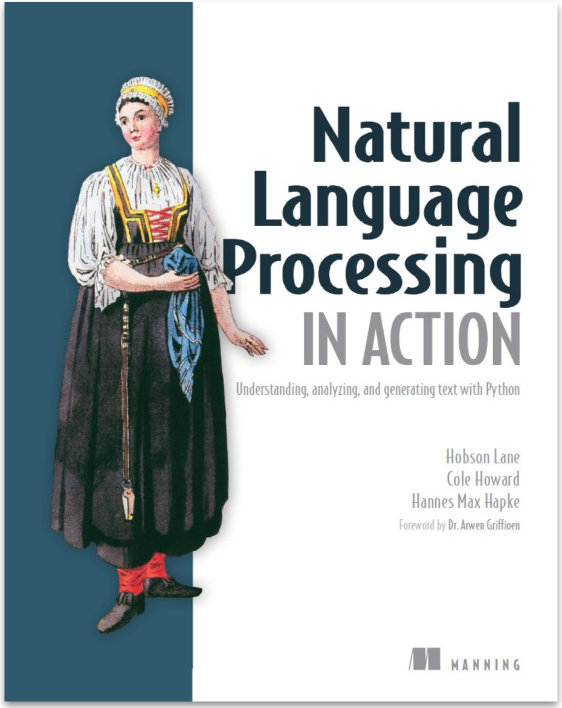
NLP

TEXT REPRESENTATION

BOOK RECOMMENDATION

Lane, Hobson, et al. *Natural Language Processing in Action: Understanding, Analyzing, and Generating Text with Python*. Manning Publications Co, 2019.

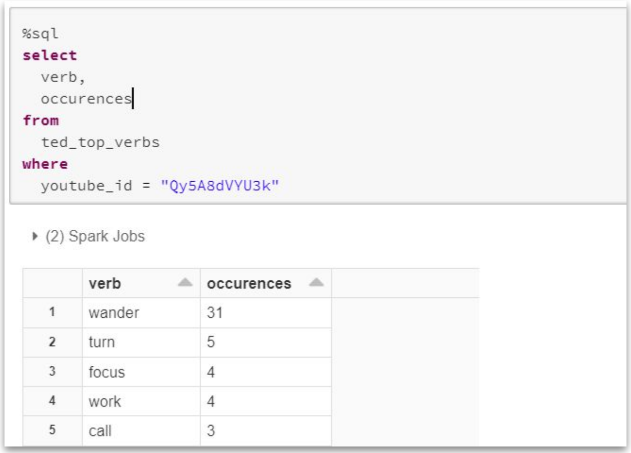
You can find the example code in this notebook.


Natural
Language
Processing
IN ACTION
Understanding, analyzing, and generating text with Python
Hobson Lane
Cole Howard
Hannes Max Hapke
Foreword by Dr. Arwen Griffioen
MANNING

BAG OF WORDS

RAW WORD COUNTS

A bag of words is a dictionary with counts of the occurrence of the single words in a text.



```
%sql
select
  verb,
  occurences
from
  ted_top_verbs
where
  youtube_id = "Qy5A8dVYU3k"
```

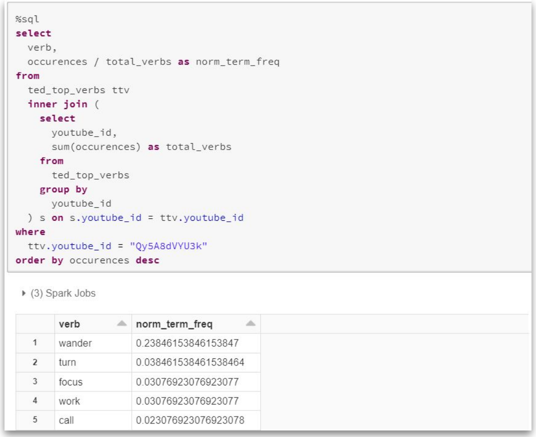
	verb	occurences
1	wander	31
2	turn	5
3	focus	4
4	work	4
5	call	3

```
{
    "wander": 31,
    "turn": 5,
    "focus": 4,
    "work": 4,
    "call": 3
    ...
}
```

BAG OF WORDS

NORMALIZED TERM FREQUENCY

Instead of raw counts, it is useful to calculate a relative occurrence to the length of the text. This is called the normalized term frequency.



```
%sql
select
  verb,
  occurences / total_verbs as norm_term_freq
from
  ted_top_verbs ttv
  inner join (
    select
      youtube_id,
      sum(occurences) as total_verbs
    from
      ted_top_verbs
    group by
      youtube_id
  ) s on s.youtube_id = ttv.youtube_id
where
  ttv.youtube_id = "Qy5A8dVYU3k"
order by occurences desc
```

▸ (3) Spark Jobs

	verb	norm_term_freq
1	wander	0.23846153846153847
2	turn	0.038461538461538464
3	focus	0.03076923076923077
4	work	0.03076923076923077
5	call	0.023076923076923078

```
{
    "work": 0.2384,
    "turn": 0.0384,
    "focus": 0.0307,
    "work": 0.0307,
    "call": 0.0230
    ...
}
```

BAG OF WORDS

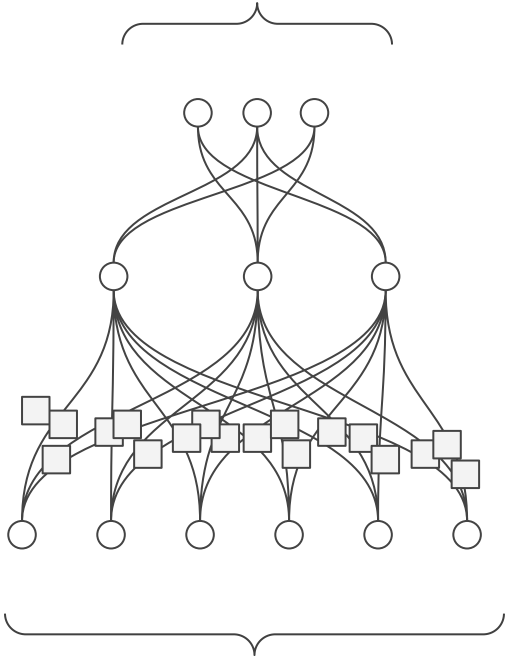
APPLICATION AND LIMITS

- Good basis for **rule-based analysis**, such as sentiment, topic identification, spam-filters

- Not suitable as input for machine learning algorithms; they require numeric values

How can we represent text numerically?

The output (prediction) is numeric, too



ML models like neural networks are purely mathematical objects and require numeric input

ONE HOT ENCODED VECTORS

SPARSE REPRESENTATION

A one hot encoded vector is a sparse vector with only `0` and a single `1` for the index of the word it represents.

`“This is my absolute undisputable favorite tea right now”`

The length of each vector depends on the size of the vocabulary. Large vectors are >99% filled with zeroes, which makes them inefficient.

absolute	0	0	0	1	0	0	0	0	0
favorite	0	0	0	0	0	1	0	0	0
is	0	1	0	0	0	0	0	0	0
my	0	0	1	0	0	0	0	0	0
now	0	0	0	0	0	0	0	0	1
right	0	0	0	0	0	0	0	1	0
tea	0	0	0	0	0	0	1	0	0
this	1	0	0	0	0	0	0	0	0
undisputable	0	0	0	0	1	0	0	0	0

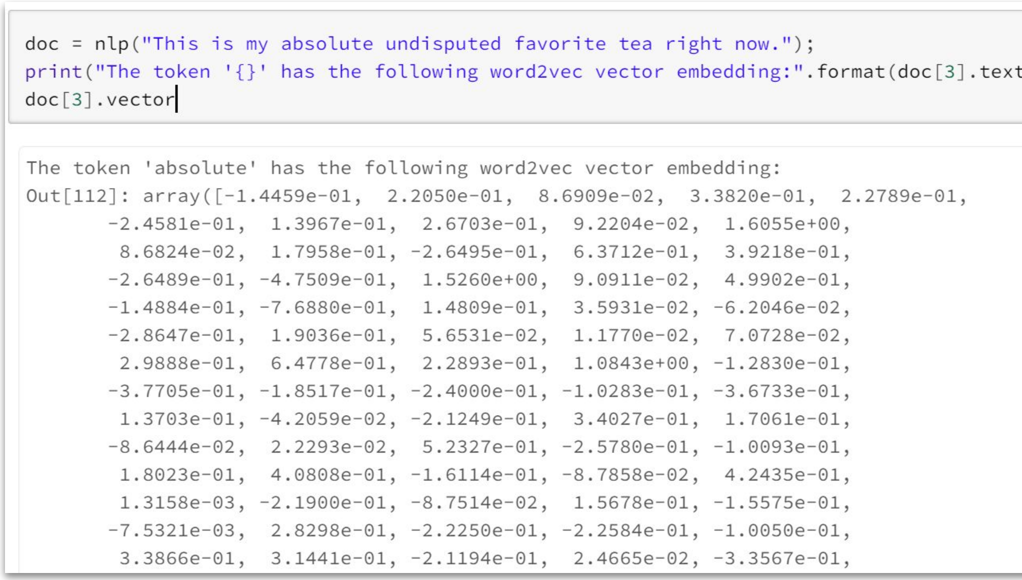
WORD EMBEDDINGS

A VECTOR OF NUMBERS

A word embedding is the representation of a word through a vector of numbers (floats).

Vectors of contextually similar words are closer to each other in the euclidean space than others.

Word embeddings are learned using a machine learning algorithm such as `word2vec`

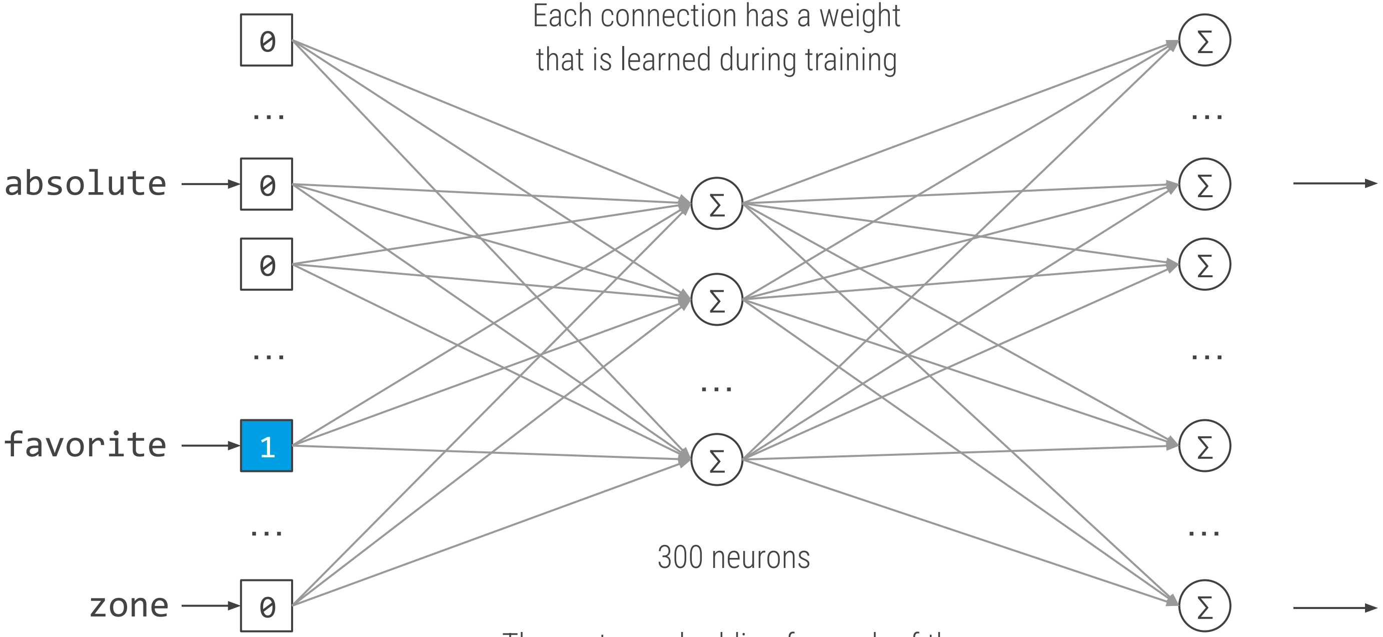


```
doc = nlp("This is my absolute undisputed favorite tea right now.");
print("The token '{}' has the following word2vec vector embedding:".format(doc[3].text
doc[3].vector
```

```
The token 'absolute' has the following word2vec vector embedding:
Out[112]: array([-1.4459e-01,  2.2050e-01,  8.6909e-02,  3.3820e-01,  2.2789e-01,
       -2.4581e-01,  1.3967e-01,  2.6703e-01,  9.2204e-02,  1.6055e+00,
        8.6824e-02,  1.7958e-01, -2.6495e-01,  6.3712e-01,  3.9218e-01,
       -2.6489e-01, -4.7509e-01,  1.5260e+00,  9.0911e-02,  4.9902e-01,
       -1.4884e-01, -7.6880e-01,  1.4809e-01,  3.5931e-02, -6.2046e-02,
       -2.8647e-01,  1.9036e-01,  5.6531e-02,  1.1770e-02,  7.0728e-02,
        2.9888e-01,  6.4778e-01,  2.2893e-01,  1.0843e+00, -1.2830e-01,
       -3.7705e-01, -1.8517e-01, -2.4000e-01, -1.0283e-01, -3.6733e-01,
        1.3703e-01, -4.2059e-02, -2.1249e-01,  3.4027e-01,  1.7061e-01,
       -8.6444e-02,  2.2293e-02,  5.2327e-01, -2.5780e-01, -1.0093e-01,
        1.8023e-01,  4.0808e-01, -1.6114e-01, -8.7858e-02,  4.2435e-01,
        1.3158e-03, -2.1900e-01, -8.7514e-02,  1.5678e-01, -1.5575e-01,
       -7.5321e-03,  2.8298e-01, -2.2250e-01, -2.2584e-01, -1.0050e-01,
        3.3866e-01,  3.1441e-01, -2.1194e-01,  2.4665e-02, -3.3567e-01,
```

WORD EMBEDDINGS

LEARNING THE VECTORS



Each connection has a weight that is learned during training

Probability that the word “absolute” appears *nearby* the word “favorite”

Probability that the word “zone” appears *nearby* the word “favorite”

300 neurons

10,000 positions

The vector embedding for each of the 10K words is the output of the network’s hidden layer for that word

WORD EMBEDDINGS

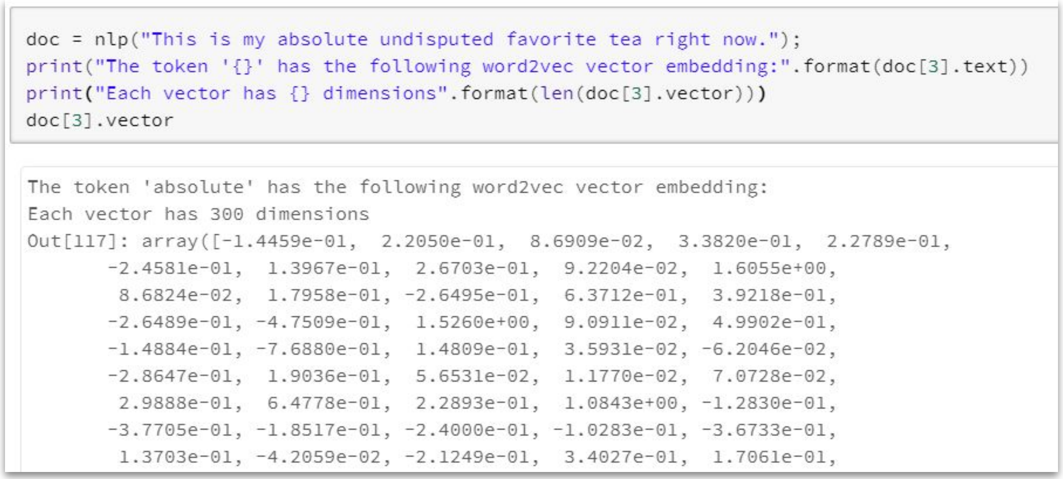
VIDEO RECOMMENDATION

WORD EMBEDDINGS

EXAMPLE spaCy

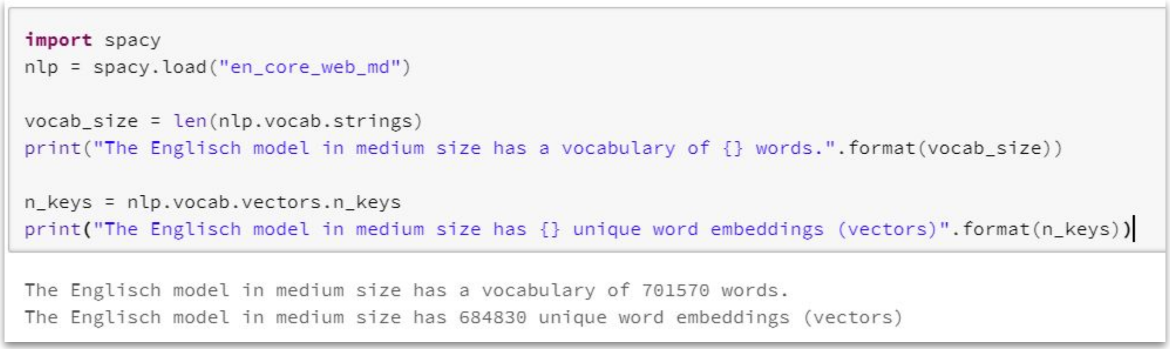
spaCy's medium English model has a **vocabulary of > 700,000 words** with vector embeddings.

A single vector has **300 dimensions**



```
doc = nlp("This is my absolute undisputed favorite tea right now.");
print("The token '{}' has the following word2vec vector embedding:".format(doc[3].text))
print("Each vector has {} dimensions".format(len(doc[3].vector)))
doc[3].vector
```

```
The token 'absolute' has the following word2vec vector embedding:
Each vector has 300 dimensions
Out[117]: array([-1.4459e-01,  2.2050e-01,  8.6909e-02,  3.3820e-01,  2.2789e-01,
       -2.4581e-01,  1.3967e-01,  2.6703e-01,  9.2204e-02,  1.6055e+00,
        8.6824e-02,  1.7958e-01, -2.6495e-01,  6.3712e-01,  3.9218e-01,
       -2.6489e-01, -4.7509e-01,  1.5260e+00,  9.0911e-02,  4.9902e-01,
       -1.4884e-01, -7.6880e-01,  1.4809e-01,  3.5931e-02, -6.2046e-02,
       -2.8647e-01,  1.9036e-01,  5.6531e-02,  1.1770e-02,  7.0728e-02,
        2.9888e-01,  6.4778e-01,  2.2893e-01,  1.0843e+00, -1.2830e-01,
       -3.7705e-01, -1.8517e-01, -2.4000e-01, -1.0283e-01, -3.6733e-01,
        1.3703e-01, -4.2059e-02, -2.1249e-01,  3.4027e-01,  1.7061e-01,
```



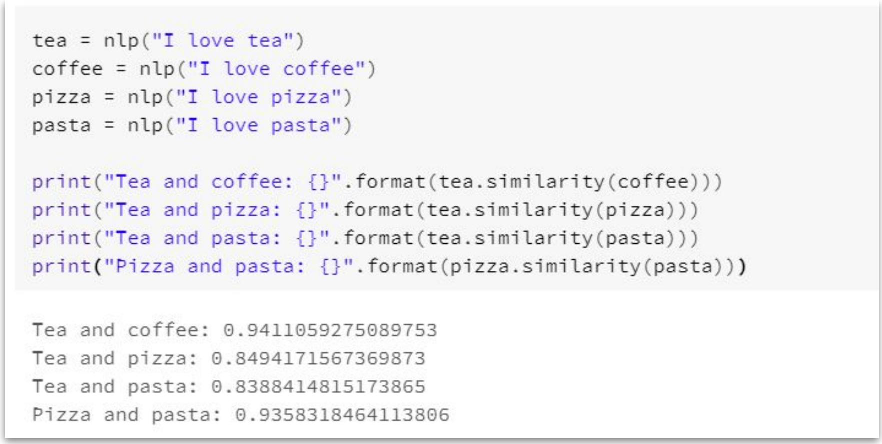
```
import spacy
nlp = spacy.load("en_core_web_md")

vocab_size = len(nlp.vocab.strings)
print("The Englisch model in medium size has a vocabulary of {} words.".format(vocab_size))

n_keys = nlp.vocab.vectors.n_keys
print("The Englisch model in medium size has {} unique word embeddings (vectors)".format(n_keys))
```

```
The Englisch model in medium size has a vocabulary of 701570 words.
The Englisch model in medium size has 684830 unique word embeddings (vectors)
```

WORD EMBEDDINGS

SIMILARITY

With word embeddings, we can calculate **similarities** between words and documents.



```
tea = nlp("I love tea")
coffee = nlp("I love coffee")
pizza = nlp("I love pizza")
pasta = nlp("I love pasta")

print("Tea and coffee: {}".format(tea.similarity(coffee)))
print("Tea and pizza: {}".format(tea.similarity(pizza)))
print("Tea and pasta: {}".format(tea.similarity(pasta)))
print("Pizza and pasta: {}".format(pizza.similarity(pasta)))
```

```
Tea and coffee: 0.9411059275089753
Tea and pizza: 0.8494171567369873
Tea and pasta: 0.8388414815173865
Pizza and pasta: 0.9358318464113806
```

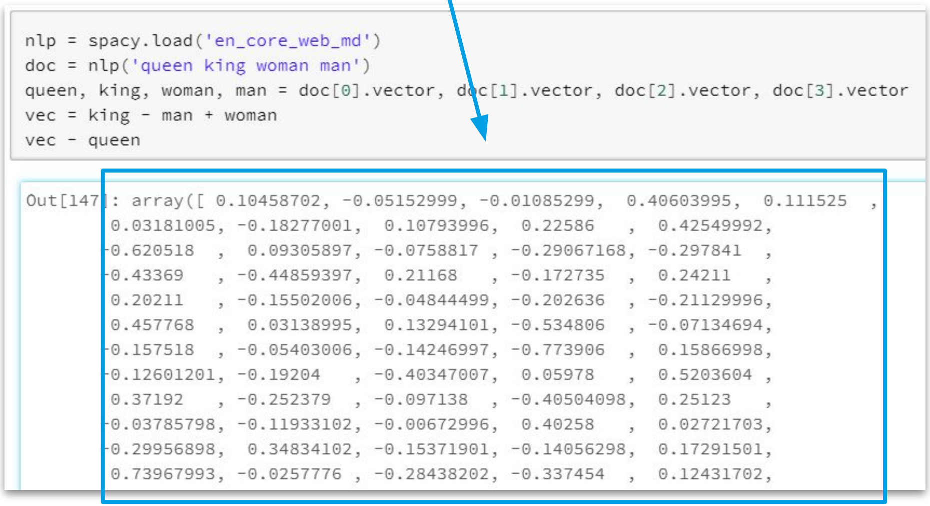
WORD EMBEDDINGS

ARITHMETIC

We can even do arithmetic based on learned vector embeddings!

`King - Man + Woman = ?`

The difference vector of
`(King - Man + Woman) - Queen`
contains only numbers close to zero.



```
nlp = spacy.load('en_core_web_md')
doc = nlp('queen king woman man')
queen, king, woman, man = doc[0].vector, doc[1].vector, doc[2].vector, doc[3].vector
vec = king - man + woman
vec - queen
```

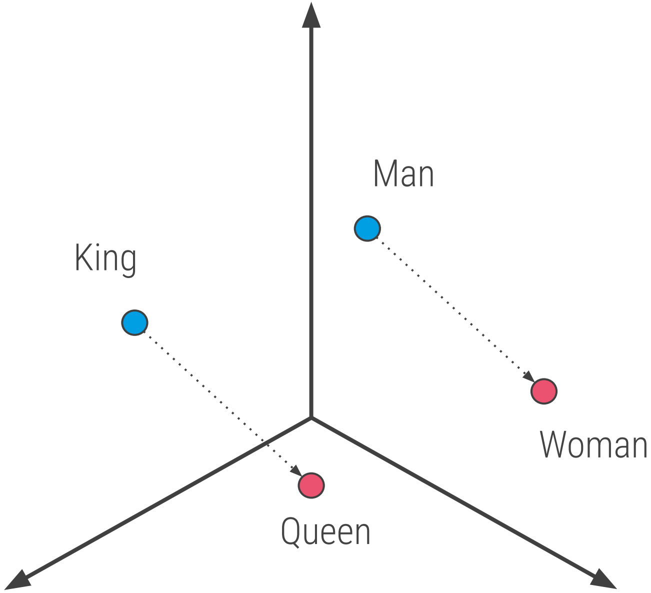
```
Out[147]: array([ 0.10458702, -0.05152999, -0.01085299,  0.40603995,  0.111525  ,
        0.03181005, -0.18277001,  0.10793996,  0.22586   ,  0.42549992,
       -0.620518  ,  0.09305897, -0.0758817 , -0.29067168, -0.297841  ,
       -0.43369   , -0.44859397,  0.21168   , -0.172735  ,  0.24211   ,
        0.20211   , -0.15502006, -0.04844499, -0.202636  , -0.21129996,
        0.457768  ,  0.03138995,  0.13294101, -0.534806  , -0.07134694,
       -0.157518  , -0.05403006, -0.14246997, -0.773906  ,  0.15866998,
       -0.12601201, -0.19204   , -0.40347007,  0.05978   ,  0.5203604 ,
        0.37192   , -0.252379  , -0.097138  , -0.40504098,  0.25123   ,
       -0.03785798, -0.11933102, -0.00672996,  0.40258   ,  0.02721703,
       -0.29956898,  0.34834102, -0.15371901, -0.14056298,  0.17291501,
        0.73967993, -0.0257776 , -0.28438202, -0.337454  ,  0.12431702,
```

WORD EMBEDDINGS

ARITHMETIC

The relative position of “King” and “Queen” in the multidimensional vector space is similar to the one of “Man” and “Woman”.

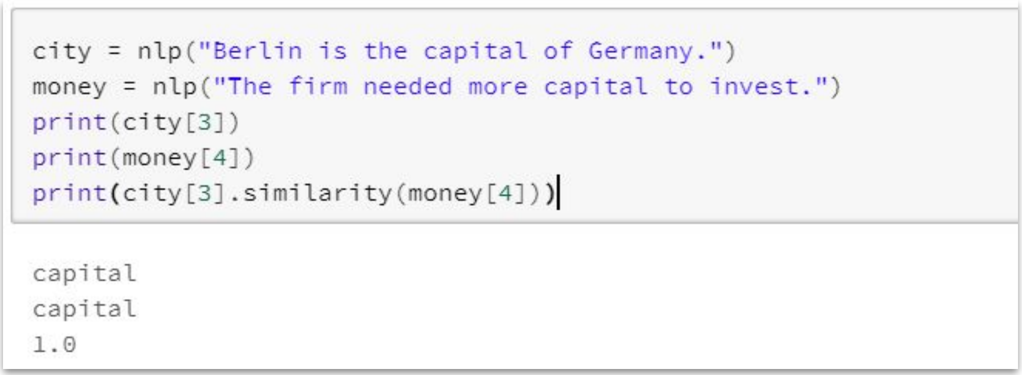
```
King - Man + Woman = Queen
```



WORD EMBEDDINGS

SIMILARITY

BUT: The same words have the same vector embeddings, no matter the context :-(



```
city = nlp("Berlin is the capital of Germany.")
money = nlp("The firm needed more capital to invest.")
print(city[3])
print(money[4])
print(city[3].similarity(money[4]))
```

```
capital
capital
1.0
```

The word “capital” can have two meanings; static word embeddings do not account for context.

TAKE CONTEXT INTO ACCOUNT

LSTM, SEQ2SEQ, TRANSFORMERS

Long short-term memory (LSTM) networks, sequence-to-sequence models and attention-based transformer networks take context into account and extend the NLP capabilities.

Transformer networks became particularly famous through the release of BERT in 2019 and GPT-3 in 2020

GPT-3 facts:

> 170 billion parameters

~ 500 billion tokens of training data

~ 4.7 million USD training costs