INFR 09028 - Foundations of Natural Language Processing

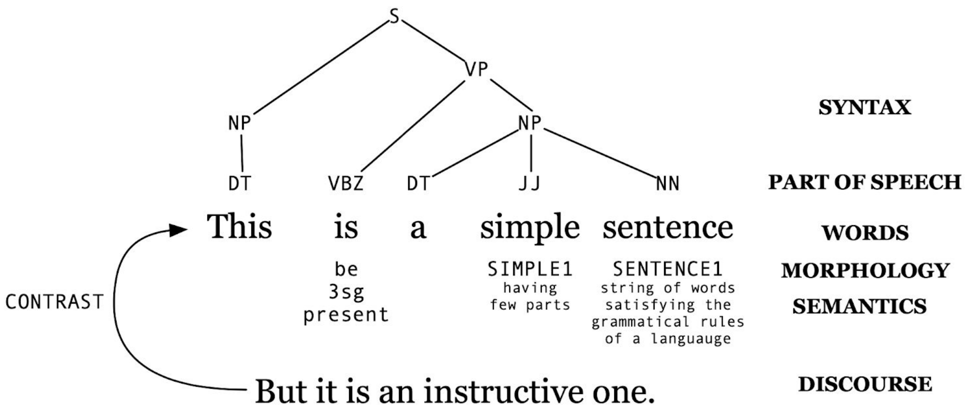
Revision Notes

(content based on Bora M. Alper's notes)

Contents

Lecture 1 - Introduction

Syntax, Part of Speech, Words, Morphology, Semantics and Discourse



Why is NLP hard?

- Because there is **ambiguity** at many levels:
  - **Word senses:** "bank" (finance or river?)
  - **Part of speech:** "chair" (noun or verb?)
  - **Syntactic structure:** "I saw a man with a telescope" (did you use a telescope to see the man or did the man have a telescope?)
  - **Quantifier scope:** "Every child loves some movie" (there exist a movie that every child loves or every child loves at least one movie)
  - **Multiple:** "I saw her duck" (you saw her ducking or you saw a duck that she had?)
  - **Reference:** "John dropped the goblet onto the glass table and it broke" (what broke - the goblet or the glass table?"
  - **Discourse:** "The meeting is cancelled. Nicholas isn't coming to the office today." (is the meeting cancelled because he isn't coming or is he not coming because the meeting is cancelled?)

Two ways of dealing with ambiguity

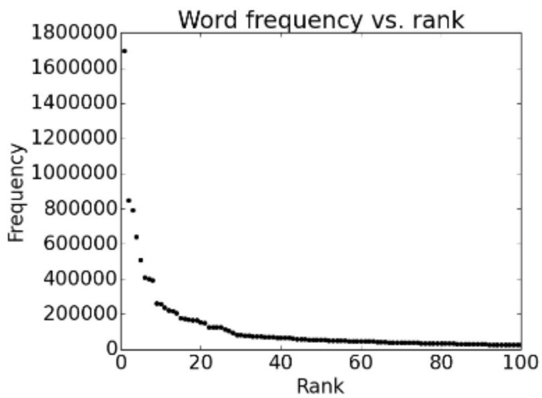
- Non-probabilistic methods, returning *all* possible answers
  - E.g. FSMs for morphology, CKY parsers for syntax
- Probabilistic methods returning the *best* possible analysis
  - E.g. HMMs for POS tagging, PCFGs for syntax, Viterbi, probabilistic CKY
  - The best analysis is only good if our model's probabilities are accurate; so where do accurate probabilities come from?

Statistical NLP

- Like most other parts of AI, NLP today is dominated by statistical
- Typically more robust than earlier rule-based methods
- Probabilities are *learned* from data
  - Usually requires *lots of data* about any particular phenomenon

Why is NLP hard again?

- Zipf's Law



- The frequency of a word is inversely proportional to its rank in the frequency table (and it's also exponential!)

$$f \times r \approx k$$

  - f for frequency, r for rank, and k for constant
  - So what is the most common word, say "the", occurs 1,000,000 times in a corpus whereas the 20th most common word, say "do", occurs only 200,000 times.
- It's a natural phenomenon that is observed in other languages and other fields as well
- Regardless of the size of your corpus!
- Can also be observed for other linguistic structure (e.g. syntactic rules in a CFG)
- These mean that we need to find clever ways to estimate probabilities for things we have rarely or never seen during training

- Variation
  - Suppose we train a Part of Speech tagger on the Wall Street Journal, which is nice and neat and copy-edited
  - What will happen if we try to use this tagger for social media?
    - E.g. Tweet: ikr smh he asked fir yo last name
- Expressivity
  - Not only can one form have different meanings (ambiguity) but the same meaning can be expressed with different forms:

    She gave the book to Tom vs. *She gave Tom the book*
    Some kids popped by vs. *A few children visited*
    Is that window still open vs. *Please close the window*
- Context dependence
  - Last example also shows that the correct interpretation is context-dependent and often requires world knowledge (that person is angry, for instance)

Lecture 2 - Text Corpora

Corpora

- A **corpus** body of utterances, as words or sentences, assumed to be *representative* of and used for lexical, grammatical, or other linguistic analysis
- To understand and model how language works, we need empirical evidence; ideally, this should be **naturally-occuring** corpora
- Aside from utterances, corpus datasets include **metadata** - side information about where the utterances come from, such as author, date, topic, publication, etc.
- Corpora with **linguistic annotations** are of particular interest for *core NLP* and therefore this course, where humans have read the text and marked categories and/or structures describing their syntax and/or meaning
    - Can be derived automatically from the original data artifact (such as star ratings) too
    - Consistency of human annotators is a big issue - unambiguous rules are required to resolve disagreements

Sentiment Analysis

- Goal: predict the *opinion* expressed in a piece of text
    - Either *positive* or *negative*
    - Or *rating* on a scale
- The simplest way is to count then number of words with positive and negative denotations/connotations

Building a Sentiment Analyzer

1. What is the input for each prediction? Sentence? Full review text? Text + metadata?
2. What are the possible outputs? Positive or negative? Stars?
3. How will it decide?
    a. When a system's behaviour is determined solely by manual rules or databases, it is said to be **rule-based**, **symbolic**, or **knowledge-driven** (early days of computational linguistics)
    b. **Learning** is the act of collecting statistics or patterns automatically from corpora to govern the system's behaviour (dominant in most areas of contemporary NLP)
        i. **Supervised learning** is when the data provides example input-output pairs
        ii. Core behaviour: **training**
        iii. Refining behaviour: **tuning**
4. How will you measure its effectiveness? This requires data!

- Before you build a system, choose a dataset for evaluation
- Why is data-driven evaluation important?
    - Good science requires controlled experimentation
    - Good engineering requires benchmarks
    - Your intuitions about typical inputs are probably wrong
- Often you should have multiple evaluation datasets: one for *development* as you hack on your system, and one reserved for *final* testing
    - So that we don't optimize for the benchmark only! (for instance by overfitting)
- **Gold labels**: correct labels
- **Evaluation**
    - Simplest measure: $accuracy = \frac{\# correct}{\# total}$

A simple sentiment classification algorithm

- Use a **sentiment lexicon** to count positive and negative words:

Positive:

absolutely	beaming	calm
adorable	beautiful	celebrated
accepted	believe	certain
acclaimed	beneficial	champ
accomplish	bliss	champion
achieve	bountiful	charming
action	bounty	cheery
active	brave	choice
admire	bravo	classic
adventure	brilliant	classical
affirm	bubbly	clean
. . .		. . .

Negative:

abysmal	bad	callous
adverse	banal	can't
alarming	barbed	clumsy
angry	belligerent	coarse
annoy	bemoan	cold
anxious	beneath	collapse
apathy	boring	confused
appalling	broken	contradictory
atrocious		contrary
awful		corrosive
		corrupt
		. . .

- Simplest rule: count positive and negative words in the text and predict whichever is greater!
- Problems
    - Hard to know whether words that *seem* positive or negative tend to actually be used that way
        - Sense ambiguity, e.g. “It was awfully beautiful.”
        - Sarcasm/irony, e.g. “Oh yeah it was definitely wonderful!”
        - Text could mention expectations or opposing viewpoints, in contrast to author’s actual opinion, e.g. “I was expecting a great movie as my friends described it as a brilliant classic but I think it was just awful.”
        - To address this problem, use a data-driven method: use **frequency counts** from *training* corpus to ascertain which words tend to be positive or negative
    - Opinion words may be describing, for example, a character’s attitude rather than being an evaluation of the film, e.g. “The villain in the movie did horrible things to the main characters.”
    - Some words act as semantic modifiers of other opinion-bearing words/phases so interpreting the full meaning requires sophistication:
        - I **can’t** stand this movie
        - I **can’t** believe how great the movie is

Preprocessing and Normalisation

- Normal written conventions often do not reflect the ‘logical’ organisation of textual symbols
    - For example, some punctuation marks are written adjacent to the previous or following word, even though they are not part of it
    - The details vary according to language and style guide
- Given a string of raw text, a **tokeniser** adds logical boundaries between separate words/punctuation **tokens** (occurrences) not separated by spaces:

    Daniels made several appearances as C-3PO on numerous TV shows and commercials, notably on a Star Wars-themed episode of The Donny and Marie Show in 1977, Disneyland’s 35th Anniversary

    =>

    Daniels made several appearances as C-3PO on numerous TV shows and commercials , notably on a Star Wars - themed episode of The Donny and Marie Show in 1977 , Disneyland ’s 35th Anniversary

    - To a large extent, this can be automated by rules. But there are always difficult cases (e.g. “C-3PO)
- English tokenisation conventions vary somewhat, for example, with respect to:
    - **Clitics** (contracted forms): ‘s, n’t, ‘re, etc.
    - **Hyphens** in compounds like *president-elect*

- Word-level tokenisation is just part of the larger process of preprocessing or normalisation, which may also include:
    - Encoding conversion
    - Removal of markup
    - Insertion of markup
    - Case conversion
    - Sentence boundary detection (called **sentence tokenisation**)
- It should be evident that a *large number of decisions* have to be made, many of them dependent on the eventual intended use fo the output, before a satisfactory preprocessor for such data can be produced
    - *Documenting* those decisions and their implementation is then a key step in establishing the credibility of any subsequent experiments
        - Documentation is especially important if the dataset is to be distributed publicly

Choice of Training and Evaluation Data

- We know that the way people use language varies considerably depending on **context**. Factors include:
    - **Mode of communication**: speech (in person, telephone, …), writing (print, SMS, web, …)
    - **Topic:** chit-chat, politics, sports, physics
    - **Genre:** news story, novel, Wikipedia article, persuasive essay, political address, tweet
    - **Audience:** formality, politeness, complexity (e.g. child-directed speech)
    - In NLP, **domain** is a cover-term for all these factors
- Statistical approaches typically assume that the training data and the test data are sampled from the same distribution
    - I.e. if you say an example data point, it would be hard to guess whether it was from the training or test data
- Things can go awry if the test data is appreciably different, for example
    - Different tokenisation conventions
    - New vocabulary
    - Longer sentences
    - More colloquial/less edited style
    - Different distribution of labels
- **Domain adaptation** techniques attempt to correct for this assumption when something about the source/characteristics of the test data is known to be different

Lecture 3 - N-gram Language Models

Probability of a sentence

- How likely is it to occur in natural language
    - Consider only a specific language (English, or even more specifically British English)
    - Not including meta-language (e.g. linguistic discussion)
    - P("the cat slept peacefully") > P("slept the peacefully cat")
        - Use case: generative NLP (abstractive summarisation)
    - P("she studies morphosyntax") > P("she studies more faux syntax")
        - Use case: audio transcription
    - It's very difficult to know the true probability of an arbitrary sequence of words
    - But we can define a **language model** to give us a good *approximation*
    - Like all models, language models will be good at capturing *some* things and *less* good for others
        - We might want different models for different tasks

Use cases of a Language Model

- Spelling correction
    - Sentence probabilities help decide correct spelling

mis-spelled text		no much effert
↓	(Error model)	
possible outputs		no much effect so much effort no much effort not much effort ...
↓	(Language model)	
best-guess output		not much effort

- Automatic speech recognition
    - Sentence probabilities help decide between similar-sounding options

speech input		
↓	(Acoustic model)	
possible outputs		She studies morphosyntax She studies more faux syntax She's studies morph or syntax ...
↓	(Language model)	
best-guess output		She studies morphosyntax

- Machine translation
    - Sentence probabilities help decide word choice and word order

non-English input		
↓	(Translation model)	
possible outputs		She is going home She is going house She is traveling to home To home she is going ...
↓	(Language model)	
best-guess output		She is going home

- Prediction

- Language models can be used for **prediction** as well as correction
- E.g. predictive text correction/completion on your mobile phone
    - Keyboard is tiny, easy to touch a spot slightly off from the letter you meant
    - Want to correct such errors as you go and also provide possible completions
    - Predicts as you are typing
    - In this case, a language model may be defined over sequences of *characters* instead of (or in addition to) sequences of *words*

Estimating Probabilities

- We want to know the probability of a word sequence $\mathbf{w} = \mathbf{w}_1 \ldots \mathbf{w}_n$ occurring in English
- Assume we have some **training data**: large corpus of general English text
- We can use this data to **estimate** the probability of **w** (even if we never see it in the corpus!)

Probability Theory vs. Estimation

- Probability theory can solve problems like:
    - I have a jar with 6 blue marbles and 4 red ones.
    - If I choose a marble uniformly at random, what is the probability that the marble is red?
- But often we don't know the *true probabilities*, we only have data:
    - I have a jar of marbles
    - I repeatedly choose a marble uniformly at random and then replace it before choosing again
    - In ten draws, I get 6 blue marbles and 4 red ones
    - On the next draw, what's the probability that I get a red marble?
    - First three facts are evidence
    - The question requires estimation theory!

Notation

- I will often omit the random variable in writing probabilities, using $P(x)$ to mean $P(X = x)$.
- When the distinction is important, I will use
    - $P(x)$ for *true* probabilities
    - $\hat{P}(x)$ for *estimated* probabilities
    - $P_{\mathrm{E}}(x)$ for estimated probabilities using a particular estimation method E.
- But since we almost always mean estimated probabilities, I may get lazy later and use $P(x)$ for those too.

Relative Frequency Estimation

- Intuitive way to estimate discrete probabilities

$$P_{RF}(x) = \frac{C(x)}{N}$$

  Where:
    - $C(x)$ is the count of x in a large dataset
    - $N = \sum_{x'} C(x')$ is the total number of items in the dataset
- This method is also known as **maximum-likelihood estimation (MLE)**

Problems

- Using MLE on full sentences doesn't work well for language model estimation

        - All sentences that have never occurred get zero probability even if they are grammatical (and meaningful)
- In general, MLE thinks anything that *hasn't occurred* will never occur (P=0)
    - Clearly not true! Such things can have *differing* and *non-zero* probabilities, for example:
        - My hair turns blue
        - I ski a black run
        - I travel to Finland
    - And similarly for word sequences that have never occurred

Sparse data

- In fact, even things that occur once or twice in our training data are a problem
- The sparse data problem is that there are **not enough observations to estimate probabilities well simply by counting observed data**
- For sentences, many (most!) will occur rarely if ever in our training data, so we need to do something far smarter

N-gram models

- One way to tackle the sparse data problem is to estimate **P(w)** by comparing the probabilities of *smaller parts* of the sentence, which will occur more frequently
- This is the intuition behind n-gram language models

Deriving an N-Gram Model

$$\begin{aligned} P(S = \text{"}the\ cat\ slept\ quietly\text{"}) &= P(the,\ cat,\ slept,\ quietly) \\ &= P(quitely \mid the,\ cat,\ slept)\ x\ P(the,\ cat,\ slept) \\ &= P(quitely \mid the,\ cat,\ slept)\ x\ P(slept \mid the,\ cat)\ x\ P(the,\ cat) \\ &= P(quitely \mid the,\ cat,\ slept)\ x\ P(slept \mid the,\ cat)\ x\ P(cat \mid the)\ x\ P(the) \end{aligned}$$

- More generally, we can use the chain rule
- But many of these conditional probabilities are just as sparse
    - If we want $P(the,\ cat,\ slept,\ quietly)$ we still need $P(quitely \mid the,\ cat,\ slept)$
- So we make an **independence assumption**: the probability of a word only depends on a fixed number of previous words (called **history**)

trigram model: $P(w_i|w_1, w_2, \ldots w_{i-1}) \approx P(w_i|w_{i-2}, w_{i-1})$
bigram model: $P(w_i|w_1, w_2, \ldots w_{i-1}) \approx P(w_i|w_{i-1})$
unigram model: $P(w_i|w_1, w_2, \ldots w_{i-1}) \approx P(w_i)$

- This assumption is not always a good one, but it does reduce the sparse data problem
- If we use MLE, we consider:
    - Out of all cases where we saw $w_{i-2},\ w_{i-1}$ (in order) as the first two words of a trigram, how many had w_i as the third word?

Beginning/End of Sequence

- To capture behaviour at beginning/end of sequences, we can augment the input with <s> and </s>
- Alternatively, we can model all sentences as one (very long) sequence, including punctuation

Costs (negative log probabilities)

- Word probabilities are typically very small

- Multiplying lots of small probabilities quickly gets so tiny that we cannot represent the numbers accurately, even with double precision floating point
- So in practice, we typically use **negative log probabilities** (also called **costs**)
  - Since lower probabilities range from 0 to 1, negative log probabilities range from 0 to infinity
  - *Lower* cost = *higher* probability
  - Instead of *multiplying* probabilities, we *add* negative log probabilities

Problems

- N-gram models can be too simplistic, length of a 'context' often varies: can be shorter or longer than an arbitrary *N*
  - Longer histories may capture more but are also more sparse
- Still suffers from assigning zero probabilities to not-seen sequences

Lecture 4 - Language Models: Evaluation and Smoothing

Evaluating a Language Model

- Intuitively, a trigram model captures more context than a bigram model, so it should be a ‘better’ model
    - That is, it should *more accurately predict the probabilities of sentences*
    - But how can we measure this?

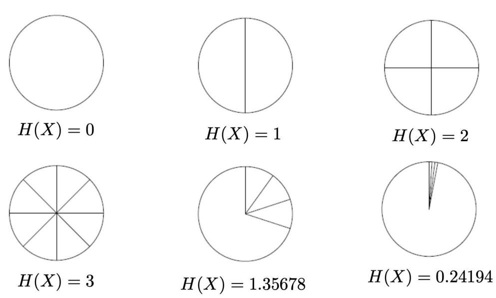
Types of Evaluation in NLP

- **Extrinsic:** measure performance on a downstream application
    - For a language model, plugging it into a machine translation, automated speech recognition, etc.
    - The most reliable evaluation, but can be time-consuming
    - And of course, we still need an evaluation measure for the downstream system!
- **Intrinsic:** design a measure that is *inherent* to the current task
    - Can be much quicker/easier during development cycle
    - But not always easy to figure out what the right measure is
        - Ideally, on that correlates well with extrinsic measures

Entropy

$$H(X) = \sum_{x} - P(x) log_2 P(x) = E[- log_2 P(X)]$$

- Intuitively, a measure of uncertainty/disorder
    - A measure of how ‘surprising’ a probability distribution is
- Example: where the area of a section is proportional to its probability



Entropy as Yes/No Questions

- Entropy is the answer to how many yes-no questions (bits) do we need to find out the outcome (or to *encode* the outcome)
- Uniform distributions with 2^n outcomes require n yes-no questions
- Average number of bits needed to encode $X \geq$ $entropy\ of\ X$

Estimates and Cross Entropy

- A good model should have low uncertainty (entropy) about what comes next
    - Lower cross entropy means that a model is better at predicting the next element (e.g. the next word)
- Cross entropy measures how close $\widehat{P}$ (estimate) is to P (true):

$$H(P, \widehat{P}) = \sum_{x} - P(x) log_2 \widehat{P}(x)$$

- Note that cross-entropy $\geq$ entropy

- A model's uncertainty can be no less than the true uncertainty
- But we still don't know $P(x)$

Estimating Cross Entropy

- For $w_1, ..., w_n$ with a large n, per-word cross-entropy is well approximated by:

$$H_M(w_1, ..., w_n) = -\frac{1}{n} log_2 P_M(w_1, ..., w_n)$$

- That is just the average negative log probability our model assigns to each word in the sequence (i.e. normalised for sequence length)

Perplexity

- Language model performance is often reported as **perplexity** rather than cross-entropy

$$perplexity = 2^{cross-entropy}$$

- The average branching factor at each decision point is 2, if our distribution were uniform
- So, 6 bits of cross-entropy means our model's perplexity is $2^6 = 64$; equivalent uncertainty to a uniform distribution over 64 outcomes

Interpreting Measures

- Cross entropy of a language model on some corpus is 5.2
- Is this *good*?
- No way to tell! Cross entropy depends on both the *model* and the *corpus*
    - **Some languages are simply more predictable** (e.g. casual speech vs. academic writing)
        - So lower cross entropy could mean that the corpus is 'easy', rather than the model is good
    - We can only compare different models on the same corpus
        - Measured on 'held-out' data

Sparse data, again

- Remember that MLE assigns zero probability to never observed sequences
- Meaning that cross-entropy would be infinite (because of $log_2 0$)
- Basically right: our model says that something should *never* occur, so our model is infinitely wrong (or rather, we are infinitely surprised) when it does occur!
- Even with a unigram model we we will run into words we never saw before
    - So even with short(est) n-grams, we need better ways to estimate probabilities from sparse data

Smoothing

- The flaw of MLE is that it estimates probabilities that make the training data maximal;y probable, by making everything else (i.e. unseen data) minimally probable
- **Smoothing** methods address the problem by stealing probability mass from seen events and (*somehow*) reallocating it to unseen events
- There are lots of different methods based on different kinds of assumptions
- In smoothing, we have to ensure that all the probabilities still sum up to 1

Add-One (Laplace) Smoothing

- Just pretend we saw everything one more time than we did

$$P_{+1}(w_i \mid w_{i-2},\ w_{i-1}) \ = \ \frac{C(w_{i-2}, w_{i-1}, w_i) + 1}{C(w_{i-2}, w_{i-1}) + v}$$

  where v is the vocabulary size.
- Problems
    - Laplace smoothing steals *way* too much from seen events
        - In fact, MLE is pretty good for frequent events, so we shouldn't want to change these much
    - Assumes that we know the vocabulary size in advance
        - And also that the size of our vocabulary is fixed
        - To remediate, we can just add a single 'unknown' (UNK) item, and use this for all unknown words

Add-α (Lidstone) Smoothing

- We can improve things by adding α < 1

$$P_{+\alpha}(w_i \mid w_{i-2},\ w_{i-1}) \ = \ \frac{C(w_{i-2}, w_{i-1}, w_i) + \alpha}{C(w_{i-2}, w_{i-1}) + \alpha v}$$

Good-Turing Smoothing

- Previous methods changed the denominator, which can have big effects on frequent events
- Good-Turing changes the numerator only
- Think of Good-Turing like this:
    - MLE divides count c of n-gram by count n of history: $P_{ML} = \frac{c}{n}$
    - Good-Turing uses **adjusted counts** c^* instead: $P_{GT} = \frac{c^*}{n}$
- There are even better methods!

Lecture 5 - More Smoothing and the Noisy Channel Model

Problems with Good-Turing

- Assumes we know the vocabulary size (i.e. no unseen words)
  - Use UNK
- Does not allow 'holes' in the counts (i.e. if $N_i > 0$ then $N_{i-1} > 0$)
  - Use linear regression
- Applies discounts even to high-frequency items
- Assigns equal probabilities to all unseen events
  - A better solution is to **use information from lower order N-grams (shorter histories)**
    - Beer drinkers (likely)
    - Beer eaters (unlikely)
  - Two methods:
    - Interpolation
    - Backoff

Interpolation

- Combine higher and lower N-gram models, since they have different strengths and weaknesses:
  - **Higher-order** n-grams are **sensitive to more context**, but have **sparse** counts
  - **Lower-order** n-grams have **limited context** but **robust** counts
- If P_N is N-gram estimate (from MLE, GT, etc; $N = 1 \text{ to } 3$), use:

  $$P_{INT}(w_3|w_1, w_2) = \lambda_1 P_1(w_3) + \lambda_2 P_2(w_3 \mid w_2) + \lambda_3 P_3(w_3 \mid w_1, w_2)$$

  E.g. $P_{INT}(three \mid I,\ spent) = \lambda_1 P_1(three) + \lambda_2 P_2(three \mid spent) + \lambda_3 P_3(three \mid I,\ spent)$
- Note that all λ_i s must sum to 1!

Fitting Interpolation Parameters

- In general, any weighted combination of distributions is called a **mixture model**
- So λ_i s are **interpolation parameters** or **mixture weights**
- The values of the λ_i s are chosen to optimise perplexity on a held-out dataset

Katz Back-Off

- Solve the problem in a similar way to Good-Turing smoothing
- Discount the trigram-based probability estimates
- This leaves some probability mass to share among the estimates from the lower order models
- Instead of distributing the mass *uniformly* over unseen items, use it for **backoff estimates**

Diversity of Histories

- "York" almost always directly follows "New", say in a corpus
- So, in unseen bigram contexts, "York" should have low probability
  - Lower than predicted by unigram model as used in interpolation/backoff

Kneser-Ney Smoothing

- Kneser-Ney smoothing takes diversity of histories into account
- Count of distinct histories for a word $N_{1+}(\cdot\, w_i) = |\{ w_{i-1} :\ c(w_{i-1},\ w_i) > 0\}|$
  - In the formula above, w_{i-1} is the history (i.e. bigram model)

- Recall: MLE of unigram language model $P_{ML}(w_i) = \frac{C(w_i)}{\sum_w C(w)}$
- In KN smoothing, replace raw counts with count of histories: $P_{KN}(w_i) = \frac{N_{1+}(\cdot w_i)}{\sum_w N_{1+}(\cdot w)}$
- The best thing about KN smoothing is that it gives you the probability of “appearing in new contexts”

Kneser-Ney in practice

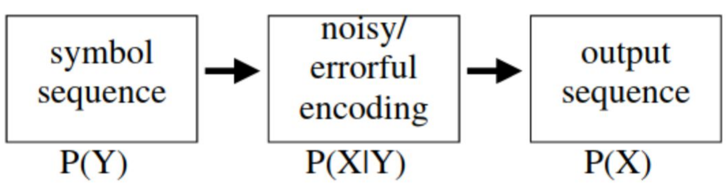
- Original version used backoff, later “modified Kneser-Ney” introduced using interpolation
- Fairly complex equations, but until recently the best smoothing method for word n-grams

Distributed Representations and Word Similarity

- E.g. Word2Vec
- Use neural networks to project words into a continuous space, so words that appear in similar contexts have similar representation
- Can $P(salmon \mid caught,\ two)$ tell us anything about $P(swordfish \mid caught,\ two)$?
    - N-gram models say no
    - But we know that both are fish and can be caught

Noisy Channel

- We imagine that someone tries to communicate a sequence to us, but noise is introduced; we only see the output sequenced
-



Application	**Y**	**X**
Speech Recognition	spoken words	acoustic signal
Machine Translation	words in L_A	words in L_B
Spelling Correction	intended words	typed words

- $P(Y)$ is the language model
- $P(X|Y)$ is the distribution describing the ‘likelihood’ of the output given the intention; we call it the **noise model**
- $P(X)$ is the resulting distribution over what we actually see
- Given some particular observation x, we want to recover the most probable y that was intended

Noisy Channel as Probabilistic Inference

- Mathematically, what we want is $argmax_y P(y|x)$
- Rewrite using Bayes’ rule:
  $argmax_y P(y|x) = argmax_y \frac{P(x|y)P(y)}{P(x)} = argmax_y P(x|y)P(y)$
    - $P(x|y)$ is the noise model
        - Varies heavily depending on the application: acoustic model, translation model, misspelling model, etc.
    - $P(y)$ is the language model

        - Fairly same for different applications
- Training conditional probabilities often requires *input/output pairs* which are often limited:
    - Misspelled words with their corrections, transcribed speech, translated text
- But language models can be trained on *huge unannotated* corpora: a better model; can help improve overall performance
- Assume we have a way to compute $P(x|y)$ and $P(y)$. Can we do the following:
    - Consider all possible intended words y
    - For each y, compute $P(x|y)P(y)$
    - Return the y with the highest $P(x|y)P(y)$ value

No, we can't. Without constraints, there are (nearly) infinite number of possible y s.

Lecture 6 - Spelling correction, Edit Distance and EM

Edit Distance

- The task: find the **optimal character alignment** between two words (the one with the fewest character changes: the **minimum edit distance** or MED)
- Example: *if all changes count equally,* MED(stall, table) is 3:

```
S T A L L
  T A L L      deletion
  T A B L      substitution
  T A B L E    insertion
```

    - Written as an alignment:

```
S T A L L
d | | s | i
- T A B L E
```

- There may be multiple best alignments
    - And lots of *non-optimal* alignments
- For now, all costs are equal: $cost(ins) = cost(del) = cost(sub) = 1$
    - But we can choose whatever costs we want! They can even depend on the particular characters involved

Finding an optimal alignment

- Brute force doesn't scale well
    - The number of alignments to check grows exponentially with the length of the sequences
- Instead we will use *dynamic programming* algorithm
    - Strings of length n and m require $O(mn)$ time and $O(mn)$ space.

Chart

		T	A	B	L	E
	0					
S						
T						
A						
L						
L						?

- $\mathrm{Chart}[i, j]$ stores two things:
    - $D(\mathrm{stall}[0..i], \mathrm{table}[0..j])$: the MED of **substrings of length** i, j
        - (row, column) addressing
    - Backpointer(s): which sub-alignment(s) used to create this one.

The idea

- **Deletion** move down
- **Insertion** move right
- **Substitution** move down and right
- If the letters are identical, it's called **Identical** and often has no cost
- Sum costs as we expand out from cell (0,0) to populate the entire matrix

Filling first cell

		T	A	B	L	E
	0					
S	↑1					
T						
A						
L						
L						

- Moving down in the chart means that we had a **deletion of S**
  - That is, we aligned (S) with (-)
- Add cost of deletion (1) and a backpointer (to where it came from)

Second column

		T	A	B	L	E
	0	←1				
S	↑1					
T	↑2					
A	↑3					
L	↑4					
L	↑5					

- Moving right in the chart (from (0,0)) means that we had an **insertion of T**
  - That is, we aligned (-) with (T)
- Add a cost of insertion (1) and backpointer (to where we came from)

Single best path

		T	A	B	L	E
	0	←1				
S	↑1	←↖↑2				
T	↑2	↖1				
A	↑3					
L	↑4					
L	↑5					

Now compute $D(ST, T)$. Take the minimum of three possibilities:

- $D(ST,-) + cost(ins) \;=\; 2 + 1 = 3$
  - Moving right from (2, 0)
- $D(S, T) + cost(del) \;=\; 2 + 1 = 3$
  - Moving down from (1, 1)
- $D(S,-) + cost(ident) \;=\; 1 + 0 = 1$
  - Moving down and right from (1,0), but since the letters are identical (T), it is not substitution but identical, the cost is 0

Completed Chart

		T	A	B	L	E
	0	←1	←2	←3	←4	←5
S	↑1	←↖↑2	←↖↑3	←4	←5	←6
T	↑2	↖1	←2	←3	←4	←5
A	↑3	↑2	↖1	←2	←3	←4
L	↑4	↑3	↑2	←↖↑3	↖2	←3
L	↑5	↑4	↑3	←↖↑4	↖↑3	←↖↑4

- You can enumerate all the optimum MEDs by starting from the bottom right cell and following the arrows until the top left cell.
  - If there are multiple arrows in a cell, it means that there are multiple optimum solutions.

Uses of Alignment and MED

- Computing distances and/or alignments between arbitrary strings can be used for:
    - Spelling correction
    - Morphological analysis (which words are likely to be related?)
    - Other fields entirely (e.g. comparing DNA sequences in biology)
    - Related algorithms are also used in speech recognition and time series data mining

Catch-22

- In our examples, we used costs of 1 (insertion and deletion) and 2 (substitution) to compute alignments
- We actually want to compute our alignments using the costs from our noise model: the most probable alignment under that model is what we are interested in
- But alas, until we have the alignments, we can't estimate the noise model

General Formulation

- This sort of problem actually happens a lot in NLP (and ML)
- We have some probabilistic model and want to estimate its **parameters** (here, the costs)
- The model also contains variables whose value is unknown (here, the correct character alignments)
- We would be able to estimate the parameters if we knew the values of the variables
    - And conversely, we would be able to infer the values of the variables if we knew the values of the parameters

Expectation-Maximisation

- Problems of this type can often be solved using a version of EM
    1. Initialise parameters to arbitrary values (e.g. set all costs to 1)
    2. Using these parameters, compute optimal values for variables (run MED to get alignments)
    3. Now using those alignments, **recompute** the parameters
        a. Just pretend that alignments are hand annotations
        b. Estimate parameters as from annotated corpus
    4. Repeat steps 2 and 3 until parameters stop changing

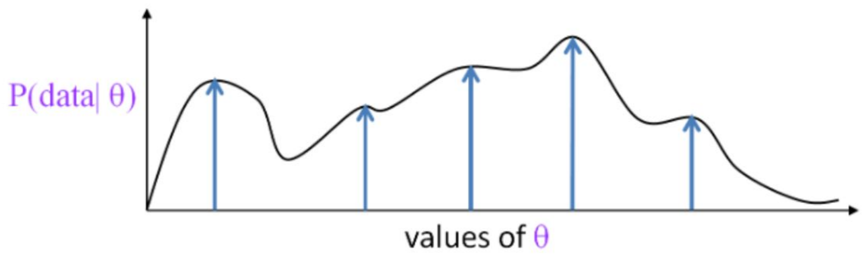
EM vs. Hard EM

- What we have just described is actually "Hard EM" (meaning: no soft/fuzzy decisions)
- Step 2 of true EM does not choose **optimal** values for variables, instead computes **expected** values
- **True EM** is guaranteed convergence to a local optimum of the **likelihood function**
    - Hard EM also converges but not to anything nicely defined mathematically
    - However it's usually easier to compute and may work fine in practice

Likelihood Function

- Let's call the parameters of our model θ
- For any value of θ, we can compute the probability of our dataset $P(data|\theta)$. This is the **likelihood**!
    - If our data includes hand-annotated character alignments, then $P(data|\theta) = \prod_{i=1}^{n} P(x_i \mid y_i)$
    - If the alignments a are latent, sum over possible alignments: $P(data|\theta) = \sum_{a} \prod_{i=1}^{n} P(x_i \mid y_i, a)$
- The likelihood $P(data|\theta)$ is a function of θ, and can have multiple local optima

- Schematically (but θ is really multidimensional)



- EM will converge to one of these local optima; hard EM won't necessarily
- Neither is guaranteed to find the global optimum!

Lecture 7 - Text Classification

Text classification

- We might want to categorise the *content* of the text:
  - Spam detection (binary: spam or not)
  - Sentiment analysis (binary or multiway)
    - Movie, restaurant, or product reviews (positive/negative or 1-5 stars)
    - Political argument (pro/con or pro/con/neutral)
  - Topic classification (multiway: sport/finance/travel/etc.)
- Or we might want to categorise the *author* of the text (**authorship attribution**)
  - Native language identification (e.g. to tailor language tutoring)
  - Diagnosis of disease (psychiatric or cognitive impairments)
  - Identification of gender, dialect, educational background, political orientation, and so on for example in forensics (legal matters), advertising/marketing, campaigning, etc.
- N-gram models can sometimes be used for classification but
  - For many tasks, sequential relationships between words are largely irrelevant: we can just consider the document as a bag of words
    - $Document \rightarrow [(word, count)]$
    - Some normalisation can be done beforehand, such as case conversion
  - On the other hand, we may want to include other kinds of features (e.g. PoS tags) that N-gram models don't include
- Here we consider two alternative models for classification:
  - Naive Bayes
  - Maximum Entropy (a.k.a. Multinomial logistic regression)

Naive Bayes

- Given document d and a set of categories C (say, spam/not-spam), we want to assign d to the most probable category $\hat{c}$

  $\hat{c} = argmax_{c \in C} P(c|d) = argmax_{c \in C} \frac{P(d|c)P(c)}{P(d)} = argmax_{c \in C} P(d|)P(c)$
- Just as in spelling correction, we need to define $P(d|c)$ and $P(c)$
  - $P(c)$ is the **prior probability** of class c before observing any data
    - Simply estimated by MLE: $\hat{P}(c) = \frac{N_c}{N}$
    - In other words, the proportion of training documents belonging to class c

Modelling $P(d|c)$ (feature probabilities)

- We represent each document d as the set of features (words) it contains: $f_1, f_2, ..., f_n$
  - So $P(d|c) = P(f_1, f_2, ..., f_n|c)$
- As in language models, we cannot accurately estimate $P(f_1, f_2, ..., f_n|c)$ due to sparse data
- So, we make a **Naive Bayes assumption**: features are conditionally independent given the class: $P(f_1, f_2, ..., f_n|c) \approx P(f_1|c)P(f_2|c)...P(f_n|c)$
- That is, the probability of a word occurring depends *only* on the class
  - Not on which words occurred before or after (as in N-grams)
  - Or even which words occurred at all
- Effectively, we only care about the **count of each feature** in each document

Calculating the feature probabilities

$P(f_i|c)$ is normally estimated with simple smoothing:

$$\widehat{P}(f_i|c) = \frac{count(f_i, c) + \alpha}{\sum_{f \in F} (count(f, c) + \alpha)}$$

- $count(f_i, c)$ is the number of times f_i occurs in class c
- F is the set of possible features
- α is the smoothing parameter, optimised on held-out data

Alternative features

- Use only **binary** values for f_i: did this word occur in d or not?
- Use only a subset of the vocabulary for F
    - Ignore **stopwords** (function words and others with little content)
    - Choose a small task-relevant set (e.g. using a sentiment lexicon)
    - Can be tricky:
        - E.g. sentiment analysis might need domain-specific non-sentiment words: such as *quiet* for computer product reviews
        - And for other tasks, stopwords might be very useful features:
            - E.g. people with schizophrenia use more 2nd-person pronouns, those with depression use more 1st-person
        - Probably better to use too many irrelevant features than not enough relevant ones
- Use more complex features (bigrams, syntactic features, morphological features)

Costs and linearity

- Multiplying large numbers of small probabilities together is problematic, thus we use costs (negative log probability) again
- In which case, we look for the **lowest cost** overall
- Naive Bayes then:

$$\widehat{c} = argmin_{c \in C}(-logP(c) + \sum_{i=1}^{n} -logP(f_i|c)$$

- This amounts to classification using a linear function (in log space) of the input features
    - So Naive Bayes is called a **linear classifier**
    - As is logistic regression

Review of Naive Bayes

- Advantages
    - Very easy to implement
    - Very fast to train, and to classify new documents (good for huge datasets)
    - Doesn't require as much training data as some other methods (good for small datasets)
    - Usually works reasonably well
    - This should be your baseline method for any classification task
- Disadvantages
    - Naive Bayes assumption is Naive
        - Consider the following categories: *travel, finance, sport*
        - Are the following features independent given the category: *beach, sun, ski, snow, pitch, palm, football, relax, ocean*?
            - No! Given *travel*, seeing *beach* makes *sun* more likely, but *ski* less likely

        - Defining finer-grained categories might help (beach travel vs ski travel), but we usually do not want to
    - In short, features are not usually independent given the class
  - Accuracy of classifier can sometimes still be OK, but it will be highly **overconfident** in its decisions
    - For example, Naive Bayes sees 5 features that all point to class 1, and treats them as five independent sources of evidence
    - It's like asking 5 friends for an opinion when some got theirs from each other

Maximum Entropy Classifiers

- Used widely in many different fields, under many different names
  - Most commonly, **multinomial logistic regression**
    - *Multinomial* if more than two possible classes
    - Otherwise (or if lazy) just *logistic* regression
  - Also called: log-linear model, one-layer neural network, single neuron classifier, etc.
  - Like Naive Bayes, Maximum Entropy assigns a document d to a class $\hat{c}$, where $\hat{c} = argmax_{c \in C} P(c|d)$
  - Unlike Naive Bayes, Maximum Entropy does not apply Bayes' rule - instead, it models $P(c|d)$ directly

Features

- Like Naive Bayes, MaxEnt models use **features** we think will be useful for classification
- However, features are treated differently in two models:
  - Naive Bayes
    - Features are *directly observed* (e.g. words in doc)
    - No difference between features and data
  - Maximum Entropy
    - We will use $\bar{x}$ to represent the observed data
    - Features are *functions* that depend on both observations $\bar{x}$ and class c
- For example, if we have three classes, our features will always come in groups of three. Imagine three binary features:

$$f_1 : contains('ski') \,\&\, c = 1$$
$$f_2 : contains('ski') \,\&\, c = 2$$
$$f_3 : contains('ski') \,\&\, c = 3$$

  - Note the format: the 'actual' feature AND class
  - Training docs from class 1 that contain *ski* will have f_1 active
  - Training docs from class 2 that contain *ski* will have f_2 active
  - Etc.
- Each feature f_i has a real-value **weight** w_i learned in training

Classification with MaxEnt

Choose the class that has highest probability according to

$$P(c|\bar{x}) = \frac{1}{Z} exp(\sum_i w_i f_i(\bar{x}|c))$$

Where normalisation constant $Z = \sum_{c'} exp(\sum_i w_i f_i(\bar{x}|c'))$

- Inside brackets is just a dot product: $\overline{w} \cdot \overline{f}$
- And $P(c|\overline{x})$ is a **monotonic function** of this dot product
- So, we will end up choosing the class for which is the highest $\overline{w} \cdot \overline{f}$
- Realise that the normalisation constant Z is not required for classification purposes

Feature Templates

- In practice, features are usually defined using **templates**

  $contains(w)\ \&\ c$

  $headerContains(w)\ \&\ c$

  $headerContains(w)\ \&\ linkInHeader\ \&\ c$
- NLP tasks often have few templates for 1,000s and 10,000s of features!

Training the Model

- Given annotated data, choose weights that make the labels most probable under the model
- That is, given examples $x^{(1)}, ..., x^{(N)}$ with labels $c^{(1)}, ..., c^{(N)}$, choose $\widehat{w} = argmax_{\overline{w}} \sum_j log P(c^{(j)}|x^{(j)})$
- Called **conditional maximum likelihood estimation (CMLE)**
  - Like MLE, CMLE will overfit so we use tricks (**regularisation**) to avoid that

Review of MaxEnt

- Supervised CMLE in MaxEnt is not so easy
  - Requires multiple iterations over the data to gradually improve weights (using *gradient ascent*)
  - Each iteration computes $P(c^{(j)}|x^{(j)})$ for all j, and each possible $c^{(j)}$
  - This can be time-consuming, especially if there are a large number of classes and/or thousands of features to extract from each training sample

Lecture 8 - Part-of-Speech Tagging and HMMs

Sequence Labelling (Tagging)

- It is often the first step towards any syntactic analysis (which in turn, is often useful for semantic analysis)
- **Named Entity Recognition** labels words as belonging to *persons*, *organisations*, *locations*, or none of the above
    - Barack/PER Obama/PER spoke/NON from/NON the/NON White/LOC House/LOC today/NON ./NON
- **Information Field Segmentation** given specific type of text (classified advert, bibliography entry, etc.), identify which words belong to which 'fields' (prize/size/location, author/title/year)
    - 3BR/SIZE flat/TYPE in/NON Bruntsfield/LOC ,/NON near/LOC main/LOC roads/LOC ./NON Bright/FEAT well/FEAT maintained/FEAT …
- In sequence labelling, deciding the correct label depends on
    - The word to be labeled
    - the labels of surrounding words
    - Hidden Markov Model combines these sources of information probabilistically

Parts of Speech

- **Open-Class Words** (or **Content Words**)
    - Nouns, verbs, adjectives, adverbs
    - Mostly *content-bearing*: they refer to objects, actions and features *in the world*
    - *Open* class, since there is no limit to what these words are, new words are added all the time (e.g. selfie, Brexit, omnishambles)
- **Close-Class Words** (or **Function Words**)
    - Pronouns, determiners, prepositions, connectives
    - There are a limited number of these
    - Mostly *functional*: to *tie* the concepts of a sentence together
    - New ones are rare
        - So far none of the attempts to introduce new gender-neutral pronouns have gotten much traction
- The **number** of parts of speech (tags) to have is both linguistic and also a practical consideration
    - Do you want to distinguish between proper nouns (names) and common nouns?
    - Singular and plural nouns?
    - Past and present tense verbs?
    - Etc.
    - Commonly used tagsets for English usually have 40-100 tags (e.g. Penn Treebank has 45)
- Morphologically rich (e.g. Turkish) languages often have compound morphosyntactic tags: Noun + A3sg + P2sg + Nom
    - Hundreds or thousands of possible combinations!
    - Predicting these requires more complex methods than what we will discuss

PoS Tagging

- The problem of finding the best tag sequence for a sentence is also called **decoding**
- PoS tagging is **hard** because
    - Ambiguity
        - Glass of water/NOUN vs. water/VERB the plants

            - wind/VERB down vs. a mighty wind/NOUN (homographs)
        - Sparse data
            - Words we haven't seen before (at all, or in this context)
            - Word-Tag pairs we haven't seen before (e.g. if we verb a noun)
- Relevant knowledge for PoS tagging
    - The word itself
        - Some words may only be nouns, e.g. *arrow*
        - Some words are ambiguous, e.g. *like, flies*
        - Probabilities may help, if one tag is more likely than another
    - Tags of surrounding words
        - Two determiners rarely follow each other
        - Two base form verbs rarely follow each other
        - A determiner is almost always followed by an adjective or a noun

A Probabilistic Model for Tagging

1. Choose a tag conditioned on previous tag (**transition probability**)
2. Choose a word conditioned on its tag (**emission probability**)
    a. Because every state *emits* a word (except <s> and </s>)

- So the model assumes
    - Each tag depends only on previous tag: a bigram (or n-gram) tag model
    - Words are independent **given a tag**
- Transition probability table

$t_{i-1} \backslash t_i$	NNP	MD	VB	JJ	NN	...
<s>	0.2767	0.0006	0.0031	0.0453	0.0449	...
NNP	0.3777	0.0110	0.0009	0.0084	0.0584	...
MD	0.0008	0.0002	0.7968	0.0005	0.0008	...
VB	0.0322	0.0005	0.0050	0.0837	0.0615	...
JJ	0.0306	0.0004	0.0001	0.0733	0.4509	...
...	...	...	...	...	...	...

- Leftmost column is the previous tag
- Topmost row is the 'next' tag
- Every row should sum up to 1

- Emission probability table

$t_i \backslash w_i$	Janet	will	back	the	...
NNP	0.000032	0	0	0.000048	...
MD	0	0.308431	0	0	...
VB	0	0.000028	0.000672	0	...
DT	0	0	0	0.506099	...
...	...	...	...	...	...

- Leftmost column is the current tag
- Topmost column is the emitted word
- Every row should sum up to 1

- In this model, **joint probability** is defined as

$$P(S,T) = \prod_{i=1}^{n} P(t_i|t_{i-1})P(w_i|t_i)$$

    - A product of transmission and emission probabilities for each word

Actual Tagging with Hidden Markov Models (HMM)

- Given a sequence of words, what is the most probable state path that generated them?
- HMMs are quite similar to what we have seen earlier:
    - **N-gram model:** a model for sequences that also makes a Markov assumption but has no hidden variables

    - **Naive Bayes:** a model with hidden variables (the classes) but no sequential dependencies
    - **HMM:** a model for sequences with hidden variables
- Find the best tag sequence T for an untagged sentence S: $argmax_T\ P(T|S)$
    - By Bayes' Rule: $argmax_T\ P(T|S) = argmax_T\ P(S|T)P(T)$
        - And $P(S|T)P(T) = P(S,T)$
- Brute-force enumeration of all the possible tag sequences takes $O(n^c)$ time for c possible tags and n words in the sentence

The Viterbi Algorithm

- Dynamic programming algorithm to memorise smaller subproblems to save time in return of space to avoid recomputation

Lecture 9 - Algorithms for HMMs

The Viterbi Table

<s>	one	dog	bit	</s>
<s>	CD	NN	NN	</s>
	NN	VB	VBD	
	PRP			

- The topmost row is the word sequence
- The cells below are the PoS tags

- Intuition: the best path of length t ending in state q must include the best path of length $t-1$ to the previous state. So:
  - Find the best path of length $t-1$ to *each state*
  - Consider extending each to those by 1 step, until state q
  - Take the best of those options as the best path to state q
  - And of course use a chart to store partial results as we go
    - And use **backtracking** to construct the path

	o_1=x	o_2=z	o_3=y
q^1	.6	.126	.00882
q^2	0	.036	.02646

- We can add up all probabilities in the last column to get the **likelihood** of (the probability of the entire) sequence
- As probabilities can get really tiny quickly, thus risking underflow, we use **costs** (negative log probabilities) instead
  - Hence take the *minimum* over *sum* of costs, instead of *maximum* over *product* of probabilities
- We can use expectation-maximisation to ‘bootstrap’ an HMM in an unsupervised fashion

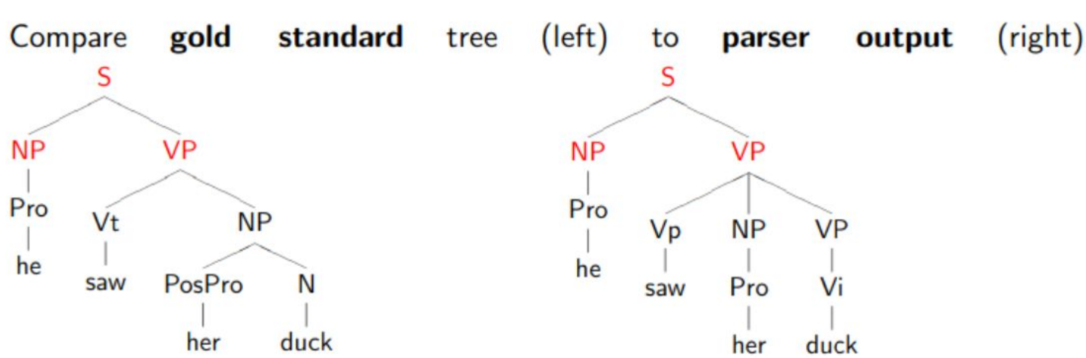
Lecture 10 - Methods in Annotation and Evaluation

Annotation
- Annotation costs time and money, you need to decide on
    - Source data: genre? Size? Licensing?
    - Annotation scheme: complexity? Guidelines?
    - Annotators: expertise? Training?
    - Annotation software: graphical interface? Scanning papers?
    - Quality control: multiple annotation? Adjudication process?
- Text might be ambiguous
- There may be grey area between categories in the annotation scheme
    - Multiple equally valid decisions can be plausible

Inter-Annotator Agreement (IAA)
- An important way to estimate the reliability of annotations is to have multiple people independently annotate a common sample, and measure *inter-annotator agreement*
    - **Raw agreement rate** is the proportion of labels in agreement
        - Some measures take knowledge about the annotation scheme into account (e.g. counting singular vs plural noun as a minor disagreement compared to noun vs preposition)
- The agreement rate can be thought of an upper bound (**human ceiling**) on the accuracy of a system evaluated on that dataset

Cross-Validation
- What if our dataset is **too small** to have a nice train/test or train/dev/test split?
- **K-fold cross-validation:** partition the data into k pieces and treat them as mini held-out sets; each **fold** is an experiment with a different held-out set, using the rest of the data for training
    - After k folds, every data point will have a held-out prediction
    - If we are tuning the system via cross-validation, it is still important to have a separate blind test set

Measuring a model's performance
- **Precision:** proportion of model's answers that are right
- **Recall:** proportion of test data that model gets right



    - Pre-terminals (lexical categories) don't count as constituents
    - Precision: ⅗
    - Recall: ¾

Bounds

- Upper bounds
  - Turing test: when using human Gold Standard, check the agreement of humans against that standard
- Lower bounds
  - Baseline: performance of a simpler model
  - Majority baseline: model always picks the most frequent/likely class

Significance

- When we are evaluating a model against each other or to a bound, how do we decide **if the differences we find are significant?**
- In other words, should we interpret the differences as down to pure chance? Or is something more going on?
- **Parametric** when the underlying distribution is **normal**
  - T-test, Z-test, etc.
- **Non-parametric** otherwise
  - Usually we do need parametric tests: remember Zipf's Law!
  - Can use McNemar's test or variants of it

Lecture 11 - Syntax and Parsing

Modelling word behaviour

- We have seen various ways to model word behaviour
    - **Bag-of-words** models ignore word order entirely
    - **N-gram models** capture a fixed-length history to predict word sequences
    - **HMMs** also capture fixed-length history, but also using latent variables
    - These are useful for various tasks, but a really accurate model of language needs more than a fixed-length history!

Long-range dependencies

- There are often long range dependencies
    - The form of one word often depend on (or agrees with) another, even when arbitrarily many words intervene:
        - *Sam/Dogs sleeps/sleep* soundly
        - *Sam*, who is my cousin, *sleeps* soundly
        - *Sam*, the man with red hair who is my cousin, *sleeps* soundly
    - We want models that can capture these dependencies: for translation, or for understanding
- We may also want to capture **substitutability** at the phrasal level
    - **POS categories** indicate which *words* are substitutable. For example, substituting *adjectives*L
        - I saw a *red* cat
        - I saw a *former* cat
    - **Phrasal categories** indicate which *phrases* are substitutable. For example, substituting *noun phrases:*
        - *Dogs* sleep soundly
        - *My next-door neighbours* sleep soundly

Theories of Syntax

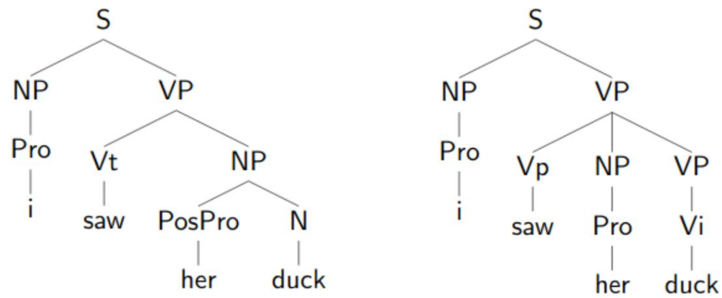
- A **theory of syntax** should explain which sentences are **well-formed** (grammatical) and which are not
    - Note that a *well-formed* sentence is distinct from *meaningful*
        - Famous example from Chomsky: *colorless green ideas sleep furiously*
    - The reason we care about syntax is mainly for interpreting meaning
- **Context-Free Grammar**
- **Dependency Grammar**

Context-Free Grammar

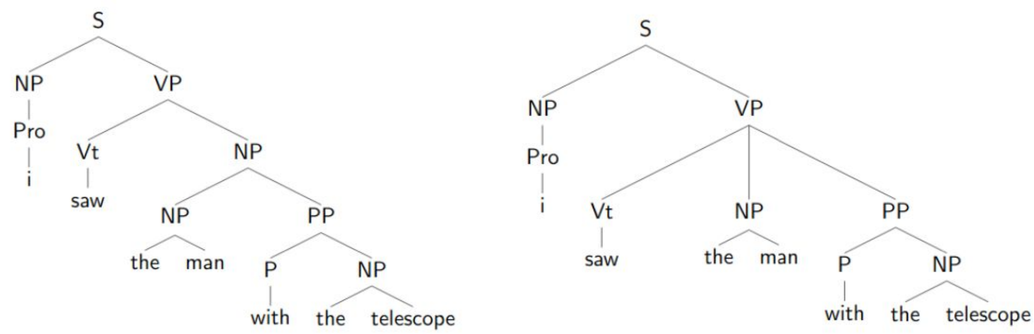
- Two types of grammar symbols:
    - **Terminals:** words
    - **Non-terminals:** phrasal categories like *S, NP, VP, PP,* etc with *S* being the *start symbol*
- Rules of the form $Non-Terminal \rightarrow \beta$ where β is any string of non-terminals and terminals
- A CFG in **Chomsky Normal Form** only has the rules of the form
    - $NT \rightarrow NT\ NT$
    - $NT \rightarrow t$
- To show that a sentence is well-formed under this CFG, we must provide a parse; one way to do this is by drawing a tree

Ambiguity

- **Structural ambiguity**



    - Some sentences have more than one parse
    - Here, the structural ambiguity is caused by **POS** ambiguity in several of the words
        - Both are types of **syntactic** ambiguity
- **Attachment Ambiguity**



"the man with the telescope" "with the telescope I saw the man

    - Some sentences have structural ambiguity even *without* POS ambiguity; this is called attachment ambiguity
    - Depends on where different phrases attach in the tree
    - Different attachments often have different meanings:
        - I saw the man with the telescope (did I see the man *using* a telescope or did I see the man that *had* a telescope?)
        - She ate the pizza on the floor (was *she* on the floor or was the *pizza* on the floor?)
        - Good boys and girls get presents from Santa (good boys *and* good girls or good boys *and* girls (regardless if they're good or bad) get presents from Santa?)

Parse Trees

- We want to use parse trees as *scaffolding for semantics*
    - **Compositional Semantics**
        - The meaning of a constituent is a function of the meaning of its children, i.e. the meaning of a whole comes from its parts
    - **Rule-to-Rule Semantics**
        - That function is determined by the rule which licenses the constituent, and the way they are combined in the whole
    - So ambiguity matters a lot!

Parsing

- Computing the structure(s) for an input string given a grammar
    - **Recognisers** tells us whether the sentence has a valid parse, but not what the parse is

- As usual, **ambiguity is a huge problem**
    - For *correctness* we need to find the right structure to get the right meaning
    - For *efficiency* searching all possible structures can be very slow
- **Global Ambiguity**
    - Multiple analyses for a full sentence
    - E.g. "I saw the man with the telescope"
- **Local Ambiguity**
    - Multiple *analyses* for *parts* of a sentence
    - E.g. "The dog bit the child"
        - The first three words could be a Noun Phrase (but aren't)
        - Building useless partial structures wastes time
        - Avoiding useless computation is a major issue in parsing
- Syntactic ambiguity is rampant; humans don't even notice because we are good at using context/semantics to disambiguate
- All parsers have two fundamental properties:
    - Directionality: the sequence in which the structures are constructed
        - Top-Down start with root category (S), choose expansions, build down to words
        - Bottom-Up build subtrees over words, build up to (S)
        - Mixed strategies are also possible (e.g. left corner parsers)
    - Search strategy: the order in which the search space of possible analyses is explored
        - Depth-First Search
            - Requires backtracking
            - Very efficient for *unambiguous* structures
            - Can be massively inefficient (exponential in sentence length) if faced with local ambiguity
                - Blind backtracking may require re-building the same structure over and over; so, simple depth-first parsers are not used in NLP
        - Breadth-First Search
            - Has higher memory requirements
        - Best-First Search
            - Requires *scoring* each partial parse and parse the highest-scoring options first

Recursive Descent Parsing

- A **recursive descent** parser treats a grammar specification of how to break down a top-level goal (find S) into subgoals (find NP VP)
    - Top-Down, Depth-First parser
        - Blindly expand non-terminals until reaching a terminal (word)
        - If multiple options are available, choose one but store current state as a backtrack point (in a stack to ensure depth-first)
        - If terminal matches next input word, continue; else, backtrack
- Recursive Descent Parsing Algorithm
    - Start with subgoal = S, them repeat until input/subgoals are empty:
        - If first subgoal in list is a non-terminal A, then pick an expansion A -> B C from grammar and replace A in subgoal list with B C
        - If first subgoal in list is a terminal w
            - If input is empty, backtrack
            - If next input is different from w, backtrack
            - If next input word is w, match (i.e. consume word input w and subgoal w)

- Move to next subgoal
- If we run out of bactrack points but not input, no parse is possible

- Example
    - Grammar

S → NP VP	VP → V	NN → bit	V → bit
NP → DT NN	DT → the	NN → dog	V → dog

- Input sequence: the dog bit

- Operations:
    - Expand (E)
    - Match (M)
    - Backtrack to step n (Bn)

Step	Op.	Subgoals	Input
0		S	the dog bit
1	E	NP VP	the dog bit
2	E	DT NN VP	the dog bit
3	E	the NN VP	the dog bit
4	M	NN VP	dog bit
5	E	bit VP	dog bit
6	B4	NN VP	dog bit
7	E	dog VP	dog bit
8	M	VP	bit
9	E	V	bit
10	E	bit	bit
11	M		

Shift-Reduce Parsing

- Search strategy and directionality are orthogonal properties
- Depth-first (like RD) but bottom-up
- Basic shift-reduce recogniser repeatedly:
    - Whenever possible, **reduces** one or more items from top of stack that match RHS of rule, replacing with LHS of rule
    - When that's not possible, **shifts** an input symbol onto a stack
- Like RD parser, it needs to maintain backtrack pointers
- Example

- Same example grammar and sentence.
- Operations:
    - Reduce (R)
    - Shift (S)
    - Backtrack to step n (Bn)
- Note that at 9 and 11 we skipped over backtracking to 7 and 5 respectively as there were actually no choices to be made at those points.

Step	Op.	Stack	Input
0			the dog bit
1	S	the	dog bit
2	R	DT	dog bit
3	S	DT dog	bit
4	R	DT V	bit
5	R	DT VP	bit
6	S	DT VP bit	
7	R	DT VP V	
8	R	DT VP VP	
9	B6	DT VP bit	
10	R	DT VP NN	
11	B4	DT V	bit
12	S	DT V bit	
13	R	DT V V	
14	R	DT V VP	
15	B3	DT dog	bit
16	R	DT NN	bit
17	R	NP	bit
…			

Lecture 12 - CKY Parsing, Treebanks and Statistical Parsing

CKY Parsing

- CKY (Cocke, Kasami, Younger) is a bottom-up, breadth-first parsing algorithm
- Original version assumes grammar in Chomsky Normal Form
- Dynamic (chart) programming algorithm
    - Add a constituent A in cell (i,j) if there is:
        - A rule $A \rightarrow B$, and a B in cell (i,j), or
        - A rule $A \rightarrow B\ C$, and a B in cell (i,k) and a C in cell (k,j)
- Fills chart in order
    - Only looks for rules that use a constituent of length n **after** finding all constituents of length less than n
    - So, guaranteed to find all possible parses
- Takes time $O(Gn^3)$, where G is the number of grammar rules and n is the number of words in the sentence

Step by Step

1.

Length 1 constituents: POS tags

	1	2	3	4
0	Pro			
1		Vt,Vp,N		
2			Pro, PosPro	
3				N,Vi
	$_0$he$_1$	$_1$saw$_2$	$_2$her$_3$	$_3$duck$_4$

- We have added **all** PoS tags that are allowed for each word
- Beware that the bottom-left half of the table (excluding the diagonal) is empty
    - We are interested in cells $(x,\ y)$ where $x \leq y$

2.

Length 1 constituents: Unary rule NP $\rightarrow$ Pro

	1	2	3	4
0	Pro, NP			
1		Vt,Vp,N		
2			Pro, PosPro	
3				N,Vi
	$_0$he$_1$	$_1$saw$_2$	$_2$her$_3$	$_3$duck$_4$

- Red shows which children create which parents
    - Normally we add pointers from parent to child to store this information permanently, here we omit them for clarity

3.

Length 1 constituents: Unary rules D $\rightarrow$ PosPro, NP $\rightarrow$ Pro and VP $\rightarrow$ Vi

	1	2	3	4
0	Pro, NP			
1		Vt,Vp,N		
2			Pro, NP, PosPro, D	
3				N, Vi, VP
	$_0$he$_1$	$_1$saw$_2$	$_2$her$_3$	$_3$duck$_4$

- More unary rule construction

4.

Length 2 constituents: Binary rule NP → D N

	1	2	3	4
0	Pro, NP			
1		Vt,Vp,N		
2			Pro, NP, PosPro, D	NP
3				N,Vi, VP
	$_o$he$_1$	$_1$saw$_2$	$_2$her$_3$	$_3$duck$_4$

- Given binary rule $NP \rightarrow D\,N$, we construct NP in cell $(2, 4)$ from D in cell $(2, 3)$ and from N in cell $(3, 4)$

5.

Length 3 constituents: Binary rule VP → Vt NP

	1	2	3	4
0	Pro, NP			
1		Vt,Vp,N		VP
2			Pro, N, PosPro, D	NP
3				N,Vi, VP
	$_o$he$_1$	$_1$saw$_2$	$_2$her$_3$	$_3$duck$_4$

- Vt from $(1, 2)$ plus NP from $(2, 4)$ makes a VP from $(1, 4)$
- For cell $(1, 4)$ we also consider $(1, 3)$ plus $(3, 4)$ but there's nothing in those cells that can combine to make a larger phrase

6.

Length 3 constituents: alternate parses

	1	2	3	4
0	Pro, NP			
1		Vt,Vp,N		VP
2			Pro, NP, PosPro, D	NP
3				N, Vi, VP
	$_o$he$_1$	$_1$saw$_2$	$_2$her$_3$	$_3$duck$_4$

- We also have another way to build the same VP $(1, 4)$
  - Add more pointers to remember this new analysis
- Not standard CKY because we need to use a ternary rule
  - In reality, we would have converted this rule into CNF, but still ended up with two are parses for VP

7.

Length 4 constituents: Binary rule S → NP VP

	1	2	3	4
0	Pro, NP			S
1		Vt,Vp,N		VP
2			Pro, PosPro, D	NP
3				N,Vi
	$_o$he$_1$	$_1$saw$_2$	$_2$her$_3$	$_3$duck$_4$

- The **top-right** cell contains the root of the parse tree, which then can be constructed using backpointers

Notes

- In general, for cell (x, y) [remembering that x is **always** less than y] you should consider all of the following:
  - $(x,\ x+1)$ and $(x+1,\ y)$
  - $(x,\ x+2)$ and $(x+2,\ y)$
  - ...

- $(x, y-1)$ and $(y-1, y)$

CKY Ordering

- We filled in all short entries, then longer ones
- Effectively, we are sweeping out diagonals beginning with the main diagonal and moving to the right
    - Other orders can work too, but it's always shorter first

CKY in Practise

- Avoids re-computing substructures so much more efficient than depth-first parsers *in worst case*
    - E.g. with natural languages, where ambiguity is none or extremely limited (e.g. formal languages), depth-first parsers can be extremely efficient!
- Still may compute a lot of unnecessary partial parses!
- Simple version requires converting the grammar to Chomsky Normal Form
    - May cause blowup
        - Remember that CKY is $O(Gn^3)$
- Various *other* chart parsing methods avoid these issues by combining top-down and bottom-up approaches
    - But rather, we will focus *statistical parsing* which can help deal with both ambiguity and efficiency issues

Treebank Grammars

- The big idea: instead of paying linguists to write a grammar, pay them to annotate real sentences with parse trees
- This way, we implicitly get a grammar (for CFG: read the rules off the trees)
- And we get probabilities for those rules (uwing any of our favourite estimation techniques)
    - We can use these probabilities to improve disambiguation and even speed up parsing

Probabilistic Context Free Grammars (PCFG)

- A **probabilistic context free grammar (PCFG)** is a CFG where each rule $NT \to \beta$ (where β is a symbol sequence) is assigned a probability $P(\beta|NT)$
- The sum over all expansions of NT must be equal to $\sum_{\beta'} P(\beta'|NT)$
- Easiest way to create a PCFG from a tree: MLE
    - Count all occurrences of $NT \to \beta$ in the treebank
    - Divide by the count of all rules **whose LHS is** NT to get $P(\beta|NT)$
    - But as usual, many rules have very low frequencies, so MLE isn't good enough and we need to smooth
- Under this model, the probability of a parse t is simply the product of all rules in the parse: $P(t) = \prod_{NT \to \beta \in t} P(NT \to \beta)$
- Given multiple trees for a sentence, choose the one with the highest probability (or lowest cost)
    - This is regarding global ambiguity
- **Probability of a sentence** is the sum of the probabilities over all the parses

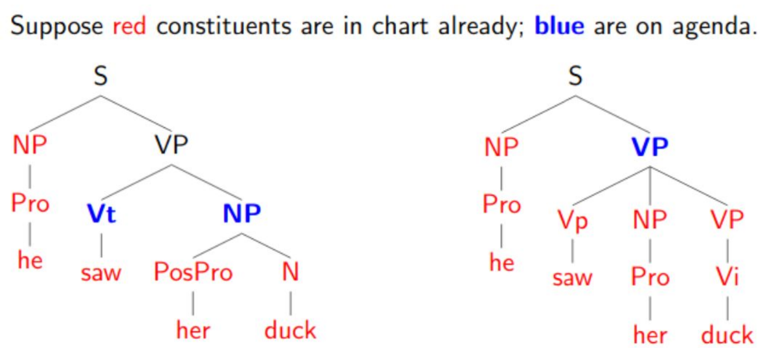
Probabilistic CYK

- Goal: return the highest probability parse of the sentence (analogous to Viterbi)
    - When we find an NT spanning (i, j), store its probability along with its label in cell (i, j)

        - If we later find an NT with the same span but higher probability, replace the probability and the backpointers for NT in cell (i, j)
    - **Inside algorithm** computes the probability of the whole sentence (analogous to *forward algorithm*)
    - **Inside-outside algorithm** is a form of EM that learns grammar rule probabilities from unannotated sentences (analogous to *forward-backward*)
    - **Exhaustive** parsing can be *really* expensive
        - **Best-first** parsing can help!

Best-First Probabilistic Parsing

- Basic idea: use probabilities of subtrees to decide which ones to build up further
    - Each time we find a new constituent, we give it a *score* ('figure of merit') and add it to an *agenda*, which is ordered by score
    - Then we pop the next item off the agenda, add it to the chart, and see which new constituents we can make using it
    - We add those to the agenda, and iterate
- Notice we are no longer filling the chart in any fixed order!
- Often limiting the size of the agenda by **pruning** out low-scoring edges (**beam search**)
- Not as great as you might first think!



    - Because higher on the tree, lower is the probability so in the majority of the cases, you will expand *all* the lower constituents before moving up
        - If we use raw probabilities for the score, **smaller** constituents will almost always have higher scores
            - Meaning we pop all the small constituents off the agenda before the larger ones
            - Which would be very much like exhaustive bottom-up parsing
        - Instead, we can divide by the **number of words** in the constituent
            - Very much like we did when comparing language models (recall *per-word* cross-entropy)
        - This works much better, but now not guaranteed to find the best parse first

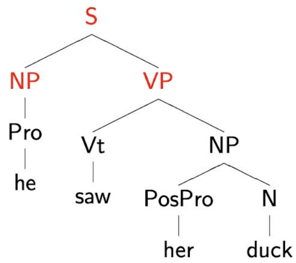
Lexical Dependencies

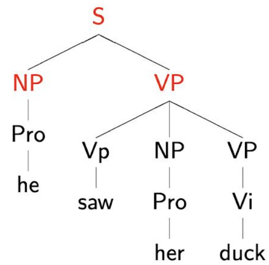
- Replacing one word with another with the same POS will never result in a different parsing decision, even though it should!
    - Example: *she stood by the door covered in tears* vs. *she stood by the door covered in ivy*
    - But PCFGs are context-free, so an NP is an NP, and will have the same expansion probabilities regardless of where it appears

Lecture 13 - Heads and Dependency Parsing

Evaluating Parse Accuracy

Compare **gold standard** tree (left) to **parser output** (right):

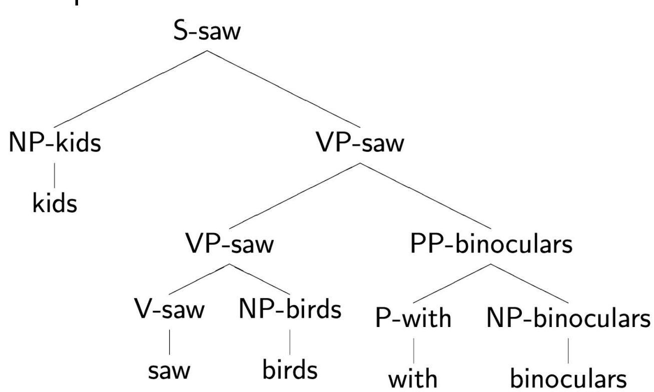




- Output constituent is counted correct if there is a gold constituent that spans the same sentence positions
- **Pre-terminals** (lexical categories) don't count as constituents

Handling Lexical Dependencies (Lexicalisation)

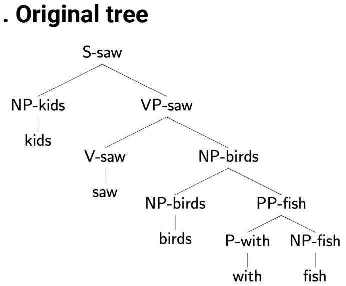
- Replacing one word with another with the same PoS will never result in a different parsing decision, even though it should!
    - *Kids saw birds with fish* vs *kids saw birds with binoculars*
- **Lexicalisation:** create new categories by adding **lexical head** of the phrase
    - Example:



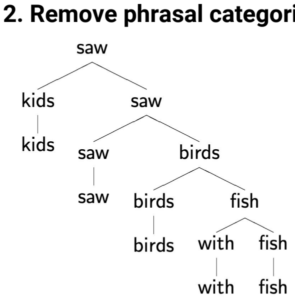
        - Now consider: VP - saw -> VP - saw PP - fish vs. VP - saw -> VP - saw PP - binoculars
- Practical issues
    - Identifying the head of every rule is not always straightforward
    - All this category-splitting makes the grammar much more **specific** (good!)
        - But leads to huge grammar blowup and very **sparse** data (bad!)
    - Do we *really* need phrase structure in the first place? Not always!

Dependency Trees

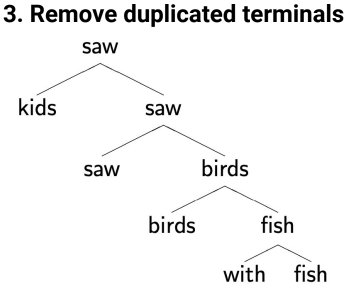
1. Original tree



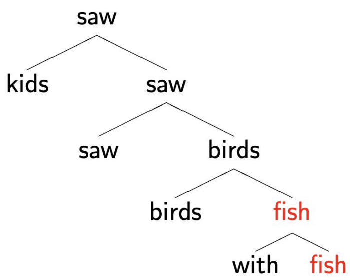
2. Remove phrasal categories



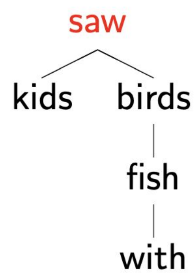
3. Remove duplicated terminals



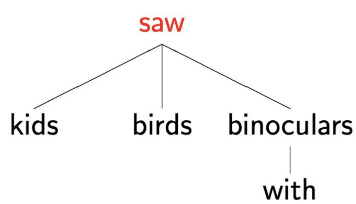
4. Collapse chains of duplicates



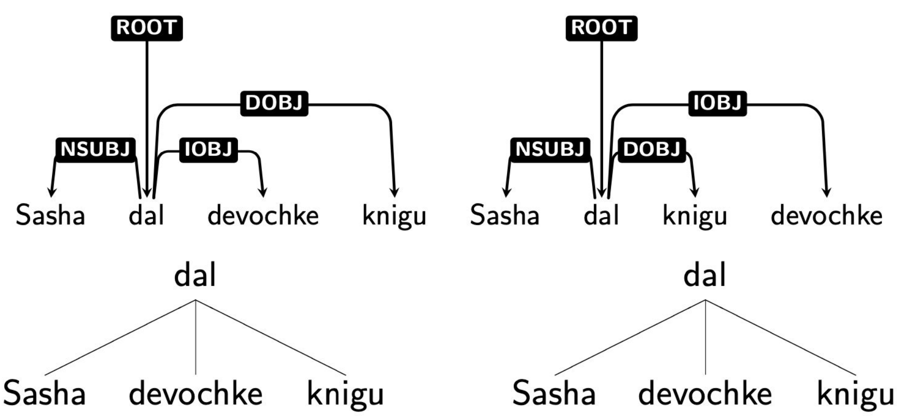
5. Result



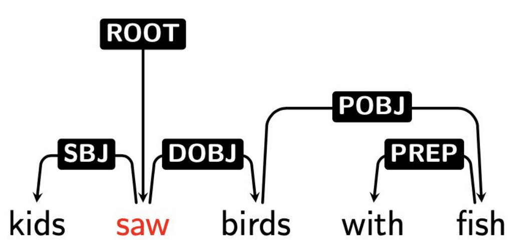
- Don't worry if the tree looks stupid to you, because it is!
  - This demonstrates how dependency trees can help with correct parsing too
  - The right one is



- Meaning of words within a sentence depend on one another, mostly in **asymmetric**, **binary** relations
  - Though some constructions don't clearly fit this pattern: e.g. coordination and relative clauses
- Also, in languages with **free word order** (e.g. Turkish, Russian), phrase structure (constituency) grammars don't make as much sense
  - E.g. we would need both $S \rightarrow NP\ VP$ and $S \rightarrow VP\ NP$
    - Not very informative about what is really going on
    - In contrast, dependency relations stay constant

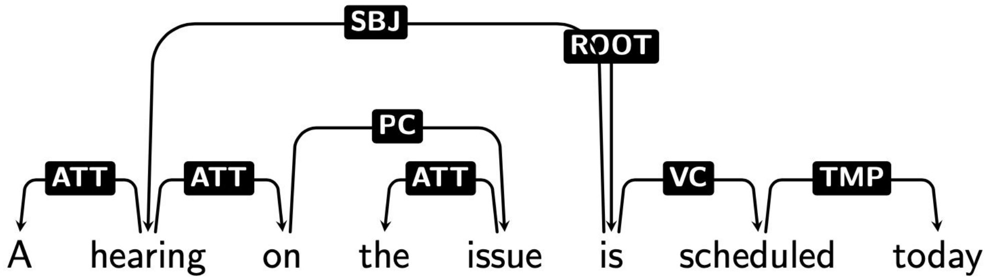


- Edge labels can help us distinguish between different kinds of $head \rightarrow modifier$ relations:



  - Important relations for English include *subject, direct object, determiner, adjective, modifier, adverbial modifier, etc.*

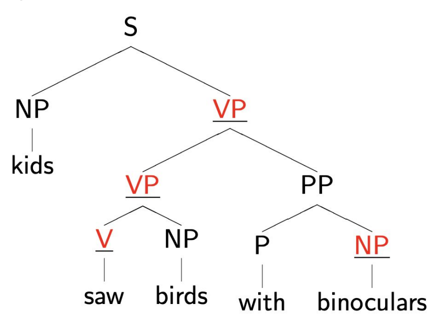
- A sentence's dependency parse is said to be **projective** if every subtree (node and all its descendants) occupies a *contiguous span* of the sentence



    - In which case, *the dependency parse can be drawn on top of the sentence without any crossing edges*
    - Non-projectivity is rare in English but quite common in many other languages

Head Rules

- How can we find each phrase's head in the first place?
- The standard solution is to use **head rules**
    - For every non-unary (P)CFG production, designate on RHS non-terminal as containing the head
        - E.g. *S -> NP VP*



        - We can also employ heuristics to scale this to large grammars: *within an NP, last immediate N child is the head*

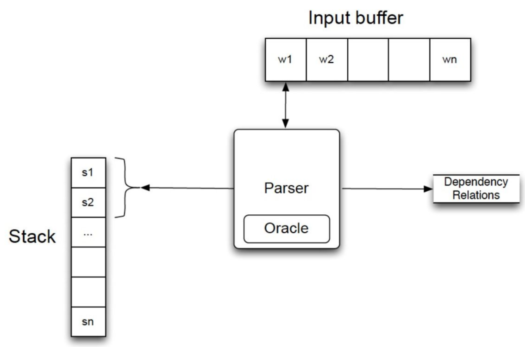
Pros and Cons

- Pros
    - Sensible framework for free word order languages
    - Identifies syntactic relations directly
        - Using CFG, how would you identify the subject of a sentence?
    - Dependency pairs/chains can make good features in classifiers, information-extractors, etc.
    - Parsers can be very fast
- Cons
    - The assumption of **asymmetric binary relations** isn't always right
        - E.g. how to parse *dogs and cats*

Direct Dependency Parsing

- **CKY** can be adapted, though efficiency is a concern: obvious approach is $O(Gn^5)$; Eisner algorithm brings it back down to $O(Gn^3)$
- **Shift-reduce** is more efficient, and doesn't even require a grammar!

Shift-Reduce Parsing



- 3 possible actions:
    - **LeftArc** assign head-dependent relation between $s1$ and $s2$; pop $s2$
    - **RightArc** assign head-dependent relation between $s2$ and $s1$; pop $s1$
    - **Shift** put $w1$ on top of the stack
- Remember, **dependency relations point from head to dependent**
- Both **LeftArc** and **RightArc** leave the head at the top of the stack

Transition-Based Parsing
- Latent structure is just edges between words
- Train a **classifier** as the oracle to predict next action (Shift, LeftArc, RightArc), and proceed left-to-right through the sentence
- $O(n)$ time complexity!
- Only finds **projective** trees (without special extensions)

Graph-Based Parsing
- From a fully connected directed graph of all possible edges, choose the best ones that form a tree
- **Edge-factored** models:
    - Classifier assigns a non-negative score to each possible edge
    - **Maximum spanning tree** algorithm finds the spanning tree with the highest total score in $O(n^2)$ time
- Can be formulated as constraint-satisfaction problem with **integer linear programming**

Comparison
- Transition-Based
    - Scoring function can look at any part of the stack
    - No optimality guarantees for search
    - Linear-time
    - (Classically) Projective only
- Graph-Based
    - Scoring function limited by factorisation
    - Optimal search within the model
    - Quadratic time
    - No projectivity constraint
- Conversion-Based
    - In terms of accuracy, *sometimes* best to first constituency-parse, then convert to dependencies (e.g. Stanford Parser)
    - Slower than direct methods and need grammar and head rules

Lecture 14 - Lexical Semantics: Word Senses, Relations and Classes

Meaning

- One grand goal of artificial intelligence is to *understand* what people mean when they talk
- But how do we know if we succeeded?
- Meaning and understanding can lead to deep 'philosophical' questions
- NLP usually takes a more pragmatic view: can the computer behave as though it understands (in order to do what we want)
  - Dialogue systems (e.g. Eliza)
  - Machine translation
  - Question answering
- What issues will we face in building such systems?

Question Answering

- We would like to build
  - A machine that answers questions in natural language
  - May have access to knowledge bases
  - May have access to vast quantities of English text
- Basically, a smarter Google
- This is typically called **Question Answering**

Semantics

- To build our QA system, we will need to deal with issues in **semantics**, i.e. *meaning*
- **Lexical semantics:** the meanings of individual words
- **Sentential semantics:** how word meanings combine (after that in a sentence)
  - Who did what to whom, when, how, why
- Some examples to highlight problems in lexical semantics:
  - *Plant* (flora) vs *plant* (infrastructure)
    - Words may have different meanings (**senses**)
    - We need to be able to disambiguate between them
  - *Vacation* and *holiday*
    - Words may have the same meaning (**synonyms**)
    - We need to be able to match them
  - *Animals* and *polar bears*
    - Words can refer to a subset (**hyponym**) or superset (**hypernym**) of the concept referred to by another word
    - We need to have a database of such **A is-a B** relationships, called **ontology**
  - *Remove* vs *eliminate*
    - Words may be related in other ways, including **similarity** and **gradation**
    - We need to be able to recognise these to give appropriate responses
  - *Poland* vs *Central Europe*
    - We need to do **inference**
    - A problem for sentential, not lexical, semantics
- Some of these problems can be solved with a good ontology, e.g. WordNet
  - WordNet is a hand-built resource containing 117k **synsets**: sets of synonymous words
  - Synsets are connected by relations such as:
    - hyponym/hypernym (IS-A: chair-furniture)

        - Meronym (PART-WHOLE: leg-chair)
        - Antonym (OPPOSITES: good-bad)
- Words are typically semantically ambiguous
    - But there's a lot of regularity (and hence predictability) in the range of *senses* a word can take
    - The senses also influence the word's syntactic behaviour
    - Word senses can be **productive**, making a dictionary model (like WordNet) inadequate
- **Lumping vs Splitting**
    - **Lump** usages of a word into small number of senses
    - **Split** senses to reflect fine-grained distinctions
- Another way to define senses is to look if occurences of the word have different translations
    - Eng. Interest -> German
        - Zins: financial charge paid for load
        - Anteil: stake in company
        - Interesse: all other sense
- **Polysemous** is a word having multiple senses

Word Sense Disambiguation (WSD)

- For many applications, we would like to disambiguate senses
    - We may be only interested in one sense
    - Searching for *chemical plant* on the web, we do not want to know about chemical bananas
- Task: given a sense ambiguous word, find the sense in a given *context*
- **WSD as classification**
    - Given a word in context, which sense (class) does it belong to?
    - We can train a supervised classifier, assuming sense-labelled training data
    - Lots of options available:
        - Naive Bayes, Maximum Entropy
        - Decision Lists
        - Decision Trees
- **Issues with WSD**
    - Not always clear how fine-grained the gold-standard should be
    - Difficult/expensive to annotate corpora with fine-grained senses
    - Classifiers must be trained separately for each word
        - Hard to learn anything for infrequent or unseen words
        - Requires new annotations for each new word

Semantic Classes

- Other approaches, such as **named entity recognition** and **supersense tagging** define coarse-grained semantic categories like *person*, *location*, *artifact*
- Like sense, can disambiguate: *Apple* as *organisation* vs *food*
- Unlike senses, which are *refinements* or particular words, classes are typically larger groupings
- Unlike senses, classes can be applied to words/names not listed in a lexicon

Named Entity Recognition (NER)

- Recognising and classifying **proper names** in text is important for many applications; a kind of **information extraction**
- Different inventories of classes:
    - **Smaller:** *person, organisation, location, miscellaneous*
    - **Larger:** also *product, work_of_art, historical_event, etc.* as well as numeric value types (*time, money*, etc.)

Supersense Tagging

- Supersense tagging does beyond NER to cover all nouns and *verbs*

<u>**Lecture 15 - Distributional Semantics**</u>

Word Similarity

- How to know if words have similar meanings?
- Can we just use a thesaurus?
  - May not have a thesaurus in every language
  - Even if we do, many words and phases will be missing
- Let's try to compute similarity automatically
- Meaning from context(s)

  A bottle of *raki* is on the table.
  Everybody likes *raki*.
  Raki makes you drunk.
  We make *raki* out of grapes.

Distributional Hypothesis

- Perhaps we can infer meaning just by looking at contexts a word occurs in
- Perhaps meaning *is* the context a word occurs in (Wittgenstein)
- Either way, similar contexts imply similar meanings
  - This idea is known as the **distributional hypothesis**
- Represent each word w_i as a vector of its contexts
  - Distributional semantic models also called **vector-space models**
- Each dimension is a context word
  - = 1 if it co-occurs with w_i
  - = 0 otherwise
- For example:

	pet	bone	fur	run	brown	screen	mouse	fetch
w_1	1	1	1	1	1	0	0	1
w_2	1	0	1	0	1	0	1	0
w_3	0	0	0	1	0	1	1	0

    - Real vectors would be far more sparse!

The Context

- Questions
  - What defines 'context'?
    - What are the dimensions?
    - What counts as co-occurrence?
  - How to weigh the context words (boolean? Counts? other?)
  - How to measure *similarity between vectors*?

Defining the context

- There are **two kinds of co-occurrence** between two words:
  - **First-Order Co-Occurrence (syntagmatic association)**
    - Typically nearby each other, *wrote* is a first-order associate of *book*
  - **Second-Order Co-Occurrence (paradigmatic association)**
    - Have similar neighbours *wrote* is second-order associate of *said* and *remarked*

- Usually ignore **stopwords** (function words and other very frequent/uninformative words)
- Usually use a large window around the target word (e.g. 100 words, maybe even whole document)
- But smaller windows allow for relations other than co-occurrence
    - E.g. dependency relation from parser
- All of these for semantic similarity
    - For **syntactic** similarity, use a small window (1-3 words) and track *only* frequent words

Weighing the context words

- Binary indicators are not very informative
- Presumably more frequent co-occurrences matter more
- Is frequency good enough?
    - Frequent (overall) words are expected to have high counts in the context-vector
        - Regardless of whether they occur more often with this word than with others
- We want to know which words occur *unusually* often in the context of w: more than we'd expect by chance?
    - E.g. 'New' and 'York'
- Put it another way, what **collocations** include w?

Pointwise Mutual Information (PMI)

$PMI(x,y) = log_2 \frac{P(x,y)}{P(x)P(y)}$

- Where
    - $P(x,y)$ is the **actual** probability of seeing words x and y together
    - $P(x)P(y)$ is the **predicted** probability of seeing words x and y together, **IF** x and y are independent!
- PMI tells us how much more/less likely the co-occurrence is than if the words were independent
- **Problems**
    - In practise, PMI is computed with counts (using MLE)
    - Therefore, it is over-sensitive to the chance co-occurrence of infrequent words

Alternatives to PMI for finding collocations

- There are a lot of alternatives!
    - Student *t*-test
    - Pearson's χ^2 statistic
    - Dice coefficient
    - Likelihood ratio test (Dunning, 1993)
    - Lin association measure (Lin, 1998)
    - Etc.
- Of those listed above, Dunning's Likelihood Ratio Test is probably the most reliable one for low counts
    - However, which works best may depend on the downstream too

Improving PMI

- Use **Positive PMI** (PPMI)
    - Change all negative PMI values to 0
    - Because of infrequent words, not enough data to accurately determine negative PMI values
- Introduce *smoothing* in PMI computation

Similarity

- Assume you have context vectors for two words $\overline{v}$ and $\overline{w}$
    - Vectors in high-dimensional space
    - Containing PMI (or PPMI) values for all context words
- Vectors seem to capture both syntactic and semantic information
- So the question is, how to measure the 'distance' between two vectors?
    - Euclidean Distance
        - Doesn't work well even if one dimension has an extreme value
    - Dot Product
        - Vectors are longer if they have higher values in each dimension
        - So more frequent words have higher dot products
            - Dot product is generally larger for longer vectors, regardless of similarity
    - Normalised Dot Product
        - Normalise through dividing by the length of each vector

$$distance_{NDP} = \frac{\overline{v} \cdot \overline{w}}{|\overline{v}|\,|\overline{w}|}$$

            - The normalised dot product is just the cosine of the angle between vectors
                - Ranges from -1 (vectors pointing to opposite directions) to 1 (same direction)
- Again, there are many other similarity measures
    - Jaccard measure
    - Dice measure
    - Jenson-Shannon divergence
    - Etc.
    - Again, depends on the downstream too

Evaluation of similarity computations

- Intrinsic evaluation is often a comparison to *psycholinguistic* data
    - Relatedness judgements
        - E.g. on a scale of 1-10, how related are the following concepts:
            - Lemon and Truth = 1/10
            - Lemon and Orange = 9/10
        - Still a funny task
        - Answers depend a lot on *how* the question is asked (e.g. *related* vs *similar*)
    - Word association
        - Upon seeing or hearing a word, say the first word that comes to mind
        - Data collected from lots of people provides probabilities of each answer
        - For example, for *Lemon*,
            - 0.16 Orange
            - 0.11 Sour
            - 0.09 Tree
- Benchmarking
    - Human judgements provide a ranked list of related words/associations for each word w
    - Computer system provides a ranked list of most similar words to w
    - Compute the Spearman Rank Correlation between the lists (how well do the rankings match)

Compact space

- So far our vectors have length V, the size of the vocabulary
- Do we really need this many dimensions?
- Can we represent words in a smaller dimensional space that preserves the similarity relationships of larger space?

Latent Semantic Analysis (LSA)

- One of the earliest methods for reducing dimensions while preserving similarity
- Like Principal Component Analysis (PCA) except that we do not subtract off the means
- LSA representations usually work better than originals for many tasks

Neural Network Methods

- Recent methods for learning reduced-dimensional representations (now often called **embeddings**)
- Train a neural network to predict context words based on input word
    - Use hidden layer(s) as the input word's vector representation
- Deep mathematical similarities to LSA, but can be faster to train

Compositionality

- One definition of collocations: **non-compositional** phrases
    - *White House* is not just a house that is white
- But a lot of language *is* compositional
    - Red barn
    - Wooden plank
- Can we capture compositionality in a vector space model?
    - More formally, compositionality implies some operator $\star$ such that $meaning(w_1 w_2) = meaning(w_1) \star meaning(w_2)$
- Current work investigates possible operators
    - Addition
    - Tensor product
    - Non-linear operations learned by neural networks
- One problem: words like 'not'
    - More like operators than points in space

Lecture 16 - Semantic Role Labelling and Argument Structure

Semantic (Thematic) Roles

- Instead of focusing on syntax, consider **semantic/thematic roles** defined by each event
- **Argument Structure and Alterations**
    - Mary opened *the door* vs *the door* opened
    - John slices *bread with a knife*
      This bread slices easily
      The knife slices cleanly
    - John gave *a present to Mary* vs John gave *Mary a present*
- Syntax $\neq$ Semantics
- The semantic roles played by different participants in the sentence are not trivially inferable from syntactic relations
    - Though there are patterns!
    - The idea of semantic roles can be combined with other aspects of meaning (beyond this course)
- Commonly used thematic roles
  Agent - *The boy* kicked his toy
  Theme - The boy kicked *his toy*
  Experiencer - *The boy* felt sad
  Result - The girl built *a shelf* with power tools
  Instrument - The girl built a shelf *with power tools*
  Source - She came *from home*
  Etc.
- **Issues with thematic roles**
    - No universally agreed-upon set of roles
    - Items with the same role (e.g. instrument) may not behave quite the same
      Sandy opened the door with a key vs *The key opened the door*
      Sandy ate the salad with a fork vs *The fork ate the salad*
    - The two main NLP resources for thematic roles avoid these problems by defining very fine-grained roles
- **Semantic role labelling** is identifying which words/phrases play which roles in an event
    - Traditional pipeline:
        1. Either assume or compute syntactic parse and predicate senses
        2. **Argument identification** (deterministic): select the predicate's argument phrases (by parsing the parse tree)
        3. **Argument classification:** select a role for each argument (with respect to the frame role for the predicate's sense)
    - Problems:
        - Numbered roles (e.g. load.01.ARG1) are predicate-specific (load.01) in PropBank
        - FrameNet tries to generalise via verb classes, but less treebank data

FrameNet

- Tries to capture relationships among word and phrase meanings by assigning them the same frame (and so captures *paraphrases*)
- ~ 1,000 frames represent scenarios
    - Most are associated with lexical units (predicates) but some are phrases

- Frames are explained with textual descriptions and linguistic examples
- Example: `Create_physical_artwork`

> Definition:
> A `Creator` creates an artefact that is typically an iconic `Representation` of an actual or imagined entity or event. The `Representation` may also be evocative of an idea while not based on resemblance.
> - **Diagrams** must be **clearly** <u>drawn</u> **on construction paper**
> - **I** <u>took</u> **his picture** and told him it came out well
>
> Frame Elements:
> Core: `creator`, `representation`
> Non-core: `manner`, `location_of_representation`

Lecture 17 - Discourse Coherence

Discourse Coherence

- Making sense of **verbal actions**
    - We assume action choice isn't arbitrary (choice is informed by the context)
    - So we infer more than we see
    - And may change these inferences as we see more
- **Representation**
    - How should discourse coherence be represented *formally* and *computationally*?
- **Construction**
    - What inference processes, and what knowledge sources, are used when *identifying coherence relations*?
- Examples:
    - "John can open Bill's safe." "He knows the combination"
        - If "He" is John: we infer *explanation* ("because")
        - If "He" is Bill: we infer (at best) *continuation* ("and") with a very vague topic
    - "John can open Bill's safe." "He should change the combination."
        - If "He" is Bill: we infer *result* ("so")
        - If "He" is John, we infer a weaker *result* (?)
        - Subjects are more likely antecedents, but not here!
        - Pronouns shall be interpreted in a way that *maximises* coherence, even if this conflicts with predictions from other knowledge sources!
- **Word Meaning**
    - "A: Did you buy the apartment?" "B: Yes, but we rented it / No, but we rented it"
        - "Yes, but we rented it" signifies that B is the landlord and is renting out the flat
        - "No, but we rented it" signifies that B is renting the flat
- **Bridging**
    - "John took an engine from Avon to Dansville" "He picked up a boxcar / He also took a boxcar"
        - "He picked up a boxcar" signifies that the boxcar was in Dansville
        - "He also took a boxcar" signifies that the boxcar was in Avon
- **Implicit Agreement**
    - M (to K and S): "Karen and I are having a fight"
      M (to K and S): "after she went out with Keith not me"
      K (to M and S): "Well Mark, you never asked me out"
        - "Well" entails implicit agreement
- **Dishonesty**
    - P: "Do you have any bank accounts in Swiss banks, Mr. Bronston?" B: "No, sir."
      P: "Have you ever?" B: "The company had an account there for about six months, in Zurich."
        - The last sentence is interpreted as an indirect answer, implying *no* (he did not have a personal bank account in Swiss banks ever)
        - His answer is *literally true*, but the *negative answer* is *false*!
            - In fact, Bronston had once had a large personal bank account in Switzerland, where over a five year period he had deposited more than $180,000
        - Supreme Court overrules conviction for perjury
            - Different ruling is probable if Bronston had said "*Only* the company had an account there for about six months, in Zurich."

- Gesture
    - Coherence relations connect speech and gesture and sequences of gestures
        - Speech *so that* gesture
        - Speech *by* gesture
        - Speech *and moreover* gesture

SDRT: The Logical Form (LF) of Monologue

- Logical form consists of
    - Set A of **labels** $\pi_1,\ \pi_2, \ldots$
        - Each label stands for a **segment** of discourse
    - A mapping F from each label to a formula representing its content
    - Vocabulary includes coherence relations
        - E.g. $Elaboration(\pi_1, \pi_2)$
- Logical Forms and Coherence
    - Coherent discourse is a single segment of rhetorically connected subsegments
    - More formally:
        - The **partial order** over A induced by F has a **unique root**
- Example

π_1 : *John can open Bill's safe.*

π_2 : *He knows the combination.*

π_0 : $Explanation(\pi_1, \pi_2)$

π_1 : $ix(safe(x)\ \&\ possess(x,\ Bill)\ \&\ can(open(e_1,\ John\ x))$

π_2 : $iy(combination(y)\ \&\ of(y, x)\ \&\ knows(John,\ y))$

- $Explanation(\pi_1, \pi_2)$, $of(y, x)$, and $knows(John,\ y)$ are specific values that go beyond content that's revealed by linguistic form
    - They are inferred via **commonsense reasoning** that's used to construct a **maximally coherent** interpretation