

# Practical Machine Learning

## Day 10: Mar22 DBDA

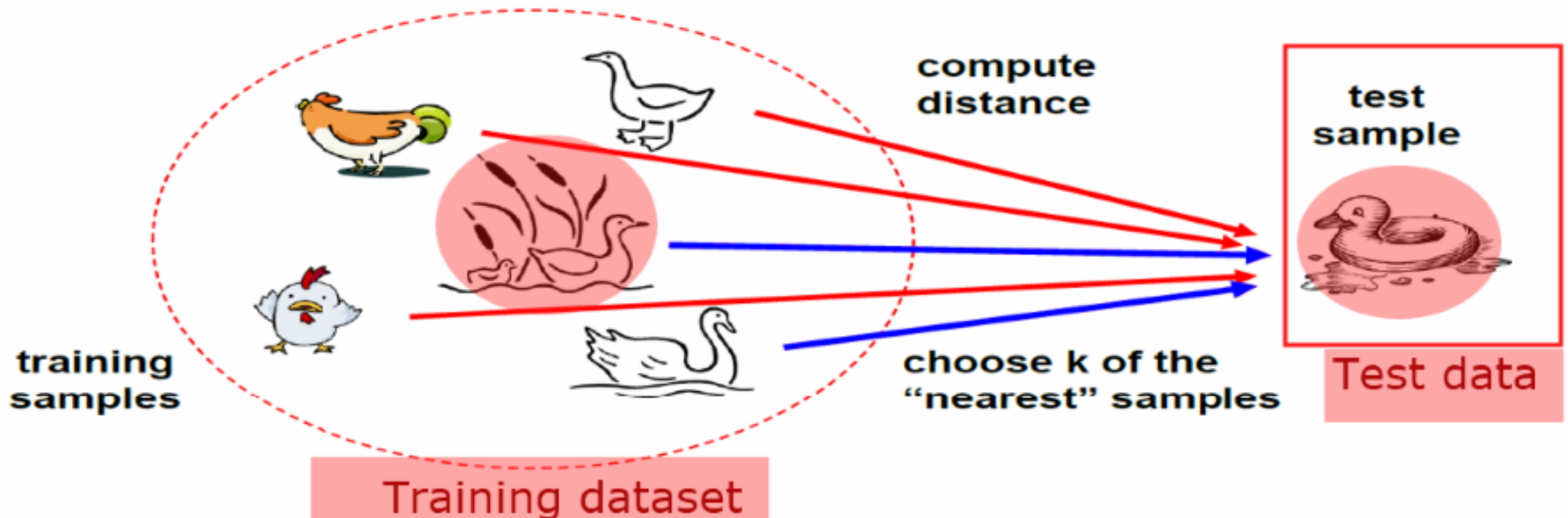
Kiran Waghmare

# Agenda

- Classification Algorithm
- kNN
- Naïve Bayes

# Nearest Neighbor Classifiers → Pattern recognition

- Basic idea: Similarity: distance
  - If it walks like a duck, quacks like a duck, then it's probably a duck



# Instance based classifiers

Set of Stored Cases

Atr1	.....	AtrN	Class
			A
			B
			B
			C
			A
			C
			B

Training dataset

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

Rules

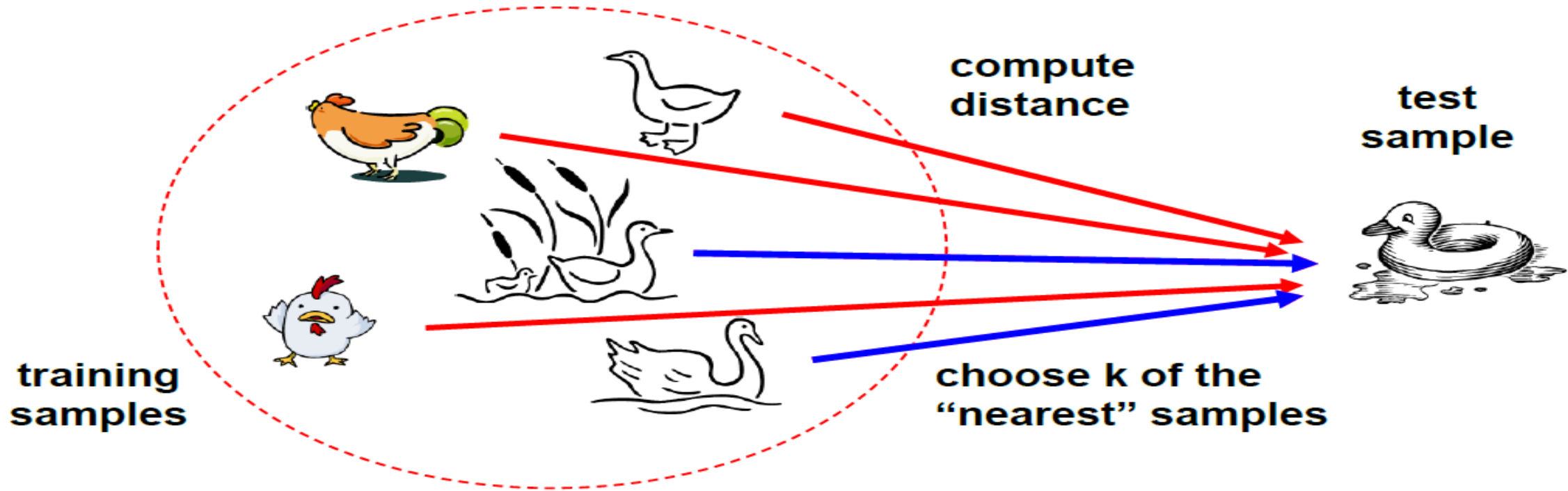
Unseen Case

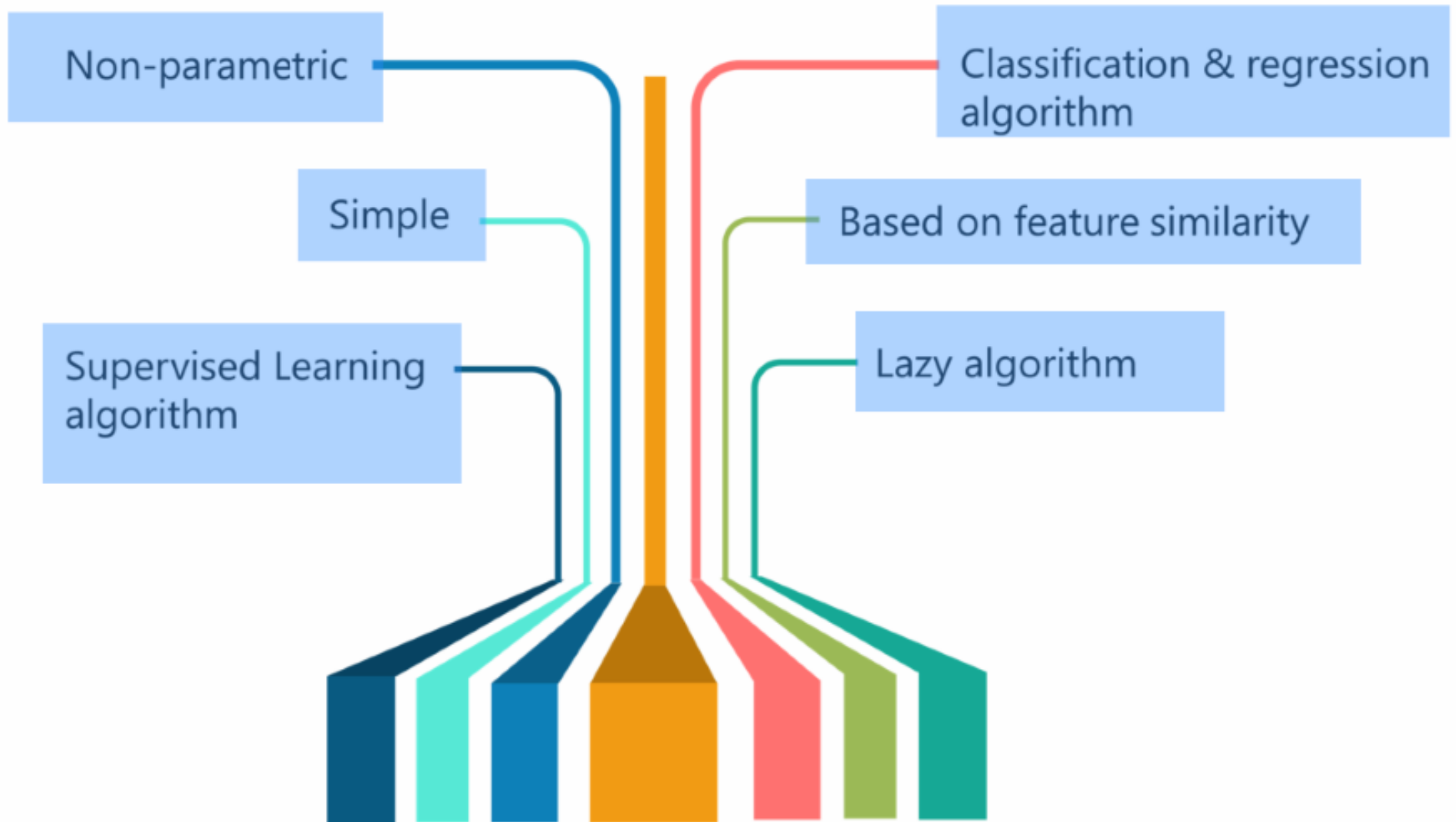
Atr1	.....	AtrN

Test case

# Nearest Neighbor Classifiers

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



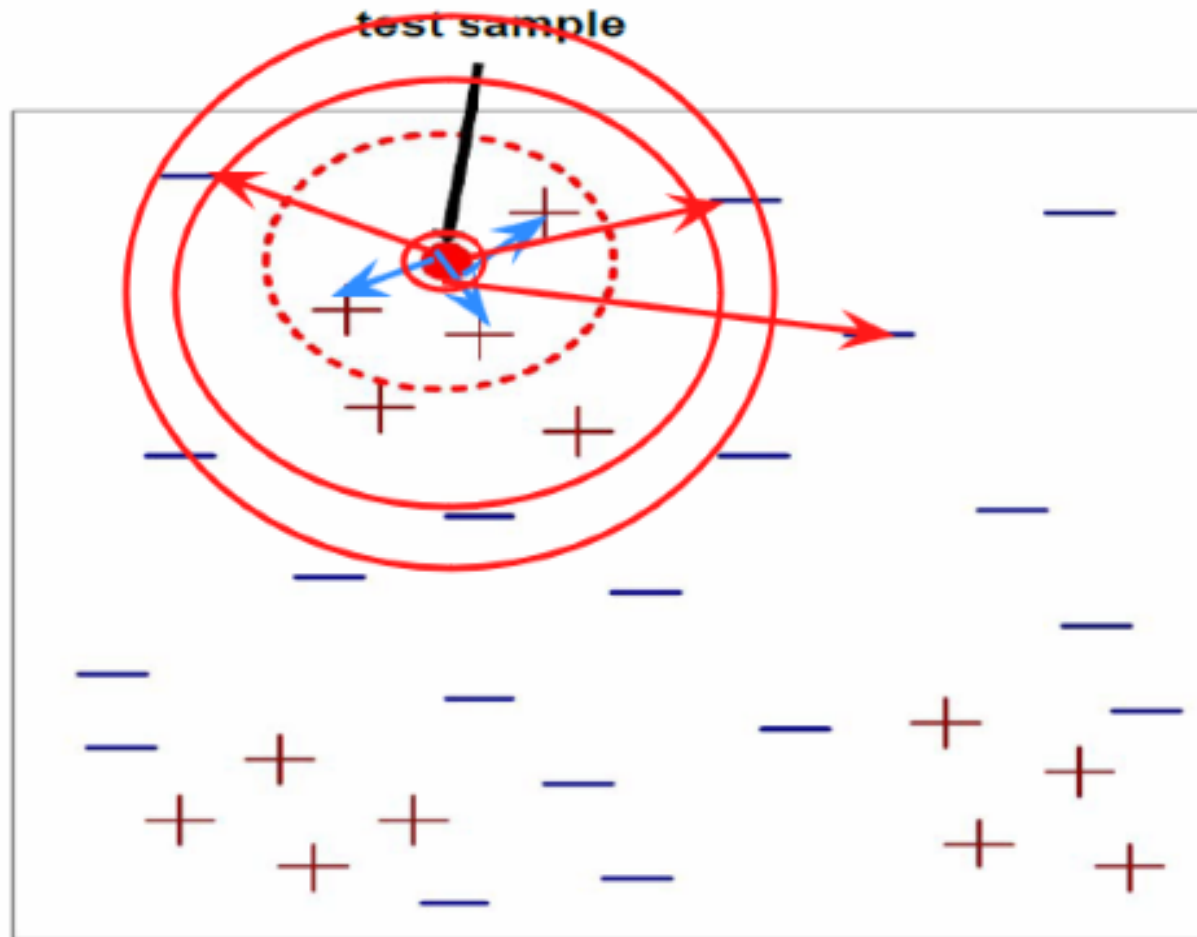


# Lazy learners

- **‘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”**



# 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



# 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

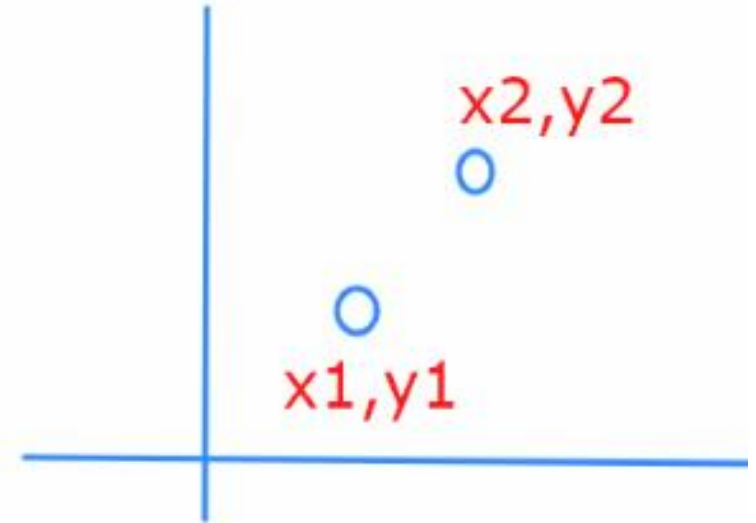
$$d(\mathbf{x}, \mathbf{y}) = \mathbf{x} \cdot \mathbf{y}$$

- Hamming distance

- String edit distance

- Kernel distance

- Many others



# 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

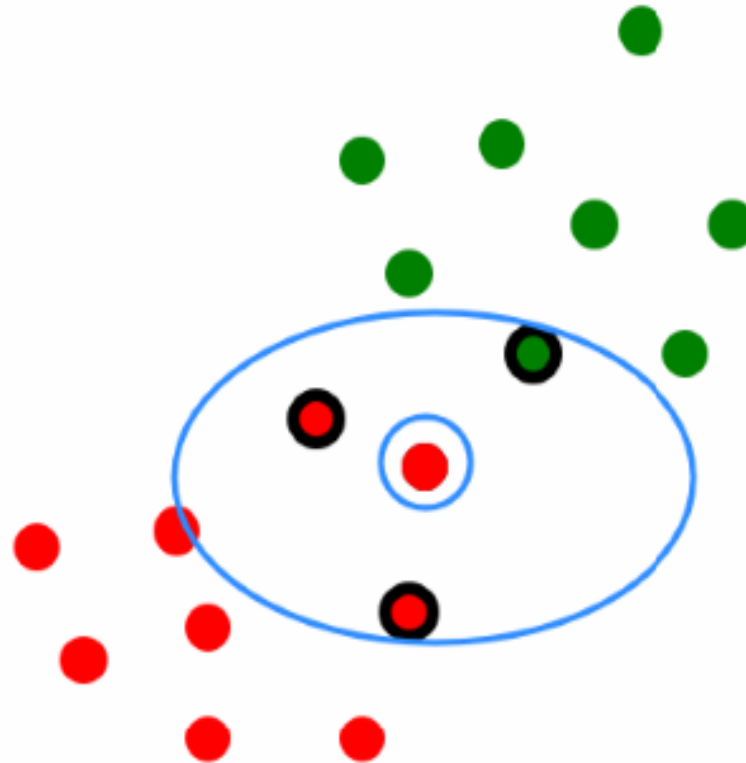
$$\left( \sum_{i=1}^k (|x_i - y_i|)^q \right)^{1/q}$$

Numeric value

# 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



# Distance Between Neighbors

- Calculate the distance between new example (E) and all examples in the training set.
- *Euclidean* distance between two examples.
  - $X = [x_1, x_2, x_3, \dots, x_n]$
  - $Y = [y_1, y_2, y_3, \dots, y_n]$
  - The Euclidean distance between  $X$  and  $Y$  is defined

as:

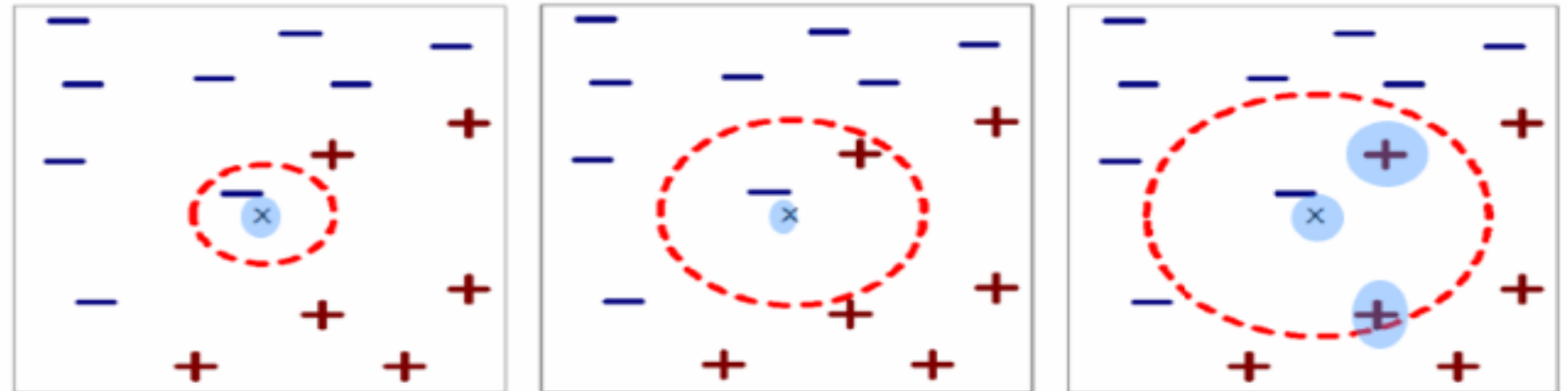
$$D(X, Y) = \sqrt{\sum_{i=1}^n (x_i - y_i)^2}$$

# Predicting class from nearest neighbors

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- 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  $w = 1 / d^2$

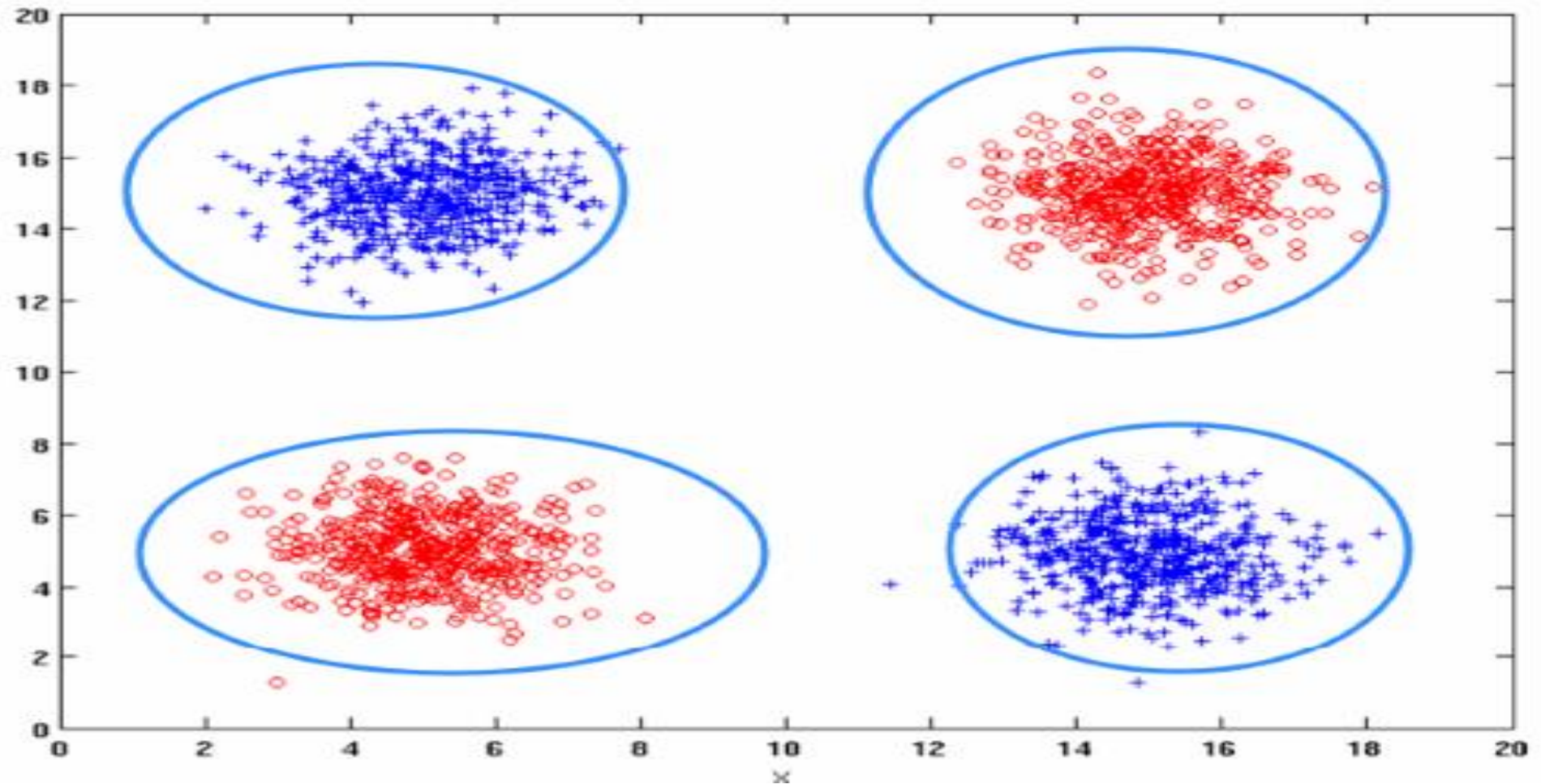
# Predicting class from nearest neighbors



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



## K-NN Classifiers: Handling attributes that are interacting

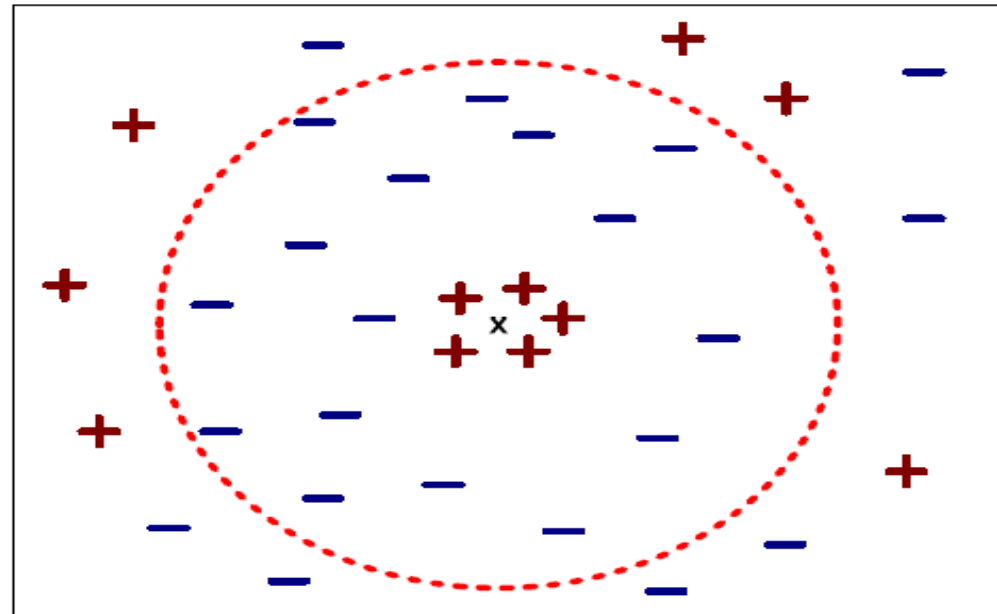




# Predicting class from nearest neighbors

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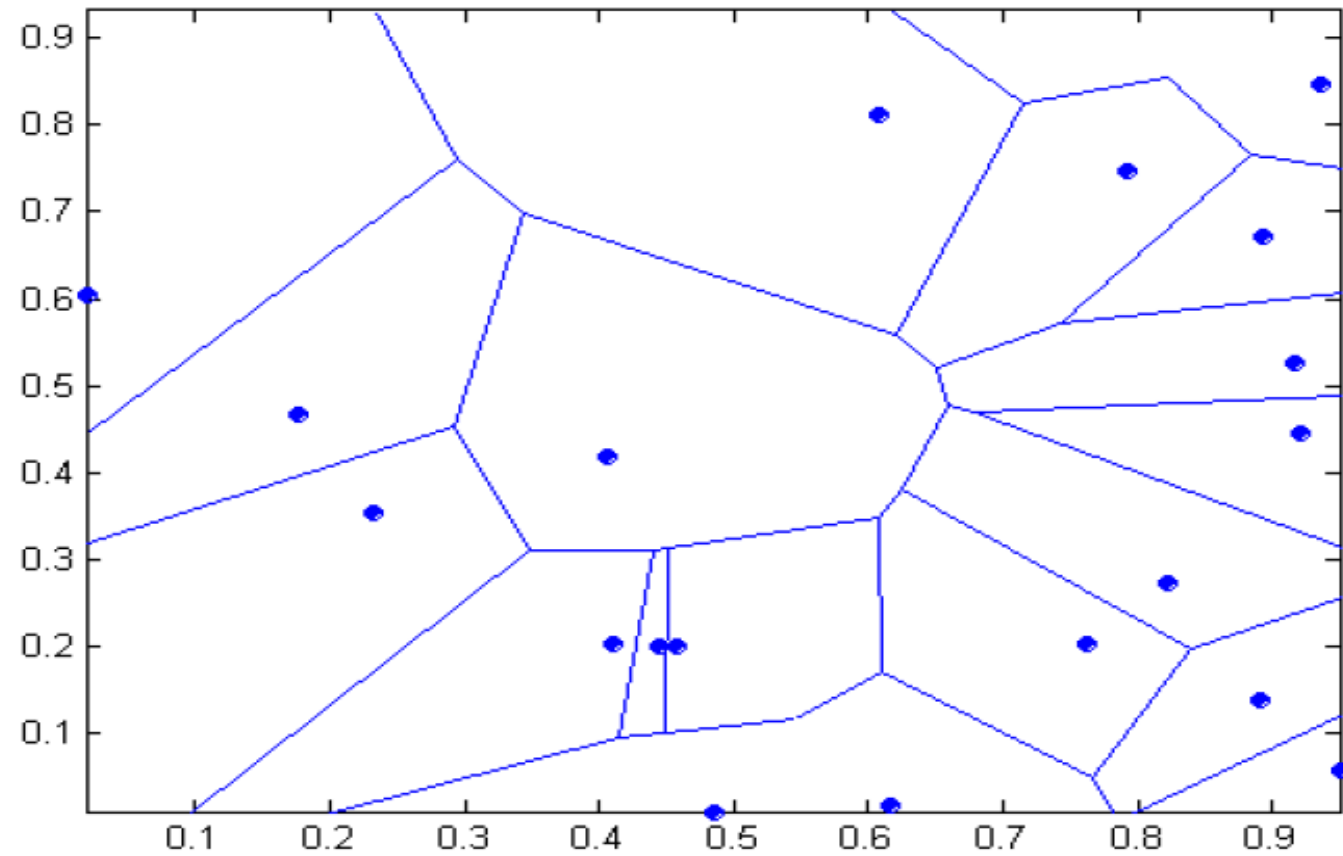
- Choosing the value of  $k$ :
  - If  $k$  is too small, sensitive to noise points
  - If  $k$  is too large, neighborhood may include points from other classes



# 1-nearest neighbor

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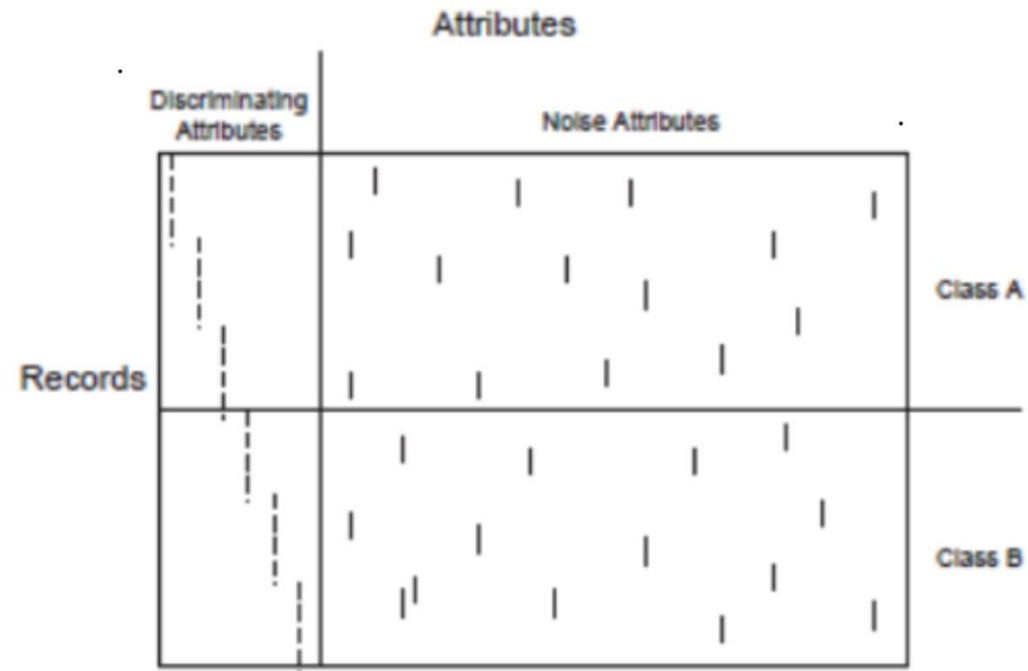
Voronoi diagram



## K-NN Classifiers...

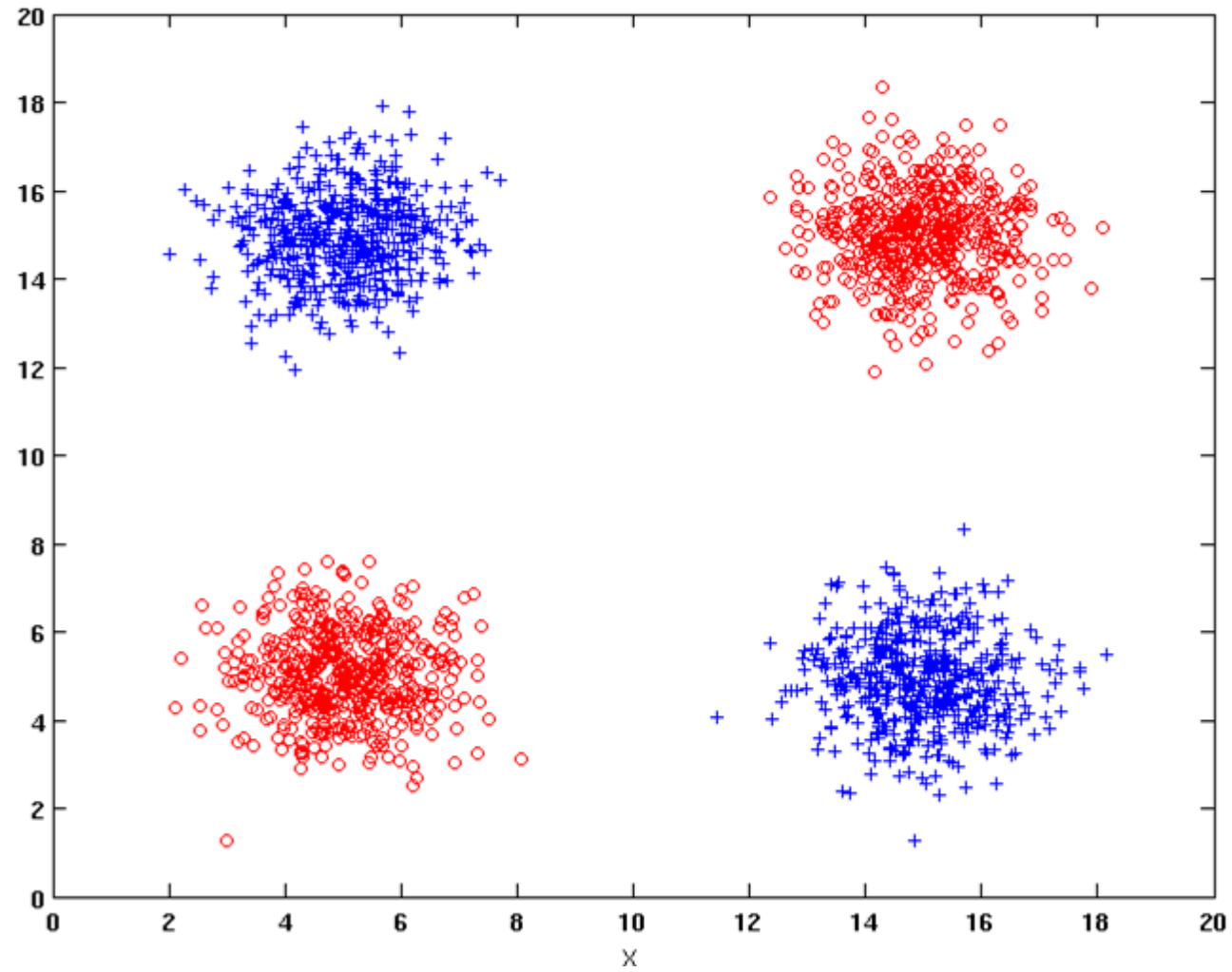
### Handling Irrelevant and Redundant Attributes

- Irrelevant attributes add noise to the proximity measure
- Redundant attributes bias the proximity measure towards certain attributes

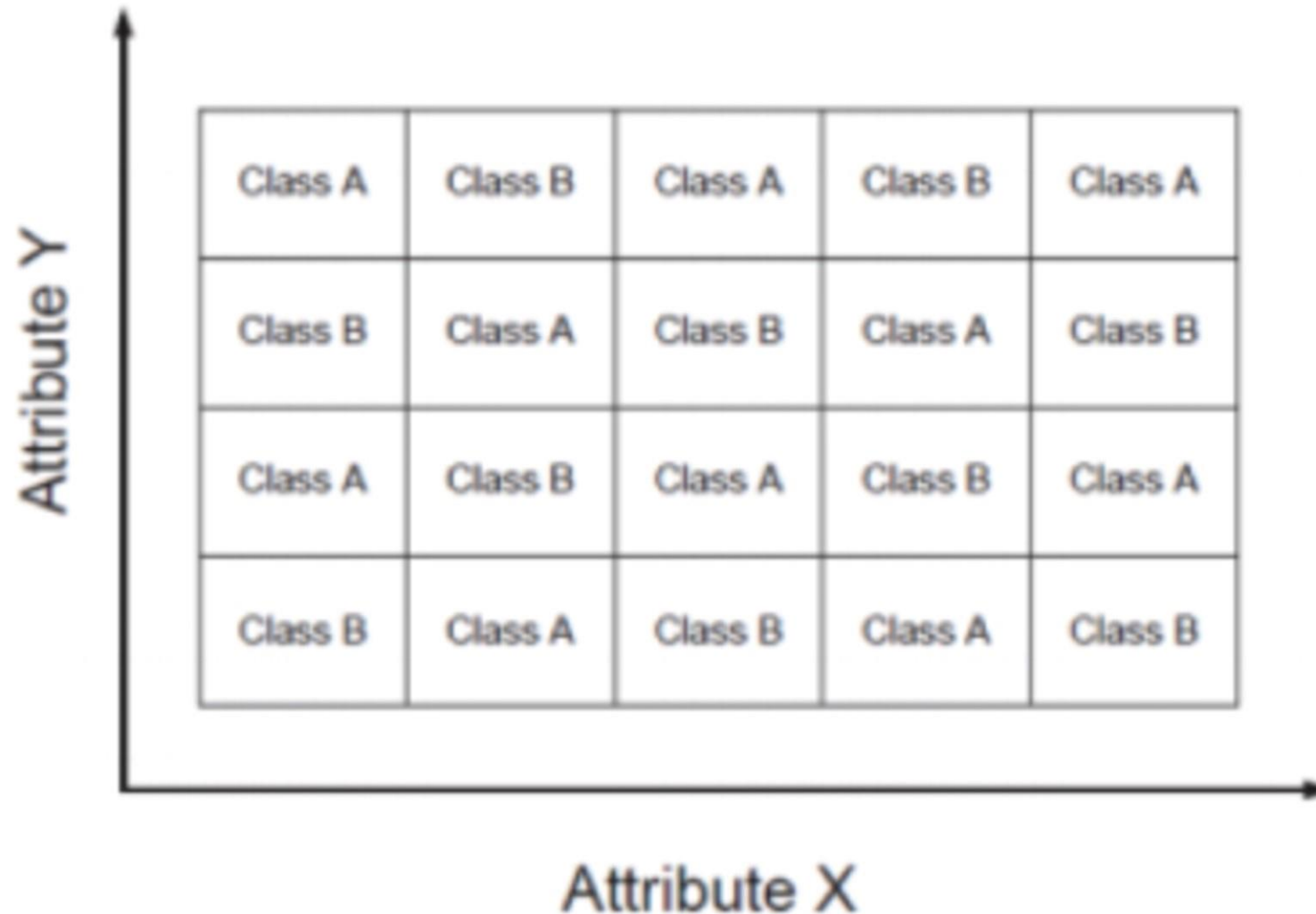


(a) Synthetic data set 1.

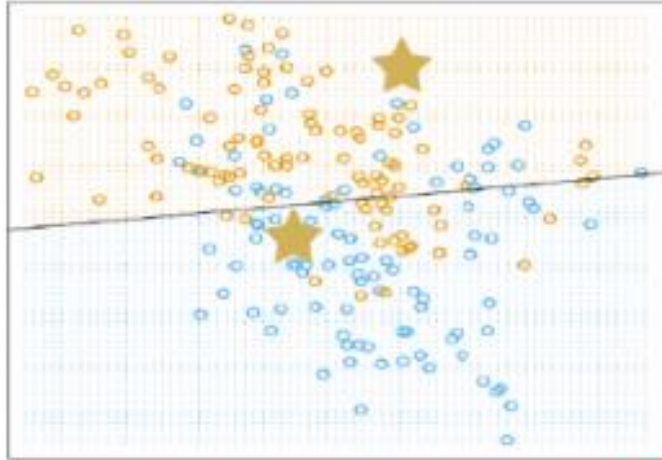
## K-NN Classifiers: Handling attributes that are interacting



# Handling attributes that are interacting



# Decision boundaries in global vs. local models



## logistic regression

- global
- stable
- can be inaccurate



## 15-nearest neighbor



## 1-nearest neighbor

- local
- unstable
- accurate

**stable:** model decision boundary not sensitive to addition or removal of samples from training set

What ultimately matters: **GENERALIZATION**



# 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

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



## 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 ✓

### Distance from John

$$\text{sqrt} [(35-37)^2 + (35-50)^2 + (3-2)^2] = 15.16 \quad \checkmark$$

$$\text{sqrt} [(22-37)^2 + (50-50)^2 + (2-2)^2] = 15 \quad \checkmark$$

$$\text{sqrt} [(63-37)^2 + (200-50)^2 + (1-2)^2] = 152.23$$

$$\text{sqrt} [(59-37)^2 + (170-50)^2 + (1-2)^2] = 122$$

$$\text{sqrt} [(25-37)^2 + (40-50)^2 + (4-2)^2] = 15.74$$

# Improving KNN Efficiency

- Avoid having to compute distance to all objects in the training set
  - Multi-dimensional access methods (k-d trees)
  - Fast approximate similarity search
  - Locality Sensitive Hashing (LSH)
- Condensing
  - Determine a smaller set of objects that give the same performance
- Editing
  - Remove objects to improve efficiency

```
Out[17]: array([[64,  4],
                [ 3, 29]], dtype=int64)
```

```
In [18]: accuracy_score(y_test,y_pred)
```

```
Out[18]: 0.93
```

```
In [19]: #Visualising the Training data
```

```
from matplotlib.colors import ListedColormap
X_set, y_set = sc.inverse_transform(X_train), y_train
X1, X2 = np.meshgrid(np.arange(start = X_set[:, 0].min() - 10, stop = X_set[:, 0].max() + 10, step = 5),
                     np.arange(start = X_set[:, 1].min() - 1000, stop = X_set[:, 1].max() + 1000, step = 1000))

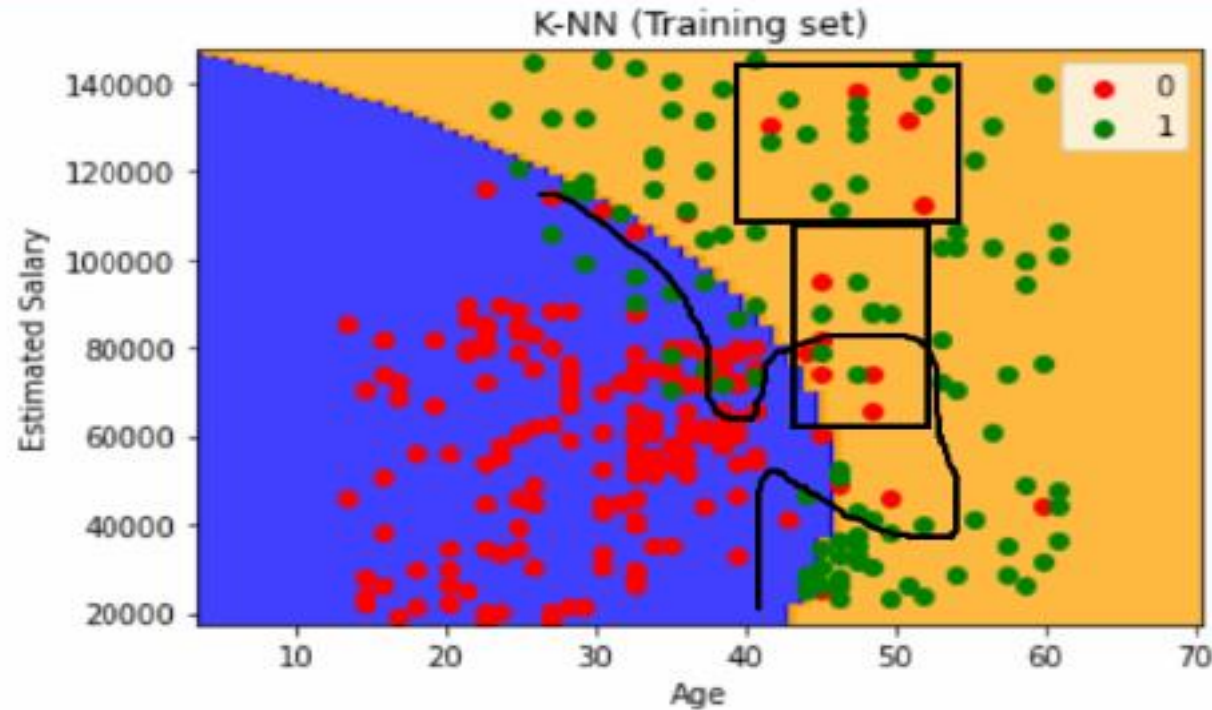
plt.contourf(X1, X2, classifier.predict(sc.transform(np.array([X1.ravel(), X2.ravel()])).reshape((-1, 2))),
             alpha = 0.75, cmap = ListedColormap(('blue', 'orange')))
plt.xlim(X1.min(), X1.max())
plt.ylim(X2.min(), X2.max())
for i, j in enumerate(np.unique(y_set)):
    plt.scatter(X_set[y_set == j, 0], X_set[y_set == j, 1], c = ListedColormap(('blue', 'orange'))[j])
plt.title('K-NN (Training set)')
plt.xlabel('Age')
plt.ylabel('Estimated Salary')
plt.legend()
plt.show()
```

\*c\* argument looks like a single numeric RGB or RGBA sequence, which should be avoided as value-mapping will have precedence in case its length matches with \*x\* & \*y\*. Please use the \*color\* keyword-argument or provide a 2D array with a single row if you intend to specify the same RGB or RGBA value for all points.





`x*` & `*y*`. Please use the `*color*` keyword-argument or provide a 2D array with a single row if you intend to specify the same RGB or RGBA value for all points.



```
In [68]: from matplotlib.colors import ListedColormap
X_set, y_set = sc.inverse_transform(X_test), y_test
X1, X2 = np.meshgrid(np.arange(start = X_set[:, 0].min() - 10, stop = X_set[:, 0].max() + 10, step = 5),
                     np.arange(start = X_set[:, 1].min() - 1000, stop = X_set[:, 1].max() + 1000, step = 1000))
plt.contourf(X1, X2, classifier.predict(sc.transform(np.array([X1.ravel(), X2.ravel()]).T)),
             alpha = 0.75, cmap = ListedColormap(('blue', 'orange')))
plt.xlim(X1.min(), X1.max())
plt.ylim(X2.min(), X2.max())
```