

Naive Bayes

Naive Bayes

What Is Bayes Therom About?

- $P(A | B)$ → Probability of A happening given B is true.
- $P(B | A)$ → Probability of B happening given A is true.
- $P(A)$ → Prior probability of A happening.
- $P(B)$ → Total probability of B happening.

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

Example: Diagnosing a Disease:

- $P(\text{Disease} | \text{Symptom})$ → Probability of having a disease given the symptom.
- $P(\text{Symptom} | \text{Disease})$ → Probability of the symptom if the person has the disease.

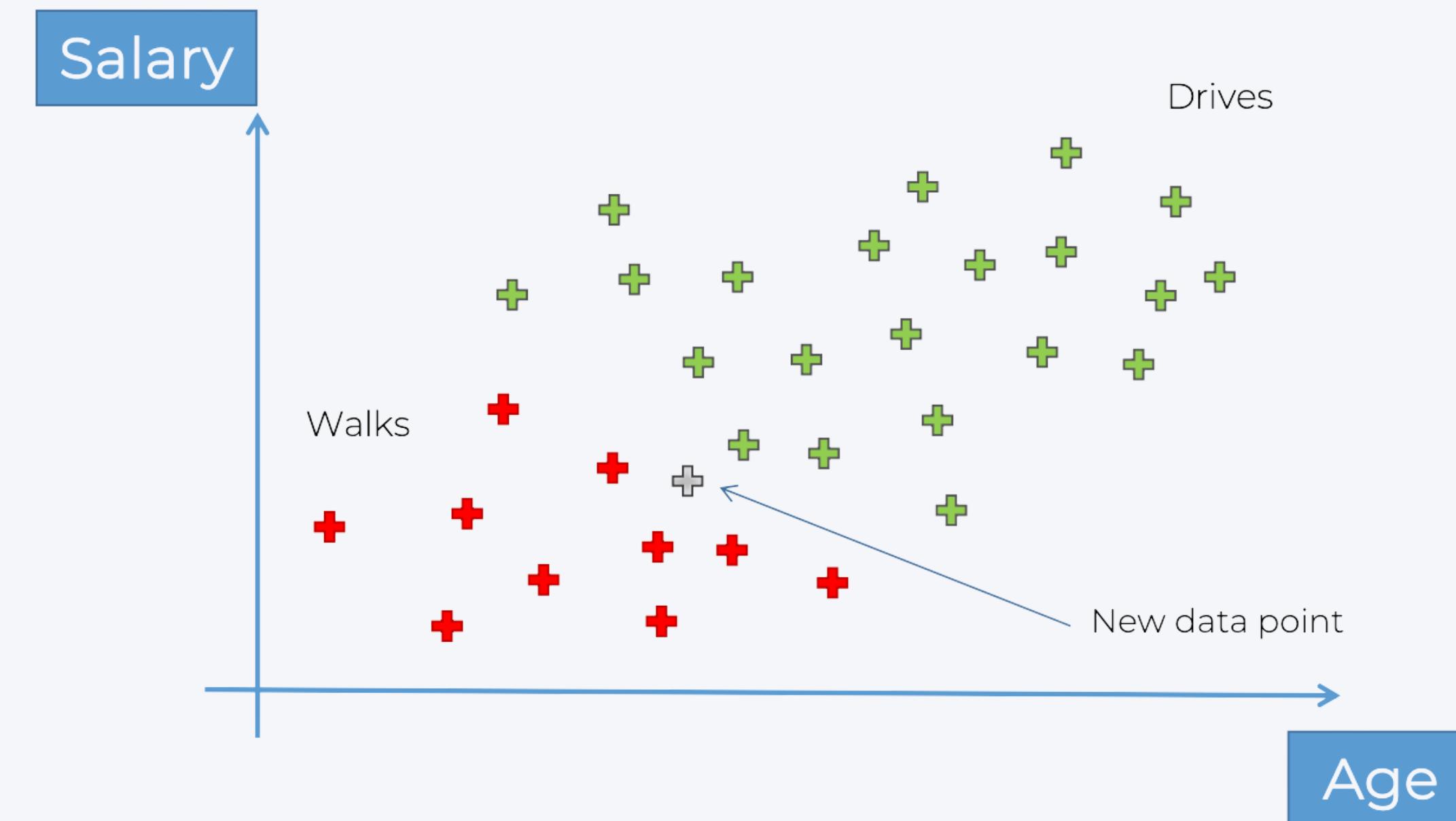
Why is Bayes' Theorem Important?

- Updates beliefs as new evidence comes in.
- Forms the foundation of Naïve Bayes Classifier for making predictions.
- Used in spam filtering, medical diagnosis, and machine learning.

Naive Bayes

How does it work ?

When a new data point is introduced, we need to classify whether this new individual is more likely to walk or drive based on given data.



Naive Bayes

Step #1

$$P(Walks|X) = \frac{P(X|Walks) * P(Walks)}{P(X)}$$

The diagram illustrates the components of the Naive Bayes formula:

- #4 Posterior Probability: The final result, $P(Walks|X)$.
- #3 Likelihood: $P(X|Walks)$, the probability of observing X given that the person walks.
- #1 Prior Probability: $P(Walks)$, the initial belief about the probability of walking.
- #2 Marginal Likelihood: $P(X)$, the overall probability of observing a data point like X.

```
graph TD; 4["#4 Posterior Probability"] --> PWalksX; 3["#3 Likelihood"] --> PXWalks; 1["#1 Prior Probability"] --> PWalks; 2["#2 Marginal Likelihood"] --> PX;
```

- Prior Probability $P(Walks)$: Initial belief about the probability of walking.
- Marginal Likelihood $P(X)$: The overall probability of observing a data point like X.
- Likelihood $P(X | Walks)$: The probability of observing XX given that the person walks.
- Posterior Probability $P(Walks | X)$: The final probability that the person belongs to the "Walks" category.

The probability of a person walking given their data point **P(Walks|X)** is computed using Bayes' Theorem.

Naive Bayes

Step #2

#4 Posterior Probability

#3 Likelihood

#1 Prior Probability

#2 Marginal Likelihood

$$P(\text{Drives}|X) = \frac{P(X|\text{Drives}) * P(\text{Drives})}{P(X)}$$

Similarly, the probability of a person driving given their data point **P(Drives|X)** is computed using the same formula.

Naive Bayes

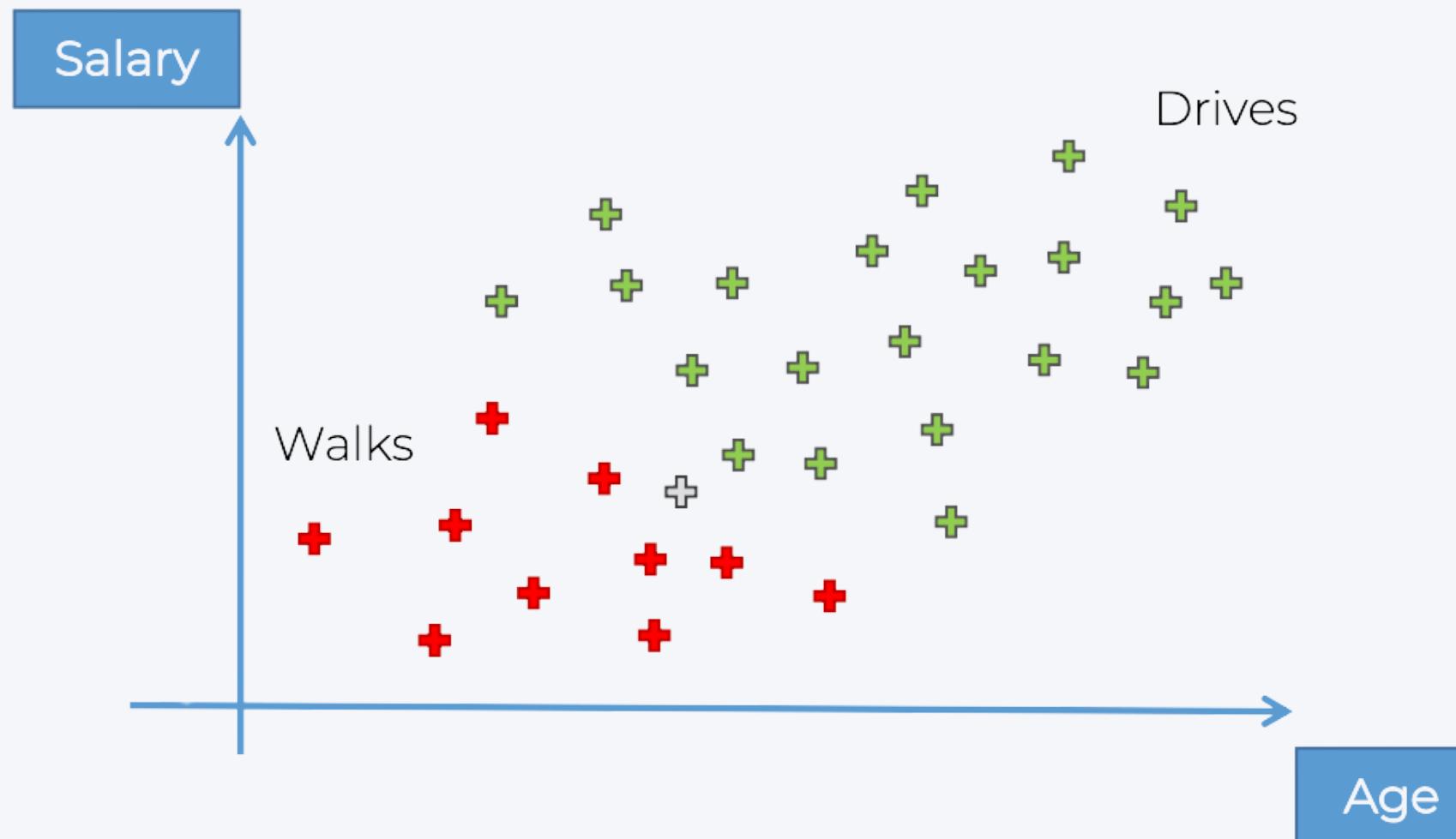
Step #3

$$P(\text{Walks} | X) \text{ v.s. } P(\text{Drives} | X)$$

- The classification decision is made by comparing **P(Walks | X) vs. P(Drives | X)**.
- The category with the higher probability is chosen.

Naive Bayes

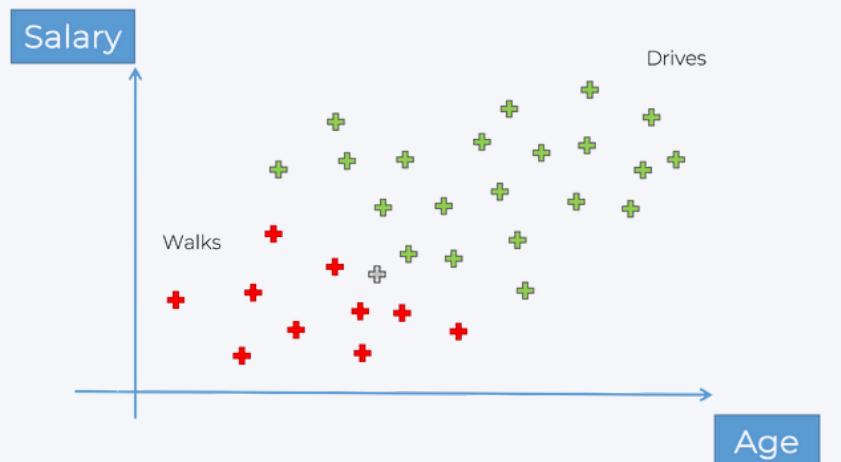
Naive bayes | In Action >> Step #1



#1. $P(\text{Walks})$

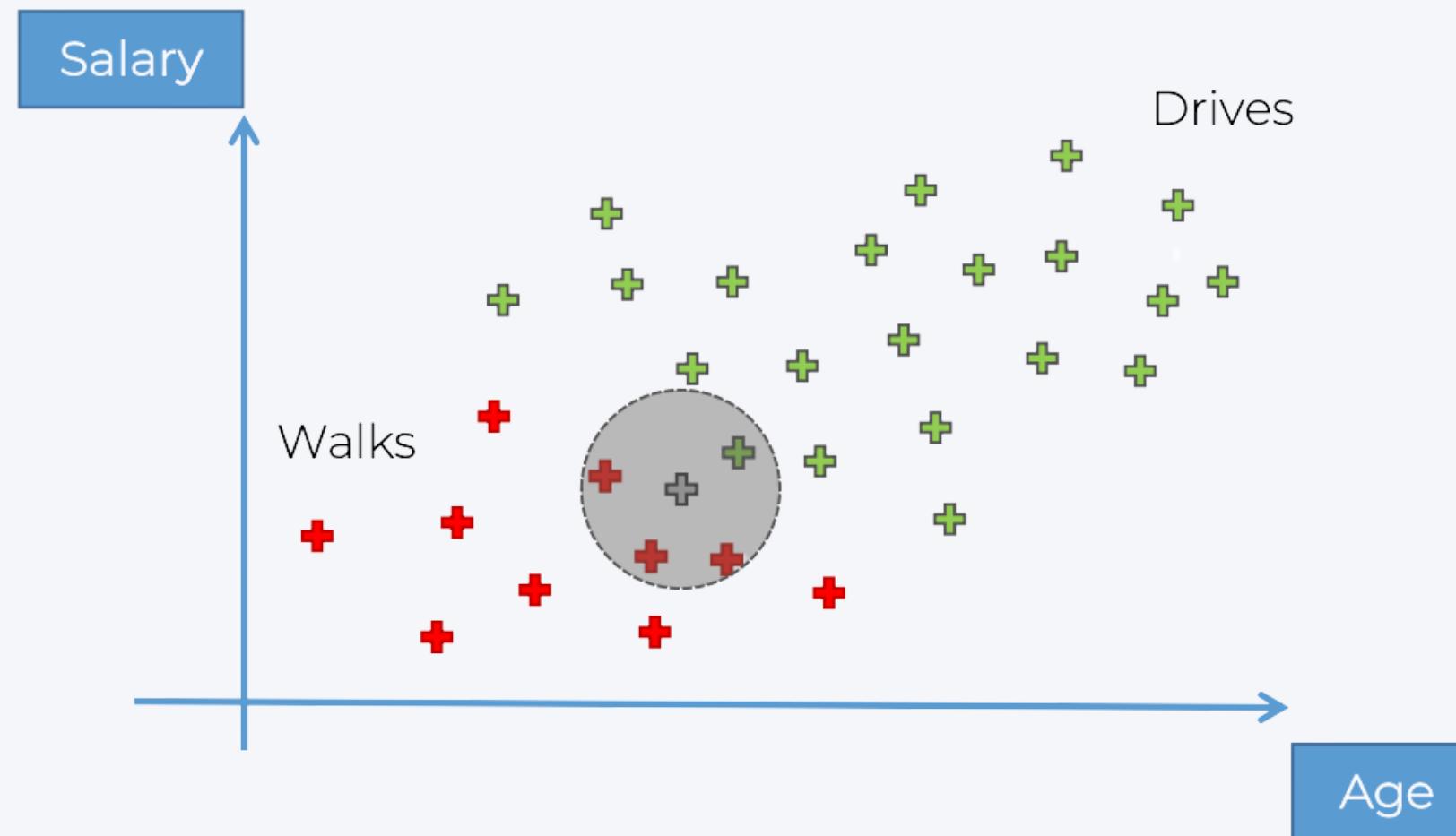
$$P(\text{Walks}) = \frac{\text{Number of Walkers}}{\text{Total Observations}}$$

$$P(\text{Walks}) = \frac{10}{30}$$



Naive Bayes

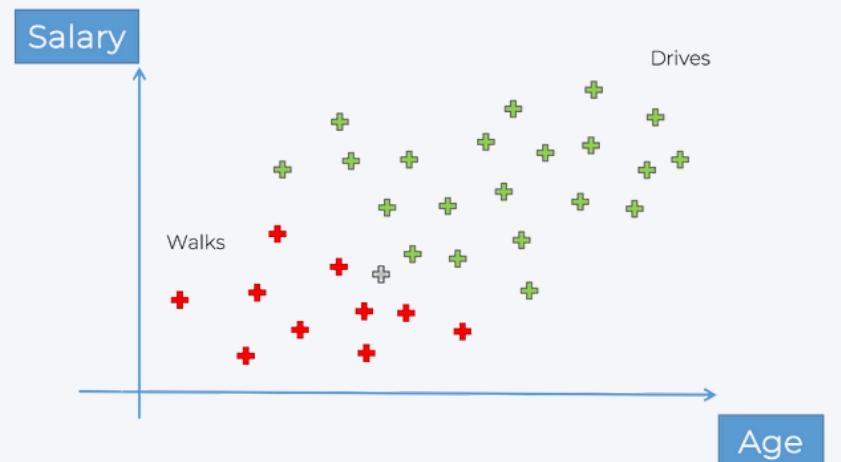
Naive bayes | In Action >> Step #1



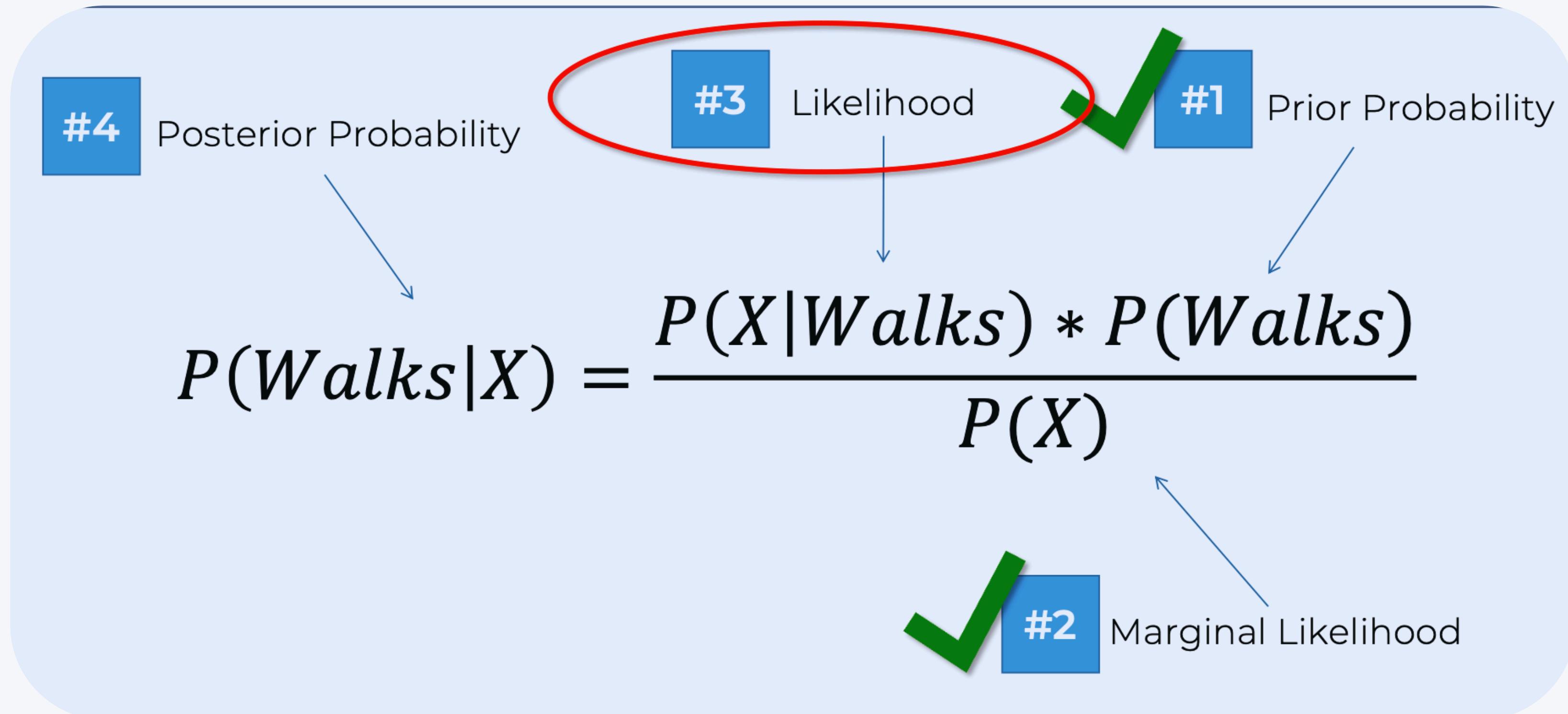
#2. $P(X)$

$$P(X) = \frac{\text{Number of Similar Observations}}{\text{Total Observations}}$$

$$P(X) = \frac{4}{30}$$

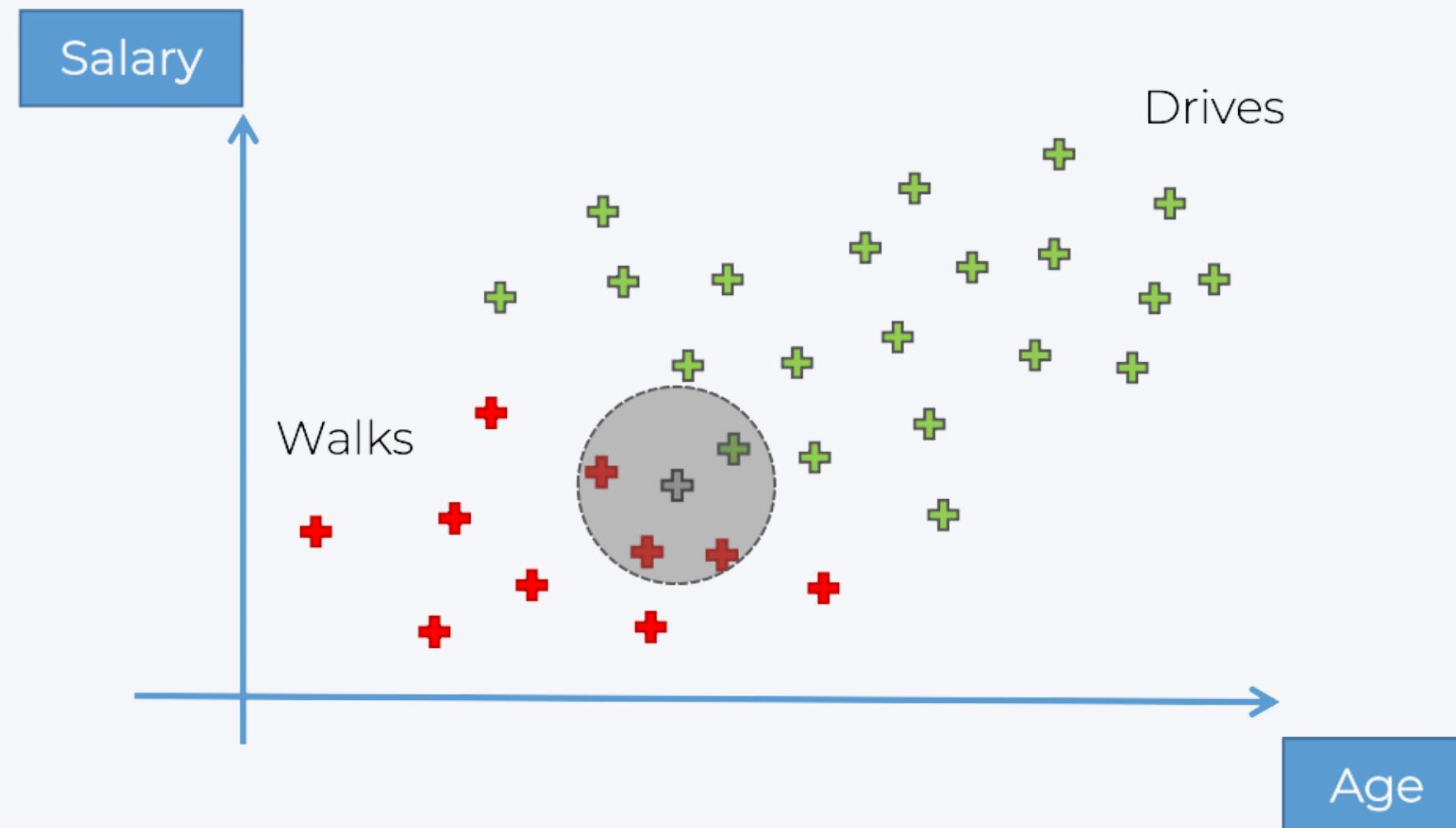


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#3. $P(X|Walks)$

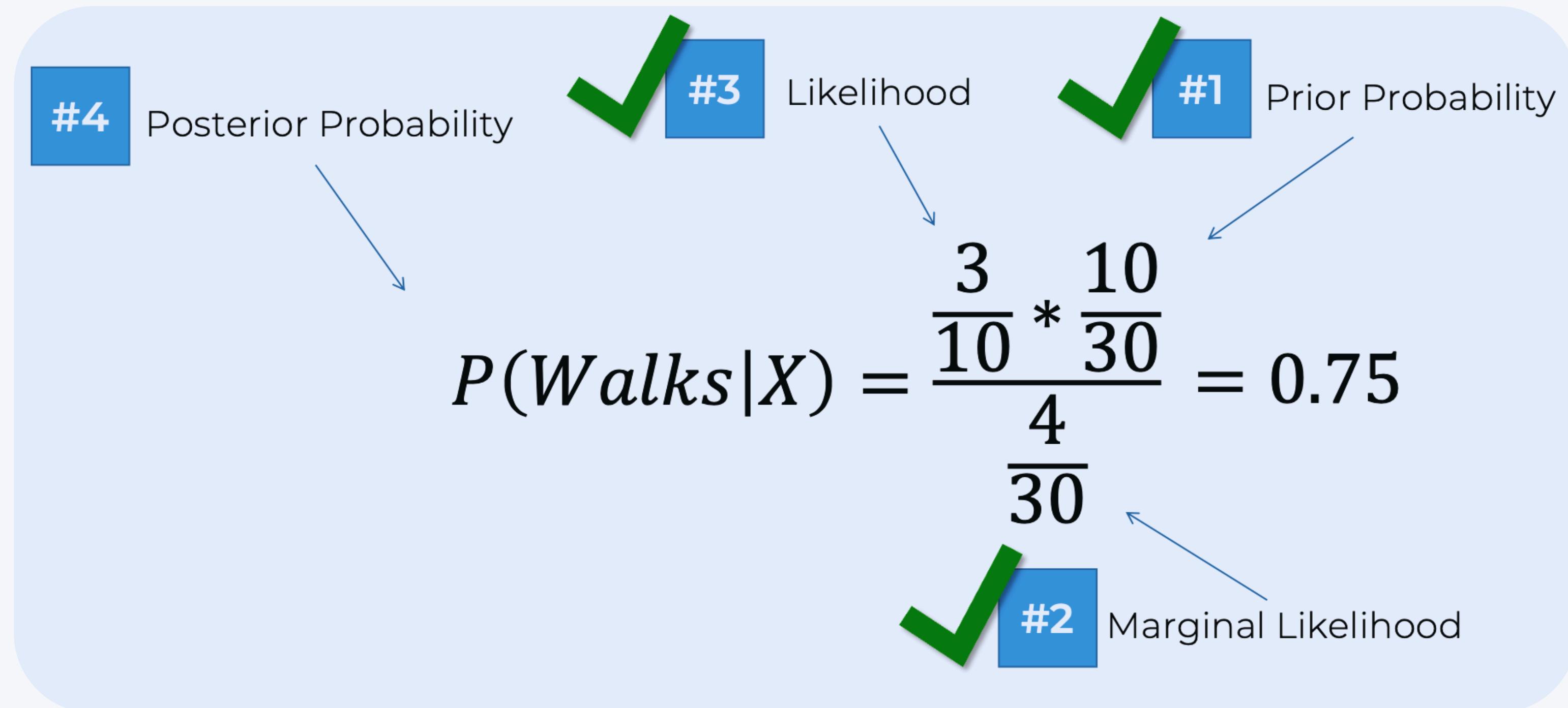
Number of Similar Observations Among those who Walk

$$P(X|Walks) = \frac{\text{Number of Similar Observations Among those who Walk}}{\text{Total number of Walkers}}$$

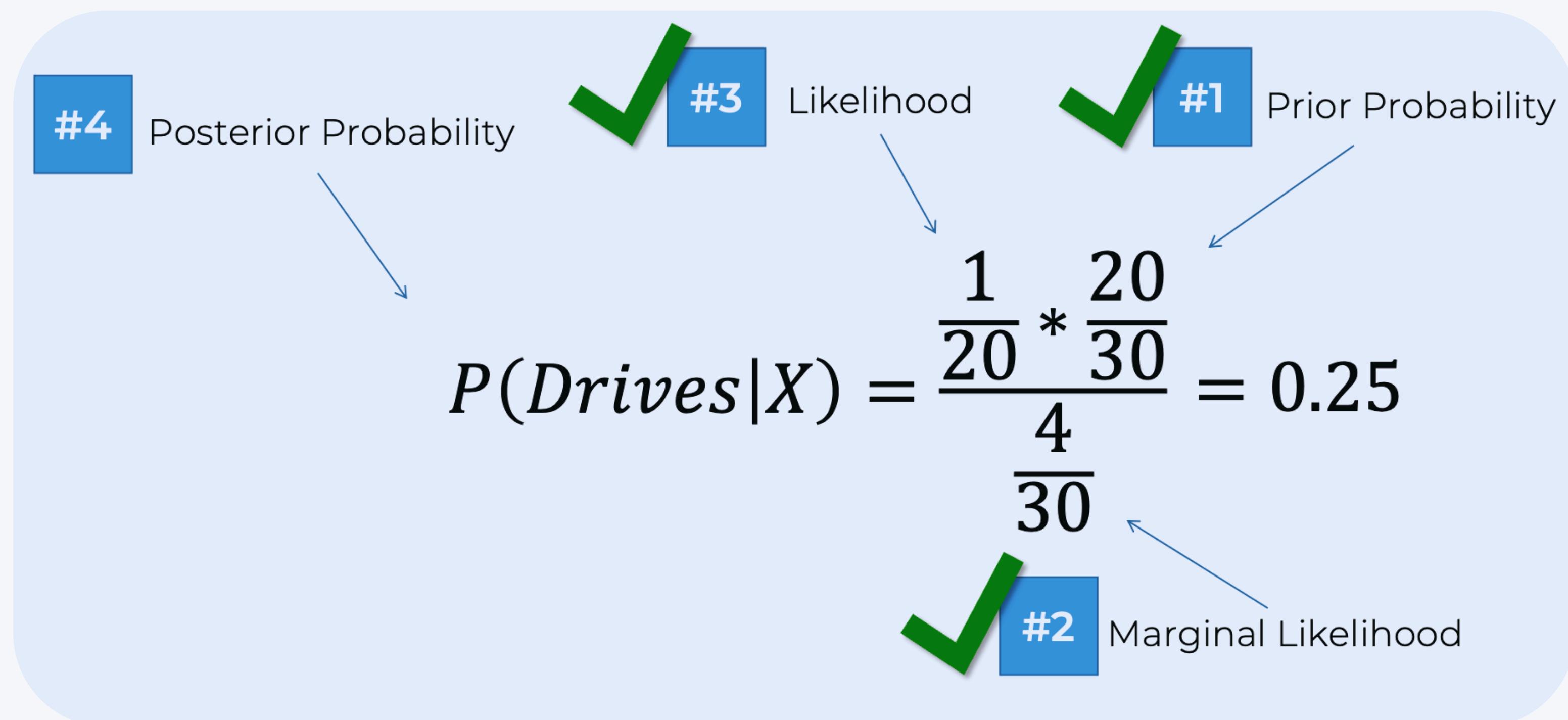
$$P(X|Walks) = \frac{3}{10}$$

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Naive bayes | In Action >> Step #1



Naive bayes | In Action >> Step #2



Naive Bayes

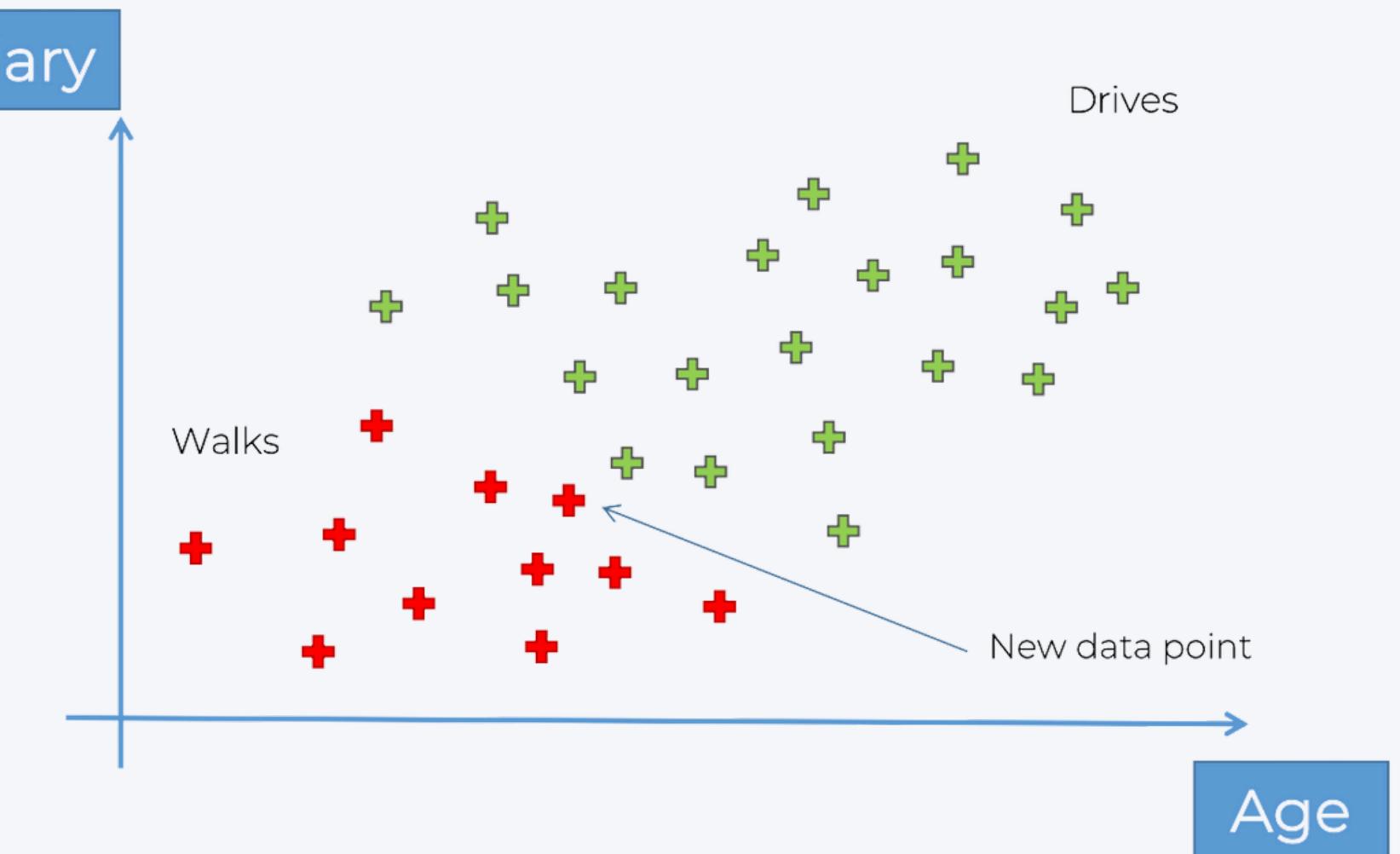
Naive bayes | In Action >> Step #2

$P(\text{Walks}|X)$ v.s. $P(\text{Drives}|X)$

0.75 v.s. 0.25

0.75 > 0.25

$P(\text{Walks}|X) > P(\text{Drives}|X)$



Why is it called "Naive"?

Because it assumes independence between features, meaning each feature contributes to the classification independently.

Why Can We Ignore $P(X)$?

- Since $P(X)$ is the same for all classes, it cancels out when comparing probabilities.

More than Two Classes?

- The method extends to multiple classes by computing the probability for each and picking the highest.

QUIZ

Naive Bayes



Hands-On Code

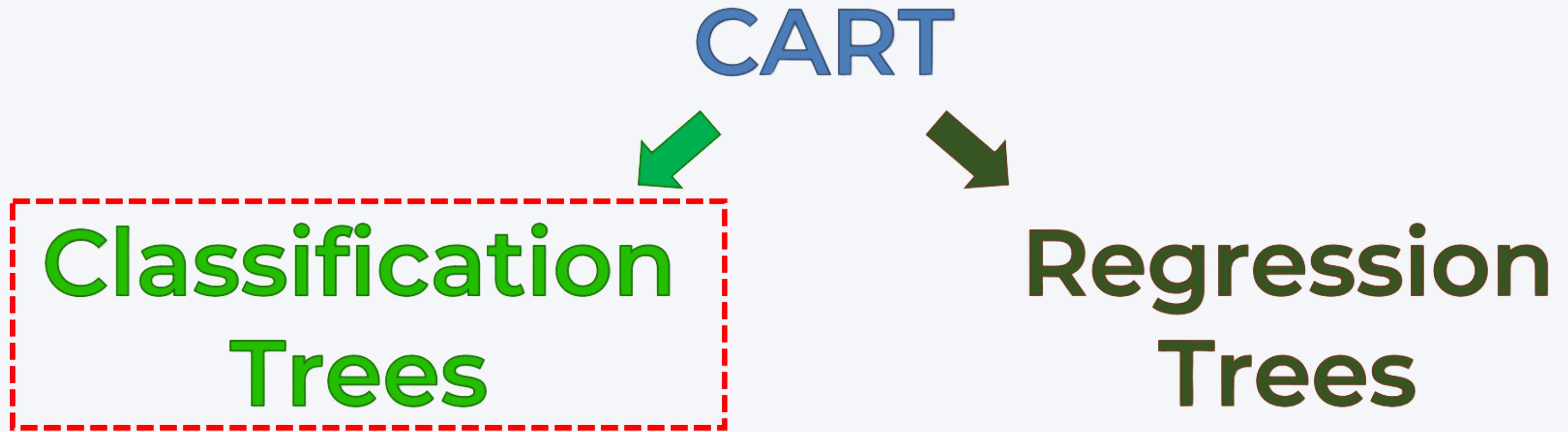
Naive Bayes



Decision Tree classification

Decision Tree Classification

CART



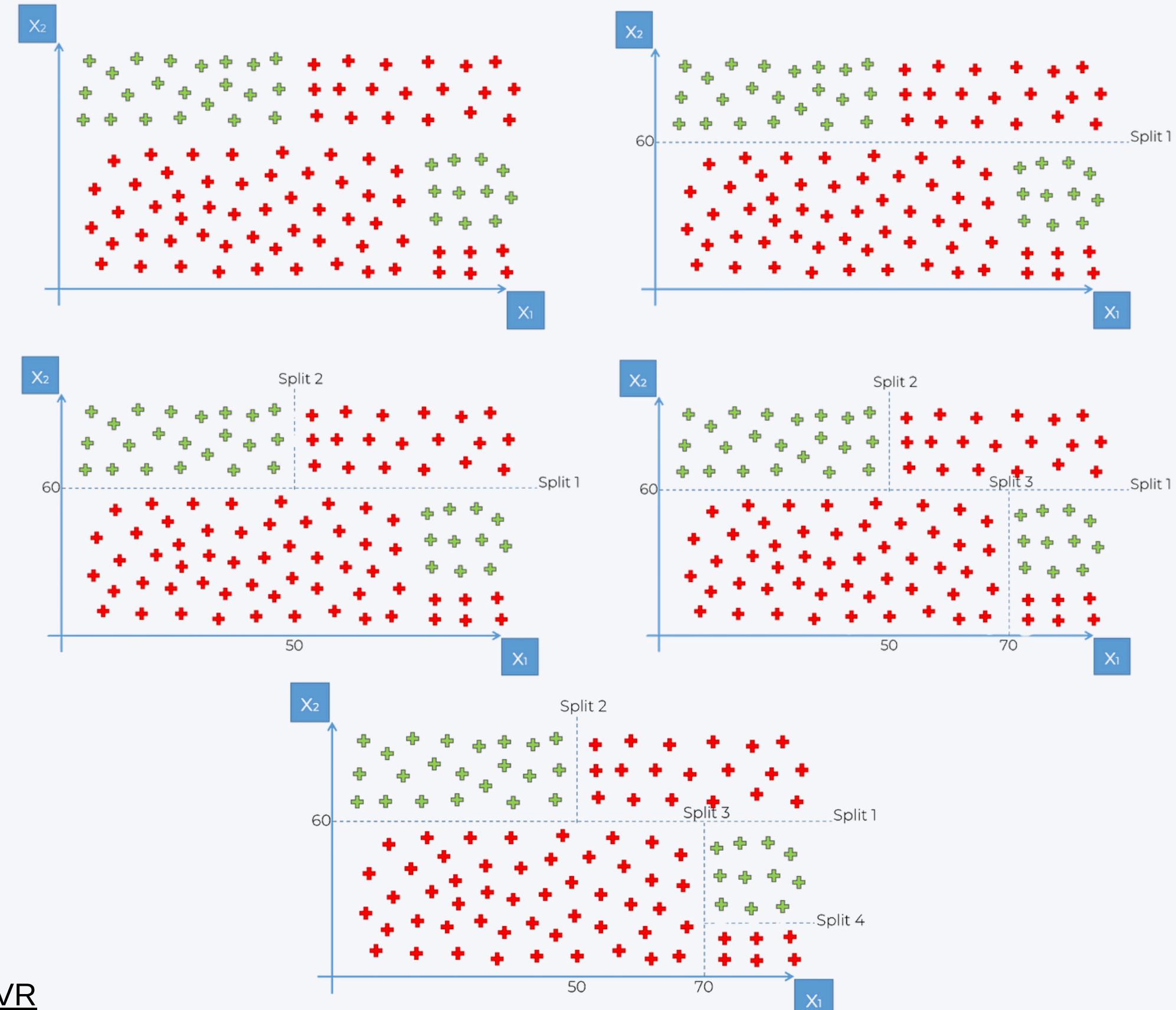
Difference Between Decision Tree Regression and Classification:

- **Decision Tree Regression:** Predicts a continuous numerical value based on input features. The tree is built using splits that minimize variance within groups.
- **Decision Tree Classification:** Assigns an input to a specific category (class) by recursively splitting the data based on features that best separate different classes.

Decision Tree Classification

Explanation of Decision Tree Classification:

- The images illustrate how a decision tree classifier works by recursively splitting the data into smaller regions.
- Each split is made based on a feature that best separates the classes (red and green points).
- The first split (Split 1) separates based on $X_2 > 60$, dividing the data into two main groups.
- The second split (Split 2) further divides one of these groups based on $X_1 < 50$.
- Additional splits (Split 3, Split 4) continue until pure or nearly pure regions are formed.



Decision Tree Classification

Explanation of Decision Tree Classification:

The tree chooses splits based on feature values that maximize class separation. This is done using:

- **Gini Impurity (default in CART trees):**

- Measures how mixed a group is.
- A lower Gini value means a purer split.

$$Gini = 1 - \sum P(i)^2$$

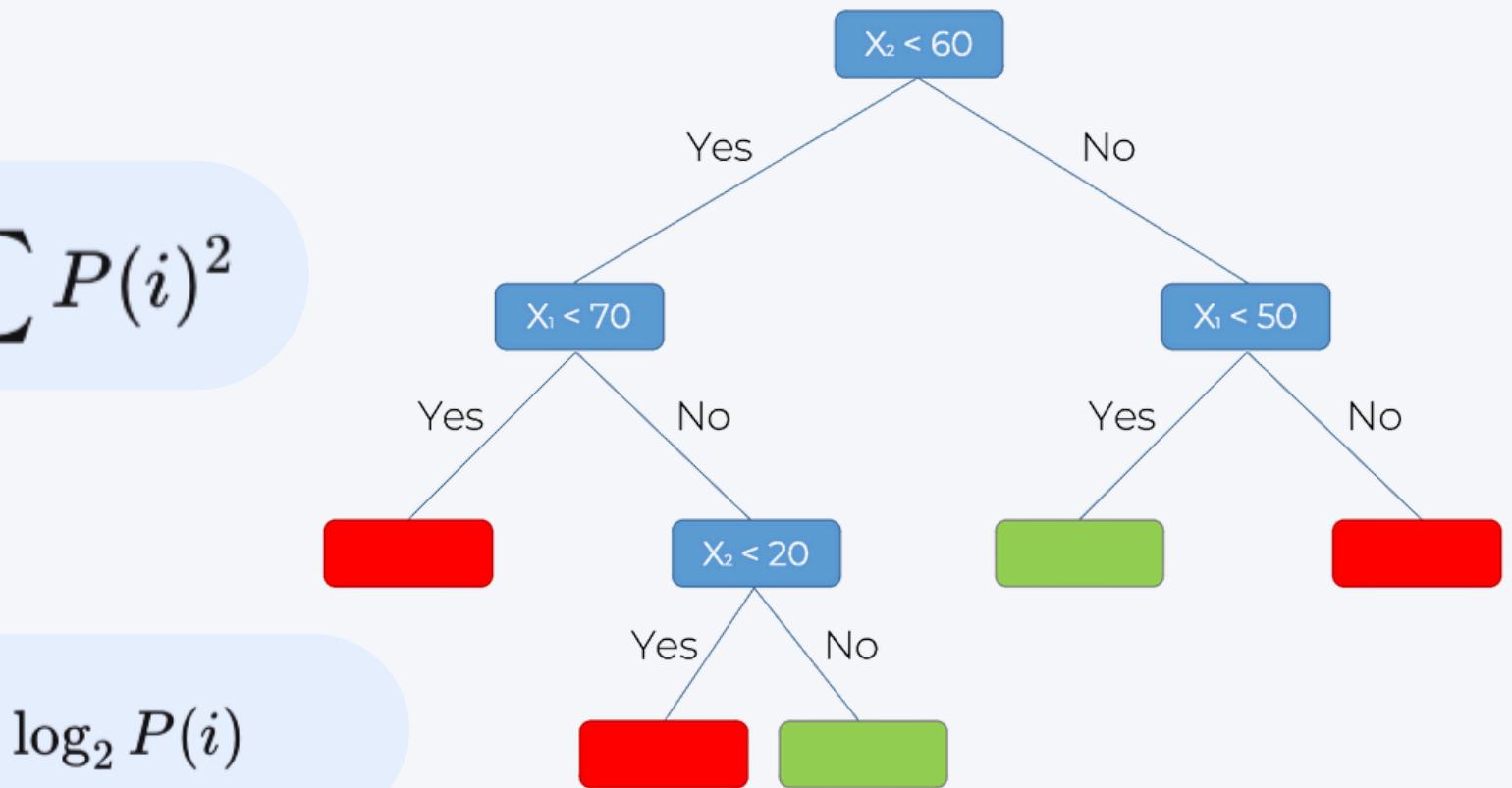
- **Entropy & Information Gain**

- Entropy measures uncertainty in data:

$$Entropy = - \sum P(i) \log_2 P(i)$$

- **Information Gain calculates how much uncertainty is reduced by a split:**

- The split that maximizes Information Gain is chosen.



$$IG = Entropy_{parent} - \sum \left(\frac{|Subset|}{|Parent|} \times Entropy_{subset} \right)$$

Hands-On Code

Decision Tree Classification

Random Forest classification

How does Random Forest do Classification?

Ensemble Learning

- **STEP 1:** Pick at random **K** data points from the Training set.
- **STEP 2:** Build the Decision Tree associated to these **K** data points.
- **STEP 3:** Choose the number **Ntree** of trees you want to build and repeat STEPS 1 & 2
- **STEP 4:** For a new data point, make each one of your **Ntree** trees predict the category to which the data point belongs, and assign the new data point to the category that wins the majority vote.

Hands-On Code

Random Forest Classification