Mid-term Reviews

Preprocessing,
language models
Sequence models,
Syntactic Parsing

Preprocessing

- What is a Lemma? What is a wordform?
- What is a word type? What is a token?
- What is tokenization?
- What is lemmatization?
- What is stemming?

How many words?

- I do uh main- mainly business data processing
  - Fragments, filled pauses
- Seuss's cat in the hat is different from other cats!
  - **Lemma**: same stem, part of speech, rough word sense
    - cat and cats = same lemma
  - **Wordform**: the full inflected surface form
    - cat and cats = different wordforms

How many words?

they lay back on the San Francisco grass and looked at the stars and their

- **Type**: an element of the vocabulary.
- **Token**: an instance of that type in running text.
- How many?
  - 15 tokens (or 14)
  - 13 types (or 12) (or 11?)

Issues in Tokenization

- `Finland's capital` → `Finland Finlands Finland's` ?
- `what're, I'm, isn't` → `What are, I am, is not`
- `Hewlett-Packard` → `Hewlett Packard` ?
- `state-of-the-art` → `state of the art` ?
- `Lowercase` → `lower-case lowercase lower case` ?
- `San Francisco` → one token or two?
- m.p.h., PhD. → ??

Lemmatization

- Reduce inflections or variant forms to base form
  - *am, are, is → be*
  - *car, cars, car's, cars' → car*
- *the boy's cars are different colors → the boy car be different color*
- Lemmatization: have to find correct dictionary headword form

Context dependent. for instance:
in our last meeting (noun, meeting).
We're meeting (verb, meet) tomorrow.

Stemming

context independent

- Reduce terms to their stems in information retrieval
- *Stemming* is crude chopping of affixes
  - language dependent
  - e.g., ***automate(s), automatic, automation*** all reduced to ***automat***.

for example compressed and compression are both accepted as equivalent to compress.

➡

for exampl compress and compress ar both accept as equival to compress

Naïve Bayes

- How to train a naïve bayes model? How to estimate prior probabilities and conditional probabilities?
- How to apply laplace smoothing?

Bayes' Rule Applied to Documents and Classes

- For a document *d* and a class *c*

$$P(c \mid d) = \frac{P(d \mid c)P(c)}{P(d)}$$

Learning the Multinomial Naïve Bayes Model

- First attempt: maximum likelihood estimates
  - simply use the frequencies in the data

$$\hat{P}(c_j) = \frac{doccount(C = c_j)}{N_{doc}}$$

$$\hat{P}(w_i \mid c_j) = \frac{count(w_i, c_j)}{\sum_{w \in V} count(w, c_j)}$$

Laplace (add-1) smoothing: unknown words

Add one extra word to the vocabulary, the "unknown word" w_u

$$\hat{P}(w_u \mid c) = \frac{count(w_u, c) + 1}{\left(\sum_{w \in V} count(w, c)\right) + |V + 1|}$$

$$= \frac{1}{\left(\sum_{w \in V} count(w, c)\right) + |V + 1|}$$

Maxent and Perceptron

- What are the differences between a generative model and a discriminate model?
- What are features in a discriminate model?
- What’s the relation between maxent and logistic regression?
- What’s the general form of maxent?
- What’s the form of a perceptron classifier?

Joint vs. Conditional Models

- We have some data {(*d*, *c*)} of paired observations *d* and hidden classes *c*.
- Joint (generative) models place probabilities over both observed data and the hidden stuff (gene-rate the observed data from hid $P(c,d)$
  - All the classic StatNLP models:
    - *n*-gram models, Naive Bayes classifiers, hidden Markov models, probabilistic context-free grammars, IBM machine translation alignment models

Joint vs. Conditional Models

- Discriminative (conditional) models take the data as given, and put a probability over hidden structure given the data:

$P(c|d)$

  - Logistic regression, conditional loglinear or maximum entropy models, conditional random fields
  - Also, SVMs, (averaged) perceptron, etc. are discriminative classifiers (but not directly probabilistic)

Features

- In NLP uses, usually a feature specifies
  1. an indicator function – a yes/no boolean matching function – of properties of the input and
  2. a particular class

$$f_i(c, d) \equiv [\Phi(d) \wedge c = c_j]$$

[Value is 0 or 1]

- Each feature picks out a data subset and suggests a label for it

Feature-Based Linear Classifiers

- Exponential (log-linear, maxent, logistic, Gibbs) models:
  - Make a probabilistic model from the linear combination $\Sigma\lambda_i f_i(c,d)$

$$P(c \mid d,\lambda) = \frac{\exp \sum_i \lambda_i f_i(c,d)}{\sum_{c'} \exp \sum_i \lambda_i f_i(c',d)}$$

Makes votes positive

Normalizes votes

  - P(LOCATION|*in Québec*) = $e^{1.8}e^{-0.6}/(e^{1.8}e^{-0.6} + e^{0.3} + e^{0}) = 0.586$
  - P(DRUG|*in Québec*) = $e^{0.3} /(e^{1.8}e^{-0.6} + e^{0.3} + e^{0}) = 0.238$
  - P(PERSON|*in Québec*) = $e^{0} /(e^{1.8}e^{-0.6} + e^{0.3} + e^{0}) = 0.176$
- The weights are the parameters of the probability model, combined via a “soft max” function

Perceptron Algorithm

- Algorithm is Very similar to logistic regression
- Not exactly computing gradients

```
Initalize weight vector w = 0
Loop for K iterations
    Loop For all training examples x_i
        if sign(w * x_i) != y_i
            w += (y_i - sign(w * x_i)) * x_i
```

Language Modeling

- How to calculate the probability of a sentence using a language model?
- What are the main Smoothing Algorithms for language models?
- Extrinsic v.s Intrinsic Evaluation
- Intrinsic Evaluation Metric of language models

Bigram estimates of sentence probabilities

P(<s> I want english food </s>) =

P(I|<s>)

× P(want|I)

× P(english|want)

× P(food|english)

× P(</s>|food)

= .000031

An example

$$P(w_i \mid w_{i-1}) = \frac{c(w_{i-1}, w_i)}{c(w_{i-1})}$$

<s> I am Sam </s>

<s> Sam I am </s>

<s> I do not like green eggs and ham </s>

$P(\texttt{I} \mid \texttt{<s>}) = \frac{2}{3} = .67$ $P(\texttt{Sam} \mid \texttt{<s>}) = \frac{1}{3} = .33$ $P(\texttt{am} \mid \texttt{I}) = \frac{2}{3} = .67$

$P(\texttt{</s>} \mid \texttt{Sam}) = \frac{1}{2} = 0.5$ $P(\texttt{Sam} \mid \texttt{am}) = \frac{1}{2} = .5$ $P(\texttt{do} \mid \texttt{I}) = \frac{1}{3} = .33$

Backoff and Interpolation

- Sometimes it helps to use **less** context
  - Condition on less context for contexts you haven't learned much about
- **Backoff:**
  - use trigram if you have good evidence,
  - otherwise bigram, otherwise unigram
- **Interpolation:**
  - mix unigram, bigram, trigram

- Interpolation works better

Advanced smoothing algorithms

- Intuition used by many smoothing algorithms
  - Good-Turing
  - Kneser-Ney
- Use the count of things we’ve **seen**
  - to help estimate the count of things we’ve **never seen**

Kneser-Ney Smoothing I (smart backoff)

- Better estimate for probabilities of lower-order unigrams!
  - Shannon game: *I can't see without my reading*___________? *Francisco* *glasses*
  - "Francisco" is more common than "glasses"
  - … but "Francisco" always follows "San"
- Instead of P(w): "How likely is w"
- $P_{continuation}(w)$: "How likely is w to appear as a novel continuation?
  - For each word, count the number of unique bigram types it completes
  - Every bigram type was a novel continuation the first time it was seen

$$P_{CONTINUATION}(w) \propto \left|\{w_{i-1} : c(w_{i-1}, w) > 0\}\right|$$

Extrinsic evaluation of N-gram models

- Best evaluation for comparing models A and B
  - Put each model in a task
    - spelling corrector, speech recognizer, MT system
  - Run the task, get an accuracy for A and for B
    - How many misspelled words corrected properly
    - How many words translated correctly
  - Compare accuracy for A and B

Perplexity

The best language model is one that best predicts an unseen test set

- Gives the highest P(sentence)

Perplexity is the inverse probability of the test set, normalized by the number of words:

$$PP(W) = P(w_1 w_2 \ldots w_N)^{-\frac{1}{N}}$$

$$= \sqrt[N]{\frac{1}{P(w_1 w_2 \ldots w_N)}}$$

Chain rule:

$$\mathrm{PP}(W) = \sqrt[N]{\prod_{i=1}^{N} \frac{1}{P(w_i|w_1 \ldots w_{i-1})}}$$

For bigrams:

$$\mathrm{PP}(W) = \sqrt[N]{\prod_{i=1}^{N} \frac{1}{P(w_i|w_{i-1})}}$$

Minimizing perplexity is the same as maximizing probability

Sequence Tagging

- What is sequence tagging? what are common sequence tagging problems in NLP?
- What is the form of Trigram HMM?
- What’s the run time complexity of the viterbi algorithm for Trigram HMM?

Part-of-Speech Tagging

INPUT:
Profits soared at Boeing Co., easily topping forecasts on Wall Street, as their CEO Alan Mulally announced first quarter results.

OUTPUT:
Profits/N soared/V at/P Boeing/N Co./N ,/, easily/ADV topping/V forecasts/N on/P Wall/N Street/N ,/, as/P their/POSS CEO/N Alan/N Mulally/N announced/V first/ADJ quarter/N results/N ./.

N = Noun
V = Verb
P = Preposition
Adv = Adverb
Adj = Adjective
...

Named Entity Extraction as Tagging

INPUT:

Profits soared at Boeing Co., easily topping forecasts on Wall Street, as their CEO Alan Mulally announced first quarter results.

OUTPUT:

Profits/NA soared/NA at/NA Boeing/SC Co./CC ,/NA easily/NA topping/NA forecasts/NA on/NA Wall/SL Street/CL ,/NA as/NA their/NA CEO/NA Alan/SP Mulally/CP announced/NA first/NA quarter/NA results/NA ./NA

NA = No entity
SC = Start Company
CC = Continue Company
SL = Start Location
CL = Continue Location
...

Why the Name?

$$p(x_1 \ldots x_n, y_1 \ldots y_n) = \underbrace{q(\mathsf{STOP}|y_{n-1}, y_n) \prod_{j=1}^{n} q(y_j \mid y_{j-2}, y_{j-1})}_{\text{Markov Chain}}$$

$$\times \underbrace{\prod_{j=1}^{n} e(x_j \mid y_j)}_{x_j\text{'s are observed}}$$

The Viterbi Algorithm with Backpointers

Input: a sentence $x_1 \ldots x_n$, parameters $q(s|u,v)$ and $e(x|s)$.

Initialization: Set $\pi(0, *, *) = 1$

Definition: $\mathcal{S}_{-1} = \mathcal{S}_0 = \{*\}$, $\mathcal{S}_k = \mathcal{S}$ for $k \in \{1 \ldots n\}$

Algorithm:

- For $k = 1 \ldots n$,
  - For $u \in \mathcal{S}_{k-1}$, $v \in \mathcal{S}_k$,

$$\begin{aligned}
\pi(k,u,v) &= \max_{w \in \mathcal{S}_{k-2}} \left(\pi(k-1,w,u) \times q(v|w,u) \times e(x_k|v)\right) \\
bp(k,u,v) &= \arg\max_{w \in \mathcal{S}_{k-2}} \left(\pi(k-1,w,u) \times q(v|w,u) \times e(x_k|v)\right)
\end{aligned}$$

- Set $(y_{n-1}, y_n) = \arg\max_{(u,v)} \left(\pi(n,u,v) \times q(\text{STOP}|u,v)\right)$
- For $k = (n-2) \ldots 1$, $y_k = bp(k+2, y_{k+1}, y_{k+2})$
- **Return** the tag sequence $y_1 \ldots y_n$

The Viterbi Algorithm: Running Time

- $O(n|\mathcal{S}|^3)$ time to calculate $q(s|u, v) \times e(x_k|s)$ for all k, s, u, v.
- $n|\mathcal{S}|^2$ entries in π to be filled in.
- $O(|\mathcal{S}|)$ time to fill in one entry
- $\Rightarrow O(n|\mathcal{S}|^3)$ time in total

Syntactic Parsing

- What’s a PCFG?
- What’s the probability of a parse tree under a PCFG?
- What’s the Chomsky normal form of CFG?
- What’s the run time complexity of the CKY algorithm?

A Probabilistic Context-Free Grammar (PCFG)

S	$\Rightarrow$	NP	VP	1.0
VP	$\Rightarrow$	Vi		0.4
VP	$\Rightarrow$	Vt	NP	0.4
VP	$\Rightarrow$	VP	PP	0.2
NP	$\Rightarrow$	DT	NN	0.3
NP	$\Rightarrow$	NP	PP	0.7
PP	$\Rightarrow$	P	NP	1.0

Vi	$\Rightarrow$	sleeps	1.0
Vt	$\Rightarrow$	saw	1.0
NN	$\Rightarrow$	man	0.7
NN	$\Rightarrow$	woman	0.2
NN	$\Rightarrow$	telescope	0.1
DT	$\Rightarrow$	the	1.0
IN	$\Rightarrow$	with	0.5
IN	$\Rightarrow$	in	0.5

- Probability of a tree t with rules

$$\alpha_1 \rightarrow \beta_1, \alpha_2 \rightarrow \beta_2, \ldots, \alpha_n \rightarrow \beta_n$$

is $p(t) = \prod_{i=1}^{n} q(\alpha_i \rightarrow \beta_i)$ where $q(\alpha \rightarrow \beta)$ is the probability for rule $\alpha \rightarrow \beta$.

Chomsky Normal Form

A context free grammar $G = (N, \Sigma, R, S)$ in Chomsky Normal Form is as follows

- N is a set of non-terminal symbols
- Σ is a set of terminal symbols
- R is a set of rules which take one of two forms:
  - $X \rightarrow Y_1 Y_2$ for $X \in N$, and $Y_1, Y_2 \in N$
  - $X \rightarrow Y$ for $X \in N$, and $Y \in \Sigma$
- $S \in N$ is a distinguished start symbol

The Full Dynamic Programming Algorithm

Input: a sentence $s = x_1 \ldots x_n$, a PCFG $G = (N, \Sigma, S, R, q)$.
Initialization:
For all $i \in \{1 \ldots n\}$, for all $X \in N$,

$$\pi(i, i, X) = \begin{cases} q(X \to x_i) & \text{if } X \to x_i \in R \\ 0 & \text{otherwise} \end{cases}$$

Algorithm:

What's the run time Complexity?

- For $l = 1 \ldots (n-1)$
  - For $i = 1 \ldots (n-l)$
    - Set $j = i + l$
    - For all $X \in N$, calculate

$$\pi(i, j, X) = \max_{\substack{X \to YZ \in R, \\ s \in \{i \ldots (j-1)\}}} \left(q(X \to YZ) \times \pi(i, s, Y) \times \pi(s+1, j, Z)\right)$$

and

$$bp(i, j, X) = \arg \max_{\substack{X \to YZ \in R, \\ s \in \{i \ldots (j-1)\}}} \left(q(X \to YZ) \times \pi(i, s, Y) \times \pi(s+1, j, Z)\right)$$

Dependency Parsing

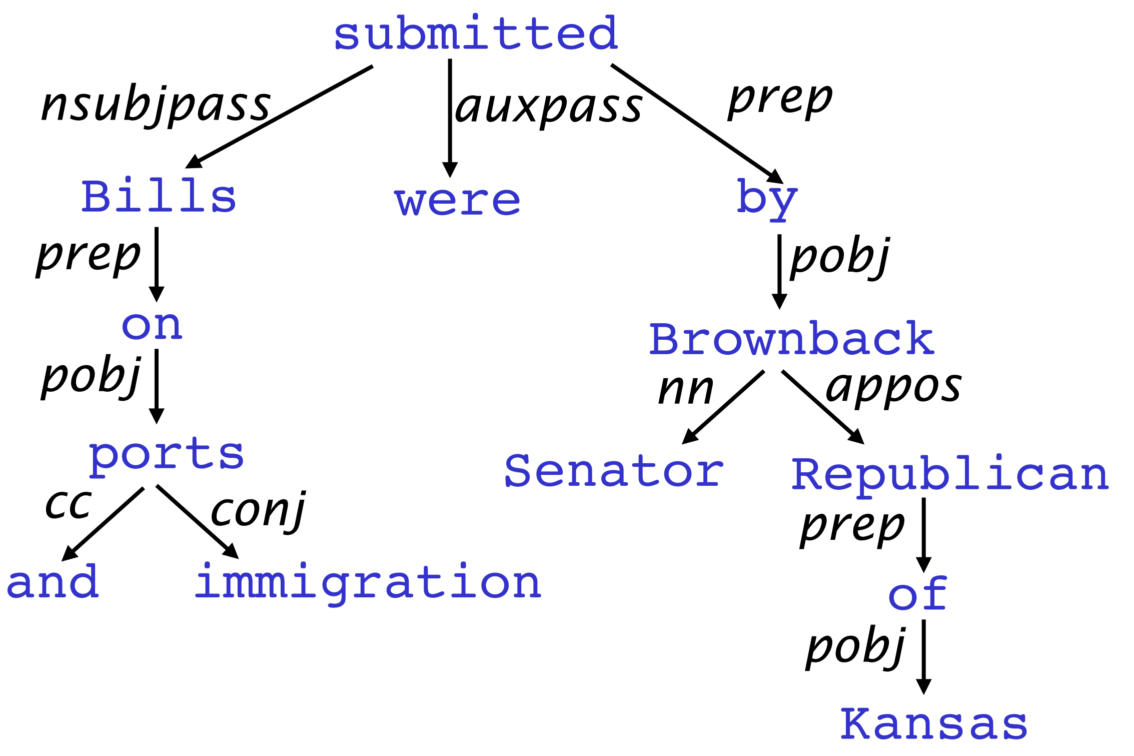
- Can you draw a dependency parse tree for a simple sentence?
- What is projectivity?

Dependency Grammar and Dependency Structure

Dependency syntax postulates that syntactic structure consists of lexical items linked by binary asymmetric relations (“arrows”) called dependencies

The arrow connects a head (governor, superior, regent) with a dependent (modifier, inferior, subordinate)

Usually, dependencies form a tree (connected, acyclic, single-head)



Projectivity

- Dependencies from a CFG tree using heads, must be projective
  - There must not be any crossing dependency arcs when the words are laid out in their linear order, with all arcs above the words.
- But dependency theory normally does allow non-projective structures to account for displaced constituents
  - You can't easily get the semantics of certain constructions right without these nonprojective dependencies