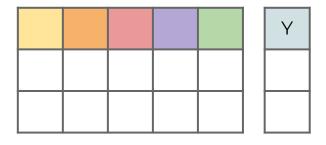
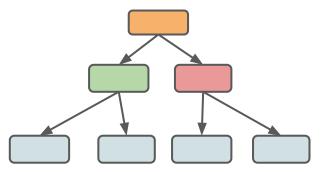






Decision Tree restricted by gini impurity:

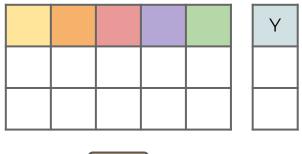


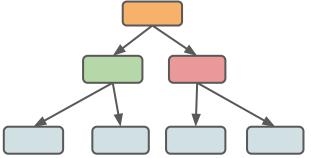






No guarantee of using all features!

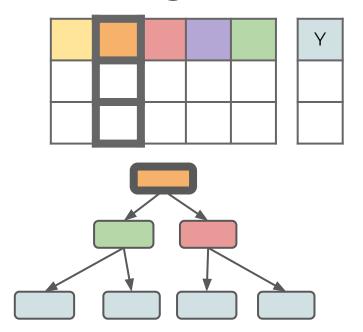








Root feature has huge influence over tree.







- We could try adjusting rules, such as:
  - Splitting Criterion (Information Gain)
  - Minimum Gini Impurity Decrease
  - Setting Depth Limits
  - Limits on number of leaf nodes





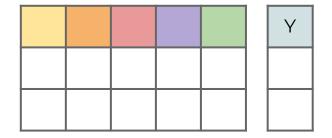
Main ideas





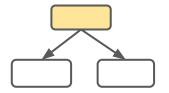
 Known as ensemble learners, since they rely on an ensemble of models (multiple decision trees).

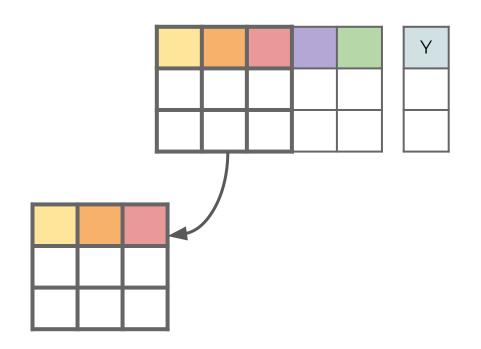




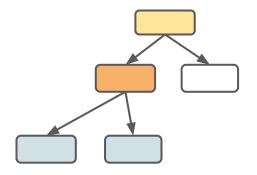
Create subsets of randomly picked features at each potential split

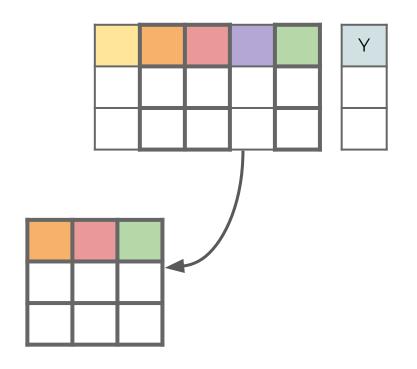




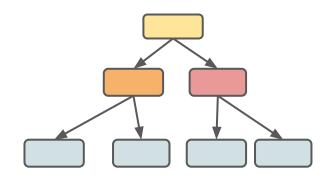


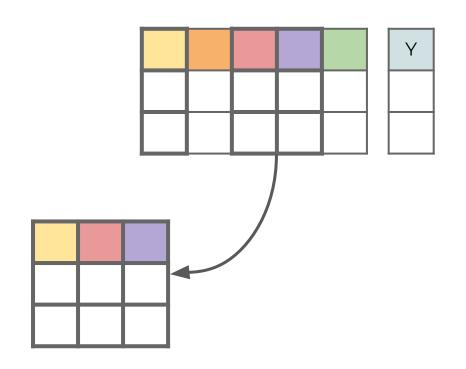




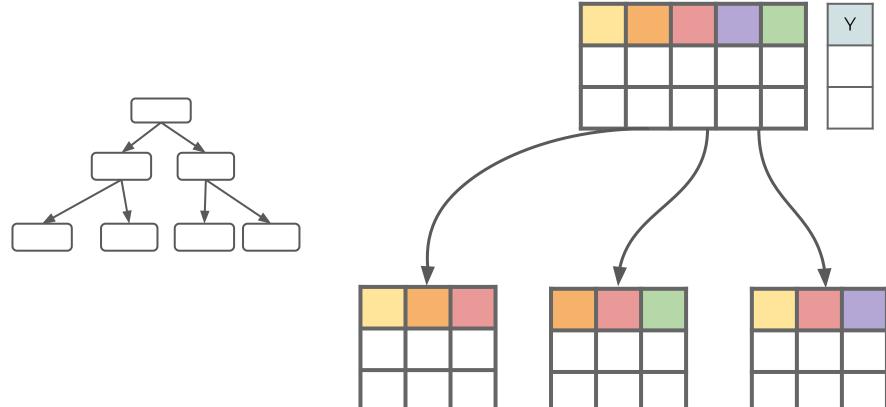


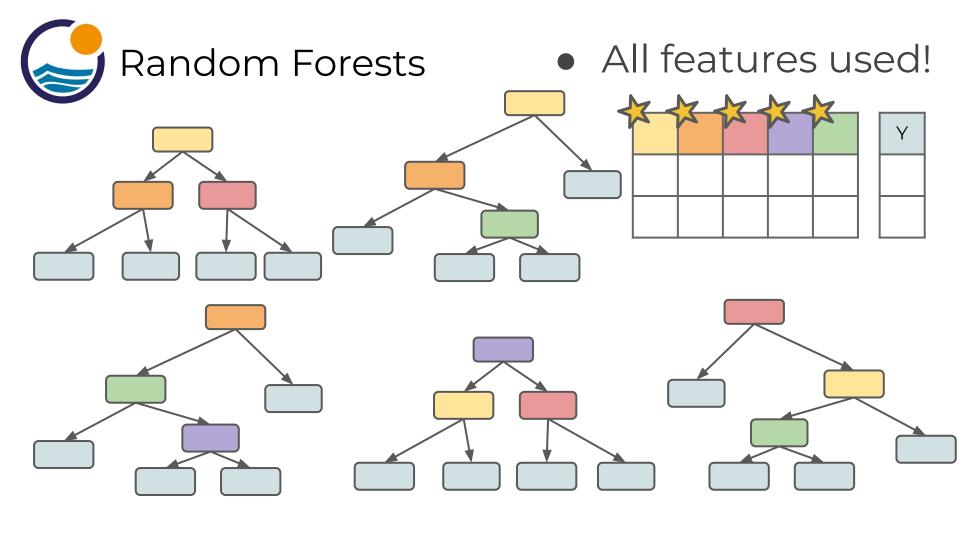




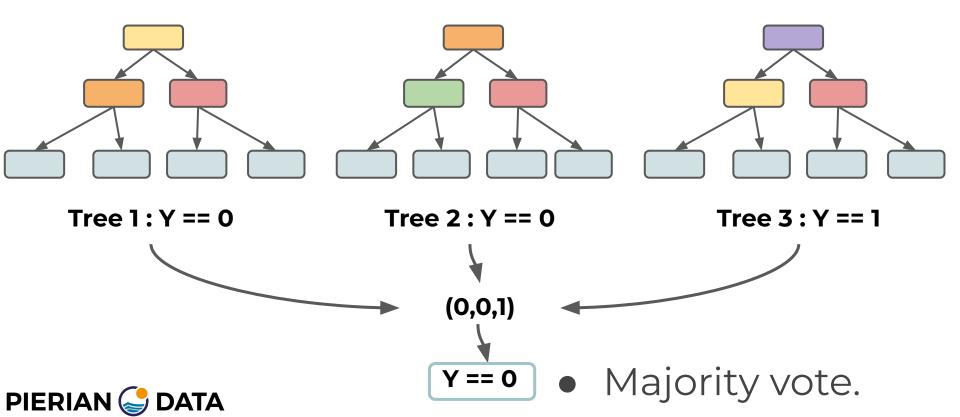




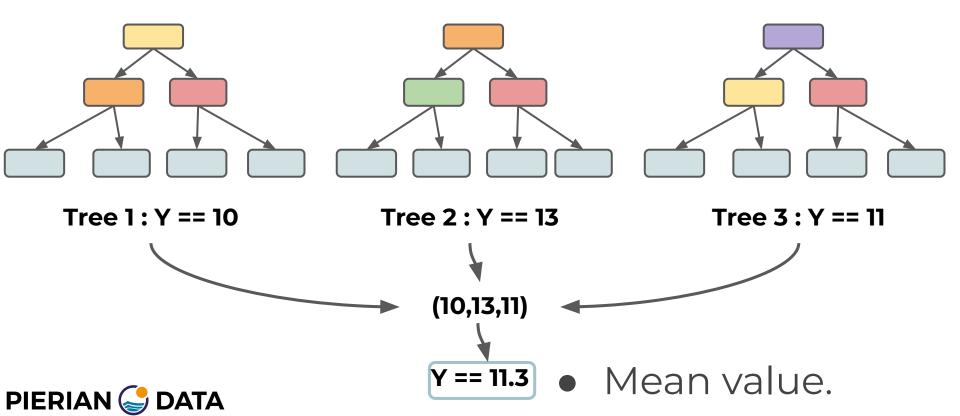














Theory and Intuition: Hyperparameters



```
class sklearn.tree.DecisionTreeClassifier(*,criterion='gini') splitter='best', max_depth=None, min_samples_split=2, min_samples_leaf=1, min_weight_fraction_leaf=0.0, max_features=None, random_state=None, max_leaf_nodes=None, min_impurity_decrease=0.0, min_impurity_split=None, class_weight=None, ccp_alpha=0.0) <math>\P [source]
```

class sklearn.ensemble. RandomForestClassifier ( $n_estimators=100$ , \*, criterion='gini', max\_depth=None, min\_samples\_split=2, min\_samples\_leaf=1, min\_weight\_fraction\_leaf=0.0, max\_features='auto', max\_leaf\_nodes=None, min\_impurity\_decrease=0.0, min\_impurity\_split=None, bootstrap=True, oob\_score=False, n\_jobs=None, random\_state=None, verbose=0, warm\_start=False, class\_weight=None, ccp\_alpha=0.0, max\_samples=None) ¶ [source]



```
class sklearn.tree. DecisionTreeClassifier(*, criterion='gini' splitter='best', max_depth=None, min_samples_split=2, min_samples_leaf=1 min_weight_fraction_leaf=0.0, max_features=None, random_state=None, max_leaf_nodes=None, min_impurity_decrease=0.0, min_impurity_split=None, class_weight=None, ccp_alpha=0.0) [source]
```

```
class sklearn.ensemble. RandomForestClassifier(n_estimators=100, *, criterion='gini', max_depth=None, min_samples_split=2, min_samples_leaf=1, min_weight_fraction_leaf=0.0, max_features='auto', max_leaf_nodes=None, min_impurity_decrease=0.0, min_impurity_split=None, bootstrap=True, oob_score=False, n_jobs=None, random_state=None, verbose=0, warm_start=False, class_weight=None ccp_alpha=0.0, max_samples=None) 1 [source]
```





class sklearn.ensemble. RandomForestClassifier  $[n_estimators=100]$ , \*, criterion='gini', max\_depth=None, min\_samples\_split=2, min\_samples\_leaf=1, min\_weight\_fraction\_leaf=0.0  $[max_e]$  max\_leaf\_nodes=None, min\_impurity\_decrease=0.0, min\_impurity\_split=None, bootstrap=True, oob\_score=False, n\_jobs=None, random\_state=None, verbose=0, warm\_start=False, class\_weight=None, ccp\_alpha=0.0, max\_samples=None) [source]





- Random Forest Hyperparameters:
  - Number of Estimators
  - Number of Features per estimator
  - Bootstrap Samples



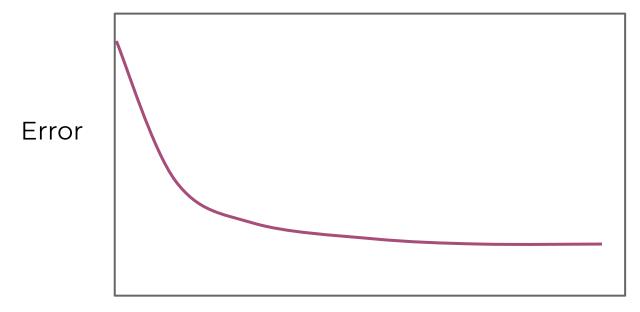


- How to choose number of trees?
  - Reasonable Default Value: 100
  - Publications suggest 64-128 trees.
  - Cross Validate a grid search of trees.
  - o Plot Error versus number of trees.
    - Should notice diminishing error reduction after some N trees (similar to KNN).





• Error vs. Trees





Number of Estimators (Trees)



- After a certain number of trees, two things that can occur:
  - Different random selections don't reveal any more information.
    - Trees become highly correlated.
  - Different random selections are simply duplicating trees that have already been created.





- Number of Features in Subset?
  - Current suggested convention is sqrt(N) in the subset given N features.
  - N/3 may be more suitable for regression tasks, typically larger than sqrt(N).
  - should be treated as a tuning parameter,
     with sqrt(N) as a good starting point.





- Hyperparameter Review:
  - Number of Estimators:
    - Start with 100 as default, feel free to grid search for lower and higher values.
  - Number of Features for Selection:
    - Start with sqrt(N), grid search for other possible values (N/3).





Theory and Intuition: Hyperparameters
Bootstrap Samples and OOB Error



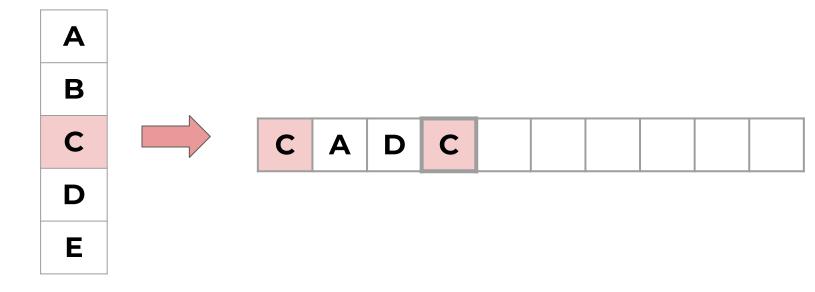


- Bootstrap Samples
  - Allow for bootstrap sampling of each training subset of features?
  - First, let's understand "bootstrapping" in general terms...





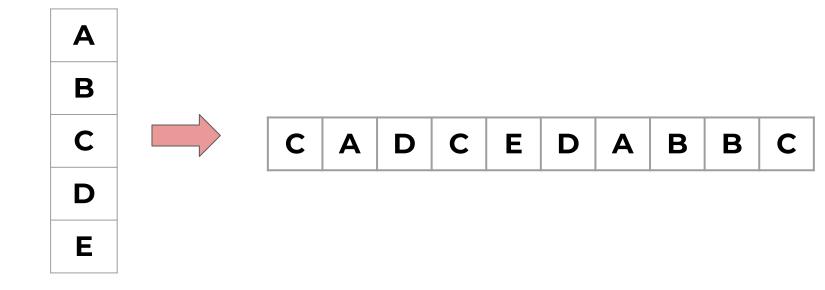
Bootstrapping = sampling with replacement.







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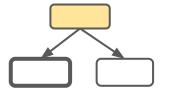


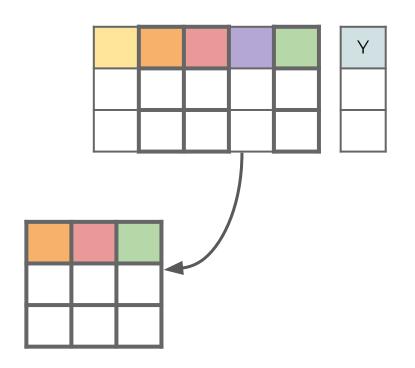




- Bootstrapping in Random Forest
  - Recall for each split we are randomly selecting a subset of features.
  - This random subset of features helps create more diverse trees that are not correlated to each other.



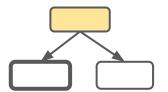






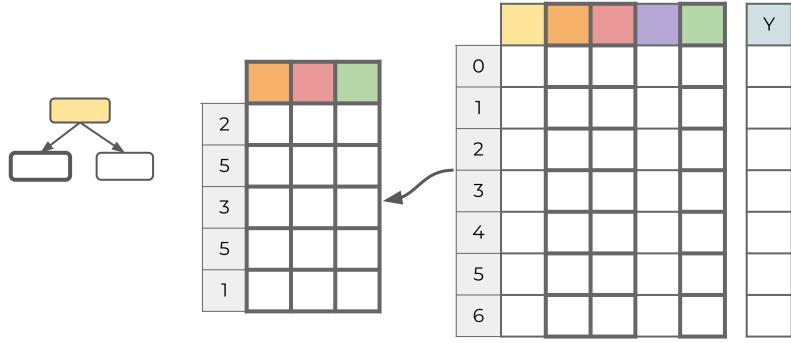
- Bootstrapping in Random Forest
  - To further differentiate trees, we could bootstrap a selection of rows for each split.
  - This results in <u>two randomized</u> training components:
    - Subset of Features Used
    - Bootstrapped rows of data





				Υ
0				
1				
2				
3				
4				
5				
6				







- Bootstrapping can be set to False during training (it is True by default).
- Bootstrapping is yet another hyperparameter meant to reduce correlation between trees, since trees are then trained on different subsets of feature columns and data rows!





- What is Bagging?
  - Recall to actually use a Random
     Forest, we use bootstrapped data and
     then calculate a prediction based on
     the aggregated prediction of the
     trees:
    - Classification: Most Voted Y Class
    - Regression: Average Predicted Ys





- What is Bagging?
  - If we performed bootstrapping when building out trees, this means that for certain trees, certain rows of data were not used for training.



