A Practical Introduction to Machine Learning in Python
Day 5 – Friday
»Transformers«

Damian Trilling
Anne Kroon

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

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Gesis

This part: State of the art and next steps

One-Hot to Continous

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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One-Hot to Continous

Encoding text in ML models

Encoding so far: BoW approach

- Our vectorizers gave a random ID to each word
- Words are *discrete* and *independent* tokens.
- This is a rather naïve assumption, with two main disadvantages:
  1. high dimensionality of the *one-hot-encodings* of the tokens
  2. they do not incorporate real-world knowledge

Token	Index	One-hot vector
aargh	0	[1,0,0]
king	1	[0,1,0]
queen	2	[0,0,1]

Continous vectors

- A more realistic view: words are continous vectors in an N dimensional space
- Their representation contains real numbers, and they can occupy a position in the N dimensionality space
- This way of *embedding* tokens is refered to as *continous* or distributed vectors, representations or *word embeddings*
- The dimensions encode meaning (implicit)

Token	Index	One-hot vector	Continous vector
aargh	0	[1,0,0]	[0.3, 1.9, -0.9]
king	1	[0,1,0]	[0.2, -0.7, 0.2]
queen	2	[0,0,1]	[0.5, 1.3, 0.9]

Language Modeling

Language modelling refers to a set of techniques that aim determine the probability of a given sequence of words occurring in a sentence.

Large Language Models

- Often referred to as ‘pretrained’ or ‘foundation’ models.
- They rely on massive amounts of training data.
- e.g., wikipedia, news archives, Reddit, etc.

Training language models: based on unstructured text – in the absence of explicit labels

Dobermann

From Wikipedia, the free encyclopedia

"Doberman" redirects here. For other uses, see Doberman (disambiguation).

This article **needs additional citations for verification**. Please help improve this article by adding citations to reliable sources. Unsourced material may be challenged and removed.
Find sources: "Dobermann" – news · newspapers · books · scholar · JSTOR
(March 2018) (*Learn how and when to remove this template message*)

The **Dobermann** (/ˈdoʊbərmən/; German pronunciation: [ˈdoːbɐman]), or **Doberman Pinscher** in the United States and Canada, is a medium-large breed of domestic dog that was originally developed around 1890 by Louis Dobermann, a tax collector from Germany.[2] The Dobermann has a long muzzle. It stands on its pads and is not usually heavy-footed. Ideally, they have an even and graceful gait. Traditionally, the ears are cropped and posted and the tail is docked. However, in some countries, these procedures are now illegal and it is often considered cruel and unnecessary. Dobermanns have markings on the chest, paws/legs, muzzle, above the eyes, and underneath the tail.

Dobermanns are known to be intelligent, alert, and tenaciously loyal companions and guard dogs.[3]

Dobermann	
Other names	Doberman Pinscher
Common nicknames	Dobie, Doberman
Origin	Germany
Traits [hide]	
Height	Dogs 68 to 72 cm (27 to 28 in)[1]
	Bitches 63 to 68 cm (25 to 27 in)[1]

Bulldog

From Wikipedia, the free encyclopedia

This article is about the English Bulldog. For other uses, see Bulldog (disambiguation).
See also: French Bulldog, American Bulldog, and Old English Bulldog

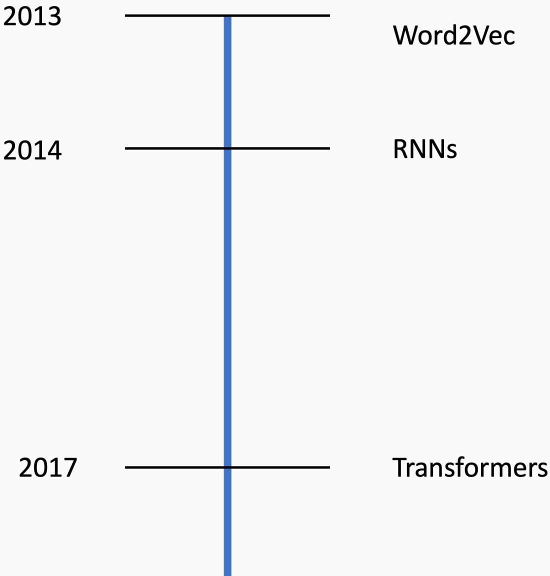
The **Bulldog** is a British breed of dog of mastiff type. It may also be known as the **English Bulldog** or **British Bulldog**. It is of medium size, a muscular, hefty dog with a wrinkled face and a distinctive pushed-in nose.[4] It is commonly kept as a companion dog; in 2013 it was in twelfth place on a list of the breeds most frequently registered worldwide.[5]

The Bulldog has a longstanding association with British culture; the BBC wrote: "to many the Bulldog is a national icon, symbolising pluck and determination".[6] During the Second World War, the Prime Minister Winston Churchill was likened to a Bulldog for his defiance of Nazi Germany.[7] The Bulldog Club (In England) was formed in 1878, and the Bulldog Club of America was formed in 1890.

Bulldog	
Other names	English Bulldog, British Bulldog
Origin	England[1]

Male English Bulldog

Key events in the history of language modeling



Non-Contextual Embeddings

"...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
- for instance, 'dobermann' and 'bulldog' should be represented by vectors that are close to each other in space, while 'kill' and 'walk' should be far from each other.

Word embeddings:Training algorithms

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-40fe4e8602ba

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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, 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

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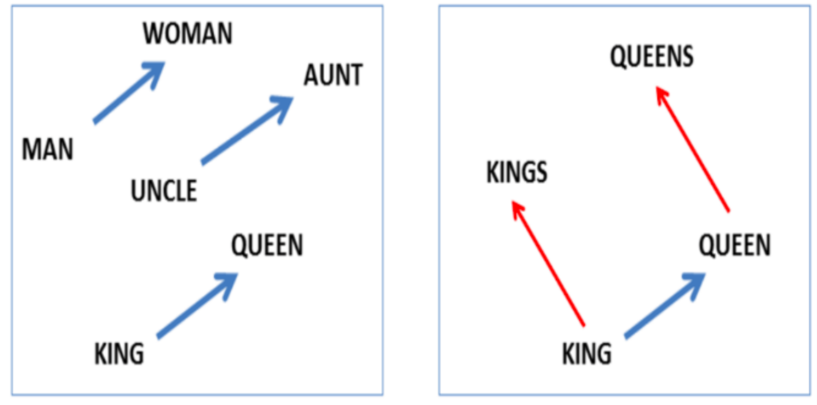
You can literally calculate with words!

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



semantic relationships vs. syntactic relationships

Non-Contextual Embeddings

Improving down-stream classification tasks

Using word embeddings to improve down-stream classification tasks.

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).

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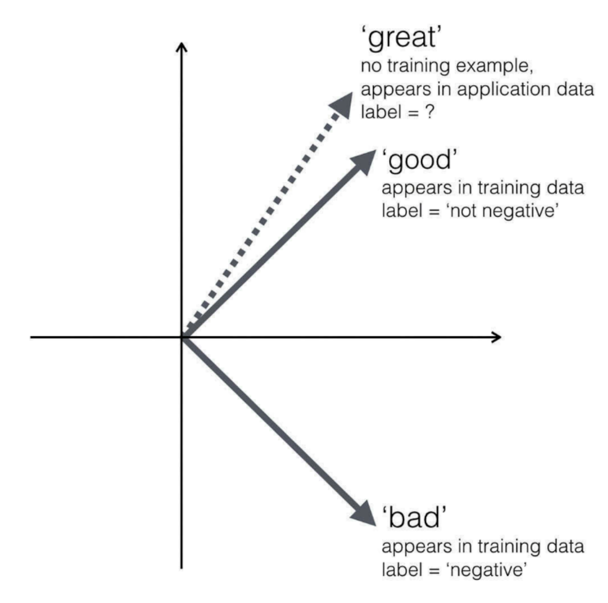

Rudkowsky, E., Haselmayer, M., Wastian, M., Jenny, M., Emrich, Š., & Sedlmair, M. (2018). More than Bags of Words: Sentiment Analysis with Word Embeddings. *Communication Methods and Measures, 12*(2–3), 140–157. doi:10.1080/19312458.2018.1455817

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

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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?

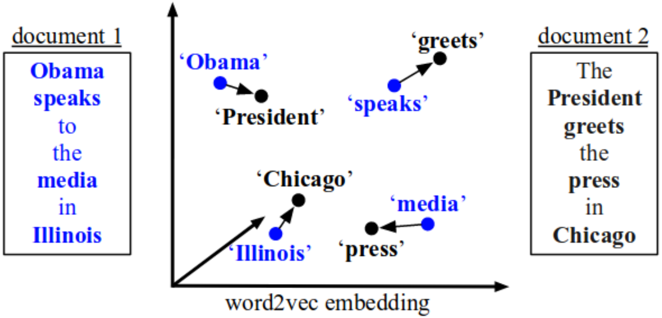

Figure 1. An illustration of the *word mover's distance*. All non-stop words (***bold***) of both documents are embedded into a *word2vec* space. The distance between the two documents is the minimum cumulative distance that all words in document 1 need to travel to exactly match document 2. (Best viewed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

Kusner, 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)

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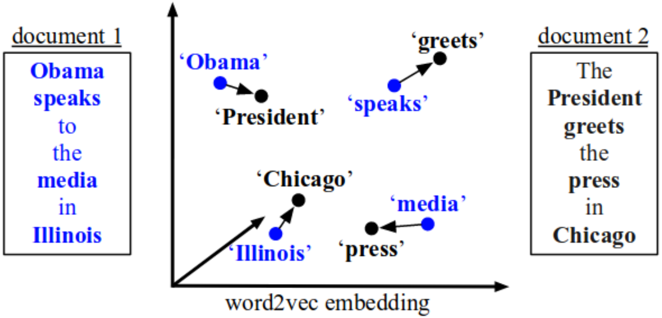

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There are several approaches

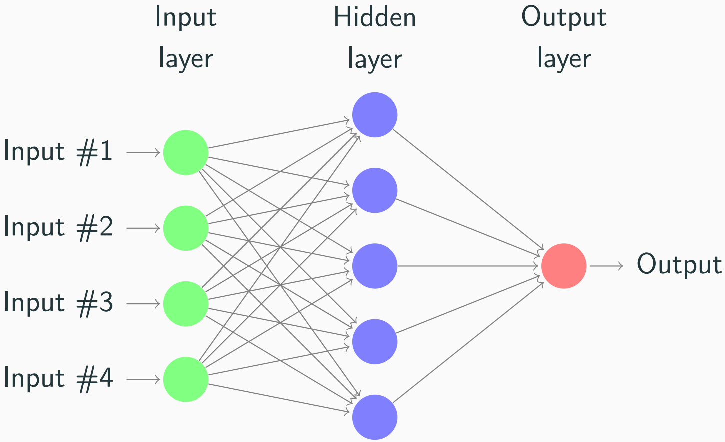
- word mover's distance
- soft cosine similarity

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

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"



⇒ 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

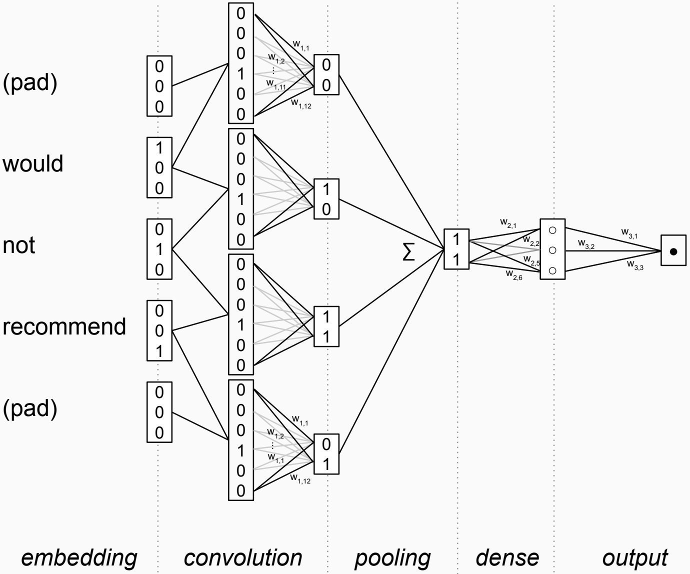
The problem with such a basic networks: just as with classic SML, we still loose all information about order (the “not good” problem).

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

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model.add(Embedding(input_dim=vocab_size, output_dim=embedding_dim,
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model.add(Conv1D(embedding_dim, 5, activation='relu'))
model.add(GlobalMaxPooling1D())
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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

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

Neural networks

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!

Contextual Embeddings

Downsides of Non-Contextual Word Embeddings

- Word2Vec and Glove produce *static* vectors: each word is represented by a single vector.
  - e.g., the vector for *date* is always the same...
  - ...however, the meaning of this word differs across domains: "she put a *date* in his lunchbox" (1); "they went on a *date*" (2); and "what's the *date* today?"

Enter: Contextual Word Embeddings

- *Transformers* create a new vector for each time a word is used in the dataset
- *Contextualized* vectors.
- *self-attention* mechanism is essential here: this is a manner to automatically decide which nearby words should influence a token's representation; the model *learns* which tokens *to attend to*

Transfer learning paradigm

The idea of transfer learning is very powerful

Transfer Learning paradigm

1. Pre-train a model on data that is at hand (e.g., Wikipedia, Google News)
2. Fine-tune the model on your downstream task (bring in your small-scale annotated dataset)

By adding 'task-specific' heads you can produce specific outputs, e.g., classification, text generation, named entity recognition, etc.

Transformer-based models

The architecture of transformers is very efficient on modern hardware; transformers process words in parallel. As they are much faster, we can use much more data.

Transformer-based models

BERT: Bidirectional Encoder Representations from Transformers (Devlin et al., 2019)

- (Huge) pre-trained model (by, e.g., Google)
- Trained on very large amount of text and can use words in context.
- State of the art performance on the General Language Understanding Evaluation benchmark (GLUE).
- BERT and other transformer-based models are used for a range of tasks;
    1. Sentiment analysis
    2. sequence-to-sequence predictions (e.g., translation)
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- (Huge) pre-trained model (by, e.g., Google)
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- State of the art performance on the General Language Understanding Evaluation benchmark (GLUE).
- BERT and other transformer-based models are used for a range of tasks;
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How to use

HuggingFace

- The ‘HuggingFace‘: Python library includes lots of datasets and transformer-based models
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Let’s look at an example (imdb.ipynb)

Transformer-based models

Do I need all this fancy stuff?

Things to consider

How important is. . .

- precision/recall? Am I satisfied with .88 when .90 is theoretically possible? .85? .80? .75?
- explainability?
- computational resources?
- generalizability and out-of-sample performance?

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- Invest in good hyperparameter-tuning (cross-validation, gridsearch) and don't forget to set aside unseen data for the *final* evaluation.
- If you (a) need to get the highest possible accuracy, or (b) have reasons to assume that the model does not generalize well enough (overfitting problems, bad out-of-sample prediction (e.g., training topics on newspaper 1, predicting topics in newspaper 2), try embedding-based approaches, transformers, etc.
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Ethical considerations

(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.

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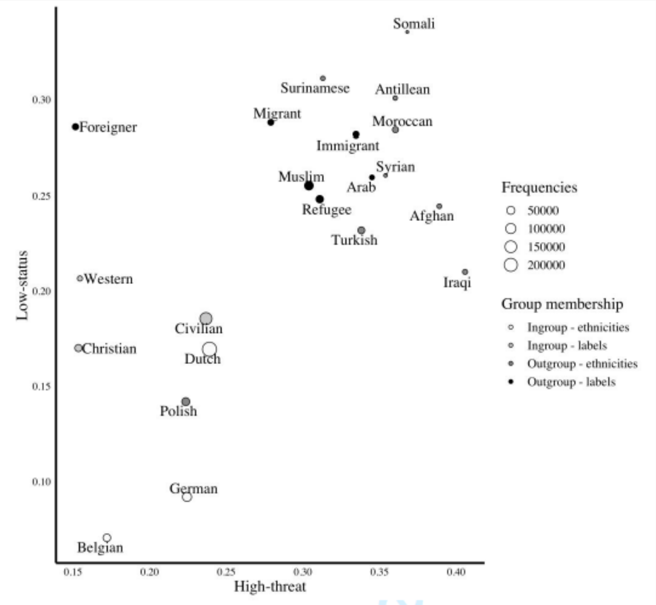
An exmaple from our research

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
Foreigner
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Immigrant
Syrian
Muslim
Arab
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Afghan
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Iraqi
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Dutch
Polish
German
Belgian
Low-status
High-threat
0.10
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Frequencies
50000
100000
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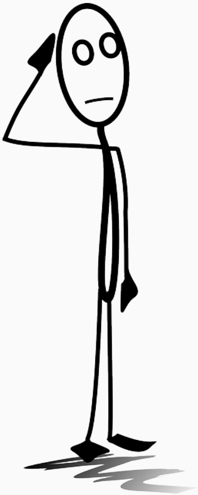
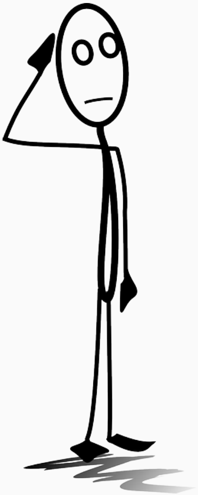
200000
Group membership
Ingroup - ethnicities
Ingroup - labels
Outgroup - ethnicities
Outgroup - labels

Your takeaway

(short recap of course)



Have your plans about how to and wether to use ML changed?



What are your next steps?

Last part: we help you working on (or discussing about) your own projects.

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

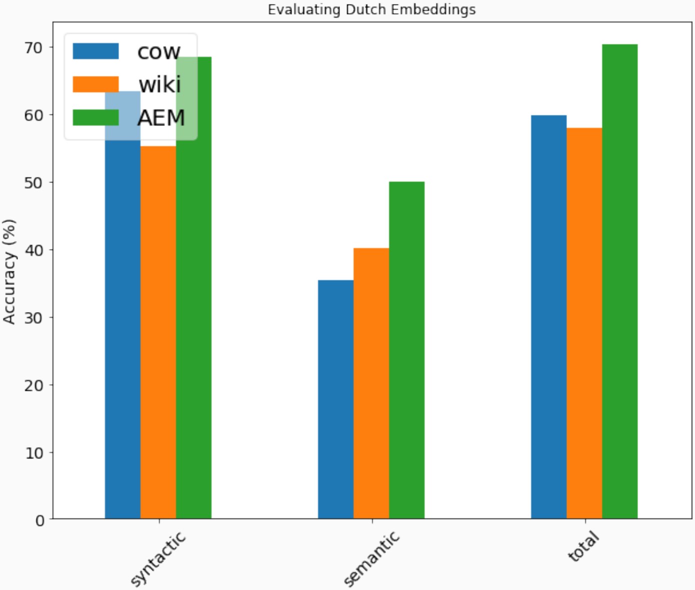
Evaluation methods

- 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

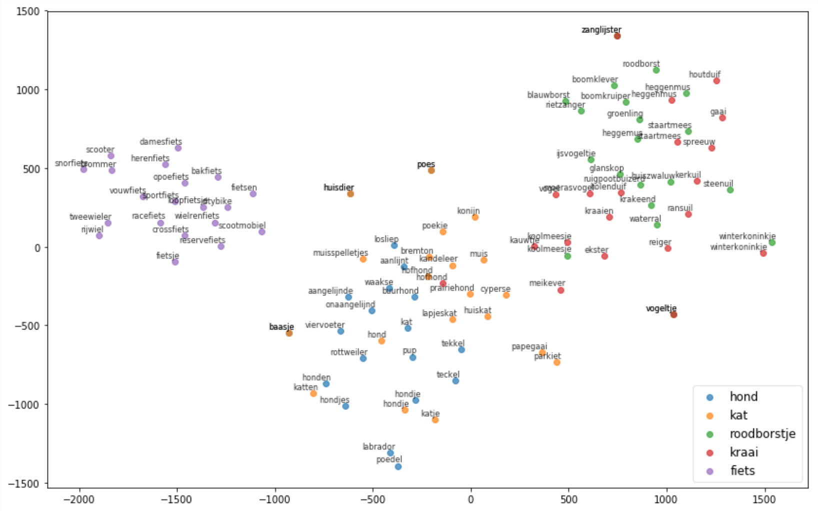
1. 'relationship'/ analogy-task (Tulkens et al., 2016)
   - **syntatic relationships**: dans dansen loop *[lopen]*
   - **semantic relationships**: denemarken kopenhagen noorwegen *[oslo]*
2. 5806 relationship tasks


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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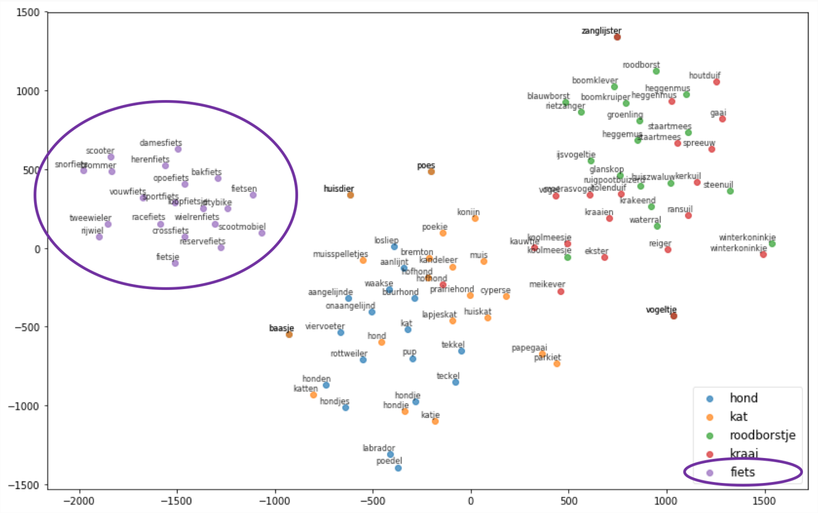
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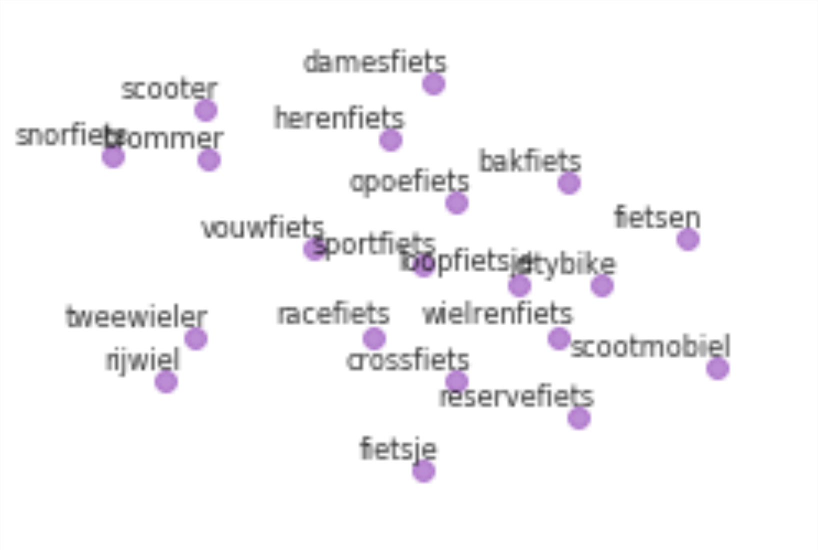
damesfiets
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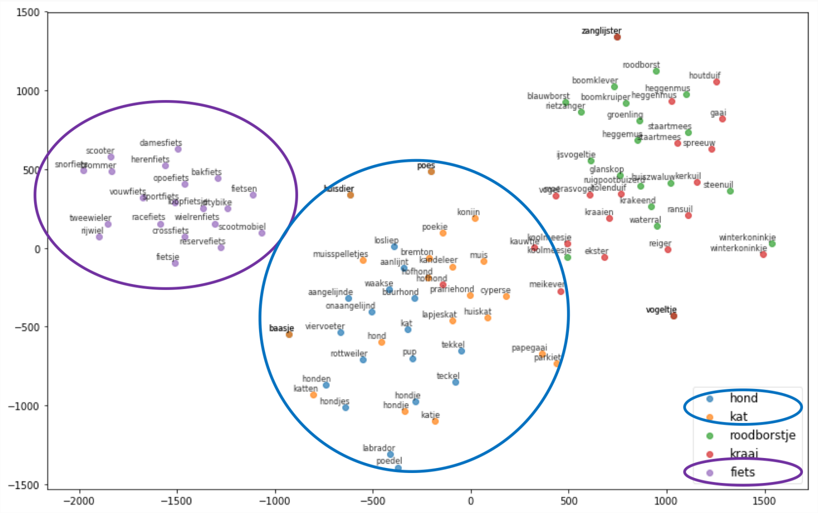
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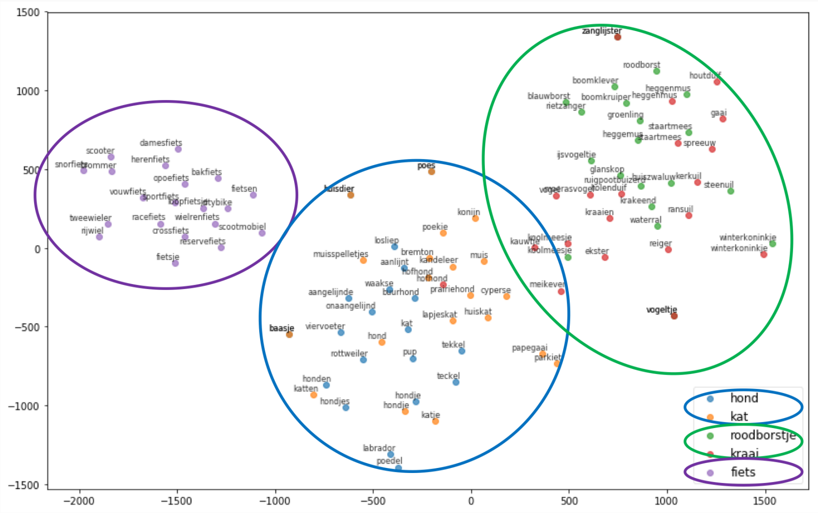
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rottweiler
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papegaai
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roodborst
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boomklever
heggenmus
blauwborst
boomkruiper
rietzanger
groenling
gaai
staartmees
spreeuw
ijsvogeltje
glanskop
huiszwaluw
kerkuil
steenuil
holenduif
krakeend
kraaien
ransuil
waterral
kauwtje
koolmeesje
ekster
reiger
winterkoninkje
meikever
vogeltje

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.

References

Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2019). BERT: Pre-training of deep bidirectional transformers for language understanding. *NAACL HLT 2019 - 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies - Proceedings of the Conference*, *1*(1950), 4171–4186.