Part I

Natural Language Processing

1 Introduction

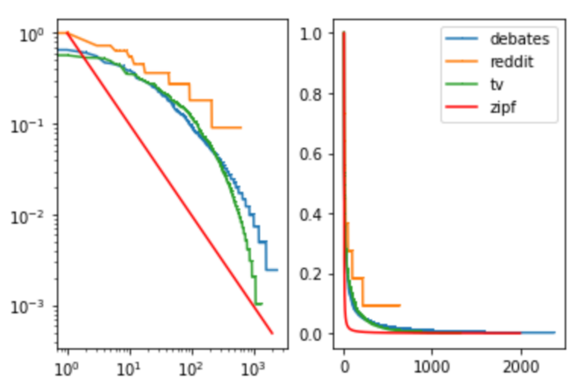
Challenges

- Complicated structure in sentence
- Syntactic ambuigities ("*time flies like an arrow*", "*get the cat with the gloves*").
- Metaphores, humor, irony, ...
- Semantics can be very rich and dependent on context, not easy to distuingish
- Language requries knowledge about the world
- Hard to really formalise the notion of "meaning"

Basic approach Gather information on word based on its context. Given a large text corpus, we can assume this to be meaningful statistics.

Zipf's Law The number of elements with a given frequency follows a power law distribution. That is, there is a small number of elements which appear very often and the majority of elements appears rarely. In its most simple form, the probability of the n-th most common word $p(n)$ is

$$p(n) = {}^{1}/_{n}$$



Elements of language We can have different points of view on language:

- Phonetics (sound)
- Grammar
  - Phonology
  - Morphology
  - Syntax
- Semantics (meaning)

Morphology How words are built up from smaller meaningful units, for instance *un-lady-like*, *dog-s*

- ***Inflection*** – variation in the form of a word (usually affix) that expresses a grammatical contrast
  - adds tense, number, person, mood, aspect, etc
  - e.g. *run*→ *run* — *running*
  - does not change word class
- ***Derivation*** – formation of a new word from another
  - e.g. nominalization (*computer*→*computerization*)
  - e.g. formation of adjectives (*computational*, *clueless*)
  - changes word class

Morphemes

- ***Root*** – equivalence class of a word when all affixes are removed; not further decomposable into meaningful elements.
- ***Stem*** – part of word that never changes when morphologically inflected, *i.e. without affixes describing tense, number, person, ...*
- ***Lemma*** – Base form of word
- From *produced*, lemma is *produce* but stem is *produc*

2 Tokenization

Token an individual occurence of a word (as opposed to a vocabulary/dictionary item)

Challenges

- Keep abbreviations, dates, numbers as single tokens
- distuingish abbreviations from words
- names and phrases (*queen of england*, *TU Wien*)
- compound words
- apostrophes, umlauts, etc and other linguistic characteristics
- encoding issues like RTL/LTR

Maximum Matching algorithm Use a dictionary of known terms. Take the longest prefix of the input string that matches a dictionary item. Does not always make sense (*"Theta bled own there"*).

3 Stemming

Stemming/Lemmatization reduce tokens to equivalence classes. Usually to gather words that are morphologically different but semantically quite similar to the same set, i.e. to improve comparability.

Porter Stemmer Rules for stripping suffixes. Applicability of rules is based on *measure* of a word w, which is the number m s.t. $w = C(VC)\{m\}V$ where C, V are arbitrary sequences of consontants, vowels, resp. — Indeed reduces the words to their *stems*.

WordNet MORPHY

- Has • a sophisticated set of rules about inflections • exception list
- Checks the result of transformation against an extensive dictionary

Note MORPHY reduces to *lemmas*, while PORTER reduces to *stems*.

- ***Over-stemming*** Two words are reduced to the same root when they should not be
- ***Under-stemming*** Should be reduced to the same root but are not.

4 POS-Tagging

Given some input text and some tags (usually word types such as *noun*, *verb*, etc.), want to assign tags to tokens. (*Sequence classification problem*).

Tagging can help with other procedures such as stemming, NER, parsing, ...

Def. Can divide words into two different classes

- ***Closed class*** — can enumerate all members, e.g. determiners, pronouns, prepositions, ...
- ***Open class*** — don't know all members, e.g. nouns, verbs, adjectives, ...

Note

- A single term (dictionary entry) can have different optimal POS-tags depending on its context.
- Tagging helps to resolve ambiguities that exist on term-level (.e.g *leaves* as NN or as VB)
- Tagging removes unnecessary distinctions e.g. all personal pronouns are PRP, determiners
- Naive method (assigning most frequent tag in training data to term) already has 90% accuracy.

Def.

- ***Informativeness*** — Assignment of tag adds information, reduces ambuigity
- ***Specifiability*** — Ease of mapping a term to a tag
- *Example*: Collapsing multiple related tags into one decreases informativeness, decreases specifiability.

Feature selection Can look at word-local features (term, pre-, suffixes, capitalization); but very often the tag of a word depends on its context in the sentence.

Main techniques

- *Probabilistic tagging* — consider lexical frequencies of tag in training data – good when large training corpora are available
- *Rule-based tagging* — use rules based on linguistic understanding – good to tailor solution to very specific problems

4.1 Probabilistic tagging

Consider the definition of *conditional probability*

$$P(A|B) = \frac{P(A,B)}{P(B)}$$

This gives rise to the *chain rule*

$$\Rightarrow P(A,B) = P(A|B) \cdot P(B)$$

or, more generally

$$P(w_1, ..., w_n) = \prod P(w_i \mid w_1, ..., w_{i-1})$$

The problem here is that we cannot realistically obtain all the components of the product because there are way too many possible sequences of words. Instead, we employ the *Markov assumption* that says that we can estimate the probabilities by only consiering only the k preceding terms

$$P(w_i \mid w_1 ..., w_{i-1}) \approx P(w_i \mid w_{i-k}, ..., w_{i-1})$$

For $k = 1$, this yields the *unigram model*, for $k = 2$ the *bigram model* (i.e. $P(w_i|w_{i-1})$).

n-gram modelling is insufficient because language has *long-distance depenencies*.

Unigram Tagger Assume that a unigram model generates the current tagging.

Assign a token w its most frequent tag, i.e.

$$t(w) := \text{argmax}_t P(t \mid w)$$

Improvement: Use Bayes' formula, i.e. $P(A|B) = \frac{P(B|A)P(B)}{P(B)}$, omitting the quotient:

$$t(w) := P(t \mid w) = \text{argmax}_t P(t) \cdot P(w \mid t)$$

TODO example

n-gram tagger Use information about the previous n tokens in addition to information about current token. Can have *word-based* and *tag-based* (tags are more common, training data covers more ground).

Assume a bigram language model (generating the sequence of POS-tags).

Pick the tag t_i for word w_i that maximises

$$P(t_i \mid t_{i-1}) \cdot P(w_i \mid t_{i-1})$$

For finding $P(t_i \mid t_{i-1})$, use the *Maximum Likelihood Estimate* (where c is the count of observations)

$$P(t_i|t_{i-1}) \approx \frac{c(w_{i-1}, w_i)}{c(w_{i-1})}$$

(Use start and end symbols to be able to calculate probs for first and last words)

TODO example

4.2 Rule-based tagging

Try to incorporate linguistic insight.

Brill tagger

1. Tag each word using a *baseline tagger* (e.g. unigram tagger, i.e. most common tag)
2. Apply patches that improve the result
   - e.g. *if one of the two preceding words is a determiner, change the tag from verb to noun*
   - Based on training data, compute the error between any two should-be/is-assigned: $(t_a, t_b, \mathit{freq})$.
   - For each error triple, apply the patch that results in the greatest improvement, apply it.
   - Repeat until no further improvement is possible.

5 Parsing

Part II

Similarity Measures

Part III

Language Modelling

Part IV

Text Data Mining

Part V

Opinion Mining & Information Extraction

6 Information Extraction

to extract • the entities and • relationships between such entities (i.e. clear, factual information)

6.1 Named Entity Extraction

used for • summarizing text • answering questions • integrating into knowlege bases • associating information (e.g. sentiments) to sentiments (e.g. of parts of printer in question)

Possible types of entities • location • time • person • ...

Supervised learning models Based on labelled training sequences (of tokens), train a classifier to predict labels (*Sequence Labelling Problem*)

- new data must fit training data
- time-consuming

To make this easier, use features that go beyond single tokens, e.g. context window of k words.

Sequence Labelling • reminiscent to POS-tagging • assuming that label is dependent on context. Typical models are • Markov models • Conditional Random Fields • Bidirectional LSTMs

Once we have identified the entities, we'd like to find relationships between them (e.g. triples of operators *is-a*, *daughter-of*, ...) *(Can save these triples in a knowledge base e.g. for question-answering; cf* RDF*-triples)*.

Relationship Extraction Try to find type of relationship between two entitties. Possibilities

- Extract RDF triples from large corpora like Wikipedia
- Use (specialised) ontologies / knowledge bases (for ex. medical applications)

Methods to extract information:

- handwritten rules – e.g. *"Y such as X", "X, especially Y", "X, including Y" all express an is-a-relationship*. – there can be more specific relations that only make sense between certain types of entities (e.g. *cures(drug, disease)*) – pros: • precise •

can be tailored to specific domains – cons: • low recall • high effort

- supervised,
- unsupervised machine learning.

semi-supervised learning: extract less common patterns based on training corpus?

Part VI

Question Answering & Text Summarization