Natural Language Processing

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Plan for Today

• Probabilistic Language Models

Probabilistic Language Modeling

- Goal: compute the probability of a sentence or sequence of words.
 P(words) is the joint probability that a sequence of words=w₁w₂...w_n is likely for a specified natural language.
- Related task: probability of an upcoming word
 P(w₅|w₁, w₂, w₃, w₄)
- A model that computes either of these:

$$P(W) \text{ or } P(w_n|w_1, w_2...w_{n-1})$$

is called a language model.

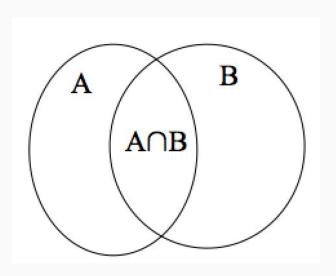
Probability Function:

- P(A) means that how likely the event A happens.
- o P(A) is a number between 0 and 1.
- \circ P(A) = 1 is a certain event.
- \circ P(A) = 0 is an impossible event.
- Unconditional Probability or Prior Probability:
 - P(A): the probability of the event A does not depend on other events.
- Conditional Probability Posterior Probability –

Likelihood:

- \circ P(A|B): this is read as the probability of A given that we know B.
- Example:
 - P(put) is the probability of to see the word put in a text.
 - P(on|put) is the probability of to see the word on after seeing the word put.

Unconditional and Conditional Probability Probability



- P(A|B) = P(A∩B)/P(B)
 P(B|A) = P(A∩B)/P(A)

Bays' Theorem

- Bayes' theorem is used to calculate P(A|B) from given P(B|A).
- We know that

$$P(A|B) = P(A \cap B)/P(B)$$

 $P(B|A) = P(A \cap B)/P(A)$

So, we will have

$$P(A|B) = rac{P(B|A)P(A)}{P(B)}$$
 $P(B|A) = rac{P(A|B)P(B)}{P(A)}$

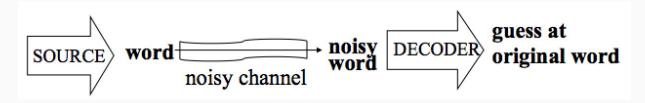
Language Models

Language Models:

- The Noisy Channel Model
- N-GRAM models are the language models which are widely used in NLP domain.

The Noisy Channel Model

The Noisy Channel Model



Many problems in Natural Language Processing can be viewed as noisy channel model.

- optical character recognition.
- spelling correction.
- speech recognition.

The Noisy Channel Model

Chain Rule

• The probability of a word sequence $w_1, w_2, \dots w_n$ is:

$$P(w_1, w_2, \ldots w_n)$$

 We can use the chain rule of the probability to decompose this probability:

$$egin{align} P(w_1^n) &= P(w_1) P(w_2|w_1) P(w_3|w_1^2) \ldots P(w_n|w_1^{n-1}) \ &= \Pi_{k=1}^n P(w_k|w_1^{k-1}) \ \end{aligned}$$

Example

P(the man from jupiter) = P(the)P(man | the)P(from | the man)P(jupiter | the man from)

N Grams

N Grams

 To collect statistics to compute the functions in the following forms is difficult (sometimes impossible):

$$P(w_n|w_1^{n-1})$$

- Here we are trying to compute the probability of w_n after seeing w_{n-1}.
- We may approximate this computation just looking N previous words:

$$P(w_n|w_1^{n-1})pprox P(w_n|w_{n-N+1}^{n-1})$$

So, a N-GRAM model:

$$P(w_1^n)pprox \Pi_{k=1}^n P(w_k|w_{k-N+1}^{k-1})$$

N Grams ...

N Grams ...

- ullet Unigrams: $P(w_1^n)pprox \Pi_{k=1}^n P(w_k)$
- ullet Bigrams: $P(w_1^n)pprox \Pi_{k=1}^n P(w_k|w_{k-1})$
- ullet Trigrams: $P(w_1^n)pprox \Pi_{k=1}^n P(w_k|w_{k-1}w_{k-2})$
- ullet Quadgrams: $P(w_1^n)pprox \Pi_{k=1}^n P(w_k|w_{k-1}w_{k-2}w_{k-3})$

N Grams Example

• Unigrams:

$$P(the\ man\ from\ jupiter)$$

• Bigrams:

$$P(the\ man\ from\ jupiter)$$

$$R pprox P(the| < s >) P(man|the) P(from|man) P(jupiter|from)$$

• Trigrams:

$$P(the\ man\ from\ jupiter)$$

$$\approx P(the| < s > < s >) P(man| < s > the) P(from|the\; man) P(jupiter|man\; from)$$

Simple Markov Models

- The assumption that the probability of a word depends only on the previous word is called Markov assumption.
- Markov models are the class of probabilistic models that assume that we can predict the probability of some future unit without looking too far into the past.
- A bigram is called a first-order Markov model (because it looks one token into the past);
- A trigram is called a second-order Markov model;
- In general a N-Gram is called a N-1 order Markov model.

Estimating N Gram Probabilities

• Estimating Bi-Gram Probabilities

$$egin{aligned} P(w_n | w_{n-1}) \ &= rac{C(w_{n-1}w_n)}{\sum_w C(w_{n-1}w)} \ &= rac{C(w_{n-1}w_n)}{C(w_{n-1})} \end{aligned}$$

- Here C is the count of that pattern in the corpus.
- Estimating N-Gram Probabilities

$$P(w_n|w_{n-N+1}^{n-1}) \ = rac{C(w_{n-N+1}^{n-1}w_n)}{C(w_{n-1}^{n-N+1})}$$

Example: Estimating N gram Probabilities

Consider a mini corpus of three sentences:

```
<s>I am Sam</s>
<s>Sam I am</s>
<s>i do not like green eggs and ham</s>
```

A few bigram probabilities from this corpus:

$$P(I| < s >) = \frac{2}{3} = 0.67$$
 $P(Sam| < s >) = \frac{1}{3} = 0.33$ $P(am|I) = \frac{2}{3} = 0.67$ $P(Sam|am) = \frac{1}{2} = 0.5$ $P(do|I) = \frac{1}{3} = 0.33$

Which N Gram?

- Which N gram should be used a language Model?
 - o Unigram, Bigram, Trigram, . . .
- Bigger N, the model will be more accurate.
 - But we may not get good estimates for N-Gram probabilities.
- The N-Gram tables will be more sparse.
- Smaller N, the model will be less accurate.
 - But we may get better estimates for N-Gram probabilities.
 - The N-Gram table will be less sparse.
- In reality, we do not use higher than **Trigram (not more than Bigram).**
- How big are N-Gram tables with 10,000 words?
 - Unigram 10,000
 - Bigram 10000*10000 = 100,000,000
 - Trigram 10000*10000*10000 = 1,000,000,000,000

References

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Thank You

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