

# Text Classification using knn

# What is Text mining?

- To discover the useful patterns/contents from the large amount of data that can be structured or unstructured.



# Text mining

- What can be used for text mining??
  - Classification/categorization
  - Clustering
  - Summarization
  - Retrieval.....



# Pre-processing of text

- Tokenisation: Separation of tokens with removal of special symbols that are not required in the text.
- Stemming: Converging the words like 'playing', 'played' into 'play'.
- Lemmatisation: Returning the base form of the word.  
Eg: heard – 'hear'
- Case folding: Conversion of case- caps to small
- Stop word removal: 'the', 'an', 'on'... are called stop words. They are of limited use when it comes to determine the weight of a document for retrieval.
- Normalisation: Equivalence classing. Use of synonyms. Spell check too can be performed here.

# Different models for representation

- Term frequency and weighing
  - Bag of words: number of occurrence of word where the exact ordering is ignored.
- Vector space model and so on....



# Term frequency

- Term frequency is the number of times, the term occurs in the document.
- Eg: 'Cricket is a game. Sam likes the game of cricket.'

| Ter<br>ms          | Cricket | is   | a    | game | Sam  | likes | the  | of   |
|--------------------|---------|------|------|------|------|-------|------|------|
| Freq               | 2       | 1    | 1    | 2    | 1    | 1     | 1    | 1    |
| nor<br>mali<br>sed | 2/10    | 1/10 | 1/10 | 2/10 | 1/10 | 1/10  | 1/10 | 1/10 |

- Each documents varies in size.
- Thus the frequency of terms differs with the size. And it impacts the smaller ones
- Thus it is normalised

# Inverse document frequency

- The whole intension for the terms generation is finding out relevant documents to one specific or to a query that is fired.
- Occurrence of a term more times cannot indicate the power or potential to determine relevance.
- Thus their weight needs to be scaled down.
- We use idf :
- $idf_t = \log \left( \frac{N}{df_t} \right)$ 
  - Where t is the terms, N = total no. of documents and
  - $df_t$  = no. of documents with t term.

- So,
- For 3 documents:
  - $D_1$  = Cricket is a game. Sam likes the game of cricket.
  - $D_2$  = Do you play cricket?
  - $D_3$  = Playing any game is good for health. I play basketball.
  - For  $D_1$ , the idf values:

|               | Cricket           | is                | a                 | game              | Sam               | likes             | the               | of                |
|---------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|
| Tf            | 2                 | 1                 | 1                 | 2                 | 1                 | 1                 | 1                 | 1                 |
| Normalised tf | 2/10              | 1/10              | 1/10              | 2/10              | 1/10              | 1/10              | 1/10              | 1/10              |
| idf           | $\text{Log}(3/2)$ | $\text{Log}(3/2)$ | $\text{Log}(3/1)$ | $\text{Log}(3/2)$ | $\text{Log}(3/1)$ | $\text{Log}(3/1)$ | $\text{Log}(3/1)$ | $\text{Log}(3/1)$ |



# Tf-idf

- To find relevant documents, generally a combined weighted approach is used called as tf-idf.
- So:
  - $w_{t,d} = tf_{t,d} * idf_t$
- Representation of set of documents as vectors in common vector space is known as vector space model.

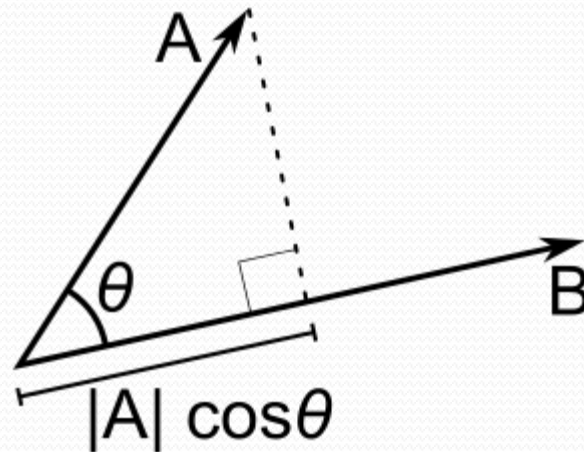


# Calculating similarities between the documents

- Often cosine similarity is used.
- It is a measure of orientation and not magnitude.
- We are interested in determining the orthogonality.



- More about Dot product:
  - When we consider the dot product of two vectors say  $\vec{a} \cdot \vec{b}$ , we are trying to project a into b. The angle between these vectors determines the orthogonality. If it is 90 degrees, the vectors are orthogonal.



# Cosine similarity

Cosine Similarity  $(d1, d2) = \text{Dot product}(d1, d2) / \|d1\| * \|d2\|$

Dot product  $(d1, d2) = d1[0] * d2[0] + d1[1] * d2[1] + \dots + d1[n] * d2[n]$

$\|d1\| = \text{square root}(d1[0]^2 + d1[1]^2 + \dots + d1[n]^2)$

$\|d2\| = \text{square root}(d2[0]^2 + d2[1]^2 + \dots + d2[n]^2)$

# Classifying the text documents

- For the given training data:
  - Calculate tf of each document
  - Normalize it
  - For a new unknown test data, calculate tf, normalise
  - Use kNN to classify this document using cosine similarity.
- Use training data:
  - D1: “This is big classroom” - classroom
  - D2: “Classroom has many benches” - classroom
  - D3: “This is house” - house
  - D4: “The house has garden” - house
  - D5: “The house is big” - house
  - Classify: ‘Big house’ - house