

# Introduction to regular expressions

Katharine Jarmul Founder, kjamistan



### What is Natural Language Processing?

- Field of study focused on making sense of language
  - Using statistics and computers
- You will learn the basics of NLP
  - Topic identification
  - Text classification
- NLP applications include:
  - Chatbots
  - Translation
  - Sentiment analysis
  - ... and many more!

### What exactly are regular expressions?

- Strings with a special syntax
- Allow us to match patterns in other strings
- Applications of regular expressions:
  - Find all web links in a document
  - Parse email addresses, remove/replace unwanted characters

```
In [1]: import re
In [2]: re.match('abc', 'abcdef')
Out[2]: <_sre.SRE_Match object; span=(0, 3), match='abc'>
In [3]: word_regex = '\w+'
In [4]: re.match(word_regex, 'hi there!')
Out[4]: <_sre.SRE_Match object; span=(0, 2), match='hi'>
```



### Common Regex Patterns

pattern	matches	example	
\W+	word	'Magic'	



### Common Regex patterns (2)

pattern	matches	example
\W+	word	'Magic'
\d	digit	9



### Common regex patterns (3)

pattern	matches	example
\W+	word	'Magic'
\d	digit	9
\s	space	11



### Common regex patterns (4)

pattern	matches	example	
\W+	word	'Magic'	
\d	digit	9	
\s	space	1.1	
*	wildcard	'username74'	



### Common regex patterns (5)

pattern	matches	example	
\W+	word	'Magic'	
\d	digit	9	
\s	space	1.1	
*	wildcard	'username74'	
+ or *	greedy match	'aaaaaa'	



### Common regex patterns (6)

pattern	matches	example	
\W+	word	'Magic'	
\d	digit	9	
\s	space	1 1	
*	wildcard	'username74'	
+ or *	greedy match	'aaaaaa'	
\S	not space	'no_spaces'	



### Common regex patterns (7)

pattern	matches	example	
/w+	word	'Magic'	
\d	digit	9	
\s	space	1.1	
*	wildcard	'username74'	
+ or *	greedy match	'aaaaaa'	
\S	not space	'no_spaces'	
[a-z]	lowercase group	'abcdefg'	

### Python's re Module

- re module
- split: split a string on regex
- findall: find all patterns in a string
- search: search for a pattern
- match: match an entire string or substring based on a pattern
- Pattern first, and the string second
- May return an iterator, string, or match object

```
In [5]: re.split('\s+', 'Split on spaces.')
Out[5]: ['Split', 'on', 'spaces.']
```





## Let's practice!





### Introduction to tokenization

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#### What is tokenization?

- Turning a string or document into tokens (smaller chunks)
- One step in preparing a text for NLP
- Many different theories and rules
- You can create your own rules using regular expressions
- Some examples:
  - Breaking out words or sentences
  - Separating punctuation
  - Separating all hashtags in a tweet



### nltk library

• nltk: natural language toolkit

```
In [1]: from nltk.tokenize import word_tokenize
In [2]: word_tokenize("Hi there!")
Out[2]: ['Hi', 'there', '!']
```



### Why tokenize?

- Easier to map part of speech
- Matching common words
- Removing unwanted tokens
- "I don't like Sam's shoes."
- "I", "do", "n't", "like", "Sam", "'s", "shoes", "."



#### Other nltk tokenizers

- sent tokenize: tokenize a document into sentences
- regexp\_tokenize: tokenize a string or document based on a regular expression pattern
- TweetTokenizer: special class just for tweet tokenization, allowing you to separate hashtags, mentions and lots of exclamation points!!!



### More regex practice

• Difference between re.search() and re.match()

```
In [1]: import re
In [2]: re.match('abc', 'abcde')
Out[2]: <_sre.SRE_Match object; span=(0, 3), match='abc'>
In [3]: re.search('abc', 'abcde')
Out[3]: <_sre.SRE_Match object; span=(0, 3), match='abc'>
In [4]: re.match('cd', 'abcde')
In [5]: re.search('cd', 'abcde')
Out[5]: <_sre.SRE_Match object; span=(2, 4), match='cd'>
```





## Let's practice!



# Advanced tokenization with regex

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### Regex groups using or "|"

- OR is represented using
- You can define a group using ()
- You can define explicit character ranges using []

```
In [1]: import re
In [2]: match_digits_and_words = ('(\d+|\w+)')
In [3]: re.findall(match_digits_and_words, 'He has 11 cats.')
Out[3]: ['He', 'has', '11', 'cats']
```



### Regex ranges and groups

pattern	matches	example
[A-Za-z]+	upper and lowercase English alphabet	'ABCDEFghijk'
[0-9]	numbers from 0 to 9	9
[A-Za-z\-\.]+	upper and lowercase English alphabet, - and .	'My-Website.com'
(a-z)	a, - and z	'a-z'
(\s+l,)	spaces or a comma	, ,



### Character range with re.match()





## Let's practice!



## Charting word length with nltk

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### Getting started with matplotlib

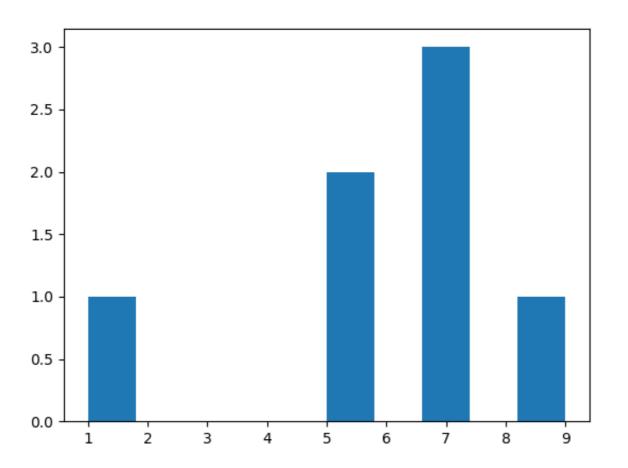
- Charting library used by many open source Python projects
- Straightforward functionality with lots of options
  - Histograms
  - Bar charts
  - Line charts
  - Scatter plots
- ... and also advanced functionality like 3D graphs and animations!



### Plotting a histogram with matplotlib



### Generated Histogram

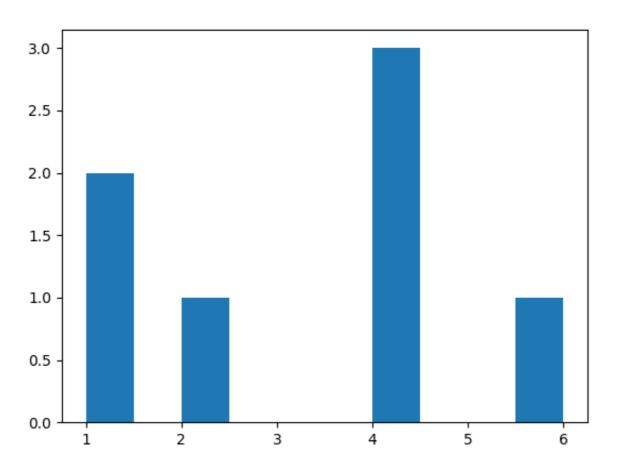




### Combining NLP data extraction with plotting



### Word length histogram







## Let's practice!



## Word counts with bag-of-words

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### Bag-of-words

- Basic method for finding topics in a text
- Need to first create tokens using tokenization
- ... and then count up all the tokens
- The more frequent a word, the more important it might be
- Can be a great way to determine the significant words in a text

### Bag-of-words example

- Text: "The cat is in the box. The cat likes the box. The box is over the cat."
- Bag of words (stripped punctuation):
  - "The": 3, "box": 3
  - "cat": 3, "the": 3
  - "is": 2
  - "in": 1, "likes": 1, "over": 1



### Bag-of-words in Python

```
In [1]: from nltk.tokenize import word tokenize
In [2]: from collections import Counter
In [3]: Counter(word tokenize(
                """The cat is in the box. The cat likes the box.
                 The box is over the cat."""))
Out[3]:
Counter({ '.': 3,
         'The': 3,
         'box': 3,
         'cat': 3,
         'in': 1,
         'the': 3})
In [4]: counter.most common(2)
Out[4]: [('The', 3), -('box', 3)]
```





## Let's practice!





# Simple text preprocessing

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#### Why preprocess?

- Helps make for better input data
  - When performing machine learning or other statistical methods
- Examples:
  - Tokenization to create a bag of words
  - Lowercasing words
- Lemmatization/Stemming
  - Shorten words to their root stems
- Removing stop words, punctuation, or unwanted tokens
- Good to experiment with different approaches



#### Preprocessing example

- Input text: Cats, dogs and birds are common pets. So are fish.
- Output tokens: cat, dog, bird, common, pet, fish



#### Text preprocessing with Python





# Let's practice!



### Introduction to gensim

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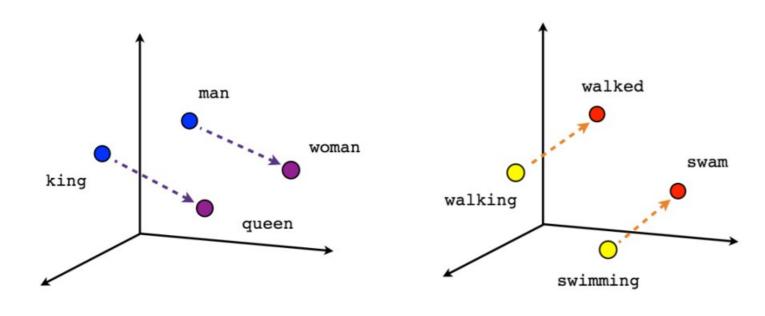


#### What is gensim?

- Popular open-source NLP library
- Uses top academic models to perform complex tasks
  - Building document or word vectors
  - Performing topic identification and document comparison

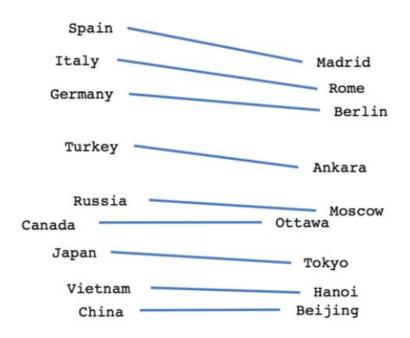


#### What is a word vector?



Male-Female

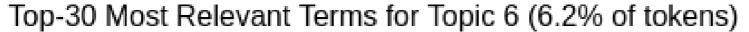
Verb tense

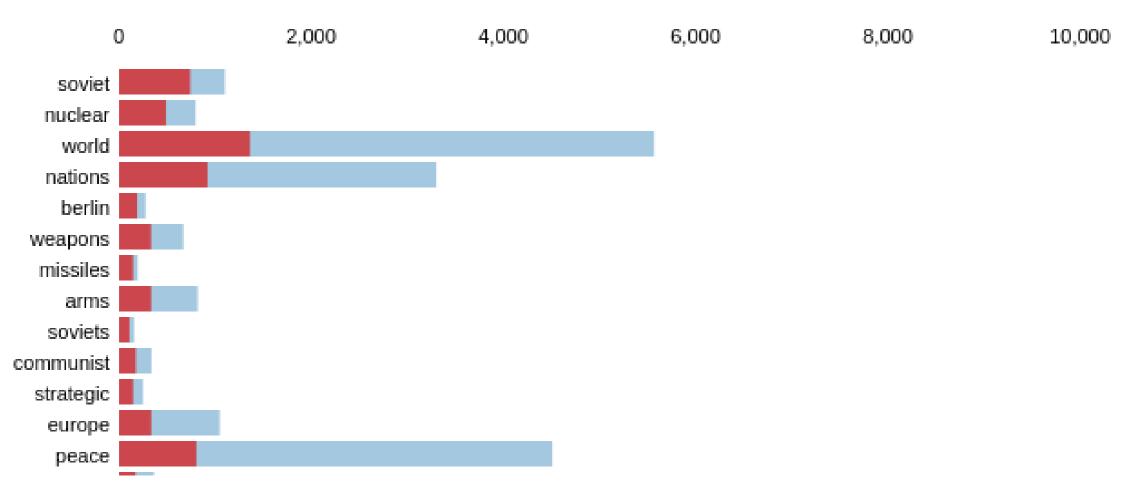


Country-Capital



#### Gensim Example





(Source: http://tlfvincent.github.io/2015/10/23/presidential-speech-topics)



#### Creating a gensim dictionary

```
In [1]: from gensim.corpora.dictionary import Dictionary
In [2]: from nltk.tokenize import word tokenize
In [3]: my documents = ['The movie was about a spaceship and aliens.',
                        'I really liked the movie!',
                        'Awesome action scenes, but boring characters.',
                        'The movie was awful! I hate alien films.',
                       'Space is cool! I liked the movie.',
                       'More space films, please!', ]
   . . . .
In [4]: tokenized docs = [word tokenize(doc.lower())
                          for doc in my documents]
   . . . .
In [5]: dictionary = Dictionary(tokenized docs)
In [6]: dictionary.token2id
Out[6]:
{'!': 11,
 ',': 17,
 '.': 7,
 'a': 2,
 'about': 4,
```



#### Creating a gensim corpus

```
In [7]: corpus = [dictionary.doc2bow(doc) for doc in tokenized_docs]
In [8]: corpus
Out[8]:
[[(0, 1), (1, 1), (2, 1), (3, 1), (4, 1), (5, 1), (6, 1), (7, 1), (8, 1)],
[(0, 1), (1, 1), (9, 1), (10, 1), (11, 1), (12, 1)],
...
]
```

- gensim models can be easily saved, updated, and reused
- Our dictionary can also be updated
- This more advanced and feature rich bag-of-words can be used in future exercises





# Let's practice!





# Tf-idf with gensim

Katharine Jarmul Founder, kjamistan



#### What is tf-idf?

- Term frequency inverse document frequency
- Allows you to determine the most important words in each document
- Each corpus may have shared words beyond just stopwords
- These words should be down-weighted in importance
- Example from astronomy: "Sky"
- Ensures most common words don't show up as key words
- Keeps document specific frequent words weighted high



#### Tf-idf formula

$$w_{i,j} = tf_{i,j} * \log(rac{N}{df_i})$$

 $w_{i,j} = \text{tf-idf weight for token } i \text{ in document } j$ 

 $tf_{i,j} = \text{number of occurrences of token } i \text{ in document } j$ 

 $df_i = \text{number of documents that contain token } i$ 

N = total number of documents



#### Tf-idf with gensim

```
In [10]: from gensim.models.tfidfmodel import TfidfModel
In [11]: tfidf = TfidfModel(corpus)

In [12]: tfidf[corpus[1]]
Out[12]:
[(0, 0.1746298276735174),
    (1, 0.1746298276735174),
    (9, 0.29853166221463673),
    (10, 0.7716931521027908),
...
]
```





# Let's practice!



# **Named Entity Recognition**

Katharine Jarmul Founder, kjamistan



#### What is Named Entity Recognition?

- NLP task to identify important named entities in the text
  - People, places, organizations
  - Dates, states, works of art
  - ... and other categories!
- Can be used alongside topic identification
  - ... or on its own!
- Who? What? When? Where?



#### Example of NER

```
In 1917, Einstein applied the general theory of relativity to model the large-scale structure of the universe. He was visiting the United States when Adolf Hitler came to power in 1938 and did not go back to Germany, where he had been a professor at the Berlin Academy of Sciences. He settled in the U.S., becoming an American citizen in 1940. On the eve of World War II, he endorsed a letter to President Franklin D. Roosevelt alerting him to the potential development of "extremely powerful bombs of a new type" and recommending that the U.S. begin similar research. This eventually led to what would become the Manhattan Project. Einstein supported defending the Allied forces, but largely denounced using the new discovery of nuclear fission as a weapon. Later, with the British philosopher Bertrand Russell, Einstein signed the Russell-Einstein Manifesto, which highlighted the danger of nuclear weapons. Einstein was affiliated with the Institute for Advanced Study in Princeton, New Jersey, until his death in 1955.
```

Tag colours:

LOCATION TIME PERSON ORGANIZATION MONEY PERCENT DATE

(Source: Europeana Newspapers (http://www.europeana-newspapers.eu))



#### nltk and the Stanford CoreNLP Library

- The Stanford CoreNLP library:
  - Integrated into Python via nltk
  - Java based
  - Support for NER as well as coreference and dependency trees



#### Using nltk for Named Entity Recognition



#### nltk's ne\_chunk()

```
In [6]: print(nltk.ne_chunk(tagged_sent))
(S
  In/IN
  (GPE New/NNP York/NNP)
  ,/,
  I/PRP
  like/VBP
  to/TO
  ride/VB
  the/DT
  (ORGANIZATION Metro/NNP)
  to/TO
  visit/VB
  (ORGANIZATION MOMA/NNP)
  and/CC
  some/DT
  restaurants/NNS
  rated/VBN
  well/RB
  by/IN
  (PERSON Ruth/NNP Reichl/NNP)
  ./.)
```





# Let's practice!





# Introduction to SpaCy

Katharine Jarmul Founder, kjamistan



#### What is SpaCy?

- NLP library similar to gensim, with different implementations
- Focus on creating NLP pipelines to generate models and corpora
- Open-source, with extra libraries and tools
  - Displacy



#### Displacy entity recognition visualizer

```
In New York GPE, I like to ride the Metro to visit MOMA ORG and some restaurants rated well by Ruth Reichl PERSON
```

(source: https://demos.explosion.ai/displacy-ent/)



#### SpaCy NER



#### Why use SpaCy for NER?

- Easy pipeline creation
- Different entity types compared to nltk
- Informal language corpora
  - Easily find entities in Tweets and chat messages
- Quickly growing!





# Let's practice!



# Multilingual NER with polyglot

Katharine Jarmul Founder, kjamistan



#### What is polyglot?

- NLP library which uses word vectors
- Why polyglot?
  - Vectors for many different languages
  - More than 130!

which ويكه India بنديا beat Bermuda بيرمودا in ين Port بورت of سباین Spain 2007 , which ويكه واس يكالليد equalled five فيفي days دایس اغو ago by South سووث Africa in their ثير فيكتوري victory over وفير West Indies بندييس Sydney سيدني



#### Spanish NER with polyglot

```
In [1]: from polyglot.text import Text
In [2]: text = """El presidente de la Generalitat de Cataluña,
                  Carles Puigdemont, ha afirmado hoy a la alcaldesa
                  de Madrid, Manuela Carmena, que en su etapa de
                  alcalde de Girona (de julio de 2011 a enero de 2016)
                  hizo una gran promoción de Madrid."""
In [3]: ptext = Text(text)
In [4]: ptext.entities
Out [4]:
[I-ORG(['Generalitat', 'de']),
 I-LOC(['Generalitat', 'de', 'Cataluña']),
 I-PER(['Carles', 'Puigdemont']),
 I-LOC(['Madrid']),
 I-PER(['Manuela', 'Carmena']),
 I-LOC(['Girona']),
 I-LOC(['Madrid'])]
```





# Let's practice!





# Classifying fake news using supervised learning with NLP

Katharine Jarmul Founder, kjamistan



#### What is supervised learning?

- Form of machine learning
  - Problem has predefined training data
  - This data has a label (or outcome) you want the model to learn
  - Classification problem
  - Goal: Make good hypotheses about the species based on geometric features

Sepal Length	Sepal Width	Petal Length	Petal Width	Species
5.1	3.5	1.4	0.2	I. setosa
7.0	3.2	4.77	1.4	I.versicolor
6.3	3.3	6.0	2.5	I.virginica



#### Supervised learning with NLP

- Need to use language instead of geometric features
- scikit-learn: Powerful open-source library
- How to create supervised learning data from text?
  - Use bag-of-words models or tf-idf as features



#### **IMDB** Movie Dataset

Plot	Sci-Fi	Action
In a post-apocalyptic world in human decay, a	1	0
Mohei is a wandering swordsman. He arrives in	0	1
#137 is a SCI/FI thriller about a girl, Marla,	1	0

- Goal: Predict movie genre based on plot summary
- Categorical features generated using preprocessing



#### Supervised learning steps

- Collect and preprocess our data
- Determine a label (Example: Movie genre)
- Split data into training and test sets
- Extract features from the text to help predict the label
  - Bag-of-words vector built into scikit-learn
- Evaluate trained model using the test set









# Building word count vectors with scikit-learn

Katharine Jarmul Founder, kjamistan



#### Predicting movie genre

- Dataset consisting of movie plots and corresponding genre
- Goal: Create bag-of-word vectors for the movie plots
  - Can we predict genre based on the words used in the plot summary?



#### Count Vectorizer with Python

```
In [1]: import pandas as pd
In [2]: from sklearn.model selection import train test split
In [3]: from sklearn.feature extraction.text import CountVectorizer
In [4]: df = ... # Load data into DataFrame
In [5]: y = df['Sci-Fi']
In [6]: X train, X test, y train, y test = train test split(
                                             df['plot'], y,
                                             test size=0.33,
                                             random state=53)
In [7]: count vectorizer = CountVectorizer(stop words='english')
In [8]: count train = count vectorizer.fit transform(X train.values)
In [9]: count test = count vectorizer.transform(X test.values)
```







# Training and testing a classification model with scikit-learn

Katharine Jarmul Founder, kjamistan



#### Naive Bayes classifier

- Naive Bayes Model
  - Commonly used for testing NLP classification problems
  - Basis in probability
- Given a particular piece of data, how likely is a particular outcome?
- Examples:
  - If the plot has a spaceship, how likely is it to be sci-fi?
  - Given a spaceship and an alien, how likely now is it sci-fi?
- Each word from CountVectorizer acts as a feature
- Naive Bayes: Simple and effective



#### Naive Bayes with scikit-learn

```
In [10]: from sklearn.naive_bayes import MultinomialNB
In [11]: from sklearn import metrics
In [12]: nb_classifier = MultinomialNB()
In [13]: nb_classifier.fit(count_train, y_train)
In [14]: pred = nb_classifier.predict(count_test)
In [15]: metrics.accuracy_score(y_test, pred)
Out [15]: 0.85841849389820424
```



#### **Confusion Matrix**

	Action	Sci-Fi
Action	6410	563
Sci-Fi	864	2242







# Simple NLP, Complex Problems

Katharine Jarmul Founder, kjamistan



#### **Translation**



(source: https://twitter.com/Lupintweets/status/865533182455685121)

#### **Sentiment Analysis**

"big men are very soft"

"freakin raging animal"

"went from the ladies tees"

"two dogs fighting"

"being able to hit"

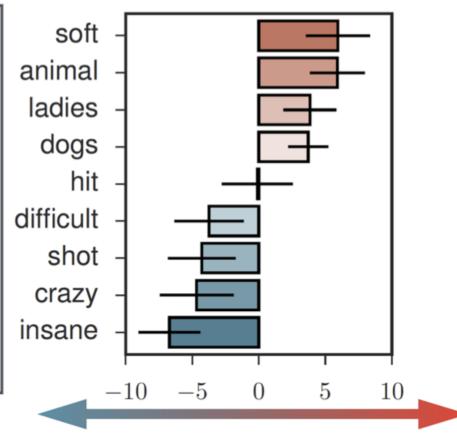
"insanely difficult saves"

"amazing shot"

"he is still crazy good"

"his stats are insane"

Ex. contexts in r/sports



"some soft pajamas"

"stuffed animal"

"lovely ladies"

"hiking with the dogs"

"it didn't really hit me"

"a difficult time"

"totally shot me down"

"overreacting crazy woman"

"people are just insane"

Ex. contexts in r/TwoX

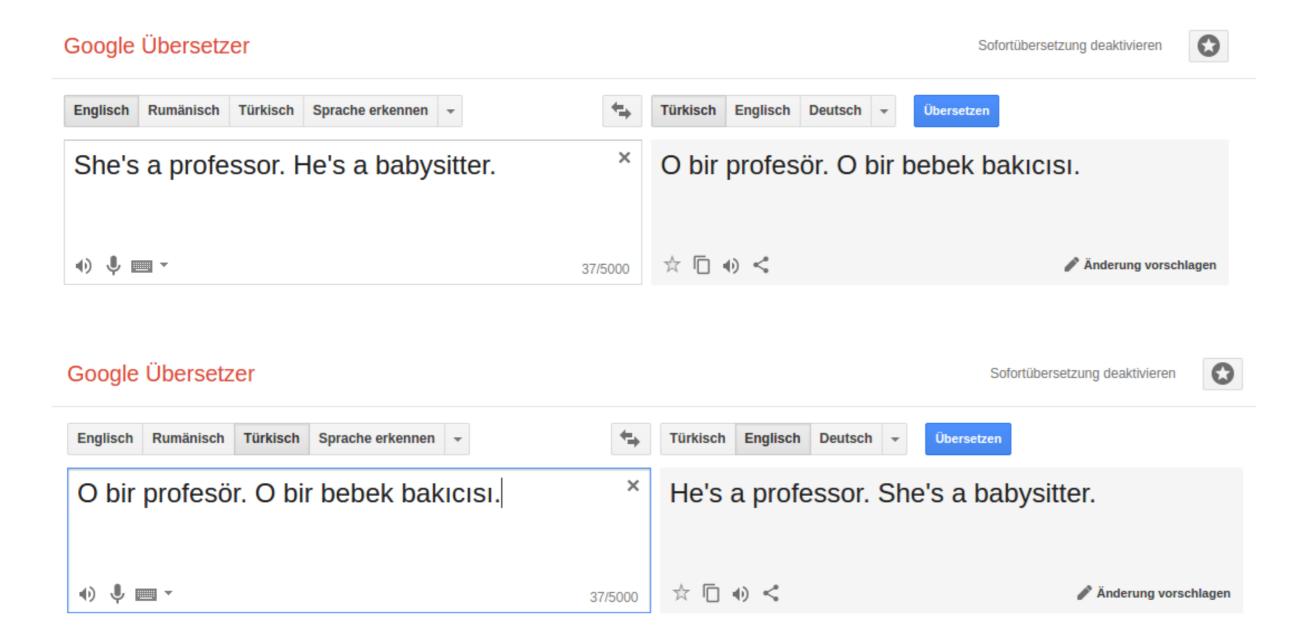
more positive in r/sports, more negative in r/TwoX

more positive in r/TwoX, more negative in r/sports

(source: https://nlp.stanford.edu/projects/socialsent/)



#### Language Biases



(related talk: https://www.youtube.com/watch?v=j7FwpZB1hWc)



