Supervised learning- Decision tree(2)

Parcours Progis

Etudes, Medias, communication, Marketing

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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.

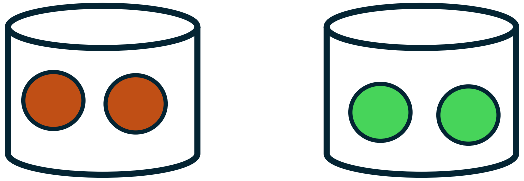
Example of Desision Tree- visual representation

Target variable

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

Which of these columns(features) best splits these labels into the largest purest buckets?

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



No

Yes

Feature x

<=50k

>50 k

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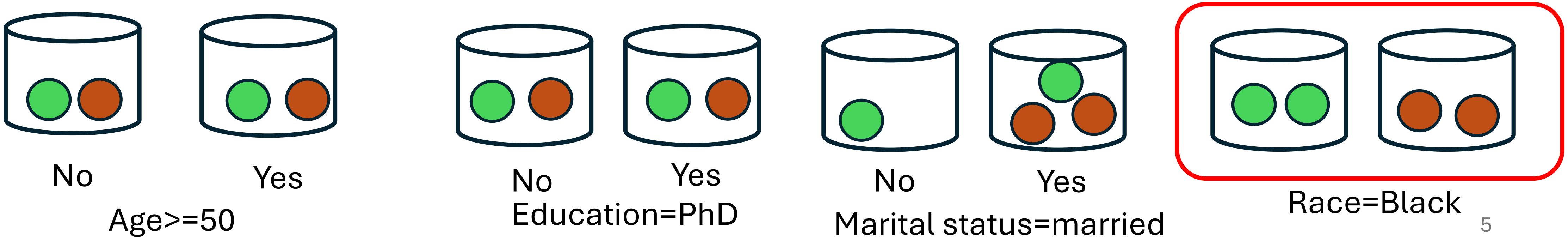
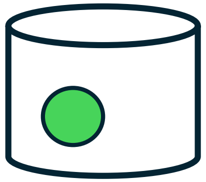
Race is a best one 100% pure

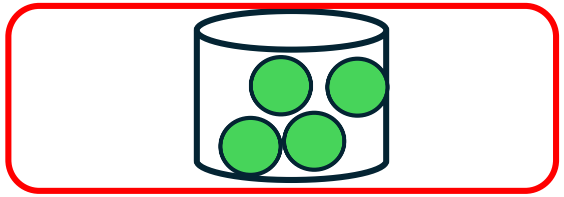


Gini impurity

- 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 bench of split points are calculated based on the differences between these numbers

What is the spilt 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
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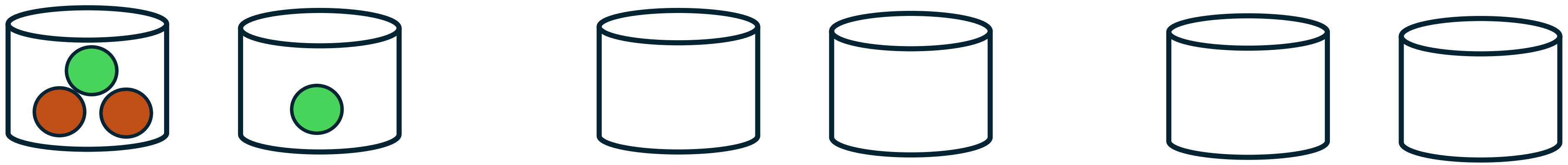

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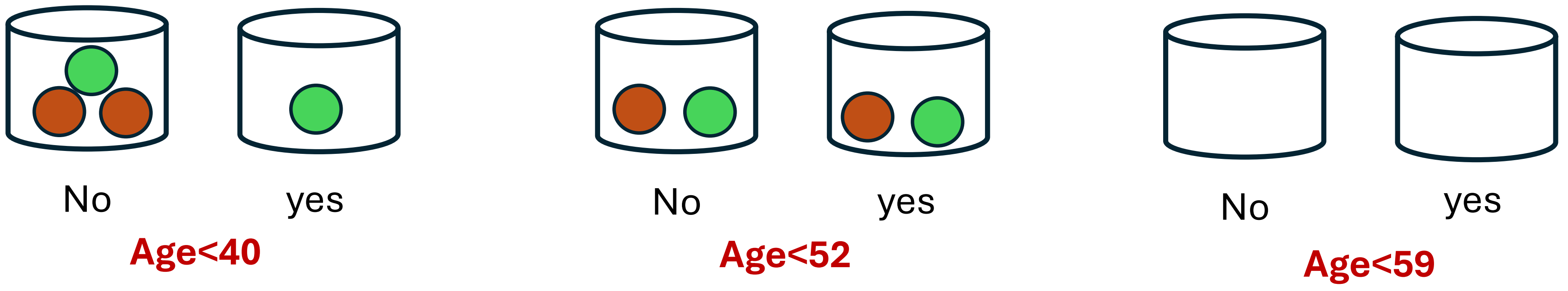

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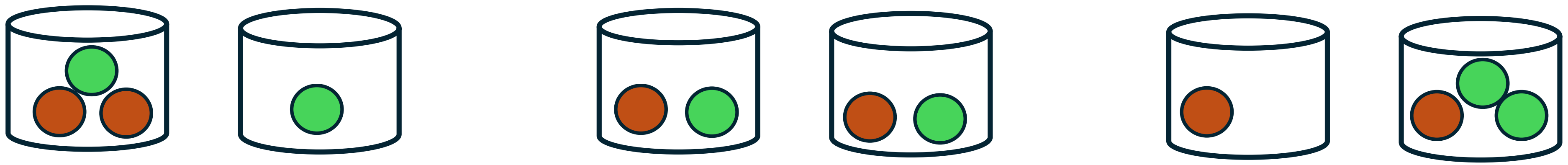
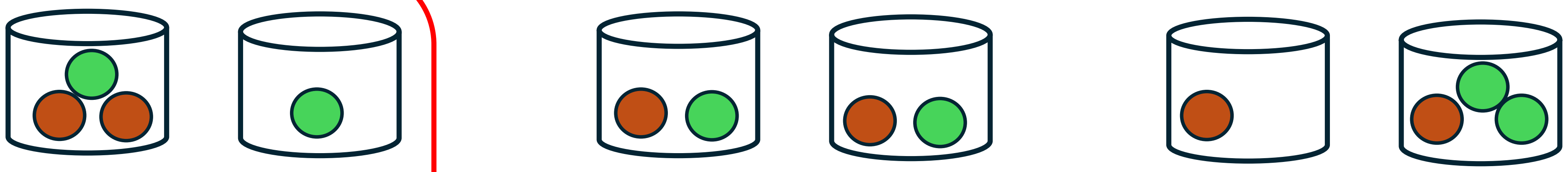


No yes
Age<40

No yes
Age<52

No yes
Age<59

- Which one has the best overall gini impurity score?



No yes
Age<40 **100%**
The first best one is chosen

No yes
Age<52
Not good 50/50

No yes
Age<59

Age<40

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

Race=black

yes

Age	Education	Marital status	Race	Sex	Hours Per Week	Label
55	PhD	married	Black	Male	45	>50 k
30	master	Never married	Black	Female	50	>50 k
50	master	married	Black	Female	55	<=50
⋮						⋮

no

Age	Education	Marital status	Race	Sex	Hours Per Week	Label
61	master	maried	White	Male	40	<=50k
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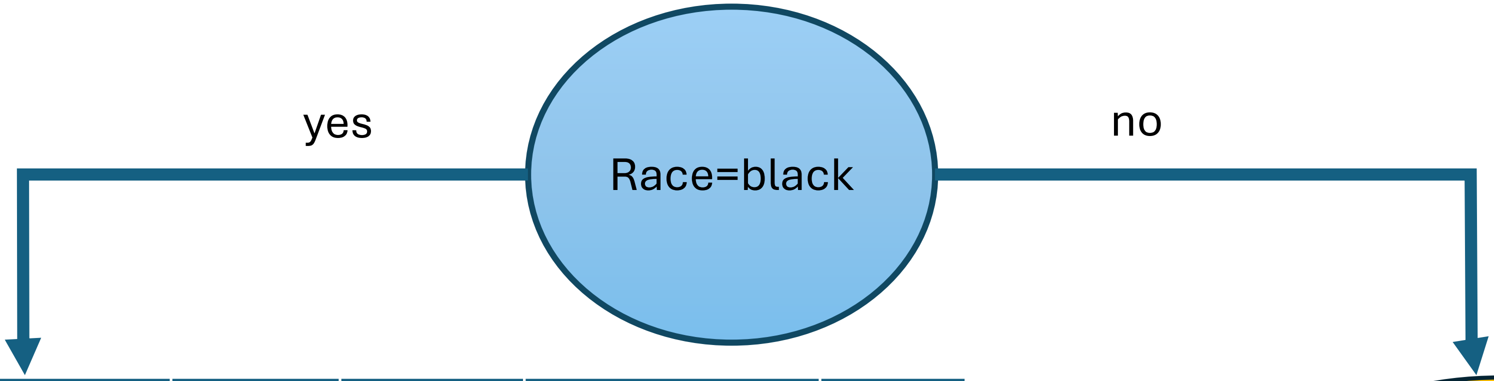
100% pure

Because we have all the same label value, it is pure



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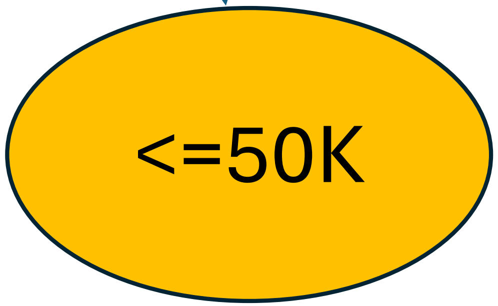
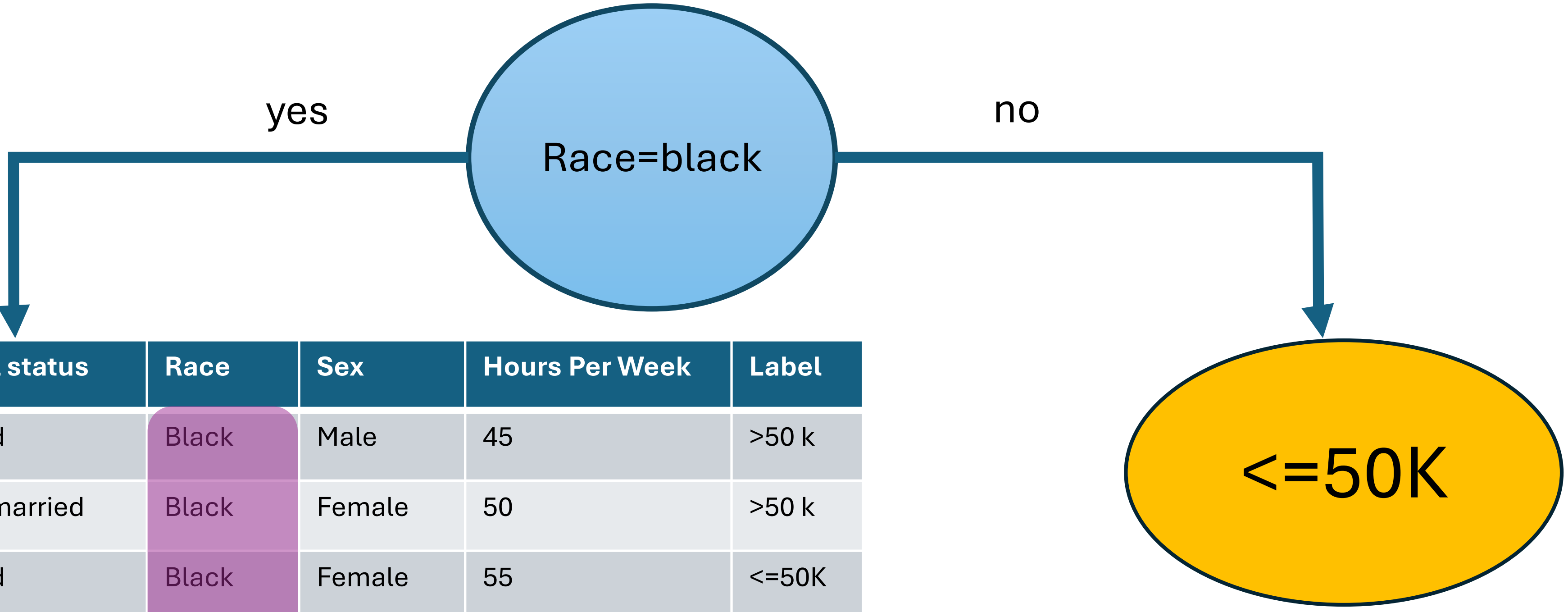


Left side: we do not have purity
So, the algorithm try to split it again

A Leaf node
With a prediction
label

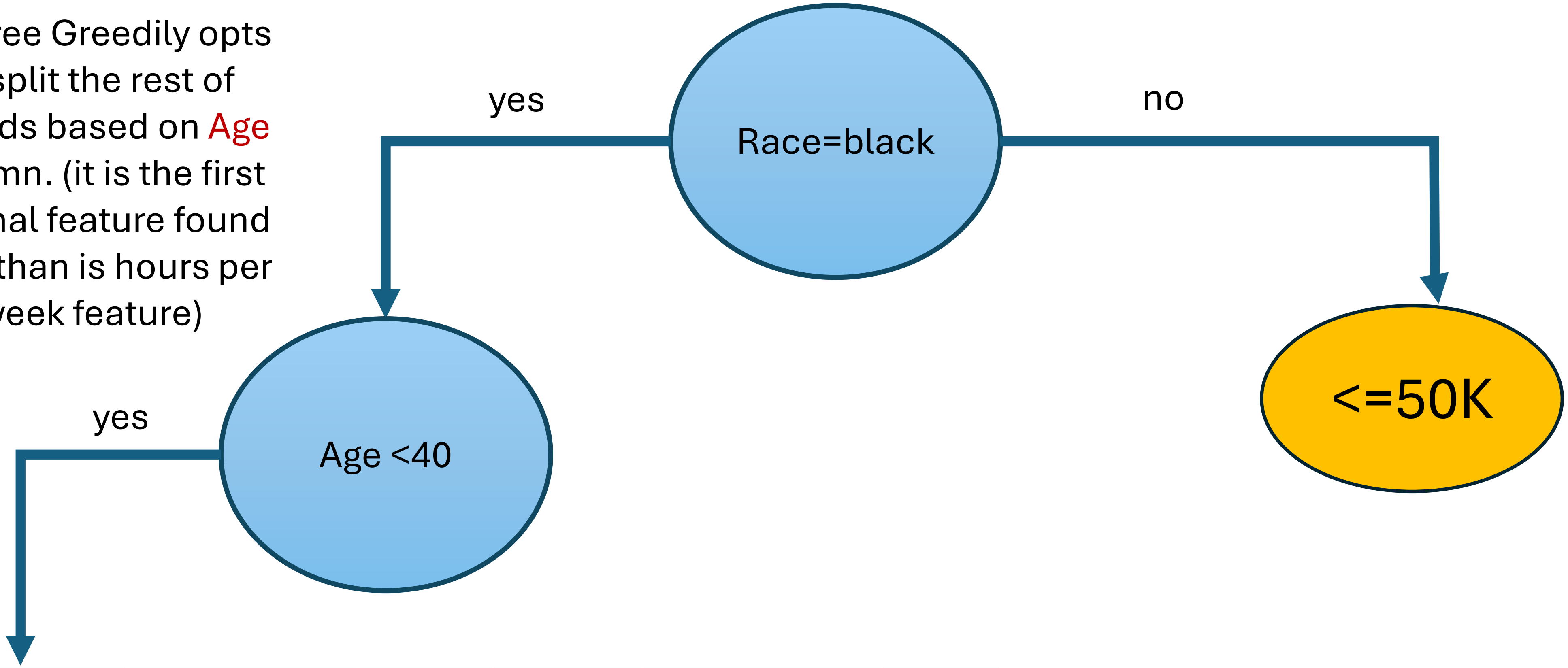


Age	Education	Marital status	Race	Sex	Hours Per Week	Label
55	PhD	married	Black	Male	45	>50 k
30	master	Never married	Black	Female	50	>50 k
50	master	married	Black	Female	55	<=50K

- 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.

A Leaf node
With a prediction
label

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)



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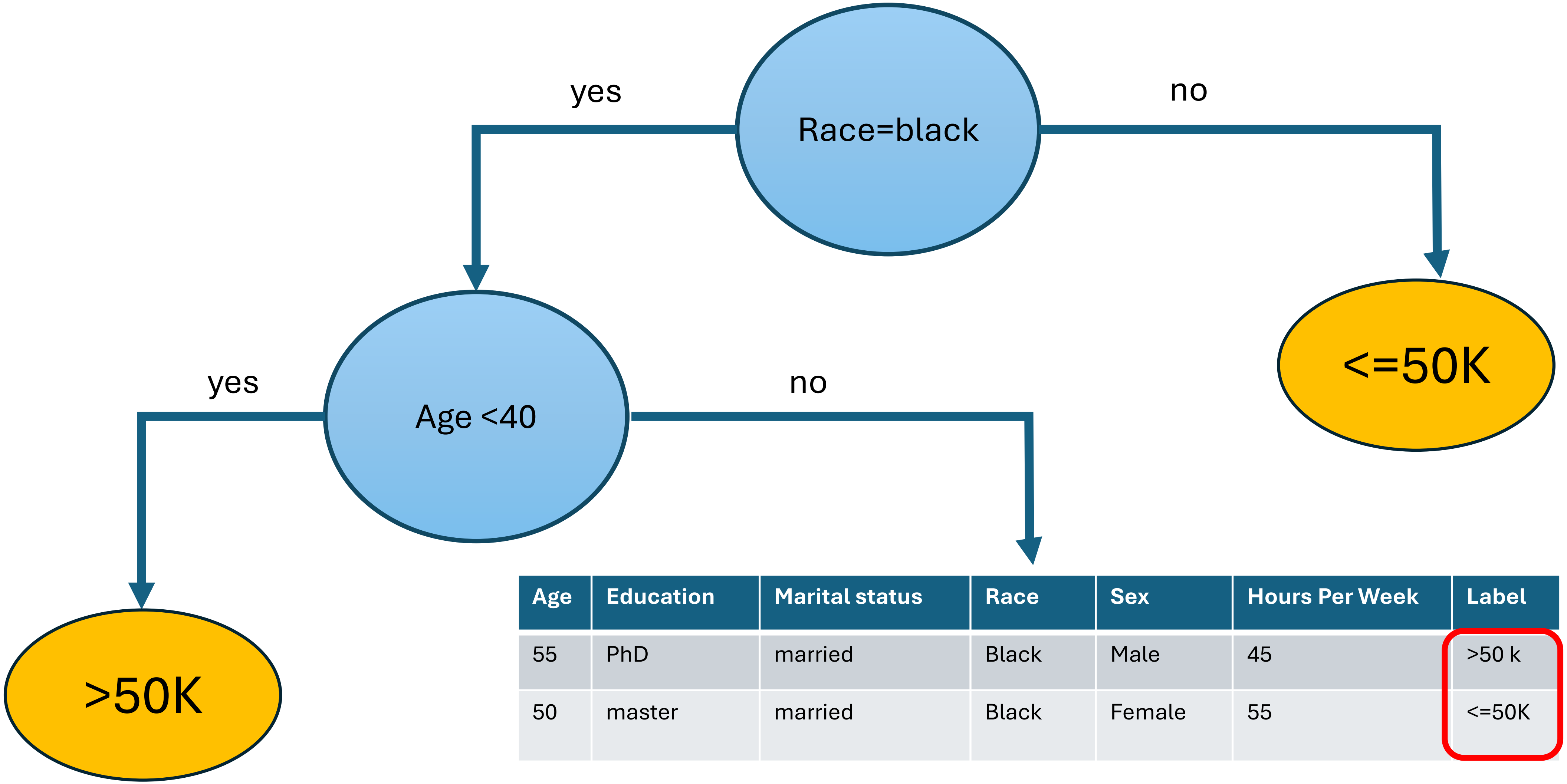

Age	Education	Marital status	Race	Sex	Hours Per Week	Label
55	PhD	married	Black	Male	45	>50 k
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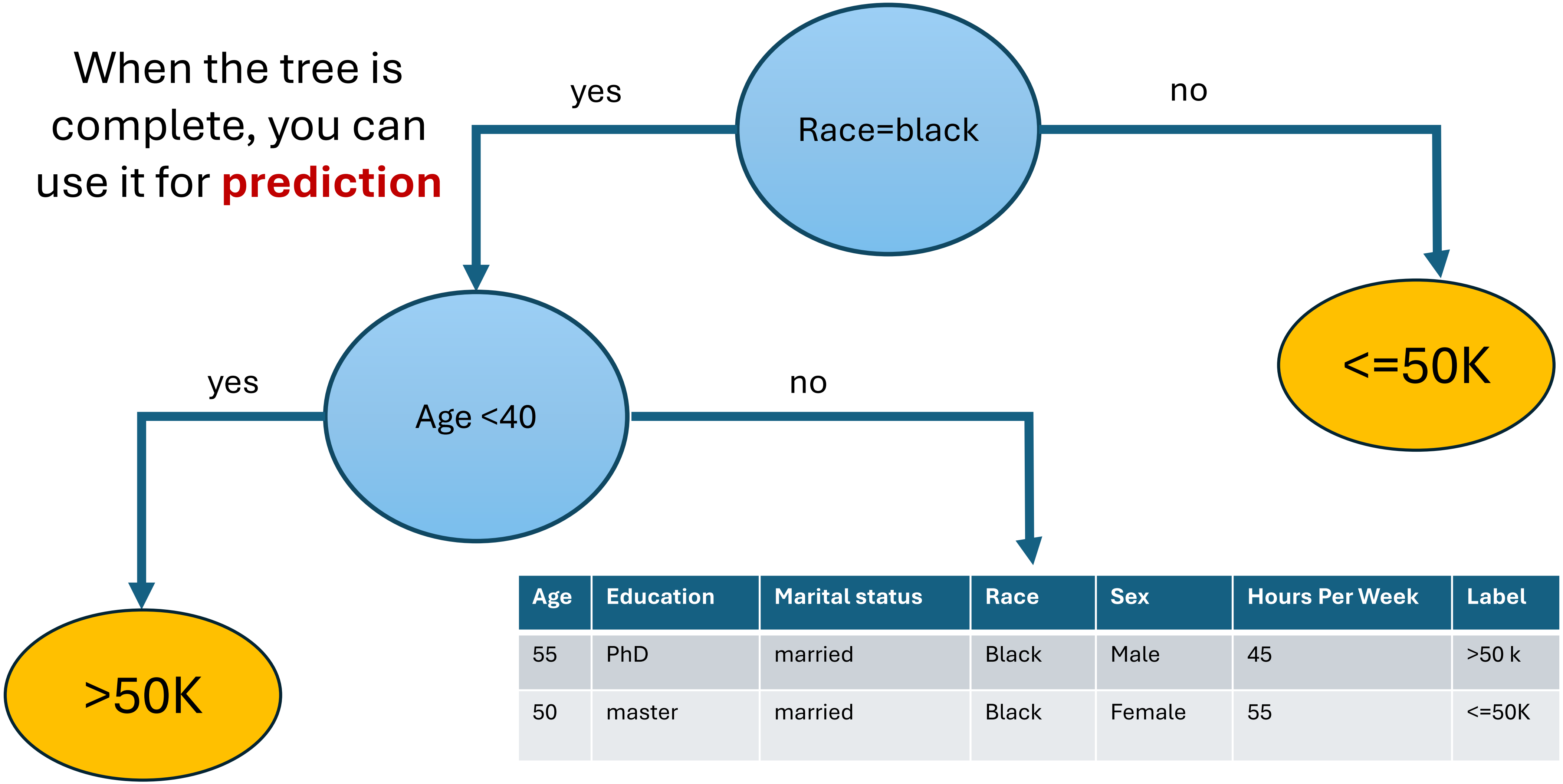
We should continue

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



Age	Education	Marital status	Race	Sex	Hours Per Week	Label
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When the algorithm stop to split

- When the node is 100% pure.
- Based on Hyperparameters
  - You can set the thresholds for such things qs:
    - 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.

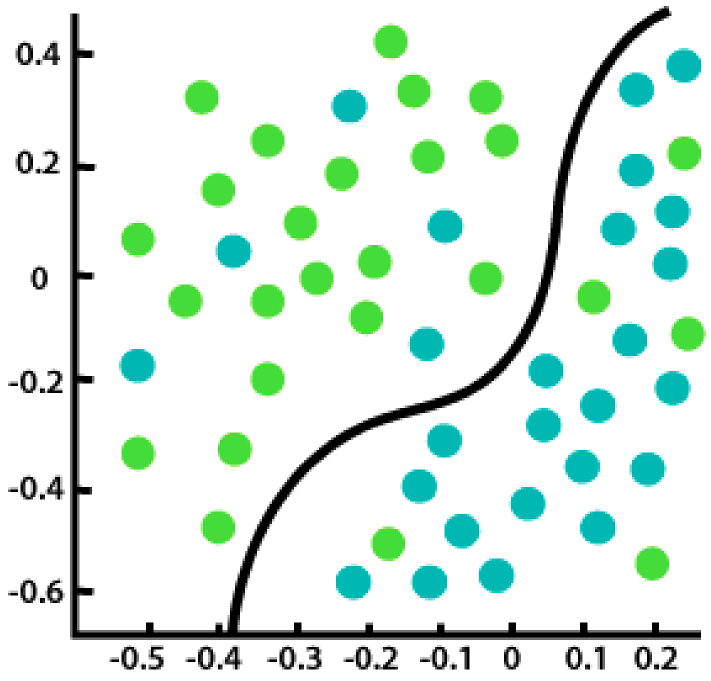
Arbres de décision

- 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.

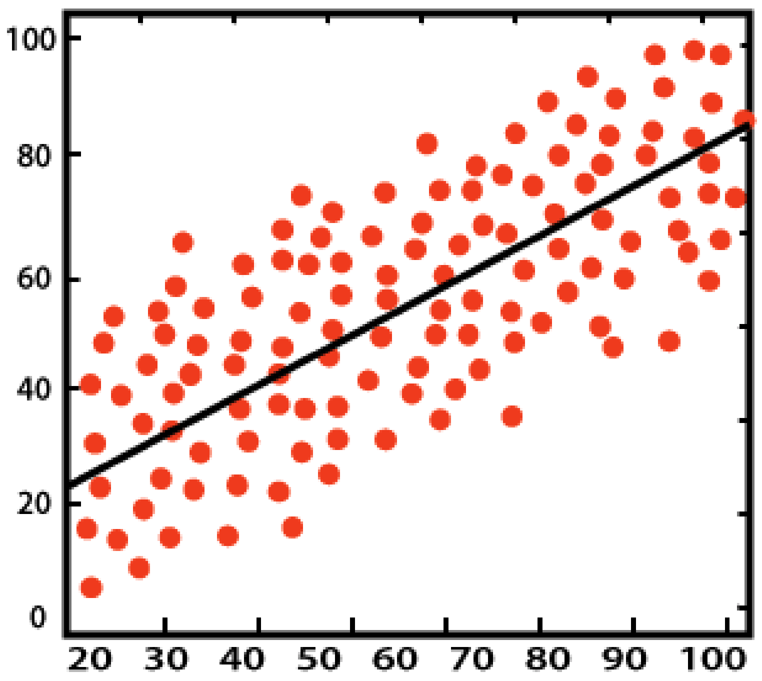
- En scikit-learn, la classe à utiliser est un DecisionTreeRegressor.

```
from sklearn.tree import DecisionTreeRegressor

regressor = DecisionTreeRegressor(max_depth=2)

regressor.fit(X, y)

y_pred = regressor.predict(X_test)
```

Supervised learning- Decision tree(2)



Classification

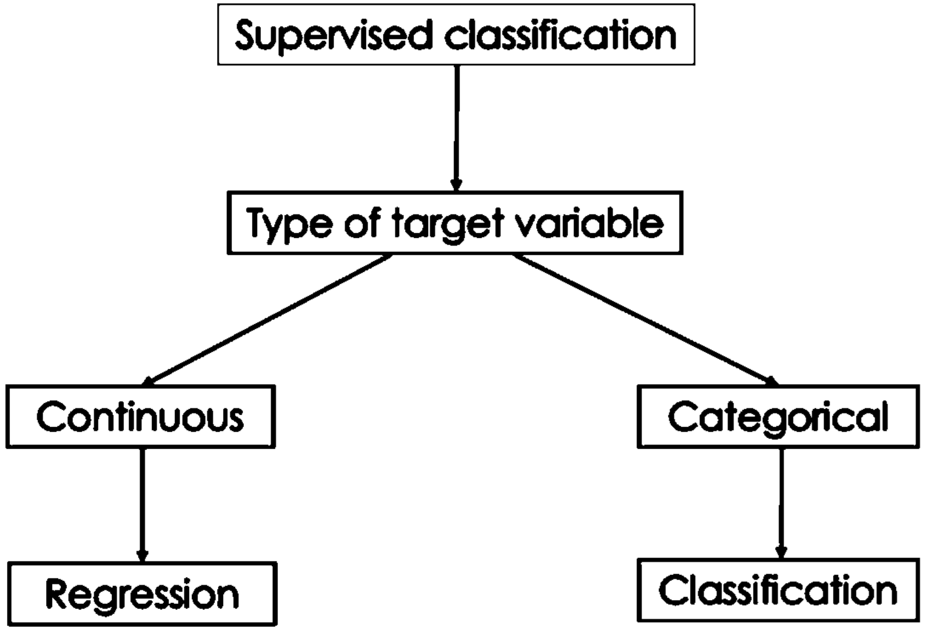


Regression

https://www.javatpoint.com/regression-vs-classification-in-machine-learning

What is Classification in Machine Learning?

- Classification is a supervised machine learning method where the model tries to predict the correct label of a given input data.
- In classification, the model is fully trained using the training data, and then it is evaluated on test data before being used to perform prediction on new unseen data.

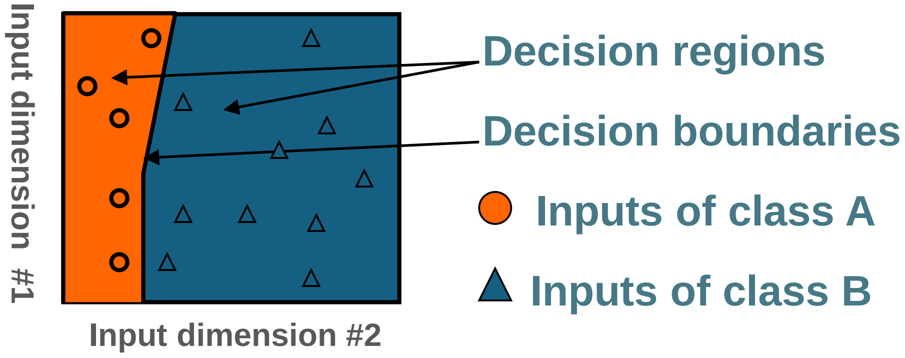


https://www.datacamp.com/blog/classification-machine-learning

Classification: Terminology

- A *classifier* can be viewed as a function of block.
- A classifier assigns one class to each point of the input space.
- The input space is thus partitioned into disjoint subsets, called *decision regions*, each associated with a class.

Classification: Terminology (cont.)



- The way a classifier classifies inputs is defined by its decision regions.
- The borderlines between decision regions are called *decision-region boundaries* or simply *decision boundaries*.