Introduction to Data Science

(Lecture 16)

Dr. Mohammad Pourhomayoun

Assistant Professor

Computer Science Department

California State University, Los Angeles


Random Forest

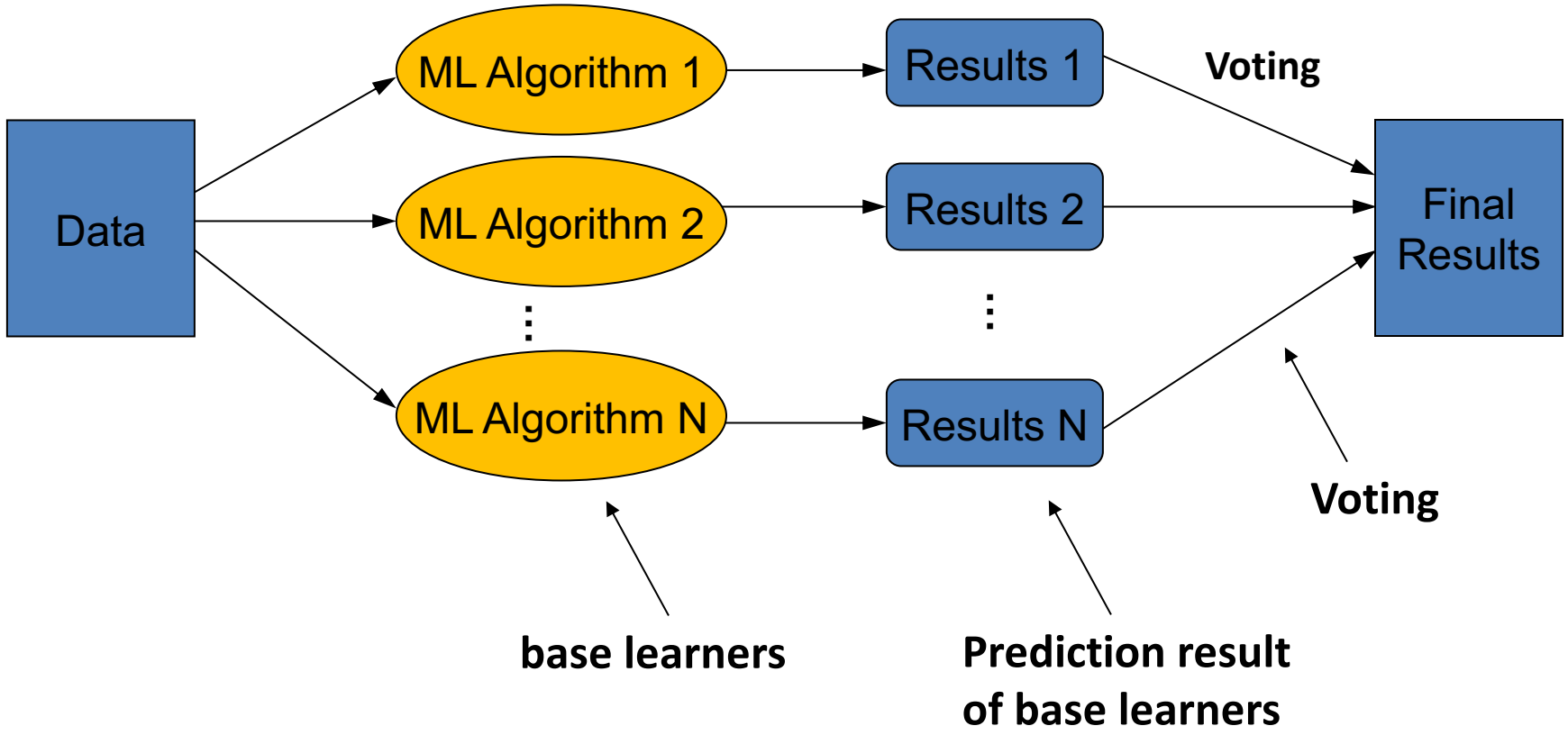
Introduction

- **Before Talking bout Random Forest Algorithm, we have to briefly define two new concepts:**
  - **Ensemble Learning**
  - **Bootstrapping**

Ensemble Learning

- **Ensemble Learning** is a popular and effective approach to improve the accuracy and performance of a machine learning problem.
- **Ensemble Learning** uses a **group of machine learning algorithms** (called **base** learners), and then combine the results of them using some techniques such as **Voting** to achieve higher accuracy.
  - **Example**: Constructing a **Strong Classifier** by combining several **Weak Classifiers!**
- Each learner (e.g. a classifier) alone may have very poor performance. But, a group of them together can achieve very accurate results.

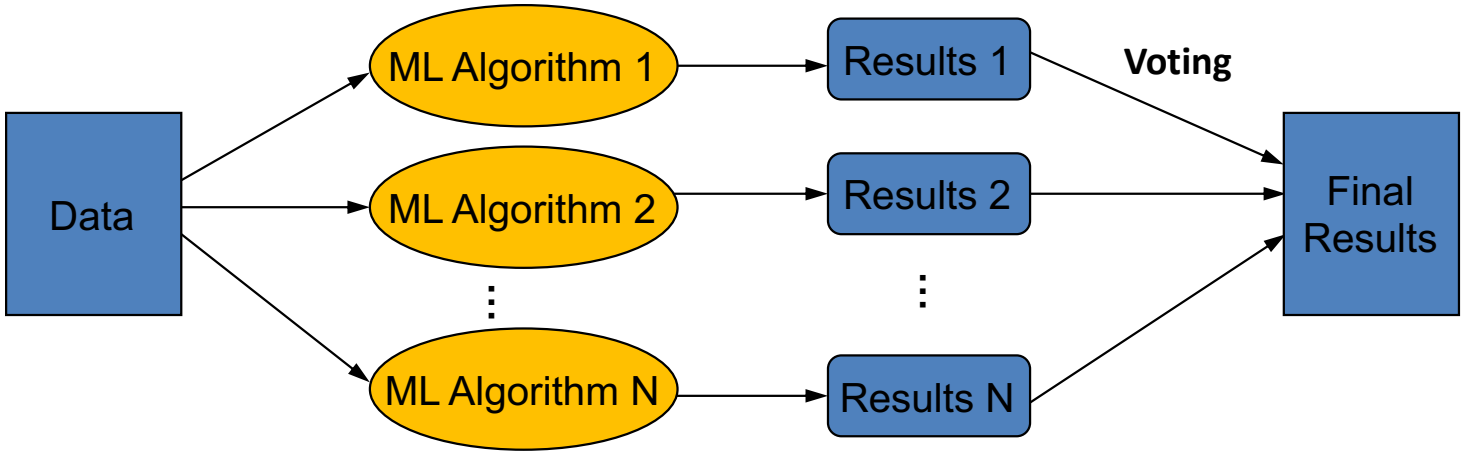
An Example of Ensemble Learning



An Important Note about Ensemble Learning

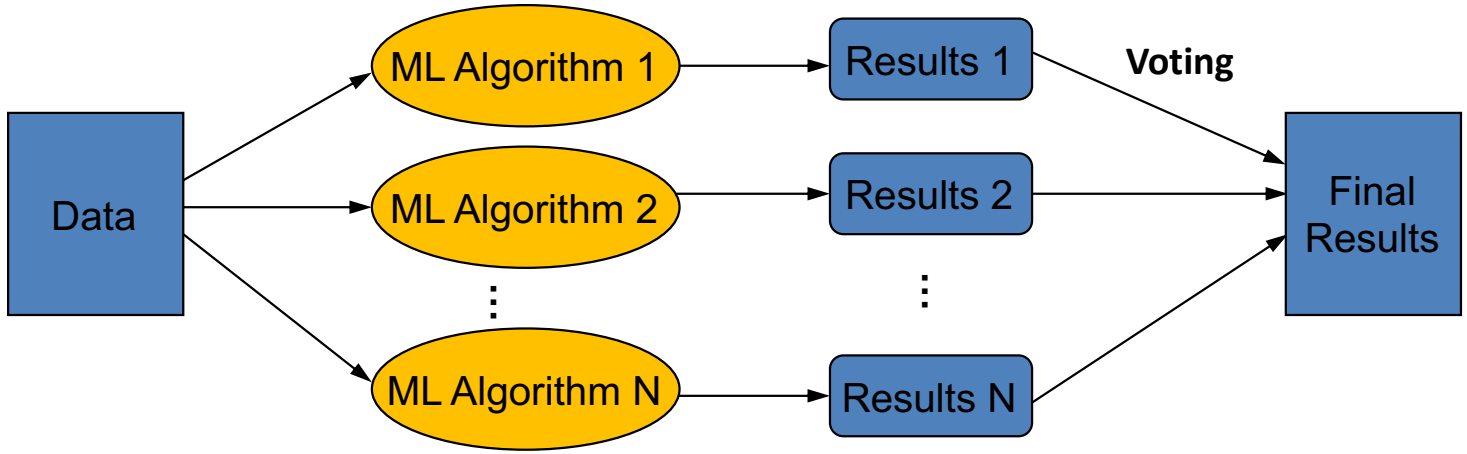
- The key in designing ensembles is **diversity** and **not necessarily high accuracy** of the base classifiers.

- Members of an ensemble group **should vary in the examples they misclassify, so that they cover each other's mistakes!**



An Important Note about Ensemble Learning

- In other word, if we have several classifiers that are pretty accurate but they all misclassify the **same samples**, then ensemble learning will not achieve any better results! Therefore, most ensemble approaches, **seek to promote diversity among the models** they combine.

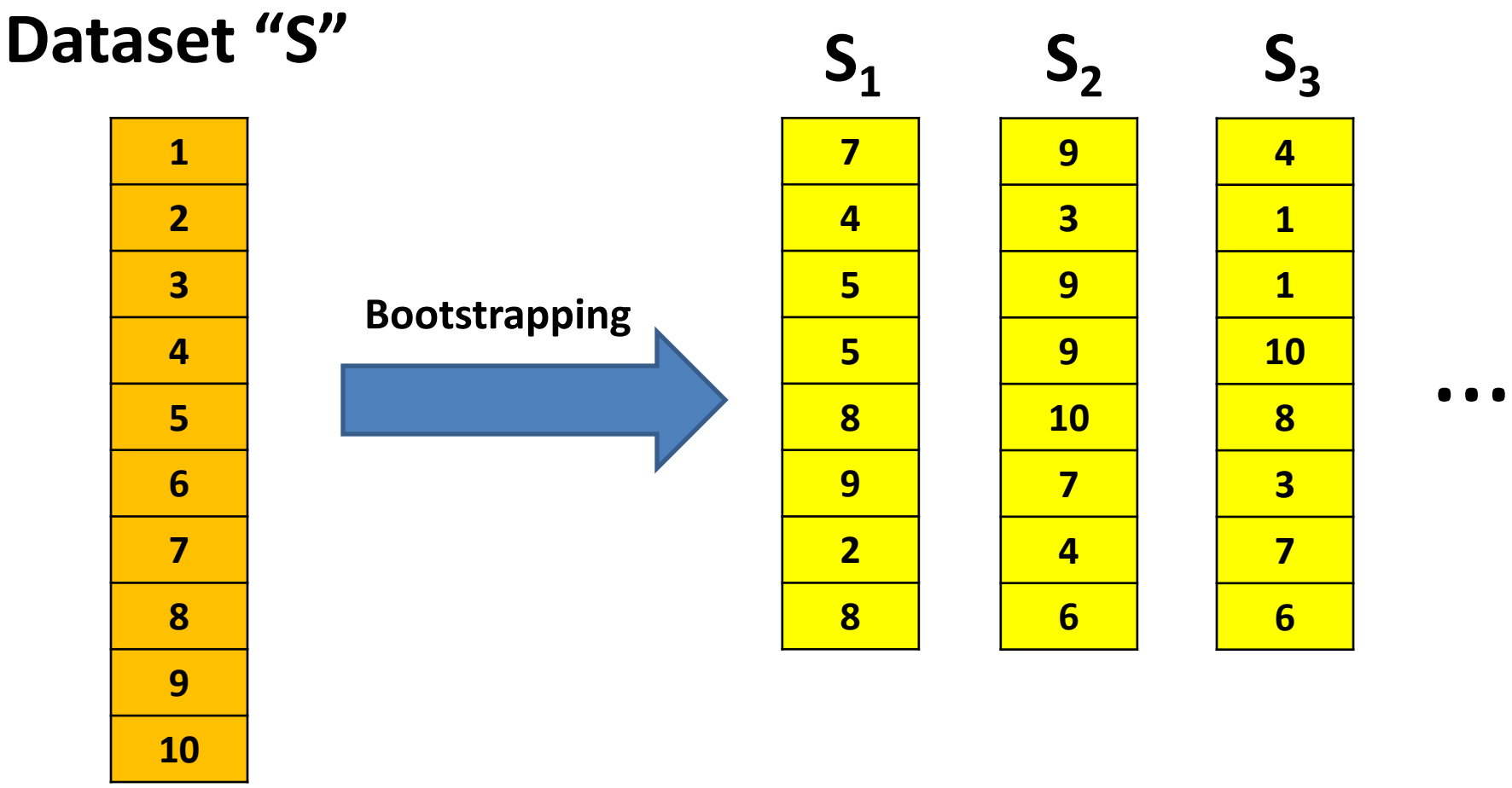


- We will talk a lot more about Ensemble Learning in CS4662!

Bootstrapping

- **Bootstrapping** or **Bootstrap Sampling** is an important step in many Ensemble Learning methods (such as Random Forest).
- **Bootstrapping**: Suppose we have a **Training Dataset S** of **size N**. Bootstrapping generates **L** new training sets $\mathbf{S_1, S_2, \ldots, S_L}$ each of **size M**, by sampling from **S** randomly and **with replacement.**
  - This type of sampling is called **Bootstrapping** or **Bootstrap Sampling.**
  - The bootstrap training sets $\mathbf{S_1, S_2, \ldots, S_L}$ may have overlap with each other.
  - By sampling with **replacement**, some data sample may be repeated in **each** $\mathbf{S_i}$.

Example for Bootstrap Sampling



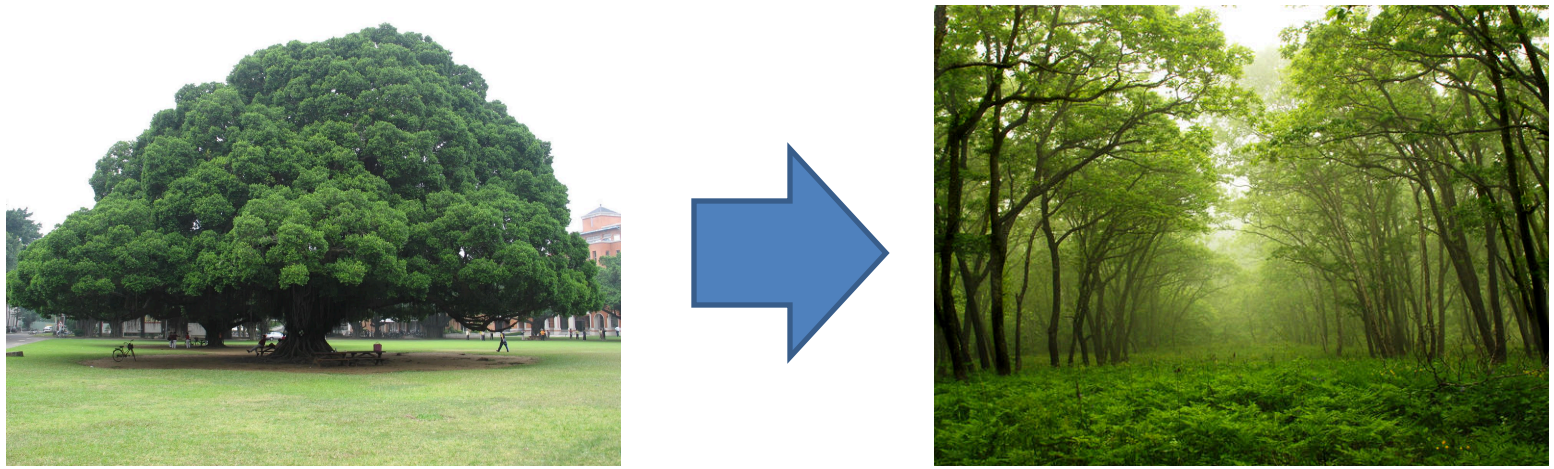

Random Forest

Random Forest

- **Random Forest** (also called Random Decision Forest) is an ensemble learning method, that operates by constructing **several decision trees** at training stage, and then combining the prediction results.
- First proposed by **Leo Breiman** in 2001.
- Random Forest algorithm resolves the well-known problem of **overfitting** in decision tree algorithms by reducing variance and instability.

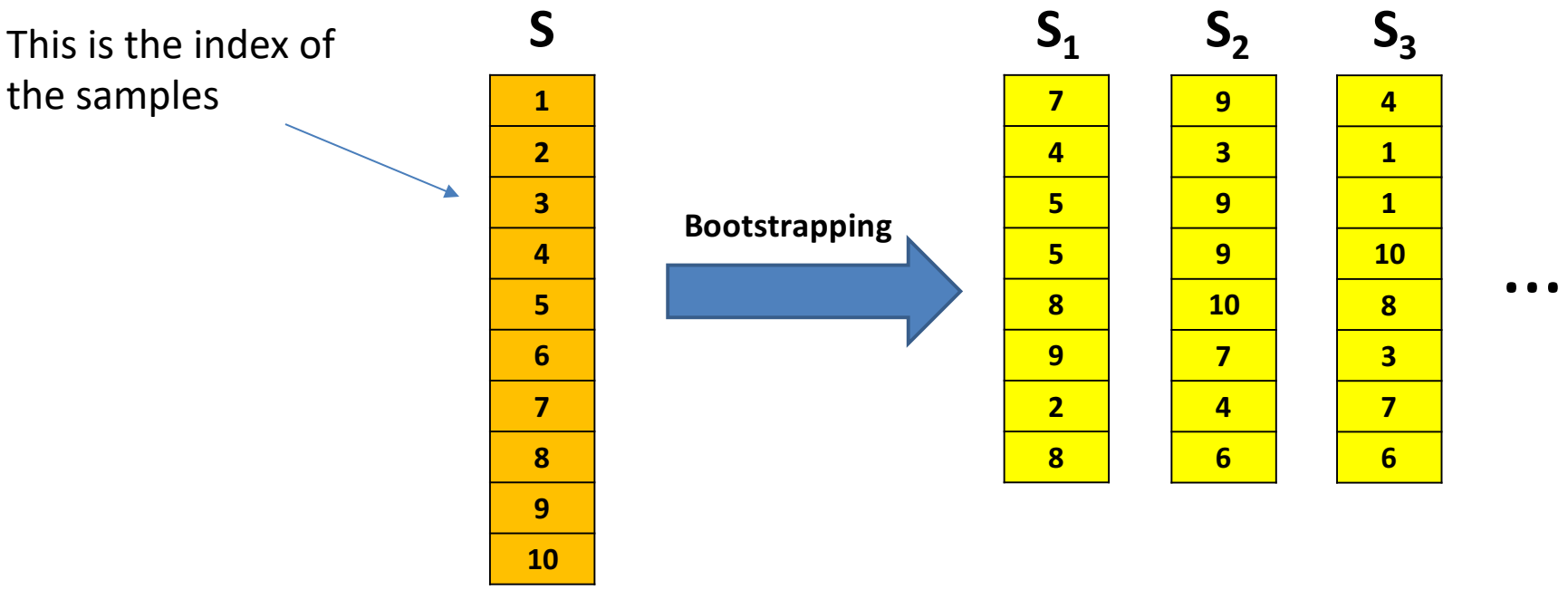
Random Forest

- **Strategy 1:** Random Forest uses **Bootstrap Sampling (randomly sampling of data)** to generate several training datasets and train a decision tree for each one.
- **Strategy 2**: Random Forest uses a **random selection of Features** to split on at each node of each decision tree.
- Both of these approaches will help the algorithm build a more accurate predictor, which is also robust to overfitting!



Random Forest Algorithm

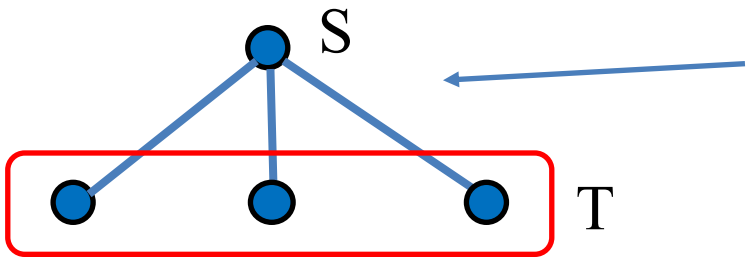
- **Step1 (Bootstrapping):** Suppose we have a training set with ***N* samples** and ***D* features**. Random Forest first uses Bootstrap Sampling (randomly sampling of data) to generate ***L*** training datasets $\mathbf{S_1, S_2, \ldots, S_L}$.



Random Forest Algorithm

- **Step2 (Training):** The *L* new training sets $S_1, S_2, \ldots, S_L$ will be used to **train *L* decision trees. HOWEVER, for each branch split, the algorithm first randomly selects a small number of features, and then use the best of them for splitting.**

- In other word, unlike regular decision tree that selects the best feature in the entire feature set, random forest select the best feature in a very small random subset of features! **Thus, the features that are used in each tree may differ from another tree!**



At each node, this is the best feature selected from a **small random subset of features.**

- **Note:** If *d* is the size of random feature subset at each node, the *d* is much smaller than the size of the entire feature set (*d*<<*D*, e.g. *d* = sqrt (*D*)).

Random Forest Algorithm

- **Step3 (Base Learner Prediction):** Given a new unknown data sample, all **trained** decision trees (*L* trees) make their prediction for the new sample.
- **Step4 (Voting):** The final decision will be made using **Voting** method. The final prediction is based on the majority vote of the *L* decision trees.

Pseudo Code for Random Forest

Given a training set S

For i = 1 to L do:

Build subset S_i by sampling with replacement from S.

Train tree T_i from dataset S_i:

At each node of tree T_i :

Choose best split from a random subset of *d* features.

Each trained tree makes prediction about a new sample.

Make final prediction according to majority vote of the *L* trees.

Advantages of random forest

- One of the most accurate classification algorithms!
- Very Robust to Noise and Overfitting.
- It can handle big data including hundreds of features.
- It can handle missing value!

Why does Random Forest work so well?

- **Question1: Why is Random Forest much better than a single Decision Tree?**

- It can reduce variance and resolve the overfitting problem by voting.

Why does Random Forest work so well?

- Question2: Why is Random Forest much better than a set of Decision Trees together?
- In other word, Why does using a subset of features at each node (rather than all features) help a lot?

Why does Random Forest work so well?

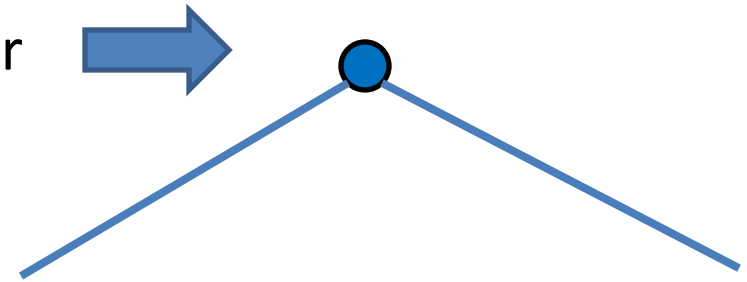
- **Question2: Why is Random Forest much better than a set of Decision Trees together?**
- **In other word, Why does using a subset of features at each node help a lot?**
- **Review:**
  - The key of designing ensembles is **diversity!**
  - Members of the ensemble **should be uncorrelated and vary in the examples they misclassify, so that they can compensate for each others mistakes!**

Why does Random Forest work so well?

- **Question2: Why is Random Forest much better than a set of Decision Trees together?**
- **In other word, Why does using a subset of features at each node help a lot?**
- If each time we select from the entire feature set, every tree always selects the **best features one after another**, and consequently, the structure of all trees will be **the same**.
- On the other hand, Selecting only from a random subset of the features at each node, makes our trees **different**.
- Random Forest tries to generate the set of tress that are **different from each other**. Nonetheless, each one does **its best in its own way**.
- After voting, the trees will **compensate for each others mistakes**, and provide the best results together.

Example: Tree1 in Random Forest for Titanic

We have total 3 features {**age, gender, pclass**} in our dataset. But, at this node, let's limit our feature subset to {**gender,pclass**}



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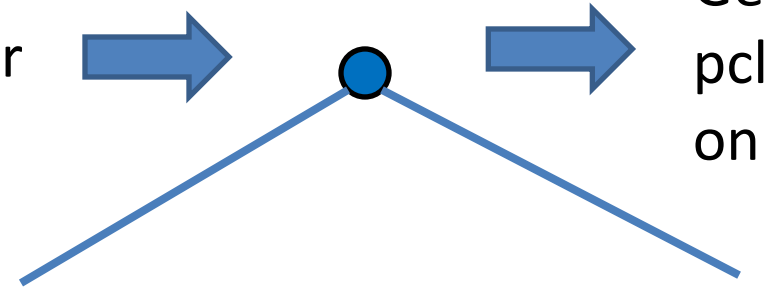

Gender is better than pclass, So I split based on gender!

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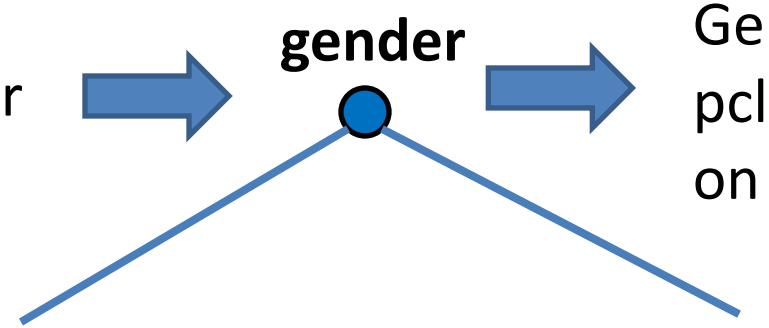

Gender is better than pclass, So I split based on gender!

And similarly for the rest of the tree …

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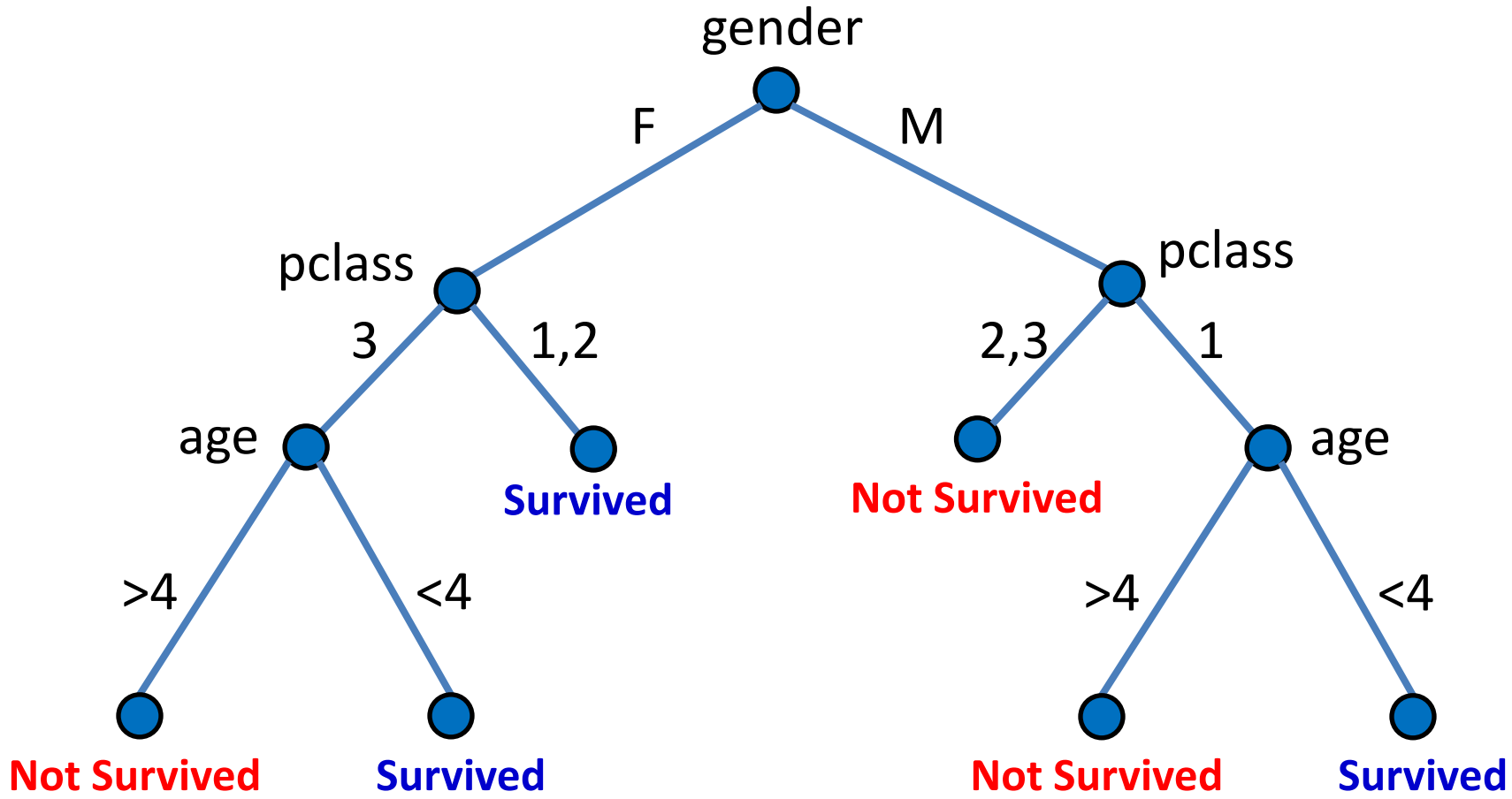
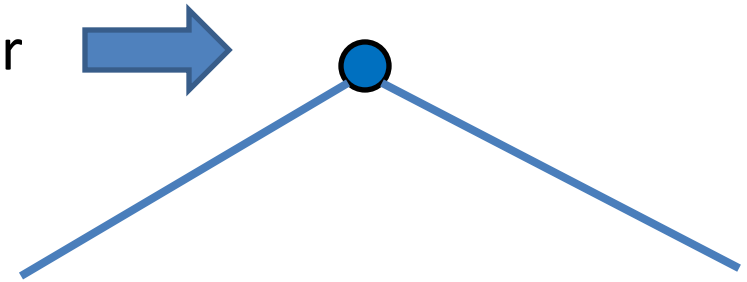


Example: Tree2 in Random Forest for Titanic

We have total 3 features {**age, gender, pclass**} in our dataset. But, at this node, let's limit our feature subset to {**age,pclass**}



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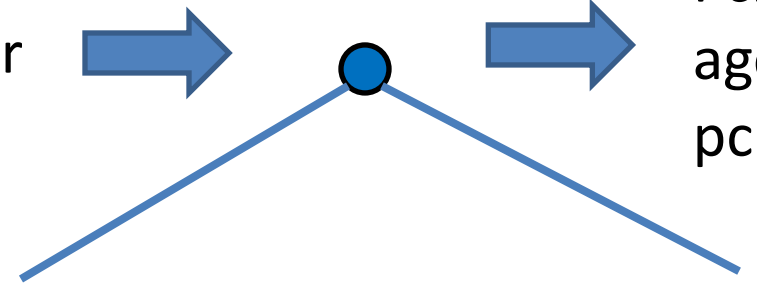

Pclass is better than age, So I split based on pclass!

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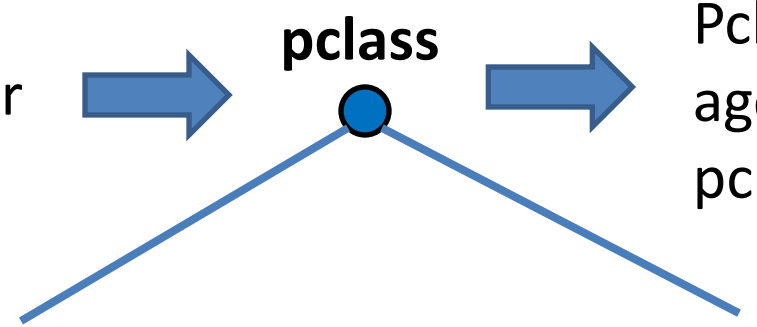

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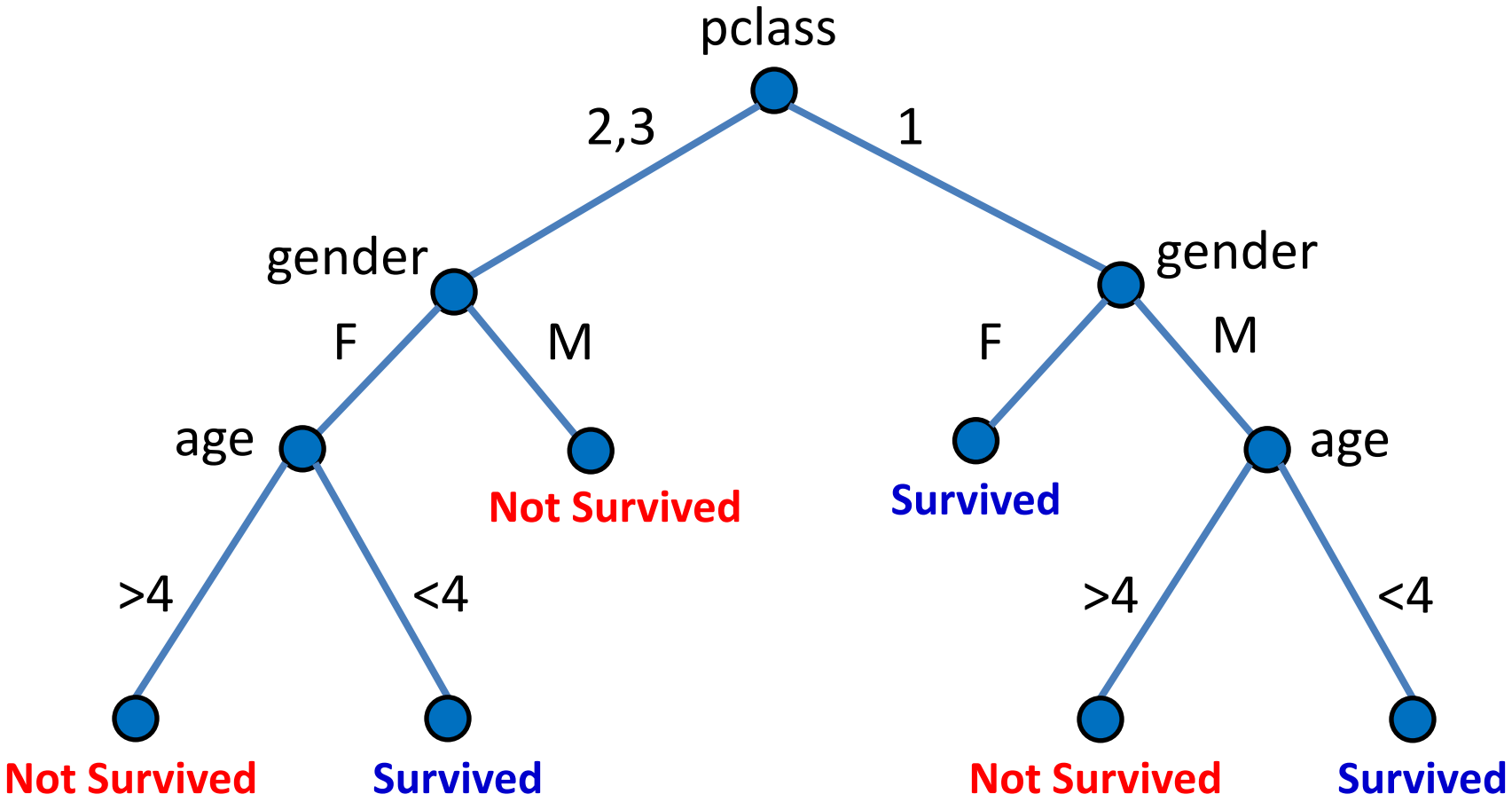

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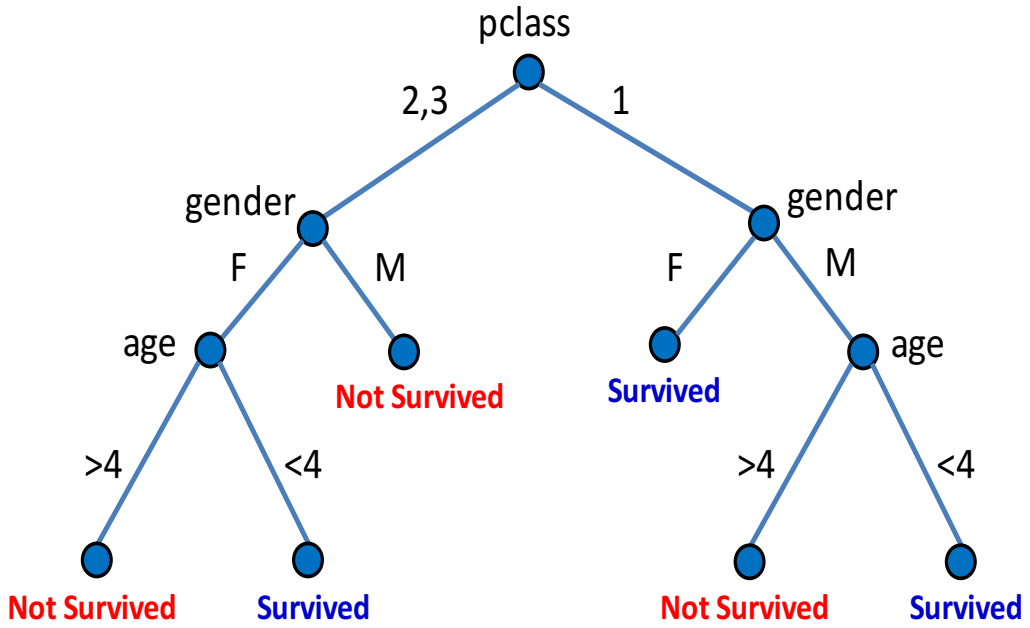

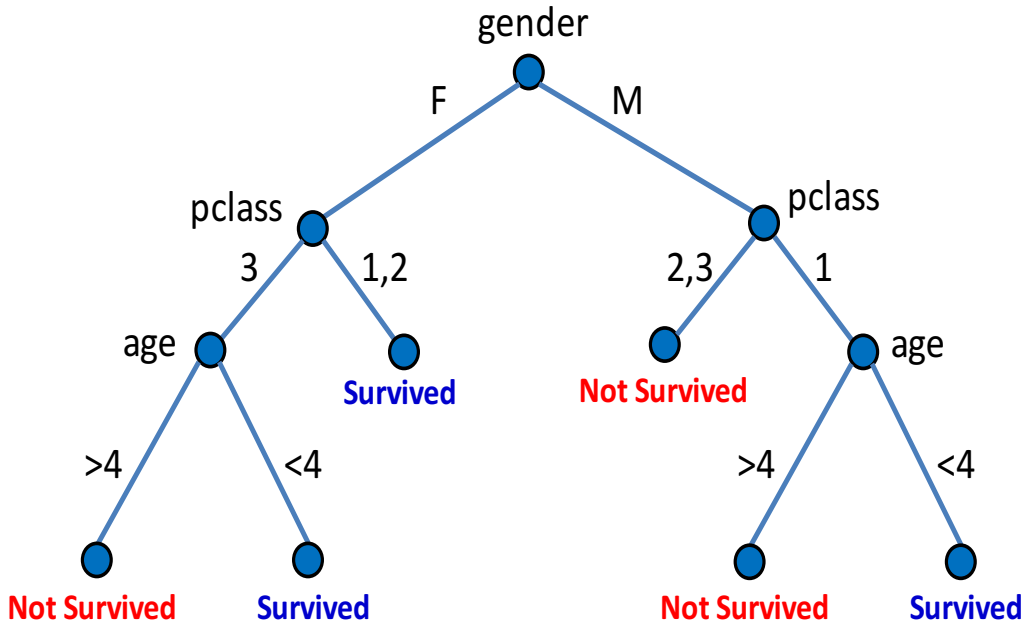

As we see, the 2 trees are completely different! And this is what we want!

Question: What is your prediction for a passenger who is adult female and has 2nd class ticket?

Thank You!

Questions?