K-Nearest Neighbors (KNN)

1. Introduction:

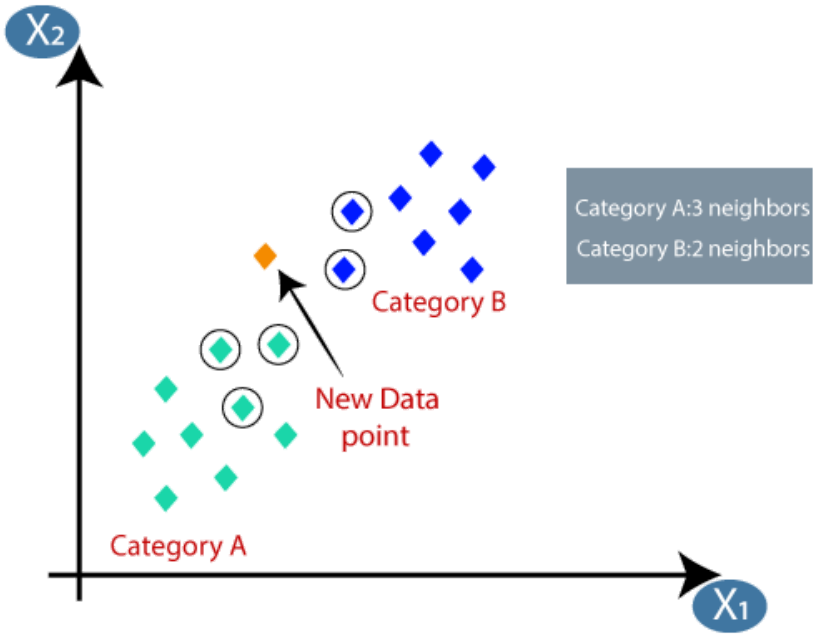
- **What it is:** KNN is a simple, versatile, and intuitive supervised machine learning algorithm used for both **classification** and **regression** tasks.
- **Algorithm Type:**
    - **Instance-Based Learning:** It doesn't learn an explicit function from the training data but relies on storing the entire dataset. Predictions are made based on similarity to stored instances.
    - **Lazy Learning:** It does minimal computation during the "training" phase (essentially just storing the data). Most of the work happens during the prediction phase.
    - **Non-parametric:** It makes no strong assumptions about the underlying data distribution.

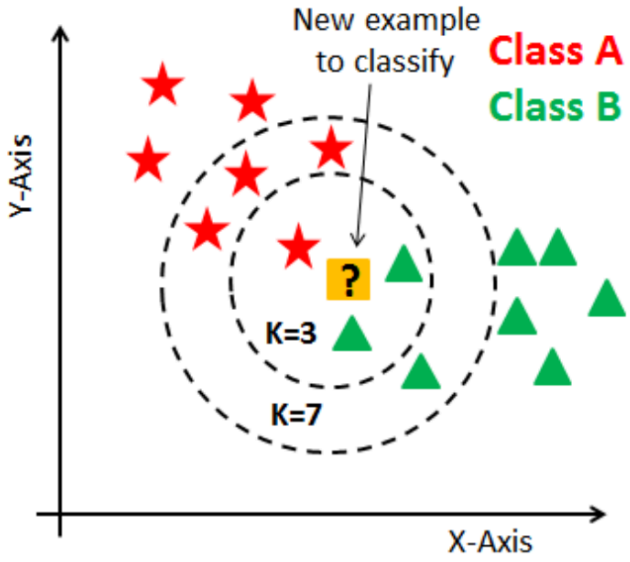
2. Core Idea:

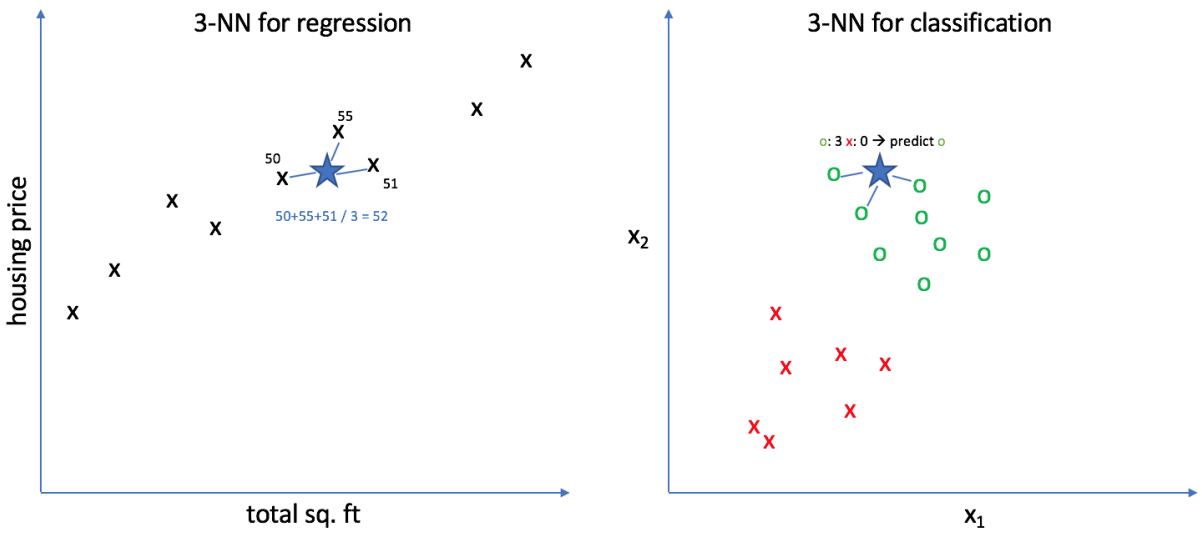
- The fundamental principle is **"similarity"** or **"proximity"**.
- To classify or predict a value for a new, unseen data point, KNN looks at the `K` closest data points (neighbors) to it in the training dataset.
- The prediction is based on the properties (class label or value) of these `K` neighbors. "Birds of a feather flock together."

3. How KNN Works (Steps):

1. **Choose the value of `K`:** Decide how many neighbors (e.g., 3, 5, 10) to consider. This is a hyperparameter.
2. **Choose a Distance Metric:** Select a method to measure the "closeness" or distance between data points (e.g., Euclidean, Manhattan).
3. **For a new data point (`x_new`):**
    - Calculate the distance between `x_new` and **every** data point in the training dataset using the chosen metric.
    - Identify the `K` training data points that have the smallest distances to `x_new`. These are the "K nearest neighbors".
    - **For Classification:** Perform a **majority vote** among the class labels of the K neighbors. The most frequent class among the neighbors is assigned as the predicted class for `x_new`. (Using an odd `K` helps avoid ties).
    - **For Regression:** Calculate the **average** (or sometimes the median) of the target values of the K neighbors. This average/median value is assigned as the predicted value for `x_new`.

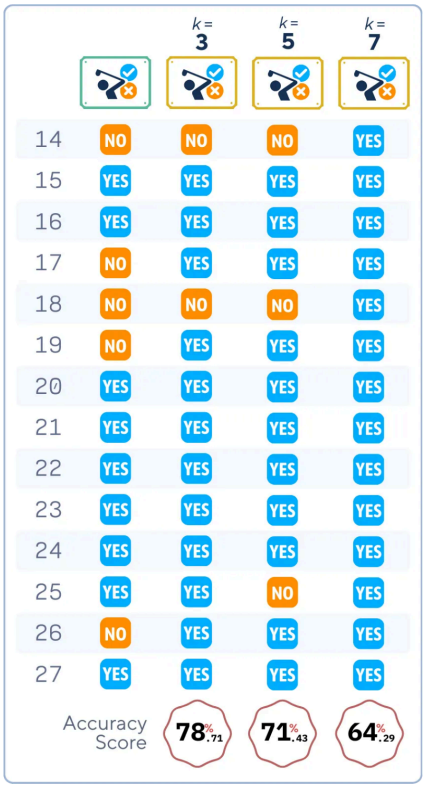

X2
Category A:3 neighbors
Category B:2 neighbors
Category B
New Data
point
Category A
X1


New example
to classify
Class A
Class B
Y-Axis
?
K=3
K=7
X-Axis

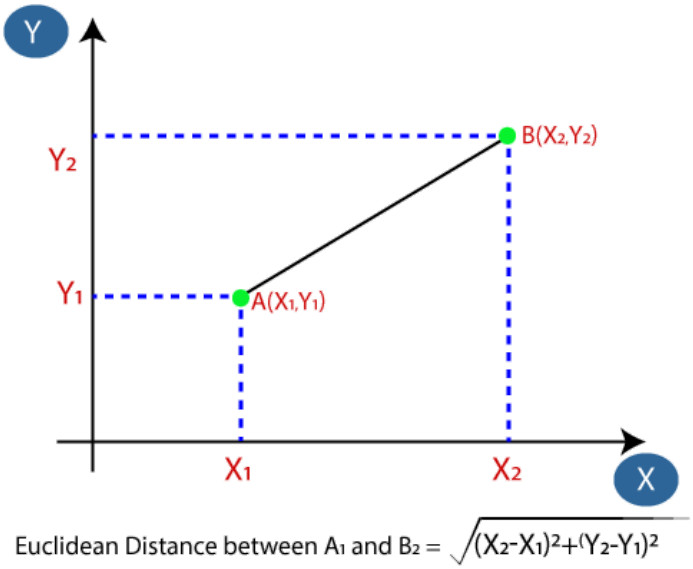


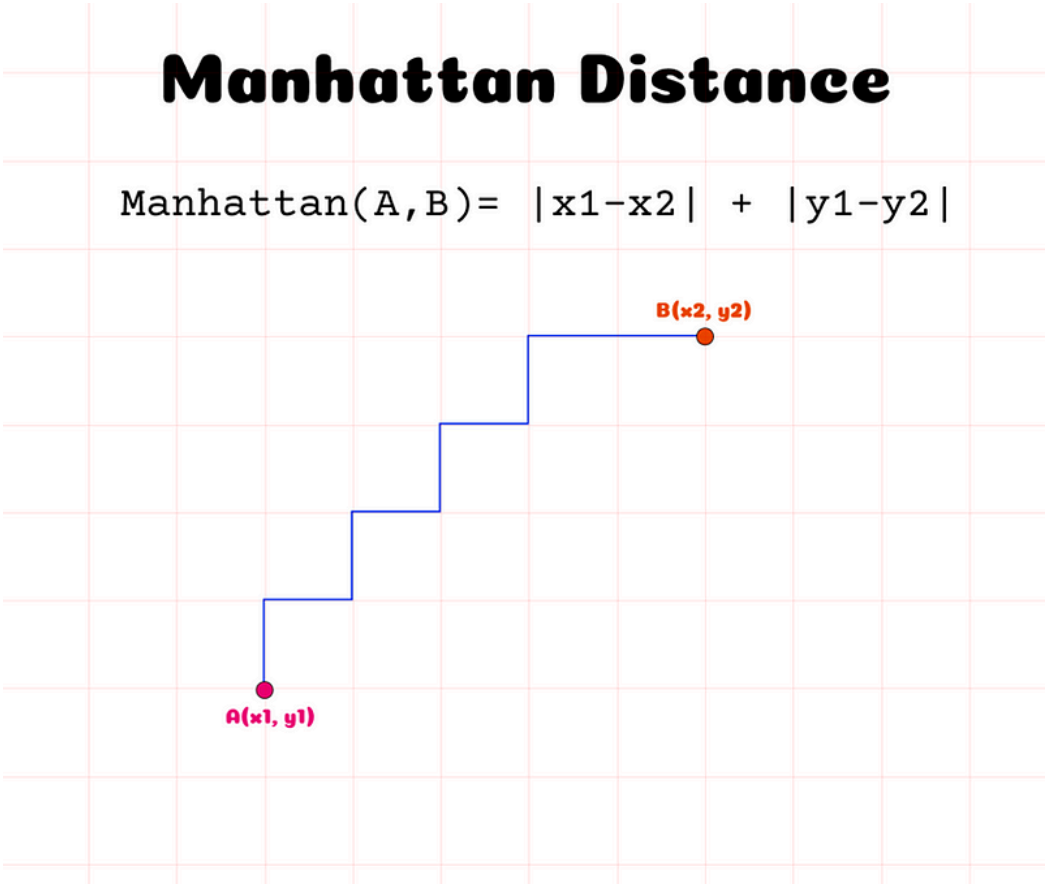
4. The Parameter K:

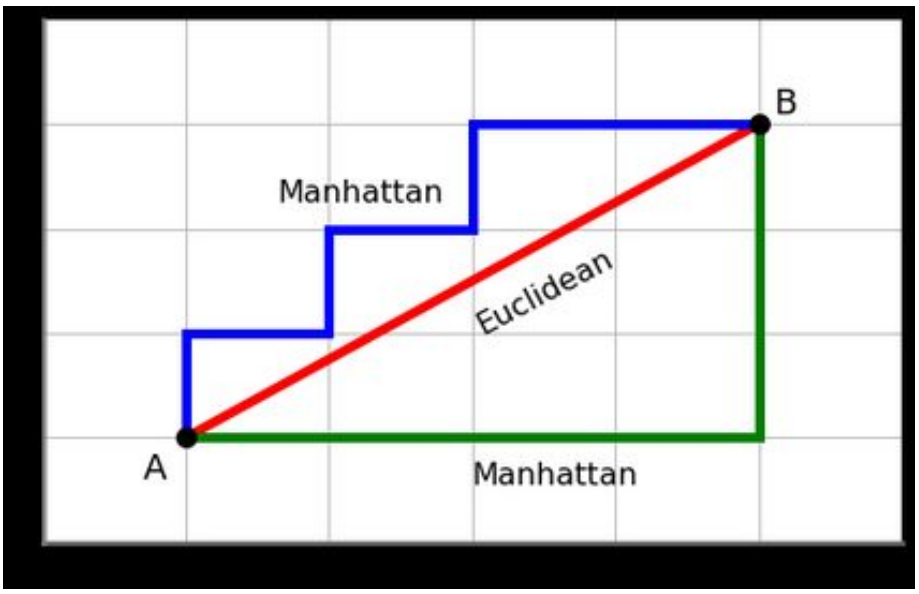
- K determines the number of neighbors influencing the prediction.
- **Choosing K:**
    - **Small K (e.g., K=1):** Model is very sensitive to noise and outliers. Decision boundary can be complex. Low bias, high variance (prone to overfitting).
    - **Large K:** Model is smoother, less sensitive to noise. Decision boundary is simpler. High bias, low variance (prone to underfitting).
    - **Selection Method:** Often chosen using cross-validation on the training set to find a K that balances bias and variance well. An odd number is usually preferred for classification to prevent ties.



5. Distance Metrics:

- Crucial for defining "closeness". Choice depends on the data type and problem context.
- Common Metrics:
  - **Euclidean Distance (L2 norm):** Most common; the straight-line distance between two points in Euclidean space. Formula: $d(x,y)=\sum_{i=1}^{n}(x_i-y_i)2$
  - 

- **Manhattan Distance (L1 norm):** Sum of the absolute differences of their coordinates ("city block" distance). Often better for high-dimensional data. Formula: $d(x,y)=\sum_{i=1}^{n}|x_i-y_i|$
- Imagine a city grid where you can only move horizontally or vertically. The Manhattan distance is the shortest path between two points in such a grid.
- 

- 

    - **Minkowski Distance:** A generalization of both Euclidean (p=2) and Manhattan (p=1). Formula: $d(x,y)=(\sum_{i=1}^{n}|x_i-y_i|^p)^{1/p}$
    - **Hamming Distance:** Used for categorical variables (measures the number of positions at which corresponding symbols are different).

6. Importance of Feature Scaling:

- **Crucial for KNN!** Since KNN relies on distances, features with larger ranges/values can disproportionately influence the distance calculation compared to features with smaller ranges.
- **Solution:** Scale features before applying KNN. Common methods include:
    - **Normalization (Min-Max Scaling):** Scales data to a fixed range, usually [0, 1].
    - **Standardization (Z-score Normalization):** Scales data to have zero mean and unit variance.

7. Advantages:

- **Simple and Intuitive:** Easy to understand and implement.
- **No Training Phase:** Just stores data (lazy learner). Can be updated easily with new data.
- **Non-parametric:** Makes no assumptions about data distribution.
- **Handles Multi-class Problems:** Works naturally with more than two classes.
- **Flexible Decision Boundaries:** Can learn complex boundaries.

8. Disadvantages:

- **Computationally Expensive Prediction:** Must compute distances to *all* training points for each prediction. Slow for large datasets.
- **High Memory Requirement:** Needs to store the entire training dataset.
- **Sensitive to Irrelevant Features:** Irrelevant features can distort distance calculations ("Curse of Dimensionality"). Feature selection/engineering is important.
- **Sensitive to Feature Scaling:** Performance heavily depends on proper scaling.
- **Performance Dependent on K and Distance Metric:** Requires careful tuning of these hyperparameters.

9. Common Applications:

- Recommendation Systems (finding similar items/users)
- Image Recognition / Computer Vision (finding similar images)
- Anomaly Detection (identifying points far from others)
- Gene Expression Analysis
- Basic classification and regression tasks, especially as a baseline model.