N-grams

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Tokenization

Tokenization is splitting text into individual words or **tokens**

Multiple challenges:

- Different delimiters: spaces, punctuation
- Contractions: "can't" $\rightarrow$ "can not"
- Special cases: dates, numbers, URLs, hashtags, email addresses

Tokenization

Input

"Natural language processing enables computers to understand human language."

Tokenized output

Natural, language, processing, enables, computers, to, understand, human, language, .

Tokenization

Input

"Dr. Smith's email, dr.smith@example.com, isn't working since 01/02/2023; try reaching out at (555) 123-4567 in San Francisco."

Tokenized output

Dr., Smith's, email, ,, dr.smith@example.com, ,, isn't, working, since, 01/02/2023, ;, try, reaching, out, at, (, 555,), 123-4567, in, San Francisco, .

Tokenization

Rule-based approach

Use predefined rules, like splitting by spaces or punctuation using regular expressions

Machine learning approach

Learn from data to handle complex cases, e.g., using Byte-Pair Encoding subword tokenization

What is a language model?

A **language model** is a probabilistic model that:

- computes the **probability of a sequence of words** S
  $P(S) = P(w_1, w_2, ..., w_n)$
- computes the **probability of an upcoming word**
  $P(w_5|w_1, w_2, w_3, w_4)$

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For example, for speech recognition:
$P(\text{I saw a van}) >> P(\text{eyes awe of an})$

How to compute P(S)?

Definition of **conditional probabilities**:

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Applying the chain rule to compute the joint probability of words in a sentence:

$$P(\text{I am Gustave}) = P(\text{I})P(\text{am}|\text{I})P(\text{Gustave}|\text{I am})$$

How to estimate these probabilities?

Can we just count and divide?

$$P(\text{processing}|\text{I am Gustave, I love natural language}) = \frac{\text{Count(I am Gustave, I love natural language processing)}}{\text{Count(I am Gustave, I love natural language)}}$$

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$\rightarrow$ We'll never see enough data for estimating long sentences

N-grams are Markov models

Markov assumption uses a limited context window to approximate $P(\text{processing}|\text{I am Gustave, I love natural language})$

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$\rightarrow$ Language has long-distance dependencies, therefore n-grams are insufficient models of language

Example: estimating bigram probabilities

Estimation using $P(w_i|w_{i-1}) = \frac{\text{count}(w_i, w_{\mathbf{i-1}})}{\text{count}(w_{\mathbf{i-1}})}$

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<s> I am Gustave </s>
<s> Gustave I am </s>
<s> I love natural language processing </s>

$$P(\text{I}|\text{am}) = \frac{\text{count}(\text{I}, \text{am})}{\text{count}(\text{am})} = \frac{2}{3}$$

How to evaluate performance?

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Therefore, a good LM assigns a higher probability to the test set than another LM

If the test set has n tokens, then $P(\text{test set}) = (w_1, w_2, ..., w_n)$

$$P_{\text{good LM}}(\text{test set}) > P_{\text{bad LM}}(\text{test set})$$

Perplexity

Probability depends on the number of tokens, the longer the text, the smaller the probability

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$\rightarrow$ We normalize by the number of tokens to have a metric per token:

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Minimizing perplexity is the same as maximizing probability

Practical issues

Due to **unknown words**, bigrams with zero probability drop sentence probabilities to zero and prevent us from calculating perplexity

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→ **Add-1 smoothing** pretends we saw each word one more time than we did

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where V is the vocabulary size

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To avoid **underflow**, every computation is performed in log space

$$\log(p_1 \times p_2 \times p_3) = \log(p_1) + \log(p_2) + \log(p_3)$$

Better n-grams using backoff or interpolation methods

Backing off through progressively shorter context models under certain conditions. For example, use trigram if count$(w_i, w_{i-1}, w_{i-2}) > 0$, otherwise use bigram.

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Interpolation methods train individual models for different n-gram orders and then interpolate them together.

$$\hat{P}(w_n|w_{n-2}, w_{n-1}) = \lambda_1 P(w_n|w_{n-2}, w_{n-1}) + \lambda_2 P(w_n|w_{n-1}) + \lambda_3 P(w_n)$$

where $\sum_{i=1}^{3} \lambda_i = 1$

From n-gram to neural network language models

Neural network language models solve major problems with n-grams

- The number of parameters increases exponentially as the n-gram order increases
- N-grams have no way to generalize from training to test set

Neural language models instead **project words into a continuous space** in which words with similar contexts have similar representations

How to represent word meaning?

Word meaning as a point in a multidimensional space

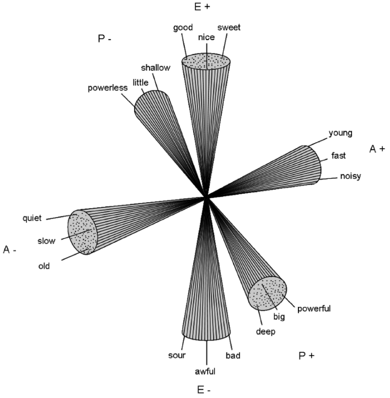


Figure: A three-dimensional affective space of connotative meaning by Osgood et al. (1957)

How to represent word meaning?

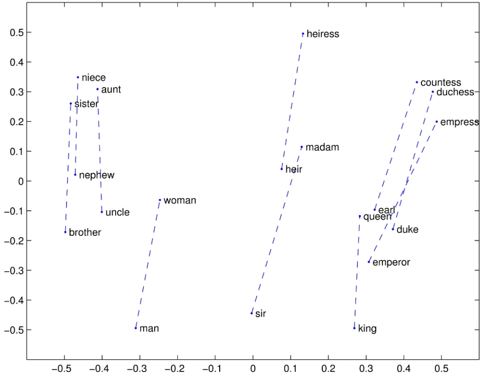
Defining meaning by linguistic distribution

The meaning of a word is its use in a language, Ludwig Wittgenstein (1953)

If A and B have almost identical environments (words around them), then they are synonyms, Zellig Harris (1954)

How to represent word meaning?

Word meaning as a point in a multidimensional space + Defining meaning by linguistic distribution = **Defining meaning as a point in a multidimensional space based on linguistic distribution**



The meaning of a word is a vector called an **embedding**

Components of a machine learning classifier

- A feature representation of the input x
- A classification function that computes the estimated class
- An objective function for learning (e.g., cross-entropy loss)
- An algorithm for optimizing the objective function (e.g., stochastic gradient descent)