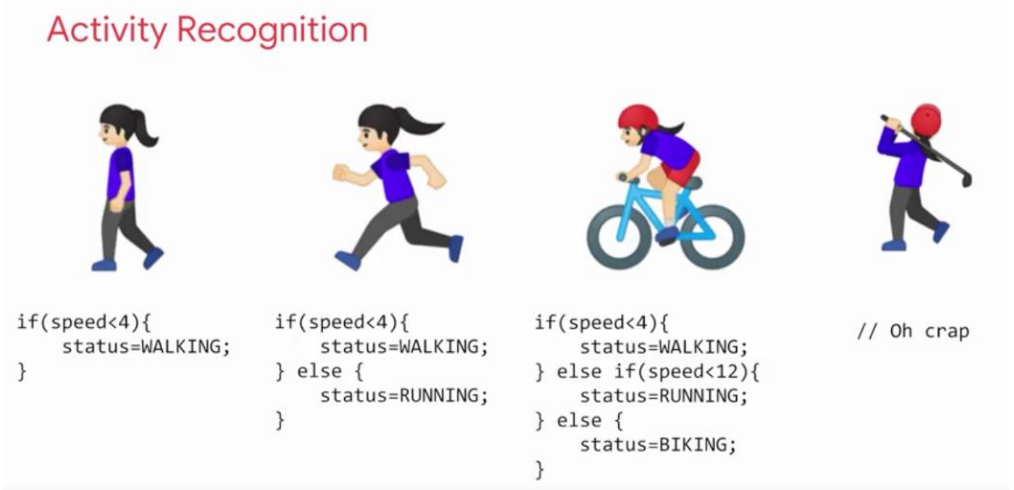
DATA SCIENCE IN MANUFACTURING

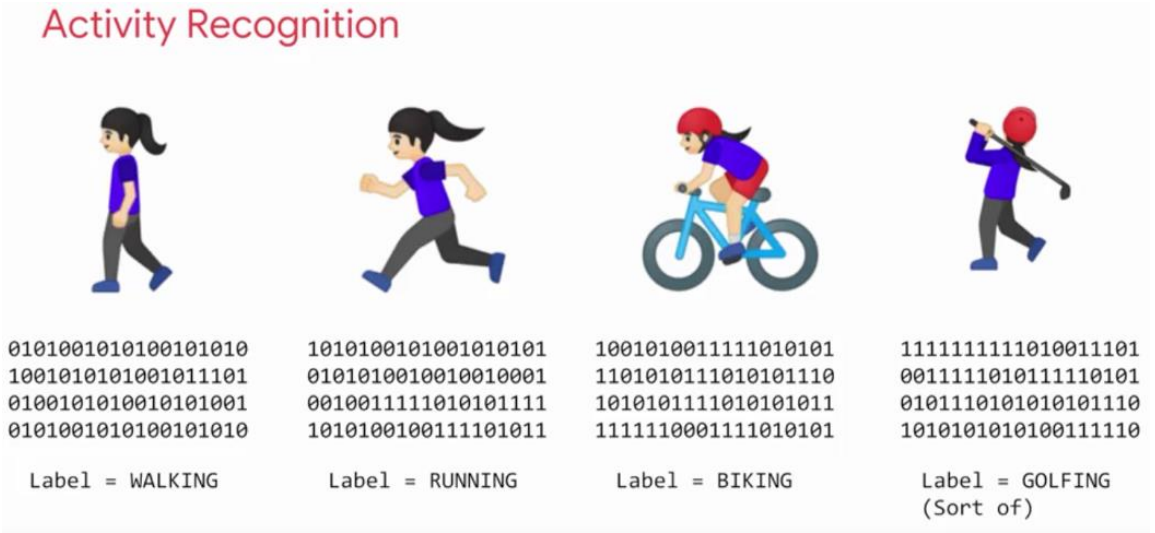
WEEK 8

ANDREW SHERLOCK, JONATHAN CORNEY, DANAI KORRE

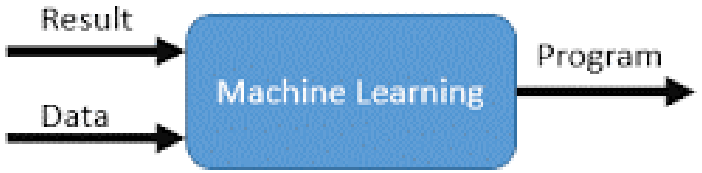
RECALL LAST WEEK



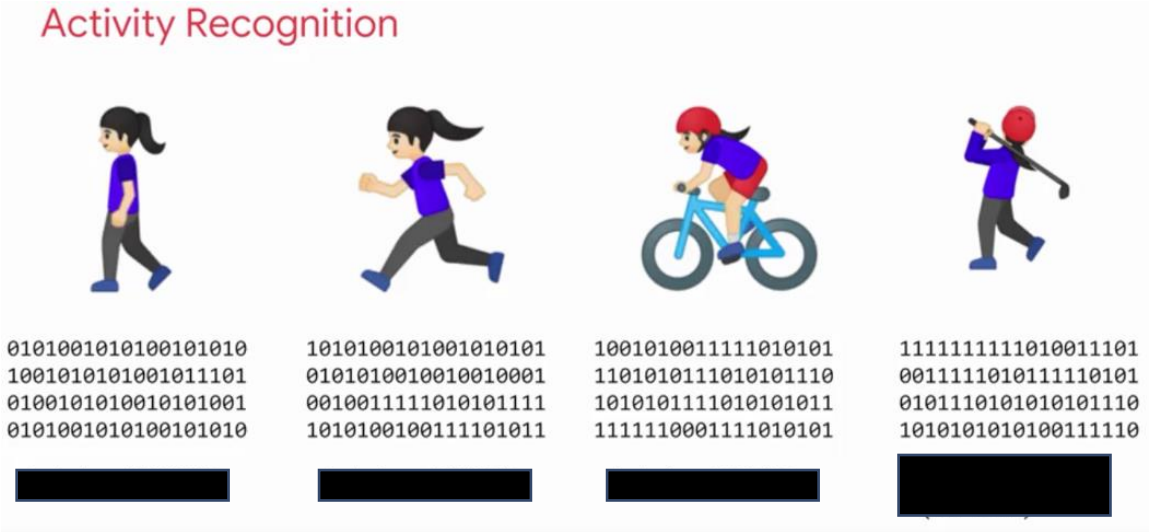
Conventional Programming



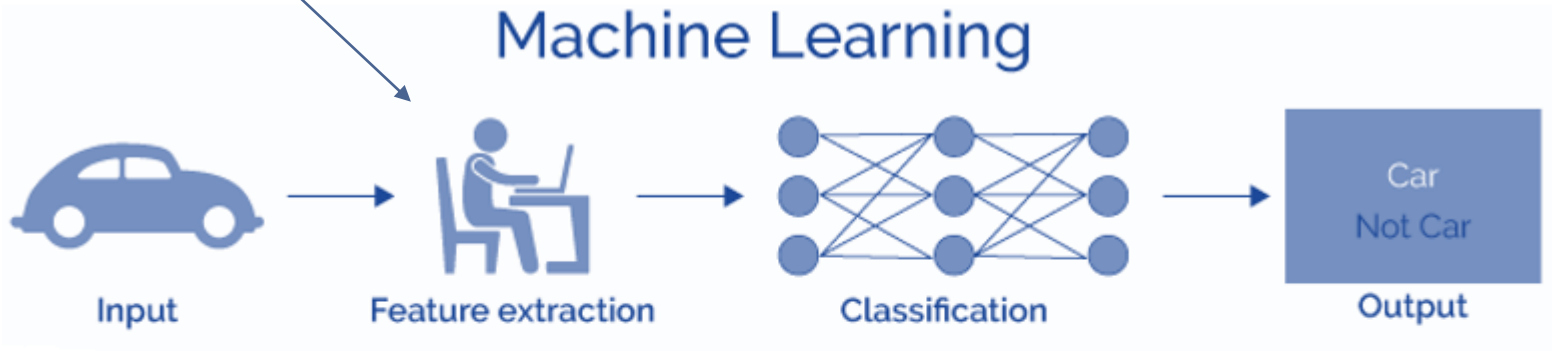
Machine Learning



UNSUPERVISED LEARNING



SUPERVISED LEARNING



UNSUPERVISED LEARNING

Supervised Learning

- Classification
- Regression

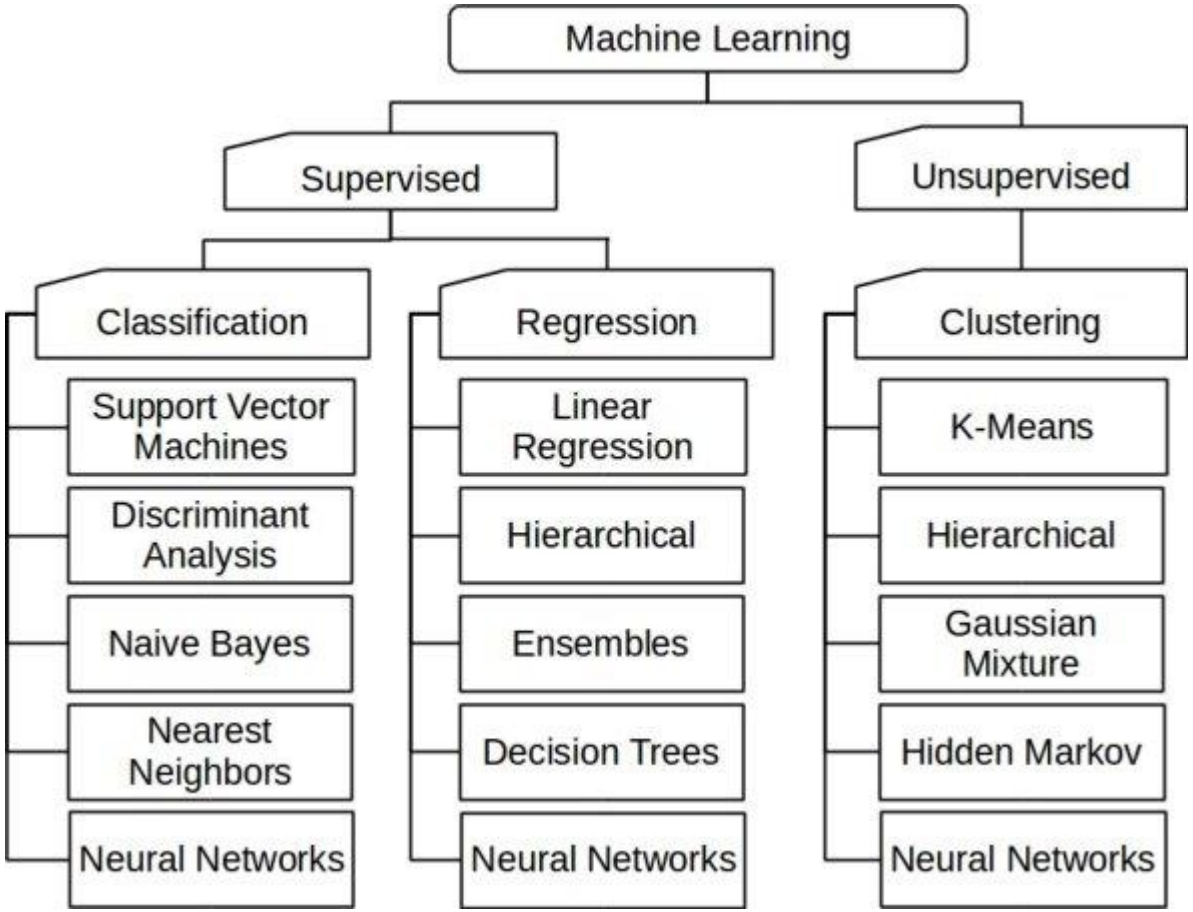
Used for predictions

Unsupervised Learning

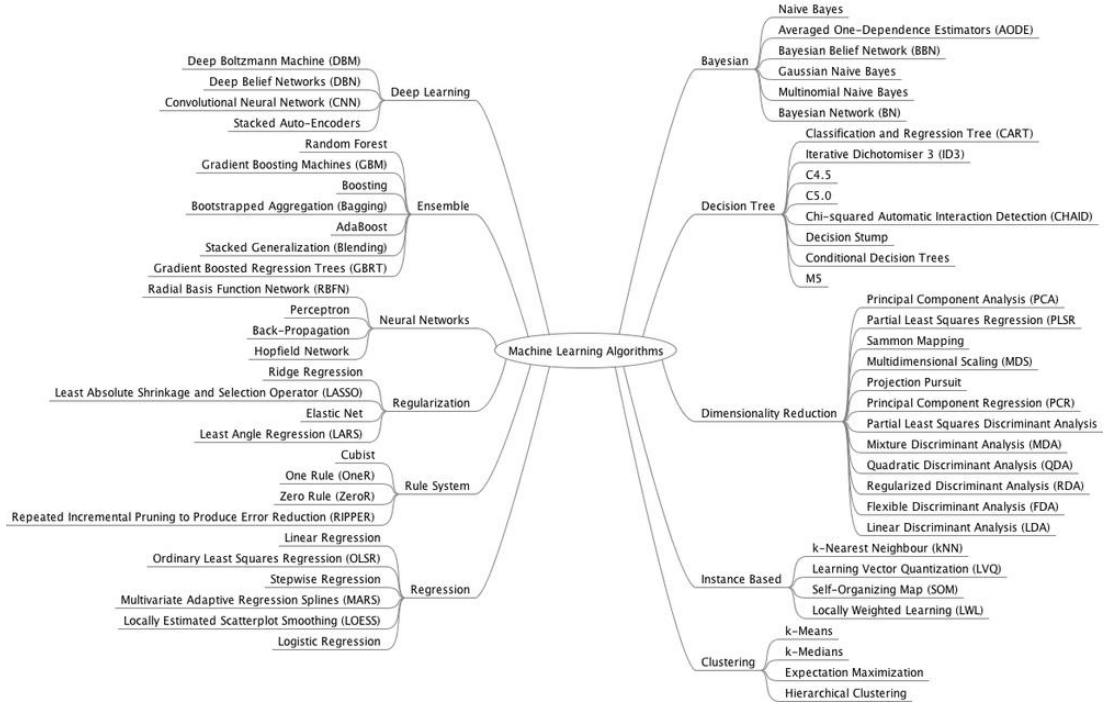
- Clustering
- Association

Used for pattern/structure discovery

A MAJOR CLASS OF MACHINE LEARNING METHODS



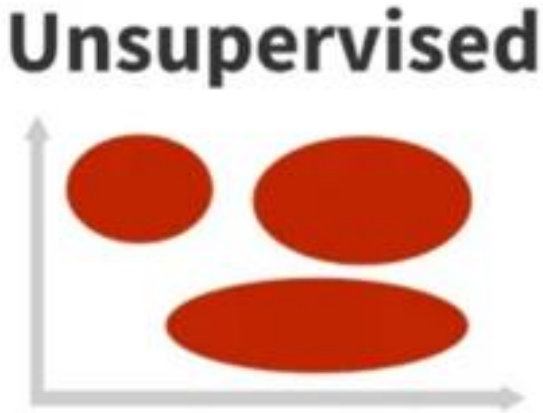
Association Rules



We are just scratching the surface of a big subject

WHAT IS UNSUPERVISED LEARNING?

Doug Rose defines unsupervised learning as “The machine makes all the observations on its own. It might now know all the different names and labels, but it will find patterns on its own.” [5]



Source: Ben Freundorfer

Google's Artificial Brain Learns to Find Cat Videos

When computer scientists at Google's mysterious X lab built a neural network of 16,000 computer processors with one billion connections and let it browse YouTube, it did what many web users might do -- it began to look for cats.

By Liat Clark, Wired UK

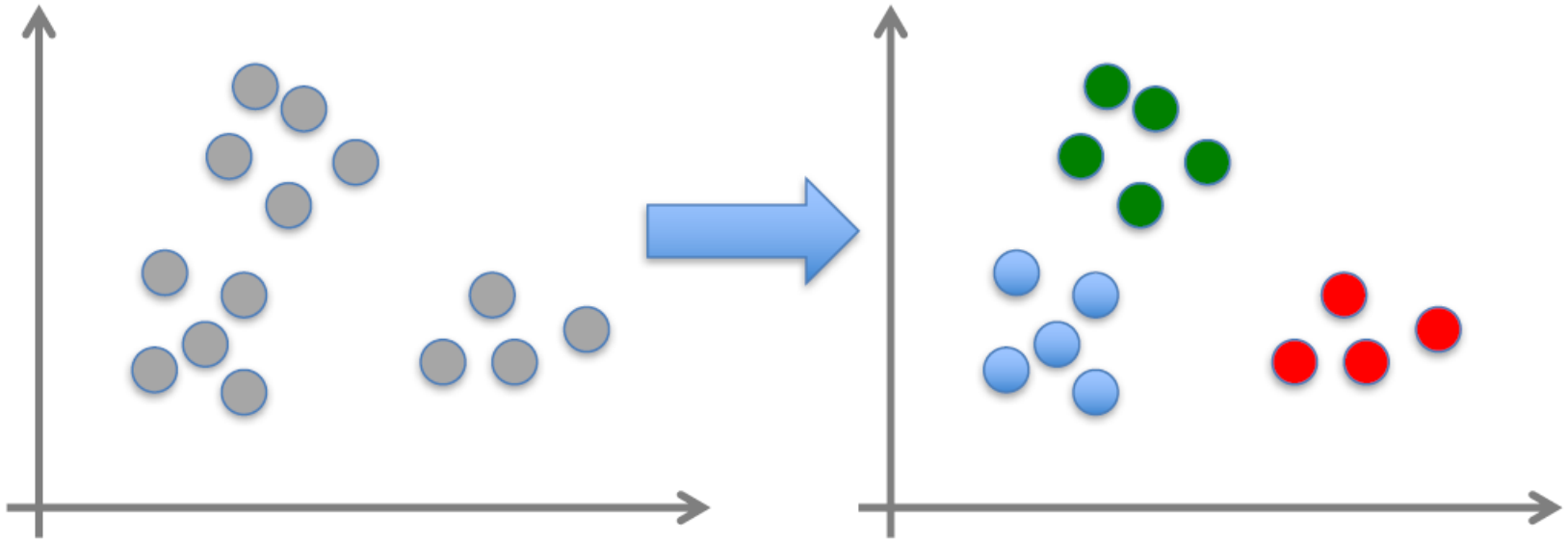
When computer scientists at Google's mysterious X lab built a neural network of 16,000 computer processors with one billion connections and let it browse YouTube, it did what many web users might do -- it began to look for cats.

[partner id="wireduk"] The "brain" simulation was exposed to 10 million randomly selected YouTube video thumbnails over the course of three days and, after being presented with a list of 20,000 different items, it began to recognize pictures of cats using a "deep learning" algorithm. This was despite being fed no information on distinguishing features that might help identify one.

Picking up on the most commonly occurring images featured on YouTube, the system achieved 81.7 percent accuracy in detecting human faces, 76.7 percent accuracy when identifying human body parts and 74.8 percent accuracy when identifying cats.

UNSUPERVISED LEARNING

- Given $x_1, x_2, \ldots, x_n$ (without labels)
- Output hidden structure behind the x's
  - E.g., clustering



Source: Eric Eaton

UNSUPERVISED LEARNING IN MANUFACTURING

Quality control

Predictive maintenance

Anomaly detection

Optimisation

ADVANTAGES AND DISADVANTAGES OF UNSUPERVISED LEARNING

Advantages:

- No need for labels in data
- Pattern detection discovery
- Scalability
- Flexibility

Disadvantages:

- Lack of interpretability
- Lack of guidance
- Sensitivity to data preprocessing
- Limited control

CLUSTERING

Clustering is one main approach to unsupervised learning.

- It finds similarity groups in data, called clusters,
  - it groups data instances that are similar to (near) each other in one cluster and data instances that are very different (far away) from each other into different clusters.

Clustering is often considered synonymous with unsupervised learning.

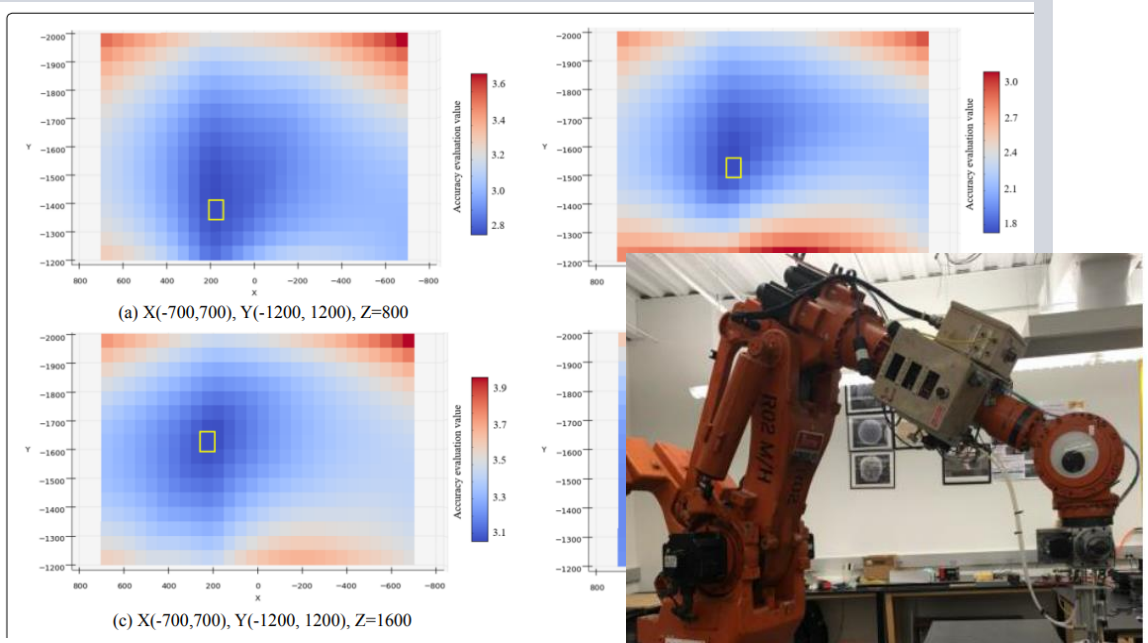
- But we'll look at some other types of pattern identification , such as association rule mining, that are also a form of unsupervised learning.

We will focuses on clustering first.

Source: Bing Liu, UIC

WHAT IS CLUSTERING FOR?

Example: Given a measurements of a robot's accuracy throughout its workspace, we want to organize them according to their content similarities,

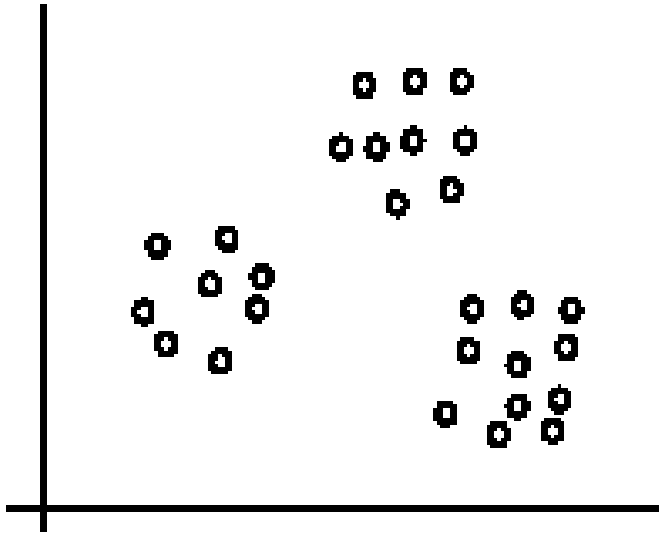


Clustering is one of the most utilized data mining techniques.

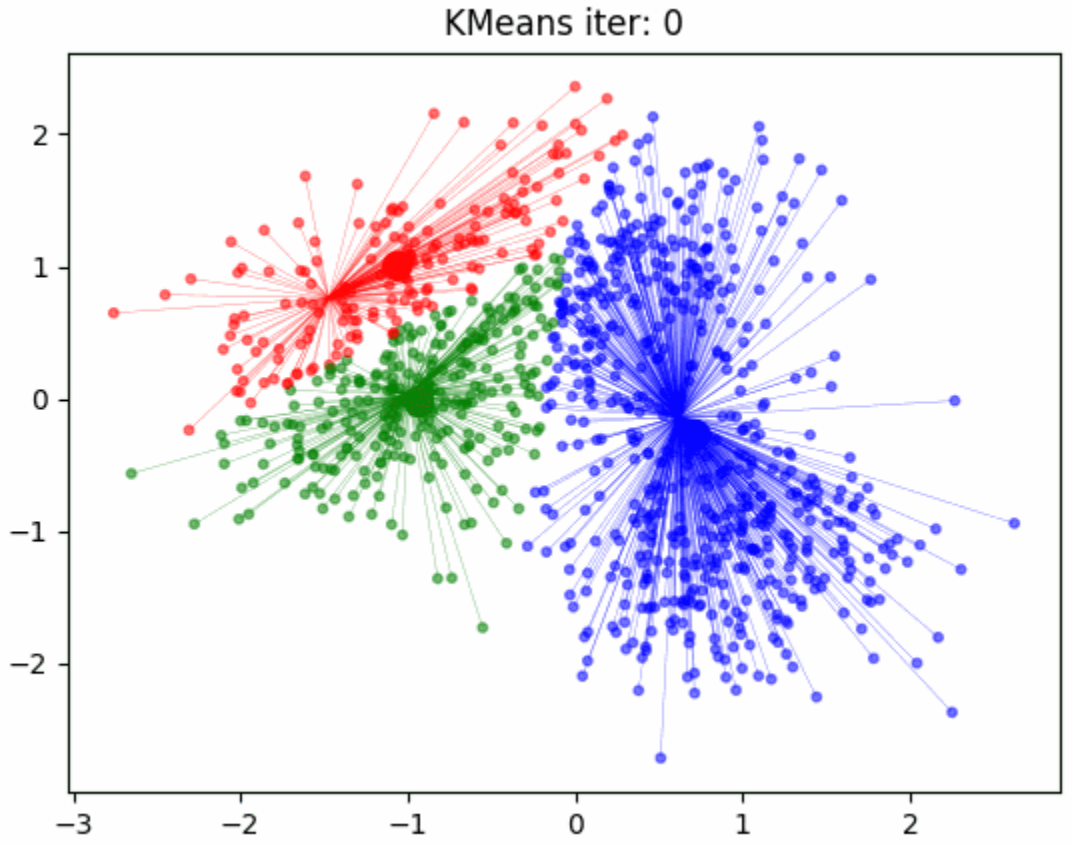
- It has a long history, and been used in almost every field, e.g., medicine, psychology, botany, sociology, biology, archeology, marketing, insurance, libraries, etc.
- In recent years, due to the rapid increase of online documents, text clustering becomes important.

Source: Bing Liu, UIC

"Easy" to cluster a data set which has three "natural" groups of data points, i.e., 3 natural clusters.



Source: Bing Liu, UIC

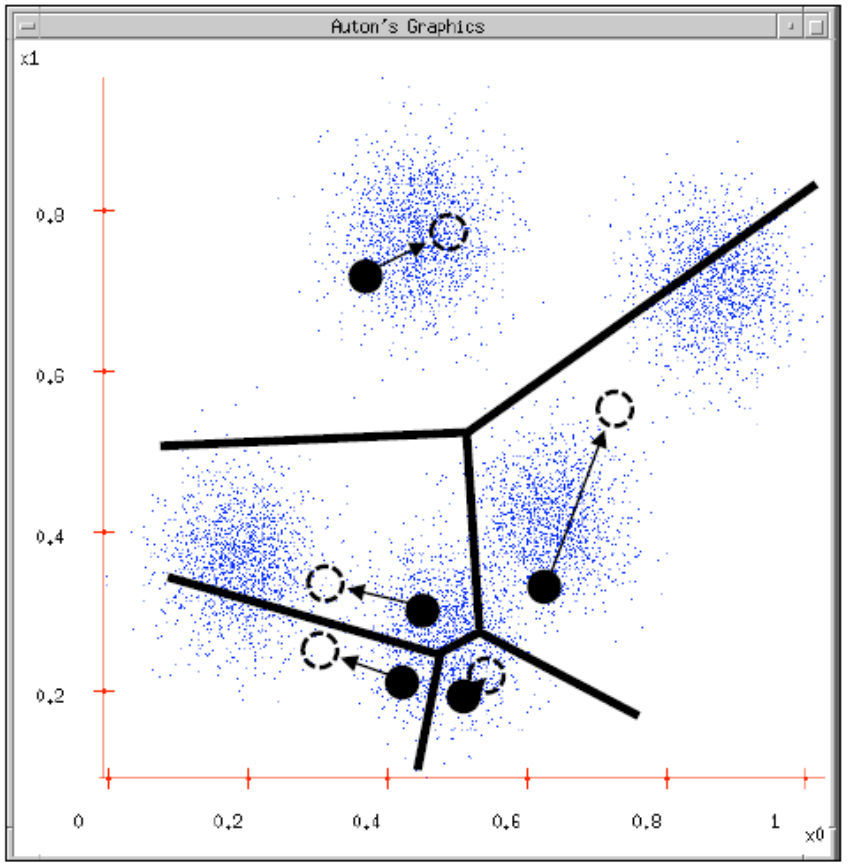


But often the clusters are not obvious so a range of algorithms have been developed to automatically collect points into groups or clusters

K-MEAN CLUSTERING

K-Means (k , X)

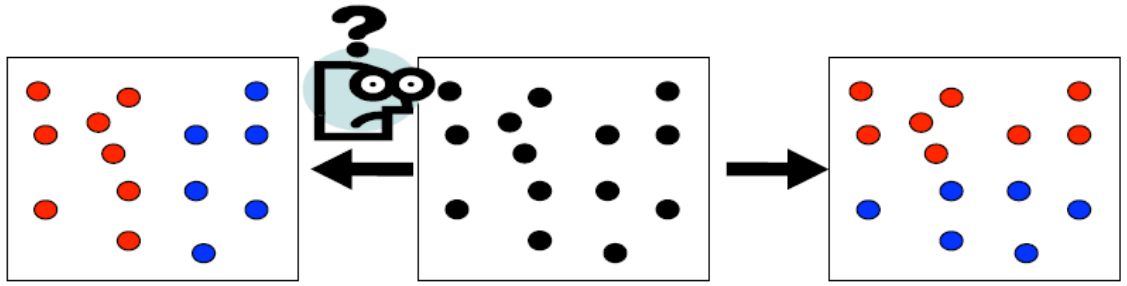
- Randomly choose k cluster center locations (centroids)
- Loop until convergence
  - Assign each point to the cluster of the closest centroid
  - Re-estimate the cluster centroids based on the data assigned to each cluster



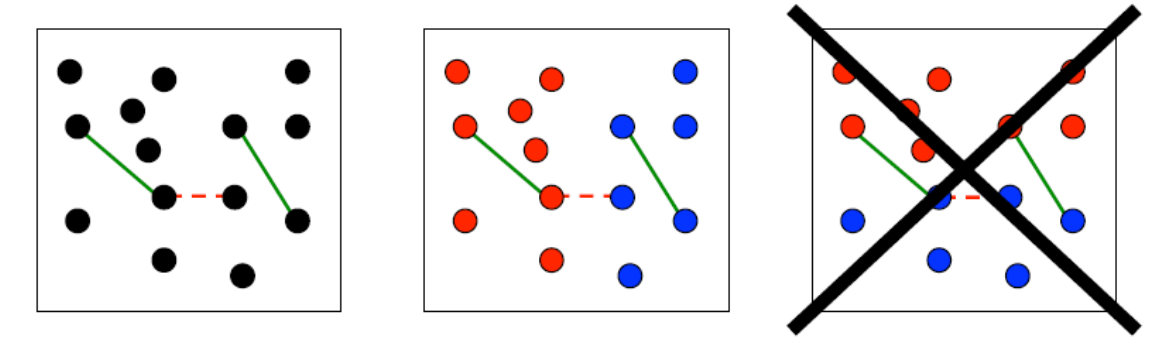
Source: Eric Eaton

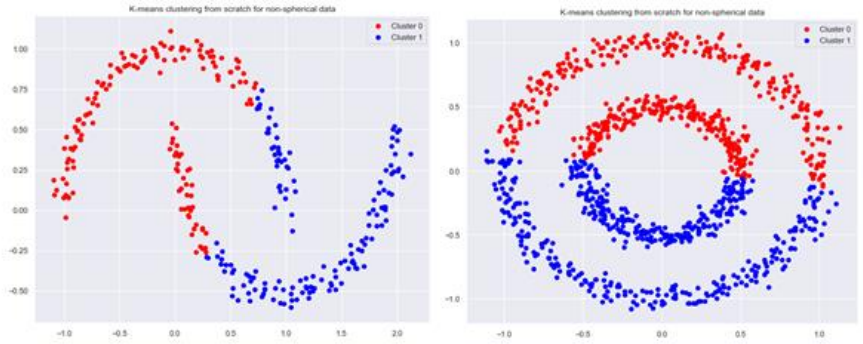
PROBLEMS WITH K-MEANS

- How do you tell it which clustering you want?



Constrained clustering techniques (semi-supervised)

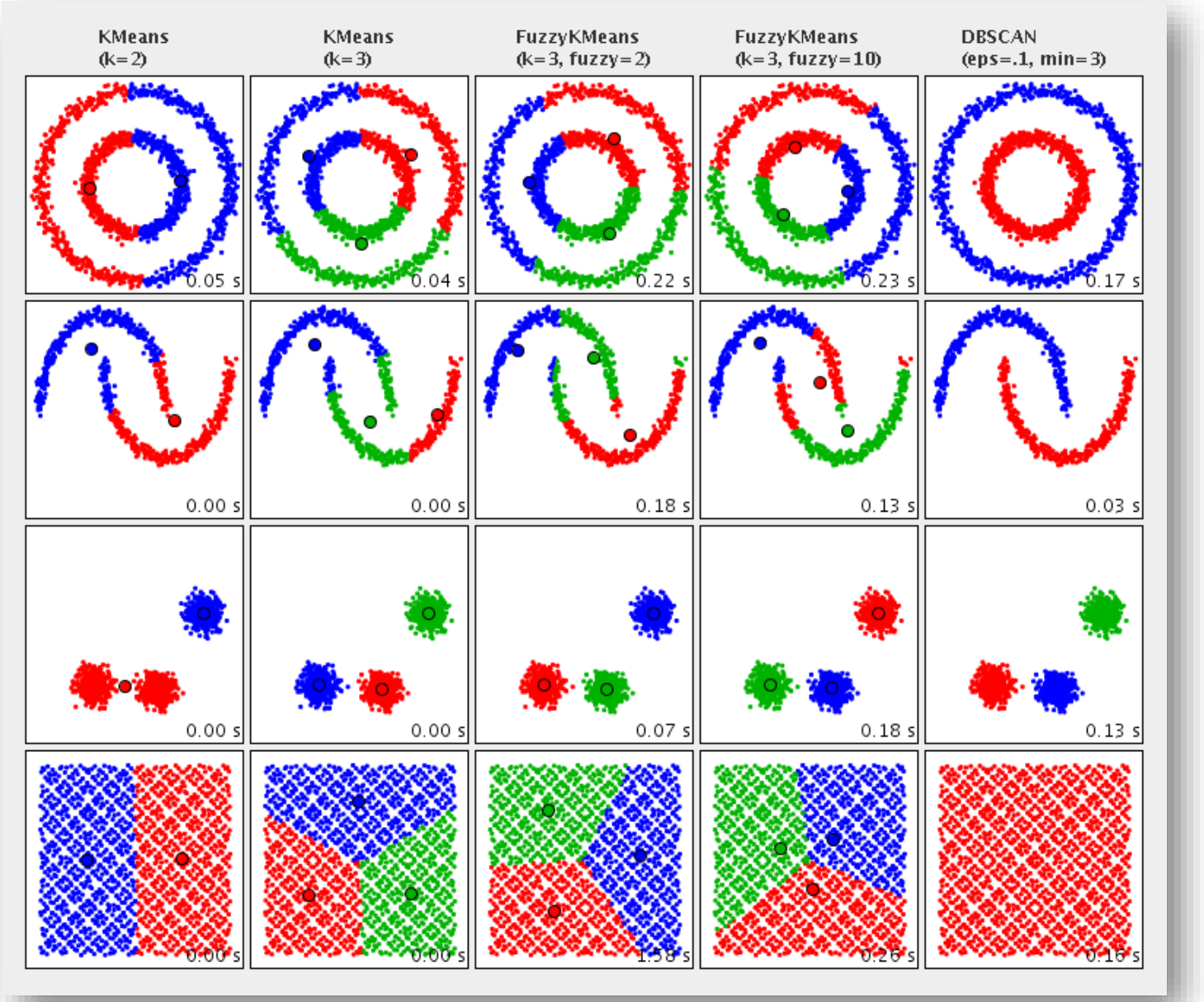




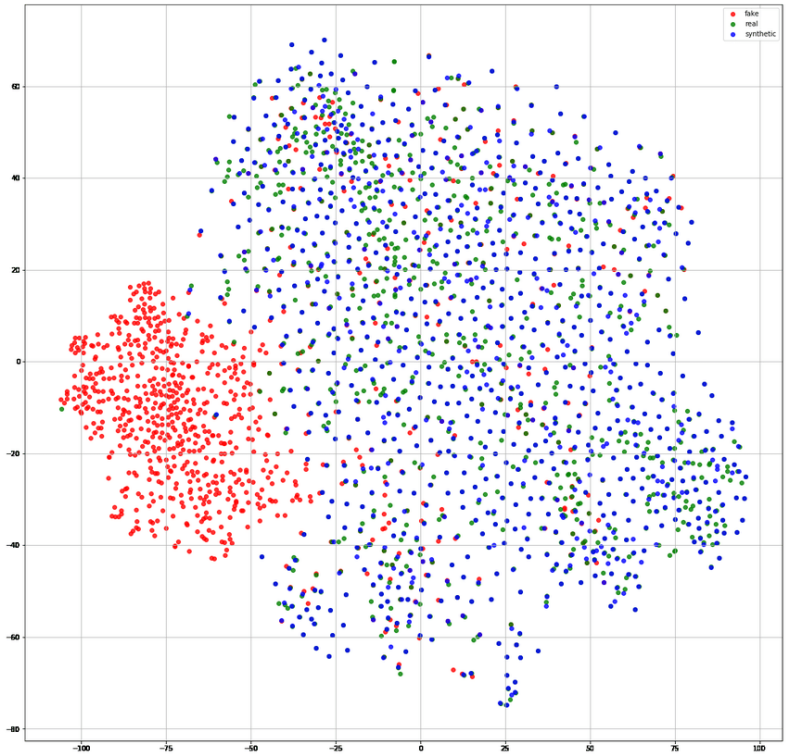
..and if your clusters are not blob shaped the results are not intuitive (i.e. what you expect)!

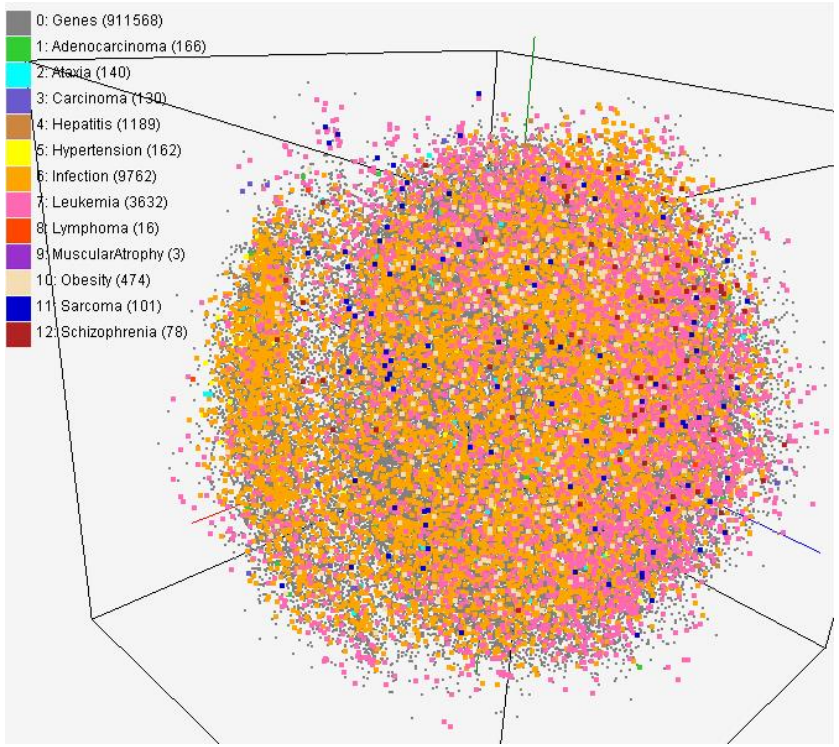
Source: Eric Eaton

CLUSTERING ALGORITHMS FOR EVERY RESULT!



DATA DIMENSIONS





Basic symbol	d [mm]	d [inch]	D [mm]	D [inch]	B [mm]	B [inch]	$r_{s\,min}$ [mm]	$r_{s\,min}$ [inch]	$d_{a\,min}$ [mm]	$d_{a\,min}$ [inch]	$d_{a\,max}$ [mm]	$d_{a\,max}$ [inch]	$D_{a\,max}$ [mm]	$D_{a\,max}$ [inch]
15875A	**15.875**	.625	**22.225**	.875	**3.967**	.156	**0.25**	.010	**16.9**	.665	**17.9**	.705	**20.6**	.811
15875A-2Z	**15.875**	.625	**22.225**	.875	**4.978**	.196	**0.25**	.010	**16.9**	.665	**17.9**	.705	**20.6**	.811
15875A-2TS	**15.875**	.625	**22.225**	.875	**4.978**	.196	**0.25**	.010	**16.9**	.665	**17.2**	.677	**20.6**	.811
19050A	**19.050**	.750	**25.400**	1.000	**3.967**	.156	**0.25**	.010	**20.1**	.791	**21.1**	.831	**23.7**	.933
19050A-2Z	**19.050**	.750	**25.400**	1.000	**4.978**	.196	**0.25**	.010	**20.1**	.791	**21.1**	.831	**23.7**	.933
19050A-2Z	**19.050**	.750	**25.400**	1.000	**4.978**	.196	**0.25**	.010	**20.1**	.791	**20.4**	.803	**23.7**	.933
22225A	**22.225**	.875	**28.575**	1.125	**3.967**	.156	**0.25**	.010	**23.3**	.917	**24.3**	.957	**26.9**	1.059
22225A-2Z	**22.225**	.875	**28.575**	1.125	**4.978**	.196	**0.25**	.010	**23.3**	.917	**24.3**	.957	**26.9**	1.059
22225A-2TS	**22.225**	.875	**28.575**	1.125	**4.978**	.196	**0.25**	.010	**23.3**	.917	**23.6**	.929	**26.9**	1.059
26988A	**26.988**	1.063	**33.338**	1.313	**3.967**	.156	**0.25**	.010	**28.1**	1.106	**29.1**	1.146	**31.7**	1.248
26988A-2Z	**26.988**	1.063	**33.338**	1.313	**4.978**	.196	**0.25**	.010	**28.1**	1.106	**29.1**	1.146	**31.7**	1.248
26988-2TS	**26.988**	1.063	**33.338**	1.313	**4.978**	.196	**0.25**	.010	**28.1**	1.106	**28.4**	1.118	**31.7**	1.248
31750A	**31.750**	1.250	**38.100**	1.500	**3.967**	.156	**0.25**	.010	**32.8**	1.291	**33.8**	1.331	**36.4**	1.433
31750A-2Z	**31.750**	1.250	**38.100**	1.500	**4.978**	.196	**0.25**	.010	**32.8**	1.291	**33.8**	1.331	**36.4**	1.433
31750A-2TS	**31.750**	1.250	**38.100**	1.500	**4.978**	.196	**0.25**	.010	**32.8**	1.291	**33.1**	1.303	**36.4**	1.433
34925A	**34.925**	1.375	**41.275**	1.625	**3.967**	.156	**0.25**	.010	**36.0**	1.417	**37.0**	1.457	**39.5**	1.555
34925A-2Z	**34.925**	1.375	**41.275**	1.625	**4.978**	.196	**0.25**	.010	**36.0**	1.417	**37.0**	1.457	**39.5**	1.555
34925A-2TS	**34.925**	1.375	**41.275**	1.625	**4.978**	.196	**0.25**	.010	**36.0**	1.417	**36.3**	1.429	**39.5**	1.555

Subject to change.

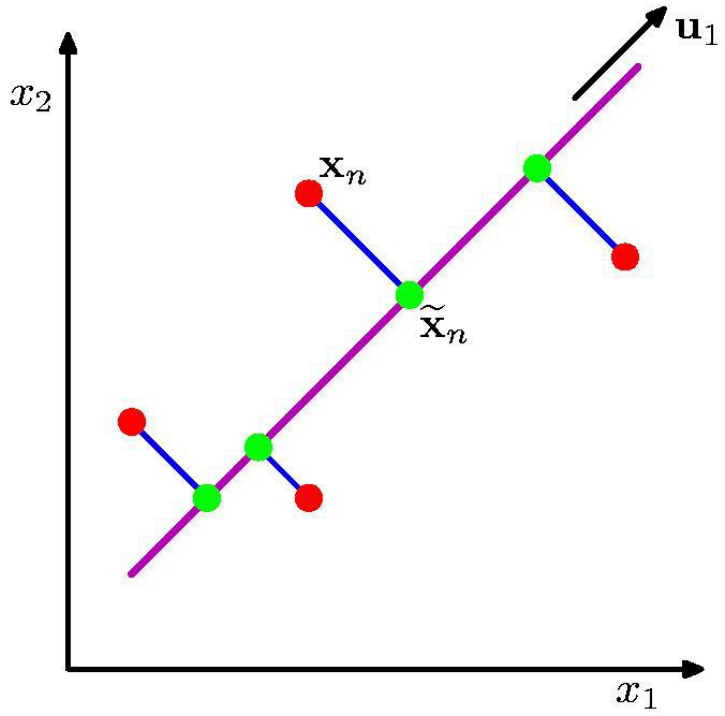
2D Data (x,y)

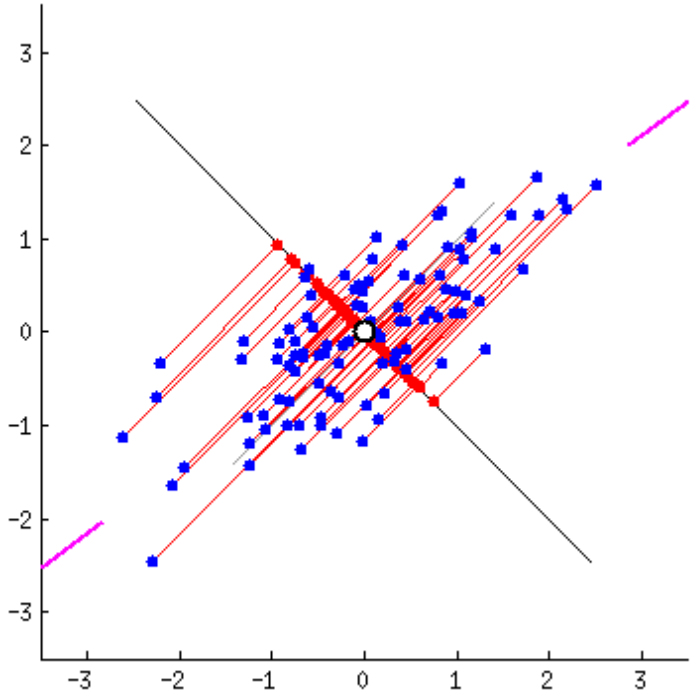
3D Data (x,y,z)

7D Data (d,D,B,r,d1,d2,D1)

You can cluster high dimensional data …but how can you visualize the results?

PRINCIPLE COMPONENT ANALYSIS (PCA)





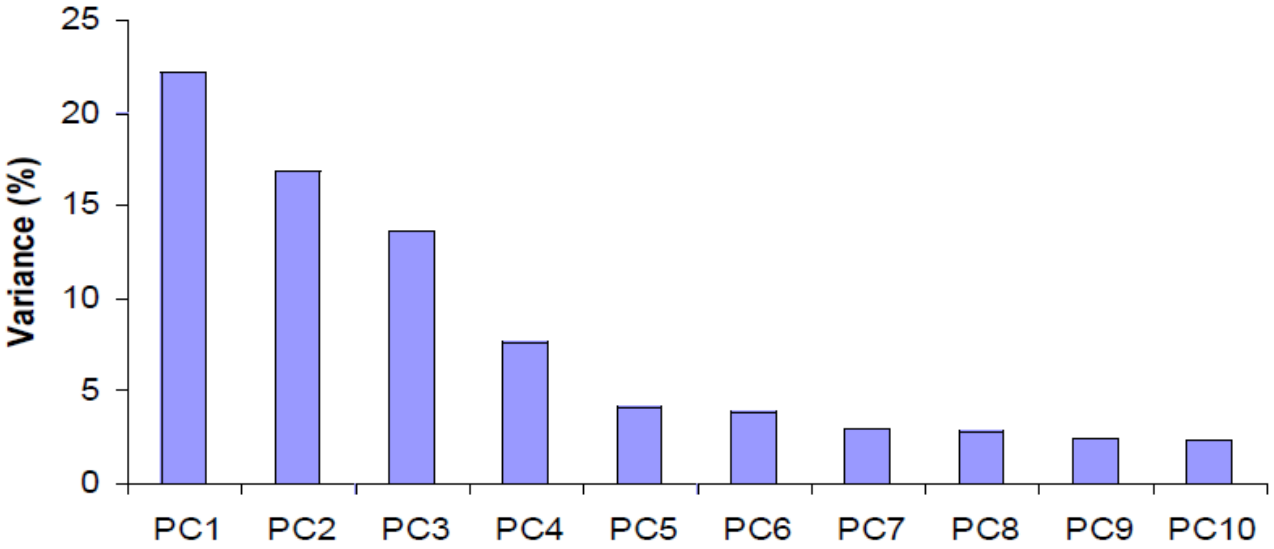
Orthogonal projection of data onto lower---dimension linear space that...

- Maximizes variance of projected data (purple line)
- Minimizes mean squared distance between data point and projections (sum of blue lines)

Source: Eric Eaton

DIMENSIONALITY REDUCTION

Can *ignore* the components of lesser significance

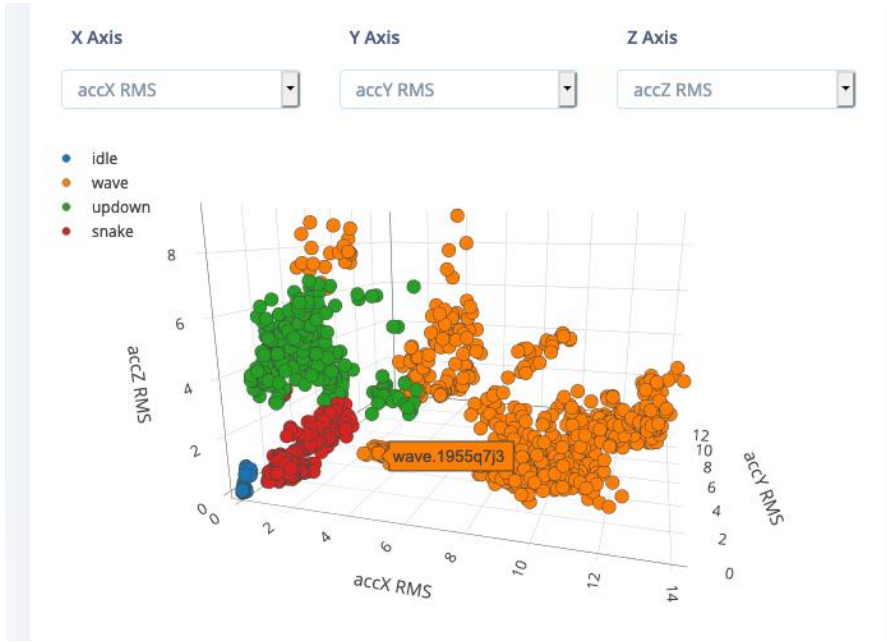


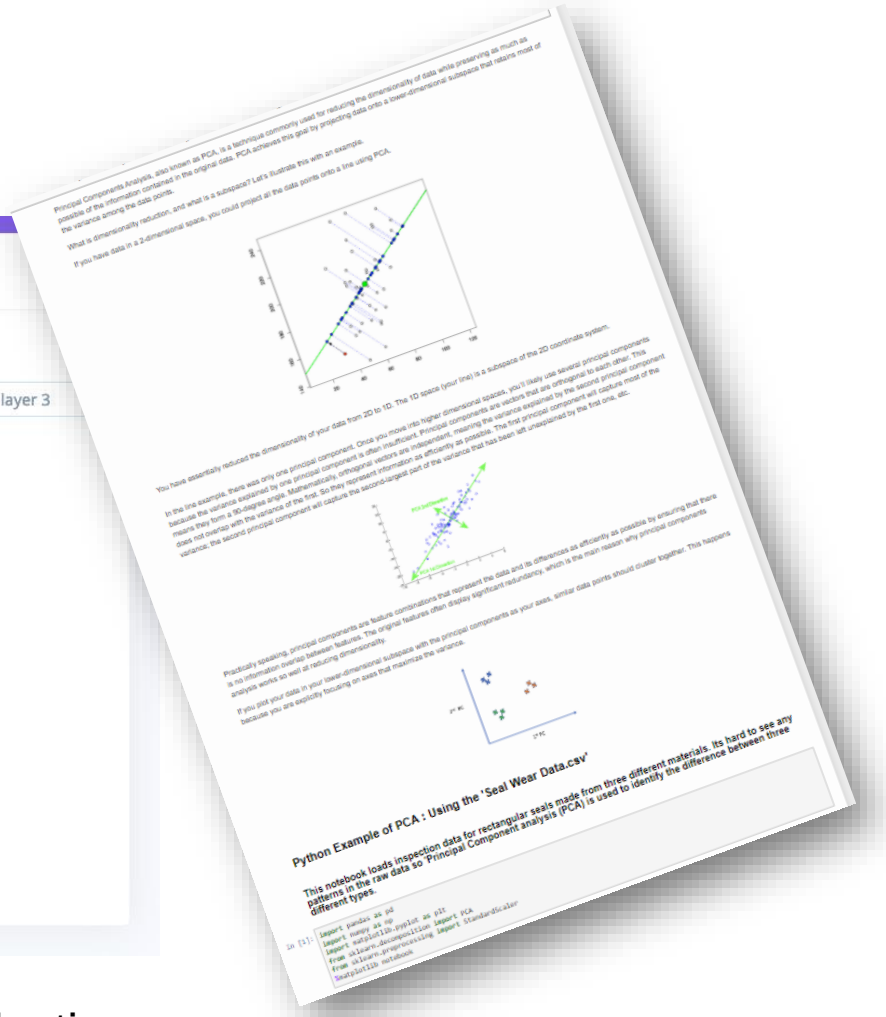
You do lose some informa1on, but if the eigenvalues are small, you don't lose much

- Choose only the first *k* eigenvectors, based on their eigenvalues
- Final data set has only *k* dimensions

Source: Eric Eaton

PCA APPLICATIONS





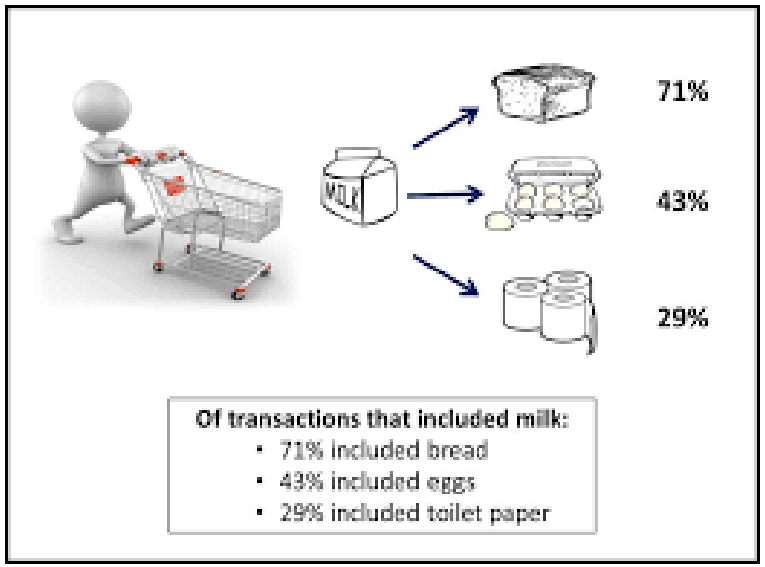
PCA is used for dimensionality reduction

It allows N-Dimensional Data to be “Projected” on to 3D or 2D spaces

After the break we will look at an example of using PCA to investigate Mechanical Seal Wear!

Source: Lyle Ungar

ITEM SETS & ASSOCIATION RULES



Example of Association Rules

{Diaper} → {Beer},
{Milk, Bread} → {Eggs,Coke},
{Beer, Bread} → {Milk},

Implication means co-occurrence, not causality!

Market-Basket transactions

TID	*Items*
1	Bread, Milk
2	Bread, Diaper, Beer, Eggs
3	Milk, Diaper, Beer, Coke
4	Bread, Milk, Diaper, Beer
5	Bread, Milk, Diaper, Coke

Itemsets

ASSOCIATION RULES
HAVE TWO PROBABILITIES ASSOCIATED WITH THEM KNOW AS SUPPORT (S) AND CONFIDENCE (C)

TID	*Items*
1	Bread, Milk
2	Bread, Diaper, Beer, Eggs
3	Milk, Diaper, Beer, Coke
4	Bread, Milk, Diaper, Beer
5	Bread, Milk, Diaper, Coke

Example of Rules:

{Milk,Diaper} → {Beer} (s=0.4, c=0.67)
{Milk,Beer} → {Diaper} (s=0.4, c=1.0)
{Diaper,Beer} → {Milk} (s=0.4, c=0.67)
{Beer} → {Milk,Diaper} (s=0.4, c=0.67)
{Diaper} → {Milk,Beer} (s=0.4, c=0.5)
{Milk} → {Diaper,Beer} (s=0.4, c=0.5)

MINING ASSOCIATION RULES

- Two-step approach:

  1. Frequent Itemset Generation

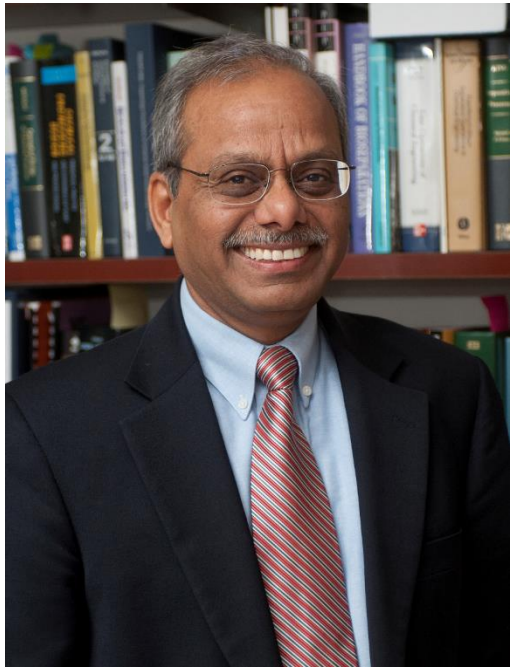
     – Generate all itemsets whose support $\geq$ minsup

  2. Rule Generation

     – Generate high confidence rules from each frequent itemset, where each rule is a binary partitioning of a frequent itemset

- However frequent itemset generation appears to be a very **computationally expensive task!**

Solution is described in one of the most cited papers in all of Computer Science….



Scholarly articles for **fast algorithms for mining association rules**

Fast algorithms for **mining association rules** - Agrawal - Cited by 21740

Fast algorithm for **mining association rules** - Margahny - Cited by 58

A **fast** distributed **algorithm** for **mining association rules** - Cheung - Cited by 630

[PDF] Fast Algorithms for Mining Association Rules - Rakesh Agrawal

rakesh.agrawal-family.com/papers/vldb94apriori.pdf ▾

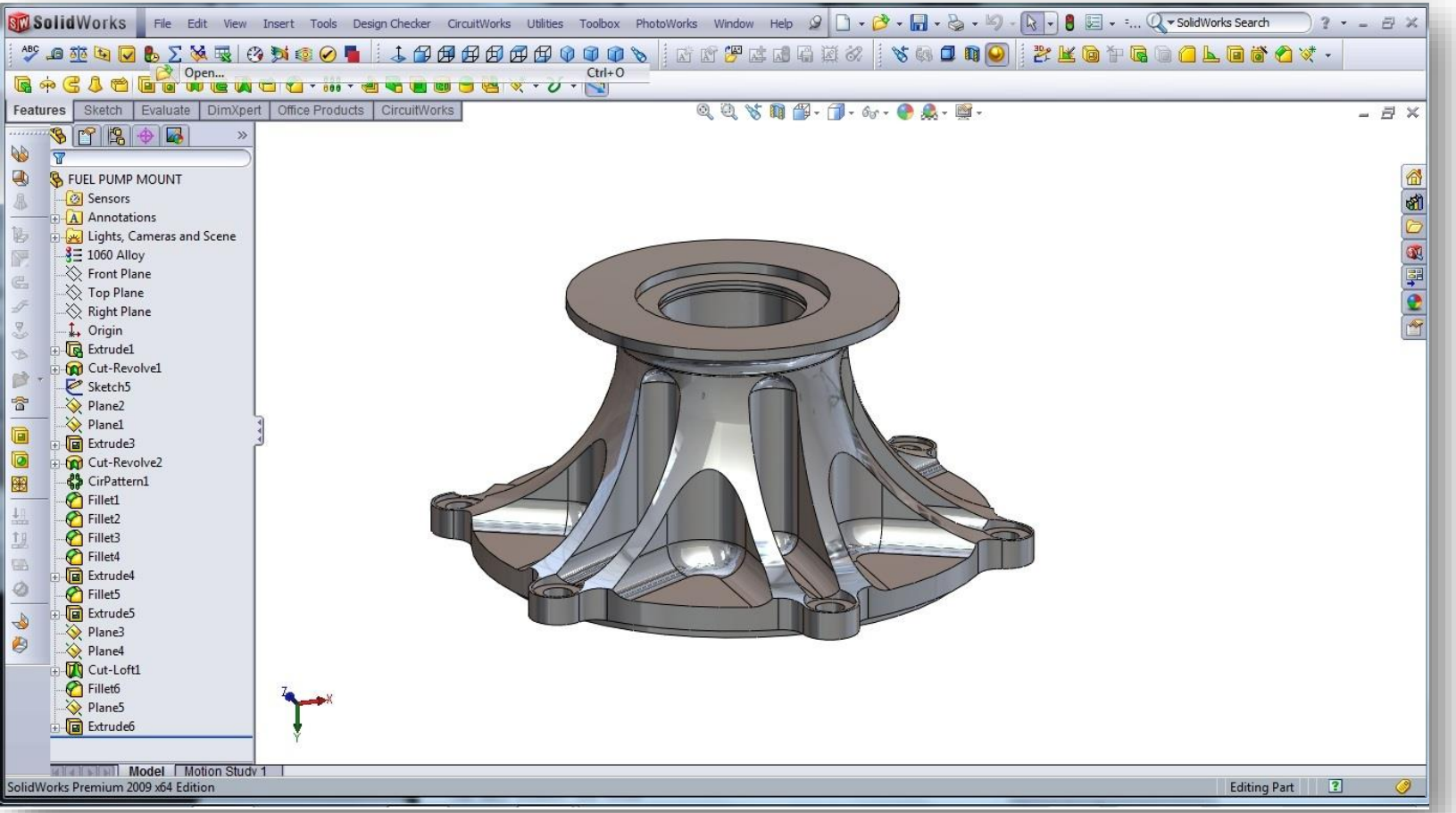
by R Agrawal - Cited by 21740 - Related articles

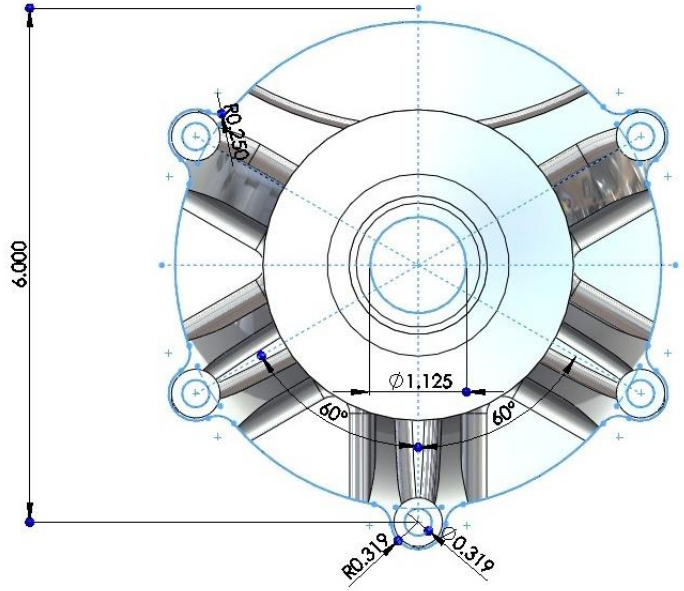
Fast Algorithms for Mining Association Rules. Rakesh Agrawal. Ramakrishnan Srikant. IBM Almaden Research Center. 650 Harry Road, San Jose, CA 95120.

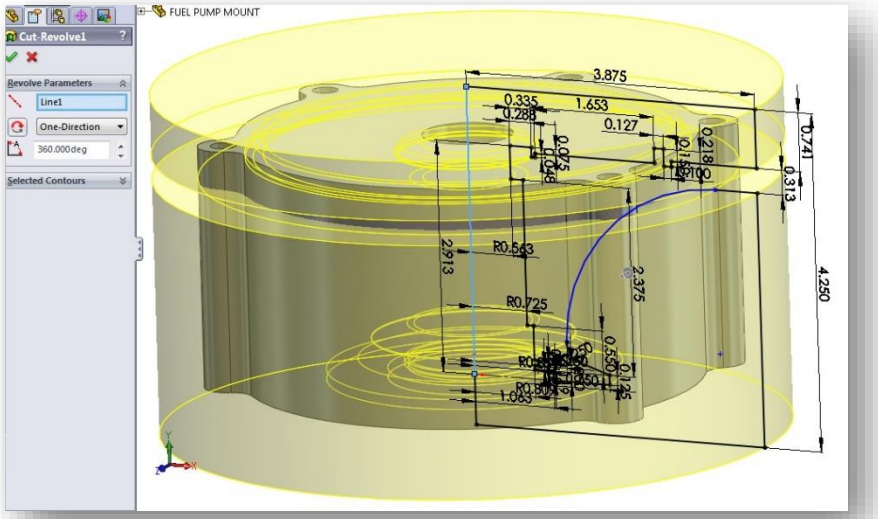
…….It's a clever tree search

EXAMPLE APPLICATION: ASSOCIATION RULE MINING OF ENGINEERING DESIGNS

CAD DATA DEFINES THE DESIGNS BUT WHERE IS THE DATA ?

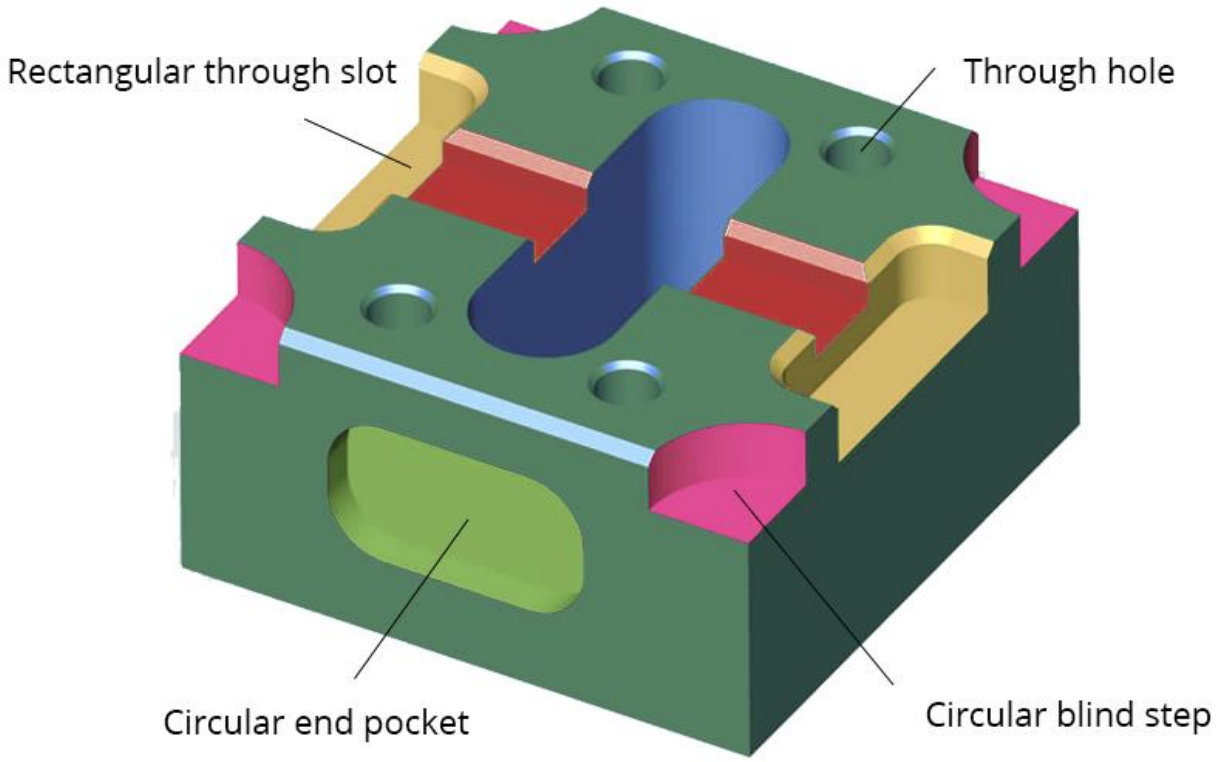


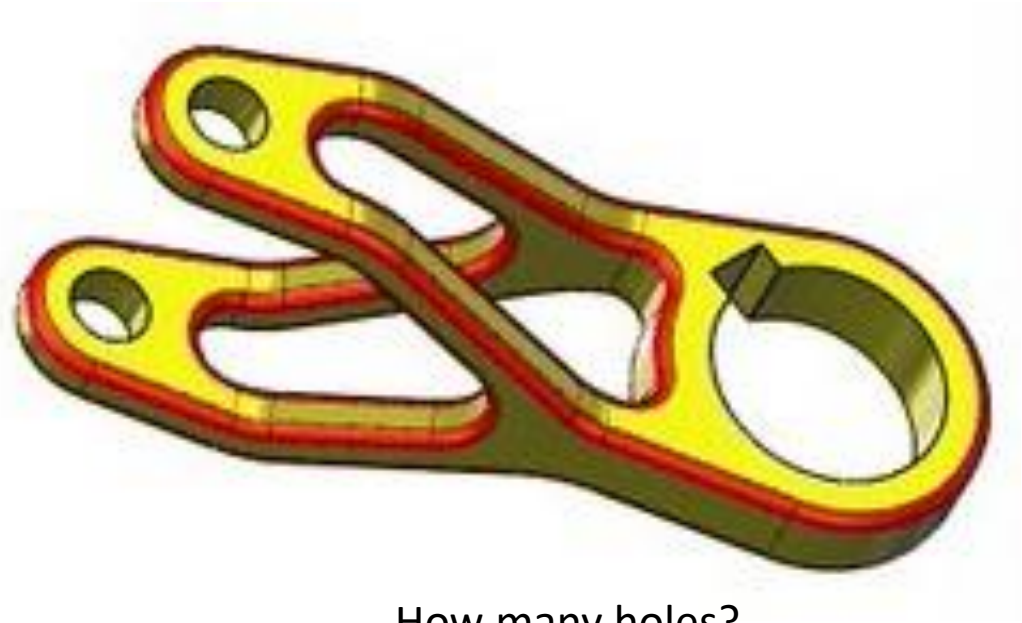




We can see it, most of the interpretation is done by the user not the computer

FOR SIMPLE SHAPES SO CALLED FEATURE INFORMATION CAN BE EXTRACTED, BUT FOR COMPLEX MODELS THE DEFINITIONS BREAKDOWN



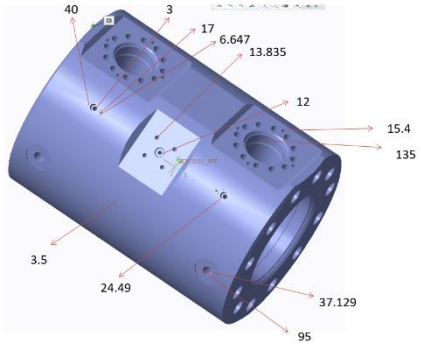


How many holes?

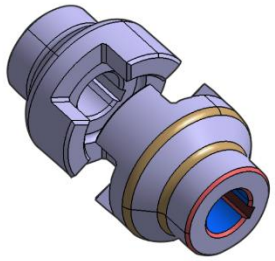
SPECTRUM OF INFORMATION EXTRACTABLE FROM CAD DATA

Mass Properties

Overall dimensions



Holes

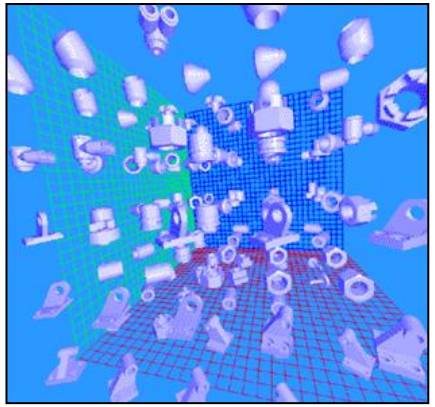


GTIN# 123 4567 890 234

GTIN# 091 2345 678 9012

Duplicates

(Same shape different part number)



Partial Similarity

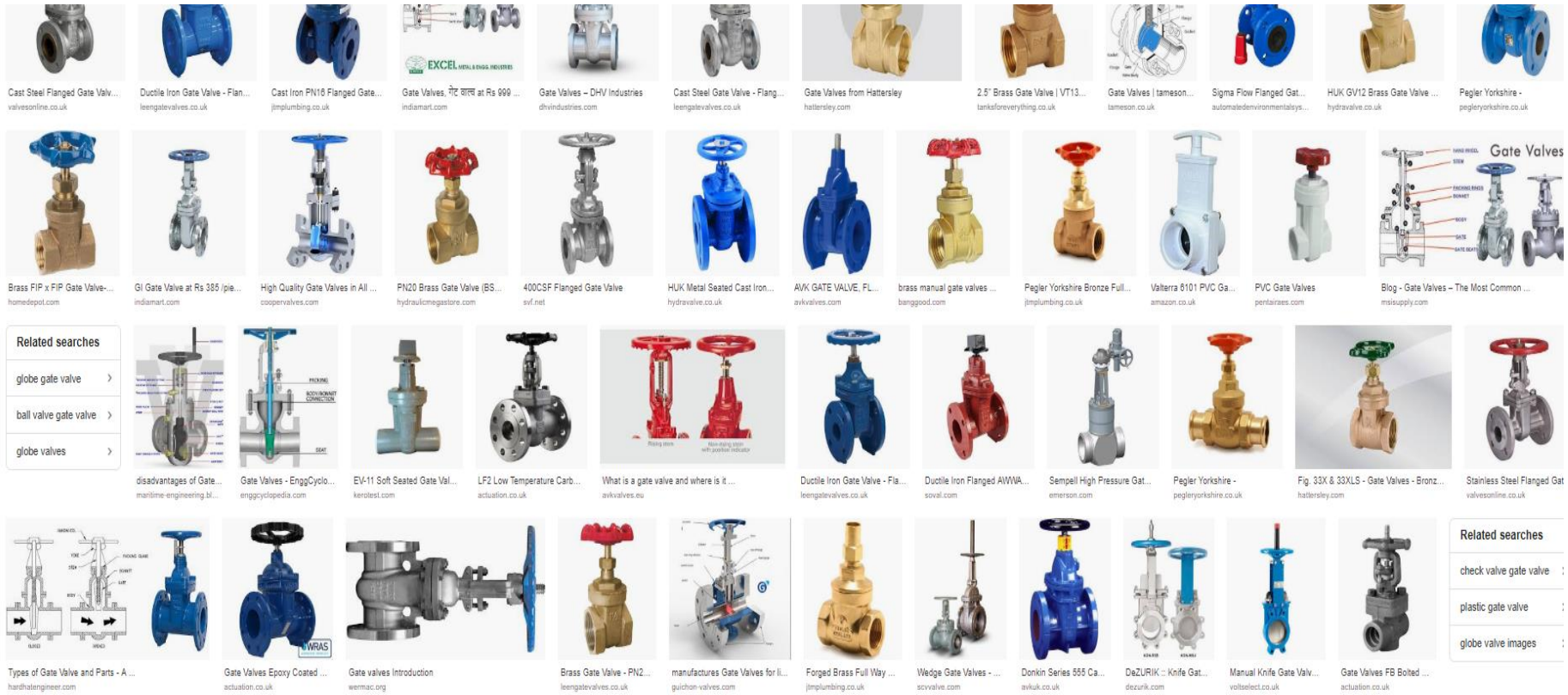
Easy

Hard

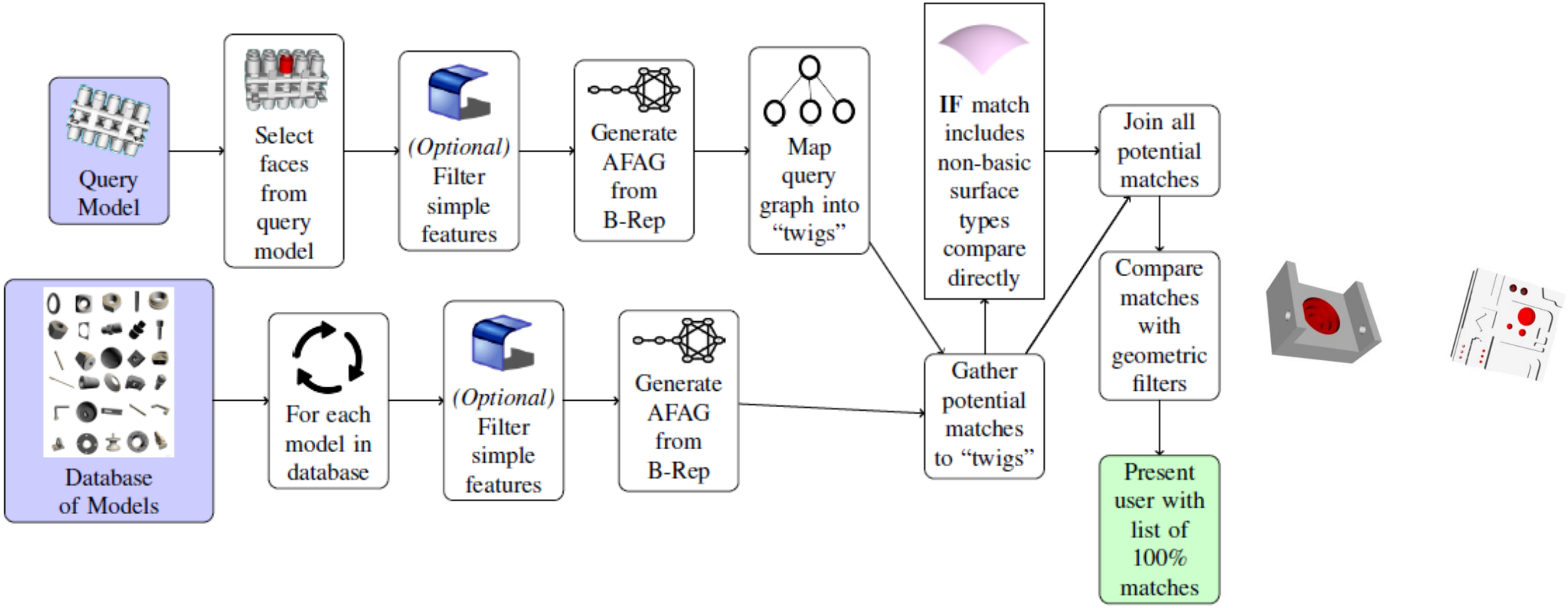
Impossible

THE UNIVERSITY of EDINBURGH
School of Engineering

3D CAD DATA FOR ONE COMPANY'S 16,000 VALVES



High speed feature recognition able to process dataset of models to extract the holes



NUMBER AND DIAMETERS OF HOLES EXTRACTED FROM EACH 3D CAD MODEL

Body

8502-3FF: 10,10,10,10,8,8,8,8, 12,12,12,12, 36, 45

Bonnet

8602WGB: 12,12,12,12,12,12,12,12, 34,38, 35

Part number: List of hole diameters

Hole Dataset

Component holes
[57.15, 12.0, 5.2, 46.375, 31.8, 3.5, 28.05, 50.0, 29.975, 84.07, 39.0, 12.85, 19.1, 63.375, 45.875, 22.025, 18.5, 17.175, 18.25, 24.915, 38.025, 54.86, 19.0, 63.88, 42.39, 26.75, 3.0, 6.647, 12.751, 15.05, 3
[1.6, 10.106, 16.307, 34.0, 13.835, 30.0, 20.7, 6.25, 3.0, 44.1, 42.2, 42.375, 45.0, 34.95, 41.7, 32.64, 45.5, 4.917, 44.4, 5.2, 3.5, 25.4, 27.15, 18.0, 58.0, 19.05, 12.751, 24.0, 32.0, 23.0, 37.0]
[20.7, 33.5, 19.065, 6.25, 5.2, 13.835, 10.592, 31.75, 101.24, 18.075, 48.625, 11.1, 44.1, 3.0, 6.35, 23.0, 40.5, 10.0, 40.0, 30.0, 3.2, 32.64, 50.4, 37.0, 12.751, 18.02, 3.5, 34.95, 58.0, 4.917]
[60.0, 12.751, 19.0, 46.8, 3.242, 29.975, 18.0, 19.177, 25.0, 3.0, 5.2, 3.5, 35.0, 24.49, 11.1, 16.307, 6.647, 10.592, 13.835, 43.78, 19.1, 51.0, 31.8, 36.0426, 38.8, 34.0, 18.5, 20.0, 15.0]
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[27.15, 32.0, 25.5, 44.1, 3.5, 1.6, 13.835, 58.0, 30.0, 41.1, 8.376, 5.0, 13.6, 34.0, 20.7, 3.0, 34.95, 17.75, 42.375, 4.917, 46.0374, 32.639, 44.4, 37.0, 32.64, 28.0, 6.25]
[13.835, 58.0, 41.1, 13.6, 20.7, 17.75, 28.0, 42.375, 34.0, 44.1, 34.95, 32.0, 5.0, 32.639, 32.64, 3.0, 6.25, 1.6, 37.0, 3.5, 46.0374, 44.4, 8.376, 30.0, 4.917, 25.5, 27.15]
[16.307, 44.4, 1.6, 26.92, 12.751, 23.95, 58.0, 32.0, 27.2, 25.4, 35.9, 5.2, 3.0, 27.4, 20.7, 4.917, 29.975, 6.25, 13.835, 44.1, 39.1, 34.0, 42.375, 7.798, 3.5, 4.0, 23.0]
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[37.0, 5.0, 27.15, 32.0, 53.025, 32.64, 13.6, 58.0, 3.5, 6.25, 30.0, 4.917, 13.835, 34.0, 42.0, 20.7, 34.95, 17.5, 44.1, 12.751, 5.2, 25.5, 44.4, 42.375, 3.0, 1.6, 18.25]
[18.25, 52.4, 46.2, 21.971, 6.0, 5.0, 60.0, 20.0, 49.5, 55.0, 35.0, 3.5, 33.5, 38.1, 329.2, 17.45, 48.0, 13.6, 53.0, 14.0, 200.0, 23.114, 29.4, 25.4, 26.05, 43.25, 13.835]
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[3.0, 41.4, 23.0, 30.0, 20.27, 25.15, 27.0, 32.75, 5.2, 24.49, 12.5, 13.835, 3.5, 30.39, 12.7, 22.23, 4.134, 19.05, 11.7, 11.1, 18.15, 25.9, 24.15, 25.1, 12.751, 10.106]
[13.5, 48.0, 5.2, 9.0, 4.917, 0.8, 12.751, 10.05, 27.65, 3.0, 10.23, 115.0, 27.025, 17.323, 13.6, 17.3, 7.798, 40.0, 25.0, 8.0, 6.35, 20.0, 10.0, 8.376, 3.242, 29.0]
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[1.6, 27.2, 29.975, 16.307, 23.0, 3.0, 27.15, 3.242, 44.4, 35.814, 26.92, 3.5, 32.0, 13.835, 23.95, 39.1, 12.751, 10.106, 42.375, 7.798, 25.4, 5.2, 20.7, 34.0, 58.0, 4.134]
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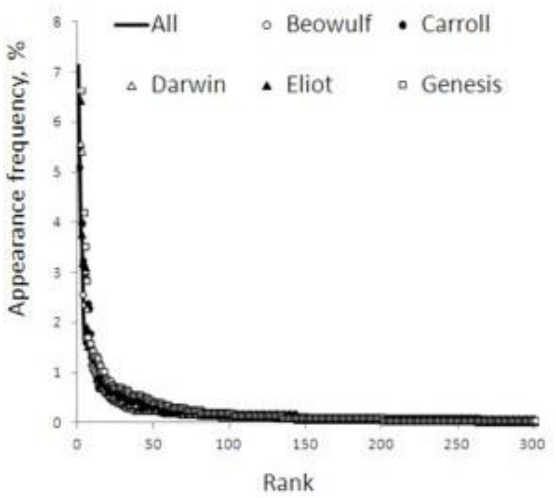
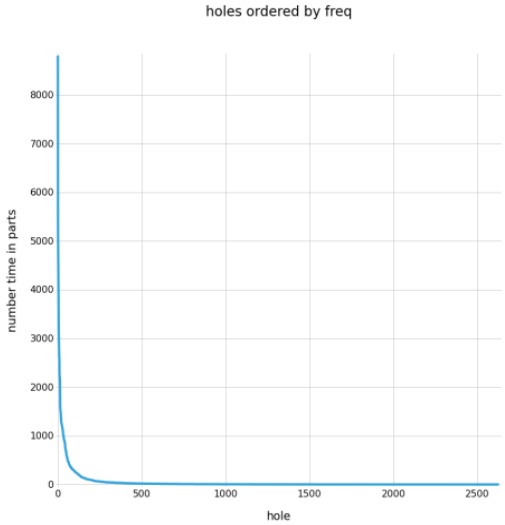
[26.92, 35.814, 3.242, 42.375, 27.15, 23.0, 5.2, 25.4, 23.95, 20.7, 16.307, 32.0, 34.0, 12.751, 3.0, 4.134, 13.835, 39.1, 44.4, 29.975, 7.798, 27.2, 1.6, 3.5, 58.0]

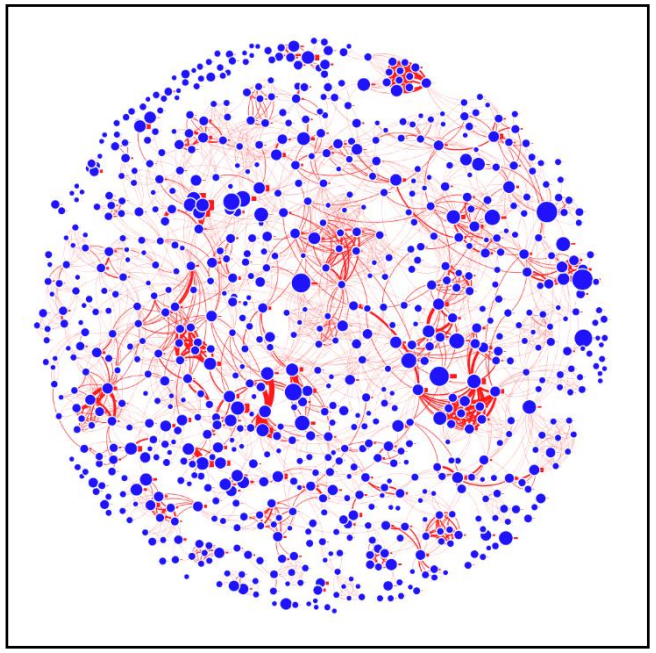
THERE ARE PATTERNS IN THE HOLE DATA



(a) Word Frequency



(b) Hole Diameter Frequency



Each node in the graph represents a specific diameter of hole: The size of the nodes is proportional to the frequency of the hole size within the CAD database. The thickness of the red arcs between nodes is proportional to the frequency with which the holes occur on the same component.

Component holes
[57.15, 12.0, 5.2, 46.375, 31.8, 3.5, 28.05, 50.0, 29.975, 84.07, 39.0, 12.85, 19.1, 63.375, 45.875, 22.025, 18.5, 17.175, 18.25, 24.915, 38.025, 54.86, 19.0, 63.88, 42.39, 26.75, 3.0, 6.647, 12.751, 15.05, 3
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[60.0, 12.751, 19.0, 46.8, 3.242, 29.975, 18.0, 19.177, 25.0, 3.0, 5.2, 3.5, 35.0, 24.49, 11.1, 16.307, 6.647, 10.592, 13.835, 43.78, 19.1, 51.0, 31.8, 36.0426, 38.8, 34.0, 18.5, 20.0, 15.0]
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[27.15, 32.0, 25.5, 44.1, 3.5, 1.6, 13.835, 58.0, 30.0, 41.1, 8.376, 5.0, 13.6, 34.0, 20.7, 3.0, 34.95, 17.75, 42.375, 4.917, 46.0374, 32.639, 44.4, 37.0, 32.64, 28.0, 6.25]
[13.835, 58.0, 41.1, 13.6, 20.7, 17.75, 28.0, 42.375, 34.0, 44.1, 34.95, 32.0, 5.0, 32.639, 32.64, 3.0, 6.25, 1.6, 37.0, 3.5, 46.0374, 44.4, 8.376, 30.0, 4.917, 25.5, 27.15]
[16.307, 44.4, 1.6, 26.92, 12.751, 23.95, 58.0, 32.0, 27.2, 25.4, 35.9, 5.2, 3.0, 27.4, 20.7, 4.917, 29.975, 6.25, 13.835, 44.1, 39.1, 34.0, 42.375, 7.798, 3.5, 4.0, 23.0]
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[18.25, 52.4, 46.2, 21.971, 6.0, 5.0, 60.0, 20.0, 49.5, 55.0, 35.0, 3.5, 33.5, 38.1, 329.2, 17.45, 48.0, 13.6, 53.0, 14.0, 200.0, 23.114, 29.4, 25.4, 26.05, 43.25, 13.835]
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[26.92, 35.814, 3.242, 42.375, 27.15, 23.0, 5.2, 25.4, 23.95, 20.7, 16.307, 32.0, 34.0, 12.751, 3.0, 4.134, 13.835, 39.1, 44.4, 29.975, 7.798, 27.2, 1.6, 3.5, 58.0]

Perhaps the collection of holes on each component could be analogous to items in shopping basket

TID	*Items*
1	Bread, Milk
2	Bread, Diaper, Beer, Eggs
3	Milk, Diaper, Beer, Coke
4	Bread, Milk, Diaper, Beer
5	Bread, Milk, Diaper, Coke

Itemsets

Example of Association Rules

{Diaper} → {Beer},
{Milk, Bread} → {Eggs,Coke},
{Beer, Bread} → {Milk},

Implication means co-occurrence, not causality!

Component holes
[57.15, 12.0, 5.2, 46.375, 31.8, 3.5, 28.05, 50.0, 29.975, 84.07, 39.0, 12.85, 19.1, 63.375, 45.875, 22.025, 18.5, 17.175, 18.25, 24.915, 38.025, 54.86, 19.0, 63.88, 42.39, 26.75, 3.0, 6.647, 12.751, 15.05, 3
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[60.0, 12.751, 19.0, 46.8, 3.242, 29.975, 18.0, 19.177, 25.0, 3.0, 5.2, 3.5, 35.0, 24.49, 11.1, 16.307, 6.647, 10.592, 13.835, 43.78, 19.1, 51.0, 31.8, 36.0426, 38.8, 34.0, 18.5, 20.0, 15.0]
[38.8, 20.0, 24.49, 5.2, 43.78, 12.751, 18.5, 35.0, 34.0, 3.5, 51.0, 11.1, 36.0426, 19.0, 31.8, 15.0, 29.975, 10.592, 60.0, 25.0, 6.647, 46.8, 18.0, 19.1, 13.835, 3.0, 3.242, 16.307]
[15.0, 14.0, 24.92, 23.8124, 20.0, 3.5, 28.05, 22.225, 4.134, 9.0, 34.25, 12.0, 3.0, 11.835, 6.647, 35.975, 27.625, 15.125, 45.7962, 26.0, 27.0, 24.69, 18.05, 45.2424, 22.0, 31.17, 12.85]
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[27.15, 32.0, 25.5, 44.1, 3.5, 1.6, 13.835, 58.0, 30.0, 41.1, 8.376, 5.0, 13.6, 34.0, 20.7, 3.0, 34.95, 17.75, 42.375, 4.917, 46.0374, 32.639, 44.4, 37.0, 32.64, 28.0, 6.25]
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[26.92, 35.814, 3.242, 42.375, 27.15, 23.0, 5.2, 25.4, 23.95, 20.7, 16.307, 32.0, 34.0,

L3						
3	3.242	5.2	support	:	119	
3	3.242	12.751	support	:	122	
3	3.242	20	support	:	74	
3	3.5	4.134	support	:	75	
3	3.5	5.2	support	:	150	
3	3.5	6.647	support	:	256	
3	3.5	8	support	:	151	
3	3.5	8.376	support	:	63	
3	3.5	10.106	support	:	65	
3	3.5	10.592	support	:	162	
3	3.5	11.1	support	:	88	
				:	205	
				:	151	
				:	196	
				:	110	
3	3.5	15.125	support	:	143	
3	3.5	16.307	support	:	157	
3	3.5	18.05	support	:	116	
3	3.5	18.1	support	:	62	
3	3.5	18.923	support	:	117	
3	3.5	20	support	:	62	
3	3.5	23	support	:	57	
3	3.5	24.49	support	:	79	
3	3.5	24.69	suppo			
3	3.5	24.915	suppo			
3	3.5	26.289	suppo			
3	3.5	28.05	suppo			

K = 3 Itemsets of hole diameters

List of Hole Diameters on each component

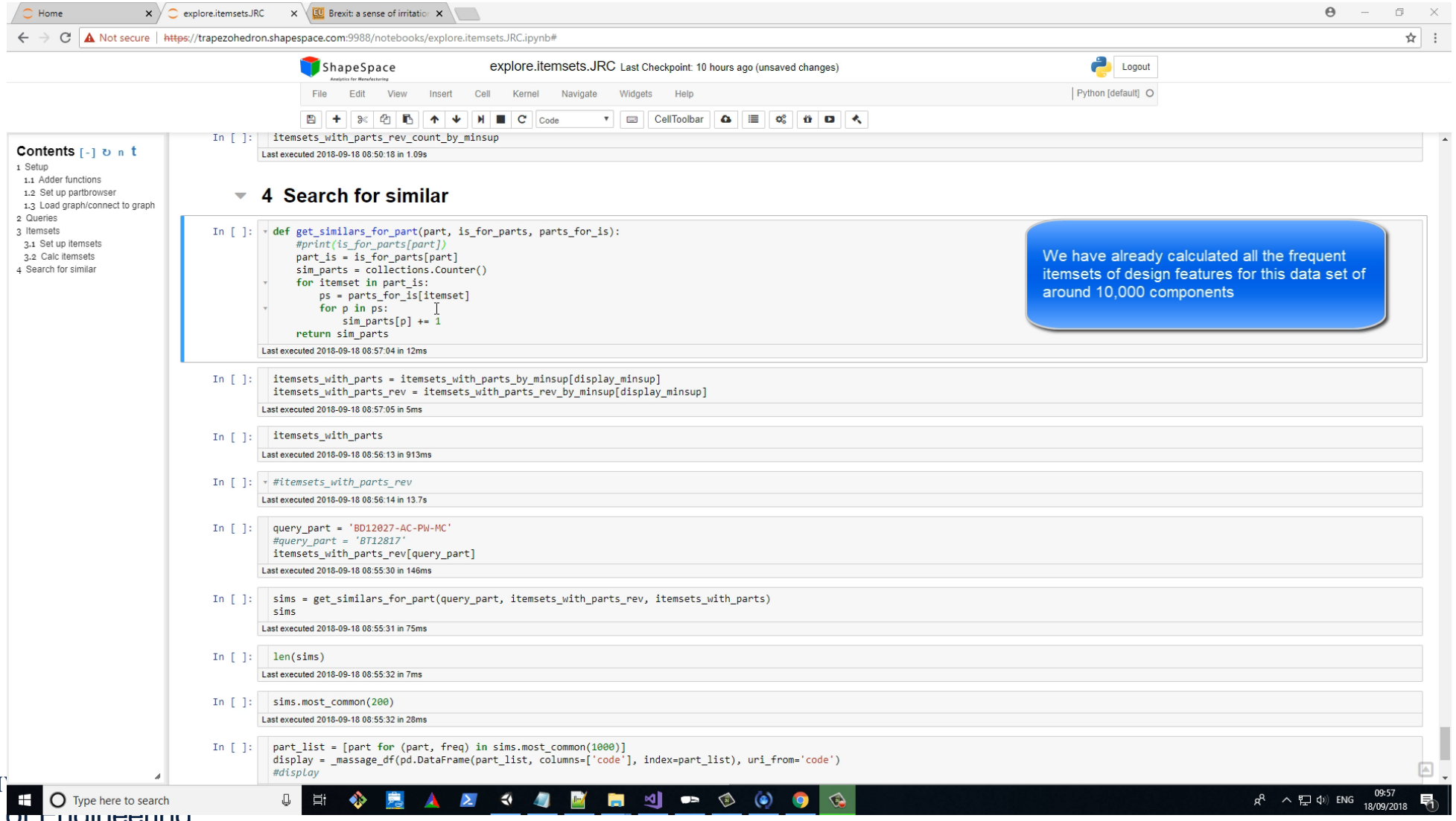
Frequency with which the Itemsets occurs

THE UNIVERSITY of EDINBURGH
School of Engineering

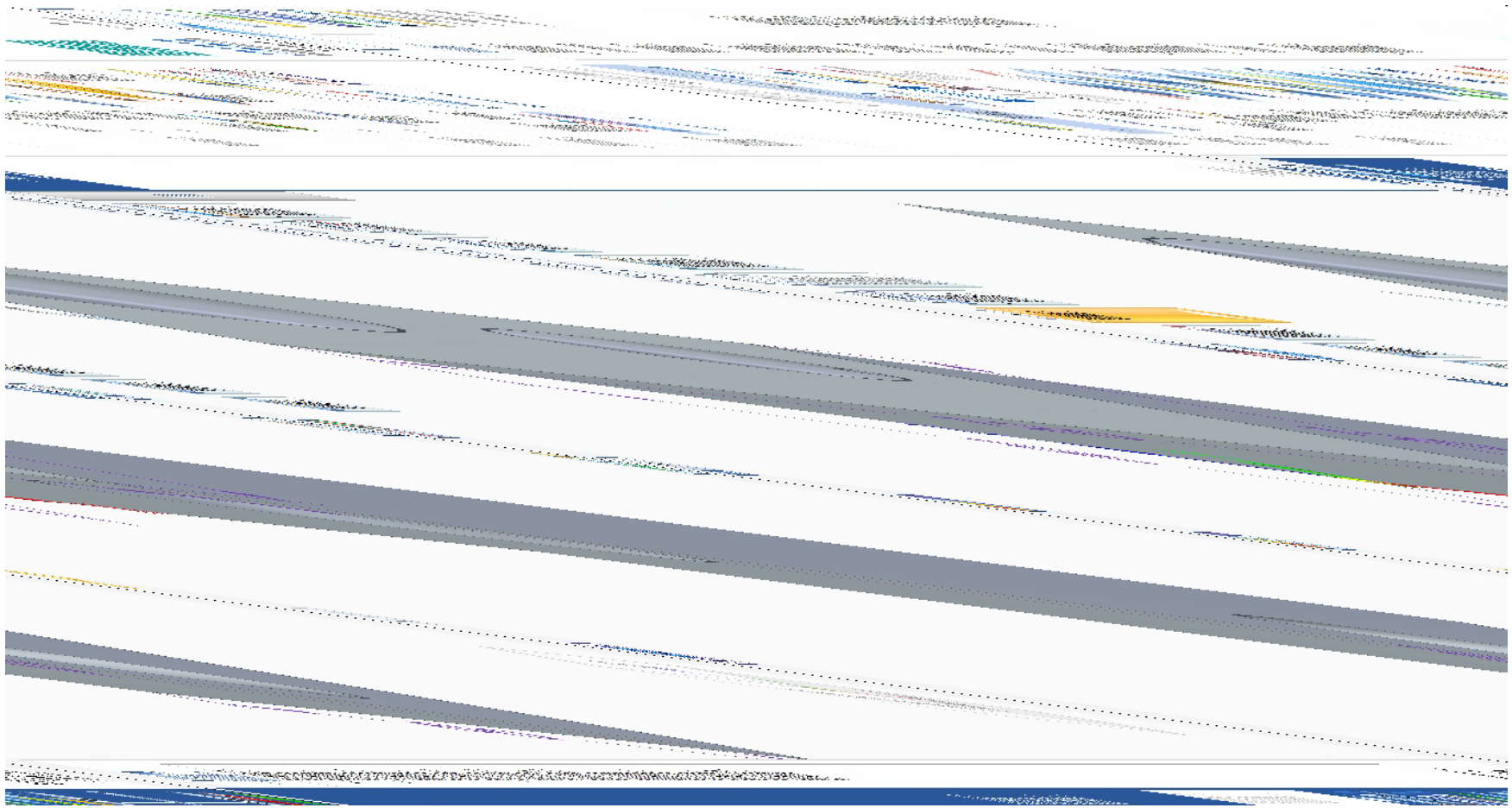
ANALYSIS OF MANY DATA SET PRODUCES MANY DIFFERENT ITEM SETS

2.5	4.8	7.75	sup=1														
2.5	5.675	6.8	sup=1														
2.5	11.2	sup=1															
2.5	32.5	42.45	42.5	44.7	sup=1												
2.5	3	sup=19															
	2.5	3	3.242	sup=14													
		2.5	3	3.242	4.917	sup=12											
			2.5	3	3.242	4.917	5.2	sup=10									
				2.5	3	3.242	4.917	5.2	6.35	7.798	sup=6						
					2.5	3	3.242	4.917	5.2	6.35	7.798	11	12.751	13	13.5	17.05	17.3228
					2.5	3	3.242	4.917	5.2	6.35	7.798	9	11	12.751	13.5	13.6	17.3228
				2.5	3	3.242	4.917	5.2	6	7.798	10.592	11	12.751	13	13.5	17.05	20
				2.5	3	3.242	4.917	5.2	7.798	sup=3							
					2.5	3	3.242	4.917	5.2	7.798	11	12.751	13	13.5	13.6	17.3228	20
					2.5	3	3.242	4.917	5.2	7.798	8	11	12.751	13	13.5	13.6	17.3228
			2.5	3	3.242	4.917	5.1	5.2	sup=2								
				2.5	3	3.242	4.917	5.1	5.2	11.835	12.751	16.667	21	24.1	25.2	25.4	30.675
				2.5	3	3.242	4.917	5.1	5.2	10.106	12.751	16.667	21	23.82	25.2	25.4	30.65
		2.5	3	3.242	5.2	sup=2											
			2.5	3	3.242	5.2	10.106	12.751	12.86	15	16.667	16.8	18	21	24.8	25.4	26.475
			2.5	3	3.242	5.2	6.35	7.798	9	11	12.751	13.6	14	17.3228	20	25	27.025
	2.5	3	5.2	sup=5													

PARTS WITH THE SAME ITEMSETS ARE SIMILAR

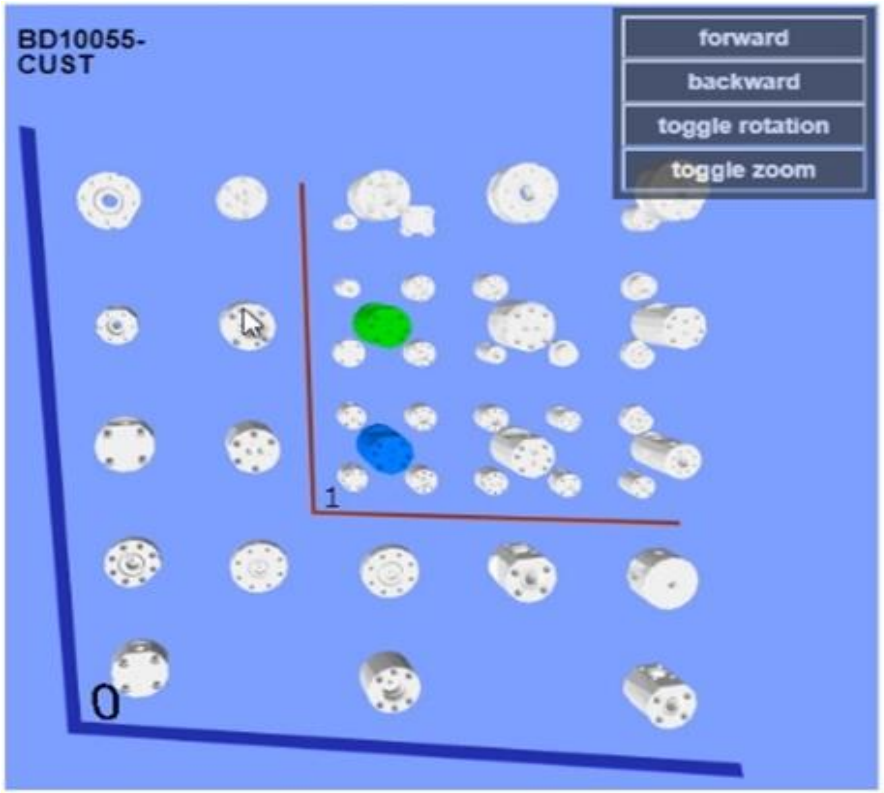


VERSION 0.1 OF OUR SOLIDEDGE "PREDICATIVE HOLE PLUG-IN"



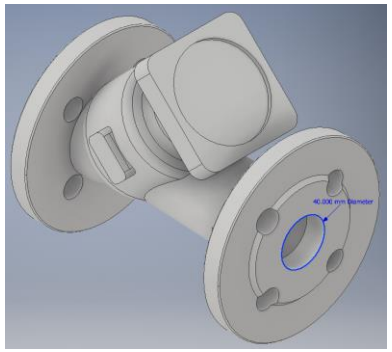
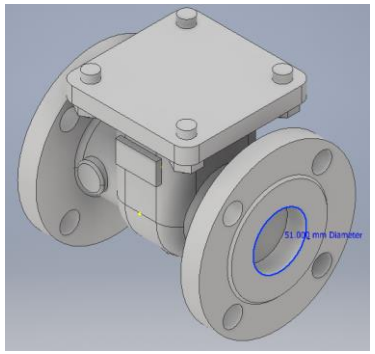
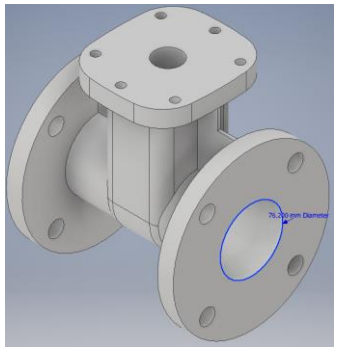
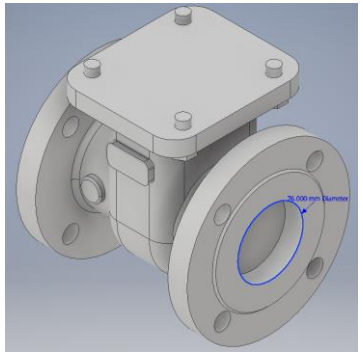
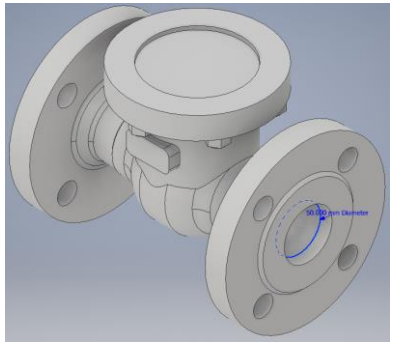
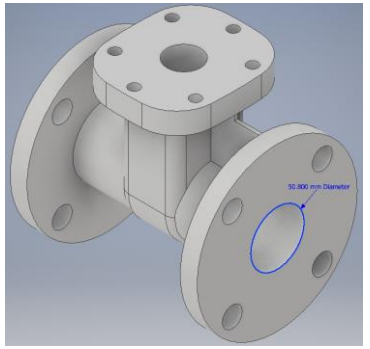
ONCE DATA IS EXTRACTED FROM THE CAD MODEL IT CAN ENABLE PORTFOLIO ANALYSES

- However each data extract process currently has to be bespoke dependent of the particular CAD systems and the CAD data



Similar Parts have Similar Itemsets
(i.e. Similar Patterns of holes

ASSOCIATION RULES CAN ALSO BE USED TO IDENTIFY SUBSTITUTABLE FEATURES

- If the patterns of holes that occur frequently together have been identified then they can be used to suggest potential ***substitutions***

AFTER THE BREAK WE WILL LOOK AT PYTHON NOTEBOOK EXAMPLE OF THE CLASSIC ITEM SET APPLICATION TO SHOPPING DATE

THE UNIVERSITY of EDINBURGH
School of Engineering

ML PREDICTION ALGORITHMS

MANY PREDICTION ALGORITHMS AVAILABLE ..THE PROBLEM IS ONE OF CHOICE

	TYPE	NAME	DESCRIPTION	ADVANTAGES	DISADVANTAGES
Linear		**Linear Regression**	**The "best fit" line** through all data points. Predictions are numerical.	Easy to understand — you clearly see what the biggest drivers of the model are.	Sometimes too simple to capture complex relationships between variables. Does poorly with correlated features.
		**Logistic Regression**	The adaptation of **linear regression** to problems of classification (e.g., yes/no questions, groups, etc.	Also easy to understand.	Sometimes too simple to capture complex relationships between variables. Does poorly with correlated features.

Source: data iku

PREDICTION ALGORITHMS (CONTINUED)

Tree-Based		**Decision Tree**	**A series of yes/no rules based on the features,** forming a tree, to match all possible outcomes of a decision.	Easy to understand.	Not often used on its own for prediction because it's also often too simple and not powerful enough for complex data.
		**Random Forest**	Takes advantage of many decision trees, with rules created from subsamples of features. Each tree is weaker than a full decision tree, but **by combining them we get better overall performance.**	A sort of "wisdom of the crowd". Tends to result in very high quality models. Fast to train.	Models can get very large. Not easy to understand predictions.
		**Gradient Boosting**	Uses even weaker decision trees, that are increasingly **focused on "hard" examples.**	High-performing.	A small change in the feature set or training set can create radical changes in the model. Not easy to understand predictions.

Source: data iku

MANY OF THESE WE HAVE SEEN BEFORE …THE COMPUTATIONAL DIFFERENCE BETWEEN

CLASSIFICATION AND PREDICTION IS OFTEN QUITE SMALL

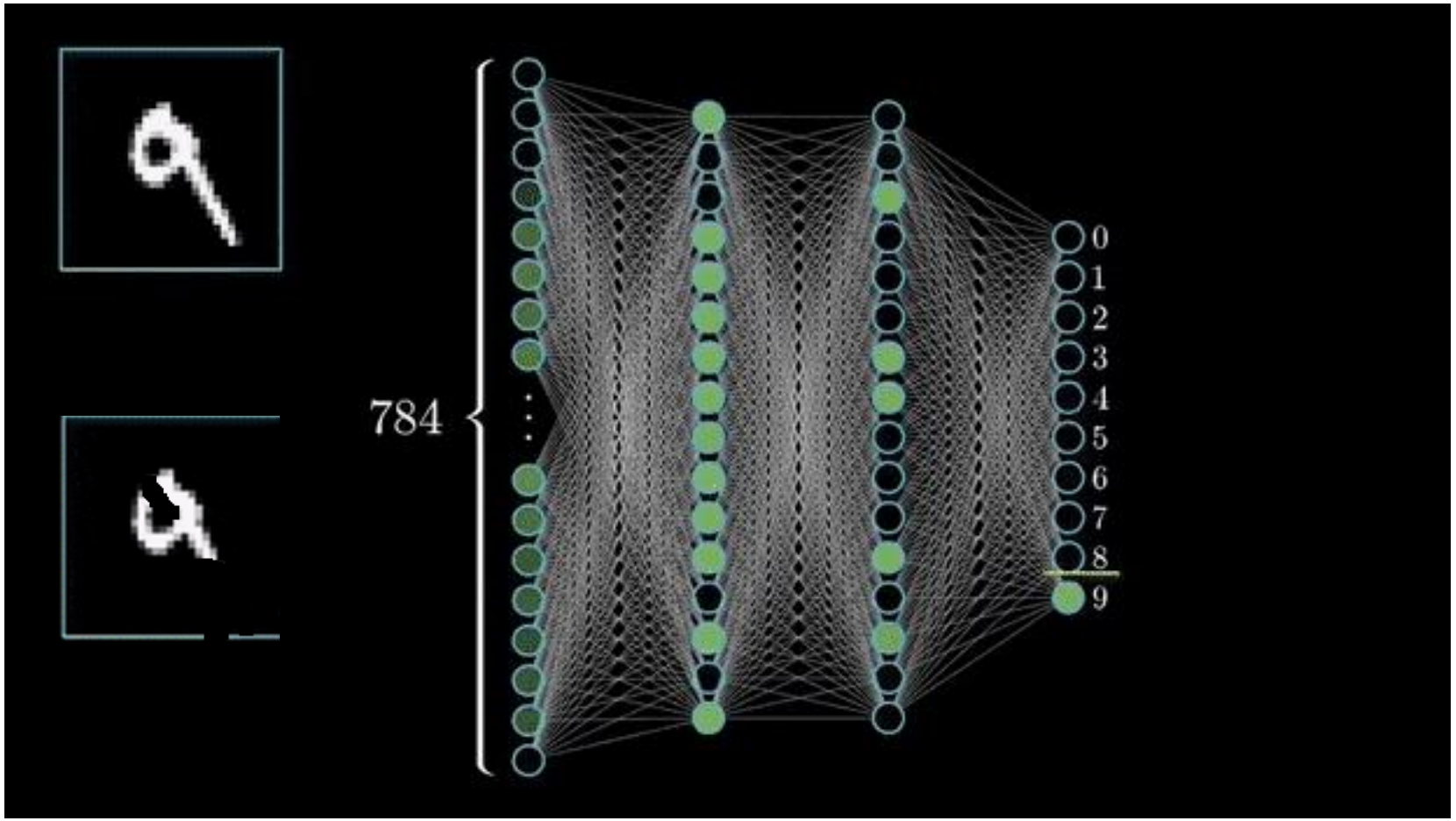
Neural Networks		**Neural Networks**	Interconnected "neurons" that pass messages to each other. Deep learning uses several **layers of neural networks stacked on top of one another.**	Can handle extremely complex tasks — no other algorithm comes close in image recognition.	Very slow to train, because they often have a very complex architecture. Almost impossible to understand predictions.

Source: data iku

RECALL THE NEURAL NETWORKS RESPONSE IS DETERMINED BY THE **WEIGHTS** APPLIED TO THE 1000'S OF ARCS CONNECTING THE "NEURONS"

784 input pixels

An incomplete input (e.g. 456 pixels) will still produce an output that could be interpreted as "predicting" what character is being drawn



The outputs each have a different "strength"; a different probability

The **weights** are calculated by the training process

SO LOTS OF CHOICE AND CONSEQUENTLY A LARGE PART OF MOST PREDICTIONS PROJECTS IS FOCUSED ON EVALUATING MODELS

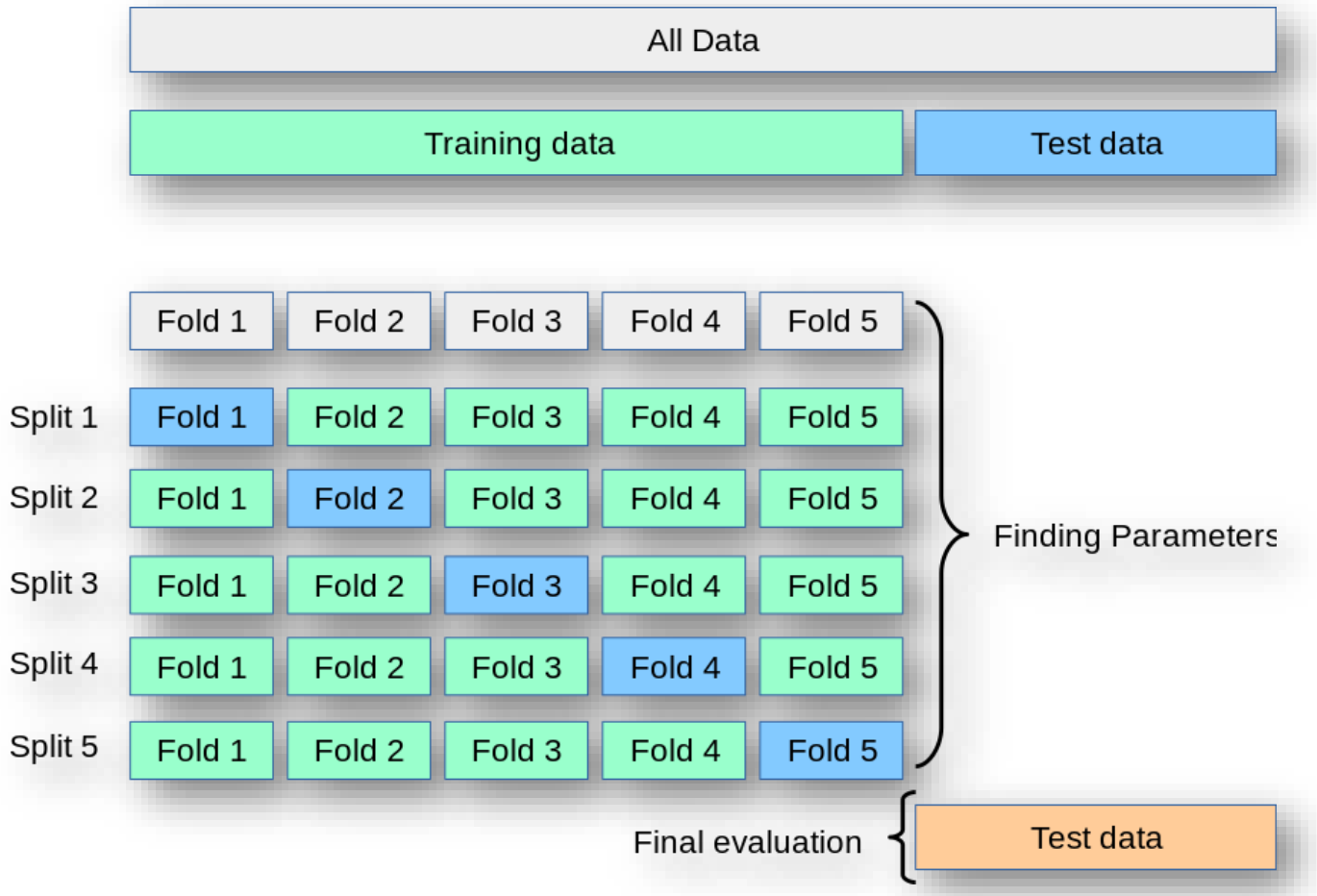
TRAINING VS. TEST DISTRIBUTION

- We generally assume that the training and test examples are independently drawn from the same overall distribution of data
  - We call this “i.i.d” which stands for “independent and identically distributed”
- If examples are not independent, requires ***collective classification***
- If test distribution is different, requires ***transfer learning***

Slide credit: Ray Mooney

AGAIN MANY METHODS OF EVALUATING MODELS

- Accuracy
- Precision and recall
- Squared error
- Likelihood
- Posterior probability
- Cost / Utility
- Margin
- Entropy
- K-L divergence
- etc.

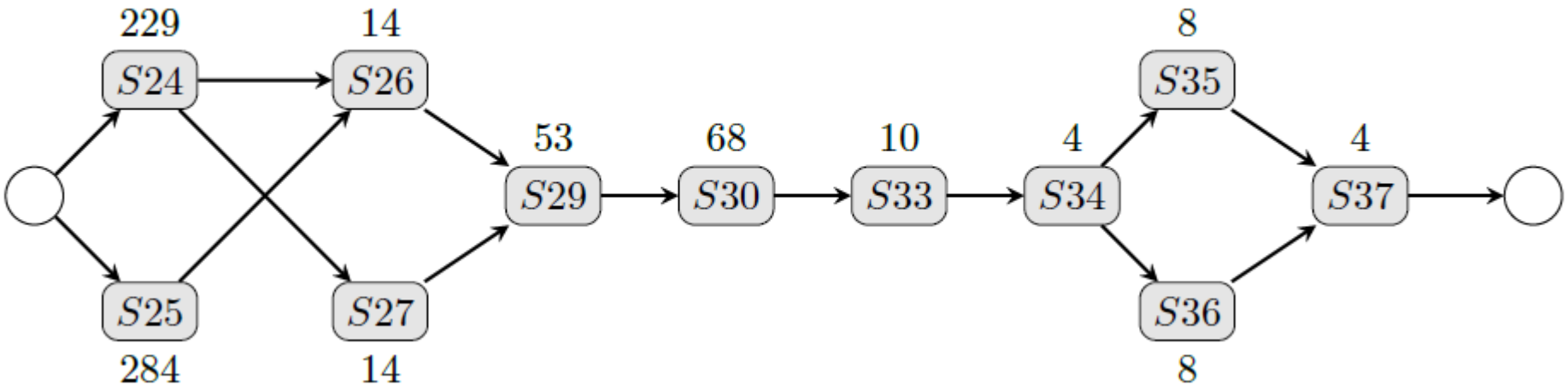


Learning the parameters of a prediction function and testing it on the same data is pointless: a model that would just repeat the labels of the samples that it has just seen would have a perfect score but would fail to predict anything useful on yet-unseen data. This situation is called overfitting. To avoid it, it is common practice when developing a machine learning implementation to hold out part of the available data as a test set

Source: Pedro Domingos

EXAMPLE : ANALYSIS OF THE BOSCH PRODUCTION DATA SET

Bosch Dataset records the time taken for products to pass through one of their production plants.The assembly line is divided into 4 segments and 52 workstations. Each workstation performs a variable number of tests and measurements on a given part, accounting in total for 4264 features. Different products may not share the same path along the assembly line, nor there seem to be a common starting or final workstation. Each of the 1,183,747 parts recorded in the dataset follows one of the 4700 unique combinations.



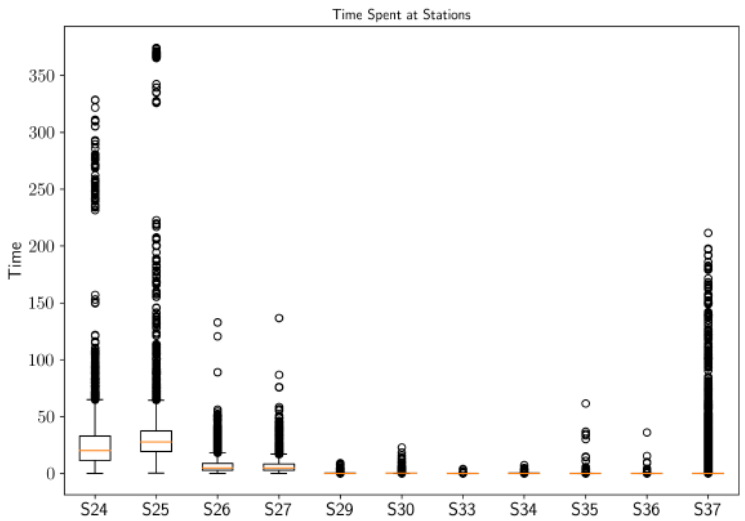


Figure 3: Distributions of time spent per station in the entire dataset (Considering involved stations in types

VALIDATION OF DIFFERENT MODELS

Table 3: Performance of SL algorithms with 10-fold cross validation for $n = 100$, $n = 200$ and $n = 270$ features selected

		$n = 100$					$n = 200$					$n = 270$(keep all features)				
Perf. Measure	Prod. Type	DNN	Ridge	RF	kNN	NN	DNN	Ridge	RF	kNN	NN	DNN	Ridge	RF	kNN	NN
R^2	1	**0.93**	0.64	0.90	0.89	0.89	**0.95**	0.67	0.91	0.89	0.90	**0.96**	0.67	0.91	0.87	0.90
	2	**0.92**	0.64	0.89	0.89	0.89	**0.95**	0.66	0.90	0.88	0.89	**0.95**	0.67	0.90	0.87	0.89
	3	**0.86**	0.62	0.83	0.83	0.81	**0.87**	0.64	0.83	0.82	0.78	**0.88**	0.65	0.83	0.80	0.75
	4	**0.88**	0.65	0.85	0.84	0.85	**0.88**	0.66	0.85	0.83	0.80	**0.89**	0.67	0.85	0.81	0.79
	5	**0.91**	0.74	**0.91**	0.89	0.88	**0.93**	0.77	0.92	0.91	0.87	**0.93**	0.77	0.91	0.89	0.85
	6	**0.91**	0.75	**0.91**	0.89	0.88	**0.94**	0.77	0.92	0.91	0.88	**0.93**	0.77	0.92	0.89	0.86
RMSE	1	**3.92**	8.64	4.64	4.74	4.69	**3.11**	8.24	4.37	4.87	4.44	**2.93**	8.22	4.43	5.15	4.54
	2	**4.06**	8.68	4.78	4.88	4.78	**3.24**	8.40	4.67	5.07	4.69	**3.10**	8.29	4.59	5.26	4.71
	3	**5.52**	9.10	6.01	6.13	6.37	**5.22**	8.82	6.03	6.33	6.93	**5.20**	8.75	6.13	6.51	7.31
	4	**5.23**	8.82	5.69	5.90	5.80	**5.08**	8.61	5.74	6.18	6.58	**4.92**	8.56	5.81	6.39	6.76
	5	4.37	7.55	**4.33**	4.85	5.04	**3.90**	7.17	4.28	4.51	5.42	**3.89**	7.15	4.32	4.87	5.69
	6	4.56	7.50	**4.38**	4.88	5.16	**3.73**	7.16	4.24	4.54	5.23	**3.84**	7.14	4.32	4.91	5.59
MAE	1	**1.95**	6.60	2.72	2.60	3.13	**1.36**	6.23	2.57	2.78	3.07	**1.32**	6.21	2.63	3.00	3.15
	2	**2.00**	6.58	2.77	2.61	3.15	**1.44**	6.31	2.73	2.85	3.21	**1.39**	6.22	2.68	3.01	3.24
	3	**3.17**	5.86	3.28	3.43	4.30	**3.14**	5.71	3.33	3.45	4.93	**3.08**	5.66	3.37	3.57	5.15
	4	**3.12**	5.80	3.22	3.49	4.02	**3.08**	5.61	3.25	3.36	4.68	**3.01**	5.58	3.29	3.52	4.80
	5	**2.22**	5.58	2.37	2.67	3.27	**1.93**	5.23	2.37	2.38	3.73	**2.02**	5.21	2.42	2.69	3.97
	6	**2.42**	5.55	**2.42**	2.81	3.37	**1.90**	5.23	2.34	2.40	3.62	**1.99**	5.21	2.40	2.72	3.92

TH
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TIME FOR BREAK: BACK IN 20MINS

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