

#### **Introduction to Artificial Intelligence- CII2M3**

Nearest Neighbor

ADF - Start 08:30













#### **Enormous Attributes**

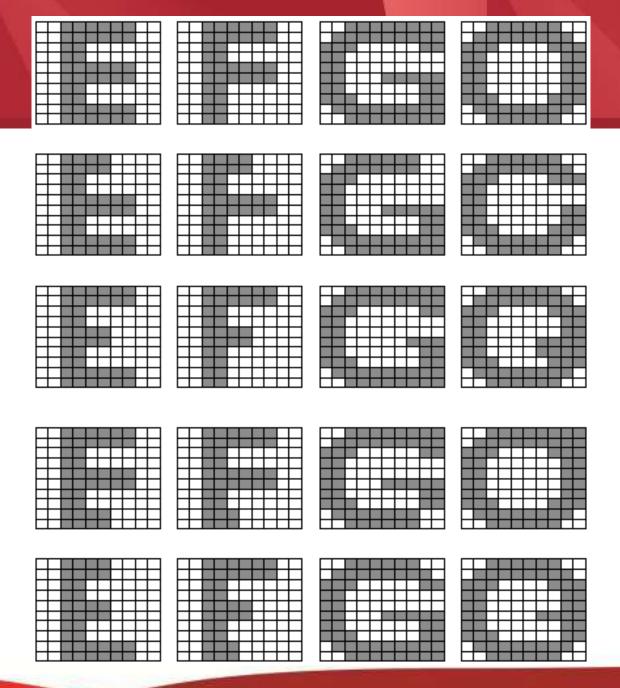
- Decision tree is good for limited and discrete attributes
- In case of classification with numerous attributes,
  the tree resulted might be too complex and prone to overfit

For example: in image classification



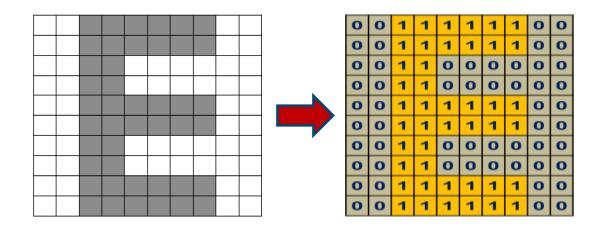
#### **Character Recognition**

20 data 10x10 pixel 4 class



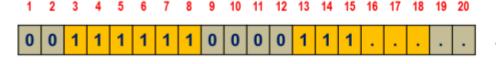


#### **Character Recognition**



To ease the computation, change data into 1D array

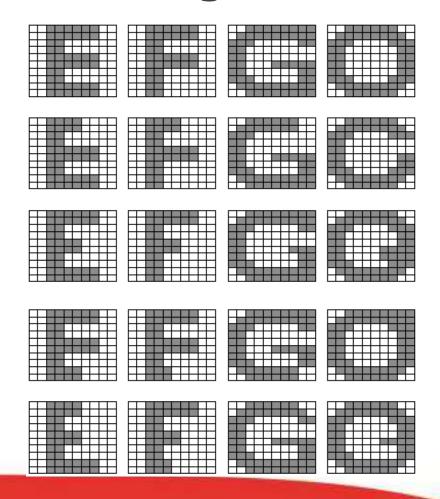








#### **Character Recognition Dataset**



	Pix 1	Pix 2	Pix 3	Pix 4	Pix 5	 Pix 100
E1	0	0	1	1	1	 0
F1	0	0	1	1	1	 0
G1	0	0	1	1	1	 0
01	0	0	1	1	1	 0
05	0	0	1	1	1	 0

20 data 100 dimensional 4 class



#### **Character Recognition – ID3**

- Let's say we try to build character classifier based on pixel input using ID3
- What will happen?

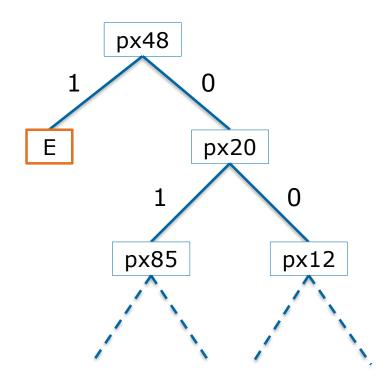


#### **Character Recognition – ID3**



#### **Character Recognition – ID3**

- The tree will be too long
- A complete ID3 will result a 100-level-depth tree (100-dimensional input)
- Not efficient







- Simple algorithm that stores all available cases and classifies new cases based on a similarity measure
- Non-parametric techniques
- Other names:
  - Memory-Based Reasoning
  - Example-Based Reasoning
  - Instance-Based Learning
  - Case-Based Reasoning
  - Lazy Learning



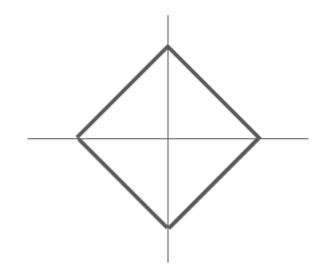
- Training Process
  - Memorize all training data and labels
- Testing Process
  - -Use L1 or L2 (or other distance choices) distance to each and every training data, return label of the closest one
  - L1: Manhattan Distance
  - L2: Euclidean Distance



#### **Distance Metric**

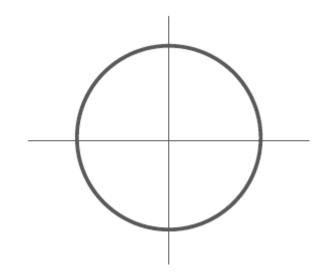
L1 (Manhattan) distance

$$d_1(x1, x2) = \sum_{p} |x1_p - x2_p|$$



L2 (Euclidean) distance

$$d_1(x1, x2) = \sqrt{\sum_{p} (x1_p - x2_p)^2}$$

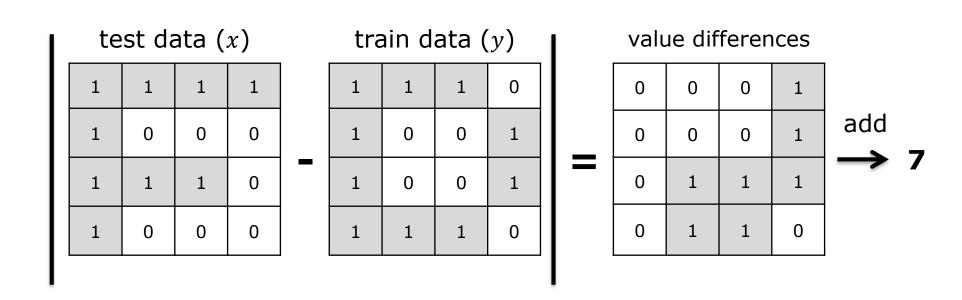




L2 distance : 
$$d_1(x_1, y_2) = \sqrt{\sum_p (x_1^p - y_2^p)^2}$$

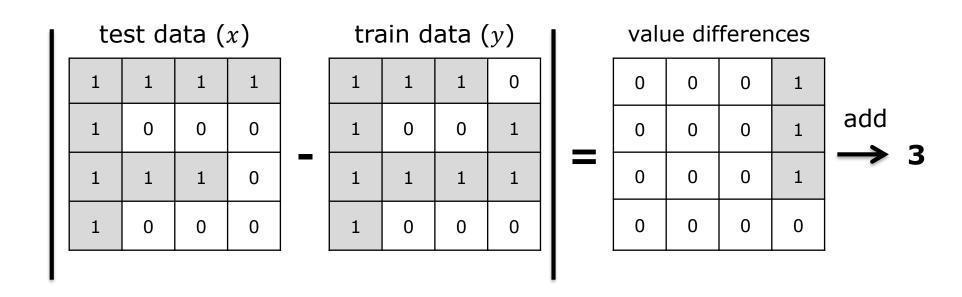


L1 distance :  $d_1(x_1, y_2) = \sum_p |x_1^p - y_2^p|$ 





L1 distance : 
$$d_1(x_1, y_2) = \sum_p |x_1^p - y_2^p|$$





#### **Nearest Neighbor Algorithm**

- For each test data A,
  - loop through all training data, calculate the distance
  - Choose the closest training data point X
  - Set the label of X as label of data test A

- Nearest neighbor intuition
  - Since A is similar to X (the attributes are close),
     then A and X must be the same class



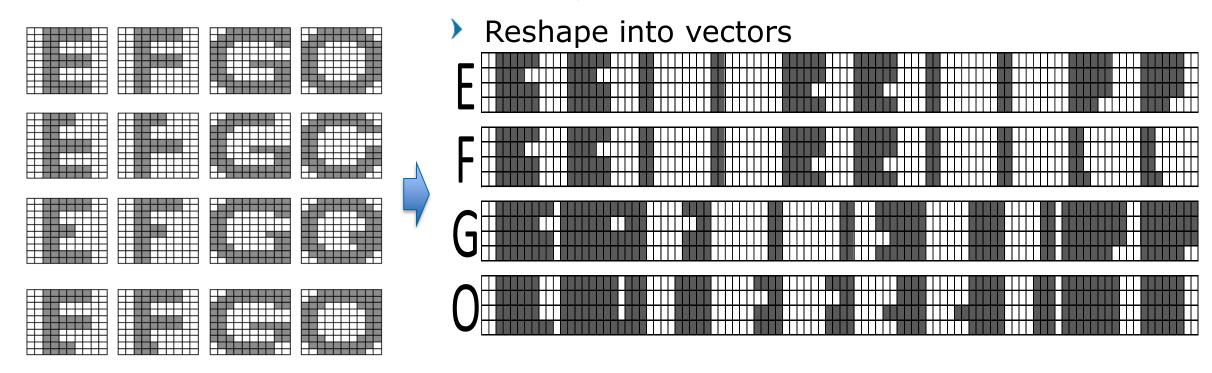
# Character Recognition with Nearest Neighbor

**Training and Testing** 



#### **Nearest Neighbor Learning Process**

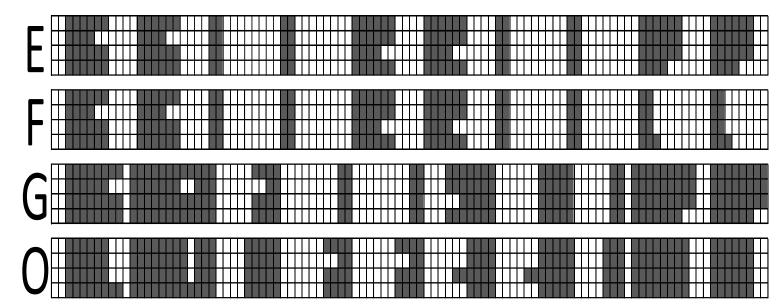
Let's say we use 16 data as training data





#### **Nearest Neighbor Learning Process**

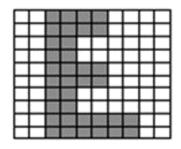
- Save to database,
- And that's it for Learning Process





#### **Nearest Neighbor Testing Process**

Now we want to classify new data using Nearest Neighbor



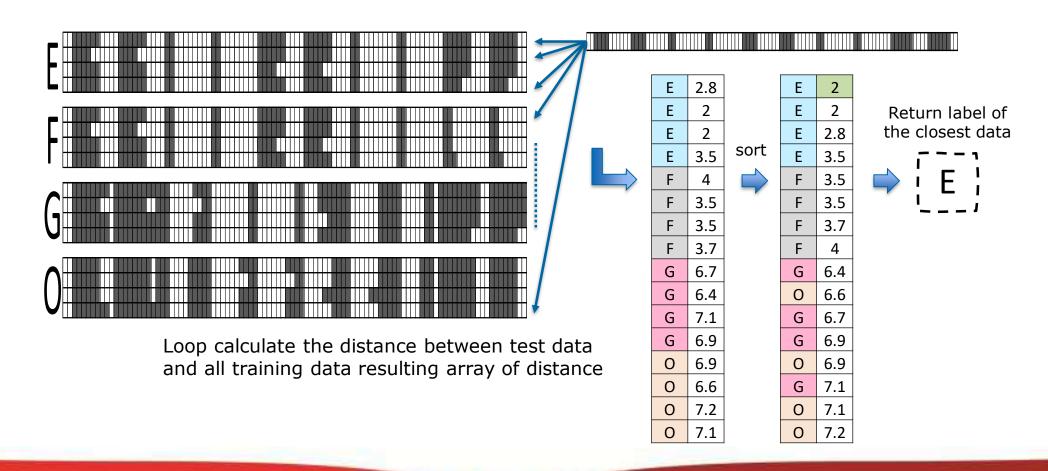
First, we change new data into 1 dimensional



Then calculate distance to the 16 data training

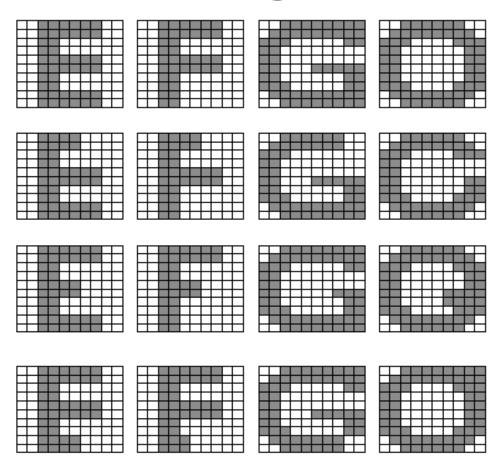


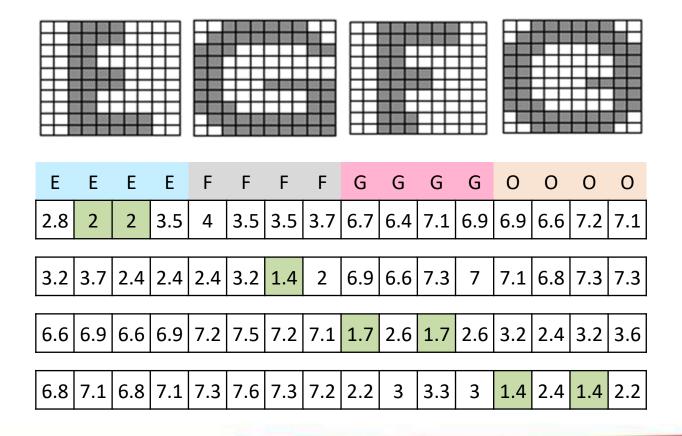
#### **Nearest Neighbor Testing Process**





#### **Nearest Neighbor Testing Process**







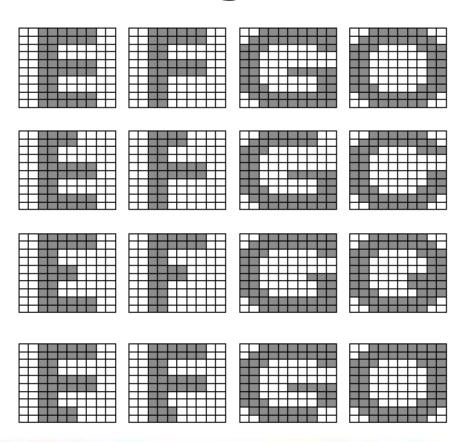
#### **Nearest Neighbor Problem**

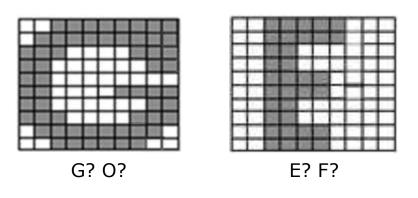


- Training Speed?
  - -0(1)
  - No training, just save all training data
- Testing Speed?
  - -O(N)
  - Linearly slower according to the size of training data



# **Character Recognition using Nearest Neighbor**





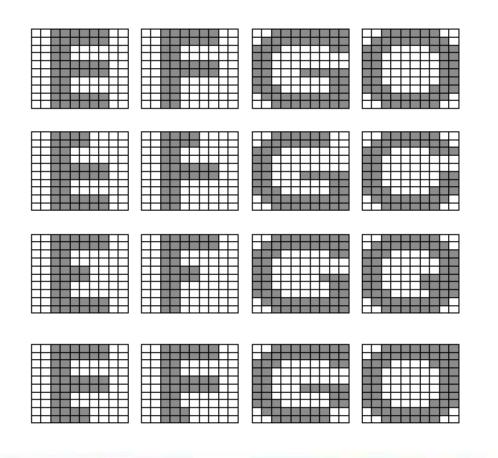
Ε	Ε	Ε	Ε	F	F	F	F	G	G	G	G	0	0	0	0
6.9	7.1	6.9	7.1	7.4	7.7	7.4	7.3	2.4	3.2	2.4	2	2.6	2.6	2.6	2
3.2	3.2	2.4	2.4	3.2	3.2	2.4	2.8	6.9	6.6	7.3	7	7.1	6.8	7.3	7.3

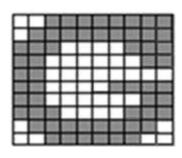




- Use many neighbors to determine the class
  - Choose k-closest data point
  - Majority vote the label
- K-NN can be use for Classification and Regression
  - For classification select the most frequent neighbor.
  - For regression calculate the average of K neighbors



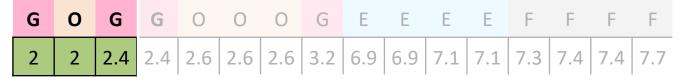




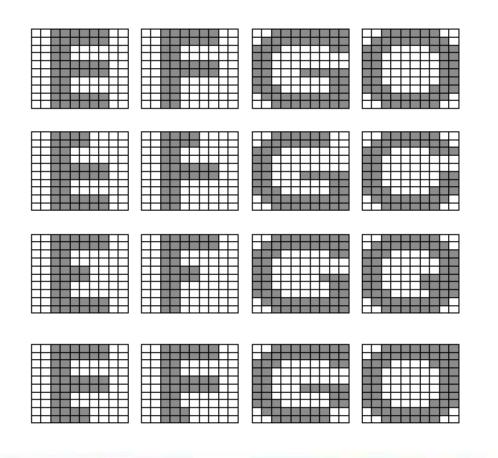
$$K = 3$$

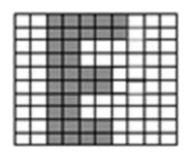
Е	Ε	Ε	Е	F	F	F	F	G	G	G	G	0	0	0	0
6.9	7.1	6.9	7.1	7.4	7.7	7.4	7.3	2.4	3.2	2.4	2	2.6	2.6	2.6	2

sort





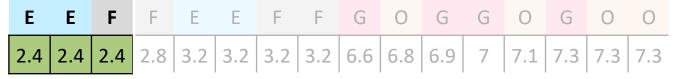




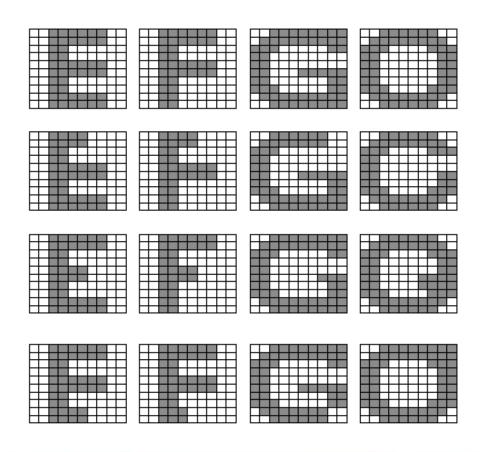
$$K = 3$$

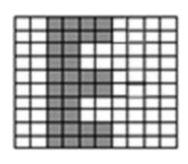
Е															
3.2	3.2	2.4	2.4	3.2	3.2	2.4	2.8	6.9	6.6	7.3	7	7.1	6.8	7.3	7.3

sort





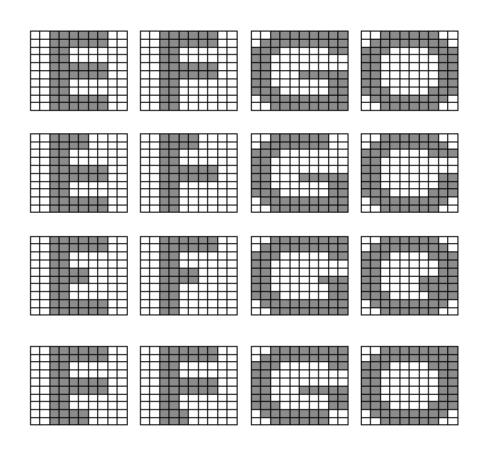


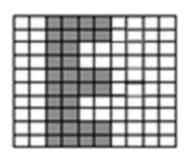


$$K = 3$$











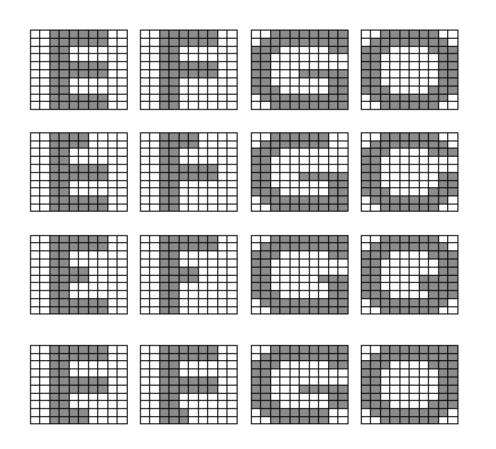
sort

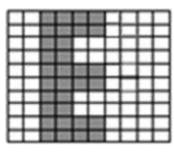
E	F	Ε	Е	F	F	Е	F	G	0	G	G	0	G	0	0
2.8	2.8	2.8	2.8	2.8	3.2	3.5	3.5	6.7	6.9	7	7.1	7.2	7.4	7.4	7.5

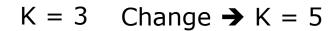
what will happened if the sorting result is

E															
2.8	2.8	2.8	2.8	2.8	3.2	3.5	3.5	6.7	6.9	7	7.1	7.2	7.4	7.4	7.5





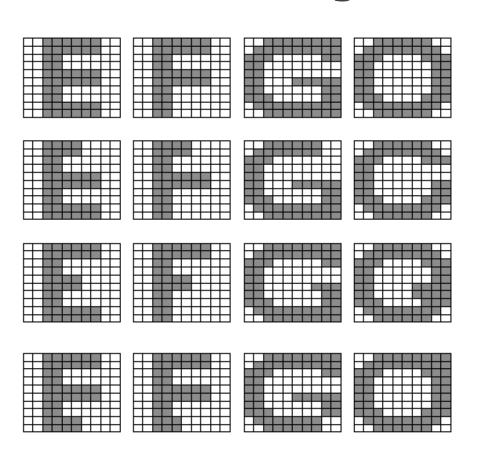




sort

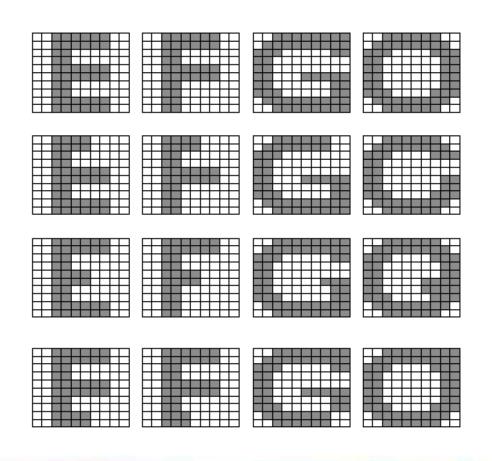
															0
2.8	2.8	2.8	2.8	2.8	3.2	3.5	3.5	6.7	6.9	7	7.1	7.2	7.4	7.4	7.5



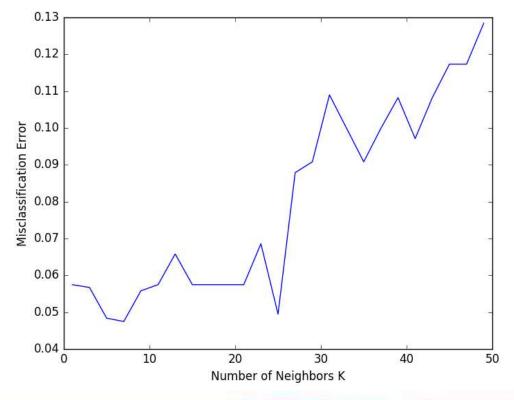


K = 3? K = 5? Which one is better? K = 7? K = 10?





Observe and determine k using validation set





#### k-Nearest Neighbors - Hyperparameters

- What is the best distance to use?
- What is the best value of k to use?

- Choices about the algorithm that we set rather than learn
- Very problem-dependent.
- Must try them all out and see what works best.
- Use train set and validation set to avoid overfitting



#### **K-Fold Cross Validation**

Start 09:30



#### **Hyperparameter Observation on Trainset?**

- We want to observe  $k = \{1, 2, 3, 4, 5\}$
- What would happen if we check the performance on train set?

Best performance will ALWAYS be k=1



#### **Example K-Fold Cross Validation**

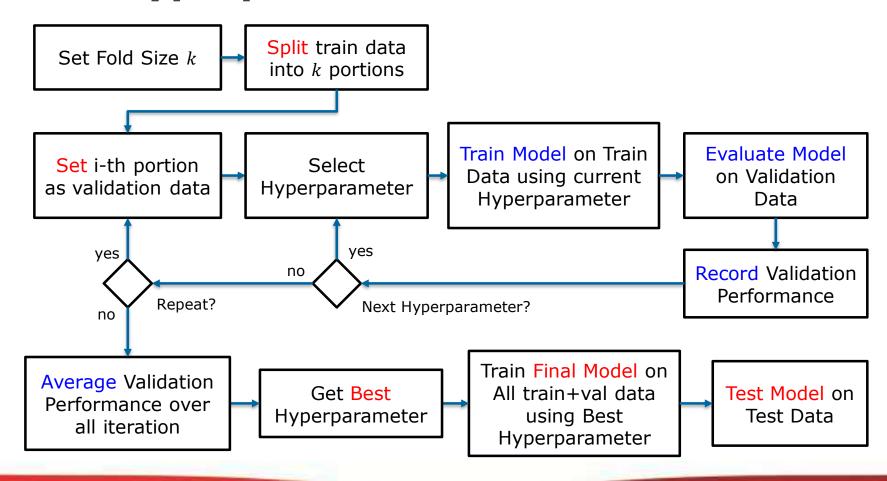
- Example K-Fold Cross Validation using 5 folds
  - Iteration 1
    - 1,2,3,4 train
    - Fold 5 validation
  - Iteration 2
    - **1,2,3,5** train
    - Fold 4 validation
  - Iteration 3
    - **1,2,4,5** train
    - Fold 3 validation

fold 1	fold 2	fold 3	fold 4	fold 5
fold 1	fold 2	fold 3	fold 4	fold 5
fold 1	fold 2	fold 3	fold 4	fold 5

- ..



#### K-Fold Val: Hyperparameter Observation





#### K-Fold Val: Hyperparameter Observation

- For each iteration
  - -Try all hyperparameters
  - Record the validation acc
- At the end of iteration, average the validation acc
- Choose best hyperparameter
- Use the chosen hyperparameter to test new data using ALL data (train+val)

	kNN validation											
Iteration	1	2	3	4	5							
1	66%	65%	83%	84%	67%							



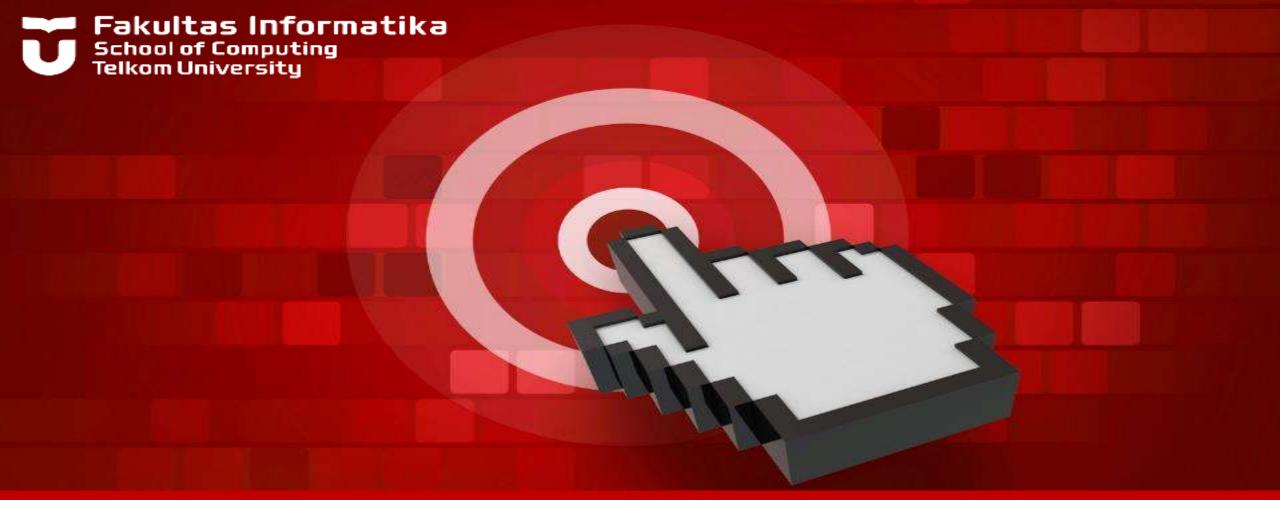
#### Note on kNN Hyperparameter Observation

Myth: k value should be an odd-number



## **Question?**





# THANK YOU