Text Preprocessing II

From textual information to numerical vector

Bag-of-Words: counting is everything

Vector Representation for Documents

- Without any deep analysis of the linguistic content of the documents, we can describe each document by features that represent the most frequent tokens.
- Each row is a document, and each column represents a feature.
- Thus, a cell in the csv/excel file is a measurement of a feature (corresponding to the column) for a document (corresponding to a row).

Bag-of-Words

- Steps
  - Build vocab i.e., set of all the words in the corpus
  - Count the occurrence of words in each document

The cat and the dog play
The cat is on the mat

corpus

and, the, cat, dog, play, on, mat, is

vocab.

1	2	1	1	1	0	0
1	2	0	0	1	1	1

countVec

Document Features

- How to define document features (i.e., entry value in the matrix)
  - Presence (0 or 1)
  - Frequencies (0,1,2,3)
  - Thresholding frequencies - three values
    - 0 (do not exit), 1 (occurred once), and 2 (occurred 2 or more times)

Term Frequency-Inverse Document Frequency

- Tf-id(w): tf(w) * idf(w), where $idf(w) = log(1 + \frac{N}{df(w)})$
    - The tf-idf weight assigned to word w is the **term frequency** (i.e., the word count) modified by a scale factor for the importance of the word.
    - The scale factor is called the **inverse document frequency**, which checks the number of documents containing word w (i.e., *df(w)*) and reverses the scaling.
    - The N is the number of documents.

Term Frequency-Inverse Document Frequency

- Intuitive logic:
  - Capture the importances of a word to document in a corpus
  - Importance of words is proportionally to the number of times a word appears
  - Importance of words is inversely proportionally to the document containing the word
  - Thus, when a word appears in many documents, it is considered unimportant and the scale is lowered, perhaps near zero, e.g., “the”, “I”, “on”, “document”, etc.

Term Frequency-Inverse Document Frequency

- When prepare the feature matrix, most of the entries will be zero.
- Most documents contain a small subset of the vocab’s words
- Rather than storing all the zeros, it may be better to represent the matrix as a set of sparse vectors, where a row is represented by a list of paris, one element of the pair being a column number and the other element being the corresponding nonzero feature value.

0	15	0	3
12	0	0	0
8	0	5	2

(2,15) (4,3)
(1,12)
(1,8) (3,5) (4,2)

Multiword Features

- A variety of measures can be used for this purpose.
  - E.g., frequent n-grams, such as “text mining”, “hip hop”
- As another method, an Association Measure AM for the multiword T, is used for evaluation multiword features, where size(T) is the number of words in phrase T and freq(T) is the number of times phrases T occurs in the document collection.

$$AM(T) = \frac{size(T) log_{10}(freq(T)) freq(T)}{\sum_{word_i \in T} freq(word_i)}$$

- Generally, multiword features are not found too frequently in a document collection, but when they do occur they are often high predictive.

Bag-of-Words

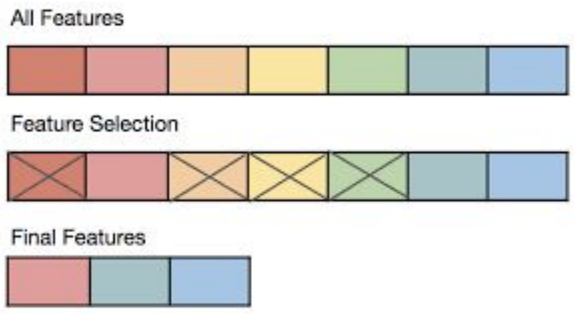
- Pros
  - Simple
  - Surprisingly effective
  - Fast

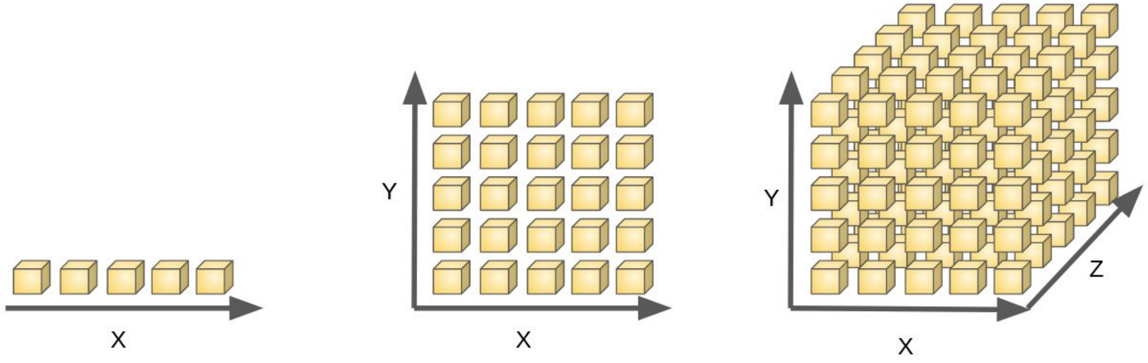
- Cons
  - Order of words does not matter
  - Cannot capture syntactic/semantic information
  - High dimensionality

Dictionary Reduction

Dictionary Reduction

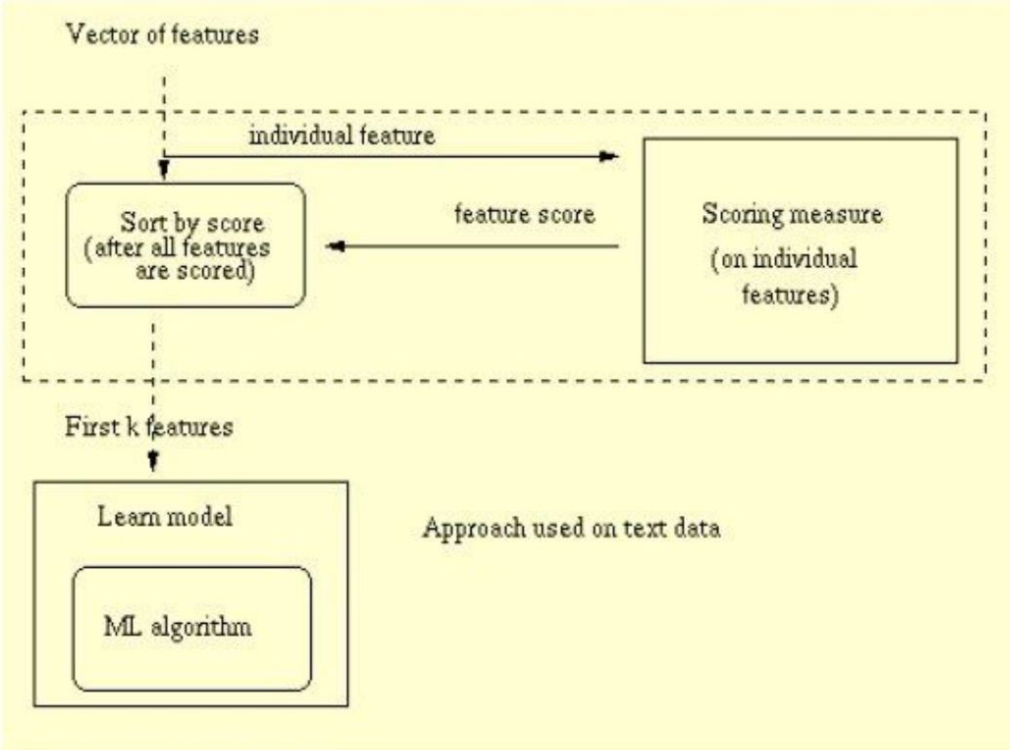
- Also called feature reduction techniques
- Due to **curse of high dimensionality**
- For BoW models:
  - Local dictionary
  - Removing Stopwords
  - Frequent Words
  - **Feature Selection**
  - Token reduction (stemming and synonyms)
  - Feature transformation (PCA, or Topic models)





Feature Selection by Attribute Ranking

- Can select a set of features (e.g., a set of words) to form a local dictionary.
- Rank feature attributes according to their predictive abilities for the category under consideration.
  - **Sports**: *soccer, football*, *etc*. **Travel**: *airport, cruise,etc*
- In this approach, simply select the top-ranking features.
- Feature Selection approaches:
  - Document Frequency
  - Information Gain
  - Mutual Information
  - CHI
  - A survey



Feature Selection based on Information Gain

On Widely Used Example

Outlook	Temperature	Humidity	Windy	Play
Sunny	Hot	High	False	***No***
Sunny	Hot	High	True	***No***
Overcast	Hot	High	False	***Yes***
Rainy	Mild	High	False	***Yes***
Rainy	Cool	Normal	False	***Yes***
Rainy	Cool	Normal	True	***No***
Overcast	Cool	Normal	True	***Yes***
Sunny	Mild	High	False	***No***
Sunny	Cool	Normal	False	***Yes***
Rainy	Mild	Normal	False	***Yes***
Sunny	Mild	Normal	True	***Yes***
Overcast	Mild	High	True	***Yes***
Overcast	Hot	Normal	False	***Yes***
Rainy	Mild	High	True	***No***

Features/ Attributes

Label

You may think the most important feature is the one that can be most related to the label.

Impurity of Splits

- S contain 20 occurrences of P and 20 of N.
- Assume each data has three binary features f1, f2, f3. Then, based on each feature, we are going to have three possible splits on the data.
- S1 means the feature is 0 and S2 means the feature is 1.
- For feature 1: S1 = 20P and S2 = 20N
- For feature 2: S1 = 10P, 10N and S2 = 10P, 10N
- For feature 3: S1 = 17P, 1N and S2 = 3P, 19N

Entropy

- Entropy is the measure of the information in a set of examples.

$$Entropy = -\sum_{i=1}^{K} p_i log_2 p_i$$

  - Where i={1,...,K}, K is the number of possible actions, pi is the proportion of each action i in the example set
  - For example: $Entropy([9*, 5+, 6-]) = -\frac{9}{20} log_2 \frac{9}{20} - \frac{5}{20} log_2 \frac{5}{20} - \frac{6}{20} log_2 \frac{6}{20}$

- High Entropy: more information
- Low Entropy: less information

Properties of Entropy

- Maximized when events are heterogeneous (impure):
  - A set of many mixed classes (say, rgb OOO) is unpredictable. High Entropy

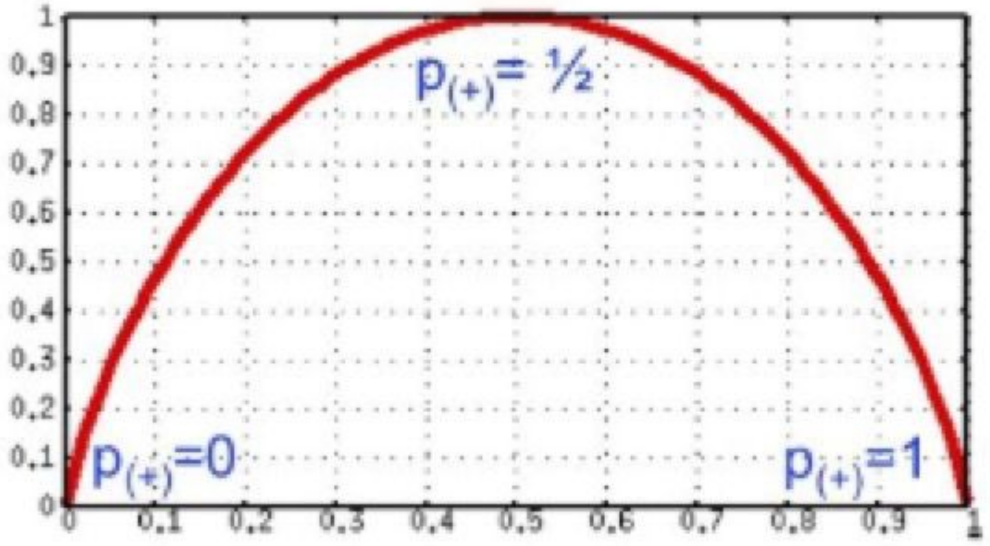
$$Entropy = log_2 K \qquad \text{if all } p_i = \frac{1}{K}$$

- Minimized when events are homogenous (pure):
  - A set of only one class (say, blue OOO) is extremely predictable. Low entropy

$$Entropy = 0 \qquad \text{if one } p_i = 1 \text{ the rest are zeros}$$

Entropy for binary case

- *S* is a sample of training examples
  - P+ is the proportion of positive examples in S
  - P- is the proportion of negative examples in S



- Entropy measures the impurity of S

$$Entropy(S) = -p_+ log_2 p_+ - p_- log_2 p_-$$

$$Entropy([9+, 5-]) = -\frac{9}{14} log_2(\frac{9}{14}) - \frac{5}{14} log_2(\frac{5}{14}) = 0.94$$

Information Gain

- Entropy:

$$E(X) = -\sum_{i=1}^{K} p(X = X_i) log_2 p(X = X_i)$$

  - **Intuition**: uncertainty of X, information contained in X, expected information bits required to represent X.
- Conditional Entropy

$$E(X|Y) = \sum_{i=1} p(Y = Y_i) E(X|Y = Y_i)$$

  - **Intuition**: given y, how much uncertainty remains in X
- **Mutual Information** (Information Gain)

$$I(X, Y) = E(X) - E(X|Y) = E(Y) - E(Y|X)$$

High IG, More Entropy Removed

  - **Intuition**: how much knowing Y reduces uncertainty about X, and vice versa.

IG: Example

Outlook	Temperature	Humidity	Windy	Play
Sunny	Hot	High	False	*No*
Sunny	Hot	High	True	*No*
Overcast	Hot	High	False	*Yes*
Rainy	Mild	High	False	*Yes*
Rainy	Cool	Normal	False	*Yes*
Rainy	Cool	Normal	True	*No*
Overcast	Cool	Normal	True	*Yes*
Sunny	Mild	High	False	*No*
Sunny	Cool	Normal	False	*Yes*
Rainy	Mild	Normal	False	*Yes*
Sunny	Mild	Normal	True	*Yes*
Overcast	Mild	High	True	*Yes*
Overcast	Hot	Normal	False	*Yes*
Rainy	Mild	High	True	*No*

$$E = -\sum_{i=1}^{K} p_k log_2 k$$

$$= -\frac{5}{14}\log_2\frac{5}{14} - \frac{9}{14}\log_2\frac{9}{14}$$
$$= 0.94$$

IG: Example

Outlook	Temperature	Humidity	Windy	Play
Sunny	Hot	High	False	*No*
Sunny	Hot	High	True	*No*
Overcast	Hot	High	False	*Yes*
Rainy	Mild	High	False	*Yes*
Rainy	Cool	Normal	False	*Yes*
Rainy	Cool	Normal	True	*No*
Overcast	Cool	Normal	True	*Yes*
Sunny	Mild	High	False	*No*
Sunny	Cool	Normal	False	*Yes*
Rainy	Mild	Normal	False	*Yes*
Sunny	Mild	Normal	True	*Yes*
Overcast	Mild	High	True	*Yes*
Overcast	Hot	Normal	False	*Yes*
Rainy	Mild	High	True	*No*

$$\Delta E(Humidity) = E - \frac{m_{i=H}}{m} E(i = H) - \frac{m_{i=N}}{m} E(i = N)$$

$$= 0.94 - \frac{7}{14} H_L - \frac{7}{14} H_R$$

IG: Example

Outlook	Temperature	Humidity	Windy	Play
Sunny	Hot	High	False	*No*
Sunny	Hot	High	True	*No*
Overcast	Hot	High	False	*Yes*
Rainy	Mild	High	False	*Yes*
Rainy	Cool	**Normal**	False	*Yes*
Rainy	Cool	**Normal**	True	*No*
Overcast	Cool	**Normal**	True	*Yes*
Sunny	Mild	High	False	*No*
Sunny	Cool	**Normal**	False	*Yes*
Rainy	Mild	**Normal**	False	*Yes*
Sunny	Mild	**Normal**	True	*Yes*
Overcast	Mild	High	True	*Yes*
Overcast	Hot	**Normal**	False	*Yes*
Rainy	Mild	High	True	*No*

$$\Delta E(Humidity) = E - \frac{m_{i=H}}{m} E(i = H) - \frac{m_{i=N}}{m} E(i = N)$$

$$= 0.94 - \frac{7}{14} H_L - \frac{7}{14} H_R$$

$$H_L = -\frac{6}{7}\log_2\frac{6}{7} - \frac{1}{7}\log_2\frac{1}{7}$$

IG: Example

Outlook	Temperature	Humidity	Windy	Play
Sunny	Hot	**High**	False	***No***
Sunny	Hot	**High**	True	***No***
Overcast	Hot	**High**	False	***Yes***
Rainy	Mild	**High**	False	***Yes***
Rainy	Cool	Normal	False	***Yes***
Rainy	Cool	Normal	True	***No***
Overcast	Cool	Normal	True	***Yes***
Sunny	Mild	**High**	False	***No***
Sunny	Cool	Normal	False	***Yes***
Rainy	Mild	Normal	False	***Yes***
Sunny	Mild	Normal	True	***Yes***
Overcast	Mild	**High**	True	***Yes***
Overcast	Hot	Normal	False	***Yes***
Rainy	Mild	**High**	True	***No***

$$\Delta E(Humidity) = E - \frac{m_{i=H}}{m} E(i = H) - \frac{m_{i=N}}{m} E(i = N)$$

$$= 0.94 - \frac{7}{14} H_L - \frac{7}{14} H_R$$

$$H_L = -\frac{6}{7}\log_2\frac{6}{7} - \frac{1}{7}\log_2\frac{1}{7}$$
$$= 0.592$$
$$H_R = -\frac{3}{7}\log_2\frac{3}{7} - \frac{4}{7}\log_2\frac{4}{7}$$
$$= 0.985$$

IG: Example

Outlook	Temperature	Humidity	Windy	Play
Sunny	Hot	High	False	***No***
Sunny	Hot	High	True	***No***
Overcast	Hot	High	False	***Yes***
Rainy	Mild	High	False	***Yes***
Rainy	Cool	Normal	False	***Yes***
Rainy	Cool	Normal	True	***No***
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Sunny	Mild	High	False	***No***
Sunny	Cool	Normal	False	***Yes***
Rainy	Mild	Normal	False	***Yes***
Sunny	Mild	Normal	True	***Yes***
Overcast	Mild	High	True	***Yes***
Overcast	Hot	Normal	False	***Yes***
Rainy	Mild	High	True	***No***

$$\Delta E(Humidity) = E - \frac{m_{i=H}}{m} E(i=H) - \frac{m_{i=N}}{m} E(i=N)$$

$$= 0.94 - \frac{7}{14} H_L - \frac{7}{14} H_R$$

$$0.94 - \frac{7}{14} 0.592 - \frac{7}{14} 0.985$$

$$= 0.94 - 0.296 - 0.4925$$

$$= 0.1515$$

IG: Example

Outlook	Temperature	Humidity	Windy	Play
Sunny	Hot	High	False	***No***
Sunny	Hot	High	True	***No***
Overcast	Hot	High	False	***Yes***
Rainy	Mild	High	False	***Yes***
Rainy	Cool	Normal	False	***Yes***
Rainy	Cool	Normal	True	***No***
Overcast	Cool	Normal	True	***Yes***
Sunny	Mild	High	False	***No***
Sunny	Cool	Normal	False	***Yes***
Rainy	Mild	Normal	False	***Yes***
Sunny	Mild	Normal	True	***Yes***
Overcast	Mild	High	True	***Yes***
Overcast	Hot	Normal	False	***Yes***
Rainy	Mild	High	True	***No***

1. Compute the information gain for the rest three features:
- outlook
- temperature
- windy

2. Should we select features with high IG or low IG?

When it comes to text mining

- The previous features/attributes will be “words” or “terms”
- The information gain of a term measures:
    - The expected reduction in entropy caused by partitioning the sample documents according to the term:

$$IG(t) = -\sum_{i=1}^{m} p(c_i) log p(c_i) + p(t) \sum_{i=1}^{m} p(c_i|t) log p(c_i|t)) + p(\bar{t}) \sum_{i=1}^{m} p(c_i|\bar{t}) log p(c_i|\bar{t}))$$

where
t is a term,
m is the total number of classes
$p(c_i)$ is the percentage of documents in category ci from total sample documents
$p(t)$ is the percentage of documents in which term t is present
$p(\bar{t})$ is the percentage of documents in which term t is absent
$p(c_i|t)$ is the conditional probability of category given term t
$p(c_i|\bar{t})$ is conditional probability of category given term t is absent