



Holistic AI



**The
Alan Turing
Institute**

Bias in Clustering Systems Part I

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Part I – Introduction to Clustering

Part II – Fairness in Clustering Tasks

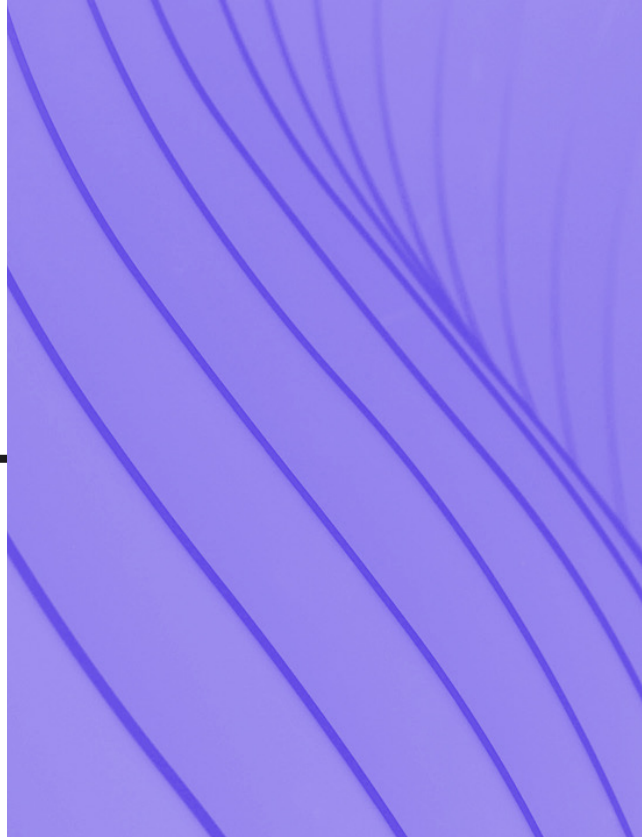
Part III – Measuring Bias in Clustering Systems

Part IV – Mitigating Bias in Clustering Systems



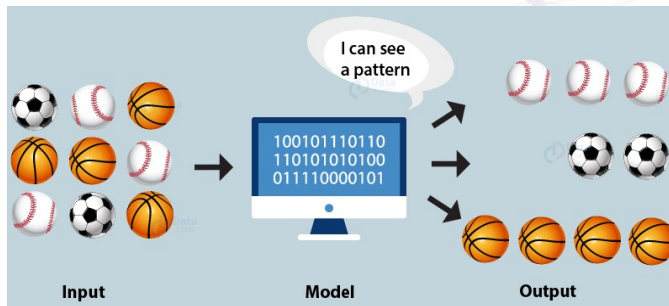
Introduction to Clustering

1. Introduce Clustering as a form of AI.
2. Provide real world examples of Clustering.
3. Motivate the importance of fairness in Clustering.



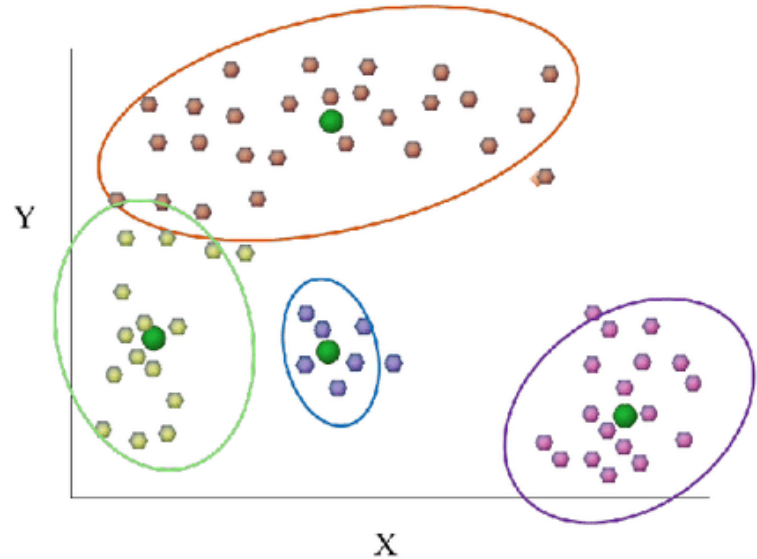
What is Clustering?

- Unsupervised learning method that groups objects into 'clusters'.
- Objects in each cluster are more 'similar' to each other than to objects in another.
- Gain insight into unlabelled datasets.
- Playlist Curation.



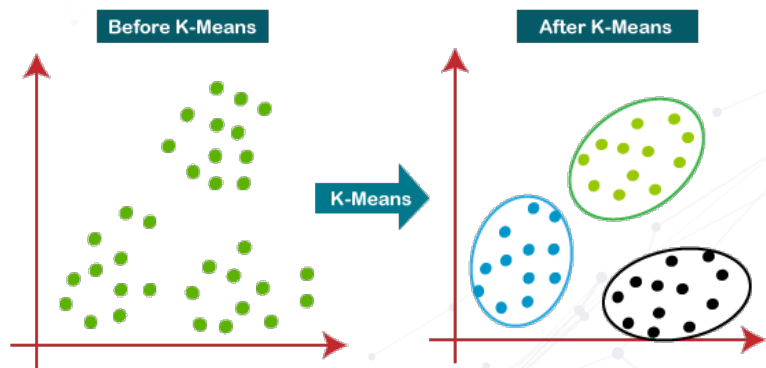
Centre-Based Clustering

- Split the data into k groups with a *centroid* to represent each cluster.
- Points are assigned to cluster with the most 'similar' centroid.
- Distance is used as a 'dissimilarity' metric.
- Aims to assign objects to the group with the closest centroid.
- K-means, K-medoids, mean-shift.



K-Means Clustering Algorithm

- Randomly choose k points as centroids.
- Measure the distance between each point and each centroid.
- Assign the cluster with the smallest centroid distance.
- Update each centroid to be the mean of the cluster.
- Repeat until the cluster assignments and centroids cease to change.



K-Means Clustering Algorithm

- Given k cluster centroids and n data points, the solution for k -means is:

$$\begin{aligned} C &\in \{c_1, c_2, \dots, c_k\}, c_i \in \mathbb{R}^d \\ a &\in \{a_1, a_2, \dots, a_n\}, a_i \in \{1, 2, \dots, k\} \\ \hat{C}, \hat{a} &= \arg \min_{C, a} \sum_i^n \|x_i - c_{a_i}\|^2 \end{aligned}$$



K-Means Clustering Algorithm

Pros

Easy to implement.

Easily interpreted.

Guaranteed to converge to a solution.

Cons

Not guaranteed to converge to optimal solution.

Strongly depends on initial choice of centroids.

Sensitive to outliers.



Example of K-Means Clustering

- Drafting players for a fantasy premier league team
- Choose similar players.
- Using the 2021-2022 Premier League season data.

(<https://github.com/vaastav/Fantasy-Premier-League/>)

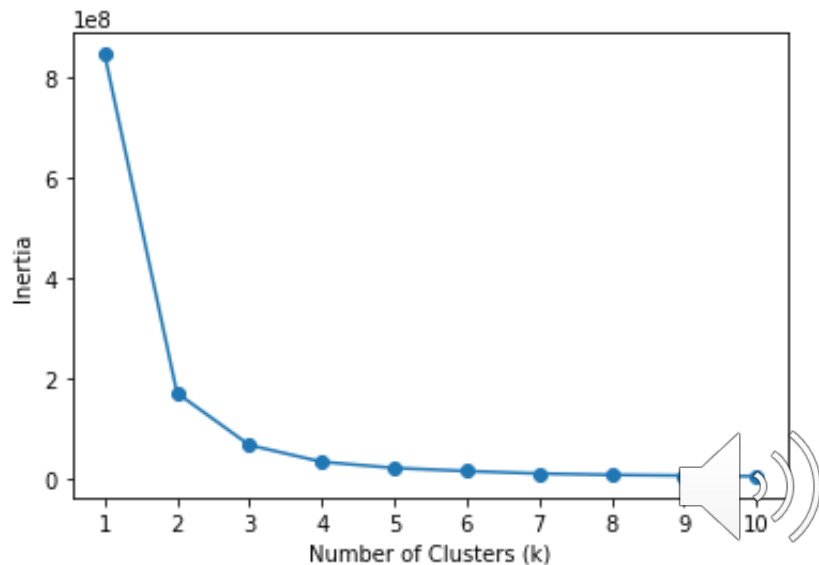
	first_name	second_name	goals_scored	assists	total_points	minutes	goals_conceded	ict_index	clean_sheets	red_cards	yellow_cards	element_type
0	Bernd	Leno	0	0	10	360	9	8.5	1	0	0	GK
1	Rúnar Alex	Rúnarsson	0	0	0	0	0	0.0	0	0	0	GK
2	Willian	Borges Da Silva	0	0	0	0	0	0.0	0	0	0	MID
3	Pierre-Emerick	Aubameyang	4	1	44	1036	16	92.9	6	0	3	FWD
4	Cédric	Soares	1	1	48	1481	27	63.0	3	0	3	DEF



Drafting a Fantasy Team with Clustering

- Train several clustering model using all numerical input features.
- Choose optimal number of clusters using elbow method.

```
# create a KMeans instance with k clusters
model = KMeans(n_clusters = k)
# fit model to samples
model.fit(data)
```



Drafting a Fantasy Team with Clustering

- Look at which players to draft based on the clusters desirable players get assigned to and choosing players from the same clusters.
- If we take the cluster that Harry Kane is in, we can see all the players that are 'similar' to him.

	first_name	second_name	goals_scored	assists	total_points	minutes	goals_conceded	ict_index	clean_sheets	red_cards	yellow_cards	element_type	cluster
19	Bukayo	Saka	11	9	179	2978	39	311.8	13	0	6	MID	3
20	Gabriel	Magalhães	5	0	146	3063	38	128.4	13	1	6	DEF	3
25	Ben	White	0	0	107	2880	35	92.5	13	0	3	DEF	3
31	Martin	Ødegaard	7	4	131	2782	39	220.3	11	0	4	MID	3
32	Aaron	Ramsdale	0	0	135	3060	39	68.0	12	0	1	DEF	3

Part 1 Question 1

Given these 4 points and distances to cluster centres, how many points get assigned to to each cluster?

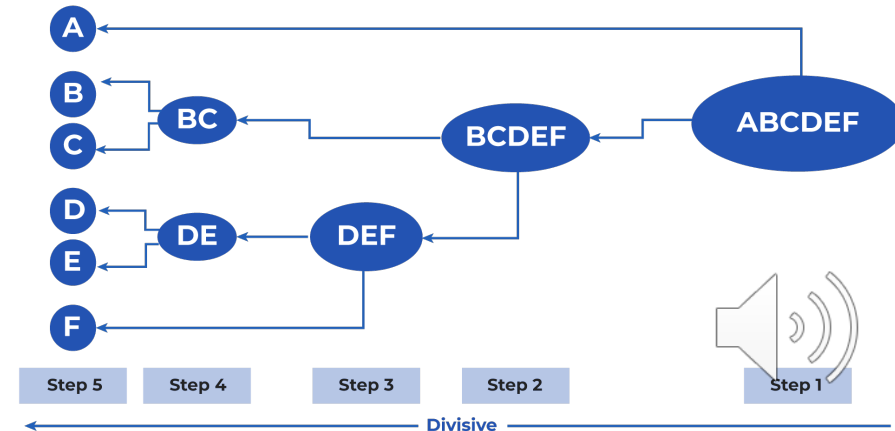
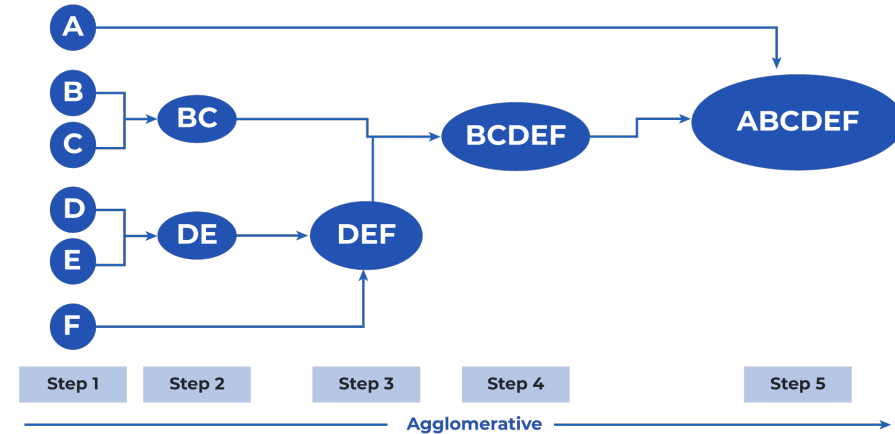
X	0.78	2.23	1.57	1.21
Y	-1.86	-2.67	-2.76	-2.55
Distance from first centroid	3.62	4.48	4.49	4.27
Distance from first centroid	4.16	5.15	5.11	4.86



Other forms of Clustering

Hierarchical

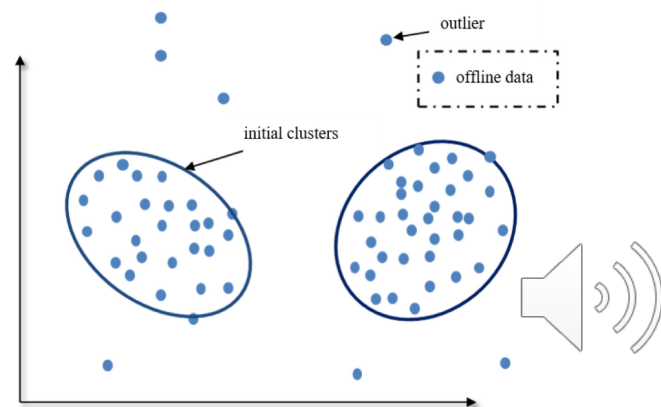
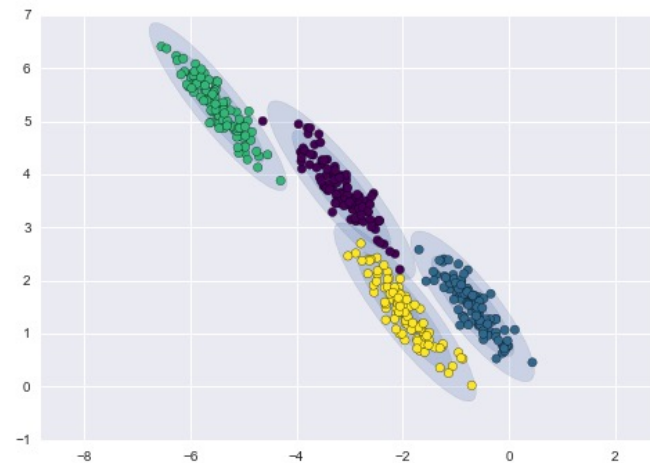
- Partitions data set into hierarchies.
- Agglomerative builds the tree from the bottom up.
- Divisive builds it from the top down.
- The root of the tree represents the entire data set while the leaves compromise singular samples.
- Removes the need to have a predefined number of clusters.
- Customer segmentation.



Other forms of Clustering

Mixture model

- Probabilistic clustering.
- Points are assigned to clusters with no fixed membership.
- Data points are assumed to come from some mixture of probability distributions.
- Distributions are assumed.
- GMM-EM for anomaly detection.



Other forms of Clustering

Spectral

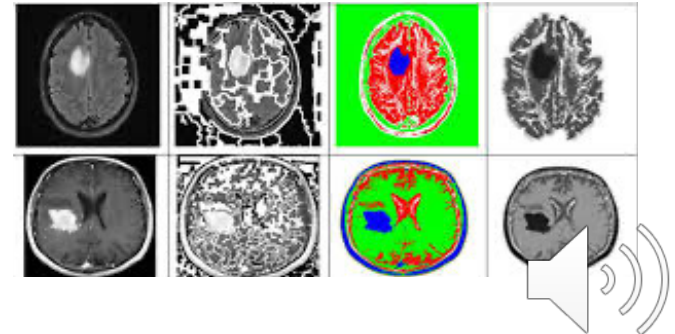
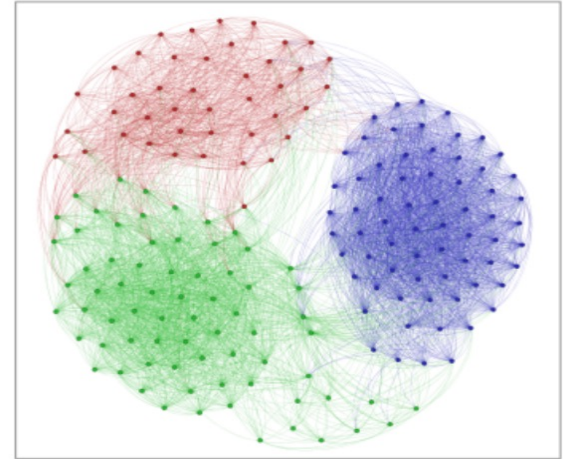
- Construct a graph to encode similarity between all data points.
- The weight of the edge between nodes is a function of how similar they are to each other.
- Weighted graph represented matrix W where $w_{i,j}$ is similarity between point x_i and point x_j .
- Degree of the i -th node is defined as $d_i = \sum_j^n w_{ij}$, can construct the degree matrix D .
- The graph Laplacian Matrix is defined as: $L = D - W$.



Other forms of Clustering

Spectral (cont.)

- The k smallest eigenvectors of L can be used to construct a low-dimensional matrix V using them as column vectors.
- From the new matrix we create a new set of data points using its row vectors: y_1, \dots, y_n .
- Cluster new dataset using k -means and assign any point x_j from the old dataset to the same cluster its corresponding point in the new dataset y_j was assigned to.
- Image segmentation.



Part 1 Question 2

What type of clustering might be best suited if you would like to automatically group documents together?

- A. Centre-Based
- B. Hierarchical
- C. Mixture Model
- D. Spectral



Part 1 Question 2

What type of clustering might be best suited if you would like to automatically group documents together?

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How Can Clustering Be Unfair?

Bank Loans

- Used to determine whether someone should get a loan based on how likely they are to default on it.
- Input features often contain proxies to protected attributes (income, education, marital status).
- Due to historical systemic discrimination, women and POC may have lower incomes.
- Married people typically have higher credit scores than single people.
- This clustering can result in rejection or higher interest rates.



How Can Clustering Be Unfair? (Cont.)

Job Shortlisting

- Group similar candidates together
- Choose who should move on to the next round
- Can reduce human bias but does not eliminate bias completely
- Features relevant to choosing a candidate may contain proxies or the protected attribute themselves



How Can Clustering Be Unfair? (Cont.)

Prisoner Recidivism

- The tendency for a prisoner to reoffend can be interpreted as a probability.
- Probability can be determined by a soft clustering algorithm (GMM-EM).
- A data point can be assigned a certain proportion of each cluster with clusters signifying the level of risk of re-offending .
- COMPAS.



Conclusion

- Introduced Clustering as a form of AI
- Seen the applications of Clustering and how it can be used in real world examples
- Explored how Clustering can be biased and the need for fairness



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