A Practical Introduction to Machine Learning in Python

Day 5 – Friday

»Next steps«

Damian Trilling
Anne Kroon

d.c.trilling@uva.nl, @damian0604
a.c.kroon@uva.nl, @annekroon

September 30, 2021

Gesis

Today: Beyond BOW

From word counts to word vectors

Training word embeddings

Using word embeddings to improve models

(Ab-)using word embeddings to detect biases

AEM: An application from our own research

Neural networks

Using pretrained embeddings

Today, we want to look into techniques that go beyond using word frequencies as features. We will talk about Word Embeddings, Neural Networks, and Transformers.

From word counts to 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

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

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

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

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

Our BOW approach until now

- 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.

$\Rightarrow$ That's the idea behind word embeddings!

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

Our BOW approach until now

- 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.

$\Rightarrow$ That's the idea behind word embeddings!

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

Our BOW approach until now

- 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.

$\Rightarrow$ That's the idea behind word embeddings!

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

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 counts 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, 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

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-40fe4e860

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, O., Goldberg, Y., & Dagan, I. (2018). Improving Distributional Similarity with Lessons Learned from Word Embeddings. *Transactions of the Association for Computational Linguistics*, *3*, 211–225. doi:10.1162/tacl_a_00134

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, O., Goldberg, Y., & Dagan, I. (2018). Improving Distributional Similarity with Lessons Learned from Word Embeddings. *Transactions of the Association for Computational Linguistics*, *3*, 211–225. doi:10.1162/tacl_a_00134

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

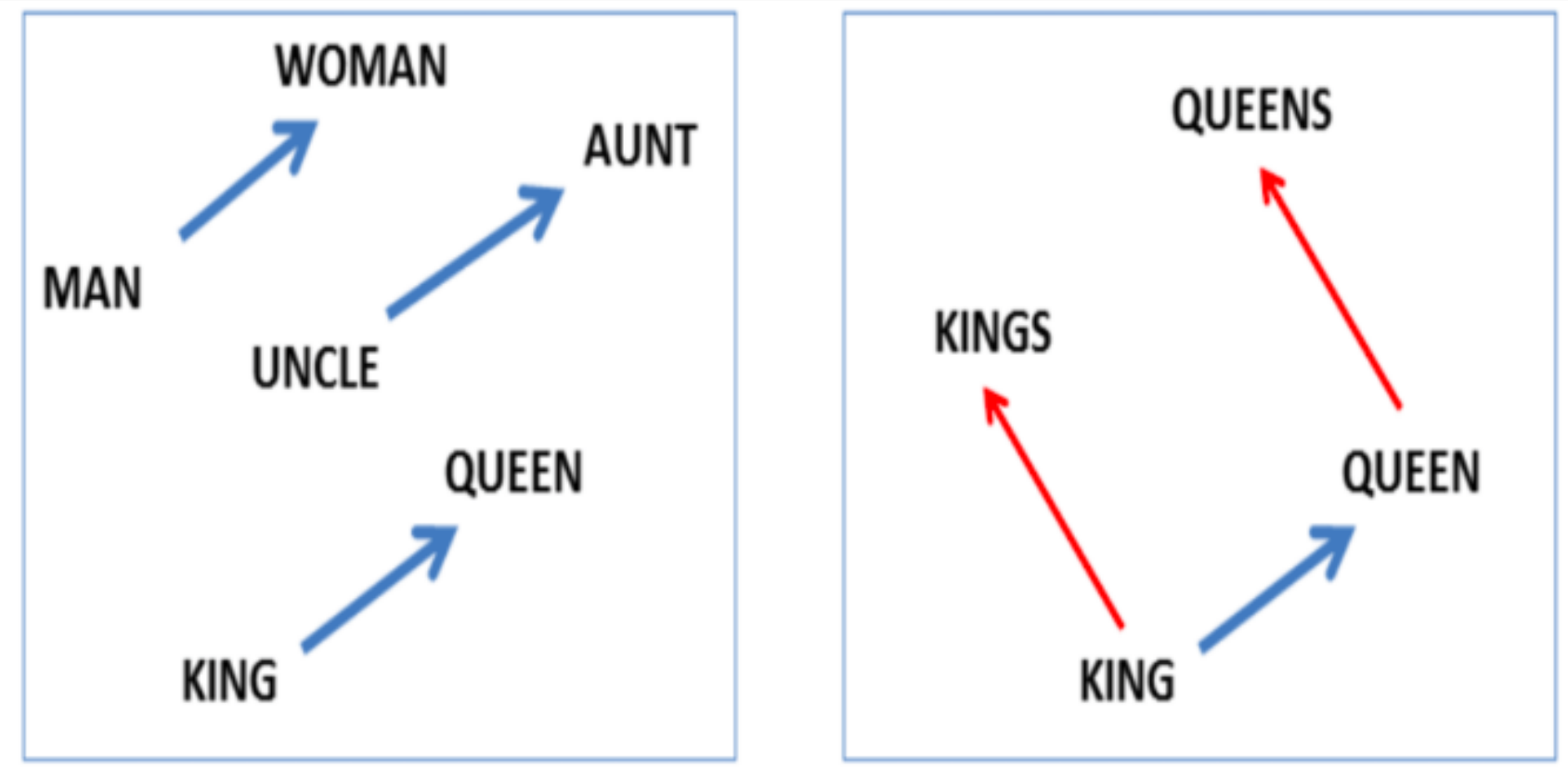
Word embeddings ...

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

Firth, J. R. (1957). A synopsis of linguistic theory, 1930-1955. Studies in linguistic analysis.

You can literally calculate with words!

And answer questions such as "Man is to woman as king is to _____?"



semantic relationships vs. syntactic relationships

Improving models

Using word embeddings to improve models

In supervised machine learning

- Modify CountVectorizer or TfIdfVector such that for each term, you do not only count how often it occurs, but also multiply with its embedding vector
- 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).

In supervised machine learning

- Modify CountVectorizer or TfIdfVector such that for each term, you do not only count how often it occurs, but also multiply with its embedding vector
- 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).

In supervised machine learning

- Modify CountVectorizer or TfIdfVector such that for each term, you do not only count how often it occurs, but also multiply with its embedding vector
- 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).

In supervised machine learning

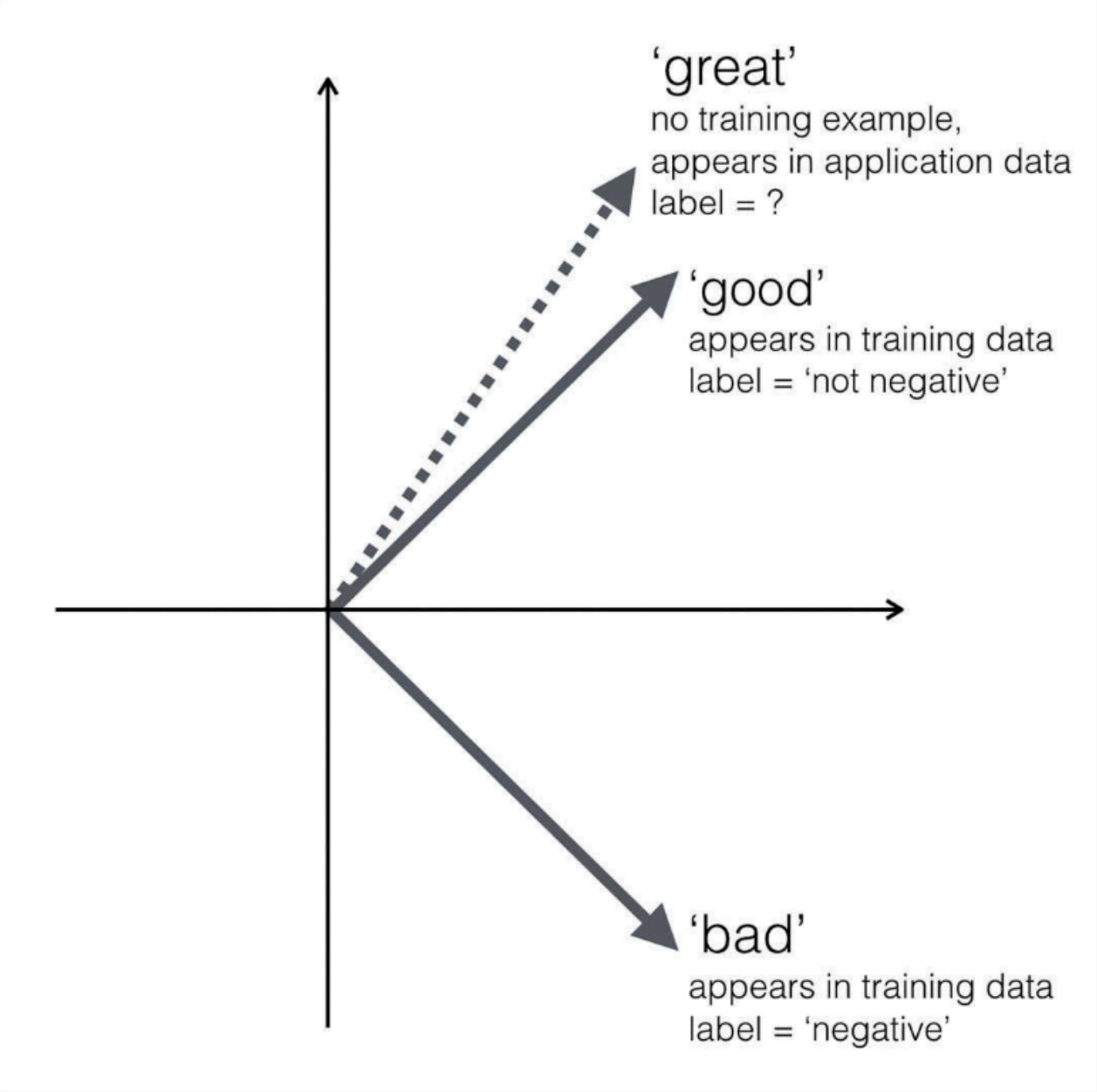
- Modify CountVectorizer or TfIdfVector such that for each term, you do not only count how often it occurs, but also multiply with its embedding vector
- Often, pre-trained embeddings (e.g., trained on the whole wikipedia) are used
- Thus, our supervised model will be able to deal with synonyms and related words!

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

In supervised machine learning

- Modify CountVectorizer or TfIdfVector such that for each term, you do not only count how often it occurs, but also multiply with its embedding vector
- 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).



Rudkowsky, E., Haselmayer, M., Wastian, M., Jenny, M., Emrich, Š., & Sedlmair, M. (2018). More than Bags of Words: Sentiment Analysis with Word Embeddings. *Communication Methods and Measures*, *12*(2–3), 140–157. doi:10.1080/19312458.2018.1455817

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, E., Haselmayer, M., Wastian, M., Jenny, M., Emrich, Š., & Sedlmair, M. (2018). More than Bags of Words: Sentiment Analysis with Word Embeddings. *Communication Methods and Measures*, *12*(2–3), 140–157. doi:10.1080/19312458.2018.1455817

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)

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)

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

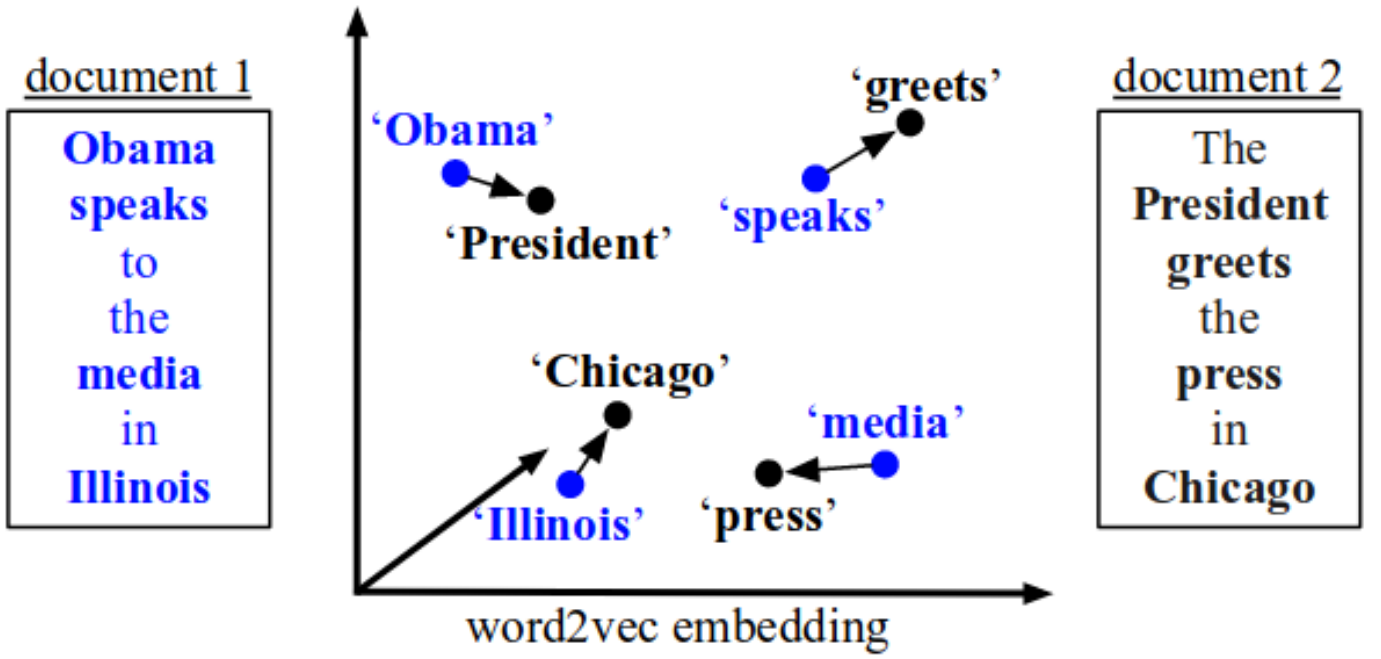


Figure 1. An illustration of the *word mover's distance*. All non-stop words (***bold***) of both documents are embedded into a *word2vec* space. The distance between the two documents is the minimum cumulative distance that all words in document 1 need to travel to exactly match document 2. (Best viewed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

Kusner, M. J., Sun, Y., Kolkin, N. I., & Weinberger, K. Q. (2015). From Word Embeddings To Document Distances. *Proceedings of The 32nd International Conference on Machine Learning* (Vol. 37, pp. 957–966)

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

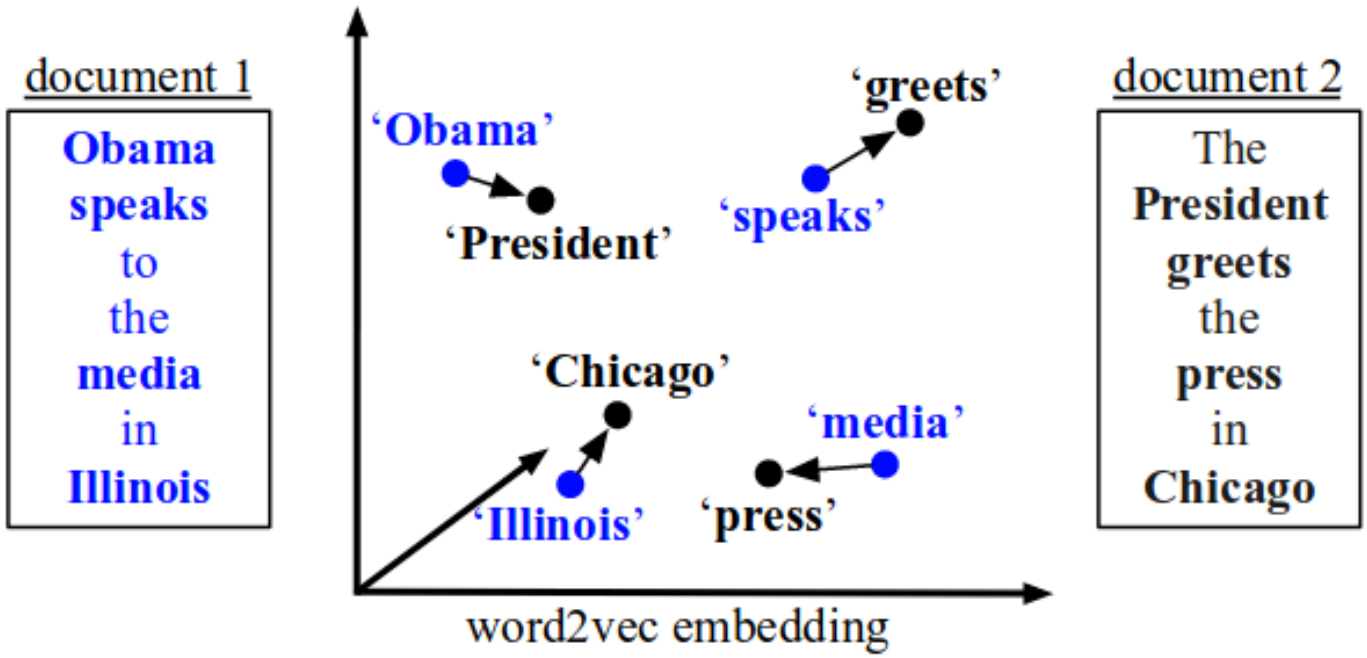


Figure 1. An illustration of the *word mover's distance*. All non-stop words (***bold***) of both documents are embedded into a *word2vec* space. The distance between the two documents is the minimum cumulative distance that all words in document 1 need to travel to exactly match document 2. (Best viewed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

Kusner, M. J., Sun, Y., Kolkin, N. I., & Weinberger, K. Q. (2015). From Word Embeddings To Document Distances. *Proceedings of The 32nd International Conference on Machine Learning* (Vol. 37, pp. 957–966)

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

Detecting biases

(Ab-)using word embeddings to detect biases

Biased embeddings

- 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

Bolukbasi, T., Chang, K.-W., Zou, J., Saligrama, V., & Kalai, A. (2016). Man is to Computer Programmer as Woman is to Homemaker? Debiasing Word Embeddings, 1–25. Retrieved from http://arxiv.org/abs/1607.06520

Biased embeddings

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

unless. . .

we actually want to chart such biases.

Biased embeddings

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

unless. . .

we actually want to chart such biases.

Biased embeddings

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

unless. . .

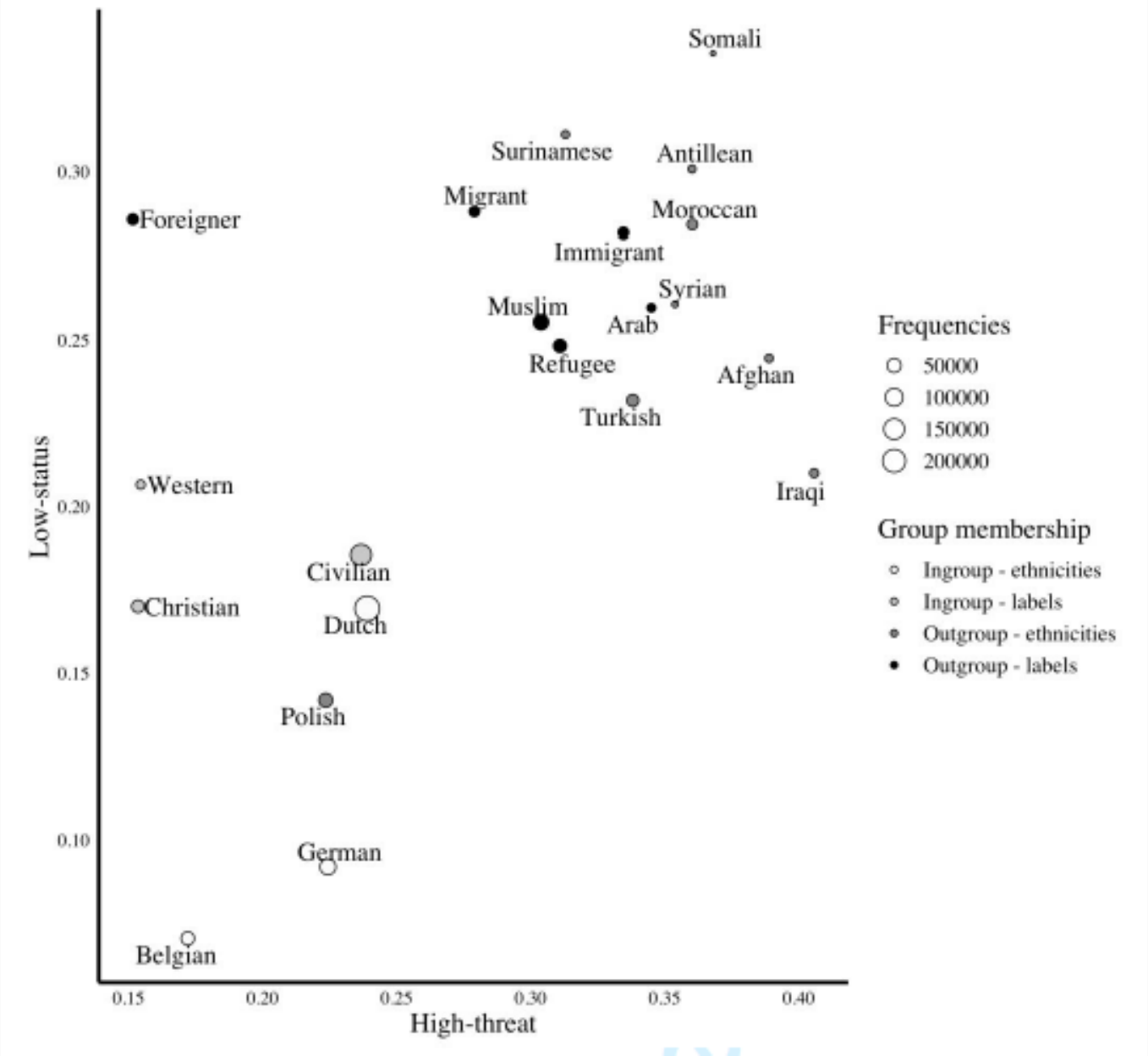
we actually want to chart such biases.

An exmaple from our research

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?

Kroon, A.C., Van der Meer, G.L.A., Jonkman, J.G.F., &Trilling, D. (in press): Guilty by Association: Using Word Embeddings to Measure Ethnic Stereotypes in News Coverage. *Journalism & Mass Communication Quarterly*


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

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

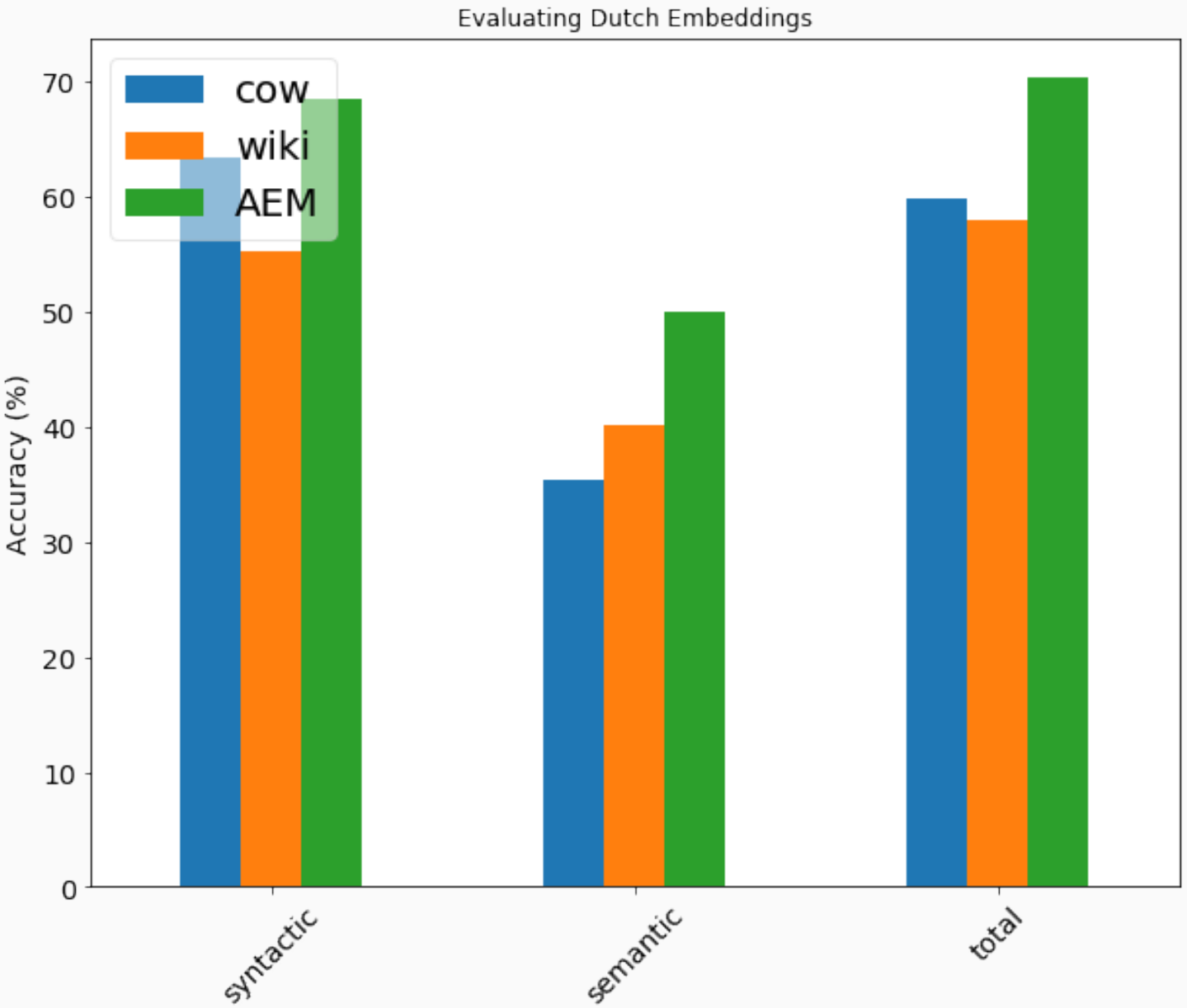
Evaluation methods

- 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

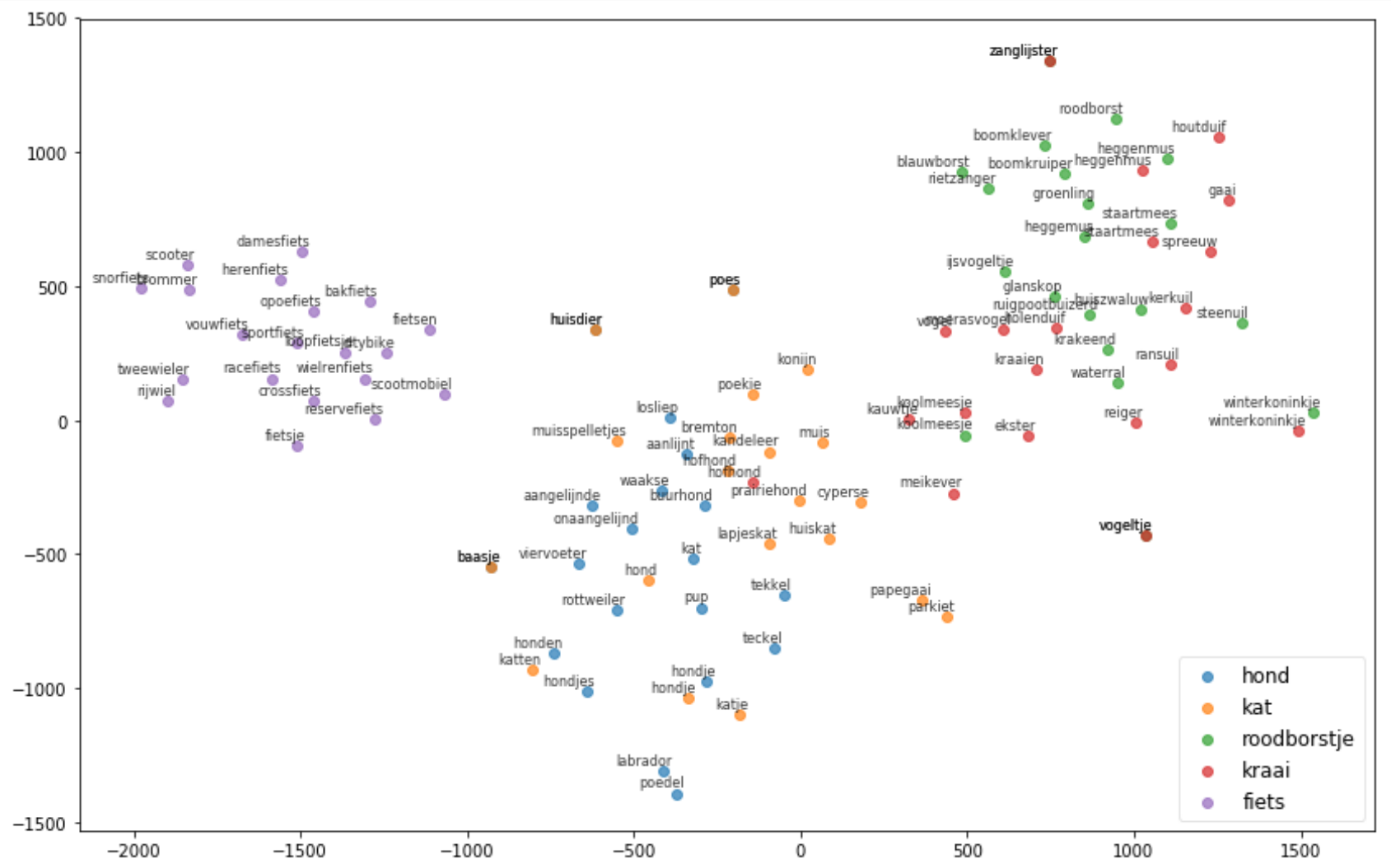
1. 'relationship'/ analogy-task (Tulkens et al., 2016)
    - **syntatic relationships**: dans dansen loop *[lopen]*
    - **semantic relationships**: denemarken kopenhagen noorwegen *[oslo]*
2. 5806 relationship tasks

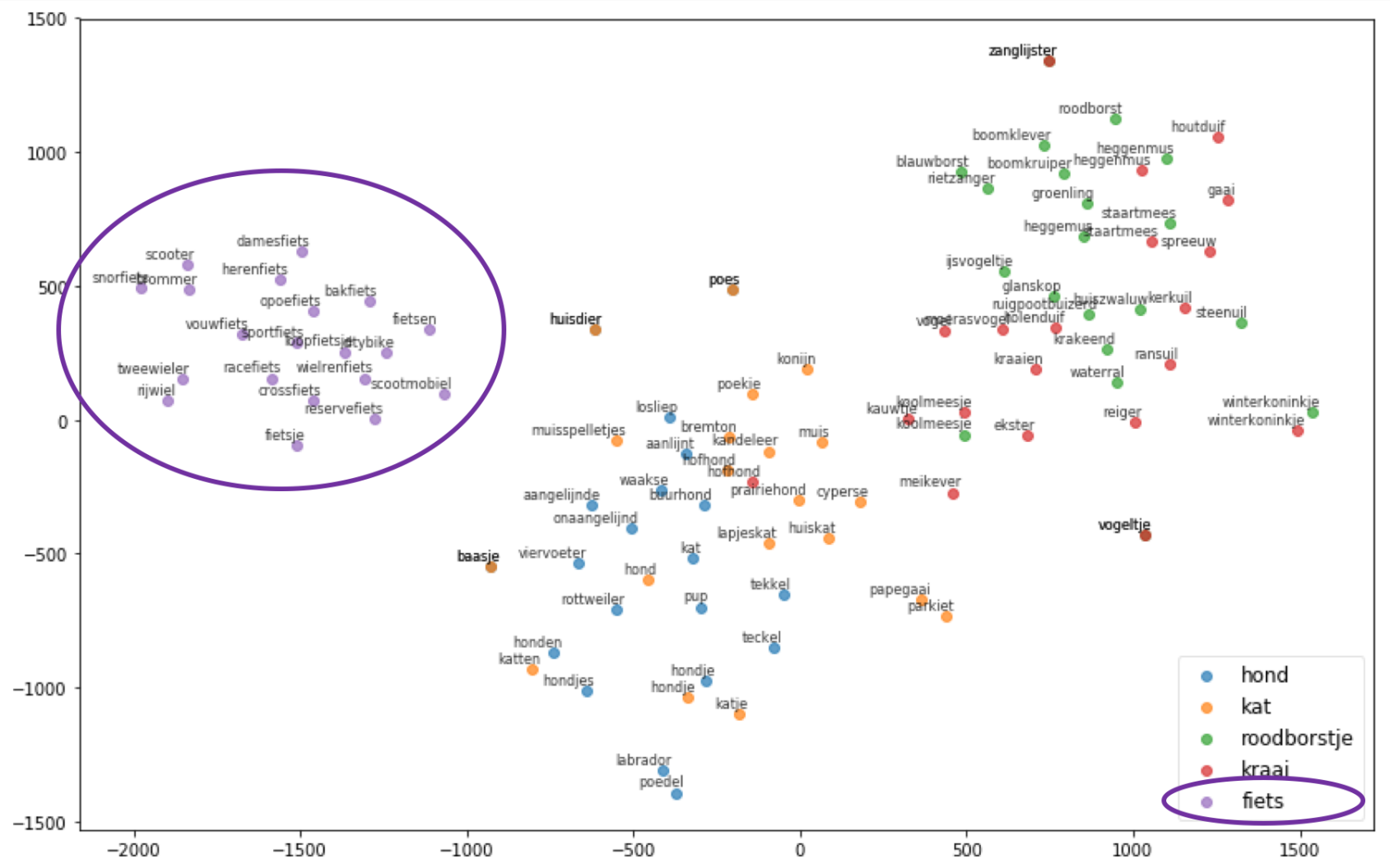

Evaluating Dutch Embeddings
cow
wiki
AEM
Accuracy (%)
0
10
20
30
40
50
60
70
syntactic
semantic
total

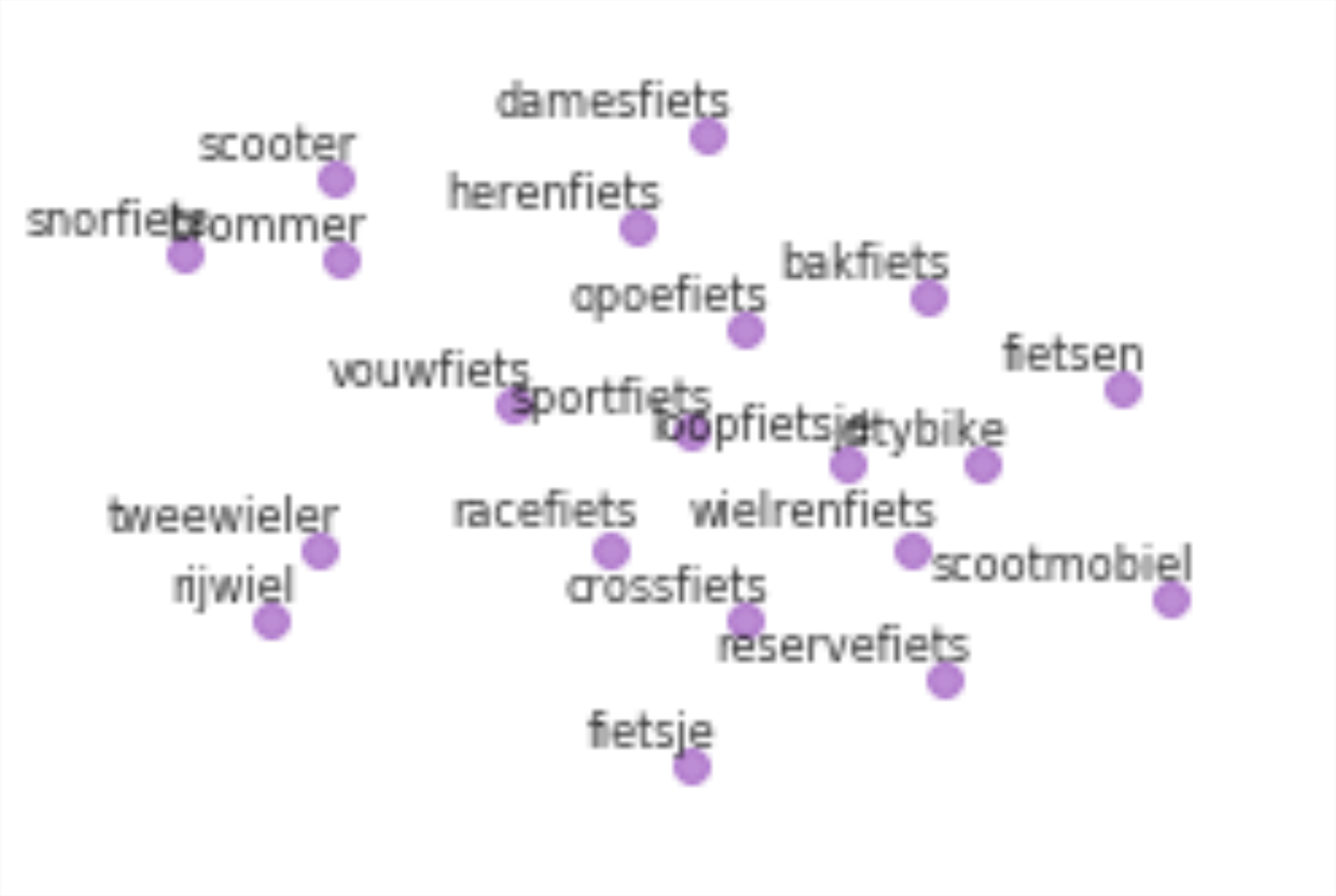
Illustration

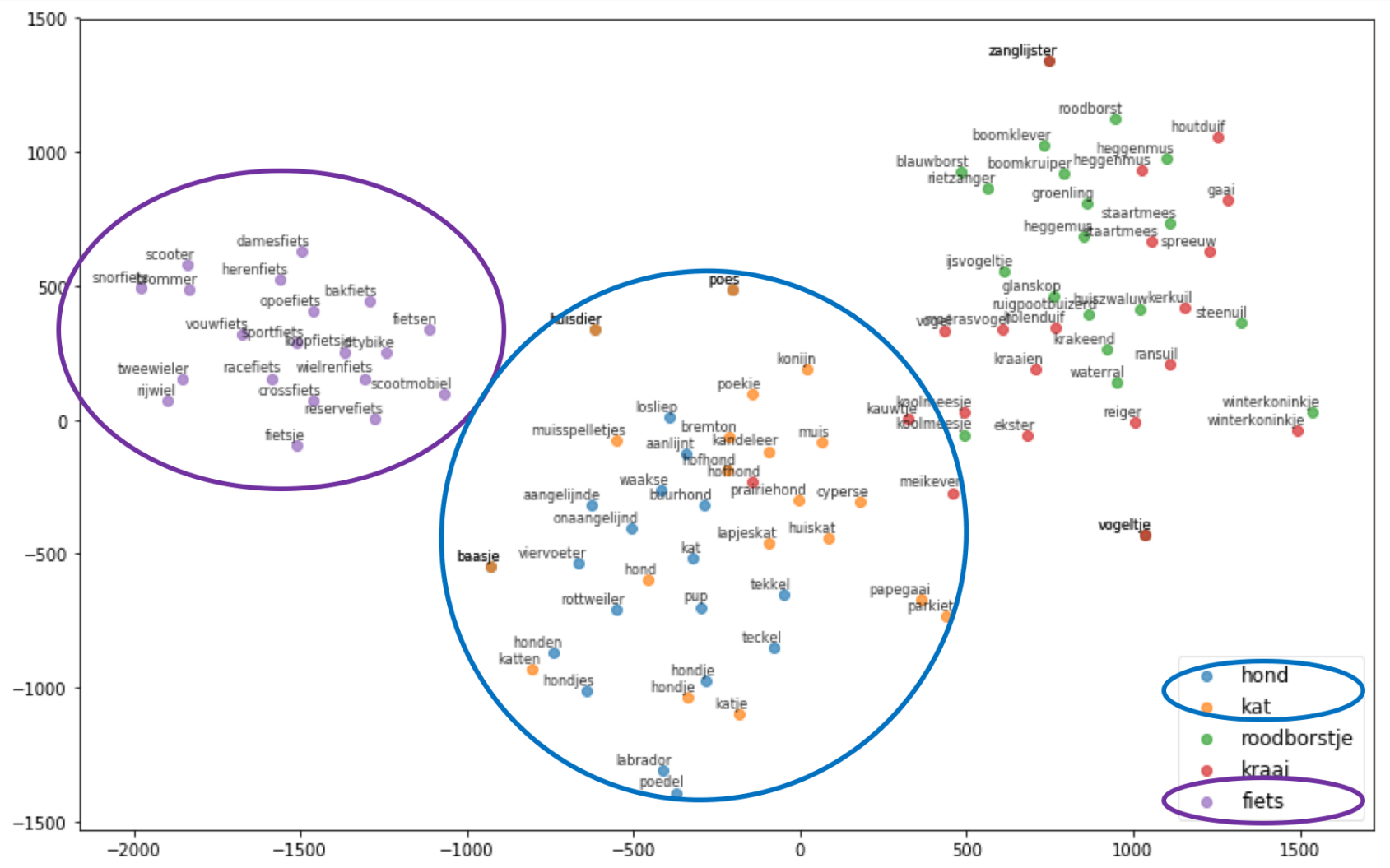
Illustration - Using the Amsterdam Embedding Model

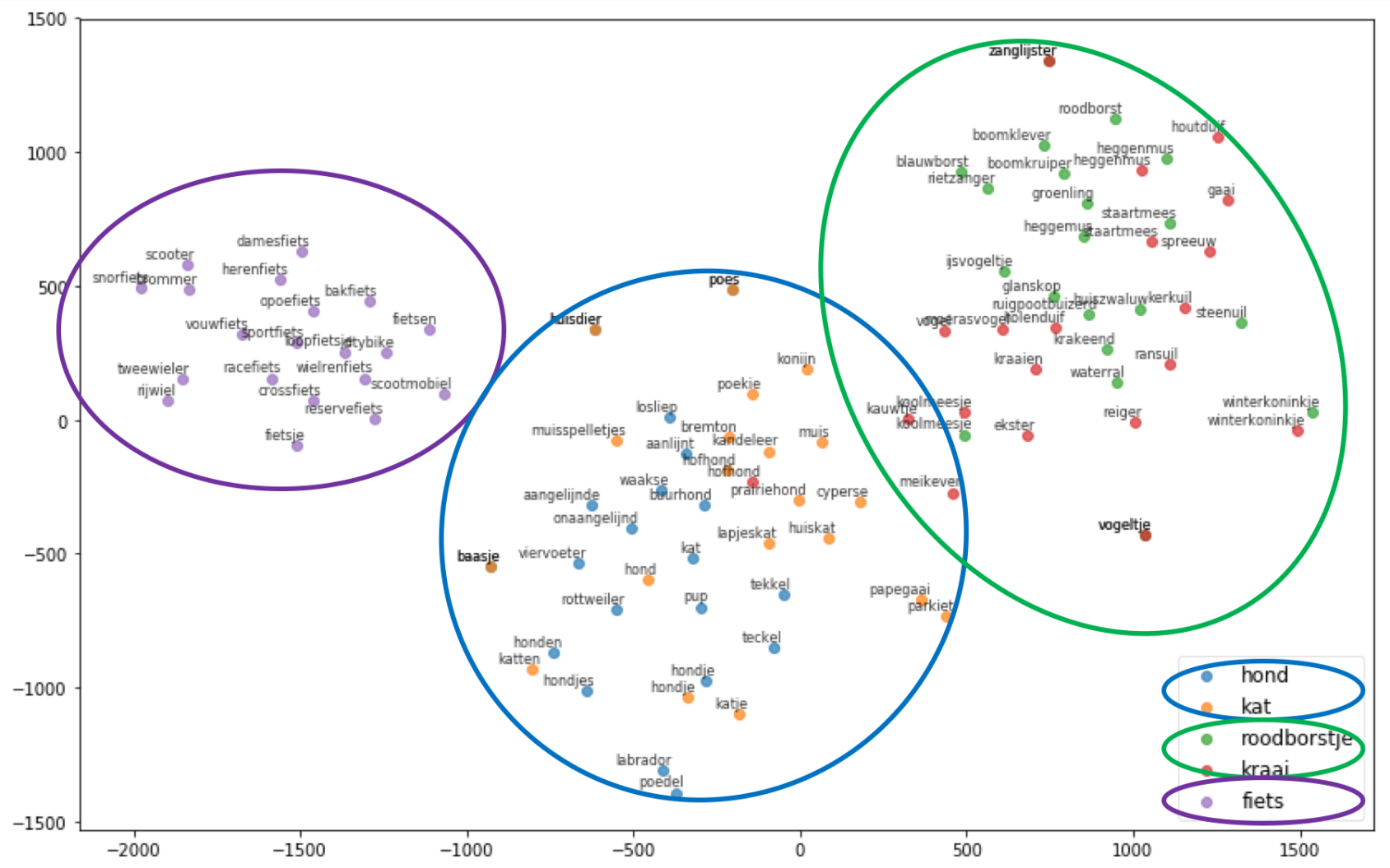
AEM


zanglijster
roodborst
houtduif
boomklever
heggenmus
blauwborst
boomkruiper
heggenmus
rietzanger
groenling
gaai
staartmees
heggemus
staartmees
spreeuw
damesfiets
scooter
herenfiets
ijsvogeltje
snorfiets
bommer
poes
glanskop
bakfiets
opoefiets
huiszwaluw
kerkuil
ruigpootbuizerd
steenuil
vouwfiets
fietsen
huisdier
vogelenduif
sportfiets
krakeend
bmxfiets
citybike
koniijn
kraaien
ransuil
tweewieler
racefiets
wielrenfiets
waterral
poekie
rijwiel
crossfiets
scootmobiel
kauwtje
winterkoninkje
losliep
koolmeesje
reiger
reservefiets
bremton
muisspelletjes
koolmeesje
ekster
winterkoninkje
fietsje
aanlijnt
kandeleer
muis
hofhond
hofhond
waakse
meikever
prairiehond
cyperse
aangelijnde
boerhond
onaangelijnd
vogeltje
lapjeskat
huiskat
kat
baasje
viervoeter
hond
tekkel
papegaai
rottweiler
pup
parkiet
teckel
honden
katten
hondje
hondje
hondjes
katje
labrador
poedel
hond
kat
roodborstje
kraai
fiets
1500
1000
500
0
−500
−1000
−1500
−2000
−1500
−1000
−500
0
500
1000
1500


zanglijster
roodborst
houtduif
boomklever
heggenmus
blauwborst
boomkruiper
heggenmus
rietzanger
gaai
groenling
staartmees
heggemus
staartmees
spreeuw
ijsvogeltje
glanskop
huiszwaluw
kerkuil
ruigpootbuizerd
steenuil
vogelenduif
krakeend
kraaien
ransuil
waterral
koolmeesje
reiger
winterkoninkje
ekster
meikever
vogeltje
papegaai
parkiet
poes
huisdier
koniijn
poekie
losliep
muisspelletjes
bremton
aanlijnt
kandeleer
muis
hofhond
waakse
aangelijnde
buurhond
prairiehond
cyperse
onaangelijnd
lapjeskat
huiskat
kat
baasje
viervoeter
hond
tekkel
rottweiler
pup
teckel
honden
katten
hondje
hondjes
katje
labrador
poedel
damesfiets
scooter
herenfiets
snorfiets
bommer
bakfiets
opoefiets
fietsen
vouwfiets
sportfiets
bmxfiets
citybike
tweewieler
racefiets
wielrenfiets
scootmobiel
rijwiel
crossfiets
reservefiets
fietsje
hond
kat
roodborstje
kraai
fiets
1500
1000
500
0
−500
−1000
−1500
−2000
−1500
−1000
−500
0
500
1000
1500


damesfiets
scooter
herenfiets
snorfiets
bommer
bakfiets
opoefiets
fietsen
vouwfiets
sportfiets
toerfiets
mountainbike
tweewieler
racefiets
wielrenfiets
scootmobiel
rijwiel
crossfiets
reservefiets
fietsje


zanglijster
roodborst
houtduif
boomklever
heggenmus
blauwborst
boomkruiper
heggenmus
rietzanger
gaai
groenling
staartmees
heggemus
staartmees
spreeuw
ijsvogeltje
glanskop
huiszwaluw
kerkuil
ruigpootbuizerd
steenuil
vogelenduif
krakeend
kraaien
ransuil
waterral
winterkoninkje
reiger
winterkoninkje
kauwtje
koolmeesje
koolmeesje
ekster
meikever
vogeltje
poes
huisdier
konijn
poekie
losliep
muisspelletjes
bremton
aanlijnt
kandeleer
muis
hofhond
hofhond
waakse
prairiehond
cyperse
aangelijnde
buurhond
onaangelijnd
lapjeskat
huiskat
baasje
viervoeter
kat
hond
tekkel
papegaai
parkiet
rottweiler
pup
teckel
honden
katten
hondje
hondje
hondjes
katje
labrador
poedel
damesfiets
scooter
herenfiets
snorfiets
bommer
bakfiets
opoefiets
fietsen
vouwfiets
sportfiets
bmxfiets
stepbike
tweewieler
racefiets
wielrenfiets
scootmobiel
rijwiel
crossfiets
reservefiets
fietsje
hond
kat
roodborstje
kraai
fiets
1500
1000
500
0
−500
−1000
−1500
−2000
−1500
−1000
−500
0
500
1000
1500


1500
1000
500
0
−500
−1000
−1500
−2000
−1500
−1000
−500
0
500
1000
1500
zanglijster
roodborst
houtduif
boomklever
heggenmus
blauwborst
boomkruiper
heggenmus
rietzanger
gaai
groenling
staartmees
heggemus
staartmees
spreeuw
ijsvogeltje
glanskop
huiszwaluw
kerkuil
ruigpootbuizerd
steenuil
vogelenduif
krakeend
kraaien
ransuil
waterral
winterkoninkje
reiger
ekster
meikever
vogeltje
papegaai
parkiet
poes
huisdier
konijn
poekie
losliep
muisspelletjes
bremton
aanlijnt
kandeleer
muis
hofhond
waakse
prairiehond
cyperse
aangelijnde
buurhond
onaangelijnd
lapjeskat
huiskat
baasje
viervoeter
kat
hond
tekkel
rottweiler
pup
teckel
honden
katten
hondje
hondjes
katje
labrador
poedel
damesfiets
scooter
herenfiets
bakfiets
opoefiets
fietsen
vouwfiets
sportfiets
bmxfiets
tybike
tweewieler
racefiets
wielrenfiets
scootmobiel
crossfiets
rijwiel
reservefiets
fietsje
hond
kat
roodborstje
kraai
fiets

Re-usability

Re-usability of the Amsterdam Embedding Model

Re-usability

Reusing model and data

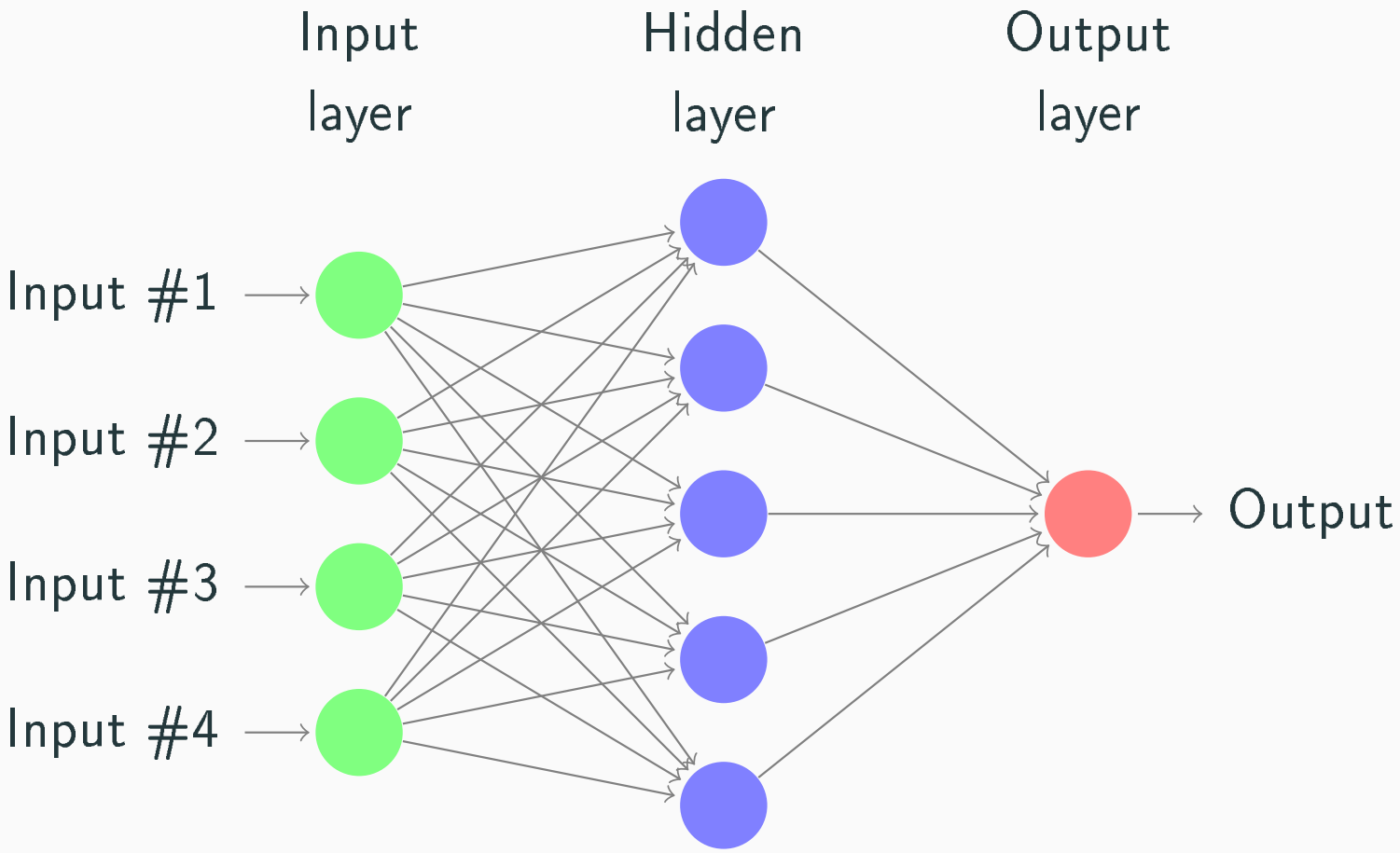
1. See https://github.com/annekroon/amsterdam-embedding-model
2. Open access to all the code

Disclaimer: I cannot give a full overview of the whole topic of deep learning here – that's a whole (extensive) course in itself. But embeddings are closely related, that's why we at least will at least get out feet wet a bit.

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"



$\Rightarrow$ 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

```
1        model.add(Dense(300, input_dim=input_dim, activation='relu'))
2        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

Simple feed forward network

```
1        model.add(Dense(300, input_dim=input_dim, activation='relu'))
2        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

Simple feed forward network

```
1        model.add(Dense(300, input_dim=input_dim, activation='relu'))
2        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

Simple feed forward network

```
1        model.add(Dense(300, input_dim=input_dim, activation='relu'))
2        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

Convolutional networks

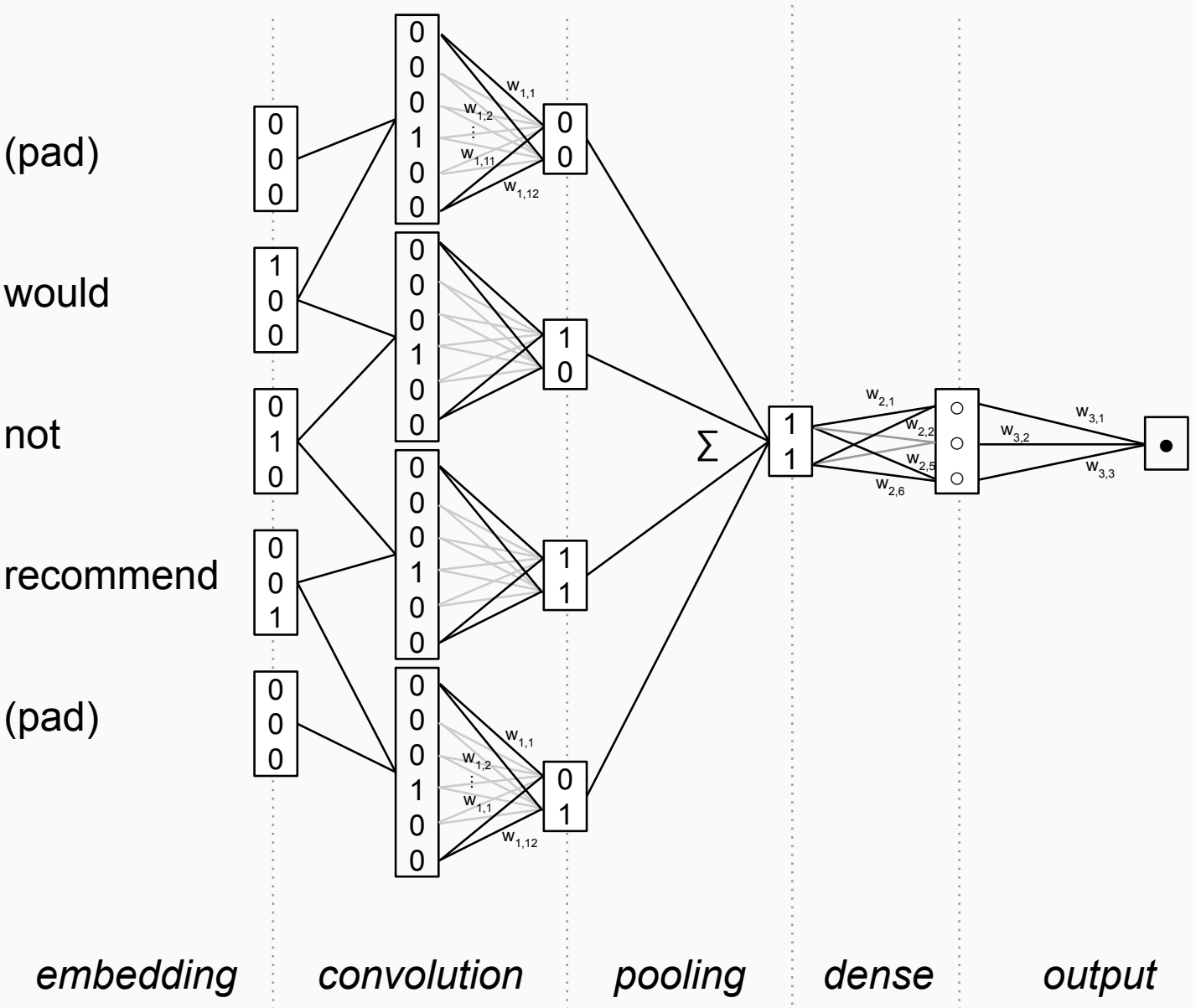
The problem with such a basic networks: just as with classic SML, we still loose all information about order (the "not good" problem).

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

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

Convolutional networks

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

Convolutional networks

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

Convolutional networks

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

Convolutional networks

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

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

LSTM (long short-term memory)

- Unlike "feed forward" neural networks, this is a "recurrent neural network" (RNN) – the training works in two directions
- Heavy in computation, very useful for predicting *sequences*
- Won't cover today

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!