Artificial Intelligence

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Intelligence

- **INTELLIGENCE**

- Who is intelligent?
- All living organisms are intelligent.
- They interact with their environment and survive.
- Examples from our own world

➢Crossing a road

➢Discovering alternate paths

➢Writing a poem, drawing a picture, creating a new recipe

Outline

- INTELLIGENCE
- ARTIFICIAL INTELLEGENCE
- ARTIFICIAL INTELLEGENCE SUBSETS
- MACHINE LEARNING
- APPLICATIONS OF MACHINE LEARNING

What is machine learning?

"Learning is any process by which a system improves performance from experience."
- Herbert Simon

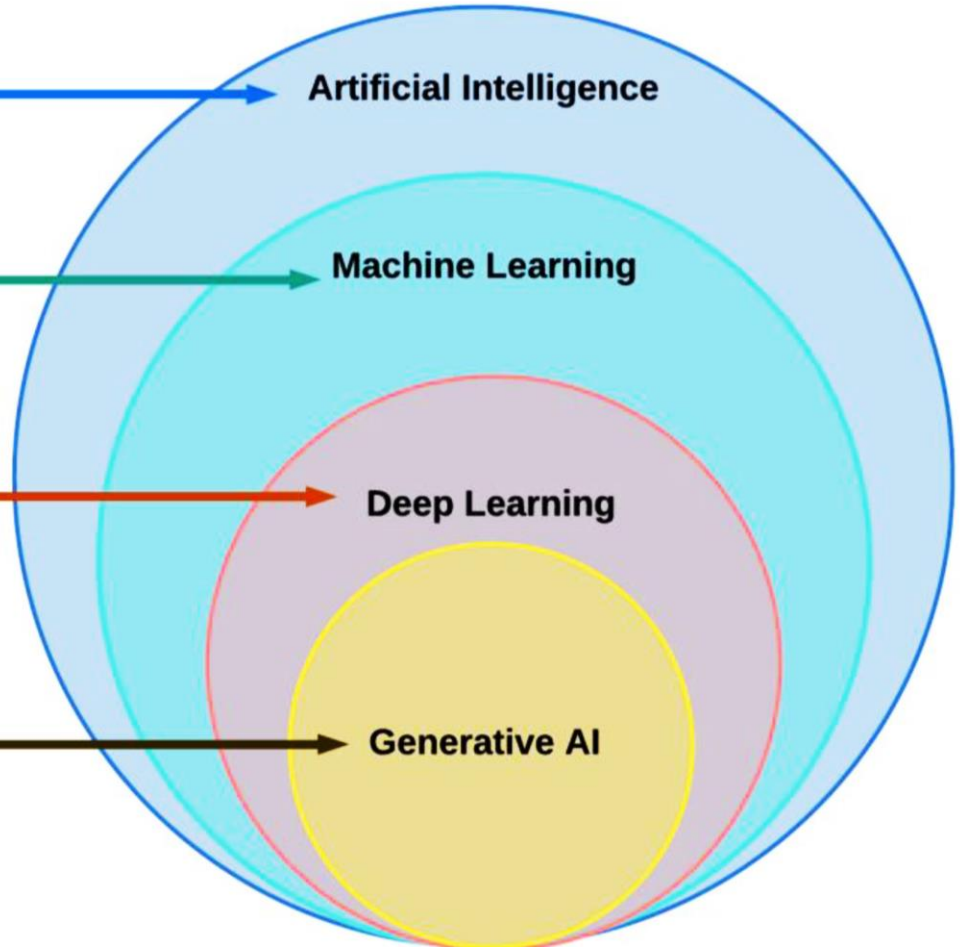
- A branch of artificial intelligence, concerned with the design and development of algorithms that allow computers to evolve behaviors based on empirical data.
- As intelligence requires knowledge, it is necessary for the computers to acquire knowledge.
- Machine learning refers to a system capable of the autonomous acquisition and integration of knowledge

Artificial Intelligence
AI involves techniques that equip computers to emulate human behavior, enabling them to learn, make decisions, recognize patterns, and solve complex problems in a manner akin to human intelligence.

Machine Learning
ML is a subset of AI, uses advanced algorithms to detect patterns in large data sets, allowing machines to learn and adapt. ML algorithms use supervised or unsupervised learning methods.

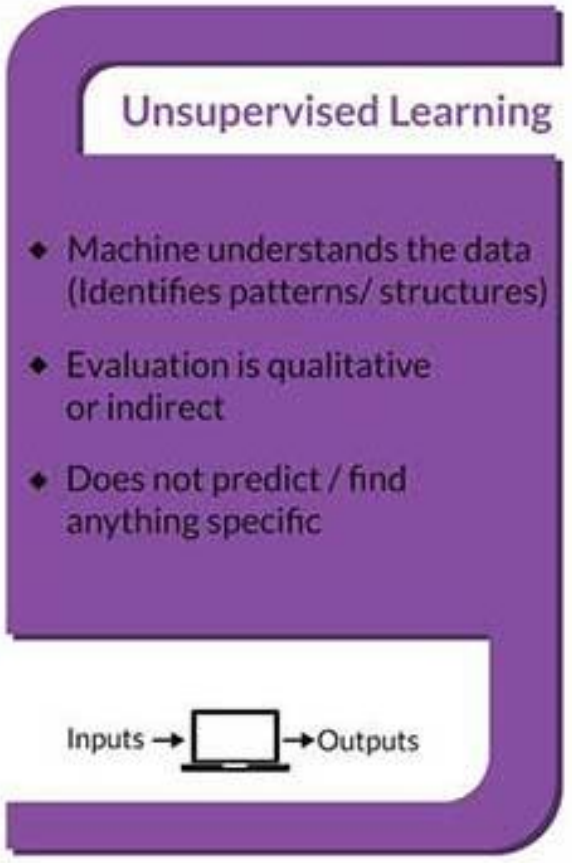
Deep Learning
DL is a subset of ML which uses neural networks for in-depth data processing and analytical tasks. DL leverages multiple layers of artificial neural networks to extract high-level features from raw input data, simulating the way human brains perceive and understand the world.

Generative AI
Generative AI is a subset of DL models that generates content like text, images, or code based on provided input. Trained on vast data sets, these models detect patterns and create outputs without explicit instruction, using a mix of supervised and unsupervised learning.



Supervised, Unsupervised learning

Training Data
Both inputs & output are given
We create a model based on the dummy data



Only input is available
Clustering
Our world for Alien

An agent performs in environment
Agent gets some penalty or reward
And makes some policy based on output (state)

Artificial Intelligence

- **ARTIFICIAL INTELLIGENCE**

- Living beings are intelligent; but are man made non living beings also intelligent???
- Can a machine
  - ➢make discoveries?
  - ➢pass a ruling order in a court?
  - ➢compose a symphony?
  - ➢go for a PLAN B?
  - ➢decide to wait or let go?

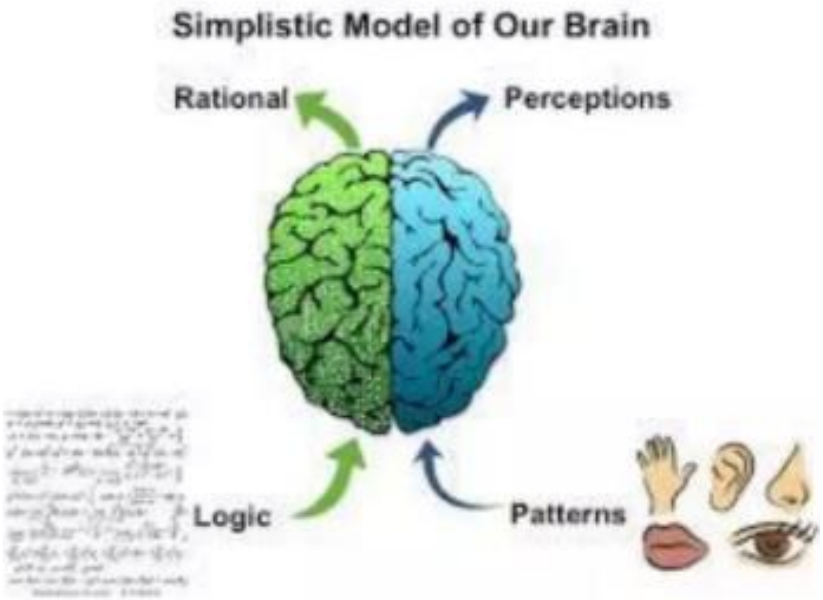
Artificial Intelligence

- **ARTIFICIAL INTELLIGENCE**

- Traditional computers are powerful but not intelligent
- They can compile MBs and GBs of code but may get stuck at a minor logical error
- Artificial intelligence is a field of computer science which aims to make computer systems that can mimic human intelligence.
- Just as we humans act when we don't have exact information about a situation but still go ahead and choose one of the many possible moves.

Artificial Intelligence

- **ARTIFICIAL INTELLIGENCE**



- Why make machines INTELLIGENT?
- To reduce our effort and help the society advance

➢share our load

➢make use of massive number crunching power of CPUs

➢perceive things and try to realize them

➢perform in our absence/ without our guidance

Artificial Intelligence

- **ARTIFICIAL INTELLIGENCE SUBSETS**

- MACHINE LEARNING
- ARTIFICIAL NEURAL NETWORKS
- DEEP LEARNING
- COMPUER VISION
- NATURAL LANGUAGE PROCESSING
- SPEECH RECOGNITION

machine learning?

- **MACHINE LEARNING**

- It is a branch of Artificial Intelligence that gives computers the capability to learn without being explicitly programmed.
- Focus is on imparting "learning" to machines
- Learning over time and iterations (similar to human experience)
- No longer dependent on rule based programming
- Real world data and observations are fed to the system

What is machine learning?

- **MACHINE LEARNING**

- ML algorithms can be broadly categorized into

➢SUPERVISED

➢UNSUPERVISED

➢REINFORCED

What is machine learning?

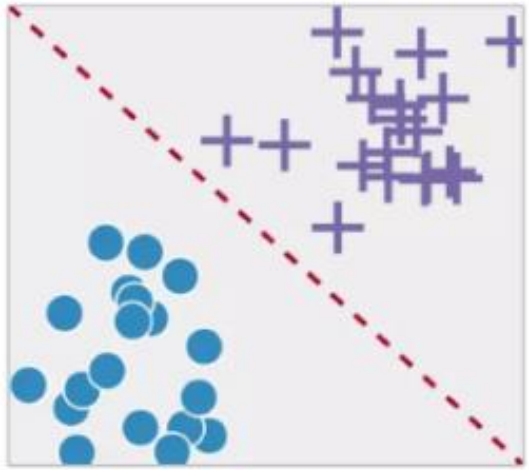
- **MACHINE LEARNING**

- **SUPERVISED LEARNING**
- Uses ground truth and labeled data
- Requires prior knowledge
- Approximates the relationship between input and output
- Mainly divided into CLASSIFICATION and REGRESSION
- Naïve Bayes, Random Forest, Support Vector Machine, Neural Networks

What is machine learning?

- **MACHINE LEARNING (SUPERVISED)**

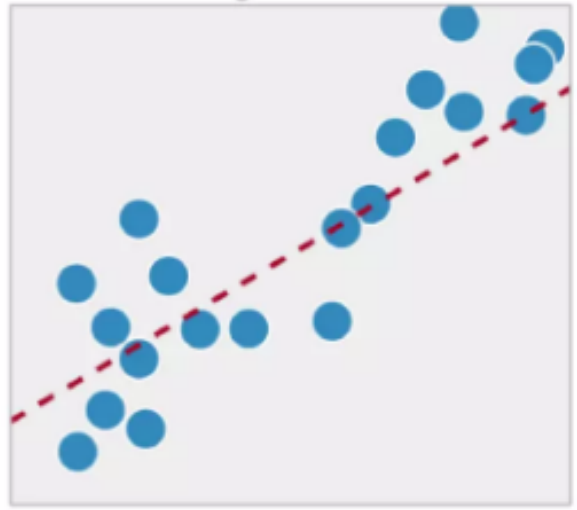
- **CLASSIFICATION**
- approximating a mapping function (f) from input variables (X) to discrete output variables (y)
- Predicting a label
- Spam/ non spam
- Positive/ negative



What is machine learning?

- **MACHINE LEARNING (SUPERVISED)**

- **REGRESSION**
- Approximating a mapping function (f) from input variables (X) to a continuous output variable (y)
- Predicting a quantity
- Predict salary from age/experience data
- Sales forecast



What is machine learning?

- **MACHINE LEARNING**

- **UNSUPERVISED LEARNING**
- No historical labels
- Learn the inherent structure of data
- Discover the trends in data
- Mainly divided into CLUSTERING and ASSOCIATION

What is machine learning?

- **MACHINE LEARNING (UNSUPERVISED)**

- **CLUSTERING**
- Dividing the population into groups
- Same group members resemble each other compared to other groups
- Connectivity/ centroid/ distribution/density models
- K Means, Hierarchical, KNN, PCA

sample

Cluster/group

What is machine learning?

- **MACHINE LEARNING (UNSUPERVISED)**

- **ASSOCIATION**
- Rule based learning model
- Discover rules that describe large portions of your data
- Product placement in malls
- Eg people that buy X also tend to buy Y

ID	Items
1	{Bread, Milk}
2	{Bread, Diapers, Beer, Eggs}
3	{Milk, Diapers, Beer, Cola}
4	{Bread, Milk, Diapers, Beer}
5	{Bread, Milk, Diapers, Cola}
...	...

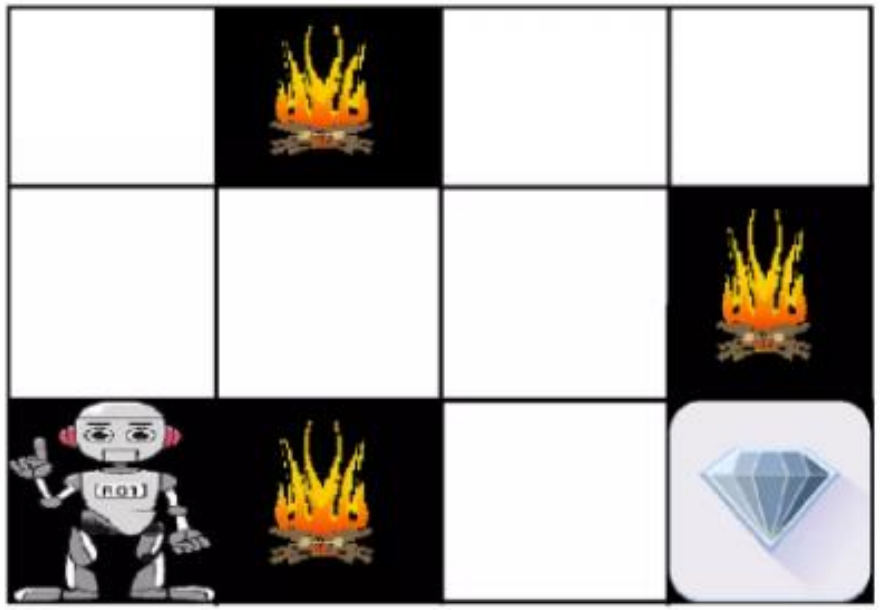
market basket transactions

{Diapers, Beer} Example of a frequent itemset

{Diapers} → {Beer} Example of an association rule

What is machine learning?

- **MACHINE LEARNING**



- **REINFORCEMENT**
- Maximize reward in a given situation
- Find the best possible behavior/ path
- Input: initial state of the model
- Output: many possible solutions to a given problem
- Training: reward or punishment
- Iterations: best solution is selected when reward is maximum

Supervised, Unsupervised learning

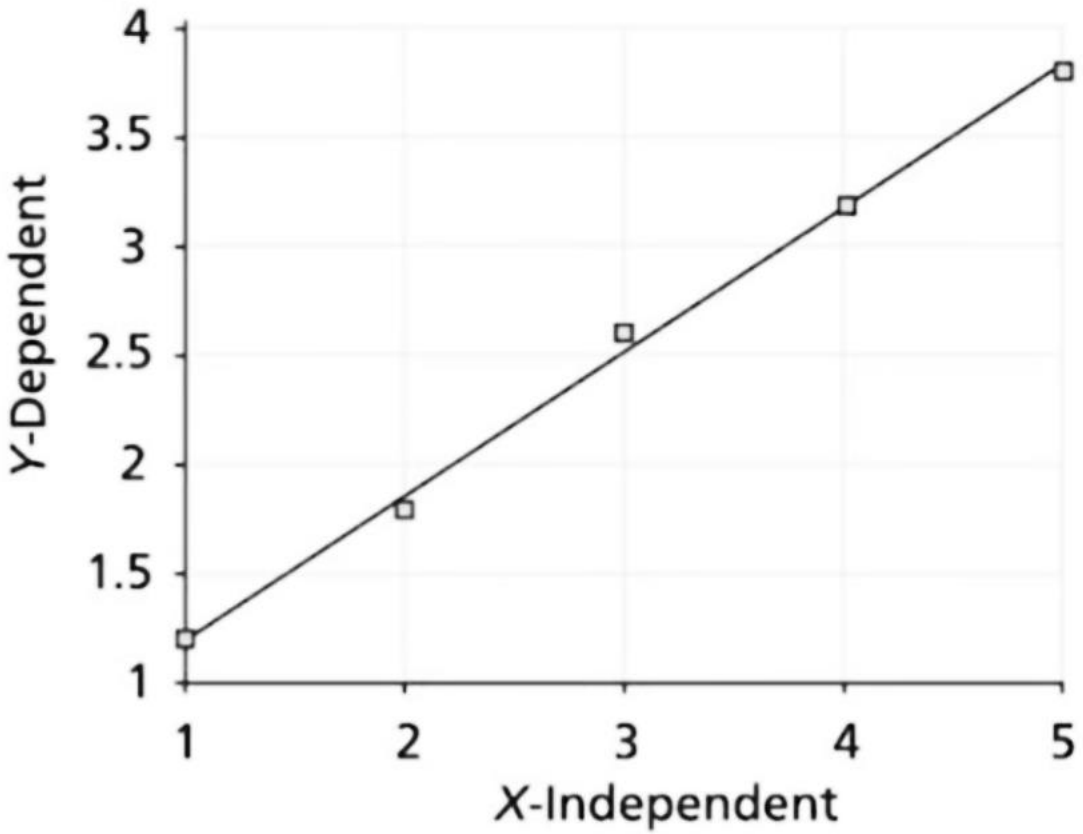
Criteria	Supervised ML	Unsupervised ML	Reinforcement ML
Definition	Learns by using labelled data	Trained using unlabelled data without any guidance.	Works on interacting with the environment
Type of data	Labelled data	Unlabelled data	No – predefined data
Type of problems	Regression and classification	Association and Clustering	Exploitation or Exploration
Supervision	Extra supervision	No supervision	No supervision
Algorithms	Linear Regression, Logistic Regression, SVM, KNN etc.	K – Means, C – Means, Apriori	Q – Learning, SARSA
Aim	Calculate outcomes	Discover underlying patterns	Learn a series of action
Application	Risk Evaluation, Forecast Sales	Recommendation System, Anomaly Detection	Self Driving Cars, Gaming, Healthcare

Linear Regression: Example 1

- Let us consider an example where the five weeks' sales data (in Thousands) is given as shown in Table.
- Apply linear regression technique to predict the 7^{th} and 12^{th} week sales.

x_i (Week)	y_j (Sales in Thousands)
1	1.2
2	1.8
3	2.6
4	3.2
5	3.8

Linear Regression: Example 1



x_i (Week)	y_j (Sales in Thousands)
1	1.2
2	1.8
3	2.6
4	3.2
5	3.8

Linear Regression: Example 1

- Linear regression equation is given by
- $y = a_0 + a_1 * x + e$
- *where*
- $a_1 = \frac{(\overline{xy}) - (\bar{x})(\bar{y})}{\overline{x^2} - \bar{x}^2}$
- $a_0 = \bar{y} - a_1 * \bar{x}$

x_i (Week)	y_j (Sales in Thousands)
1	1.2
2	1.8
3	2.6
4	3.2
5	3.8

Linear Regression: Example 1

- Here, there are 5 items, i.e., i = 1, 2, 3, 4, 5.

	x_i (Week)	y_j (Sales in Thousands)	x_i^2	$x_i * y_j$
	1	1.2	1	1.2
	2	1.8	4	3.6
	3	2.6	9	7.8
	4	3.2	16	12.8
	5	3.8	25	19
Sum	15	12.6	55	44.4
Average	$\bar{x} = 3$	$\bar{y} = 2.52$	$\overline{x^2} = 11$	$\overline{xy} = 8.88$

Linear Regression: Example 1

- $\bar{x} = 3$ $\bar{y} = 2.52$ $\overline{x^2} = 11$ $\overline{xy} = 8.88$

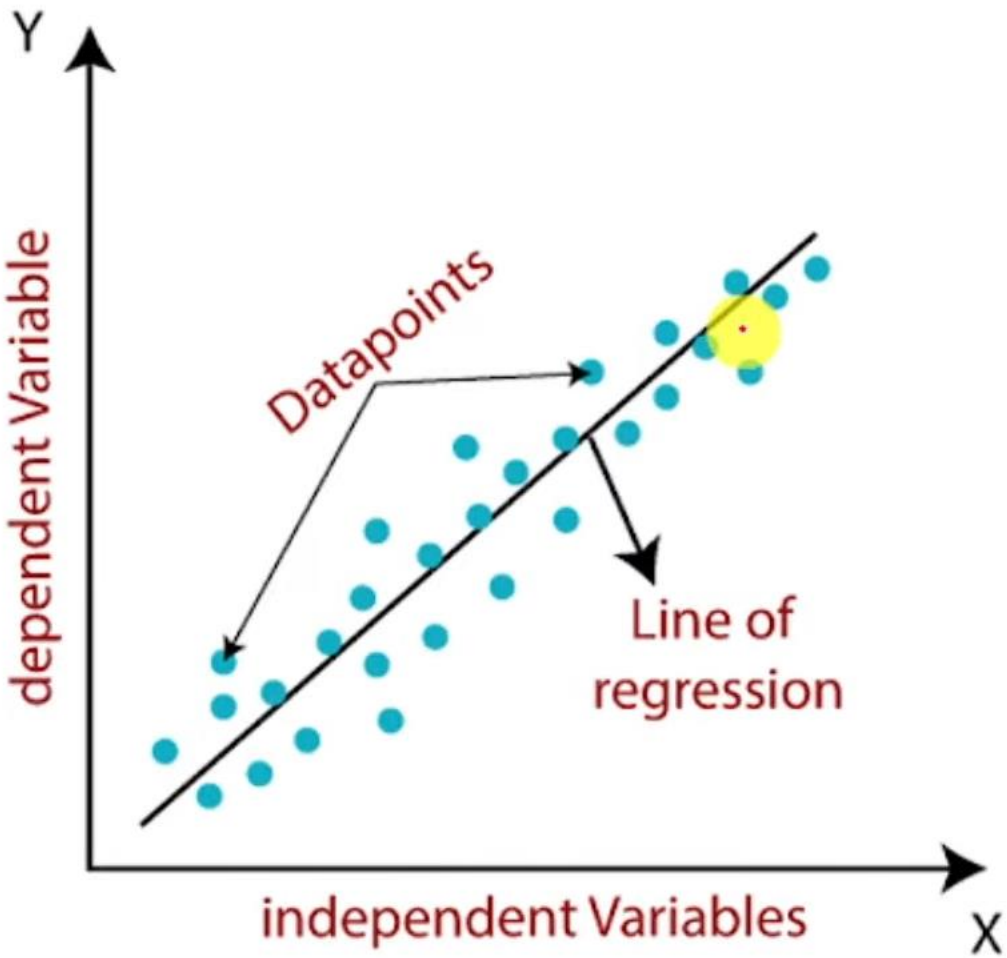
- $a_1 = \frac{(\overline{xy})-(\bar{x})(\bar{y})}{\overline{x^2}-\bar{x}^2} = \frac{8.88-3*2.52}{11-3^2} = 0.66$
- $a_0 = \bar{y} - a_1 * \bar{x} = 2.52 - 0.66 * 3 = 0.54$
- **Regression equation is**
- $y = a_0 + a_1 * x$
- $y = 0.54 + 0.66 * x$

Linear Regression: Example 1

- **Regression equation is**
- $y = a_0 + a_1 * x$
- $y = 0.54 + 0.66 * x$
- The predicted 7th week sale (when x = 7) is,
- **y = 0.54 + 0.66 x 7 = 5.16**
- the predicted 12th week sale (when x = 12) is,
- **y = 0.54 + 0.66 x 12 = 8.46**

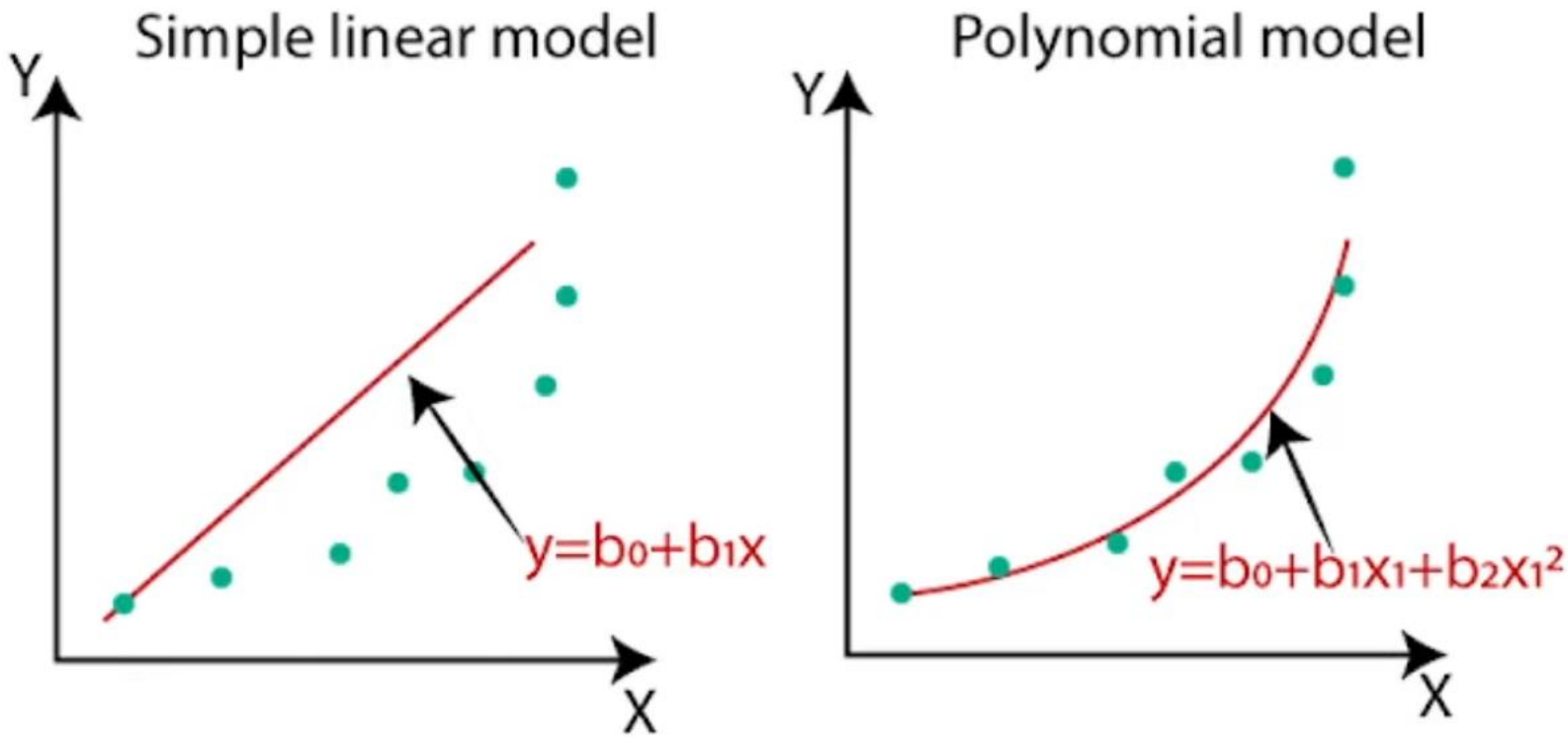
When Linear Regression not works?

- If the relationship between the independent and dependent variables is linear, then we can use a straight line to fit the given data.



Linear and Polynomial Regression

- If the relationship between the independent and dependent variables is not linear, then linear regression cannot be used as it will result in large errors.



Classification

- Linear regression predicts the numerical response but is not suitable for predicting the categorical variables.
- When categorical variables are involved, it is called classification problem.
- Logistic regression is suitable for binary classification problem.

Where Classification is used?

For example, the following scenarios are instances of predicting categorical variables.

1. Is the mail spam or not spam? The answer is yes or no. Thus, categorical dependent variable is a binary response of yes or no.
2. If the student should be admitted or not is based on entrance examination marks. Here, categorical variable response is admitted or not.
3. The student being pass or fail is based on marks secured.

How Logistic regression works but not classify!

How Does the Logistic Regression Algorithm Work?

- Consider the following example:
- An organization wants to determine an employee's salary increase based on their performance.
- For this purpose, a linear regression algorithm will help them decide.
- Plotting a regression line by considering the employee's performance as the independent variable, and the salary increase as the dependent variable will make their task easier.

If you want to calculate the performance-based salary hike!

Classification Regression: KNN Classifier Example 1

Sepal Length	Sepal Width	Species
5.3	3.7	Setosa
5.1	3.8	Setosa
7.2	3.0	Virginica
5.4	3.4	Setosa
5.1	3.3	Setosa
5.4	3.9	Setosa
7.4	2.8	Virginica
6.1	2.8	Verscicolor
7.3	2.9	Virginica
6.0	2.7	Verscicolor
5.8	2.8	Virginica
6.3	2.3	Verscicolor
5.1	2.5	Verscicolor
6.3	2.5	Verscicolor
5.5	2.4	Verscicolor

Sepal Length	Sepal Width	Species
5.2	3.1	?

Iris flower

Classification Regression: KNN Classifier Example 1

Sepal Length	Sepal Width	Species
5.3	3.7	Setosa
5.1	3.8	Setosa
7.2	3.0	Virginica
5.4	3.4	Setosa
5.1	3.3	Setosa
5.4	3.9	Setosa
7.4	2.8	Virginica
6.1	2.8	Verscicolor
7.3	2.9	Virginica
6.0	2.7	Verscicolor
5.8	2.8	Virginica
6.3	2.3	Verscicolor
5.1	2.5	Verscicolor
6.3	2.5	Verscicolor
5.5	2.4	Verscicolor

Sepal Length	Sepal Width	Species
5.2	3.1	?

Step 1: Find Distance

$$\text{Distance (Sepal Length, Sepal Width)} = \sqrt{(x-a)^2 + (y-b)^2}$$

$$\text{Distance (Sepal Length, Sepal Width)} = \sqrt{(5.2-5.3)^2 + (3.1-3.7)^2}$$

$$\text{Distance (Sepal Length, Sepal Width)} = 0.608$$

Sepal Length	Sepal Width	Species	Distance
5.3	3.7	Setosa	0.608

Classification Regression: KNN Classifier Example 1

Sepal Length	Sepal Width	Species	Distance	Rank
5.3	3.7	Setosa	0.608	3
5.1	3.8	Setosa	0.707	6
7.2	3.0	Virginica	2.002	13
5.4	3.4	Setosa	0.36	2
5.1	3.3	Setosa	0.22	1
5.4	3.9	Setosa	0.82	8
7.4	2.8	Virginica	2.22	15
6.1	2.8	Verscicolor	0.94	10
7.3	2.9	Virginica	2.1	14
6.0	2.7	Verscicolor	0.89	9
5.8	2.8	Virginica	0.67	5
6.3	2.3	Verscicolor	1.36	12
5.1	2.5	Verscicolor	0.60	4
6.3	2.5	Verscicolor	1.25	11
5.5	2.4	Verscicolor	0.75	7

Step 2: Find Rank

Classification Regression: KNN Classifier Example 1

Sepal Length	Sepal Width	Species	Distance	Rank
5.3	3.7	Setosa	0.608	3
5.1	3.8	Setosa	0.707	6
7.2	3.0	Virginica	2.002	13
5.4	3.4	Setosa	0.36	2
5.1	3.3	Setosa	0.22	1
5.4	3.9	Setosa	0.82	8
7.4	2.8	Virginica	2.22	15
6.1	2.8	Verscicolor	0.94	10
7.3	2.9	Virginica	2.1	14
6.0	2.7	Verscicolor	0.89	9
5.8	2.8	Virginica	0.67	5
6.3	2.3	Verscicolor	1.36	12
5.1	2.5	Verscicolor	0.60	4
6.3	2.5	Verscicolor	1.25	11
5.5	2.4	Verscicolor	0.75	7

Step 3: Find the Nearest Neighbor

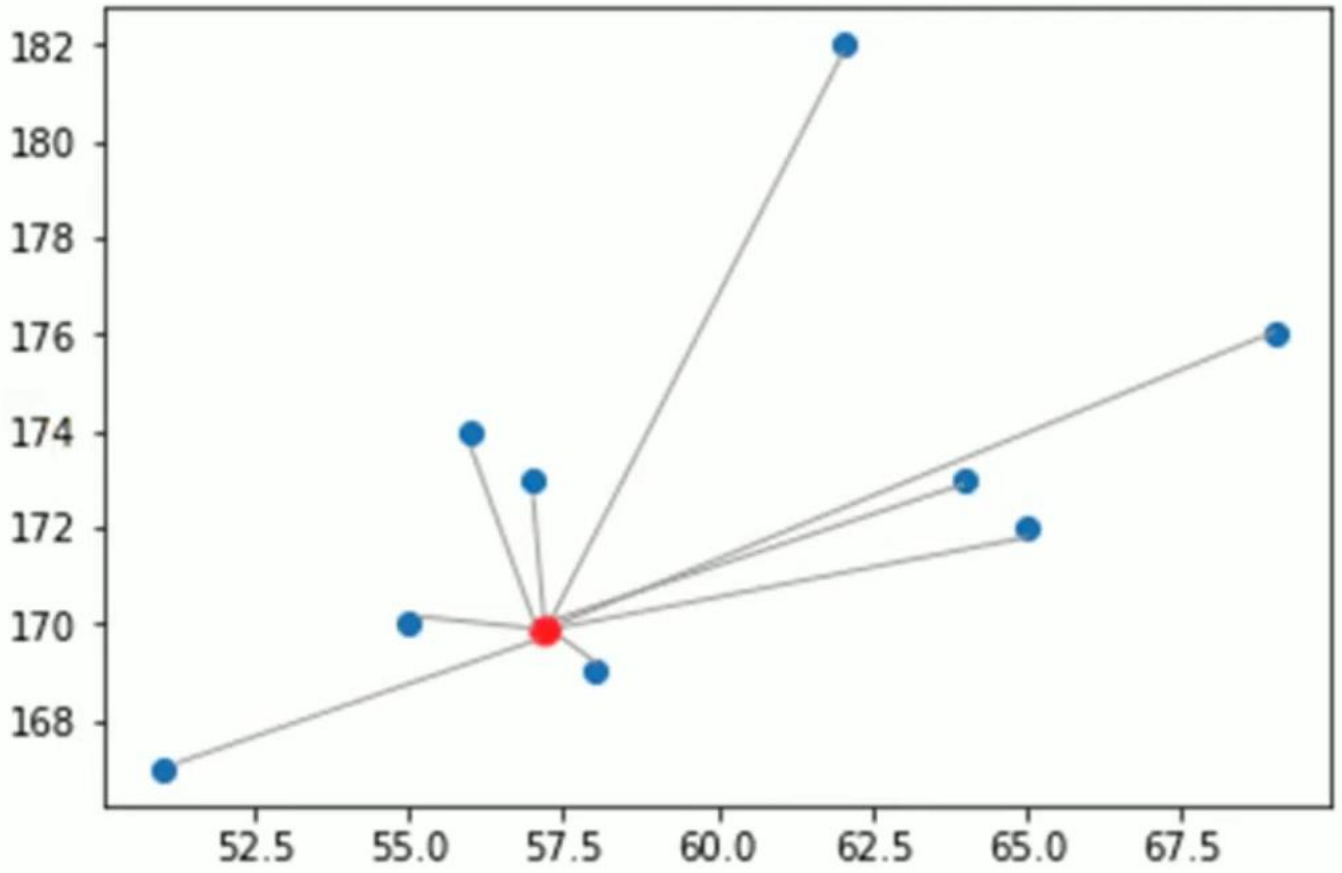
If k = 1 – Setosa

If k = 2 – Setosa

If k = 5 – Setosa

Classification Regression: KNN Classifier Example 2

Height (CM)	Weight (KG)	Class
167	51	Underweight
182	62	Normal
176	69	Normal
173	64	Normal
172	65	Normal
174	56	Underweight
169	58	Normal
173	57	Normal
170	55	Normal
170	57	?



Classification Regression: KNN Classifier Example 2

Height (CM)	Weight (KG)	Class
167	51	Underweight
182	62	Normal
176	69	Normal
173	64	Normal
172	65	Normal
174	56	Underweight
169	58	Normal
173	57	Normal
170	55	Normal
170	57	?

THE DISTANCE FORMULA

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

Classification Regression: KNN Classifier Example 2

Height (CM)	Weight (KG)	Class
167	51	Underweight
182	62	Normal
176	69	Normal
173	64	Normal
172	65	Normal
174	56	Underweight
169	58	Normal
173	57	Normal
170	55	Normal
170	57	?

Distance	Rank
1.4	1
2	2
3	3
4.1	4
6.7	5
7.6	6
8.2	7
13	8
13.4	9

- If K=1, Normal
- If K=2, Normal
- If K=3, Normal
- If K=4, Normal
- If K=5, Normal

Naïve Bayes Classifier Example1

- Estimate conditional probabilities of each attributes {color, legs, height, smelly} for the species classes: {M, H} using the data given in the table.
- Using these probabilities estimate the probability values for the new instance – (Color=Green, legs=2, Height=Tall, and Smelly=No).

No	Color	Legs	Height	Smelly	Species
1	White	3	Short	Yes	M
2	Green	2	Tall	No	M
3	Green	3	Short	Yes	M
4	White	3	Short	Yes	M
5	Green	2	Short	No	H
6	White	2	Tall	No	H
7	White	2	Tall	No	H
8	White	2	Short	Yes	H

Naïve Bayes Classifier Example1

No	Color	Legs	Height	Smelly	Species
1	White	3	Short	Yes	M
2	Green	2	Tall	No	M
3	Green	3	Short	Yes	M
4	White	3	Short	Yes	M
5	Green	2	Short	No	H
6	White	2	Tall	No	H
7	White	2	Tall	No	H
8	White	2	Short	Yes	H

New Instance

(Color=Green, legs=2, Height=Tall, and Smelly=No)

$$P(M) = \frac{4}{8} = 0.5 \quad P(H) = \frac{4}{8} = 0.5$$

Color	M	H
White	2/4	3/4
Green	2/4	1/4

Legs	M	H
2	1/4	4/4
3	3/4	0/4

Height	M	H
Tall	1/4	2/4
Short	3/4	2/4

Smelly	M	H
Yes	3/4	1/4
No	1/4	3/4

Naïve Bayes Classifier Example1

$$P(M) = \frac{4}{8} = 0.5 \quad P(H) = \frac{4}{8} = 0.5$$

Color	M	H
White	2/4	3/4
Green	2/4	1/4

Legs	M	H
2	1/4	4/4
3	3/4	0/4

Height	M	H
Tall	1/4	2/4
Short	3/4	2/4

Smelly	M	H
Yes	3/4	1/4
No	1/4	3/4

$$p(M|New\ Instance) = p(M) * p(Color = Green|M) * p(Legs = 2|M) * p(Height = tall|M) * p(Smelly = no\ |M)$$

$$p(M|New\ Instance) = 0.5 * \frac{2}{4} * \frac{1}{4} * \frac{1}{4} * \frac{1}{4} = \mathbf{0.003906}$$

$$p(H|New\ Instance) = p(H) * p(Color = Green|H) * p(Legs = 2|H) * p(Height = tall|H) * p(Smelly = no\ |H)$$

$$p(H|New\ Instance) = 0.5 * \frac{1}{4} * \frac{4}{4} * \frac{2}{4} * \frac{3}{4} = 0.047$$

$$p(H|New\ Instance) > p(M|New\ Instance)$$

Hence the new instance belongs to Speices H

Naïve Bayes Classifier Example2

Day	*Outlook*	*Temperature*	*Humidity*	*Wind*	*PlayTennis*
D1	Sunny	Hot	High	Weak	No
D2	Sunny	Hot	High	Strong	No
D3	Overcast	Hot	High	Weak	Yes
D4	Rain	Mild	High	Weak	Yes
D5	Rain	Cool	Normal	Weak	Yes
D6	Rain	Cool	Normal	Strong	No
D7	Overcast	Cool	Normal	Strong	Yes
D8	Sunny	Mild	High	Weak	No
D9	Sunny	Cool	Normal	Weak	Yes
D10	Rain	Mild	Normal	Weak	Yes
D11	Sunny	Mild	Normal	Strong	Yes
D12	Overcast	Mild	High	Strong	Yes
D13	Overcast	Hot	Normal	Weak	Yes
D14	Rain	Mild	High	Strong	No

$$\langle Outlook = sunny, Temperature = cool, Humidity = high, Wind = strong \rangle$$

Naïve Bayes Classifier

$$P(PlayTennis = yes) = 9/14 = .64$$

$$P(PlayTennis = no) = 5/14 = .36$$

Outlook	Y	N
sunny	2/9	3/5
overcast	4/9	0
rain	3/9	2/5
Tempreature		
hot	2/9	2/5
mild	4/9	2/5
cool	3/9	1/5

Humidity	Y	N
high	3/9	4/5
normal	6/9	1/5
Windy		
Strong	3/9	3/5
Weak	6/9	2/5