



Supervised learning- Decision tree(2)



Parcours Progis
Etudes, Medias, communication, Marketing

Bahareh Afshinpour.

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References

- <https://www.geeksforgeeks.org/k-nearest-neighbours/>
- <https://www.youtube.com/watch?v=pR-Of1ua6Dc>

- There are two main methods that are commonly used to split the data:
 - a) Gini impurity and
 - b) entropy information gain.

Example of Desision Tree-visual representation

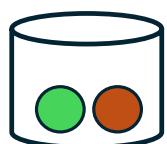
Age	Education	Marital status	Race	Sex	Hours Per Week	Label
61	master	maried	White	Male	40	<=50k
48	PhD	divorse	White	Female	16	<=50k
55	PhD	married	Black	Male	45	>50 k
30	master	Never married	Black	Female	50	>50 k

Target variable

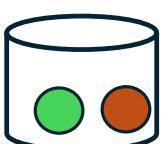


Race is a best one

100% pure

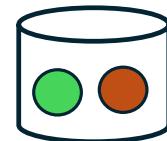


No

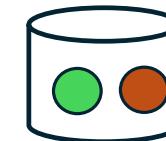


Yes

Age >= 50



No

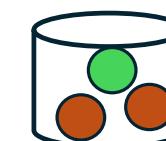


Yes

Education=PhD

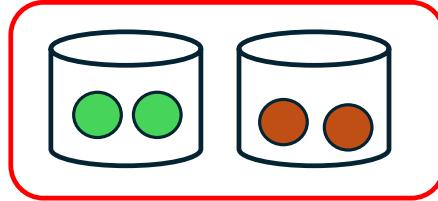


No



Yes

Marital status=married



Race=Black

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Example of Desision Tree-visual representation

Age	Education	Marital status	Race	Sex	Hours Per Week	Label
61	master	maried	White	Male	40	<=50k
48	PhD	divorse	White	Female	16	<=50
55	PhD	married	Black	Male	45	>50 k
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Which of these columns(features) best splits these labels into the largest purest buckets?

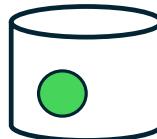
We have two rows
less than 50k and
two more than 50k



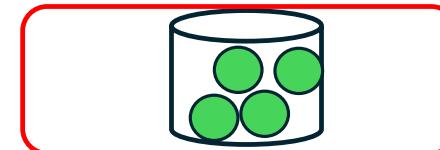
Gini impurity

- The probability that decision tree made a mistake.
 - High Gini ipmurity is bad
 - Low Gini impurity is good
- The algorithm goes to check a features one by one (like we just saw), and it calculates this gini impurity score for each one of the features.
- One that it picks is the one with the best that is the **lowest** gini impurity score.
- Gini consider bothe the **purity** and the **weight** of the leaves.

Not much weight



We have much weight.



Binning

- We need to convert the numeric feature into multiple classes (like $age > 50$)
- Finding a cut off (finding the rule for a numeric column is a non-trivial task)
- We are going to create a rule (hypothetical decision)
- How does efficiently the algorithm find these thresholds for the rules
 - $age < 30$ or $age > 50$ or

- ✓ It finds split point
- ✓ It takes a copy of that numeric data and then it sorts it(ascending order)

Binning example

Age	Education	Marital status	Race	Sex	Hours Per Week	Label
61	master	maried	White	Male	40	<=50k
48	PhD	divorse	White	Female	16	<=50
55	PhD	married	Black	Male	45	>50 k
30	master	Never married	Black	Female	50	>50 k

30  48  55  61
 39 51.5 58
 <40 <52 <59

We are going to find the split points :

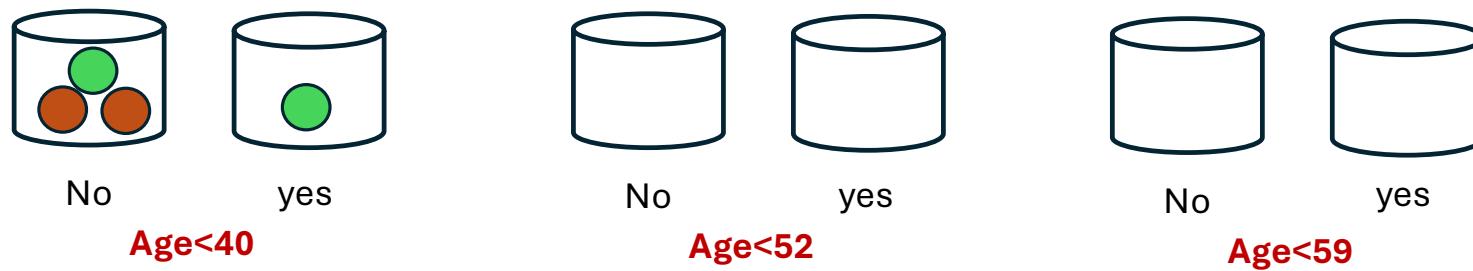
A bunch of split points are calculated based on the differences between these numbers

What is the split point? The midpoint between adjacent values.

Binning example

- Which one has the best overall gini impurity score?

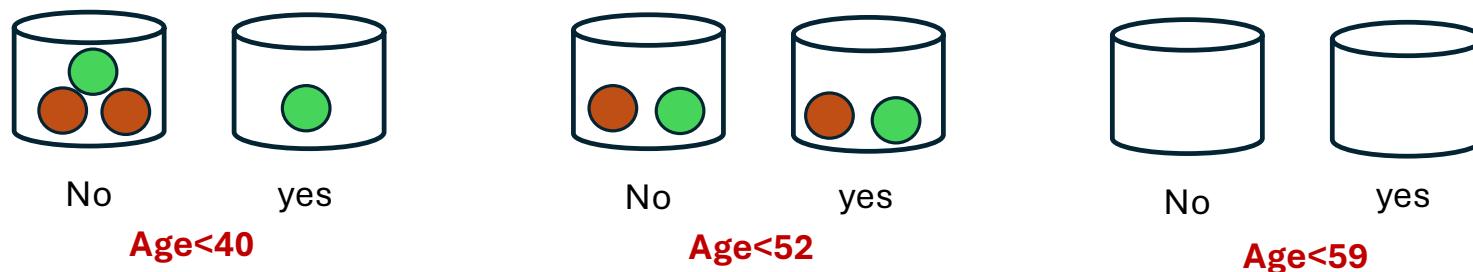
Age	Education	Marital status	Race	Sex	Hours Per Week	Label
61	master	maried	White	Male	40	<=50k
48	PhD	divorse	White	Female	16	<=50
55	PhD	married	Black	Male	45	>50 k
30	master	Never married	Black	Female	50	>50 k



Binning example

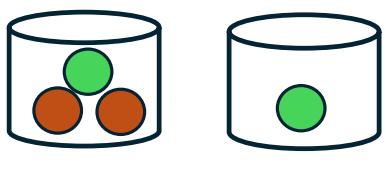
- Which one has the best overall gini impurity score?

Age	Education	Marital status	Race	Sex	Hours Per Week	Label
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30	master	Never married	Black	Female	50	>50 k

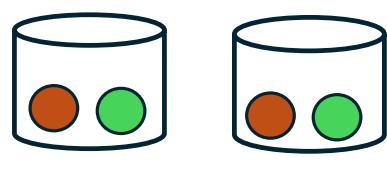


- Which one has the best overall gini impurity score?

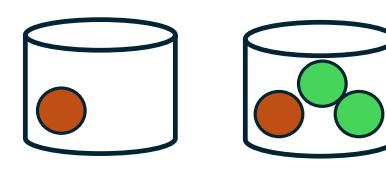
Age	Education	Marital status	Race	Sex	Hours Per Week	Label
61	master	maried	White	Male	40	$\leq 50k$
48	PhD	divorse	White	Female	16	≤ 50
55	PhD	married	Black	Male	45	$> 50k$
30	master	Never married	Black	Female	50	$> 50k$



Age<40

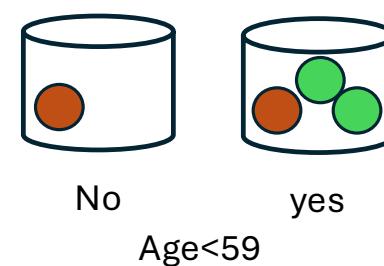
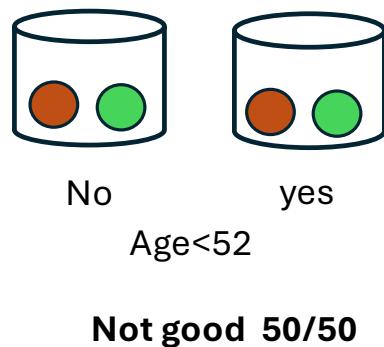
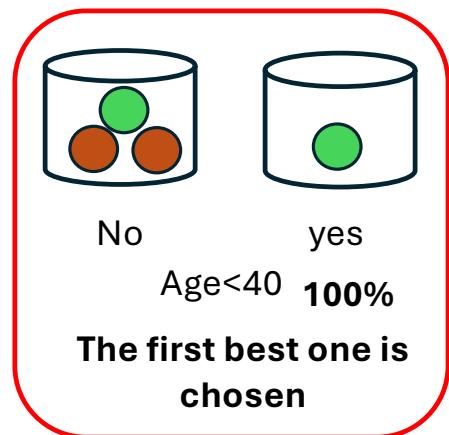


Age<52



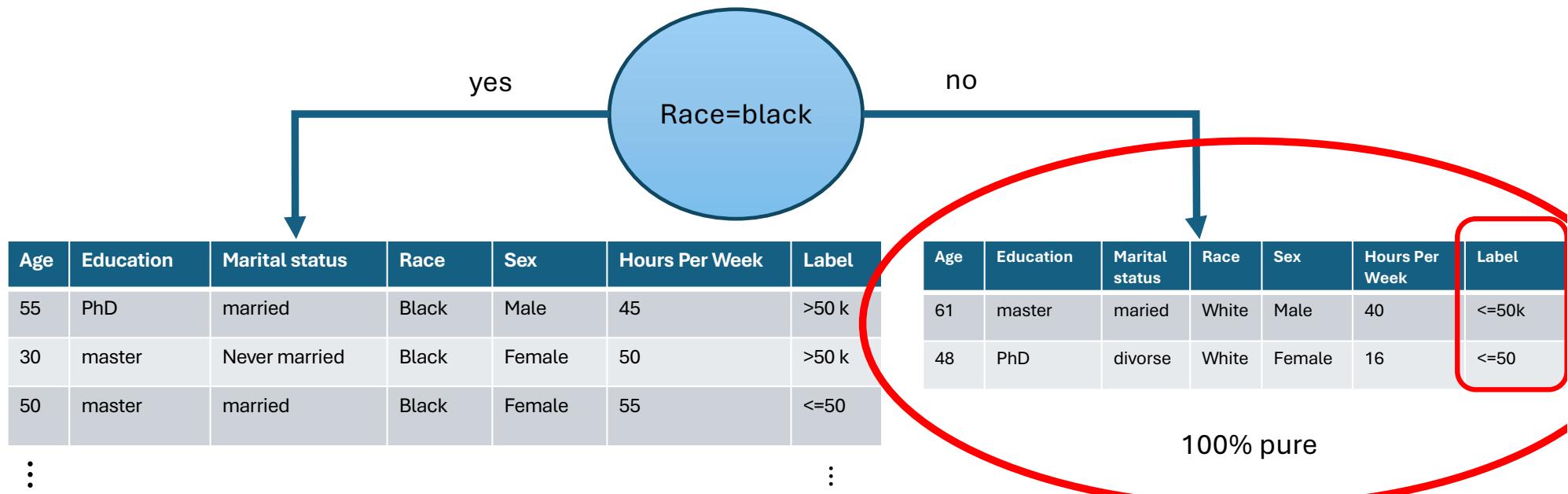
Age<59

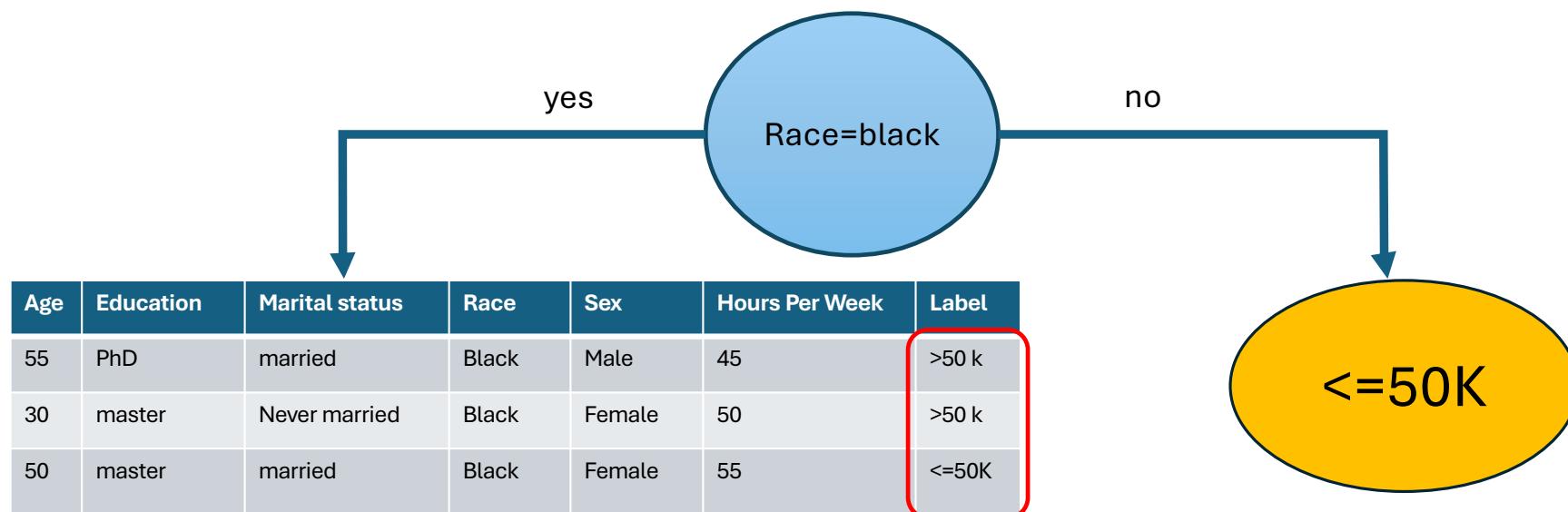
- Which one has the best overall gini impurity score?



Age < 40

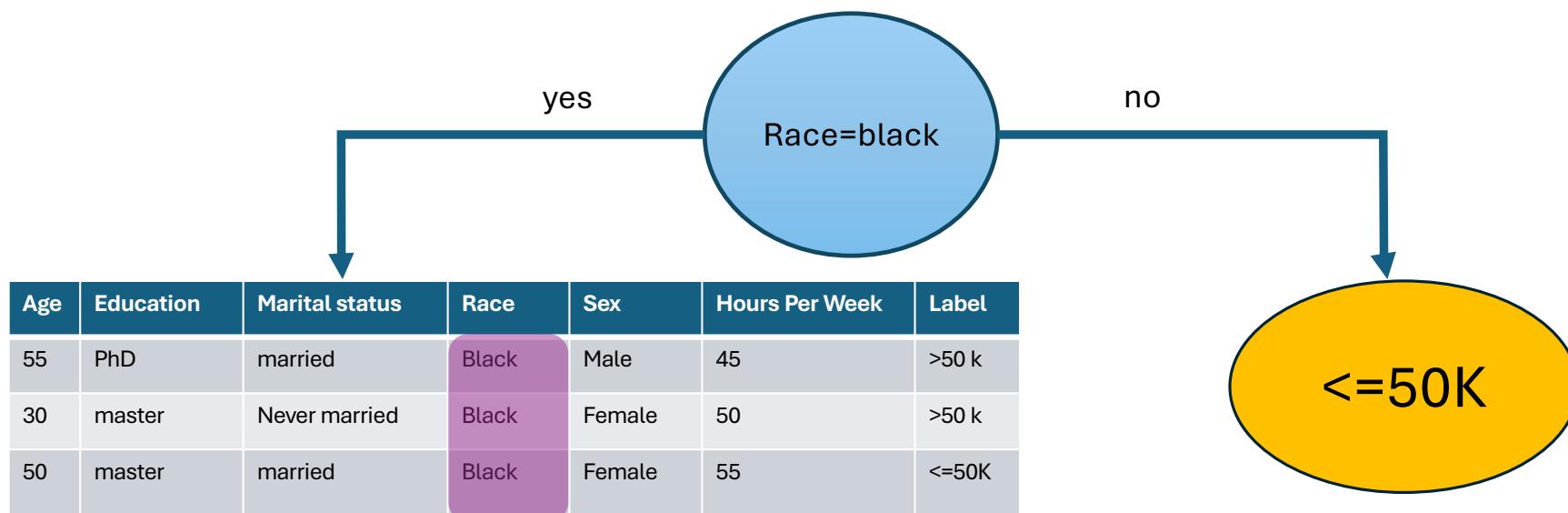
Imagine we have many rows (records) in our dataset.





Left side: we do not have purity
So, the algorithm try to split it again

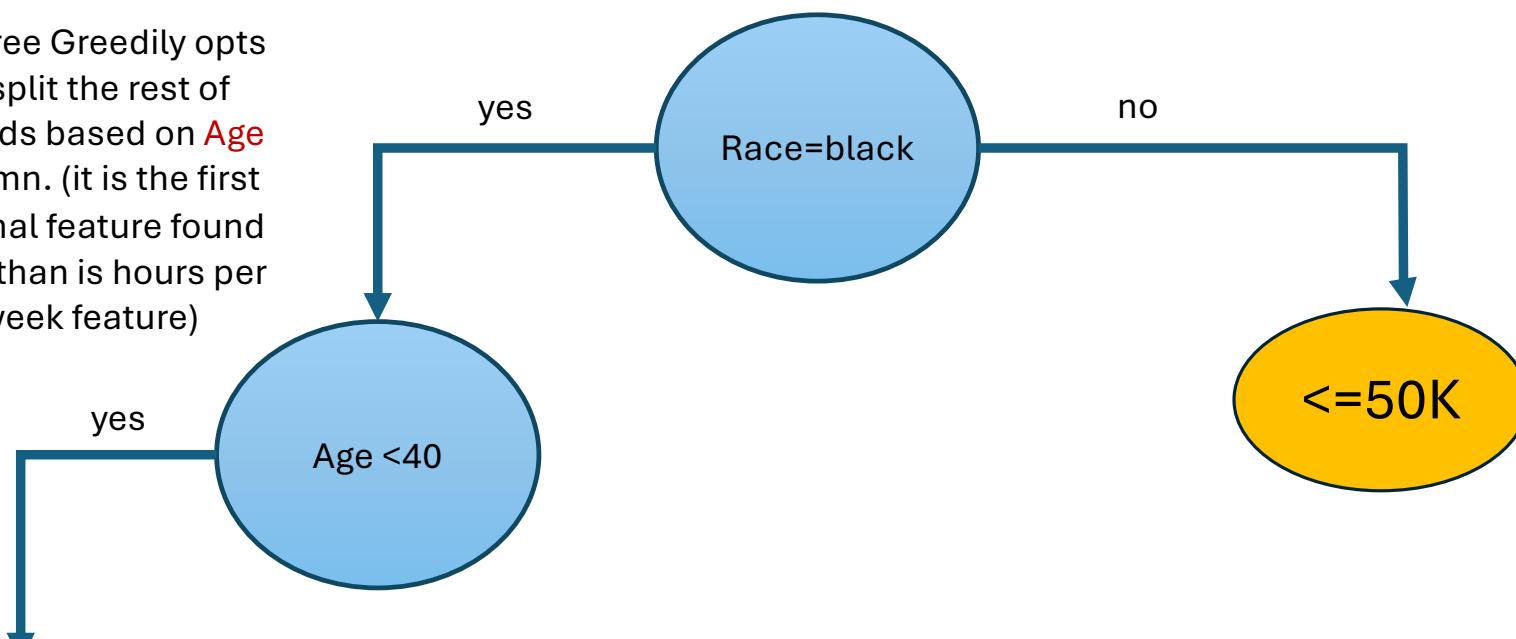
A Leaf node
With a prediction
label



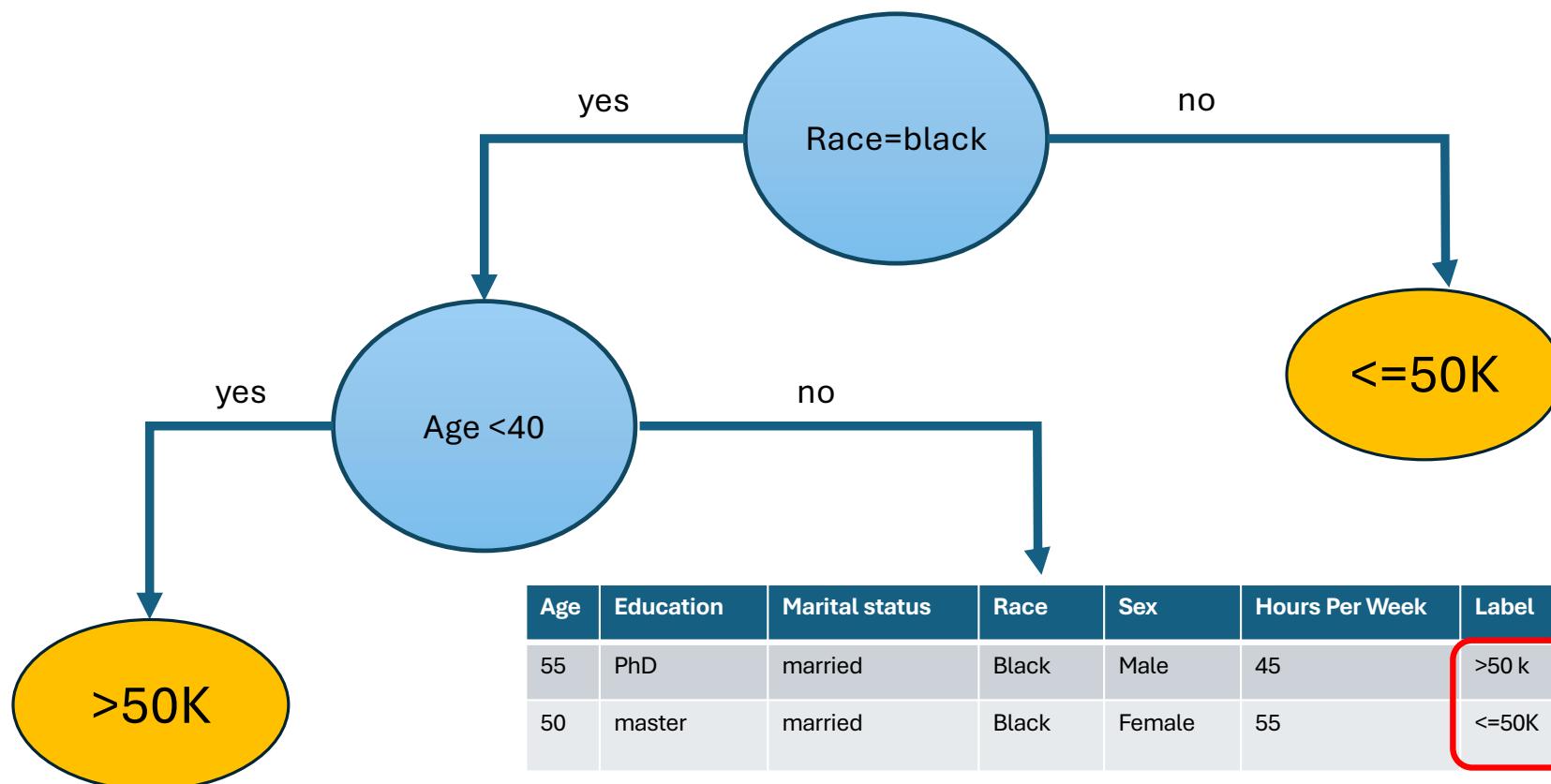
A Leaf node
With a prediction
label

- But all the values in the Race column are the same.
- The algorithm **masks** them since they have no useful information.
- The algorithm starts to find the best column for the next condition.

The tree Greedily opts to split the rest of records based on **Age** column. (it is the first optimal feature found after than is hours per week feature)

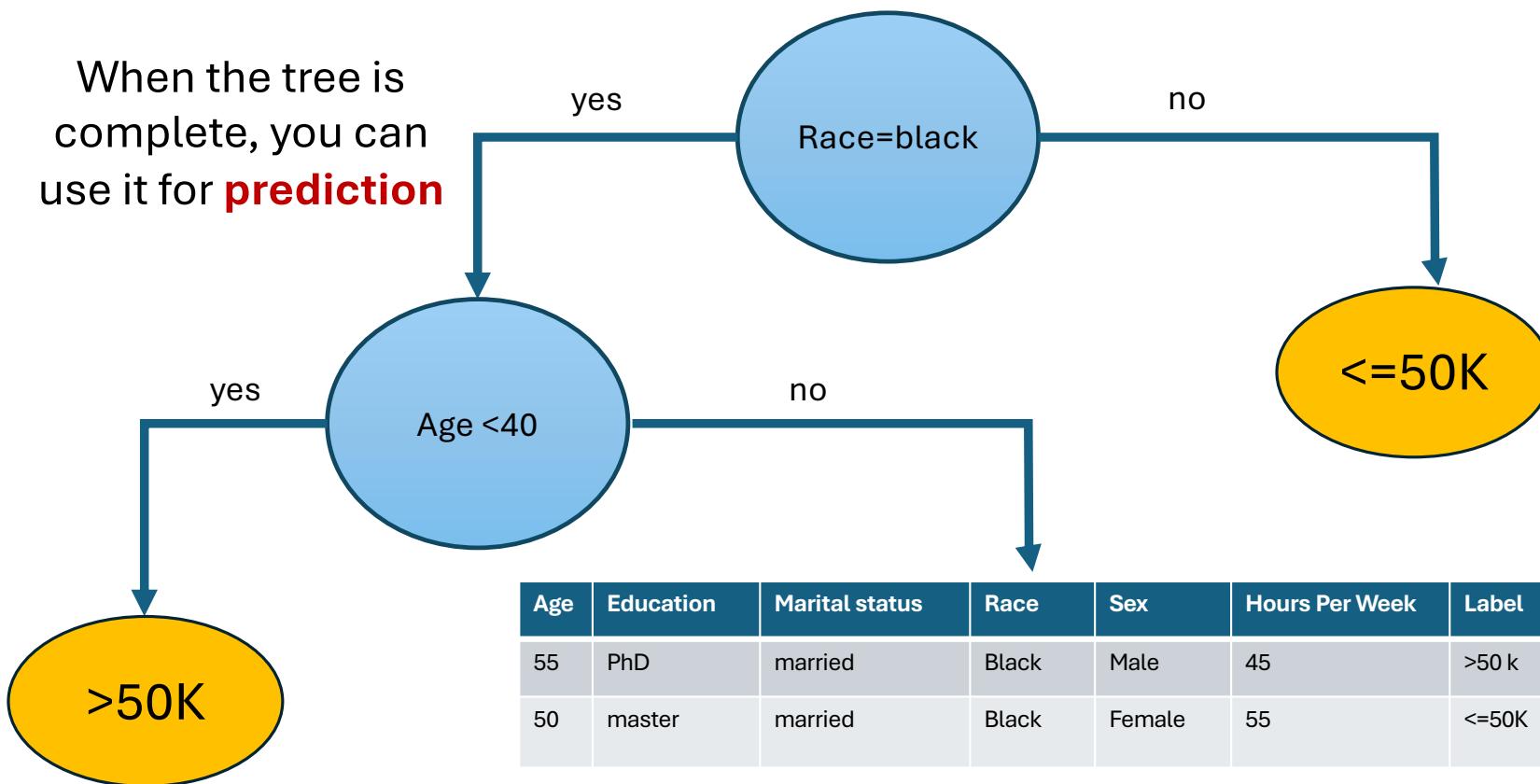


Age	Education	Marital status	Race	Sex	Hours Per Week	Label
30	master	Never married	Black	Female	50	>50 k



We should
continue
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When the tree is complete, you can use it for **prediction**



Age	Education	Marital status	Race	Sex	Hours Per Week	Label
55	PhD	married	Black	Male	45	>50 k
50	master	married	Black	Female	55	<=50K

When the algorithm stop to split

- When the node is 100% pure.
- Based on Hyperparameters
 - You can set the thresholds for such things as:
 - The max dept of the tree
 - The min number of record that fall into a leaf node
 -

A **hyperparameter**, on the other hand, is a variable that is set before the training process begins.

Hyperparameters are not learned from the data but are instead set by the user or determined through a process known as hyperparameter optimization.

Arbres de décision

- Les arbres de décision sont utilisables pour faire de la régression. Au lieu d'associer une classe à chaque feuille, c'est la valeur moyenne de la variable cible des éléments dans cette feuille qui sera utilisée.
- En scikit-learn, la classe à utiliser est un DecisionTreeRegressor.

```
from sklearn.tree import DecisionTreeRegressor
```

```
regressor = DecisionTreeRegressor(max_depth=2)
```

```
regressor.fit(X, y) Hyperparameter
```

```
y_pred = regressor.predict(X_test)
```