A Practical Introduction to Machine Learning in Python Day 3 - Wednesday »Unsupervised Machine Learning«

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Gesis

Today

Recap: Types of Automated Content Analysis

Finding similar variables

- An introduction to dimensionality reduction
- Principal Component Analysis and Singular Value Decomposition

Finding similar cases

- k-means clustering
- Hierarchical clustering

Important notes

Recap

Recap: Types of Automated Content Analysis

Recap

Top-down vs. bottom-up

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

deductive **inductive**

section[Recap]Recap: Top-down vs bottom-up

Boumans2016

The same logic applies to non-textual data!

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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

Unsupervised machine learning

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

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

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Let's distinguish four use cases...

1. Finding similar variables (dimensionality reduction) – unsupervised
2. Finding similar cases (clustering) – unsupervised
3. Predicting a continous variable (regression) – supervised
4. Predicting group membership (classification) – supervised

	x1	x2	x3	x4	x5	y
case1	110	110	110	110	110	110
case2	110	110	110	110	110	110
case3	110	110	110	110	110	110
case4	110	110	110	110	110	110

	x1	x2	x3	x4	x5	(y)
case1	110	110	110	110	110	(110)
case2	110	110	110	110	110	(110)
case3	110	110	110	110	110	(110)
case4	110	110	110	110	110	(110)

Dimensionality reduction: finding similar variables (features)

	x1	x2	x3	x4	x5	(y)
case1	110	110	110	110	110	(110)
case2	110	110	110	110	110	(110)
case3	110	110	110	110	110	(110)
case4	110	110	110	110	110	(110)

Clustering: finding similar cases

	x1	x2	x3	x4	x5	→	y
case1	110	110	110	110	110	→	110
case2	110	110	110	110	110	→	110
case3	110	110	110	110	110	→	110
case4	110	110	110	110	110	→	110
new case	110	110	110	110	110	→	?

Regression and classification: learn how to predict y.

Note, again, that the 110 signs can be *anything*. For us, often word counts or $tf \cdot$ idf scores (x) and, for supervised approaches, a topic, a sentiment, or similar (y).

But it could also be pixel colors or clicks on links or anything else.

	x1	x2	x3	x4	x5	y
case1	110	110	110	110	110	110
case2	110	110	110	110	110	110
case3	110	110	110	110	110	110
case4	110	110	110	110	110	110

A lot of applications and use cases, . . .

. . . but we'll distinguish two today:

1. Finding similar variables (dimension reduction)
2. Finding similar cases (clustering)

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

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Finding similar variables

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An introduction to dimensionality reduction

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Dimensionality reduction

dimensionality = the number of features we have

(1) Explorative data analysis and visualization

- No good way to visualize 10,000 dimensions (or even 4)

(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

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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 and Singular Value Decomposition

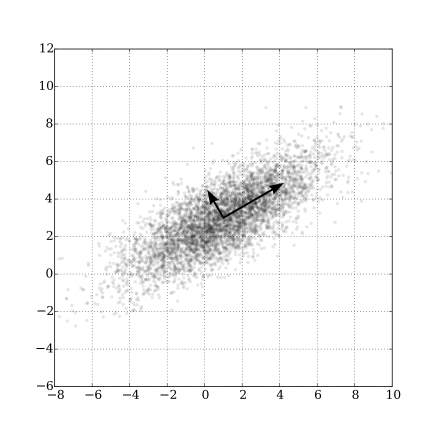
Finding similar variables

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*.

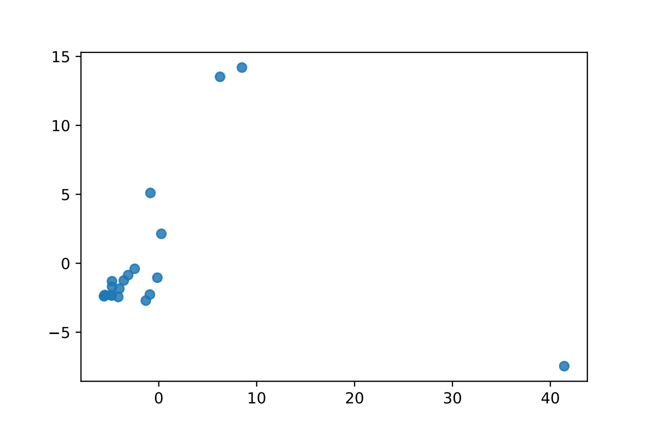
```
myvec = CountVectorizer(texts, max_df=.5, min_df=5)
mypca = PCA(n_components=2)

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).

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

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Finding similar cases

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k-means clustering

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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.

But:

- We do not learn anything about *which* texts (cases) belong to which topic
- We could use the component scores returned by `.fit_transform()` to then group our cases

⇒ **Alternative: Choose the opposite approach and first find out which cases are most similar, *then* describe what**

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k-means clustering

- Goal: group cases into *k* clusters
- *k* is set in advance
- Algorithm to determine *k* centroids (points in the middle of the cases that belong to it) such that the distances between the cases and their centroids are minimized
- 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

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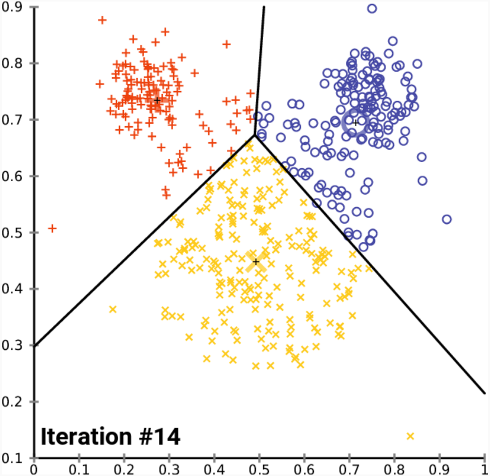

https://upload.wikimedia.org/wikipedia/commons/e/ea/K-means_convergence.gif

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!

- `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

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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()
```

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
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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 ks
- 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)

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

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Finding similar cases

Hierarchical clustering

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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

Different options

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

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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

Important notes for all types of clustering

Important notes

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!

Pay attention outliers/extreme cases

Extreme cases or outliers can have a strong influence.

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).

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Exercise

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!

This afternoon we will discuss one of the most popular unsupervised methods of the moment – topic modeling.