Big Data and Automated Content Analysis Part I+II

Week 11 – Wednesday

»Unsupervised Machine Learning I«

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Today

1. Recap: Types of Automated Content Analysis
2. Finding similar variables
   - An introduction to dimensionality reduction
   - Principal Component Analysis and Singular Value Decomposition
   - Multidimensional scaling
3. Finding similar cases
   - k-means clustering
   - Hierarchical clustering
4. Important notes
5. Next meetings

Recap: Types of Automated Content Analysis

	Methodological approach		
	Counting and Dictionary	*Supervised Machine Learning*	*Unsupervised Machine Learning*
Typical research interests and content features	visibility analysis sentiment analysis subjectivity analysis	frames topics gender bias	frames topics
Common statistical procedures	string comparisons counting	support vector machines naive Bayes	principal component analysis cluster analysis latent dirichlet allocation semantic network analysis

Some terminology

Supervised machine learning

You have a dataset with both predictor and outcome (independent and dependent variables; features and labels) — a *labeled* dataset.

Some terminology

Supervised machine learning

You have a dataset with both predictor and outcome (independent and dependent variables; features and labels) — a *labeled* dataset. Think of regression: You measured `x1`, `x2`, `x3` and you want to predict `y`, which you also measured

Some terminology

Supervised machine learning

You have a dataset with both predictor and outcome (independent and dependent variables; features and labels) — a *labeled* dataset.

Unsupervised machine learning

You have no labels.

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Supervised machine learning

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Unsupervised machine learning

You have no labels. (You did not measure y)

Some terminology

Unsupervised machine learning

You have no labels.

Again, you already know some techniques to find out how `x1`, `x2`,... `x_i` co-occur from other courses:

- Principal Component Analysis (PCA) and Singular Value Decomposition (SVD)
- Cluster analysis
- Topic modelling (Non-negative matrix factorization and Latent Dirichlet Allocation)
- ...

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. . . but we'll distinguish two today:

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2. Finding similar cases (clustering)

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... but we'll distinguish two today:

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Are we more interested in which features "belong together" or which cases "belong together"?

There are many other techniques than those presented today, and vice versa, those presented today can also be used for other purposes

Finding similar variables

An introduction to dimensionality reduction

Dimensionality reduction

dimensionality = the number of features we have

(1) Explorative data analysis and visualization

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(2) The curse of dimensionality

More features means more data (good!), but:

- Too many features can lead to unfeasible computation times
- We need more training cases to increase the likelihood that the possible combinations actually occur

Dimensionality reduction

First approach: feature selection

- Only choose the features that are really relevant

Example: Exclude all terms that occur in more than 50% of the documents, or in less than $n = 5$ documents:

```
vec = CountVectorizer(max_df=0.5, min_df=5)
```

https://scikit-learn.org/stable/modules/generated/sklearn.feature_extraction.text.CountVectorizer.html

Dimensionality reduction

Second approach: feature extraction

- Create a smaller set of features
- E.g.: 1,000 features $\rightarrow$ PCA to reduce to 50 components $\rightarrow$ SML with these 50 component scores as features

Dimensionality reduction

So, we can use unsuvised ML as a dimension reduction step in a supervised ML pipeline. But it can also be a goal in itself, to

understand the data better or to visualize them.

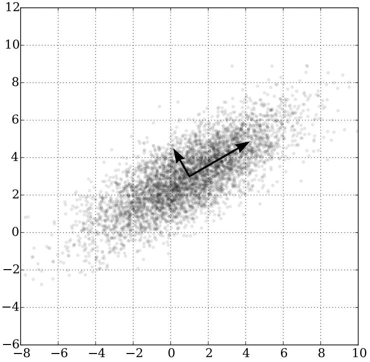
Finding similar variables

Principal Component Analysis (PCA) and Singular Value Decomposition (SVD)

PCA

- related to and often confused with Factor Analysis (same menu item in SPSS – many people who believe they run FA actually run PCA!)
- Components are ordered (first explains most variance)
- Components do *not* necessarily carry a meaningful interpretation

PCA



https://upload.wikimedia.org/wikipedia/commons/f/f5/GaussianScatterPCA.svg

Preparation: Import modules and get some texts

```
from sklearn import datasets
from sklearn.decomposition import PCA
from sklearn.decomposition import TruncatedSVD
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import FunctionTransformer
import matplotlib.pyplot as plt
%matplotlib inline

autotexts = datasets.fetch_20newsgroups('rec.autos', remove=('headers',
     'footers', 'quotes'), subset='train')['data']
religiontexts = datasets.fetch_20newsgroups('soc.religion.christian',
     remove=('headers', 'footers', 'quotes'), subset='train')['data']

texts = autotexts[:20] + religiontexts[:20]
```

Running PCA

PCA does not accept a *sparse matrix* as input (but the CountVectorizer gives one as output), so we need to transform it into a *dense matrix*.

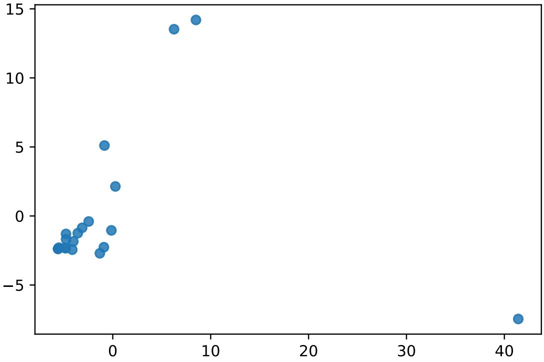
```
myvec = CountVectorizer(texts, max_df=.5, min_df=5)
mypca = PCA(n_components=2)

mypipe = make_pipeline(myvec, FunctionTransformer(lambda x: x.todense(), accept_sparse=True), mypca)

r = mypipe.fit_transform(texts)
```

Plotting the result

```
plt.scatter([e[0] for e in r], [e[1] for e in r], alpha=.6)
```



Singular value decomposition

The need to use a dense matrix is *really* a problem for large feature sets (which we have in NLP).

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The need to use a dense matrix is *really* a problem for large feature sets (which we have in NLP).
We therefore can better use SVD, which is essentially* the same and very simple to use:

```
mysvd = TruncatedSVD(n_components=2)
mypipe = make_pipeline(myvec, mysvd)
r = mypipe.fit_transform(texts)
```

(In this specific case, we even get exactly the same plot. . .)
* It's mathematically different, but you can SVD is even used "under the hood" by several PCA modules to solve PCA problems.
More info and background: `https://towardsdatascience.com/pca-and-svd-explained-with-numpy-5d13b0d2a4d8`

Finding similar variables
Multidimensional Scaling (MDS)

Multidimensional scaling

Assume we have a $n \times n$ matrix in which in which the cell entries indicate the distance between ech of our n features to each other feature based on their co-occurrence (= a dissimilarity matrix).

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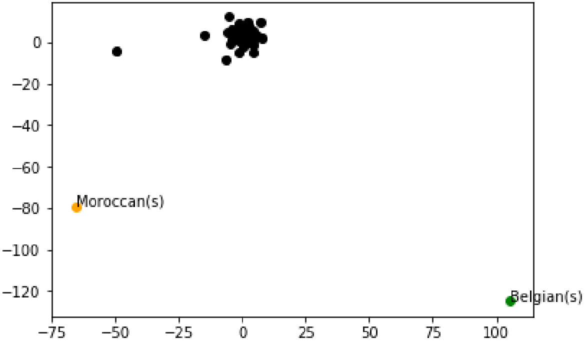

Multidimensiponal scaling

- Low-dimensional representation of the data in which the *distances* respect well the distances in the original high-dimensional space
- With $D = 2$ and $D = 3$ often used for visualization (e.g., in political science)

Finding similar cases

k-means clustering

Grouping features vs grouping cases

Let's consider a corpus of several thousand user comments.
We could use SVD, MDS, or similar techniques to

- figure out relationships between features
- see which features stand out
- get a first sense what topics are in the corpus.

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$\Rightarrow$ **Alternative: Choose the opposite approach and first find out which cases are most similar, *then* describe what features characterize each group of cases**

k-means clustering

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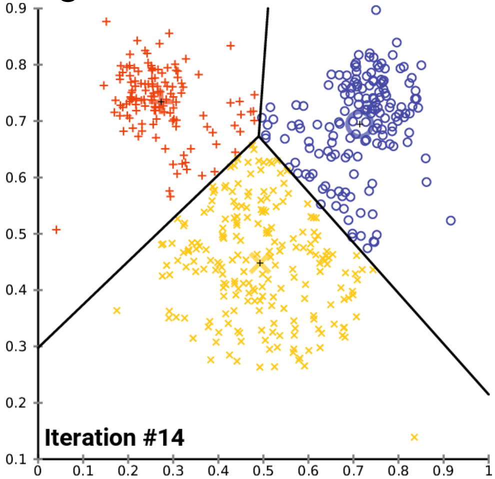
- non-deterministic: starts with a randomly choosen centroids (there are other versions)
- Cheap to compute: works even with large number of cases
- We can run PCA first to reduce the number of features if we want/need to

k-means clustering



https://upload.wikimedia.org/wikipedia/commons/e/ea/K-means_convergence.gif

Notice the big symbols indicating the centroids.

```
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.cluster import KMeans

k = 5
texts = ['text1 ejkh ek ekh', 'ekyerykel'] # a list of texts

vec = TfidfVectorizer(min_df=5, max_df=.4)
features = vec.fit_transform(texts)
km = KMeans(n_clusters=k, init='k-means++', max_iter=100, n_init=1)
predictions = km.fit_predict(features)
```

That's it!

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That's it!

- `predictions` is a list of integers indicated the predicted cluster number. We can thus use `zip(predictions, texts)` to put them together.
- We could also use `.fit()` and `.transform()` sperately and use our `km` to predict clusters for additional cases we have not used to train the model

Let's get the terms closest to the centroids

```
order_centroids = km.cluster_centers_.argsort()[:, ::-1]
terms = vec.get_feature_names()

print("Top terms per cluster:")

for i in range(k):
    print("Cluster {}: ".format(i), end='')
    for ind in order_centroids[i, :10]:
        print("{} ".format(terms[ind]), end='')
        print()
```

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```

returns something like:

```
Top terms per cluster:
Cluster 0: heard could if opinions info day how really just around
Cluster 1: systems would ken pc am if as care summary ibm
Cluster 2: year car years was my no one higher single than
Cluster 3: which like seen 1000 few easily based personal work used
Cluster 4: as was he if they my all will get has
```

Using k-means clustering. . .

- we get the cluster membership for each text; and
- we get the terms that are most characteristic for the documents in each cluster.

Finding the optimal *k*

- The only way to find *k* is to estimate multiple models with different *k*s
- No single best solution; finding a balance between error within clusters (distances from centroid) and low number of clusters.
- An elbow plot can be helpful (see example in Burscher et al, 2016)

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Code-example for creating an elbow plot:
`https://pythonprogramminglanguage.com/kmeans-elbow-method/`
(Don't forget to insert `%matplotlib inline` to actually see the plot)

Burscher, B., Vliegenthart, R., & de Vreese, C. H. (2016). Frames beyond words: Applying cluster and sentiment analysis to news coverage of the nuclear power issue. *Social Science Computer Review, 34*(5), 530-545. doi:10.1177/0894439315596385

Finding similar cases

Hierarchical clustering

Downsides of k-means clustering

k-means is fast, but has problems:

- *k* can only be determined by fitting multiple models and comparing them
- bad results if the wrong *k* is chosen
- bad results if the (real) clusters are non-spherical
- bad results if the (real) clusters are not evenly sized

Hiearchical clusttering

General idea

- To start, each case has its own cluster
- Merge the two clusters that are most similar
- Repeat until desired number of clusters is reached

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Different options

- Stopping criterion: based on numerical statistic (e.g., Duda-Hart) or dendrogram
- Linkage: how to determine which two clusters should be merged?

Let's look into some options

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

$\Rightarrow$ Ward's linkage is a good default all-rounder choice, especially if you encounter the problem that other linkages lead to almost all cases ending up in one cluster.

Hierarchical clustering takeaway

- The main reason *not* to use hierarchical methods (but k-means) is their computational cost: when clustering survey data of media users, never use *k*-means!
- But for NLP/ML, costs may be too high (if not used carefully)
- Very much worth considering, though, if you are really into grouping cases!

Important notes for all types of clustering

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Consider the scales of measurement

Clustering is based on distances – if your features are not measured on the same scale, or if it is not meaningful to calculate a numerical distance, it won't produce meaningful results!
Consider standardizing/whitening your features!

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Pay attention outliers/extreme cases

Extreme cases or outliers can have a strong influence.

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Do proper pre-processing

To reduce the number of features, but also to have *meaningful* features (dimensions on which you expect high distances between the clusters).

Exercise (as always, Anne and Damian available for questions on Friday)

1. Go to https://figshare.com/articles/News-Processed-Dataset/5296357 and download WSJ_20170607_to_20170726_10AmTo4Pm.json (the small file of 9 MB)
2. You can read the file as follows:

```
import json
data = []
with  open('/home/damian/Downloads/WSJ_20170607_to_20170726_10AmTo4Pm.
     json') as f:
  for line in f:
    data.append(json.loads(line))
texts = [e['content'] for e in data]
```

3. Use unsupervised machine learning techniques (and/or other techniques) to draw inferences about topics of (groups of) texts!