ITMO UNIVERSITY

NLP Basic and Selected Topics

A Practical and Easy Introduction to Selected Topics

Aug 31st, 2019

Overview of the Unit Today

1) Applications of NLP / Introduction (30min)

2) Practical NLP (NLTK / pythainlp) (45min)

3) **Modern NLP with ML/DL (45min)**

4) Example: Word Similarity and WordNet (30min)

5) Modern NLP with fastAI / flair (30min)

Traditional NLP

- Traditional NLP often based on dictionaries and a large processing pipeline
- Often with rules and feature engineering

- **Example:** Sentiment
  - Dictionary
  - POS / NE-extraction – apply dict only for adjectives
  - Negation Rules
  - Maybe feature engineering for machine learning, rules/patterns

Modern NLP

- Often done end-to-end with deep learning
- Algorithm finds all the features, and what it needs by itself
- But: we need (lots of) training data

Modern NLP

- Explain basic idea of a deep neural network

Modern NLP

- A neural network needs numbers as input – it does not understand strings!

- Every word needs to be a vector of numbers – how can we make a word into a vector of numbers?
- The numbers need to represent **the meaning** of a word somehow.
  - What does this mean?
  - How could it be done?

Count-based Word Vectors

- Explain word – document matrix
- Explain word-word matrix
- Similarity of 2 words in a word-word matrix

Term-Term Matrices

- In IR systems we typically use Term-Document matrices
- But in many NLP applications we are interested in **term-term co-occurrence** matrices
- Co-occurrence can be measured in diferent ways, for example
  - Within a unit like a **sentence** or **paragraph**
  - Within a **word window** (left and/or right) of the target word – eg. a word window of 5
  - Q: when could a co-occurrence matrix be useful?

Co-occurrence matrix - Example

1. I enjoy flying.
2. I like NLP.
3. I like deep learning.

The resulting counts matrix will then be:

$$X = \begin{array}{c} \\ I \\ like \\ enjoy \\ deep \\ learning \\ NLP \\ flying \\ . \end{array} \begin{array}{c} \begin{array}{cccccccc} I & like & enjoy & deep & learning & NLP & flying & . \end{array} \\ \begin{bmatrix} 0 & 2 & 1 & 0 & 0 & 0 & 0 & 0 \\ 2 & 0 & 0 & 1 & 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 \end{bmatrix} \end{array}$$

Co-occurrence Matrices

Distributional hypothesis – "a word is characterized by the company it keeps"

- Words are defned by their context (words)

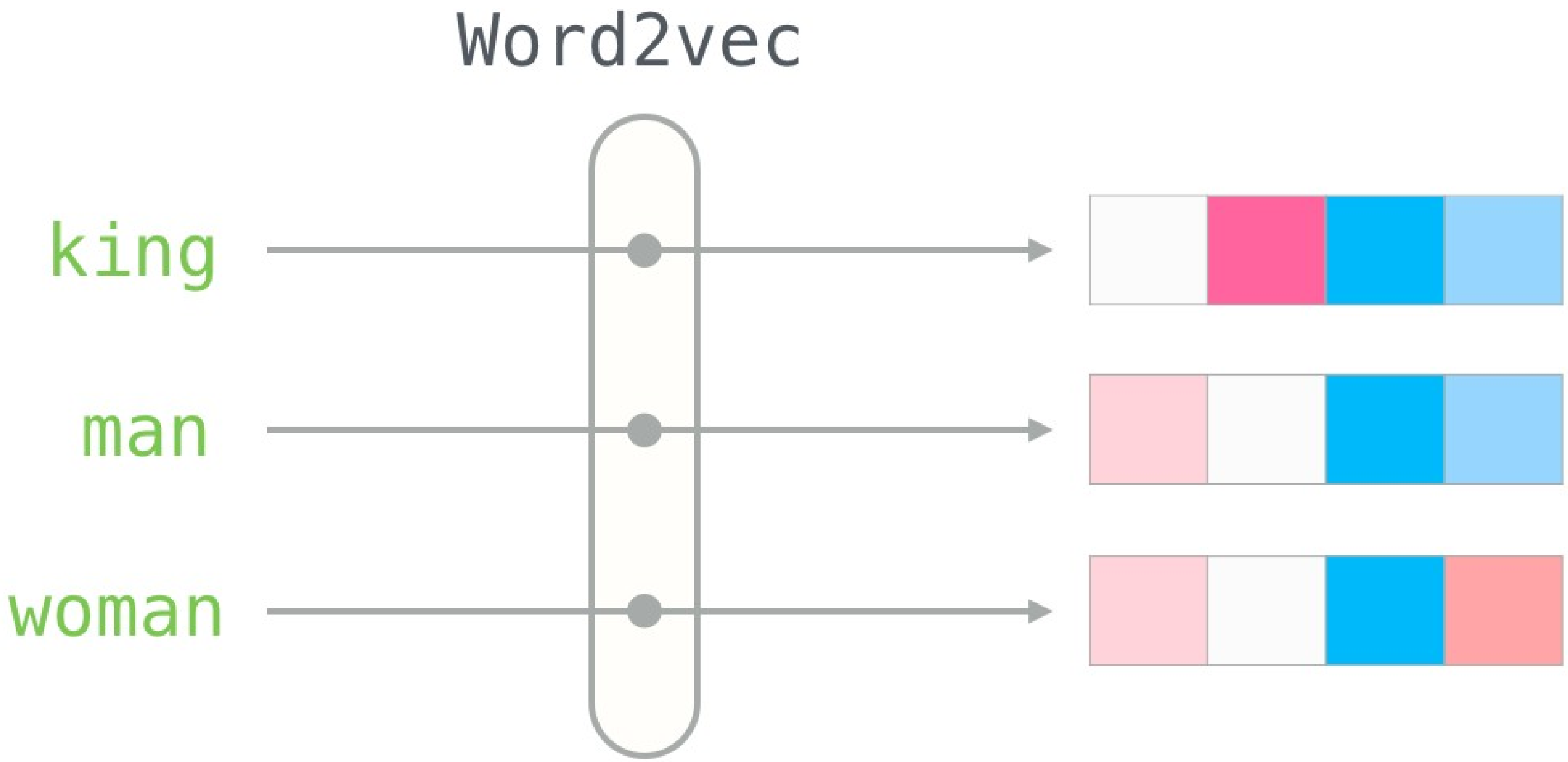
A bottle of **tesgüino** is on the table
Everybody likes **tesgüino**
Tesgüino makes you drunk
We make **tesgüino** out of corn.

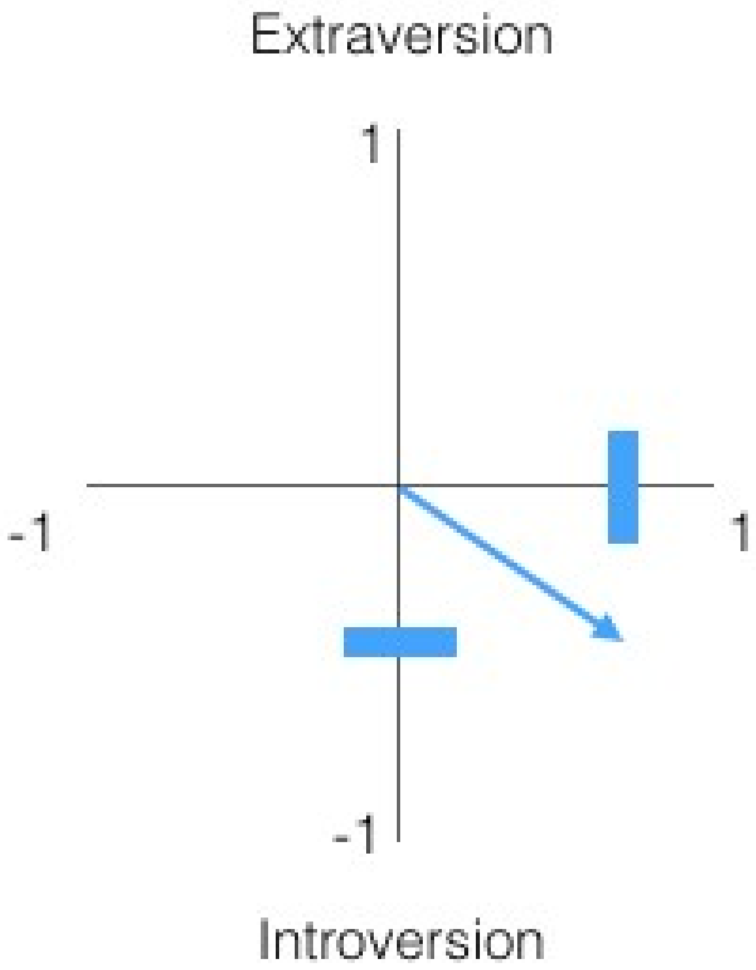
Count-based Word Vectors

- Once we have the co-occurrence matrix, we can apply PCA, SVD etc to compress the matrix to have eg only 300 dimensions per word

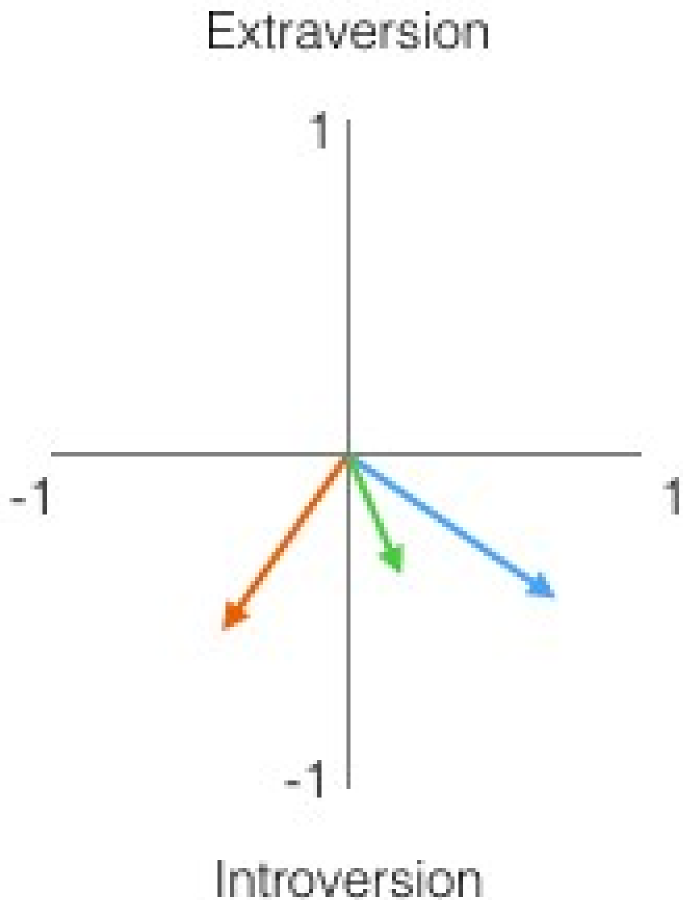
Prediction-based word vectors

- Using neural nets
- Most famous: word2vec
- Very good explanation http://jalammar.github.io/illustrated-word2vec/


Word2vec
king
man
woman

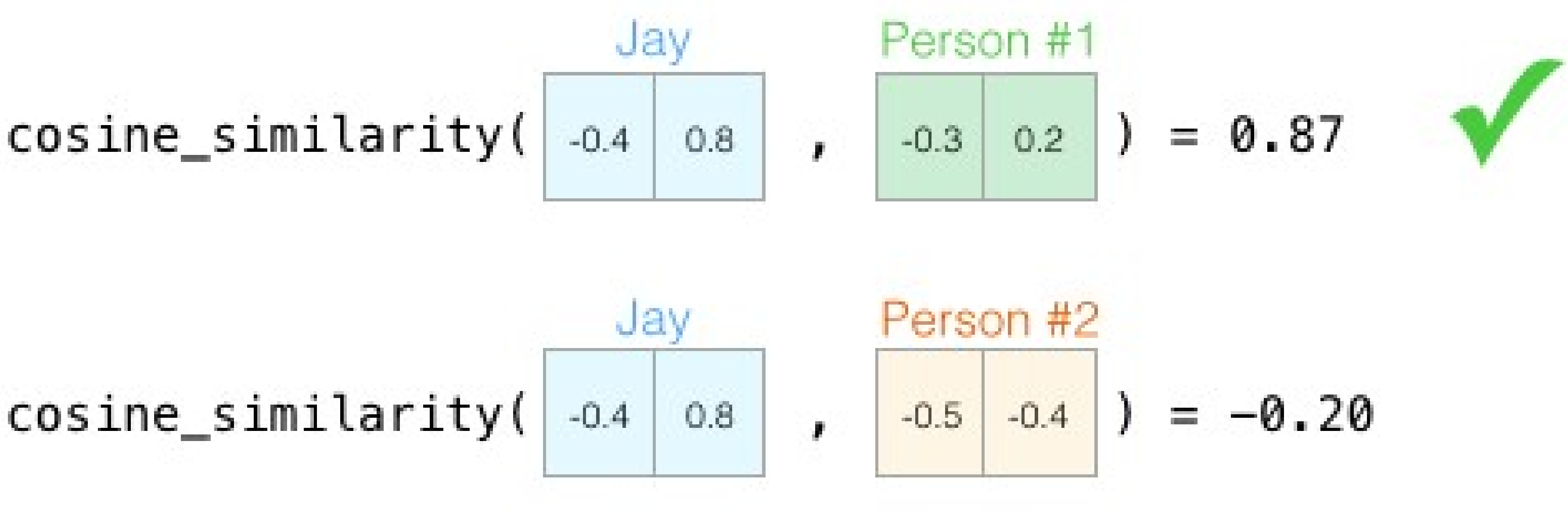


	Trait #1	Trait #2			
Jay	-0.4	0.8			

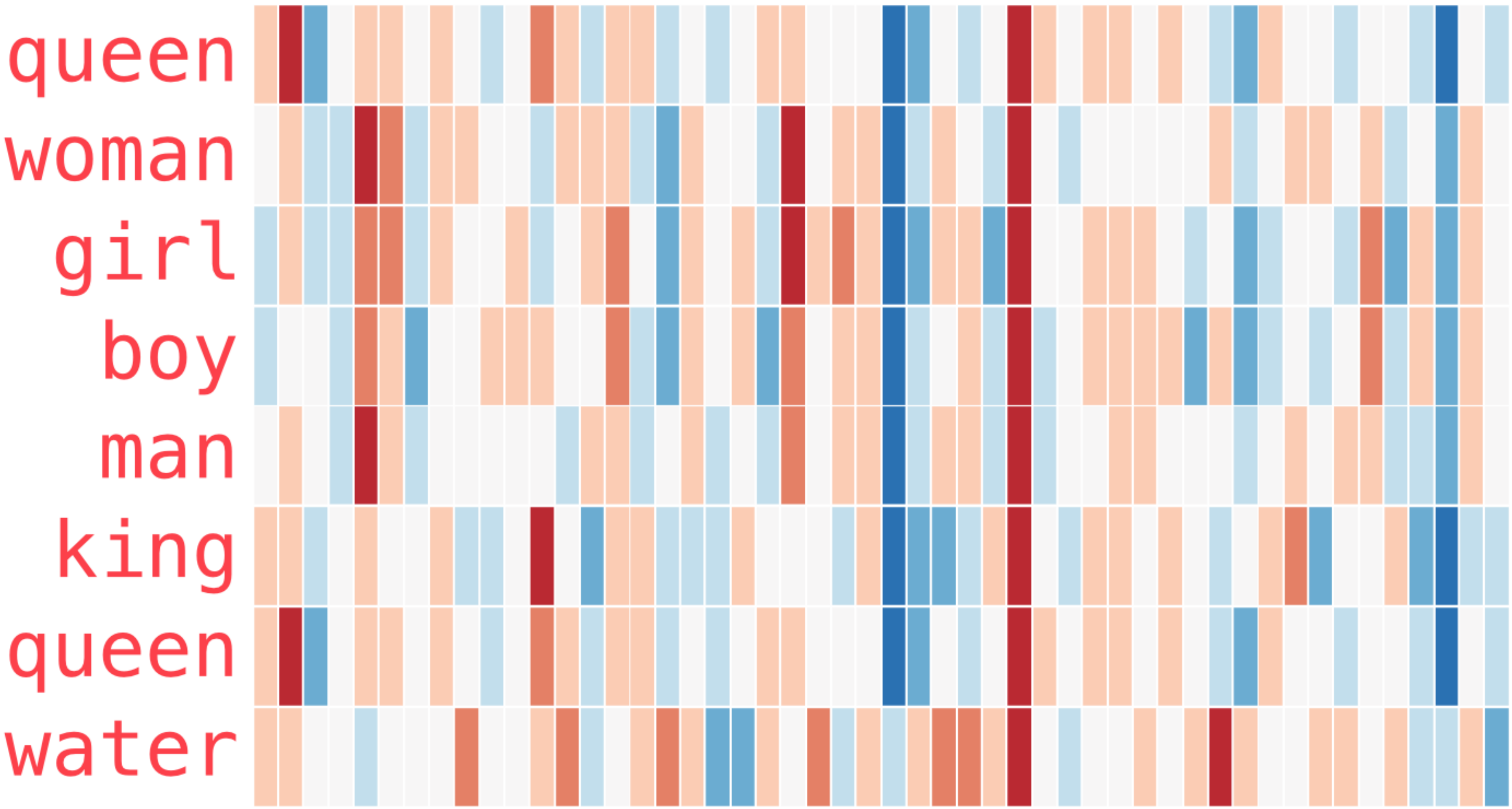


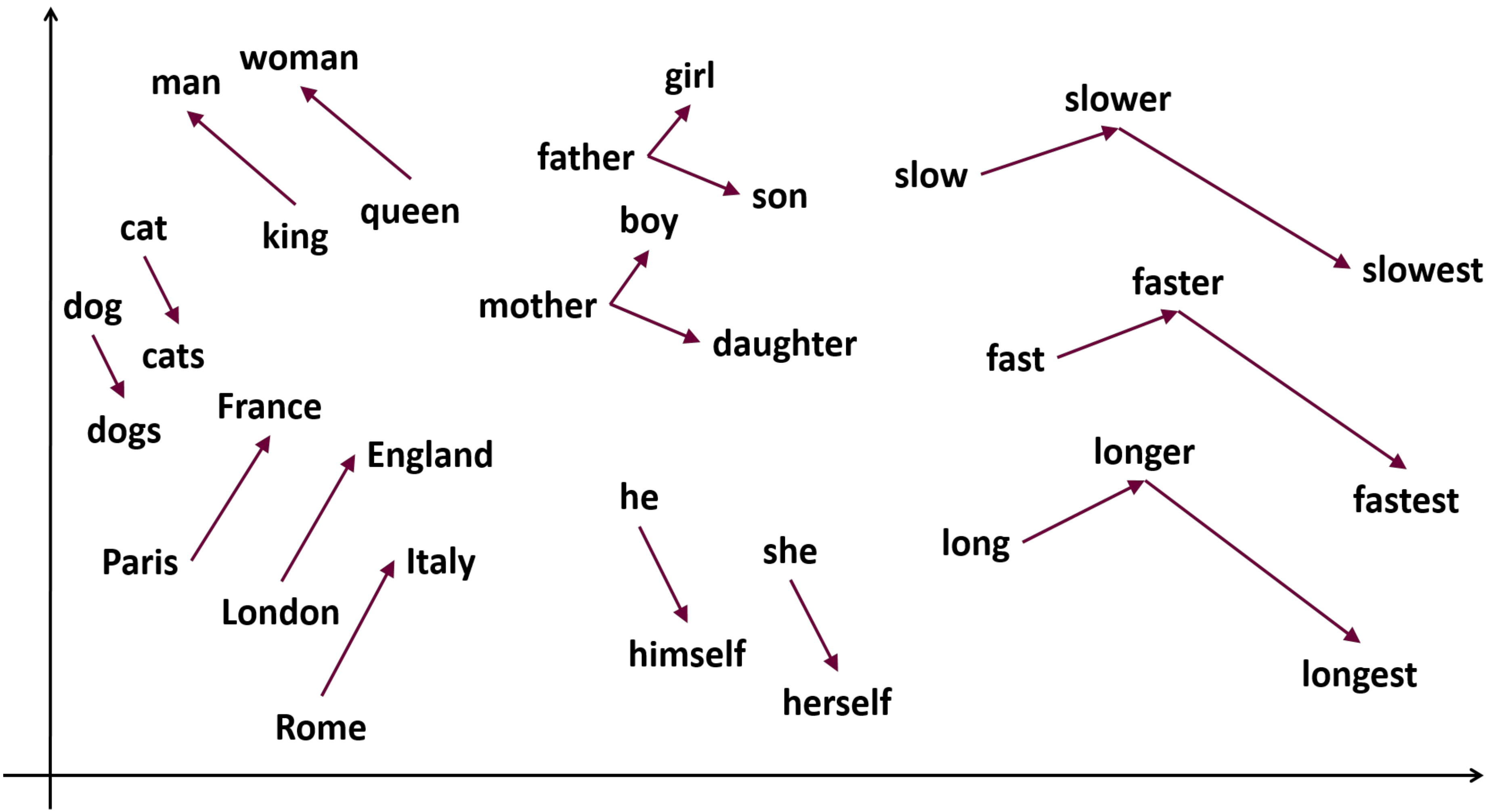
	Trait #1	Trait #2			
Jay	-0.4	0.8			
Person #1	-0.3	0.2			
Person #2	-0.5	-0.4			

Similarity in Vector Space



Word vectors




man
woman
king
queen
cat
cats
dog
dogs
France
Paris
England
London
Italy
Rome
girl
father
son
boy
mother
daughter
he
himself
she
herself
slower
slow
slowest
faster
fast
fastest
longer
long
longest

Training models

- Word2vec models can be easily trained
- You just need an input corpus
- For example Wikipedia
- But also domain specific, for example a book

- The result will be a model file like this:

Word vectors

```
the 0.418 0.24968 -0.41242 0.1217 0.34527 -0.044457 -0.49688 -0.17862
-0.00066023 -0.6566 0.27843 -0.14767 -0.55677 0.14658 -0.0095095 0.011658
0.10204 -0.12792 -0.8443 -0.12181 -0.016801 -0.33279 -0.1552 -0.23131
-0.19181 -1.8823 -0.76746 0.099051 -0.42125 -0.19526 4.0071 -0.18594
-0.52287 -0.31681 0.00059213 0.0074449 0.17778 -0.15897 0.012041 -0.054223
-0.29871 -0.15749 -0.34758 -0.045637 -0.44251 0.18785 0.0027849 -0.18411
-0.11514 -0.78581
, 0.013441 0.23682 -0.16899 0.40951 0.63812 0.47709 -0.42852 -0.55641
-0.364 -0.23938 0.13001 -0.063734 -0.39575 -0.48162 0.23291 0.090201
-0.13324 0.078639 -0.41634 -0.15428 0.10068 0.48891 0.31226 -0.1252
-0.037512 -1.5179 0.12612 -0.02442 -0.042961 -0.28351 3.5416 -0.11956
-0.014533 -0.1499 0.21864 -0.33412 -0.13872 0.31806 0.70358 0.44858
-0.080262 0.63003 0.32111 -0.46765 0.22786 0.36034 -0.37818 -0.56657
0.044691 0.30392
```

Training models

- But: we don’t want to train models now.
- There are many pretrained models

Use models

- You can use the Gensim library for Python
- See Colab!
- https://rare-technologies.com/word2vec-tutorial/

Exercise

- Open Colab
- Load a model (copy !wget etc code)
- Test the `most_similar` function
- Test the `doesnt_match` function
- Look at the vector of some word

What to the with those embeddings?

- Can we do sentence / document classification with the embeddings? How?
- How to improve (tf-idf)

- Use as input in for example machine translation with an RNN – for example on POS tagging
  - Show on whiteboard

What to the with those embeddings?

- How can we use embedding in a search system to get more results?!

- Example search query: “Bangkok animal shelter”

What to the with those embeddings?

- Example search query: “Bangkok animal shelter”

What to the with those embeddings? Classification with CNN