08 K-NN

- K-Nearest Neighbors (KNN) is a simple, yet powerful machine learning algorithm used for classification and regression task
- KNN operates on the principle that similar data points are likely to be found near each other
- Given a data point whose classification or value is unknown, KNN will look at the 'k' nearest data points (neighbors) in the training dataset to make a prediction

KNN Steps

1. Choose the value of 'k'

- The first step is to decide how many neighbors (k) you want to consider when making the prediction
- Common values for k are small positive integers like 3, 5, or 7

2. Calculate Distance

- To find the nearest neighbors, KNN calculates the distance between the data point in question and all the points in the training data
 - Euclidean distance: The most common metric, which is the straight-line distance between two points in Euclidean space

$$d(\mathbf{x}_i,\mathbf{x}_j) = \sqrt{\sum_{k=1}^n (x_{ik} - x_{jk})^2}$$

 Manhattan distance: The sum of the absolute differences between coordinates

$$d(\mathbf{x}_i, \mathbf{x}_j) = \sum_{k=1}^n |x_{ik} - x_{jk}|$$

 Minkowski distance: A generalization that includes both Euclidean and Manhattan distances

$$d(\mathbf{x}_i,\mathbf{x}_j) = \left(\sum_{k=1}^n |x_{ik}-x_{jk}|^p
ight)^{rac{1}{p}}$$

Chebyshev Distance : A special case of the Minkowski distance

$$d(\mathbf{x}_i,\mathbf{x}_j) = \max_{k=1}^n |x_{ik} - x_{jk}|$$

3. Find Nearest Neighbors

 Once the distances are calculated, KNN identifies the k closest data points (the knearest neighbors)

4. Predict the Outcome

 For classification: The algorithm assigns the class that is most frequent among the k-nearest neighbors • For regression: The algorithm averages the values of the k-nearest neighbors to predict the outcome

Choosing 'k'

- Small k: Leads to a model that is sensitive to noise in the data (high variance)
- Large k : Leads to smoother decision boundaries but might oversimplify the model (high bias)

Advantages of KNN

- Simple and intuitive: No assumptions about the data distribution are required
- Flexible: Can be used for both classification and regression tasks

Disadvantages of KNN

- **Computationally expensive :** Especially with large datasets since it calculates distances to all training points
- Sensitive to the choice of k : Different k values can lead to different results
- Affected by irrelevant features: Feature scaling or dimensionality reduction (like PCA) might be necessary

Practical Considerations

- Feature scaling: Standardizing or normalizing features is important because KNN relies on distance metrics
- Handling large datasets: Techniques like KD-Trees or Ball Trees can optimize the search for nearest neighbors