Machine Learning I

Mohamed Hussien

Decision Trees & Random Forest

Lecture Overview

- Simple Decision Tree
- Mobile Apps Recommendation Example
- Split Using Accuracy
- Split Using Gini Impurity
- Split Using Entropy
- Tree Hyperparameters
- One-hot Encoded Features
- Continues Features
- Decision Tree For Regression
- Random Forest

Wear a jacket?

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You want to decide if you should wear a jacket today. What does the decision process look like?

- You may look outside and check if it’s raining. If it’s raining, then you definitely wear a jacket.
- If it’s not, then it could be that it’s hot outside, or cold. So then you check the temperature, and if it is hot, then you don’t wear a jacket, but if it is cold, then you wear a jacket.

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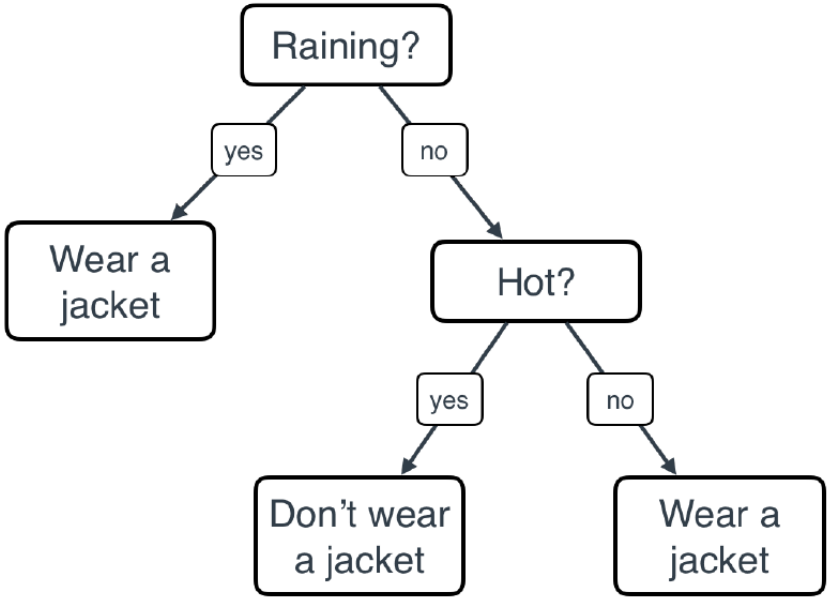
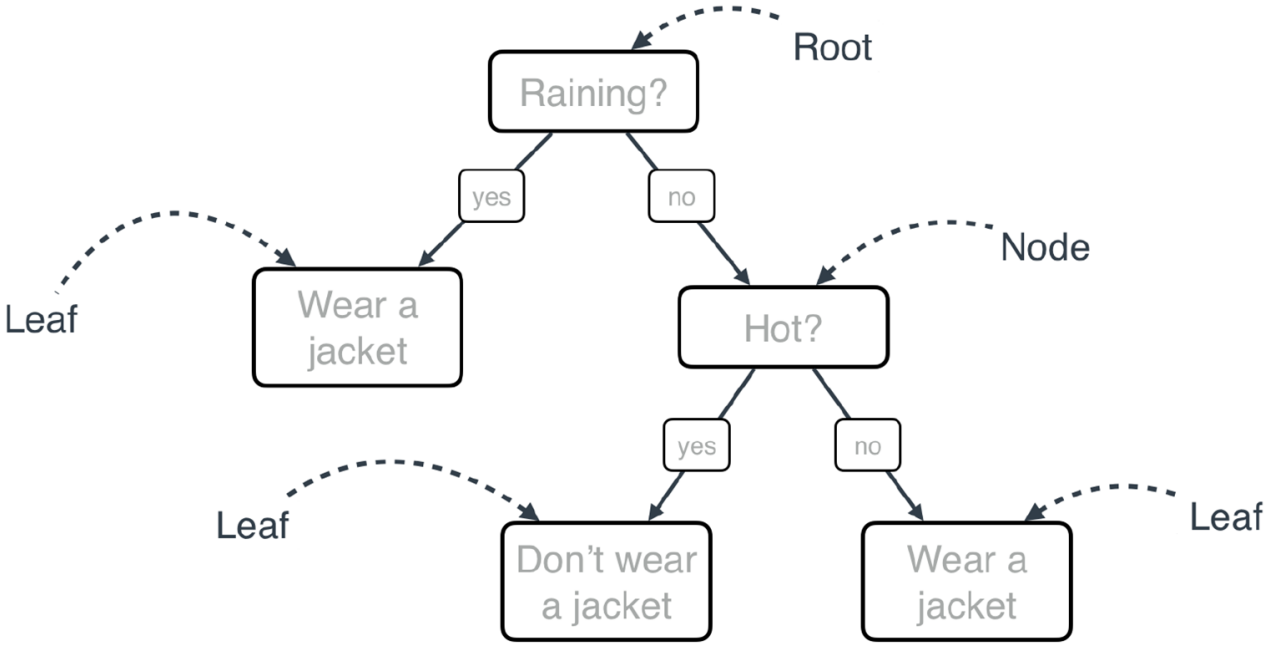


Simple Decision Tree



Simple Decision Tree

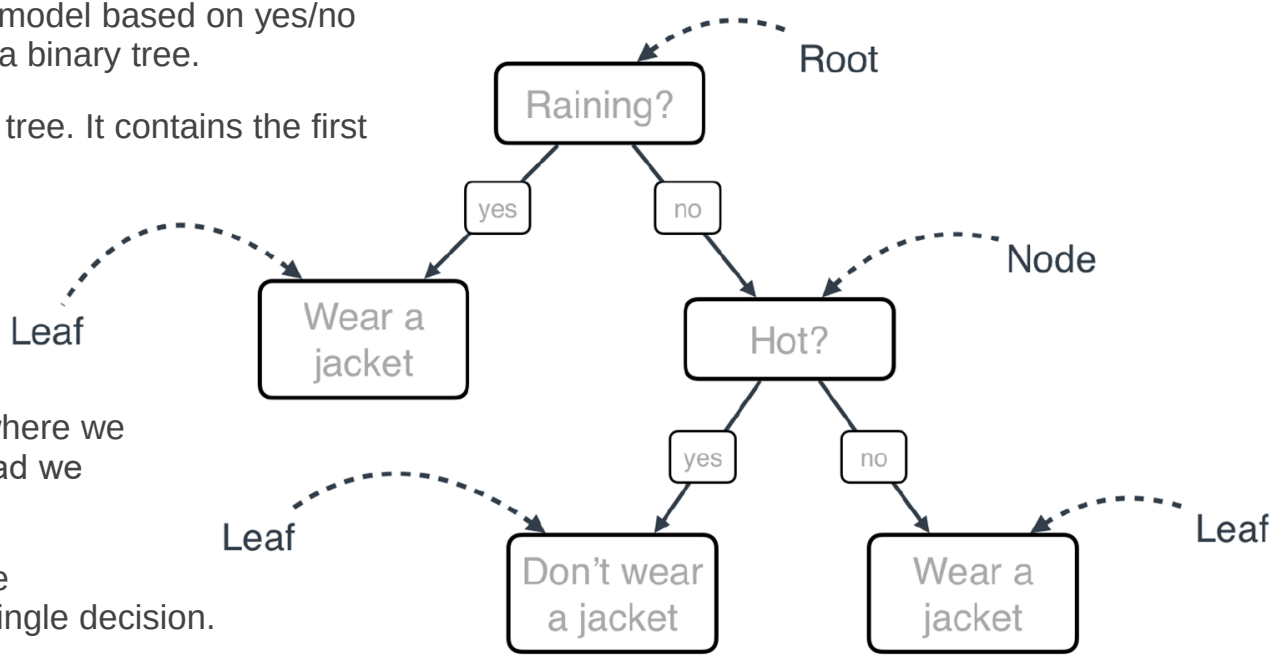
Decision tree A classification model based on yes/no questions and represented by a binary tree.

Root The topmost node of the tree. It contains the first yes/no question.

Node Each yes/no question is represented by a node, or decision stump, with two branches emanating from it.

Leaf When we reach a point where we don't ask a question and instead we make a decision

Stub A tree with only one node and 2 leaves. It represents a single decision.



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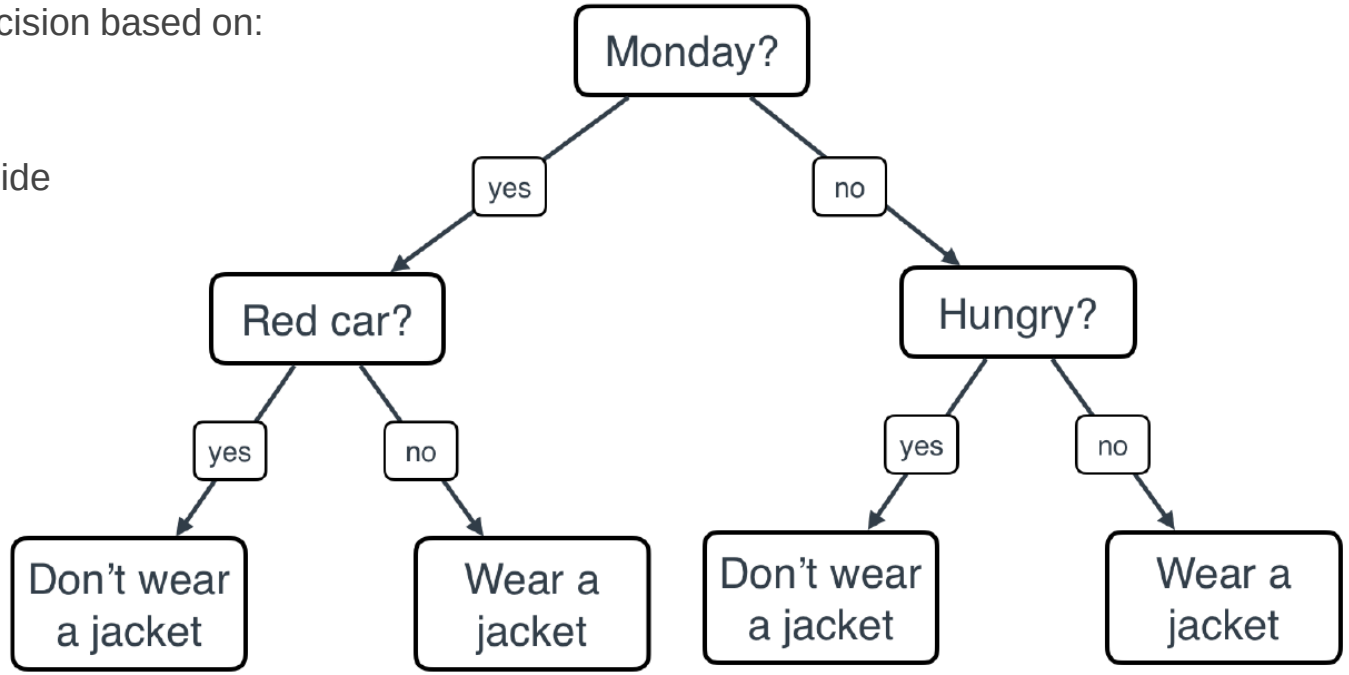

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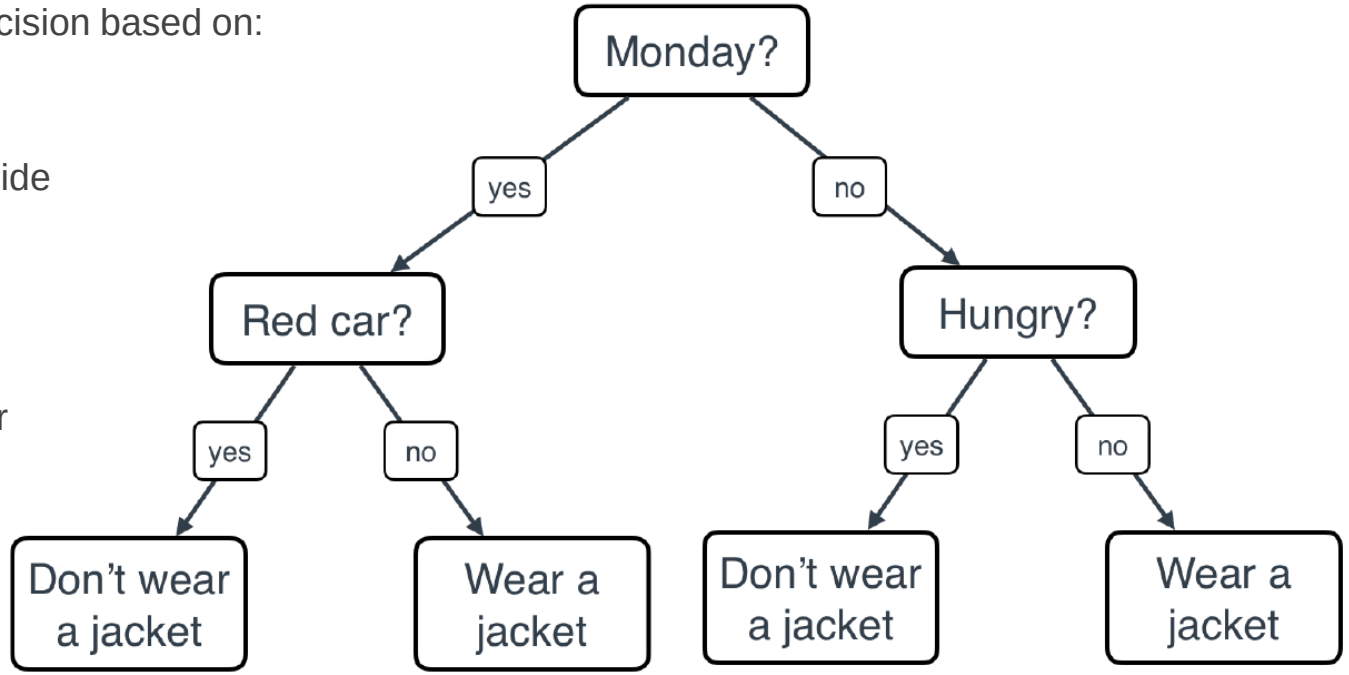
Which mode is better?
And how does computer know that?



Another Decision Tree

Picking our first question:

1. Is it raining?
2. Is it hot outside?
3. Am I hungry?
4. Is there a red car outside?
5. Is it Monday?

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Neglecting the last three questions, data says that wearing a jacket was true:
- 250 times based on raining or not
- 200 times based on hot or not

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Can we enhance this model?

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Let’s say we noticed that the right part of the tree is very accurate.
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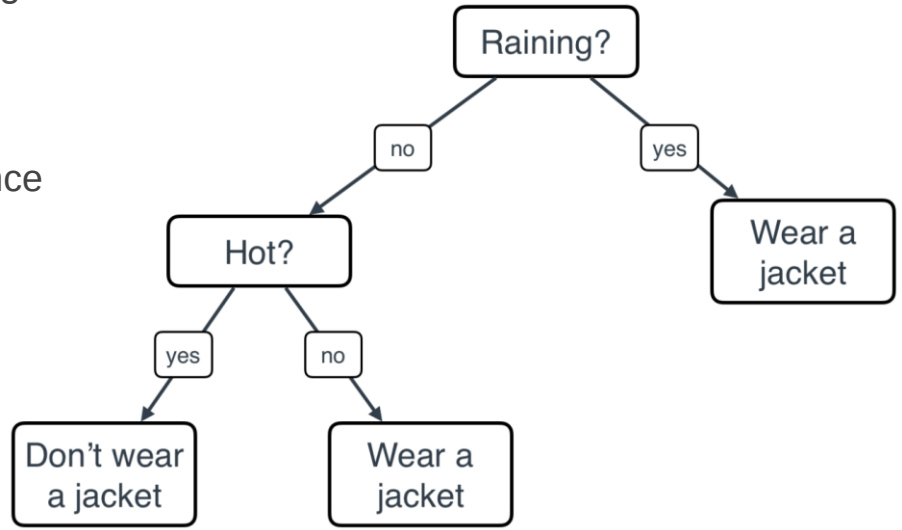

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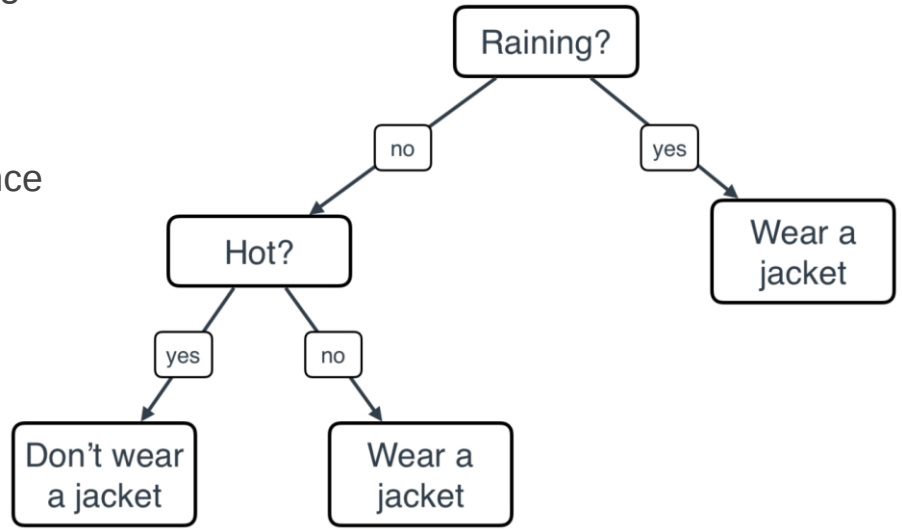

How we choose the best question each time?

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Mobile Apps Recommendation System Example

Gender	Age	App
F	15	Snapchat
F	25	SHEIN
M	32	Fantasy Premier League
F	35	SHEIN
M	12	Snapchat
M	14	Snapchat

Mobile Apps Recommendation System Example

Guess which app to recommend to these customers:

- A girl aged 13
- A woman aged 28
- A man aged 34

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How we know that?

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Mobile Apps Recommendation System Example

Which question would be better to start with?

Gender	Age	App
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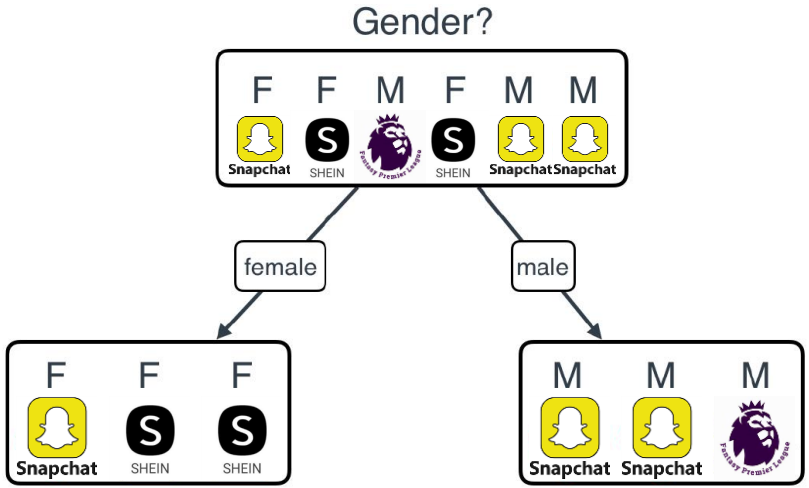

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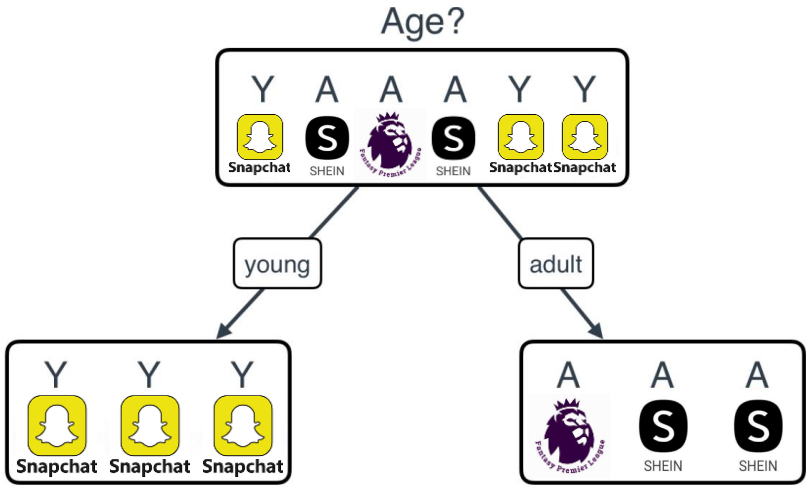

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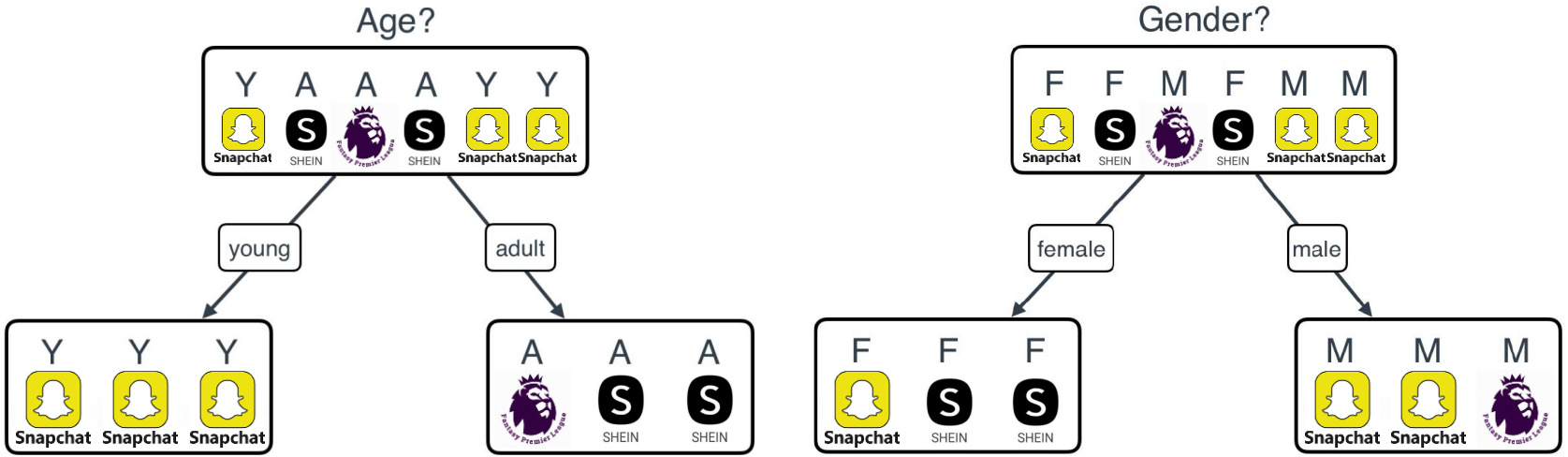

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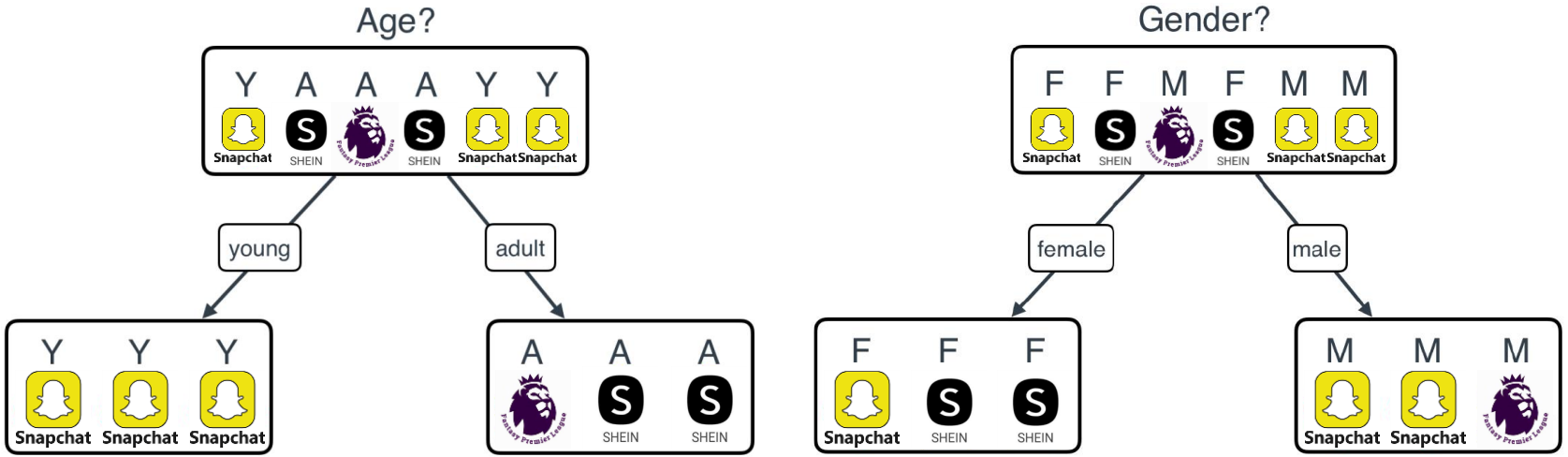

How does computer know that asking about age is better?

Mobile Apps Recommendation System Example

Using Accuracy:

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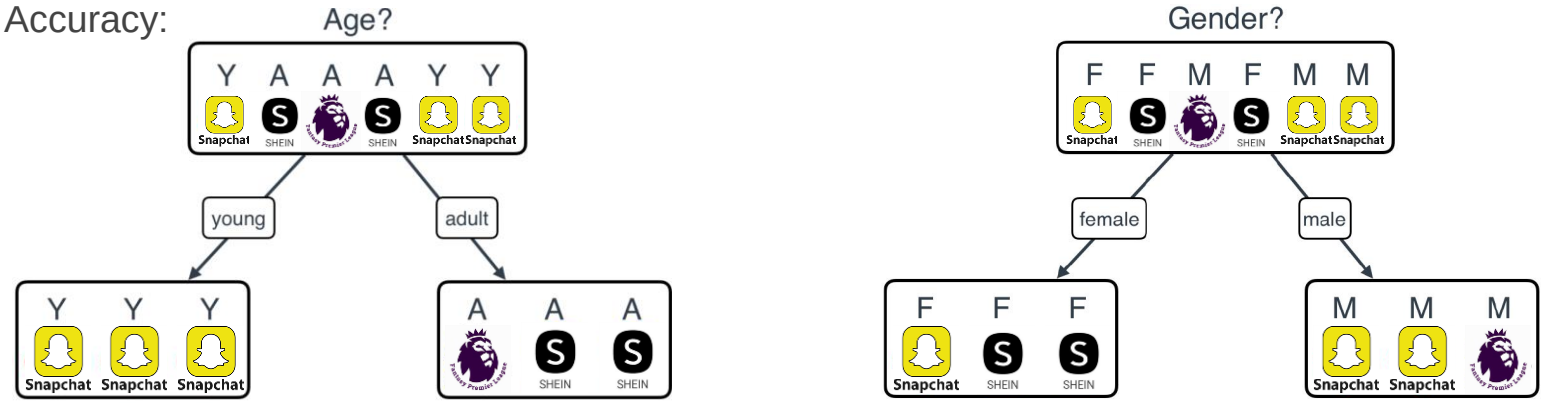

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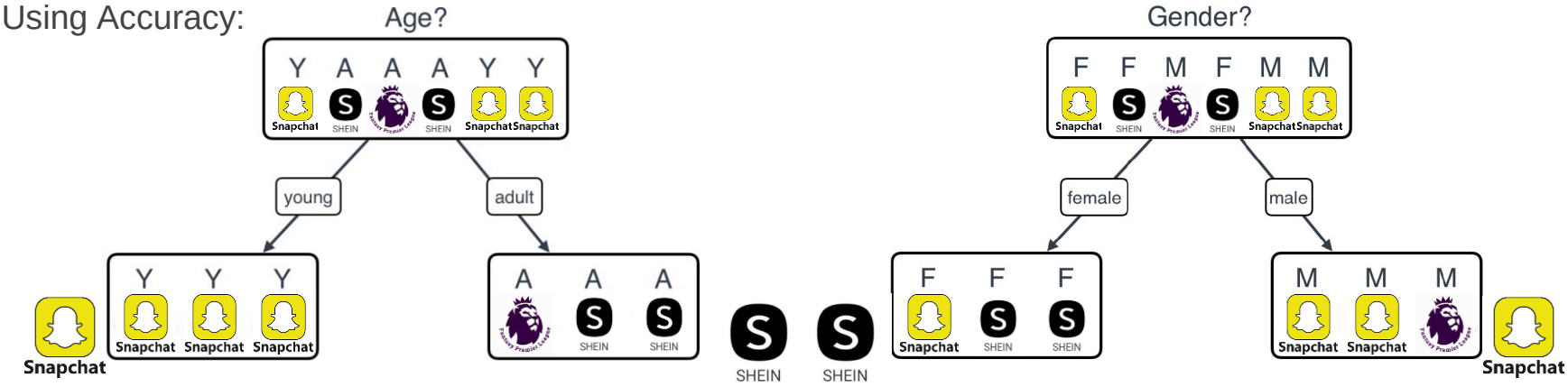

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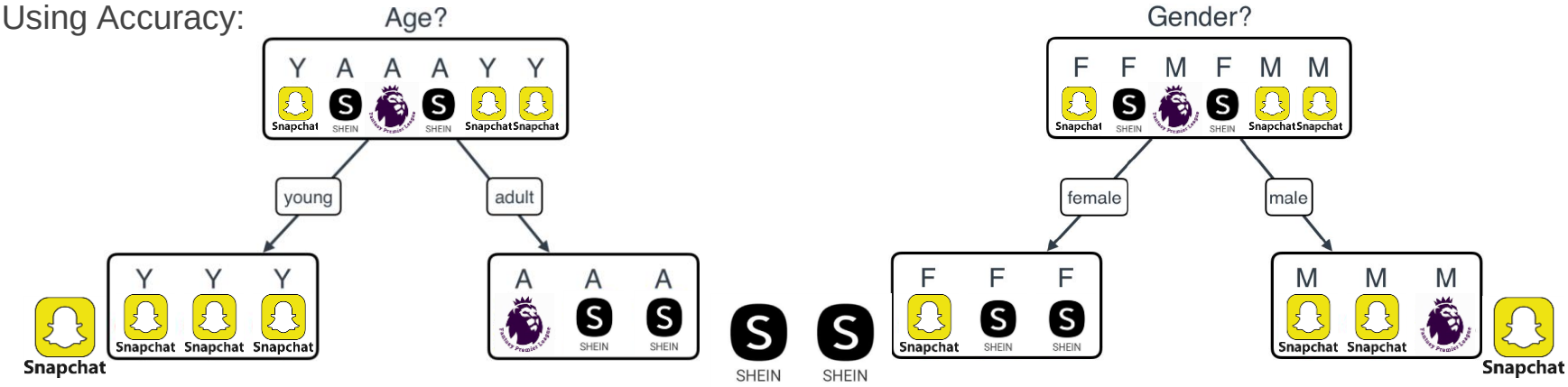

Correct 5 out of 6 times

Mobile Apps Recommendation System Example

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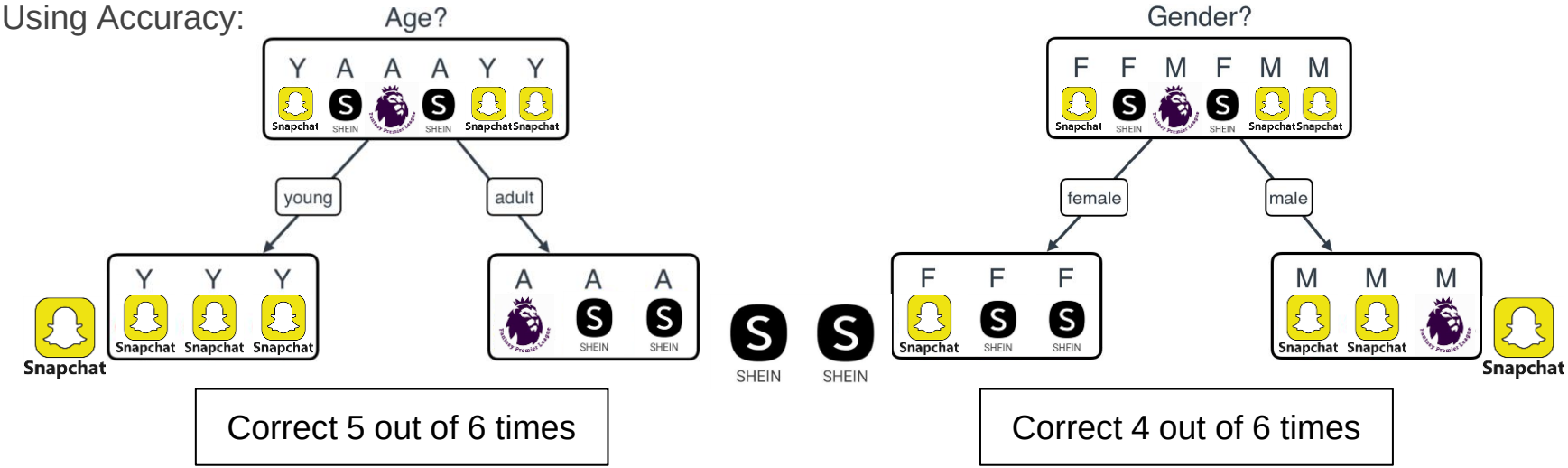

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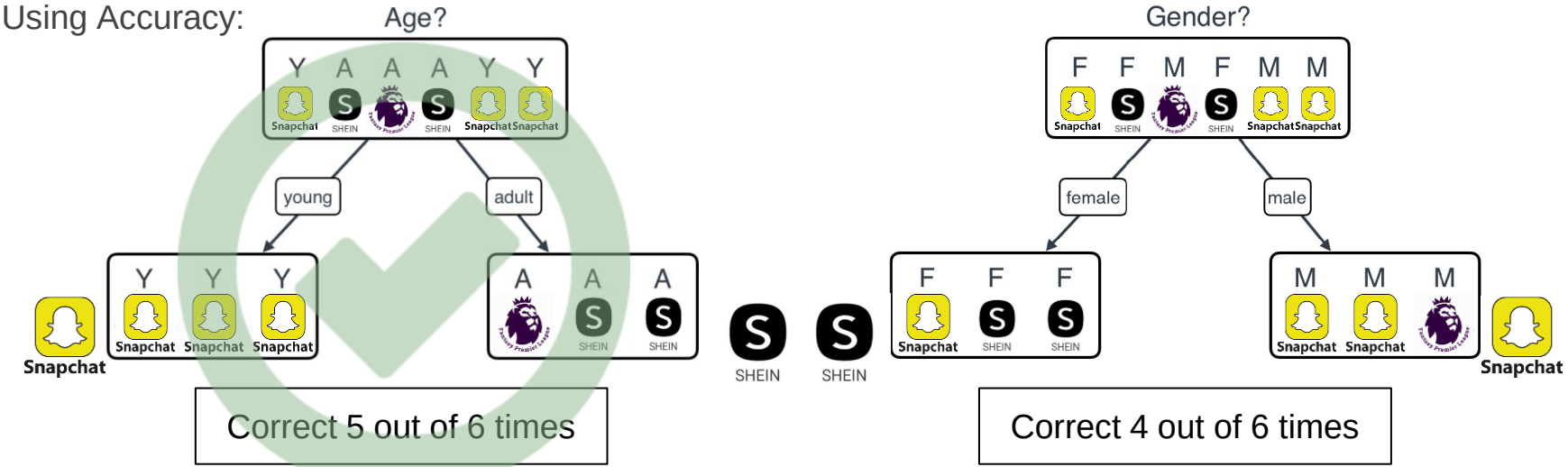

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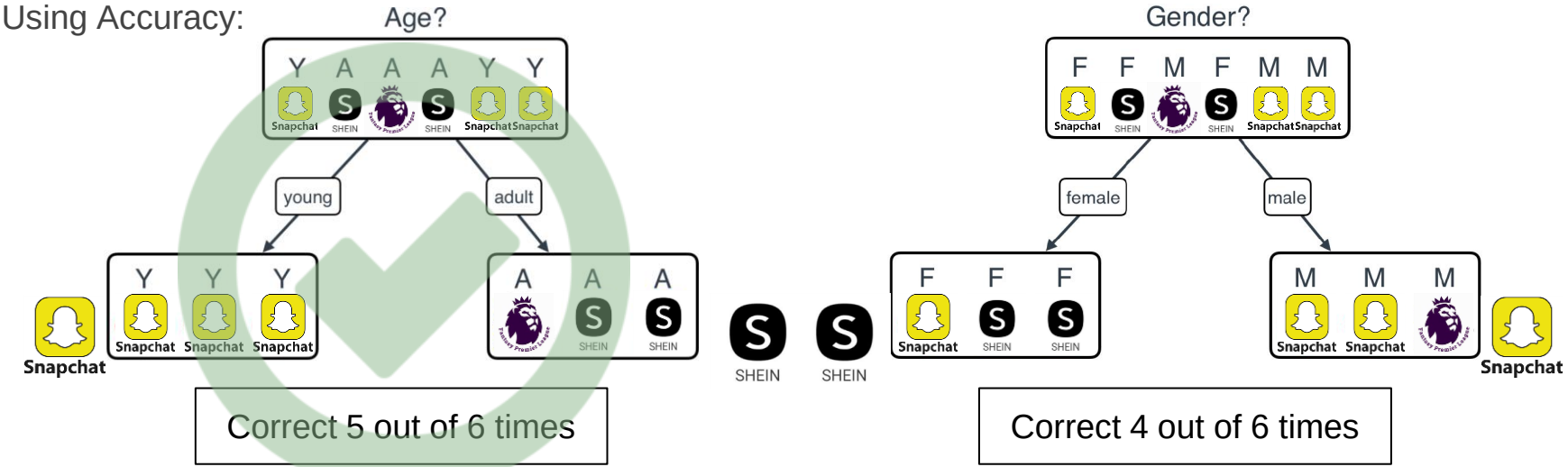

What are next steps?

Iterate by asking the best question every time

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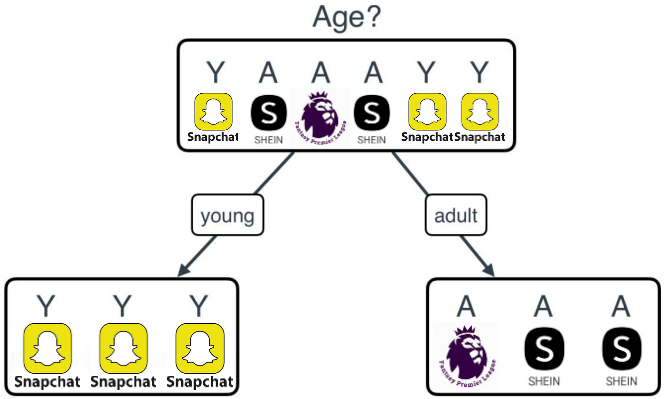

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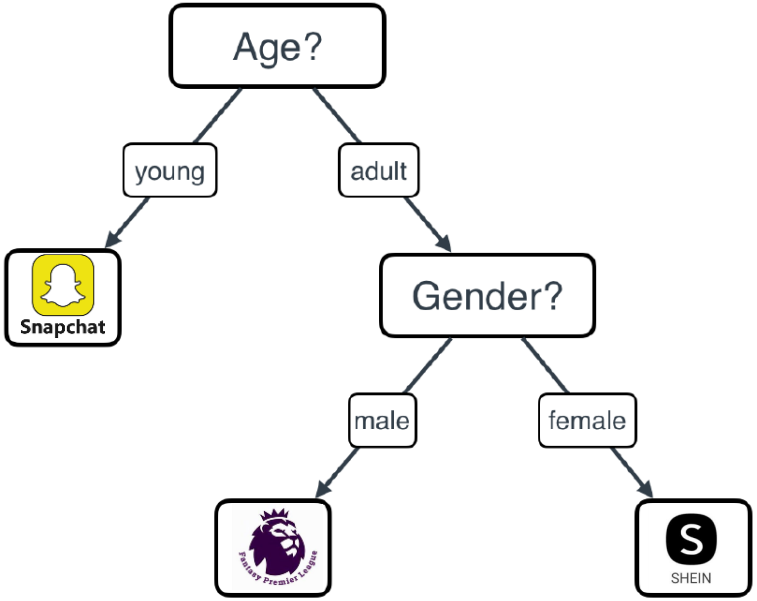

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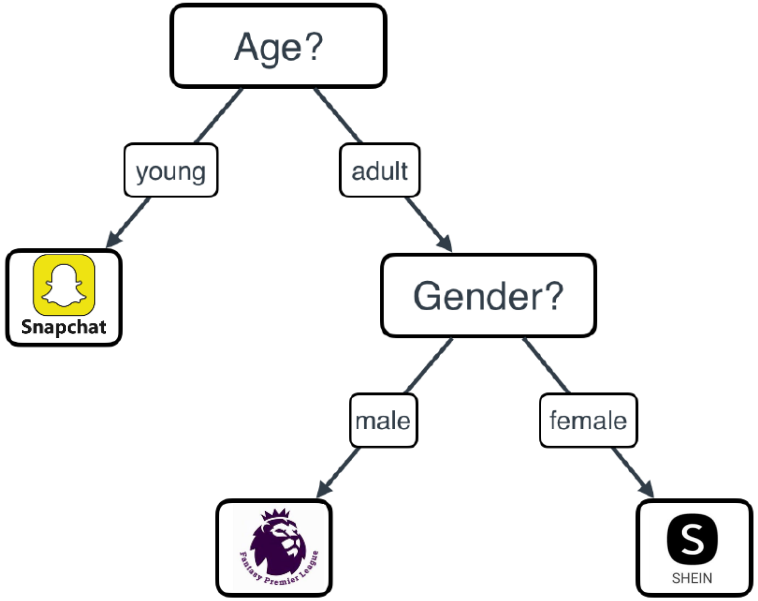

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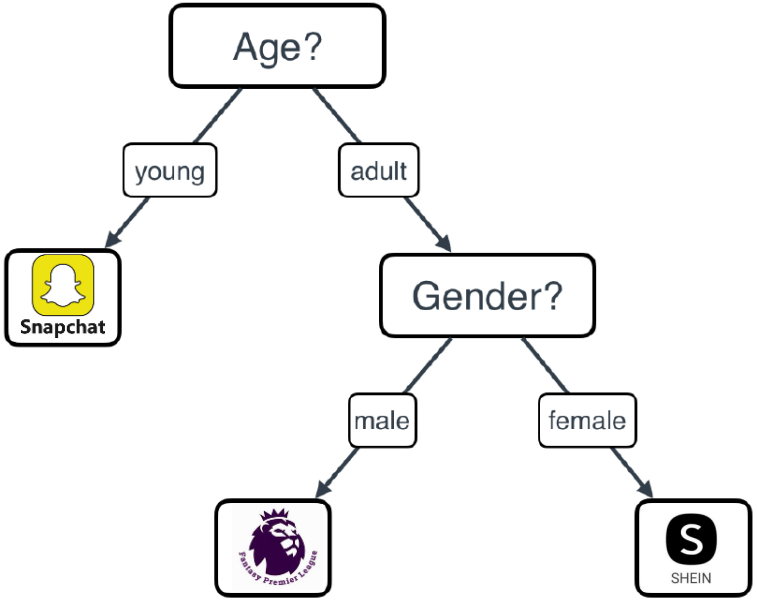

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Predict these examples: 1) A **girl** aged **13**

2) A **woman** aged **28**

3) A **man** aged **34**

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How to pick the right feature to split

Gender	Age	Location	App
Female	Young	A	1
Male	Young	A	1
Female	Young	A	1
Male	Adult	A	1
Female	Young	B	2
Male	Adult	B	2
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How to pick the right feature to split

We can use three methods:

1- Accuracy

2- Gini impurity

3- Entropy and information gain

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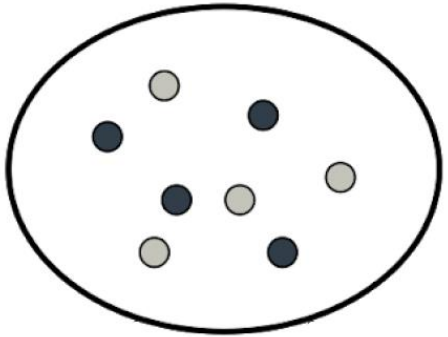

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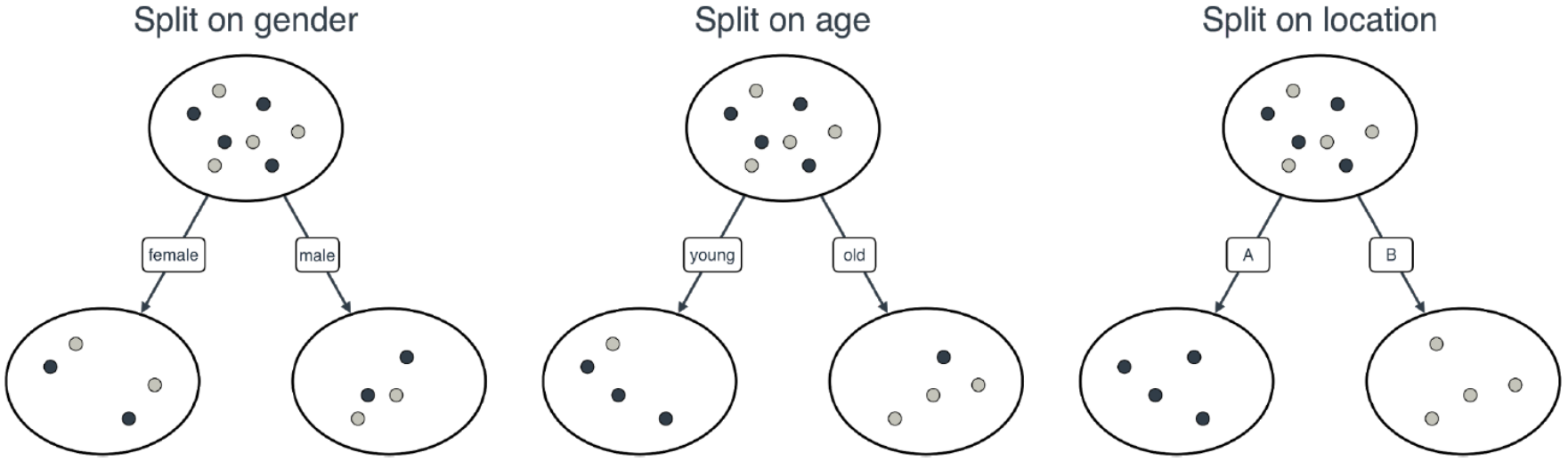

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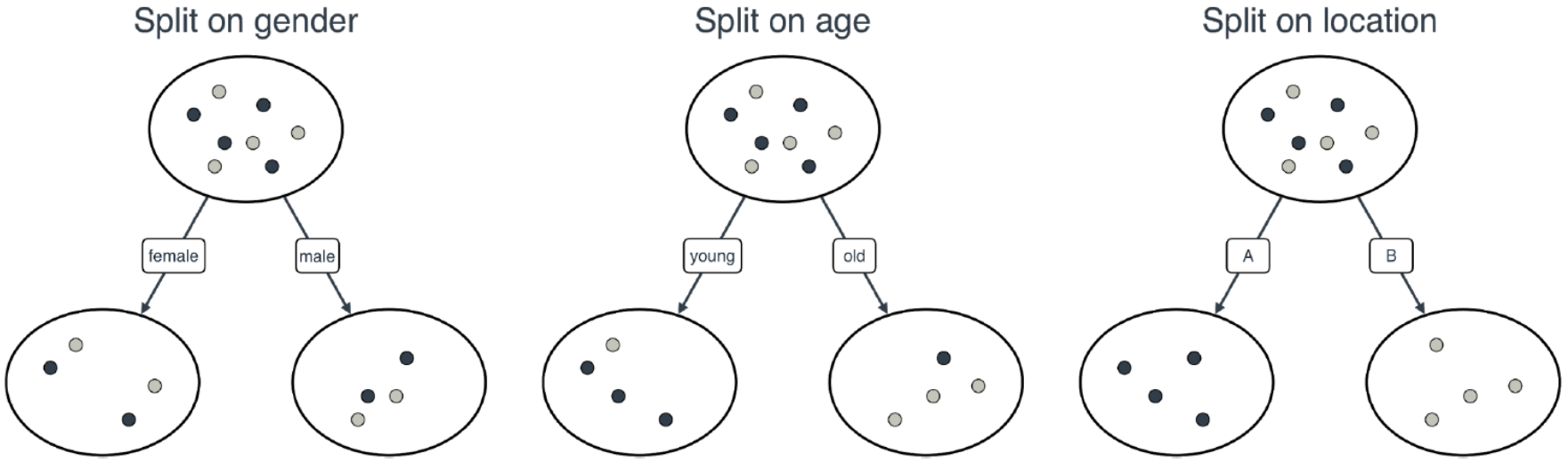

What is the right feature to split from your point of view?

How to pick the right feature to split

Using **Accuracy**:

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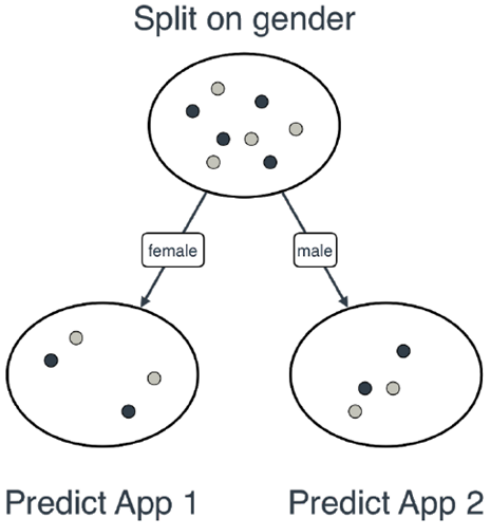

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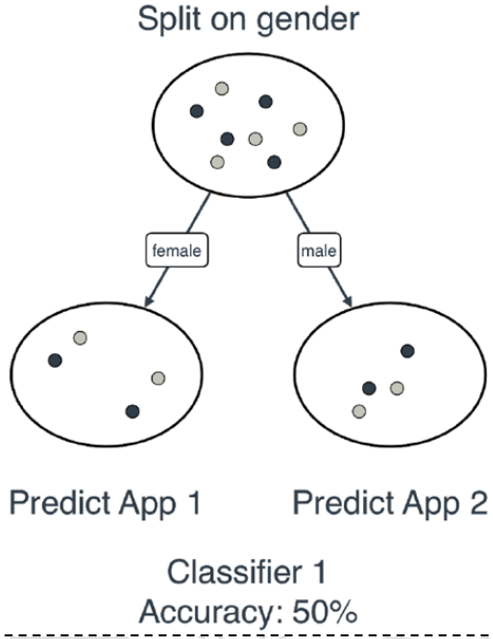

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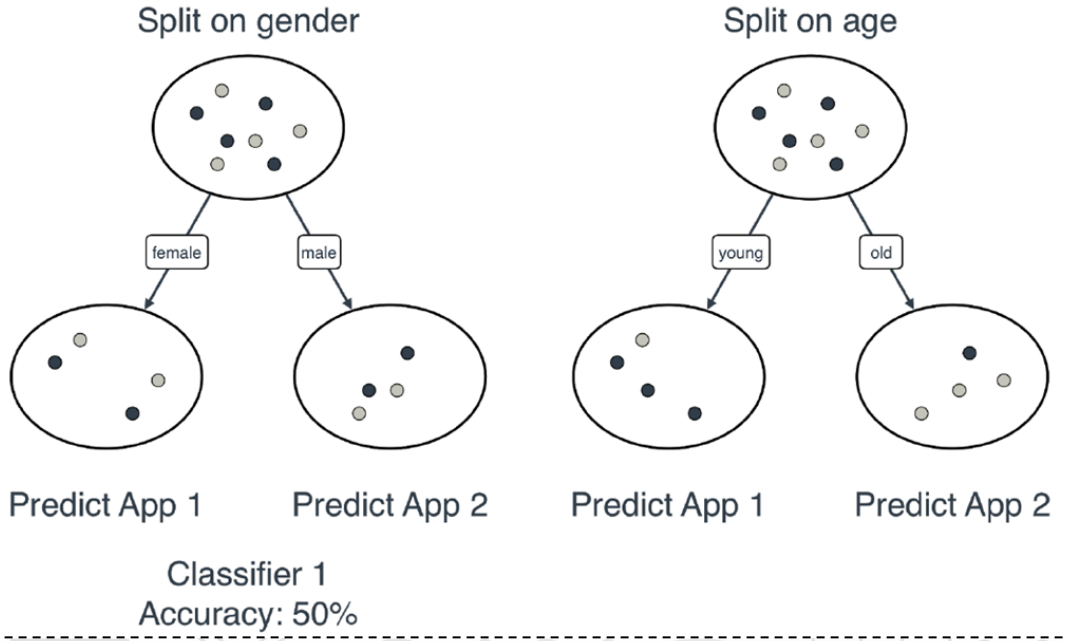

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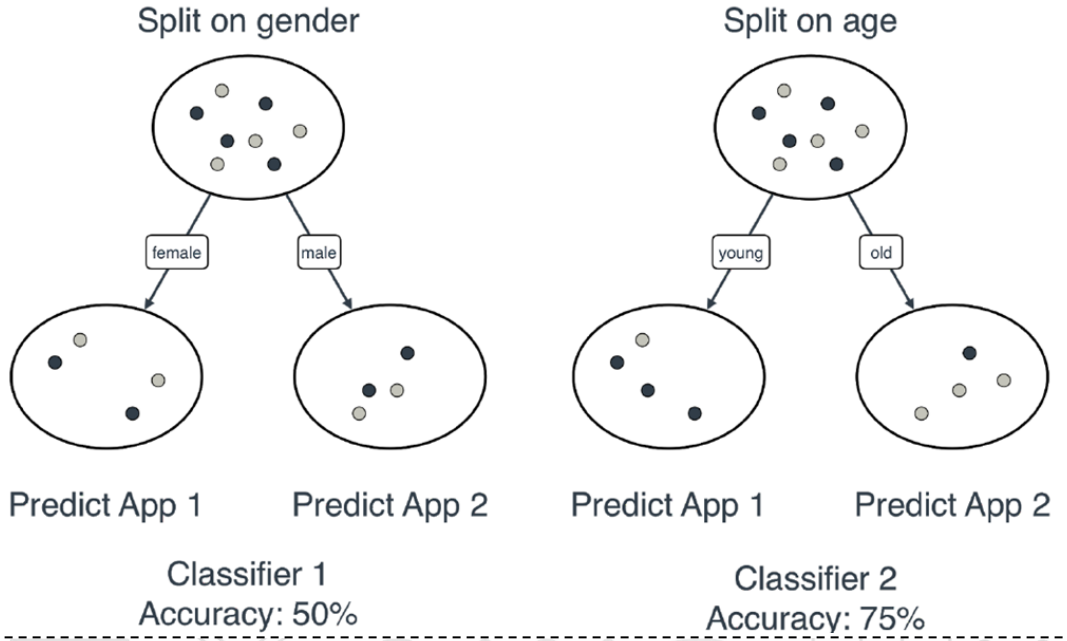

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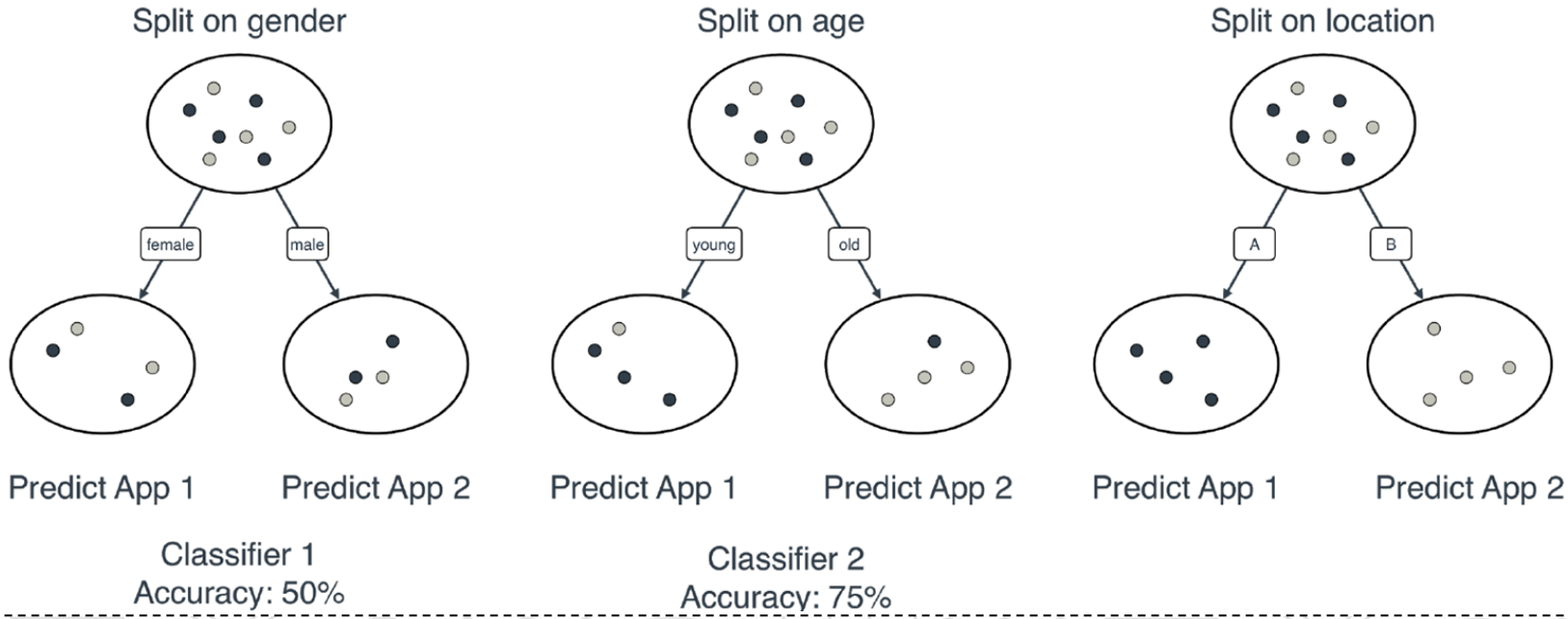

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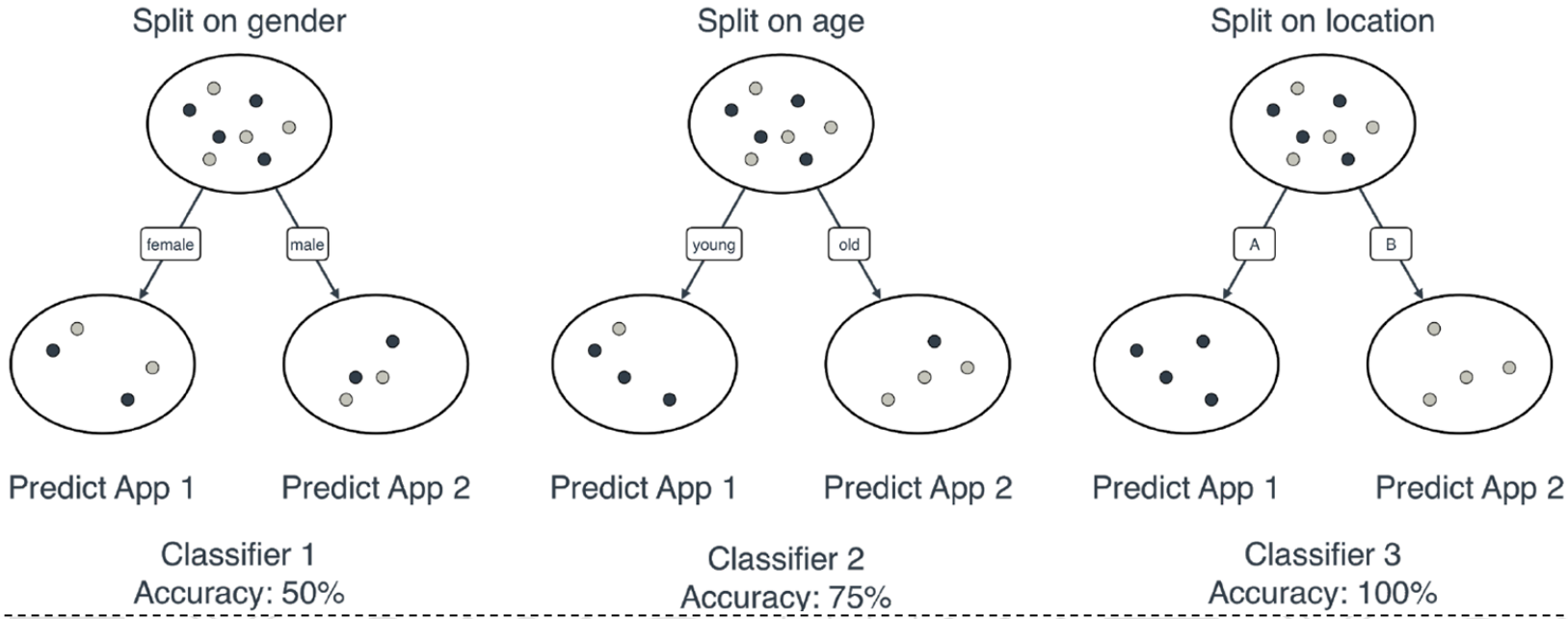

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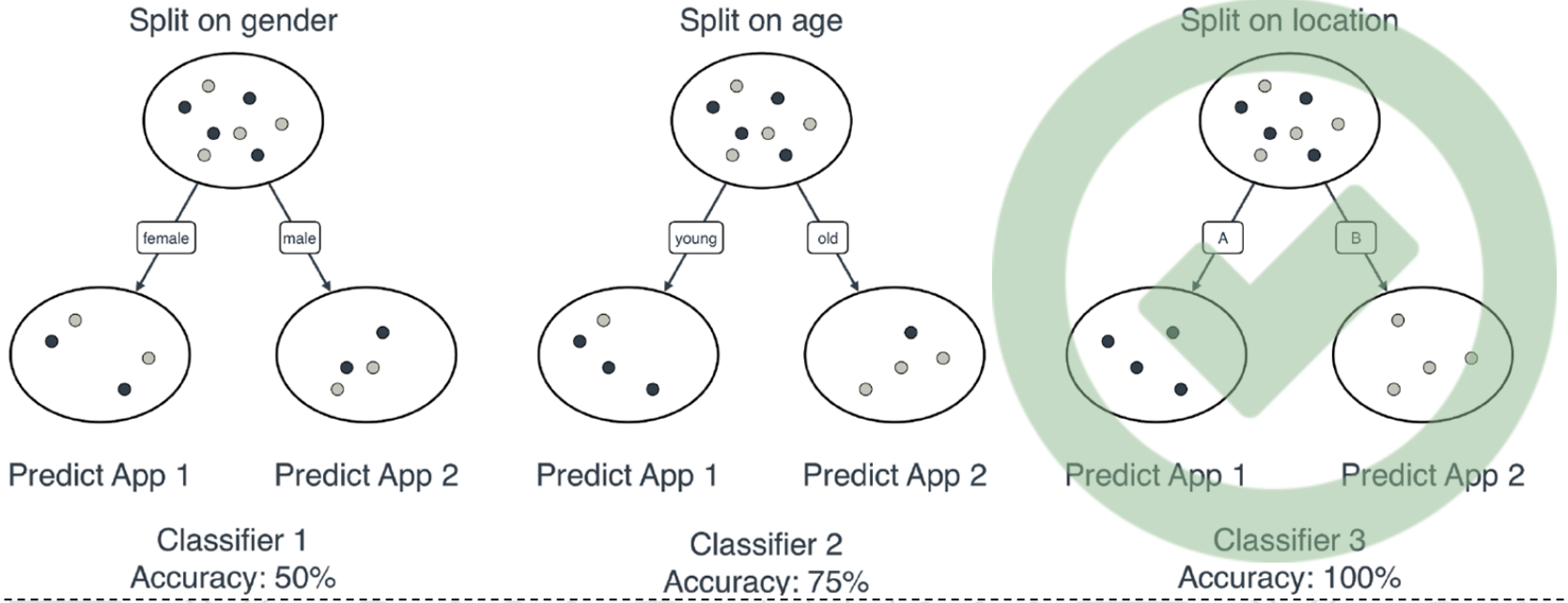

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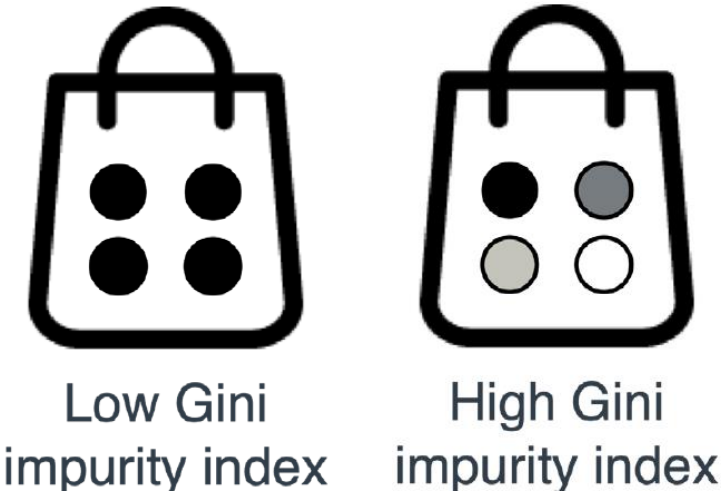

How to pick the right feature to split

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Possible sets:

- Set 1: App 1, App 1, App 1, App 1.
- Set 2: App 1, App 1, App 1, App 2.
- Set 3: App 1, App 1, App 2, App 2.
- Set 4: App 1, App 2, App 2, App 2.
- Set 5: App 2, App 2, App 2, App 2.

Low Gini impurity index

High Gini impurity index

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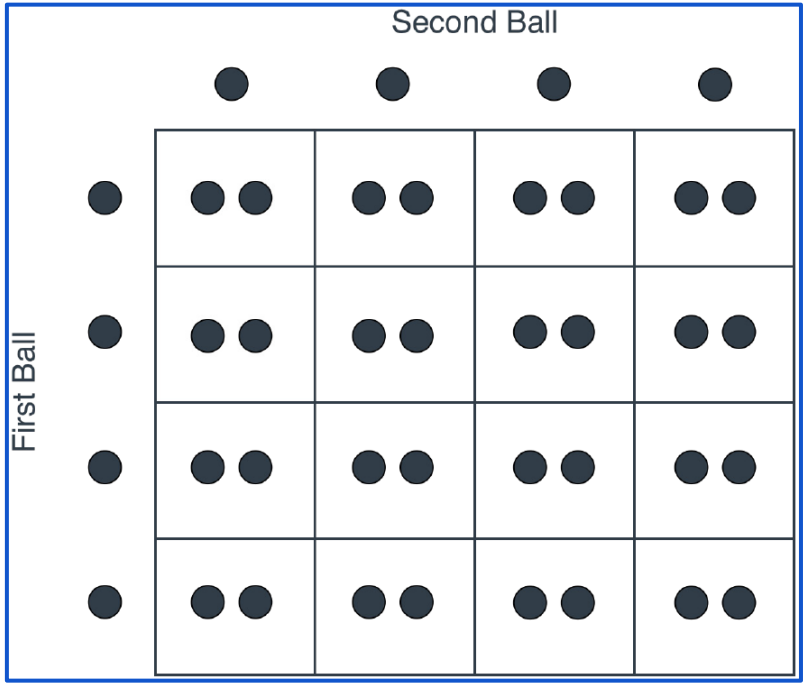

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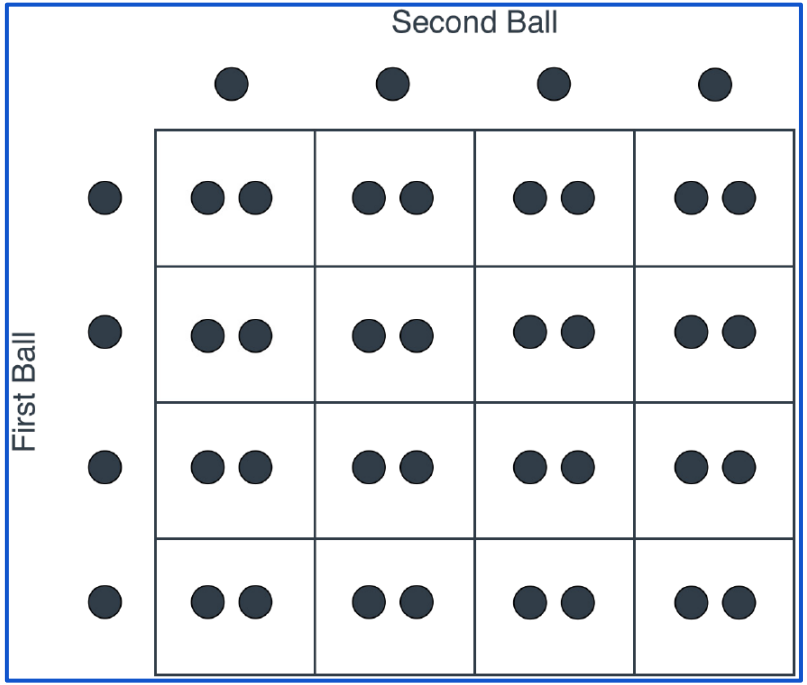
• Set 2: App 1, App 1, App 1, App 2.	
• Set 3: App 1, App 1, App 2, App 2.	
• Set 4: App 1, App 2, App 2, App 2.	
• Set 5: App 2, App 2, App 2, App 2.	**0**

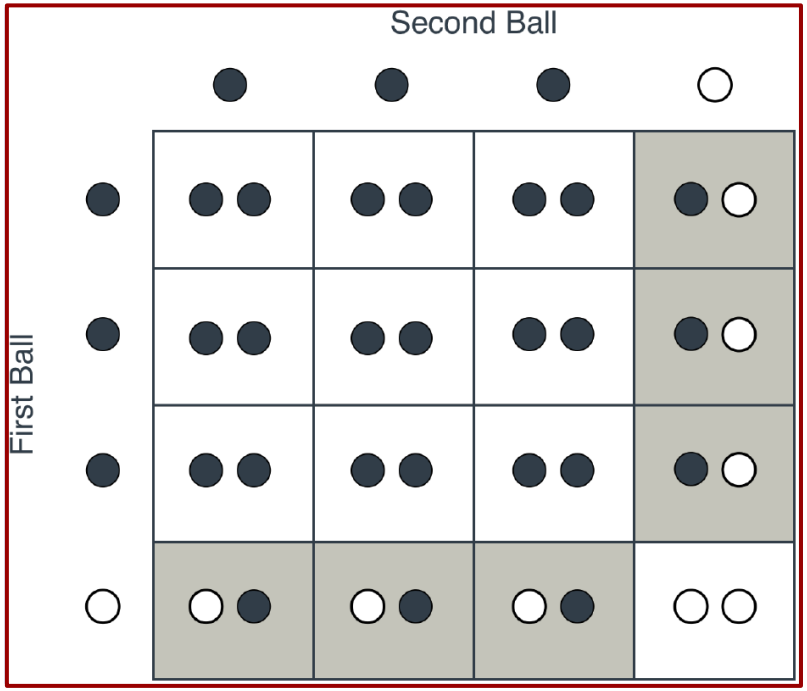


How to pick the right feature to split

Using **Gini Impurity**:

Gini impurity is a measure of
Non-homogeneity in a set.

Possible sets:	**Gini Index**
• Set 1: App 1, App 1, App 1, App 1.	**0**
• Set 2: App 1, App 1, App 1, App 2.	
• Set 3: App 1, App 1, App 2, App 2.	
• Set 4: App 1, App 2, App 2, App 2.	
• Set 5: App 2, App 2, App 2, App 2.	**0**

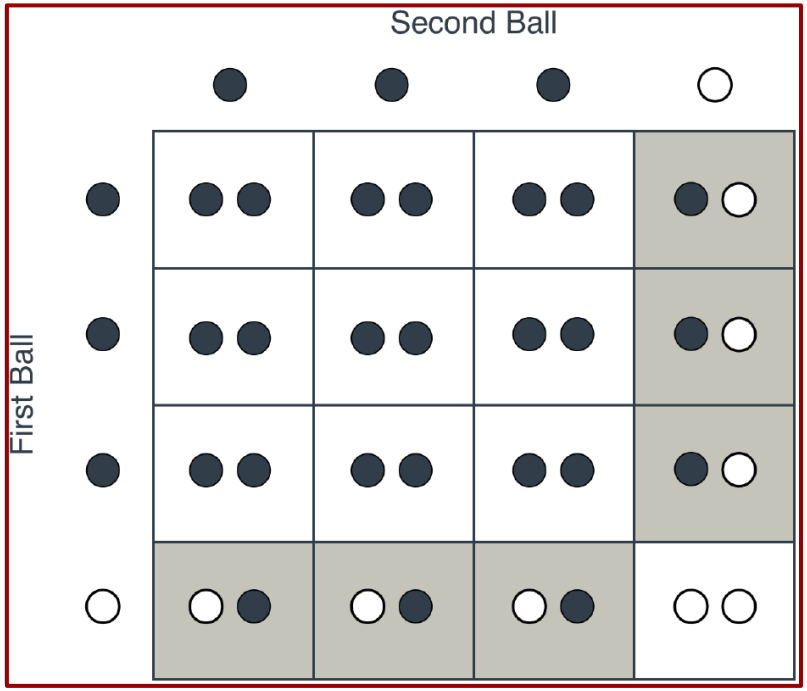


How to pick the right feature to split

Using **Gini Impurity**:

Gini impurity is a measure of
Non-homogeneity in a set.

Possible sets:	**Gini Index**
• Set 1: App 1, App 1, App 1, App 1.	**0**
• Set 2: App 1, App 1, App 1, App 2.	**0.375**
• Set 3: App 1, App 1, App 2, App 2.	
• Set 4: App 1, App 2, App 2, App 2.	**0.375**
• Set 5: App 2, App 2, App 2, App 2.	**0**

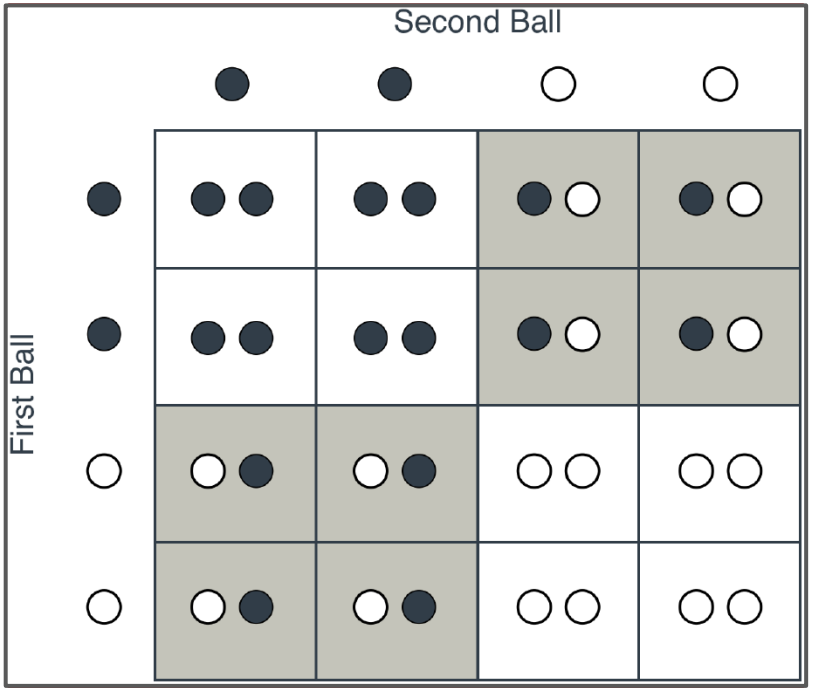


How to pick the right feature to split

Using **Gini Impurity**:

Gini impurity is a measure of
Non-homogeneity in a set.

Possible sets:	**Gini Index**
• Set 1: App 1, App 1, App 1, App 1.	**0**
• Set 2: App 1, App 1, App 1, App 2.	**0.375**
• Set 3: App 1, App 1, App 2, App 2.	
• Set 4: App 1, App 2, App 2, App 2.	**0.375**
• Set 5: App 2, App 2, App 2, App 2.	**0**

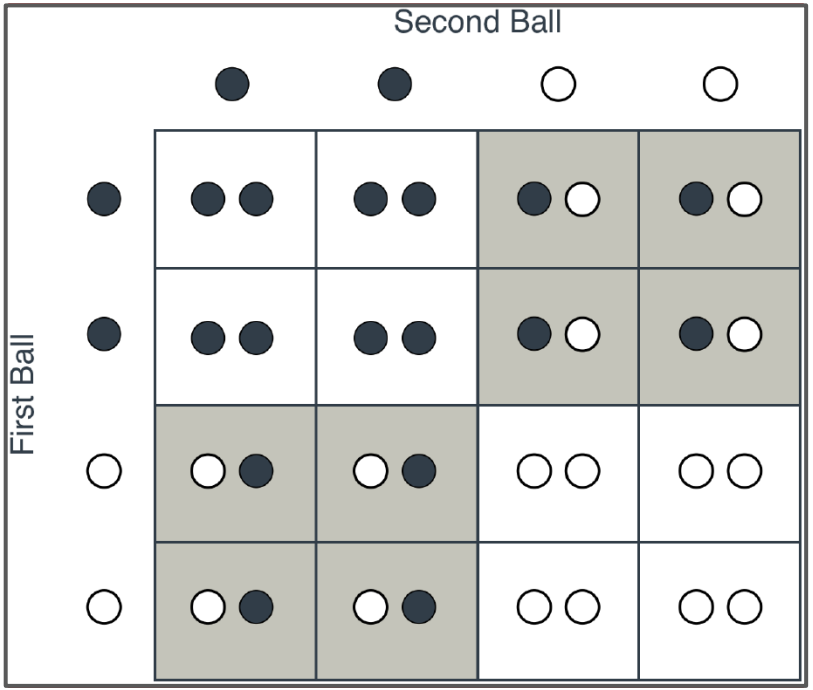


How to pick the right feature to split

Using **Gini Impurity**:

Gini impurity is a measure of
Non-homogeneity in a set.

Possible sets:	**Gini Index**
• Set 1: App 1, App 1, App 1, App 1.	**0**
• Set 2: App 1, App 1, App 1, App 2.	**0.375**
• Set 3: App 1, App 1, App 2, App 2.	**0.5**
• Set 4: App 1, App 2, App 2, App 2.	**0.375**
• Set 5: App 2, App 2, App 2, App 2.	**0**



How to pick the right feature to split

Using **Gini Impurity**:

How to pick the right feature to split

How to pick the right feature to split

Using **Gini Impurity**:
Formula:

What is the probability of picking the same ball color twice with replacement if probability of this color is P?

Probability of picking the color twice: $P_1^2 + P_2^2 + P_3^2 + P_4^2 + ...$

Gini Impurity index: $1 - P_1^2 - P_2^2 - P_3^2 - P_4^2 - .....$

How to pick the right feature to split

Using **Gini Impurity**:

Formula:

What is the probability of picking the same ball color twice with replacement if probability of this color is P?

Probability of picking the color twice: $P_1^2 + P_2^2 + P_3^2 + P_4^2 + ...$

Gini Impurity index: $1 - P_1^2 - P_2^2 - P_3^2 - P_4^2 - .....$

Gini Impurity Index = P(picking two balls of different color)

$$= 1 - \left(\frac{3}{6}\right)^2 - \left(\frac{2}{6}\right)^2 - \left(\frac{1}{6}\right)^2$$

P(Both balls are black)

P(Both balls are grey)

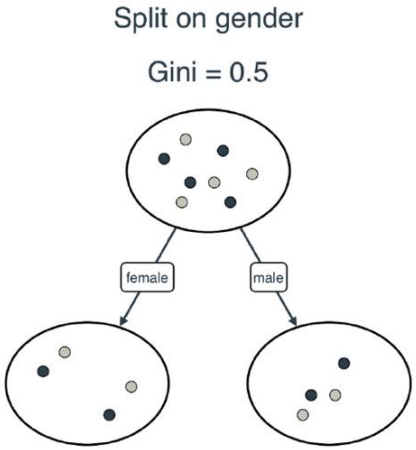
P(Both balls are white)

How to pick the right feature to split

Using **Gini Impurity**:

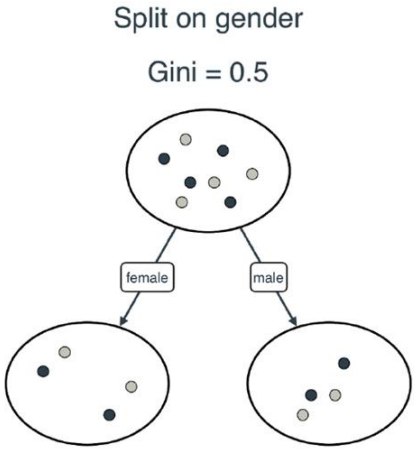
How to pick the right feature to split

Using **Gini Impurity**:



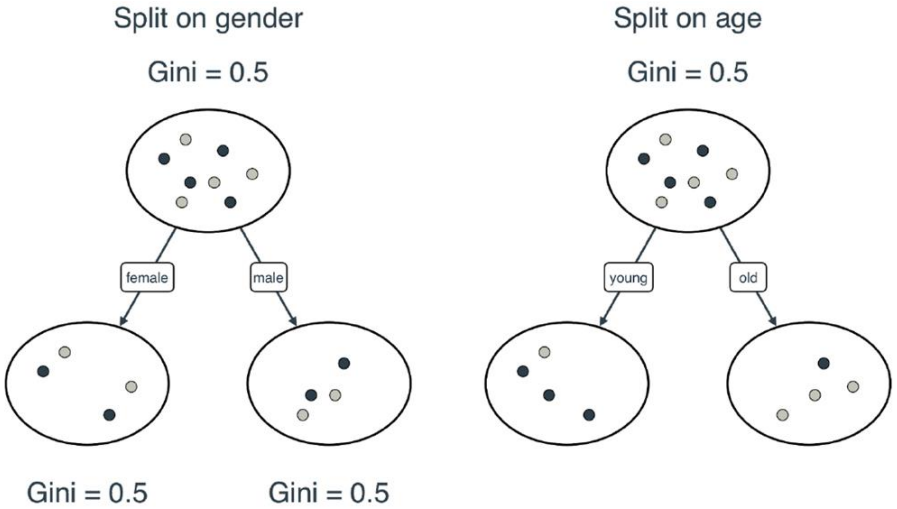
How to pick the right feature to split

Using **Gini Impurity**:



How to pick the right feature to split

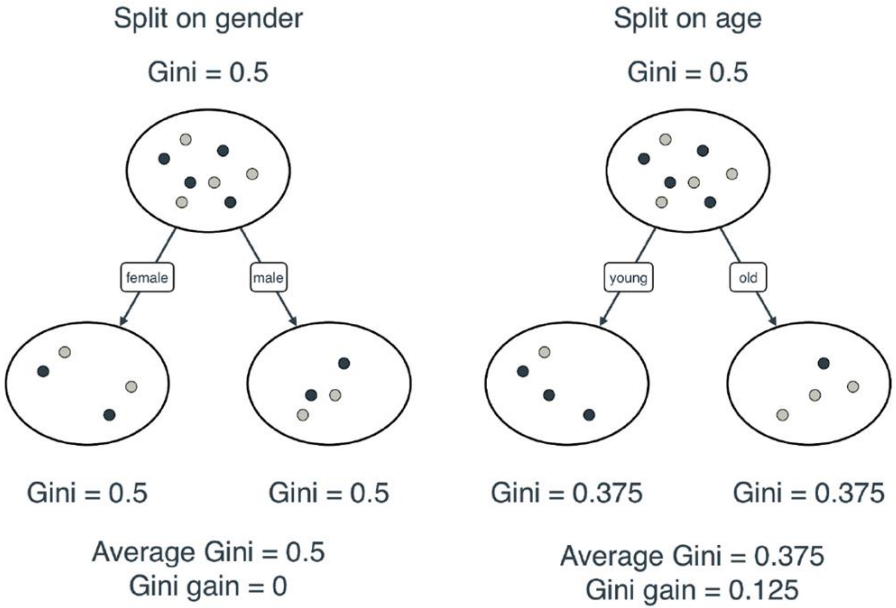
Using **Gini Impurity**:



Average Gini = 0.5
Gini gain = 0

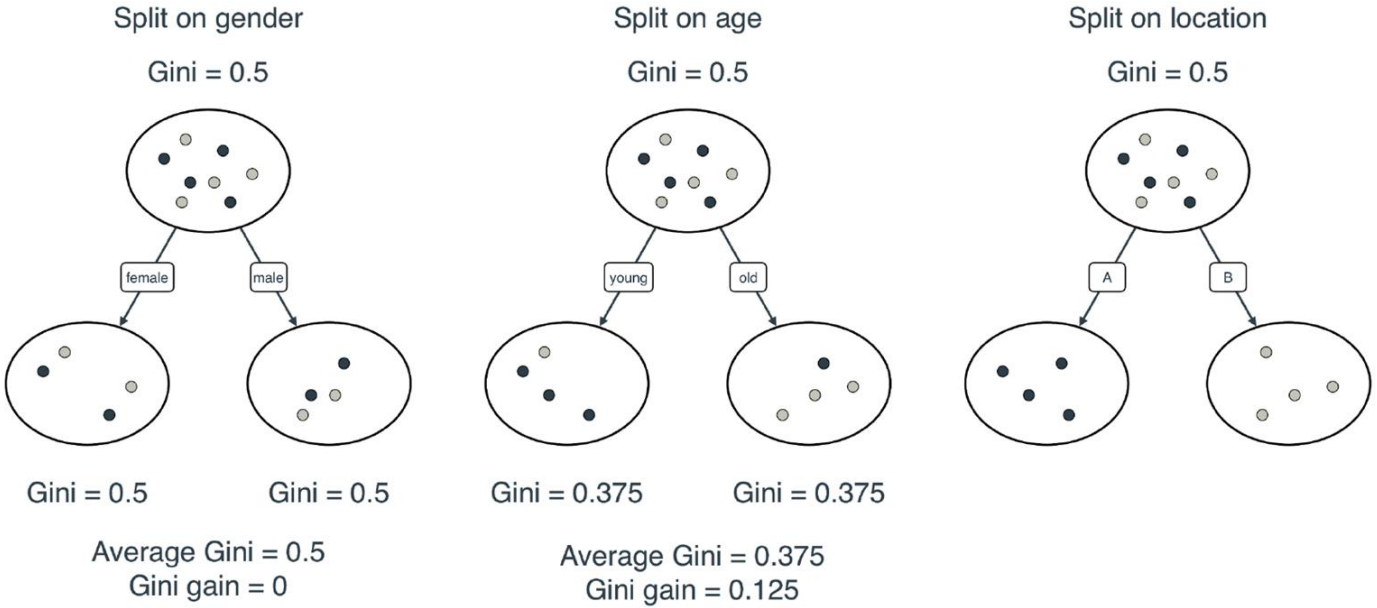
How to pick the right feature to split

Using **Gini Impurity**:



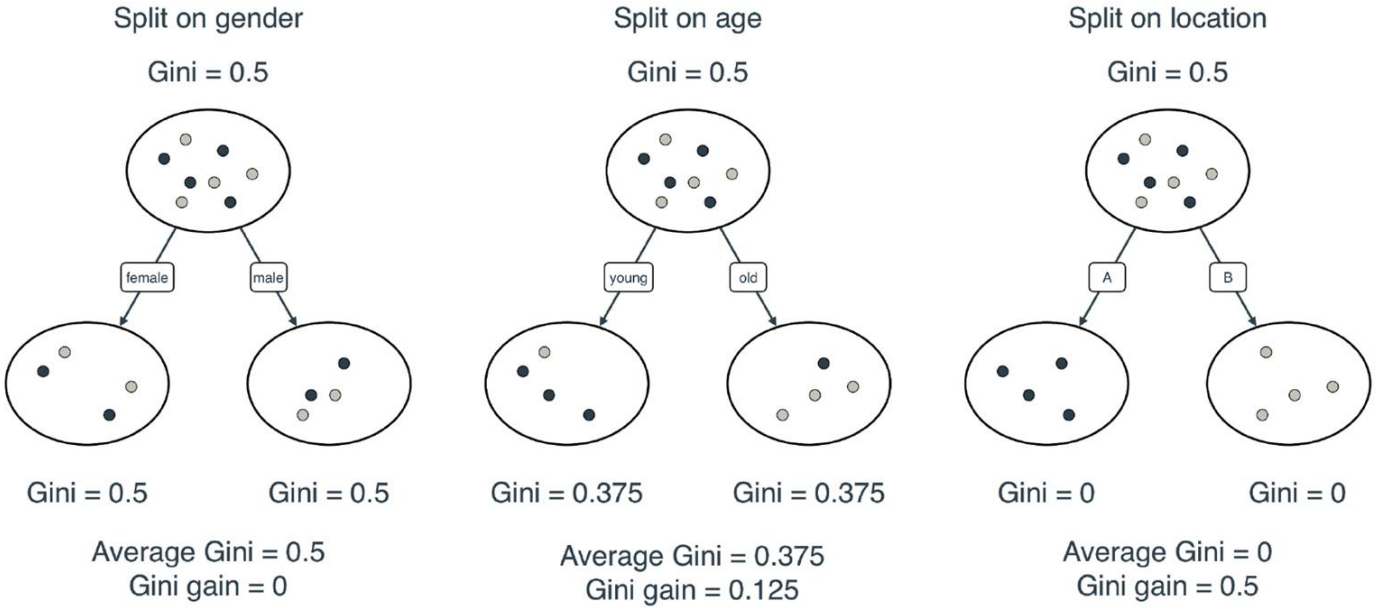
How to pick the right feature to split

Using **Gini Impurity**:



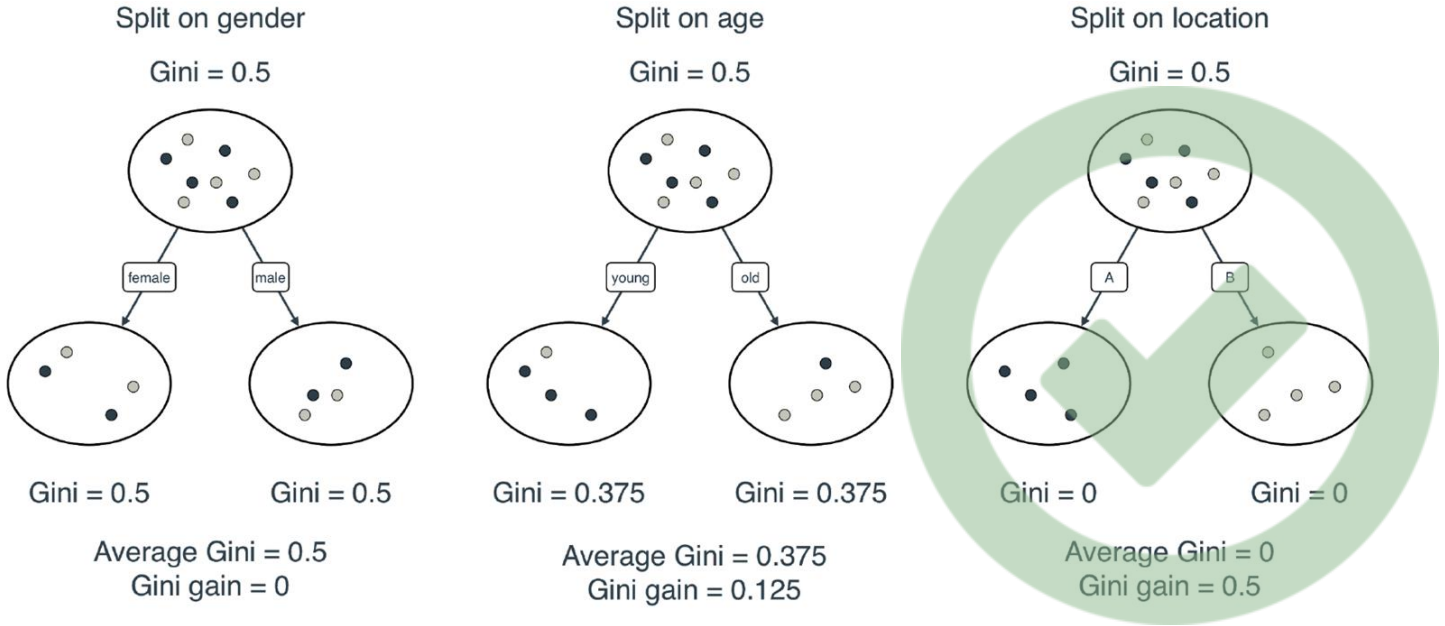
How to pick the right feature to split

Using **Gini Impurity**:



How to pick the right feature to split

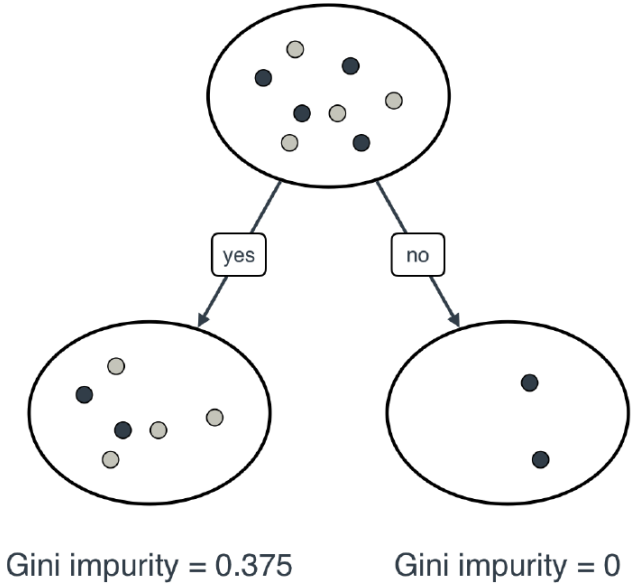
Using **Gini Impurity**:



How to pick the right feature to split

Using **Gini Impurity**:

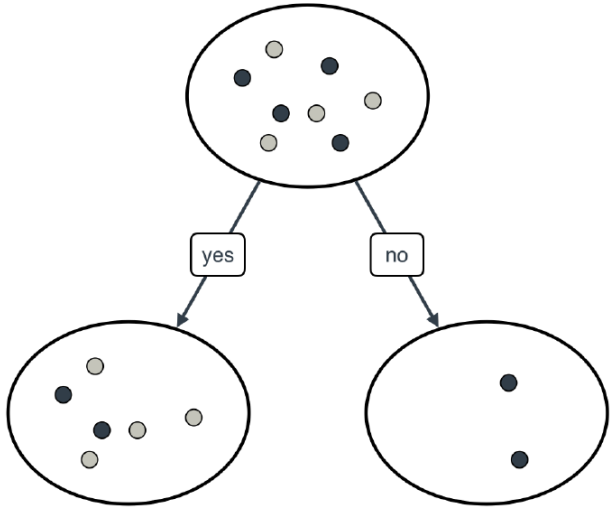
Weighted Gini Impurity:



How to pick the right feature to split

Using **Gini Impurity**:

Weighted Gini Impurity:



$$\text{Weighted average} = 0.375\left(\frac{6}{8}\right) + 0\left(\frac{2}{8}\right) = 0.25$$

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How to pick the right feature to split

Using **Entropy**:

Formula: $E = -p_1 \, log_2(p_1) - p_2 \, log_2(p_2) - \cdots - p_k \, log_2(p_k).$

How to pick the right feature to split

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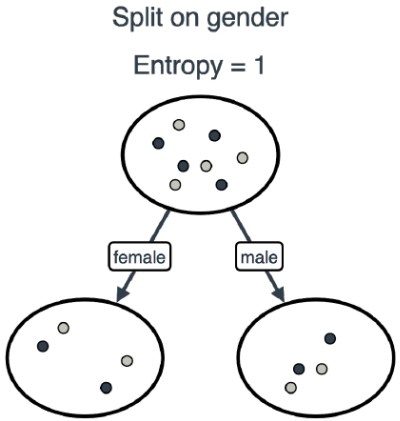

How to pick the right feature to split

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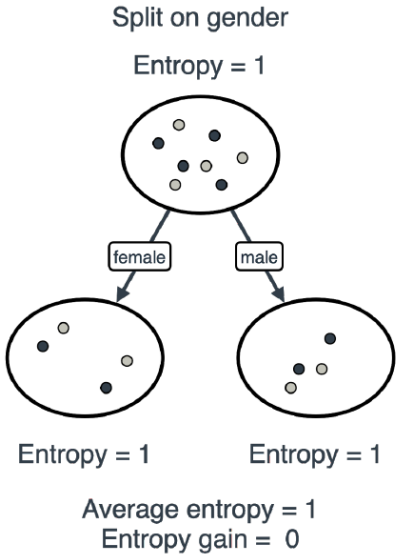

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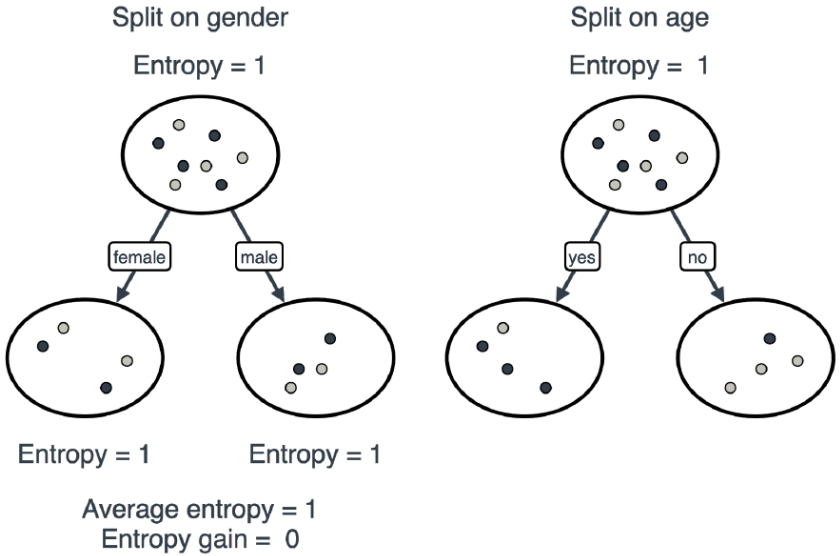

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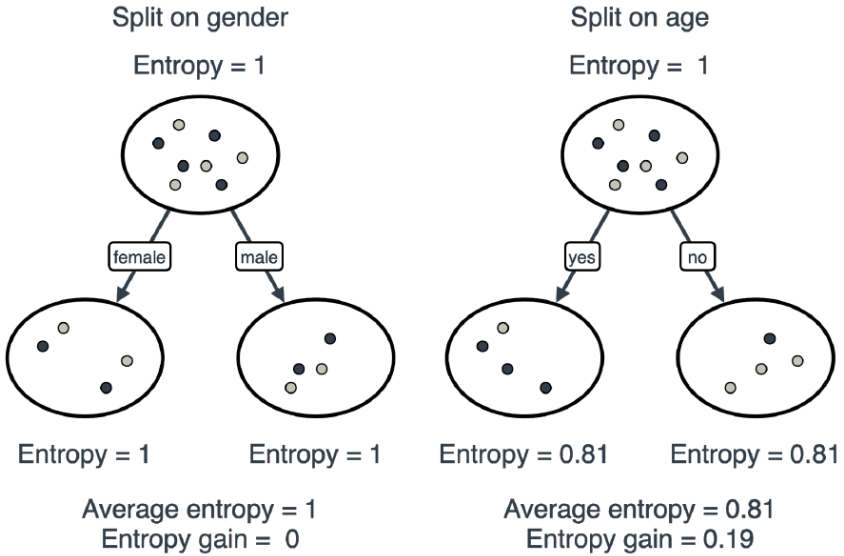

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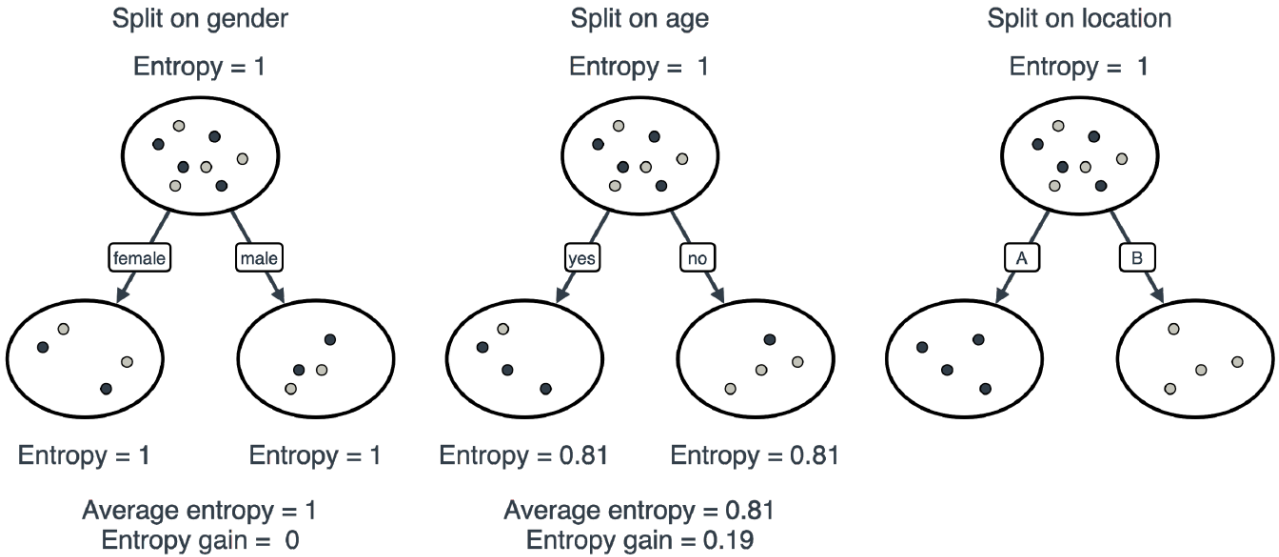

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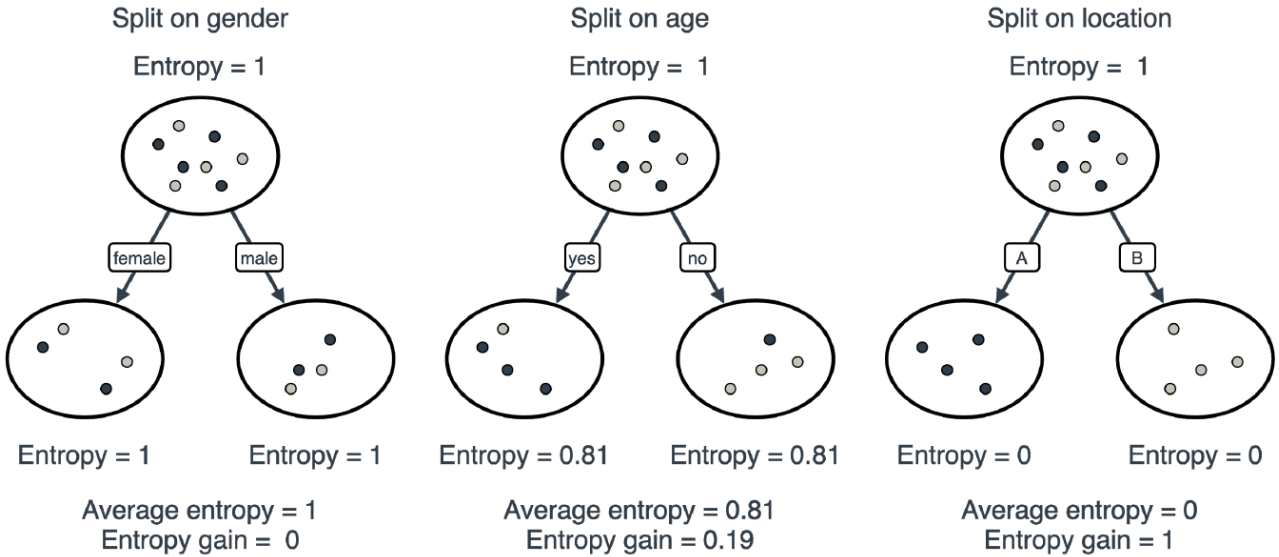

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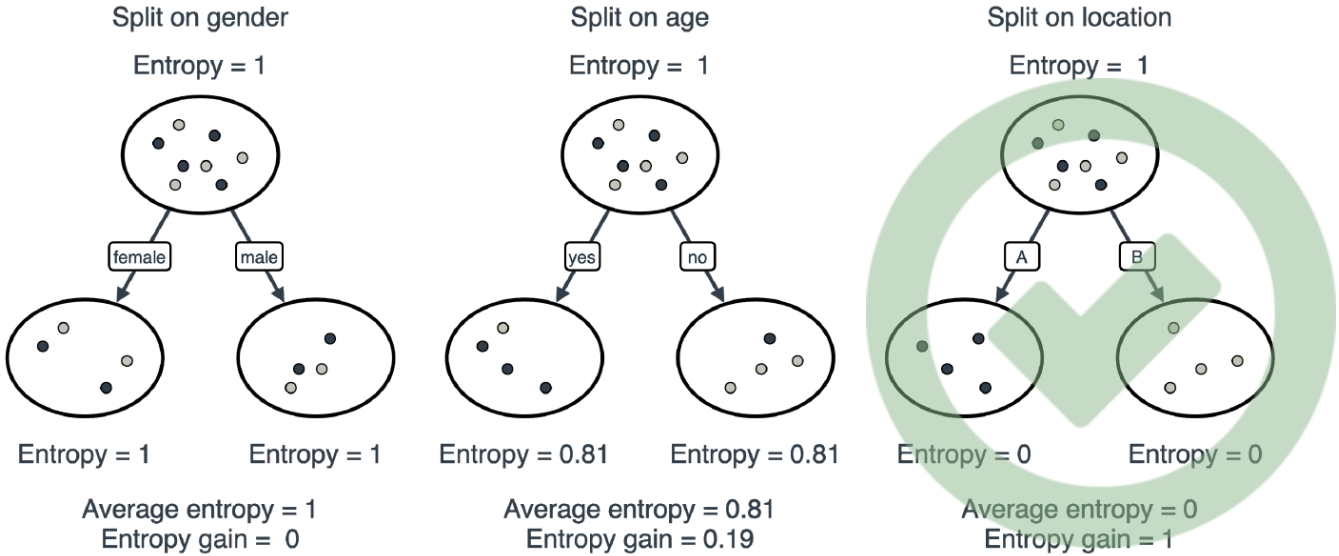
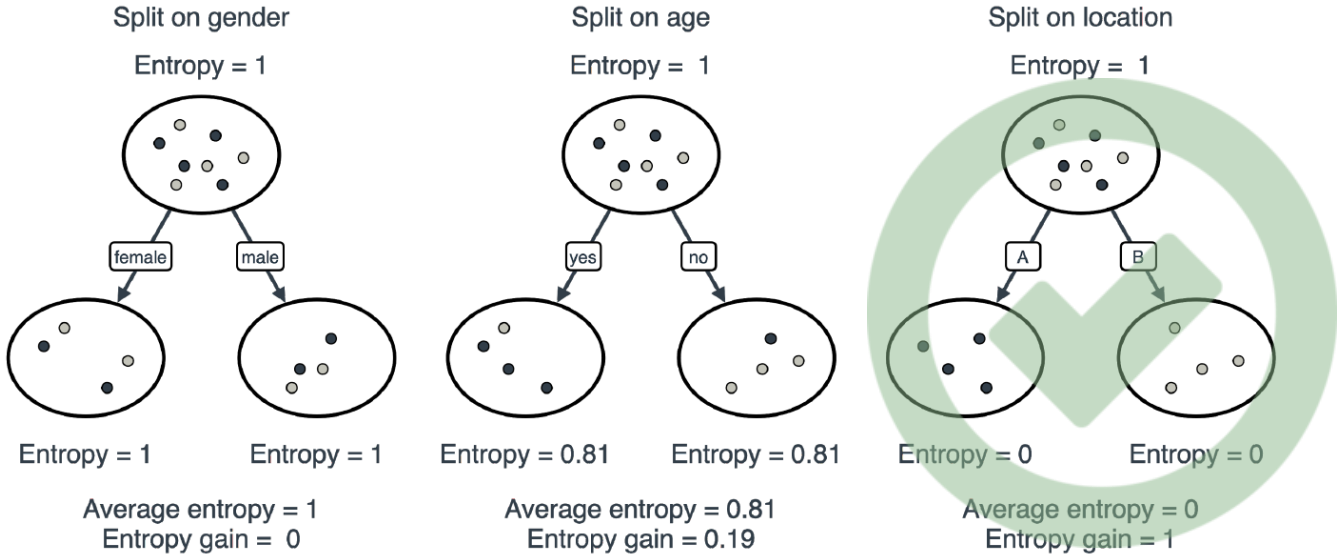


How to pick the right feature to split

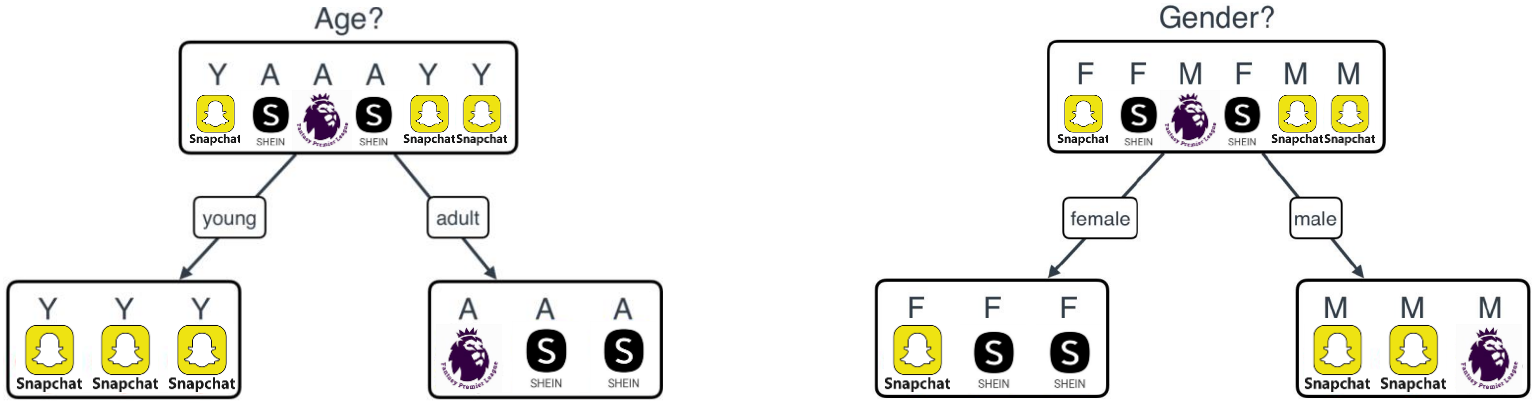
Using **Entropy**:

Formula: $E = -p_1 \log_2(p_1) - p_2 \log_2(p_2) - \cdots - p_k \log_2(p_k).$

As we did with the Gini impurity, we can also find the weighted information gain when the leaves don't have the same size.



Back To Our Recommendation System



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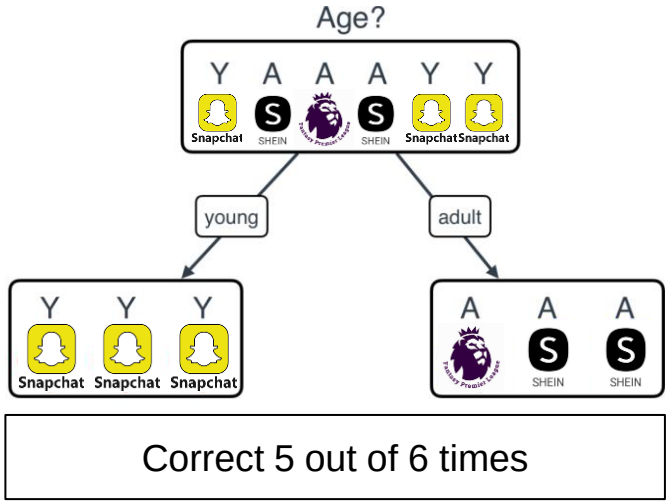

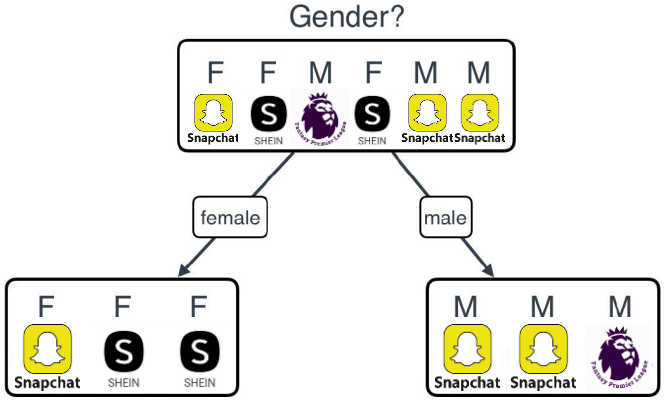

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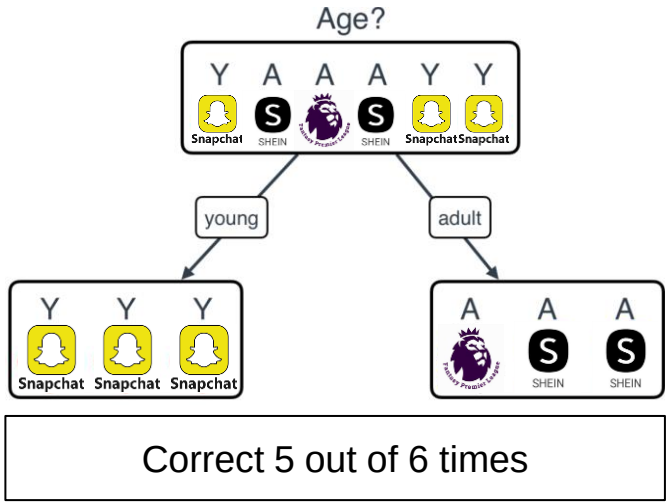

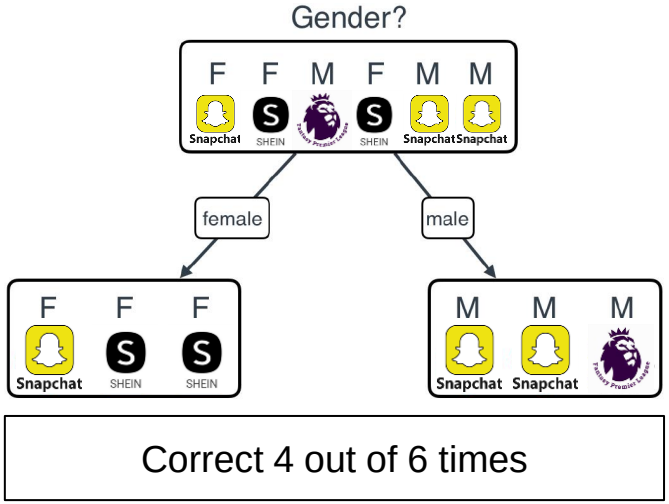

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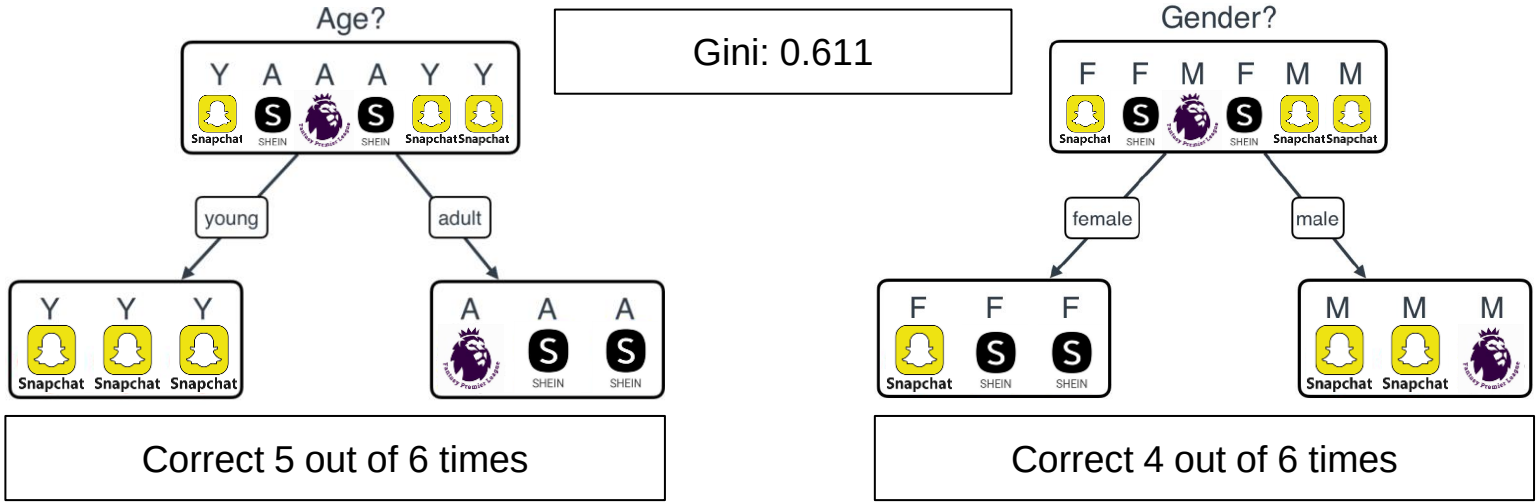

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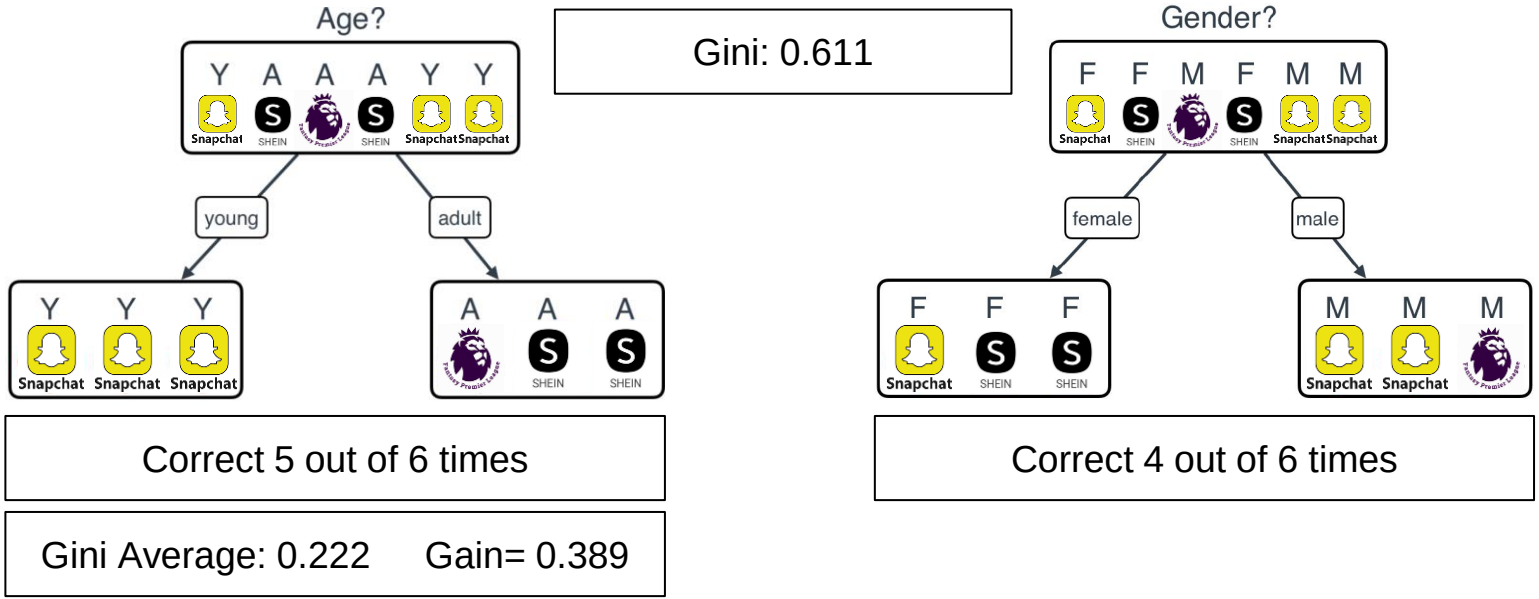

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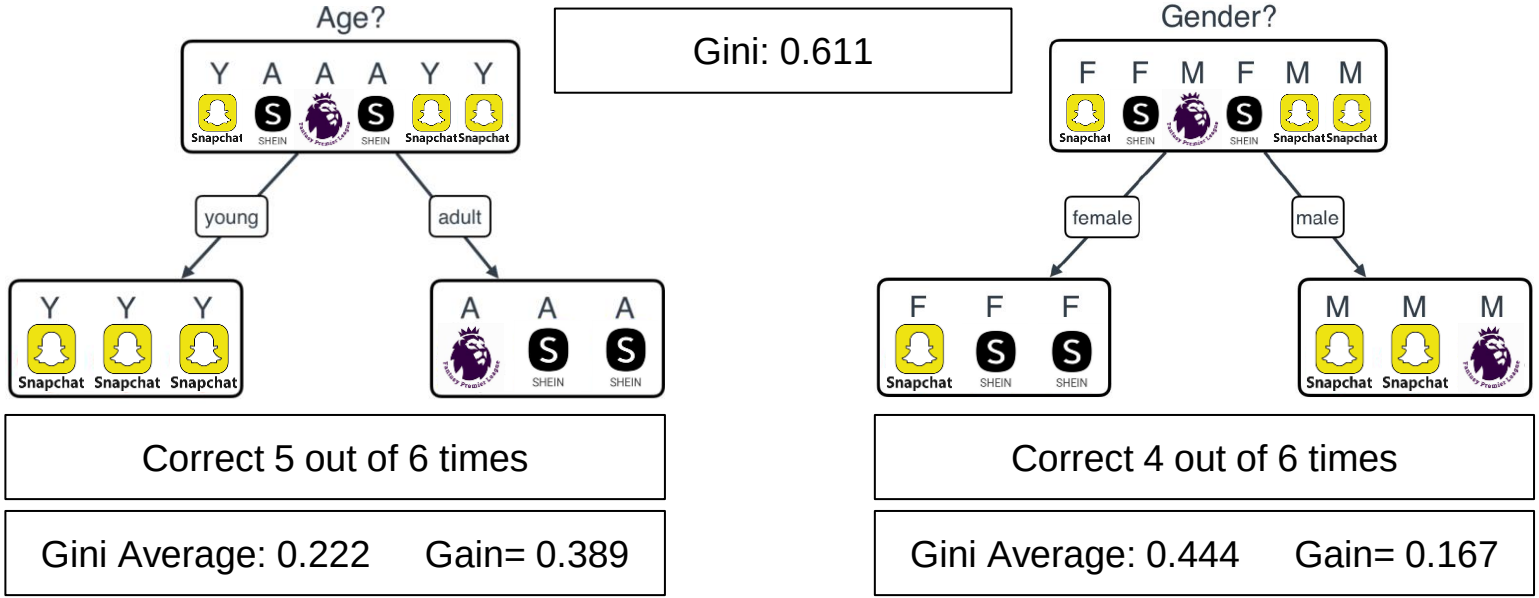

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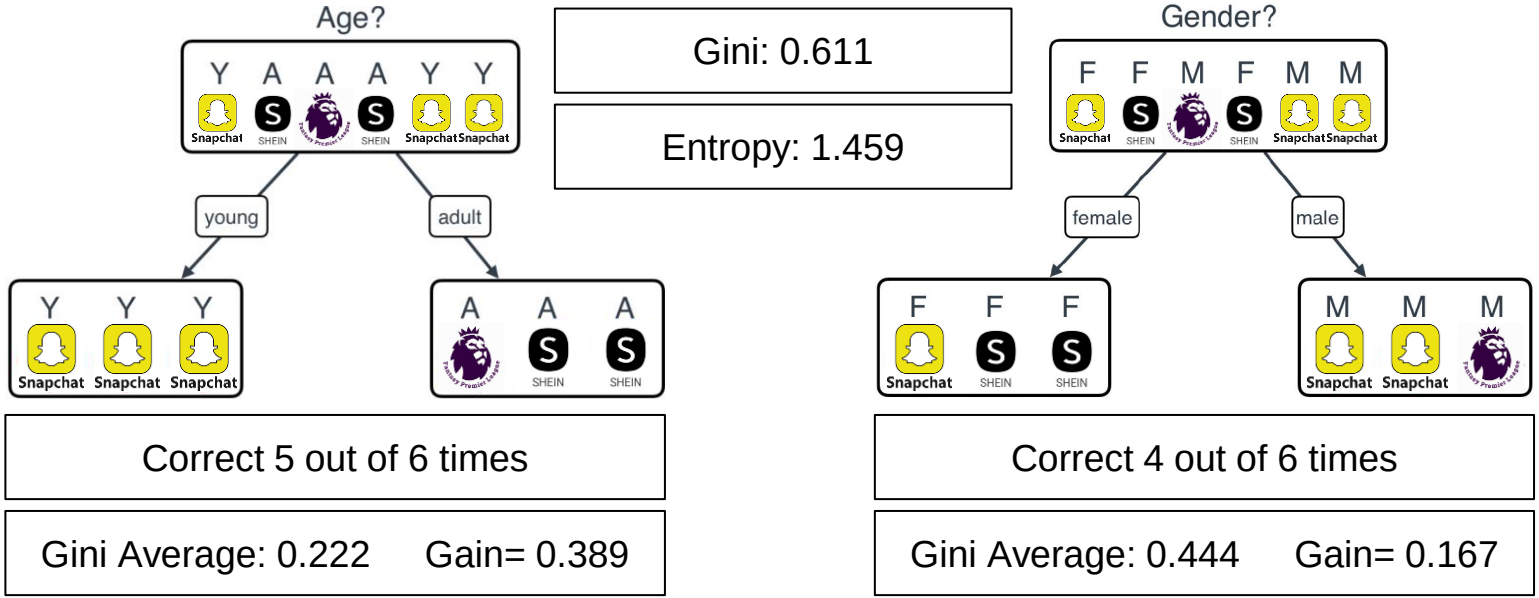

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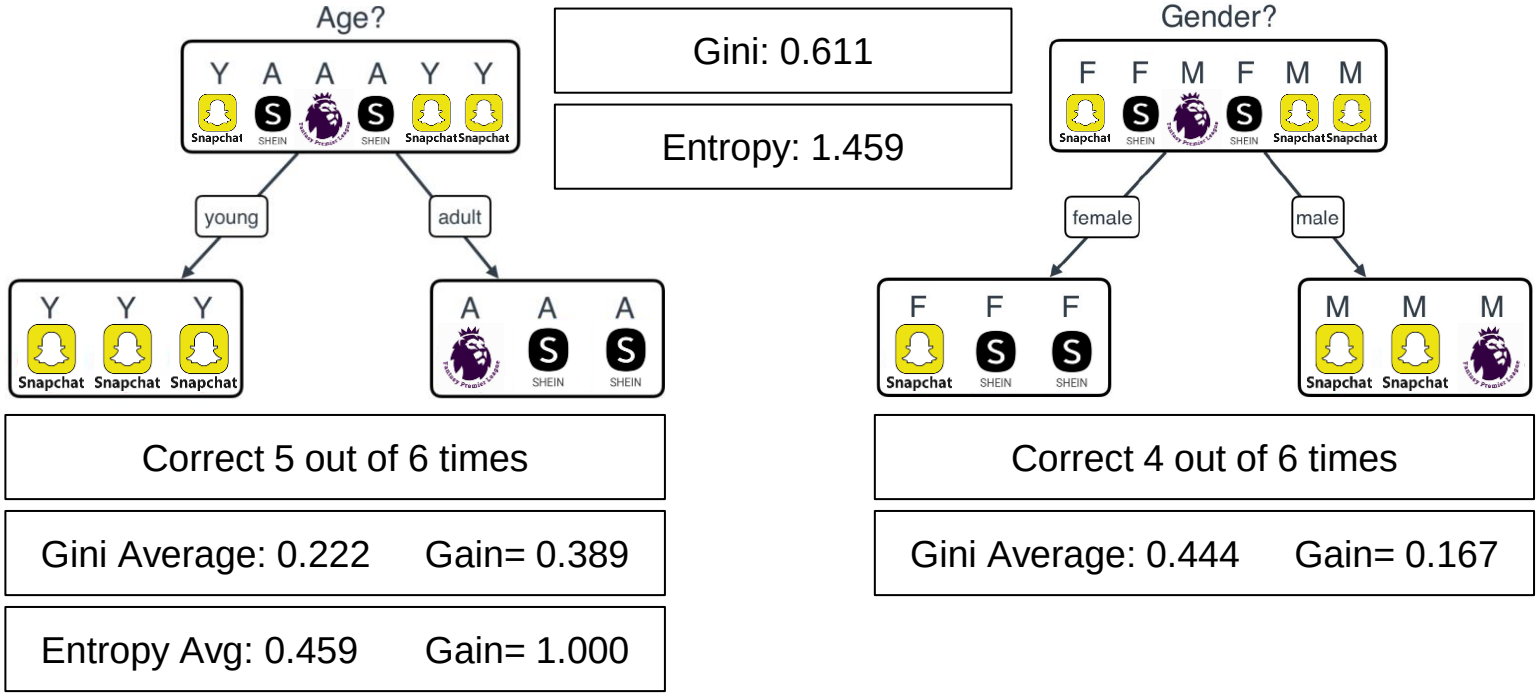

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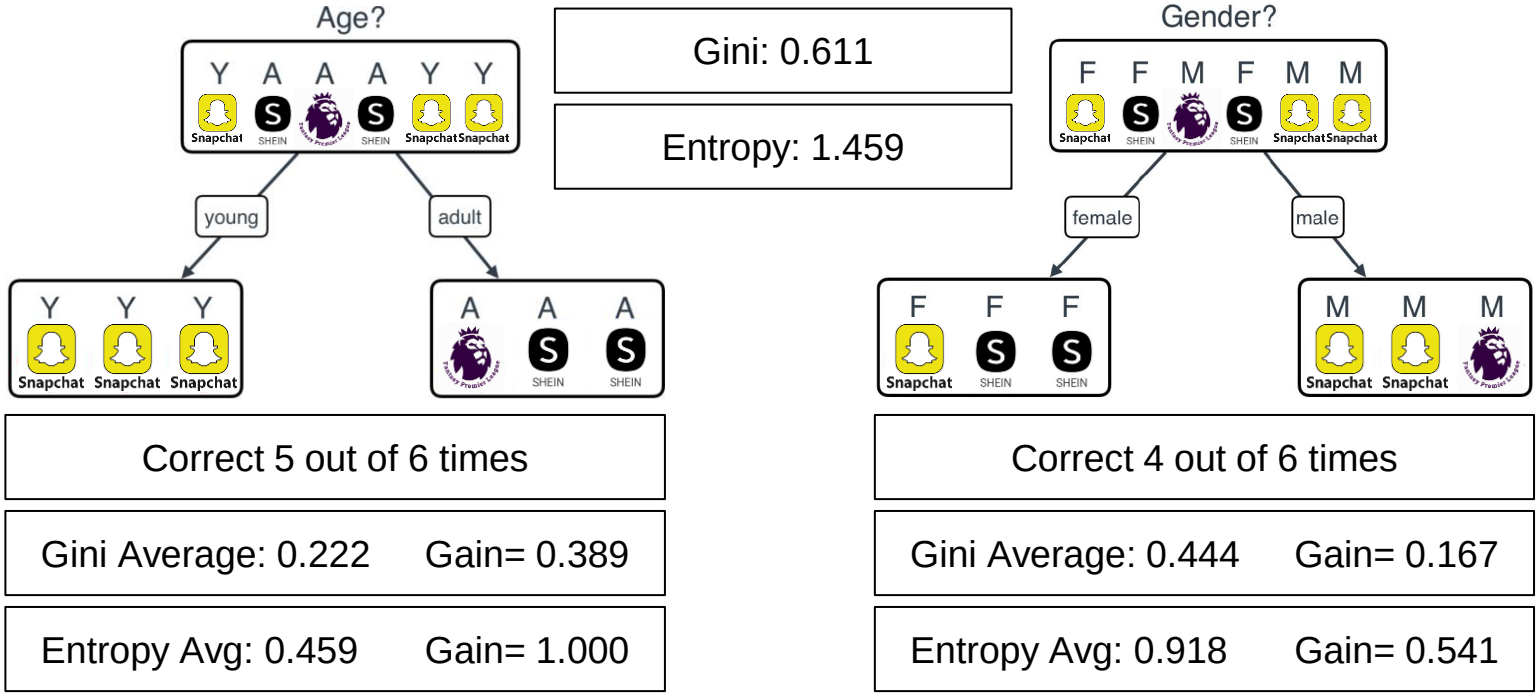

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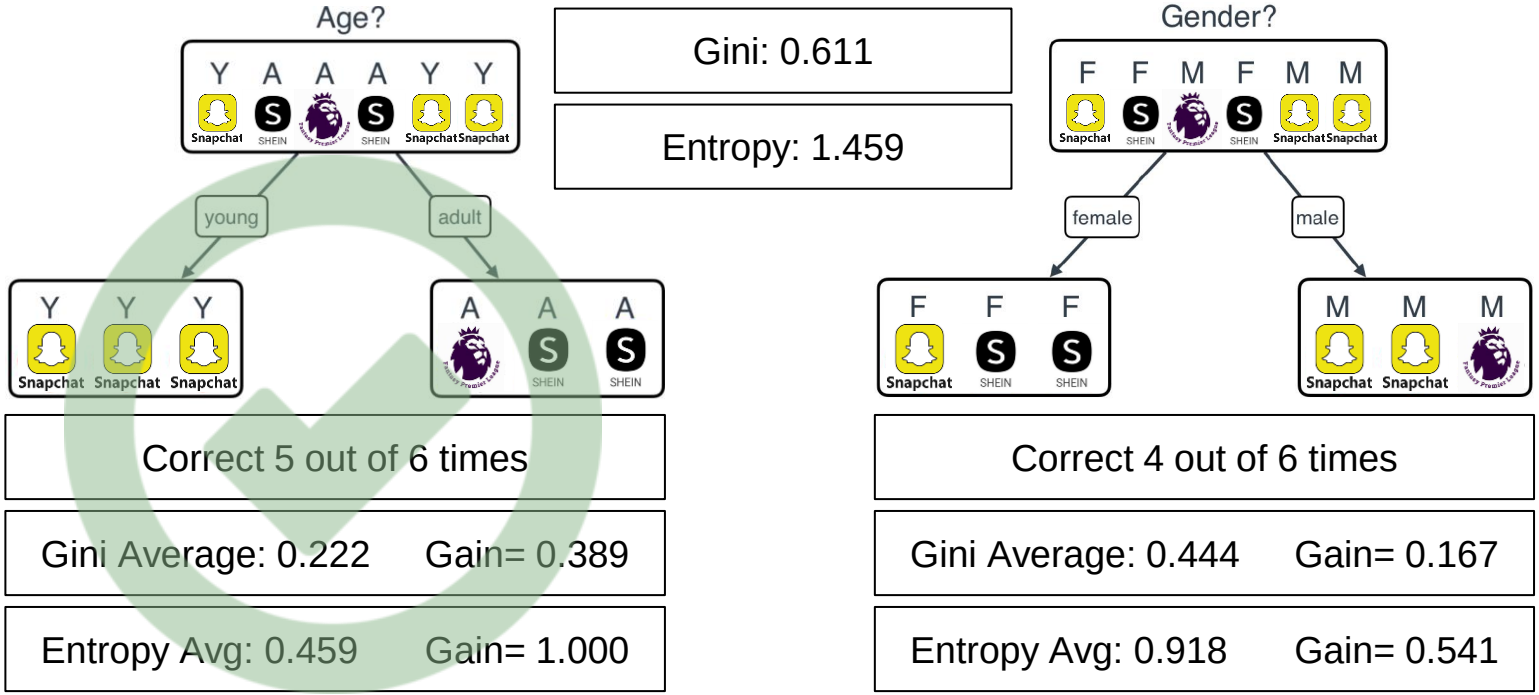

Lecture Overview

- Simple Decision Tree
- Mobile Apps Recommendation Example
- Split Using Accuracy
- Split Using Gini Impurity
- Split Using Entropy
- Tree Hyperparameters
- One-hot Encoded Features
- Continues Features
- Decision Tree For Regression
- Random Forest

When Do We Stop Building The Tree?

When Do We Stop Building The Tree?

These are hyperparameters:

- The gain of Gini index or Entropy is below some threshold.
- If node has less than a certain number of elements.
- Reach a certain number of levels.

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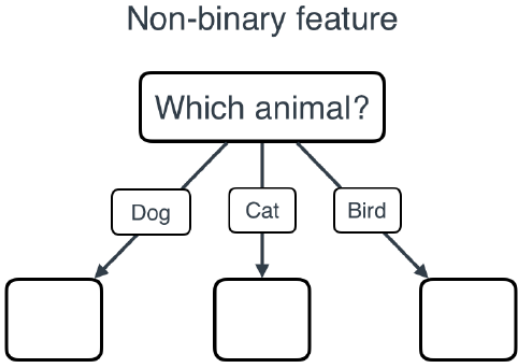
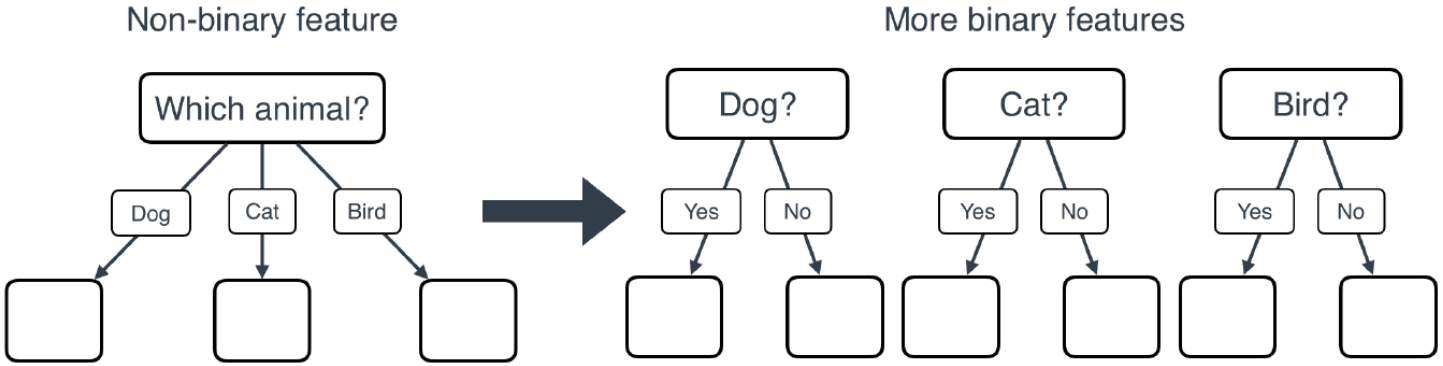
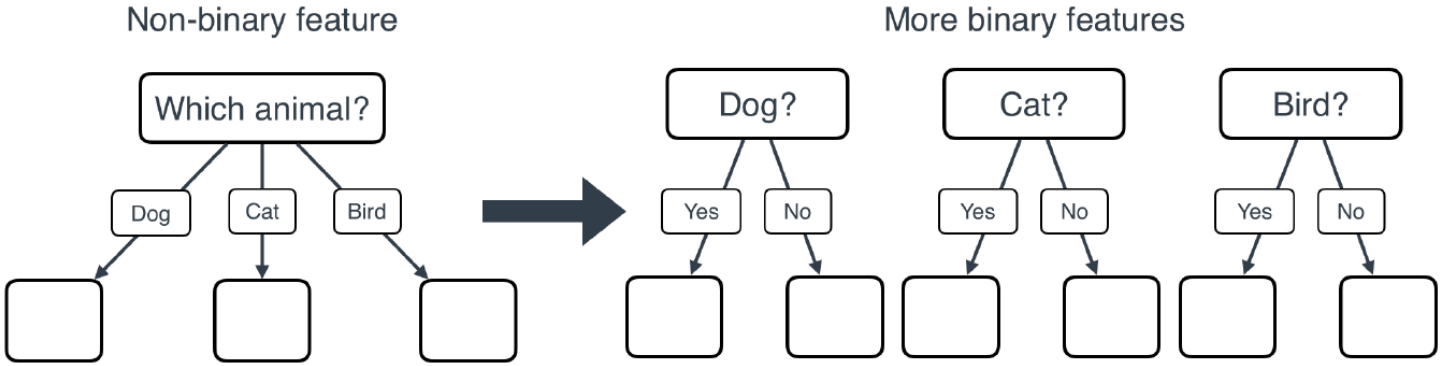
Features With More Than Two Categories



Features With More Than Two Categories



Features With More Than Two Categories



Animal
Dog
Cat
Bird
Dog
Bird

One-hot encoding

Dog?	Cat?	Bird?
1	0	0
0	1	0
0	0	1
1	0	0
0	0	1

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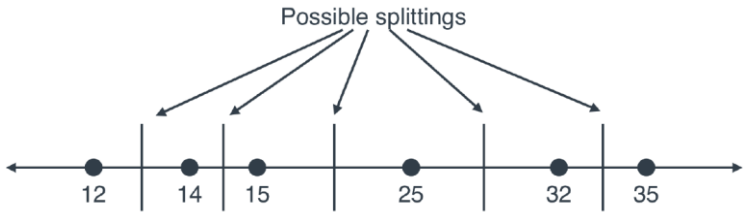
Continuous Features

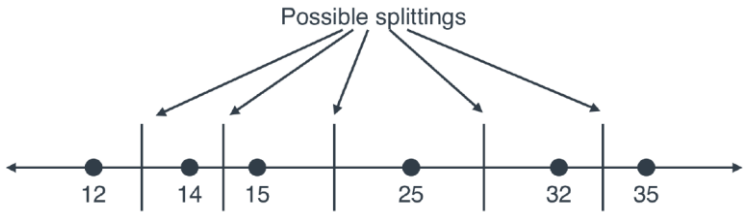
Gender	Age	App
F	15	Snapchat
F	25	SHEIN
M	32	Fantasy Premier League
F	35	SHEIN
M	12	Snapchat
M	14	Snapchat

Continuous Features



Gender	Age	App
F	15	Snapchat
F	25	SHEIN
M	32	Fantasy Premier League
F	35	SHEIN
M	12	Snapchat
M	14	Snapchat

Continuous Features



Question	First set	Second set
Is the user younger than 13?	12	14, 15, 25, 32, 35
Is the user younger than 14.5?	12, 14	15, 25, 32, 35
Is the user younger than 20?	12, 14, 15	25, 32, 35
Is the user younger than 27?	12, 14, 15, 25	32, 35
Is the user younger than 33?	12, 14, 15, 25, 32	35

Gender	Age	App
F	15	Snapchat
F	25	SHEIN
M	32	Fantasy Premier League
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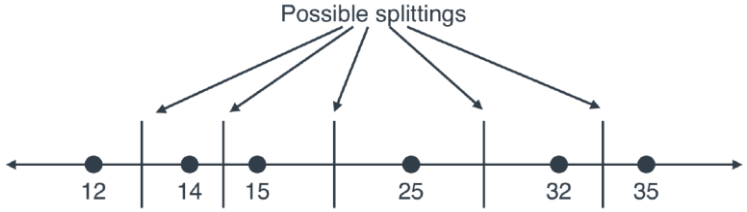
Continuous Features



Question	First set	Second set
Is the user younger than 13?	12	14, 15, 25, 32, 35
Is the user younger than 14.5?	12, 14	15, 25, 32, 35
Is the user younger than 20?	12, 14, 15	25, 32, 35
Is the user younger than 27?	12, 14, 15, 25	32, 35
Is the user younger than 33?	12, 14, 15, 25, 32	35

Add all these 5 questions to the age question and use accuracy, Gini-index or entropy to choose the question to split

Gender	Age	App
F	15	Snapchat
F	25	SHEIN
M	32	Fantasy Premier League
F	35	SHEIN
M	12	Snapchat
M	14	Snapchat

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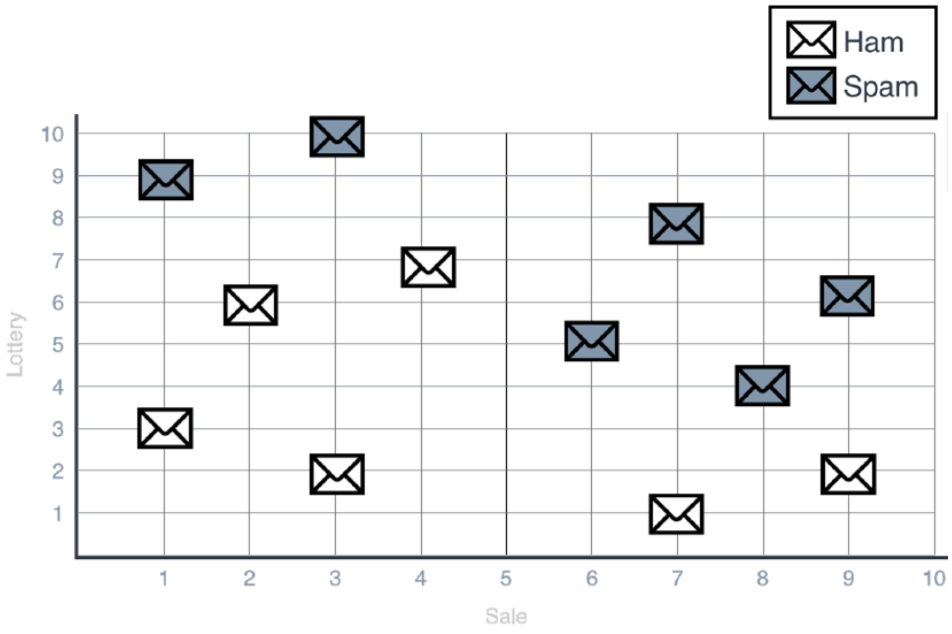
Graphical Example: Spam Detector

Lottery	Sale	Spam
7	1	No
3	2	No
3	9	No
1	3	No
2	6	No
4	7	No
1	9	Yes
3	10	Yes
6	5	Yes
7	8	Yes
8	4	Yes
9	6	Yes

Graphical Example: Spam Detector



Lottery	Sale	Spam
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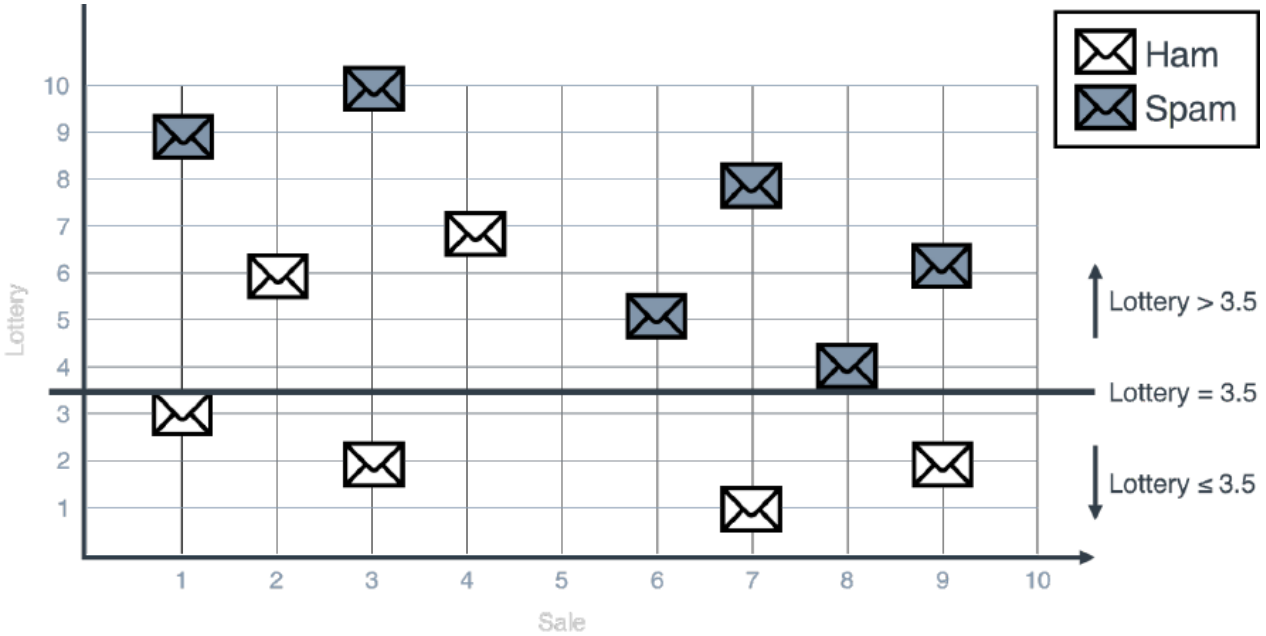
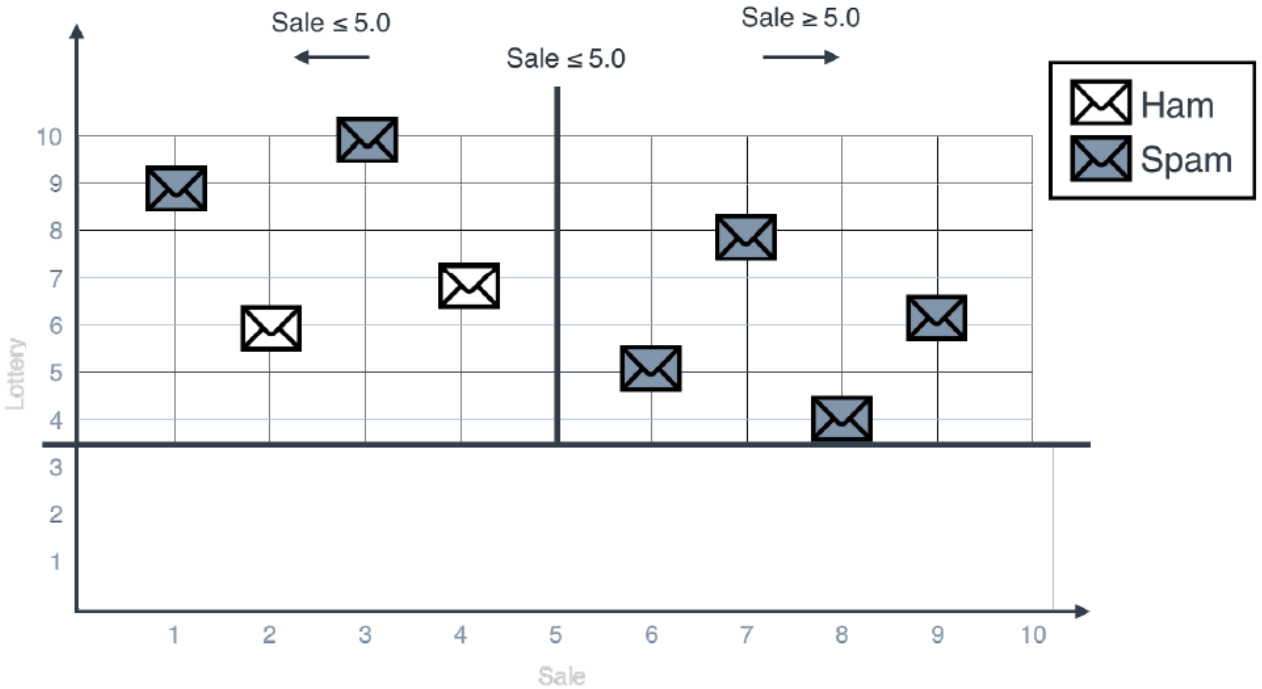
Graphical Example: Spam Detector



Graphical Example: Spam Detector



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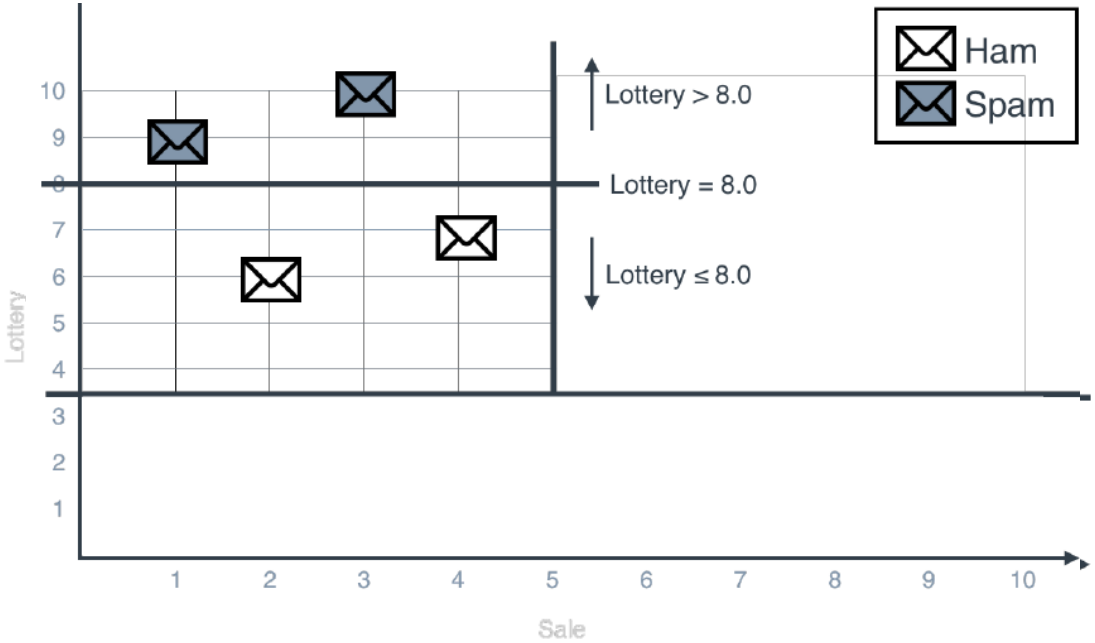

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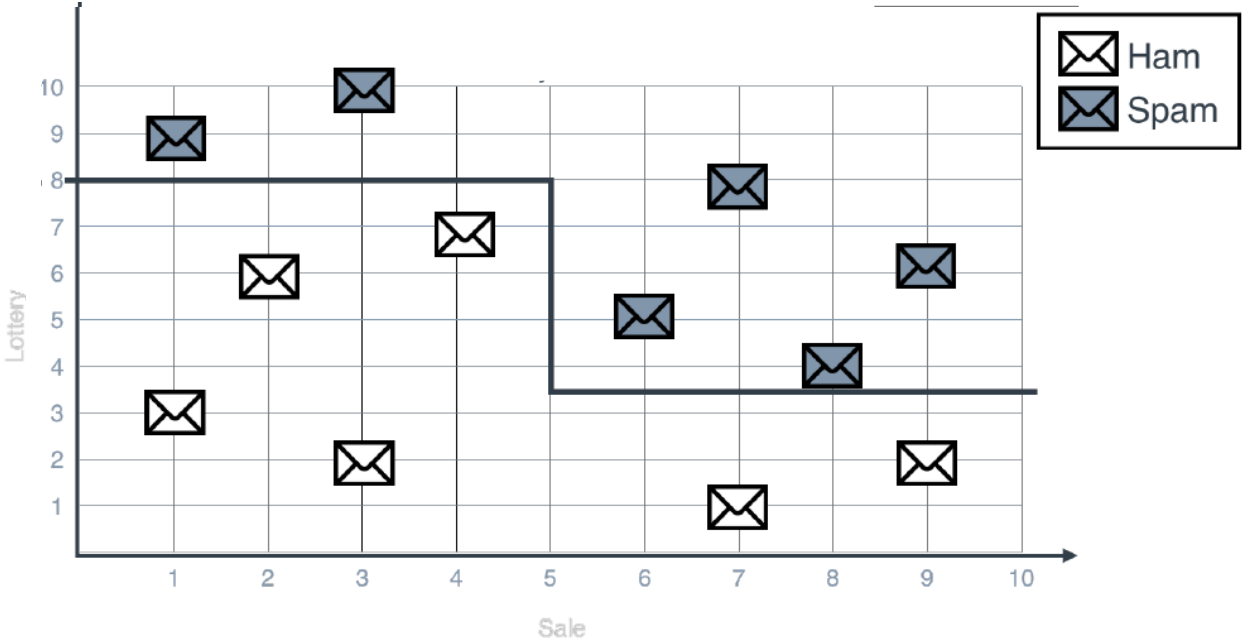
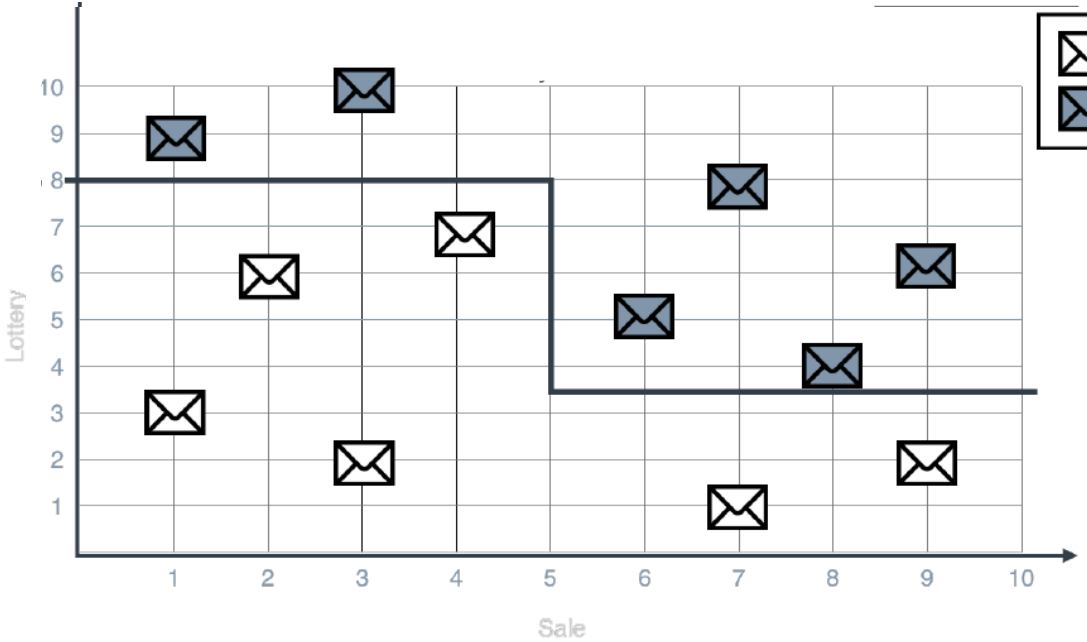


Graphical Example: Spam Detector



Each Stub represents vertical or horizontal line

Decision Tree For Classification

Use colab to open this github notebook:

“s7s/machine_learning_1/decision_trees/decision_trees.ipynb”

Decision Trees For Regression

Decision Trees For Regression

For regression,

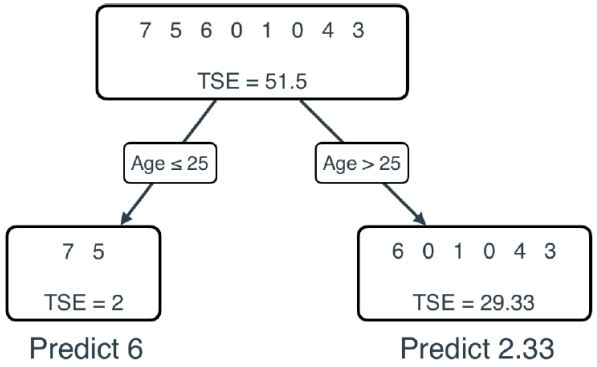
- The decision is **the average** of the set.
- The error is **Total Square Error(TSE)** from the average.
- The best question that gives **the least error**.

Decision Trees For Regression

Decision Trees For Regression

Age	Engagement
10	7
20	5
30	6
40	0
50	1
60	0
70	4
80	3

Decision Trees For Regression



TSE = 51.5

TSE = 31.33

TSE gain = 20.17

Age	Engagement
10	7
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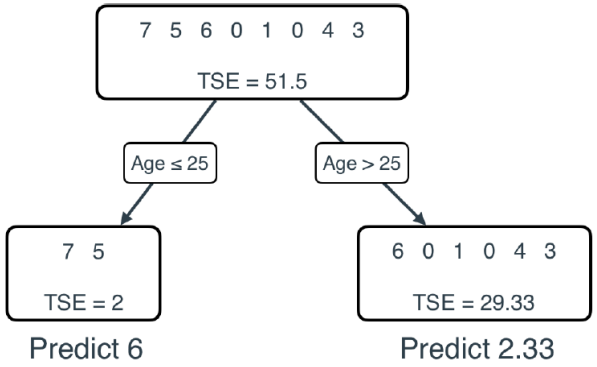
Decision Trees For Regression



TSE = 51.5

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Age	Engagement
10	7
20	5
30	6
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50	1
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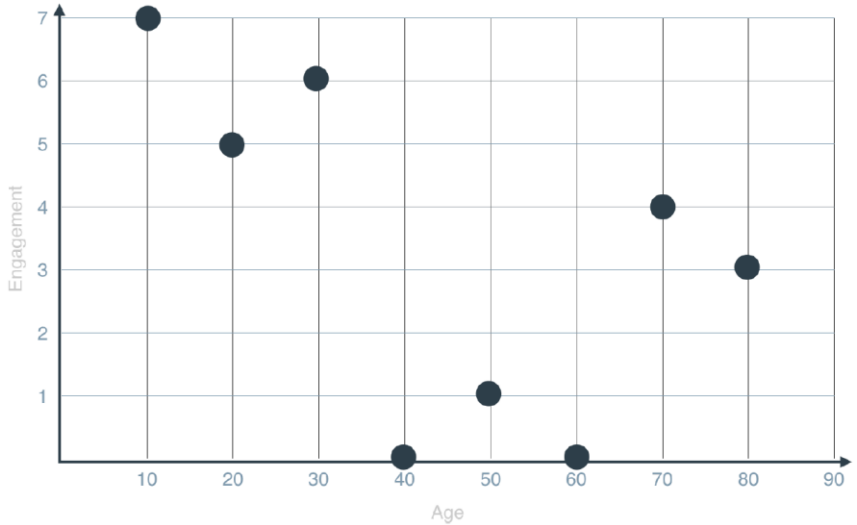
70	4
80	3

TSE example (root):

$$(5-3.25)^2+(6-3.25)^2+(7-3.25)^2+(0-3.25)^2+(1-3.25)^2+$$
$$(0-3.25)^2+(4-3.25)^2+(3-3.25)^2 = 51.5.$$

Decision Trees For Regression



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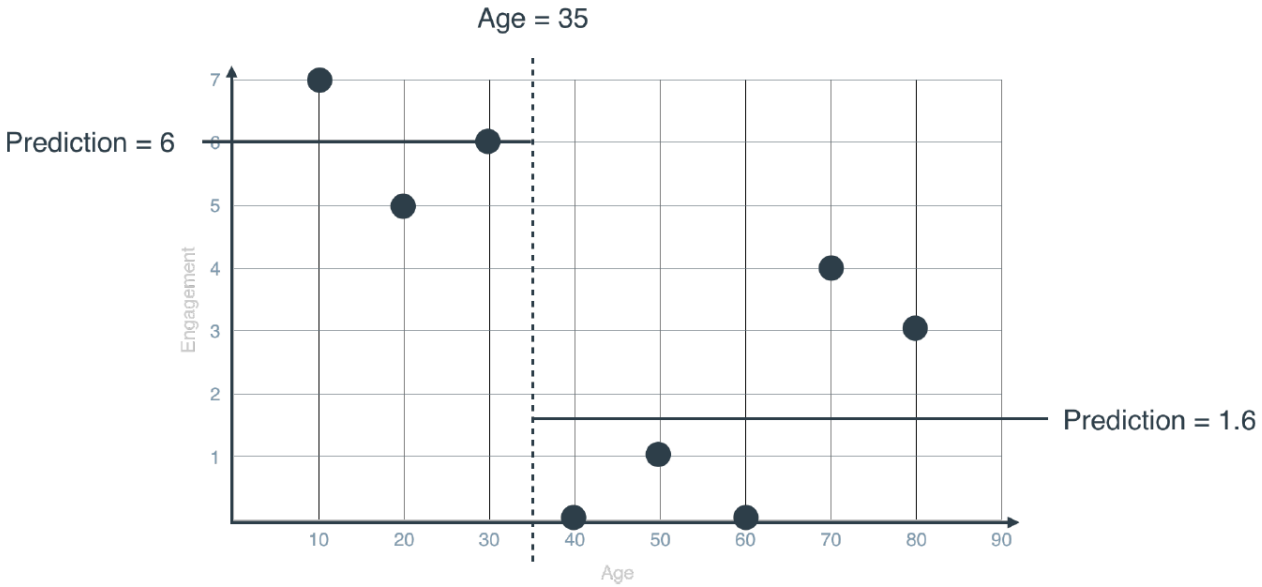
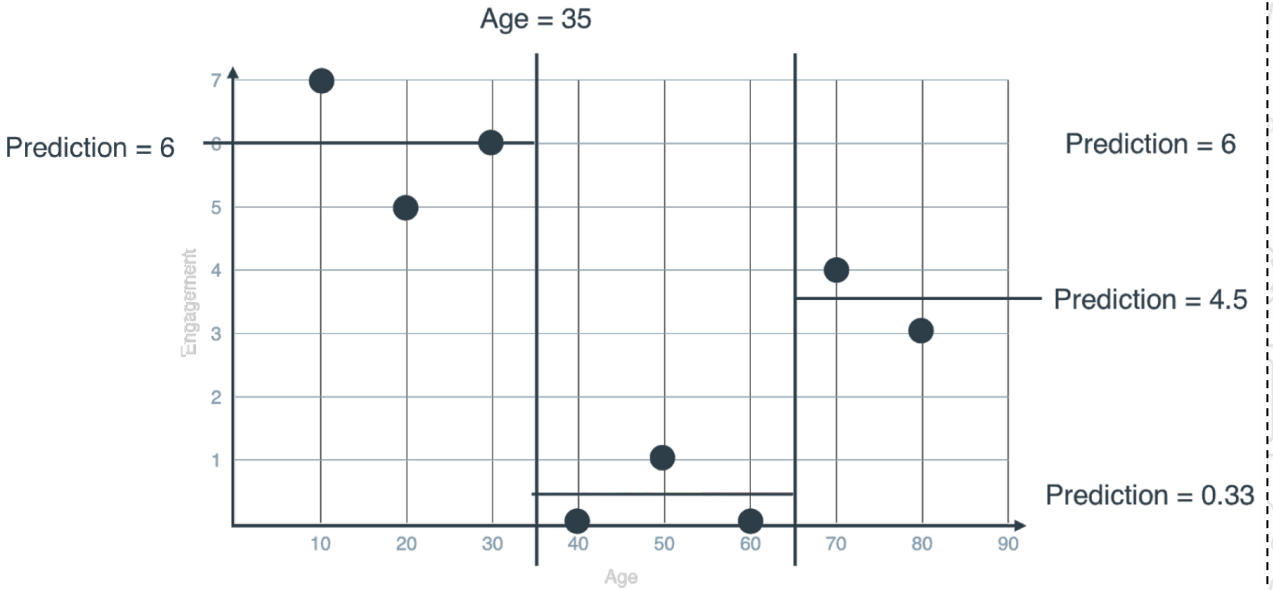
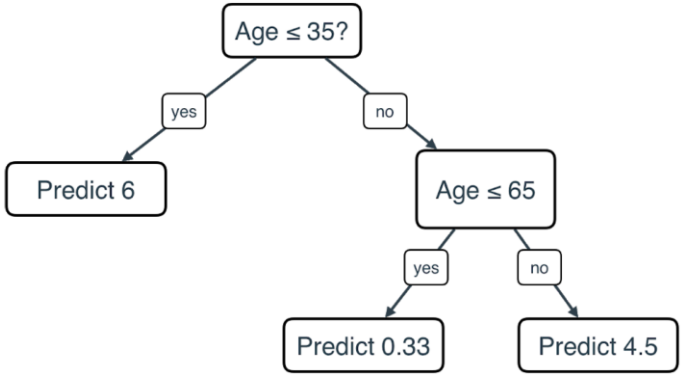
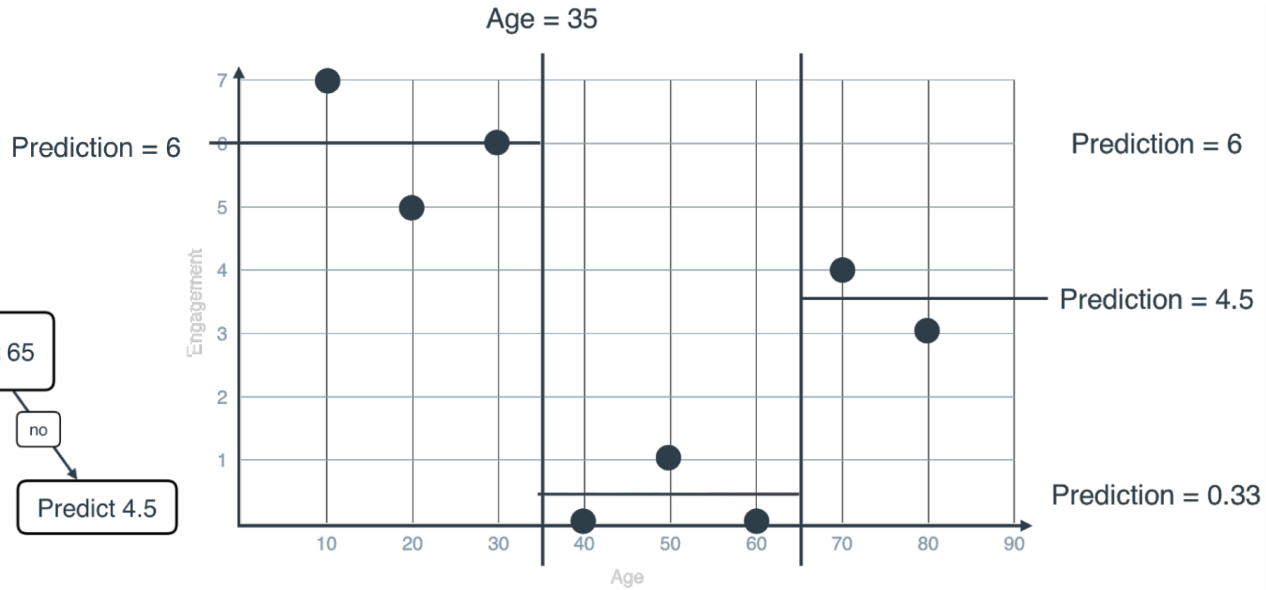


Decision Trees For Regression



Decision Trees For Regression





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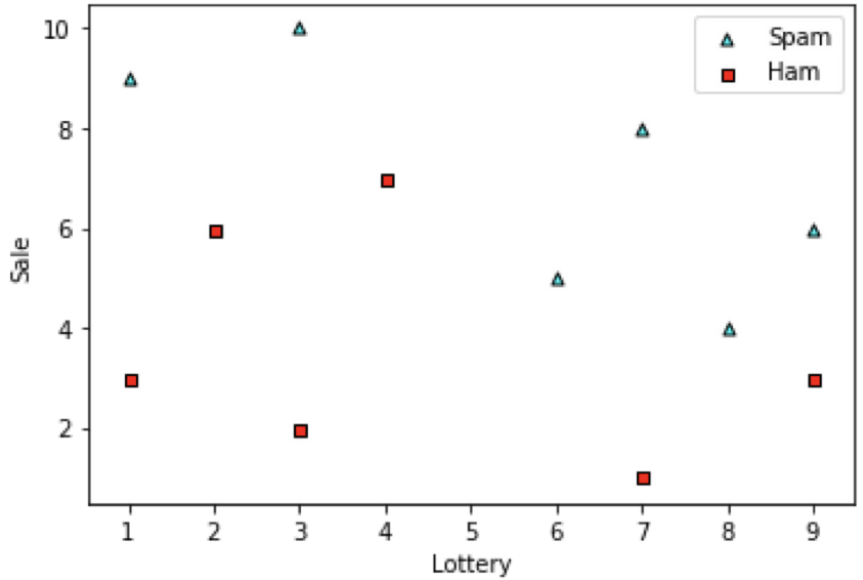
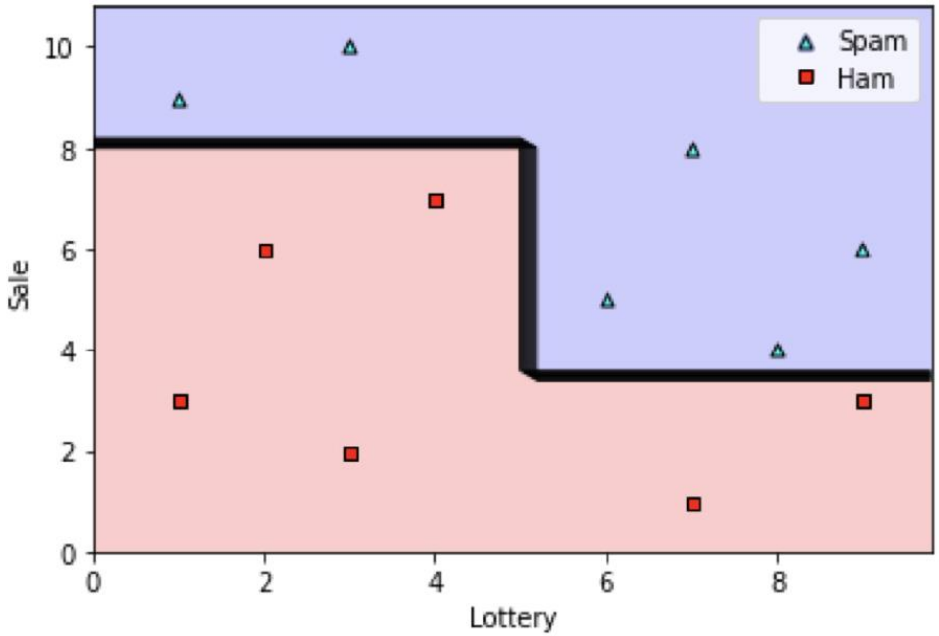
Random Forest

Using norma Decision Tree



Random Forest

Using norma Decision Tree



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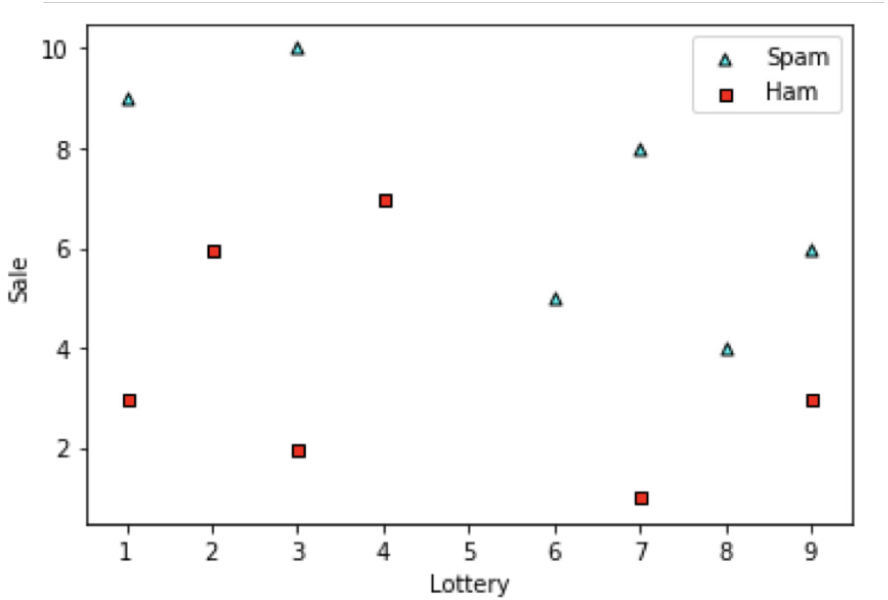

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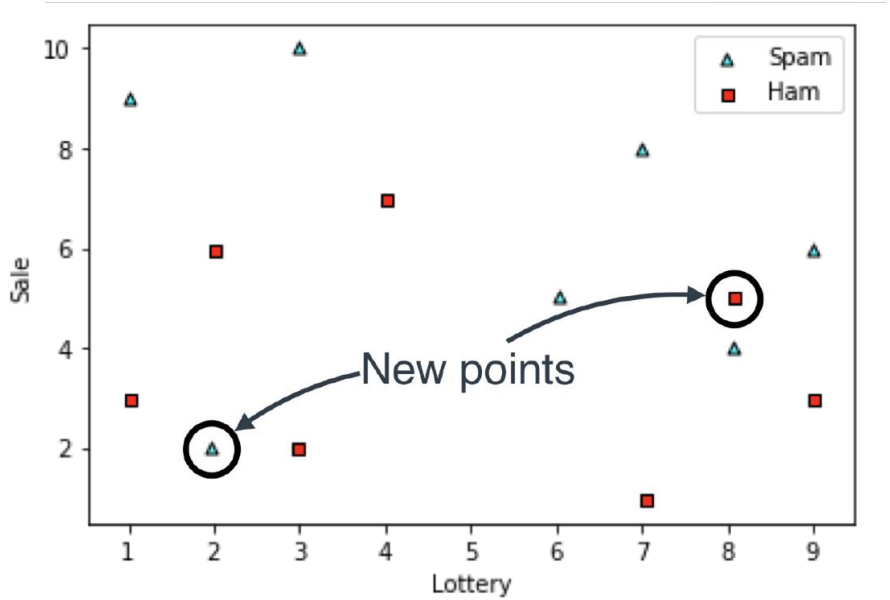

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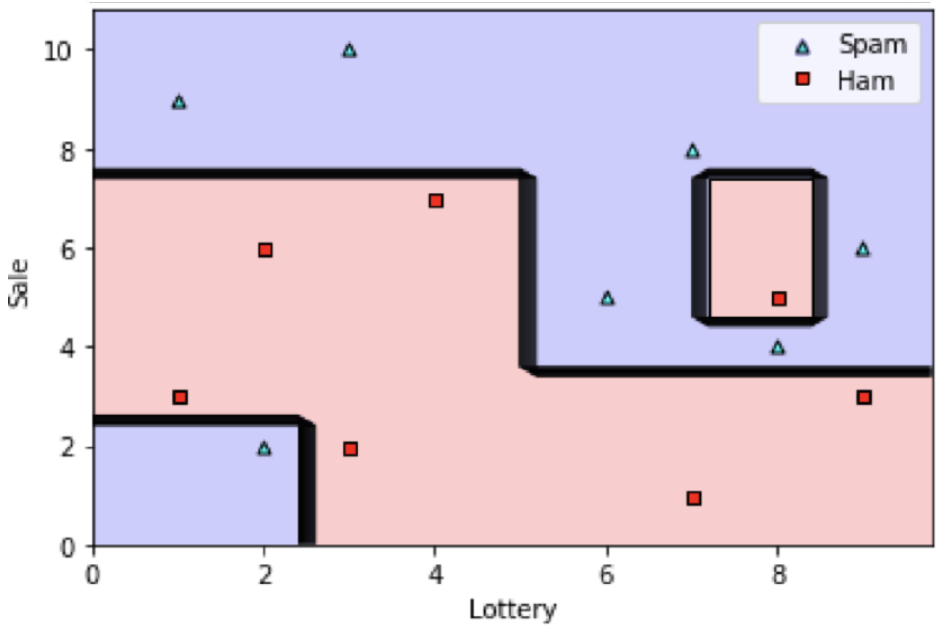

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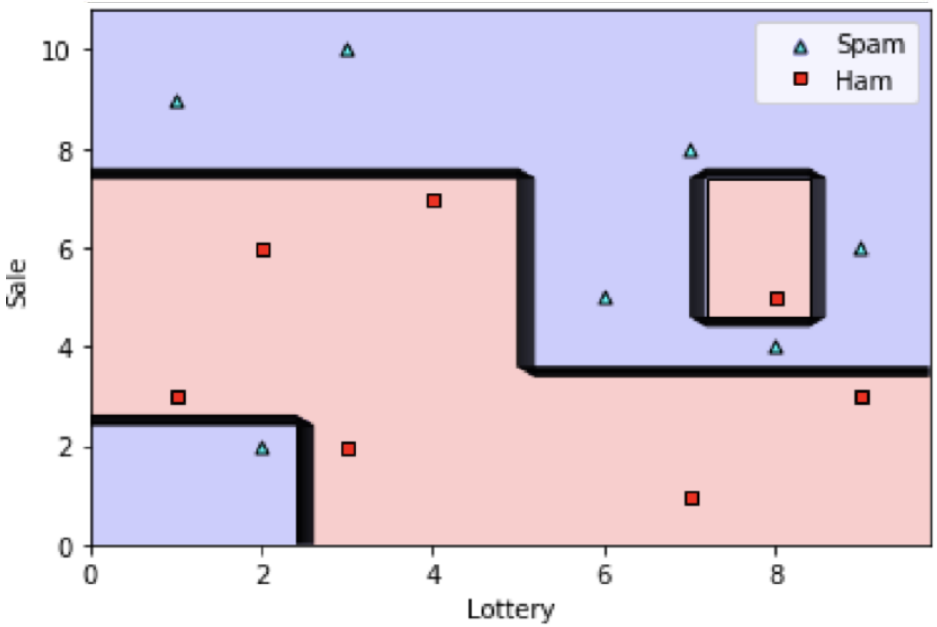
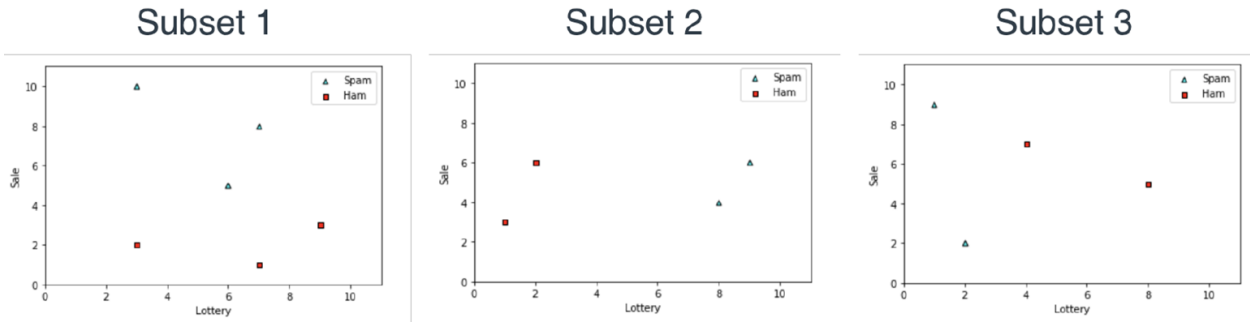


Do you notice the overfitting?

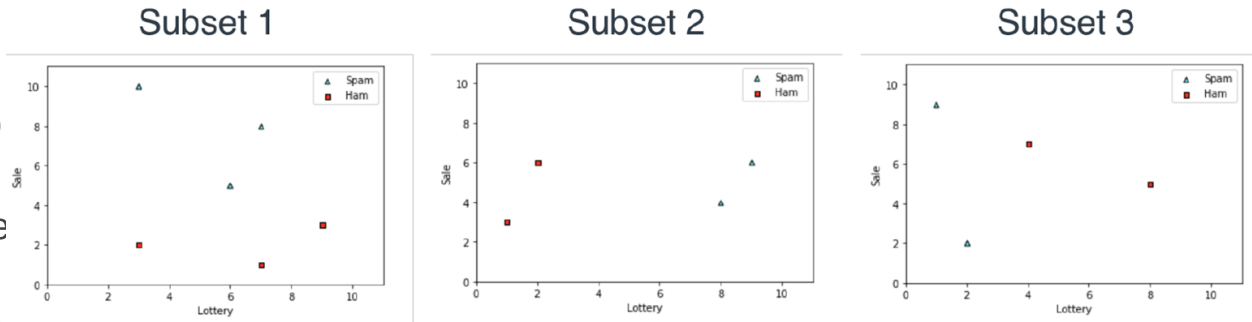
Random Forest



Random Forest

Random Forest Steps:

- Split data randomly into sets:
- Train each decision tree at one of these sets.
- Take decision based on vote between these models.



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Feedback