VL Deep Learning for Natural Language Processing

4. Word Embeddings I

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AG Information Profiling and Retrieval

Summary of Previous Session

- Preprocessing
  - OCR, speech recognition
  - Tokenization
  - Normalization
- Morphological analysis
  - Stemming, lemmatization
  - Part-of-speech tagging
- Syntactic analysis
  - Sentence splitting
  - Parsing
- Semantic analysis
  - Lexical semantics
  - Relational semantics
  - Discourse

Pipeline

- Applications
  - Document Classification
  - Document Clustering
  - Topic Modeling
  - Machine translation (MT)
  - Information retrieval (IR)
    - Information extraction (IE)
    - Question answering (QA)
    - Automatic summarization
    - Recommender Systems (RS)
  - Knowledge Graphs (KG)
  - Natural language generation (NLG)
  - Natural language understanding (NLU)

Semester Schedule

Week	Date	Exercise (Mon)	Lecture (Thu)	Assignments
1	15.4.24	No Exercise	Introduction	
2	22.4.24	Python/Pytorch/Colab	Neural Networks	Hand-out A1
3	29.4.24	Neural Network Implementation	NLP+TM	
4	6.5.24	Text Classification	Holiday	Hand-in A1
5	13.5.24	Assignment 1 Discussion	Word Embeddings I	Hand-out A2
6	20.5.24	Holiday	Word Embeddings II	
7	27.5.24	Word Embeddings Applications	Word Classifiers	
8	3.6.24	Deep Learning in Practice	Language Models	Hand-out A3
9	10.6.24	RNNs+CNN	Recurrent Neural Networks	Hand-in A2
10	17.6.24	Assignment 2 Discussion	Sequence-to-Sequence Models	
11	24.6.24	Seq2Seq & Hugging Face	Transformer Models	
12	1.7.24	Transformers	Large Language Models	Hand-in A3
13	8.7.24	Assignment 3 Discussion	Generation and Prompting	

Introduction

Basics

Advanced

Deep Learning for Natural Language Processing

In contrast to deep learning for non-perceptional tasks

- Not NLP
- Not CV

Meaning!

In contrast to machine learning for natural language processing

- Statistics
- Rule-based

Text from a data science perspective

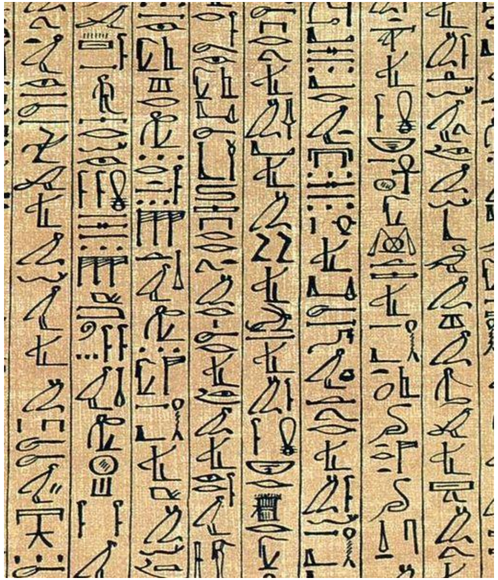
- A sequence of characters or words (tokens) (or sub-words)
- DL algorithms for sequences
  - Recurrent neural networks (RNN)
  - 1D convolutional neural networks (CNN)
  - Transformer
  - Large language models (LLM)

What is Meaning

- What‘s the meaning of this sentence?
  - *The weather is nice.*
  - *Time flies like an arrow; fruit flies like a banana.*

- What‘s the meaning of these words?
  - *Bank*
  - *Jaguar*
  - *Java*

- Is cold positive or negative?
  - *Cold beer*
  - *Cold coffee*



https://www.historyonthenet.com/the-egyptians-hieroglyphs

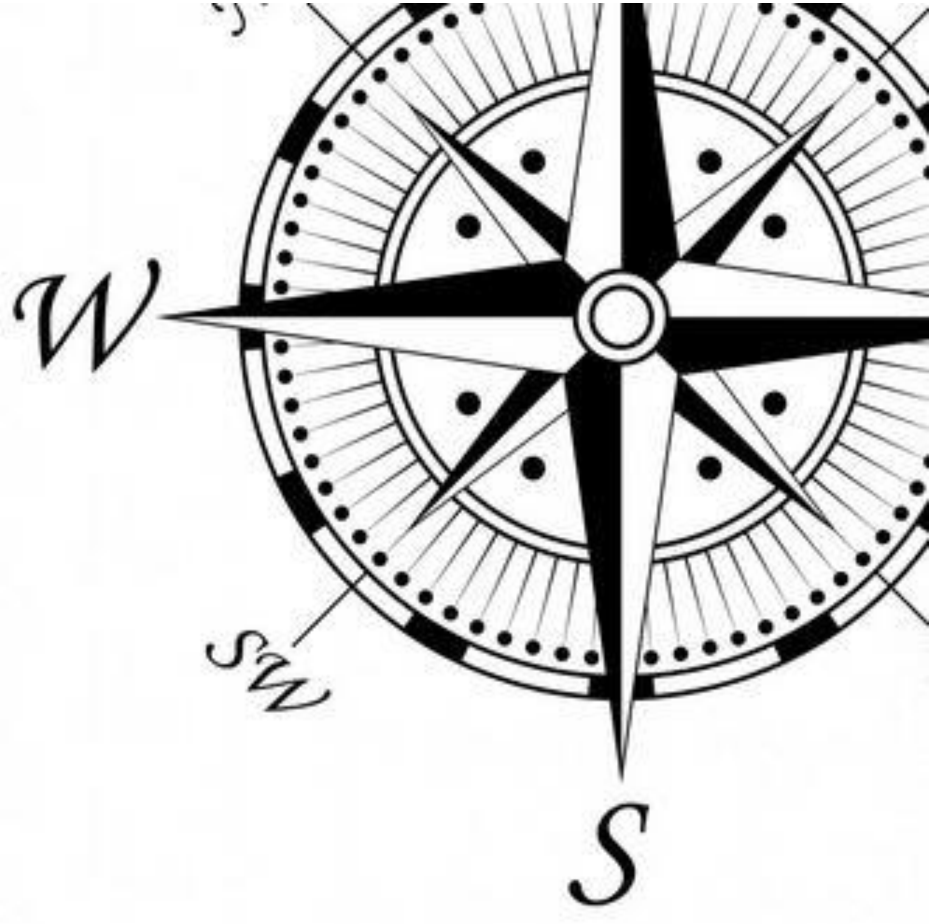
Learning Goals for this Chapter

- Whats the meaning of meaning?
- Know representations for words
  - Pros and cons
- Understand word2vec
  - CBOW/skip-gram

- Relevant chapters:
  - P6.1
  - S1 (2021) https://www.youtube.com/watch?v=rmVRLeJRkl4

Topics Today

1. **Word Meaning**
2. LSA
3. Word2vec



What‘s the Meaning of Meaning?

- Merriam-Webster (https://www.merriam-webster.com/dictionary/meaning)
  - **Meaning** noun (mean·ing | ˈmē-niŋ)
  - ***Definition of meaning***
    - 1a **:** the thing one intends to convey especially by language **:** purport
      // Do not mistake my meaning.
    - 1b **:** the thing that is conveyed especially by language **:** import
      // Many words have more than one meaning.
    - 2 **:** something meant or intended **:** aim
      // a mischievous meaning was apparent
    - 3 **:** significant quality
      especially **:** implication of a hidden or special significance
      // a glance full of meaning
    - 4a **:** the logical connotation of a word or phrase
    - 4b **:** the logical denotation or extension of a word or phrase

How do Humans Understand Words?

- Wikipedia (https://de.wikipedia.org/wiki/Bedeutung_(Sprachphilosophie))
  - Meaning means the knowledge of the usual **use** of a word or phrase within a **language community** and given **context**.
  - Meaning means what someone **understands** based on a sign or a linguistic expression.
  - In **reference** theory, meaning is the **object** denoted by a word.
  - In **lexical** meaning theory, the meaning is expressed by a **list of properties** that includes a term.

- Decisive for determining the meaning are
  - word and sentence structure (**syntax**),
  - content of the expression (**semantics**), and
  - the context of use of an utterance (**pragmatics**)

How Can a Computer Understand Words?

- Easy, using a dictionary!
  - E.g. WordNet, SentiWordNet
    - Collection of words organized in synsets (synonym sets) and in „is-a“-Hierarchy

```
import nltk
nltk.download('wordnet')
from nltk.corpus import wordnet as wn
for synset in wn.synsets("bank"):
    print ("(%s)" % synset.pos(), ", ".join([l.name() for l
    in synset.lemmas()]), "Def: %s " % synset.definition())
>>>(n) bank
   Def: sloping land (especially the slope beside a body of water)
>>>(n) depository_financial_institution, bank, banking_concern, banking_company
   Def: a financial institution that accepts deposits and channels the money into lending activities
>>>(v) bank
   Def: tip laterally
```

```
fox = wn.synset("fox.n.01")
hyper = lambda s: s.hypernyms()
list(fox.closure(hyper))

[Synset('canine.n.02'),
 Synset('carnivore.n.01'),
 Synset('placental.n.01'),
 Synset('mammal.n.01'),
 Synset('vertebrate.n.01'),
 Synset('chordate.n.01'),
 Synset('animal.n.01'),
 Synset('organism.n.01'),
 Synset('living_thing.n.01'),
 Synset('whole.n.02'),
 Synset('object.n.01'),
 Synset('physical_entity.n.01'),
 Synset('entity.n.01')]
```

Problems with Dictionaries such as WordNet

- In general useful, e.g. to answer the questions
  - Is this word ‚positive‘?
  - Is this word related to a particular topic?
- But:
  - Not very sophisticated
    - *proficient* is only in certain context a synonym for *good*
  - New words not included at all
    - *Ninja, wizard, genius*
  - Subjective, since man made
  - Very costly to create and maintain
  - Meaning of n-grams unclear
  - Similartiy of words hard to measure
    - Distance in WordNet-Hierarchy

Words as Discrete Symbols

- Bag-of-words, vector space model
  - Words and n-grams correspond to positions in a vector
    - Also possible on character level: character and character n-grams
  - Length of vector = vocabulary size
    - Between 20k and 500k
  - Advantage:
    - Very successul in IR
    - Input data are vectors
    - Can be processed by a DNNs
    - Documents can be represented as sum of all their words' vectors

Web 1T corpus: one billion tokens; 13.5 million unigrams

$$\text{aunt}=\begin{array}{c} c \\ 0 \\ 0 \\ 0 \\ 0 \\ 1 \\ 0 \\ \vdots \\ 0 \end{array} \qquad \text{uncle}=\begin{array}{c} c \\ 0 \\ \vdots \\ 0 \\ 0 \\ 0 \\ 0 \\ 1 \\ 0 \end{array}$$

Vectorization

- **One-hot-encoding**
  - Vectorization of words

$$
\begin{aligned}
house &= [0\ 0\ 1\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0 \ldots 0] \\
mouse &= [0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 1\ 0\ 0\ 0\ 0\ 0\ 0 \ldots 0] \\
home &= [0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 1\ 0 \ldots 0]
\end{aligned}
$$

- Problem:
  - Vectors of similar words are orthogonal
  - One-hot-encoding has no concept of similarity

- Solution:
  - Make use of Wordnet to find synonyms?
  - **Better: include similarity already in vector representation**

Represent Words by their Context

- Idea: The meaning of a word is defined by the words that appear often in its vicinity.
  - *"You shall know a word by the company it keeps"* (Firth 1957)
  - Most successful concept in modern, statistical NLP

- The context of a word *w* in a text are the words in its vicinity.
  - Typically a window of fixed size
    - Between two and five on both sides
- One word is then represented by all its contexts:

*…proud to own a **house** in this neighborhood…*
*The **house** of cultures offers…*
*…on main street, the **house** of her parents was…*

These contexts then represents the word *house*

John Rupert Firth (1957). "A synopsis of linguistic theory 1930-1955." In *Special Volume of the Philological Society.* Oxford: Oxford University Press.

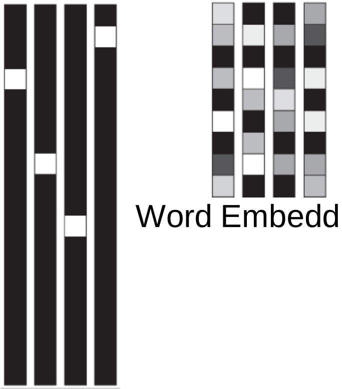
Word Vectors

- Idea: each word is represented by a **dense** vector.
  - Similar words have similar vector representations
  - $house = \begin{bmatrix} -0.345 \\ 0.422 \\ -0.114 \\ -0.225 \\ 0.135 \\ 0.452 \\ -0.164 \\ -0.398 \\ 0.145 \end{bmatrix} mouse = \begin{bmatrix} 0.441 \\ 0.125 \\ -0.514 \\ 0.156 \\ 0.532 \\ -0.216 \\ -0.379 \\ 0.294 \\ 0.542 \end{bmatrix} home = \begin{bmatrix} -0.465 \\ 0.222 \\ -0.165 \\ -0.123 \\ 0.415 \\ 0.392 \\ -0.183 \\ -0.382 \\ 0.1 \end{bmatrix}$
  - These word vectors are called **word embeddings**.
- Two types of word embeddings
  - Learning of the vectors as **part of the machine learning problem**
  - **Pretrained vectors** as input for a DNN
    - Pretrained word embeddings: word2vec, GloVe, fastText

Sparse vs. Dense

High vs. Low dimensional

Hard-coded vs. Learned from data



Word Embeddings

One-Hot-coded Vectors

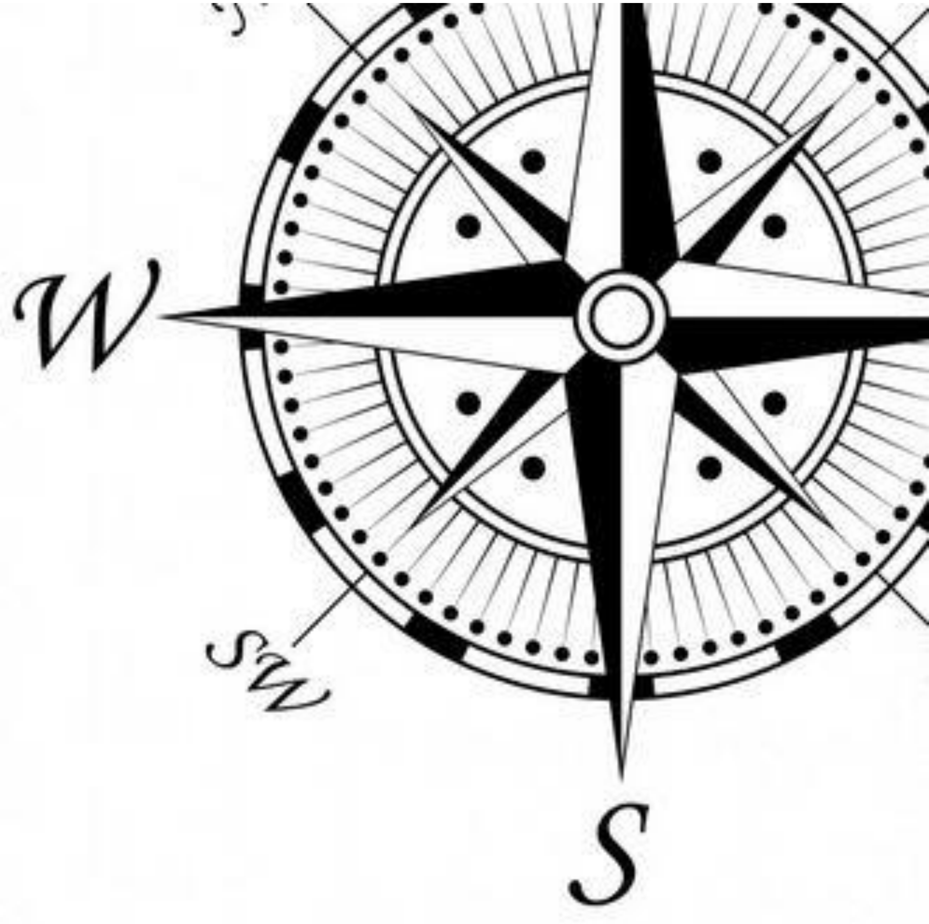
Word Meaning

- How could you determine the sentiment of a sentence using word vectors?
  - E.g movie reviews: „This movie was boring“ vs. „Great movie, highly recommended“

Start 5 4 3 2 1 End

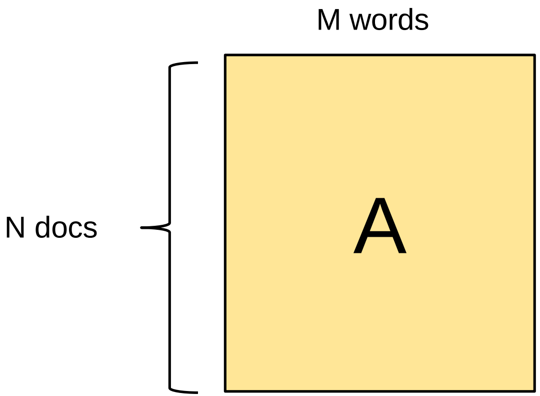
Topics Today

1. Word Meaning
2. **LSA**
3. Word2vec



Latent Semantic Analysis

- Aka latent semantic indexing (LSA/LSI)
- Based on **bag-of-words model**
- Given a matrix ***A*** encoding some documents:
  - A_{ij} is the count of word ***j*** in document ***i***.
  - Often tf-idf or other "squashing" functions of the count are used
  - Most entries are 0.



Scott Deerwester et al. "Indexing by latent semantic analysis". Journal of the American society for information science (1990).

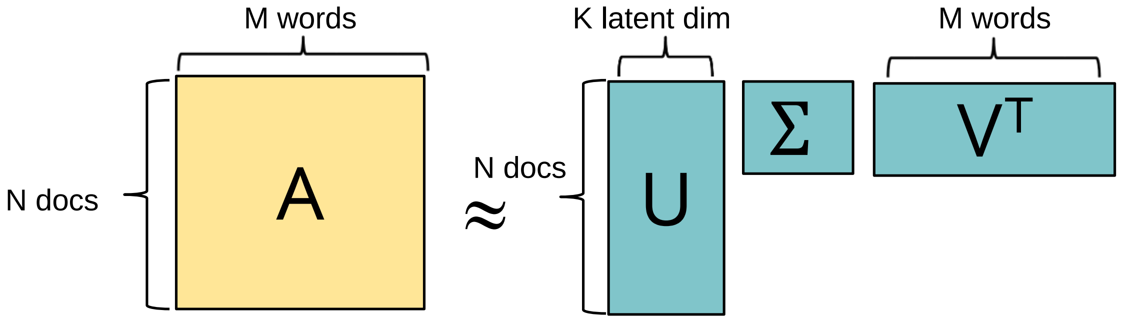
Latent Semantic Analysis

- Low-rank **singular value decomposition (SVD)**:

$$A_{[m\times n]} = U_{[m\times r]}\Sigma_{[r\times r]}(V_{[n\times r]})^T$$

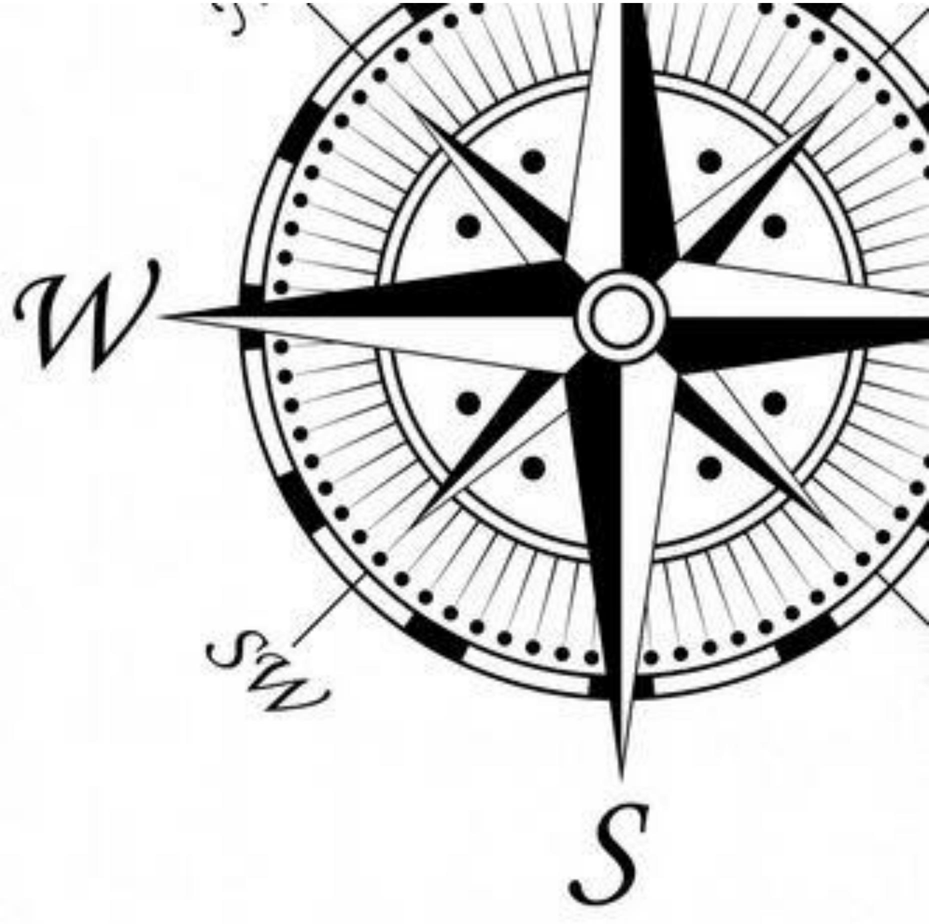
  - U : document-to-concept similarities matrix (orthogonal matrix)
  - V : word-to-concept similarities matrix (orthogonal matrix)
  - Σ : strength of each concept
- Then given a word ***w*** (column of ***A***):
  - $\varsigma = w^T \times U$ is the embedding (encoding) of the word ***w*** in the latent space
  - $w \approx U \times \varsigma^T = U \times (w^T \times U)^T$ is the decoding of the word ***w*** from its embedding

An SVD factorization gives the best possible reconstructions of a word *w* from its embedding



Topics Today

1. Word Meaning
2. LSA
3. **Word2vec**



Word Embeddings

- **Word2vec** is a framework to to compute word vectors (**word embeddings**) using a deep neural network architecture.
- Idea:
  1. Given a very, very large text corpus
     - E.g. the web, large digital libraries, at least Wikipedia
  2. Represent each word of the vocabulary as a dense vector.
     - Number of dimensions: 50-300
  3. Iterate over each word *c* (center) in the text and look at its context *o* (outside).
  4. Learn to predict the center word *c*, given the context word vectors.
     - $P(c|o)$; Multi-class classification problem; or vice versa $P(o|c)$
  5. Change/adapt the word vectors in a way to maximize these probabilities.
     - Similar context results in similar word vectors!

Mikolov, T., Sutskever, I., Chen, K., Corrado, G. S., & Dean, J. (2013). Distributed representations of words and phrases and their compositionality. In *Advances in Neural Information Processing Systems (NIPS).* pp. 3111-3119.

Word2vec

- Two variants of Word2vec
  1. **Skip-grams** (SG)
     - Predict the context words given the center word
  2. **Continuous Bag of Words** (CBOW)
     - Predict the center word given the bag-of-words of its context

Independent of exact position

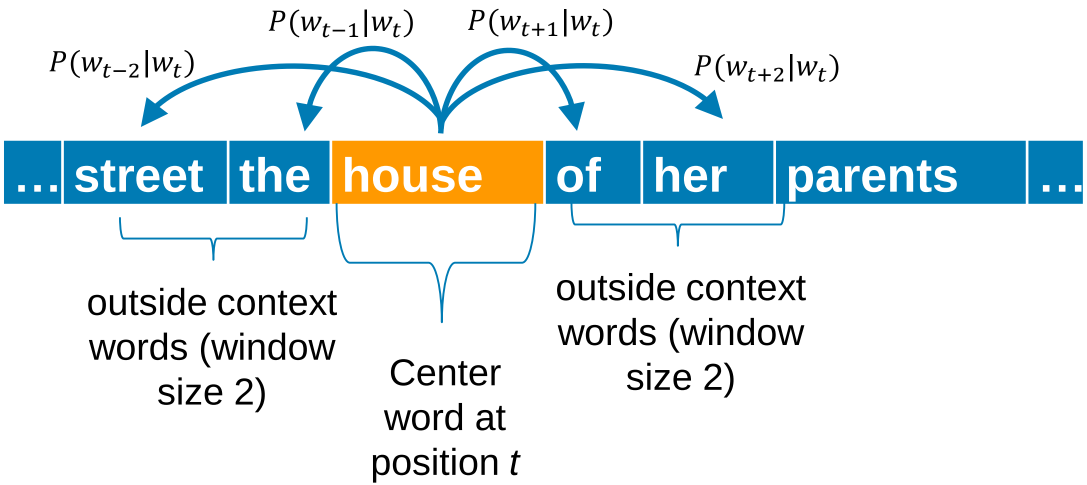
- Two more or less efficient methods to learn the word vectors
  1. Hierarchical softmax
  2. Negative sampling

  – We look at naive softmax
     - VERY inefficient ;) but easier to understand ☺

Mikolov, T., Sutskever, I., Chen, K., Corrado, G. S., & Dean, J. (2013). Distributed representations of words and phrases and their compositionality. In *Advances in Neural Information Processing Systems (NIPS).* pp. 3111-3119.

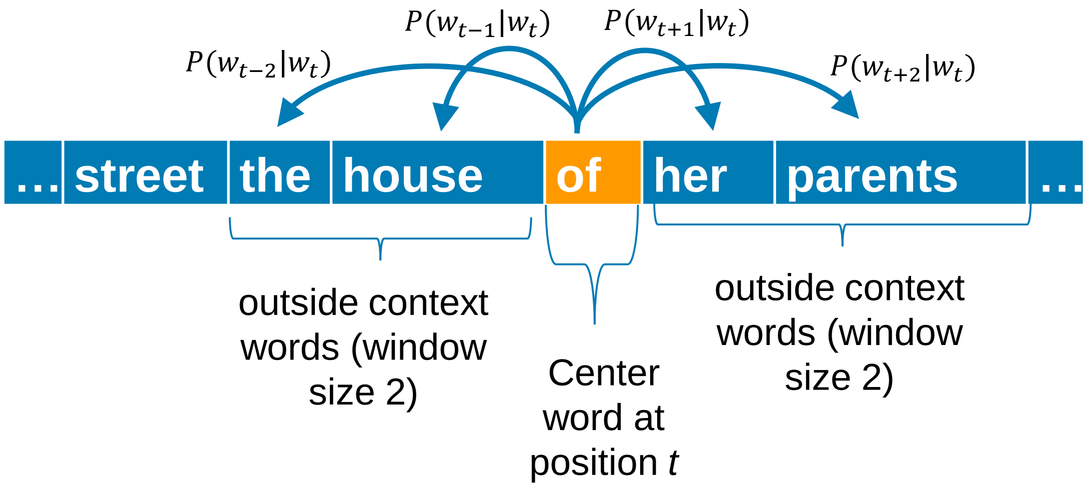
Example

- Calculation of $P(w_{t+x}|w_t)$ for window size x

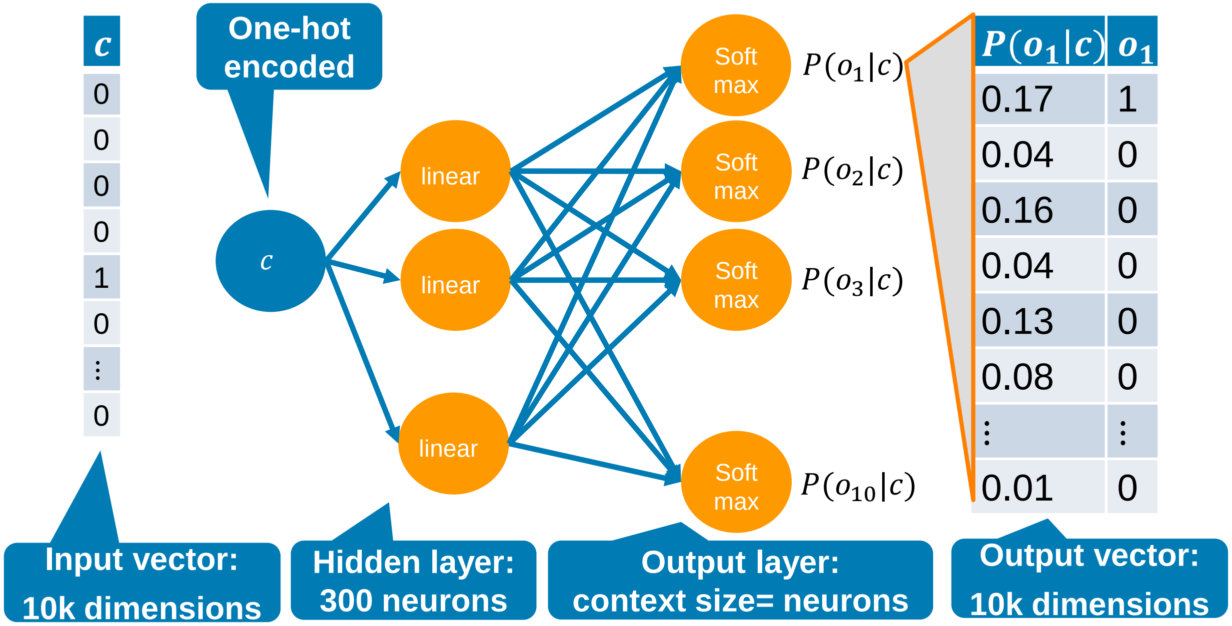


Example

- Calculation of $P(w_{t+x}|w_t)$ for window size x



Network Architecture



Loss Function

- For each position $t = 1, \ldots, T$ predict the context words in window of size m for a given center word w_t.

$$J'(\theta) = \prod_{t=1}^{T} \prod_{\substack{-m \leq j \leq m \\ j \neq 0}} P(w_{t+j} | w_t; \theta)$$

- The loss function $J(\theta)$ is then the (average) negative log likelihood:

$$J(\theta) = -\frac{1}{T} \log J'(\theta) = -\frac{1}{T} \sum_{t=1}^{T} \sum_{\substack{-m \leq j \leq m \\ j \neq 0}} log P(w_{t+j} | w_t; \theta)$$

- Minimizing the loss function $\Leftrightarrow$ Maximizing the prediction accuracy

Computing the Loss Function I

- Minimizing the loss function

$$J(\theta) = -\frac{1}{T}\sum_{t=1}^{T}\sum_{\substack{-m\leq j\leq m\\ j\neq 0}} logP(w_{t+1}|w_t;\theta)$$

- How to compute $P(w_{t+1}|w_t;\theta)$?
- For each word w there are two vectors:
  - v_w if w is a center word
  - u_w if w is a context word
- Then, for a given center word c and a given context word o you can compute:

$$P(o|c) = \frac{e^{u_o^T v_c}}{\sum_{w\in V} e^{u_w^T v_c}}$$

Scalar product compares the similarity of *o* and *c*.

Normalization across the complete vocabulary

Computing the Loss Function II

$$P(o|c) = \frac{e^{u_o^T v_c}}{\sum_{w \in V} e^{u_w^T v_c}}$$

- A version of the softmax function
- Reminder:

$$softmax(x_i) = \frac{e^{x_i}}{\sum_j e^{x_j}} = p_i$$

  – The softmax function maps arbitrary values x_i to a probability distribution p_i.
    - „max“, because large values are maped to excessively large probability values
    - „soft“, because also very small values get mapped to a small probability value

Parameters of the Model

- Optimize all parameters so that loss fuction is minimized!

$$J(\theta) = -\frac{1}{T}\sum_{t=1}^{T}\sum_{\substack{-m\leq j\leq m \\ j\neq 0}} log\,\frac{e^{u_o^T v_c}}{\sum_{w\in V} e^{u_w^T v_c}}$$

- Find two vector representations for each word in a way that similar words have similar vectors.
- Compute gradients per window for all parameters
- Why two vectors per word?
  - Easier to optimize
  - Use average at the end!

$$\theta = \begin{bmatrix} v_{aachen} \\ v_{aake} \\ \vdots \\ v_{zuse} \\ u_{aachen} \\ u_{aake} \\ \vdots \\ u_{zuse} \end{bmatrix} \in \mathbb{R}^{2dV}$$

Gradients

- How to change each vector v and u to minimize loss function?
- For each window and context word, we need to compute $\frac{\partial J}{\partial v_c}$ and $\frac{\partial J}{\partial u_o}$:

$$\frac{\partial}{\partial v_c} log \frac{e^{u_o^T v_c}}{\sum_{w \in V} e^{u_w^T v_c}} = \underbrace{\frac{\partial}{\partial v_c} log e^{u_o^T v_c}}_{A} - \underbrace{\frac{\partial}{\partial v_c} log \sum_{w \in V} e^{u_w^T v_c}}_{B}$$

- A: $\frac{\partial}{\partial v_c} u_o^T v_c = u_o^T$
- B: $\frac{\partial}{\partial v_c} log \sum_{w \in V} e^{u_w^T v_c} = \frac{1}{\sum_{w \in V} e^{u_w^T v_c}} \cdot \frac{\partial}{\partial v_c} \sum_{x \in V} e^{u_w^T v_c} = \frac{1}{\sum_{w \in V} e^{u_w^T v_c}} \cdot \sum_{x \in V} \frac{\partial}{\partial v_c} e^{u_x^T v_c}$

  $= \frac{1}{\sum_{w \in V} e^{u_w^T v_c}} \cdot \sum_{x \in V} e^{u_x^T v_c} \frac{\partial}{\partial v_c} u_x^T v_c = \frac{1}{\sum_{w \in V} e^{u_w^T v_c}} \cdot \sum_{x \in V} e^{u_x^T v_c} u_x^T$

  $= \sum_{x \in V} \frac{e^{u_x^T v_c}}{\sum_{w \in V} e^{u_w^T v_c}} u_x^T = \sum_{x \in V} P(x|c)\, u_x^T$
- A-B: $u_o - \sum_{x \in V} P(x|c)\, u_x^T$

Learning Embeddings

- Imagine a corpus with only three (meaningful) words
  - house, home, mouse
  - Further there are stop words and verbs.
  - Assume the corpus contains 10k sentences

- Go through the process of learning word embeddings manually using the network architecture and the loss function
  - How does backpropagation changes the weights?

Start 5 4 3 2 1 End

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  - S1 (2021) https://www.youtube.com/watch?v=rmVRLeJRkl4

Literature

- Efficient Estimation of Word Representations in Vector Space
  – (original word2vec paper)
- Distributed Representations of Words and Phrases and their Compositionality
  – (negative sampling paper)
- GloVe: Global Vectors for Word Representation
  – (original GloVe paper)
- Improving Distributional Similarity with Lessons Learned from Word Embeddings
- word2vec parameter learning explained