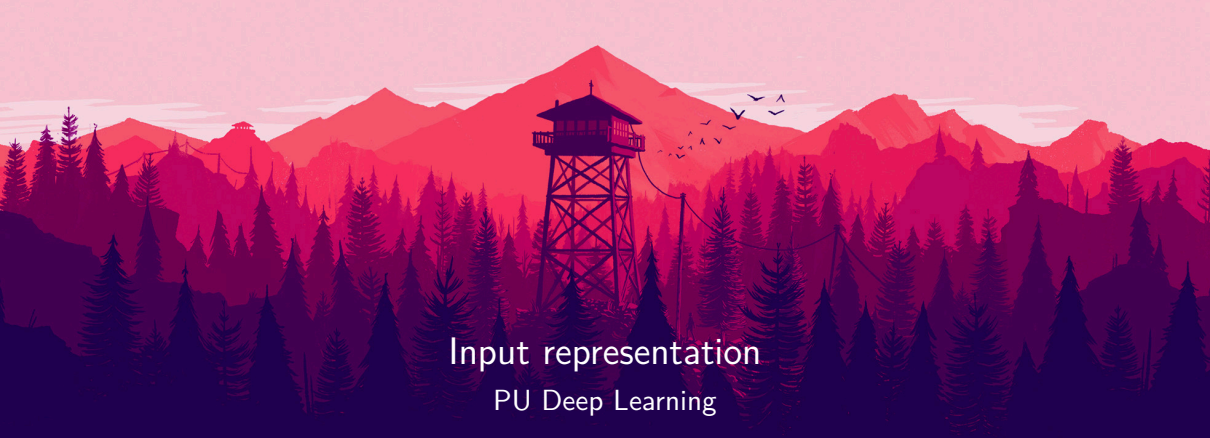

Input representation

PU Deep Learning

Nils Reiter, nils.reiter@uni-koeln.de

June 8, 2021 (Summer term 2021)

Recap

Bag of words

- Count words, disregard their order
- Document → vector → input for neural network
- scikit-learn: `CountVectorizer`

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- No strict, deterministic decision
- Regularization: Add something to loss function
- Dropout: Randomly remove edges during training, force the network to create redundancies

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Exercise 7

Administration

- Modulprüfungen
  - Modul: Angewandte Linguistische Datenverarbeitung
  - Anmeldung: Bis 30.07.
  - Abmeldung: Bis 14.09.
  - Modus: Hausarbeit mit praktischem Anteil/Experiment
    - Kann, muss aber nicht, Bezug zum HS Computational Literary Studies haben
    - ...oder zu einem Modul-HS aus den letzten Semestern
  - Abgabedatum: 15.09.
    - Abweichung in Absprache möglich

Today

Input Representation

Embeddings

Implementing Embeddings in Keras

Exercise

Section 1

Input Representation

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  - Makes things a lot easier
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Last Week: Bag of Words

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  - Makes things a lot easier
  - But it's not how language works
- Example
  - »This remake was even greater than the original.«
  - »Deciding to make the script into a 3D movie led to an even greater failure.«
- How could we represent words in order and context with feed-forward neural networks?

Sequential Input

- Enumerate all words and replace the strings with index numbers
- Use n words at once as input features

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- »The best soundtrack ever to anything: […]«
  Bag of Words

$$text = \begin{bmatrix} a & 5 \\ an & 2 \\ animal & 0 \end{bmatrix}$$

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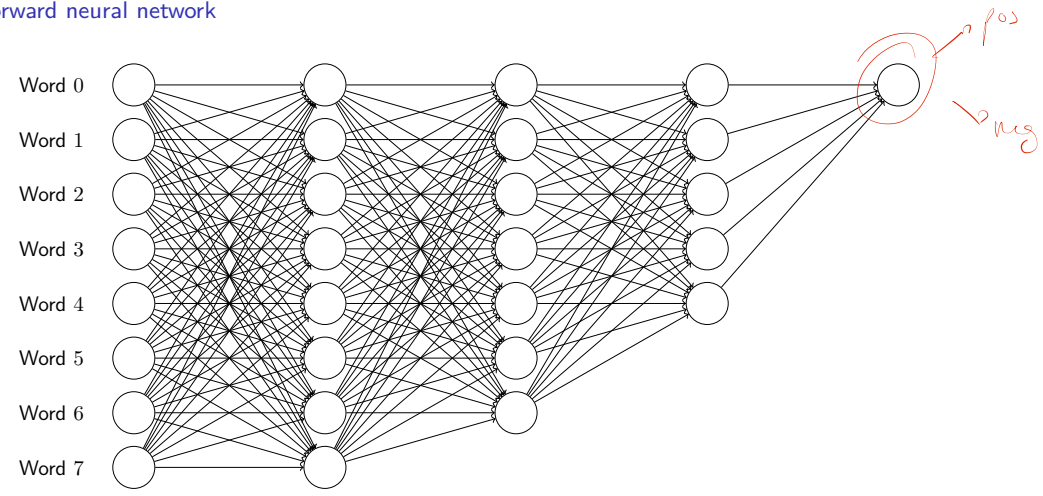
Sequential word indices

$$text = \begin{bmatrix} the & 5 \\ best & 124 \\ soundtrack & 15 \end{bmatrix}$$

Sequential Input

In a feed-forward neural network



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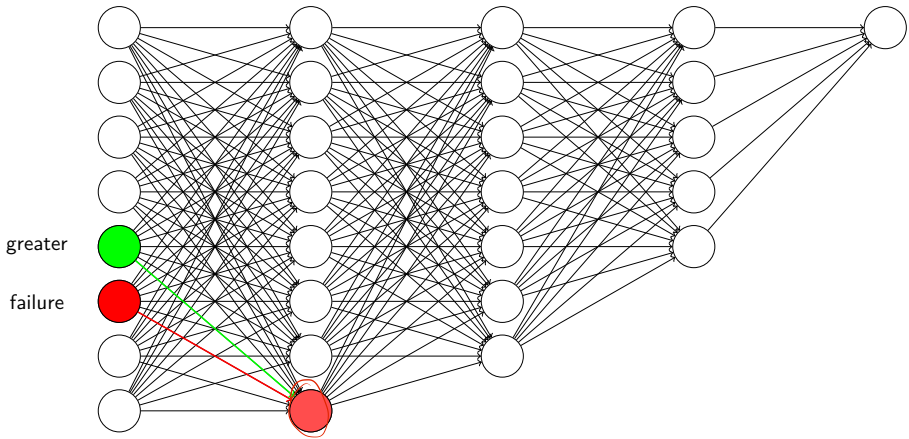

Sequential Input

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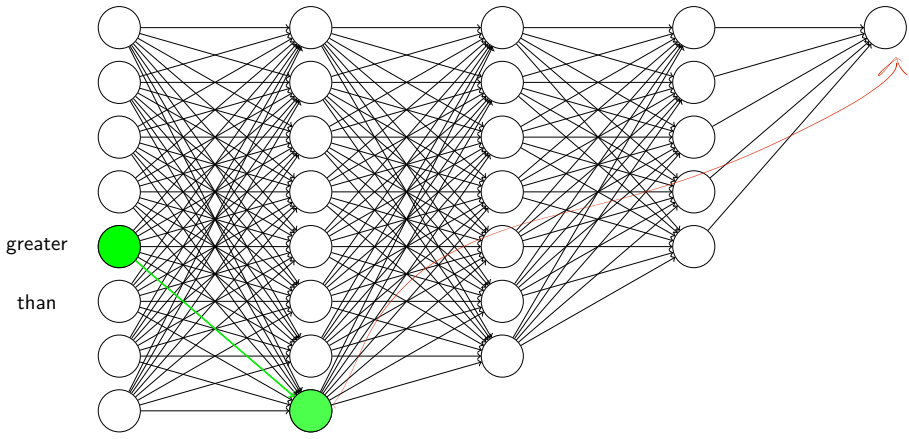

Sequential Input

Problems

- Fixed word positions
  No connection between these sentences:
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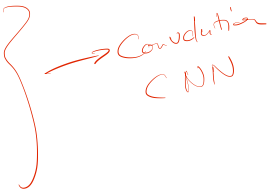

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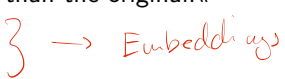

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- No generalization across small variations
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- No connection irrespective of the position

Section 2

Embeddings

Motivation

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  - Things are ›embedded‹ in a vector space

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Motivation

- An embedding is a mapping of words or documents to vectors
  - Things are ›embedded‹ in a vector space
- Why do we need this?
  - Classically, words are discrete symbols
    - For neural networks, each word is replaced by a word index
- We can do better
  - Representing a word as a vector allows calculating similarity between words
  - If the embedding works well, similarity between word *meanings*

Documents as vectors

Document	Dog	Cat
1	10	2
2	5	0
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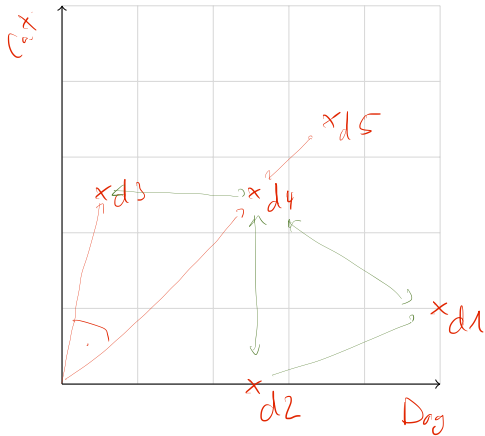

Documents as vectors

Document	Dog	Cat
1	10	2
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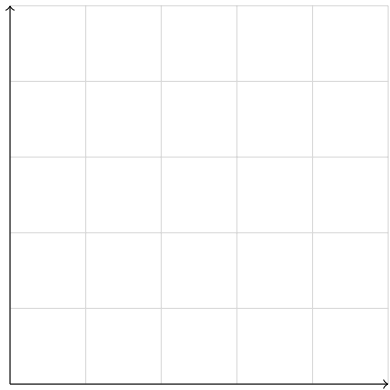
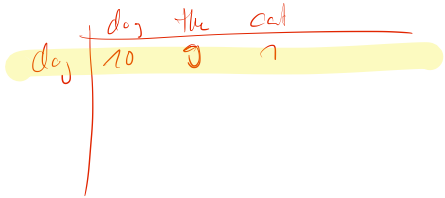
- Document-term-matrix
  Sparsely populated!
- Count vector
- Similarity based on vector angle



Words as vectors



- Co-occurrence windows: Count how often a word co-occurs with every other word
  - ›Vocabulary V‹: Set of words in entire corpus
  - Results in $|V| \times |V|$ matrix
  - Mostly zeros (because of the Zipf distribution)

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- Singular value decomposition (SVD): Mathematically reduce dimensions

Word Embeddings (after 2013)

Bojanowski et al. (2016), Mikolov et al. (2013), and Pennington et al. (2014), ...

- Dense representations of words in vector space
- Word vectors: Weights learned by a simple neural network with a classification target
  - word2vec: Given word w_i, how likely is it that w_j appears in its context?
- Idea
  - Embeddings are learned using a neural network
  - Classification task: Given a word, predict its context words
    - Training data in abundance
  - Use learned weights as embeddings

Embeddings and neural networks

- Existing (pre-trained) embeddings can be plugged in
- Specific embeddings can be trained, just like all other weights

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- Glove (Stanford University): `https://nlp.stanford.edu/projects/glove/`
- FastText (facebook research): `https://fasttext.cc` (multiple languages)

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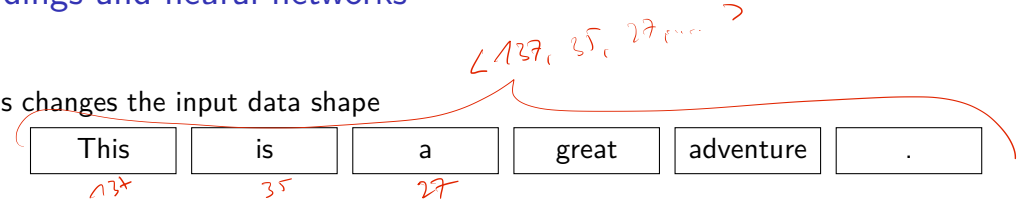
```
adventure 0.0292 -0.0269 0.0273 0.0792 -0.0617 0.1370 -0.0628 0.0420
0.0743 0.0979 -0.0136 0.0488 -0.0267 -0.0227 0.0592 0.0410 0.0314 0.0378
-0.0455 0.0616 -0.0380 0.0232 -0.0218 0.0000 -0.0699 -0.1327 -0.0393
0.0467 0.0413 0.0089 -0.0046 0.0372 -0.0590 0.0740 0.0214 0.0625 0.0067
-0.0063 0.0218 -0.0447 -0.0298 0.0186 -0.0207 0.0158 -0.0508 -0.0297
-0.0807 -0.0619 -0.0194 -0.0153 0.0909 -0.0037 0.0999 -0.0110 ...
```

Embeddings and neural networks

- This changes the input data shape



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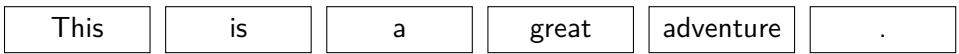

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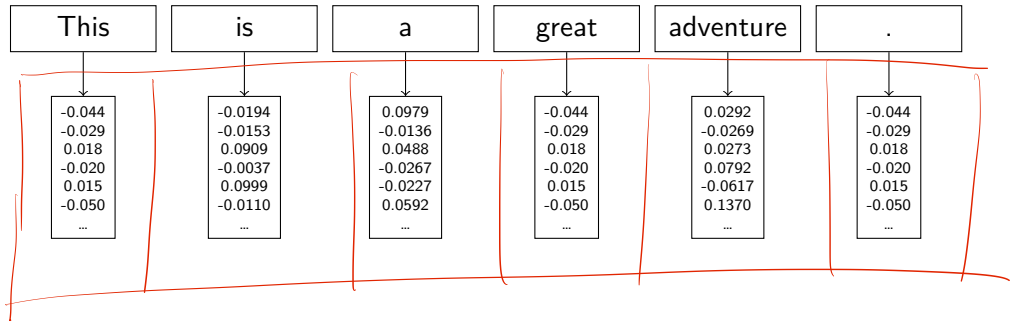

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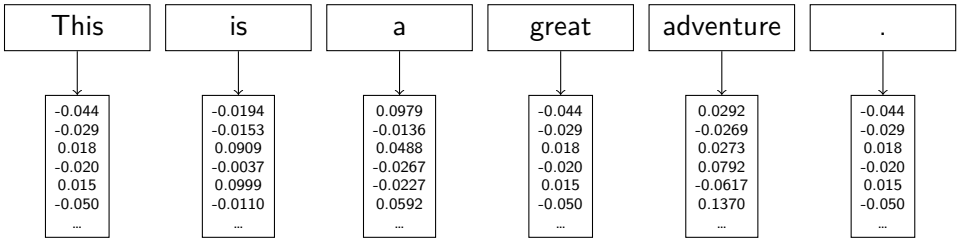

- This is a matrix!
  - I.e., by embedding tokens into a vector space, we have changed the shape of our data from 1D to 2D

Fixed Length of Input

- Our input now consists of a matrix (per instance)
- Matrix size needs to be predefined
  - Embedding dimension: Parameter we can set freely
  - Length: To be set on training data

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- Padding
  - Extend shorter inputs so that they have the same length
  - Truncate longer inputs
  - Keras: Function `tensorflow.keras.preprocessing.sequence.pad_sequences(...)`

Section 3

Implementing Embeddings in Keras

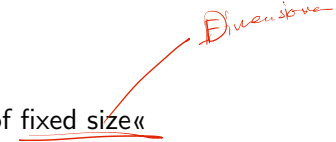
Implementing Embeddings in Keras

- Two relevant new layers
  - `tensorflow.python.keras.layers.Embedding()`
  - `tensorflow.python.keras.layers.Flatten()`
- Preparations
  - `tensorflow.keras.preprocessing.text.Tokenizer()`
  - `tensorflow.keras.preprocessing.text.text_to_word_sequence()`
  - `tensorflow.keras.preprocessing.sequence.pad_sequences()`

Embeddings

`tensorflow.python.keras.layers.Embedding(...)`

- Must be the first layer of the model
- »Turns positive integers (indexes) into dense vectors of fixed size«



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- Parameters
  - `input_dim`: Size of the vocabulary (i.e., how many words to distinguish)
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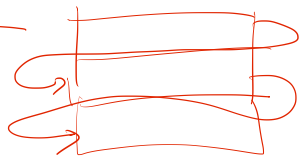
  - `output_dim`: How many elements to word vectors have?
  - `input_length`: Length of input vectors (e.g., sentences)
- Pre-trained embeddings
  - Documentation: `https://keras.io/examples/nlp/pretrained_word_embeddings/`
  - Parameters
    - `embeddings_initializer=keras.initializers.Constant(embedding_matrix)`
    - `trainable=False`
  - `embedding_matrix` is a numpy matrix that contains the vectors loaded from a file

Flatten

- Network structure so far: Only 1-dimensional vectors
- Result of embedding layer: matrices (2D)
- Flatten layer: Combine all rows of a matrix to a long vector
- `layers.Flatten()`
  - Usually used after an embedding layer



Preparations

1. Tokenizer
   - Establish vocabulary
   - Assign each type an integer number
2. Map token sequences to integer sequences
3. Padding
   - Ensure that all sequences have the same length by truncating or adding

Full Example

```
tokenizer = Tokenizer()
tokenizer.fit_on_texts(train_texts)
vocab_size = len(tokenizer.word_index) + 1
train_texts = tokenizer.texts_to_sequences(train_texts)

MAX_LENGTH = max(len(train_ex) for train_ex in train_texts)

train_texts = pad_sequences(train_texts, maxlen=MAX_LENGTH, padding="post")

model = models.Sequential()
model.add(layers.Input(shape=(MAX_LENGTH)))
model.add(layers.Embedding(vocab_size, 100, input_length=MAX_LENGTH))
model.add(layers.Flatten())
model.add(layers.Dense(10, activation="sigmoid"))
model.add(layers.Dropout(0.5))
model.add(layers.Dense(1, activation="sigmoid"))

model.summary()
```

Section 4

Exercise

Exercise 08

https://github.com/idh-cologne-deep-learning/exercise-08