COMP9414: Artificial Intelligence

Lecture 5b: Language Models

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Probabilistic Language Models

- Based on statistics derived from large corpus of text/speech
  - Brown Corpus (1960s) – 1 million words
  - Penn Treebank (1980s) – 7 million words
  - North American News (1990s) – 350 million words
  - IBM – 1 billion words
  - Google, Facebook & Microsoft – Trillions of words
- Contrary to view that language ability based on (innate) knowledge
- Idea is language ability can be learnt . . . with enough data . . .

This Lecture

- Part of Speech Tagging
  - n-gram Models
  - Hidden Markov Models
  - Viterbi Algorithm
- Word Sense Disambiguation
  - Mutual Information
  - Class-Based Models

Penn Treebank Tagset

Tag	Description	Example	Tag	Description	Example
CC	coord. conjunction	*and, or*	RB	adverb	*extremely*
CD	cardinal number	*one, two*	RBR	adverb, comparative	*never*
DT	determiner	*a, the*	RBS	adverb, superlative	*fastest*
EX	existential there	*there*	RP	particle	*up, off*
FW	foreign word	*noire*	SYM	symbol	*+, %*
IN	preposition or sub-conjunction	*of, in*	TO	"to"	*to*
JJ	adjective	*small*	UH	interjection	*oops, oh*
JJR	adject., comparative	*smaller*	VB	verb, base form	*fly*
JJS	adject., superlative	*smallest*	VBD	verb, past tense	*flew*
LS	list item marker	*1, one*	VBG	verb, gerund	*flying*
MD	modal	*can, could*	VBN	verb, past participle	*flown*
NN	noun, singular or mass	*dog*	VBP	verb, non-3sg pres	*fly*
NNS	noun, plural	*dogs*	VBZ	verb, 3sg pres	*flies*
NNP	proper noun, sing.	*London*	WDT	wh-determiner	*which, that*
NNPS	proper noun, plural	*Azores*	WP	wh-pronoun	*who, what*
PDT	predeterminer	*both, lot of*	WP$	possessive wh-	*whose*
POS	possessive ending	*'s*	WRB	wh-adverb	*where, how*
PRP	personal pronoun	*he, she*			

Part of Speech Tagging

- The/DT grand/JJ jury/NN commented/VBD on/IN a/DT number/NN of/IN other/JJ topics/NNS ./.
- There/EX are/VBP 70/CD children/NNS there/RB
- Preliminary/JJ findings/NNS were/VBD reported/VBN in/IN today/NN 's/POS New/NNP England/NNP Journal/NNP of/IN Medicine/NNP ./.

Why is this Hard?

Ambiguity, e.g. back

- earnings growth took a back/JJ seat
- a small building in the back/NN
- a clear majority of senators back/VBP the bill
- Dave began to back/VB toward the door
- enable the country to buy back/RP debt
- I was twenty-one back/RB then

Probabilistic Formulation

- Events: Occurrence of word w, occurrence of a word with tag t
- Given sequence of words $w_1, \cdots, w_n$, choose $t_1, \cdots, t_n$ so that – $P(t_1, \cdots, t_n | w_1, \cdots, w_n)$ is maximized
- Apply Bayes' Rule
  - $P(t_1, \cdots, t_n | w_1, \cdots, w_n) = \frac{P(w_1, \cdots, w_n | t_1, \cdots, t_n).P(t_1, \cdots, t_n)}{P(w_1, \cdots, w_n)}$
  - Therefore maximize $P(w_1, \cdots, w_n | t_1, \cdots, t_n).P(t_1, \cdots, t_n)$

Unigram Model

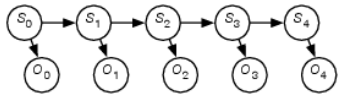
Maximize $P(w_1, \cdots, w_n | t_1, \cdots, t_n).P(t_1, \cdots, t_n)$

- Apply independence assumptions
  - $P(w_1, \cdots, w_n | t_1, \cdots, t_n) = P(w_1 | t_1). \cdots .P(w_n | t_n)$
  - Probability of word w generated by t independent of context
  - $P(t_1, \cdots, t_n) = P(t_1). \cdots .P(t_n)$
  - Probability of tag sequence independent of order
- Estimate probabilities
  - $P(w|t)$ = #(w occurs with tag t)/#(words with tag t)
  - $P(t)$ = #(words with tag t)/#words
  - Choose tag sequence that maximizes $\Pi P(t_i | w_i)$
  - Chooses most common tag for each word
- Accuracy around 90% – but still ≈1 word wrong in every sentence!

Markov Chain

- Bayesian network
  - $P(S_0)$ specifies initial conditions
  - $P(S_{i+1}|S_i)$ specifies dynamics (stationary if same for each i)
- Independence assumptions
  - $P(S_{i+1}|S_0,\cdots,S_i) = P(S_{i+1}|S_i)$
  - Transition probabilities dependent only on current state S_i – independent of history to reach that state $S_0,\cdots,S_{i-1}$
  - The future is independent of the past, given the present

Hidden Markov Models



- Bayesian network
  - $P(S_0)$ specifies initial conditions
  - $P(S_{i+1}|S_i)$ specifies dynamics
  - $P(O_i|S_i)$ specifies "observations"
- Independence Assumptions
  - $P(S_{i+1}|S_0,\cdots,S_i) = P(S_{i+1}|S_i)$ (Markov Chain)
  - $P(O_i|S_0,\cdots,S_{i-1},S_i,O_0,\cdots,O_{i-1}) = P(O_i|S_i)$
  - Observations (words) depend only on current state (tag)

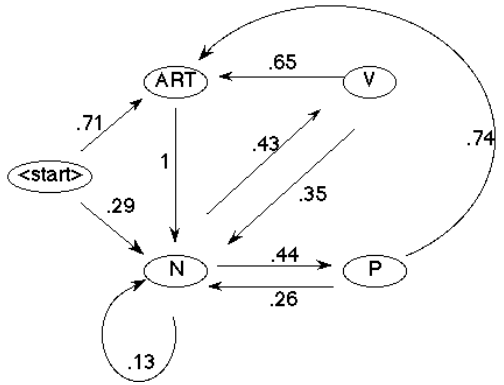
Bigram Model

Maximize $P(w_1,\cdots,w_n|t_1,\cdots,t_n).P(t_1,\cdots,t_n)$

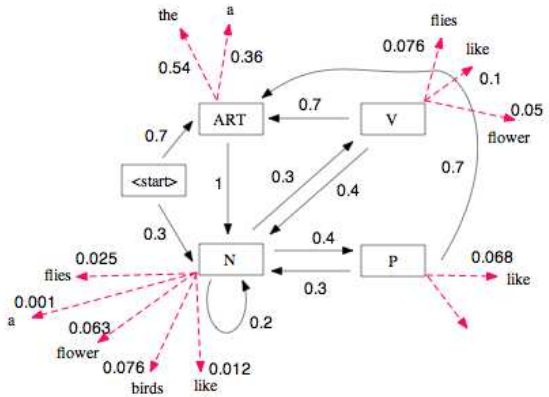
- Apply independence assumptions (Markov assumptions)
  - $P(w_1,\cdots,w_n|t_1,\cdots,t_n) = \Pi P(w_i|t_i)$
  - Observations (words) depend only on states (tags)
  - $P(t_1,\cdots,t_n) = P(t_n|t_{n-1}).\cdots.P(t_1|\phi)$, where ϕ = start
  - Bigram model: state (tag) depends only on previous state (tag)
- Estimate probabilities
  - $P(t_i|t_j)$ = #((t_j,t_i) occurs)/#(t_j starts a bigram)
  - Choose tag sequence that maximizes $\Pi P(w_i|t_i).P(t_i|t_{i-1})$
  - Parts of speech generated by finite state machine

Markov Model for POS Tagging

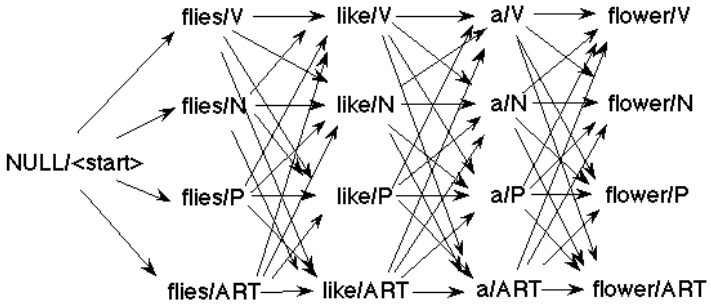
Transition probabilities define stationary distribution



Hidden Markov Model for POS Tagging



Computing Probabilities



Example

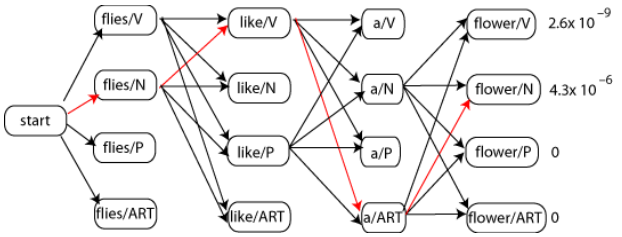
w	$P(w\|\text{ART})$	$P(w\|\text{N})$	$P(w\|\text{P})$	$P(w\|\text{V})$
a	0.36	0	0	0
flies	0	0.025	0	0.076
flower	0	0.063	0	0.05
like	0	0.012	0	0.1

P(flies/N like/V a/ART flower/N) =
$= P(\text{N}|\text{start}).P(\text{flies}|\text{N}).P(\text{V}|\text{N}).P(\text{like}|\text{V}).P(\text{ART}|\text{V}).P(\text{a}|\text{ART}).P(\text{N}|\text{ART}).P(\text{flower}|\text{N})$
$= 0.29 \times 0.025 \times 0.43 \times 0.1 \times 0.65 \times 0.36 \times 1 \times 0.063$

Most likely sequence, even though $P(\text{flies/V}) > P(\text{flies/N})$

Viterbi Algorithm

1. Sweep forward (one word at a time) saving only the most likely sequence (and its probability) for each tag t_i of w_i
2. Select highest probability final state
3. Follow chain backwards to extract tag sequence



Word Sense Disambiguation

Example

> I should have changed that stupid lock and made you leave your key, if I'd known for just one second you'd be back to bother me.

lock = $\cdots$

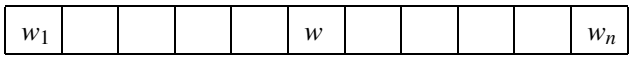
leave = $\cdots$

second = $\cdots$

back = $\cdots$

Windows

- Consider co-occurrences in a window about w



- Senses of word should co-occur with classes of "related" words
- Choose sense s of w to maximize $P(w \text{ as } s|w_1,\cdots,w_n)$
- Apply Bayes' Rule
  - Maximize $\frac{P(w_1,\cdots,w_n|w \text{ as } s).P(w \text{ as } s)}{P(w_1,\cdots,w_n)}$
- Apply independence assumptions
  - $P(w_1,\cdots,w_n|w \text{ as } s) = \Pi P(w_i|w \text{ as } s)$
- Estimate probabilities: $P(w_i|w \text{ as } s)$
  - #(w_i in n-word window around w as s)/#(windows on w as s)

Simple (Made Up) Example

Word	bridge/structure	bridge/dental	any window
teeth	1	10	300
suspension	200	1	2000
the	5500	180	500 000
dentist	2	35	900
TOTAL	5651	194	501 500

P(bridge/structure) = 5651/501 500 = 0.0113
P(bridge/dental) = 194/501 500 = 3.87 x 10^{-4}
P(teeth|bridge/structure) = 1/5651 = 1.77 x 10^{-4}
P(teeth|bridge/dental) = 10/194 = 0.052

bridge/dental preferred if window contains 'teeth'

Mutual Information

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

$$MI(sense(w_1),w_2) = \log_2 \frac{N.\#(sense(w_1),w_2)}{\#(sense(w_1)).\#(w_2)}$$

where N is the size of the corpus

- $MI = 0$: $sense(w_1)$ and w_2 are conditionally independent
- $MI < 0$: $sense(w_1)$ and w_2 occur together less than randomly
- $MI > 0$: $sense(w_1)$ and w_2 occur together more than randomly
- Adding mutual information is equivalent to assuming independence
- Choose sense s for $w = \arg\max_{s \in senses(w)} \Sigma_{w_i \in window(w)} MI(s,w_i)$

Class-Based Methods

- Use predefined "sense classes", e.g. WordNet, Wikipedia
  - lock $\rightarrow$ *Mechanical Devices* $\leftarrow$ tool, crank, cog, $\cdots$
  - lock $\rightarrow$ *Body Part* $\leftarrow$ hair, eyes, hands, $\cdots$
- Calculate counts for word senses by adding those for words
- Take all $P(w \text{ as } s)$ to be just $P(s)$, i.e. $P(\textbf{any}$ word with sense $s)$
- Advantages
  - Reduces space and time complexity
  - Reduces data sparsity
  - Allows unsupervised learning

Conclusion

- Statistical (and neural network) models perform well on many tasks
  - Part-of-speech tagging
  - Word sense disambiguation
  - Control of traditional parser
  - Probabilistic parsing
- Problems
  - Unrealistic simplifying assumptions (that seem to work)
  - Requirement for very large amount of (labelled) text
  - Sparsity of word occurrences in (even large) text corpora
  - Changes in word usage over time (e.g. *Senator* Obama)