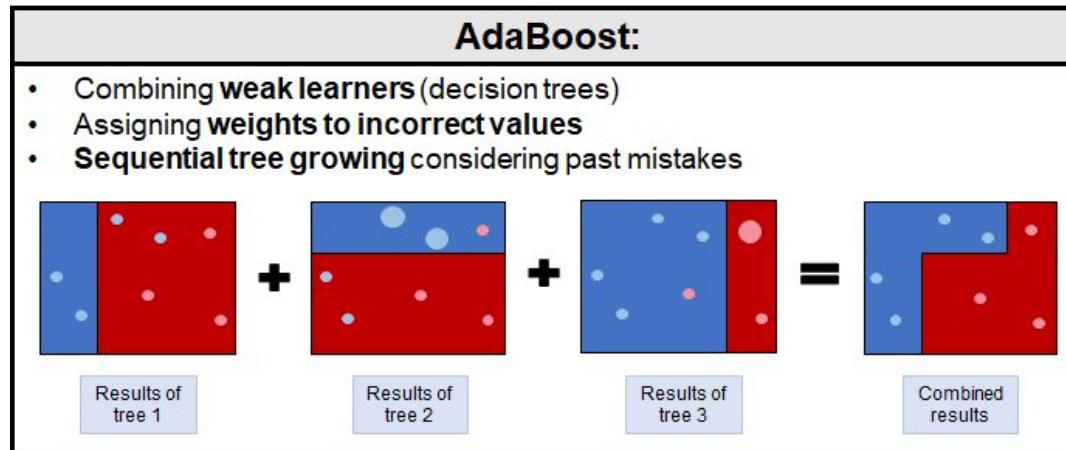


Boosting

AdaBoost

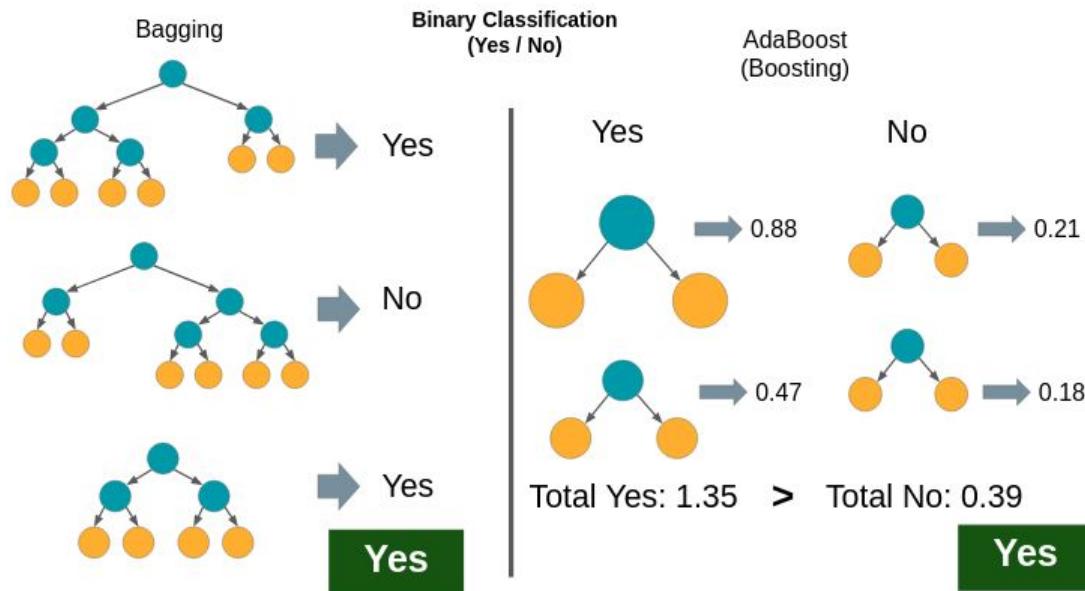
- AdaBoost Adaptive boosting is a **boosting** algorithm, which also works on the principle of the **stagewise addition method** where multiple **weak** learners are used for getting **strong** learners.



How AdaBoost Works

- **Step 1:** A **weak classifier** (e.g. a decision stump) is made on top of the training data based on the **weighted samples**. Here, the **weights of each sample** indicate how **important** it is **to be correctly classified**. Initially, for the first stump, we give all the samples **equal weights**.
- **Step 2:** We create a decision **stump** for **each variable** and see **how well** each stump classifies samples to their target classes.
- **Step 3:** **More weight** is assigned to the **incorrectly classified** samples so that they're classified correctly in the next decision stump. **Weight** is also assigned to **each classifier** based on the **accuracy of the classifier**, which means **high accuracy = high weight!**
- **Step 4:** **Reiterate** from Step 2 until all the data points have been correctly classified, **the error function does not change**, or **the maximum iteration level** has been reached.

How AdaBoost Works



An Example of How AdaBoost Works

- Suppose we have the sample data below, with three features (x_1 , x_2 , x_3) and an output (Y). Note that $T = \text{True}$ and $F = \text{False}$.

x_1	x_2	x_3	Y
T	T	F	T
T	T	F	F
T	F	F	T
T	T	T	F
F	T	F	F
T	F	F	T

An Example of How AdaBoost Works

- Step 1: Assign a sample weight for each sample

$$\text{sample weight} = \frac{1}{\# \text{ of samples}}$$

x1	x2	x3	Y	Sample Weight
T	T	F	T	1/6
T	T	F	F	1/6
T	F	F	T	1/6
T	T	T	F	1/6
F	T	F	F	1/6
T	F	F	T	1/6

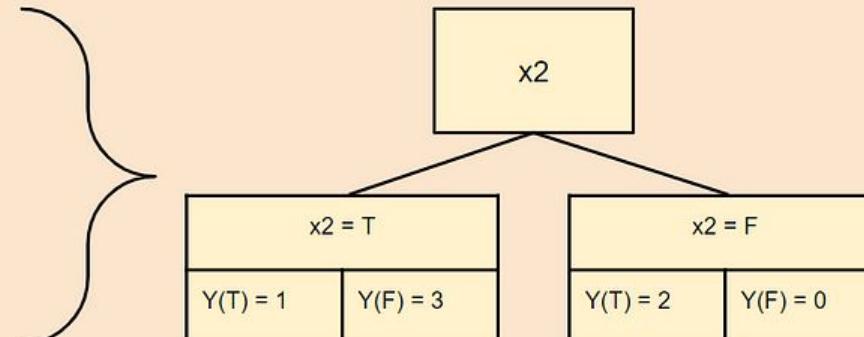
An Example of How AdaBoost Works

- Step 2: Calculate the Gini Impurity for each variable

This is done to determine which variable to use to create the first stump.

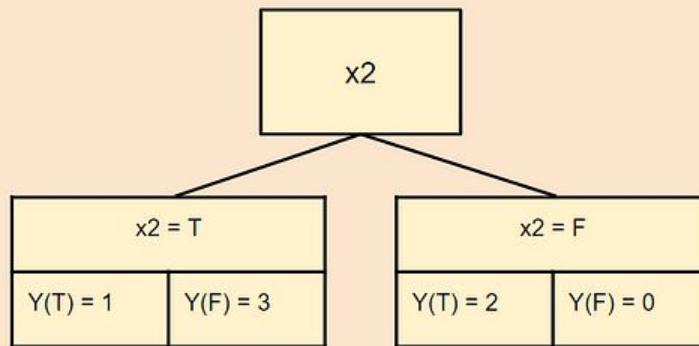
$$\text{Gini Impurity} = 1 - (\text{the probability of True})^2 - (\text{the probability of False})^2$$

x2	Y = T	Y = F
X2 = T	1	3
X2 = F	2	0



An Example of How AdaBoost Works

x2 has the lowest Gini Impurity, so x2 will be used to create the first stump.



$$\text{Gini Impurity} = 1 - (\text{the probability of True})^2 - (\text{the probability of False})^2$$

$$\text{Gini Impurity} = 1 - \left(\frac{1}{1+3}\right)^2 - \left(\frac{3}{1+3}\right)^2$$

$$\text{Gini Impurity} = 0.375$$

$$\text{Gini Impurity} = 1 - (\text{the probability of True})^2 - (\text{the probability of False})^2$$

$$\text{Gini Impurity} = 1 - \left(\frac{2}{2+0}\right)^2 - \left(\frac{0}{2+0}\right)^2$$

$$\text{Gini Impurity} = 0$$

$$\text{Total Impurity} = 0.375 \left(\frac{4}{4+2}\right) + 0 \left(\frac{2}{4+2}\right)$$

$$\text{Total Impurity} = 0.25$$

the Gini Impurity for $x_2 = 0.25$.

An Example of How AdaBoost Works

- Step 3: Calculate the **Amount of Say** for the stump that was created

Total Error is equal to the sum of the weights of the incorrectly classified samples.

Since one of the samples was incorrectly classified for x_2 , the total error is equal to $1/6$.

$$\text{Amount of say} = \frac{1}{2} \log \left(\frac{1 - \text{total error}}{\text{total error}} \right)$$

$$\text{Amount of say} = \frac{1}{2} \log \left(\frac{1 - \frac{1}{6}}{\frac{1}{6}} \right) = 0.35$$

An Example of How AdaBoost Works

- Step 4: Calculate the **new sample weights** for the next stump

we're going to increase the sample weights of samples that were incorrectly classified and decrease the sample weights of samples that were correctly classified using the following equations:

$$\text{New Sample Weight For Incorrect Samples} = \text{Sample weight} * e^{\text{amount of say}}$$

$$\text{New Sample Weight For Correct Samples} = \text{Sample weight} * e^{-\text{amount of say}}$$

An Example of How AdaBoost Works

Need to divide each weight by 0.84 

Total: 0.84

x1	x2	x3	Y	New Sample Weight	Normalized Sample Weights
T	T	F	T	0.24	0.29
T	T	F	F	0.12	0.14
T	F	F	T	0.12	0.14
T	T	T	F	0.12	0.14
F	T	F	F	0.12	0.14
T	F	F	T	0.12	0.14

An Example of How AdaBoost Works

- Step 5: Create a **bootstrapped dataset** with the odds of each sample being chosen based on their new sample weights.

x1	x2	x3	Y	Normalized Sample Weights
T	T	F	T	0.29
T	T	F	F	0.14
T	T	F	T	0.29
T	T	T	F	0.14
T	T	F	T	0.29
T	F	F	T	0.14

An Example of How AdaBoost Works

- Step 6: Repeat the process n number of times
- Lastly, this process is repeated until n number of stumps are created, each with its own amount of say. Once this is done, the model is complete and new points can be classified.
- New points are classified by running them through all of the stumps and seeing how they're classified. Then, the amount of say is summed for each class, and the class with the higher amount of say is the classification of the new point.

Difference Between Boosting Algorithms

Algorithms	Gradient Boosting	AdaBoost	XGBoost	CatBoost	LightGBM
Year	–	1995	2014	2017	2017
Handling Categorical Variables	May require preprocessing like one-hot encoding	No	NO	Automatically handles categorical variables	No
Speed/Scalability	Moderate	Fast	Fast	Moderate	Fast
Memory Usage	Moderate	Low	Moderate	High	Low
Regularization	NO	No	Yes	Yes	Yes
Parallel Processing	No	No	Yes	Yes	Yes
GPU Support	No	No	Yes	Yes	Yes
Feature Importance	Available	Available	Available	Available	Available

[Copy Code](#)

AdaBoost Code

<https://www.analyticsvidhya.com/blog/2015/11/quick-introduction-boosting-algorithms-machine-learning/>

```
# Importing dependencies numpy and keras
import pandas as pd
from sklearn.ensemble import AdaBoostClassifier #For Classification
from sklearn.ensemble import AdaBoostRegressor #For Regression
from sklearn.tree import DecisionTreeClassifier

# reading the data
df = pd.read_csv('train-data.csv')

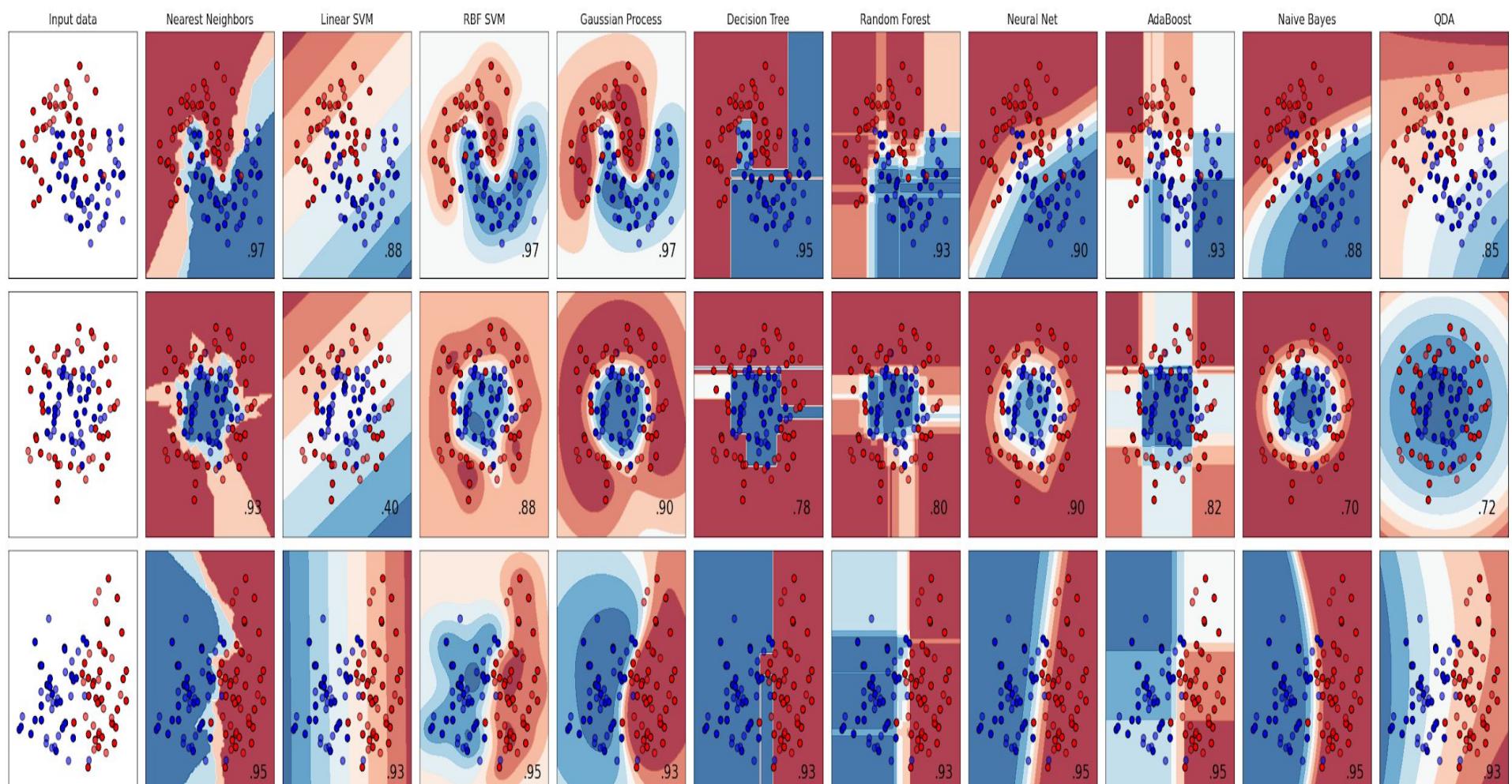
# first five rows of the data
print(df.head())

# shape of the data
print('\nShape : ', df.shape)

# separating the independent and dependent variables
# independent variable
x_train = df.drop('Survived', axis=1)
# dependent variable
y_train = df['Survived']

# Now we will use decision tree as a base estimator, you can use any ML learner as base es
dt = DecisionTreeClassifier()
clf = AdaBoostClassifier(n_estimators=100, base_estimator=dt,learning_rate=1)

# training the model
clf.fit(x_train,y_train)
```



Classifier comparison — scikit-learn 1.3.0

• :Decision tree

- Split data (nodes, branches , leafs)
- اكثراً عرضة لل overfitting > إذا كانت depth deep
- تغيير بسيط بالبيانات يمكنه تغيير كل ال trees

• Random forest

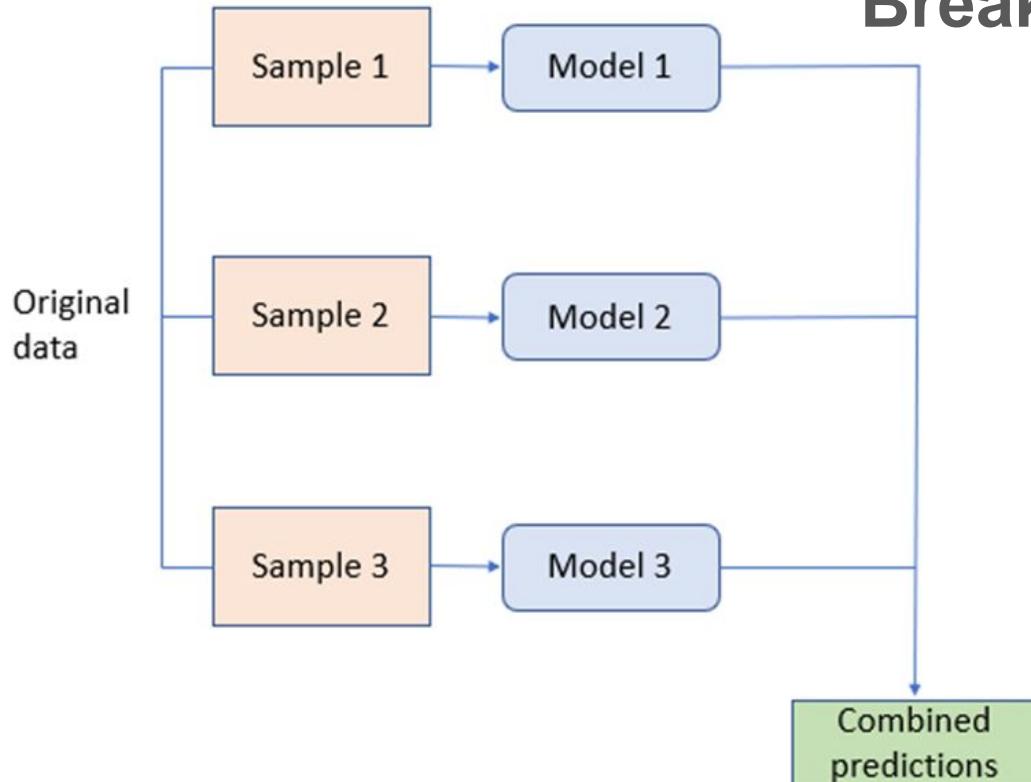
- مجموعة من DT تتتدرب على عينات مختلفة من البيانات ويفيتشر عشوائية والنتيجة بتطبع عن طريق تصويت Bagging > **decrease variance**
- Ensemble learning
- overfitting حل مشكلة ال

• Adaboost

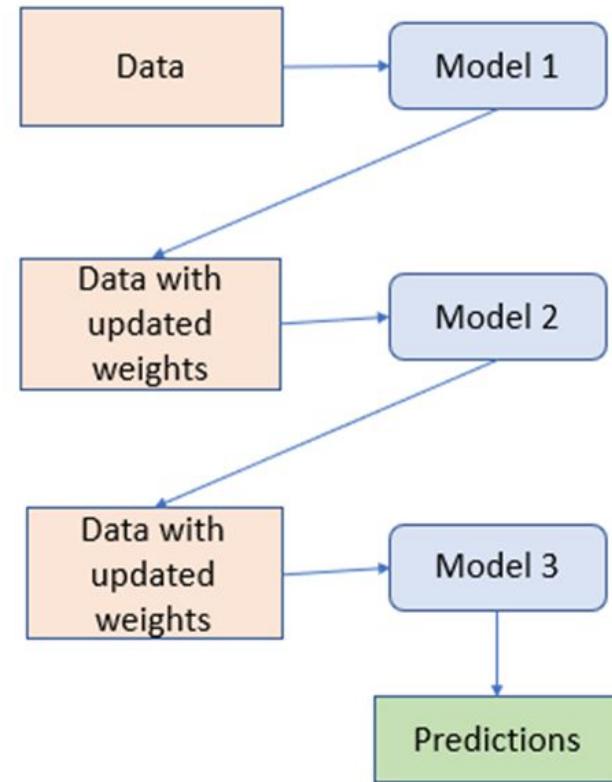
- بناء الـ decision stumps لـ sequential trees حسب الاداء rows samples
- الدقة أعلى من RF لأنها تقلل **bais** وتركتز على الخطأ لأنها تعطي أهمية وأولوية أكثر للغلطان حتى يتعلم من يحي فهاد معناه أن الدقة هنزيد
- حساسة لـ outliers

6:50 PM Break

Bagging



Boosting



★ Bagging is used mainly in reducing variance and it is a parallel process

★ Boosting is used mainly in reducing bias and it is a sequential process