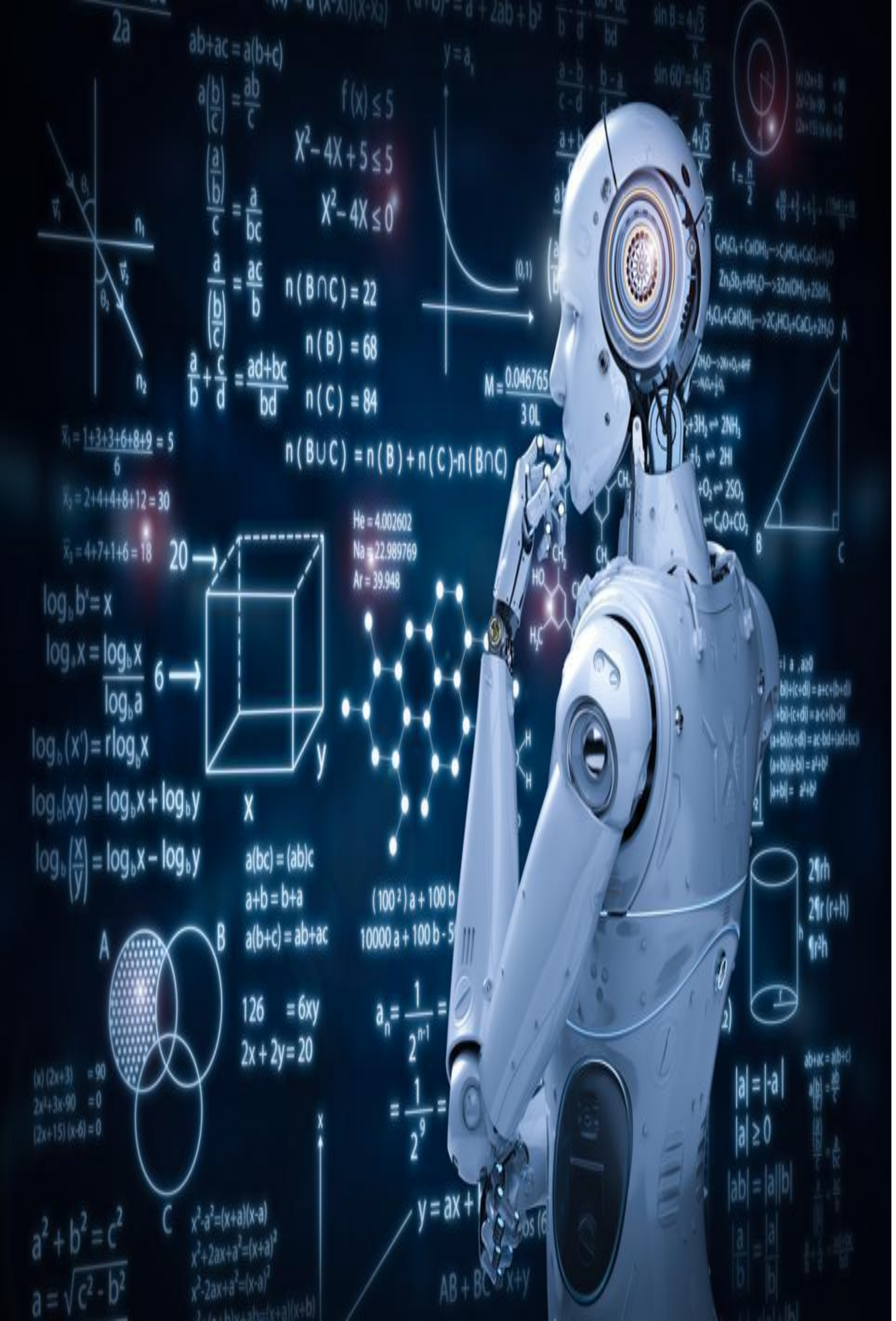


Practical Machine Learning

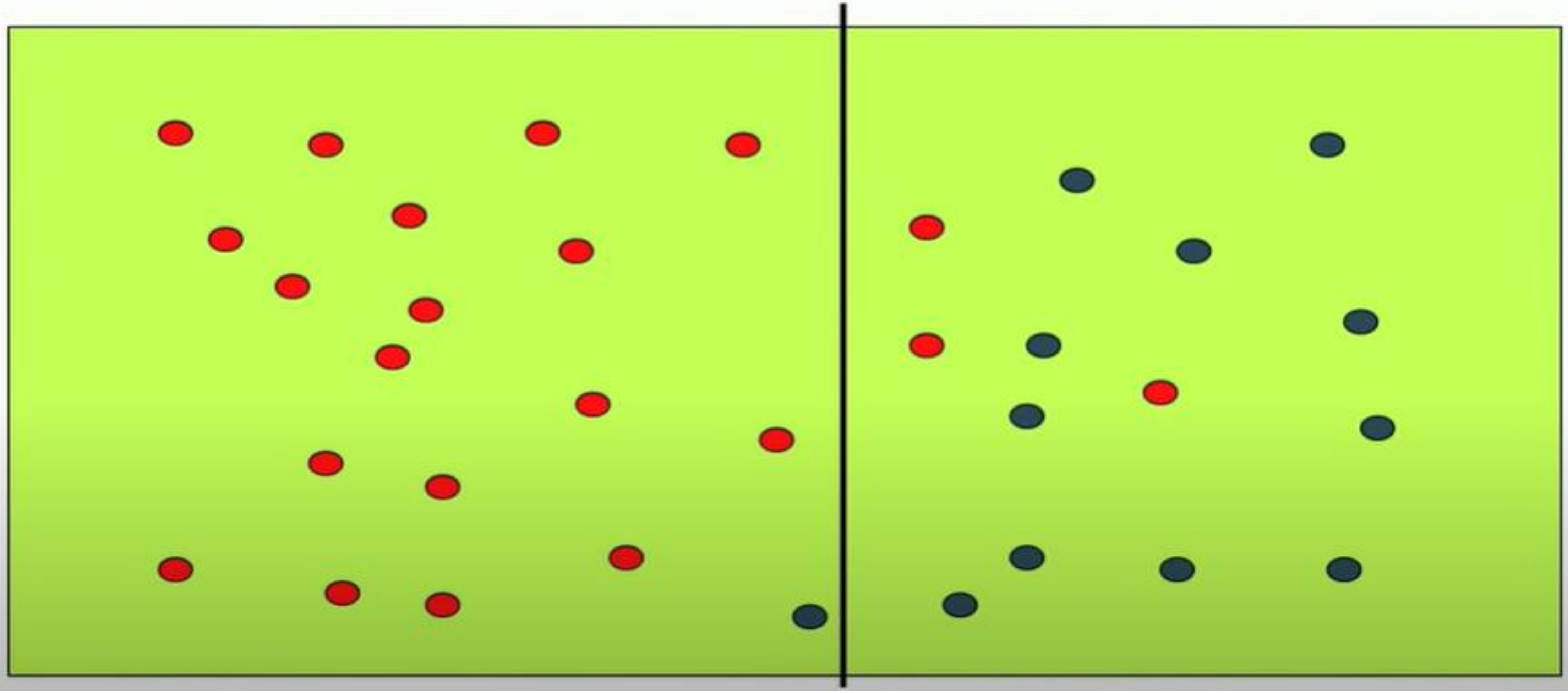
Day 10: Mar22 DBDA

Kiran Waghmare

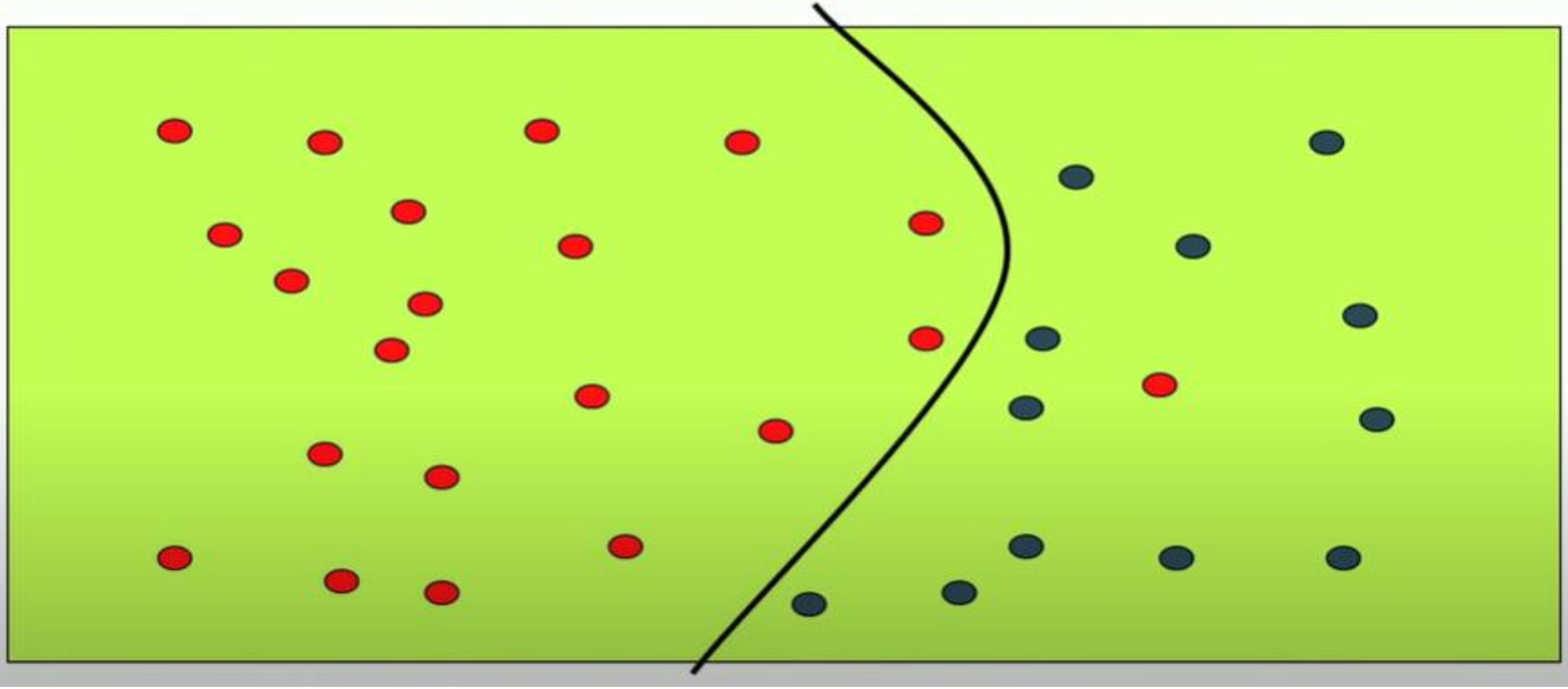
Agenda

- Classification Algorithm
- kNN
- Naïve Bayes

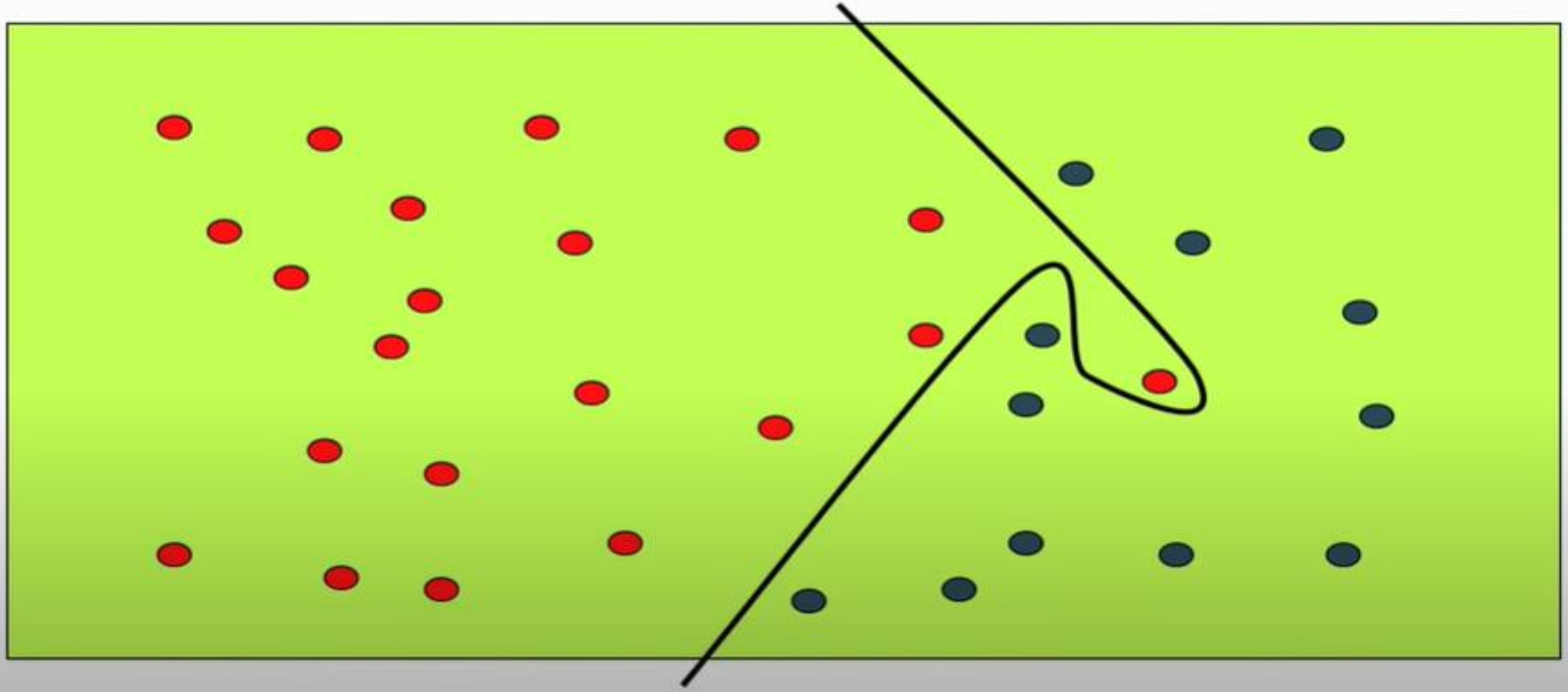
Possible Classifiers



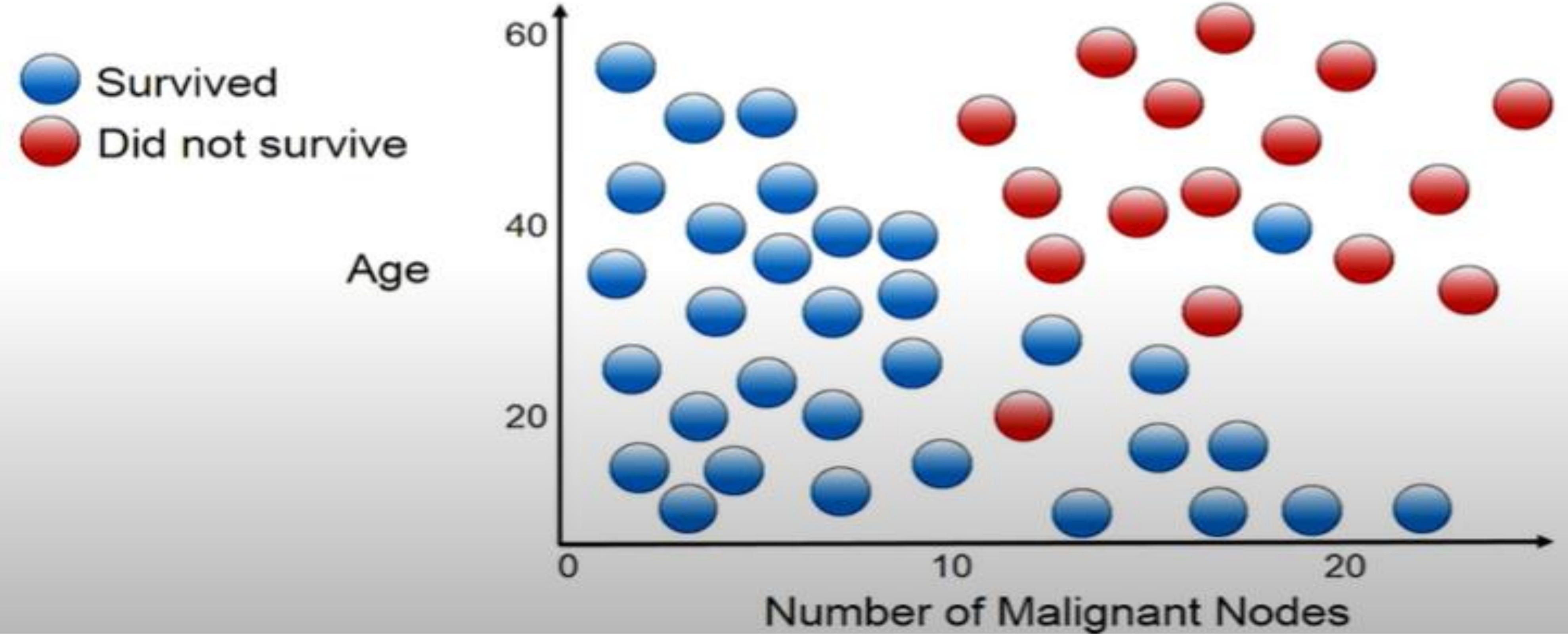
Possible Classifiers



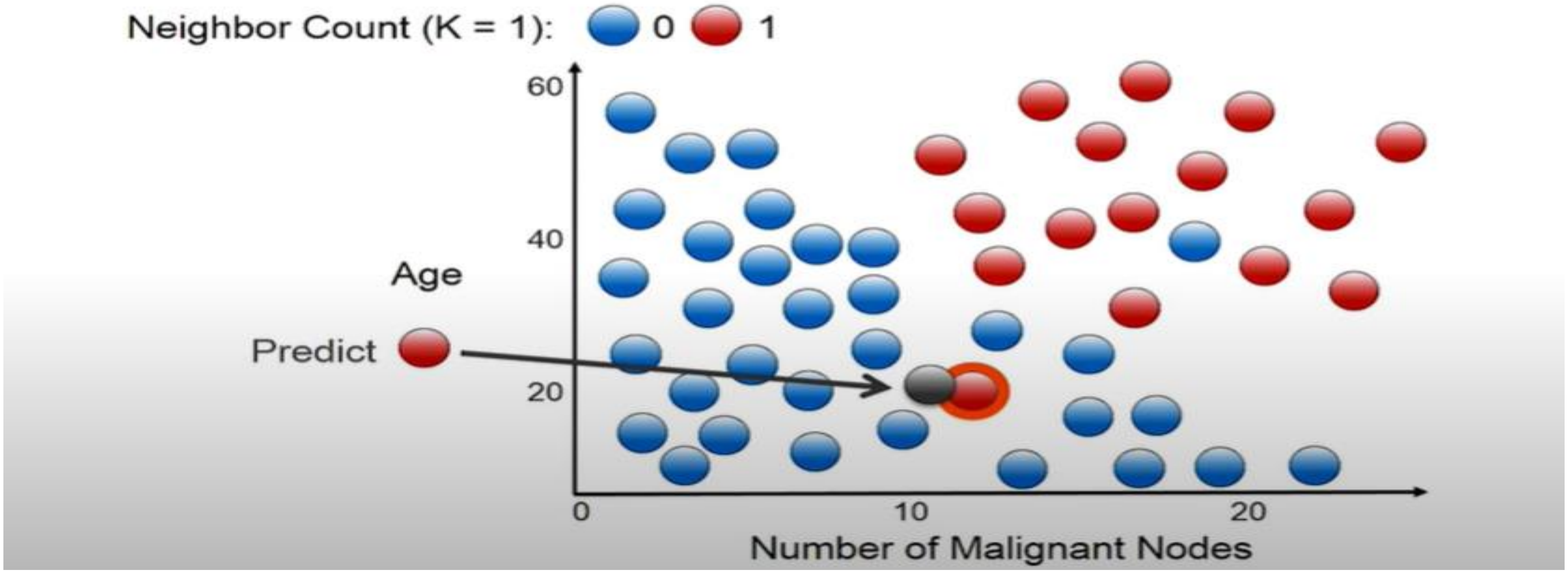
Possible Classifiers



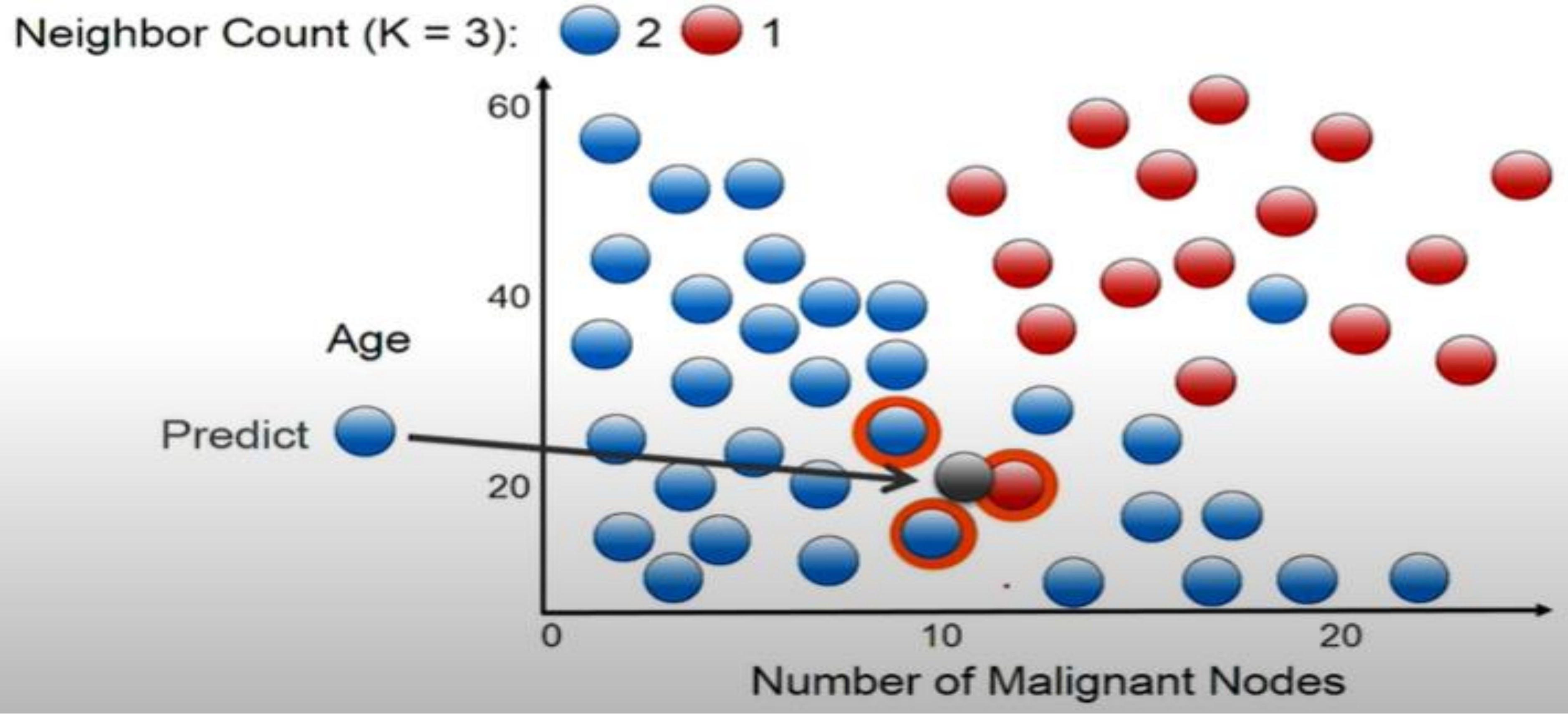
K-Nearest Neighbour- Classification



.. Classification



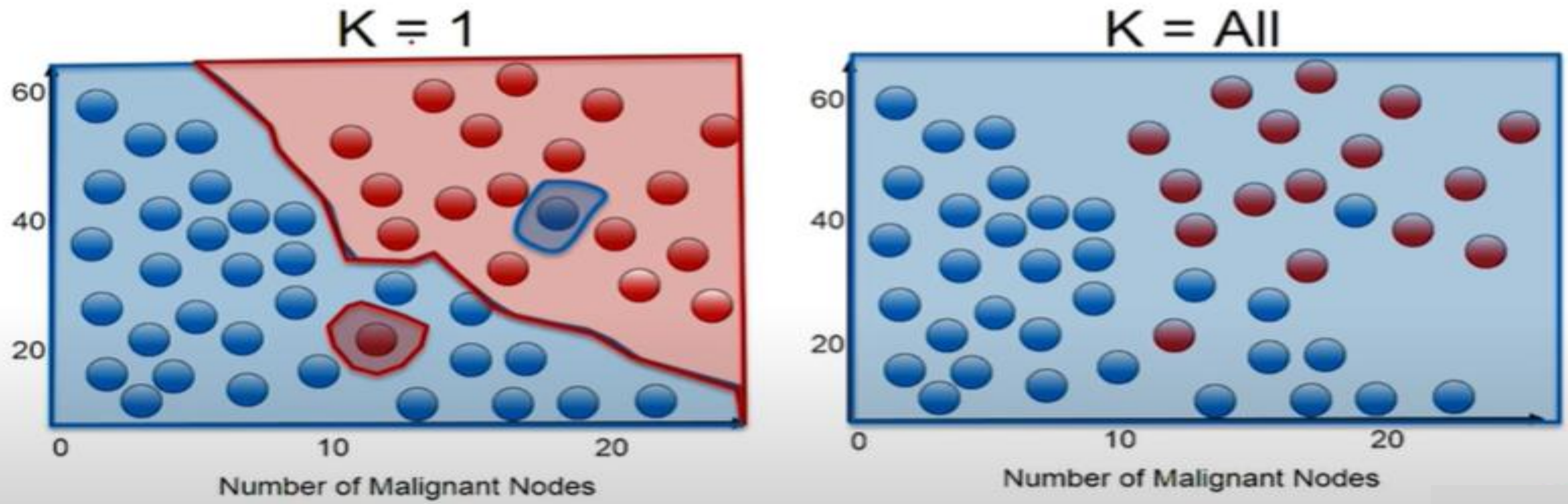
...Classification



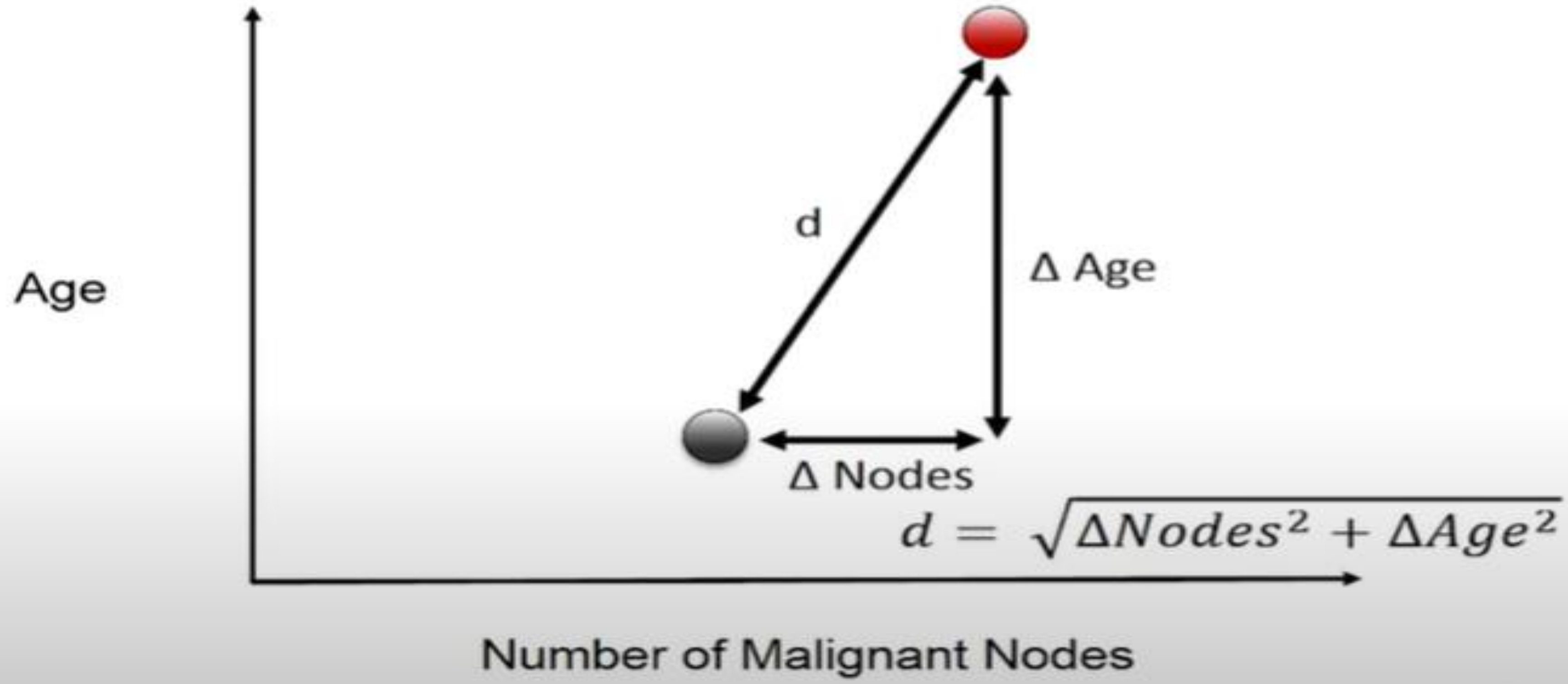
KNN parameters

- K – nearest neighbours
- Distance metric

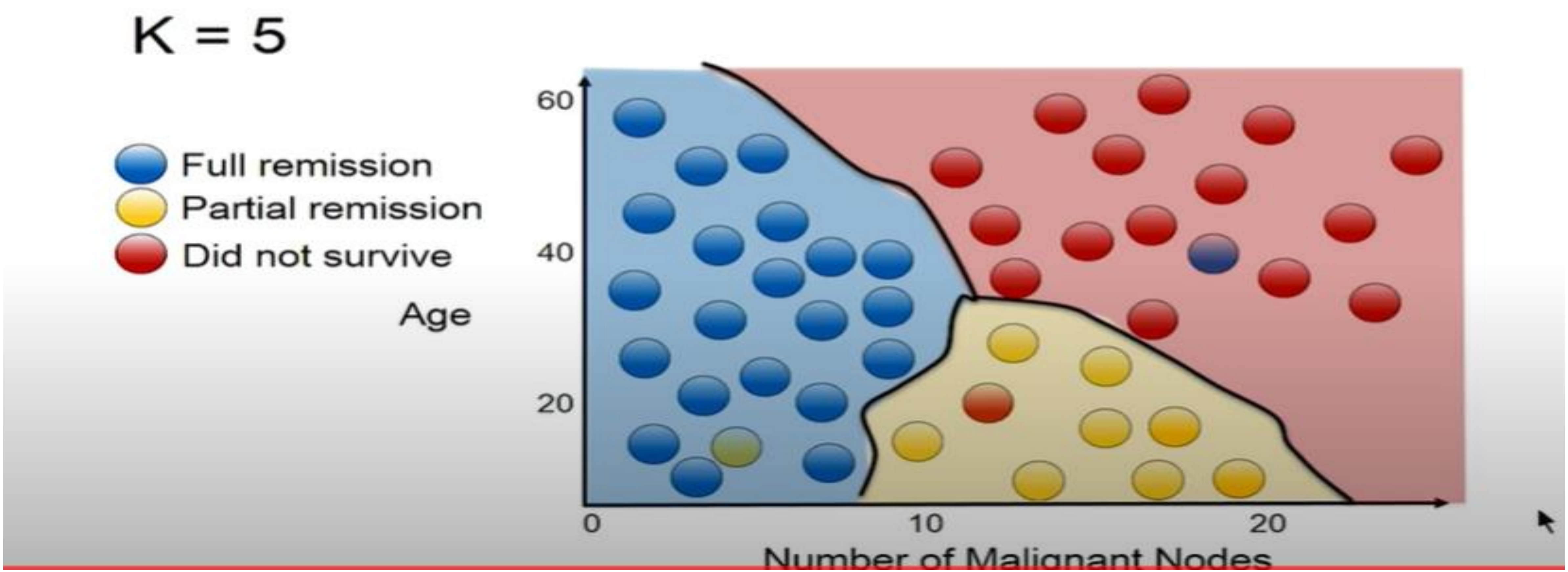
Choosing K


K = 1
K = All
60
40
20
0
10
20
Number of Malignant Nodes
60
40
20
0
10
20
Number of Malignant Nodes

Distance Metric- Euclidean Distance



Multiple Classes



Instance based classifiers

Set of Stored Cases

Atr1	………	AtrN	Class
			A
			B
			B
			C
			A
			C
			B

- Store the training samples
- Use training samples to predict the class label of test samples

Unseen Case

Atr1	………	AtrN

What is KNN?

- A powerful classification algorithm used in pattern recognition.
- K nearest neighbors stores all available cases and classifies new cases based on a *similarity measure*(e.g **distance function**)
- One of the top data mining algorithms used today.
- A non-parametric lazy learning algorithm (An Instance-based Learning method).

Nearest neighbor classification

- *k*-Nearest neighbor classifier is a lazy learner.
  - Does not build model explicitly.
  - Unlike eager learners such as decision tree induction and rule-based systems.
  - Classifying unknown samples is relatively expensive.
- *k*-Nearest neighbor classifier is a local model, vs. global models of linear classifiers.
- *k*-Nearest neighbor classifier is a non-parametric model, vs. parametric models of linear classifiers.

Lazy learners

•‘**Lazy**’: Do not create a model of the training instances in advance

•When an instance arrives for testing, runs the algorithm to get the class prediction

•**Example, K** – nearest neighbor classifier

(K – NN classifier)

“One is known by the company one keeps”

Simple Analogy..

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

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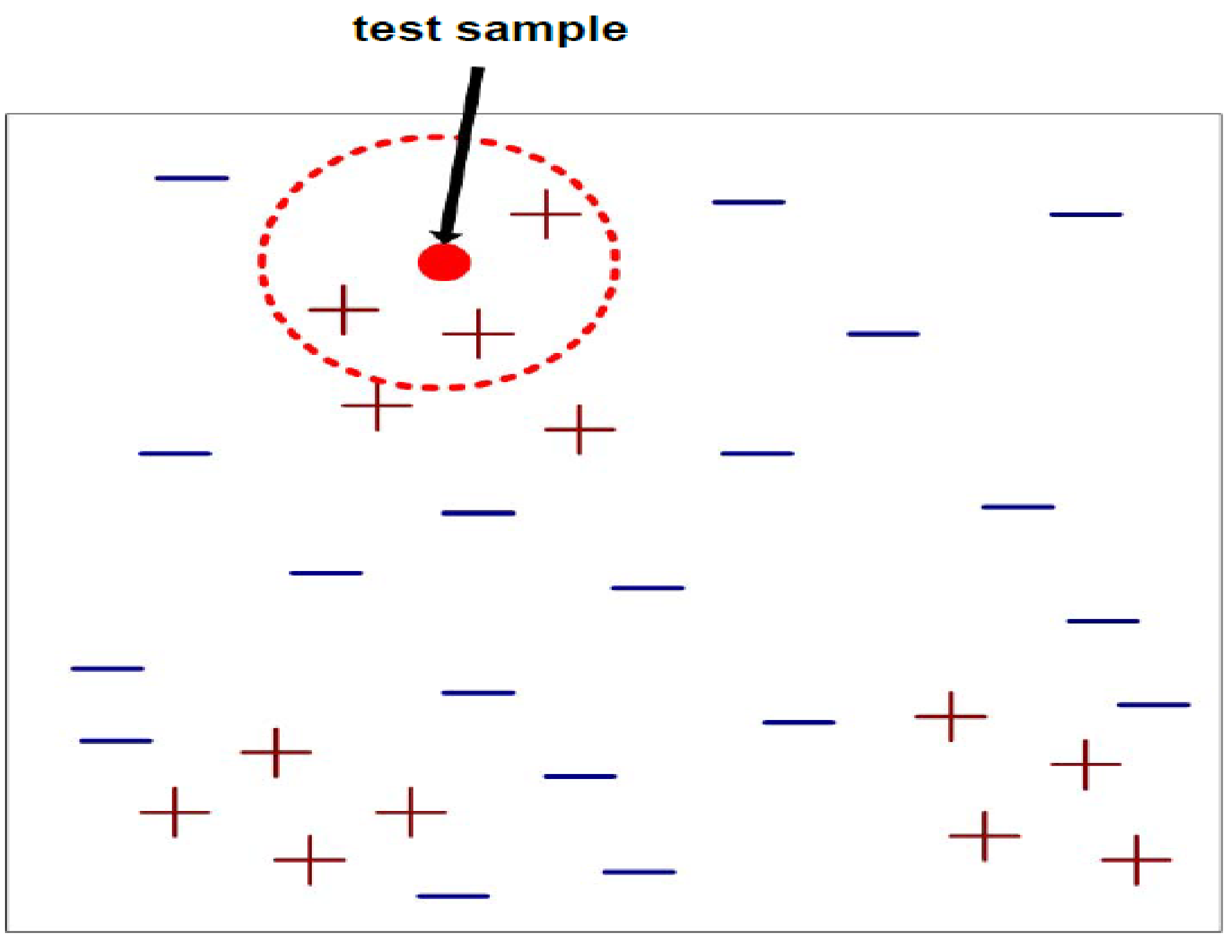
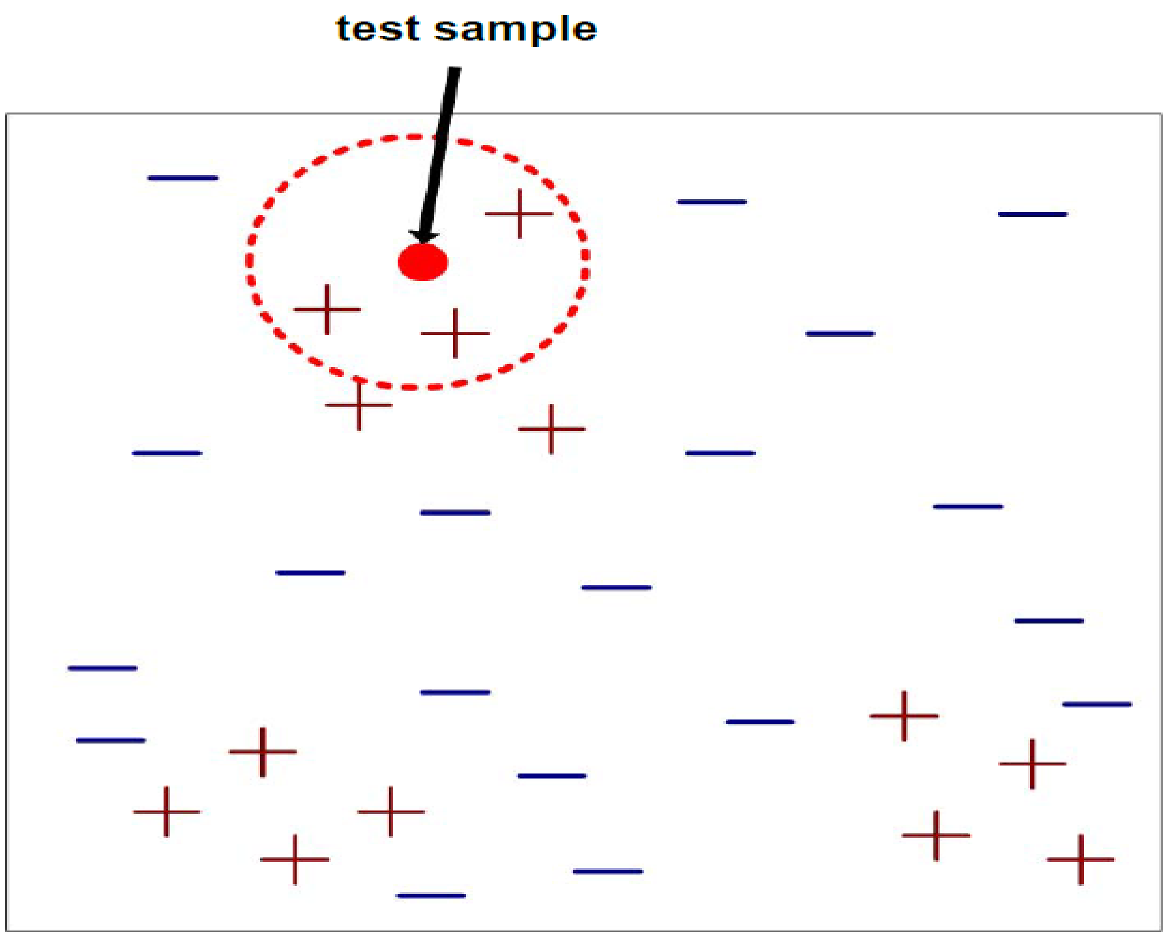
Nearest Neighbor Classifiers



Requires three inputs:

1. The set of stored samples
2. Distance metric to compute distance between samples
3. The value of *k*, the number of nearest neighbors to retrieve

Nearest Neighbor Classifiers

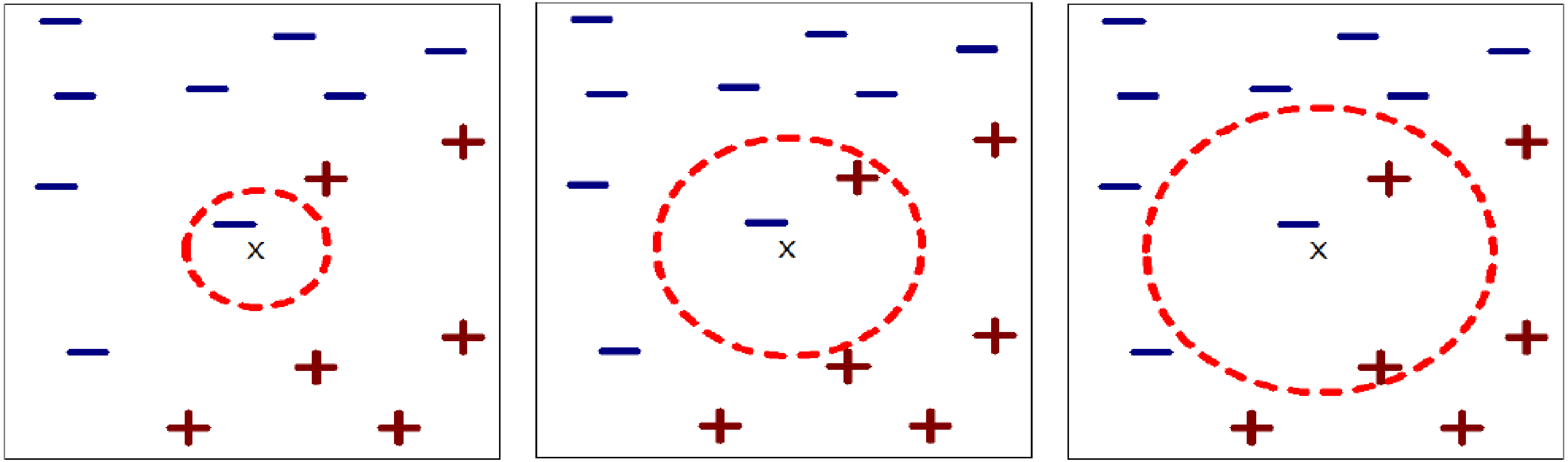


To classify test sample:

1. Compute distances to samples in training set
2. Identify *k* nearest neighbors
3. Use class labels of nearest neighbors to determine class label of test sample (e.g. by taking majority vote)

Definition of Nearest Neighbors

k-nearest neighbors of test sample x are training samples that have the *k* smallest distances to x



1-nearest neighbor **2-nearest neighbor** **3-nearest neighbor**

Distances for nearest neighbors

- Options for computing distance between two samples:
  - Euclidean distance

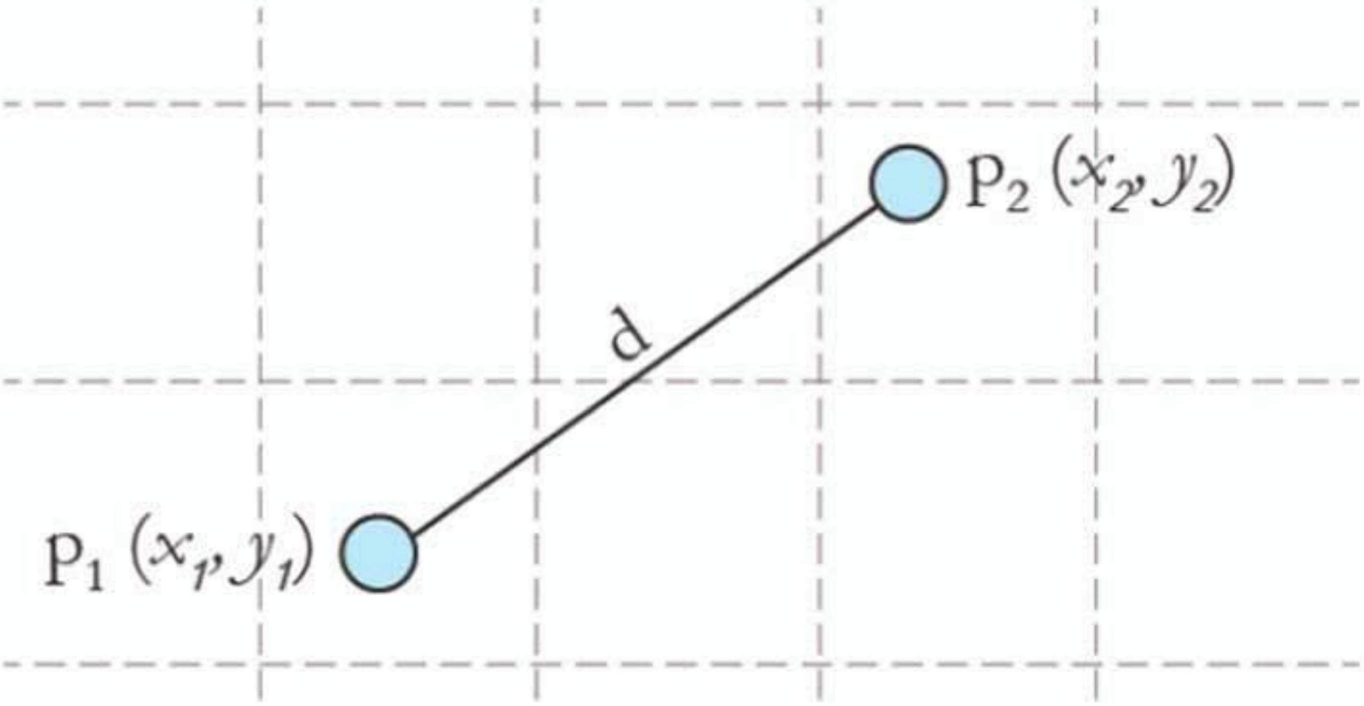
$$d(\mathbf{x},\mathbf{y}) = \sqrt{\sum_i (x_i - y_i)^2}$$

  - Cosine similarity

$$d(\mathbf{x},\mathbf{y}) = \mathbf{x} \cdot \mathbf{y}$$

  - Hamming distance
  - String edit distance
  - Kernel distance
  - Many others

What is **Euclidean distance?**



Euclidean distance (d) $= \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$

Distance measure for Continuous Variables

Distance functions

Euclidean $$\sqrt{\sum_{i=1}^{k}(x_i - y_i)^2}$$

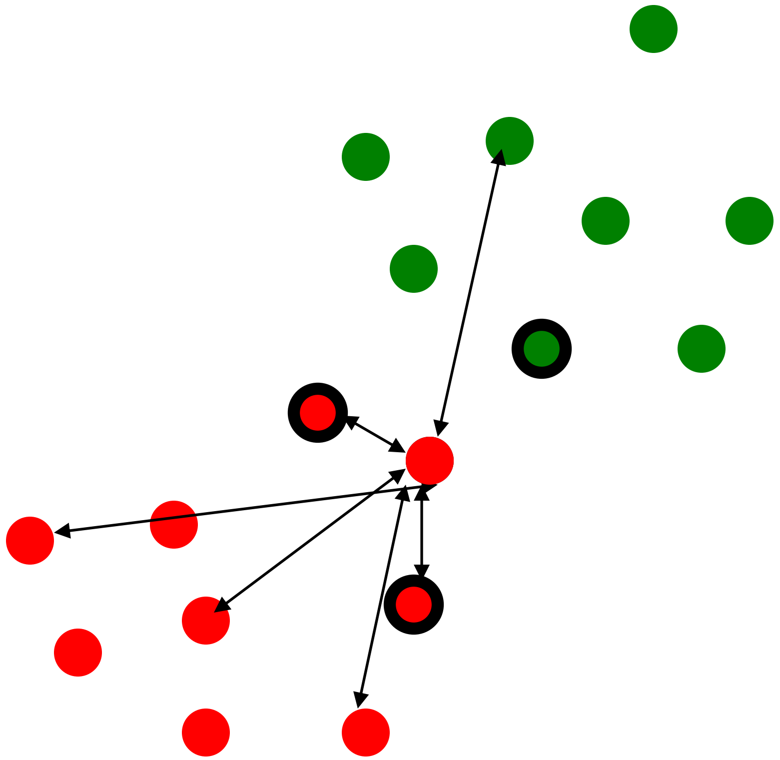
Manhattan $$\sum_{i=1}^{k}|x_i - y_i|$$

Minkowski $$\left(\sum_{i=1}^{k}(|x_i - y_i|)^q\right)^{1/q}$$

K-NN classifier schematic

For a test instance,

1) Calculate distances from training pts.
2) Find K-nearest neighbours (say, K = 3)
3) Assign class label based on majority



$$dist(X_1, X_2) = \sqrt{\sum_{i=1}^{n} (x_{1i} - x_{2i})^2}.$$

$$v' = \frac{v - min_A}{max_A - min_A},$$

Distance Between Neighbors

- Calculate the distance between new example (E) and all examples in the training set.

- *Euclidean* distance between two examples.
  - $X = [x_1, x_2, x_3, .., x_n]$
  - $Y = [y_1, y_2, y_3, ..., y_n]$

  - The Euclidean distance between X and Y is defined as:

$$D(X,Y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2}$$

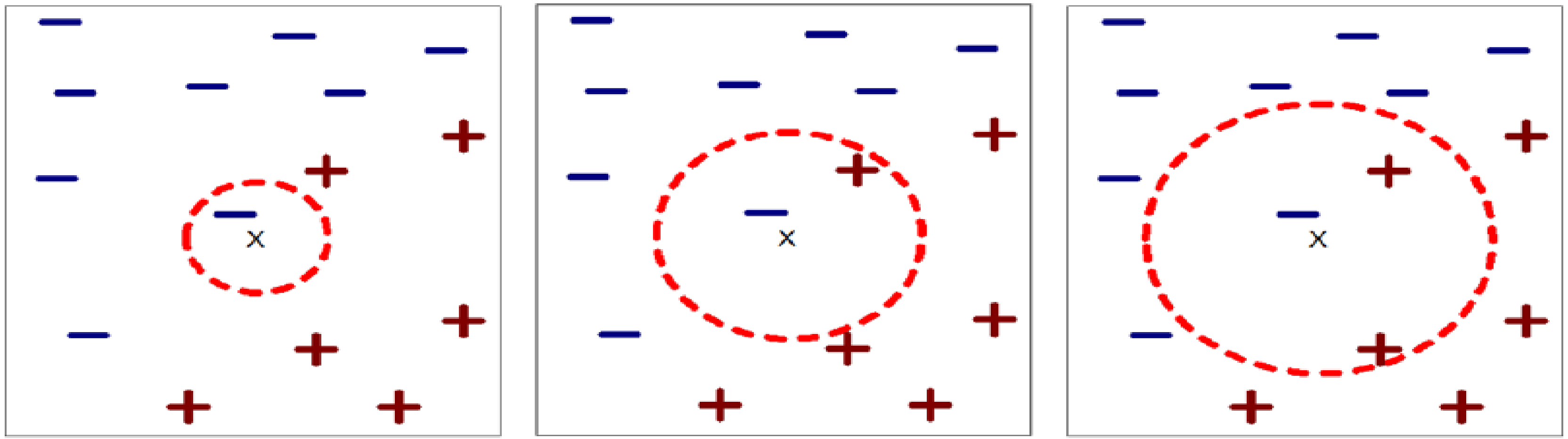
Distances for nearest neighbors

- Scaling issues
  - Attributes may have to be scaled to prevent distance measures from being dominated by one of the attributes
  - Example:
    - height of a person may vary from 1.5 m to 1.8 m
    - weight of a person may vary from 90 lb to 300 lb
    - income of a person may vary from $10K to $1M

Predicting class from nearest neighbors

- Options for predicting test class from nearest neighbor list
  - Take majority vote of class labels among the *k*-nearest neighbors
  - Weight the votes according to distance
    - example: weight factor $w = 1 / d^2$

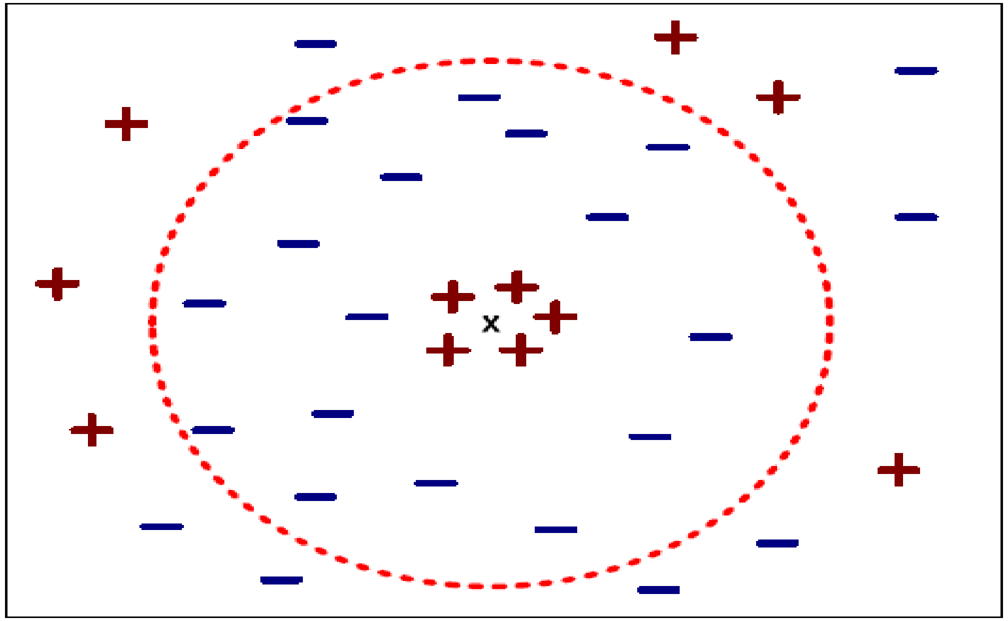
Predicting class from nearest neighbors



nearest neighbors	1	2	3
majority vote	–	?	+
distance-weighted vote	–	–	– or +

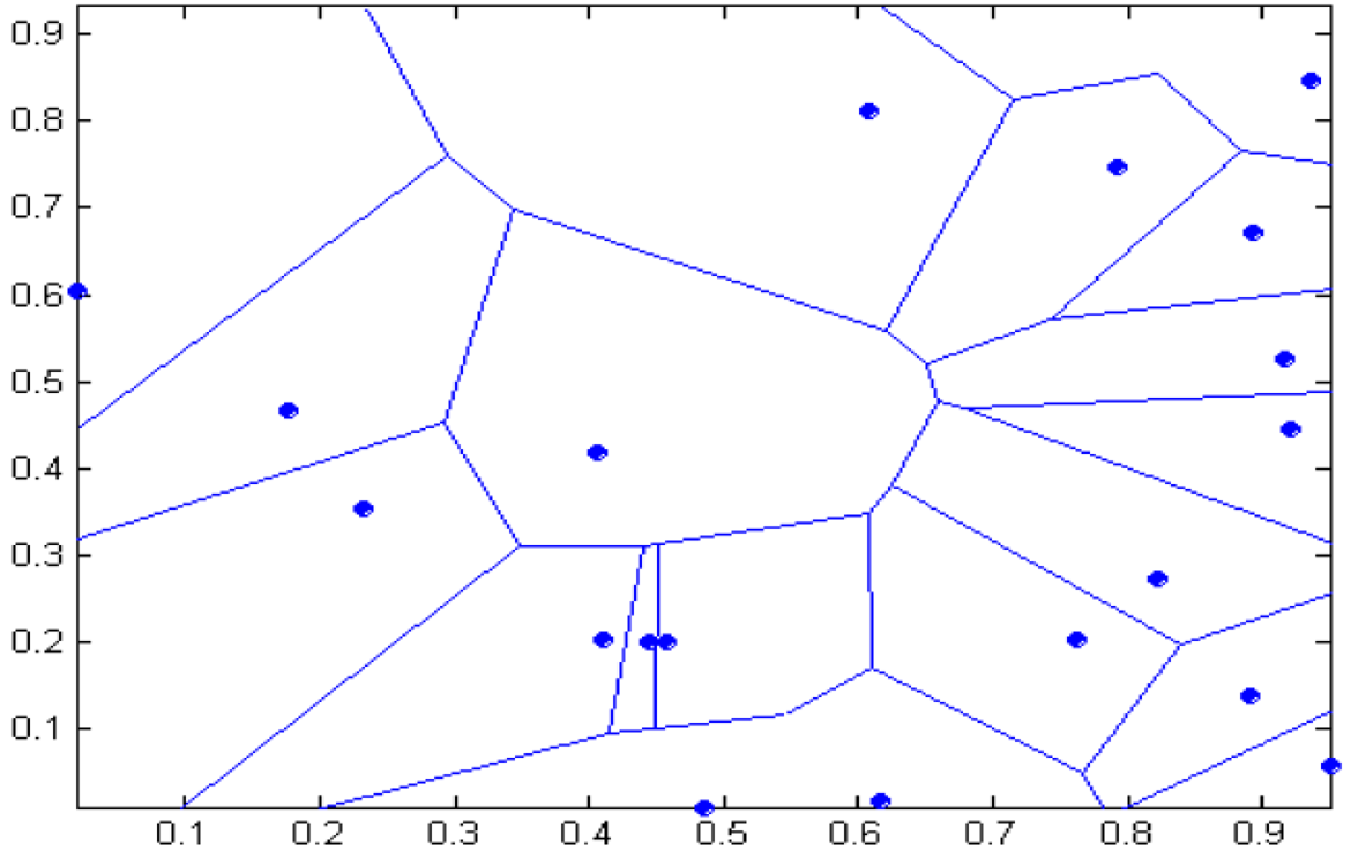
Predicting class from nearest neighbors

- Choosing the value of *k*:
  - If *k* is too small, sensitive to noise points
  - If *k* is too large, neighborhood may include points from other classes



1-nearest neighbor

Voronoi diagram



K-Nearest Neighbor Algorithm

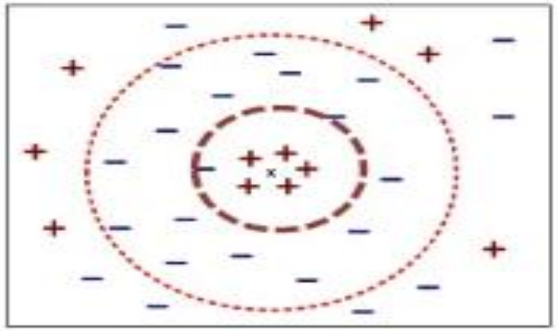
- All the instances correspond to points in an n-dimensional feature space.
- Each instance is represented with a set of numerical attributes.
- Each of the training data consists of a set of vectors and a class label associated with each vector.
- Classification is done by comparing feature vectors of different K nearest points.
- Select the K-nearest examples to E in the training set.
- Assign E to the most common class among its K-nearest neighbors.

Nearest Neighbor Classification…

- **How to handle missing values in training and test sets?**
  - Proximity computations normally require the presence of all attributes
  - Some approaches use the subset of attributes present in two instances
    - This may not produce good results since it effectively uses different proximity measures for each pair of instances
    - Thus, proximities are not comparable

How to choose K?

- If K is too small it is sensitive to noise points.
- Larger K works well. But too large K may include majority points from other classes.



- Rule of thumb is K < sqrt(n), n is number of examples.

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KNN Feature Weighting

- Scale each feature by its importance for classification

$$D(a,b) = \sqrt{\sum_k \boxed{w_k} (a_k - b_k)^2}$$

- Can use our prior knowledge about which features are more important
- Can learn the weights $\mathbf{w_k}$ using **cross-validation** (to be covered later)

Nominal/Categorical Data

- Distance works naturally with numerical attributes.
- Binary value categorical data attributes can be regarded as 1 or 0.

Hamming Distance

$$D_H = \sum_{i=1}^{k} |x_i - y_i|$$

$$x = y \Rightarrow D = 0$$

$$x \neq y \Rightarrow D = 1$$

X	Y	Distance
Male	Male	0
Male	Female	1

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KNN Classification – Distance

Age	Loan	Default	Distance
25	$40,000	N	102000
35	$60,000	N	82000
45	$80,000	N	62000
20	$20,000	N	122000
35	$120,000	N	22000
52	$18,000	N	124000
23	$95,000	Y	47000
40	$62,000	Y	80000
60	$100,000	Y	42000
48	$220,000	Y	78000
33	$150,000	Y	8000
48	**$142,000**	**?**	

Euclidean Distance

$$D = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}$$

KNN Classification – Standardized Distance

Age	Loan	Default	Distance
0.125	0.11	N	0.7652
0.375	0.21	N	0.5200
0.625	0.31	N	0.3160
0	0.01	N	0.9245
0.375	0.50	N	0.3428
0.8	0.00	N	0.6220
0.075	0.38	Y	0.6669
0.5	0.22	Y	0.4437
1	0.41	Y	0.3650
0.7	1.00	Y	0.3861
0.325	0.65	Y	0.3771
0.7	0.61	?	

Standardized Variable

$$X_s = \frac{X - Min}{Max - Min}$$

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3-KNN: Example(1)

Customer	Age	Income	No. credit cards	Class
George	35	35K	3	No
Rachel	22	50K	2	Yes
Steve	63	200K	1	No
Tom	59	170K	1	No
Anne	25	40K	4	Yes
John	37	50K	2	YES

Example: PEBLS

Tid	Refund	Marital Status	Taxable Income	Cheat
1	Yes	Single	125K	No
2	No	Married	100K	No
3	No	Single	70K	No
4	Yes	Married	120K	No
5	No	Divorced	95K	Yes
6	No	Married	60K	No
7	Yes	Divorced	220K	No
8	No	Single	85K	Yes
9	No	Married	75K	No
10	No	Single	90K	Yes

Example: PEBLS

Tid	Refund	Marital Status	Taxable Income	Cheat
1	Yes	Single	125K	No
2	No	Married	100K	No
3	No	Single	70K	No
4	Yes	Married	120K	No
5	No	Divorced	95K	Yes
6	No	Married	60K	No
7	Yes	Divorced	220K	No
8	No	Single	85K	Yes
9	No	Married	75K	No
10	No	Single	90K	Yes

Distance between nominal attribute values:

d(Single,Married)

= | 2/4 – 0/4 | + | 2/4 – 4/4 | = 1

d(Single,Divorced)

= | 2/4 – 1/2 | + | 2/4 – 1/2 | = 0

d(Married,Divorced)

= | 0/4 – 1/2 | + | 4/4 – 1/2 | = 1

d(Refund=Yes,Refund=No)

= | 0/3 – 3/7 | + | 3/3 – 4/7 | = 6/7

Class	Marital Status		
	Single	Married	Divorced
Yes	2	0	1
No	2	4	1

Class	Refund	
	Yes	No
Yes	0	3
No	3	4

$$d(V_1, V_2) = \sum_i \left| \frac{n_{1i}}{n_1} - \frac{n_{2i}}{n_2} \right|$$

Example: PEBLS

Tid	Refund	Marital Status	Taxable Income	Cheat
X	Yes	Single	125K	No
Y	No	Married	100K	No

Distance between record X and record Y:

$$\Delta(X,Y) = w_X w_Y \sum_{i=1}^{d} d(X_i, Y_i)^2$$

where:

$$w_X = \frac{\text{Number of times X is used for prediction}}{\text{Number of times X predicts correctly}}$$

$w_X \cong 1$ if X makes accurate prediction most of the time

$w_X > 1$ if X is not reliable for making predictions

Problem Statement

Outlook	Temp	Humidity	Windy	Play Golf
Rainy	Hot	High	False	No
Rainy	Hot	High	True	No
Overcast	Hot	High	False	Yes
Sunny	Mild	High	False	Yes
Sunny	Cool	Normal	False	Yes
Sunny	Cool	Normal	True	No
Overcast	Cool	Normal	True	Yes
Rainy	Mild	High	False	No
Rainy	Cool	Normal	False	Yes
Sunny	Mild	Normal	False	Yes
Rainy	Mild	Normal	True	Yes
Overcast	Mild	High	True	Yes
Overcast	Hot	Normal	False	Yes
Sunny	Mild	High	True	No