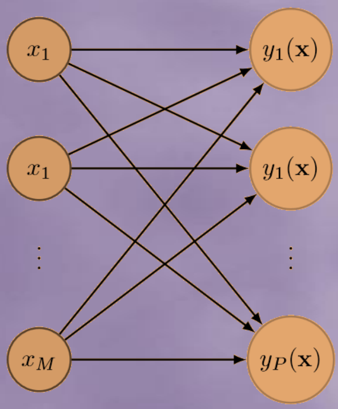

Machine Learning for Natural Language

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0.1 Introduction

[TBW]

0.2 Tokenization

Tokenization or text-processing is the process for cleaning text and converting it into standard format:

- Remove redundant tokens, e.g. HTML tags.
- Finding word boundaries, using white-spaces and punctuation. One needs to be careful about different type of punctuation, for example *st., B.Sc, km, miles, ...* could have different interpretation if they are considered separately.
- Stemming/Lemmatization: In many languages, one family of words might appear in different forms. For example in English, *go*, could be used in any of the following forms, *went, goes, gone, etc* depending the structure of the sentence. To make the input easier to be processed (at least from some specific models' point of view), one can replaces all such occurrences with *go*. The most important stemming is Porter Stemming. The SnowBall is also a very important language preprocessing package.
- Removing stop-words: Removing many of the words in the sentences which don't have much of semantic meaning, e.g. *of, that, the, a, an, ...*. One such list could be found here .
- Removing capitalization: In many cases it would help to remove the the capitalization. One standard counterexample is *US vs. us*.

[1] This is part of my notes; to find the complete list of notes visit `http://web.engr.illinois.edu/~khashab2/learn.html`. This document is updated on April 6, 2014.

Many of the above steps, may or may not be needed, depending on the target problem.

0.3 Language models

0.3.1 Language as a stochastic process

Assume that words of a language is sampled from a Multinomial distribution,

0.4 tf.idf

The *tf.idf* is one of the features that could be used for modeling documents. The *tf* vectors are base on the relative word frequencies, i.e. the most frequent word has the most *tf* value:

$$tf_w = \frac{c(w,d)}{\max_v c(v,d)}$$

where $c(w,d)$ is the word count in document d. The *idf* is aiming at eliminating stop-words which appear in most of the documents, like "the".

$$itf_w = \log \frac{N}{n_w}$$

where n_w is the number of the documents that w appears in. If the word appears in almost all of the documents, we have $n_w \approx N$, then *idf* ≈ 0. The *tf.idf* score of a word is:

$$tf.idf(w) = tf_w \times itf_w$$

0.5 Parsing

0.5.1 Inside-Outside algorithm

Inside-Outside could be considered as generalization of forward-backward algorithm in HMMs, for model probability estimation in probabilistic context-free grammars. In context-free grammar we only have the rules of only the following form:

$$i \to jk \text{ and } i \to w$$

in which i, j, k are integers which correspond to unique internal nodes. In the Probabilistic Context-Free Grammar, we describe each of these rules via some probability distributions:

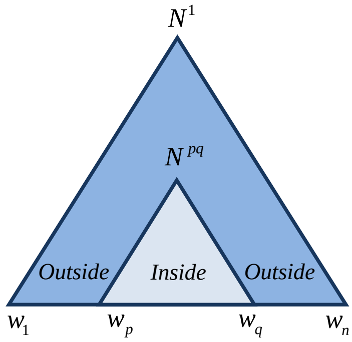
$$\mathbb{P}(i \to jk) \text{ and } \mathbb{P}(i \to w)$$

with the proper probability distribution on each of the rules:

$$\sum_{i,j,k} \mathbb{P}(i \to jk) + \sum_{i} \mathbb{P}(i \to w) = 1$$

Similar to HMMs we ask the following three important questions:

- Given grammar $\mathcal{G}$, what is the probability of a sentence, i.e. $\mathbb{P}(w_{1:m}|\mathcal{G})$?
- Given a grammar and a sentence, what is the most-likely parse tree, i.e. $\arg\max_t \mathbb{P}(t|\mathcal{G}, w_{1:m})$?



- Given a sentence, what is the grammar that maximizes its probability of observation, i.e. $\arg\max_{\mathcal{G}} \mathbb{P}(w_{1:m}|\mathcal{G})$?

To define the above probabilities, we define the following two probability distributions, to make the derivation and its interpretation easier. Here the notation, and partly the representation is from ?. A good reference for this algorithm is ?.

Definition 0.1 — Inside and Outside probabilities.
Inside probability: $\beta_j(p, q)$, $(p \leq q)$ is the probability of generating $w_p \ldots w_q$, given the nonterminal node N_j, i.e. $\mathbb{P}(w_{p:q}|N^j_{pq}, \mathcal{G})$.
Outside probability: $\alpha_j(p, q)$, $(p \leq q)$ is the probability of generating $w_1 \ldots w_{p-1}$ and $w_{q+1} \ldots w_n$, beginning with the nonterminal node N_1 and generating the nonterminal node N^j_{pq}, i.e. $\mathbb{P}(w_{1:p-1}, N^j_{pq}, w_{q+1:n}|\mathcal{G})$

It can be shown that we have the following recursive formulas for the inside and outside formula:

$$\beta_j(p, q) = \sum_{r,s} \sum_{i=p}^{q-1} \mathbb{P}(N^j \to N^r N^s) \beta_r(p, i) \beta_s(i+1, q)$$

$$\alpha_j(p, q) = \sum_{r,s \neq j} \sum_{i=q+1}^{n} \alpha_r(p, i) \mathbb{P}(N^r \to N^j N^s) \beta_s(q+1, i) + \sum_{r,s} \sum_{i=1}^{p-1} \alpha_r(i, q) \mathbb{P}(N^r \to N^s N^j) \beta_s(i, p-1)$$

The probability a specific sentence, given the grammar

The probability of observing one specific sentence is the following:

$$\mathbb{P}(w_{1:n}|\mathcal{G}) = \sum_j \alpha_j(p, q) \beta_j(p, q)$$

The max-likely parse tree

Define the following variable:

$\delta_i(p, q) :=$ Max probability of the parse tree, that spans p to q, rooted at the internal node N^i

We can expand this variable recursively in the following way:

$$\delta_i(p, q) = \begin{cases} \max_{1 \leq j,k \leq n, p \leq r < q} \mathbb{P}(N^i \to N^j N^k) \delta_j(p, r) \delta_k(r+1, q) & \\ \mathbb{P}(N^i \to w_p) & \text{if } p = q \end{cases}$$

Using the above recursive definition and memoization of the values for $\delta_j(.)$ we can calculate the value of $\delta_1(1, n)$, which contains the value of the best parse tree for the whole sentence, in time $O(n^3 g^3)$. If we save the decisions while memoizations, we can backtrack the decisions and recover the optimal tree.