Natural Language Processing 3: Transfer learning, Transformer models

HS Sprachtechnologie für eine bessere Welt (Winter term 2022/23)

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Neural Networks

- Neural network consists of layers of neurons
- Training goal: Find weights, such that the training instances are correctly predicted
- Training method: Gradient descent
- Training does not have to be completed in one go
  - Pausing at any time is possible
  - Training can continue with a different data set

Section 1

Word2Vec

Introduction

- Embeddings: Words are *embedded* into a high-dimensional vector space
  - (and not simply indexed any more)
- Word2Vec
  - A method to represent words in a (high-dimensional) vector space
  - No end-user task

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- Word2Vec
  - A method to represent words in a (high-dimensional) vector space
  - No end-user task
- A vector representation for “köln”

```
0.0539 -0.0030 0.0203 -0.1084 -0.0099 0.0705 -0.0546 -0.0433 -0.0096 0.0561 -0.0095 0.0280 0.1726 0.0190 0.0369 0.0217 -0.0002
-0.0309 0.0347 -0.0749 -0.0202 0.0151 -0.0195 0.0001 0.0232 0.0243 -0.0170 -0.0090 -0.0108 -0.0943 0.0376 0.1118 -0.0324 0.0148
-0.0033 0.0537 -0.0681 -0.0733 -0.0201 -0.0329 0.1242 0.0324 -0.0744 -0.0149 -0.0047 -0.0484 -0.0483 0.0481 0.0107 0.0101 -0.0704
0.0500 0.0112 -0.0227 0.0499 -0.0259 -0.0441 0.0712 -0.0157 -0.1271 0.0407 -0.0495 -0.0359 0.0202 0.0024 0.0764 0.0196 0.0267
-0.0117 0.0026 0.0171 -0.0121 -0.1374 -0.0370 0.0247 -0.0113 -0.0094 0.0322 -0.0347 -0.0866 0.0042 -0.0014 0.0067 0.0591 0.0009
0.0085 0.0310 0.0479 -0.0511 0.0198 -0.0886 -0.0274 -0.1364 0.0322 -0.1638 -0.0689 0.0016 -0.1039 0.0059 0.0757 -0.0034 0.1013
-0.0034 -0.0065 -0.0468 0.1577 -0.0065 -0.0478 -0.0004 0.0682 0.0045 -0.0607 -0.0590 0.0343 0.0036 -0.1014 -0.0136 -0.0063 0.0801
0.0360 0.0579 -0.0039 0.0975 0.0500 -0.0558 -0.0095 0.0057 -0.0246 0.1070 -0.0186 0.0669 -0.0781 -0.0569 -0.1286 -0.0834 0.0106
-0.0672 -0.0205 0.0613 0.0290 -0.0545 -0.0481 -0.0882 -0.0489 0.0622 -0.0730 -0.0192 -0.0415 -0.0287 0.0218 -0.0427 -0.0046
0.0255 -0.1164 0.0077 -0.0546 -0.0786 0.0000 -0.0456 0.0943 0.0157 -0.0117 -0.0441 -0.0015 -0.0556 -0.0508 0.0088 0.0418 0.0030
-0.1450 -0.0663 0.0800 0.0172 -0.0289 0.1178 -0.0973 0.0888 0.0637 -0.0295 0.0212 0.0100 -0.0860 0.0035 0.0730 0.0425 -0.0080
0.0885 -0.0166 -0.0765 0.0004 -0.0118 0.0138 -0.0093 -0.0606 -0.0447 -0.0746 0.0131 -0.0447 -0.0763 0.0032 0.1181 0.0542 0.0431
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-0.0266 -0.0287 -0.0874 0.0797 -0.0784 -0.0920 0.0380 0.0411 0.0859 0.0369 0.0595 0.0446 0.0363 -0.0353 -0.0044 -0.0061 0.1134
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-0.0634 0.0317 -0.0022 0.0882 -0.0240 0.0031 -0.0370 0.0747 -0.0097 -0.0315 0.0405 0.0124 -0.1416 -0.0768 0.0363 -0.1248 -0.0134
0.0702 -0.0905 -0.0387 0.0683 -0.0784 0.0886 0.0640 0.0611 -0.0199 -0.0447 -0.1331 -0.1247 0.0540 0.0499 -0.0212 -0.0544 -0.1161
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Embeddings

Why is that useful?

1. Input Representation for Neural Networks
   - Example Task: Sentiment Analysis
   - Take a sentence, classify it as positive or negative

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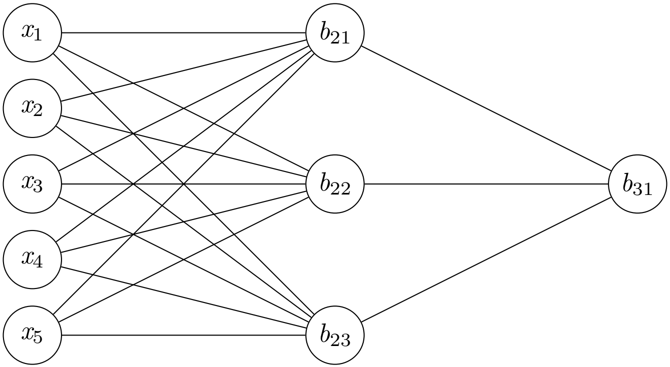

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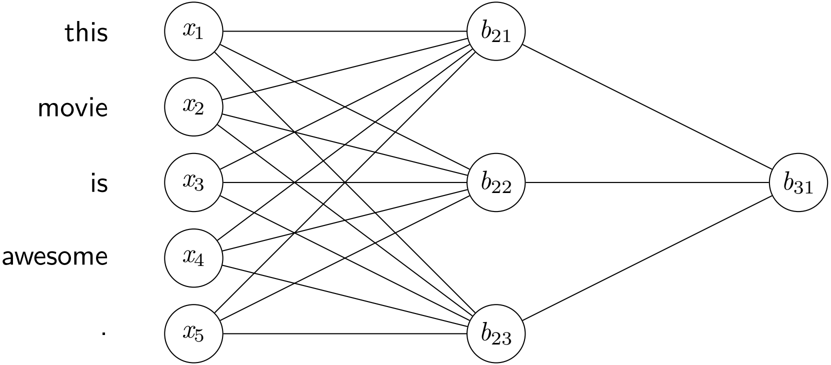

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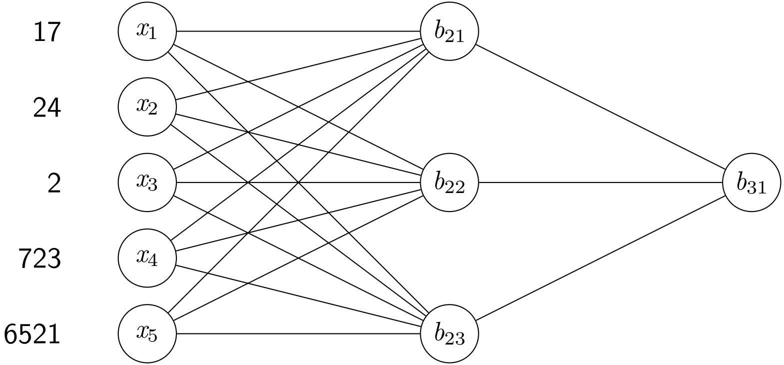

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$$\langle -0.0353, -0.0044, -0.0061, 0.1134 \rangle$$

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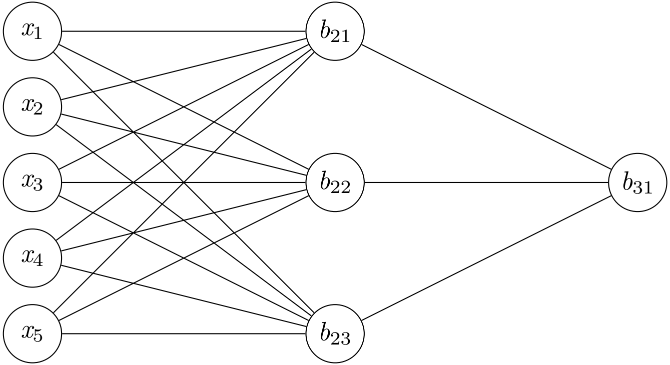
$$\langle -0.0689, 0.0016, -0.1039, 0.0059 \rangle$$



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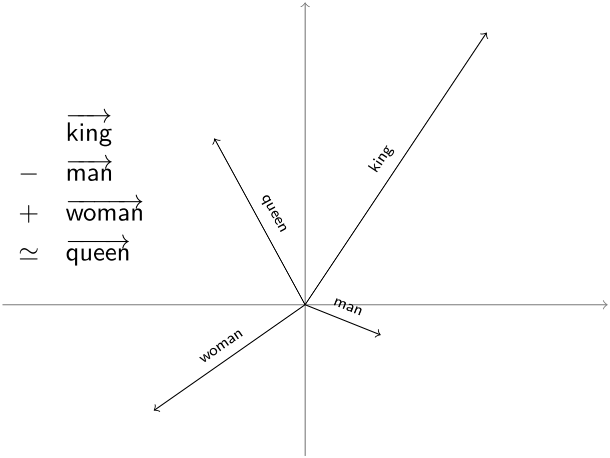
2. For semantic calculations

$$\begin{array}{ll} & \overrightarrow{\text{king}} \\ - & \overrightarrow{\text{man}} \\ + & \overrightarrow{\text{woman}} \\ \simeq & \overrightarrow{\text{queen}} \end{array}$$



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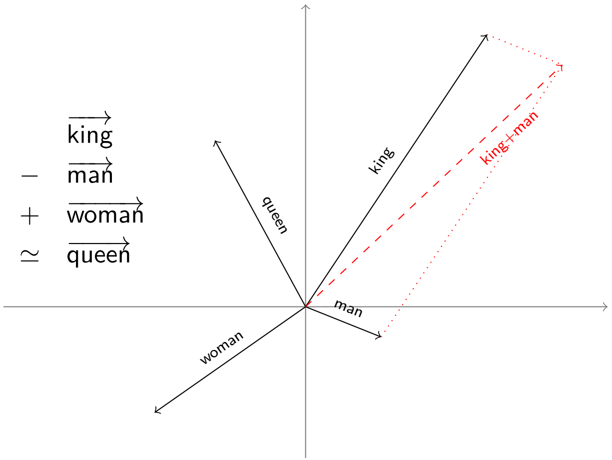

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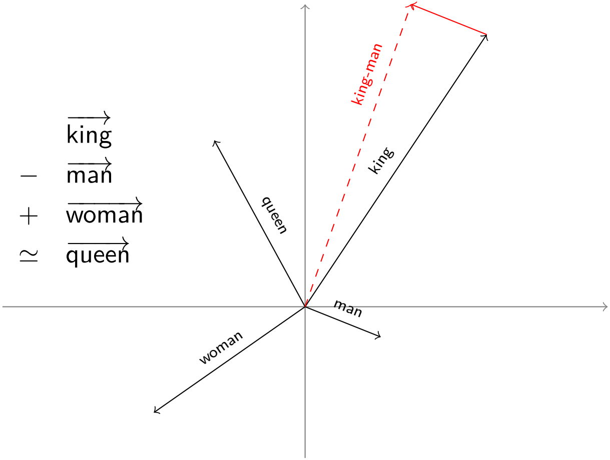

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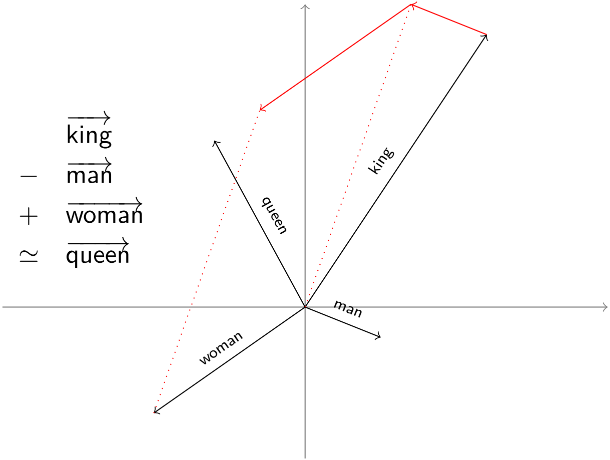

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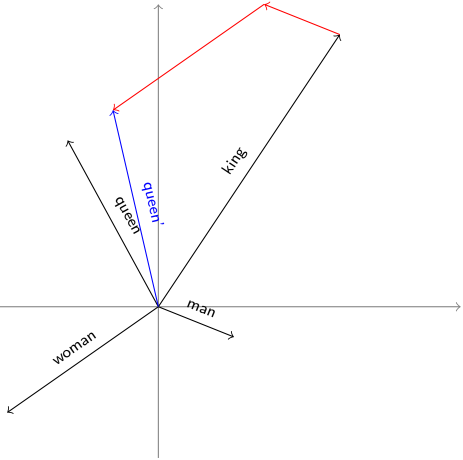

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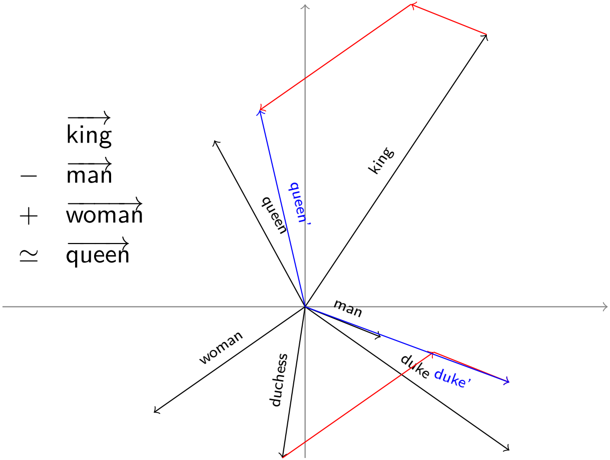


Subsection 1

Generating Word Embeddings with Word2Vec

Literature basis

Two very influential papers by Mikolov et al.

Tomáš Mikolov/Kai Chen/Greg Corrado/Jeffrey Dean (2013). "Efficient Estimation of Word Representations in Vector Space". In: *arXiv cs.CL*. URL: https://arxiv.org/pdf/1301.3781.pdf

Tomáš Mikolov/Ilya Sutskever/Kai Chen/Greg S Corrado/Jeff Dean (2013). "Distributed Representations of Words and Phrases and their Compositionality". In: *Advances in Neural Information Processing Systems 26*. Ed. by C. J. C. Burges/L. Bottou/M. Welling/Z. Ghahramani/K. Q. Weinberger. Curran Associates, Inc., pp. 3111–3119. URL: http://papers.nips.cc/paper/5021-distributed-representations-of-words-and-phrases-and-their-compositionality.pdf

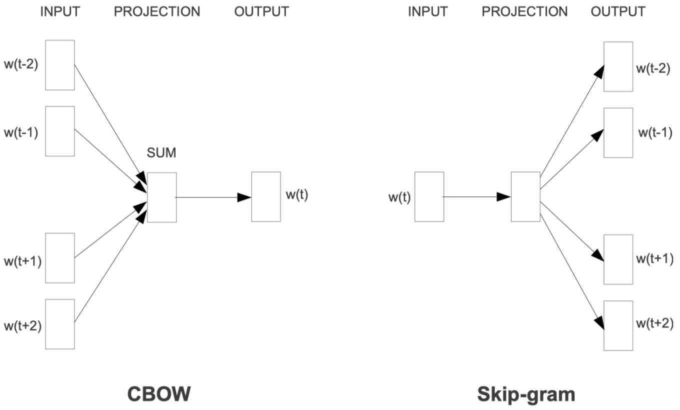
Textbook recommendation

Dan Jurafsky/James H. Martin (2019). *Speech and Language Processing*. 3rd ed. Draft of October 16, 2019. Prentice Hall

Core Idea

- Define a classification task for which we have huge training data sets
  - Given a word, predict predict possible context words
  - Training data: Any text collection (e.g., Wikipedia)
- Train a neural network
- Extract learned weights and use as embeddings

Two tasks



Continuous Bag of Words (CBOW)

Context words used to predict a single word

Skip-Gram

One word used to predict its context

Word2Vec

Skip-Gram

- Context: ± 2 words around target word t

```
... lemon, a [tablespoon of apricot jam, a] pinch ...
              c1          c2 t          c3   c4
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Skip-Gram

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- Classifier:
  - Predict for (t, c) wether c are *really* context words for t
  - Probability of $\vec{t}$ and $\vec{c}$ being positive examples: $p(+|\vec{t}, \vec{c})$

Word2Vec Training

- NN training: We start with random vectors, and iteratively improve them
- Vector similarity can be measured easily
  - Dot product / cosine!
- "a word is likely to occur near the target if its embedding is similar to the target embedding" Jurafsky/Martin (JM19, 112)
  - Probability is based on similarity
  - Similarity $\rightarrow$ probability? Sigmoid / logistic function!

When are vectors similar?

- Metric that takes two vectors and returns a similarity score
- Linear algebra: dot product ("Skalarprodukt")

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$$\vec{a} \cdot \vec{b} \;=\; \sum_{i=1}^{N} a_i b_i$$

Dot product

Example

$$
\begin{aligned}
\vec{a} &= [0, 0, 1, 1] \\
\vec{b} &= [0, 0, 1, 0.95] \\
\vec{a} \cdot \vec{b} &= 1.95
\end{aligned}
$$

Dot product

Example

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\begin{aligned}
\vec{a} &= [0, 0, 1, 1] \\
\vec{b} &= [0, 0, 1, 0.95] \\
\vec{a} \cdot \vec{b} &= 1.95 \\
\vec{a}' &= 10\vec{a} = [0, 0, 10, 10] \\
\vec{b}' &= 10\vec{b} = [0, 0, 10, 9.5]
\end{aligned}
$$

Dot product

Example

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\vec{b}' &= 10\vec{b} = [0,0,10,9.5] \\
\vec{a}'\cdot\vec{b}' &= 195
\end{aligned}
$$

Dot product as similarity metric?

- Favours high frequent words
  - For the word ‘Cologne’, it’s easier to be similar to ‘the’ than to ‘Düsseldorf’
  - Because ‘the’ is more frequent (= has more higher numbers in its vector) than ‘Cologne’

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  - Normalisation can mostly done by dividing by something

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$$\frac{\vec{a} \cdot \vec{b}}{|\vec{a}||\vec{b}|} = \frac{\sum_{i=1}^{N} a_i b_i}{|\vec{a}||\vec{b}|}$$

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\vec{a} \cdot \vec{b} &= \sum_{i=1}^{N} a_i b_i \\
\frac{\vec{a} \cdot \vec{b}}{|\vec{a}||\vec{b}|} &= \frac{\sum_{i=1}^{N} a_i b_i}{|\vec{a}||\vec{b}|} \\
&= \frac{\sum_{i=1}^{N} a_i b_i}{\sum_{i=1}^{N} a_i^2 \sum_{i=1}^{N} b_i^2} = \cos \sphericalangle(\vec{a}, \vec{b})
\end{aligned}
$$

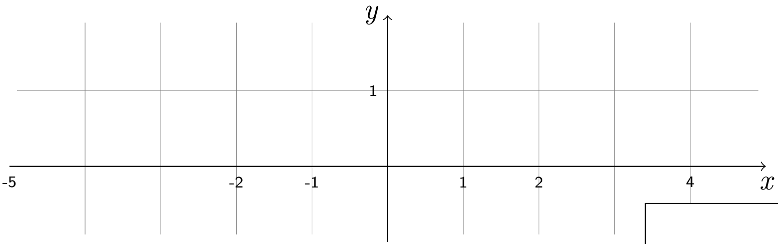
Cosine Similarity Metric

$$\cos \sphericalangle(\vec{a}, \vec{b}) = \frac{\sum_{i=1}^{N} a_i b_i}{\sum_{i=1}^{N} a_i^2 \sum_{i=1}^{N} b_i^2}$$

- Independent of length (measures the angle between the vectors)
- Simple to calculate

The Logistic Function

Turn Similarities into Probabilities



$$y = \frac{1}{1+e^{-x}} = \frac{1}{1+e^{-(ax+b)}}$$

$$e = \sum_{n=0}^{\infty} \frac{1}{n!} = 2.71828$$

(Euler's Number)

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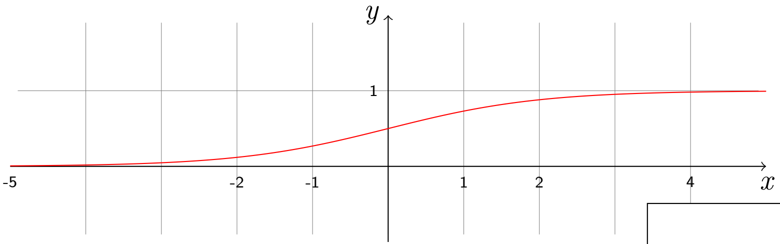

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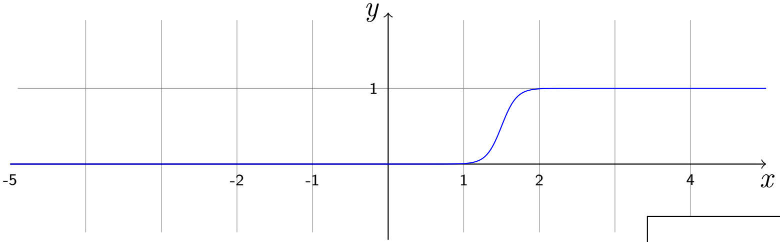

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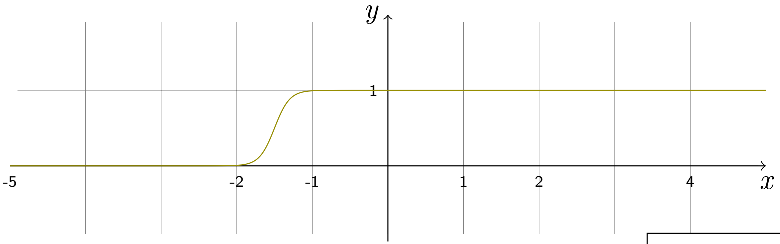

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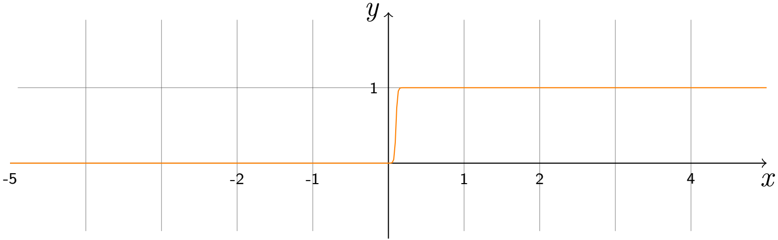

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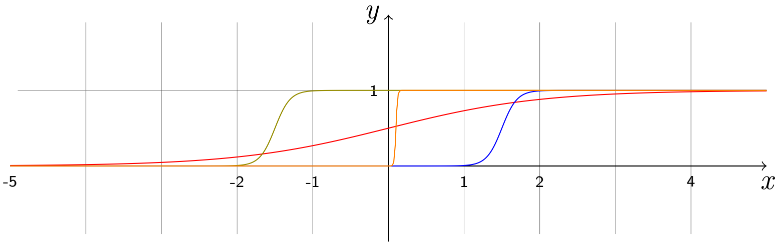

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Skip-gram

Notation

t, c: words

$\vec{t}$, $\vec{c}$: vectors for the words

(this is different from JM19)

cosine similarity

$$p(+|t,c) = \frac{1}{1+e^{-\vec{t}\cdot\vec{c}}} = \sigma(\vec{t}\cdot\vec{c})$$

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$$
\begin{aligned}
p(+|t,c_{1:k}) &= \prod_{i=1}^{k} \frac{1}{1+e^{-\vec{t}\cdot\vec{c}_i}} \\
\log p(+|t,c_{1:k}) &= \sum_{i=1}^{k} \log \frac{1}{1+e^{-\vec{t}\cdot\vec{c}_i}}
\end{aligned}
$$

Skip-gram

- So far, we have assumed that we have vector $\vec{t}$ for word t, but where do they come from?
- Basic gradient descent: We start randomly, and iteratively improve

Skip-gram

Negative sampling

- Negative examples
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  - For every positive tuple (t, c), we add k negative tuples
  - Negative tuple (t, c_n), with c_n randomly selected (and $t \neq c_n$)

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- Negative sampling
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  - Negative tuple (t, c_n), with c_n randomly selected (and $t \neq c_n$)
  - Select noise words according to their weighted frequency
  - $p_\alpha(w) = \frac{count(w)^\alpha}{\sum_{w'} count(w')^\alpha}$
    - This leads to rare words being more frequently selected, frequent words less

Skip-gram

Negative sampling

- Negative examples
  - Training a classifier needs negative examples, i.e., words that are not in the context of each other
- Negative sampling
  - For every positive tuple (t, c), we add k negative tuples
  - Negative tuple (t, c_n), with c_n randomly selected (and $t \neq c_n$)
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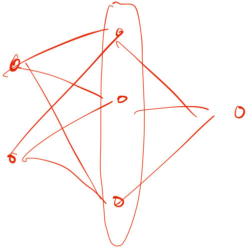
    - This leads to rare words being more frequently selected, frequent words less
- Two more hyperparameters on this slide: k and α

Section 2

Encoder-Attention-Decoder Architecture

Different Layer Types



- So far: fully connected layer
- Other layers
  - Convolutional layer
  - Dropout layer
  - Recurrent layer
  - Long short-term memory (LSTM) layer
  - ...

Sequence

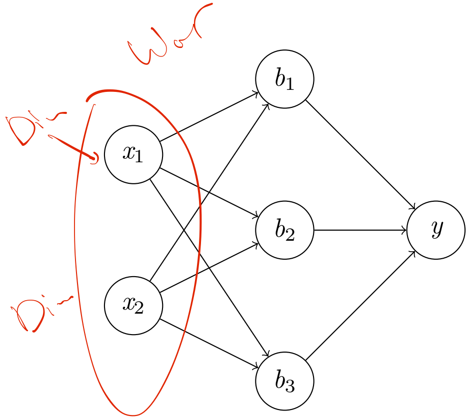
Different Layer Types

- So far: fully connected layer
- Other layers
  - Convolutional layer
  - Dropout layer
  - Recurrent layer
  - Long short-term memory (LSTM) layer
  - ...

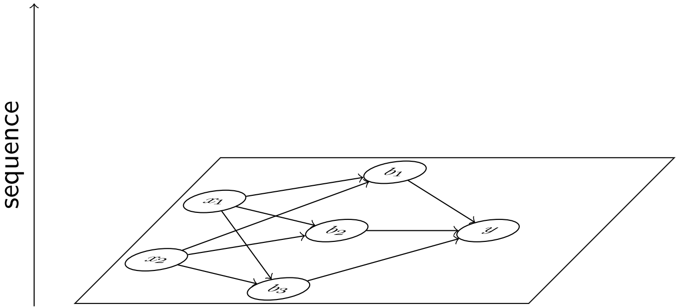
Sequences are important for NLP

- Many NLP tasks are sequential tasks: The outcome of one item has impact on the next item (e.g., part of speech)
- Recurrent and LSTM layers add new connections
- Instead of processing one item at a time, they look at sequences
- Connections along the sequence (i.e., the neuron knows its output for the previous item)

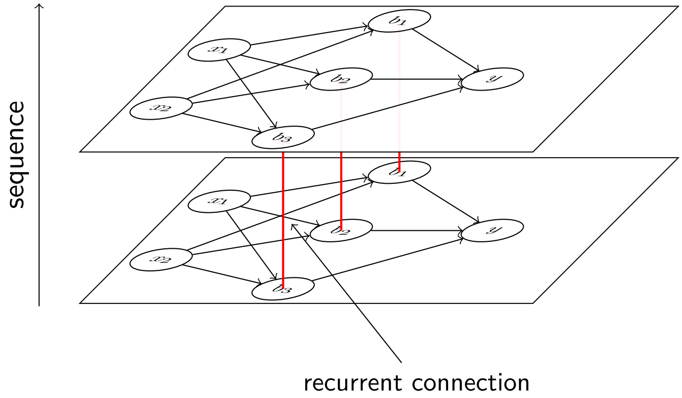
Recurrent Neural Networks



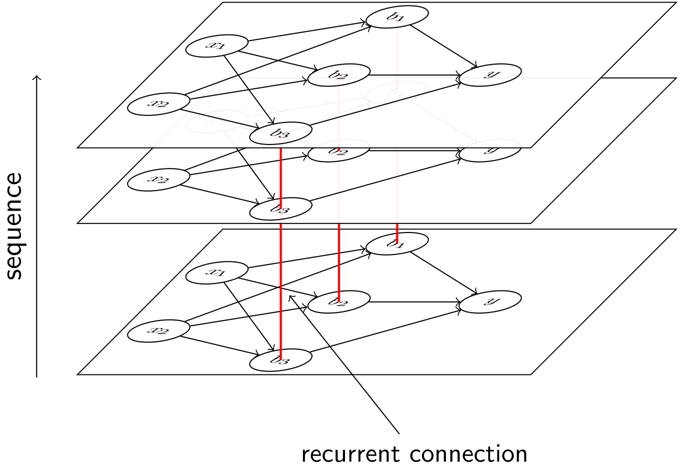
Recurrent Neural Networks



Recurrent Neural Networks



Recurrent Neural Networks

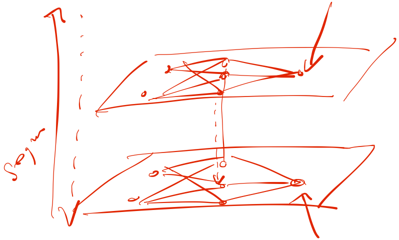


Recurrent Neural Networks

- Feed-forward neural networks: Weights between neurons
- Recurrent neural networks
  - Weights between neurons
  - Weight(s) for recurrent connections

Recurrent Neural Networks

- Feed-forward neural networks: Weights between neurons
- Recurrent neural networks
  - Weights between neurons
  - Weight(s) for recurrent connections
- Also possible in two directions



Encoder-Decoder-Architecture

- Often: No 1-to-1 relation between input and output
  - I.e.: Not as many output items as input items (e.g., machine translation)

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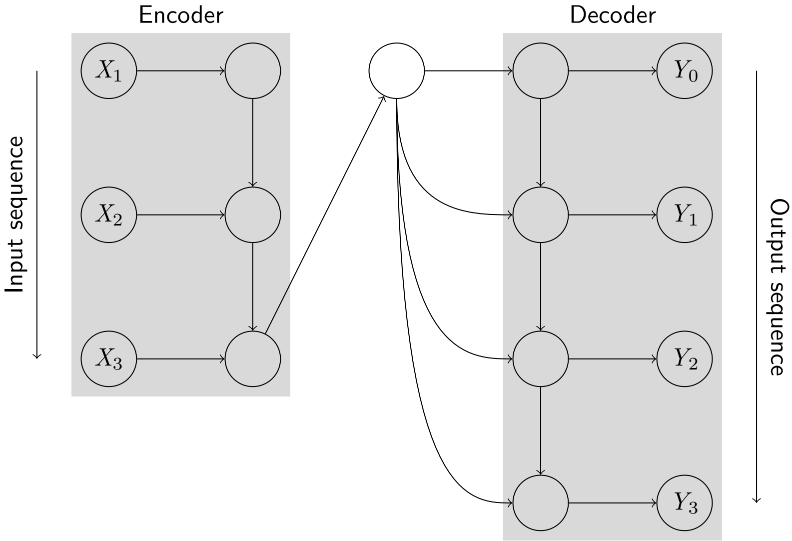
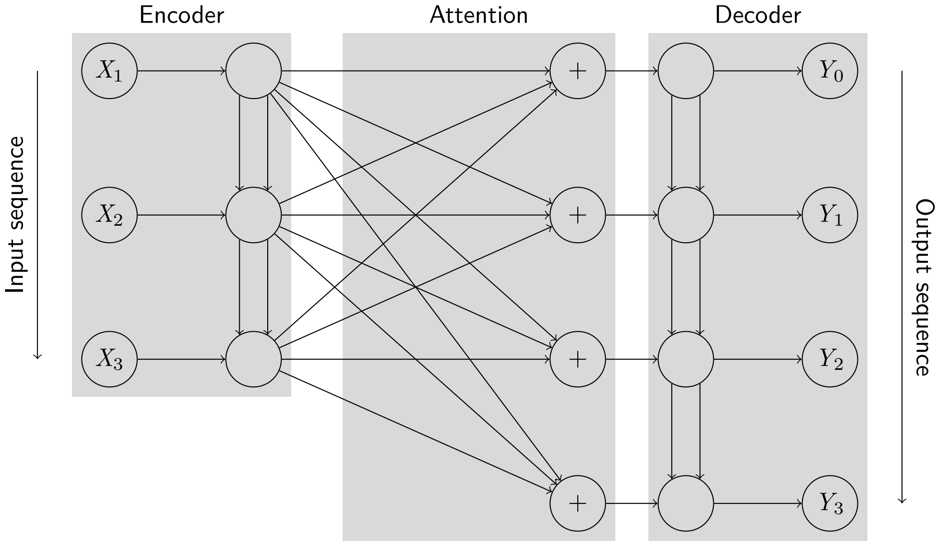
  - I.e.: Not as many output items as input items (e.g., machine translation)
- Encorder-decoder-network has two parts:
  - Encoder maps from input data to an internal representation
  - Decoder maps from internal representation to the output
- Internal representation
  - Use the output or internal state of last recurrent cell
  - Not interpretable

From Encoder-Decoder to Attention



From Encoder-Decoder to Attention



Section 3

BERT

Introduction

- BERT has outperformed the state of the art in many tasks
- Breakthrough in natural language processing

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- BERT has outperformed the state of the art in many tasks
- Breakthrough in natural language processing
- General idea
  - Encoder-Attention-Decoder architecture (= transformer)
  - Process whole input at once (max. 512 tokens, = bidirectional)
  - Pre-training and fine-tuning on different tasks

Jacob Devlin/Ming-Wei Chang/Kenton Lee/Kristina Toutanova (2019). "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding". In: *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*. Minneapolis, Minnesota: Association for Computational Linguistics, pp. 4171–4186. DOI: 10.18653/v1/N19-1423. URL: https://aclanthology.org/N19-1423

Pre-Training and Fine-Tuning

- BERT models are trained on huge data sets
- Training one from scratch requires significant resources (time/money)
- Pre-trained models are shared freely
- Recipe: Take a pre-trained model and fine-tune it on your task
  - Pre-trained model contains an abstract language representation

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- Recipe: Take a pre-trained model and fine-tune it on your task
  - Pre-trained model contains an abstract language representation
- Fine-tuning
  - Any language-related task!

BERT Training Tasks

Masked Language Modeling (MLM)

- Sentence-wise
- 15% of the tokens are "masked" by a special token
- Model predicts these, having access to all other tokens

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- Sentence-wise
- 15% of the tokens are “masked” by a special token
- Model predicts these, having access to all other tokens

Next sentence prediction (NSP)

- Two (masked) sentences are concatenated
- Model has to predict wether second sentence follows on the first or not

Section 4

Summary

Summary

Word2Vec

- Take learned weights as vector representation for input
- Allows “semantic calculation”

BERT

- Split up training process into two
  - Pretraining on simple, generic tasks
  - Fine-tuning on specific tasks
- Use bidirectional NN architecture
- Use huge data sets for pretraining

References I

Devlin, Jacob/Ming-Wei Chang/Kenton Lee/Kristina Toutanova (2019). “BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding”. In: *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*. Minneapolis, Minnesota: Association for Computational Linguistics, pp. 4171–4186. DOI: 10.18653/v1/N19-1423. URL: https://aclanthology.org/N19-1423.

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