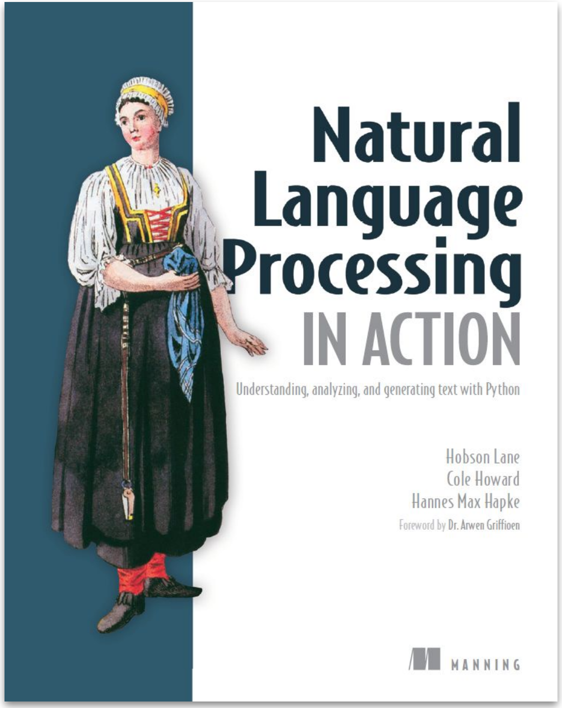
# NLP

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.



# 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"
```

▸ (2) Spark Jobs

| | 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.

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

```sql
%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
```

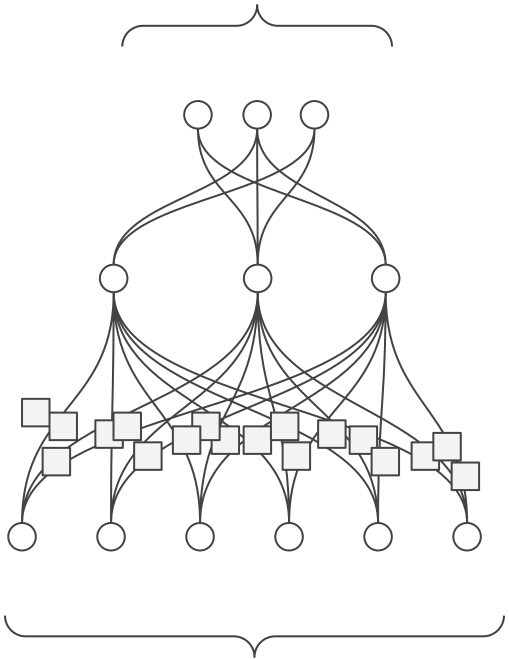
▸ (3) Spark Jobs

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

- 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

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

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”

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 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.

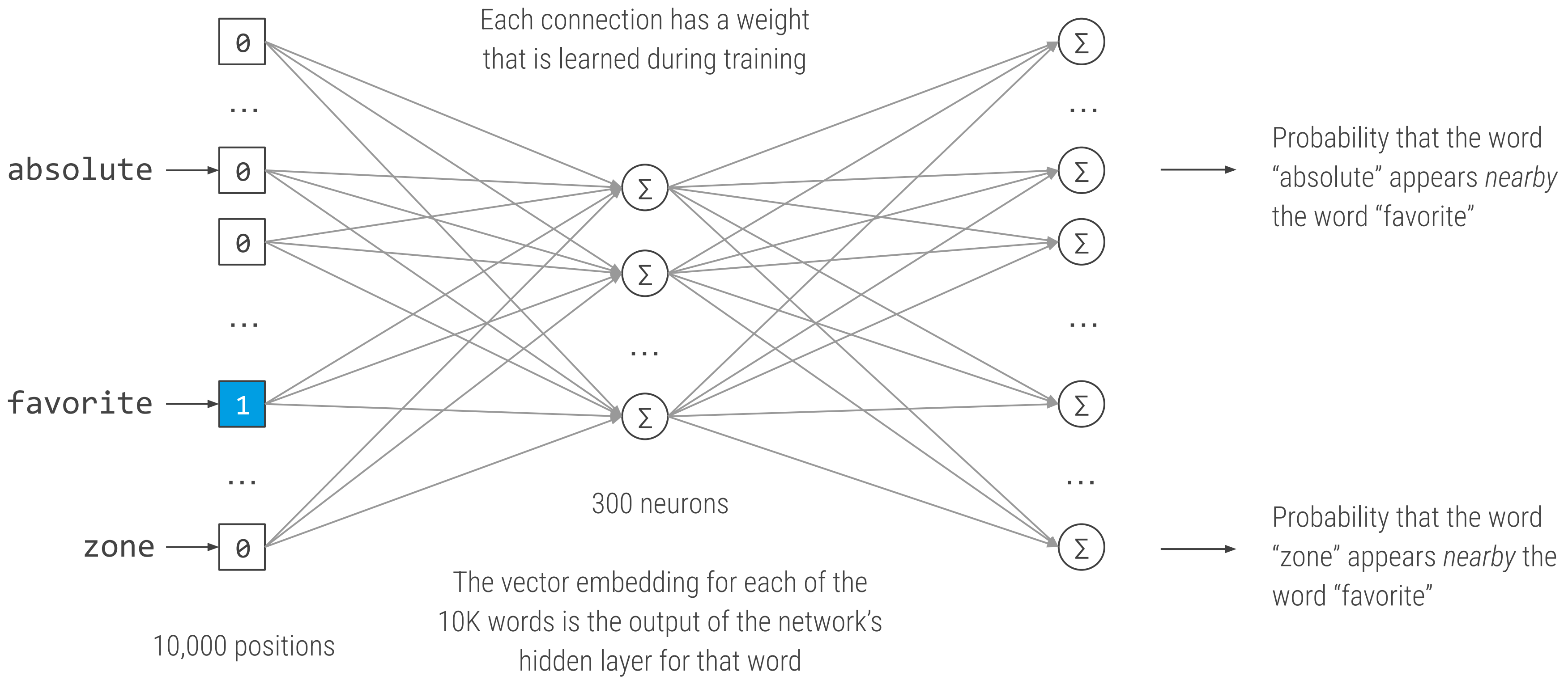
Word embeddings are learned using a machine learning algorithm such as `word2vec`

```
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



# WORD EMBEDDINGS

## VIDEO RECOMMENDATION

# WORD EMBEDDINGS

## EXAMPLE spaCy

```
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,
```

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

A single vector has **300 dimensions**

```
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)
```

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

The difference vector of

`(King - Man + Woman) - Queen`

contains only numbers close to zero.

We can even do arithmetic based on learned vector embeddings!

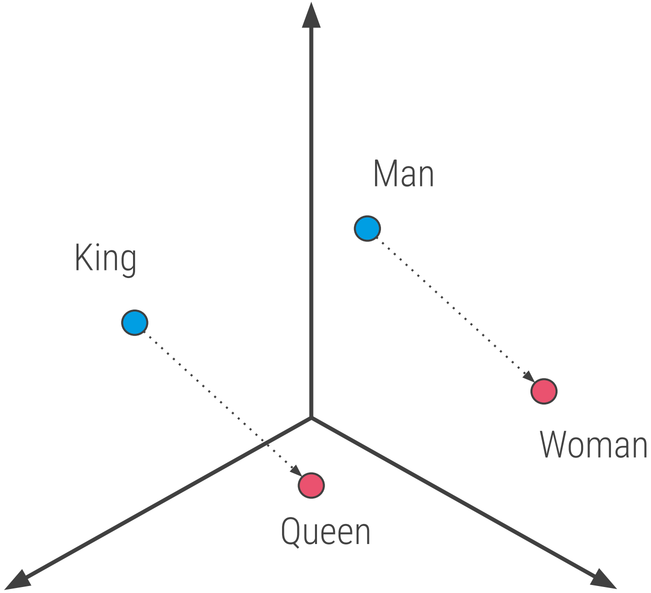
`King - Man + Woman = ?`

```python
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,
```

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
```



**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.

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