TEXT MINING

- Text is everywhere.
  - Twitter
  - Blogs
  - Articles
  - Emails
  - Books
  - surveys
  - Etc
- What do we do with it?
- Unstructured: How do we represent it?

TEXT MINING

- Application Topics:
  - Information Retrieval: retrieve information
  - Search: Search engines
  - Classification: Categorize documents
  - Clustering: Organize
  - Topic Modelling: Find the topic, theme of text
  - Sentiment Analysis: What is the sentiment
  - POS: Parts of speech tagging
  - Record Linkage: Link data sources
  - Speech to text
  - Machine Translation

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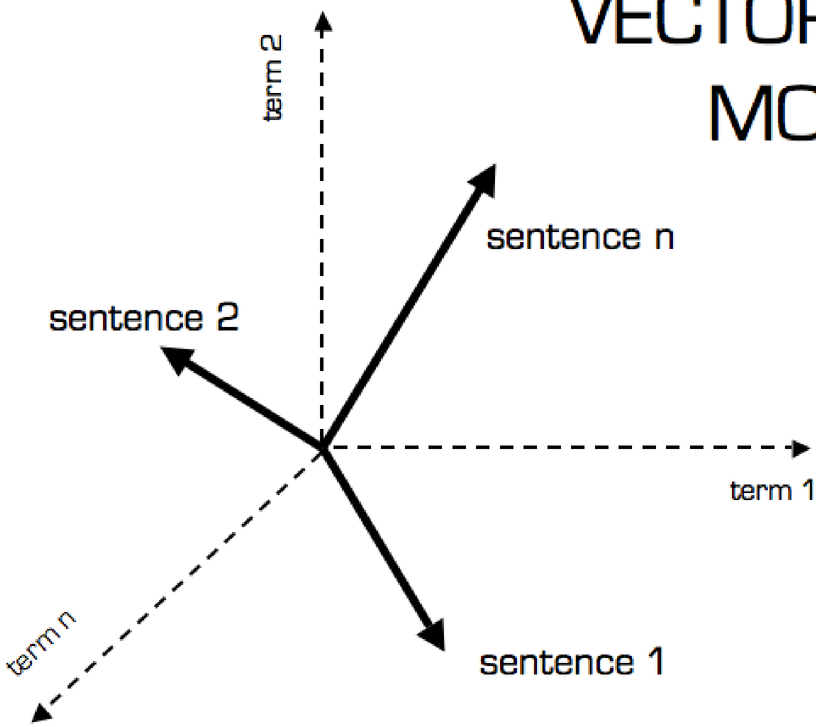
  - Each document can be represented as a vector

VECTOR SPACE MODEL



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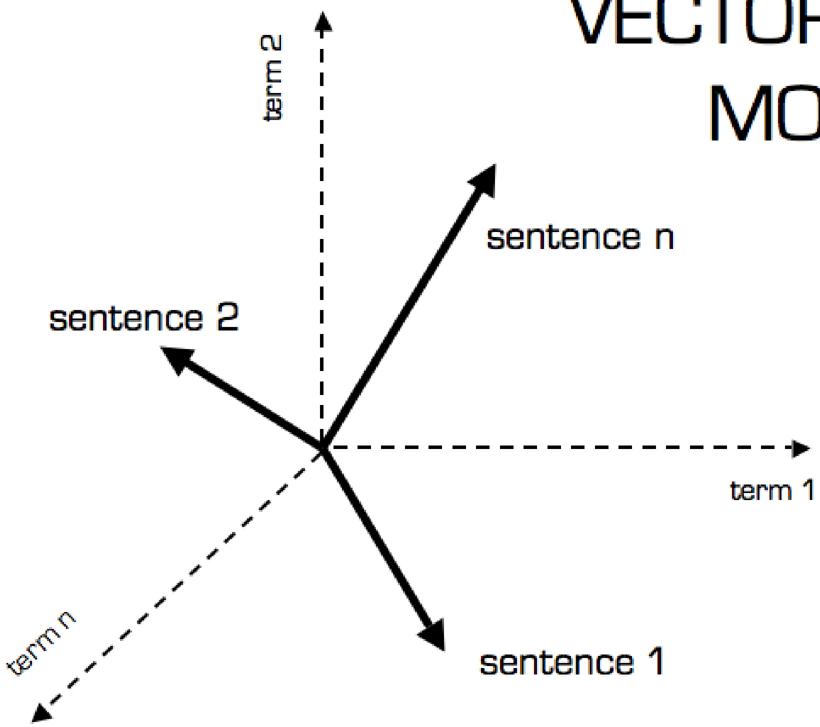
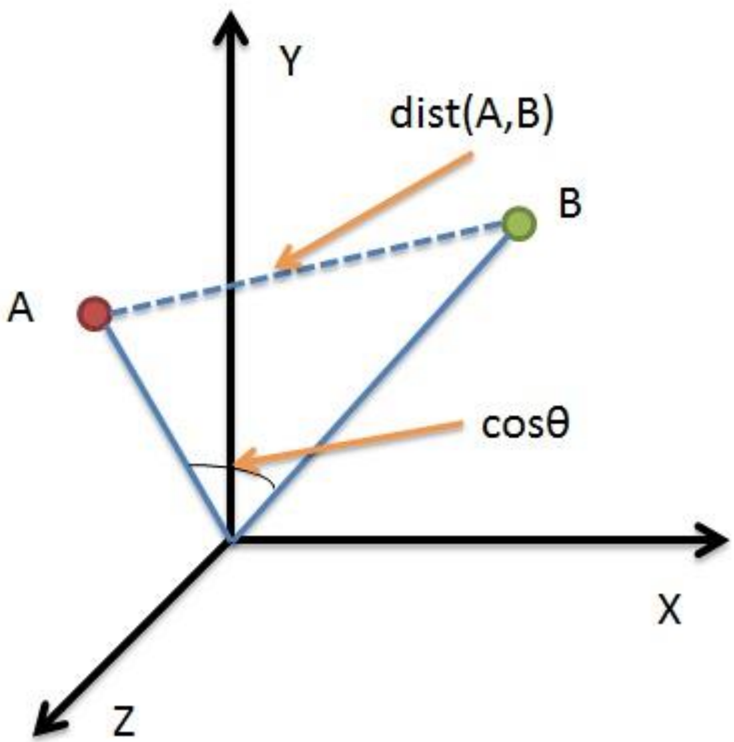


Document:

- Classification
- Clustering
  - Distance
  - Cosine similarity

$$similarity = \cos(\theta) = \frac{A \cdot B}{\|A\| \|B\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2} \sqrt{\sum_{i=1}^{n} B_i^2}}$$


Y
dist(A,B)
B
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X
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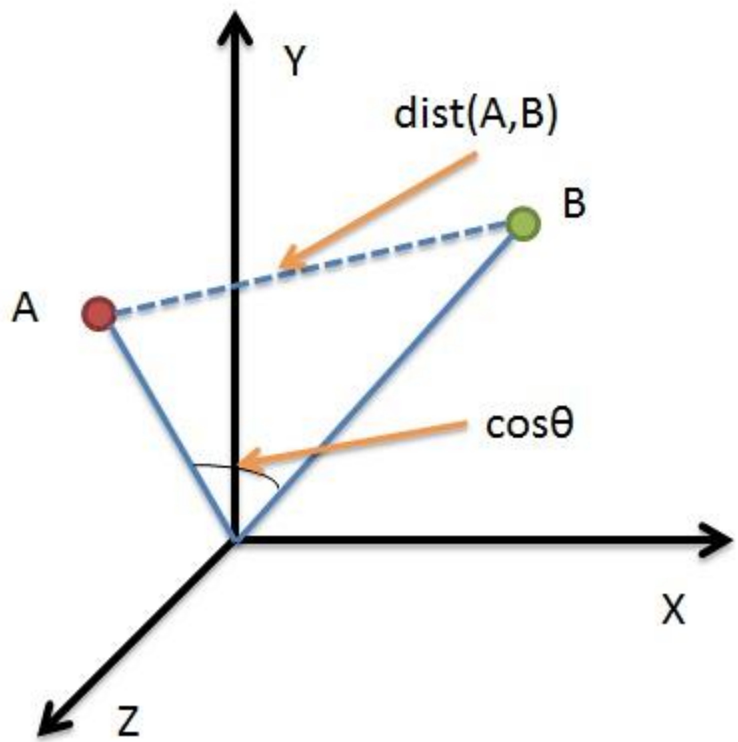

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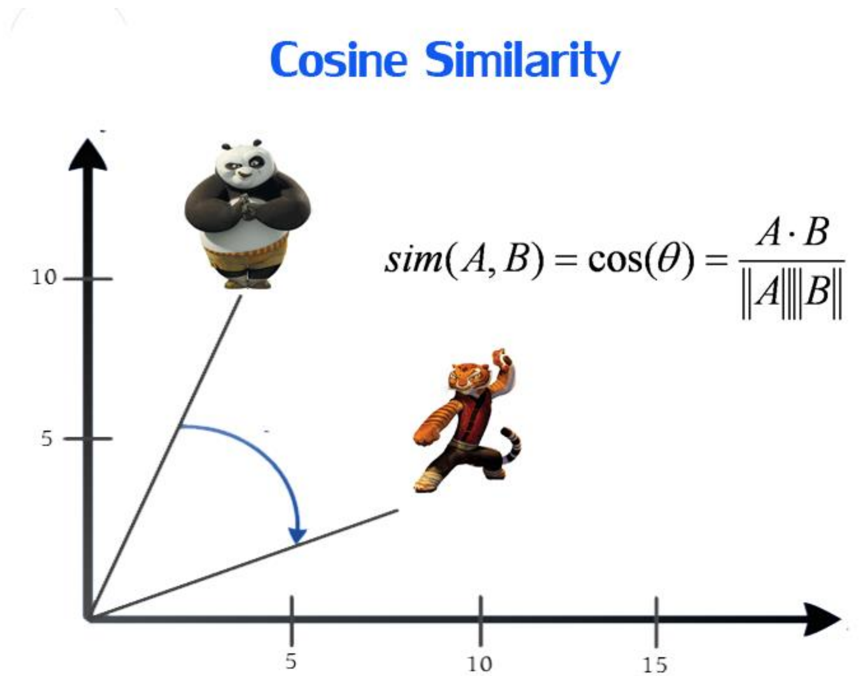

Cosine Similarity
$sim(A,B) = \cos(\theta) = \frac{A \cdot B}{\|A\|\|B\|}$
10
5
5
10
15

- Observations:
  - High dimensional: Lot’s of tokens, characters, etc
  - Sparse: Most documents have a small number of tokens
  - Common words: The, I, and, etc
  - Word similarity: grocery, groceries
  - Word ordering: Only considers presence of words not ordering
    - Is this the first document
    - This is the first document
  - Misspelling, Acronyms, Ambiguity, etc

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- Stemming: Reduce word to its stem, root
  - Stem, stemming, stemmer, stemmed -> stem

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  - Log(1) = 0
  - So common words IDF value goes to 0 thus TF-IDF gets small

Topic Modelling: Finding the topics, themes occurring in a collection of documents

- LDA: Latent Dirichlet Allocation
  - Blei, Ng, Jordan 2003
  - Each document assumed to be a mixture of topics
  - Probability of document to topic
  - Words associated with topics
- Matrix Factorization
- Etc

Useful Python Tools:

- NLTK
- Sklearn
- LDA