Natural Language Processing Basics

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Natural language Processing (NLP)

- The processing of the human languages by computers

- One of the oldest AI tasks
- One of the most important AI tasks
- One of the hottest AI tasks nowadays

Difficulty

- Difficulty 1: ambiguous, typically no formal description

- Example: “*We saw her duck.*”

How many different meanings?

Difficulty

- Difficulty 1: ambiguous, typically no formal description

- Example: "*We saw her duck.*"
- 1. We looked at a duck that belonged to her.
- 2. We looked at her quickly squat down to avoid something.
- 3. We use a saw to cut her duck.

Difficulty

- Difficulty 2: computers do not have human concepts
- Example: "*She like little animals. For example, yesterday we saw her duck.*"
- 1. We looked at a duck that belonged to her.
- 2. We looked at her quickly squat down to avoid something.
- 3. We use a saw to cut her duck.

Words

Preprocess

Zipf's Law

Preprocess

- Corpus: often a set of text documents
- Tokenization or text normalization: turn corpus into sequence(s) of tokens

1. Remove unwanted stuff: HTML tags, encoding tags
2. Determine word boundaries: usually white space and punctuations
   - Sometimes can be tricky, like Ph.D.

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2. Determine word boundaries: usually white space and punctuations
   - Sometimes can be tricky, like Ph.D.
3. Remove stopwords: the, of, a, with, …
4. Case folding: lower-case all characters.
   - Sometimes can be tricky, like US and us
5. Stemming/Lemmatization (optional): looks, looked, looking → look

Vocabulary

Given the preprocessed text

- Word token: occurrences of a word
- Word type: unique word as a dictionary entry (i.e., unique tokens)

- Vocabulary: the set of word types
  - Often 10k to 1 million on different corpora
  - Often remove too rare words

Zipf's Law

- Word count f, word rank r
- Zipf's law: $f * r \approx \text{constant}$

Word	Count f	rank r	fr
the	3332	1	3332
and	2972	2	5944
a	1775	3	5235
he	877	10	8770
but	410	20	8400
be	294	30	8820
there	222	40	8880
one	172	50	8600
two	104	100	10400
turned	51	200	10200
comes	16	500	8000
family	8	1000	8000
brushed	4	2000	8000
Could	2	4000	8000
Applausive	1	8000	8000

Zipf's law on the corpus *Tom Sawyer*

Text: Bag-of-Words Representation

Bag-of-Words

tf-idf

Bag-of-Words

How to represent a piece of text (sentence/document) as numbers?

- Let m denote the size of the vocabulary
- Given a document d, let $c(w, d)$ denote the #occurrence of w in d
- Bag-of-Words representation of the document

$$v_d = [c(w_1, d), c(w_2, d), \dots, c(w_m, d)]/Z_d$$

- Often $Z_d = \sum_w c(w, d)$

Example

- Preprocessed text: *this is a good sentence this is another good sentence*

- BoW representation:
  $$[c('a', d)/Z_d, c('is', d)/Z_d, \ldots, c('example', d)/Z_d]$$
- What is Z_d?
- What is $c('a', d)/Z_d$?
- What is $c('example', d)/Z_d$?

tf-idf

- tf: normalized term frequency

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

- idf: inverse document frequency

$$idf_w = \log \frac{\text{total \#doucments}}{\text{\#documents containing } w}$$

- tf-idf: $tf\text{-}idf_w = tf_w * idf_w$
- Representation of the document

$$v_d = [tf\text{–}idf_{w_1}, tf\text{–}idf_{w_2}, \dots, tf\text{–}idf_{w_m}]$$

Cosine Similarity

How to measure similarities between pieces of text?

- Given the document vectors, can use any similarity notion on vectors
- Commonly used in NLP: cosine of the angle between the two vectors

$$sim(x, y) = \frac{x^\top y}{\sqrt{x^\top x}\sqrt{y^\top y}}$$

Text: statistical Language Model

Statistical language model

N-gram

Smoothing

Probabilistic view

- Use probabilistic distribution to model the language
- Dates back to Shannon (information theory; bits in the message)

Statistical language model

- Language model: probability distribution over sequences of tokens
- Typically, tokens are words, and distribution is discrete

- Tokens can also be characters or even bytes

- Sentence: "*the quick brown fox jumps over the lazy dog*"

Tokens: x_1 x_2 x_3 x_4 x_5 x_6 x_7 x_8 x_9

Statistical language model

- For simplification, consider fixed length sequence of tokens (sentence)

$$(x_1, x_2, x_3, \dots, x_{\tau-1}, x_\tau)$$

- Probabilistic model:

$$\mathrm{P}\,[x_1, x_2, x_3, \dots, x_{\tau-1}, x_\tau]$$

Unigram model

- Unigram model: define the probability of the sequence as the product of the probabilities of the tokens in the sequence

$$\mathrm{P}[x_1, x_2, \ldots, x_\tau] = \prod_{t=1}^{\tau} \mathrm{P}[x_t]$$

- Independence!

A simple unigram example

- Sentence: "*the dog ran away*"

$$\hat{\mathrm{P}}[the\ dog\ ran\ away] = \hat{\mathrm{P}}[the]\,\hat{\mathrm{P}}[dog]\,\hat{\mathrm{P}}[ran]\,\hat{\mathrm{P}}[away]$$

- How to estimate $\hat{\mathrm{P}}[the]$ on the training corpus?

A simple unigram example

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- How to estimate $\hat{\mathrm{P}}[the]$ on the training corpus?

Word	Count f
the	3332
and	2972
a	1775
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but	410
be	294
there	222
one	172

n-gram model

- n-gram: sequence of n tokens

- n-gram model: define the conditional probability of the n-th token given the preceding $n-1$ tokens

$$\mathrm{P}[x_1, x_2, \ldots, x_\tau] = \mathrm{P}[x_1, \ldots, x_{n-1}] \prod_{t=n}^{\tau} \mathrm{P}[x_t | x_{t-n+1}, \ldots, x_{t-1}]$$

n-gram model

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Markovian assumptions

Typical $\boldsymbol{n}$-gram model

- $n = 1$: unigram
- $n = 2$: bigram
- $n = 3$: trigram

Training n-gram model

- Straightforward counting: counting the co-occurrence of the grams

For all grams $(x_{t-n+1}, \dots, x_{t-1}, x_t)$

1. count and estimate $\hat{\mathrm{P}}[x_{t-n+1}, \dots, x_{t-1}, x_t]$
2. count and estimate $\hat{\mathrm{P}}[x_{t-n+1}, \dots, x_{t-1}]$
3. compute

$$\hat{\mathrm{P}}[x_t | x_{t-n+1}, \dots, x_{t-1}] = \frac{\hat{\mathrm{P}}[x_{t-n+1}, \dots, x_{t-1}, x_t]}{\hat{\mathrm{P}}[x_{t-n+1}, \dots, x_{t-1}]}$$

A simple trigram example

- Sentence: "*the dog ran away*"

$$\hat{\mathrm{P}}[the\ dog\ ran\ away] = \hat{\mathrm{P}}[the\ dog\ ran]\ \hat{\mathrm{P}}[away|dog\ ran]$$

$$\hat{\mathrm{P}}[the\ dog\ ran\ away] = \hat{\mathrm{P}}[the\ dog\ ran]\frac{\hat{\mathrm{P}}[dog\ ran\ away]}{\hat{\mathrm{P}}[dog\ ran]}$$

Drawback

- Sparsity issue: $\hat{\mathrm{P}}[\dots]$ most likely to be 0

- Bad case: *"dog ran away"* never appear in the training corpus, so $\hat{\mathrm{P}}[dog\ ran\ away] = 0$
- Even worse: *"dog ran"* never appear in the training corpus, so $\hat{\mathrm{P}}[dog\ ran] = 0$

Rectify: smoothing

- Basic method: adding non-zero probability mass to zero entries

- Example: Laplace smoothing that adds one count to all n-grams
  $\text{pseudocount}[dog] = \text{actualcount}[dog] + 1$

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  $\text{pseudocount}[dog] = \text{actualcount}[dog] + 1$

$$\hat{\mathrm{P}}[dog] = \frac{\text{pseudocount}[dog]}{\text{pseudo length of the corpus}} = \frac{\text{pseudocount}[dog]}{\text{actual length of the corpus } + |V|}$$

Rectify: smoothing

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- Example: Laplace smoothing that adds one count to all n-grams

  $\text{pseudocount}[dog\ ran\ away] = \text{actualcount}[dog\ ran\ away] + 1$

  $\text{pseudocount}[dog\ ran] = ?$

Rectify: smoothing

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- Example: Laplace smoothing that adds one count to all n-grams

  $\text{pseudocount}[dog\ ran\ away] = \text{actualcount}[dog\ ran\ away] + 1$

  $\text{pseudocount}[dog\ ran] = \text{actualcount}[dog\ ran] + |V|$

$$\hat{\mathrm{P}}[away|dog\ ran] \approx \frac{\text{pseudocount}[dog\ ran\ away]}{\text{pseudocount}\ [dog\ ran]}$$

since #bigrams $\approx$#trigrams on the corpus

Example

- Preprocessed text: *this is a good sentence this is another good sentence*

- How many unigrams?
- How many bigrams?
- Estimate $\hat{\mathrm{P}}[is|this]$ without using Laplace smoothing
- Estimate $\hat{\mathrm{P}}[is|this]$ using Laplace smoothing (|V| = 10000)

Rectify: smoothing

- Basic method: adding non-zero probability mass to zero entries
  - Example: Laplace smoothing
- Back-off methods: restore to lower order statistics
  - Example: if $\hat{\mathrm{P}}[away|dog\ ran]$ does not work, use $\hat{\mathrm{P}}[away|ran]$ as replacement
- Mixture methods: use a linear combination of $\hat{\mathrm{P}}[away|ran]$ and $\hat{\mathrm{P}}[away|dog\ ran]$

Another drawback

- High dimesion: # of grams too large

- Vocabulary size: about 10k=2^14
- #trigram: about 2^42

Rectify: clustering

- Class-based language models: cluster tokens into classes; replace each token with its class
- Significantly reduces the vocabulary size; also address sparsity issue

- Combinations of smoothing and clustering are also possible