

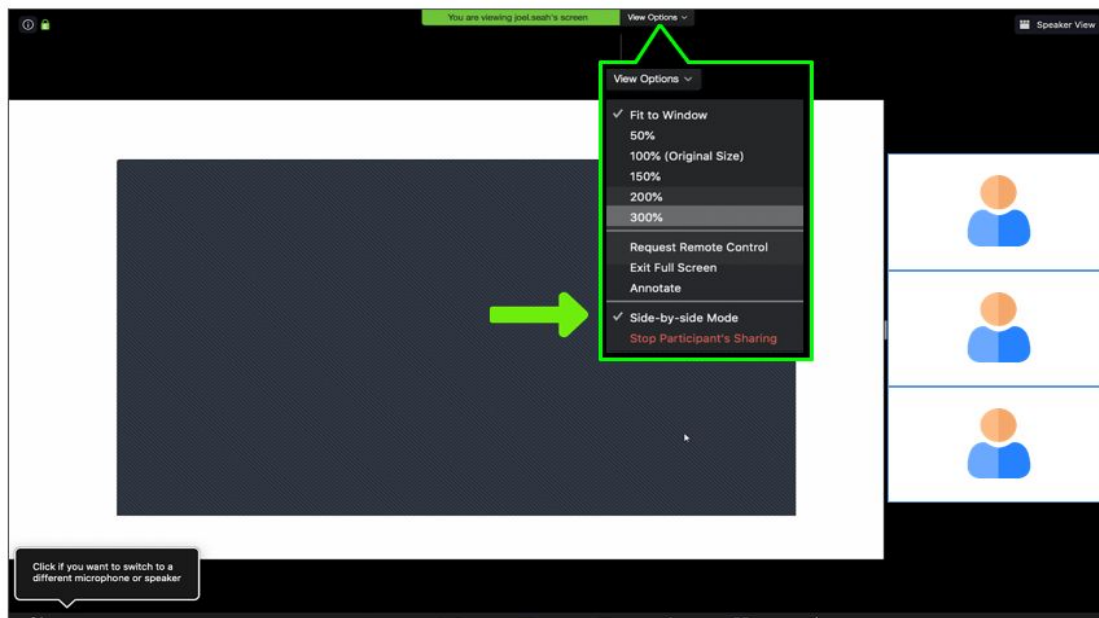


# We'll Be Starting Shortly!

To help us run the workshop smoothly, kindly:

- Submit all questions using the Q&A function
- If you have an urgent request, please use the "Raise Hand" function

# Using Zoom: Viewing Mode



## Side-By-Side Mode

- When sharing screen (slide share)
- With small thumbnails of people on the sidebar

### STEPS:

1. View Options
2. Side-By-Side Mode



# NLP - Sentiment Analysis

Smartcademy

ENGLISH

CHINESE

# Natural Language Processing

PYTHON

JAVA



# Natural Language Processing

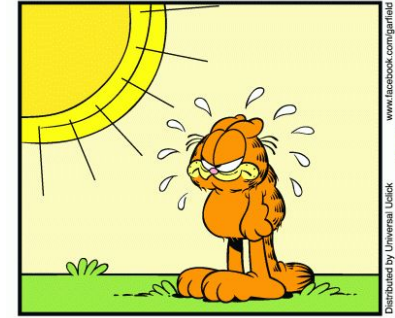


# Natural Language Processing

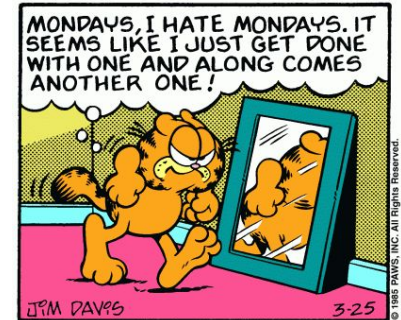


**Garfield was trying to  
stay cool**

■ GARFIELD WAS TRYING TO STAY COOL



■ GARFIELD WAS TRYING TO STAY COOL



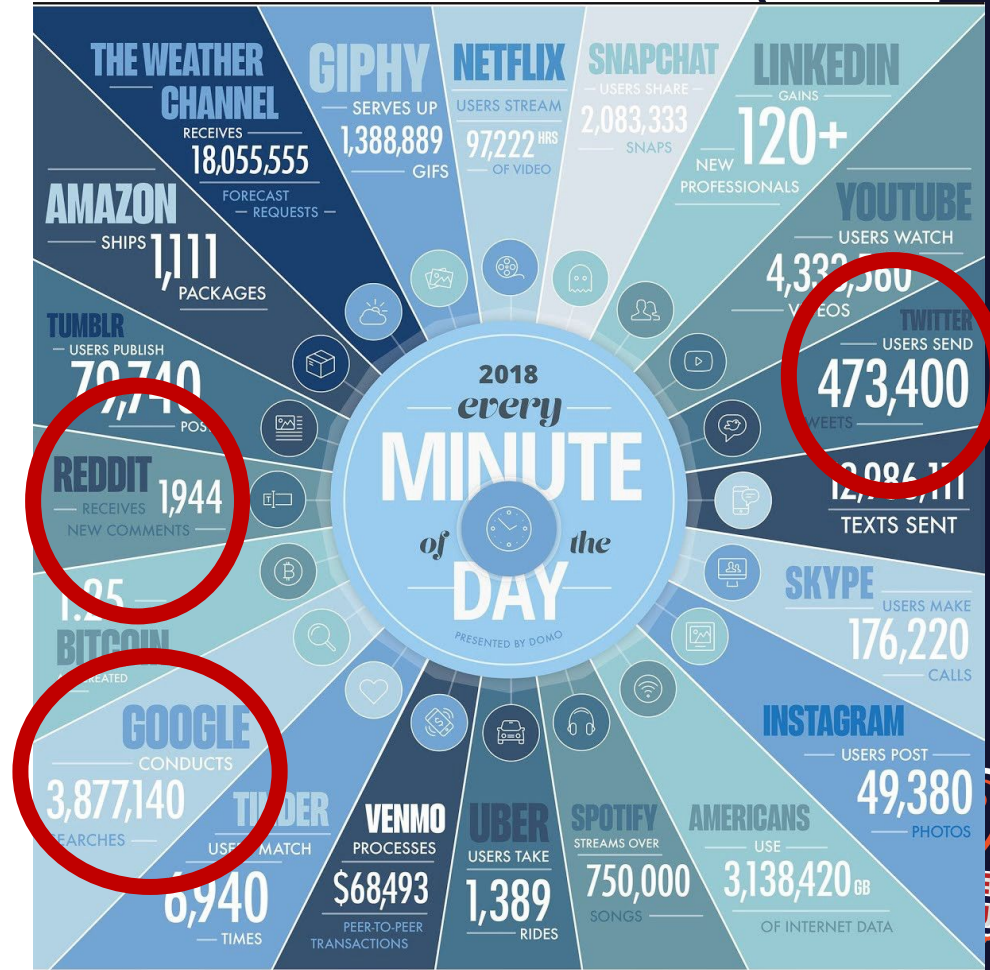
■ GARFIELD WAS TRYING TO STAY COOL





# WHY

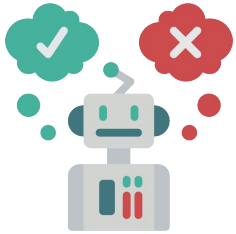
- Natural Language
- Convey information between 2 people
- Structured Vs Unstructured Data
- NLP is the interdisciplinary field combining computer science and linguistics



Source:

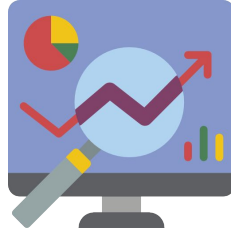
<https://www.domo.com/solution/data-never-sleeps/>

# Natural Language Processing - NLP



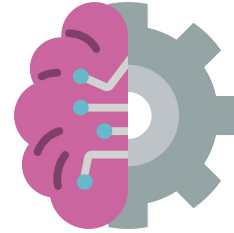
- MACHINE CAN INTERPRET HUMAN LANGUAGE

- Facilitates the Human Machine Interaction
- Enables the Machine to Machine Interaction



- DATA DRIVEN AND KNOWLEDGE DRIVEN

- Machine Learning for data classification and generation
- Semantic reasoning for data discovery and disambiguation

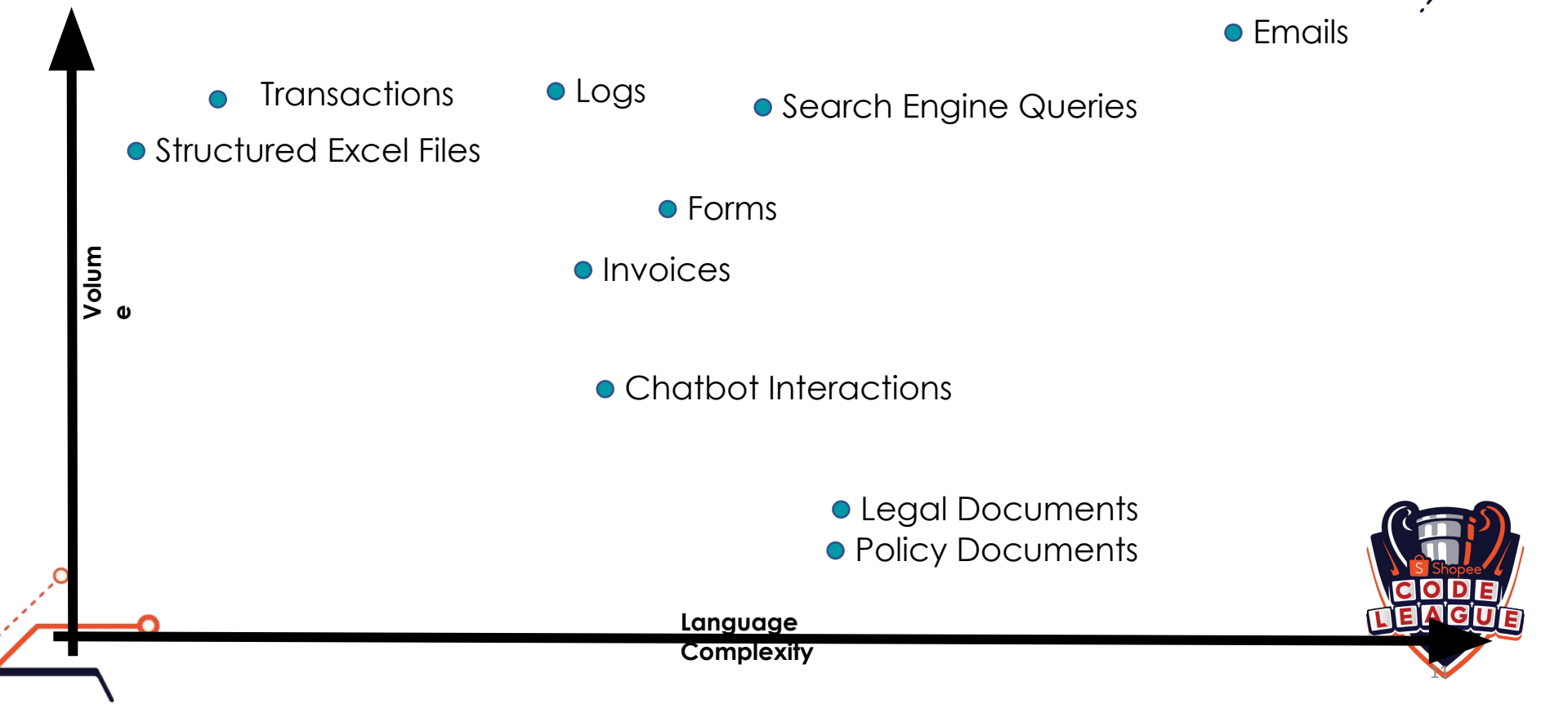


- SIMULATING HUMAN BRAIN

- Current models performs well at individual task, still needs improvements for multiple tasks



# WHY



# Applications of NLP

1. Sentiment analysis
2. Chatbot
3. Speech recognition
4. Language Translation
5. Information retrieval/extraction
6. Advertisement matching



# Applications of NLP

1. Sentiment analysis
2. Chatbot
3. Speech recognition
4. Language Translation
5. Information retrieval/extraction
6. Advertisement matching

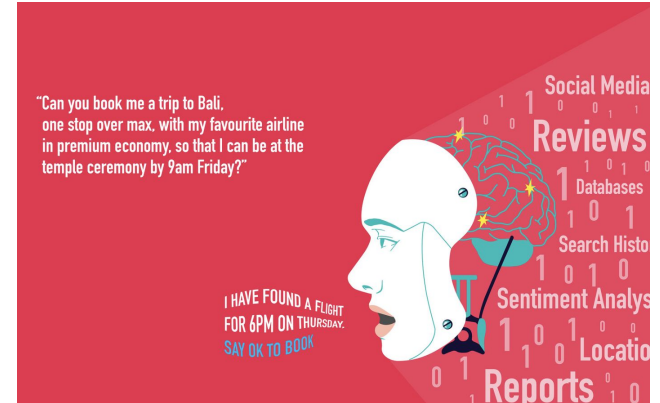


**Nordstrom digs into 5-star  
customer reviews and  
finds a shipping problem.**



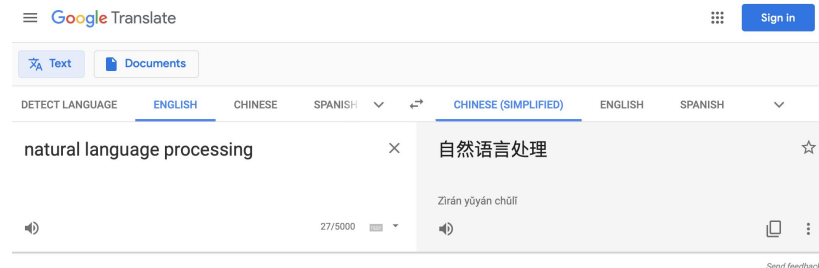
## Applications of NLP

1. Sentiment analysis
2. Chatbot
3. Speech recognition
4. Language Translation
5. Information retrieval/extraction
6. Advertisement matching



# Applications of NLP

1. Sentiment analysis
2. Chatbot
3. Speech recognition
4. Language Translation
5. Information retrieval/extraction
6. Advertisement matching



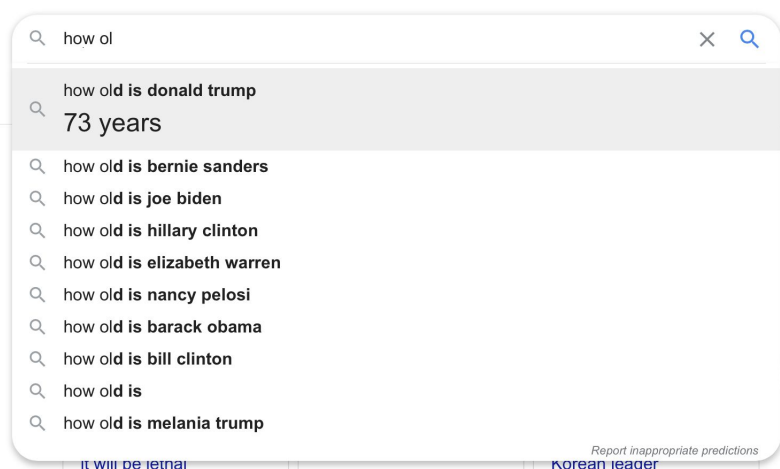
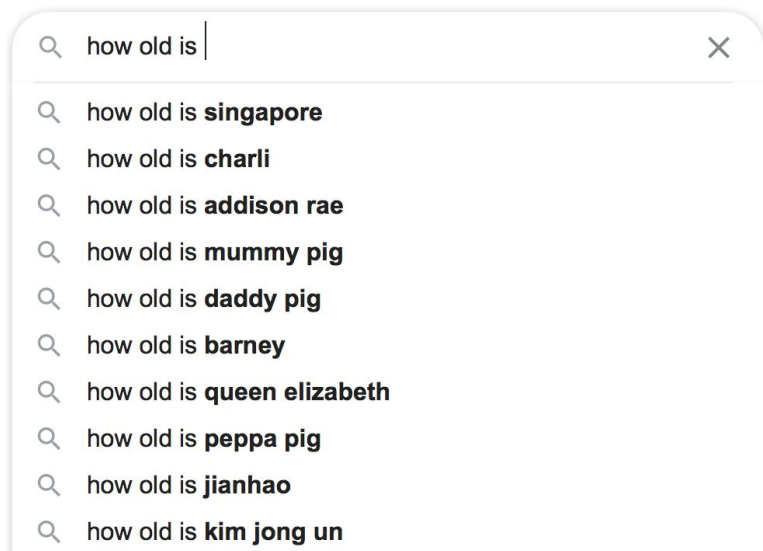


# Applications of NLP

1. Sentiment analysis
2. Chatbot
3. Speech recognition
4. Language Translation
5. Information retrieval/extraction
6. Advertisement matching



# E.g. Semantic search engine





**Walmart's semantic  
search engine  
increased  
conversion rates by  
10-15%**

# Applications of NLP

1. Sentiment analysis
2. Chatbot
3. Speech recognition
4. Language Translation
5. Information retrieval/extraction
6. Advertisement matching



# Natural Language Understanding



# TEXT NORMALISATION

She bought 10 apples and 10 oranges from the nearby grocer .

- CONVERTING ALL LETTERS TO LOWER OR UPPER CASE

she bought 10 apples and 10 oranges from the nearby grocer .

- CONVERTING NUMBERS INTO WORDS OR REMOVING NUMBERS

she bought apples and oranges from the nearby grocer .

- REMOVING PUNCTUATIONS, ACCENT MARKS AND OTHER DIACRITICS

she bought apples and oranges from the nearby grocer

- REMOVING WHITE SPACES

she bought apples and oranges from the nearby grocer

- REMOVING STOP WORDS, AND PARTICULAR WORDS

bought apples oranges nearby grocer

You can add your own Stop word. Go to your NLTK download **directory path** -> **corpora** -> **stopwords** -> update the stop word **file** depends on your language which one you are using. Here we are using english (stopwords.words('english')).



# PRE-PROCESSING

She bought 10 red apples and 10 cans of coca cola from the nearby grocer.

---

TOKENISATION "bought" "red" "apples" "cans" "coca" "cola" "nearby" "grocer"

N-GRAMS "red apples" "coca cola" "nearby grocer"

STEMMING "bought" "appl" "can" "coca" "cola" "nearbi"  
"grocer"

PART OF  
SPEECH (POS)  
TAGGING [ ('She', 'PRP'), ('bought', 'VBD'), ('10', 'CD'), ('apples', 'NNS'), ('and', 'CC'), ('10', 'CD'), ('cans', 'NNS'), ('of', 'IN'), ('coca', 'NN'), ('cola', 'NN'), ('from', 'IN'), ('the', 'DT'), ('nearby', 'JJ'), ('grocer', 'NN') ]

NAMED ENTITY  
RECOGNITION (\$ She/PRP bought/VBD 10/CD apples/NNS and/CC 10/CD cans/NNS of/IN (NP coca/NN) (NP cola/NN) from/IN (NP the/DT nearby/JJ grocer/NN))



# Tokenisation

Taking a text or set of text and breaking it up into its individual tokens (sentences, words, characters)

**She bought 10 red apples and 10 cans of coca cola from the nearby grocer.**

TOKENISATION      “bought” “red” “apples” “cans” “coca” “cola” “nearby” “grocer”

---

- New York, Los Angeles, Singapore Management University

- **Language specific:**

Chinese: 地铁站

French: L'ensemble

- **Context is often missing: “can”**





# N-GRAMS

Sequence of N words, good for putting keywords into local context

**bought red apples cans coca cola nearby grocer**

**NGRAMS**    “bought red”   “red apples”   “apples can”   “coca cola”   “nearby grocer”

---

**BIGRAMS**

“Coca cola”

- Compression algorithms (the PPM variety especially) where the length of the grams depends on how much data is available for providing specific contexts.

**TRIGRAMS**

The Three Musketeers

- Approximate string matching (e.g. BLAST for genetic sequence matching)

**4-GRAMS**

National University of Singapore

**5-GRAMS**

etc

- Predictive models (e.g. name generators)

- Speech recognition (phonemes grams are used to help evaluate likelihood of possibilities for the current phoneme undergoing recognition)



# STEMMING & LEMMATISATION

Reduce inflectional forms and sometimes derivationally related forms of a word to a **common base form**, to **bring variant forms of a word together**

**She bought 10 red apples and 10 oranges from the nearby grocer.**

STEM                    “bought” “appl” “orang” “nearbi” “grocer”

LEMMATIZE           “buy” “apple” “orange” “nearby” “grocer”

## SUFFIX

-ing

-ed

-es

-s

...

```
application
  Stemming: applic Lemmatizing: application
applying
  Stemming: appli Lemmatizing: apply
applies
  Stemming: appli Lemmatizing: apply
applied
  Stemming: appli Lemmatizing: apply
apply
  Stemming: appli Lemmatizing: apply
apples
  Stemming: appl Lemmatizing: apples
apple
  Stemming: appl Lemmatizing: apple
```

**Porter:** Most commonly used stemmer, and provides Java support.

**Snowball:** Improvement over the Porter algorithm, even Porter admits it is better than his original algorithm. Slightly faster computation time than porter, with a fairly large community around it.

To view the entire algorithm: <http://people.scs.carleton.ca/~armyunis/projects/KAPI/porter.pdf>



# PART OF SPEECH TAGGING

Marking up a word in a corpus to a corresponding part of a speech tag, based on its context and definition

I **left** my keys in my **left** pocket.

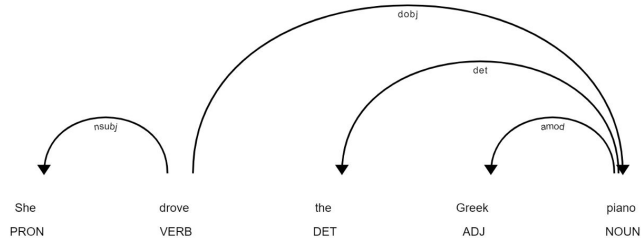
## PART OF SPEECH (POS) TAGGING

[( 'I', 'PRP'), (**'left'**, 'VBD'), ('my', 'PRP\$'), ('keys', 'NNS'), ('in', 'IN'), ('my', 'PRP\$'), (**'left'**, 'JJ'), ('pocket', 'NN')]

Left - VBD verb, past tense  
took

Left - JJ adjective

Building parse trees, which are used in building Named Entity Recognisers and extracting relations between words, helps in Syntactic and semantic analysis



Types:

1. Lexical Based Methods
2. Rule-Based Methods
3. Probabilistic Methods
4. Deep Learning Methods



# NAMED ENTITY Recognition

Identify all textual mentions of the named entities and classify them into pre-defined categories

**She bought 10 red apples and 10 cans of coca cola from the nearby grocer.**

**NAMED ENTITY RECOGNITION** (S She/PRP bought/VBD 10/CD apples/NNS and/CC 10/CD cans/NNS of/IN (NP coca/NN) (NP cola/NN) from/IN (NP the/DT nearby/JJ grocer/NN))

Stanford's Named Entity Recognizer is based on an implementation of linear chain Conditional Random Field (CRF) sequence models. Model is only trained on instances of **PERSON**, **ORGANIZATION** and **LOCATION** types.

Based on training data, the model will support different types of entities:

<https://spacy.io/api/annotation#section-named-entities>

Samples of Pre-defined categories	Examples
Names of people	Joan, Jeremy, Adam
Organisations	Accenture, Apple, GoJek
Locations	City Hall, Mount Fuji,
Expressions of times	June, 1980, 2008-03-10
Percent	100%, Twenty pct,
Monetary value	18 Euros, \$19, 600 Yen

Each POS tag is attached to a single word, while NER tags can be attached to multiple words.



# PRE-PROCESSING

She bought 10 red apples and 10 cans of coca cola from the nearby grocer.

---

TOKENISATION      "bought" "red" "apples" "cans" "coca" "cola" "nearby" "grocer"

N-GRAMS            "red apples" "coca cola" "nearby grocer"

STEMMING          "bought" "appl" "can" "coca" "cola" "nearbi"  
"grocer"

PART OF  
SPEECH (POS)  
TAGGING            [('She', 'PRP'), ('bought', 'VBD'), ('10', 'CD'), ('apples', 'NNS'), ('and', 'CC'), ('10', 'CD'), ('cans', 'NNS'), ('of', 'IN'), ('coca', 'NN'), ('cola', 'NN'), ('from', 'IN'), ('the', 'DT'), ('nearby', 'JJ'), ('grocer', 'NN')]

NAMED ENTITY  
RECOGNITION      (\$ She/PRP bought/VBD 10/CD apples/NNS and/CC 10/CD cans/NNS of/IN (NP coca/NN) (NP cola/NN) from/IN (NP the/DT nearby/JJ grocer/NN))



# DOCUMENT TERM MATRIX

1

## ORIGINAL STATEMENT

D1: Natural language processing is fun!

D2: Natural language processing is not fun!

D3: Drinking beer is fun!

2

## PROCESSED STATEMENT

D1: natur languag process fun

D2: natur languag process fun

D3: drink beer fun

3

## VECTOR OUTPUT

	natur	languag	process	fun	drink	beer
D1	1	1	1	1		
D2	1	1	1	1		
D3				1	1	1

Final vectors:

D1: (1,1,1,1,0,0)

D2: (1,1,1,1,0,0)

D3: (0,0,0,1,1,1)



# TERM FREQUENCY VS. TERM FREQUENCY – INVERSE DOCUMENT FREQUENCY

- TERM FREQUENCY (TF)
- Frequency of the term in the document
- i.e. if the word appears twice, the frequency in the vector will be 2

- TERM FREQUENCY - INVERSE DOCUMENT FREQUENCY (TF-IDF)

- Words that appear across multiple documents are less important (less discriminative)
- Give higher weightage to words that appear less
- $IDF(W) = \log \frac{N}{df(W)}$
- $N$  = Number of documents
- $df(W)$  = Number of documents the word appears in
- $TF - IDF(W) = TF(W) \times IDF(W)$

$$IDF(W) = \log \frac{100}{20}$$

$$TF - IDF(W) = 25 \times \log \frac{100}{20}$$

100 movie reviews  
20 on movie reviews  
'Avengers' □ 25  
times



## Hands-on

- 01 NLU.ipynb





# Your Feedback Matters!



[bit.ly/3hmJ3Nr](https://bit.ly/3hmJ3Nr)