

# Machine Learning

## Nearest Neighbors Model

---

DR. BHARGAVI R

PROFESSOR

SCOPE

VIT CHENNAI

# Classification - Types

---

**Binary Classification:** Involves categorizing data into one of the two classes

- Online transactions – Fraudulent / Not Fraudulent
- Email – Spam/ Not spam ?
- Tumor classification – Malignant/Benign

**Multi-class Classification:** Involves more than two classes. i.e A data instance can belong to one of many possible classes

- Optical Character Recognition
- Face classification

# Classification Types (cont...)

---

## Multi-Label Classification

A variant of the classification problem where multiple nonexclusive labels may be assigned to each instance.

- Photo tagging feature where each photo can have multiple tags such as 'Beach', 'Friends', 'Summer', and 'Vacation'. Each tag is a different label, and multiple tags can be correct for a single photo.

# Nearest Neighbor Classification - Intuition

---

Can you recognize me?



?



?

# How did we answer?

Similar inputs => Similar outputs



# Nearest Neighbors - Introduction

---

- Popular, intuitive and simple to understand.
- Supervised learning algorithm.
- Non Parametric Learning model – No functional form assumption.
- Lazy Learner – All the computations (similarity or distance computations) are postponed till the prediction time.
- Memorize the training instances (Memory based learning) and use at the time of prediction.
- Used for classification and regression.

# Use case: House Number Identification

---

- How do you identify the house number from the image captured?



# What are the *Challenges* we see here

---

- How to represent the data?
- Which instances are nearest neighbors?
- How to find the similarity?
- How many nearest neighbors are to be considered for decision making?

Bhargavi R



# How to Represent the Data? (cont...)

## Structured Data

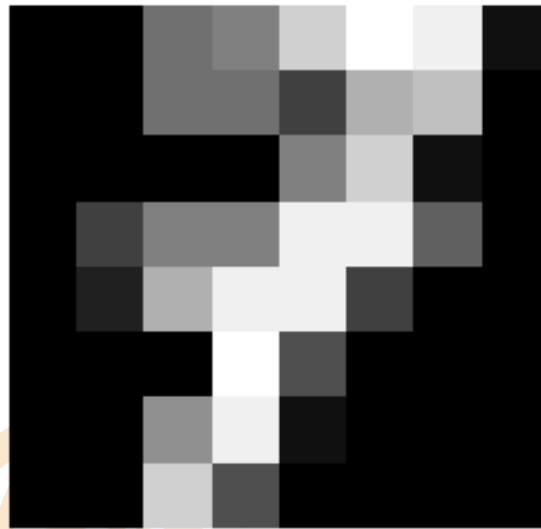


| Feature      | Value (cms) |
|--------------|-------------|
| sepal length | 6.3         |
| sepal width  | 3.3         |
| petal length | 6           |
| petal width  | 2.5         |

| Id | Sepal Length | Sepal Width (cm) | Petal Length | Petal Width (cm) | Species     |
|----|--------------|------------------|--------------|------------------|-------------|
| 1  | 5.1          | 3.5              | 1.4          | 0.2              | Iris-setosa |
| 2  | 4.9          | 3.0              | 1.4          | 0.2              | Iris-setosa |
| 3  | 4.7          | 3.2              | 1.3          | 0.2              | Iris-setosa |
| 4  | 4.6          | 3.1              | 1.5          | 0.2              | Iris-setosa |
| 5  | 5.0          | 3.6              | 1.4          | 0.2              | Iris-setosa |

# How to Represent the Data? (cont...)

## Unstructured Data



|   |   |    |    |    |    |    |   |
|---|---|----|----|----|----|----|---|
| 0 | 0 | 7  | 8  | 13 | 16 | 15 | 1 |
| 0 | 0 | 7  | 7  | 4  | 11 | 12 | 0 |
| 0 | 0 | 0  | 0  | 8  | 13 | 1  | 0 |
| 0 | 4 | 8  | 8  | 15 | 15 | 6  | 0 |
| 0 | 2 | 11 | 15 | 15 | 4  | 0  | 0 |
| 0 | 0 | 0  | 16 | 5  | 0  | 0  | 0 |
| 0 | 0 | 9  | 15 | 1  | 0  | 0  | 0 |
| 0 | 0 | 13 | 5  | 0  | 0  | 0  | 0 |

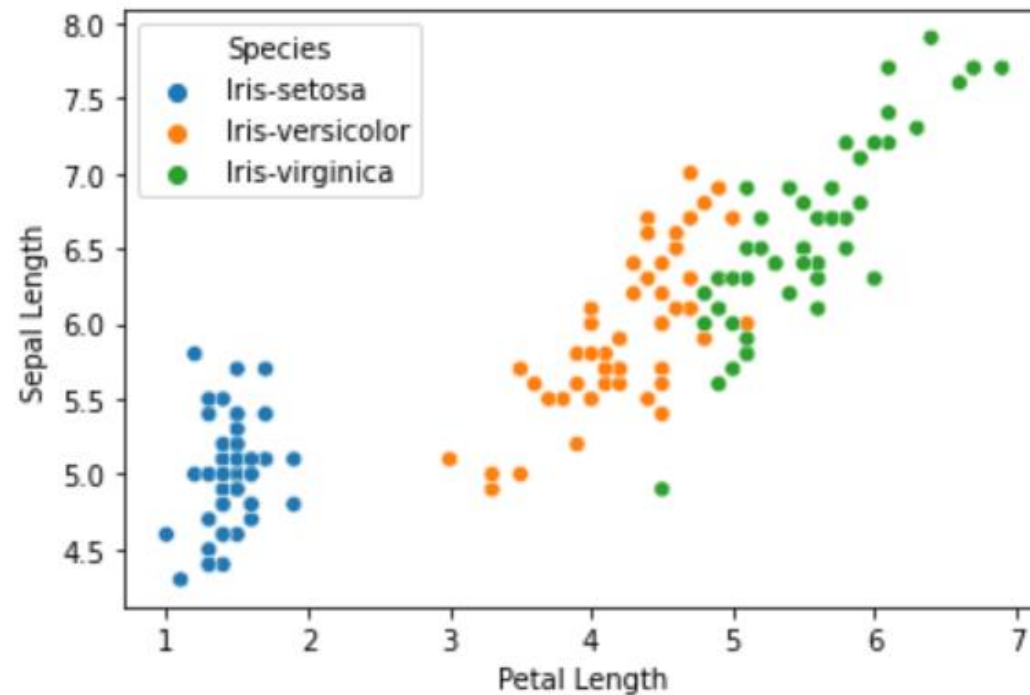
|   |   |   |   |    |    |    |   |       |   |   |    |   |   |   |   |   |
|---|---|---|---|----|----|----|---|-------|---|---|----|---|---|---|---|---|
| 0 | 0 | 7 | 8 | 13 | 16 | 15 | 1 | ----- | 0 | 0 | 13 | 5 | 0 | 0 | 0 | 0 |
|---|---|---|---|----|----|----|---|-------|---|---|----|---|---|---|---|---|

# What are Nearest Neighbors

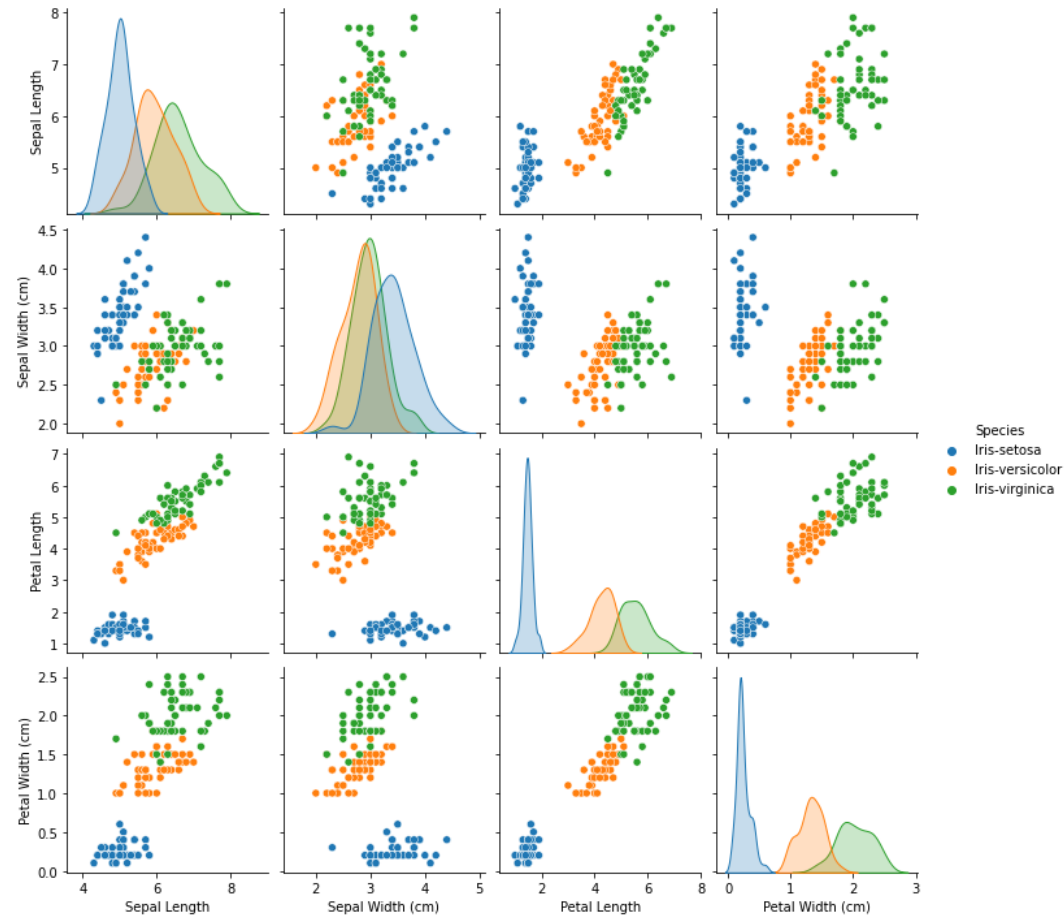
---

Which instances are nearest neighbors?

Different classes seem to be well separated from the other



# Neighbors (cont...)



# One NN Classification

Input data

|   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 |
| 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 |
| 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 |
| 5 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 5 |
| 6 | 6 | 6 | 6 | 6 | 6 | 6 | 6 | 6 | 6 | 6 | 6 | 6 | 6 | 6 | 6 |
| 7 | 7 | 7 | 7 | 7 | 7 | 7 | 7 | 7 | 7 | 7 | 7 | 7 | 7 | 7 | 7 |
| 8 | 8 | 8 | 8 | 8 | 8 | 8 | 8 | 8 | 8 | 8 | 8 | 8 | 8 | 8 | 8 |
| 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 | 9 |



Labels or Ground Truth

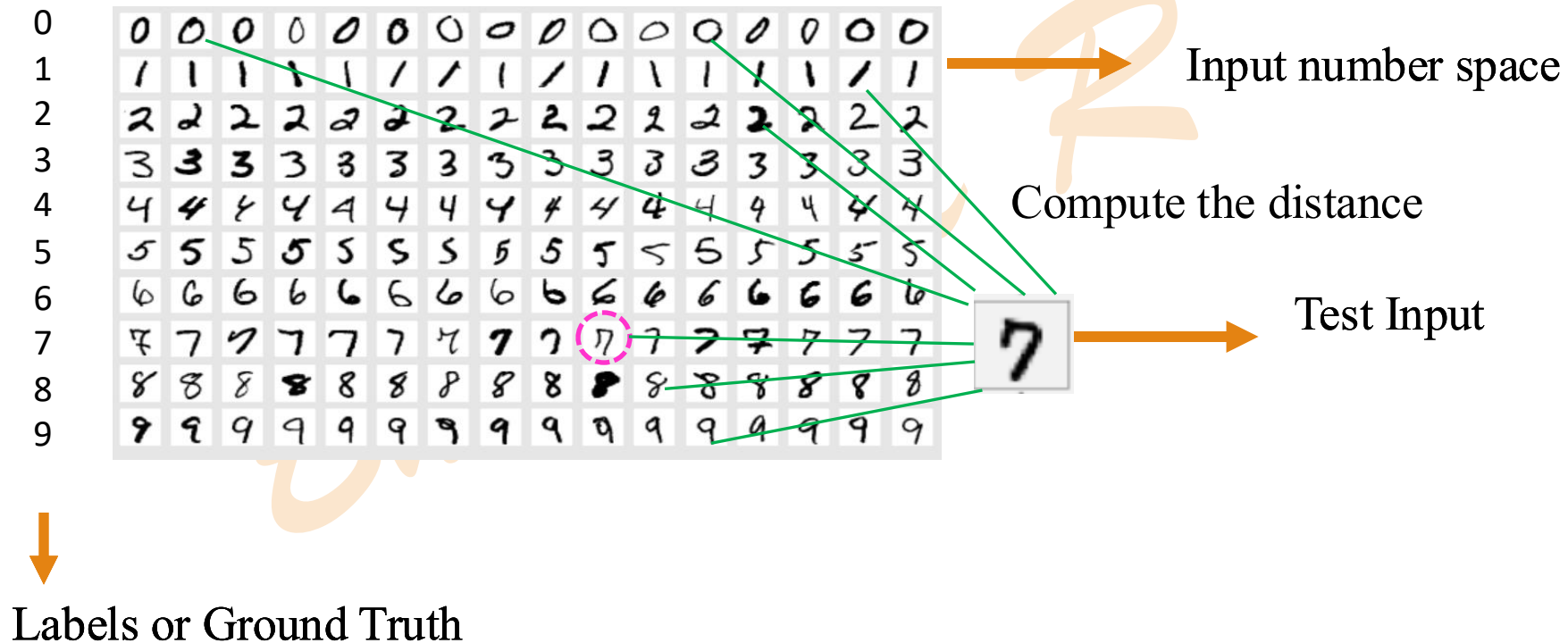
Input number space



Test Input

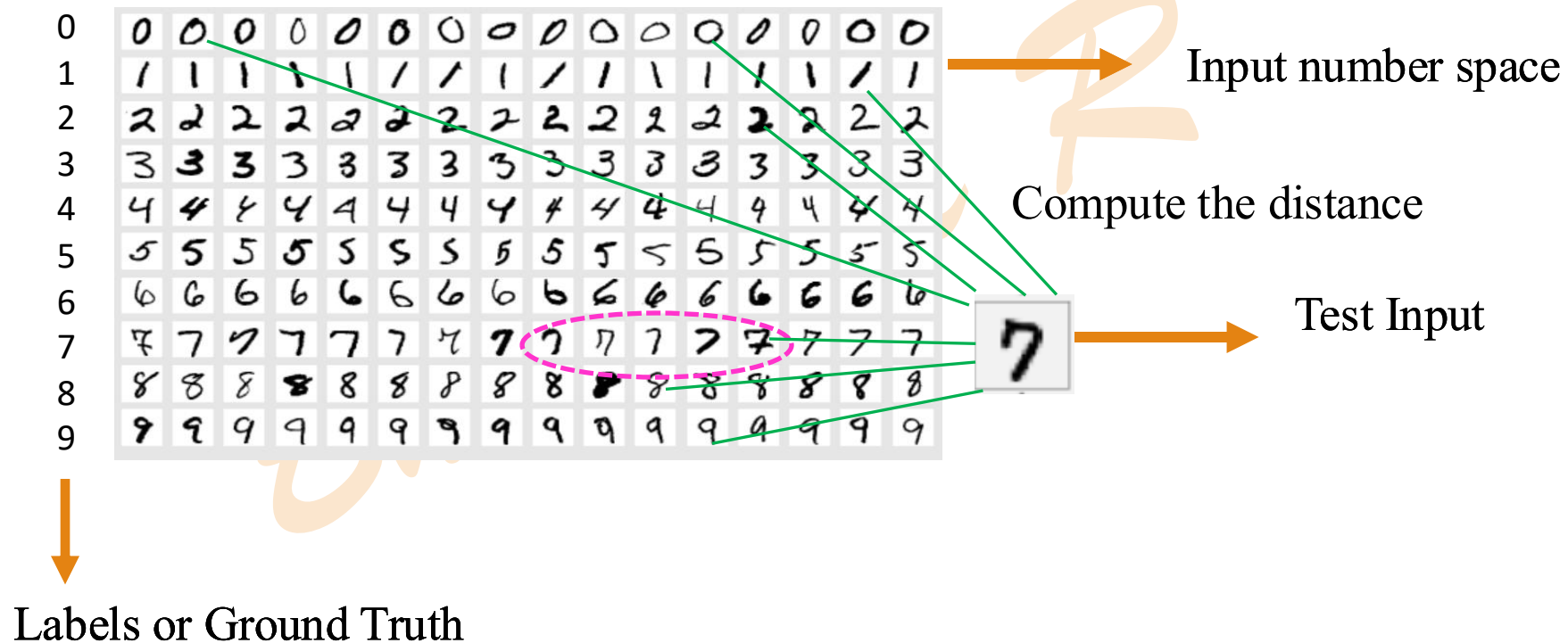
# One NN Classification (cont...)

*Choose the minimum distance or most similar input instance* and label the test input with the corresponding input instance's label



# K NN Classification

*Choose the set of minimum distances or most similar input instances and label the test input with the label of the majority class from the set*



# How to find the most similar/nearest instances?

---

## Distance Metrics

- Similarity – Domain specific
- Euclidian distance: Euclidean distance between two vectors  $x_i$  and  $y_i$  is

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

- In 1 Dimension Distance between  $x_i$  and  $y_i$  is given by  $D(x, y) = |x - y|$
- The more the distance is, less similar the data points are.



# Distance Metrics (cont ...)

---

- Manhattan distance: Manhattan distance between two vectors  $x_i$  and  $y_i$  is

$$D(x_i, y_i) = \sum_{i=1}^n |x_i - y_i|$$

- The more the distance is, less similar the data points are.

Bhargavi R

# Distance Metrics (cont ...)

---

- Scaled Euclidean
- Mahalanobis
- Correlation
- Cosine Similarity
- Jaccard etc

*Bhargavi R*

# One NN Example

---

Consider the dataset of humans indicating the age of the person (input) and the stage (label/output) to which the person belongs to.

| Sl.No | Age | Category     |
|-------|-----|--------------|
| 1     | 1   | Child        |
| 2     | 12  | Child        |
| 3     | 13  | Adolescence  |
| 4     | 18  | Adolescence  |
| 5     | 19  | Adult        |
| 6     | 59  | Adult        |
| 7     | 60  | Senior Adult |
| 8     | 100 | Senior Adult |

What is the category of a person who is 35 years old?

# One NN Example

| Sl.No | Age | Category     | Distance from test data |
|-------|-----|--------------|-------------------------|
| 1     | 1   | Child        | 34                      |
| 2     | 12  | Child        | 23                      |
| 3     | 13  | Adolescence  | 22                      |
| 4     | 18  | Adolescence  | 17                      |
| 5     | 19  | Adult        | 16                      |
| 6     | 59  | Adult        | 24                      |
| 7     | 60  | Senior Adult | 25                      |
| 8     | 100 | Senior Adult | 65                      |

Nearest  
neighbor to  
x\_test (35).  
So, prediction  
= Adult

Therefore, the person with Age = 35 belongs to Adult category.

# K-NN Example

| Sl.No | Age | Category     | Distance from test data |
|-------|-----|--------------|-------------------------|
| 1     | 1   | Child        | 34                      |
| 2     | 12  | Child        | 23                      |
| 3     | 13  | Adolescence  | 22                      |
| 4     | 18  | Adolescence  | 17                      |
| 5     | 19  | Adult        | 16                      |
| 6     | 59  | Adult        | 24                      |
| 7     | 60  | Senior Adult | 25                      |
| 8     | 100 | Senior Adult | 65                      |

3 Nearest  
neighbor to  
x\_test (35).  
So, prediction  
= Adolescence

With  $k = 3$ , the person with Age = 35 belongs to Adolescence category.

# Another Example

---

Consider the dataset given below, indicating the age, salary of the person (input) and the loan approval status (label/output).

| Sl.No | Age | Salary   | Loan Approval Status |
|-------|-----|----------|----------------------|
| 1     | 25  | 40,000   | N                    |
| 2     | 35  | 60,000   | N                    |
| 3     | 45  | 80,000   | N                    |
| 4     | 23  | 95,000   | Y                    |
| 5     | 40  | 62,000   | Y                    |
| 6     | 60  | 1,00,000 | Y                    |

What's the Loan approval status of a person who is 48 years old & salary of 90000?

# Example (cont...)

Normalize the data with min-max normalization

$$(x_i^{\text{test}} - \min(x_i)) / (\max(x_i) - \min(x_i))$$

| Sl.No | Age   | Salary | Status |
|-------|-------|--------|--------|
| 1     | 0.054 | 0      | N      |
| 2     | 0.324 | 0.333  | N      |
| 3     | 0.595 | 0.667  | N      |
| 4     | 0     | 0.917  | Y      |
| 5     | 0.459 | 0.367  | Y      |
| 6     | 1     | 1      | Y      |

Normalizing the test input  $48 = 0.675$ ,  $90000 = 0.833$

# Example (cont...)

Compute the distance

| Sl.No | Age   | Salary | Status | Distance |
|-------|-------|--------|--------|----------|
| 1     | 0.054 | 0      | N      | 1.04     |
| 2     | 0.324 | 0.333  | N      | 0.611    |
| 3     | 0.595 | 0.667  | N      | 0.185    |
| 4     | 0     | 0.917  | Y      | 0.681    |
| 5     | 0.459 | 0.367  | Y      | 0.514    |
| 6     | 1     | 1      | Y      | 0.365    |

3 Nearest  
Neighbors

With  $K = 3$  Loan approval status is predicted as “Yes” with majority class prediction



# K-NN Classification Algorithm

---

Input : input, label pairs  $(\mathbf{x}_1, y_1), (\mathbf{x}_2, y_2), \dots, (\mathbf{x}_i, y_i), \mathbf{x}_q$  (test sample for which label needs to be predicted).

Output:  $y_q$  (Predicted label for  $\mathbf{x}_q$ )

Procedure:

- (a) Find K most similar (nearest) examples to  $\mathbf{x}_q$  from the training dataset based on some distance measure.
- (b) Get the labels of these K nearest examples.
- (c) Predict the label of  $\mathbf{x}_q$  by applying some aggregation (eg. Majority voting) on these labels of the K nearest neighbours.

# K-NN Regression

---

Consider the employee dataset indicating the age, years of experience of the employee (input) and the Salary (output).

| Age | Experience(yrs) | Salary (Lakhs) |
|-----|-----------------|----------------|
| 28  | 3               | 22             |
| 26  | 4               | 25             |
| 30  | 5               | 30             |
| 34  | 8               | 35             |
| 38  | 15              | 40             |
| 46  | 20              | 42             |
| 48  | 25              | 47             |
| 55  | 30              | 70             |
| 52  | 23              | 60             |

What is the Expected salary of a person who is 32 years old with 7 years Experience?

# K-NN Regression (cont...)

| Age | Experience (Yrs) | Salary (Lakhs) | Distance (Euclidean) |
|-----|------------------|----------------|----------------------|
| 28  | 3                | 22             | 5.656854             |
| 26  | 4                | 25             | 6.708204             |
| 30  | 5                | 30             | 2.828427             |
| 34  | 8                | 35             | 2.236068             |
| 38  | 15               | 40             | 10                   |
| 46  | 20               | 42             | 19.10497             |
| 48  | 25               | 47             | 24.08319             |
| 55  | 30               | 70             | 32.52691             |
| 52  | 23               | 60             | 25.6125              |

3 Nearest  
Neighbors

With  $K = 3$  Expected salary of the person is 29 Lakhs which is average of Nearest neighbors

# Nearest Neighbors - Advantages

---

- Simple computations, easy to implement.
- Can learn complex decision boundaries.
- Performs well when a single function can not fit the entire input space.



# Limitations/Disadvantages

---

- Intensive computations in the case of large data sets.
- Do not work well with high dimensional input (curse of Dimensionality)
  - Curse of Dimensionality: Distance metrics become less informative
  - Volume of data increases exponentially.
  - Chances more sparsity of input feature space due to data unavailability for all the features.
  - Computational complexity increases.
  - Models tend to overfit.
  - Difficulty in visualization
- Since K-NN is memory based, entire data needs to be preserved and carried around for predictions.
- Choosing the right distance metric and the value of 'K' can be difficult.