Big Data and Automated Content Analysis (12EC)
Week 11: »Beyond Bag-of-Words«
Friday

Damian Trilling
d.c.trilling@uva.nl, @damian0604

April 25, 2022

UvA RM Communication Science

Today

From word counts to word vectors

- Training word embeddings
- Using word embeddings to improve models
- Document similarity
- (Ab-)using word embeddings to detect biases
- AEM: An application from our own research
- Downstream tasks

Neural Networks and Deep Learning

- Neural Networks in Keras
- Using pretrained embeddings

Next steps

Before we start: Questions from last week?

Today: Beyond BOW: word embeddings, neural networks, and deep learning

Word vectors

Our BOW approach until now

Representing a document by word frequency counts

Result of preprocessing and vectorizing:

0. `He took the dog for a walk to the dog playground`

$\Rightarrow$ `took dog walk dog playground`

$\Rightarrow$ `'took':1, 'dog': 2, walk: 1, playground: 1`

Consider these other sentences

1. He took the doberman for a walk to the dog playground
2. He took the cat for a walk to the dog playground
3. He killed the dog on his walk to the dog playground

The vectorized representations of these sentences have a "distance" (dissimilarity) of 1 each, but arguably, sentences 0 and 1 should be "closer" than others

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- Our vectorizers gave a random ID to each word
- What if we instead would represent each word by another vector representing its meaning?
- For, instance, 'doberman' and 'dog' should be represented by vectors that are close to each other in space, while 'kill' and 'walk' should be far from each other.

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Or, more broadly: Can computers understand meanings, semantic relationships, different types of contexts?

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Word vectors

Training word embeddings

GloVe vs Word2Vec

There are two popular approaches to training word embeddings: GloVe and word2vec.

- GloVe is count-based: dimensionality reduction on the co-occurrence count matrix.
- Word2Vec is a predictive model: neural network to predict words/contexts
- That means that GloVe takes *global* context into account, word2vec *local* context
- Some technical implications for how training can be implemented
- **However, often only subtle differences in final result.**

Word2Vec: Continous Bag of Words (CBOW) vs skipgram

Example sentence: "the quick brown fox jumped over the lazy dog"

CBOW: Predict a word given its context

Dataset:

`([the, brown], quick), ([quick, fox], brown), ([brown, jumped], fox), ...`

skipgram: Predict the context given the word

`(quick, the), (quick, brown), (brown, quick), (brown, fox), ...`

Example taken from here: https://medium.com/explore-artificial-intelligence/word2vec-a-baby-step-in-deep-learning-but-a-giant-leap-towards-natural-language-processing-40fe4e86

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Continous Bag of Words (CBOW) vs skipgram

- CBOW is faster
- skipgram works better for infrequent words
- Both are often used
- Usually, we use larger window sizes (e.g, 5)
- We need to specify the number of dimensions (typically 100–300)

*In any event, as a result of the prediction task, we end up with a {100|200|300}-dimensional vector representation of each word.**

* If that makes you think of PCA/SVD, that's not completely crazy, see Levy et al., 2018

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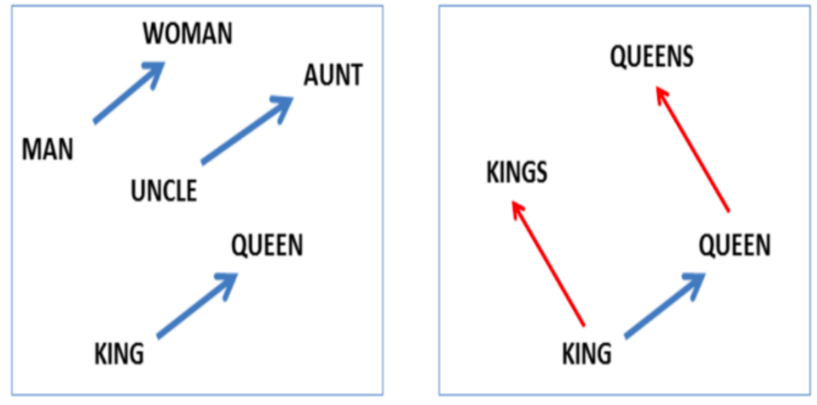
"...a word is characterized by the company it keeps..."(Firth, 1957)

Word embeddings ...

- help capturing the meaning of text
- are low-dimensional vector representations that capture semantic meaning
- are very common in NLP...

You can literally calculate with words!

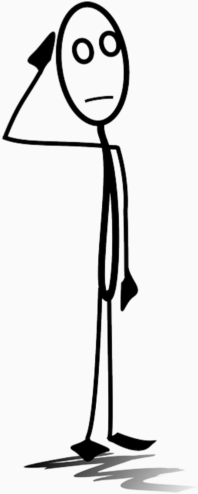
And answer questions such as “Man is to woman as king is to ____?”



semantic relationships vs. syntactic relationships

Word vectors

Improving models



What can we use word embeddings for?

In supervised machine learning

- For instance, we could modify our vectorizer such that for each term, you do not only count how often it occurs, but also multiply with its embedding vector
- Aggregate these embeddings (e.g., sum or mean) and represent document with 300 instead of 10,000 dimensions!
- Often, pre-trained embeddings (e.g., trained on the whole wikipedia) are used
- Thus, our supervised model will be able to deal with synonyms and related words!

Let's look at an example for using supervised sentiment analysis (i.e., what we did with IMDB-data before).

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In classical SML:

- we represent each document by a vector of word frequencies (or tf$\cdot$ idf scores)
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	ability	about	above	...	zippered	zealotry	→	topic
text1	■	■	■	...	■	■	→	■
text2	■	■	■	...	■	■	→	■
text3	■	■	■	...	■	■	→	■
text4	■	■	■	...	■	■	→	■
new case	■	■	■	...	■	■	→	?

For instance, topic can be [“sports”, “economy”, “politics”] and the other entries are word frequencies

The idea

We modify our vectorizer such that

- for each word in the document, we look up its embedding
- we then aggregate these embeddings (e.g., mean, max, or sum)
- For each document, we now have a 300-dimensional instead of a 10,000-dimensional vector[1]

Example implementation at https://github.com/ccs-amsterdam/embeddingvectorizer

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What does that mean?

A couple of things:

- Our model is smaller
- We can use words in the prediction dataset *even if it's not in the training dataset*[2]
- We can learn from similar training samples even if they do not use the same words
- But we also may loose some nuance

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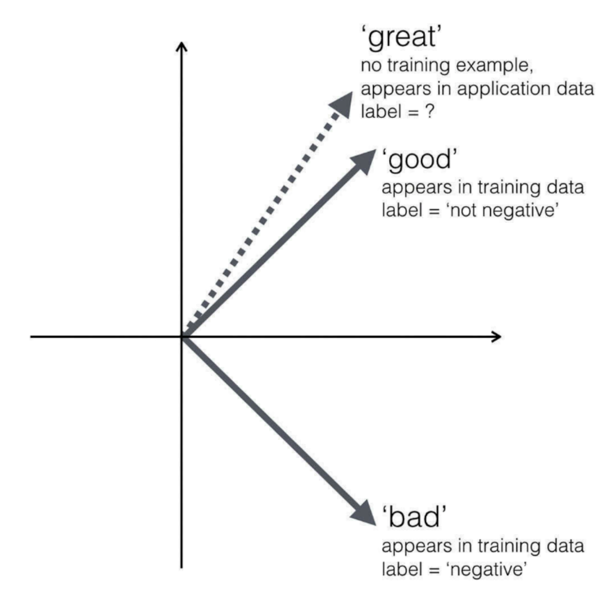
Let's look at an example

As we see, not *all* embedding models are improving downstream tasks – but good ones can: https://github.com/annekroon/amsterdam-embedding-model

[explain results in README.md]



Rudkowsky et al., 2018

It's not always black/white. . .

Sometimes, BOW may be just fine (for very negative sentences, it doesn't matter). But especially in less clear cases ('slightly negative'), embeddings increased performance.

Table 1. Precision, recall, and F1 score for the bag of words approach.

	Actual	Predicted	Precision	Recall	F1 Score
not/slightly negative	524.3	205.6	0.33	0.83	0.47
negative	805.7	1188.7	0.71	0.48	0.57
very negative	730	665.7	0.53	0.58	0.56

Table 2. Precision, recall, and F1 score for the Word Embeddings approach.

	Actual	Predicted	Precision	Recall	F1 Score
not/slightly negative	522.4	575	0.65	0.59	0.61
negative	799.2	771.6	0.52	0.53	0.53
very negative	739.4	714.4	0.55	0.57	0.56

Rudkowsky et al., 2018

Word vectors

Document similarity

In document similarity calculation

Use cases

- plagiarism detection
- Are press releases/news agency copy/...taken over?
- Event detection

Traditional measures

- Levenshtein distance (How many characters|words do I need to change to transform string A into string B?)
- Cosine similarity ("correlation" between the BOW-representations of string A and string B)

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BUT: This only works for literal overlap. What if the writer chooses synonyms?

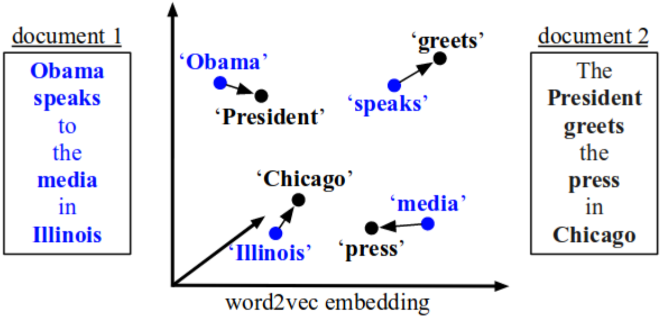

Figure 1. An illustration of the *word mover's distance*. All non-stop words (***bold***) of both documents are embedded into a *word2vec* space. The distance between the two documents is the minimum cumulative distance that all words in document 1 need to travel to exactly match document 2. (Best viewed in color.)

Kusner et al., 2015

There are several approaches

- word mover's distance
- soft cosine similarity

In common: we use pre-trained embeddings to replace words (that otherwise would just have a random identifier and be unrelated) with vectors representing their meaning, when calculating our measure of interest

Word vectors

Detecting biases

Biased embeddings Bolukbasi et al., 2016

- word embeddings are trained on large corpora
- As the task is to learn how to predict a word from its context (CBOW) or vice versa (skip-gram), biased texts produce biased embeddings
- If in the training corpus, the words "man" and "computer programmer" are used in the same context, then we will learn such a gender bias

Biased embeddings

Usually, we do not want that (and it has a huge potential for a shitstorm)

unless. . .

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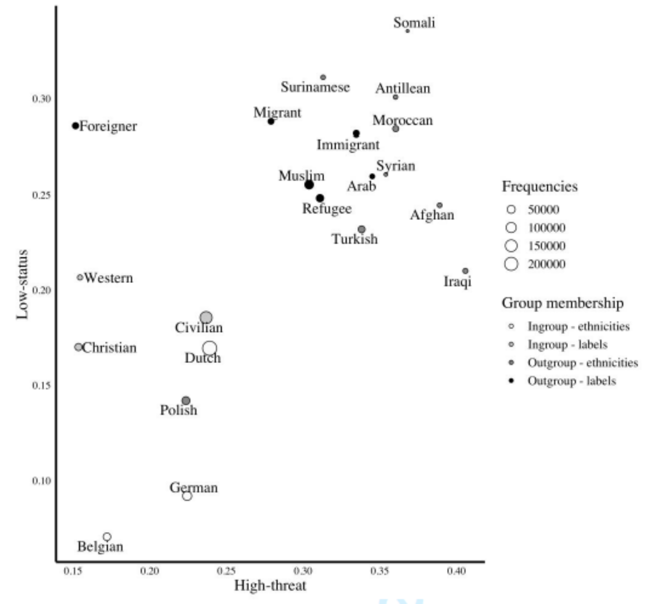
An exmaple from our research (Kroon et al., 2021)

We trained word embeddings on 3.3 million Dutch news articles.

Are vector representations of outgroups (Maroccans, Muslims) closer to representations of negative stereotype words than ingroups?


Somali
Surinamese
Antillean
Migrant
Moroccan
Foreigner
Immigrant
Syrian
Muslim
Arab
Refugee
Afghan
Turkish
Iraqi
Western
Civilian
Christian
Dutch
Polish
German
Belgian
0.30
0.25
0.20
0.15
0.10
Low-status
0.15
0.20
0.25
0.30
0.35
0.40
High-threat
Frequencies
50000
100000
150000
200000
Group membership
Ingroup - ethnicities
Ingroup - labels
Outgroup - ethnicities
Outgroup - labels

Word vectors

AEM

We can use pre-trained embeddings – but can we make even better ones? **The Amsterdam Embedding Model (AEM)**

Anne Kroon, Antske Fokkens, Damian Trilling, Felicia Loecherbach, Judith Moeller, Mariken A. C. G. van der Velden, Wouter van Atteveldt

Why do this?

- Embedding models are of great interest to communication scholars
- yet... Most publicly available models represent **English** language
- The preparation of good-performing embedding models require a significant amount of **time** and **access to a large amount of data sets**
- Few Dutch embedding models are available, but trained on ordinary human language from the World Wide Web.
- These models do not capture the specifics of news article data and are therefore less suitable to study and understand dynamics of this domain
- $\Rightarrow$ No model is available trained on Dutch news data

Project's Aim

Aim of the current project

1. Develop and evaluate a high-quality embedding model
2. Assess performance in downstream tasks of interest to Communication Science (such as topic classification of newspaper data).
3. Facilitate distribution and use of the model
4. Offer clear methodological recommendations for researchers interested using our Dutch embedding model

Training data

Training data set

- Dataset: diverse print and online news sources
- Preprocessing: duplicate sentences were removed
- Telegraaf (print & online), NRC Handelsblad (print & online), Volkskrant (print & online), Algemeen Dabldad (print & online), Trouw (print & online), nu.nl , nos.nl
- # words: 1.18b (1181701742)
- # sentences: 77.1M (77151321)

Training model

Training model

- We trained the model using Gensim's Word2Vec package in Python
- Skip-gram with negative sampling, window size of 5, 300-dimensional word vectors

Evaluation

Evaluation of the Amsterdam Embedding Model

Evaluation

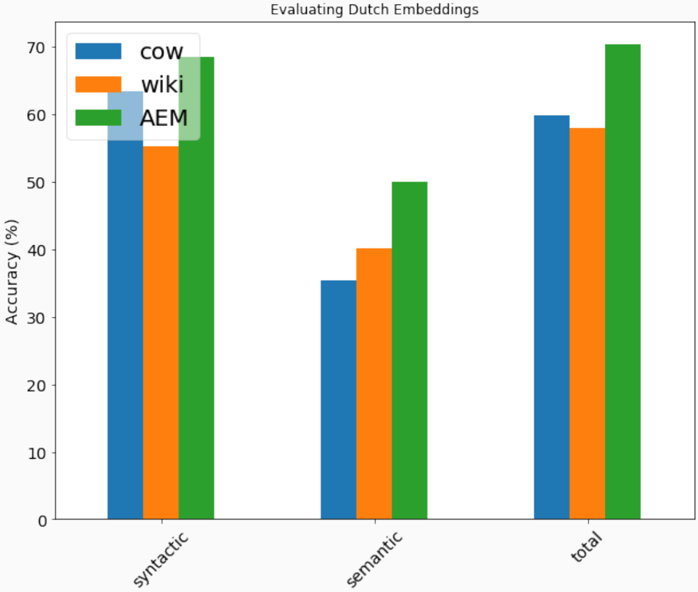
Evaluation methods

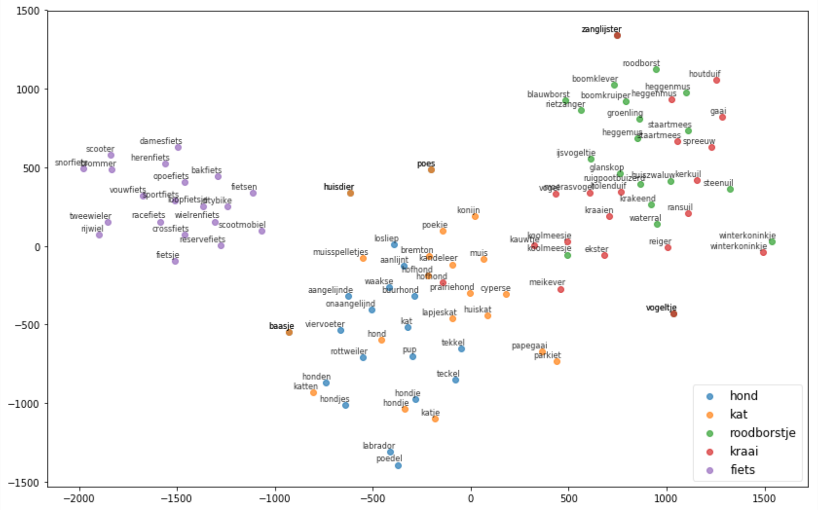
- To evaluate the model, we compare it to two other publicly available embedding models
  - ⇒ **'Wiki'**: Embedding model trained on Wikipedia data (FastText)
  - ⇒ **'Cow'**: Embedding model trained on diverse .nl and .be sites (Schafer & Bildhauer, 2012; Tulkens et al., 2016)
  - ⇒ **'AEM'**: Amsterdam Embedding Model

Evaluation data

Evaluation data

1. 'relationship'/ analogy-task (Tulkens et al., 2016)
   - **syntatic relationships**: dans dansen loop *[lopen]*
   - **semantic relationships**: denemarken kopenhagen noorwegen *[oslo]*
2. 5806 relationship tasks


Evaluating Dutch Embeddings
cow
wiki
AEM
Accuracy (%)
0
10
20
30
40
50
60
70
syntactic
semantic
total


hond
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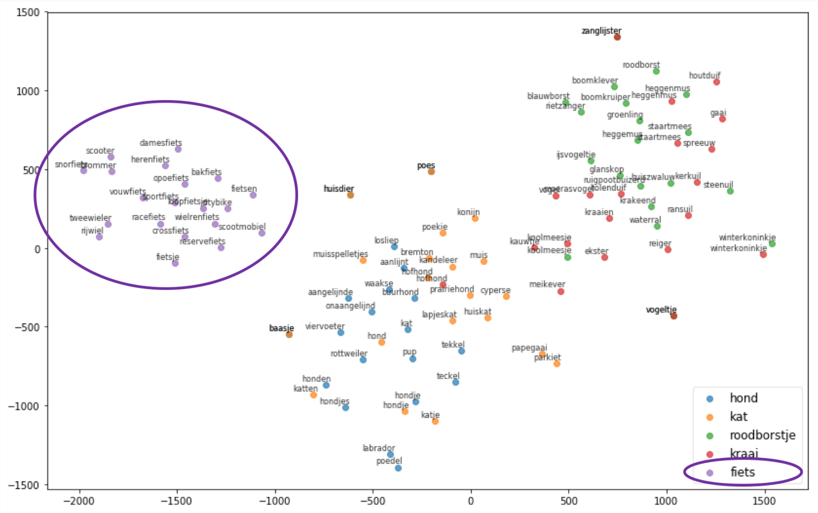
kraai
fiets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heggemus
spreeuw
ijsvogeltje
glanskop
steenuil
kraaien
krakeend
ransuil
waterral
winterkoninkje
reiger
ekster
koolmeesje
meikever
vogeltje
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damesfiets
scooter
snorfiets
brommer
herenfiets
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sportfiets
citybike
tweewieler
racefiets
wielrenfiets
scootmobiel
rijwiel
crossfiets
reservefiets
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poes
huisdier
konijn
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losliep
bremton
muisspelletjes
aanlijnt
kandeleer
muis
waakse
buurhond
prairiehond
cyperse
aangelijnde
onaangelijnd
lapjeskat
huiskat
baasje
viervoeter
kat
hond
tekkel
rottweiler
pup
teckel
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labrador
poedel
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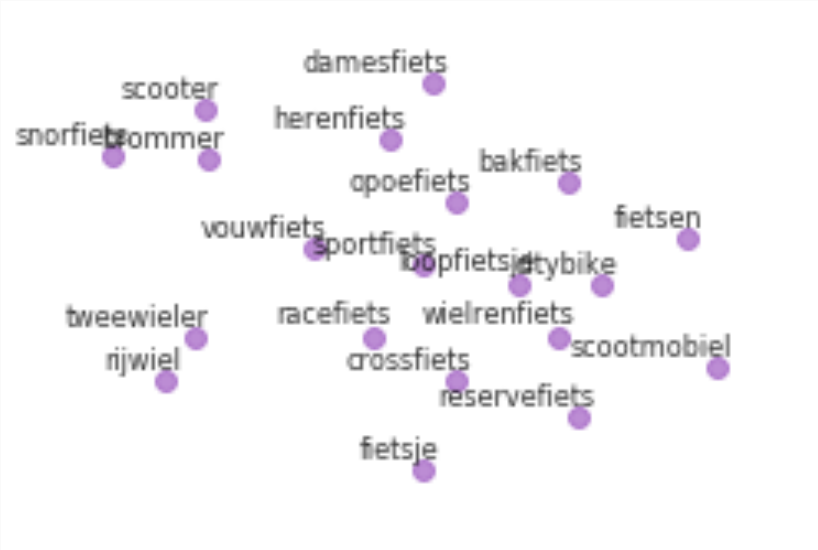
roodborstje
kraai
fiets


damesfiets
scooter
herenfiets
bakfiets
opoefiets
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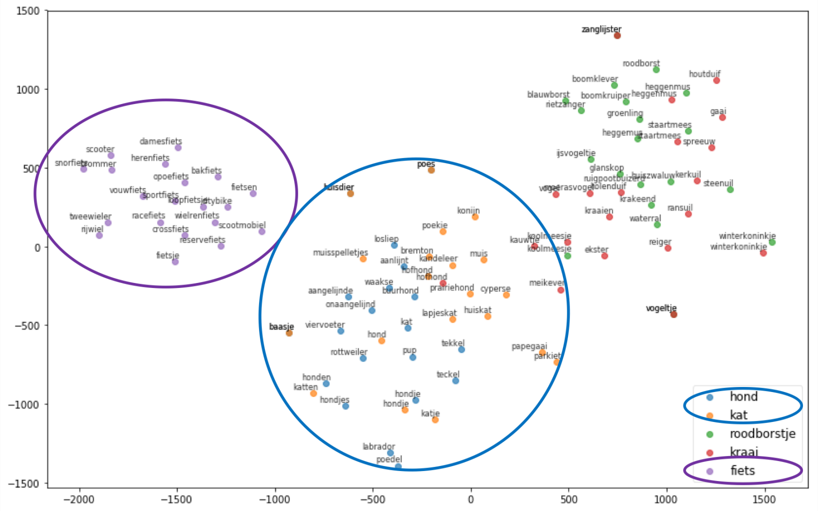
vouwfiets
sportfiets
tweewieler
racefiets
wielrenfiets
rijwiel
scootmobiel
crossfiets
reservefiets
fietsje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opoefiets
fietsen
vouwfiets
sportfiets
loopfietsje
citybike
tweewieler
racefiets
wielrenfiets
scootmobiel
rijwiel
crossfiets
reservefiets
fietsje
poes
huisdier
konijn
poekie
losliep
muisspelletjes
bremton
kandeleer
muis
aanlijnt
hofhond
waakse
aangelijnde
buurhond
prairiehond
cyperse
onaangelijnd
lapjeskat
huiskat
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baasje
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hond
tekkel
rottweiler
pup
papegaai
parkiet
teckel
honden
katten
hondjes
hondje
katje
labrador
poedel
zanglijster
roodborst
houtduif
boomklever
heggenmus
blauwborst
boomkruiper
rietzanger
groenling
gaai
staartmees
heggemus
spreeuw
ijsvogeltje
glanskop
ruigpootbuizerd
huiszwaluw
kerkuil
steenuil
vogel
roofvogel
holenduif
krakeend
kraaien
ransuil
waterral
kauwtje
koolmeesje
winterkoninkje
reiger
ekster
meikever
vogeltje
1500
1000
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0
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0
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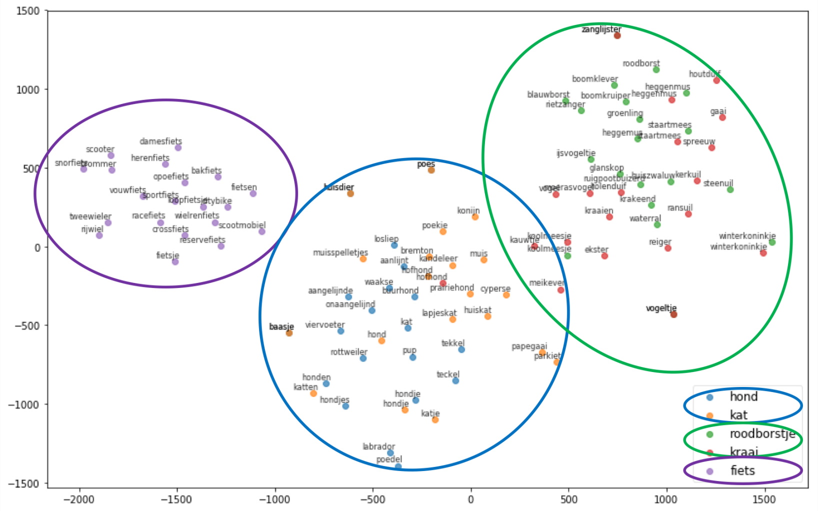

hond
kat
roodborstje
kraai
fiets

Re-usability

Re-usability of the Amsterdam Embedding Model

Re-usability

Reusing model and data

1. See https://github.com/annekroon/amsterdam-embedding-model
2. Open access to all the code

Word vectors

Downstream tasks

Document comparison: An example (Trilling & van Hoof, 2020)

Let's say we have a large corpus of news articles and what to find those that are about the same events.

Data

- 45K articles
- 6 months
- volkskrant.nl, ad.nl, nu.nl

Step 1: Get candidate articles

Comparing everything with everything is

- computationally infeasible
- theoretical nonsensical

Our solution

- Three-day moving window (but "chaining" possible)
- Saturday/Sunday merged into one day

Step 2: Get similarity scores

How to determine similarity between articles?

Our solution

Compare combinations of

- different measures (in particular, $tf \cdot idf$ cosine similarity vs. softcosine similarity
- different thresholds (to get rid of the overwhelming majority of close-to-zero edges)

Step 3: Network clustering

How to determine events?

After experimenting *a lot*:

Our final solution

- One network for all (instead of one per window)
- Articles are nodes, similarity scores = edge weights
- all edges with weight < threshold removed
- Leiden algorithm (Traag et al., 2019) with Surprise method (Traag et al., 2015) (very suitable for smaller, but more clusters)

Number of articles per event

Table 1: Descriptives for different threshold/similarity combinations

	cosine					softcosine				
	0.2	0.3	0.4	0.5	0.6	0.2	0.3	0.4	0.5	0.6
mean	2.03	1.58	1.35	1.21	1.12	6.78	2.89	1.88	1.51	1.27
std	3.48	2.00	1.22	0.71	0.45	30.41	10.04	4.27	2.27	1.07
max	88	53	41	21	15	551	367	161	70	30
single-art. events	15626	21854	27135	32232	36348	4262	11043	18305	24337	30700
multi-art. events	6685	6777	6241	5165	3899	2460	4736	5961	5940	5257

What does that mean?

- Use a high threshold!
- Soft-cosine finds some more events, leaves less articles unassigned (good), but that comes at the expense of slightly lower precision
- Example from our data: Because soft-cosine “understands” that Nike and Puma are both sports brands, it incorrectly assigned economic coverage about the two to one event.

How correct are the events?

We manually checked 6×100 events, qualitatively (not shown) and quantitatively:

Similarity	Threshold	Prec. 1 (%)	Prec. 2 (%)	TP/max. TP
cosine	0.4	74	88.52	223/268
cosine	0.5	78	89.02	217/253
cosine	0.6	89	94.39	204/225
softcosine	0.4	56	76.20	234/521
softcosine	0.5	65	81.77	236/379
softcosine	0.6	75	86.92	222/289

Note. *Precision 1:* The percentage of news events that are entirely clustered correctly. *Precision 2:* The percentage of news articles that are correctly clustered. *max. TP* is the number of articles that are assigned to an event in the sample; hence, the maximum number of true positives that can be achieved.

Cosine vs Softcosine

Also a matter of computational costs

- the document needs to be converted into embeddings
- but once that is done, our document vectors only have 300 instead of thousands of dimensions!

Neural Networks and Deep Learning

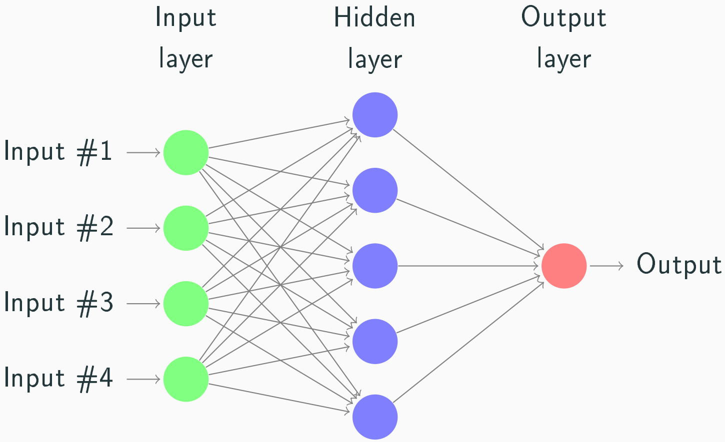
Neural Networks and Deep Learning

Neural networks

Neural Networks

- In “classical” machine learning, we predict an outcome directly based on the input features
- In neural networks, we can have “hidden layers” that we predict
- These layers are not necessarily interpretable
- “Neurons” that “fire” based on an “activation function”

Note that in our earlier example with our EmbeddingVectorizer, we essentially added a “layer” between the input and the output. Now, we generalize this idea.



⇒ If we had multiple hidden layers in a row, we'd call it a *deep* network.

Why neural networks?

- learn hidden structures (e.g., embeddings (!))
- go beyond the idea that there is a direct relationship between occurrence of word X and label (or occurrence of pixel [R,G,B] and a label)
- images, machine translation — and more and more general NLP, sentiment analysis, etc.

Example of a comparatively easy introduction:
https://towardsdatascience.com/neural-network-embeddings-explained-4d028e6f0526

Simple feed forward network

```
model.add(Dense(300, input_dim=input_dim, activation='relu'))
model.add(Dense(1, activation='sigmoid'))
```

- Our first layer reduces the input features (e.g., the 10,000 features our CountVectorizer creates) to 300 neurons
- It does so using the relu function $f(x) = max(0, x)$ (as our counts cannot be negartive, just a linear function)
- The second layer reduces the 300 neurons to 1 output neuron using the sigmoid function (the S curve you know fron logistic regression)
- Of course, we can add multiple layers in between if we want to

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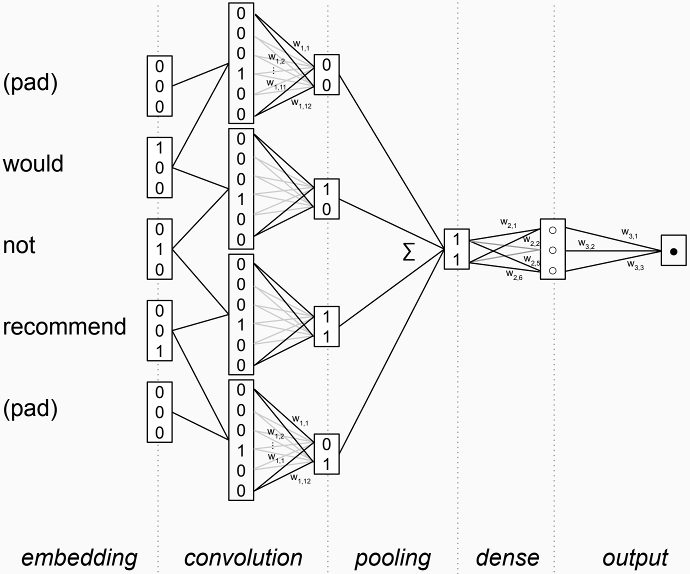
Convolutional networks

The problem with such a basic networks: just as with classic SML, we still loose all information about order (the "not good" problem). Therefore,

- We concatenate the vectors of neighboring words
- We apply some filter (essentially, we detect patterns)
- and then pool the results (e.g., taking the maximum)

This means that we now excplitly take into acount *the temporal structure* of a sentence.

Convolutional networks



Convolutional networks

```
model.add(Embedding(input_dim=vocab_size, output_dim=embedding_dim,
    input_length=maxlen))
model.add(Conv1D(embedding_dim, 5, activation='relu'))
model.add(GlobalMaxPooling1D())
model.add(Dense(300, activation='relu'))
model.add(Dense(1, activation='sigmoid'))
```

The layers:

1. train an embedding model
2. apply the convolution with 5 “timestamps”
3. pool using the maximum
4. another layer with 300 dimensions
5. the final layer with 1 output neuron

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Convolutional networks

Note that the preprocessing differs!

- We do not take a word vector per document as input any more, but *a sequence of words*
- For concatenating, these sequences need to have equal length, which is why we *pad* then

Neural Networks and Deep Learning

Using pretrained embeddings

The embedding layer

- Often, the first layer is creating word embeddings
- Good embeddings need a lot of training data
- Training good embeddings needs time
- Therefore, we can replace that layer with a pre-trained embedding layer (!)
- We can even use a hybrid approach and allow the pre-trained embedding layer to be re-trained!

Next steps

Take-home exam

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