Natural Language Processing

And why it's not that opaque

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Agenda

NLP: Why?

Where to use?

How to?

NLP: Why?

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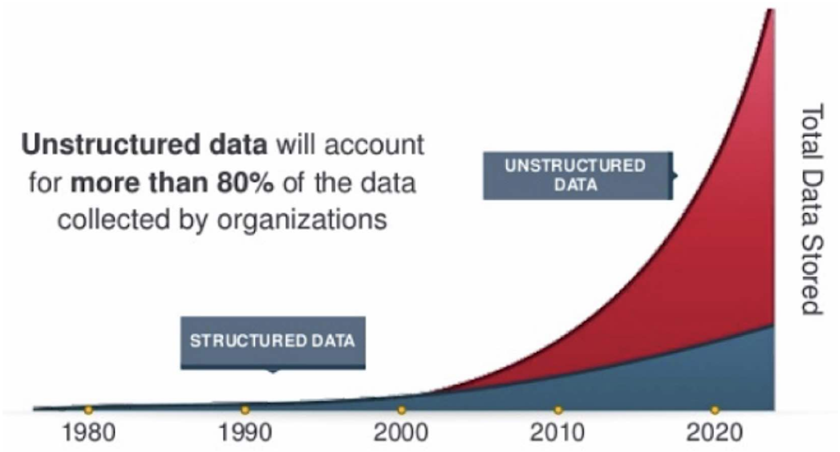
Big Data

Is for the most unstructured



What would you do if you had 1000s of reliable and extremely fast assistants at hand?

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Where to use?

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3 main use-cases

An ad-hoc taxonomy

- Holistic exploration of the "discourse" – Document is the unit of analysis
- Identify and extract some elements and their relationships
- Use text for labeling of other some other observations (e.g. sentiments, classes etc.)

How to?

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- Text $\rightarrow$ tokens
- preprocessing: filters, stemmers, lemmatizers, bigram encoders
- Bag of words vs. Sequence
- Modelling: Depends on the task

So many great papers on neural networks $\rightarrow$ 'So', 'many', 'great','papers','on,'neural','networks'$\rightarrow$ 'many', 'great', 'paper', 'neural_network'

R

- R: *tidytext* `https://www.tidytextmining.com`
- topicmodels, quanteda

Python

- Python: *NLTK* `https://www.nltk.org/book/`
- TextBlob (simple API for NLTK)
- Fuzzywuzzy (string-matching)
- Polyglot (multilanguage - jobs)
- gensim (high-performance ML on text)
- spaCy (modern all in one high-level NLP)

NER

Identifying things in text

```python
import spacy
from spacy import displacy

text = """But Google is starting from behind. The company made a late push
into hardware, and Apple’s Siri, available on iPhones, and Amazon’s Alexa
software, which runs on its Echo and Dot devices, have clear leads in
consumer adoption."""

nlp = spacy.load('custom_ner_model')
doc = nlp(text)
displacy.serve(doc, style='ent')
```

But Google **ORG** is starting from behind. The company made a late push into hardware, and Apple **ORG** ’s Siri **PRODUCT** , available on iPhones **PRODUCT** , and Amazon **ORG** ’s Alexa **PRODUCT** software, which runs on its Echo **PRODUCT** and Dot **PRODUCT** devices, have clear leads in consumer adoption.

(O-H-E, TF-IDF) LSI, LDA & Co.

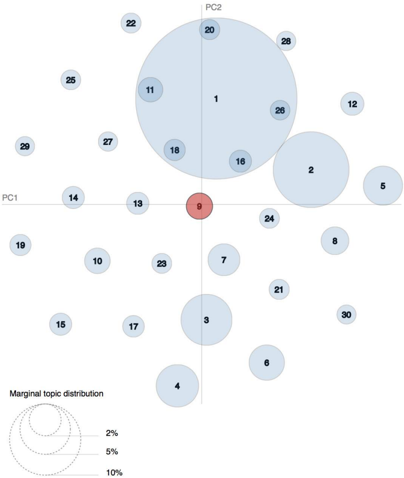
Check out Gensim: `https://radimrehurek.com/gensim/`

- Co-occurence of terms in docs
- Returns matrix of documents to topics
- Dot-product with transpose $\rightarrow$ Document-similarity adjacency matrix
- LDA mainly for topic discovery

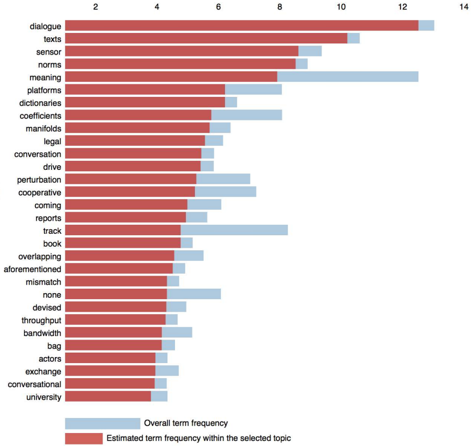
LDA

topic modelling, visualisation: `https://github.com/cpsievert/LDAvis`

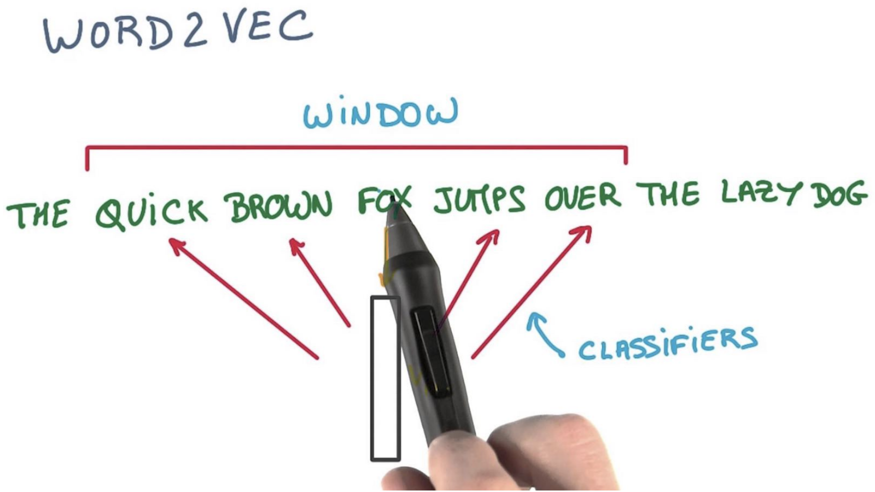
Intertopic Distance Map (via multidimensional scaling)



Top-30 Most Relevant Terms for Topic 9 (1.4% of tokens)



1. saliency(term w) = frequency(w) * [sum_t p(t | w) * log(p(t | w)/p(t))] for topics t; see Chuang et. al (2012)
2. relevance(term w | topic t) = λ * p(w | t) + (1 - λ) * p(w | t)/p(w); see Sievert & Shirley (2014)


WORD2VEC
WINDOW
THE QUICK BROWN FOX JUMPS OVER THE LAZY DOG
CLASSIFIERS

Embeddings

Word2Vec, GloVe, Fasttext & Co.

```
]: w2v_model.wv.most_similar('rnn')

]: [('lstm', 0.9124458432197571),
    ('gru', 0.7881952524185181),
    ('crf', 0.7548298835754395),
    ('long_short', 0.7546945810317993),
    ('lstms', 0.7449157238006592),
    ('recurrent_network', 0.7438251972198486),
    ('attention_mechanism', 0.7428297996520996),
    ('autoencoder', 0.7388468384742737),
    ('cnn', 0.7268193960189819),
    ('encoder_decoder', 0.7267674803733826)]
```

```
In [24]: w2v_model.wv.most_similar(positive=(['neural']), negative=['cv'])

Out[24]: [('recurrent_neural', 0.4580277502536737),
          ('recurrent', 0.45371636748313904),
          ('rnns', 0.42905929684638977),
          ('rnn', 0.4164518117904663),
          ('hierarchical', 0.40013378858566284),
          ('sequence_to_sequence', 0.39685627818107605),
          ('compositional', 0.39215320348739624),
          ('term_memory', 0.38211631774902344),
          ('generative', 0.38072299957275390),
          ('lstm', 0.37855387258529663)]
```

Sentence Embedding

Doc2Vec, Avg. embeddings, TF-IDF weighted, Seq2Seq and other autoencoder based

- Average of all word vectors (easier filtering due to preceding w2v training.
- Weighted average – TF-IDF (great performance)
- Account for patterns and sequences: Autoencoder approaches (More complex) using the encoder part of a trained model to generate latent “thought vectors”.

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Sentence Embedding
Autoencoders for NLP