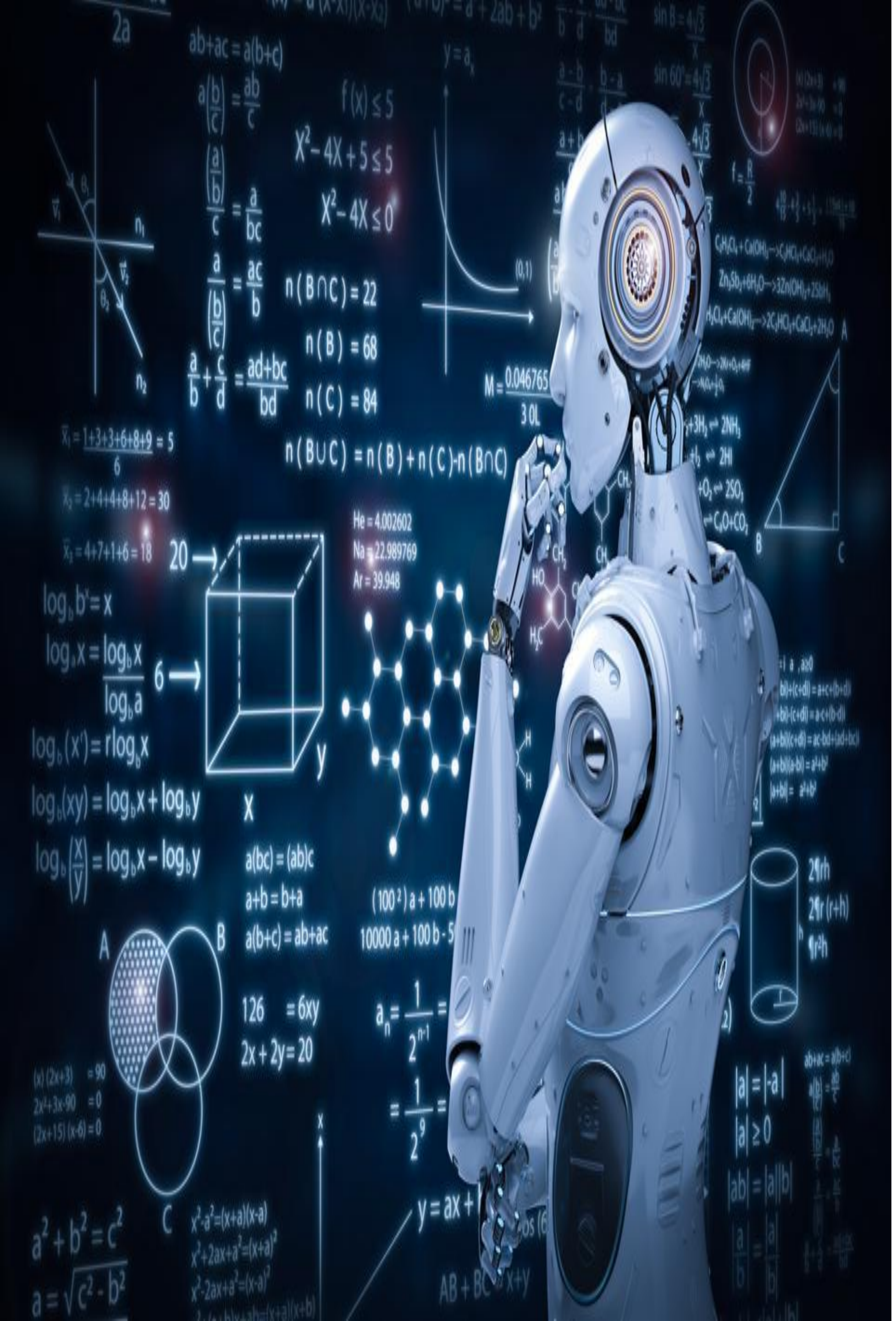


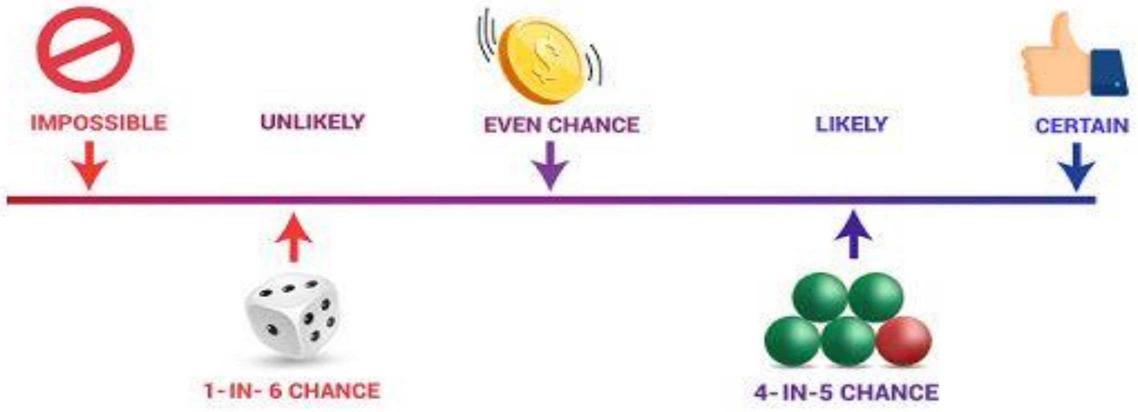
Practical Machine Learning

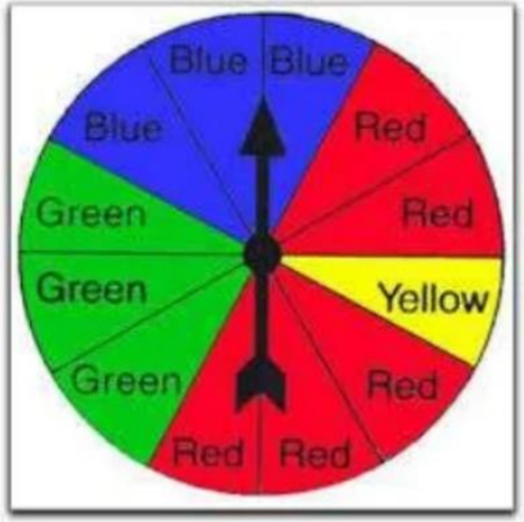
Day 9: Mar22 DBDA

Kiran Waghmare

Agenda

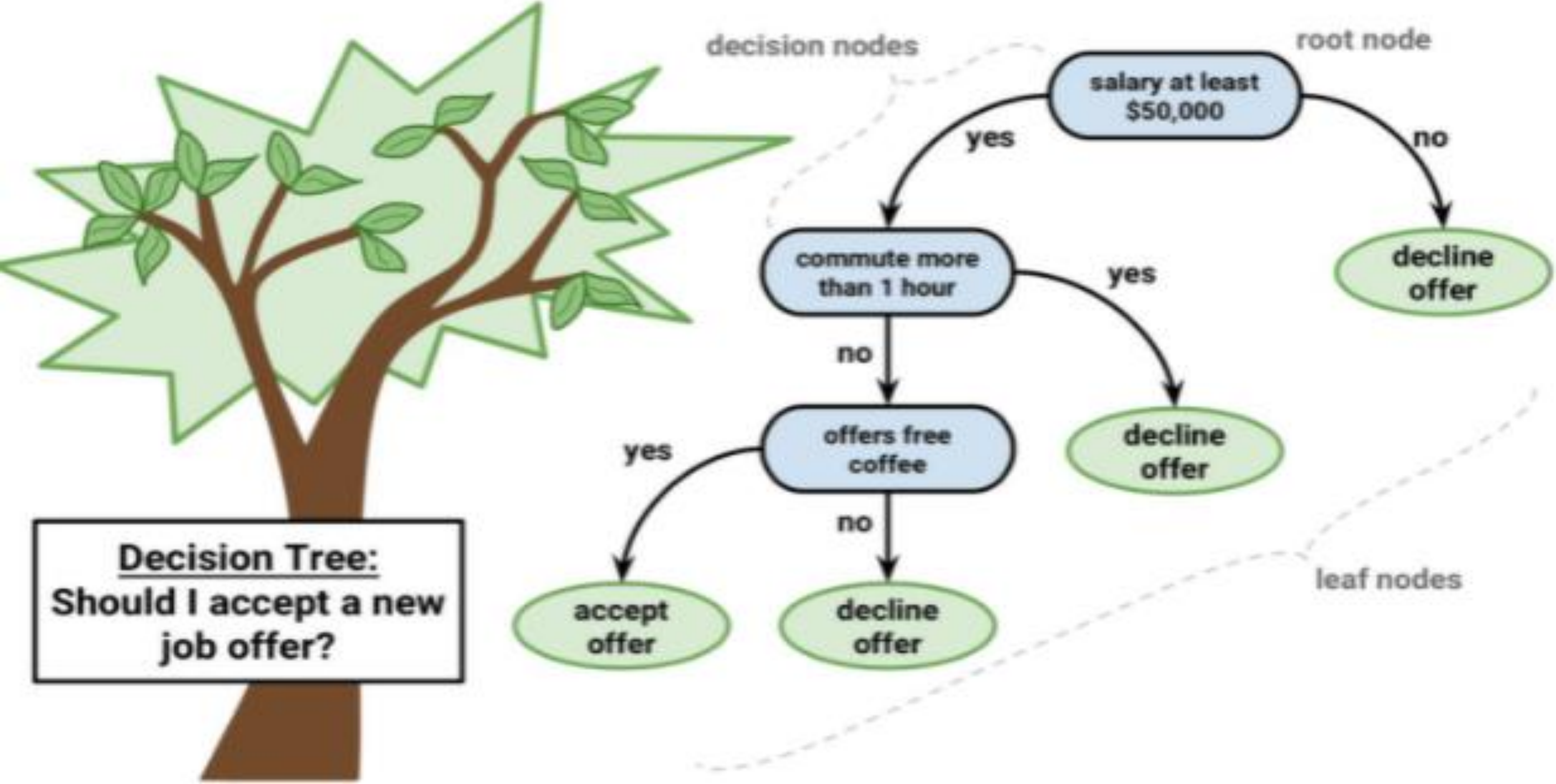
- Naïve Bayes





PROBABILITY

GETTING KNOWLEDGE READY


decision nodes
root node
salary at least $50,000
yes
no
commute more than 1 hour
yes
decline offer
no
offers free coffee
decline offer
yes
no
accept offer
decline offer
leaf nodes
Decision Tree:
Should I accept a new job offer?

THE PROBABILITY IN EVERY LIFE

Pick a random card, what is the probability of getting a queen?

Pick a random card, you know it is a diamond. Now what is the probability of that card being a queen?

Conditional Probability

$$P(\text{queen}/\text{diamond}) = 1/13$$

P(A/B)= Probability of event A knowing that event B has already occurred

Conditional Probability Formula

Probability of A and B

$$P(A \mid B) = \frac{P(A \cap B)}{P(B)}$$

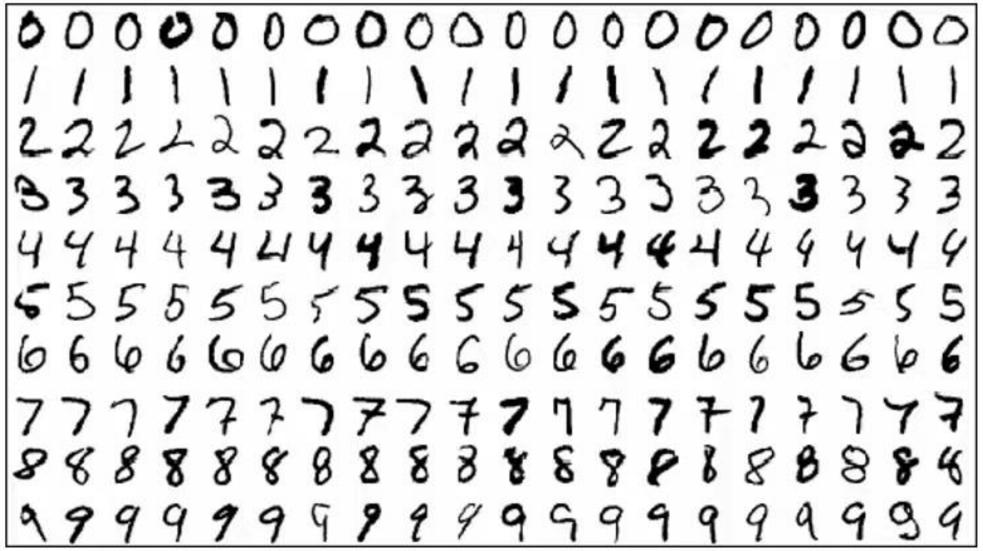
Probability of A given B

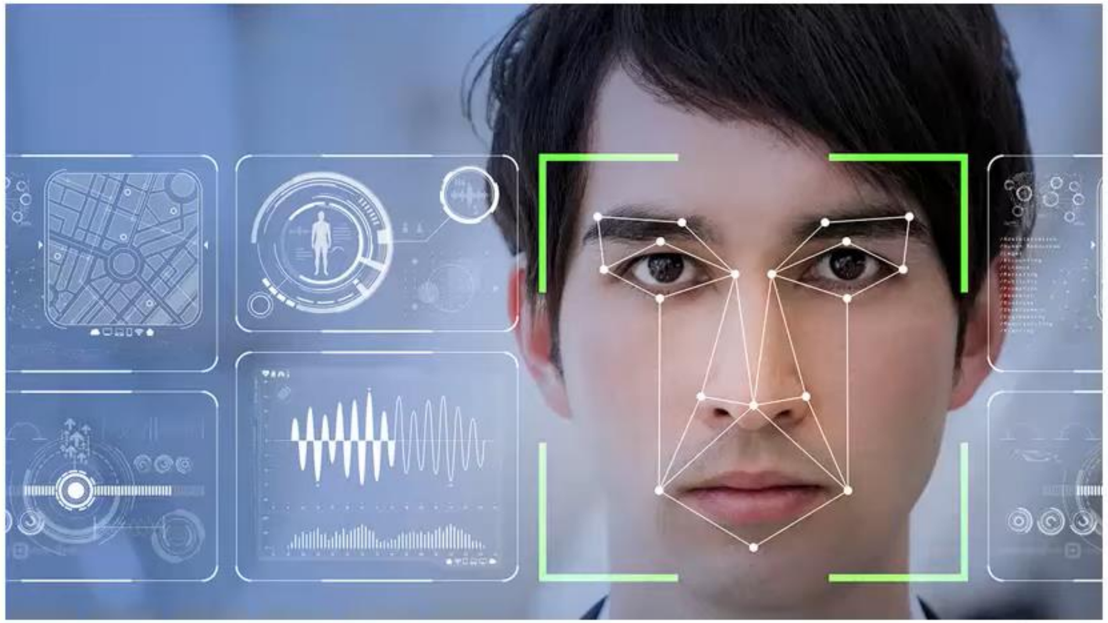
Probability of B

Thomas Bayes

$$P(A/B) = \frac{P(B/A) * P(A)}{P(B)}$$


EMAIL
SPAM
SPAM






NEWS

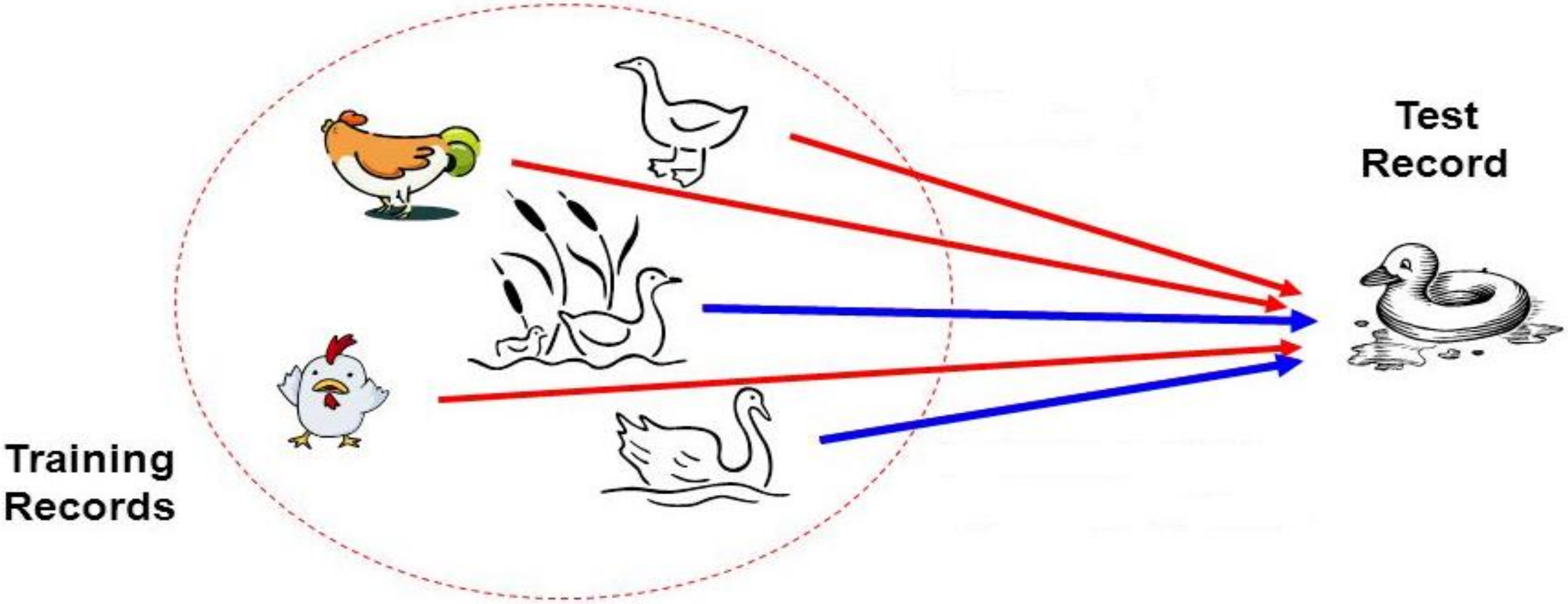
Examples of Classification in Data Analytics

- Life Science: Predicting tumor cells as benign or malignant
- Security: Classifying credit card transactions as legitimate or fraudulent
- Prediction: Weather, voting, political dynamics, etc.
- Entertainment: Categorizing news stories as finance, weather, entertainment, sports, etc.
- Social media: Identifying the current trend and future growth

Bayesian Classifier

Bayesian Classifier

- Principle
  - If it walks like a duck, quacks like a duck, then it is probably a duck



Bayesian Classifier

- **A statistical classifier**
  - Performs *probabilistic prediction*, *i.e.,* predicts class membership probabilities
- **Foundation**
  - Based on Bayes' Theorem.
- **Assumptions**
  1. The classes are mutually exclusive and exhaustive.
  2. The attributes are independent given the class.
- **Called "Naïve" classifier because of these assumptions.**
  - Empirically proven to be useful.
  - Scales very well.

Probability Basics

- Prior, conditional and joint probability
  - Prior probability: $P(X)$
  - Conditional probability: $P(X_1 | X_2), P(X_2 | X_1)$
  - Joint probability: $\mathbf{X} = (X_1, X_2), P(\mathbf{X}) = P(X_1, X_2)$
  - Relationship: $P(X_1, X_2) = P(X_2 | X_1)P(X_1) = P(X_1 | X_2)P(X_2)$
  - Independence: $P(X_2 | X_1) = P(X_2), P(X_1 | X_2) = P(X_1), P(X_1, X_2) = P(X_1)P(X_2)$
- Bayesian Rule

$$P(C | \mathbf{X}) = \frac{P(\mathbf{X} | C)P(C)}{P(\mathbf{X})} \qquad Posterior = \frac{Likelihood \times Prior}{Evidence}$$

BAYES THEOREM

- Bayes theorem is the cornerstone of Bayesian learning methods because it provides a way to calculate the posterior probability **P(h|D), from**
- **the prior** probability **P(h),**
- **Probability over the data set P(D) and**
- **Current probability P(D(h)**

$$P(h|D) = \frac{P(D|h)p(h)}{P(D)}$$

Maximum A Posteriori (MAP)

- **Goal:** To find the most probable hypothesis h from a set of candidate hypotheses H given the observed data D.
- ***MAP Hypothesis, h_{MAP}***

$$h_{map} = \arg\max_{h \in H} (P(h \mid D))$$

$$= \arg\max_{h \in H} \left(\frac{P(D \mid h) P(h)}{P(D)} \right)$$

$$= \arg\max_{h \in H} (P(D \mid h) P(h))$$

Probabilistic Classification

- Establishing a probabilistic model for classification
  - Discriminative model

$$\boxed{P(C \mid \mathbf{X}) \quad C = c_1, \cdots, c_L, \mathbf{X} = (X_1, \cdots, X_n)}$$

  - Generative model

$$\boxed{P(\mathbf{X} \mid C) \quad C = c_1, \cdots, c_L, \mathbf{X} = (X_1, \cdots, X_n)}$$

- MAP classification rule
  - MAP: Maximum A Posterior
  - Assign x to c^* if $P(C = c^* \mid \mathbf{X} = \mathbf{x}) > P(C = c \mid \mathbf{X} = \mathbf{x}) \quad c \neq c^*, \ c = c_1, \cdots, c_L$
- Generative classification with the MAP rule
  - Apply Bayesian rule to convert: $P(C \mid \mathbf{X}) = \dfrac{P(\mathbf{X} \mid C) P(C)}{P(\mathbf{X})} \propto P(\mathbf{X} \mid C) P(C)$

NAIVE BAYES CLASSIFIER – Example -1

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

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

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

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

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

NAIVE BAYES CLASSIFIER

Example - 1

Day	*Outlook*	*Temperature*	*Humidity*	*Wind*	*PlayTennis*
D1	Sunny	Hot	High	Weak	No
D2	Sunny	Hot	High	Strong	No
D3	Overcast	Hot	High	Weak	Yes
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D5	Rain	Cool	Normal	Weak	Yes
D6	Rain	Cool	Normal	Strong	No
D7	Overcast	Cool	Normal	Strong	Yes
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D14	Rain	Mild	High	Strong	No

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

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

NAIVE BAYES CLASSIFIER

Example - 1

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

NAIVE BAYES CLASSIFIER – Example -1

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

$$v_{NB} = \underset{v_j \in \{yes,no\}}{\operatorname{argmax}} P(v_j) \prod_i P(a_i|v_j)$$

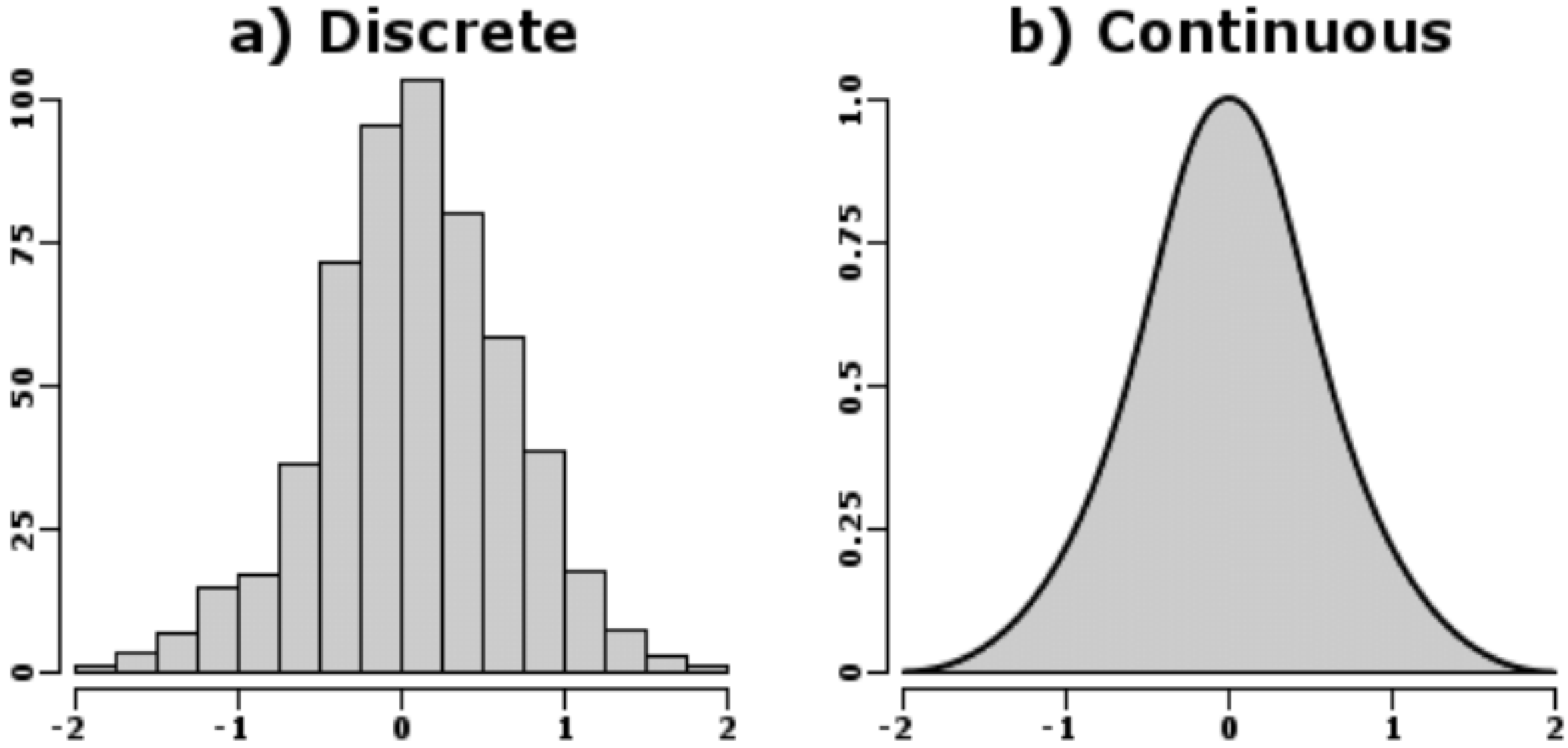
$$= \underset{v_j \in \{yes,no\}}{\operatorname{argmax}} P(v_j) \quad P(Outlook = sunny|v_j) P(Temperature = cool|v_j)$$

$$\cdot P(Humidity = high|v_j) P(Wind = strong|v_j)$$

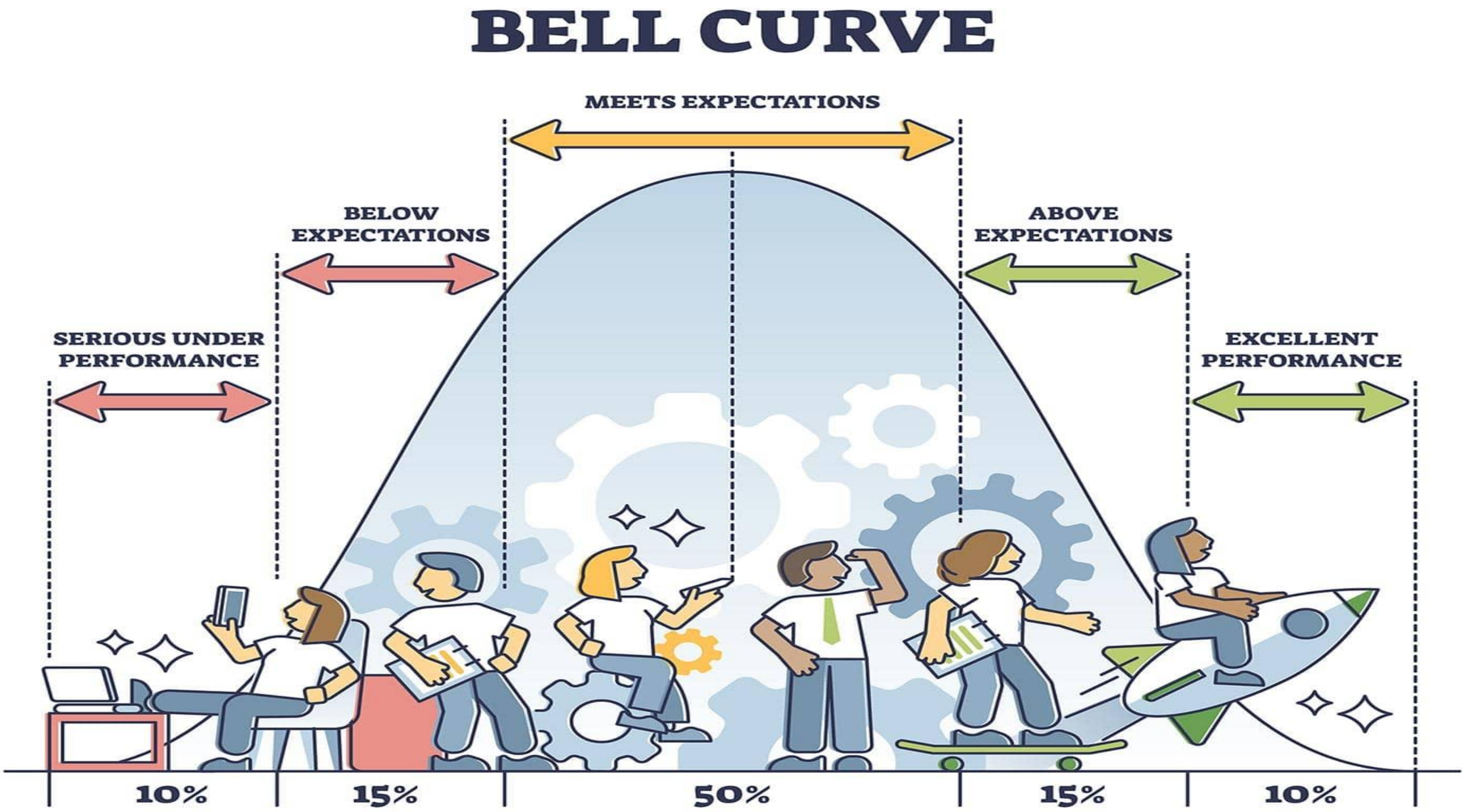
$$v_{NB}(yes) = P(yes)\ P(sunny|yes)\ P(cool|yes)\ P(high|yes)\ P(strong|yes) = .0053$$

$$v_{NB}(no) = P(no)\ P(sunny|no)\ P(cool|no)\ P(high|no)\ P(strong|no) = .0206$$

$$v_{NB}(yes) = \frac{v_{NB}(yes)}{v_{NB}(yes) + v_{NB}(no)} = 0.205 \qquad v_{NB}(no) = \frac{v_{NB}(no)}{v_{NB}(yes) + v_{NB}(no)} = 0.795$$



Discrete Vs Continuous


BELL CURVE
MEETS EXPECTATIONS
BELOW EXPECTATIONS
ABOVE EXPECTATIONS
SERIOUS UNDER PERFORMANCE
EXCELLENT PERFORMANCE
10%
15%
50%
15%
10%