

Machine Learning

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# K Nearest Neighbors

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- A supervised learning method
- Though it is a supervised learning method, it is a ‘lazy learner’, i.e. does not construct a model using training data
- Classification is determined based on a majority vote of the nearest neighbors of each point
- Suitable for classification where items in a class tend to be fairly homogenous on the values of attributes
- Not suitable if the data is too noisy or the target classes do not have clear demarcation in terms of attribute values

# K Nearest Neighbors

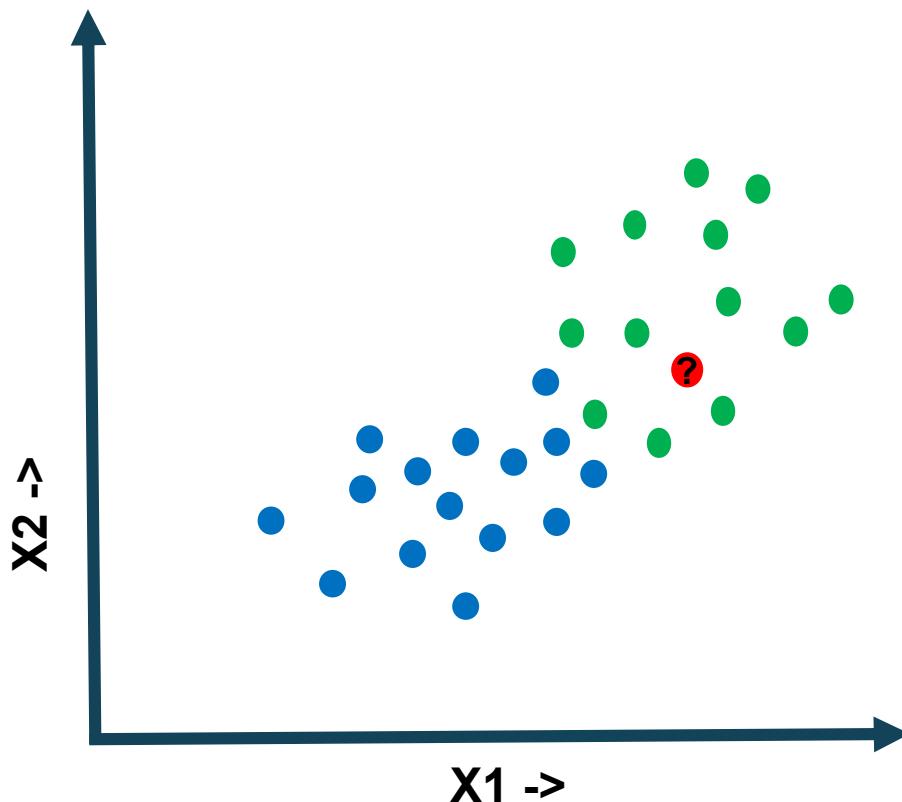
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- Nonparametric model: distribution-free tests because no assumption of the data needing to follow a specific distribution
- Commonly used for classification
- Can also be used for regression

# K Nearest Neighbors

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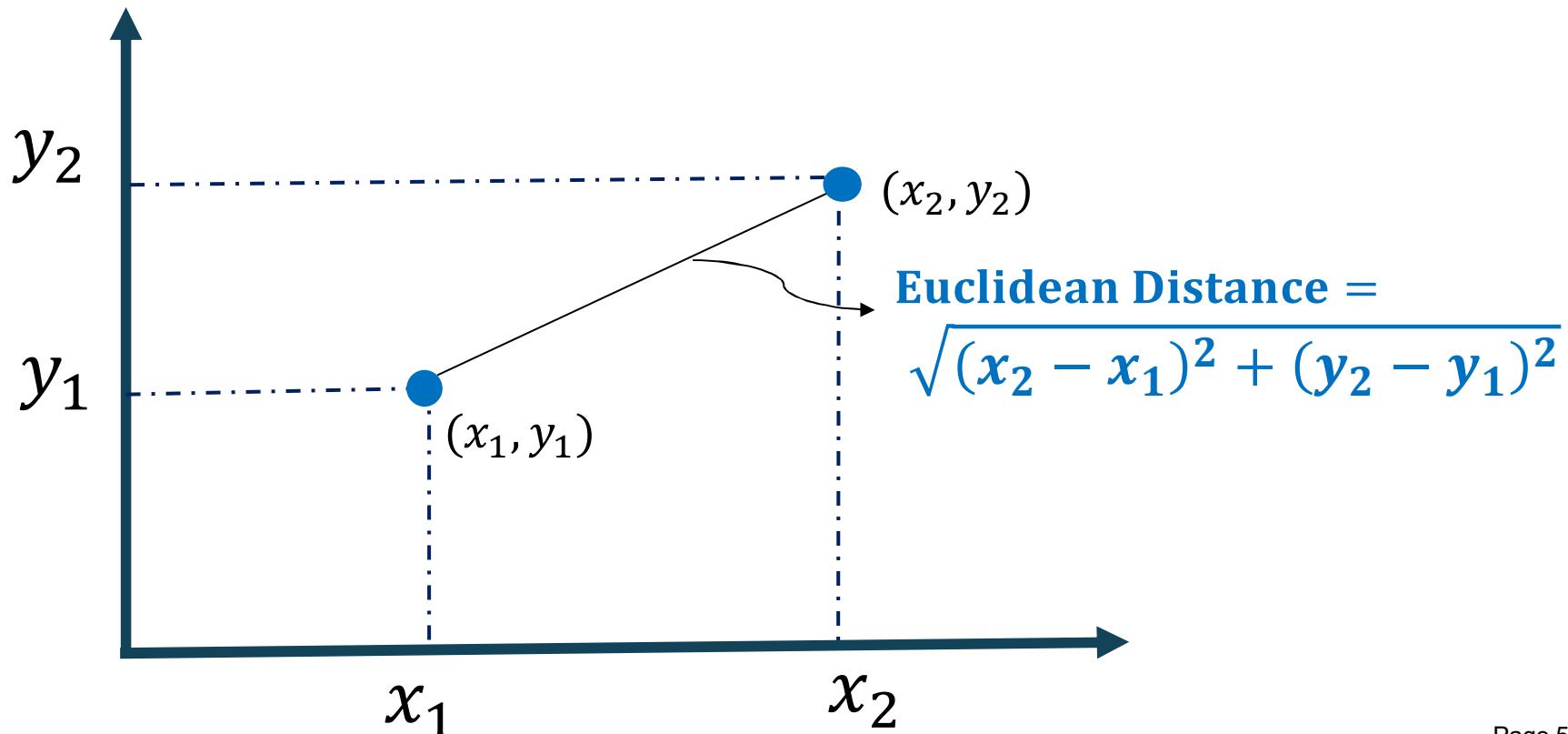
- New data point is assigned a class which has the most data points in the nearest neighbors of the point



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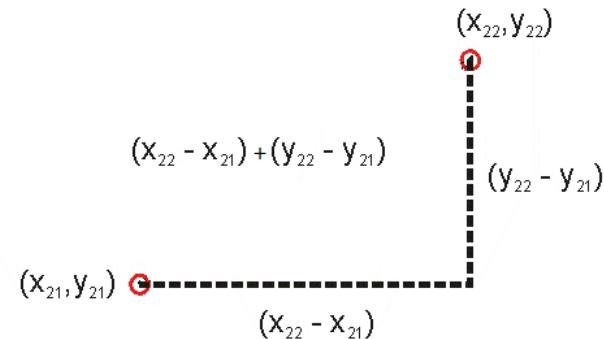
- Nearest neighbors are calculated based on shortest distance.
- Most commonly used distance measure is Euclidean distance (default)



# K Nearest Neighbors

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- Manhattan / Taxi Distance: Also called L1 norm. It is the sum of the differences in each dimension.



- Mahalanobis distance – takes into account the covariance between attributes
- Jaccard distance (for Boolean data) = number of non-equal dimensions / number of nonzero dimensions.
- Matching distance (for Boolean data) = number of non-equal dimensions / number of dimensions

# K Nearest Neighbors

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- To ensure all the dimensions have similar scale, it is necessary to normalize the data. Common way to normalize data is
- Z-score standardization using formula 
$$z_i = \frac{x_i - \bar{x}}{s}$$
- Min-max scaler
  - $X_{\text{std}} = (X - \text{min}) / (\text{max} - \text{min})$

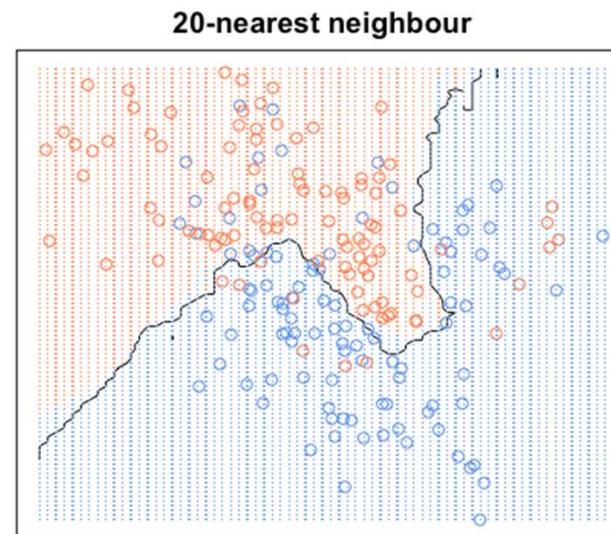
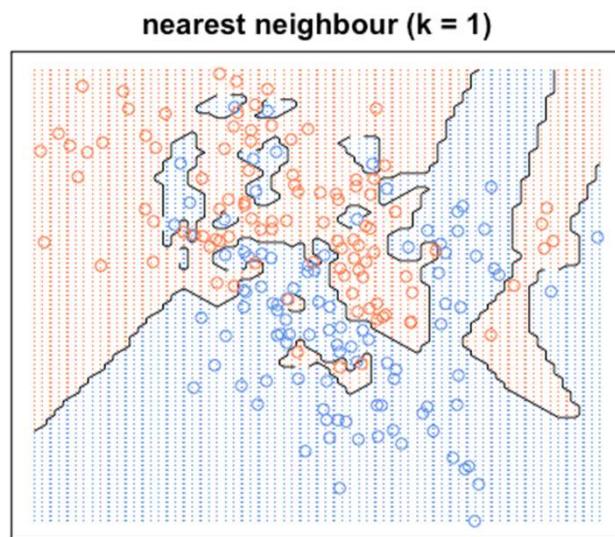
# K Nearest Neighbors

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- Advantages -
  - Makes no assumptions about distributions of data
  - Easy to understand and implement
  - Not impacted by outliers
  - Able to segregate classes using non-linear boundary
- Dis-advantages -
  - Determining the optimal value of K is a challenge
  - Not effective when the class distributions have large overlap
  - Does not output any models. Calculates distances for every new point.  
Hence very computation intensive

# Selecting value of K

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- $K$  is a hyperparameter must be picked in order to get the best possible fit for the data set
- $K$  controls the shape of the decision boundary we talked about earlier
- A small value of  $k$  means that noise will have a higher influence on the result

# K Nearest Neighbors

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- Hands-on exercise

# Confusion Matrix

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		Predicted		
		A	B	C
Actual	A	15	0	0
	B	0	19	2
	C	0	0	17

- . Classification accuracy = correct predictions / total predictions
- . Precision is the proportion of the predicted positive cases that were correct.
  - . Precision of C =  $17 / (17+2)$
- . Recall is the proportion of positive cases that were correctly identified
  - . Recall for B =  $19 / (19+2)$
- . F1 Score =  $2 * (\text{Recall} * \text{Precision}) / (\text{Recall} + \text{Precision})$

# Confusion Matrix

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		Predicted	
		Positive	Negative
Actual	Positive	TP	FN
	Negative	FP	TN

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad \text{Precision} = \frac{TP}{TP + FP}$$

- True Positive (TP) : Observation is positive, and is predicted to be positive.
  - False Negative (FN) : Observation is positive, but is predicted negative.
  - True Negative (TN) : Observation is negative, and is predicted to be negative.
  - False Positive (FP) : Observation is negative, but is predicted positive.
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- Note that in binary classification, recall of the positive class is also known as “sensitivity”; recall of the negative class is “specificity”.
  - High recall, low precision: This means that most of the positive examples are correctly recognized (low FN) but there are a lot of false positives.
  - Low recall, high precision: This shows that we miss a lot of positive examples (high FN) but those we predict as positive are indeed positive (low FP)