Statistical Natural Language Processing

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CS430 lecture

Natural Language Processing

Some subproblems are partially solved

- Spelling correction, grammar checking
- Information retrieval with keywords
- Semi-automatic translation in narrow domains, e.g., travel planning
- Information extraction in narrow domains
- Speech recognition

Challenges

- Common-sense reasoning
- Language understanding at a deep level
- Semantics-based information retrieval
- Knowledge representation and inference
- A model of learning semantics or meaning
- Robust learning of grammars

Language Models

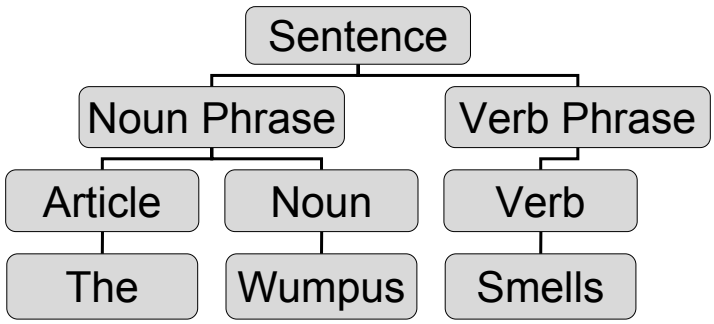
- Unigram models
  For every word *w*, learn the prior *P(w)*
- Bigram models
  For every word pair, (W_i, W_j) learn the probability of W_j following W_i : $P(W_j \mid W_i)$
- Trigram models: $P(W_k \mid W_i, W_j)$
  probability of W_k following W_i and W_j . Of

None of these sufficiently capture grammar!

Context-free Grammars

- Variables
  - Noun Phrase, Verb Phrase, Noun, Verb etc.
- Terminals (words)
  - Book, a, smells, wumpus, the, etc.
- Production Rules
  - [Sentence] -> [Noun Phrase] [Verb Phrase]
  - [Noun Phrase] -> [Article] [Noun]
  - [Verb Phrase] -> [Verb] [Noun Phrase]
- Start Symbol: [Sentence]

Parse Tree



Natural language is ambiguous – needs a “softer” grammar.

Probabilistic CFGs

- Context-free grammars with probabilities attached to each production
- The probabilities of different productions with the same left hand side sum to 1
- Semantics: the conditional probability of a variable generating the right hand side

  [Noun Phrase] -> [Noun] (0.1) |

  [Article] [Noun] (0.8)|

  [Article] [Adjective] [Noun] (0.1)

Learning PCFGs

- From Sentences and their parse trees:

  Counting: Count the number of times each variable occurs in the parse trees and generates each possible r.h.s.

$$\text{Probability} = \frac{\#\text{of times A-> rhs occurs}}{\#\text{of times A occurs}}$$

Inside-Outside Algorithm

- Applicable when parse trees are not given
- An instance of the EM Algorithm: treat the parse trees as “hidden variables” of EM
  - Start with an intial random PCFG
  - Repeat until convergence
    - E-step: Estimate the probability that each subsequence is generated by each rule
    - M-step: Estimate the probability of each rule

Information Retrieval

- Given a query, how to retrieve documents that answers the query?
- So far semantics-based methods are not as successful as word-based methods
- The documents and the query are treated as bags of words, disregarding the syntax.
- Stemming (removing suffixes like “ing”) and “stop words” (eg, “the”) removal are found useful.

Vector Space Model

- TF-IDF computed for each word-doc pair
- There are many versions of this measure
- TF is the term frequency: the number of times a term (word) occurs in the doc
- IDF is "inverse document frequency" of the word = *log(|D|/DF(w)),* where *DF(w)* is the number of documents in which w occurs and D is the set of all documents.
- Common words like "all" "the" etc. have high document frequency and low IDF

Rocchio Method

- Each document is described as a vector in an n-dimensional space, where

  each dimension represents a term

  Doc1 = [t(1,1),t(1,2),…,t(1,n)]

  Doc2 = [t(2,1),t(2,2),…,t(2,n)]

  t[I,j] is the tf-idf of document *i* and term *j*.
- Two vectors are similar if their cosine distance (normalized dot product) is small.

Cosine Distance

- *Doc1 = [t(1,1),t(1,2),…,t(1,n)]*
  Doc2 = [t(2,1),t(2,2),…,t(2,n)]
- *CosineDistance(Doc1,Doc2) =*

$$\frac{t(1,1)*t(2,1)+\ldots+t(1,n)*t(2,n)}{\sqrt{t(1,1)^2+\ldots+t(1,n)^2}\sqrt{t(2,1)^2+\ldots+t(2,n)^2}}$$

- The documents are ranked by their cosine distance to the query, treated as another document

Naïve Bayes

- Naïve Bayes is very effective for document retrieval
- Naïve Bayes assumes that the features *X* are independent, given the class *Y*
- Medical diagnosis: Class *Y* = disease
  Features *X* = symptoms
- Information retrieval: Class *Y* = document
  Features *X* = words

Naïve Bayes for Retrieval

- Build a unigram model for each document: Estimate $P(W_j | D_i)$ for each document D_i and W_j (easily done by counting).
- Each document D_i has a prior probability $P(D_i)$ of being relevant regardless of any query, e.g., today's newspaper has much higher prior than, say, yesterday's paper.

Naïve Bayes for Retrieval

- The posterior probability of a document's relevance given the query is $P(D_i|W_1 \ldots W_n)$
  $= \alpha\ P(D_i)\ P(W_1 \ldots W_n | D_i)$ [Bayes Rule]
  $= \alpha\ P(D_i)\ P(W_1| D_i) \ldots P(W_n| D_i)$
  [conditional independence of features]
  where α is a normalizing factor and the same for all documents (so ignored)
- To avoid zero probabilities, a pseudo-count of 1 is added for each W_j -D_i pair (Laplace correction)

Evaluating IR Systems

	Relevant	Not relevant
Retrieved	15	10
Not retrieved	20	55

Accuracy = (15+55)/100 = 70%. It is misleading!
Accuracy if no docs are retrieved = 65%.

Recall = number of retrieved docs as a percentage of relevant documents =15/35 = 43%

Precision = number of relevant docs as a percentage of retrieved documents =15/25 = 60%

Precision Recall Curves

We want high precision and high recall.

Usually there is a controllable parameter that can tradeoff one against the other