IEMS 5780
Building and Deploying Scalable Machine Learning Services

Lecture 3 - Text Classification (1)

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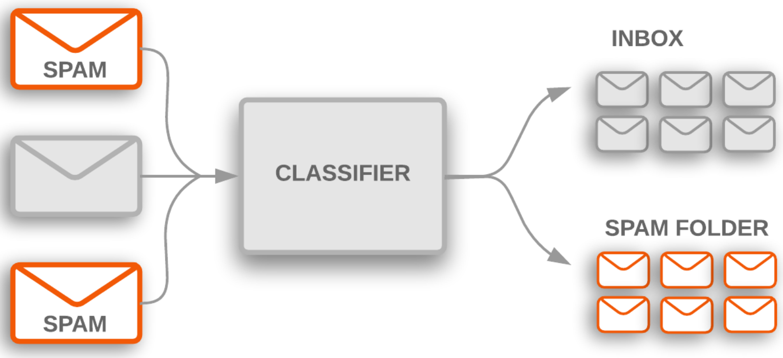
Text Classification

What is Text Classification?

- Putting a piece of **text** into a suitable **category**
- Categories / classes are **pre-defined**
- An example of **supervised learning**
- **Inputs**
  - text (e.g. news article, user reviews, email content)
- **Output**
  - topics / categories (e.g. sports / financial / technology news. or spam / non-spam emails)
  - polarity of opinions (e.g. positive, neutral, negative)
  - relevancy
  - tags (multi-label classification task, e.g. predicting tags for stackoverflow questions

Spam Email Detection

- https://developers.google.com/machine-learning/guides/text-classification/



Characteristics of Text Classification

- Highly **unstructured** (not in tabular format)
- Data can be very **noisy**
- Unput can be very short (e.g. "Nice restaurant!"), and can also be very long (e.g. a detailed report of an event on a newspaper)
- unseen data very likely to contain **unseen features** (new words, phrases, symbols or codes)
- Many new features might come up over time (e.g. new jargons, new words)
- Things can become very different across **different languages**
- ...

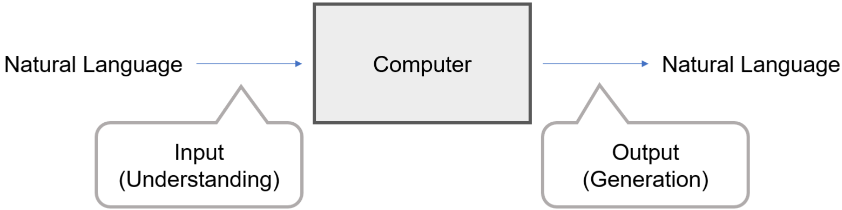
Features & Representation

- Since texts are **not structured** input, we need some ways to convert a text into a **vector representation** (feature vectors)
- What would be the **features** X of a text document?
  - Individual **words** / **phrases** / **sentences**
- Can also consider:
  - **Length** of the text
  - Existence of special **entities** in the text (e.g. person names, organizations, countries, etc.)
  - Source (e.g. which newspaper it is from)
  - **Date/time** of creation, publication, modification, etc.
  - ...

Natural Language Processing

Natural Language Processing

- NLP involves making the computer **understand** natural language input and **generate** natural language output
- It is a field that involves computer science, linguistics, artificial intelligence, human-computer interface, etc.



Examples: Real-time Speech Translation

- Real-time Skype Translator by Microsoft Research
- AI Powered Machine Translation
- Skype Translator: Speak Chinese like a local

How is NLP Done?

- Natural languages are usually **unstructured**, in which we find **alphabets**, **symbols**, **numbers and codes**, and even **emojis**.
- We need to apply different **pre-processing** algorithms before we can use the data for analysis and machine learning
- Common preprocessing tasks:
  - Tokenization
  - Stemming
  - Term Weighting
  - Parsing
  - Part-of-Speech (POS) Tagging
  - Pattern extraction using regular expressions

Tokenization

- **Token** is a unit in natural language processing
- Usually it is a word in English (or other languages using Latin alphabets), separated by space
- **Tokenization** = breaking up the raw text into words (or other meaningful units)
- Problems:
  - How do we treat punctuations?
  - John’s book (John + ‘s + book ?)
  - Doesn't (does + not, or does + n’t ?)
  - Hyphenated words: so-called, high-risk, anti-social

Chinese (Asian Languages) Segmentation

- There is no space between words/phrases in Chinese and other **Asian languages** such as Japanese and Korean

```
超強颱風「山竹」目前集結太平洋地區，料明日登陸菲律賓，周日再吹襲香港。
美國氣象學家警告，「山竹」威力相等於5級颶風，比吹襲美東颶風「佛羅倫斯」
更強。菲律賓政府嚴陣以待，並已疏散120萬名沿岸居民。
```

```
大阪府北部地震や台風２１号など度重なる災害を受け、京都市は１４日、
各省庁への要望活動を始めた。停電の早期解消に向けた関西電力の指導や、
二条城などの文化財の復旧を支援する制度の拡充を国に求めた。
```

```
스마트폰과 4세대(4G) 롱텀에볼루션(LTE)으로 재편된 휴대전화 시장에
2세대(2G)폰이 2년 만에 나온다. 삼성전자는 이달 중 폴더폰 '와이즈2 2G(모델명
SHC-Z160S)'를 SK텔레콤을 통해 출시한다. 국내 휴대전화 시장에 2G폰이 출시되는
것은 2011년 LG전자
```

Tokenizing in Python

- A commonly used tokenizer in **English** is the one provided by the [Natural Language ToolKit (NLTK)]
- Example:

```
import nltk

sentence = "Antoni Gaudí was a Spanish architect from Catalonia."
nltk.word_tokenize(sentence)
# ['Antoni', 'Gaudí', 'was', 'a', 'Spanish', 'architect', 'from', 'Catalonia', '.']

sentence = "Every morning I wake up at about seven o'clock."
nltk.word_tokenize(sentence)
# ['Every', 'morning', 'I', 'wake', 'up', 'at', 'about', 'seven', "o'clock", '.']
```

Tokenizing in Python

- In Chinese, a commonly used open source package is called [jieba]
- Example:

```
import jieba

sentence = "超強颱風「山竹」目前集結太平洋地區，料明日登陸菲律賓，周日再吹襲香港。"
tokens = list(jieba.cut(s))
# ['超強', '颱', '風', '「', '山竹', '」', '目前', '集結', '太平洋',
#  '地區', '，', '料', '明日', '登陸菲律賓', '，', '周日', '再吹襲',
#  '香港', '。']
```

Normalization

- A related issue: words in uppercase or lowercase
- E.g. Usually we do not want to treat `house`, `House` and `HOUSE` differently
- Normally, we convert all words into lowercases (lowercasing) (*Problem?*)
- Truecasing: try to preserve uppercase in entity names, in order to distinguish between something like `Mr. Brown` and `brown colour`.

Stemming

- A word may appear in different forms, consider:
  - cat, cats / bus, buses
  - run, running, runs
  - fun, funny / beautiful, beautifully
- **Stemming** is the action of reducing words to its **stem** or **root**
  - cat, cats --> cat
  - run, running, runs --> run
- Many different ways to do this:
  - Lookup table
  - Rule-based (Suffix stripping)
  - Stochastic methods (machine learning)

Stemming

- The widely used stemming method used is the Porter Stemmer, invented by Martin F. Porter in 1980.
- Available in many different programming languages (e.g. C, C++, Python, Java, etc.)
- Demo available at: http://qaa.ath.cx/porter_js_demo.html

```python
from nltk.stem.porter import PorterStemmer

stemmer = PorterStemmer()

stemmer.stem("running"), stemmer.stem("run"), stemmer.stem("runs")
# All returns 'run'

stemmer.stem("beauty"), stemmer.stem("beautiful")
# All returns 'beauti'
```

Parts of Speech

- Words have different **roles** in a sentence:
  - **nouns** (e.g. house, car, people)
  - **verbs** (e.g. run, walk, pay, eat)
  - **adjectives** (e.g. beautiful, quick)
- Roughly, we can divide words into two broad categories:
  - Content words (e.g. nouns, verbs)
  - Function words (e.g. prepositions)
- **Content words** are also called **open-class** words (not a finite set of words, word can be created or become obsolete)
- **Function words** are called **close-class** words, because usually, they do not change over a long period of time.

Parts of Speech

Figure 2.5 Part-of-speech tags of the Penn tree bank.

- **Nouns** refer to abstract or real objects in the word. Nouns (singular: *house*/NN, plural: *houses*/NNS) are distinguished from proper nouns (singular: *Britain*/NP, plural: *Americas*/NPS)
- **Verbs** refer to actions. Base form: *go*/VB, past tense: *went*/VBD, past participle: *gone*/VBN, gerund: *going*/VBG, 3rd person singular present: *goes*/VBZ, other singular present: *am*/VBP. Special cases: modals *can*/MD, particles *switch on*/RP.
- **Adjectives** refer to properties of nouns. Regular: *green*/JJ, comparative: *greener*/JJR, superlative: *greenest*/JJS
- **Adverbs** refer to properties of verbs or adjectives. Regular: *happily/RB*, comparative: *ran faster*/RBR, superlative: *ran fastest*/RBS, wh-adverbs: *how*/WRB *fast*
- **Determiners** (also called **articles**) qualify or replace nouns. Regular: *the*/DT *house*, pre-determiner: *all*/PDT *the houses*, wh-determiner: *which*/WDT.
- **Pronouns** refer to previously mentioned nouns. Personal pronoun: *she*/PP, possessive pronoun: *her*/PP$, wh-pronoun: *who*/WP, possessive wh-pronoun: *whose*/WP$.
- **Prepositions** precede noun phrases or clauses and indicate their role in the sentence: *from*/IN *here*. Special case *to*/TO.
- **Coordinating conjunctions**: *and*/CC.
- **Numbers**: *17*/CD
- **Possessive marker**: *Joe 's*/POS
- **List item markers**: *A.*/LS
- **Symbols**: *$*/SYM
- **Foreign words**: *de*/FW *facto*/FW
- **Interjections**: *oh*/UH

- [Penn tree bank POS Tags]

Parts of Speech

- **POS tagging** can be treated as a **machine learning** problem
- Given a token and its features (e.g. the word itself, previous word, next word, prefix/suffix of the word), predict its POS tag
- A **trained model** can be found in NLTK

```
import nltk

sentence = "Antoni Gaudí was a Spanish architect from Catalonia."
tokens = nltk.word_tokenize(sentence)
pos_tagged = nltk.pos_tag(tokens)

# [('Antoni', 'NNP'), ('Gaudí', 'NNP'), ('was', 'VBD'), ('a', 'DT'),
#  ('Spanish', 'JJ'), ('architect', 'NN'), ('from', 'IN'),
#  ('Catalonia', 'NNP'), ('.', '.')]
```

Document Representation

Document Representation

- How do we **represent** a document in a program?
- We need to represent documents as a **feature vector** before we can **classify** them
- A commonly used representation is called the **bag-of-words model (bow)**
- Ignore any grammar, dependencies, punctuations, part-of-speech, etc.
- Order of word is assumed to be **NOT** important

Bag-of-words Model

- Once each document is represented by a **bag of words**, we can use a **vector** to represent each of them
- Firstly, let N be the total number of unique words (i.e. the **size** of our *vocabulary**)
- We can use a vector of length N (N-dimension) to represent a document
  - Each element in the vector corresponds to **one unique word**
  - The element is 1 if the document contains the word, otherwise it is 0
- This is called **one-hot encoding**
- For example, if we have a vocabulary of (0="boy", 1="girl", 2="school"), a document with two words **`boy`** and **`school`** will be represented by the following vector:

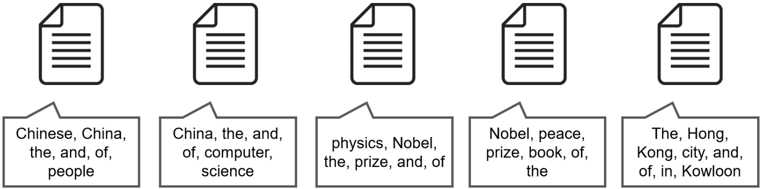
$$v = (1, 0, 1)$$

Vector Space Representation

- This **vector space representation** of document can be extended
- The value in the vectors can be assigned **different** meanings
  - Existence of individual words (0 or 1)
  - Number of times a word appears (0, 1, 2, ...)
  - A certain weighting assigned to the word (any real number)
- Intuitively, a word that appears more than the others should be more important
- However, some words are commonly used in general
  - articles (a, an, the)
  - pronouns (his, her, we, you, ...)
  - prepositions (of, in, over, ...)
- How can we assign a **meaningful weight**?

Term Weighting

- A commonly used **term weighting** scheme is called **tf-idf** (term frequency-inverse document frequency)
- Determine the **importance** of a word to a document by how often they appear across the whole corpus
- Consider a corpus with five documents:



TF-IDF

- Term Frequency (tf)

$$tf(w,d) = \text{Number of times } w \text{ appears in } d$$

- Document Frequency (df)

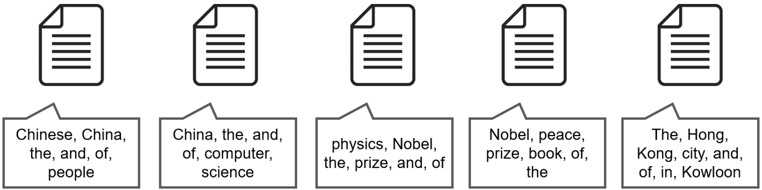
$$df(w) = \text{Number of documents that contain } w$$

- Inverse Document Frequency (idf)
    - Rare words has high idf, frequent words has low idf

$$idf(w) = log(N/df(w))$$

$$tfidf(w,d) = tf(w,d) \times idf(w)$$

TF-IDF



- Example: comparing importance of the word **`china`** vs. **and**

$$tfidf(\text{china}, d_2) = 1 \times log\frac{5}{2} = 0.3979$$

$$tfidf(\text{and}, d_2) = 1 \times log\frac{5}{4} = 0.0969$$

Transforming Documents in Scikit-learn

- In Python, you can use the [CountVectorizer]() or [TfidfVectorizer]() to convert texts into vectors

```
from sklearn.feature_extraction.text import CountVectorizer

docs = [
    "CUHK is located in Shatin",
    "CUHK has a large campus",
    "Shatin is a district in the New Territories"
]
vectorizer = CountVectorizer()
vectorizer.fit(docs)  # Create the vocabulary
vectorizer.vocabulary
# {'located': 7, 'has': 3, 'new': 8, 'shatin': 9, 'the': 11, 'cuhk': 1,
#  'territories': 10, 'district': 2, 'is': 5, 'in': 4, 'campus': 0, 'large': 6}

vectorizer.transform(["CUHK is in Shatin"]).todense()
# matrix([[0, 1, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0]])
```

TfidfVectorizer

```
from sklearn.feature_extraction.text import TfidfVectorizer

docs = [
    "CUHK is located in Shatin",
    "CUHK has a large campus",
    "Shatin is a district in the New Territories"
]
vectorizer = TfidfVectorizer()
vectorizer.fit(docs)  # Create the vocabulary
vectorizer.vocabulary
# {'located': 7, 'has': 3, 'new': 8, 'shatin': 9, 'the': 11, 'cuhk': 1,
#  'territories': 10, 'district': 2, 'is': 5, 'in': 4, 'campus': 0, 'large': 6}

vectorizer.transform(["CUHK is in Shatin"]).todense()
# matrix([[0. , 0.5, 0. , 0. , 0.5, 0.5, 0. , 0. , 0. , 0.5, 0. , 0. ]])
```

Models for Text Classification

Models for Text Classification

Characteristics of data

- Huge number of features (high dimensionality)
- Very sparse data (most words appear only appear a few times)

Suitable Models

- Logistic Regression
- SVM
- Naive Bayes
- Neural networks (next lecture)

Logistic Regression

- Recall that logistic regression is a **linear model** for classification

$$y = g(\theta^T x) = \frac{1}{1 + e^{-\theta^T x}}$$

- $\boldsymbol{x}$ is a feature vector of an input
- Using the vector space model, each document is represented as a feature vector $\boldsymbol{x}_i$, whose dimension is N (size of vocabulary)
- What is our **assumptions** in such a model?
    - Each word is **independent**
    - Each word **contributes** some information (+ve or -ve) to whether the document belongs to one class or another

Logistic Regression

- Let's try this on a toy example to classify whether a text is about CUHK
- Check the documentation of Logistic Regression on scikit-learn
- Notebook: https://drive.google.com/file/d/1tKfPsEhBKmyBgDaV5_vD-xy039fnc-Tg/view?usp=sharing
- Our data:

```
docs = [
    "CUHK is a university in Hong Kong",
    "Hong Kong is a city in Southeast Asia",
    "Asia is the most populous continent",
    "CUHK is located in Shatin"
]
labels = [1, 0, 0, 1]
```

Naïve Bayes Classifiers

- **Naïve Bayes classifier** is a simple yet powerful probability-based classifier that can be applied to many different problems
- Idea: Probability of a **document** belonging to a class depending on the probability of the **words** in the document belonging to the class
- Some notations:

$$P(c) - \text{Probability of the class } c$$
$$P(d|c) - \text{Probability of a document given class } c$$
$$P(c|d) - \text{Probability of class } c \text{ given document } d$$
$$P(w|c) - \text{Probability of a word } w \text{ given class } c$$

Naïve Bayes Classifiers

- Given a new document d, we want to decide which class it belongs to, i.e. we want to find a class c such that the following probability is the largest (compared to other classes)

$$P(c|d)$$

- How do we do so?
- We can break the problem into smaller problems:
  - A document is composed of **individual words**
  - Let's assume that each word is **independent**
  - Each word has a different **probability** of appearing in a document of a class

Some Maths

$$\begin{aligned} P(c|d) &= \frac{P(d|c)P(c)}{P(d)} \\ &\propto P(c) \times P(d|c) \\ &\propto P(c) \times P(w_1 w_2 \ldots w_{n_d}|c) \\ &\propto P(c) \times \prod_{1 \leq k \leq n_d} P(w_k|c) \end{aligned}$$

- $P(w_1 w_2 \ldots w_{n_d}|c)$ is the joint probability of all words that appear in document d given that it is in class c
- If we assume that each word appears independently, then the above can be simplified as the **product** of the probabilities of indiviudal words w_i
- $P(c)$ is the **prior probability** of class c

Training a Naive Bayes Classifier

- When training a NB classifier, we actually want to estimate $P(c)$ and $P(w_k|c)$

$$P(c) = \frac{\text{Number of documents in class } c}{\text{Total number of documents}} = \frac{N_c}{N}$$

$$P(w|c) = \text{Probability of } w \text{ appearing in class } c = \frac{f(w,c)}{\sum_{w_i} f(w_i,c)}$$

- This is called the **maximum likelihood estimation** of the parameters in the Naive Bayes model

Naive Bayes Classifier

- Let's try the toy example again using Naive Bayes classifier this time
- Check the documentation of Naive Bayes classifier in scikit-learn
- Notebook: https://colab.research.google.com/drive/1lK0AT5vf8c4crF9F2mp1j7MGOxbcn0ei

Logistic Regression vs. Naive Bayes

- The two models are very similar
- Both assume that words are **independent** in a document
- **Logistic Regression** is a **discriminative model** --> it tries to find out $p(y|x)$
  - Directly classifies the inputs into one of the classes
- **Naive Bayes** is a **generative model** --> it tries to find out $p(x,y)$
  - Tries to model how data is generated, and use that information to perform classification
  - Models the differences in the probabilities of different classes (useful in the case of imbalanced dataset)
- If you are interested, check out [a paper comparing logistic regression and naive bayes]

Practical Example

- Let's go through an example using the data below:
  - [SMS Spam Collection Dataset](): 4,827 "ham" messages, 747 "spam" messages
- We will use the following modules in scikit-learn:
  - `sklearn.feature_extraction.text.CountVectorizer`
  - `sklearn.naive_bayes.MultinomialNB`
  - `sklearn.pipeline.Pipeline`
    (combining the count vectorizer and Naive Bayes model into a pipeline)
  - `sklearn.model_selection.train_test_split`
    (for splitting data into train and test sets)
  - `roc_auc_score`, `precision_score`, `recall_score` in `sklearn.metrics`
    (for evaluating our trained model)

Reading the Data

- We can use **pandas** to read in the tab-separated data easily:

```
import pandas as pd

# The data is tab-separated, and there is no header row
df = pd.read_csv("data/sms/SMSSpamCollection", sep="\t", header=None)

# Add column names, convert ham to 0 and spam to 1
df.columns = ["label", "text"]
df.loc[:, "label"] = df["label"].apply(lambda x: 0 if x == "ham" else 1)
```

	label	text
0	0	Go until jurong point, crazy.. Available only in bugis n great world la...
1	0	Ok lar... Joking wif u oni...
2	1	Free entry in 2 a wkly comp to win FA Cup final tkts 21st May 2005. Tex...
3	0	U dun say so early hor... U c already then say...
4	0	Nah I don't think he goes to usf, he lives around here though

Splitting in Train and Test Sets

- We use **`train_test_split`** to split the dataset into train and test sets
- Note that the data is **highly imbalanced**, so we need to use **[stratified sampling]()**

```
from sklearn.model_selection import train_test_split
X = df["text"]
y = df["label"]

# We want to use 30% of the data as test data
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.3, stratify=y, random_state=100)
```

- Note: Always specify an integer for **`random_state`** so that you can **reproduce the experiment**
- You can check that the ratio of ham to spam in **`X`**, **`X_train`** and **`X_test`** are all 0.87 : 0.13.

Model Training

- To train our model, we create a scikit-learn pipeline that:
  - Takes the input texts and convert them into word vectors
  - Use the word vectors and their labels to train the model

```
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.naive_bayes import MultinomialNB
from sklearn.pipeline import Pipeline

clf = Pipeline([                      # Creating a pipeline
    ('vec', CountVectorizer()),       # The count vectorizer using default params
    ('nb', MultinomialNB())           # The multinomial NB using default params
])
clf.fit(X_train, y_train)             # Use the training data to fit the model
```

Evaluation

- We can check our model performance using the following scores:
  - **AUC score**
  - **Precision** and **Recall** of the spam class

```
from sklearn.metrics import roc_auc_score, precision_score, recall_score

y_pred = clf.predict(X_test)
print("AUC      : {:.4f}".format(roc_auc_score(y_test, y_pred)))
print("Precision: {:.4f}".format(precision_score(y_test, y_pred)))
print("Recall   : {:.4f}".format(recall_score(y_test, y_pred)))

# Prints the following
#
# Precision: 0.9624
# Recall   : 0.9152
```

- (The scores you obtain will probably be slightly different from above)

Evaluation

- Instead of computing the precision and recall scores separately, you can also use **`sklearn.metrics.classification_report`** to obtain a full report of the classification results on the test set

```
from sklearn.metrics import classification_report

print(classification_report(y_test, y_pred))

# Prints the following
#
#               precision   recall   f1-score   support
# 0             0.99        0.99     0.99       1448
# 1             0.96        0.92     0.94       224
# avg / total   0.98        0.98     0.98       1672
```

What's Next?

- We have gone through the basic steps of training a text classifier
- Consider this your **baseline** model
- How do you improve your model?
  - **Investigate** when does the model make mistakes
  - Check if your model **overfits** or **underfits**
  - Consider **pre-processing** of the data
  - Consider tunning the **hyper-parameters** of the model
  - Consider using **another algorithm / model**
  - Try **cross validation**
  - Do **feature selection**
  - ...

Model Persistence

- To use your model elsewhere (e.g. in **another program**), you need to **save** or **persist** your trained model
- Assuming that you will only load the model in **Python** again, we can use the `joblib` module

```
from sklearn.externals import joblib

...
model.fit(X, y)   # Training a model
...

joblib.dump(model, "model.pkl")  # Save the model into a file named 'model.pkl'
```

Loading a Model

- To load a model that was dumped using `joblib` before:

```
from sklearn.externals import joblib

model = joblib.load("model.pkl")
...
predictions = model.predict(X_test)  # apply the loaded model on new data
```

- Note that in addition to the model itself, you should keep track of:
  - The **version of scikit-learn** that you used to train your model
  - The **performance** (e.g. cross-validation scores) of the model
  - The **training data** used to train the model
  - The **source code** for preprocessing the data

Putting the Model in Production

- When using a model in a production system, in addition to the accuracy/precision/recall of the model, we need to consider:
  - **Size** of the model --> would it be too big to be copied around?
  - **Memory usage** --> how much memory will it take up after loaded?
  - **CPU usage** --> how much CPU resources needed to generate a prediction?
  - **Time to predict** --> time requried to generate a prediction
  - **Preprocessing** --> how complicated is the preprocessing steps?

End of Lecture 3