

Artificial Intelligence and Data Analytics for Engineers (AIDAE)

Lecture 7 June, 19<sup>th</sup>

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Today's Lecturer

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### Artificial Intelligence and Data Analytics for Engineers Overview Lectures 1 – 4



Introduction to Data Analytics and Artificial Intelligence in Engineering: Organizational matters (e.g. exam, exercises, dates). Goals, Challenges, Obstacles, and Processes.



Introduction into the primary programming language of the lecture, Python: Syntax, libraries, IDEs etc. Why is Python the *lingua franca* of the Data Scientist?



**Data Preparation**: Cleansing and Transformation. How do real world data sets look like and why is cleaning and transformation an integral part of a Data Scientist's workflow?



**Data Integration**: Architectures, Challenges, and Approaches. How can you integrate various data sources into an overarching consolidating schema and why is this important?







### Artificial Intelligence and Data Analytics for Engineers Overview Lectures 5 – 8



**Data Representation**: Feature Extraction and Selection. How to pick relevant features for the task at hand. Manual vs automatic methods. What is the curse of dimensionality?



**Data-Driven Learning**: Supervised (Classification, Regression) methods and algorithms. What is an artificial neural net? What methods are there for evaluation of your model?

7

**Data-Driven Learning**: Unsupervised (Clustering) methods and algorithms. How can machines learn without labels? What methods are there for evaluation of your model?







## Today's Lecture







# Unsupervised Learning

What is it?

Methods

Applying







## Learning Objectives



Learning Objective w.r.t. Knowledge/Understanding.

After successfully completing this lecture, the students will have achieved the following learning outcomes:

- Have an understanding of what unsupervised learning is.
- Know the different families of unsupervised learning algorithms.
- Learn how to use unsupervised learning algorithms.







## Motivation and Introduction



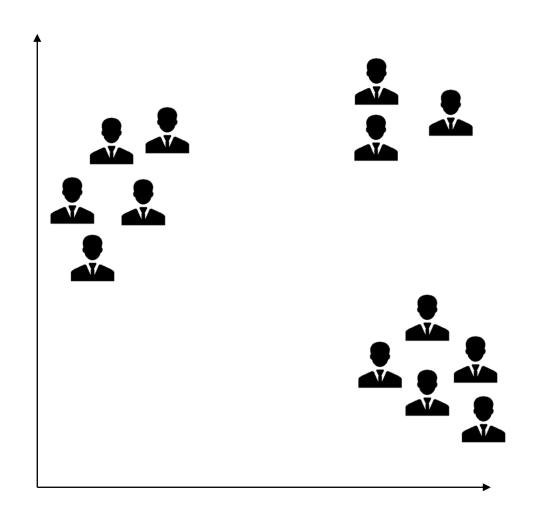




## Unsupervised Learning in Different Industries

By using **clustering algorithms** to segment markets, companies can:

- Identify your most profitable group of customers.
- Focus your marketing on segments most likely to purchase.
- Discover potential niche markets.
- Develop or improve products to meet customer needs of groups of customers.





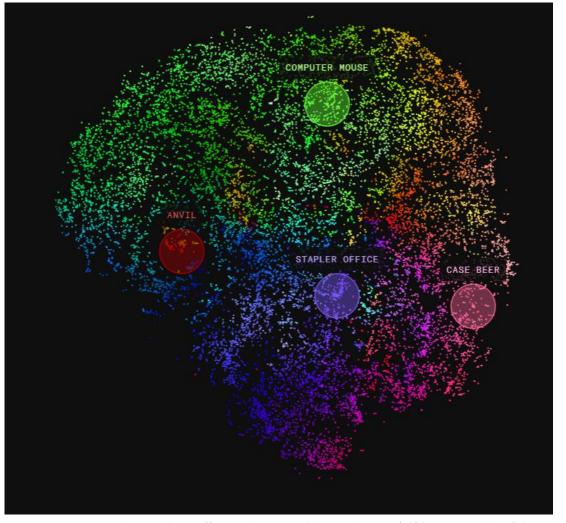




## Unsupervised Learning in Different Industries

- Unsupervised learning algorithms such as manifold learning are often used to get a more understandable representation of a high dimensional dataset.
- Examples of this are applications that create sound maps of
  - Instruments
  - bird songs
  - Images
  - machine noises

in order to find out more about the data.



Source: https://experiments.withgoogle.com/ai/drum-machine/view

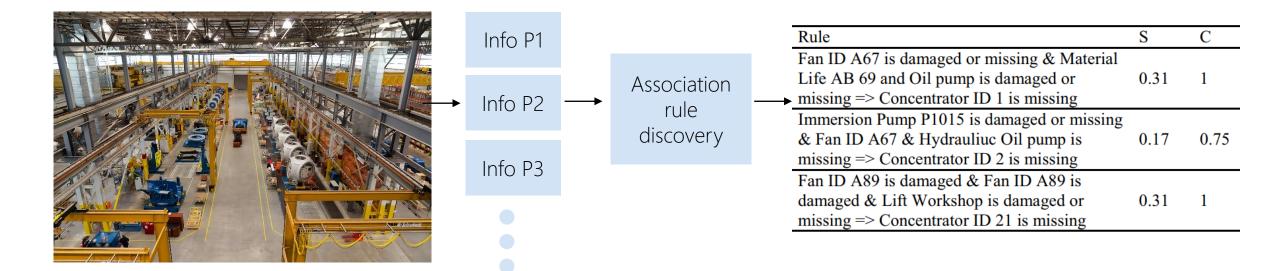






## Unsupervised Learning in Different Industries

In the manufacturing industry, **Association rule discovery** is used over SCADA logs of events and alerts to better understand the relations between the failures in multiple machines.









## Introduction





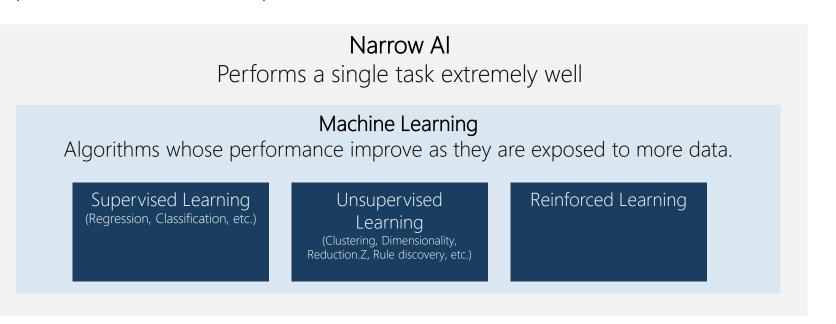


### Introduction

• Brief view into Artificial intelligence and Machine Learning

## Artificial Intelligence: Any technique which enables a computer to mimic human behaviour.

General AI (GAI)
Transfer knowledge
across domains.







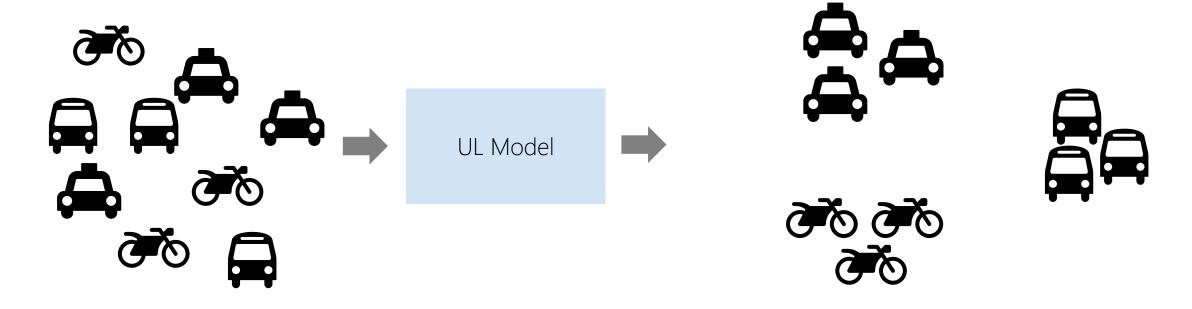


## What is supervised learning?



### Working Definition

Unsupervised learning deals with problems in which your dataset doesn't have labels. Instead, the model is allowed to discover relations in the data on its own.







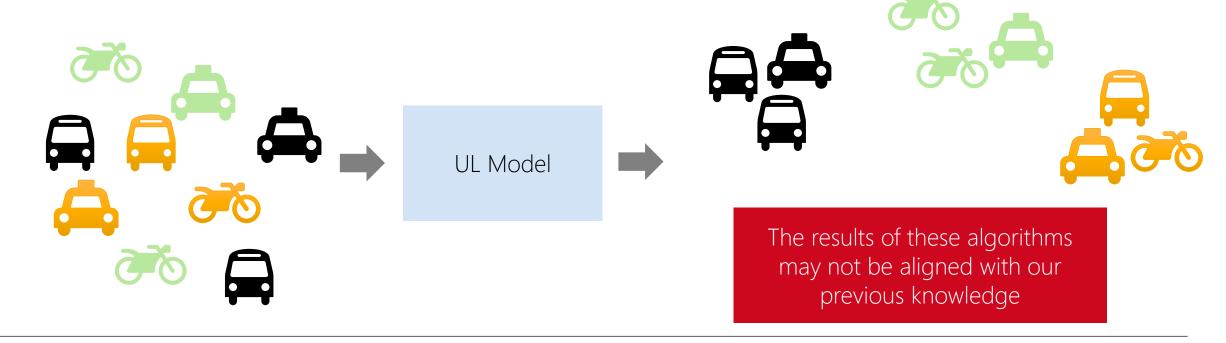


## What is supervised learning?



### Working Definition

Unsupervised learning deals with problems in which your dataset doesn't have labels. Instead, the model is allowed to discover relations in the data on its own.









## What is supervised learning?



What Kind of Unsupervised learning algorithms exist?

### **Finding clusters**

Clustering



Anomaly Detection



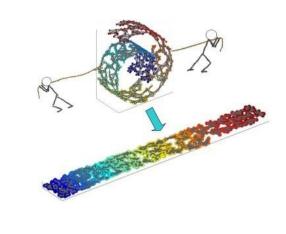
### **Association rule mining**

Association:
"If product X is bought,
it's likely product Y is
bought as well."



### **Dimensionality Reduction**

Reduce data to fewer Dimensions.









## Clustering



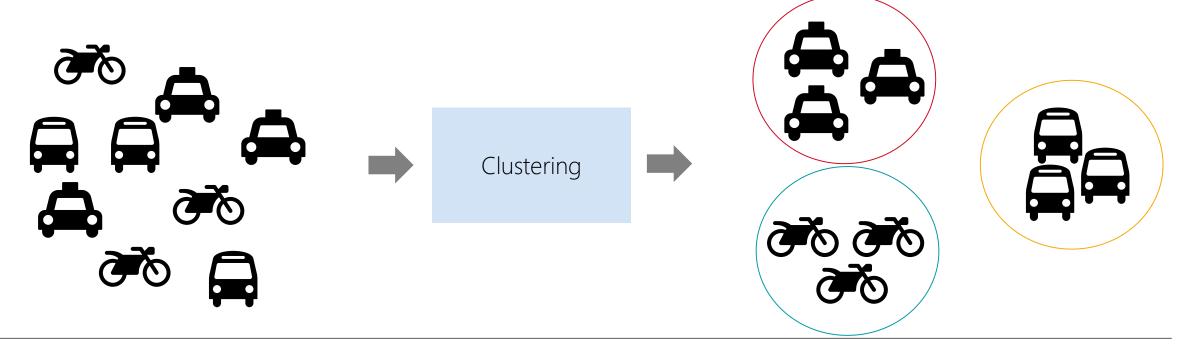






### Working Definition

Clustering is the task of **grouping** sets of objects (**clusters**), so that more **similar** items are in the same group and less **similar** items are in separate groups (**clusters**).











3 main families of techniques for clustering

### Hierarchical clustering

Finding a cluster-hierarchy, e.g. beginning with as many clusters as data-objects.

- Single-Linkage
- Wards method

### Partitioning Clustering

Optimizing cluster centers to minimize the distance to the data-objects to a cluster.

- K-means
- Fuzzy C-means
- Affinity-Propagation
- EM-Clustering (GMM)

### **Density-based Clustering**

Locates high-density regions separated form one another by regions of low density.

- DBSCAN
- Mean-Shift
- OPTICS



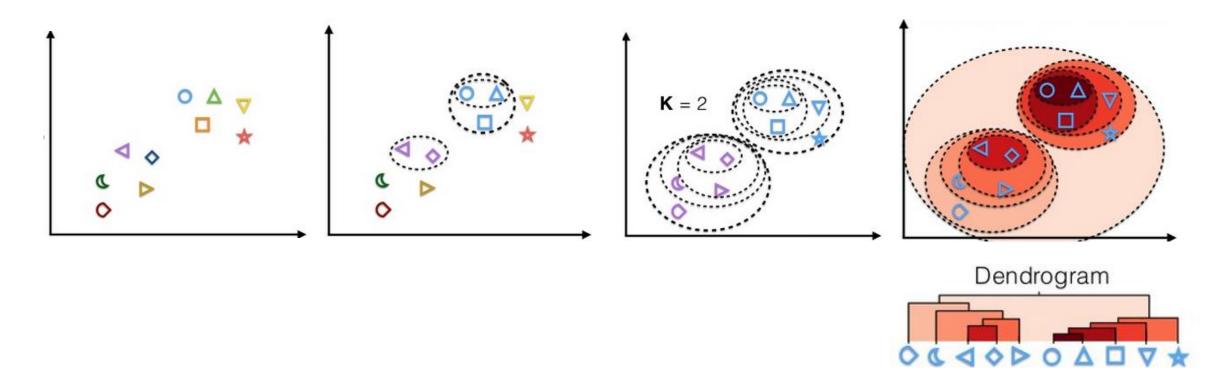






### **Hierarchical clustering**

Finding a cluster-hierarchy, e.g. beginning with as many clusters as data-objects.





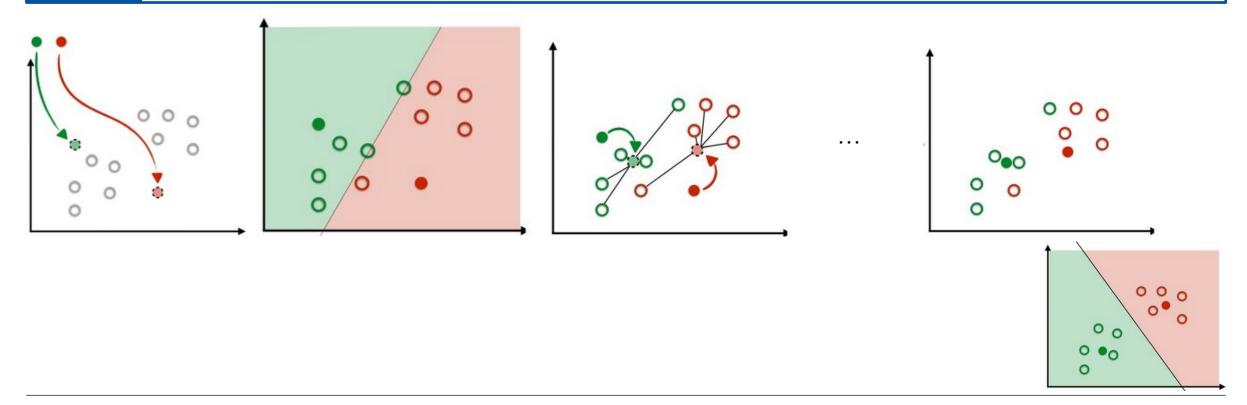






### **Partitioning Clustering**

Optimizing cluster centers to minimize the distance to the data-objects to a cluster.







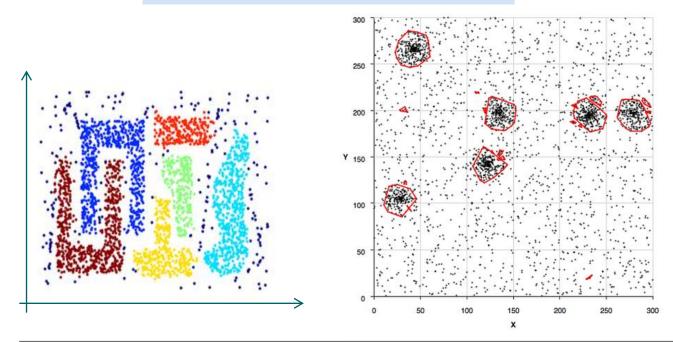




### **Density-based Clustering**

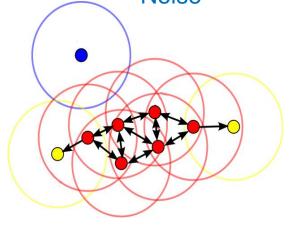
Locates high-density regions separated form one another by regions of low density.

### How do they look?



### Belonging/borders and noise

Core objects
Border objects
Noise











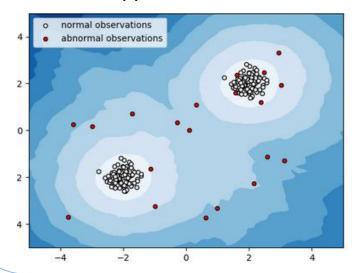
### How do we use clustering for anomaly detection?

### **Using clustering algorithms**

→ Objects outside clusters

### Example:

One-Class Support Vector Machine:

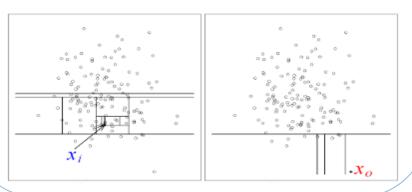


### **Anomaly Detection algorithm**

### Example:

Isolation Forest Algorithm

- Objects are isolated by dividing the data space
- Small number of isolation steps
- → High chance for an anomaly











#### K-means

Optimizing cluster centers to minimize the distance to the data-objects to a cluster.

1) Randomly initialize k data 8.0 points (means or centroids). 0.7 0.6 0.5 3) Recompute the centroids: 2) Associate each item to its Calculate the mean of all 0.4 closest mean (based on the items currently associated 0.3 squared Euclidean distance) with the centroid 0.2 Iteration #0

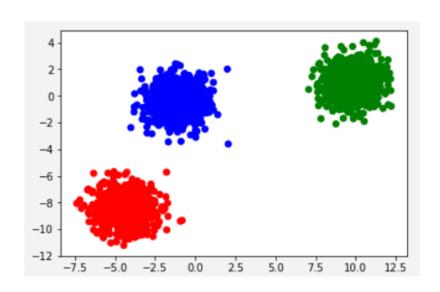






### **Example: K-means**

```
# %% load data
from sklearn import datasets
import numpy as np
X, y = datasets.make_blobs(n_samples=2000, random_state=45)
# cluster data
from sklearn.cluster import KMeans
kmeans = KMeans(n_clusters=3, random_state=0).fit(X)
predicted_clusters = kmeans.labels_
# plot
c = [{0:"b",1:"g",2:"r"}[c] for c in predicted_clusters]
plt.scatter(X[:,0],X[:,1],c=c)
```







## Association rule mining









### Working Definition

Association rule mining methods try to **discover** interesting **associations** (relationships or dependencies) between **variables** hidden in large datasets of **items**.

Customer 1 milk, bread

Customer 2 bread, butter

Customer 3 beer

Customer 4 milk, bread, butter

Customer 5 bread, butter

. . .





Rule: bread → butter









A dataset for association rule mining is composed by **transactions**, which have a unique id and contain a subset of **items**.

$$D = \{t_1, t_2, \ldots, t_m\}$$

Customer 1 milk, bread

Customer 2 bread, butter

Customer 3 beer

Customer 4 milk, bread, butter

Customer 5 bread, butter

. . .

$$I = \{i_1, i_2, \dots, i_n\}$$
 = {Milk, bread, butter, beer,...}









An association rule is an implication expression of the form " $X \rightarrow Y$ " where X and Y are itemsets

### Rules evaluation metrics:

- Support (s):
- is the fraction of transactions that contain both X and Y.
- Confidence (c):
- measures how often items in Y appear in transactions that contain X.







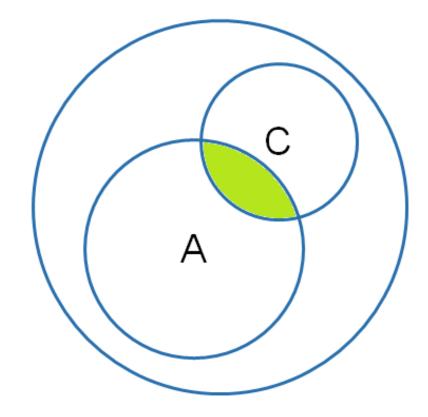


### How does it work?

1) Find rules which have the highest support.

### Support

Percentage of instances which match antecedent "A" and consequent "C".











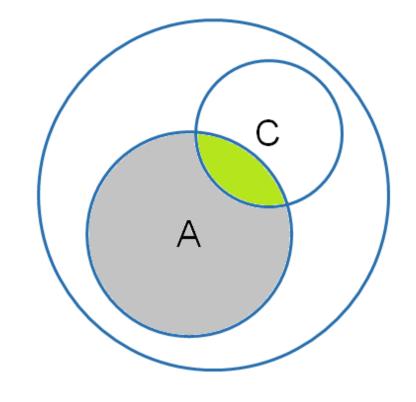
### How does it work?

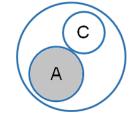
2) Select the relevant rules above a confidence threshold

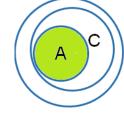
#### Confidence

Percentage of instances in the antecedent which also contain the consequent.









0% Confidence

100% Confidence









### **Brute force approach?**

- 1) List all possible association rules
- 2) Compute the support and confidence for each rule
- 3) Prune rules that fail the minimum thresholds

But..... For medium or large datasets it's computationally expensive (seriously, don't do it this way)









### Other approaches: Apriori algorithm

- 1) Let k=1
- Generate frequent itemsets of length 1
- 3) Repeat until no new frequent itemsets are identified
- Generate length k+1 candidate itemsets from length k that are frequent
- Prune candidate itemsets containing subsets of length k that are infrequent
- Compute support
- Filter infrequent candidates

Other alternatives such as the eclat algorithm also exist, but most are computationally expensive.







### **Example: apriori**

```
from apyori import apriori
```

```
transactions = [
['beer', 'nuts'],
['beer', 'cheese'],
['nuts', 'cheese'],
['nuts'],
['nuts'],
['cheese', 'banana'],
['cheese', 'beer'],
['cheese', 'beer']
]
```

	confidence	rule_if	rule_then	support
0	0.125	banana	-	0.125
1	1.000	banana	cheese	0.125
2	0.250	nuts	beer	0.125
3	0.200	nuts	cheese	0.125
4	0.750	beer	cheese	0.375
5	0.500	beer	-	0.500
6	0.500	nuts	-	0.500
7	0.625	cheese	-	0.625

```
association_rules = list(apriori(transactions))
```







## Dimensionality Reduction



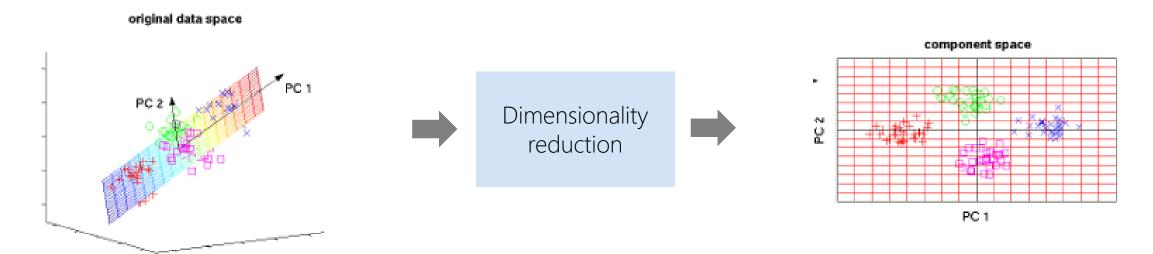






### Working Definition

Dimensionality reduction techniques are meant to reduce the number of dimensions of a featureset.



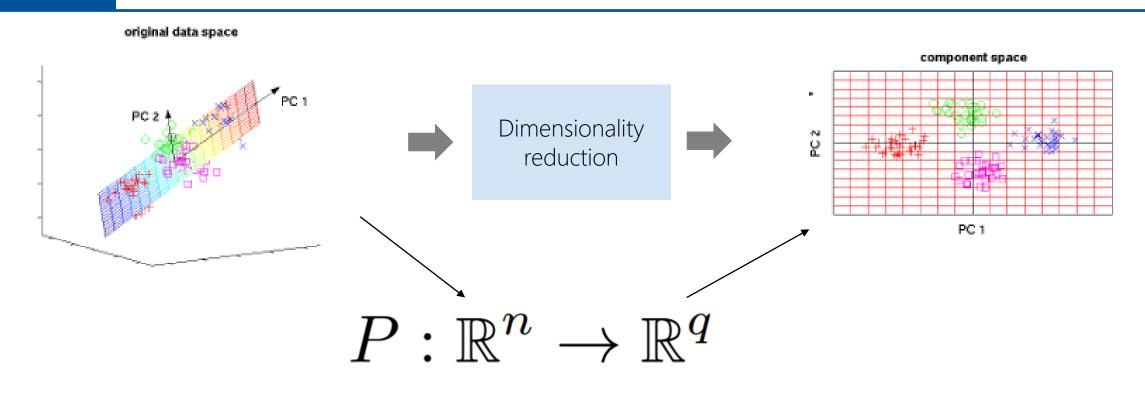






### Working Definition

Dimensionality reduction techniques are meant to reduce the number of dimensions of a featureset.











### Why?

- Storage space
- Model complexity / computational cost
- Curse of dimensionality can affect some models
- Helps visualize data (humans are not good at understanding many dimensions)









### How?

- Feature selection
- Linear projections (normally component based)
- Non linear projections (Manifold learning)









#### Feature selection

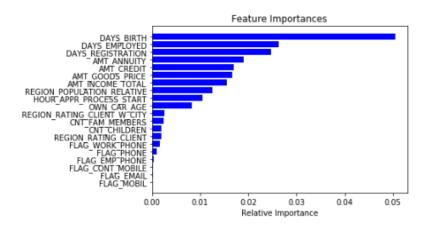
Techniques that focus on only keeping the most relevant variables from the original featureset

### Feature filtering

- Missing values
- Low variance
- Correlation filter

### Random forest

Gini importance (Mean Decrease in Impurity)







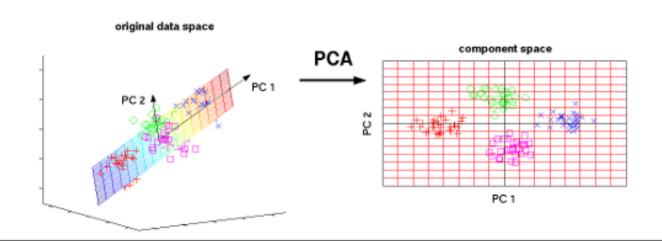




### Linear projections (normally component based)

These family of techniques look for the main components of the data. Common working principles are to look for uncorrelated variables, to group correlated variables or to search eigenvectors of latent variables.

- Principal Component Analysis(PCA)
- Singular Value Decomposition(SVD)
- Independent Component Analysis(ICA)







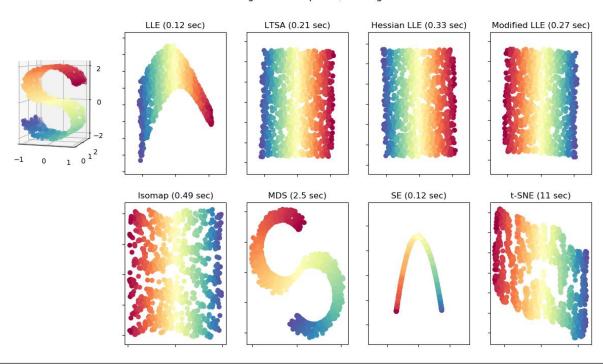




### Non linear projections (Manifold learning)

Algorithms on this family are based on the idea that the dimensionality of many datasets is artificially high. They try to maintain local or global distance metrics while transforming the feature space.

#### Manifold Learning with 1000 points, 10 neighbors



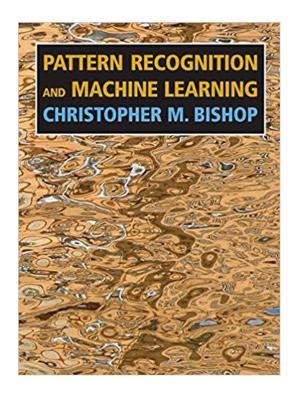


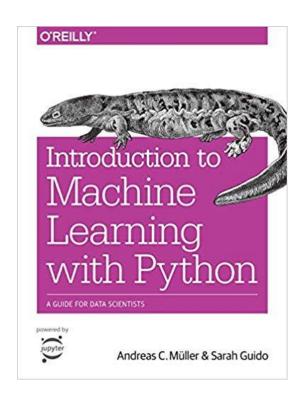




## Further Reading Material

- <a href="https://www.youtube.com/watch?v=bQI5uDxrFfA">https://www.youtube.com/watch?v=bQI5uDxrFfA</a> [ Introduction Supervised Learning, Andrew Ng]
- <a href="https://scikit-learn.org/stable/supervised learning.html">https://scikit-learn.org/stable/supervised learning.html</a> [Short Explanation and Code Snippets]











Thank you for your attention!

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