Maschinelle Sprachverarbeitung

Part-Of-Speech Tagging and Hidden Markov Models

Ulf Leser

Content of this Lecture

- Language as stochastic processes

- Language and Markov Models
- Data sparsity
- POS Tagging

Language Models

- Given a prefix of a sentence: Predict the next word
  - "At 5 o'clock, we usually drink …"
    - "tea" – quite likely
    - "beer" – quite unlikely
    - "a beer" – slightly more likely, but still
    - "biscuits" – semantically wrong
    - "the windows need cleaning" – syntactically wrong
- Abstract formulation: Given a language L and the prefix S[1..n] of a sequence S, S$\in$L: Predict S[n+1]
- This is a ranking problem – no single solution

Applications

- Speech/character recognition
  - Given a transcribed prefix of a sentence – which word do we expect next?
- Automatic translation
  - Given a translated prefix of a sentence – what do we expect next?
- General: Use probabilities of next word as a-priori probability for interpreting the next signal
  - Helps to disambiguate between different options
  - Helps to make useful suggestions
  - Helps to point to likely errors (observation ≠ expectation)

N-Grams over Words

- Popular and simple approach: N-gram models
  - "Indeed, it is difficult to beat a trigram model on the purely linear task of predicting the next word" [MS99]
- Definition
  A (word) n-gram is a sequence of n words.
- Usage
  - Given a corpus, perform sentence splitting and tokenization
  - Count frequencies of all n-grams in this corpus
    - Slide window of size n over sentences and keep counter for each n-gram ever seen
  - Given a sentence prefix, predict most probable continuation(s) based on n-gram frequencies – how?

N-Grams for Language Modeling

- Assume a sentence prefix with n-1 words $<w_1,...,w_{n-1}>$
- Look-up counts of all n-grams starting with $<w_1,...,w_{n-1}>$
  - I.e., n-grams $<w_1,...,w_{n-1},w_x>$
- Choose w_x whose n-gram is the most frequent one
- More formally
  - Compute, for every possibly w_x,

$$p(w_x) = p(w_x \mid w_1,..., w_{n-1}) = \frac{p(w_1,..., w_x)}{p(w_1,...w_{n-1})}$$

  - Choose w_x which maximizes $p(w_x)$
- Which n?
  - Too short: Bad predictions; too large: data sparsity

Markov Models

- Definition
  Assume an alphabet Σ. A Markov Model of order 1 is a sequential stochastic process with $|\Sigma|$ states $s_1, \ldots, s_n$ with
  - *Every state emits exactly one symbol w_i from Σ*
  - *No two states emit the same symbol*
  - *For a sequence $<s_1,s_2,\ldots>$ of states, the following holds*

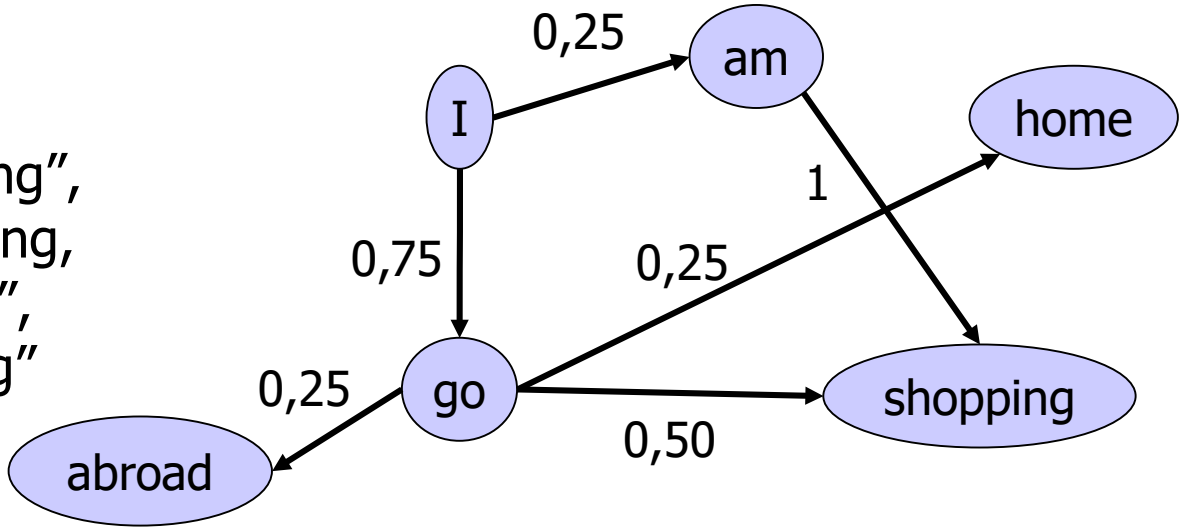
    $$p(w_n=s_n|w_{n-1}=s_{n-1}, w_{n-2}=s_{n-2},\ldots, w_1=s_1) = p(w_n=s_n|w_{n-1}=s_{n-1})$$
  - For all s_i, it holds that

    $$\sum_{s_{i+1}} p(w_{i+1} = s_{i+1} \mid w_i = s_i) = 1$$

- Remarks
  - $a_{i,j} = p(w_n=s_j|w_{n-1}=s_i)$ are called transition probabilities
  - In language modeling, Σ = {set of all words of a language}
  - Computing good start probabilities is an issue we essentially ignore

Visualization

- Since every state emits exactly one word, we can merge states and words
- State transition graph
  - Nodes are states (labeled with their emission)
  - Arcs are transitions labeled with a non-zero probability
  - Probabilities of all outgoing edges of a state sum up to 1
- Example
  - "I go home",
    "I go shopping",
    "I am shopping,
    "I go abroad",
    "Go shopping"



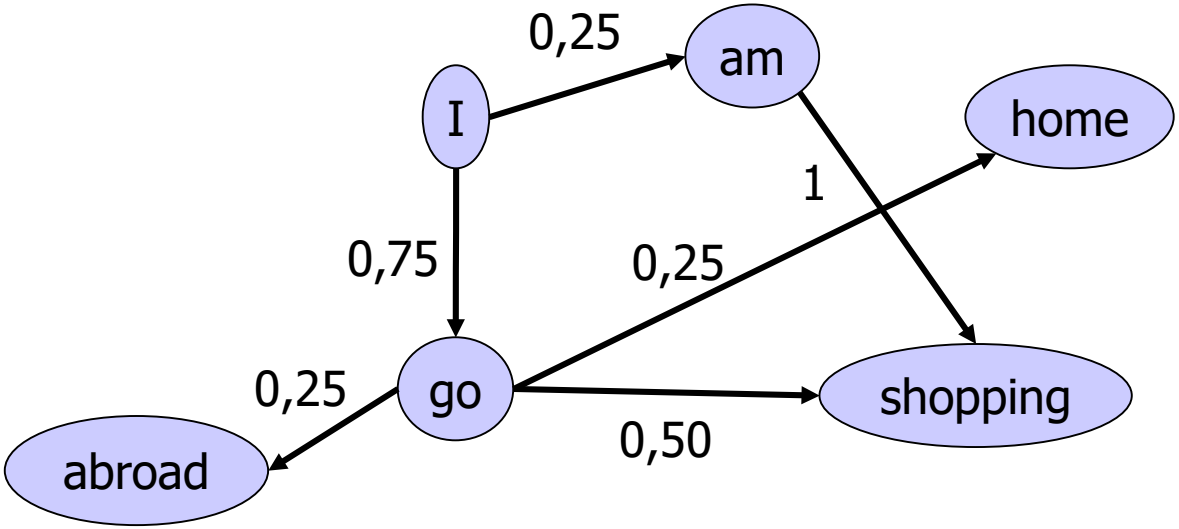
Probability of a Sequence of States (=a Sentence)

- Assume a Markov Model M and a sequence S of states with |S|=n
- With which probability was S generated by M, i.e., what is the value of p(S|M)?

$$p(S \mid M) = p(w_1 = S[1]) * \prod_{i=2..n} p(w_i = S[i] \mid w_{i-1} = S[i-1])$$

$$= a_{0,S[1]} * \prod_{i=2..n} a_{S[i-1],S[i]} = a_{0,1} * \prod_{i=2..n} a_{i-1,i}$$

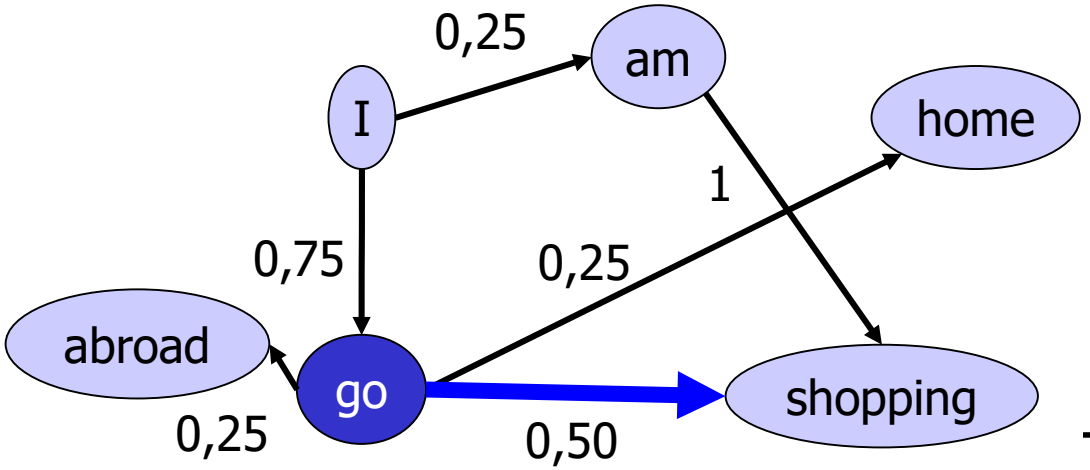
Example



- p("I go home") = $p(w_1=„I“|w_0)$* $p(w_2=„go“|w_1=„I“)$ * $p(w_3=„home“|w_2=„go“)$
  = 1 * 0.75* 0.25 = 0.1875
- Problem: Pairs not in the training data get probability 0
  - Example: "I am abroad"
  - With this small "corpus", almost all transitions get p=0

Predicting the Next State

- For language modeling, we do not need the probability of an entire sequence, but we only reason about the next state given some previous states
- Consider an order-1 Markov Model



$$p(w_n) = p(w_n \mid w_1, \ldots, w_{n-1})$$
$$= p(w_n \mid w_{n-1})$$
$$= \frac{p(w_{n-1}, w_n)}{p(w_{n-1})}$$
$$\sim p(w_{n-1}, w_n)$$

This is the most frequent bi-gram with prefix w_{n-1}

Content of this Lecture

- Language and Markov Models
- Data sparsity
- POS Tagging

Problem

- We learn our transition probabilities from a limited sample
- Thus, we only estimate the true transition probabilities
- Introduces a systematic error which we can try to alleviate
  - Sample selection is important
  - Problem is researched a lot in statistics
- Extreme cases: Transitions we do not see in the corpus
  - Get a probability of 0
  - Will never be predicted
  - This does not mean that they are non-existing in the language
- Our model (yet) cannot adequately cope with data sparsity

Smoothing I: Laplace's Law

- Give some probability mass to unseen events
- Oldest (and simplest) suggestion: "Adding one"

$$p_{LAP}(w_1,\ldots,w_n) = \frac{count(w_1,\ldots,w_n)+1}{N+B}$$

  - Where B is the number of possible n-grams, i.e., K^n
  - All n-grams get a probability≠0
- But – moves too much mass to the unknown
  - Estimates for seen n-grams are scaled down dramatically
  - Estimates for unseen n-grams are small, but there are so many
    - And many of them are truly impossible
  - In a corpus of 40 M words with K~400T, 99.7% of the total probability mass is spend in unseen events

Smoothing II: Lidstone's Law

- Laplace not suitable if there are many events, but few seen
- Lidstone's law gives less probability mass to unseen events

$$p_{LIP}(w_1,\ldots,w_n) = \frac{count(w_1,\ldots,w_n)+\lambda}{N+\lambda * B}$$

  - Small λ: More mass is given to seen events
  - Typical estimate is λ=0.5
  - Appropriate values can be learned (next slide)
- Still: Estimate of seen events is linear in the MLE estimate
  - Not a good approximation of empirical distributions
- Other: Good-Turing Estimator, n-gram interpolations, …

Content of this Lecture

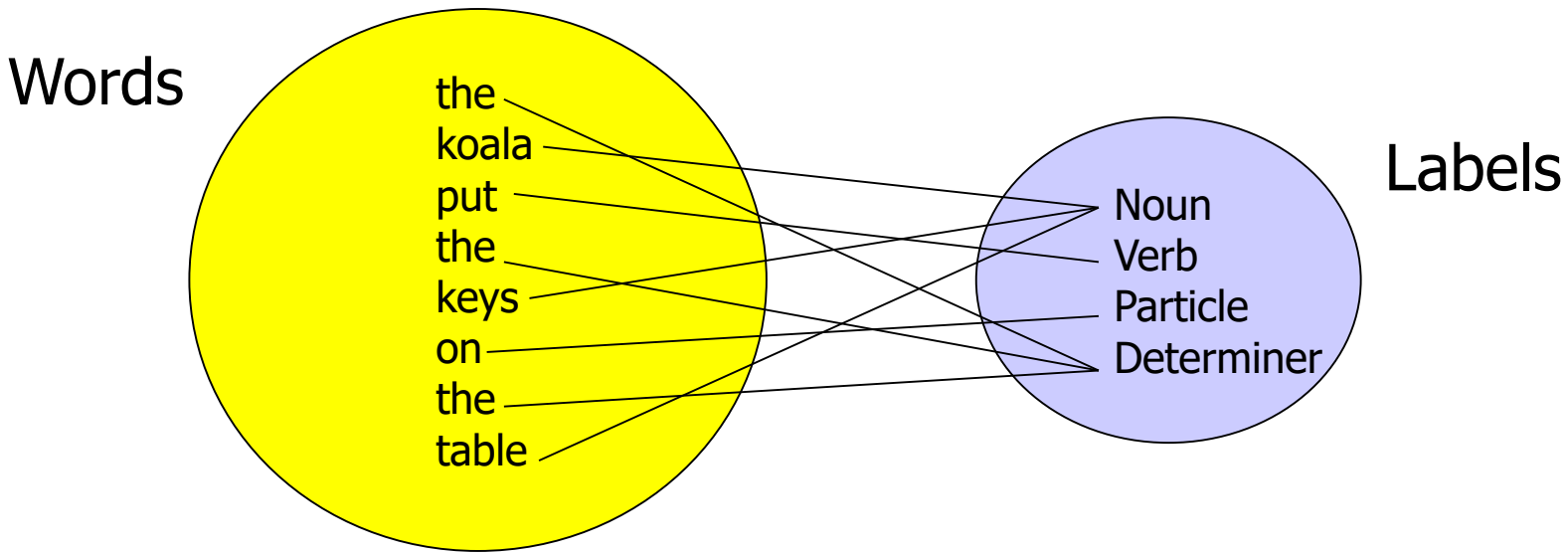
- Language and Markov Models
- Data sparsity
- POS Tagging
  - Part-Of-Speech (POS)
  - Simple methods for POS tagging
  - Hidden Markov Models
- Closing Remarks

Material from

- [MS99], Chapter 9/10
- Rabiner, L. R. (1988). "A Tutorial on Hidden Markov Models and Selected Applications in Speech Recognition." *Proceedings of the IEEE* **77**(2): 257-286.

Part-of-Speech (POS)

- In a sentence, each word has a grammatical class
- Simplest case: Noun, verb, adjective, adverb, article, …
  - That's not a grammatical role: Subject, object, …



Tag Sets

- (POS-) tag set: Set of labels representing POS-classes
  - Simple tag set: Only broad word classes
  - Complex tag sets: Include morphological information
    - Noun: Gender, case, number
    - Verb: Tense, number, person
    - Adjective: normal, comparative, superlative
    - …
- Word classes even within a language are not really defined
  - London-Lund Corpus of Spoken English: 197 tags
  - Lancaster-Oslo/ Bergen: 135 tags
  - Penn tag set: 45 tags
  - Brown tag set: 87 tags
  - STTS (Stuttgart-Tübingen Tagset): ~50 tags

U-Penn TreeBank Tag Set (45 tags)

Tag	Description	Example	Tag	Description	Example
CC	Coordin. Conjunction	*and, but, or*	SYM	Symbol	+,%, &
CD	Cardinal number	*one, two, three*	TO	"to"	*to*
DT	Determiner	*a, the*	UH	Interjection	*ah, oops*
EX	Existential 'there'	*there*	VB	Verb, base form	*eat*
FW	Foreign word	*mea culpa*	VBD	Verb, past tense	*ate*
IN	Preposition/sub-conj	*of, in, by*	VBG	Verb, gerund	*eating*
JJ	Adjective	*yellow*	VBN	Verb, past participle	*eaten*
JJR	Adj., comparative	*bigger*	VBP	Verb, non-3sg pres	*eat*
JJS	Adj., superlative	*wildest*	VBZ	Verb, 3sg pres	*eats*
LS	List item marker	*1, 2, One*	WDT	Wh-determiner	*which, that*
MD	Modal	*can, should*	WP	Wh-pronoun	*what, who*
NN	Noun, sing. or mass	*llama*	WP$	Possessive wh-	*whose*
NNS	Noun, plural	*llamas*	WRB	Wh-adverb	*how, where*
NNP	Proper noun, singular	*IBM*	$	Dollar sign	$
NNPS	Proper noun, plural	*Carolinas*	#	Pound sign	#
PDT	Predeterminer	*all, both*	"	Left quote	(' or ")
POS	Possessive ending	*'s*	"	Right quote	(' or ")
PRP	Personal pronoun	*I, you, he*	(	Left parenthesis	([, (, {, <)
PRP$	Possessive pronoun	*your, one's*	)	Right parenthesis	( ],), }, >)
RB	Adverb	*quickly, never*	,	Comma	,
RBR	Adverb, comparative	*faster*	.	Sentence-final punc	(. ! ?)
RBS	Adverb, superlative	*fastest*	:	Mid-sentence punc	(: ; ... – -)
RP	Particle	*up, off*			

Tagged Sentences

- Simple tag set
  - The/**D** koala/**N** put/**V** the/**D** keys/**N** on/**P** the/**D** table/**N**
- Including morphological information
  - The/**D** koala/**Ns** put/**V-past-3rd** the/**D** keys/**N-p** on/**P** …
- Using Penn tag set
  - The/**DT** koala/**NN** put/**VBN** the/**DT** keys/**NNS** on/**P** …

The	koala	put	the	keys	on	the	table
D	N	V	D	N	P	D	N
D	N-sing	V-past-3rd	D	N-plu	P	D	N-sing
DT	NN	VBN	DT	NNS	P	DT	NN

Why POS Tagging?

- Parsing a sentence usually starts with POS tagging
- Finding phrases (shallow parsing) requires POS tagging
  - Noun phrases, verb phrases, adverbial phrases, …
- POS tags are beneficial for word sense disambiguation
- Applications in all areas of Text Mining
  - NER: ~10% boost using POS-features for single-token entities
  - NER: ~20% boost using POS-tags during post-processing of multi-token entities
- High accuracy with relative simple methods (97%)
- Many tagger available (BRILL, TNT, MedPost, …)

POS Tagging

- Maybe each term has a single intrinsic grammatical class?
  - Peter, deliberately, school, the, better (?), …
- No: Homonyms
  - One term can represent many words (senses)
  - Different senses can have different word classes
  - "ist modern"–"Balken modern", "Win a grant"–"to grant access"
- No: Words intentionally used in different word classes
  - "We flour the pan", "Put the buy here", "the buy back of …"
  - In German, things are easier: kaufen – Einkauf, gabeln – Gabelung
    - Of course, there are exceptions: wir essen – das Essen
- Still, most words have a preferred class

Problems

- Correct class depends on context within the sentence
  - The back door = JJ
  - On my back = NN
  - Win the voters back = RB
  - Promised to back the bill = VB
- Note: Also sentences may be ambiguous
  - The representative put chairs on the table
    - The/**DT** representative/**NN** put/**VBD** chairs/**NNS** on/**IN** the/**DT** table/**NN**
    - The/**DT** representative/**JJ** put/**NN** chairs/**VBZ** on/**IN** the/**DT** table/**NN**
  - Presumably the first is more probable than the second
- Another big problem (prob. the biggest): Unseen words
  - Recall Zipf's law – there will always be unseen words

A Real Issue

		Original 87-tag corpus		Treebank 45-tag corpus	
Unambiguous (1 tag)		**44,019**		**38,857**	
Ambiguous (2–7 tags)		**5,490**		**8844**	
Details:	2 tags	4,967		6,731	
	3 tags	411		1621	
	4 tags	91		357	
	5 tags	17		90	
	6 tags	2	(*well*, *beat*)	32	
	7 tags	2	(*still*, *down*)	6	(*well*, *set*, *round*, *open*, *fit*, *down*)
	8 tags			4	(*'s*, *half*, *back*, *a*)
	9 tags			3	(*that*, *more*, *in*)

Source: Jurasky / Martin

Content of this Lecture

- Part-Of-Speech (POS)
- Simple methods for POS tagging
  - Most frequent class
  - Syntagmatic rules
- Hidden Markov Models
- Closing Remarks

Simplest Method: Most Frequent Class

- Words have a preferred POS
  - The POS tag which a word most often gets assigned to
  - Recall school: We use words such as “adjektiviertes Verb”, “adjektiviertes Nomen”, “a noun being used as an adjective”
- Method: Tag each word with its preferred POS

Using Syntagmatic Information

- Syntagmatic: „the relationship between linguistic units in a construction or sequence“
  - [http://www.thefreedictionary.com]
- Idea: Look at surrounding POS tags
  - Some POS-tag sequences are frequent, others impossible
  - DT JJ NN versus DT JJ VBZ
- Idea: Count frequencies of POS-patterns in a tagged corpus
  - Count all tag bi-grams, tag tri-grams, …
  - Count regular expressions (DT * NN versus DT * VBZ)
  - … (many ways to define a pattern)

Usage for Tagging

- Start with words with unique POS tags (the, to, lady, …)
  - But: "The The"
- Find and apply the most frequent patterns over these tags
  - Assume <DT JJ> and <JJ NN> are frequent
  - "The blue car" -> DT * * -> DT JJ * -> DT JJ NN
  - But: "The representative put chairs" -> DT * * * -> DT JJ * * -> DT JJ NN *
- Needs conflict resolution
  - Assume frequent bi-grams <DT JJ> and <VBZ IN>
  - How to tag "the bank in" -> DT * IN
- Pattern-cover problem: Cover a sentence with patterns such that the sum of their relative frequencies is maximal

Content of this Lecture

- Part-Of-Speech (POS)
- Simple methods for POS tagging
- Hidden Markov Models
  - Definition and Application
  - Learning the Model
  - Tagging
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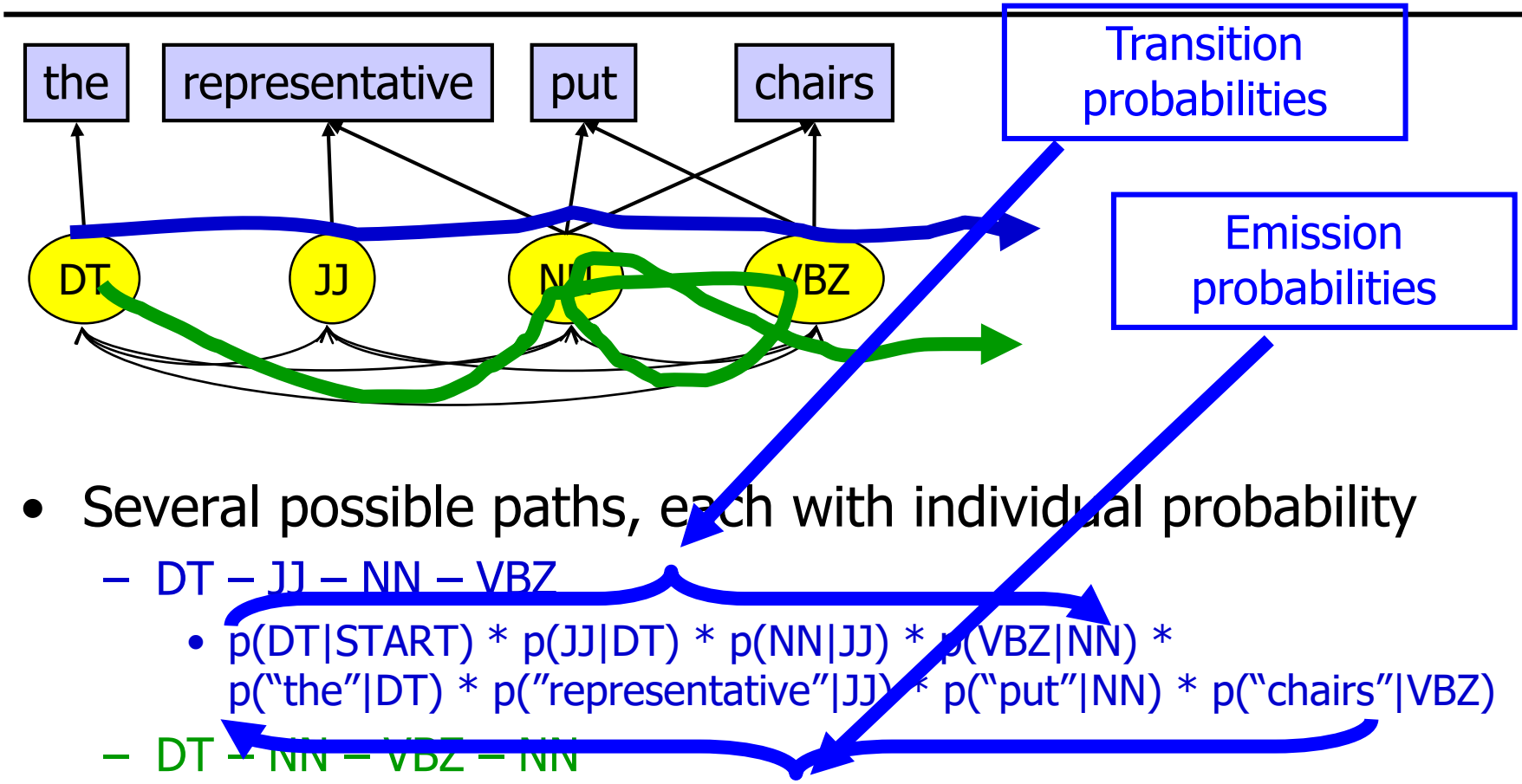
Sequential Probabilistic Model

- Recall Markov Models (1st order)
  - *A Markov Model is a stochastic process with states s_1, …, s_n with …*
    - *Every state emits exactly one symbol from Σ*
    - *No two states emit the same symbol*
    - *$p(w_n=s_n/w_{n-1}=s_{n-1}, w_{n-2}=s_{n-2},…, w_1=s_1) = p(w_t=s_t/w_{n-1}=s_{n-1})$*
- That doesn't help: Relationship POS – WORD is m:n
- We need an extension
  - We assume one state per POS tag
  - Each state may emit any word with a given probability
  - This is a Hidden Markov Model
  - When seeing a sentence, we can only observe the sequence of emissions, but not the underlying sequence of (hidden) states

Example

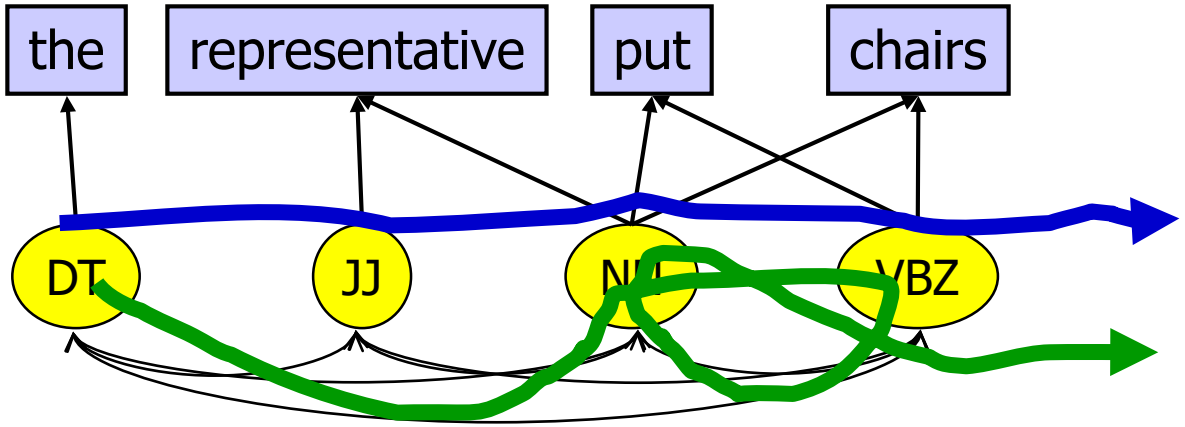


- Several possible paths, each with individual probability
  - DT – JJ – NN – VBZ
    - p(DT|START) * p(JJ|DT) * p(NN|JJ) * p(VBZ|NN) * p("the"|DT) * p("representative"|JJ) * p("put"|NN) * p("chairs"|VBZ)
  - DT – NN – VBZ – NN
    - p(DT|START) * p(NN|DT) * p(VBZ|NN) * p(NN|VBZ) * p("the"|DT) * p("representative"|NN) * p("put"|VBZ) * p("chairs"|NN)

Definition

- Definition
  A Hidden Markov Model of order one is a sequential stochastic process with k states $s_1, \ldots, s_k$ with
  - *Every state s emits every symbol $x \in \Sigma$ with probability p(x|s)*
  - *The sequence of states is a 1st order Markov Model*
  - *The $a_{0,1}$ are called start probabilities*
  - *The $a_{t-1,t}$ are called transition probabilities*
  - *The $e_s(x)=p(x|s)$ are called emission probabilities*
- Note
  - A given sequence of symbols can be emitted by many different sequences of states
  - These have individual probabilities depending on the transition probabilities and the emission probabilities in the state sequence

Example



	DT	JJ	NN	VBZ
DT	0	0,4	0,6	0
JJ	0	0,3	0,6	0,1
NN	0	0,2	0,2	0,6
VBZ	0,2	0	0,7	0,1

- DT – JJ – NN – VBZ

  p(DT|START) * p(JJ|DT) * p(NN|JJ) * p(VBZ|NN) *
  p("the"|DT) * p("representative"|JJ) * p("put"|NN) * p("chairs"|VBZ)
  = … * 0,4 * 0,6 * 0,6 * …

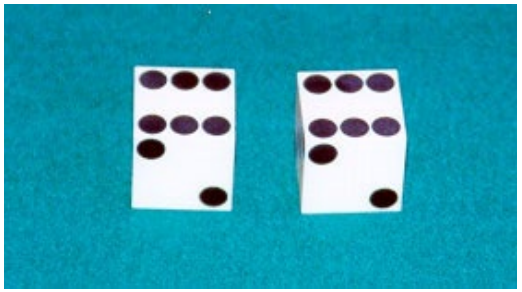
- DT – NN – VBZ – NN

  p(DT|START) * p(NN|DT) * p(VBZ|NN) * p(NN|VBZ) *
  p("the"|DT) * p("representative"|NN) * p("put"|VBZ) * p("chairs"|NN)
  = … * 0,6 * 0,6 * 0,7 * …

HMM: Classical Problems

- Decoding/parsing: Given a sequence S of symbols and a HMM M: Which sequence of states did most likely emit S?
  - This is our tagging problem once we have the model
  - Solution: Viterbi algorithm
- Evaluation: Given a sequence S of symbols and a HMM M: With which probability did M emit S?
  - Fit of the model for the observation
  - Different than parsing, as many sequence may have emitted S
  - Solution: Forward/Backward algorithm (skipped here)
- Learning: Given a tagged sequence S: Which HMM emits S with the highest probability?
  - We need to learn start, emission, and transition probabilities
  - Solution: MLE or Baum-Welch algorithm (skipped here)

Another Example: The Dishonest Casino



A casino has two dice:

- Fair die
  p(1)=p(2)=p(3)=p(4)=p(5)=p(6)=1/6
- Loaded die
  p(1)=p(2)=p(3)=p(4)=p(5)=1/10
  p(6) = 1/2

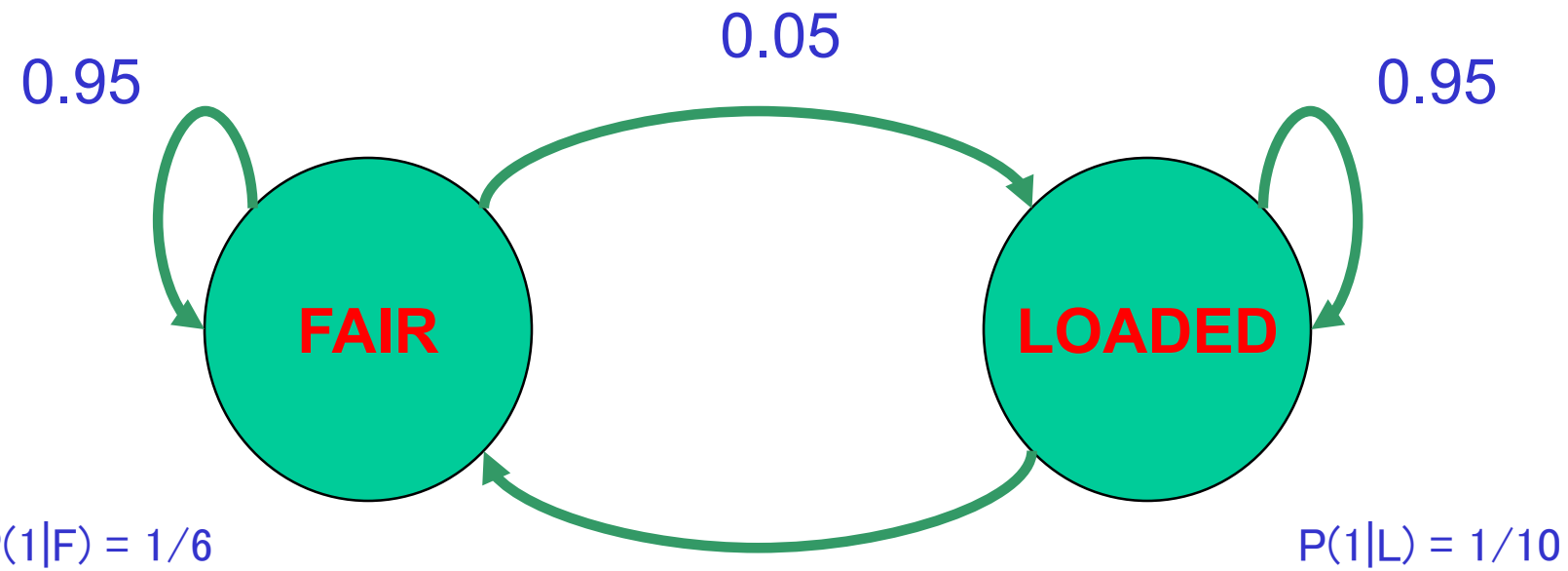
Casino occasionally switches between dice
(and you want to know when)

Game:

1. You bet $1
2. You roll (always with a fair die)
3. You may bet more or surrender
4. Casino player rolls (with some die…)
5. Highest number wins

Quelle: Batzoglou, Stanford

The dishonest casino model



P(1|F) = 1/6
P(2|F) = 1/6
P(3|F) = 1/6
P(4|F) = 1/6
P(5|F) = 1/6
P(6|F) = 1/6

P(1|L) = 1/10
P(2|L) = 1/10
P(3|L) = 1/10
P(4|L) = 1/10
P(5|L) = 1/10
P(6|L) = 1/2

Question # 1 – Decoding

GIVEN A sequence of rolls by the casino player

6214614613613666166466163661636616361651561511514612356234 4

QUESTION What portion of the sequence was generated with the fair die, and what portion with the loaded die?

This is the **DECODING** question

Question # 2 – Evaluation

GIVEN A sequence of rolls by the casino player

6214614613613666166466163661636616361651561511514612356 2344

QUESTION How likely is this sequence, given our model of how the casino works?

This is the **EVALUATION** problem

Question # 3 – Learning

GIVEN A sequence of rolls by the casino player

6146136136661664661636616366163616515615115146123562344

QUESTION

How "loaded" is the loaded die? How "fair" is the fair die? How often does the casino player change from fair to loaded, and back?

This is the **LEARNING** question

[Note: We need to know how many dice there are!]

Content of this Lecture

- Part-Of-Speech (POS)
- Simple methods for POS tagging
- Hidden Markov Models
  - Definition and Application
  - Learning the Model
  - Tagging
- Concluding Remarks

Learning a HMM

- We always assume the set of states (POS tags) as fixed
- We need to learn start, emission and transition probabilities
- Assuming a large, tagged corpus, MLE does the job
  - Count relative frequencies of all starts, emissions, and transitions

MLE for Transition and Emission Probabilities

- Transitions
  - Count frequencies of all state transitions s $\rightarrow$ t
  - Transform in relative frequencies for each outgoing state
    - Let A_{st} be the number of transitions s$\rightarrow$t

$$a_{st} = p(t \mid s) = \frac{A_{st}}{\sum_{t' \in M} A_{st'}}$$

- Emissions
  - Count frequencies of emissions over all symbols and states
  - Transform in relative frequencies for each state
    - Let $E_s(x)$ be the number of times that state s emits symbol x

$$e_s(x) = \frac{E_s(x)}{\sum_{x' \in \Sigma} E_s(x')}$$

Overfitting

- We have a data sparsity problem
  - Not so bad for the state transitions
    - Not too many POS Tags
    - But some classes are very rare
  - Quite bad for emission probabilities
    - As large as the corpus might be, most rare emissions are never seen and would (falsely) be assigned probability 0
- Need to apply smoothing
  - See previous lecture

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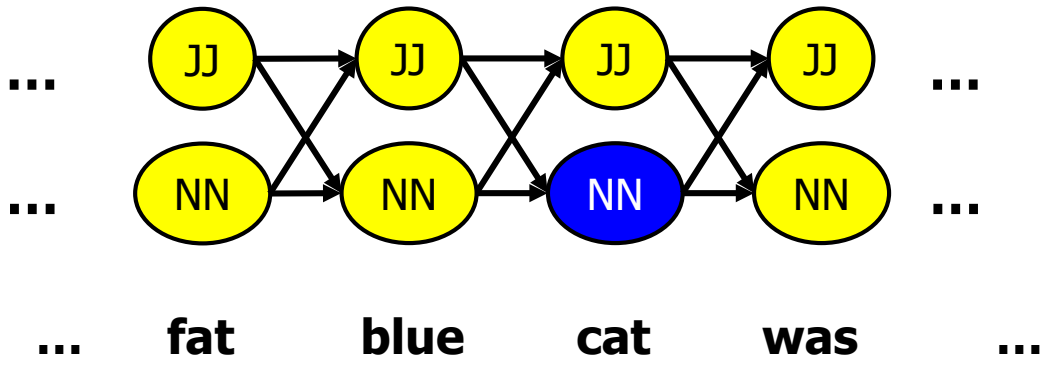
Viterbi Algorithm

- Definition
  Let M be a HMM and S a sequence of symbols. The parsing problem is to find a (or all) state sequence of M that generated S with the highest probability
- Very often, we call a sequence of states a path
- Naïve solution
  - Let's assume that $a_{ij}>0$ and $e_i(x)>0$ for all x,i,j and i,j≤k
  - Then there exist k^n path
  - We cannot look at all of them
- Viterbi-Algorithm
  - Viterbi, A. J. (1967). "Error bounds for convolution codes and an asymptotically optimal decoding algorithm." *IEEE Transact. on Information Theory* **13**: 260-269.

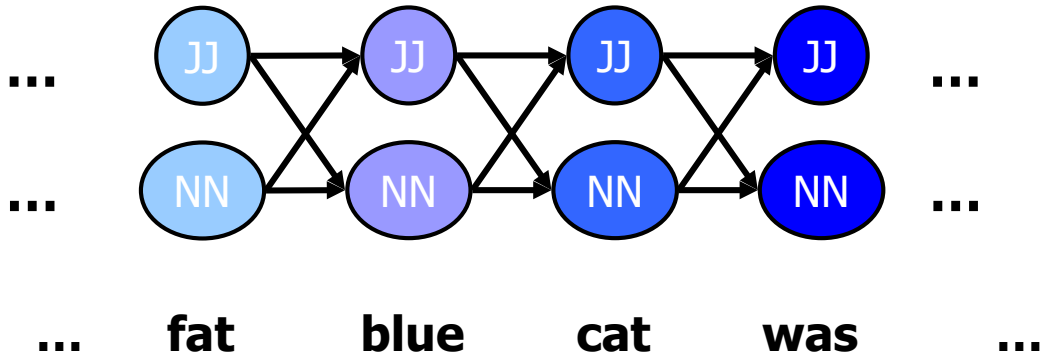
Idea: Dynamic Programming

- Every potential state s at position i in S is reachable by many paths
- However, one of those must be the most probable one
- All continuations of the path for S from s at position i only need this highest probability over all paths reaching s at i
- Compute maximal probabilities iteratively for all positions



Viterbi: Dynamic Programming

- We compute optimal (= most probable) paths for increasingly long prefixes of S
- Let $v_t(i)$ be the probability of the optimal path for S[..i] ending in state t
- We want to express $v_t(i)$ using only the $v_{s \in M}(i-1)$ values
- Once we have found this formula, we may iteratively compute $v_s(1)$, $v_s(2)$, …, $v_s(|S|)$ (for all $s \in M$)



Recursion

- Let $v_s(i)$ be the probability of the optimal path for S[..i] ending in state s
- Assume we proceed from s in position i to t in position i+1
- What is the probability of the path ending in t passing through s before?
  - The probability of s (=$v_s(i)$)
  - * the transition probability from s to t (a_{st})
  - * the probability that t emits S[i+1] (=$e_t(S[i+1])$)
- Of course, we may reach t from any state at position i
- This gives

$$v_t(i+1) = e_t(S[i+1]) * \max_{s \in M}(v_s(i) * a_{st})$$

Tabular Computation

		The	fat	blue
S_0	1	0	0	
DT	0	1	0	0
JJ	0	0	…	…
NN	0	0	…	…
NNS	0	0	…	…
VB	0	0	…	…
VBZ	0	0	…	…
…				

- Use table for storing $v_s(i)$
- Special start state with prob. 1; all other states have start prob. 0
- Compute column-wise
- Every cell can be reached from every cell in the previous column
  - If a state never emits a certain symbol, all probabilities in columns with this symbol will be 0

Result

		The	fat	blue	…	cake.
S_0	1	0	0	0	…	0
DT	0	1	0	0	…	0,004
JJ	0	0	…	…	…	0,0012
NN	0	0	…	…	…	0,034
NNS	0	0	…	…	…	0,0001
VB	0	0	…	…	…	0,002
VBZ	0	0	…	…	…	0,013
…						0,008

- The probability of the most probably parse(s) is the largest value in the right-most column
- Most probable tag sequence is determined by traceback

Complexity

- Let |S|=n, |M|=k (states)
- This gives
  - The table has n*k cells
  - For computing a cell value, we need to access all potential predecessor states (=k)
  - Together: $O(n*k^2)$

Numerical Difficulties

- Naturally, the numbers are getting extremely small
  - We are multiplying small probabilities (all <<1)
- We need to take care of not running into problems with computational accuracy
- Solution: Use logarithms
  - Instead of

$$v_t(i+1) = e_t(S[i+1]) * \max_{s \in M}(v_s(i) * a_{st}))$$

  - Compute

$$v_t(i+1) = \log\left(e_t(S[i+1])\right) + \max_{s \in M}(v_s(i) + \log\left(a_{st}\right))$$

Unknown Words

- HMM do not help in tagging unknown words
- The treatment of unknown words is one of the major differentiating features in different POS taggers
- Simple approach: Consider all tags with equal probability
  - Tags are influenced only by the transition probabilities
  - Not very accurate – even closed word classes are considered
- More sophisticated approach: Use syntactical hints
  - Morphological clues: suffixes (-ed mostly is past tense of a verb)
  - Likelihood of a POS class of allowing a new word
    - Some classes are closed: Determiner, pronouns, …
  - Special characters, "Greek" syllables, … (hint to proper names)

Content of this Lecture

- Part-Of-Speech (POS)
- Simple methods for POS tagging
- Hidden Markov Models
- Concluding Remarks

Wrap-Up

- Advantages of HMM
  - Clean framework
  - Relative simple math, linear in the sentence length
  - Good performance with POS-tri-grams
    - But 3-grams already need quite a large training corpus
- Disadvantages
  - Cannot capture non-local dependencies
    - Beyond the "n" of n-grams
  - Cannot condition probability of tags on concrete preceding words (but only on preceding tags)
    - But language has such constraints
- Extensions exist, but don't seem to be necessary for POS
  - Conditional Random Fields, Markov Logic Networks, …

POS Tagger Today

- Brill, TnT, TreeTagger, OpenNLP MaxEnt tagger, …
- Choosing a tagger: Which corpus was used to learn the model? Domain specificity? Can I retrain it? Treatment of unknown words? Tag-Set?
- Some figures
  - Brill tagger has ~87% accuracy on Medline abstracts
    - When learned on Brown corpus = bad model for Medline
  - Performance of >97% accuracy is possible
    - MedPost: HMM-based, with a dictionary of fixed (word / POS-tag) assignments for the 10.000 most frequent "unknown" Medline terms
    - TnT / MaxEnt tagger reach 95-98 on newspaper corpora
- Further improvements hit inter-annotator agreement
  - And depend on the tag set – the richer, the more difficult

References

- Brill, E. (1992). "A simple rule-based part of speech tagger". Conf Applied Natural Language Processing, Trento, Italy
- Brants, T. (2000). "TnT - a statistical part-of-speech tagger". Conf Applied Natural Language Processing, Seattle, USA
- Smith, L., Rindflesch, T. and Wilbur, W. J. (2004). "MedPost: a part-of-speech tagger for biomedical text." Bioinformatics

Self-Assessment

- Give a formal definition of a Hidden Markov Model, order 1.
- Consider the following sequence of observations XYZ. Derive the set of states of a Markov Model of order 2 for this sequence and specify all transition probabilities.
- Assume the following HMM: XYZ. Compute the probability of this HMM producing the sequence ABC.
- What is the worst-case complexity of the Viterbi algorithm for HMMs? What is the average complexity?
- What is the typical size of a POS tag set for English? 0-30, 40-150, 150-300 tags?
- Where and why is data sparsity a problem in POS tagging using HMM? What can be done to overcome it?