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Natural Language Processing

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3

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322 Notation

323 As a general rule, words, word counts, and other types of observations are indicated with
324 Roman letters (a, b, c); parameters are indicated with Greek letters (α, β, θ). Vectors are
325 indicated with bold script for both random variables \mathbf{x} and parameters $\boldsymbol{\theta}$. Other useful
326 notations are indicated in the table below.

Basics

$\exp x$	the base-2 exponent, 2^x
$\log x$	the base-2 logarithm, $\log_2 x$
$\{x_n\}_{n=1}^N$	the set $\{x_1, x_2, \dots, x_N\}$
x_i^j	x_i raised to the power j
$x_i^{(j)}$	indexing by both i and j

Linear algebra

$\mathbf{x}^{(i)}$	a column vector of feature counts for instance i , often word counts
$\mathbf{x}_{j:k}$	elements j through k (inclusive) of a vector \mathbf{x}
$[\mathbf{x}; \mathbf{y}]$	vertical concatenation of two column vectors
$[\mathbf{x}, \mathbf{y}]$	horizontal concatenation of two column vectors
\mathbf{e}_n	a “one-hot” vector with a value of 1 at position n , and zero everywhere else
$\boldsymbol{\theta}^\top$	the transpose of a column vector $\boldsymbol{\theta}$
$\boldsymbol{\theta} \cdot \mathbf{x}^{(i)}$	the dot product $\sum_{j=1}^N \theta_j \times x_j^{(i)}$
\mathbf{X}	a matrix
$x_{i,j}$	row i , column j of matrix \mathbf{X}
$\text{Diag}(\mathbf{x})$	a matrix with \mathbf{x} on the diagonal, e.g., $\begin{pmatrix} x_1 & 0 & 0 \\ 0 & x_2 & 0 \\ 0 & 0 & x_3 \end{pmatrix}$
\mathbf{X}^{-1}	the inverse of matrix \mathbf{X}

Text datasets

w_m	word token at position m
N	number of training instances
M	length of a sequence (of words or tags)
V	number of words in vocabulary
$y^{(i)}$	the true label for instance i
\hat{y}	a predicted label
\mathcal{Y}	the set of all possible labels
K	number of possible labels $K = \mathcal{Y} $
\square	the start token
\blacksquare	the stop token
$\mathbf{y}^{(i)}$	a structured label for instance i , such as a tag sequence
$\mathcal{Y}(\mathbf{w})$	the set of possible labelings for the word sequence \mathbf{w}
\diamond	the start tag
\blacklozenge	the stop tag

Probabilities

$\Pr(A)$	probability of event A
$\Pr(A B)$	probability of event A , conditioned on event B
$p_B(b)$	the marginal probability of random variable B taking value b ; written $p(b)$ when the choice of random variable is clear from context
$p_{B A}(b a)$	the probability of random variable B taking value b , conditioned on A taking value a ; written $p(b a)$ when clear from context
$A \sim p$	the random variable A is distributed according to distribution p . For example, $X \sim \mathcal{N}(0, 1)$ states that the random variable X is drawn from a normal distribution with zero mean and unit variance.
$A B \sim p$	conditioned on the random variable B , A is distributed according to p . ¹

Machine learning

$\Psi(\mathbf{x}^{(i)}, y)$	the score for assigning label y to instance i
$\mathbf{f}(\mathbf{x}^{(i)}, y)$	the feature vector for instance i with label y
θ	a (column) vector of weights
$\ell^{(i)}$	loss on an individual instance i
L	objective function for an entire dataset
\mathcal{L}	log-likelihood of a dataset
λ	the amount of regularization

327 **Chapter 1**

328 **Introduction**

329 Natural language processing is the set of methods for making human language accessible
330 to computers. In the past decade, natural language processing has become embedded
331 in our daily lives: automatic machine translation is ubiquitous on the web and in social
332 media; text classification keeps emails from collapsing under a deluge of spam; search
333 engines have moved beyond string matching and network analysis to a high degree of
334 linguistic sophistication; dialog systems provide an increasingly common and effective
335 way to get and share information.

336 These diverse applications are based on a common set of ideas, drawing on algo-
337 rithms, linguistics, logic, statistics, and more. The goal of this text is to provide a survey
338 of these foundations. The technical fun starts in the next chapter; the rest of this current
339 chapter situates natural language processing with respect to other intellectual disciplines,
340 identifies some high-level themes in contemporary natural language processing, and ad-
341 vises the reader on how best to approach the subject.

342 **1.1 Natural language processing and its neighbors**

343 One of the great pleasures of working in this field is the opportunity to draw on many
344 other intellectual traditions, from formal linguistics to statistical physics. This section
345 briefly situates natural language processing with respect to some of its closest neighbors.

346 **Computational Linguistics** Most of the meetings and journals that host natural lan-
347 guage processing research bear the name “computational linguistics”, and the terms may
348 be thought of as essentially synonymous. But while there is substantial overlap, there is
349 an important difference in focus. In linguistics, language is the object of study. Compu-
350 tational methods may be brought to bear, just as in scientific disciplines like computational
351 biology and computational astronomy, but they play only a supporting role. In contrast,

352 natural language processing is focused on the design and analysis of computational al-
 353 gorithms and representations for processing natural human language. The goal of natu-
 354 ral language processing is to provide new computational capabilities around human lan-
 355 guage: for example, extracting information from texts, translating between languages, an-
 356 swering questions, holding a conversation, taking instructions, and so on. Fundamental
 357 linguistic insights may be crucial for accomplishing these tasks, but success is ultimately
 358 measured by whether and how well the job gets done.

359 **Machine Learning** Contemporary approaches to natural language processing rely heav-
 360 ily on machine learning, which makes it possible to build complex computer programs
 361 from examples. Machine learning provides an array of general techniques for tasks like
 362 converting a sequence of discrete tokens in one vocabulary to a sequence of discrete to-
 363 kens in another vocabulary — a generalization of what normal people might call “transla-
 364 tion.” Much of today’s natural language processing research can be thought of as applied
 365 machine learning. However, natural language processing has characteristics that distin-
 366 guish it from many of machine learning’s other application domains.

- 367 • Unlike images or audio, text data is fundamentally discrete, with meaning created
 368 by combinatorial arrangements of symbolic units. This is particularly consequential
 369 for applications in which text is the output, such as translation and summarization,
 370 because it is not possible to gradually approach an optimal solution.
- 371 • Although the set of words is discrete, new words are always being created. Further-
 372 more, the distribution over words (and other linguistic elements) resembles that of a
 373 **power law** (Zipf, 1949): there will be a few words that are very frequent, and a long
 374 tail of words that are rare. A consequence is that natural language processing algo-
 375 rithms must be especially robust to observations that do not occur in the training
 376 data.
- 377 • Language is **recursive**: units such as words can combine to create phrases, which
 378 can combine by the very same principles to create larger phrases. For example, a
 379 **noun phrase** can be created by combining a smaller noun phrase with a **preposi-**
 380 **tional phrase**, as in *the whiteness of the whale*. The prepositional phrase is created by
 381 combining a preposition (in this case, *of*) with another noun phrase (*the whale*). In
 382 this way, it is possible to create arbitrarily long phrases, such as,

383 (1.1) ...huge globular pieces of the whale of the bigness of a human head.¹

384 The meaning of such a phrase must be analyzed in accord with the underlying hier-
 385 archical structure. In this case, *huge globular pieces of the whale* acts as a single noun
 386 phrase, which is conjoined with the prepositional phrase of *the bigness of a human*

¹Throughout the text, this notation will be used to introduce linguistic examples.

387 *head*. The interpretation would be different if instead, *huge globular pieces* were con-
 388 joined with the prepositional phrase *of the whale of the bigness of a human head* —
 389 implying a disappointingly small whale. Even though text appears as a sequence,
 390 machine learning methods must account for its implicit recursive structure.

391 **Artificial Intelligence** The goal of artificial intelligence is to build software and robots
 392 with the same range of abilities as humans (Russell and Norvig, 2009). Natural language
 393 processing is relevant to this goal in several ways. The capacity for language is one of the
 394 central features of human intelligence, and no artificial intelligence program could be said
 395 to be complete without the ability to communicate in words.²

396 Much of artificial intelligence research is dedicated to the development of systems
 397 that can reason from premises to a conclusion, but such algorithms are only as good as
 398 what they know (Dreyfus, 1992). Natural language processing is a potential solution to
 399 the “knowledge bottleneck”, by acquiring knowledge from natural language texts, and
 400 perhaps also from conversations; This idea goes all the way back to Turing’s 1949 pa-
 401 per *Computing Machinery and Intelligence*, which proposed the **Turing test** and helped to
 402 launch the field of artificial intelligence (Turing, 2009).

403 Conversely, reasoning is sometimes essential for basic tasks of language processing,
 404 such as determining who a pronoun refers to. **Winograd schemas** are examples in which
 405 a single word changes the likely referent of a pronoun, in a way that seems to require
 406 knowledge and reasoning to decode (Levesque et al., 2011). For example,

407 (1.2) The trophy doesn’t fit into the brown suitcase because **it** is too [small/large].
 408 When the final word is *small*, then the pronoun *it* refers to the suitcase; when the final
 409 word is *large*, then *it* refers to the trophy. Solving this example requires spatial reasoning;
 410 other schemas require reasoning about actions and their effects, emotions and intentions,
 411 and social conventions.

412 The Winograd schemas demonstrate that natural language understanding cannot be
 413 achieved in isolation from knowledge and reasoning. Yet the history of artificial intelli-
 414 gence has been one of increasing specialization: with the growing volume of research in
 415 subdisciplines such as natural language processing, machine learning, and computer vi-

²This view seems to be shared by some, but not all, prominent researchers in artificial intelligence. Michael Jordan, a specialist in machine learning, has said that if he had a billion dollars to spend on any large research project, he would spend it on natural language processing (https://www.reddit.com/r/MachineLearning/comments/2fxi6v/ama_michael_i_jordan/). On the other hand, in a public discussion about the future of artificial intelligence in February 2018, computer vision researcher Yann LeCun argued that language was perhaps the “50th most important” thing to work on, and that it would be a great achievement if AI could attain the capabilities of an orangutan, which presumably do not include language (<http://www.abigailsee.com/2018/02/21/deep-learning-structure-and-innate-priors.html>).

416 sion, it is difficult for anyone to maintain expertise across the entire field. Still, recent work
417 has demonstrated interesting connections between natural language processing and other
418 areas of AI, including computer vision (e.g., Antol et al., 2015) and game playing (e.g.,
419 Branavan et al., 2009). The dominance of machine learning throughout artificial intel-
420 ligence has led to a broad consensus on representations such as graphical models and
421 knowledge graphs, and on algorithms such as backpropagation and combinatorial opti-
422 mization. Many of the algorithms and representations covered in this text are part of this
423 consensus.

424 **Computer Science** The discrete and recursive nature of natural language invites the ap-
425 plication of theoretical ideas from computer science. Linguists such as Chomsky and
426 Montague have shown how formal language theory can help to explain the syntax and
427 semantics of natural language. Theoretical models such as finite-state and pushdown au-
428 tomata are the basis for many practical natural language processing systems. Algorithms
429 for searching the combinatorial space of analyses of natural language utterances can be
430 analyzed in terms of their computational complexity, and theoretically motivated approx-
431 imations can sometimes be applied.

432 The study of computer systems is also relevant to natural language processing. Pro-
433 cessing large datasets of unlabeled text is a natural application for parallelization tech-
434 niques like MapReduce (Dean and Ghemawat, 2008; Lin and Dyer, 2010); handling high-
435 volume streaming data sources such as social media is a natural application for approx-
436 imate streaming and sketching techniques (Goyal et al., 2009). When deep neural net-
437 works are implemented in production systems, it is possible to eke out speed gains using
438 techniques such as reduced-precision arithmetic (Wu et al., 2016). Many classical natu-
439 ral language processing algorithms are not naturally suited to graphics processing unit
440 (GPU) parallelization, suggesting directions for further research at the intersection of nat-
441 ural language processing and computing hardware (Yi et al., 2011).

442 **Speech Processing** Natural language is often communicated in spoken form, and speech
443 recognition is the task of converting an audio signal to text. From one perspective, this is
444 a signal processing problem, which might be viewed as a preprocessing step before nat-
445 ural language processing can be applied. However, context plays a critical role in speech
446 recognition by human listeners: knowledge of the surrounding words influences percep-
447 tion and helps to correct for noise (Miller et al., 1951). For this reason, speech recognition
448 is often integrated with text analysis, particularly with statistical **language model**, which
449 quantify the probability of a sequence of text (see chapter 6). Beyond speech recognition,
450 the broader field of speech processing includes the study of speech-based dialogue sys-
451 tems, which are briefly discussed in chapter 19. Historically, speech processing has often
452 been pursued in electrical engineering departments, while natural language processing

453 has been the purview of computer scientists. For this reason, the extent of interaction
454 between these two disciplines is less than it might otherwise be.

455 **Others** Natural language processing plays a significant role in emerging interdisciplinary
456 fields like **computational social science** and the **digital humanities**. Text classification
457 (chapter 4), clustering (chapter 5), and information extraction (chapter 17) are particularly
458 useful tools; another is probabilistic **topic models** (Blei, 2012), which are not covered in
459 this text. **Information retrieval** (Manning et al., 2008) makes use of similar tools, and
460 conversely, techniques such as latent semantic analysis (§ 14.3) have roots in information
461 retrieval. **Text mining** is sometimes used to refer to the application of data mining tech-
462 niques, especially classification and clustering, to text. While there is no clear distinction
463 between text mining and natural language processing (nor between data mining and ma-
464 chine learning), text mining is typically less concerned with linguistic structure, and more
465 interested in fast, scalable algorithms.

466 1.2 Three themes in natural language processing

467 Natural language processing covers a diverse range of tasks, methods, and linguistic phe-
468 nomena. But despite the apparent incommensurability between, say, the summarization
469 of scientific articles (§ 16.3.4.1) and the identification of suffix patterns in Spanish verbs
470 (§ 9.1.4.3), some general themes emerge. Each of these themes can be expressed as an
471 opposition between two extreme viewpoints on how to process natural language, and in
472 each case, existing approaches can be placed on a continuum between these two extremes.

473 1.2.1 Learning and knowledge

474 A recurring topic of debate is the relative importance of machine learning and linguistic
475 knowledge. On one extreme, advocates of “natural language processing from scratch” (Col-
476 lobert et al., 2011) propose to use machine learning to train end-to-end systems that trans-
477 mute raw text into any desired output structure: e.g., a summary, database, or transla-
478 tion. On the other extreme, the core work of natural language processing is sometimes
479 taken to be transforming text into a stack of general-purpose linguistic structures: from
480 subword units called **morphemes**, to word-level **parts-of-speech**, to tree-structured repre-
481 sentations of grammar, and beyond, to logic-based representations of meaning. In theory,
482 these general-purpose structures should then be able to support any desired application.

483 The end-to-end learning approach has been buoyed by recent results in computer vi-
484 sion and speech recognition, in which advances in machine learning have swept away
485 expert-engineered representations based on the fundamentals of optics and phonology (Krizhevsky
486 et al., 2012; Graves and Jaitly, 2014). But while some amount of machine learning is an el-
487 ement of nearly every contemporary approach to natural language processing, linguistic

488 representations such as syntax trees have not yet gone the way of the visual edge detector
 489 or the auditory triphone. Linguists have argued for the existence of a “language faculty”
 490 in all human beings, which encodes a set of abstractions specially designed to facilitate
 491 the understanding and production of language. The argument for the existence of such
 492 a language faculty is based on the observation that children learn language faster and
 493 from fewer examples than would be reasonably possible, if language was learned from
 494 experience alone.³ Regardless of the cognitive validity of these arguments, it seems that
 495 linguistic structures are particularly important in scenarios where training data is limited.

496 Moving away from the extreme ends of the continuum, there are a number of ways in
 497 which knowledge and learning can be combined in natural language processing. Many
 498 supervised learning systems make use of carefully engineered **features**, which transform
 499 the data into a representation that can facilitate learning. For example, in a task like doc-
 500 ument classification, it may be useful to identify each word’s **stem**, so that a learning
 501 system can more easily generalize across related terms such as *whale*, *whales*, *whalers*, and
 502 *whaling*. This is particularly important in the many languages that exceed English in the
 503 complexity of the system of affixes that can attach to words. Such features could be ob-
 504 tained from a hand-crafted resource, like a dictionary that maps each word to a single
 505 root form. Alternatively, features can be obtained from the output of a general-purpose
 506 language processing system, such as a parser or part-of-speech tagger, which may itself
 507 be built on supervised machine learning.

508 Another synthesis of learning and knowledge is in model structure: building machine
 509 learning models whose architectures are inspired by linguistic theories. For example, the
 510 organization of sentences is often described as **compositional**, with meaning of larger
 511 units gradually constructed from the meaning of their smaller constituents. This idea
 512 can be built into the architecture of a deep neural network, which is then trained using
 513 contemporary deep learning techniques (Dyer et al., 2016).

514 The debate about the relative importance of machine learning and linguistic knowl-
 515 edge sometimes becomes heated. No machine learning specialist likes to be told that their
 516 engineering methodology is unscientific alchemy;⁴ nor does a linguist want to hear that
 517 the search for general linguistic principles and structures has been made irrelevant by big
 518 data. Yet there is clearly room for both types of research: we need to know how far we
 519 can go with end-to-end learning alone, while at the same time, we continue the search for
 520 linguistic representations that generalize across applications, scenarios, and languages.
 521 For more on the history of this debate, see Church (2011); for an optimistic view of the
 522 potential symbiosis between computational linguistics and deep learning, see Manning

³The *Language Instinct* (Pinker, 2003) articulates these arguments in an engaging and popular style. For arguments against the innateness of language, see Elman et al. (1998).

⁴Ali Rahimi argued that much of deep learning research was similar to “alchemy” in a presentation at the 2017 conference on Neural Information Processing Systems. He was advocating for more learning theory, not more linguistics.

523 (2015).

524 **1.2.2 Search and learning**

525 Many natural language processing problems can be written mathematically in the form
 526 of optimization,⁵

$$\hat{\mathbf{y}} = \operatorname{argmax}_{\mathbf{y} \in \mathcal{Y}(\mathbf{x})} \Psi(\mathbf{x}, \mathbf{y}; \boldsymbol{\theta}), \quad [1.1]$$

527 where,

- 528 • \mathbf{x} is the input, which is an element of a set \mathcal{X} ;
- 529 • \mathbf{y} is the output, which is an element of a set $\mathcal{Y}(\mathbf{x})$;
- 530 • Ψ is a scoring function (also called the **model**), which maps from the set $\mathcal{X} \times \mathcal{Y}$ to
 531 the real numbers;
- 532 • $\boldsymbol{\theta}$ is a vector of parameters for Ψ ;
- 533 • $\hat{\mathbf{y}}$ is the predicted output, which is chosen to maximize the scoring function.

534 This basic structure can be used across a huge range of problems. For example, the
 535 input \mathbf{x} might be a social media post, and the output \mathbf{y} might be a labeling of the emotional
 536 sentiment expressed by the author (chapter 4); or \mathbf{x} could be a sentence in French, and the
 537 output \mathbf{y} could be a sentence in Tamil (chapter 18); or \mathbf{x} might be a sentence in English,
 538 and \mathbf{y} might be a representation of the syntactic structure of the sentence (chapter 10); or
 539 \mathbf{x} might be a news article and \mathbf{y} might be a structured record of the events that the article
 540 describes (chapter 17).

541 By adopting this formulation, we make an implicit decision that language processing
 542 algorithms will have two distinct modules:

543 **Search.** The search module is responsible for computing the argmax of the function Ψ . In
 544 other words, it finds the output $\hat{\mathbf{y}}$ that gets the best score with respect to the input
 545 \mathbf{x} . This is easy when the search space $\mathcal{Y}(\mathbf{x})$ is small enough to enumerate, or when
 546 the scoring function Ψ has a convenient decomposition into parts. In many cases,
 547 we will want to work with scoring functions that do not have these properties, moti-
 548 vating the use of more sophisticated search algorithms. Because the outputs are
 549 usually discrete in language processing problems, search often relies on the machin-
 550 ery of **combinatorial optimization**.

⁵Throughout this text, equations will be numbered by square brackets, and linguistic examples will be numbered by parentheses.

551 **Learning.** The learning module is responsible for finding the parameters θ . This is typ-
 552 ically (but not always) done by processing a large dataset of labeled examples,
 553 $\{(\mathbf{x}^{(i)}, \mathbf{y}^{(i)})\}_{i=1}^N$. Like search, learning is also approached through the framework
 554 of optimization, as we will see in chapter 2. Because the parameters are usually
 555 continuous, learning algorithms generally rely on **numerical optimization**, search-
 556 ing over vectors of real numbers for parameters that optimize some function of the
 557 model and the labeled data. Some basic principles of numerical optimization are
 558 reviewed in Appendix B.

559 The division of natural language processing into separate modules for search and
 560 learning makes it possible to reuse generic algorithms across a range of different tasks
 561 and models. This means that the work of natural language processing can be focused on
 562 the design of the model Ψ , while reaping the benefits of decades of progress in search,
 563 optimization, and learning. Much of this textbook will focus on specific classes of scoring
 564 functions, and on the algorithms that make it possible to search and learn efficiently with
 565 them.

566 When a model is capable of making subtle linguistic distinctions, it is said to be *expres-*
 567 *sive*. Expressiveness is often traded off against the efficiency of search and learning. For
 568 example, a word-to-word translation model makes search and learning easy, but it is not
 569 expressive enough to distinguish good translations from bad ones. Unfortunately many
 570 of the most important problems in natural language processing seem to require expres-
 571 sive models, in which the complexity of search grows exponentially with the size of the
 572 input. In these models, exact search is usually impossible. Intractability threatens the neat
 573 modular decomposition between search and learning: if search requires a set of heuristic
 574 approximations, then it may be advantageous to learn a model that performs well under
 575 these specific heuristics. This has motivated some researchers to take a more integrated
 576 approach to search and learning, as briefly mentioned in chapters 11 and 15.

577 1.2.3 Relational, compositional, and distributional perspectives

578 Any element of language — a word, a phrase, a sentence, or even a sound — can be
 579 described from at least three perspectives. Consider the word *journalist*. A *journalist* is a
 580 subcategory of a *profession*, and an *anchorwoman* is a subcategory of *journalist*; furthermore,
 581 a *journalist* performs *journalism*, which is often, but not always, a subcategory of *writing*.
 582 This relational perspective on meaning is the basis for semantic **ontologies** such as **Word-**
 583 **Net** (Fellbaum, 2010), which enumerate the relations that hold between words and other
 584 elementary semantic units. The power of the relational perspective is illustrated by the
 585 following example:

586 (1.3) Umashanthi interviewed Ana. She works for the college newspaper.

587 Who works for the college newspaper? The word *journalist*, while not stated in the ex-
588 ample, implicitly links the *interview* to the *newspaper*, making *Umashanthi* the most likely
589 referent for the pronoun. (A general discussion of how to resolve pronouns is found in
590 chapter 15.)

591 Yet despite the inferential power of the relational perspective, it is not easy to formalize
592 computationally. Exactly which elements are to be related? Are *journalists* and *reporters*
593 distinct, or should we group them into a single unit? Is the kind of *interview* performed by
594 a journalist the same as the kind that one undergoes when applying for a job? Ontology
595 designers face many such thorny questions, and the project of ontology design hearkens
596 back to Borges' (1993) *Celestial Emporium of Benevolent Knowledge*, which divides animals
597 into:

598 (a) belonging to the emperor; (b) embalmed; (c) tame; (d) suckling pigs; (e)
599 sirens; (f) fabulous; (g) stray dogs; (h) included in the present classification;
600 (i) frenzied; (j) innumerable; (k) drawn with a very fine camelhair brush; (l) et
601 cetera; (m) having just broken the water pitcher; (n) that from a long way off
602 resemble flies.

603 Difficulties in ontology construction have led some linguists to argue that there is no task-
604 independent way to partition up word meanings (Kilgarriff, 1997).

605 Some problems are easier. Each member in a group of *journalists* is a *journalist*: the -s
606 suffix distinguishes the plural meaning from the singular in most of the nouns in English.
607 Similarly, a *journalist* can be thought of, perhaps colloquially, as someone who produces or
608 works on a *journal*. (Taking this approach even further, the word *journal* derives from the
609 French *jour+nal*, or *day+ly* = *daily*.) In this way, the meaning of a word is constructed from
610 the constituent parts — the principle of **compositionality**. This principle can be applied
611 to larger units: phrases, sentences, and beyond. Indeed, one of the great strengths of the
612 compositional view of meaning is that it provides a roadmap for understanding entire
613 texts and dialogues through a single analytic lens, grounding out in the smallest parts of
614 individual words.

615 But alongside *journalists* and *anti-parliamentarians*, there are many words that seem to
616 be linguistic atoms: think, for example, of *whale*, *blubber*, and *Nantucket*. Furthermore,
617 idiomatic phrases like *kick the bucket* and *shoot the breeze* have meanings that are quite
618 different from the sum of their parts (Sag et al., 2002). Composition is of little help for such
619 words and expressions, but their meanings can be ascertained — or at least approximated
620 — from the contexts in which they appear. Take, for example, *blubber*, which appears in
621 such contexts as:

- 622 (1.4) The blubber served them as fuel.
623 (1.5) ... extracting it from the blubber of the large fish ...

624 (1.6) Amongst oily substances, blubber has been employed as a manure.

625 These contexts form the **distributional properties** of the word *blubber*, and they link it to
 626 words which can appear in similar constructions: *fat*, *pelts*, and *barnacles*. This distribu-
 627 tional perspective makes it possible to learn about meaning from unlabeled data alone;
 628 unlike relational and compositional semantics, no manual annotation or expert knowl-
 629 edge is required. Distributional semantics is thus capable of covering a huge range of
 630 linguistic phenomena. However, it lacks precision: *blubber* is similar to *fat* in one sense, to
 631 *pelts* in another sense, and to *barnacles* in still another. The question of *why* all these words
 632 tend to appear in the same contexts is left unanswered.

633 The relational, compositional, and distributional perspectives all contribute to our un-
 634 derstanding of linguistic meaning, and all three appear to be critical to natural language
 635 processing. Yet they are uneasy collaborators, requiring seemingly incompatible repre-
 636 sentations and algorithmic approaches. This text presents some of the best known and
 637 most successful methods for working with each of these representations, but it is hoped
 638 that future research will reveal new ways to combine them.

639 1.3 Learning to do natural language processing

640 This text began with the notes that I use for teaching Georgia Tech’s undergraduate and
 641 graduate courses on natural language processing, CS 4650 and 7650. There are several
 642 other good resources (e.g., Manning and Schütze, 1999; Jurafsky and Martin, 2009; Smith,
 643 2011; Collins, 2013), but the goal of this text is focus on a core subset of the field, uni-
 644 fied by the concepts of learning and search. A remarkable thing about natural language
 645 processing is that so many problems can be solved by a compact set of methods:

646 **Search.** Viterbi, CKY, minimum spanning tree, shift-reduce, integer linear programming,
 647 beam search.

648 **Learning.** Naïve Bayes, logistic regression, perceptron, expectation-maximization, matrix
 649 factorization, backpropagation, recurrent neural networks.

650 This text explains how these methods work, and how they can be applied to problems
 651 that arise in the computer processing of natural language: document classification, word
 652 sense disambiguation, sequence labeling (part-of-speech tagging and named entity recog-
 653 nition), parsing, coreference resolution, relation extraction, discourse analysis, language
 654 modeling, and machine translation.

655 1.3.1 Background

656 Because natural language processing draws on many different intellectual traditions, al-
 657 most everyone who approaches it feels underprepared in one way or another. Here is a

658 summary of what is expected, and where you can learn more:

659 **Mathematics and machine learning.** The text assumes a background in multivariate cal-
660 culus and linear algebra: vectors, matrices, derivatives, and partial derivatives. You
661 should also be familiar with probability and statistics. A review of basic proba-
662 bility is found in Appendix A, and a minimal review of numerical optimization is
663 found in Appendix B. For linear algebra, the online course and textbook from Strang
664 (2016) are excellent sources of review material. Deisenroth et al. (2018) are currently
665 preparing a textbook on *Mathematics for Machine Learning*, and several chapters can
666 be found online.⁶ For an introduction to probabilistic modeling and estimation, see
667 James et al. (2013); for a more advanced and comprehensive discussion of the same
668 material, the classic reference is Hastie et al. (2009).

669 **Linguistics.** This book assumes no formal training in linguistics, aside from elementary
670 concepts like nouns and verbs, which you have probably encountered in the study
671 of English grammar. Ideas from linguistics are introduced throughout the text as
672 needed, including discussions of morphology and syntax (chapter 9), semantics
673 (chapters 12 and 13), and discourse (chapter 16). Linguistic issues also arise in the
674 application-focused chapters 4, 8, and 18. A short guide to linguistics for students
675 of natural language processing is offered by Bender (2013); you are encouraged to
676 start there, and then pick up a more comprehensive introductory textbook (e.g., Ak-
677 majian et al., 2010; Fromkin et al., 2013).

678 **Computer science.** The book is targeted at computer scientists, who are assumed to have
679 taken introductory courses on the analysis of algorithms and complexity theory. In
680 particular, you should be familiar with asymptotic analysis of the time and memory
681 costs of algorithms, and should have seen dynamic programming. The classic text
682 on algorithms is offered by Cormen et al. (2009); for an introduction to the theory of
683 computation, see Arora and Barak (2009) and Sipser (2012).

684 1.3.2 How to use this book

685 The textbook is organized into four main units:

686 **Learning.** This section builds up a set of machine learning tools that will be used through-
687 out the rest of the textbook. Because the focus is on machine learning, the text
688 representations and linguistic phenomena are mostly simple: “bag-of-words” text
689 classification is treated as a model example. Chapter 4 describes some of the more
690 linguistically interesting applications of word-based text analysis.

⁶<https://mml-book.github.io/>

691 **Sequences and trees.** This section introduces the treatment of language as a structured
 692 phenomena. It describes sequence and tree representations and the algorithms that
 693 they facilitate, as well as the limitations that these representations impose. Chapter
 694 9 introduces finite state automata and briefly overviews a context-free account of
 695 English syntax.

696 **Meaning.** This section takes a broad view of efforts to represent and compute meaning
 697 from text, ranging from formal logic to neural word embeddings. It also includes
 698 two topics that are closely related to semantics: resolution of ambiguous references,
 699 and analysis of multi-sentence discourse structure.

700 **Applications.** The final section offers chapter-length treatments on three of the most prominent
 701 applications of natural language processing: information extraction, machine
 702 translation, and text generation. Each of these applications merits a textbook length
 703 treatment of its own (Koehn, 2009; Grishman, 2012; Reiter and Dale, 2000); the chapters
 704 here explain some of the most well known systems using the formalisms and
 705 methods built up earlier in the book, while introducing methods such as neural attention.
 706

707 Each chapter contains some advanced material, which is marked with an asterisk.
 708 This material can be safely omitted without causing misunderstandings later on. But
 709 even without these advanced sections, the text is too long for a single semester course, so
 710 instructors will have to pick and choose among the chapters.

711 Chapters 2 and 3 provide building blocks that will be used throughout the book, and
 712 chapter 4 describes some critical aspects of the practice of language technology. Lan-
 713 guage models (chapter 6), sequence labeling (chapter 7), and parsing (chapter 10 and 11)
 714 are canonical topics in natural language processing, and distributed word embeddings
 715 (chapter 14) are so ubiquitous that students will complain if you leave them out. Of the
 716 applications, machine translation (chapter 18) is the best choice: it is more cohesive than
 717 information extraction, and more mature than text generation. In my experience, nearly
 718 all students benefit from the review of probability in Appendix A.

- 719 • A course focusing on machine learning should add the chapter on unsupervised
 720 learning (chapter 5). The chapters on predicate-argument semantics (chapter 13),
 721 reference resolution (chapter 15), and text generation (chapter 19) are particularly
 722 influenced by recent machine learning innovations, including deep neural networks
 723 and learning to search.
- 724 • A course with a more linguistic orientation should add the chapters on applica-
 725 tions of sequence labeling (chapter 8), formal language theory (chapter 9), semantics
 726 (chapter 12 and 13), and discourse (chapter 16).

- 727 • For a course with a more applied focus — for example, a course targeting under-
728 graduates — I recommend the chapters on applications of sequence labeling (chap-
729 ter 8), predicate-argument semantics (chapter 13), information extraction (chapter 17),
730 and text generation (chapter 19).

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744

Part I

745

Learning

746

Chapter 2

747

Linear text classification

748 We'll start with the problem of **text classification**: given a text document, assign it a dis-
749 crete label $y \in \mathcal{Y}$, where \mathcal{Y} is the set of possible labels. This problem has many appli-
750 cations, from spam filtering to analysis of electronic health records. Text classification is
751 also a building block that is used throughout more complex natural language processing
752 tasks.

753 To perform this task, the first question is how to represent each document. A common
754 approach is to use a vector of word counts, e.g., $\mathbf{x} = [0, 1, 1, 0, 0, 2, 0, 1, 13, 0 \dots]^T$, where
755 x_j is the count of word j . The length of \mathbf{x} is $V \triangleq |\mathcal{V}|$, where \mathcal{V} is the set of possible words
756 in the vocabulary.

757 The object \mathbf{x} is a vector, but colloquially we call it a **bag of words**, because it includes
758 only information about the count of each word, and not the order in which the words
759 appear. We have thrown out grammar, sentence boundaries, paragraphs — everything
760 but the words. Yet the bag of words model is surprisingly effective for text classification.
761 If you see the word *freeee* in an email, is it a spam email? What if you see the word
762 *Bayesian*? For many labeling problems, individual words can be strong predictors.

763 To predict a label from a bag-of-words, we can assign a score to each word in the
764 vocabulary, measuring the compatibility with the label. In the spam filtering case, we
765 might assign a positive score to the word *freeee* for the label SPAM, and a negative score
766 to the word *Bayesian*. These scores are called **weights**, and they are arranged in a column
767 vector θ .

768 Suppose that you want a multiclass classifier, where $K \triangleq |\mathcal{Y}| > 2$. For example, we
769 might want to classify news stories about sports, celebrities, music, and business. The goal
770 is to predict a label \hat{y} , given the bag of words \mathbf{x} , using the weights θ . For each label $y \in \mathcal{Y}$,
771 we compute a score $\Psi(\mathbf{x}, y)$, which is a scalar measure of the compatibility between the
772 bag-of-words \mathbf{x} and the label y . In a linear bag-of-words classifier, this score is the vector

773 inner product between the weights θ and the output of a **feature function** $f(x, y)$,

$$\Psi(x, y) = \theta \cdot f(x, y). \quad [2.1]$$

774 As the notation suggests, f is a function of two arguments, the word counts x and the
 775 label y , and it returns a vector output. For example, given arguments x and y , element j
 776 of this feature vector might be,

$$f_j(x, y) = \begin{cases} x_{freeee}, & \text{if } y = \text{SPAM} \\ 0, & \text{otherwise} \end{cases} \quad [2.2]$$

777 This function returns the count of the word *freeee* if the label is SPAM, and it returns zero
 778 otherwise. The corresponding weight θ_j then scores the compatibility of the word *freeee*
 779 with the label SPAM. A positive score means that this word makes the label more likely.

To formalize this feature function, we define $f(x, y)$ as a column vector,

$$f(x, y = 1) = [x; \underbrace{0; 0; \dots; 0}_{(K-1) \times V}] \quad [2.3]$$

$$f(x, y = 2) = [\underbrace{0; 0; \dots; 0}_V; x; \underbrace{0; 0; \dots; 0}_{(K-2) \times V}] \quad [2.4]$$

$$f(x, y = K) = [\underbrace{0; 0; \dots; 0}_{(K-1) \times V}; x], \quad [2.5]$$

780 where $\underbrace{[0; 0; \dots; 0]}_{(K-1) \times V}$ is a column vector of $(K - 1) \times V$ zeros, and the semicolon indicates
 781 vertical concatenation. This arrangement is shown in Figure 2.1; the notation may seem
 782 awkward at first, but it generalizes to an impressive range of learning settings.

Given a vector of weights, $\theta \in \mathbb{R}^{V \times K}$, we can now compute the score $\Psi(x, y)$. This
 inner product gives a scalar measure of the compatibility of the observation x with label
 y .¹ For any document x , we predict the label \hat{y} ,

$$\hat{y} = \operatorname{argmax}_{y \in \mathcal{Y}} \Psi(x, y) \quad [2.6]$$

$$\Psi(x, y) = \theta \cdot f(x, y). \quad [2.7]$$

783 This inner product notation gives a clean separation between the *data* (x and y) and the
 784 *parameters* (θ). This notation also generalizes nicely to **structured prediction**, in which

¹Only $V \times (K - 1)$ features and weights are necessary. By stipulating that $\Psi(x, y = K) = 0$ regardless of x , it is possible to implement any classification rule that can be achieved with $V \times K$ features and weights. This is the approach taken in binary classification rules like $y = \text{Sign}(\beta \cdot x + a)$, where β is a vector of weights, a is an offset, and the label set is $\mathcal{Y} = \{-1, 1\}$. However, for multiclass classification, it is more concise to write $\theta \cdot f(x, y)$ for all $y \in \mathcal{Y}$.

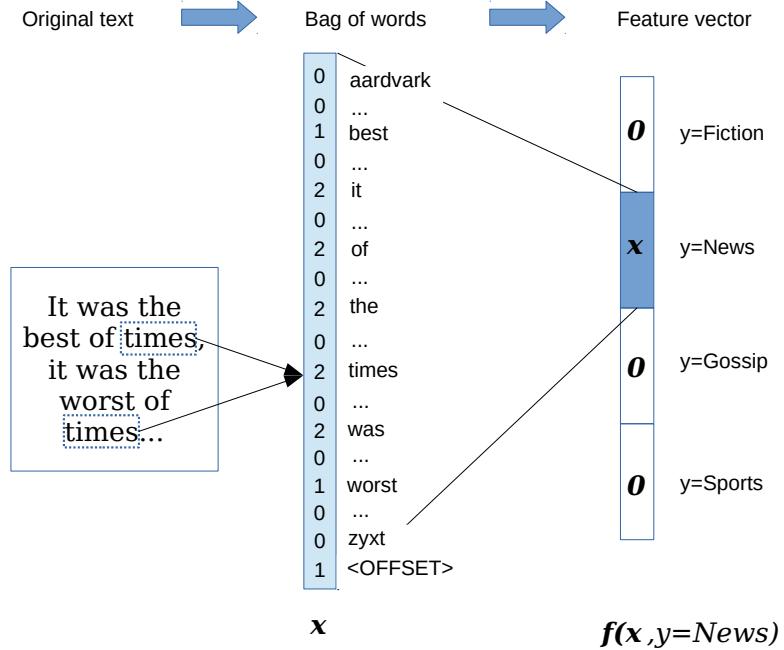


Figure 2.1: The bag-of-words and feature vector representations, for a hypothetical text classification task.

785 the space of labels \mathcal{Y} is very large, and we want to model shared substructures between
786 labels.

787 It is common to add an **offset feature** at the end of the vector of word counts x , which
788 is always 1. We then have to also add an extra zero to each of the zero vectors, to make the
789 vector lengths match. This gives the entire feature vector $f(x, y)$ a length of $(V + 1) \times K$.
790 The weight associated with this offset feature can be thought of as a bias for or against
791 each label. For example, if we expect most documents to be spam, then the weight for
792 the offset feature for $y = \text{SPAM}$ should be larger than the weight for the offset feature for
793 $y = \text{HAM}$.

Returning to the weights θ , where do they come from? One possibility is to set them by hand. If we wanted to distinguish, say, English from Spanish, we can use English and Spanish dictionaries, and set the weight to one for each word that appears in the

associated dictionary. For example,²

$$\begin{array}{ll} \theta_{(E,bicycle)} = 1 & \theta_{(S,bicycle)} = 0 \\ \theta_{(E,bicicleta)} = 0 & \theta_{(S,bicicleta)} = 1 \\ \theta_{(E,con)} = 1 & \theta_{(S,con)} = 1 \\ \theta_{(E,ordinateur)} = 0 & \theta_{(S,ordinateur)} = 0. \end{array}$$

794 Similarly, if we want to distinguish positive and negative sentiment, we could use positive
795 and negative **sentiment lexicons** (see § 4.1.2), which are defined by social psychologists
796 (Tausczik and Pennebaker, 2010).

797 But it is usually not easy to set classification weights by hand, due to the large number
798 of words and the difficulty of selecting exact numerical weights. Instead, we will learn the
799 weights from data. Email users manually label messages as SPAM; newspapers label their
800 own articles as BUSINESS or STYLE. Using such **instance labels**, we can automatically
801 acquire weights using **supervised machine learning**. This chapter will discuss several
802 machine learning approaches for classification. The first is based on probability. For a
803 review of probability, consult Appendix A.

804 2.1 Naïve Bayes

805 The **joint probability** of a bag of words \mathbf{x} and its true label y is written $p(\mathbf{x}, y)$. Suppose
806 we have a dataset of N labeled instances, $\{(\mathbf{x}^{(i)}, y^{(i)})\}_{i=1}^N$, which we assume are **independ-**
807 **ent and identically distributed (IID)** (see § A.3). Then the joint probability of the entire
808 dataset, written $p(\mathbf{x}^{(1:N)}, y^{(1:N)})$, is equal to $\prod_{i=1}^N p_{X,Y}(\mathbf{x}^{(i)}, y^{(i)})$.³

What does this have to do with classification? One approach to classification is to set the weights $\boldsymbol{\theta}$ so as to maximize the joint probability of a **training set** of labeled documents. This is known as **maximum likelihood estimation**:

$$\hat{\boldsymbol{\theta}} = \operatorname{argmax}_{\boldsymbol{\theta}} p(\mathbf{x}^{(1:N)}, y^{(1:N)}; \boldsymbol{\theta}) \quad [2.8]$$

$$= \operatorname{argmax}_{\boldsymbol{\theta}} \prod_{i=1}^N p(\mathbf{x}^{(i)}, y^{(i)}; \boldsymbol{\theta}) \quad [2.9]$$

$$= \operatorname{argmax}_{\boldsymbol{\theta}} \sum_{i=1}^N \log p(\mathbf{x}^{(i)}, y^{(i)}; \boldsymbol{\theta}). \quad [2.10]$$

²In this notation, each tuple (language, word) indexes an element in $\boldsymbol{\theta}$, which remains a vector.

³The notation $p_{X,Y}(\mathbf{x}^{(i)}, y^{(i)})$ indicates the joint probability that random variables X and Y take the specific values $\mathbf{x}^{(i)}$ and $y^{(i)}$ respectively. The subscript will often be omitted when it is clear from context. For a review of random variables, see Appendix A.

Algorithm 1 Generative process for the Naïve Bayes classifier

for Document $i \in \{1, 2, \dots, N\}$ **do**:

Draw the label $y^{(i)} \sim \text{Categorical}(\boldsymbol{\mu})$;

Draw the word counts $\mathbf{x}^{(i)} | y^{(i)} \sim \text{Multinomial}(\boldsymbol{\phi}_{y^{(i)}})$.

809 The notation $p(\mathbf{x}^{(i)}, y^{(i)}; \boldsymbol{\theta})$ indicates that $\boldsymbol{\theta}$ is a *parameter* of the probability function. The
 810 product of probabilities can be replaced by a sum of log-probabilities because the log func-
 811 tion is monotonically increasing over positive arguments, and so the same $\boldsymbol{\theta}$ will maxi-
 812 mize both the probability and its logarithm. Working with logarithms is desirable because
 813 of numerical stability: on a large dataset, multiplying many probabilities can **underflow**
 814 to zero.⁴

815 The probability $p(\mathbf{x}^{(i)}, y^{(i)}; \boldsymbol{\theta})$ is defined through a **generative model** — an idealized
 816 random process that has generated the observed data.⁵ Algorithm 1 describes the gener-
 817 ative model describes the **Naïve Bayes** classifier, with parameters $\boldsymbol{\theta} = \{\boldsymbol{\mu}, \boldsymbol{\phi}\}$.

- 818 • The first line of this generative model encodes the assumption that the instances are
 819 mutually independent: neither the label nor the text of document i affects the label
 820 or text of document j .⁶ Furthermore, the instances are identically distributed: the
 821 distributions over the label $y^{(i)}$ and the text $\mathbf{x}^{(i)}$ (conditioned on $y^{(i)}$) are the same
 822 for all instances i .
- 823 • The second line of the generative model states that the random variable $y^{(i)}$ is drawn
 824 from a categorical distribution with parameter $\boldsymbol{\mu}$. Categorical distributions are like
 825 weighted dice: the vector $\boldsymbol{\mu} = [\mu_1, \mu_2, \dots, \mu_K]^\top$ gives the probabilities of each la-
 826 bel, so that the probability of drawing label y is equal to μ_y . For example, if $\mathcal{Y} =$
 827 $\{\text{POSITIVE}, \text{NEGATIVE}, \text{NEUTRAL}\}$, we might have $\boldsymbol{\mu} = [0.1, 0.7, 0.2]^\top$. We require
 828 $\sum_{y \in \mathcal{Y}} \mu_y = 1$ and $\mu_y \geq 0, \forall y \in \mathcal{Y}$.⁷
- 829 • The third line describes how the bag-of-words counts $\mathbf{x}^{(i)}$ are generated. By writing
 830 $\mathbf{x}^{(i)} | y^{(i)}$, this line indicates that the word counts are conditioned on the label, so

⁴Throughout this text, you may assume all logarithms and exponents are base 2, unless otherwise indicated. Any reasonable base will yield an identical classifier, and base 2 is most convenient for working out examples by hand.

⁵Generative models will be used throughout this text. They explicitly define the assumptions underlying the form of a probability distribution over observed and latent variables. For a readable introduction to generative models in statistics, see Blei (2014).

⁶Can you think of any cases in which this assumption is too strong?

⁷Formally, we require $\boldsymbol{\mu} \in \Delta^{K-1}$, where Δ^{K-1} is the $K - 1$ **probability simplex**, the set of all vectors of K nonnegative numbers that sum to one. Because of the sum-to-one constraint, there are $K - 1$ degrees of freedom for a vector of size K .

831 that the joint probability is factored using the chain rule,

$$p_{X,Y}(x^{(i)}, y^{(i)}) = p_{X|Y}(x^{(i)} | y^{(i)}) \times p_Y(y^{(i)}). \quad [2.11]$$

The specific distribution $p_{X|Y}$ is the **multinomial**, which is a probability distribution over vectors of non-negative counts. The probability mass function for this distribution is:

$$p_{\text{mult}}(x; \phi) = B(x) \prod_{j=1}^V \phi_j^{x_j} \quad [2.12]$$

$$B(x) = \frac{(\sum_{j=1}^V x_j)!}{\prod_{j=1}^V (x_j)!} \quad [2.13]$$

832 As in the categorical distribution, the parameter ϕ_j can be interpreted as a proba-
 833 bility: specifically, the probability that any given token in the document is the word
 834 j . The multinomial distribution involves a product over words, with each term in
 835 the product equal to the probability ϕ_j , exponentiated by the count x_j . Words that
 836 have zero count play no role in this product, because $\phi_j^0 = 1$. The term $B(x)$ doesn't
 837 depend on ϕ , and can usually be ignored. Can you see why we need this term at
 838 all?⁸

839 The notation $p(x | y; \phi)$ indicates the conditional probability of word counts x given
 840 label y , with parameter ϕ , which is equal to $p_{\text{mult}}(x; \phi_y)$. By specifying the multino-
 841 mial distribution, we describe the **multinomial naïve Bayes** classifier. Why “naïve”?
 842 Because the multinomial distribution treats each word token independently: the
 843 probability mass function factorizes across the counts.⁹

844 2.1.1 Types and tokens

845 A slight modification to the generative model of Naïve Bayes is shown in Algorithm 2.
 846 Instead of generating a vector of counts of **types**, x , this model generates a *sequence of*
 847 **tokens**, $w = (w_1, w_2, \dots, w_M)$. The distinction between types and tokens is critical: $x_j \in$
 848 $\{0, 1, 2, \dots, M\}$ is the count of word type j in the vocabulary, e.g., the number of times
 849 the word *cannibal* appears; $w_m \in \mathcal{V}$ is the identity of token m in the document, e.g. $w_m =$
 850 *cannibal*.

⁸Technically, a multinomial distribution requires a second parameter, the total number of word counts in x . In the bag-of-words representation is equal to the number of words in the document. However, this parameter is irrelevant for classification.

⁹You can plug in any probability distribution to the generative story and it will still be Naïve Bayes, as long as you are making the “naïve” assumption that the features are conditionally independent, given the label. For example, a multivariate Gaussian with diagonal covariance is naïve in exactly the same sense.

Algorithm 2 Alternative generative process for the Naïve Bayes classifier

```

for Document  $i \in \{1, 2, \dots, N\}$  do:
    Draw the label  $y^{(i)} \sim \text{Categorical}(\boldsymbol{\mu})$ ;
    for Token  $m \in \{1, 2, \dots, M_i\}$  do:
        Draw the token  $w_m^{(i)} | y^{(i)} \sim \text{Categorical}(\boldsymbol{\phi}_{y^{(i)}})$ .

```

851 The probability of the sequence \mathbf{w} is a product of categorical probabilities. Algo-
 852 rithm 2 makes a conditional independence assumption: each token $w_m^{(i)}$ is independent
 853 of all other tokens $w_{n \neq m}^{(i)}$, conditioned on the label $y^{(i)}$. This is identical to the “naïve”
 854 independence assumption implied by the multinomial distribution, and as a result, the
 855 optimal parameters for this model are identical to those in multinomial Naïve Bayes. For
 856 any instance, the probability assigned by this model is proportional to the probability un-
 857 der multinomial Naïve Bayes. The constant of proportionality is the factor $B(\mathbf{x})$, which
 858 appears in the multinomial distribution. Because $B(\mathbf{x}) \geq 1$, the probability for a vector
 859 of counts \mathbf{x} is at least as large as the probability for a list of words \mathbf{w} that induces the
 860 same counts: there can be many word sequences that correspond to a single vector of
 861 counts. For example, *man bites dog* and *dog bites man* correspond to an identical count vec-
 862 tor, $\{bites : 1, dog : 1, man : 1\}$, and $B(\mathbf{x})$ is equal to the total number of possible word
 863 orderings for count vector \mathbf{x} .

864 Sometimes it is useful to think of instances as counts of types, \mathbf{x} ; other times, it is
 865 better to think of them as sequences of tokens, \mathbf{w} . If the tokens are generated from a
 866 model that assumes conditional independence, then these two views lead to probability
 867 models that are identical, except for a scaling factor that does not depend on the label or
 868 the parameters.

869 **2.1.2 Prediction**

The Naïve Bayes prediction rule is to choose the label y which maximizes $\log p(\mathbf{x}, y; \boldsymbol{\mu}, \boldsymbol{\phi})$:

$$\hat{y} = \underset{y}{\operatorname{argmax}} \log p(\mathbf{x}, y; \boldsymbol{\mu}, \boldsymbol{\phi}) \quad [2.14]$$

$$= \underset{y}{\operatorname{argmax}} \log p(\mathbf{x} | y; \boldsymbol{\phi}) + \log p(y; \boldsymbol{\mu}) \quad [2.15]$$

Now we can plug in the probability distributions from the generative story.

$$\log p(\mathbf{x} \mid y; \boldsymbol{\phi}) + \log p(y; \boldsymbol{\mu}) = \log \left[B(\mathbf{x}) \prod_{j=1}^V \phi_{y,j}^{x_j} \right] + \log \mu_y \quad [2.16]$$

$$= \log B(\mathbf{x}) + \sum_{j=1}^V x_j \log \phi_{y,j} + \log \mu_y \quad [2.17]$$

$$= \log B(\mathbf{x}) + \boldsymbol{\theta} \cdot \mathbf{f}(\mathbf{x}, y), \quad [2.18]$$

where

$$\boldsymbol{\theta} = [\boldsymbol{\theta}^{(1)}; \boldsymbol{\theta}^{(2)}; \dots; \boldsymbol{\theta}^{(K)}] \quad [2.19]$$

$$\boldsymbol{\theta}^{(y)} = [\log \phi_{y,1}; \log \phi_{y,2}; \dots; \log \phi_{y,V}; \log \mu_y] \quad [2.20]$$

870 The feature function $\mathbf{f}(\mathbf{x}, y)$ is a vector of V word counts and an offset, padded by
 871 zeros for the labels not equal to y (see Equations 2.3-2.5, and Figure 2.1). This construction
 872 ensures that the inner product $\boldsymbol{\theta} \cdot \mathbf{f}(\mathbf{x}, y)$ only activates the features whose weights are
 873 in $\boldsymbol{\theta}^{(y)}$. These features and weights are all we need to compute the joint log-probability
 874 $\log p(\mathbf{x}, y)$ for each y . This is a key point: through this notation, we have converted the
 875 problem of computing the log-likelihood for a document-label pair (\mathbf{x}, y) into the compu-
 876 tation of a vector inner product.

877 2.1.3 Estimation

878 The parameters of the categorical and multinomial distributions have a simple interpre-
 879 tation: they are vectors of expected frequencies for each possible event. Based on this
 880 interpretation, it is tempting to set the parameters empirically,

$$\phi_{y,j} = \frac{\text{count}(y, j)}{\sum_{j'=1}^V \text{count}(y, j')} = \frac{\sum_{i:y^{(i)}=y} x_j^{(i)}}{\sum_{j'=1}^V \sum_{i:y^{(i)}=y} x_{j'}^{(i)}}, \quad [2.21]$$

881 where $\text{count}(y, j)$ refers to the count of word j in documents with label y .

882 Equation 2.21 defines the **relative frequency estimate** for ϕ . It can be justified as a
 883 **maximum likelihood estimate**: the estimate that maximizes the probability $p(\mathbf{x}^{(1:N)}, y^{(1:N)}; \boldsymbol{\theta})$.
 884 Based on the generative model in Algorithm 1, the log-likelihood is,

$$\mathcal{L}(\boldsymbol{\phi}, \boldsymbol{\mu}) = \sum_{i=1}^N \log p_{\text{mult}}(\mathbf{x}^{(i)}; \boldsymbol{\phi}_{y^{(i)}}) + \log p_{\text{cat}}(y^{(i)}; \boldsymbol{\mu}), \quad [2.22]$$

which is now written as a function \mathcal{L} of the parameters ϕ and μ . Let's continue to focus on the parameters ϕ . Since $p(y)$ is constant with respect to ϕ , we can drop it:

$$\mathcal{L}(\phi) = \sum_{i=1}^N \log p_{\text{mult}}(\mathbf{x}^{(i)}; \phi_{y^{(i)}}) = \sum_{i=1}^N \log B(\mathbf{x}^{(i)}) + \sum_{j=1}^V x_j^{(i)} \log \phi_{y^{(i)}, j}, \quad [2.23]$$

where $B(\mathbf{x}^{(i)})$ is constant with respect to ϕ .

We would now like to optimize the log-likelihood \mathcal{L} , by taking derivatives with respect to ϕ . But before we can do that, we have to deal with a set of constraints:

$$\sum_{j=1}^V \phi_{y,j} = 1 \quad \forall y \quad [2.24]$$

These constraints can be incorporated by adding a set of Lagrange multipliers (see Appendix B for more details). Solving separately for each label y , we obtain the Lagrangian,

$$\ell(\phi_y) = \sum_{i:y^{(i)}=y} \sum_{j=1}^V x_j^{(i)} \log \phi_{y,j} - \lambda \left(\sum_{j=1}^V \phi_{y,j} - 1 \right). \quad [2.25]$$

It is now possible to differentiate the Lagrangian with respect to the parameter of interest,

$$\frac{\partial \ell(\phi_y)}{\partial \phi_{y,j}} = \sum_{i:y^{(i)}=y} x_j^{(i)} / \phi_{y,j} - \lambda \quad [2.26]$$

The solution is obtained by setting each element in this vector of derivatives equal to zero,

$$\lambda \phi_{y,j} = \sum_{i:y^{(i)}=y} x_j^{(i)} \quad [2.27]$$

$$\phi_{y,j} \propto \sum_{i:y^{(i)}=y} x_j^{(i)} = \sum_{i=1}^N \delta(y^{(i)} = y) x_j^{(i)} = \text{count}(y, j), \quad [2.28]$$

where $\delta(y^{(i)} = y)$ is a **delta function**, also sometimes called an **indicator function**, which returns one if $y^{(i)} = y$, and zero otherwise. Equation 2.28 shows three different notations for the same thing: a sum over the word counts for all documents i such that the label $y^{(i)} = y$. This gives a solution for each ϕ_y up to a constant of proportionality. Now recall the constraint $\sum_{j=1}^V \phi_{y,j} = 1$, which arises because ϕ_y represents a vector of probabilities for each word in the vocabulary. This constraint leads to an exact solution,

$$\phi_{y,j} = \frac{\text{count}(y, j)}{\sum_{j'=1}^V \text{count}(y, j')}. \quad [2.29]$$

890 This is equal to the relative frequency estimator from Equation 2.21. A similar derivation
 891 gives $\mu_y \propto \sum_{i=1}^N \delta(y^{(i)} = y)$.

892 2.1.4 Smoothing and MAP estimation

893 With text data, there are likely to be pairs of labels and words that never appear in the
 894 training set, leaving $\phi_{y,j} = 0$. For example, the word *Bayesian* may have never yet ap-
 895 peared in a spam email. But choosing a value of $\phi_{\text{SPAM}, \text{Bayesian}} = 0$ would allow this single
 896 feature to completely veto a label, since $p(\text{SPAM} | x) = 0$ if $x_{\text{Bayesian}} > 0$.

897 This is undesirable, because it imposes high **variance**: depending on what data hap-
 898 pens to be in the training set, we could get vastly different classification rules. One so-
 899 lution is to **smooth** the probabilities, by adding a “pseudocount” of α to each count, and
 900 then normalizing.

$$\phi_{y,j} = \frac{\alpha + \text{count}(y, j)}{V\alpha + \sum_{j'=1}^V \text{count}(y, j')} \quad [2.30]$$

901 This is called **Laplace smoothing**.¹⁰ The pseudocount α is a **hyperparameter**, because it
 902 controls the form of the log-likelihood function, which in turn drives the estimation of ϕ .

903 Smoothing reduces variance, but it takes us away from the maximum likelihood esti-
 904 mate: it imposes a **bias**. In this case, the bias points towards uniform probabilities. Ma-
 905 chine learning theory shows that errors on heldout data can be attributed to the sum of
 906 bias and variance (Mohri et al., 2012). Techniques for reducing variance typically increase
 907 the bias, leading to a **bias-variance tradeoff**.

- 908 • Unbiased classifiers may **overfit** the training data, yielding poor performance on
 909 unseen data.
- 910 • But if the smoothing is too large, the resulting classifier can **underfit** instead. In the
 911 limit of $\alpha \rightarrow \infty$, there is zero variance: you get the same classifier, regardless of the
 912 data. However, the bias is likely to be large.

913 2.1.5 Setting hyperparameters

914 How should we choose the best value of hyperparameters like α ? Maximum likelihood
 915 will not work: the maximum likelihood estimate of α on the training set will always be
 916 $\alpha = 0$. In many cases, what we really want is **accuracy**: the number of correct predictions,
 917 divided by the total number of predictions. (Other measures of classification performance
 918 are discussed in § 4.4.) As we will see, it is hard to optimize for accuracy directly. But for
 919 scalar hyperparameters like α can be tuned by a simple heuristic called **grid search**: try a

¹⁰Laplace smoothing has a Bayesian justification, in which the generative model is extended to include ϕ as a random variable. The resulting estimate is called **maximum a posteriori**, or MAP.

920 set of values (e.g., $\alpha \in \{0.001, 0.01, 0.1, 1, 10\}$), compute the accuracy for each value, and
921 choose the setting that maximizes the accuracy.

922 The goal is to tune α so that the classifier performs well on *unseen* data. For this reason,
923 the data used for hyperparameter tuning should not overlap the training set, where very
924 small values of α will be preferred. Instead, we hold out a **development set** (also called
925 a **tuning set**) for hyperparameter selection. This development set may consist of a small
926 fraction of the labeled data, such as 10%.

927 We also want to predict the performance of our classifier on unseen data. To do this,
928 we must hold out a separate subset of data, called the **test set**. It is critical that the test set
929 not overlap with either the training or development sets, or else we will overestimate the
930 performance that the classifier will achieve on unlabeled data in the future. The test set
931 should also not be used when making modeling decisions, such as the form of the feature
932 function, the size of the vocabulary, and so on (these decisions are reviewed in chapter 4.)
933 The ideal practice is to use the test set only once — otherwise, the test set is used to guide
934 the classifier design, and test set accuracy will diverge from accuracy on truly unseen
935 data. Because annotated data is expensive, this ideal can be hard to follow in practice,
936 and many test sets have been used for decades. But in some high-impact applications like
937 machine translation and information extraction, new test sets are released every year.

938 When only a small amount of labeled data is available, the test set accuracy can be
939 unreliable. *K*-fold **cross-validation** is one way to cope with this scenario: the labeled
940 data is divided into *K* folds, and each fold acts as the test set, while training on the other
941 folds. The test set accuracies are then aggregated. In the extreme, each fold is a single data
942 point; this is called **leave-one-out** cross-validation. To perform hyperparameter tuning in
943 the context of cross-validation, another fold can be used for grid search. It is important
944 not to repeatedly evaluate the cross-validated accuracy while making design decisions
945 about the classifier, or you will overstate the accuracy on truly unseen data.

946 2.2 Discriminative learning

947 Naïve Bayes is easy to work with: the weights can be estimated in closed form, and the
948 probabilistic interpretation makes it relatively easy to extend. However, the assumption
949 that features are independent can seriously limit its accuracy. Thus far, we have defined
950 the **feature function** $f(\mathbf{x}, y)$ so that it corresponds to bag-of-words features: one feature
951 per word in the vocabulary. In natural language, bag-of-words features violate the as-
952 sumption of conditional independence — for example, the probability that a document
953 will contain the word *naïve* is surely higher given that it also contains the word *Bayes* —
954 but this violation is relatively mild.

955 However, good performance on text classification often requires features that are richer
956 than the bag-of-words:

- 957 • To better handle out-of-vocabulary terms, we want features that apply to multiple
 958 words, such as prefixes and suffixes (e.g., *anti-*, *un-*, *-ing*) and capitalization.
 959 • We also want *n*-gram features that apply to multi-word units: **bigrams** (e.g., *not*
 960 *good*, *not bad*), **trigrams** (e.g., *not so bad*, *lacking any decency*, *never before imagined*), and
 961 beyond.

These features flagrantly violate the Naïve Bayes independence assumption. Consider what happens if we add a prefix feature. Under the Naïve Bayes assumption, we make the following approximation:¹¹

$$\Pr(\text{word} = \textit{unfit}, \text{prefix} = \textit{un-} \mid y) \approx \Pr(\text{prefix} = \textit{un-} \mid y) \times \Pr(\text{word} = \textit{unfit} \mid y).$$

To test the quality of the approximation, we can manipulate the left-hand side by applying the chain rule,

$$\Pr(\text{word} = \textit{unfit}, \text{prefix} = \textit{un-} \mid y) = \Pr(\text{prefix} = \textit{un-} \mid \text{word} = \textit{unfit}, y) \quad [2.31]$$

$$\times \Pr(\text{word} = \textit{unfit} \mid y) \quad [2.32]$$

But $\Pr(\text{prefix} = \textit{un-} \mid \text{word} = \textit{unfit}, y) = 1$, since *un-* is guaranteed to be the prefix for the word *unfit*. Therefore,

$$\Pr(\text{word} = \textit{unfit}, \text{prefix} = \textit{un-} \mid y) = 1 \times \Pr(\text{word} = \textit{unfit} \mid y) \quad [2.33]$$

$$\gg \Pr(\text{prefix} = \textit{un-} \mid y) \times \Pr(\text{word} = \textit{unfit} \mid y), \quad [2.34]$$

962 because the probability of any given word starting with the prefix *un-* is much less than
 963 one. Naïve Bayes will systematically underestimate the true probabilities of conjunctions
 964 of positively correlated features. To use such features, we need learning algorithms that
 965 do not rely on an independence assumption.

966 The origin of the Naïve Bayes independence assumption is the learning objective,
 967 $p(\mathbf{x}^{(1:N)}, y^{(1:N)})$, which requires modeling the probability of the observed text. In clas-
 968 sification problems, we are always given \mathbf{x} , and are only interested in predicting the label
 969 y , so it seems unnecessary to model the probability of \mathbf{x} . **Discriminative learning** algo-
 970 rithms focus on the problem of predicting y , and do not attempt to model the probability
 971 of the text \mathbf{x} .

972 2.2.1 Perceptron

973 In Naïve Bayes, the weights can be interpreted as parameters of a probabilistic model. But
 974 this model requires an independence assumption that usually does not hold, and limits

¹¹The notation $\Pr(\cdot)$ refers to the probability of an event, and $p(\cdot)$ refers to the probability density or mass for a random variable (see Appendix A).

Algorithm 3 Perceptron learning algorithm

```

1: procedure PERCEPTRON( $\mathbf{x}^{(1:N)}, y^{(1:N)}$ )
2:    $t \leftarrow 0$ 
3:    $\boldsymbol{\theta}^{(0)} \leftarrow \mathbf{0}$ 
4:   repeat
5:      $t \leftarrow t + 1$ 
6:     Select an instance  $i$ 
7:      $\hat{y} \leftarrow \operatorname{argmax}_y \boldsymbol{\theta}^{(t-1)} \cdot \mathbf{f}(\mathbf{x}^{(i)}, y)$ 
8:     if  $\hat{y} \neq y^{(i)}$  then
9:        $\boldsymbol{\theta}^{(t)} \leftarrow \boldsymbol{\theta}^{(t-1)} + \mathbf{f}(\mathbf{x}^{(i)}, y^{(i)}) - \mathbf{f}(\mathbf{x}^{(i)}, \hat{y})$ 
10:    else
11:       $\boldsymbol{\theta}^{(t)} \leftarrow \boldsymbol{\theta}^{(t-1)}$ 
12:    until tired
13:   return  $\boldsymbol{\theta}^{(t)}$ 

```

975 our choice of features. Why not forget about probability and learn the weights in an error-
 976 driven way? The **perceptron** algorithm, shown in Algorithm 3, is one way to do this.

977 Here's what the algorithm says: if you make a mistake, increase the weights for fea-
 978 tures that are active with the correct label $y^{(i)}$, and decrease the weights for features that
 979 are active with the guessed label \hat{y} . This is an **online learning** algorithm, since the clas-
 980 sifier weights change after every example. This is different from Naïve Bayes, which
 981 computes corpus statistics and then sets the weights in a single operation — Naïve Bayes
 982 is a **batch learning** algorithm. Algorithm 3 is vague about when this online learning pro-
 983 cedure terminates. We will return to this issue shortly.

984 The perceptron algorithm may seem like a cheap heuristic: Naïve Bayes has a solid
 985 foundation in probability, but the perceptron is just adding and subtracting constants from
 986 the weights every time there is a mistake. Will this really work? In fact, there is some nice
 987 theory for the perceptron, based on the concept of **linear separability**:

988 **Definition 1** (Linear separability). *The dataset $\mathcal{D} = \{(\mathbf{x}^{(i)}, y^{(i)})\}_{i=1}^N$ is linearly separable iff
 989 there exists some weight vector $\boldsymbol{\theta}$ and some margin ρ such that for every instance $(\mathbf{x}^{(i)}, y^{(i)})$, the
 990 inner product of $\boldsymbol{\theta}$ and the feature function for the true label, $\boldsymbol{\theta} \cdot \mathbf{f}(\mathbf{x}^{(i)}, y^{(i)})$, is at least ρ greater
 991 than inner product of $\boldsymbol{\theta}$ and the feature function for every other possible label, $\boldsymbol{\theta} \cdot \mathbf{f}(\mathbf{x}^{(i)}, y')$.*

$$\exists \boldsymbol{\theta}, \rho > 0 : \forall (\mathbf{x}^{(i)}, y^{(i)}) \in \mathcal{D}, \quad \boldsymbol{\theta} \cdot \mathbf{f}(\mathbf{x}^{(i)}, y^{(i)}) \geq \rho + \max_{y' \neq y^{(i)}} \boldsymbol{\theta} \cdot \mathbf{f}(\mathbf{x}^{(i)}, y'). \quad [2.35]$$

992 Linear separability is important because of the following guarantee: if your data is

993 linearly separable, then the perceptron algorithm will find a separator (Novikoff, 1962).¹²
 994 So while the perceptron may seem heuristic, it is guaranteed to succeed, if the learning
 995 problem is easy enough.

996 How useful is this proof? Minsky and Papert (1969) famously proved that the simple
 997 logical function of *exclusive-or* is not separable, and that a perceptron is therefore inca-
 998 pable of learning this function. But this is not just an issue for the perceptron: any linear
 999 classification algorithm, including Naïve Bayes, will fail on this task. In natural language
 1000 classification problems usually involve high dimensional feature spaces, with thousands
 1001 or millions of features. For these problems, it is very likely that the training data is indeed
 1002 separable. And even if the data is not separable, it is still possible to place an upper bound
 1003 on the number of errors that the perceptron algorithm will make (Freund and Schapire,
 1004 1999).

1005 2.2.2 Averaged perceptron

1006 The perceptron iterates over the data repeatedly — until “tired”, as described in Algo-
 1007 rithm 3. If the data is linearly separable, the perceptron will eventually find a separator,
 1008 and we can stop once all training instances are classified correctly. But if the data is not
 1009 linearly separable, the perceptron can *thrash* between two or more weight settings, never
 1010 converging. In this case, how do we know that we can stop training, and how should
 1011 we choose the final weights? An effective practical solution is to *average* the perceptron
 1012 weights across all iterations.

1013 This procedure is shown in Algorithm 4. The learning algorithm is nearly identical,
 1014 but we also maintain a vector of the sum of the weights, \mathbf{m} . At the end of the learning
 1015 procedure, we divide this sum by the total number of updates t , to compute the average
 1016 weights, $\bar{\theta}$. These average weights are then used for prediction. In the algorithm sketch,
 1017 the average is computed from a running sum, $\mathbf{m} \leftarrow \mathbf{m} + \theta$. However, this is inefficient,
 1018 because it requires $|\theta|$ operations to update the running sum. When $f(\mathbf{x}, y)$ is sparse,
 1019 $|\theta| \gg |f(\mathbf{x}, y)|$ for any individual (\mathbf{x}, y) . This means that computing the running sum will
 1020 be much more expensive than computing of the update to θ itself, which requires only
 1021 $2 \times |f(\mathbf{x}, y)|$ operations. One of the exercises is to sketch a more efficient algorithm for
 1022 computing the averaged weights.

1023 Even if the data is not separable, the averaged weights will eventually converge. One
 1024 possible stopping criterion is to check the difference between the average weight vectors
 1025 after each pass through the data: if the norm of the difference falls below some predefined
 1026 threshold, we can stop training. Another stopping criterion is to hold out some data,
 1027 and to measure the predictive accuracy on this heldout data. When the accuracy on the
 1028 heldout data starts to decrease, the learning algorithm has begun to **overfit** the training

¹²It is also possible to prove an upper bound on the number of training iterations required to find the separator. Proofs like this are part of the field of **statistical learning theory** (Mohri et al., 2012).

Algorithm 4 Averaged perceptron learning algorithm

```

1: procedure AVG-PERCEPTRON( $\mathbf{x}^{(1:N)}, \mathbf{y}^{(1:N)}$ )
2:    $t \leftarrow 0$ 
3:    $\boldsymbol{\theta}^{(0)} \leftarrow 0$ 
4:   repeat
5:      $t \leftarrow t + 1$ 
6:     Select an instance  $i$ 
7:      $\hat{y} \leftarrow \operatorname{argmax}_y \boldsymbol{\theta}^{(t-1)} \cdot \mathbf{f}(\mathbf{x}^{(i)}, y)$ 
8:     if  $\hat{y} \neq y^{(i)}$  then
9:        $\boldsymbol{\theta}^{(t)} \leftarrow \boldsymbol{\theta}^{(t-1)} + \mathbf{f}(\mathbf{x}^{(i)}, y^{(i)}) - \mathbf{f}(\mathbf{x}^{(i)}, \hat{y})$ 
10:    else
11:       $\boldsymbol{\theta}^{(t)} \leftarrow \boldsymbol{\theta}^{(t-1)}$ 
12:     $\mathbf{m} \leftarrow \mathbf{m} + \boldsymbol{\theta}^{(t)}$ 
13:   until tired
14:    $\bar{\boldsymbol{\theta}} \leftarrow \frac{1}{t} \mathbf{m}$ 
15:   return  $\bar{\boldsymbol{\theta}}$ 

```

1029 set. At this point, it is probably best to stop; this stopping criterion is known as **early**
 1030 **stopping**.

1031 **Generalization** is the ability to make good predictions on instances that are not in
 1032 the training data. Averaging can be proven to improve generalization, by computing an
 1033 upper bound on the generalization error (Freund and Schapire, 1999; Collins, 2002).

1034 **2.3 Loss functions and large-margin classification**

1035 Naïve Bayes chooses the weights $\boldsymbol{\theta}$ by maximizing the joint log-likelihood $\log p(\mathbf{x}^{(1:N)}, \mathbf{y}^{(1:N)})$.
 1036 By convention, optimization problems are generally formulated as minimization of a **loss**
 1037 **function**. The input to a loss function is the vector of weights $\boldsymbol{\theta}$, and the output is a non-
 1038 negative scalar, measuring the performance of the classifier on a training instance. The
 1039 loss $\ell(\boldsymbol{\theta}; \mathbf{x}^{(i)}, y^{(i)})$ is then a measure of the performance of the weights $\boldsymbol{\theta}$ on the instance
 1040 $(\mathbf{x}^{(i)}, y^{(i)})$. The goal of learning is to minimize the sum of the losses across all instances in
 1041 the training set.

We can trivially reformulate maximum likelihood as a loss function, by defining the

loss function to be the *negative log-likelihood*:

$$\log p(\mathbf{x}^{(1:N)}, y^{(1:N)}; \boldsymbol{\theta}) = \sum_{i=1}^N \log p(\mathbf{x}^{(i)}, y^{(i)}; \boldsymbol{\theta}) \quad [2.36]$$

$$\ell_{\text{NB}}(\boldsymbol{\theta}; \mathbf{x}^{(i)}, y^{(i)}) = -\log p(\mathbf{x}^{(i)}, y^{(i)}; \boldsymbol{\theta}) \quad [2.37]$$

$$\hat{\boldsymbol{\theta}} = \operatorname{argmin}_{\boldsymbol{\theta}} \sum_{i=1}^N \ell_{\text{NB}}(\boldsymbol{\theta}; \mathbf{x}^{(i)}, y^{(i)}) \quad [2.38]$$

$$= \operatorname{argmax}_{\boldsymbol{\theta}} \sum_{i=1}^N \log p(\mathbf{x}^{(i)}, y^{(i)}; \boldsymbol{\theta}). \quad [2.39]$$

1042 The problem of minimizing ℓ_{NB} is thus identical to the problem of maximum-likelihood
1043 estimation.

1044 Loss functions provide a general framework for comparing machine learning objectives.
1045 For example, an alternative loss function is the **zero-one loss**,

$$\ell_{0-1}(\boldsymbol{\theta}; \mathbf{x}^{(i)}, y^{(i)}) = \begin{cases} 0, & y^{(i)} = \operatorname{argmax}_y \boldsymbol{\theta} \cdot \mathbf{f}(\mathbf{x}^{(i)}, y) \\ 1, & \text{otherwise} \end{cases} \quad [2.40]$$

1046 The zero-one loss is zero if the instance is correctly classified, and one otherwise. The
1047 sum of zero-one losses is proportional to the error rate of the classifier on the training
1048 data. Since a low error rate is often the ultimate goal of classification, this may seem
1049 ideal. But the zero-one loss has several problems. One is that it is **non-convex**,¹³ which
1050 means that there is no guarantee that gradient-based optimization will be effective. A
1051 more serious problem is that the derivatives are useless: the partial derivative with respect
1052 to any parameter is zero everywhere, except at the points where $\boldsymbol{\theta} \cdot \mathbf{f}(\mathbf{x}^{(i)}, y) = \boldsymbol{\theta} \cdot \mathbf{f}(\mathbf{x}^{(i)}, \hat{y})$
1053 for some \hat{y} . At those points, the loss is discontinuous, and the derivative is undefined.

1054 The perceptron optimizes the following loss function:

$$\ell_{\text{PERCEPTRON}}(\boldsymbol{\theta}; \mathbf{x}^{(i)}, y^{(i)}) = \max_{y \in \mathcal{Y}} \boldsymbol{\theta} \cdot \mathbf{f}(\mathbf{x}^{(i)}, y) - \boldsymbol{\theta} \cdot \mathbf{f}(\mathbf{x}^{(i)}, y^{(i)}), \quad [2.41]$$

1055 When $\hat{y} = y^{(i)}$, the loss is zero; otherwise, it increases linearly with the gap between the
1056 score for the predicted label \hat{y} and the score for the true label $y^{(i)}$. Plotting this loss against
1057 the input $\max_{y \in \mathcal{Y}} \boldsymbol{\theta} \cdot \mathbf{f}(\mathbf{x}^{(i)}, y) - \boldsymbol{\theta} \cdot \mathbf{f}(\mathbf{x}^{(i)}, y^{(i)})$ gives a hinge shape, motivating the name
1058 **hinge loss**.

¹³A function f is **convex** iff $\alpha f(x_i) + (1-\alpha)f(x_j) \geq f(\alpha x_i + (1-\alpha)x_j)$, for all $\alpha \in [0, 1]$ and for all x_i and x_j on the domain of the function. In words, any weighted average of the output of f applied to any two points is larger than the output of f when applied to the weighted average of the same two points. Convexity implies that any local minimum is also a global minimum, and there are many effective techniques for optimizing convex functions (Boyd and Vandenberghe, 2004). See Appendix B for a brief review.

1059 To see why this is the loss function optimized by the perceptron, take the derivative
 1060 with respect to θ ,

$$\frac{\partial}{\partial \theta} \ell_{\text{PERCEPTRON}}(\theta; \mathbf{x}^{(i)}, y^{(i)}) = \mathbf{f}(\mathbf{x}^{(i)}, \hat{y}) - \mathbf{f}(\mathbf{x}^{(i)}, y^{(i)}). \quad [2.42]$$

1061 At each instance perceptron algorithm takes a step of magnitude one in the opposite direction
 1062 of this **gradient**, $\nabla_{\theta} \ell_{\text{PERCEPTRON}} = \frac{\partial}{\partial \theta} \ell_{\text{PERCEPTRON}}(\theta; \mathbf{x}^{(i)}, y^{(i)})$. As we will see in § 2.5,
 1063 this is an example of the optimization algorithm **stochastic gradient descent**, applied to
 1064 the objective in Equation 2.41.

1065 **Breaking ties with subgradient descent** Careful readers will notice the tacit assumption
 1066 that there is a unique \hat{y} that maximizes $\theta \cdot \mathbf{f}(\mathbf{x}^{(i)}, y)$. What if there are two or more labels
 1067 that maximize this function? Consider binary classification: if the maximizer is $y^{(i)}$, then
 1068 the gradient is zero, and so is the perceptron update; if the maximizer is $\hat{y} \neq y^{(i)}$, then the
 1069 update is the difference $\mathbf{f}(\mathbf{x}^{(i)}, y^{(i)}) - \mathbf{f}(\mathbf{x}^{(i)}, \hat{y})$. The underlying issue is that the perceptron
 1070 loss is not **smooth**, because the first derivative has a discontinuity at the hinge point,
 1071 where the score for the true label $y^{(i)}$ is equal to the score for some other label \hat{y} . At this
 1072 point, there is no unique gradient; rather, there is a set of **subgradients**. A vector v is a
 1073 subgradient of the function g at u_0 iff $g(u) - g(u_0) \geq v \cdot (u - u_0)$ for all u . Graphically,
 1074 this defines the set of hyperplanes that include $g(u_0)$ and do not intersect g at any other
 1075 point. As we approach the hinge point from the left, the gradient is $\mathbf{f}(\mathbf{x}, \hat{y}) - \mathbf{f}(\mathbf{x}, y)$; as we
 1076 approach from the right, the gradient is 0. At the hinge point, the subgradients include all
 1077 vectors that are bounded by these two extremes. In subgradient descent, *any* subgradient
 1078 can be used (Bertsekas, 2012). Since both 0 and $\mathbf{f}(\mathbf{x}, \hat{y}) - \mathbf{f}(\mathbf{x}, y)$ are subgradients at the
 1079 hinge point, either one can be used in the perceptron update.

1080 **Perceptron versus Naïve Bayes** The perceptron loss function has some pros and cons
 1081 with respect to the negative log-likelihood loss implied by Naïve Bayes.

- 1082 • Both ℓ_{NB} and $\ell_{\text{PERCEPTRON}}$ are convex, making them relatively easy to optimize. However,
 1083 ℓ_{NB} can be optimized in closed form, while $\ell_{\text{PERCEPTRON}}$ requires iterating over
 1084 the dataset multiple times.
- 1085 • ℓ_{NB} can suffer **infinite** loss on a single example, since the logarithm of zero probabil-
 1086 ity is negative infinity. Naïve Bayes will therefore overemphasize some examples,
 1087 and underemphasize others.
- 1088 • $\ell_{\text{PERCEPTRON}}$ treats all correct answers equally. Even if θ only gives the correct answer
 1089 by a tiny margin, the loss is still zero.

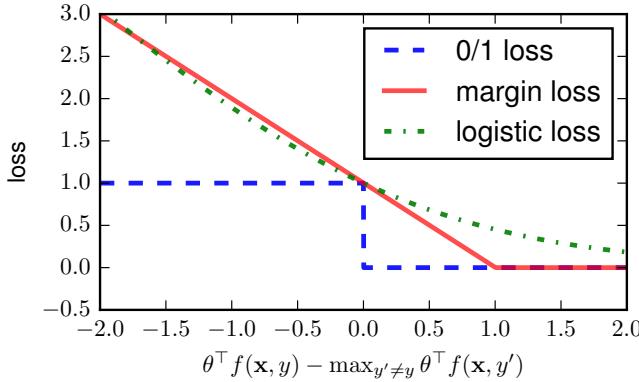


Figure 2.2: Margin, zero-one, and logistic loss functions.

1090 **2.3.1 Large margin classification**

1091 This last comment suggests a potential problem with the perceptron. Suppose a test ex-
 1092 ample is very close to a training example, but not identical. If the classifier only gets the
 1093 correct answer on the training example by a small margin, then it may get the test instance
 1094 wrong. To formalize this intuition, define the **margin** as,

$$\gamma(\boldsymbol{\theta}; \mathbf{x}^{(i)}, y^{(i)}) = \boldsymbol{\theta} \cdot \mathbf{f}(\mathbf{x}^{(i)}, y^{(i)}) - \max_{y \neq y^{(i)}} \boldsymbol{\theta} \cdot \mathbf{f}(\mathbf{x}^{(i)}, y). \quad [2.43]$$

The margin represents the difference between the score for the correct label $y^{(i)}$, and the score for the highest-scoring label. The intuition behind **large margin classification** is that it is not enough just to label the training data correctly — the correct label should be separated from other labels by a comfortable margin. This idea can be encoded into a loss function,

$$\ell_{\text{MARGIN}}(\boldsymbol{\theta}; \mathbf{x}^{(i)}, y^{(i)}) = \begin{cases} 0, & \gamma(\boldsymbol{\theta}; \mathbf{x}^{(i)}, y^{(i)}) \geq 1, \\ 1 - \gamma(\boldsymbol{\theta}; \mathbf{x}^{(i)}, y^{(i)}), & \text{otherwise} \end{cases} \quad [2.44]$$

$$= (1 - \gamma(\boldsymbol{\theta}; \mathbf{x}^{(i)}, y^{(i)}))_+, \quad [2.45]$$

1095 where $(x)_+ = \max(0, x)$. The loss is zero if there is a margin of at least 1 between the
 1096 score for the true label and the best-scoring alternative \hat{y} . This is almost identical to the
 1097 perceptron loss, but the hinge point is shifted to the right, as shown in Figure 2.2. The
 1098 margin loss is a convex upper bound on the zero-one loss.

1099 **2.3.2 Support vector machines**

If a dataset is linearly separable, then there is some hyperplane θ that correctly classifies all training instances with margin ρ (by Definition 1). This margin can be increased to any desired value by multiplying the weights by a constant. Now, for any datapoint $(x^{(i)}, y^{(i)})$, the geometric distance to the separating hyperplane is given by $\frac{\gamma(\theta; x^{(i)}, y^{(i)})}{\|\theta\|_2}$,

where the denominator is the norm of the weights, $\|\theta\|_2 = \sqrt{\sum_j \theta_j^2}$. The geometric distance is sometimes called the **geometric margin**, in contrast to the **functional margin** $\gamma(\theta; x^{(i)}, y^{(i)})$. Both are shown in Figure 2.3. The geometric margin is a good measure of the robustness of the separator: if the functional margin is large, but the norm $\|\theta\|_2$ is also large, then a small change in $x^{(i)}$ could cause it to be misclassified. We therefore seek to maximize the minimum geometric margin, subject to the constraint that the functional margin is at least one:

$$\begin{aligned} \max_{\theta} . & \quad \min_i . & & \frac{\gamma(\theta; x^{(i)}, y^{(i)})}{\|\theta\|_2} \\ \text{s.t.} & \quad \gamma(\theta; x^{(i)}, y^{(i)}) \geq 1, \quad \forall i. & & [2.46] \end{aligned}$$

1100 This is a **constrained optimization** problem, where the second line describes constraints
 1101 on the space of possible solutions θ . In this case, the constraint is that the functional
 1102 margin always be at least one, and the objective is that the minimum geometric margin
 1103 be as large as possible.

Any scaling factor on θ will cancel in the numerator and denominator of the geometric margin. This means that if the data is linearly separable at ρ , we can increase this margin to 1 by rescaling θ . We therefore need only minimize the denominator $\|\theta\|_2$, subject to the constraint on the functional margin. The minimizer of $\|\theta\|_2$ is also the minimizer of $\frac{1}{2}\|\theta\|_2^2 = \frac{1}{2}\sum_{j=1}^V \theta_j^2$, which is easier to work with. This gives the optimization problem,

$$\begin{aligned} \min_{\theta} . & \quad \frac{1}{2}\|\theta\|_2^2 \\ \text{s.t.} & \quad \gamma(\theta; x^{(i)}, y^{(i)}) \geq 1, \quad \forall i. & & [2.47] \end{aligned}$$

1104 This optimization problem is a **quadratic program**: the objective is a quadratic function
 1105 of the parameters, and the constraints are all linear inequalities. The resulting classifier
 1106 is better known as the **support vector machine**. The name derives from one of the
 1107 solutions, which is to incorporate the constraints through Lagrange multipliers $\alpha_i \geq 0, i =$
 1108 $1, 2, \dots, N$. The instances for which $\alpha_i > 0$ are the **support vectors**; other instances are
 1109 irrelevant to the classification boundary.



Figure 2.3: Functional and geometric margins for a binary classification problem. All separators that satisfy the margin constraint are shown. The separator with the largest geometric margin is shown in bold.

1110 2.3.3 Slack variables

If a dataset is not linearly separable, then there is no θ that satisfies the margin constraint. To add more flexibility, we introduce a set of **slack variables** $\xi_i \geq 0$. Instead of requiring that the functional margin be greater than or equal to one, we require that it be greater than or equal to $1 - \xi_i$. Ideally there would not be any slack, so the slack variables are penalized in the objective function:

$$\begin{aligned} \min_{\theta, \xi} \quad & \frac{1}{2} \|\theta\|_2^2 + C \sum_{i=1}^N \xi_i \\ \text{s.t.} \quad & \gamma(\theta; \mathbf{x}^{(i)}, y^{(i)}) + \xi_i \geq 1, \quad \forall i \\ & \xi_i \geq 0, \quad \forall i. \end{aligned} \quad [2.48]$$

1111 The hyperparameter C controls the tradeoff between violations of the margin con-
 1112 straint and the preference for a low norm of θ . As $C \rightarrow \infty$, slack is infinitely expensive,
 1113 and there is only a solution if the data is separable. As $C \rightarrow 0$, slack becomes free, and
 1114 there is a trivial solution at $\theta = 0$. Thus, C plays a similar role to the smoothing parame-
 1115 ter in Naïve Bayes (§ 2.1.4), trading off between a close fit to the training data and better
 1116 generalization. Like the smoothing parameter of Naïve Bayes, C must be set by the user,
 1117 typically by maximizing performance on a heldout development set.

1118 To solve the constrained optimization problem defined in Equation 2.48, we can first

1119 solve for the slack variables,

$$\xi_i \geq (1 - \gamma(\boldsymbol{\theta}; \mathbf{x}^{(i)}, y^{(i)}))_+. \quad [2.49]$$

The inequality is tight, because the slack variables are penalized in the objective, and there is no advantage to increasing them beyond the minimum value (Ratliff et al., 2007; Smith, 2011). The problem can therefore be transformed into the unconstrained optimization,

$$\min_{\boldsymbol{\theta}} \quad \frac{\lambda}{2} \|\boldsymbol{\theta}\|_2^2 + \sum_{i=1}^N (1 - \gamma(\boldsymbol{\theta}; \mathbf{x}^{(i)}, y^{(i)}))_+, \quad [2.50]$$

1120 where each ξ_i has been substituted by the right-hand side of Equation 2.49, and the factor
 1121 of C on the slack variables has been replaced by an equivalent factor of $\lambda = \frac{1}{C}$ on the
 1122 norm of the weights.

1123 Now define the **cost** of a classification error as,¹⁴

$$c(y^{(i)}, \hat{y}) = \begin{cases} 1, & y^{(i)} \neq \hat{y} \\ 0, & \text{otherwise.} \end{cases} \quad [2.51]$$

Equation 2.50 can be rewritten using this cost function,

$$\min_{\boldsymbol{\theta}} \quad \frac{\lambda}{2} \|\boldsymbol{\theta}\|_2^2 + \sum_{i=1}^N \left(\max_{y \in \mathcal{Y}} (\boldsymbol{\theta} \cdot \mathbf{f}(\mathbf{x}^{(i)}, y) + c(y^{(i)}, y)) - \boldsymbol{\theta} \cdot \mathbf{f}(\mathbf{x}^{(i)}, y^{(i)}) \right)_+. \quad [2.52]$$

1124 This objective maximizes over all $y \in \mathcal{Y}$, in search of labels that are both *strong*, as measured by $\boldsymbol{\theta} \cdot \mathbf{f}(\mathbf{x}^{(i)}, y)$, and *wrong*, as measured by $c(y^{(i)}, y)$. This maximization is known
 1125 as **cost-augmented decoding**, because it augments the maximization objective to favor
 1126 high-cost predictions. If the highest-scoring label is $y = y^{(i)}$, then the margin constraint is
 1127 satisfied, and the loss for this instance is zero. Cost-augmentation is only for learning: it
 1128 is not applied when making predictions on unseen data.

Differentiating Equation 2.52 with respect to the weights gives,

$$\nabla_{\boldsymbol{\theta}} L_{\text{SVM}} = \lambda \boldsymbol{\theta} + \sum_{i=1}^N \mathbf{f}(\mathbf{x}^{(i)}, \hat{y}) - \mathbf{f}(\mathbf{x}^{(i)}, y^{(i)}) \quad [2.53]$$

$$\hat{y} = \operatorname{argmax}_{y \in \mathcal{Y}} \boldsymbol{\theta} \cdot \mathbf{f}(\mathbf{x}^{(i)}, y) + c(y^{(i)}, y), \quad [2.54]$$

1130 where L_{SVM} refers to minimization objective in Equation 2.52. This gradient is very similar
 1131 to the perceptron update. One difference is the additional term $\lambda \boldsymbol{\theta}$, which **regularizes** the

¹⁴We can also define specialized cost functions that heavily penalize especially undesirable errors (Tsacharidis et al., 2004). This idea is revisited in chapter 7.

weights towards 0. The other difference is the cost $c(y^{(i)}, y)$, which is added to $\theta \cdot \mathbf{f}(\mathbf{x}, y)$ when choosing \hat{y} during training. This term derives from the margin constraint: large margin classifiers learn not only from instances that are incorrectly classified, but also from instances for which the correct classification decision was not sufficiently confident.

2.4 Logistic regression

Thus far, we have seen two broad classes of learning algorithms. Naïve Bayes is a probabilistic method, where learning is equivalent to estimating a joint probability distribution. The perceptron and support vector machine are discriminative, error-driven algorithms: the learning objective is closely related to the number of errors on the training data. Probabilistic and error-driven approaches each have advantages: probability makes it possible to quantify uncertainty about the predicted labels, but the probability model of Naïve Bayes makes unrealistic independence assumptions that limit the features that can be used.

Logistic regression combines advantages of discriminative and probabilistic classifiers. Unlike Naïve Bayes, which starts from the **joint probability** $p_{X,Y}$, logistic regression defines the desired **conditional probability** $p_{Y|X}$ directly. Think of $\theta \cdot \mathbf{f}(\mathbf{x}, y)$ as a scoring function for the compatibility of the base features \mathbf{x} and the label y . To convert this score into a probability, we first exponentiate, obtaining $\exp(\theta \cdot \mathbf{f}(\mathbf{x}, y))$, which is guaranteed to be non-negative. Next, we normalize, dividing over all possible labels $y' \in \mathcal{Y}$. The resulting conditional probability is defined as,

$$p(y | \mathbf{x}; \theta) = \frac{\exp(\theta \cdot \mathbf{f}(\mathbf{x}, y))}{\sum_{y' \in \mathcal{Y}} \exp(\theta \cdot \mathbf{f}(\mathbf{x}, y'))}. \quad [2.55]$$

Given a dataset $\mathcal{D} = \{(\mathbf{x}^{(i)}, y^{(i)})\}_{i=1}^N$, the weights θ are estimated by **maximum conditional likelihood**,

$$\log p(\mathbf{y}^{(1:N)} | \mathbf{x}^{(1:N)}; \theta) = \sum_{i=1}^N \log p(y^{(i)} | \mathbf{x}^{(i)}; \theta) \quad [2.56]$$

$$= \sum_{i=1}^N \theta \cdot \mathbf{f}(\mathbf{x}^{(i)}, y^{(i)}) - \log \sum_{y' \in \mathcal{Y}} \exp(\theta \cdot \mathbf{f}(\mathbf{x}^{(i)}, y')). \quad [2.57]$$

The final line is obtained by plugging in Equation 2.55 and taking the logarithm.¹⁵ Inside

¹⁵The log-sum-exp term is a common pattern in machine learning. It is numerically unstable, because it will underflow if the inner product is small, and overflow if the inner product is large. Scientific computing libraries usually contain special functions for computing `logsumexp`, but with some thought, you should be able to see how to create an implementation that is numerically stable.

1146 the sum, we have the (additive inverse of the) **logistic loss**,

$$\ell_{\text{LOGREG}}(\boldsymbol{\theta}; \mathbf{x}^{(i)}, y^{(i)}) = -\boldsymbol{\theta} \cdot \mathbf{f}(\mathbf{x}^{(i)}, y^{(i)}) + \log \sum_{y' \in \mathcal{Y}} \exp(\boldsymbol{\theta} \cdot \mathbf{f}(\mathbf{x}^{(i)}, y')) \quad [2.58]$$

1147 The logistic loss is shown in Figure 2.2. A key difference from the zero-one and hinge
 1148 losses is that logistic loss is never zero. This means that the objective function can always
 1149 be improved by assigning higher confidence to the correct label.

1150 2.4.1 Regularization

1151 As with the support vector machine, better generalization can be obtained by penalizing
 1152 the norm of $\boldsymbol{\theta}$. This is done by adding a term of $\frac{\lambda}{2} \|\boldsymbol{\theta}\|_2^2$ to the minimization objective.
 1153 This is called L_2 regularization, because $\|\boldsymbol{\theta}\|_2^2$ is the squared L_2 norm of the vector $\boldsymbol{\theta}$.
 1154 Regularization forces the estimator to trade off performance on the training data against
 1155 the norm of the weights, and this can help to prevent overfitting. Consider what would
 1156 happen to the unregularized weight for a base feature j that is active in only one instance
 1157 $\mathbf{x}^{(i)}$: the conditional log-likelihood could always be improved by increasing the weight
 1158 for this feature, so that $\boldsymbol{\theta}_{(j,y^{(i)})} \rightarrow \infty$ and $\boldsymbol{\theta}_{(j,\tilde{y} \neq y^{(i)})} \rightarrow -\infty$, where (j, y) is the index of
 1159 feature associated with $x_j^{(i)}$ and label y in $\mathbf{f}(\mathbf{x}^{(i)}, y)$.

In § 2.1.4, we saw that smoothing the probabilities of a Naïve Bayes classifier can be justified in a hierarchical probabilistic model, in which the parameters of the classifier are themselves random variables, drawn from a prior distribution. The same justification applies to L_2 regularization. In this case, the prior is a zero-mean Gaussian on each term of $\boldsymbol{\theta}$. The log-likelihood under a zero-mean Gaussian is,

$$\log N(\theta_j; 0, \sigma^2) \propto -\frac{1}{2\sigma^2} \theta_j^2, \quad [2.59]$$

1160 so that the regularization weight λ is equal to the inverse variance of the prior, $\lambda = \frac{1}{\sigma^2}$.

1161 **2.4.2 Gradients**

Logistic loss is minimized by optimization along the gradient. Here is the gradient with respect to the logistic loss on a single example,

$$\ell_{\text{LOGREG}} = -\boldsymbol{\theta} \cdot \mathbf{f}(\mathbf{x}^{(i)}, y^{(i)}) + \log \sum_{y' \in \mathcal{Y}} \exp(\boldsymbol{\theta} \cdot \mathbf{f}(\mathbf{x}^{(i)}, y')) \quad [2.60]$$

$$\frac{\partial \ell}{\partial \boldsymbol{\theta}} = -\mathbf{f}(\mathbf{x}^{(i)}, y^{(i)}) + \frac{1}{\sum_{y'' \in \mathcal{Y}} \exp(\boldsymbol{\theta} \cdot \mathbf{f}(\mathbf{x}^{(i)}, y''))} \times \sum_{y' \in \mathcal{Y}} \exp(\boldsymbol{\theta} \cdot \mathbf{f}(\mathbf{x}^{(i)}, y')) \times \mathbf{f}(\mathbf{x}^{(i)}, y') \quad [2.61]$$

$$= -\mathbf{f}(\mathbf{x}^{(i)}, y^{(i)}) + \sum_{y' \in \mathcal{Y}} \frac{\exp(\boldsymbol{\theta} \cdot \mathbf{f}(\mathbf{x}^{(i)}, y'))}{\sum_{y'' \in \mathcal{Y}} \exp(\boldsymbol{\theta} \cdot \mathbf{f}(\mathbf{x}^{(i)}, y''))} \times \mathbf{f}(\mathbf{x}^{(i)}, y') \quad [2.62]$$

$$= -\mathbf{f}(\mathbf{x}^{(i)}, y^{(i)}) + \sum_{y' \in \mathcal{Y}} p(y' | \mathbf{x}^{(i)}; \boldsymbol{\theta}) \times \mathbf{f}(\mathbf{x}^{(i)}, y') \quad [2.63]$$

$$= -\mathbf{f}(\mathbf{x}^{(i)}, y^{(i)}) + E_{Y|X}[\mathbf{f}(\mathbf{x}^{(i)}, y)]. \quad [2.64]$$

1162 The final step employs the definition of a conditional expectation (§ A.5). The gradient of
 1163 the logistic loss is equal to the difference between the expected counts under the current
 1164 model, $E_{Y|X}[\mathbf{f}(\mathbf{x}^{(i)}, y)]$, and the observed feature counts $\mathbf{f}(\mathbf{x}^{(i)}, y^{(i)})$. When these two
 1165 vectors are equal for a single instance, there is nothing more to learn from it; when they
 1166 are equal in sum over the entire dataset, there is nothing more to learn from the dataset as
 1167 a whole. The gradient of the hinge loss is nearly identical, but it involves the features of
 1168 the predicted label under the current model, $\mathbf{f}(\mathbf{x}^{(i)}, \hat{y})$, rather than the expected features
 1169 $E_{Y|X}[\mathbf{f}(\mathbf{x}^{(i)}, y)]$ under the conditional distribution $p(y | \mathbf{x}; \boldsymbol{\theta})$.

The regularizer contributes $\lambda \boldsymbol{\theta}$ to the overall gradient:

$$L_{\text{LOGREG}} = \frac{\lambda}{2} \|\boldsymbol{\theta}\|_2^2 - \sum_{i=1}^N \left(\boldsymbol{\theta} \cdot \mathbf{f}(\mathbf{x}^{(i)}, y^{(i)}) - \log \sum_{y' \in \mathcal{Y}} \exp \boldsymbol{\theta} \cdot \mathbf{f}(\mathbf{x}^{(i)}, y') \right) \quad [2.65]$$

$$\nabla_{\boldsymbol{\theta}} L_{\text{LOGREG}} = \lambda \boldsymbol{\theta} - \sum_{i=1}^N \left(\mathbf{f}(\mathbf{x}^{(i)}, y^{(i)}) - E_{y|\mathbf{x}}[\mathbf{f}(\mathbf{x}^{(i)}, y)] \right). \quad [2.66]$$

1170 **2.5 Optimization**

1171 Each of the classification algorithms in this chapter can be viewed as an optimization
 1172 problem:

- 1173 • In Naïve Bayes, the objective is the joint likelihood $\log p(\mathbf{x}^{(1:N)}, \mathbf{y}^{(1:N)})$. Maximum
 1174 likelihood estimation yields a closed-form solution for $\boldsymbol{\theta}$.

- 1175 • In the support vector machine, the objective is the regularized margin loss,

$$L_{\text{SVM}} = \frac{\lambda}{2} \|\boldsymbol{\theta}\|_2^2 + \sum_{i=1}^N (\max_{y \in \mathcal{Y}} (\boldsymbol{\theta} \cdot \mathbf{f}(\mathbf{x}^{(i)}, y) + c(y^{(i)}, y)) - \boldsymbol{\theta} \cdot \mathbf{f}(\mathbf{x}^{(i)}, y^{(i)}))_+, \quad [2.67]$$

1176 There is no closed-form solution, but the objective is convex. The perceptron algo-
1177 rithm minimizes a similar objective.

- 1178 • In logistic regression, the objective is the regularized negative log-likelihood,

$$L_{\text{LOGREG}} = \frac{\lambda}{2} \|\boldsymbol{\theta}\|_2^2 - \sum_{i=1}^N \left(\boldsymbol{\theta} \cdot \mathbf{f}(\mathbf{x}^{(i)}, y^{(i)}) - \log \sum_{y \in \mathcal{Y}} \exp(\boldsymbol{\theta} \cdot \mathbf{f}(\mathbf{x}^{(i)}, y)) \right) \quad [2.68]$$

1179 Again, there is no closed-form solution, but the objective is convex.

1180 These learning algorithms are distinguished by *what* is being optimized, rather than
1181 *how* the optimal weights are found. This decomposition is an essential feature of con-
1182 temporary machine learning. The domain expert's job is to design an objective function
1183 — or more generally, a **model** of the problem. If the model has certain characteristics,
1184 then generic optimization algorithms can be used to find the solution. In particular, if an
1185 objective function is differentiable, then gradient-based optimization can be employed;
1186 if it is also convex, then gradient-based optimization is guaranteed to find the globally
1187 optimal solution. The support vector machine and logistic regression have both of these
1188 properties, and so are amenable to generic **convex optimization** techniques (Boyd and
1189 Vandenberghe, 2004).

1190 **2.5.1 Batch optimization**

In **batch optimization**, each update to the weights is based on a computation involving the entire dataset. One such algorithm is **gradient descent**, which iteratively updates the weights,

$$\boldsymbol{\theta}^{(t+1)} \leftarrow \boldsymbol{\theta}^{(t)} - \eta^{(t)} \nabla_{\boldsymbol{\theta}} L, \quad [2.69]$$

1191 where $\nabla_{\boldsymbol{\theta}} L$ is the gradient computed over the entire training set, and $\eta^{(t)}$ is the **step size**
1192 at iteration t . If the objective L is a convex function of $\boldsymbol{\theta}$, then this procedure is guaranteed
1193 to terminate at the global optimum, for appropriate schedule of learning rates, $\eta^{(t)}$.¹⁶

¹⁶Specifically, the learning rate must have the following properties (Bottou et al., 2016):

$$\sum_{t=1}^{\infty} \eta^{(t)} = \infty \quad [2.70]$$

$$\sum_{t=1}^{\infty} (\eta^{(t)})^2 < \infty. \quad [2.71]$$

1194 In practice, gradient descent can be slow to converge, as the gradient can become
 1195 infinitesimally small. Faster convergence can be obtained by second-order Newton opti-
 1196 mization, which incorporates the inverse of the **Hessian matrix**,

$$H_{i,j} = \frac{\partial^2 L}{\partial \theta_i \partial \theta_j} \quad [2.72]$$

1197 The size of the Hessian matrix is quadratic in the number of features. In the bag-of-words
 1198 representation, this is usually too big to store, let alone invert. **Quasi-Network optimiza-**
 1199 **tion** techniques maintain a low-rank approximation to the inverse of the Hessian matrix.
 1200 Such techniques usually converge more quickly than gradient descent, while remaining
 1201 computationally tractable even for large feature sets. A popular quasi-Newton algorithm
 1202 is **L-BFGS** (Liu and Nocedal, 1989), which is implemented in many scientific computing
 1203 environments, such as `scipy` and `Matlab`.

1204 For any gradient-based technique, the user must set the learning rates $\eta^{(t)}$. While con-
 1205 vergence proofs usually employ a decreasing learning rate, in practice, it is common to fix
 1206 $\eta^{(t)}$ to a small constant, like 10^{-3} . The specific constant can be chosen by experimentation,
 1207 although there is research on determining the learning rate automatically (Schaul et al.,
 1208 2013; Wu et al., 2018).

1209 2.5.2 Online optimization

1210 Batch optimization computes the objective on the entire training set before making an up-
 1211 date. This may be inefficient, because at early stages of training, a small number of train-
 1212 ing examples could point the learner in the correct direction. **Online learning** algorithms
 1213 make updates to the weights while iterating through the training data. The theoretical
 1214 basis for this approach is a stochastic approximation to the true objective function,

$$\sum_{i=1}^N \ell(\boldsymbol{\theta}; \mathbf{x}^{(i)}, y^{(i)}) \approx N \times \ell(\boldsymbol{\theta}; \mathbf{x}^{(j)}, y^{(j)}), \quad (\mathbf{x}^{(j)}, y^{(j)}) \sim \{(\mathbf{x}^{(i)}, y^{(i)})\}_{i=1}^N, \quad [2.73]$$

1215 where the instance $(\mathbf{x}^{(j)}, y^{(j)})$ is sampled at random from the full dataset.

1216 In **stochastic gradient descent**, the approximate gradient is computed by randomly
 1217 sampling a single instance, and an update is made immediately. This is similar to the
 1218 perceptron algorithm, which also updates the weights one instance at a time. In **mini-**
 1219 **batch** stochastic gradient descent, the gradient is computed over a small set of instances.
 1220 A typical approach is to set the minibatch size so that the entire batch fits in memory on a
 1221 graphics processing unit (GPU; Neubig et al., 2017). It is then possible to speed up learn-
 1222 ing by parallelizing the computation of the gradient over each instance in the minibatch.

These properties can be obtained by the learning rate schedule $\eta^{(t)} = \eta^{(0)} t^{-\alpha}$ for $\alpha \in [1, 2]$.

Algorithm 5 Generalized gradient descent. The function BATCHER partitions the training set into B batches such that each instance appears in exactly one batch. In gradient descent, $B = 1$; in stochastic gradient descent, $B = N$; in minibatch stochastic gradient descent, $1 < B < N$.

```

1: procedure GRADIENT-DESCENT( $\mathbf{x}^{(1:N)}, \mathbf{y}^{(1:N)}, L, \eta^{(1:\infty)}$ , BATCHER,  $T_{\max}$ )
2:    $\boldsymbol{\theta} \leftarrow \mathbf{0}$ 
3:    $t \leftarrow 0$ 
4:   repeat
5:      $(\mathbf{b}^{(1)}, \mathbf{b}^{(2)}, \dots, \mathbf{b}^{(B)}) \leftarrow \text{BATCHER}(N)$ 
6:     for  $n \in \{1, 2, \dots, B\}$  do
7:        $t \leftarrow t + 1$ 
8:        $\boldsymbol{\theta}^{(t)} \leftarrow \boldsymbol{\theta}^{(t-1)} - \eta^{(t)} \nabla_{\boldsymbol{\theta}} L(\boldsymbol{\theta}^{(t-1)}; \mathbf{x}^{(b_1^{(n)}, b_2^{(n)}, \dots)}, \mathbf{y}^{(b_1^{(n)}, b_2^{(n)}, \dots)})$ 
9:       if Converged( $\boldsymbol{\theta}^{(1, 2, \dots, t)}$ ) then
10:        return  $\boldsymbol{\theta}^{(t)}$ 
11:   until  $t \geq T_{\max}$ 
12:   return  $\boldsymbol{\theta}^{(t)}$ 

```

1223 Algorithm 5 offers a generalized view of gradient descent. In standard gradient de-
 1224 scent, the batcher returns a single batch with all the instances. In stochastic gradient de-
 1225 scent, it returns N batches with one instance each. In mini-batch settings, the batcher
 1226 returns B minibatches, $1 < B < N$.

There are many other techniques for online learning, and the field is currently quite active (Bottou et al., 2016). Some algorithms use an adaptive step size, which can be different for every feature (Duchi et al., 2011). Features that occur frequently are likely to be updated frequently, so it is best to use a small step size; rare features will be updated infrequently, so it is better to take larger steps. The **AdaGrad** (adaptive gradient) algorithm achieves this behavior by storing the sum of the squares of the gradients for each feature, and rescaling the learning rate by its inverse:

$$\mathbf{g}_t = \nabla_{\boldsymbol{\theta}} L(\boldsymbol{\theta}^{(t)}; \mathbf{x}^{(i)}, y^{(i)}) \quad [2.74]$$

$$\theta_j^{(t+1)} \leftarrow \theta_j^{(t)} - \frac{\eta^{(t)}}{\sqrt{\sum_{t'=1}^t g_{t,j}^2}} g_{t,j}, \quad [2.75]$$

1227 where j iterates over features in $\mathbf{f}(\mathbf{x}, y)$.

1228 In most cases, the number of active features for any instance is much smaller than the
 1229 number of weights. If so, the computation cost of online optimization will be dominated
 1230 by the update from the regularization term, $\lambda \boldsymbol{\theta}$. The solution is to be “lazy”, updating
 1231 each θ_j only as it is used. To implement lazy updating, store an additional parameter τ_j ,
 1232 which is the iteration at which θ_j was last updated. If θ_j is needed at time t , the $t - \tau$

1233 regularization updates can be performed all at once. This strategy is described in detail
 1234 by Kummerfeld et al. (2015).

1235 2.6 *Additional topics in classification

1236 Throughout this text, advanced topics will be marked with an asterisk.

1237 2.6.1 Feature selection by regularization

1238 In logistic regression and large-margin classification, generalization can be improved by
 1239 regularizing the weights towards 0, using the L_2 norm. But rather than encouraging
 1240 weights to be small, it might be better for the model to be **sparse**: it should assign weights
 1241 of exactly zero to most features, and only assign non-zero weights to features that are
 1242 clearly necessary. This idea can be formalized by the L_0 norm, $L_0 = \|\theta\|_0 = \sum_j \delta(\theta_j \neq 0)$,
 1243 which applies a constant penalty for each non-zero weight. This norm can be thought
 1244 of as a form of **feature selection**: optimizing the L_0 -regularized conditional likelihood is
 1245 equivalent to trading off the log-likelihood against the number of active features. Reduc-
 1246 ing the number of active features is desirable because the resulting model will be fast,
 1247 low-memory, and should generalize well, since irrelevant features will be pruned away.
 1248 Unfortunately, the L_0 norm is non-convex and non-differentiable. Optimization under L_0
 1249 regularization is **NP-hard**, meaning that it can be solved efficiently only if P=NP (Ge et al.,
 1250 2011).

1251 A useful alternative is the L_1 norm, which is equal to the sum of the absolute values
 1252 of the weights, $\|\theta\|_1 = \sum_j |\theta_j|$. The L_1 norm is convex, and can be used as an approxima-
 1253 tion to L_0 (Tibshirani, 1996). Conveniently, the L_1 norm also performs feature selection,
 1254 by driving many of the coefficients to zero; it is therefore known as a **sparsity inducing**
 1255 **regularizer**. The L_1 norm does not have a gradient at $\theta_j = 0$, so we must instead optimize
 1256 the L_1 -regularized objective using **subgradient** methods. The associated stochastic sub-
 1257 gradient descent algorithms are only somewhat more complex than conventional SGD;
 1258 Sra et al. (2012) survey approaches for estimation under L_1 and other regularizers.

1259 Gao et al. (2007) compare L_1 and L_2 regularization on a suite of NLP problems, finding
 1260 that L_1 regularization generally gives similar accuracy to L_2 regularization, but that L_1
 1261 regularization produces models that are between ten and fifty times smaller, because more
 1262 than 90% of the feature weights are set to zero.

1263 2.6.2 Other views of logistic regression

In binary classification, we can dispense with the feature function, and choose y based on
 the inner product of $\theta \cdot x$. The conditional probability $p_{Y|X}$ is obtained by passing this

inner product through a **logistic function**,

$$\sigma(a) \triangleq \frac{\exp(a)}{1 + \exp(a)} = (1 + \exp(-a))^{-1} \quad [2.76]$$

$$p(y | \mathbf{x}; \boldsymbol{\theta}) = \sigma(\boldsymbol{\theta} \cdot \mathbf{x}). \quad [2.77]$$

1264 This is the origin of the name **logistic regression**. Logistic regression can be viewed as
 1265 part of a larger family of **generalized linear models** (GLMs), in which various other “link
 1266 functions” convert between the inner product $\boldsymbol{\theta} \cdot \mathbf{x}$ and the parameter of a conditional
 1267 probability distribution.

1268 In the early NLP literature, logistic regression is frequently called **maximum entropy**
 1269 classification (Berger et al., 1996). This name refers to an alternative formulation, in
 1270 which the goal is to find the maximum entropy probability function that satisfies **moment-**
 1271 **matching** constraints. These constraints specify that the empirical counts of each feature
 1272 should match the expected counts under the induced probability distribution $p_{Y|X;\boldsymbol{\theta}}$.

$$\sum_{i=1}^N f_j(\mathbf{x}^{(i)}, y^{(i)}) = \sum_{i=1}^N \sum_{y \in \mathcal{Y}} p(y | \mathbf{x}^{(i)}; \boldsymbol{\theta}) f_j(\mathbf{x}^{(i)}, y), \quad \forall j \quad [2.78]$$

1273 The moment-matching constraint is satisfied exactly when the derivative of the condi-
 1274 tional log-likelihood function (Equation 2.64) is equal to zero. However, the constraint
 1275 can be met by many values of $\boldsymbol{\theta}$, so which should we choose?

1276 The **entropy** of the conditional probability distribution $p_{Y|X}$ is,

$$H(p_{Y|X}) = - \sum_{\mathbf{x} \in \mathcal{X}} p_X(\mathbf{x}) \sum_{y \in \mathcal{Y}} p_{Y|X}(y | \mathbf{x}) \log p_{Y|X}(y | \mathbf{x}), \quad [2.79]$$

1277 where \mathcal{X} is the set of all possible feature vectors, and $p_X(\mathbf{x})$ is the probability of observing
 1278 the base features \mathbf{x} . The distribution p_X is unknown, but it can be estimated by summing
 1279 over all the instances in the training set,

$$\tilde{H}(p_{Y|X}) = - \frac{1}{N} \sum_{i=1}^N \sum_{y \in \mathcal{Y}} p_{Y|X}(y | \mathbf{x}^{(i)}) \log p_{Y|X}(y | \mathbf{x}^{(i)}). \quad [2.80]$$

1280 If the entropy is large, the likelihood function is smooth across possible values of y ;
 1281 if it is small, the likelihood function is sharply peaked at some preferred value; in the
 1282 limiting case, the entropy is zero if $p(y | x) = 1$ for some y . The maximum-entropy cri-
 1283 terion chooses to make the weakest commitments possible, while satisfying the moment-
 1284 matching constraints from Equation 2.78. The solution to this constrained optimization
 1285 problem is identical to the maximum conditional likelihood (logistic-loss) formulation
 1286 that was presented in § 2.4.

1287 2.7 Summary of learning algorithms

1288 It is natural to ask which learning algorithm is best, but the answer depends on what
 1289 characteristics are important to the problem you are trying to solve.

1290 **Naïve Bayes** *Pros:* easy to implement; estimation is fast, requiring only a single pass over
 1291 the data; assigns probabilities to predicted labels; controls overfitting with smoothing
 1292 parameter. *Cons:* often has poor accuracy, especially with correlated features.

1293 **Perceptron** *Pros:* easy to implement; online; error-driven learning means that accuracy
 1294 is typically high, especially after averaging. *Cons:* not probabilistic; hard to know
 1295 when to stop learning; lack of margin can lead to overfitting.

1296 **Support vector machine** *Pros:* optimizes an error-based metric, usually resulting in high
 1297 accuracy; overfitting is controlled by a regularization parameter. *Cons:* not proba-
 1298 bilistic.

1299 **Logistic regression** *Pros:* error-driven and probabilistic; overfitting is controlled by a reg-
 1300 ularization parameter. *Cons:* batch learning requires black-box optimization; logistic
 1301 loss can “overtrain” on correctly labeled examples.

1302 One of the main distinctions is whether the learning algorithm offers a probability
 1303 over labels. This is useful in modular architectures, where the output of one classifier
 1304 is the input for some other system. In cases where probability is not necessary, the sup-
 1305 port vector machine is usually the right choice, since it is no more difficult to implement
 1306 than the perceptron, and is often more accurate. When probability is necessary, logistic
 1307 regression is usually more accurate than Naïve Bayes.

1308 Additional resources

1309 For more on classification, you can consult a textbook on machine learning (e.g., Mur-
 1310 phy, 2012), although the notation will differ slightly from what is typical in natural lan-
 1311 guage processing. Probabilistic methods are surveyed by Hastie et al. (2009), and Mohri
 1312 et al. (2012) emphasize theoretical considerations. Online learning is a rapidly moving
 1313 subfield of machine learning, and Bottou et al. (2016) describes progress through 2016.
 1314 Kummerfeld et al. (2015) empirically review several optimization algorithms for large-
 1315 margin learning. The python toolkit `scikit-learn` includes implementations of all of
 1316 the algorithms described in this chapter (Pedregosa et al., 2011).

1317 **Exercises**

- 1318 1. Let \mathbf{x} be a bag-of-words vector such that $\sum_{j=1}^V x_j = 1$. Verify that the multinomial
 1319 probability $p_{\text{mult}}(\mathbf{x}; \phi)$, as defined in Equation 2.12, is identical to the probability of
 1320 the same document under a categorical distribution, $p_{\text{cat}}(\mathbf{w}; \phi)$.
- 1321 2. Derive the maximum-likelihood estimate for the parameter μ in Naïve Bayes.
- 1322 3. As noted in the discussion of averaged perceptron in § 2.2.2, the computation of the
 1323 running sum $\mathbf{m} \leftarrow \mathbf{m} + \boldsymbol{\theta}$ is unnecessarily expensive, requiring $K \times V$ operations.
 1324 Give an alternative way to compute the averaged weights $\bar{\boldsymbol{\theta}}$, with complexity that is
 1325 independent of V and linear in the sum of feature sizes $\sum_{i=1}^N |\mathbf{f}(\mathbf{x}^{(i)}, y^{(i)})|$.
- 1326 4. Consider a dataset that is comprised of two identical instances $\mathbf{x}^{(1)} = \mathbf{x}^{(2)}$ with
 1327 distinct labels $y^{(1)} \neq y^{(2)}$. Assume all features are binary $x_j \in \{0, 1\}$ for all j .

1328 Now suppose that the averaged perceptron always chooses $i = 1$ when t is even,
 1329 and $i = 2$ when t is odd, and that it will terminate under the following condition:

$$\epsilon \geq \max_j \left| \frac{1}{t} \sum_t \theta_j^{(t)} - \frac{1}{t-1} \sum_t \theta_j^{(t-1)} \right|. \quad [2.81]$$

1330 In words, the algorithm stops when the largest change in the averaged weights is
 1331 less than or equal to ϵ . Compute the number of iterations before the averaged per-
 1332 ceptron terminates.

- 1333 5. Suppose you have two labeled datasets D_1 and D_2 , with the same features and la-
 1334 bels.
- 1335 • Let $\boldsymbol{\theta}^{(1)}$ be the unregularized logistic regression (LR) coefficients from training
 1336 on dataset D_1 .
 - 1337 • Let $\boldsymbol{\theta}^{(2)}$ be the unregularized LR coefficients (same model) from training on
 1338 dataset D_2 .
 - 1339 • Let $\boldsymbol{\theta}^*$ be the unregularized LR coefficients from training on the combined
 1340 dataset $D_1 \cup D_2$.

Under these conditions, prove that for any feature j ,

$$\begin{aligned} \theta_j^* &\geq \min(\theta_j^{(1)}, \theta_j^{(2)}) \\ \theta_j^* &\leq \max(\theta_j^{(1)}, \theta_j^{(2)}). \end{aligned}$$

1341

1342

Chapter 3

1343

Nonlinear classification

1344 Linear classification may seem like all we need for natural language processing. The bag-
1345 of-words representation is inherently high dimensional, and the number of features is
1346 often larger than the number of training instances. This means that it is usually possible
1347 to find a linear classifier that perfectly fits the training data. Moving to nonlinear classifi-
1348 cation may therefore only increase the risk of overfitting. For many tasks, **lexical features**
1349 (words) are meaningful in isolation, and can offer independent evidence about the in-
1350 stance label — unlike computer vision, where individual pixels are rarely informative,
1351 and must be evaluated holistically to make sense of an image. For these reasons, natu-
1352 ral language processing has historically focused on linear classification to a greater extent
1353 than other machine learning application domains.

1354 But in recent years, nonlinear classifiers have swept through natural language pro-
1355 cessing, and are now the default approach for many tasks (Manning, 2016). There are at
1356 least three reasons for this change.

- 1357 • There have been rapid advances in **deep learning**, a family of nonlinear meth-
1358 ods that learn complex functions of the input through multiple layers of computa-
1359 tion (Goodfellow et al., 2016).
- 1360 • Deep learning facilitates the incorporation of **word embeddings**, which are dense
1361 vector representations of words. Word embeddings can be learned from large amounts
1362 of unlabeled data, and enable generalization to words that do not appear in the an-
1363notated training data (word embeddings are discussed in detail in chapter 14).
- 1364 • A third reason for the rise of deep nonlinear learning algorithms is hardware. Many
1365 deep learning models can be implemented efficiently on graphics processing units
1366 (GPUs), offering substantial performance improvements over CPU-based comput-
1367 ing.

1368 This chapter focuses on **neural networks**, which are the dominant approach for non-

1369 linear classification in natural language processing today.¹ Historically, a few other non-
 1370 linear learning methods have been applied to language data:

- 1371 • **Kernel methods** are generalizations of the **nearest-neighbor** classification rule, which
 1372 classifies each instance by the label of the most similar example in the training
 1373 set (Hastie et al., 2009). The application of the **kernel support vector machine** to
 1374 information extraction is described in chapter 17.
- 1375 • **Decision trees** classify instances by checking a set of conditions. Scaling decision
 1376 trees to bag-of-words inputs is difficult, but decision trees have been successful in
 1377 problems such as coreference resolution (chapter 15), where more compact feature
 1378 sets can be constructed (Soon et al., 2001).
- 1379 • **Boosting** and related **ensemble methods** work by combining the predictions of sev-
 1380 eral “weak” classifiers, each of which may consider only a small subset of features.
 1381 Boosting has been successfully applied to text classification (Schapire and Singer,
 1382 2000) and syntactic analysis (Abney et al., 1999), and remains one of the most suc-
 1383 cessful methods on machine learning competition sites such as Kaggle (Chen and
 1384 Guestrin, 2016).

1385 3.1 Feedforward neural networks

1386 Consider the problem of building a classifier for movie reviews. The goal is to predict
 1387 a label $y \in \{\text{GOOD}, \text{BAD}, \text{OKAY}\}$ from a representation of the text of each document, x .
 1388 But what makes a good movie? The story, acting, cinematography, soundtrack, and so
 1389 on. Now suppose the training set contains labels for each of these additional features,
 1390 $z = [z_1, z_2, \dots, z_{K_z}]^\top$. With such information, we could build a two-step classifier:

- 1391 1. **Use the text x to predict the features z .** Specifically, train a logistic regression clas-
 1392 sifier to compute $p(z_k | x)$, for each $k \in \{1, 2, \dots, K_z\}$.
- 1393 2. **Use the features z to predict the label y .** Again, train a logistic regression classifier
 1394 to compute $p(y | z)$. On test data, z is unknown, so we use the probabilities $p(z | x)$
 1395 from the first layer as the features.

1396 This setup is shown in Figure 3.1, which describes the proposed classifier in a **compu-
 1397 tation graph**: the text features x are connected to the middle layer z , which in turn is
 1398 connected to the label y .

1399 Since each $z_k \in \{0, 1\}$, we can treat $p(z_k | x)$ as a binary classification problem, using
 1400 binary logistic regression:

$$\Pr(z_k = 1 | x; \Theta^{(x \rightarrow z)}) = \sigma(\boldsymbol{\theta}_k^{(x \rightarrow z)} \cdot x) = (1 + \exp(-\boldsymbol{\theta}_k^{(x \rightarrow z)} \cdot x))^{-1}, \quad [3.1]$$

¹I will use “deep learning” and “neural networks” interchangeably.

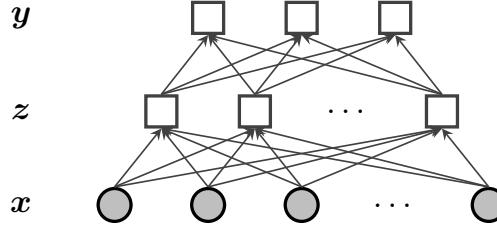


Figure 3.1: A feedforward neural network. Shaded circles indicate observed features, usually words; squares indicate nodes in the computation graph, which are computed from the information carried over the incoming arrows.

1401 where $\sigma(\cdot)$ is the **sigmoid** function (shown in Figure 3.2), and the matrix $\Theta^{(x \rightarrow z)} \in \mathbb{R}^{K_z \times V}$
 1402 is constructed by stacking the weight vectors for each z_k ,

$$\Theta^{(x \rightarrow z)} = [\theta_1^{(x \rightarrow z)}, \theta_2^{(x \rightarrow z)}, \dots, \theta_{K_z}^{(x \rightarrow z)}]^\top. \quad [3.2]$$

1403 We will assume that x contains a term with a constant value of 1, so that a corresponding
 1404 offset parameter is included in each $\theta_k^{(x \rightarrow z)}$.

1405 The output layer is computed by the multi-class logistic regression probability,

$$\Pr(y = j \mid z; \Theta^{(z \rightarrow y)}, b) = \frac{\exp(\theta_j^{(z \rightarrow y)} \cdot z + b_j)}{\sum_{j' \in \mathcal{Y}} \exp(\theta_{j'}^{(z \rightarrow y)} \cdot z + b_{j'})}, \quad [3.3]$$

1406 where b_j is an offset for label j , and the output weight matrix $\Theta^{(z \rightarrow y)} \in \mathbb{R}^{K_y \times K_z}$ is again
 1407 constructed by concatenation,

$$\Theta^{(z \rightarrow y)} = [\theta_1^{(z \rightarrow y)}, \theta_2^{(z \rightarrow y)}, \dots, \theta_{K_y}^{(z \rightarrow y)}]^\top. \quad [3.4]$$

1408 The vector of probabilities over each possible value of y is denoted,

$$p(y \mid z; \Theta^{(z \rightarrow y)}, b) = \text{SoftMax}(\Theta^{(z \rightarrow y)} z + b), \quad [3.5]$$

1409 where element j in the output of the **SoftMax** function is computed as in Equation 3.3.

We have now defined a multilayer classifier, which can be summarized as,

$$p(z \mid x; \Theta^{(x \rightarrow z)}) = \sigma(\Theta^{(x \rightarrow z)} x) \quad [3.6]$$

$$p(y \mid z; \Theta^{(z \rightarrow y)}, b) = \text{SoftMax}(\Theta^{(z \rightarrow y)} z + b), \quad [3.7]$$

1410 where $\sigma(\cdot)$ is now applied **elementwise** to the vector of inner products,

$$\sigma(\Theta^{(x \rightarrow z)} x) = [\sigma(\theta_1^{(x \rightarrow z)} \cdot x), \sigma(\theta_2^{(x \rightarrow z)} \cdot x), \dots, \sigma(\theta_{K_z}^{(x \rightarrow z)} \cdot x)]^\top. \quad [3.8]$$

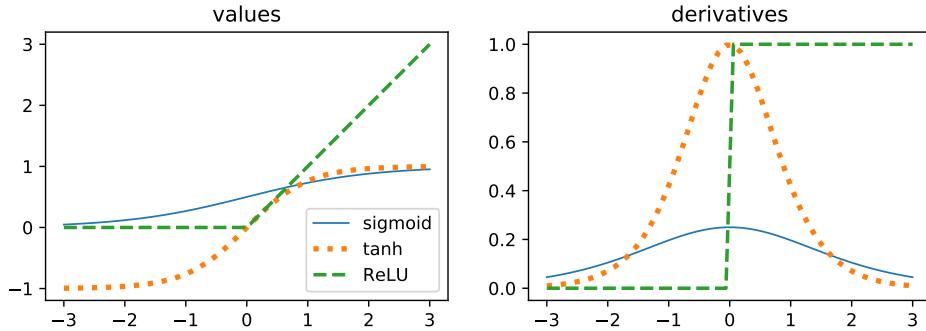


Figure 3.2: The sigmoid, tanh, and ReLU activation functions

Now suppose that the hidden features z are never observed, even in the training data. We can still construct the architecture in Figure 3.1. Instead of predicting y from a discrete vector of predicted values z , we use the probabilities $\sigma(\theta_k \cdot x)$. The resulting classifier is barely changed:

$$z = \sigma(\Theta^{(x \rightarrow z)} x) \quad [3.9]$$

$$p(y | x; \Theta^{(z \rightarrow y)}, b) = \text{SoftMax}(\Theta^{(z \rightarrow y)} z + b). \quad [3.10]$$

This defines a classification model that predicts the label $y \in \mathcal{Y}$ from the base features x , through a “hidden layer” z . This is a **feedforward neural network**.²

3.2 Designing neural networks

This feedforward neural network can be generalized in a number of ways.

3.2.1 Activation functions

If the hidden layer is viewed as a set of latent features, then the sigmoid function represents the extent to which each of these features is “activated” by a given input. However, the hidden layer can be regarded more generally as a nonlinear transformation of the input. This opens the door to many other activation functions, some of which are shown in Figure 3.2. At the moment, the choice of activation functions is more art than science, but a few points can be made about the most popular varieties:

- The range of the sigmoid function is $(0, 1)$. The bounded range ensures that a cascade of sigmoid functions will not “blow up” to a huge output, and this is impor-

²The architecture is sometimes called a **multilayer perceptron**, but this is misleading, because each layer is not a perceptron as defined in Algorithm 3.

tant for deep networks with several hidden layers. The derivative of the sigmoid is $\frac{\partial}{\partial a} \sigma(a) = \sigma(a)(1 - \sigma(a))$. This derivative becomes small at the extremes, which can make learning slow; this is called the **vanishing gradient** problem.

- The range of the **tanh activation function** is $(-1, 1)$: like the sigmoid, the range is bounded, but unlike the sigmoid, it includes negative values. The derivative is $\frac{\partial}{\partial a} \tanh(a) = 1 - \tanh(a)^2$, which is steeper than the logistic function near the origin (LeCun et al., 1998). The tanh function can also suffer from vanishing gradients at extreme values.
- The **rectified linear unit (ReLU)** is zero for negative inputs, and linear for positive inputs (Glorot et al., 2011),

$$\text{ReLU}(a) = \begin{cases} a, & a \geq 0 \\ 0, & \text{otherwise.} \end{cases} \quad [3.11]$$

The derivative is a step function, which is 1 if the input is positive, and zero otherwise. Once the activation is zero, the gradient is also zero. This can lead to the problem of **dead neurons**, where some ReLU nodes are zero for all inputs, throughout learning. A solution is the **leaky ReLU**, which has a small positive slope for negative inputs (Maas et al., 2013),

$$\text{Leaky-ReLU}(a) = \begin{cases} a, & a \geq 0 \\ .0001a, & \text{otherwise.} \end{cases} \quad [3.12]$$

Sigmoid and tanh are sometimes described as **squashing functions**, because they squash an unbounded input into a bounded range. Glorot and Bengio (2010) recommend against the use of the sigmoid activation in deep networks, because its mean value of $\frac{1}{2}$ can cause the next layer of the network to be saturated, with very small gradients on their own parameters. Several other activation functions are reviewed by Goodfellow et al. (2016), who recommend ReLU as the “default option.”

3.2.2 Network structure

Deep networks stack up several hidden layers, with each $\mathbf{z}^{(d)}$ acting as the input to the next layer, $\mathbf{z}^{(d+1)}$. As the total number of nodes in the network increases, so does its capacity to learn complex functions of the input. For a fixed number of nodes, an architectural decision is whether to emphasize width (large K_z at each layer) or depth (many layers). At present, this tradeoff is not well understood.³

³With even a single hidden layer, a neural network can approximate any continuous function on a closed and bounded subset of \mathbb{R}^N to an arbitrarily small non-zero error; see section 6.4.1 of Goodfellow et al. (2016) for a survey of these theoretical results. However, depending on the function to be approximated, the width

1451 It is also possible to “short circuit” a hidden layer, by propagating information directly
 1452 from the input to the next higher level of the network. This is the idea behind **residual net-**
 1453 **works**, which propagate information directly from the input to the subsequent layer (He
 1454 et al., 2016),

$$z = f(\Theta^{(x \rightarrow z)} \mathbf{x}) + \mathbf{x}, \quad [3.13]$$

where f is any nonlinearity, such as sigmoid or ReLU. A more complex architecture is the **highway network** (Srivastava et al., 2015; Kim et al., 2016), in which an addition **gate** controls an interpolation between $f(\Theta^{(x \rightarrow z)} \mathbf{x})$ and \mathbf{x} :

$$t = \sigma(\Theta^{(t)} \mathbf{x} + \mathbf{b}^{(t)}) \quad [3.14]$$

$$z = t \odot f(\Theta^{(x \rightarrow z)} \mathbf{x}) + (1 - t) \odot \mathbf{x}, \quad [3.15]$$

1455 where \odot refers to an elementwise vector product, and $\mathbf{1}$ is a column vector of ones. The
 1456 sigmoid function is applied elementwise to its input; recall that the output of this function
 1457 is restricted to the range $[0, 1]$. Gating is also used in the **long short-term memory (LSTM)**,
 1458 which is discussed in chapter 6. Residual and highway connections address a problem
 1459 with deep architectures: repeated application of a nonlinear activation function can make
 1460 it difficult to learn the parameters of the lower levels of the network, which are too distant
 1461 from the supervision signal.

1462 3.2.3 Outputs and loss functions

In the multi-class classification example, a softmax output produces probabilities over each possible label. This aligns with a negative **conditional log-likelihood**,

$$-\mathcal{L} = -\sum_{i=1}^N \log p(y^{(i)} | \mathbf{x}^{(i)}; \Theta). \quad [3.16]$$

1463 where $\Theta = \{\Theta^{(x \rightarrow z)}, \Theta^{(z \rightarrow y)}, \mathbf{b}\}$ is the entire set of parameters.

This loss can be written alternatively as follows:

$$\tilde{y}_j \triangleq \Pr(y = j | \mathbf{x}^{(i)}; \Theta) \quad [3.17]$$

$$-\mathcal{L} = -\sum_{i=1}^N e_{y^{(i)}} \cdot \log \tilde{y} \quad [3.18]$$

1464 where $e_{y^{(i)}}$ is a **one-hot vector** of zeros with a value of 1 at position $y^{(i)}$. The inner product
 1465 between $e_{y^{(i)}}$ and $\log \tilde{y}$ is also called the multinomial **cross-entropy**, and this terminology
 1466 is preferred in many neural networks papers and software packages.

of the hidden layer may need to be arbitrarily large. Furthermore, the fact that a network has the capacity to approximate any given function does not say anything about whether it is possible to *learn* the function using gradient-based optimization.

It is also possible to train neural networks from other objectives, such as a margin loss. In this case, it is not necessary to use softmax at the output layer: an affine transformation of the hidden layer is enough:

$$\Psi(y; \mathbf{x}^{(i)}, \Theta) = \theta_y^{(z \rightarrow y)} \cdot z + b_y \quad [3.19]$$

$$\ell_{\text{MARGIN}}(\Theta; \mathbf{x}^{(i)}, y^{(i)}) = \max_{y \neq y^{(i)}} \left(1 + \Psi(y; \mathbf{x}^{(i)}, \Theta) - \Psi(y^{(i)}; \mathbf{x}^{(i)}, \Theta) \right)_+ \quad [3.20]$$

- 1467 In regression problems, the output is a scalar or vector (see § 4.1.2). For these problems, a
1468 typical loss function is the squared error $(y - \hat{y})^2$ or squared norm $\|\mathbf{y} - \hat{\mathbf{y}}\|_2^2$.

1469 **3.2.4 Inputs and lookup layers**

1470 In text classification, the input layer \mathbf{x} can refer to a bag-of-words vector, where x_j is
1471 the count of word j . The input to the hidden unit z_k is then $\sum_{j=1}^V \theta_{j,k}^{(x \rightarrow z)} x_j$, and word j is
1472 represented by the vector $\theta_j^{(x \rightarrow z)}$. This vector is sometimes described as the **embedding** of
1473 word j , and can be learned from unlabeled data, using techniques discussed in chapter 14.
1474 The columns of $\Theta^{(x \rightarrow z)}$ are each K_z -dimensional word embeddings.

1475 Chapter 2 presented an alternative view of text documents, as a sequence of word
1476 tokens, w_1, w_2, \dots, w_M . In a neural network, each word token w_m is represented with
1477 a one-hot vector, $e_{w_m} \in \mathbb{R}^V$. The matrix-vector product $\Theta^{(x \rightarrow z)} e_{w_m}$ returns the embed-
1478 ding of word w_m . The complete document can be represented by horizontally concatenating
1479 these one-hot vectors, $\mathbf{W} = [e_{w_1}, e_{w_2}, \dots, e_{w_M}]$, and the bag-of-words representation can
1480 be recovered from the matrix-vector product $\mathbf{W} \mathbf{1}$, which simply sums each row over the
1481 tokens $m = \{1, 2, \dots, M\}$. The matrix product $\Theta^{(x \rightarrow z)} \mathbf{W}$ contains the horizontally con-
1482 catenated embeddings of each word in the document, which will be useful as the starting
1483 point for **convolutional neural networks** (see § 3.4). This is sometimes called a **lookup**
1484 **layer**, because the first step is to lookup the embeddings for each word in the input text.

1485 **3.3 Learning neural networks**

The feedforward network in Figure 3.1 can now be written in a more general form,

$$z \leftarrow f(\Theta^{(x \rightarrow z)} \mathbf{x}^{(i)}) \quad [3.21]$$

$$\tilde{\mathbf{y}} \leftarrow \text{SoftMax} \left(\Theta^{(z \rightarrow y)} z + b \right) \quad [3.22]$$

$$\ell^{(i)} \leftarrow -e_{y^{(i)}} \cdot \log \tilde{\mathbf{y}}, \quad [3.23]$$

- 1486 where f is an elementwise activation function, such as σ or ReLU.

Let us now consider how to estimate the parameters $\Theta^{(x \rightarrow z)}$, $\Theta^{(z \rightarrow y)}$ and \mathbf{b} , using online gradient-based optimization. The simplest such algorithm is stochastic gradient descent (Algorithm 5). The relevant updates are,

$$\mathbf{b} \leftarrow \mathbf{b} - \eta^{(t)} \nabla_{\mathbf{b}} \ell^{(i)} \quad [3.24]$$

$$\boldsymbol{\theta}_k^{(z \rightarrow y)} \leftarrow \boldsymbol{\theta}_k^{(z \rightarrow y)} - \eta^{(t)} \nabla_{\boldsymbol{\theta}_k^{(z \rightarrow y)}} \ell^{(i)} \quad [3.25]$$

$$\boldsymbol{\theta}_k^{(x \rightarrow z)} \leftarrow \boldsymbol{\theta}_k^{(x \rightarrow z)} - \eta^{(t)} \nabla_{\boldsymbol{\theta}_k^{(x \rightarrow z)}} \ell^{(i)}, \quad [3.26]$$

where $\eta^{(t)}$ is the learning rate on iteration t , $\ell^{(i)}$ is the loss at instance (or minibatch) i , and $\boldsymbol{\theta}_k^{(x \rightarrow z)}$ is column k of the matrix $\Theta^{(x \rightarrow z)}$, and $\boldsymbol{\theta}_k^{(z \rightarrow y)}$ is column k of $\Theta^{(z \rightarrow y)}$.

The gradients of the negative log-likelihood on \mathbf{b} and $\boldsymbol{\theta}_k^{(z \rightarrow y)}$ are very similar to the gradients in logistic regression,

$$\nabla_{\boldsymbol{\theta}_k^{(z \rightarrow y)}} \ell^{(i)} = \left[\frac{\partial \ell^{(i)}}{\partial \theta_{k,1}^{(z \rightarrow y)}}, \frac{\partial \ell^{(i)}}{\partial \theta_{k,2}^{(z \rightarrow y)}}, \dots, \frac{\partial \ell^{(i)}}{\partial \theta_{k,K_y}^{(z \rightarrow y)}} \right]^\top \quad [3.27]$$

$$\frac{\partial \ell^{(i)}}{\partial \theta_{k,j}^{(z \rightarrow y)}} = - \frac{\partial}{\partial \theta_{k,j}^{(z \rightarrow y)}} \left(\boldsymbol{\theta}_{y^{(i)}}^{(z \rightarrow y)} \cdot \mathbf{z} - \log \sum_{y \in \mathcal{Y}} \exp \boldsymbol{\theta}_y^{(z \rightarrow y)} \cdot \mathbf{z} \right) \quad [3.28]$$

$$= \left(\Pr(y = j \mid \mathbf{z}; \Theta^{(z \rightarrow y)}, \mathbf{b}) - \delta(j = y^{(i)}) \right) z_k, \quad [3.29]$$

where $\delta(j = y^{(i)})$ is a function that returns one when $j = y^{(i)}$, and zero otherwise. The gradient $\nabla_{\mathbf{b}} \ell^{(i)}$ is similar to Equation 3.29.

The gradients on the input layer weights $\Theta^{(x \rightarrow z)}$ can be obtained by applying the chain rule of differentiation:

$$\frac{\partial \ell^{(i)}}{\partial \theta_{n,k}^{(x \rightarrow z)}} = \frac{\partial \ell^{(i)}}{\partial z_k} \frac{\partial z_k}{\partial \theta_{n,k}^{(x \rightarrow z)}} \quad [3.30]$$

$$= \frac{\partial \ell^{(i)}}{\partial z_k} \frac{\partial f(\boldsymbol{\theta}_k^{(x \rightarrow z)} \cdot \mathbf{x})}{\partial \theta_{n,k}^{(x \rightarrow z)}} \quad [3.31]$$

$$= \frac{\partial \ell^{(i)}}{\partial z_k} \times f'(\boldsymbol{\theta}_k^{(x \rightarrow z)} \cdot \mathbf{x}) \times x_n, \quad [3.32]$$

where $f'(\boldsymbol{\theta}_k^{(x \rightarrow z)} \cdot \mathbf{x})$ is the derivative of the activation function f , applied at the input

$\theta_k^{(x \rightarrow z)} \cdot \mathbf{x}$. For example, if f is the sigmoid function, then the derivative is,

$$\frac{\partial \ell^{(i)}}{\partial \theta_{n,k}^{(x \rightarrow z)}} = \frac{\partial \ell^{(i)}}{\partial z_k} \times \sigma(\theta_k^{(x \rightarrow z)} \cdot \mathbf{x}) \times (1 - \sigma(\theta_k^{(x \rightarrow z)} \cdot \mathbf{x})) \times x_n \quad [3.33]$$

$$= \frac{\partial \ell^{(i)}}{\partial z_k} \times z_k \times (1 - z_k) \times x_n. \quad [3.34]$$

1491 For intuition, consider each of the terms in the product.

- 1492 • If the negative log-likelihood $\ell^{(i)}$ does not depend much on z_k , $\frac{\partial \ell^{(i)}}{\partial z_k} \rightarrow 0$, then it
1493 doesn't matter how z_k is computed, and so $\frac{\partial \ell^{(i)}}{\partial \theta_{n,k}^{(x \rightarrow z)}} \rightarrow 0$.
- 1494 • If z_k is near 1 or 0, then the curve of the sigmoid function (Figure 3.2) is nearly flat,
1495 and changing the inputs will make little local difference. The term $z_k \times (1 - z_k)$ is
1496 maximized at $z_k = \frac{1}{2}$, where the slope of the sigmoid function is steepest.
- 1497 • If $x_n = 0$, then it does not matter how we set the weights $\theta_{n,k}^{(x \rightarrow z)}$, so $\frac{\partial \ell^{(i)}}{\partial \theta_{n,k}^{(x \rightarrow z)}} = 0$.

1498 3.3.1 Backpropagation

1499 In the equations above, the value $\frac{\partial \ell^{(i)}}{\partial z_k}$ is reused in the derivatives with respect to each
1500 $\theta_{n,k}^{(x \rightarrow z)}$. It should therefore be computed once, and then cached. Furthermore, we should
1501 only compute any derivative once we have already computed all of the necessary "inputs"
1502 demanded by the chain rule of differentiation. This combination of sequencing, caching,
1503 and differentiation is known as **backpropagation**. It can be generalized to any directed
1504 acyclic **computation graph**.

1505 A computation graph is a declarative representation of a computational process. At
1506 each node t , compute a value v_t by applying a function f_t to a (possibly empty) list of
1507 parent nodes, π_t . For example, in a feedforward network with one hidden layer, there are
1508 nodes for the input $\mathbf{x}^{(i)}$, the hidden layer \mathbf{z} , the predicted output $\tilde{\mathbf{y}}$, and the parameters
1509 $\{\Theta^{(x \rightarrow z)}, \Theta^{(z \rightarrow y)}, \mathbf{b}\}$. During training, there is also a node for the observed label $y^{(i)}$ and
1510 the loss $\ell^{(i)}$. Computation graphs have three main types of nodes:

1511 **Variables.** The variables include the *inputs* \mathbf{x} , the *hidden nodes* \mathbf{z} , the outputs \mathbf{y} , and the
1512 loss function. Inputs are variables that do not have parents. Backpropagation com-
1513putes the gradients with respect to all variables except the inputs, but does not up-
1514date the variables during learning.

1515 **Parameters.** In a feedforward network, the parameters include the weights and offsets.
1516 Parameter nodes do not have parents, and they are updated during learning.

Algorithm 6 General backpropagation algorithm. In the computation graph G , every node contains a function f_t and a set of parent nodes π_t ; the inputs to the graph are $x^{(i)}$.

```

1: procedure BACKPROP( $G = \{f_t, \pi_t\}_{t=1}^T, x^{(i)}$ )
2:    $v_{t(n)} \leftarrow x_n^{(i)}$  for all  $n$  and associated computation nodes  $t(n)$ .
3:   for  $t \in \text{TOPLOGICALSORT}(G)$  do  $\triangleright$  Forward pass: compute value at each node
4:     if  $|\pi_t| > 0$  then
5:        $v_t \leftarrow f_t(v_{\pi_{t,1}}, v_{\pi_{t,2}}, \dots, v_{\pi_{t,N_t}})$ 
6:      $g_{\text{objective}} = 1$   $\triangleright$  Backward pass: compute gradients at each node
7:     for  $t \in \text{REVERSE}(\text{TOPLOGICALSORT}(G))$  do
8:        $g_t \leftarrow \sum_{t': t \in \pi_{t'}} g_{t'} \times \nabla_{v_t} v_{t'}$   $\triangleright$  Sum over all  $t'$  that are children of  $t$ , propagating
        the gradient  $g_{t'}$ , scaled by the local gradient  $\nabla_{v_t} v_{t'}$ 
9:   return  $\{g_1, g_2, \dots, g_T\}$ 

```

1517 **Objective.** The *objective* node is not the parent of any other node. Backpropagation begins
 1518 by computing the gradient with respect to this node.

1519 If the computation graph is a directed acyclic graph, then it is possible to order the
 1520 nodes with a topological sort, so that if node t is a parent of node t' , then $t < t'$. This
 1521 means that the values $\{v_t\}_{t=1}^T$ can be computed in a single forward pass. The topolog-
 1522 ical sort is reversed when computing gradients: each gradient g_t is computed from the
 1523 gradients of the children of t , implementing the chain rule of differentiation. The general
 1524 backpropagation algorithm for computation graphs is shown in Algorithm 6, and illus-
 1525 trated in Figure 3.3.

1526 While the gradients with respect to each parameter may be complex, they are com-
 1527 posed of products of simple parts. For many networks, all gradients can be computed
 1528 through **automatic differentiation**. This means that end users need only specify the feed-
 1529 forward computation, and the gradients necessary for learning can be obtained automati-
 1530 cally. There are many software libraries that perform automatic differentiation on compu-
 1531 tation graphs, such as Torch (Collobert et al., 2011), TensorFlow (Abadi et al., 2016), and
 1532 DyNet (Neubig et al., 2017). One important distinction between these libraries is whether
 1533 they support **dynamic computation graphs**, in which the structure of the computation
 1534 graph varies across instances. Static computation graphs are compiled in advance, and
 1535 can be applied to fixed-dimensional data, such as bag-of-words vectors. In many natu-
 1536 ral language processing problems, each input has a distinct structure, requiring a unique
 1537 computation graph.

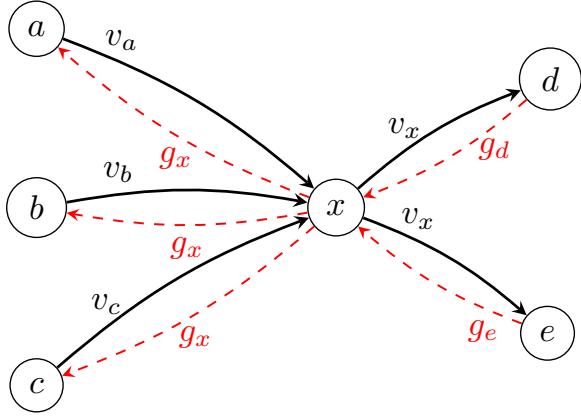


Figure 3.3: Backpropagation at a single node x in the computation graph. The values of the predecessors v_a, v_b, v_c are the inputs to x , which computes v_x , and passes it on to the successors d and e . The gradients at the successors g_d and g_e are passed back to x , where they are incorporated into the gradient g_x , which is then passed back to the predecessors a, b , and c .

1538 3.3.2 Regularization and dropout

1539 In linear classification, overfitting was addressed by augmenting the objective with a reg-
 1540 ularization term, $\lambda \|\theta\|_2^2$. This same approach can be applied to feedforward neural net-
 1541 works, penalizing each matrix of weights:

$$L = \sum_{i=1}^N \ell^{(i)} + \lambda_{z \rightarrow y} \|\Theta^{(z \rightarrow y)}\|_F^2 + \lambda_{x \rightarrow z} \|\Theta^{(x \rightarrow z)}\|_F^2, \quad [3.35]$$

1542 where $\|\Theta\|_F^2 = \sum_{i,j} \theta_{i,j}^2$ is the squared **Frobenius norm**, which generalizes the L_2 norm
 1543 to matrices. The bias parameters b are not regularized, as they do not contribute to the
 1544 sensitivity of the classifier to the inputs. In gradient-based optimization, the practical
 1545 effect of Frobenius norm regularization is that the weights “decay” towards zero at each
 1546 update, motivating the alternative name **weight decay**.

1547 Another approach to controlling model complexity is **dropout**, which involves ran-
 1548 domly setting some computation nodes to zero during training (Srivastava et al., 2014).
 1549 For example, in the feedforward network, on each training instance, with probability ρ we
 1550 set each input x_n and each hidden layer node z_k to zero. Srivastava et al. (2014) recom-
 1551 mend $\rho = 0.5$ for hidden units, and $\rho = 0.2$ for input units. Dropout is also incorpo-
 1552 rated in the gradient computation, so if node z_k is dropped, then none of the weights $\theta_k^{(x \rightarrow z)}$
 1553 will be updated for this instance. Dropout prevents the network from learning to depend too
 1554 much on any one feature or hidden node, and prevents **feature co-adaptation**, in which a

hidden unit is only useful in combination with one or more other hidden units. Dropout is a special case of **feature noising**, which can also involve adding Gaussian noise to inputs or hidden units (Holmstrom and Koistinen, 1992). Wager et al. (2013) show that dropout is approximately equivalent to “adaptive” L_2 regularization, with a separate regularization penalty for each feature.

3.3.3 *Learning theory

Chapter 2 emphasized the importance of **convexity** for learning: for convex objectives, the global optimum can be found efficiently. The negative log-likelihood and hinge loss are convex functions of the parameters of the output layer. However, the output of a feed-forward network is generally not a convex function of the parameters of the input layer, $\Theta^{(x \rightarrow z)}$. Feedforward networks can be viewed as function composition, where each layer is a function that is applied to the output of the previous layer. Convexity is generally not preserved in the composition of two convex functions — and furthermore, “squashing” activation functions like tanh and sigmoid are not convex.

The non-convexity of hidden layer neural networks can also be seen by permuting the elements of the hidden layer, from $z = [z_1, z_2, \dots, z_{K_z}]$ to $\tilde{z} = [z_{\pi(1)}, z_{\pi(2)}, \dots, z_{\pi(K_z)}]$. This corresponds to applying π to the rows of $\Theta^{(x \rightarrow z)}$ and the columns of $\Theta^{(z \rightarrow y)}$, resulting in permuted parameter matrices $\Theta_\pi^{(x \rightarrow z)}$ and $\Theta_\pi^{(z \rightarrow y)}$. As long as this permutation is applied consistently, the loss will be identical, $L(\Theta) = L(\Theta_\pi)$: it is *invariant* to this permutation. However, the loss of the linear combination $L(\alpha\Theta + (1 - \alpha)\Theta_\pi)$ will generally not be identical to the loss under Θ or its permutations. If $L(\Theta)$ is better than the loss at any points in the immediate vicinity, and if $L(\Theta) = L(\Theta_\pi)$, then the loss function does not satisfy the definition of convexity (see § 2.3). One of the exercises asks you to prove this more rigorously.

In practice, the existence of multiple optima is not necessarily problematic, if all such optima are permutations of the sort described in the previous paragraph. In contrast, “bad” local optima are better than their neighbors, but much worse than the global optimum. Fortunately, in large feedforward neural networks, most local optima are nearly as good as the global optimum (Choromanska et al., 2015), which helps to explain why back-propagation works in practice. More generally, a **critical point** is one at which the gradient is zero. Critical points may be local optima, but they may also be **saddle points**, which are local minima in some directions, but local *maxima* in other directions. For example, the equation $x_1^2 - x_2^2$ has a saddle point at $x = (0, 0)$.⁴ In large networks, the overwhelming majority of critical points are saddle points, rather than local minima or maxima (Dauphin et al., 2014). Saddle points can pose problems for gradient-based optimization, since learning will slow to a crawl as the gradient goes to zero. However, the noise introduced by

⁴Thanks to Rong Ge’s blogpost for this example, <http://www.offconvex.org/2016/03/22/saddlepoints/>

1591 stochastic gradient descent, and by feature noising techniques such as dropout, can help
 1592 online optimization to escape saddle points and find high-quality optima (Ge et al., 2015).
 1593 Other techniques address saddle points directly, using local reconstructions of the Hessian
 1594 matrix (Dauphin et al., 2014) or higher-order derivatives (Anandkumar and Ge, 2016).

1595 **3.3.4 Tricks**

1596 Getting neural networks to work effectively sometimes requires heuristic “tricks” (Bottou,
 1597 2012; Goodfellow et al., 2016; Goldberg, 2017b). This section presents some tricks that are
 1598 especially important.

Initialization Initialization is not especially important for linear classifiers, since convexity ensures that the global optimum can usually be found quickly. But for multilayer neural networks, it is helpful to have a good starting point. One reason is that if the magnitude of the initial weights is too large, a sigmoid or tanh nonlinearity will be saturated, leading to a small gradient, and slow learning. Large gradients are also problematic. Initialization can help avoid these problems, by ensuring that the variance over the initial gradients is constant and bounded throughout the network. For networks with tanh activation functions, this can be achieved by sampling the initial weights from the following uniform distribution (Glorot and Bengio, 2010),

$$\theta_{i,j} \sim U \left[-\frac{\sqrt{6}}{\sqrt{d_{\text{in}}(n) + d_{\text{out}}(n)}}, \frac{\sqrt{6}}{\sqrt{d_{\text{in}}(n) + d_{\text{out}}(n)}} \right], \quad [3.36]$$

[3.37]

1599 For the weights leading to a ReLU activation function, He et al. (2015) use similar argu-
 1600 mentation to justify sampling from a zero-mean Gaussian distribution,

$$\theta_{i,j} \sim N(0, \sqrt{2/d_{\text{in}}(n)}) \quad [3.38]$$

Rather than initializing the weights independently, it can be beneficial to initialize each layer jointly as an **orthonormal matrix**, ensuring that $\Theta^\top \Theta = \mathbb{I}$ (Saxe et al., 2014). Orthonormal matrices preserve the norm of the input, so that $\|\Theta x\| = \|x\|$, which prevents the gradients from exploding or vanishing. Orthogonality ensures that the hidden units are uncorrelated, so that they correspond to different features of the input. Orthonormal initialization can be performed by applying **singular value decomposition** to a matrix of

values sampled from a standard normal distribution:

$$a_{i,j} \sim N(0, 1) \quad [3.39]$$

$$\mathbf{A} = \{a_{i,j}\}_{i=1,j=1}^{d_{\text{in}}(j), d_{\text{out}}(j)} \quad [3.40]$$

$$\mathbf{U}, \mathbf{S}, \mathbf{V}^\top = \text{SVD}(\mathbf{A}) \quad [3.41]$$

$$\Theta^{(j)} \leftarrow \mathbf{U}. \quad [3.42]$$

1601 The matrix \mathbf{U} contains the **singular vectors** of \mathbf{A} , and is guaranteed to be orthonormal.
 1602 For more on singular value decomposition, see chapter 14.

1603 Even with careful initialization, there can still be significant variance in the final re-
 1604 sults. It can be useful to make multiple training runs, and select the one with the best
 1605 performance on a heldout development set.

1606 **Clipping and normalizing the gradients** As already discussed, the magnitude of the
 1607 gradient can pose problems for learning: too large, and learning can diverge, with suc-
 1608 ccessive updates thrashing between increasingly extreme values; too small, and learning can
 1609 grind to a halt. Several heuristics have been proposed to address this issue.

1610 • In **gradient clipping** (Pascanu et al., 2013), an upper limit is placed on the norm of
 1611 the gradient, and the gradient is rescaled when this limit is exceeded,

$$\text{CLIP}(\hat{\mathbf{g}}) = \begin{cases} \mathbf{g} & \|\hat{\mathbf{g}}\| < \tau \\ \frac{\tau}{\|\mathbf{g}\|} \mathbf{g} & \text{otherwise.} \end{cases} \quad [3.43]$$

1612 • In **batch normalization** (Ioffe and Szegedy, 2015), the inputs to each computation
 1613 node are recentered by their mean and variance across all of the instances in the
 minibatch \mathcal{B} (see § 2.5.2). For example, in a feedforward network with one hidden
 layer, batch normalization would transform the inputs to the hidden layer as follows:

$$\boldsymbol{\mu}^{(\mathcal{B})} = \frac{1}{|\mathcal{B}|} \sum_{i \in \mathcal{B}} \mathbf{x}^{(i)} \quad [3.44]$$

$$\mathbf{s}^{(\mathcal{B})} = \frac{1}{|\mathcal{B}|} \sum_{i \in \mathcal{B}} (\mathbf{x}^{(i)} - \boldsymbol{\mu}^{(\mathcal{B})})^2 \quad [3.45]$$

$$\bar{\mathbf{x}}^{(i)} = (\mathbf{x}^{(i)} - \boldsymbol{\mu}^{(\mathcal{B})}) / \sqrt{\mathbf{s}^{(\mathcal{B})}}. \quad [3.46]$$

1612 Empirically, this speeds convergence of deep architectures. One explanation is that
 1613 it helps to correct for changes in the distribution of activations during training.

- In **layer normalization** (Ba et al., 2016), the inputs to each nonlinear activation function are recentered across the layer:

$$\mathbf{a} = \Theta^{(x \rightarrow z)} \mathbf{x} \quad [3.47]$$

$$\mu = \frac{1}{K_z} \sum_{k=1}^{K_z} a_k \quad [3.48]$$

$$s = \frac{1}{K_z} \sum_{k=1}^{K_z} (a_k - \mu)^2 \quad [3.49]$$

$$z = (\mathbf{a} - \mu) / \sqrt{s}. \quad [3.50]$$

1614 Layer normalization has similar motivations to batch normalization, but it can be
 1615 applied across a wider range of architectures and training conditions.

Online optimization The trend towards deep learning has spawned a cottage industry of **online optimization** algorithms, which attempt to improve on stochastic gradient descent. **AdaGrad** was reviewed in § 2.5.2; its main innovation is to set adaptive learning rates for each parameter by storing the sum of squared gradients. Rather than using the sum over the entire training history, we can keep a running estimate,

$$v_j^{(t)} = \beta v_j^{(t-1)} + (1 - \beta) g_{t,j}^2, \quad [3.51]$$

1616 where $g_{t,j}$ is the gradient with respect to parameter j at time t , and $\beta \in [0, 1]$. This term
 1617 places more emphasis on recent gradients, and is employed in the **AdaDelta** (Zeiler, 2012)
 1618 and **Adam** (Kingma and Ba, 2014) optimizers. Online optimization and its theoretical
 1619 background are reviewed by Bottou et al. (2016). **Early stopping**, mentioned in § 2.2.2,
 1620 can help to avoid overfitting, by terminating training after reaching a plateau in the per-
 1621 formance on a heldout validation set.

1622 3.4 Convolutional neural networks

1623 A basic weakness of the bag-of-words model is its inability to account for the ways in
 1624 which words combine to create meaning, including even simple reversals such as *not*
 1625 *pleasant, hardly a generous offer*, and *I wouldn't mind missing the flight*. Similarly, computer
 1626 vision faces the challenge of identifying the semantics of images from pixel features that
 1627 are uninformative in isolation. An earlier generation of computer vision research fo-
 1628 cused on designing *filters* to aggregate local pixel-level features into more meaningful
 1629 representations, such as edges and corners (e.g., Canny, 1987). Similarly, earlier NLP re-
 1630 search attempted to capture multiword linguistic phenomena by hand-designed lexical
 1631 patterns (Hobbs et al., 1997). In both cases, the output of the filters and patterns could

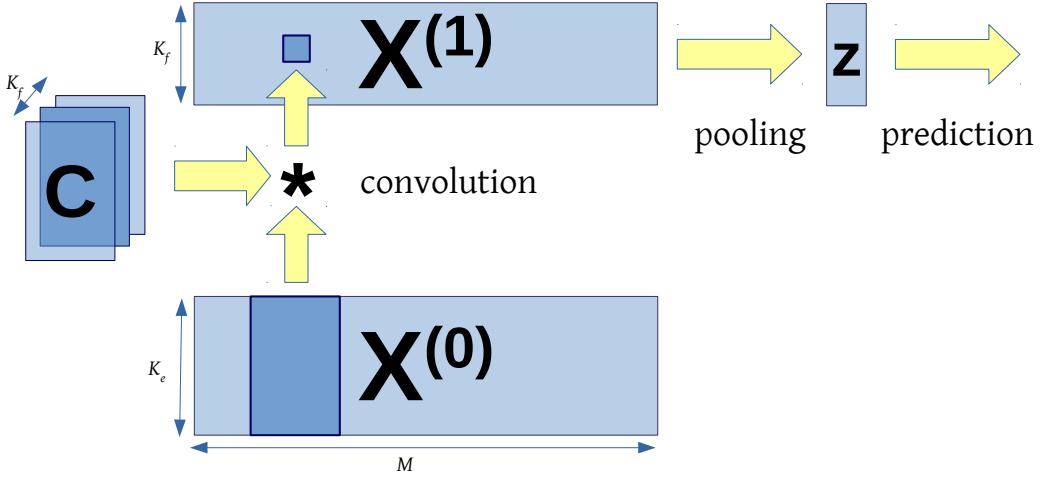


Figure 3.4: A convolutional neural network for text classification

then act as base features in a linear classifier. But rather than designing these feature extractors by hand, a better approach is to learn them, using the magic of backpropagation. This is the idea behind **convolutional neural networks**.

Following § 3.2.4, define the base layer of a neural network as,

$$\mathbf{X}^{(0)} = \Theta^{(x \rightarrow z)}[\mathbf{e}_{w_1}, \mathbf{e}_{w_2}, \dots, \mathbf{e}_{w_M}], \quad [3.52]$$

where \mathbf{e}_{w_m} is a column vector of zeros, with a 1 at position w_m . The base layer has dimension $\mathbf{X}^{(0)} \in \mathbb{R}^{K_e \times M}$, where K_e is the size of the word embeddings. To merge information across adjacent words, we *convolve* $\mathbf{X}^{(0)}$ with a set of filter matrices $\mathbf{C}^{(k)} \in \mathbb{R}^{K_e \times h}$. Convolution is indicated by the symbol $*$, and is defined,

$$\mathbf{X}^{(1)} = f(\mathbf{b} + \mathbf{C} * \mathbf{X}^{(0)}) \implies x_{k,m}^{(1)} = f \left(b_k + \sum_{k'=1}^{K_e} \sum_{n=1}^h c_{k',n}^{(k)} \times x_{k',m+n-1}^{(0)} \right), \quad [3.53]$$

where f is an activation function such as tanh or ReLU, and \mathbf{b} is a vector of offsets. The convolution operation slides the matrix $\mathbf{C}^{(k)}$ across the columns of $\mathbf{X}^{(0)}$; at each position m , compute the elementwise product $\mathbf{C}^{(k)} \odot \mathbf{X}_{m:m+h-1}^{(0)}$, and take the sum.

A simple filter might compute a weighted average over nearby words,

$$\mathbf{C}^{(k)} = \begin{bmatrix} 0.5 & 1 & 0.5 \\ 0.5 & 1 & 0.5 \\ \dots & \dots & \dots \\ 0.5 & 1 & 0.5 \end{bmatrix}, \quad [3.54]$$

1640 thereby representing trigram units like *not so unpleasant*. In **one-dimensional convolution**,
 1641 each filter matrix $\mathbf{C}^{(k)}$ is constrained to have non-zero values only at row k (Kalchbrenner et al., 2014).

1643 To deal with the beginning and end of the input, the base matrix $\mathbf{X}^{(0)}$ may be padded
 1644 with h column vectors of zeros at the beginning and end; this is known as **wide convolution**. If padding is not applied, then the output from each layer will be $h - 1$ units smaller
 1645 than the input; this is known as **narrow convolution**. The filter matrices need not have
 1646 identical filter widths, so more generally we could write h_k to indicate width of filter
 1647 $\mathbf{C}^{(k)}$. As suggested by the notation $\mathbf{X}^{(0)}$, multiple layers of convolution may be applied,
 1648 so that $\mathbf{X}^{(d)}$ is the input to $\mathbf{X}^{(d+1)}$.

After D convolutional layers, we obtain a matrix representation of the document $\mathbf{X}^{(D)} \in \mathbb{R}^{K_z \times M}$. If the instances have variable lengths, it is necessary to aggregate over all M word positions to obtain a fixed-length representation. This can be done by a **pooling** operation, such as max-pooling (Collobert et al., 2011) or average-pooling,

$$\mathbf{z} = \text{MaxPool}(\mathbf{X}^{(D)}) \implies z_k = \max(x_{k,1}^{(D)}, x_{k,2}^{(D)}, \dots, x_{k,M}^{(D)}) \quad [3.55]$$

$$\mathbf{z} = \text{AvgPool}(\mathbf{X}^{(D)}) \implies z_k = \frac{1}{M} \sum_{m=1}^M x_{k,m}^{(D)}. \quad [3.56]$$

1650 The vector \mathbf{z} can now act as a layer in a feedforward network, culminating in a prediction
 1651 \hat{y} and a loss $\ell^{(i)}$. The setup is shown in Figure 3.4.

Just as in feedforward networks, the parameters $(\mathbf{C}^{(k)}, \mathbf{b}, \Theta)$ can be learned by backpropagating from the classification loss. This requires backpropagating through the max-pooling operation, which is a discontinuous function of the input. But because we need only a local gradient, backpropagation flows only through the argmax m :

$$\frac{\partial z_k}{\partial x_{k,m}^{(D)}} = \begin{cases} 1, & x_{k,m}^{(D)} = \max(x_{k,1}^{(D)}, x_{k,2}^{(D)}, \dots, x_{k,M}^{(D)}) \\ 0, & \text{otherwise.} \end{cases} \quad [3.57]$$

1652 The computer vision literature has produced a huge variety of convolutional architectures,
 1653 and many of these bells and whistles can be applied to text data. One avenue for
 1654 improvement is more complex pooling operations, such as k -max pooling (Kalchbrenner
 1655 et al., 2014), which returns a matrix of the k largest values for each filter. Another innovation
 1656 is the use of **dilated convolution** to build multiscale representations (Yu and Koltun,
 1657 2016). At each layer, the convolutional operator applied in *strides*, skipping ahead by s
 1658 steps after each feature. As we move up the hierarchy, each layer is s times smaller than
 1659 the layer below it, effectively summarizing the input. This idea is shown in Figure 3.5.
 1660 Multi-layer convolutional networks can also be augmented with “shortcut” connections,
 1661 as in the ResNet model from § 3.2.2 (Johnson and Zhang, 2017).

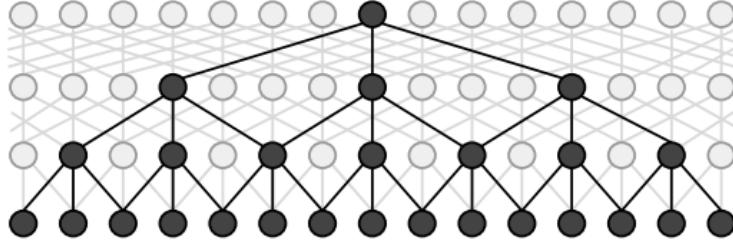


Figure 3.5: A dilated convolutional neural network captures progressively larger context through recursive application of the convolutional operator (Strubell et al., 2017) [todo: permission]

1662 Additional resources

1663 The deep learning textbook by Goodfellow et al. (2016) covers many of the topics in this
 1664 chapter in more detail. For a comprehensive review of neural networks in natural lan-
 1665 guage processing, see (Goldberg, 2017b). A seminal work on deep learning in natural
 1666 language processing is the aggressively titled “Natural Language Processing (Almost)
 1667 from Scratch”, which uses convolutional neural networks to perform a range of language
 1668 processing tasks (Collobert et al., 2011). This chapter focuses on feedforward and con-
 1669 volutional neural networks, but recurrent neural networks are one of the most important
 1670 deep learning architectures for natural language processing. They are covered extensively
 1671 in chapters 6 and 7.

1672 The role of deep learning in natural language processing research has caused angst
 1673 in some parts of the natural language processing research community (e.g., Goldberg,
 1674 2017a), especially as some of the more zealous deep learning advocates have argued that
 1675 end-to-end learning from “raw” text can eliminate the need for linguistic constructs such
 1676 as sentences, phrases, and even words (Zhang et al., 2015, originally titled *Text understand-
 1677 ing from scratch*). These developments were surveyed by Manning (2016).

1678 Exercises

- 1679 1. Prove that the softmax and sigmoid functions are equivalent when the number of
 1680 possible labels is two. Specifically, for any $\Theta^{(z \rightarrow y)}$ (omitting the offset b for sim-
 1681 plicity), show how to construct a vector of weights θ such that,

$$\text{SoftMax}(\Theta^{(z \rightarrow y)} z)[0] = \sigma(\theta \cdot z). \quad [3.58]$$

1682 2. Design a feedforward network to compute the XOR function:

$$f(x_1, x_2) = \begin{cases} -1, & x_1 = 1, x_2 = 1 \\ 1, & x_1 = 1, x_2 = 0 \\ 1, & x_1 = 0, x_2 = 1 \\ -1, & x_1 = 0, x_2 = 0 \end{cases}. \quad [3.59]$$

1683 Your network should have a single output node which uses the Sign activation function.
 1684 Use a single hidden layer, with ReLU activation functions. Describe all weights
 1685 and offsets.

1686 3. Consider the same network as above (with ReLU activations for the hidden layer),
 1687 with an arbitrary differentiable loss function $\ell(y^{(i)}, \tilde{y})$, where \tilde{y} is the activation of
 1688 the output node. Suppose all weights and offsets are initialized to zero. Prove that
 1689 gradient-based optimization cannot learn the desired function from this initializa-
 1690 tion.

1691 4. The simplest solution to the previous problem relies on the use of the ReLU activa-
 1692 tion function at the hidden layer. Now consider a network with arbitrary activations
 1693 on the hidden layer. Show that if the initial weights are any uniform constant, then
 1694 it is not possible to learn the desired function.

1695 5. Consider a network in which: the base features are all binary, $\mathbf{x} \in \{0, 1\}^M$; the
 1696 hidden layer activation function is sigmoid, $z_k = \sigma(\theta_k \cdot \mathbf{x})$; and the initial weights
 1697 are sampled independently from a standard normal distribution, $\theta_{j,k} \sim N(0, 1)$.

- 1698 • Show how the probability of a small initial gradient on any weight, $\frac{\partial z_k}{\partial \theta_{j,k}} < \alpha$,
 1699 depends on the size of the input M . **Hint:** use the lower bound,

$$\Pr(\sigma(\theta_k \cdot \mathbf{x}) \times (1 - \sigma(\theta_k \cdot \mathbf{x})) < \alpha) \geq 2 \Pr(\sigma(\theta_k \cdot \mathbf{x}) < \alpha), \quad [3.60]$$

1700 and relate this probability to the variance $V[\theta_k \cdot \mathbf{x}]$.

- 1701 • Design an alternative initialization that removes this dependence.

6. Suppose that the parameters $\Theta = \{\Theta^{(x \rightarrow z)}, \Theta(z \rightarrow y), \mathbf{b}\}$ are a local optimum of a feedforward network in the following sense: there exists some $\epsilon > 0$ such that,

$$\begin{aligned} & \left(\|\tilde{\Theta}^{(x \rightarrow z)} - \Theta^{(x \rightarrow z)}\|_F^2 + \|\tilde{\Theta}^{(z \rightarrow y)} - \Theta^{(z \rightarrow y)}\|_F^2 + \|\tilde{\mathbf{b}} - \mathbf{b}\|_2^2 < \epsilon \right) \\ & \Rightarrow \left(L(\tilde{\Theta}) > L(\Theta) \right) \end{aligned} \quad [3.61]$$

1702 Define the function π as a permutation on the hidden units, as described in § 3.3.3,
 1703 so that for any Θ , $L(\Theta) = L(\Theta_\pi)$. Prove that if a feedforward network has a local
 1704 optimum in the sense of Equation 3.61, then its loss is not a convex function of the
 1705 parameters Θ , using the definition of convexity from § 2.3

1706 **Chapter 4**

1707 **Linguistic applications of
1708 classification**

1709 Having learned some techniques for classification, this chapter shifts the focus from math-
1710 ematics to linguistic applications. Later in the chapter, we will consider the design deci-
1711 sions involved in text classification, as well as evaluation practices.

1712 **4.1 Sentiment and opinion analysis**

1713 A popular application of text classification is to automatically determine the **sentiment**
1714 or **opinion polarity** of documents such as product reviews and social media posts. For
1715 example, marketers are interested to know how people respond to advertisements, ser-
1716 vices, and products (Hu and Liu, 2004); social scientists are interested in how emotions
1717 are affected by phenomena such as the weather (Hannak et al., 2012), and how both opin-
1718 ions and emotions spread over social networks (Coviello et al., 2014; Miller et al., 2011).
1719 In the field of **digital humanities**, literary scholars track plot structures through the flow
1720 of sentiment across a novel (Jockers, 2015).¹

1721 Sentiment analysis can be framed as a direct application of document classification,
1722 assuming reliable labels can be obtained. In the simplest case, sentiment analysis is a
1723 two or three-class problem, with sentiments of POSITIVE, NEGATIVE, and possibly NEU-
1724 TRAL. Such annotations could be annotated by hand, or obtained automatically through
1725 a variety of means:

- 1726 • Tweets containing happy emoticons can be marked as positive, sad emoticons as
1727 negative (Read, 2005; Pak and Paroubek, 2010).

¹Comprehensive surveys on sentiment analysis and related problems are offered by Pang and Lee (2008) and Liu (2015).

- Reviews with four or more stars can be marked as positive, two or fewer stars as negative (Pang et al., 2002).
- Statements from politicians who are voting for a given bill are marked as positive (towards that bill); statements from politicians voting against the bill are marked as negative (Thomas et al., 2006).

The bag-of-words model is a good fit for sentiment analysis at the document level: if the document is long enough, we would expect the words associated with its true sentiment to overwhelm the others. Indeed, **lexicon-based sentiment analysis** avoids machine learning altogether, and classifies documents by counting words against positive and negative sentiment word lists (Taboada et al., 2011).

Lexicon-based classification is less effective for short documents, such as single-sentence reviews or social media posts. In these documents, linguistic issues like **negation** and **irrealis** (Polanyi and Zaenen, 2006) — events that are hypothetical or otherwise non-factual — can make bag-of-words classification ineffective. Consider the following examples:

- 1742 (4.1) That's not bad for the first day.
- 1743 (4.2) This is not the worst thing that can happen.
- 1744 (4.3) It would be nice if you acted like you understood.
- 1745 (4.4) There is no reason at all to believe that the polluters are suddenly going to be-
1746 come reasonable. (Wilson et al., 2005)
- 1747 (4.5) This film should be brilliant. The actors are first grade. Stallone plays a happy,
1748 wonderful man. His sweet wife is beautiful and adores him. He has a fascinat-
1749 ing gift for living life fully. It sounds like a great plot, **however**, the film is a
1750 failure. (Pang et al., 2002)

A minimal solution is to move from a bag-of-words model to a bag-of-**bigrams** model, where each base feature is a pair of adjacent words, e.g.,

$$(that's, not), (not, bad), (bad, for), \dots \quad [4.1]$$

Bigrams can handle relatively straightforward cases, such as when an adjective is immediately negated; trigrams would be required to extend to larger contexts (e.g., *not the worst*). But this approach will not scale to more complex examples like (4.4) and (4.5). More sophisticated solutions try to account for the syntactic structure of the sentence (Wilson et al., 2005; Socher et al., 2013), or apply more complex classifiers such as **convolutional neural networks** (Kim, 2014), which are described in chapter 3.

1759 **4.1.1 Related problems**

1760 **Subjectivity** Closely related to sentiment analysis is **subjectivity detection**, which re-
1761 quires identifying the parts of a text that express subjective opinions, as well as other non-
1762 factual content such as speculation and hypotheticals (Riloff and Wiebe, 2003). This can be
1763 done by treating each sentence as a separate document, and then applying a bag-of-words
1764 classifier: indeed, Pang and Lee (2004) do exactly this, using a training set consisting of
1765 (mostly) subjective sentences gathered from movie reviews, and (mostly) objective sen-
1766 tences gathered from plot descriptions. They augment this bag-of-words model with a
1767 graph-based algorithm that encourages nearby sentences to have the same subjectivity
1768 label.

1769 **Stance classification** In debates, each participant takes a side: for example, advocating
1770 for or against proposals like adopting a vegetarian lifestyle or mandating free college ed-
1771 ucation. The problem of stance classification is to identify the author’s position from the
1772 text of the argument. In some cases, there is training data available for each position,
1773 so that standard document classification techniques can be employed. In other cases, it
1774 suffices to classify each document as whether it is in support or opposition of the argu-
1775 ment advanced by a previous document (Anand et al., 2011). In the most challenging
1776 case, there is no labeled data for any of the stances, so the only possibility is group docu-
1777 ments that advocate the same position (Somasundaran and Wiebe, 2009). This is a form
1778 of **unsupervised learning**, discussed in chapter 5.

1779 **Targeted sentiment analysis** The expression of sentiment is often more nuanced than a
1780 simple binary label. Consider the following examples:

1781 (4.6) The vodka was good, but the meat was rotten.

1782 (4.7) Go to Heaven for the climate, Hell for the company. —Mark Twain

1783 These statements display a mixed overall sentiment: positive towards some entities (e.g.,
1784 *the vodka*), negative towards others (e.g., *the meat*). **Targeted sentiment analysis** seeks to
1785 identify the writer’s sentiment towards specific entities (Jiang et al., 2011). This requires
1786 identifying the entities in the text and linking them to specific sentiment words — much
1787 more than we can do with the classification-based approaches discussed thus far. For
1788 example, Kim and Hovy (2006) analyze sentence-internal structure to determine the topic
1789 of each sentiment expression.

1790 **Aspect-based opinion mining** seeks to identify the sentiment of the author of a review
1791 towards predefined aspects such as PRICE and SERVICE, or, in the case of (4.7), CLIMATE
1792 and COMPANY (Hu and Liu, 2004). If the aspects are not defined in advance, it may again
1793 be necessary to employ **unsupervised learning** methods to identify them (e.g., Branavan
1794 et al., 2009).

1795 **Emotion classification** While sentiment analysis is framed in terms of positive and neg-
 1796 ative categories, psychologists generally regard **emotion** as more multifaceted. For ex-
 1797 ample, Ekman (1992) argues that there are six basic emotions — happiness, surprise, fear,
 1798 sadness, anger, and contempt — and that they are universal across human cultures. Alm
 1799 et al. (2005) build a linear classifier for recognizing the emotions expressed in children’s
 1800 stories. The ultimate goal of this work was to improve text-to-speech synthesis, so that
 1801 stories could be read with intonation that reflected the emotional content. They used bag-
 1802 of-words features, as well as features capturing the story type (e.g., jokes, folktales), and
 1803 structural features that reflect the position of each sentence in the story. The task is diffi-
 1804 cult: even human annotators frequently disagreed with each other, and the best classifiers
 1805 achieved accuracy between 60-70%.

1806 4.1.2 Alternative approaches to sentiment analysis

1807 **Regression** A more challenging version of sentiment analysis is to determine not just
 1808 the class of a document, but its rating on a numerical scale (Pang and Lee, 2005). If the
 1809 scale is continuous, it is most natural to apply **regression**, identifying a set of weights θ
 1810 that minimize the squared error of a predictor $\hat{y} = \theta \cdot x + b$, where b is an offset. This
 1811 approach is called **linear regression**, and sometimes **least squares**, because the regression
 1812 coefficients θ are determined by minimizing the squared error, $(y - \hat{y})^2$. If the weights are
 1813 regularized using a penalty $\lambda \|\theta\|_2^2$, then it is **ridge regression**. Unlike logistic regression,
 1814 both linear regression and ridge regression can be solved in closed form as a system of
 1815 linear equations.

1816 **Ordinal ranking** In many problems, the labels are ordered but discrete: for example,
 1817 product reviews are often integers on a scale of 1 – 5, and grades are on a scale of A – F.
 1818 Such problems can be solved by discretizing the score $\theta \cdot x$ into “ranks”,

$$\hat{y} = \underset{r: \theta \cdot x \geq b_r}{\operatorname{argmin}} r, \quad [4.2]$$

1819 where $\mathbf{b} = [b_1 = -\infty, b_2, b_3, \dots, b_K]$ is a vector of boundaries. It is possible to learn the
 1820 weights and boundaries simultaneously, using a perceptron-like algorithm (Crammer and
 1821 Singer, 2001).

1822 **Lexicon-based classification** Sentiment analysis is one of the only NLP tasks where
 1823 hand-crafted feature weights are still widely employed. In **lexicon-based classification** (Taboada
 1824 et al., 2011), the user creates a list of words for each label, and then classifies each docu-
 1825 ment based on how many of the words from each list are present. In our linear classifica-
 1826 tion framework, this is equivalent to choosing the following weights:

$$\theta_{y,j} = \begin{cases} 1, & j \in \mathcal{L}_y \\ 0, & \text{otherwise,} \end{cases} \quad [4.3]$$

1827 where \mathcal{L}_y is the lexicon for label y . Compared to the machine learning classifiers discussed
 1828 in the previous chapters, lexicon-based classification may seem primitive. However, su-
 1829 pervised machine learning relies on large annotated datasets, which are time-consuming
 1830 and expensive to produce. If the goal is to distinguish two or more categories in a new
 1831 domain, it may be simpler to start by writing down a list of words for each category.

1832 An early lexicon was the *General Inquirer* (Stone, 1966). Today, popular sentiment lex-
 1833 cons include sentiwordnet (Esuli and Sebastiani, 2006) and an evolving set of lexicons
 1834 from Liu (2015). For emotions and more fine-grained analysis, *Linguistic Inquiry and Word*
 1835 *Count* (LIWC) provides a set of lexicons (Tausczik and Pennebaker, 2010). The MPQA lex-
 1836 icon indicates the polarity (positive or negative) of 8221 terms, as well as whether they are
 1837 strongly or weakly subjective (Wiebe et al., 2005). A comprehensive comparison of senti-
 1838 ment lexicons is offered by Ribeiro et al. (2016). Given an initial **seed lexicon**, it is possible
 1839 to automatically expand the lexicon by looking for words that frequently co-occur with
 1840 words in the seed set (Hatzivassiloglou and McKeown, 1997; Qiu et al., 2011).

1841 4.2 Word sense disambiguation

1842 Consider the the following headlines:

- 1843 (4.8) Iraqi head seeks arms
- 1844 (4.9) Prostitutes appeal to Pope
- 1845 (4.10) Drunk gets nine years in violin case²

1846 These headlines are ambiguous because they contain words that have multiple mean-
 1847 ings, or **senses**. Word sense disambiguation is the problem of identifying the intended
 1848 sense of each word token in a document. Word sense disambiguation is part of a larger
 1849 field of research called **lexical semantics**, which is concerned with meanings of the words.

1850 At a basic level, the problem of word sense disambiguation is to identify the correct
 1851 sense for each word token in a document. Part-of-speech ambiguity (e.g., noun versus
 1852 verb) is usually considered to be a different problem, to be solved at an earlier stage.
 1853 From a linguistic perspective, senses are not properties of words, but of **lemmas**, which
 1854 are canonical forms that stand in for a set of inflected words. For example, *arm*/N is a
 1855 lemma that includes the inflected form *arms*/N — the /N indicates that it we are refer-
 1856 ring to the noun, and not its **homonym** *arm*/V, which is another lemma that includes
 1857 the inflected verbs (*arm*/V, *arms*/V, *armed*/V, *arming*/V). Therefore, word sense disam-
 1858 biguation requires first identifying the correct part-of-speech and lemma for each token,

²These examples, and many more, can be found at <http://www.ling.upenn.edu/~beatrice/humor/headlines.html>

1859 and then choosing the correct sense from the inventory associated with the corresponding
 1860 lemma.³ (Part-of-speech tagging is discussed in § 8.1.)

1861 **4.2.1 How many word senses?**

1862 Words sometimes have many more than two senses, as exemplified by the word *serve*:

- 1863 • [FUNCTION]: *The tree stump served as a table*
- 1864 • [CONTRIBUTE TO]: *His evasive replies only served to heighten suspicion*
- 1865 • [PROVIDE]: *We serve only the rawest fish*
- 1866 • [ENLIST]: *She served in an elite combat unit*
- 1867 • [JAIL]: *He served six years for a crime he didn't commit*
- 1868 • [LEGAL]: *They were served with subpoenas*⁴

1869 These sense distinctions are annotated in **WordNet** (<http://wordnet.princeton.edu>), a lexical semantic database for English. WordNet consists of roughly 100,000 **synsets**,
 1870 which are groups of lemmas (or phrases) that are synonymous. An example synset is
 1871 {*chump*¹, *fool*², *sucker*¹, *mark*⁹}, where the superscripts index the sense of each lemma that
 1872 is included in the synset: for example, there are at least eight other senses of *mark* that
 1873 have different meanings, and are not part of this synset. A lemma is **polysemous** if it
 1874 participates in multiple synsets.

1876 WordNet defines the scope of the word sense disambiguation problem, and, more
 1877 generally, formalizes lexical semantic knowledge of English. (WordNets have been cre-
 1878 ated for a few dozen other languages, at varying levels of detail.) Some have argued
 1879 that WordNet's sense granularity is too fine (Ide and Wilks, 2006); more fundamentally,
 1880 the premise that word senses can be differentiated in a task-neutral way has been criti-
 1881 cized as linguistically naïve (Kilgarriff, 1997). One way of testing this question is to ask
 1882 whether people tend to agree on the appropriate sense for example sentences: accord-
 1883 ing to Mihalcea et al. (2004), people agree on roughly 70% of examples using WordNet
 1884 senses; far better than chance, but less than agreement on other tasks, such as sentiment
 1885 annotation (Wilson et al., 2005).

1886 ***Other lexical semantic relations** Besides **synonymy**, WordNet also describes many
 1887 other lexical semantic relationships, including:

- 1888 • **antonymy**: *x* means the opposite of *y*, e.g. FRIEND-ENEMY;

³Navigli (2009) provides a survey of approaches for word-sense disambiguation.

⁴Several of the examples are adapted from WordNet (Fellbaum, 2010).

- **hyponymy:** x is a special case of y , e.g. RED-COLOR; the inverse relationship is **hyperonymy**;
- **meronymy:** x is a part of y , e.g., WHEEL-BICYCLE; the inverse relationship is **holonymy**.

Classification of these relations can be performed by searching for characteristic patterns between pairs of words, e.g., X , *such as* Y , which signals hyponymy (Hearst, 1992), or X *but* Y , which signals antonymy (Hatzivassiloglou and McKeown, 1997). Another approach is to analyze each term's **distributional statistics** (the frequency of its neighboring words). Such approaches are described in detail in chapter 14.

4.2.2 Word sense disambiguation as classification

How can we tell living *plants* from manufacturing *plants*? The context is often critical:

- (4.11) Town officials are hoping to attract new manufacturing plants through weakened environmental regulations.
- (4.12) The endangered plants play an important role in the local ecosystem.

It is possible to build a feature vector using the bag-of-words representation, by treating each context as a pseudo-document. The feature function is then,

$$\begin{aligned} f((\text{plant}, \text{The endangered plants play an ...}), y) = \\ \{(the, y) : 1, (\text{endangered}, y) : 1, (\text{play}, y) : 1, (\text{an}, y) : 1, \dots\} \end{aligned}$$

As in document classification, many of these features are irrelevant, but a few are very strong predictors. In this example, the context word *endangered* is a strong signal that the intended sense is biology rather than manufacturing. We would therefore expect a learning algorithm to assign high weight to (*endangered*, BIOLOGY), and low weight to (*endangered*, MANUFACTURING).⁵

It may also be helpful to go beyond the bag-of-words: for example, one might encode the position of each context word with respect to the target, e.g.,

$$\begin{aligned} f((\text{bank}, I \text{ went to the bank to deposit my paycheck}), y) = \\ \{(i - 3, \text{went}, y) : 1, (i + 2, \text{deposit}, y) : 1, (i + 4, \text{paycheck}, y) : 1\} \end{aligned}$$

These are called **collocation features**, and they give more information about the specific role played by each context word. This idea can be taken further by incorporating additional syntactic information about the grammatical role played by each context feature, such as the **dependency path** (see chapter 11).

⁵The context bag-of-words can be also used to perform word-sense disambiguation without machine learning: the Lesk (1986) algorithm selects the word sense whose dictionary definition best overlaps the local context.

Using such features, a classifier can be trained from labeled data. A **semantic concordance** is a corpus in which each open-class word (nouns, verbs, adjectives, and adverbs) is tagged with its word sense from the target dictionary or thesaurus. SemCor is a semantic concordance built from 234K tokens of the Brown corpus (Francis and Kucera, 1982), annotated as part of the WordNet project (Fellbaum, 2010). SemCor annotations look like this:

(4.13) As of Sunday¹_N night¹_N there was⁴_V no word²_N ...,

with the superscripts indicating the annotated sense of each polysemous word, and the subscripts indicating the part-of-speech.

As always, supervised classification is only possible if enough labeled examples can be accumulated. This is difficult in word sense disambiguation, because each polysemous lemma requires its own training set: having a good classifier for the senses of *serve* is no help towards disambiguating *plant*. For this reason, **unsupervised** and **semisupervised** methods are particularly important for word sense disambiguation (e.g., Yarowsky, 1995). These methods will be discussed in chapter 5. Unsupervised methods typically lean on the heuristic of “one sense per discourse”, which means that a lemma will usually have a single, consistent sense throughout any given document (Gale et al., 1992). Based on this heuristic, we can propagate information from high-confidence instances to lower-confidence instances in the same document (Yarowsky, 1995).

4.3 Design decisions for text classification

Text classification involves a number of design decisions. In some cases, the design decision is clear from the mathematics: if you are using regularization, then a regularization weight λ must be chosen. Other decisions are more subtle, arising only in the low level “plumbing” code that ingests and processes the raw data. Such decision can be surprisingly consequential for classification accuracy.

4.3.1 What is a word?

The bag-of-words representation presupposes that extracting a vector of word counts from text is unambiguous. But text documents are generally represented as sequences of characters (in an encoding such as ascii or unicode), and the conversion to bag-of-words presupposes a definition of the “words” that are to be counted.

4.3.1.1 Tokenization

The first subtask for constructing a bag-of-words vector is **tokenization**: converting the text from a sequence of characters to a sequence of **word tokens**. A simple approach is

Whitespace	Isn't	Ahab,	Ahab?	;)
Treebank	Is	n't	Ahab	,	Ahab ? ;)
Tweet	Isn't	Ahab	,	Ahab ? ;))
TokTok (Dehdari, 2014)	Isn	'	t	Ahab ,	Ahab ? ;)

Figure 4.1: The output of four `nltk` tokenizers, applied to the string *Isn't Ahab, Ahab? ;)*

1944 to define a subset of characters as whitespace, and then split the text on these tokens.
 1945 However, whitespace-based tokenization is not ideal: we may want to split conjunctions
 1946 like *isn't* and hyphenated phrases like *prize-winning* and *half-asleep*, and we likely want
 1947 to separate words from commas and periods that immediately follow them. At the same
 1948 time, it would be better not to split abbreviations like *U.S.* and *Ph.D.* In languages with
 1949 Roman scripts, tokenization is typically performed using regular expressions, with mod-
 1950 ules designed to handle each of these cases. For example, the `nltk` package includes a
 1951 number of tokenizers (Loper and Bird, 2002); the outputs of four of the better-known tok-
 1952 enizers are shown in Figure 4.1. Social media researchers have found that emoticons and
 1953 other forms of orthographic variation pose new challenges for tokenization, leading to the
 1954 development of special purpose tokenizers to handle these phenomena (O'Connor et al.,
 1955 2010).

1956 Tokenization is a language-specific problem, and each language poses unique chal-
 1957 lenges. For example, Chinese does not include spaces between words, nor any other
 1958 consistent orthographic markers of word boundaries. A “greedy” approach is to scan the
 1959 input for character substrings that are in a predefined lexicon. However, Xue et al. (2003)
 1960 notes that this can be ambiguous, since many character sequences could be segmented in
 1961 multiple ways. Instead, he trains a classifier to determine whether each Chinese character,
 1962 or *hanzi*, is a word boundary. More advanced sequence labeling methods for word seg-
 1963 mentation are discussed in § 8.4. Similar problems can occur in languages with alphabetic
 1964 scripts, such as German, which does not include whitespace in compound nouns, yield-
 1965 ing examples such as *Freundschaftsbezeigungen* (demonstration of friendship) and *Dilett-
 1966 tantenaufdringlichkeiten* (the importunities of dilettantes). As Twain (1997) argues, “*These
 1967 things are not words, they are alphabetic processions.*” Social media raises similar problems
 1968 for English and other languages, with hashtags such as `#TrueLoveInFourWords` requiring
 1969 decomposition for analysis (Brun and Roux, 2014).

1970 4.3.1.2 Normalization

1971 After splitting the text into tokens, the next question is which tokens are really distinct.
 1972 Is it necessary to distinguish *great*, *Great*, and *GREAT*? Sentence-initial capitalization may
 1973 be irrelevant to the classification task. Going further, the complete elimination of case
 1974 distinctions will result in a smaller vocabulary, and thus smaller feature vectors. However,

Original	The	Williams	sisters	are	leaving	this	tennis	centre
Porter stemmer	the	william	sister	are	leav	thi	tenni	centr
Lancaster stemmer	the	william	sist	ar	leav	thi	ten	cent
WordNet lemmatizer	The	Williams	sister	are	leaving	this	tennis	centre

Figure 4.2: Sample outputs of the Porter (1980) and Lancaster (Paice, 1990) stemmers, and the WordNet lemmatizer

1975 case distinctions might be relevant in some situations: for example, *apple* is a delicious
 1976 pie filling, while *Apple* is a company that specializes in proprietary dongles and power
 1977 adapters.

1978 For Roman script, case conversion can be performed using unicode string libraries.
 1979 Many scripts do not have case distinctions (e.g., the Devanagari script used for South
 1980 Asian languages, the Thai alphabet, and Japanese kana), and case conversion for all scripts
 1981 may not be available in every programming environment. (Unicode support is an im-
 1982 portant distinction between Python’s versions 2 and 3, and is a good reason for mi-
 1983 grating to Python 3 if you have not already done so. Compare the output of the code
 1984 "\à l\'hôtel".upper() in the two language versions.)⁶

1985 Case conversion is a type of **normalization**, which refers to string transformations that
 1986 remove distinctions that are irrelevant to downstream applications (Sproat et al., 2001).
 1987 Other normalizations include the standardization of numbers (e.g., 1,000 to 1000) and
 1988 dates (e.g., August 11, 2015 to 2015/11/08). Depending on the application, it may even be
 1989 worthwhile to convert all numbers and dates to special tokens, !NUM and !DATE. In social
 1990 media, there are additional orthographic phenomena that may be normalized, such as ex-
 1991 pressive lengthening, e.g., *coooooool* (Aw et al., 2006; Yang and Eisenstein, 2013). Similarly,
 1992 historical texts feature spelling variations that may need to be normalized to a contempo-
 1993 rary standard form (Baron and Rayson, 2008).

1994 A more extreme form of normalization is to eliminate **inflectional affixes**, such as the
 1995 -ed and -s suffixes in English. On this view, *bike*, *bikes*, *biking*, and *biked* all refer to the
 1996 same underlying concept, so they should be grouped into a single feature. A **stemmer** is
 1997 a program for eliminating affixes, usually by applying a series of regular expression sub-
 1998 stitutions. Character-based stemming algorithms are necessarily approximate, as shown
 1999 in Figure 4.2: the Lancaster stemmer incorrectly identifies -ers as an inflectional suffix of
 2000 *sisters* (by analogy to *fix/fixer*s), and both stemmers incorrectly identify -s as a suffix of *this*
 2001 and *Williams*. Fortunately, even inaccurate stemming can improve bag-of-words classifi-
 2002 cation models, by merging related strings and thereby reducing the vocabulary size.

2003 Accurately handling irregular orthography requires word-specific rules. **Lemmatizers**

⁶[todo: I want to make this a footnote, but can't figure out how.]

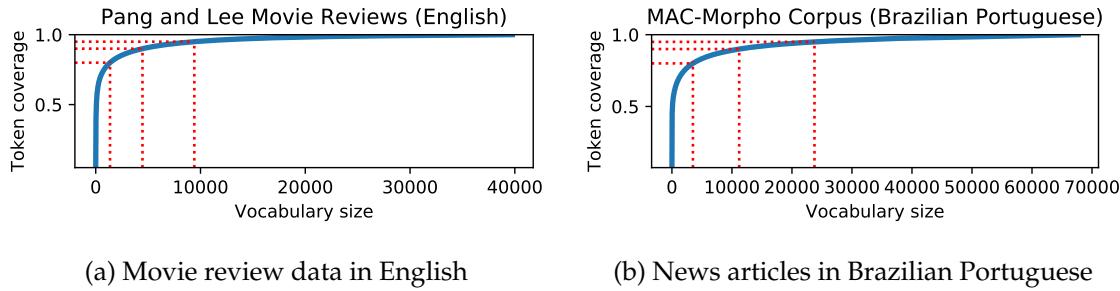


Figure 4.3: Tradeoff between token coverage (y-axis) and vocabulary size, on the `nltk` movie review dataset, after sorting the vocabulary by decreasing frequency. The red dashed lines indicate 80%, 90%, and 95% coverage.

2004 are systems that identify the underlying lemma of a given wordform. They must avoid the
 2005 over-generalization errors of the stemmers in Figure 4.2, and also handle more complex
 2006 transformations, such as *geese*→*goose*. The output of the WordNet lemmatizer is shown in
 2007 the final line of Figure 4.2. Both stemming and lemmatization are language-specific: an
 2008 English stemmer or lemmatizer is of little use on a text written in another language. The
 2009 discipline of **morphology** relates to the study of word-internal structure, and is described
 2010 in more detail in § 9.1.2.

2011 The value of normalization depends on the data and the task. Normalization re-
 2012 duces the size of the feature space, which can help in generalization. However, there
 2013 is always the risk of merging away linguistically meaningful distinctions. In supervised
 2014 machine learning, regularization and smoothing can play a similar role to normalization
 2015 — preventing the learner from overfitting to rare features — while avoiding the language-
 2016 specific engineering required for accurate normalization. In unsupervised scenarios, such
 2017 as content-based information retrieval (Manning et al., 2008) and topic modeling (Blei
 2018 et al., 2003), normalization is more critical.

2019 4.3.2 How many words?

2020 Limiting the size of the feature vector reduces the memory footprint of the resulting mod-
 2021 els, and increases the speed of prediction. Normalization can help to play this role, but
 2022 a more direct approach is simply to limit the vocabulary to the N most frequent words
 2023 in the dataset. For example, in the `movie-reviews` dataset provided with `nltk` (orig-
 2024 inally from Pang et al., 2002), there are 39,768 word types, and 1.58M tokens. As shown
 2025 in Figure 4.3a, the most frequent 4000 word types cover 90% of all tokens, offering an
 2026 order-of-magnitude reduction in the model size. Such ratios are language-specific: in for
 2027 example, in the Brazilian Portuguese Mac-Morpho corpus (Aluísio et al., 2003), attain-
 2028 ing 90% coverage requires more than 10000 word types (Figure 4.3b). This reflects the

2029 morphological complexity of Portuguese, which includes many more inflectional suffixes
 2030 than English.

2031 Eliminating rare words is not always advantageous for classification performance: for
 2032 example, names, which are typically rare, play a large role in distinguishing topics of news
 2033 articles. Another way to reduce the size of the feature space is to eliminate **stopwords** such
 2034 as *the*, *to*, and *and*, which may seem to play little role in expressing the topic, sentiment,
 2035 or stance. This is typically done by creating a **stoplist** (e.g., `nltk.corpus.stopwords`),
 2036 and then ignoring all terms that match the list. However, corpus linguists and social psy-
 2037 chologists have shown that seemingly inconsequential words can offer surprising insights
 2038 about the author or nature of the text (Biber, 1991; Chung and Pennebaker, 2007). Further-
 2039 more, high-frequency words are unlikely to cause overfitting in discriminative classifiers.
 2040 As with normalization, stopword filtering is more important for unsupervised problems,
 2041 such as term-based document retrieval.

2042 Another alternative for controlling model size is **feature hashing** (Weinberger et al.,
 2043 2009). Each feature is assigned an index using a hash function. If a hash function that
 2044 permits collisions is chosen (typically by taking the hash output modulo some integer),
 2045 then the model can be made arbitrarily small, as multiple features share a single weight.
 2046 Because most features are rare, accuracy is surprisingly robust to such collisions (Ganchev
 2047 and Dredze, 2008).

2048 4.3.3 Count or binary?

2049 Finally, we may consider whether we want our feature vector to include the *count* of each
 2050 word, or its *presence*. This gets at a subtle limitation of linear classification: it worse to
 2051 have two *failures* than one, but is it really twice as bad? Motivated by this intuition, Pang
 2052 et al. (2002) use binary indicators of presence or absence in the feature vector: $f_j(x, y) \in$
 2053 $\{0, 1\}$. They find that classifiers trained on these binary vectors tend to outperform feature
 2054 vectors based on word counts. One explanation is that words tend to appear in clumps:
 2055 if a word has appeared once in a document, it is likely to appear again (Church, 2000).
 2056 These subsequent appearances can be attributed to this tendency towards repetition, and
 2057 thus provide little additional information about the class label of the document.

2058 4.4 Evaluating classifiers

2059 In any supervised machine learning application, it is critical to reserve a held-out test set.
 2060 This data should be used for only one purpose: to evaluate the overall accuracy of a single
 2061 classifier. Using this data more than once would cause the estimated accuracy to be overly
 2062 optimistic, because the classifier would be customized to this data, and would not perform
 2063 as well as on unseen data in the future. It is usually necessary to set hyperparameters or

2064 perform feature selection, so you may need to construct a **tuning** or **development set** for
 2065 this purpose, as discussed in § 2.1.5.

2066 There are a number of ways to evaluate classifier performance. The simplest is **accuracy**:
 2067 the number of correct predictions, divided by the total number of instances,

$$\text{acc}(\mathbf{y}, \hat{\mathbf{y}}) = \frac{1}{N} \sum_i^N \delta(y^{(i)} = \hat{y}). \quad [4.4]$$

2068 Exams are usually graded by accuracy. Why are other metrics necessary? The main
 2069 reason is **class imbalance**. Suppose you are building a classifier to detect whether an
 2070 electronic health record (EHR) describes symptoms of a rare disease, which appears in
 2071 only 1% of all documents in the dataset. A classifier that reports $\hat{y} = \text{NEGATIVE}$ for
 2072 all documents would achieve 99% accuracy, but would be practically useless. We need
 2073 metrics that are capable of detecting the classifier's ability to discriminate between classes,
 2074 even when the distribution is skewed.

2075 One solution is to build a **balanced test set**, in which each possible label is equally rep-
 2076 resented. But in the EHR example, this would mean throwing away 98% of the original
 2077 dataset! Furthermore, the detection threshold itself might be a design consideration: in
 2078 health-related applications, we might prefer a very sensitive classifier, which returned a
 2079 positive prediction if there is even a small chance that $y^{(i)} = \text{POSITIVE}$. In other applica-
 2080 tions, a positive result might trigger a costly action, so we would prefer a classifier that
 2081 only makes positive predictions when absolutely certain. We need additional metrics to
 2082 capture these characteristics.

2083 4.4.1 Precision, recall, and F-MEASURE

2084 For any label (e.g., positive for presence of symptoms of a disease), there are two possible
 2085 errors:

- 2086 • **False positive**: the system incorrectly predicts the label.
- 2087 • **False negative**: the system incorrectly fails to predict the label.

2088 Similarly, for any label, there are two ways to be correct:

- 2089 • **True positive**: the system correctly predicts the label.
- 2090 • **True negative**: the system correctly predicts that the label does not apply to this
 2091 instance.

Classifiers that make a lot of false positives are too sensitive; classifiers that make a
 lot of false negatives are not sensitive enough. These two conditions are captured by the

metrics of **recall** and **precision**:

$$\text{RECALL}(\mathbf{y}, \hat{\mathbf{y}}, k) = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad [4.5]$$

$$\text{PRECISION}(\mathbf{y}, \hat{\mathbf{y}}, k) = \frac{\text{TP}}{\text{TP} + \text{FP}}. \quad [4.6]$$

2092 Recall and precision are both conditional likelihoods of a correct prediction, which is why
 2093 their numerators are the same. Recall is conditioned on k being the correct label, $y^{(i)} = k$,
 2094 so the denominator sums over true positive and false negatives. Precision is conditioned
 2095 on k being the prediction, so the denominator sums over true positives and false positives.
 2096 Note that true negatives are not considered in either statistic. The classifier that labels
 2097 every document as “negative” would achieve zero recall; precision would be $\frac{0}{0}$.

2098 Recall and precision are complementary. A high-recall classifier is preferred when
 2099 false negatives are cheaper than false positives: for example, in a preliminary screening
 2100 for symptoms of a disease, the cost of a false positive might be an additional test, while a
 2101 false negative would result in the disease going untreated. Conversely, a high-precision
 2102 classifier is preferred when false positives are more expensive: for example, in spam de-
 2103tection, a false negative is a relatively minor inconvenience, while a false positive might
 2104 mean that an important message goes unread.

The ***F*-MEASURE** combines recall and precision into a single metric, using the harmonic mean:

$$\text{F-MEASURE}(\mathbf{y}, \hat{\mathbf{y}}, k) = \frac{2rp}{r + p}, \quad [4.7]$$

2105 where r is recall and p is precision.⁷

Evaluating multi-class classification Recall, precision, and ***F*-MEASURE** are defined with respect to a specific label k . When there are multiple labels of interest (e.g., in word sense disambiguation or emotion classification), it is necessary to combine the ***F*-MEASURE** across each class. **Macro *F*-MEASURE** is the average ***F*-MEASURE** across several classes,

$$\text{Macro-}F(\mathbf{y}, \hat{\mathbf{y}}) = \frac{1}{|\mathcal{K}|} \sum_{k \in \mathcal{K}} \text{F-MEASURE}(\mathbf{y}, \hat{\mathbf{y}}, k) \quad [4.8]$$

2106 In multi-class problems with unbalanced class distributions, the macro ***F*-MEASURE** is a
 2107 balanced measure of how well the classifier recognizes each class. In **micro *F*-MEASURE**,
 2108 we compute true positives, false positives, and false negatives for each class, and then add
 2109 them up to compute a single recall, precision, and ***F*-MEASURE**. This metric is balanced
 2110 across instances rather than classes, so it weights each class in proportion to its frequency
 2111 — unlike macro ***F*-MEASURE**, which weights each class equally.

⁷ F -MEASURE is sometimes called F_1 , and generalizes to $F_\beta = \frac{(1+\beta^2)rp}{\beta^2p+r}$. The β parameter can be tuned to emphasize recall or precision.

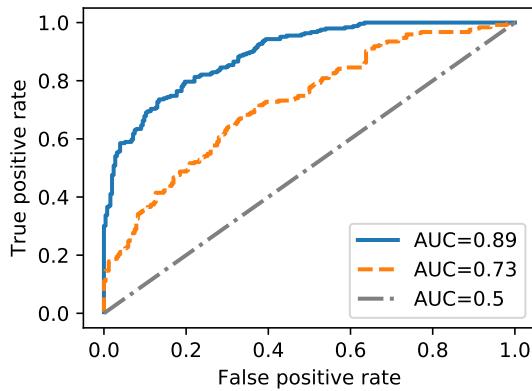


Figure 4.4: ROC curves for three classifiers of varying discriminative power, measured by AUC (area under the curve)

2112 4.4.2 Threshold-free metrics

2113 In binary classification problems, it is possible to trade off between recall and precision by
 2114 adding a constant “threshold” to the output of the scoring function. This makes it possible
 2115 to trace out a curve, where each point indicates the performance at a single threshold. In
 2116 the **receiver operating characteristic (ROC)** curve,⁸ the *x*-axis indicates the **false positive**
 2117 **rate**, $\frac{FP}{FP+TN}$, and the *y*-axis indicates the recall, or **true positive rate**. A perfect classifier
 2118 attains perfect recall without any false positives, tracing a “curve” from the origin (0,0) to
 2119 the upper left corner (0,1), and then to (1,1). In expectation, a non-discriminative classifier
 2120 traces a diagonal line from the origin (0,0) to the upper right corner (1,1). Real classifiers
 2121 tend to fall between these two extremes. Examples are shown in Figure 4.4.

2122 The ROC curve can be summarized in a single number by taking its integral, the **area**
 2123 **under the curve (AUC)**. The AUC can be interpreted as the probability that a randomly-
 2124 selected positive example will be assigned a higher score by the classifier than a randomly-
 2125 selected negative example. A perfect classifier has AUC = 1 (all positive examples score
 2126 higher than all negative examples); a non-discriminative classifier has AUC = 0.5 (given
 2127 a randomly selected positive and negative example, either could score higher with equal
 2128 probability); a perfectly wrong classifier would have AUC = 0 (all negative examples score
 2129 higher than all positive examples). One advantage of AUC in comparison to *F*-MEASURE
 2130 is that the baseline rate of 0.5 does not depend on the label distribution.

⁸The name “receiver operator characteristic” comes from the metric’s origin in signal processing applications (Peterson et al., 1954). Other threshold-free metrics include **precision-recall curves**, **precision-at-*k***, and **balanced *F*-MEASURE**; see Manning et al. (2008) for more details.

2131 **4.4.3 Classifier comparison and statistical significance**

2132 Natural language processing research and engineering often involves comparing different
 2133 classification techniques. In some cases, the comparison is between algorithms, such as
 2134 logistic regression versus averaged perceptron, or L_2 regularization versus L_1 . In other
 2135 cases, the comparison is between feature sets, such as the bag-of-words versus positional
 2136 bag-of-words (see § 4.2.2). **Ablation testing** involves systematically removing (ablating)
 2137 various aspects of the classifier, such as feature groups, and testing the **null hypothesis**
 2138 that the ablated classifier is as good as the full model.

2139 A full treatment of hypothesis testing is beyond the scope of this text, but this section
 2140 contains a brief summary of the techniques necessary to compare classifiers. The main
 2141 aim of hypothesis testing is to determine whether the difference between two statistics
 2142 — for example, the accuracies of two classifiers — is likely to arise by chance. We will
 2143 be concerned with chance fluctuations that arise due to the finite size of the test set.⁹ An
 2144 improvement of 10% on a test set with ten instances may reflect a random fluctuation that
 2145 makes the test set more favorable to classifier c_1 than c_2 ; on another test set with a different
 2146 ten instances, we might find that c_2 does better than c_1 . But if we observe the same 10%
 2147 improvement on a test set with 1000 instances, this is highly unlikely to be explained
 2148 by chance. Such a finding is said to be **statistically significant** at a level p , which is the
 2149 probability of observing an effect of equal or greater magnitude when the null hypothesis
 2150 is true. The notation $p < .05$ indicates that the likelihood of an equal or greater effect is
 2151 less than 5%, assuming the null hypothesis is true.¹⁰

2152 **4.4.3.1 The binomial test**

2153 The statistical significance of a difference in accuracy can be evaluated using classical tests,
 2154 such as the **binomial test**.¹¹ Suppose that classifiers c_1 and c_2 disagree on N instances in a
 2155 test set with binary labels, and that c_1 is correct on k of those instances. Under the null hy-
 2156 pothesis that the classifiers are equally accurate, we would expect k/N to be roughly equal
 2157 to 1/2, and as N increases, k/N should be increasingly close to this expected value. These
 2158 properties are captured by the **binomial distribution**, which is a probability over counts

⁹Other sources of variance include the initialization of non-convex classifiers such as neural networks, and the ordering of instances in online learning such as stochastic gradient descent and perceptron.

¹⁰Statistical hypothesis testing is useful only to the extent that the existing test set is representative of the instances that will be encountered in the future. If, for example, the test set is constructed from news documents, no hypothesis test can predict which classifier will perform best on documents from another domain, such as electronic health records.

¹¹A well-known alternative to the binomial test is **McNemar's test**, which computes a **test statistic** based on the number of examples that are correctly classified by one system and incorrectly classified by the other. The null hypothesis distribution for this test statistic is known to be drawn from a chi-squared distribution with a single degree of freedom, so a p -value can be computed from the cumulative density function of this distribution (Dietterich, 1998). Both tests give similar results in most circumstances, but the binomial test is easier to understand from first principles.

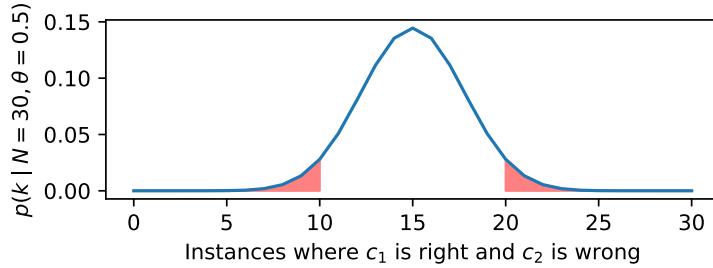


Figure 4.5: Probability mass function for the binomial distribution. The pink highlighted areas represent the cumulative probability for a significance test on an observation of $k = 10$ and $N = 30$.

of binary random variables. We write $k \sim \text{Binom}(\theta, N)$ to indicate that k is drawn from a binomial distribution, with parameter N indicating the number of random “draws”, and θ indicating the probability of “success” on each draw. Each draw is an example on which the two classifiers disagree, and a “success” is a case in which c_1 is right and c_2 is wrong. (The label space is assumed to be binary, so if the classifiers disagree, exactly one of them is correct. The test can be generalized to multi-class classification by focusing on the examples in which exactly one classifier is correct.)

The probability mass function (PMF) of the binomial distribution is,

$$p_{\text{Binom}}(k; N, \theta) = \binom{N}{k} \theta^k (1 - \theta)^{N-k}, \quad [4.9]$$

with θ^k representing the probability of the k successes, $(1 - \theta)^{N-k}$ representing the probability of the $N - k$ unsuccessful draws. The expression $\binom{N}{k} = \frac{N!}{k!(N-k)!}$ is a binomial coefficient, representing the number of possible orderings of events; this ensures that the distribution sums to one over all $k \in \{0, 1, 2, \dots, N\}$.

Under the null hypothesis, when the classifiers disagree, each classifier is equally likely to be right, so $\theta = \frac{1}{2}$. Now suppose that among N disagreements, c_1 is correct $k < \frac{N}{2}$ times. The probability of c_1 being correct k or fewer times is the **one-tailed p-value**, because it is computed from the area under the binomial probability mass function from 0 to k , as shown in the left tail of Figure 4.5. This **cumulative probability** is computed as a sum over all values $i \leq k$,

$$\Pr_{\text{Binom}} \left(\text{count}(\hat{y}_2^{(i)} = y^{(i)} \neq \hat{y}_1^{(i)}) \leq k; N, \theta = \frac{1}{2} \right) = \sum_{i=0}^k p_{\text{Binom}} \left(i; N, \theta = \frac{1}{2} \right). \quad [4.10]$$

The one-tailed p-value applies only to the asymmetric null hypothesis that c_1 is at least as accurate as c_2 . To test the **two-tailed** null hypothesis that c_1 and c_2 are equally accu-

Algorithm 7 Bootstrap sampling for classifier evaluation. The original test set is $\{\mathbf{x}^{(1:N)}, \mathbf{y}^{(1:N)}\}$, the metric is $\delta(\cdot)$, and the number of samples is M .

```

procedure BOOTSTRAP-SAMPLE( $\mathbf{x}^{(1:N)}, \mathbf{y}^{(1:N)}, \delta(\cdot), M$ )
    for  $t \in \{1, 2, \dots, M\}$  do
        for  $i \in \{1, 2, \dots, N\}$  do
             $j \sim \text{UniformInteger}(1, N)$ 
             $\tilde{\mathbf{x}}^{(i)} \leftarrow \mathbf{x}^{(j)}$ 
             $\tilde{\mathbf{y}}^{(i)} \leftarrow \mathbf{y}^{(j)}$ 
             $d^{(t)} \leftarrow \delta(\tilde{\mathbf{x}}^{(1:N)}, \tilde{\mathbf{y}}^{(1:N)})$ 
    return  $\{d^{(t)}\}_{t=1}^M$ 
```

2173 rate, we would take the sum of one-tailed p -values, where the second term is computed
 2174 from the right tail of Figure 4.5. The binomial distribution is symmetric, so this can be
 2175 computed by simply doubling the one-tailed p -value.

2176 Two-tailed tests are more stringent, but they are necessary in cases in which there is
 2177 no prior intuition about whether c_1 or c_2 is better. For example, in comparing logistic
 2178 regression versus averaged perceptron, a two-tailed test is appropriate. In an ablation
 2179 test, c_2 may contain a superset of the features available to c_1 . If the additional features are
 2180 thought to be likely to improve performance, then a one-tailed test would be appropriate,
 2181 if chosen in advance. However, such a test can only prove that c_2 is more accurate than
 2182 c_1 , and not the reverse.

2183 **4.4.3.2 *Randomized testing**

2184 The binomial test is appropriate for accuracy, but not for more complex metrics such as
 2185 F -MEASURE. To compute statistical significance for arbitrary metrics, we can apply ran-
 2186 domization. Specifically, draw a set of M **bootstrap samples** (Efron and Tibshirani, 1993),
 2187 by resampling instances from the original test set with replacement. Each bootstrap sam-
 2188 ple is itself a test set of size N . Some instances from the original test set will not appear
 2189 in any given bootstrap sample, while others will appear multiple times; but overall, the
 2190 sample will be drawn from the same distribution as the original test set. We can then com-
 2191 pute any desired evaluation on each bootstrap sample, which gives a distribution over the
 2192 value of the metric. Algorithm 7 shows how to perform this computation.

2193 To compare the F -MEASURE of two classifiers c_1 and c_2 , we set the function $\delta(\cdot)$ to
 2194 compute the difference in F -MEASURE on the bootstrap sample. If the difference is less
 2195 than or equal to zero in at least 5% of the samples, then we cannot reject the one-tailed
 2196 null hypothesis that c_2 is at least as good as c_1 (Berg-Kirkpatrick et al., 2012). We may
 2197 also be interested in the 95% **confidence interval** around a metric of interest, such as
 2198 the F -MEASURE of a single classifier. This can be computed by sorting the output of

2199 Algorithm 7, and then setting the top and bottom of the 95% confidence interval to the
 2200 values at the 2.5% and 97.5% percentiles of the sorted outputs. Alternatively, you can fit
 2201 a normal distribution to the set of differences across bootstrap samples, and compute a
 2202 Gaussian confidence interval from the mean and variance.

2203 As the number of bootstrap samples goes to infinity, $M \rightarrow \infty$, the bootstrap estimate
 2204 is increasingly accurate. A typical choice for M is 10^4 or 10^5 ; larger numbers of samples
 2205 are necessary for smaller p -values. One way to validate your choice of M is to run the test
 2206 multiple times, and ensure that the p -values are similar; if not, increase M by an order of
 2207 magnitude. This is a heuristic measure of the **variance** of the test, which can decrease
 2208 with the square root \sqrt{M} (Robert and Casella, 2013).

2209 4.4.4 *Multiple comparisons

2210 Sometimes it is necessary to perform multiple hypothesis tests, such as when compar-
 2211 ing the performance of several classifiers on multiple datasets. Suppose you have five
 2212 datasets, and you compare four versions of your classifier against a baseline system, for a
 2213 total of 20 comparisons. Even if none of your classifiers is better than the baseline, there
 2214 will be some chance variation in the results, and in expectation you will get one statis-
 2215 tically significant improvement at $p = 0.05 = \frac{1}{20}$. It is therefore necessary to adjust the
 2216 p -values when reporting the results of multiple comparisons.

2217 One approach is to require a threshold of $\frac{\alpha}{m}$ to report a p value of $p < \alpha$ when per-
 2218 forming m tests. This is known as the **Bonferroni correction**, and it limits the overall
 2219 probability of incorrectly rejecting the null hypothesis at α . Another approach is to bound
 2220 the **false discovery rate** (FDR), which is the fraction of null hypothesis rejections that are
 2221 incorrect. Benjamini and Hochberg (1995) propose a p -value correction that bounds the
 2222 fraction of false discoveries at α : sort the p -values of each individual test in ascending
 2223 order, and set the significance threshold equal to largest k such that $p_k \leq \frac{k}{m}\alpha$. If $k > 1$, the
 2224 FDR adjustment is more permissive than the Bonferroni correction.

2225 4.5 Building datasets

2226 Sometimes, if you want to build a classifier, you must first build a dataset of your own.
 2227 This includes selecting a set of documents or instances to annotate, and then performing
 2228 the annotations. The scope of the dataset may be determined by the application: if you
 2229 want to build a system to classify electronic health records, then you must work with a
 2230 corpus of records of the type that your classifier will encounter when deployed. In other
 2231 cases, the goal is to build a system that will work across a broad range of documents. In
 2232 this case, it is best to have a *balanced* corpus, with contributions from many styles and
 2233 genres. For example, the Brown corpus draws from texts ranging from government doc-
 2234 uments to romance novels (Francis, 1964), and the Google Web Treebank includes an-

2235 notations for five “domains” of web documents: question answers, emails, newsgroups,
2236 reviews, and blogs (Petrov and McDonald, 2012).

2237 4.5.1 Metadata as labels

2238 Annotation is difficult and time-consuming, and most people would rather avoid it. It
2239 is sometimes possible to exploit existing metadata to obtain labels for training a classi-
2240 fier. For example, reviews are often accompanied by a numerical rating, which can be
2241 converted into a classification label (see § 4.1). Similarly, the nationalities of social media
2242 users can be estimated from their profiles (Dredze et al., 2013) or even the time zones of
2243 their posts (Gouws et al., 2011). More ambitiously, we may try to classify the political af-
2244 filiations of social media profiles based on their social network connections to politicians
2245 and major political parties (Rao et al., 2010).

2246 The convenience of quickly constructing large labeled datasets without manual an-
2247 notation is appealing. However this approach relies on the assumption that unlabeled
2248 instances — for which metadata is unavailable — will be similar to labeled instances.
2249 Consider the example of labeling the political affiliation of social media users based on
2250 their network ties to politicians. If a classifier attains high accuracy on such a test set,
2251 is it safe to assume that it accurately predicts the political affiliation of all social media
2252 users? Probably not. Social media users who establish social network ties to politicians
2253 may be more likely to mention politics in the text of their messages, as compared to the
2254 average user, for whom no political metadata is available. If so, the accuracy on a test set
2255 constructed from social network metadata would give an overly optimistic picture of the
2256 method’s true performance on unlabeled data.

2257 4.5.2 Labeling data

2258 In many cases, there is no way to get ground truth labels other than manual annotation.
2259 An annotation protocol should satisfy several criteria: the annotations should be *expressive*
2260 enough to capture the phenomenon of interest; they should be *replicable*, meaning that
2261 another annotator or team of annotators would produce very similar annotations if given
2262 the same data; and they should be *scalable*, so that they can be produced relatively quickly.
2263 Hovy and Lavid (2010) propose a structured procedure for obtaining annotations that
2264 meet these criteria, which is summarized below.

- 2265 1. **Determine what the annotations are to include.** This is usually based on some
2266 theory of the underlying phenomenon: for example, if the goal is to produce an-
2267 notations about the emotional state of a document’s author, one should start with a
2268 theoretical account of the types or dimensions of emotion (e.g., Mohammad and Tur-
2269 ney, 2013). At this stage, the tradeoff between expressiveness and scalability should

2270 be considered: a full instantiation of the underlying theory might be too costly to
2271 annotate at scale, so reasonable approximations should be considered.

- 2272 2. Optionally, one may **design or select a software tool to support the annotation**
2273 **effort**. Existing general-purpose annotation tools include BRAT (Stenetorp et al.,
2274 2012) and MMAX2 (Müller and Strube, 2006).
- 2275 3. **Formalize the instructions for the annotation task.** To the extent that the instruc-
2276 tions are not explicit, the resulting annotations will depend on the intuitions of the
2277 annotators. These intuitions may not be shared by other annotators, or by the users
2278 of the annotated data. Therefore explicit instructions are critical to ensuring the an-
2279 notations are replicable and usable by other researchers.
- 2280 4. **Perform a pilot annotation** of a small subset of data, with multiple annotators for
2281 each instance. This will give a preliminary assessment of both the replicability and
2282 scalability of the current annotation instructions. Metrics for computing the rate of
2283 agreement are described below. Manual analysis of specific disagreements should
2284 help to clarify the instructions, and may lead to modifications of the annotation task
2285 itself. For example, if two labels are commonly conflated by annotators, it may be
2286 best to merge them.
- 2287 5. **Annotate the data.** After finalizing the annotation protocol and instructions, the
2288 main annotation effort can begin. Some, if not all, of the instances should receive
2289 multiple annotations, so that inter-annotator agreement can be computed. In some
2290 annotation projects, instances receive many annotations, which are then aggregated
2291 into a “consensus” label (e.g., Danescu-Niculescu-Mizil et al., 2013). However, if the
2292 annotations are time-consuming or require significant expertise, it may be preferable
2293 to maximize scalability by obtaining multiple annotations for only a small subset of
2294 examples.
- 2295 6. **Compute and report inter-annotator agreement, and release the data.** In some
2296 cases, the raw text data cannot be released, due to concerns related to copyright or
2297 privacy. In these cases, one solution is to publicly release **stand-off annotations**,
2298 which contain links to document identifiers. The documents themselves can be re-
2299 leased under the terms of a licensing agreement, which can impose conditions on
2300 how the data is used. It is important to think through the potential consequences of
2301 releasing data: people may make personal data publicly available without realizing
2302 that it could be redistributed in a dataset and publicized far beyond their expecta-
2303 tions (boyd and Crawford, 2012).

2304 **4.5.2.1 Measuring inter-annotator agreement**

2305 To measure the replicability of annotations, a standard practice is to compute the extent to
 2306 which annotators agree with each other. If the annotators frequently disagree, this casts
 2307 doubt on either their reliability or on the annotation system itself. For classification, one
 2308 can compute the frequency with which the annotators agree; for rating scales, one can
 2309 compute the average distance between ratings. These raw agreement statistics must then
 2310 be compared with the rate of **chance agreement** — the level of agreement that would be
 2311 obtained between two annotators who ignored the data.

2312 **Cohen's Kappa** is widely used for quantifying the agreement on discrete labeling
 2313 tasks (Cohen, 1960; Carletta, 1996),¹²

$$\kappa = \frac{\text{agreement} - E[\text{agreement}]}{1 - E[\text{agreement}]}. \quad [4.11]$$

2314 The numerator is the difference between the observed agreement and the chance agree-
 2315 ment, and the denominator is the difference between perfect agreement and chance agree-
 2316 ment. Thus, $\kappa = 1$ when the annotators agree in every case, and $\kappa = 0$ when the annota-
 2317 tors agree only as often as would happen by chance. Various heuristic scales have been
 2318 proposed for determining when κ indicates "moderate", "good", or "substantial" agree-
 2319 ment; for reference, Lee and Narayanan (2005) report $\kappa \approx 0.45 - 0.47$ for annotations
 2320 of emotions in spoken dialogues, which they describe as "moderate agreement"; Stolcke
 2321 et al. (2000) report $\kappa = 0.8$ for annotations of **dialogue acts**, which are labels for the pur-
 2322 pose of each turn in a conversation.

2323 When there are two annotators, the expected chance agreement is computed as,

$$E[\text{agreement}] = \sum_k \hat{\Pr}(Y = k)^2, \quad [4.12]$$

2324 where k is a sum over labels, and $\hat{\Pr}(Y = k)$ is the empirical probability of label k across
 2325 all annotations. The formula is derived from the expected number of agreements if the
 2326 annotations were randomly shuffled. Thus, in a binary labeling task, if one label is applied
 2327 to 90% of instances, chance agreement is $.9^2 + .1^2 = .82$.

2328 **4.5.2.2 Crowdsourcing**

2329 Crowdsourcing is often used to rapidly obtain annotations for classification problems.
 2330 For example, **Amazon Mechanical Turk** makes it possible to define "human intelligence
 2331 tasks (hits)", such as labeling data. The researcher sets a price for each set of annotations
 2332 and a list of minimal qualifications for annotators, such as their native language and their

¹² For other types of annotations, Krippendorff's alpha is a popular choice (Hayes and Krippendorff, 2007; Artstein and Poesio, 2008).

2333 satisfaction rate on previous tasks. The use of relatively untrained “crowdworkers” con-
 2334 trasts with earlier annotation efforts, which relied on professional linguists (Marcus et al.,
 2335 1993). However, crowdsourcing has been found to produce reliable annotations for many
 2336 language-related tasks (Snow et al., 2008). Crowdsourcing is part of the broader field of
 2337 **human computation** (Law and Ahn, 2011).

2338 Additional resources

2339 Many of the preprocessing issues discussed in this chapter also arise in information re-
 2340 trieval. See (Manning et al., 2008, chapter 2) for discussion of tokenization and related
 2341 algorithms.

2342 Exercises

2343 1. As noted in § 4.3.3, words tend to appear in clumps, with subsequent occurrences
 2344 of a word being more probable. More concretely, if word j has probability $\phi_{y,j}$
 2345 of appearing in a document with label y , then the probability of two appearances
 2346 ($x_j^{(i)} = 2$) is greater than $\phi_{y,j}^2$.

2347 Suppose you are applying Naïve Bayes to a binary classification. Focus on a word j
 2348 which is more probable under label $y = 1$, so that,

$$\Pr(w = j \mid y = 1) > \Pr(w = j \mid y = 0). \quad [4.13]$$

2349 Now suppose that $x_j^{(i)} > 1$. All else equal, will the classifier overestimate or under-
 2350 estimate the posterior $\Pr(y = 1 \mid x)$?

2351 2. Prove that F-measure is never greater than the arithmetic mean of recall and pre-
 2352 cision, $\frac{r+p}{2}$. Your solution should also show that F-measure is equal to $\frac{r+p}{2}$ iff $r = p$.

2353 3. Given a binary classification problem in which the probability of the “positive” label
 2354 is equal to α , what is the expected F-MEASURE of a random classifier which ignores
 2355 the data, and selects $\hat{y} = +1$ with probability $\frac{1}{2}$? (Assume that $p(\hat{y}) \perp p(y)$.) What is
 2356 the expected F-MEASURE of a classifier that selects $\hat{y} = +1$ with probability α (also
 2357 independent of $y^{(i)}$)? Depending on α , which random classifier will score better?

2358 4. Suppose that binary classifiers c_1 and c_2 disagree on $N = 30$ cases, and that c_1 is
 2359 correct in $k = 10$ of those cases.

- 2360 • Write a program that uses primitive functions such as `exp` and `factorial` to com-
 2361 pute the **two-tailed** p -value — you may use an implementation of the “choose”
 2362 function if one is available. Verify your code against the output of a library for

- 2363 computing the binomial test or the binomial CDF, such as `scipy.stats.binom`
 2364 in Python.
- 2365 • Then use a randomized test to try to obtain the same p -value. In each sample,
 2366 draw from a binomial distribution with $N = 30$ and $\theta = \frac{1}{2}$. Count the fraction
 2367 of samples in which $k \leq 10$. This is the one-tailed p -value; double this to
 2368 compute the two-tailed p -value.
 - 2369 • Try this with varying numbers of bootstrap samples: $M \in \{100, 1000, 5000, 10000\}$.
 2370 For $M = 100$ and $M = 1000$, run the test 10 times, and plot the resulting p -
 2371 values.
 - 2372 • Finally, perform the same tests for $N = 70$ and $k = 25$.
- 2373 5. SemCor 3.0 is a labeled dataset for word sense disambiguation. You can download
 2374 it,¹³ or access it in `nltk.corpora.semcor`.
- 2375 Choose a word that appears at least ten times in SemCor (*find*), and annotate its
 2376 WordNet senses across ten randomly-selected examples, without looking at the ground
 2377 truth. Use online WordNet to understand the definition of each of the senses.¹⁴ Have
 2378 a partner do the same annotations, and compute the raw rate of agreement, expected
 2379 chance rate of agreement, and Cohen's kappa.
- 2380 6. Download the Pang and Lee movie review data, currently available from <http://www.cs.cornell.edu/people/pabo/movie-review-data/>. Hold out a
 2381 randomly-selected 400 reviews as a test set.
- 2383 Download a sentiment lexicon, such as the one currently available from Bing Liu,
 2384 <https://www.cs.uic.edu/~liub/FBS/sentiment-analysis.html>. Tokenize
 2385 the data, and classify each document as positive iff it has more positive sentiment
 2386 words than negative sentiment words. Compute the accuracy and *F*-MEASURE on
 2387 detecting positive reviews on the test set, using this lexicon-based classifier.
- 2388 Then train a discriminative classifier (averaged perceptron or logistic regression) on
 2389 the training set, and compute its accuracy and *F*-MEASURE on the test set.
- 2390 Determine whether the differences are statistically significant, using two-tailed hy-
 2391 pothesis tests: Binomial for the difference in accuracy, and bootstrap for the differ-
 2392 ence in macro-*F*-MEASURE.
- 2393 2394 The remaining problems will require you to build a classifier and test its properties. Pick
 a multi-class text classification dataset, such as RCV1¹⁵). Divide your data into training

¹³e.g., https://github.com/google-research-datasets/word_sense_disambiguation_corpora or <http://globalwordnet.org/wordnet-annotated-corpora/>

¹⁴<http://wordnetweb.princeton.edu/perl/webwn>

¹⁵http://www.ai.mit.edu/projects/jmlr/papers/volume5/lewis04a/lyrl2004_rcv1v2_README.htm

2395 (60%), development (20%), and test sets (20%), if no such division already exists. [todo:
2396 this dataset is already tokenized, find something else]

2397 7. Compare various vocabulary sizes of $10^2, 10^3, 10^4, 10^5$, using the most frequent words
2398 in each case (you may use any reasonable tokenizer). Train logistic regression clas-
2399 sifiers for each vocabulary size, and apply them to the development set. Plot the
2400 accuracy and Macro-*F*-MEASURE with the increasing vocabulary size. For each vo-
2401 cabulary size, tune the regularizer to maximize accuracy on a subset of data that is
2402 held out from the training set.

2403 8. Compare the following tokenization algorithms:

- 2404 • Whitespace, using a regular expression
2405 • Penn Treebank
2406 • Split input into five-character units, regardless of whitespace or punctuation

2407 Compute the token/type ratio for each tokenizer on the training data, and explain
2408 what you find. Train your classifier on each tokenized dataset, tuning the regularizer
2409 on a subset of data that is held out from the training data. Tokenize the development
2410 set, and report accuracy and Macro-*F*-MEASURE.

2411 9. Apply the Porter and Lancaster stemmers to the training set, using any reasonable
2412 tokenizer, and compute the token/type ratios. Train your classifier on the stemmed
2413 data, and compute the accuracy and Macro-*F*-MEASURE on stemmed development
2414 data, again using a held-out portion of the training data to tune the regularizer.

2415 10. Identify the best combination of vocabulary filtering, tokenization, and stemming
2416 from the previous three problems. Apply this preprocessing to the test set, and
2417 compute the test set accuracy and Macro-*F*-MEASURE. Compare against a baseline
2418 system that applies no vocabulary filtering, whitespace tokenization, and no stem-
2419 ming.

2420 Use the binomial test to determine whether your best-performing system is signifi-
2421 cantly more accurate than the baseline.

2422 Use the bootstrap test with $M = 10^4$ to determine whether your best-performing
2423 system achieves significantly higher macro-*F*-MEASURE.

2424 Chapter 5

2425 Learning without supervision

2426 So far we've assumed the following setup:

- 2427 a **training set** where you get observations x and labels y ;
- 2428 a **test set** where you only get observations x .

2429 Without labeled data, is it possible to learn anything? This scenario is known as **unsu-**
2430 **pervised learning**, and we will see that indeed it is possible to learn about the underlying
2431 structure of unlabeled observations. This chapter will also explore some related scenarios:
2432 **semi-supervised learning**, in which only some instances are labeled, and **domain adap-**
2433 **tation**, in which the training data differs from the data on which the trained system will
2434 be deployed.

2435 5.1 Unsupervised learning

2436 To motivate unsupervised learning, consider the problem of word sense disambiguation
2437 (§ 4.2). Our goal is to classify each instance of a word, such as *bank* into a sense,

- 2438 bank#1: a financial institution
- 2439 bank#2: the land bordering a river

2440 It is difficult to obtain sufficient training data for word sense disambiguation, because
2441 even a large corpus will contain only a few instances of all but the most common words.
2442 Is it possible to learn anything about these different senses without labeled data?

2443 Word sense disambiguation is usually performed using feature vectors constructed
2444 from the local context of the word to be disambiguated. For example, for the word

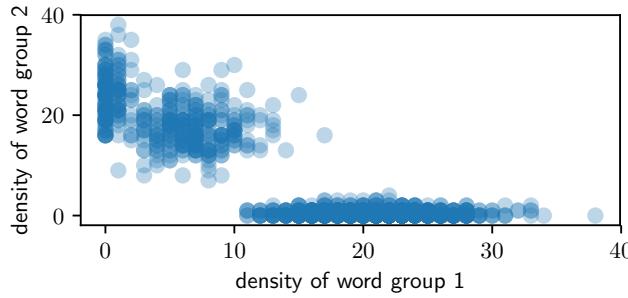


Figure 5.1: Counts of words from two different context groups

2445 *bank*, the immediate context might typically include words from one of the following two
 2446 groups:

- 2447 1. *financial, deposits, credit, lending, capital, markets, regulated, reserve, liquid, assets*
- 2448 2. *land, water, geography, stream, river, flow, deposits, discharge, channel, ecology*

2449 Now consider a scatterplot, in which each point is a document containing the word *bank*.
 2450 The location of the document on the x -axis is the count of words in group 1, and the
 2451 location on the y -axis is the count for group 2. In such a plot, shown in Figure 5.1, two
 2452 “blobs” might emerge, and these blobs correspond to the different senses of *bank*.

2453 Here’s a related scenario, from a different problem. Suppose you download thousands
 2454 of news articles, and make a scatterplot, where each point corresponds to a document:
 2455 the x -axis is the frequency of the group of words (*hurricane, winds, storm*); the y -axis is the
 2456 frequency of the group (*election, voters, vote*). This time, three blobs might emerge: one
 2457 for documents that are largely about a hurricane, another for documents largely about a
 2458 election, and a third for documents about neither topic.

2459 These clumps represent the underlying structure of the data. But the two-dimensional
 2460 scatter plots are based on groupings of context words, and in real scenarios these word
 2461 lists are unknown. Unsupervised learning applies the same basic idea, but in a high-
 2462 dimensional space with one dimension for every context word. This space can’t be di-
 2463 rectly visualized, but the idea is the same: try to identify the underlying structure of the
 2464 observed data, such that there are a few clusters of points, each of which is internally
 2465 coherent. **Clustering** algorithms are capable of finding such structure automatically.

2466 5.1.1 **K-means** clustering

2467 Clustering algorithms assign each data point to a discrete cluster, $z_i \in 1, 2, \dots, K$. One of
 2468 the best known clustering algorithms is ***K-means***, an iterative algorithm that maintains

Algorithm 8 K -means clustering algorithm

```

1: procedure  $K$ -MEANS( $\mathbf{x}_{1:N}, K$ )
2:   for  $i \in 1 \dots N$  do                                 $\triangleright$  initialize cluster memberships
3:      $z^{(i)} \leftarrow \text{RandomInt}(1, K)$ 
4:   repeat
5:     for  $k \in 1 \dots K$  do                           $\triangleright$  recompute cluster centers
6:        $\boldsymbol{\nu}_k \leftarrow \frac{1}{\delta(z^{(i)}=k)} \sum_{i=1}^N \delta(z^{(i)} = k) \mathbf{x}^{(i)}$ 
7:     for  $i \in 1 \dots N$  do                       $\triangleright$  reassing instances to nearest clusters
8:        $z^{(i)} \leftarrow \operatorname{argmin}_k \|\mathbf{x}^{(i)} - \boldsymbol{\nu}_k\|^2$ 
9:   until converged
10:  return  $\{z^{(i)}\}$                                  $\triangleright$  return cluster assignments

```

2469 a cluster assignment for each instance, and a central (“mean”) location for each cluster.
 2470 K -means iterates between updates to the assignments and the centers:

- 2471 1. each instance is placed in the cluster with the closest center;
 2472 2. each center is recomputed as the average over points in the cluster.

2473 This is formalized in Algorithm 8. The term $\|\mathbf{x}^{(i)} - \boldsymbol{\nu}\|^2$ refers to the squared Euclidean
 2474 norm, $\sum_{j=1}^V (x_j^{(i)} - \nu_j)^2$.

2475 **Soft K -means** is a particularly relevant variant. Instead of directly assigning each
 2476 point to a specific cluster, soft K -means assigns each point a **distribution** over clusters
 2477 $\mathbf{q}^{(i)}$, so that $\sum_{k=1}^K q^{(i)}(k) = 1$, and $\forall_k, q^{(i)}(k) \geq 0$. The soft weight $q^{(i)}(k)$ is computed from
 2478 the distance of $\mathbf{x}^{(i)}$ to the cluster center $\boldsymbol{\nu}_k$. In turn, the center of each cluster is computed
 2479 from a **weighted average** of the points in the cluster,

$$\boldsymbol{\nu}_k = \frac{1}{\sum_{i=1}^N q^{(i)}(k)} \sum_{i=1}^N q^{(i)}(k) \mathbf{x}^{(i)}. \quad [5.1]$$

2480 We will now explore a probabilistic version of soft K -means clustering, based on **expectation**
 2481 **maximization** (EM). Because EM clustering can be derived as an approximation to
 2482 maximum-likelihood estimation, it can be extended in a number of useful ways.

2483 **5.1.2 Expectation Maximization (EM)**

Expectation maximization combines the idea of soft K -means with Naïve Bayes classification. To review, Naïve Bayes defines a probability distribution over the data,

$$\log p(\mathbf{x}, \mathbf{y}; \boldsymbol{\phi}, \boldsymbol{\mu}) = \sum_{i=1}^N \log \left(p(\mathbf{x}^{(i)} | y^{(i)}; \boldsymbol{\phi}) \times p(y^{(i)}; \boldsymbol{\mu}) \right) \quad [5.2]$$

Now suppose that you never observe the labels. To indicate this, we'll refer to the label of each instance as $z^{(i)}$, rather than $y^{(i)}$, which is usually reserved for observed variables. By marginalizing over the **latent** variables \mathbf{z} , we compute the marginal probability of the observed instances \mathbf{x} :

$$\log p(\mathbf{x}; \boldsymbol{\phi}, \boldsymbol{\mu}) = \sum_{i=1}^N \log p(\mathbf{x}^{(i)}; \boldsymbol{\phi}, \boldsymbol{\mu}) \quad [5.3]$$

$$= \sum_{i=1}^N \log \sum_{z=1}^K p(\mathbf{x}^{(i)}, z; \boldsymbol{\phi}, \boldsymbol{\mu}) \quad [5.4]$$

$$= \sum_{i=1}^N \log \sum_{z=1}^K p(\mathbf{x}^{(i)} | z; \boldsymbol{\phi}) \times p(z; \boldsymbol{\mu}). \quad [5.5]$$

2484 To estimate the parameters $\boldsymbol{\phi}$ and $\boldsymbol{\mu}$, we can maximize the marginal likelihood in Equa-
 2485 tion 5.5. Why is this the right thing to maximize? Without labels, discriminative learning
 2486 is impossible — there's nothing to discriminate. So maximum likelihood is all we have.

2487 When the labels are observed, we can estimate the parameters of the Naïve Bayes
 2488 probability model separately for each label. But marginalizing over the labels couples
 2489 these parameters, making direct optimization of $\log p(\mathbf{x})$ intractable. We will approximate
 2490 the log-likelihood by introducing an *auxiliary variable* $\mathbf{q}^{(i)}$, which is a distribution over the
 2491 label set $\mathcal{Z} = \{1, 2, \dots, K\}$. The optimization procedure will alternate between updates to
 2492 \mathbf{q} and updates to the parameters $(\boldsymbol{\phi}, \boldsymbol{\mu})$. Thus, $\mathbf{q}^{(i)}$ plays here as in soft K -means.

To derive the updates for this optimization, multiply the right side of Equation 5.5 by

the ratio $\frac{q^{(i)}(z)}{q^{(i)}(z)} = 1$,

$$\log p(\mathbf{x}; \phi, \mu) = \sum_{i=1}^M \log \sum_{z=1}^K p(\mathbf{x}^{(i)} | z; \phi) \times p(z; \mu) \times \frac{q^{(i)}(z)}{q^{(i)}(z)} \quad [5.6]$$

$$= \sum_{i=1}^M \log \sum_{z=1}^K q^{(i)}(z) \times p(\mathbf{x}^{(i)} | z; \phi) \times p(z; \mu) \times \frac{1}{q^{(i)}(z)} \quad [5.7]$$

$$= \sum_{i=1}^M \log E_{\mathbf{q}^{(i)}} \left[\frac{p(\mathbf{x}^{(i)} | z; \phi) p(z; \mu)}{q^{(i)}(z)} \right], \quad [5.8]$$

where $E_{\mathbf{q}^{(i)}} [f(z)] = \sum_{z=1}^K q^{(i)}(z) \times f(z)$ refers to the expectation of the function f under the distribution $z \sim \mathbf{q}^{(i)}$.

Jensen's inequality says that because \log is a concave function, we can push it inside the expectation, and obtain a lower bound.

$$\log p(\mathbf{x}; \phi, \mu) \geq \sum_{i=1}^N E_{\mathbf{q}^{(i)}} \left[\log \frac{p(\mathbf{x}^{(i)} | z; \phi) p(z; \mu)}{q^{(i)}(z)} \right] \quad [5.9]$$

$$J \triangleq \sum_{i=1}^N E_{\mathbf{q}^{(i)}} \left[\log p(\mathbf{x}^{(i)} | z; \phi) + \log p(z; \mu) - \log q^{(i)}(z) \right] \quad [5.10]$$

$$= \sum_{i=1}^N E_{\mathbf{q}^{(i)}} \left[\log p(\mathbf{x}^{(i)}, z; \phi, \mu) \right] + H(\mathbf{q}^{(i)}) \quad [5.11]$$

We will focus on Equation 5.10, which is the lower bound on the marginal log-likelihood of the observed data, $\log p(\mathbf{x})$. Equation 5.11 shows the connection to the information theoretic concept of **entropy**, $H(\mathbf{q}^{(i)}) = -\sum_{z=1}^K q^{(i)}(z) \log q^{(i)}(z)$, which measures the average amount of information produced by a draw from the distribution $q^{(i)}$. The lower bound J is a function of two groups of arguments:

- the distributions $\mathbf{q}^{(i)}$ for each instance;
- the parameters μ and ϕ .

The expectation-maximization (EM) algorithm maximizes the bound with respect to each of these arguments in turn, while holding the other fixed.

5.1.2.1 The E-step

The step in which we update $\mathbf{q}^{(i)}$ is known as the **E-step**, because it updates the distribution under which the expectation is computed. To derive this update, first write out the

expectation in the lower bound as a sum,

$$J = \sum_{i=1}^N \sum_{z=1}^K q^{(i)}(z) \left[\log p(\mathbf{x}^{(i)} | z; \boldsymbol{\phi}) + \log p(z; \boldsymbol{\mu}) - \log q^{(i)}(z) \right]. \quad [5.12]$$

When optimizing this bound, we must also respect a set of “sum-to-one” constraints, $\sum_{z=1}^K q^{(i)}(z) = 1$ for all i . Just as in Naïve Bayes, this constraint can be incorporated into a Lagrangian:

$$J_q = \sum_{i=1}^N \sum_{z=1}^K q^{(i)}(z) \left(\log p(\mathbf{x}^{(i)} | z; \boldsymbol{\phi}) + \log p(z; \boldsymbol{\mu}) - \log q^{(i)}(z) \right) + \lambda^{(i)} \left(1 - \sum_{z=1}^K q^{(i)}(z) \right), \quad [5.13]$$

where $\lambda^{(i)}$ is the Lagrange multiplier for instance i .

The Lagrangian is maximized by taking the derivative and solving for $q^{(i)}$:

$$\frac{\partial J_q}{\partial q^{(i)}(z)} = \log p(\mathbf{x}^{(i)} | z; \boldsymbol{\phi}) + \log p(z; \boldsymbol{\mu}) - \log q^{(i)}(z) - 1 - \lambda^{(i)} \quad [5.14]$$

$$\log q^{(i)}(z) = \log p(\mathbf{x}^{(i)} | z; \boldsymbol{\phi}) + \log p(z; \boldsymbol{\mu}) - 1 - \lambda^{(i)} \quad [5.15]$$

$$q^{(i)}(z) \propto p(\mathbf{x}^{(i)} | z; \boldsymbol{\phi}) \times p(z; \boldsymbol{\mu}). \quad [5.16]$$

Applying the sum-to-one constraint gives an exact solution,

$$q^{(i)}(z) = \frac{p(\mathbf{x}^{(i)} | z; \boldsymbol{\phi}) \times p(z; \boldsymbol{\mu})}{\sum_{z'=1}^K p(\mathbf{x}^{(i)} | z'; \boldsymbol{\phi}) \times p(z'; \boldsymbol{\mu})} \quad [5.17]$$

$$= p(z | \mathbf{x}^{(i)}; \boldsymbol{\phi}, \boldsymbol{\mu}). \quad [5.18]$$

After normalizing, each $q^{(i)}$ — which is the soft distribution over clusters for data $\mathbf{x}^{(i)}$ — is set to the posterior probability $p(z | \mathbf{x}^{(i)}; \boldsymbol{\phi}, \boldsymbol{\mu})$ under the current parameters. Although the Lagrange multipliers $\lambda^{(i)}$ were introduced as additional parameters, they drop out during normalization.

5.1.2.2 The M-step

Next, we hold fixed the soft assignments $q^{(i)}$, and maximize with respect to the parameters, $\boldsymbol{\phi}$ and $\boldsymbol{\mu}$. Let’s focus on the parameter $\boldsymbol{\phi}$, which parametrizes the likelihood $p(\mathbf{x} | z; \boldsymbol{\phi})$, and leave $\boldsymbol{\mu}$ for an exercise. The parameter $\boldsymbol{\phi}$ is a distribution over words for each cluster, so it is optimized under the constraint that $\sum_{j=1}^V \phi_{z,j} = 1$. To incorporate this

constraint, we introduce a set of Lagrange multipliers $\{\lambda_z\}_{z=1}^K$, and from the Lagrangian,

$$J_\phi = \sum_{i=1}^N \sum_{z=1}^K q^{(i)}(z) \left(\log p(\mathbf{x}^{(i)} | z; \boldsymbol{\phi}) + \log p(z; \mu) - \log q^{(i)}(z) \right) + \sum_{z=1}^K \lambda_z \left(1 - \sum_{j=1}^V \phi_{z,j} \right). \quad [5.19]$$

2511 The term $\log p(\mathbf{x}^{(i)} | z; \boldsymbol{\phi})$ is the conditional log-likelihood for the multinomial, which
 2512 expands to,

$$\log p(\mathbf{x}^{(i)} | z, \boldsymbol{\phi}) = C + \sum_{j=1}^V x_j \log \phi_{z,j}, \quad [5.20]$$

2513 where C is a constant with respect to $\boldsymbol{\phi}$ — see Equation 2.12 in § 2.1 for more discussion
 2514 of this probability function.

Setting the derivative of J_ϕ equal to zero,

$$\frac{\partial J_\phi}{\partial \phi_{z,j}} = \sum_{i=1}^N q^{(i)}(z) \times \frac{x_j^{(i)}}{\phi_{z,j}} - \lambda_z \quad [5.21]$$

$$\phi_{z,j} \propto \sum_{i=1}^N q^{(i)}(z) \times x_j^{(i)}. \quad [5.22]$$

Because ϕ_z is constrained to be a probability distribution, the exact solution is computed as,

$$\phi_{z,j} = \frac{\sum_{i=1}^N q^{(i)}(z) \times x_j^{(i)}}{\sum_{j'=1}^V \sum_{i=1}^N q^{(i)}(z) \times x_{j'}^{(i)}} = \frac{E_q [\text{count}(z, j)]}{\sum_{j'=1}^V E_q [\text{count}(z, j')]} \quad [5.23]$$

2515 where the counter $j \in \{1, 2, \dots, V\}$ indexes over base features, such as words.

2516 This update sets ϕ_z equal to the relative frequency estimate of the *expected counts* under
 2517 the distribution q . As in supervised Naïve Bayes, we can smooth these counts by adding
 2518 a constant α . The update for μ is similar: $\mu_z \propto \sum_{i=1}^N q^{(i)}(z) = E_q [\text{count}(z)]$, which is the
 2519 expected frequency of cluster z . These probabilities can also be smoothed. In sum, the
 2520 M-step is just like Naïve Bayes, but with expected counts rather than observed counts.

2521 The multinomial likelihood $p(\mathbf{x} | z)$ can be replaced with other probability distribu-
 2522 tions: for example, for continuous observations, a Gaussian distribution can be used. In
 2523 some cases, there is no closed-form update to the parameters of the likelihood. One ap-
 2524 proach is to run gradient-based optimization at each M-step; another is to simply take a
 2525 single step along the gradient step and then return to the E-step (Berg-Kirkpatrick et al.,
 2526 2010).

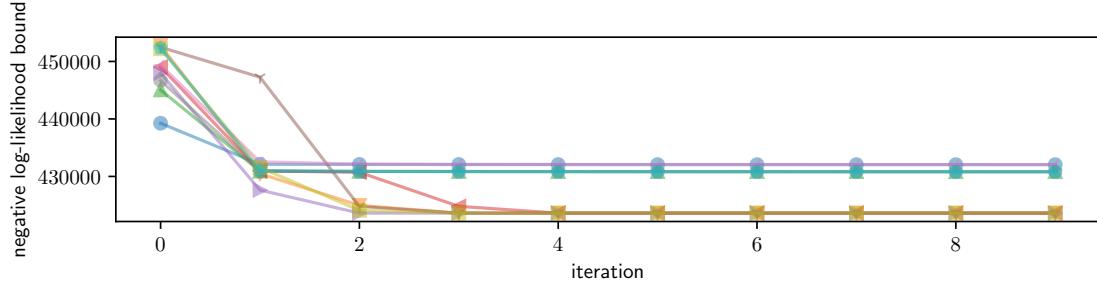


Figure 5.2: Sensitivity of expectation maximization to initialization. Each line shows the progress of optimization from a different random initialization.

2527 5.1.3 EM as an optimization algorithm

2528 Algorithms that alternate between updating subsets of the parameters are called **coordi-**
 2529 **nate ascent** algorithms. The objective J (the lower bound on the marginal likelihood of
 2530 the data) is separately convex in q and (μ, ϕ) , but it is not jointly convex in all terms; this
 2531 condition is known as **biconvexity**. Each step of the expectation-maximization algorithm
 2532 is guaranteed not to decrease the lower bound J , which means that EM will converge
 2533 towards a solution at which no nearby points yield further improvements. This solution
 2534 is a **local optimum** — it is as good or better than any of its immediate neighbors, but is
 2535 *not* guaranteed to be optimal among all possible configurations of (q, μ, ϕ) .

2536 The fact that there is no guarantee of global optimality means that initialization is
 2537 important: where you start can determine where you finish. To illustrate this point,
 2538 Figure 5.2 shows the objective function for EM with ten different random initializations:
 2539 while the objective function improves monotonically in each run, it converges to several
 2540 different values.¹ For the convex objectives that we encountered in chapter 2, it was not
 2541 necessary to worry about initialization, because gradient-based optimization guaranteed
 2542 to reach the global minimum. But in expectation-maximization — and in the deep neural
 2543 networks from chapter 3 — initialization matters.

2544 In **hard EM**, each $q^{(i)}$ distribution assigns probability of 1 to a single label $\hat{z}^{(i)}$, and zero
 2545 probability to all others (Neal and Hinton, 1998). This is similar in spirit to K -means clus-
 2546 tering, and can outperform standard EM in some cases (Spitkovsky et al., 2010). Another
 2547 variant of expectation maximization incorporates stochastic gradient descent (SGD): after
 2548 performing a local E-step at each instance $x^{(i)}$, we immediately make a gradient update
 2549 to the parameters (μ, ϕ) . This algorithm has been called **incremental expectation maxi-**
 2550 **mization** (Neal and Hinton, 1998) and **online expectation maximization** (Sato and Ishii,
 2551 2000; Cappé and Moulines, 2009), and is especially useful when there is no closed-form

¹The figure shows the upper bound on the *negative* log-likelihood, because optimization is typically framed as minimization rather than maximization.

2552 optimum for the likelihood $p(\mathbf{x} \mid z)$, and in online settings where new data is constantly
 2553 streamed in (see Liang and Klein, 2009, for a comparison for online EM variants).

2554 **5.1.4 How many clusters?**

2555 So far, we have assumed that the number of clusters K is given. In some cases, this as-
 2556 sumption is valid. For example, a lexical semantic resource like WordNet might define the
 2557 number of senses for a word. In other cases, the number of clusters could be a parameter
 2558 for the user to tune: some readers want a coarse-grained clustering of news stories into
 2559 three or four clusters, while others want a fine-grained clustering into twenty or more.
 2560 But many times there is little extrinsic guidance for how to choose K .

2561 One solution is to choose the number of clusters to maximize a metric of clustering
 2562 quality. The other parameters μ and ϕ are chosen to maximize the log-likelihood bound
 2563 J , so this might seem a potential candidate for tuning K . However, J will never decrease
 2564 with K : if it is possible to obtain a bound of J_K with K clusters, then it is always possible
 2565 to do at least as well with $K + 1$ clusters, by simply ignoring the additional cluster and
 2566 setting its probability to zero in q and μ . It is therefore necessary to introduce a penalty
 2567 for model complexity, so that fewer clusters are preferred. For example, the Akaike Infor-
 2568 mation Crition (AIC; Akaike, 1974) is the linear combination of the number of parameters
 2569 and the log-likelihood,

$$\text{AIC} = 2M - 2J, \quad [5.24]$$

2570 where M is the number of parameters. In an expectation-maximization clustering algo-
 2571 rithm, $M = K \times V + K$. Since the number of parameters increases with the number of
 2572 clusters K , the AIC may prefer more parsimonious models, even if they do not fit the data
 2573 quite as well.

2574 Another choice is to maximize the **predictive likelihood** on heldout data. This data
 2575 is not used to estimate the model parameters ϕ and μ , and so it is not the case that the
 2576 likelihood on this data is guaranteed to increase with K . Figure 5.3 shows the negative
 2577 log-likelihood on training and heldout data, as well as the AIC.

2578 ***Bayesian nonparametrics** An alternative approach is to treat the number of clusters as
 2579 another latent variable. This requires statistical inference over a set of models with a vari-
 2580 able number of clusters. This is not possible within the framework of expectation max-
 2581 imization, but there are several alternative inference procedures which can be applied,
 2582 including **Markov Chain Monte Carlo (MCMC)**, which is briefly discussed in § 5.5 (for
 2583 more details, see Chapter 25 of Murphy, 2012). Bayesian nonparametrics have been ap-
 2584 plied to the problem of unsupervised word sense induction, learning not only the word
 2585 senses but also the number of senses per word (Reisinger and Mooney, 2010).

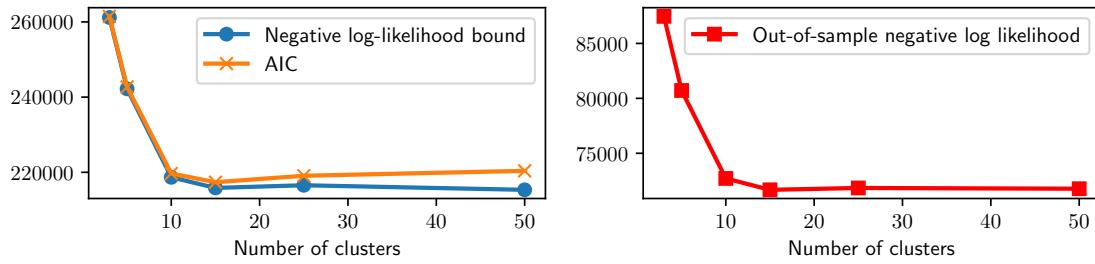


Figure 5.3: The negative log-likelihood and AIC for several runs of expectation maximization, on synthetic data. Although the data was generated from a model with $K = 10$, the optimal number of clusters is $\hat{K} = 15$, according to AIC and the heldout log-likelihood. The training set log-likelihood continues to improve as K increases.

2586 5.2 Applications of expectation-maximization

2587 EM is not really an “algorithm” like, say, quicksort. Rather, it is a framework for learning
2588 with missing data. The recipe for using EM on a problem of interest is:

- 2589 • Introduce latent variables z , such that it is easy to write the probability $P(x, z)$. It
2590 should also be easy to estimate the associated parameters, given knowledge of z .
- 2591 • Derive the E-step updates for $q(z)$, which is typically factored as $q(z) = \prod_{i=1}^N q_{z(i)}(z^{(i)})$,
2592 where i is an index over instances.
- 2593 • The M-step updates typically correspond to the soft version of a probabilistic super-
2594 vised learning algorithm, like Naïve Bayes.

2595 This section discusses a few of the many applications of this general framework.

2596 5.2.1 Word sense induction

2597 The chapter began by considering the problem of word sense disambiguation when the
2598 senses are not known in advance. Expectation-maximization can be applied to this prob-
2599 lem by treating each cluster as a word sense. Each instance represents the use of an
2600 ambiguous word, and $x^{(i)}$ is a vector of counts for the other words that appear nearby:
2601 Schütze (1998) uses all words within a 50-word window. The probability $p(x^{(i)} | z)$ can be
2602 set to the multinomial distribution, as in Naïve Bayes. The EM algorithm can be applied
2603 directly to this data, yielding clusters that (hopefully) correspond to the word senses.

Better performance can be obtained by first applying truncated **singular value decom-
position (SVD)** to the matrix of context-counts $C_{ij} = \text{count}(i, j)$, where $\text{count}(i, j)$ is the

count of word j in the context of instance i . Truncated singular value decomposition approximates the matrix \mathbf{C} as a product of three matrices, $\mathbf{U}, \mathbf{S}, \mathbf{V}$, under the constraint that \mathbf{U} and \mathbf{V} are orthonormal, and \mathbf{S} is diagonal:

$$\begin{aligned} & \min_{\mathbf{U}, \mathbf{S}, \mathbf{V}} \|\mathbf{C} - \mathbf{USV}^\top\|_F \\ & \text{s.t. } \mathbf{U} \in \mathbb{R}^{V \times K}, \mathbf{UU}^\top = \mathbb{I} \\ & \quad \mathbf{S} = \text{Diag}(s_1, s_2, \dots, s_K) \\ & \quad \mathbf{V}^\top \in \mathbb{R}^{N_p \times K}, \mathbf{VV}^\top = \mathbb{I}, \end{aligned} \quad [5.25]$$

where $\|\cdot\|_F$ is the Frobenius norm, $\|X\|_F = \sqrt{\sum_{i,j} X_{i,j}^2}$. The matrix \mathbf{U} contains the left singular vectors of \mathbf{C} , and the rows of this matrix can be used as low-dimensional representations of the count vectors \mathbf{c}_i . EM clustering can be made more robust by setting the instance descriptions $\mathbf{x}^{(i)}$ equal to these rows, rather than using raw counts (Schütze, 1998). However, because the instances are now dense vectors of continuous numbers, the probability $p(\mathbf{x}^{(i)} | z)$ must be defined as a multivariate Gaussian distribution.

In truncated singular value decomposition, the hyperparameter K is the truncation limit: when K is equal to the rank of \mathbf{C} , the norm of the difference between the original matrix \mathbf{C} and its reconstruction \mathbf{USV}^\top will be zero. Lower values of K increase the reconstruction error, but yield vector representations that are smaller and easier to learn from. Singular value decomposition is discussed in more detail in chapter 14.

5.2.2 Semi-supervised learning

Expectation-maximization can also be applied to the problem of **semi-supervised learning**: learning from both labeled and unlabeled data in a single model. Semi-supervised learning makes use of ground truth annotations, ensuring that each label y corresponds to the desired concept. By adding unlabeled data, it is possible cover a greater fraction of the features than would be possible using labeled data alone. Other methods for semi-supervised learning are discussed in § 5.3, but for now, let's approach the problem within the framework of expectation-maximization (Nigam et al., 2000).

Suppose we have labeled data $\{(\mathbf{x}^{(i)}, y^{(i)})\}_{i=1}^{N_\ell}$, and unlabeled data $\{\mathbf{x}^{(i)}\}_{i=N_\ell+1}^{N_\ell+N_u}$, where N_ℓ is the number of labeled instances and N_u is the number of unlabeled instances. We can learn from the combined data by maximizing a lower bound on the joint log-likelihood,

$$\mathcal{L} = \sum_{i=1}^{N_\ell} \log p(\mathbf{x}^{(i)}, y^{(i)}; \boldsymbol{\mu}, \boldsymbol{\phi}) + \sum_{j=N_\ell+1}^{N_\ell+N_u} \log p(\mathbf{x}^{(j)}; \boldsymbol{\mu}, \boldsymbol{\phi}) \quad [5.26]$$

$$= \sum_{i=1}^{N_\ell} \left(\log p(\mathbf{x}^{(i)} | y^{(i)}; \boldsymbol{\phi}) + \log p(y^{(i)}; \boldsymbol{\mu}) \right) + \sum_{j=N_\ell+1}^{N_\ell+N_u} \log \sum_{y=1}^K p(\mathbf{x}^{(j)}, y; \boldsymbol{\mu}, \boldsymbol{\phi}). \quad [5.27]$$

Algorithm 9 Generative process for the Naïve Bayes classifier with hidden components

for Document $i \in \{1, 2, \dots, N\}$ **do**:

Draw the label $y^{(i)} \sim \text{Categorical}(\mu)$;

Draw the component $z^{(i)} \sim \text{Categorical}(\beta_{y^{(i)}})$;

Draw the word counts $x^{(i)} | y^{(i)}, z^{(i)} \sim \text{Multinomial}(\phi_{z^{(i)}})$.

2623 The left sum is identical to the objective in Naïve Bayes; the right sum is the marginal log-
 2624 likelihood for expectation-maximization clustering, from Equation 5.5. We can construct a
 2625 lower bound on this log-likelihood by introducing distributions $q^{(j)}$ for all $j \in \{N_\ell + 1, \dots, N_\ell + N_u\}$.
 2626 The E-step updates these distributions; the M-step updates the parameters ϕ and μ , us-
 2627 ing the expected counts from the unlabeled data and the observed counts from the labeled
 2628 data.

2629 A critical issue in semi-supervised learning is how to balance the impact of the labeled
 2630 and unlabeled data on the classifier weights, especially when the unlabeled data is much
 2631 larger than the labeled dataset. The risk is that the unlabeled data will dominate, caus-
 2632 ing the parameters to drift towards a “natural clustering” of the instances — which may
 2633 not correspond to a good classifier for the labeled data. One solution is to heuristically
 2634 reweight the two components of Equation 5.26, tuning the weight of the two components
 2635 on a heldout development set (Nigam et al., 2000).

2636 **5.2.3 Multi-component modeling**

2637 As a final application, let’s return to fully supervised classification. A classic dataset for
 2638 text classification is 20 newsgroups, which contains posts to a set of online forums, called
 2639 newsgroups. One of the newsgroups is `comp.sys.mac.hardware`, which discusses Ap-
 2640 ple computing hardware. Suppose that within this newsgroup there are two kinds of
 2641 posts: reviews of new hardware, and question-answer posts about hardware problems.
 2642 The language in these *components* of the `mac.hardware` class might have little in com-
 2643 mon; if so, it would be better to model these components separately, rather than treating
 2644 their union as a single class. However, the component responsible for each instance is not
 2645 directly observed.

2646 Recall that Naïve Bayes is based on a generative process, which provides a stochastic
 2647 explanation for the observed data. In Naïve Bayes, each label is drawn from a categorical
 2648 distribution with parameter μ , and each vector of word counts is drawn from a multi-
 2649 nominal distribution with parameter ϕ_y . For multi-component modeling, we envision a
 2650 slightly different generative process, incorporating both the observed label $y^{(i)}$ and the
 2651 latent component $z^{(i)}$. This generative process is shown in Algorithm 9. A new parameter
 2652 $\beta_{y^{(i)}}$ defines the distribution of components, conditioned on the label $y^{(i)}$. The component,
 2653 and not the class label, then parametrizes the distribution over words.

-
- (5.1) ☺ Villeneuve a bel et bien **réussi** son pari de changer de perspectives tout en assurant une cohérence à la franchise.²
- (5.2) ☺ Il est également trop **long** et bancal dans sa narration, tiède dans ses intentions, et tirailé entre deux personnages et directions qui ne parviennent pas à coexister en harmonie.³
- (5.3) Denis Villeneuve a **réussi** une suite **parfaitemment** maîtrisée⁴
- (5.4) **Long, bavard**, hyper design, à peine agité (le comble de l'action : une bagarre dans la flotte), métaphysique et, surtout, ennuyeux jusqu'à la catalepsie.⁵
- (5.5) Une suite d'une écrasante puissance, mêlant **parfaitemment** le contemplatif au narratif.⁶
- (5.6) Le film impitoyablement **bavard** finit quand même par se taire quand se lève l'espèce de bouquet final où semble se déchaîner, comme en libre parcours de poulets décapiés, l'armée des graphistes numériques griffant nerveusement la palette graphique entre agonie et orgasme.⁷

Table 5.1: Labeled and unlabeled reviews of the films *Blade Runner 2049* and *Transformers: The Last Knight*.

The labeled data includes $(\mathbf{x}^{(i)}, y^{(i)})$, but not $z^{(i)}$, so this is another case of missing data. Again, we sum over the missing data, applying Jensen's inequality to as to obtain a lower bound on the log-likelihood,

$$\log p(\mathbf{x}^{(i)}, y^{(i)}) = \log \sum_{z=1}^{K_z} p(\mathbf{x}^{(i)}, y^{(i)}, z; \boldsymbol{\mu}, \boldsymbol{\phi}, \boldsymbol{\beta}) \quad [5.28]$$

$$\geq \log p(y^{(i)}; \boldsymbol{\mu}) + E_{q_{Z|Y}^{(i)}} [\log p(\mathbf{x}^{(i)} | z; \boldsymbol{\phi}) + \log p(z | y^{(i)}; \boldsymbol{\beta}) - \log q^{(i)}(z)]. \quad [5.29]$$

We are now ready to apply expectation maximization. As usual, the E-step updates the distribution over the missing data, $q_{Z|Y}^{(i)}$. The M-step updates the parameters,

$$\beta_{y,z} = \frac{E_q [\text{count}(y, z)]}{\sum_{z'=1}^{K_z} E_q [\text{count}(y, z')]} \quad [5.30]$$

$$\phi_{z,j} = \frac{E_q [\text{count}(z, j)]}{\sum_{j'=1}^V E_q [\text{count}(z, j')]} \quad [5.31]$$

2654 5.3 Semi-supervised learning

2655 In semi-supervised learning, the learner makes use of both labeled and unlabeled data.
 2656 To see how this could help, suppose you want to do sentiment analysis in French. In Ta-

ble 5.1, there are two labeled examples, one positive and one negative. From this data, a learner could conclude that *réussi* is positive and *long* is negative. This isn't much! However, we can propagate this information to the unlabeled data, and potentially learn more.

- If we are confident that *réussi* is positive, then we might guess that (5.3) is also positive.
- That suggests that *parfaitement* is also positive.
- We can then propagate this information to (5.5), and learn from this words in this example.
- Similarly, we can propagate from the labeled data to (5.4), which we guess to be negative because it shares the word *long*. This suggests that *bavard* is also negative, which we propagate to (5.6).

Instances (5.3) and (5.4) were "similar" to the labeled examples for positivity and negativity, respectively. By using these instances to expand the models for each class, it became possible to correctly label instances (5.5) and (5.6), which didn't share any important features with the original labeled data. This requires a key assumption: that similar instances will have similar labels.

In § 5.2.2, we discussed how expectation maximization can be applied to semi-supervised learning. Using the labeled data, the initial parameters ϕ would assign a high weight for *réussi* in the positive class, and a high weight for *long* in the negative class. These weights helped to shape the distributions q for instances (5.3) and (5.4) in the E-step. In the next iteration of the M-step, the parameters ϕ are updated with counts from these instances, making it possible to correctly label the instances (5.5) and (5.6).

However, expectation-maximization has an important disadvantage: it requires using a generative classification model, which restricts the features that can be used for classification. In this section, we explore non-probabilistic approaches, which impose fewer restrictions on the classification model.

5.3.1 Multi-view learning

EM semi-supervised learning can be viewed as **self-training**: the labeled data guides the initial estimates of the classification parameters; these parameters are used to compute a label distribution over the unlabeled instances, $q^{(i)}$; the label distributions are used to update the parameters. The risk is that self-training drifts away from the original labeled data. This problem can be ameliorated by **multi-view learning**. Here we take the assumption that the features can be decomposed into multiple "views", each of which is conditionally independent, given the label. For example, consider the problem of classifying a name as a person or location: one view is the name itself; another is the context in which it appears. This situation is illustrated in Table 5.2.

	$\mathbf{x}^{(1)}$	$\mathbf{x}^{(2)}$	y
1.	Peachtree Street	located on	LOC
2.	Dr. Walker	said	PER
3.	Zanzibar	located in	? → LOC
4.	Zanzibar	flew to	? → LOC
5.	Dr. Robert	recommended	? → PER
6.	Oprah	recommended	? → PER

Table 5.2: Example of multiview learning for named entity classification

2693 **Co-training** is an iterative multi-view learning algorithm, in which there are separate
 2694 classifiers for each view (Blum and Mitchell, 1998). At each iteration of the algorithm, each
 2695 classifier predicts labels for a subset of the unlabeled instances, using only the features
 2696 available in its view. These predictions are then used as ground truth to train the classifiers
 2697 associated with the other views. In the example shown in Table 5.2, the classifier on $\mathbf{x}^{(1)}$
 2698 might correctly label instance #5 as a person, because of the feature *Dr*; this instance would
 2699 then serve as training data for the classifier on $\mathbf{x}^{(2)}$, which would then be able to correctly
 2700 label instance #6, thanks to the feature *recommended*. If the views are truly independent,
 2701 this procedure is robust to drift. Furthermore, it imposes no restrictions on the classifiers
 2702 that can be used for each view.

2703 Word-sense disambiguation is particularly suited to multi-view learning, thanks to the
 2704 heuristic of “one sense per discourse”: if a polysemous word is used more than once in
 2705 a given text or conversation, all usages refer to the same sense (Gale et al., 1992). This
 2706 motivates a multi-view learning approach, in which one view corresponds to the local
 2707 context (the surrounding words), and another view corresponds to the global context at
 2708 the document level (Yarowsky, 1995). The local context view is first trained on a small
 2709 seed dataset. We then identify its most confident predictions on unlabeled instances. The
 2710 global context view is then used to extend these confident predictions to other instances
 2711 within the same documents. These new instances are added to the training data to the
 2712 local context classifier, which is retrained and then applied to the remaining unlabeled
 2713 data.

2714 5.3.2 Graph-based algorithms

2715 Another family of approaches to semi-supervised learning begins by constructing a graph,
 2716 in which pairs of instances are linked with symmetric weights $\omega_{i,j}$, e.g.,

$$\omega_{i,j} = \exp(-\alpha \times \|\mathbf{x}^{(i)} - \mathbf{x}^{(j)}\|^2). \quad [5.32]$$

2717 The goal is to use this weighted graph to propagate labels from a small set of labeled
 2718 instances to larger set of unlabeled instances.

2719 In **label propagation**, this is done through a series of matrix operations (Zhu et al.,
 2720 Let \mathbf{Q} be a matrix of size $N \times K$, in which each row $\mathbf{q}^{(i)}$ describes the labeling
 2721 of instance i . When ground truth labels are available, then $\mathbf{q}^{(i)}$ is an indicator vector,
 2722 with $q_{y^{(i)}}^{(i)} = 1$ and $q_{y' \neq y^{(i)}}^{(i)} = 0$. Let us refer to the submatrix of rows containing labeled
 2723 instances as \mathbf{Q}_L , and the remaining rows as \mathbf{Q}_U . The rows of \mathbf{Q}_U are initialized to assign
 2724 equal probabilities to all labels, $q_{i,k} = \frac{1}{K}$.

2725 Now, let $T_{i,j}$ represent the “transition” probability of moving from node j to node i ,

$$T_{i,j} \triangleq \Pr(j \rightarrow i) = \frac{\omega_{i,j}}{\sum_{k=1}^N \omega_{k,j}}. \quad [5.33]$$

We compute values of $T_{i,j}$ for all instances j and all *unlabeled* instances i , forming a matrix
 of size $N_U \times N$. If the dataset is large, this matrix may be expensive to store and manip-
 ulate; a solution is to sparsify it, by keeping only the κ largest values in each row, and
 setting all other values to zero. We can then “propagate” the label distributions to the
 unlabeled instances,

$$\tilde{\mathbf{Q}}_U \leftarrow \mathbf{T}\mathbf{Q} \quad [5.34]$$

$$\mathbf{s} \leftarrow \tilde{\mathbf{Q}}_U \mathbf{1} \quad [5.35]$$

$$\mathbf{Q}_U \leftarrow \text{Diag}(\mathbf{s})^{-1} \tilde{\mathbf{Q}}_U. \quad [5.36]$$

2726 The expression $\tilde{\mathbf{Q}}_U \mathbf{1}$ indicates multiplication of $\tilde{\mathbf{Q}}_U$ by a column vector of ones, which is
 2727 equivalent to computing the sum of each row of $\tilde{\mathbf{Q}}_U$. The matrix $\text{Diag}(\mathbf{s})$ is a diagonal
 2728 matrix with the elements of \mathbf{s} on the diagonals. The product $\text{Diag}(\mathbf{s})^{-1} \tilde{\mathbf{Q}}_U$ has the effect
 2729 of normalizing the rows of $\tilde{\mathbf{Q}}_U$, so that each row of \mathbf{Q}_U is a probability distribution over
 2730 labels.

2731 5.4 Domain adaptation

2732 In many practical scenarios, the labeled data differs in some key respect from the data
 2733 to which the trained model is to be applied. A classic example is in consumer reviews:
 2734 we may have labeled reviews of movies (the **source domain**), but we want to predict the
 2735 reviews of appliances (the **target domain**). A similar issues arise with genre differences:
 2736 most linguistically-annotated data is news text, but application domains range from social
 2737 media to electronic health records. In general, there may be several source and target
 2738 domains, each with their own properties; however, for simplicity, this discussion will
 2739 focus mainly on the case of a single source and target domain.

2740 The simplest approach is “direct transfer”: train a classifier on the source domain,
 2741 and apply it directly to the target domain. The accuracy of this approach depends on the
 2742 extent to which features are shared across domains. In review text, words like *outstanding*

and *disappointing* will apply across both movies and appliances; but others, like *terrifying*, may have meanings that are domain-specific. **Domain adaptation** algorithms attempt to do better than direct transfer, by learning from data in both domains. There are two main families of domain adaptation algorithms, depending on whether any labeled data is available in the target domain.

5.4.1 Supervised domain adaptation

In supervised domain adaptation, there is a small amount of labeled data in the target domain, and a large amount of data in the source domain. The simplest approach would be to ignore domain differences, and simply merge the training data from the source and target domains. There are several other baseline approaches to dealing with this scenario (Daumé III, 2007):

Interpolation. Train a classifier for each domain, and combine their predictions. For example,

$$\hat{y} = \operatorname{argmax}_y \lambda_s \Psi_s(\mathbf{x}, y) + (1 - \lambda_s) \Psi_t(\mathbf{x}, y), \quad [5.37]$$

where Ψ_s and Ψ_t are the scoring functions from the source and target domain classifiers respectively, and λ_s is the interpolation weight.

Prediction. Train a classifier on the source domain data, use its prediction as an additional feature in a classifier trained on the target domain data.

Priors. Train a classifier on the source domain data, and use its weights as a prior distribution on the weights of the classifier for the target domain data. This is equivalent to regularizing the target domain weights towards the weights of the source domain classifier (Chelba and Acero, 2006),

$$\ell(\boldsymbol{\theta}_t) = \sum_{i=1}^N \ell^{(i)}(\mathbf{x}^{(i)}, y^{(i)}; \boldsymbol{\theta}_t) + \lambda \|\boldsymbol{\theta}_t - \boldsymbol{\theta}_s\|_2^2, \quad [5.38]$$

where $\ell^{(i)}$ is the prediction loss on instance i , and λ is the regularization weight.

An effective and “frustratingly simple” alternative is EasyAdapt (Daumé III, 2007), which creates copies of each feature: one for each domain and one for the cross-domain setting. For example, a negative review of the film *Wonder Woman* begins, *As boring and flavorless as a three-day-old grilled cheese sandwich....*⁸ The resulting bag-of-words feature

⁸<http://www.colesmithey.com/capsules/2017/06/wonder-woman.HTML>, accessed October 9, 2017.

vector would be,

$$\begin{aligned} \mathbf{f}(\mathbf{x}, y, d) = & \{(boring, -, \text{MOVIE}) : 1, (boring, -, *) : 1, \\ & (flavorless, -, \text{MOVIE}) : 1, (flavorless, -, *) : 1, \\ & (three-day-old, -, \text{MOVIE}) : 1, (three-day-old, -, *) : 1, \\ & \dots\}, \end{aligned}$$

with $(boring, -, \text{MOVIE})$ indicating the word *boring* appearing in a negative labeled document in the MOVIE domain, and $(boring, -, *)$ indicating the same word in a negative labeled document in *any* domain. It is up to the learner to allocate weight between the domain-specific and cross-domain features: for words that facilitate prediction in both domains, the learner will use the cross-domain features; for words that are relevant only to a single domain, the domain-specific features will be used. Any discriminative classifier can be used with these augmented features.⁹

5.4.2 Unsupervised domain adaptation

In unsupervised domain adaptation, there is no labeled data in the target domain. Unsupervised domain adaptation algorithms cope with this problem by trying to make the data from the source and target domains as similar as possible. This is typically done by learning a **projection function**, which puts the source and target data in a shared space, in which a learner can generalize across domains. This projection is learned from data in both domains, and is applied to the base features — for example, the bag-of-words in text classification. The projected features can then be used both for training and for prediction.

5.4.2.1 Linear projection

In linear projection, the cross-domain representation is constructed by a matrix-vector product,

$$\mathbf{g}(\mathbf{x}^{(i)}) = \mathbf{U}\mathbf{x}^{(i)}. \quad [5.39]$$

The projected vectors $\mathbf{g}(\mathbf{x}^{(i)})$ can then be used as base features during both training (from the source domain) and prediction (on the target domain).

The projection matrix \mathbf{U} can be learned in a number of different ways, but many approaches focus on compressing and reconstructing the base features (Ando and Zhang, 2005). For example, we can define a set of **pivot features**, which are typically chosen because they appear in both domains: in the case of review documents, pivot features might include evaluative adjectives like *outstanding* and *disappointing* (Blitzer et al., 2007). For each pivot feature j , we define an auxiliary problem of predicting whether the feature is

⁹EasyAdapt can be explained as a hierarchical Bayesian model, in which the weights for each domain are drawn from a shared prior (Finkel and Manning, 2009).

2791 present in each example, using the remaining base features. Let ϕ_j denote the weights of
 2792 this classifier, and us horizontally concatenate the weights for each of the N_p pivot features
 2793 into a matrix $\Phi = [\phi_1, \phi_2, \dots, \phi_{N_p}]$.

2794 We then perform truncated singular value decomposition on Φ , as described in § 5.2.1,
 2795 obtaining $\Phi \approx \mathbf{U}\mathbf{S}\mathbf{V}^\top$. The rows of the matrix \mathbf{U} summarize information about each base
 2796 feature: indeed, the truncated singular value decomposition identifies a low-dimension
 2797 basis for the weight matrix Φ , which in turn links base features to pivot features. Sup-
 2798 pose that a base feature *reliable* occurs only in the target domain of appliance reviews.
 2799 Nonetheless, it will have a positive weight towards some pivot features (e.g., *outstanding*,
 2800 *recommended*), and a negative weight towards others (e.g., *worthless*, *unpleasant*). A base
 2801 feature such as *watchable* might have the same associations with the pivot features, and
 2802 therefore, $\mathbf{u}_{\text{reliable}} \approx \mathbf{u}_{\text{watchable}}$. The matrix \mathbf{U} can thus project the base features into a
 2803 space in which this information is shared.

2804 5.4.2.2 Non-linear projection

2805 Non-linear transformations of the base features can be accomplished by implementing
 2806 the transformation function as a deep neural network, which is trained from an auxiliary
 2807 objective.

2808 **Denoising objectives** One possibility is to train a projection function to reconstruct a
 2809 corrupted version of the original input. The original input can be corrupted in various
 2810 ways: by the addition of random noise (Glorot et al., 2011; Chen et al., 2012), or by the
 2811 deletion of features (Chen et al., 2012; Yang and Eisenstein, 2015). Denoising objectives
 2812 share many properties of the linear projection method described above: they enable the
 2813 projection function to be trained on large amounts of unlabeled data from the target do-
 2814 main, and allow information to be shared across the feature space, thereby reducing sen-
 2815 sitivity to rare and domain-specific features.

2816 **Adversarial objectives** The ultimate goal is for the transformed representations $\mathbf{g}(\mathbf{x}^{(i)})$
 2817 to be domain-general. This can be made an explicit optimization criterion by comput-
 2818 ing the similarity of transformed instances both within and between domains (Tzeng
 2819 et al., 2015), or by formulating an auxiliary classification task, in which the domain it-
 2820 self is treated as a label (Ganin et al., 2016). This setting is **adversarial**, because we want
 2821 to learn a representation that makes this classifier perform poorly. At the same time, we
 2822 want $\mathbf{g}(\mathbf{x}^{(i)})$ to enable accurate predictions of the labels $y^{(i)}$.

2823 To formalize this idea, let $d^{(i)}$ represent the domain of instance i , and let $\ell_d(\mathbf{g}(\mathbf{x}^{(i)}), d^{(i)}; \theta_d)$
 2824 represent the loss of a classifier (typically a deep neural network) trained to predict $d^{(i)}$
 2825 from the transformed representation $\mathbf{g}(\mathbf{x}^{(i)})$, using parameters θ_d . Analogously, let $\ell_y(\mathbf{g}(\mathbf{x}^{(i)}), y^{(i)}; \theta_y)$
 2826 represent the loss of a classifier trained to predict the label $y^{(i)}$ from $\mathbf{g}(\mathbf{x}^{(i)})$, using param-

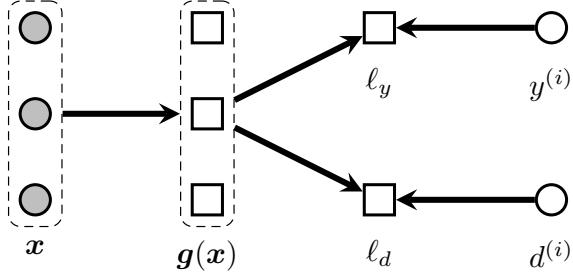


Figure 5.4: A schematic view of adversarial domain adaptation. The loss ℓ_y is computed only for instances from the source domain, where labels $y^{(i)}$ are available.

eters θ_y . The transformation g can then be trained from two criteria: it should yield accurate predictions of the labels $y^{(i)}$, while making *inaccurate* predictions of the domains $d^{(i)}$. This can be formulated as a joint optimization problem,

$$\min_{f, \theta_g, \theta_y, \theta_d} \sum_{i=1}^{N_\ell+N_u} \ell_d(g(\mathbf{x}^{(i)}; \theta_g), d^{(i)}; \theta_d) - \sum_{i=1}^{N_\ell} \ell_y(g(\mathbf{x}^{(i)}), y^{(i)}; \theta_y), \quad [5.40]$$

where N_ℓ is the number of labeled instances and N_u is the number of unlabeled instances, with the labeled instances appearing first in the dataset. This setup is shown in Figure 5.4. The loss can be optimized by stochastic gradient descent, jointly training the parameters of the non-linear transformation θ_g , and the parameters of the prediction models θ_d and θ_y .

5.5 *Other approaches to learning with latent variables

Expectation maximization provides a general approach to learning with latent variables, but it has limitations. One is the sensitivity to initialization; in practical applications, considerable attention may need to be devoted to finding a good initialization. A second issue is that EM tends to be easiest to apply in cases where the latent variables have a clear decomposition (in the cases we have considered, they decompose across the instances). For these reasons, it is worth briefly considering some alternatives to EM.

5.5.1 Sampling

In EM clustering, there is a distribution $q^{(i)}$ for the missing data related to each instance. The M-step consists of updating the parameters of this distribution. An alternative is to draw samples of the latent variables. If the sampling distribution is designed correctly, this procedure will eventually converge to drawing samples from the true posterior over the missing data, $p(z^{(1:N_z)} | \mathbf{x}^{(1:N_x)})$. For example, in the case of clustering, the missing

2848 data $\mathbf{z}^{(1:N_z)}$ is the set of cluster memberships, $\mathbf{y}^{(1:N)}$, so we draw samples from the pos-
 2849 terior distribution over clusterings of the data. If a single clustering is required, we can
 2850 select the one with the highest conditional likelihood, $\hat{\mathbf{z}} = \operatorname{argmax}_{\mathbf{z}} p(\mathbf{z}^{(1:N_z)} | \mathbf{x}^{(1:N_x)})$.

This general family of algorithms is called **Markov Chain Monte Carlo (MCMC)**: “Monte Carlo” because it is based on a series of random draws; “Markov Chain” because the sampling procedure must be designed such that each sample depends only on the previous sample, and not on the entire sampling history. **Gibbs sampling** is an MCMC algorithm in which each latent variable is sampled from its posterior distribution,

$$\mathbf{z}^{(n)} | \mathbf{x}, \mathbf{z}^{(-n)} \sim p(\mathbf{z}^{(n)} | \mathbf{x}, \mathbf{z}^{(-n)}), \quad [5.41]$$

where $\mathbf{z}^{(-n)}$ indicates $\{\mathbf{z} \setminus \mathbf{z}^{(n)}\}$, the set of all latent variables except for $\mathbf{z}^{(n)}$. Repeatedly drawing samples over all latent variables constructs a Markov chain, and which is guaranteed to converge to a sequence of samples from, $p(\mathbf{z}^{(1:N_z)} | \mathbf{x}^{(1:N_x)})$. In probabilistic clustering, the sampling distribution has the following form,

$$p(\mathbf{z}^{(i)} | \mathbf{x}, \mathbf{z}^{(-i)}) = \frac{p(\mathbf{x}^{(i)} | z^{(i)}; \boldsymbol{\phi}) \times p(z^{(i)}; \boldsymbol{\mu})}{\sum_{z=1}^K p(\mathbf{x}^{(i)} | z; \boldsymbol{\phi}) \times p(z; \boldsymbol{\mu})} \quad [5.42]$$

$$\propto \text{Multinomial}(\mathbf{x}^{(i)}; \boldsymbol{\phi}_{z^{(i)}}) \times \boldsymbol{\mu}_{z^{(i)}}. \quad [5.43]$$

2851 In this case, the sampling distribution does not depend on the other instances $\mathbf{x}^{(-i)}, \mathbf{z}^{(-i)}$:
 2852 given the parameters $\boldsymbol{\phi}$ and $\boldsymbol{\mu}$, the posterior distribution over each $z^{(i)}$ can be computed
 2853 from $\mathbf{x}^{(i)}$ alone.

2854 In sampling algorithms, there are several choices for how to deal with the parameters.
 2855 One possibility is to sample them too. To do this, we must add them to the generative
 2856 story, by introducing a prior distribution. For the multinomial and categorical parameters
 2857 in the EM clustering model, the **Dirichlet distribution** is a typical choice, since it defines
 2858 a probability on exactly the set of vectors that can be parameters: vectors that sum to one
 2859 and include only non-negative numbers.¹⁰

2860 To incorporate this prior, the generative model must augmented to indicate that each
 2861 $\boldsymbol{\phi}_z \sim \text{Dirichlet}(\boldsymbol{\alpha}_\phi)$, and $\boldsymbol{\mu} \sim \text{Dirichlet}(\boldsymbol{\alpha}_\mu)$. The hyperparameters $\boldsymbol{\alpha}$ are typically set to

¹⁰If $\sum_i^K \theta_i = 1$ and $\theta_i \geq 0$ for all i , then $\boldsymbol{\theta}$ is said to be on the $K - 1$ **simplex**. A Dirichlet distribution with parameter $\boldsymbol{\alpha} \in \mathbb{R}_+^K$ has support over the $K - 1$ simplex,

$$p_{\text{Dirichlet}}(\boldsymbol{\theta} | \boldsymbol{\alpha}) = \frac{1}{B(\boldsymbol{\alpha})} \prod_{i=1}^K \theta_i^{\alpha_i - 1} \quad [5.44]$$

$$B(\boldsymbol{\alpha}) = \frac{\prod_{i=1}^K \Gamma(\alpha_i)}{\Gamma(\sum_{i=1}^K \alpha_i)}, \quad [5.45]$$

with $\Gamma(\cdot)$ indicating the gamma function, a generalization of the factorial function to non-negative reals.

2862 a constant vector $\alpha = [\alpha, \alpha, \dots, \alpha]$. When α is large, the Dirichlet distribution tends to
 2863 generate vectors that are nearly uniform; when α is small, it tends to generate vectors that
 2864 assign most of their probability mass to a few entries. Given prior distributions over ϕ
 2865 and μ , we can now include them in Gibbs sampling, drawing values for these parameters
 2866 from posterior distributions that are conditioned on the other variables in the model.

2867 Unfortunately, sampling ϕ and μ usually leads to slow convergence, meaning that a
 2868 large number of samples is required before the Markov chain breaks free from the initial
 2869 conditions. The reason is that the sampling distributions for these parameters are tightly
 2870 constrained by the cluster memberships $y^{(i)}$, which in turn are tightly constrained by the
 2871 parameters. There are two solutions that are frequently employed:

- 2872 • **Empirical Bayesian** methods maintain ϕ and μ as parameters rather than latent
 2873 variables. They still employ sampling in the E-step of the EM algorithm, but they
 2874 update the parameters using expected counts that are computed from the samples
 2875 rather than from parametric distributions. This EM-MCMC hybrid is also known
 2876 as Monte Carlo Expectation Maximization (MCEM; Wei and Tanner, 1990), and is
 2877 well-suited for cases in which it is difficult to compute $q^{(i)}$ directly.
- 2878 • In **collapsed Gibbs sampling**, we analytically integrate ϕ and μ out of the model.
 2879 The cluster memberships $y^{(i)}$ are the only remaining latent variable; we sample them
 2880 from the compound distribution,

$$p(y^{(i)} | \mathbf{x}^{(1:N)}, \mathbf{y}^{(-i)}; \alpha_\phi, \alpha_\mu) = \int_{\phi, \mu} p(\phi, \mu | \mathbf{y}^{(-i)}, \mathbf{x}^{(1:N)}; \alpha_\phi, \alpha_\mu) p(y^{(i)} | \mathbf{x}^{(1:N)}, \mathbf{y}^{(-i)}, \phi, \mu) d\phi d\mu. \quad [5.46]$$

2881 For multinomial and Dirichlet distributions, the sampling distribution can be com-
 2882 puted in closed form.

2883 MCMC algorithms are guaranteed to converge to the true posterior distribution over
 2884 the latent variables, but there is no way to know how long this will take. In practice, the
 2885 rate of convergence depends on initialization, just as expectation-maximization depends
 2886 on initialization to avoid local optima. Thus, while Gibbs Sampling and other MCMC
 2887 algorithms provide a powerful and flexible array of techniques for statistical inference in
 2888 latent variable models, they are not a panacea for the problems experienced by EM.

2889 5.5.2 Spectral learning

Another approach to learning with latent variables is based on the **method of moments**, which makes it possible to avoid the problem of non-convex log-likelihood. Write $\bar{\mathbf{x}}^{(i)}$ for the normalized vector of word counts in document i , so that $\bar{\mathbf{x}}^{(i)} = \mathbf{x}^{(i)} / \sum_{j=1}^V x_j^{(i)}$. Then

we can form a matrix of word-word co-occurrence probabilities,

$$\mathbf{C} = \sum_{i=1}^N \bar{\mathbf{x}}^{(i)} (\bar{\mathbf{x}}^{(i)})^\top. \quad [5.47]$$

The expected value of this matrix under $p(\mathbf{x} | \phi, \mu)$, as

$$E[\mathbf{C}] = \sum_{i=1}^N \sum_{k=1}^K \Pr(Z^{(i)} = k; \boldsymbol{\mu}) \phi_k \phi_k^\top \quad [5.48]$$

$$= \sum_k^K N \mu_k \phi_k \phi_k^\top \quad [5.49]$$

$$= \Phi \text{Diag}(N\mu) \Phi^\top, \quad [5.50]$$

where Φ is formed by horizontally concatenating $\phi_1 \dots \phi_K$, and $\text{Diag}(N\mu)$ indicates a diagonal matrix with values $N\mu_k$ at position (k, k) . Setting \mathbf{C} equal to its expectation gives,

$$\mathbf{C} = \Phi \text{Diag}(N\mu) \Phi^\top, \quad [5.51]$$

which is similar to the eigendecomposition $\mathbf{C} = \mathbf{Q}\Lambda\mathbf{Q}^\top$. This suggests that simply by finding the eigenvectors and eigenvalues of \mathbf{C} , we could obtain the parameters ϕ and μ , and this is what motivates the name **spectral learning**.

While moment-matching and eigendecomposition are similar in form, they impose different constraints on the solutions: eigendecomposition requires orthonormality, so that $\mathbf{Q}\mathbf{Q}^\top = \mathbb{I}$; in estimating the parameters of a text clustering model, we require that μ and the columns of Φ are probability vectors. Spectral learning algorithms must therefore include a procedure for converting the solution into vectors that are non-negative and sum to one. One approach is to replace eigendecomposition (or the related singular value decomposition) with non-negative matrix factorization (Xu et al., 2003), which guarantees that the solutions are non-negative (Arora et al., 2013).

After obtaining the parameters ϕ and μ , the distribution over clusters can be computed from Bayes' rule:

$$p(z^{(i)} | \mathbf{x}^{(i)}; \phi, \mu) \propto p(\mathbf{x}^{(i)} | z^{(i)}; \phi) \times p(z^{(i)}; \mu). \quad [5.52]$$

Spectral learning yields provably good solutions without regard to initialization, and can be quite fast in practice. However, it is more difficult to apply to a broad family of generative models than more generic techniques like EM and Gibbs Sampling. For more on applying spectral learning across a range of latent variable models, see Anandkumar et al. (2014).

2908 Additional resources

2909 There are a number of other learning paradigms that deviate from supervised learning.

- 2910 • **Active learning:** the learner selects unlabeled instances and requests annotations (Settles, 2012).
- 2912 • **Multiple instance learning:** labels are applied to bags of instances, with a positive label applied if at least one instance in the bag meets the criterion (Dietterich et al., 2913 1997; Maron and Lozano-Pérez, 1998).
- 2915 • **Constraint-driven learning:** supervision is provided in the form of explicit constraints on the learner (Chang et al., 2007; Ganchev et al., 2010).
- 2917 • **Distant supervision:** noisy labels are generated from an external resource (Mintz 2918 et al., 2009, also see § 17.2.3).
- 2919 • **Multitask learning:** the learner induces a representation that can be used to solve 2920 multiple classification tasks (Collobert et al., 2011).
- 2921 • **Transfer learning:** the learner must solve a classification task that differs from the 2922 labeled data (Pan and Yang, 2010).

2923 Expectation maximization was introduced by Dempster et al. (1977), and is discussed
 2924 in more detail by Murphy (2012). Like most machine learning treatments, Murphy focus
 2925 on continuous observations and Gaussian likelihoods, rather than the discrete observa-
 2926 tions typically encountered in natural language processing. Murphy (2012) also includes
 2927 an excellent chapter on MCMC; for a textbook-length treatment, see Robert and Casella
 2928 (2013). For still more on Bayesian latent variable models, see Barber (2012), and for ap-
 2929 plications of Bayesian models to natural language processing, see Cohen (2016). Surveys
 2930 are available for semi-supervised learning (Zhu and Goldberg, 2009) and domain adapta-
 2931 tion (Søgaard, 2013), although both pre-date the current wave of interest in deep learning.

2932 Exercises

- 2933 1. Derive the expectation maximization update for the parameter μ in the EM cluster-
 ing model.
- 2935 2. The expectation maximization lower bound \mathcal{J} is defined in Equation 5.10. Prove
 that the inverse $-\mathcal{J}$ is convex in q . You can use the following facts about convexity:
 - 2937 • $f(\mathbf{x})$ is convex in \mathbf{x} iff $\alpha f(\mathbf{x}_1) + (1 - \alpha)f(\mathbf{x}_2) \geq f(\alpha\mathbf{x}_1 + (1 - \alpha)\mathbf{x}_2)$ for all
 $\alpha \in [0, 1]$.
 - 2939 • If $f(\mathbf{x})$ and $g(\mathbf{x})$ are both convex in \mathbf{x} , then $f(\mathbf{x}) + g(\mathbf{x})$ is also convex in \mathbf{x} .

- 2940 • $\log(x + y) \leq \log x + \log y.$

2941 3. Derive the E-step and M-step updates for the following generative model. You may
 2942 assume that the labels $y^{(i)}$ are observed, but $z_m^{(i)}$ is not.

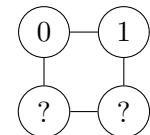
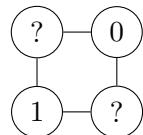
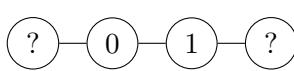
- 2943 • For each instance i ,

- 2944 – Draw label $y^{(i)} \sim \text{Categorical}(\boldsymbol{\mu})$
- 2945 – For each token $m \in \{1, 2, \dots, M^{(i)}\}$
 - 2946 * Draw $z_m^{(i)} \sim \text{Categorical}(\boldsymbol{\pi})$
 - 2947 * If $z_m^{(i)} = 0$, draw the current token from a label-specific distribution,
 $w_m^{(i)} \sim \boldsymbol{\phi}_{y^{(i)}}$
 - 2948 * If $z_m^{(i)} = 1$, draw the current token from a document-specific distribu-
 $w_m^{(i)} \sim \boldsymbol{\nu}^{(i)}$

2951 4. Use expectation-maximization clustering to train a word-sense induction system,
 2952 applied to the word *say*.

- 2953 • Import `nltk`, run `nltk.download()` and select `semcor`. Import `semcor`
 2954 from `nltk.corpus`.
- 2955 • The command `semcor.tagged_sentences(tag='sense')` returns an iter-
 2956 ator over sense-tagged sentences in the corpus. Each sentence can be viewed as
 2957 an iterator over `tree` objects. For `tree` objects that are sense-annotated words,
 2958 you can access the annotation as `tree.label()`, and the word itself with
 2959 `tree.leaves()`. So `semcor.tagged_sentences(tag='sense')[0][2].label()`
 2960 would return the sense annotation of the third word in the first sentence.
- 2961 • Extract all sentences containing the senses `say.v.01` and `say.v.02`.
- 2962 • Build bag-of-words vectors $\mathbf{x}^{(i)}$, containing the counts of other words in those
 2963 sentences, including all words that occur in at least two sentences.
- 2964 • Implement and run expectation-maximization clustering on the merged data.
- 2965 • Compute the frequency with which each cluster includes instances of `say.v.01`
 2966 and `say.v.02`.

2967 5. Using the iterative updates in Equations 5.34-5.36, compute the outcome of the label
 2968 propagation algorithm for the following examples.



2969 The value inside the node indicates the label, $y^{(i)} \in \{0, 1\}$, with $y^{(i)} = ?$ for unlabeled
 2970 nodes. The presence of an edge between two nodes indicates $w_{i,j} = 1$, and the
 2971 absence of an edge indicates $w_{i,j} = 0$. For the third example, you need only compute
 2972 the first three iterations, and then you can guess at the solution in the limit.

2973 In the remaining exercises, you will try out some approaches for semisupervised learning
 2974 and domain adaptation. You will need datasets in multiple domains. You can obtain
 2975 product reviews in multiple domains here: https://www.cs.jhu.edu/~mdredze/datasets/sentiment/processed_acl.tar.gz. Choose a source and target domain,
 2976 e.g. dvds and books, and divide the data for the target domain into training and test sets
 2977 of equal size.
 2978

- 2979 6. First, quantify the cost of cross-domain transfer.
- 2980 • Train a logistic regression classifier on the source domain training set, and eval-
 2981 uate it on the target domain test set.
 - 2982 • Train a logistic regression classifier on the target domain training set, and eval-
 2983 uate it on the target domain test set. This is the “direct transfer” baseline.

2984 Compute the difference in accuracy, which is a measure of the transfer loss across
 2985 domains.

- 2986 7. Next, apply the **label propagation** algorithm from § 5.3.2.

2987 As a baseline, using only 5% of the target domain training set, train a classifier, and
 2988 compute its accuracy on the target domain test set.

2989 Next, apply label propagation:

- 2990 • Compute the label matrix \mathbf{Q}_L for the labeled data (5% of the target domain
 2991 training set), with each row equal to an indicator vector for the label (positive
 2992 or negative).
- 2993 • Iterate through the target domain instances, including both test and training
 2994 data. At each instance i , compute all w_{ij} , using Equation 5.32, with $\alpha = 0.01$.
 2995 Use these values to fill in column i of the transition matrix \mathbf{T} , setting all but the
 2996 ten largest values to zero for each column i . Be sure to normalize the column
 2997 so that the remaining values sum to one. You may need to use a sparse matrix
 2998 for this to fit into memory.
- 2999 • Apply the iterative updates from Equations 5.34-5.36 to compute the outcome
 3000 of the label propagation algorithm for the unlabeled examples.

3001 Select the test set instances from \mathbf{Q}_U , and compute the accuracy of this method.
 3002 Compare with the supervised classifier trained only on the 5% sample of the target
 3003 domain training set.

- 3004 8. Using only 5% of the target domain training data (and all of the source domain train-
3005 ing data), implement one of the supervised domain adaptation baselines in § 5.4.1.
3006 See if this improves on the “direct transfer” baseline from the previous problem
- 3007 9. Implement EasyAdapt (§ 5.4.1), again using 5% of the target domain training data
3008 and all of the source domain data.
- 3009 10. Now try unsupervised domain adaptation, using the “linear projection” method
3010 described in § 5.4.2. Specifically:
- 3011 • Identify 500 pivot features as the words with the highest frequency in the (com-
3012 plete) training data for the source and target domains. Specifically, let x_i^d be the
3013 count of the word i in domain d : choose the 500 words with the largest values
3014 of $\min(x_i^{\text{source}}, x_i^{\text{target}})$.
- 3015 • Train a classifier to predict each pivot feature from the remaining words in the
3016 document.
- 3017 • Arrange the features of these classifiers into a matrix Φ , and perform truncated
3018 singular value decomposition, with $k = 20$
- 3019 • Train a classifier from the source domain data, using the combined features
3020 $\mathbf{x}^{(i)} \oplus \mathbf{U}^\top \mathbf{x}^{(i)}$ — these include the original bag-of-words features, plus the pro-
3021 jected features.
- 3022 • Apply this classifier to the target domain test set, and compute the accuracy.

3023

Part II

3024

Sequences and trees

3025

Chapter 6

3026

Language models

3027 In probabilistic classification, the problem is to compute the probability of a label, conditioned
3028 on the text. Let's now consider the inverse problem: computing the probability of
3029 text itself. Specifically, we will consider models that assign probability to a sequence of
3030 word tokens, $p(w_1, w_2, \dots, w_M)$, with $w_m \in \mathcal{V}$. The set \mathcal{V} is a discrete vocabulary,

$$\mathcal{V} = \{aardvark, abacus, \dots, zither\}. \quad [6.1]$$

3031 Why would you want to compute the probability of a word sequence? In many applications,
3032 the goal is to produce word sequences as output:

- 3033 • In **machine translation** (chapter 18), we convert from text in a source language to
3034 text in a target language.
- 3035 • In **speech recognition**, we convert from audio signal to text.
- 3036 • In **summarization** (§ 16.3.4.1; § 19.2), we convert from long texts into short texts.
- 3037 • In **dialogue systems** (§ 19.3), we convert from the user's input (and perhaps an
3038 external knowledge base) into a text response.

3039 In many of the systems for performing these tasks, there is a subcomponent that computes
3040 the probability of the output text. The purpose of this component is to generate
3041 texts that are more **fluent**. For example, suppose we want to translate a sentence from
3042 Spanish to English.

3043 (6.1) El cafe negro me gusta mucho.

3044 Here is a literal word-for-word translation (a **gloss**):

3045 (6.2) The coffee black me pleases much.

3046 A good language model of English will tell us that the probability of this translation is
 3047 low, in comparison with more grammatical alternatives,

$$p(\text{The coffee black me pleases much}) < p(\text{I love dark coffee}). \quad [6.2]$$

3048 How can we use this fact? Warren Weaver, one of the early leaders in machine trans-
 3049 lation, viewed it as a problem of breaking a secret code (Weaver, 1955):

3050 When I look at an article in Russian, I say: 'This is really written in English,
 3051 but it has been coded in some strange symbols. I will now proceed to decode.'

3052 This observation motivates a generative model (like Naïve Bayes):

3053 • The English sentence $w^{(e)}$ is generated from a **language model**, $p_e(w^{(e)})$.

3054 • The Spanish sentence $w^{(s)}$ is then generated from a **translation model**, $p_{s|e}(w^{(s)} | w^{(e)})$.

Given these two distributions, we can then perform translation by Bayes rule:

$$p_{e|s}(w^{(e)} | w^{(s)}) \propto p_{e,s}(w^{(e)}, w^{(s)}) \quad [6.3]$$

$$= p_{s|e}(w^{(s)} | w^{(e)}) \times p_e(w^{(e)}). \quad [6.4]$$

3055 This is sometimes called the **noisy channel model**, because it envisions English text
 3056 turning into Spanish by passing through a noisy channel, $p_{s|e}$. What is the advantage of
 3057 modeling translation this way, as opposed to modeling $p_{e|s}$ directly? The crucial point is
 3058 that the two distributions $p_{s|e}$ (the translation model) and p_e (the language model) can be
 3059 estimated from separate data. The translation model requires examples of correct trans-
 3060 lations, but the language model requires only text in English. Such monolingual data is
 3061 much more widely available. Furthermore, once estimated, the language model p_e can be
 3062 reused in any application that involves generating English text, from summarization to
 3063 speech recognition.

3064 6.1 *N*-gram language models

A simple approach to computing the probability of a sequence of tokens is to use a **relative frequency estimate**. For example, consider the quote, attributed to Picasso, "*computers are useless, they can only give you answers.*" We can estimate the probability of this sentence,

$$\begin{aligned} p(\text{Computers are useless, they can only give you answers}) \\ = \frac{\text{count}(\text{Computers are useless, they can only give you answers})}{\text{count(all sentences ever spoken)}} \end{aligned} \quad [6.5]$$

3065 This estimator is **unbiased**: in the theoretical limit of infinite data, the estimate will
 3066 be correct. But in practice, we are asking for accurate counts over an infinite number of
 3067 events, since sequences of words can be arbitrarily long. Even with an aggressive upper
 3068 bound of, say, $M = 20$ tokens in the sequence, the number of possible sequences is V^{20} . A
 3069 small vocabulary for English would have $V = 10^4$, so there are 10^{80} possible sequences.
 3070 Clearly, this estimator is very data-hungry, and suffers from high variance: even gram-
 3071 matical sentences will have probability zero if have not occurred in the training data.¹ We
 3072 therefore need to introduce bias to have a chance of making reliable estimates from finite
 3073 training data. The language models that follow in this chapter introduce bias in various
 3074 ways.

We begin with n -gram language models, which compute the probability of a sequence as the product of probabilities of subsequences. The probability of a sequence $p(w) = p(w_1, w_2, \dots, w_M)$ can be refactored using the chain rule (see § A.2):

$$p(w) = p(w_1, w_2, \dots, w_M) \quad [6.6]$$

$$= p(w_1) \times p(w_2 | w_1) \times p(w_3 | w_2, w_1) \times \dots \times p(w_M | w_{M-1}, \dots, w_1) \quad [6.7]$$

Each element in the product is the probability of a word given all its predecessors. We can think of this as a *word prediction* task: given the context *Computers are*, we want to compute a probability over the next token. The relative frequency estimate of the probability of the word *useless* in this context is,

$$\begin{aligned} p(\text{useless} | \text{computers are}) &= \frac{\text{count}(\text{computers are useless})}{\sum_{x \in \mathcal{V}} \text{count}(\text{computers are } x)} \\ &= \frac{\text{count}(\text{computers are useless})}{\text{count}(\text{computers are})}. \end{aligned}$$

3075 We haven't made any approximations yet, and we could have just as well applied the
 3076 chain rule in reverse order,

$$p(w) = p(w_M) \times p(w_{M-1} | w_M) \times \dots \times p(w_1 | w_2, \dots, w_M), \quad [6.8]$$

3077 or in any other order. But this means that we also haven't really made any progress:
 3078 to compute the conditional probability $p(w_M | w_{M-1}, w_{M-2}, \dots, w_1)$, we would need to
 3079 model V^{M-1} contexts. Such a distribution cannot be estimated from any realistic sample
 3080 of text.

¹Chomsky has famously argued that this is evidence against the very concept of probabilistic language models: no such model could distinguish the grammatical sentence *colorless green ideas sleep furiously* from the ungrammatical permutation *furiously sleep ideas green colorless*. Indeed, even the bigrams in these two examples are unlikely to occur — at least, not in texts written before Chomsky proposed this example.

To solve this problem, n -gram models make a crucial simplifying approximation: condition on only the past $n - 1$ words.

$$p(w_m | w_{m-1} \dots w_1) \approx p(w_m | w_{m-1}, \dots, w_{m-n+1}) \quad [6.9]$$

This means that the probability of a sentence w can be approximated as

$$p(w_1, \dots, w_M) \approx \prod_m^M p(w_m | w_{m-1}, \dots, w_{m-n+1}) \quad [6.10]$$

To compute the probability of an entire sentence, it is convenient to pad the beginning and end with special symbols \square and \blacksquare . Then the bigram ($n = 2$) approximation to the probability of *I like black coffee* is:

$$p(I \text{ like black coffee}) = p(I | \square) \times p(\text{like} | I) \times p(\text{black} | \text{like}) \times p(\text{coffee} | \text{black}) \times p(\blacksquare | \text{coffee}). \quad [6.11]$$

3081 This model requires estimating and storing the probability of only V^n events, which is
 3082 exponential in the order of the n -gram, and not V^M , which is exponential in the length of
 3083 the sentence. The n -gram probabilities can be computed by relative frequency estimation,

$$p(w_m | w_{m-1}, w_{m-2}) = \frac{\text{count}(w_{m-2}, w_{m-1}, w_m)}{\sum_{w'} \text{count}(w_{m-2}, w_{m-1}, w')} \quad [6.12]$$

3084 The hyperparameter n controls the size of the context used in each conditional proba-
 3085 bility. If this is misspecified, the language model will perform poorly. Let's consider the
 3086 potential problems concretely.

3087 **When n is too small.** Consider the following sentences:

3088 (6.3) **Gorillas** always like to groom **their** friends.

3089 (6.4) The **computer** that's on the 3rd floor of our office building **crashed**.

3090 In each example, the bolded words depend on each other: the likelihood of *their*
 3091 depends on knowing that *gorillas* is plural, and the likelihood of *crashed* depends on
 3092 knowing that the subject is a *computer*. If the n -grams are not big enough to capture
 3093 this context, then the resulting language model would offer probabilities that are too
 3094 low for these sentences, and too high for sentences that fail basic linguistic tests like
 3095 number agreement.

3096 **When n is too big.** In this case, it is hard to get good estimates of the n -gram parameters from
 3097 our dataset, because of data sparsity. To handle the *gorilla* example, it is necessary to
 3098 model 6-grams, which means accounting for V^6 events. Under a very small vocabulary of $V = 10^4$, this means estimating the probability of 10^{24} distinct events.

3100 These two problems point to another **bias-variance tradeoff** (see § 2.1.4). A small n -
 3101 gram size introduces high bias, and a large n -gram size introduces high variance. But
 3102 in reality we often have both problems at the same time! Language is full of long-range
 3103 dependencies that we cannot capture because n is too small; at the same time, language
 3104 datasets are full of rare phenomena, whose probabilities we fail to estimate accurately
 3105 because n is too large. One solution is to try to keep n large, while still making low-
 3106 variance estimates of the underlying parameters. To do this, we will introduce a different
 3107 sort of bias: **smoothing**.

3108 **6.2 Smoothing and discounting**

3109 Limited data is a persistent problem in estimating language models. In § 6.1, we presented
 3110 n -grams as a partial solution. sparse data can be a problem even for low-order n -grams;
 3111 at the same time, many linguistic phenomena, like subject-verb agreement, cannot be in-
 3112 corporated into language models without high-order n -grams. It is therefore necessary to
 3113 add additional inductive biases to n -gram language models. This section covers some of
 3114 the most intuitive and common approaches, but there are many more (Chen and Good-
 3115 man, 1999).

3116 **6.2.1 Smoothing**

3117 A major concern in language modeling is to avoid the situation $p(w) = 0$, which could
 3118 arise as a result of a single unseen n-gram. A similar problem arose in Naïve Bayes, and
 3119 the solution was **smoothing**: adding imaginary “pseudo” counts. The same idea can be
 3120 applied to n -gram language models, as shown here in the bigram case,

$$P_{\text{smooth}}(w_m \mid w_{m-1}) = \frac{\text{count}(w_{m-1}, w_m) + \alpha}{\sum_{w' \in \mathcal{V}} \text{count}(w_{m-1}, w') + V\alpha}. \quad [6.13]$$

3121 This basic framework is called **Lidstone smoothing**, but special cases have other names:

- 3122 • **Laplace smoothing** corresponds to the case $\alpha = 1$.
- 3123 • **Jeffreys-Perks law** corresponds to the case $\alpha = 0.5$. Manning and Schütze (1999)
 3124 offer more insight on the justifications for this setting.

3125 To maintain normalization, anything that we add to the numerator (α) must also ap-
 3126 pear in the denominator ($V\alpha$). This idea is reflected in the concept of **effective counts**:

$$c_i^* = (c_i + \alpha) \frac{M}{M + V\alpha}, \quad [6.14]$$

	counts	unsmoothed probability	Lidstone smoothing, $\alpha = 0.1$		Discounting, $d = 0.1$	
			effective counts	smoothed probability	effective counts	smoothed probability
<i>impropriety</i>	8	0.4	7.826	0.391	7.9	0.395
<i>offense</i>	5	0.25	4.928	0.246	4.9	0.245
<i>damage</i>	4	0.2	3.961	0.198	3.9	0.195
<i>deficiencies</i>	2	0.1	2.029	0.101	1.9	0.095
<i>outbreak</i>	1	0.05	1.063	0.053	0.9	0.045
<i>infirmity</i>	0	0	0.097	0.005	0.25	0.013
<i>cephalopods</i>	0	0	0.097	0.005	0.25	0.013

Table 6.1: Example of Lidstone smoothing and absolute discounting in a bigram language model, for the context *(alleged, -)*, for a toy corpus with a total of twenty counts over the seven words shown. Note that discounting decreases the probability for all but the unseen words, while Lidstone smoothing increases the effective counts and probabilities for *deficiencies* and *outbreak*.

where c_i is the count of event i , c_i^* is the effective count, and $M = \sum_{i=1}^V c_i$ is the total number of tokens in the dataset (w_1, w_2, \dots, w_M) . This term ensures that $\sum_{i=1}^V c_i^* = \sum_{i=1}^V c_i = M$. The **discount** for each n-gram is then computed as,

$$d_i = \frac{c_i^*}{c_i} = \frac{(c_i + \alpha)}{c_i} \frac{M}{(M + V\alpha)}.$$

3127 6.2.2 Discounting and backoff

3128 Discounting “borrows” probability mass from observed n -grams and redistributes it. In
 3129 Lidstone smoothing, the borrowing is done by increasing the denominator of the relative
 3130 frequency estimates. The borrowed probability mass is then redistributed by increasing
 3131 the numerator for all n -grams. Another approach would be to borrow the same amount
 3132 of probability mass from all observed n -grams, and redistribute it among only the unob-
 3133 served n -grams. This is called **absolute discounting**. For example, suppose we set an
 3134 absolute discount $d = 0.1$ in a bigram model, and then redistribute this probability mass
 3135 equally over the unseen words. The resulting probabilities are shown in Table 6.1.

Discounting reserves some probability mass from the observed data, and we need not redistribute this probability mass equally. Instead, we can **backoff** to a lower-order language model: if you have trigrams, use trigrams; if you don’t have trigrams, use bigrams; if you don’t even have bigrams, use unigrams. This is called **Katz backoff**. In the simple

case of backing off from bigrams to unigrams, the bigram probabilities are computed as,

$$c^*(i, j) = c(i, j) - d \quad [6.15]$$

$$p_{\text{Katz}}(i | j) = \begin{cases} \frac{c^*(i, j)}{c(j)} & \text{if } c(i, j) > 0 \\ \alpha(j) \times \frac{p_{\text{unigram}}(i)}{\sum_{i': c(i', j)=0} p_{\text{unigram}}(i')} & \text{if } c(i, j) = 0. \end{cases} \quad [6.16]$$

3136 The term $\alpha(j)$ indicates the amount of probability mass that has been discounted for
 3137 context j . This probability mass is then divided across all the unseen events, $\{i' : c(i', j) =$
 3138 $0\}$, proportional to the unigram probability of each word i' . The discount parameter d can
 3139 be optimized to maximize performance (typically held-out log-likelihood) on a develop-
 3140 ment set.

3141 6.2.3 *Interpolation

3142 Backoff is one way to combine different order n -gram models. An alternative approach
 3143 is **interpolation**: setting the probability of a word in context to a weighted sum of its
 3144 probabilities across progressively shorter contexts.

Instead of choosing a single n for the size of the n -gram, we can take the weighted average across several n -gram probabilities. For example, for an interpolated trigram model,

$$\begin{aligned} p_{\text{Interpolation}}(w_m | w_{m-1}, w_{m-2}) &= \lambda_3 p_3^*(w_m | w_{m-1}, w_{m-2}) \\ &\quad + \lambda_2 p_2^*(w_m | w_{m-1}) \\ &\quad + \lambda_1 p_1^*(w_m). \end{aligned}$$

3145 In this equation, p_n^* is the unsmoothed empirical probability given by an n -gram lan-
 3146 guage model, and λ_n is the weight assigned to this model. To ensure that the interpolated
 3147 $p(w)$ is still a valid probability distribution, the values of λ must obey the constraint,
 3148 $\sum_{n=1}^{n_{\max}} \lambda_n = 1$. But how to find the specific values?

3149 An elegant solution is **expectation maximization**. Recall from chapter 5 that we can
 3150 think about EM as learning with *missing data*: we just need to choose missing data such
 3151 that learning would be easy if it weren't missing. What's missing in this case? Think of
 3152 each word w_m as drawn from an n -gram of unknown size, $z_m \in \{1 \dots n_{\max}\}$. This z_m is
 3153 the missing data that we are looking for. Therefore, the application of EM to this problem
 3154 involves the following **generative process**:

3155 **for** Each token $w_m, m = 1, 2, \dots, M$ **do**:
 3156 draw the n -gram size $z_m \sim \text{Categorical}(\lambda)$;
 3157 draw $w_m \sim p_{z_m}^*(w_m | w_{m-1}, \dots, w_{m-z_m})$.

If the missing data $\{Z_m\}$ were known, then λ could be estimated as the relative frequency,

$$\lambda_z = \frac{\text{count}(Z_m = z)}{M} \quad [6.17]$$

$$\propto \sum_{m=1}^M \delta(Z_m = z). \quad [6.18]$$

But since we do not know the values of the latent variables Z_m , we impute a distribution q_m in the E-step, which represents the degree of belief that word token w_m was generated from a n -gram of order z_m ,

$$q_m(z) \triangleq \Pr(Z_m = z \mid \mathbf{w}_{1:m}; \lambda) \quad [6.19]$$

$$= \frac{p(w_m \mid \mathbf{w}_{1:m-1}, Z_m = z) \times p(z)}{\sum_{z'} p(w_m \mid \mathbf{w}_{1:m-1}, Z_m = z') \times p(z')} \quad [6.20]$$

$$\propto p_z^*(w_m \mid \mathbf{w}_{1:m-1}) \times \lambda_z. \quad [6.21]$$

In the M-step, λ is computed by summing the expected counts under q ,

$$\lambda_z \propto \sum_{m=1}^M q_m(z). \quad [6.22]$$

3159 A solution is obtained by iterating between updates to q and λ . The complete algorithm
3160 is shown in Algorithm 10.

Algorithm 10 Expectation-maximization for interpolated language modeling

```

1: procedure ESTIMATE INTERPOLATED  $n$ -GRAM ( $\mathbf{w}_{1:M}, \{p_n^*\}_{n \in 1:n_{\max}}$ ) ▷ Initialization
2:   for  $z \in \{1, 2, \dots, n_{\max}\}$  do
3:      $\lambda_z \leftarrow \frac{1}{n_{\max}}$ 
4:   repeat
5:     for  $m \in \{1, 2, \dots, M\}$  do ▷ E-step
6:       for  $z \in \{1, 2, \dots, n_{\max}\}$  do
7:          $q_m(z) \leftarrow p_z^*(w_m \mid \mathbf{w}_{1:m-1}) \times \lambda_z$ 
8:        $q_m \leftarrow \text{Normalize}(q_m)$ 
9:     for  $z \in \{1, 2, \dots, n_{\max}\}$  do ▷ M-step
10:       $\lambda_z \leftarrow \frac{1}{M} \sum_{m=1}^M q_m(z)$ 
11:    until tired
12:    return  $\lambda$ 

```

3161 6.2.4 *Kneser-Ney smoothing

3162 Kneser-Ney smoothing is based on absolute discounting, but it redistributes the result-
 3163 ing probability mass in a different way from Katz backoff. Empirical evidence points
 3164 to Kneser-Ney smoothing as the state-of-art for n -gram language modeling (Goodman,
 3165 2001). To motivate Kneser-Ney smoothing, consider the example: *I recently visited ..*
 3166 Which of the following is more likely?

- 3167 • *Francisco*
 3168 • *Duluth*

3169 Now suppose that both bigrams *visited Duluth* and *visited Francisco* are unobserved in
 3170 the training data, and furthermore, the unigram probability $p_1^*(\text{Francisco})$ is greater than
 3171 $p^*(\text{Duluth})$. Nonetheless we would still guess that $p(\text{visited Duluth}) > p(\text{visited Francisco})$,
 3172 because *Duluth* is a more “versatile” word: it can occur in many contexts, while *Francisco*
 3173 usually occurs in a single context, following the word *San*. This notion of versatility is the
 3174 key to Kneser-Ney smoothing.

Writing u for a context of undefined length, and $\text{count}(w, u)$ as the count of word w in
 context u , we define the Kneser-Ney bigram probability as

$$p_{KN}(w | u) = \begin{cases} \frac{\text{count}(w, u) - d}{\text{count}(u)}, & \text{count}(w, u) > 0 \\ \alpha(u) \times p_{\text{continuation}}(w), & \text{otherwise} \end{cases} \quad [6.23]$$

$$p_{\text{continuation}}(w) = \frac{|u : \text{count}(w, u) > 0|}{\sum_{w' \in \mathcal{V}} |u' : \text{count}(w', u') > 0|}. \quad [6.24]$$

First, note that we reserve probability mass using absolute discounting d , which is taken from all unobserved n -grams. The total amount of discounting in context u is $d \times |w : \text{count}(w, u) > 0|$, and we divide this probability mass equally among the unseen n -grams,

$$\alpha(u) = |w : \text{count}(w, u) > 0| \times \frac{d}{\text{count}(u)}. \quad [6.25]$$

3175 This is the amount of probability mass left to account for versatility, which we define via
 3176 the *continuation probability* $p_{\text{continuation}}(w)$ as proportional to the number of observed con-
 3177 texts in which w appears. The numerator of the continuation probability is the number of
 3178 contexts u in which w appears; the denominator normalizes the probability by summing
 3179 the same quantity over all words w' .

3180 The idea of modeling versatility by counting contexts may seem heuristic, but there is
 3181 an elegant theoretical justification from Bayesian nonparametrics (Teh, 2006). Kneser-Ney
 3182 smoothing on n -grams was the dominant language modeling technique before the arrival
 3183 of neural language models.

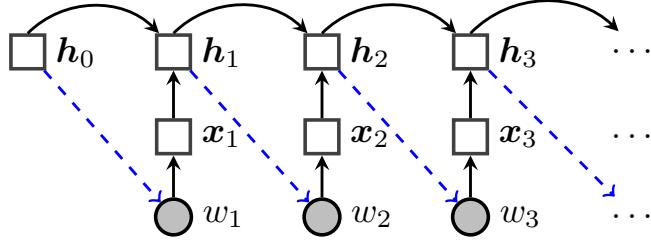


Figure 6.1: The recurrent neural network language model, viewed as an “unrolled” computation graph. Solid lines indicate direct computation, dotted blue lines indicate probabilistic dependencies, circles indicate random variables, and squares indicate computation nodes.

3184 6.3 Recurrent neural network language models

3185 N -gram language models have been largely supplanted by **neural networks**. These mod-
 3186 els do not make the n -gram assumption of restricted context; indeed, they can incorpo-
 3187 rate arbitrarily distant contextual information, while remaining computationally and statisti-
 3188 cally tractable.

3189 The first insight behind neural language models is to treat word prediction as a *dis-
 3190 criminative* learning task.² The goal is to compute the probability $p(w | u)$, where $w \in \mathcal{V}$ is
 3191 a word, and u is the context, which depends on the previous words. Rather than directly
 3192 estimating the word probabilities from (smoothed) relative frequencies, we can treat
 3193 language modeling as a machine learning problem, and estimate parameters that maxi-
 3194 mize the log conditional probability of a corpus.

3195 The second insight is to reparametrize the probability distribution $p(w | u)$ as a func-
 3196 tion of two dense K -dimensional numerical vectors, $\beta_w \in \mathbb{R}^K$, and $v_u \in \mathbb{R}^K$,

$$p(w | u) = \frac{\exp(\beta_w \cdot v_u)}{\sum_{w' \in \mathcal{V}} \exp(\beta_{w'} \cdot v_u)}, \quad [6.26]$$

3197 where $\beta_w \cdot v_u$ represents a dot product. As usual, the denominator ensures that the prob-
 3198 ability distribution is properly normalized. This vector of probabilities is equivalent to
 3199 applying the **softmax** transformation (see § 3.1) to the vector of dot-products,

$$p(\cdot | u) = \text{SoftMax}([\beta_1 \cdot v_u, \beta_2 \cdot v_u, \dots, \beta_V \cdot v_u]). \quad [6.27]$$

The word vectors β_w are parameters of the model, and are estimated directly. The context vectors v_u can be computed in various ways, depending on the model. A simple

²This idea predates neural language models (e.g., Rosenfeld, 1996; Roark et al., 2007).

but effective neural language model can be built from a **recurrent neural network** (RNN; Mikolov et al., 2010). The basic idea is to recurrently update the context vectors while moving through the sequence. Let \mathbf{h}_m represent the contextual information at position m in the sequence. RNN language models are defined,

$$\mathbf{x}_m \triangleq \phi_{w_m} \quad [6.28]$$

$$\mathbf{h}_m = \text{RNN}(\mathbf{x}_m, \mathbf{h}_{m-1}) \quad [6.29]$$

$$p(w_{m+1} | w_1, w_2, \dots, w_m) = \frac{\exp(\beta_{w_{m+1}} \cdot \mathbf{h}_m)}{\sum_{w' \in \mathcal{V}} \exp(\beta_{w'} \cdot \mathbf{h}_m)}, \quad [6.30]$$

where ϕ is a matrix of **input word embeddings**, and \mathbf{x}_m denotes the embedding for word w_m . The conversion of w_m to \mathbf{x}_m is sometimes known as a **lookup layer**, because we simply lookup the embeddings for each word in a table; see § 3.2.4.

The **Elman unit** defines a simple recurrent operation (Elman, 1990),

$$\text{RNN}(\mathbf{x}_m, \mathbf{h}_{m-1}) \triangleq g(\Theta \mathbf{h}_{m-1} + \mathbf{x}_m), \quad [6.31]$$

where $\Theta \in \mathbb{R}^{K \times K}$ is the recurrence matrix and g is a non-linear transformation function, often defined as the elementwise hyperbolic tangent \tanh (see § 3.1).³ The \tanh acts as a **squashing function**, ensuring that each element of \mathbf{h}_m is constrained to the range $[-1, 1]$.

Although each w_m depends on only the context vector \mathbf{h}_{m-1} , this vector is in turn influenced by *all* previous tokens, w_1, w_2, \dots, w_{m-1} , through the recurrence operation: w_1 affects \mathbf{h}_1 , which affects \mathbf{h}_2 , and so on, until the information is propagated all the way to \mathbf{h}_{m-1} , and then on to w_m (see Figure 6.1). This is an important distinction from n -gram language models, where any information outside the n -word window is ignored. In principle, the RNN language model can handle long-range dependencies, such as number agreement over long spans of text — although it would be difficult to know where exactly in the vector \mathbf{h}_m this information is represented. The main limitation is that information is attenuated by repeated application of the squashing function g . **Long short-term memories** (LSTMs), described below, are a variant of RNNs that address this issue, using memory cells to propagate information through the sequence without applying nonlinearities (Hochreiter and Schmidhuber, 1997).

The denominator in Equation 6.30 is a computational bottleneck, because it involves a sum over the entire vocabulary. One solution is to use a **hierarchical softmax** function, which computes the sum more efficiently by organizing the vocabulary into a tree (Mikolov et al., 2011). Another strategy is to optimize an alternative metric, such as **noise-contrastive estimation** (Gutmann and Hyvärinen, 2012), which learns by distinguishing observed instances from artificial instances generated from a noise distribution (Mnih and Teh, 2012). Both of these strategies are described in § 14.5.3.

³In the original Elman network, the sigmoid function was used in place of \tanh . For an illuminating mathematical discussion of the advantages and disadvantages of various nonlinearities in recurrent neural networks, see the lecture notes from Cho (2015).

3226 **6.3.1 Backpropagation through time**

3227 The recurrent neural network language model has the following parameters:

- 3228 • $\phi_i \in \mathbb{R}^K$, the “input” word vectors (these are sometimes called **word embeddings**,
3229 since each word is embedded in a K -dimensional space);
- 3230 • $\beta_i \in \mathbb{R}^K$, the “output” word vectors;
- 3231 • $\Theta \in \mathbb{R}^{K \times K}$, the recurrence operator;
- 3232 • \mathbf{h}_0 , the initial state.

3233 Each of these parameters can be estimated by formulating an objective function over the
3234 training corpus, $L(\mathbf{w})$, and then applying **backpropagation** to obtain gradients on the
3235 parameters from a minibatch of training examples (see § 3.3.1). Gradient-based updates
3236 can be computed from an online learning algorithm such as stochastic gradient descent
3237 (see § 2.5.2).

3238 The application of backpropagation to recurrent neural networks is known as **back-**
3239 **propagation through time**, because the gradients on units at time m depend in turn on the
3240 gradients of units at earlier times $n < m$. Let ℓ_{m+1} represent the negative log-likelihood
3241 of word $m + 1$,

$$\ell_{m+1} = -\log p(w_{m+1} | w_1, w_2, \dots, w_m). \quad [6.32]$$

We require the gradient of this loss with respect to each parameter, such as $\theta_{k,k'}$, an individual element in the recurrence matrix Θ . Since the loss depends on the parameters only through \mathbf{h}_m , we can apply the chain rule of differentiation,

$$\frac{\partial \ell_{m+1}}{\partial \theta_{k,k'}} = \frac{\partial \ell_{m+1}}{\partial \mathbf{h}_m} \frac{\partial \mathbf{h}_m}{\partial \theta_{k,k'}}. \quad [6.33]$$

The vector \mathbf{h}_m depends on Θ in several ways. First, \mathbf{h}_m is computed by multiplying Θ by the previous state \mathbf{h}_{m-1} . But the previous state \mathbf{h}_{m-1} also depends on Θ :

$$\mathbf{h}_m = g(\mathbf{x}_m, \mathbf{h}_{m-1}) \quad [6.34]$$

$$\frac{\partial h_{m,k}}{\partial \theta_{k,k'}} = g'(\mathbf{x}_{m,k} + \boldsymbol{\theta}_k \cdot \mathbf{h}_{m-1})(h_{m-1,k'} + \boldsymbol{\theta}_k \cdot \frac{\partial \mathbf{h}_{m-1}}{\partial \theta_{k,k'}}), \quad [6.35]$$

3242 where g' is the local derivative of the nonlinear function g . The key point in this equation
3243 is that the derivative $\frac{\partial \mathbf{h}_m}{\partial \theta_{k,k'}}$ depends on $\frac{\partial \mathbf{h}_{m-1}}{\partial \theta_{k,k'}}$, which will depend in turn on $\frac{\partial \mathbf{h}_{m-2}}{\partial \theta_{k,k'}}$, and
3244 so on, until reaching the initial state \mathbf{h}_0 .

3245 Each derivative $\frac{\partial \mathbf{h}_m}{\partial \theta_{k,k'}}$ will be reused many times: it appears in backpropagation from
3246 the loss ℓ_m , but also in all subsequent losses $\ell_{n>m}$. Neural network toolkits such as
3247 Torch (Collobert et al., 2011) and DyNet (Neubig et al., 2017) compute the necessary

derivatives automatically, and cache them for future use. An important distinction from the feedforward neural networks considered in chapter 3 is that the size of the computation graph is not fixed, but varies with the length of the input. This poses difficulties for toolkits that are designed around static computation graphs, such as TensorFlow (Abadi et al., 2016).⁴

6.3.2 Hyperparameters

The RNN language model has several hyperparameters that must be tuned to ensure good performance. The model capacity is controlled by the size of the word and context vectors K , which play a role that is somewhat analogous to the size of the n -gram context. For datasets that are large with respect to the vocabulary (i.e., there is a large token-to-type ratio), we can afford to estimate a model with a large K , which enables more subtle distinctions between words and contexts. When the dataset is relatively small, then K must be smaller too, or else the model may “memorize” the training data, and fail to generalize. Unfortunately, this general advice has not yet been formalized into any concrete formula for choosing K , and trial-and-error is still necessary. Overfitting can also be prevented by **dropout**, which involves randomly setting some elements of the computation to zero (Srivastava et al., 2014), forcing the learner not to rely too much on any particular dimension of the word or context vectors. The dropout rate must also be tuned on development data.

6.3.3 Gated recurrent neural networks

In principle, recurrent neural networks can propagate information across infinitely long sequences. But in practice, repeated applications of the nonlinear recurrence function causes this information to be quickly attenuated. The same problem affects learning: back-propagation can lead to **vanishing gradients** that decay to zero, or **exploding gradients** that increase towards infinity (Bengio et al., 1994). The exploding gradient problem can be addressed by clipping gradients at some maximum value (Pascanu et al., 2013). The other issues must be addressed by altering the model itself.

The **long short-term memory (LSTM)** (Hochreiter and Schmidhuber, 1997) is a popular variant of RNNs that is more robust to these problems. This model augments the hidden state \mathbf{h}_m with a **memory cell** c_m . The value of the memory cell at each time m is a gated sum of two quantities: its previous value c_{m-1} , and an “update” \tilde{c}_m , which is computed from the current input x_m and the previous hidden state \mathbf{h}_{m-1} . The next state \mathbf{h}_m is then computed from the memory cell. Because the memory cell is not passed through a non-linear squashing function during the update, it is possible for information to propagate through the network over long distances.

⁴See <https://www.tensorflow.org/tutorials/recurrent> (retrieved Feb 8, 2018).

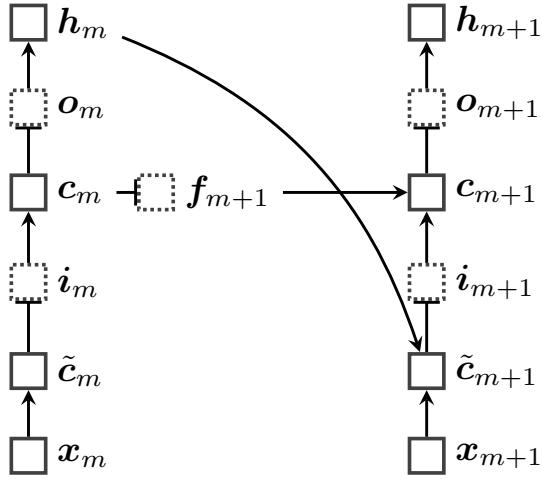


Figure 6.2: The long short-term memory (LSTM) architecture. Gates are shown in boxes with dotted edges. In an LSTM language model, each h_m would be used to predict the next word w_{m+1} .

The gates are functions of the input and previous hidden state. They are computed from elementwise sigmoid activations, $\sigma(x) = (1 + \exp(-x))^{-1}$, ensuring that their values will be in the range $[0, 1]$. They can therefore be viewed as soft, differentiable logic gates. The LSTM architecture is shown in Figure 6.2, and the complete update equations are:

$$f_{m+1} = \sigma(\Theta^{(h \rightarrow f)} h_m + \Theta^{(x \rightarrow f)} x_{m+1} + b_f) \quad \text{forget gate} \quad [6.36]$$

$$i_{m+1} = \sigma(\Theta^{(h \rightarrow i)} h_m + \Theta^{(x \rightarrow i)} x_{m+1} + b_i) \quad \text{input gate} \quad [6.37]$$

$$\tilde{c}_{m+1} = \tanh(\Theta^{(h \rightarrow c)} h_m + \Theta^{(x \rightarrow c)} x_{m+1}) \quad \text{update candidate} \quad [6.38]$$

$$c_{m+1} = f_{m+1} \odot c_m + i_{m+1} \odot \tilde{c}_{m+1} \quad \text{memory cell update} \quad [6.39]$$

$$o_{m+1} = \sigma(\Theta^{(h \rightarrow o)} h_m + \Theta^{(x \rightarrow o)} x_{m+1} + b_o) \quad \text{output gate} \quad [6.40]$$

$$h_{m+1} = o_{m+1} \odot \tanh(c_{m+1}) \quad \text{output.} \quad [6.41]$$

3282 The operator \odot is an elementwise (Hadamard) product. Each gate is controlled by a vec-
 3283 tor of weights, which parametrize the previous hidden state (e.g., $\Theta^{(h \rightarrow f)}$) and the current
 3284 input (e.g., $\Theta^{(x \rightarrow f)}$), plus a vector offset (e.g., b_f). The overall operation can be infor-
 3285 mally summarized as $(h_m, c_m) = \text{LSTM}(x_m, (h_{m-1}, c_{m-1}))$, with (h_m, c_m) representing
 3286 the LSTM state after reading token m .

3287 The LSTM outperforms standard recurrent neural networks across a wide range of
 3288 problems. It was first used for language modeling by Sundermeyer et al. (2012), but can
 3289 be applied more generally: the vector h_m can be treated as a complete representation of

3290 the input sequence up to position m , and can be used for any labeling task on a sequence
 3291 of tokens, as we will see in the next chapter.

3292 There are several LSTM variants, of which the Gated Recurrent Unit (Cho et al., 2014)
 3293 is one of the more well known. Many software packages implement a variety of RNN
 3294 architectures, so choosing between them is simple from a user’s perspective. Jozefowicz
 3295 et al. (2015) provide an empirical comparison of various modeling choices circa 2015.

3296 6.4 Evaluating language models

3297 Language modeling is not usually an application in itself: language models are typically
 3298 components of larger systems, and they would ideally be evaluated **extrinsically**. This
 3299 means evaluating whether the language model improves performance on the application
 3300 task, such as machine translation or speech recognition. But this is often hard to do, and
 3301 depends on details of the overall system which may be irrelevant to language modeling.
 3302 In contrast, **intrinsic evaluation** is task-neutral. Better performance on intrinsic metrics
 3303 may be expected to improve extrinsic metrics across a variety of tasks, but there is always
 3304 the risk of over-optimizing the intrinsic metric. This section discusses some intrinsic met-
 3305 rics, but keep in mind the importance of performing extrinsic evaluations to ensure that
 3306 intrinsic performance gains carry over to the applications that we care about.

3307 6.4.1 Held-out likelihood

The goal of probabilistic language models is to accurately measure the probability of sequences of word tokens. Therefore, an intrinsic evaluation metric is the likelihood that the language model assigns to **held-out data**, which is not used during training. Specifically, we compute,

$$\ell(\mathbf{w}) = \sum_{m=1}^M \log p(w_m | w_{m-1}, \dots, w_1), \quad [6.42]$$

3308 treating the entire held-out corpus as a single stream of tokens.

3309 Typically, unknown words are mapped to the $\langle \text{UNK} \rangle$ token. This means that we have
 3310 to estimate some probability for $\langle \text{UNK} \rangle$ on the training data. One way to do this is to fix
 3311 the vocabulary \mathcal{V} to the $V - 1$ words with the highest counts in the training data, and then
 3312 convert all other tokens to $\langle \text{UNK} \rangle$. Other strategies for dealing with out-of-vocabulary
 3313 terms are discussed in § 6.5.

3314 **6.4.2 Perplexity**

Held-out likelihood is usually presented as **perplexity**, which is a deterministic transformation of the log-likelihood into an information-theoretic quantity,

$$\text{Perplex}(\mathbf{w}) = 2^{-\frac{\ell(\mathbf{w})}{M}}, \quad [6.43]$$

3315 where M is the total number of tokens in the held-out corpus.

3316 Lower perplexities correspond to higher likelihoods, so lower scores are better on this
3317 metric — it is better to be less perplexed. Here are some special cases:

- 3318 • In the limit of a perfect language model, probability 1 is assigned to the held-out
3319 corpus, with $\text{Perplex}(\mathbf{w}) = 2^{-\frac{1}{M} \log_2 1} = 2^0 = 1$.
- 3320 • In the opposite limit, probability zero is assigned to the held-out corpus, which cor-
3321 responds to an infinite perplexity, $\text{Perplex}(\mathbf{w}) = 2^{-\frac{1}{M} \log_2 0} = 2^\infty = \infty$.
- 3322 • Assume a uniform, unigram model in which $p(w_i) = \frac{1}{V}$ for all words in the vocab-
3323 ular. Then,

$$\begin{aligned} \log_2(\mathbf{w}) &= \sum_{m=1}^M \log_2 \frac{1}{V} = - \sum_{m=1}^M \log_2 V = -M \log_2 V \\ \text{Perplex}(\mathbf{w}) &= 2^{\frac{1}{M} M \log_2 V} \\ &= 2^{\log_2 V} \\ &= V. \end{aligned}$$

3322 This is the “worst reasonable case” scenario, since you could build such a language
3323 model without even looking at the data.

3324 In practice, language models tend to give perplexities in the range between 1 and V .
3325 A small benchmark dataset is the **Penn Treebank**, which contains roughly a million to-
3326 kens; its vocabulary is limited to 10,000 words, with all other tokens mapped a special
3327 $\langle \text{UNK} \rangle$ symbol. On this dataset, a well-smoothed 5-gram model achieves a perplexity of
3328 141 (Mikolov and Zweig, Mikolov and Zweig), and an LSTM language model achieves
3329 perplexity of roughly 80 (Zaremba, Sutskever, and Vinyals, Zaremba et al.). Various en-
3330 hancements to the LSTM architecture can bring the perplexity below 60 (Merity et al.,
3331 2018). A larger-scale language modeling dataset is the 1B Word Benchmark (Chelba et al.,
3332 2013), which contains text from Wikipedia. On this dataset, a perplexities of around 25
3333 can be obtained by averaging together multiple LSTM language models (Jozefowicz et al.,
3334 2016).

3335 6.5 Out-of-vocabulary words

3336 So far, we have assumed a **closed-vocabulary** setting — the vocabulary \mathcal{V} is assumed to be
 3337 a finite set. In realistic application scenarios, this assumption may not hold. Consider, for
 3338 example, the problem of translating newspaper articles. The following sentence appeared
 3339 in a Reuters article on January 6, 2017:⁵

3340 The report said U.S. intelligence agencies believe Russian military intelligence,
 3341 the **GRU**, used intermediaries such as **WikiLeaks**, **DCLeaks.com** and the **Guc-**
 3342 **cifer** 2.0 "persona" to release emails...

3343 Suppose that you trained a language model on the Gigaword corpus,⁶ which was released
 3344 in 2003. The bolded terms either did not exist at this date, or were not widely known; they
 3345 are unlikely to be in the vocabulary. The same problem can occur for a variety of other
 3346 terms: new technologies, previously unknown individuals, new words (e.g., *hashtag*), and
 3347 numbers.

3348 One solution is to simply mark all such terms with a special token, $\langle \text{UNK} \rangle$. While
 3349 training the language model, we decide in advance on the vocabulary (often the K most
 3350 common terms), and mark all other terms in the training data as $\langle \text{UNK} \rangle$. If we do not want
 3351 to determine the vocabulary size in advance, an alternative approach is to simply mark
 3352 the first occurrence of each word type as $\langle \text{UNK} \rangle$.

3353 But it is often better to make distinctions about the likelihood of various unknown words.
 3354 This is particularly important in languages that have rich morphological systems, with
 3355 many inflections for each word. For example, Portuguese is only moderately complex
 3356 from a morphological perspective, yet each verb has dozens of inflected forms (see Fig-
 3357 ure 4.3b). In such languages, there will be many word types that we do not encounter in a
 3358 corpus, which are nonetheless predictable from the morphological rules of the language.
 3359 To use a somewhat contrived English example, if *transfenestrate* is in the vocabulary, our
 3360 language model should assign a non-zero probability to the past tense *transfenestrated*,
 3361 even if it does not appear in the training data.

3362 One way to accomplish this is to supplement word-level language models with **character-**
3363 level language models. Such models can use n -grams or RNNs, but with a fixed vocab-
 3364 uary equal to the set of ASCII or Unicode characters. For example Ling et al. (2015)
 3365 propose an LSTM model over characters, and Kim (2014) employ a **convolutional neural**
 3366 **network** (LeCun and Bengio, 1995). A more linguistically motivated approach is to seg-
 3367 ment words into meaningful subword units, known as **morphemes** (see chapter 9). For

⁵Bayoumy, Y. and Strobel, W. (2017, January 6). U.S. intel report: Putin directed cy-
 ber campaign to help Trump. *Reuters*. Retrieved from <http://www.reuters.com/article/us-usa-russia-cyber-idUSKBN14Q1T8> on January 7, 2017.

⁶<https://catalog.ldc.upenn.edu/LDC2003T05>

3368 example, Botha and Blunsom (2014) induce vector representations for morphemes, which
3369 they build into a log-bilinear language model; Bhatia et al. (2016) incorporate morpheme
3370 vectors into an LSTM.

3371 Additional resources

3372 A variety of neural network architectures have been applied to language modeling. No-
3373 table earlier non-recurrent architectures include the neural probabilistic language model (Ben-
3374 gio et al., 2003) and the log-bilinear language model (Mnih and Hinton, 2007). Much more
3375 detail on these models can be found in the text by Goodfellow et al. (2016).

3376 Exercises

3377 1. exercises tk

3378 **Chapter 7**

3379 **Sequence labeling**

3380 The goal of sequence labeling is to assign tags to words, or more generally, to assign dis-
3381 crete labels to discrete elements in a sequence. There are many applications of sequence
3382 labeling in natural language processing, and chapter 8 presents an overview. A classic ap-
3383 plication is **part-of-speech tagging**, which involves tagging each word by its grammatical
3384 category. Coarse-grained grammatical categories include **NOUNs**, which describe things,
3385 properties, or ideas, and **VERBs**, which describe actions and events. Consider a simple
3386 input:

3387 (7.1) They can fish.

3388 A dictionary of coarse-grained part-of-speech tags might include **NOUN** as the only valid
3389 tag for *they*, but both **NOUN** and **VERB** as potential tags for *can* and *fish*. An accurate se-
3390 quence labeling algorithm should select the verb tag for both *can* and *fish* in (7.1), but it
3391 should select the noun tags for the same two words in the phrase *can of fish*.

3392 **7.1 Sequence labeling as classification**

One way to solve a tagging problem is to turn it into a classification problem. Let $f((\mathbf{w}, m), y)$ indicate the feature function for tag y at position m in the sequence $\mathbf{w} = (w_1, w_2, \dots, w_M)$. A simple tagging model would have a single base feature, the word itself:

$$f((\mathbf{w} = \text{they can fish}, m = 1), \text{N}) = (\text{they}, \text{N}) \quad [7.1]$$

$$f((\mathbf{w} = \text{they can fish}, m = 2), \text{V}) = (\text{can}, \text{V}) \quad [7.2]$$

$$f((\mathbf{w} = \text{they can fish}, m = 3), \text{V}) = (\text{fish}, \text{V}). \quad [7.3]$$

3393 Here the feature function takes three arguments as input: the sentence to be tagged (e.g.,
3394 *they can fish*), the proposed tag (e.g., N or V), and the index of the token to which this tag

3395 is applied. This simple feature function then returns a single feature: a tuple including
 3396 the word to be tagged and the tag that has been proposed. If the vocabulary size is V
 3397 and the number of tags is K , then there are $V \times K$ features. Each of these features must
 3398 be assigned a weight. These weights can be learned from a labeled dataset using a clas-
 3399 sification algorithm such as perceptron, but this isn't necessary in this case: it would be
 3400 equivalent to define the classification weights directly, with $\theta_{w,y} = 1$ for the tag y most
 3401 frequently associated with word w , and $\theta_{w,y} = 0$ for all other tags.

However, it is easy to see that this simple classification approach cannot correctly tag both *they can fish* and *can of fish*, because *can* and *fish* are grammatically ambiguous. To handle both of these cases, the tagger must rely on context, such as the surrounding words. We can build context into the feature set by incorporating the surrounding words as additional features:

$$\begin{aligned} f((\mathbf{w} = \text{they can fish}, 1), \mathbf{N}) = & \{(w_m = \text{they}, y_m = \mathbf{N}), \\ & (w_{m-1} = \square, y_m = \mathbf{N}), \\ & (w_{m+1} = \text{can}, y_m = \mathbf{N})\} \end{aligned} \quad [7.4]$$

$$\begin{aligned} f((\mathbf{w} = \text{they can fish}, 2), \mathbf{V}) = & \{(w_m = \text{can}, y_m = \mathbf{V}), \\ & (w_{m-1} = \text{they}, y_m = \mathbf{V}), \\ & (w_{m+1} = \text{fish}, y_m = \mathbf{V})\} \end{aligned} \quad [7.5]$$

$$\begin{aligned} f((\mathbf{w} = \text{they can fish}, 3), \mathbf{V}) = & \{(w_m = \text{fish}, y_m = \mathbf{V}), \\ & (w_{m-1} = \text{can}, y_m = \mathbf{V}), \\ & (w_{m+1} = \blacksquare, y_m = \mathbf{V})\}. \end{aligned} \quad [7.6]$$

3402 These features contain enough information that a tagger should be able to choose the
 3403 right tag for the word *fish*: words that come after *can* are likely to be verbs, so the feature
 3404 $(w_{m-1} = \text{can}, y_m = \mathbf{V})$ should have a large positive weight.

3405 However, even with this enhanced feature set, it may be difficult to tag some se-
 3406 quences correctly. One reason is that there are often relationships between the tags them-
 3407 selves. For example, in English it is relatively rare for a verb to follow another verb —
 3408 particularly if we differentiate MODAL verbs like *can* and *should* from more typical verbs,
 3409 like *give*, *transcend*, and *befuddle*. We would like to incorporate preferences against tag se-
 3410 quences like VERB-VERB, and in favor of tag sequences like NOUN-VERB. The need for
 3411 such preferences is best illustrated by a **garden path sentence**:

3412 (7.2) The old man the boat.

3413 Grammatically, the word *the* is a DETERMINER. When you read the sentence, what
 3414 part of speech did you first assign to *old*? Typically, this word is an ADJECTIVE — abbrevi-
 3415 ated as J — which is a class of words that modify nouns. Similarly, *man* is usually a noun.
 3416 The resulting sequence of tags is D J N D N. But this is a mistaken “garden path” inter-
 3417 pretation, which ends up leading nowhere. It is unlikely that a determiner would directly

follow a noun,¹ and it is particularly unlikely that the entire sentence would lack a verb. The only possible verb in (7.2) is the word *man*, which can refer to the act of maintaining and piloting something — often boats. But if *man* is tagged as a verb, then *old* is seated between a determiner and a verb, and must be a noun. And indeed, adjectives often have a second interpretation as nouns when used in this way (e.g., *the young*, *the restless*). This reasoning, in which the labeling decisions are intertwined, cannot be applied in a setting where each tag is produced by an independent classification decision.

7.2 Sequence labeling as structure prediction

As an alternative, think of the entire sequence of tags as a label itself. For a given sequence of words $\mathbf{w} = (w_1, w_2, \dots, w_M)$, there is a set of possible taggings $\mathcal{Y}(\mathbf{w}) = \mathcal{Y}^M$, where $\mathcal{Y} = \{\text{N, V, D, ...}\}$ refers to the set of individual tags, and \mathcal{Y}^M refers to the set of tag sequences of length M . We can then treat the sequence labeling problem as a classification problem in the label space $\mathcal{Y}(\mathbf{w})$,

$$\hat{\mathbf{y}} = \underset{\mathbf{y} \in \mathcal{Y}(\mathbf{w})}{\operatorname{argmax}} \Psi(\mathbf{w}, \mathbf{y}), \quad [7.7]$$

where $\mathbf{y} = (y_1, y_2, \dots, y_M)$ is a sequence of M tags, and Ψ is a scoring function on pairs of sequences, $V^M \times \mathcal{Y}^M \mapsto \mathbb{R}$. Such a function can include features that capture the relationships between tagging decisions, such as the preference that determiners not follow nouns, or that all sentences have verbs.

Given that the label space is exponentially large in the length of the sequence M , can it ever be practical to perform tagging in this way? The problem of making a series of interconnected labeling decisions is known as **inference**. Because natural language is full of interrelated grammatical structures, inference is a crucial aspect of natural language processing. In English, it is not unusual to have sentences of length $M = 20$; part-of-speech tag sets vary in size from 10 to several hundred. Taking the low end of this range, we have $|\mathcal{Y}(\mathbf{w}_{1:M})| \approx 10^{20}$, one hundred billion billion possible tag sequences. Enumerating and scoring each of these sequences would require an amount of work that is exponential in the sequence length, so inference is intractable.

However, the situation changes when we restrict the scoring function. Suppose we choose a function that decomposes into a sum of local parts,

$$\Psi(\mathbf{w}, \mathbf{y}) = \sum_{m=1}^{M+1} \psi(\mathbf{w}, y_m, y_{m-1}, m), \quad [7.8]$$

where each $\psi(\cdot)$ scores a local part of the tag sequence. Note that the sum goes up to $M+1$, so that we can include a score for a special end-of-sequence tag, $\psi(\mathbf{w}_{1:M}, \diamond, y_M, M+1)$. We also define a special tag to begin the sequence, $y_0 \triangleq \diamond$.

¹The main exception occurs with ditransitive verbs, such as *They gave the winner a trophy*.

3447 In a linear model, local scoring function can be defined as a dot product of weights
 3448 and features,

$$\psi(\mathbf{w}_{1:M}, y_m, y_{m-1}, m) = \boldsymbol{\theta} \cdot \mathbf{f}(\mathbf{w}, y_m, y_{m-1}, m). \quad [7.9]$$

3449 The feature vector \mathbf{f} can consider the entire input \mathbf{w} , and can look at pairs of adjacent
 3450 tags. This is a step up from per-token classification: the weights can assign low scores
 3451 to infelicitous tag pairs, such as noun-determiner, and high scores for frequent tag pairs,
 3452 such as determiner-noun and noun-verb.

In the example *they can fish*, a minimal feature function would include features for word-tag pairs (sometimes called **emission features**) and tag-tag pairs (sometimes called **transition features**):

$$\mathbf{f}(\mathbf{w} = \text{they can fish}, \mathbf{y} = \text{N V V}) = \sum_{m=1}^{M+1} \mathbf{f}(\mathbf{w}, y_m, y_{m-1}, m) \quad [7.10]$$

$$\begin{aligned} &= \mathbf{f}(\mathbf{w}, \text{N}, \diamond, 1) \\ &\quad + \mathbf{f}(\mathbf{w}, \text{V}, \text{N}, 2) \\ &\quad + \mathbf{f}(\mathbf{w}, \text{V}, \text{V}, 3) \\ &\quad + \mathbf{f}(\mathbf{w}, \blacklozenge, \text{V}, 4) \end{aligned} \quad [7.11]$$

$$\begin{aligned} &= (w_m = \text{they}, y_m = \text{N}) + (y_m = \text{N}, y_{m-1} = \diamond) \\ &\quad + (w_m = \text{can}, y_m = \text{V}) + (y_m = \text{V}, y_{m-1} = \text{N}) \\ &\quad + (w_m = \text{fish}, y_m = \text{V}) + (y_m = \text{V}, y_{m-1} = \text{V}) \\ &\quad + (y_m = \blacklozenge, y_{m-1} = \text{V}). \end{aligned} \quad [7.12]$$

3453 There are seven active features for this example: one for each word-tag pair, and one
 3454 for each tag-tag pair, including a final tag $y_{M+1} = \blacklozenge$. These features capture the two main
 3455 sources of information for part-of-speech tagging in English: which tags are appropriate
 3456 for each word, and which tags tend to follow each other in sequence. Given appropriate
 3457 weights for these features, taggers can achieve high accuracy, even for difficult cases like
 3458 *the old man the boat*. We will now discuss how this restricted scoring function enables
 3459 efficient inference, through the **Viterbi algorithm** (Viterbi, 1967).

3460 **7.3 The Viterbi algorithm**

By decomposing the scoring function into a sum of local parts, it is possible to rewrite the tagging problem as follows:

$$\hat{\mathbf{y}} = \operatorname{argmax}_{\mathbf{y} \in \mathcal{Y}(\mathbf{w})} \Psi(\mathbf{w}, \mathbf{y}) \quad [7.13]$$

$$= \operatorname{argmax}_{\mathbf{y}_{1:M}} \sum_{m=1}^{M+1} \psi(\mathbf{w}, y_m, y_{m-1}, m) \quad [7.14]$$

$$= \operatorname{argmax}_{\mathbf{y}_{1:M}} \sum_{m=1}^{M+1} s_m(y_m, y_{m-1}), \quad [7.15]$$

3461 where the final line simplifies the notation with the shorthand,

$$s_m(y_m, y_{m-1}) \triangleq \psi(\mathbf{w}_{1:M}, y_m, y_{m-1}, m). \quad [7.16]$$

This inference problem can be solved efficiently using **dynamic programming**, a algorithmic technique for reusing work in recurrent computations. As is often the case in dynamic programming, we begin by solving an auxiliary problem: rather than finding the best tag sequence, we simply compute the *score* of the best tag sequence,

$$\max_{\mathbf{y}_{1:M}} \Psi(\mathbf{w}, \mathbf{y}_{1:M}) = \max_{\mathbf{y}_{1:M}} \sum_{m=1}^{M+1} s_m(y_m, y_{m-1}). \quad [7.17]$$

This score involves a maximization over all tag sequences of length M , written $\max_{\mathbf{y}_{1:M}}$. This maximization can be broken into two pieces,

$$\max_{\mathbf{y}_{1:M}} \Psi(\mathbf{w}, \mathbf{y}_{1:M}) = \max_{y_M} \max_{\mathbf{y}_{1:M-1}} \sum_{m=1}^{M+1} s_m(y_m, y_{m-1}), \quad [7.18]$$

which simply says that we maximize over the final tag y_M , and we maximize over all “prefixes”, $\mathbf{y}_{1:M-1}$. But within the sum of scores, only the final term $s_{M+1}(\blacklozenge, y_M)$ depends on y_M . We can pull this term out of the second maximization,

$$\max_{\mathbf{y}_{1:M}} \Psi(\mathbf{w}, \mathbf{y}_{1:M}) = \max_{y_M} s_{M+1}(\blacklozenge, y_M) + \max_{\mathbf{y}_{1:M-1}} \sum_{m=1}^M s_m(y_m, y_{m-1}). \quad [7.19]$$

This same reasoning can be applied recursively to the second term of Equation 7.19, pulling out $s_M(y_M, y_{M-1})$, and so on. We can formalize this idea by defining an auxiliary

Algorithm 11 The Viterbi algorithm. Each $s_m(k, k')$ is a local score for tag $y_m = k$ and $y_{m-1} = k'$.

```

for  $k \in \{0, \dots, K\}$  do
     $v_1(k) = s_1(k, \diamond)$ 
for  $m \in \{2, \dots, M\}$  do
    for  $k \in \{0, \dots, K\}$  do
         $v_m(k) = \max_{k'} s_m(k, k') + v_{m-1}(k')$ 
         $b_m(k) = \operatorname{argmax}_{k'} s_m(k, k') + v_{m-1}(k')$ 
     $y_M = \operatorname{argmax}_k s_{M+1}(\blacklozenge, k) + v_M(k)$ 
    for  $m \in \{M-1, \dots, 1\}$  do
         $y_m = b_m(y_{m+1})$ 
return  $\mathbf{y}_{1:M}$ 
```

Viterbi variable,

$$v_m(y_m) \triangleq \max_{\mathbf{y}_{1:m-1}} \sum_{n=1}^m s_n(y_n, y_{n-1}) \quad [7.20]$$

$$= \max_{y_{m-1}} s_m(y_m, y_{m-1}) + \max_{\mathbf{y}_{1:m-2}} \sum_{n=1}^{m-1} s_n(y_n, y_{n-1}) \quad [7.21]$$

$$= \max_{y_{m-1}} s_m(y_m, y_{m-1}) + v_{m-1}(y_{m-1}). \quad [7.22]$$

3462 The variable $v_m(k)$ represents the score of the best sequence of length m ending in tag k .

Each set of Viterbi variables is computed from the local score $s_m(y_m, y_{m-1})$, and from the previous set of Viterbi variables. The initial condition of the recurrence is simply the first score,

$$v_1(y_1) \triangleq s_1(y_1, \diamond). \quad [7.23]$$

The maximum overall score for the sequence is then the final Viterbi variable,

$$\max_{\mathbf{y}_{1:M}} \Psi(\mathbf{w}_{1:M}, \mathbf{y}_{1:M}) = v_{M+1}(\blacklozenge). \quad [7.24]$$

3463 Thus, the score of the best labeling for the sequence can be computed in a single forward
 3464 sweep: first compute all variables $v_1(\cdot)$ from Equation 7.23, and then compute all variables
 3465 $v_2(\cdot)$ from the recurrence Equation 7.22, and continue until reaching the final variable
 3466 $v_{M+1}(\blacklozenge)$.

3467 Graphically, it is customary to arrange these variables in a structure known as a **trellis**,
 3468 shown in Figure 7.1. Each column indexes a token m in the sequence, and each row

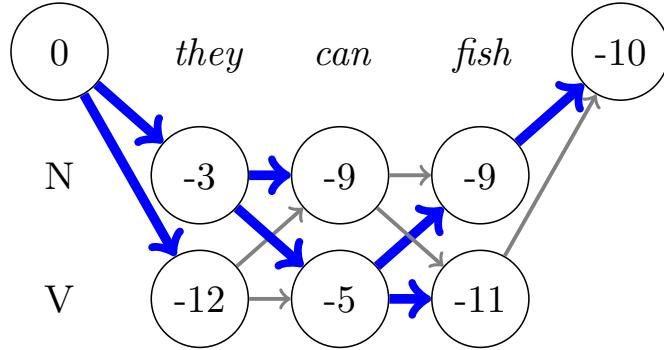


Figure 7.1: The trellis representation of the Viterbi variables, for the example *they can fish*, using the weights shown in Table 7.1.

3469 indexes a tag in \mathcal{Y} ; every $v_{m-1}(k)$ is connected to every $v_m(k')$, that $v_m(k')$ is computed
 3470 from $v_{m-1}(k)$. Special nodes are set aside for the start and end states.

3471 Our real goal is to find the best scoring sequence, not simply to compute its score.
 3472 But solving the auxiliary problem gets us almost all the way there. Recall that each $v_m(k)$
 3473 represents the score of the best tag sequence ending in that tag k in position m . To compute
 3474 this, we maximize over possible values of y_{m-1} . If we keep track of the “argmax” tag that
 3475 maximizes this choice at each step, then we can walk backwards from the final tag, and
 3476 recover the optimal tag sequence. This is indicated in Figure 7.1 by the solid blue lines,
 3477 which we trace back from the final position. These “back-pointers” are written $b_m(k)$,
 3478 indicating the optimal tag y_{m-1} on the path to $Y_m = k$.

3479 The complete Viterbi algorithm is shown in Algorithm 11. When computing the initial
 3480 Viterbi variables $v_1(\cdot)$, we use a special tag, \diamond , to indicate the start of the sequence. When
 3481 computing the final tag Y_M , we use another special tag, \blacklozenge , to indicate the end of the
 3482 sequence. Linguistically, these special tags enable the use of transition features for the tags
 3483 that begin and end the sequence: for example, conjunctions are unlikely to end sentences
 3484 in English, so we would like a low score for $s_{M+1}(\blacklozenge, CC)$; nouns are relatively likely to
 3485 appear at the beginning of sentences, so we would like a high score for $s_1(N, \diamond)$, assuming
 3486 the noun tag is compatible with the first word token w_1 .

3487 **Complexity** If there are K tags and M positions in the sequence, then there are $M \times K$
 3488 Viterbi variables to compute. Computing each variable requires finding a maximum over
 3489 K possible predecessor tags. The total time complexity of populating the trellis is therefore
 3490 $\mathcal{O}(MK^2)$, with an additional factor for the number of active features at each position.
 3491 After completing the trellis, we simply trace the backwards pointers to the beginning of
 3492 the sequence, which takes $\mathcal{O}(M)$ operations.

	<i>they</i>	<i>can</i>	<i>fish</i>	
N	-2	-3	-3	
V	-10	-1	-3	

(a) Weights for emission features.

	N	V	♦
◊	-1	-2	$-\infty$
N	-3	-1	-1
V	-1	-3	-1

(b) Weights for transition features. The “from” tags are on the columns, and the “to” tags are on the rows.

Table 7.1: Feature weights for the example trellis shown in Figure 7.1. Emission weights from \diamond and ♦ are implicitly set to $-\infty$.3493 **7.3.1 Example**

3494 Consider the minimal tagset $\{N, V\}$, corresponding to nouns and verbs. Even in this
 3495 tagset, there is considerable ambiguity: for example, the words *can* and *fish* can each take
 3496 both tags. Of the $2 \times 2 \times 2 = 8$ possible taggings for the sentence *they can fish*, four are
 3497 possible given these possible tags, and two are grammatical.²

3498 The values in the trellis in Figure 7.1 are computed from the feature weights defined in
 3499 Table 7.1. We begin with $v_1(N)$, which has only one possible predecessor, the start tag \diamond .
 3500 This score is therefore equal to $s_1(N, \diamond) = -2 - 1 = -3$, which is the sum of the scores for
 3501 the emission and transition features respectively; the backpointer is $b_1(N) = \diamond$. The score
 3502 for $v_1(V)$ is computed in the same way: $s_1(V, \diamond) = -10 - 2 = -12$, and again $b_1(V) = \diamond$.
 3503 The backpointers are represented in the figure by thick lines.

Things get more interesting at $m = 2$. The score $v_2(N)$ is computed by maximizing over the two possible predecessors,

$$v_2(N) = \max(v_1(N) + s_2(N, N), v_1(V) + s_2(N, V)) \quad [7.25]$$

$$= \max(-3 - 3 - 3, -12 - 3 - 1) = -9 \quad [7.26]$$

$$b_2(N) = N. \quad [7.27]$$

This continues until reaching $v_4(\diamond)$, which is computed as,

$$v_4(\diamond) = \max(v_3(N) + s_4(\diamond, N), v_3(V) + s_4(\diamond, V)) \quad [7.28]$$

$$= \max(-9 + 0 - 1, -11 + 0 - 1) \quad [7.29]$$

$$= -10, \quad [7.30]$$

3504 so $b_4(\diamond) = N$. As there is no emission w_4 , the emission features have scores of zero.

²The tagging *they*/N *can*/V *fish*/N corresponds to the scenario of putting fish into cans, or perhaps of firing them.

3505 To compute the optimal tag sequence, we walk backwards from here, next checking
 3506 $b_3(N) = V$, and then $b_2(V) = N$, and finally $b_1(N) = \diamond$. This yields $y = (N, V, N)$, which
 3507 corresponds to the linguistic interpretation of the fishes being put into cans.

3508 **7.3.2 Higher-order features**

3509 The Viterbi algorithm was made possible by a restriction of the scoring function to local
 3510 parts that consider only pairs of adjacent tags. We can think of this as a bigram language
 3511 model over tags. A natural question is how to generalize Viterbi to tag trigrams, which
 3512 would involve the following decomposition:

$$\Psi(\mathbf{w}, \mathbf{y}) = \sum_{m=1}^{M+2} f(\mathbf{w}, y_m, y_{m-1}, y_{m-2}, m), \quad [7.31]$$

3513 where $y_{-1} = \diamond$ and $y_{M+2} = \blacklozenge$.

3514 One solution is to create a new tagset $\mathcal{Y}^{(2)}$ from the Cartesian product of the original
 3515 tagset with itself, $\mathcal{Y}^{(2)} = \mathcal{Y} \times \mathcal{Y}$. The tags in this product space are ordered pairs, rep-
 3516 resenting adjacent tags at the token level: for example, the tag (N, V) would represent a
 3517 noun followed by a verb. Transitions between such tags must be consistent: we can have a
 3518 transition from (N, V) to (V, N) (corresponding to the tag sequence $N V N$), but not from
 3519 (N, V) to (N, N) , which would not correspond to any coherent tag sequence. This con-
 3520 straint can be enforced in feature weights, with $\theta_{((a,b),(c,d))} = -\infty$ if $b \neq c$. The remaining
 3521 feature weights can encode preferences for and against various tag trigrams.

3522 In the Cartesian product tag space, there are K^2 tags, suggesting that the time com-
 3523 plexity will increase to $\mathcal{O}(MK^4)$. However, it is unnecessary to max over predecessor tag
 3524 bigrams that are incompatible with the current tag bigram. By exploiting this constraint,
 3525 it is possible to limit the time complexity to $\mathcal{O}(MK^3)$. The space complexity grows to
 3526 $\mathcal{O}(MK^2)$, since the trellis must store all possible predecessors of each tag. In general, the
 3527 time and space complexity of higher-order Viterbi grows exponentially with the order of
 3528 the tag n -grams that are considered in the feature decomposition.

3529 **7.4 Hidden Markov Models**

3530 Let us now consider how to learn the scores $s_m(y, y')$ that parametrize the Viterbi sequence
 3531 labeling algorithm, beginning with a probabilistic approach. Recall from § 2.1 that the
 3532 probabilistic Naïve Bayes classifier selects the label y to maximize $p(y | \mathbf{x}) \propto p(y, \mathbf{x})$. In
 3533 probabilistic sequence labeling, our goal is similar: select the tag sequence that maximizes
 3534 $p(\mathbf{y} | \mathbf{w}) \propto p(\mathbf{y}, \mathbf{w})$. The locality restriction in Equation 7.8 can be viewed as a conditional
 3535 independence assumption on the random variables \mathbf{y} .

Algorithm 12 Generative process for the hidden Markov model

```

 $y_0 \leftarrow \diamond,$     $m \leftarrow 1$ 
repeat
     $y_m \sim \text{Categorical}(\lambda_{y_{m-1}})$             $\triangleright$  sample the current tag
     $w_m \sim \text{Categorical}(\phi_{y_m})$             $\triangleright$  sample the current word
until  $y_m = \blacklozenge$             $\triangleright$  terminate when the stop symbol is generated

```

3536 Naïve Bayes was introduced as a generative model — a probabilistic story that ex-
 3537 plains the observed data as well as the hidden label. A similar story can be constructed
 3538 for probabilistic sequence labeling: first, the tags are drawn from a prior distribution; next,
 3539 the tokens are drawn from a conditional likelihood. However, for inference to be tractable,
 3540 additional independence assumptions are required. First, the probability of each token
 3541 depends only on its tag, and not on any other element in the sequence:

$$p(w | y) = \prod_{m=1}^M p(w_m | y_m). \quad [7.32]$$

3542 Second, each tag y_m depends only on its predecessor,

$$p(y) = \prod_{m=1}^M p(y_m | y_{m-1}), \quad [7.33]$$

3543 where $y_0 = \diamond$ in all cases. Due to this **Markov assumption**, probabilistic sequence labeling
 3544 models are known as **hidden Markov models** (HMMs).

3545 The generative process for the hidden Markov model is shown in Algorithm 12. Given
 3546 the parameters λ and ϕ , we can compute $p(w, y)$ for any token sequence w and tag se-
 3547 quence y . The HMM is often represented as a **graphical model** (Wainwright and Jordan,
 3548 2008), as shown in Figure 7.2. This representation makes the independence assumptions
 3549 explicit: if a variable v_1 is probabilistically conditioned on another variable v_2 , then there
 3550 is an arrow $v_2 \rightarrow v_1$ in the diagram. If there are no arrows between v_1 and v_2 , they
 3551 are **conditionally independent**, given each variable's **Markov blanket**. In the hidden
 3552 Markov model, the Markov blanket for each tag y_m includes the “parent” y_{m-1} , and the
 3553 “children” y_{m+1} and w_m .³

3554 It is important to reflect on the implications of the HMM independence assumptions.
 3555 A non-adjacent pair of tags y_m and y_n are conditionally independent; if $m < n$ and we
 3556 are given y_{n-1} , then y_m offers no additional information about y_n . However, if we are
 3557 not given any information about the tags in a sequence, then all tags are probabilistically
 3558 coupled.

³In general graphical models, a variable's Markov blanket includes its parents, children, and its children's other parents (Murphy, 2012).

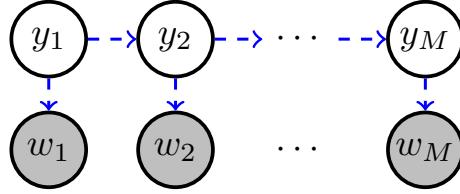


Figure 7.2: Graphical representation of the hidden Markov model. Arrows indicate probabilistic dependencies.

3559 7.4.1 Estimation

3560 The hidden Markov model has two groups of parameters:

3561 **Emission probabilities.** The probability $p_e(w_m | y_m; \phi)$ is the emission probability, since
3562 the words are treated as probabilistically “emitted”, conditioned on the tags.

3563 **Transition probabilities.** The probability $p_t(y_m | y_{m-1}; \lambda)$ is the transition probability,
3564 since it assigns probability to each possible tag-to-tag transition.

Both of these groups of parameters are typically computed from smoothed relative frequency estimation on a labeled corpus (see § 6.2 for a review of smoothing). The unsmoothed probabilities are,

$$\begin{aligned}\phi_{k,i} &\triangleq \Pr(W_m = i | Y_m = k) = \frac{\text{count}(W_m = i, Y_m = k)}{\text{count}(Y_m = k)} \\ \lambda_{k,k'} &\triangleq \Pr(Y_m = k' | Y_{m-1} = k) = \frac{\text{count}(Y_m = k', Y_{m-1} = k)}{\text{count}(Y_{m-1} = k)}.\end{aligned}$$

3565 Smoothing is more important for the emission probability than the transition probability,
3566 because the vocabulary is much larger than the number of tags.

3567 7.4.2 Inference

3568 The goal of inference in the hidden Markov model is to find the highest probability tag
3569 sequence,

$$\hat{y} = \underset{y}{\operatorname{argmax}} p(y | w). \quad [7.34]$$

3570 As in Naïve Bayes, it is equivalent to find the tag sequence with the highest *log*-probability,
3571 since the logarithm is a monotonically increasing function. It is furthermore equivalent
3572 to maximize the joint probability $p(y, w) = p(y | w) \times p(w) \propto p(y | w)$, which is pro-
3573 portional to the conditional probability. Putting these observations together, the inference

3574 problem can be reformulated as,

$$\hat{\mathbf{y}} = \operatorname{argmax}_{\mathbf{y}} \log p(\mathbf{y}, \mathbf{w}). \quad [7.35]$$

We can now apply the HMM independence assumptions:

$$\log p(\mathbf{y}, \mathbf{w}) = \log p(\mathbf{y}) + \log p(\mathbf{w} \mid \mathbf{y}) \quad [7.36]$$

$$= \sum_{m=1}^{M+1} \log p_Y(y_m \mid y_{m-1}) + \log p_{W|Y}(w_m \mid y_m) \quad [7.37]$$

$$= \sum_{m=1}^{M+1} \log \lambda_{y_m, y_{m-1}} + \log \phi_{y_m, w_m} \quad [7.38]$$

$$= \sum_{m=1}^{M+1} s_m(y_m, y_{m-1}), \quad [7.39]$$

where,

$$s_m(y_m, y_{m-1}) \triangleq \log \lambda_{y_m, y_{m-1}} + \log \phi_{y_m, w_m}, \quad [7.40]$$

3575 and,

$$\phi_{\diamond, w} = \begin{cases} 1, & w = \blacksquare \\ 0, & \text{otherwise,} \end{cases} \quad [7.41]$$

3576 which ensures that the stop tag \diamond can only be applied to the final token \blacksquare .

This derivation shows that HMM inference can be viewed as an application of the Viterbi decoding algorithm, given an appropriately defined scoring function. The local score $s_m(y_m, y_{m-1})$ can be interpreted probabilistically,

$$s_m(y_m, y_{m-1}) = \log p_y(y_m \mid y_{m-1}) + \log p_{w|y}(w_m \mid y_m) \quad [7.42]$$

$$= \log p(y_m, w_m \mid y_{m-1}). \quad [7.43]$$

Now recall the definition of the Viterbi variables,

$$v_m(y_m) = \max_{y_{m-1}} s_m(y_m, y_{m-1}) + v_{m-1}(y_{m-1}) \quad [7.44]$$

$$= \max_{y_{m-1}} \log p(y_m, w_m \mid y_{m-1}) + v_{m-1}(y_{m-1}). \quad [7.45]$$

By setting $v_{m-1}(y_{m-1}) = \max_{\mathbf{y}_{1:m-2}} \log p(\mathbf{y}_{1:m-1}, \mathbf{w}_{1:m-1})$, we obtain the recurrence,

$$v_m(y_m) = \max_{y_{m-1}} \log p(y_m, w_m \mid y_{m-1}) + \max_{\mathbf{y}_{1:m-2}} \log p(\mathbf{y}_{1:m-1}, \mathbf{w}_{1:m-1}) \quad [7.46]$$

$$= \max_{\mathbf{y}_{1:m-1}} \log p(y_m, w_m \mid y_{m-1}) + \log p(\mathbf{y}_{1:m-1}, \mathbf{w}_{1:m-1}) \quad [7.47]$$

$$= \max_{\mathbf{y}_{1:m-1}} \log p(\mathbf{y}_{1:m}, \mathbf{w}_{1:m}). \quad [7.48]$$

In words, the Viterbi variable $v_m(y_m)$ is the log probability of the best tag sequence ending in y_m , joint with the word sequence $w_{1:m}$. The log probability of the best complete tag sequence is therefore,

$$\max_{\mathbf{y}_{1:M}} \log p(\mathbf{y}_{1:M+1}, \mathbf{w}_{1:M+1}) = v_{M+1}(\spadesuit) \quad [7.49]$$

***Viterbi as an example of the max-product algorithm** The Viterbi algorithm can also be implemented using probabilities, rather than log-probabilities. In this case, each $v_m(y_m)$ is equal to,

$$v_m(y_m) = \max_{\mathbf{y}_{1:m-1}} p(\mathbf{y}_{1:m-1}, y_m, \mathbf{w}_{1:m}) \quad [7.50]$$

$$= \max_{y_{m-1}} p(y_m, w_m | y_{m-1}) \times \max_{\mathbf{y}_{1:m-2}} p(\mathbf{y}_{1:m-2}, y_{m-1}, \mathbf{w}_{1:m-1}) \quad [7.51]$$

$$= \max_{y_{m-1}} p(y_m, w_m | y_{m-1}) \times v_{m-1}(y_{m-1}) \quad [7.52]$$

$$= p_{w|y}(w_m | y_m) \times \max_{y_{m-1}} p_y(y_m | y_{m-1}) \times v_{m-1}(y_{m-1}). \quad [7.53]$$

3577 Each Viterbi variable is computed by *maximizing* over a set of *products*. Thus, the Viterbi
 3578 algorithm is a special case of the **max-product algorithm** for inference in graphical mod-
 3579 els (Wainwright and Jordan, 2008). However, the product of probabilities tends towards
 3580 zero over long sequences, so the log-probability version of Viterbi is recommended in
 3581 practical implementations.

3582 7.5 Discriminative sequence labeling with features

3583 Today, hidden Markov models are rarely used for supervised sequence labeling. This is
 3584 because HMMs are limited to only two phenomena:

- 3585 • word-tag compatibility, via the emission probability $p_{W|Y}(w_m | y_m)$;
- 3586 • local context, via the transition probability $p_Y(y_m | y_{m-1})$.

3587 The Viterbi algorithm permits the inclusion of richer information in the local scoring func-
 3588 tion $\psi(\mathbf{w}_{1:M}, y_m, y_{m-1}, m)$, which can be defined as a weighted sum of arbitrary local *fea-*
 3589 *tures*,

$$\psi(\mathbf{w}, y_m, y_{m-1}, m) = \boldsymbol{\theta} \cdot \mathbf{f}(\mathbf{w}, y_m, y_{m-1}, m), \quad [7.54]$$

3590 where \mathbf{f} is a locally-defined feature function, and $\boldsymbol{\theta}$ is a vector of weights.

The local decomposition of the scoring function Ψ is reflected in a corresponding decomposition of the feature function:

$$\Psi(\mathbf{w}, \mathbf{y}) = \sum_{m=1}^{M+1} \psi(\mathbf{w}, y_m, y_{m-1}, m) \quad [7.55]$$

$$= \sum_{m=1}^{M+1} \boldsymbol{\theta} \cdot \mathbf{f}(\mathbf{w}, y_m, y_{m-1}, m) \quad [7.56]$$

$$= \boldsymbol{\theta} \cdot \sum_{m=1}^{M+1} \mathbf{f}(\mathbf{w}, y_m, y_{m-1}, m) \quad [7.57]$$

$$= \boldsymbol{\theta} \cdot \mathbf{f}^{(\text{global})}(\mathbf{w}, \mathbf{y}_{1:M}), \quad [7.58]$$

3591 where $\mathbf{f}^{(\text{global})}(\mathbf{w}, \mathbf{y})$ is a global feature vector, which is a sum of local feature vectors,

$$\mathbf{f}^{(\text{global})}(\mathbf{w}, \mathbf{y}) = \sum_{m=1}^{M+1} \mathbf{f}(\mathbf{w}_{1:M}, y_m, y_{m-1}, m), \quad [7.59]$$

3592 with $y_{M+1} = \diamond$ and $y_0 = \diamond$ by construction.

3593 Let's now consider what additional information these features might encode.

3594 **Word affix features.** Consider the problem of part-of-speech tagging on the first four
3595 lines of the poem *Jabberwocky* (Carroll, 1917):

3596 (7.3) 'Twas brillig, and the slithy toves
3597 Did gyre and gimble in the wabe:
3598 All mimsy were the borogoves,
3599 And the mome raths outgrabe.

3600 Many of these words were made up by the author of the poem, so a corpus would offer
3601 no information about their probabilities of being associated with any particular part of
3602 speech. Yet it is not so hard to see what their grammatical roles might be in this passage.
3603 Context helps: for example, the word *slithy* follows the determiner *the*, so it is probably a
3604 noun or adjective. Which do you think is more likely? The suffix *-thy* is found in a number
3605 of adjectives, like *frothy*, *healthy*, *pithy*, *worthy*. It is also found in a handful of nouns — e.g.,
3606 *apathy*, *sympathy* — but nearly all of these have the longer coda *-pathy*, unlike *slithy*. So the
3607 suffix gives some evidence that *slithy* is an adjective, and indeed it is: later in the text we
3608 find that it is a combination of the adjectives *lithe* and *slimy*.⁴

⁴Morphology is the study of how words are formed from smaller linguistic units. Computational approaches to morphological analysis are touched on in chapter 9; Bender (2013) provides a good overview of the underlying linguistic principles.

3609 **Fine-grained context.** The hidden Markov model captures contextual information in the
 3610 form of part-of-speech tag bigrams. But sometimes, the necessary contextual information
 3611 is more specific. Consider the noun phrases *this fish* and *these fish*. Many part-of-speech
 3612 tagsets distinguish between singular and plural nouns, but do not distinguish between
 3613 singular and plural determiners.⁵ A hidden Markov model would be unable to correctly
 3614 label *fish* as singular or plural in both of these cases, because it only has access to two
 3615 features: the preceding tag (determiner in both cases) and the word (*fish* in both cases).
 3616 The classification-based tagger discussed in § 7.1 had the ability to use preceding and suc-
 3617 ceeding words as features, and it can also be incorporated into a Viterbi-based sequence
 3618 labeler as a local feature.

Example Consider the tagging D J N (determiner, adjective, noun) for the sequence *the slithy toves*, so that

$$\mathbf{w} = \text{the slithy toves}$$

$$\mathbf{y} = \text{D J N}.$$

Let's create the feature vector for this example, assuming that we have word-tag features (indicated by W), tag-tag features (indicated by T), and suffix features (indicated by M). You can assume that you have access to a method for extracting the suffix *-thy* from *slithy*, *-es* from *toves*, and \emptyset from *the*, indicating that this word has no suffix.⁶ The resulting feature vector is,

$$\begin{aligned} f(\text{the slithy toves, D J N}) &= f(\text{the slithy toves, D}, \diamond, 1) \\ &\quad + f(\text{the slithy toves, J}, D, 2) \\ &\quad + f(\text{the slithy toves, N}, J, 3) \\ &\quad + f(\text{the slithy toves}, \blacklozenge, N, 4) \\ &= \{(T : \diamond, D), (W : \text{the}, D), (M : \emptyset, D), \\ &\quad (T : D, J), (W : \text{slithy}, J), (M : -thy, J), \\ &\quad (T : J, N), (W : \text{toves}, N), (M : -es, N) \\ &\quad (T : N, \blacklozenge)\}. \end{aligned}$$

3619 These examples show that local features can incorporate information that lies beyond
 3620 the scope of a hidden Markov model. Because the features are local, it is possible to apply
 3621 the Viterbi algorithm to identify the optimal sequence of tags. The remaining question

⁵For example, the Penn Treebank tagset follows these conventions.

⁶Such a system is called a **morphological segmenter**. The task of morphological segmentation is briefly described in § 9.1.4.4; a well known segmenter is Morfessor (Creutz and Lagus, 2007). In real applications, a typical approach is to include features for all orthographic suffixes up to some maximum number of characters: for *slithy*, we would have suffix features for *-y*, *-hy*, and *-thy*.

3622 is how to estimate the weights on these features. § 2.2 presented three main types of
 3623 discriminative classifiers: perceptron, support vector machine, and logistic regression.
 3624 Each of these classifiers has a structured equivalent, enabling it to be trained from labeled
 3625 sequences rather than individual tokens.

3626 **7.5.1 Structured perceptron**

The perceptron classifier is trained by increasing the weights for features that are associated with the correct label, and decreasing the weights for features that are associated with incorrectly predicted labels:

$$\hat{y} = \operatorname{argmax}_{y \in \mathcal{Y}} \theta \cdot f(\mathbf{x}, y) \quad [7.60]$$

$$\theta^{(t+1)} \leftarrow \theta^{(t)} + f(\mathbf{x}, y) - f(\mathbf{x}, \hat{y}). \quad [7.61]$$

We can apply exactly the same update in the case of structure prediction,

$$\hat{\mathbf{y}} = \operatorname{argmax}_{\mathbf{y} \in \mathcal{Y}(\mathbf{w})} \theta \cdot f(\mathbf{w}, \mathbf{y}) \quad [7.62]$$

$$\theta^{(t+1)} \leftarrow \theta^{(t)} + f(\mathbf{w}, \mathbf{y}) - f(\mathbf{w}, \hat{\mathbf{y}}). \quad [7.63]$$

3627 This learning algorithm is called **structured perceptron**, because it learns to predict the
 3628 structured output \mathbf{y} . The only difference is that instead of computing \hat{y} by enumerating
 3629 the entire set \mathcal{Y} , the Viterbi algorithm is used to efficiently search the set of possible tag-
 3630 gings, \mathcal{Y}^M . Structured perceptron can be applied to other structured outputs as long as
 3631 efficient inference is possible. As in perceptron classification, weight averaging is crucial
 3632 to get good performance (see § 2.2.2).

Example For the example *they can fish*, suppose that the reference tag sequence is $\mathbf{y}^{(i)} =$
 N V V, but the tagger incorrectly returns the tag sequence $\hat{\mathbf{y}} = \text{N V N}$. Assuming a model
 with features for emissions (w_m, y_m) and transitions (y_{m-1}, y_m) , the corresponding structured
 perceptron update is:

$$\theta_{(fish,V)} \leftarrow \theta_{(fish,V)} + 1, \quad \theta_{(fish,N)} \leftarrow \theta_{(fish,N)} - 1 \quad [7.64]$$

$$\theta_{(V,V)} \leftarrow \theta_{(V,V)} + 1, \quad \theta_{(V,N)} \leftarrow \theta_{(V,N)} - 1 \quad [7.65]$$

$$\theta_{(V,\blacklozenge)} \leftarrow \theta_{(V,\blacklozenge)} + 1, \quad \theta_{(N,\blacklozenge)} \leftarrow \theta_{(N,\blacklozenge)} - 1. \quad [7.66]$$

3633 **7.5.2 Structured support vector machines**

3634 Large-margin classifiers such as the support vector machine improve on the perceptron by
 3635 pushing the classification boundary away from the training instances. The same idea can

3636 be applied to sequence labeling. A support vector machine in which the output is a struc-
 3637 tured object, such as a sequence, is called a **structured support vector machine** (Tsochan-
 3638 taridis et al., 2004).⁷

3639 In classification, we formalized the large-margin constraint as,

$$\forall \mathbf{y} \neq \mathbf{y}^{(i)}, \boldsymbol{\theta} \cdot \mathbf{f}(\mathbf{x}, \mathbf{y}^{(i)}) - \boldsymbol{\theta} \cdot \mathbf{f}(\mathbf{x}, \mathbf{y}) \geq 1, \quad [7.67]$$

3640 requiring a margin of at least 1 between the scores for all labels \mathbf{y} that are not equal to the
 3641 correct label $\mathbf{y}^{(i)}$. The weights $\boldsymbol{\theta}$ are then learned by constrained optimization (see § 2.3.2).

3642 This idea can be applied to sequence labeling by formulating an equivalent set of con-
 3643 straints for all possible labelings $\mathcal{Y}(\mathbf{w})$ for an input \mathbf{w} . However, there are two problems.
 3644 First, in sequence labeling, some predictions are more wrong than others: we may miss
 3645 only one tag out of fifty, or we may get all fifty wrong. We would like our learning algo-
 3646 rithm to be sensitive to this difference. Second, the number of constraints is equal to the
 3647 number of possible labelings, which is exponentially large in the length of the sequence.

3648 The first problem can be addressed by adjusting the constraint to require larger mar-
 3649 gins for more serious errors. Let $c(\mathbf{y}^{(i)}, \hat{\mathbf{y}}) \geq 0$ represent the *cost* of predicting label $\hat{\mathbf{y}}$ when
 3650 the true label is $\mathbf{y}^{(i)}$. We can then generalize the margin constraint,

$$\forall \mathbf{y}, \boldsymbol{\theta} \cdot \mathbf{f}(\mathbf{w}^{(i)}, \mathbf{y}^{(i)}) - \boldsymbol{\theta} \cdot \mathbf{f}(\mathbf{w}^{(i)}, \mathbf{y}) \geq c(\mathbf{y}^{(i)}, \mathbf{y}). \quad [7.68]$$

3651 This cost-augmented margin constraint specializes to the constraint in Equation 7.67 if we
 3652 choose the delta function $c(\mathbf{y}^{(i)}, \mathbf{y}) = \delta((\mathbf{y}^{(i)} \neq \mathbf{y}))$. A more expressive cost function is
 3653 the **Hamming cost**,

$$c(\mathbf{y}^{(i)}, \mathbf{y}) = \sum_{m=1}^M \delta(y_m^{(i)} \neq y_m), \quad [7.69]$$

3654 which computes the number of errors in \mathbf{y} . By incorporating the cost function as the
 3655 margin constraint, we require that the true labeling be separated from the alternatives by
 3656 a margin that is proportional to the number of incorrect tags in each alternative labeling.

The second problem is that the number of constraints is exponential in the length
 of the sequence. This can be addressed by focusing on the prediction $\hat{\mathbf{y}}$ that *maximally*
 violates the margin constraint. This prediction can be identified by solving the following
cost-augmented decoding problem:

$$\hat{\mathbf{y}} = \operatorname{argmax}_{\mathbf{y} \neq \mathbf{y}^{(i)}} \boldsymbol{\theta} \cdot \mathbf{f}(\mathbf{w}^{(i)}, \mathbf{y}) - \boldsymbol{\theta} \cdot \mathbf{f}(\mathbf{w}^{(i)}, \mathbf{y}^{(i)}) + c(\mathbf{y}^{(i)}, \mathbf{y}) \quad [7.70]$$

$$= \operatorname{argmax}_{\mathbf{y} \neq \mathbf{y}^{(i)}} \boldsymbol{\theta} \cdot \mathbf{f}(\mathbf{w}^{(i)}, \mathbf{y}) + c(\mathbf{y}^{(i)}, \mathbf{y}), \quad [7.71]$$

⁷This model is also known as a **max-margin Markov network** (Taskar et al., 2003), emphasizing that the scoring function is constructed from a sum of components, which are Markov independent.

3657 where in the second line we drop the term $\theta \cdot f(\mathbf{w}^{(i)}, \mathbf{y}^{(i)})$, which is constant in \mathbf{y} .

We can now reformulate the margin constraint for sequence labeling,

$$\theta \cdot f(\mathbf{w}^{(i)}, \mathbf{y}^{(i)}) - \max_{\mathbf{y} \in \mathcal{Y}(\mathbf{w})} (\theta \cdot f(\mathbf{w}^{(i)}, \mathbf{y}) + c(\mathbf{y}^{(i)}, \mathbf{y})) \geq 0. \quad [7.72]$$

3658 If the score for $\theta \cdot f(\mathbf{w}^{(i)}, \mathbf{y}^{(i)})$ is greater than the cost-augmented score for all alternatives,
 3659 then the constraint will be met. The name “cost-augmented decoding” is due to the fact
 3660 that the objective includes the standard decoding problem, $\max_{\hat{\mathbf{y}} \in \mathcal{Y}(\mathbf{w})} \theta \cdot f(\mathbf{w}, \hat{\mathbf{y}})$, plus
 3661 an additional term for the cost. Essentially, we want to train against predictions that are
 3662 strong and wrong: they should score highly according to the model, yet incur a large loss
 3663 with respect to the ground truth. Training adjusts the weights to reduce the score of these
 3664 predictions.

3665 For cost-augmented decoding to be tractable, the cost function must decompose into
 3666 local parts, just as the feature function $f(\cdot)$ does. The Hamming cost, defined above,
 3667 obeys this property. To perform cost-augmented decoding using the Hamming cost, we
 3668 need only to add features $f_m(y_m) = \delta(y_m \neq y_m^{(i)})$, and assign a constant weight of 1 to
 3669 these features. Decoding can then be performed using the Viterbi algorithm.⁸

As with large-margin classifiers, it is possible to formulate the learning problem in an unconstrained form, by combining a regularization term on the weights and a Lagrangian for the constraints:

$$\min_{\theta} \frac{1}{2} \|\theta\|_2^2 - C \left(\sum_i \theta \cdot f(\mathbf{w}^{(i)}, \mathbf{y}^{(i)}) - \max_{\mathbf{y} \in \mathcal{Y}(\mathbf{w}^{(i)})} [\theta \cdot f(\mathbf{w}^{(i)}, \mathbf{y}) + c(\mathbf{y}^{(i)}, \mathbf{y})] \right), \quad [7.73]$$

3670 In this formulation, C is a parameter that controls the tradeoff between the regularization
 3671 term and the margin constraints. A number of optimization algorithms have been
 3672 proposed for structured support vector machines, some of which are discussed in § 2.3.2.
 3673 An empirical comparison by Kummerfeld et al. (2015) shows that stochastic subgradient
 3674 descent — which is essentially a cost-augmented version of the structured perceptron —
 3675 is highly competitive.

3676 7.5.3 Conditional random fields

3677 The **conditional random field** (CRF; Lafferty et al., 2001) is a conditional probabilistic
 3678 model for sequence labeling; just as structured perceptron is built on the perceptron clas-
 3679 sifier, conditional random fields are built on the logistic regression classifier.⁹ The basic

⁸Are there cost functions that do not decompose into local parts? Suppose we want to assign a constant loss c to any prediction $\hat{\mathbf{y}}$ in which k or more predicted tags are incorrect, and zero loss otherwise. This loss function is combinatorial over the predictions, and thus we cannot decompose it into parts.

⁹The name “Conditional Random Field” is derived from **Markov random fields**, a general class of models in which the probability of a configuration of variables is proportional to a product of scores across pairs (or

3680 probability model is,

$$p(\mathbf{y} \mid \mathbf{w}) = \frac{\exp(\Psi(\mathbf{w}, \mathbf{y}))}{\sum_{\mathbf{y}' \in \mathcal{Y}(\mathbf{w})} \exp(\Psi(\mathbf{w}, \mathbf{y}'))}. \quad [7.74]$$

3681 This is almost identical to logistic regression, but because the label space is now tag
 3682 sequences, we require efficient algorithms for both **decoding** (searching for the best tag
 3683 sequence given a sequence of words \mathbf{w} and a model θ) and for **normalizing** (summing
 3684 over all tag sequences). These algorithms will be based on the usual locality assumption
 3685 on the scoring function, $\Psi(\mathbf{w}, \mathbf{y}) = \sum_{m=1}^{M+1} \psi(\mathbf{w}, y_m, y_{m-1}, m)$.

3686 **7.5.3.1 Decoding in CRFs**

Decoding — finding the tag sequence $\hat{\mathbf{y}}$ that maximizes $p(\mathbf{y} \mid \mathbf{w})$ — is a direct application of the Viterbi algorithm. The key observation is that the decoding problem does not depend on the denominator of $p(\mathbf{y} \mid \mathbf{w})$,

$$\begin{aligned} \hat{\mathbf{y}} &= \operatorname{argmax}_{\mathbf{y}} \log p(\mathbf{y} \mid \mathbf{w}) \\ &= \operatorname{argmax}_{\mathbf{y}} \Psi(\mathbf{y}, \mathbf{w}) - \log \sum_{\mathbf{y}' \in \mathcal{Y}(\mathbf{w})} \exp \Psi(\mathbf{y}', \mathbf{w}) \\ &= \operatorname{argmax}_{\mathbf{y}} \Psi(\mathbf{y}, \mathbf{w}) = \operatorname{argmax}_{\mathbf{y}} \sum_{m=1}^{M+1} s(y_m, y_{m-1}). \end{aligned}$$

3687 This is identical to the decoding problem for structured perceptron, so the same Viterbi
 3688 recurrence as defined in Equation 7.22 can be used.

3689 **7.5.3.2 Learning in CRFs**

As with logistic regression, the weights θ are learned by minimizing the regularized negative log-probability,

$$\ell = \frac{\lambda}{2} \|\theta\|^2 - \sum_{i=1}^N \log p(\mathbf{y}^{(i)} \mid \mathbf{w}^{(i)}; \theta) \quad [7.75]$$

$$= \frac{\lambda}{2} \|\theta\|^2 - \sum_{i=1}^N \theta \cdot f(\mathbf{w}^{(i)}, \mathbf{y}^{(i)}) + \log \sum_{\mathbf{y}' \in \mathcal{Y}(\mathbf{w}^{(i)})} \exp (\theta \cdot f(\mathbf{w}^{(i)}, \mathbf{y}')), \quad [7.76]$$

more generally, cliques) of variables in a **factor graph**. In sequence labeling, the pairs of variables include all adjacent tags (y_m, y_{m-1}). The probability is *conditioned* on the words \mathbf{w} , which are always observed, motivating the term “conditional” in the name.

3690 where λ controls the amount of regularization. The final term in Equation 7.76 is a sum
 3691 over all possible labelings. This term is the log of the denominator in Equation 7.74, some-
 3692 times known as the **partition function**.¹⁰ There are $|\mathcal{Y}|^M$ possible labelings of an input of
 3693 size M , so we must again exploit the decomposition of the scoring function to compute
 3694 this sum efficiently.

The sum $\sum_{\mathbf{y} \in \mathcal{Y}^{w(i)}} \exp \Psi(\mathbf{y}, \mathbf{w})$ can be computed efficiently using the **forward recurrence**, which is closely related to the Viterbi recurrence. We first define a set of **forward variables**, $\alpha_m(y_m)$, which is equal to the sum of the scores of all paths leading to tag y_m at position m :

$$\alpha_m(y_m) \triangleq \sum_{\mathbf{y}_{1:m-1}} \exp \sum_{n=1}^m s_n(y_n, y_{n-1}) \quad [7.77]$$

$$= \sum_{\mathbf{y}_{1:m-1}} \prod_{n=1}^m \exp s_n(y_n, y_{n-1}). \quad [7.78]$$

Note the similarity to the definition of the Viterbi variable, $v_m(y_m) = \max_{\mathbf{y}_{1:m-1}} \sum_{n=1}^m s_n(y_n, y_{n-1})$. In the hidden Markov model, the Viterbi recurrence had an alternative interpretation as the max-product algorithm (see Equation 7.53); analogously, the forward recurrence is known as the **sum-product algorithm**, because of the form of [7.78]. The forward variable can also be computed through a recurrence:

$$\alpha_m(y_m) = \sum_{\mathbf{y}_{1:m-1}} \prod_{n=1}^m \exp s_n(y_n, y_{n-1}) \quad [7.79]$$

$$= \sum_{y_{m-1}} (\exp s_m(y_m, y_{m-1})) \sum_{\mathbf{y}_{1:m-2}} \prod_{n=1}^{m-1} \exp s_n(y_n, y_{n-1}) \quad [7.80]$$

$$= \sum_{y_{m-1}} (\exp s_m(y_m, y_{m-1})) \times \alpha_{m-1}(y_{m-1}). \quad [7.81]$$

Using the forward recurrence, it is possible to compute the denominator of the conditional probability,

$$\sum_{\mathbf{y} \in \mathcal{Y}(\mathbf{w})} \Psi(\mathbf{w}, \mathbf{y}) = \sum_{\mathbf{y}_{1:M}} s_{M+1}(\blacklozenge, y_M) \prod_{m=1}^M s_m(y_m, y_{m-1}) \quad [7.82]$$

$$= \alpha_{M+1}(\blacklozenge). \quad [7.83]$$

¹⁰The terminology of “potentials” and “partition functions” comes from statistical mechanics (Bishop, 2006).

The conditional log-likelihood can be rewritten,

$$\ell = \frac{\lambda}{2} \|\boldsymbol{\theta}\|^2 - \sum_{i=1}^N \boldsymbol{\theta} \cdot \mathbf{f}(\mathbf{w}^{(i)}, \mathbf{y}^{(i)}) + \log \alpha_{M+1}(\blacklozenge). \quad [7.84]$$

- 3695 Probabilistic programming environments, such as `Torch` (Collobert et al., 2011) and `dynet` (Neu-
 3696 big et al., 2017), can compute the gradient of this objective using automatic differentiation.
 3697 The programmer need only implement the forward algorithm as a computation graph.

As in logistic regression, the gradient of the likelihood with respect to the parameters is a difference between observed and expected feature counts:

$$\frac{d\ell}{d\theta_j} = \lambda \theta_j + \sum_{i=1}^N E[f_j(\mathbf{w}^{(i)}, \mathbf{y})] - f_j(\mathbf{w}^{(i)}, \mathbf{y}^{(i)}), \quad [7.85]$$

- 3698 where $f_j(\mathbf{w}^{(i)}, \mathbf{y}^{(i)})$ refers to the count of feature j for token sequence $\mathbf{w}^{(i)}$ and tag se-
 3699 quence $\mathbf{y}^{(i)}$. The expected feature counts are computed “under the hood” when automatic
 3700 differentiation is applied to Equation 7.84 (Eisner, 2016).

- 3701 Before the widespread use of automatic differentiation, it was common to compute
 3702 the feature expectations from marginal tag probabilities $p(y_m | \mathbf{w})$. These marginal prob-
 3703 abilities are sometimes useful on their own, and can be computed using the **forward-**
 3704 **backward algorithm**. This algorithm combines the forward recurrence with an equivalent
 3705 **backward recurrence**, which traverses the input from w_M back to w_1 .

3706 7.5.3.3 *Forward-backward algorithm

Marginal probabilities over tag bigrams can be written as,¹¹

$$\Pr(Y_{m-1} = k', Y_m = k | \mathbf{w}) = \frac{\sum_{\mathbf{y}: Y_m=k, Y_{m-1}=k'} \prod_{n=1}^M \exp s_n(y_n, y_{n-1})}{\sum_{\mathbf{y}'} \prod_{n=1}^M \exp s_n(y'_n, y'_{n-1})}. \quad [7.86]$$

The numerator sums over all tag sequences that include the transition $(Y_{m-1} = k') \rightarrow (Y_m = k)$. Because we are only interested in sequences that include the tag bigram, this sum can be decomposed into three parts: the *prefixes* $\mathbf{y}_{1:m-1}$, terminating in $Y_{m-1} = k'$; the

¹¹Recall the notational convention of upper-case letters for random variables, e.g. Y_m , and lower case letters for specific values, e.g., y_m , so that $Y_m = k$ is interpreted as the event of random variable Y_m taking the value k .

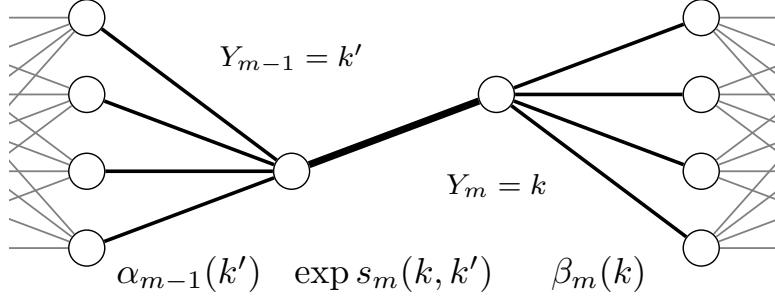


Figure 7.3: A schematic illustration of the computation of the marginal probability $\Pr(Y_{m-1} = k', Y_m = k)$, using the forward score $\alpha_{m-1}(k')$ and the backward score $\beta_m(k)$.

transition $(Y_{m-1} = k') \rightarrow (Y_m = k)$; and the suffixes $\mathbf{y}_{m:M}$, beginning with the tag $Y_m = k$:

$$\sum_{\mathbf{y}: Y_m = k, Y_{m-1} = k'} \prod_{n=1}^M \exp s_n(y_n, y_{n-1}) = \sum_{\mathbf{y}_{1:m-1}: Y_{m-1} = k'} \prod_{n=1}^{m-1} \exp s_n(y_n, y_{n-1}) \times \exp s_m(k, k') \times \sum_{\mathbf{y}_{m:M}: Y_m = k} \prod_{n=m+1}^{M+1} \exp s_n(y_n, y_{n-1}). \quad [7.87]$$

The result is product of three terms: a score that sums over all the ways to get to the position $(Y_{m-1} = k')$, a score for the transition from k' to k , and a score that sums over all the ways of finishing the sequence from $(Y_m = k)$. The first term of Equation 7.87 is equal to the **forward variable**, $\alpha_{m-1}(k')$. The third term — the sum over ways to finish the sequence — can also be defined recursively, this time moving over the trellis from right to left, which is known as the **backward recurrence**:

$$\beta_m(k) \triangleq \sum_{\mathbf{y}_{m:M}: Y_m = k} \prod_{n=m}^{M+1} \exp s_n(y_n, y_{n-1}) \quad [7.88]$$

$$= \sum_{k' \in \mathcal{Y}} \exp s_{m+1}(k', k) \sum_{\mathbf{y}_{m+1:M}: Y_m = k'} \prod_{n=m+1}^{M+1} \exp s_n(y_n, y_{n-1}) \quad [7.89]$$

$$= \sum_{k' \in \mathcal{Y}} \exp s_{m+1}(k', k) \times \beta_{m+1}(k'). \quad [7.90]$$

³⁷⁰⁷ To understand this computation, compare with the forward recurrence in Equation 7.81.

In practice, numerical stability demands that we work in the log domain,

$$\log \alpha_m(k) = \log \sum_{k' \in \mathcal{Y}} \exp (\log s_m(k, k') + \log \alpha_{m-1}(k')) \quad [7.91]$$

$$\log \beta_{m-1}(k) = \log \sum_{k' \in \mathcal{Y}} \exp (\log s_m(k', k) + \log \beta_m(k')). \quad [7.92]$$

The application of the forward and backward probabilities is shown in Figure 7.3. Both the forward and backward recurrences operate on the trellis, which implies a space complexity $\mathcal{O}(MK)$. Because both recurrences require computing a sum over K terms at each node in the trellis, their time complexity is $\mathcal{O}(MK^2)$.

7.6 Neural sequence labeling

In neural network approaches to sequence labeling, we construct a vector representation for each tagging decision, based on the word and its context. Neural networks can perform tagging as a per-token classification decision, or they can be combined with the Viterbi algorithm to tag the entire sequence globally.

7.6.1 Recurrent neural networks

Recurrent neural networks (RNNs) were introduced in chapter 6 as a language modeling technique, in which the context at token m is summarized by a recurrently-updated vector,

$$\mathbf{h}_m = g(\mathbf{x}_m, \mathbf{h}_{m-1}), \quad m = 1, 2, \dots, M,$$

where \mathbf{x}_m is the vector **embedding** of the token w_m and the function g defines the recurrence. The starting condition \mathbf{h}_0 is an additional parameter of the model. The long short-term memory (LSTM) is a more complex recurrence, in which a memory cell is through a series of gates, avoiding repeated application of the non-linearity. Despite these bells and whistles, both models share the basic architecture of recurrent updates across a sequence, and both will be referred to as RNNs here.

A straightforward application of RNNs to sequence labeling is to score each tag y_m as a linear function of \mathbf{h}_m :

$$\psi_m(y) = \beta_y \cdot \mathbf{h}_m \quad [7.93]$$

$$\hat{y}_m = \operatorname{argmax}_y \psi_m(y). \quad [7.94]$$

The score $\psi_m(y)$ can also be converted into a probability distribution using the usual softmax operation,

$$p(y | \mathbf{w}_{1:m}) = \frac{\exp \psi_m(y)}{\sum_{y' \in \mathcal{Y}} \exp \psi_m(y')} \quad [7.95]$$

3726 Using this transformation, it is possible to train the tagger from the negative log-likelihood
 3727 of the tags, as in a conditional random field. Alternatively, a hinge loss or margin loss
 3728 objective can be constructed from the raw scores $\psi_m(y)$.

The hidden state \mathbf{h}_m accounts for information in the input leading up to position m , but it ignores the subsequent tokens, which may also be relevant to the tag y_m . This can be addressed by adding a second RNN, in which the input is reversed, running the recurrence from w_M to w_1 . This is known as a **bidirectional recurrent neural network** (Graves and Schmidhuber, 2005), and is specified as:

$$\overleftarrow{\mathbf{h}}_m = g(\mathbf{x}_m, \overleftarrow{\mathbf{h}}_{m+1}), \quad m = 1, 2, \dots, M. \quad [7.96]$$

3729 The hidden states of the left-to-right RNN are denoted $\overrightarrow{\mathbf{h}}_m$. The left-to-right and right-to-
 3730 left vectors are concatenated, $\mathbf{h}_m = [\overleftarrow{\mathbf{h}}_m; \overrightarrow{\mathbf{h}}_m]$. The scoring function in Equation 7.93 is
 3731 applied to this concatenated vector.

3732 Bidirectional RNN tagging has several attractive properties. Ideally, the representa-
 3733 tion \mathbf{h}_m summarizes the useful information from the surrounding context, so that it is not
 3734 necessary to design explicit features to capture this information. If the vector \mathbf{h}_m is an ad-
 3735 equate summary of this context, then it may not even be necessary to perform the tagging
 3736 jointly: in general, the gains offered by joint tagging of the entire sequence are diminished
 3737 as the individual tagging model becomes more powerful. Using backpropagation, the
 3738 word vectors \mathbf{x} can be trained “end-to-end”, so that they capture word properties that are
 3739 useful for the tagging task. Alternatively, if limited labeled data is available, we can use
 3740 word embeddings that are “pre-trained” from unlabeled data, using a language modeling
 3741 objective (as in § 6.3) or a related word embedding technique (see chapter 14). It is even
 3742 possible to combine both fine-tuned and pre-trained embeddings in a single model.

3743 **Neural structure prediction** The bidirectional recurrent neural network incorporates in-
 3744 formation from throughout the input, but each tagging decision is made independently.
 3745 In some sequence labeling applications, there are very strong dependencies between tags:
 3746 it may even be impossible for one tag to follow another. In such scenarios, the tagging
 3747 decision must be made jointly across the entire sequence.

3748 Neural sequence labeling can be combined with the Viterbi algorithm by defining the
 3749 local scores as:

$$s_m(y_m, y_{m-1}) = \beta_{y_m} \cdot \mathbf{h}_m + \eta_{y_{m-1}, y_m}, \quad [7.97]$$

3750 where \mathbf{h}_m is the RNN hidden state, β_{y_m} is a vector associated with tag y_m , and η_{y_{m-1}, y_m}
 3751 is a scalar parameter for the tag transition (y_{m-1}, y_m) . These local scores can then be
 3752 incorporated into the Viterbi algorithm for inference, and into the forward algorithm for
 3753 training. This model is shown in Figure 7.4. It can be trained from the conditional log-
 3754 likelihood objective defined in Equation 7.76, backpropagating to the tagging parameters

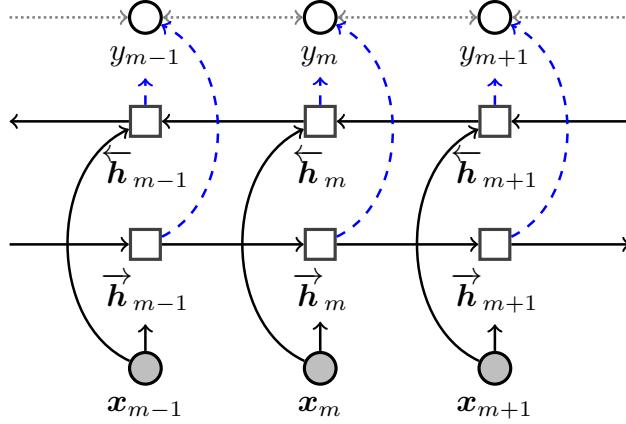


Figure 7.4: Bidirectional LSTM for sequence labeling. The solid lines indicate computation, the dashed lines indicate probabilistic dependency, and the dotted lines indicate the optional additional probabilistic dependencies between labels in the biLSTM-CRF.

3755 β and η , as well as the parameters of the RNN. This model is called the **LSTM-CRF**, due
 3756 to its combination of aspects of the long short-term memory and conditional random field
 3757 models (Huang et al., 2015).

3758 The LSTM-CRF is especially effective on the task of **named entity recognition** (Lample
 3759 et al., 2016), a sequence labeling task that is described in detail in § 8.3. This task has strong
 3760 dependencies between adjacent tags, so structure prediction is especially important.

3761 7.6.2 Character-level models

3762 As in language modeling, rare and unseen words are a challenge: if we encounter a word
 3763 that was not in the training data, then there is no obvious choice for the word embed-
 3764 ding x_m . One solution is to use a generic **unseen word** embedding for all such words.
 3765 However, in many cases, properties of unseen words can be guessed from their spellings.
 3766 For example, *whimsical* does not appear in the Universal Dependencies (UD) English Tree-
 3767 bank, yet the suffix *-al* makes it likely to be adjective; by the same logic, *unflinchingly* is
 3768 likely to be an adverb, and *barnacle* is likely to be a noun.

3769 In feature-based models, these morphological properties were handled by suffix fea-
 3770 tures; in a neural network, they can be incorporated by constructing the embeddings of
 3771 unseen words from their spellings or morphology. One way to do this is to incorporate
 3772 an additional layer of bidirectional RNNs, one for each word in the vocabulary (Ling
 3773 et al., 2015). For each such character-RNN, the inputs are the characters, and the output
 3774 is the concatenation of the final states of the left-facing and right-facing passes, $\phi_w =$

[$\vec{h}_{N_w}^{(w)}; \overleftarrow{h}_0^{(w)}$], where $\vec{h}_{N_w}^{(w)}$ is the final state of the right-facing pass for word w , and N_w is the number of characters in the word. The character RNN model is trained by back-propagation from the tagging objective. On the test data, the trained RNN is applied to out-of-vocabulary words (or all words), yielding inputs to the word-level tagging RNN. Other approaches to compositional word embeddings are described in § 14.7.1.

7.6.3 Convolutional Neural Networks for Sequence Labeling

One disadvantage of recurrent neural networks is that the architecture requires iterating through the sequence of inputs and predictions: each hidden vector h_m must be computed from the previous hidden vector h_{m-1} , before predicting the tag y_m . These iterative computations are difficult to parallelize, and fail to exploit the speedups offered by **graphics processing units (GPUs)** on operations such as matrix multiplication. **Convolutional neural networks** achieve better computational performance by predicting each label y_m from a set of matrix operations on the neighboring word embeddings, $x_{m-k:m+k}$ (Collobert et al., 2011). Because there is no hidden state to update, the predictions for each y_m can be computed in parallel. For more on convolutional neural networks, see § 3.4. Character-based word embeddings can also be computed using convolutional neural networks (Santos and Zadrozny, 2014).

7.7 *Unsupervised sequence labeling

In unsupervised sequence labeling, the goal is to induce a hidden Markov model from a corpus of *unannotated* text ($w^{(1)}, w^{(2)}, \dots, w^{(N)}$), where each $w^{(i)}$ is a sequence of length $M^{(i)}$. This is an example of the general problem of **structure induction**, which is the unsupervised version of structure prediction. The tags that result from unsupervised sequence labeling might be useful for some downstream task, or they might help us to better understand the language’s inherent structure. For part-of-speech tagging, it is common to use a tag dictionary that lists the allowed tags for each word, simplifying the problem (Christodoulopoulos et al., 2010).

Unsupervised learning in hidden Markov models can be performed using the **Baum-Welch algorithm**, which combines the forward-backward algorithm (§ 7.5.3.3) with expectation-maximization (EM; § 5.1.2). In the M-step, the HMM parameters from expected counts:

$$\Pr(W = i \mid Y = k) = \phi_{k,i} = \frac{E[\text{count}(W = i, Y = k)]}{E[\text{count}(Y = k)]}$$

$$\Pr(Y_m = k \mid Y_{m-1} = k') = \lambda_{k',k} = \frac{E[\text{count}(Y_m = k, Y_{m-1} = k')]}{E[\text{count}(Y_{m-1} = k')]} \quad \text{[Equation 7.10]}$$

3801 The expected counts are computed in the E-step, using the forward and backward
 3802 recurrences. The local scores follow the usual definition for hidden Markov models,

$$s_m(k, k') = \log p_E(w_m | Y_m = k; \phi) + \log p_T(Y_m = k | Y_{m-1} = k'; \lambda). \quad [7.98]$$

The expected transition counts for a single instance are,

$$E[\text{count}(Y_m = k, Y_{m-1} = k') | \mathbf{w}] = \sum_{m=1}^M \Pr(Y_{m-1} = k', Y_m = k | \mathbf{w}) \quad [7.99]$$

$$= \frac{\sum_{\mathbf{y}: Y_m=k, Y_{m-1}=k'} \prod_{n=1}^M \exp s_n(y_n, y_{n-1})}{\sum_{\mathbf{y}'} \prod_{n=1}^M \exp s_n(y'_n, y'_{n-1})}. \quad [7.100]$$

As described in § 7.5.3.3, these marginal probabilities can be computed from the forward-backward recurrence,

$$\Pr(Y_{m-1} = k', Y_m = k | \mathbf{w}) = \frac{\alpha_{m-1}(k') \times s_m(k, k') \times \beta_m(k)}{\alpha_{M+1}(\blacklozenge)}. \quad [7.101]$$

In a hidden Markov model, each element of the forward-backward computation has a special interpretation:

$$\alpha_{m-1}(k') = p(Y_{m-1} = k', \mathbf{w}_{1:m-1}) \quad [7.102]$$

$$s_m(k, k') = p(Y_m = k, w_m | Y_{m-1} = k') \quad [7.103]$$

$$\beta_m(k) = p(\mathbf{w}_{m+1:M} | Y_m = k). \quad [7.104]$$

Applying the conditional independence assumptions of the hidden Markov model (defined in Algorithm 12), the product is equal to the joint probability of the tag bigram and the entire input,

$$\begin{aligned} \alpha_{m-1}(k') \times s_m(k, k') \times \beta_m(k) &= p(Y_{m-1} = k', \mathbf{w}_{1:m-1}) \\ &\quad \times p(Y_m = k, w_m | Y_{m-1} = k') \\ &\quad \times p(\mathbf{w}_{m+1:M} | Y_m = k) \\ &= p(Y_{m-1} = k', Y_m = k, \mathbf{w}_{1:M}). \end{aligned} \quad [7.105]$$

Dividing by $\alpha_{M+1}(\blacklozenge) = p(\mathbf{w}_{1:M})$ gives the desired probability,

$$\frac{\alpha_{m-1}(k') \times s_m(k, k') \times \beta_m(k)}{\alpha_{M+1}(\blacklozenge)} = \frac{p(Y_{m-1} = k', Y_m = k, \mathbf{w}_{1:M})}{p(\mathbf{w}_{1:M})} \quad [7.106]$$

$$= \Pr(Y_{m-1} = k', Y_m = k | \mathbf{w}_{1:M}). \quad [7.107]$$

3803 The expected emission counts can be computed in a similar manner, using the product
 3804 $\alpha_m(k) \times \beta_m(k)$.

3805 **7.7.1 Linear dynamical systems**

3806 The forward-backward algorithm can be viewed as Bayesian state estimation in a discrete
 3807 state space. In a continuous state space, $\mathbf{y}_m \in \mathbb{R}^K$, the equivalent algorithm is the **Kalman**
 3808 **smoother**. It also computes marginals $p(\mathbf{y}_m | \mathbf{x}_{1:M})$, using a similar two-step algorithm
 3809 of forward and backward passes. Instead of computing a trellis of values at each step, the
 3810 Kalman smoother computes a probability density function $q_{\mathbf{y}_m}(\mathbf{y}_m; \boldsymbol{\mu}_m, \Sigma_m)$, character-
 3811 ized by a mean $\boldsymbol{\mu}_m$ and a covariance Σ_m around the latent state. Connections between the
 3812 Kalman Smoother and the forward-backward algorithm are elucidated by Minka (1999)
 3813 and Murphy (2012).

3814 **7.7.2 Alternative unsupervised learning methods**

As noted in § 5.5, expectation-maximization is just one of many techniques for structure induction. One alternative is to use **Markov Chain Monte Carlo (MCMC)** sampling algorithms, which are briefly described in § 5.5.1. For the specific case of sequence labeling, Gibbs sampling can be applied by iteratively sampling each tag y_m conditioned on all the others (Finkel et al., 2005):

$$p(y_m | \mathbf{y}_{-m}, \mathbf{w}_{1:M}) \propto p(w_m | y_m) p(y_m | \mathbf{y}_{-m}). \quad [7.108]$$

3815 Gibbs Sampling has been applied to unsupervised part-of-speech tagging by Goldwater
 3816 and Griffiths (2007). **Beam sampling** is a more sophisticated sampling algorithm, which
 3817 randomly draws entire sequences $\mathbf{y}_{1:M}$, rather than individual tags y_m ; this algorithm
 3818 was applied to unsupervised part-of-speech tagging by Van Gael et al. (2009). Spectral
 3819 learning (see § 5.5.2) can also be applied to sequence labeling. By factoring matrices of
 3820 co-occurrence counts of word bigrams and trigrams (Song et al., 2010; Hsu et al., 2012), it
 3821 is possible to obtain globally optimal estimates of the transition and emission parameters,
 3822 under mild assumptions.

3823 **7.7.3 Semiring Notation and the Generalized Viterbi Algorithm**

The Viterbi and Forward recurrences can each be performed over probabilities or log probabilities, yielding a total of four closely related recurrences. These four recurrence scan in fact be expressed as a single recurrence in a more general notation, known as **semiring algebra**. Let the symbol \oplus represent generalized addition, and the symbol \otimes represent generalized multiplication.¹² Given these operators, we can denote a general-

¹²In a semiring, the addition and multiplication operators must both obey associativity, and multiplication must distribute across addition; the addition operator must be commutative; there must be additive and multiplicative identities $\bar{0}$ and $\bar{1}$, such that $a \oplus \bar{0} = a$ and $a \otimes \bar{1} = a$; and there must be a multiplicative annihilator $\bar{0}$, such that $a \otimes \bar{0} = \bar{0}$.

ized Viterbi recurrence as,

$$v_m(k) = \bigoplus_{k' \in \mathcal{Y}} s_m(k, k') \otimes v_{m-1}(k'). \quad [7.109]$$

3824 Each recurrence that we have seen so far is a special case of this generalized Viterbi
3825 recurrence:

- 3826 • In the max-product Viterbi recurrence over probabilities, the \oplus operation corre-
3827 sponds to maximization, and the \otimes operation corresponds to multiplication.
- 3828 • In the forward recurrence over probabilities, the \oplus operation corresponds to addi-
3829 tion, and the \otimes operation corresponds to multiplication.
- 3830 • In the max-product Viterbi recurrence over log-probabilities, the \oplus operation corre-
3831 sponds to maximization, and the \otimes operation corresponds to addition.¹³
- 3832 • In the forward recurrence over log-probabilities, the \oplus operation corresponds to log-
3833 addition, $a \oplus b = \log(e^a + e^b)$. The \otimes operation corresponds to addition.

3834 The mathematical abstraction offered by semiring notation can be applied to the soft-
3835 ware implementations of these algorithms, yielding concise and modular implemen-
3836 tations. The OPENFST library (Allauzen et al., 2007) is an example of a software package in
3837 which the algorithms are parametrized by the choice of semiring.

3838 Exercises

- 3839 1. Consider the garden path sentence, *The old man the boat*. Given word-tag and tag-tag
3840 features, what inequality in the weights must hold for the correct tag sequence to
3841 outscore the garden path tag sequence for this example?
- 3842 2. Sketch out an algorithm for a variant of Viterbi that returns the top- n label se-
3843 quences. What is the time and space complexity of this algorithm?
- 3844 3. Show how to compute the marginal probability $\Pr(y_{m-2} = k, y_m = k' \mid \mathbf{w}_{1:M})$, in
3845 terms of the forwards and backward variables, and the potentials $s_n(y_n, y_{n-1})$.
- 3846 4. Suppose you receive a stream of text, where some of tokens have been replaced at
3847 random with *NOISE*. For example:
 - 3848 • Source: *I try all things, I achieve what I can*
 - 3849 • Message received: *I try NOISE NOISE, I NOISE what I NOISE*

¹³This is sometimes called the **tropical semiring**, in honor of the Brazilian mathematician Imre Simon.

3850 Assume you have access to a pre-trained bigram language model, which gives prob-
3851 abilities $p(w_m \mid w_{m-1})$. These probabilities can be assumed to be non-zero for all
3852 bigrams.

- 3853 a) Show how to use the Viterbi algorithm to try to recover the source by maxi-
3854 mizing the bigram language model log-probability. Specifically, set the scores
3855 $s_m(y_m, y_{m-1})$ so that the Viterbi algorithm selects a sequence of words that
3856 maximizes the bigram language model log-probability, *while leaving the non-*
3857 *noise tokens intact*. Your solution should not modify the logic of the Viterbi
3858 algorithm, it should only set the scores $s_m(y_m, y_{m-1})$.
- 3859 b) An alternative solution is to iterate through the text from $m \in \{1, 2, \dots, M\}$,
3860 replacing each noise token with the word that maximizes $P(w_m \mid w_{m-1})$ ac-
3861 cording to the bigram language model. Given an upper bound on the expected
3862 fraction of tokens for which the two approaches will disagree.
- 3863 5. Consider an RNN tagging model with a tanh activation function on the hidden
3864 layer, and a hinge loss on the output. (The problem also works for the margin loss
3865 and negative log-likelihood.) Suppose you initialize all parameters to zero: this
3866 includes the word embeddings that make up \mathbf{x} , the transition matrix Θ , the out-
3867 put weights β , and the initial hidden state \mathbf{h}_0 . Prove that for any data and for any
3868 gradient-based learning algorithm, all parameters will be stuck at zero.
3869 Extra credit: would a sigmoid activation function avoid this problem?

3870 Chapter 8

3871 Applications of sequence labeling

3872 Sequence labeling has applications throughout natural language processing. This chap-
3873 ter focuses on part-of-speech tagging, morpho-syntactic attribute tagging, named entity
3874 recognition, and tokenization. It also touches briefly on two applications to interactive
3875 settings: dialogue act recognition and the detection of code-switching points between
3876 languages.

3877 8.1 Part-of-speech tagging

3878 The **syntax** of a language is the set of principles under which sequences of words are
3879 judged to be grammatically acceptable by fluent speakers. One of the most basic syntactic
3880 concepts is the **part-of-speech** (POS), which refers to the syntactic role of each word in a
3881 sentence. This concept was used informally in the previous chapter, and you may have
3882 some intuitions from your own study of English. For example, in the sentence *We like*
3883 *vegetarian sandwiches*, you may already know that *we* and *sandwiches* are nouns, *like* is a
3884 verb, and *vegetarian* is an adjective. These labels depend on the context in which the word
3885 appears: in *she eats like a vegetarian*, the word *like* is a preposition, and the word *vegetarian*
3886 is a noun.

3887 Parts-of-speech can help to disentangle or explain various linguistic problems. Recall
3888 Chomsky's proposed distinction in chapter 6:

- 3889 (8.1) Colorless green ideas sleep furiously.
- 3890 (8.2) *Ideas colorless furiously green sleep.

3891 One difference between these two examples is that the first contains part-of-speech transitions
3892 that are typical in English: adjective to adjective, adjective to noun, noun to verb, and verb
3893 to adverb. The second example contains transitions that are unusual: noun to adjective
3894 and adjective to verb. The ambiguity in a headline like,

3895 (8.3) Teacher Strikes Idle Children

3896 can also be explained in terms of parts of speech: in the interpretation that was likely
 3897 intended, *strikes* is a noun and *idle* is a verb; in the alternative explanation, *strikes* is a verb
 3898 and *idle* is an adjective.

3899 Part-of-speech tagging is often taken as a early step in a natural language processing
 3900 pipeline. Indeed, parts-of-speech provide features that can be useful for many of the
 3901 tasks that we will encounter later, such as parsing (chapter 10), coreference resolution
 3902 (chapter 15), and relation extraction (chapter 17).

3903 **8.1.1 Parts-of-Speech**

3904 The **Universal Dependencies** project (UD) is an effort to create syntactically-annotated
 3905 corpora across many languages, using a single annotation standard (Nivre et al., 2016). As
 3906 part of this effort, they have designed a part-of-speech **tagset**, which is meant to capture
 3907 word classes across as many languages as possible.¹ This section describes that inventory,
 3908 giving rough definitions for each of tags, along with supporting examples.

3909 Part-of-speech tags are **morphosyntactic**, rather than **semantic**, categories. This means
 3910 that they describe words in terms of how they pattern together and how they are inter-
 3911 nally constructed (e.g., what suffixes and prefixes they include). For example, you may
 3912 think of a noun as referring to objects or concepts, and verbs as referring to actions or
 3913 events. But events can also be nouns:

3914 (8.4) ... the **howling** of the **shrieking** storm.

3915 Here *howling* and *shrieking* are events, but grammatically they act as a noun and adjective
 3916 respectively.

3917 **8.1.1.1 The Universal Dependency part-of-speech tagset**

3918 The UD tagset is broken up into three groups: open class tags, closed class tags, and
 3919 “others.”

3920 **Open class tags** Nearly all languages contain nouns, verbs, adjectives, and adverbs.²
 3921 These are all **open word classes**, because new words can easily be added to them. The
 3922 UD tagset includes two other tags that are open classes: proper nouns and interjections.

3923 • **Nouns** (UD tag: NOUN) tend to describe entities and concepts, e.g.,

¹The UD tagset builds on earlier work from Petrov et al. (2012), in which a set of twelve universal tags was identified by creating mappings from tagsets for individual languages.

²One prominent exception is Korean, which some linguists argue does not have adjectives Kim (2002).

3924 (8.5) **Toes** are scarce among veteran **blubber men**.

3925 In English, nouns tend to follow determiners and adjectives, and can play the subject
 3926 role in the sentence. They can be marked for the plural number by an -s suffix.

- 3927 • **Proper nouns** (PROPN) are tokens in names, which uniquely specify a given entity,

3928 (8.6) “**Moby Dick?**” shouted **Ahab**.

- 3929 • **Verbs** (VERB), according to the UD guidelines, “typically signal events and ac-
 3930 tions.” But they are also defined grammatically: they “can constitute a minimal
 3931 predicate in a clause, and govern the number and types of other constituents which
 3932 may occur in a clause.”³

3933 (8.7) “**Moby Dick?**” shouted Ahab.

3934 (8.8) Shall we **keep chasing** this murderous fish?

3935 English verbs tend to come in between the subject and some number of direct ob-
 3936 jects, depending on the verb. They can be marked for **tense** and **aspect** using suffixes
 3937 such as *-ed* and *-ing*. (These suffixes are an example of **inflectional morphology**,
 3938 which is discussed in more detail in § 9.1.4.)

- 3939 • **Adjectives** (ADJ) describe properties of entities,

3940 (8.9) Shall we keep chasing this **murderous** fish?

3941 (8.10) Toes are **scarce** among **veteran** blubber men.

3942 In the second example, *scarce* is a predicative adjective, linked to the subject by the
 3943 **copula verb** *are*. This means that In contrast, *murderous* and *veteran* are attribute
 3944 adjectives, modifying the noun phrase in which they are embedded.

- 3945 • **Adverbs** (ADV) describe properties of events, and may also modify adjectives or
 3946 other adverbs:

3947 (8.11) It is not down on any map; true places **never** are.

3948 (8.12) ... **treacherously** hidden beneath the loveliest tints of azure

3949 (8.13) Not drowned **entirely**, though.

- 3950 • **Interjections** (INTJ) are used in exclamations, e.g.,

3951 (8.14) **Aye aye!** it was that accursed white whale that razed me.

³<http://universaldependencies.org/u/pos/VERB.html>

3952 **Closed class tags** Closed word classes rarely receive new members. They are sometimes
 3953 referred to as **function words** — as opposed to **content words** — as they have little lexical
 3954 meaning of their own, but rather, help to organize the components of the sentence.

- 3955 • **Adpositions** (ADP) describe the relationship between a complement (usually a noun
 3956 phrase) and another unit in the sentence, typically a noun or verb phrase.

- 3957 (8.15) Toes are scarce **among** veteran blubber men.
 3958 (8.16) It is not **down on** any map.
 3959 (8.17) Give not thyself **up** then.

3960 As the examples show, English generally uses prepositions, which are adpositions
 3961 that appear before their complement. (An exception is *ago*, as in, *we met three days*
 3962 *ago*). Postpositions are used in other languages, such as Japanese and Turkish.

- 3963 • **Auxiliary verbs** (AUX) are a closed class of verbs that add information such as
 3964 tense, aspect, person, and number.

- 3965 (8.18) **Shall** we keep chasing this murderous fish?
 3966 (8.19) What the white whale was to Ahab, **has been** hinted.
 3967 (8.20) Ahab **must** use tools.
 3968 (8.21) Meditation and water **are** wedded forever.
 3969 (8.22) Toes **are** scarce among veteran blubber men.

3970 The final example is a copula verb, which is also tagged as an auxiliary in the UD
 3971 corpus.

- 3972 • **Coordinating conjunctions** (CCONJ) express relationships between two words or
 3973 phrases, which play a parallel role:

- 3974 (8.23) Meditation **and** water are wedded forever.

- 3975 • **Subordinating conjunctions** (SCONJ) link two elements, making one syntactically
 3976 subordinate to the other:

- 3977 (8.24) There is wisdom **that** is woe.

- 3978 • **Pronouns** (PRON) are words that substitute for nouns or noun phrases.

- 3979 (8.25) Be **it what it will**, I'll go to **it** laughing.
 3980 (8.26) **I** try all things, **I** achieve **what I can**.

3981 The example includes the personal pronouns *I* and *it*, as well as the relative pronoun
3982 *what*. Other pronouns include *myself*, *somebody*, and *nothing*.

- 3983 • **Determiners** (DET) provide additional information about the nouns or noun phrases
3984 that they modify:

3985 (8.27) What **the** white whale was to Ahab, has been hinted.

3986 (8.28) It is not down on **any** map.

3987 (8.29) I try **all** things ...

3988 (8.30) Shall we keep chasing **this** murderous fish?

3989 Determiners include articles (*the*), possessive determiners (*their*), demonstratives
3990 (*this murderous fish*), and quantifiers (*any map*).

- 3991 • **Numerals** (NUM) are an infinite but closed class, which includes integers, fractions,
3992 and decimals, regardless of whether spelled out or written in numerical form.

3993 (8.31) How then can this **one** small heart beat.

3994 (8.32) I am going to put him down for the **three hundredth**.

- 3995 • **Particles** (PART) are a catch-all of function words that combine with other words or
3996 phrases, but do not meet the conditions of the other tags. In English, this includes
3997 the infinitival *to*, the possessive marker, and negation.

3998 (8.33) Better **to** sleep with a sober cannibal than a drunk Christian.

3999 (8.34) So man's insanity is heaven's sense

4000 (8.35) It is **not** down on any map

4001 As the second example shows, the possessive marker is not considered part of the
4002 same token as the word that it modifies, so that *man's* is split into two tokens. (Tok-
4003 enization is described in more detail in § 8.4.) A non-English example of a particle
4004 is the Japanese question marker *ka*, as in,⁴

4005 (8.36) *Sensei desu ka*

 Teacher are ?

4006 Is she a teacher?

⁴In this notation, the first line is the transliterated Japanese text, the second line is a token-to-token **gloss**, and the third line is the translation.

4007 **Other** The remaining UD tags include punctuation (PUN) and symbols (SYM). Punc-
 4008 tuation is purely structural — e.g., commas, periods, colons — while symbols can carry
 4009 content of their own. Examples of symbols include dollar and percentage symbols, math-
 4010 ematical operators, emoticons, emojis, and internet addresses. A final catch-all tag is X,
 4011 which is used for words that cannot be assigned another part-of-speech category. The X
 4012 tag is also used in cases of **code switching** (between languages), described in § 8.5.

4013 **8.1.1.2 Other tagsets**

4014 Prior to the Universal Dependency treebank, part-of-speech tagging was performed us-
 4015 ing language-specific tagsets. The dominant tagset for English was designed as part of
 4016 the **Penn Treebank** (PTB), and it includes 45 tags — more than three times as many as
 4017 the UD tagset. This granularity is reflected in distinctions between singular and plural
 4018 nouns, verb tenses and aspects, possessive and non-possessive pronouns, comparative
 4019 and superlative adjectives and adverbs (e.g., *faster, fastest*), and so on. The Brown corpus
 4020 includes a tagset that is even more detailed, with 87 tags Francis (1964), including special
 4021 tags for individual auxiliary verbs such as *be, do, and have*.

4022 Different languages make different distinctions, and so the PTB and Brown tagsets are
 4023 not appropriate for a language such as Chinese, which does not mark the verb tense (Xia,
 4024 2000); nor for Spanish, which marks every combination of person and number in the
 4025 verb ending; nor for German, which marks the case of each noun phrase. Each of these
 4026 languages requires more detail than English in some areas of the tagset, and less in other
 4027 areas. The strategy of the Universal Dependencies corpus is to design a coarse-grained
 4028 tagset to be used across all languages, and then to additionally annotate language-specific
 4029 **morphosyntactic attributes**, such as number, tense, and case. The attribute tagging task
 4030 is described in more detail in § 8.2.

4031 Social media such as Twitter have been shown to require tagsets of their own (Gimpel
 4032 et al., 2011). Such corpora contain some tokens that are not equivalent to anything en-
 4033 countered in a typical written corpus: e.g., emoticons, URLs, and hashtags. Social media
 4034 also includes dialectal words like *gonna* ('going to', e.g. *We gonna be fine*) and *Ima* ('I'm
 4035 going to', e.g., *Ima tell you one more time*), which can be analyzed either as non-standard
 4036 orthography (making tokenization impossible), or as lexical items in their own right. In
 4037 either case, it is clear that existing tags like NOUN and VERB cannot handle cases like *Ima*,
 4038 which combine aspects of the noun and verb. Gimpel et al. (2011) therefore propose a new
 4039 set of tags to deal with these cases.

4040 **8.1.2 Accurate part-of-speech tagging**

4041 Part-of-speech tagging is the problem of selecting the correct tag for each word in a sen-
 4042 tence. Success is typically measured by accuracy on an annotated test set, which is simply
 4043 the fraction of tokens that were tagged correctly.

4044 8.1.2.1 Baselines

4045 A simple baseline for part-of-speech tagging is to choose the most common tag for each
4046 word. For example, in the Universal Dependencies treebank, the word *talk* appears 96
4047 times, and 85 of those times it is labeled as a VERB: therefore, this baseline will always
4048 predict VERB for this word. For words that do not appear in the training corpus, the base-
4049 line simply guesses the most common tag overall, which is NOUN. In the Penn Treebank,
4050 this simple baseline obtains accuracy above 92%. A more rigorous evaluation is the accu-
4051 racy on **out-of-vocabulary words**, which are not seen in the training data. Tagging these
4052 words correctly requires attention to the context and the word's internal structure.

4053 8.1.2.2 Contemporary approaches

4054 Conditional random fields and structured perceptron perform at or near the state-of-the-
4055 art for part-of-speech tagging in English. For example, (Collins, 2002) achieved 97.1%
4056 accuracy on the Penn Treebank, using a structured perceptron with the following base
4057 features (originally introduced by Ratnaparkhi (1996)):

- 4058 • current word, w_m
- 4059 • previous words, w_{m-1}, w_{m-2}
- 4060 • next words, w_{m+1}, w_{m+2}
- 4061 • previous tag, y_{m-1}
- 4062 • previous two tags, (y_{m-1}, y_{m-2})
- 4063 • for rare words:
 - 4064 – first k characters, up to $k = 4$
 - 4065 – last k characters, up to $k = 4$
 - 4066 – whether w_m contains a number, uppercase character, or hyphen.

4067 Similar results for the PTB data have been achieved using conditional random fields (CRFs;
4068 Toutanova et al., 2003).

4069 More recent work has demonstrated the power of neural sequence models, such as the
4070 **long short-term memory (LSTM)** (§ 7.6). Plank et al. (2016) apply a CRF and a bidirec-
4071 tional LSTM to twenty-two languages in the UD corpus, achieving an average accuracy
4072 of 94.3% for the CRF, and 96.5% with the bi-LSTM. Their neural model employs three
4073 types of embeddings: fine-tuned word embeddings, which are updated during training;
4074 pre-trained word embeddings, which are never updated, but which help to tag out-of-
4075 vocabulary words; and character-based embeddings. The character-based embeddings
4076 are computed by running an LSTM on the individual characters in each word, thereby
4077 capturing common orthographic patterns such as prefixes, suffixes, and capitalization.
4078 Extensive evaluations show that these additional embeddings are crucial to their model's
4079 success.

word	PTB tag	UD tag	UD attributes
<i>The</i>	DT	DET	DEFINITE=DEF PRONTYPE=ART
<i>German</i>	JJ	ADJ	DEGREE=POS
<i>Expressionist</i>	NN	NOUN	NUMBER=SING
<i>movement</i>	NN	NOUN	NUMBER=SING
<i>was</i>	VBD	AUX	MOOD=IND NUMBER=SING PERSON=3 TENSE=PAST VERBFORM=FIN
<i>destroyed</i>	VBN	VERB	TENSE=PAST VERBFORM=PART VOICE=PASS
<i>as</i>	IN	ADP	
<i>a</i>	DT	DET	DEFINITE=IND PRONTYPE=ART
<i>result</i>	NN	NOUN	NUMBER=SING
.	.	PUNCT	

Figure 8.1: UD and PTB part-of-speech tags, and UD morphosyntactic attributes. Example selected from the UD 1.4 English corpus.

4080 8.2 Morphosyntactic Attributes

4081 There is considerably more to say about a word than whether it is a noun or a verb: in En-
 4082 glish, verbs are distinguish by features such tense and aspect, nouns by number, adjectives
 4083 by degree, and so on. These features are language-specific: other languages distinguish
 4084 other features, such as **case** (the role of the noun with respect to the action of the sen-
 4085 tence, which is marked in languages such as Latin and German⁵) and **evidentiality** (the
 4086 source of information for the speaker’s statement, which is marked in languages such as
 4087 Turkish). In the UD corpora, these attributes are annotated as feature-value pairs for each
 4088 token.⁶

4089 An example is shown in Figure 8.1. The determiner *the* is marked with two attributes:
 4090 PRONTYPE=ART, which indicates that it is an **article** (as opposed to another type of deter-

⁵Case is marked in English for some personal pronouns, e.g., *She saw her, They saw them*.

⁶The annotation and tagging of morphosyntactic attributes can be traced back to earlier work on Turkish (Oflazer and Kuruöz, 1994) and Czech (Hajič and Hladká, 1998). MULTEXT-East was an early multilingual corpus to include morphosyntactic attributes (Dimitrova et al., 1998).

miner or pronominal modifier), and DEFINITE=DEF, which indicates that it is a **definite article** (referring to a specific, known entity). The verbs are each marked with several attributes. The auxiliary verb *was* is third-person, singular, past tense, finite (conjugated), and indicative (describing an event that has happened or is currently happenings); the main verb *destroyed* is in participle form (so there is no additional person and number information), past tense, and passive voice. Some, but not all, of these distinctions are reflected in the PTB tags VBD (past-tense verb) and VBN (past participle).

While there are thousands of papers on part-of-speech tagging, there is comparatively little work on automatically labeling morphosyntactic attributes. Faruqui et al. (2016) train a support vector machine classification model, using a minimal feature set that includes the word itself, its prefixes and suffixes, and type-level information listing all possible morphosyntactic attributes for each word and its neighbors. Mueller et al. (2013) use a conditional random field (CRF), in which the tag space consists of all observed combinations of morphosyntactic attributes (e.g., the tag would be DEF+ART for the word *the* in Figure 8.1). This massive tag space is managed by decomposing the feature space over individual attributes, and pruning paths through the trellis. More recent work has employed bidirectional LSTM sequence models. For example, Pinter et al. (2017) train a bidirectional LSTM sequence model. The input layer and hidden vectors in the LSTM are shared across attributes, but each attribute has its own output layer, culminating in a softmax over all attribute values, e.g. $y_t^{\text{NUMBER}} \in \{\text{SING}, \text{PLURAL}, \dots\}$. They find that character-level information is crucial, especially when the amount of labeled data is limited.

Evaluation is performed by first computing recall and precision for each attribute. These scores can then be averaged at either the type or token level to obtain micro- or macro-*F*-MEASURE. Pinter et al. (2017) evaluate on 23 languages in the UD treebank, reporting a median micro-*F*-MEASURE of 0.95. Performance is strongly correlated with the size of the labeled dataset for each language, with a few outliers: for example, Chinese is particularly difficult, because although the dataset is relatively large (10^5 tokens in the UD 1.4 corpus), only 6% of tokens have any attributes, offering few useful labeled instances.

8.3 Named Entity Recognition

A classical problem in information extraction is to recognize and extract mentions of **named entities** in text. In news documents, the core entity types are people, locations, and organizations; more recently, the task has been extended to include amounts of money, percentages, dates, and times. In item 8.37 (Figure 8.2), the named entities include: *The U.S. Army*, an organization; *Atlanta*, a location; and *May 14, 1864*, a date. Named entity recognition is also a key task in **biomedical natural language processing**, with entity types including proteins, DNA, RNA, and cell lines (e.g., Collier et al., 2000; Ohta et al., 2002). Figure 8.2 shows an example from the GENIA corpus of biomedical research ab-

- (8.37) *The U.S. Army captured Atlanta on May 14, 1864*
 B-ORG I-ORG I-ORG O B-LOC O B-DATE I-DATE I-DATE I-DATE
 (8.38) *Number of glucocorticoid receptors in lymphocytes and ...*
 O O B-PROTEIN I-PROTEIN O B-CELLTYPE O ...

Figure 8.2: BIO notation for named entity recognition. Example (8.38) is drawn from the GENIA corpus of biomedical documents (Ohta et al., 2002).

4129 stracts.

4130 A standard approach to tagging named entity spans is to use discriminative sequence
 4131 labeling methods such as conditional random fields. However, the named entity recogni-
 4132 tion (NER) task would seem to be fundamentally different from sequence labeling tasks
 4133 like part-of-speech tagging: rather than tagging each token, the goal is to recover *spans*
 4134 of tokens, such as *The United States Army*.

4135 This is accomplished by the **BIO notation**, shown in Figure 8.2. Each token at the
 4136 beginning of a name span is labeled with a B- prefix; each token within a name span is la-
 4137 beled with an I- prefix. These prefixes are followed by a tag for the entity type, e.g. B-LOC
 4138 for the beginning of a location, and I-PROTEIN for the inside of a protein name. Tokens
 4139 that are not parts of name spans are labeled as O. From this representation, the entity
 4140 name spans can be recovered unambiguously. This tagging scheme is also advantageous
 4141 for learning: tokens at the beginning of name spans may have different properties than
 4142 tokens within the name, and the learner can exploit this. This insight can be taken even
 4143 further, with special labels for the last tokens of a name span, and for unique tokens in
 4144 name spans, such as *Atlanta* in the example in Figure 8.2. This is called BILOU notation,
 4145 and it can yield improvements in supervised named entity recognition (Ratinov and Roth,
 4146 2009).

Feature-based sequence labeling Named entity recognition was one of the first applications of conditional random fields (McCallum and Li, 2003). The use of Viterbi decoding restricts the feature function $f(\mathbf{w}, \mathbf{y})$ to be a sum of local features, $\sum_m f(\mathbf{w}, y_m, y_{m-1}, m)$, so that each feature can consider only local adjacent tags. Typical features include tag transitions, word features for w_m and its neighbors, character-level features for prefixes and suffixes, and “word shape” features for capitalization and other orthographic properties. As an example, base features for the word *Army* in the example in (8.37) include:

(CURR-WORD:*Army*, PREV-WORD:*U.S.*, NEXT-WORD:*captured*, PREFIX-1:*A-*,
 PREFIX-2:*Ar-*, SUFFIX-1:*-y*, SUFFIX-2:*-my*, SHAPE:*Xxxx*)

4147 Another source of features is to use **gazetteers**: lists of known entity names. For example,
 4148 the U.S. Social Security Administration provides a list of tens of thousands of given names

- (1) 日文 章魚 怎麼 說?
 Japanese octopus how say
 How to say octopus in Japanese?
- (2) 日 文章 魚 怎麼 說?
 Japan essay fish how say

Figure 8.3: An example of tokenization ambiguity in Chinese (Sproat et al., 1996)

4149 — more than could be observed in any annotated corpus. Tokens or spans that match an
 4150 entry in a gazetteer can receive special features; this provides a way to incorporate hand-
 4151 crafted resources such as name lists in a learning-driven framework.

4152 **Neural sequence labeling for NER** Current research has emphasized neural sequence
 4153 labeling, using similar LSTM models to those employed in part-of-speech tagging (Ham-
 4154 merton, 2003; Huang et al., 2015; Lample et al., 2016). The bidirectional LSTM-CRF (Fig-
 4155 ure 7.4 in § 7.6) does particularly well on this task, due to its ability to model tag-to-tag
 4156 dependencies. However, Strubell et al. (2017) show that **convolutional neural networks**
 4157 can be equally accurate, with significant improvement in speed due to the efficiency of
 4158 implementing ConvNets on **graphics processing units (GPUs)**. The key innovation in
 4159 this work was the use of **dilated convolution**, which is described in more detail in § 3.4.

4160 8.4 Tokenization

4161 A basic problem for text analysis, first discussed in § 4.3.1, is to break the text into a se-
 4162 quence of discrete tokens. For alphabetic languages such as English, deterministic scripts
 4163 suffice to achieve accurate tokenization. However, in logographic writing systems such
 4164 as Chinese script, words are typically composed of a small number of characters, with-
 4165 out intervening whitespace. The tokenization must be determined by the reader, with
 4166 the potential for occasional ambiguity, as shown in Figure 8.3. One approach is to match
 4167 character sequences against a known dictionary (e.g., Sproat et al., 1996), using additional
 4168 statistical information about word frequency. However, no dictionary is completely com-
 4169 prehensive, and dictionary-based approaches can struggle with such out-of-vocabulary
 4170 words.

4171 Chinese tokenization has therefore been approached as a supervised sequence label-
 4172 ing problem. Xue et al. (2003) train a logistic regression classifier to make independent
 4173 segmentation decisions while moving a sliding window across the document. A set of
 4174 rules is then used to convert these individual classification decisions into an overall tok-
 4175 enization of the input. However, these individual decisions may be globally suboptimal,
 4176 motivating a structure prediction approach. Peng et al. (2004) train a conditional random

4177 field to predict labels of START or NONSTART on each character. More recent work has
 4178 employed neural network architectures. For example, Chen et al. (2015) use an LSTM-
 4179 CRF architecture, as described in § 7.6: they construct a trellis, in which each tag is scored
 4180 according to the hidden state of an LSTM, and tag-tag transitions are scored according
 4181 to learned transition weights. The best-scoring segmentation is then computed by the
 4182 Viterbi algorithm.

4183 8.5 Code switching

4184 Multilingual speakers and writers do not restrict themselves to a single language. **Code**
4185 **switching** is the phenomenon of switching between languages in speech and text (Auer,
4186 2013; Poplack, 1980). Written code switching has become more common in online social
4187 media, as in the following extract from Justin Trudeau's website:⁷

- 4188 (8.39) *Although everything written on this site est disponible en anglais*
is available in English
4189 *and in French, my personal videos seront bilingues*
will be bilingual

4190 Accurately analyzing such texts requires first determining which languages are being
4191 used. Furthermore, quantitative analysis of code switching can provide insights on the
4192 languages themselves and their relative social positions.

Code switching can be viewed as a sequence labeling problem, where the goal is to label each token as a candidate switch point. In the example above, the words *est*, *and*, and *seront* would be labeled as switch points. Solorio and Liu (2008) detect English-Spanish switch points using a supervised classifier, with features that include the word, its part-of-speech in each language (according to a supervised part-of-speech tagger), and the probabilities of the word and part-of-speech in each language. Nguyen and Dogruöz (2013) apply a conditional random field to the problem of detecting code switching between Turkish and Dutch.

Code switching is a special case of the more general problem of word level language identification, which Barman et al. (2014) address in the context of trilingual code switching between Bengali, English, and Hindi. They further observe an even more challenging phenomenon: intra-word code switching, such as the use of English suffixes with Bengali roots. They therefore mark each token as either (1) belonging to one of the three languages; (2) a mix of multiple languages; (3) “universal” (e.g., symbols, numbers, emoticons); or (4) undefined.

⁷As quoted in <http://blogues.lapresse.ca/lagace/2008/09/08/justin-trudeau-really-parfait-bilingue/>, accessed August 21, 2017.

Speaker	Dialogue Act	Utterance
A	YES-NO-QUESTION	<i>So do you go college right now?</i>
A	ABANDONED	<i>Are yo-</i>
B	YES-ANSWER	<i>Yeah,</i>
B	STATEMENT	<i>It's my last year [laughter].</i>
A	DECLARATIVE-QUESTION	<i>You're a, so you're a senior now.</i>
B	YES-ANSWER	<i>Yeah,</i>
B	STATEMENT	<i>I'm working on my projects trying to graduate [laughter]</i>
A	APPRECIATION	<i>Oh, good for you.</i>
B	BACKCHANNEL	<i>Yeah.</i>

Figure 8.4: An example of dialogue act labeling (Stolcke et al., 2000)

4208 8.6 Dialogue acts

4209 The sequence labeling problems that we have discussed so far have been over sequences
 4210 of word tokens or characters (in the case of tokenization). However, sequence labeling
 4211 can also be performed over higher-level units, such as **utterances**. **Dialogue acts** are la-
 4212 bels over utterances in a dialogue, corresponding roughly to the speaker’s intention —
 4213 the utterance’s **illocutionary force** (Austin, 1962). For example, an utterance may state a
 4214 proposition (*it is not down on any map*), pose a question (*shall we keep chasing this murderous*
 4215 *fish?*), or provide a response (*aye aye!*). Stolcke et al. (2000) describe how a set of 42 dia-
 4216 logue acts were annotated for the 1,155 conversations in the Switchboard corpus (Godfrey
 4217 et al., 1992).⁸

4218 An example is shown in Figure 8.4. The annotation is performed over UTTERANCES,
 4219 with the possibility of multiple utterances per **conversational turn** (in cases such as inter-
 4220 ruptions, an utterance may split over multiple turns). Some utterances are clauses (e.g., *So*
 4221 *do you go to college right now?*), while others are single words (e.g., *yeah*). Stolcke et al. (2000)
 4222 report that hidden Markov models (HMMs) achieve 96% accuracy on supervised utter-
 4223 ance segmentation. The labels themselves reflect the conversational goals of the speaker:
 4224 the utterance *yeah* functions as an answer in response to the question *you’re a senior now*,
 4225 but in the final line of the excerpt, it is a **backchannel** (demonstrating comprehension).

4226 For task of dialogue act labeling, Stolcke et al. (2000) apply a hidden Markov model.
 4227 The probability $p(w_m | y_m)$ must generate the entire sequence of words in the utterance,
 4228 and it is modeled as a trigram language model (§ 6.1). Stolcke et al. (2000) also account
 4229 for acoustic features, which capture the **prosody** of each utterance — for example, tonal
 4230 and rhythmic properties of speech, which can be used to distinguish dialogue acts such

⁸Dialogue act modeling is not restricted to speech; it is relevant in any interactive conversation. For example, Jeong et al. (2009) annotate a more limited set of **speech acts** in a corpus of emails and online forums.

4231 as questions and answers. These features are handled with an additional emission distri-
4232 bution, $p(a_m | y_m)$, which is modeled with a probabilistic decision tree (Murphy, 2012).
4233 While acoustic features yield small improvements overall, they play an important role in
4234 distinguish questions from statements, and agreements from backchannels.

4235 Recurrent neural architectures for dialogue act labeling have been proposed by Kalch-
4236 brenner and Blunsom (2013) and Ji et al. (2016), with strong empirical results. Both models
4237 are recurrent at the utterance level, so that each complete utterance updates a hidden state.
4238 The recurrent-convolutional network of Kalchbrenner and Blunsom (2013) uses convolu-
4239 tion to obtain a representation of each individual utterance, while Ji et al. (2016) use a
4240 second level of recurrence, over individual words. This enables their method to also func-
4241 tion as a language model, giving probabilities over sequences of words in a document.

4242 Exercises

- 4243 1. [todo: exercises tk]

4244

Chapter 9

4245

Formal language theory

4246 We have now seen methods for learning to label individual words, vectors of word counts,
4247 and sequences of words; we will soon proceed to more complex structural transfor-
4248 mations. Most of these techniques could apply to counts or sequences from any discrete vo-
4249 cabulary; there is nothing fundamentally linguistic about, say, a hidden Markov model.
4250 This raises a basic question that this text has not yet considered: what is a language?

4251 This chapter will take the perspective of **formal language theory**, in which a language
4252 is defined as a set of **strings**, each of which is a sequence of elements from a finite alphabet.
4253 For interesting languages, there are an infinite number of strings that are in the language,
4254 and an infinite number of strings that are not. For example:

- 4255 • the set of all even-length sequences from the alphabet $\{a, b\}$, e.g., $\{\emptyset, aa, ab, ba, bb, aaaa, aaab, \dots\}$;
- 4256 • the set of all sequences from the alphabet $\{a, b\}$ that contain *aaa* as a substring, e.g.,
4257 $\{aaa, aaaa, baaa, aaab, \dots\}$;
- 4258 • the set of all sequences of English words (drawn from a finite dictionary) that con-
4259 tain at least one verb (a finite subset of the dictionary);
- 4260 • the `python` programming language.

4261 Formal language theory defines classes of languages and their computational prop-
4262 erties. Of particular interest is the computational complexity of solving the **membership**
4263 **problem** — determining whether a string is in a language. The chapter will focus on
4264 three classes of formal languages: regular, context-free, and “mildly” context-sensitive
4265 languages.

4266 A key insight of 20th century linguistics is that formal language theory can be usefully
4267 applied to natural languages such as English, by designing formal languages that cap-
4268 ture as many properties of the natural language as possible. For many such formalisms, a
4269 useful linguistic analysis comes as a byproduct of solving the membership problem. The

4270 membership problem can be generalized to the problems of *scoring* strings for their ac-
 4271 ceptability (as in language modeling), and of **transducing** one string into another (as in
 4272 translation).

4273 9.1 Regular languages

4274 Sooner or later, most computer scientists will write a **regular expression**. If you have,
 4275 then you have defined a **regular language**, which is any language that can be defined by
 4276 a regular expression. Formally, a regular expression can include the following elements:

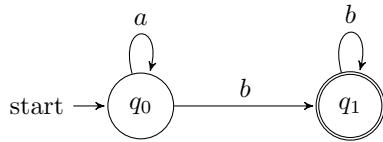
- 4277 • A **literal character** drawn from some finite alphabet Σ .
- 4278 • The **empty string** ϵ .
- 4279 • The concatenation of two regular expressions RS , where R and S are both regular
 4280 expressions. The resulting expression accepts any string that can be decomposed
 4281 $x = yz$, where y is accepted by R and z is accepted by S .
- 4282 • The alternation $R \mid S$, where R and S are both regular expressions. The resulting
 4283 expression accepts a string x if it is accepted by R or it is accepted by S .
- 4284 • The **Kleene star** R^* , which accepts any string x that can be decomposed into a se-
 4285 quence of strings which are all accepted by R .
- 4286 • Parenthesization ((R)), which is used to limit the scope of the concatenation, alterna-
 4287 tion, and Kleene star operators.

4288 Here are some example regular expressions:

- 4289 • The set of all even length strings on the alphabet $\{a, b\}$: $((aa)|(ab)|(ba)|(bb))^*$
- 4290 • The set of all sequences of the alphabet $\{a, b\}$ that contain aaa as a substring: $(a|b)^*aaa(a|b)^*$
- 4291 • The set of all sequences of English words that contain at least one verb: W^*VW^* ,
 4292 where W is an alternation between all words in the dictionary, and V is an alterna-
 4293 tion between all verbs ($V \subseteq W$).

4294 This list does not include a regular expression for the Python programming language,
 4295 because this language is not regular — there is no regular expression that can capture its
 4296 syntax. We will discuss why towards the end of this section.

4297 Regular languages are **closed** under union, intersection, and concatenation. This means,
 4298 for example, that if two languages L_1 and L_2 are regular, then so are the languages $L_1 \cup L_2$,
 4299 $L_1 \cap L_2$, and the language of strings that can be decomposed as $s = tu$, with $s \in L_1$ and
 4300 $t \in L_2$. Regular languages are also closed under negation: if L is regular, then so is the
 4301 language $\bar{L} = \{s \notin L\}$.

Figure 9.1: State diagram for the finite state acceptor M_1 .

4302 **9.1.1 Finite state acceptors**

4303 A regular expression defines a regular language, but does not give an algorithm for de-
 4304 termining whether a string is in the language that it defines. **Finite state automata** are
 4305 theoretical models of computation on regular languages, which involve transitions be-
 4306 tween a finite number of states. The most basic type of finite state automaton is the **finite**
 4307 **state acceptor (FSA)**, which describes the computation involved in testing if a string is
 4308 a member of a language. Formally, a finite state acceptor is a tuple $M = (Q, \Sigma, q_0, F, \delta)$,
 4309 consisting of:

- 4310 • a finite alphabet Σ of input symbols;
- 4311 • a finite set of states $Q = \{q_0, q_1, \dots, q_n\}$;
- 4312 • a start state $q_0 \in Q$;
- 4313 • a set of final states $F \subseteq Q$;
- 4314 • a transition function $\delta : Q \times (\Sigma \cup \{\epsilon\}) \rightarrow 2^Q$. The transition function maps from a
 4315 state and an input symbol (or empty string ϵ) to a *set* of possible resulting states.

4316 A **path** in M is a sequence of transitions, $\pi = t_1, t_2, \dots, t_N$, where each t_i traverses an
 4317 arc in the transition function δ . The finite state acceptor M accepts a string ω if there is
 4318 a **accepting path**, in which the initial transition t_1 begins at the start state q_0 , the final
 4319 transition t_N terminates in a final state in Q , and the entire input ω is consumed.

4320 **9.1.1.1 Example**

Consider the following FSA, M_1 .

$$\Sigma = \{a, b\} \quad [9.1]$$

$$Q = \{q_0, q_1\} \quad [9.2]$$

$$F = \{q_1\} \quad [9.3]$$

$$\delta = \{(q_0, a) \rightarrow q_0, (q_0, b) \rightarrow q_1, (q_1, b) \rightarrow q_1\}. \quad [9.4]$$

4321 This FSA defines a language over an alphabet of two symbols, a and b . The transition
 4322 function δ is written as a set of arcs: $(q_0, a) \rightarrow q_0$ says that if the machine is in state

4323 q_0 and reads symbol a , it stays in q_0 . Figure 9.1 provides a graphical representation of
 4324 M_1 . Because each pair of initial state and symbol has at most one resulting state, M_1 is
 4325 **deterministic**: each string ω induces at most one accepting path. Note that there are no
 4326 transitions for the symbol a in state q_1 ; if a is encountered in q_1 , then the acceptor is stuck,
 4327 and the input string is rejected.

4328 What strings does M_1 accept? The start state is q_0 , and we have to get to q_1 , since this
 4329 is the only final state. Any number of a symbols can be consumed in q_0 , but a b symbol is
 4330 required to transition to q_1 . Once there, any number of b symbols can be consumed, but
 4331 an a symbol cannot. So the regular expression corresponding to the language defined by
 4332 M_1 is a^*bb^* .

4333 9.1.1.2 Computational properties of finite state acceptors

4334 The key computational question for finite state acceptors is: how fast can we determine
 4335 whether a string is accepted? For deterministic FSAs, this computation can be performed
 4336 by Dijkstra's algorithm, with time complexity $\mathcal{O}(V \log V + E)$, where V is the number of
 4337 vertices in the FSA, and E is the number of edges (Cormen et al., 2009). Non-deterministic
 4338 FSAs (NFSAs) can include multiple transitions from a given symbol and state. Any NSFA
 4339 can be converted into a deterministic FSA, but the resulting automaton may have a num-
 4340 ber of states that is exponential in the number of size of the original NFSFA (Mohri et al.,
 4341 2002).

4342 9.1.2 Morphology as a regular language

4343 Many words have internal structure, such as prefixes and suffixes that shape their mean-
 4344 ing. The study of word-internal structure is the domain of **morphology**, of which there
 4345 are two main types:

- 4346 • **Derivational morphology** describes the use of affixes to convert a word from one
 4347 grammatical category to another (e.g., from the noun *grace* to the adjective *graceful*),
 4348 or to change the meaning of the word (e.g., from *grace* to *disgrace*).
- 4349 • **Inflectional morphology** describes the addition of details such as gender, number,
 4350 person, and tense (e.g., the *-ed* suffix for past tense in English).

4351 Morphology is a rich topic in linguistics, deserving of a course in its own right.¹ The
 4352 focus here will be on the use of finite state automata for morphological analysis. The

¹A good starting point would be a chapter from a linguistics textbook (e.g., Akmajian et al., 2010; Bender, 2013). A key simplification in this chapter is the focus on affixes at the sole method of derivation and inflection. English makes use of affixes, but also incorporates **apophony**, such as the inflection of *foot* to *feet*. Semitic languages like Arabic and Hebrew feature a template-based system of morphology, in which roots are triples of consonants (e.g., *ktb*), and words are created by adding vowels: *kataba* (Arabic: he wrote), *kutub* (books), *maktab* (desk). For more detail on morphology, see texts from Haspelmath and Sims (2013) and Lieber (2015).

4353 current section deals with derivational morphology; inflectional morphology is discussed
4354 in § 9.1.4.3.

4355 Suppose that we want to write a program that accepts only those words that are con-
4356 structed in accordance with the rules of English derivational morphology:

- 4357 (9.1) grace, graceful, gracefully, *gracelyful
4358 (9.2) disgrace, *ungrace, disgraceful, disgracefully
4359 (9.3) allure, *allureful, alluring, alluringly
4360 (9.4) fairness, unfair, *disfair, fairly

4361 (Recall that the asterisk indicates that a linguistic example is judged unacceptable by flu-
4362 ent speakers of a language.) These examples cover only a tiny corner of English deriva-
4363 tional morphology, but a number of things stand out. The suffix *-ful* converts the nouns
4364 *grace* and *disgrace* into adjectives, and the suffix *-ly* converts adjectives into adverbs. These
4365 suffixes must be applied in the correct order, as shown by the unacceptability of **grace-*
4366 *lyful*. The *-ful* suffix works for only some words, as shown by the use of *alluring* as the
4367 adjectival form of *allure*. Other changes are made with prefixes, such as the derivation
4368 of *disgrace* from *grace*, which roughly corresponds to a negation; however, *fair* is negated
4369 with the *un-* prefix instead. Finally, while the first three examples suggest that the direc-
4370 tion of derivation is noun → adjective → adverb, the example of *fair* suggests that the
4371 adjective can also be the base form, with the *-ness* suffix performing the conversion to a
4372 noun.

4373 Can we build a computer program that accepts only well-formed English words, and
4374 rejects all others? This might at first seem trivial to solve with a brute-force attack: simply
4375 make a dictionary of all valid English words. But such an approach fails to account for
4376 morphological **productivity** — the applicability of existing morphological rules to new
4377 words and names, such as *Trump* to *Trumpy* and *Trumpkin*, and *Clinton* to *Clintonian* and
4378 *Clintonite*. We need an approach that represents morphological rules explicitly, and for
4379 this we will try a finite state acceptor.

4380 The dictionary approach can be implemented as a finite state acceptor, with the vo-
4381 cabulary Σ equal to the vocabulary of English, and a transition from the start state to the
4382 accepting state for each word. But this would of course fail to generalize beyond the origi-
4383 nal vocabulary, and would not capture anything about the **morphotactic** rules that govern
4384 derivations from new words. The first step towards a more general approach is shown in
4385 Figure 9.2, which is the state diagram for a finite state acceptor in which the vocabulary
4386 consists of **morphemes**, which include **stems** (e.g., *grace*, *allure*) and **affixes** (e.g., *dis-*, *-ing*,
4387 *-ly*). This finite state acceptor consists of a set of paths leading away from the start state,
4388 with derivational affixes added along the path. Except for q_{neg} , the states on these paths
4389 are all final, so the FSA will accept *disgrace*, *disgraceful*, and *disgracefully*, but not *dis-*.

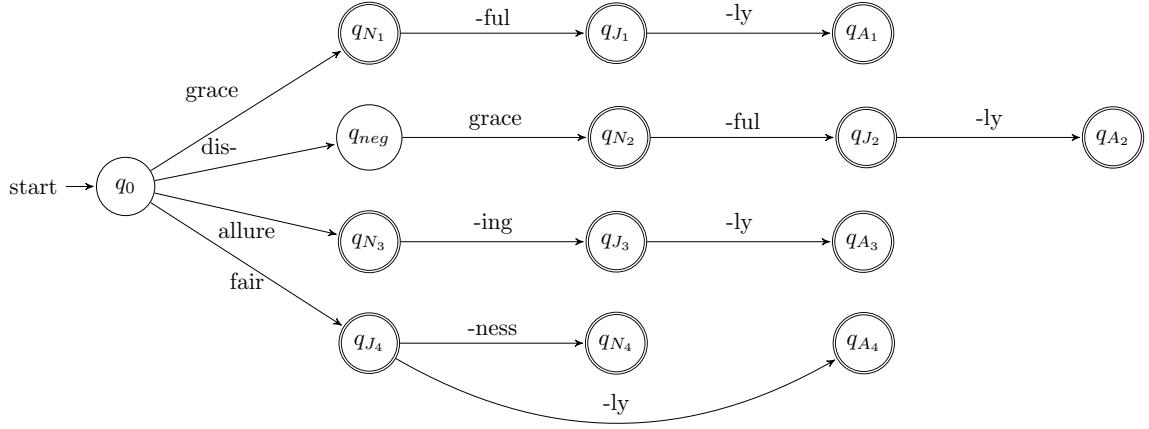


Figure 9.2: A finite state acceptor for a fragment of English derivational morphology. Each path represents possible derivations from a single root form.

4390 This FSA can be **minimized** to the form shown in Figure 9.3, which makes the generality of the finite state approach more apparent. For example, the transition from q_0 to
 4391 q_{J_2} can be made to accept not only *fair* but any single-morpheme (**monomorphemic**) adjective that takes *-ness* and *-ly* as suffixes. In this way, the finite state acceptor can easily
 4392 be extended: as new word stems are added to the vocabulary, their derived forms will be
 4393 accepted automatically. Of course, this FSA would still need to be extended considerably
 4394 to cover even this small fragment of English morphology. As shown by cases like *music*
 4395 → *musical*, *athlete* → *athletic*, English includes several classes of nouns, each with its own
 4396 rules for derivation.

4399 The FSAs shown in Figure 9.2 and 9.3 accept *allureing*, not *alluring*. This reflects a distinction between morphology — the question of which morphemes to use, and in what order — and **orthography** — the question of how the morphemes are rendered in written language. Just as orthography requires dropping the *e* preceding the *-ing* suffix, **phonology** imposes a related set of constraints on how words are rendered in speech. As we will see soon, these issues are handled through **finite state transducers**, which are finite state automata that take inputs and produce outputs.

4406 9.1.3 Weighted finite state acceptors

4407 According to the FSA treatment of morphology, every word is either in or out of the language, with no wiggle room. Perhaps you agree that *musicky* and *fishful* are not valid
 4408 English words; but if forced to choose, you probably find *a fishful stew* or *a musicky trib-
 4409 ute* preferable to *behaving disgracelyful*. Rather than asking whether a word is acceptable,
 4410 we might like to ask how acceptable it is. Aronoff (1976, page 36) puts it another way:

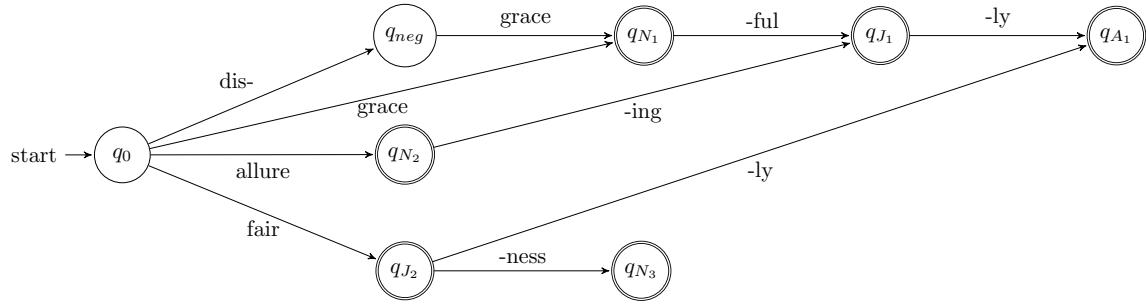


Figure 9.3: Minimization of the finite state acceptor shown in Figure 9.2.

4412 “Though many things are possible in morphology, some are more possible than others.”
 4413 But finite state acceptors give no way to express preferences among technically valid
 4414 choices.

4415 **Weighted finite state acceptors (WFSAs)** are generalizations of FSAs, in which each
 4416 accepting path is assigned a score, computed from the transitions, the initial state, and the
 4417 final state. Formally, a weighted finite state acceptor $M = (Q, \Sigma, \lambda, \rho, \delta)$ consists of:

- 4418 • a finite set of states $Q = \{q_0, q_1, \dots, q_n\}$;
- 4419 • a finite alphabet Σ of input symbols;
- 4420 • an initial weight function, $\lambda : Q \mapsto \mathbb{R}$;
- 4421 • a final weight function $\rho : Q \mapsto \mathbb{R}$;
- 4422 • a transition function $\delta : Q \times \Sigma \times Q \mapsto \mathbb{R}$.

4423 WFSAs depart from the FSA formalism in three ways: every state can be an initial
 4424 state, with score $\lambda(q)$; every state can be an accepting state, with score $\rho(q)$; transitions are
 4425 possible between any pair of states on any input, with a score $\delta(q_i, \omega, q_j)$. Nonetheless,
 4426 FSAs can be viewed as a special case: for any FSA M we can build an equivalent WFSA
 4427 by setting $\lambda(q) = \infty$ for all $q \neq q_0$, $\rho(q) = \infty$ for all $q \notin F$, and $\delta(q_i, \omega, q_j) = \infty$ for all
 4428 transitions $\{(q_1, \omega) \rightarrow q_2\}$ that are not permitted by the transition function of M .

4429 The total score for any path $\pi = t_1, t_2, \dots, t_N$ is equal to the sum of these scores,

$$d(\pi) = \lambda(\text{from-state}(t_1)) + \sum_n^N \delta(t_n) + \rho(\text{to-state}(t_N)). \quad [9.5]$$

4430 A **shortest-path algorithm** is used to find the minimum-cost path through a WFSA for
 4431 string ω , with time complexity $\mathcal{O}(E + V \log V)$, where E is the number of edges and V is
 4432 the number of vertices (Cormen et al., 2009).²

²Shortest-path algorithms find the path with the minimum cost. In many cases, the path weights are log

4433 **9.1.3.1 N-gram language models as WFSAs**

4434 In **n-gram language models** (see § 6.1), the probability of a sequence of tokens w_1, w_2, \dots, w_M
 4435 is modeled as,

$$p(w_1, \dots, w_M) \approx \prod_{m=1}^M p_n(w_m | w_{m-1}, \dots, w_{m-n+1}). \quad [9.6]$$

The log probability under an n -gram language model can be modeled in a WFSA. First consider a unigram language model. We need only a single state q_0 , with transition scores $\delta(q_0, \omega, q_0) = \log p_1(\omega)$. The initial and final scores can be set to zero. Then the path score for w_1, w_2, \dots, w_M is equal to,

$$0 + \sum_m^M \delta(q_0, w_m, q_0) + 0 = \sum_m^M \log p_1(w_m). \quad [9.7]$$

For an n -gram language model with $n > 1$, we need probabilities that condition on the past history. For example, in a bigram language model, the transition weights must represent $\log p_2(w_m | w_{m-1})$. The transition scoring function must somehow “remember” the previous word or words. This can be done by adding more states: to model the bigram probability $p_2(w_m | w_{m-1})$, we need a state for every possible w_{m-1} — a total of V states. The construction indexes each state q_i by a context event $w_{m-1} = i$. The weights are then assigned as follows:

$$\begin{aligned} \delta(q_i, \omega, q_j) &= \begin{cases} \log \Pr(w_m = j | w_{m-1} = i), & \omega = j \\ -\infty, & \omega \neq j \end{cases} \\ \lambda(q_i) &= \log \Pr(w_1 = i | w_0 = \square) \\ \rho(q_i) &= \log \Pr(w_{M+1} = \blacksquare | w_M = i). \end{aligned}$$

4436 The transition function is designed to ensure that the context is recorded accurately:
 4437 we can move to state j on input ω only if $\omega = j$; otherwise, transitioning to state j is
 4438 forbidden by the weight of $-\infty$. The initial weight function $\lambda(q_i)$ is the log probability of
 4439 receiving i as the first token, and the final weight function $\rho(q_i)$ is the log probability of
 4440 receiving an “end-of-string” token after observing $w_M = i$.

4441 **9.1.3.2 *Semiring weighted finite state acceptors**

4442 The n -gram language model WFSA is deterministic: each input has exactly one accepting
 4443 path, for which the WFSA computes a score. In non-deterministic WFSAs, a given input

probabilities, so we want the path with the maximum score, which can be accomplished by making each local score into a *negative* log-probability. The remainder of this section will refer to **best-path algorithms**, which are assumed to “do the right thing.”

4444 may have multiple accepting paths. In some applications, the score for the input is ag-
 4445 gregated across all such paths. Such aggregate scores can be computed by generalizing
 4446 WFSAs with **semiring notation**, first introduced in § 7.7.3.

4447 Let $d(\pi)$ represent the total score for path $\pi = t_1, t_2, \dots, t_N$, which is computed as,

$$d(\pi) = \lambda(\text{from-state}(t_1)) \otimes \delta(t_1) \otimes \delta(t_2) \otimes \dots \otimes \delta(t_N) \otimes \rho(\text{to-state}(t_N)). \quad [9.8]$$

4448 This is a generalization of Equation 9.5 to semiring notation, using the semiring multipli-
 4449 cation operator \otimes in place of addition.

4450 Now let $s(\omega)$ represent the total score for all paths $\Pi(\omega)$ that consume input ω ,

$$s(\omega) = \bigoplus_{\pi \in \Pi(\omega)} d(\pi). \quad [9.9]$$

4451 Here, semiring addition (\oplus) is used to combine the scores of multiple paths.

4452 The generalization to semirings covers a number of useful special cases. In the log-
 4453 probability semiring, multiplication is defined as $\log p(x) \otimes \log p(y) = \log p(x) + \log p(y)$,
 4454 and addition is defined as $\log p(x) \oplus \log p(y) = \log(p(x) + p(y))$. Thus, $s(\omega)$ represents
 4455 the log-probability of accepting input ω , marginalizing over all paths $\pi \in \Pi(\omega)$. In the
 4456 **boolean semiring**, the \otimes operator is logical conjunction, and the \oplus operator is logical
 4457 disjunction. This reduces to the special case of unweighted finite state acceptors, where
 4458 the score $s(\omega)$ is a boolean indicating whether there exists any accepting path for ω . In
 4459 the **tropical semiring**, the \oplus operator is a maximum, so the resulting score is the score of
 4460 the best-scoring path through the WFSAs. The OpenFST toolkit uses semirings and poly-
 4461 morphism to implement general algorithms for weighted finite state automata (Allauzen
 4462 et al., 2007).

4463 9.1.3.3 *Interpolated n -gram language models

4464 Recall from § 6.2.3 that an **interpolated n -gram language model** combines the probabili-
 4465 ties from multiple n -gram models. For example, an interpolated bigram language model
 4466 computes probability,

$$\hat{p}(w_m | w_{m-1}) = \lambda_1 p_1(w_m) + \lambda_2 p_2(w_m | w_{m-1}), \quad [9.10]$$

4467 with \hat{p} indicating the interpolated probability, p_2 indicating the bigram probability, and
 4468 p_1 indicating the unigram probability. We set $\lambda_2 = (1 - \lambda_1)$ so that the probabilities sum
 4469 to one.

4470 Interpolated bigram language models can be implemented using a non-deterministic
 4471 WFSAs (Knight and May, 2009). The basic idea is shown in Figure 9.4. In an interpolated
 4472 bigram language model, there is one state for each element in the vocabulary — in this

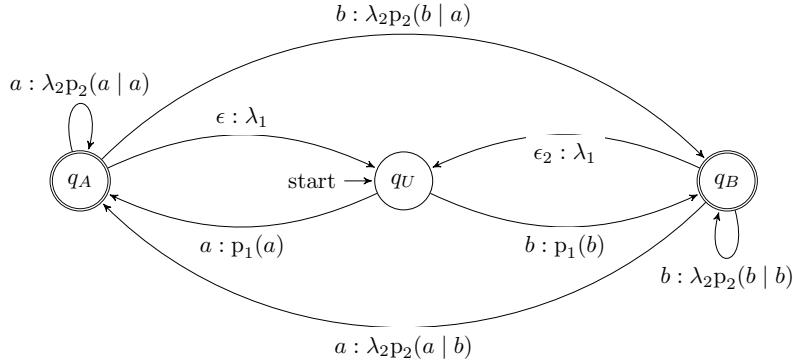


Figure 9.4: WFSA implementing an interpolated bigram/unigram language model, on the alphabet $\Sigma = \{a, b\}$. For simplicity, the WFSA is constrained to force the first token to be generated from the unigram model, and does not model the emission of the end-of-sequence token.

4473 case, the states q_A and q_B — which capture the contextual conditioning in the bigram
 4474 probabilities. To model unigram probabilities, there is an additional state q_U , which “for-
 4475 gets” the context. Transitions out of q_U involve unigram probabilities, $p_1(a)$ and $p_2(b)$;
 4476 transitions into q_U emit the empty symbol ϵ , and have probability λ_1 , reflecting the inter-
 4477 polation weight for the unigram model. The interpolation weight for the bigram model is
 4478 included in the weight of the transition $q_A \rightarrow q_B$.

4479 The epsilon transitions into q_U make this WFSA non-deterministic. Consider the score
 4480 for the sequence (a, b, b) . The initial state is q_U , so the symbol a is generated with score
 4481 $p_1(a)$ ³ Next, we can generate b from the unigram model by taking the transition $q_A \rightarrow q_B$,
 4482 with score $\lambda_2 p_2(b | a)$. Alternatively, we can take a transition back to q_U with score λ_1 ,
 4483 and then emit b from the unigram model with score $p_1(b)$. To generate the final b token,
 4484 we face the same choice: emit it directly from the self-transition to q_B , or transition to q_U
 4485 first.

The total score for the sequence (a, b, b) is the semiring sum over all accepting paths,

$$\begin{aligned}
 s(a, b, b) &= (p_1(a) \otimes \lambda_2 p_2(b | a) \otimes \lambda_2 p_2(b | b)) \\
 &\oplus (p_1(a) \otimes \lambda_1 \otimes p_1(b) \otimes \lambda_2 p_2(b | b)) \\
 &\oplus (p_1(a) \otimes \lambda_2 p_2(b | a) \otimes p_1(b) \otimes p_1(b)) \\
 &\oplus (p_1(a) \otimes \lambda_1 \otimes p_1(b) \otimes p_1(b) \otimes p_1(b)). \tag{[9.11]}
 \end{aligned}$$

4486 Each line in Equation 9.11 represents the probability of a specific path through the WFSA.
 4487 In the probability semiring, \otimes is multiplication, so that each path is the product of each

³We could model the sequence-initial bigram probability $p_2(a | \square)$, but for simplicity the WFSA does not admit this possibility, which would require another state.

4488 transition weight, which are themselves probabilities. The \oplus operator is addition, so that
 4489 the total score is the sum of the scores (probabilities) for each path. This corresponds to
 4490 the probability under the interpolated bigram language model.

4491 **9.1.4 Finite state transducers**

4492 Finite state acceptors can determine whether a string is in a regular language, and weighted
 4493 finite state acceptors can compute a score for every string over a given alphabet. **Finite**
 4494 **state transducers** (FSTs) extend the formalism further, by adding an output symbol to each
 4495 transition. Formally, a finite state transducer is a tuple $T = (Q, \Sigma, \Omega, \lambda, \rho, \delta)$, with Ω repre-
 4496 senting an output vocabulary and the transition function $\delta : Q \times (\Sigma \cup \epsilon) \times (\Omega \cup \epsilon) \times Q \rightarrow \mathbb{R}$
 4497 mapping from states, input symbols, and output symbols to states. The remaining ele-
 4498 ments (Q, Σ, λ, ρ) are identical to their definition in weighted finite state acceptors (§ 9.1.3).
 4499 Thus, each path through the FST T transduces the input string into an output.

4500 **9.1.4.1 String edit distance**

The **edit distance** between two strings s and t is a measure of how many operations are required to transform one string into another. There are several ways to compute edit distance, but one of the most popular is the **Levenshtein edit distance**, which counts the minimum number of insertions, deletions, and substitutions. This can be computed by a one-state weighted finite state transducer, in which the input and output alphabets are identical. For simplicity, consider the alphabet $\Sigma = \Omega = \{a, b\}$. The edit distance can be computed by a one-state transducer with the following transitions,

$$\delta(q, a, a, q) = \delta(q, b, b, q) = 0 \quad [9.12]$$

$$\delta(q, a, b, q) = \delta(q, b, a, q) = 1 \quad [9.13]$$

$$\delta(q, a, \epsilon, q) = \delta(q, b, \epsilon, q) = 1 \quad [9.14]$$

$$\delta(q, \epsilon, a, q) = \delta(q, \epsilon, b, q) = 1. \quad [9.15]$$

4501 The state diagram is shown in Figure 9.5.

4502 For a given string pair, there are multiple paths through the transducer: the best-
 4503 scoring path from *dessert* to *desert* involves a single deletion, for a total score of 1; the
 4504 worst-scoring path involves seven deletions and six additions, for a score of 13.

4505 **9.1.4.2 The Porter stemmer**

The Porter (1980) stemming algorithm is a “lexicon-free” algorithm for stripping suffixes from English words, using a sequence of character-level rules. Each rule can be described

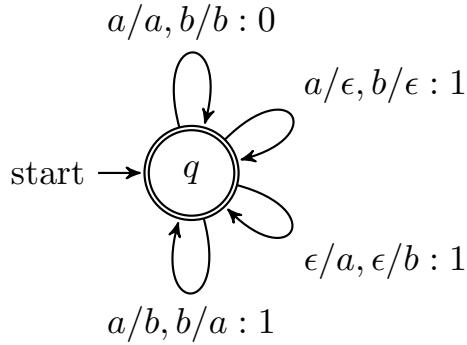


Figure 9.5: State diagram for the Levenshtein edit distance finite state transducer. The label $x/y : c$ indicates a cost of c for a transition with input x and output y .

by an unweighted finite state transducer. The first rule is:

-sses → -ss e.g., *dresses* → *dress* [9.16]

-ies → -i e.g., *parties* → *parti* [9.17]

-ss → -ss e.g., *dress* → *dress* [9.18]

-s → ε e.g., *cats* → *cat* [9.19]

4506 The final two lines appear to conflict; they are meant to be interpreted as an instruction
 4507 to remove a terminal *-s* unless it is part of an *-ss* ending. A state diagram to handle just
 4508 these final two lines is shown in Figure 9.6. Make sure you understand how this finite
 4509 state transducer handles *cats*, *steps*, *bass*, and *basses*.

4510 9.1.4.3 Inflectional morphology

4511 In **inflectional morphology**, word **lemmas** are modified to add grammatical information
 4512 such as tense, number, and case. For example, many English nouns are pluralized by the
 4513 suffix *-s*, and many verbs are converted to past tense by the suffix *-ed*. English's inflectional
 4514 morphology is considerably simpler than many of the world's languages. For example,
 4515 Romance languages (derived from Latin) feature complex systems of verb suffixes which
 4516 must agree with the person and number of the verb, as shown in Table 9.1.

4517 The task of **morphological analysis** is to read a form like *canto*, and output an analysis
 4518 like CANTAR+VERB+PRESIND+1P+SING, where +PRESIND describes the tense as present
 4519 indicative, +1P indicates the first-person, and +SING indicates the singular number. The
 4520 task of **morphological generation** is the reverse, going from CANTAR+VERB+PRESIND+1P+SING
 4521 to *canto*. Finite state transducers are an attractive solution, because they can solve both
 4522 problems with a single model (Beesley and Karttunen, 2003). As an example, Figure 9.7
 4523 shows a fragment of a finite state transducer for Spanish inflectional morphology. The

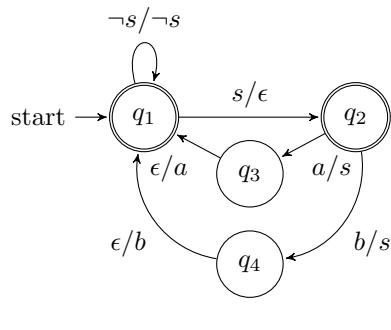


Figure 9.6: State diagram for final two lines of step 1a of the Porter stemming diagram. States q_3 and q_4 “remember” the observations a and b respectively; the ellipsis \dots represents additional states for each symbol in the input alphabet. The notation $\neg s / \neg s$ is not part of the FST formalism; it is a shorthand to indicate a set of self-transition arcs for every input/output symbol except s .

infinitive	cantar (to sing)	comer (to eat)	vivir (to live)
yo (1st singular)	canto	como	vivo
tu (2nd singular)	cantas	comes	vives
él, ella, usted (3rd singular)	canta	come	vive
nosotros (1st plural)	cantamos	comemos	vivimos
vosotros (2nd plural, informal)	cantáis	coméis	vívís
ellos, ellas (3rd plural); ustedes (2nd plural)	cantan	comen	viven

Table 9.1: Spanish verb inflections for the present indicative tense. Each row represents a person and number, and each column is a regular example from a class of verbs, as indicated by the ending of the infinitive form.

4524 input vocabulary Σ corresponds to the set of letters used in Spanish spelling, and the out-
 4525 put vocabulary Ω corresponds to these same letters, plus the vocabulary of morphological
 4526 features (e.g., +SING, +VERB). In Figure 9.7, there are two paths that take *canto* as input,
 4527 corresponding to the verb and noun meanings; the choice between these paths could be
 4528 guided by a part-of-speech tagger. By **inversion**, the inputs and outputs for each trans-
 4529ition are switched, resulting in a finite state generator, capable of producing the correct
 4530 **surface form** for any morphological analysis.

4531 Finite state morphological analyzers and other unweighted transducers can be de-
 4532 signed by hand. The designer’s goal is to avoid **overgeneration** — accepting strings or
 4533 making transductions that are not valid in the language — as well as **undergeneration** —

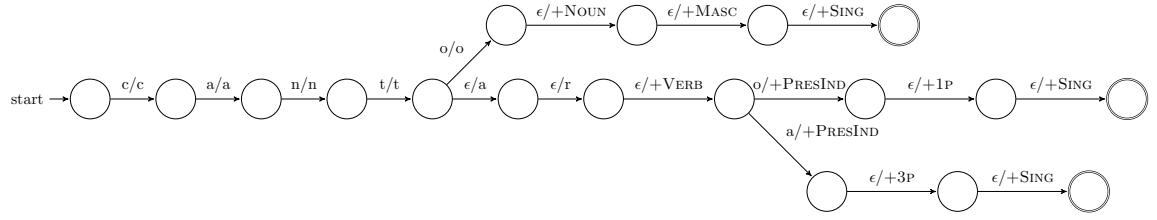


Figure 9.7: Fragment of a finite state transducer for Spanish morphology. There are two accepting paths for the input *canto*: *canto+NOUN+MASC+SING* (masculine singular noun, meaning a song), and *cantar+VERB+PRESIND+1P+SING* (I sing). There is also an accepting path for *canta*, with output *cantar+VERB+PRESIND+3P+SING* (he/she sings).

4534 failing to accept strings or transductions that are valid. For example, a pluralization trans-
 4535 ducer that does not accept *foot/feet* would undergenerate. Suppose we “fix” the transducer
 4536 to accept this example, but as a side effect, it now accepts *boot/beet*; the transducer would
 4537 then be said to overgenerate. A transducer that accepts *foot/foots* but not *foot/feet* would
 4538 both overgenerate and undergenerate.

4539 9.1.4.4 Finite state composition

4540 Designing finite state transducers to capture the full range of morphological phenomena
 4541 in any real language is a huge task. Modularization is a classic computer science approach
 4542 for this situation: decompose a large and unwieldy problem into a set of subproblems,
 4543 each of which will hopefully have a concise solution. Finite state automata can be mod-
 4544 ularized through **composition**: feeding the output of one transducer T_1 as the input to
 4545 another transducer T_2 , written $T_2 \circ T_1$. Formally, if there exists some y such that $(x, y) \in T_1$
 4546 (meaning that T_1 produces output y on input x), and $(y, z) \in T_2$, then $(x, z) \in (T_2 \circ T_1)$.
 4547 Because finite state transducers are closed under composition, there is guaranteed to be
 4548 a single finite state transducer that $T_3 = T_2 \circ T_1$, which can be constructed as a machine
 4549 with one state for each pair of states in T_1 and T_2 (Mohri et al., 2002).

4550 **Example: Morphology and orthography** In English morphology, the suffix *-ed* is added
 4551 to signal the past tense for many verbs: *cook*→*cooked*, *want*→*wanted*, etc. However, English
 4552 **orthography** dictates that this process cannot produce a spelling with consecutive e’s, so
 4553 that *bake*→*baked*, not *bakeed*. A modular solution is to build separate transducers for mor-
 4554 phology and orthography. The morphological transducer T_M transduces from *bake+PAST*
 4555 to *bake+ed*, with the + symbol indicating a segment boundary. The input alphabet of T_M
 4556 includes the lexicon of words and the set of morphological features; the output alphabet
 4557 includes the characters *a-z* and the + boundary marker. Next, an orthographic transducer
 4558 T_O is responsible for the transductions *cook+ed*→*cooked*, and *bake+ed*→*baked*. The input
 4559 alphabet of T_O must be the same as the output alphabet for T_M , and the output alphabet

4560 is simply the characters *a-z*. The composed transducer ($T_O \circ T_M$) then transduces from
 4561 *bake*+PAST to the spelling *baked*. The design of T_O is left as an exercise.

Example: Hidden Markov models Hidden Markov models (chapter 7) can be viewed as weighted finite state transducers, and they can be constructed by transduction. Recall that a hidden Markov model defines a joint probability over words and tags, $p(w, y)$, which can be computed as a path through a **trellis** structure. This trellis is itself a weighted finite state acceptor, with edges between all adjacent nodes $q_{m-1,i} \rightarrow q_{m,j}$ on input $Y_m = j$. The edge weights are log-probabilities,

$$\delta(q_{m-1,i}, Y_m = j, q_{m,j}) = \log p(w_m, Y_m = j | Y_{m-1} = i) \quad [9.20]$$

$$= \log p(w_m | Y_m = j) + \log \Pr(Y_m = j | Y_{m-1} = i). \quad [9.21]$$

4562 Because there is only one possible transition for each tag Y_m , this WFSA is deterministic.
 4563 The score for any tag sequence $\{y_m\}_{m=1}^M$ is the sum of these log-probabilities, correspond-
 4564 ing to the total log probability $\log p(w, y)$. Furthermore, the trellis can be constructed by
 4565 the composition of simpler FSTs.

- 4566 • First, construct a “transition” transducer to represent a bigram probability model
 4567 over tag sequences, T_T . This transducer is almost identical to the n -gram language
 4568 model acceptor in § 9.1.3.1: there is one state for each tag, and the edge weights
 4569 equal to the transition log-probabilities, $\delta(q_i, j, j, q_j) = \log \Pr(Y_m = j | Y_{m-1} = i)$.
 4570 Note that T_T is a transducer, with identical input and output at each arc; this makes
 4571 it possible to compose T_T with other transducers.
- 4572 • Next, construct an “emission” transducer to represent the probability of words given
 4573 tags, T_E . This transducer has only a single state, with arcs for each word/tag pair,
 4574 $\delta(q_0, i, j, q_0) = \log \Pr(W_m = j | Y_m = i)$. The input vocabulary is the set of all tags,
 4575 and the output vocabulary is the set of all words.
- 4576 • The composition $T_E \circ T_T$ is a finite state transducer with one state per tag, as shown
 4577 in Figure 9.8. Each state has $V \times K$ outgoing edges, representing transitions to each
 4578 of the K other states, with outputs for each of the V words in the vocabulary. The
 4579 weights for these edges are equal to,

$$\delta(q_i, Y_m = j, w_m, q_j) = \log p(w_m, Y_m = j | Y_{m-1} = i). \quad [9.22]$$

- 4580 • The trellis is a structure with $M \times K$ nodes, for each of the M words to be tagged and
 4581 each of the K tags in the tagset. It can be built by composition of $(T_E \circ T_T)$ against an
 4582 unweighted **chain FSA** $M_A(w)$ that is specially constructed to accept only a given
 4583 input w_1, w_2, \dots, w_M , shown in Figure 9.9. The trellis for input w is built from the
 4584 composition $M_A(w) \circ (T_E \circ T_T)$. Composing with the unweighted $M_A(w)$ does not
 4585 affect the edge weights from $(T_E \circ T_T)$, but it selects the subset of paths that generate
 4586 the word sequence w .

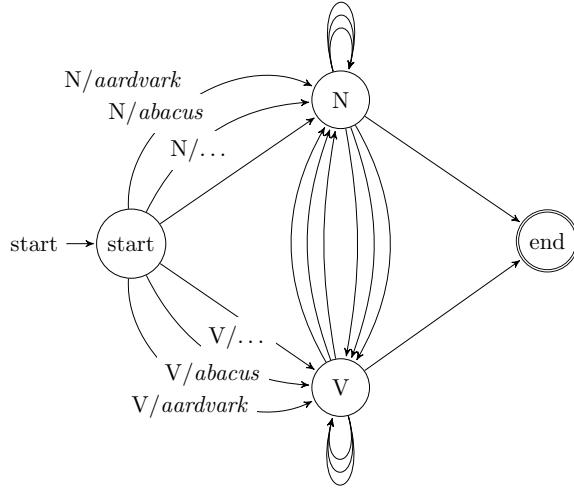


Figure 9.8: Finite state transducer for hidden Markov models, with a small tagset of nouns and verbs. For each pair of tags (including self-loops), there is an edge for every word in the vocabulary. For simplicity, input and output are only shown for the edges from the start state. Weights are also omitted from the diagram; for each edge from q_i to q_j , the weight is equal to $\log p(w_m, Y_m = j \mid Y_{m-1} = i)$, except for edges to the end state, which are equal to $\log \Pr(Y_m = \diamond \mid Y_{m-1} = i)$.

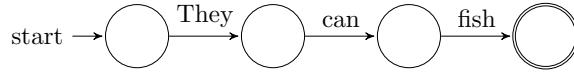


Figure 9.9: Chain finite state acceptor for the input *They can fish*.

4587 9.1.5 *Learning weighted finite state automata

4588 In generative models such as n -gram language models and hidden Markov models, the
 4589 edge weights correspond to log probabilities, which can be obtained from relative fre-
 4590 quency estimation. However, in other cases, we wish to learn the edge weights from in-
 4591 put/output pairs. This is difficult in non-deterministic finite state automata, because we
 4592 do not observe the specific arcs that are traversed in accepting the input, or in transducing
 4593 from input to output. The path through the automaton is a **latent variable**.

4594 Chapter 5 presented one method for learning with latent variables: expectation max-
 4595 imization (EM). This involves computing a distribution $q(\cdot)$ over the latent variable, and
 4596 iterating between updates to this distribution and updates to the parameters — in this
 4597 case, the arc weights. The **forward-backward algorithm** (§ 7.5.3.3) describes a dynamic
 4598 program for computing a distribution over arcs in the trellis structure of a hidden Markov

model, but this is a special case of the more general problem for finite state automata. Eisner (2002) describes an **expectation semiring**, which enables the expected number of transitions across each arc to be computed through a semiring shortest-path algorithm. Alternative approaches for generative models include Markov Chain Monte Carlo (Chiang et al., 2010) and spectral learning (Balle et al., 2011).

Further afield, we can take a perceptron-style approach, with each arc corresponding to a feature. The classic perceptron update would update the weights by subtracting the difference between the feature vector corresponding to the predicted path and the feature vector corresponding to the correct path. Since the path is not observed, we resort to a **hidden variable perceptron**. The model is described formally in § 12.4, but the basic idea is to compute an update from the difference between the features from the predicted path and the features for the best-scoring path that generates the correct output.

9.2 Context-free languages

Beyond the class of regular languages lie the context-free languages. An example of a language that is context-free but not finite state is the set of arithmetic expressions with balanced parentheses. Intuitively, to accept only strings in this language, an FSA would have to “count” the number of left parentheses, and make sure that they are balanced against the number of right parentheses. An arithmetic expression can be arbitrarily long, yet by definition an FSA has a finite number of states. Thus, for any FSA, there will be a string that with too many parentheses to count. More formally, the **pumping lemma** is a proof technique for showing that languages are not regular. It is typically demonstrated for the simpler case $a^n b^n$, the language of strings containing a sequence of a 's, and then an equal-length sequence of b 's.⁴

There are at least two arguments for the relevance of non-regular formal languages to linguistics. First, there are natural language phenomena that are argued to be isomorphic to $a^n b^n$. For English, the classic example is **center embedding**, shown in Figure 9.10. The initial expression *the dog* specifies a single dog. Embedding this expression into *the cat ... chased* specifies a particular cat — the one chased by the dog. This cat can then be embedded again to specify a goat, in the less felicitous but arguably grammatical expression, *the goat the cat the dog chased kissed*, which refers to the goat who was kissed by the cat which was chased by the dog. Chomsky (1957) argues that to be grammatical, a center-embedded construction must be balanced: if it contains n noun phrases (e.g., *the cat*), they must be followed by exactly $n - 1$ verbs. An FSA that could recognize such expressions would also be capable of recognizing the language $a^n b^n$. Because we can prove that no FSA exists for $a^n b^n$, no FSA can exist for center embedded constructions either. En-

⁴Details of the proof can be found in an introductory computer science theory textbook (e.g., Sipser, 2012).

			the dog	
	the cat	the dog	chased	
the goat	the cat	the dog	chased	kissed
			...	

Figure 9.10: Three levels of center embedding

4634 glish includes center embedding, and so the argument goes, English grammar as a whole
 4635 cannot be regular.⁵

4636 A more practical argument for moving beyond regular languages is modularity. Many
 4637 linguistic phenomena — especially in syntax — involve constraints that apply at long
 4638 distance. Consider the problem of determiner-noun number agreement in English: we
 4639 can say *the coffee* and *these coffees*, but not **these coffee*. By itself, this is easy enough to model
 4640 in an FSA. However, fairly complex modifying expressions can be inserted between the
 4641 determiner and the noun:

- 4642 (9.5) the burnt coffee
- 4643 (9.6) the badly-ground coffee
- 4644 (9.7) the burnt and badly-ground Italian coffee
- 4645 (9.8) these burnt and badly-ground Italian coffees
- 4646 (9.9) *these burnt and badly-ground Italian coffee

4647 Again, an FSA can be designed to accept modifying expressions such as *burnt and badly-*
 4648 *ground Italian*. Let's call this FSA F_M . To reject the final example, a finite state acceptor
 4649 must somehow "remember" that the determiner was plural when it reaches the noun *cof-*
 4650 *fee* at the end of the expression. The only way to do this is to make two identical copies
 4651 of F_M : one for singular determiners, and one for plurals. While this is possible in the
 4652 finite state framework, it is inconvenient — especially in languages where more than one
 4653 attribute of the noun is marked by the determiner. **Context-free languages** facilitate mod-
 4654 ularity across such long-range dependencies.

4655 9.2.1 Context-free grammars

4656 Context-free languages are specified by **context-free grammars (CFGs)**, which are tuples
 4657 (N, Σ, R, S) consisting of:

⁵The claim that arbitrarily deep center-embedded expressions are grammatical has drawn skepticism. Corpus evidence shows that embeddings of depth greater than two are exceedingly rare (Karlsson, 2007), and that embeddings of depth greater than three are completely unattested. If center-embedding is capped at some finite depth, then it is regular.

$$\begin{aligned}
 S &\rightarrow S \text{ OP } S \mid \text{NUM} \\
 \text{OP} &\rightarrow + \mid - \mid \times \mid \div \\
 \text{NUM} &\rightarrow \text{NUM DIGIT} \mid \text{DIGIT} \\
 \text{DIGIT} &\rightarrow 0 \mid 1 \mid 2 \mid \dots \mid 9
 \end{aligned}$$

Figure 9.11: A context-free grammar for arithmetic expressions

- 4658 • a finite set of **non-terminals** N ;
 4659 • a finite alphabet Σ of **terminal symbols**;
 4660 • a set of **production rules** R , each of the form $A \rightarrow \beta$, where $A \in N$ and $\beta \in (\Sigma \cup N)^*$;
 4661 • a designated start symbol S .

4662 In the production rule $A \rightarrow \beta$, the left-hand side (LHS) A must be a non-terminal;
 4663 the right-hand side (RHS) can be a sequence of terminals or non-terminals, $\{n, \sigma\}^*, n \in$
 4664 $N, \sigma \in \Sigma$. A non-terminal can appear on the left-hand side of many production rules.
 4665 A non-terminal can appear on both the left-hand side and the right-hand side; this is a
 4666 **recursive production**, and is analogous to self-loops in finite state automata. The name
 4667 “context-free” is based on the property that the production rule depends only on the LHS,
 4668 and not on its ancestors or neighbors; this is analogous to Markov property of finite state
 4669 automata, in which the behavior at each step depends only on the current state, on not on
 4670 the path by which that state was reached.

4671 A **derivation** τ is a sequence of steps from the start symbol S to a surface string $w \in \Sigma^*$,
 4672 which is the **yield** of the derivation. A string w is in a context-free language if there is
 4673 some derivation from S yielding w . **Parsing** is the problem of finding a derivation for a
 4674 string in a grammar. Algorithms for parsing are described in chapter 10.

4675 Like regular expressions, context-free grammars define the language but not the com-
 4676 putation necessary to recognize it. The context-free analogues to finite state acceptors are
 4677 **pushdown automata**, a theoretical model of computation in which input symbols can be
 4678 pushed onto a stack with potentially infinite depth. For more details, see Sipser (2012).

4679 9.2.1.1 Example

4680 Figure 9.11 shows a context-free grammar for arithmetic expressions such as $1 + 2 \div 3 - 4$.
 4681 In this grammar, the terminal symbols include the digits $\{1, 2, \dots, 9\}$ and the op-
 4682 erators $\{+, -, \times, \div\}$. The rules include the $|$ symbol, a notational convenience that makes
 4683 it possible to specify multiple right-hand sides on a single line: the statement $A \rightarrow x | y$

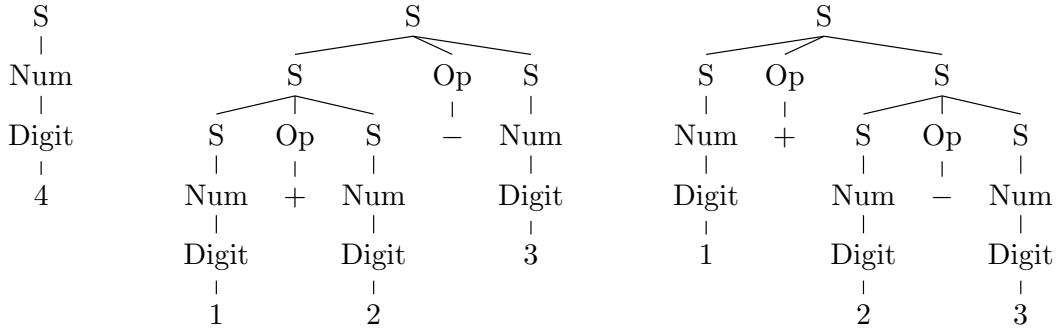


Figure 9.12: Some example derivations from the arithmetic grammar in Figure 9.11

4684 defines *two* productions, $A \rightarrow x$ and $A \rightarrow y$. This grammar is recursive: the non-termals S
4685 and NUM can produce themselves.

4686 Derivations are typically shown as trees, with production rules applied from the top
4687 to the bottom. The tree on the left in Figure 9.12 describes the derivation of a single digit,
4688 through the sequence of productions $S \rightarrow \text{NUM} \rightarrow \text{DIGIT} \rightarrow 4$ (these are all **unary produc-**
4689 **tions**, because the right-hand side contains a single element). The other two trees in
4690 Figure 9.12 show alternative derivations of the string $1 + 2 - 3$. The existence of multiple
4691 derivations for a string indicates that the grammar is **ambiguous**.

Context-free derivations can also be written out according to the pre-order tree traversal.⁶ For the two derivations of $1 + 2 - 3$ in Figure 9.12, the notation is:

$$(S (S (S (\text{Num} (Digit 1))) (\text{Op} +) (S (\text{Num} (Digit 2))))) (\text{Op} -) (S (\text{Num} (Digit 3)))) \quad [9.23]$$

$$(S (S (\text{Num} (Digit 1))) (\text{Op} +) (S (\text{Num} (Digit 2)) (\text{Op} -) (S (\text{Num} (Digit 3)))))). \quad [9.24]$$

4692 9.2.1.2 Grammar equivalence and Chomsky Normal Form

A single context-free language can be expressed by more than one context-free grammar. For example, the following two grammars both define the language $a^n b^n$ for $n > 0$.

$$\begin{aligned} S &\rightarrow aSb \mid ab \\ S &\rightarrow aSb \mid aabb \mid ab \end{aligned}$$

4693 Two grammars are **weakly equivalent** if they generate the same strings. Two grammars
4694 are **strongly equivalent** if they generate the same strings via the same derivations. The
4695 grammars above are only weakly equivalent.

⁶This is a depth-first left-to-right search that prints each node the first time it is encountered (Cormen et al., 2009, chapter 12).

In **Chomsky Normal Form (CNF)**, the right-hand side of every production includes either two non-terminals, or a single terminal symbol:

$$A \rightarrow BC$$

$$A \rightarrow a$$

- 4696 All CFGs can be converted into a CNF grammar that is weakly equivalent. To convert a
 4697 grammar into CNF, we first address productions that have more than two non-terminals
 4698 on the RHS by creating new “dummy” non-terminals. For example, if we have the pro-
 4699 duction,

$$W \rightarrow X Y Z, \quad [9.25]$$

it is replaced with two productions,

$$W \rightarrow X W \setminus X \quad [9.26]$$

$$W \setminus X \rightarrow Y Z. \quad [9.27]$$

- 4700 In these productions, $W \setminus X$ is a new dummy non-terminal. This transformation **binarizes**
 4701 the grammar, which is critical for efficient bottom-up parsing, as we will see in chapter 10.
 4702 Productions whose right-hand side contains a mix of terminal and non-terminal symbols
 4703 can be replaced in a similar fashion.

- 4704 Unary non-terminal productions $A \rightarrow B$ are replaced as follows: identify all produc-
 4705 tions $B \rightarrow \alpha$, and add $A \rightarrow \alpha$ to the grammar. For example, in the grammar described in
 4706 Figure 9.11, we would replace $\text{NUM} \rightarrow \text{DIGIT}$ with $\text{NUM} \rightarrow 1 \mid 2 \mid \dots \mid 9$. However, we
 4707 keep the production $\text{NUM} \rightarrow \text{NUM DIGIT}$, which is a valid binary production.

4708 9.2.2 Natural language syntax as a context-free language

- 4709 Context-free grammars are widely used to represent **syntax**, which is the set of rules that
 4710 determine whether an utterance is judged to be grammatical. If this representation were
 4711 perfectly faithful, then a natural language such as English could be transformed into a
 4712 formal language, consisting of exactly the (infinite) set of strings that would be judged to
 4713 be grammatical by a fluent English speaker. We could then build parsing software that
 4714 would automatically determine if a given utterance were grammatical.⁷

- 4715 Contemporary theories generally do *not* consider natural languages to be context-free
 4716 (see § 9.3), yet context-free grammars are widely used in natural language parsing. The
 4717 reason is that context-free representations strike a good balance: they cover a broad range
 4718 of syntactic phenomena, and they can be parsed efficiently. This section therefore de-
 4719 scribes how to handle a core fragment of English syntax in context-free form, following

⁷You are encouraged to move beyond this cursory treatment of syntax by consulting a textbook on linguistics (e.g., Akmajian et al., 2010; Bender, 2013).

4720 the conventions of the **Penn Treebank** (PTB; Marcus et al., 1993), a large-scale annotation
 4721 of English language syntax. The generalization to “mildly” context-sensitive languages is
 4722 discussed in § 9.3.

4723 The Penn Treebank annotation is a **phrase-structure grammar** of English. This means
 4724 that sentences are broken down into **constituents**, which are contiguous sequences of
 4725 words that function as coherent units for the purpose of linguistic analysis. Constituents
 4726 generally have a few key properties:

4727 **Movement.** Constituents can often be moved around sentences as units.

- 4728 (9.10) Abigail gave (her brother) (a fish).
 4729 (9.11) Abigail gave (a fish) to (her brother).

4730 In contrast, *gave her* and *brother a* cannot easily be moved while preserving gram-
 4731 maticality.

4732 **Substitution.** Constituents can be substituted by other phrases of the same type.

- 4733 (9.12) Max thanked (his older sister).
 4734 (9.13) Max thanked (her).

4735 In contrast, substitution is not possible for other contiguous units like *Max thanked*
 4736 and *thanked his*.

4737 **Coordination.** Coordinators like *and* and *or* can conjoin constituents.

- 4738 (9.14) (Abigail) and (her younger brother) bought a fish.
 4739 (9.15) Abigail (bought a fish) and (gave it to Max).
 4740 (9.16) Abigail (bought) and (greedily ate) a fish.

4741 Units like *brother bought* and *bought a* cannot easily be coordinated.

4742 These examples argue for units such as *her brother* and *bought a fish* to be treated as con-
 4743 stituents. Other sequences of words in these examples, such as *Abigail gave* and *brother*
a fish, cannot be moved, substituted, and coordinated in these ways. In phrase-structure
 4744 grammar, constituents are nested, so that *the senator from New Jersey* contains the con-
 4745 stituent *from New Jersey*, which in turn contains *New Jersey*. The sentence itself is the max-
 4746 imal constituent; each word is a minimal constituent, derived from a unary production
 4747 from a part-of-speech tag. Between part-of-speech tags and sentences are **phrases**. In
 4748 phrase-structure grammar, phrases have a type that is usually determined by their **head**
 4749 **word**: for example, a **noun phrase** corresponds to a noun and the group of words that

4751 modify it, such as *her younger brother*; a **verb phrase** includes the verb and its modifiers,
4752 such as *bought a fish* and *greedily ate it*.

4753 In context-free grammars, each phrase type is a non-terminal, and each constituent is
4754 the substring that the non-terminal yields. Grammar design involves choosing the right
4755 set of non-terminals. Fine-grained non-terminals make it possible to represent more fine-
4756 grained linguistic phenomena. For example, by distinguishing singular and plural noun
4757 phrases, it is possible to have a grammar of English that generates only sentences that
4758 obey subject-verb agreement. However, enforcing subject-verb agreement is considerably
4759 more complicated in languages like Spanish, where the verb must agree in both person
4760 and number with subject. In general, grammar designers must trade off between **over-**
4761 **generation** — a grammar that permits ungrammatical sentences — and **undergeneration**
4762 — a grammar that fails to generate grammatical sentences. Furthermore, if the grammar is
4763 to support manual annotation of syntactic structure, it must be simple enough to annotate
4764 efficiently.

4765 9.2.3 A phrase-structure grammar for English

4766 To better understand how phrase-structure grammar works, let's consider the specific
4767 case of the Penn Treebank grammar of English. The main phrase categories in the Penn
4768 Treebank (PTB) are based on the main part-of-speech classes: noun phrase (NP), verb
4769 phrase (VP), prepositional phrase (PP), adjectival phrase (ADJP), and adverbial phrase
4770 (ADVP). The top-level category is S, which conveniently stands in for both "sentence"
4771 and the "start" symbol. **Complement clauses** (e.g., *I take the good old fashioned ground that*
4772 *the whale is a fish*) are represented by the non-terminal SBAR. The terminal symbols in
4773 the grammar are individual words, which are generated from unary productions from
4774 part-of-speech tags (the PTB tagset is described in § 8.1).

4775 This section explores the productions from the major phrase-level categories, explain-
4776 ing how to generate individual tag sequences. The production rules are approached in a
4777 "theory-driven" manner: first the syntactic properties of each phrase type are described,
4778 and then some of the necessary production rules are listed. But it is important to keep
4779 in mind that the Penn Treebank was produced in a "data-driven" manner. After the set
4780 of non-terminals was specified, annotators were free to analyze each sentence in what-
4781 ever way seemed most linguistically accurate, subject to some high-level guidelines. The
4782 grammar of the Penn Treebank is simply the set of productions that were required to ana-
4783 lyze the several million words of the corpus. By design, the grammar overgenerates — it
4784 does not exclude ungrammatical sentences.

4785 **9.2.3.1 Sentences**

The most common production rule for sentences is,

$$S \rightarrow NP VP \quad [9.28]$$

which accounts for simple sentences like *Abigail ate the kimchi* — as we will see, the direct object *the kimchi* is part of the verb phrase. But there are more complex forms of sentences as well:

$$S \rightarrow ADVP NP VP \quad \text{Unfortunately } Abigail \text{ ate the kimchi.} \quad [9.29]$$

$$S \rightarrow S CC S \quad \text{Abigail ate the kimchi and Max had a burger.} \quad [9.30]$$

$$S \rightarrow VP \quad \text{Eat the kimchi.} \quad [9.31]$$

- 4786 where ADVP is an adverbial phrase (e.g., *unfortunately*, *very unfortunately*) and CC is a
 4787 coordinating conjunction (e.g., *and*, *but*).⁸

4788 **9.2.3.2 Noun phrases**

Noun phrases refer to entities, real or imaginary, physical or abstract: *Asha*, *the steamed dumpling*, *parts and labor*, *nobody*, *the whiteness of the whale*, and *the rise of revolutionary syndicalism in the early twentieth century*. Noun phrase productions include “bare” nouns, which may optionally follow determiners, as well as pronouns:

$$NP \rightarrow NN | NNS | NNP | PRP \quad [9.32]$$

$$NP \rightarrow DET NN | DET NNS | DET NNP \quad [9.33]$$

- 4789 The tags NN, NNS, and NNP refer to singular, plural, and proper nouns; PRP refers to
 4790 personal pronouns, and DET refers to determiners. The grammar also contains terminal
 4791 productions from each of these tags, e.g., $PRP \rightarrow I | you | we | \dots$.

Noun phrases may be modified by adjectival phrases (ADJP; e.g., *the small Russian dog*) and numbers (CD; e.g., *the five pastries*), each of which may optionally follow a determiner:

$$NP \rightarrow ADJP NN | ADJP NNS | DET ADJP NN | DET ADJP NNS \quad [9.34]$$

$$NP \rightarrow CD NNS | DET CD NNS | \dots \quad [9.35]$$

Some noun phrases include multiple nouns, such as *the liberation movement* and *an antelope horn*, necessitating additional productions:

$$NP \rightarrow NN NN | NN NNS | DET NN NN | \dots \quad [9.36]$$

⁸Notice that the grammar does not include the recursive production $S \rightarrow ADVP S$. It may be helpful to think about why this production would cause the grammar to overgenerate.

4792 These multiple noun constructions can be combined with adjectival phrases and cardinal
 4793 numbers, leading to a large number of additional productions.

Recursive noun phrase productions include coordination, prepositional phrase attachment, subordinate clauses, and verb phrase adjuncts:

$NP \rightarrow NP\ Cc\ NP$	<i>e.g., the red and the black</i>	[9.37]
$NP \rightarrow NP\ PP$	<i>e.g., the President of the Georgia Institute of Technology</i>	[9.38]
$NP \rightarrow NP\ SBAR$	<i>e.g., a whale which he had wounded</i>	[9.39]
$NP \rightarrow NP\ VP$	<i>e.g., a whale taken near Shetland</i>	[9.40]

4794 These recursive productions are a major source of ambiguity, because the VP and PP non-
 4795 terminals can also generate NP children. Thus, the *the President of the Georgia Institute of*
 4796 *Technology* can be derived in two ways, as can *a whale taken near Shetland in October*.

4797 But aside from these few recursive productions, the noun phrase fragment of the Penn
 4798 Treebank grammar is relatively flat, containing a large of number of productions that go
 4799 from NP directly to a sequence of parts-of-speech. If noun phrases had more internal
 4800 structure, the grammar would need fewer rules, which, as we will see, would make pars-
 4801 ing faster and machine learning easier. Vadas and Curran (2011) propose to add additional
 4802 structure in the form of a new non-terminal called a **nominal modifier** (NML), e.g.,

4803 (9.17) (NP (NN crude) (NN oil) (NNS prices)) (PTB analysis)
 4804 (NP (NML (NN crude) (NN oil)) (NNS prices)) (NML-style analysis)

4805 Another proposal is to treat the determiner as the head of a **determiner phrase** (DP;
 4806 Abney, 1987). There are linguistic arguments for and against determiner phrases (e.g.,
 4807 Van Eynde, 2006). From the perspective of context-free grammar, DPs enable more struc-
 4808 tured analyses of some constituents, e.g.,

4809 (9.18) (NP (DT the) (JJ white) (NN whale)) (PTB analysis)
 4810 (DP (DT the) (NP (JJ white) (NN whale))) (DP-style analysis).

4811 9.2.3.3 Verb phrases

Verb phrases describe actions, events, and states of being. The PTB tagset distinguishes several classes of verb inflections: base form (VB; *she likes to snack*), present-tense third-person singular (VBD; *she snacks*), present tense but not third-person singular (VBP; *they snack*), past tense (VBD; *they snacked*), present participle (VBG; *they are snacking*), and past participle (VBN; *they had snacked*).⁹ Each of these forms can constitute a verb phrase on its

⁹It bears emphasis the principles governing this tagset design are entirely English-specific: VBP is a meaningful category only because English morphology distinguishes third-person singular from all person-number combinations.

own:

$$\text{VP} \rightarrow \text{VB} \mid \text{VBZ} \mid \text{VBD} \mid \text{VBN} \mid \text{VBG} \mid \text{VBP} \quad [9.41]$$

More complex verb phrases can be formed by a number of recursive productions, including the use of coordination, modal verbs (MD; *she should snack*), and the infinitival *to* (TO):

$\text{VP} \rightarrow \text{MD VP}$	<i>She will snack</i>	[9.42]
$\text{VP} \rightarrow \text{VBD VP}$	<i>She had snacked</i>	[9.43]
$\text{VP} \rightarrow \text{VBZ VP}$	<i>She has been snacking</i>	[9.44]
$\text{VP} \rightarrow \text{VBN VP}$	<i>She has been snacking</i>	[9.45]
$\text{VP} \rightarrow \text{TO VP}$	<i>She wants to snack</i>	[9.46]
$\text{VP} \rightarrow \text{VP CC VP}$	<i>She buys and eats many snacks</i>	[9.47]

- 4812 Each of these productions uses recursion, with the VP non-terminal appearing in both the
 4813 LHS and RHS. This enables the creation of complex verb phrases, such as *She will have*
 4814 *wanted to have been snacking*.

Transitive verbs take noun phrases as direct objects, and ditransitive verbs take two direct objects:

$\text{VP} \rightarrow \text{VBZ NP}$	<i>She teaches algebra</i>	[9.48]
$\text{VP} \rightarrow \text{VBG NP}$	<i>She has been teaching algebra</i>	[9.49]
$\text{VP} \rightarrow \text{VBD NP NP}$	<i>She taught her brother algebra</i>	[9.50]

These productions are *not* recursive, so a unique production is required for each verb part-of-speech. They also do not distinguish transitive from intransitive verbs, so the resulting grammar overgenerates examples like **She sleeps sushi* and **She learns Boyang algebra*. Sentences can also be direct objects:

$\text{VP} \rightarrow \text{VBZ S}$	<i>Asha wants to eat the kimchi</i>	[9.51]
$\text{VP} \rightarrow \text{VBZ SBAR}$	<i>Asha knows that Boyang eats the kimchi</i>	[9.52]

- 4815 The first production overgenerates, licensing sentences like **Asha sees Boyang eats the kim-*
 4816 *chi*. This problem could be addressed by designing a more specific set of sentence non-
 4817 terminals, indicating whether the main verb can be conjugated.

Verbs can also be modified by prepositional phrases and adverbial phrases:

$\text{VP} \rightarrow \text{VBZ PP}$	<i>She studies at night</i>	[9.53]
$\text{VP} \rightarrow \text{VBZ ADVP}$	<i>She studies intensively</i>	[9.54]
$\text{VP} \rightarrow \text{ADVP VBG}$	<i>She is not studying</i>	[9.55]

4818 Again, because these productions are not recursive, the grammar must include produc-
 4819 tions for every verb part-of-speech.

A special set of verbs, known as **copula**, can take **predicative adjectives** as direct ob-
 jects:

$VP \rightarrow VBZ\ ADJP$	<i>She is hungry</i>	[9.56]
$VP \rightarrow VBP\ ADJP$	<i>Success seems increasingly unlikely</i>	[9.57]

4820 The PTB does not have a special non-terminal for copular verbs, so this production gen-
 4821 erates non-grammatical examples such as **She eats tall*.

Particles (PRT as a phrase; RP as a part-of-speech) work to create phrasal verbs:

$VP \rightarrow VB\ PRT$	<i>She told them to fuck off</i>	[9.58]
$VP \rightarrow VBD\ PRT\ NP$	<i>They gave up their ill-gotten gains</i>	[9.59]

4822 As the second production shows, particle productions are required for all configura-
 4823 tions of verb parts-of-speech and direct objects.

4824 9.2.3.4 Other constituents

The remaining constituents require far fewer productions. **Prepositional phrases** almost
 always consist of a preposition and a noun phrase,

$PP \rightarrow IN\ NP$	<i>the whiteness of the whale</i>	[9.60]
$PP \rightarrow TO\ NP$	<i>What the white whale was to Ahab, has been hinted.</i>	[9.61]

Similarly, complement clauses consist of a complementizer (usually a preposition, pos-
 sibly null) and a sentence,

$SBAR \rightarrow IN\ S$	<i>She said that it was spicy</i>	[9.62]
$SBAR \rightarrow S$	<i>She said it was spicy</i>	[9.63]

Adverbial phrases are usually bare adverbs ($ADVP \rightarrow RB$), with a few exceptions:

$ADVP \rightarrow RB\ RBR$	<i>They went considerably further</i>	[9.64]
$ADVP \rightarrow ADVP\ PP$	<i>They went considerably further than before</i>	[9.65]

4825 The tag RBR is a comparative adverb.

Adjectival phrases extend beyond bare adjectives ($\text{ADJP} \rightarrow \text{JJ}$) in a number of ways:

$\text{ADJP} \rightarrow \text{RB JJ}$	<i>very hungry</i>	[9.66]
$\text{ADJP} \rightarrow \text{RBR JJ}$	<i>more hungry</i>	[9.67]
$\text{ADJP} \rightarrow \text{JJS JJ}$	<i>best possible</i>	[9.68]
$\text{ADJP} \rightarrow \text{RB JJR}$	<i>even bigger</i>	[9.69]
$\text{ADJP} \rightarrow \text{JJ CC JJ}$	<i>high and mighty</i>	[9.70]
$\text{ADJP} \rightarrow \text{JJ JJ}$	<i>West German</i>	[9.71]
$\text{ADJP} \rightarrow \text{RB VBN}$	<i>previously reported</i>	[9.72]

4826 The tags JJR and JJS refer to comparative and superlative adjectives respectively.

All of these phrase types can be coordinated:

$\text{PP} \rightarrow \text{PP CC PP}$	<i>on time and under budget</i>	[9.73]
$\text{ADVP} \rightarrow \text{ADVP CC ADVP}$	<i>now and two years ago</i>	[9.74]
$\text{ADJP} \rightarrow \text{ADJP CC ADJP}$	<i>quaint and rather deceptive</i>	[9.75]
$\text{SBar} \rightarrow \text{SBar CC SBar}$	<i>whether they want control</i>	[9.76]
	<i>or whether they want exports</i>	

4827 9.2.4 Grammatical ambiguity

4828 Context-free parsing is useful not only because it determines whether a sentence is grammatical, but mainly because the constituents and their relations can be applied to tasks 4829 such as information extraction (chapter 17) and sentence compression (Jing, 2000; Clarke 4830 and Lapata, 2008). However, the **ambiguity** of wide-coverage natural language grammars 4831 poses a serious problem for such potential applications. As an example, Figure 9.13 shows 4832 two possible analyses for the simple sentence *We eat sushi with chopsticks*, depending on 4833 whether the *chopsticks* modify *eat* or *sushi*. Realistic grammars can license thousands or 4834 even millions of parses for individual sentences. **Weighted context-free grammars** solve 4835 this problem by attaching weights to each production, and selecting the derivation with 4836 the highest score. This is the focus of chapter 10. 4837

4838 9.3 *Mildly context-sensitive languages

4839 Beyond context-free languages lie **context-sensitive languages**, in which the expansion 4840 of a non-terminal depends on its neighbors. In the general class of context-sensitive 4841 languages, computation becomes much more challenging: the membership problem for 4842 context-sensitive languages is PSPACE-complete. Since PSPACE contains the complexity 4843 class NP (problems that can be solved in polynomial time on a non-deterministic Turing

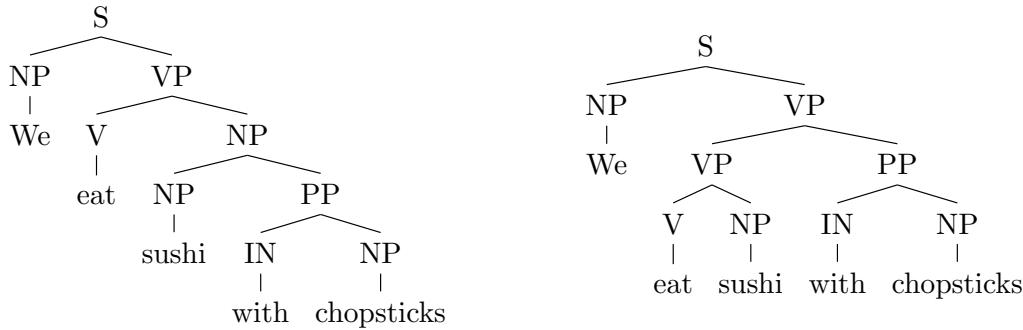


Figure 9.13: Two derivations of the same sentence

4844 machine), PSPACE-complete problems cannot be solved efficiently if $P \neq NP$. Thus, de-
 4845 signing an efficient parsing algorithm for the full class of context-sensitive languages is
 4846 probably hopeless.¹⁰

4847 However, Joshi (1985) identifies a set of properties that define **mildly context-sensitive**
 4848 **languages**, which are a strict subset of context-sensitive languages. Like context-free lan-
 4849 guages, mildly context-sensitive languages are efficiently parseable. However, the mildly
 4850 context-sensitive languages include non-context-free languages, such as the “copy lan-
 4851 guage” $\{ww \mid w \in \Sigma^*\}$ and the language $a^m b^n c^m d^n$. Both are characterized by **cross-**
 4852 **serial dependencies**, linking symbols at long distance across the string.¹¹ For example, in
 4853 the language $a^n b^m c^n d^m$, each a symbol is linked to exactly one c symbol, regardless of the
 4854 number of intervening b symbols.

4855 9.3.1 Context-sensitive phenomena in natural language

4856 Such phenomena are occasionally relevant to natural language. A classic example is found
 4857 in Swiss-German (Shieber, 1985), in which sentences such as *we let the children help Hans*
 4858 *paint the house* are realized by listing all nouns before all verbs, i.e., *we the children Hans the*
 4859 *house let help paint*. Furthermore, each noun’s determiner is dictated by the noun’s **case**
 4860 **marking** (the role it plays with respect to the verb). Using an argument that is analogous
 4861 to the earlier discussion of center-embedding (§ 9.2), Shieber argues that these case mark-
 4862 ing constraints are a cross-serial dependency, homomorphic to $a^m b^n c^m d^n$, and therefore
 4863 not context-free.

¹⁰If $P \neq NP$, then it contains problems that cannot be solved in polynomial time on a non-deterministic Turing machine; equivalently, solutions to these problems cannot even be checked in polynomial time (Arora and Barak, 2009).

¹¹A further condition of the set of mildly-context-sensitive languages is *constant growth*: if the strings in the language are arranged by length, the gap in length between any pair of adjacent strings is bounded by some language specific constant. This condition excludes languages such as $\{a^{2^n} \mid n \geq 0\}$.

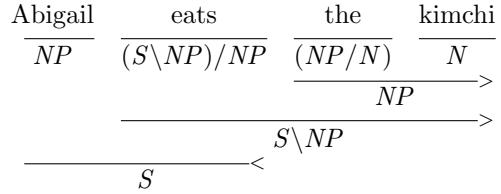


Figure 9.14: A syntactic analysis in CCG involving forward and backward function application

As with the move from regular to context-free languages, mildly context-sensitive languages can be motivated by expedience. While infinite sequences of cross-serial dependencies cannot be handled by context-free grammars, even finite sequences of cross-serial dependencies are more convenient to handle using a mildly context-sensitive formalism like **tree-adjoining grammar** (TAG) and **combinatory categorial grammar** (CCG). Furthermore, TAG-inspired parsers have been shown to be particularly effective in parsing the Penn Treebank (Collins, 1997; Carreras et al., 2008), and CCG plays a leading role in current research on semantic parsing (Zettlemoyer and Collins, 2005). Furthermore, these two formalisms are weakly equivalent: any language that can be specified in TAG can also be specified in CCG, and vice versa (Joshi et al., 1991). The remainder of the chapter gives a brief overview of CCG, but you are encouraged to consult Joshi and Schabes (1997) and Steedman and Baldridge (2011) for more detail on TAG and CCG respectively.

9.3.2 Combinatory categorial grammar

In combinatory categorial grammar, structural analyses are built up through a small set of generic combinatorial operations, which apply to immediately adjacent sub-structures. These operations act on the categories of the sub-structures, producing a new structure with a new category. The basic categories include S (sentence), NP (noun phrase), VP (verb phrase) and N (noun). The goal is to label the entire span of text as a sentence, S .

Complex categories, or types, are constructed from the basic categories, parentheses, and forward and backward slashes: for example, S/NP is a complex type, indicating a sentence that is lacking a noun phrase to its right; $S\backslash NP$ is a sentence lacking a noun phrase to its left. Complex types act as functions, and the most basic combinatory operations are function application to either the right or left neighbor. For example, the type of a verb phrase, such as *eats*, would be $S\backslash NP$. Applying this function to a subject noun phrase to its left results in an analysis of *Abigail eats* as category S , indicating a successful parse.

Transitive verbs must first be applied to the direct object, which in English appears to the right of the verb, before the subject, which appears on the left. They therefore have the more complex type $(S\backslash NP)/NP$. Similarly, the application of a determiner to the noun at

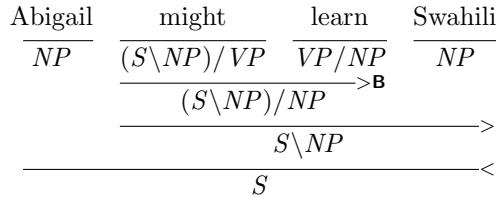


Figure 9.15: A syntactic analysis in CCG involving function composition (example modified from Steedman and Baldridge, 2011)

4893 its right results in a noun phrase, so determiners have the type NP/N. Figure 9.14 pro-
 4894 vides an example involving a transitive verb and a determiner. A key point from this
 4895 example is that it can be trivially transformed into phrase-structure tree, by treating each
 4896 function application as a constituent phrase. Indeed, when CCG's only combinatory op-
 4897 erators are forward and backward function application, it is equivalent to context-free
 4898 grammar. However, the location of the “effort” has changed. Rather than designing good
 4899 productions, the grammar designer must focus on the **lexicon** — choosing the right cate-
 4900 gories for each word. This makes it possible to parse a wide range of sentences using only
 4901 a few generic combinatory operators.

4902 Things become more interesting with the introduction of two additional operators:
 4903 **composition** and **type-raising**. Function composition enables the combination of com-
 4904 plex types: $X/Y \circ Y/Z \Rightarrow_B X/Z$ (forward composition) and $Y \setminus Z \circ X \setminus Y \Rightarrow_B X \setminus Z$ (back-
 4905 ward composition).¹² Composition makes it possible to “look inside” complex types, and
 4906 combine two adjacent units if the “input” for one is the “output” for the other. Figure 9.15
 4907 shows how function composition can be used to handle modal verbs. While this sen-
 4908 tence can be parsed using only function application, the composition-based analysis is
 4909 preferable because the unit *might learn* functions just like a transitive verb, as in the exam-
 4910 ple *Abigail studies Swahili*. This in turn makes it possible to analyze conjunctions such as
 4911 *Abigail studies and might learn Swahili*, attaching the direct object *Swahili* to the entire con-
 4912 joined verb phrase *studies and might learn*. The Penn Treebank grammar fragment from
 4913 § 9.2.3 would be unable to handle this case correctly: the direct object *Swahili* could attach
 4914 only to the second verb *learn*.

4915 Type raising converts an element of type X to a more complex type: $X \Rightarrow_T T / (T \setminus X)$
 4916 (forward type-raising to type T), and $X \Rightarrow_T T \setminus (T / X)$ (backward type-raising to type
 4917 T). Type-raising makes it possible to reverse the relationship between a function and its
 4918 argument — by transforming the argument into a function over functions over arguments!
 4919 An example may help. Figure 9.15 shows how to analyze an object relative clause, *a story*
 4920 *that Abigail tells*. The problem is that *tells* is a transitive verb, expecting a direct object to
 4921 its right. As a result, *Abigail tells* is not a valid constituent. The issue is resolved by raising

¹²The subscript **B** follows notation from Curry and Feys (1958).

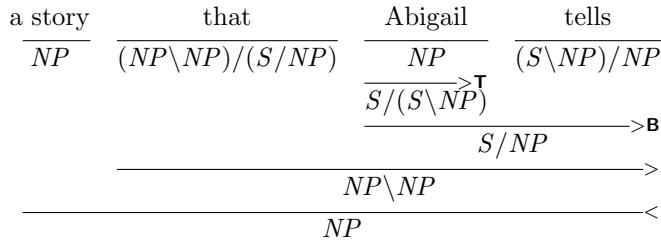


Figure 9.16: A syntactic analysis in CCG involving an object relative clause (based on slides from Alex Clark)

4922 *Abigail* from NP to the complex type $(S/NP) \setminus NP$. This function can then be combined
 4923 with the transitive verb *tells* by forward composition, resulting in the type (S/NP) , which
 4924 is a sentence lacking a direct object to its right.¹³ From here, we need only design the
 4925 lexical entry for the complementizer *that* to expect a right neighbor of type (S/NP) , and
 4926 the remainder of the derivation can proceed by function application.

4927 Composition and type-raising give CCG considerable power and flexibility, but at a price.
 4928 The simple sentence *Abigail tells Max* can be parsed in two different ways: by function
 4929 application (first forming the verb phrase *tells Max*), and by type-raising and compo-
 4930 sition (first forming the non-constituent *Abigail tells*). This **derivational ambiguity** does
 4931 not affect the resulting linguistic analysis, so it is sometimes known as **spurious ambi-**
 4932 **guity**. Hockenmaier and Steedman (2007) present a translation algorithm for converting
 4933 the Penn Treebank into CCG derivations, using composition and type-raising only when
 4934 necessary.

4935 Exercises

- 4936 1. Sketch out the state diagram for finite-state acceptors for the following languages
 4937 on the alphabet $\{a, b\}$.
- 4938 a) Even-length strings. (Be sure to include 0 as an even number.)
- 4939 b) Strings that contain *aaa* as a substring.
- 4940 c) Strings containing an even number of *a* and an odd number of *b* symbols.
- 4941 d) Strings in which the substring *bbb* must be terminal if it appears — the string
 4942 need not contain *bbb*, but if it does, nothing can come after it.
- 4943 2. Levenshtein edit distance is the number of insertions, substitutions, or deletions
 4944 required to convert one string to another.

¹³The missing direct object would be analyzed as a **trace** in CFG-like approaches to syntax, including the Penn Treebank.

- 4945 a) Define a finite-state acceptor that accepts all strings with edit distance 1 from
 4946 the target string, *target*.
 4947 b) Now think about how to generalize your design to accept all strings with edit
 4948 distance from the target string equal to d . If the target string has length ℓ , what
 4949 is the minimal number of states required?
- 4950 3. Construct an FSA in the style of Figure 9.3, which handles the following examples:

- 4951 • *nation*/N, *national*/ADJ, *nationalize*/V, *nationalizer*/N
 4952 • *America*/N, *American*/ADJ, *Americanize*/V, *Americanizer*/N

4953 Be sure that your FSA does not accept any further derivations, such as **nationalizeral*
 4954 and **Americanizern*.

- 4955 4. Show how to construct a trigram language model in a weighted finite-state acceptor.
 4956 Make sure that you handle the edge cases at the beginning and end of the sequence
 4957 accurately.
- 4958 5. Extend the FST in Figure 9.6 to handle the other two parts of rule 1a of the Porter
 4959 stemmer: *-sses* → *ss*, and *-ies* → *-i*.

- 4960 6. § 9.1.4.4 describes T_O , a transducer that captures English orthography by transduc-
 4961 ing *cook + ed* → *cooked* and *bake + ed* → *baked*. Design an unweighted finite-state
 4962 transducer that captures this property of English orthography.

4963 Next, augment the transducer to appropriately model the suffix *-s* when applied to
 4964 words ending in *s*, e.g. *kiss+s* → *kisses*.

- 4965 7. Add parenthesization to the grammar in Figure 9.11 so that it is no longer ambigu-
 4966 ous.
- 4967 8. Construct three examples — a noun phrase, a verb phrase, and a sentence — which
 4968 can be derived from the Penn Treebank grammar fragment in § 9.2.3, yet are not
 4969 grammatical. Avoid reusing examples from the text. Optionally, propose corrections
 4970 to the grammar to avoid generating these cases.
- 4971 9. Produce parses for the following sentences, using the Penn Treebank grammar frag-
 4972 ment from § 9.2.3.

- 4973 (9.19) This aggression will not stand.
 4974 (9.20) I can get you a toe.
 4975 (9.21) Sometimes you eat the bar and sometimes the bar eats you.

4976 Then produce parses for three short sentences from a news article from this week.

4977 10. * One advantage of CCG is its flexibility in handling coordination:

4978 (9.22) *Abigail and Max speak Swahili*

4979 (9.23) *Abigail speaks and Max understands Swahili*

Define the lexical entry for *and* as

$$\textit{and} := (X/X) \setminus X, \quad [9.77]$$

4980 where X can refer to any type. Using this lexical entry, show how to parse the two
4981 examples above. In the second example, *Swahili* should be combined with the coor-
4982 dination *Abigail speaks and Max understands*, and not just with the verb *understands*.

4983 **Chapter 10**

4984 **Context-free parsing**

4985 Parsing is the task of determining whether a string can be derived from a given context-
4986 free grammar, and if so, how. The parse structure can answer basic questions of who-did-
4987 what-to-whom, and is useful for various downstream tasks, such as semantic analysis
4988 (chapter 12 and 13) and information extraction (chapter 17).

For a given input and grammar, how many parse trees are there? Consider a minimal context-free grammar with only one non-terminal, X , and the following productions:

$$\begin{aligned} X \rightarrow & X \ X \\ X \rightarrow & aardvark \mid abacus \mid \dots \mid zyther \end{aligned}$$

The second line indicates unary productions to every nonterminal in Σ . In this grammar, the number of possible derivations for a string w is equal to the number of binary bracketings, e.g.,

$$(((w_1 w_2) w_3) w_4) w_5), \quad (((w_1 (w_2 w_3)) w_4) w_5), \quad ((w_1 (w_2 (w_3 w_4))) w_5), \quad \dots$$

4989 The number of such bracketings is a **Catalan number**, which grows super-exponentially
4990 in the length of the sentence, $C_n = \frac{(2n)!}{(n+1)n!}$. As with sequence labeling, it is only possible to
4991 exhaustively search the space of parses by resorting to locality assumptions, which make it
4992 possible to search efficiently by reusing shared substructures with dynamic programming.
4993 This chapter focuses on a bottom-up dynamic programming algorithm, which enables
4994 exhaustive search of the space of possible parses, but imposes strict limitations on the
4995 form of scoring function. These limitations can be relaxed by abandoning exhaustive
4996 search. Non-exact search methods will be briefly discussed at the end of this chapter, and
4997 one of them — **transition-based parsing** — will be the focus of chapter 11.

S	\rightarrow	NP VP
NP	\rightarrow	NP PP <i>we</i> <i>sushi</i> <i>chopsticks</i>
PP	\rightarrow	IN NP
IN	\rightarrow	<i>with</i>
VP	\rightarrow	V NP VP PP
V	\rightarrow	<i>eat</i>

Table 10.1: A toy example context-free grammar

4998 10.1 Deterministic bottom-up parsing

4999 The **CKY algorithm**¹ is a bottom-up approach to parsing in a context-free grammar. It
 5000 efficiently tests whether a string is in a language, without enumerating all possible parses.
 5001 The algorithm first forms small constituents, and then tries to merge them into larger
 5002 constituents.

5003 To understand the algorithm, consider the input, *We eat sushi with chopsticks*. According-
 5004 ing to the toy grammar in Table 10.1, each terminal symbol can be generated by exactly
 5005 one unary production, resulting in the sequence NP V NP IN NP. Next, we try to apply
 5006 binary productions to merge adjacent symbols into larger constituents: for example, V
 5007 NP can be merged into a verb phrase (VP), and IN NP can be merged into a prepositional
 5008 phrase (PP). Bottom-up parsing tries to find some series of mergers that ultimately results
 5009 in the start symbol S covering the entire input.

5010 The CKY algorithm systematizes this approach, incrementally constructing a table t in
 5011 which each cell $t[i, j]$ contains the set of nonterminals that can derive the span $w_{i+1:j}$. The
 5012 algorithm fills in the upper right triangle of the table; it begins with the diagonal, which
 5013 corresponds to substrings of length 1, and then computes derivations for progressively
 5014 larger substrings, until reaching the upper right corner $t[0, M]$, which corresponds to the
 5015 entire input, $w_{1:M}$. If the start symbol S is in $t[0, M]$, then the string w is in the language
 5016 defined by the grammar. This process is detailed in Algorithm 13, and the resulting data
 5017 structure is shown in Figure 10.1. Informally, here's how it works:

- 5018 • Begin by filling in the diagonal: the cells $t[m - 1, m]$ for all $m \in \{1, 2, \dots, M\}$. These
 5019 cells are filled with terminal productions that yield the individual tokens; for the
 5020 word $w_2 = \text{sushi}$, we fill in $t[1, 2] = \{\text{NP}\}$, and so on.
- 5021 • Then fill in the next diagonal, in which each cell corresponds to a subsequence of
 5022 length two: $t[0, 2], t[1, 3], \dots, t[M - 2, M]$. These cells are filled in by looking for
 5023 binary productions capable of producing at least one entry in each of the cells corre-

¹The name is for Cocke-Kasami-Younger, the inventors of the algorithm. It is a special case **chart parsing**, because its stores reusable computations in a chart-like data structure.

Algorithm 13 The CKY algorithm for parsing a sequence $w \in \Sigma^*$ in a context-free grammar $G = (N, \Sigma, R, S)$, with non-terminals N , production rules R , and start symbol S . The grammar is assumed to be in Chomsky normal form (§ 9.2.1.2). The function $\text{PICKFROM}(b[i, j, X])$ selects an element of the set $b[i, j, X]$ arbitrarily. All values of t and b are initialized to \emptyset .

```

1: procedure CKY( $w, G = (N, \Sigma, R, S)$ )
2:   for  $m \in \{1 \dots M\}$  do
3:      $t[m - 1, m] \leftarrow \{X : (X \rightarrow w_m) \in R\}$ 
4:   for  $\ell \in \{2, 3, \dots, M\}$  do                                 $\triangleright$  Iterate over constituent lengths
5:     for  $m \in \{0, 1, \dots, M - \ell\}$  do           $\triangleright$  Iterate over left endpoints
6:       for  $k \in \{m + 1, m + 2, \dots, m + \ell - 1\}$  do       $\triangleright$  Iterate over split points
7:         for  $(X \rightarrow Y Z) \in R$  do           $\triangleright$  Iterate over rules
8:           if  $Y \in t[m, k] \wedge Z \in t[k, m + \ell]$  then
9:              $t[m, m + \ell] \leftarrow t[m, m + \ell] \cup X$            $\triangleright$  Add non-terminal to table
10:             $b[m, m + \ell, X] \leftarrow b[m, m + \ell, X] \cup (Y, Z, k)$        $\triangleright$  Add back-pointers
11:   if  $S \in t[0, M]$  then
12:     return TRACEBACK( $S, 0, M, b$ )
13:   else
14:     return  $\emptyset$ 
15: procedure TRACEBACK( $X, i, j, b$ )
16:   if  $j = i + 1$  then
17:     return  $X$ 
18:   else
19:      $(Y, Z, k) \leftarrow \text{PICKFROM}(b[i, j, X])$ 
20:     return  $X \rightarrow (\text{TRACEBACK}(Y, i, k, b), \text{TRACEBACK}(Z, k, j, b))$ 

```

5024 sponding to left and right children. For example, the cell $t[1, 3]$ includes VP because
 5025 the grammar includes the production $\text{VP} \rightarrow \text{V NP}$, and the chart contains $\text{V} \in t[1, 2]$
 5026 and $\text{NP} \in t[2, 3]$.

- 5027 • At the next diagonal, the entries correspond to spans of length three. At this level,
 5028 there is an additional decision at each cell: where to split the left and right children.
 5029 The cell $t[i, j]$ corresponds to the subsequence $w_{i+1:j}$, and we must choose some
 5030 *split point* $i < k < j$, so that $w_{i+1:k}$ is the left child and $w_{k+1:j}$ is the right child. We
 5031 consider all possible k , looking for productions that generate elements in $t[i, k]$ and
 5032 $t[k, j]$; the left-hand side of all such productions can be added to $t[i, j]$. When it is
 5033 time to compute $t[i, j]$, the cells $t[i, k]$ and $t[k, j]$ are guaranteed to be complete, since
 5034 these cells correspond to shorter sub-strings of the input.
- 5035 • The process continues until we reach $t[0, M]$.

5036 Figure 10.1 shows the chart that arises from parsing the sentence *We eat sushi with chop-*
 5037 *sticks* using the grammar defined above.

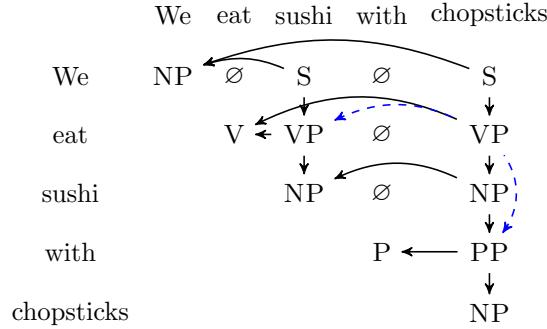


Figure 10.1: An example completed CKY chart. The solid and dashed lines show the back pointers resulting from the two different derivations of VP in position $t[1, 5]$.

5038 10.1.1 Recovering the parse tree

5039 As with the Viterbi algorithm, it is possible to identify a successful parse by storing and
 5040 traversing an additional table of back-pointers. If we add an entry X to cell $t[i, j]$ by using
 5041 the production $X \rightarrow YZ$ and the split point k , then we store the back-pointer $b[i, j, X] =$
 5042 (Y, Z, k) . Once the table is complete, we can recover a parse by tracing this pointers,
 5043 starting at $b[0, M, S]$, and stopping when they ground out at terminal productions.

5044 For ambiguous sentences, there will be multiple paths to reach $S \in t[0, M]$. For exam-
 5045 ple, in Figure 10.1, the goal state $S \in t[0, M]$ is reached through the state $VP \in t[1, 5]$, and
 5046 there are two different ways to generate this constituent: one with *(eat sushi)* and *(with
 5047 chopsticks)* as children, and another with *(eat)* and *(sushi with chopsticks)* as children. The
 5048 presence of multiple paths indicates that the input can be generated by the grammar in
 5049 more than one way. In Algorithm 13, one of these derivations is selected arbitrarily. As
 5050 discussed in § 10.3, **weighted context-free grammars** can select a single parse that maxi-
 5051 mizes a scoring function.

5052 10.1.2 Non-binary productions

5053 The CKY algorithm assumes that all productions with non-terminals on the right-hand
 5054 side (RHS) are binary. But in real grammars, such as the one considered in chapter 9,
 5055 there will be productions with more than two elements on the right-hand side, and other
 5056 productions with only a single element.

- 5057 • Productions with more than two elements on the right-hand side can be **binarized**
 5058 by creating additional non-terminals, as described in § 9.2.1.2. For example, given
 5059 the production $VP \rightarrow V NP NP$ (for ditransitive verbs), we can convert to $VP \rightarrow$
 5060 $VP_{ditrans}/NP NP$, and then add the production $VP_{ditrans}/NP \rightarrow V NP$.

- What about unary productions like $VP \rightarrow V$? In practice, this is handled by making a second pass on each diagonal, in which each cell $t[i, j]$ is augmented with all possible unary productions capable of generating each item already in the cell — formally, $t[i, j]$ is extended to its **unary closure**. Suppose the example grammar in Table 10.1 were extended to include the production $VP \rightarrow V$, enabling sentences with intransitive verb phrases, like *we eat*. Then the cell $t[1, 2]$ — corresponding to the word *eat* — would first include the set $\{V\}$, and would be augmented to the set $\{V, VP\}$ during this second pass.

10.1.3 Complexity

For an input of length M and a grammar with R productions and N non-terminals, the space complexity of the CKY algorithm is $\mathcal{O}(M^2N)$: the number of cells in the chart is $\mathcal{O}(M^2)$, and each cell must hold $\mathcal{O}(N)$ elements. The time complexity is $\mathcal{O}(M^3R)$: each cell is computed by searching over $\mathcal{O}(M)$ split points, with R possible productions for each split point. Both the time and space complexity are considerably worse than the Viterbi algorithm, which is linear in the length of the input.

10.2 Ambiguity

Syntactic ambiguity is endemic to natural language. Here are a few broad categories:

- **Attachment ambiguity:** e.g., *We eat sushi with chopsticks, I shot an elephant in my pajamas*. In these examples, the prepositions (*with, in*) can attach to either the verb or the direct object.
- **Modifier scope:** e.g., *southern food store, plastic cup holder*. In these examples, the first word could be modifying the subsequent adjective, or the final noun.
- **Particle versus preposition:** e.g., *The puppy tore up the staircase*. Phrasal verbs like *tore up* often include particles which could also act as prepositions. This has structural implications: if *up* is a preposition, then *up the staircase* is a prepositional phrase; if *up* is a particle, then *the staircase* is the direct object to the verb.
- **Complement structure:** e.g., *The students complained to the professor that they didn't understand*. This is another form of attachment ambiguity, where the complement *that they didn't understand* could attach to the main verb (*complained*), or to the indirect object (*the professor*).
- **Coordination scope:** e.g., *"I see," said the blind man, as he picked up the hammer and saw*. In this example, the lexical ambiguity for *saw* enables it to be coordinated either with the noun *hammer* or the verb *picked up*.

These forms of ambiguity can combine, so that seemingly simple headlines like *Fed raises interest rates* have dozens of possible analyses even in a minimal grammar. In a broad coverage grammar, typical sentences can have millions of parses. While careful grammar design can chip away at this ambiguity, a better strategy is to combine broad coverage parsers with data driven strategies for identifying the correct analysis.

10.2.1 Parser evaluation

Before continuing to parsing algorithms that are able to handle ambiguity, we stop to consider how to measure parsing performance. Suppose we have a set of *reference parses* — the ground truth — and a set of *system parses* that we would like to score. A simple solution would be per-sentence accuracy: the parser is scored by the proportion of sentences on which the system and reference parses exactly match.² But as any good student knows, it is better to get *partial credit*, which we can assign to analyses that correctly match parts of the reference parse. The PARSEval metrics (Grishman et al., 1992) score each system parse via:

Precision: the fraction of constituents in the system parse that match a constituent in the reference parse.

Recall: the fraction of constituents in the reference parse that match a constituent in the system parse.

In **labeled precision** and **recall**, the system must also match the phrase type for each constituent; in **unlabeled precision** and **recall**, it is only required to match the constituent structure. As in chapter 4, the precision and recall can be combined into an *F*-MEASURE, $F = \frac{2 \times P \times R}{P + R}$.

In Figure 10.2, suppose that the left tree is the system parse and the right tree is the reference parse. We have the following spans:

- $S \rightarrow w_{1:5}$ is *true positive*, because it appears in both trees.
- $VP \rightarrow w_{2:5}$ is *true positive* as well.
- $NP \rightarrow w_{3:5}$ is *false positive*, because it appears only in the system output.
- $PP \rightarrow w_{4:5}$ is *true positive*, because it appears in both trees.
- $VP \rightarrow w_{2:3}$ is *false negative*, because it appears only in the reference.

²Most parsing papers do not report results on this metric, but Finkel et al. (2008) find that a strong parser finds the exact correct parse on 35% of sentences of length ≤ 40 , and on 62% of parses of length ≤ 15 in the Penn Treebank.

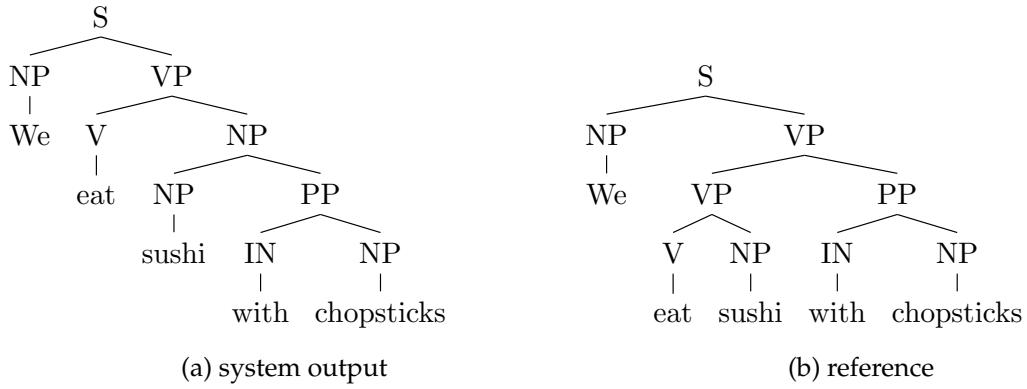


Figure 10.2: Two possible analyses from the grammar in Table 10.1

5123 The labeled and unlabeled precision of this parse is $\frac{3}{4} = 0.75$, and the recall is $\frac{3}{4} = 0.75$, for
 5124 an F-measure of 0.75. For an example in which precision and recall are not equal, suppose
 5125 the reference parse instead included the production $VP \rightarrow V NP PP$. In this parse, the
 5126 reference does not contain the constituent $w_{2:3}$, so the recall would be 1.³

5127 10.2.2 Local solutions

5128 Some ambiguity can be resolved locally. Consider the following examples,

5129 (10.1) We met the President on Monday.

5130 (10.2) We met the President of Mexico.

Each case ends with a preposition, which can be attached to the verb *met* or the noun phrase *the president*. This ambiguity can be resolved by using a labeled corpus to compare the likelihood of observing the preposition alongside each candidate attachment point,

$$p(on \mid met) \geq p(on \mid President) \quad [10.1]$$

$$p(of \mid met) \geq p(of \mid President). \quad [10.2]$$

5131 A comparison of these probabilities would successfully resolve this case (Hindle and
5132 Rooth, 1993). Other cases, such as the example ... *eat sushi with chopsticks*, require consider-
5133 ing the object of the preposition — consider the alternative ... *eat sushi with soy sauce*. With
5134 sufficient labeled data, the problem of prepositional phrase attachment can be treated as
5135 a classification task (Ratnaparkhi et al., 1994).

³While the grammar must be binarized before applying the CKY algorithm, evaluation is performed on the original parses. It is therefore necessary to “unbinarize” the output of a CKY-based parser, converting it back to the original grammar.

5136 However, there are inherent limitations to local solutions. While toy examples may
 5137 have just a few ambiguities to resolve, realistic sentences have thousands or millions of
 5138 possible parses. Furthermore, attachment decisions are interdependent, as shown in the
 5139 garden path example:

5140 (10.3) Cats scratch people with claws with knives.

5141 We may want to attach *with claws* to *scratch*, as would be correct in the shorter sentence
 5142 in *cats scratch people with claws*. But this leaves nowhere to attach *with knives*. The cor-
 5143 rect interpretation can be identified only by considering the attachment decisions jointly.
 5144 The huge number of potential parses may seem to make exhaustive search impossible.
 5145 But as with sequence labeling, locality assumptions make it possible to search this space
 5146 efficiently.

5147 10.3 Weighted Context-Free Grammars

5148 Let us define a derivation τ as a set of **anchored productions**,

$$\tau = \{X \rightarrow \alpha, (i, j, k)\}, \quad [10.3]$$

5149 with X corresponding to the left-hand side non-terminal and α corresponding to the right-
 5150 hand side. For grammars in Chomsky normal form, α is either a pair of non-terminals or
 5151 a terminal symbol. The indices i, j, k anchor the production in the input, with X deriving
 5152 the span $w_{i+1:j}$. For binary productions, $w_{i+1:k}$ indicates the span of the left child, and
 5153 $w_{k+1:j}$ indicates the span of the right child; for unary productions, k is ignored. For an
 5154 input w , the optimal parse is then,

$$\hat{\tau} = \underset{\tau \in \mathcal{T}(w)}{\operatorname{argmax}} \Psi(\tau), \quad [10.4]$$

5155 where $\mathcal{T}(w)$ is the set of derivations that yield the input w .

5156 The scoring function Ψ decomposes across anchored productions,

$$\Psi(\tau) = \sum_{(X \rightarrow \alpha, (i, j, k)) \in \tau} \psi(X \rightarrow \alpha, (i, j, k)). \quad [10.5]$$

5157 This is a locality assumption, akin to the assumption in Viterbi sequence labeling. In this
 5158 case, the assumption states that the overall score is a sum over scores of productions,
 5159 which are computed independently. In a **weighted context-free grammar** (WCFG), the
 5160 score of each anchored production $X \rightarrow (\alpha, i, j, k)$ is simply $\psi(X \rightarrow \alpha)$, ignoring the
 5161 anchors (i, j, k) . In other parsing models, the anchors can be used to access features of the
 5162 input, while still permitting efficient bottom-up parsing.

		$\psi(\cdot)$	$\exp \psi(\cdot)$
S	$\rightarrow \text{NP VP}$	0	1
NP	$\rightarrow \text{NP PP}$	-1	$\frac{1}{2}$
	$\rightarrow \text{we}$	-2	$\frac{1}{4}$
	$\rightarrow \text{sushi}$	-3	$\frac{1}{8}$
	$\rightarrow \text{chopsticks}$	-3	$\frac{1}{8}$
PP	$\rightarrow \text{IN NP}$	0	1
IN	$\rightarrow \text{with}$	0	1
VP	$\rightarrow \text{V NP}$	-1	$\frac{1}{2}$
	$\rightarrow \text{VP PP}$	-2	$\frac{1}{4}$
	$\rightarrow \text{MD V}$	-2	$\frac{1}{4}$
V	$\rightarrow \text{eat}$	0	1

Table 10.2: An example weighted context-free grammar (WCFG). The weights are chosen so that $\exp \psi(\cdot)$ sums to one over right-hand sides for each non-terminal; this is required by probabilistic context-free grammars, but not by WCFGs in general.

Example Consider the weighted grammar shown in Table 10.2, and the analysis in Figure 10.2b.

$$\begin{aligned} \Psi(\tau) = & \psi(S \rightarrow \text{NP VP}) + \psi(VP \rightarrow \text{VP PP}) + \psi(VP \rightarrow \text{V NP}) + \psi(PP \rightarrow \text{IN NP}) \\ & + \psi(\text{NP} \rightarrow \text{We}) + \psi(\text{V} \rightarrow \text{eat}) + \psi(\text{NP} \rightarrow \text{sushi}) + \psi(\text{IN} \rightarrow \text{with}) + \psi(\text{NP} \rightarrow \text{chopsticks}) \end{aligned} \quad [10.6]$$

$$= 0 - 2 - 1 + 0 - 2 + 0 - 3 + 0 - 3 = -11. \quad [10.7]$$

5163 In the alternative parse in Figure 10.2a, the production $VP \rightarrow VP PP$ (with score -2) is
 5164 replaced with the production $NP \rightarrow NP PP$ (with score -1); all other productions are the
 5165 same. As a result, the score for this parse is -10.

5166 This example hints at a big problem with WCFG parsing on non-terminals such as
 5167 NP, VP, and PP: a WCFG will *always* prefer either VP or NP attachment, without regard
 5168 to what is being attached! This problem is addressed in § 10.5.

5169 10.3.1 Parsing with weighted context-free grammars

5170 The optimization problem in Equation 10.4 can be solved by modifying the CKY algo-
 5171 rithm. In the deterministic CKY algorithm, each cell $t[i, j]$ stored a set of non-terminals
 5172 capable of deriving the span $w_{i+1:j}$. We now augment the table so that the cell $t[i, j, X]$
 5173 is the *score of the best derivation of $w_{i+1:j}$ from non-terminal X* . This score is computed
 5174 recursively: for the anchored binary production $(X \rightarrow Y Z, (i, j, k))$, we compute:

Algorithm 14 CKY algorithm for parsing a string $w \in \Sigma^*$ in a weighted context-free grammar (N, Σ, R, S) , where N is the set of non-terminals and R is the set of weighted productions. The grammar is assumed to be in Chomsky normal form (§ 9.2.1.2). The function TRACEBACK is defined in Algorithm 13.

```

procedure WCKY( $w, G = (N, \Sigma, R, S)$ )
  for all  $i, j, X$  do ▷ Initialization
     $t[i, j, X] \leftarrow 0$ 
     $b[i, j, X] \leftarrow \emptyset$ 
  for  $m \in \{1, 2, \dots, M\}$  do
    for all  $X \in N$  do
       $t[m, m + 1, X] \leftarrow \psi(X \rightarrow w_m, (m, m + 1, m))$ 
  for  $\ell \in \{2, 3, \dots, M\}$  do
    for  $m \in \{0, 1, \dots, M - \ell\}$  do
      for  $k \in \{m + 1, m + 2, \dots, m + \ell - 1\}$  do
         $t[m, m + \ell, X] \leftarrow \max_{k, Y, Z} \psi(X \rightarrow Y Z, (m, m + \ell, k)) + t[m, k, Y] + t[k, m + \ell, Z]$ 
         $b[m, m + \ell, X] \leftarrow \operatorname{argmax}_{k, Y, Z} \psi(X \rightarrow Y Z, (m + \ell, k)) + t[m, k, Y] + t[k, m + \ell, Z]$ 
  return TRACEBACK( $S, 0, M, b$ )

```

- 5175 • the score of the anchored production, $\psi(X \rightarrow Y Z, (i, j, k))$;
- 5176 • the score of the best derivation of the left child, $t[i, k, Y]$;
- 5177 • the score of the best derivation of the right child, $t[k, j, Z]$.

5178 These scores are combined by addition. As in the unscored CKY algorithm, the table
 5179 is constructed by considering spans of increasing length, so the scores for spans $t[i, k, Y]$
 5180 and $t[k, j, Z]$ are guaranteed to be available at the time we compute the score $t[i, j, X]$. The
 5181 value $t[0, M, S]$ is the score of the best derivation of w from the grammar. Algorithm 14
 5182 formalizes this procedure.

5183 As in unweighted CKY, the parse is recovered from the table of back pointers b , where
 5184 each $b[i, j, X]$ stores the argmax split point k and production $X \rightarrow Y Z$ in the derivation of
 5185 $w_{i+1:j}$ from X . The best parse can be obtained by tracing these pointers backwards from
 5186 $b[0, M, S]$, all the way to the terminal symbols. This is analogous to the computation of the
 5187 best sequence of labels in the Viterbi algorithm by tracing pointers backwards from the
 5188 end of the trellis. Note that we need only store back-pointers for the *best* path to $t[i, j, X]$;
 5189 this follows from the locality assumption that the global score for a parse is a combination
 5190 of the local scores of each production in the parse.

Example Let's revisit the parsing table in Figure 10.1. In a weighted CFG, each cell would include a score for each non-terminal; non-terminals that cannot be generated are

Algorithm 15 Generative model for derivations from probabilistic context-free grammars in Chomsky Normal Form (CNF).

```

procedure DRAWSUBTREE(X)
    sample  $(X \rightarrow \alpha) \sim p(\alpha | X)$ 
    if  $\alpha = (Y Z)$  then
        return DRAWSUBTREE(Y)  $\cup$  DRAWSUBTREE(Z)
    else
        return  $(X \rightarrow \alpha)$             $\triangleright$  In CNF, all unary productions yield terminal symbols

```

assumed to have a score of $-\infty$. The first diagonal contains the scores of unary productions: $t[0, 1, \text{NP}] = -2$, $t[1, 2, \text{V}] = 0$, and so on. At the next diagonal, we compute the scores for spans of length 2: $t[1, 3, \text{VP}] = -1 + 0 - 3 = -4$, $t[3, 5, \text{PP}] = 0 + 0 - 3 = -3$, and so on. Things get interesting when we reach the cell $t[1, 5, \text{VP}]$, which contains the score for the derivation of the span $w_{2:5}$ from the non-terminal VP. This score is computed as a max over two alternatives,

$$t[1, 5, \text{VP}] = \max(\psi(\text{VP} \rightarrow \text{VP PP}, (1, 3, 5)) + t[1, 3, \text{VP}] + t[3, 5, \text{PP}], \\ \psi(\text{VP} \rightarrow \text{V NP}, (1, 2, 5)) + t[1, 2, \text{V}] + t[2, 5, \text{NP}]) \quad [10.8]$$

$$= \max(-2 - 4 - 3, -1 + 0 - 7) = -8. \quad [10.9]$$

5191 Since the second case is the argmax, we set the back-pointer $b[1, 5, \text{VP}] = (\text{V}, \text{NP}, 2)$, enabling the optimal derivation to be recovered.

5193 **10.3.2 Probabilistic context-free grammars**

5194 **Probabilistic context-free grammars (PCFGs)** are a special case of weighted context-
5195 free grammars that arises when the weights correspond to probabilities. Specifically, the
5196 weight $\psi(X \rightarrow \alpha, (i, j, k)) = \log p(\alpha | X)$, where the probability of the right-hand side
5197 α is conditioned on the non-terminal X . These probabilities must be normalized over all
5198 possible right-hand sides, so that $\sum_\alpha p(\alpha | X) = 1$, for all X . For a given parse τ , the prod-
5199 uct of the probabilities of the productions is equal to $p(\tau)$, under the **generative model**
5200 $\tau \sim \text{DRAWSUBTREE}(S)$, where the function DRAWSUBTREE is defined in Algorithm 15.

5201 The conditional probability of a parse given a string is,

$$p(\tau | w) = \frac{p(\tau)}{\sum_{\tau' \in \mathcal{T}(w)} p(\tau')} = \frac{\exp \Psi(\tau)}{\sum_{\tau' \in \mathcal{T}(w)} \exp \Psi(\tau')}, \quad [10.10]$$

5202 where $\Psi(\tau) = \sum_{X \rightarrow \alpha, (i, j, k) \in \tau} \psi(X \rightarrow \alpha)$; the anchor is ignored. Because the probability
5203 is monotonic in the score $\Psi(\tau)$, the maximum likelihood parse can be identified by the
5204 CKY algorithm without modification. If a normalized probability $p(\tau | w)$ is required,
5205 the denominator of Equation 10.10 can be computed by the **inside recurrence**, described
5206 below.

Example The WCFG in Table 10.2 is designed so that the weights are log-probabilities, satisfying the constraint $\sum_{\alpha} \exp \psi(X \rightarrow \alpha) = 1$. As noted earlier, there are two parses in $\mathcal{T}(\text{we eat sushi with chopsticks})$, with scores $\Psi(\tau_1) = \log p(\tau_1) = -10$ and $\Psi(\tau_2) = \log p(\tau_2) = -11$. Therefore, the conditional probability $p(\tau_1 | \mathbf{w})$ is equal to,

$$p(\tau_1 | \mathbf{w}) = \frac{p(\tau_1)}{p(\tau_1) + p(\tau_2)} = \frac{\exp \Psi(\tau_1)}{\exp \Psi(\tau_1) + \exp \Psi(\tau_2)} = \frac{2^{-10}}{2^{-10} + 2^{-11}} = \frac{2}{3}. \quad [10.11]$$

5207 **The inside recurrence** The denominator of Equation 10.10 can be viewed as a language
5208 model, summing over all valid derivations of the string \mathbf{w} ,

$$p(\mathbf{w}) = \sum_{\tau': \text{yield}(\tau') = \mathbf{w}} p(\tau'). \quad [10.12]$$

Just as the CKY algorithm makes it possible to maximize over all such analyses, with a few modifications it can also compute their sum. Each cell $t[i, j, X]$ must store the log probability of deriving $\mathbf{w}_{i+1:j}$ from non-terminal X . To compute this, we replace the maximization over split points k and productions $X \rightarrow Y Z$ with a “log-sum-exp” operation, which exponentiates the log probabilities of the production and the children, sums them in probability space, and then converts back to the log domain:

$$t[i, j, X] = \log \sum_{k, Y, Z} \exp (\psi(X \rightarrow Y Z) + t[i, k, Y] + t[k, j, Z]) \quad [10.13]$$

$$= \log \sum_{k, Y, Z} \exp (\log p(Y Z | X) + \log p(Y \rightarrow \mathbf{w}_{i+1:k}) + \log p(Z \rightarrow \mathbf{w}_{k+1:j})) \quad [10.14]$$

$$= \log \sum_{k, Y, Z} p(Y Z | X) \times p(Y \rightarrow \mathbf{w}_{i+1:k}) \times p(Z \rightarrow \mathbf{w}_{k+1:j}) \quad [10.15]$$

$$= \log \sum_{k, Y, Z} p(Y Z, \mathbf{w}_{i+1:k}, \mathbf{w}_{k+1:j} | X) \quad [10.16]$$

$$= \log p(X \rightarrow \mathbf{w}_{i+1:j}). \quad [10.17]$$

5209 This is called the **inside recurrence**, because it computes the probability of each subtree
5210 as a combination of the probabilities of the smaller subtrees that are inside of it. The
5211 name implies a corresponding **outside recurrence**, which computes the probability of
5212 a non-terminal X spanning $\mathbf{w}_{i+1:j}$, joint with the outside context $(\mathbf{w}_{1:i}, \mathbf{w}_{j+1:M})$. This
5213 recurrence is described in § 10.4.3. The inside and outside recurrences are analogous to the
5214 forward and backward recurrences in probabilistic sequence labeling (see § 7.5.3.3). They
5215 can be used to compute the marginal probabilities of individual anchored productions,
5216 $p(X \rightarrow \alpha, (i, j, k) | \mathbf{w})$, summing over all possible derivations of \mathbf{w} .

5217 **10.3.3 *Semiring weighted context-free grammars**

The weighted and unweighted CKY algorithms can be unified with the inside recurrence using the same semiring notation described in § 7.7.3. The generalized recurrence is:

$$t[i, j, X] = \bigoplus_{k, Y, Z} \psi(X \rightarrow Y Z, (i, j, k)) \otimes t[i, k, Y] \otimes t[k, j, Z]. \quad [10.18]$$

5218 This recurrence subsumes all of the algorithms that we have encountered in this chapter.

5219 **Unweighted CKY.** When $\psi(X \rightarrow \alpha, (i, j, k))$ is a *Boolean truth value* $\{\top, \perp\}$, \otimes is logical
5220 conjunction, and \bigoplus is logical disjunction, then we derive the CKY recurrence for
5221 unweighted context-free grammars, discussed in § 10.1 and Algorithm 13.

5222 **Weighted CKY.** When $\psi(X \rightarrow \alpha, (i, j, k))$ is a scalar score, \otimes is addition, and \bigoplus is maxi-
5223 mization, then we derive the CKY recurrence for weighted context-free grammars,
5224 discussed in § 10.3 and Algorithm 14. When $\psi(X \rightarrow \alpha, (i, j, k)) = \log p(\alpha \mid X)$,
5225 this same setting derives the CKY recurrence for finding the maximum likelihood
5226 derivation in a probabilistic context-free grammar.

5227 **Inside recurrence.** When $\psi(X \rightarrow \alpha, (i, j, k))$ is a log probability, \otimes is addition, and $\bigoplus =$
5228 $\log \sum \exp$, then we derive the inside recurrence for probabilistic context-free gram-
5229 mmars, discussed in § 10.3.2. It is also possible to set $\psi(X \rightarrow \alpha, (i, j, k))$ directly equal
5230 to the probability $p(\alpha \mid X)$. In this case, \otimes is multiplication, and \bigoplus is addition.
5231 While this may seem more intuitive than working with log probabilities, there is the
5232 risk of underflow on long inputs.

5233 Regardless of how the scores are combined, the key point is the locality assumption:
5234 the score for a derivation is the combination of the independent scores for each anchored
5235 production, and these scores do not depend on any other part of the derivation. For exam-
5236 ple, if two non-terminals are siblings, the scores of productions from these non-terminals
5237 are computed independently. This locality assumption is analogous to the first-order
5238 Markov assumption in sequence labeling, where the score for transitions between tags
5239 depends only on the previous tag and current tag, and not on the history. As with se-
5240 quence labeling, this assumption makes it possible to find the optimal parse efficiently; its
5241 linguistic limitations are discussed in § 10.5.

5242 **10.4 Learning weighted context-free grammars**

5243 Like sequence labeling, context-free parsing is a form of structure prediction. As a result,
5244 WCFGs can be learned using the same set of algorithms: generative probabilistic models,
5245 structured perceptron, maximum conditional likelihood, and maximum margin learning.

5246 In all cases, learning requires a **treebank**, which is a dataset of sentences labeled with
 5247 context-free parses. Parsing research was catalyzed by the **Penn Treebank** (Marcus et al.,
 5248 1993), the first large-scale dataset of this type (see § 9.2.2). Phrase structure treebanks exist
 5249 for roughly two dozen other languages, with coverage mainly restricted to European and
 5250 East Asian languages, plus Arabic and Urdu.

5251 **10.4.1 Probabilistic context-free grammars**

Probabilistic context-free grammars are similar to hidden Markov models, in that they are generative models of text. In this case, the parameters of interest correspond to probabilities of productions, conditional on the left-hand side. As with hidden Markov models, these parameters can be estimated by relative frequency:

$$\psi(X \rightarrow \alpha) = \log p(X \rightarrow \alpha) \quad [10.19]$$

$$\hat{p}(X \rightarrow \alpha) = \frac{\text{count}(X \rightarrow \alpha)}{\text{count}(X)}. \quad [10.20]$$

5252 For example, the probability of the production $NP \rightarrow DET\ NN$ is the corpus count of
 5253 this production, divided by the count of the non-terminal NP . This estimator applies
 5254 to terminal productions as well: the probability of $NN \rightarrow whale$ is the count of how often
 5255 *whale* appears in the corpus as generated from an NN tag, divided by the total count of the
 5256 NN tag. Even with the largest treebanks — currently on the order of one million tokens
 5257 — it is difficult to accurately compute probabilities of even moderately rare events, such
 5258 as $NN \rightarrow whale$. Therefore, smoothing is critical for making PCFGs effective.

5259 **10.4.2 Feature-based parsing**

5260 The scores for each production can be computed as an inner product of weights and fea-
 5261 tures,

$$\psi(X \rightarrow \alpha) = \boldsymbol{\theta} \cdot \mathbf{f}(X, \alpha, (i, j, k), \mathbf{w}), \quad [10.21]$$

5262 where the feature vector $\mathbf{f}(X, \alpha)$ is a function of the left-hand side X , the right-hand side
 5263 α , the anchor indices (i, j, k) , and the input \mathbf{w} .

5264 The basic feature $\mathbf{f}(X, \alpha, (i, j, k)) = \{(X, \alpha)\}$ encodes only the identity of the pro-
 5265 duction itself, which is a discriminatively-trained model with the same expressiveness as
 5266 a PCFG. Features on anchored productions can include the words that border the span
 5267 w_i, w_{j+1} , the word at the split point w_{k+1} , the presence of a verb or noun in the left child
 5268 span $w_{i+1:k}$, and so on (Durrett and Klein, 2015). Scores on anchored productions can be
 5269 incorporated into CKY parsing without any modification to the algorithm, because it is
 5270 still possible to compute each element of the table $t[i, j, X]$ recursively from its immediate
 5271 children.

5272 Other features can be obtained by grouping elements on either the left-hand or right-
 5273 hand side: for example it can be particularly beneficial to compute additional features
 5274 by clustering terminal symbols, with features corresponding to groups of words with
 5275 similar syntactic properties. The clustering can be obtained from unlabeled datasets that
 5276 are much larger than any treebank, improving coverage. Such methods are described in
 5277 chapter 14.

Feature-based parsing models can be estimated using the usual array of discriminative learning techniques. For example, a structure perceptron update can be computed as (Carreras et al., 2008),

$$\mathbf{f}(\tau, \mathbf{w}^{(i)}) = \sum_{(X \rightarrow \alpha, (i, j, k)) \in \tau} \mathbf{f}(X, \alpha, (i, j, k), \mathbf{w}^{(i)}) \quad [10.22]$$

$$\hat{\tau} = \operatorname{argmax}_{\tau \in \mathcal{T}(\mathbf{w})} \mathbf{f}(\tau, \mathbf{w}^{(i)}) \quad [10.23]$$

$$\boldsymbol{\theta} \leftarrow \mathbf{f}(\tau^{(i)}, \mathbf{w}^{(i)}) - \mathbf{f}(\hat{\tau}, \mathbf{w}^{(i)}). \quad [10.24]$$

5278 A margin-based objective can be optimized by selecting $\hat{\tau}$ through cost-augmented decoding (§ 2.3.2), enforcing a margin of $\Delta(\hat{\tau}, \tau)$ between the hypothesis and the reference parse,
 5279 where Δ is a non-negative cost function, such as the Hamming loss (Stern et al., 2017). It
 5280 is also possible to train feature-based parsing models by conditional log-likelihood, as
 5281 described in the next section.

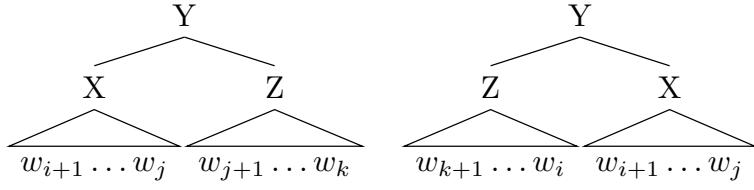
5283 10.4.3 *Conditional random field parsing

5284 The score of a derivation $\Psi(\tau)$ can be converted into a probability by normalizing over all
 5285 possible derivations,

$$p(\tau | \mathbf{w}) = \frac{\exp \Psi(\tau)}{\sum_{\tau' \in \mathcal{T}(\mathbf{w})} \exp \Psi(\tau')}. \quad [10.25]$$

5286 Using this probability, a WCFG can be trained by maximizing the conditional log-likelihood
 5287 of a labeled corpus.

5288 Just as in logistic regression and the conditional random field over sequences, the
 5289 gradient of the conditional log-likelihood is the difference between the observed and ex-
 5290 pected counts of each feature. The expectation $E_{\tau|\mathbf{w}}[\mathbf{f}(\tau, \mathbf{w}^{(i)}); \boldsymbol{\theta}]$ requires summing over
 5291 all possible parses, and computing the marginal probabilities of anchored productions,
 5292 $p(X \rightarrow \alpha, (i, j, k) | \mathbf{w})$. In CRF sequence labeling, marginal probabilities over tag bigrams
 5293 are computed by the two-pass **forward-backward algorithm** (§ 7.5.3.3). The analogue for
 5294 context-free grammars is the **inside-outside algorithm**, in which marginal probabilities
 5295 are computed from terms generated by an upward and downward pass over the parsing
 5296 chart:

Figure 10.3: The two cases faced by the outside recurrence in the computation of $\beta(i, j, X)$

- The upward pass is performed by the **inside recurrence**, which is described in § 10.3.2. Each inside variable $\alpha(i, j, X)$ is the score of deriving $w_{i+1:j}$ from the non-terminal X . In a PCFG, this corresponds to the log-probability $\log p(w_{i+1:j} \mid X)$. This is computed by the recurrence,

$$\alpha(i, j, X) \triangleq \log \sum_{(X \rightarrow Y \ Z)} \sum_{k=i+1}^j \exp (\psi(X \rightarrow Y \ Z, (i, j, k)) + \alpha(i, k, Y) + \alpha(k, j, Z)). \quad [10.26]$$

5297 The initial condition of this recurrence is $\alpha(m - 1, m, X) = \psi(X \rightarrow w_m)$. The de-
5298 nominator $\sum_{\tau \in \mathcal{T}(w)} \exp \Psi(\tau)$ is equal to $\exp \alpha(0, M, S)$.

- The downward pass is performed by the **outside recurrence**, which recursively populates the same table structure, starting at the root of the tree. Each outside variable $\beta(i, j, X)$ is the score of having a phrase of type X covering the span $(i + 1 : j)$, joint with the exterior context $w_{1:i}$ and $w_{j+1:M}$. In a PCFG, this corresponds to the log probability $\log p((X, i + 1, j), w_{1:i}, w_{j+1:M})$. Each outside variable is computed by the recurrence,

$$\exp \beta(i, j, X) \triangleq \sum_{(Y \rightarrow X \ Z)} \sum_{k=j+1}^M \exp [\psi(Y \rightarrow X \ Z, (i, k, j)) + \alpha(j, k, Z) + \beta(i, k, Y)] \quad [10.27]$$

$$+ \sum_{(Y \rightarrow Z \ X)} \sum_{k=0}^{i-1} \exp [\psi(Y \rightarrow Z \ X, (k, i, j)) + \alpha(k, i, Z) + \beta(k, j, Y)]. \quad [10.28]$$

5299 The first line of Equation 10.28 is the score under the condition that X is a left child
5300 of its parent, which spans $w_{i+1:k}$, with $k > j$; the second line is the score under the
5301 condition that X is a right child of its parent Y , which spans $w_{k+1:j}$, with $k < i$.
5302 The two cases are shown in Figure 10.3. In each case, we sum over all possible
5303 productions with X on the right-hand side. The parent Y is bounded on one side

5304 by either i or j , depending on whether X is a left or right child of Y ; we must sum
 5305 over all possible values for the other boundary. The initial conditions for the outside
 5306 recurrence are $\beta(0, M, S) = 0$ and $\beta(0, M, X \neq S) = -\infty$.

The marginal probability of a non-terminal X over span $w_{i+1:j}$ is written $p(X \rightsquigarrow w_{i+1:j} | w)$, and can be computed from the inside and outside scores,

$$p(X \rightsquigarrow w_{i+1:j} | w) = \frac{p(X \rightsquigarrow w_{i+1:j}, w)}{p(w)} \quad [10.29]$$

$$= \frac{p(w_{i+1:j} | X) \times p(X, w_{1:i}, w_{j+1:M})}{p(w)} \quad [10.30]$$

$$= \frac{\exp(\alpha(i, j, X) + \beta(i, j, X))}{\exp \alpha(0, M, S)}. \quad [10.31]$$

5307 Marginal probabilities of individual productions can be computed similarly (see exercise
 5308 2). These marginal probabilities can be used for training a conditional random field parser,
 5309 and also for the task of unsupervised **grammar induction**, in which a PCFG is estimated
 5310 from a dataset of unlabeled text (Lari and Young, 1990; Pereira and Schabes, 1992).

5311 10.4.4 Neural context-free grammars

5312 Recent work has applied neural representations to parsing, representing each span with
 5313 a dense numerical vector (Socher et al., 2013; Durrett and Klein, 2015; Cross and Huang,
 5314 2016).⁴ For example, the anchor (i, j, k) and sentence w can be associated with a fixed-
 5315 length column vector,

$$\mathbf{v}_{(i,j,k)} = [\mathbf{u}_{w_{i-1}}; \mathbf{u}_{w_i}; \mathbf{u}_{w_{j-1}}; \mathbf{u}_{w_j}; \mathbf{u}_{w_{k-1}}; \mathbf{u}_{w_k}], \quad [10.32]$$

where \mathbf{u}_{w_i} is a word embedding associated with the word w_i . The vector $\mathbf{v}_{i,j,k}$ can then be passed through a feedforward neural network, and used to compute the score of the anchored production. For example, this score can be computed as a bilinear product (Durrett and Klein, 2015),

$$\tilde{\mathbf{v}}_{(i,j,k)} = \text{FeedForward}(\mathbf{v}_{(i,j,k)}) \quad [10.33]$$

$$\psi(X \rightarrow \alpha, (i, j, k)) = \tilde{\mathbf{v}}_{(i,j,k)}^\top \Theta \mathbf{f}(X \rightarrow \alpha), \quad [10.34]$$

5316 where $\mathbf{f}(X \rightarrow \alpha)$ is a vector of discrete features of the production, and Θ is a parameter
 5317 matrix. The matrix Θ and the parameters of the feedforward network can be learned by
 5318 backpropagating from an objective such as the margin loss or the negative conditional
 5319 log-likelihood.

⁴Earlier work on neural constituent parsing used transition-based parsing algorithms (§ 10.6.2) rather than CKY-style chart parsing (Henderson, 2004; Titov and Henderson, 2007).

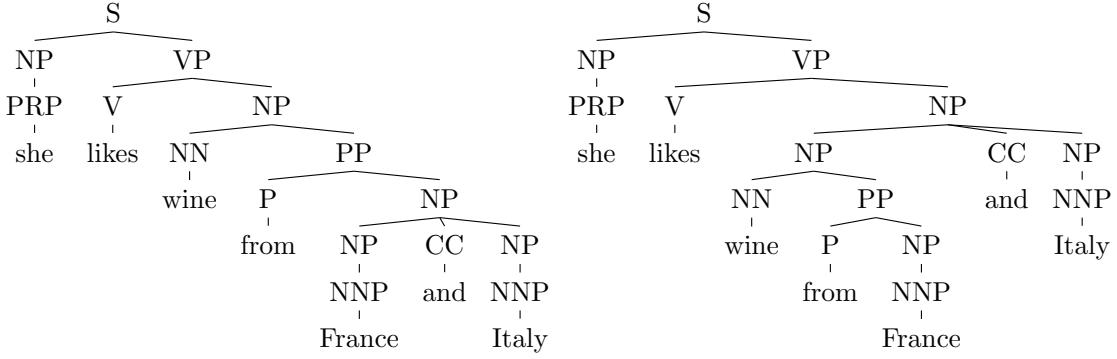


Figure 10.4: The left parse is preferable because of the conjunction of phrases headed by *France* and *Italy*, but these parses cannot be distinguished by a WCFG.

5320 10.5 Grammar refinement

5321 The locality assumptions underlying CFG parsing depend on the granularity of the non-
 5322 terminals. For the Penn Treebank non-terminals, there are several reasons to believe that
 5323 these assumptions are too strong to enable accurate parsing (Johnson, 1998):

- 5324 • The context-free assumption is too strict: for example, the probability of the produc-
 5325 tion $NP \rightarrow NP\ PP$ is much higher (in the PTB) if the parent of the noun phrase is a
 5326 verb phrase (indicating that the NP is a direct object) than if the parent is a sentence
 5327 (indicating that the NP is the subject of the sentence).
- 5328 • The Penn Treebank non-terminals are too coarse: there are many kinds of noun
 5329 phrases and verb phrases, and accurate parsing sometimes requires knowing the
 5330 difference. As we have already seen, when faced with prepositional phrase at-
 5331 tachment ambiguity, a weighted CFG will either always choose NP attachment (if
 5332 $\psi(NP \rightarrow NP\ PP) > \psi(VP \rightarrow VP\ PP)$), or it will always choose VP attachment. To
 5333 get more nuanced behavior, more fine-grained non-terminals are needed.
- 5334 • More generally, accurate parsing requires some amount of **semantics** — understand-
 5335 ing the meaning of the text to be parsed. Consider the example *cats scratch people with*
 5336 *claws*: knowledge of about *cats*, *claws*, and scratching is necessary to correctly resolve
 5337 the attachment ambiguity.

5338 An extreme example is shown in Figure 10.4. The analysis on the left is preferred
 5339 because of the conjunction of similar entities *France* and *Italy*. But given the non-terminals
 5340 shown in the analyses, there is no way to differentiate these two parses, since they include
 5341 exactly the same productions. What is needed seems to be more precise non-terminals.
 5342 One possibility would be to rethink the linguistics behind the Penn Treebank, and ask

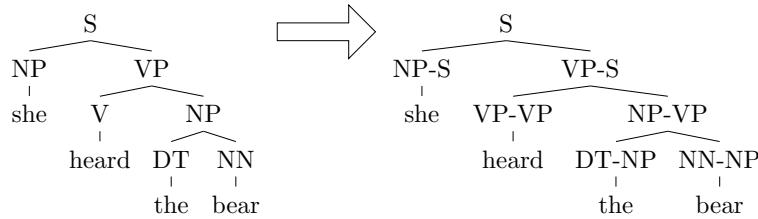


Figure 10.5: Parent annotation in a CFG derivation

5343 the annotators to try again. But the original annotation effort took five years, and there
 5344 is a little appetite for another annotation effort of this scope. Researchers have therefore
 5345 turned to automated techniques.

5346 10.5.1 Parent annotations and other tree transformations

The key assumption underlying context-free parsing is that productions depend only on the identity of the non-terminal on the left-hand side, and not on its ancestors or neighbors. The validity of this assumption is an empirical question, and it depends on the non-terminals themselves: ideally, every noun phrase (and verb phrase, etc) would be distributionally identical, so the assumption would hold. But in the Penn Treebank, the observed probability of productions often depends on the parent of the left-hand side. For example, noun phrases are more likely to be modified by prepositional phrases when they are in the object position (e.g., *they amused the students from Georgia*) than in the subject position (e.g., *the students from Georgia amused them*). This means that the $\text{NP} \rightarrow \text{NP PP}$ production is more likely if the entire constituent is the child of a VP than if it is the child of S. The observed statistics are (Johnson, 1998):

$$\Pr(\text{NP} \rightarrow \text{NP PP}) = 11\% \quad [10.35]$$

$$\Pr(\text{NP under S} \rightarrow \text{NP PP}) = 9\% \quad [10.36]$$

$$\Pr(\text{NP under VP} \rightarrow \text{NP PP}) = 23\%. \quad [10.37]$$

5347 This phenomenon can be captured by **parent annotation** (Johnson, 1998), in which each
 5348 non-terminal is augmented with the identity of its parent, as shown in Figure 10.5). This is
 5349 sometimes called **vertical Markovization**, since a Markov dependency is introduced be-
 5350 tween each node and its parent (Klein and Manning, 2003). It is analogous to moving from
 5351 a bigram to a trigram context in a hidden Markov model. In principle, parent annotation
 5352 squares the size of the set of non-terminals, which could make parsing considerably less
 5353 efficient. But in practice, the increase in the number of non-terminals that actually appear
 5354 in the data is relatively modest (Johnson, 1998).

5355 Parent annotation weakens the WCFG locality assumptions. This improves accuracy
 5356 by enabling the parser to make more fine-grained distinctions, which better capture real
 5357 linguistic phenomena. However, each production is more rare, and so careful smoothing
 5358 or regularization is required to control the variance over production scores.

5359 10.5.2 Lexicalized context-free grammars

5360 The examples in § 10.2.2 demonstrate the importance of individual words in resolving
 5361 parsing ambiguity: the preposition *on* is more likely to attach to *met*, while the preposition
 5362 *of* is more likely to attachment to *President*. But of all word pairs, which are relevant to
 5363 attachment decisions? Consider the following variants on the original examples:

- 5364 (10.4) We met the President of Mexico.
- 5365 (10.5) We met the first female President of Mexico.
- 5366 (10.6) They had supposedly met the President on Monday.

5367 The underlined words are the **head words** of their respective phrases: *met* heads the verb
 5368 phrase, and *President* heads the direct object noun phrase. These heads provide useful
 5369 semantic information. But they break the context-free assumption, which states that the
 5370 score for a production depends only on the parent and its immediate children, and not
 5371 the substructure under each child.

The incorporation of head words into context-free parsing is known as **lexicalization**,
 and is implemented in rules of the form,

$$\text{NP}(\text{President}) \rightarrow \text{NP}(\text{President}) \text{ PP}(of) \quad [10.38]$$

$$\text{NP}(\text{President}) \rightarrow \text{NP}(\text{President}) \text{ PP}(on). \quad [10.39]$$

5372 Lexicalization was a major step towards accurate PCFG parsing. It requires solving three
 5373 problems: identifying the heads of all constituents in a treebank; parsing efficiently while
 5374 keeping track of the heads; and estimating the scores for lexicalized productions.

5375 10.5.2.1 Identifying head words

5376 The head of a constituent is the word that is the most useful for determining how that
 5377 constituent is integrated into the rest of the sentence.⁵ The head word of a constituent is
 5378 determined recursively: for any non-terminal production, the head of the left-hand side
 5379 must be the head of one of the children. The head is typically selected according to a set of
 5380 deterministic rules, sometimes called **head percolation rules**. In many cases, these rules
 5381 are straightforward: the head of a noun phrase in a $\text{NP} \rightarrow \text{DET NN}$ production is the head

⁵This is a pragmatic definition, befitting our goal of using head words to improve parsing; for a more formal definition, see (Bender, 2013, chapter 7).

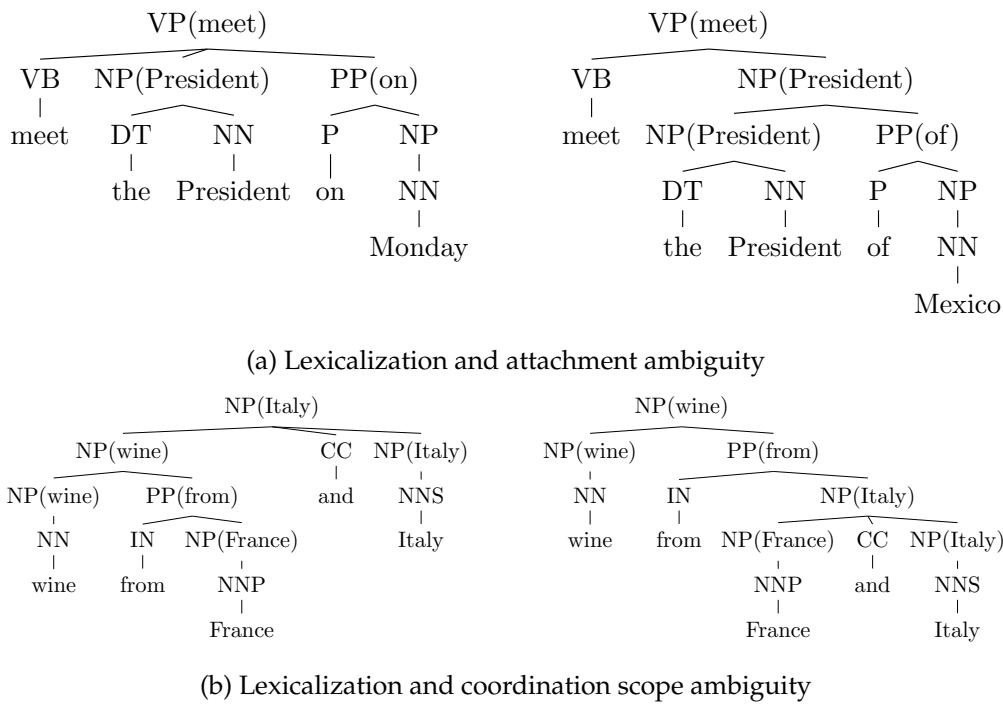


Figure 10.6: Examples of lexicalization

5382 of the noun; the head of a sentence in a $S \rightarrow NP\ VP$ production is the head of the verb
5383 phrase.

Table 10.3 shows a fragment of the head percolation rules used in many English parsing systems. The meaning of the first rule is that to find the head of an S constituent, first look for the rightmost VP child; if you don't find one, then look for the rightmost SBAR child, and so on down the list. Verb phrases are headed by left verbs (the head of *can plan on walking* is *planned*, since the modal verb *can* is tagged MD); noun phrases are headed by the rightmost noun-like non-terminal (so the head of *the red cat* is *cat*),⁶ and prepositional phrases are headed by the preposition (the head of *at Georgia Tech* is *at*). Some of these rules are somewhat arbitrary — there's no particular reason why the head of *cats and dogs* should be *dogs* — but the point here is just to get some lexical information that can support parsing, not to make deep claims about syntax. Figure 10.6 shows the application of these rules to two of the running examples.

⁶The noun phrase non-terminal is sometimes treated as a special case. Collins (1997) uses a heuristic that looks for the rightmost child which is a noun-like part-of-speech (e.g., NN, NNP), a possessive marker, or a superlative adjective (e.g., *the greatest*). If no such child is found, the heuristic then looks for the *leftmost* NP. If there is no child with tag NP, the heuristic then applies another priority list, this time from right to left.

Non-terminal	Direction	Priority
S	right	VP SBAR ADJP UCP NP
VP	left	VBD VBN MD VBZ TO VB VP VBG VBP ADJP NP
NP	right	N* EX \$ CD QP PRP ...
PP	left	IN TO FW

Table 10.3: A fragment of head percolation rules for English, from <http://www.cs.columbia.edu/~mcollins/papers/heads>

5395 10.5.2.2 Parsing lexicalized context-free grammars

5396 A naïve application of lexicalization would simply increase the set of non-terminals by
 5397 taking the cross-product with the set of terminal symbols, so that the non-terminals now
 5398 include symbols like $\text{NP}(\text{President})$ and $\text{VP}(\text{meet})$. Under this approach, the CKY parsing
 5399 algorithm could be applied directly to the lexicalized production rules. However, the
 5400 complexity would be cubic in the size of the vocabulary of terminal symbols, which would
 5401 clearly be intractable.

Another approach is to augment the CKY table with an additional index, keeping track of the head of each constituent. The cell $t[i, j, h, X]$ stores the score of the best derivation in which non-terminal X spans $w_{i+1:j}$ with head word h , where $i < h \leq j$. To compute such a table recursively, we must consider the possibility that each phrase gets its head from either its left or right child. The scores of the best derivations in which the head comes from the left and right child are denoted t_ℓ and t_r respectively, leading to the following recurrence:

$$t_\ell[i, j, h, X] = \max_{(X \rightarrow Y Z)} \max_{k > h} \max_{k < h' \leq j} t[i, k, h, Y] + t[k, j, h', Z] + \psi(X(h) \rightarrow Y(h)Z(h')) \quad [10.40]$$

$$t_r[i, j, h, X] = \max_{(X \rightarrow Y Z)} \max_{k < h} \max_{i < h' \leq k} t[i, k, h', Y] + t[k, j, h, Z] + (\psi(X(h) \rightarrow Y(h')Z(h))) \quad [10.41]$$

$$t[i, j, h, X] = \max(t_\ell[i, j, h, X], t_r[i, j, h, X]). \quad [10.42]$$

5402 To compute t_ℓ , we maximize over all split points $k > h$, since the head word must be in
 5403 the left child. We then maximize again over possible head words h' for the right child. An
 5404 analogous computation is performed for t_r . The size of the table is now $\mathcal{O}(M^3N)$, where
 5405 M is the length of the input and N is the number of non-terminals. Furthermore, each
 5406 cell is computed by performing $\mathcal{O}(M^2)$ operations, since we maximize over both the split
 5407 point k and the head h' . The time complexity of the algorithm is therefore $\mathcal{O}(RM^5N)$,
 5408 where R is the number of rules in the grammar. Fortunately, more efficient solutions are
 5409 possible. In general, the complexity of parsing can be reduced to $\mathcal{O}(M^4)$ in the length of

5410 the input; for a broad class of lexicalized CFGs, the complexity can be made cubic in the
 5411 length of the input, just as in unlexicalized CFGs (Eisner, 2000).

5412 **10.5.2.3 Estimating lexicalized context-free grammars**

5413 The final problem for lexicalized parsing is how to estimate weights for lexicalized pro-
 5414 ductions $X(i) \rightarrow Y(j) Z(k)$. These productions are said to be **bilexical**, because they
 5415 involve scores over pairs of words: in the example *meet the President of Mexico*, we hope
 5416 to choose the correct attachment point by modeling the bilexical affinities of (*meet, of*) and
 5417 (*President, of*). The number of such word pairs is quadratic in the size of the vocabulary,
 5418 making it difficult to estimate the weights of lexicalized production rules directly from
 5419 data. This is especially true for probabilistic context-free grammars, in which the weights
 5420 are obtained from smoothed relative frequency. In a treebank with a million tokens, a
 5421 vanishingly small fraction of the possible lexicalized productions will be observed more
 5422 than once.⁷ The Charniak (1997) and Collins (1997) parsers therefore focus on approxi-
 5423 mating the probabilities of lexicalized productions, using various smoothing techniques
 5424 and independence assumptions.

In discriminatively-trained weighted context-free grammars, the scores for each production can be computed from a set of features, which can be made progressively more fine-grained (Finkel et al., 2008). For example, the score of the lexicalized production $\text{NP}(\text{President}) \rightarrow \text{NP}(\text{President}) \text{ PP}(of)$ can be computed from the following features:

$$\begin{aligned} f(\text{NP}(\text{President}) \rightarrow \text{NP}(\text{President}) \text{ PP}(of)) = & \{\text{NP}(\text{*}) \rightarrow \text{NP}(\text{*}) \text{ PP}(\text{*}), \\ & \text{NP}(\text{President}) \rightarrow \text{NP}(\text{President}) \text{ PP}(\text{*}), \\ & \text{NP}(\text{*}) \rightarrow \text{NP}(\text{*}) \text{ PP}(of), \\ & \text{NP}(\text{President}) \rightarrow \text{NP}(\text{President}) \text{ PP}(of)\} \end{aligned}$$

5425 The first feature scores the unlexicalized production $\text{NP} \rightarrow \text{NP PP}$; the next two features
 5426 lexicalize only one element of the production, thereby scoring the appropriateness of NP
 5427 attachment for the individual words *President* and *of*; the final feature scores the specific
 5428 bilexical affinity of *President* and *of*. For bilexical pairs that are encountered frequently in
 5429 the treebank, this bilexical feature can play an important role in parsing; for pairs that are
 5430 absent or rare, regularization will drive its weight to zero, forcing the parser to rely on the
 5431 more coarse-grained features.

5432 In chapter 14, we will encounter techniques for clustering words based on their **distribu-**
 5433 **tional** properties — the contexts in which they appear. Such a clustering would group
 5434 rare and common words, such as *whale*, *shark*, *Leviathan*. Word clusters can be used

⁷The real situation is even more difficult, because non-binary context-free grammars can involve **trilexical** or higher-order dependencies, between the head of the constituent and multiple of its children (Carreras et al., 2008).

5435 as features in discriminative lexicalized parsing, striking a middle ground between full
 5436 lexicalization and non-terminals (Finkel et al., 2008). In this way, labeled examples con-
 5437 taining relatively common words like *whale* can help to improve parsing for rare words
 5438 like *beluga*, as long as those two words are clustered together.

5439 **10.5.3 *Refinement grammars**

5440 Lexicalization improves on context-free parsing by adding detailed information in the
 5441 form of lexical heads. However, estimating the scores of lexicalized productions is dif-
 5442 ficult. Klein and Manning (2003) argue that the right level of linguistic detail is some-
 5443 where between treebank categories and individual words. Some parts-of-speech and non-
 5444 terminals are truly substitutable: for example, *cat*/N and *dog*/N. But others are not: for
 5445 example, the preposition *of* exclusively attaches to nouns, while the preposition *as* is more
 5446 likely to modify verb phrases. Klein and Manning (2003) obtained a 2% improvement in
 5447 *F*-MEASURE on a parent-annotated PCFG parser by making a single change: splitting the
 5448 preposition category into six subtypes. They propose a series of linguistically-motivated
 5449 refinements to the Penn Treebank annotations, which in total yielded a 40% error reduc-
 5450 tion.

5451 Non-terminal refinement process can be automated by treating the refined categories
 5452 as latent variables. For example, we might split the noun phrase non-terminal into NP1, NP2, NP3, ...,
 5453 without defining in advance what each refined non-terminal corresponds to. This can
 5454 be treated as **partially supervised learning**, similar to the multi-component document
 5455 classification model described in § 5.2.3. A latent variable PCFG can be estimated by
 5456 expectation-maximization (Matsuzaki et al., 2005):

- 5457 • In the E-step, estimate a marginal distribution q over the refinement type of each
 5458 non-terminal in each derivation. These marginals are constrained by the original
 5459 annotation: an NP can be reannotated as NP4, but not as VP3. Marginal probabili-
 5460 ties over refined productions can be computed from the **inside-outside algorithm**,
 5461 as described in § 10.4.3, where the E-step enforces the constraints imposed by the
 5462 original annotations.
- 5463 • In the M-step, recompute the parameters of the grammar, by summing over the
 5464 probabilities of anchored productions that were computed in the E-step:

$$E[\text{count}(X \rightarrow Y Z)] = \sum_{i=0}^M \sum_{j=i}^M \sum_{k=i}^j p(X \rightarrow Y Z, (i, j, k) | \mathbf{w}). \quad [10.43]$$

5465 As usual, this process can be iterated to convergence. To determine the number of re-
 5466 finement types for each tag, Petrov et al. (2006) apply a split-merge heuristic; Liang et al.
 5467 (2007) and Finkel et al. (2007) apply **Bayesian nonparametrics** (Cohen, 2016).

Proper nouns			
NNP-14	<i>Oct.</i>	<i>Nov.</i>	<i>Sept.</i>
NNP-12	<i>John</i>	<i>Robert</i>	<i>James</i>
NNP-2	<i>J.</i>	<i>E.</i>	<i>L.</i>
NNP-1	<i>Bush</i>	<i>Noriega</i>	<i>Peters</i>
NNP-15	<i>New</i>	<i>San</i>	<i>Wall</i>
NNP-3	<i>York</i>	<i>Francisco</i>	<i>Street</i>
Personal Pronouns			
PRP-0	<i>It</i>	<i>He</i>	<i>I</i>
PRP-1	<i>it</i>	<i>he</i>	<i>they</i>
PRP-2	<i>it</i>	<i>them</i>	<i>him</i>

Table 10.4: Examples of automatically refined non-terminals and some of the words that they generate (Petrov et al., 2006).

5468 Some examples of refined non-terminals are shown in Table 10.4. The proper nouns
 5469 differentiate months, first names, middle initials, last names, first names of places, and
 5470 second names of places; each of these will tend to appear in different parts of grammatical
 5471 productions. The personal pronouns differentiate grammatical role, with PRP-0 appear-
 5472 ing in subject position at the beginning of the sentence (note the capitalization), PRP-1
 5473 appearing in subject position but not at the beginning of the sentence, and PRP-2 appear-
 5474 ing in object position.

5475 10.6 Beyond context-free parsing

5476 In the context-free setting, the score for a parse is a combination of the scores of individual
 5477 productions. As we have seen, these models can be improved by using finer-grained non-
 5478 terminals, via parent-annotation, lexicalization, and automated refinement. However, the
 5479 inherent limitations to the expressiveness of context-free parsing motivate the consider-
 5480 ation of other search strategies. These strategies abandon the optimality guaranteed by
 5481 bottom-up parsing, in exchange for the freedom to consider arbitrary properties of the
 5482 proposed parses.

5483 10.6.1 Reranking

5484 A simple way to relax the restrictions of context-free parsing is to perform a two-stage pro-
 5485 cess, in which a context-free parser generates a k -best list of candidates, and a **reranker**
 5486 then selects the best parse from this list (Charniak and Johnson, 2005; Collins and Koo,
 5487 2005). The reranker can be trained from an objective that is similar to multi-class classi-
 5488 fication: the goal is to learn weights that assign a high score to the reference parse, or to

5489 the parse on the k -best list that has the lowest error. In either case, the reranker need only
 5490 evaluate the K best parses, and so no context-free assumptions are necessary. This opens
 5491 the door to more expressive scoring functions:

- 5492 • It is possible to incorporate arbitrary non-local features, such as the structural par-
 5493 allelism and right-branching orientation of the parse (Charniak and Johnson, 2005).
 5494 • Reranking enables the use of **recursive neural networks**, in which each constituent
 5495 span $w_{i+1:j}$ receives a vector $u_{i,j}$ which is computed from the vector representa-
 5496 tions of its children, using a composition function that is linked to the production
 5497 rule (Socher et al., 2013), e.g.,

$$u_{i,j} = f \left(\Theta_{X \rightarrow Y} Z \begin{bmatrix} u_{i,k} \\ u_{k,j} \end{bmatrix} \right) \quad [10.44]$$

5498 The overall score of the parse can then be computed from the final vector, $\Psi(\tau) =$
 5499 $\theta u_{0,M}$.

5500 Reranking can yield substantial improvements in accuracy. The main limitation is that it
 5501 can only find the best parse among the K -best offered by the generator, so it is inherently
 5502 limited by the ability of the bottom-up parser to find high-quality candidates.

5503 10.6.2 Transition-based parsing

5504 Structure prediction can be viewed as a form of search. An alternative to bottom-up pars-
 5505 ing is to read the input from left-to-right, gradually building up a parse structure through
 5506 a series of **transitions**. Transition-based parsing is described in more detail in the next
 5507 chapter, in the context of dependency parsing. However, it can also be applied to CFG
 5508 parsing, as briefly described here.

5509 For any context-free grammar, there is an equivalent **pushdown automaton**, a model
 5510 of computation that accepts exactly those strings that can be derived from the grammar.
 5511 This computational model consumes the input from left to right, while pushing and pop-
 5512 ping elements on a stack. This architecture provides a natural transition-based parsing
 5513 framework for context-free grammars, known as **shift-reduce parsing**.

5514 Shift-reduce parsing is a type of transition-based parsing, in which the parser can take
 5515 the following actions:

- 5516 • *shift* the next terminal symbol onto the stack;
 5517 • *unary-reduce* the top item on the stack, using a unary production rule in the gram-
 5518 mar;
 5519 • *binary-reduce* the top two items onto the stack, using a binary production rule in the
 5520 grammar.

5521 The set of available actions is constrained by the situation: the parser can only shift if
 5522 there are remaining terminal symbols in the input, and it can only reduce if an applicable
 5523 production rule exists in the grammar. If the parser arrives at a state where the input
 5524 has been completely consumed, and the stack contains only the element S, then the input
 5525 is accepted. If the parser arrives at a non-accepting state where there are no possible
 5526 actions, the input is rejected. A parse error occurs if there is some action sequence that
 5527 would accept an input, but the parser does not find it.

5528 **Example** Consider the input *we eat sushi* and the grammar in Table 10.1. The input can
 5529 be parsed through the following sequence of actions:

- 5530 1. **Shift** the first token *we* onto the stack.
- 5531 2. **Reduce** the top item on the stack to NP, using the production $NP \rightarrow we$.
- 5532 3. **Shift** the next token *eat* onto the stack, and **reduce** it to V with the production $V \rightarrow eat$.
- 5534 4. **Shift** the final token *sushi* onto the stack, and **reduce** it to NP. The input has been
 5535 completely consumed, and the stack contains [NP, V, NP].
- 5536 5. **Reduce** the top two items using the production $VP \rightarrow V NP$. The stack now con-
 5537 tains [VP, NP].
- 5538 6. **Reduce** the top two items using the production $S \rightarrow NP VP$. The stack now contains
 5539 [S]. Since the input is empty, this is an accepting state.

5540 One thing to notice from this example is that the number of shift actions is equal to the length of the input. The number of reduce actions is equal to the number of non-terminals in the analysis, which grows linearly in the length of the input. Thus, the overall time complexity of shift-reduce parsing is linear in the length of the input (assuming the complexity of each individual classification decision is constant in the length of the input).
 5545 This is far better than the cubic time complexity required by CKY parsing.

5546 **Transition-based parsing as inference** In general, it is not possible to guarantee that a transition-based parser will find the optimal parse, $\text{argmax}_\tau \Psi(\tau; \mathbf{w})$, even under the usual CFG independence assumptions. We could assign a score to each anchored parsing action in each context, with $\psi(a, c)$ indicating the score of performing action a in context c .
 5549 One might imagine that transition-based parsing could efficiently find the derivation that maximizes the sum of such scores. But this too would require backtracking and searching over an exponentially large number of possible action sequences: if a bad decision is made at the beginning of the derivation, then it may be impossible to recover the optimal action sequence without backtracking to that early mistake. This is known as a **search error**. Transition-based parsers can incorporate arbitrary features, without the restrictive

5556 independence assumptions required by chart parsing; search errors are the price that must
 5557 be paid for this flexibility.

5558 **Learning transition-based parsing** Transition-based parsing can be combined with ma-
 5559 chine learning by training a classifier to select the correct action in each situation. This
 5560 classifier is free to choose any feature of the input, the state of the parser, and the parse
 5561 history. However, there is no optimality guarantee: the parser may choose a suboptimal
 5562 parse, due to a mistake at the beginning of the analysis. Nonetheless, some of the strongest
 5563 CFG parsers are based on the shift-reduce architecture, rather than CKY. A recent genera-
 5564 tion of models links shift-reduce parsing with recurrent neural networks, updating a
 5565 hidden state vector while consuming the input (e.g., Cross and Huang, 2016; Dyer et al.,
 5566 2016). Learning algorithms for transition-based parsing are discussed in more detail in
 5567 § 11.3.

5568 Exercises

1. Consider the following PCFG:

$$p(X \rightarrow X X) = \frac{1}{2} \quad [10.45]$$

$$p(X \rightarrow Y) = \frac{1}{2} \quad [10.46]$$

$$p(Y \rightarrow \sigma) = \frac{1}{|\Sigma|}, \forall \sigma \in \Sigma \quad [10.47]$$

5569 a) Compute the probability $p(\hat{\tau})$ of the maximum probability parse for a string
 5570 $w \in \Sigma^M$.

5571 b) Compute the marginal probability $p(w) = \sum_{\tau: \text{yield}(\tau)=w} p(\tau)$.

5572 c) Compute the conditional probability $p(\hat{\tau} | w)$.

2. Use the inside and outside scores to compute the marginal probability $p(X_{i:j} \rightarrow Y_{i:k-1} Z_{k:j} | w)$,
 indicating that Y spans $w_{i:k-1}$, Z spans $w_{k:j}$, and X is the parent of Y and Z , span-
 ning $w_{i:j}$.
3. Suppose that the potentials $\Psi(X \rightarrow \alpha)$ are log-probabilities, so that $\sum_{\alpha} \exp \Psi(X \rightarrow \alpha) = 1$
 for all X . Verify that the semiring inside recurrence from Equation 10.26 generates
 the log-probability $\log p(w) = \log \sum_{\tau: \text{yield}(\tau)=w} p(\tau)$.
4. more exercises tk

5580

Chapter 11

5581

Dependency parsing

5582 The previous chapter discussed algorithms for analyzing sentences in terms of nested con-
5583 stituents, such as noun phrases and verb phrases. However, many of the key sources of
5584 ambiguity in phrase-structure analysis relate to questions of **attachment**: where to attach a
5585 prepositional phrase or complement clause, how to scope a coordinating conjunction, and
5586 so on. These attachment decisions can be represented with a more lightweight structure:
5587 a directed graph over the words in the sentence, known as a **dependency parse**. Syntac-
5588 tic annotation has shifted its focus to such dependency structures: at the time of this
5589 writing, the **Universal Dependencies** project offers more than 100 dependency treebanks
5590 for more than 60 languages.¹ This chapter will describe the linguistic ideas underlying
5591 dependency grammar, and then discuss exact and transition-based parsing algorithms.
5592 The chapter will also discuss recent research on **learning to search** in transition-based
5593 structure prediction.

5594

11.1 Dependency grammar

5595 While **dependency grammar** has a rich history of its own (Tesnière, 1966; Kübler et al.,
5596 2009), it can be motivated by extension from the lexicalized context-free grammars that
5597 we encountered in previous chapter (§ 10.5.2). Recall that lexicalization augments each
5598 non-terminal with a **head word**. The head of a constituent is identified recursively, using
5599 a set of **head rules**, as shown in Table 10.3. An example of a lexicalized context-free parse
5600 is shown in Figure 11.1a. In this sentence, the head of the S constituent is the main verb,
5601 *scratch*; this non-terminal then produces the noun phrase *the cats*, whose head word is
5602 *cats*, and from which we finally derive the word *the*. Thus, the word *scratch* occupies the
5603 central position for the sentence, with the word *cats* playing a supporting role. In turn, *cats*

¹universaldependencies.org

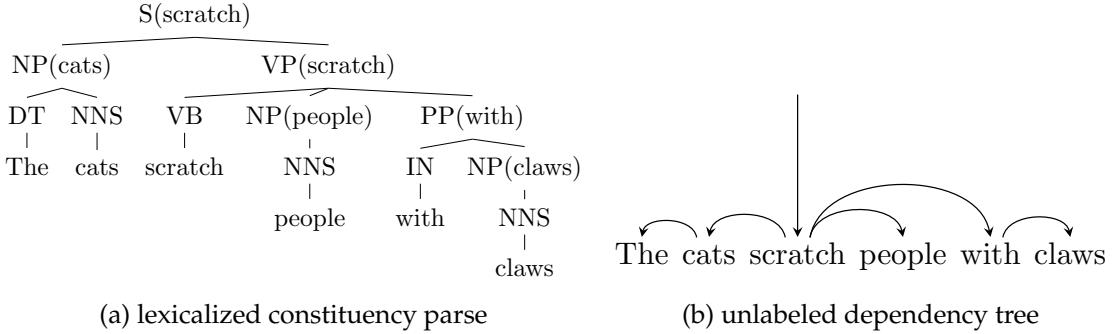


Figure 11.1: Dependency grammar is closely linked to lexicalized context free grammars: each lexical head has a dependency path to every other word in the constituent. (This example is based on the lexicalization rules from § 10.5.2, which make the preposition the head of a prepositional phrase. In the more contemporary Universal Dependencies annotations, the head of *with claws* would be *claws*, so there would be an edge *scratch* → *claws*.)

5604 occupies the central position for the noun phrase, with the word *the* playing a supporting
5605 role.

5606 The relationships between words in a sentence can be formalized in a directed graph,
5607 based on the lexicalized phrase-structure parse: create an edge (i, j) iff word i is the head
5608 of a phrase whose child is a phrase headed by word j . Thus, in our example, we would
5609 have *scratch* → *cats* and *cats* → *the*. We would not have the edge *scratch* → *the*, because
5610 although $S(\text{scratch})$ dominates $\text{DET}(\text{the})$ in the phrase-structure parse tree, it is not its im-
5611 mediate parent. These edges describe **syntactic dependencies**, a bilexical relationship
5612 between a **head** and a **dependent**, which is at the heart of dependency grammar.

5613 Continuing to build out this **dependency graph**, we will eventually reach every word
5614 in the sentence, as shown in Figure 11.1b. In this graph — and in all graphs constructed
5615 in this way — every word has exactly one incoming edge, except for the root word, which
5616 is indicated by a special incoming arrow from above. Furthermore, the graph is *weakly*
5617 *connected*: if the directed edges were replaced with undirected edges, there would be a
5618 path between all pairs of nodes. From these properties, it can be shown that there are no
5619 cycles in the graph (or else at least one node would have to have more than one incoming
5620 edge), and therefore, the graph is a tree. Because the graph includes all vertices, it is a
5621 **spanning tree**.

5622 11.1.1 Heads and dependents

5623 A dependency edge implies an asymmetric syntactic relationship between the head and
5624 dependent words, sometimes called **modifiers**. For a pair like *the cats* or *cats scratch*, how

5625 do we decide which is the head? Here are some possible criteria:

- 5626 • The head sets the syntactic category of the construction: for example, nouns are the
5627 heads of noun phrases, and verbs are the heads of verb phrases.
- 5628 • The modifier may be optional while the head is mandatory: for example, in the
5629 sentence *cats scratch people with claws*, the subtrees *cats scratch* and *cats scratch people*
5630 are grammatical sentences, but *with claws* is not.
- 5631 • The head determines the morphological form of the modifier: for example, in lan-
5632 guages that require gender agreement, the gender of the noun determines the gen-
5633 der of the adjectives and determiners.
- 5634 • Edges should first connect content words, and then connect function words.

5635 As always, these guidelines sometimes conflict. The Universal Dependencies (UD)
5636 project has attempted to identify a set of principles that can be applied to dozens of dif-
5637 ferent languages (Nivre et al., 2016).² These guidelines are based on the universal part-
5638 of-speech tags from chapter 8. They differ somewhat from the head rules described in
5639 § 10.5.2: for example, on the principle that dependencies should relate content words, the
5640 prepositional phrase *with claws* would be headed by *claws*, resulting in an edge *scratch* →
5641 *claws*, and another edge *claws* → *with*.

5642 One objection to dependency grammar is that not all syntactic relations are asymmet-
5643 ric. Coordination is one of the most obvious examples (Popel et al., 2013): in the sentence,
5644 *Abigail and Max like kimchi* (Figure 11.2), which word is the head of the coordinated noun
5645 phrase *Abigail and Max*? Choosing either *Abigail* or *Max* seems arbitrary; fairness argues
5646 for making *and* the head, but this seems like the least important word in the noun phrase,
5647 and selecting it would violate the principle of linking content words first. The Universal
5648 Dependencies annotation system arbitrarily chooses the left-most item as the head — in
5649 this case, *Abigail* — and includes edges from this head to both *Max* and the coordinating
5650 conjunction *and*. These edges are distinguished by the labels CONJ (for the thing begin
5651 conjoined) and CC (for the coordinating conjunction). The labeling system is discussed
5652 next.

5653 11.1.2 Labeled dependencies

5654 Edges may be **labeled** to indicate the nature of the syntactic relation that holds between
5655 the two elements. For example, in Figure 11.2, the label NSUBJ on the edge from *like* to
5656 *Abigail* indicates that the subtree headed by *Abigail* is the noun subject of the verb *like*;
5657 similarly, the label OBJ on the edge from *like* to *kimchi* indicates that the subtree headed by

²The latest and most specific guidelines are available at universaldependencies.org/guidelines.html

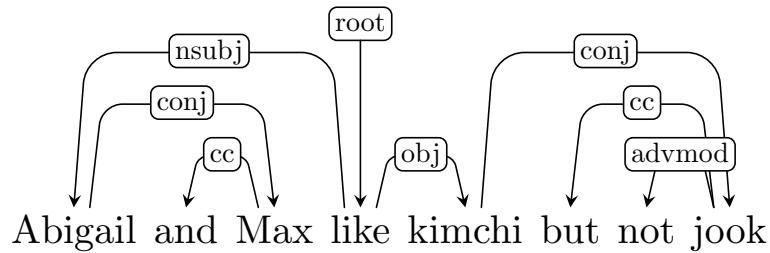


Figure 11.2: In the Universal Dependencies annotation system, the left-most item of a coordination is the head.

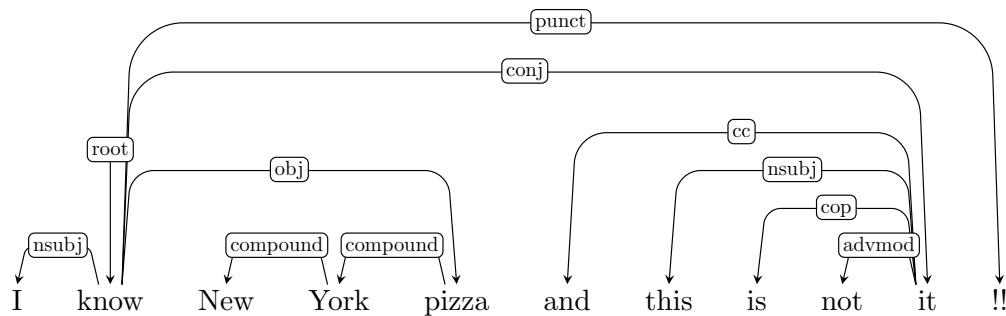


Figure 11.3: A labeled dependency parse from the English UD Treebank (reviews-361348-0006)

5658 *kimchi* is the object.³ The negation *not* is treated as an adverbial modifier (ADVMOD) on
5659 the noun *jook*.

5660 A slightly more complex example is shown in Figure 11.3. The multiword expression
5661 *New York pizza* is treated as a “flat” unit of text, with the elements linked by the COM-
5662 POUND relation. The sentence includes two clauses that are conjoined in the same way
5663 that noun phrases are conjoined in Figure 11.2. The second clause contains a copula verb
5664 (see § 8.1.1). For such clauses, we treat the “object” of the verb as the root — in this case,
5665 *it* — and label the verb as a dependent, with the COP relation. This example also shows
5666 how punctuations are treated, with label PUNCT.

5667 11.1.3 Dependency subtrees and constituents

5668 Dependency trees hide information that would be present in a CFG parse. Often what
5669 is hidden is in fact irrelevant: for example, Figure 11.4 shows three different ways of

³Earlier work distinguished direct and indirect objects (De Marneffe and Manning, 2008), but this has been dropped in version 2.0 of the Universal Dependencies annotation system.

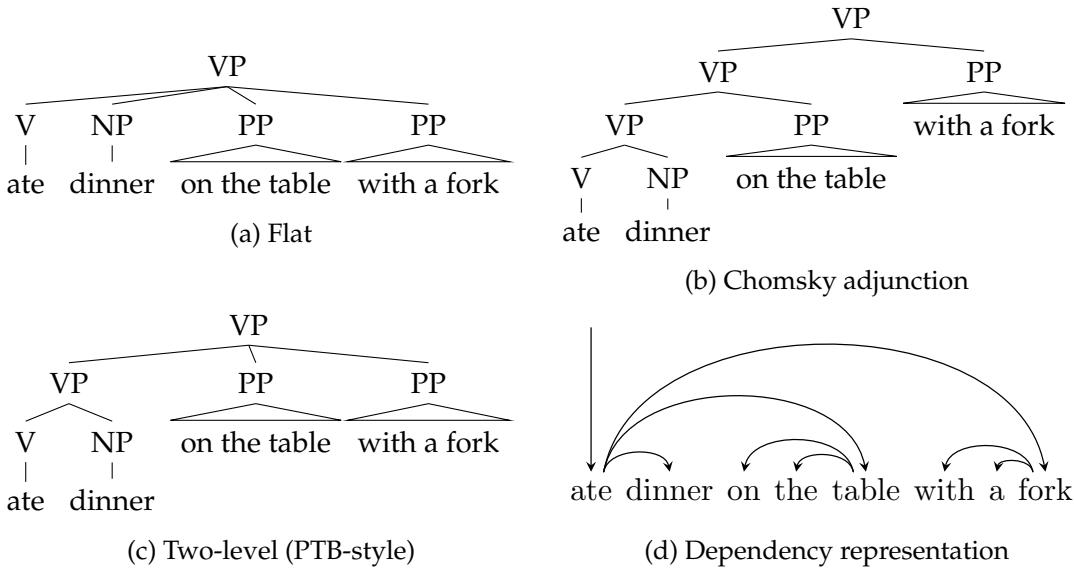


Figure 11.4: The three different CFG analyses of this verb phrase all correspond to a single dependency structure.

representing prepositional phrase adjuncts to the verb *ate*. Because there is apparently no meaningful difference between these analyses, the Penn Treebank decides by convention to use the two-level representation (see Johnson, 1998, for a discussion). As shown in Figure 11.4d, these three cases all look the same in a dependency parse.

But dependency grammar imposes its own set of annotation decisions, such as the identification of the head of a coordination (§ 11.1.1); without lexicalization, context-free grammar does not require either element in a coordination to be privileged in this way. Dependency parses can be disappointingly flat: for example, in the sentence *Yesterday, Abigail was reluctantly giving Max kimchi*, the root *giving* is the head of every dependency! The constituent parse arguably offers a more useful structural analysis for such cases.

Projectivity Thus far, we have defined dependency trees as spanning trees over a graph in which each word is a vertex. As we have seen, one way to construct such trees is by connecting the heads in a lexicalized constituent parse. However, there are spanning trees that cannot be constructed in this way. Syntactic constituents are *contiguous spans*. In a spanning tree constructed from a lexicalized constituent parse, the head h of any constituent that spans the nodes from i to j must have a path to every node in this span. This property is known as **projectivity**, and projective dependency parses are a restricted class of spanning trees. Informally, projectivity means that “crossing edges” are prohibited. The formal definition follows:

	% non-projective edges	% non-projective sentences
Czech	1.86%	22.42%
English	0.39%	7.63%
German	2.33%	28.19%

Table 11.1: Frequency of non-projective dependencies in three languages (Kuhlmann and Nivre, 2010)

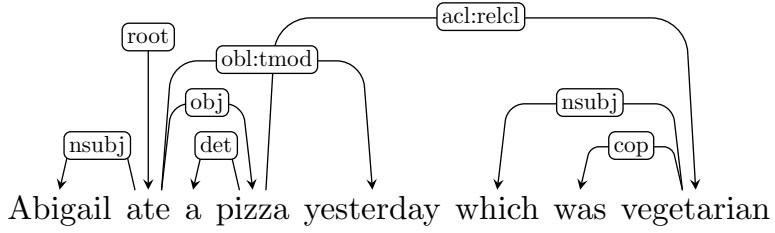


Figure 11.5: An example of a non-projective dependency parse. The “crossing edge” arises from the relative clause *which was vegetarian* and the oblique temporal modifier *yesterday*.

5689 **Definition 2** (Projectivity). *An edge from i to j is projective iff all k between i and j are descendants of i . A dependency parse is projective iff all its edges are projective.*

5691 Figure 11.5 gives an example of a non-projective dependency graph in English. This
 5692 dependency graph does not correspond to any constituent parse. As shown in Table 11.1,
 5693 non-projectivity is more common in languages such as Czech and German. Even though
 5694 relatively few dependencies are non-projective in these languages, many sentences have
 5695 at least one such dependency. As we will soon see, projectivity has important algorithmic
 5696 consequences.

5697 11.2 Graph-based dependency parsing

5698 Let $\mathbf{y} = \{i \xrightarrow{r} j\}$ represent a dependency graph, in which each edge is a relation r from
 5699 head word $i \in \{1, 2, \dots, M, \text{ROOT}\}$ to modifier $j \in \{1, 2, \dots, M\}$. The special node ROOT
 5700 indicates the root of the graph, and M is the length of the input $|\mathbf{w}|$. Given a scoring
 5701 function $\Psi(\mathbf{y}, \mathbf{w}; \theta)$, the optimal parse is,

$$\hat{\mathbf{y}} = \underset{\mathbf{y} \in \mathcal{Y}(\mathbf{w})}{\operatorname{argmax}} \Psi(\mathbf{y}, \mathbf{w}; \theta), \quad [11.1]$$

5702 where $\mathcal{Y}(\mathbf{w})$ is the set of valid dependency parses on the input \mathbf{w} . As usual, the number
 5703 of possible labels $|\mathcal{Y}(\mathbf{w})|$ is exponential in the length of the input (Wu and Chao, 2004).

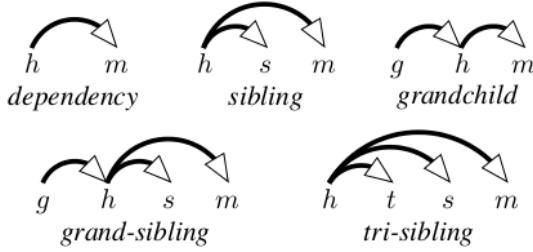


Figure 11.6: Feature templates for higher-order dependency parsing (Koo and Collins, 2010) [todo: permission]

5704 Algorithms that search over this space of possible graphs are known as **graph-based de-**
 5705 **pendency parsers.**

In sequence labeling and constituent parsing, it was possible to search efficiently over an exponential space by choosing a feature function that decomposes into a sum of local feature vectors. A similar approach is possible for dependency parsing, by requiring the scoring function to decompose across dependency arcs $i \rightarrow j$:

$$\Psi(\mathbf{y}, \mathbf{w}; \boldsymbol{\theta}) = \sum_{i \xrightarrow{r} j \in \mathbf{y}} \psi(i \xrightarrow{r} j, \mathbf{w}; \boldsymbol{\theta}). \quad [11.2]$$

5706 Dependency parsers that operate under this assumption are known as **arc-factored**, since
 5707 the overall score is a product of scores over all arcs.

Higher-order dependency parsing The arc-factored decomposition can be relaxed to allow higher-order dependencies. In **second-order dependency parsing**, the scoring function may include grandparents and siblings, as shown by the templates in Figure 11.6. The scoring function is,

$$\begin{aligned} \Psi(\mathbf{y}, \mathbf{w}; \boldsymbol{\theta}) = & \sum_{i \xrightarrow{r} j \in \mathbf{y}} \sum_{k \xrightarrow{r'} i \in \mathbf{y}} \psi_{\text{grandparent}}(i \xrightarrow{r} j, k, r', \mathbf{w}; \boldsymbol{\theta}) \\ & \sum_{\substack{i \xrightarrow{r'} s \in \mathbf{y} \\ s \neq j}} \psi_{\text{sibling}}(i \xrightarrow{r} j, s, r', \mathbf{w}; \boldsymbol{\theta}). \end{aligned} \quad [11.3]$$

5708 The top line scores computes a scoring function that includes the grandparent k ; the
 5709 bottom line computes a scoring function for each sibling s . For projective dependency
 5710 graphs, there are efficient algorithms for second-order and third-order dependency pars-
 5711 ing (Eisner, 1996; McDonald and Pereira, 2006; Koo and Collins, 2010); for non-projective
 5712 dependency graphs, second-order dependency parsing is NP-hard (McDonald and Pereira,
 5713 2006). The specific algorithms are discussed in the next section.

5714 **11.2.1 Graph-based parsing algorithms**

5715 The distinction between projective and non-projective dependency trees (§ 11.1.3) plays
 5716 a key role in the choice of algorithms. Because projective dependency trees are closely
 5717 related to (and can be derived from) lexicalized constituent trees, lexicalized parsing al-
 5718 gorithms can be applied directly. For the more general problem of parsing to arbitrary
 5719 spanning trees, a different class of algorithms is required. In both cases, arc-factored de-
 5720 pendency parsing relies on precomputing the scores $\psi(i \xrightarrow{r} j, w; \theta)$ for each potential
 5721 edge. There are $\mathcal{O}(M^2 R)$ such scores, where M is the length of the input and R is the
 5722 number of dependency relation types, and this is a lower bound on the time and space
 5723 complexity of any exact algorithm for arc-factored dependency parsing.

5724 **11.2.1.1 Projective dependency parsing**

5725 Any lexicalized constituency tree can be converted into a projective dependency tree by
 5726 creating arcs between the heads of constituents and their parents, so any algorithm for
 5727 lexicalized constituent parsing can be converted into an algorithm for projective depen-
 5728 dency parsing, by converting arc scores into scores for lexicalized productions. As noted
 5729 in § 10.5.2, there are cubic time algorithms for lexicalized constituent parsing, which are
 5730 extensions of the CKY algorithm. Therefore, arc-factored projective dependency parsing
 5731 can be performed in cubic time in the length of the input.

5732 Second-order projective dependency parsing can also be performed in cubic time, with
 5733 minimal modifications to the lexicalized parsing algorithm (Eisner, 1996). It is possible to
 5734 go even further, to **third-order dependency parsing**, in which the scoring function may
 5735 consider great-grandparents, grand-siblings, and “tri-siblings”, as shown in Figure 11.6.
 5736 Third-order dependency parsing can be performed in $\mathcal{O}(M^4)$ time, which can be made
 5737 practical through the use of pruning to eliminate unlikely edges (Koo and Collins, 2010).

5738 **11.2.1.2 Non-projective dependency parsing**

5739 In non-projective dependency parsing, the goal is to identify the highest-scoring span-
 5740 ning tree over the words in the sentence. The arc-factored assumption ensures that the
 5741 score for each spanning tree will be computed as a sum over scores for the edges, which
 5742 are precomputed. Based on these scores, we build a weighted connected graph. Arc-
 5743 factored non-projective dependency parsing is then equivalent to finding the spanning
 5744 tree that achieves the maximum total score, $\Psi(y, w) = \sum_{i \xrightarrow{r} j \in y} \psi(i \xrightarrow{r} j, w)$. The **Chu-**
 5745 **Liu-Edmonds algorithm** (Chu and Liu, 1965; Edmonds, 1967) computes this **maximum**
 5746 **spanning tree** efficiently. It does this by first identifying the best incoming edge $i \xrightarrow{r} j$ for
 5747 each vertex j . If the resulting graph does not contain cycles, it is the maximum spanning
 5748 tree. If there is a cycle, it is collapsed into a super-vertex, whose incoming and outgoing
 5749 edges are based on the edges to the vertices in the cycle. The algorithm is then applied

5750 recursively to the resulting graph, and process repeats until a graph without cycles is
 5751 obtained.

5752 The time complexity of identifying the best incoming edge for each vertex is $\mathcal{O}(M^2R)$,
 5753 where M is the length of the input and R is the number of relations; in the worst case, the
 5754 number of cycles is $\mathcal{O}(M)$. Therefore, the complexity of the Chu-Liu-Edmonds algorithm
 5755 is $\mathcal{O}(M^3R)$. This complexity can be reduced to $\mathcal{O}(M^2N)$ by storing the edge scores in a
 5756 Fibonacci heap (Gabow et al., 1986). For more detail on graph-based parsing algorithms,
 5757 see Eisner (1997) and Kübler et al. (2009).

5758 **Higher-order non-projective dependency parsing** Given the tractability of higher-order
 5759 projective dependency parsing, you may be surprised to learn that non-projective second-
 5760 order dependency parsing is NP-Hard. This can be proved by reduction from the vertex
 5761 cover problem (Neuhaus and Bröker, 1997). A heuristic solution is to do projective pars-
 5762 ing first, and then post-process the projective dependency parse to add non-projective
 5763 edges (Nivre and Nilsson, 2005). More recent work has applied techniques for approxi-
 5764 mate inference in graphical models, including belief propagation (Smith and Eisner, 2008),
 5765 integer linear programming (Martins et al., 2009), variational inference (Martins et al.,
 5766 2010), and Markov Chain Monte Carlo (Zhang et al., 2014).

5767 11.2.2 Computing scores for dependency arcs

The arc-factored scoring function $\psi(i \xrightarrow{r} j, \mathbf{w}; \boldsymbol{\theta})$ can be defined in several ways:

$$\text{Linear} \quad \psi(i \xrightarrow{r} j, \mathbf{w}; \boldsymbol{\theta}) = \boldsymbol{\theta} \cdot \mathbf{f}(i \xrightarrow{r} j, \mathbf{w}) \quad [11.4]$$

$$\text{Neural} \quad \psi(i \xrightarrow{r} j, \mathbf{w}; \boldsymbol{\theta}) = \text{Feedforward}([\mathbf{u}_{w_i}; \mathbf{u}_{w_j}]; \boldsymbol{\theta}) \quad [11.5]$$

$$\text{Generative} \quad \psi(i \xrightarrow{r} j, \mathbf{w}; \boldsymbol{\theta}) = \log p(w_j, r | w_i). \quad [11.6]$$

5768 11.2.2.1 Linear feature-based arc scores

5769 Linear models for dependency parsing incorporate many of the same features used in
 5770 sequence labeling and discriminative constituent parsing. These include:

- 5771 • the length and direction of the arc;
- 5772 • the words w_i and w_j linked by the dependency relation;
- 5773 • the prefixes, suffixes, and parts-of-speech of these words;
- 5774 • the neighbors of the dependency arc, $w_{i-1}, w_{i+1}, w_{j-1}, w_{j+1}$;
- 5775 • the prefixes, suffixes, and part-of-speech of these neighbor words.

5776 Each of these features can be conjoined with the dependency edge label r . Note that
 5777 features in an arc-factored parser can refer to words other than w_i and w_j . The restriction
 5778 is that the features consider only a single arc.

Bilexical features (e.g., *sushi* → *chopsticks*) are powerful but rare, so it is useful to augment them with coarse-grained alternatives, by “backing off” to the part-of-speech or affix. For example, the following features are created by backing off to part-of-speech tags in an unlabeled dependency parser:

$$\begin{aligned} f(3 \rightarrow 5, \text{we eat sushi with chopsticks}) = & \langle \text{sushi} \rightarrow \text{chopsticks}, \\ & \text{sushi} \rightarrow \text{NNS}, \\ & \text{NN} \rightarrow \text{chopsticks}, \\ & \text{NNS} \rightarrow \text{NN} \rangle. \end{aligned}$$

5779 Regularized discriminative learning algorithms can then trade off between features at
 5780 varying levels of detail. McDonald et al. (2005) take this approach as far as *tetralexical*
 5781 features (e.g., $(w_i, w_{i+1}, w_{j-1}, w_j)$). Such features help to avoid choosing arcs that are un-
 5782 likely due to the intervening words: for example, there is unlikely to be an edge between
 5783 two nouns if the intervening span contains a verb. A large list of first and second-order
 5784 features is provided by Bohnet (2010), who uses a hashing function to store these features
 5785 efficiently.

5786 11.2.2.2 Neural arc scores

Given vector representations \mathbf{x}_i for each word w_i in the input, a set of arc scores can be computed from a feedforward neural network:

$$\psi(i \xrightarrow{r} j, \mathbf{w}; \boldsymbol{\theta}) = \text{FeedForward}([\mathbf{x}_i; \mathbf{x}_j]; \boldsymbol{\theta}_r), \quad [11.7]$$

where unique weights $\boldsymbol{\theta}_r$ are available for each arc type (Pei et al., 2015; Kiperwasser and Goldberg, 2016). Kiperwasser and Goldberg (2016) use a feedforward network with a single hidden layer,

$$\mathbf{z} = g(\boldsymbol{\Theta}_r[\mathbf{x}_i; \mathbf{x}_j] + \mathbf{b}_r^{(z)}) \quad [11.8]$$

$$\psi(i \xrightarrow{r} j) = \boldsymbol{\beta}_r \mathbf{z} + \mathbf{b}_r^{(y)}, \quad [11.9]$$

5787 where $\boldsymbol{\Theta}_r$ is a matrix, $\boldsymbol{\beta}_r$ is a vector, each \mathbf{b}_r is a scalar, and the function g is an elementwise
 5788 \tanh activation function.

5789 The vector \mathbf{x}_i can be set equal to the word embedding, which may be pre-trained or
 5790 learned by backpropagation (Pei et al., 2015). Alternatively, contextual information can
 5791 be incorporated by applying a bidirectional recurrent neural network across the input, as
 5792 described in § 7.6. The RNN hidden states at each word can be used as inputs to the arc
 5793 scoring function (Kiperwasser and Goldberg, 2016).

5794 **11.2.2.3 Probabilistic arc scores**

If each arc score is equal to the log probability $\log p(w_j, r \mid w_i)$, then the sum of scores gives the log probability of the sentence and arc labels, by the chain rule. For example, consider the unlabeled parse of *we eat sushi with rice*,

$$\mathbf{y} = \{(ROOT, 2), (2, 1), (2, 3), (3, 5), (5, 4)\} \quad [11.10]$$

$$\log p(\mathbf{w} \mid \mathbf{y}) = \sum_{(i \rightarrow j) \in \mathbf{y}} \log p(w_j \mid w_i) \quad [11.11]$$

$$\begin{aligned} &= \log p(eat \mid ROOT) + \log p(we \mid eat) + \log p(sushi \mid eat) \\ &\quad + \log p(rice \mid sushi) + \log p(with \mid rice). \end{aligned} \quad [11.12]$$

5795 Probabilistic generative models are used in combination with expectation-maximization
 5796 (chapter 5) for unsupervised dependency parsing (Klein and Manning, 2004).

5797 **11.2.3 Learning**

Having formulated graph-based dependency parsing as a structure prediction problem, we can apply similar learning algorithms to those used in sequence labeling. Given a loss function $\ell(\boldsymbol{\theta}; \mathbf{w}^{(i)}, \mathbf{y}^{(i)})$, we can compute gradient-based updates to the parameters. For a model with feature-based arc scores and a perceptron loss, we obtain the usual structured perceptron update,

$$\hat{\mathbf{y}} = \operatorname{argmax}_{\mathbf{y}' \in \mathcal{Y}(\mathbf{w})} \boldsymbol{\theta} \cdot \mathbf{f}(\mathbf{w}, \mathbf{y}') \quad [11.13]$$

$$\boldsymbol{\theta} = \boldsymbol{\theta} + \mathbf{f}(\mathbf{w}, \mathbf{y}) - \mathbf{f}(\mathbf{w}, \hat{\mathbf{y}}) \quad [11.14]$$

5798 In this case, the argmax requires a maximization over all dependency trees for the sen-
 5799 tence, which can be computed using the algorithms described in § 11.2.1. We can apply
 5800 all the usual tricks from § 2.2: weight averaging, a large margin objective, and regular-
 5801 ization. McDonald et al. (2005) were the first to treat dependency parsing as a structure
 5802 prediction problem, using MIRA, an online margin-based learning algorithm. Neural arc
 5803 scores can be learned in the same way, backpropagating from a margin loss to updates on
 5804 the feedforward network that computes the score for each edge.

A conditional random field for arc-factored dependency parsing is built on the probability model,

$$p(\mathbf{y} \mid \mathbf{w}) = \frac{\exp \sum_{i \xrightarrow{r} j \in \mathbf{y}} \psi(i \xrightarrow{r} j, \mathbf{w}; \boldsymbol{\theta})}{\sum_{\mathbf{y}' \in \mathcal{Y}(\mathbf{w})} \exp \sum_{i \xrightarrow{r} j \in \mathbf{y}'} \psi(i \xrightarrow{r} j, \mathbf{w}; \boldsymbol{\theta})} \quad [11.15]$$

5805 Such a model is trained to minimize the negative log conditional-likelihood. Just as in
 5806 CRF sequence models (§ 7.5.3) and the logistic regression classifier (§ 2.4), the gradients

5807 involve marginal probabilities $p(i \xrightarrow{r} j \mid \mathbf{w}; \theta)$, which in this case are probabilities over
 5808 individual dependencies. In arc-factored models, these probabilities can be computed
 5809 in polynomial time. For projective dependency trees, the marginal probabilities can be
 5810 computed in cubic time, using a variant of the inside-outside algorithm (Lari and Young,
 5811 1990). For non-projective dependency parsing, marginals can also be computed in cubic
 5812 time, using the **matrix-tree theorem** (Koo et al., 2007; McDonald et al., 2007; Smith and
 5813 Smith, 2007). Details of these methods are described by Kübler et al. (2009).

5814 11.3 Transition-based dependency parsing

5815 Graph-based dependency parsing offers exact inference, meaning that it is possible to re-
 5816 cover the best-scoring parse for any given model. But this comes at a price: the scoring
 5817 function is required to decompose into local parts — in the case of non-projective parsing,
 5818 these parts are restricted to individual arcs. These limitations are felt more keenly in de-
 5819 pendency parsing than in sequence labeling, because second-order dependency features
 5820 are critical to correctly identify some types of attachments. For example, prepositional
 5821 phrase attachment depends on the attachment point, the object of the preposition, and
 5822 the preposition itself; arc-factored scores cannot account for all three of these features si-
 5823 multaneously. Graph-based dependency parsing may also be criticized on the basis of
 5824 intuitions about human language processing: people read and listen to sentences *sequen-*
 5825 *tially*, incrementally building mental models of the sentence structure and meaning before
 5826 getting to the end (Jurafsky, 1996). This seems hard to reconcile with graph-based algo-
 5827 rithms, which perform bottom-up operations on the entire sentence, requiring the parser
 5828 to keep every word in memory. Finally, from a practical perspective, graph-based depen-
 5829 dency parsing is relatively slow, running in cubic time in the length of the input.

5830 Transition-based algorithms address all three of these objections. They work by mov-
 5831 ing through the sentence sequentially, while performing actions that incrementally up-
 5832 date a stored representation of what has been read thus far. As with the shift-reduce
 5833 parser from § 10.6.2, this representation consists of a stack, onto which parsing substruc-
 5834 tures can be pushed and popped. In shift-reduce, these substructures were constituents;
 5835 in the transition systems that follow, they will be projective dependency trees over partial
 5836 spans of the input.⁴ Parsing is complete when the input is consumed and there is only
 5837 a single structure on the stack. The sequence of actions that led to the parse is known as
 5838 the **derivation**. One problem with transition-based systems is that there may be multiple
 5839 derivations for a single parse structure — a phenomenon known as **spurious ambiguity**.

⁴Transition systems also exist for non-projective dependency parsing (e.g., Nivre, 2008).

5840 **11.3.1 Transition systems for dependency parsing**

5841 A **transition system** consists of a representation for describing configurations of the parser,
 5842 and a set of transition actions, which manipulate the configuration. There are two main
 5843 transition systems for dependency parsing: **arc-standard**, which is closely related to shift-
 5844 reduce, and **arc-eager**, which adds an additional action that can simplify derivations (Ab-
 5845 ney and Johnson, 1991). In both cases, transitions are between **configurations** that are
 5846 represented as triples, $C = (\sigma, \beta, A)$, where σ is the stack, β is the input buffer, and A is
 5847 the list of arcs that have been created (Nivre, 2008). In the initial configuration,

$$C_{\text{initial}} = ([\text{ROOT}], \mathbf{w}, \emptyset), \quad [11.16]$$

5848 indicating that the stack contains only the special node ROOT, the entire input is on the
 5849 buffer, and the set of arcs is empty. An accepting configuration is,

$$C_{\text{accept}} = ([\text{ROOT}], \emptyset, A), \quad [11.17]$$

5850 where the stack contains only ROOT, the buffer is empty, and the arcs A define a spanning
 5851 tree over the input. The arc-standard and arc-eager systems define a set of transitions
 5852 between configurations, which are capable of transforming an initial configuration into
 5853 an accepting configuration. In both of these systems, the number of actions required to
 5854 parse an input grows linearly in the length of the input, making transition-based parsing
 5855 considerably more efficient than graph-based methods.

5856 **11.3.1.1 Arc-standard**

5857 The **arc-standard** transition system is closely related to shift-reduce, and to the LR algo-
 5858 rithm that is used to parse programming languages (Aho et al., 2006). It includes the
 5859 following classes of actions:

- 5860 • SHIFT: move the first item from the input buffer on to the top of the stack,

$$(\sigma, i|\beta, A) \Rightarrow (\sigma|i, \beta, A), \quad [11.18]$$

5861 where we write $i|\beta$ to indicate that i is the leftmost item in the input buffer, and $\sigma|i$
 5862 to indicate the result of pushing i on to stack σ .

- 5863 • ARC-LEFT: create a new left-facing arc of type r between the item on the top of the
 5864 stack and the first item in the input buffer. The head of this arc is j , which remains
 5865 at the front of the input buffer. The arc $j \xrightarrow{r} i$ is added to A . Formally,

$$(\sigma|i, j|\beta, A) \Rightarrow (\sigma, j|\beta, A \oplus j \xrightarrow{r} i), \quad [11.19]$$

5866 where r is the label of the dependency arc, and \oplus concatenates the new arc $j \xrightarrow{r} i$ to
 5867 the list A .

σ	β	action	arc added to \mathcal{A}
1. [ROOT]	<i>they like bagels with lox</i>	SHIFT	
2. [ROOT, <i>they</i>]	<i>like bagels with lox</i>	ARC-LEFT	(<i>they</i> \leftarrow <i>like</i>)
3. [ROOT]	<i>like bagels with lox</i>	SHIFT	
4. [ROOT, <i>like</i>]	<i>bagels with lox</i>	SHIFT	
5. [ROOT, <i>like</i> , <i>bagels</i>]	<i>with lox</i>	SHIFT	
6. [ROOT, <i>like</i> , <i>bagels</i> , <i>with</i>]	<i>lox</i>	ARC-LEFT	(<i>with</i> \leftarrow <i>lox</i>)
7. [ROOT, <i>like</i> , <i>bagels</i>]	<i>lox</i>	ARC-RIGHT	(<i>bagels</i> \rightarrow <i>lox</i>)
8. [ROOT, <i>like</i>]	<i>bagels</i>	ARC-RIGHT	(<i>like</i> \rightarrow <i>bagels</i>)
9. [ROOT]	<i>like</i>	ARC-RIGHT	(ROOT \rightarrow <i>like</i>)
10. [ROOT]	\emptyset	DONE	

Table 11.2: Arc-standard derivation of the unlabeled dependency parse for the input *they like bagels with lox*.

- 5868 • ARC-RIGHT: creates a new right-facing arc of type r between the item on the top of
 5869 the stack and the first item in the input buffer. The head of this arc is i , which is
 5870 “popped” from the stack and pushed to the front of the input buffer. The arc $i \xrightarrow{r} j$
 5871 is added to A . Formally,

$$(\sigma | i, j | \beta, A) \Rightarrow (\sigma, i | \beta, A \oplus i \xrightarrow{r} j), \quad [11.20]$$

5872 where again r is the label of the dependency arc.

5873 Each action has preconditions. The SHIFT action can be performed only when the buffer
 5874 has at least one element. The ARC-LEFT action cannot be performed when the root node
 5875 ROOT is on top of the stack, since this node must be the root of the entire tree. The ARC-
 5876 LEFT and ARC-RIGHT remove the modifier words from the stack (in the case of ARC-LEFT)
 5877 and from the buffer (in the case of ARC-RIGHT), so it is impossible for any word to have
 5878 more than one parent. Furthermore, the end state can only be reached when every word is
 5879 removed from the buffer and stack, so the set of arcs is guaranteed to constitute a spanning
 5880 tree. An example arc-standard derivation is shown in Table 11.2.

5881 11.3.1.2 Arc-eager dependency parsing

5882 In the arc-standard transition system, a word is completely removed from the parse once
 5883 it has been made the modifier in a dependency arc. At this time, any dependents of
 5884 this word must have already been identified. Right-branching structures are common in
 5885 English (and many other languages), with words often modified by units such as prepo-
 5886 sitional phrases to their right. In the arc-standard system, this means that we must first
 5887 shift all the units of the input onto the stack, and then work backwards, creating a series of

5888 arcs, as occurs in Table 11.2. Note that the decision to shift *bagels* onto the stack guarantees
 5889 that the prepositional phrase *with lox* will attach to the noun phrase, and that this decision
 5890 must be made before the prepositional phrase is itself parsed. This has been argued to be
 5891 cognitively implausible (Abney and Johnson, 1991); from a computational perspective, it
 5892 means that a parser may need to look several steps ahead to make the correct decision.

5893 **Arc-eager dependency parsing** changes the ARC-RIGHT action so that right depen-
 5894 dents can be attached before all of their dependents have been found. Rather than re-
 5895 moving the modifier from both the buffer and stack, the ARC-RIGHT action pushes the
 5896 modifier on to the stack, on top of the head. Because the stack can now contain elements
 5897 that already have parents in the partial dependency graph, two additional changes are
 5898 necessary:

- 5899 • A precondition is required to ensure that the ARC-LEFT action cannot be applied
 5900 when the top element on the stack already has a parent in A .
- 5901 • A new REDUCE action is introduced, which can remove elements from the stack if
 5902 they already have a parent in A :

$$(\sigma|i, \beta, A) \Rightarrow (\sigma, \beta, A). \quad [11.21]$$

5903 As a result of these changes, it is now possible to create the arc *like* \rightarrow *bagels* before parsing
 5904 the prepositional phrase *with lox*. Furthermore, this action does not imply a decision about
 5905 whether the prepositional phrase will attach to the noun or verb. Noun attachment is
 5906 chosen in the parse in Table 11.3, but verb attachment could be achieved by applying the
 5907 REDUCE action at step 5 or 7.

5908 11.3.1.3 Projectivity

5909 The arc-standard and arc-eager transition systems are guaranteed to produce projective
 5910 dependency trees, because all arcs are between the word at the top of the stack and the
 5911 left-most edge of the buffer (Nivre, 2008). Non-projective transition systems can be con-
 5912 structed by adding actions that create arcs with words that are second or third in the
 5913 stack (Attardi, 2006), or by adopting an alternative configuration structure, which main-
 5914 tains a list of all words that do not yet have heads (Covington, 2001). In **pseudo-projective**
 5915 **dependency parsing**, a projective dependency parse is generated first, and then a set of
 5916 graph transformation techniques are applied, producing non-projective edges (Nivre and
 5917 Nilsson, 2005).

5918 11.3.1.4 Beam search

5919 In “greedy” transition-based parsing, the parser tries to make the best decision at each
 5920 configuration. This can lead to search errors, when an early decision locks the parser into

σ	β	action	arc added to \mathcal{A}
1. [ROOT]	<i>they like bagels with lox</i>	SHIFT	
2. [ROOT, <i>they</i>]	<i>like bagels with lox</i>	ARC-LEFT	(<i>they</i> \leftarrow <i>like</i>)
3. [ROOT]	<i>like bagels with lox</i>	ARC-RIGHT	(ROOT \rightarrow <i>like</i>)
4. [ROOT, <i>like</i>]	<i>bagels with lox</i>	ARC-RIGHT	(<i>like</i> \rightarrow <i>bagels</i>)
5. [ROOT, <i>like</i> , <i>bagels</i>]	<i>with lox</i>	SHIFT	
6. [ROOT, <i>like</i> , <i>bagels</i> , <i>with</i>]	<i>lox</i>	ARC-LEFT	(<i>with</i> \leftarrow <i>lox</i>)
7. [ROOT, <i>like</i> , <i>bagels</i>]	<i>lox</i>	ARC-RIGHT	(<i>bagels</i> \rightarrow <i>lox</i>)
8. [ROOT, <i>like</i> , <i>bagels</i> , <i>lox</i>]	\emptyset	REDUCE	
9. [ROOT, <i>like</i> , <i>bagels</i>]	\emptyset	REDUCE	
10. [ROOT, <i>like</i>]	\emptyset	REDUCE	
11. [ROOT]	\emptyset	DONE	

Table 11.3: Arc-eager derivation of the unlabeled dependency parse for the input *they like bagels with lox*.

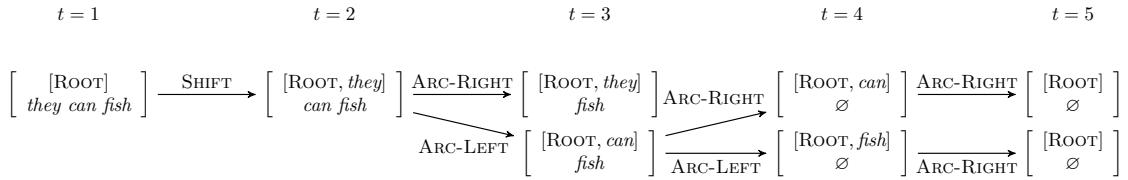


Figure 11.7: Beam search for unlabeled dependency parsing, with beam size $K = 2$. The arc lists for each configuration are not shown, but can be computed from the transitions.

5921 a poor derivation. For example, in Table 11.2, if ARC-RIGHT were chosen at step 4, then
 5922 the parser would later be forced to attach the prepositional phrase *with lox* to the verb
 5923 *likes*. Note that the *likes* \rightarrow *bagels* arc is indeed part of the correct dependency parse, but
 5924 the arc-standard transition system requires it to be created later in the derivation.

Beam search addresses this issue by maintaining a set of hypothetical derivations, called a beam. At step t of the derivation, there is a set of k hypotheses, each of which is a tuple of a score and a sequence of actions,

$$h_t^{(k)} = (s_t^{(k)}, A_t^{(k)}) \quad [11.22]$$

5925 Each hypothesis is then “expanded” by considering the set of all valid actions from the
 5926 current configuration $c_t^{(k)}$, written $\mathcal{A}(c_t^{(k)})$. This yields a large set of new hypotheses. For
 5927 each action $a \in \mathcal{A}(c_t^{(k)})$, we score the new hypothesis $A_t^{(k)} \oplus a$. The top k hypotheses by
 5928 this scoring metric are kept, and parsing proceeds to the next step (Zhang and Clark,

5929 2008). Note that beam search requires a scoring function for action *sequences*, rather than
 5930 individual actions. This issue will be revisited in the next section.

5931 An example of beam search is shown in Figure 11.7, with a beam size of $K = 2$. For the
 5932 first transition, the only valid action is SHIFT, so there is only one possible configuration
 5933 at $t = 2$. From this configuration, there are three possible actions. The top two are ARC-
 5934 RIGHT and ARC-LEFT, and so the resulting hypotheses from these actions are on the beam
 5935 at $t = 3$. From these configurations, there are three possible actions each, but the best
 5936 two are expansions of the bottom hypothesis at $t = 3$. Parsing continues until $t = 5$, at
 5937 which point both hypotheses reach an accepting state. The best-scoring hypothesis is then
 5938 selected as the parse.

5939 11.3.2 Scoring functions for transition-based parsers

Transition-based parsing requires selecting a series of actions. In greedy transition-based
 parsing, this can be done by training a classifier,

$$\hat{a} = \underset{a \in \mathcal{A}(c)}{\operatorname{argmax}} \Psi(a, c, \mathbf{w}; \boldsymbol{\theta}), \quad [11.23]$$

5940 where $\mathcal{A}(c)$ is the set of admissible actions in the current configuration c , \mathbf{w} is the input,
 5941 and Ψ is a scoring function with parameters $\boldsymbol{\theta}$ (Yamada and Matsumoto, 2003).

5942 A feature-based score can be computed, $\Psi(a, c, \mathbf{w}) = \boldsymbol{\theta} \cdot \mathbf{f}(a, c, \mathbf{w})$, using features that
 5943 may consider any aspect of the current configuration and input sequence. Typical features
 5944 for transition-based dependency parsing include: the word and part-of-speech of the top
 5945 element on the stack; the word and part-of-speech of the first, second, and third elements
 5946 on the input buffer; pairs and triples of words and parts-of-speech from the top of the
 5947 stack and the front of the buffer; the distance (in tokens) between the element on the top
 5948 of the stack and the element in the front of the input buffer; the number of modifiers of
 5949 each of these elements; and higher-order dependency features as described above in the
 5950 section on graph-based dependency parsing (see, e.g., Zhang and Nivre, 2011).

5951 Parse actions can also be scored by neural networks. For example, Chen and Manning
 5952 (2014) build a feedforward network in which the input layer consists of the concatenation
 5953 of embeddings of several words and tags:

- 5954 • the top three words on the stack, and the first three words on the buffer;
- 5955 • the first and second leftmost and rightmost children (dependents) of the top two
 5956 words on the stack;
- 5957 • the leftmost and right most grandchildren of the top two words on the stack;
- 5958 • embeddings of the part-of-speech tags of these words.

Let us call this base layer $\mathbf{x}(c, \mathbf{w})$, defined as,

$$c = (\sigma, \beta, A)$$

$$\mathbf{x}(c, \mathbf{w}) = [\mathbf{v}_{w_{\sigma_1}}, \mathbf{v}_{t_{\sigma_1}} \mathbf{v}_{w_{\sigma_2}}, \mathbf{v}_{t_{\sigma_2}}, \mathbf{v}_{w_{\sigma_3}}, \mathbf{v}_{t_{\sigma_3}}, \mathbf{v}_{w_{\beta_1}}, \mathbf{v}_{t_{\beta_1}}, \mathbf{v}_{w_{\beta_2}}, \mathbf{v}_{t_{\beta_2}}, \dots],$$

where $\mathbf{v}_{w_{\sigma_1}}$ is the embedding of the first word on the stack, $\mathbf{v}_{t_{\beta_2}}$ is the embedding of the part-of-speech tag of the second word on the buffer, and so on. Given this base encoding of the parser state, the score for the set of possible actions is computed through a feedforward network,

$$\mathbf{z} = g(\Theta^{(x \rightarrow z)} \mathbf{x}(c, \mathbf{w})) \quad [11.24]$$

$$\psi(a, c, \mathbf{w}; \boldsymbol{\theta}) = \Theta_a^{(z \rightarrow y)} \mathbf{z}, \quad [11.25]$$

5959 where the vector \mathbf{z} plays the same role as the features $\mathbf{f}(a, c, \mathbf{w})$, but is a learned representation.
 5960 Chen and Manning (2014) use a cubic elementwise activation function, $g(x) = x^3$,
 5961 so that the hidden layer models products across all triples of input features. The learning
 5962 algorithm updates the embeddings as well as the parameters of the feedforward network.

5963 11.3.3 Learning to parse

5964 Transition-based dependency parsing suffers from a mismatch between the supervision,
 5965 which comes in the form of dependency trees, and the classifier's prediction space, which
 5966 is a set of parsing actions. One solution is to create new training data by converting parse
 5967 trees into action sequences; another is to derive supervision directly from the parser's
 5968 performance.

5969 11.3.3.1 Oracle-based training

5970 A transition system can be viewed as a function from action sequences (also called **derivations**)
 5971 to parse trees. The inverse of this function is a mapping from parse trees to derivations,
 5972 which is called an **oracle**. For the arc-standard and arc-eager parsing system, an
 5973 oracle can be computed in linear time in the length of the derivation (Kübler et al., 2009,
 5974 page 32). Both the arc-standard and arc-eager transition systems suffer from **spurious**
 5975 **ambiguity**: there exist dependency parses for which multiple derivations are possible,
 5976 such as $1 \leftarrow 2 \rightarrow 3$. The oracle must choose between these different derivations. For exam-
 5977 ple, the algorithm described by Kübler et al. (2009) would first create the left arc ($1 \leftarrow 2$),
 5978 and then create the right arc, $(1 \leftarrow 2) \rightarrow 3$; another oracle might begin by shifting twice,
 5979 resulting in the derivation $1 \leftarrow (2 \rightarrow 3)$.

Given such an oracle, a dependency treebank can be converted into a set of oracle action sequences $\{A^{(i)}\}_{i=1}^N$. The parser can be trained by stepping through the oracle action sequences, and optimizing on an classification-based objective that rewards selecting the

oracle action. For transition-based dependency parsing, maximum conditional likelihood is a typical choice (Chen and Manning, 2014; Dyer et al., 2015):

$$p(a | c, \mathbf{w}) = \frac{\exp \Psi(a, c, \mathbf{w}; \boldsymbol{\theta})}{\sum_{a' \in \mathcal{A}(c)} \exp \Psi(a', c, \mathbf{w}; \boldsymbol{\theta})} \quad [11.26]$$

$$\hat{\boldsymbol{\theta}} = \underset{\boldsymbol{\theta}}{\operatorname{argmax}} \sum_{i=1}^N \sum_{t=1}^{|A^{(i)}|} \log p(a_t^{(i)} | c_t^{(i)}, \mathbf{w}), \quad [11.27]$$

5980 where $|A^{(i)}|$ is the length of the action sequence $A^{(i)}$.

5981 Recall that beam search requires a scoring function for action sequences. Such a score
 5982 can be obtained by adding the log-likelihoods (or hinge losses) across all actions in the
 5983 sequence (Chen and Manning, 2014).

5984 11.3.3.2 Global objectives

5985 The objective in Equation 11.27 is **locally-normalized**: it is the product of normalized
 5986 probabilities over individual actions. A similar characterization could be made of non-
 5987 probabilistic algorithms in which hinge-loss objectives are summed over individual ac-
 5988 tions. In either case, training on individual actions can be sub-optimal with respect to
 5989 global performance, due to the **label bias problem** (Lafferty et al., 2001; Andor et al.,
 5990 2016).

5991 As a stylized example, suppose that a given configuration appears 100 times in the
 5992 training data, with action a_1 as the oracle action in 51 cases, and a_2 as the oracle action in
 5993 the other 49 cases. However, in cases where a_2 is correct, choosing a_1 results in a cascade
 5994 of subsequent errors, while in cases where a_1 is correct, choosing a_2 results in only a single
 5995 error. A classifier that is trained on a local objective function will learn to always choose
 5996 a_1 , but choosing a_2 would minimize the overall number of errors.

5997 This observation motivates a global objective, such as the globally-normalized condi-
 5998 tional likelihood,

$$p(A^{(i)} | \mathbf{w}; \boldsymbol{\theta}) = \frac{\exp \sum_{t=1}^{|A^{(i)}|} \Psi(a_t^{(i)}, c_t^{(i)}, \mathbf{w})}{\sum_{A' \in \mathbb{A}(\mathbf{w})} \exp \sum_{t=1}^{|A'|} \Psi(a'_t, c'_t, \mathbf{w})}, \quad [11.28]$$

where the denominator sums over the set of all possible action sequences, $\mathbb{A}(\mathbf{w})$.⁵ In the conditional random field model for sequence labeling (§ 7.5.3), it was possible to compute

⁵Andor et al. (2016) prove that the set of globally-normalized conditional distributions is a strict superset of the set of locally-normalized conditional distributions, and that globally-normalized conditional models are therefore strictly more expressive.

this sum explicitly, using dynamic programming. In transition-based parsing, this is not possible. However, the sum can be approximated using beam search,

$$\sum_{A' \in \mathbb{A}(\mathbf{w})} \exp \sum_{t=1}^{|A'|} \Psi(a'_t, c'_t, \mathbf{w}) \approx \sum_{k=1}^K \exp \sum_{t=1}^{|A^{(k)}|} \Psi(a_t^{(k)}, c_t^{(k)}, \mathbf{w}), \quad [11.29]$$

where $A^{(k)}$ is an action sequence on a beam of size K . This gives rise to the following loss function,

$$L(\boldsymbol{\theta}) = - \sum_{t=1}^{|A^{(i)}|} \Psi(a_t^{(i)}, c_t^{(i)}, \mathbf{w}) + \log \sum_{k=1}^K \exp \sum_{t=1}^{|A^{(k)}|} \Psi(a_t^{(k)}, c_t^{(k)}, \mathbf{w}). \quad [11.30]$$

5999 The derivatives of this loss involve expectations with respect to a probability distribution
6000 over action sequences on the beam.

6001 11.3.3.3 *Early update and the incremental perceptron

6002 When learning in the context of beam search, the goal is to learn a decision function so that
6003 the gold dependency parse is always reachable from at least one of the partial derivations
6004 on the beam. (The combination of a transition system (such as beam search) and a scoring
6005 function for actions is known as a **policy**.) To achieve this, we can make an **early update**
6006 as soon as the oracle action sequence “falls off” the beam, even before a complete analysis
6007 is available (Collins and Roark, 2004; Daumé III and Marcu, 2005). The loss can be based
6008 on the best-scoring hypothesis on the beam, or the sum of all hypotheses (Huang et al.,
6009 2012).

6010 For example, consider the beam search in Figure 11.7. In the correct parse, *fish* is the
6011 head of dependency arcs to both of the other two words. In the arc-standard system,
6012 this can be achieved only by using SHIFT for the first two actions. At $t = 3$, the oracle
6013 action sequence has fallen off the beam. The parser should therefore stop, and update the
6014 parameters by the gradient $\frac{\partial}{\partial \boldsymbol{\theta}} L(A_{1:3}^{(i)}, \{A_{1:3}^{(k)}\}; \boldsymbol{\theta})$, where $A_{1:3}^{(i)}$ is the first three actions of the
6015 oracle sequence, and $\{A_{1:3}^{(k)}\}$ is the beam.

6016 This integration of incremental search and learning was first developed in the **incremental**
6017 **perceptron** (Collins and Roark, 2004). This method updates the parameters with
6018 respect to a hinge loss, which compares the top-scoring hypothesis and the gold action
6019 sequence, up to the current point t . Several improvements to this basic protocol are pos-
6020 sible:

- 6021 • As noted earlier, the gold dependency parse can be derived by multiple action se-
6022 quences. Rather than checking for the presence of a single oracle action sequence on
6023 the beam, we can check if the gold dependency parse is *reachable* from the current
6024 beam, using a **dynamic oracle** (Goldberg and Nivre, 2012).

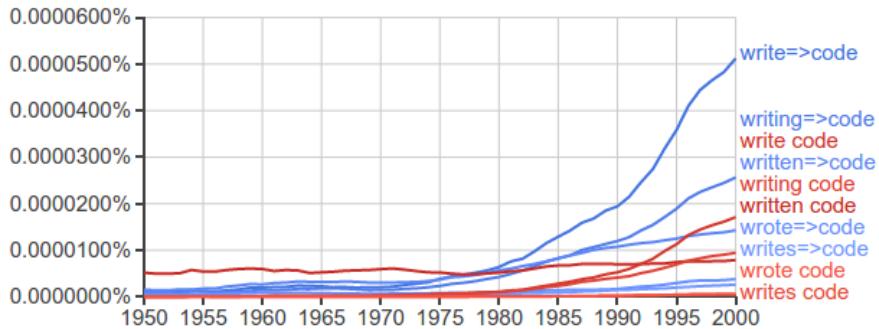


Figure 11.8: Google n-grams results for the bigram *write code* and the dependency arc *write => code* (and their morphological variants)

- By maximizing the score of the gold action sequence, we are training a decision function to find the correct action given the gold context. But in reality, the parser will make errors, and the parser is not trained to find the best action given a context that may not itself be optimal. This issue is addressed by various generalizations of incremental perceptron, known as **learning to search** (Daumé III et al., 2009). Some of these methods are discussed in chapter 15.

11.4 Applications

Dependency parsing is used in many real-world applications: any time you want to know about pairs of words which might not be adjacent, you can use dependency arcs instead of regular expression search patterns. For example, you may want to match strings like *delicious pastries*, *delicious French pastries*, and *the pastries are delicious*.

It is possible to search the Google *n*-gramscorpus by dependency edges, finding the trend in how often a dependency edge appears over time. For example, we might be interested in knowing when people started talking about *writing code*, but we also want *write some code*, *write good code*, *write all the code*, etc. The result of a search on the dependency edge *write → code* is shown in Figure 11.8. This capability has been applied to research in digital humanities, such as the analysis of gender in Shakespeare Muralidharan and Hearst (2013).

A classic application of dependency parsing is **relation extraction**, which is described

in chapter 17. The goal of relation extraction is to identify entity pairs, such as

(MELVILLE, MOBY-DICK)
 (TOLSTOY, WAR AND PEACE)
 (MARQUÉZ, 100 YEARS OF SOLITUDE)
 (SHAKESPEARE, A MIDSUMMER NIGHT'S DREAM),

6043 which stand in some relation to each other (in this case, the relation is authorship). Such
 6044 entity pairs are often referenced via consistent chains of dependency relations. Therefore,
 6045 dependency paths are often a useful feature in supervised systems which learn to detect
 6046 new instances of a relation, based on labeled examples of other instances of the same
 6047 relation type (Culotta and Sorensen, 2004; Fundel et al., 2007; Mintz et al., 2009).

6048 Cui et al. (2005) show how dependency parsing can improve automated question an-
 6049 swering. Suppose you receive the following query:

6050 (11.1) What percentage of the nation's cheese does Wisconsin produce?

6051 The corpus contains this sentence:

6052 (11.2) In Wisconsin, where farmers produce 28% of the nation's cheese, ...

6053 The location of *Wisconsin* in the surface form of this string makes it a poor match for the
 6054 query. However, in the dependency graph, there is an edge from *produce* to *Wisconsin* in
 6055 both the question and the potential answer, raising the likelihood that this span of text is
 6056 relevant to the question.

6057 A final example comes from sentiment analysis. As discussed in chapter 4, the polarity
 6058 of a sentence can be reversed by negation, e.g.

6059 (11.3) *There is no reason at all to believe the polluters will suddenly become reasonable.*

6060 By tracking the sentiment polarity through the dependency parse, we can better iden-
 6061 tify the overall polarity of the sentence, determining when key sentiment words are re-
 6062 versed (Wilson et al., 2005; Nakagawa et al., 2010).

6063 Additional resources

6064 More details on dependency grammar and parsing algorithms can be found in the manuscript
 6065 by Kübler et al. (2009). For a comprehensive but whimsical overview of graph-based de-
 6066 pendency parsing algorithms, see Eisner (1997). Jurafsky and Martin (2018) describe an
 6067 **agenda-based** version of beam search, in which the beam contains hypotheses of varying
 6068 lengths. New hypotheses are added to the beam only if their score is better than the worst

6069 item currently on the beam. Another search algorithm for transition-based parsing is
6070 **easy-first**, which abandons the left-to-right traversal order, and adds the highest-scoring
6071 edges first, regardless of where they appear (Goldberg and Elhadad, 2010). Goldberg et al.
6072 (2013) note that although transition-based methods can be implemented in linear time in
6073 the length of the input, naïve implementations of beam search will require quadratic time,
6074 due to the cost of copying each hypothesis when it is expanded on the beam. This issue
6075 can be addressed by using a more efficient data structure for the stack.

6076 Exercises

- 6077 1. The dependency structure $1 \leftarrow 2 \rightarrow 3$, with 2 as the root, can be obtained from more
6078 than one set of actions in arc-standard parsing. List both sets of actions that can
6079 obtain this parse.
- 6080 2. Suppose you have a set of unlabeled arc scores $\psi(i \rightarrow j)$, where the score depends
6081 only on the identity of the two words. The scores include $\psi(\text{ROOT} \rightarrow j)$.
 - 6082 • Assuming each word occurs only once in the sentence ($(i \neq j) \Leftarrow (w_i \neq w_j)$),
6083 how would you construct a weighted lexicalized context-free grammar so that
6084 the score of *any* projective dependency tree is equal to the score of some equiv-
6085 alent derivation in the lexicalized context-free grammar?
 - 6086 • Verify that your method works for a simple example like *they eat fish*.
 - 6087 • How would you adapt your method to handle the case an individual word
6088 may appear multiple times in the sentence?
- 6089 3. Provide the UD-style dependency parse for the sentence *Xi-Lan eats shoots and leaves*,
6090 assuming *leaves* is a verb. Provide arc-standard and arc-eager derivations for this
6091 dependency parse.

6092

Part III

6093

Meaning

6094 Chapter 12

6095 Logical semantics

6096 The previous few chapters have focused on building systems that reconstruct the **syntax**
6097 of natural language — its structural organization — through tagging and parsing. But
6098 some of the most exciting and promising potential applications of language technology
6099 involve going beyond syntax to **semantics** — the underlying meaning of the text:

- 6100 • Answering questions, such as *where is the nearest coffeeshop?* or *what is the middle name*
6101 *of the mother of the 44th President of the United States?*.
- 6102 • Building a robot that can follow natural language instructions to execute tasks.
- 6103 • Translating a sentence from one language into another, while preserving the under-
6104 lying meaning.
- 6105 • Fact-checking an article by searching the web for contradictory evidence.
- 6106 • Logic-checking an argument by identifying contradictions, ambiguity, and unsup-
6107 ported assertions.

6108 Semantic analysis involves converting natural language into a **meaning representa-**
6109 **tion**. To be useful, a meaning representation must meet several criteria:

- 6110 • **c1**: it should be unambiguous: unlike natural language, there should be exactly one
6111 meaning per statement;
- 6112 • **c2**: it should provide a way to link language to external knowledge, observations,
6113 and actions;
- 6114 • **c3**: it should support computational **inference**, so that meanings can be combined
6115 to derive additional knowledge;
- 6116 • **c4**: it should be expressive enough to cover the full range of things that people talk
6117 about in natural language.

6118 Much more than this can be said about the question of how best to represent knowledge
 6119 for computation (e.g., Sowa, 2000), but this chapter will focus on these four criteria.

6120 12.1 Meaning and denotation

6121 The first criterion for a meaning representation is that statements in the representation
 6122 should be unambiguous — they should have only one possible interpretation. Natural
 6123 language does not have this property: as we saw in chapter 10, sentences like *cats scratch*
 6124 *people with claws* have multiple interpretations.

6125 But what does it mean for a statement to be unambiguous? Programming languages
 6126 provide a useful example: the output of a program is completely specified by the rules of
 6127 the language and the properties of the environment in which the program is run. For ex-
 6128 ample, the python code $5 + 3$ will have the output 8, as will the codes $(4 * 4) - (3 * 3) + 1$
 6129 and $((8))$. This output is known as the **denotation** of the program, and can be written
 6130 as,

$$\llbracket 5+3 \rrbracket = \llbracket (4 * 4) - (3 * 3) + 1 \rrbracket = \llbracket ((8)) \rrbracket = 8. \quad [12.1]$$

6131 The denotations of these arithmetic expressions are determined by the meaning of the
 6132 **constants** (e.g., 5, 3) and the **relations** (e.g., $+$, $*$, $(,)$). Now let's consider another snippet
 6133 of python code, `double(4)`. The denotation of this code could be, $\llbracket \text{double}(4) \rrbracket = 8$, or
 6134 it could be $\llbracket \text{double}(4) \rrbracket = 44$ — it depends on the meaning of `double`. This meaning
 6135 is defined in a **world model** \mathcal{M} as an infinite set of pairs. We write the denotation with
 6136 respect to model \mathcal{M} as $\llbracket \cdot \rrbracket_{\mathcal{M}}$, e.g., $\llbracket \text{double} \rrbracket_{\mathcal{M}} = \{(0, 0), (1, 2), (2, 4), \dots\}$. The world
 6137 model would also define the (infinite) list of constants, e.g., $\{0, 1, 2, \dots\}$. As long as the
 6138 denotation of string ϕ in model \mathcal{M} can be computed unambiguously, the language can be
 6139 said to be unambiguous.

6140 This approach to meaning is known as **model-theoretic semantics**, and it addresses
 6141 not only criterion *c1* (no ambiguity), but also *c2* (connecting language to external knowl-
 6142 edge, observations, and actions). For example, we can connect a representation of the
 6143 meaning of a statement like *the capital of Georgia* with a world model that includes knowl-
 6144 edge base of geographical facts, obtaining the denotation `Atlanta`. We might populate
 6145 a world model by applying an image analysis algorithm to Figure 12.1, and then use this
 6146 world model to evaluate **propositions** like *a man is riding a moose*. Another desirable prop-
 6147 erty of model-theoretic semantics is that when the facts change, the denotations change
 6148 too: the meaning representation of *President of the USA* would have a different denotation
 6149 in the model \mathcal{M}_{2014} as it would in \mathcal{M}_{2022} .



Figure 12.1: A (doctored) image, which could be the basis for a world model

6150 12.2 Logical representations of meaning

6151 Criterion *c3* requires that the meaning representation support inference — for example,
 6152 automatically deducing new facts from known premises. While many representations
 6153 have been proposed that meet these criteria, the most mature is the language of first-order
 6154 logic.¹

6155 12.2.1 Propositional logic

6156 The bare bones of logical meaning representation are Boolean operations on propositions:

6157 **Propositional symbols.** Greek symbols like ϕ and ψ will be used to represent **proposi-**
 6158 **tions**, which are statements that are either true or false. For example, ϕ may corre-
 6159 **spond to the proposition, *bagels are delicious*.**

6160 **Boolean operators.** We can build up more complex propositional formulas from Boolean
 6161 operators. These include:

- 6162 • Negation $\neg\phi$, which is true if ϕ is false.

¹Alternatives include the “variable-free” representation used in semantic parsing of geographical queries (Zelle and Mooney, 1996) and robotic control (Ge and Mooney, 2005), and dependency-based compositional semantics (Liang et al., 2013).

- 6163 • Conjunction, $\phi \wedge \psi$, which is true if both ϕ and ψ are true.
- 6164 • Disjunction, $\phi \vee \psi$, which is true if at least one of ϕ and ψ is true
- 6165 • Implication, $\phi \Rightarrow \psi$, which is true unless ϕ is true and ψ is false. Implication
6166 has identical truth conditions to $\neg\phi \vee \psi$.
- 6167 • Equivalence, $\phi \Leftrightarrow \psi$, which is true if ϕ and ψ are both true or both false. Equiv-
6168 alence has identical truth conditions to $(\phi \Rightarrow \psi) \wedge (\psi \Rightarrow \phi)$.

6169 It is not strictly necessary to have all five Boolean operators: readers familiar with
6170 Boolean logic will know that it is possible to construct all other operators from either the
6171 NAND (not-and) or NOR (not-or) operators. Nonetheless, it is clearest to use all five
6172 operators. From the truth conditions for these operators, it is possible to define a number
6173 of “laws” for these Boolean operators, such as,

- 6174 • *Commutativity*: $\phi \wedge \psi = \psi \wedge \phi$, $\phi \vee \psi = \psi \vee \phi$
- 6175 • *Associativity*: $\phi \wedge (\psi \wedge \chi) = (\phi \wedge \psi) \wedge \chi$, $\phi \vee (\psi \vee \chi) = (\phi \vee \psi) \vee \chi$
- 6176 • *Complementation*: $\phi \wedge \neg\phi = \perp$, $\phi \vee \neg\phi = \top$, where \top indicates a true proposition
6177 and \perp indicates a false proposition.

These laws can be combined to derive further equivalences, which can support logical inferences. For example, suppose $\phi = \text{The music is loud}$ and $\psi = \text{Max can't sleep}$. Then if we are given,

$$\begin{aligned} \phi \Rightarrow \psi & \quad \text{If the music is loud, Max can't sleep.} \\ \phi & \quad \text{The music is loud.} \end{aligned}$$

6178 we can derive ψ (*Max can't sleep*) by application of **modus ponens**, which is one of a
6179 set of **inference rules** that can be derived from more basic laws and used to manipulate
6180 propositional formulas. **Automated theorem provers** are capable of applying inference
6181 rules to a set of premises to derive desired propositions (Loveland, 2016).

6182 12.2.2 First-order logic

6183 Propositional logic is so named because it treats propositions as its base units. However,
6184 the criterion *c4* states that our meaning representation should be sufficiently expressive.
6185 Now consider the sentence pair,

- 6186 (12.1) If anyone is making noise, then Max can't sleep.
6187 Abigail is making noise.

6188 People are capable of making inferences from this sentence pair, but such inferences re-
6189 quire formal tools that are beyond propositional logic. To understand the relationship

6190 between the statement *anyone is making noise* and the statement *Abigail is making noise*, our
 6191 meaning representation requires the additional machinery of **first-order logic** (FOL).

6192 In FOL, logical propositions can be constructed from relationships between entities.
 6193 Specifically, FOL extends propositional logic with the following classes of terms:

6194 **Constants.** These are elements that name individual entities in the model, such as MAX
 6195 and ABIGAIL. The denotation of each constant in a model \mathcal{M} is an element in the
 6196 model, e.g., $[\![\text{MAX}]\!] = m$ and $[\![\text{ABIGAIL}]\!] = a$.

6197 **Relations.** Relations can be thought of as sets of entities, or sets of tuples. For example,
 6198 the relation CAN-SLEEP is defined as the set of entities who can sleep, and has the
 6199 denotation $[\![\text{CAN-SLEEP}]\!] = \{a, m, \dots\}$. To test the truth value of the proposition
 6200 CAN-SLEEP(MAX), we ask whether $[\![\text{MAX}]\!] \in [\![\text{CAN-SLEEP}]\!]$. Logical relations that are
 6201 defined over sets of entities are sometimes called **properties**.

6202 Relations may also be ordered tuples of entities. For example BROTHER(MAX,ABIGAIL)
 6203 expresses the proposition that MAX is the brother of ABIGAIL. The denotation of
 6204 such relations is a set of tuples, $[\![\text{BROTHER}]\!] = \{(m, a), (x, y), \dots\}$. To test the
 6205 truth value of the proposition BROTHER(MAX,ABIGAIL), we ask whether the tuple
 6206 $([\![\text{MAX}]\!], [\![\text{ABIGAIL}]\!])$ is in the denotation $[\![\text{BROTHER}]\!]$.

Using constants and relations, it is possible to express statements like *Max can't sleep* and *Max is Abigail's brother*:

$$\neg \text{CAN-SLEEP}(\text{MAX}) \\ \text{BROTHER}(\text{MAX}, \text{ABIGAIL}).$$

These statements can also be combined using Boolean operators, such as,

$$(\text{BROTHER}(\text{MAX}, \text{ABIGAIL}) \vee \text{BROTHER}(\text{MAX}, \text{STEVE})) \Rightarrow \neg \text{CAN-SLEEP}(\text{MAX}).$$

6207 This fragment of first-order logic permits only statements about specific entities. To
 6208 support inferences about statements like *If anyone is making noise, then Max can't sleep*,
 6209 two more elements must be added to the meaning representation:

6210 **Variables.** Variables are mechanisms for referring to entities that are not locally specified.
 6211 We can then write CAN-SLEEP(x) or BROTHER(x , ABIGAIL). In these cases, x is a **free
 6212 variable**, meaning that we have not committed to any particular assignment.

6213 **Quantifiers.** Variables are bound by quantifiers. There are two quantifiers in first-order
 6214 logic.²

- 6215 • The **existential quantifier** \exists , which indicates that there must be at least one en-
 6216 tity to which the variable can bind. For example, the statement $\exists x \text{MAKES-NOISE}(x)$
 6217 indicates that there is at least one entity for which MAKES-NOISE is true.
 6218 • The **universal quantifier** \forall , which indicates that the variable must be able to
 6219 bind to any entity in the model. For example, the statement,

$$\text{MAKES-NOISE(ABIGAIL)} \Rightarrow (\forall x \neg \text{CAN-SLEEP}(x)) \quad [12.3]$$

6220 asserts that if Abigail makes noise, no one can sleep.

6221 The expressions $\exists x$ and $\forall x$ make x into a **bound variable**. A formula that contains
 6222 no free variables is a **sentence**.

6223 **Functions.** Functions map from entities to entities, e.g., $\llbracket \text{CAPITAL-OF(GEORGIA)} \rrbracket = \llbracket \text{ATLANTA} \rrbracket$.
 6224 With functions, it is convenient to add an equality operator, supporting statements
 6225 like,

$$\forall x \exists y \text{MOTHER-OF}(x) = \text{DAUGHTER-OF}(y). \quad [12.4]$$

6226 Note that MOTHER-OF is a functional analogue of the relation MOTHER, so that
 6227 $\text{MOTHER-OF}(x) = y$ if $\text{MOTHER}(x, y)$. Any logical formula that uses functions can be
 6228 rewritten using only relations and quantification. For example,

$$\text{MAKES-NOISE}(\text{MOTHER-OF(ABIGAIL)}) \quad [12.5]$$

6229 can be rewritten as $\exists x \text{MAKES-NOISE}(x) \wedge \text{MOTHER}(x, \text{ABIGAIL})$.

An important property of quantifiers is that the order can matter. Unfortunately, natural language is rarely clear about this! The issue is demonstrated by examples like *everyone speaks a language*, which has the following interpretations:

$$\forall x \exists y \text{ SPEAKS}(x, y) \quad [12.6]$$

$$\exists y \forall x \text{ SPEAKS}(x, y). \quad [12.7]$$

6230 In the first case, y may refer to several different languages, while in the second case, there
 6231 is a single y that is spoken by everyone.

²In first-order logic, it is possible to quantify only over entities. In **second-order logic**, it is possible to quantify over properties, supporting statements like *Butch has every property that a good boxer has* (example from Blackburn and Bos, 2005),

$$\forall P \forall x ((\text{GOOD-BOXER}(x) \Rightarrow P(x)) \Rightarrow P(\text{BUTCH})). \quad [12.2]$$

6232 12.2.2.1 Truth-conditional semantics

6233 One way to look at the meaning of an FOL sentence ϕ is as a set of **truth conditions**,
 6234 or models under which ϕ is satisfied. But how to determine whether a sentence is true
 6235 or false in a given model? We will approach this inductively, starting with a predicate
 6236 applied to a tuple of constants. The truth of such a sentence depends on whether the
 6237 tuple of denotations of the constants is in the denotation of the predicate. For example,
 6238 CAPITAL(GEORGIA,ATLANTA) is true in model \mathcal{M} iff,

$$(\llbracket \text{GEORGIA} \rrbracket_{\mathcal{M}}, \llbracket \text{ATLANTA} \rrbracket_{\mathcal{M}}) \in \llbracket \text{CAPITAL} \rrbracket_{\mathcal{M}}. \quad [12.8]$$

6239 The Boolean operators \wedge, \vee, \dots provide ways to construct more complicated sentences,
 6240 and the truth of such statements can be assessed based on the truth tables associated with
 6241 these operators. The statement $\exists x\phi$ is true if there is some assignment of the variable x
 6242 to an entity in the model such that ϕ is true; the statement $\forall x\phi$ is true if ϕ is true under
 6243 all possible assignments of x . More formally, we would say that ϕ is **satisfied** under \mathcal{M} ,
 6244 written as $\mathcal{M} \models \phi$.

6245 Truth conditional semantics allows us to define several other properties of sentences
 6246 and pairs of sentences. Suppose that in every \mathcal{M} under which ϕ is satisfied, another
 6247 formula ψ is also satisfied; then ϕ **entails** ψ , which is also written as $\phi \models \psi$. For example,

$$\text{CAPITAL(GEORGIA,ATLANTA)} \models \exists x \text{CAPITAL(GEORGIA, } x\text{)}. \quad [12.9]$$

6248 A statement that is satisfied under any model, such as $\phi \vee \neg\phi$, is **valid**, written $\models (\phi \vee$
 6249 $\neg\phi)$. A statement that is not satisfied under any model, such as $\phi \wedge \neg\phi$, is **unsatisfiable**,
 6250 or **inconsistent**. A **model checker** is a program that determines whether a sentence ϕ
 6251 is satisfied in \mathcal{M} . A **model builder** is a program that constructs a model in which ϕ
 6252 is satisfied. The problems of checking for consistency and validity in first-order logic
 6253 are **undecidable**, meaning that there is no algorithm that can automatically determine
 6254 whether an FOL formula is valid or inconsistent.

6255 12.2.2.2 Inference in first-order logic

6256 Our original goal was to support inferences that combine general statements *If anyone is*
making noise, then Max can't sleep with specific statements like *Abigail is making noise*. We
 6257 can now represent such statements in first-order logic, but how are we to perform the
 6258 inference that *Max can't sleep*? One approach is to use “generalized” versions of proposi-
 6259 tional inference rules like modus ponens, which can be applied to FOL formulas. By
 6260 repeatedly applying such inference rules to a knowledge base of facts, it is possible to
 6261 produce proofs of desired propositions. To find the right sequence of inferences to derive
 6262 a desired theorem, classical artificial intelligence search algorithms like backward chain-
 6263 ing can be applied. Such algorithms are implemented in interpreters for the `prolog` logic
 6264 programming language (Pereira and Shieber, 2002).

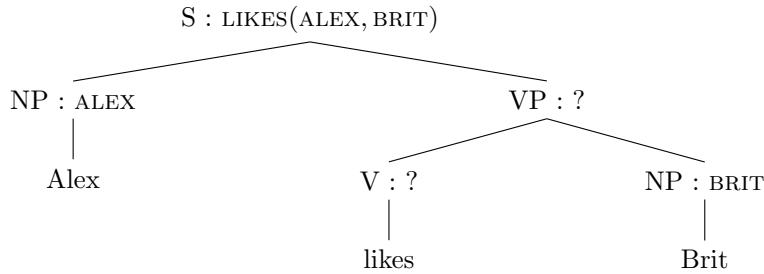


Figure 12.2: The principle of compositionality requires that we identify meanings for the constituents *likes* and *likes Brit* that will make it possible to compute the meaning for the entire sentence.

6266 12.3 Semantic parsing and the lambda calculus

6267 The previous section laid out a lot of formal machinery; the remainder of this chapter
 6268 links these formalisms back to natural language. Given an English sentence like *Alex likes*
 6269 *Brit*, how can we obtain the desired first-order logical representation, $\text{LIKES}(\text{ALEX}, \text{BRIT})$?
 6270 This is the task of **semantic parsing**. Just as a syntactic parser is a function from a natu-
 6271 ral language sentence to a syntactic structure such as a phrase structure tree, a semantic
 6272 parser is a function from natural language to logical formulas.

6273 As in syntactic analysis, semantic parsing is difficult because the space of inputs and
 6274 outputs is very large, and their interaction is complex. Our best hope is that, like syntactic
 6275 parsing, semantic parsing can somehow be decomposed into simpler sub-problems. This
 6276 idea, usually attributed to the German philosopher Gottlob Frege, is called the **principle**
 6277 **of compositionality**: the meaning of a complex expression is a function of the meanings of
 6278 that expression's constituent parts. We will define these “constituent parts” as syntactic
 6279 constituents: noun phrases and verb phrases. These constituents are combined using
 6280 function application: if the syntactic parse contains the production $x \rightarrow y z$, then the
 6281 semantics of x , written $x.\text{sem}$, will be computed as a function of the semantics of the
 6282 constituents, $y.\text{sem}$ and $z.\text{sem}$.³ ⁴

³§ 9.3.2 briefly discusses Combinatory Categorial Grammar (CCG) as an alternative to a phrase-structure analysis of syntax. CCG is argued to be particularly well-suited to semantic parsing (Hockenmaier and Steedman, 2007), and is used in much of the contemporary work on machine learning for semantic parsing, summarized in § 12.4.

⁴The approach of algorithmically building up meaning representations from a series of operations on the syntactic structure of a sentence is generally attributed to the philosopher Richard Montague, who published a series of influential papers on the topic in the early 1970s (e.g., Montague, 1973).

6283 **12.3.1 The lambda calculus**

6284 Let's see how this works for a simple sentence like *Alex likes Brit*, whose syntactic structure
 6285 is shown in Figure 12.2. Our goal is the formula, LIKES(ALEX,BRIT), and it is clear that the
 6286 meaning of the constituents *Alex* and *Brit* should be ALEX and BRIT. That leaves two more
 6287 constituents: the verb *likes*, and the verb phrase *likes Brit*. The meanings of these units
 6288 must be defined in a way that makes it possible to recover the desired meaning for the
 6289 entire sentence by function application. If the meanings of *Alex* and *Brit* are constants,
 6290 then the meanings of *likes* and *likes Brit* must be functional expressions, which can be
 6291 applied to their siblings to produce the desired analyses.

6292 Modeling these partial analyses requires extending the first-order logic meaning rep-
 6293 resentation. We do this by adding **lambda expressions**, which are descriptions of anonym-
 6294 ous functions,⁵ e.g.,

$$\lambda x.\text{LIKES}(x, \text{BRIT}). \quad [12.10]$$

6295 This functional expression is the meaning of the verb phrase *likes Brit*; it takes a single
 6296 argument, and returns the result of substituting that argument for x in the expression
 6297 $\text{LIKES}(x, \text{BRIT})$. We write this substitution as,

$$(\lambda x.\text{LIKES}(x, \text{BRIT}))@\text{ALEX} = \text{LIKES}(\text{ALEX}, \text{BRIT}), \quad [12.11]$$

6298 with the symbol "@" indicating function application. Function application in the lambda
 6299 calculus is sometimes called **β -reduction** or **β -conversion**. The expression $\phi@\psi$ indicates
 6300 a function application to be performed by β -reduction, and $\phi(\psi)$ indicates a function or
 6301 predicate in the final logical form.

6302 Equation 12.11 shows how to obtain the desired semantics for the sentence *Alex likes*
 6303 *Brit*: by applying the lambda expression $\lambda x.\text{LIKES}(x, \text{BRIT})$ to the logical constant ALEX.
 6304 This rule of composition can be specified in a **syntactic-semantic grammar**, in which
 6305 syntactic productions are paired with semantic operations. For the syntactic production
 6306 $S \rightarrow NP VP$, we have the semantic rule $VP.sem @ NP.sem$.

The meaning of the transitive verb phrase *likes Brit* can also be obtained by function
 application on its syntactic constituents. For the syntactic production $VP \rightarrow V NP$, we
 apply the semantic rule,

$$VP.sem = (V.sem) @ NP.sem \quad [12.12]$$

$$= (\lambda y. \lambda x. \text{LIKES}(x, y)) @ (\text{BRIT}) \quad [12.13]$$

$$= \lambda x. \text{LIKES}(x, \text{BRIT}). \quad [12.14]$$

⁵Formally, all first-order logic formulas are lambda expressions; in addition, if ϕ is a lambda expression, then $\lambda x.\phi$ is also a lambda expression. Readers who are familiar with functional programming will recognize lambda expressions from their use in programming languages such as Lisp and Python.

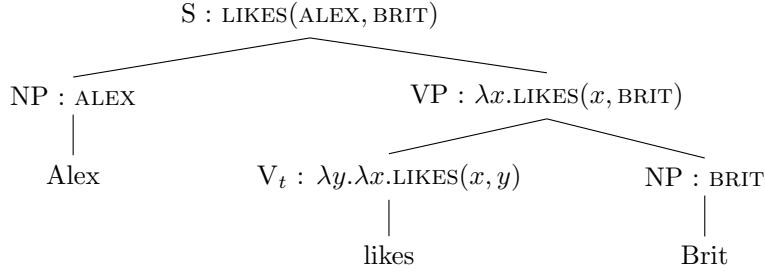


Figure 12.3: Derivation of the semantic representation for *Alex likes Brit* in the grammar G_1 .

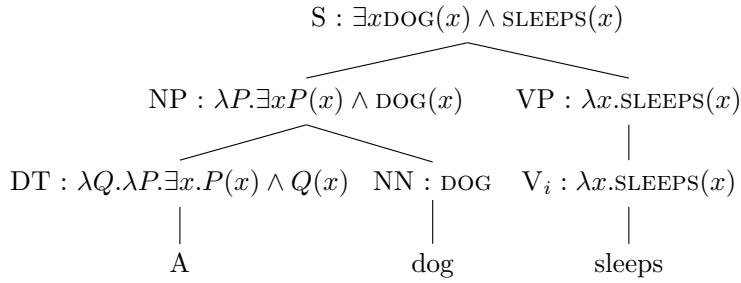
S	\rightarrow	NP VP	VP.sem@NP.sem
VP	\rightarrow	V _t NP	V _t .sem@NP.sem
VP	\rightarrow	V _i	V _i .sem
V _t	\rightarrow	likes	$\lambda y. \lambda x. \text{LIKES}(x, y)$
V _i	\rightarrow	sleeps	$\lambda x. \text{SLEEPS}(x)$
NP	\rightarrow	Alex	ALEX
NP	\rightarrow	Brit	BRIT

Table 12.1: G_1 , a minimal syntactic-semantic context-free grammar

6307 Thus, the meaning of the transitive verb *likes* is a lambda expression whose output is
 6308 *another* lambda expression: it takes y as an argument to fill in one of the slots in the LIKES
 6309 relation, and returns a lambda expression that is ready to take an argument to fill in the
 6310 other slot.⁶

6311 Table 12.1 shows a minimal syntactic-semantic grammar fragment, G_1 . The complete
 6312 **derivation** of *Alex likes Brit* in G_1 is shown in Figure 12.3. In addition to the transitive
 6313 verb *likes*, the grammar also includes the intransitive verb *sleeps*; it should be clear how
 6314 to derive the meaning of sentences like *Alex sleeps*. For verbs that can be either transitive
 6315 or intransitive, such as *eats*, we would have two terminal productions, one for each sense
 6316 (terminal productions are also called the **lexical entries**). Indeed, most of the grammar is
 6317 in the **lexicon** (the terminal productions), since these productions select the basic units of
 6318 the semantic interpretation.

⁶This can be written in a few different ways. The notation $\lambda y. x. \text{LIKES}(x, y)$ is a somewhat informal way to indicate a lambda expression that takes two arguments; this would be acceptable in functional programming. Logicians (e.g., Carpenter, 1997) often prefer the more formal notation $\lambda y. \lambda x. \text{LIKES}(x)(y)$, indicating that each lambda expression takes exactly one argument.

Figure 12.4: Derivation of the semantic representation for *A dog sleeps*, in grammar G_2 6319 **12.3.2 Quantification**

6320 Things get more complicated when we move from sentences about named entities to sen-
 6321 tences that involve more general noun phrases. Let's consider the example, *A dog sleeps*,
 6322 which has the meaning $\exists x\text{DOG}(x) \wedge \text{SLEEPS}(x)$. Clearly, the DOG relation will be intro-
 6323 duced by the word *dog*, and the SLEEP relation will be introduced by the word *sleeps*.⁷
 6324 The existential quantifier \exists must be introduced by the lexical entry for the determiner *a*.⁷
 6325 However, this seems problematic for the compositional approach taken in the grammar
 6326 G_1 : if the semantics of the noun phrase *a dog* is an existentially quantified expression, how
 6327 can it be the argument to the semantics of the verb *sleeps*, which expects an entity? And
 6328 where does the logical conjunction come from?

6329 There are a few different approaches to handling these issues.⁸ We will begin by re-
 6330 versing the semantic relationship between subject NPs and VPs, so that the production
 6331 $S \rightarrow \text{NP VP}$ has the semantics $\text{NP.sem}@\text{VP.sem}$: the meaning of the sentence is now the
 6332 semantics of the noun phrase applied to the verb phrase. The implications of this change
 6333 are best illustrated by exploring the derivation of the example, shown in Figure 12.4. Let's
 6334 start with the indefinite article *a*, to which we assign the rather intimidating semantics,

$$\lambda P. \lambda Q. \exists x P(x) \wedge Q(x). \quad [12.15]$$

This is a lambda expression that takes two **relations** as arguments, P and Q . The relation P is scoped to the outer lambda expression, so it will be provided by the immediately

⁷Conversely, the sentence *Every dog sleeps* would involve a universal quantifier, $\forall x\text{DOG}(x) \Rightarrow \text{SLEEPS}(x)$. The definite article *the* requires more consideration, since *the dog* must refer to some dog which is uniquely identifiable, perhaps from contextual information external to the sentence. Carpenter (1997, pp. 96-100) summarizes recent approaches to handling definite descriptions.

⁸Carpenter (1997) offers an alternative treatment based on combinatory categorial grammar.

adjacent noun, which in this case is DOG. Thus, the noun phrase *a dog* has the semantics,

$$\text{NP.sem} = \text{DET.sem} @ \text{NN.sem} \quad [12.16]$$

$$= (\lambda P. \lambda Q. \exists x P(x) \wedge Q(x)) @ (\text{DOG}) \quad [12.17]$$

$$= \lambda Q. \exists x \text{DOG}(x) \wedge Q(x). \quad [12.18]$$

6335 This is a lambda expression that is expecting another relation, Q , which will be provided
 6336 by the verb phrase, SLEEPS. This gives the desired analysis, $\exists x \text{DOG}(x) \wedge \text{SLEEPS}(x)$.⁹

6337 If noun phrases like *a dog* are interpreted as lambda expressions, then proper nouns
 6338 like *Alex* must be treated in the same way. This is achieved by **type-raising** from con-
 6339 stants to lambda expressions, $x \Rightarrow \lambda P. P(x)$. After type-raising, the semantics of *Alex* is
 6340 $\lambda P. P(\text{ALEX})$ — a lambda expression that expects a relation to tell us something about
 6341 *ALEX*.¹⁰ Again, make sure you see how the analysis in Figure 12.4 can be applied to the
 6342 sentence *Alex sleeps*.

6343 Direct objects are handled by applying the same type-raising operation to transitive
 6344 verbs: the meaning of verbs such as *likes* is raised to,

$$\lambda P. \lambda x. P(\lambda y. \text{LIKES}(x, y)) \quad [12.19]$$

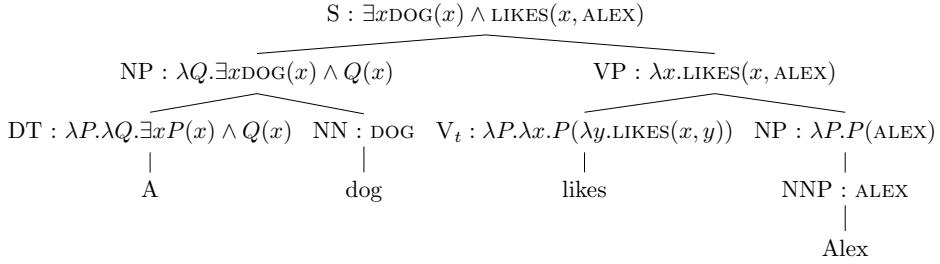
As a result, we can keep the verb phrase production $\text{VP.sem} = \text{V.sem} @ \text{NP.sem}$, knowing
 that the direct object will provide the function P in Equation 12.19. To see how this works,
 let's analyze the verb phrase *likes a dog*. After uniquely relabeling each lambda variable,
 we have,

$$\begin{aligned} \text{VP.sem} &= \text{V.sem} @ \text{NP.sem} \\ &= (\lambda P. \lambda x. P(\lambda y. \text{LIKES}(x, y))) @ (\lambda Q. \exists z \text{DOG}(z) \wedge Q(z)) \\ &= \lambda x. (\lambda Q. \exists z \text{DOG}(z) \wedge Q(z)) @ (\lambda y. \text{LIKES}(x, y)) \\ &= \lambda x. \exists z \text{DOG}(z) \wedge (\lambda y. \text{LIKES}(x, y)) @ z \\ &= \lambda x. \exists z \text{DOG}(z) \wedge \text{LIKES}(x, z). \end{aligned}$$

6345 These changes are summarized in the revised grammar G_2 , shown in Table 12.2. Fig-
 6346 ure 12.5 shows a derivation that involves a transitive verb, an indefinite noun phrase, and
 6347 a proper noun.

⁹When applying β -reduction to arguments that are themselves lambda expressions, be sure to use unique variable names to avoid confusion. For example, it is important to distinguish the x in the semantics for *a* from the x in the semantics for *likes*. Variable names are abstractions, and can always be changed — this is known as **α -conversion**. For example, $\lambda x. P(x)$ can be converted to $\lambda y. P(y)$, etc.

¹⁰Compositional semantic analysis is often supported by **type systems**, which make it possible to check whether a given function application is valid. The base types are entities e and truth values t . A property, such as DOG, is a function from entities to truth values, so its type is written $\langle e, t \rangle$. A transitive verb has type

Figure 12.5: Derivation of the semantic representation for *A dog likes Alex*.

S	\rightarrow NP VP	NP.sem@VP.sem
VP	\rightarrow V _t NP	V _t .sem@NP.sem
VP	\rightarrow V _i	V _i .sem
NP	\rightarrow DET NN	DET.sem@NN.sem
NP	\rightarrow NNP	$\lambda P. P(\text{NNP.sem})$
DET	$\rightarrow a$	$\lambda P. \lambda Q. \exists x P(x) \wedge Q(x)$
DET	\rightarrow every	$\lambda P. \lambda Q. \forall x (P(x) \Rightarrow Q(x))$
V _t	\rightarrow likes	$\lambda P. \lambda x. P(\lambda y. \text{LIKES}(x, y))$
V _i	\rightarrow sleeps	$\lambda x. \text{SLEEPS}(x)$
NN	\rightarrow dog	DOG
NNP	\rightarrow Alex	ALEX
NNP	\rightarrow Brit	BRIT

Table 12.2: G_2 , a syntactic-semantic context-free grammar fragment, which supports quantified noun phrases

6348 12.4 Learning semantic parsers

6349 As with syntactic parsing, any syntactic-semantic grammar with sufficient coverage risks
 6350 producing many possible analyses for any given sentence. Machine learning is the dom-
 6351 inant approach to selecting a single analysis. We will focus on algorithms that learn to
 6352 score logical forms by attaching weights to features of their derivations (Zettlemoyer
 6353 and Collins, 2005). Alternative approaches include transition-based parsing (Zelle and
 6354 Mooney, 1996; Misra and Artzi, 2016) and methods inspired by machine translation (Wong
 6355 and Mooney, 2006). Methods also differ in the form of supervision used for learning,

$\langle e, \langle e, t \rangle \rangle$: after receiving the first entity (the direct object), it returns a function from entities to truth values, which will be applied to the subject of the sentence. The type-raising operation $x \Rightarrow \lambda P. P(x)$ corresponds to a change in type from e to $\langle \langle e, t \rangle, t \rangle$: it expects a function from entities to truth values, and returns a truth value.

which can range from complete derivations to much more limited training signals. We will begin with the case of complete supervision, and then consider how learning is still possible even when seemingly key information is missing.

Datasets Early work on semantic parsing focused on natural language expressions of geographical database queries, such as *What states border Texas*. The GeoQuery dataset of Zelle and Mooney (1996) was originally coded in prolog, but has subsequently been expanded and converted into the SQL database query language by Popescu et al. (2003) and into first-order logic with lambda calculus by Zettlemoyer and Collins (2005), providing logical forms like $\lambda x.\text{STATE}(x) \wedge \text{BORDERS}(x, \text{TEXAS})$. Another early dataset consists of instructions for RoboCup robot soccer teams (Kate et al., 2005). More recent work has focused on broader domains, such as the Freebase database (Bollacker et al., 2008), for which queries have been annotated by Krishnamurthy and Mitchell (2012) and Cai and Yates (2013). Other recent datasets include child-directed speech (Kwiatkowski et al., 2012) and elementary school science exams (Krishnamurthy, 2016).

12.4.1 Learning from derivations

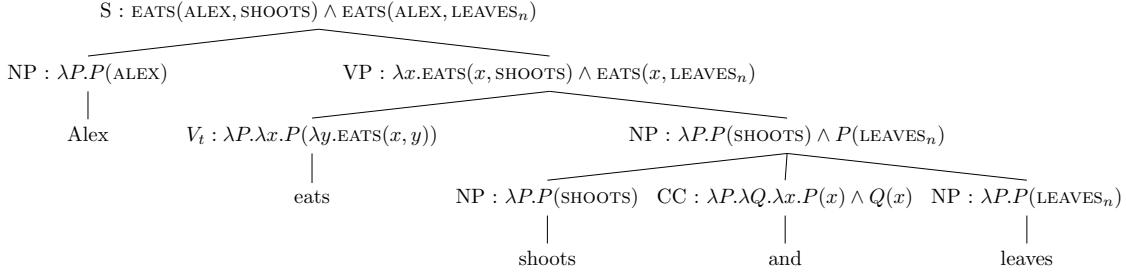
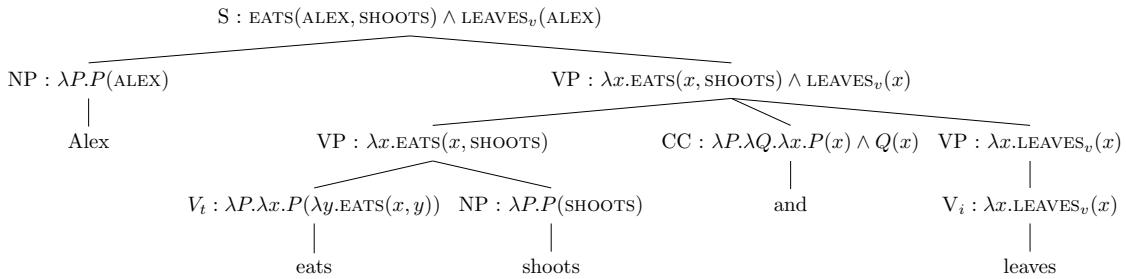
Let $w^{(i)}$ indicate a sequence of text, and let $y^{(i)}$ indicate the desired logical form. For example:

$$\begin{aligned} w^{(i)} &= \text{Alex eats shoots and leaves} \\ y^{(i)} &= \text{EATS(ALEX,SHOOTS)} \wedge \text{EATS(ALEX,LEAVES)} \end{aligned}$$

In the standard supervised learning paradigm that was introduced in § 2.2, we first define a feature function, $f(w, y)$, and then learn weights on these features, so that $y^{(i)} = \operatorname{argmax}_y \theta \cdot f(w, y)$. The weight vector θ is learned by comparing the features of the true label $f(w^{(i)}, y^{(i)})$ against either the features of the predicted label $f(w^{(i)}, \hat{y})$ (perceptron, support vector machine) or the expected feature vector $E_{y|w}[f(w^{(i)}, y)]$ (logistic regression).

While this basic framework seems similar to discriminative syntactic parsing, there is a crucial difference. In (context-free) syntactic parsing, the annotation $y^{(i)}$ contains all of the syntactic productions; indeed, the task of identifying the correct set of productions is identical to the task of identifying the syntactic structure. In semantic parsing, this is not the case: the logical form $\text{EATS(ALEX,SHOOTS)} \wedge \text{EATS(ALEX,LEAVES)}$ does not reveal the syntactic-semantic productions that were used to obtain it. Indeed, there may be **spurious ambiguity**, so that a single logical form can be reached by multiple derivations. (We previously encountered spurious ambiguity in transition-based dependency parsing, § 11.3.2.)

These ideas can be formalized by introducing an additional variable z , representing the **derivation** of the logical form y from the text w . Assume that the feature function de-

Figure 12.6: Derivation for gold semantic analysis of *Alex eats shoots and leaves*Figure 12.7: Derivation for incorrect semantic analysis of *Alex eats shoots and leaves*

6388 composes across the productions in the derivation, $f(\mathbf{w}, \mathbf{z}, \mathbf{y}) = \sum_{t=1}^T f(\mathbf{w}, z_t, \mathbf{y})$, where
 6389 z_t indicates a single syntactic-semantic production. For example, we might have a feature
 6390 for the production $S \rightarrow NP VP : NP.sem@VP.sem$, as well as for terminal productions
 6391 like $NNP \rightarrow Alex : ALEX$. Under this decomposition, it is possible to compute scores
 6392 for each semantically-annotated subtree in the analysis of \mathbf{w} , so that bottom-up parsing
 6393 algorithms like CKY (§ 10.1) can be applied to find the best-scoring semantic analysis.

6394 Figure 12.6 shows a derivation of the correct semantic analysis of the sentence *Alex*
 6395 *eats shoots and leaves*, in a simplified grammar in which the plural noun phrases *shoots*
 6396 and *leaves* are interpreted as logical constants *SHOOTS* and *LEAVES_n*. Figure 12.7 shows a
 6397 derivation of an incorrect analysis. Assuming one feature per production, the perceptron
 6398 update is shown in Table 12.3. From this update, the parser would learn to prefer the
 6399 noun interpretation of *leaves* over the verb interpretation. It would also learn to prefer
 6400 noun phrase coordination over verb phrase coordination.

6401 While the update is explained in terms of the perceptron, it would be easy to replace
 6402 the perceptron with a conditional random field. In this case, the online updates would be
 6403 based on feature expectations, which can be computed using the inside-outside algorithm
 6404 (§ 10.6).

$NP_1 \rightarrow NP_2 CC NP_3$	$(CC.sem @ (NP_2.sem)) @ (NP_3.sem)$	+1
$VP_1 \rightarrow VP_2 CC VP_3$	$(CC.sem @ (VP_2.sem)) @ (VP_3.sem)$	-1
$NP \rightarrow leaves$	$LEAVES_n$	+1
$VP \rightarrow V_i$	$V_i.sem$	-1
$V_i \rightarrow leaves$	$\lambda x.LEAVES_v$	-1

Table 12.3: Perceptron update for analysis in Figure 12.6 (gold) and Figure 12.7 (predicted)

6405 **12.4.2 Learning from logical forms**

Complete derivations are expensive to annotate, and are rarely available.¹¹ One solution is to focus on learning from logical forms directly, while treating the derivations as **latent variables** (Zettlemoyer and Collins, 2005). In a conditional probabilistic model over logical forms y and derivations z , we have,

$$p(y, z | w) = \frac{\exp(\theta \cdot f(w, z, y))}{\sum_{y', z'} \exp(\theta \cdot f(w, z', y'))}, \quad [12.20]$$

6406 which is the standard log-linear model, applied to the logical form y and the derivation
6407 z .

Since the derivation z unambiguously determines the logical form y , it may seem silly to model the joint probability over y and z . However, since z is unknown, it can be marginalized out,

$$p(y | w) = \sum_z p(y, z | w). \quad [12.21]$$

The semantic parser can then select the logical form with the maximum log marginal probability,

$$\log \sum_z p(y, z | w) = \log \sum_z \frac{\exp(\theta \cdot f(w, z, y))}{\sum_{y', z'} \exp(\theta \cdot f(w, z', y'))} \quad [12.22]$$

$$\propto \log \sum_z \exp(\theta \cdot f(w, z', y')) \quad [12.23]$$

$$\geq \max_z \theta \cdot f(w, z, y). \quad [12.24]$$

6408 It is impossible to push the log term inside the sum over z , so our usual linear scoring
6409 function does not apply. We can recover this scoring function only in approximation, by
6410 taking the max (rather than the sum) over derivations z , which provides a lower bound.

¹¹An exception is the work of Ge and Mooney (2005), who annotate the meaning of each syntactic constituents for several hundred sentences.

Learning can be performed by maximizing the log marginal likelihood,

$$\ell(\boldsymbol{\theta}) = \sum_{i=1}^N \log p(\mathbf{y}^{(i)} \mid \mathbf{w}^{(i)}; \boldsymbol{\theta}) \quad [12.25]$$

$$= \sum_{i=1}^N \log \sum_z p(\mathbf{y}^{(i)}, \mathbf{z}^{(i)} \mid \mathbf{w}^{(i)}; \boldsymbol{\theta}). \quad [12.26]$$

6411 This log-likelihood is not **convex** in $\boldsymbol{\theta}$, unlike the log-likelihood of a fully-observed conditional random field. This means that learning can give different results depending on the
 6412 initialization.
 6413

The derivative of Equation 12.26 is,

$$\frac{\partial \ell_i}{\partial \boldsymbol{\theta}} = \sum_z p(z \mid \mathbf{y}, \mathbf{w}; \boldsymbol{\theta}) \mathbf{f}(\mathbf{w}, z, \mathbf{y}) - \sum_{z'} p(z' \mid \mathbf{y}, \mathbf{w}; \boldsymbol{\theta}) \mathbf{f}(\mathbf{w}, z', \mathbf{y}) \quad [12.27]$$

$$= E_{z|\mathbf{y}, \mathbf{w}} \mathbf{f}(\mathbf{w}, z, \mathbf{y}) - E_{y, z|\mathbf{w}} \mathbf{f}(\mathbf{w}, z, \mathbf{y}) \quad [12.28]$$

6414 Both expectations can be computed via bottom-up algorithms like inside-outside. Alternatively, we can again maximize rather than marginalize over derivations for an approximating solution. In either case, the first term of the gradient requires us to identify derivations z that are compatible with the logical form \mathbf{y} . This can be done in a bottom-up dynamic programming algorithm, by having each cell in the table $t[i, j, X]$ include the set of all possible logical forms for $X \rightsquigarrow \mathbf{w}_{i+1:j}$. The resulting table may therefore be much larger than in syntactic parsing. This can be controlled by using pruning to eliminate intermediate analyses that are incompatible with the final logical form \mathbf{y} (Zettlemoyer and Collins, 2005), or by using beam search and restricting the size of each cell to some fixed constant (Liang et al., 2013).

6424 If we replace each expectation in Equation 12.28 with argmax and then apply stochastic
 6425 gradient descent to learn the weights, we obtain the **latent variable perceptron**, a simple
 6426 and general algorithm for learning with missing data. The algorithm is shown in its most
 6427 basic form in Algorithm 16, but the usual tricks such as averaging and margin loss can
 6428 be applied (Yu and Joachims, 2009). Aside from semantic parsing, the latent variable
 6429 perceptron has been used in tasks such as machine translation (Liang et al., 2006) and
 6430 named entity recognition (Sun et al., 2009). In **latent conditional random fields**, we use
 6431 the full expectations rather than maximizing over the hidden variable. This model has
 6432 also been employed in a range of problems beyond semantic parsing, including parse
 6433 reranking (Koo and Collins, 2005) and gesture recognition (Quattoni et al., 2007).

6434 12.4.3 Learning from denotations

Logical forms are easier to obtain than complete derivations, but the annotation of logical forms still requires considerable expertise. However, it is relatively easy to obtain deno-

Algorithm 16 Latent variable perceptron

```

1: procedure LATENTVARIABLEPERCEPTRON( $\mathbf{w}^{(1:N)}, \mathbf{y}^{(1:N)}$ )
2:    $\theta \leftarrow 0$ 
3:   repeat
4:     Select an instance  $i$ 
5:      $\mathbf{z}^{(i)} \leftarrow \text{argmax}_{\mathbf{z}} \theta \cdot \mathbf{f}(\mathbf{w}^{(i)}, \mathbf{z}, \mathbf{y}^{(i)})$ 
6:      $\hat{\mathbf{y}}, \hat{\mathbf{z}} \leftarrow \text{argmax}_{\mathbf{y}', \mathbf{z}'} \theta \cdot \mathbf{f}(\mathbf{w}^{(i)}, \mathbf{z}', \mathbf{y}')$ 
7:      $\theta \leftarrow \theta + \mathbf{f}(\mathbf{w}^{(i)}, \mathbf{z}^{(i)}, \mathbf{y}^{(i)}) - \mathbf{f}(\mathbf{w}^{(i)}, \hat{\mathbf{z}}, \hat{\mathbf{y}})$ 
8:   until tired
9:   return  $\theta$ 

```

tations for many natural language sentences. For example, in the geography domain, the denotation of a question would be its answer (Clarke et al., 2010; Liang et al., 2013):

Text :*What states border Georgia?*
Logical form : $\lambda x.\text{STATE}(x) \wedge \text{BORDER}(x, \text{GEORGIA})$
Denotation :{Alabama, Florida, North Carolina,
South Carolina, Tennessee}

6435 Similarly, in a robotic control setting, the denotation of a command would be an action or
6436 sequence of actions (Artzi and Zettlemoyer, 2013). In both cases, the idea is to reward the
6437 semantic parser for choosing an analysis whose denotation is correct: the right answer to
6438 the question, or the right action.

Learning from logical forms was made possible by summing or maxing over derivations. This idea can be carried one step further, summing or maxing over all logical forms with the correct denotation. Let $v_i(\mathbf{y}) \in \{0, 1\}$ be a **validation function**, which assigns a binary score indicating whether the denotation $[\mathbf{y}]$ for the text $\mathbf{w}^{(i)}$ is correct. We can then learn by maximizing a conditional-likelihood objective,

$$\ell^{(i)}(\boldsymbol{\theta}) = \log \sum_{\mathbf{y}} v_i(\mathbf{y}) \times p(\mathbf{y} \mid \mathbf{w}; \boldsymbol{\theta}) \quad [12.29]$$

$$= \log \sum_{\mathbf{y}} v_i(\mathbf{y}) \times \sum_{\mathbf{z}} p(\mathbf{y}, \mathbf{z} \mid \mathbf{w}; \boldsymbol{\theta}), \quad [12.30]$$

6439 which sums over all derivations \mathbf{z} of all valid logical forms, $\{\mathbf{y} : v_i(\mathbf{y}) = 1\}$. This cor-
6440 responds to the log-probability that the semantic parser produces a logical form with a
6441 valid denotation.

Differentiating with respect to θ , we obtain,

$$\frac{\partial \ell^{(i)}}{\partial \theta} = \sum_{\mathbf{y}, \mathbf{z}: v_i(\mathbf{y})=1} p(\mathbf{y}, \mathbf{z} | \mathbf{w}) \mathbf{f}(\mathbf{w}, \mathbf{z}, \mathbf{y}) - \sum_{\mathbf{y}', \mathbf{z}'} p(\mathbf{y}', \mathbf{z}' | \mathbf{w}) \mathbf{f}(\mathbf{w}, \mathbf{z}', \mathbf{y}'), \quad [12.31]$$

which is the usual difference in feature expectations. The positive term computes the expected feature expectations conditioned on the denotation being valid, while the second term computes the expected feature expectations according to the current model, without regard to the ground truth. Large-margin learning formulations are also possible for this problem. For example, Artzi and Zettlemoyer (2013) generate a set of valid and invalid derivations, and then impose a constraint that all valid derivations should score higher than all invalid derivations. This constraint drives a perceptron-like learning rule.

Additional resources

A key issue not considered here is how to handle **semantic underspecification**: cases in which there are multiple semantic interpretations for a single syntactic structure. Quantifier scope ambiguity is a classic example. Blackburn and Bos (2005) enumerate a number of approaches to this issue, and also provide links between natural language semantics and computational inference techniques. Much of the contemporary research on semantic parsing uses the framework of combinatory categorial grammar (CCG). Carpenter (1997) provides a comprehensive treatment of how CCG can support compositional semantic analysis. Another recent area of research is the semantics of multi-sentence texts. This can be handled with models of **dynamic semantics**, such as dynamic predicate logic (Groenendijk and Stokhof, 1991).

Alternative readings on formal semantics include an “informal” reading from Levy and Manning (2009), and a more involved introduction from Briscoe (2011). To learn more about ongoing research on data-driven semantic parsing, readers may consult the survey article by Liang and Potts (2015), tutorial slides and videos by Artzi and Zettlemoyer (2013),¹² and the source code by Yoav Artzi¹³ and Percy Liang.¹⁴

Exercises

- Derive the **modus ponens** inference rule, which states that if we know $\phi \Rightarrow \psi$ and ϕ , then ψ must be true. The derivation can be performed using the definition of the \Rightarrow operator and some of the laws provided in § 12.2.1, plus one additional identity: $\perp \vee \phi = \phi$.

¹²Videos are currently available at <http://yoavartzi.com/tutorial/>

¹³<http://yoavartzi.com/spf>

¹⁴<https://github.com/percyliang/sempre>

- 6470 2. Convert the following examples into first-order logic, using the relations CAN-SLEEP,
 6471 MAKES-NOISE, and BROTHER.
- 6472 • If Abigail makes noise, no one can sleep.
 6473 • If Abigail makes noise, someone cannot sleep.
 6474 • None of Abigail's brothers can sleep.
 6475 • If one of Abigail's brothers makes noise, Abigail cannot sleep.
- 6476 3. Extend the grammar fragment G_1 to include the ditransitive verb *teaches* and the
 6477 proper noun *Swahili*. Show how to derive the interpretation for the sentence *Alex*
 6478 *teaches Brit Swahili*, which should be $\text{TEACHES}(\text{ALEX}, \text{BRIT}, \text{SWAHILI})$. The grammar
 6479 need not be in Chomsky Normal Form. For the ditransitive verb, use NP_1 and NP_2
 6480 to indicate the two direct objects.
- 6481 4. Derive the semantic interpretation for the sentence *Alex likes every dog*, using gram-
 6482 mar fragment G_2 .
- 6483 5. Extend the grammar fragment G_2 to handle adjectives, so that the meaning of *an
 6484 angry dog* is $\lambda P. \exists x \text{DOG}(x) \wedge \text{ANGRY}(x) \wedge P(x)$. Specifically, you should supply the
 6485 lexical entry for the adjective *angry*, and you should specify the syntactic-semantic
 6486 productions $\text{NP} \rightarrow \text{DET } \text{NOM}$, $\text{NOM} \rightarrow \text{JJ } \text{NOM}$, and $\text{NOM} \rightarrow \text{NN}$.
- 6487 6. Extend your answer to the previous question to cover copula constructions with
 6488 predicative adjectives, such as *Alex is angry*. The interpretation should be $\text{ANGRY}(\text{ALEX})$.
 6489 You should add a verb phrase production $\text{VP} \rightarrow \text{V}_{\text{cop}} \text{ JJ}$, and a terminal production
 6490 $\text{V}_{\text{cop}} \rightarrow \text{is}$. Show why your grammar extensions result in the correct interpretation.
- 6491 7. In Figure 12.6 and Figure 12.7, we treat the plurals *shoots* and *leaves* as entities. Revise
 6492 G_2 so that the interpretation of *Alex eats leaves* is $\forall x. (\text{LEAF}(x) \Rightarrow \text{EATS}(\text{ALEX}, x))$, and
 6493 show the resulting perceptron update.
- 6494 8. Statements like *every student eats a pizza* have two possible interpretations, depend-
 6495 ing on quantifier scope:

$$\forall x \exists y \text{PIZZA}(y) \wedge (\text{STUDENT}(x) \Rightarrow \text{EATS}(x, y)) \quad [12.32]$$

$$\exists y \forall x \text{PIZZA}(y) \wedge (\text{STUDENT}(x) \Rightarrow \text{EATS}(x, y)) \quad [12.33]$$

6494 Explain why these interpretations really are different, and modify the grammar G_2
 6495 so that it can produce both interpretations.

6496 9. Derive Equation 12.27.

6497 10. In the GeoQuery domain, give a natural language query that has multiple plausible
 6498 semantic interpretations with the same denotation. List both interpretations and the
 6499 denotation.

6500 **Hint:** There are many ways to do this, but one approach involves using toponyms
6501 (place names) that could plausibly map to several different entities in the model.

6502

Chapter 13

6503

Predicate-argument semantics

6504 This chapter considers more “lightweight” semantic representations, which discard some
6505 aspects of first-order logic, but focus on predicate-argument structures. Let’s begin by
6506 thinking about the semantics of events, with a simple example:

6507 (13.1) Asha gives Boyang a book.

6508 A first-order logical representation of this sentence is,

$$\exists x. \text{BOOK}(x) \wedge \text{GIVE}(\text{ASHA}, \text{BOYANG}, x) \quad [13.1]$$

6509 In this representation, we define variable x for the book, and we link the strings *Asha* and
6510 *Boyang* to entities ASHA and BOYANG. Because the action of giving involves a giver, a
6511 recipient, and a gift, the predicate GIVE must take three arguments.

6512 Now suppose we have additional information about the event:

6513 (13.2) Yesterday, Asha reluctantly gave Boyang a book.

6514 One possible solution is to extend the predicate GIVE to take additional arguments,

$$\exists x. \text{BOOK}(x) \wedge \text{GIVE}(\text{ASHA}, \text{BOYANG}, x, \text{YESTERDAY}, \text{RELUCTANTLY}) \quad [13.2]$$

But this is clearly unsatisfactory: *yesterday* and *reluctantly* are optional arguments, and we would need a different version of the GIVE predicate for every possible combination of arguments. **Event semantics** solves this problem by **reifying** the event as an existentially quantified variable e ,

$$\begin{aligned} \exists e, x. & \text{GIVE-EVENT}(e) \wedge \text{GIVER}(e, \text{ASHA}) \wedge \text{GIFT}(e, x) \wedge \text{BOOK}(e, x) \wedge \text{RECIPIENT}(e, \text{BOYANG}) \\ & \wedge \text{TIME}(e, \text{YESTERDAY}) \wedge \text{MANNER}(e, \text{RELUCTANTLY}) \end{aligned}$$

6515 In this way, each argument of the event — the giver, the recipient, the gift — can be rep-
 6516 resented with a relation of its own, linking the argument to the event e . The expression
 6517 GIVER(e , ASHA) says that ASHA plays the **role** of GIVER in the event. This reformulation
 6518 handles the problem of optional information such as the time or manner of the event,
 6519 which are called **adjuncts**. Unlike arguments, adjuncts are not a mandatory part of the
 6520 relation, but under this representation, they can be expressed with additional logical rela-
 6521 tions that are conjoined to the semantic interpretation of the sentence.¹

6522 The event semantic representation can be applied to nested clauses, e.g.,

6523 (13.3) Chris sees Asha pay Boyang.

This is done by using the event variable as an argument:

$$\begin{aligned} \exists e_1 \exists e_2 \text{SEE-EVENT}(e_1) \wedge \text{SEER}(e_1, \text{CHRIS}) \wedge \text{SIGHT}(e_1, e_2) \\ \wedge \text{PAY-EVENT}(e_2) \wedge \text{PAYER}(e_2, \text{ASHA}) \wedge \text{PAYEE}(e_2, \text{BOYANG}) \end{aligned} \quad [13.3]$$

6524 As with first-order logic, the goal of event semantics is to provide a representation that
 6525 generalizes over many surface forms. Consider the following paraphrases of (13.1):

- 6526 (13.4) Asha gives a book to Boyang.
- 6527 (13.5) A book is given to Boyang by Asha.
- 6528 (13.6) A book is given by Asha to Boyang.
- 6529 (13.7) The gift of a book from Asha to Boyang ...

6530 All have the same event semantic meaning as Equation 13.1, but the ways in which the
 6531 meaning can be expressed are diverse. The final example does not even include a verb:
 6532 events are often introduced by verbs, but as shown by (13.7), the noun *gift* can introduce
 6533 the same predicate, with the same accompanying arguments.

6534 **Semantic role labeling** (SRL) is a relaxed form of semantic parsing, in which each
 6535 semantic role is filled by a set of tokens from the text itself. This is sometimes called
 6536 “shallow semantics” because, unlike model-theoretic semantic parsing, role fillers need
 6537 not be symbolic expressions with denotations in some world model. A semantic role
 6538 labeling system is required to identify all predicates, and then specify the spans of text
 6539 that fill each role. To give a sense of the task, here is a more complicated example:

- 6540 (13.8) Boyang wants Asha to give him a linguistics book.

¹This representation is often called **Neo-Davidsonian event semantics**. The use of existentially-quantified event variables was proposed by Davidson (1967) to handle the issue of optional adjuncts. In Neo-Davidsonian semantics, this treatment of adjuncts is extended to mandatory arguments as well (e.g., Parsons, 1990).

6541 In this example, there are two predicates, expressed by the verbs *want* and *give*. Thus, a
 6542 semantic role labeler might return the following output:

- 6543 • (PREDICATE : *wants*, WANTED : *Boyang*, DESIRE : *Asha to give him a linguistics book*)
 6544 • (PREDICATE : *give*, GIVER : *Asha*, RECIPIENT : *him*, GIFT : *a linguistics book*)

6545 *Boyang* and *him* may refer to the same person, but the semantic role labeling is not re-
 6546 quired to resolve this reference. Other predicate-argument representations, such as **Ab-**
 6547 **stract Meaning Representation (AMR)**, do require reference resolution. We will return to
 6548 AMR in § 13.3, but first, let us further consider the definition of semantic roles.

6549 **13.1 Semantic roles**

6550 In event semantics, it is necessary to specify a number of additional logical relations to
 6551 link arguments to events: GIVER, RECIPIENT, SEER, SIGHT, etc. Indeed, every predicate re-
 6552 quires a set of logical relations to express its own arguments. In contrast, adjuncts such as
 6553 TIME and MANNER are shared across many types of events. A natural question is whether
 6554 it is possible to treat mandatory arguments more like adjuncts, by identifying a set of
 6555 generic argument types that are shared across many event predicates. This can be further
 6556 motivated by examples involving related verbs:

- 6557 (13.9) Asha gave Boyang a book.
 6558 (13.10) Asha loaned Boyang a book.
 6559 (13.11) Asha taught Boyang a lesson.
 6560 (13.12) Asha gave Boyang a lesson.

6561 The respective roles of Asha, Boyang, and the book are nearly identical across the first
 6562 two examples. The third example is slightly different, but the fourth example shows that
 6563 the roles of GIVER and TEACHER can be viewed as related.

6564 One way to think about the relationship between roles such as GIVER and TEACHER is
 6565 by enumerating the set of properties that an entity typically possesses when it fulfills these
 6566 roles: givers and teachers are usually **animate** (they are alive and sentient) and **volitional**
 6567 (they choose to enter into the action).² In contrast, the thing that gets loaned or taught is
 6568 usually not animate or volitional; furthermore, it is unchanged by the event.

6569 Building on these ideas, **thematic roles** generalize across predicates by leveraging the
 6570 shared semantic properties of typical role fillers (Fillmore, 1968). For example, in exam-
 6571 ples (13.9-13.12), Asha plays a similar role in all four sentences, which we will call the

²There are always exceptions. For example, in the sentence *The C programming language has taught me a lot about perseverance*, the “teacher” is the *The C programming language*, which is presumably not animate or volitional.

	<i>Asha</i>	<i>gave</i>	<i>Boyang</i>	<i>a book</i>
VerbNet	AGENT		RECIPIENT	THEME
PropBank	ARG0: giver		ARG2: entity given to	ARG1: thing given
FrameNet	DONOR		RECIPIENT	THEME
	<i>Asha</i>	<i>taught</i>	<i>Boyang</i>	<i>algebra</i>
VerbNet	AGENT		RECIPIENT	TOPIC
PropBank	ARG0: teacher		ARG2: student	ARG1: subject
FrameNet	TEACHER		STUDENT	SUBJECT

Figure 13.1: Example semantic annotations according to VerbNet, PropBank, and FrameNet

6572 **agent.** This reflects several shared semantic properties: she is the one who is actively and
 6573 intentionally performing the action, while Boyang is a more passive participant; the book
 6574 and the lesson would play a different role, as non-animate participants in the event.

6575 Example annotations from three well known systems are shown in Figure 13.1. We
 6576 will now discuss these systems in more detail.

6577 13.1.1 VerbNet

6578 **VerbNet** (Kipper-Schuler, 2005) is a lexicon of verbs, and it includes thirty “core” thematic
 6579 roles played by arguments to these verbs. Here are some example roles, accompanied by
 6580 their definitions from the VerbNet Guidelines.³

- 6581 • AGENT: “ACTOR in an event who initiates and carries out the event intentionally or
 6582 consciously, and who exists independently of the event.”
- 6583 • PATIENT: “UNDERGOER in an event that experiences a change of state, location or
 6584 condition, that is causally involved or directly affected by other participants, and
 6585 exists independently of the event.”
- 6586 • RECIPIENT: “DESTINATION that is animate”
- 6587 • THEME: “UNDERGOER that is central to an event or state that does not have control
 6588 over the way the event occurs, is not structurally changed by the event, and/or is
 6589 characterized as being in a certain position or condition throughout the state.”
- 6590 • TOPIC: “THEME characterized by information content transferred to another partic-
 6591 ipant.”

³http://verbs.colorado.edu/verb-index/VerbNet_Guidelines.pdf

6592 VerbNet roles are organized in a hierarchy, so that a TOPIC is a type of THEME, which in
 6593 turn is a type of UNDERGOER, which is a type of PARTICIPANT, the top-level category.

6594 In addition, VerbNet organizes verb senses into a class hierarchy, in which verb senses
 6595 that have similar meanings are grouped together. Recall from § 4.2 that multiple meanings
 6596 of the same word are called **senses**, and that WordNet identifies senses for many English
 6597 words. VerbNet builds on WordNet, so that verb classes are identified by the WordNet
 6598 senses of the verbs that they contain. For example, the verb class give-13.1 includes
 6599 the first WordNet sense of *loan* and the second WordNet sense of *lend*.

6600 Each VerbNet class or subclass takes a set of thematic roles. For example, give-13.1
 6601 takes arguments with the thematic roles of AGENT, THEME, and RECIPIENT;⁴ the pred-
 6602 icate TEACH takes arguments with the thematic roles AGENT, TOPIC, RECIPIENT, and
 6603 SOURCE.⁵ So according to VerbNet, *Asha* and *Boyang* play the roles of AGENT and RECIP-
 6604 IENT in the sentences,

6605 (13.13) Asha gave Boyang a book.

6606 (13.14) Asha taught Boyang algebra.

6607 The *book* and *algebra* are both THEMES, but *algebra* is a subcategory of THEME — a TOPIC
 6608 — because it consists of information content that is given to the receiver.

6609 13.1.2 Proto-roles and PropBank

6610 Detailed thematic role inventories of the sort used in VerbNet are not universally accepted.
 6611 For example, Dowty (1991, pp. 547) notes that “Linguists have often found it hard to agree
 6612 on, and to motivate, the location of the boundary between role types.” He argues that a
 6613 solid distinction can be identified between just two **proto-roles**:

6614 **Proto-Agent.** Characterized by volitional involvement in the event or state; sentience
 6615 and/or perception; causing an event or change of state in another participant; move-
 6616 ment; exists independently of the event.

6617 **Proto-Patient.** Undergoes change of state; causally affected by another participant; sta-
 6618 tionary relative to the movement of another participant; does not exist indepen-
 6619 dently of the event.⁶

⁴<https://verbs.colorado.edu/verb-index/vn/give-13.1.php>

⁵https://verbs.colorado.edu/verb-index/vn/transfer_mesg-37.1.1.php

⁶Reisinger et al. (2015) ask crowd workers to annotate these properties directly, finding that annotators tend to agree on the properties of each argument. They also find that in English, arguments having more proto-agent properties tend to appear in subject position, while arguments with more proto-patient properties appear in object position.

6620 In the examples in Figure 13.1, Asha has most of the proto-agent properties: in giving
 6621 the book to Boyang, she is acting volitionally (as opposed to *Boyang got a book from Asha*, in
 6622 which it is not clear whether Asha gave up the book willingly); she is sentient; she causes
 6623 a change of state in Boyang; she exists independently of the event. Boyang has some
 6624 proto-agent properties: he is sentient and exists independently of the event. But he also
 6625 some proto-patient properties: he is the one who is causally affected and who undergoes
 6626 change of state. The book that Asha gives Boyang has even fewer of the proto-agent
 6627 properties: it is not volitional or sentient, and it has no causal role. But it also lacks many
 6628 of the proto-patient properties: it does not undergo change of state, exists independently
 6629 of the event, and is not stationary.

6630 The **Proposition Bank**, or PropBank (Palmer et al., 2005), builds on this basic agent-
 6631 patient distinction, as a middle ground between generic thematic roles and roles that are
 6632 specific to each predicate. Each verb is linked to a list of numbered arguments, with ARG0
 6633 as the proto-agent and ARG1 as the proto-patient. Additional numbered arguments are
 6634 verb-specific. For example, for the predicate TEACH,⁷ the arguments are:

- 6635 • ARG0: the teacher
- 6636 • ARG1: the subject
- 6637 • ARG2: the student(s)

6638 Verbs may have any number of arguments: for example, WANT and GET have five, while
 6639 EAT has only ARG0 and ARG1. In addition to the semantic arguments found in the frame
 6640 files, roughly a dozen general-purpose **adjuncts** may be used in combination with any
 6641 verb. These are shown in Table 13.1.

6642 PropBank-style semantic role labeling is annotated over the entire Penn Treebank. This
 6643 annotation includes the sense of each verbal predicate, as well as the argument spans.

6644 13.1.3 FrameNet

6645 Semantic **frames** are descriptions of situations or events. Frames may be *evoked* by one
 6646 of their **lexical units** (often a verb, but not always), and they include some number of
 6647 **frame elements**, which are like roles (Fillmore, 1976). For example, the act of teaching
 6648 is a frame, and can be evoked by the verb *taught*; the associated frame elements include
 6649 the teacher, the student(s), and the subject being taught. Frame semantics has played a
 6650 significant role in the history of artificial intelligence, in the work of Minsky (1974) and
 6651 Schank and Abelson (1977). In natural language processing, the theory of frame semantics
 6652 has been implemented in **FrameNet** (Fillmore and Baker, 2009), which consists of a lexicon

⁷<http://verbs.colorado.edu/propbank/framesets-english-aliases/teach.html>

TMP	time	<i>Boyang ate a bagel</i> [AM-TMP <i>yesterday</i>].
LOC	location	<i>Asha studies in</i> [AM-LOC <i>Stuttgart</i>]
MOD	modal verb	<i>Asha</i> [AM-MOD <i>will</i>] <i>study in Stuttgart</i>
ADV	general purpose	[AM-ADV <i>Luckily</i>], <i>Asha knew algebra</i> .
MNR	manner	<i>Asha ate</i> [AM-MNR <i>aggressively</i>].
DIS	discourse connective	[AM-DIS <i>However</i>], <i>Asha prefers algebra</i> .
PRP	purpose	<i>Barry studied</i> [AM-PRP <i>to pass the bar</i>].
DIR	direction	<i>Workers dumped burlap sacks</i> [AM-DIR <i>into a bin</i>].
NEG	negation	<i>Asha does</i> [AM-NEG <i>not</i>] <i>speak Albanian</i> .
EXT	extent	<i>Prices increased</i> [AM-EXT <i>4%</i>].
CAU	cause	<i>Boyang returned the book</i> [AM-CAU <i>because it was overdue</i>].

Table 13.1: PropBank adjuncts (Palmer et al., 2005), sorted by frequency in the corpus

6653 of roughly 1000 frames, and a corpus of more than 200,000 “exemplar sentences,” in which
 6654 the frames and their elements are annotated.⁸

6655 Rather than seeking to link semantic roles such as TEACHER and GIVER into the-
 6656 matic roles such as AGENT, FrameNet aggressively groups verbs into frames, and links
 6657 semantically-related roles across frames. For example, the following two sentences would
 6658 be annotated identically in FrameNet:

6659 (13.15) Asha taught Boyang algebra.

6660 (13.16) Boyang learned algebra from Asha.

6661 This is because *teach* and *learn* are both lexical units in the EDUCATION-TEACHING frame.
 6662 Furthermore, roles can be shared even when the frames are distinct, as in the following
 6663 two examples:

6664 (13.17) Asha gave Boyang a book.

6665 (13.18) Boyang got a book from Asha.

6666 The GIVING and GETTING frames both have RECIPIENT and THEME elements, so Boyang
 6667 and the book would play the same role. Asha’s role is different: she is the DONOR in the
 6668 GIVING frame, and the SOURCE in the GETTING frame. FrameNet makes extensive use of
 6669 multiple inheritance to share information across frames and frame elements: for example,
 6670 the COMMERCE-SELL and LENDING frames inherit from GIVING frame.

⁸Current details and data can be found at <https://framenet.icsi.berkeley.edu/>

6671 13.2 Semantic role labeling

6672 The task of semantic role labeling is to identify the parts of the sentence comprising the
 6673 semantic roles. In English, this task is typically performed on the PropBank corpus, with
 6674 the goal of producing outputs in the following form:

6675 (13.19) [ARG0 Asha] [GIVE.01 gave] [ARG2 Boyang's mom] [ARG1 a book] [AM-TMP yesterday].

6676 Note that a single sentence may have multiple verbs, and therefore a given word may be
 6677 part of multiple role-fillers:

6678 (13.20) [ARG0 Asha] [WANT.01 wanted]
 Asha wanted

6679 [ARG1 Boyang to give her the book].
 [ARG0 Boyang] [GIVE.01 to give] [ARG2 her] [ARG1 the book].

6680 13.2.1 Semantic role labeling as classification

6681 PropBank is annotated on the Penn Treebank, and annotators used phrasal constituents
 6682 (\S 9.2.2) to fill the roles. PropBank semantic role labeling can be viewed as the task of as-
 6683 signing to each phrase a label from the set $\mathcal{R} = \{\emptyset, \text{PRED}, \text{ARG0}, \text{ARG1}, \text{ARG2}, \dots, \text{AM-LOC}, \text{AM-TMP}, \dots\}$
 6684 with respect to each predicate. If we treat semantic role labeling as a classification prob-
 6685 lem, we obtain the following functional form:

$$\hat{y}_{(i,j)} = \underset{y}{\operatorname{argmax}} \psi(\mathbf{w}, y, i, j, \rho, \tau), \quad [13.4]$$

6686 where,

- 6687 • (i, j) indicates the span of a phrasal constituent $(w_{i+1}, w_{i+2}, \dots, w_j)$;⁹
- 6688 • \mathbf{w} represents the sentence as a sequence of tokens;
- 6689 • ρ is the index of the predicate verb in \mathbf{w} ;
- 6690 • τ is the structure of the phrasal constituent parse of \mathbf{w} .

6691 Early work on semantic role labeling focused on discriminative feature-based models,
 6692 where $\psi(\mathbf{w}, y, i, j, \rho, \tau) = \theta \cdot f(\mathbf{w}, y, i, j, \rho, \tau)$. Table 13.2 shows the features used in a sem-
 6693 inal paper on FrameNet semantic role labeling (Gildea and Jurafsky, 2002). By 2005 there

⁹PropBank roles can also be filled by **split constituents**, which are discontinuous spans of text. This situation most frequently in reported speech, e.g. [ARG1 *By addressing these problems*], *Mr. Maxwell said*, [ARG1 *the new funds have become extremely attractive.*] (example adapted from Palmer et al., 2005). This issue is typically addressed by defining “continuation arguments”, e.g. C-ARG1, which refers to the continuation of ARG1 after the split.

Predicate lemma and POS tag	The lemma of the predicate verb and its part-of-speech tag
Voice	Whether the predicate is in active or passive voice, as determined by a set of syntactic patterns for identifying passive voice constructions
Phrase type	The constituent phrase type for the proposed argument in the parse tree, e.g. NP, PP
Headword and POS tag	The head word of the proposed argument and its POS tag, identified using the Collins (1997) rules
Position	Whether the proposed argument comes before or after the predicate in the sentence
Syntactic path	The set of steps on the parse tree from the proposed argument to the predicate (described in detail in the text)
Subcategorization	The syntactic production from the first branching node above the predicate. For example, in Figure 13.2, the subcategorization feature around <i>taught</i> would be VP → VBD NP PP.

Table 13.2: Features used in semantic role labeling by Gildea and Jurafsky (2002).

were several systems for PropBank semantic role labeling, and their approaches and feature sets are summarized by Carreras and Márquez (2005). Typical features include: the phrase type, head word, part-of-speech, boundaries, and neighbors of the proposed argument $w_{i+1:j}$; the word, lemma, part-of-speech, and voice of the verb w_ρ (active or passive), as well as features relating to its frameset; the distance and path between the verb and the proposed argument. In this way, semantic role labeling systems are high-level “consumers” in the NLP stack, using features produced from lower-level components such as part-of-speech taggers and parsers. More comprehensive feature sets are enumerated by Das et al. (2014) and Täckström et al. (2015).

A particularly powerful class of features relate to the **syntactic path** between the argument and the predicate. These features capture the sequence of moves required to get from the argument to the verb by traversing the phrasal constituent parse of the sentence. The idea of these features is to capture syntactic regularities in how various arguments are realized. Syntactic path features are best illustrated by example, using the parse tree in Figure 13.2:

- The path from *Asha* to the verb *taught* is NNP↑NP↑S↓VP↓VBD. The first part of the path, NNP↑NP↑S, means that we must travel up the parse tree from the NNP tag (proper noun) to the S (sentence) constituent. The second part of the path, S↓VP↓VBD, means that we reach the verb by producing a VP (verb phrase) from

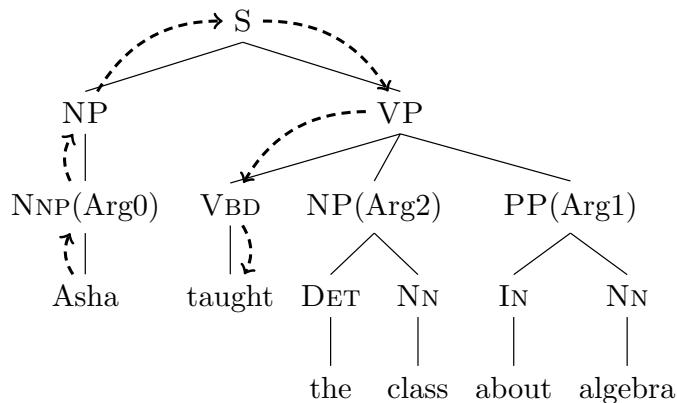


Figure 13.2: Semantic role labeling on the phrase-structure parse tree for a sentence. The dashed line indicates the syntactic path from *Asha* to the predicate verb *taught*.

6713 the S constituent, and then by producing a VBD (past tense verb). This feature is
 6714 consistent with *Asha* being in subject position, since the path includes the sentence
 6715 root S.

- 6716 • The path from *the class* to *taught* is NP↑VP↓VBD. This is consistent with *the class*
 6717 being in object position, since the path passes through the VP node that dominates
 6718 the verb *taught*.

6719 Because there are many possible path features, it can also be helpful to look at smaller
 6720 parts: for example, the upward and downward parts can be treated as separate features;
 6721 another feature might consider whether S appears anywhere in the path.

6722 Rather than using the constituent parse, it is also possible to build features from the
 6723 **dependency path** between the head word of each argument and the verb (Pradhan et al.,
 6724 2005). Using the Universal Dependency part-of-speech tagset and dependency relations (Nivre
 6725 et al., 2016), the dependency path from *Asha* to *taught* is PROPN $\xleftarrow[\text{NSUBJ}]{} \text{VERB}$, because *taught*
 6726 is the head of a relation of type $\xleftarrow[\text{NSUBJ}]{} \text{VERB}$ with *Asha*. Similarly, the dependency path from *class*
 6727 to *taught* is NOUN $\xleftarrow[\text{DOBJ}]{} \text{VERB}$, because *class* heads the noun phrase that is a direct object of
 6728 *taught*. A more interesting example is *Asha wanted to teach the class*, where the path from
 6729 *Asha* to *teach* is PROPN $\xleftarrow[\text{NSUBJ}]{} \text{VERB} \rightarrow[\text{XCOMP}] \text{VERB}$. The right-facing arrow in second relation
 6730 indicates that *wanted* is the head of its XCOMP relation with *teach*.

6731 **13.2.2 Semantic role labeling as constrained optimization**

6732 A potential problem with treating SRL as a classification problem is that there are a num-
 6733 ber of sentence-level **constraints**, which a classifier might violate.

- 6734 • For a given verb, there can be only one argument of each type (ARG0, ARG1, etc.)
 6735 • Arguments cannot overlap. This problem arises when we are labeling the phrases
 6736 in a constituent parse tree, as shown in Figure 13.2: if we label the PP *about algebra*
 6737 as an argument or adjunct, then its children *about* and *algebra* must be labeled as \emptyset .
 6738 The same constraint also applies to the syntactic ancestors of this phrase.

6739 These constraints introduce dependencies across labeling decisions. In structure pre-
 6740 diction problems such as sequence labeling and parsing, such dependencies are usually
 6741 handled by defining a scoring over the entire structure, \mathbf{y} . Efficient inference requires
 6742 that the global score decomposes into local parts: for example, in sequence labeling, the
 6743 scoring function decomposes into scores of pairs of adjacent tags, permitting the applica-
 6744 tion of the Viterbi algorithm for inference. But the constraints that arise in semantic role
 6745 labeling are less amenable to local decomposition.¹⁰ We therefore consider **constrained**
 6746 **optimization** as an alternative solution.

Let the set $\mathcal{C}(\tau)$ refer to all labelings that obey the constraints introduced by the parse τ . The semantic role labeling problem can be reformulated as a constrained optimization over $\mathbf{y} \in \mathcal{C}(\tau)$,

$$\begin{aligned} \max_{\mathbf{y}} \quad & \sum_{(i,j) \in \tau} \psi(\mathbf{w}, y_{i,j}, i, j, \rho, \tau) \\ \text{s.t. } \quad & \mathbf{y} \in \mathcal{C}(\tau). \end{aligned} \quad [13.5]$$

6747 In this formulation, the objective (shown on the first line) is a separable function of each
 6748 individual labeling decision, but the constraints (shown on the second line) apply to the
 6749 overall labeling. The sum $\sum_{(i,j) \in \tau}$ indicates that we are summing over all constituent
 6750 spans in the parse τ . The expression s.t. in the second line means that we maximize the
 6751 objective *subject to* the constraint $\mathbf{y} \in \mathcal{C}(\tau)$.

6752 A number of practical algorithms exist for restricted forms of constrained optimiza-
 6753 tion. One such restricted form is **integer linear programming**, in which the objective and
 6754 constraints are linear functions of integer variables. To formulate SRL as an integer linear
 6755 program, we begin by rewriting the labels as a set of binary variables $\mathbf{z} = \{z_{i,j,r}\}$ (Pun-
 6756 yakanok et al., 2008),

$$z_{i,j,r} = \begin{cases} 1, & y_{i,j} = r \\ 0, & \text{otherwise,} \end{cases} \quad [13.6]$$

¹⁰Dynamic programming solutions have been proposed by Tromble and Eisner (2006) and Täckström et al. (2015), but they involve creating a trellis structure whose size is exponential in the number of labels.

6757 where $r \in \mathcal{R}$ is a label in the set $\{\text{ARG0}, \text{ARG1}, \dots, \text{AM-LOC}, \dots, \emptyset\}$. Thus, the variables
 6758 \mathbf{z} are a binarized version of the semantic role labeling \mathbf{y} .

The objective can then be formulated as a linear function of \mathbf{z} .

$$\sum_{(i,j) \in \tau} \psi(\mathbf{w}, y_{i,j}, i, j, \rho, \tau) = \sum_{i,j,r} \psi(\mathbf{w}, r, i, j, \rho, \tau) \times z_{i,j,r}, \quad [13.7]$$

6759 which is the sum of the scores of all relations, as indicated by $z_{i,j,r}$.

Constraints Integer linear programming permits linear inequality constraints, of the general form $\mathbf{A}\mathbf{z} \leq \mathbf{b}$, where the parameters \mathbf{A} and \mathbf{b} define the constraints. To make this more concrete, let's start with the constraint that each non-null role type can occur only once in a sentence. This constraint can be written,

$$\forall r \neq \emptyset, \quad \sum_{(i,j) \in \tau} z_{i,j,r} \leq 1. \quad [13.8]$$

6760 Recall that $z_{i,j,r} = 1$ iff the span (i, j) has label r ; this constraint says that for each possible
 6761 label $r \neq \emptyset$, there can be at most one (i, j) such that $z_{i,j,r} = 1$. Rewriting this constraint
 6762 can be written in the form $\mathbf{A}\mathbf{z} \leq \mathbf{b}$, as you will find if you complete the exercises at the
 6763 end of the chapter.

Now consider the constraint that labels cannot overlap. Let's define the convenience function $o((i, j), (i', j')) = 1$ iff (i, j) overlaps (i', j') , and zero otherwise. Thus, o will indicate if a constituent (i', j') is either an ancestor or descendant of (i, j) . The constraint is that if two constituents overlap, only one can have a non-null label:

$$\forall (i, j) \in \tau, \quad \sum_{(i', j') \in \tau} \sum_{r \neq \emptyset} o((i, j), (i', j')) \times z_{i',j',r} \leq 1, \quad [13.9]$$

6764 where $o((i, j), (i, j)) = 1$.

In summary, the semantic role labeling problem can thus be rewritten as the following integer linear program,

$$\max_{\mathbf{z} \in \{0,1\}^{|\tau|}} \quad \sum_{(i,j) \in \tau} \sum_{r \in \mathcal{R}} z_{i,j,r} \psi_{i,j,r} \quad [13.10]$$

$$s.t. \quad \forall r \neq \emptyset, \quad \sum_{(i,j) \in \tau} z_{i,j,r} \leq 1. \quad [13.11]$$

$$\forall (i, j) \in \tau, \quad \sum_{(i', j') \in \tau} \sum_{r \neq \emptyset} o((i, j), (i', j')) \times z_{i',j',r} \leq 1. \quad [13.12]$$

6765 **Learning with constraints** Learning can be performed in the context of constrained op-
 6766 timization using the usual perceptron or large-margin classification updates. Because
 6767 constrained inference is generally more time-consuming, a key question is whether it is
 6768 necessary to apply the constraints during learning. Chang et al. (2008) find that better per-
 6769 formance can be obtained by learning *without* constraints, and then applying constraints
 6770 only when using the trained model to predict semantic roles for unseen data.

6771 **How important are the constraints?** Das et al. (2014) find that an unconstrained, classification-
 6772 based method performs nearly as well as constrained optimization for FrameNet parsing;
 6773 while it commits many violations of the “no-overlap” constraint, the overall F_1 score is
 6774 less than one point worse than the score at the constrained optimum. Similar results
 6775 were obtained for PropBank semantic role labeling by Punyakanok et al. (2008). He et al.
 6776 (2017) find that constrained inference makes a bigger impact if the constraints are based
 6777 on manually-labeled “gold” syntactic parses. This implies that errors from the syntac-
 6778 tic parser may limit the effectiveness of the constraints. Punyakanok et al. (2008) hedge
 6779 against parser error by including constituents from several different parsers; any con-
 6780 stituent can be selected from any parse, and additional constraints ensure that overlap-
 6781 ping constituents are not selected.

6782 **Implementation** Integer linear programming solvers such as `glpk`,¹¹ `cplex`,¹² and `Gurobi`¹³
 6783 allow inequality constraints to be expressed directly in the problem definition, rather than
 6784 in the matrix form $\mathbf{A}z \leq b$. The time complexity of integer linear programming is theoreti-
 6785 cally exponential in the number of variables $|z|$, but in practice these off-the-shelf solvers
 6786 obtain good solutions efficiently. Das et al. (2014) report that the `cplex` solver requires 43
 6787 seconds to perform inference on the FrameNet test set, which contains 4,458 predicates.

6788 Recent work has shown that many constrained optimization problems in natural lan-
 6789 guage processing can be solved in a highly parallelized fashion, using optimization tech-
 6790 niques such as **dual decomposition**, which are capable of exploiting the underlying prob-
 6791 lem structure (Rush et al., 2010). Das et al. (2014) apply this technique to FrameNet se-
 6792 mantic role labeling, obtaining an order-of-magnitude speedup over `cplex`.

6793 13.2.3 Neural semantic role labeling

6794 Neural network approaches to SRL have tended to treat it as a sequence labeling task,
 6795 using a labeling scheme such as the **BIO notation**, which we previously saw in named
 6796 entity recognition (§ 8.3). In this notation, the first token in a span of type ARG1 is labeled

¹¹<https://www.gnu.org/software/glpk/>

¹²<https://www-01.ibm.com/software/commerce/optimization/cplex-optimizer/>

¹³<http://www.gurobi.com/>

6797 B-ARG1; all remaining tokens in the span are *inside*, and are therefore labeled I-ARG1.
 6798 Tokens outside any argument are labeled O. For example:

- 6799 (13.21) *Asha taught Boyang 's mom about algebra*
 B-ARG0 PRED B-ARG2 I-ARG2 I-ARG2 B-ARG1 I-ARG1

Recurrent neural networks are a natural approach to this tagging task. For example, Zhou and Xu (2015) apply a deep bidirectional multilayer LSTM (see § 7.6) to PropBank semantic role labeling. In this model, each bidirectional LSTM serves as input for another, higher-level bidirectional LSTM, allowing complex non-linear transformations of the original input embeddings, $\mathbf{X} = [\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_M]$. The hidden state of the final LSTM is $\mathbf{Z}^{(K)} = [\mathbf{z}_1^{(K)}, \mathbf{z}_2^{(K)}, \dots, \mathbf{z}_M^{(K)}]$. The “emission” score for each tag $Y_m = y$ is equal to the inner product $\theta_y \cdot \mathbf{z}_m^{(K)}$, and there is also a transition score for each pair of adjacent tags. The complete model can be written,

$$\mathbf{Z}^{(1)} = \text{BiLSTM}(\mathbf{X}) \quad [13.13]$$

$$\mathbf{Z}^{(i)} = \text{BiLSTM}(\mathbf{Z}^{(i-1)}) \quad [13.14]$$

$$\hat{\mathbf{y}} = \underset{\mathbf{y}}{\operatorname{argmax}} \sum_{m=1}^M \Theta^{(y)} \mathbf{z}_m^{(K)} + \psi_{y_{m-1}, y_m}. \quad [13.15]$$

6800 Note that the final step maximizes over the entire labeling \mathbf{y} , and includes a score for
 6801 each tag transition ψ_{y_{m-1}, y_m} . This combination of LSTM and pairwise potentials on tags
 6802 is an example of an **LSTM-CRF**. The maximization over \mathbf{y} is performed by the Viterbi
 6803 algorithm.

6804 This model strongly outperformed alternative approaches at the time, including con-
 6805 strained decoding and convolutional neural networks.¹⁴ More recent work has combined
 6806 recurrent neural network models with constrained decoding, using the A^* search algo-
 6807 rithm to search over labelings that are feasible with respect to the constraints (He et al.,
 6808 2017). This yields small improvements over the method of Zhou and Xu (2015). He et al.
 6809 (2017) obtain larger improvements by creating an **ensemble** of SRL systems, each trained
 6810 on an 80% subsample of the corpus. The average prediction across this ensemble is more
 6811 robust than any individual model.

6812 13.3 Abstract Meaning Representation

6813 Semantic role labeling transforms the task of semantic parsing to a labeling task. Consider
 6814 the sentence,

¹⁴The successful application of convolutional neural networks to semantic role labeling by Collobert and Weston (2008) was an influential early result in the most recent wave of neural networks in natural language processing.

```
(w / want-01
  :ARG0 (b / boy)
  :ARG1 (g / go-02
    :ARG0 b))
```

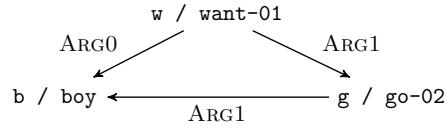


Figure 13.3: Two views of the AMR representation for the sentence *The boy wants to go.*

6815 (13.22) The boy wants to go.

6816 The PropBank semantic role labeling analysis is:

6817 • (PREDICATE : *wants*, ARG0 : *the boy*, ARG1 : *to go*)

6818 • (PREDICATE : *go*, ARG1 : *the boy*)

6819 The **Abstract Meaning Representation (AMR)** unifies this analysis into a graph structure, in which each node is a **variable**, and each edge indicates a **concept** (Banarescu et al., 2013). This can be written in two ways, as shown in Figure 13.3. On the left is the 6820 PENMAN notation (Matthiessen and Bateman, 1991), in which each set of parentheses 6821 introduces a variable. Each variable is an **instance** of a concept, which is indicated with 6822 the slash notation: for example, *w / want-01* indicates that the variable *w* is an instance 6823 of the concept *want-01*, which in turn refers to the PropBank frame for the first sense 6824 of the verb *want*. Relations are introduced with colons: for example, *:ARG0 (b / boy)* 6825 indicates a relation of type *ARG0* with the newly-introduced variable *b*. Variables can be 6826 reused, so that when the variable *b* appears again as an argument to *g*, it is understood to 6827 refer to the same boy in both cases. This arrangement is indicated compactly in the graph 6828 structure on the right, with edges indicating concepts. 6829
6830

6831 One way in which AMR differs from PropBank-style semantic role labeling is that it 6832 reifies each entity as a variable: for example, *the boy* in (13.22) is reified in the variable 6833 *b*, which is reused as *ARG0* in its relationship with *w / want-01*, and as *ARG1* in its 6834 relationship with *g / go-02*. Reifying entities as variables also makes it possible to 6835 represent the substructure of noun phrases more explicitly. For example, *Asha borrowed* 6836 *the algebra book* would be represented as:

```
6837 (b / borrow-01
  :ARG0 (p / person
    :name (n / name
      :op1 "Asha"))
  :ARG1 (b2 / book
    :topic (a / algebra)))
```

6843 This indicates that the variable *p* is a person, whose name is the variable *n*; that name
 6844 has one token, the string *Asha*. Similarly, the variable *b2* is a book, and the topic of *b2*
 6845 is a variable *a* whose type is algebra. The relations name and topic are examples of
 6846 **non-core roles**, which are similar to adjunct modifiers in PropBank. However, AMR’s
 6847 inventory is more extensive, including more than 70 non-core roles, such as negation,
 6848 time, manner, frequency, and location. Lists and sequences — such as the list of tokens in
 6849 a name — are described using the roles *op1*, *op2*, etc.

6850 Another feature of AMR is that a semantic predicate can be introduced by any syntac-
 6851 tic element, as in the following examples from Banarescu et al. (2013):

- 6852 (13.23) The boy destroyed the room.
- 6853 (13.24) the destruction of the room by the boy ...
- 6854 (13.25) the boy’s destruction of the room ...

6855 All these examples have the same semantics in AMR,

```
6856 (d / destroy-01
6857   :ARG0 (b / boy)
6858   :ARG1 (r / room))
```

6859 The noun *destruction* is linked to the verb *destroy*, which is captured by the PropBank
 6860 frame *destroy-01*. This can happen with adjectives as well: in the phrase *the attractive*
 6861 *spy*, the adjective *attractive* is linked to the PropBank frame *attract-01*:

```
6862 (s / spy
6863   :ARG0-of (a / attract-01))
```

6864 In this example, *ARG0-of* is an **inverse relation**, indicating that *s* is the *ARG0* of the
 6865 predicate *a*. Inverse relations make it possible for all AMR parses to have a single root
 6866 concept, which should be the **focus** of the utterance.

6867 While AMR goes farther than semantic role labeling, it does not link semantically-
 6868 related frames such as buy/sell (as FrameNet does), does not handle quantification (as
 6869 first-order predicate calculus does), and makes no attempt to handle noun number and
 6870 verb tense (as PropBank does). A recent survey by Abend and Rappoport (2017) situ-
 6871 ates AMR with respect to several other semantic representation schemes. Other linguistic
 6872 features of AMR are summarized in the original paper (Banarescu et al., 2013) and the
 6873 tutorial slides by Schneider et al. (2015).

6874 13.3.1 AMR Parsing

6875 Abstract Meaning Representation is not a labeling of the original text — unlike PropBank
6876 semantic role labeling, and most of the other tagging and parsing tasks that we have
6877 encountered thus far. The AMR for a given sentence may include multiple concepts for
6878 single words in the sentence: as we have seen, the sentence *Asha likes algebra* contains both
6879 person and name concepts for the word *Asha*. Conversely, words in the sentence may not
6880 appear in the AMR: in *Boyang made a tour of campus*, the **light verb** *make* would not appear
6881 in the AMR, which would instead be rooted on the predicate *tour*. As a result, AMR
6882 is difficult to parse, and even evaluating AMR parsing involves considerable algorithmic
6883 complexity (Cai and Yates, 2013).

6884 A further complexity is that AMR labeled datasets do not explicitly show the **align-**
6885 **ment** between the AMR annotation and the words in the sentence. For example, the link
6886 between the word *wants* and the concept *want-01* is not annotated. To acquire train-
6887 ing data for learning-based parsers, it is therefore necessary to first perform an alignment
6888 between the training sentences and their AMR parses. Flanigan et al. (2014) introduce a
6889 rule-based parser, which links text to concepts through a series of increasingly high-recall
6890 steps.

6891 **Graph-based parsing** One family of approaches to AMR parsing is similar to the graph-
6892 based methods that we encountered in syntactic dependency parsing (chapter 11). For
6893 these systems (Flanigan et al., 2014), parsing is a two-step process:

- 6894 1. **Concept identification** (Figure 13.4a). This involves constructing concept subgraphs
6895 for individual words or spans of adjacent words. For example, in the sentence,
6896 *Asha likes algebra*, we would hope to identify the minimal subtree including just the
6897 concept *like-01* for the word *like*, and the subtree (*p / person :name (n /*
6898 *name :op1 Asha)*) for the word *Asha*.
- 6899 2. **Relation identification** (Figure 13.4b). This involves building a directed graph over
6900 the concepts, where the edges are labeled by the relation type. AMR imposes a
6901 number of constraints on the graph: all concepts must be included, the graph must
6902 be **connected** (there must be a path between every pair of nodes in the undirected
6903 version of the graph), and every node must have at most one outgoing edge of each
6904 type.

6905 Both of these problems are solved by structure prediction. Concept identification re-
6906 quires simultaneously segmenting the text into spans, and labeling each span with a graph
6907 fragment containing one or more concepts. This is done by computing a set of features
6908 for each candidate span *s* and concept labeling *c*, and then returning the labeling with the
6909 highest overall score.

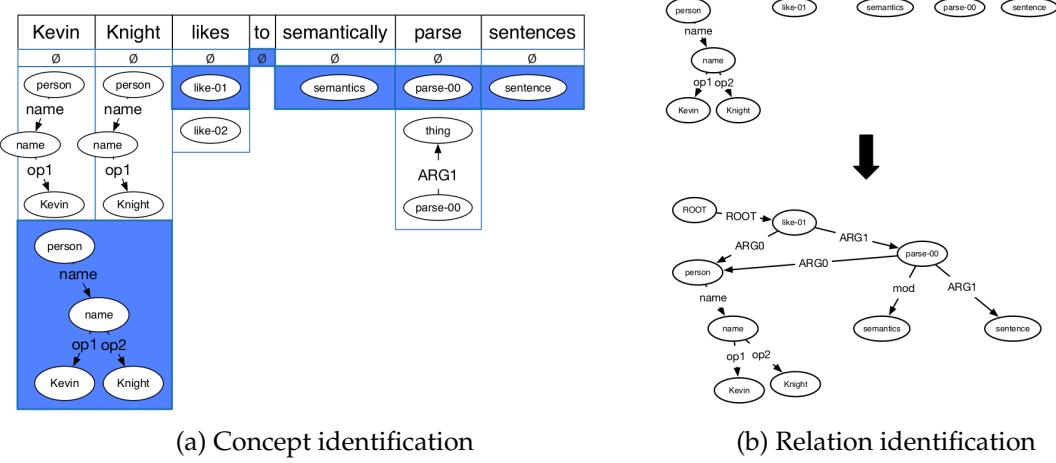


Figure 13.4: Subtasks for Abstract Meaning Representation parsing, from Schneider et al. (2015). [todo: permission]

6910 Relation identification can be formulated as search for the maximum spanning sub-
 6911 graph, under a set of constraints. Each labeled edge has a score, which is computed
 6912 from features of the concepts. We then search for the set of labeled edges that maximizes
 6913 the sum of these scores, under the constraint that the resulting graph is a well-formed
 6914 AMR (Flanigan et al., 2014). This constrained search can be performed by optimization
 6915 techniques such as integer linear programming, as described in § 13.2.2.

6916 **Transition-based parsing** In many cases, AMR parses are structurally similar to syn-
 6917 tactic dependency parses. Figure 13.5 shows one such example. This motivates an alter-
 6918 native approach to AMR parsing: modify the syntactic dependency parse until it looks
 6919 like a good AMR parse. Wang et al. (2015) propose a transition-based method, based on
 6920 incremental modifications to the syntactic dependency tree (transition-based dependency
 6921 parsing is discussed in § 11.3). At each step, the parser performs an action: for example,
 6922 adding an AMR relation label to the current dependency edge, swapping the direction of
 6923 a syntactic dependency edge, or cutting an edge and reattaching the orphaned subtree to
 6924 a new parent. The overall system is trained as a classifier, learning to choose the action as
 6925 would be given by an **oracle** that is capable of reproducing the ground-truth parse.

6926 13.4 Applications of Predicate-Argument Semantics

6927 **Question answering** Factoid questions have answers that are single words or phrases,
 6928 such as *who discovered prions?*, *where was Barack Obama born?*, and *in what year did the Knicks*
 6929 *last win the championship?* Semantic role labeling can be used to answer such questions,

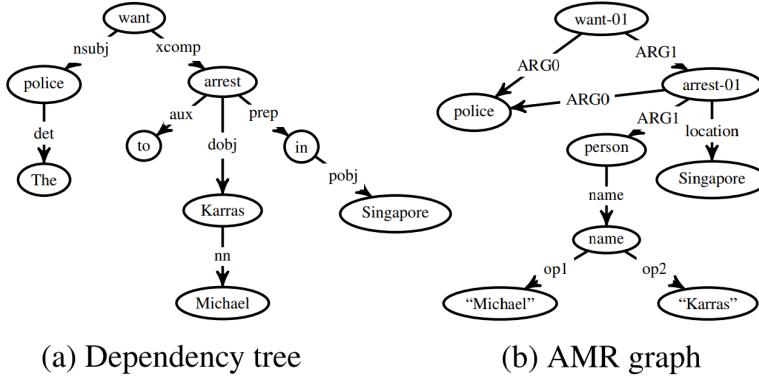


Figure 13.5: Syntactic dependency parse and AMR graph for the sentence *The police want to arrest Michael Karras in Singapore* (borrowed from Wang et al. (2015)) [todo: permission]

6930 by linking questions to sentences in a corpus of text. Shen and Lapata (2007) perform
 6931 FrameNet semantic role labeling on the query, and then construct a weighted **bipartite**
 6932 **graph**¹⁵ between FrameNet semantic roles and the words and phrases in the sentence.
 6933 This is done by first scoring all pairs of semantic roles and assignments, as shown in the
 6934 top half of Figure 13.6. They then find the bipartite edge cover, which is the minimum
 6935 weighted subset of edges such that each vertex has at least one edge, as shown in the
 6936 bottom half of Figure 13.6. After analyzing the question in this manner, Shen and Lapata
 6937 then find semantically-compatible sentences in the corpus, by performing graph matching
 6938 on the bipartite graphs for the question and candidate answer sentences. Finally, the
 6939 *expected answer phrase* in the question — typically the *wh*-word — is linked to a phrase in
 6940 the candidate answer source, and that phrase is returned as the answer.

6941 **Relation extraction** The task of **relation extraction** involves identifying pairs of entities
 6942 for which a given semantic relation holds (see § 17.2. For example, we might like to find
 6943 all pairs (i, j) such that i is the INVENTOR-OF j . PropBank semantic role labeling can
 6944 be applied to this task by identifying sentences whose verb signals the desired relation,
 6945 and then extracting ARG1 and ARG2 as arguments. (To fully solve this task, these argu-
 6946 ments must then be linked to entities, as described in chapter 17.) Christensen et al. (2010)
 6947 compare a semantic role labeling system against a simpler approach based on surface pat-
 6948 terns (Banko et al., 2007). They find that the SRL system is considerably more accurate,
 6949 but that it is several orders of magnitude slower. Conversely, Barnickel et al. (2009) apply
 6950 SENNA, a convolutional neural network SRL system (Collobert and Weston, 2008) to the
 6951 task of identifying biomedical relations (e.g., which genes inhibit or activate each other).

¹⁵A bipartite graph is one in which the vertices can be divided into two disjoint sets, and every edge connects a vertex in one set to a vertex in the other.

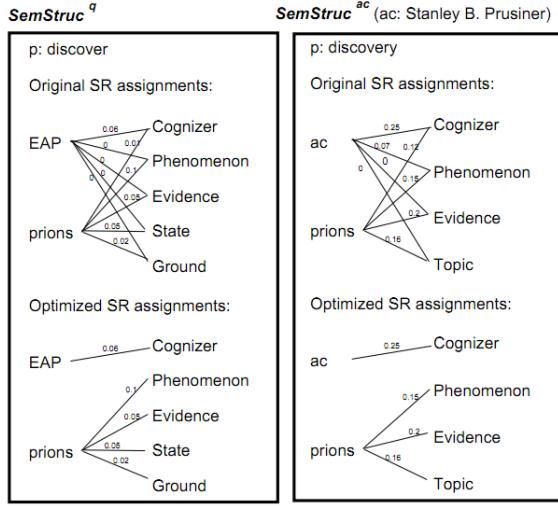


Figure 13.6: FrameNet semantic role labeling is used in factoid question answering, by aligning the semantic roles in the question (q) against those of sentences containing answer candidates (ac). “EAP” is the expected answer phrase, replacing the word *who* in the question. Figure reprinted from Shen and Lapata (2007) [todo: permission]

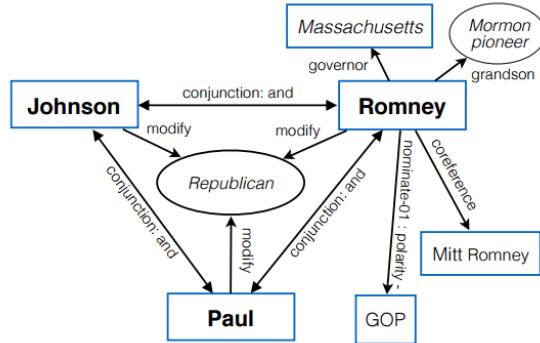


Figure 13.7: Fragment of AMR knowledge network for entity linking. Figure reprinted from Pan et al. (2015) [todo: permission]

6952 In comparison with a strong baseline that applies a set of rules to syntactic dependency
 6953 structures (Fundel et al., 2007), the SRL system is faster but less accurate. One possible
 6954 explanation for these divergent results is that Fundel et al. compare against a baseline
 6955 which is carefully tuned for performance in a relatively narrow domain, while the system
 6956 of Banko et al. is designed to analyze text across the entire web.

6957 **Entity linking** Another core task in information extraction is to link mentions of entities
6958 (e.g., *Republican candidates like Romney, Paul, and Johnson* ...) to entities in a knowledge
6959 base (e.g., LYNDON JOHNSON or GARY JOHNSON). This task, which is described in § 17.1,
6960 is often performed by examining nearby “collaborator” mentions — in this case, *Romney*
6961 and *Paul*. By jointly linking all such mentions, it is possible to arrive at a good overall
6962 solution. Pan et al. (2015) apply AMR to this problem. For each entity, they construct a
6963 knowledge network based on its semantic relations with other mentions within the same
6964 sentence. They then rerank a set of candidate entities, based on the overlap between
6965 the entity’s knowledge network and the semantic relations present in the sentence (Figure
6966 13.7).

6967 **Exercises**

- 6968 1. Write out an event semantic representation for the following sentences. You may
6969 make up your own predicates.
 - 6970 (13.26) *Abigail shares with Max.*
 - 6971 (13.27) *Abigail reluctantly shares a toy with Max.*
 - 6972 (13.28) *Abigail hates to share with Max.*
 - 6973 2. Find the PropBank framesets for *share* and *hate* at <http://verbs.colorado.edu/propbank/framesets-english-aliases/>, and rewrite your answers from the
6974 previous question, using the thematic roles ARG0, ARG1, and ARG2.
6975
 - 6976 3. Compute the syntactic path features for Abigail and Max in each of the example sentences (13.26) and (13.28) in Question 1, with respect to the verb *share*. If you’re not
6977 sure about the parse, you can try an online parser such as <http://nlp.stanford.edu:8080/parser/>.
6978
 - 6979 4. Compute the dependency path features for Abigail and Max in each of the example sentences (13.26) and (13.28) in Question 1, with respect to the verb *share*. Again, if
6980 you’re not sure about the parse, you can try an online parser such as <http://nlp.stanford.edu:8080/parser/>. As a hint, the dependency relation between *share*
6981 and *Max* is OBL according to the Universal Dependency treebank (version 2).
6982
 - 6983 5. PropBank semantic role labeling includes **reference arguments**, such as,
6984
- 6985 (13.29) [AM-LOC The bed] on [R-AM-LOC which] I slept broke.¹⁶

¹⁶Example from 2013 NAACL tutorial slides by Shumin Wu

6987 The label R-AM-LOC indicates that word *which* is a reference to *The bed*, which ex-
 6988 presses the location of the event. Reference arguments must have referents: the tag
 6989 R-AM-LOC can appear only when AM-LOC also appears in the sentence. Show how
 6990 to express this as a linear constraint, specifically for the tag R-AM-LOC. Be sure to
 6991 correctly handle the case in which neither AM-LOC nor R-AM-LOC appear in the
 6992 sentence.

- 6993 6. Explain how to express the constraints on semantic role labeling in Equation 13.8
 6994 and Equation 13.9 in the general form $Az \geq b$.
- 6995 7. Download the FrameNet sample data (<https://framenet.icsi.berkeley.edu/fndrupal/fulltextIndex>), and train a bag-of-words classifier to predict the
 6996 frame that is evoked by each verb in each example. Your classifier should build
 6997 a bag-of-words from the sentence in which the frame-evoking lexical unit appears.
 6998 [**todo: Somehow limit to one or a few lexical units.**] [**todo: use NLTK if possible**]
- 7000 8. Download the PropBank sample data, using NLTK (<http://www.nltk.org/howto/propbank.html>). Use a deep learning toolkit such as PyTorch or DyNet to train an
 7001 LSTM to predict tags. You will have to convert the downloaded instances to a BIO
 7002 sequence labeling representation first.
- 7004 9. Produce the AMR annotations for the following examples:

- 7005 (13.30) The girl likes the boy.
- 7006 (13.31) The girl was liked by the boy.
- 7007 (13.32) Abigail likes Maxwell Aristotle.
- 7008 (13.33) The spy likes the attractive boy.
- 7009 (13.34) The girl doesn't like the boy.
- 7010 (13.35) The girl likes her dog.

7011 For (13.32), recall that multi-token names are created using op1, op2, etc. You will
 7012 need to consult Banerjee et al. (2013) for (13.34), and Schneider et al. (2015) for
 7013 (13.35). You may assume that *her* refers to *the girl* in this example.

- 7014 10. Using an off-the-shelf PropBank SRL system,¹⁷ build a simplified question answer-
 7015 ing system in the style of Shen and Lapata (2007). Specifically, your system should
 7016 do the following:

¹⁷At the time of writing, the following systems are available: SENNA (<http://ronan.collobert.com/senna/>), Illinois Semantic Role Labeler (https://cogcomp.cs.illinois.edu/page/software_view/SRL), and mate-tools (<https://code.google.com/archive/p/mate-tools/>).

- For each document in a collection, it should apply the semantic role labeler, and should store the output as a tuple.
- For a question, your system should again apply the semantic role labeler. If any of the roles are filled by a *wh*-pronoun, you should mark that role as the expected answer phrase (EAP).
- To answer the question, search for a stored tuple which matches the question as well as possible (same predicate, no incompatible semantic roles, and as many matching roles as possible). Align the EAP against its role filler in the stored tuple, and return this as the answer.

To evaluate your system, download a set of three news articles on the same topic, and write down five factoid questions that should be answerable from the articles. See if your system can answer these questions correctly. (If this problem is assigned to an entire class, you can build a large-scale test set and compare various approaches.)

7031 Chapter 14

7032 Distributional and distributed 7033 semantics

7034 A recurring theme in natural language processing is the complexity of the mapping from
7035 words to meaning. In chapter 4, we saw that a single word form, like *bank*, can have mul-
7036 tiple meanings; conversely, a single meaning may be created by multiple surface forms,
7037 a lexical semantic relationship known as **synonymy**. Despite this complex mapping be-
7038 tween words and meaning, natural language processing systems usually rely on words
7039 as the basic unit of analysis. This is especially true in semantics: the logical and frame
7040 semantic methods from the previous two chapters rely on hand-crafted lexicons that map
7041 from words to semantic predicates. But how can we analyze texts that contain words
7042 that we haven't seen before? This chapter describes methods that learn representations
7043 of word meaning by analyzing unlabeled data, vastly improving the generalizability of
7044 natural language processing systems. The theory that makes it possible to acquire mean-
7045 ingful representations from unlabeled data is the **distributional hypothesis**.

7046 14.1 The distributional hypothesis

7047 Here's a word you may not know: *tezgüino* (the example is from Lin, 1998). If you do not
7048 know the meaning of *tezgüino*, then you are in the same situation as a natural language
7049 processing system when it encounters a word that did not appear in its training data.
7050 Now suppose you see that *tezgüino* is used in the following contexts:

- 7051 (14.1) A bottle of _____ is on the table.
- 7052 (14.2) Everybody likes _____.
- 7053 (14.3) Don't have _____ before you drive.
- 7054 (14.4) We make _____ out of corn.

	(14.1)	(14.2)	(14.3)	(14.4)	...
<i>tezgüino</i>	1	1	1	1	
<i>loud</i>	0	0	0	0	
<i>motor oil</i>	1	0	0	1	
<i>tortillas</i>	0	1	0	1	
<i>choices</i>	0	1	0	0	
<i>wine</i>	1	1	1	0	

Table 14.1: Distributional statistics for *tezgüino* and five related terms

What other words fit into these contexts? How about: *loud*, *motor oil*, *tortillas*, *choices*, *wine*? Each row of Table 14.1 is a vector that summarizes the contextual properties for each word, with a value of one for contexts in which the word can appear, and a value of zero for contexts in which it cannot. Based on these vectors, we can conclude: *wine* is very similar to *tezgüino*; *motor oil* and *tortillas* are fairly similar to *tezgüino*; *loud* is completely different.

These vectors, which we will call **word representations**, describe the **distributional** properties of each word. Does vector similarity imply semantic similarity? This is the **distributional hypothesis**, stated by Firth (1957) as: “You shall know a word by the company it keeps.” The distributional hypothesis has stood the test of time: distributional statistics are a core part of language technology today, because they make it possible to leverage large amounts of unlabeled data to learn about rare words that do not appear in labeled training data.

Distributional statistics have a striking ability to capture lexical semantic relationships such as analogies. Figure 14.1 shows two examples, based on two-dimensional projections of distributional **word embeddings**, discussed later in this chapter. In each case, word-pair relationships correspond to regular linear patterns in this two dimensional space. No labeled data about the nature of these relationships was required to identify this underlying structure.

Distributional semantics are computed from context statistics. **Distributed** semantics are a related but distinct idea: that meaning can be represented by numerical vectors rather than symbolic structures. Distributed representations are often estimated from distributional statistics, as in latent semantic analysis and WORD2VEC, described later in this chapter. However, distributed representations can also be learned in a supervised fashion from labeled data, as in the neural classification models encountered in chapter 3.

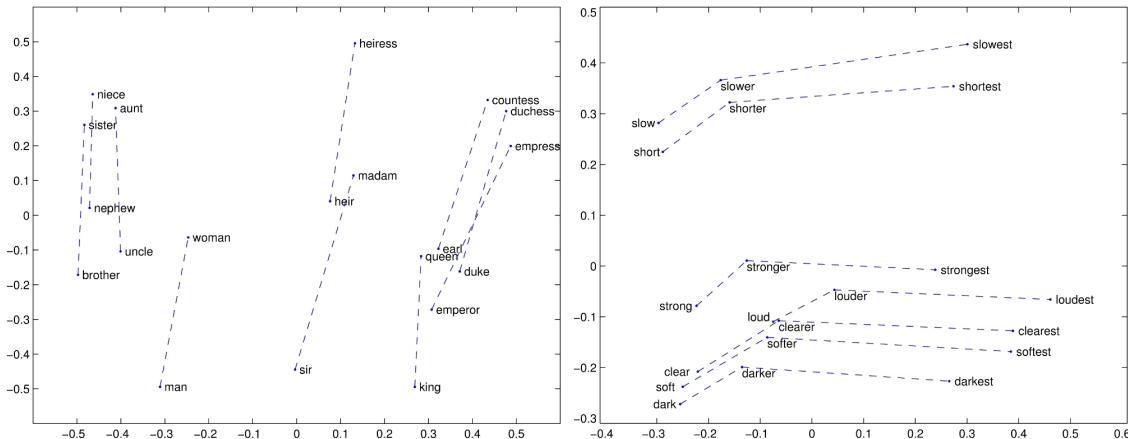


Figure 14.1: Lexical semantic relationships have regular linear structures in two dimensional projections of distributional statistics. From [http://nlp.stanford.edu/projects/glove/.\[todo: redo to make words bigger?\]](http://nlp.stanford.edu/projects/glove/.[todo: redo to make words bigger?])

7080 14.2 Design decisions for word representations

7081 There are many approaches for computing word representations, but most can be distin-
 7082 guished on three main dimensions: the nature of the representation, the source of context-
 7083 ual information, and the estimation procedure.

7084 14.2.1 Representation

7085 Today, the dominant word representations are k -dimensional vectors of real numbers,
 7086 known as **word embeddings**. (The name is due to the fact that each discrete word is em-
 7087 bedded in a continuous vector space.) This representation dates back at least to the late
 7088 1980s (Deerwester et al., 1990), and is used in popular techniques such as WORD2VEC (Mikolov
 7089 et al., 2013).

7090 Word embeddings are well suited for neural networks, where they can be plugged
 7091 in as inputs. They can also be applied in linear classifiers and structure prediction mod-
 7092 els (Turian et al., 2010), although it can be difficult to learn linear models that employ
 7093 real-valued features (Kummerfeld et al., 2015). A popular alternative is bit-string rep-
 7094 resentations, such as **Brown clusters** (§ 14.4), in which each word is represented by a
 7095 variable-length sequence of zeros and ones (Brown et al., 1992).

7096 Another representational question is whether to estimate one embedding per surface
 7097 form (e.g., *bank*), or to estimate distinct embeddings for each word sense or synset. In-
 7098 tuitively, if word representations are to capture the meaning of individual words, then
 7099 words with multiple meanings should have multiple embeddings. This can be achieved

The moment one learns English, complications set in (Alfau, 1999)

Brown Clusters (Brown et al., 1992)	{one}
WORD2VEC (Mikolov et al., 2013) ($h = 2$)	{moment, one, English, complications}
Structured WORD2VEC (Ling et al., 2015) ($h = 2$)	$\{(moment, -2), (one, -1), (English, +1), (complications, +2)\}$
Dependency contexts (Levy and Goldberg, 2014)	$\{(one, \text{NSUBJ}), (English, \text{DOBJ}), (moment, \text{ACL}^{-1})\}$

Table 14.2: Contexts for the word *learns*, according to various word representations. For dependency context, *(one, NSUBJ)* means that there is a relation of type NSUBJ (nominal subject) **to** the word *one*, and *(moment, ACL⁻¹)* means that there is a relation of type ACL (adjectival clause) **from** the word *moment*.

7100 by integrating unsupervised clustering with word embedding estimation (Huang and
 7101 Yates, 2012; Li and Jurafsky, 2015). However, Arora et al. (2016) argue that it is unnec-
 7102 essary to model distinct word senses explicitly, because the embeddings for each surface
 7103 form are a linear combination of the embeddings of the underlying senses.

7104 14.2.2 Context

7105 The distributional hypothesis says that word meaning is related to the “contexts” in which
 7106 the word appears, but context can be defined in many ways. In the *tezgiiino* example, con-
 7107 texts are entire sentences, but in practice there are far too many sentences. At the oppo-
 7108 site extreme, the context could be defined as the immediately preceding word; this is the
 7109 context considered in Brown clusters. WORD2VEC takes an intermediate approach, using
 7110 local neighborhoods of words (e.g., $h = 5$) as contexts (Mikolov et al., 2013). Contexts
 7111 can also be much larger: for example, in **latent semantic analysis**, each word’s context
 7112 vector includes an entry per document, with a value of one if the word appears in the
 7113 document (Deerwester et al., 1990); in **explicit semantic analysis**, these documents are
 7114 Wikipedia pages (Gabrilovich and Markovitch, 2007).

7115 Words in context can be labeled by their position with respect to the target word w_m
 7116 (e.g., two words before, one word after), which makes the resulting word representations
 7117 more sensitive to syntactic differences (Ling et al., 2015). Another way to incorporate
 7118 syntax is to perform parsing as a preprocessing step, and then form context vectors from
 7119 the dependency edges (Levy and Goldberg, 2014) or predicate-argument relations (Lin,
 7120 1998). The resulting context vectors for several of these methods are shown in Table 14.2.

7121 The choice of context has a profound effect on the resulting representations, which

7122 can be viewed in terms of word similarity. Applying latent semantic analysis (§ 14.3) to
 7123 contexts of size $h = 2$ and $h = 30$ yields the following nearest-neighbors for the word
 7124 *dog*:¹

- 7125 • ($h = 2$): *cat, horse, fox, pet, rabbit, pig, animal, mongrel, sheep, pigeon*
 7126 • ($h = 30$): *kennel, puppy, pet, bitch, terrier, rottweiler, canine, cat, to bark, Alsatian*

7127 Which word list is better? Each word in the $h = 2$ list is an animal, reflecting the fact that
 7128 locally, the word *dog* tends to appear in the same contexts as other animal types (e.g., *pet*
 7129 *the dog, feed the dog*). In the $h = 30$ list, nearly everything is dog-related, including specific
 7130 breeds such as *rottweiler* and *Alsatian*. The list also includes words that are not animals
 7131 (*kennel*), and in one case (*to bark*), is not a noun at all. The 2-word context window is more
 7132 sensitive to syntax, while the 30-word window is more sensitive to topic.

7133 14.2.3 Estimation

7134 Word embeddings are estimated by optimizing some objective: the likelihood of a set of
 7135 unlabeled data (or a closely related quantity), or the reconstruction of a matrix of context
 7136 counts, similar to Table 14.1.

7137 **Maximum likelihood estimation** Likelihood-based optimization is derived from the
 7138 objective $\log p(\mathbf{w}; \mathbf{U})$, where $\mathbf{U} \in \mathbb{R}^{K \times V}$ is matrix of word embeddings, and $\mathbf{w} =$
 7139 $\{\mathbf{w}_m\}_{m=1}^M$ is a corpus, represented as a list of M tokens. Recurrent neural network lan-
 7140 guage models (§ 6.3) optimize this objective directly, backpropagating to the input word
 7141 embeddings through the recurrent structure. However, state-of-the-art word embeddings
 7142 employ huge corpora with hundreds of billions of tokens, and recurrent architectures are
 7143 difficult to scale to such data. As a result, likelihood-based word embeddings are usually
 7144 based on simplified likelihoods or heuristic approximations.

Matrix factorization The matrix $\mathbf{C} = \{\text{count}(i, j)\}$ stores the co-occurrence counts of
 word i and context j . Word representations can be obtained by approximately factoring
 this matrix, so that $\text{count}(i, j)$ is approximated by a function of a word embedding \mathbf{u}_i and
 a context embedding \mathbf{v}_j . These embeddings can be obtained by minimizing the norm of
 the reconstruction error,

$$\min_{\mathbf{u}, \mathbf{v}} \|\mathbf{C} - \tilde{\mathbf{C}}(\mathbf{u}, \mathbf{v})\|_F, \quad [14.1]$$

¹The example is from lecture slides by Marco Baroni, Alessandro Lenci, and Stefan Evert, who applied latent semantic analysis to the British National Corpus. You can find an online demo here: <http://clic.cimec.unitn.it/infomap-query/>

7145 where $\tilde{\mathbf{C}}(\mathbf{u}, \mathbf{v})$ is the approximate reconstruction resulting from the embeddings \mathbf{u} and
 7146 \mathbf{v} , and $\|\mathbf{X}\|_F$ indicates the Frobenius norm, $\sum_{i,j} x_{i,j}^2$. Rather than factoring the matrix of
 7147 word-context counts directly, it is often helpful to transform these counts using information-
 7148 theoretic metrics such as **pointwise mutual information** (PMI), described in the next sec-
 7149 tion.

7150 **14.3 Latent semantic analysis**

Latent semantic analysis (LSA) is one of the oldest approaches to distributed semantics (Deerwester et al., 1990). It induces continuous vector representations of words by factoring a matrix of word and context counts, using **truncated singular value decomposition** (SVD),

$$\min_{\mathbf{U} \in \mathbb{R}^{V \times K}, \mathbf{S} \in \mathbb{R}^{K \times K}, \mathbf{V} \in \mathbb{R}^{|\mathcal{C}| \times K}} \|\mathbf{C} - \mathbf{USV}^\top\|_F \quad [14.2]$$

$$\text{s.t. } \mathbf{U}^\top \mathbf{U} = \mathbb{I} \quad [14.3]$$

$$\mathbf{V}^\top \mathbf{V} = \mathbb{I} \quad [14.4]$$

$$\forall i \neq j, \mathbf{S}_{i,j} = 0, \quad [14.5]$$

7151 where V is the size of the vocabulary, $|\mathcal{C}|$ is the number of contexts, and K is size of the
 7152 resulting embeddings, which are set equal to the rows of the matrix \mathbf{U} . The matrix \mathbf{S} is
 7153 constrained to be diagonal (these diagonal elements are called the singular values), and
 7154 the columns of the product \mathbf{SV}^\top provide descriptions of the contexts. Each element $c_{i,j}$ is
 7155 then reconstructed as a **bilinear product**,

$$c_{i,j} \approx \sum_{k=1}^K u_{i,k} s_k v_{j,k}. \quad [14.6]$$

7156 The objective is to minimize the sum of squared approximation errors. The orthonormality
 7157 constraints $\mathbf{U}^\top \mathbf{U} = \mathbf{V}^\top \mathbf{V} = \mathbb{I}$ ensure that all pairs of dimensions in \mathbf{U} and \mathbf{V} are
 7158 uncorrelated, so that each dimension conveys unique information. Efficient implemen-
 7159 tations of truncated singular value decomposition are available in numerical computing
 7160 packages such as `scipy` and `matlab`.²

Latent semantic analysis is most effective when the count matrix is transformed before the application of SVD. One such transformation is **pointwise mutual information** (PMI; Church and Hanks, 1990), which captures the degree of association between word i and

²An important implementation detail is to represent \mathbf{C} as a **sparse matrix**, so that the storage cost is equal to the number of non-zero entries, rather than the size $V \times |\mathcal{C}|$.

context j ,

$$\text{PMI}(i, j) = \log \frac{p(i, j)}{p(i)p(j)} = \log \frac{p(i | j)p(j)}{p(i)p(j)} = \log \frac{p(i | j)}{p(i)} \quad [14.7]$$

$$= \log \text{count}(i, j) - \log \sum_{i'=1}^V \text{count}(i', j) \quad [14.8]$$

$$- \log \sum_{j' \in \mathcal{C}} \text{count}(i, j') + \log \sum_{i'=1}^V \sum_{j' \in \mathcal{C}} \text{count}(i', j'). \quad [14.9]$$

7161 The pointwise mutual information can be viewed as the logarithm of the ratio of the con-
 7162 ditional probability of word i in context j to the marginal probability of word i in all
 7163 contexts. When word i is statistically associated with context j , the ratio will be greater
 7164 than one, so $\text{PMI}(i, j) > 0$. The PMI transformation focuses latent semantic analysis on re-
 7165 constructing strong word-context associations, rather than on reconstructing large counts.

7166 The PMI is negative when a word and context occur together less often than if they
 7167 were independent, but such negative correlations are unreliable because counts of rare
 7168 events have high variance. Furthermore, the PMI is undefined when $\text{count}(i, j) = 0$. One
 7169 solution to these problems is to use the **Positive PMI** (PPMI),

$$\text{PPMI}(i, j) = \begin{cases} \text{PMI}(i, j), & p(i | j) > p(i) \\ 0, & \text{otherwise.} \end{cases} \quad [14.10]$$

7170 Bullinaria and Levy (2007) compare a range of matrix transformations for latent se-
 7171 mantic analysis, using a battery of tasks related to word meaning and word similarity
 7172 (for more on evaluation, see § 14.6). They find that PPMI-based latent semantic analysis
 7173 yields strong performance on a battery of tasks related to word meaning: for example,
 7174 PPMI-based LSA vectors can be used to solve multiple-choice word similarity questions
 7175 from the Test of English as a Foreign Language (TOEFL), obtaining 85% accuracy.

7176 14.4 Brown clusters

7177 Learning algorithms like perceptron and conditional random fields often perform better
 7178 with discrete feature vectors. A simple way to obtain discrete representations from distri-
 7179 butional statistics is by clustering (§ 5.1.1), so that words in the same cluster have similar
 7180 distributional statistics. This can help in downstream tasks, by sharing features between
 7181 all words in the same cluster. However, there is an obvious tradeoff: if the number of clus-
 7182 ters is too small, the words in each cluster will not have much in common; if the number
 7183 of clusters is too large, then the learner will not see enough examples from each cluster to
 7184 generalize.

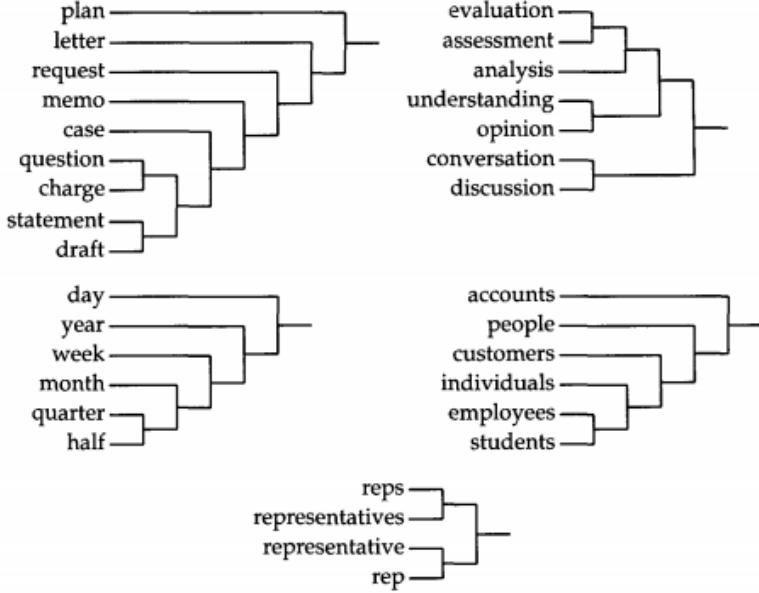


Figure 14.2: Some subtrees produced by bottom-up Brown clustering (Miller et al., 2004) on news text [todo: permission]

7185 A solution to this problem is **hierarchical clustering**: using the distributional statistics
 7186 to induce a tree-structured representation. Fragments of **Brown cluster** trees are shown in
 7187 Figure 14.2 and Table 14.3. Each word’s representation consists of a binary string describ-
 7188 ing a path through the tree: 0 for taking the left branch, and 1 for taking the right branch.
 7189 In the subtree in the upper right of the figure, the representation of the word *conversation*
 7190 is 10; the representation of the word *assessment* is 0001. Bitstring prefixes capture simila-
 7191 rity at varying levels of specificity, and it is common to use the first eight, twelve, sixteen,
 7192 and twenty bits as features in tasks such as named entity recognition (Miller et al., 2004)
 7193 and dependency parsing (Koo et al., 2008).

Hierarchical trees can be induced from a likelihood-based objective, using a discrete latent variable $k_i \in \{1, 2, \dots, K\}$ to represent the cluster of word i :

$$\log p(\mathbf{w}; \mathbf{k}) \approx \sum_{m=1}^M \log p(w_m | w_{m-1}; \mathbf{k}) \quad [14.11]$$

$$\triangleq \sum_{m=1}^M \log p(w_m | k_{w_m}) + \log p(k_{w_m} | k_{w_{m-1}}). \quad [14.12]$$

7194 This is similar to a hidden Markov model, with the crucial difference that each word can

bitstring	ten most frequent words
01111010 0111	<i>excited thankful grateful stoked pumped anxious hyped psyched exited geeked</i>
01111010 100	<i>talking talkin complaining talkn bitching tlkn tlkin bragging rav- ing +k</i>
01111010 1010	<i>thinking thinkin dreaming worrying thinkn speakin reminiscing dreamin daydreaming fantasizing</i>
01111010 1011	<i>saying sayin suggesting stating sayn jokin talmbout implying insisting 5'2</i>
01111010 1100	<i>wonder dunno wondered duno donno dno doно wonda wounder dunnoe</i>
01111010 1101	<i>wondering wonders debating deciding pondering unsure won- derin debatin woundering wondern</i>
01111010 1110	<i>sure suree suuure suure sure- surre sures shuree</i>

Table 14.3: Fragment of a Brown clustering of Twitter data (Owoputi et al., 2013). Each row is a leaf in the tree, showing the ten most frequent words. This part of the tree emphasizes verbs of communicating and knowing, especially in the present participle. Each leaf node includes orthographic variants (*thinking*, *thinkin*, *thinkn*), semantically related terms (*excited*, *thankful*, *grateful*), and some outliers (*5'2*, *+k*). See http://www.cs.cmu.edu/~ark/TweetNLP/cluster_viewer.html for more.

7195 be emitted from only a single cluster: $\forall k \neq k_{w_m}, p(w_m | k) = 0$.

Using the objective in Equation 14.12, the Brown clustering tree can be constructed from the bottom up: begin with each word in its own cluster, and incrementally merge clusters until only a single cluster remains. At each step, we merge the pair of clusters such that the objective in Equation 14.12 is maximized. Although the objective seems to involve a sum over the entire corpus, the score for each merger can be computed from the cluster-to-cluster co-occurrence counts. These counts can be updated incrementally as the clustering proceeds. The optimal merge at each step can be shown to maximize the **average mutual information**,

$$I(\mathbf{k}) = \sum_{k_1=1}^K \sum_{k_2=1}^K p(k_1, k_2) \times \text{PMI}(k_1, k_2) \quad [14.13]$$

$$p(k_1, k_2) = \frac{\text{count}(k_1, k_2)}{\sum_{k_{1'}=1}^K \sum_{k_{2'}=1}^K \text{count}(k_{1'}, k_{2'})},$$

7196 where $p(k_1, k_2)$ is the joint probability of a bigram involving a word in cluster k_1 followed
7197 by a word in k_2 . This probability and the PMI are both computed from the co-occurrence

Algorithm 17 Exchange clustering algorithm. Assumes that words are sorted by frequency, and that MAXMI finds the cluster pair whose merger maximizes the mutual information, as defined in Equation 14.13.

```

procedure EXCHANGECLUSTERING({count( $\cdot, \cdot$ )},  $K$ )
    for  $i \in 1 \dots K$  do                                 $\triangleright$  Initialization
         $k_i \leftarrow i$ ,  $i = 1, 2, \dots, K$ 
        for  $j \in 1 \dots K$  do
             $c_{i,j} \leftarrow \text{count}(i, j)$ 
         $\tau \leftarrow \{(i)\}_{i=1}^K$ 
        for  $i \in \{K + 1, K + 2, \dots, V\}$  do       $\triangleright$  Iteratively add each word to the clustering
             $\tau \leftarrow \tau \cup (i)$ 
            for  $k \in \tau$  do
                 $c_{k,i} \leftarrow \text{count}(k, i)$ 
                 $c_{i,k} \leftarrow \text{count}(i, k)$ 
             $\hat{i}, \hat{j} \leftarrow \text{MAXMI}(\mathbf{C})$ 
             $\tau, \mathbf{C} \leftarrow \text{MERGE}(\hat{i}, \hat{j}, \mathbf{C}, \tau)$ 
        repeat                                          $\triangleright$  Merge the remaining clusters into a tree
             $\hat{i}, \hat{j} \leftarrow \text{MAXMI}(\mathbf{C}, \tau)$ 
             $\tau, \mathbf{C} \leftarrow \text{MERGE}(\hat{i}, \hat{j}, \mathbf{C}, \tau)$ 
        until  $|\tau| = 1$ 
        return  $\tau$ 
procedure MERGE( $i, j, \mathbf{C}, \tau$ )
     $\tau \leftarrow \tau \setminus i \setminus j \cup (i, j)$            $\triangleright$  Merge the clusters in the tree
    for  $k \in \tau$  do                                 $\triangleright$  Aggregate the counts across the merged clusters
         $c_{k,(i,j)} \leftarrow c_{k,i} + c_{k,j}$ 
         $c_{(i,j),k} \leftarrow c_{i,k} + c_{j,k}$ 
    return  $\tau, \mathbf{C}$ 

```

7198 counts between clusters. After each merger, the co-occurrence vectors for the merged
 7199 clusters are simply added up, so that the next optimal merger can be found efficiently.

7200 This bottom-up procedure requires iterating over the entire vocabulary, and evaluating
 7201 K_t^2 possible mergers at each step, where K_t is the current number of clusters at step t
 7202 of the algorithm. Furthermore, computing the score for each merger involves a sum over
 7203 K_t^2 clusters. The maximum number of clusters is $K_0 = V$, which occurs when every word
 7204 is in its own cluster at the beginning of the algorithm. The time complexity is thus $\mathcal{O}(V^5)$.

7205 To avoid this complexity, practical implementations use a heuristic approximation
 7206 called **exchange clustering**. The K most common words are placed in clusters of their
 7207 own at the beginning of the process. We then consider the next most common word, and

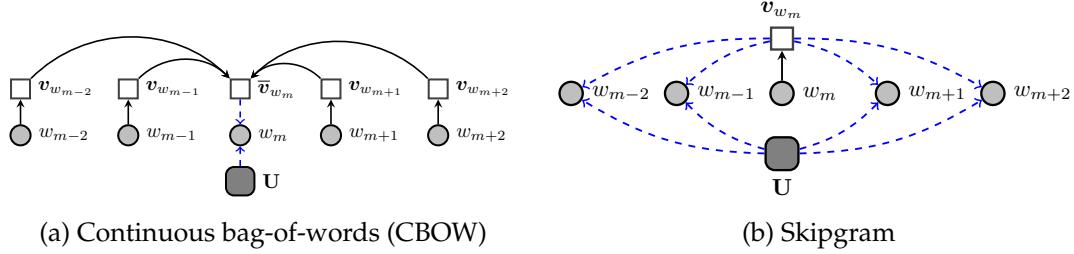


Figure 14.3: The CBOW and skipgram variants of WORD2VEC. The parameter \mathbf{U} is the matrix of word embeddings, and each \mathbf{v}_m is the context embedding for word w_m .

7208 merge it with one of the existing clusters. This continues until the entire vocabulary has
 7209 been incorporated, at which point the K clusters are merged down to a single cluster,
 7210 forming a tree. The algorithm never considers more than $K + 1$ clusters at any step, and
 7211 the complexity is $\mathcal{O}(VK + V \log V)$, with the second term representing the cost of sorting
 7212 the words at the beginning of the algorithm.

7213 14.5 Neural word embeddings

7214 Neural word embeddings combine aspects of the previous two methods: like latent se-
 7215 mantic analysis, they are a continuous vector representation; like Brown clusters, they are
 7216 trained from a likelihood-based objective. Let the vector \mathbf{u}_i represent the K -dimensional
7217 embedding for word i , and let \mathbf{v}_j represent the K -dimensional embedding for context
 7218 j . The inner product $\mathbf{u}_i \cdot \mathbf{v}_j$ represents the compatibility between word i and context j .
 7219 By incorporating this inner product into an approximation to the log-likelihood of a cor-
 7220 pus, it is possible to estimate both parameters by backpropagation. WORD2VEC (Mikolov
 7221 et al., 2013) includes two such approximations: continuous bag-of-words (CBOW) and
 7222 skipgrams.

7223 14.5.1 Continuous bag-of-words (CBOW)

7224 In recurrent neural network language models, each word w_m is conditioned on a recurrently-
 7225 updated state vector, which is based on word representations going all the way back to the
 7226 beginning of the text. The **continuous bag-of-words (CBOW)** model is a simplification:
 7227 the local context is computed as an average of embeddings for words in the immediate
 7228 neighborhood $m - h, m - h + 1, \dots, m + h - 1, m + h$,

$$\bar{\mathbf{v}}_m = \frac{1}{2h} \sum_{n=1}^h \mathbf{v}_{w_{m+n}} + \mathbf{v}_{w_{m-n}}. \quad [14.14]$$

7229 Thus, CBOW is a bag-of-words model, because the order of the context words does not
 7230 matter; it is continuous, because rather than conditioning on the words themselves, we
 7231 condition on a continuous vector constructed from the word embeddings. The parameter
 7232 h determines the neighborhood size, which Mikolov et al. (2013) set to $h = 4$.

The CBOW model optimizes an approximation to the corpus log-likelihood,

$$\log p(\mathbf{w}) \approx \sum_{m=1}^M \log p(w_m | w_{m-h}, w_{m-h+1}, \dots, w_{m+h-1}, w_{m+h}) \quad [14.15]$$

$$= \sum_{m=1}^M \log \frac{\exp(\mathbf{u}_{w_m} \cdot \bar{\mathbf{v}}_m)}{\sum_{j=1}^V \exp(\mathbf{u}_j \cdot \bar{\mathbf{v}}_m)} \quad [14.16]$$

$$= \sum_{m=1}^M \mathbf{u}_{w_m} \cdot \bar{\mathbf{v}}_m - \log \sum_{j=1}^V \exp(\mathbf{u}_j \cdot \bar{\mathbf{v}}_m). \quad [14.17]$$

7233 14.5.2 Skipgrams

In the CBOW model, words are predicted from their context. In the **skipgram** model, the context is predicted from the word, yielding the objective:

$$\log p(\mathbf{w}) \approx \sum_{m=1}^M \sum_{n=1}^{h_m} \log p(w_{m-n} | w_m) + \log p(w_{m+n} | w_m) \quad [14.18]$$

$$= \sum_{m=1}^M \sum_{n=1}^{h_m} \log \frac{\exp(\mathbf{u}_{w_{m-n}} \cdot \mathbf{v}_{w_m})}{\sum_{j=1}^V \exp(\mathbf{u}_j \cdot \mathbf{v}_{w_m})} + \log \frac{\exp(\mathbf{u}_{w_{m+n}} \cdot \mathbf{v}_{w_m})}{\sum_{j=1}^V \exp(\mathbf{u}_j \cdot \mathbf{v}_{w_m})} \quad [14.19]$$

$$= \sum_{m=1}^M \sum_{n=1}^{h_m} \mathbf{u}_{w_{m-n}} \cdot \mathbf{v}_{w_m} + \mathbf{u}_{w_{m+n}} \cdot \mathbf{v}_{w_m} - 2 \log \sum_{j=1}^V \exp(\mathbf{u}_j \cdot \mathbf{v}_{w_m}). \quad [14.20]$$

7234 In the skipgram approximation, each word is generated multiple times; each time it is con-
 7235 ditioned only on a single word. This makes it possible to avoid averaging the word vec-
 7236 tors, as in the CBOW model. The local neighborhood size h_m is randomly sampled from
 7237 a uniform categorical distribution over the range $\{1, 2, \dots, h_{\max}\}$; Mikolov et al. (2013) set
 7238 $h_{\max} = 10$. Because the neighborhood grows outward with h , this approach has the effect
 7239 of weighting near neighbors more than distant ones. Skipgram performs better on most
 7240 evaluations than CBOW (see § 14.6 for details of how to evaluate word representations),
 7241 but CBOW is faster to train (Mikolov et al., 2013).

7242 14.5.3 Computational complexity

7243 The WORD2VEC models can be viewed as an efficient alternative to recurrent neural net-
 7244 work language models, which involve a recurrent state update whose time complexity

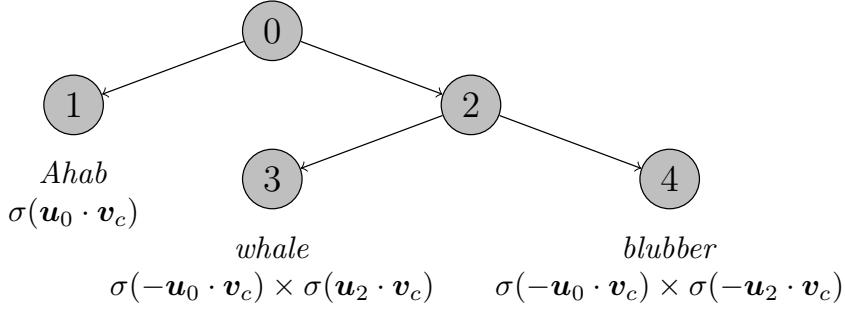


Figure 14.4: A fragment of a hierarchical softmax tree. The probability of each word is computed as a product of probabilities of local branching decisions in the tree.

is quadratic in the size of the recurrent state vector. CBOW and skipgram avoid this computation, and incur only a linear time complexity in the size of the word and context representations. However, all three models compute a normalized probability over word tokens; a naïve implementation of this probability requires summing over the entire vocabulary. The time complexity of this sum is $\mathcal{O}(V \times K)$, which dominates all other computational costs. There are two solutions: **hierarchical softmax**, a tree-based computation that reduces the cost to a logarithm of the size of the vocabulary; and **negative sampling**, an approximation that eliminates the dependence on vocabulary size. Both methods are also applicable to RNN language models.

14.5.3.1 Hierarchical softmax

In Brown clustering, the vocabulary is organized into a binary tree. Mnih and Hinton (2008) show that the normalized probability over words in the vocabulary can be reparametrized as a probability over paths through such a tree. This **hierarchical softmax** probability is computed as a product of binary decisions over whether to move left or right through the tree, with each binary decision represented as a sigmoid function of the inner product between the context embedding v_c and an output embedding associated with the node u_n ,

$$\Pr(\text{left at } n \mid c) = \sigma(u_n \cdot v_c) \quad [14.21]$$

$$\Pr(\text{right at } n \mid c) = 1 - \sigma(u_n \cdot v_c) = \sigma(-u_n \cdot v_c), \quad [14.22]$$

where σ refers to the sigmoid function, $\sigma(x) = \frac{1}{1+\exp(-x)}$. The range of the sigmoid is the interval $(0, 1)$, and $1 - \sigma(x) = \sigma(-x)$.

As shown in Figure 14.4, the probability of generating each word is redefined as the product of the probabilities across its path. The sum of all such path probabilities is guaranteed to be one, for any context vector $v_c \in \mathbb{R}^K$. In a balanced binary tree, the depth is

7260 logarithmic in the number of leaf nodes, and thus the number of multiplications is equal
 7261 to $\mathcal{O}(\log V)$. The number of non-leaf nodes is equal to $\mathcal{O}(2V - 1)$, so the number of pa-
 7262 rameters to be estimated increases by only a small multiple. The tree can be constructed
 7263 using an incremental clustering procedure similar to hierarchical Brown clusters (Mnih
 7264 and Hinton, 2008), or by using the Huffman (1952) encoding algorithm for lossless com-
 7265 pression.

7266 **14.5.3.2 Negative sampling**

Likelihood-based methods are computationally intensive because each probability must be normalized over the vocabulary. These probabilities are based on scores for each word in each context, and it is possible to design an alternative objective that is based on these scores more directly: we seek word embeddings that maximize the score for the word that was really observed in each context, while minimizing the scores for a set of randomly selected **negative samples**:

$$\psi(i, j) = \log \sigma(\mathbf{u}_i \cdot \mathbf{v}_j) + \sum_{i' \in \mathcal{W}_{\text{neg}}} \log(1 - \sigma(\mathbf{u}_{i'} \cdot \mathbf{v}_j)), \quad [14.23]$$

7267 where $\psi(i, j)$ is the score for word i in context j , and \mathcal{W}_{neg} is the set of negative samples.
 7268 The objective is to maximize the sum over the corpus, $\sum_{m=1}^M \psi(w_m, c_m)$, where w_m is
 7269 token m and c_m is the associated context.

7270 The set of negative samples \mathcal{W}_{neg} is obtained by sampling from a unigram language
 7271 model. Mikolov et al. (2013) construct this unigram language model by exponentiating
 7272 the empirical word probabilities, setting $\hat{p}(i) \propto (\text{count}(i))^{\frac{3}{4}}$. This has the effect of redi-
 7273 tributing probability mass from common to rare words. The number of negative samples
 7274 increases the time complexity of training by a constant factor. Mikolov et al. (2013) report
 7275 that 5-20 negative samples works for small training sets, and that two to five samples
 7276 suffice for larger corpora.

7277 **14.5.4 Word embeddings as matrix factorization**

7278 The negative sampling objective in Equation 14.23 can be justified as an efficient approx-
 7279 imation to the log-likelihood, but it is also closely linked to the matrix factorization ob-
 7280 jective employed in latent semantic analysis. For a matrix of word-context pairs in which
 7281 all counts are non-zero, negative sampling is equivalent to factorization of the matrix M ,
 7282 where $M_{ij} = \text{PMI}(i, j) - \log k$: each cell in the matrix is equal to the pointwise mutual
 7283 information of the word and context, shifted by $\log k$, with k equal to the number of neg-
 7284 ative samples (Levy and Goldberg, 2014). For word-context pairs that are not observed in
 7285 the data, the pointwise mutual information is $-\infty$, but this can be addressed by consid-
 7286 ering only PMI values that are greater than $\log k$, resulting in a matrix of **shifted positive**

7287 **pointwise mutual information,**

$$M_{ij} = \max(0, \text{PMI}(i, j) - \log k). \quad [14.24]$$

7288 Word embeddings are obtained by factoring this matrix with truncated singular value
7289 decomposition.

GloVe (“global vectors”) are a closely related approach (Pennington et al., 2014), in which the matrix to be factored is constructed from log co-occurrence counts, $M_{ij} = \log \text{count}(i, j)$. The word embeddings are estimated by minimizing the sum of squares,

$$\begin{aligned} \min_{\mathbf{u}, \mathbf{v}, b, \tilde{b}} \quad & \sum_{j=1}^V \sum_{j \in C} f(M_{ij}) \left(\widehat{\log M_{ij}} - \log M_{ij} \right)^2 \\ \text{s.t.} \quad & \widehat{\log M_{ij}} = \mathbf{u}_i \cdot \mathbf{v}_j + b_i + \tilde{b}_j, \end{aligned} \quad [14.25]$$

7290 where b_i and \tilde{b}_j are offsets for word i and context j , which are estimated jointly with the
7291 embeddings \mathbf{u} and \mathbf{v} . The weighting function $f(M_{ij})$ is set to be zero at $M_{ij} = 0$, thus
7292 avoiding the problem of taking the logarithm of zero counts; it saturates at $M_{ij} = m_{\max}$,
7293 thus avoiding the problem of overcounting common word-context pairs. This heuristic
7294 turns out to be critical to the method’s performance.

7295 The time complexity of sparse matrix reconstruction is determined by the number of
7296 non-zero word-context counts. Pennington et al. (2014) show that this number grows
7297 sublinearly with the size of the dataset: roughly $\mathcal{O}(N^{0.8})$ for typical English corpora. In
7298 contrast, the time complexity of WORD2VEC is linear in the corpus size. Computing the co-
7299 occurrence counts also requires linear time in the size of the corpus, but this operation can
7300 easily be parallelized using MapReduce-style algorithms (Dean and Ghemawat, 2008).

7301 14.6 Evaluating word embeddings

7302 Distributed word representations can be evaluated in two main ways. **Intrinsic** evalua-
7303 tions test whether the representations cohere with our intuitions about word meaning.
7304 **Extrinsic** evaluations test whether they are useful for downstream tasks, such as sequence
7305 labeling.

7306 14.6.1 Intrinsic evaluations

7307 A basic question for word embeddings is whether the similarity of words i and j is re-
7308 flected in the similarity of the vectors \mathbf{u}_i and \mathbf{u}_j . **Cosine similarity** is typically used to
7309 compare two word embeddings,

$$\cos(\mathbf{u}_i, \mathbf{u}_j) = \frac{\mathbf{u}_i \cdot \mathbf{u}_j}{\|\mathbf{u}_i\|_2 \times \|\mathbf{u}_j\|_2}. \quad [14.26]$$

word 1	word 2	similarity
<i>love</i>	<i>sex</i>	6.77
<i>stock</i>	<i>jaguar</i>	0.92
<i>money</i>	<i>cash</i>	9.15
<i>development</i>	<i>issue</i>	3.97
<i>lad</i>	<i>brother</i>	4.46

Table 14.4: Subset of the WS-353 (Finkelstein et al., 2002) dataset of word similarity ratings (examples from Faruqui et al. (2016)).

7310 For any embedding method, we can evaluate whether the cosine similarity of word em-
 7311 beddings is correlated with human judgments of word similarity. The WS-353 dataset (Finkel-
 7312 stein et al., 2002) includes similarity scores for 353 word pairs (Table 14.4). To test the
 7313 accuracy of embeddings for rare and morphologically complex words, Luong et al. (2013)
 7314 introduce a dataset of “rare words.” Outside of English, word similarity resources are
 7315 limited, mainly consisting of translations of WS-353.

7316 Word analogies (e.g., *king:queen :: man:woman*) have also been used to evaluate word
 7317 embeddings (Mikolov et al., 2013). In this evaluation, the system is provided with the first
 7318 three parts of the analogy ($i_1 : j_1 :: i_2 : ?$), and the final element is predicted by finding the
 7319 word embedding most similar to $\mathbf{u}_{i_1} - \mathbf{u}_{j_1} + \mathbf{u}_{i_2}$. Another evaluation tests whether word
 7320 embeddings are related to broad lexical semantic categories called **supersenses** (Caramita
 7321 and Johnson, 2003): verbs of motion, nouns that describe animals, nouns that describe
 7322 body parts, and so on. These supersenses are annotated for English synsets in Word-
 7323 Net (Fellbaum, 2010). This evaluation is implemented in the `qvec` metric, which tests
 7324 whether the matrix of supersenses can be reconstructed from the matrix of word embed-
 7325 dings (Tsvetkov et al., 2015).

7326 Levy et al. (2015) compared several dense word representations for English — includ-
 7327 ing latent semantic analysis, WORD2VEC, and GloVe — using six word similarity metrics
 7328 and two analogy tasks. None of the embeddings outperformed the others on every task,
 7329 but skipgrams were the most broadly competitive. Hyperparameter tuning played a key
 7330 role: any method will perform badly if the wrong hyperparameters are used. Relevant
 7331 hyperparameters include the embedding size, as well as algorithm-specific details such
 7332 as the neighborhood size and the number of negative samples.

7333 14.6.2 Extrinsic evaluations

7334 Word representations contribute to downstream tasks like sequence labeling and docu-
 7335 ment classification by enabling generalization across words. The use of distributed repre-
 7336 sentations as features is a form of **semi-supervised learning**, in which performance on a

7337 supervised learning problem is augmented by learning distributed representations from
 7338 unlabeled data (Miller et al., 2004; Koo et al., 2008; Turian et al., 2010). These **pre-trained**
 7339 **word representations** can be used as features in a linear prediction model, or as the input
 7340 layer in a neural network, such as a Bi-LSTM tagging model (§ 7.6). Word representations
 7341 can be evaluated by the performance of the downstream systems that consume them:
 7342 for example, GloVe embeddings are convincingly better than Latent Semantic Analysis
 7343 as features in the downstream task of named entity recognition (Pennington et al., 2014).
 7344 Unfortunately, extrinsic and intrinsic evaluations do not always point in the same direc-
 7345 tion, and the best word representations for one downstream task may perform poorly on
 7346 another task (Schnabel et al., 2015).

7347 When word representations are updated from labeled data in the downstream task,
 7348 they are said to be **fine-tuned**. When labeled data is plentiful, pre-training may be un-
 7349 necessary; when labeled data is scarce, fine-tuning may lead to overfitting. Various com-
 7350 binations of pre-training and fine-tuning can be employed. Pre-trained embeddings can
 7351 be used as initialization before fine-tuning, and this can substantially improve perfor-
 7352 mance (Lample et al., 2016). Alternatively, both fine-tuned and pre-trained embeddings
 7353 can be used as inputs in a single model (Kim, 2014).

7354 In semi-supervised scenarios, pretrained word embeddings can be replaced by “con-
 7355 textualized” word representations (Peters et al., 2018). These contextualized represen-
 7356 tations are set to the hidden states of a deep bi-directional LSTM, which is trained as a
 7357 bi-directional language model, motivating the name **ELMo (embeddings from language**
 7358 **models**). Given a supervised learning problem, the language model generates contextu-
 7359 alized representations, which are then used as the base layer in a task-specific supervised
 7360 neural network. This approach yields significant gains over pretrained word embeddings
 7361 on several tasks, presumably because the contextualized embeddings use unlabeled data
 7362 to learn how to integrate linguistic context into the base layer of the supervised neural
 7363 network.

7364 14.7 Distributed representations beyond distributional statistics

7365 Distributional word representations can be estimated from huge unlabeled datasets, thereby
 7366 covering many words that do not appear in labeled data: for example, GloVe embeddings
 7367 are estimated from 800 billion tokens of web data,³ while the largest labeled datasets for
 7368 NLP tasks are on the order of millions of tokens. Nonetheless, even a dataset of hundreds
 7369 of billions of tokens will not cover every word that may be encountered in the future.
 7370 Furthermore, many words will appear only a few times, making their embeddings un-
 7371 reliable. Many languages exceed English in morphological complexity, and thus have
 7372 lower token-to-type ratios. When this problem is coupled with small training corpora, it

³<http://commoncrawl.org/>

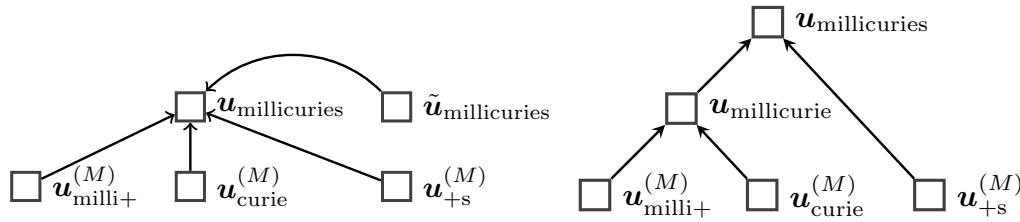


Figure 14.5: Two architectures for building word embeddings from subword units. On the left, morpheme embeddings $u^{(m)}$ are combined by addition with the non-compositional word embedding \tilde{u} (Botha and Blunsom, 2014). On the right, morpheme embeddings are combined in a recursive neural network (Luong et al., 2013).

7373 becomes especially important to leverage other sources of information beyond distributional statistics.

7375 14.7.1 Word-internal structure

7376 One solution is to incorporate word-internal structure into word embeddings. Purely
7377 distributional approaches consider words as atomic units, but in fact, many words have
7378 internal structure, so that their meaning can be **composed** from the representations of
7379 sub-word units. Consider the following terms, all of which are missing from Google's
7380 pre-trained WORD2VEC embeddings:⁴

7381 **millicuries** This word has **morphological** structure (see § 9.1.2 for more on morphology):
7382 the prefix *milli-* indicates an amount, and the suffix *-s* indicates a plural. (A *millicurie*
7383 is an unit of radioactivity.)

7384 **caesium** This word is a single morpheme, but the characters *-ium* are often associated
7385 with chemical elements. (*Caesium* is the British spelling of a chemical element,
7386 spelled *cesium* in American English.)

7387 **IAEA** This term is an acronym, as suggested by the use of capitalization. The prefix *I-* frequently
7388 refers to international organizations, and the suffix *-A* often refers to agencies or associations. (*IAEA* is the International Atomic Energy Agency.)

7390 **Zhezhan** This term is in title case, suggesting the name of a person or place, and the
7391 character bigram *zh* indicates that it is likely a transliteration. (*Zhezhan* is a mining
7392 facility in Kazakhstan.)

⁴<https://code.google.com/archive/p/word2vec/>, accessed September 20, 2017

7393 How can word-internal structure be incorporated into word representations? One
7394 approach is to construct word representations from embeddings of the characters or mor-
7395 phemes. For example, if word i has morphological segments \mathcal{M}_i , then its embedding can
7396 be constructed by addition (Botha and Blunsom, 2014),

$$\mathbf{u}_i = \tilde{\mathbf{u}}_i + \sum_{j \in \mathcal{M}_i} \mathbf{u}_j^{(M)}, \quad [14.27]$$

7397 where $\mathbf{u}_m^{(M)}$ is a morpheme embedding and $\tilde{\mathbf{u}}_i$ is a non-compositional embedding of the
7398 whole word, which is an additional free parameter of the model (Figure 14.5, left side).
7399 All embeddings are estimated from a **log-bilinear language model** (Mnih and Hinton,
7400 2007), which is similar to the CBOW model (§ 14.5), but includes only contextual informa-
7401 tion from preceding words. The morphological segments are obtained using an unsuper-
7402 vised segmenter (Creutz and Lagus, 2007). For words that do not appear in the training
7403 data, the embedding can be constructed directly from the morphemes, assuming that each
7404 morpheme appears in some other word in the training data. The free parameter $\tilde{\mathbf{u}}$ adds
7405 flexibility: words with similar morphemes are encouraged to have similar embeddings,
7406 but this parameter makes it possible for them to be different.

7407 Word-internal structure can be incorporated into word representations in various other
7408 ways. Here are some of the main parameters.

7409 **Subword units.** Examples like *IAEA* and *Zhezhgan* are not based on morphological com-
7410 position, and a morphological segmenter is unlikely to identify meaningful sub-
7411 word units for these terms. Rather than using morphemes for subword embeddings,
7412 one can use characters (Santos and Zadrozny, 2014; Ling et al., 2015; Kim et al., 2016),
7413 character n -grams (Wieting et al., 2016; Bojanowski et al., 2017), and **byte-pair en-**
7414 **codings**, a compression technique which captures frequent substrings (Gage, 1994;
7415 Sennrich et al., 2016).

7416 **Composition.** Combining the subword embeddings by addition does not differentiate
7417 between orderings, nor does it identify any particular morpheme as the **root**. A
7418 range of more flexible compositional models have been considered, including re-
7419 currence (Ling et al., 2015), convolution (Santos and Zadrozny, 2014; Kim et al.,
7420 2016), and **recursive neural networks** (Luong et al., 2013), in which representa-
7421 tions of progressively larger units are constructed over a morphological parse, e.g.
7422 $((milli+curie)+s)$, $((in+flam)+able)$, $(in+(vis+ible))$. A recursive embedding model is
7423 shown in the right panel of Figure 14.5.

7424 **Estimation.** Estimating subword embeddings from a full dataset is computationally ex-
7425 pensive. An alternative approach is to train a subword model to match pre-trained
7426 word embeddings (Cotterell et al., 2016; Pinter et al., 2017). To train such a model, it
7427 is only necessary to iterate over the vocabulary, and the not the corpus.

7428 **14.7.2 Lexical semantic resources**

Resources such as WordNet provide another source of information about word meaning; if we know that *caesium* is a synonym of *cesium*, or that a *millicurie* is a type of *measurement unit*, then this should help to provide embeddings for the unknown words, and to smooth embeddings of rare words. One way to do this is to **retrofit** pre-trained word embeddings across a network of lexical semantic relationships (Faruqui et al., 2015) by minimizing the following objective,

$$\min_{\mathbf{U}} \sum_{j=1}^V \|\mathbf{u}_i - \hat{\mathbf{u}}_i\|_2 + \sum_{(i,j) \in \mathcal{L}} \beta_{ij} \|\mathbf{u}_i - \mathbf{u}_j\|_2, \quad [14.28]$$

7429 where $\hat{\mathbf{u}}_i$ is the pretrained embedding of word i , and $\mathcal{L} = \{(i,j)\}$ is a lexicon of word
 7430 relations. The hyperparameter β_{ij} controls the importance of adjacent words having
 7431 similar embeddings; Faruqui et al. (2015) set it to the inverse of the degree of word i ,
 7432 $\beta_{ij} = |\{j : (i,j) \in \mathcal{L}\}|^{-1}$. Retrofitting improves performance on a range of intrinsic evalua-
 7433 tions, and gives small improvements on an extrinsic document classification task.

7434 **14.8 Distributed representations of multiword units**

7435 Can distributed representations extend to phrases, sentences, paragraphs, and beyond?
 7436 Before exploring this possibility, recall the distinction between distributed and distri-
 7437 butional representations. Neural embeddings such as WORD2VEC are both distributed
 7438 (vector-based) and distributional (derived from counts of words in context). As we con-
 7439 sider larger units of text, the counts decrease: in the limit, a multi-paragraph span of text
 7440 would never appear twice, except by plagiarism. Thus, the meaning of a large span of
 7441 text cannot be determined from distributional statistics alone; it must be computed com-
 7442 positionally from smaller spans. But these considerations are orthogonal to the question
 7443 of whether distributed representations — dense numerical vectors — are sufficiently ex-
 7444 pressive to capture the meaning of phrases, sentences, and paragraphs.

7445 **14.8.1 Purely distributional methods**

7446 Some multiword phrases are non-compositional: the meaning of such phrases is not de-
 7447 rived from the meaning of the individual words using typical compositional semantics.
 7448 This includes proper nouns like *San Francisco* as well as idiomatic expressions like *kick*
 7449 *the bucket* (Baldwin and Kim, 2010). For these cases, purely distributional approaches
 7450 can work. A simple approach is to identify multiword units that appear together fre-
 7451 quently, and then treat these units as words, learning embeddings using a technique such
 7452 as WORD2VEC. The problem of identifying multiword units is sometimes called **colloca-**
 7453 **tion extraction**, and can be approached using metrics such as pointwise mutual informa-
 7454 tion: two-word units are extracted first, and then larger units are extracted. Mikolov et al.

7455 (2013) identify such units and then treat them as words when estimating skipgram em-
7456 beddings, showing that the resulting embeddings perform reasonably on a task of solving
7457 phrasal analogies, e.g. *New York : New York Times :: Baltimore : Baltimore Sun*.

7458 14.8.2 Distributional-compositional hybrids

7459 To move beyond short multiword phrases, composition is necessary. A simple but sur-
7460 prisingly powerful approach is to represent a sentence with the average of its word em-
7461 beddings (Mitchell and Lapata, 2010). This can be considered a hybrid of the distribu-
7462 tional and compositional approaches to semantics: the word embeddings are computed
7463 distributionally, and then the sentence representation is computed by composition.

7464 The WORD2VEC approach can be stretched considerably further, embedding entire
7465 sentences using a model similar to skipgrams, in the “skip-thought” model of Kiros et al.
7466 (2015). Each sentence is *encoded* into a vector using a recurrent neural network: the encod-
7467 ing of sentence t is set to the RNN hidden state at its final token, $h_{M_t}^{(t)}$. This vector is then
7468 a parameter in a *decoder* model that is used to generate the previous and subsequent sen-
7469 tences: the decoder is another recurrent neural network, which takes the encoding of the
7470 neighboring sentence as an additional parameter in its recurrent update. (This **encoder-**
7471 **decoder model** is discussed at length in chapter 18.) The encoder and decoder are trained
7472 simultaneously from a likelihood-based objective, and the trained encoder can be used to
7473 compute a distributed representation of any sentence. Skip-thought can also be viewed
7474 as a hybrid of distributional and compositional approaches: the vector representation of
7475 each sentence is computed compositionally from the representations of the individual
7476 words, but the training objective is distributional, based on sentence co-occurrence across
7477 a corpus.

7478 **Autoencoders** are a variant of encoder-decoder models in which the decoder is trained
7479 to produce the same text that was originally encoded, using only the distributed encod-
7480 ing vector (Li et al., 2015). The encoding acts as a bottleneck, so that generalization is
7481 necessary if the model is to successfully fit the training data. In **denoising autoencoders**,
7482 the input is a corrupted version of the original sentence, and the auto-encoder must re-
7483 construct the uncorrupted original (Vincent et al., 2010; Hill et al., 2016). By interpolating
7484 between distributed representations of two sentences, $\alpha \mathbf{u}_i + (1 - \alpha) \mathbf{u}_j$, it is possible to gen-
7485 erate sentences that combine aspects of the two inputs, as shown in Figure 14.6 (Bowman
7486 et al., 2016).

7487 Autoencoders can also be applied to longer texts, such as paragraphs and documents.
7488 This enables applications such as **question answering**, which can be performed by match-
7489 ing the encoding of the question with encodings of candidate answers (Miao et al., 2016).

this was the only way
 it was the only way
 it was her turn to blink
 it was hard to tell
 it was time to move on
 he had to do it again
 they all looked at each other
 they all turned to look back
 they both turned to face him
they both turned and walked away

Figure 14.6: By interpolating between the distributed representations of two sentences (in bold), it is possible to generate grammatical sentences that combine aspects of both (Bowman et al., 2016)

7490 14.8.3 Supervised compositional methods

7491 Given a supervision signal, such as a label describing the sentiment or meaning of a sen-
 7492 tence, a wide range of compositional methods can be applied to compute a distributed
 7493 representation that then predicts the label. The simplest is to average the embeddings
 7494 of each word in the sentence, and pass this average through a feedforward neural net-
 7495 work (Iyyer et al., 2015). Convolutional and recurrent neural networks go further, with
 7496 the ability to effectively capturing multiword phenomena such as negation (Kalchbrenner
 7497 et al., 2014; Kim, 2014; Li et al., 2015; Tang et al., 2015). Another approach is to incorpo-
 7498 rate the syntactic structure of the sentence into a **recursive neural networks**, in which the
 7499 representation for each syntactic constituent is computed from the representations of its
 7500 children (Socher et al., 2012). However, in many cases, recurrent neural networks perform
 7501 as well or better than recursive networks (Li et al., 2015).

7502 Whether convolutional, recurrent, or recursive, a key question is whether supervised
 7503 sentence representations are task-specific, or whether a single supervised sentence repre-
 7504 sentation model can yield useful performance on other tasks. Wieting et al. (2015) train a
 7505 variety of sentence embedding models for the task of labeling pairs of sentences as **para-**
 7506 **phrases**. They show that the resulting sentence embeddings give good performance for
 7507 sentiment analysis. The **Stanford Natural Language Inference corpus** classifies sentence
 7508 pairs as **entailments** (the truth of sentence i implies the truth of sentence j), **contradictions**
 7509 (the truth of sentence i implies the falsity of sentence j), and neutral (i neither entails nor
 7510 contradicts j). Sentence embeddings trained on this dataset transfer to a wide range of
 7511 classification tasks (Conneau et al., 2017).

7512 14.8.4 Hybrid distributed-symbolic representations

7513 The power of distributed representations is in their generality: the distributed representation
7514 of a unit of text can serve as a summary of its meaning, and therefore as the input
7515 for downstream tasks such as classification, matching, and retrieval. For example, dis-
7516 tributed sentence representations can be used to recognize the paraphrase relationship
7517 between closely related sentences like the following:

- 7518 (14.5) Donald thanked Vlad profusely.
7519 (14.6) Donald conveyed to Vlad his profound appreciation.
7520 (14.7) Vlad was showered with gratitude by Donald.

7521 Symbolic representations are relatively brittle to this sort of variation, but are better
7522 suited to describe individual entities, the things that they do, and the things that are done
7523 to them. In examples (14.5)-(14.7), we not only know that somebody thanked someone
7524 else, but we can make a range of inferences about what has happened between the en-
7525 tities named *Donald* and *Vlad*. Because distributed representations do not treat entities
7526 symbolically, they lack the ability to reason about the roles played by entities across a sen-
7527 tence or larger discourse.⁵ A hybrid between distributed and symbolic representations
7528 might give the best of both worlds: robustness to the many different ways of describing
7529 the same event, plus the expressiveness to support inferences about entities and the roles
7530 that they play.

7531 A “top-down” hybrid approach is to begin with logical semantics (of the sort de-
7532 scribed in the previous two chapters), and but replace the predefined lexicon with a set
7533 of distributional word clusters (Poon and Domingos, 2009; Lewis and Steedman, 2013). A
7534 “bottom-up” approach is to add minimal symbolic structure to existing distributed repre-
7535 sentations, such as vector representations for each entity (Ji and Eisenstein, 2015; Wiseman
7536 et al., 2016). This has been shown to improve performance on two problems that we will
7537 encounter in the following chapters: classification of **discourse relations** between adj-
7538 cent sentences (chapter 16; Ji and Eisenstein, 2015), and **coreference resolution** of entity
7539 mentions (chapter 15; Wiseman et al., 2016; Ji et al., 2017). Research on hybrid seman-
7540 tic representations is still in an early stage, and future representations may deviate more
7541 boldly from existing symbolic and distributional approaches.

7542 Additional resources

7543 Turney and Pantel (2010) survey a number of facets of vector word representations, fo-
7544 cusing on matrix factorization methods. Schnabel et al. (2015) highlight problems with

⁵At a 2014 workshop on semantic parsing, this critique of distributed representations was expressed by Ray Mooney — a leading researcher in computational semantics — in a now well-known quote, “you can’t cram the meaning of a whole sentence into a single vector!”

7545 similarity-based evaluations of word embeddings, and present a novel evaluation that
 7546 controls for word frequency. Baroni et al. (2014) address linguistic issues that arise in
 7547 attempts to combine distributed and compositional representations.

7548 In bilingual and multilingual distributed representations, embeddings are estimated
 7549 for translation pairs or tuples, such as (*dog, perro, chien*). These embeddings can improve
 7550 machine translation (Zou et al., 2013; Klementiev et al., 2012), transfer natural language
 7551 processing models across languages (Täckström et al., 2012), and make monolingual word
 7552 embeddings more accurate (Faruqui and Dyer, 2014). A typical approach is to learn a pro-
 7553 jection that maximizes the correlation of the distributed representations of each element
 7554 in a translation pair, which can be obtained from a bilingual dictionary. Distributed rep-
 7555 resentations can also be linked to perceptual information, such as image features. Bruni
 7556 et al. (2014) use textual descriptions of images to obtain visual contextual information for
 7557 various words, which supplements traditional distributional context. Image features can
 7558 also be inserted as contextual information in log bilinear language models (Kiros et al.,
 7559 2014), making it possible to automatically generate text descriptions of images.

7560 Exercises

- 7561 1. Prove that the sum of probabilities of paths through a hierarchical softmax tree is
 7562 equal to one.
- 7563 2. In skipgram word embeddings, the negative sampling objective can be written as,

$$\mathcal{L} = \sum_{i \in \mathcal{V}} \sum_{j \in \mathcal{C}} \text{count}(i, j) \psi(i, j), \quad [14.29]$$

7564 with $\psi(i, j)$ is defined in Equation 14.23.

7565 Suppose we draw the negative samples from the empirical unigram distribution
 $\hat{p}(i) = p_{\text{unigram}}(i)$. First, compute the expectation of \mathcal{L} with respect this probability.

7566 Next, take the derivative of this expectation with respect to the score of a single word
 7567 context pair $\sigma(\mathbf{u}_i \cdot \mathbf{v}_j)$, and solve for the pointwise mutual information $\text{PMI}(i, j)$. You
 7568 should be able to show that at the optimum, the PMI is a simple function of $\sigma(\mathbf{u}_i \cdot \mathbf{v}_j)$
 7569 and the number of negative samples.

- 7570 3. * In Brown clustering, prove that the cluster merge that maximizes the average mu-
 7571 tual information (Equation 14.13) also maximizes the log-likelihood objective (Equa-
 7572 tion 14.12).

7573 For the next two problems, download a set of pre-trained word embeddings, such as the
 7574 WORD2VEC or polyglot embeddings.

7575 4. Use cosine similarity to find the most similar words to: *dog, whale, before, however, fabricate.*

7577 5. Use vector addition and subtraction to compute target vectors for the analogies below. After computing each target vector, find the top three candidates by cosine
7578 similarity.

- 7580 • *dog:puppy :: cat: ?*
7581 • *speak:speaker :: sing:?*
7582 • *France:French :: England:?*
7583 • *France:wine :: England:?*

7584 The remaining problems will require you to build a classifier and test its properties. Pick
7585 a multi-class text classification dataset, such as RCV1⁶). Divide your data into training
7586 (60%), development (20%), and test sets (20%), if no such division already exists.

7587 6. Train a convolutional neural network, with inputs set to pre-trained word embed-
7588 dings from the previous problem. Use a special, fine-tuned embedding for out-of-
7589 vocabulary words. Train until performance on the development set does not im-
7590 prove. You can also use the development set to tune the model architecture, such
7591 as the convolution width and depth. Report *F-MEASURE* and accuracy, as well as
7592 training time.

7593 7. Now modify your model from the previous problem to fine-tune the word embed-
7594 dings. Report *F-MEASURE*, accuracy, and training time.

7595 8. Try a simpler approach, in which word embeddings in the document are averaged,
7596 and then this average is passed through a feed-forward neural network. Again, use
7597 the development data to tune the model architecture. How close is the accuracy to
7598 the convolutional networks from the previous problems?

⁶http://www.ai.mit.edu/projects/jmlr/papers/volume5/lewis04a/lyrl2004_rcv1v2_README.htm

7599

Chapter 15

7600

Reference Resolution

7601 References are one of the most noticeable forms of linguistic ambiguity, afflicting not just
7602 automated natural language processing systems, but also fluent human readers. Warnings
7603 to avoid “ambiguous pronouns” are ubiquitous in manuals and tutorials on writing
7604 style. But referential ambiguity is not limited to pronouns, as shown in the text in Fig-
7605 ure 15.1. Each of the bracketed substrings refers to an entity that is introduced earlier
7606 in the passage. These references include the pronouns *he* and *his*, but also the shortened
7607 name *Cook*, and **nominals** such as *the firm* and *the firm’s biggest growth market*.

7608 **Reference resolution** subsumes several subtasks. This chapter will focus on **corefer-
7609 ence resolution**, which is the task of grouping spans of text that refer to a single underly-
7610 ing entity, or, in some cases, a single event: for example, the spans *Tim Cook*, *he*, and *Cook*
7611 are all **coreferent**. These individual spans are called **mentions**, because they mention an
7612 entity; the entity is sometimes called the **referent**. Each mention has a set of **antecedents**,
7613 which are preceding mentions that are coreferent; for the first mention of an entity, the an-
7614 tecedent set is empty. The task of **pronominal anaphora resolution** requires identifying
7615 only the antecedents of pronouns. In **entity linking**, references are resolved not to other
7616 spans of text, but to entities in a knowledge base. This task is discussed in chapter 17.

7617 Coreference resolution is a challenging problem for several reasons. Resolving differ-
7618 ent types of **referring expressions** requires different types of reasoning: the features and
7619 methods that are useful for resolving pronouns are different from those that are useful
7620 to resolve names and nominals. Coreference resolution involves not only linguistic rea-
7621 soning, but also world knowledge and pragmatics: you may not have known that China
7622 was Apple’s biggest growth market, but it is likely that you effortlessly resolved this ref-
7623 erence while reading the passage in Figure 15.1.¹ A further challenge is that coreference

¹This interpretation is based in part on the assumption that a **cooperative** author would not use the expression *the firm’s biggest growth market* to refer to an entity not yet mentioned in the article (Grice, 1975). **Pragmatics** is the discipline of linguistics concerned with the formalization of such assumptions (Huang,

- (15.1) *[[Apple Inc] Chief Executive Tim Cook] has jetted into [China] for talks with government officials as [he] seeks to clear up a pile of problems in [[the firm] 's biggest growth market] ... [Cook] is on [his] first trip to [the country] since taking over...*

Figure 15.1: Running example (Yee and Jones, 2012). Coreferring entity mentions are underlined and bracketed.

resolution decisions are often entangled: each mention adds information about the entity, which affects other coreference decisions. This means that coreference resolution must be addressed as a structure prediction problem. But as we will see, there is no dynamic program that allows the space of coreference decisions to be searched efficiently.

15.1 Forms of referring expressions

There are three main forms of referring expressions — pronouns, names, and nominals.

15.1.1 Pronouns

Pronouns are a closed class of words that are used for references. A natural way to think about pronoun resolution is SMASH (Kehler, 2007):

- Search for candidate antecedents;
- Match against hard agreement constraints;
- And Select using Heuristics, which are “soft” constraints such as recency, syntactic prominence, and parallelism.

15.1.1.1 Search

In the search step, candidate antecedents are identified from the preceding text or speech.² Any noun phrase can be a candidate antecedent, and pronoun resolution usually requires

2015).

²Pronouns whose referents come later are known as **cataphora**, as in this example from Márquez (1970):

- (15.1) Many years later, as [he] faced the firing squad, [Colonel Aureliano Buendía] was to remember that distant afternoon when his father took him to discover ice.

7640 parsing the text to identify all such noun phrases.³ Filtering heuristics can help to prune
 7641 the search space to noun phrases that are likely to be coreferent (Lee et al., 2013; Durrett
 7642 and Klein, 2013). In nested noun phrases, mentions are generally considered to be the
 7643 largest unit with a given head word: thus, *Apple Inc. Chief Executive Tim Cook* would be
 7644 included as a mention, but *Tim Cook* would not, since they share the same head word,
 7645 *Cook*.

7646 15.1.1.2 Matching constraints for pronouns

7647 References and their antecedents must agree on semantic features such as number, person,
 7648 gender, and animacy. Consider the pronoun *he* in this passage from the running example:

7649 (15.2) Tim Cook has jetted in for talks with officials as [he] seeks to clear up a pile of
 7650 problems...

7651 The pronoun and possible antecedents have the following features:

- 7652 • *he*: singular, masculine, animate, third person
- 7653 • *officials*: plural, animate, third person
- 7654 • *talks*: plural, inanimate, third person
- 7655 • *Tim Cook*: singular, masculine, animate, third person

7656 The SMASH method searches backwards from *he*, discarding *officials* and *talks* because they
 7657 do not satisfy the agreements constraints.

7658 Another source of constraints comes from syntax — specifically, from the phrase struc-
 7659 ture trees discussed in chapter 10. Consider a parse tree in which both *x* and *y* are phrasal
 7660 constituents. The constituent *x* **c-commands** the constituent *y* iff the first branching node
 7661 above *x* also dominates *y*. For example, in Figure 15.2a, *Abigail* c-commands *her*, because
 7662 the first branching node above *Abigail*, *S*, also dominates *her*. Now, if *x* c-commands *y*,
 7663 **government and binding theory** (Chomsky, 1982) states that *y* can refer to *x* only if it is
 7664 a **reflexive pronoun** (e.g., *herself*). Furthermore, if *y* is a reflexive pronoun, then its an-
 7665 tecedent must c-command it. Thus, in Figure 15.2a, *her* cannot refer to *Abigail*; conversely,
 7666 if we replace *her* with *herself*, then the reflexive pronoun *must* refer to *Abigail*, since this is
 7667 the only candidate antecedent that c-commands it.

7668 Now consider the example shown in Figure 15.2b. Here, *Abigail* does not c-command
 7669 *her*, but *Abigail's mom* does. Thus, *her* can refer to *Abigail* — and we cannot use reflexive

³In the OntoNotes coreference annotations, verbs can also be antecedents, if they are later referenced by nominals (Pradhan et al., 2011):

(15.1) Sales of passenger cars [grew] 22%. [The strong growth] followed year-to-year increases.

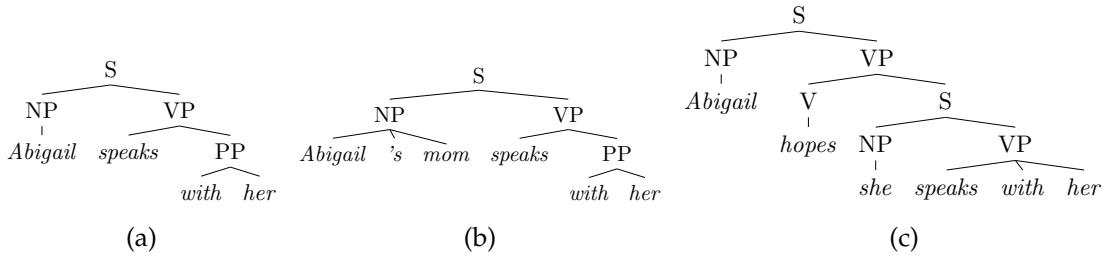


Figure 15.2: In (a), *Abigail* c-commands *her*; in (b), *Abigail* does not c-command *her*, but *Abigail's mom* does; in (c), the scope of *Abigail* is limited by the S non-terminal, so that *she* or *her* can bind to *Abigail*, but not both.

7670 *herself* in this context, unless we are talking about *Abigail*'s mom. However, *her* does not
 7671 have to refer to *Abigail*. Finally, Figure 15.2c shows how these constraints are limited.
 7672 In this case, the pronoun *she* can refer to *Abigail*, because the S non-terminal puts *Abigail*
 7673 outside the domain of *she*. Similarly, *her* can also refer to *Abigail*. But *she* and *her* cannot be
 7674 coreferent, because *she* c-commands *her*.

7675 15.1.1.3 Heuristics

7676 After applying constraints, heuristics are applied to select among the remaining candidates.
 7677 Recency is a particularly strong heuristic. All things equal, readers will prefer
 7678 the more recent referent for a given pronoun, particularly when comparing referents that
 7679 occur in different sentences. Jurafsky and Martin (2009) offer the following example:

- 7680 (15.3) The doctor found an old map in the captain's chest. Jim found an even older map
 7681 hidden on the shelf. [It] described an island.

7682 Readers are expected to prefer the older map as the referent for the pronoun *it*.

7683 However, subjects are often preferred over objects, and this can contradict the preference
 7684 for recency when two candidate referents are in the same sentence. For example,

- 7685 (15.4) Asha loaned Mei a book on Spanish. [She] is always trying to help people.

7686 Here, we may prefer to link *she* to *Asha* rather than *Mei*, because of *Asha*'s position in the
 7687 subject role of the preceding sentence. (Arguably, this preference would not be strong
 7688 enough to select *Asha* if the second sentence were *She is visiting Valencia next month*.)

7689 A third heuristic is parallelism:

- 7690 (15.5) Asha loaned Mei a book on Spanish. Olya loaned [her] a book on Portuguese.

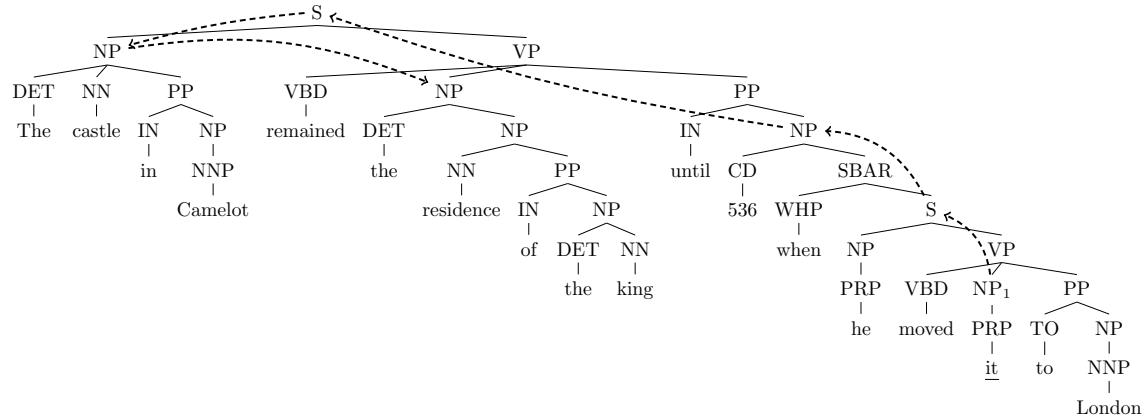


Figure 15.3: Left-to-right breadth-first tree traversal (Hobbs, 1978), indicating that the search for an antecedent for *it* (NP₁) would proceed in the following order: 536; *the castle in Camelot*; *the residence of the king*; *the king*. Hobbs (1978) proposes semantic constraints to eliminate 536 and *the castle in Camelot* as candidates, since they are unlikely to be the direct object of the verb *move*.

7691 Here *Mei* is preferred as the referent for *her*, contradicting the preference for the subject
 7692 *Asha* in the preceding sentence.

7693 The recency and subject role heuristics can be unified by traversing the document in
 7694 a syntax-driven fashion (Hobbs, 1978): each preceding sentence is traversed breadth-first,
 7695 left-to-right (Figure 15.3). This heuristic successfully handles (15.4): *Asha* is preferred as
 7696 the referent for *she* because the subject NP is visited first. It also handles (15.3): the older
 7697 map is preferred as the referent for *it* because the more recent sentence is visited first. (An
 7698 alternative unification of recency and syntax is proposed by **centering theory** (Grosz et al.,
 7699 1995), which is discussed in detail in chapter 16.)

7700 In early work on reference resolution, the number of heuristics was small enough that
 7701 a set of numerical weights could be set by hand (Lappin and Leass, 1994). More recent
 7702 work uses machine learning to quantify the importance of each of these factors. However,
 7703 pronoun resolution cannot be completely solved by constraints and heuristics alone. This
 7704 is shown by the classic example pair (Winograd, 1972):

7705 (15.6) The [city council] denied [the protesters] a permit because [they] advocated / feared
 7706 violence.

7707 Without reasoning about the motivations of the city council and protesters, it is unlikely
 7708 that any system could correctly resolve both versions of this example.

7709 **15.1.1.4 Non-referential pronouns**

7710 While pronouns are generally used for reference, they need not refer to entities. The fol-
 7711 lowing examples show how pronouns can refer to propositions, events, and speech acts.

- 7712 (15.7) They told me that I was too ugly for show business, but I didn't believe [it].
 7713 (15.8) Asha saw Babak get angry, and I saw [it] too.
 7714 (15.9) Asha said she worked in security. I suppose [that]'s one way to put it.

7715 These forms of reference are generally not annotated in large-scale coreference resolution
 7716 datasets such as OntoNotes (Pradhan et al., 2011).

7717 Pronouns may also have **generic referents**:

- 7718 (15.10) A poor carpenter blames [her] tools.
 7719 (15.11) On the moon, [you] have to carry [your] own oxygen.
 7720 (15.12) Every farmer who owns a donkey beats [it]. (Geach, 1962)

7721 In the OntoNotes dataset, coreference is not annotated for generic referents, even in cases
 7722 like these examples, in which the same generic entity is mentioned multiple times.

7723 Some pronouns do not refer to anything at all:

- 7724 (15.13) *[It]'s raining.*
 [Il] pleut. (Fr)
 7725 (15.14) [It] 's money that she's really after.
 7726 (15.15) [It] is too bad that we have to work so hard.

7727 How can we automatically distinguish these usages of *it* from referential pronouns?
 7728 Consider the the difference between the following two examples (Bergsma et al., 2008):

- 7729 (15.16) You can make [it] in advance.
 7730 (15.17) You can make [it] in showbiz.

7731 In the second example, the pronoun *it* is non-referential. One way to see this is by substi-
 7732 tuting another pronoun, like *them*, into these examples:

- 7733 (15.18) You can make [them] in advance.
 7734 (15.19) ? You can make [them] in showbiz.

7735 The questionable grammaticality of the second example suggests that *it* is not referential.
 7736 Bergsma et al. (2008) operationalize this idea by comparing distributional statistics for the

7737 *n*-grams around the word *it*, testing how often other pronouns or nouns appear in the
 7738 same context. In cases where nouns and other pronouns are infrequent, the *it* is unlikely
 7739 to be referential.

7740 15.1.2 Proper Nouns

7741 If a proper noun is used as a referring expression, it often corefers with another proper
 7742 noun, so that the coreference problem is simply to determine whether the two names
 7743 match. Subsequent proper noun references often use a shortened form, as in the running
 7744 example (Figure 15.1):

7745 (15.20) Apple Inc Chief Executive [Tim Cook] has jetted into China ... [Cook] is on his
 7746 first business trip to the country ...

7747 A typical solution for proper noun coreference is to match the syntactic **head words**
 7748 of the reference with the referent. In § 10.5.2, we saw that the head word of a phrase can
 7749 be identified by applying head percolation rules to the phrasal parse tree; alternatively,
 7750 the head can be identified as the root of the dependency subtree covering the name. For
 7751 sequences of proper nouns, the head word will be the final token.

7752 There are a number of caveats to the practice of matching head words of proper nouns.

- 7753 • In the European tradition, family names tend to be more specific than given names,
 7754 and family names usually come last. However, other traditions have other practices:
 7755 for example, in Chinese names, the family name typically comes first; in Japanese,
 7756 honorifics come after the name, as in *Nobu-San* (*Mr. Nobu*).
- 7757 • In organization names, the head word is often not the most informative, as in *Georgia*
 7758 *Tech* and *Virginia Tech*. Similarly, *Lebanon* does not refer to the same entity as *Southern Lebanon*, necessitating special rules for the specific case of geographical modi-
 7759 fiers (Lee et al., 2011).
- 7761 • Proper nouns can be nested, as in [*the CEO of [Microsoft]*], resulting in head word
 7762 match without coreference.

7763 Despite these difficulties, proper nouns are the easiest category of references to re-
 7764 solve (Stoyanov et al., 2009). In machine learning systems, one solution is to include a
 7765 range of matching features, including exact match, head match, and string inclusion. In
 7766 addition to matching features, competitive systems (e.g., Bengtson and Roth, 2008) in-
 7767 clude large lists, or **gazetteers**, of acronyms (e.g., *the National Basketball Association/NBA*),
 7768 demonymns (e.g., *the Israelis/Israel*), and other aliases (e.g., *the Georgia Institute of Technol-*
 7769 *ogy/Georgia Tech*).

7770 **15.1.3 Nominals**

7771 In coreference resolution, noun phrases that are neither pronouns nor proper nouns are
 7772 referred to as **nominals**. In the running example (Figure 15.1), nominal references include:
 7773 *the firm (Apple Inc); the firm's biggest growth market (China); and the country (China)*.

7774 Nominals are especially difficult to resolve (Denis and Baldridge, 2007; Durrett and
 7775 Klein, 2013), and the examples above suggest why this may be the case: world knowledge
 7776 is required to identify *Apple Inc* as a *firm*, and *China* as a *growth market*. Other difficult
 7777 examples include the use of colloquial expressions, such as coreference between *Clinton*
 7778 *campaign officials* and *the Clinton camp* (Soon et al., 2001).

7779 **15.2 Algorithms for coreference resolution**

The ground truth training data for coreference resolution is a set of mention sets, where all mentions within each set refer to a single entity.⁴ In the running example from Figure 15.1, the ground truth coreference annotation is:

$$c_1 = \{Apple\ Inc_{1:2}, the\ firm_{27:28}\} \quad [15.1]$$

$$c_2 = \{Apple\ Inc\ Chief\ Executive\ Tim\ Cook_{1:6}, he_{17}, Cook_{33}, his_{36}\} \quad [15.2]$$

$$c_3 = \{China_{10}, the\ firm\ 's\ biggest\ growth\ market_{27:32}, the\ country_{40:41}\} \quad [15.3]$$

7780 Each row specifies the token spans that mention an entity. (“Singleton” entities, which are
 7781 mentioned only once (e.g., *talks, government officials*), are excluded from the annotations.)
 7782 Equivalently, if given a set of M mentions, $\{m_i\}_{i=1}^M$, each mention i can be assigned to a
 7783 cluster z_i , where $z_i = z_j$ if i and j are coreferent. The cluster assignments z are invariant
 7784 under permutation. The unique clustering associated with the assignment z is written
 7785 $c(z)$.

7786 **Mention identification** The task of identifying mention spans for coreference resolution
 7787 is often performed by applying a set of heuristics to the phrase structure parse of each
 7788 sentence. A typical approach is to start with all noun phrases and named entities, and
 7789 then apply filtering rules to remove nested noun phrases with the same head (e.g., [*Apple*
 7790 *CEO [Tim Cook]*]), numeric entities (e.g., [*100 miles*], [*97%*]), non-referential *it*, etc (Lee
 7791 et al., 2013; Durrett and Klein, 2013). In general, these deterministic approaches err in
 7792 favor of recall, since the mention clustering component can choose to ignore false positive
 7793 mentions, but cannot recover from false negatives. An alternative is to consider all spans

⁴In many annotations, the term **markable** is used to refer to spans of text that can *potentially* mention an entity. The set of markables includes non-referential pronouns, which does not mention any entity. Part of the job of the coreference system is to avoid incorrectly linking these non-referential markables to any mention chains.

7794 (up to some finite length) as candidate mentions, performing mention identification and
 7795 clustering jointly (Daumé III and Marcu, 2005; Lee et al., 2017).

7796 **Mention clustering** The overwhelming majority of research on coreference resolution
 7797 addresses the subtask of mention clustering, and this will be the focus of the remainder of
 7798 this chapter. There are two main sets of approaches. In *mention-based models*, the scoring
 7799 function for a coreference clustering decomposes over pairs of mentions. These pairwise
 7800 decisions are then aggregated, using a clustering heuristic. Mention-based coreference
 7801 clustering can be treated as a fairly direct application of supervised classification or rank-
 7802 ing. However, the mention-pair locality assumption can result in incoherent clusters, like
 7803 $\{\text{Hillary Clinton} \leftarrow \text{Clinton} \leftarrow \text{Mr Clinton}\}$, in which the pairwise links score well, but the
 7804 overall result is unsatisfactory. *Entity-based models* address this issue by scoring entities
 7805 holistically. This can make inference more difficult, since the number of possible entity
 7806 groupings is exponential in the number of mentions.

7807 15.2.1 Mention-pair models

7808 In the **mention-pair model**, a binary label $y_{i,j} \in \{0, 1\}$ is assigned to each pair of mentions
 7809 (i, j) , where $i < j$. If i and j corefer ($z_i = z_j$), then $y_{i,j} = 1$; otherwise, $y_{i,j} = 0$. The
 7810 mention *he* in Figure 15.1 is preceded by five other mentions: (1) *Apple Inc*; (2) *Apple Inc*
 7811 *Chief Executive Tim Cook*; (3) *China*; (4) *talks*; (5) *government officials*. The correct mention
 7812 pair labeling is $y_{2,6} = 1$ and $y_{i \neq 2,6} = 0$ for all other i . If a mention j introduces a new entity,
 7813 such as mention 3 in the example, then $y_{i,j} = 0$ for all i . The same is true for “mentions”
 7814 that do not refer to any entity, such as non-referential pronouns. If mention j refers to an
 7815 entity that has been mentioned more than once, then $y_{i,j} = 1$ for all $i < j$ that mention the
 7816 referent.

7817 By transforming coreference into a set of binary labeling problems, the mention-pair
 7818 model makes it possible to apply an off-the-shelf binary classifier (Soon et al., 2001). This
 7819 classifier is applied to each mention j independently, searching backwards from j until
 7820 finding an antecedent i which corefers with j with high confidence. After identifying a
 7821 single **antecedent**, the remaining mention pair labels can be computed by transitivity: if
 7822 $y_{i,j} = 1$ and $y_{j,k} = 1$, then $y_{i,k} = 1$.

7823 Since the ground truth annotations give entity chains c but not individual mention-
 7824 pair labels y , an additional heuristic must be employed to convert the labeled data into
 7825 training examples for classification. A typical approach is to generate at most one pos-
 7826 itive labeled instance $y_{a_j,j} = 1$ for mention j , where a_j is the index of the most recent
 7827 antecedent, $a_j = \max\{i : i < j \wedge z_i = z_j\}$. Negative labeled instances are generated for
 7828 all for all $i \in \{a_j + 1, \dots, j\}$. In the running example, the most recent antecedent of the
 7829 pronoun *he* is $a_6 = 2$, so the training data would be $y_{2,6} = 1$ and $y_{3,6} = y_{4,6} = y_{5,6} = 0$.

7830 The variable $y_{1,6}$ is not part of the training data, because the first mention appears before
 7831 the true antecedent $a_6 = 2$.

7832 **15.2.2 Mention-ranking models**

In **mention ranking** (Denis and Baldridge, 2007), the classifier learns to identify a single antecedent $a_i \in \{\epsilon, 1, 2, \dots, i-1\}$ for each referring expression i ,

$$\hat{a}_i = \operatorname{argmax}_{a \in \{\epsilon, 1, 2, \dots, i-1\}} \psi_M(a, i), \quad [15.4]$$

7833 where $\psi_M(a, i)$ is a score for the mention pair (a, i) . If $a = \epsilon$, then mention i does not refer
 7834 to any previously-introduced entity — it is not **anaphoric**. Mention-ranking is similar to
 7835 the mention-pair model, but all candidates are considered simultaneously, and at most
 7836 a single antecedent is selected. The mention-ranking model explicitly accounts for the
 7837 possibility that mention i is not anaphoric, through the score $\psi_M(\epsilon, i)$. The determination
 7838 of anaphoricity can be made by a special classifier in a preprocessing step, so that non- ϵ
 7839 antecedents are identified only for spans that are determined to be anaphoric (Denis and
 7840 Baldridge, 2008).

7841 As a learning problem, ranking can be trained using the same objectives as in dis-
 7842 criminative classification. For each mention i , we can define a gold antecedent a_i^* , and an
 7843 associated loss, such as the hinge loss, $\ell_i = (1 - \psi_M(a_i^*, i) + \psi_M(\hat{a}, i))_+$ or the negative
 7844 log-likelihood, $\ell_i = -\log p(a_i^* | i; \theta)$. (For more on learning to rank, see § 17.1.1.) But as
 7845 with the mention-pair model, there is a mismatch between the labeled data, which comes
 7846 in the form of mention sets, and the desired supervision, which would indicate the spe-
 7847 cific antecedent of each mention. The antecedent variables $\{a_i\}_{i=1}^M$ relate to the mention
 7848 sets in a many-to-one mapping: each set of antecedents induces a single clustering, but a
 7849 clustering can correspond to many different settings of antecedent variables.

A heuristic solution is to set $a_i^* = \max\{j : j < i \wedge z_j = z_i\}$, the most recent mention in
 the same cluster as i . But the most recent mention may not be the most informative: in the
 running example, the most recent antecedent of the mention *Cook* is the pronoun *he*, but
 a more useful antecedent is the earlier mention *Apple Inc Chief Executive Tim Cook*. Rather
 than selecting a specific antecedent to train on, the antecedent can be treated as a latent
 variable, in the manner of the **latent variable perceptron** from § 12.4.2 (Fernandes et al.,

2014):

$$\hat{\mathbf{a}} = \operatorname{argmax}_{\mathbf{a}} \sum_{i=1}^M \psi_M(a_i, i) \quad [15.5]$$

$$\mathbf{a}^* = \operatorname{argmax}_{\mathbf{a} \in \mathcal{A}(c)} \sum_{i=1}^M \psi_M(a_i, i) \quad [15.6]$$

$$\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} + \sum_{i=1}^M \frac{\partial L}{\partial \boldsymbol{\theta}} \psi_M(a_i^*, i) - \sum_{i=1}^M \frac{\partial L}{\partial \boldsymbol{\theta}} \psi_M(\hat{a}_i, i) \quad [15.7]$$

where $\mathcal{A}(c)$ is the set of antecedent structures that is compatible with the ground truth coreference clustering c . Another alternative is to sum over all the conditional probabilities of antecedent structures that are compatible with the ground truth clustering (Durrett and Klein, 2013; Lee et al., 2017). For the set of mention \mathbf{m} , we compute the following probabilities:

$$p(c | \mathbf{m}) = \sum_{\mathbf{a} \in \mathcal{A}(c)} p(\mathbf{a} | \mathbf{m}) = \sum_{\mathbf{a} \in \mathcal{A}(c)} \prod_{i=1}^M p(a_i | i, \mathbf{m}) \quad [15.8]$$

$$p(a_i | i, \mathbf{m}) = \frac{\exp(\psi_M(a_i, i))}{\sum_{a' \in \{\epsilon, 1, 2, \dots, i-1\}} \exp(\psi_M(a', i))}. \quad [15.9]$$

7850 This objective rewards models that assign high scores for all valid antecedent structures.
 7851 In the running example, this would correspond to summing the probabilities of the two
 7852 valid antecedents for *Cook, he* and *Apple Inc Chief Executive Tim Cook*. In one of the exer-
 7853 cises, you will compute the number of valid antecedent structures for a given clustering.

7854 15.2.3 Transitive closure in mention-based models

A problem for mention-based models is that individual mention-level decisions may be incoherent. Consider the following mentions:

$$m_1 = \text{Hillary Clinton} \quad [15.10]$$

$$m_2 = \text{Clinton} \quad [15.11]$$

$$m_3 = \text{Bill Clinton} \quad [15.12]$$

7855 A mention-pair system might predict $\hat{y}_{1,2} = 1, \hat{y}_{2,3} = 1, \hat{y}_{1,3} = 0$. Similarly, a mention-
 7856 ranking system might choose $\hat{a}_2 = 1$ and $\hat{a}_3 = 2$. Logically, if mentions 1 and 3 are both
 7857 coreferent with mention 2, then all three mentions must refer to the same entity. This
 7858 constraint is known as **transitive closure**.

Transitive closure can be applied *post hoc*, revising the independent mention-pair or mention-ranking decisions. However, there are many possible ways to enforce transitive closure: in the example above, we could set $\hat{y}_{1,3} = 1$, or $\hat{y}_{1,2} = 0$, or $\hat{y}_{2,3} = 0$. For documents with many mentions, there may be many violations of transitive closure, and many possible fixes. Transitive closure can be enforced by always adding edges, so that $\hat{y}_{1,3} = 1$ is preferred (e.g., Soon et al., 2001), but this can result in overclustering, with too many mentions grouped into too few entities.

Mention-pair coreference resolution can be viewed as a constrained optimization problem,

$$\begin{aligned} \max_{\mathbf{y} \in \{0,1\}^M} \quad & \sum_{j=1}^M \sum_{i=1}^j \psi_M(i, j) \times y_{i,j} \\ \text{s.t.} \quad & y_{i,j} + y_{j,k} - 1 \leq y_{i,k}, \quad \forall i < j < k, \end{aligned}$$

with the constraint enforcing transitive closure. This constrained optimization problem is equivalent to graph partitioning with positive and negative edge weights: construct a graph where the nodes are mentions, and the edges are the pairwise scores $\psi_M(i, j)$; the goal is to partition the graph so as to maximize the sum of the edge weights between all nodes within the same partition (McCallum and Wellner, 2004). This problem is NP-hard, motivating approximations such as correlation clustering (Bansal et al., 2004) and **integer linear programming** (Klenner, 2007; Finkel and Manning, 2008, also see § 13.2.2).

15.2.4 Entity-based models

A weakness of mention-based models is that they treat coreference resolution as a classification or ranking problem, when it is really a clustering problem: the goal is to group the mentions together into clusters that correspond to the underlying entities. Entity-based approaches attempt to identify these clusters directly. Such methods require a scoring function at the entity level, measuring whether each set of mentions is internally consistent. Coreference resolution can then be viewed as the following optimization,

$$\max_{\mathbf{z}} \quad \sum_{e=1} \psi_E(\{i : z_i = e\}), \tag{15.13}$$

where z_i indicates the entity referenced by mention i , and $\psi_E(\{i : z_i = e\})$ is a scoring function applied to all mentions i that are assigned to entity e .

Entity-based coreference resolution is conceptually similar to the unsupervised clustering problems encountered in chapter 5: the goal is to obtain clusters of mentions that are internally coherent. The number of possible clusterings is the **Bell number**, which is

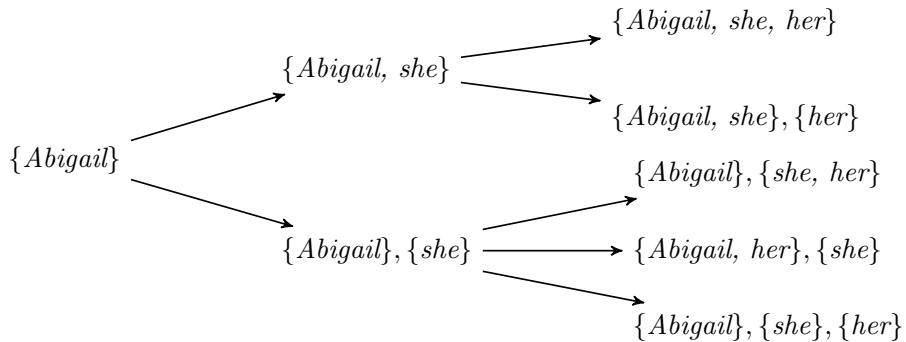


Figure 15.4: The Bell Tree for the sentence *Abigail hopes she speaks with her*. Which paths are excluded by the syntactic constraints mentioned in § 15.1.1?

defined by the following recurrence (Bell, 1934; Luo et al., 2004),

$$B_n = \sum_{k=0}^{n-1} B_k \binom{n-1}{k} = \frac{1}{e} \sum_{k=0}^{\infty} \frac{k^n}{k!}. \quad [15.14]$$

This recurrence is illustrated by the Bell tree, which is applied to a short coreference problem in Figure 15.4. The Bell number B_n grows exponentially with n , making exhaustive search of the space of clusterings impossible. For this reason, entity-based coreference resolution typically involves incremental search, in which clustering decisions are based on local evidence, in the hope of approximately optimizing the full objective in Equation 15.13. This approach is sometimes called **cluster ranking**, in contrast to mention ranking.

***Generative models of coreference** Entity-based cooreference can be approached through probabilistic **generative models**, in which the mentions in the document are conditioned on a set of latent entities (Haghghi and Klein, 2007, 2010). An advantage of these methods is that they can be learned from unlabeled data (Poon and Domingos, 2008, e.g.); a disadvantage is that probabilistic inference is required not just for learning, but also for prediction. Furthermore, generative models require independence assumptions that are difficult to apply in coreference resolution, where the diverse and heterogeneous features do not admit an easy decomposition into mutually independent subsets.

15.2.4.1 Incremental cluster ranking

The SMASH method (§ 15.1.1) can be extended to entity-based coreference resolution by building up coreference clusters while moving through the document (Cardie and Wagstaff, 1999). At each mention, the algorithm iterates backwards through possible antecedent

7895 clusters; but unlike SMASH, a cluster is selected only if *all* members of its cluster are compatible
 7896 with the current mention. As mentions are added to a cluster, so are their features
 7897 (e.g., gender, number, animacy). In this way, incoherent chains like *{Hillary Clinton, Clinton, Bill Clinton}*
 7898 can be avoided. However, an incorrect assignment early in the document — a **search error**
 7899 — might lead to a cascade of errors later on.

7900 More sophisticated search strategies can help to ameliorate the risk of search errors.
 7901 One approach is **beam search** (§ 11.3), in which a set of hypotheses is maintained through-
 7902 out search. Each hypothesis represents a path through the Bell tree (Figure 15.4). Hy-
 7903 potheses are “expanded” either by adding the next mention to an existing cluster, or by
 7904 starting a new cluster. Each expansion receives a score, based on Equation 15.13, and the
 7905 top K hypotheses are kept on the beam as the algorithm moves to the next step.

7906 Incremental cluster ranking can be made more accurate by performing multiple passes
 7907 over the document, applying rules (or “sieves”) with increasing recall and decreasing
 7908 precision at each pass (Lee et al., 2013). In the early passes, coreference links are pro-
 7909 posed only between mentions that are highly likely to corefer (e.g., exact string match
 7910 for full names and nominals). Information can then be shared among these mentions,
 7911 so that when more permissive matching rules are applied later, agreement is preserved
 7912 across the entire cluster. For example, in the case of *{Hillary Clinton, Clinton, she}*, the
 7913 name-matching sieve would link *Clinton* and *Hillary Clinton*, and the pronoun-matching
 7914 sieve would then link *she* to the combined cluster. A deterministic multi-pass system
 7915 won nearly every track of the 2011 CoNLL shared task on coreference resolution (Prad-
 7916 han et al., 2011). Given the dominance of machine learning in virtually all other areas
 7917 of natural language processing — and more than fifteen years of prior work on machine
 7918 learning for coreference — this was a surprising result, even if learning-based methods
 7919 have subsequently regained the upper hand (e.g., Lee et al., 2017, the state-of-the-art at
 7920 the time of this writing).

7921 15.2.4.2 Incremental perceptron

Incremental coreference resolution can be learned with the **incremental perceptron**, as described in § 11.3.2. At mention i , each hypothesis on the beam corresponds to a clustering of mentions $1 \dots i - 1$, or equivalently, a path through the Bell tree up to position $i - 1$. As soon as none of the hypotheses on the beam are compatible with the gold coreference clustering, a perceptron update is made (Daumé III and Marcu, 2005). For concreteness, consider a linear cluster ranking model,

$$\psi_E(\{i : z_i = e\}) = \sum_{i:z_i=e} \theta \cdot f(i, \{j : j < i \wedge z_j = e\}), \quad [15.15]$$

7922 where the score for each cluster is computed as the sum of scores of all mentions that are
 7923 linked into the cluster, and $f(i, \emptyset)$ is a set of features for the non-anaphoric mention that
 7924 initiates the cluster.

7925 Using Figure 15.4 as an example, suppose that the ground truth is,

$$\mathbf{c}^* = \{\text{Abigail}, \text{her}\}, \{\text{she}\}, \quad [15.16]$$

7926 but that with a beam of size one, the learner reaches the hypothesis,

$$\hat{\mathbf{c}} = \{\text{Abigail}, \text{she}\}. \quad [15.17]$$

This hypothesis is incompatible with \mathbf{c}^* , so an update is needed:

$$\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} + \mathbf{f}(\mathbf{c}^*) - \mathbf{f}(\hat{\mathbf{c}}) \quad [15.18]$$

$$= \boldsymbol{\theta} + (\mathbf{f}(\text{Abigail}, \emptyset) + \mathbf{f}(\text{she}, \emptyset)) - (\mathbf{f}(\text{Abigail}, \emptyset) + \mathbf{f}(\text{she}, \{\text{Abigail}\})) \quad [15.19]$$

$$= \boldsymbol{\theta} + \mathbf{f}(\text{she}, \emptyset) - \mathbf{f}(\text{she}, \{\text{Abigail}\}). \quad [15.20]$$

7927 This style of incremental update can also be applied to a margin loss between the gold
 7928 clustering and the top clustering on the beam. By backpropagating from this loss, it is also
 7929 possible to train a more complicated scoring function, such as a neural network in which
 7930 the score for each entity is a function of embeddings for the entity mentions (Wiseman
 7931 et al., 2015).

7932 15.2.4.3 Reinforcement learning

7933 **Reinforcement learning** is a topic worthy of a textbook of its own (Sutton and Barto,
 7934 1998),⁵ so this section will provide only a very brief overview, in the context of coreference
 7935 resolution. A stochastic **policy** assigns a probability to each possible **action**, conditional
 7936 on the context. The goal is to learn a policy that achieves a high expected reward, or
 7937 equivalently, a low expected cost.

7938 In incremental cluster ranking, a complete clustering on M mentions can be produced
 7939 by a sequence of M actions, in which the action z_i either merges mention i with an existing
 7940 cluster or begins a new cluster. We can therefore create a stochastic policy using the cluster
 7941 scores (Clark and Manning, 2016),

$$\Pr(z_i = e; \boldsymbol{\theta}) = \frac{\exp \psi_E(i \cup \{j : z_j = e\}; \boldsymbol{\theta})}{\sum_{e'} \exp \psi_E(i \cup \{j : z_j = e'\}; \boldsymbol{\theta})}, \quad [15.21]$$

7942 where $\psi_E(i \cup \{j : z_j = e\}; \boldsymbol{\theta})$ is the score under parameters $\boldsymbol{\theta}$ for assigning mention i to
 7943 cluster e . This score can be an arbitrary function of the mention i , the cluster e and its
 7944 (possibly empty) set of mentions; it can also include the history of actions taken thus far.

⁵A draft of the second edition can be found here: <http://incompleteideas.net/book/the-book-2nd.html>. Reinforcement learning has been used in spoken dialogue systems (Walker, 2000) and text-based game playing (Branavan et al., 2009), and was applied to coreference resolution by Clark and Manning (2015).

7945 If a policy assigns probability $p(c; \theta)$ to clustering c , then its expected loss is,

$$L(\theta) = \sum_{c \in \mathcal{C}(m)} p_\theta(c) \times \ell(c), \quad [15.22]$$

7946 where $\mathcal{C}(m)$ is the set of possible clusterings for mentions m . The loss $\ell(c)$ can be based on
 7947 any arbitrary scoring function, including the complex evaluation metrics used in corefer-
 7948 ence resolution (see § 15.4). This is an advantage of reinforcement learning, which can be
 7949 trained directly on the evaluation metric — unlike traditional supervised learning, which
 7950 requires a loss function that is differentiable and decomposable across individual deci-
 7951 sions.

Rather than summing over the exponentially many possible clusterings, we can approximate the expectation by sampling trajectories of actions, $z = (z_1, z_2, \dots, z_M)$, from the current policy. Each action z_i corresponds to a step in the Bell tree: adding mention m_i to an existing cluster, or forming a new cluster. Each trajectory z corresponds to a single clustering c , and so we can write the loss of an action sequence as $\ell(c(z))$. The **policy gradient** algorithm computes the gradient of the expected loss as an expectation over trajectories (Sutton et al., 2000),

$$\frac{\partial}{\partial \theta} L(\theta) = E_{z \sim \mathcal{Z}(m)} \ell(c(z)) \sum_{i=1}^M \frac{\partial}{\partial \theta} \log p(z_i | z_{1:i-1}, m) \quad [15.23]$$

$$\approx \frac{1}{K} \sum_{k=1}^K \ell(c(z^{(k)})) \sum_{i=1}^M \frac{\partial}{\partial \theta} \log p(z_i^{(k)} | z_{1:i-1}^{(k)}, m) \quad [15.24]$$

[15.25]

7952 where the action sequence $z^{(k)}$ is sampled from the current policy. Unlike the incremental
 7953 perceptron, an update is not made until the complete action sequence is available.

7954 15.2.4.4 Learning to search

7955 Policy gradient can suffer from high variance: while the average loss over K samples is
 7956 asymptotically equal to the expected reward of a given policy, this estimate may not be
 7957 accurate unless K is very large. This can make it difficult to allocate credit and blame to
 7958 individual actions. In **learning to search**, this problem is addressed through the addition
 7959 of an **oracle** policy, which is known to receive zero or small loss. The oracle policy can be
 7960 used in two ways:

- 7961 • The oracle can be used to generate partial hypotheses that are likely to score well,
 7962 by generating i actions from the initial state. These partial hypotheses are then used
 7963 as starting points for the learned policy. This is known as **roll-in**.

Algorithm 18 Learning to search for entity-based coreference resolution

```

1: procedure COMPUTE-GRADIENT(mentions  $m$ , loss function  $\ell$ , parameters  $\theta$ )
2:    $L(\theta) \leftarrow 0$ 
3:    $z \sim p(z | m; \theta)$                                  $\triangleright$  Sample a trajectory from the current policy
4:   for  $i \in \{1, 2, \dots, M\}$  do
5:     for action  $z \in \mathcal{Z}(z_{1:i-1}, m)$  do           $\triangleright$  All possible actions after history  $z_{1:i-1}$ 
6:        $h \leftarrow z_{1:i-1} \oplus z$                        $\triangleright$  Concatenate history  $z_{1:i-1}$  with action  $z$ 
7:       for  $j \in \{i+1, i+2, \dots, M\}$  do            $\triangleright$  Roll-out
8:          $h_j \leftarrow \operatorname{argmin}_h \ell(h_{1:j-1} \oplus h)$      $\triangleright$  Oracle selects action with minimum loss
9:        $L(\theta) \leftarrow L(\theta) + p(z | z_{1:i-1}, m; \theta) \times \ell(h)$        $\triangleright$  Update expected loss
10:      return  $\frac{\partial}{\partial \theta} L(\theta)$ 

```

- 7964 • The oracle can be used to compute the minimum possible loss from a given state, by
 7965 generating $M - i$ actions from the current state until completion. This is known as
 7966 **roll-out**.

7967 The oracle can be combined with the existing policy during both roll-in and roll-out, sam-
 7968 pling actions from each policy (Daumé III et al., 2009). One approach is to gradually
 7969 decrease the number of actions drawn from the oracle over the course of learning (Ross
 7970 et al., 2011).

7971 In the context of entity-based coreference resolution, Clark and Manning (2016) use
 7972 the learned policy for roll-in and the oracle policy for roll-out. Algorithm 18 shows how
 7973 the gradients on the policy weights are computed in this case. In this application, the
 7974 oracle is “noisy”, because it selects the action that minimizes only the *local* loss — the
 7975 accuracy of the coreference clustering up to mention i — rather than identifying the action
 7976 sequence that will lead to the best final coreference clustering on the entire document.
 7977 When learning from noisy oracles, it can be helpful to mix in actions from the current
 7978 policy with the oracle during roll-out (Chang et al., 2015).

7979 **15.3 Representations for coreference resolution**

7980 Historically, coreference resolution has employed an array of hand-engineered features
 7981 to capture the linguistic constraints and preferences described in § 15.1 (Soon et al., 2001).
 7982 Later work has documented the utility of lexical and bilexical features on mention pairs (Björkelund
 7983 and Nugues, 2011; Durrett and Klein, 2013). The most recent and successful methods re-
 7984 place many (but not all) of these features with distributed representations of mentions
 7985 and entities (Wiseman et al., 2015; Clark and Manning, 2016; Lee et al., 2017).

7986 **15.3.1 Features**

7987 Coreference features generally rely on a preprocessing pipeline to provide part-of-speech
 7988 tags and phrase structure parses. This pipeline makes it possible to design features that
 7989 capture many of the phenomena from § 15.1, and is also necessary for typical approaches
 7990 to mention identification. However, the pipeline may introduce errors that propagate
 7991 to the downstream coreference clustering system. Furthermore, the existence of such
 7992 a pipeline presupposes resources such as treebanks, which do not exist for many lan-
 7993 guages.⁶

7994 **15.3.1.1 Mention features**

7995 Features of individual mentions can help to predict anaphoricity. In systems where men-
 7996 tion detection is performed jointly with coreference resolution, these features can also
 7997 predict whether a span of text is likely to be a mention. For mention i , typical features
 7998 include:

7999 **Mention type.** Each span can be identified as a pronoun, name, or nominal, using the
 8000 part-of-speech of the head word of the mention: both the Penn Treebank and Uni-
 8001 versal Dependencies tagsets (§ 8.1.1) include tags for pronouns and proper nouns,
 8002 and all other heads can be marked as nominals (Haghghi and Klein, 2009).

8003 **Mention width.** The number of tokens in a mention is a rough predictor of its anaphor-
 8004 icity, with longer mentions being less likely to refer back to previously-defined enti-
 8005 ties.

8006 **Lexical features.** The first, last, and head words can help to predict anaphoricity; they are
 8007 also useful in conjunction with features such as mention type and part-of-speech,
 8008 providing a rough measure of agreement (Björkelund and Nugues, 2011). The num-
 8009 ber of lexical features can be very large, so it can be helpful to select only frequently-
 8010 occurring features (Durrett and Klein, 2013).

8011 **Morphosyntactic features.** These features include the part-of-speech, number, gender,
 8012 and dependency ancestors.

8013 The features for mention i and candidate antecedent a can be conjoined, producing
 8014 joint features that can help to assess the compatibility of the two mentions. For example,
 8015 Durrett and Klein (2013) conjoin each feature with the mention types of the anaphora
 8016 and the antecedent. Coreference resolution corpora such as ACE and OntoNotes contain

⁶The Universal Dependencies project has produced dependency treebanks for more than sixty languages. However, coreference features and mention detection are generally based on phrase structure trees, which exist for roughly two dozen languages. A list is available here: <https://en.wikipedia.org/wiki/Treebank>

8017 documents from various genres. By conjoining the genre with other features, it is possible
8018 to learn genre-specific feature weights.

8019 **15.3.1.2 Mention-pair features**

8020 For any pair of mentions i and j , typical features include:

8021 **Distance.** The number of intervening tokens, mentions, and sentences between i and j
8022 can all be used as distance features. These distances can be computed on the surface
8023 text, or on a transformed representation reflecting the breadth-first tree traversal
8024 (Figure 15.3). Rather than using the distances directly, they are typically binned,
8025 creating binary features.

8026 **String match.** A variety of string match features can be employed: exact match, suffix
8027 match, head match, and more complex matching rules that disregard irrelevant
8028 modifiers (Soon et al., 2001).

8029 **Compatibility.** Building on the model, features can measure the anaphor and antecedent
8030 agree with respect to morphosyntactic attributes such as gender, number, and ani-
8031 macy.

8032 **Nesting.** If one mention is nested inside another (e.g., *[The President of [France]]*), they
8033 generally cannot corefer.

8034 **Same speaker.** For documents with quotations, such as news articles, personal pronouns
8035 can be resolved only by determining the speaker for each mention (Lee et al., 2013).
8036 Coreference is also more likely between mentions from the same speaker.

8037 **Gazetteers.** These features indicate that the anaphor and candidate antecedent appear in
8038 a gazetteer of acronyms (e.g., *USA/United States*, *GATech/Georgia Tech*), demonymns
8039 (e.g., *Israel/Israeli*), or other aliases (e.g., *Knickerbockers/New York Knicks*).

8040 **Lexical semantics.** These features use a lexical resource such as WordNet to determine
8041 whether the head words of the mentions are related through synonymy, antonymy,
8042 and hypernymy (§ 4.2).

8043 **Dependency paths.** The dependency path between the anaphor and candidate antecedent
8044 can help to determine whether the pair can corefer, under the government and bind-
8045 ing constraints described in § 15.1.1.

8046 Comprehensive lists of mention-pair features are offered by Bengtson and Roth (2008) and
8047 Rahman and Ng (2011). Neural network approaches use far fewer mention-pair features:
8048 for example, Lee et al. (2017) include only speaker, genre, distance, and mention width
8049 features.

8050 **Semantics** In many cases, coreference seems to require knowledge and semantic in-
 8051 ferences, as in the running example, where we link *China* with a *country* and a *growth*
 8052 *market*. Some of this information can be gleaned from WordNet, which defines a graph
 8053 over **synsets** (see § 4.2). For example, one of the synsets of *China* is an instance of an
 8054 *Asian_nation#1*, which in turn is a hyponym of *country#2*, a synset that includes
 8055 *country*.⁷ Such paths can be used to measure the similarity between concepts (Pedersen
 8056 et al., 2004), and this similarity can be incorporated into coreference resolution as a fea-
 8057 ture (Ponzetto and Strube, 2006). Similar ideas can be applied to knowledge graphs in-
 8058 duced from Wikipedia (Ponzetto and Strube, 2007). But while such approaches improve
 8059 relatively simple classification-based systems, they have proven less useful when added
 8060 to the current generation of techniques.⁸ For example, Durrett and Klein (2013) employ
 8061 a range of semantics-based features — WordNet synonymy and hypernymy relations on
 8062 head words, named entity types (e.g., person, organization), and unsupervised clustering
 8063 over nominal heads — but find that these features give minimal improvement over a
 8064 baseline system using surface features.

8065 15.3.1.3 Entity features

8066 Many of the features for entity-mention coreference are generated by aggregating mention-
 8067 pair features over all mentions in the candidate entity (Culotta et al., 2007; Rahman and
 8068 Ng, 2011). Specifically, for each binary mention-pair feature $f(i, j)$, we compute the fol-
 8069 lowing entity-mention features for mention i and entity $e = \{j : j < i \wedge z_j = e\}$.

- 8070 • ALL-TRUE: Feature $f(i, j)$ holds for all mentions $j \in e$.
- 8071 • MOST-TRUE: Feature $f(i, j)$ holds for at least half and fewer than all mentions $j \in e$.
- 8072 • MOST-FALSE: Feature $f(i, j)$ holds for at least one and fewer than half of all men-
 8073 tions $j \in e$.
- 8074 • NONE: Feature $f(i, j)$ does not hold for any mention $j \in e$.

8075 For scalar mention-pair features (e.g., distance features), aggregation can be performed by
 8076 computing the minimum, maximum, and median values across all mentions in the cluster.
 8077 Additional entity-mention features include the number of mentions currently clustered in
 8078 the entity, and ALL-X and MOST-X features for each mention type.

8079 15.3.2 Distributed representations of mentions and entities

8080 Recent work has emphasized distributed representations of both mentions and entities.
 8081 One potential advantage is that pre-trained embeddings could help to capture the se-

⁷teletype font is used to indicate wordnet synsets, and *italics* is used to indicate strings.

⁸This point was made by Michael Strube at a 2015 workshop, noting that as the quality of the machine learning models in coreference has improved, the benefit of including semantics has become negligible.

8082 mantic compatibility underlying nominal coreference, helping with difficult cases like
 8083 (*Apple, the firm*) and (*China, the firm's biggest growth market*). Furthermore, a distributed
 8084 representation of entities can be trained to capture semantic features that are added by
 8085 each mention.

8086 **15.3.2.1 Mention embeddings**

8087 Entity mentions can be embedded into a vector space, providing the base layer for neural
 8088 networks that score coreference decisions (Wiseman et al., 2015).

8089 **Constructing the mention embedding** Various approaches for embedding multiword
 8090 units can be applied (see § 14.8). Figure 15.5 shows a recurrent neural network approach,
 8091 which begins by running a bidirectional LSTM over the entire text, obtaining hidden states
 8092 from the left-to-right and right-to-left passes, $\mathbf{h}_m = [\overleftarrow{\mathbf{h}}_m; \overrightarrow{\mathbf{h}}_m]$. Each candidate mention
 8093 span (s, t) is then represented by the vertical concatenation of four vectors:

$$\mathbf{u}^{(s,t)} = [\mathbf{u}_{\text{first}}^{(s,t)}; \mathbf{u}_{\text{last}}^{(s,t)}; \mathbf{u}_{\text{head}}^{(s,t)}; \phi^{(s,t)}], \quad [15.26]$$

8094 where $\mathbf{u}_{\text{first}}^{(s,t)} = \mathbf{h}_{s+1}$ is the embedding of the first word in the span, $\mathbf{u}_{\text{last}}^{(s,t)} = \mathbf{h}_t$ is the
 8095 embedding of the last word, $\mathbf{u}_{\text{head}}^{(s,t)}$ is the embedding of the “head” word, and $\phi^{(s,t)}$ is a
 8096 vector of surface features, such as the length of the span (Lee et al., 2017).

Attention over head words Rather than identifying the head word from the output of a parser, it can be computed from a neural **attention mechanism**:

$$\tilde{\alpha}_m = \theta_\alpha \cdot \mathbf{h}_m \quad [15.27]$$

$$\mathbf{a}^{(s,t)} = \text{SoftMax}([\tilde{\alpha}_{s+1}, \tilde{\alpha}_{s+2}, \dots, \tilde{\alpha}_t]) \quad [15.28]$$

$$\mathbf{u}_{\text{head}}^{(s,t)} = \sum_{m=s+1}^t a_m^{(s,t)} \mathbf{h}_m. \quad [15.29]$$

8097 Each token m gets a scalar score $\tilde{\alpha}_m = \theta_\alpha \cdot \mathbf{h}_m$, which is the dot product of the LSTM
 8098 hidden state \mathbf{h}_m and a vector of weights θ_α . The vector of scores for tokens in the span
 8099 $m \in \{s + 1, s + 2, \dots, t\}$ is then passed through a softmax layer, yielding a vector $\mathbf{a}^{(s,t)}$
 8100 that allocates one unit of attention across the span. This eliminates the need for syntactic
 8101 parsing to recover the head word; instead, the model learns to identify the most important
 8102 words in each span. Attention mechanisms were introduced in neural machine transla-
 8103 tion (Bahdanau et al., 2014), and are described in more detail in § 18.3.1.

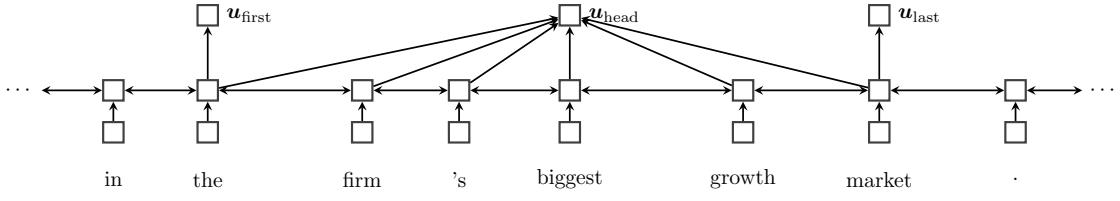


Figure 15.5: A bidirectional recurrent model of mention embeddings. The mention is represented by its first word, its last word, and an estimate of its head word, which is computed from a weighted average (Lee et al., 2017).

Using mention embeddings Given a set of mention embeddings, each mention i and candidate antecedent a is scored as,

$$\psi(a, i) = \psi_S(a) + \psi_S(i) + \psi_M(a, i) \quad [15.30]$$

$$\psi_S(a) = \text{FeedForward}_S(\mathbf{u}^{(a)}) \quad [15.31]$$

$$\psi_S(i) = \text{FeedForward}_S(\mathbf{u}^{(i)}) \quad [15.32]$$

$$\psi_M(a, i) = \text{FeedForward}_M([\mathbf{u}^{(a)}; \mathbf{u}^{(i)}; \mathbf{u}^{(a)} \odot \mathbf{u}^{(i)}; \mathbf{f}(a, i, \mathbf{w})]), \quad [15.33]$$

where $\mathbf{u}^{(a)}$ and $\mathbf{u}^{(i)}$ are the embeddings for spans a and i respectively, as defined in Equation 15.26.

- The scores $\psi_S(a)$ quantify whether span a is likely to be a coreferring mention, independent of what it corefers with. This allows the model to learn identify mentions directly, rather than identifying mentions with a preprocessing step.
- The score $\psi_M(a, i)$ computes the compatibility of spans a and i . Its base layer is a vector that includes the embeddings of spans a and i , their elementwise product $\mathbf{u}^{(a)} \odot \mathbf{u}^{(i)}$, and a vector of surface features $\mathbf{f}(a, i, \mathbf{w})$, including distance, speaker, and genre information.

Lee et al. (2017) provide an error analysis that shows how this method can correctly link a *blaze* and a *fire*, while incorrectly linking *pilots* and *fight attendants*. In each case, the coreference decision is based on similarities in the word embeddings.

Rather than embedding individual mentions, Clark and Manning (2016) embed mention pairs. At the base layer, their network takes embeddings of the words in and around each mention, as well as **one-hot** vectors representing a few surface features, such as the distance and string matching features. This base layer is then passed through a multilayer feedforward network with ReLU nonlinearities, resulting in a representation of the mention pair. The output of the mention pair encoder $\mathbf{u}_{i,j}$ is used in the scoring function of a mention-ranking model, $\psi_M(i, j) = \theta \cdot \mathbf{u}_{i,j}$. A similar approach is used to score cluster

8123 pairs, constructing a cluster-pair encoding by **pooling** over the mention-pair encodings
8124 for all pairs of mentions within the two clusters.

8125 **15.3.2.2 Entity embeddings**

8126 In entity-based coreference resolution, each entity should be represented by properties of
8127 its mentions. In a distributed setting, we maintain a set of vector entity embeddings, v_e .
8128 Each candidate mention receives an embedding u_i ; Wiseman et al. (2016) compute this
8129 embedding by a single-layer neural network, applied to a vector of surface features. The
8130 decision of whether to merge mention i with entity e can then be driven by a feedforward
8131 network, $\psi_E(i, e) = \text{Feedforward}([v_e; u_i])$. If i is added to entity e , then its representa-
8132 tion is updated recurrently, $v_e \leftarrow f(v_e, u_i)$, using a recurrent neural network such as a
8133 long short-term memory (LSTM; chapter 6). Alternatively, we can apply a **pooling** oper-
8134 ation, such as max-pooling or average-pooling (chapter 3), setting $v_e \leftarrow \text{Pool}(v_e, u_i)$. In
8135 either case, the update to the representation of entity e can be thought of as adding new
8136 information about the entity from mention i .

8137 **15.4 Evaluating coreference resolution**

8138 The state of coreference evaluation is aggravatingly complex. Early attempts at sim-
8139 ple evaluation metrics were found to under-penalize trivial baselines, such as placing
8140 each mention in its own cluster, or grouping all mentions into a single cluster. Follow-
8141 ing Denis and Baldridge (2009), the CoNLL 2011 shared task on coreference (Pradhan
8142 et al., 2011) formalized the practice of averaging across three different metrics: MUC (Vi-
8143 lain et al., 1995), B-CUBED (Bagga and Baldwin, 1998a), and CEAf (Luo, 2005). Refer-
8144 ence implementations of these metrics are available from Pradhan et al. (2014) at <https://github.com/conll/reference-coreference-scorers>.
8145

8146 **Additional resources**

8147 Ng (2010) surveys coreference resolution through 2010. Early work focused exclusively
8148 on pronoun resolution, with rule-based (Lappin and Leass, 1994) and probabilistic meth-
8149 ods (Ge et al., 1998). The full coreference resolution problem was popularized in a shared
8150 task associated with the sixth Message Understanding Conference, which included coref-
8151 erence annotations for training and test sets of thirty documents each (Grishman and
8152 Sundheim, 1996). An influential early paper was the decision tree approach of Soon et al.
8153 (2001), who introduced mention ranking. A comprehensive list of surface features for
8154 coreference resolution is offered by Bengtson and Roth (2008). Durrett and Klein (2013)
8155 improved on prior work by introducing a large lexicalized feature set; subsequent work
8156 has emphasized neural representations of entities and mentions (Wiseman et al., 2015).

8157 **Exercises**

8158 1. Select an article from today's news, and annotate coreference for the first twenty
 8159 noun phrases that appear in the article (include nested noun phrases). That is,
 8160 group the noun phrases into entities, where each entity corresponds to a set of noun
 8161 phrases. Then specify the mention-pair training data that would result from the first
 8162 five noun phrases.

8163 2. Using your annotations from the preceding problem, compute the following statistics:
 8164

- 8165 • The number of times new entities are introduced by each of the three types of
 8166 referring expressions: pronouns, proper nouns, and nominals. Include "single-
 8167 ton" entities that are mentioned only once.
- 8168 • For each type of referring expression, compute the fraction of mentions that are
 8169 anaphoric.

8170 3. Apply a simple heuristic to all pronouns in the article from the previous exercise.
 8171 Specifically, link each pronoun to the closest preceding noun phrase that agrees in
 8172 gender, number, animacy, and person. Compute the following evaluation:

- 8173 • True positive: a pronoun that is linked to a noun phrase with which it is coref-
 8174 erent, or is correctly labeled as the first mention of an entity.
- 8175 • False positive: a pronoun that is linked to a noun phrase with which it is not
 8176 coreferent. (This includes mistakenly linking singleton or non-referential pro-
 8177 nouns.)
- 8178 • False negative: a pronoun that is not linked to a noun phrase with which it is
 8179 coreferent.

8180 Compute the *F-MEASURE* for your method, and for a trivial baseline in which ev-
 8181 ery mention is its own entity. Are there any additional heuristics that would have
 8182 improved the performance of this method?

8183 4. Durrett and Klein (2013) compute the probability of the gold coreference clustering
 8184 by summing over all antecedent structures that are compatible with the clustering.
 8185 Compute the number of antecedent structures for a single entity with K mentions.

8186 5. Use the policy gradient algorithm to compute the gradient for the following sce-
 8187 nario, based on the Bell tree in Figure 15.4:

- 8188 • The gold clustering c^* is $\{Abigail, her\}, \{she\}$.

- Drawing a single sequence of actions ($K = 1$) from the current policy, you obtain the following incremental clusterings:

$$\begin{aligned}\mathbf{c}(a_1) &= \{\text{Abigail}\} \\ \mathbf{c}(\mathbf{a}_{1:2}) &= \{\text{Abigail}, \text{she}\} \\ \mathbf{c}(\mathbf{a}_{1:3}) &= \{\text{Abigail}, \text{she}\}, \{\text{her}\}.\end{aligned}$$

- 8189 • At each mention t , the action space \mathcal{A}_t is to merge the mention with each existing cluster, or the empty cluster, with probability,
- 8190

$$\Pr(\text{Merge}(m_t, \mathbf{c}(\mathbf{a}_{1:t-1}))) \propto \exp \psi_E(m_t \cup \mathbf{c}(\mathbf{a}_{1:t-1})), \quad [15.34]$$

8191 where the cluster score $\psi_E(m_t \cup c)$ is defined in Equation 15.15.

8192 Compute the gradient $\frac{\partial}{\partial \theta} L(\theta)$ in terms of the loss $\ell(c(a))$ and the features of each
 8193 (potential) cluster. Explain the differences between the gradient-based update $\theta \leftarrow \theta - \frac{\partial}{\partial \theta} L(\theta)$
 8194 and the incremental perceptron update from this sample example.

8195 **Chapter 16**

8196 **Discourse**

8197 Applications of natural language processing often concern multi-sentence documents:
8198 from paragraph-long restaurant reviews, to 500-word newspaper articles, to 500-page
8199 novels. Yet most of the methods that we have discussed thus far are concerned with
8200 individual sentences. This chapter discusses theories and methods for handling multi-
8201 sentence linguistic phenomena, known collectively as **discourse**. There are diverse char-
8202 acterizations of discourse structure, and no single structure is ideal for every computa-
8203 tional application. This chapter covers some of the most well studied discourse repre-
8204 sentations, while highlighting computational models for identifying and exploiting these
8205 structures.

8206 **16.1 Segments**

8207 A document or conversation can be viewed as a sequence of **segments**, each of which is
8208 **cohesive** in its content and/or function. In Wikipedia biographies, these segments often
8209 pertain to various aspects to the subject's life: early years, major events, impact on others,
8210 and so on. This segmentation is organized around **topics**. Alternatively, scientific research
8211 articles are often organized by **functional themes**: the introduction, a survey of previous
8212 research, experimental setup, and results.

8213 Written texts often mark segments with section headers and related formatting de-
8214 vices. However, such formatting may be too coarse-grained to support applications such
8215 as the retrieval of specific passages of text that are relevant to a query (Hearst, 1997).
8216 Unformatted speech transcripts, such as meetings and lectures, are also an application
8217 scenario for segmentation (Carletta, 2007; Glass et al., 2007; Janin et al., 2003).

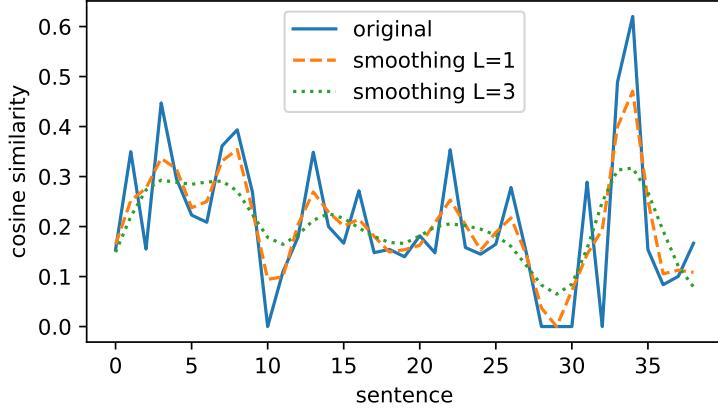


Figure 16.1: Smoothed cosine similarity among adjacent sentences in a news article. Local minima at $m = 10$ and $m = 29$ indicate likely segmentation points.

8218 16.1.1 Topic segmentation

A cohesive topic segment forms a unified whole, using various linguistic devices: repeated references to an entity or event; the use of conjunctions to link related ideas; and the repetition of meaning through lexical choices (Halliday and Hasan, 1976). Each of these cohesive devices can be measured, and then used as features for topic segmentation. A classical example is the use of lexical cohesion in the `TextTiling` method for topic segmentation (Hearst, 1997). The basic idea is to compute the textual similarity between each pair of adjacent blocks of text (sentences or fixed-length units), using a formula such as the smoothed **cosine similarity** of their bag-of-words vectors,

$$s_m = \frac{\mathbf{x}_m \cdot \mathbf{x}_{m+1}}{\|\mathbf{x}_m\|_2 \times \|\mathbf{x}_{m+1}\|_2} \quad [16.1]$$

$$\bar{s}_m = \sum_{\ell=0}^L k_\ell (s_{m+\ell} + s_{m-\ell}), \quad [16.2]$$

8219 with k_ℓ representing the value of a smoothing kernel of size L , e.g. $\mathbf{k} = [1, 0.5, 0.25]^\top$.
 8220 Segmentation points are then identified at local minima in the smoothed similarities \bar{s} ,
 8221 since these points indicate changes in the overall distribution of words in the text. An
 8222 example is shown in Figure 16.1.

8223 Text segmentation can also be formulated as a probabilistic model, in which each seg-
 8224 ment has a unique language model that defines the probability over the text in the seg-
 8225 ment (Utiyama and Isahara, 2001; Eisenstein and Barzilay, 2008; Du et al., 2013).¹ A good

¹There is a rich literature on how latent variable models (such as **latent Dirichlet allocation**) can track

8226 segmentation achieves high likelihood by grouping segments with similar word distribu-
8227 tions. This probabilistic approach can be extended to **hierarchical topic segmentation**, in
8228 which each topic segment is divided into subsegments (Eisenstein, 2009). All of these ap-
8229 proaches are unsupervised. While labeled data can be obtained from well-formatted texts
8230 such as textbooks, such annotations may not generalize to speech transcripts in alterna-
8231 tive domains. Supervised methods have been tried in cases where in-domain labeled data
8232 is available, substantially improving performance by learning weights on multiple types
8233 of features (Galley et al., 2003).

8234 16.1.2 Functional segmentation

8235 In some genres, there is a canonical set of communicative *functions*: for example, in sci-
8236 entific research articles, one such function is to communicate the general background for
8237 the article, another is to introduce a new contribution, or to describe the aim of the re-
8238 search (Teufel et al., 1999). A **functional segmentation** divides the document into con-
8239 tiguous segments, sometimes called **rhetorical zones**, in which each sentence has the same
8240 function. Teufel and Moens (2002) train a supervised classifier to identify the functional
8241 of each sentence in a set of scientific research articles, using features that describe the sen-
8242 tence's position in the text, its similarity to the rest of the article and title, tense and voice of
8243 the main verb, and the functional role of the previous sentence. Functional segmentation
8244 can also be performed without supervision. Noting that some types of Wikipedia arti-
8245 cles have very consistent functional segmentations (e.g., articles about cities or chemical
8246 elements), Chen et al. (2009) introduce an unsupervised model for functional segmenta-
8247 tion, which learns both the language model associated with each function and the typical
8248 patterning of functional segments across the article.

8249 16.2 Entities and reference

8250 Another dimension of discourse relates to which entities are mentioned throughout the
8251 text, and how. Consider the examples in Figure 16.2: Grosz et al. (1995) argue that the first
8252 discourse is more coherent. Do you agree? The examples differ in their choice of **refe-
8253 ring expressions** for the protagonist *John*, and in the syntactic constructions in sentences
8254 (b) and (d). The examples demonstrate the need for theoretical models to explain how
8255 referring expressions are chosen, and where they are placed within sentences. Such mod-
8256 els can then be used to help interpret the overall structure of the discourse, to measure
8257 discourse coherence, and to generate discourses in which referring expressions are used
8258 coherently.

topics across documents (Blei et al., 2003; Blei, 2012).

- | | |
|--|---|
| (16.1) a. John went to his favorite music store to buy a piano.
b. He had frequented the store for many years.
c. He was excited that he could finally buy a piano.
d. He arrived just as the store was closing for the day | (16.2) a. John went to his favorite music store to buy a piano.
b. It was a store John had frequented for many years.
c. He was excited that he could finally buy a piano.
d. It was closing just as John arrived. |
|--|---|

Figure 16.2: Two tellings of the same story (Grosz et al., 1995). The discourse on the left uses referring expressions coherently, while the one on the right does not.

8259 16.2.1 Centering theory

8260 The relationship between discourse and entity reference is most elaborated in **centering**
8261 **theory** (Grosz et al., 1995). According to the theory, every utterance in the discourse is
8262 characterized by a set of entities, known as *centers*.

- 8263 • The **forward-looking centers** in utterance m are all the entities that are mentioned
8264 in the utterance, $c_f(w_m) = \{e_1, e_2, \dots\}$. The forward-looking centers are partially
8265 ordered by their syntactic prominence, favoring subjects over other positions.
8266 • The **backward-looking center** $c_b(w_m)$ is the highest-ranked element in the set of
8267 forward-looking centers from the previous utterance $c_f(w_{m-1})$ that is also men-
8268 tioned in w_m .

8269 Given these two definitions, centering theory makes the following predictions about
8270 the form and position of referring expressions:

- 8271 1. If a pronoun appears in the utterance w_m , then the backward-looking center $c_b(w_m)$
8272 must also be realized as a pronoun. This rule argues against the use of *it* to refer
8273 to the piano store in Example (16.2d), since JOHN is the backward looking center of
8274 (16.2d), and he is mentioned by name and not by a pronoun.
8275 2. Sequences of utterances should retain the same backward-looking center if possible,
8276 and ideally, the backward-looking center should also be the top-ranked element in
8277 the list of forward-looking centers. This rule argues in favor of the preservation of
8278 JOHN as the backward-looking center throughout Example (16.1).

8279 Centering theory unifies aspects of syntax, discourse, and anaphora resolution. However,
8280 it can be difficult to clarify exactly how to rank the elements of each utterance, or even
8281 how to partition a text or dialog into utterances (Poesio et al., 2004).

	SKYLER	WALTER	DANGER	A GUY	THE DOOR
<i>You don't know who you're talking to,</i>	S	-	-	-	-
<i>so let me clue you in.</i>	O	O	-	-	-
<i>I am not in danger, Skyler.</i>	X	S	X	-	-
<i>I am the danger.</i>	-	S	O	-	-
<i>A guy opens his door and gets shot,</i>	-	-	-	S	O
<i>and you think that of me?</i>	S	X	-	-	-
<i>No. I am the one who knocks!</i>	-	S	-	-	-

Figure 16.3: The entity grid representation for a dialogue from the television show *Breaking Bad*.

16.2.2 The entity grid

One way to formalize the ideas of centering theory is to arrange the entities in a text or conversation in an **entity grid**. This is a data structure with one row per sentence, and one column per entity (Barzilay and Lapata, 2008). Each cell $c(m, i)$ can take the following values:

$$c(m, i) = \begin{cases} S, & \text{entity } i \text{ is in subject position in sentence } m \\ O, & \text{entity } i \text{ is in object position in sentence } m \\ X, & \text{entity } i \text{ appears in sentence } m, \text{ in neither subject nor object position} \\ -, & \text{entity } i \text{ does not appear in sentence } m. \end{cases} \quad [16.3]$$

To populate the entity grid, syntactic parsing is applied to identify subject and object positions, and coreference resolution is applied to link multiple mentions of a single entity. An example is shown in Figure 16.3.

After the grid is constructed, the coherence of a document can be measured by the transitions between adjacent cells in each column. For example, the transition $(S \rightarrow S)$ keeps an entity in subject position across adjacent sentences; the transition $(O \rightarrow S)$ promotes an entity from object position to subject position; the transition $(S \rightarrow -)$ drops the subject of one sentence from the next sentence. The probabilities of each transition can be estimated from labeled data, and an entity grid can then be scored by the sum of the log-probabilities across all columns and all transitions, $\sum_{i=1}^{N_e} \sum_{m=1}^M \log p(c(m, i) | c(m-1, i))$. The resulting probability can be used as a proxy for the coherence of a text. This has been shown to be useful for a range of tasks: determining which of a pair of articles is more readable (Schwartz and Ostendorf, 2005), correctly ordering the sentences in a scrambled

8300 text (Lapata, 2003), and disentangling multiple conversational threads in an online multi-
 8301 party chat (Elsner and Charniak, 2010).

8302 **16.2.3 *Formal semantics beyond the sentence level**

8303 An alternative view of the role of entities in discourse focuses on formal semantics, and the
 8304 construction of meaning representations for multi-sentence units. Consider the following
 8305 two sentences (from Bird et al., 2009):

- 8306 (16.3) a. Angus owns a dog.
 8307 b. It bit Irene.

8308 We would like to recover the formal semantic representation,

$$\exists x. \text{DOG}(x) \wedge \text{OWN}(\text{ANGUS}, x) \wedge \text{BITE}(x, \text{IRENE}). \quad [16.4]$$

However, the semantic representations of each individual sentence are:

$$\exists x. \text{DOG}(x) \wedge \text{OWN}(\text{ANGUS}, x) \quad [16.5]$$

$$\text{BITE}(y, \text{IRENE}). \quad [16.6]$$

8309 Unifying these two representations into the form of Equation 16.4 requires linking the
 8310 unbound variable y from [16.6] with the quantified variable x in [16.5]. Discourse under-
 8311 standing therefore requires the reader to update a set of assignments, from variables
 8312 to entities. This update would (presumably) link the *dog* in the first sentence of [16.3]
 8313 with the unbound variable y in the second sentence, thereby licensing the conjunction in
 8314 [16.4].² This basic idea is at the root of **dynamic semantics** (Groenendijk and Stokhof,
 8315 1991). **Segmented discourse representation theory** links dynamic semantics with a set
 8316 of **discourse relations**, which explain how adjacent units of text are rhetorically or con-
 8317 ceptually related (Lascarides and Asher, 2007). The next section explores the theory of
 8318 discourse relations in more detail.

8319 **16.3 Relations**

8320 In dependency grammar, sentences are characterized by a graph (usually a tree) of syntac-
 8321 tic relations between words, such as NSUBJ and DET. A similar idea can be applied at the
 8322 document level, identifying relations between discourse units, such as clauses, sentences,
 8323 or paragraphs. The task of **discourse parsing** involves identifying discourse units and
 8324 the relations that hold between them. These relations can then be applied to tasks such as
 8325 document classification and summarization, as discussed in § 16.3.4.

²This linking task is similar to coreference resolution (see chapter 15), but here the connections are between semantic variables, rather than spans of text.

- TEMPORAL
 - Asynchronous
 - Synchronous: precedence, succession
- CONTINGENCY
 - Cause: result, reason
 - Pragmatic cause: justification
 - Condition: hypothetical, general, unreal present, unreal past, real present, real past
 - Pragmatic condition: relevance, implicit assertion
- COMPARISON
 - Contrast: juxtaposition, opposition
 - Pragmatic contrast
 - Concession: expectation, contra-expectation
 - Pragmatic concession
- EXPANSION
 - Conjunction
 - Instantiation
 - Restatement: specification, equivalence, generalization
 - Alternative: conjunctive, disjunctive, chosen alternative
 - Exception
 - List

Table 16.1: The hierarchy of discourse relation in the Penn Discourse Treebank annotations (Prasad et al., 2008). For example, PRECEDENCE is a subtype of SYNCHRONOUS, which is a type of TEMPORAL relation.

8326 16.3.1 Shallow discourse relations

8327 The existence of discourse relations is hinted by **discourse connectives**, such as *however*,
 8328 *moreover*, *meanwhile*, and *if . . . then*. These connectives explicitly specify the relationship
 8329 between adjacent units of text: *however* signals a contrastive relationship, *moreover* signals
 8330 that the subsequent text elaborates or strengthens the point that was made immediately
 8331 beforehand, *meanwhile* indicates that two events are contemporaneous, and *if . . . then* sets
 8332 up a conditional relationship. Discourse connectives can therefore be viewed as a starting
 8333 point for the analysis of discourse relations.

8334 In **lexicalized tree-adjoining grammar for discourse (D-LTAG)**, each connective an-
 8335 chors a relationship between two units of text (Webber, 2004). This model provides the
 8336 theoretical basis for the **Penn Discourse Treebank (PDTB)**, the largest corpus of discourse
 8337 relations in English (Prasad et al., 2008). It includes a hierarchical inventory of discourse
 8338 relations (shown in Table 16.1), which is created by abstracting the meanings implied by
 8339 the discourse connectives that appear in real texts (Knott, 1996). These relations are then
 8340 annotated on the same corpus of news text used in the Penn Treebank (see § 9.2.2), adding
 8341 the following information:

- Each connective is annotated for the discourse relation or relations that it expresses, if any — many discourse connectives have senses in which they do not signal a discourse relation (Pitler and Nenkova, 2009).
- For each discourse relation, the two arguments of the relation are specified as ARG1 and ARG2, where ARG2 is constrained to be adjacent to the connective. These arguments may be sentences, but they may also smaller or larger units of text.
- Adjacent sentences are annotated for **implicit discourse relations**, which are not marked by any connective. When a connective could be inserted between a pair of sentence, the annotator supplies it, and also labels its sense (e.g., example 16.5). In some cases, there is no relationship at all between a pair of adjacent sentences; in other cases, the only relation is that the adjacent sentences mention one or more shared entity. These phenomena are annotated as NOREL and ENTRREL (entity relation), respectively.

Examples of Penn Discourse Treebank annotations are shown in (16.4). In (16.4), the word *therefore* acts as an explicit discourse connective, linking the two adjacent units of text. The Treebank annotations also specify the “sense” of each relation, linking the connective to a relation in the sense inventory shown in Table 16.1: in (16.4), the relation is PRAGMATIC CAUSE:JUSTIFICATION because it relates to the author’s communicative intentions. The word *therefore* can also signal causes in the external world (e.g., *He was therefore forced to relinquish his plan*). In **discourse sense classification**, the goal is to determine which discourse relation, if any, is expressed by each connective. A related task is the classification of implicit discourse relations, as in (16.5). In this example, the relationship between the adjacent sentences could be expressed by the connective *because*, indicating a CAUSE:REASON relationship.

16.3.1.1 Classifying explicit discourse relations and their arguments

As suggested by the examples above, many connectives can be used to invoke multiple types of discourse relations. Similarly, some connectives have senses that are unrelated to discourse: for example, *and* functions as a discourse connective when it links propositions, but not when it links noun phrases (Lin et al., 2014). Nonetheless, the senses of explicitly-marked discourse relations in the Penn Treebank are relatively easy to classify, at least at the coarse-grained level. When classifying the four top-level PDTB relations, 90% accuracy can be obtained simply by selecting the most common relation for each connective (Pitler and Nenkova, 2009). At the more fine-grained levels of the discourse relation hierarchy, connectives are more ambiguous. This fact is reflected both in the accuracy of automatic sense classification (Versley, 2011) and in interannotator agreement, which falls to 80% for level-3 discourse relations (Prasad et al., 2008).

- (16.4) *...as this business of whaling has somehow come to be regarded among landsmen as a rather unpoetical and disreputable pursuit; therefore, I am all anxiety to convince ye, ye landsmen, of the injustice hereby done to us hunters of whales.*
- (16.5) But a few funds have taken other defensive steps. *Some have raised their cash positions to record levels. Implicit = BECAUSE High cash positions help buffer a fund when the market falls.*
- (16.6) Michelle lives in a hotel room, and although **she drives a canary-colored Porsche**, *she hasn't time to clean or repair it.*
- (16.7) *Most oil companies, when they set exploration and production budgets for this year, forecast revenue of \$15 for each barrel of crude produced.*

Figure 16.4: Example annotations of discourse relations. In the style of the Penn Discourse Treebank, the discourse connective is underlined, the first argument is shown in italics, and the second argument is shown in bold. Examples (16.5-16.7) are quoted from Prasad et al. (2008).

8378 A more challenging task for explicitly-marked discourse relations is to identify the
 8379 scope of the arguments. Discourse connectives need not be adjacent to ARG1, as shown
 8380 in item 16.6, where ARG1 follows ARG2; furthermore, the arguments need not be contigu-
 8381 ous, as shown in (16.7). For these reasons, recovering the arguments of each discourse
 8382 connective is a challenging subtask. Because intra-sentential arguments are often syn-
 8383 tactic constituents (see chapter 10), many approaches train a classifier to predict whether
 8384 each constituent is an appropriate argument for each explicit discourse connective (Well-
 8385 ner and Pustejovsky, 2007; Lin et al., 2014, e.g.,).

8386 16.3.1.2 Classifying implicit discourse relations

Implicit discourse relations are considerably more difficult to classify and to annotate.³ Most approaches are based on an encoding of each argument, which is then used as input to a non-linear classifier:

$$\mathbf{z}^{(i)} = \text{Encode}(\mathbf{w}^{(i)}) \quad [16.7]$$

$$\mathbf{z}^{(i+1)} = \text{Encode}(\mathbf{w}^{(i+1)}) \quad [16.8]$$

$$\hat{y}_i = \underset{y}{\operatorname{argmax}} \Psi(y, \mathbf{z}^{(i)}, \mathbf{z}^{(i+1)}). \quad [16.9]$$

³In the dataset for the 2015 shared task on shallow discourse parsing, the interannotator agreement was 91% for explicit discourse relations and 81% for non-explicit relations, across all levels of detail (Xue et al., 2015).

8387 This basic framework can be instantiated in several ways, including both feature-based
 8388 and neural encoders. Several recent approaches are compared in the 2015 and 2016 shared
 8389 tasks at the Conference on Natural Language Learning (Xue et al., 2015, 2016).

8390 **Feature-based approaches** Each argument can be encoded into a vector of surface fea-
 8391 tures. The encoding typically includes lexical features (all words, or all content words, or
 8392 a subset of words such as the first three and the main verb), Brown clusters of individ-
 8393 ual words (§ 14.4), and syntactic features such as terminal productions and dependency
 8394 arcs (Pitler et al., 2009; Lin et al., 2009; Rutherford and Xue, 2014). The classification func-
 8395 tion then has two parts. First, it creates a joint feature vector by combining the encodings
 8396 of each argument, typically by computing the cross-product of all features in each encod-
 8397 ing:

$$\mathbf{f}(y, \mathbf{z}^{(i)}, \mathbf{z}^{(i+1)}) = \{(a \times b \times y) : (\mathbf{z}_a^{(i)} \mathbf{z}_b^{(i+1)})\} \quad [16.10]$$

8398 The size of this feature set grows with the square of the size of the vocabulary, so it can be
 8399 helpful to select a subset of features that are especially useful on the training data (Park
 8400 and Cardie, 2012). After \mathbf{f} is computed, any classifier can be trained to compute the final
 8401 score, $\Psi(y, \mathbf{z}^{(i)}, \mathbf{z}^{(i+1)}) = \boldsymbol{\theta} \cdot \mathbf{f}(y, \mathbf{z}^{(i)}, \mathbf{z}^{(i+1)})$.

8402 **Neural network approaches** In neural network architectures, the encoder is learned
 8403 jointly with the classifier as an end-to-end model. Each argument can be encoded using
 8404 a variety of neural architectures (surveyed in § 14.8): recursive (§ 10.6.1; Ji and Eisenstein,
 8405 2015), recurrent (§ 6.3; Ji et al., 2016), and convolutional (§ 3.4; Qin et al., 2017). The clas-
 8406 sification function can then be implemented as a feedforward neural network on the two
 8407 encodings (chapter 3; for examples, see Rutherford et al., 2017; Qin et al., 2017), or as a
 8408 simple bilinear product, $\Psi(y, \mathbf{z}^{(i)}, \mathbf{z}^{(i+1)}) = (\mathbf{z}^{(i)})^\top \boldsymbol{\Theta}_y \mathbf{z}^{(i+1)}$ (Ji and Eisenstein, 2015). The
 8409 encoding model can be trained by backpropagation from the classification objective, such
 8410 as the margin loss. Rutherford et al. (2017) show that neural architectures outperform
 8411 feature-based approaches in most settings. While neural approaches require engineering
 8412 the network architecture (e.g., embedding size, number of hidden units in the classifier),
 8413 feature-based approaches also require significant engineering to incorporate linguistic re-
 8414 sources such as Brown clusters and parse trees, and to select a subset of relevant features.

8415 16.3.2 Hierarchical discourse relations

8416 In sentence parsing, adjacent phrases combine into larger constituents, ultimately pro-
 8417 ducing a single constituent for the entire sentence. The resulting tree structure enables
 8418 structured analysis of the sentence, with subtrees that represent syntactically coherent
 8419 chunks of meaning. **Rhetorical Structure Theory (RST)** extends this style of hierarchical
 8420 analysis to the discourse level (Mann and Thompson, 1988).

8421 The basic element of RST is the **discourse unit**, which refers to a contiguous span of
 8422 text. **Elementary discourse units** (EDUs) are the atomic elements in this framework, and
 8423 are typically (but not always) clauses.⁴ Each discourse relation combines two or more
 8424 adjacent discourse units into a larger, composite discourse unit; this process ultimately
 8425 unites the entire text into a tree-like structure.⁵

8426 **Nuclearity** In many discourse relations, one argument is primary. For example:

8427 (16.8) [LaShawn loves animals]_N
 8428 [She has nine dogs and one pig]_S

8429 In this example, the second sentence provides EVIDENCE for the point made in the first
 8430 sentence. The first sentence is thus the **nucleus** of the discourse relation, and the second
 8431 sentence is the **satellite**. The notion of **nuclearity** is analogous to the head-modifier struc-
 8432 ture of dependency parsing (see § 11.1.1). However, in RST, some relations have multiple
 8433 nuclei. For example, the arguments of the CONTRAST relation are equally important:

8434 (16.9) [The clash of ideologies survives this treatment]_N
 8435 [but the nuance and richness of Gorky's individual characters have vanished in the scuffle]_N⁶

8436 Relations that have multiple nuclei are called **coordinating**; relations with a single nu-
 8437 cleus are called **subordinating**. Subordinating relations are constrained to have only two
 8438 arguments, while coordinating relations (such as CONJUNCTION) may have more than
 8439 two.

8440 **RST Relations** Rhetorical structure theory features a large inventory of discourse rela-
 8441 tions, which are divided into two high-level groups: subject matter relations, and presen-
 8442 tational relations. Presentational relations are organized around the intended beliefs of
 8443 the reader. For example, in (16.8), the second discourse unit provides evidence intended
 8444 to increase the reader's belief in the proposition expressed by the first discourse unit, that
 8445 *LaShawn loves animals*. In contrast, subject-matter relations are meant to communicate ad-
 8446 dditional facts about the propositions contained in the discourse units that they relate:

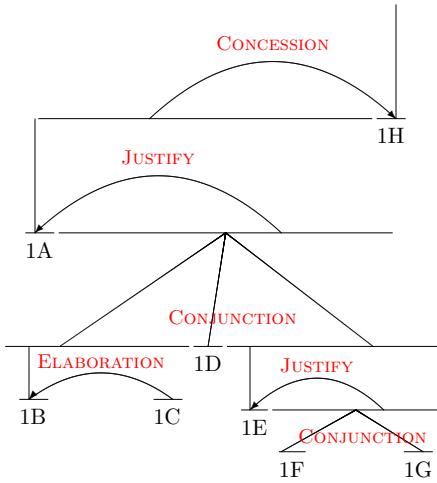
⁴Details of discourse segmentation can be found in the RST annotation manual (Carlson and Marcu, 2001).

⁵While RST analyses are typically trees, this should be taken as a strong theoretical commitment to the principle that all coherent discourses have a tree structure. Taboada and Mann (2006) write:

It is simply the case that trees are convenient, easy to represent, and easy to understand. There is, on the other hand, no theoretical reason to assume that trees are the only possible representation of discourse structure and of coherence relations.

The appropriateness of tree structures to discourse has been challenged, e.g., by Wolf and Gibson (2005), who propose a more general graph-structured representation.

⁶from the RST Treebank (Carlson et al., 2002)



[It could have been a great movie]^{1A} [It does have beautiful scenery,]^{1B} [some of the best since Lord of the Rings.]^{1C} [The acting is well done,]^{1D} [and I really liked the son of the leader of the Samurai.]^{1E} [He was a likable chap,]^{1F} [and I hated to see him die.]^{1G} [But, other than all that, this movie is nothing more than hidden rip-offs.]^{1H}

Figure 16.5: A rhetorical structure theory analysis of a short movie review, adapted from Voll and Taboada (2007). Positive and negative sentiment words are underlined, indicating RST’s potential utility in document-level sentiment analysis.

8447 (16.10) [the debt plan was rushed to completion]_N
 8448 [in order to be announced at the meeting]_S⁷

8449 In this example, the satellite describes a world state that is realized by the action described
 8450 in the nucleus. This relationship is about the world, and not about the author’s commu-
 8451 nicative intentions.

8452 **Example** Figure 16.5 depicts an RST analysis of a paragraph from a movie review. Asym-
 8453 metric (subordinating) relations are depicted with an arrow from the satellite to the nu-
 8454 cleus; symmetric (coordinating) relations are depicted with lines. The elementary dis-
 8455 course units 1F and 1G are combined into a larger discourse unit with the symmetric
 8456 CONJUNCTION relation. The resulting discourse unit is then the satellite in a JUSTIFY
 8457 relation with 1E.

⁷from the RST Treebank (Carlson et al., 2002)

8458 **16.3.2.1 Hierarchical discourse parsing**

8459 The goal of discourse parsing is to recover a hierarchical structural analysis from a doc-
 8460 ument text, such as the analysis in Figure 16.5. For now, let's assume a segmentation
 8461 of the document into elementary discourse units (EDUs); segmentation algorithms are
 8462 discussed below. After segmentation, discourse parsing can be viewed as a combination
 8463 of two components: the discourse relation classification techniques discussed in § 16.3.1.2,
 8464 and algorithms for phrase-structure parsing, such as chart parsing and shift-reduce, which
 8465 were discussed in chapter 10.

8466 Both chart parsing and shift-reduce require encoding composite discourse units, ei-
 8467 ther in a discrete feature vector or a dense neural representation.⁸ Some discourse parsers
 8468 rely on the **strong compositionality criterion** (Marcu, 1996), which states the assumption
 8469 that a composite discourse unit can be represented by its nucleus. This criterion is used in
 8470 feature-based discourse parsing to determine the feature vector for a composite discourse
 8471 unit (Hernault et al., 2010); it is used in neural approaches to setting the vector encod-
 8472 ing for a composite discourse unit equal to the encoding of its nucleus (Ji and Eisenstein,
 8473 2014). An alternative neural approach is to learn a composition function over the compo-
 8474 nents of a composite discourse unit (Li et al., 2014), using a recursive neural network (see
 8475 § 14.8.3).

8476 **Bottom-up discourse parsing** Assume a segmentation of the text into N elementary
 8477 discourse units with base representations $\{z^{(i)}\}_{i=1}^N$, and assume a composition function
 8478 COMPOSE $(z^{(i)}, z^{(j)}, \ell)$, which maps two encodings and a discourse relation ℓ into a new
 8479 encoding. The composition function can follow the strong compositionality criterion and
 8480 simply select the encoding of the nucleus, or it can do something more complex. We
 8481 also need a scoring function $\Psi(z^{(i,k)}, z^{(k,j)}, \ell)$, which computes a scalar score for the (bi-
 8482 narized) discourse relation ℓ with left child covering the span $i + 1 : k$, and the right
 8483 child covering the span $k + 1 : j$. Given these components, we can construct vector rep-
 8484 resentations for each span, and this is the basic idea underlying **compositional vector**
 8485 **grammars** (Socher et al., 2013).

8486 These same components can also be used in bottom-up parsing, in a manner that is
 8487 similar to the CKY algorithm for weighted context-free grammars (see § 10.1): compute
 8488 the score and best analysis for each possible span of increasing lengths, while storing
 8489 back-pointers that make it possible to recover the optimal parse of the entire input. How-
 8490 ever, there is an important distinction from CKY parsing: for each labeled span (i, j, ℓ) , we
 8491 must use the composition function to construct a representation $z^{(i,j,\ell)}$. This representa-
 8492 tion is then used to combine the discourse unit spanning $i + 1 : j$ in higher-level discourse
 8493 relations. The representation $z^{(i,j,\ell)}$ depends on the entire substructure of the unit span-

⁸To use these algorithms, is also necessary to binarize all discourse relations during parsing, and then to “unbinarize” them to reconstruct the desired structure (e.g., Hernault et al., 2010).

8494 ning $i + 1 : j$, and this violates the locality assumption that underlie CKY’s optimality
 8495 guarantee. Bottom-up parsing with recursively constructed span representations is gen-
 8496 erally not guaranteed to find the best-scoring discourse parse. This problem is explored
 8497 in an exercise at the end of the chapter.

8498 **Transition-based discourse parsing** One drawback of bottom-up parsing is its cubic
 8499 time complexity in the length of the input. For long documents, transition-based parsing
 8500 is an appealing alternative. The shift-reduce algorithm can be applied to discourse parsing
 8501 fairly directly (Sagae, 2009): the stack stores a set of discourse units and their repres-
 8502 entations, and each action is chosen by a function of these representations. This function
 8503 could be a linear product of weights and features, or it could be a neural network ap-
 8504 plied to encodings of the discourse units. The REDUCE action then performs composition
 8505 on the two discourse units at the top of the stack, yielding a larger composite discourse
 8506 unit, which goes on top of the stack. All of the techniques for integrating learning and
 8507 transition-based parsing, described in § 11.3, are applicable to discourse parsing.

8508 16.3.2.2 Segmenting discourse units

8509 In rhetorical structure theory, elementary discourse units do not cross the sentence bound-
 8510 ary, so discourse segmentation can be performed within sentences, assuming the sentence
 8511 segmentation is given. The segmentation of sentences into elementary discourse units is
 8512 typically performed using features of the syntactic analysis (Braud et al., 2017). One ap-
 8513 proach is to train a classifier to determine whether each syntactic constituent is an EDU,
 8514 using features such as the production, tree structure, and head words (Soricut and Marcu,
 8515 2003; Hernault et al., 2010). Another approach is to train a sequence labeling model, such
 8516 as a conditional random field (Sporleder and Lapata, 2005; Xuan Bach et al., 2012; Feng
 8517 et al., 2014). This is done using the BIO formalism for segmentation by sequence labeling,
 8518 described in § 8.3.

8519 16.3.3 Argumentation

8520 An alternative view of text-level relational structure focuses on **argumentation** (Stab and
 8521 Gurevych, 2014b). Each segment (typically a sentence or clause) may support or rebut
 8522 another segment, creating a graph structure over the text. In the following example (from
 8523 Peldszus and Stede, 2013), segment S_2 provides argumentative support for the proposi-
 8524 tion in the segment S_1 :

8525 (16.11) [We should tear the building down] $_{S1}$
 8526 [because it is full of asbestos] $_{S2}$.

8527 Assertions may also support or rebut proposed links between two other assertions, cre-
 8528 ating a **hypergraph**, which is a generalization of a graph to the case in which edges can

8529 join any number of vertices. This can be seen by introducing another sentence into the
8530 example:

8531 (16.12) [In principle it is possible to clean it up.]_{S3}
8532 [but according to the mayor that is too expensive.]_{S4}

8533 S3 acknowledges the validity of *S2*, but undercuts its support of *S1*. This can be repre-
8534 sented by introducing a hyperedge, $(S3, S2, S1)_{\text{undercut}}$, indicating that *S3* undercuts the
8535 proposed relationship between *S2* and *S1*. *S4* then undercuts the relevance of *S3*.

8536 **Argumentation mining** is the task of recovering such structures from raw texts. At
8537 present, annotations of argumentation structure are relatively small: Stab and Gurevych
8538 (2014a) have annotated a collection of 90 persuasive essays, and Peldszus and Stede (2015)
8539 have solicited and annotated a set of 112 paragraph-length “microtexts” in German.

8540 16.3.4 Applications of discourse relations

8541 The predominant application of discourse parsing is to select content within a document.
8542 In rhetorical structure theory, the nucleus is considered the more important element of
8543 the relation, and is more likely to be part of a summary of the document; it may also
8544 be more informative for document classification. The D-LTAG theory that underlies the
8545 Penn Discourse Treebank lacks this notion of nuclearity, but arguments may have varying
8546 importance, depending on the relation type. For example, the span of text constituting
8547 ARG1 of an expansion relation is more likely to appear in a summary, while the sentence
8548 constituting ARG2 of an implicit relation is less likely (Louis et al., 2010). Discourse rela-
8549 tions may also signal segmentation points in the document structure. Explicit discourse
8550 markers have been shown to correlate with changes in subjectivity, and identifying such
8551 change points can improve document-level sentiment classification, by helping the clas-
8552 sifier to focus on the subjective parts of the text (Trivedi and Eisenstein, 2013; Yang and
8553 Cardie, 2014).

8554 16.3.4.1 Extractive Summarization

8555 Text **summarization** is the problem of converting a longer text into a shorter one, while
8556 still conveying the key facts, events, ideas, and sentiments from the original. In **extractive**
8557 **summarization**, the summary is a subset of the original text; in **abstractive summariza-**
8558 **tion**, the summary is produced *de novo*, by paraphrasing the original, or by first encoding
8559 it into a semantic representation (see § 19.2). The main strategy for extractive summa-
8560 rization is to maximize **coverage**, choosing a subset of the document that best covers the
8561 concepts mentioned in the document as a whole; typically, coverage is approximated by
8562 bag-of-words overlap (Nenkova and McKeown, 2012). Coverage-based objectives can be
8563 supplemented by hierarchical discourse relations, using the principle of nuclearity: in any
8564 subordinating discourse relation, the nucleus is more critical to the overall meaning of the

8565 text, and is therefore more important to include in an extractive summary (Marcu, 1997a).⁹
 8566 This insight can be generalized from individual relations using the concept of **discourse**
 8567 **depth** (Hirao et al., 2013): for each elementary discourse unit e , the discourse depth d_e is
 8568 the number of relations in which a discourse unit containing e is the satellite.

8569 Both discourse depth and nuclearity can be incorporated into extractive summarization
 8570 using constrained optimization. Let \mathbf{x}_n be a bag-of-words vector representation of
 8571 elementary discourse unit n , let $y_n \in \{0, 1\}$ indicate whether n is included in the summary,
 8572 and let d_n be the depth of unit n . Furthermore, let each discourse unit have a “head” h ,
 8573 which is defined recursively:

- 8574 • if a discourse unit is produced by a subordinating relation, then its head is the head
 8575 of the (unique) nucleus;
- 8576 • if a discourse unit is produced by a coordinating relation, then its head is the head
 8577 of the left-most nucleus;
- 8578 • for each elementary discourse unit, its parent $\pi(n) \in \{\emptyset, 1, 2, \dots, N\}$ is the head of
 8579 the smallest discourse unit containing n whose head is not n ;
- 8580 • if n is the head of the discourse unit spanning the whole document, then $\pi(n) = \emptyset$.

With these definitions in place, discourse-driven extractive summarization can be formalized as (Hirao et al., 2013),

$$\begin{aligned} & \max_{y=\{0,1\}^N} \sum_{n=1}^N y_n \frac{\Psi(\mathbf{x}_n, \{\mathbf{x}_{1:N}\})}{d_n} \\ & \text{s.t. } \sum_{n=1}^N y_n \left(\sum_{j=1}^V x_{n,j} \right) \leq L \\ & \quad y_{\pi(n)} \geq y_n, \quad \forall n \end{aligned} \tag{16.11}$$

8581 where $\Psi(\mathbf{x}_n, \{\mathbf{x}_{1:N}\})$ measures the coverage of elementary discourse unit n with respect
 8582 to the rest of the document, and $\sum_{j=1}^V x_{n,m}$ is the number of tokens in \mathbf{x}_n . The first con-
 8583 straint ensures that the number of tokens in the summary has an upper bound L . The
 8584 second constraint ensures that no elementary discourse unit is included unless its parent
 8585 is also included. In this way, the discourse structure is used twice: to downweight the
 8586 contributions of elementary discourse units that are not central to the discourse, and to
 8587 ensure that the resulting structure is a subtree of the original discourse parse. The opti-

⁹Conversely, the arguments of a multi-nuclear relation should either both be included in the summary, or both excluded (Durrett et al., 2016).

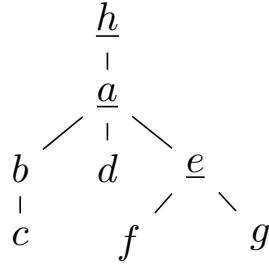


Figure 16.6: A **discourse depth tree** (Hirao et al., 2013) for the discourse parse from Figure 16.5, in which each elementary discourse unit is connected to its parent. The discourse units in one valid summary are underlined.

8588 mization problem in 16.11 can be solved with **integer linear programming**, described in
 8589 § 13.2.2.¹⁰

8590 Figure 16.6 shows a **discourse depth tree** for the RST analysis from Figure 16.5, in
 8591 which each elementary discourse is connected to (and below) its parent. The figure also
 8592 shows a valid summary, corresponding to:

8593 (16.13) It could have been a great movie, and I really liked the son of the leader of the
 8594 Samurai. But, other than all that, this movie is nothing more than hidden rip-offs.

8595 16.3.4.2 Document classification

8596 Hierarchical discourse structures lend themselves naturally to text classification: in a sub-
 8597 ordinating discourse relation, the nucleus should play a stronger role in the classification
 8598 decision than the satellite. Various implementations of this idea have been proposed.

- 8599 • Focusing on within-sentence discourse relations and lexicon-based classification (see
 8600 § 4.1.2), Voll and Taboada (2007) simply ignore the text in the satellites of each dis-
 8601 course relation.
- 8602 • At the document level, elements of each discourse relation argument can be reweighted,
 8603 favoring words in the nucleus, and disfavoring words in the satellite (Heerschop
 8604 et al., 2011; Bhatia et al., 2015). This approach can be applied recursively, computing
 8605 weights across the entire document. The weights can be relation-specific, so that the
 8606 features from the satellites of contrastive relations are discounted or even reversed.
- 8607 • Alternatively, the hierarchical discourse structure can define the structure of a **re-
 8608 cursive neural network** (see § 10.6.1). In this network, the representation of each

¹⁰Formally, 16.11 is a special case of the **knapsack problem**, in which the goal is to find a subset of items with maximum value, constrained by some maximum weight (Cormen et al., 2009).

8609 discourse unit is computed from its arguments and from a parameter corresponding
 8610 to the discourse relation (Ji and Smith, 2017).

8611 Shallow, non-hierarchical discourse relations have also been applied to document clas-
 8612 sification. One approach is to impose a set of constraints on the analyses of individual
 8613 discourse units, so that adjacent units have the same polarity when they are connected
 8614 by a discourse relation indicating agreement, and opposite polarity when connected by a
 8615 contrastive discourse relation, indicating disagreement (Somasundaran et al., 2009; Zirn
 8616 et al., 2011). Yang and Cardie (2014) apply explicitly-marked relations from the Penn
 8617 Discourse Treebank to the problem of sentence-level sentiment polarity classification (see
 8618 § 4.1). They impose the following soft constraints:

- 8619 • When a CONTRAST relation appears between two sentences, those sentences should
 8620 have opposite sentiment polarity.
- 8621 • When an EXPANSION or CONTINGENCY relation appears between two sentences,
 8622 they should have the same polarity.
- 8623 • When a CONTRAST relation appears *within* a sentence, it should have neutral polar-
 8624 ity, since it is likely to express both sentiments.

8625 These discourse-driven constraints are shown to improve performance on two datasets of
 8626 product reviews.

8627 16.3.4.3 Coherence

8628 Just as **grammaticality** is the property shared by well-structured sentences, **coherence** is
 8629 the property shared by well-structured discourses. One application of discourse process-
 8630 ing is to measure (and maximize) the coherence of computer-generated texts like transla-
 8631 tions and summaries (Kibble and Power, 2004). Coherence assessment is also used to eval-
 8632 uate human-generated texts, such as student essays (e.g., Miltsakaki and Kukich, 2004;
 8633 Burstein et al., 2013).

8634 Coherence subsumes a range of phenomena, many of which have been highlighted
 8635 earlier in this chapter: e.g., that adjacent sentences should be lexically cohesive (Foltz
 8636 et al., 1998; Ji et al., 2015; Li and Jurafsky, 2017), and that entity references should follow
 8637 the principles of centering theory (Barzilay and Lapata, 2008; Nguyen and Joty, 2017).
 8638 Discourse relations also bear on the coherence of a text in a variety of ways:

- 8639 • Hierarchical discourse relations tend to have a “canonical ordering” of the nucleus
 8640 and satellite (Mann and Thompson, 1988): for example, in the ELABORATION rela-
 8641 tion from rhetorical structure theory, the nucleus always comes first, while in the
 8642 JUSTIFICATION relation, the satellite tends to be first (Marcu, 1997b).

- Discourse relations should be signaled by connectives that are appropriate to the semantic or functional relationship between the arguments: for example, a coherent text would be more likely to use *however* to signal a COMPARISON relation than a *temporal* relation (Kibble and Power, 2004).
- Discourse relations tend to appear in predictable sequences: for example, COMPARISON relations tend to immediately precede CONTINGENCY relations (Pitler et al., 2008). This observation can be formalized by generalizing the entity grid model (§ 16.2.2), so that each cell (i, j) provides information about the role of the discourse argument containing a mention of entity j in sentence i (Lin et al., 2011). For example, if the first sentence is ARG1 of a comparison relation, then any entity mentions in the sentence would be labeled COMP.ARG1. This approach can also be applied to RST discourse relations (Feng et al., 2014).

Datasets One difficulty with evaluating metrics of discourse coherence is that human-generated texts usually meet some minimal threshold of coherence. For this reason, much of the research on measuring coherence has focused on synthetic data. A typical setting is to permute the sentences of a human-written text, and then determine whether the original sentence ordering scores higher according to the proposed coherence measure (Barzilay and Lapata, 2008). There are also small datasets of human evaluations of the coherence of machine summaries: for example, human judgments of the summaries from the participating systems in the 2003 Document Understanding Conference are available online.¹¹ Researchers from the Educational Testing Service (an organization which administers several national exams in the United States) have studied the relationship between discourse coherence and student essay quality (Burstein et al., 2003, 2010). A public dataset of essays from second-language learners, with quality annotations, has been made available by researchers at Cambridge University (Yannakoudakis et al., 2011). At the other extreme, Louis and Nenkova (2013) analyze the structure of professionally written scientific essays, finding that discourse relation transitions help to distinguish prize-winning essays from other articles in the same genre.

Additional resources

For a manuscript-length discussion of discourse processing, see Stede (2011). Article-length surveys are offered by Webber et al. (2012) and Webber and Joshi (2012).

¹¹<http://homepages.inf.ed.ac.uk/mlap/coherence/>

8674 **Exercises**

- 8675 1.
 - Implement the smoothed cosine similarity metric from Equation 16.2, using the smoothing kernel $k = [.5, .3, .15, .05]$.
 - Download the text of a news article with at least ten paragraphs.
 - Compute and plot the smoothed similarity \bar{s} over the length of the article.
 - Identify *local minima* in \bar{s} as follows: first find all sentences m such that $\bar{s}_m < \bar{s}_{m\pm1}$. Then search among these points to find the five sentences with the lowest \bar{s}_m .
 - How often do the five local minima correspond to paragraph boundaries?
 - The fraction of local minima that are paragraph boundaries is the **precision-at- k** , where in this case, $k = 5$.
 - The fraction of paragraph boundaries which are local minima is the **recall-at- k** .
 - Compute precision-at- k and recall-at- k for $k = 3$ and $k = 10$.
- 8688 2. This exercise is to be done in pairs. Each participant selects an article from today's news, and replaces all mentions of individual people with special tokens like PERSON1, PERSON2, and so on. The other participant should then use the rules of centering theory to guess each type of referring expression: full name (*Captain Ahab*), partial name (e.g., *Ahab*), nominal (e.g., *the ship's captain*), or pronoun. Check whether the predictions match the original article, and whether the original article conforms to the rules of centering theory.
- 8695 3. In § 16.3.2.1, it is noted that bottom-up parsing with compositional representations of each span is not guaranteed to be optimal. In this exercise, you will construct a minimal example proving this point. Consider a discourse with four units, with base representations $\{z^{(i)}\}_{i=1}^4$. Construct a scenario in which the parse selected by bottom-up parsing is not optimal, and give the precise mathematical conditions that must hold for this suboptimal parse to be selected. You may ignore the relation labels ℓ for the purpose of this example.

8702

Part IV

8703

Applications

8704 Chapter 17

8705 Information extraction

8706 Computers offer powerful capabilities for searching and reasoning about structured records
8707 and relational data. Some even argue that the most important limitation of artificial intel-
8708 ligence is not inference or learning, but simply having too little knowledge (Lenat et al.,
8709 1990). Natural language processing provides an appealing solution: automatically con-
8710 struct a structured **knowledge base** by reading natural language text.

8711 For example, many Wikipedia pages have an “infobox” that provides structured in-
8712 formation about an entity or event. An example is shown in Figure 17.1a: each row rep-
8713 resents one or more properties of the entity IN THE AEROPLANE OVER THE SEA, a record
8714 album. The set of properties is determined by a predefined **schema**, which applies to all
8715 record albums in Wikipedia. As shown in Figure 17.1b, the values for many of these fields
8716 are indicated directly in the first few sentences of text on the same Wikipedia page.

8717 The task of automatically constructing (or “populating”) an infobox from text is an
8718 example of **information extraction**. Much of information extraction can be described in
8719 terms of **entities**, **relations**, and **events**.

- 8720 • **Entities** are uniquely specified objects in the world, such as people (JEFF MANGUM),
8721 places (ATHENS, GEORGIA), organizations (MERGE RECORDS), and times (FEBRUARY
8722 10, 1998). Chapter 8 described the task of **named entity recognition**, which labels
8723 tokens as parts of entity spans. Now we will see how to go further, **linking** each
8724 entity **mention** to an element in a **knowledge base**.
- 8725 • **Relations** include a **predicate** and two **arguments**: for example, CAPITAL(GEORGIA, ATLANTA).
- **Events** involve multiple typed arguments. For example, the production and release

Studio album by Neutral Milk Hotel	
Released	February 10, 1998
Recorded	July–September 1997
Studio	Pet Sounds Studio, Denver, Colorado
Genre	Indie rock • psychedelic folk • lo-fi
Length	39:55
Label	Merge • Domino
Producer	Robert Schneider

(a) A Wikipedia infobox

- (17.1) In the Aeroplane Over the Sea is the second and final studio album by the American indie rock band Neutral Milk Hotel.
- (17.2) It was released in the United States on February 10, 1998 on Merge Records and May 1998 on Blue Rose Records in the United Kingdom.
- (17.3) Jeff Mangum moved from Athens, Georgia to Denver, Colorado to prepare the bulk of the album's material with producer Robert Schneider, this time at Schneider's newly created Pet Sounds Studio at the home of Jim McIntyre.

- (b) The first few sentences of text. Strings that match fields or field names in the infobox are underlined; strings that mention other entities are wavy underlined.

Figure 17.1: From the Wikipedia page for the album “In the Aeroplane Over the Sea”, retrieved October 26, 2017.

of the album described in Figure 17.1 is described by the event,

```
<TITLE : IN THE AEROPLANE OVER THE SEA,
ARTIST : NEUTRAL MILK HOTEL,
RELEASE-DATE : 1998-FEB-10,...>
```

8726 The set of arguments for an event type is defined by a **schema**. Events often refer to
 8727 time-delimited occurrences: weddings, protests, purchases, terrorist attacks.

8728 Information extraction is similar to semantic role labeling (chapter 13): we may think
 8729 of predicates as corresponding to events, and the arguments as defining slots in the event
 8730 representation. However, the goals of information extraction are different. Rather than
 8731 accurately parsing every sentence, information extraction systems often focus on recog-
 8732 nizing a few key relation or event types, or on the task of identifying all properties of a
 8733 given entity. Information extraction is often evaluated by the correctness of the resulting
 8734 knowledge base, and not by how many sentences were accurately parsed. The goal is
 8735 sometimes described as **macro-reading**, as opposed to **micro-reading**, in which each sen-
 8736 tence must be analyzed correctly. Macro-reading systems are not penalized for ignoring
 8737 difficult sentences, as long as they can recover the same information from other, easier-
 8738 to-read sources. However, macro-reading systems must resolve apparent inconsistencies

8739 (was the album released on MERGE RECORDS or BLUE ROSE RECORDS?), requiring rea-
8740 soning across the entire dataset.

8741 In addition to the basic tasks of recognizing entities, relations, and events, information
8742 extraction systems must handle negation, and must be able to distinguish statements of
8743 fact from hopes, fears, hunches, and hypotheticals. Finally, information extraction is of-
8744 ten paired with the problem of **question answering**, which requires accurately parsing a
8745 query, and then selecting or generating a textual answer. Question answering systems can
8746 be built on knowledge bases that are extracted from large text corpora, or may attempt to
8747 identify answers directly from the source texts.

8748 17.1 Entities

8749 The starting point for information extraction is to identify mentions of entities in text.
8750 Consider the following example:

8751 (17.4) *The United States Army captured a hill overlooking Atlanta on May 14, 1864.*

8752 For this sentence, there are two goals:

- 8753 1. *Identify* the spans *United States Army*, *Atlanta*, and *May 14, 1864* as entity mentions.
8754 (The hill is not uniquely identified, so it is not a *named* entity.) We may also want to
8755 recognize the **named entity types**: organization, location, and date. This is **named**
8756 **entity recognition**, and is described in chapter 8.
- 8757 2. *Link* these spans to entities in a knowledge base: U.S. ARMY, ATLANTA, and 1864-
8758 MAY-14. This task is known as **entity linking**.

8759 The strings to be linked to entities are **mentions** — similar to the use of this term in
8760 coreference resolution. In some formulations of the entity linking task, only named enti-
8761 ties are candidates for linking. This is sometimes called **named entity linking** (Ling et al.,
8762 2015). In other formulations, such as **Wikification** (Milne and Witten, 2008), any string
8763 can be a mention. The set of target entities often corresponds to Wikipedia pages, and
8764 Wikipedia is the basis for more comprehensive knowledge bases such as YAGO (Suchanek
8765 et al., 2007), DBPedia (Auer et al., 2007), and Freebase (Bollacker et al., 2008). Entity link-
8766 ing may also be performed in more “closed” settings, where a much smaller list of targets
8767 is provided in advance. The system must also determine if a mention does not refer to
8768 any entity in the knowledge base, sometimes called a **NIL entity** (McNamee and Dang,
8769 2009).

8770 Returning to (17.4), the three entity mentions may seem unambiguous. But the Wikipedia
8771 disambiguation page for the string *Atlanta* says otherwise:¹ there are more than twenty

¹[https://en.wikipedia.org/wiki/Atlanta_\(disambiguation\)](https://en.wikipedia.org/wiki/Atlanta_(disambiguation)), retrieved November 1, 2017.

8772 different towns and cities, five United States Navy vessels, a magazine, a television show,
 8773 a band, and a singer — each prominent enough to have its own Wikipedia page. We now
 8774 consider how to choose among these dozens of possibilities. In this chapter we will focus
 8775 on supervised approaches. Unsupervised entity linking is closely related to the problem
 8776 of **cross-document coreference resolution**, where the task is to identify pairs of mentions
 8777 that corefer, across document boundaries (Bagga and Baldwin, 1998b; Singh et al., 2011).

8778 17.1.1 Entity linking by learning to rank

8779 Entity linking is often formulated as a **ranking** problem,

$$\hat{y} = \operatorname{argmax}_{y \in \mathcal{Y}(x)} \Psi(y, x, c), \quad [17.1]$$

8780 where y is a target entity, x is a description of the mention, $\mathcal{Y}(x)$ is a set of candidate
 8781 entities, and c is a description of the context — such as the other text in the document,
 8782 or its metadata. The function Ψ is a scoring function, which could be a linear model,
 8783 $\Psi(y, x, c) = \theta \cdot f(y, x, c)$, or a more complex function such as a neural network. In either
 8784 case, the scoring function can be learned by minimizing a margin-based **ranking loss**,

$$\ell(\hat{y}, y^{(i)}, x^{(i)}, c^{(i)}) = (\Psi(\hat{y}, x^{(i)}, c^{(i)}) - \Psi(y^{(i)}, x^{(i)}, c^{(i)}) + 1)_+, \quad [17.2]$$

8785 where $y^{(i)}$ is the ground truth and $\hat{y} \neq y^{(i)}$ is the predicted target for mention $x^{(i)}$ in
 8786 context $c^{(i)}$ (Joachims, 2002; Dredze et al., 2010).

8787 **Candidate identification** For computational tractability, it is helpful to restrict the set of
 8788 candidates, $\mathcal{Y}(x)$. One approach is to use a **name dictionary**, which maps from strings
 8789 to the entities that they might mention. This mapping is many-to-many: a string such as
 8790 *Atlanta* can refer to multiple entities, and conversely, an entity such as ATLANTA can be
 8791 referenced by multiple strings. A name dictionary can be extracted from Wikipedia, with
 8792 links between each Wikipedia entity page and the anchor text of all hyperlinks that point
 8793 to the page (Bunescu and Pasca, 2006; Ratinov et al., 2011). To improve recall, the name
 8794 dictionary can be augmented by partial and approximate matching (Dredze et al., 2010),
 8795 but as the set of candidates grows, the risk of false positives increases. For example, the
 8796 string *Atlanta* is a partial match to *the Atlanta Fed* (a name for the FEDERAL RESERVE BANK
 8797 OF ATLANTA), and a noisy match (edit distance of one) from *Atalanta* (a heroine in Greek
 8798 mythology and an Italian soccer team).

8799 **Features** Feature-based approaches to entity ranking rely on three main types of local
 8800 information (Dredze et al., 2010):

- The similarity of the mention string to the canonical entity name, as quantified by string similarity. This feature would elevate the city ATLANTA over the basketball team ATLANTA HAWKS for the string *Atlanta*.
- The popularity of the entity, which can be measured by Wikipedia page views or PageRank in the Wikipedia link graph. This feature would elevate ATLANTA, GEORGIA over the unincorporated community of ATLANTA, OHIO.
- The entity type, as output by the named entity recognition system. This feature would elevate the city of ATLANTA over the magazine ATLANTA in contexts where the mention is tagged as a location.

In addition to these local features, the document context can also help. If *Jamaica* is mentioned in a document about the Caribbean, it is likely to refer to the island nation; in the context of New York, it is likely to refer to the neighborhood in Queens; in the context of a menu, it might refer to a hibiscus tea beverage. Such hints can be formalized by computing the similarity between the Wikipedia page describing each candidate entity and the mention context $c^{(i)}$, which may include the bag-of-words representing the document (Dredze et al., 2010; Hoffart et al., 2011) or a smaller window of text around the mention (Ratinov et al., 2011). For example, we can compute the cosine similarity between bag-of-words vectors for the context and entity description, typically weighted using **inverse document frequency** to emphasize rare words.²

Neural entity linking An alternative approach is to compute the score for each entity candidate using distributed vector representations of the entities, mentions, and context. For example, for the task of entity linking in Twitter, Yang et al. (2016) employ the bilinear scoring function,

$$\Psi(y, x, c) = v_y^\top \Theta^{(y,x)} x + v_y^\top \Theta^{(y,c)} c, \quad [17.3]$$

with $v_y \in \mathbb{R}^{K_y}$ as the vector embedding of entity y , $x \in \mathbb{R}^{K_x}$ as the embedding of the mention, $c \in \mathbb{R}^{K_c}$ as the embedding of the context, and the matrices $\Theta^{(y,x)}$ and $\Theta^{(y,c)}$ as parameters that score the compatibility of each entity with respect to the mention and context. Each of the vector embeddings can be learned from an end-to-end objective, or pre-trained on unlabeled data.

- Pretrained **entity embeddings** can be obtained from an existing knowledge base (Bordes et al., 2011, 2013), or by running a word embedding algorithm such as WORD2VEC

²The **document frequency** of word j is $DF(j) = \frac{1}{N} \sum_{i=1}^N \delta(x_j^{(i)} > 0)$, equal to the number of documents in which the word appears. The contribution of each word to the cosine similarity of two bag-of-words vectors can be weighted by the **inverse document frequency** $\frac{1}{DF(j)}$ or $\log \frac{1}{DF(j)}$, to emphasize rare words (Spärck Jones, 1972).

- 8831 on the text of Wikipedia, with hyperlinks substituted for the anchor text.³
- 8832 • The embedding of the mention x can be computed by averaging the embeddings
 8833 of the words in the mention (Yang et al., 2016), or by the compositional techniques
 8834 described in § 14.8.
- 8835 • The embedding of the context c can also be computed from the embeddings of the
 8836 words in the context. A **denoising autoencoder** learns a function from raw text to
 8837 dense K -dimensional vector encodings by minimizing a reconstruction loss (Vin-
 8838 cent et al., 2010),

$$\min_{\theta_g, \theta_h} \sum_{i=1}^N \|\mathbf{x}^{(i)} - g(h(\tilde{\mathbf{x}}^{(i)}; \theta_h); \theta_g)\|^2, \quad [17.4]$$

8835 where $\tilde{\mathbf{x}}^{(i)}$ is a noisy version of the bag-of-words counts $\mathbf{x}^{(i)}$, which is produced by
 8836 randomly setting some counts to zero; $h : \mathbb{R}^V \mapsto \mathbb{R}^K$ is an encoder with parameters
 8837 θ_h ; and $g : \mathbb{R}^K \mapsto \mathbb{R}^V$, with parameters θ_g . The encoder and decoder functions
 8838 are typically implemented as feedforward neural networks. To apply this model to
 8839 entity linking, each entity and context are initially represented by the encoding of
 8840 their bag-of-words vectors, $h(e)$ and $g(c)$, and these encodings are then fine-tuned
 8841 from labeled data (He et al., 2013). The context vector c can also be obtained by
 8842 convolution on the embeddings of words in the document (Sun et al., 2015), or by
 8843 examining metadata such as the author’s social network (Yang et al., 2016).

8844 The remaining parameters $\Theta^{(y,x)}$ and $\Theta^{(y,c)}$ can be trained by backpropagation from the
 8845 margin loss in Equation 17.2.

8846 17.1.2 Collective entity linking

8847 Entity linking can be more accurate when it is performed jointly across a document. To
 8848 see why, consider the following lists:

- 8849 (17.5) California, Oregon, Washington
- 8850 (17.6) Baltimore, Washington, Philadelphia
- 8851 (17.7) Washington, Adams, Jefferson

8852 In each case, the term *Washington* refers to a different entity, and this reference is strongly
 8853 suggested by the other entries on the list. In the last list, all three names are highly am-
 8854 biguous — there are dozens of other *Adams* and *Jefferson* entities in Wikipedia. But a

³Pre-trained entity embeddings can be downloaded from <https://code.google.com/archive/p/word2vec/>.

8855 preference for coherence motivates **collectively** linking these references to the first three
 8856 U.S. presidents.

8857 A general approach to collective entity linking is to introduce a compatibility score
 8858 $\psi_c(\mathbf{y})$. Collective entity linking is then performed by optimizing the global objective,

$$\hat{\mathbf{y}} = \underset{\mathbf{y} \in \mathbb{Y}(\mathbf{x})}{\operatorname{argmax}} \Psi_c(\mathbf{y}) + \sum_{i=1}^N \Psi_\ell(y^{(i)}, \mathbf{x}^{(i)}, \mathbf{c}^{(i)}), \quad [17.5]$$

8859 where $\mathbb{Y}(\mathbf{x})$ is the set of all possible collective entity assignments for the mentions in \mathbf{x} ,
 8860 and ψ_ℓ is the local scoring function for each entity i . The compatibility function is typically
 8861 decomposed into a sum of pairwise scores, $\Psi_c(\mathbf{y}) = \sum_{i=1}^N \sum_{j \neq i}^N \Psi_c(y^{(i)}, y^{(j)})$. These scores
 8862 can be computed in a number of different ways:

- 8863 • Wikipedia defines high-level categories for entities (e.g., *living people*, *Presidents of*
 8864 *the United States*, *States of the United States*), and Ψ_c can reward entity pairs for the
 8865 number of categories that they have in common (Cucerzan, 2007).
- 8866 • Compatibility can be measured by the number of incoming hyperlinks shared by
 8867 the Wikipedia pages for the two entities (Milne and Witten, 2008).
- 8868 • In a neural architecture, the compatibility of two entities can be set equal to the inner
 8869 product of their embeddings, $\Psi_c(y^{(i)}, y^{(j)}) = \mathbf{v}_{y^{(i)}} \cdot \mathbf{v}_{y^{(j)}}$.
- 8870 • A non-pairwise compatibility score can be defined using a type of latent variable
 8871 model known as a **probabilistic topic model** (Blei et al., 2003; Blei, 2012). In this
 8872 framework, each latent topic is a probability distribution over entities, and each
 8873 document has a probability distribution over topics. Each entity helps to determine
 8874 the document's distribution over topics, and in turn these topics help to resolve am-
 8875 biguous entity mentions (Newman et al., 2006). Inference can be performed using
 8876 the sampling techniques described in chapter 5.

8877 Unfortunately, collective entity linking is **NP-hard** even for pairwise compatibility func-
 8878 tions, so exact optimization is almost certainly intractable. Various approximate inference
 8879 techniques have been proposed, including **integer linear programming** (Cheng and Roth,
 8880 2013), **Gibbs sampling** (Han and Sun, 2012), and graph-based algorithms (Hoffart et al.,
 8881 2011; Han et al., 2011).

8882 17.1.3 *Pairwise ranking loss functions

8883 The loss function defined in Equation 17.2 considers only the highest-scoring prediction
 8884 \hat{y} , but in fact, the true entity $y^{(i)}$ should outscore *all* other entities. A loss function based on
 8885 this idea would give a gradient against the features or representations of several entities,

Algorithm 19 WARP approximate ranking loss

```

1: procedure WARP( $y^{(i)}$ ,  $\mathbf{x}^{(i)}$ )
2:    $N \leftarrow 0$ 
3:   repeat
4:     Randomly sample  $y \sim \mathcal{Y}(\mathbf{x}^{(i)})$ 
5:      $N \leftarrow N + 1$ 
6:     if  $\psi(y, \mathbf{x}^{(i)}) + 1 > \psi(y^{(i)}, \mathbf{x}^{(i)})$  then            $\triangleright$  check for margin violation
7:        $r \leftarrow \lfloor |\mathcal{Y}(\mathbf{x}^{(i)})|/N \rfloor$                           $\triangleright$  compute approximate rank
8:       return  $L_{\text{rank}}(r) \times (\psi(y, \mathbf{x}^{(i)}) + 1 - \psi(y^{(i)}, \mathbf{x}^{(i)}))$ 
9:     until  $N \geq |\mathcal{Y}(\mathbf{x}^{(i)})| - 1$                             $\triangleright$  no violation found
10:    return 0                                          $\triangleright$  return zero loss

```

8886 not just the top-scoring prediction. Usunier et al. (2009) define a general ranking error
 8887 function,

$$L_{\text{rank}}(k) = \sum_{j=1}^k \alpha_j, \quad \text{with } \alpha_1 \geq \alpha_2 \geq \dots \geq 0, \quad [17.6]$$

8888 where k is equal to the number of labels ranked higher than the correct label $y^{(i)}$. This
 8889 function defines a class of ranking errors: if $\alpha_j = 1$ for all j , then the ranking error is
 8890 equal to the rank of the correct entity; if $\alpha_1 = 1$ and $\alpha_{j>1} = 0$, then the ranking error is
 8891 one whenever the correct entity is not ranked first; if α_j decreases smoothly with j , as in
 8892 $\alpha_j = \frac{1}{j}$, then the error is between these two extremes.

This ranking error can be integrated into a margin objective. Remember that large margin classification requires not only the correct label, but also that the correct label outscores other labels by a substantial margin. A similar principle applies to ranking: we want a high rank for the correct entity, and we want it to be separated from other entities by a substantial margin. We therefore define the margin-augmented rank,

$$r(y^{(i)}, \mathbf{x}^{(i)}) \triangleq \sum_{y \in \mathcal{Y}(\mathbf{x}^{(i)}) \setminus y^{(i)}} \delta \left(1 + \psi(y, \mathbf{x}^{(i)}) \geq \psi(y^{(i)}, \mathbf{x}^{(i)}) \right), \quad [17.7]$$

8893 where $\delta(\cdot)$ is a delta function, and $\mathcal{Y}(\mathbf{x}^{(i)}) \setminus y^{(i)}$ is the set of all entity candidates minus
 8894 the true entity $y^{(i)}$. The margin-augmented rank is the rank of the true entity, after aug-
 8895 menting every other candidate with a margin of one, under the current scoring function
 8896 ψ . (The context c is omitted for clarity, and can be considered part of x .)

For each instance, a hinge loss is computed from the ranking error associated with this

margin-augmented rank, and the violation of the margin constraint,

$$\ell(y^{(i)}, \mathbf{x}^{(i)}) = \frac{L_{\text{rank}}(r(y^{(i)}, \mathbf{x}^{(i)}))}{r(y^{(i)}, \mathbf{x}^{(i)})} \sum_{y \in \mathcal{Y}(\mathbf{x}) \setminus y^{(i)}} \left(\psi(y, \mathbf{x}^{(i)}) - \psi(y^{(i)}, \mathbf{x}^{(i)}) + 1 \right)_+, \quad [17.8]$$

8897 The sum in Equation 17.8 includes non-zero values for every label that is ranked at least as
 8898 high as the true entity, after applying the margin augmentation. Dividing by the margin-
 8899 augmented rank of the true entity thus gives the average violation.

8900 The objective in Equation 17.8 is expensive to optimize when the label space is large,
 8901 as is usually the case for entity linking against large knowledge bases. This motivates a
 8902 randomized approximation called **WARP** (Weston et al., 2011), shown in Algorithm 19. In
 8903 this procedure, we sample random entities until one violates the pairwise margin con-
 8904 straint, $\psi(y, \mathbf{x}^{(i)}) + 1 \geq \psi(y^{(i)}, \mathbf{x}^{(i)})$. The number of samples N required to find such
 8905 a violation yields an approximation of the margin-augmented rank of the true entity,
 8906 $r(y^{(i)}, \mathbf{x}^{(i)}) \approx \left\lfloor \frac{|\mathcal{Y}(\mathbf{x})|}{N} \right\rfloor$. If a violation is found immediately, $N = 1$, the correct entity
 8907 probably ranks below many others, $r \approx |\mathcal{Y}(\mathbf{x})|$. If many samples are required before a
 8908 violation is found, $N \rightarrow |\mathcal{Y}(\mathbf{x})|$, then the correct entity is probably highly ranked, $r \rightarrow 1$.
 8909 A computational advantage of WARP is that it is not necessary to find the highest-scoring
 8910 label, which can impose a non-trivial computational cost when $\mathcal{Y}(\mathbf{x}^{(i)})$ is large. The objec-
 8911 tive is conceptually similar to the **negative sampling** objective in WORD2VEC (chapter 14),
 8912 which compares the observed word against randomly sampled alternatives.

8913 17.2 Relations

8914 After identifying the entities that are mentioned in a text, the next step is to determine
 8915 how they are related. Consider the following example:

8916 (17.8) George Bush traveled to France on Thursday for a summit.

8917 This sentence introduces a relation between the entities referenced by *George Bush* and
 8918 *France*. In the Automatic Content Extraction (ACE) ontology (Linguistic Data Consortium,
 8919 2005), the type of this relation is PHYSICAL, and the subtype is LOCATED. This relation
 8920 would be written,

$$\text{PHYSICAL.LOCATED(GEORGE BUSH, FRANCE)}. \quad [17.9]$$

8921 Relations take exactly two arguments, and the order of the arguments matters.

8922 In the ACE datasets, relations are annotated between entity mentions, as in the exam-
 8923 ple above. Relations can also hold between nominals, as in the following example from
 8924 the SemEval-2010 shared task (Hendrickx et al., 2009):

CAUSE-EFFECT	<i>those cancers were caused by radiation exposures</i>
INSTRUMENT-AGENCY	<i>phone operator</i>
PRODUCT-PRODUCER	<i>a factory manufactures suits</i>
CONTENT-CONTAINER	<i>a bottle of honey was weighed</i>
ENTITY-ORIGIN	<i>letters from foreign countries</i>
ENTITY-DESTINATION	<i>the boy went to bed</i>
COMPONENT-WHOLE	<i>my apartment has a large kitchen</i>
MEMBER-COLLECTION	<i>there are many trees in the forest</i>
COMMUNICATION-TOPIC	<i>the lecture was about semantics</i>

Table 17.1: Relations and example sentences from the SemEval-2010 dataset (Hendrickx et al., 2009)

8925 (17.9) The cup contained tea from dried ginseng.

8926 This sentence describes a relation of type ENTITY-ORIGIN between *tea* and *ginseng*. Nominal
 8927 relation extraction is closely related to **semantic role labeling** (chapter 13). The main
 8928 difference is that relation extraction is restricted to a relatively small number of relation
 8929 types; for example, Table 17.1 shows the ten relation types from SemEval-2010.

8930 17.2.1 Pattern-based relation extraction

8931 Early work on relation extraction focused on hand-crafted patterns (Hearst, 1992). For
 8932 example, the appositive *Starbuck, a native of Nantucket* signals the relation ENTITY-ORIGIN
 8933 between *Starbuck* and *Nantucket*. This pattern can be written as,

$$\text{PERSON , } a \text{ native of LOCATION} \Rightarrow \text{ENTITY-ORIGIN(PERSON, LOCATION)}. \quad [17.10]$$

8934 This pattern will be “triggered” whenever the literal string *, a native of* occurs between an
 8935 entity of type PERSON and an entity of type LOCATION. Such patterns can be generalized
 8936 beyond literal matches using techniques such as lemmatization, which would enable the
 8937 words (*buy, buys, buying*) to trigger the same patterns (see § 4.3.1.2). A more aggressive
 8938 strategy would be to group all words in a WordNet synset (§ 4.2), so that, e.g., *buy* and
 8939 *purchase* trigger the same patterns.

8940 Relation extraction patterns can be implemented in finite-state automata (§ 9.1). If the
 8941 named entity recognizer is also a finite-state machine, then the systems can be combined
 8942 by finite-state transduction (Hobbs et al., 1997). This makes it possible to propagate uncer-
 8943 tainty through the finite-state cascade, and disambiguate from higher-level context. For
 8944 example, suppose the entity recognizer cannot decide whether *Starbuck* refers to either a
 8945 PERSON or a LOCATION; in the composed transducer, the relation extractor would be free
 8946 to select the PERSON annotation when it appears in the context of an appropriate pattern.

8947 **17.2.2 Relation extraction as a classification task**

8948 Relation extraction can be formulated as a classification problem,

$$\hat{r}_{(i,j),(m,n)} = \operatorname{argmax}_{r \in \mathcal{R}} \Psi(r, (i, j), (m, n), \mathbf{w}), \quad [17.11]$$

8949 where $r \in \mathcal{R}$ is a relation type (possibly NIL), $\mathbf{w}_{i+1:j}$ is the span of the first argument, and
 8950 $\mathbf{w}_{m+1:n}$ is the span of the second argument. The argument $\mathbf{w}_{m+1:n}$ may appear before
 8951 or after $\mathbf{w}_{i+1:j}$ in the text, or they may overlap; we stipulate only that $\mathbf{w}_{i+1:j}$ is the first
 8952 argument of the relation. We now consider three alternatives for computing the scoring
 8953 function.

8954 **17.2.2.1 Feature-based classification**

8955 In a feature-based classifier, the scoring function is defined as,

$$\Psi(r, (i, j), (m, n), \mathbf{w}) = \boldsymbol{\theta} \cdot \mathbf{f}(r, (i, j), (m, n), \mathbf{w}), \quad [17.12]$$

8956 with $\boldsymbol{\theta}$ representing a vector of weights, and $\mathbf{f}(\cdot)$ a vector of features. The pattern-based
 8957 methods described in § 17.2.1 suggest several features:

- 8958 • Local features of $\mathbf{w}_{i+1:j}$ and $\mathbf{w}_{m+1:n}$, including: the strings themselves; whether they
 8959 are recognized as entities, and if so, which type; whether the strings are present in a
 8960 **gazetteer** of entity names; each string's syntactic **head** (§ 9.2.2).
- 8961 • Features of the span between the two arguments, $\mathbf{w}_{j+1:m}$ or $\mathbf{w}_{n+1:i}$ (depending on
 8962 which argument appears first): the length of the span; the specific words that appear
 8963 in the span, either as a literal sequence or a bag-of-words; the wordnet synsets (§ 4.2)
 8964 that appear in the span between the arguments.
- 8965 • Features of the syntactic relationship between the two arguments, typically the **de-**
 8966 **pendency path** between the arguments (§ 13.2.1). Example dependency paths are
 8967 shown in Table 17.2.

8968 **17.2.2.2 Kernels**

8969 Suppose that the first line of Table 17.2 is a labeled example, and the remaining lines are
 8970 instances to be classified. A feature-based approach would have to decompose the depen-
 8971 dency paths into features that capture individual edges, with or without their labels, and
 8972 then learn weights for each of these features: for example, the second line contains identi-
 8973 cal dependencies, but different arguments; the third line contains a different inflection of
 8974 the word *travel*; the fourth and fifth lines each contain an additional edge on the depen-
 8975 dency path; and the sixth example uses an entirely different path. Rather than attempting
 8976 to create local features that capture all of the ways in which these dependencies paths

1. <i>George Bush traveled to France</i>	<i>George Bush</i> \leftarrow <i>traveled</i> \rightarrow <i>France</i> NSUBJ OBL
2. <i>Ahab traveled to Nantucket</i>	<i>Ahab</i> \leftarrow <i>traveled</i> \rightarrow <i>Nantucket</i> NSUBJ OBL
3. <i>George Bush will travel to France</i>	<i>George Bush</i> \leftarrow <i>travel</i> \rightarrow <i>France</i> NSUBJ OBL
4. <i>George Bush wants to travel to France</i>	<i>George Bush</i> \leftarrow <i>wants</i> \rightarrow <i>travel</i> \rightarrow <i>France</i> NSUBJ XCOMP OBL
5. <i>Ahab traveled to a city in France</i>	<i>Ahab</i> \leftarrow <i>traveled</i> \rightarrow <i>city</i> \rightarrow <i>France</i> NSUBJ OBL NMOD
6. <i>We await Ahab's visit to France</i>	<i>Ahab</i> \leftarrow <i>visit</i> \rightarrow <i>France</i> NMOD:POSS NMOD

Table 17.2: Candidates instances for the PHYSICAL.LOCATED relation, and their dependency paths

8977 are similar and different, we can instead define a similarity function κ , which computes a
 8978 score for any pair of instances, $\kappa : \mathcal{X} \times \mathcal{X} \mapsto \mathbb{R}_+$. The score for any pair of instances (i, j)
 8979 is $\kappa(\mathbf{x}^{(i)}, \mathbf{x}^{(j)}) \geq 0$, with $\kappa(i, j)$ being large when instances $\mathbf{x}^{(i)}$ and $\mathbf{x}^{(j)}$ are similar. If the
 8980 function κ obeys a few key properties it is a valid **kernel function**.⁴

Given a valid kernel function, we can build a non-linear classifier without explicitly defining a feature vector or neural network architecture. For a binary classification problem $y \in \{-1, 1\}$, we have the decision function,

$$\hat{y} = \text{Sign}(b + \sum_{i=1}^N y^{(i)} \alpha^{(i)} \kappa(\mathbf{x}^{(i)}, \mathbf{x})) \quad [17.13]$$

8981 where b and $\{\alpha^{(i)}\}_{i=1}^N$ are parameters that must be learned from the training set, under
 8982 the constraint $\forall_i, \alpha^{(i)} \geq 0$. Intuitively, each α_i specifies the importance of the instance $\mathbf{x}^{(i)}$
 8983 towards the classification rule. Kernel-based classification can be viewed as a weighted
 8984 form of the **nearest-neighbor** classifier (Hastie et al., 2009), in which test instances are
 8985 assigned the most common label among their near neighbors in the training set. This
 8986 results in a non-linear classification boundary. The parameters are typically learned from
 8987 a margin-based objective (see § 2.3), leading to the **kernel support vector machine**. To
 8988 generalize to multi-class classification, we can train separate binary classifiers for each
 8989 label (sometimes called **one-versus-all**), or train binary classifiers for each pair of possible
 8990 labels (**one-versus-one**).

8991 Dependency kernels are particularly effective for relation extraction, due to their ability
 8992 to capture syntactic properties of the path between the two candidate arguments. One
 8993 class of dependency tree kernels is defined recursively, with the score for a pair of trees

⁴The **Gram matrix** \mathbf{K} arises from computing the kernel function between all pairs in a set of instances. For a valid kernel, the Gram matrix must be symmetric ($\mathbf{K} = \mathbf{K}^\top$) and positive semi-definite ($\forall \mathbf{a}, \mathbf{a}^\top \mathbf{K} \mathbf{a} \geq 0$). For more on kernel-based classification, see chapter 14 of Murphy (2012).

equal to the similarity of the root nodes and the sum of similarities of matched pairs of child subtrees (Zelenko et al., 2003; Culotta and Sorensen, 2004). Alternatively, Bunescu and Mooney (2005) define a kernel function over sequences of unlabeled dependency edges, in which the score is computed as a product of scores for each pair of words in the sequence: identical words receive a high score, words that share a synset or part-of-speech receive a small non-zero score (e.g., *travel* / *visit*), and unrelated words receive a score of zero.

17.2.2.3 Neural relation extraction

Convolutional neural networks were an early neural architecture for relation extraction (Zeng et al., 2014; dos Santos et al., 2015). For the sentence (w_1, w_2, \dots, w_M) , obtain a matrix of word embeddings \mathbf{X} , where $x_m \in \mathbb{R}^K$ is the embedding of w_m . Now, suppose the candidate arguments appear at positions a_1 and a_2 ; then for each word in the sentence, its position with respect to each argument is $m - a_1$ and $m - a_2$. (Following Zeng et al. (2014), this is a restricted version of the relation extraction task in which the arguments are single tokens.) To capture any information conveyed by these positions, the word embeddings are concatenated with embeddings of the positional offsets, $x_{m-a_1}^{(p)}$ and $x_{m-a_2}^{(p)}$. The complete base representation of the sentence is,

$$\mathbf{X}(a_1, a_2) = \begin{pmatrix} \mathbf{x}_1 & \mathbf{x}_2 & \cdots & \mathbf{x}_M \\ \mathbf{x}_{1-a_1}^{(p)} & \mathbf{x}_{2-a_1}^{(p)} & \cdots & \mathbf{x}_{M-a_1}^{(p)} \\ \mathbf{x}_{1-a_2}^{(p)} & \mathbf{x}_{2-a_2}^{(p)} & \cdots & \mathbf{x}_{M-a_2}^{(p)} \end{pmatrix}, \quad [17.14]$$

where each column is a vertical concatenation of a word embedding, represented by the column vector \mathbf{x}_m , and two positional embeddings, specifying the position with respect to a_1 and a_2 . The matrix $\mathbf{X}(a_1, a_2)$ is then taken as input to a convolutional layer (see § 3.4), and max-pooling is applied to obtain a vector. The final scoring function is then,

$$\Psi(r, i, j, \mathbf{X}) = \theta_r \cdot \text{MaxPool}(\text{ConvNet}(\mathbf{X}(i, j); \phi)), \quad [17.15]$$

where ϕ defines the parameters of the convolutional operator, and the θ_r defines a set of weights for relation r . The model can be trained using a margin objective,

$$\hat{r} = \underset{r}{\operatorname{argmax}} \Psi(r, i, j, \mathbf{X}) \quad [17.16]$$

$$\ell = (1 + \psi(\hat{r}, i, j, \mathbf{X}) - \psi(r, i, j, \mathbf{X}))_+. \quad [17.17]$$

Recurrent neural networks have also been applied to relation extraction, using a network such as an bidirectional LSTM to encode the words or dependency path between the two arguments. Xu et al. (2015) segment each dependency path into left and right subpaths: the path $George \xleftarrow[\text{NSUBJ}]{} Bush \xrightarrow[\text{XCOMP}]{} wants \xrightarrow[\text{OBL}]{} travel \xrightarrow{} France$ is segmented into the subpaths,

9020 (17.10) *George Bush* $\xleftarrow{\text{NSUBJ}}$ *wants*

9021 (17.11) *wants* $\xrightarrow{\text{XCOMP}}$ *travel* $\xrightarrow{\text{OBL}}$ *France*.

Xu et al. (2015) then run recurrent networks from the arguments to the root word (in this case, *wants*), obtaining the final representation by max pooling across all the recurrent states along each path. This process can be applied across separate “channels”, in which the inputs consist of embeddings for the words, parts-of-speech, dependency relations, and WordNet hypernyms. To define the model formally, let $s(m)$ define the successor of word m in either the left or right subpath (in a dependency path, each word can have a successor in at most one subpath). Let $\mathbf{x}_m^{(c)}$ indicate the embedding of word (or relation) m in channel c , and let $\overleftarrow{\mathbf{h}}_m^{(c)}$ and $\overrightarrow{\mathbf{h}}_m^{(c)}$ indicate the associated recurrent states in the left and right subtrees respectively. Then the complete model is specified as follows,

$$\mathbf{h}_{s(m)}^{(c)} = \text{RNN}(\mathbf{x}_{s(m)}^{(c)}, \mathbf{h}_m^{(c)}) \quad [17.18]$$

$$\mathbf{z}^{(c)} = \text{MaxPool}(\overleftarrow{\mathbf{h}}_i^{(c)}, \overleftarrow{\mathbf{h}}_{s(i)}^{(c)}, \dots, \overleftarrow{\mathbf{h}}_{\text{root}}^{(c)}, \overrightarrow{\mathbf{h}}_j^{(c)}, \overrightarrow{\mathbf{h}}_{s(j)}^{(c)}, \dots, \overrightarrow{\mathbf{h}}_{\text{root}}^{(c)}) \quad [17.19]$$

$$\Psi(r, i, j) = \theta \cdot [\mathbf{z}^{(\text{word})}; \mathbf{z}^{(\text{POS})}; \mathbf{z}^{(\text{dependency})}; \mathbf{z}^{(\text{hypernym})}] \quad [17.20]$$

9022 Note that \mathbf{z} is computed by applying max-pooling to the *matrix* of horizontally concatenated vectors \mathbf{h} , while Ψ is computed from the *vector* of vertically concatenated vectors 9023 \mathbf{z} . Xu et al. (2015) pass the score Ψ through a **softmax** layer to obtain a probability 9024 $p(r | i, j, w)$, and train the model by regularized **cross-entropy**. Miwa and Bansal (2016) 9025 show that a related model can solve the more challenging “end-to-end” relation extraction 9026 task, in which the model must simultaneously detect entities and then extract their 9027 relations.

9029 17.2.3 Knowledge base population

9030 In many applications, what matters is not what fraction of sentences are analyzed correctly, but how much accurate knowledge can be extracted. **Knowledge base population** 9031 (**KBP**) refers to the task of filling in Wikipedia-style infoboxes, as shown in Figure 17.1a. 9032 Knowledge base population can be decomposed into two subtasks: **entity linking** (described in § 17.1), and **slot filling** (Ji and Grishman, 2011). Slot filling has two key differences from the formulation of relation extraction presented above: the relations hold 9033 between entities rather than spans of text, and the performance is evaluated at the *type* 9034 level (on entity pairs), rather than on the *token level* (on individual sentences).

9035 From a practical standpoint, there are three other important differences between slot 9036 filling and per-sentence relation extraction.

- KBP tasks are often formulated from the perspective of identifying attributes of a few “query” entities. As a result, these systems often start with an **information retrieval** phase, in which relevant passages of text are obtained by search.
- For many entity pairs, there will be multiple passages of text that provide evidence. Slot filling systems must aggregate this evidence to predict a single relation type (or set of relations).
- Labeled data is usually available in the form of pairs of related entities, rather than annotated passages of text. Training from such type-level annotations is a challenge: two entities may be linked by several relations, or they may appear together in a passage of text that nonetheless does not describe their relation to each other.

Information retrieval is beyond the scope of this text (see Manning et al., 2008). The remainder of this section describes approaches to information fusion and learning from type-level annotations.

17.2.3.1 Information fusion

In knowledge base population, there will often be multiple pieces of evidence for (and sometimes against) a single relation. For example, a search for the entity MAYNARD JACKSON, JR. may return several passages that reference the entity ATLANTA:⁵

- (17.12) Elected mayor of Atlanta in 1973, **Maynard Jackson** was the first African American to serve as mayor of a major southern city.
- (17.13) **Atlanta**’s airport will be renamed to honor **Maynard Jackson**, the city’s first Black mayor .
- (17.14) Born in Dallas, Texas in 1938, **Maynard Holbrook Jackson, Jr.** moved to Atlanta when he was 8.
- (17.15) **Maynard Jackson** has gone from one of the worst high schools in **Atlanta** to one of the best.

The first and second examples provide evidence for the relation **MAYOR** holding between the entities **ATLANTA** and **MAYNARD JACKSON, JR.**. The third example provides evidence for a different relation between these same entities, **LIVED-IN**. The fourth example poses an entity linking problem, referring to **MAYNARD JACKSON HIGH SCHOOL**. Knowledge base population requires aggregating this sort of textual evidence, and predicting the relations that are most likely to hold.

⁵First three examples from: <http://www.georgiaencyclopedia.org/articles/government-politics/maynard-jackson-1938-2003>; JET magazine, November 10, 2003; www.todayingeorgiahistory.org/content/maynard-jackson-elected

9071 One approach is to run a single-document relation extraction system (using the tech-
 9072 niques described in § 17.2.2), and then aggregate the results (Li et al., 2011). Relations
 9073 that are detected with high confidence in multiple documents are more likely to be valid,
 9074 motivating the heuristic,

$$\psi(r, e_1, e_2) = \sum_{i=1}^N (\text{p}(r(e_1, e_2) | \mathbf{w}^{(i)}))^\alpha, \quad [17.21]$$

9075 where $\text{p}(r(e_1, e_2) | \mathbf{w}^{(i)})$ is the probability of relation r between entities e_1 and e_2 condi-
 9076 tioned on the text $\mathbf{w}^{(i)}$, and $\alpha \gg 1$ is a tunable hyperparameter. Using this heuristic, it is
 9077 possible to rank all candidate relations, and trace out a **precision-recall curve** as more rel-
 9078 ations are extracted.⁶ Alternatively, features can be aggregated across multiple passages
 9079 of text, feeding a single type-level relation extraction system (Wolfe et al., 2017).

9080 Precision can be improved by introducing constraints across multiple relations. For
 9081 example, if we are certain of the relation $\text{PARENT}(e_1, e_2)$, then it cannot also be the case
 9082 that $\text{PARENT}(e_2, e_1)$. Integer linear programming makes it possible to incorporate such
 9083 constraints into a global optimization (Li et al., 2011). Other pairs of relations have pos-
 9084 itive correlations, such $\text{MAYOR}(e_1, e_2)$ and $\text{LIVED-IN}(e_1, e_2)$. Compatibility across relation
 9085 types can be incorporated into probabilistic graphical models (e.g., Riedel et al., 2010).

9086 17.2.3.2 Distant supervision

9087 Relation extraction is “annotation hungry,” because each relation requires its own la-
 9088 beled data. Rather than relying on annotations of individual documents, it would be
 9089 preferable to use existing knowledge resources — such as the many facts that are al-
 9090 ready captured in knowledge bases like DBpedia. However such annotations raise the
 9091 inverse of the information fusion problem considered above: the existence of the relation
 9092 $\text{MAYOR}(\text{MAYNARD JACKSON JR., ATLANTA})$ provides only **distant supervision** for the
 9093 example texts in which this entity pair is mentioned.

9094 One approach is to treat the entity pair as the instance, rather than the text itself (Mintz
 9095 et al., 2009). Features are then aggregated across all sentences in which both entities are
 9096 mentioned, and labels correspond to the relation (if any) between the entities in a knowl-
 9097 edge base, such as FreeBase. Negative instances are constructed from entity pairs that are
 9098 not related in the knowledge base. In some cases, two entities are related, but the knowl-
 9099 edge base is missing the relation; however, because the number of possible entity pairs is
 9100 huge, these missing relations are presumed to be relatively rare. This approach is shown
 9101 in Figure 17.2.

⁶The precision-recall curve is similar to the ROC curve shown in Figure 4.4, but it includes the precision $\frac{\text{TP}}{\text{TP} + \text{FP}}$ rather than the false positive rate $\frac{\text{FP}}{\text{FP} + \text{TN}}$.

- **Label** : MAYOR(ATLANTA, MAYNARD JACKSON)
 - Elected mayor of **Atlanta** in 1973, **Maynard Jackson** ...
 - **Atlanta**'s airport will be renamed to honor **Maynard Jackson**, the city's first Black mayor
 - Born in Dallas, Texas in 1938, **Maynard Holbrook Jackson, Jr.** moved to **Atlanta** when he was 8.
- **Label** : MAYOR(NEW YORK, FIORELLO LA GUARDIA)
 - **Fiorello La Guardia** was Mayor of **New York** for three terms ...
 - **Fiorello La Guardia**, then serving on the **New York** City Board of Aldermen...
- **Label** : BORN-IN(DALLAS, MAYNARD JACKSON)
 - Born in **Dallas**, Texas in 1938, **Maynard Holbrook Jackson, Jr.** moved to Atlanta when he was 8.
 - **Maynard Jackson** was raised in **Dallas** ...
- **Label** : NIL(NEW YORK, MAYNARD JACKSON)
 - **Jackson** married Valerie Richardson, whom he had met in **New York**...
 - **Jackson** was a member of the Georgia and **New York** bars ...

Figure 17.2: Four training instances for relation classification using **distant supervision** Mintz et al. (2009). The first two instances are positive for the MAYOR relation, and the third instance is positive for the BORN-IN relation. The fourth instance is a negative example, constructed from a pair of entities (NEW YORK, MAYNARD JACKSON) that do not appear in any Freebase relation. Each instance's features are computed by aggregating across all sentences in which the two entities are mentioned.

9102 In **multiple instance learning**, labels are assigned to *sets* of instances, of which only
 9103 an unknown subset are actually relevant (Dietterich et al., 1997; Maron and Lozano-Pérez,
 9104 1998). This formalizes the framework of distant supervision: the relation $\text{REL}(A, B)$ acts
 9105 as a label for the entire set of sentences mentioning entities A and B, even when only a
 9106 subset of these sentences actually describes the relation. One approach to multi-instance
 9107 learning is to introduce a binary **latent variable** for each sentence, indicating whether the
 9108 sentence expresses the labeled relation (Riedel et al., 2010). A variety of inference tech-
 9109 niques have been employed for this probabilistic model of relation extraction: Surdeanu
 9110 et al. (2012) use expectation maximization, Riedel et al. (2010) use sampling, and Hoff-
 9111 mann et al. (2011) use a custom graph-based algorithm. Expectation maximization and
 9112 sampling are surveyed in chapter 5, and are covered in more detail by Murphy (2012);
 9113 graph-based methods are surveyed by Mihalcea and Radev (2011).

Task	Relation ontology	Supervision
PropBank semantic role labeling	VerbNet	sentence
FrameNet semantic role labeling	FrameNet	sentence
Relation extraction	ACE, TAC, SemEval, etc	sentence
Slot filling	ACE, TAC, SemEval, etc	relation
Open Information Extraction	open	seed relations or patterns

Table 17.3: Various relation extraction tasks and their properties. VerbNet and FrameNet are described in chapter 13. ACE (Linguistic Data Consortium, 2005), TAC (McNamee and Dang, 2009), and SemEval (Hendrickx et al., 2009) refer to shared tasks, each of which involves an ontology of relation types.

9114 17.2.4 Open information extraction

9115 In classical relation extraction, the set of relations is defined in advance, using a **schema**.
 9116 The relation for any pair of entities can then be predicted using multi-class classification.
 9117 In **open information extraction** (OpenIE), a relation can be any triple of text. The example
 9118 sentence (17.12) instantiates several “relations” of this sort:

- 9119 • (*mayor of, Maynard Jackson, Atlanta*),
- 9120 • (*elected, Maynard Jackson, mayor of Atlanta*),
- 9121 • (*elected in, Maynard Jackson, 1973*),

9122 and so on. Extracting such tuples can be viewed as a lightweight version of **semantic role**
 9123 **labeling** (chapter 13), with only two argument types: first slot and second slot. The task is
 9124 generally evaluated on the relation level, rather than on the level of sentences: precision is
 9125 measured by the number of extracted relations that are accurate, and recall is measured by
 9126 the number of true relations that were successfully extracted. OpenIE systems are trained
 9127 from distant supervision or bootstrapping, rather than from labeled sentences.

9128 An early example is the TextRunner system (Banko et al., 2007), which identifies re-
 9129 lations with a set of handcrafted syntactic rules. The examples that are acquired from the
 9130 handcrafted rules are then used to train a classification model that uses part-of-speech pat-
 9131 terns as features. Finally, the relations that are extracted by the classifier are aggregated,
 9132 removing redundant relations and computing the number of times that each relation is
 9133 mentioned in the corpus. TextRunner was the first in a series of systems that performed
 9134 increasingly accurate open relation extraction by incorporating more precise linguistic fea-
 9135 tures (Etzioni et al., 2011), distant supervision from Wikipedia infoboxes (Wu and Weld,
 9136 2010), and better learning algorithms (Zhu et al., 2009).

17.3 Events

Relations link pairs of entities, but many real-world situations involve more than two entities. Consider again the example sentence (17.12), which describes the **event** of an election, with four properties: the office (MAYOR), the district (ATLANTA), the date (1973), and the person elected (MAYNARD JACKSON, JR.). In **event detection**, a schema is provided for each event type (e.g., an election, a terrorist attack, or a chemical reaction), indicating all the possible properties of the event. The system is then required to fill in as many of these properties as possible (Doddington et al., 2004).

Event detection systems generally involve a retrieval component (finding relevant documents and passages of text) and an extraction component (determining the properties of the event based on the retrieved texts). Early approaches focused on finite-state patterns for identify event properties (Hobbs et al., 1997); such patterns can be automatically induced by searching for patterns that are especially likely to appear in documents that match the event query (Riloff, 1996). Contemporary approaches employ techniques that are similar to FrameNet semantic role labeling (§ 13.2), such as structured prediction over local and global features (Li et al., 2013) and bidirectional recurrent neural networks (Feng et al., 2016). These methods detect whether an event is described in a sentence, and if so, what are its properties.

Event coreference Because multiple sentences may describe unique properties of a single event, **event coreference** is required to link event mentions across a single passage of text, or between passages (Humphreys et al., 1997). Bejan and Harabagiu (2014) define event coreference as the task of identifying event mentions that share the same event participants (i.e., the slot-filling entities) and the same event properties (e.g., the time and location), within or across documents. Event coreference resolution can be performed using supervised learning techniques in a similar way to entity coreference, as described in chapter 15: move left-to-right through the document, and use a classifier to decide whether to link each event reference to an existing cluster of coreferent events, or to create a new cluster (Ahn, 2006). Each clustering decision is based on the compatibility of features describing the participants and properties of the event. Due to the difficulty of annotating large amounts of data for entity coreference, unsupervised approaches are especially desirable (Chen and Ji, 2009; Bejan and Harabagiu, 2014).

Relations between events Just as entities are related to other entities, events may be related to other events: for example, the event of winning an election both *precedes* and *causes* the event of serving as mayor; moving to Atlanta *precedes* and *enables* the event of becoming mayor of Atlanta; moving from Dallas to Atlanta *prevents* the event of later becoming mayor of Dallas. As these examples show, events may be related both temporally and causally. The **TimeML** annotation scheme specifies a set of six temporal relations

	Positive (+)	Negative (-)	Underspecified (u)
Certain (CT)	Fact: CT+	Counterfact: CT-	Certain, but unknown: CTU
Probable (PR)	Probable: PR+	Not probable: PR-	(NA)
Possible (PS)	Possible: PS+	Not possible: PS-	(NA)
Underspecified (U)	(NA)	(NA)	Unknown or uncommitted: UU

Table 17.4: Table of factuality values from the FactBank corpus (Saurí and Pustejovsky, 2009). The entry (NA) indicates that this combination is not annotated.

9174 between events (Pustejovsky et al., 2005), derived in part from **interval algebra** (Allen,
9175 1984). The TimeBank corpus provides TimeML annotations for 186 documents (Pustejovsky
9176 et al., 2003). Methods for detecting these temporal relations combine supervised
9177 machine learning with temporal constraints, such as transitivity (e.g. Mani et al., 2006;
9178 Chambers and Jurafsky, 2008).

9179 More recent annotation schemes and datasets combine temporal and causal relations (Mirza
9180 et al., 2014; Dunietz et al., 2017): for example, the CaTeRS dataset includes annotations of
9181 320 five-sentence short stories (Mostafazadeh et al., 2016). Abstracting still further, **processes**
9182 are networks of causal relations between multiple events. A small dataset of bi-
9183 ological processes is annotated in the ProcessBank dataset (Berant et al., 2014), with the
9184 goal of supporting automatic question answering on scientific textbooks.

9185 17.4 Hedges, denials, and hypotheticals

9186 The methods described thus far apply to **propositions** about the way things are in the
9187 real world. But natural language can also describe events and relations that are likely or
9188 unlikely, possible or impossible, desired or feared. The following examples hint at the
9189 scope of the problem (Prabhakaran et al., 2010):

- 9190 (17.16) GM will lay off workers.
- 9191 (17.17) A spokesman for GM said GM will lay off workers.
- 9192 (17.18) GM may lay off workers.
- 9193 (17.19) The politician claimed that GM will lay off workers.
- 9194 (17.20) Some wish GM would lay off workers.
- 9195 (17.21) Will GM lay off workers?
- 9196 (17.22) Many wonder whether GM will lay off workers.

9197 Accurate information extraction requires handling these **extra-propositional** aspects
9198 of meaning, which are sometimes summarized under the terms **modality** and **negation**.⁷
9199 Modality refers to expressions of the speaker's attitude towards her own statements, in-
9200 cluding "degree of certainty, reliability, subjectivity, sources of information, and perspec-
9201 tive" (Morante and Sporleder, 2012). Various systematizations of modality have been
9202 proposed (e.g., Palmer, 2001), including categories such as future, interrogative, imper-
9203 ative, conditional, and subjective. Information extraction is particularly concerned with
9204 negation and certainty. For example, Saurí and Pustejovsky (2009) link negation with
9205 a modal calculus of certainty, likelihood, and possibility, creating the two-dimensional
9206 schema shown in Table 17.4. This is the basis for the FactBank corpus, with annotations
9207 of the **factuality** of all sentences in 208 documents of news text.

9208 A related concept is **hedging**, in which speakers limit their commitment to a proposi-
9209 tion (Lakoff, 1973):

- 9210 (17.23) These results **suggest** that expression of c-jun, jun B and jun D genes **might** be in-
9211 volved in terminal granulocyte differentiation... (Morante and Daelemans, 2009)
- 9212 (17.24) A whale is **technically** a mammal (Lakoff, 1973)

9213 In the first example, the hedges *suggest* and *might* communicate uncertainty; in the second
9214 example, there is no uncertainty, but the hedge *technically* indicates that the evidence for
9215 the proposition will not fully meet the reader's expectations. Hedging has been studied
9216 extensively in scientific texts (Medlock and Briscoe, 2007; Morante and Daelemans, 2009),
9217 where the goal of large-scale extraction of scientific facts is obstructed by hedges and spec-
9218 ulation. Still another related aspect of modality is **evidentiality**, in which speakers mark
9219 the source of their information. In many languages, it is obligatory to mark evidentiality
9220 through affixes or particles (Aikhenvald, 2004); while evidentiality is not grammaticalized
9221 in English, authors are expected to express this information in contexts such as journal-
9222 ism (Kovach and Rosenstiel, 2014) and Wikipedia.⁸

9223 Methods for handling negation and modality generally include two phases:

- 9224 1. detecting negated or uncertain events;
- 9225 2. identifying the scope and focus of the negation or modal operator.

⁷The classification of negation as extra-propositional is controversial: Packard et al. (2014) argue that negation is a "core part of compositionally constructed logical-form representations." Negation is an element of the semantic parsing tasks discussed in chapter 12 and chapter 13 — for example, negation markers are treated as adjuncts in PropBank semantic role labeling. However, many of the relation extraction methods mentioned in this chapter do not handle negation directly. A further consideration is that negation interacts closely with aspects of modality that are generally not considered in propositional semantics, such as certainty and subjectivity.

⁸<https://en.wikipedia.org/wiki/Wikipedia:Verifiability>

9226 A considerable body of work on negation has employed rule-based techniques such as
 9227 regular expressions (Chapman et al., 2001) to detect negated events. Such techniques
 9228 match lexical cues (e.g., *Norwood was **not** elected Mayor*), while avoiding “double nega-
 9229 tives” (e.g., *surely all this is **not without** meaning*). More recent approaches employ classi-
 9230 fiers over lexical and syntactic features (Uzuner et al., 2009) and sequence labeling (Prab-
 9231 hakaran et al., 2010).

9232 The tasks of scope and focus resolution are more fine grained, as shown in the example
 9233 from Morante and Sporleder (2012):

- 9234 (17.25) [After his habit he said] **nothing**, and after mine I asked no questions.
 9235 After his habit he said nothing, and [after mine I asked] **no** [questions].

9236 In this sentence, there are two negation cues (*nothing* and *no*). Each negates an event,
 9237 indicated by the underlined verbs *said* and *asked* (this is the focus of negation), and each
 9238 occurs within a scope: *after his habit he said* and *after mine I asked* ____ *questions*. These tasks
 9239 are typically formalized as sequence labeling problems, with each word token labeled
 9240 as beginning, inside, or outside of a cue, focus, or scope span (see § 8.3). Conventional
 9241 sequence labeling approaches can then be applied, using surface features as well as syn-
 9242 tax (Velldal et al., 2012) and semantic analysis (Packard et al., 2014). Labeled datasets
 9243 include the BioScope corpus of biomedical texts (Vincze et al., 2008) and a shared task
 9244 dataset of detective stories by Arthur Conan Doyle (Morante and Blanco, 2012).

9245 17.5 Question answering and machine reading

9246 The victory of the Watson question-answering system against three top human players on
 9247 the game show *Jeopardy!* was a landmark moment for natural language processing (Fer-
 9248 rucci et al., 2010). Game show questions are usually answered by **factoids**: entity names
 9249 and short phrases.⁹ The task of factoid question answering is therefore closely related to
 9250 information extraction, with the additional problem of accurately parsing the question.

9251 17.5.1 Formal semantics

9252 Semantic parsing is an effective method for question-answering in restricted domains
 9253 such as questions about geography and airline reservations (Zettlemoyer and Collins,
 9254 2005), and has also been applied in “open-domain” settings such as question answering
 9255 on Freebase (Berant et al., 2013) and biomedical research abstracts (Poon and Domingos,
 9256 2009). One approach is to convert the question into a lambda calculus expression that

⁹The broader landscape of question answering includes “why” questions (*Why did Ahab continue to pursue the white whale?*), “how questions” (*How did Queequeg die?*), and requests for summaries (*What was Ishmael’s attitude towards organized religion?*). For more, see Hirschman and Gaizauskas (2001).

9257 returns a boolean value: for example, the question *who is the mayor of the capital of Georgia?*
 9258 would be converted to,

$$\lambda x. \exists y \text{ CAPITAL(GEORGIA, } y) \wedge \text{MAYOR}(y, x). \quad [17.22]$$

9259 This lambda expression can then be used to query an existing knowledge base, returning
 9260 “true” for all entities that satisfy it.

9261 17.5.2 Machine reading

9262 Recent work has focused on answering questions about specific textual passages, similar
 9263 to the reading comprehension examinations for young students (Hirschman et al., 1999).
 9264 This task has come to be known as **machine reading**.

9265 17.5.2.1 Datasets

9266 The machine reading problem can be formulated in a number of different ways. The most
 9267 important distinction is what form the answer should take.

- 9268 • **Multiple-choice question answering**, as in the MCTest dataset of stories (Richard-
 9269 son et al., 2013) and the New York Regents Science Exams (Clark, 2015). In MCTest,
 9270 the answer is deducible from the text alone, while in the science exams, the system
 9271 must make inferences using an existing model of the underlying scientific phenom-
 9272 ena. Here is an example from MCTest:

9273 (17.26) James the turtle was always getting into trouble. Sometimes he'd reach into
 9274 the freezer and empty out all the food ...

9275 Q: What is the name of the trouble making turtle?
 9276 (a) Fries
 9277 (b) Pudding
 9278 (c) James
 9279 (d) Jane

- 9280 • **Cloze-style “fill in the blank”** questions, as in the CNN/Daily Mail comprehension
 9281 task (Hermann et al., 2015), the Children’s Book Test (Hill et al., 2016), and the Who-
 9282 did-What dataset (Onishi et al., 2016). In these tasks, the system must guess which
 9283 word or entity completes a sentence, based on reading a passage of text. Here is an
 9284 example from Who-did-What:

9285 (17.27) Q: Tottenham manager Juande Ramos has hinted he will allow ____ to leave
 9286 if the Bulgaria striker makes it clear he is unhappy. (Onishi et al., 2016)

9287 The query sentence may be selected either from the story itself, or from an external
 9288 summary. In either case, datasets can be created automatically by processing large
 9289 quantities existing documents. An additional constraint is that that missing element
 9290 from the cloze must appear in the main passage of text: for example, in Who-did-
 9291 What, the candidates include all entities mentioned in the main passage. In the
 9292 CNN/Daily Mail dataset, each entity name is replaced by a unique identifier, e.g.,
 9293 ENTITY37. This ensures that correct answers can only be obtained by accurately
 9294 reading the text, and not from external knowledge about the entities.

- 9295 • **Extractive** question answering, in which the answer is drawn from the original text.
 9296 In WikiQA, answers are sentences (Yang et al., 2015). In the Stanford Question An-
 9297 swering Dataset (SQuAD), answers are words or short phrases (Rajpurkar et al.,
 9298 2016):

9299 (17.28) In metereology, precipitation is any product of the condensation of atmo-
 9300 spheric water vapor that falls under gravity.
 9301 Q: What causes precipitation to fall? A: gravity

9302 In both WikiQA and SQuAD, the original texts are Wikipedia articles, and the ques-
 9303 tions are generated by crowdworkers.

9304 **17.5.2.2 Methods**

9305 A baseline method is to search the text for sentences or short passages that overlap with
 9306 both the query and the candidate answer (Richardson et al., 2013). In example (17.26), this
 9307 baseline would select the correct answer, since *James* appears in a sentence that includes
 9308 the query terms *trouble* and *turtle*.

This baseline can be implemented as a neural architecture, using an **attention mechanism** (see § 18.3.1), which scores the similarity of the query to each part of the source text (Chen et al., 2016). The first step is to encode the passage $w^{(p)}$ and the query $w^{(q)}$, using two bidirectional LSTMs (§ 7.6).

$$\mathbf{h}^{(q)} = \text{BiLSTM}(\mathbf{w}^{(q)}; \Theta^{(q)}) \quad [17.23]$$

$$\mathbf{h}^{(p)} = \text{BiLSTM}(\mathbf{w}^{(p)}; \Theta^{(p)}). \quad [17.24]$$

The query is represented by vertically concatenating the final states of the left-to-right and right-to-left passes:

$$\mathbf{u} = [\overrightarrow{\mathbf{h}}^{(q)}_{M_q}; \overleftarrow{\mathbf{h}}^{(q)}_0]. \quad [17.25]$$

The attention vector is computed as a softmax over a vector of bilinear products, and the expected representation is computed by summing over attention values,

$$\tilde{\alpha}_m = (\mathbf{u}^{(q)})^\top \mathbf{W}_a \mathbf{h}_m^{(p)} \quad [17.26]$$

$$\boldsymbol{\alpha} = \text{SoftMax}(\tilde{\boldsymbol{\alpha}}) \quad [17.27]$$

$$\mathbf{o} = \sum_{m=1}^M \alpha_m \mathbf{h}_m^{(p)}. \quad [17.28]$$

Each candidate answer c is represented by a vector \mathbf{x}_c . Assuming the candidate answers are spans from the original text, these vectors can be set equal to the corresponding element in $\mathbf{h}^{(p)}$. The score for each candidate answer a is computed by the inner product,

$$\hat{c} = \underset{c}{\operatorname{argmax}} \mathbf{o} \cdot \mathbf{x}_c. \quad [17.29]$$

9309 This architecture can be trained end-to-end from a loss based on the log-likelihood of the
 9310 correct answer. A number of related architectures have been proposed (e.g., Hermann
 9311 et al., 2015; Kadlec et al., 2016; Dhingra et al., 2017; Cui et al., 2017), and the relationships
 9312 between these methods are surveyed by Wang et al. (2017).

9313 Additional resources

9314 The field of information extraction is surveyed in course notes by Grishman (2012), and
 9315 more recently in a short survey paper (Grishman, 2015). Shen et al. (2015) survey the task
 9316 of entity linking, and Ji and Grishman (2011) survey work on knowledge base popula-
 9317 tion. This chapter’s discussion of non-propositional meaning was strongly influenced by
 9318 Morante and Sporleder (2012), who introduced a special issue of the journal *Computational
 9319 Linguistics* dedicated to recent work on modality and negation.

9320 Exercises

9321 1. Consider the following heuristic for entity linking:

- 9322 • Among all entities that have the same type as the mention (e.g., LOC, PER),
 9323 choose the one whose name has the lowest edit distance from the mention.
- 9324 • If more than one entity has the right type and the lowest edit distance from the
 9325 mention, choose the most popular one.
- 9326 • If no candidate entity has the right type, choose NIL.

Now suppose you have the following feature function:

$$f(y, \mathbf{x}) = [\text{edit-dist}(\text{name}(y), \mathbf{x}), \text{same-type}(y, \mathbf{x}), \text{popularity}(y), \delta(y = \text{NIL})]$$

Design a set of ranking weights θ that match the heuristic. You may assume that edit distance and popularity are always in the range [0, 100], and that the NIL entity has values of zero for all features except δ ($y = \text{NIL}$).

2. Now consider another heuristic:

- Among all candidate entities that have edit distance zero from the mention and the right type, choose the most popular one.
- If no entity has edit distance zero from the mention, choose the one with the right type that is most popular, regardless of edit distance.
- If no entity has the right type, choose NIL.

Using the same features and assumptions from the previous problem, prove that there is no set of weights that could implement this heuristic. Then show that the heuristic can be implemented by adding a single feature. Your new feature should consider only the edit distance.

3. * Consider the following formulation for collective entity linking, which rewards sets of entities that are all of the same type, where “types” can be elements of any set:

$$\psi_c(\mathbf{y}) = \begin{cases} \alpha & \text{all entities in } \mathbf{y} \text{ have the same type} \\ \beta & \text{more than half of the entities in } \mathbf{y} \text{ have the same type} \\ 0 & \text{otherwise.} \end{cases} \quad [17.30]$$

Show how to implement this model of collective entity linking in an **integer linear program**. You may want to review § 13.2.2.

To get started, here is an integer linear program for entity linking, without including the collective term ψ_c :

$$\begin{aligned} \max_{z_{i,y} \in \{0,1\}} \quad & \sum_{i=1}^N \sum_{y \in \mathcal{Y}(\mathbf{x}^{(i)})} s_{i,y} z_{i,y} \\ \text{s.t.} \quad & \sum_{y \in \mathcal{Y}(\mathbf{x}^{(i)})} z_{i,y} \leq 1 \quad \forall i \in \{1, 2, \dots, N\} \end{aligned}$$

where $z_{i,y} = 1$ if entity y is linked to mention i , and $s_{i,y}$ is a parameter that scores the quality of this individual ranking decision, e.g., $s_{i,y} = \theta \cdot f(y, \mathbf{x}^{(i)}, \mathbf{c}^{(i)})$.

To incorporate the collective linking score, you may assume parameters r ,

$$r_{y,\tau} = \begin{cases} 1, & \text{entity } y \text{ has type } \tau \\ 0, & \text{otherwise.} \end{cases} \quad [17.31]$$

Hint: You will need to define several auxiliary variables to optimize over.

- 9349 4. Run `nltk.corpus.download('reuters')` to download the Reuters corpus in
 9350 NLTK, and run `from nltk.corpus import reuters` to import it. The com-
 9351 mand `reuters.words()` returns an iterator over the tokens in the corpus.
- 9352 a) Apply the pattern *_____, such as _____* to this corpus, obtaining candidates for the
 9353 IS-A relation, e.g. `IS-A(ROMANIA, COUNTRY)`. What are three pairs that this
 9354 method identifies correctly? What are three different pairs that it gets wrong?
- 9355 b) Design a pattern for the PRESIDENT relation, e.g. `PRESIDENT(PHILIPPINES, CORAZON AQUINO)`.
 9356 In this case, you may want to augment your pattern matcher with the ability
 9357 to match multiple token wildcards, perhaps using case information to detect
 9358 proper names. Again, list three correct
- 9359 c) Preprocess the Reuters data by running a named entity recognizer, replacing
 9360 tokens with named entity spans when applicable. Apply your PRESIDENT
 9361 matcher to this new data. Does the accuracy improve? Compare 20 randomly-
 9362 selected pairs from this pattern and the one you designed in the previous part.
- 9363 5. Represent the dependency path $\mathbf{x}^{(i)}$ as a sequence of words and dependency arcs
 9364 of length M_i , ignoring the endpoints of the path. In example 1 of Table 17.2, the
 9365 dependency path is,

$$\mathbf{x}^{(1)} = (\xleftarrow[\text{NSUBJ}]{}, \text{traveled}, \xrightarrow[\text{OBL}]{}) \quad [17.32]$$

9366 If $x_m^{(i)}$ is a word, then let $\text{pos}(x_m^{(i)})$ be its part-of-speech, using the tagset defined in
 9367 chapter 8.

We can define the following kernel function over pairs of dependency paths (Bunescu and Mooney, 2005):

$$\kappa(\mathbf{x}^{(i)}, \mathbf{x}^{(j)}) = \begin{cases} 0, & M_i \neq M_j \\ \prod_{m=1}^{M_i} c(x_m^{(i)}, x_m^{(j)}), & M_i = M_j \end{cases}$$

$$c(x_m^{(i)}, x_m^{(j)}) = \begin{cases} 2, & x_m^{(i)} = x_m^{(j)} \\ 1, & x_m^{(i)} \text{ and } x_m^{(j)} \text{ are words and } \text{pos}(x_m^{(i)}) = \text{pos}(x_m^{(j)}) \\ 0, & \text{otherwise.} \end{cases}$$

9368 Using this kernel function, compute the kernel similarities of example 1 from Ta-
 9369 ble 17.2 with the other five examples.

6. Continuing from the previous problem, suppose that the instances have the following labels:

$$y_2 = 1, y_3 = -1, y_4 = -1, y_5 = 1, y_6 = 1 \quad [17.33]$$

9370 Identify the conditions for α and b under which $\hat{y}_1 = 1$. Remember the constraint
 9371 that $\alpha_i \geq 0$ for all i .

9372 Chapter 18

9373 Machine translation

9374 Machine translation (MT) is one of the “holy grail” problems in artificial intelligence,
9375 with the potential to transform society by facilitating communication between people
9376 anywhere in the world. As a result, MT has received significant attention and funding
9377 since the early 1950s. However, it has proved remarkably challenging, and while there
9378 has been substantial progress towards usable MT systems — especially for high-resource
9379 language pairs like English-French — we are still far from translation systems that match
9380 the nuance and depth of human translations.

9381 18.1 Machine translation as a task

9382 Machine translation can be formulated as an optimization problem:

$$\hat{\mathbf{w}}^{(t)} = \underset{\mathbf{w}^{(t)}}{\operatorname{argmax}} \Psi(\mathbf{w}^{(s)}, \mathbf{w}^{(t)}), \quad [18.1]$$

9383 where $\mathbf{w}^{(s)}$ is a sentence in a **source** language, $\mathbf{w}^{(t)}$ is a sentence in the **target language**,
9384 and Ψ is a scoring function. As usual, this formalism requires two components: a decod-
9385 ing algorithm for computing $\hat{\mathbf{w}}^{(t)}$, and a learning algorithm for estimating the parameters
9386 of the scoring function Ψ .

9387 Decoding is difficult for machine translation because of the huge space of possible
9388 translations. We have faced large label spaces before: for example, in sequence labeling,
9389 the set of possible label sequences is exponential in the length of the input. In these cases,
9390 it was possible to search the space quickly by introducing locality assumptions: for ex-
9391 ample, that each tag depends only on its predecessor, or that each production depends
9392 only on its parent. In machine translation, no such locality assumptions seem possible:
9393 human translators reword, reorder, and rearrange words; they replace single words with
9394 multi-word phrases, and vice versa. This flexibility means that in even relatively simple

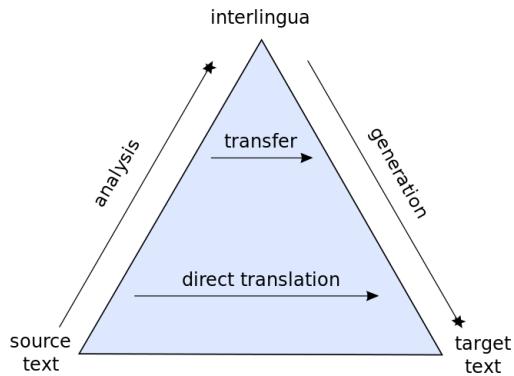


Figure 18.1: The Vauquois Pyramid http://commons.wikimedia.org/wiki/File:Direct_translation_and_transfer_translation_pyramind.svg

9395 translation models, decoding is NP-hard (Knight, 1999). Approaches for dealing with this
 9396 complexity are described in § 18.4.

Estimating translation models is difficult as well. Labeled translation data usually comes in the form parallel sentences, e.g.,

$$\begin{aligned} w^{(s)} &= A \text{ } Vinay \text{ } le \text{ } gusta \text{ } las \text{ } manzanas. \\ w^{(t)} &= Vinay \text{ likes apples.} \end{aligned}$$

9397 A useful feature function would note the translation pairs (*gusta, likes*), (*manzanas, apples*),
 9398 and even (*Vinay, Vinay*). But this word-to-word **alignment** is not given in the data. One
 9399 solution is to treat this alignment as a **latent variable**; this is the approach taken by clas-
 9400 **statistical machine translation** (SMT) systems, described in § 18.2. Another solution
 9401 is to model the relationship between $w^{(t)}$ and $w^{(s)}$ through a more complex and expres-
 9402 sive function; this is the approach taken by **neural machine translation** (NMT) systems,
 9403 described in § 18.3.

9404 The **Vauquois Pyramid** is a theory of how translation should be done. At the lowest
 9405 level, the translation system operates on individual words, but the horizontal distance
 9406 at this level is large, because languages express ideas differently. If we can move up the
 9407 triangle to syntactic structure, the distance for translation is reduced; we then need only
 9408 produce target-language text from the syntactic representation, which can be as simple
 9409 as reading off a tree. Further up the triangle lies semantics; translating between semantic
 9410 representations should be easier still, but mapping between semantics and surface text is
 9411 a difficult, unsolved problem. At the top of the triangle is **interlingua**, a semantic repre-
 9412 **sentation** that is so generic that it is identical across all human languages. Philosophers

	Adequate?	Fluent?
<i>To Vinay it like Python</i>	yes	no
<i>Vinay debugs memory leaks</i>	no	yes
<i>Vinay likes Python</i>	yes	yes

Table 18.1: Adequacy and fluency for translations of the Spanish sentence *A Vinay le gusta Python*.

debate whether such a thing as interlingua is really possible (Derrida, 1985). While the first-order logic representations discussed in chapter 12 might be considered to be language independent, it is built on an inventory of relations that is suspiciously similar to a subset of English words (Nirenburg and Wilks, 2001). Nonetheless, the idea of linking translation and semantic understanding may still be a promising path, if the resulting translations better preserve the meaning of the original text.

18.1.1 Evaluating translations

There are two main criteria for a translation, summarized in Table 18.1.

- **Adequacy:** The translation $w^{(t)}$ should adequately reflect the linguistic content of $w^{(s)}$. For example, if $w^{(s)} = A Vinay le gusta Python$, the gloss¹ $w^{(t)} = To Vinay it like Python$ is considered adequate because it contains all the relevant content. The output $w^{(t)} = Vinay debugs memory leaks$ is not adequate.
- **Fluency:** The translation $w^{(t)}$ should read like fluent text in the target language. By this criterion, the gloss $w^{(t)} = To Vinay it like Python$ will score poorly, and $w^{(t)} = Vinay debugs memory leaks$ will be preferred.

Automated evaluations of machine translations typically merge both of these criteria, by comparing the system translation with one or more **reference translations**, produced by professional human translators. The most popular quantitative metric is **BLEU** (bilingual evaluation understudy; Papineni et al., 2002), which is based on n -gram precision: what fraction of n -grams in the system translation appear in the reference? Specifically, for each n -gram length, the precision is defined as,

$$p_n = \frac{\text{number of } n\text{-grams appearing in both reference and hypothesis translations}}{\text{number of } n\text{-grams appearing in the hypothesis translation}}. \quad [18.2]$$

The n -gram precisions for three hypothesis translations are shown in Figure 18.2.

¹A gloss is a word-for-word translation.

	Translation	p_1	p_2	p_3	p_4	BP	BLEU
<i>Reference</i>	<i>Vinay likes programming in Python</i>						
<i>Sys1</i>	<i>To Vinay it like to program Python</i>	$\frac{2}{7}$	0	0	0	1	.21
<i>Sys2</i>	<i>Vinay likes Python</i>	$\frac{3}{3}$	$\frac{1}{2}$	0	0	.51	.33
<i>Sys3</i>	<i>Vinay likes programming in his pajamas</i>	$\frac{4}{6}$	$\frac{3}{5}$	$\frac{2}{4}$	$\frac{1}{3}$	1	.76

Figure 18.2: A reference translation and three system outputs. For each output, p_n indicates the precision at each n -gram, and BP indicates the brevity penalty.

9435 The BLEU score is then based on the average, $\exp \frac{1}{N} \sum_{n=1}^N \log p_n$. Two modifications
 9436 of Equation 18.2 are necessary: (1) to avoid computing $\log 0$, all precisions are smoothed
 9437 to ensure that they are positive; (2) each n -gram in the source can be used at most once,
 9438 so that *to to to to to* does not achieve $p_1 = 1$ against the reference *to be or not to be*.
 9439 Furthermore, precision-based metrics are biased in favor of short translations, which can
 9440 achieve high scores by minimizing the denominator in [18.2]. To avoid this issue, a **brevity**
 9441 **penalty** is applied to translations that are shorter than the reference. This penalty is indi-
 9442 cated as “BP” in Figure 18.2.

9443 Automated metrics like BLEU have been validated by correlation with human judg-
 9444 ments of translation quality. Nonetheless, it is not difficult to construct examples in which
 9445 the BLEU score is high, yet the translation is disfluent or carries a completely different
 9446 meaning from the original. To give just one example, consider the problem of translating
 9447 pronouns. Because pronouns refer to specific entities, a single incorrect pronoun can obliti-
 9448 onate the semantics of the original sentence. Existing state-of-the-art systems generally
 9449 do not attempt the reasoning necessary to correctly resolve pronominal anaphora (Hard-
 9450 meier, 2012). Despite the importance of pronouns for semantics, they have a marginal
 9451 impact on BLEU, which may help to explain why existing systems do not make a greater
 9452 effort to translate them correctly.

9453 **Fairness and bias** The problem of pronoun translation intersects with issues of fairness
 9454 and bias. In many languages, such as Turkish, the third person singular pronoun is gender
 9455 neutral. Today’s state-of-the-art systems produce the following Turkish-English transla-
 9456 tions (Caliskan et al., 2017):

- 9457 (18.1) *O bir doktor.*
 He is a doctor.
 9458 (18.2) *O bir hemşire.*
 She is a nurse.

9459 The same problem arises for other professions that have stereotypical genders, such as
9460 engineers, soldiers, and teachers, and for other languages that have gender-neutral pro-
9461 nouns. This bias was not directly programmed into the translation model; it arises from
9462 statistical tendencies in existing datasets. This highlights a general problem with data-
9463 driven approaches, which can perpetuate biases that negatively impact disadvantaged
9464 groups. Worse, machine learning can *amplify* biases in data (Bolukbasi et al., 2016): if a
9465 dataset has even a slight tendency towards men as doctors, the resulting translation model
9466 may produce translations in which doctors are always *he*, and nurses are always *she*.

9467 **Other metrics** A range of other automated metrics have been proposed for machine
9468 translation. One potential weakness of BLEU is that it only measures precision; METEOR
9469 is a weighted *F*-MEASURE, which is a combination of recall and precision (see § 4.4.1).
9470 **Translation Error Rate (TER)** computes the string **edit distance** (see § 9.1.4.1) between the
9471 reference and the hypothesis (Snover et al., 2006). For language pairs like English and
9472 Japanese, there are substantial differences in word order, and word order errors are not
9473 sufficiently captured by *n*-gram based metrics. The **RIBES** metric applies rank correla-
9474 tion to measure the similarity in word order between the system and reference transla-
9475 tions (Isozaki et al., 2010).

9476 18.1.2 Data

9477 Data-driven approaches to machine translation rely primarily on **parallel corpora**: sentence-
9478 level translations. Early work focused on government records, in which fine-grained offi-
9479 cial translations are often required. For example, the IBM translation systems were based
9480 on the proceedings of the Canadian Parliament, called **Hansards**, which are recorded in
9481 English and French (Brown et al., 1990). The growth of the European Union led to the
9482 development of the **EuroParl corpus**, which spans 21 European languages (Koehn, 2005).
9483 While these datasets helped to launch the field of machine translation, they are restricted
9484 to narrow domains and a formal speaking style, limiting their applicability to other types
9485 of text. As more resources are committed to machine translation, new translation datasets
9486 have been commissioned. This has broadened the scope of available data to news,² movie
9487 subtitles,³ social media (Ling et al., 2013), dialogues (Fordyce, 2007), TED talks (Paul et al.,
9488 2010), and scientific research articles (Nakazawa et al., 2016).

9489 Despite this growing set of resources, the main bottleneck in machine translation data
9490 is the need for parallel corpora that are aligned at the sentence level. Many languages have
9491 sizable parallel corpora with some high-resource language, but not with each other. The
9492 high-resource language can then be used as a “pivot” or “bridge” (Boitet, 1988; Utiyama

²https://catalog.ldc.upenn.edu/LDC2010T10_translation-task.html <http://www.statmt.org/wmt15/>

³<http://opus.nlpl.eu/>

and Isahara, 2007): for example, De Gispert and Marino (2006) use Spanish as a bridge for translation between Catalan and English. For most of the 6000 languages spoken today, the only source of translation data remains the Judeo-Christian Bible (Resnik et al., 1999). While relatively small, at less than a million tokens, the Bible has been translated into more than 2000 languages, far outpacing any other corpus. Some research has explored the possibility of automatically identifying parallel sentence pairs from unaligned parallel texts, such as web pages and Wikipedia articles (Kilgarriff and Grefenstette, 2003; Resnik and Smith, 2003; Adafre and De Rijke, 2006). Another approach is to create large parallel corpora through crowdsourcing (Zaidan and Callison-Burch, 2011).

18.2 Statistical machine translation

The previous section introduced adequacy and fluency as the two main criteria for machine translation. A natural modeling approach is to represent them with separate scores,

$$\Psi(\mathbf{w}^{(s)}, \mathbf{w}^{(t)}) = \Psi_A(\mathbf{w}^{(s)}, \mathbf{w}^{(t)}) + \Psi_F(\mathbf{w}^{(t)}). \quad [18.3]$$

The fluency score Ψ_F need not even consider the source sentence; it only judges $\mathbf{w}^{(t)}$ on whether it is fluent in the target language. This decomposition is advantageous because it makes it possible to estimate the two scoring functions on separate data. While the adequacy model must be estimated from aligned sentences — which are relatively expensive and rare — the fluency model can be estimated from monolingual text in the target language. Large monolingual corpora are now available in many languages, thanks to resources such as Wikipedia.

An elegant justification of the decomposition in Equation 18.3 is provided by the **noisy channel model**, in which each scoring function is a log probability:

$$\Psi_A(\mathbf{w}^{(s)}, \mathbf{w}^{(t)}) \triangleq \log p_{S|T}(\mathbf{w}^{(s)} | \mathbf{w}^{(t)}) \quad [18.4]$$

$$\Psi_F(\mathbf{w}^{(t)}) \triangleq \log p_T(\mathbf{w}^{(t)}) \quad [18.5]$$

$$\Psi(\mathbf{w}^{(s)}, \mathbf{w}^{(t)}) = \log p_{S|T}(\mathbf{w}^{(s)} | \mathbf{w}^{(t)}) + \log p_T(\mathbf{w}^{(t)}) = \log p_{S,T}(\mathbf{w}^{(s)}, \mathbf{w}^{(t)}). \quad [18.6]$$

By setting the scoring functions equal to the logarithms of the prior and likelihood, their sum is equal to $\log p_{S,T}$, which is the logarithm of the joint probability of the source and target. The sentence $\hat{\mathbf{w}}^{(t)}$ that maximizes this joint probability is also the maximizer of the conditional probability $p_{T|S}$, making it the most likely target language sentence, conditioned on the source.

The noisy channel model can be justified by a generative story. The target text is originally generated from a probability model p_T . It is then encoded in a “noisy channel” $p_{S|T}$, which converts it to a string in the source language. In decoding, we apply Bayes’ rule to recover the string $\mathbf{w}^{(t)}$ that is maximally likely under the conditional probability

	<i>A</i>	<i>Vinay</i>	<i>le</i>	<i>gusta</i>	<i>python</i>
<i>Vinay</i>		■			
<i>likes</i>			■	■	
<i>python</i>					■

Figure 18.3: An example word-to-word alignment

9521 $p_{T|S}$. Under this interpretation, the target probability p_T is just a language model, and
 9522 can be estimated using any of the techniques from chapter 6. The only remaining learning
 9523 problem is to estimate the translation model $p_{S|T}$.

9524 18.2.1 Statistical translation modeling

9525 The simplest decomposition of the translation model is word-to-word: each word in the
 9526 source should be aligned to a word in the translation. This approach presupposes an
 9527 **alignment** $\mathcal{A}(\mathbf{w}^{(s)}, \mathbf{w}^{(t)})$, which contains a list of pairs of source and target tokens. For
 9528 example, given $\mathbf{w}^{(s)} = A\ Vinay\ le\ gusta\ Python$ and $\mathbf{w}^{(t)} = Vinay\ likes\ Python$, one possible
 9529 word-to-word alignment is,

$$\mathcal{A}(\mathbf{w}^{(s)}, \mathbf{w}^{(t)}) = \{(A, \emptyset), (Vinay, Vinay), (le, likes), (gusta, likes), (Python, Python)\}. \quad [18.7]$$

9530 This alignment is shown in Figure 18.3. Another, less promising, alignment is:

$$\mathcal{A}(\mathbf{w}^{(s)}, \mathbf{w}^{(t)}) = \{(A, Vinay), (Vinay, likes), (le, Python), (gusta, \emptyset), (Python, \emptyset)\}. \quad [18.8]$$

9531 Each alignment contains exactly one tuple for each word in the *source*, which serves to
 9532 explain how the source word could be translated from the target, as required by the trans-
 9533 lation probability $p_{S|T}$. If no appropriate word in the target can be identified for a source
 9534 word, it is aligned to \emptyset — as is the case for the Spanish function word *a* in the example,
 9535 which glosses to the English word *to*. Words in the target can align with multiple words
 9536 in the source, so that the target word *likes* can align to both *le* and *gusta* in the source.

The joint probability of the alignment and the translation can be defined conveniently

as,

$$p(\mathbf{w}^{(s)}, \mathcal{A} | \mathbf{w}^{(t)}) = \prod_{m=1}^{M^{(s)}} p(w_m^{(s)}, a_m | w_{a_m}^{(t)}, m, M^{(s)}, M^{(t)}) \quad [18.9]$$

$$= \prod_{m=1}^{M^{(s)}} p(a_m | m, M^{(s)}, M^{(t)}) \times p(w_m^{(s)} | w_{a_m}^{(t)}). \quad [18.10]$$

9537 This probability model makes two key assumptions:

9538 • The alignment probability factors across tokens,

$$p(\mathcal{A} | \mathbf{w}^{(s)}, \mathbf{w}^{(t)}) = \prod_{m=1}^{M^{(s)}} p(a_m | m, M^{(s)}, M^{(t)}). \quad [18.11]$$

9539 This means that each alignment decision is independent of the others, and depends
9540 only on the index m , and the sentence lengths $M^{(s)}$ and $M^{(t)}$.

9541 • The translation probability also factors across tokens,

$$p(\mathbf{w}^{(s)} | \mathbf{w}^{(t)}, \mathcal{A}) = \prod_{m=1}^{M^{(s)}} p(w_m^{(s)} | w_{a_m}^{(t)}), \quad [18.12]$$

9542 so that each word in $\mathbf{w}^{(s)}$ depends only on its aligned word in $\mathbf{w}^{(t)}$. This means that
9543 translation is word-to-word, ignoring context. The hope is that the target language
9544 model $p(\mathbf{w}^{(t)})$ will correct any disfluencies that arise from word-to-word translation.

To translate with such a model, we could sum or max over all possible alignments,

$$p(\mathbf{w}^{(s)}, \mathbf{w}^{(t)}) = \sum_{\mathcal{A}} p(\mathbf{w}^{(s)}, \mathbf{w}^{(t)}, \mathcal{A}) \quad [18.13]$$

$$= p(\mathbf{w}^{(t)}) \sum_{\mathcal{A}} p(\mathcal{A}) \times p(\mathbf{w}^{(s)} | \mathbf{w}^{(t)}, \mathcal{A}) \quad [18.14]$$

$$\geq p(\mathbf{w}^{(t)}) \max_{\mathcal{A}} p(\mathcal{A}) \times p(\mathbf{w}^{(s)} | \mathbf{w}^{(t)}, \mathcal{A}). \quad [18.15]$$

The term $p(\mathcal{A})$ defines the prior probability over alignments. A series of alignment models with increasingly relaxed independence assumptions was developed by researchers at IBM in the 1980s and 1990s, known as IBM Models 1-6 (Och and Ney, 2003). IBM Model 1 makes the strongest independence assumption:

$$p(a_m | m, M^{(s)}, M^{(t)}) = \frac{1}{M^{(t)}}. \quad [18.16]$$

9545 In this model, every alignment is equally likely. This is almost surely wrong, but it re-
 9546 sults in a convex learning objective, yielding a good initialization for the more complex
 9547 alignment models (Brown et al., 1993; Koehn, 2009).

9548 18.2.2 Estimation

9549 Let us define the parameter $\theta_{u \rightarrow v}$ as the probability of translating target word u to source
 9550 word v . If word-to-word alignments were annotated, these probabilities could be com-
 9551 puted from relative frequencies,

$$\hat{\theta}_{u \rightarrow v} = \frac{\text{count}(u, v)}{\text{count}(u)}, \quad [18.17]$$

9552 where $\text{count}(u, v)$ is the count of instances in which word v was aligned to word u in
 9553 the training set, and $\text{count}(u)$ is the total count of the target word u . The smoothing
 9554 techniques mentioned in chapter 6 can help to reduce the variance of these probability
 9555 estimates.

9556 Conversely, if we had an accurate translation model, we could estimate the likelihood
 9557 of each alignment decision,

$$q_m(a_m | \mathbf{w}^{(s)}, \mathbf{w}^{(t)}) \propto p(a_m | m, M^{(s)}, M^{(t)}) \times p(w_m^{(s)} | w_{a_m}^{(t)}), \quad [18.18]$$

where $q_m(a_m | \mathbf{w}^{(s)}, \mathbf{w}^{(t)})$ is a measure of our confidence in aligning source word $w_m^{(s)}$
 to target word $w_{a_m}^{(t)}$. The relative frequencies could then be computed from the *expected
 counts*,

$$\hat{\theta}_{u \rightarrow v} = \frac{E_q[\text{count}(u, v)]}{\text{count}(u)} \quad [18.19]$$

$$E_q[\text{count}(u, v)] = \sum_m q_m(a_m | \mathbf{w}^{(s)}, \mathbf{w}^{(t)}) \delta(w_m^{(s)} = v) \delta(w_{a_m}^{(t)} = u). \quad [18.20]$$

9558 The **expectation-maximization** (EM) algorithm proceeds by iteratively updating q_m
 9559 and $\hat{\Theta}$. The algorithm is described in general form in chapter 5. For statistical machine
 9560 translation, the steps of the algorithm are:

- 9561 1. **E-step:** Update beliefs about word alignment using Equation 18.18.
- 9562 2. **M-step:** Update the translation model using Equations 18.19 and 18.20.

9563 As discussed in chapter 5, the expectation maximization algorithm is guaranteed to con-
 9564 verge, but not to a global optimum. However, for IBM Model 1, it can be shown that EM
 9565 optimizes a convex objective, and global optimality is guaranteed. For this reason, IBM
 9566 Model 1 is often used as an initialization for more complex alignment models. For more
 9567 detail, see Koehn (2009).

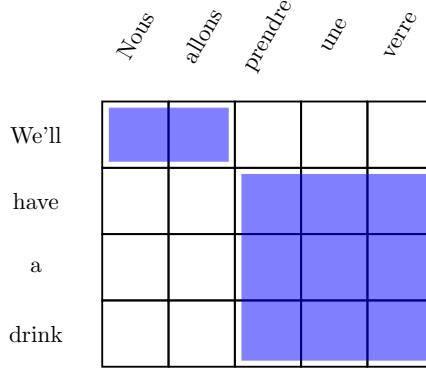


Figure 18.4: A phrase-based alignment between French and English, corresponding to example (18.3)

9568 18.2.3 Phrase-based translation

9569 Real translations are not word-to-word substitutions. One reason is that many multiword
9570 expressions are not translated literally, as shown in this example from French:

- 9571 (18.3) *Nous allons prendre un verre*
 We will take a glass
 9572 We'll have a drink

9573 The line *we will take a glass* is the word-for-word gloss of the French sentence; the transla-
 9574 tion *we'll have a drink* is shown on the third line. Such examples are difficult for word-to-
 9575 word translation models, since they require translating *prendre* to *have* and *verre* to *drink*.
 9576 These translations are only correct in the context of these specific phrases.

Phrase-based translation generalizes on word-based models by building translation tables and alignments between multiword spans. (These “phrases” are not necessarily syntactic constituents like the noun phrases and verb phrases described in chapters 9 and 10.) The generalization from word-based translation is surprisingly straightforward: the translation tables can now condition on multi-word units, and can assign probabilities to multi-word units; alignments are mappings from spans to spans, $((i, j), (k, \ell))$, so that

$$p(\mathbf{w}^{(s)} | \mathbf{w}^{(t)}, \mathcal{A}) = \prod_{((i, j), (k, \ell)) \in \mathcal{A}} p_{w^{(s)}|w^{(t)}}(\{w_{i+1}^{(s)}, w_{i+2}^{(s)}, \dots, w_j^{(s)}\} | \{w_{k+1}^{(t)}, w_{k+2}^{(t)}, \dots, w_\ell^{(t)}\}). \quad [18.21]$$

9577 The phrase alignment $((i, j), (k, \ell))$ indicates that the span $\mathbf{w}_{i+1:j}^{(s)}$ is the translation of the
 9578 span $\mathbf{w}_{k+1:\ell}^{(t)}$. An example phrasal alignment is shown in Figure 18.4. Note that the align-

ment set \mathcal{A} is required to cover all of the tokens in the source, just as in word-based translation. The probability model $p_{w^{(s)}|w^{(t)}}$ must now include translations for all phrase pairs, which can be learned from expectation-maximization just as in word-based statistical machine translation.

18.2.4 *Syntax-based translation

The Vauquois Pyramid (Figure 18.1) suggests that translation might be easier if we take a higher-level view. One possibility is to incorporate the syntactic structure of the source, the target, or both. This is particularly promising for language pairs that consistent syntactic differences. For example, English adjectives almost always precede the nouns that they modify, while in Romance languages such as French and Spanish, the adjective often follows the noun: thus, *angry fish* would translate to *pez (fish) enojado (angry)* in Spanish. In word-to-word translation, these reorderings cause the alignment model to be overly permissive. It is not that the order of *any* pair of English words can be reversed when translating into Spanish, but only adjectives and nouns within a noun phrase. Similar issues arise when translating between verb-final languages such as Japanese (in which verbs usually follow the subject and object), verb-initial languages like Tagalog and classical Arabic, and verb-medial languages such as English.

An elegant solution is to link parsing and translation in a **synchronous context-free grammar** (SCFG; Chiang, 2007).⁴ An SCFG is a set of productions of the form $X \rightarrow (\alpha, \beta, \sim)$, where X is a non-terminal, α and β are sequences of terminals or non-terminals, and \sim is a one-to-one alignment of items in α with items in β . To handle the English-Spanish adjective-noun ordering, an SCFG would include productions such as,

$$\text{NP} \rightarrow (\text{DET}_1 \text{NN}_2 \text{JJ}_3, \quad \text{DET}_1 \text{JJ}_3 \text{NN}_2), \quad [18.22]$$

with subscripts indicating the alignment between the Spanish (left) and English (right) parts of the right-hand side. Terminal productions yield translation pairs,

$$\text{JJ} \rightarrow (\text{enojado}_1, \text{angry}_1). \quad [18.23]$$

A synchronous derivation begins with the start symbol S , and derives a pair of sequences of terminal symbols.

Given an SCFG in which each production yields at most two symbols in each language (Chomsky Normal Form; see § 9.2.1.2), a sentence can be parsed using only the CKY algorithm (chapter 10). The resulting derivation also includes productions in the other language, all the way down to the surface form. Therefore, SCFGs make translation very similar to parsing. In a weighted SCFG, the log probability $\log p_{S|T}$ can be computed from

⁴Key earlier work includes syntax-driven transduction (Lewis II and Stearns, 1968) and stochastic inversion transduction grammars (Wu, 1997).

the sum of the log-probabilities of the productions. However, combining SCFGs with a target language model is computationally expensive, necessitating approximate search algorithms (Huang and Chiang, 2007).

Synchronous context-free grammars are an example of **tree-to-tree translation**, because they model the syntactic structure of both the target and source language. In **string-to-tree translation**, string elements are translated into constituent tree fragments, which are then assembled into a translation (Yamada and Knight, 2001; Galley et al., 2004); in **tree-to-string translation**, the source side is parsed, and then transformed into a string on the target side (Liu et al., 2006). A key question for syntax-based translation is the extent to which we phrasal constituents align across translations (Fox, 2002), because this governs the extent to which we can rely on monolingual parsers and treebanks. For more on syntax-based machine translation, see the monograph by Williams et al. (2016).

18.3 Neural machine translation

Neural network models for machine translation are based on the **encoder-decoder** architecture (Cho et al., 2014). The encoder network converts the source language sentence into a vector or matrix representation; the decoder network then converts the encoding into a sentence in the target language.

$$z = \text{ENCODE}(\mathbf{w}^{(s)}) \quad [18.24]$$

$$\mathbf{w}^{(t)} \mid \mathbf{w}^{(s)} \sim \text{DECODE}(z), \quad [18.25]$$

where the second line means that the function $\text{DECODE}(z)$ defines the conditional probability $p(\mathbf{w}^{(t)} \mid \mathbf{w}^{(s)})$.

The decoder is typically a recurrent neural network, which generates the target language sentence one word at a time, while recurrently updating a hidden state. The encoder and decoder networks are trained end-to-end from parallel sentences. If the output layer of the decoder is a logistic function, then the entire architecture can be trained to maximize the conditional log-likelihood,

$$\log p(\mathbf{w}^{(t)} \mid \mathbf{w}^{(s)}) = \sum_{m=1}^{M^{(t)}} p(w_m^{(t)} \mid \mathbf{w}_{1:m-1}^{(t)}, z) \quad [18.26]$$

$$p(w_m^{(t)} \mid \mathbf{w}_{1:m-1}^{(t)}, \mathbf{w}^{(s)}) \propto \exp \left(\boldsymbol{\beta}_{w_m^{(t)}} \cdot \mathbf{h}_{m-1}^{(t)} \right) \quad [18.27]$$

where the hidden state $\mathbf{h}_{m-1}^{(t)}$ is a recurrent function of the previously generated text $\mathbf{w}_{1:m-1}^{(t)}$ and the encoding z . The second line is equivalent to writing,

$$w_m^{(t)} \mid \mathbf{w}_{1:m-1}^{(t)}, \mathbf{w}^{(s)} \sim \text{SoftMax} \left(\boldsymbol{\beta} \cdot \mathbf{h}_{m-1}^{(t)} \right), \quad [18.28]$$

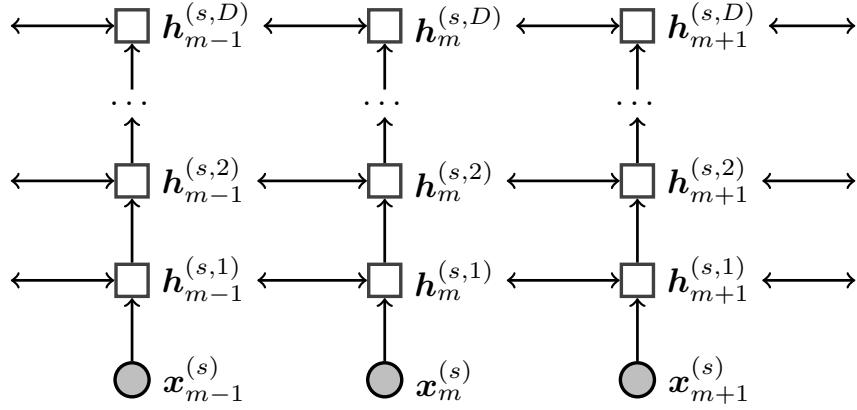


Figure 18.5: A deep bidirectional LSTM encoder

9625 where $\beta \in \mathbb{R}^{(V^{(t)} \times K)}$ is the matrix of output word vectors for the $V^{(t)}$ words in the target
 9626 language vocabulary.

The simplest encoder-decoder architecture is the **sequence-to-sequence** model (Sutskever et al., 2014). In this model, the encoder is set to the final hidden state of a **long short-term memory (LSTM)** (see § 6.3.3) on the source sentence:

$$\mathbf{h}_m^{(s)} = \text{LSTM}(\mathbf{x}_m^{(s)}, \mathbf{h}_{m-1}^{(s)}) \quad [18.29]$$

$$\mathbf{z} \triangleq \mathbf{h}_{M^{(s)}}^{(s)}, \quad [18.30]$$

where $\mathbf{x}_m^{(s)}$ is the embedding of source language word $w_m^{(s)}$. The encoding then provides the initial hidden state for the decoder LSTM:

$$\mathbf{h}_0^{(t)} = \mathbf{z} \quad [18.31]$$

$$\mathbf{h}_m^{(t)} = \text{LSTM}(\mathbf{x}_m^{(t)}, \mathbf{h}_{m-1}^{(t)}), \quad [18.32]$$

9627 where $\mathbf{x}_m^{(t)}$ is the embedding of the target language word $w_m^{(t)}$.

9628 Sequence-to-sequence translation is nothing more than wiring together two LSTMs:
 9629 one to read the source, and another to generate the target. To make the model work well,
 9630 some additional tweaks are needed:

- 9631 • Most notably, the model works much better if the source sentence is reversed, reading
 9632 from the end of the sentence back to the beginning. In this way, the words at the
 9633 beginning of the source have the greatest impact on the encoding \mathbf{z} , and therefore

9634 impact the words at the beginning of the target sentence. Later work on more ad-
 9635 vanced encoding models, such as **neural attention** (see § 18.3.1), has eliminated the
 9636 need for reversing the source sentence.

- The encoder and decoder can be implemented as **deep LSTMs**, with multiple layers of hidden states. As shown in Figure 18.5, each hidden state $\mathbf{h}_m^{(s,i)}$ at layer i is treated as the input to an LSTM at layer $i + 1$:

$$\mathbf{h}_m^{(s,1)} = \text{LSTM}(\mathbf{x}_m^{(s)}, \mathbf{h}_{m-1}^{(s)}) \quad [18.33]$$

$$\mathbf{h}_m^{(s,i+1)} = \text{LSTM}(\mathbf{h}_m^{(s,i)}, \mathbf{h}_{m-1}^{(s)}), \quad \forall i \geq 1. \quad [18.34]$$

9637 The original work on sequence-to-sequence translation used four layers; in 2016,
 9638 Google’s commercial machine translation system used eight layers (Wu et al., 2016).⁵

- 9639 • Significant improvements can be obtained by creating an **ensemble** of translation
 9640 models, each trained from a different random initialization. For an ensemble of size
 9641 N , the per-token decoding probability is set equal to,

$$p(w^{(t)} | \mathbf{z}, \mathbf{w}_{1:m-1}^{(t)}) = \frac{1}{N} \sum_{i=1}^N p_i(w^{(t)} | \mathbf{z}, \mathbf{w}_{1:m-1}^{(t)}), \quad [18.35]$$

9642 where p_i is the decoding probability for model i . Each translation model in the
 9643 ensemble includes its own encoder and decoder networks.

- 9644 • The original sequence-to-sequence model used a fairly standard training setup: stochas-
 9645 tic gradient descent with an exponentially decreasing learning rate after the first five
 9646 epochs; mini-batches of 128 sentences, chosen to have similar length so that each
 9647 sentence on the batch will take roughly the same amount of time to process; gradi-
 9648 ent clipping (see § 3.3.4) to ensure that the norm of the gradient never exceeds some
 9649 predefined value.

9650 18.3.1 Neural attention

9651 The sequence-to-sequence model discussed in the previous section was a radical depart-
 9652 ure from statistical machine translation, in which each word or phrase in the target lan-
 9653 guage is conditioned on a single word or phrase in the source language. Both approaches
 9654 have advantages. Statistical translation leverages the idea of compositionality — transla-
 9655 tions of large units should be based on the translations of their component parts — and
 9656 this seems crucial if we are to scale translation to longer units of text. But the translation
 9657 of each word or phrase often depends on the larger context, and encoder-decoder models
 9658 capture this context at the sentence level.

⁵Google reports that this system took six days to train for English-French translation, using 96 NVIDIA K80 GPUs, which would have cost roughly half a million dollars at the time.

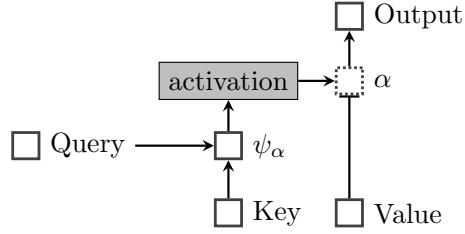


Figure 18.6: A general view of neural attention. The dotted box indicates that each $\alpha_{m \rightarrow n}$ can be viewed as a **gate** on value n .

Is it possible for translation to be both contextualized and compositional? One approach is to augment neural translation with an **attention mechanism**. The idea of neural attention was described in § 17.5, but its application to translation bears further discussion. In general, attention can be thought of as using a query to select from a memory of key-value pairs. However, the query, keys, and values are all vectors, and the entire operation is differentiable. For each key n in the memory, we compute a score $\psi_\alpha(m, n)$ with respect to the query m . That score is a function of the compatibility of the key and the query, and can be computed using a small feedforward neural network. The vector of scores is passed through an activation function, such as softmax. The output of this activation function is a vector of non-negative numbers $[\alpha_{m \rightarrow 1}, \alpha_{m \rightarrow 2}, \dots, \alpha_{m \rightarrow N}]^\top$, with length N equal to the size of the memory. Each value in the memory v_n is multiplied by the attention $\alpha_{m \rightarrow n}$; the sum of these scaled values is the output. This process is shown in Figure 18.6. In the extreme case that $\alpha_{m \rightarrow n} = 1$ and $\alpha_{m \rightarrow n'} = 0$ for all other n' , then the attention mechanism simply selects the value v_n from the memory.

Neural attention makes it possible to integrate alignment into the encoder-decoder architecture. Rather than encoding the entire source sentence into a fixed length vector z , it can be encoded into a matrix $Z \in \mathbb{R}^{K \times M^{(S)}}$, where K is the dimension of the hidden state, and $M^{(S)}$ is the number of tokens in the source input. Each column of Z represents the state of a recurrent neural network over the source sentence. These vectors are constructed from a **bidirectional LSTM** (see § 7.6), which can be a deep network as shown in Figure 18.5. These columns are both the keys and the values in the attention mechanism.

At each step m in decoding, the attentional state is computed by executing a query, which is equal to the state of the decoder, $h_m^{(t)}$. The resulting compatibility scores are,

$$\psi_\alpha(m, n) = v_\alpha \cdot \tanh(\Theta_\alpha[h_m^{(t)}; h_n^{(s)}]). \quad [18.36]$$

The function ψ is thus a two layer feedforward neural network, with weights v_α on the output layer, and weights Θ_α on the input layer. To convert these scores into attention weights, we apply an activation function, which can be vector-wise softmax or an

9683 element-wise sigmoid:

Softmax attention

$$\alpha_{m \rightarrow n} = \frac{\exp \psi_\alpha(m, n)}{\sum_{n'=1}^{M^{(s)}} \exp \psi_\alpha(m, n')} \quad [18.37]$$

Sigmoid attention

$$\alpha_{m \rightarrow n} = \sigma(\psi_\alpha(m, n)) \quad [18.38]$$

The attention α is then used to compute an **context vector** c_m by taking a weighted average over the columns of Z ,

$$c_m = \sum_{n=1}^{M^{(s)}} \alpha_{m \rightarrow n} z_n, \quad [18.39]$$

where $\alpha_{m \rightarrow n} \in [0, 1]$ is the amount of attention from word m of the target to word n of the source. The context vector can be incorporated into the decoder's word output probability model, by adding another layer to the decoder (Luong et al., 2015):

$$\tilde{h}_m^{(t)} = \tanh(\Theta_c[h_m^{(t)}; c_m]) \quad [18.40]$$

$$p(w_{m+1}^{(t)} | w_{1:m}^{(t)}, w^{(s)}) \propto \exp\left(\beta_{w_{m+1}^{(t)}} \cdot \tilde{h}_m^{(t)}\right). \quad [18.41]$$

9684 Here the decoder state $h_m^{(t)}$ is concatenated with the context vector, forming the input
 9685 to compute a final output vector $\tilde{h}_m^{(t)}$. The context vector can be incorporated into the
 9686 decoder recurrence in a similar manner (Bahdanau et al., 2014).

9687 **18.3.2 *Neural machine translation without recurrence**

In the encoder-decoder model, attention's “keys and values” are the hidden state representations in the encoder network, z , and the “queries” are state representations in the decoder network $h^{(t)}$. It is also possible to completely eliminate recurrence from neural translation, by applying **self-attention** (Lin et al., 2017; Kim et al., 2017) within the encoder and decoder, as in the **transformer architecture** (Vaswani et al., 2017). For level i , the basic equations of the encoder side of the transformer are:

$$z_m^{(i)} = \sum_{n=1}^{M^{(s)}} \alpha_{m \rightarrow n}^{(i)} (\Theta_v h_n^{(i-1)}) \quad [18.42]$$

$$h_m^{(i)} = \Theta_2 \text{ReLU}\left(\Theta_1 z_m^{(i)} + b_1\right) + b_2. \quad [18.43]$$

9688 For each token m at level i , we compute self-attention over the entire source sentence:
 9689 the keys, values, and queries are all projections of the vector $\mathbf{h}^{(i-1)}$. The attention scores
 9690 $\alpha_{m \rightarrow n}^{(i)}$ are computed using a scaled form of softmax attention,

$$\alpha_{m \rightarrow n} \propto \exp(\psi_\alpha(m, n)/M), \quad [18.44]$$

9691 where M is the length of the input. This encourages the attention to be more evenly
 9692 dispersed across the input. Self-attention is applied across multiple “heads”, each using
 9693 different projections of $\mathbf{h}^{(i-1)}$ to form the keys, values, and queries.

9694 The output of the self-attentional layer is the representation $\mathbf{z}_m^{(i)}$, which is then passed
 9695 through a two-layer feed-forward network, yielding the input to the next layer, $\mathbf{h}^{(i)}$. To
 9696 ensure that information about word order in the source is integrated into the model, the
 9697 encoder includes **positional encodings** of the index of each word in the source. These
 9698 encodings are vectors for each position $m \in \{1, 2, \dots, M\}$. The positional encodings are
 9699 concatenated with the word embeddings \mathbf{x}_m at the base layer of the model.⁶

9700 Convolutional neural networks (see § 3.4) have also been applied as encoders in neu-
 9701 ral machine translation. For each word $w_m^{(s)}$, a convolutional network computes a rep-
 9702 resentation $\mathbf{h}_m^{(s)}$ from the embeddings of the word and its neighbors. This procedure is
 9703 applied several times, creating a deep convolutional network. The recurrent decoder then
 9704 computes a set of attention weights over these convolutional representations, using the
 9705 decoder’s hidden state $\mathbf{h}^{(t)}$ as the queries. This attention vector is used to compute a
 9706 weighted average over the outputs of *another* convolutional neural network of the source,
 9707 yielding an averaged representation c_m , which is then fed into the decoder. As with the
 9708 transformer, speed is the main advantage over recurrent encoding models; another sim-
 9709 ilarity is that word order information is approximated through the use of positional en-
 9710 codings. It seems likely that there are limitations to how well positional encodings can
 9711 account for word order and deeper linguistic structure. But for the moment, the com-
 9712 putational advantages of such approaches have put them on par with the best recurrent
 9713 translation models.⁷

9714 18.3.3 Out-of-vocabulary words

9715 Thus far, we have treated translation as a problem at the level of words or phrases. For
 9716 words that do not appear in the training data, all such models will struggle. There are
 9717 two main reasons for the presence of out-of-vocabulary (OOV) words:

⁶The transformer architecture relies on several additional tricks, including **layer normalization** (see § 3.3.4) and residual connections around the nonlinear activations (see § 3.2.2).

⁷A recent evaluation found that best performance was obtained by using a recurrent network for the decoder, and a transformer for the encoder (Chen et al., 2018). The transformer was also found to significantly outperform a convolutional neural network.

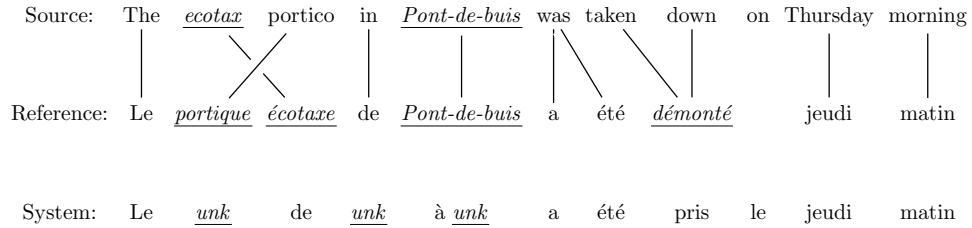


Figure 18.7: Translation with *unknown words*. The system outputs *unk* to indicate words that are outside its vocabulary. Figure adapted from Luong et al. (2015).

- New proper nouns, such as family names or organizations, are constantly arising — particularly in the news domain. The same is true, to a lesser extent, for technical terminology. This issue is shown in Figure 18.7.
- In many languages, words have complex internal structure, known as **morphology**. An example is German, which uses compounding to form nouns like *Abwasserbehandlungsanlage* (*sewage water treatment plant*; example from Sennrich et al. (2016)). While compounds could in principle be addressed by better tokenization (see § 8.4), other morphological processes involve more complex transformations of subword units.

Names and technical terms can be handled in a postprocessing step: after first identifying alignments between unknown words in the source and target, we can look up each aligned source word in a dictionary, and choose a replacement (Luong et al., 2015). If the word does not appear in the dictionary, it is likely to be a proper noun, and can be copied directly from the source to the target. This approach can also be integrated directly into the translation model, rather than applying it as a postprocessing step (Jean et al., 2015).

Words with complex internal structure can be handled by translating subword units rather than entire words. A popular technique for identifying subword units is **byte-pair encoding** (BPE; Gage, 1994; Sennrich et al., 2016). The initial vocabulary is defined as the set of characters used in the text. The most common character bigram is then merged into a new symbol, and the vocabulary is updated. The merging operation is applied repeatedly, until the vocabulary reaches some maximum size. For example, given the dictionary $\{fish, fished, want, wanted, bike, biked\}$, we would first merge $e+d$ into the subword unit ed , since this bigram appears in three words of the six words. Next, there are several bigrams that each appear in a pair of words: $f+i$, $i+s$, $s+h$, $w+a$, $a+n$, etc. These can be merged in any order, resulting in the segmentation, $\{fish, fish+ed, want, want+ed, bik+e, bik+ed\}$. At this point, there are no subword bigrams that appear more than once. In real data, merging is performed until the number of subword units reaches some predefined threshold,

9745 such as 10^4 .

9746 Each subword unit is treated as a token for translation, in both the encoder (source
 9747 side) and decoder (target side). BPE can be applied jointly to the union of the source and
 9748 target vocabularies, identifying subword units that appear in both languages. For lan-
 9749 guages that have different scripts, such as English and Russian, **transliteration** between
 9750 the scripts should be applied first.⁸

9751 18.4 Decoding

Given a trained translation model, the decoding task is:

$$\hat{\mathbf{w}}^{(t)} = \underset{\mathbf{w} \in \mathcal{V}^*}{\operatorname{argmax}} \Psi(\mathbf{w}, \mathbf{w}^{(s)}), \quad [18.45]$$

9752 where $\mathbf{w}^{(t)}$ is a sequence of tokens from the target vocabulary \mathcal{V} . It is not possible to
 9753 efficiently obtain exact solutions to the decoding problem, for even minimally effective
 9754 models in either statistical or neural machine translation. Today's state-of-the-art transla-
 9755 tion systems use **beam search** (see § 11.3.1.4), which is an incremental decoding algorithm
 9756 that maintains a small constant number of competitive hypotheses. Such greedy approxi-
 9757 mations are reasonably effective in practice, and this may be in part because the decoding
 9758 objective is only loosely correlated with measures of translation quality, so that exact op-
 9759 timization of [18.45] may not greatly improve the resulting translations.

Decoding in neural machine translation is somewhat simpler than in phrase-based
 statistical machine translation.⁹ The scoring function Ψ is defined,

$$\Psi(\mathbf{w}^{(t)}, \mathbf{w}^{(s)}) = \sum_{m=1}^{M^{(t)}} \psi(w_m^{(t)}; \mathbf{w}_{1:m-1}^{(t)}, \mathbf{z}) \quad [18.46]$$

$$\psi(w^{(t)}; \mathbf{w}_{1:m-1}^{(t)}, \mathbf{z}) = \beta_{w_m^{(t)}} \cdot \mathbf{h}_m^{(t)} - \log \sum_{w \in \mathcal{V}} \exp(\beta_w \cdot \mathbf{h}_m^{(t)}), \quad [18.47]$$

9760 where \mathbf{z} is the encoding of the source sentence $\mathbf{w}^{(s)}$, and $\mathbf{h}_m^{(t)}$ is a function of the encoding
 9761 \mathbf{z} and the decoding history $\mathbf{w}_{1:m-1}^{(t)}$. This formulation subsumes the attentional translation
 9762 model, where \mathbf{z} is a matrix encoding of the source.

Now consider the incremental decoding algorithm,

$$\hat{w}_m^{(t)} = \underset{w \in \mathcal{V}}{\operatorname{argmax}} \psi(w; \hat{\mathbf{w}}_{1:m-1}^{(t)}, \mathbf{z}), \quad m = 1, 2, \dots \quad [18.48]$$

⁸Transliteration is crucial for converting names and other foreign words between languages that do not share a single script, such as English and Japanese. It is typically approached using the finite-state methods discussed in chapter 9 (Knight and Graehl, 1998).

⁹For more on decoding in phrase-based statistical models, see Koehn (2009).

9763 This algorithm selects the best target language word at position m , assuming that it has
 9764 already generated the sequence $\hat{w}_{1:m-1}^{(t)}$. (Termination can be handled by augmenting
 9765 the vocabulary \mathcal{V} with a special end-of-sequence token, ■.) The incremental algorithm
 9766 is likely to produce a suboptimal solution to the optimization problem defined in Equa-
 9767 tion 18.45, because selecting the highest-scoring word at position m can set the decoder
 9768 on a “garden path,” in which there are no good choices at some later position $n > m$. We
 9769 might hope for some dynamic programming solution, as in sequence labeling (§ 7.3). But
 9770 the Viterbi algorithm and its relatives rely on a Markov decomposition of the objective
 9771 function into a sum of local scores: for example, scores can consider locally adjacent tags
 9772 (y_m, y_{m-1}), but not the entire tagging history $y_{1:m}$. This decomposition is not applicable
 9773 to recurrent neural networks, because the hidden state $h_m^{(t)}$ is impacted by the entire his-
 9774 tory $w_{1:m}^{(t)}$; this sensitivity to long-range context is precisely what makes recurrent neural
 9775 networks so effective.¹⁰ In fact, it can be shown that decoding from any recurrent neural
 9776 network is NP-complete (Siegelmann and Sontag, 1995; Chen et al., 2018).

9777 **Beam search** Beam search is a general technique for avoiding search errors when ex-
 9778 haustive search is impossible; it was first discussed in § 11.3.1.4. Beam search can be
 9779 seen as a variant of the incremental decoding algorithm sketched in Equation 18.48, but
 9780 at each step m , a set of K different hypotheses are kept on the beam. For each hypothesis
 9781 $k \in \{1, 2, \dots, K\}$, we compute both the current score $\sum_{m=1}^{M^{(t)}} \psi(w_{k,m}^{(t)}; w_{k,1:m-1}^{(t)}, z)$ as well as
 9782 the current hidden state $h_k^{(t)}$. At each step in the beam search, the K top-scoring children
 9783 of each hypothesis currently on the beam are “expanded”, and the beam is updated. For
 9784 a detailed description of beam search for RNN decoding, see Graves (2012).

9785 **Learning and search** Conventionally, the learning algorithm is trained to predict the
 9786 right token in the translation, conditioned on the translation history being correct. But
 9787 if decoding must be approximate, then we might do better by modifying the learning
 9788 algorithm to be robust to errors in the translation history. **Scheduled sampling** does this
 9789 by training on histories that sometimes come from the ground truth, and sometimes come
 9790 from the model’s own output (Bengio et al., 2015).¹¹ As training proceeds, the training
 9791 wheels come off: we increase the fraction of tokens that come from the model rather than
 9792 the ground truth. Another approach is to train on an objective that relates directly to beam
 9793 search performance (Wiseman et al., 2016). **Reinforcement learning** has also been applied
 9794 to decoding of RNN-based translation models, making it possible to directly optimize
 9795 translation metrics such as BLEU (Ranzato et al., 2016).

¹⁰Note that this problem does not impact RNN-based sequence labeling models (see § 7.6). This is because the tags produced by these models do not affect the recurrent state.

¹¹Scheduled sampling builds on earlier work on learning to search (Daumé III et al., 2009; Ross et al., 2011), which are also described in § 15.2.4.

9796 18.5 Training towards the evaluation metric

9797 In likelihood-based training, the objective is to maximize the probability of a parallel
 9798 corpus. However, translations are not evaluated in terms of likelihood: metrics like BLEU
 9799 consider only the correctness of a single output translation, and not the range of prob-
 9800 abilities that the model assigns. It might therefore be better to train translation models
 9801 to achieve the highest BLEU score possible — to the extent that we believe BLEU mea-
 9802 sures translation quality. Unfortunately, BLEU and related metrics are not friendly for
 9803 optimization: they are discontinuous, non-differentiable functions of the parameters of
 9804 the translation model.

Consider an error function $\Delta(\hat{\mathbf{w}}^{(t)}, \mathbf{w}^{(t)})$, which measures the discrepancy between the system translation $\hat{\mathbf{w}}^{(t)}$ and the reference translation $\mathbf{w}^{(t)}$; this function could be based on BLEU or any other metric on translation quality. One possible criterion would be to select the parameters θ that minimize the error of the system's preferred translation,

$$\hat{\mathbf{w}}^{(t)} = \operatorname{argmax}_{\mathbf{w}^{(t)}} \Psi(\mathbf{w}^{(t)}, \mathbf{w}^{(s)}; \theta) \quad [18.49]$$

$$\hat{\theta} = \operatorname{argmin}_{\theta} \Delta(\hat{\mathbf{w}}^{(t)}, \mathbf{w}^{(s)}) \quad [18.50]$$

9805 However, identifying the top-scoring translation $\hat{\mathbf{w}}^{(t)}$ is usually intractable, as described
 9806 in the previous section. In **minimum error-rate training (MERT)**, $\hat{\mathbf{w}}^{(t)}$ is selected from a
 9807 set of candidate translations $\mathcal{Y}(\mathbf{w}^{(s)})$; this is typically a strict subset of all possible transla-
 9808 tions, so that it is only possible to optimize an approximation to the true error rate (Och
 9809 and Ney, 2003).

A further issue is that the objective function in Equation 18.50 is discontinuous and non-differentiable, due to the argmax over translations: an infinitesimal change in the parameters θ could cause another translation to be selected, with a completely different error. To address this issue, we can instead minimize the **risk**, which is defined as the expected error rate,

$$R(\theta) = E_{\hat{\mathbf{w}}^{(t)} | \mathbf{w}^{(s)}, \theta} [\Delta(\hat{\mathbf{w}}^{(t)}, \mathbf{w}^{(t)})] \quad [18.51]$$

$$= \sum_{\hat{\mathbf{w}}^{(t)} \in \mathcal{Y}(\mathbf{w}^{(s)})} p(\hat{\mathbf{w}}^{(t)} | \mathbf{w}^{(s)}) \times \Delta(\hat{\mathbf{w}}^{(t)}, \mathbf{w}^{(t)}). \quad [18.52]$$

9810 **Minimum risk training** minimizes the sum of $R(\theta)$ across all instances in the training set.

The risk can be generalized by exponentiating the translation probabilities,

$$\tilde{p}(\mathbf{w}^{(t)}; \theta, \alpha) \propto \left(p(\mathbf{w}^{(t)} | \mathbf{w}^{(s)}; \theta) \right)^\alpha \quad [18.53]$$

$$\tilde{R}(\theta) = \sum_{\hat{\mathbf{w}}^{(t)} \in \mathcal{Y}(\mathbf{w}^{(s)})} \tilde{p}(\hat{\mathbf{w}}^{(t)} | \mathbf{w}^{(s)}; \alpha, \theta) \times \Delta(\hat{\mathbf{w}}^{(t)}, \mathbf{w}^{(t)}) \quad [18.54]$$

where $\mathcal{Y}(\mathbf{w}^{(s)})$ is now the set of *all* possible translations for $\mathbf{w}^{(s)}$. Exponentiating the probabilities in this way is known as **annealing** (Smith and Eisner, 2006). When $\alpha = 1$, then $\tilde{R}(\boldsymbol{\theta}) = R(\boldsymbol{\theta})$; when $\alpha = \infty$, then $\tilde{R}(\boldsymbol{\theta})$ is equivalent to the sum of the errors of the maximum probability translations for each sentence in the dataset.

Clearly the set of candidate translations $\mathcal{Y}(\mathbf{w}^{(s)})$ is too large to explicitly sum over. Because the error function Δ generally does not decompose into smaller parts, there is no efficient dynamic programming solution to sum over this set. We can approximate the sum $\sum_{\mathbf{w}^{(t)} \in \mathcal{Y}(\mathbf{w}^{(s)})}$ with a sum over a finite number of samples, $\{\mathbf{w}_1^{(t)}, \mathbf{w}_2^{(t)}, \dots, \mathbf{w}_K^{(t)}\}$. If these samples were drawn uniformly at random, then the (annealed) risk would be approximated as (Shen et al., 2016),

$$\tilde{R}(\boldsymbol{\theta}) \approx \frac{1}{Z} \sum_{k=1}^K \tilde{p}(\mathbf{w}_k^{(t)} | \mathbf{w}^{(s)}; \boldsymbol{\theta}, \alpha) \times \Delta(\mathbf{w}_k^{(t)}, \mathbf{w}^{(t)}) \quad [18.55]$$

$$Z = \sum_{k=1}^K \tilde{p}(\mathbf{w}_k^{(t)} | \mathbf{w}^{(s)}; \boldsymbol{\theta}, \alpha). \quad [18.56]$$

Shen et al. (2016) report that performance plateaus at $K = 100$ for minimum risk training of neural machine translation.

Uniform sampling over the set of all possible translations is undesirable, because most translations have very low probability. A solution from Monte Carlo estimation is **importance sampling**, in which we draw samples from a **proposal distribution** $q(\mathbf{w}^{(t)})$. This distribution can be set equal to the current translation model $p(\mathbf{w}^{(t)} | \mathbf{w}^{(s)}; \boldsymbol{\theta})$. Each sample is then weighted by an **importance score**, $\omega_k = \frac{\tilde{p}(\mathbf{w}_k^{(t)} | \mathbf{w}^{(s)})}{q(\mathbf{w}_k^{(t)})}$. The effect of this weighting is to correct for any mismatch between the proposal distribution q and the true distribution \tilde{p} . The risk can then be approximated as,

$$\mathbf{w}_k^{(t)} \sim q(\mathbf{w}^{(t)}) \quad [18.57]$$

$$\omega_k = \frac{\tilde{p}(\mathbf{w}_k^{(t)} | \mathbf{w}^{(s)})}{q(\mathbf{w}_k^{(t)})} \quad [18.58]$$

$$\tilde{R}(\boldsymbol{\theta}) \approx \frac{1}{\sum_{k=1}^K \omega_k} \sum_{k=1}^K \omega_k \times \Delta(\mathbf{w}_k^{(t)}, \mathbf{w}^{(t)}). \quad [18.59]$$

Importance sampling will generally give a more accurate approximation with a given number of samples. The only formal requirement is that the proposal assigns non-zero probability to every $\mathbf{w}^{(t)} \in \mathcal{Y}(\mathbf{w}^{(s)})$. For more on importance sampling and related methods, see Robert and Casella (2013).

9821 Additional resources

9822 A complete textbook on machine translation is available from Koehn (2009). While this
9823 book precedes recent work on neural translation, a more recent draft chapter on neural
9824 translation models is also available (Koehn, 2017). Neubig (2017) provides a comprehen-
9825 sive tutorial on neural machine translation, starting from first principles. The course notes
9826 from Cho (2015) are also useful.

9827 Several neural machine translation systems are available, in connection with each of
9828 the major neural computing libraries: `lamtram` is an implementation of neural machine
9829 translation in the `dynet` (Neubig et al., 2017); `OpenNMT` (Klein et al., 2017) is an imple-
9830 mentation primarily in `Torch`; `tensor2tensor` is an implementation of several of the
9831 Google translation models in `tensorflow` (Abadi et al., 2016).

9832 Literary translation is especially challenging, even for expert human translators. Mes-
9833 sud (2014) describes some of these issues in her review of an English translation of *L'étranger*,
9834 the 1942 French novel by Albert Camus.¹² She compares the new translation by Sandra
9835 Smith against earlier translations by Stuart Gilbert and Matthew Ward, focusing on the
9836 difficulties presented by a single word in the first sentence:

9837 Then, too, Smith has reconsidered the book's famous opening. Camus's
9838 original is deceptively simple: "*Aujourd'hui, maman est morte.*" Gilbert influ-
9839 enced generations by offering us "Mother died today"—inscribing in Meur-
9840 sault [the narrator] from the outset a formality that could be construed as
9841 heartlessness. But *maman*, after all, is intimate and affectionate, a child's name
9842 for his mother. Matthew Ward concluded that it was essentially untranslatable
9843 ("mom" or "mummy" being not quite apt), and left it in the original French:
9844 "Maman died today." There is a clear logic in this choice; but as Smith has
9845 explained, in an interview in *The Guardian*, *maman* "didn't really tell the reader
9846 anything about the connotation." She, instead, has translated the sentence as
9847 "My mother died today."

9848 I chose "My mother" because I thought about how someone would
9849 tell another person that his mother had died. Meursault is speaking
9850 to the reader directly. "My mother died today" seemed to me the
9851 way it would work, and also implied the closeness of "maman" you
9852 get in the French.

9853 Elsewhere in the book, she has translated *maman* as "mama" — again, striving
9854 to come as close as possible to an actual, colloquial word that will carry the
9855 same connotations as *maman* does in French.

¹²The book review is currently available online at <http://www.nybooks.com/articles/2014/06/05/camus-new-letranger/>.

9856 The passage is a useful reminder that while the quality of machine translation has
9857 improved dramatically in recent years, expert human translations draw on considerations
9858 that are beyond the ken of any known computational approach.

9859 **Exercises**

9860 1. Give a synchronized derivation (§ 18.2.4) for the Spanish-English translation,

9861 (18.4) *El pez enojado atacado.*
 The fish angry attacked.
9862 The angry fish attacked.

9863 As above, the second line shows a word-for-word gloss, and the third line shows
9864 the desired translation. Use the synchronized production rule in [18.22], and design
9865 the other production rules necessary to derive this sentence pair. You may derive
9866 (*atacado*, *attacked*) directly from VP.

9867 Chapter 19

9868 Text generation

9869 In many of the most interesting problems in natural language processing, language is
9870 the output. The previous chapter described the specific case of machine translation, but
9871 there are many other applications, from summarization of research articles, to automated
9872 journalism, to dialogue systems. This chapter emphasizes three main scenarios: data-to-
9873 text, in which text is generated to explain or describe a structured record or unstructured
9874 perceptual input; text-to-text, which typically involves fusing information from multiple
9875 linguistic sources into a single coherent summary; and dialogue, in which text is generated
9876 as part of an interactive conversation with one or more human participants.

9877 19.1 Data-to-text generation

9878 In data-to-text generation, the input ranges from structured records, such as the descrip-
9879 tion of an weather forecast (as shown in Figure 19.1), to unstructured perceptual data,
9880 such as a raw image or video; the output may be a single sentence, such as an image cap-
9881 tion, or a multi-paragraph argument. Despite this diversity of conditions, all data-to-text
9882 systems share some of the same challenges (Reiter and Dale, 2000):

- 9883 • determining what parts of the data to describe;
- 9884 • planning a presentation of this information;
- 9885 • **lexicalizing** the data into words and phrases;
- 9886 • organizing words and phrases into well-formed sentences and paragraphs.

9887 The earlier stages of this process are sometimes called **content selection** and **text plan-**
9888 **ning**; the later stages are often called **surface realization**.

9889 Early systems for data-to-text generation were modular, with separate software com-
9890 ponents for each task. Artificial intelligence **planning** algorithms can be applied to both

Database:	Temperature			Cloud Sky Cover		
	time	min	mean	max	time	percent (%)
	06:00-21:00	9	15	21	06:00-09:00	25-50
	09:00-12:00				09:00-12:00	50-75
Wind Speed			Wind Direction			
			time	mode		
	06:00-21:00	15	20	30	06:00-21:00	S

Text: Cloudy, with temperatures between 10 and 20 degrees. South wind around 20 mph.

Figure 19.1: An example input-output pair for the task of generating text descriptions of weather forecasts (Konstas and Lapata, 2013). [todo: permission]

the high-level information structure and the organization of individual sentences, ensuring that communicative goals are met (McKeown, 1992; Moore and Paris, 1993). Surface realization can be performed by grammars or templates, which link specific types of data to candidate words and phrases. A simple example template is offered by Wiseman et al. (2017), for generating descriptions of basketball games:

(19.1) The <team1> (<wins1>-<losses1>) defeated the <team2> (<wins2>-<losses2>),
<pts1>-<pts2>. The New York Knicks (45-5) defeated the Boston Celtics (11-38), 115-79.

For more complex cases, it may be necessary to apply morphological inflections such as pluralization and tense marking — even in the simple example above, languages such as Russian would require case marking suffixes for the team names. Such inflections can be applied as a postprocessing step. Another difficult challenge for surface realization is the generation of varied **referring expressions** (e.g., *The Knicks*, *New York*, *they*), which is critical to avoid repetition. As discussed in § 16.2.1, the form of referring expressions is constrained by the discourse and information structure.

An example at the intersection of rule-based and statistical techniques is the Nitrogen system (Langkilde and Knight, 1998). The input to Nitrogen is an abstract meaning representation (AMR; see § 13.3) of semantic content to be expressed in a single sentence. In data-to-text scenarios, the abstract meaning representation is the output of a higher-level text planning stage. A set of rules then converts the abstract meaning representation into various sentence plans, which may differ in both the high-level structure (e.g., active versus passive voice) as well as the low-level details (e.g., word and phrase choice). Some examples are shown in Figure 19.2. To control the combinatorial explosion in the number of possible realizations for any given meaning, the sentence plans are unified into a single finite-state acceptor, in which word tokens are represented by arcs (see § 9.1.1). A bigram

```
(a / admire-01
  :ARG0 (v / visitor
    :ARG1-of (c / arrive-01
      :ARG4 (j / Japan)))
  :ARG1 (m / "Mount Fuji"))
```

- Visitors who came to Japan admire Mount Fuji.
- Visitors who came in Japan admire Mount Fuji.
- Mount Fuji is admired by the visitor who came in Japan.

Figure 19.2: Abstract meaning representation and candidate surface realizations from the Nitrogen system. Example adapted from Langkilde and Knight (1998).

language model is then used to compute weights on the arcs, so that the shortest path is also the surface realization with the highest bigram language model probability.

More recent systems are unified models that are trained end-to-end using backpropagation. Data-to-text generation shares many properties with machine translation, including a problem of **alignment**: labeled examples provide the data and the text, but they do not specify which parts of the text correspond to which parts of the data. For example, to learn from Figure 19.1, the system must align the word *cloudy* to records in CLOUD SKY COVER, the phrases *10* and *20 degrees* to the MIN and MAX fields in TEMPERATURE, and so on. As in machine translation, both latent variables and neural attention have been proposed as solutions.

19.1.1 Latent data-to-text alignment

Given a dataset of texts and associated records $\{(\mathbf{w}^{(i)}, \mathbf{y}^{(i)})\}_{i=1}^N$, our goal is to learn a model Ψ , so that

$$\hat{\mathbf{w}} = \underset{\mathbf{w} \in \mathcal{V}^*}{\operatorname{argmax}} \Psi(\mathbf{w}, \mathbf{y}; \theta), \quad [19.1]$$

where \mathcal{V}^* is the set of strings over a discrete vocabulary, and θ is a vector of parameters. The relationship between \mathbf{w} and \mathbf{y} is complex: the data \mathbf{y} may contain dozens of records, and \mathbf{w} may extend to several sentences. To facilitate learning and inference, it would be helpful to decompose the scoring function Ψ into subcomponents. This would be possible if given an **alignment**, specifying which element of \mathbf{y} is expressed in each part of \mathbf{w} (Angeli et al., 2010):

$$\Psi(\mathbf{w}, \mathbf{y}; \theta) = \sum_{m=1}^M \psi_{w,y}(\mathbf{w}_m, \mathbf{y}_{z_m}) + \psi_z(z_m, z_{m-1}), \quad [19.2]$$

where z_m indicates the record aligned to word m . For example, in Figure 19.1, z_1 might specify that the word *cloudy* is aligned to the record *cloud-sky-cover:percent*. The score for this alignment would then be given by the weight on features such as

$$(\textit{cloudy}, \textit{cloud-sky-cover:percent}), \quad [19.3]$$

which could be learned from labeled data $\{(\mathbf{w}^{(i)}, \mathbf{y}^{(i)}, \mathbf{z}^{(i)})\}_{i=1}^N$. The function ψ_z can learn to assign higher scores to alignments that are coherent, referring to the same records in adjacent parts of the text.¹

Several datasets include structured records and natural language text (Barzilay and McKeown, 2005; Chen and Mooney, 2008; Liang and Klein, 2009), but the alignments between text and records are usually not available.² One solution is to model the problem probabilistically, treating the alignment as a latent variable (Liang et al., 2009; Konstas and Lapata, 2013). The model can then be estimated using expectation maximization or sampling (see chapter 5).

19.1.2 Neural data-to-text generation

The **encoder-decoder model** and **neural attention** were introduced in § 18.3 as methods for neural machine translation. They can also be applied to data-to-text generation, with the data acting as the source language (Mei et al., 2016). In neural machine translation, the attention mechanism linked words in the source to words in the target; in data-to-text generation, the attention mechanism can link each part of the generated text back to a record in the data. The biggest departure from translation is in the encoder, which depends on the form of the data.

19.1.2.1 Data encoders

In some types of structured records, all values are drawn from discrete sets. For example, the birthplace of an individual is drawn from a discrete set of possible locations; the diagnosis and treatment of a patient are drawn from an exhaustive list of clinical codes (Johnson et al., 2016). In such cases, vector embeddings can be estimated for each field and possible value: for example, a vector embedding for the field BIRTHPLACE, and another embedding for the value BERKELEY_CALIFORNIA (Bordes et al., 2011). The table of such embeddings serves as the encoding of a structured record (He et al., 2017). It is also possible to compress the entire table into a single vector representation, by **pooling** across the embeddings of each field and value (Lebret et al., 2016).

Sequences Some types of structured records have a natural ordering, such as events in a game (Chen and Mooney, 2008) and steps in a recipe (Tutin and Kittredge, 1992). For example, the following records describe a sequence of events in a robot soccer match (Mei

¹More expressive decompositions of Ψ are possible. For example, Wong and Mooney (2007) use a synchronous context-free grammar (see § 18.2.4) to “translate” between a meaning representation and natural language text.

²An exception is a dataset of records and summaries from American football games, containing annotations of alignments between sentences and records (Snyder and Barzilay, 2007).

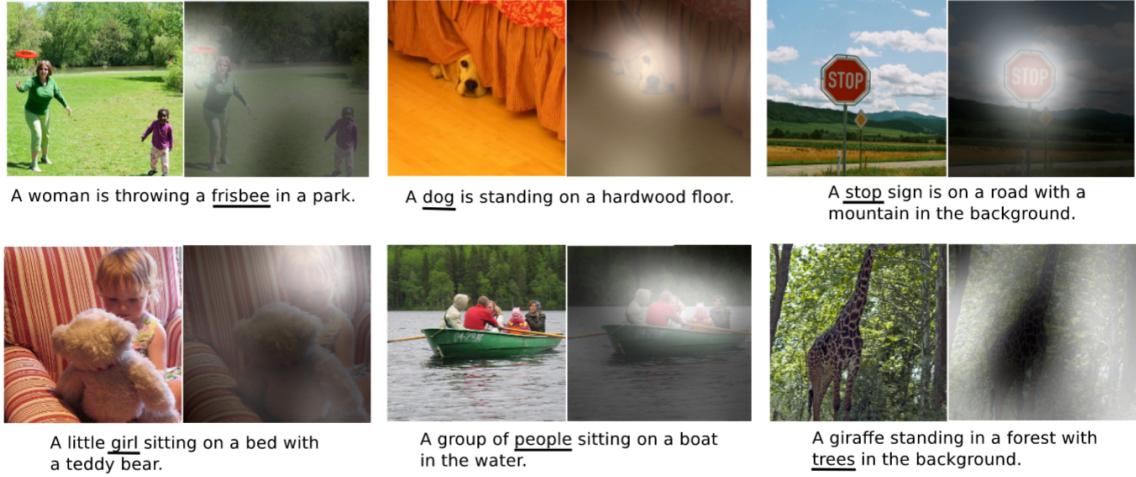


Figure 19.3: Examples of the image captioning task, with attention masks shown for each of the underlined words. From Xu et al. (2015). [todo: permission]

et al., 2016):

```
PASS(arg1 = PURPLE6,arg2 = PURPLE3)
KICK(arg1 = PURPLE3)
BADPASS(arg1 = PURPLE3,arg2 = PINK9).
```

9965 Each event is a single record, and can be encoded by a concatenation of vector representations for the event type (e.g., PASS), the field (e.g., arg1), and the values (e.g., PURPLE3),
9966 e.g.,
9967

$$\mathbf{X} = [\mathbf{u}_{\text{PASS}}, \mathbf{u}_{\text{arg1}}, \mathbf{u}_{\text{PURPLE6}}, \mathbf{u}_{\text{arg2}}, \mathbf{u}_{\text{PURPLE3}}]. \quad [19.4]$$

9968 This encoding can then act as the input layer for a recurrent neural network, yielding a
9969 sequence of vector representations $\{z_r\}_{r=1}^R$, where r indexes over records. Interestingly,
9970 this sequence-based approach is effective even in cases where there is no natural ordering
9971 over the records, such as the weather data in Figure 19.1 (Mei et al., 2016).

9972 **Images** Another flavor of data-to-text generation is the generation of text captions for
9973 images. Examples from this task are shown in Figure 19.3. Images are naturally repre-
9974 sented as tensors: a color image of 320×240 pixels would be stored as a tensor with
9975 $320 \times 240 \times 3$ intensity values. The dominant approach to image classification is to en-
9976 code images as vectors using a combination of convolution and pooling (Krizhevsky et al.,
9977 2012). Chapter 3 explains how to use convolutional networks for text; for images, convo-
9978 lution is applied across the vertical, horizontal, and color dimensions. By pooling the re-
9979 sults of successive convolutions, the image is converted to a vector representation, which

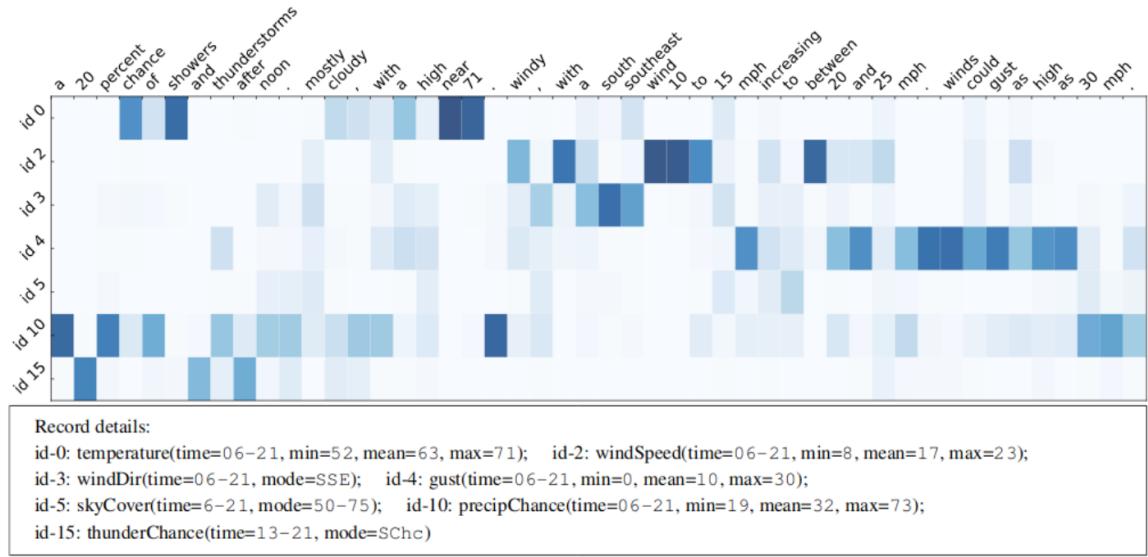


Figure 19.4: Neural attention in text generation. Figure from Mei et al. (2016).[todo: permission]

9980 can then be fed directly into the decoder as the initial state (Vinyals et al., 2015), just as
 9981 in the sequence-to-sequence translation model (see § 18.3). Alternatively, one can apply
 9982 a set of convolutional networks, yielding vector representations for different parts of the
 9983 image, which can then be combined using neural attention (Xu et al., 2015).

9984 19.1.2.2 Attention

Given a set of embeddings of the data $\{\mathbf{z}_r\}_{r=1}^R$ and a decoder state \mathbf{h}_m , the attention vector over the data can be computed using the same technique described in § 18.3.1. When generating word m of the output, a softmax attention mechanism computes the weighted average \mathbf{c}_m ,

$$\psi_\alpha(m, r) = \beta_\alpha \cdot f(\Theta_\alpha[\mathbf{h}_m; \mathbf{z}_r]) \quad [19.5]$$

$$\boldsymbol{\alpha}_m = \text{SoftMax}([\psi_\alpha(m, 1), \psi_\alpha(m, 2), \dots, \psi_\alpha(m, R)]) \quad [19.6]$$

$$\mathbf{c}_m = \sum_{r=1}^R \alpha_{m \rightarrow r} \mathbf{z}_r, \quad [19.7]$$

9985 where f is an elementwise nonlinearity such as tanh or ReLU (see § 3.2.1). The weighted
 9986 average \mathbf{c}_m can then be included in the recurrent update to the decoder state, or in the
 9987 emission probabilities, as described in § 18.3.1. Figure 19.4 shows the attention to compo-
 9988 nents of a weather record, while generating the text shown on the x -axis.

9989 Adapting this architecture to image captioning is straightforward. A convolutional
 9990 neural networks is applied to a set of image locations, and the output at each location ℓ is
 9991 represented with a vector z_ℓ . Attention can then be computed over the image locations,
 9992 as shown in the right panels of each pair of images in Figure 19.3.

9993 Various modifications to this basic mechanism have been proposed. In **coarse-to-fine**
 9994 **attention** (Mei et al., 2016), each record receives a global attention $a_r \in [0, 1]$, which is in-
 9995 dependent of the decoder state. This global attention, which represents the overall impor-
 9996 tance of the record, is multiplied with the decoder-based attention scores, before comput-
 9997 ing the final normalized attentions. In **structured attention**, the attention vector $\alpha_{m \rightarrow \cdot}$ can
 9998 include structural biases, which can favor assigning higher attention values to contiguous
 9999 segments or to dependency subtrees (Kim et al., 2017). Structured attention vectors can
 10000 be computed by running the forward-backward algorithm to obtain marginal attention
 10001 probabilities (see § 7.5.3.3). Because each step in the forward-backward algorithm is dif-
 10002 ferentiable, it can be encoded in a computation graph, and end-to-end learning can be
 10003 performed by backpropagation.

10004 19.1.2.3 Decoder

10005 Given the encoding, the decoder can function just as in neural machine translation (see
 10006 § 18.3.1), using the attention-weighted encoder representation in the decoder recurrence
 10007 and/or output computation. As in machine translation, beam search can help to avoid
 10008 search errors (Lebret et al., 2016).

Many applications require generating words that do not appear in the training vocabulary. For example, a weather record may contain a previously unseen city name; a sports record may contain a previously unseen player name. Such tokens can be generated in the text by copying them over from the input (e.g., Gulcehre et al., 2016).³ First introduce an additional variable $s_m \in \{\text{gen}, \text{copy}\}$, indicating whether token $w_m^{(t)}$ should be generated or copied. The decoder probability is then,

$$p(w^{(t)} | w_{1:m-1}^{(t)}, \mathbf{Z}, s_m) = \begin{cases} \text{SoftMax}(\beta_{w^{(t)}} \cdot h_{m-1}^{(t)}), & s_m = \text{gen} \\ \sum_{r=1}^R \delta(w_r^{(s)} = w^{(t)}) \times \alpha_{m \rightarrow r}, & s_m = \text{copy}, \end{cases} \quad [19.8]$$

10009 where $\delta(w_r^{(s)} = w^{(t)})$ is an indicator function, taking the value 1 iff the text of the record
 10010 $w_r^{(s)}$ is identical to the target word $w^{(t)}$. The probability of copying record r from the source
 10011 is $\delta(s_m = \text{copy}) \times \alpha_{m \rightarrow r}$, the product of the copy probability by the local attention. Note
 10012 that in this model, the attention weights α_m are computed from the *previous* decoder state
 10013 h_{m-1} . The computation graph therefore remains a feedforward network, with recurrent
 10014 paths such as $h_{m-1}^{(t)} \rightarrow \alpha_m \rightarrow w_m^{(t)} \rightarrow h_m^{(t)}$.

³A number of variants of this strategy have been proposed (e.g., Gu et al., 2016; Merity et al., 2017). See Wiseman et al. (2017) for an overview.

10015 To facilitate end-to-end training, the switching variable s_m can be represented by a
 10016 gate π_m , which is computed from a two-layer feedforward network, whose input consists
 10017 of the concatenation of the decoder state $\mathbf{h}_{m-1}^{(t)}$ and the attention-weighted representation
 10018 of the data, $\mathbf{c}_m = \sum_{r=1}^R \alpha_{m \rightarrow r} \mathbf{z}_r$,

$$\pi_m = \sigma(\Theta^{(2)} f(\Theta^{(1)}[\mathbf{h}_{m-1}^{(t)}; \mathbf{c}_m])). \quad [19.9]$$

The full generative probability at token m is then,

$$p(w^{(t)} | \mathbf{w}_{1:m}^{(t)}, \mathbf{Z}) = \pi_m \times \underbrace{\frac{\exp \beta_{w^{(t)}} \cdot \mathbf{h}_{m-1}^{(t)}}{\sum_{j=1}^V \exp \beta_j \cdot \mathbf{h}_{m-1}^{(t)}}}_{\text{generate}} + (1 - \pi_m) \times \underbrace{\sum_{r=1}^R \delta(w_r^{(s)} = w^{(t)}) \times \alpha_{m \rightarrow r}}_{\text{copy}}. \quad [19.10]$$

10019 19.2 Text-to-text generation

10020 Text-to-text generation includes problems of summarization and simplification:

- 10021 • reading a novel and outputting a paragraph-long summary of the plot;⁴
- 10022 • reading a set of blog posts about politics, and outputting a bullet list of the various
 10023 issues and perspectives;
- 10024 • reading a technical research article about the long-term health consequences of drink-
 10025 ing kombucha, and outputting a summary of the article in language that non-experts
 10026 can understand.

10027 These problems can be approached in two ways: through the encoder-decoder architec-
 10028 ture discussed in the previous section, or by operating directly on the input text.

10029 19.2.1 Neural abstractive summarization

10030 **Sentence summarization** is the task of shortening a sentence while preserving its mean-
 10031 ing, as in the following examples (Knight and Marcu, 2000; Rush et al., 2015):

- 10032 (19.2) The documentation is typical of Epson quality: excellent.
 10033 Documentation is excellent.

⁴In § 16.3.4.1, we encountered a special case of single-document summarization, which involved extracting the most important sentences or discourse units. We now consider the more challenging problem of **abstractive summarization**, in which the summary can include words that do not appear in the original text.

- 10035 (19.3) Russian defense minister Ivanov called sunday for the creation of a joint front for
 10036 combating global terrorism.
 10037 Russia calls for joint front against terrorism.
 10038

10039 Sentence summarization is closely related to **sentence compression**, in which the sum-
 10040 mary is produced by deleting words or phrases from the original (Clarke and Lapata,
 10041 2008). But as shown in (19.3), a sentence summary can also introduce new words, such as
 10042 *against*, which replaces the phrase *for combatting*.

10043 Sentence summarization can be treated as a machine translation problem, using the at-
 10044 tentional encoder-decoder translation model discussed in § 18.3.1 (Rush et al., 2015). The
 10045 longer sentence is encoded into a sequence of vectors, one for each token. The decoder
 10046 then computes attention over these vectors when updating its own recurrent state. As
 10047 with data-to-text generation, it can be useful to augment the encoder-decoder model with
 10048 the ability to copy words directly from the source. Rush et al. (2015) train this model by
 10049 building four million sentence pairs from news articles. In each pair, the longer sentence is
 10050 the first sentence of the article, and the summary is the article headline. Sentence summa-
 10051 rization can also be trained in a semi-supervised fashion, using a probabilistic formulation
 10052 of the encoder-decoder model called a **variational autoencoder** (Miao and Blunsom, 2016,
 10053 also see § 14.8.2).

When summarizing longer documents, an additional concern is that the summary not be repetitive: each part of the summary should cover new ground. This can be addressed by maintaining a vector of the sum total of all attention values thus far, $t_m = \sum_{n=1}^m \alpha_n$. This total can be used as an additional input to the computation of the attention weights,

$$\alpha_{m \rightarrow n} \propto \exp \left(\mathbf{v}_\alpha \cdot \tanh(\Theta_\alpha[\mathbf{h}_m^{(t)}; \mathbf{h}_n^{(s)}; \mathbf{t}_m]) \right), \quad [19.11]$$

which enables the model to learn to prefer parts of the source which have not been attended to yet (Tu et al., 2016). To further encourage diversity in the generated summary, See et al. (2017) introduce a **coverage loss** to the objective function,

$$\ell_m = \sum_{n=1}^{M^{(s)}} \min(\alpha_{m \rightarrow n}, t_{m \rightarrow n}). \quad [19.12]$$

10054 This loss will be low if $\alpha_{m \rightarrow \cdot}$ assigns little attention to words that already have large
 10055 values in $t_{m \rightarrow \cdot}$. Coverage loss is similar to the concept of **marginal relevance**, in which
 10056 the reward for adding new content is proportional to the extent to which it increases
 10057 the overall amount of information conveyed by the summary (Carbonell and Goldstein,
 10058 1998).

10059 **19.2.2 Sentence fusion for multi-document summarization**

10060 In **multi-document summarization**, the goal is to produce a summary that covers the
 10061 content of several documents (McKeown et al., 2002). One approach to this challenging
 10062 problem is to identify sentences across multiple documents that relate to a single theme,
 10063 and then to fuse them into a single sentence (Barzilay and McKeown, 2005). As an exam-
 10064 ple, consider the following two sentences (McKeown et al., 2010):

- 10065 (19.4) Palin actually turned against the bridge project only after it became a national
 10066 symbol of wasteful spending.
 10067 (19.5) Ms. Palin supported the bridge project while running for governor, and aban-
 10068 doned it after it became a national scandal.

10069 An *intersection* preserves only the content that is present in both sentences:

- 10070 (19.6) Palin turned against the bridge project after it became a national scandal.

10071 A *union* includes information from both sentences:

- 10072 (19.7) Ms. Palin supported the bridge project while running for governor, but turned
 10073 against it when it became a national scandal and a symbol of wasteful spending.

Dependency parsing is often used as a technique for sentence fusion. After parsing each sentence, the resulting dependency trees can be aggregated into a lattice (Barzilay and McKeown, 2005) or a graph structure (Filippova and Strube, 2008), in which identical or closely related words (e.g., *Palin*, *bridge*, *national*) are fused into a single node. The resulting graph can then be pruned back to a tree by solving an **integer linear program** (see § 13.2.2),

$$\max_{\mathbf{y}} \sum_{i,j,r} \psi(i \xrightarrow{r} j, \mathbf{w}; \boldsymbol{\theta}) \times y_{i,j,r} \quad [19.13]$$

$$\text{s.t. } \mathbf{y} \in \mathcal{C}, \quad [19.14]$$

10074 where the variable $y_{i,j,r} \in \{0, 1\}$ indicates whether there is an edge from i to j of type r ,
 10075 the score of this edge is $\psi(i \xrightarrow{r} j, \mathbf{w}; \boldsymbol{\theta})$, and \mathcal{C} is a set of constraints, described below. As
 10076 usual, \mathbf{w} is the list of words in the graph, and $\boldsymbol{\theta}$ is a vector of parameters. The score $\psi(i \xrightarrow{r} j, \mathbf{w}; \boldsymbol{\theta})$
 10077 reflects the “importance” of the modifier j to the overall meaning: in intersective
 10078 fusion, this score indicates the extent to which the content in this edge is expressed in all
 10079 sentences; in union fusion, the score indicates whether the content in the edge is expressed
 10080 in any sentence.

10081 The constraint set \mathcal{C} ensures that \mathbf{y} forms a valid dependency graph. It can also im-
 10082 pose additional linguistic constraints: for example, ensuring that coordinated nouns are

10083 sufficiently similar. The resulting tree must then be **linearized** into a sentence. This is
 10084 typically done by generating a set of candidate linearizations, and choosing the one with
 10085 the highest score under a language model (Langkilde and Knight, 1998; Song et al., 2016).

10086 19.3 Dialogue

10087 **Dialogue systems** are capable of conversing with a human interlocutor, often to per-
 10088 form some task (Grosz, 1979), but sometimes just to chat (Weizenbaum, 1966). While re-
 10089 search on dialogue systems goes back several decades (Carbonell, 1970; Winograd, 1972),
 10090 commercial systems such as Alexa and Siri have recently brought this technology into
 10091 widespread use. Nonetheless, there is a significant gap between research and practice:
 10092 many practical dialogue systems remain scripted and inflexible, while research systems
 10093 emphasize abstractive text generation, “on-the-fly” decision making, and probabilistic
 10094 reasoning about the user’s intentions.

10095 19.3.1 Finite-state and agenda-based dialogue systems

10096 Finite-state automata were introduced in chapter 9 as a formal model of computation,
 10097 in which string inputs and outputs are linked to transitions between a finite number of
 10098 discrete states. This model naturally fits simple task-oriented dialogues, such as the one
 10099 shown in the left panel of Figure 19.5. This (somewhat frustrating) dialogue can be repre-
 10100 sented with a finite-state transducer, as shown in the right panel of the figure. The accept-
 10101 ing state is reached only when the two needed pieces of information are provided, and the
 10102 human user confirms that the order is correct. In this simple scenario, the TOPPING and
 10103 ADDRESS are the two **slots** associated with the activity of ordering a pizza, which is called
 10104 a **frame**. Frame representations can be hierarchical: for example, an ADDRESS could have
 10105 slots of its own, such as STREET and CITY.

10106 In the example dialogue in Figure 19.5, the user provides the precise inputs that are
 10107 needed in each turn (e.g., *anchovies*; *the College of Computing building*). Some users may
 10108 prefer to communicate more naturally, with phrases like *I’d, uh, like some anchovies please*.
 10109 One approach to handling such utterances is to design a custom grammar, with non-
 10110 terminals for slots such as TOPPING and LOCATION. However, context-free parsing of
 10111 unconstrained speech input is challenging. A more lightweight alternative is BIO-style
 10112 sequence labeling (see § 8.3), e.g.:

10113 (19.9) *I’d like anchovies , and please bring it to the College of Computing*
 10114 *Building .*

O	O	B-TOPPING	O	O	O	O	O	O	B-ADDR	I-ADDR	I-ADDR	I-ADDR	I-ADDR
I-ADDR	O												

- (19.8) A: I want to order a pizza.
 B: What toppings?
 A: Anchovies.
 B: Ok, what address?
 A: The College of Computing building.
 B: Please confirm: one pizza with artichokes, to be delivered to the College of Computing building.
 A: No.
 B: What toppings?
 ...

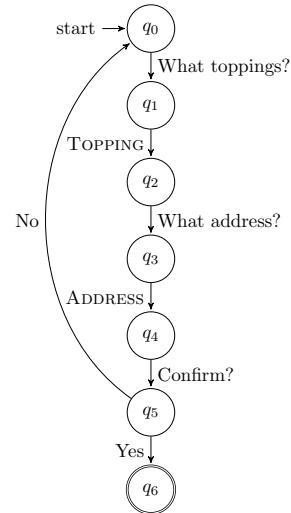


Figure 19.5: An example dialogue and the associated finite-state model. In the finite-state model, SMALL CAPS indicates that the user must provide information of this type in their answer.

10115 The tagger can be driven by a bi-directional recurrent neural network, similar to recurrent
 10116 approaches to semantic role labeling described in § 13.2.3.

10117 The input in (19.9) could not be handled by the finite-state system from Figure 19.5,
 10118 which forces the user to provide the topping first, and then the location. In this sense,
 10119 the **initiative** is driven completely by the system. **Agenda-based dialogue systems** ex-
 10120 tend finite-state architectures by attempting to recognize all slots that are filled by the
 10121 user’s reply, thereby handling these more complex examples. Agenda-based systems dy-
 10122 namically pose additional questions until the frame is complete (Bobrow et al., 1977; Allen
 10123 et al., 1995; Rudnicky and Xu, 1999). Such systems are said to be **mixed-initiative**, because
 10124 both the user and the system can drive the direction of the dialogue.

10125 **19.3.2 Markov decision processes**

10126 The task of dynamically selecting the next move in a conversation is known as **dialogue**
 10127 **management**. This problem can be framed as a **Markov decision process**, which is a
 10128 theoretical model that includes a discrete set of states, a discrete set of actions, a function
 10129 that computes the probability of transitions between states, and a function that computes
 10130 the cost or reward of action-state pairs. Let’s see how each of these elements pertains to
 10131 the pizza ordering dialogue system.

- 10132 • Each state is a tuple of information about whether the topping and address are

10133 known, and whether the order has been confirmed. For example,

$$(KNOWN\ TOPPING,\ UNKNOWN\ ADDRESS,\ NOT\ CONFIRMED) \quad [19.15]$$

10134 is a possible state. Any state in which the pizza order is confirmed is a terminal
 10135 state, and the Markov decision process stops after entering such a state.

- 10136 • The set of actions includes querying for the topping, querying for the address, and
 10137 requesting confirmation. Each action induces a probability distribution over states,
 10138 $p(s_t | a_t, s_{t-1})$. For example, requesting confirmation of the order is not likely to
 10139 result in a transition to the terminal state if the topping is not yet known. This
 10140 probability distribution over state transitions may be learned from data, or it may
 10141 be specified in advance.
- 10142 • Each state-action-state tuple earns a reward, $r_a(s_t, s_{t+1})$. In the context of the pizza
 10143 ordering system, a simple reward function would be,

$$r_a(s_t, s_{t+1}) = \begin{cases} 0, & a = \text{CONFIRM}, s_{t+1} = (*, *, \text{CONFIRMED}) \\ -10, & a = \text{CONFIRM}, s_{t+1} = (*, *, \text{NOT CONFIRMED}) \\ -1, & a \neq \text{CONFIRM} \end{cases} \quad [19.16]$$

10144 This function assigns zero reward for successful transitions to the terminal state, a
 10145 large negative reward to a rejected request for confirmation, and a small negative re-
 10146 ward for every other type of action. The system is therefore rewarded for reaching
 10147 the terminal state in few steps, and penalized for prematurely requesting confirma-
 10148 tion.

10149 In a Markov decision process, a **policy** is a function $\pi : \mathcal{S} \mapsto \mathcal{A}$ that maps from states to
 10150 actions (see § 15.2.4.3). The value of a policy is the expected sum of discounted rewards,
 10151 $E_\pi[\sum_{t=1}^T \gamma^t r_{a_t}(s_t, s_{t+1})]$, where γ is the discount factor, $\gamma \in [0, 1)$. Discounting has the
 10152 effect of emphasizing rewards that can be obtained immediately over less certain rewards
 10153 in the distant future.

10154 An optimal policy can be obtained by dynamic programming, by iteratively updating
 10155 the **value function** $V(s)$, which is the expectation of the cumulative reward from s under
 10156 the optimal action a ,

$$V(s) \leftarrow \max_{a \in \mathcal{A}} \sum_{s' \in \mathcal{S}} p(s' | s, a)[r_a(s, s') + \gamma V(s')]. \quad [19.17]$$

10157 The value function $V(s)$ is computed in terms of $V(s')$ for all states $s' \in \mathcal{S}$. A series
 10158 of iterative updates to the value function will eventually converge to a stationary point.
 10159 This algorithm is known as **value iteration**. Given the converged value function $V(s)$, the

10160 optimal action at each state is the argmax,

$$\pi(s) = \operatorname{argmax}_{a \in \mathcal{A}} \sum_{s' \in \mathcal{S}} p(s' | s, a)[r_a(s, s') + \gamma V(s')]. \quad [19.18]$$

10161 Value iteration and related algorithms are described in detail by Sutton and Barto (1998).
 10162 For applications to dialogue systems, see Levin et al. (1998) and Walker (2000).

10163 The Markov decision process framework assumes that the current state of the dialogue
 10164 is known. In reality, the system may misinterpret the user’s statements — for example,
 10165 believing that a specification of the delivery location (PEACHTREE) is in fact a specification
 10166 of the topping (PEACHES). In a **partially observable Markov decision process (POMDP)**,
 10167 the system receives an *observation* o , which is probabilistically conditioned on the state,
 10168 $p(o | s)$. It must therefore maintain a distribution of beliefs about which state it is in, with
 10169 $q_t(s)$ indicating the degree of belief that the dialogue is in state s at time t . The POMDP
 10170 formulation can help to make dialogue systems more robust to errors, particularly in the
 10171 context of spoken language dialogues, where the speech itself may be misrecognized (Roy
 10172 et al., 2000; Williams and Young, 2007). However, finding the optimal policy in a POMDP
 10173 is computationally intractable, requiring additional approximations.

10174 **19.3.3 Neural chatbots**

10175 Chatting is a lot easier when you don’t need to get anything done. **Chatbots** are systems
 10176 that parry the user’s input with a response that keeps the conversation going. They can be
 10177 built from the encoder-decoder architecture discussed in § 18.3 and § 19.1.2: the encoder
 10178 converts the user’s input into a vector, and the decoder produces a sequence of words as a
 10179 response. For example, Shang et al. (2015) apply the attentional encoder-decoder transla-
 10180 tion model, training on a dataset of posts and responses from the Chinese microblogging
 10181 platform Sina Weibo.⁵ This approach is capable of generating replies that relate themati-
 10182 cally to the input, as shown in the following examples:⁶

10183 (19.10) A: High fever attacks me every New Year’s day.
 10184 Get B: well soon and stay healthy!

10185 (19.11) A: I gain one more year. Grateful to my group, so happy.
 10186 B: Getting old now. Time has no mercy.

10187 While encoder-decoder models can generate responses that make sense in the con-
 10188 text of the immediately preceding turn, they struggle to maintain coherence over longer

⁵Twitter is also frequently used for construction of dialogue datasets (Ritter et al., 2011; Sordoni et al., 2015). Another source is technical support chat logs from the Ubuntu linux distribution (Uthus and Aha, 2013; Lowe et al., 2015).

⁶All examples are translated from Chinese by Shang et al. (2015).

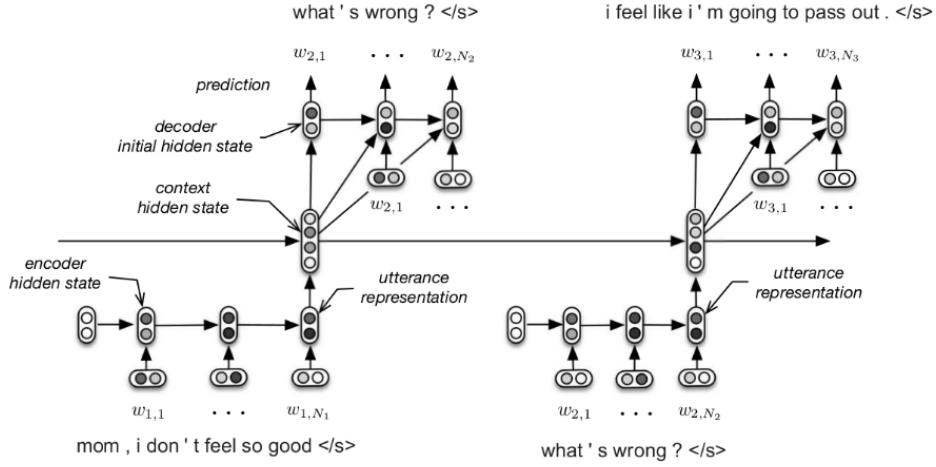


Figure 19.6: A hierarchical recurrent neural network for dialogue, with recurrence over both words and turns, from Serban et al. (2016). [todo: permission]

conversations. One solution is to model the dialogue context recurrently. This creates a **hierarchical recurrent network**, including both word-level and turn-level recurrences. The turn-level hidden state is then used as additional context in the decoder (Serban et al., 2016), as shown in Figure 19.6.

An open question is how to integrate the encoder-decoder architecture into task-oriented dialogue systems. Neural chatbots can be trained end-to-end: the user’s turn is analyzed by the encoder, and the system output is generated by the decoder. This architecture can be trained by log-likelihood using backpropagation (e.g., Sordoni et al., 2015; Serban et al., 2016), or by more elaborate objectives, using reinforcement learning (Li et al., 2016). In contrast, the task-oriented dialogue systems described in § 19.3.1 typically involve a set of specialized modules: one for recognizing the user input, another for deciding what action to take, and a third for arranging the text of the system output.

Recurrent neural network decoders can be integrated into Markov Decision Process dialogue systems, by conditioning the decoder on a representation of the information that is to be expressed in each turn (Wen et al., 2015). Specifically, the long short-term memory (LSTM; § 6.3) architecture is augmented so that the memory cell at turn m takes an additional input d_m , which is a representation of the slots and values to be expressed in the next turn. However, this approach still relies on additional modules to recognize the user’s utterance and to plan the overall arc of the dialogue.

Another promising direction is to create embeddings for the elements in the domain: for example, the slots in a record and the entities that can fill them. The encoder then

10210 encodes not only the words of the user’s input, but the embeddings of the elements that
 10211 the user mentions. Similarly, the decoder is endowed with the ability to refer to specific
 10212 elements in the knowledge base. He et al. (2017) show that such a method can learn to
 10213 play a collaborative dialogue game, in which both players are given a list of entities and
 10214 their properties, and the goal is to find an entity that is on both players’ lists.

10215 **Further reading**

10216 Gatt and Krahmer (2018) provide a comprehensive recent survey on text generation. For
 10217 a book-length treatment of earlier work, see Reiter and Dale (2000). For a survey on image
 10218 captioning, see Bernardi et al. (2016); for a survey of pre-neural approaches to dialogue
 10219 systems, see Rieser and Lemon (2011). **Dialogue acts** were introduced in § 8.6 as a labeling
 10220 scheme for human-human dialogues; they also play a critical role in task-based dialogue
 10221 systems (e.g., Allen et al., 1996). The incorporation of theoretical models of dialogue into
 10222 computational systems is reviewed by Jurafsky and Martin (2009, chapter 24).

10223 While this chapter has focused on the informative dimension of text generation, another
 10224 line of research aims to generate text with configurable stylistic properties (Walker
 10225 et al., 1997; Mairesse and Walker, 2011; Ficler and Goldberg, 2017; Hu et al., 2017). This
 10226 chapter also does not address the generation of creative text such as narratives (Riedl and
 10227 Young, 2010), jokes (Ritchie, 2001), poems (Colton et al., 2012), and song lyrics (Gonçalo Oliveira
 10228 et al., 2007).

10229 **Exercises**

10230 1. The SimpleNLG system produces surface realizations from representations of de-
 10231 sired syntactic structure (Gatt and Reiter, 2009). This system can be accessed on
 10232 github at <https://github.com/simpleNLG/simpleNLG>. Download the sys-
 10233 tem, and produce realizations of the following examples:

- 10234 (19.12) Call me Ismael.
 10235 (19.13) I try all things.
 10236 (19.14) I achieve what I can.

10237 Then convert each example to a question. [todo: Can’t get SimpleNLG to work with
 10238 python anymore]

10239 **Appendix A**

10240 **Probability**

10241 Probability theory provides a way to reason about random events. The sorts of random
10242 events that are typically used to explain probability theory include coin flips, card draws,
10243 and the weather. It may seem odd to think about the choice of a word as akin to the flip of
10244 a coin, particularly if you are the type of person to choose words carefully. But random or
10245 not, language has proven to be extremely difficult to model deterministically. Probability
10246 offers a powerful tool for modeling and manipulating linguistic data.

10247 Probability can be thought of in terms of **random outcomes**: for example, a single coin
10248 flip has two possible outcomes, heads or tails. The set of possible outcomes is the **sample**
10249 **space**, and a subset of the **sample space** is an **event**. For a sequence of two coin flips,
10250 there are four possible outcomes, $\{HH, HT, TH, TT\}$, representing the ordered sequences
10251 heads-head, heads-tails, tails-heads, and tails-tails. The event of getting exactly one head
10252 includes two outcomes: $\{HT, TH\}$.

10253 Formally, a probability is a function from events to the interval between zero and one:
10254 $\Pr : \mathcal{F} \mapsto [0, 1]$, where \mathcal{F} is the set of possible events. An event that is certain has proba-
10255 bility one; an event that is impossible has probability zero. For example, the probability
10256 of getting fewer than three heads on two coin flips is one. Each outcome is also an event
10257 (a set with exactly one element), and for two flips of a fair coin, the probability of each
10258 outcome is,

$$\Pr(\{HH\}) = \Pr(\{HT\}) = \Pr(\{TH\}) = \Pr(\{TT\}) = \frac{1}{4}. \quad [\text{A.1}]$$

10259 **A.1 Probabilities of event combinations**

10260 Because events are sets of outcomes, we can use set-theoretic operations such as comple-
10261 ment, intersection, and union to reason about the probabilities of events and their combi-
10262 nations.

10263 For any event A , there is a **complement** $\neg A$, such that:

- 10264 • The probability of the union $A \cup \neg A$ is $\Pr(A \cup \neg A) = 1$;
- 10265 • The intersection $A \cap \neg A = \emptyset$ is the empty set, and $\Pr(A \cap \neg A) = 0$.

10266 In the coin flip example, the event of obtaining a single head on two flips corresponds to
 10267 the set of outcomes $\{HT, TH\}$; the complement event includes the other two outcomes,
 10268 $\{TT, HH\}$.

10269 A.1.1 Probabilities of disjoint events

10270 When two events have an empty intersection, $A \cap B = \emptyset$, they **disjoint**. The probability
 10271 of the union of two disjoint events is equal to the sum of their probabilities,

$$A \cap B = \emptyset \Rightarrow \Pr(A \cup B) = \Pr(A) + \Pr(B). \quad [A.2]$$

10272 This is the **third axiom of probability**, and it can be generalized to any countable sequence
 10273 of disjoint events.

In the coin flip example, this axiom can derive the probability of the event of getting a single head on two flips. This event is the set of outcomes $\{HT, TH\}$, which is the union of two simpler events, $\{HT, TH\} = \{HT\} \cup \{TH\}$. The events $\{HT\}$ and $\{TH\}$ are disjoint. Therefore,

$$\Pr(\{HT, TH\}) = \Pr(\{HT\} \cup \{TH\}) = \Pr(\{HT\}) + \Pr(\{TH\}) \quad [A.3]$$

$$= \frac{1}{4} + \frac{1}{4} = \frac{1}{2}. \quad [A.4]$$

10274 In the general, the probability of the union of two events is,

$$\Pr(A \cup B) = \Pr(A) + \Pr(B) - \Pr(A \cap B). \quad [A.5]$$

This can be seen visually in Figure A.1, and it can be derived from the third axiom of probability. Consider an event that includes all outcomes in B that are not in A , denoted as $B - (A \cap B)$. By construction, this event is disjoint from A . We can therefore apply the additive rule,

$$\Pr(A \cup B) = \Pr(A) + \Pr(B - (A \cap B)). \quad [A.6]$$

Furthermore, the event B is the union of two disjoint events: $A \cap B$ and $B - (A \cap B)$.

$$\Pr(B) = \Pr(B - (A \cap B)) + \Pr(A \cap B). \quad [A.7]$$

Reorganizing and substituting into Equation A.6 gives the desired result:

$$\Pr(B - (A \cap B)) = \Pr(B) - \Pr(A \cap B) \quad [A.8]$$

$$\Pr(A \cup B) = \Pr(A) + \Pr(B) - \Pr(A \cap B). \quad [A.9]$$

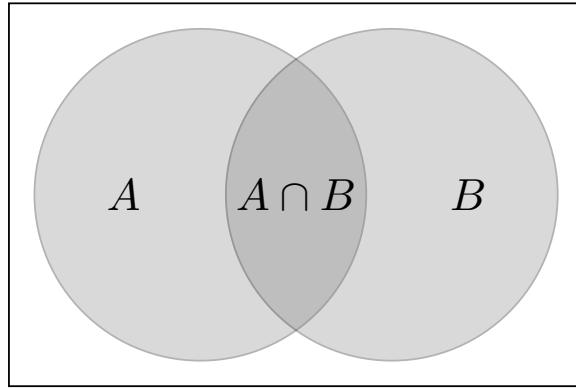


Figure A.1: A visualization of the probability of non-disjoint events A and B .

10275 A.1.2 Law of total probability

10276 A set of events $\mathcal{B} = \{B_1, B_2, \dots, B_N\}$ is a **partition** of the sample space iff each pair of
 10277 events is disjoint ($B_i \cap B_j = \emptyset$), and the union of the events is the entire sample space.
 10278 The law of total probability states that we can **marginalize** over these events as follows,

$$\Pr(A) = \sum_{B_n \in \mathcal{B}} \Pr(A \cap B_n). \quad [\text{A.10}]$$

10279 For any event B , the union $B \cup \neg B$ is a partition of the sample space. Therefore, a special
 10280 case of the law of total probability is,

$$\Pr(A) = \Pr(A \cap B) + \Pr(A \cap \neg B). \quad [\text{A.11}]$$

10281 A.2 Conditional probability and Bayes' rule

A **conditional probability** is an expression like $\Pr(A \mid B)$, which is the probability of the event A , assuming that event B happens too. For example, we may be interested in the probability of a randomly selected person answering the phone by saying *hello*, conditioned on that person being a speaker of English. Conditional probability is defined as the ratio,

$$\Pr(A \mid B) = \frac{\Pr(A \cap B)}{\Pr(B)}. \quad [\text{A.12}]$$

The **chain rule of probability** states that $\Pr(A \cap B) = \Pr(A \mid B) \times \Pr(B)$, which is just

Jacob Eisenstein. Draft of June 6, 2018. Copyright MIT Press, CC-BY-NC-ND license.

a rearrangement of terms from Equation A.12. The chain rule can be applied repeatedly:

$$\begin{aligned}\Pr(A \cap B \cap C) &= \Pr(A | B \cap C) \times \Pr(B \cap C) \\ &= \Pr(A | B \cap C) \times \Pr(B | C) \times \Pr(C).\end{aligned}$$

Bayes' rule (sometimes called Bayes' law or Bayes' theorem) gives us a way to convert between $\Pr(A | B)$ and $\Pr(B | A)$. It follows from the definition of conditional probability and the chain rule:

$$\Pr(A | B) = \frac{\Pr(A \cap B)}{\Pr(B)} = \frac{\Pr(B | A) \times \Pr(A)}{\Pr(B)} \quad [\text{A.13}]$$

10282 Each term in Bayes rule has a name, which we will occasionally use:

- 10283 • Pr(A) is the **prior**, since it is the probability of event A without knowledge about
10284 whether B happens or not.
- 10285 • Pr($B | A$) is the **likelihood**, the probability of event B given that event A has oc-
10286 curred.
- 10287 • Pr($A | B$) is the **posterior**, the probability of event A with knowledge that B has
10288 occurred.

10289 **Example** The classic examples for Bayes' rule involve tests for rare diseases, but Man-
10290 ning and Schütze (1999) reframe this example in a linguistic setting. Suppose that you are
10291 interested in a rare syntactic construction, such as *parasitic gaps*, which occur on average
10292 once in 100,000 sentences. Here is an example of a parasitic gap:

10293 (A.1) *Which class did you attend ... without registering for ...?*

10294 Lana Linguist has developed a complicated pattern matcher that attempts to identify
10295 sentences with parasitic gaps. It's pretty good, but it's not perfect:

- 10296 • If a sentence has a parasitic gap, the pattern matcher will find it with probability
10297 0.95. (This is the **recall**, which is one minus the **false positive rate**.)
- 10298 • If the sentence doesn't have a parasitic gap, the pattern matcher will wrongly say it
10299 does with probability 0.005. (This is the **false positive rate**, which is one minus the
10300 **precision**.)

10301 Suppose that Lana's pattern matcher says that a sentence contains a parasitic gap. What
10302 is the probability that this is true?

Let G be the event of a sentence having a parasitic gap, and T be the event of the test being positive. We are interested in the probability of a sentence having a parasitic gap given that the test is positive. This is the conditional probability $\Pr(G | T)$, and it can be computed by Bayes' rule:

$$\Pr(G | T) = \frac{\Pr(T | G) \times \Pr(G)}{\Pr(T)}. \quad [\text{A.14}]$$

10303 We already know both terms in the numerator: $\Pr(T | G)$ is the recall, which is 0.95; $\Pr(G)$
10304 is the prior, which is 10^{-5} .

10305 We are not given the denominator, but it can be computed using tools developed earlier
10306 in this section. First apply the law of total probability, using the partition $\{G, \neg G\}$:

$$\Pr(T) = \Pr(T \cap G) + \Pr(T \cap \neg G). \quad [\text{A.15}]$$

This says that the probability of the test being positive is the sum of the probability of a **true positive** ($T \cap G$) and the probability of a **false positive** ($T \cap \neg G$). The probability of each of these events can be computed using the chain rule:

$$\Pr(T \cap G) = \Pr(T | G) \times \Pr(G) = 0.95 \times 10^{-5} \quad [\text{A.16}]$$

$$\Pr(T \cap \neg G) = \Pr(T | \neg G) \times \Pr(\neg G) = 0.005 \times (1 - 10^{-5}) \approx 0.005 \quad [\text{A.17}]$$

$$\Pr(T) = \Pr(T \cap G) + \Pr(T \cap \neg G) \quad [\text{A.18}]$$

$$= 0.95 \times 10^{-5} + 0.005. \quad [\text{A.19}]$$

Plugging these terms into Bayes' rule gives the desired posterior probability,

$$\Pr(G | T) = \frac{\Pr(T | G) \Pr(G)}{\Pr(T)} \quad [\text{A.20}]$$

$$= \frac{0.95 \times 10^{-5}}{0.95 \times 10^{-5} + 0.005 \times (1 - 10^{-5})} \quad [\text{A.21}]$$

$$\approx 0.002. \quad [\text{A.22}]$$

10307 Lana's pattern matcher seems accurate, with false positive and false negative rates
10308 below 5%. Yet the extreme rarity of the phenomenon means that a positive result from the
10309 detector is most likely to be wrong.

10310 A.3 Independence

Two events are independent if the probability of their intersection is equal to the product of their probabilities: $\Pr(A \cap B) = \Pr(A) \times \Pr(B)$. For example, for two flips of a fair

coin, the probability of getting heads on the first flip is independent of the probability of getting heads on the second flip:

$$\Pr(\{HT, HH\}) = \Pr(HT) + \Pr(HH) = \frac{1}{4} + \frac{1}{4} = \frac{1}{2} \quad [A.23]$$

$$\Pr(\{HH, TH\}) = \Pr(HH) + \Pr(TH) = \frac{1}{4} + \frac{1}{4} = \frac{1}{2} \quad [A.24]$$

$$\Pr(\{HT, HH\}) \times \Pr(\{HH, TH\}) = \frac{1}{2} \times \frac{1}{2} = \frac{1}{4} \quad [A.25]$$

$$\Pr(\{HT, HH\} \cap \{HH, TH\}) = \Pr(HH) = \frac{1}{4} \quad [A.26]$$

$$= \Pr(\{HT, HH\}) \times \Pr(\{HH, TH\}). \quad [A.27]$$

If $\Pr(A \cap B \mid C) = \Pr(A \mid C) \times \Pr(B \mid C)$, then the events A and B are **conditionally independent**, written $A \perp B \mid C$. Conditional independence plays a important role in probabilistic models such as Naïve Bayes chapter 2.

A.4 Random variables

Random variables are functions from events to \mathbb{R}^n , where \mathbb{R} is the set of real numbers. This subsumes several useful special cases:

- An **indicator random variable** is a functions from events to the set $\{0, 1\}$. In the coin flip example, we can define Y as an indicator random variable, taking the value 1 when the coin has come up heads on at least one flip. This would include the outcomes $\{HH, HT, TH\}$. The probability $\Pr(Y = 1)$ is the sum of the probabilities of these outcomes, $\Pr(Y = 1) = \frac{1}{4} + \frac{1}{4} + \frac{1}{4} = \frac{3}{4}$.
- A **discrete random variable** is a function from events to a discrete subset of \mathbb{R} . Consider the coin flip example: the number of heads on two flips, X , can be viewed as a discrete random variable, $X \in \{0, 1, 2\}$. The event probability $\Pr(X = 1)$ can again be computed as the sum of the probabilities of the events in which there is one head, $\{HT, TH\}$, giving $\Pr(X = 1) = \frac{1}{4} + \frac{1}{4} = \frac{1}{2}$.

Each possible value of a random variable is associated with a subset of the sample space. In the coin flip example, $X = 0$ is associated with the event $\{TT\}$, $X = 1$ is associated with the event $\{HT, TH\}$, and $X = 2$ is associated with the event $\{HH\}$. Assuming a fair coin, the probabilities of these events are, respectively, $1/4$, $1/2$, and $1/4$. This list of numbers represents the **probability distribution** over X , written p_X , which maps from the possible values of X to the non-negative reals. For a specific value x , we write $p_X(x)$, which is equal to the event probability $\Pr(X = x)$.¹ The function p_X is called

¹In general, capital letters (e.g., X) refer to random variables, and lower-case letters (e.g., x) refer to specific values. When the distribution is clear from context, I will simply write $p(x)$.

a probability **mass** function (pmf) if X is discrete; it is called a probability **density** function (pdf) if X is continuous. In either case, the function must sum to one, and all values must be non-negative:

$$\int_x p_X(x)dx = 1 \quad [A.28]$$

$$\forall x, p_X(x) \geq 0. \quad [A.29]$$

Probabilities over multiple random variables can written as **joint probabilities**, e.g., $p_{A,B}(a,b) = \Pr(A = a \cap B = b)$. Several properties of event probabilities carry over to probability distributions over random variables:

- The **marginal probability distribution** is $p_A(a) = \sum_b p_{A,B}(a,b)$.
- The **conditional probability distribution** is $p_{A|B}(a | b) = \frac{p_{A,B}(a,b)}{p_B(b)}$.
- Random variables A and B are independent iff $p_{A,B}(a,b) = p_A(a) \times p_B(b)$.

A.5 Expectations

Sometimes we want the **expectation** of a function, such as $E[g(x)] = \sum_{x \in \mathcal{X}} g(x)p(x)$. Expectations are easiest to think about in terms of probability distributions over discrete events:

- If it is sunny, Lucia will eat three ice creams.
- If it is rainy, she will eat only one ice cream.
- There's a 80% chance it will be sunny.
- The expected number of ice creams she will eat is $0.8 \times 3 + 0.2 \times 1 = 2.6$.

If the random variable X is continuous, the expectation is an integral:

$$E[g(x)] = \int_{\mathcal{X}} g(x)p(x)dx \quad [A.30]$$

For example, a fast food restaurant in Quebec has a special offer for cold days: they give a 1% discount on poutine for every degree below zero. Assuming a thermometer with infinite precision, the expected price would be an integral over all possible temperatures,

$$E[\text{price}(x)] = \int_{\mathcal{X}} \min(1, 1+x) \times \text{original-price} \times p(x)dx. \quad [A.31]$$

10345 **A.6 Modeling and estimation**

10346 **Probabilistic models** provide a principled way to reason about random events and ran-
10347 dom variables. Let's consider the coin toss example. Each toss can be modeled as a ran-
10348 dom event, with probability θ of the event H , and probability $1 - \theta$ of the complementary
10349 event T . If we write a random variable X as the total number of heads on three coin
10350 flips, then the distribution of X depends on θ . In this case, X is distributed as a **binomial**
10351 **random variable**, meaning that it is drawn from a binomial distribution, with **parameters**
10352 $(\theta, N = 3)$. This is written,

$$X \sim \text{Binomial}(\theta, N = 3). \quad [\text{A.32}]$$

10353 The properties of the binomial distribution enable us to make statements about the X ,
10354 such as its expected value and the likelihood that its value will fall within some interval.

Now suppose that θ is unknown, but we have run an experiment, in which we exe-
 cuted N trials, and obtained x heads. We can **estimate** θ by the principle of **maximum**
likelihood:

$$\hat{\theta} = \operatorname{argmax}_{\theta} p_X(x; \theta, N). \quad [\text{A.33}]$$

This says that the estimate $\hat{\theta}$ should be the value that maximizes the likelihood of the
 data. The semicolon indicates that θ and N are parameters of the probability function.
 The likelihood $p_X(x; \theta, N)$ can be computed from the binomial distribution,

$$p_X(x; \theta, N) = \frac{N!}{x!(N-x)!} \theta^x (1-\theta)^{N-x}. \quad [\text{A.34}]$$

10355 This likelihood is proportional to the product of the probability of individual out-
10356 comes: for example, the sequence T, H, H, T, H would have probability $\theta^3(1-\theta)^2$. The
10357 term $\frac{N!}{x!(N-x)!}$ arises from the many possible orderings by which we could obtain x heads
10358 on N trials. This term does not depend on θ , so it can be ignored during estimation.

In practice, we maximize the log-likelihood, which is a monotonic function of the like-
 lihood. Under the binomial distribution, the log-likelihood is a **convex** function of θ (see

§ 2.3), so it can be maximized by taking the derivative and setting it equal to zero.

$$\ell(\theta) = x \log \theta + (N - x) \log(1 - \theta) \quad [\text{A.35}]$$

$$\frac{\partial \ell(\theta)}{\partial \theta} = \frac{x}{\theta} - \frac{N - x}{1 - \theta} \quad [\text{A.36}]$$

$$\frac{N - x}{1 - \theta} = \frac{x}{\theta} \quad [\text{A.37}]$$

$$\frac{N - x}{x} = \frac{1 - \theta}{\theta} \quad [\text{A.38}]$$

$$\frac{N}{x} - 1 = \frac{1}{\theta} - 1 \quad [\text{A.39}]$$

$$\hat{\theta} = \frac{x}{N}. \quad [\text{A.40}]$$

10359 In this case, the maximum likelihood estimate is equal to $\frac{x}{N}$, the fraction of trials that
 10360 came up heads. This intuitive solution is also known as the **relative frequency estimate**,
 10361 since it is equal to the relative frequency of the outcome.

Is maximum likelihood estimation always the right choice? Suppose you conduct one trial, and get heads. Would you conclude that $\theta = 1$, meaning that the coin is guaranteed to come up heads? If not, then you must have some **prior expectation** about θ . To incorporate this prior information, we can treat θ as a random variable, and use Bayes' rule:

$$p(\theta | x; N) = \frac{p(x | \theta) \times p(\theta)}{p(x)} \quad [\text{A.41}]$$

$$\propto p(x | \theta) \times p(\theta) \quad [\text{A.42}]$$

$$\hat{\theta} = \operatorname{argmax}_{\theta} p(x | \theta) \times p(\theta). \quad [\text{A.43}]$$

10362 This is the **maximum a posteriori** (MAP) estimate. Given a form for $p(\theta)$, you can de-
 10363 rive the MAP estimate using the same approach that was used to derive the maximum
 10364 likelihood estimate.

10365 Additional resources

10366 A good introduction to probability theory is offered by Manning and Schütze (1999),
 10367 which helped to motivate this section. For more detail, Sharon Goldwater provides an-
 10368 other useful reference, <http://homepages.inf.ed.ac.uk/sgwater/teaching/general/probability.pdf>. A historical and philosophical perspective on probability is offered
 10369 by Diaconis and Skyrms (2017).

10371 **Appendix B**

10372 **Numerical optimization**

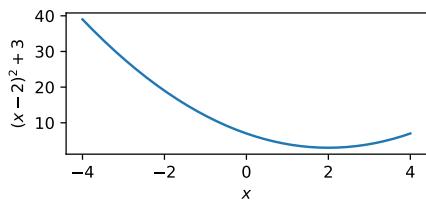
10373 Unconstrained numerical optimization involves solving problems of the form,

$$\min_{\mathbf{x} \in \mathbb{R}^D} f(\mathbf{x}), \quad [\text{B.1}]$$

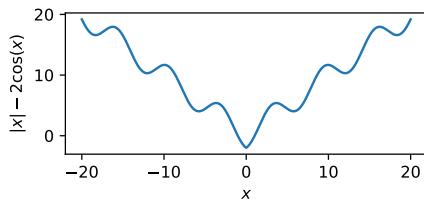
10374 where $\mathbf{x} \in \mathbb{R}^D$ is a vector of D real numbers.

10375 Differentiation is fundamental to continuous optimization. Suppose that at some \mathbf{x}^* ,
10376 every partial derivative is equal to 0: formally, $\frac{\partial f}{\partial x_i}\Big|_{\mathbf{x}^*} = 0$. Then \mathbf{x}^* is said to be a **critical**
10377 **point** of f . For a **convex** function f (defined in § 2.3), $f(\mathbf{x}^*)$ is equal to the global minimum
10378 of f iff \mathbf{x}^* is a critical point of f .

As an example, consider the convex function $f(x) = (x - 2)^2 + 3$, shown in Figure B.1a. The derivative is $\frac{\partial f}{\partial x} = 2x - 4$. A unique minimum can be obtained by setting the derivative equal to zero and solving for x , obtaining $x^* = 2$. Now consider the multivariate convex function $f(\mathbf{x}) = \frac{1}{2}\|\mathbf{x} - [2, 1]^\top\|^2$, where $\|\mathbf{x}\|^2$ is the squared Euclidean norm. The partial



(a) The function $f(x) = (x - 2)^2 + 3$



(b) The function $f(x) = |x| - 2\cos(x)$

Figure B.1: Two functions with unique global minima

derivatives are,

$$\frac{\partial d}{\partial x_1} = x_1 - 2 \quad [B.2]$$

$$\frac{\partial d}{\partial x_2} = x_2 - 1 \quad [B.3]$$

10379 The unique minimum is $\mathbf{x}^* = [2, 1]^\top$.

10380 For non-convex functions, critical points are not necessarily global minima. A **local**
 10381 **minimum** \mathbf{x}^* is a point at which the function takes a smaller value than at all nearby
 10382 neighbors: formally, \mathbf{x}^* is a local minimum if there is some positive ϵ such that $f(\mathbf{x}^*) \leq$
 10383 $f(\mathbf{x})$ for all \mathbf{x} within distance ϵ of \mathbf{x}^* . Figure B.1b shows the function $f(x) = |x| - 2 \cos(x)$,
 10384 which has many local minima, as well as a unique global minimum at $x = 0$. A critical
 10385 point may also be the local or global maximum of the function; it may be a **saddle point**,
 10386 which is a minimum with respect to at least one coordinate, and a maximum with respect
 10387 to at least one other coordinate; it may be an **inflection point**, which is neither a minimum
 10388 nor maximum. When available, the second derivative of f can help to distinguish these
 10389 cases.

10390 B.1 Gradient descent

For many convex functions, it is not possible to solve for \mathbf{x}^* in closed form. In gradient descent, we compute a series of solutions, $\mathbf{x}^{(0)}, \mathbf{x}^{(1)}, \dots$ by taking steps along the local gradient $\nabla_{\mathbf{x}^{(t)}} f$, which is the vector of partial derivatives of the function f , evaluated at the point $\mathbf{x}^{(t)}$. Each solution $\mathbf{x}^{(t+1)}$ is computed,

$$\mathbf{x}^{(t+1)} \leftarrow \mathbf{x}^{(t)} - \eta^{(t)} \nabla_{\mathbf{x}^{(t)}} f. \quad [B.4]$$

10391 where $\eta^{(t)} > 0$ is a **step size**. If the step size is chosen appropriately, this procedure will
 10392 find the global minimum of a differentiable convex function. For non-convex functions,
 10393 gradient descent will find a local minimum. The extension to non-differentiable convex
 10394 functions is discussed in § 2.3.

10395 B.2 Constrained optimization

Optimization must often be performed under constraints: for example, when optimizing the parameters of a probability distribution, the probabilities of all events must sum to one. Constrained optimization problems can be written,

$$\min_{\mathbf{x}} f(\mathbf{x}) \quad [B.5]$$

$$\text{s.t. } g_c(\mathbf{x}) \leq 0, \quad \forall c = 1, 2, \dots, C \quad [B.6]$$

where each $g_i(\mathbf{x})$ is a scalar function of \mathbf{x} . For example, suppose that \mathbf{x} must be non-negative, and that its sum cannot exceed a budget b . Then there are $D + 1$ inequality constraints,

$$g_i(\mathbf{x}) = -x_i, \quad \forall i = 1, 2, \dots, D \quad [\text{B.7}]$$

$$g_{D+1}(\mathbf{x}) = -b + \sum_{i=1}^D x_i. \quad [\text{B.8}]$$

Inequality constraints can be combined with the original objective function f by forming a **Lagrangian**,

$$L(\mathbf{x}, \boldsymbol{\lambda}) = f(\mathbf{x}) + \sum_{c=1}^C \lambda_c g_c(\mathbf{x}), \quad [\text{B.9}]$$

where λ_c is a **Lagrange multiplier**. For any Lagrangian, there is a corresponding **dual form**, which is a function of $\boldsymbol{\lambda}$:

$$D(\boldsymbol{\lambda}) = \min_{\mathbf{x}} L(\mathbf{x}, \boldsymbol{\lambda}). \quad [\text{B.10}]$$

The Lagrangian L can be referred to as the **primal form**.

B.3 Example: Passive-aggressive online learning

Sometimes it is possible to solve a constrained optimization problem by manipulating the Lagrangian. One example is maximum-likelihood estimation of a Naïve Bayes probability model, as described in § 2.1.3. In that case, it is unnecessary to explicitly compute the Lagrange multiplier. Another example is illustrated by the **passive-aggressive** algorithm for online learning (Crammer et al., 2006). This algorithm is similar to the perceptron, but the goal at each step is to make the most conservative update that gives zero margin loss on the current example.¹ Each update can be formulated as a constrained optimization over the weights $\boldsymbol{\theta}$:

$$\min_{\boldsymbol{\theta}} \frac{1}{2} \|\boldsymbol{\theta} - \boldsymbol{\theta}^{(i-1)}\|^2 \quad [\text{B.11}]$$

$$\text{s.t. } \ell^{(i)}(\boldsymbol{\theta}) = 0 \quad [\text{B.12}]$$

where $\boldsymbol{\theta}^{(i-1)}$ is the previous set of weights, and $\ell^{(i)}(\boldsymbol{\theta})$ is the margin loss on instance i . As in § 2.3.1, this loss is defined as,

$$\ell^{(i)}(\boldsymbol{\theta}) = 1 - \boldsymbol{\theta} \cdot \mathbf{f}(\mathbf{x}^{(i)}, y^{(i)}) + \max_{y \neq y^{(i)}} \boldsymbol{\theta} \cdot \mathbf{f}(\mathbf{x}^{(i)}, y). \quad [\text{B.13}]$$

¹This is the basis for the name of the algorithm: it is passive when the loss is zero, but it aggressively moves to make the loss zero when necessary.

When the margin loss is zero for $\theta^{(i-1)}$, the optimal solution is simply to set $\theta^* = \theta^{(i-1)}$, so we will focus on the case where $\ell^{(i)}(\theta^{(i-1)}) > 0$. The Lagrangian for this problem is,

$$L(\theta, \lambda) = \frac{1}{2} \|\theta - \theta^{(i-1)}\|^2 + \lambda \ell^{(i)}(\theta), \quad [\text{B.14}]$$

Holding λ constant, we can solve for θ by differentiating,

$$\nabla_{\theta} L = \theta - \theta^{(i-1)} + \lambda \frac{\partial}{\partial \theta} \ell^{(i)}(\theta) \quad [\text{B.15}]$$

$$\theta^* = \theta^{(i-1)} + \lambda \delta, \quad [\text{B.16}]$$

where $\delta = f(x^{(i)}, y^{(i)}) - f(x^{(i)}, \hat{y})$ and $\hat{y} = \operatorname{argmax}_{y \neq y^{(i)}} \theta \cdot f(x^{(i)}, y)$.

The Lagrange multiplier λ acts as the learning rate in a perceptron-style update to θ . We can solve for λ by plugging θ^* back into the Lagrangian, obtaining the dual function,

$$D(\lambda) = \frac{1}{2} \|\theta^{(i-1)} + \lambda \delta - \theta^{(i-1)}\|^2 + \lambda(1 - (\theta^{(i-1)} + \lambda \delta) \cdot \delta) \quad [\text{B.17}]$$

$$= \frac{\lambda^2}{2} \|\delta\|^2 - \lambda^2 \|\delta\|^2 + \lambda(1 - \theta^{(i-1)} \cdot \delta) \quad [\text{B.18}]$$

$$= -\frac{\lambda^2}{2} \|\delta\|^2 + \lambda \ell^{(i)}(\theta^{(i-1)}). \quad [\text{B.19}]$$

Differentiating and solving for λ ,

$$\frac{\partial D}{\partial \lambda} = -\lambda \|\delta\|^2 + \ell^{(i)}(\theta^{(i-1)}) \quad [\text{B.20}]$$

$$\lambda^* = \frac{\ell^{(i)}(\theta^{(i-1)})}{\|\delta\|^2}. \quad [\text{B.21}]$$

The complete update equation is therefore:

$$\theta^* = \theta^{(i-1)} + \frac{\ell^{(i)}(\theta^{(i-1)})}{\|f(x^{(i)}, y^{(i)}) - f(x^{(i)}, \hat{y})\|^2} (f(x^{(i)}, y^{(i)}) - f(x^{(i)}, \hat{y})). \quad [\text{B.22}]$$

This update has strong intuitive support. The numerator of the learning rate grows with the loss. The denominator grows with the norm of the difference between the feature vectors associated with the correct and predicted label. If this norm is large, then the step with respect to each feature should be small, and vice versa.

10413

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