Introduction to Natural Language Processing (NLP)

LECTURE 1

Lisa Andreevna Chalaguine

Lecture

About me and my Research

What is NLP

Importance/Applications of NLP

Challenges

Practical

Python Libraries needed

Choice of Dataset

Text Cleaning and Preprocessing

- Stopword removal
- Tokenisation
- Punctuation Removal
- Lemmatisation/Stemming

Lisa A. Chalaguine

PhD Student (Intelligent Systems Group)

Develop Chatbots that argue with people

Converted from Law to Computer Science

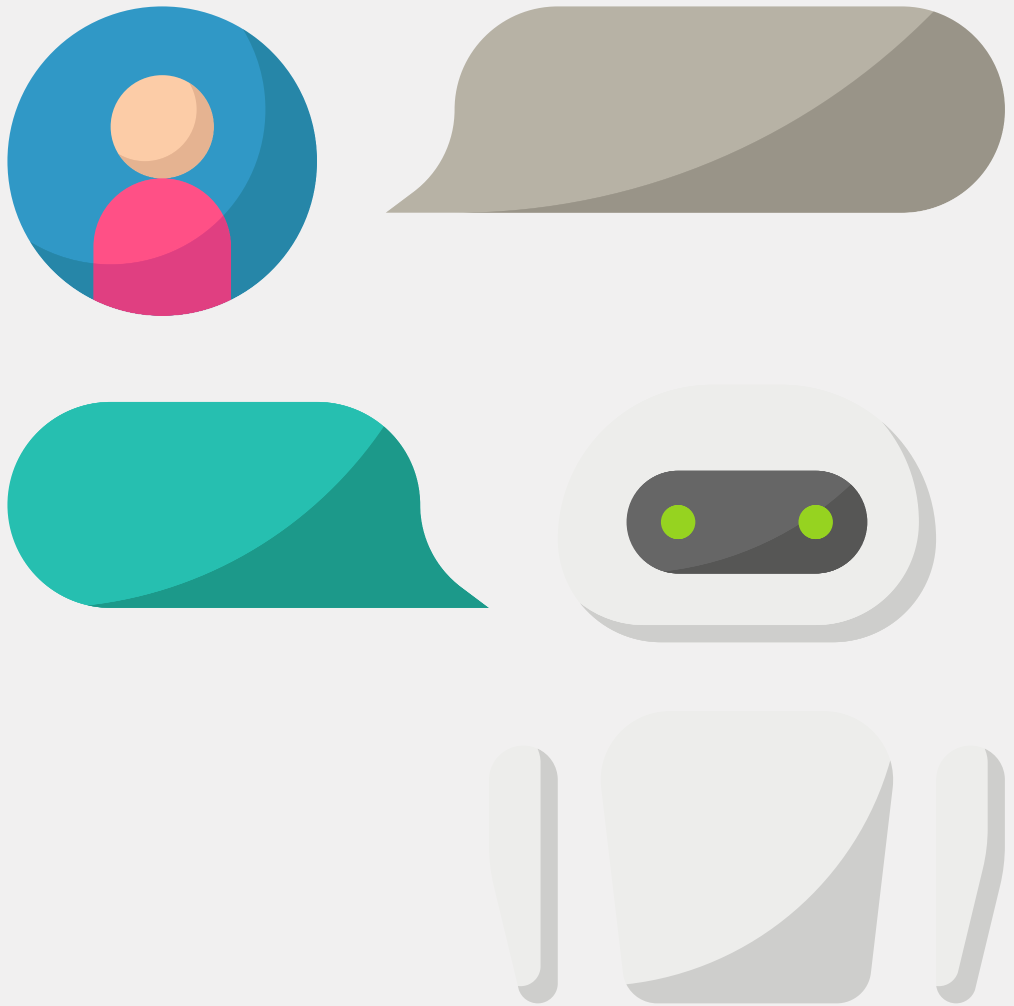
Discovered that being a Penny is better than a being Rachel Zane

Originally from Belarus

And since August most people finally know this country exists…

Demo of latest Project

Chatbot that tries to convince people to get a COVID-19 vaccine, once one is developed and becomes available



Applications

Sentiment/Opinion Analysis (e.g. social media, product reviews...)

Chatbots/Virtual Assistants (Siri, Alexa, Cortana, Google Assistant...)

- Speech Recognition
- Natural Language Generation

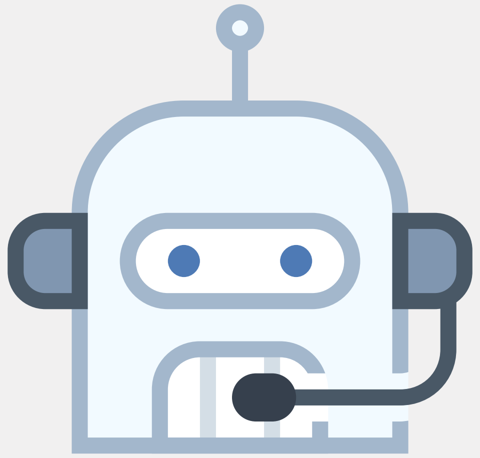
Text Classification (e.g. spam filtering)

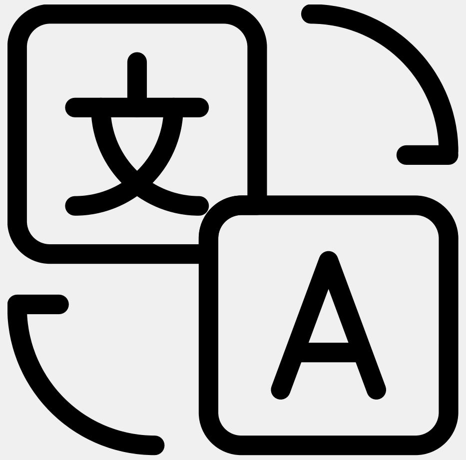
Information extraction

Machine Translation

Text Summarisation

Auto-Correct





Challenges of NLP

Unstructured data

Ambiguity of language (same word - different meaning)

Synonymy (same meaning - different words)

Coreference (what/who do pronouns refer to in subsequent sentences)

Irony, Sarcasm...

What is NLP?

NLP is a field of AI that gives machines the ability to read, understand and derive meaning from human languages

Discipline that focuses on the interaction between data science and human language.

Programming computers to process and analyse large amounts of natural language data.

Any questions so far?

Practical - stuff you need

Firstly you need ...

- A laptop
- Python 3.6+
- Jupyter Notebooks

Python libraries (for now)

- Pandas
- NLTK

Python libraries for next week

- scikit-learn

(requires NumPy & SciPy)

Anaconda comes with most the required libraries and Jupyter!!

Practical - GitHub page

I will post all of the materials on the following GitHub page

https://github.com/lisanka93/UCL_F2F_NLP101

Try yourself

Select one of the datasets in the dropbox datasets folder and apply some of the preprocessing techniques yourself

For next week

Find a (bigger, more complex) corpus that interests you and that can be used for classification.

NOTE - it will probably not be in .csv format. Your homework is then to write some code to read the corpus into Python

Recap

Last week we covered how to preprocess textual data

If you were not here please access the following GitHub repository and familiarise yourself with the content from Week 1

https://github.com/lisanka93/UCL_F2F_NLP101

Preprocessing

You should be able to understand what sort of preprocessing is necessary and adequate for different types of textual data.

Preprocecssing includes

- **Removal of unwanted characters**
- **Normalisation**
- **Tokenisation**
- **Stopword Removal**
- **Lemmatising/Stemming**

Lecture

Word Vectors

Classification Algorithms

Measuring Model Performance

Practical

Choice of Dataset

(for those who weren't here last week)

Training a classifier

- Preprocessing
- Vectorisation
- Training & Cross Validation
- Measuring Model Performance

Representing text in computer-readable format

A computer (obviously) cannot understand words. So we need to somehow convert text to numbers (vectors). There are several ways of doing that

- **Bag of Words**
- **Tf-idf**
- **Pre-trained word vectors**

Bag of words

"apples are great but so are pears, however, sometimes I feel like oranges and on other days I like bananas"

The sentence contains 17 distinct words. The following three sentences can then be represented as vectors using our vocabulary:

- **"I like apples" -->** [1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0]
- **"Bananas are great. Bananas are awesome" -->** [0, 2, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 2] **or** [0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1]
- **"She eats kiwis" -->** [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]

tf-idf

T

tf-idf stands for "term-frequency-inverse-document-frequency.
It indicates what the importance of a word is in order to understand the document or dataset.

Example: Students write essay on the topic "My family". The word "family" will come up in every single essay and is therefore not informative. Other words like "grandmother", "dog", "separated" will carry more information.

tf-idf calculation

T

TF(t) = (Number of times term t appears in a document) / (Total number of terms in the document)

tf gives equal importance to every single word so we need to define some weighing down of the frequent terms while scaling up the rare ones, which decides the importance of each word

IDF(t) = log10(Total number of documents / Number of documents with term t in it)

tf-idf(t) = tf(t) * idf(t)

tf-idf numerical example

Step 1 : Calculate TF

Step 1.1 : Term Count for each document

Document 1

Term	Term Count
this	1
is	1
a	2
sample	1

Document 2

Term	Term Count
this	1
is	1
another	2
example	3

Step 1.2 : Now calculate total nuber of words in each document

Document 1 : Total words are = 5
Document 2 : Total words are = 7

Step 1.3 : Now calculate TF

TF(t) = (Number of times term t appears in a document) / (Total number of terms in the document)

$$\mathrm{tf}(''\mathsf{this}'', d_1) = \frac{1}{5} = 0.2$$

$$\mathrm{tf}(''\mathsf{this}'', d_2) = \frac{1}{7} \approx 0.14$$

tf-idf numerical example

Step 2 : Calculate IDF

Step 2.1 : IDF calculation

IDF(t) = log(Total number of documents / Number of documents with term t in it)

So here there are 2 document and term "this" appears in both of them
So IDF is given below.

$$\mathrm{idf}(''\mathsf{this}'', D) = \log\left(\frac{2}{2}\right) = 0$$

Step 3 : TF x IDF calculation

$$\mathrm{tfidf}(''\mathsf{this}'', d_1) = 0.2 \times 0 = 0$$
$$\mathrm{tfidf}(''\mathsf{this}'', d_2) = 0.14 \times 0 = 0$$

zero implies that the word is not very informative

For other words is given below

$$\mathrm{tf}(''\mathsf{example}'', d_1) = \frac{0}{5} = 0$$

$$\mathrm{tf}(''\mathsf{example}'', d_2) = \frac{3}{7} \approx 0.429$$

$$\mathrm{idf}(''\mathsf{example}'', D) = \log\left(\frac{2}{1}\right) = 0.301$$

Step 4: TF X IDF for word example

$$\mathrm{tfidf}(''\mathsf{example}'', d_1) = \mathrm{tf}(''\mathsf{example}'', d_1) \times \mathrm{idf}(''\mathsf{example}'', D) = 0 \times 0.301 = 0$$
$$\mathrm{tfidf}(''\mathsf{example}'', d_2) = \mathrm{tf}(''\mathsf{example}'', d_2) \times \mathrm{idf}(''\mathsf{example}'', D) = 0.429 \times 0.301 \approx 0.13$$

Pre-trained word vectors

Word2Vec is one of the most popular techniques to learn word embeddings using a shallow neural network

developed by Tomas Mikolov in 2013 at Google

"Have a good day"* and *"Have a great day"
very similar meaning

One-hot encoded vectors of our vocabulary:
Have = [1,0,0,0,0]
a=[0,1,0,0,0]
good=[0,0,1,0,0]
great=[0,0,0,1,0]
day=[0,0,0,0,1]

words are independend of each other

Pre-trained word vectors

objective is to have words with similar context occupy close spatial positions. Mathematically, the cosine of the angle between such vectors should be close to 1, i.e. angle close to 0

solution: distributed representations
we introduce some dependence of one word on the other words. The words in context of this word would get a greater share of this dependence

Word2Vec is a method to construct such an embedding

- **Skip Gram**
- **Common Bag Of Words (CBOW)**

CBOW

Will not go deep into the maths. In short: CBOW works by training a neural network on a vocabulary of words where the input are one-hot encoded vectors (context) and the outcome is a target word. The NN updates the weightsin the hidden layer in order to predict the target word given the context words. The trained weights are the word embeddings

Example

	fruit	animal	edible
Apple	0.9	0.01	0.85
Orange	0.8	0.02	0.9
Elephant	0.1	0.95	0.02

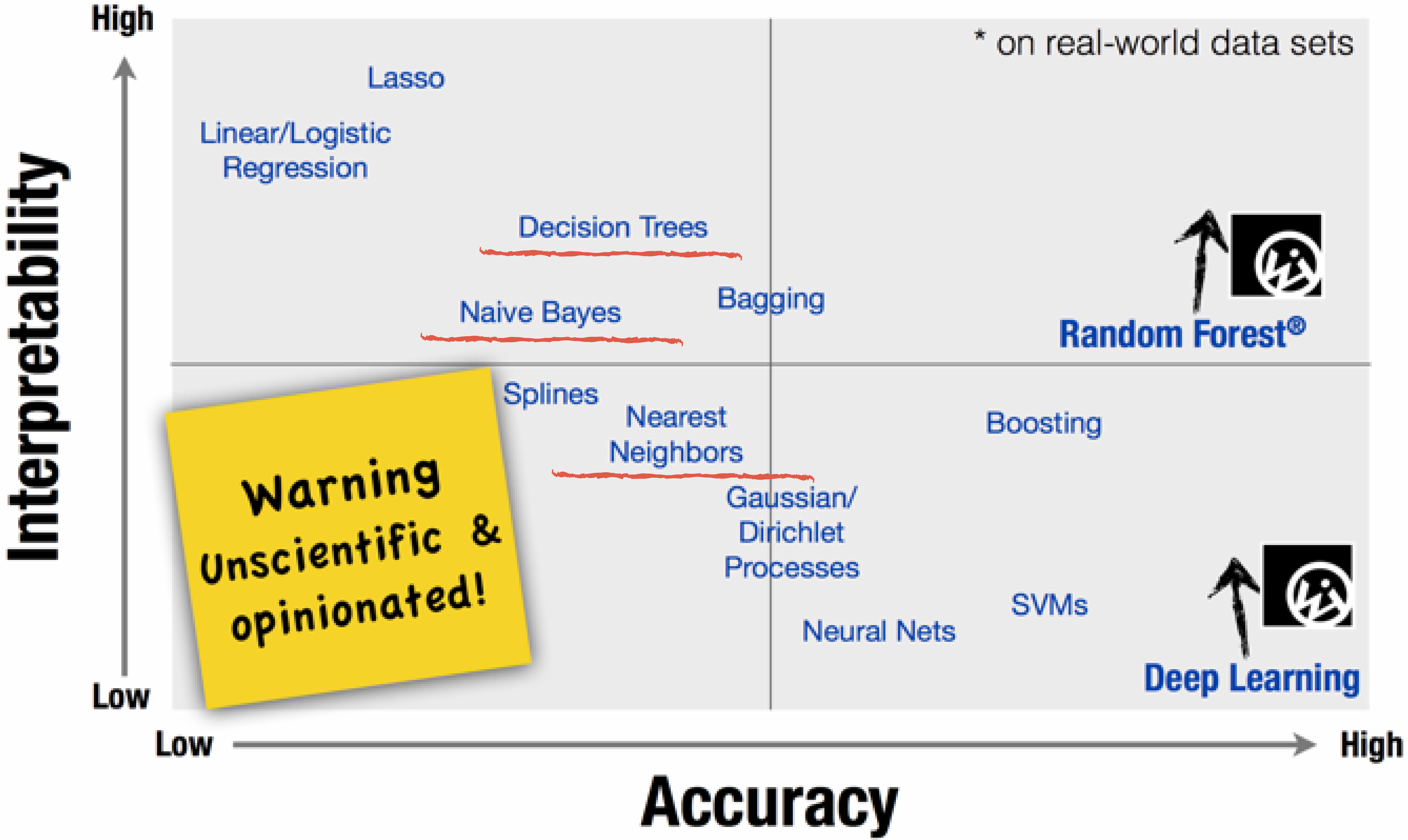
Classification Algorithms

(for today)

- **Naive Bayes**
- **KNN (K-Nearest Neighbour)**
- **Decision Trees**

Note: scikit-learn makes it quite easy to experiment with different algorithms, so feel free to test out any others (e.g. SVM)

ML Algorithmic Trade-Off



(Multinomial) Naive Bayes

- **based on Bayes' Theorem (probabilistic algorithm)**
- **works particularly well with NLP problems**

Example

Text	Tag
“A great game”	Sports
“The election was over”	Not Sports
“Very clean match”	Sports
“A clean but forgettable game”	Sports
“It was a close election”	Not Sports

(Multinomial) Naive Bayes

- Since Naive Bayes is a probabilistic classifier, we want to calculate the probability that the sentence "A very close game" is Sports and the probability that it's Not Sports
- Written mathematically, what we want is P(Sports | a very close game) — the probability that the tag of a sentence is *Sports* given that the sentence is "A very close game"
- We ignore the word order and sentence construction (hence, NAIVE bayes)
- Features will be the counts of each of these words

(Multinomial) Naive Bayes

Example: A very close game

P(Sports) = 3/5 and P(Not Sports) = 2/5

P(a very close game | Sports) = P(a | Sports) * P(very | Sports) * P(close | Sports) * P(game | Sports)

Problem: “close” is not in any Sports texts. Since we are multiplying, we will end up with P = 0!

Solution: laplace smoothing: adding 1 to every count, so it’s never 0. To balance this,

we add the number of possible words to the divisor (so division will never be greater than 1)

Word	P(word | Sports)	P(word | Not Sports)
a	$\frac{2+1}{11+14}$	$\frac{1+1}{9+14}$
very	$\frac{1+1}{11+14}$	$\frac{0+1}{9+14}$
close	$\frac{0+1}{11+14}$	$\frac{1+1}{9+14}$
game	$\frac{2+1}{11+14}$	$\frac{0+1}{9+14}$

Text	Tag
“A great game”	Sports
“The election was over”	Not Sports
“Very clean match”	Sports
“A clean but forgettable game”	Sports
“It was a close election”	Not Sports

And Finally...

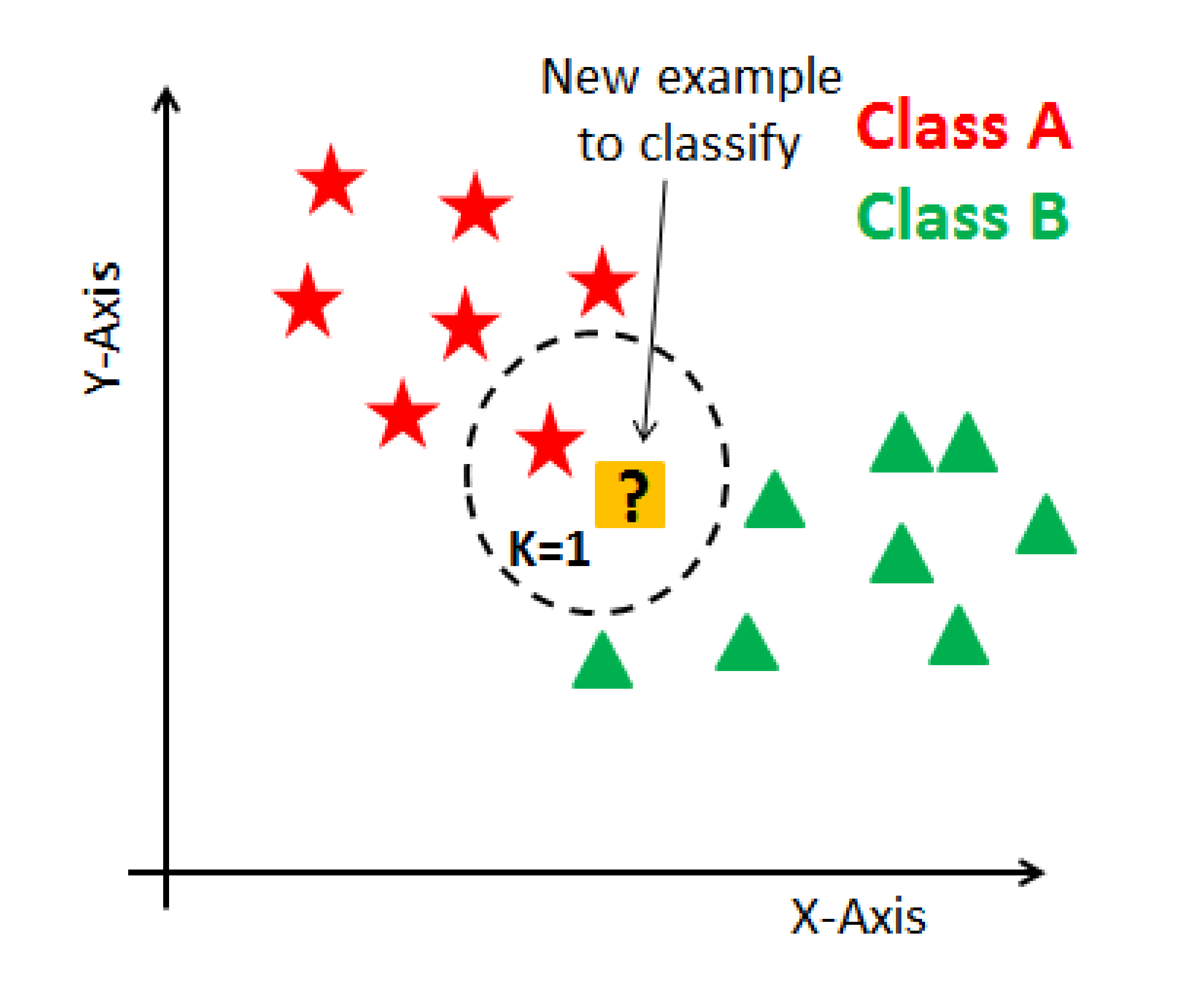
Now we just multiply all the probabilities, and see who is bigger:

$$P(a|Sports) \times P(very|Sports) \times P(close|Sports) \times P(game|Sports) \times P(Sports)$$
$$= 2.76 \times 10^{-5}$$
$$= 0.0000276$$

$$P(a|Not\,Sports) \times P(very|Not\,Sports) \times P(close|Not\,Sports) \times P(game|Not\,Sports) \times P(Not\,Sports)$$
$$= 0.572 \times 10^{-5}$$
$$= 0.00000572$$

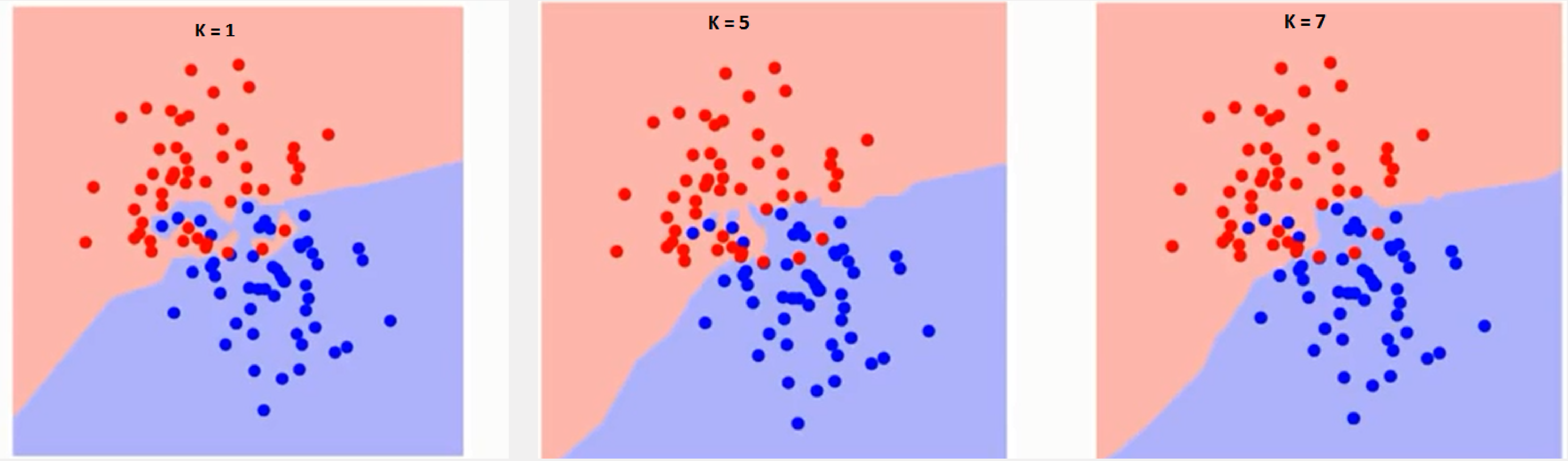
Excellent! Our classifier gives “A very close game” the **Sports** tag.

KNN



KNN

- with a given K value we can make boundaries of each class
- These boundaries will segregate the classes
- let’s see the effect of the value for K on the class boundaries



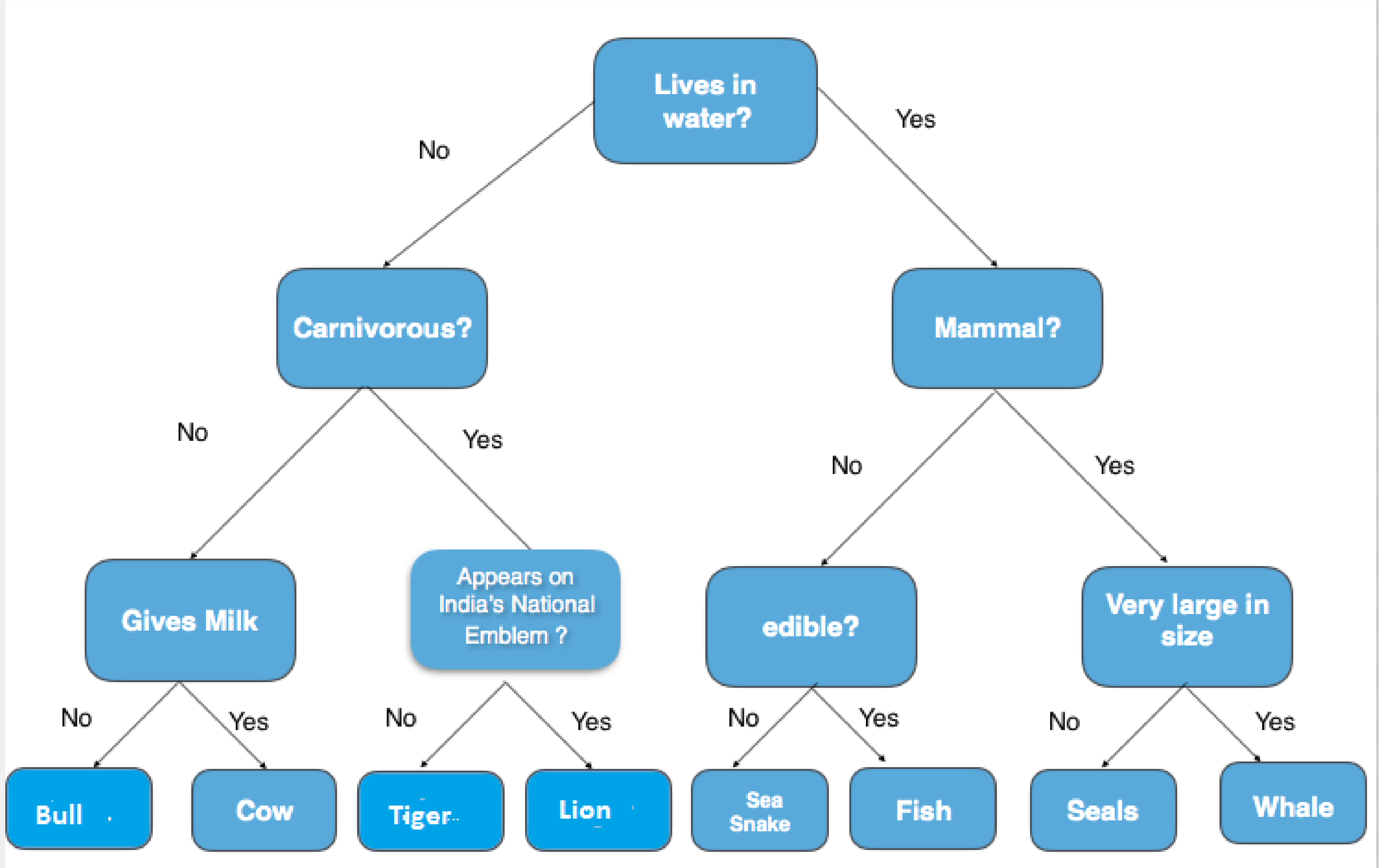
OVERFITTING!

Algorithm

- Initialize K to your chosen number of neighbors
- For each example in the data
    - Calculate the distance between the query example and the current example from the data
    - Add the distance and the index of the example to an ordered collection
- Sort the ordered collection of distances and indices from smallest to largest (in ascending order) by the distances
- Pick the first K entries from the sorted collection
- Get the labels of the selected K entries
- If regression, return the mean of the K labels/If classification, return the mode of the K labels

Decision Trees

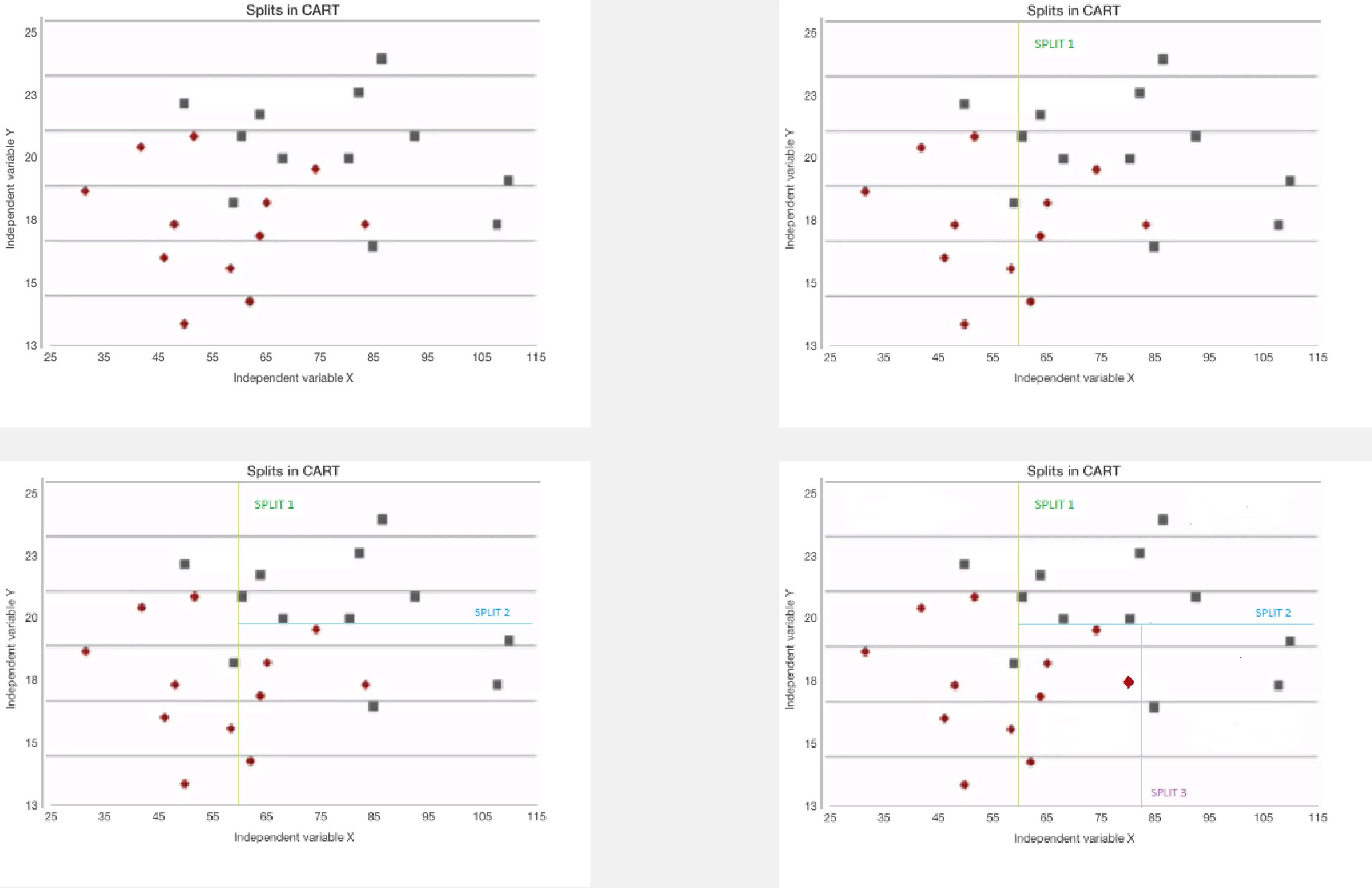
- **Advantage: very easy to interpret**
- **Disadvantage: easy to overfit**



Algorithm

- **repeatedly partitioning the data into multiple sub-spaces, so that the outcomes in each final sub-space is as homogeneous as possible**
- **recursive partitioning**
  - **Given a subset of training data, find the best feature for predicting the labels on that subset.**
  - **Find a split on that feature that best separates the labels, and split into two new subsets**
  - **Repeat steps one and two recursively until you meet a stopping criterion**

Example



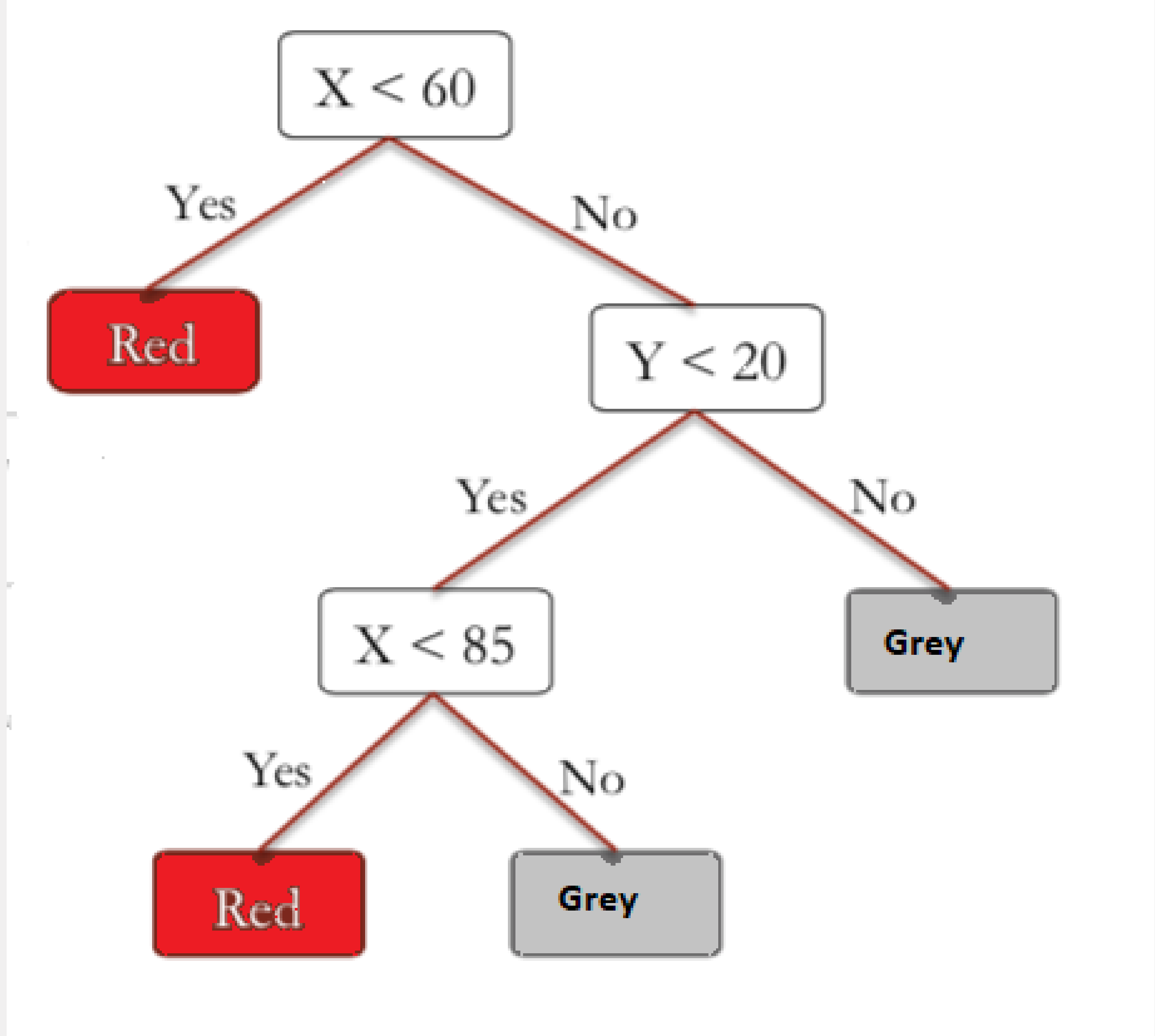
Ways of splitting:

- Gini
- Entropy
- Info Gain

Example

**If a new observation fell into any of the subsets,
it would now be decided by the majority of the observations
in that particular subset**

The tree for the splits looks like this:

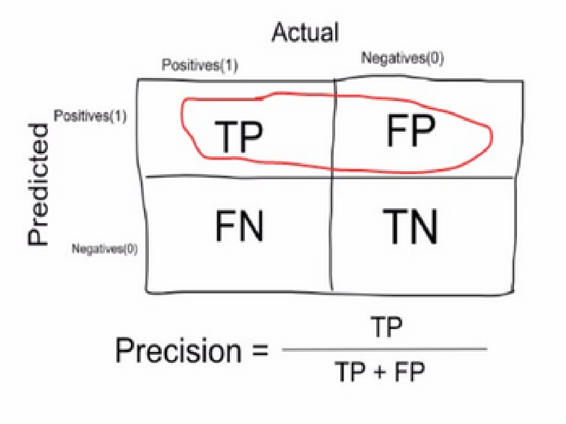


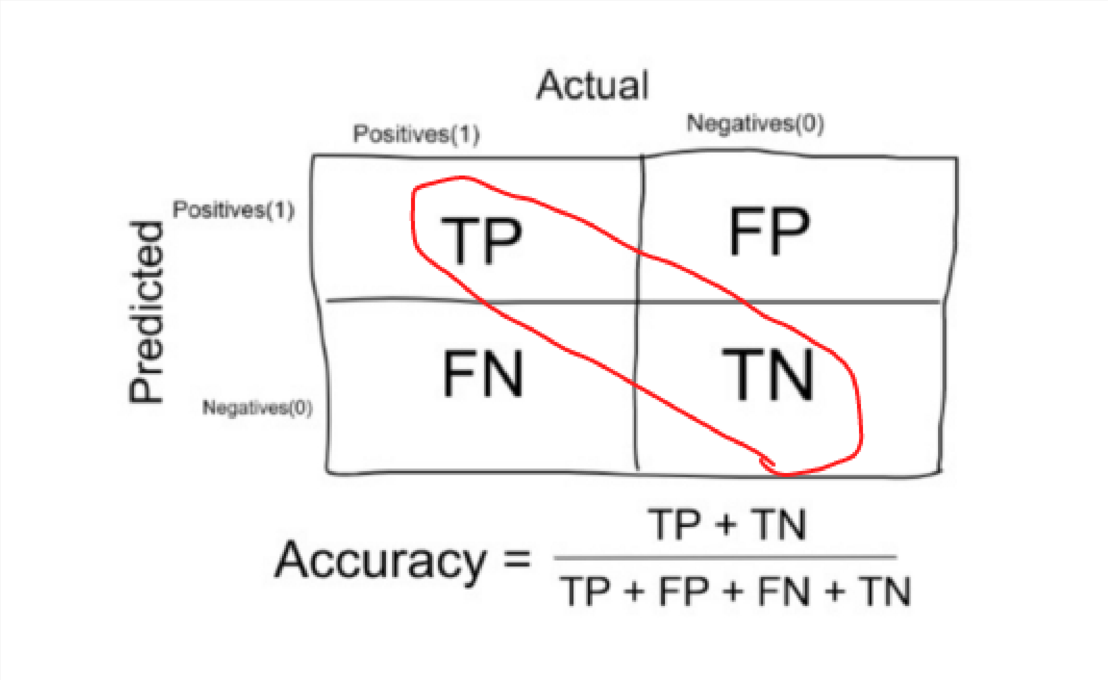
Measuring Model Performance

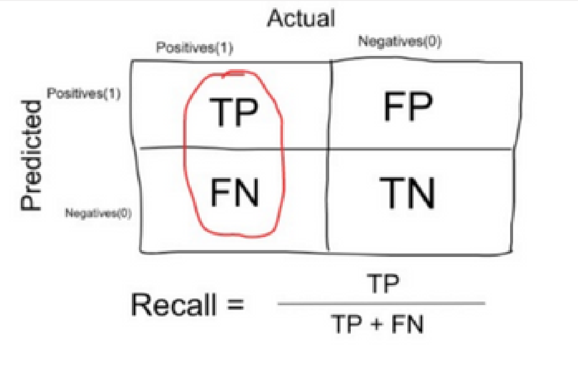
As usual,depends on problem...

Accuracy: Good measure when target variable classes in the data are nearly balanced

Precision and Recall: If data is unbalanced







F1 Score

Unpractical to carry around precision and recall every time we make a model for solving a classification problem

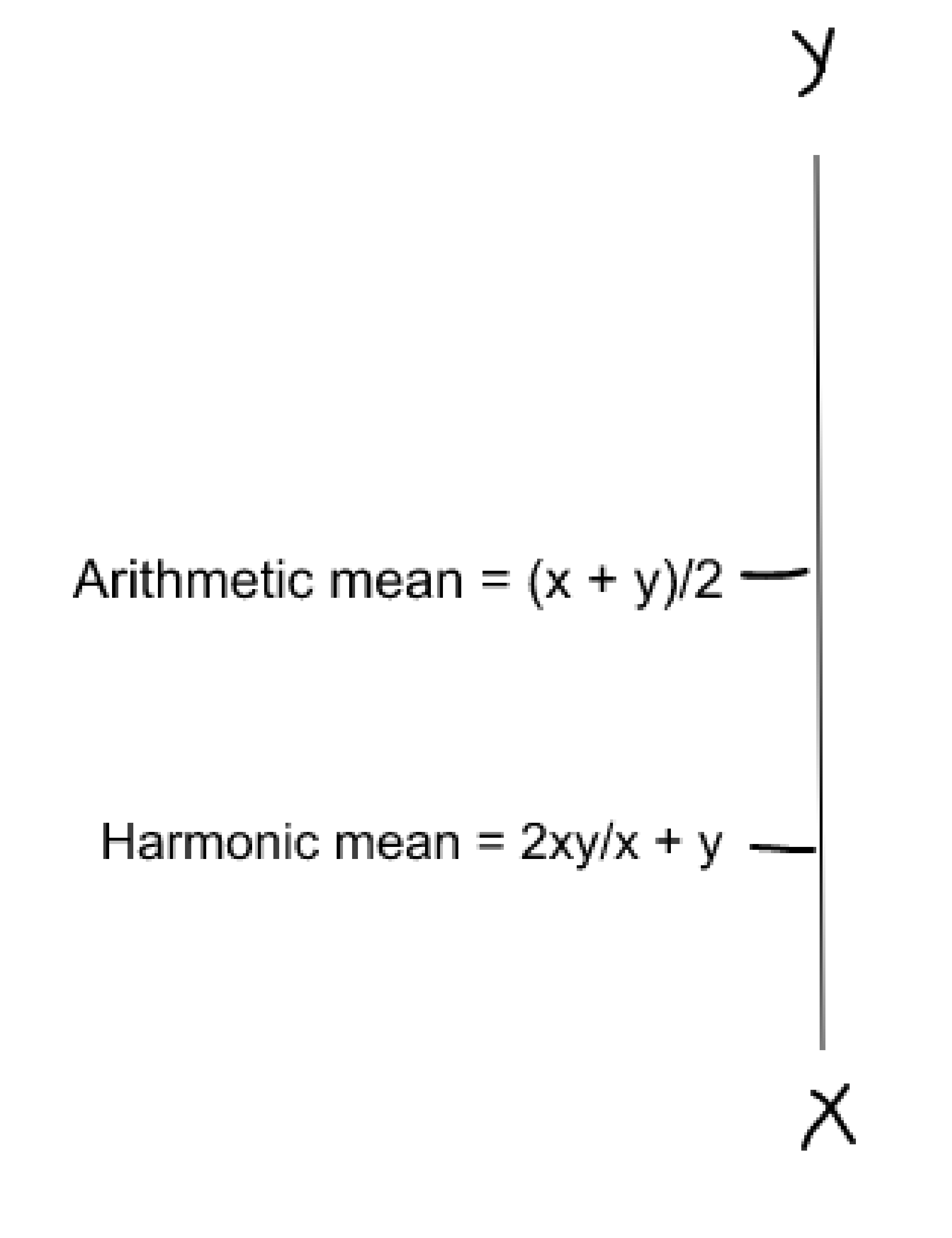
Solution: Single Score that represents Precision and Recall

Example: 100 credit card transactions: 97 legit, 3 fraud. Model predicts everything as fraud.

F1 Score = **2 * Precision * Recall / (Precision + Recall)**

= 2*3*100/103 = 5%

Harmonic Mean



Harmonic mean is kind of an average when x and y are equal. But when x and y are different, then it's closer to the smaller number as compared to the larger number.

For next week

I have decided to stick with what I know and have experience in and will show you how to host a chatbot on Facebook. We will train a bot using the chatterbot library and we will cover sentence similarity algorithms

If there is anything else you are particularly interested in, please tell me in this Google Form and I will make sure to compile a list of useful resources or maybe give another lecture series next term (because I am just looking for reason to distract me from writing my thesis...)

Lecture

Chatbots

Similarity Measures

Practical

Example of a Chatbot

Ways to host one

What is a Chatbot

- **A chatbot is an artificial intelligence (AI) software that can simulate a conversation (or a chat) with a user in natural language** through messaging applications, websites, mobile apps or through the telephone
- A chatbot is often described as one of the most advanced and promising expressions of interaction between humans and machines
- However, from a technological point of view, a chatbot only represents the natural evolution of a Question Answering system leveraging NLP

Chatbots

- Mainly used in customer service environments but now being used in a variety of other roles
- Go under many names: AI bot/assistant, intelligent virtual assistant, conversational agent etc.
- Growing in popularity
- Varying degrees of intelligence

How does a chatbot work

- **Human interacts with chatbot**
- If it is via voice - **Automatic Speech Recognition (ASR)** is used to turn speech to text
- **Chatbot analyses the text input, considers the best response and delivers it back to the user**
- if it is via voice - **Text to Speech (TTS)** tools are used
- **NLP**: used to split the user input into sentences and words, standardise and vectorise the text
- **NLU**: helps the chatbot to understand what the user said using general and domain specific objects such as lexicons, ontologies and knowledge graphs, used in conjunction with algorithms and/or rules to construct dialogue flows and tell the chatbot how to respond

Evolution of Chatbots

- **Turing Test, 1950** -

designed to test the ability of a machine to exhibit intelligent, human-like behavior. To pass the test, the machine’s replies would have to be indistinguishable from a human's in a five-minute test.

- **ELIZA, 1966** -

MIT computer scientist Joseph Weizenbaum started development on ELIZA, what would turn out to be the first machine capable of NLP. ELIZA was able to fool many people into believing they were talking to a human simply by substituting their own words into scripts and feeding them back to users to maintain the conversation.

- **Loebner Prize, 1990** -

The Loebner Prize was launched in 1990 by Hugh Loebner. It takes the format of a standard Turing Test with judges awarding the most human-like computer program.

- **ALICE, 1995 -**

A.L.I.C.E. (Artificial Linguistic Internet Computer Entity) is an NLP chatbot, who has won the Loebner prize three times.

Evolution of Chatbots

- **IBM Watson, 2006 -**

was originally developed to compete on the American TV program, 'Jeopardy!', where it defeated two of the former champions in 2011.

- **Siri, 2010**
- **Google Now, 2012**
- **Alexa, 2015**
- **Cortana, 2015**
- **Facebook Chatbots, 2016**
- **Woebot, 2017**

Woebot developed by Woebot Labs is an AI-enabled therapy chatbot designed to help users learn about their emotions with "intelligent mood tracking."

Types of Chatbots

- **Rule-Based Chatbots**

Basically **if-else statements**. But delivers the fine-tuned control and flexibility that is missing in ML chatbots. These are the most common type of bots, of which many of us have likely interacted with – either on a live chat, through an e-commerce website, or on Facebook messenger.

- **Machine Learning (AI Chatbots)**

Chatbots powered by AI are more complex than rule-based chatbots. They are data-driven and tend to be more conversational. **Over time with data they are more contextually** aware and leverage natural language understanding and apply predictive intelligence to personalise a user's experience. But, to perform even at the most rudimentary level, such systems **often require staggering amounts of training data** and highly trained skilled human specialists. In addition, a machine learning chatbot functions as a black box. If something goes wrong with the model it can be hard to intervene, let alone to optimise and improve.

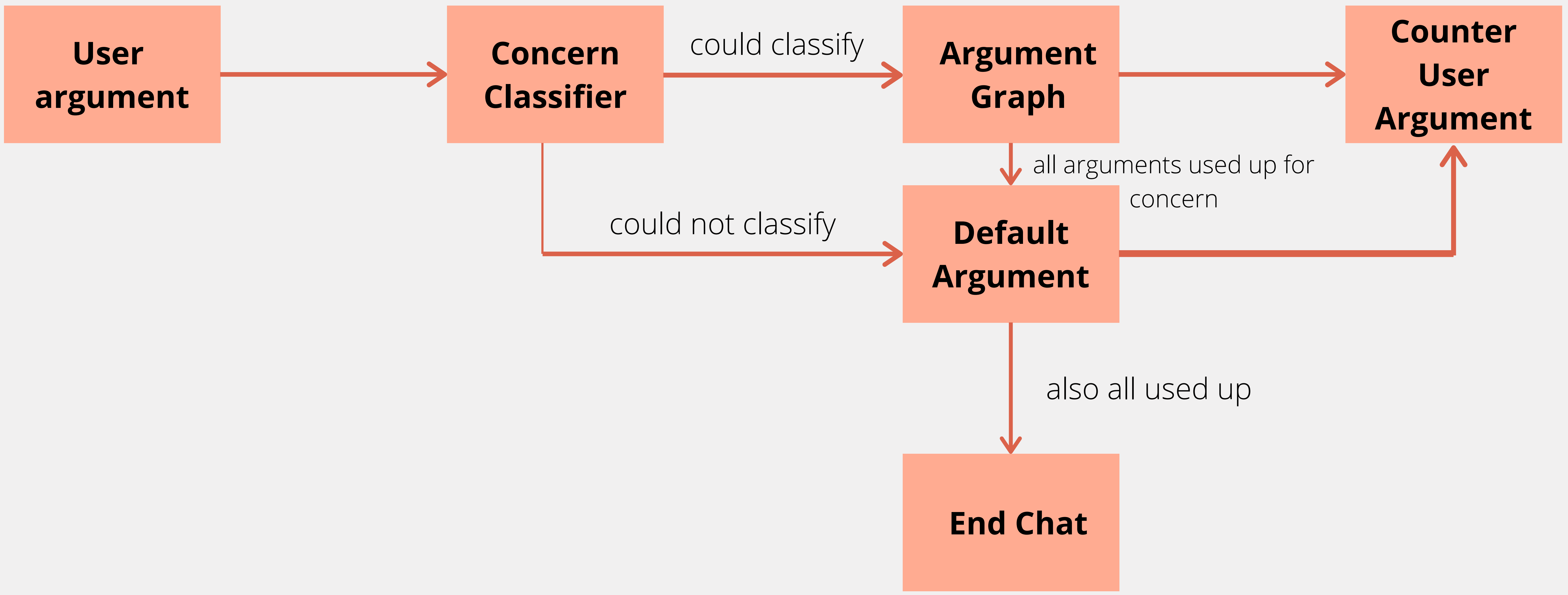
Hybrid Model -

- delivers the best chatbot experience
- key advantages:
  - does not require (that much) data
  - provides transparency on how it operates
  - uses ML where linguistic rules are impossible to use

Hybrid Model - Example

- my COVID-19 vaccine chatbot (and previous ones)
- engages in argumentative dialogues
- designed to fulfill specific task (closed domain)
- contains small database of arguments for getting a vaccine
- equipped with "concern classifier" trained on small amount of data (arguments for not getting a vaccine) - **ML part**
- selects most suitable argument to counter user argument by classifying user argument by concern
- if no concern can be classified or all arguments used up, uses default argument - **if-else part**

Dialogue Flow



Hybrid Model - Example

- In the past I have also used similarity measurements in order to match user arguments to similar arguments in the chatbots knowledge to select appropriate counterarguments **(ML part)**

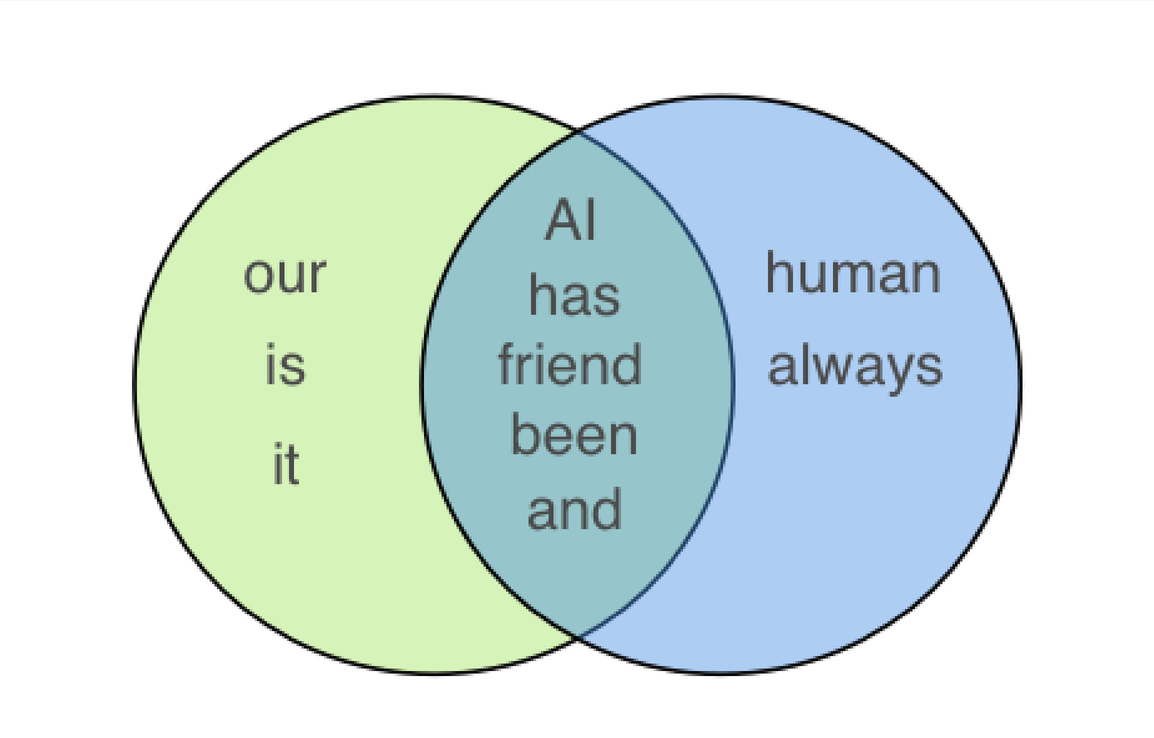
Similarity Measures - Quick Overview

- In the past I have also used a similarity measurement in order to match user arguments to similar arguments in the chatbots knowledge to select appropriate counterarguments **(ML part)**
- Let's look at some text similarity measurements

Jaccard Similarity

- Jaccard similarity or intersection over union is defined as **size of intersection divided by size of union of two sets**

Sentence 1: AI is our friend and it has been friendly
Sentence 2: AI and humans have always been friendly



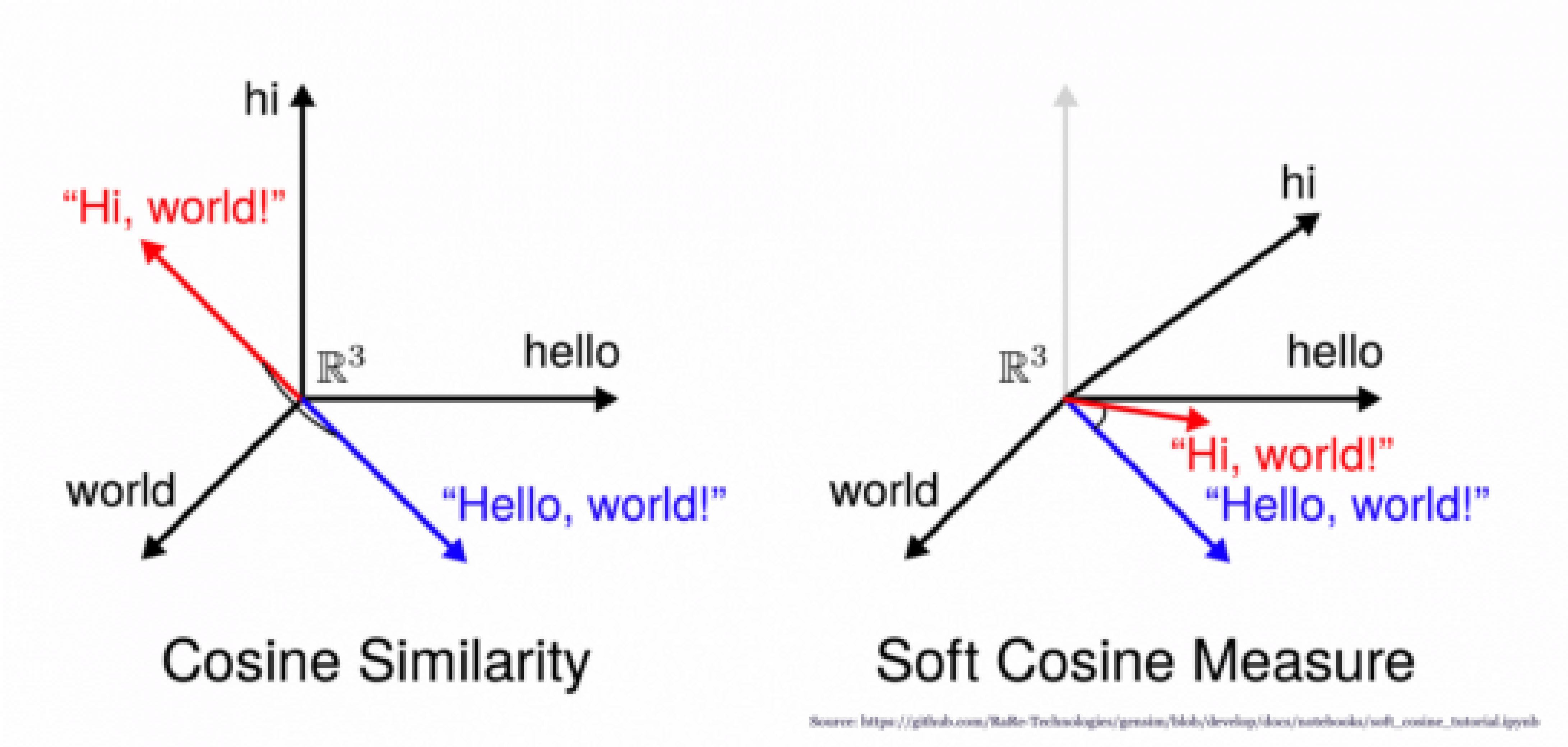
But what about
Sentence 1: President greets the press in Chicago
Sentence 2: Obama speaks in Illinois

Cosine Similarity

- Mathematically speaking, Cosine similarity is a measure of similarity between two non-zero vectors of an **inner product space that measures the cosine of the angle between them**
- Without word embeddings (using BOW or tf-idf) - maybe better than Jaccard but still bad as it does not take similar and related words into account

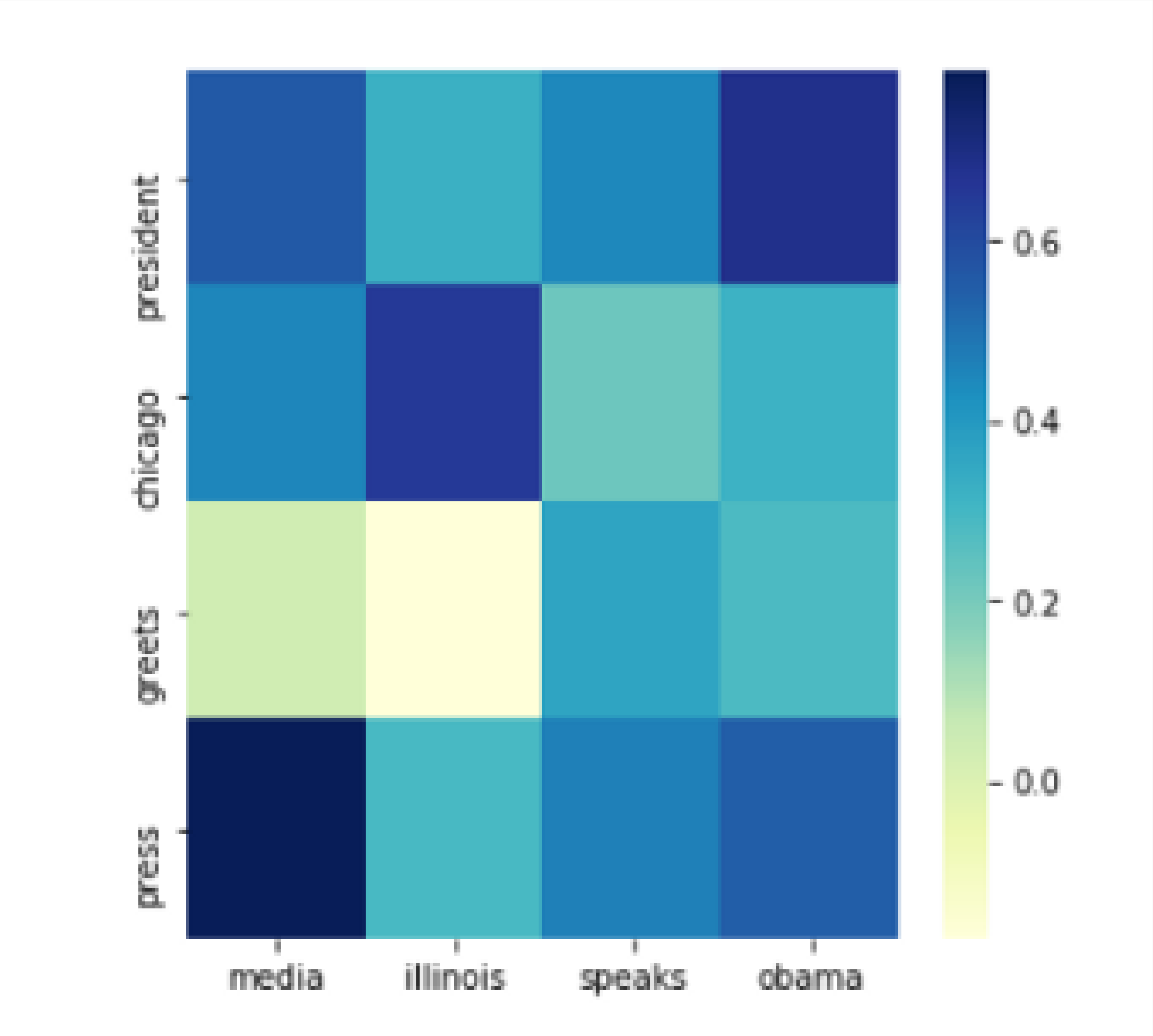
Cosine Similarity 0
Sentence 1: President greets the press in Chicago
Sentence 2: Obama speaks in Illinois

Cosine Similarity + Word Embeddings



Cosine Similarity + Word Embeddings

Cosine Similarity 80%
Sentence 1: President greets the press in Chicago
Sentence 2: Obama speaks in Illinois



Practical