# COMP8210 — Big Data Technologies

## Week 9 Lecture 1: Practical Text Analytics

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# Programme



## Reading

- Lecture notes.

# Programme

# Web Demos

- Explosion AI: https://explosion.ai/demos/
- Analysis of tweets: https://www.csc2.ncsu.edu/faculty/healey/tweet_viz/tweet_app/
- Analysis of news: https://developer.aylien.com/text-api-demo
- Coronavirus news tracker: https://coronavirus.aylien.com/
- APIs and Demos: http://text-processing.com/
- ...

# Programming Libraries

- gensim https://radimrehurek.com/gensim/
- Spacy https://spacy.io/
- Natural Language Toolkit (NLTK) https://www.nltk.org/
- Scikit-Learn http://scikit-learn.org/stable/
- Keras https://keras.io/
- ...

# Graphical Interfaces

Usually integrated in general machine learning tools

- RapidMiner https://rapidminer.com/
- Weka https://www.cs.waikato.ac.nz/ml/weka/
- SAS Enterprise Miner, SAS Viya https://www.sas.com
- ...

# Cloud Services

- Azure Machine Learning Studio https://docs.microsoft.com/en-us/azure/machine-learning/studio-module-reference/text-analytics
- Aylien https://aylien.com/text-api/
- ...

# Comparison of Named Entity Recognition Systems

Text APIs compared in these two posts:

- https://medium.com/@boab.dale/text-analytics-apis-part-1-the-bigger-players-3ce8a93577bd
- https://becominghuman.ai/text-analytics-apis-part-2-the-smaller-players-c9e608cf7810

Table 2. *Results on the CoNLL shared task data; all values are percentages*

| | Amazon comprehend | | | Google NL | | | IBM NL | | |
|---|---|---|---|---|---|---|---|---|---|
| | Prec'n | Recall | $F_{\beta=1}$ | Prec'n | Recall | $F_{\beta=1}$ | Prec'n | Recall | $F_{\beta=1}$ |
| LOC | **76.13** | 72.66 | 74.36 | 58.81 | **86.45** | 70.00 | 70.17 | 86.15 | **77.34** |
| MISC | **58.40** | 10.40 | 17.65 | 36.76 | **19.37** | **25.37** | 2.08 | 0.14 | 0.27 |
| ORG | **74.72** | **59.24** | **66.08** | 68.03 | 48.16 | 56.40 | 69.86 | 27.63 | 39.60 |
| PER | **87.14** | 82.99 | **85.02** | 82.45 | **83.36** | 82.90 | 73.13 | 76.07 | 74.57 |
| Overall | **78.95** | 63.93 | **70.65** | 66.15 | **65.97** | 66.06 | 70.51 | 55.36 | 62.03 |

https://medium.com/@boab.dale/text-analytics-apis-part-1-the-bigger-players-3ce8a93577bd

# Programme

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# Feature Extraction and Vectorizers

- Often we want to convert text into a vector.
- This process is called feature extraction.
- This way it can be fed to data analytics modules.
- Machines do not really understand text but they are good at numbers.

# Vectorizers in Scikit-Learn

https://scikit-learn.org/stable/modules/feature_extraction.html#text-feature-extraction

## CountVectorizer

- Each vector element represents a word in the vocabulary.
- The vector element indicates the count of the word in the document.

## TfidfVectorizer

- Each vector element indicates the *tf.idf* value of the word.

## HashingVectorizer

- Uses the hashing trick to handle large text collections.
- Now, we do not know what word is mapped to what vector element.
- It can still give good results in practice, at the expense of interpretability.

# A Simple Example I

## Training a CountVectorizer

The following example uses a small corpus with just 4 sentences to train a CountVectorizer. In the process, sklearn determines the vocabulary and assigns each element of the vector to one word from the vocabulary.

```
>>> from sklearn.feature_extraction.text import CountVectorizer
>>> vectorizer = CountVectorizer()
>>> corpus = [
...     'This is the first document.',
...     'This is the second second document.',
...     'And the third one.',
...     'Is this the first document?',
... ]
>>> X = vectorizer.fit_transform(corpus)
```

# A Simple Example II

## Printing the vocabulary and the TfIdf matrix

In the following example, note how we need to use .toarray() to print the document matrix. This is because X is a sparse matrix. In the printed matrix, each row indicates one document, and each column indicates the counts of the word in each document.

```
>>> vectorizer.get_feature_names()
['and', 'document', 'first', 'is', 'one', 'second',
 'the', 'third', 'this'])

>>> X.toarray()
array([[0, 1, 1, 1, 0, 0, 1, 0, 1],
       [0, 1, 0, 1, 0, 2, 1, 0, 1],
       [1, 0, 0, 0, 1, 0, 1, 1, 0],
       [0, 1, 1, 1, 0, 0, 1, 0, 1]])
```

# A Simple Example III

## Finding the document vector of new text

Only words in the vocabulary will be used to build the vectors. So it is important that the corpus used to train the vectoriser has a representative vocabulary.

```
>>> vectorizer.transform(
      ['Something completely new.']
    ).toarray()
array([[0, 0, 0, 0, 0, 0, 0, 0, 0]])
>>> vectorizer.transform(
      ['A document with repeated document word']
    ).toarray()
array([[0, 2, 0, 0, 0, 0, 0, 0, 0]])
```

# A Simple Example IV

## Computing document similarities

Once we have converted document to vectors, we can compute document similarities, e.g. pairwise cosine similarities.

```
>>> from sklearn.metrics.pairwise import cosine_similarity
>>> cosine_similarity(X)
array([[1.        , 0.63245553, 0.2236068 , 1.        ],
       [0.63245553, 1.        , 0.1767767 , 0.63245553],
       [0.2236068 , 0.1767767 , 1.        , 0.2236068 ],
       [1.        , 0.63245553, 0.2236068 , 1.        ]])
```

# Example with TfidfVectorizer

The TfidfVectorizer uses the same API as the CountVectorizer.

```
>>> from sklearn.feature_extraction.text import TfidfVectorizer
>>> vectorizer = TfidfVectorizer()
>>> X_tfidf = vectorizer.fit_transform(corpus)
>>> X_tfidf.toarray()
array([[0.        , 0.43877674, 0.54197657, 0.43877674, 0.        ,
        0.        , 0.35872874, 0.        , 0.43877674],
       [0.        , 0.27230147, 0.        , 0.27230147, 0.        ,
        0.85322574, 0.22262429, 0.        , 0.27230147],
       [0.55280532, 0.        , 0.        , 0.        , 0.55280532,
        0.        , 0.28847675, 0.55280532, 0.        ],
       [0.        , 0.43877674, 0.54197657, 0.43877674, 0.        ,
        0.        , 0.35872874, 0.        , 0.43877674]])
>>> cosine_similarity(X_tfidf)
array([[1.        , 0.43830038, 0.1034849 , 1.        ],
       [0.43830038, 1.        , 0.06422193, 0.43830038],
       [0.1034849 , 0.06422193, 1.        , 0.1034849 ],
       [1.        , 0.43830038, 0.1034849 , 1.        ]])
```

# HashingVectorizer

- For large data sets, just keeping the large vocabulary and intermediate operations in memory can be too expensive.
- sklearn provides HashingVectorizer, which is like CountVectorizer but it does not keep track of a vocabulary.
- Instead, it uses the hashing trick:
  - Use a hash function to map a word to a number.
  - Normally, different words will map to different numbers.
  - But in large vocabularies, some words might map to the same number, creating collisions.
  - There is a tradeoff between speed (number of features) and precision/interpretability since now we do not know what word (or words) is represented in each column of the document matrix.

# Example of Use of HashingVectorizer

This example defines a HashingVectorizer with 5 features. Normally we want a large number of features. The default is $2^{20}$, roughly 1 million features.

```
>>> from sklearn.feature_extraction.text import HashingVectorizer
>>> hv = HashingVectorizer(n_features=5)
>>> hv.transform(corpus).toarray()
array([[ 0.        , -0.57735027,  0.57735027, -0.57735027,  0.        ],
       [ 0.81649658,  0.        ,  0.40824829, -0.40824829,  0.        ],
       [-0.5       ,  0.5       ,  0.        , -0.5       , -0.5       ],
       [ 0.        , -0.57735027,  0.57735027, -0.57735027,  0.        ]])
>>> cosine_similarity(hv.transform(corpus))
array([[ 1.        ,  0.47140452,  0.        ,  1.        ],
       [ 0.47140452,  1.        , -0.20412415,  0.47140452],
       [ 0.        , -0.20412415,  1.        ,  0.        ],
       [ 1.        ,  0.47140452,  0.        ,  1.        ]])
```

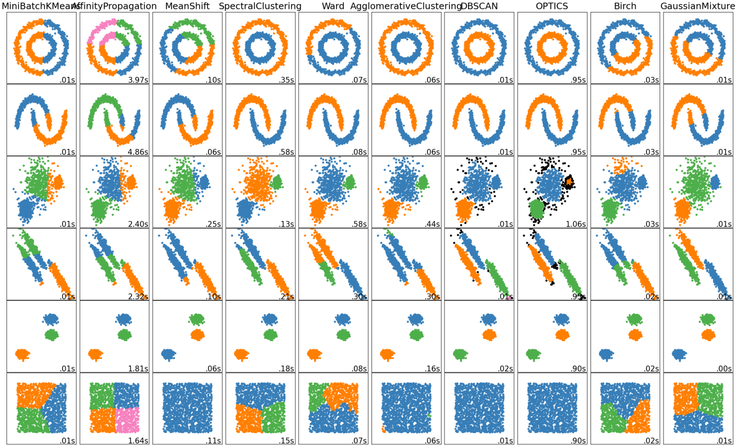
# Programme

# Clustering

https://scikit-learn.org/stable/modules/clustering.html

- Clustering is an example of unsupervised machine learning.
  - We do not need to manually annotate the data.
  - The system learns to find some structure in the data.
- Clustering identifies groups ("clusters") of documents based on their similarity.
- Clustering needs to know how to compute the similarity between two documents.
  - Several similarity metrics are possible, e.g. Euclidean (distance), cosine (similarity), ...
  - https://scikit-learn.org/stable/modules/classes.html#module-sklearn.metrics.pairwise
- sklean provides many types of clustering algorithms.

# Sklearn's Cluster Comparison chart



# An Example with KMeans Clustering

https://scikit-learn.org/stable/modules/generated/sklearn.cluster.KMeans.html

```
>>> from sklearn.cluster import KMeans
>>> import numpy as np
>>> X = np.array([[1, 2], [1, 4], [1, 0],
...               [10, 2], [10, 4], [10, 0]])
>>> kmeans = KMeans(n_clusters=2, random_state=0).fit(X)
>>> kmeans.labels_
array([1, 1, 1, 0, 0, 0], dtype=int32)
>>> kmeans.predict([[0, 0], [12, 3]])
array([1, 0], dtype=int32)
>>> kmeans.cluster_centers_
array([[10.,  2.],
       [ 1.,  2.]])
```

# An Example with Real Text

(see notebook for text clustering of tweets)

# Topic Modelling

- Topic modelling is another example of unsupervised machine learning.
- Whereas clustering is a generic algorithm for many kinds of data, topic modelling is specific to text.
- Topic modelling can be used to convert documents to vectors.
- It can be also used to identify specific topics in a document.

# Topic Modelling with Latent Dirichlet Allocation

- LDA is a generative model.
  - It assumes that each document has been generated by picking random words from a pre-defined set of topics.
- The task of LDA is to try to unravel:
  - For each document, what percentage of words come from each topic.
  - For each topic, what is the distribution of words.

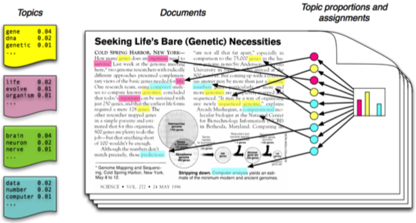



Figure source: Blei, D. M. (2012). Probabilistic topic models. *Communications of the ACM*, *55*(4), 77-84.

# LDA in SKLearn

- SKLearn's LatentDirichletAllocation offers the same API as with other tools, plus some specialised methods.
    - https://scikit-learn.org/stable/auto_examples/applications/plot_topics_extraction_wi
- In addition, pyLADvis is a library that can be used to visualise the topics.
- (See related notebook)

# Take-home Messages

- There are a wide range of text demos and APIs on the web. Explore them, use them for this unit's exercises and assignment.
- We have explored how to process text using Scikit-Learn but there are more tools available in Python and other programming languages.

# What's Next

## Week 10

- Visual Analytics.