### **K-Medoids Algorithm**

The mean in k-means clustering is sensitive to outliers. Since an object with an extremely high value may substantially distort the distribution of data. Hence, we move to k-medoids. Instead of taking mean of cluster we take the most centrally located point in cluster as its center. These are called medoids.

The K-Medoids algorithm is a clustering method similar to K-Means, but instead of using the mean of the points in a cluster as the center, it uses an actual data point (medoid) to represent the cluster. This makes it more robust to outliers.

1. **Input**:
   * A dataset with multiple data points.
   * The desired number of clusters (k).
2. **Steps**:

**Step 1**: **Initialize Medoids**  
Randomly select k data points from the dataset as the initial medoids. These medoids represent the initial "center" of each cluster.

**Step 2**: **Assign Points to Clusters**  
For each data point in the dataset, assign it to the cluster whose medoid is the closest.

**Step 3**: **Update Medoids**  
For each cluster, find the point within the cluster that minimizes the total distance to all other points in the cluster. This point becomes the new medoid for that cluster.

**Step 4**: **Repeat Steps 2 and 3**  
Reassign all points to their closest medoid and update the medoids until the clusters and medoids no longer change significantly.

1. **Stopping Conditions**:
   * The medoids no longer change after updating.
   * A maximum number of iterations is reached.
2. **Output**:
   * The final clusters with their respective data points.
   * The kkk medoids, which represent the centers of each cluster.

**Conclusion**

K-Medoids is a reliable clustering algorithm that improves data analysis in AI by selecting actual data points as cluster centers, making it more robust than K-Means.

**Key Takeaways:**

**Robust to Outliers** – Unlike K-Means, K-Medoids minimizes the impact of extreme values by using actual data points as cluster centers.  
**Higher Computational Cost** – The algorithm requires more processing time due to pairwise distance calculations, making it less efficient for large datasets.  
**Improved Interpretability** – Since medoids are real data points, clusters are more meaningful and easier to interpret.

While K-Medoids has computational challenges, its robustness and accuracy make it a valuable tool in AI. Future optimizations and hybrid approaches will continue to enhance its efficiency for large-scale data-driven tasks.

