Digital Technologies and Value Creation

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Learning objectives of today

Goals:

- Understand the inspiration and ideas behind tree methods
- Understand how to apply CART in Python
- Understand how bagging, random forests and boosting are generalizations of CART

How will we do this?

- Start by thinking about how we make classifications as humans
- Titanic dataset: how does CART predict survivors?
- Visuals to explain the underlying concepts

Tree-based methods

A short introduction to tree-based methods

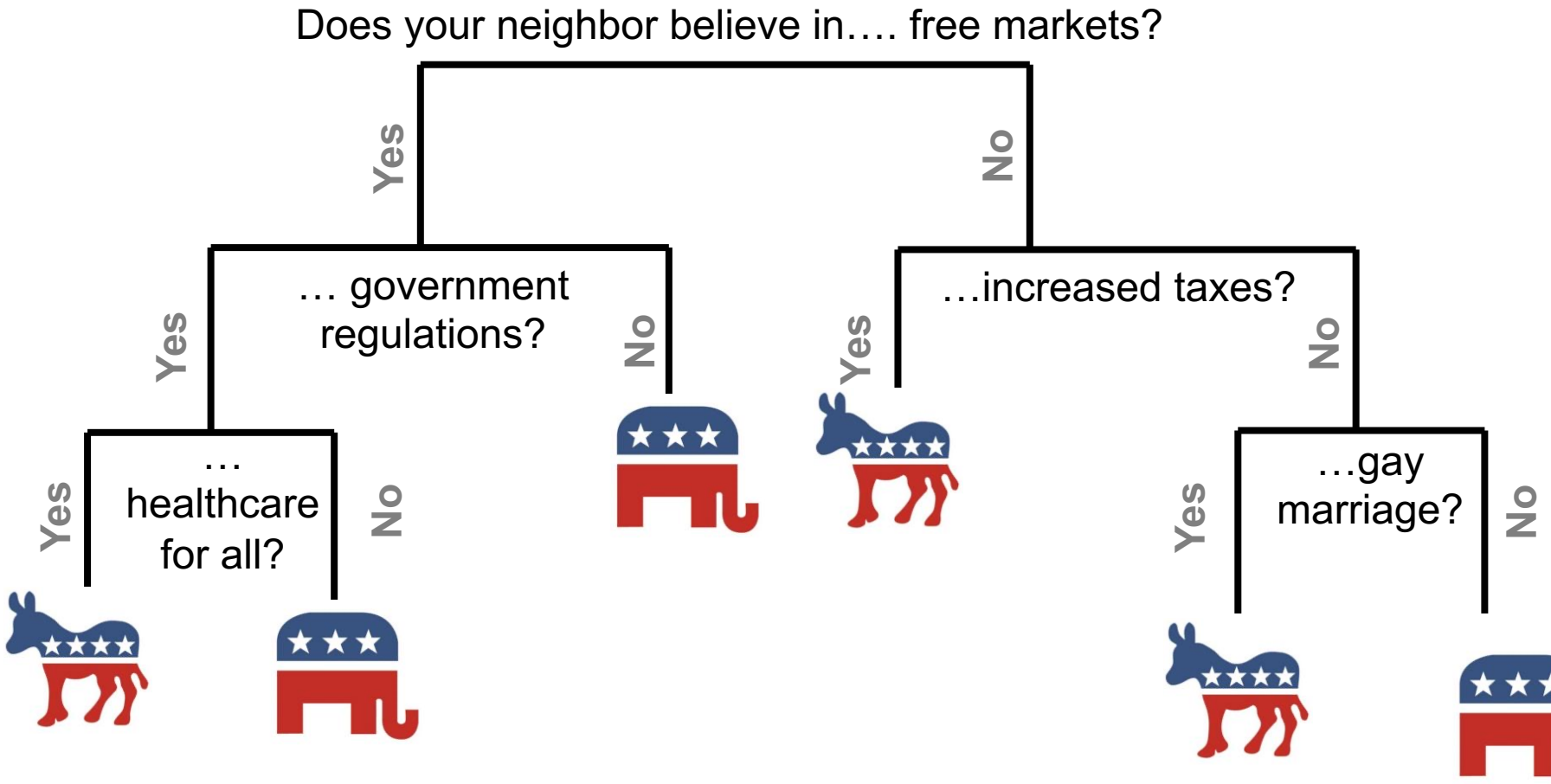
Suppose you are in the following scenario:

- you are at a dinner party in the US
- you want to figure out whether your neighbor aligns with the democratic or republican party more
- you don’t know anything about your neighbor
- for politeness reasons, you cannot ask them outright

Through conversation, **how would you figure out** which party they align with?

A possible decision tree

Caveat: Strategy which is (i) very US-centric; (ii) very schematic



This is exactly tree-based classification!

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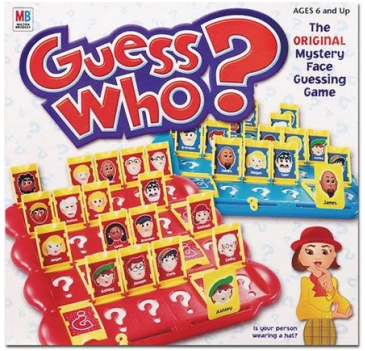
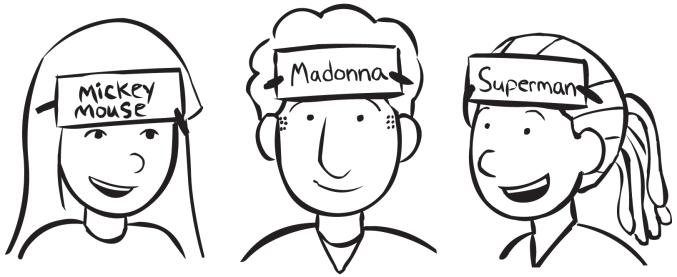
Tree-based classification

It's everywhere!





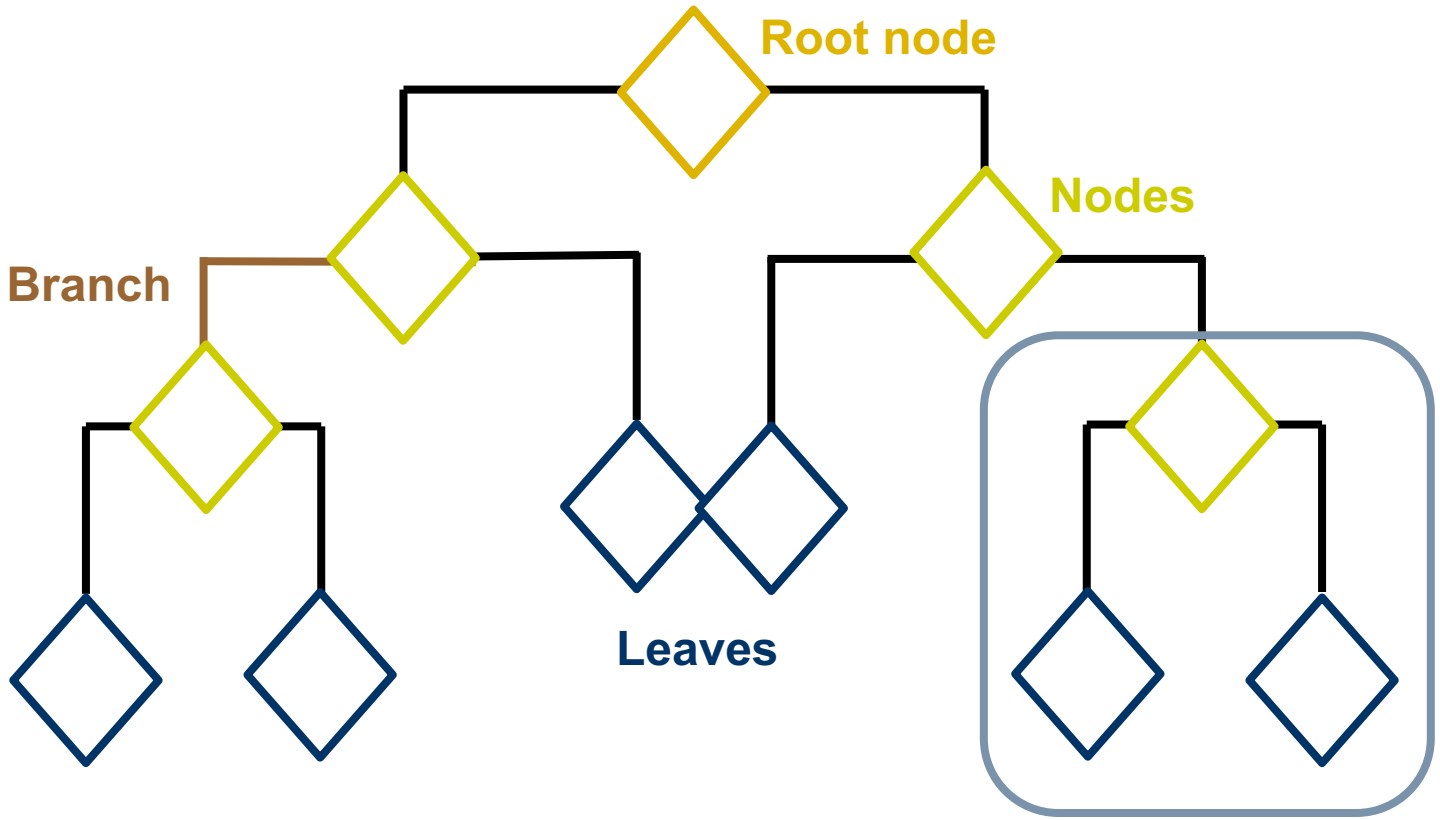
Idea:

Given a set of **features,** we obtain a **decision rule** for **classification.**

In tree-based classification, this decision rule is obtained **by recursive splitting of the features. The "end nodes"** contain **the prediction.**

Questions: **How do we split? When do we stop?**

Tree vocabulary



Branching/splitting : the act of creating new nodes
Pruning: removing leaves

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When classification is a matter of life and death: Titanic

- Dataset of passengers on Titanic and who died/survived

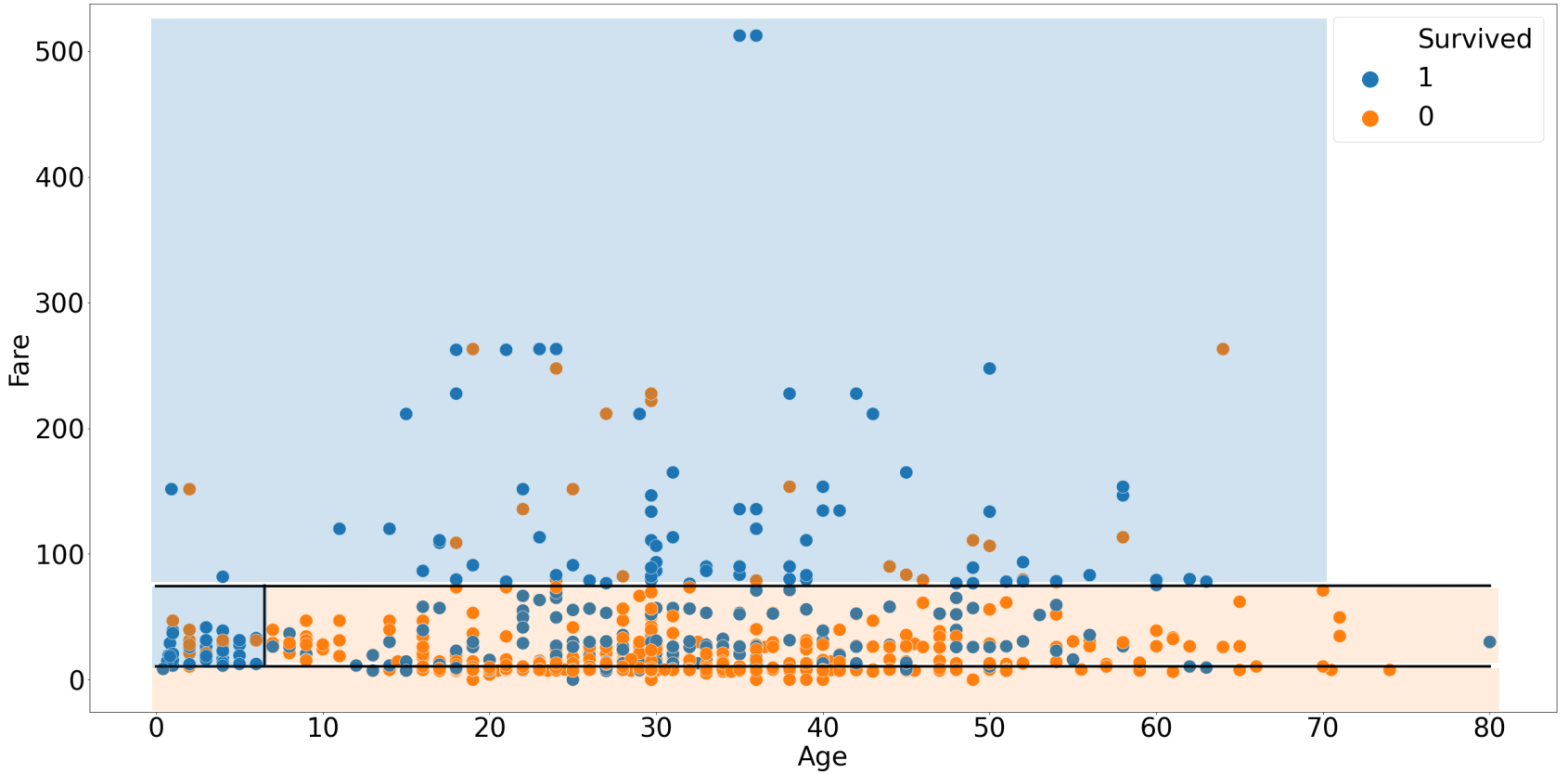
	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	S

- We will use CART to predict whether Jack and Rose the two main (fictitious) characters in the movie would have died or survived.

	Name	Pclass	Age	Fare	Family_Presence	Sex_male	Embarked_Q	Embarked_S
0	Jack Dawson	3	23	13	0	1	0	1
1	Rose DeWitt Bukater	1	17	247	1	0	0	1

CART: Classification and regression trees

- CART can be run for both regression and classification
- We start with classification supposing we only had two features: fare and age.
- CART **divides the predictor space** (here the fare and age space) into boxes and then **classifies** based on the majority in that box



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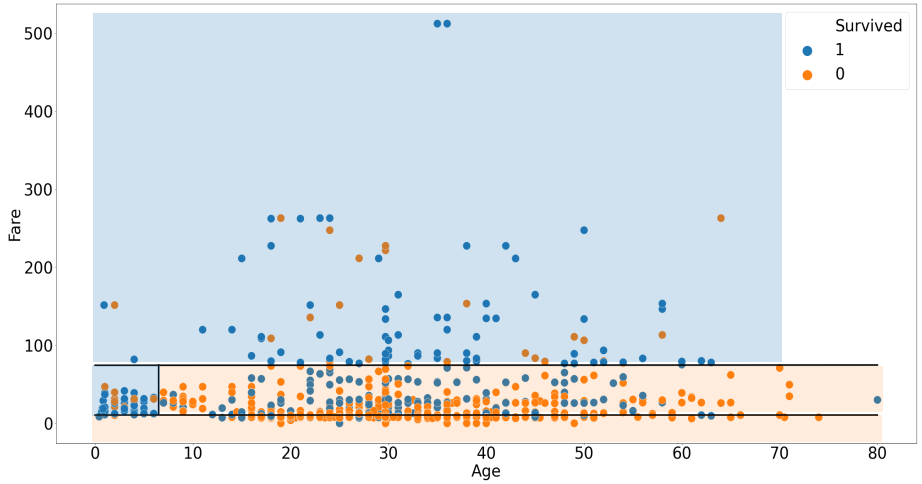
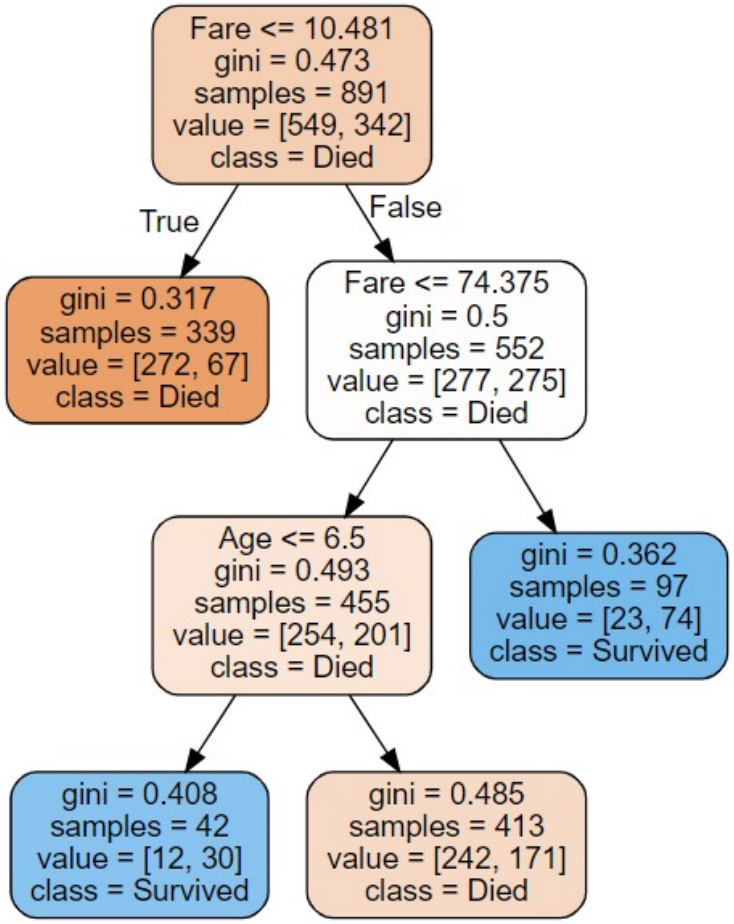
The CART decision tree

This division corresponds to a tree:





How do we know:

- On which variable to divide first? (Fare here)
- Which number to pick for the division? (10.481 e.g.)
- When to stop?

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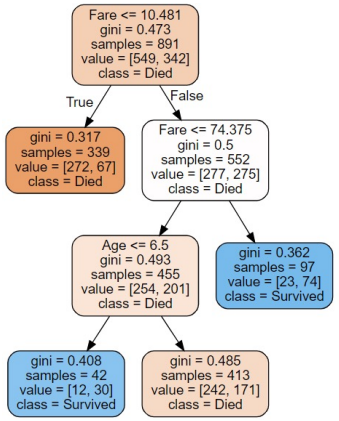
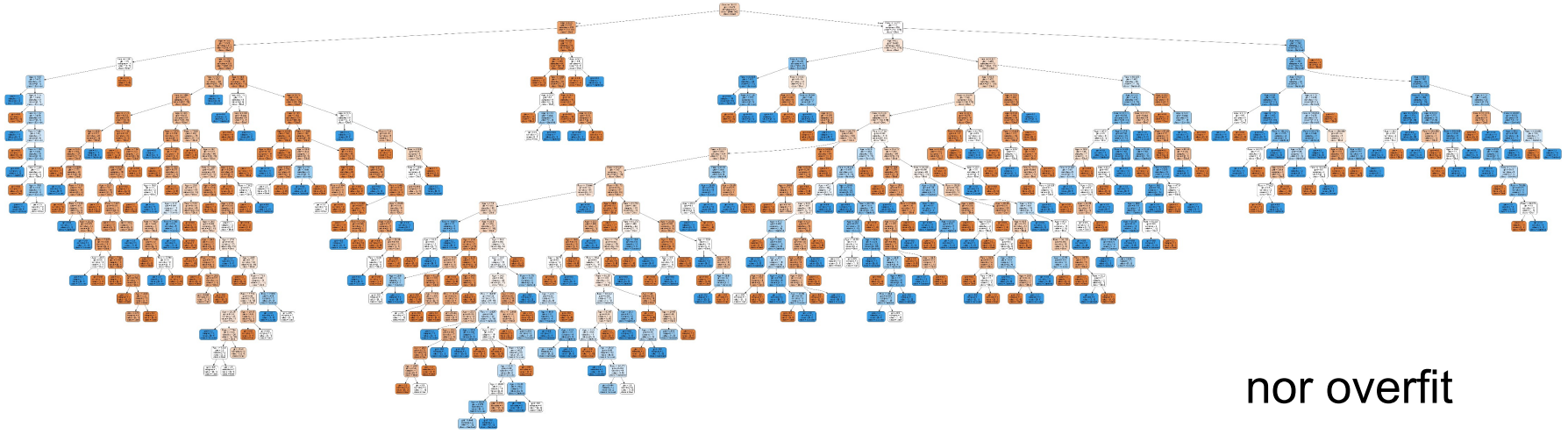
When to stop?

How to choose between…



Don’t want to underfit

Or…



nor overfit

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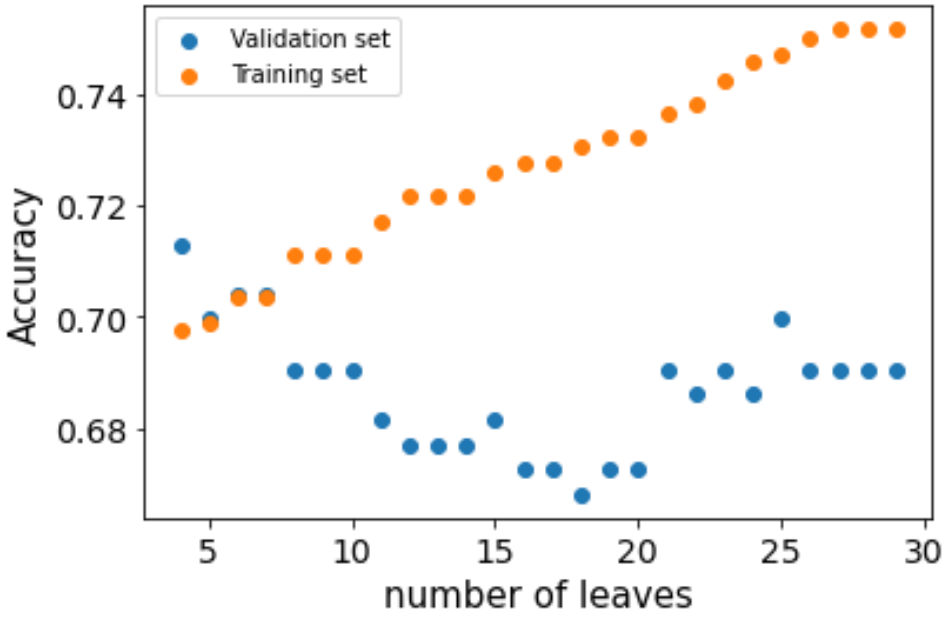
When to stop?

- **Many ways of doing this:** constraining number of leaves/number of samples per leaf/ pruning large tree
- Discuss **constraining number of leaves**
- Train the model on training set
- Determine **max number of leaves** based on **validation set: p**lot **accuracy of model** (1-proportion of misclassified points) as a function of **number of leaves**



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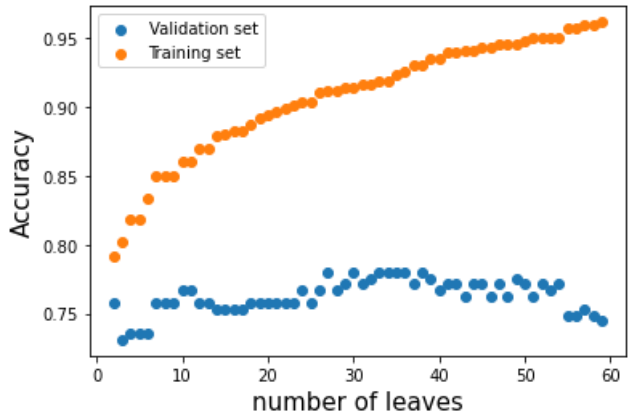
Should Rose and Jack have died?

Try it yourself: pull up the video-exercise notebook and make sure to download the appropriate dataset. Then, complete part 1.

Activity recap



Pick around 10 leaves, retrain the model on training+validation and obtain tree

Accuracy on test set: 82%

```
accuracy_score(ytest,y_pred)
```

```
0.820627802690583
```

	Name	Pclass	Age	Fare	Family_Presence	Sex_male	Embarked_Q	Embarked_S
0	Jack Dawson	3	23	13	0	1	0	1
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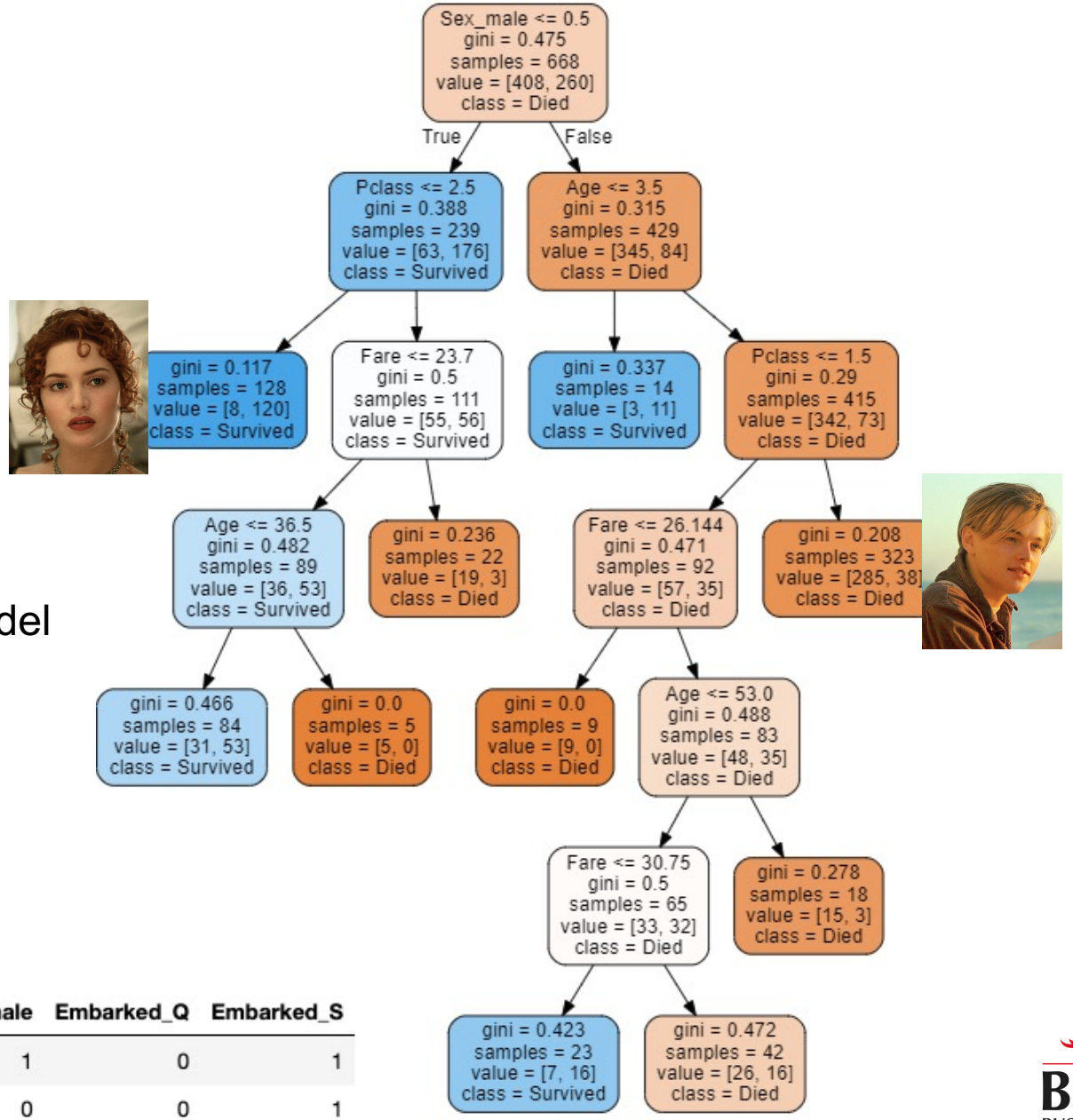

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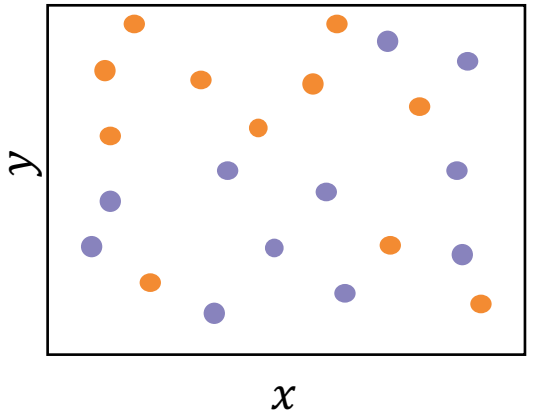
CART: Classification AND regression trees

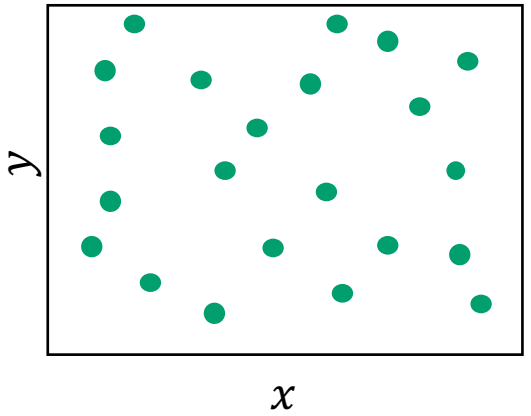
CART models can also be used for regression.

Classification



Predicted **class** of a region is the **most frequent class** that appears

Regression



Predicted **value** of a region is the **mean of all values** in the region

Pros & Cons of CART

Pros:

- Easy to explain to people
- Easy to understand and use (especially if small)
- “Mirrors” human way of thinking (see intro)

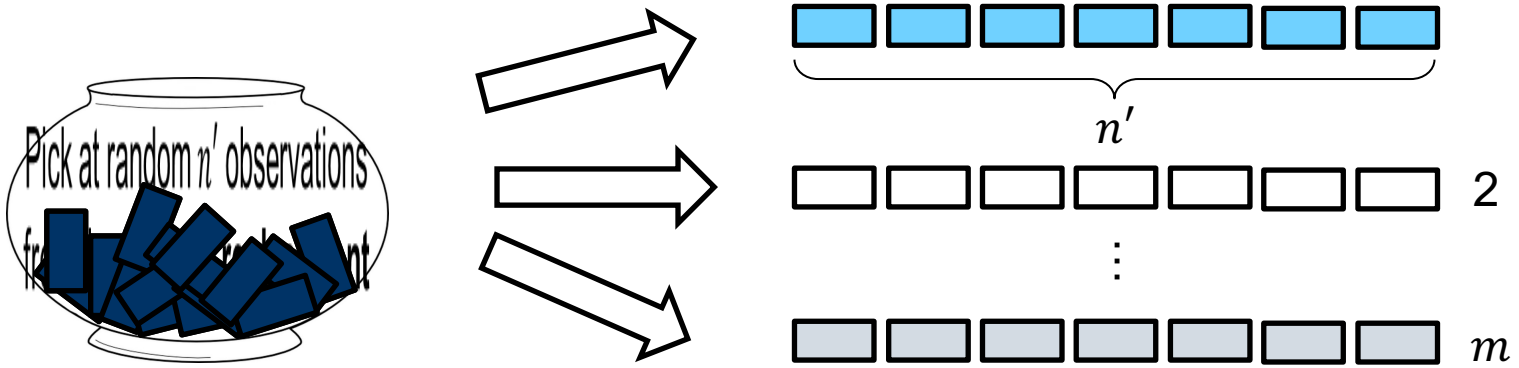
Cons:

- Not as good at the predictive aspect (accuracy generally not as good, etc.)
- **Not very robust:** changing the training data can lead to large variations in tree

→ Motivated the introduction of **bagging/random forest/boosting**

Extensions of CART

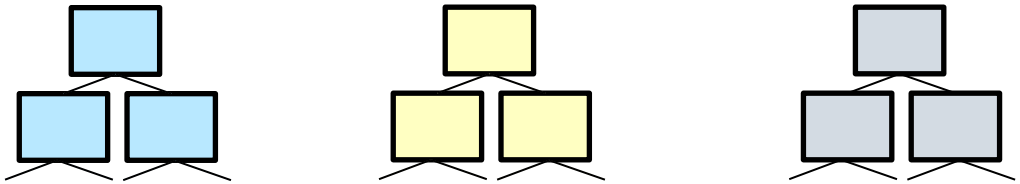
Bagging



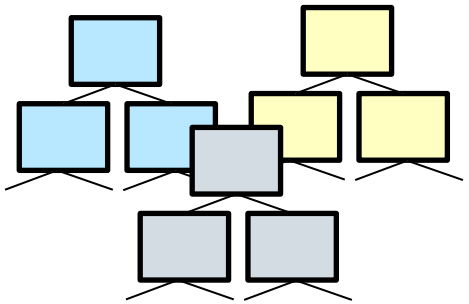
Do this m times

Pick at random n' observations from the urn **with replacement**

Train m trees, one on each set



How is each observation classified?



Each tree "**votes**" for where the observation should be classified and the majority wins

→ makes the process more **robust**

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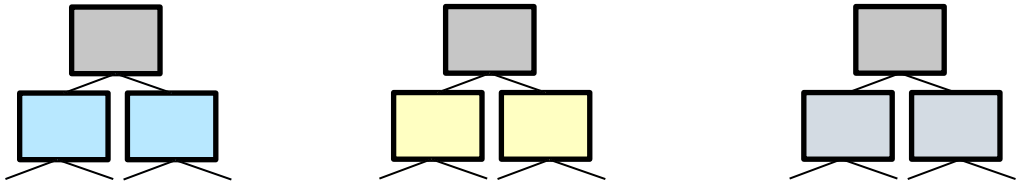
Random forests

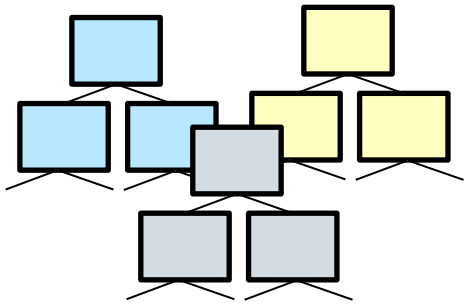
Very similar to bagging: train m trees on each set but **constrain** the training



If there is one “very predictive” feature in the dataset, then even if the training sets are different, the trees end up looking very similar (“correlated”) → **votes are the same.**

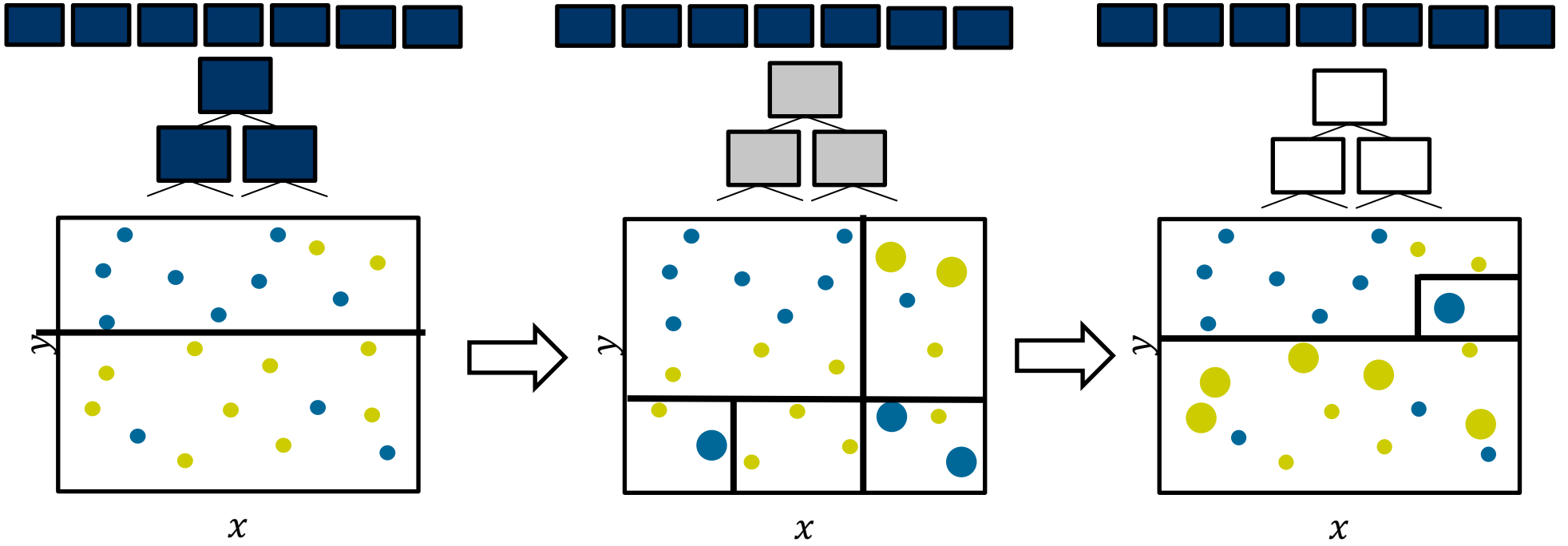
Idea: Only let the splitting occur within a **random subset of features** (typically if p features, can only split within subset of $\sqrt{p}$ for classification, $p/3$ for regression)

→ Ensures the **trees are different** enough.



Then **vote** as usual with majority winning!

Boosting



(1) Train a tree on initial data
(2) Compute misclass. error

(3) Train a new tree on weighted data
(4) Compute misclass. error

(5) Train a new tree on weighted data
(6) Compute misclass. error

- Each tree is an **expert** in some areas (and not so good in others)
- Each tree then **votes** on the right outcome, but the voting is **weighted** depending on its **misclassification error** (the higher, the less weight)

Further study

- Part 2 of the video-exercise notebook contains an example of running CART for regression, instead of classification
- Here, you can also try out running bagging, random forest, and boosting algorithms

From supervised to unsupervised learning

Supervised learning is all about **prediction.**

Predicting a **value: Regression**	Predicting a **category: Classification**
Methods: Linear/polynomial regression, CART & related	**Methods**: Logistic regression, CART & related

Input to supervised learning:

$$(\boldsymbol{X}, \boldsymbol{y})$$

X: feature matrix (i.e., columns are features and rows are observations)

y: label (predicted value or category) for each observation

Unsupervised learning – no predictions!

Unsupervised learning **cannot do** prediction. Why?

Input to unsupervised learning:

$$\boldsymbol{X}$$

i.e., just the feature matrix – no labels, so no way of predicting.

What does unsupervised learning do?

Tries to **draw patterns or other information** out of X

What does unsupervised learning do?

This week: **Dimension reduction**

How can we construct, from our set of features, a smaller number of new features while keeping all the information?

Next week: **Clustering**

Can I group my data into similar groups?

Other possible topics: anomaly detection, association rules

“Issues” for unsupervised learning

- No simple goal for unsupervised learning: generally used in an **exploratory data analysis,** and as an **input to supervised learning**
- **No notion of “true answer”**: no immediate way of evaluating our work – often subjective
- As a consequence, no training/testing/validation/cross-validation possible


See you in class!