Maschinelle Sprachverarbeitung

Part-Of-Speech Tagging and Hidden Markov Models

Ulf Leser

Terminänderung

- Vorlesung vom 23.11.
- wird auf den 25.11., 11.00 Uhr, Raum 3.113
- verschoben

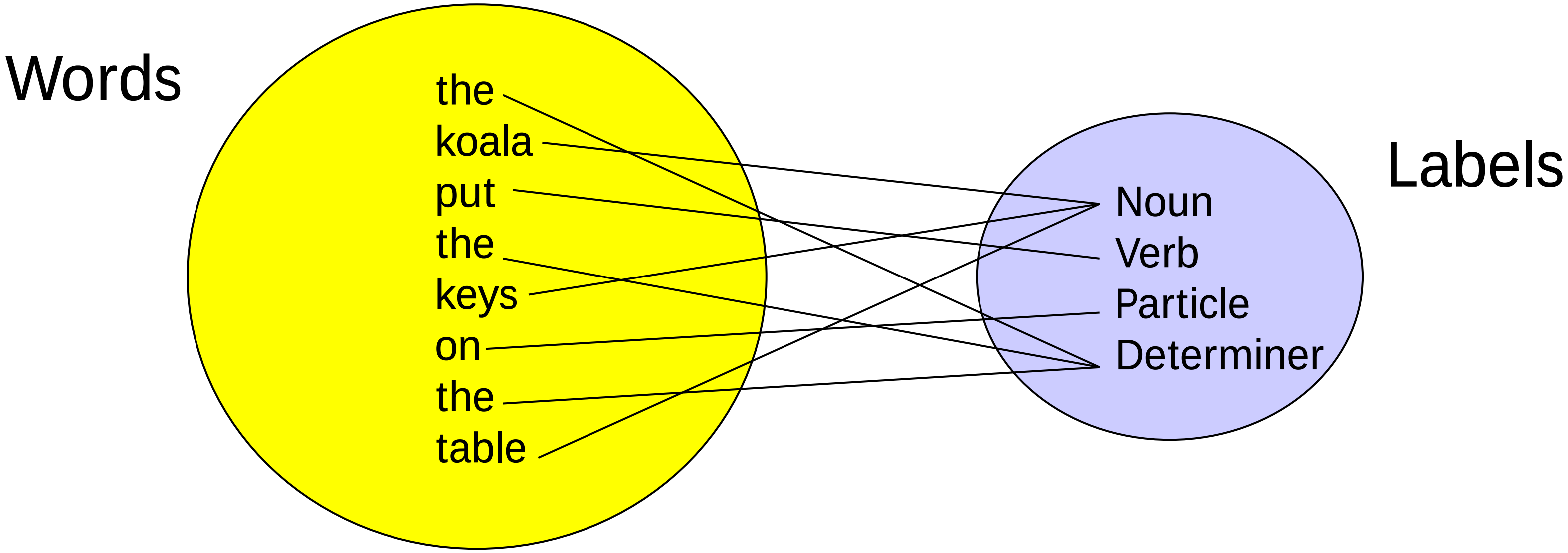
Content of this Lecture

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

- Most material from
  - [MS99], Chapter 9/10
  - Durbin, R., Eddy, S., Krogh, A. and Mitchison, G. (1998). "Biological Sequence Analysis: Probablistic Models of Proteins and Nucleic Acids". Cambridge University Press.
  - 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 for the same language are not 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

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

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, ...)

Content of this Lecture

- Part-Of-Speech (POS)
- Simple methods for POS tagging
  - Most frequent class
  - Syntagmatic rules
  - Transformation-based tagging
- 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: “the bank in” -> DT * IN
  - Assume frequent bi-grams <DT JJ> and <VBZ IN>
- Pattern-cover problem: Cover a sentence with patterns such that the sum of their relative frequencies is maximal

Transformation-Based Tagger

- Brill: „Transformation-Based Error-Driven Learning and Natural Language Processing: A Case Study in Part-of-Speech Tagging“, Computational Linguistics, 1995.
- Idea: Identify „typical situations“ in a tagged corpus
  - Example: After “to”, there usually comes a verb
  - Situations may combine words, tags, morphological information, etc.
- Capture “situations” by transformation rules
- Apply when seeing untagged text
- Sort-of generalization of the syntagmatic approach

Transformation-Based Tagging

- Learning rules
  - We simulate the real case: “Untag” a tagged corpus
  - Tag each word with its most probably POS-tag
  - Find the most frequent differences between the original (tagged) text and the retagged text and encode as a rule
    - These are the most typical errors one performs when using only the most probable classes
    - Their correction (using the gold standard) is learned
- Tagging
  - Assign each word its most probable POS tag
  - Apply transformation rules to rewrite tag sequence
  - Issues: Order of application of rules? Termination?

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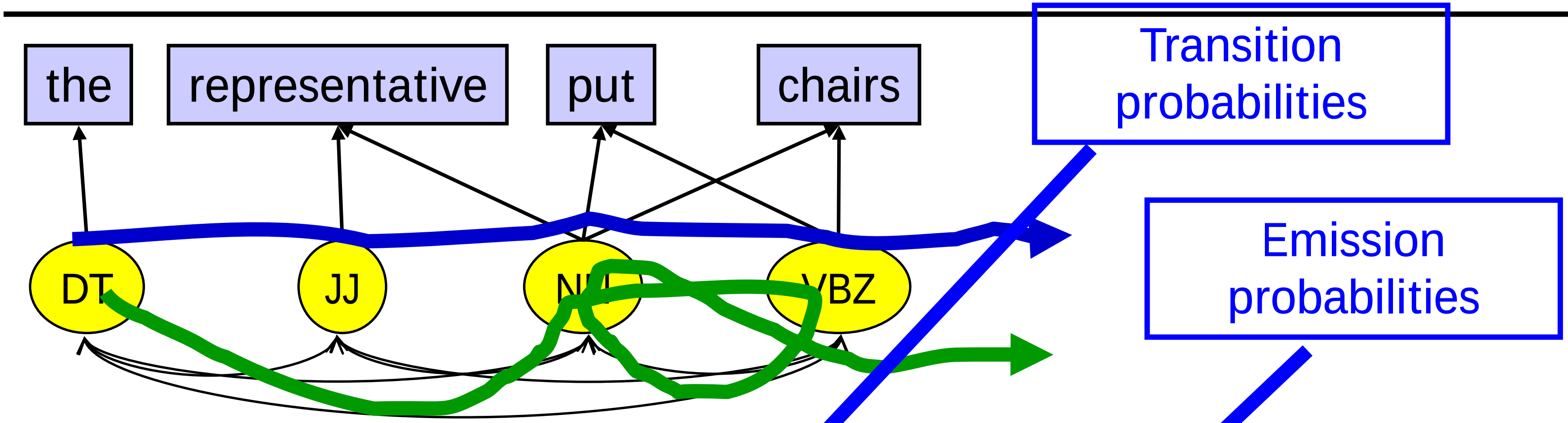
Sequential Probabilistic Model

- Recall Markov Models (1st order)
  - *A Markov Model is a stochastic process with states $s_1, \ldots, s_n$ with ...*
    - *Every state emits exactly one symbol from Σ*
    - *No two states emit the same symbol*
    - $p(w_n=s_n|w_{n-1}=s_{n-1}, w_{n-2}=s_{n-2},\ldots, w_1=s_1) = p(w_t=s_t|w_{n-1}=s_{n-1})$
- 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

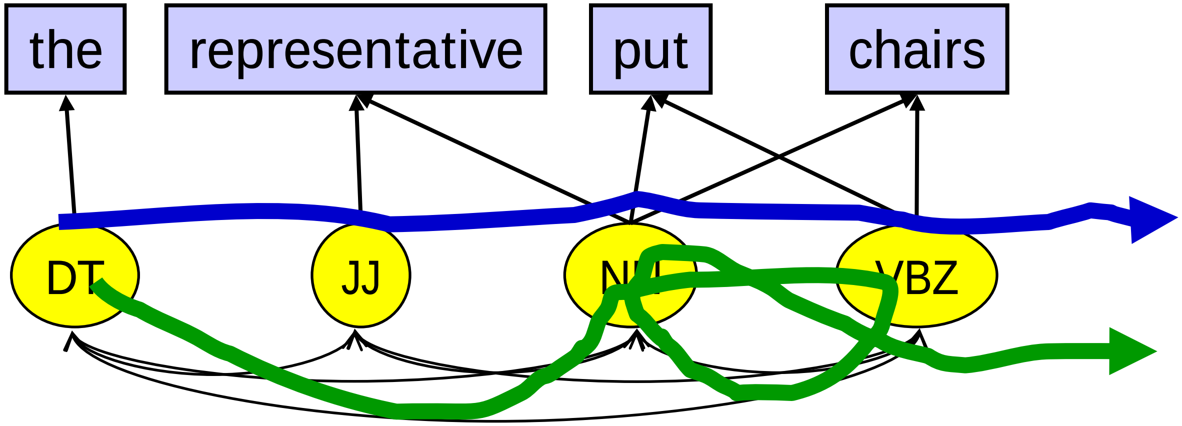


- Several possible paths, each with individual probability
  - DT – JJ – NN – VBZ
    - p(DT|"start") * p(JJ|DT) * p(NN|JJ) * p(VBZ|NN) * p(the|DT) * p(representative|JJ) * p(put|NN) * p(chairs|VBZ)
  - DT – NN – VBZ – NN
    - p(DT|"start") * p(NN|DT) * p(VBZ|NN) * p(NN|VBZ) * p(the|DT) * p(representative|NN)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

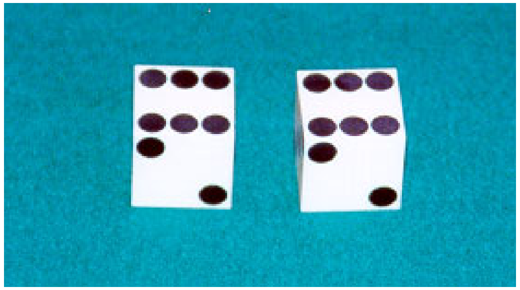
- DT – NN – VBZ – NN

  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 sequence S and a set of states: 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

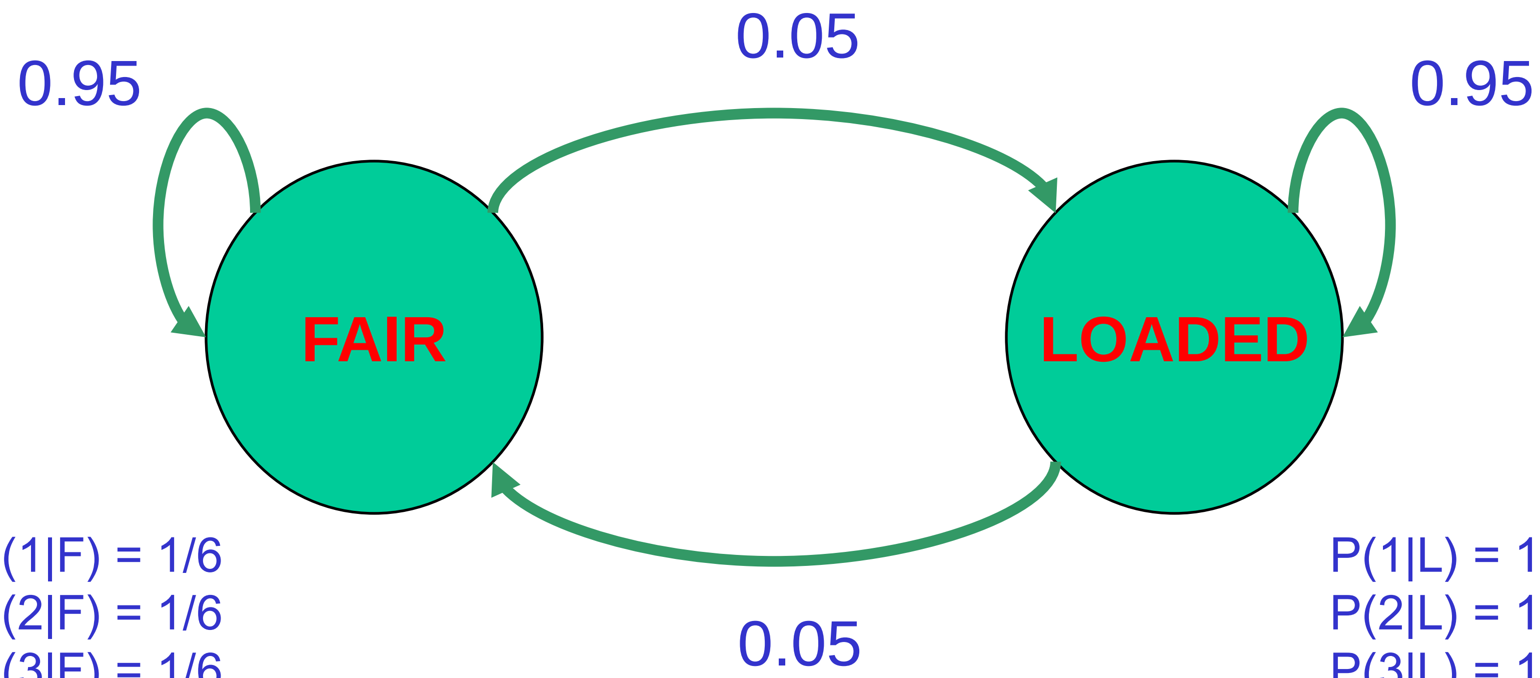
Casino occasionally switches between dice
(and you want to know when)

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

62146146136136661664661636616366163616515615115146123562344

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

6214614613613666166466163661636616361651561511514612356234

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!]

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- Part-Of-Speech (POS)
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- Hidden Markov Models
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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, transitions
  - Start probabilities are straight-forward and skipped

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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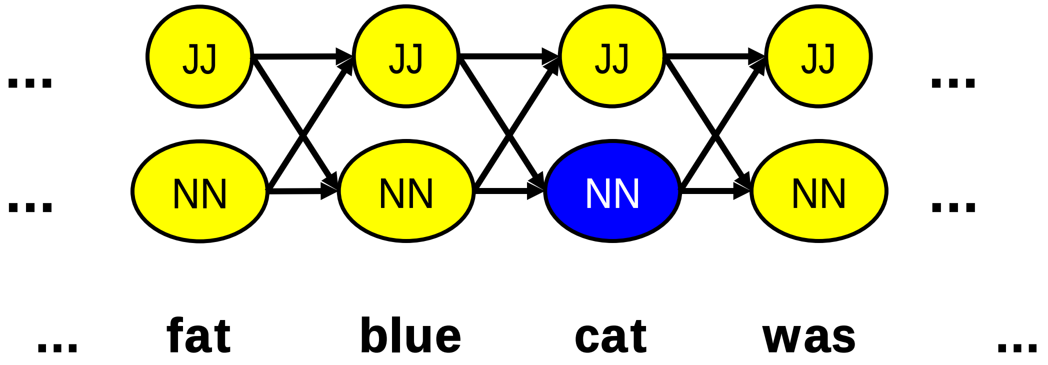
Viterbi Algorithm

- 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 $i,j \le k$
  - 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.

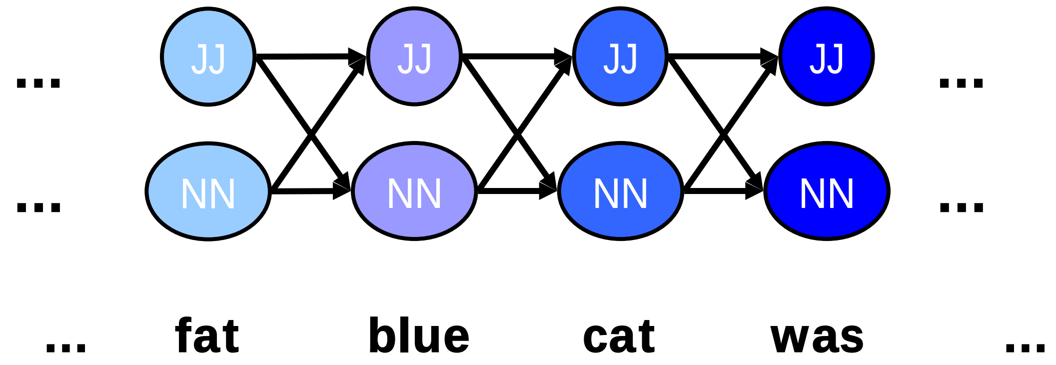
Idea: Dynamic Programming

- 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 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: Are emitted by all tags with equal prob.
  - Their tags are estimated only by the transition probabilities
  - Not very accurate
- Information one may use
  - 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)

Wrap-Up

- Advantages of HMM
  - Clean framework
  - Relative simple math
  - Good performance when learning/predicting POS-tri-grams
    - Needs large learning 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 these are not trivial
  - Conditional Random Fields, Markov Logic Networks, ...

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Evaluation (English)

- Most frequent: ~85% accuracy
- Rule-based: <90% accuracy
- Probabilistic: >90% accuracy
- Domain-specific: ~97% accuracy

POS Tagging 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

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