

# Machine Learning

## Lecture 13: k-Nearest Neighbors

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COURSE CODE: CSE451

2023



# Course Teacher

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**Dr. Mrinal Kanti Baowaly**

Associate Professor

Department of Computer Science and  
Engineering, Bangabandhu Sheikh  
Mujibur Rahman Science and  
Technology University, Bangladesh.

Email: [mkbaowaly@gmail.com](mailto:mkbaowaly@gmail.com)



# Instance Based Learning

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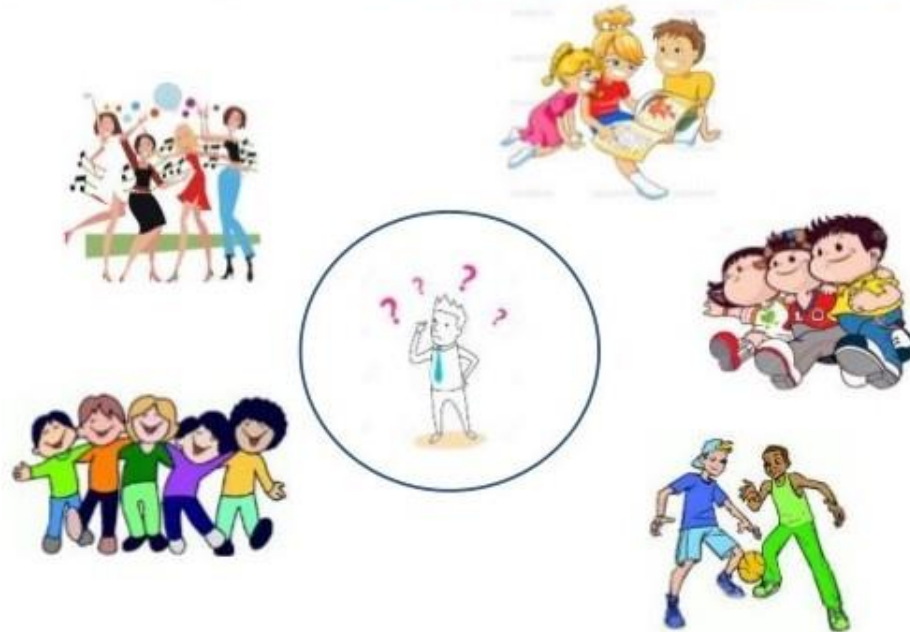
- No model is learned
- It does not learn from the training set immediately instead it stores the dataset and uses them at the time of prediction(hence also called lazy learning).
- It classifies/predicts the test data based on its similarity to the stored training data.
- Example: KNN algorithm

# What is k-Nearest Neighbors (kNN) learning?

- A type of instance-based learning in which an unknown object is classified with the most common class among its k-closest objects

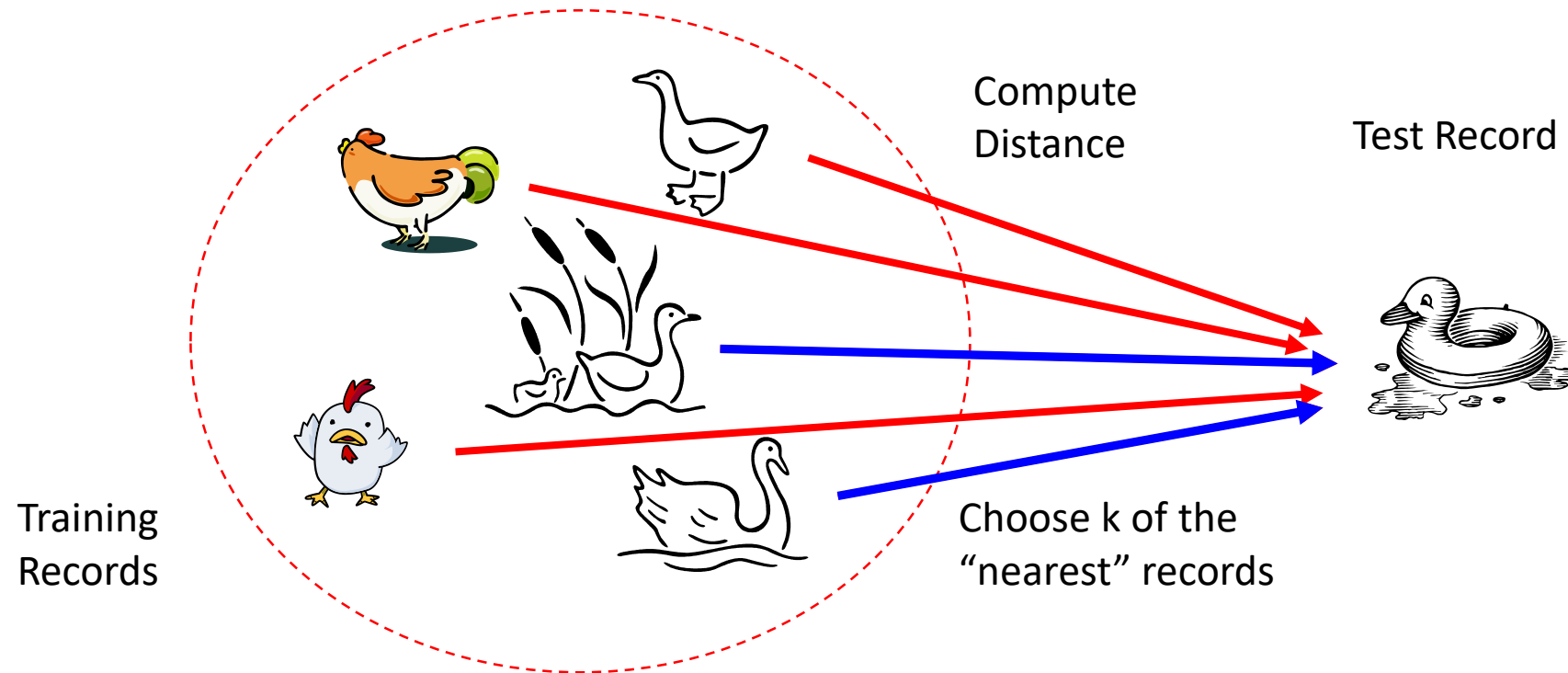
Tell me about your friends(who your neighbors are) and *I will tell you who you are.*

**Basic Idea:**  
Analogy for kNN

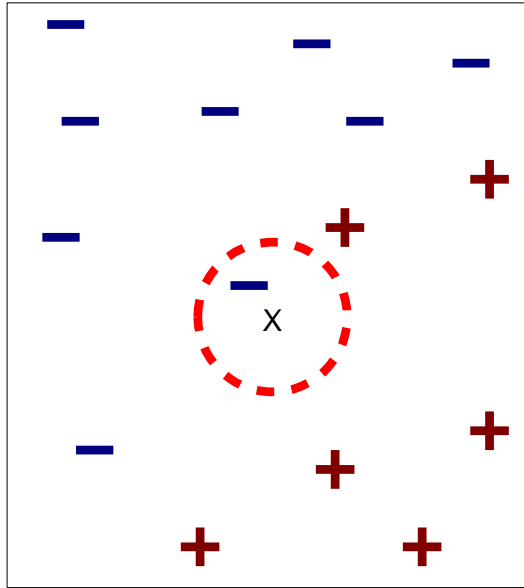


# Another Analogy for kNN

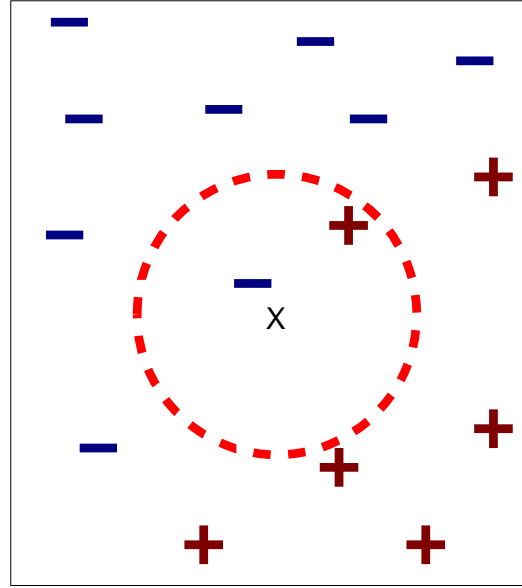
- If it walks like a duck, quacks like a duck, then it's probably a duck



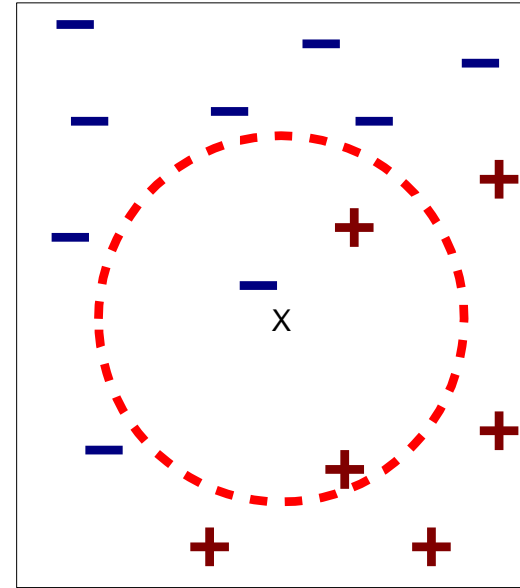
# What are k-Nearest Neighbors?



(a) 1-nearest neighbor



(b) 2-nearest neighbor



(c) 3-nearest neighbor

k-Nearest Neighbors of a record  $x$  are data points that have the  $k$  smallest distance to  $x$

# kNN algorithm

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- To classify an unknown record
  - Compute distance to all other training records
  - Identify k-nearest records (neighbors)
  - Find the most common class of the nearest k-neighbors and assign the class for the unknown record

# Distance measures

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- **Euclidean distance:** It is useful in low dimensions, it doesn't work well in high dimensions and for categorical variables.
- **Hamming distance:** Calculate the distance between binary vectors.
- **Manhattan distance:** Calculate the distance between real vectors using the sum of their absolute difference. Also called City Block Distance.
- **Minkowski distance:** Generalization of Euclidean and Manhattan distance.

**Note:** Both Euclidean and Manhattan distances are used in case of continuous variables, whereas hamming distance is used in case of categorical variable.

Detail: [Distance Metrics in Machine Learning](#)



# How to choose the value of k?

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- Choice of k is very critical – A small value of k means that noise will have a higher influence on the result. A large value make it computationally expensive and may defeat the basic philosophy behind kNN (that objects that are near might have similar classes).
- A simple approach to select  $k = \sqrt{n}$ , where  $n$  is the number of samples in the training data.
- Sometimes it is best to run through each possible value for k (e.g., start with k=1 and then increase it) and then decide the value of k that outputs the best performance with respect to training and test data
- Choose an odd number for the binary classification

# How to decide the class label?

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- Take the majority vote of class labels from the k-Nearest Neighbors
- Weigh the vote according to distance weight factor,  $w = 1/d^2$

# Example of kNN

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- Suppose you have height, weight and T-shirt size of some customers
- You need to predict the T-shirt size of a new customer named 'Monica' who has height 161cm and weight 61kg.

Detail: [ListenData](#), [Revoledu](#)

# Example of kNN

161 ✓

- Consider  $k=5$
- Calculate distance of all the customers with Monica and calculates the rank in terms of distance
- Find 5 customers closest to Monica.
- 4 of them had 'Medium T shirt sizes' and 1 had 'Large T shirt size'
- Monica is 'Medium T shirt'

		fx =SQRT((\$A\$21-A6)^2+(\$B\$21-B6)^2)			
	A	B	C	D	E
	Height (in cms)	Weight (in kgs)	T Shirt Size	Distance	
1					
2	158	58	M	4.2	
3	158	59	M	3.6	
4	158	63	M	3.6	
5	160	59	M	2.2	3
6	160	60	M	1.4	1
7	163	60	M	2.2	3
8	163	61	M	2.0	2
9	160	64	L	3.2	5
10	163	64	L	3.6	
11	165	61	L	4.0	
12	165	62	L	4.1	
13	165	65	L	5.7	
14	168	62	L	7.1	
15	168	63	L	7.3	
16	168	66	L	8.6	
17	170	63	L	9.2	
18	170	64	L	9.5	
19	170	68	L	11.4	
20					
21	161	61			

# Characteristics of kNN

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- Non-parametric (i.e. it does not make any assumption on underlying data)
- Lazy learner/instance-based  
(Find what is Eager Vs. Lazy Learners? Source: [Datacamp](#) )
- Very simple and easy to implement
- Minimal training but expensive testing
- Choosing the value of k is crucial
- Variables should be normalized/standardized else higher range variables can bias it (source: [ListenData](#))
- Susceptible of high number of independent variables

# Some Learning Materials

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[Datacamp: KNN Classification using Scikit-learn](#)

[Javatpoint: K-Nearest Neighbor\(KNN\) Algorithm for Machine Learning](#)

[ListenData: K NEAREST NEIGHBOR : STEP BY STEP TUTORIAL](#)

[AnalyticsVidhya: Introduction to k-Nearest Neighbors](#)