Text Mining 1

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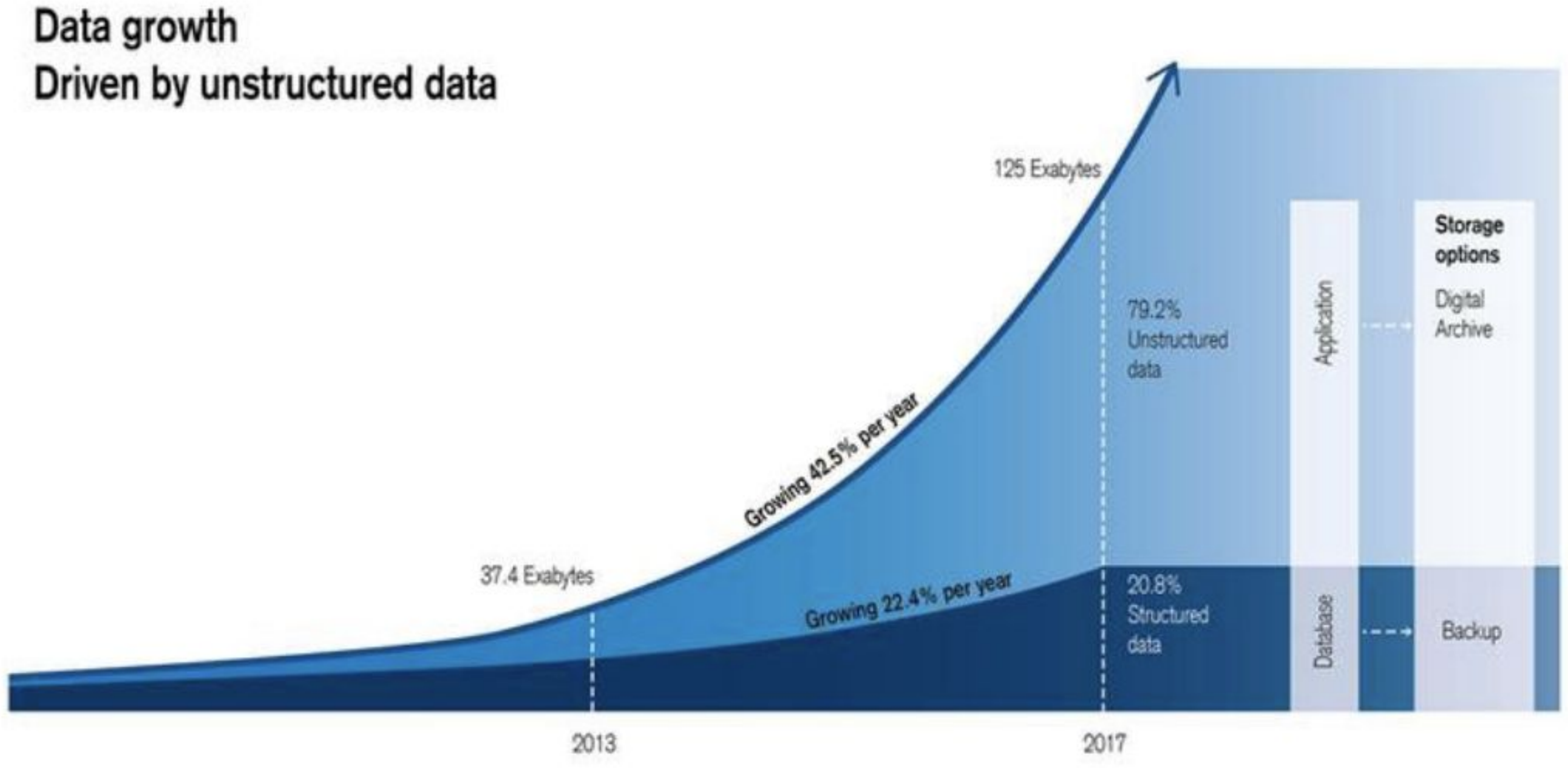
Text Analytics

^[\w-\.]+@([\w-]+\.)+[\w-]{2,4}$

Why Text Mining?

- 80-90% of all corporate data is in some kind of unstructured form (e.g. text)
- Benefits of text mining are (or will be) obvious especially in text-rich data environments
  - Email and spam filtering
  - Law (Court-orders)
  - Financial Disclosures
  - Medicine (discharge summaries, doctor notes)
  - Marketing (Customer comments and reviews)
  - Customer Support (In-bound help, problems with ordering, FAQs, etc.)
  - Survey research and analysis of open-ended results
  - Content Management



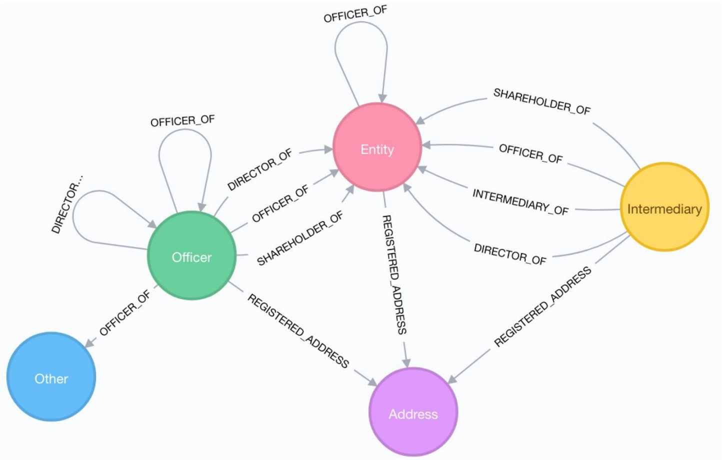
125 Exabytes of enterprise data was stored in 2017; 80% was unstructured data. (Source: Credit Suisse)

Who is the senior Trump official who wrote the New York Times op-ed?

The frenzied guessing game in the White House and on Twitter, explained.

By Andrew Prokop | andrew@vox.com | Sep 6, 2018, 1:05pm EDT

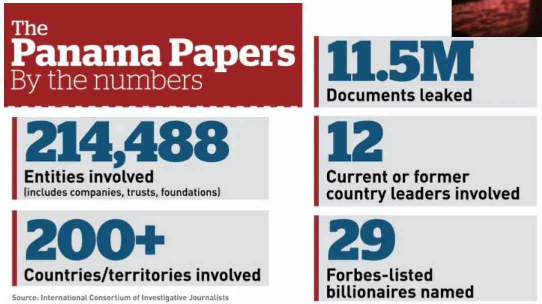
Are there linguistic clues to the author's identity?



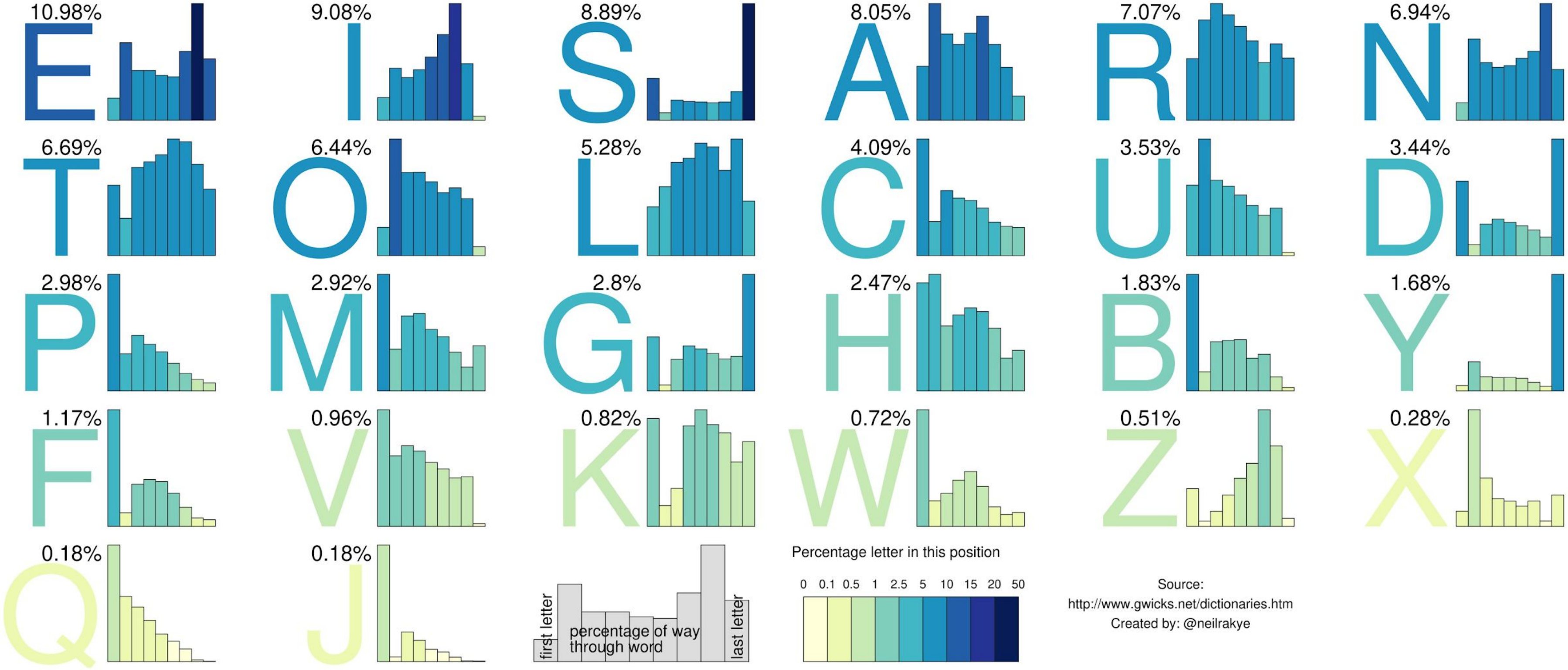
WHAT THE ENRON E-MAILS SAY ABOUT US

Scholars have spent years analyzing the corporation's vast digital archive. What have they discovered?

By Nathan Heller
July 17, 2017



Frequency of letters in English words and where they occur in the word



Source:
http://www.gwicks.net/dictionaries.htm
Created by: @neilrakye

Objectives

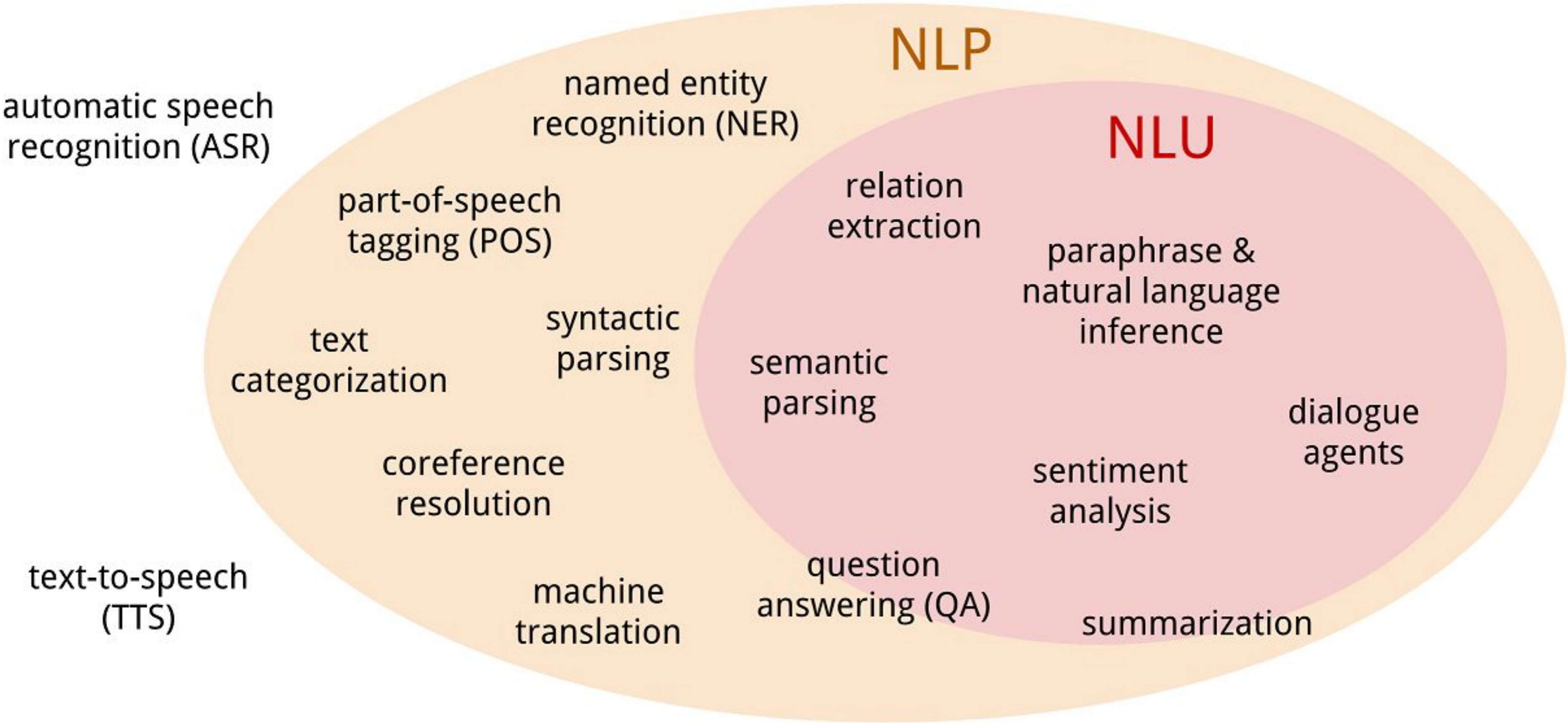
- Pattern Discovery (Unsupervised Learning)
- Prediction (Supervised Learning)

These are the **same goals** for **all of the tasks** we have covered in in the program. It's just about putting the data together **properly**, for our **need**.

- Data acquisition, cleaning, reshaping, compression

In addition, text mining can be applied to look "inside" a document to:

- Identify targets of positive/negative sentiments
- Predict the intent
- Extract entities and relationships
- Identify the level of complexity in a document
    - E.g. Find the proper educational material for children


NLP
NLU
automatic speech recognition (ASR)
named entity recognition (NER)
part-of-speech tagging (POS)
text categorization
syntactic parsing
coreference resolution
text-to-speech (TTS)
machine translation
relation extraction
paraphrase & natural language inference
semantic parsing
dialogue agents
sentiment analysis
question answering (QA)
summarization

Text Mining Setup

NLP

- Data Mining techniques allow us to combine **natural language processing** with **ML methods** in order to identify patterns and make predictions

- All the classification and clustering techniques we have discussed are applicable, as soon as we transfer and parse the data into a familiar row-column format.
  - This is the format we will mostly focus on for our text work

There is a highly active community in python when it comes to building tools to work with text as a datasource. Unfortunately it's not as well as concentrated as there are "competing" projects that put their spin on core tasks and work.

variations of the same theme

Toolkits in python (an abbreviated list!)

nltk	sckit-learn	gensim	spacy	newspaper3k	TextBlob
coreNLP	pattern	PyNLPl	Monkeylearn	rasa	vaderSentiment
emoji	wordcloud	Vocabulary	Quepy	flair	AllenNLP
Transformers	fasttext	Tensorflow Text	pyLDAviz	OpenNLP	fastAI
graphBrain	polyglot	pyTextRank	stop-words	tokenwiser	textacy

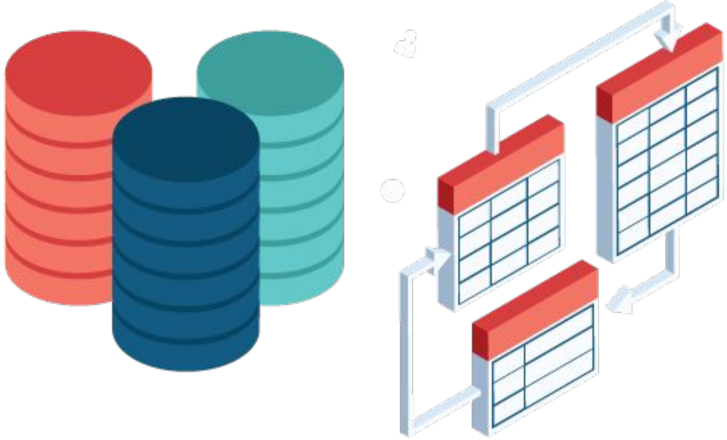
What makes this more *interesting* is that the packages depend on each other. Simply, some packages use other packages in the background.

Toolkits in R (an abbreviated list!)

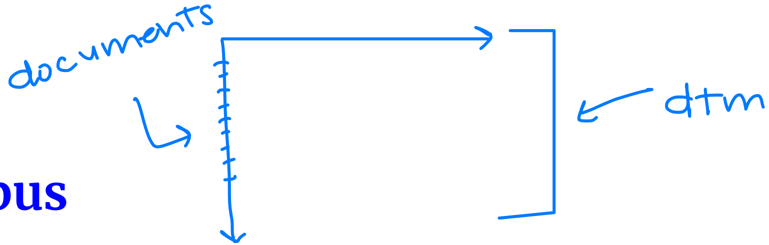
tm	tidytext	**quanteda**	udpipe	stm	topicmodels
textfeatures	Crfsuite	sentimentr	stopwords	tokenizers	cleanNLP
openNLP	textclean	textstem	textrecipes	wactor	text2vec
textmineR	ruimtehol	btm	qdap	rake	lexicon
readtext	spelling	hunspell	meanr	wordword	wordVectors

In case you are inteRested in R

Data Sources



(Higher Level) Definitions



Corpus: A collection of **documents** is a **corpus**

Document: An individual text composed of **tokens**. A document could be a tweet, a book, a news article, a blog post, a song's lyrics, customer support request, a financial disclosure ...

Token: A token is a contiguous set of characters that does not contain a **separator**

- In other contexts, can be N-grams, or a sequence of tokens (golf club)

Separator: How do we define breaks between tokens? Whitespace? Punctuation? Every character?

spaces

Example - Document Term Matrix Construction

- The collection of sentences is the corpus ← list of sentences
- Each sentence is the document
- Each word boundary is the token
- Each value is the simple term count, or occurrence
- Various python packages construct these, with slight differences

document ↙ ↙ token

Sentence	hockey	ftw	i	like	golf
I like golf!			1	1	1
I like hockey.	1		1	1	
Hockey and golf ftw	1	1			1

↑ # of times word occurred

Text Mining Process - Word inclusion and weighting

Create the Document-Term Matrix (also seen noted as: DTM, TDM, DFM)

Should all terms (N-grams) be included?

- Stopwords
- Stemming/Lemmatization

$$w_{x,y} = tf_{x,y} \times \log\left(\frac{N}{df_x}\right)$$

TF-IDF

Term x within document y

$tf_{x,y}$ = frequency of x in y

df_x = number of documents containing x

N = total number of documents

What is the best representation of values in the cells?

- Raw counts/frequencies? Binary values? Log of the counts?
- Inverse document frequency

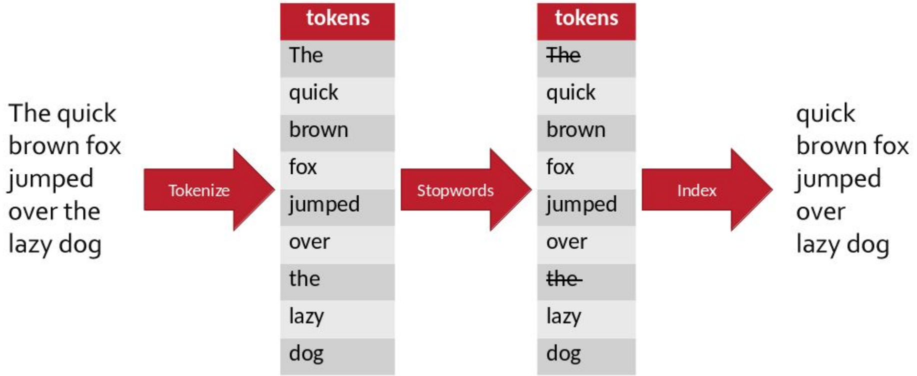
Compiling the Dictionary: Stop/Rare Words

Remove domain-specific Stopwords

Common words are typically removed as well, but it’s always good to review the stopwords for domain-specific projects

Also want to consider removing extremely rare and frequent words

- Either too rare it won’t add value
- Too common, it just adds noise



The Vocabulary: Stemming & Lemmatization

In order to reduce the term space dimensionality, we want to root of the word

Stemming

Big, bigger, biggest = **big**

reach, Reached, Reaching = **reach**

work, works, worked, Working = **work**

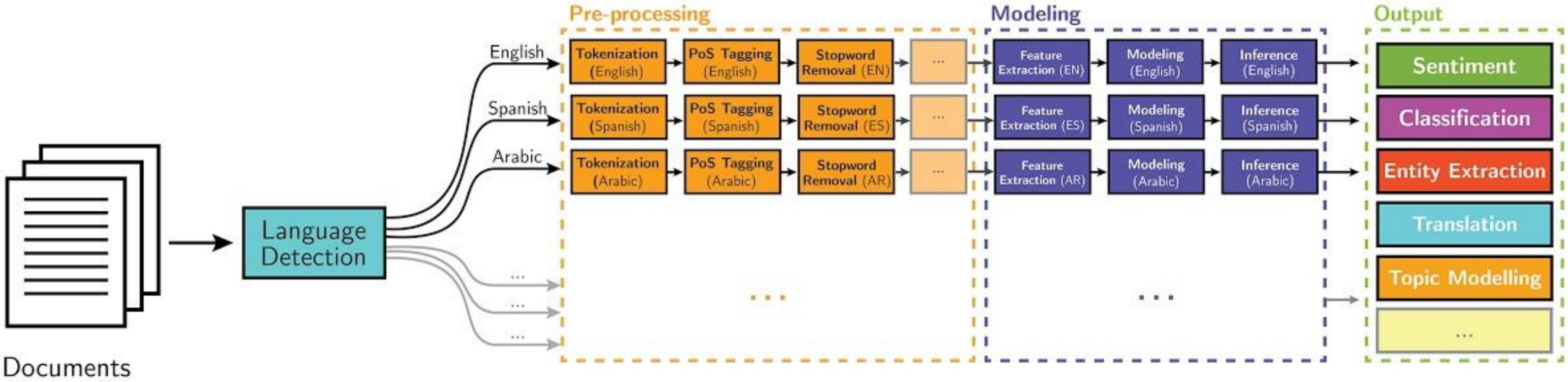
Lemmatization

drive, drove, driven = **drive**

Are, am, being = **be**

Of course there are different approaches to each
We usually perform one of these tasks, but try everything!
Decisions loosely depend on how compressed you want the feature space to be for the task ahead.

Once our data is processed, everything we have covered still applies



Text Analytics Mechanics

-by hand to build intuition-

python™

BU

Team Challenge (Next Session)

Use Text Analytics to SMS Spam

Your analytics firm was hired to monitor spam messages that are now increasingly being sent as unsolicited SMS messages.

The datasets can be found on Big Query (questrom.SMSspam). The tables are train, and test. There is also an example submission file (that you will submit as a csv file).

You should consider combining the various techniques we have covered to date (data cleaning, clustering, dimensionality reduction,etc.) and use that work in concert with whatever classification method you feel is most appropriate.

Your submission to the leaderboard will be based on the accuracy.

HINT: Start simple and work towards complexity

Notes

- label is the label, and should be modeled as a classification problem
- Handle the data any way that you see fit
- Use test table as the data to apply your model and score the dataset with a label of ham/spam
- See the next slide for the format of your submission, which must be a csv
- Use any method you want to fit the classification model

Tips and Tricks - What is our best, naive guess?

- Don’t be afraid to start simple and try different variations.
- Think about how to create columns/features from the dataset given the string of text
- Don’t try to build complex workflows right away, keep it simple for faster iteration and to see if you can improve your correlation score along the way
- What is our baseline assumption (naive guess)?

- Each team member can try a different approach to see who is getting better accuracy score

Submission CSV

- Filename does not matter
- Two column csv file with the id column and the predicted value as text
  - id
  - label
- You can submit as many times as you like
- Notice the prediction is ham/spam (string)
- NOTE: when writing your csv from pandas, remember, index=False
  - We only want those two columns

id	prediction(l...
4	ham
5	spam
11	ham
19	ham
21	ham
52	ham
59	ham
70	ham
76	ham
78	spam
93	spam
97	ham
99	ham
111	ham
113	spam
126	ham

Classification Evaluation

		Predicted	
		Negative	**Positive**
Actual	**Negative**	True Negative	False Positive
	Positive	False Negative	True Positive

- Accuracy
  - What percentage of the predictions were correct?
- Precision
  - How often were the model's predictions accurate? TP / TP + FP
- Recall
  - What percentage of known positive cases were correctly identified? TP / TP + FN
- F1
  - Balance of Precision and Recall
  - Helpful when there is class imbalance

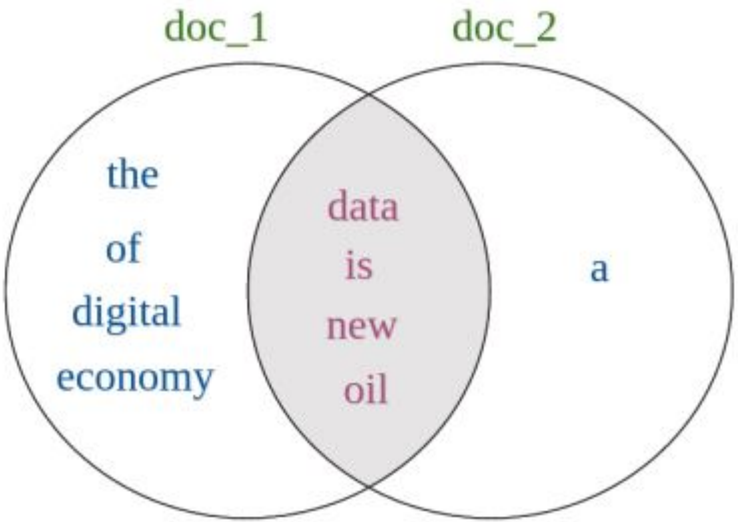
$$F1 = 2 \times \frac{Precision * Recall}{Precision + Recall}$$

Confusion Matrix and the Core Calculations

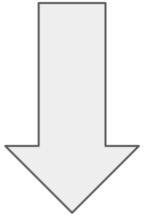
	Actual True/Yes	Actual False/No	
Predicted True/Yes	True positive shaded T_p *(Correct)*	False positive shaded F_p *(Incorrect)*	Precision/Positive Predictive Value (PPV) $\frac{T_p}{T_p + F_p}$ x 100%
Predicted False/No	False negative unshaded F_n *(Incorrect)*	True negative unshaded T_n *(Correct)*	Negative Predictive Value (NPV) $\frac{T_n}{T_n + F_n}$ x 100
	Sensitivity/Recall Rate (RR) $\frac{T_p}{T_p + F_n}$ x 100%	Specificity Rate (SR) $\frac{T_n}{T_n + F_p}$ x 100%	

- Depending on the source, actual or predicted could be rows or columns **so be careful**
- Green diagonal is the total correct cases. Accuracy rate is the green diagonal divided by total number of cases
- Red Diagonal is the total incorrect. Misclassification rate is the red diagonal divided by the total number of cases

All the (S|U)ML tasks still apply!



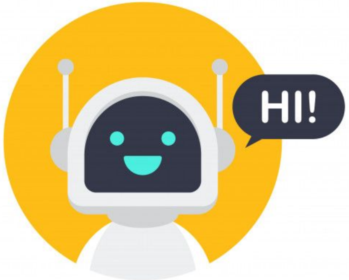
	I	love	dogs	hate	and	knitting	is	my	hobby	passion
Doc 1	1	1	1							
Doc 2	1		1	1	1	1				
Doc 3					1	1	1	2	1	1



Tokenization

Let’s think about the possibilities!

- You **can** annotate a dataset for your specific problem
  - Customer support requests
  - HR requests (time off, support)
  - FAQ
  - Label Studio!
- Put your dataset into a dtm/embedding space
  - Remember, the words/tokens and their weights now represent that document in a feature space!
- When a new document comes in
  - Find “N” most similar documents
  - Suggest answers, label, or use it to predict a label (i.e. intent)
  - Duplicate detection
- You could easily serve this with an API via fastAPI!



Text Mining 2: Sentiment

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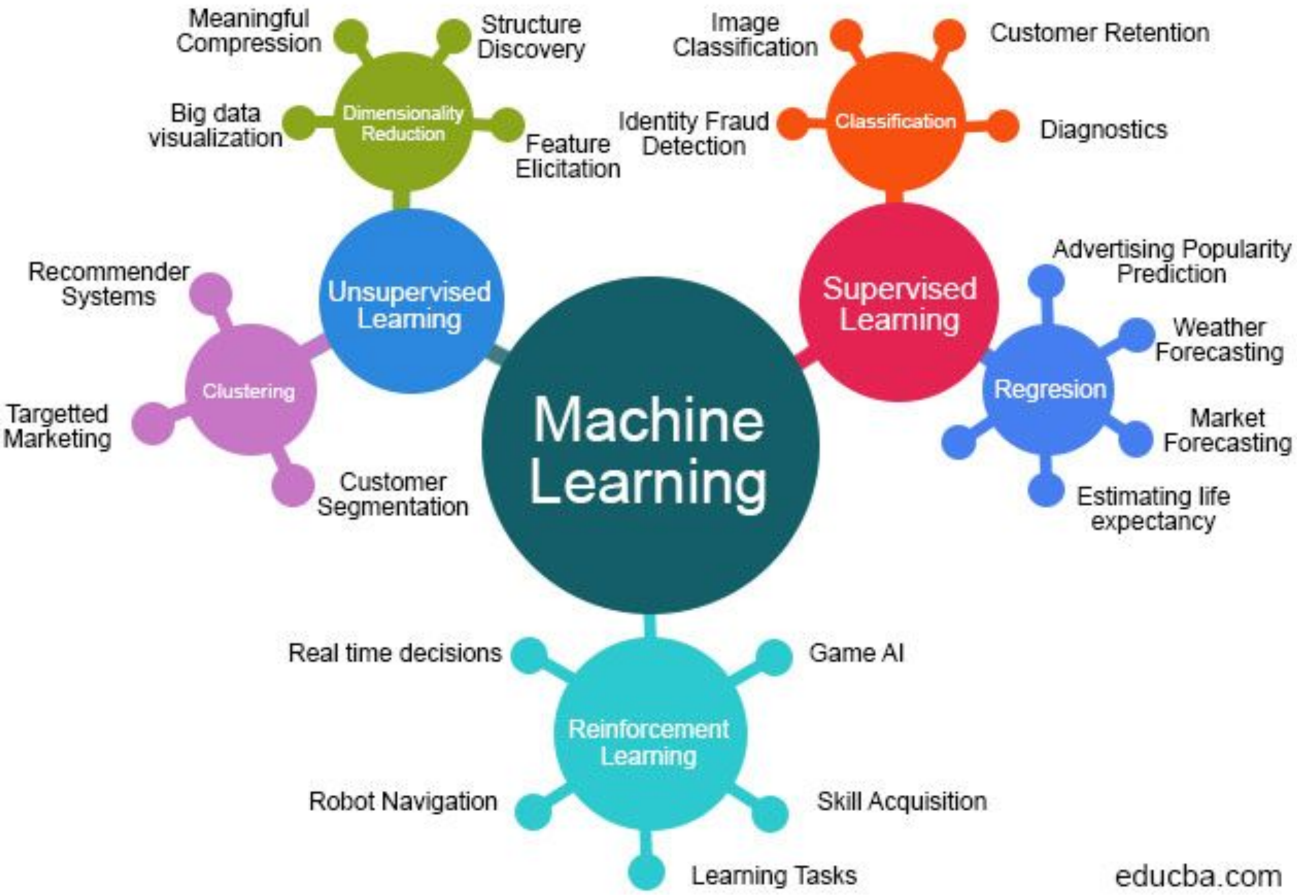
Outline

- Sentiment Analysis landscape
- Hands on in python
- Another example of how ML applications still apply

Let’s set the landscape again

Machine Learning Algorithms



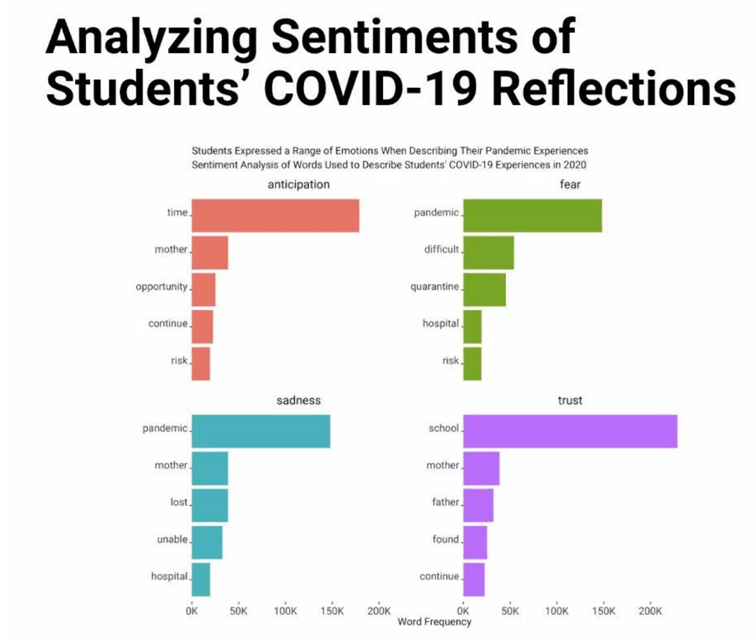
educba.com

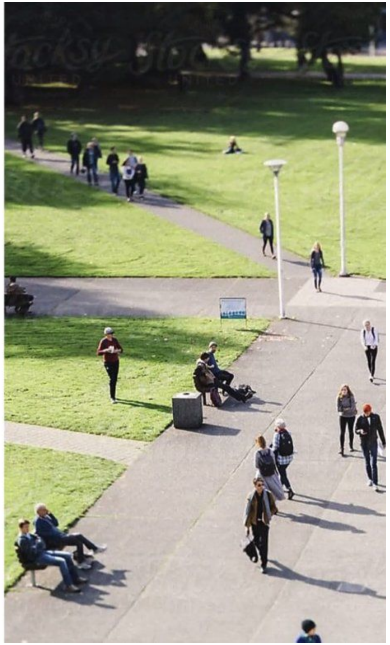
Sentiment Analysis

SENTIMENT ANALYSIS

Discovering people opinions, emotions and feelings about a product or service

This just happened! Why copy/paste code is bad





Ultimately, what are we trying to do?

An example of breaking down text

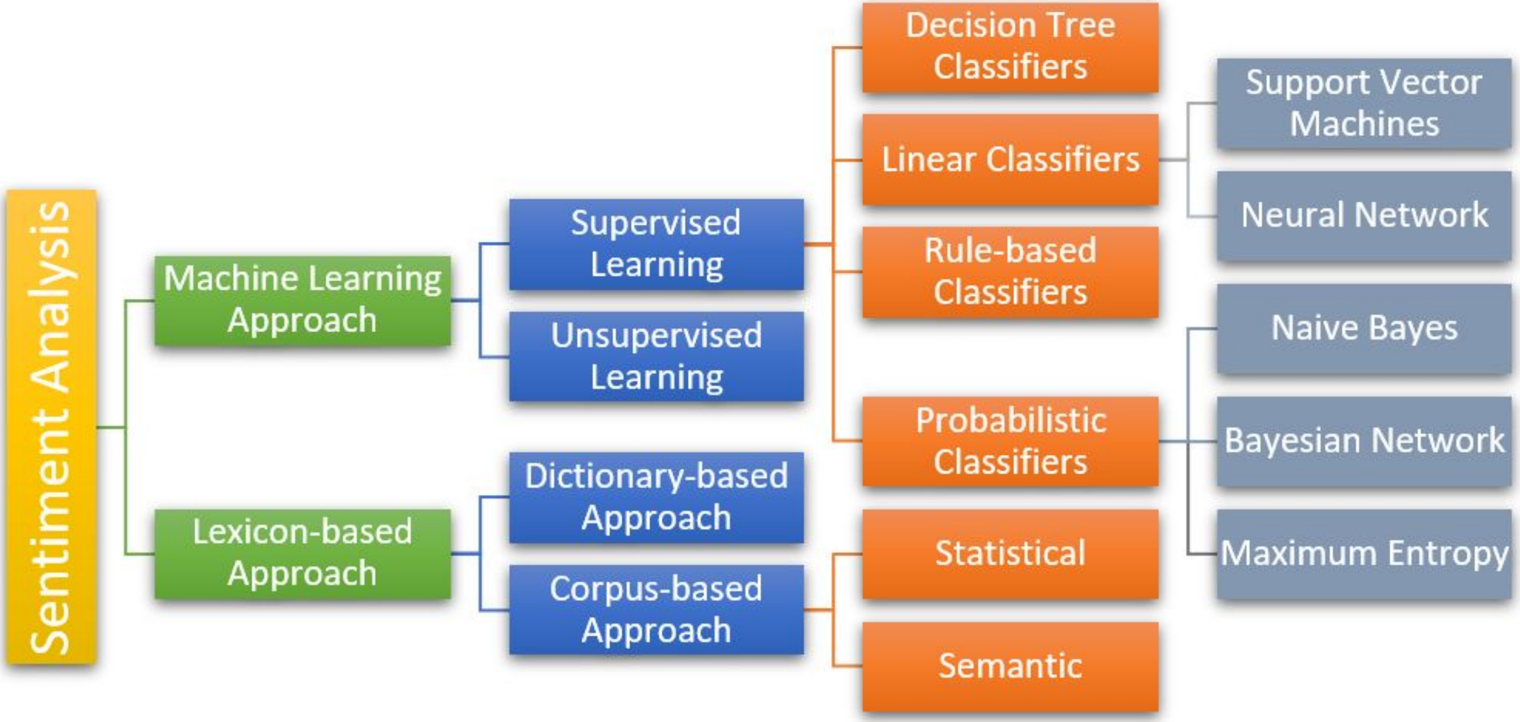
"The **room** was **great**, but the **staff** was **unfriendly**."

Sentiment Analysis → Negative sentiment

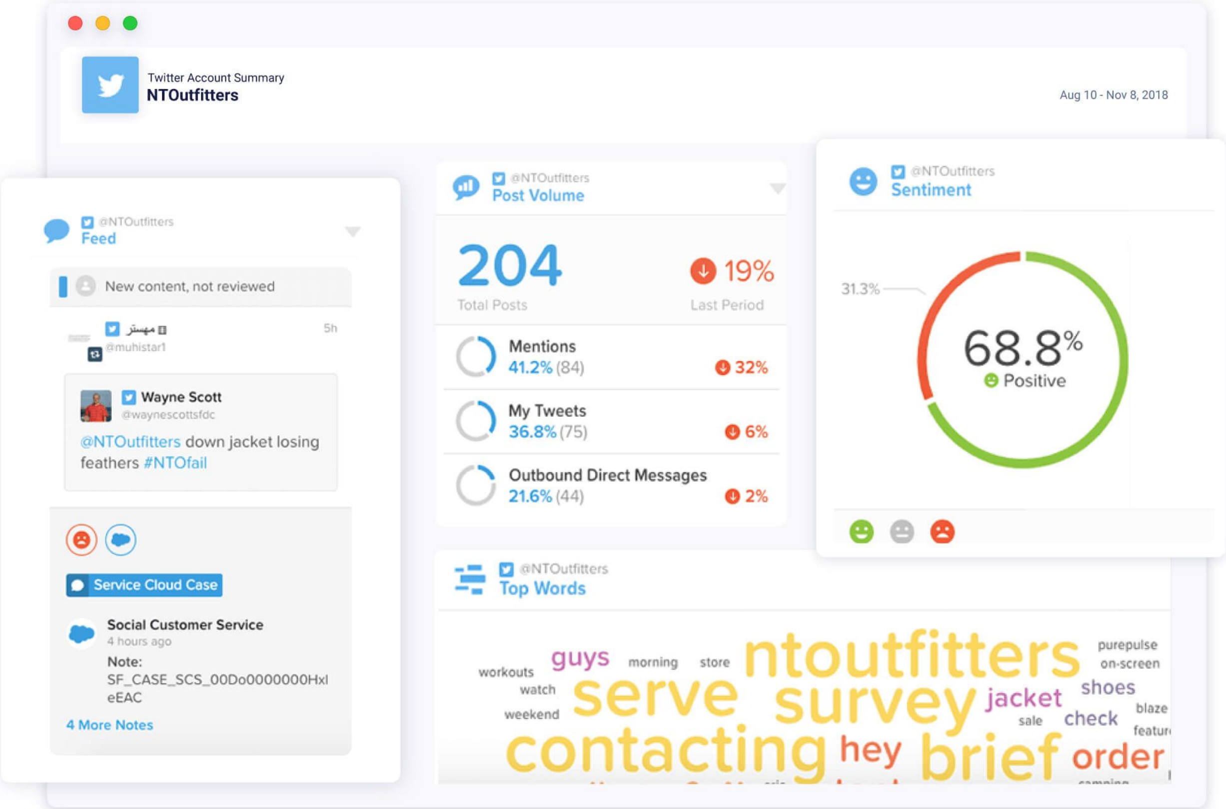
Opinion Mining →

Subject (aspect)	Opinion	Sentiment
Room	Great	Positive
Staff	Unfriendly	Negative

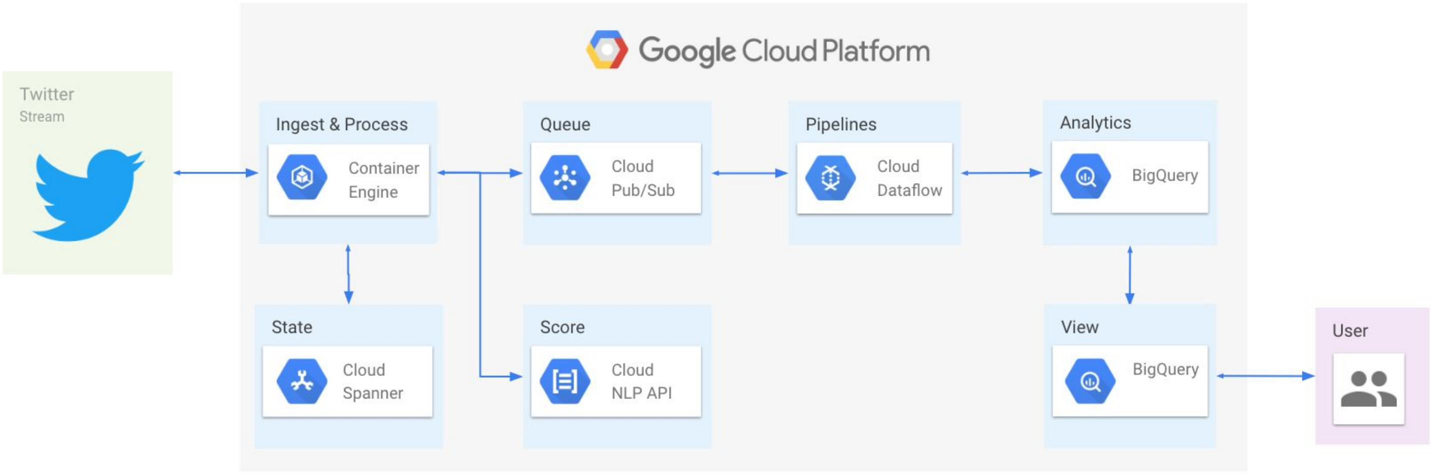
Various approaches

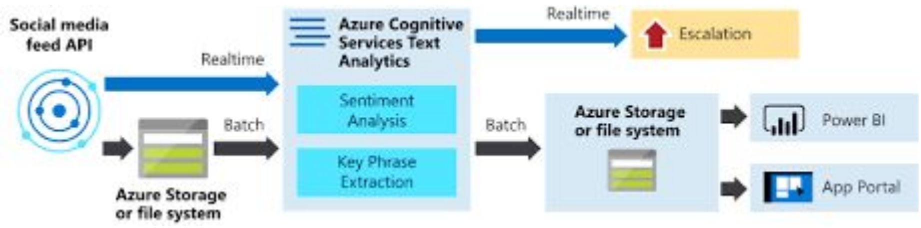


$$$$ Software (Just one example)



Cloud Services/Tools/API (just two below)





Text Analytics: Sentiment

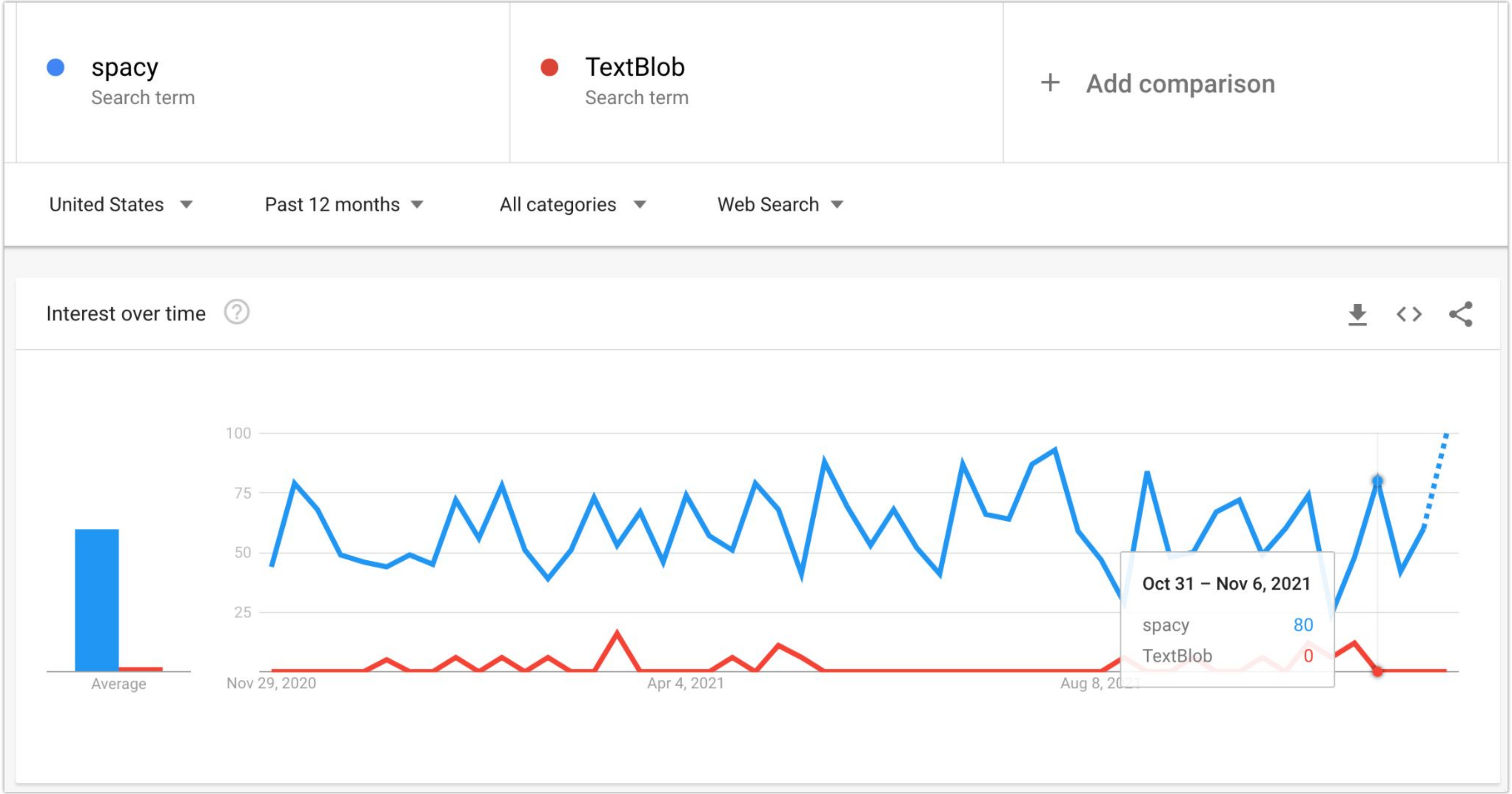
Module 11 – Spacy

NLP Pipelines

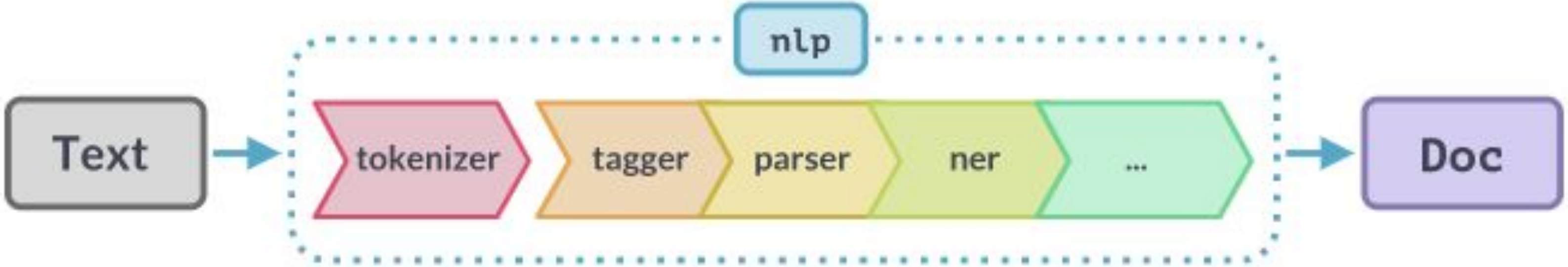
Agenda

- NLP via spacy in python!
  - I am going to use Colab for this session. Some of the tools didn’t behave as I expected in VS Code
- Named Entity Recognition ← NER
- Custom NER via spacy and label studio
  - Data annotation is a necessary task in practice!

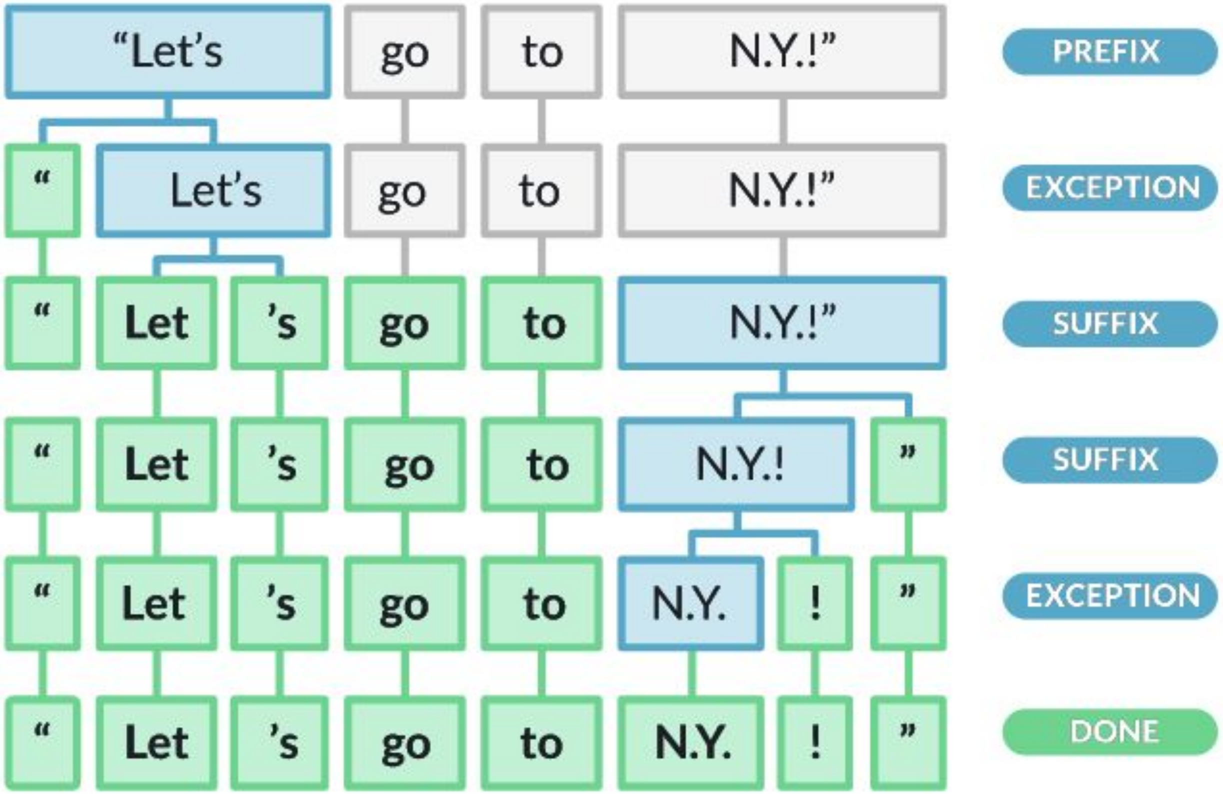
Google trends



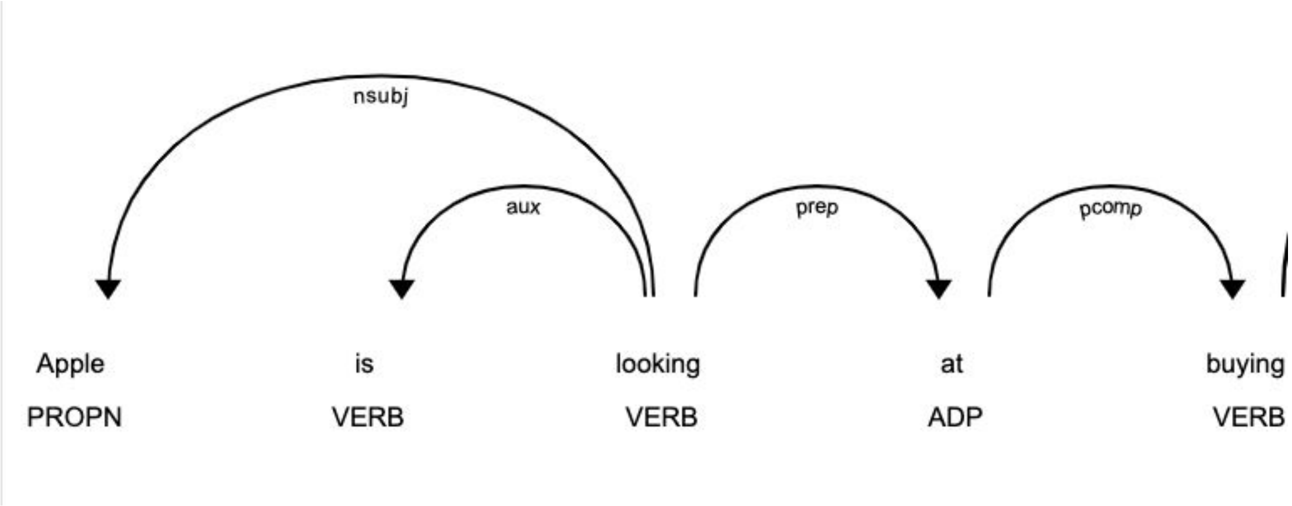
spaCy - NLP pipelines



Tokenization - more than just a regex



Visualization tools included



Robust (framework)

NAME	DESCRIPTION
Tokenization	Segmenting text into words, punctuations marks etc.
Part-of-speech (POS) **Tagging**	Assigning word types to tokens, like verb or noun.
Dependency Parsing	Assigning syntactic dependency labels, describing the relations between individual tokens, like subject or object.
Lemmatization	Assigning the base forms of words. For example, the lemma of “was” is “be”, and the lemma of “rats” is “rat”.
Sentence Boundary Detection (SBD)	Finding and segmenting individual sentences.
Named Entity Recognition (NER)	Labelling named “real-world” objects, like persons, companies or locations.
Entity Linking (EL)	Disambiguating textual entities to unique identifiers in a knowledge base.
Similarity	Comparing words, text spans and documents and how similar they are to each other.
Text Classification	Assigning categories or labels to a whole document, or parts of a document.
Rule-based Matching	Finding sequences of tokens based on their texts and linguistic annotations, similar to regular expressions.
Training	Updating and improving a statistical model’s predictions.
Serialization	Saving objects to files or byte strings.

spaCy