EPL660: Information Retrieval and Search Engines – Lab 11

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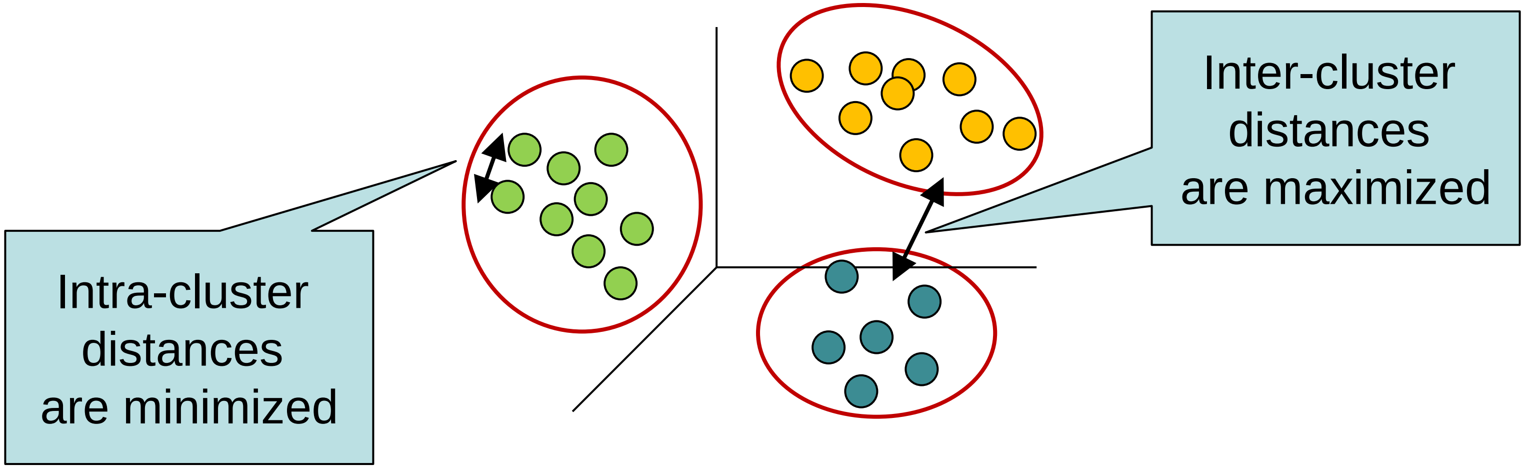
Text Clustering & Classification

Text Clustering Problem

- Input: a set of text-based, **un-labeled** documents (e.g. newspaper articles, emails, movie reviews, movie abstracts)
- Output: partition unlabeled unclustered docs into disjoint subsets – *clusters* – (hard clustering) such that:
  - Docs within a cluster are very similar
  - Docs in different clusters are very different



Text Classification Problem

- Input: a set of text-based, **labeled** documents
  - newspaper articles classified as sports / politics, …
  - emails classified as spam / not spam
  - movie reviews classified as positive / negative / neutral

  and a set of text-based, **un-labeled** documents
- Output: choose correct class label for each un-labeled document

Clustering: Unsupervised learning
Classification: Supervised learning

Text Clustering Applications

- Improving search applications
  - Improving search recall
    - When a query matches a document its whole cluster can be returned
  - Better user interface and navigation: search with less typing
  - Speeding up vector space retrieval
    - Cluster-based retrieval gives faster search
- Forensic data analysis
  - analyze patterns and detect suspicious & fraudulent activities in a large set of unstructured text files (emails, log files, social media accounts, etc.)

Text Clustering Applications

- Detect the current hot topics on twitter
  - Find what people are talking about (generally or in a specific geographic area)
- Find what topics people at a conference talk about, such as, what paper they liked most or who to network with as likes similar topics
- Use the cluster to pre-populate suggest-box to autocomplete tags when users type
- Cluster movies based on abstract and description and show related movies (augment recommendations)

Preprocessing steps

- Obtain dataset
- Clean dataset
  - Remove unneeded information from documents e.g. html tags (if text comes from websites), numbers
  - Convert to lowercase
- Tokenization
  - Parse documents into smaller units (tokens) such as words and phrases (n-grams)
    - Token separators: whitespaces and punctuation
  - Create vocabulary (list of words)
- Remove stop words
  - Stop words: frequently occurring words that don't carry much meaning e.g. and, of, in, …

Preprocessing steps

- Stemming and lemmatization
  - Different tokens might carry out similar information (e.g. tokenization and tokenizing)
  - Avoid calculating similar information repeatedly by reducing all tokens to its base form using various stemming and lemmatization dictionaries
- Features Creation
  - Transform dataset in a format supported by machine learning algorithms → create features for each document
    - e.g. convert document to a numerical vector: [0,2,1,0,0,7]
  - **bag of words** model, **tf/idf** model (see appendix)
- Feature extraction (minimize # of features)
  - singular vector decomposition (SVD), principal component analysis (PCA), Linear Discr. Analysis (LDA)

Machine Learning Methods

- Standard (text) clustering methods:
  - K-means
  - Bisecting K-means [N/A sklearn; download here]
  - Agglomerative Hierarchical Clustering
- Standard (text) classification methods:
  - Support Vector Classifier
  - Random Forest (decision tree) Classifier
  - Naïve Bayes Classifier

Hands-on

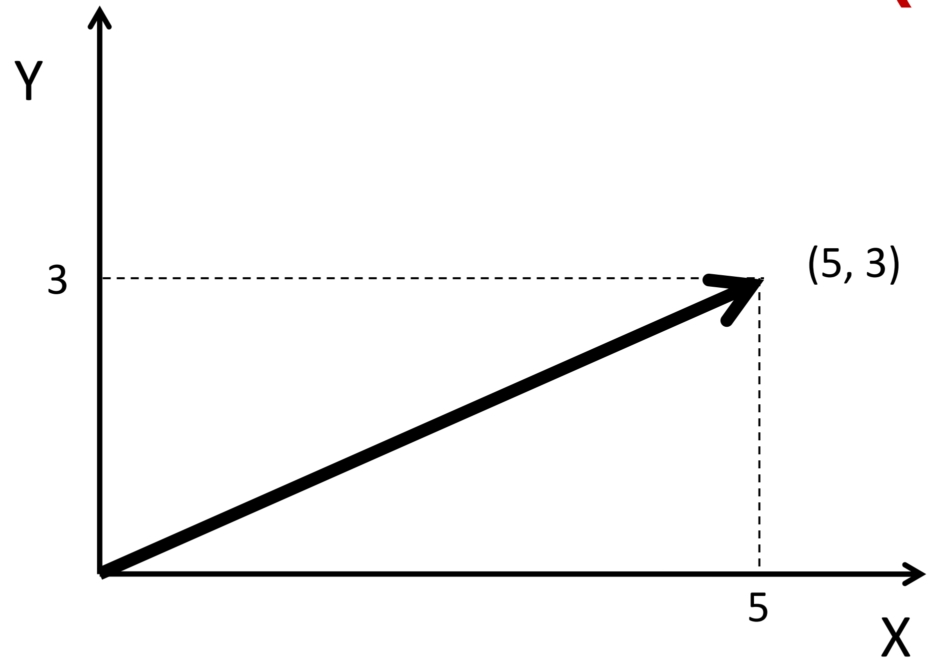
- All software needed in installed on VM. If you want to install software to your machine:
  - Install Anaconda Data Science Platform
  - Install Natural Language Toolkit that involves tokenizers, stopwords, stemmers, datasets, etc
    - `conda install nltk`
  - Install html parsing library
    - `conda install beautifulsoup4`
- Download lab tutorial and go through the steps
- After finalizing lab instructions submit the python file to Moodle.

Vector Space Model: Bag of words & tf/idf models

Appendix

Data as Vectors

- Machine learning text clustering/classification methods require vectors of numbers → convert **raw text documents into vectors (vector space model)**



weights

- The vector denoted by point (5, 3) is simply 5 x + 3 y
  - Array([5, 3]) or HashMap([0 => 5], [1 => 3])

Data as Vectors

- Document vector: v = a1*v1 + a2*v2 + …
  - a1, a2, … : weights
  - v1, v2, … : components (terms in document vectors)
- The **weight** of a component of a document vector can be represented by **term frequency (tf)** and combination of term frequency and **inverse document frequency (idf)**
- Term Frequency denoted by tf, is the number of occurrences of a term t in the document D
  - E.g. given document "hello world hello", document vector = 2 * "hello" + 1 * "world"
  - This is the **Bag of words model**

Data as Vectors

- Problem: all terms are equally important
  - certain terms have little or no discriminating power in determining relevance on a query
    - e.g. collection of documents on the auto industry is likely to have the term auto in almost every document
- Inverse Document Frequency of a term t, denoted by idf, is log(N/df), where:
  - N: total number of documents in the space,
  - df: total number of documents that contain the term t
- small idf:
  - a term occurs in many documents
- high idf:
  - a term occurs in a small number of docs

Vectors: the tf-idf model

- The combination of tf and idf is the most popular weight used in case of documents similarity exercises

- $\text{tf-idf}_{t,d} = \text{tf}_{t,d} * \text{idf}_t$

- Weight is the highest, when term t occurs many times within a small number of documents
- Weight is the lowest, when term t occurs fewer times in a document or occurs in many documents

tf-idf example

- **D1 = “Shipment of gold damaged in a fire”**
- **D2 = “Delivery of silver arrived in a silver truck”**
- **D3 = “Shipment of gold arrived in a truck”**

Document vector of D1

Terms	**tf_i**					**IDF_i**	**Weights = tf_i * IDF_i**		
	D1	D2	D3	df_i	N/df_i		D1	D2	D3
a	1	1	1	3	1	0	0.0000	0.0000	0.0000
arrived	0	1	1	2	1.5	0.1761	0.0000	0.1761	0.1761
damaged	1	0	0	1	3	0.4771	0.4771	0.0000	0.0000
delivery	0	1	0	1	3	0.4771	0.0000	0.4771	0.0000
gold	1	0	1	2	1.5	0.1761	0.1761	0.0000	0.1761
fire	1	0	0	1	3	0.4771	0.4771	0.0000	0.0000
in	1	1	1	3	1	0	0.0000	0.0000	0.0000
of	1	1	1	3	1	0	0.0000	0.0000	0.0000
shipment	1	0	1	2	1.5	0.1761	0.1761	0.0000	0.1761
silver	0	2	0	1	3	0.4771	0.0000	0.9542	0.0000
truck	0	1	1	2	1.5	0.1761	0.0000	0.1761	0.1761

Improving search recall

- *Cluster hypothesis* - Documents in the same cluster behave similarly with respect to relevance to information needs
- Therefore, to improve search recall:
  - Cluster docs in corpus a priori
  - When a query matches a doc *D*, also return other docs in the cluster containing *D*
- Hope if we do this: The query “car” will also return docs containing *automobile*
  - Because clustering grouped together docs containing *car* with those containing *automobile. Why?*

Speeding up vector space retrieval

- Using vector space retrieval model, documents closest to the query need to be found
- Calculate the similarity of the query to each document in the corpus
  - Very slow!
- Cluster docs in corpus a priori
  - Calculate similarity of the query to centroids
  - Return documents in the cluster of the most similar centroid