POLITÉCNICA
"Ingeniamos el futuro"

CAMPUS
DE EXCELENCIA
INTERNACIONAL

Text Mining 4
Information Extraction

Madrid Summer School on
Advanced Statistics and Data Mining

Florian Leitner
Data Catalytics, S.L.
leitner@datacatytics.com

Collocations (and idioms)

A **Collocation** is an expression consisting of two or more words that correspond to some conventional way of saying things.

"Collocations of a given word are statements of the habitual or customary places of that word." -Firth (1957: 181)

Collocations are **non-compositional** (i.e., the meaning of the expression cannot be understood [viz., composed] from its parts): meaning is added to the term (making it a special version of the linguistic concept of a **term**).

strong tea, weapons of mass destruction, to make up, the rich and powerful, stiff breeze, broad daylight, white wine, ...

collocation test: Is a literal word-by-word translation to another language possible? (if not, its probably a collocation)

Manning and Schütze. Foundations of Statistical Natural Language Processing. 2000

Detecting collocations: standard statistical methods

- Frequency-based methods
  - Measure the likelihood of bigram co-occurrence to detect "collocation-ness"

- **t-test** (using the **expected** probability p of a candidate bigram as the variance σ^2)
  - has problems with more frequent words and is typically only used to **rank** collocations (rather than detect them)
- **χ^2-test** (using the ratios of either word being pre-/proceeded by the other)
  - has problems when the frequency of words being compared is very small
- **PMI** (point-wise mutual information; log-ratio of the joint over the expected probability of the bigram)
  - as the other tests, has problems with data sparseness (i.e., bigrams with few examples; more robust variants use a frequency-weighted PMI) *e.g. gensim*

Detecting collocations: likelihood ratio test

- MLE assuming a **binomial distribution of bigrams** B
- For bigram "word$_1$ word$_2$", with counts c and total words N:

$$\lambda = -2\ log \frac{B(c_{12}, c_1, p_2)B(c_2 - c_{12}, N - c_1, p_2)}{B(c_{12}, c_1, p_{2|1})B(c_2 - c_{12}, N - c_1, p_{2|\neg 1})}$$

$$B(k, n, p) = \binom{n}{k} p^k (1-p)^{n-k} \qquad p_2 = \frac{c_2}{N} \qquad p_{2|1} = \frac{c_{12}}{c_1} \qquad p_{2|\neg 1} = \frac{c_2 - c_{12}}{N - c_1}$$

- Asymptotically χ^2-distributed (explaining the "-2" multiplier)
- Can use the χ^2 statistic to find the critical values for λ
  NB: d.f. is always 1 (→bigrams!); $\lambda > 10.83$ is pretty solid
- Fairly **robust** with both frequent words and infrequent bigrams

Dunning. Accurate methods for the statistics of surprise and coincidence. 1993, Comp. Ling.

Detecting collocations: phrasal filtering rules

- Select only terms that are valid noun and verb phrases
  - NB: not all collocations are noun phrases, e.g. "to make up".
  - Advantage: Can be applied after any statistical selection method.
  - Disadvantage: Requires tagging tokens with their part-of-speech.
    - i.e., this is a fully supervised approach
    - [Part-of-speech tagging is coming up later in this lecture]
  - Justeson & Katz, Comp. Ling., 1995, suggested the following rules:
    - [Adjective | Noun] - [Noun] → *"strong tea", "noun phrase"*
    - [Adjective] - [Adjective | Noun] - Noun → *"free legal advice", "online web tutorial"*
    - Noun - [Adjective | Noun] - Noun → *"mean squared error", "New York City"*
    - Noun - Preposition - Noun → *"parts of speech", "rich and powerful"*

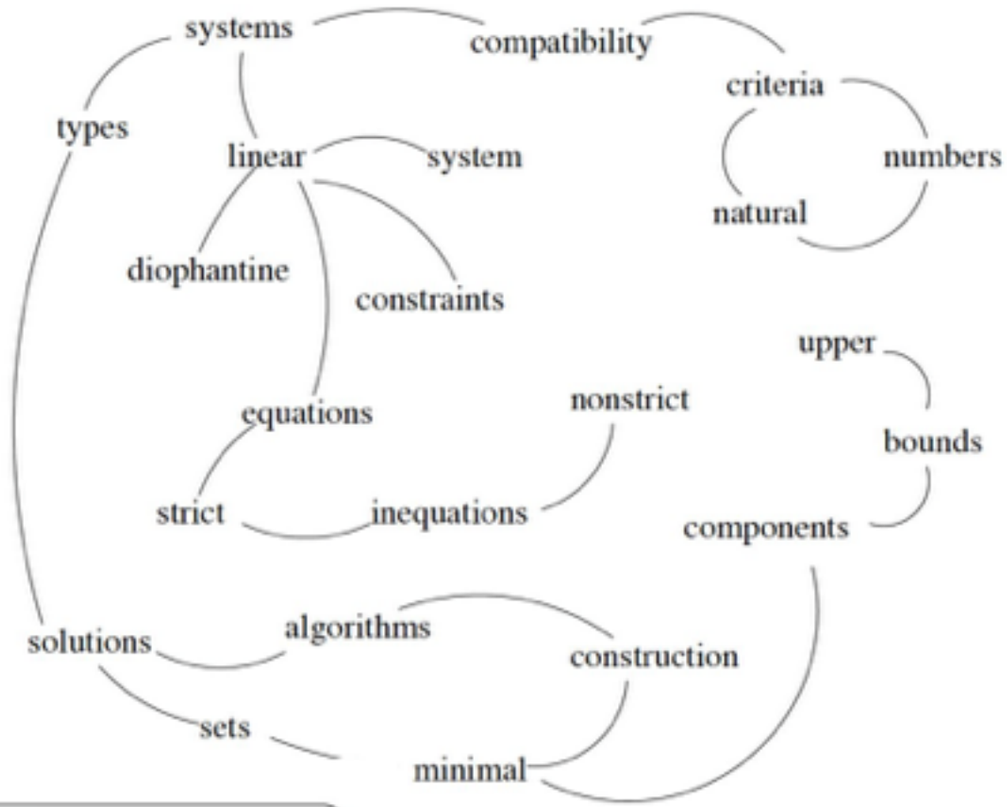
NB: no rules for verb phrases were suggested (far more tricky)

to use PoS tags in gensim, install the "pattern" package

Keyword extraction with TextRank using Co-occurrence

see day 2 for details

Compatibility of systems of linear constraints over the set of natural numbers. Criteria of compatibility of a system of linear Diophantine equations, strict inequations, and nonstrict inequations are considered. Upper bounds for components of a minimal set of solutions and algorithms of construction of minimal generating sets of solutions for all types of systems are given. These criteria and the corresponding algorithms for constructing a minimal supporting set of solutions can be used in solving all the considered types systems and systems of mixed types.



Keywords assigned by TextRank:
linear constraints; linear diophantine equations; natural numbers; nonstrict inequations; strict inequations; upper bounds

Keywords assigned by human annotators:
linear constraints; linear diophantine equations; minimal generating sets; non–strict inequations; set of natural numbers; strict inequations; upper bounds

Mihalcea, R., and Tarau, P. (2004). TextRank: Bringing order into texts.

Keyword extraction using phrase-breaking lists: RAKE

- Split sentences, then phrases, at stop-words and punctuation.
- Next, proceed with the same "word graph" evaluation as TextRank
- The authors claim RAKE performs (slightly) better than TextRank
  - Caveat emptor: manual stop-word tuning required
  - Performance depends on stop-word quality (wrt. both hits, and misses)
  - requires a language where stop-words are not common inside keywords (e.g., in Spanish, "de", commonly used to chain noun phrases, might be an issue)

Rose, S., Engel, D., Cramer, N., and Cowley, W. (2010). Automatic keyword extraction from individual documents.

Keyword extraction alternatives

- Use the PageRank (here: "TextRank") approach as foundation

- But instead of stop-word delimiters or all n-grams, use
  - **Collocations** (*beginning of this day*)
  - **Noun phrases and named entities** (*in the practical*)

Probabilistic language modeling

- Manning & Schütze. Statistical Natural Language Processing. 1999
- A sentence W is defined as a **sequence** of words $w_1, \ldots, w_n$
- Probability of **next word** w_n in a sentence is: $P(w_n | w_1, \ldots, w_{n-1})$
  - a **conditional probability**
- The probability of the **whole sentence** is: $P(W) = P(w_1, \ldots, w_n)$
  - the **chain rule of conditional probability**
- These counts & probabilities form the **language model** [for a given document collection (=**corpus**)].
  - the model variables are **discrete** (counts)
  - only needs to deal with **probability mass** (not density)

Modeling the stochastic process of "generating words" using the chain rule

"This is a long sentence with many words…" ➡

$$P(W) = P(\text{this}) \times$$

$$P(\text{is} \mid \text{this}) \times$$

$$P(\text{a} \mid \text{this, is}) \times$$

$$P(\text{long} \mid \text{this, is, a}) \times$$

$$P(\text{sentence} \mid \text{this, is, a, long}) \times$$

$$P(\text{with} \mid \text{this, is, a, long, sentence}) \times$$

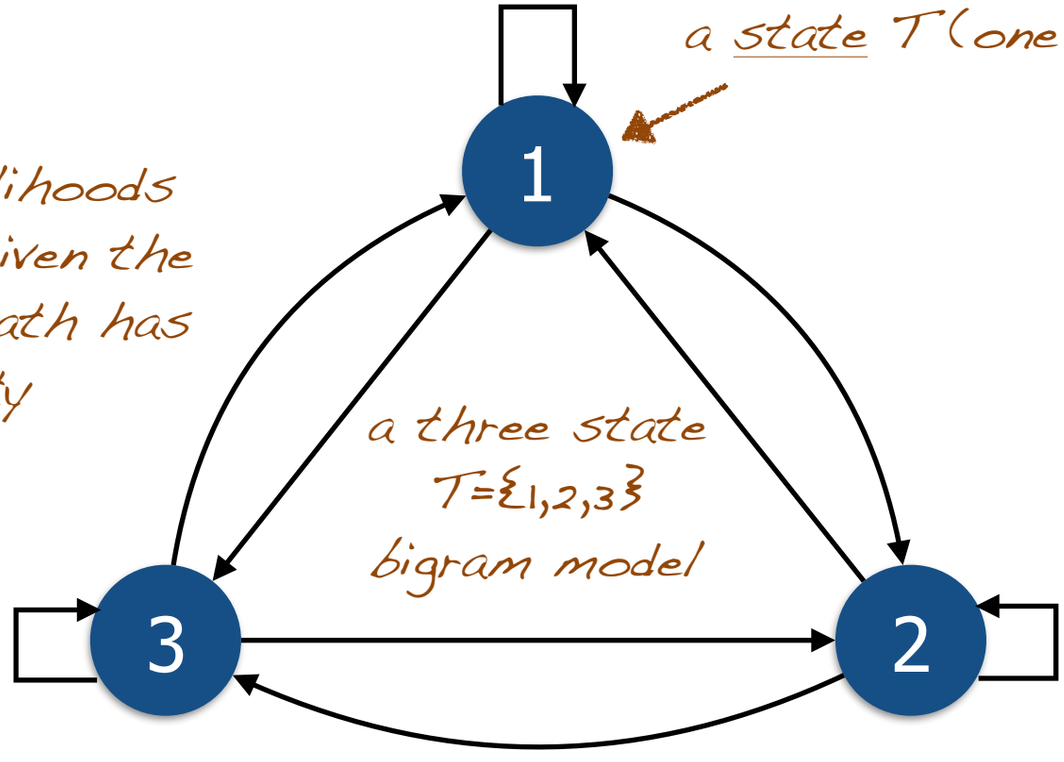
$$P(\text{many} \mid \text{this, is, a, long, sentence, with}) \times$$

….

n-grams for n > 5:
insufficient (**sparse**) data
(and expensive to calculate)

The Markov property

A Markov process is a stochastic process who's future (next) state only depends on the current state T, but not its past. ← a bigram!



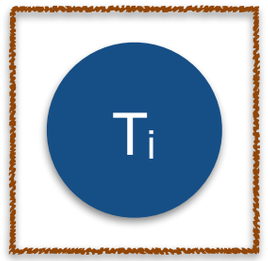
transitions with likelihoods for the (next) word given the current word: each path has some probability

A. A. Markov (1886).

Modeling the stochastic process of "generating words" assuming it is Markovian

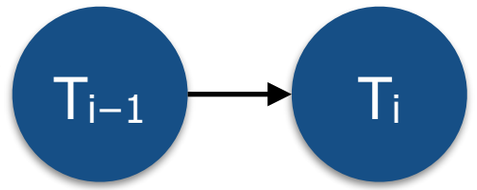
$$\prod P(w_i|w_1^{i-1}) \approx \prod P(w_i|w_{i-k}^{i-1})$$

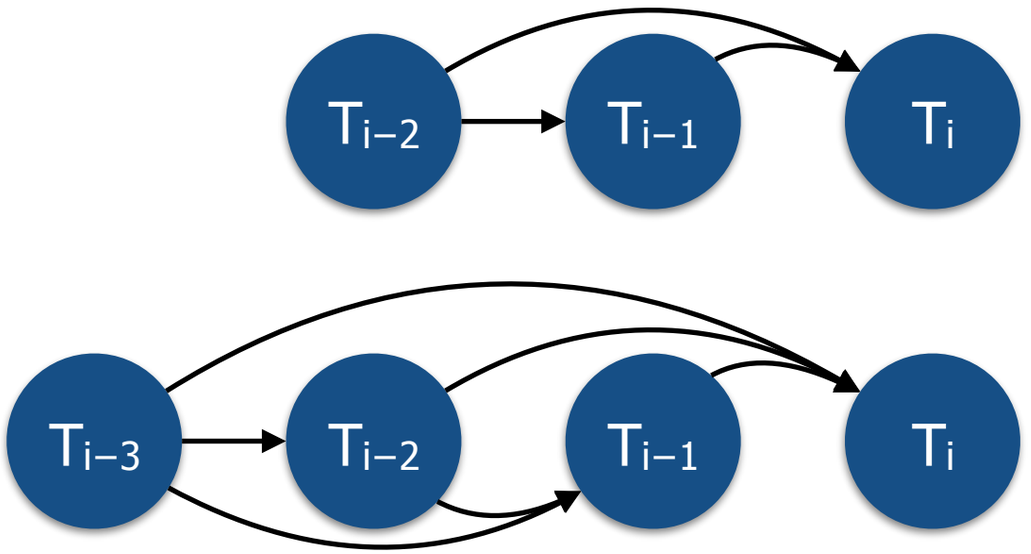
stochastic process: "Unigram Model"



- 1st Order Markov Chains
  - Bigram Model, k=1, P(be | this)
- 2nd Order Markov Chains
  - Trigram Model, k=2, P(long | this, be)
- 3rd Order Markov Chains
  - Quadrigram Model, k=3, P(sentence | this, be, long)
- …

simplified version of the former diagram ("The Markov property")





dependencies could span over a dozen tokens, but these sizes are generally sufficient to work by

Measuring n-gram (transition) probabilities

- Unigrams:

$$P(w_i) = \frac{count(w_i)}{N}$$

N = total word count

- Bigrams:

$$P(w_i|w_{i-1}) = \frac{count(w_{i-1}, w_i)}{count(w_{i-1})}$$

- **N-grams** (n=k+1):

$$P(w_i|w_{i-k}^{i-1}) = \frac{count(w_{i-k}^{i})}{count(w_{i-k}^{i-1})}$$

k = n-gram size - 1

- **Language Model:**

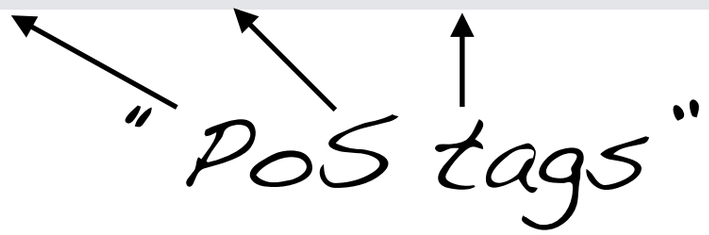
$$P(W) = \prod P(w_i|w_{i-k}^{i-1}) =$$

$$= \prod P(w_i|w_{i-k}, ...w_{i-1})$$

Programming tip: transform probabilities to logs to avoid underflows and work with addition

The Parts of Speech (PoS)

I	ate	the	pizza	with	green	peppers	.
PRP	VB	DT	NN	IN	JJ	NN	.



- The Parts of Speech:
  - noun: NN, verb: VB, adjective: JJ, adverb: RB, preposition: IN, personal pronoun: PRP, …
  - e.g. the full **Penn Treebank PoS tagset** contains 48 tags:
  - 34 grammatical tags (i.e., "real" parts-of-speech) for words
  - one for cardinal numbers ("CD"; i.e., a series of digits)
  - 13 for [mathematical] "SYM" and currency "$" symbols, various types of punctuation, as well as for opening/closing parenthesis and quotes

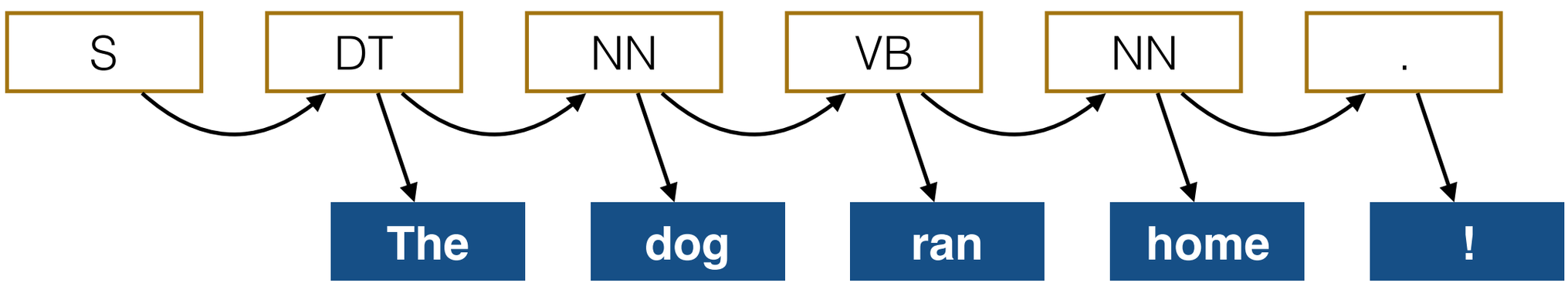
The Parts of Speech (2/2)

I	ate	the	pizza	with	green	peppers	.
PRP	VB	DT	NN	IN	JJ	NN	.

- Automatic PoS tagging ➡ supervised machine learning
  - Maximum Entropy Markov models
  - **Conditional Random Fields**
  - **Convolutional Neural Networks**
  - Ensemble methods (bagging, boosting, etc.)

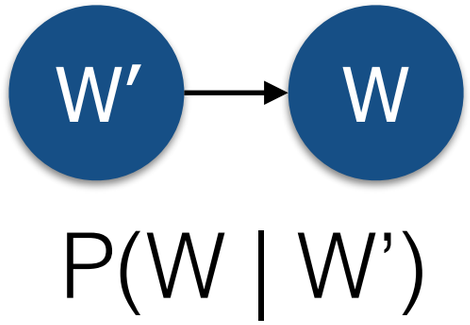
A language-based intuition for HMMs

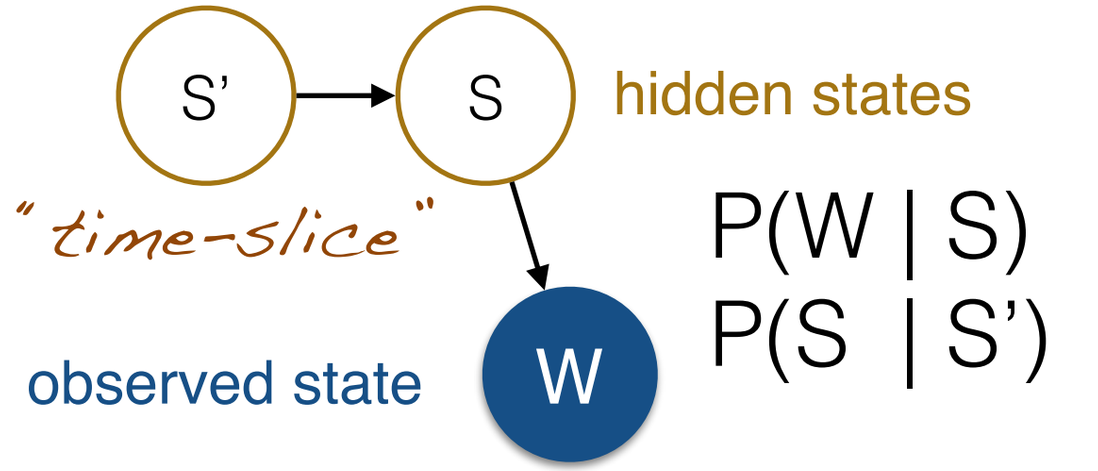
- A Markov Chain: $P(W) = \prod P(w \mid w')$
  - assumes the observed words are in and of themselves the cause of the observed sequence.
- A HMM: $P(S, W) = \prod P(s \mid s') P(w \mid s)$
  - assumes the observed words are emitted by a hidden (not observable) sequence, for example the chain of part-of-speech-states.



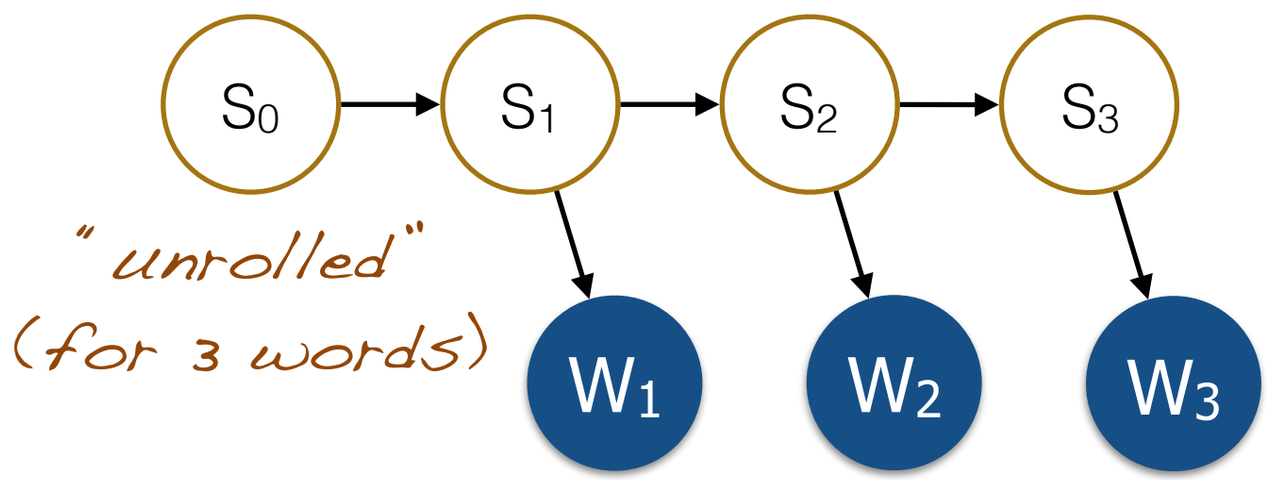
NB, this is the "unrolled" model that does not depict the conditional dependencies

From a Markov chain to a *first order* Hidden Markov Model (HMM)





W depends on S and S in turn depends on S'

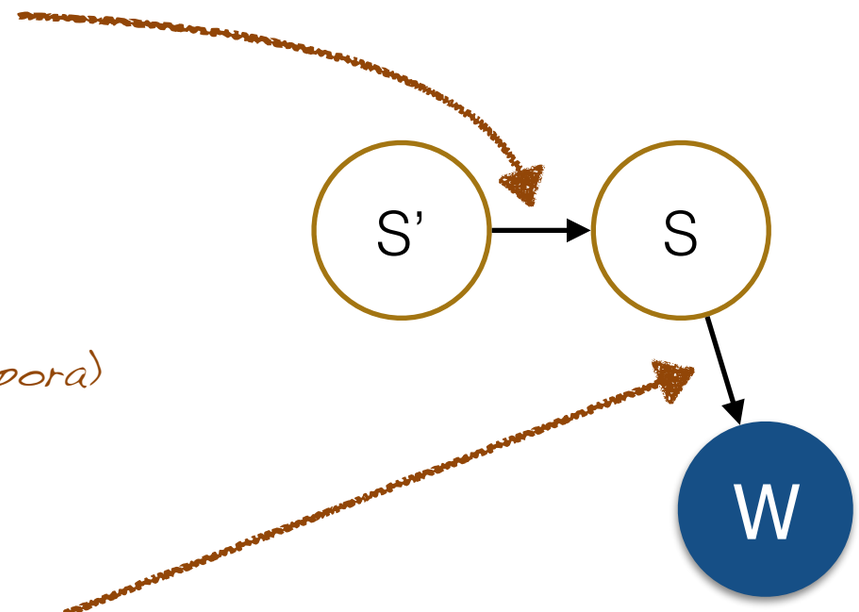


The two matrices of a HMM

a.k.a. "CPDs": Conditional Probability Distributions

P(s | s')	DT	NN	VB	…
DT	0.03	0.7	0	
NN	0	0	0.5	
VB	0	0.5	0.2	
…				

Transition Matrix



(measured as discrete factor tables from annotated PoS corpora)

P(w | s)	$word_1$	$word_2$	$word_3$	…
DT	0.3	0	0	
NN	0.0001	0.002	0	
VB	0	0	0.001	
…				

underflow danger ➡ use "log Ps"!

Observation Matrix

very sparse (W is large)
➡ Smoothing!

Three limitations of HMMs

Markov assumption: The next state only depends on the current state.

Example issue: trigrams (long-range dependencies!)

"unsolved" (CRF)

Output assumption: The output (observed value) is independent of all previous outputs (given the current state).

Example issue: word morphology (inflection, declension!)

MEMM

Stationary assumption: Transition probabilities are independent of the actual time when they take place.

Example issue: position in sentence

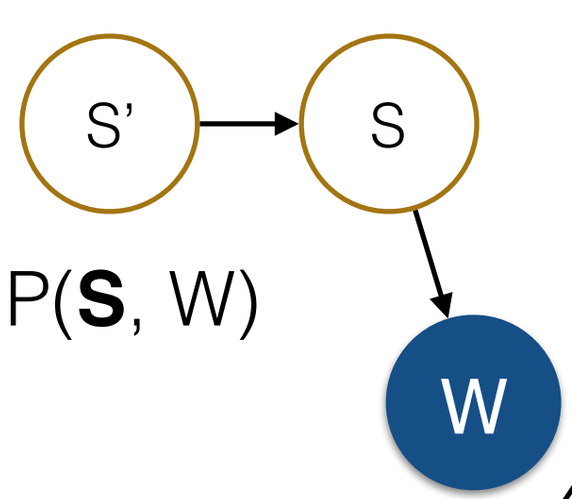
(label bias problem, see next!)

CRF

From generative to discriminative sequence models

Hidden Markov Model

(first oder version)

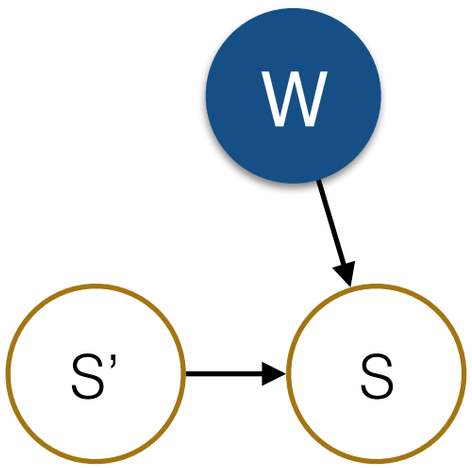


P(**S**, W)

generative model; lower bias is beneficial for small training sets

Maximum Entropy Markov Model

(first oder version)

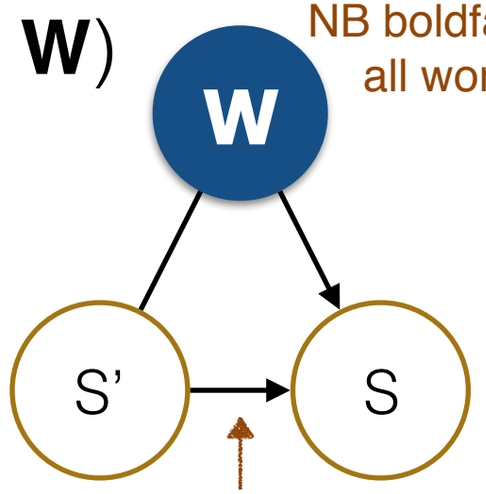


P(S | S', W)

Conditional Random Field

(linear chain version)

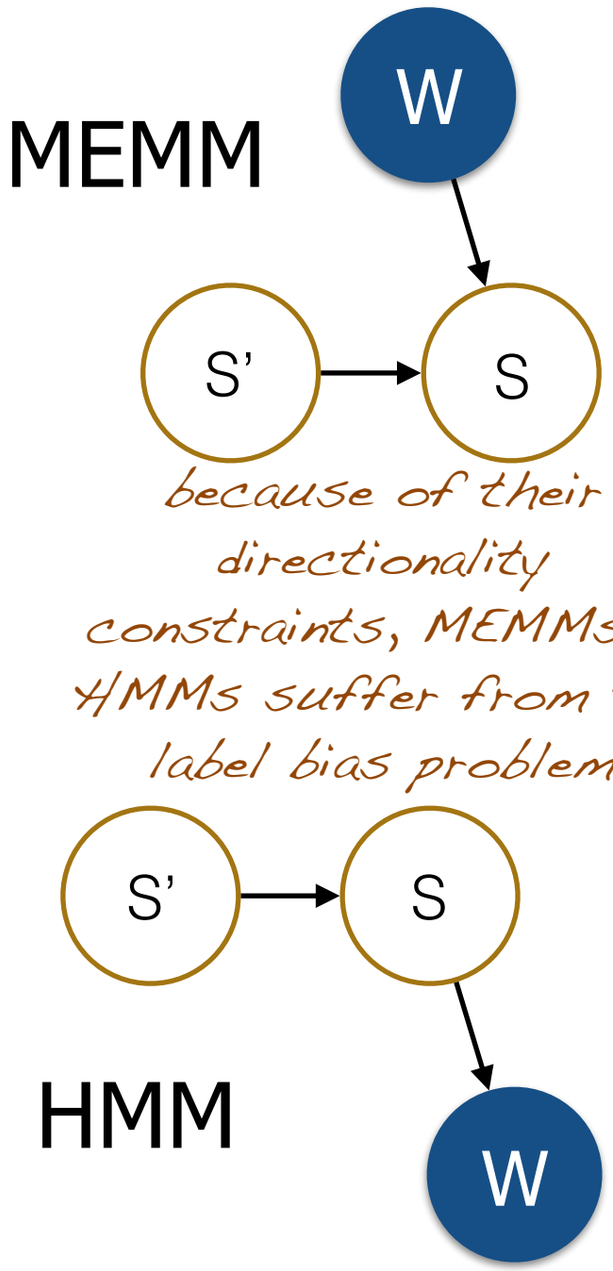
P(S | S', **W**)



NB boldface W: all words!

this "clique" makes CRFs expensive to compute

The label bias problem of directional Markov models



The robot wheels Fred around.

DT **NN** **VB** NN RB

The robot wheels were broken.

DT **NN** **NN** VB JJ

The robot wheels are round.

DT **NN** **??** yet unseen!

Wallach. Efficient Training of CRFs. MSc 2002

Model summaries: HMM, MEMM, CRF

- A **HMM**
  - **generative** model
  - **efficient** to learn and deploy
  - trains with **little data**
  - generalizes well (**low bias**)
- A **MEMM**
  - better labeling **performance**
  - modeling of **features**
  - **label bias** problem
- **CRF**
  - conditioned on **entire observation**
  - **complex features** over full input
  - training time **scales exponentially**
    - $O(NTM^2G)$
    - N: # of sequence pairs;
      T: E[sequence length];
      M: # of (hidden) states;
      G: # of gradient computations for parameter estimation

a PoS model w/45 states and 1M words can take a week to train...

LSTM: s.o.t.a. deep learning model

Sutton & McCallum. An Introduction to CRFs for Relational Learning. 2006

The Parts of Speech

I	ate	the	pizza	with	green	peppers	.
PRP	VB	DT	NN	IN	JJ	NN	.

- **Corpora** for the [supervised] **training** of PoS taggers
  - **Brown** Corpus (AE from ~1961)
  - British National Corpus: **BNC** (20th century British)
  - Wall Street Journal Corpus: **WSJ Corpus** (AE from the 80s)
  - American National Corpus: **ANC** (AE from the 90s)
  - Lancaster Corpus of Mandarin Chinese: **LCMC** (Books in Mandarin)
  - The **GENIA** corpus (Biomedical abstracts from PubMed)
  - **NEGR@** (German Newswire from the 90s)
  - Spanish and Arabian corpora should be (commercially…) available… ???

Best tip: Ask on the “corpora list” mailing list!

Linguistic morphology

➡ token normalization

- [Verbal] **Inflections**
  - conjugation (Indo-European languages)
  - tense (“availability” and use varies across languages)
  - modality (subjunctive, conditional, imperative)
  - voice (active/passive)
  - …
- **Contractions**
  - don’t say you’re in a man**’s** world…

not a contraction: possessive s

- **Declensions**
  - on nouns, pronouns, adjectives, determiners
  - case (nominative, accusative, dative, ablative, genitive, …)
  - gender (female, male, neuter)
  - number forms (singular, plural, dual)
  - possessive pronouns (I→my, you→your, she→her, it→its, … car)
  - reflexive pronouns (for myself, yourself, …)
  - …

Stemming → Lemmatization

➡ token normalization

a.k.a. token "regularization"

(although that is technically the wrong wording)

- Stemming
  - produced by "**stemmers**"
  - produces a word's "stem"
  - am → am
  - the going → the go
  - having → hav
  - fast and simple (pattern-based)
  - **Snowball**; **Lovins**; **Porter**
- Lemmatization
  - produced by "**lemmatizers**"
  - produces a word's "lemma"
  - am → be
  - the going → the going
  - having → have
  - requires: a dictionary for the mappings and the **PoS tags (!)**
  - **LemmaGen**; **morpha**; **BioLemmatizer**; **geniatagger**

Noun and verb phrase chunking with BIO-encoded labels

"shallow parsing"

a pangram (hint: check the letters → full alphabet)

The brown fox	quickly jumps	over	the lazy dog	.
DT JJ NN	RB VBZ	IN	DT JJ NN	.
B-N I-N I-N	B-V I-V	O	B-N I-N I-N	O

Performance (2nd order CRF) ~ 94%
Main problem: embedded & chained NPs (N of N and N)

Chunking is "more robust to the highly diverse corpus of text on the Web" and [exponentially] faster than [deep] parsing.

Banko et al. Open Information Extraction from the Web. IJCAI 2007 a paper with over 700 citations
Wermter et al. Recognizing noun phrases in biomedical text. SMBM 2005 **error sources**

PoS tagging and lemmatization for Named Entity Recognition (NER)

N.B.: This is all supervised (i.e., manually annotated corpora)!

de facto standard PoS tagset {NN, JJ, DT, VBZ, …}
Penn Treebank

Token	PoS	Lemma	NER
Constitutive	JJ	constitutive	O
binding	NN	binding	O
to	TO	to	O
the	DT	the	O
peri-κ	NN	peri-kappa	B-DNA
B	NN	B	I-DNA
site	NN	site	I-DNA
is	VBZ	be	O
seen	VBN	see	O
in	IN	in	O
monocytes	NNS	monocyte	B-cell
.	.	.	O

chunk

noun-phrase (chunk)

Begin-Inside-Outside
of the (relevant) token
B-I-O
chunk encoding

common alternatives:
I-O
I-E-O
B-I-E-W-O

End token

(unigram) **W**ord

Named Entity Recognition (NER)

How much training data do I need? "corpora list"

Image Source: v@s3k [a GATE session; http://vas3k.ru/blog/354/]

The departure of Mr Hogan, who originally moved to British Midland as service director from Hertz International in 1997, surprised aviation analysts, as it was believed that he had been brought into the senior executive team of the airline, as part of the group's management succession planning.

He played a leading role in the strategic planning for the rebranding of the airline as BMI in preparation for its entry this year into the scheduled long haul market with the launch of services from Manchester to the US.

BMI has taken on the costs of entry into the North Atlantic market at an unfortunate time, as airlines in North America are facing the toughest conditions for 20 years with many carriers plunging into loss.

BMI, in which Lufthansa of Germany and SAS Scandinavian Airlines each own stakes of 20 per cent, suffered a 26 per cent fall in pre-tax profits last year from £11.1m ($15.7m) to £8.2m on a turnover that grew 16.5 per cent to £739.2m.

In the first six months this year it is understood that passenger volumes have fallen by around two per cent. The share of available seats filled, the load factor, has declined by around two percentage points, but this has been offset by a strong increase in yields, or average fare levels, by more than ten per cent.

Date
Location
Money
Organization
Percentage
Person

- ➡ Conditional Random Field
- ➡ Ensemble Methods; +SVM, HMM, MEMM, … ➡ `pyensemble`

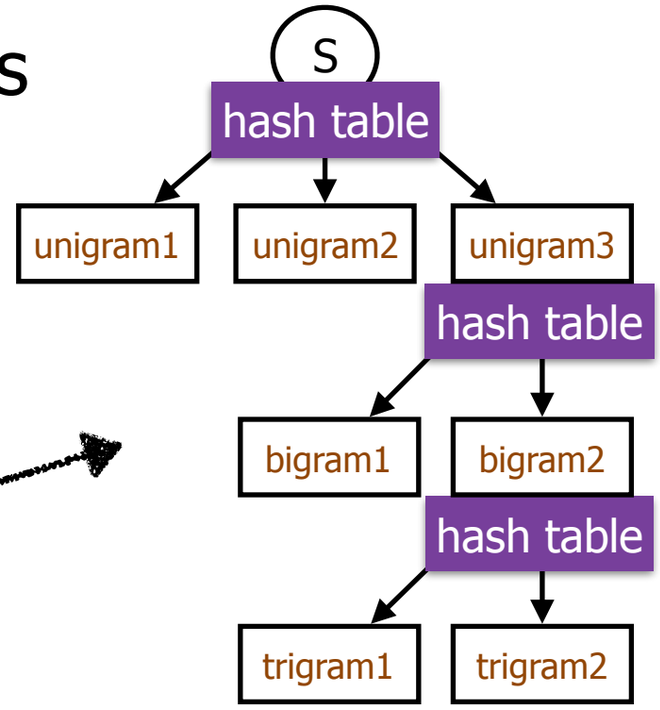
NB these are **corpus**-based approaches (supervised)

CoNLL03: http://www.cnts.ua.ac.be/conll2003/ner/

A token-based recipe for the Aho-Corasick algorithm.

Gazetteers: Dictionary matching

- Finding all tokens that match dictionary entries
  - hash table lookups: constant complexity - $O(1)$
- **Exact**, single token matches
  - regular hash table lookup (e.g., MURMUR3)
- Exact, multiple tokens
  - **prefix trie** of (hashed) tokens



- **Approximate**, single tokens *e.g. Jaro-Winkler similarity*
  - use some string metric - but do not compare all n-to-m cases…
- **Approximate**, multiple tokens
  - various "fuzzy" sequence matching algos

efficient/traditional approach: character n-gram similarity (e.g. databases)