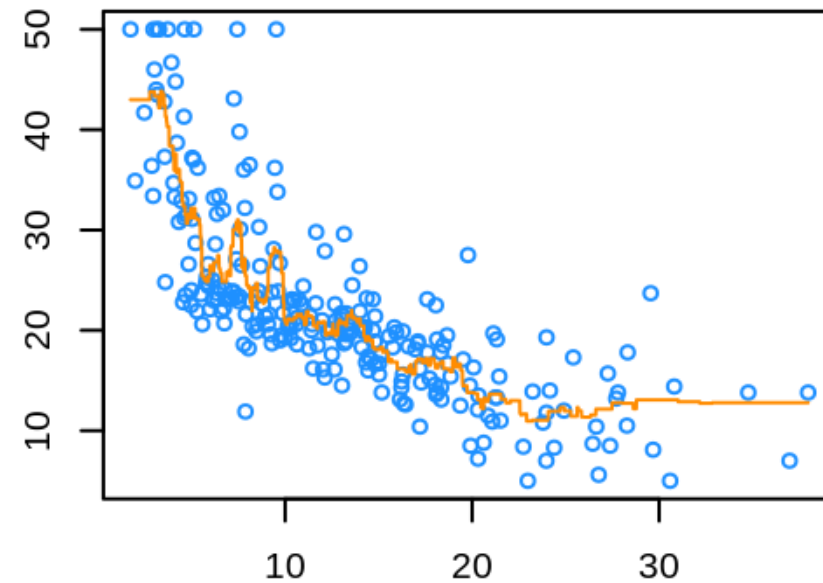
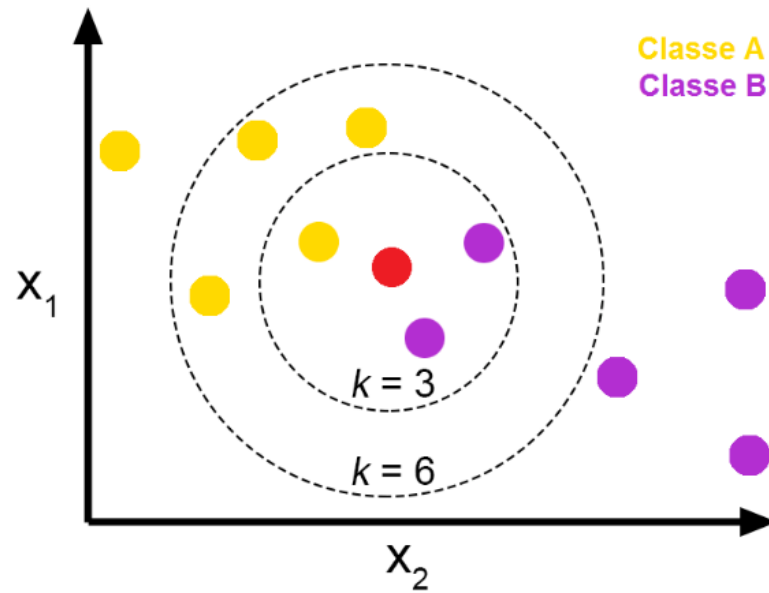


# Class 12 – KNN

## K-Nearest Neighbors

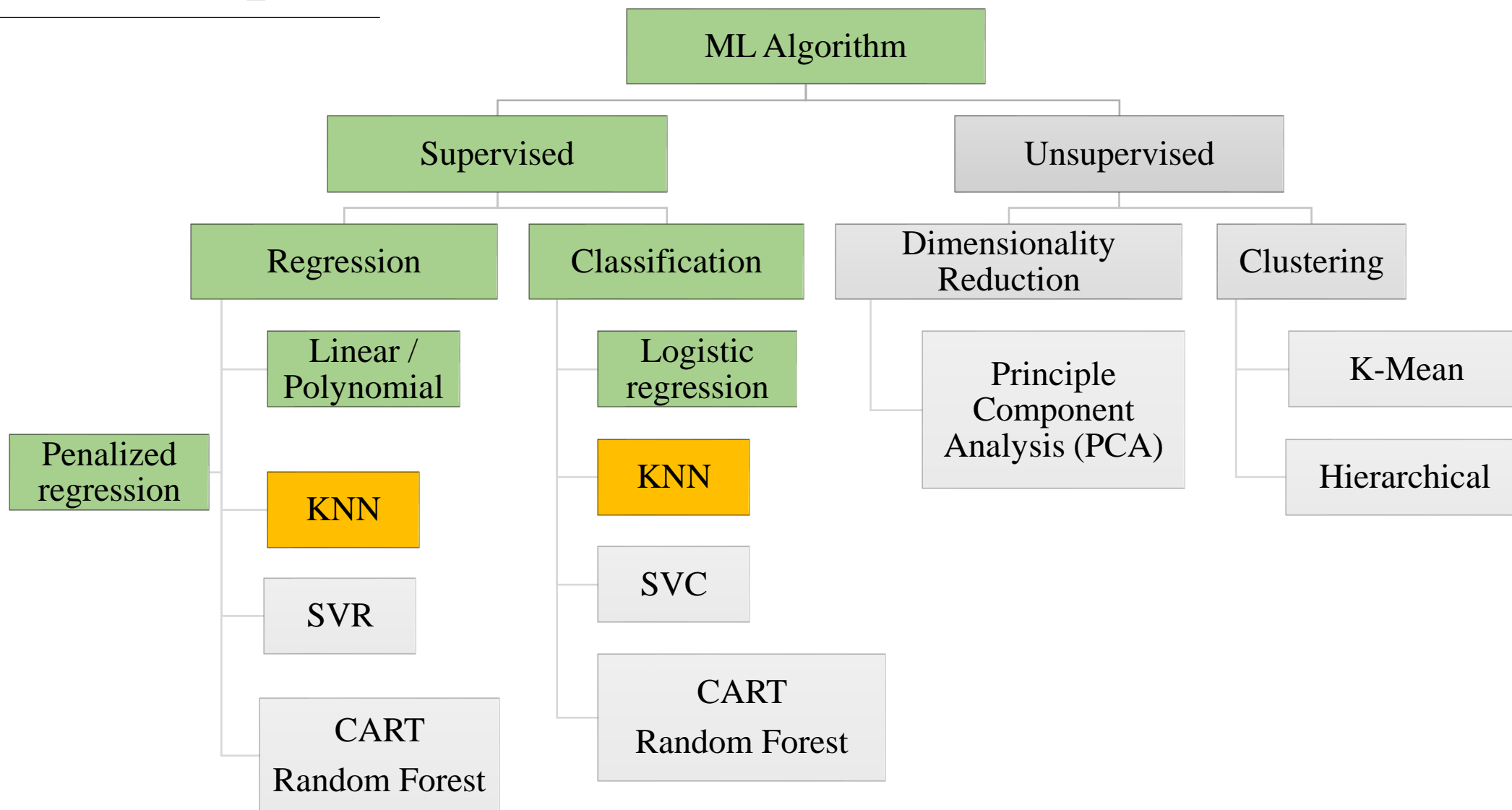


Prof. Pedram Jahangiry





# Road map





# Topics

## Part I

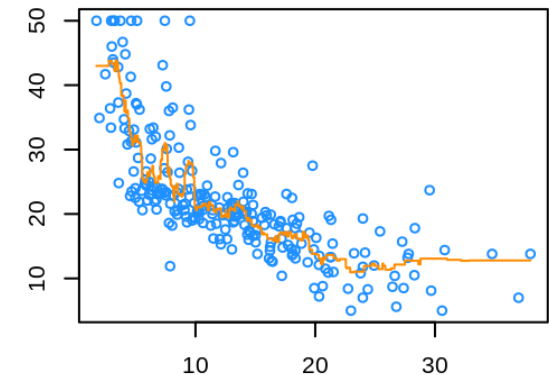
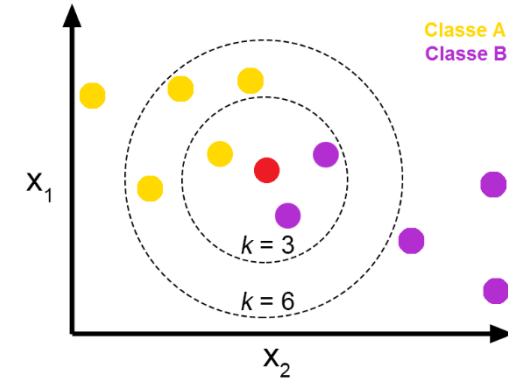
1. KNN Classification
2. Performance metrics and choice of K

## Part II

1. KNN Regression
2. KNN vs Linear Regression
3. Performance metrics and choice of K

## Part III

1. Curse of Dimensionality
2. Pros and Cons of KNN



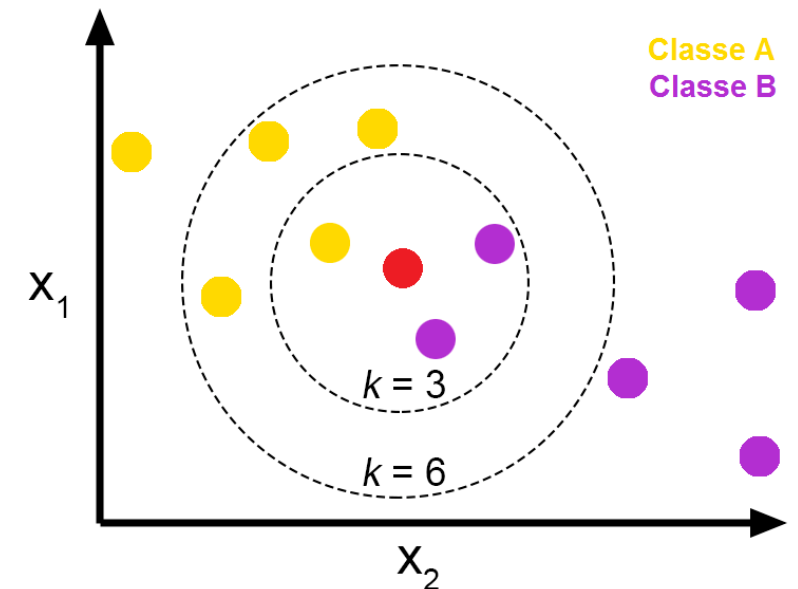
# Part I

## KNN Classification

# → KNN (K-Nearest Neighbors)

**K-nearest neighbor (KNN)** is one of the simplest and best-known **non-parametric supervised** learning technique most often used for **classification**. The idea is to classify a new observation by finding **similarities** (“nearness”) between it and its  $k$ -nearest neighbors in the existing dataset.

- Contrary to other learning algorithms that allow discarding the training data after the model is built, KNN **keeps all training examples in memory**.
- The choice of the **distance metric**, as well as the **value for  $k$** , are the choices the analyst makes before running the algorithm. So, these are **hyperparameters**.



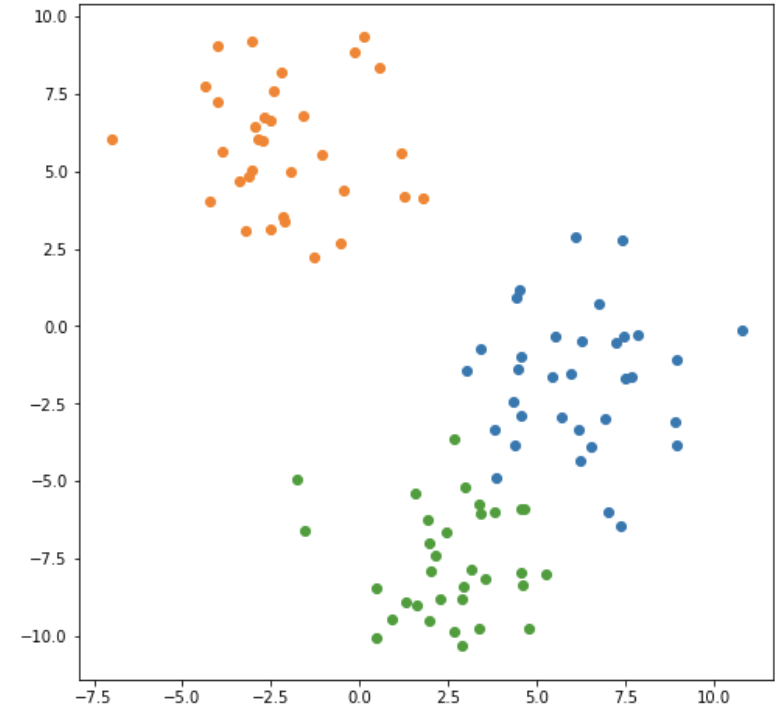


# KNN steps

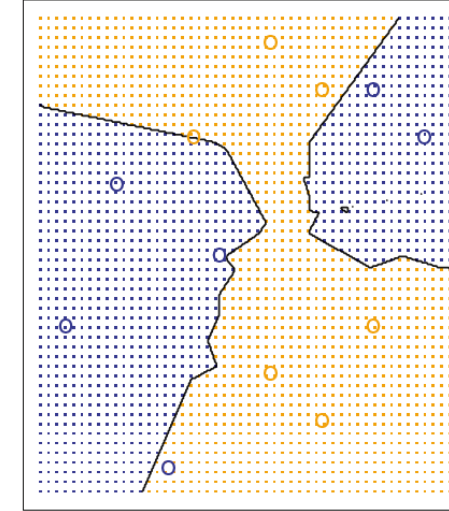
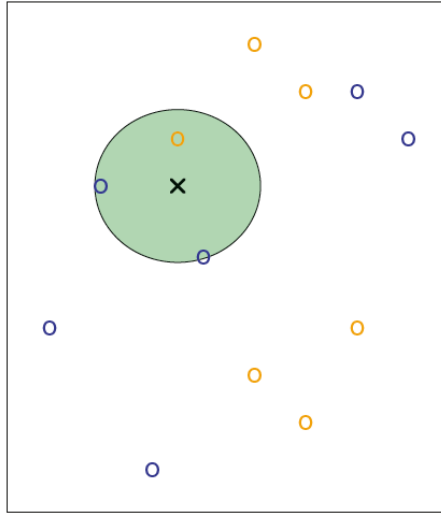
1. Choose number of neighbors **K** (positive integer)
2. Choose the distance metric (Minkowski, Euclidian, Manhattan, etc.)
3. Identify the K points in the training data that are closest to  $x_{te}$  in the test set. This **neighborhood** is represented by  $N_0$ .
4. Estimate the **conditional probability** for class j as the fraction of points in  $N_0$  whose response values equal j:

$$\Pr(Y = j \mid X = x_{te}) = \frac{1}{K} \sum_{i \in N_0} I(y_i = j)$$

5. Classifies the test observation  $x_{te}$  to the class with the largest probability.

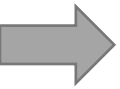


# → KNN Decision Boundary



- Two classes: blue and orange!
- Black cross: a test observation.
- When  $K=3$ , black cross is classified as:  
Blue
- Repeat this process for every potential element in the feature space!

- KNN **decision boundary** is shown in **black**.
- The blue grid indicates the region in which a test observation will be assigned to the blue class, and
- the orange grid indicates the region in which it will be assigned to the orange class.



# Performance metrics

- Error rate =  $1 - \text{Accuracy}$



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

$$\frac{1}{n} \sum_{i=1}^n I(y_i \neq \hat{y}_i)$$

		Predictions	
		0 negative	1 positive
Actual	0 negative	TN	FP
	1 positive	FN	TP

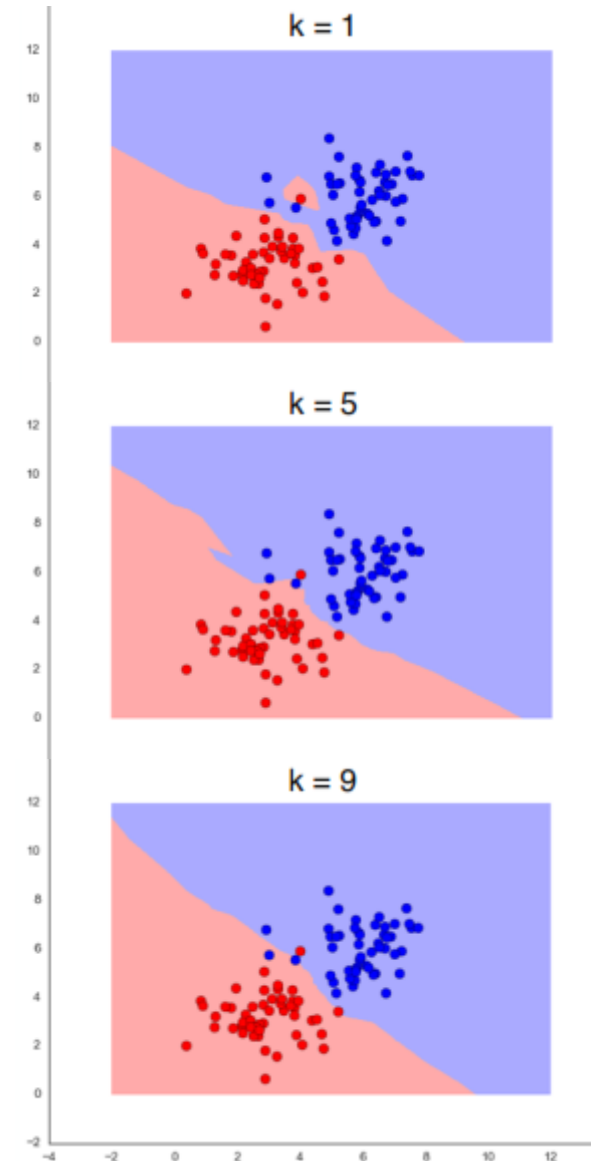
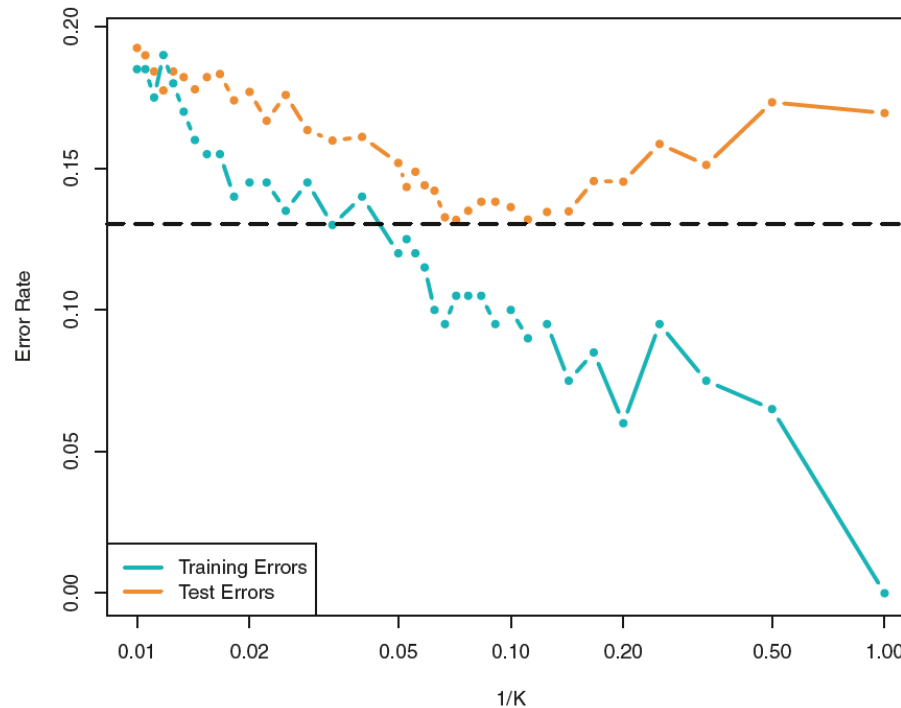
- A good classifier is one for which the **test error** is smallest.
- Like any other classifier, if the data is highly imbalanced, then we should use f1score, precision and recall instead of the error rate.





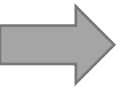
# Choice of K (Bias Variance Trade Off)

- $K=1$  very flexible model: Low bias but high variance.
- As  $K$  grows, less flexible model, decision boundary gets close to linear. This corresponds to a low variance but high bias.
- Optimal value of  $K$ :



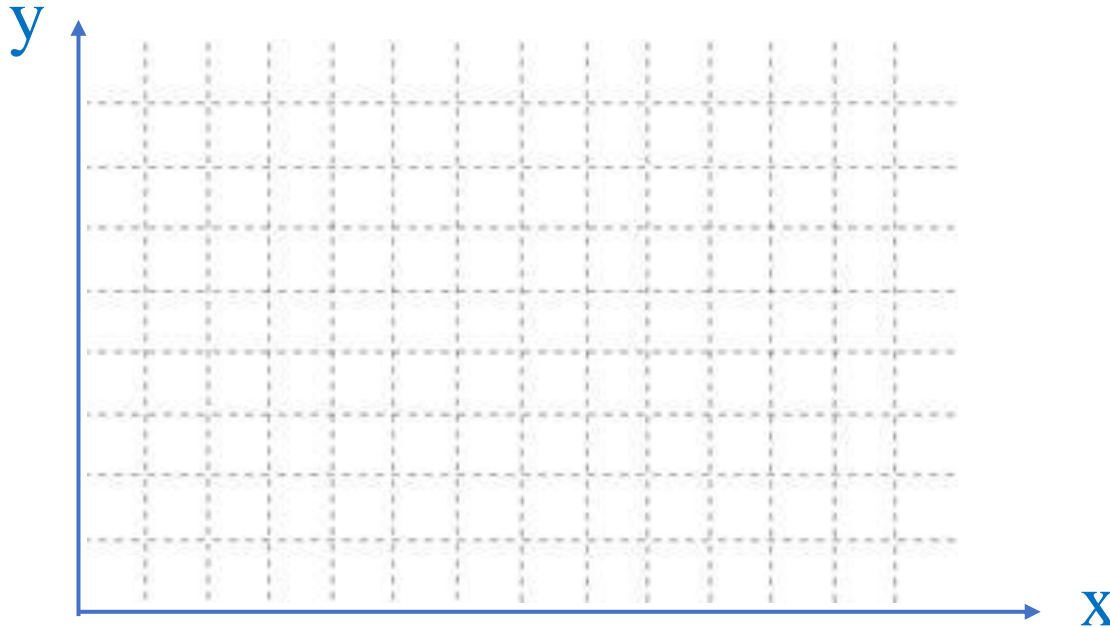
# Part II

## KNN Regression



# KNN Regression

- The KNN regression method is closely related to the KNN classifier

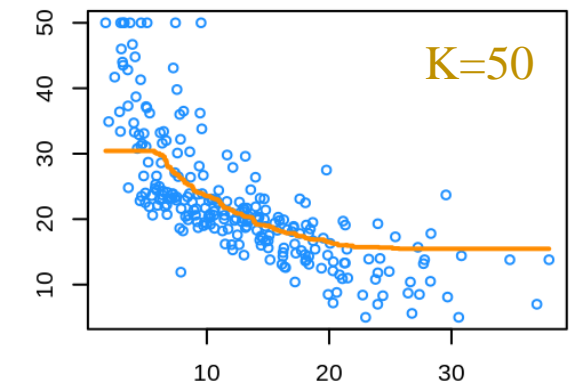
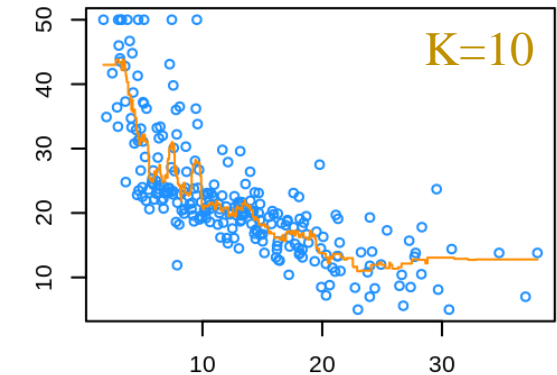
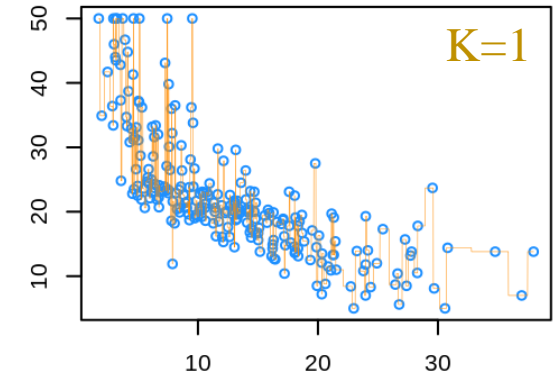
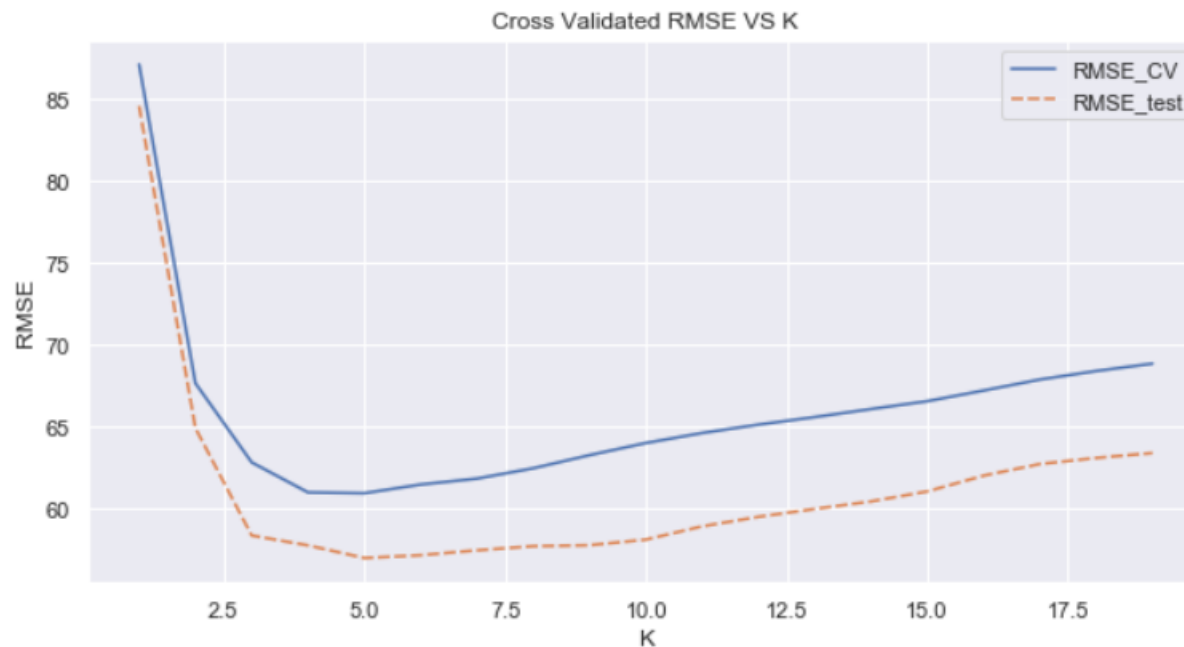


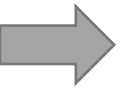
$$\hat{f}(x_{te}) = \frac{1}{K} \sum_{i \in N_0} y_i$$



# Choice of K (Bias Variance Trade Off)

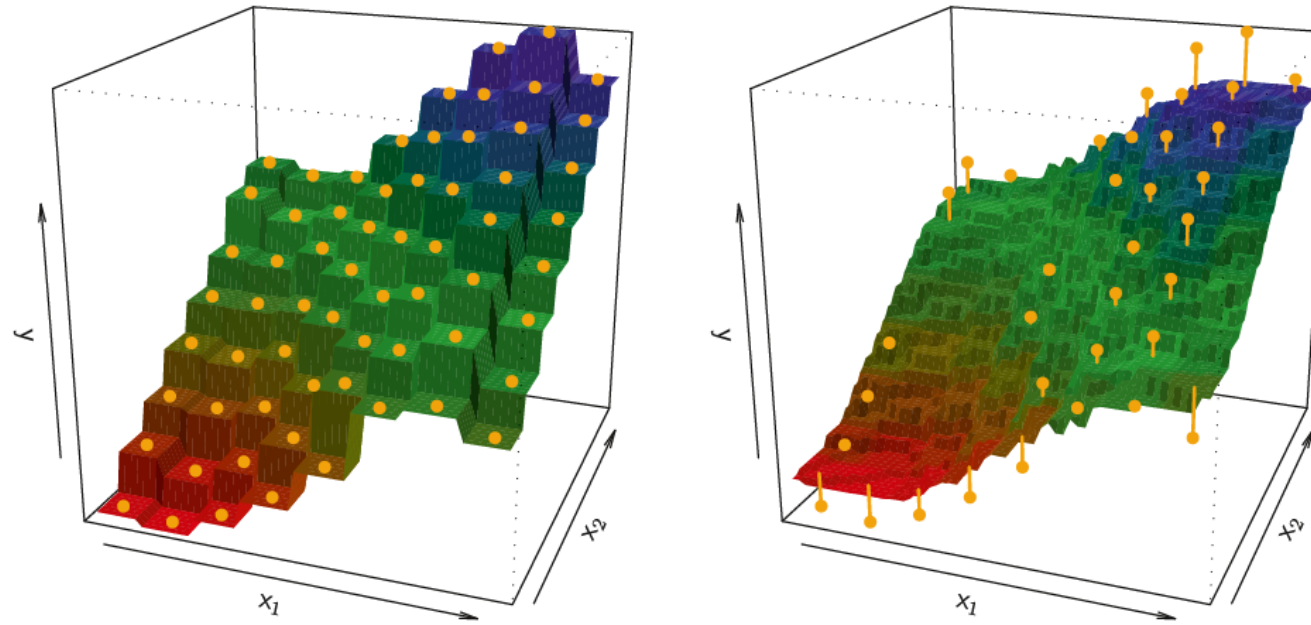
- $K=1$  very flexible model: Low bias but high variance.
- As  $K$  grows, less flexible model, regression fit gets smoother and smoother. This corresponds to a low variance but high bias.
- Optimal value of  $K$ :

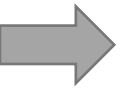




# Choice of K (Bias Variance Trade Off)

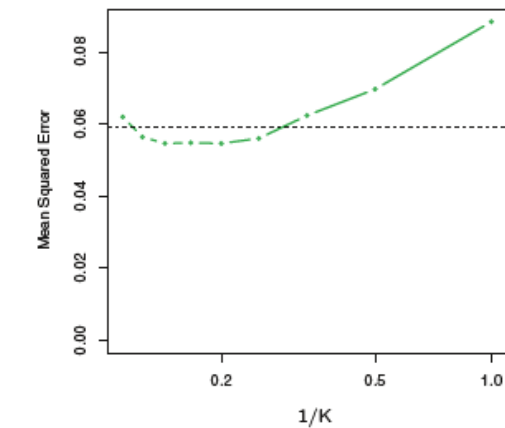
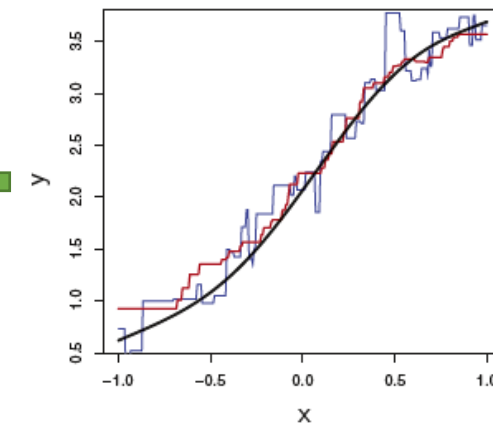
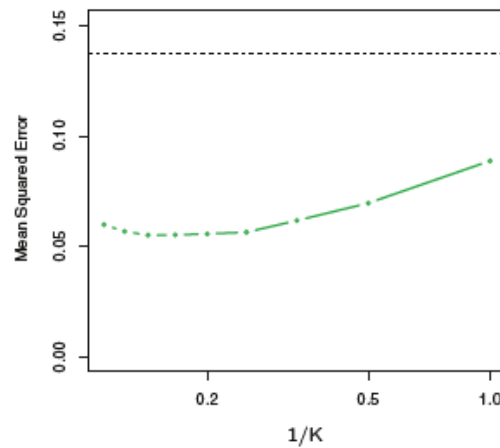
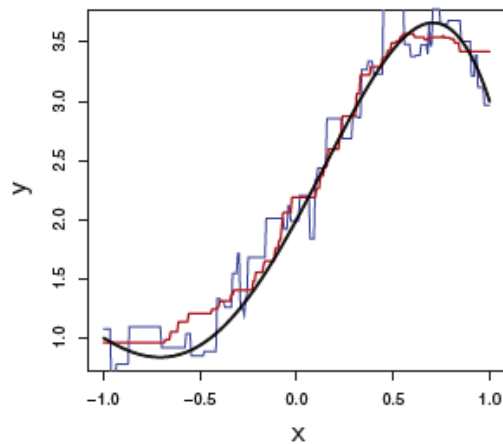
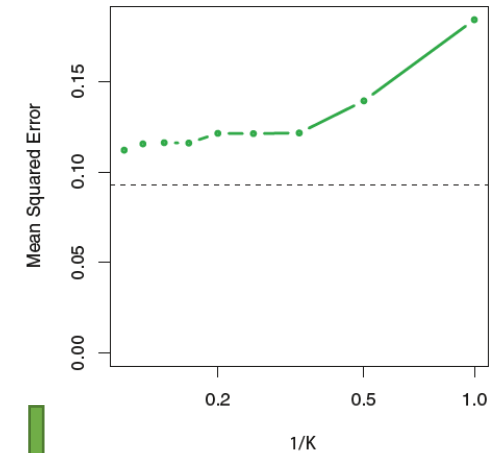
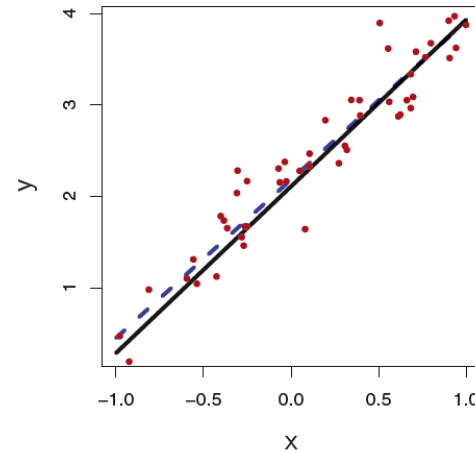
- $K=1$  very flexible model: Low bias but high variance.
- As  $K$  grows, less flexible model, regression fit gets smoother and smoother. This corresponds to a low variance but high bias.





# Linear regression vs KNN regression

- Black curve is the true relationship between  $y$  and  $X$
- Green dashed line: KNN  $MSE_{test}$
- Black dashed line: OLS  $MSE_{test}$
- The more non-linear the true relationship, the better performance of KNN compared to OLS.



# Part III

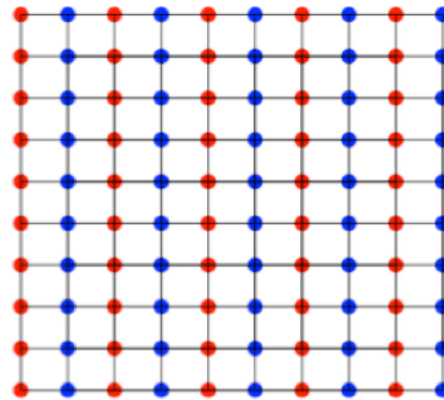
## Pros and Cons

# → Curse of Dimensionality

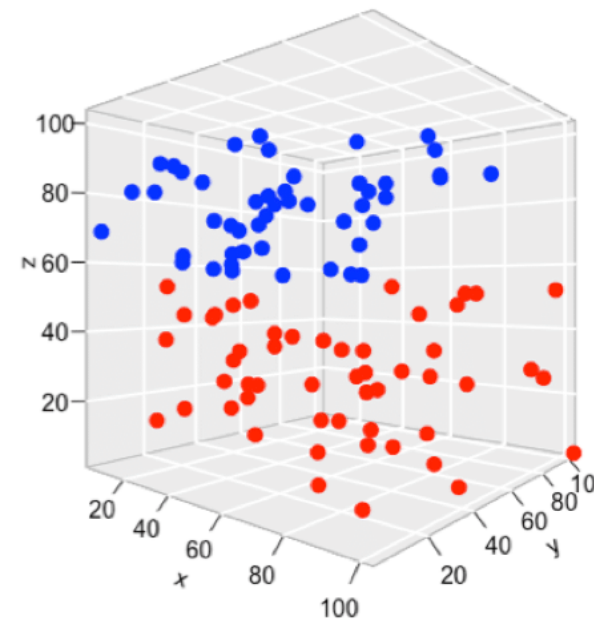
- The “Curse of Dimensionality” is a problem with the relationship between **dimensionality** and **volume**.
- Sparsity of data occurs when moving to higher dimensions. the volume of the space represented grows so quickly that the data **cannot keep up** and thus becomes sparse. (*Bellman, 1957*)



(A) 1-D



(B) 2-D

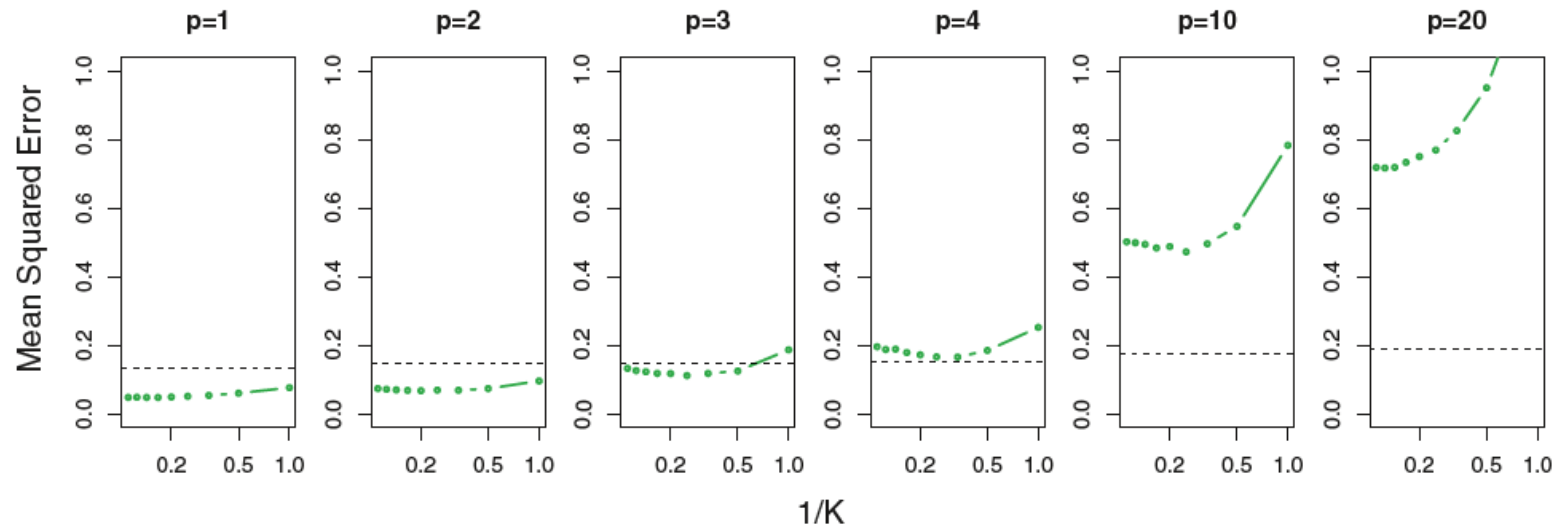
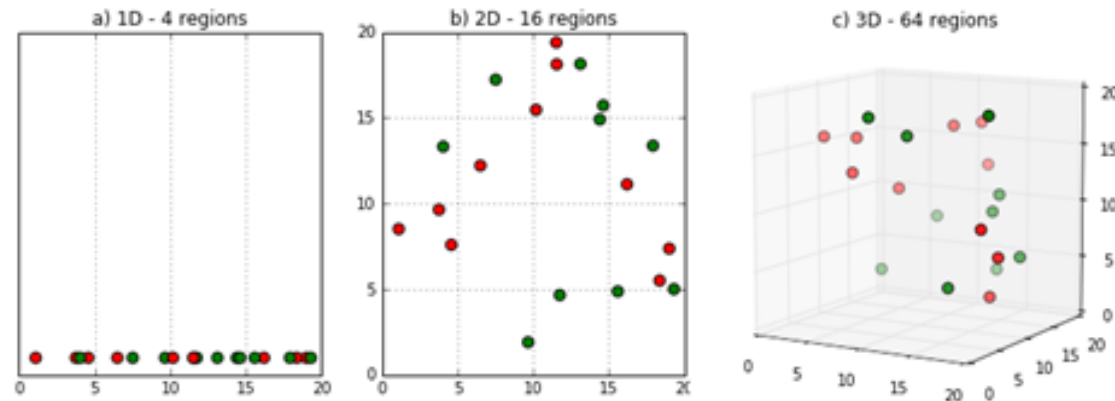


(C) 3-D





# KNN and the Curse of Dimensionality





# KNN's Pros and Cons

## Pros:

- Intuitive and simple
- No assumption (non-parametric)
- Easy to implement for multi-class problem
- Used both for classification and regression
- Few parameters/hyper-parameters

## Cons:

- Slow (memory-based approach)
- Curse of dimensionality
- Not good with multiple categorical features
- Choice of K
- No interpretation (None!)



# → KNN Applications in finance

- Bankruptcy prediction
- Stock price prediction (buy/sell/hold)
- Corporate bond credit rating assignments
- Money laundering analysis
- Bank customer profiling
- Loan management
- Customized equity and bond index creation

