Machine Learning Techniques for Text

Module 2: Detecting Spam Emails

Dr. Nikos Tsourakis

Course outline

- Module 0: Python Crash Course
- Module 1: Intro to Machine Learning
- **Module 2: Detecting Spam Emails**
- Module 3: Classifying Topics of Newsgroup Posts
- Module 4: Extracting Sentiments from Product Reviews
- Module 5: Recommending Music Titles
- Module 6: Teaching Machines to Translate
- Module 7: Summarizing Wikipedia Articles
- Module 8: Detecting Hateful and Offensive Language
- Module 9: Generating Text in Chatbots
- Module 10: Clustering Speech-to-Text Transcriptions

Overview

- Electronic mail is one of the most ubiquitous Internet services to exchange messages asynchronously
- The problem in this communication scheme is identifying and blocking unsolicited and unwanted messages
- We deal with this problem from a machine learning perspective and unfolds as a series of steps for developing and evaluating a typical ***spam detector***
  - We elaborate on the limitations of performing spam detection using traditional programming
  - Next, we introduce the basic techniques for text representation and preprocessing
  - Finally, we implement two classifiers using an open-source dataset and evaluate their performance on standard metrics

Module objectives

After completing this module, you should be able to:

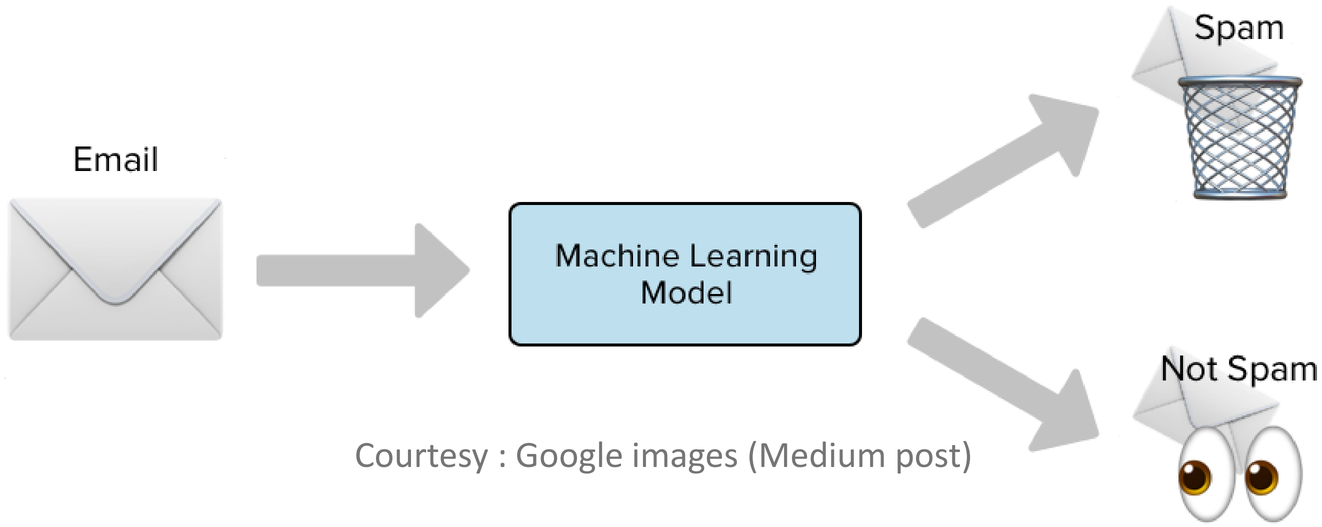
- Obtaining the data
- Understanding its content
- Preparing the datasets for the analysis
- Training the classification models
- Realizing the tradeoffs of the algorithms
- Assessing the performance of the models

Machine Learning Techniques for Text

Section 1: Understanding spam detection

Spam detection

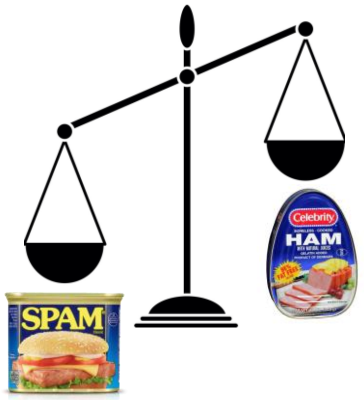
- Software inside the mail server that decides whether an incoming email is spam or not
- Without a spam detector the inbox will be flooded with irrelevant and possibly dangerous correspondence
- A serious technical, economic and even social threat!
- If you were to implement a detector program from scratch how would you do it?



Courtesy : Google images (Medium post)

Spam detection

- How can we build a spam detector for the following email?



From:	kmitnick@jakqd.com
To:	tjones@tsourakis.net
Subject:	Urgent!

Dear MR tjones,

You have noticed lately that your laptop is runing slow! This is because I gained access to your machine, and I installed a harmful VIRUS!!!

Even if you change your password my virus CANNOT BE intercept!

The only SOLUTION is to following my instractions here: https://bit.ly/33rhdNM

You have 48 hour before the virus is activated! ...OTHERWISE...GOOD LUCK!!!!

Spam detection

- Let's try to think of possible strategies for the detector

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```

➢ **T1** – The text in the subject field is typical for spam. It is characterized by a manipulative style that creates unnecessary urgency and pressure

Spam detection

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- **T2** – The message begins with the phrase *Dear MR tjones*. The last word was probably extracted automatically from the recipient's email address

Spam detection

- Let's try to think of possible strategies for the detector

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- **T3** – Bad spelling and the incorrect use of grammar are potential spam indicators

Spam detection

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```

➢ **T4** – The text in the body of the message contains sequences with multiple punctuation marks or capital letters

Write the code

- We can now implement a program taking into account the four triggers
- When a new email arrives, the detector runs the following code and decides whether it is a spam

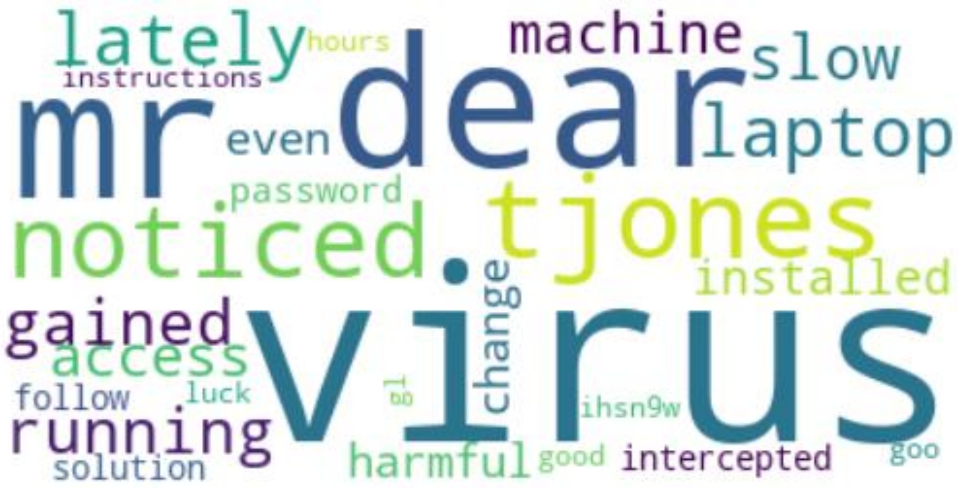
```
IF (subject is typical for spam)
    AND IF (message uses recipients email address)
        AND IF (spelling and grammar errors)
            AND IF (multiple sequences of marks-caps) THEN
                print("It's a SPAM!")
```

***Pseudocode** is an informal high-level description of a program or an algorithm.*

- Obviously, this is not the best detector ever built!

Add more triggers

- Words can also serve as part of our separation criteria
- Visualize the text data using ***word clouds*** (also known as tag clouds)



- The image suggests that the most common word in our spam message is "**virus**"

Add more triggers

- Next, we adapt the pseudocode

```
...
      AND IF (multiple sequences of marks-caps) THEN
          AND IF (common word = "virus") THEN
              print("It's a SPAM!")
```

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...
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- Is this new version of the program better?

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     ...
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  - Slightly ☹
  - We can engineer even more criteria, but the problem becomes insurmountable at some point

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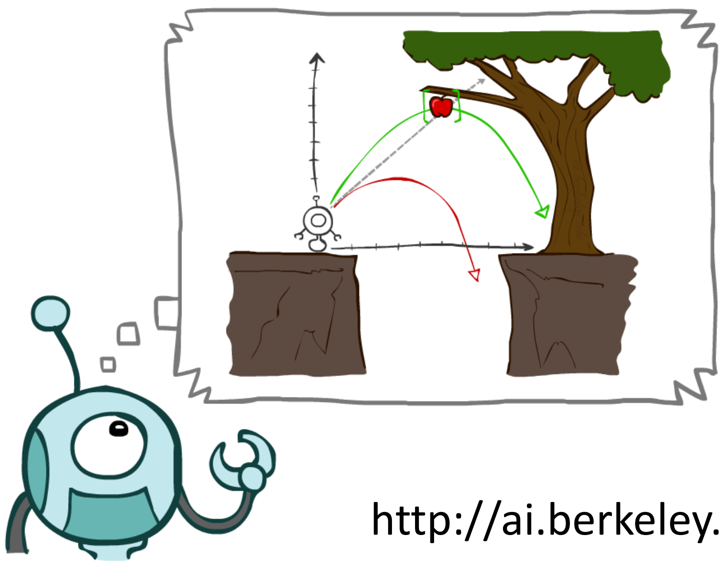
- Is this new version of the program better?
  - Slightly ☹
  - We can engineer even more criteria, but the problem becomes insurmountable at some point
- This is where machine learning algorithms become handy and can help us to solve this problem

Learn by example

- As humans learn by example; touching something very hot (input) causes pain (output), we can train a machine to read emails (input) and classify them automatically into spam/non-spam (output)



http://ai.berkeley.edu/

Feature engineering

- The input to the learning algorithm was not the actual emails text but some kind of information extracted from those (***T1***-***T4***)
- These are called ***features*** and the process of creating them is called ***feature engineering***
- Identifying a suitable list of features for any ML task requires ***domain knowledge*** – comprehending the problem you want to solve in-depth.
- How you choose them directly impacts the algorithm's performance and determines its success to a significant degree:
  - certain features can overlap with others
  - specific features might be less relevant

Feature engineering

- Let’s see a few examples and propose good features

Problem	Features
Classify movie reviews as positive or negative	[redacted]
Separate images that contain either forests or the sea	[redacted]
Classify flowers into specific categories	[redacted]
Identify angry customers from telephone recordings	[redacted]
Predict the value of an apartment in a specific area	[redacted]

Feature engineering

- Let's see a few examples and propose good features

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- But as we are dealing with text, and we need pertinent features

Machine Learning Techniques for Text

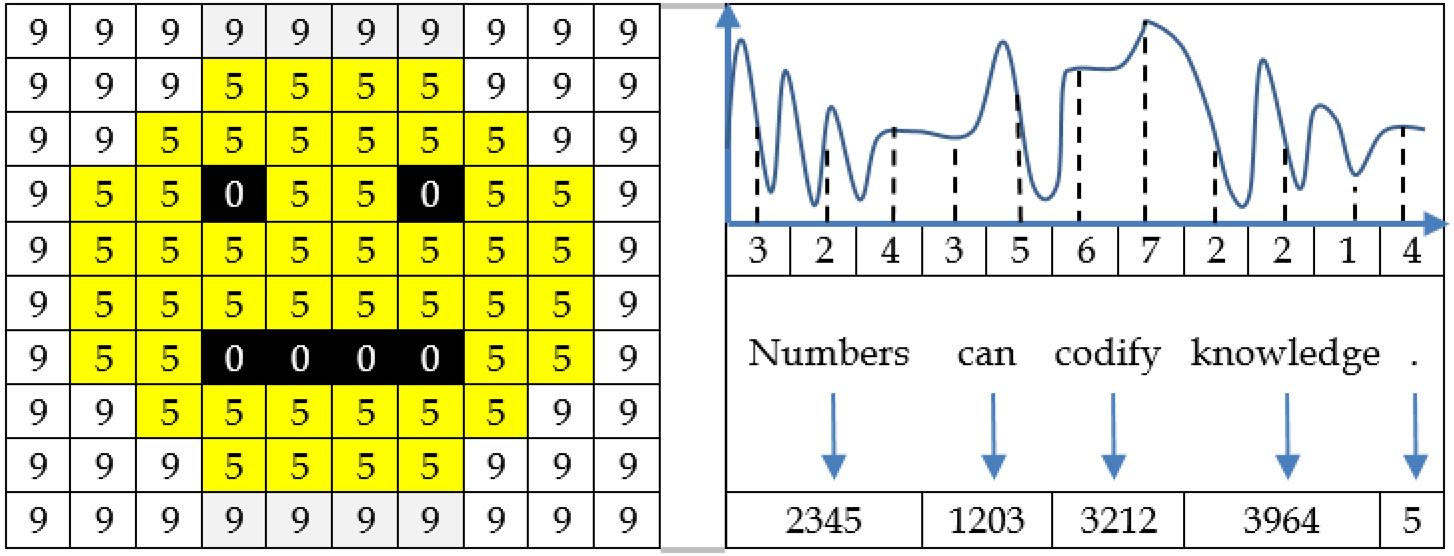
Section 2: Extracting word representations

Data representation

- What does a word mean to a computer? What about an image or an audio file?
  - To put it simply, nothing!
- A computer circuit can only process signals that contain two voltage levels or states, similar to an on-off switch
- This representation is the well-known binary system where every quantity is expressed as a sequence of ***1s*** (high voltage) and ***0s*** (low voltage)
- All data should be represented numerically

Word representations

- Numbers can codify a word, the pixels of an image, the audio samples of an audio file, etc.



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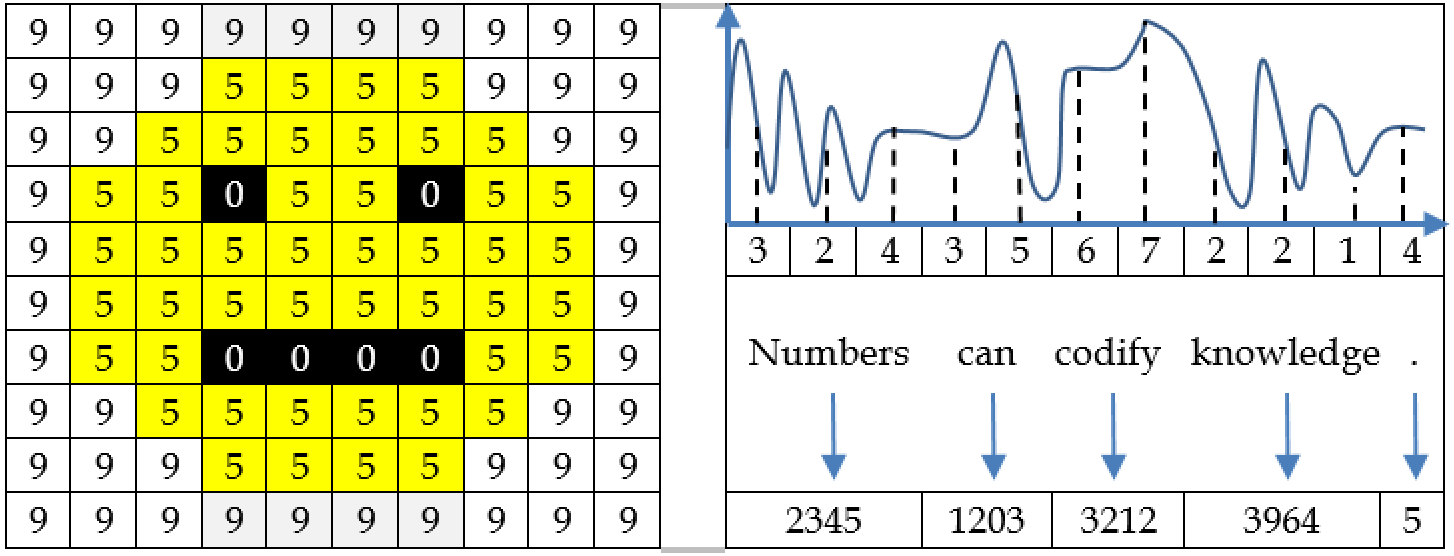


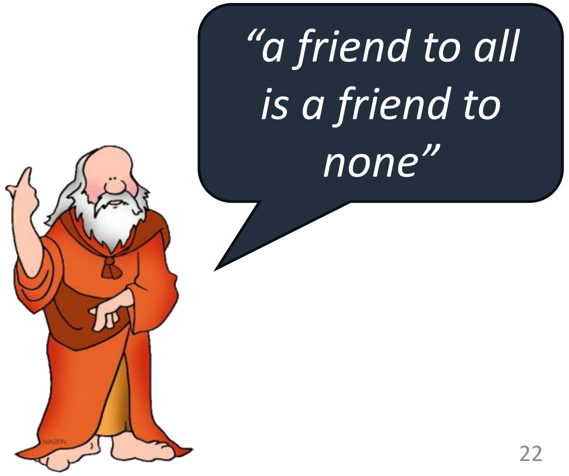
- There are various ways to represent words in machine learning problems

Using label encoding

- Consider this quote from Aristotle *“a friend to all is a friend to none”*
- Using ***label encoding*** we can produce the following mapping:

Input								
a	friend	to	all	is	a	friend	to	none
0	2	5	1	3	0	2	5	4

- This representation, however, implies some short of order (because 0 < 2 < 5), which is not true



Using one-hot encoding

- One-hot encoding codifies every word as a vector with zeros and a single one
  - no two words exist with the same one-hot vector

	Input								
Unique words	A	friend	to	all	is	a	friend	to	none
a	1	0	0	0	0	1	0	0	0
all	0	0	0	1	0	0	0	0	0
friend	0	1	0	0	0	0	1	0	0
is	0	0	0	0	1	0	0	0	0
none	0	0	0	0	0	0	0	0	1
to	0	0	1	0	0	0	0	1	0

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	Input								
Unique words	A	friend	to	all	is	a	friend	to	none
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is	0	0	0	0	1	0	0	0	0
none	0	0	0	0	0	0	0	0	1
to	0	0	1	0	0	0	0	1	0

- The majority of the elements in the array are zeros and can pose challenges due to the memory required to store them

Using one-hot encoding

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is	0	0	0	0	1	0	0	0	0
none	0	0	0	0	0	0	0	0	1
to	0	0	1	0	0	0	0	1	0

tip

Matrixes of this kind are called sparse

- The majority of the elements in the array are zeros and can pose challenges due to the memory required to store them

Using token count encoding

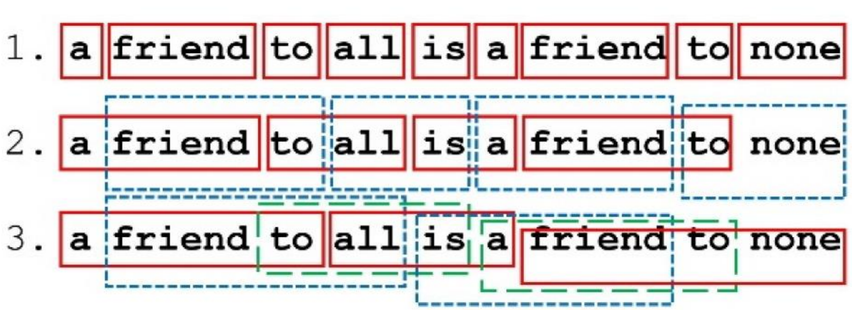
- Also known as ***bag-of-words*** (BoW) counts the absolute frequency of each word within a sentence or a document
- The input is represented as a bag of words without taking into account grammar or word order
- Create a table (***Term Document Matrix***) where each cell represents the number of times a word from the vocabulary appears the quote

Unique words							
a	all	friend	is	me	none	to	world
2	1	2	1	0	1	2	0

“a friend to all is a friend to none”

N-grams as tokens

- Certain word combinations are more frequent than others in any human language
- Consist of a single word (***unigrams***), two words (***bigrams***), three words (***trigrams***), etc.



1. Unigrams	2. Bigrams	3. Trigrams
a	a friend	a friend to
all	friend to	friend to all
friend	to all	to all is
is	all is	all is a
none	is a	is a friend
to	to none	friend to none

Using tf-idf encoding

- One limitation of BoW representations is that they do not consider the value of words inside the corpus
- If solely frequency were of prime importance, articles such as ***a*** or ***the*** would provide the most information for a document
- The ***term frequency-inverse document frequency*** (tf-idf) encoding scheme:
  - penalizes these frequent words
  - allows us to weigh each word in the text
- Heuristic where more common words tend to be less relevant for most semantic classification tasks, and the weighting reflects this approach

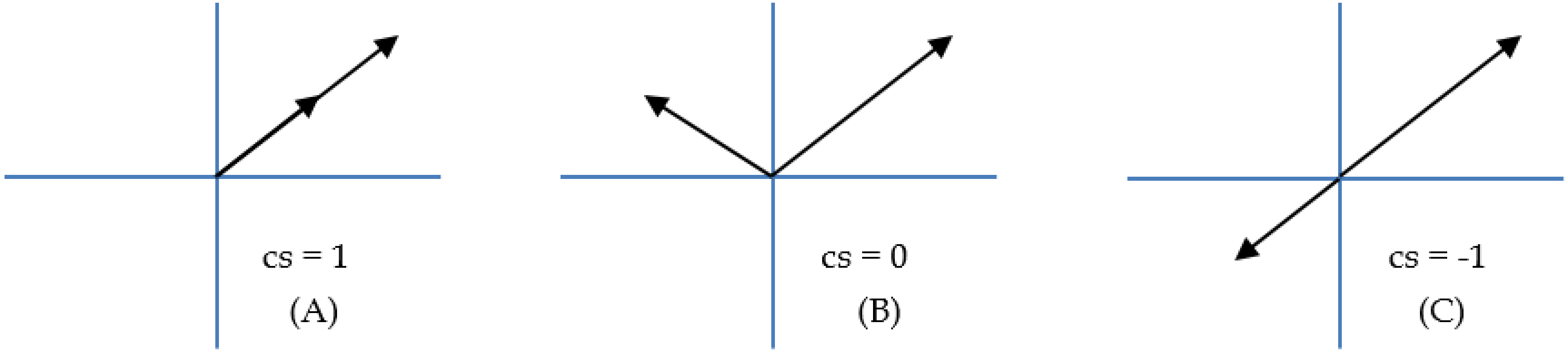
Using tf-idf encoding

- From a virtual dataset with 10 million emails, we randomly pick one containing 100 words
- Suppose that the word ***virus*** appears three times in this email, so its term frequency (tf) is: $\frac{3}{100} = 0.03$
- Moreover, the same word appears in 1000 emails in the corpus, so the inverse document frequency (idf) is: $\log(\frac{10000000}{1000}) = 4$
- The tf-idf weight is simply the product of these two statistics:

  0.03 * 4 = 0.12

Calculating vector similarity

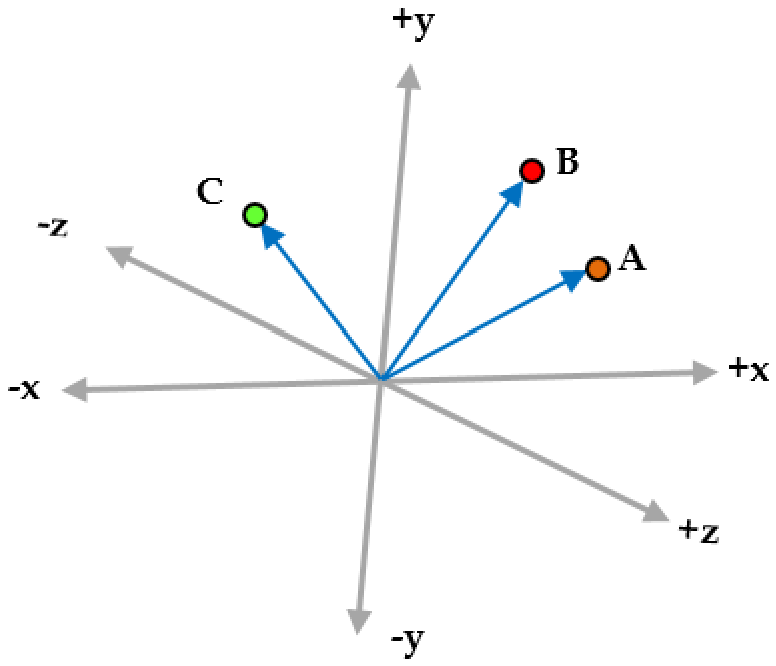
- ***Cosine similarity*** is the degree to which two vectors point in the same direction
- It targets orientation, rather than magnitude
- When the two vectors are aligned to the same direction cosine similarity is ***1***, when they are perpendicular it is ***0***, and when they point in opposite directions it is ***-1***



Cosine similarity

- Which vectors are more similar (A, B or C)?

A=(4, 4, 4),
B=(1, 7, 5)
C=(-5, 5, 1)



Cosine similarity

- Given that: $\cos(V, U) = \frac{V \bullet \mathrm{U}}{\|V\| \times \|U\|}$
- A=(4, 4, 4), B=(1, 7, 5) and C=(-5, 5, 1)
- We have:

$$A \bullet B = 4 \times 1 + 4 \times 7 + 4 \times 5 = 52$$
$$A \bullet C = 4 \times (-5) + 4 \times 5 + 4 \times 1 = 4$$
$$B \bullet C = 1 \times (-5) + 7 \times 5 + 5 \times 1 = 35$$

$\|A\| = \sqrt{4^2 + 4^2 + 4^2} = \sqrt{48}$, $\|B\| = \sqrt{75}$ and $\|C\| = \sqrt{51}$

- We obtain:

$\cos(A, B) = \frac{52}{\sqrt{48} \times \sqrt{75}} \cong 0.87$, $\cos(A, C) = \frac{4}{\sqrt{48} \times \sqrt{51}} \cong 0.08$ and $\cos(B, C) = \frac{35}{\sqrt{75} \times \sqrt{51}} \cong 0.57$

Machine Learning Techniques for Text

Section 3: Executing data preprocessing

Tokenizing the input

- During ***tokenization*** we split textual data into smaller components called ***tokens***
- These can be words, phrases, symbols, or other meaningful elements
- We can use ***regular expressions*** (regexp) that can assist with the creation of a tokenizer

“The best course ever taught about Text Mining”

↓

“The”, “best”, “course”, “ever”, “taught”, “about”, “Text”, “Mining”

Understanding regular expressions

- ***Regular expressions*** (regexp) are used to:
  - find a string in a document
  - replace part of the text with something else
  - examine the conformity of some textual input

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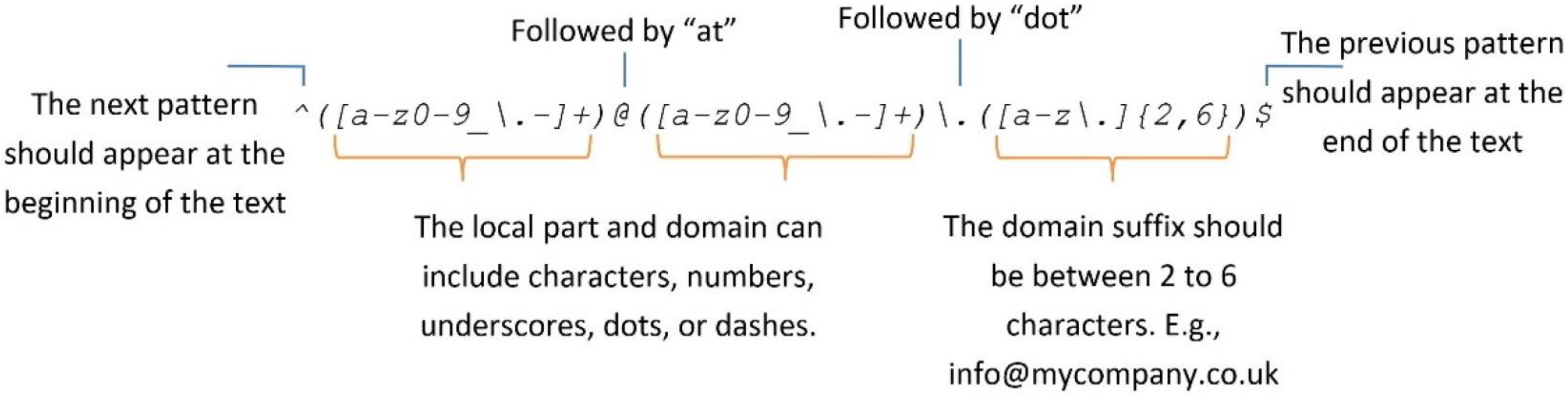
regexp	**matches**
[A-Za-z0-9]	Any character, letter, or digit, in the range A to Z, a to z, or 0 to 9 – for example, `G`.
[A-Za-z0-9]+	Any sequence of characters, letters, or digits, in the range A to Z, a to z, or 0 to 9. The plus sign signifies at least one occurrence – for example, `Hello2You`.
[a-z]{2,5}	Any sequence of lowercase letters containing two to five characters – for example, `hello`.
^([0-9][a-z]+)	Any sequence of characters beginning with a number and followed by lowercase letters – for example, `4ever`.
([A-Z]+[0-9])$	Any sequence of characters with uppercase letters that ends with a number – for example, `ME2`.

Understanding regular expressions

- Check the validity of an email address



\. = the dot character needs to be escaped otherwise it will match any character
[ ] = defines character ranges
( ) = defines a group

Removing stop words

- A typical task during the preprocessing phase is removing all the words that presumably help us focus on the most important information in the text
- These are called ***stop words*** and there is no universal list in English or any other language
- Examples of stop words include determiners (such ***as*** another and ***the***), conjunctions (such as ***but*** and ***or***), and prepositions (such as ***before*** and ***in***)

tokenization *"The", "best", "course", "ever", "taught", "about", "Text", "Mining"*

↓ ↓

stop word removal *"best", "course", "ever", "taught", "Text", "Mining"*

Stemming the words

- Map words with the same core meaning to a central word or symbol
- During ***stemming*** we cut off the end (suffix) or the beginning (prefix) of an inflected word and ending up with its stem (the root word)
- For example, the stem of the word ***plays*** is ***play***

stop word removal — *"best", "course", "ever", "taught", "Text", "Mining"*

↓

stemming or/and lemmatization — *"best", "course", "ever", "teach", "text", "mine"*

Lemmatizing the words

- Another approach for reducing the inflectional forms of a word to a base root is called ***lemmatization***
- The method performs morphological analysis of the word and obtains its proper lemma (the base form under which it appears in a dictionary)
- For example, the lemma of ***led*** is ***lead***
- Lemmatization differs from stemming, as it requires detailed dictionaries to look up a word

stop word removal	*“best”, “course”, “ever”, “taught”, “Text”, “Mining”*
↓	↓
stemming or/and lemmatization	*“best”, “course”, “ever”, “teach”, “text”, “mine”*

Let’s practice!

Tasks

- Word representations
- Data preprocessing

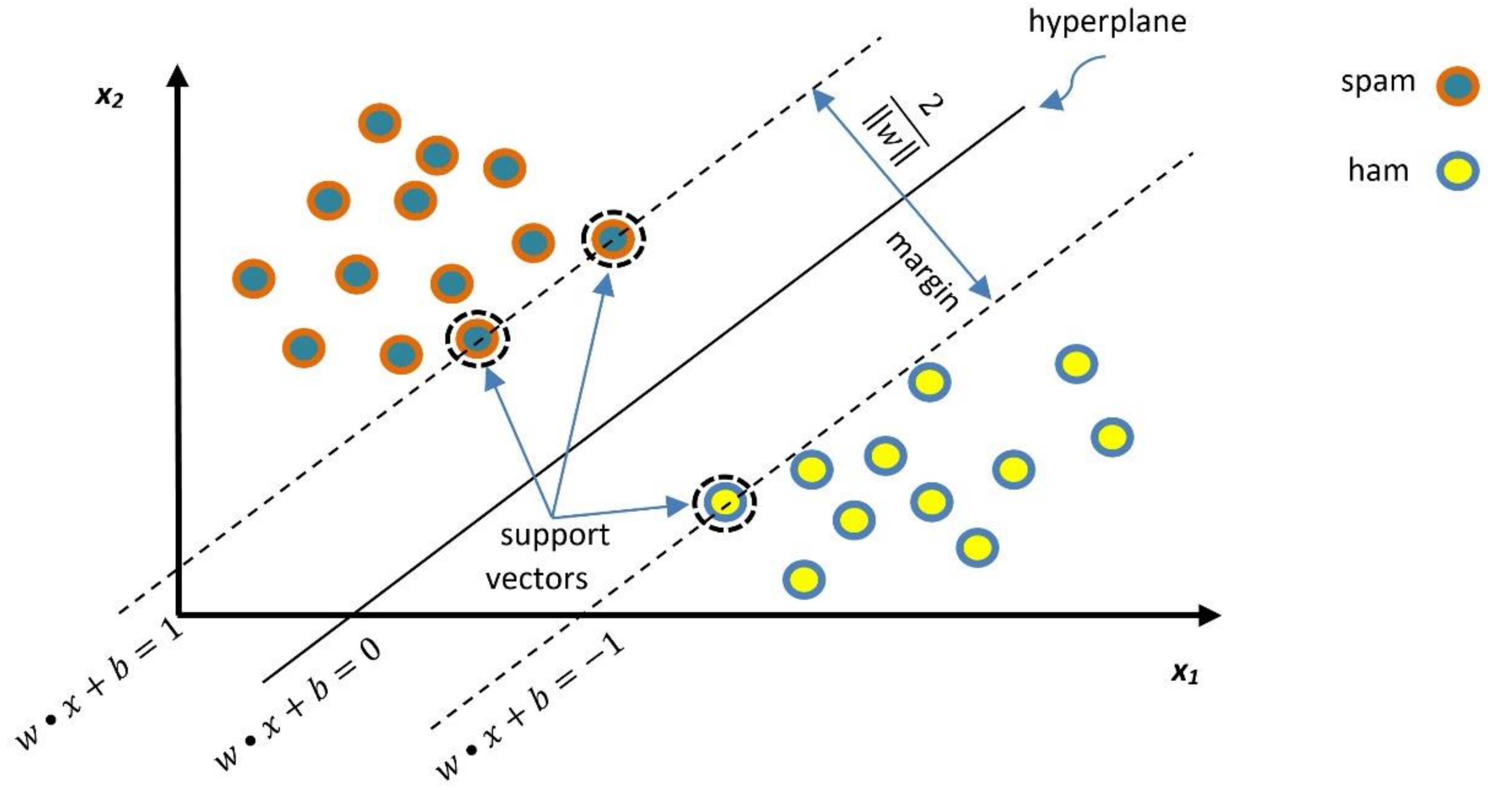
https://colab.research.google.com/github/PacktPublishing/Machine-Learning-Techniques-for-Text/blob/main/chapter-02/spam-detection.ipynb

Machine Learning Techniques for Text

Section 4: Performing classification

Support Vector Machines

- ***Support Vector Machines*** is a supervised machine learning algorithm



Support Vector Machines

- The data below is separated with two different lines. Which separation is better?

Support Vector Machines

- The data below is separated with two different lines. Which separation is better?

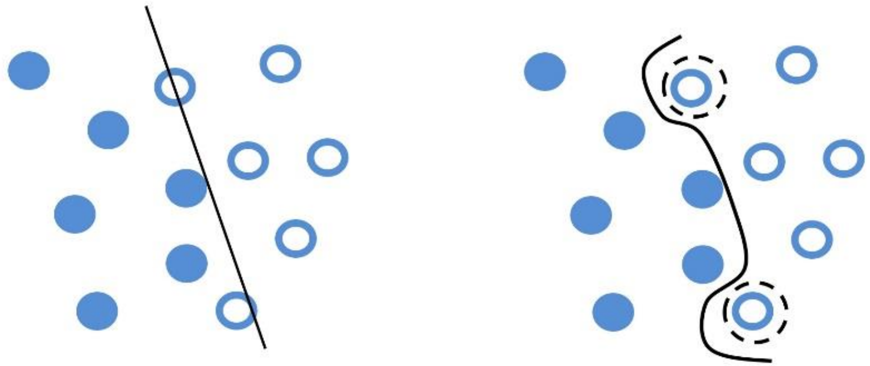
- The line in the left plot has a higher classification error
- The margin in the second is small and therefore the model lacks in generalization

Hyperparameter ***C***

- The SVM algorithm permits the adjustment of the training accuracy versus generalization tradeoff using the hyperparameter ***C***
- A frequent point of confusion is that hyperparameters and model parameters are the same things, but this is not true
  - Hyperparameters are parameters whose values are used to control the learning process
  - On the other hand, model parameters update their value in very training iteration until we obtain a good classification model
- We can direct the SVM to create the most efficient model for each problem by adjusting the hyperparameter ***C***

Support Vector Machines

- Which one seems to work better this time?



- At first glance, the curved line in the plot on the right perfectly separates the data into two classes
- But getting too specific boundaries entails the risk of ***overfitting***
  - The model learns the training data perfectly but fails to classify a slightly different example correctly

Overfitting

- Most of us have grown in a certain cultural context, trained (overfit) to interpret social signals like body posture, facial expressions, voice tone, etc. in a certain way
- When socializing with people of diverse social cultures we might fail to interpret similar social signals correctly (generalization)

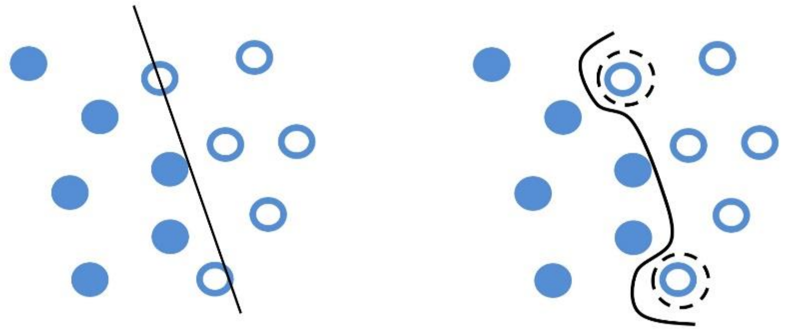
Overfitting

- Most of us have grown in a certain cultural context, trained (overfit) to interpret social signals like body posture, facial expressions, voice tone, etc. in a certain way
- When socializing with people of diverse social cultures we might fail to interpret similar social signals correctly (generalization)

There is always a tradeoff between ***accuracy*** during training and ***generalization*** during inference

Hyperparameter ***gamma***

- We can also prevent overfitting by adjusting the ***gamma*** hyperparameter
- Defines how far the influence of a single training example reaches
- The curvature of the decision boundary can also be affected by points that are pretty far from it.
- The takeaway here is that both ***C*** and ***gamma*** hyperparameters help us create more efficient models but identifying their best values demands experimentation



Data pipeline

- Getting the data
  - Use the ***SpamAssassin*** public mail corpus is a selection of mail messages, suitable for use in testing spam filtering systems
  - https://spamassassin.apache.org/old/publiccorpus/
- Creating the train and test sets
  - We choose a 75:25 split between the training and test sets, attributing the larger proposition to the training data
- Preprocessing the data
  - tokenization, stop word removal, and lemmatization
- Extracting the features
  - tf-idf vectorization

Let’s practice!

Tasks

- Word representations
- Data preprocessing
- Classification

https://colab.research.google.com/github/PacktPublishing/Machine-Learning-Techniques-for-Text/blob/main/chapter-02/spam-detection.ipynb

Machine Learning Techniques for Text

Section 5: Measuring classification performance

Accuracy

- ***Accuracy*** is the percentage of correctly classified examples by an algorithm divided by the total number of examples, defined as:

$$Accuracy = \frac{Number\ of\ correctly\ classified\ examples}{Total\ number\ of\ examples}$$

- If we had to choose the best algorithm this should probably be the one with the highest accuracy
- The argument is that the algorithm with the highest number of correct classifications should be the right choice
- Although this is not far from the truth, it is not always the case

Accuracy

- A model classifies 1000 emails that we already know whether they spam or ham
- A possible result of classifying these emails is shown in the table below, known as ***confusion matrix***

	spam	ham
spam	True Positive (TP) Reality: spam Prediction: spam Total number: 15	False Positive (FP) Reality: ham Prediction: spam Total number: 20
ham	False Negative (FN) Reality: spam Prediction: ham Total number: 85	True Negative (TN) Reality: ham Prediction: ham Total number: 880

Accuracy

- Rewrite the f*ormula*

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} = \frac{15 + 880}{15 + 880 + 20 + 85} = 0.895$$

	spam	**ham**
spam	True Positive (TP) Reality: spam Prediction: spam Total number: 15	False Positive (FP) Reality: ham Prediction: spam Total number: 20
ham	False Negative (FN) Reality: spam Prediction: ham Total number: 85	True Negative (TN) Reality: ham Prediction: ham Total number: 880

Accuracy

- Rewrite the formula

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} = \frac{15 + 880}{15 + 880 + 20 + 85} = 0.895$$

	spam	ham
spam	True Positive (TP) Reality: spam Prediction: spam Total number: 15	False Positive (FP) Reality: ham Prediction: spam Total number: 20
ham	False Negative (FN) Reality: spam Prediction: ham Total number: 85	True Negative (TN) Reality: ham Prediction: ham Total number: 880

- Out of the 1000 spam emails (TP + FN) only 15 were correctly identified and the other 85 were considered as ham emails

Accuracy

- To assess the performance of a model correctly, we need to make this analysis and consider the ***type of errors*** that are most important within the task

- Is it better to have a ***strict*** model that can block a legitimate email for the sake of fewer spam ones (increased FPs)?
- Or is it preferable to have a ***lenient*** model that doesn't block most ham emails but allows more undetected spam in your mailbox (increased FNs)?

	spam	**ham**
spam	True Positive (TP) Reality: spam Prediction: spam Total number: 15	False Positive (FP) Reality: ham Prediction: spam Total number: 20
ham	False Negative (FN) Reality: spam Prediction: ham Total number: 85	True Negative (TN) Reality: ham Prediction: ham Total number: 880

Accuracy

- Similar questions arise in all ML problems and generally in many real-world situations
- For example, wrong affirmative decisions (FPs) in a fire alarm system are preferable to wrong negative ones (FNs)
  - In the first case, we get a false alert of a fire that didn't occur
- Conversely, declaring innocent a guilty prisoner implies higher FNs, which is preferable to finding guilty an innocent one (higher FPs)
- Accuracy is a good metric when the test data is balanced and the classes are equally important

Precision and Recall

- ***Precision*** us the proportion of positive identifications that are, in reality, correct, given by:

$$Precision = \frac{TP}{TP + FP} = \frac{15}{15 + 20} = 0.43$$

- ***Recall*** tells us the proportion of the actual positives that are identified correctly, given by:

$$Recall = \frac{TP}{TP + FN} = \frac{15}{15 + 85} = 0.15$$

- Improving precision often deteriorates recall and vice versa

F-score

- We can combine precision and recall (harmonic mean) in one more reliable ***F-score*** metric

$$\text{F-score} = 2 * \frac{precision * recall}{precision + recall} = 2 * \frac{0.43 * 0.15}{0.43 + 0.15} = 0.22$$

- When precision and recall reach their perfect score (equal to 1), the F-score becomes 1
- Based on this metric we can evaluate more reliably different ML models

ROC and AUC

- When the classifier returns some kind of confidence score for each prediction, we can use another technique for evaluating performance called the ***Receiver Operator Characteristic*** (ROC) curve
- A ROC curve is a graphical plot that shows the model's performance at all classification thresholds
- It utilizes two rates, namely the ***True Positive Rate*** (TPR), the same as recall, and the ***False Positive Rate*** (FPR)

ROC and AUC

- ***True Positive Rate (TPR)***

$$TPR = \frac{TP}{TP + FN}$$

- ***False Positive Rate (FPR)***

$$FPR = \frac{FP}{FP + TN}$$

- The benefit of ROC curves is that they help us visually identify the trade-offs between the TPR and FPR
- In this way, we can find which classification threshold better suits the problem under study

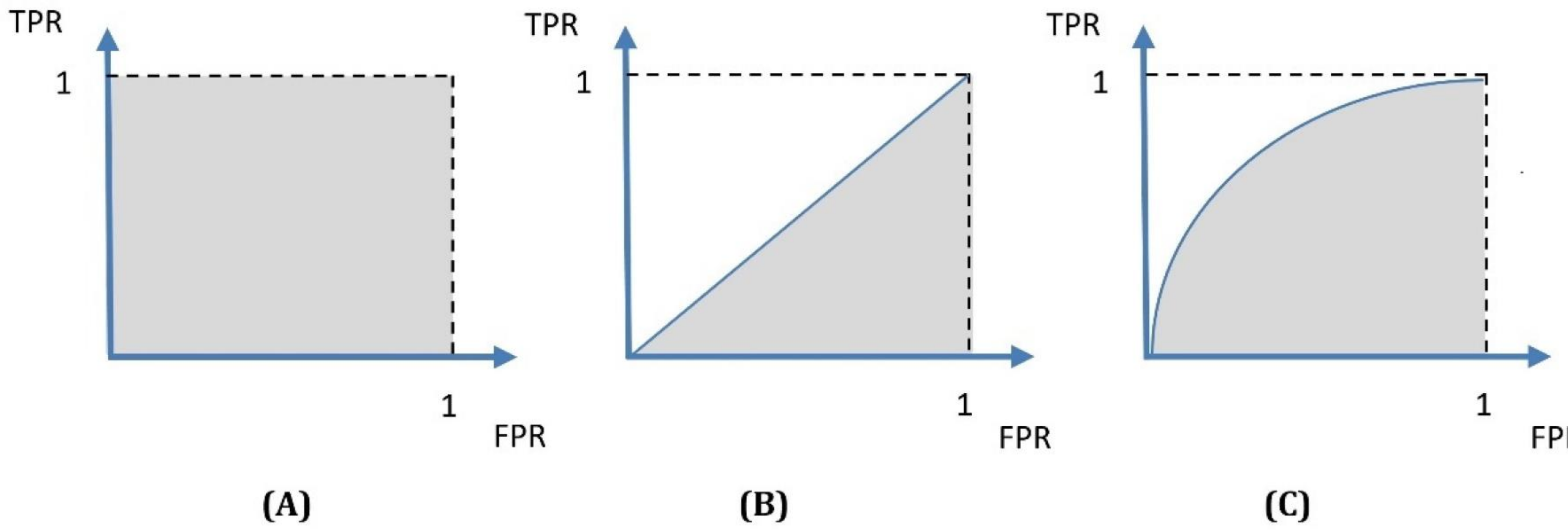
ROC and AUC

- A simplified example with 10 emails
- 7 thresholds are used
- For each prediction a probability score is generated by the model

Reality ● ham ○ spam	Pred. prob.	Threshold 0.0	0.55	0.65	0.75	0.85	0.95	1.0
●	0.1	○	●	●	●	●	●	●
●	0.2	○	●	●	●	●	●	●
●	0.3	○	●	●	●	●	●	●
●	0.4	○	●	●	●	●	●	●
●	0.5	○	●	●	●	●	●	●
○	0.6	○	○	●	●	●	●	●
●	0.7	○	○	○	●	●	●	●
●	0.8	○	○	○	○	●	●	●
○	0.9	○	○	○	○	○	●	●
○	0.99	○	○	○	○	○	○	●
		3 7	3 2	2 2	2 1	2 0	1 0	0 0
		0 0	0 5	1 5	1 6	1 7	2 7	3 7
	TPR	1	1	0.67	0.67	0.67	0.33	0
	FPR	1	0.29	0.29	0.14	0	0	0

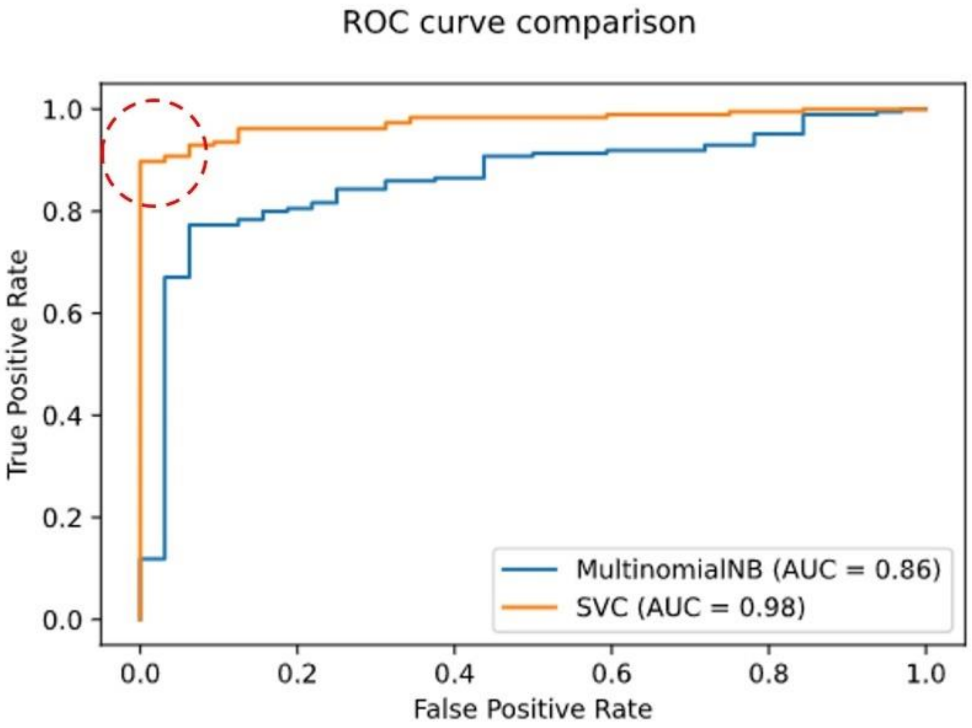
ROC and AUC

- The grayed area in these plots, called the ***Area Under the ROC Curve*** (AUC), is related to the quality of our model; the higher its surface, the better it is



AUC for two models

- The model based the support vector machines provides better results



Precision-recall curves

- ROC curves can sometimes perform too optimistically with imbalanced datasets
- For example, using the TN factor during the FPR calculation can skew the results
- The solution, in this case, is to generate another visualization called the ***Precision-Recall curve***
- Fortunately, this factor is not part of the precision or recall formulas
- We must scrutinize both ROC and precision-recall curves to understand the models' performance and the differences between the classifiers

Let's practice!

Tasks

- Word representations
- Data preprocessing
- Classification
- Performance

https://colab.research.google.com/github/PacktPublishing/Machine-Learning-Techniques-for-Text/blob/main/chapter-02/spam-detection.ipynb

Machine Learning Techniques for Text

Section 6: Typical pipeline

input “*The best course ever taught about Text Mining*” input → "The best course ever taught about Text Mining"

tokenization → *"The", "best", "course", "ever", "taught", "about", "Text", "Mining"*

input	*“The best course ever taught about Text Mining”*
↓	↓
tokenization	*“The”, “best”, “course”, “ever”, “taught”, “about”, “Text”, “Mining”*
↓	↓
stop word removal	*“best”, “course”, “ever”, “taught”, “Text”, “Mining”*

input	*“The best course ever taught about Text Mining”*
↓	↓
tokenization	*“The”, “best”, “course”, “ever”, “taught”, “about”, “Text”, “Mining”*
↓	↓
stop word removal	*“best”, “course”, “ever”, “taught”, “Text”, “Mining”*
↓	↓
stemming or/and lemmatization	*“best”, “course”, “ever”, “teach”, “text”, “mine”*

input → *“The best course ever taught about Text Mining”*

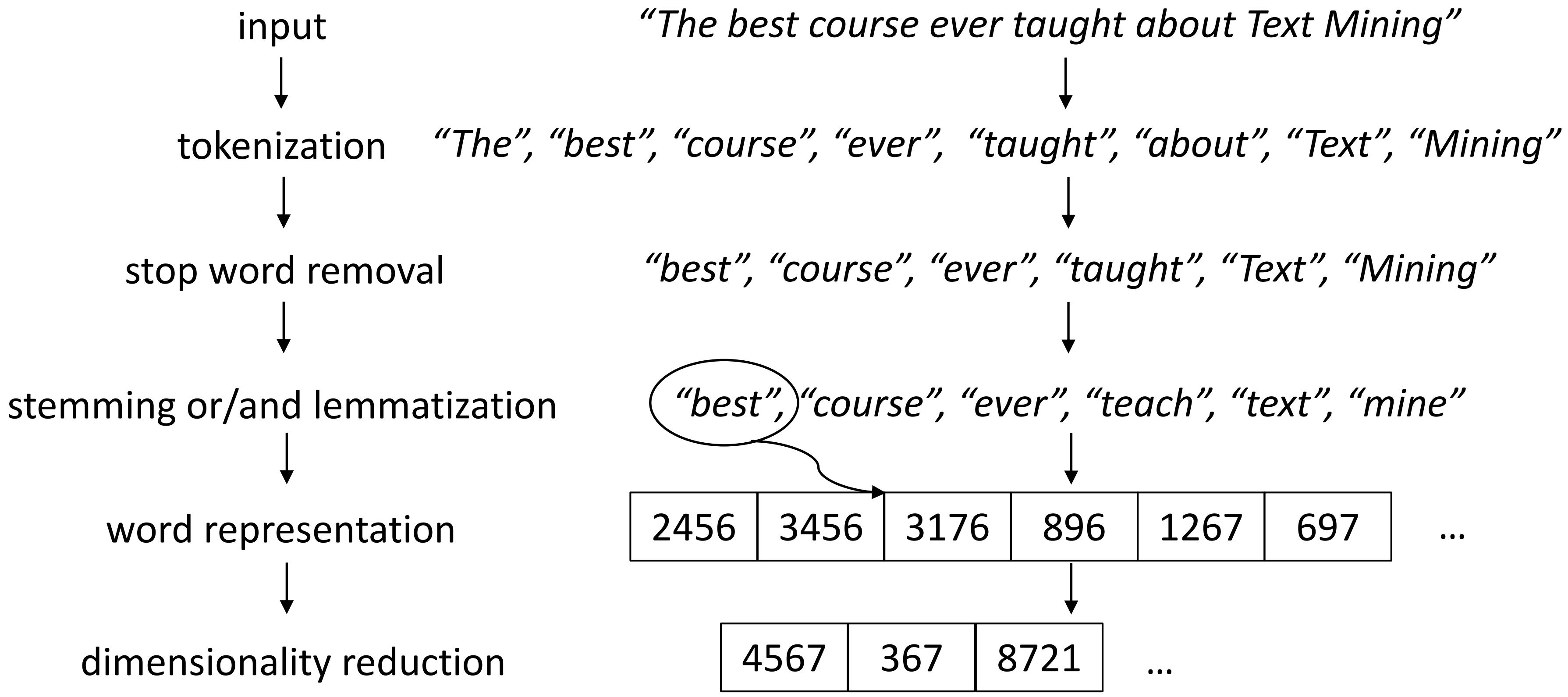
tokenization → *“The”, “best”, “course”, “ever”, “taught”, “about”, “Text”, “Mining”*

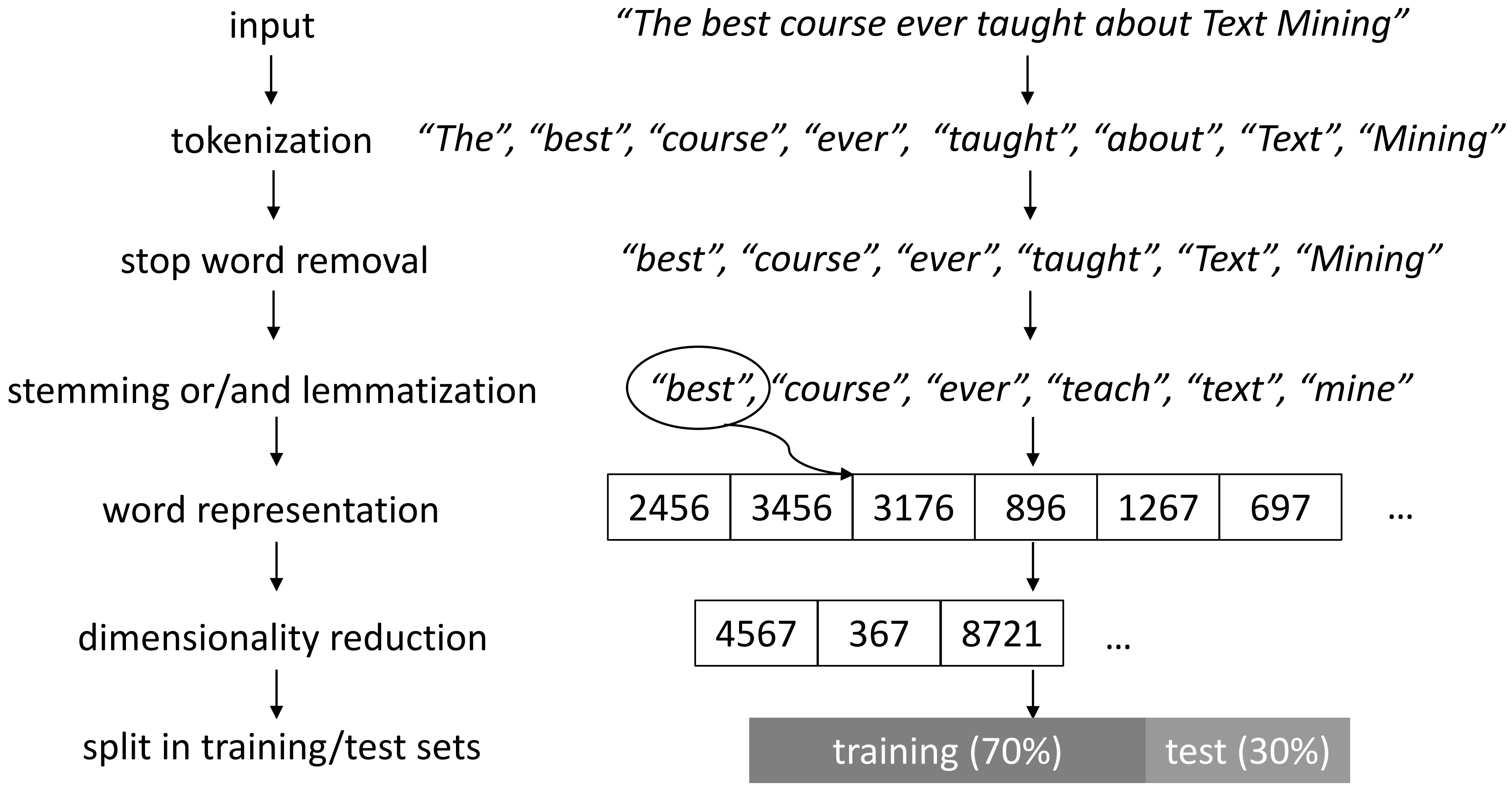
stop word removal → *“best”, “course”, “ever”, “taught”, “Text”, “Mining”*

stemming or/and lemmatization → *“best”, “course”, “ever”, “teach”, “text”, “mine”*

word representation →

2456	3456	3176	896	1267	697	…


input
"The best course ever taught about Text Mining"
tokenization
"The", "best", "course", "ever", "taught", "about", "Text", "Mining"
stop word removal
"best", "course", "ever", "taught", "Text", "Mining"
stemming or/and lemmatization
"best", "course", "ever", "teach", "text", "mine"
word representation
2456
3456
3176
896
1267
697
…
dimensionality reduction
4567
367
8721
…


input
“The best course ever taught about Text Mining”
tokenization
“The”, “best”, “course”, “ever”, “taught”, “about”, “Text”, “Mining”
stop word removal
“best”, “course”, “ever”, “taught”, “Text”, “Mining”
stemming or/and lemmatization
“best”, “course”, “ever”, “teach”, “text”, “mine”
word representation
2456 | 3456 | 3176 | 896 | 1267 | 697 …
dimensionality reduction
4567 | 367 | 8721 …
split in training/test sets
training (70%)
test (30%)

input	*“The best course ever taught about Text Mining”*
↓	↓
tokenization	*“The”, “best”, “course”, “ever”, “taught”, “about”, “Text”, “Mining”*
↓	↓
stop word removal	*“best”, “course”, “ever”, “taught”, “Text”, “Mining”*
↓	↓
stemming or/and lemmatization	*“best”, “course”, “ever”, “teach”, “text”, “mine”*
↓	↓
word representation	2456 | 3456 | 3176 | 896 | 1267 | 697 …
↓	↓
dimensionality reduction	4567 | 367 | 8721 …
↓	↓
split in training/test sets	training (70%) | test (30%)
↓	↓
classification	algorithm=KNN, k=9

input	*“The best course ever taught about Text Mining”*
tokenization	*“The”, “best”, “course”, “ever”, “taught”, “about”, “Text”, “Mining”*
stop word removal	*“best”, “course”, “ever”, “taught”, “Text”, “Mining”*
stemming or/and lemmatization	*“best”, “course”, “ever”, “teach”, “text”, “mine”*
word representation	2456 | 3456 | 3176 | 896 | 1267 | 697 …
dimensionality reduction	4567 | 367 | 8721 …
split in training/test sets	training (70%) | test (30%)
classification	algorithm=KNN, k=9
performance assessment	accuracy=90%

input	*“The best course ever taught about Text Mining”*
tokenization	*“The”, “best”, “course”, “ever”, “taught”, “about”, “Text”, “Mining”*
stop word removal	*“best”, “course”, “ever”, “taught”, “Text”, “Mining”*
stemming or/and lemmatization	*“best”, “course”, “ever”, “teach”, “text”, “mine”*
word representation	2456 | 3456 | 3176 | 896 | 1267 | 697 …
dimensionality reduction	4567 | 367 | 8721 …
split in training/test sets	training (70%) | test (30%)
classification	algorithm=KNN, k=9
performance assessment	accuracy=90%
hyperparameter tuning	k=1-100

input

input

↓

tokenization

input

↓

tokenization

↓

stop word removal

input

↓

tokenization

↓

stop word removal

↓

stemming or/and lemmatization

Porter Stemmer, Wordnet

input

↓

tokenization

↓

stop word removal

↓

stemming or/and lemmatization — Porter Stemmer, Wordnet

↓

word representation — Label, One-hot, Token count, tf-idf, Word Embedding

input

↓

tokenization

↓

stop word removal

↓

stemming or/and lemmatization — Porter Stemmer, Wordnet

↓

word representation — Label, One-hot, Token count, tf-idf, Word Embedding

↓

dimensionality reduction — PCA, LDA, SVD, t-SNE

input

↓

tokenization

↓

stop word removal

↓

stemming or/and lemmatization — Porter Stemmer, Wordnet

↓

word representation — Label, One-hot, Token count, tf-idf, Word Embedding

↓

dimensionality reduction — PCA, LDA, SVD, t-SNE

↓

split in training/test sets

input

↓

tokenization

↓

stop word removal

↓

stemming or/and lemmatization — Porter Stemmer, Wordnet

↓

word representation — Label, One-hot, Token count, tf-idf, Word Embedding

↓

dimensionality reduction — PCA, LDA, SVD, t-SNE

↓

split in training/test sets

↓

classification — SVM, Naïve Bayes, K-Nearest Neighbor, Random Forest, Logistic Regression, Neural Networks

input	
tokenization	
stop word removal	
stemming or/and lemmatization	Porter Stemmer, Wordnet
word representation	Label, One-hot, Token count, tf-idf, Word Embedding
dimensionality reduction	PCA, LDA, SVD, t-SNE
split in training/test sets	
classification	SVM, Naïve Bayes, K-Nearest Neighbor, Random Forest, Logistic Regression, Neural Networks
performance assessment	Accuracy, Precision, Recall, F-score, Confusion matrix

input	
↓	
tokenization	
↓	
stop word removal	
↓	
stemming or/and lemmatization	Porter Stemmer, Wordnet
↓	
word representation	Label, One-hot, Token count, tf-idf, Word Embedding
↓	
dimensionality reduction	PCA, LDA, SVD, t-SNE
↓	
split in training/test sets	
↓	
classification	SVM, Naïve Bayes, K-Nearest Neighbor, Random Forest, Logistic Regression, Neural Networks
↓	
performance assessment	Accuracy, Precision, Recall, F-score, Confusion matrix
↓	
hyperparameter tuning	Grid search

Key takeaways

Visualizations

- Word clouds

Text representations

- Label encoding
- One-hot encoding
- Token count encoding
- Tf-idf encoding

ML algorithms & models

- Support Vector Machines
- Naïve Bayes

Text preprocessing

- Tokenization
- Stop words removal
- Stemming
- Lemmatization
- Regular expressions

ML concepts

- Supervised learning
- Creating train and test sets
- Feature engineering
- Overfitting

Performance metrics

- Accuracy
- Precision
- Recall
- F-score
- ROC and AUC
- True Positive Rate

Machine Learning Techniques for Text

Questions?