Natural Language Processing

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28/11/2019

“Natural language processing is the set of methods for making human language accessible to computers.”

Photo by Gabriel Sollmann on Unsplash

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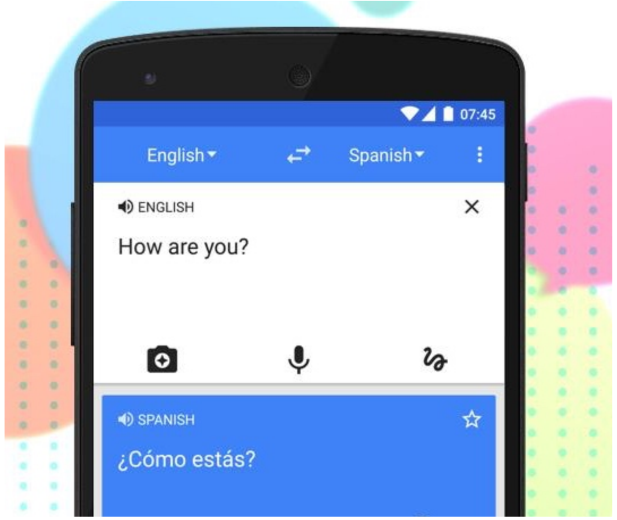
Examples of NLP applications



Machine translation

Text classification

Dialog systems

NLP tasks

- Tokenization
- Part-of-speech tagging
- Sentiment analysis
- Named-entity recognition
- Topic modelling
- Machine translation
- Text classification
- …

Why relevant for TLDs?

- Detect (active) use of domains
- Classify content of webpages
- Domain name recommendation
- Clean WHOIS database
- …

- What's your interest?
- What's your experience?

Today's topics

Tools:

- Jupyter Notebooks
- Scikit-learn
- NLTK

Concepts:

- Bag of Words
- Cross validation
- Model selection

Techniques:

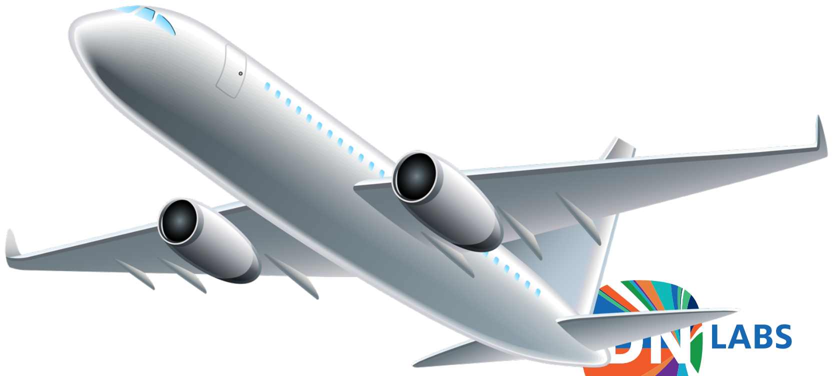
- Normalization
- Stemming/lemmatization
- TF-IDF
- Latent Dirichlet Allocation
- Random forest
- Support vector machine

Agenda

- Task 0: Text encoding (9:15-9:45)
- Task 1: Topic extraction (9:45-10:30)

- Coffee break? - -

- Task 2: Text classification (10:45-11:30)



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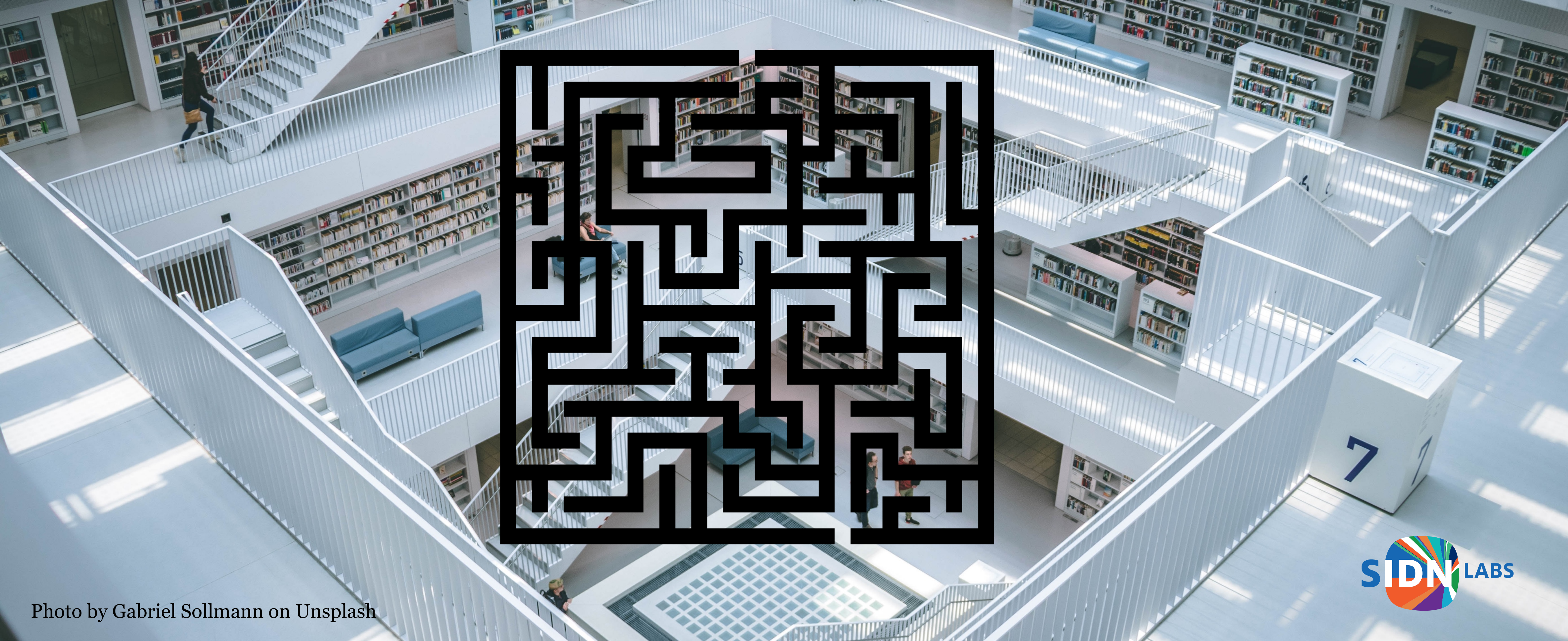


Photo by Gabriel Sollmann on Unsplash

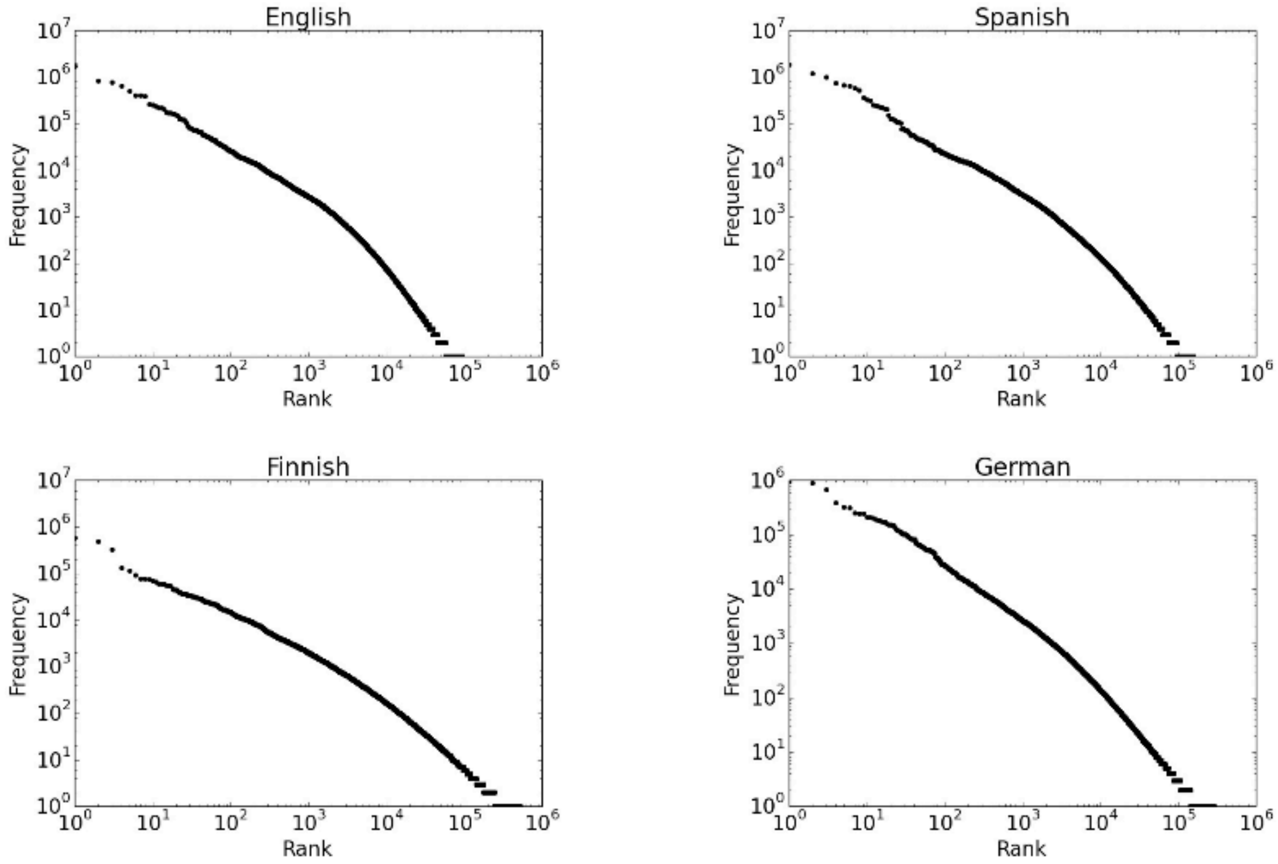
Why is NLP hard? Language is ambiguous

- Word senses: bank (finance or river?)
- Part of speech: chair (noun or verb?)
- Syntactic structure: I saw a man with a telescope
- Quantifier scope: Every child loves some movie
- Reference: John dropped the goblet onto the glass table and it broke.
- Discourse: The meeting is cancelled. Nicholas isn’t coming to the office today.

https://www.inf.ed.ac.uk/teaching/courses/fnlp/lectures/01_slides.pdf

Why is NLP hard?

Sparse data due to Zipf's Law:

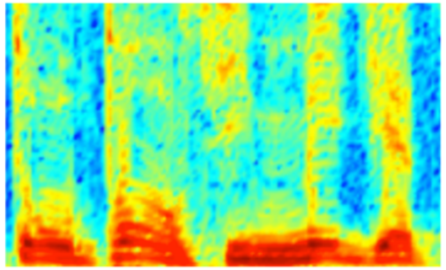


https://www.inf.ed.ac.uk/teaching/courses/fnlp/lectures/01_slides.pdf

Why is NLP hard?

- Algorithms cannot work with raw text directly;
- Text must be converted into numbers.

AUDIO



Audio Spectrogram

DENSE

IMAGES

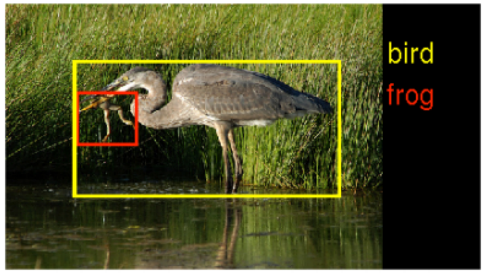


Image pixels

DENSE

TEXT

0	0	0	0.2	0	0.7	0	0	0	...	...

Word, context, or document vectors

SPARSE

https://www.tensorflow.org/tutorials/text/word_embeddings

Text encoding: Bag-of-Words model

Bag-of-Words (BoW)

Two steps:

- Construct vocabulary of known words (the items).
- Measure of the presence of known words documents (what’s in the bag).

	is	this	a	an	question	answer
Is this a question?	1	1	1	0	1	0
This is an answer.	1	1	0	1	0	1

https://machinelearningmastery.com/gentle-introduction-bag-words-model/

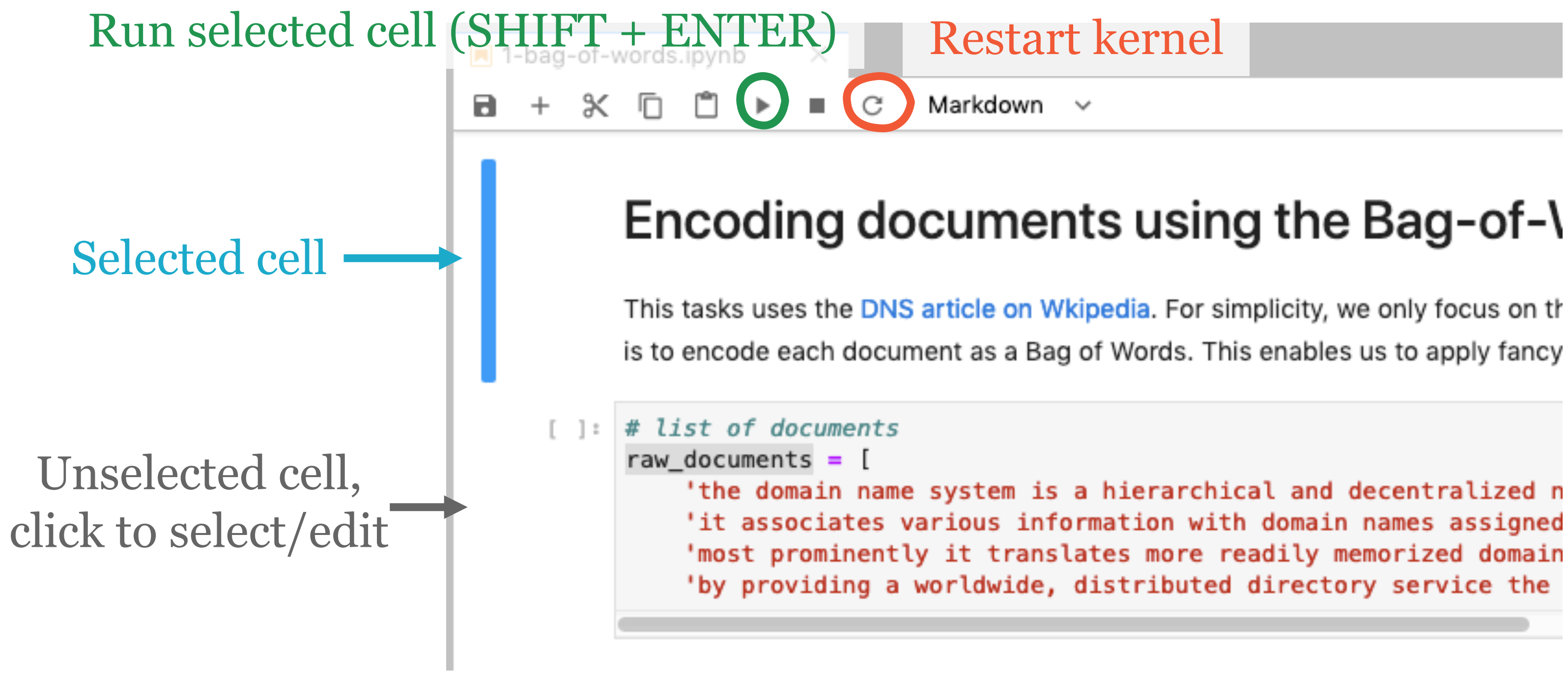
Warm up task: create Bag-of-Words (BoW)

- We will use Jupyter Notebooks
- Collaboration is encouraged, ensure experience is balanced

- Open [http://nlp-workshop.sidnlabs.nl/notebook-*[your-number*]](http://nlp-workshop.sidnlabs.nl/notebook-[your-number])
- Enter the password `centrpasswordverysafestring`

Warm up task: create Bag-of-Words (BoW)

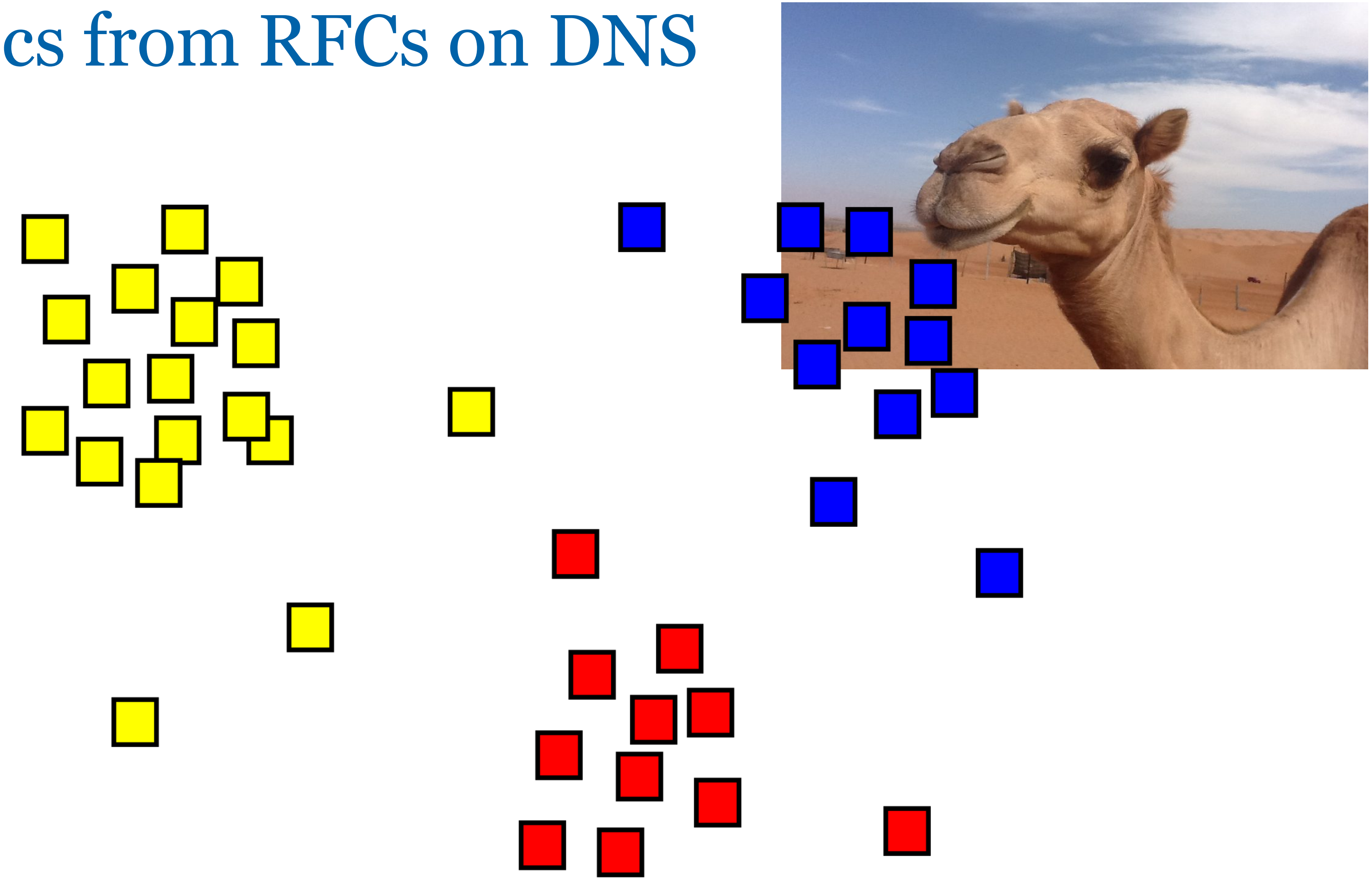
- Open `task-0/1-bag-of-words.ipynb`
- Run the cells. Try to understand what happens.



Bag-of-Word challenges

- Word order ignored (unless large n-grams)
- Sparse vectors (choose right algorithm)
- Noisy data
  - Pre-processing
  - Remove stop words
  - Use significant words only
- No awareness of word semantics
  - Not necessarily a problem
  - Use word embeddings

Extract topics from RFCs on DNS



Task 1: Latent Dirichlet Allocation (LDA)

Goal:

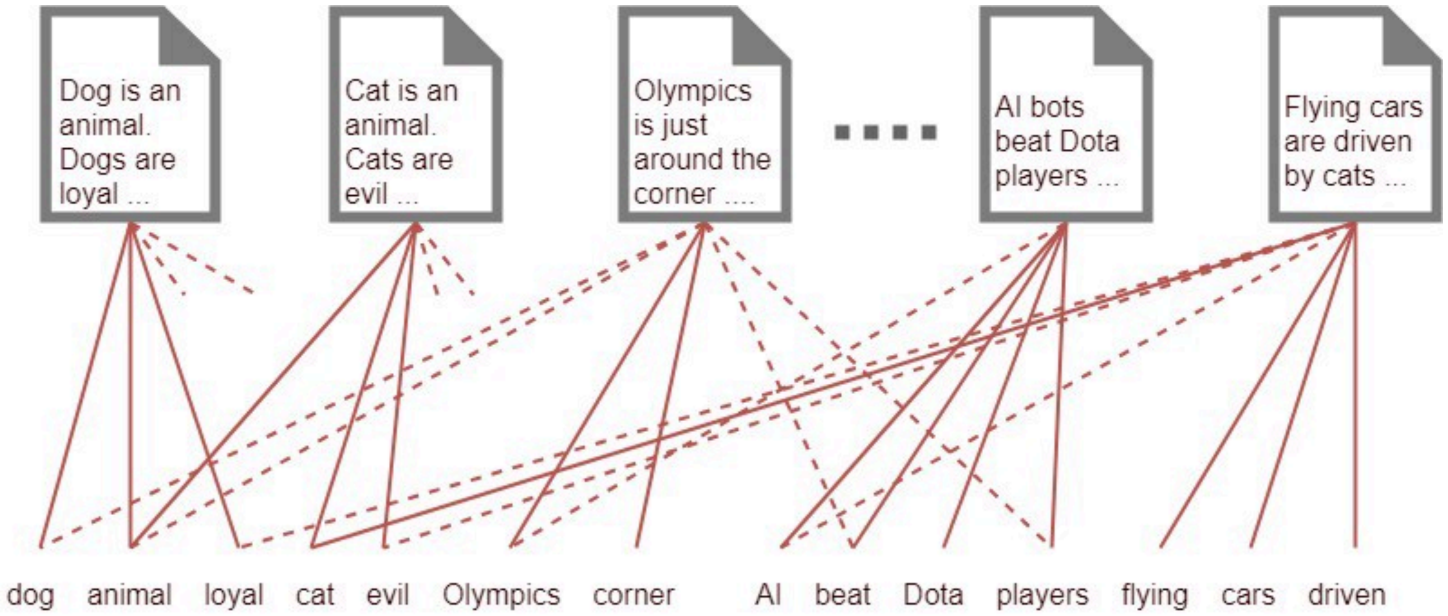
- Identify topics within documents (unsupervised)

Assumptions:

- Each document can be described by a distribution of topics, and each topic can be described by a distribution of words.
- Word and document order is not important.
- The number of topics known in advance.
- The same word can belong to multiple topics.

https://dzone.com/articles/lda-for-text-summarization-and-topic-detection

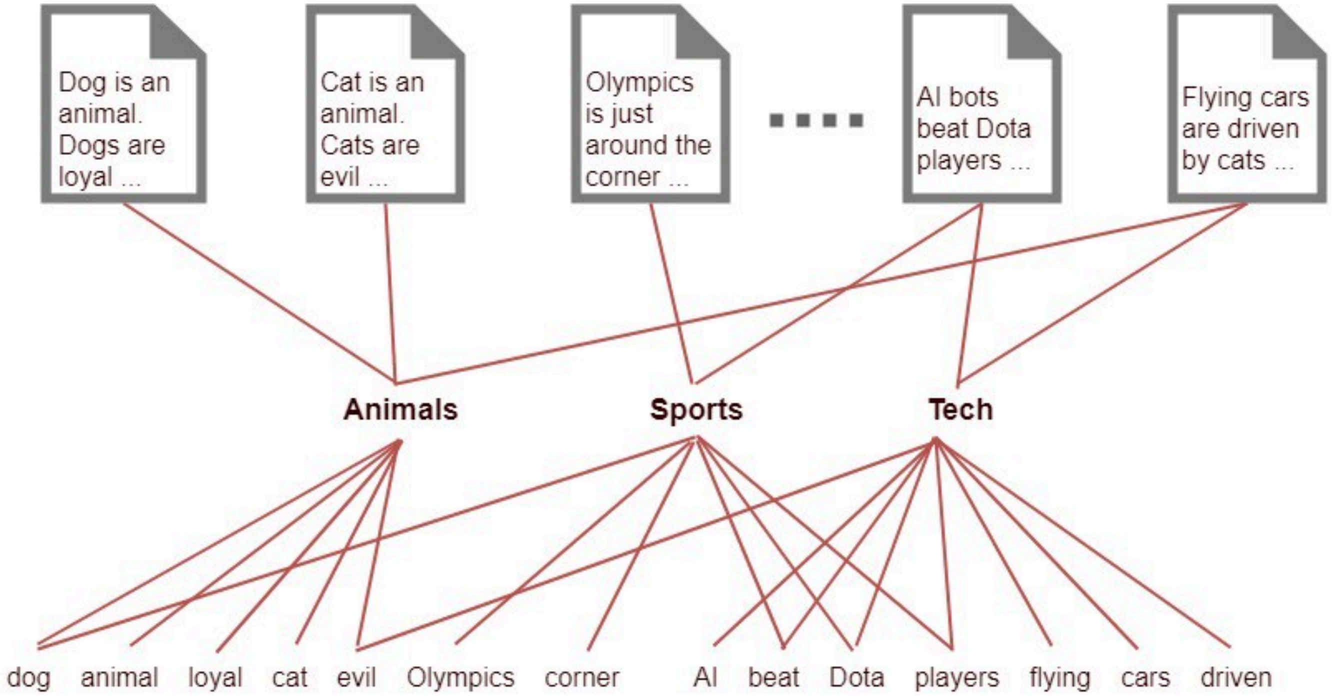
Brute force topic detection



https://towardsdatascience.com/light-on-math-machine-learning-intuitive-guide-to-latent-dirichlet-allocation

Optimized topic detection with LDA

Latent topics



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Task 1: topic modeling

- Open `task-1/1-topic-modelling.ipynb`
- Write pre-processing methods
- Fit LDA model
- Explore extracted topics

Data ingest → Pre-processing → Feature extraction (BoW) → Topic extraction (LDA) → Evaluation

Pre-processing methods

```
def remove_punctuation(document):
        filters = '!"\'#$%&()*+,-./:;<=>?@[\\]^_`{|}~\t\n'
        translate_dict = dict((c, ' ') for c in filters)
        translate_map = str.maketrans(translate_dict)
        return document.translate(translate_map)


def remove_numbers_only(document):
        return re.sub(r'\b[0-9]+\b\s*', '', document)


def remove_short_words(document):
        return ' '.join(token for token in document.split() if len(token) > 1)
```

Topic modelling results

- Can you label the topics? Do they make sense?
- What are the best parameters?

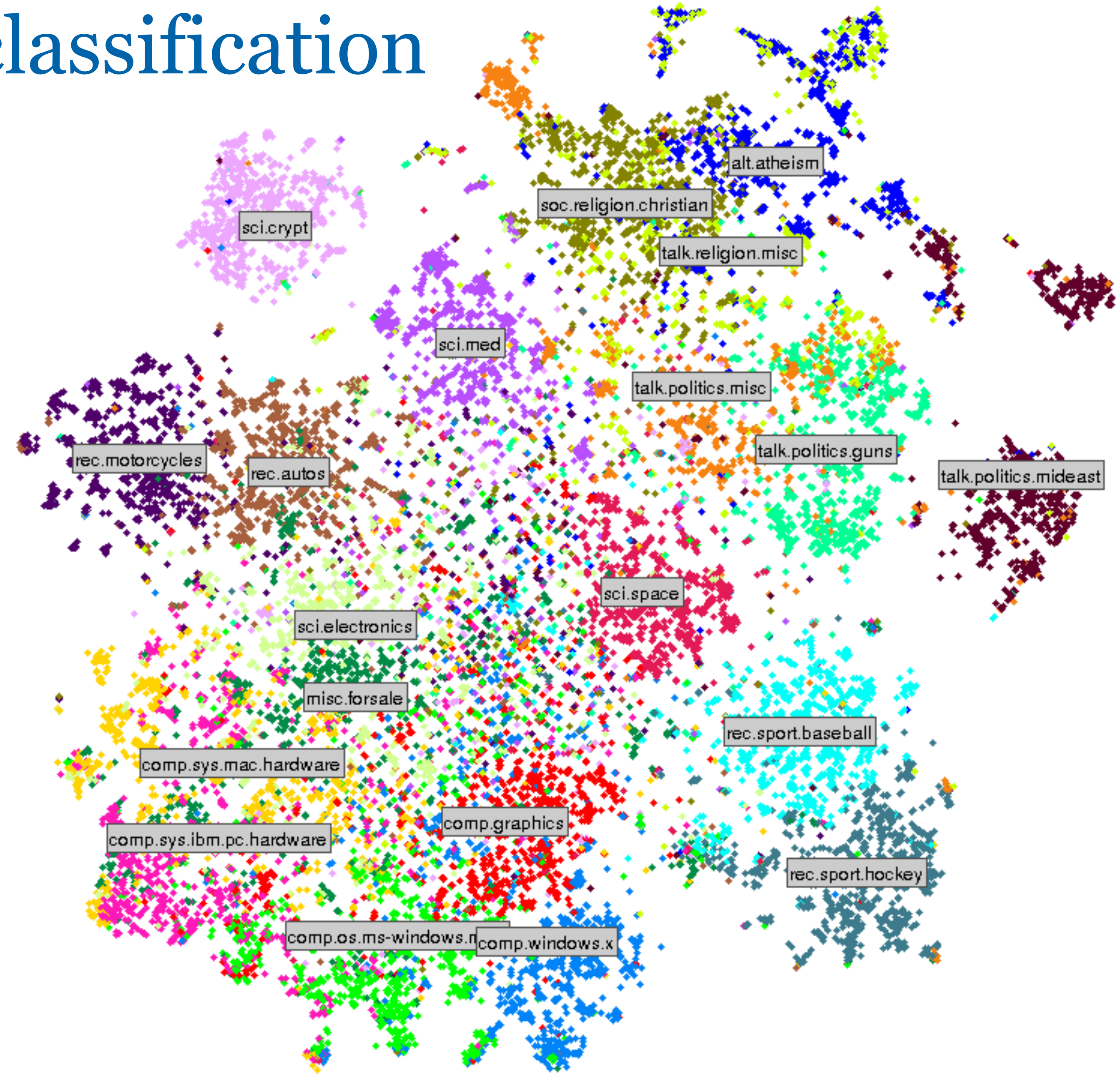
- What's the influence of pre-processing steps?
- Did you lemmatize and stem words?

- Did anyone implement "trending topics"?

Coffee break?

Please shutdown kernels to release memory.

Document classification



Text classification

Goal: assigns a label to unseen document based on its content

- Input (x): text of document
- Target (y): label of document

Supervised method: ground truth is required for training!

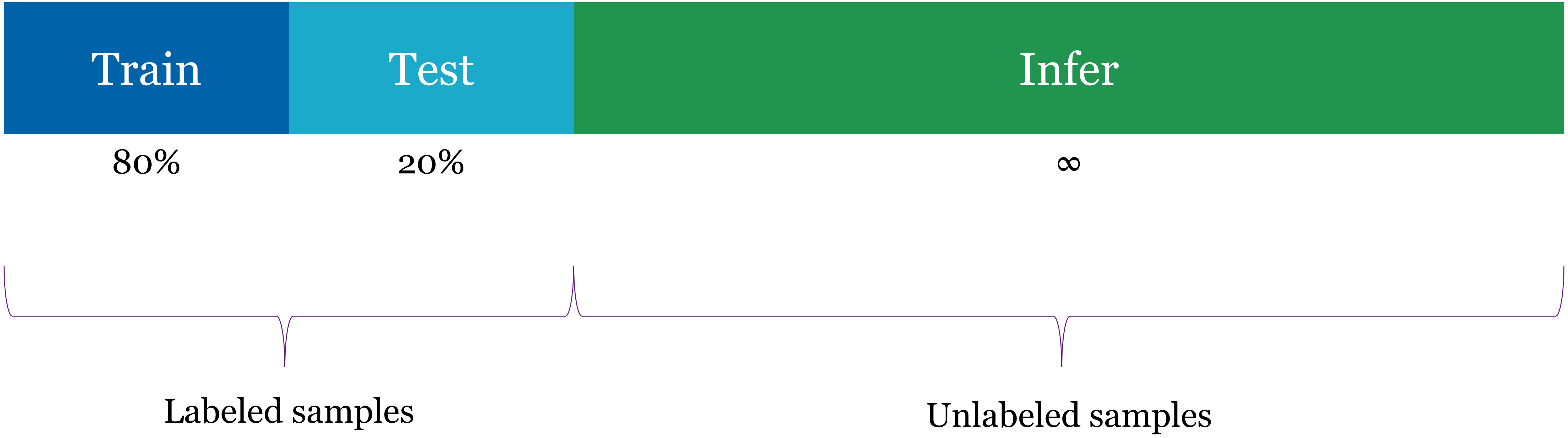
Example:

- Classify page type (parking page, eCommerce website, etc.)

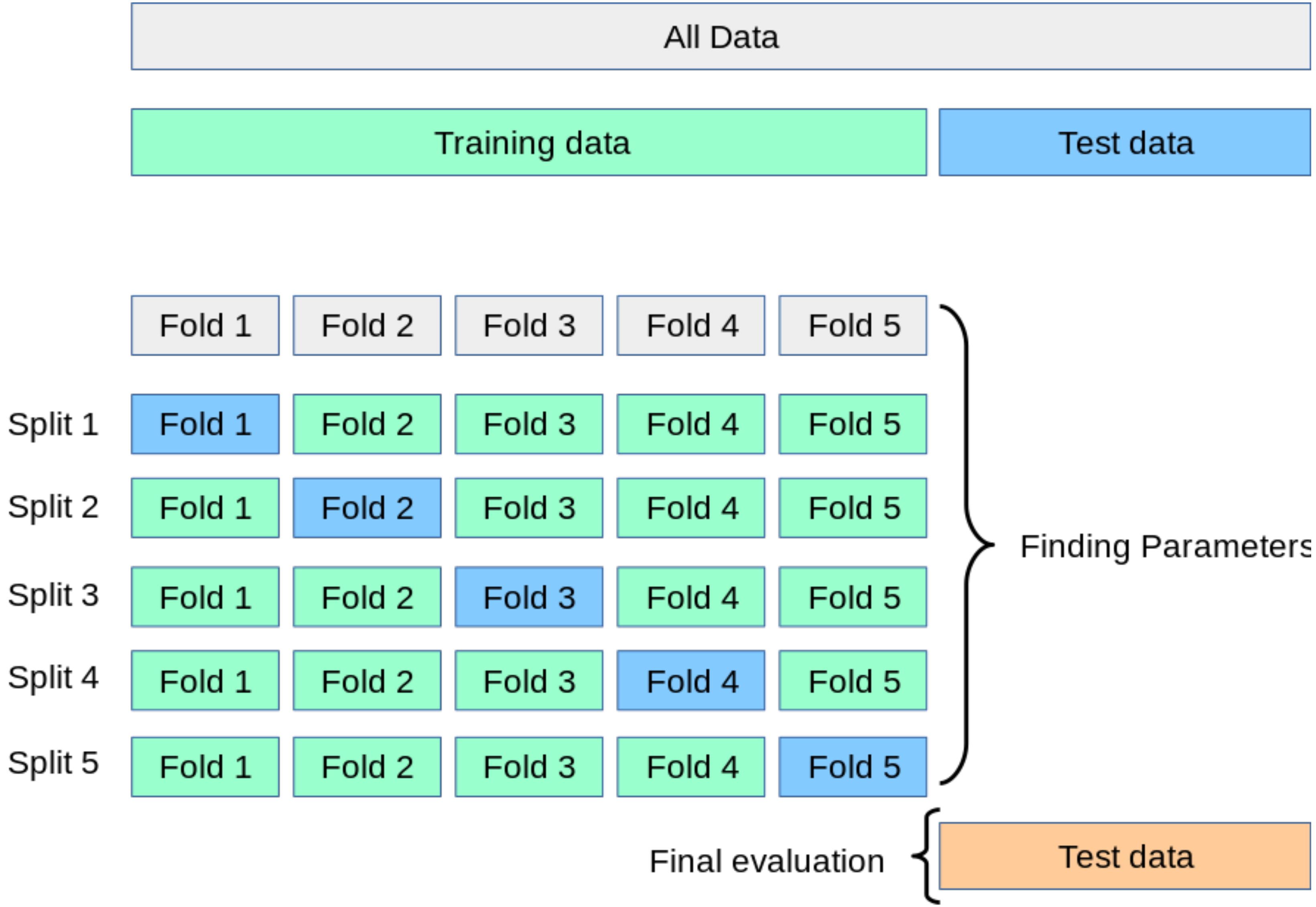
How do machines learn from data?

Train → **Test** → **Infer**

Data is used for one purpose only



Re-use training samples with cross validation



Task 2: text classification

- 3k newsgroup articles from 5 categories
- Focus on conducting experiments and model validation

- Explore 2 document encodings:
  - Term Frequency (TF)
  - TF-IDF
- Explore 2 classification methods:
  - Random Forest
  - Support Vector Machine

TF-IDF: find relevant terms

Intuition:

- A words that occurs multiple times in a single document is more relevant (TF)
- A words that occurs in many documents is less relevant (IDF)

Example:

A. The *car* is driven on the *road*.

B. The *truck* is driven on the *highway*.

Word	TF		IDF	TF*IDF	
	A	B		A	B
The	1/7	1/7	log(2/2) = 0	0	0
Car	1/7	0	log(2/1) = 0.3	0.043	0
Truck	0	1/7	log(2/1) = 0.3	0	0.043
Is	1/7	1/7	log(2/2) = 0	0	0
Driven	1/7	1/7	log(2/2) = 0	0	0
On	1/7	1/7	log(2/2) = 0	0	0
The	1/7	1/7	log(2/2) = 0	0	0
Road	1/7	0	log(2/1) = 0.3	0.043	0
Highway	0	1/7	log(2/1) = 0.3	0	0.043

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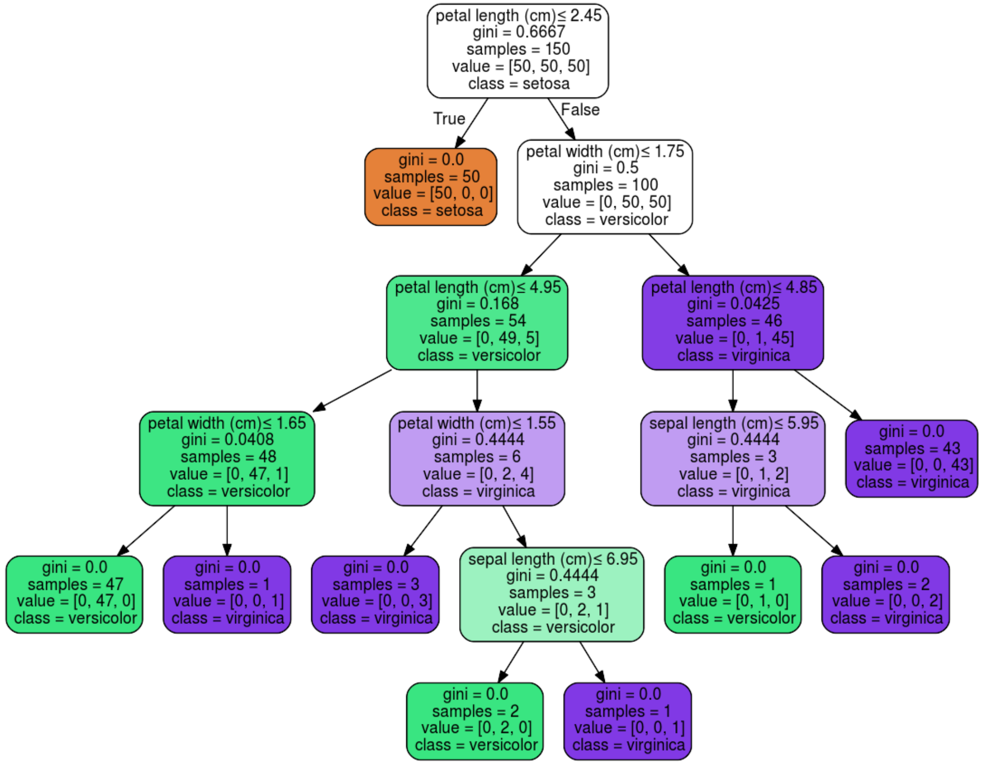
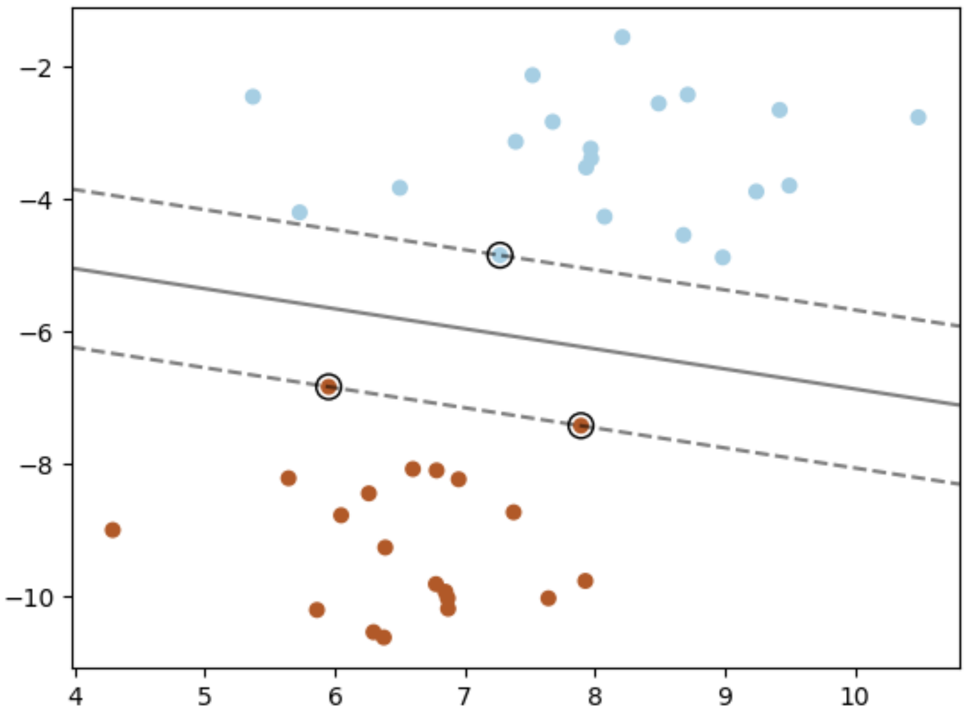
Example taken from medium.freecodecamp.org (Tripathi, 2018)



Random Forest



Support Vector Machine

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Task 2: text classification

- Open `task-2/1-text-classification.ipynb`
- Write 4 pipelines
  - TF & RF
  - TF & SGD
  - TF-IDF & RF
  - TF-IDF & SGD
- Train and evaluate on training data (wrong approach!)
- Train and evaluate using cross-validation

Task 2: text classification

- Do test results differ with cross-validation?
- Which pipeline performs the best? Using what metric?

- Optimal parameters?

Zijn er nog vragen?

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Dankjewel voor je aandacht!

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