USC Viterbi
School of Engineering
Department of Computer Science

CSCI 544
Applied Natural Language Processing

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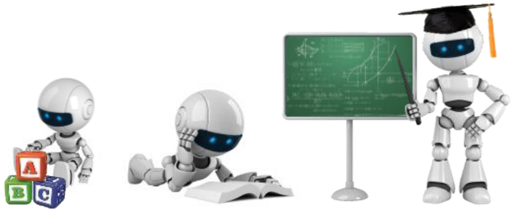
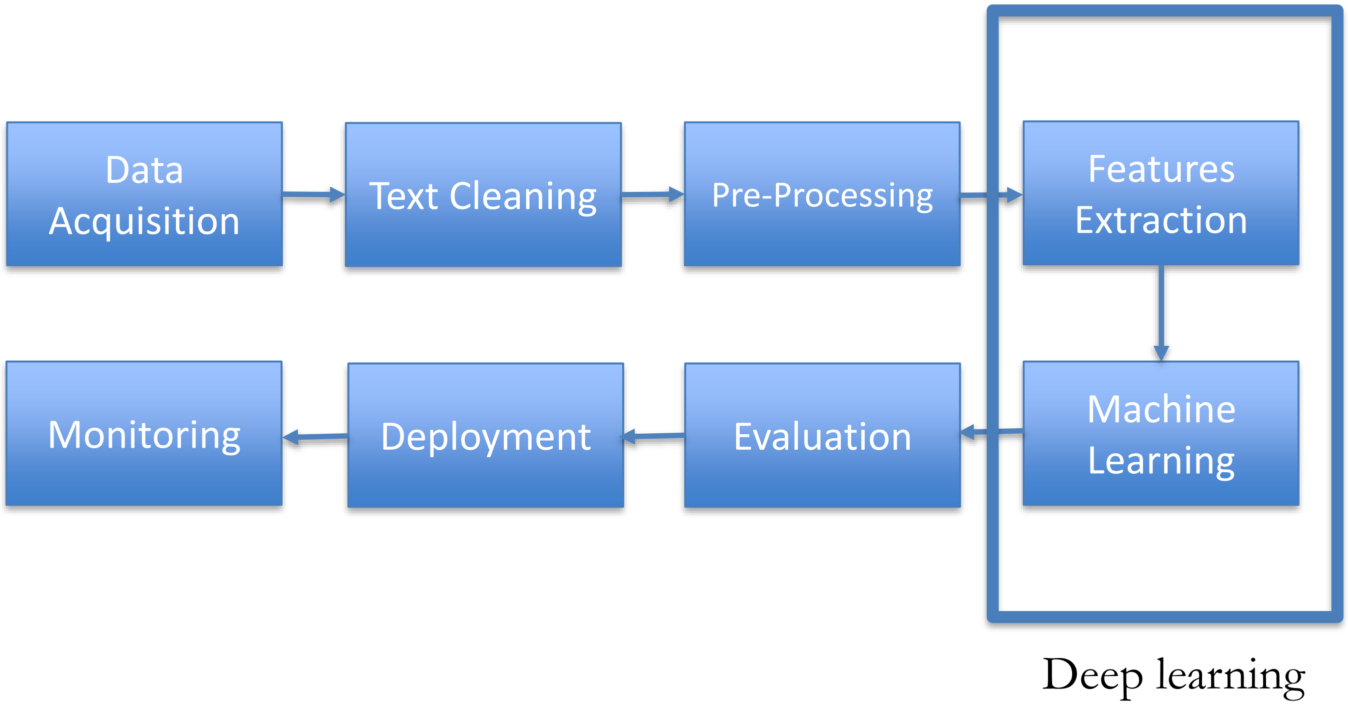


Logistical Notes

- HW1 will be out next session: start working early
  - NLTK
  - Sklearn
- Quiz1: Blackboard
  - At the beginning of the class
  - 10 questions and 10 minutes available from 5:35 till 5:50
- Recorded lectures: blackboard -> tools -> usc zoom pro meeting -> cloud recordings.
- Groups: Continue to form your groups soon.
- Happy to see some people started to form groups and already learning using NLTK
- D-Clearance, second section

NLP Pipeline

- We will mostly explore the stages between text cleaning and evaluation



Text Classification

Sentiment Analysis:

- If u want a plush authentic looking & feeling oriental rug this is NOT the rug for u ! If u want something pretty & functional to block & PROTECT ur other nice rugs from kids & dogs & all their daily sand & mud that's easy to take care of as well buy a FEW !

Preprocessing

- **Tokenization**: splitting the text into units for processing

Feature Extraction

- **Bag of Words**
- **TF-IDF:** converting text to helpful vectors

Classification Algorithms

- **Naïve Bayes**
- **Perceptron**

Classification

- Categorizing instances of data into "classes", where class members share some notion of similarity, e.g., having positive sentiment

Parametric Model:

Learning $\approx$ Choosing and selecting the **best** model

$$y_i = h(\theta) \approx \theta^\top x_i, \theta \in \mathbb{R}^d$$

Model Selection:

$$\hat{\theta} = \arg \min_{\theta \in \Omega(\theta)} \underbrace{\sum_i \mathcal{L}(\theta^\top x_i, y_i)}_{\text{Empirical Error}}$$

Class 0

Class 1

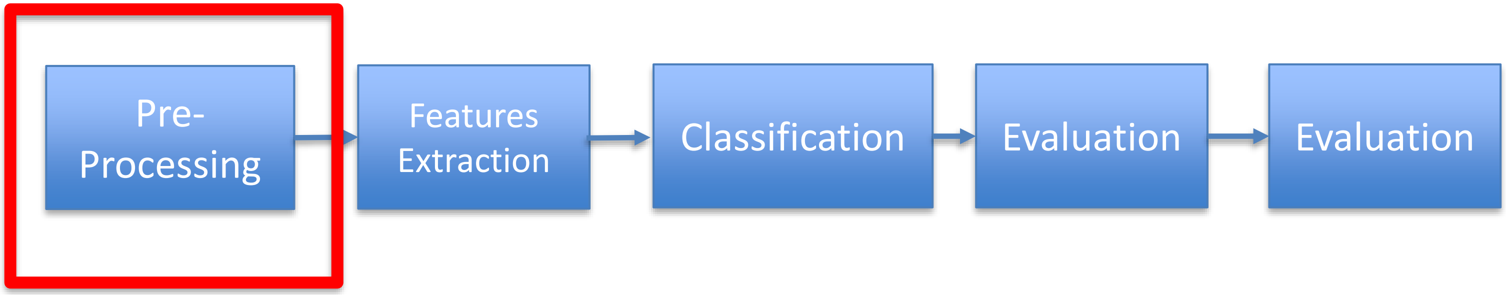
$$\mathbf{X} = [x_1, \ldots, x_N] \in \mathbb{R}^{d \times N}, \mathbf{Y} \in \{0, 1\}^N$$

Training Dataset

Testing Dataset

Features!

Sentiment Analysis Pipeline



Preprocessing

Tokenization: splitting the text into units for processing

- Removing extra spaces: the quality   is high
- Removing stop words: article, propositions, etc.

```
['i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'ourselves', 'you', "you're", "you've", "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselves', 'he', 'him', 'his', 'himself',
'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'its', 'itself', 'they', 'them', 'their', 'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'this', 'that', "that'll", 'these',
'those', 'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have', 'has', 'had', 'having', 'do', 'does', 'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or', 'because', 'as',
'until', 'while', 'of', 'at', 'by', 'for', 'with', 'about', 'against', 'between', 'into', 'through', 'during', 'before', 'after', 'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out',
'on', 'off', 'over', 'under', 'again', 'further', 'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'all', 'any', 'both', 'each', 'few', 'more', 'most', 'other', 'some',
'such', 'no', 'nor', 'not', 'only', 'own', 'same', 'so', 'than', 'too', 'very', 's', 't', 'can', 'will', 'just', 'don', "don't", 'should', "should've", 'now', 'd', 'll', 'm', 'o', 're', 've', 'y',
'ain', 'aren', "aren't", 'couldn', "couldn't", 'didn', "didn't", 'doesn', "doesn't", 'hadn', "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "isn't", 'ma', 'mightn',
"mightn't", 'mustn', "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn', "shouldn't", 'wasn', "wasn't", 'weren', "weren't", 'won', "won't", 'wouldn',
"wouldn't"]
```

- Contractions are standardized: won’t -> will not
- Removing unhelpful words, e.g., external URL links
- Removing unhelpful characters, e.g., non-alphabetical characters.
- Converting capital letter to lowercase

Preprocessing

- **Stemming:** wordform stripped of some characters
- **Lemmatization**: the base (or citation) form of a word
- Example:

- ordered could fill pandora bracelet right away wan na wait holiday filled liked fact lot pink charm barely got shipment still charm bracelet wear often since turn wrist green

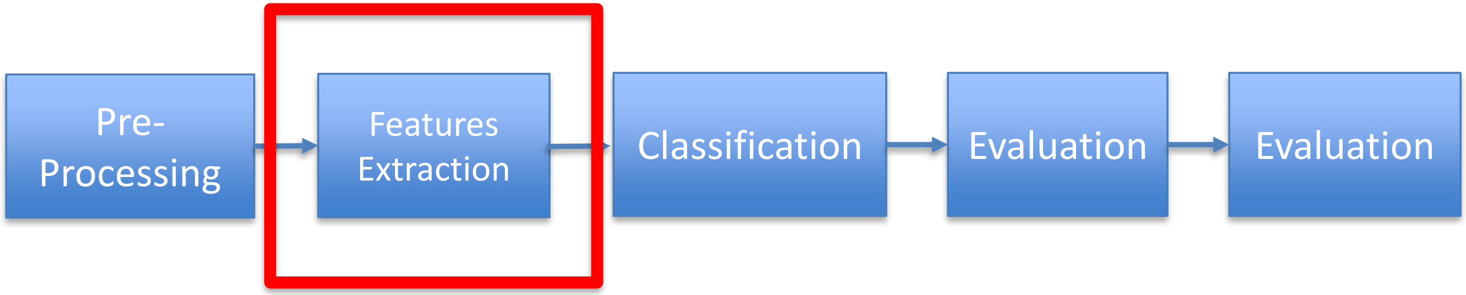
```
ps = nltk.stem.porter.PorterStemmer()
print([ps.stem(word) for word in txt])
```

```
['order', 'could', 'fill', 'pandora', 'bracelet', 'right', 'away', 'wan', 'na', 'wait', 'holi
day', 'fill', 'like', 'fact', 'lot', 'pink', 'charm', 'bare', 'got', 'shipment', 'still', 'ch
arm', 'bracelet', 'wear', 'often', 'sinc', 'turn', 'wrist', 'green']
```

```
ps = nltk.stem.WordNetLemmatizer()
print([ps.lemmatize(word) for word in txt])
```

```
['ordered', 'could', 'fill', 'pandora', 'bracelet', 'right', 'away', 'wan', 'na', 'wait', 'ho
liday', 'filled', 'liked', 'fact', 'lot', 'pink', 'charm', 'barely', 'got', 'shipment', 'stil
l', 'charm', 'bracelet', 'wear', 'often', 'since', 'turn', 'wrist', 'green']
```

Sentiment Analysis Pipeline



Feature Extraction

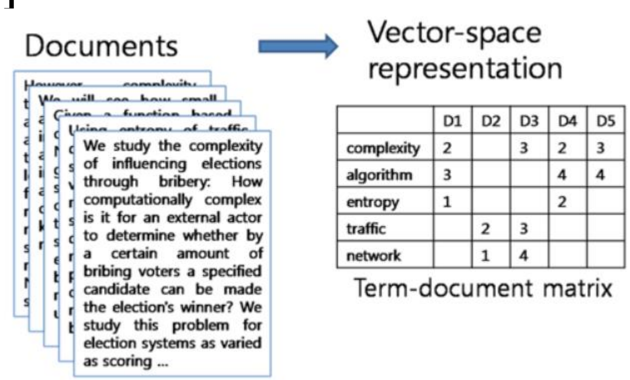
- We start from raw data, e.g., text, and build values, i.e., features, intended to be informative and non-redundant to help the subsequent learning and generalization steps.

- Is a non-trivial task and specific to the application
- The quality is judged by performance
- A tedious task as applications become more abstract, e.g., document categorization vs document summarization

- Example: Are you satisfied with our service?

Bag of Words (BoW)

- Simple example: counting the number of "informative" words in the input text
- Bag of words:
- we pick a dictionary of words and then put an arbitrary order on the words, e.g., alphabetical order
- We convert the text into a feature vector by reporting the frequency of occurrence of the words in the text
- Ex:
- Dic = [good, bad, nice, expensive, love]
- [I love this shirt because it is nice and worm. The color also is nice and matches my skin tone] -> [0, 0, 2, 0, 1]



Bag of Words (BoW)

- Limitations of bag of ward:
- Insensitive to language structure: “I wanna eat ice cream” vs “wanna eat ice cream?”
- Information in word dependencies is overlooked: “new york” vs “new book”
- The resulting vectors are highly sparse which leads to high computational costs
- Common words
- Why do we use BoW?
- Simple
- Leads to acceptable performance in some applications

Term Frequency - Inverse Document Frequency

- Core idea: reflect how important a word is to an instance in the dataset.
- Term Frequency: a measure of how frequently a term, t, appears in an instance (document), d:

$$tf_{t,d} = \frac{n_{t,d}}{Number\ of\ terms\ in\ the\ document}$$

- The frequency of occurrence is normalized

- Inverse Document Frequency: a measurement of how distinguishing a term is in the dataset.

$$idf_t = \log \frac{number\ of\ documents}{number\ of\ documents\ with\ term\ 't'}$$

Term Frequency - Inverse Document Frequency

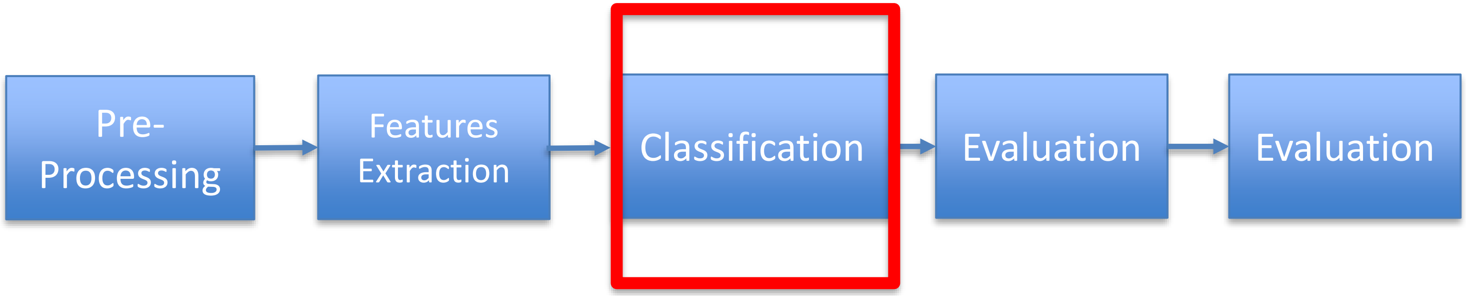
- TF-IDF score: reflects importance of the word for a particular instance and informative to categorize the documents

$$(tf\_idf)_{t,d} = tf_{t,d} * idf_t$$

- We use TF-IDF to extract the feature vector
- Ex: What is TF-IDF score for stop words?

Implemented in NLTK

Sentiment Analysis Pipeline



Statistical Learning

- Problem: finding a **predictive** function based on an annotated training dataset using probability theory $(\mathbf{x}_i, \mathbf{y}_i) \sim p(\mathbf{x}, \mathbf{y})$

- Goal: given the value of an input vector *X*, i.e., features, make a good prediction $\hat{Y}$ of the output *Y* (i.e., $\hat{Y} = Y$ with high probability) using the predictive function

- Maximum posterior estimation: $P(Y|X)$

True Error/Risk

Generative vs. Discriminative Models

Generative

- Learn a model of the joint probability P(X, Y)
- Use Bayes' Rule to calculate P(Y|X)
- Return the class that most likely to have generated that instance
- Examples: Naïve Bayes

Discriminative

- Model posterior probability P(Y|X) directly
- Class is a function of feature vector
- Find the exact function that minimizes classification errors on the training dataset and use it for prediction
- Examples: Linear classifier Logistic regression, Neural Networks (NNs), Support Vector Machines (SVMs)

Discriminative vs. Generative Classifiers

- Discriminative classifiers are generally more effective, since they directly optimize the classification accuracy. But
  - They are all sensitive to the choice of features, and in traditional ML these features are extracted heuristically
- Generative classifiers directly model the joint probability which is helpful when generating text is necessary but:
  - Modeling the joint probability is a harder problem than classification if only classification is our goal

Bayes Classifier

- Bayes Rule:

Posterior Prior Likelihood

$$P(Y|X) = \frac{P(Y)P(X|Y)}{P(X)}$$

- Bayes Optimal Classifier:

$$\hat{Y} = \arg\max_Y P(Y)P(X|Y)$$

- We use multiple features

$$\hat{Y} = \arg\max_Y P(Y)P(X_1, \ldots, X_n|Y)$$

(Multinomial) Naïve Bayes Classifier

- Challenges for the Bayes optimal classifier

- Computing the joint likelihood probability is practically almost impossible

- Assuming statistical independence between the features:

$$\hat{Y} = \arg\max_{Y} P(Y) P(X_1, \ldots, X_n | Y)$$
$$= \arg\max_{Y} P(Y) \Pi_{i=1}^{n} P(X_i | Y)$$

(Multinomial) Naïve Bayes Classifier

- Challenges for the Bayes classifier
- Computing the likelihood probability even for single features is practically difficult because many words are not frequently used: superb vs good

$$\hat{Y} = \arg\max_{Y} P(Y)P(X_1, \ldots, X_n|Y)$$
$$= \arg\max_{Y} P(Y)\Pi_{i=1}^{n} P(X_i|Y)$$

- Zero probabilities cannot be conditioned away, irrespective of the other evidence!
- Smoothing: we add small non-zero probabilities to avoid zero probabilities

Example

- Features/Dic = {I , hate, love, blue, shirt}

  ~ {X1, X2 , X3 , X4 , X5 }
- Training
  - I hate blue shirt (Y=0)
  - Love blue shirt (Y=1)

$$\text{Features}=\begin{bmatrix}1 & 1 & 0 & 1 & 1\\ 0 & 0 & 1 & 1 & 1\end{bmatrix}$$

- What is P(Y|X)?

- P(Xi=k|Y=j) = #(documents with Xi=k and Y=j)/ #(documents with Y=j)

$$P(X|Y)=\begin{bmatrix}P(X1=0|Y=0) & P(X2=0|Y=0) & P(X3=0|Y=0) & P(X4=0|Y=0) & P(X5=0|Y=0)\\ P(X1=0|Y=1) & P(X2=0|Y=1) & P(X3=0|Y=1) & P(X4=0|Y=1) & P(X5=0|Y=1)\\ P(X1=1|Y=0) & P(X2=1|Y=0) & P(X3=1|Y=0) & P(X4=1|Y=0) & P(X5=1|Y=0)\\ P(X1=1|Y=1) & P(X2=1|Y=1) & P(X3=1|Y=1) & P(X4=1|Y=1) & P(X5=1|Y=1)\end{bmatrix}$$

- Prior p(Y) $P(Y)=[P(Y=0) \quad P(Y=1)]$

- P(Y=j) = #(documents with Y=j)/ #(all documents)

- Testing
  - hate shirt {x2,X5}

$$P(Y|X)\propto[P(Y=0)\times P(X2=1|Y=0)\times P(X5=1|Y=0) \quad P(Y=1)\times P(X2=1|Y=1)\times P(X5=1|Y=1)]$$

Example

- Features = {I, hate, love, this, shirt}
- Training
  - I hate this shirt
  - Love this shirt
- What is P(Y|X)?
- Prior p(Y)
- Testing
  - hate shirt

$$P(X|Y)=\begin{bmatrix}0 & 0 & 1 & 0 & 0\\ 1 & 1 & 0 & 0 & 0\\ 1 & 1 & 0 & 1 & 1\\ 0 & 0 & 1 & 1 & 1\end{bmatrix}$$

$$P(Y) = [1/2 \quad 1/2]$$

$$P(Y|X) \propto [1/2 \times 1 \times 1 \quad 1/2 \times 0 \times 1] \propto [1\ 0]$$

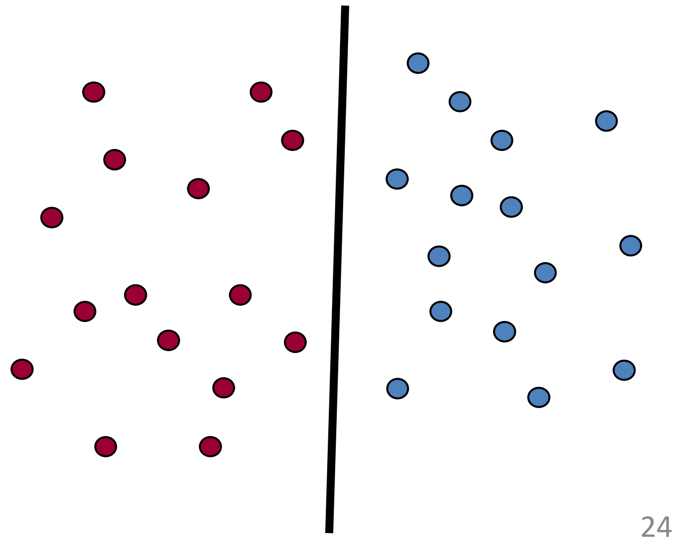
Implemented in sklearn

Linear Classifier

- An interpretation for discriminative models is that we find a boundary between the two classes in the **geometrical** features space

- A linear classifier assumes that the data points are linearly separable in the feature space

- The goal is to find a boundary



Linear models

- A linear function in *n*-dimensional space (i.e. we have *n* features) is define by *n*+1 weights:

$$Y = \sum_{i=0}^{n} \beta_i X_i$$

- We find the model weights such that the linear function acts as a good predictive model

- Is not necessarily unique!