

Boosting and Stacking

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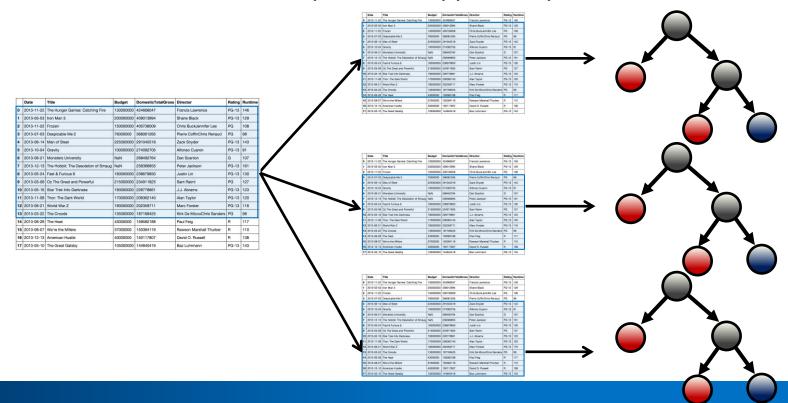


Learning Objectives

- Explain how the boosting algorithm helps reduce variance and bias.
- Apply Intel® Extension for Scikit-learn* to leverage underlying compute capabilities of hardware



Grow decision tree from multiple bootstrapped samples

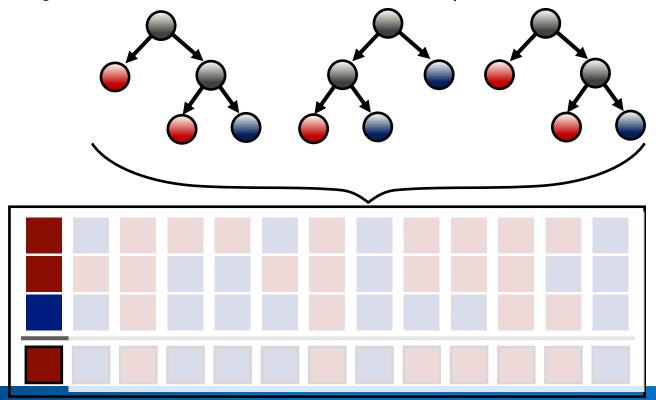




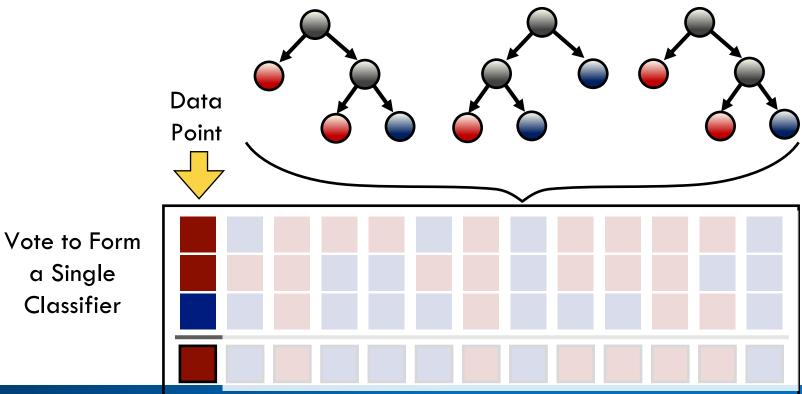
Vote to Form

a Single

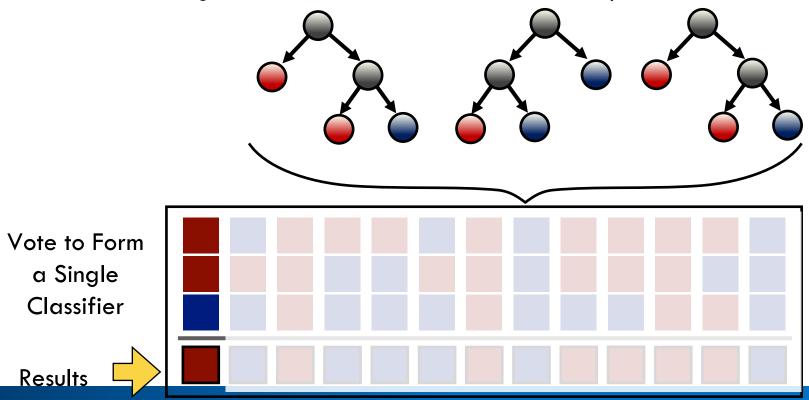
Classifier









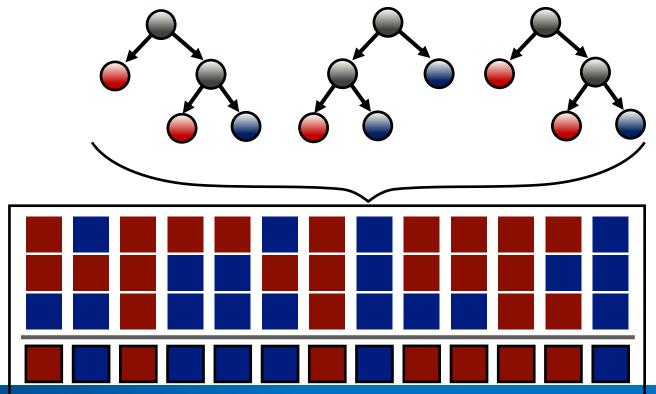




Vote to Form

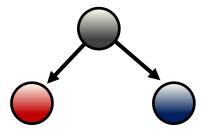
a Single

Classifier

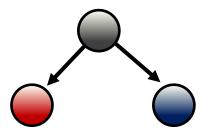




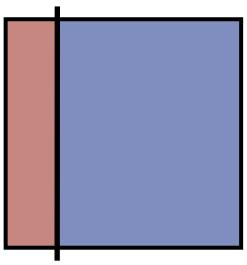
Temperature >50°F



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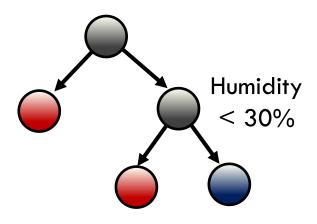




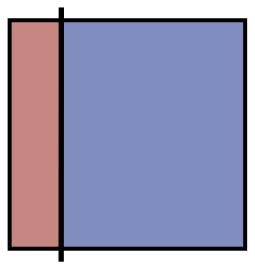




Temperature >50°F

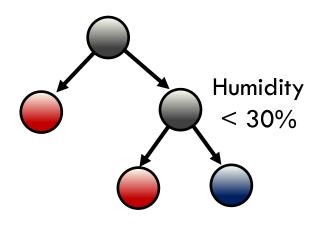


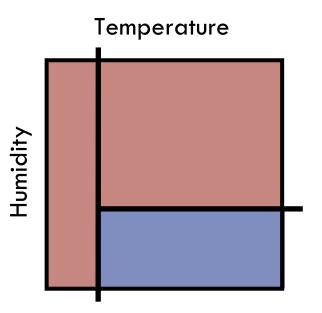










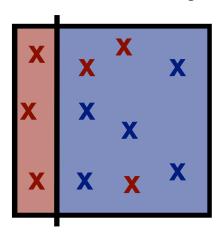




Create initial decision stump

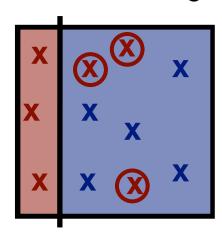


Fit to data and calculate residuals



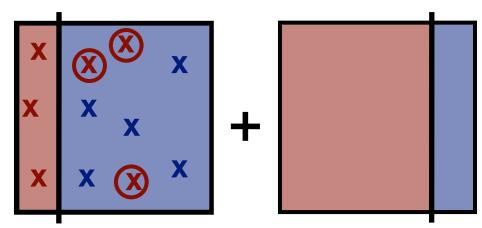


Adjust weight of points



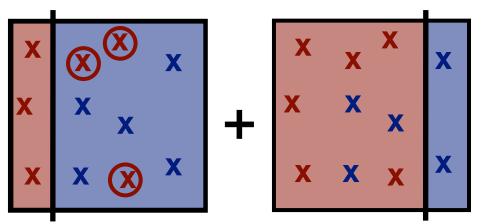


Find new decision stump to fit weighted residuals



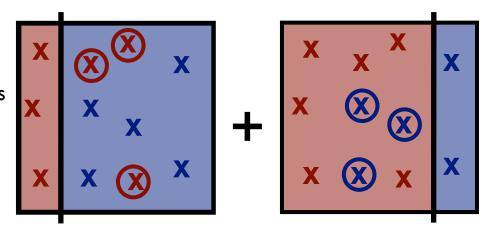


Fit new decision stump to current residuals



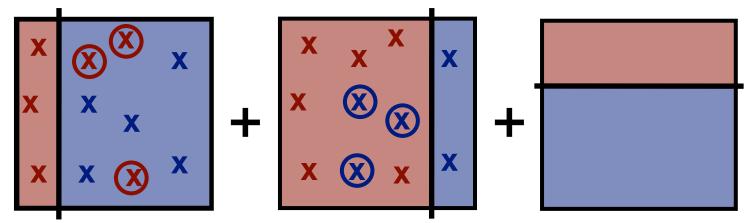


Calculate errors and weight data points



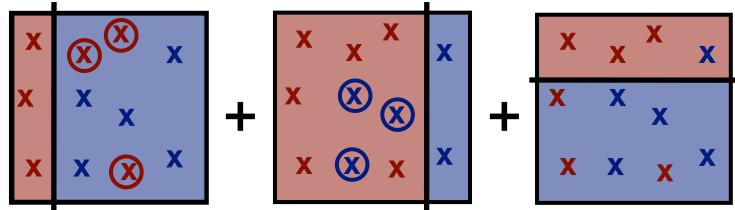


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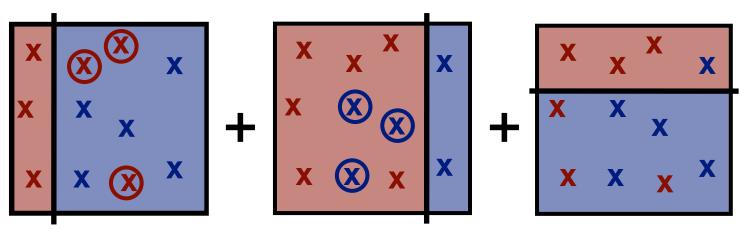




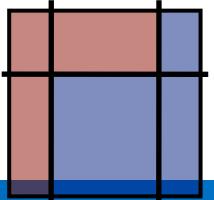
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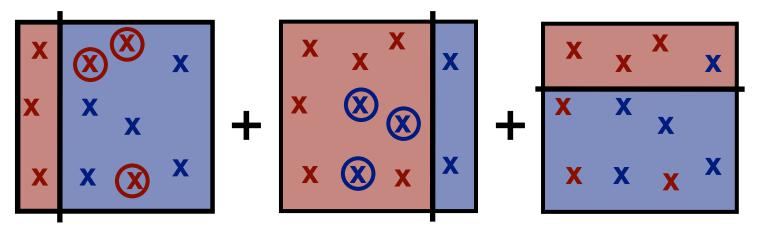




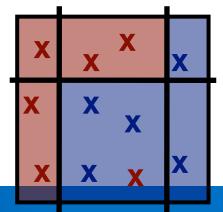
Combine to form a single classifier



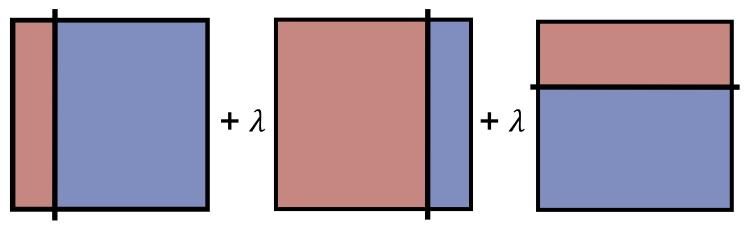




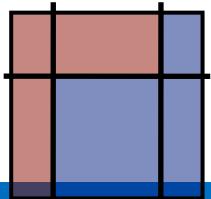
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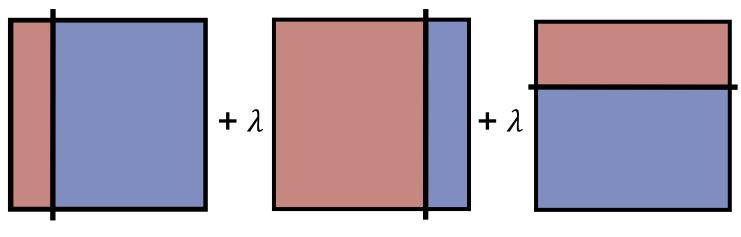




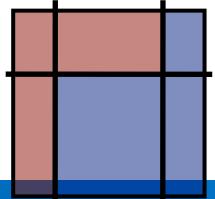
Result is weighted sum of all classifiers



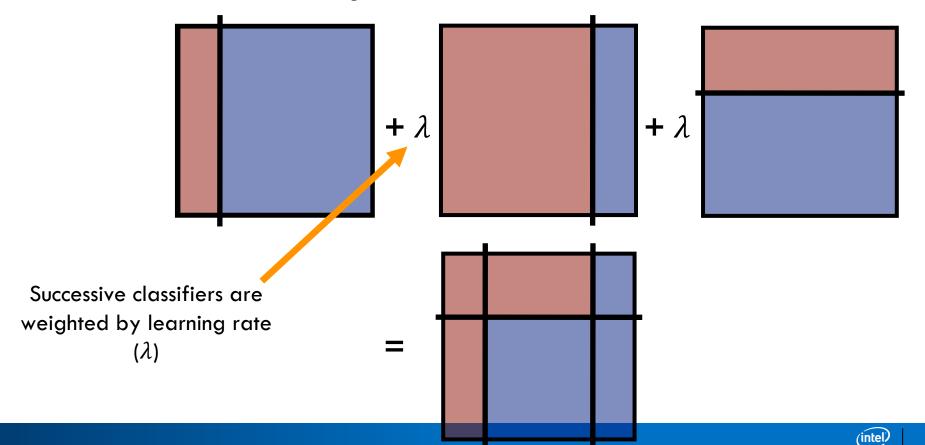


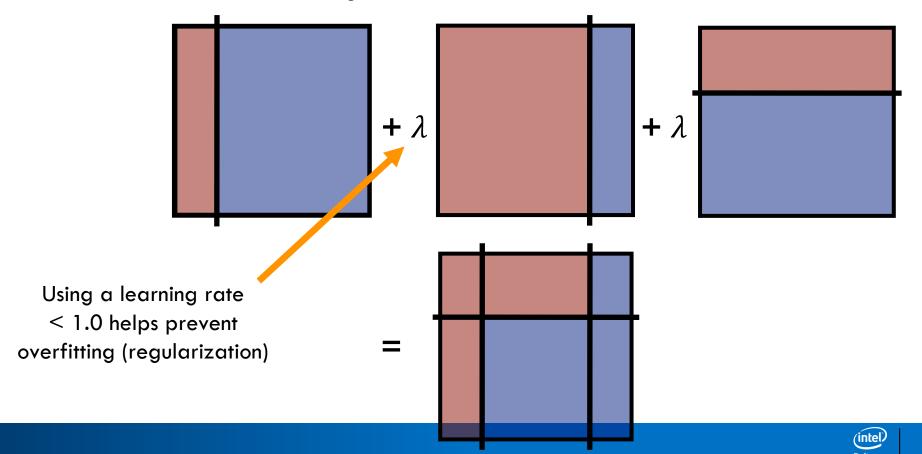


Successive classifiers are weighted by learning rate (λ)









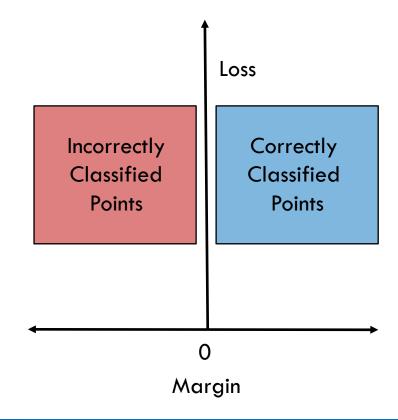
Boosting Specifics

- Boosting utilizes different loss functions
- At each stage, the margin is determined for each point



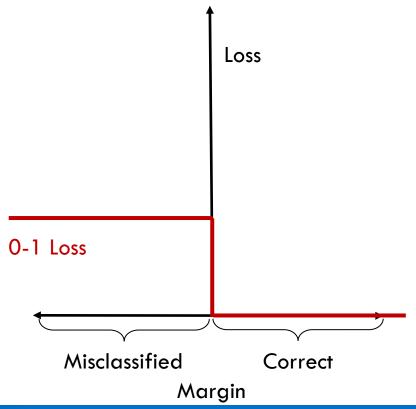
Boosting Specifics

- Boosting utilizes different loss functions
- At each stage, the margin is determined for each point
- Margin is positive for correctly classified points and negative for misclassifications
- Value of loss function is calculated from margin



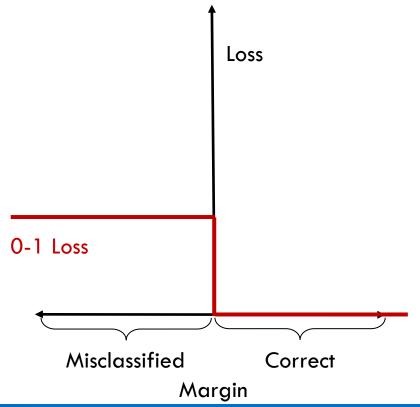


 The 0 – 1 Loss multiplies misclassified points by 1



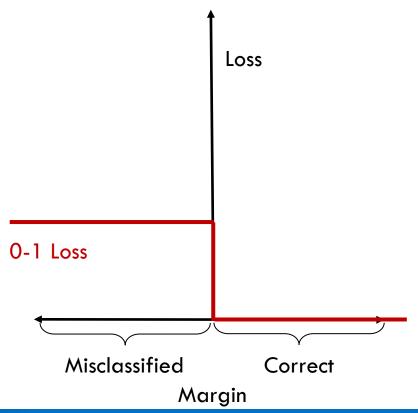


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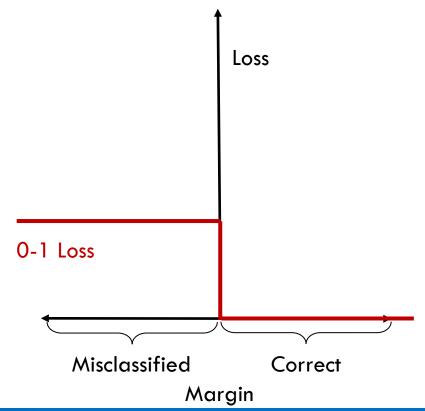


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- Theoretical "ideal" loss function
- Difficult to optimize—non-smooth





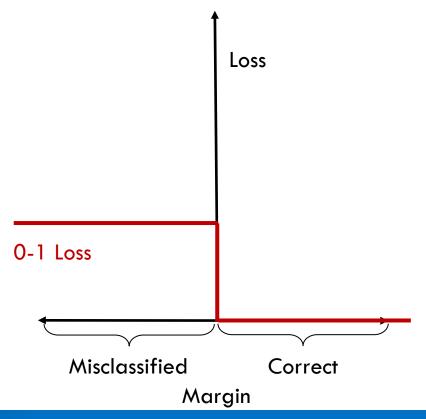
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AdaBoost Loss Function

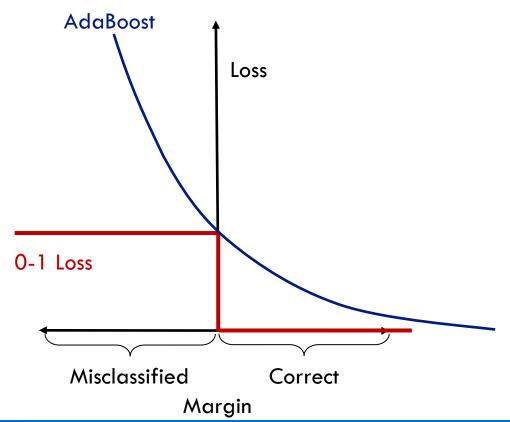
AdaBoost = Adaptive Boosting





AdaBoost Loss Function

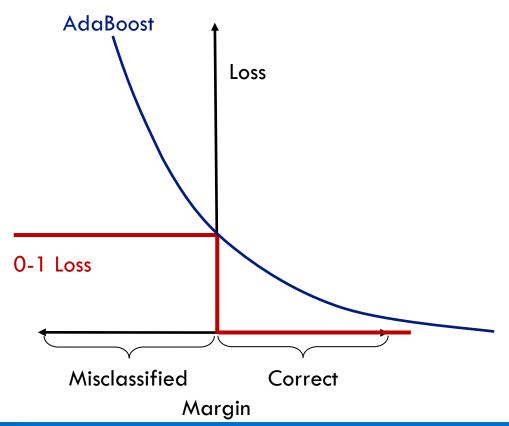
- AdaBoost = Adaptive Boosting
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AdaBoost Loss Function

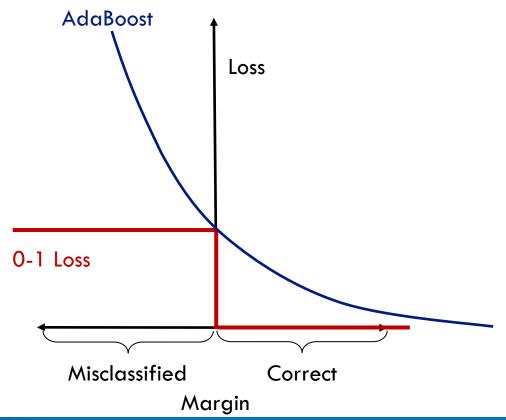
- AdaBoost = Adaptive Boosting
- Loss function is exponential: $e^{(-margin)}$
- Makes AdaBoost more sensitive to outliers than other types of boosting





Gradient Boosting Loss Function

- Generalized boosting method that can use different loss functions
- Common implementation uses

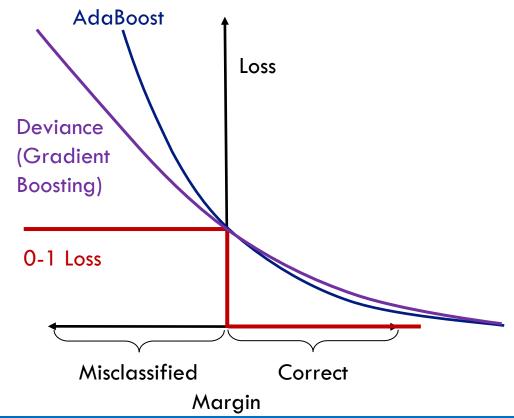




Gradient Boosting Loss Function

- Generalized boosting method that can use different loss functions
- Common implementation uses binomial log likelihood loss function (deviance):

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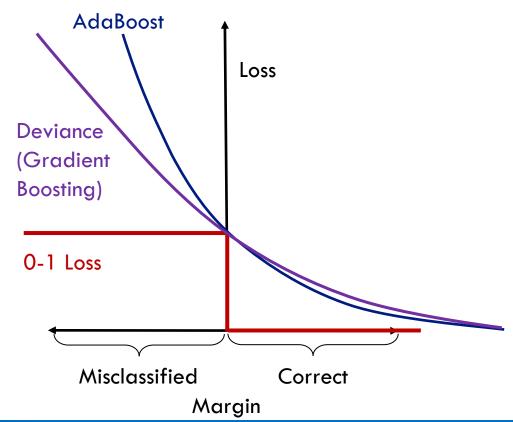


Gradient Boosting Loss Function

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$$\log(1 + e^{(-margin)})$$

 More robust to outliers than AdaBoost





Bagging

Bootstrapped samples

Boosting

• Fit entire data set



Bagging

- Bootstrapped samples
- Base trees created independently

- Fit entire data set
- Base trees created successively



Bagging

- Bootstrapped samples
- Base trees created independently
- Only data points considered

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- Use residuals from previous models



Bagging

- Bootstrapped samples
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- Excess trees will not overfit

- Fit entire data set
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- Use residuals from previous models
- Up-weight misclassified points
- Beware of overfittina



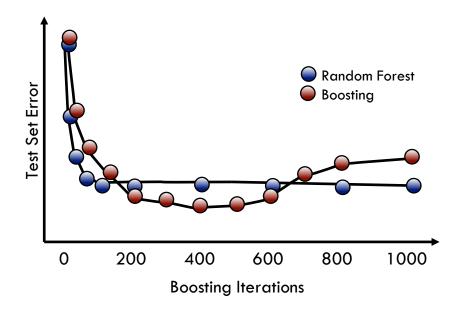
Bagging

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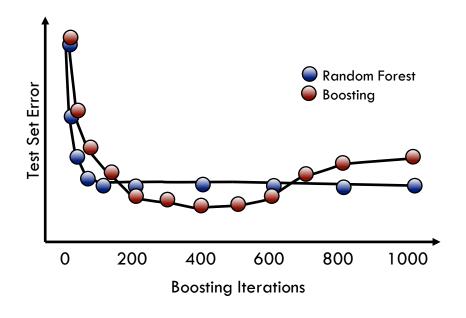
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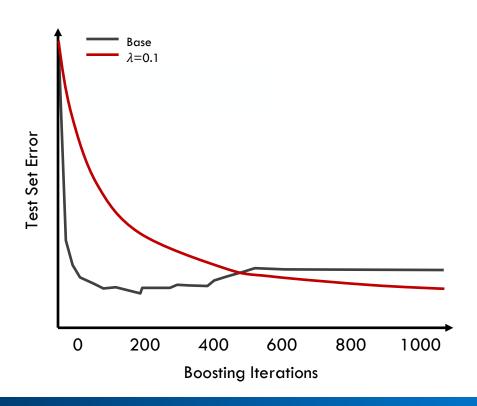
 Boosting is additive, so possible to overfit





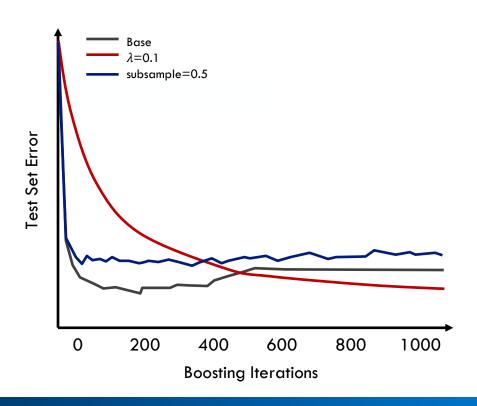
- Boosting is additive, so possible to overfit
- Use cross validation to set number of trees





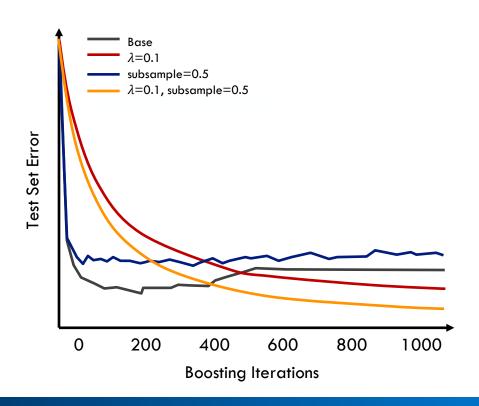
• Learning rate (λ): set to <1.0 for regularization. That's also called "shrinkage"





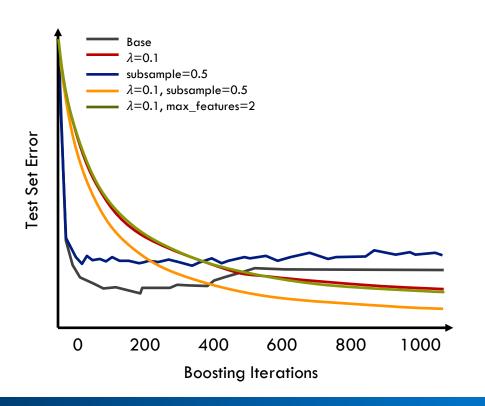
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- Subsample: set to <1.0 to use fraction of data for base learners (stochastic gradient boosting)





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- Subsample: set to <1.0 to use fraction of data for base learners (stochastic gradient boosting)
- Max_features: number of features to consider in base learners when splitting.



Import the class containing the classification method

from sklearn.ensemble import GradientBoostingClassifier



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Create an instance of the class

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GBC = GradientBoostingClassifier(learning_rate=0.1, max_features=1, subsample=0.5, n_estimators=200)
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Fit the instance on the data and then predict the expected value

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GBC = GBC.fit (X_train, y_train)
y_predict = GBC.predict(X_test)
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Tune with cross-validation. Use GradientBoostingRegressor for regression.



Import the class containing the classification method

from sklearn.ensemble import AdaBoostClassifier from sklearn.tree import DecisionTreeClassifier

To use the Intel® Extension for Scikit-learn* variant of this algorithm:

- Install <u>Intel® oneAPI AI Analytics Toolkit</u> (AI Kit)
- Add the following two lines of code after the above code:

```
import patch_sklearn
patch_sklearn()
```



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ABC = AdaBoostClassifier(base_estimator=DecisionTreeClassifier(), learning rate=0.1, n estimators=200)



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base learner can be set manually



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can also set max depth here



Import the class containing the classification method

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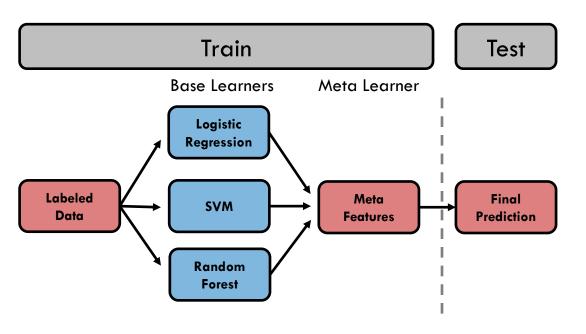
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Fit the instance on the data and then predict the expected value

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ABC = ABC.fit(X_train, y_train)
y_predict = ABC.predict(X_test)
```

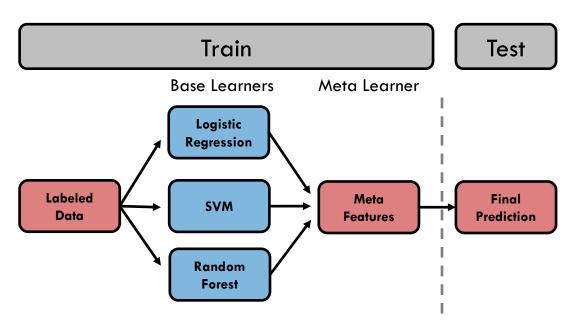
Tune parameters with cross-validation. Use AdaBoostRegressor for regression.





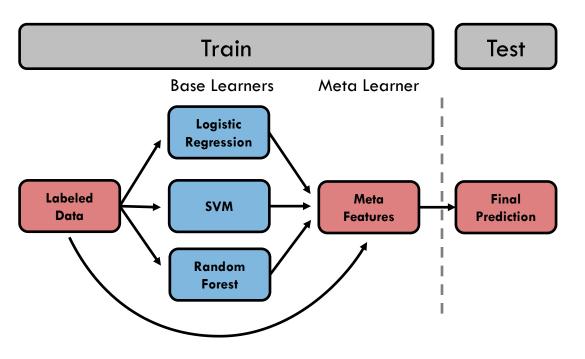
 Models of any kind combined to create stacked model





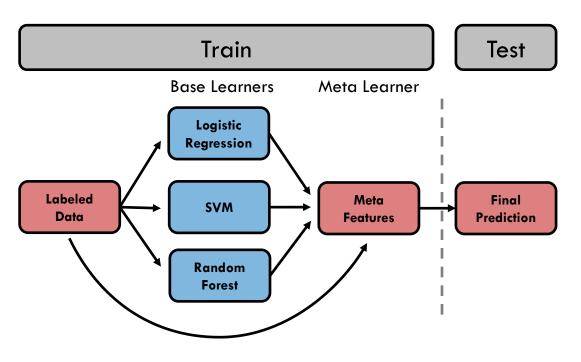
- Models of any kind combined to create stacked model
- Like bagging but not limited to decision trees





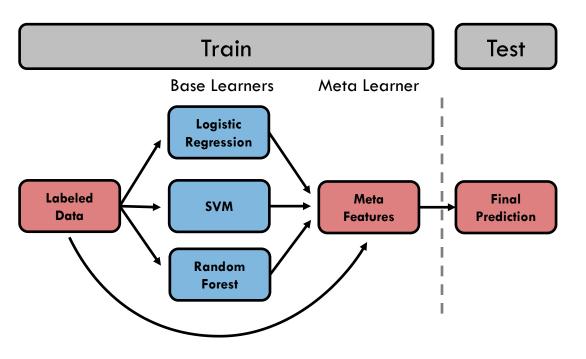
- Models of any kind combined to create stacked model
- Like bagging but not limited to decision trees
- Output of base learners creates features, can recombine with data





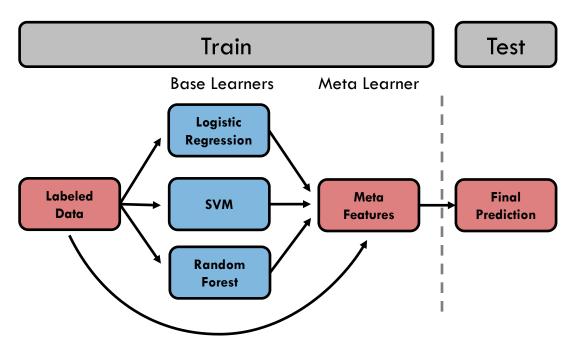
 Output of base learners can be combined via majority vote or weighted





- Output of base learners can be combined via majority vote or weighted
- Additional hold-out data needed if meta learner parameters are used





- Output of base learners can be combined via majority vote or weighted
- Additional hold-out data needed if meta learner parameters are used
- Be aware of increasing model complexity



Import the class containing the classification method

from sklearn.ensemble import VotingClassifier



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Import the class containing the classification method

from sklearn.ensemble import VotingClassifier

Create an instance of the class

Fit the instance on the data and then predict the expected value

```
VC = VC.fit(X_train, y_train)
y_predict = VC.predict(X_test)
```

Tune with an ADDITIONAL LEVEL of cross-validation or hold-out set.



