# SNS COLLEGE OF TECHNOLOGY

**Coimbatore-35**
**An Autonomous Institution**

Accredited by NBA – AICTE and Accredited by NAAC – UGC with 'A++' Grade
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## DEPARTMENT OF ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING

## 23AMB201 - MACHINE LEARNING

II YEAR IV SEM

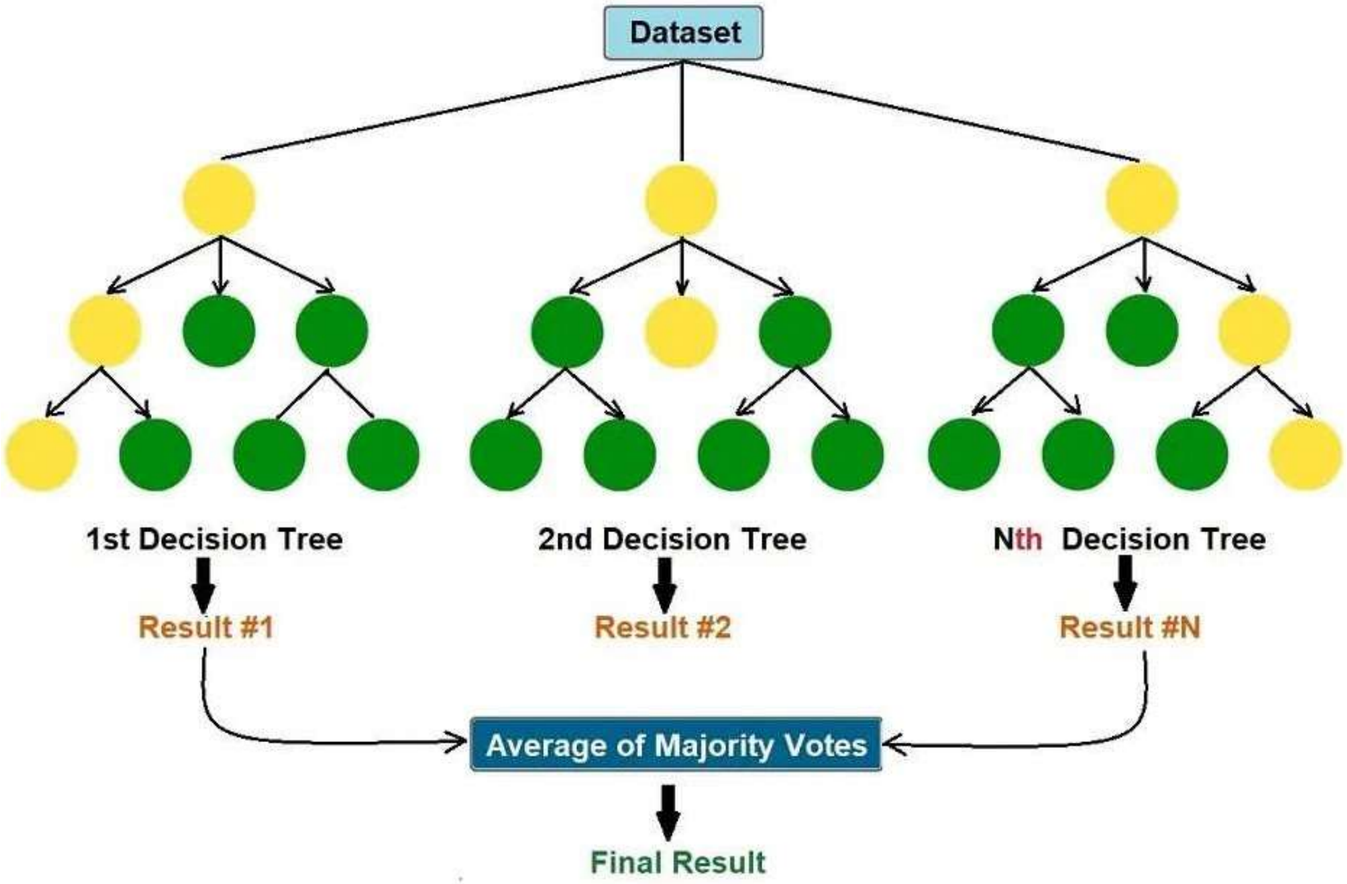
UNIT III – GENERATIVE MODELS AND BOOSTING

TOPIC 18, 19, 20 – Random Forest, Ensemble learning and Boosting

# Random Forest

A Random Forest Algorithm is a supervised machine learning algorithm that is extremely popular and is used for Classification and Regression problems in Machine Learning.

Random Forest is a classifier that contains several decision trees on various subsets of the given dataset and takes the average to improve the predictive accuracy of that dataset.



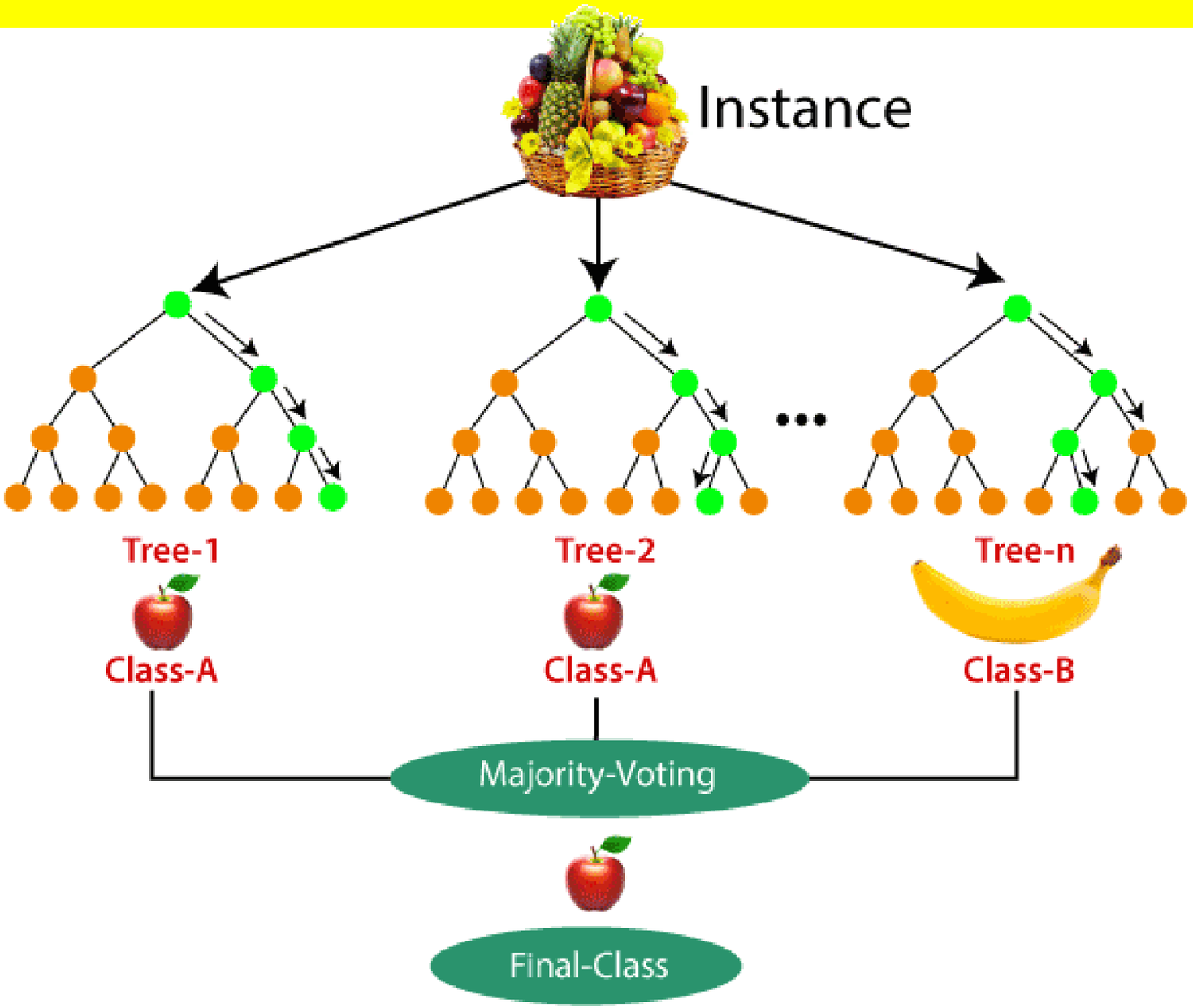
# Why Random Forest?

1. Reduced risk of overfitting
2. Provides flexibility
3. Easy to determine feature importance

**How does Random Forest algorithm work?**

1. Step-1: Select random K data points from the training set.
2. Step-2: Build the decision trees associated with the selected data points (Subsets).
3. Step-3: Choose the number N for decision trees that you want to build.
4. Step-4: Repeat Step 1 & 2.
5. Step-5: For new data points, find the predictions of each decision tree, and assign the new data points to the category that wins the majority votes.

# Example

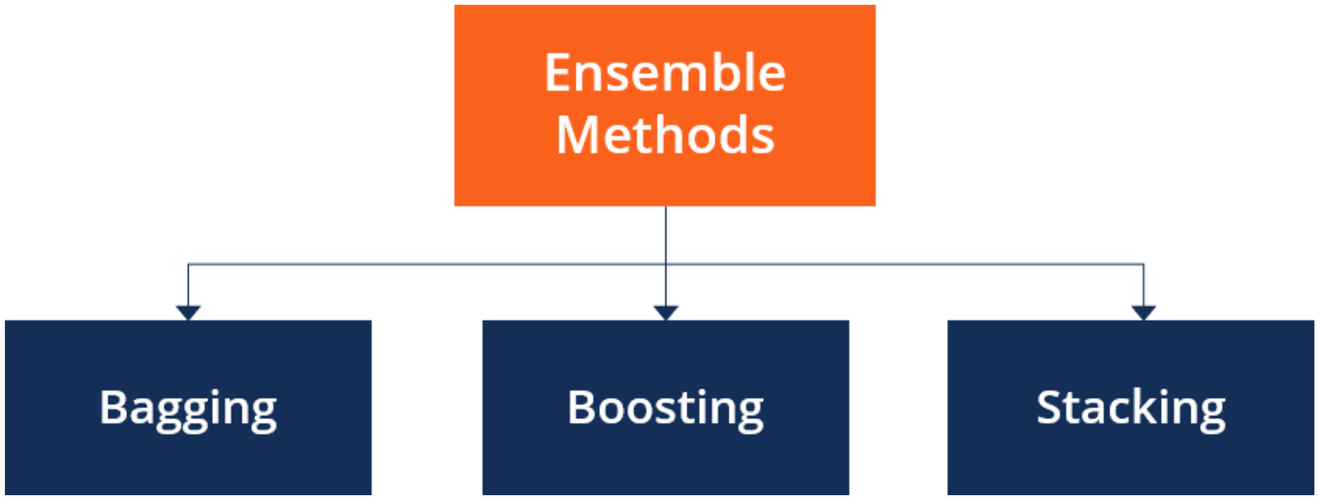

Instance
Tree-1
Tree-2
Tree-n
Class-A
Class-A
Class-B
Majority-Voting
Final-Class

# Program

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score

# Load dataset
iris = load_iris()
X_train, X_test, y_train, y_test = train_test_split(iris.data, iris.target, test_size=0.2)

# Train Random Forest
clf = RandomForestClassifier(n_estimators=100, random_state=42)
clf.fit(X_train, y_train)

# Predictions
y_pred = clf.predict(X_test)

# Accuracy
print("Accuracy:", accuracy_score(y_test, y_pred))
```

# Ensemble

**Ensemble Learning:** C ombine the decisions from multiple models to improve the overall performance.



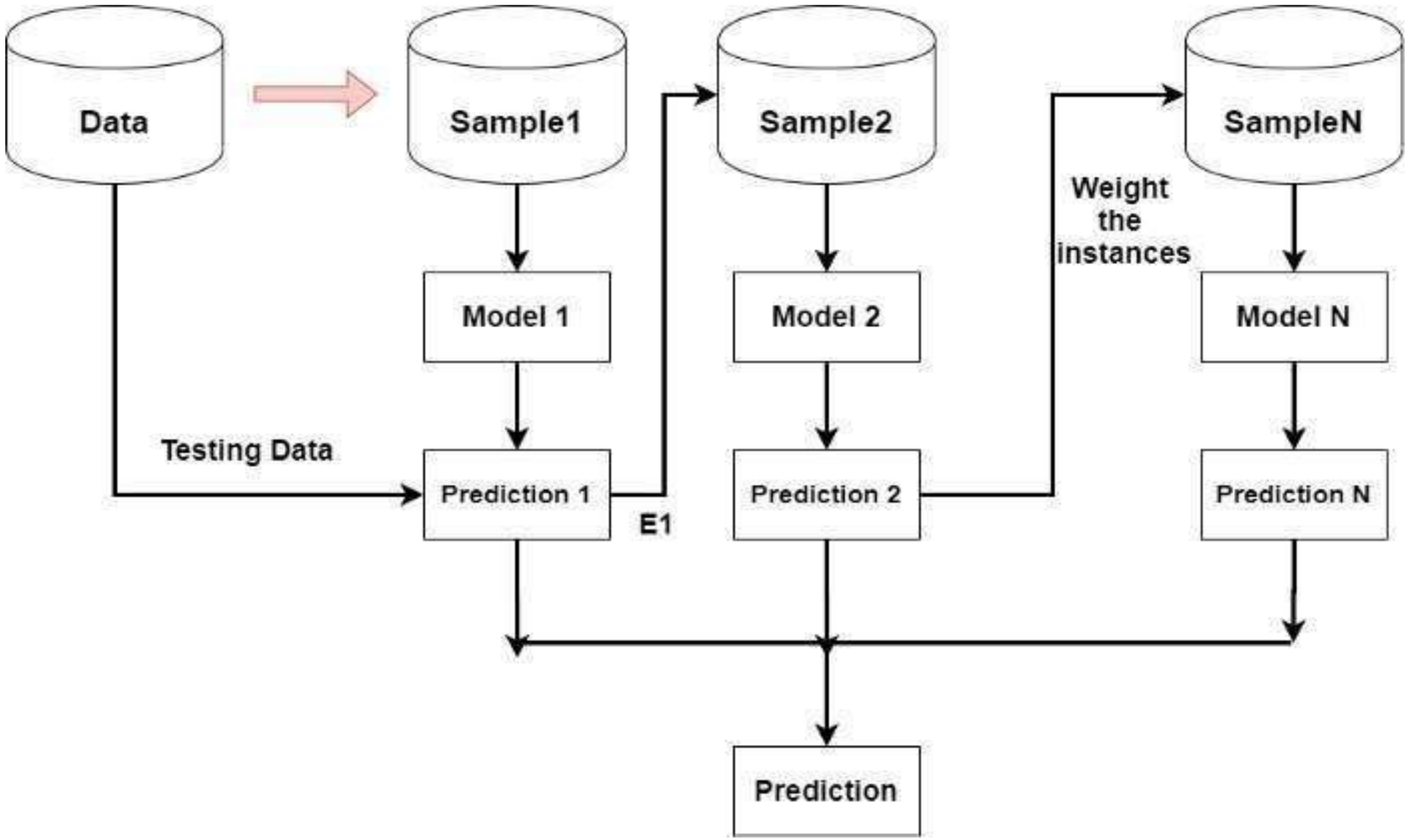
# Ensemble

1. An ensemble is itself a supervised learning algorithm because it can be trained and then used to make predictions.
2. It combine several decision trees classifiers to produce better predictive performance than a single decision tree classifier.
3. Main principle is to group of **weak learners come together to form a strong learner**
4. To increasing the accuracy of the model.
5. Ensemble helps to reduce noise, variance and bias

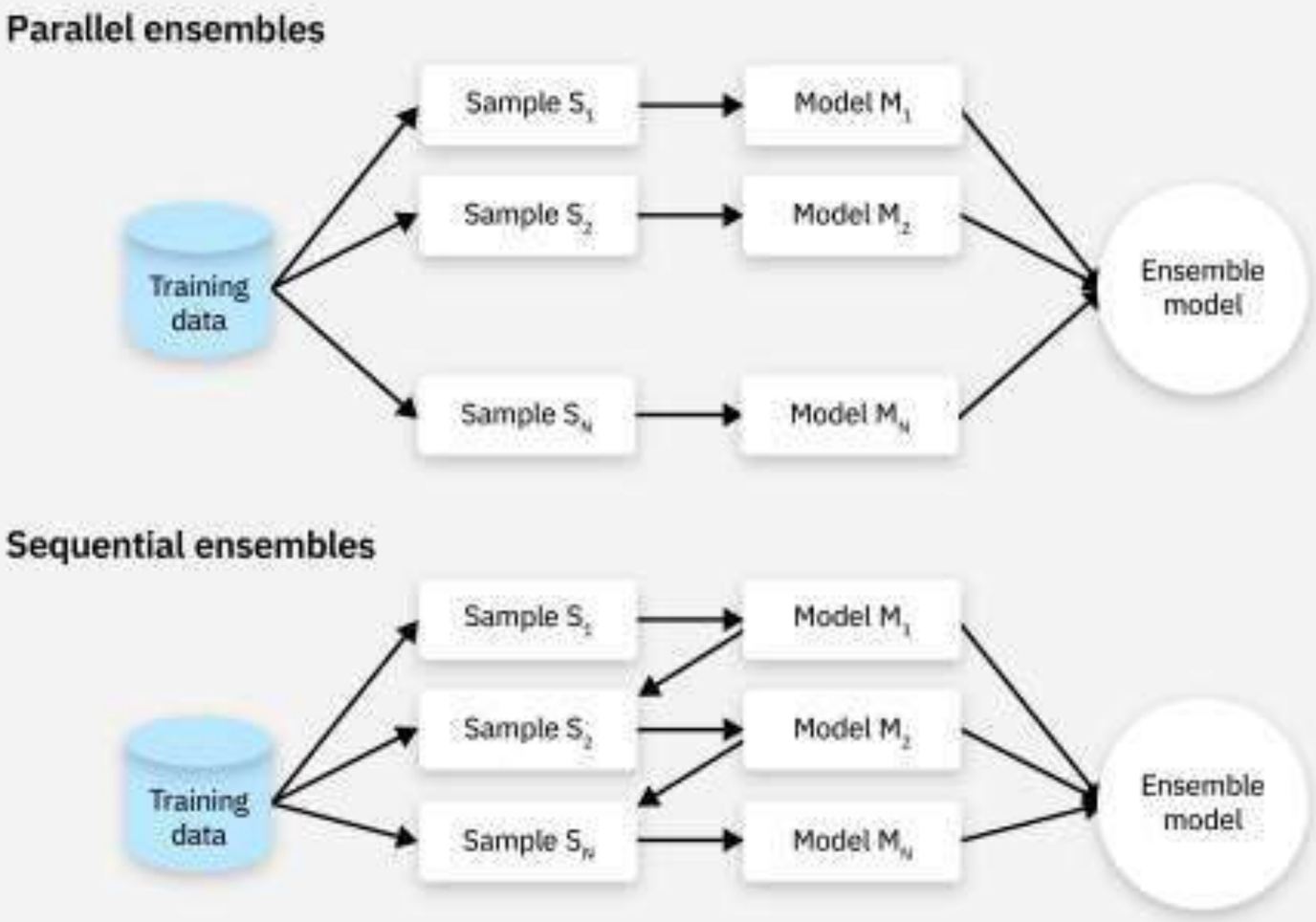
Total error can be expressed as follows:

**Total Error = Bias + Variance + Irreducible Error**

# Ensemble


Data
Sample1
Sample2
SampleN
Weight the instances
Model 1
Model 2
Model N
Testing Data
Prediction 1
E1
Prediction 2
Prediction N
Prediction

# Types of Ensemble



# Basic Ensemble Techniques and Methods

1. Max Voting
2. Averaging
3. Weighted Average

1. Bootstrap
2. Bagging
3. Stocking

# Max Voting

| PassengerId | Survived | Pclass | Name | Sex | Age | SibSp | Parch |
|---|---|---|---|---|---|---|---|
| 1 | 0 | 3 | Braund, Mr. Owen Harris | male | 22.0 | 1 | 0 |
| 2 | 1 | 1 | Cumings, Mrs. John Bradley (Florence Briggs Th... | female | 38.0 | 1 | 0 |
| 3 | 1 | 3 | Heikkinen, Miss. Laina | female | 26.0 | 0 | 0 |
| 4 | 1 | 1 | Futrelle, Mrs. Jacques Heath (Lily May Peel) | female | 35.0 | 1 | 0 |
| 5 | 0 | 3 | Allen, Mr. William Henry | male | 35.0 | 0 | 0 |

| PassengerId | Survived |
|---|---|
| 1 | 0 |
| 2 | 1 |
| 3 | 1 |
| 4 | 1 |
| 5 | 0 |

M1 M2 M3

| Pred 1 | Pred 2 | Pred 3 |
|---|---|---|
| 0 | 1 | 0 |
| 0 | 1 | 1 |
| 1 | 1 | 0 |
| 1 | 0 | 1 |
| 0 | 0 | 0 |

M1: logistic regression
M2: KNN
M3: SVM

M1 M2 M3

| Pred 1 | Pred 2 | Pred 3 | Final Pred |
|---|---|---|---|
| 0 | 1 | 0 | ? |
| 0 | 1 | 1 | ? |
| 1 | 1 | 0 | ? |
| 1 | 0 | 1 | ? |
| 0 | 0 | 0 | ? |

M1 M2 M3 Vote

| Pred 1 | Pred 2 | Pred 3 | Final Pred |
|---|---|---|---|
| 0 | 1 | 0 | 0 |
| 0 | 1 | 1 | 1 |
| 1 | 1 | 0 | 1 |
| 1 | 0 | 0 | **0** |
| 0 | 0 | 0 | 0 |

# Averaging

| | Item_Outlet_Sales |
|---|---|
| 0 | 3735.1380 |
| 1 | 443.4228 |
| 2 | 2097.2700 |
| 3 | 732.3800 |
| 4 | 994.7052 |

| M1 | M2 | M3 |
|---|---|---|
| Predicted Values 1 | Predicted Values 2 | Predicted Values 3 |
| 3900 | 3000 | 3500 |
| 390 | 340 | 500 |
| 2000 | 1900 | 2600 |
| 700 | 600 | 750 |
| 950 | 800 | 1060 |

| M1 | M2 | M3 | |
|---|---|---|---|
| Predicted Values 1 | Predicted Values 2 | Predicted Values 3 | Average |
| 3900 | 3000 | 3500 | 3466.66 |
| 390 | 340 | 500 | 410.00 |
| 2000 | 1900 | 2600 | 2166.66 |
| 700 | 600 | 750 | 683.33 |
| 950 | 800 | 1060 | 936.66 |

M1: logistic regression
M2: KNN
M3: SVM

# Weighted Average

| | | |
|---|---|---|
| M1 | 0.6 | 2 |
| M2 | 0.4 | 1 |
| M3 | 0.6 | 2 |

M1: logistic regression
M2: KNN
M3: SVM

2

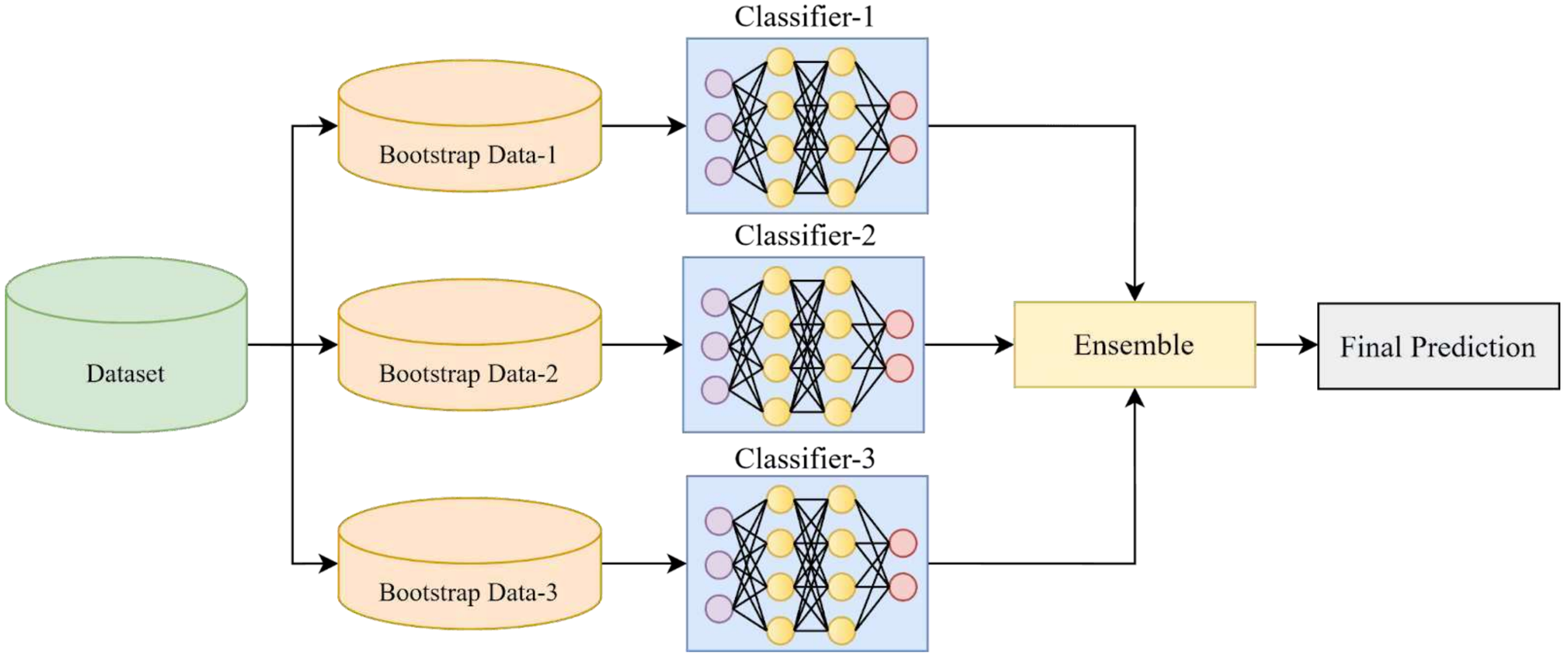
| ID | Actual Values | Predicted Values 1 | Predicted Values 2 | Predicted Values 3 |
|---|---|---|---|---|
| 0 | 3735.13 | 7800 | 3000 | 3500 |
| 1 | 443.422 | 780 | 340 | 500 |
| 2 | 2097.27 | 4000 | 1900 | 2600 |
| 3 | 732.380 | 1400 | 600 | 750 |
| 4 | 994.705 | 1900 | 800 | 1060 |

2

| ID | Actual Values | Predicted Values 1 | Predicted Values 2 | Predicted Values 3 |
|---|---|---|---|---|
| 0 | 3735.13 | 7800 | 3000 | 7000 |
| 1 | 443.422 | 780 | 340 | 1000 |
| 2 | 2097.27 | 4000 | 1900 | 5200 |
| 3 | 732.380 | 1400 | 600 | 1500 |
| 4 | 994.705 | 1900 | 800 | 2120 |

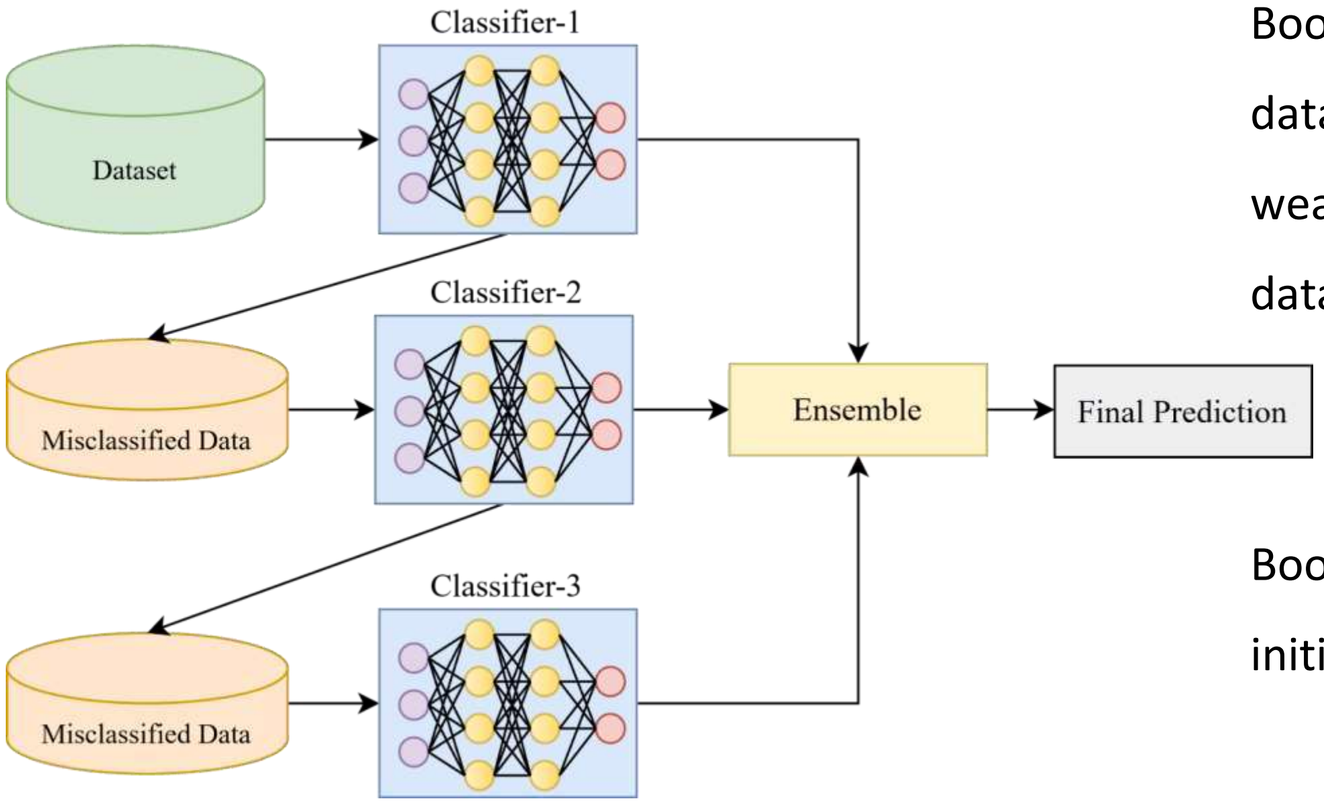
| ID | Actual Values | Predicted Values 1 | Predicted Values 2 | Predicted Values 3 | Average |
|---|---|---|---|---|---|
| 0 | 3735.13 | 7800 | 3000 | 7000 | 3560 |
| 1 | 443.422 | 780 | 340 | 1000 | 424 |
| 2 | 2097.27 | 4000 | 1900 | 5200 | 2220 |
| 3 | 732.380 | 1400 | 600 | 1500 | 700 |
| 4 | 994.705 | 1900 | 800 | 2120 | 964 |

# Ensemble Learning Methods – Bagging




Subsamples from a dataset are created and they are called “bootstrap sampling.” To put it simply, random subsets of a dataset are created using replacement, meaning that the same data point may be present in several subsets.

# Ensemble Learning Methods - Boosting

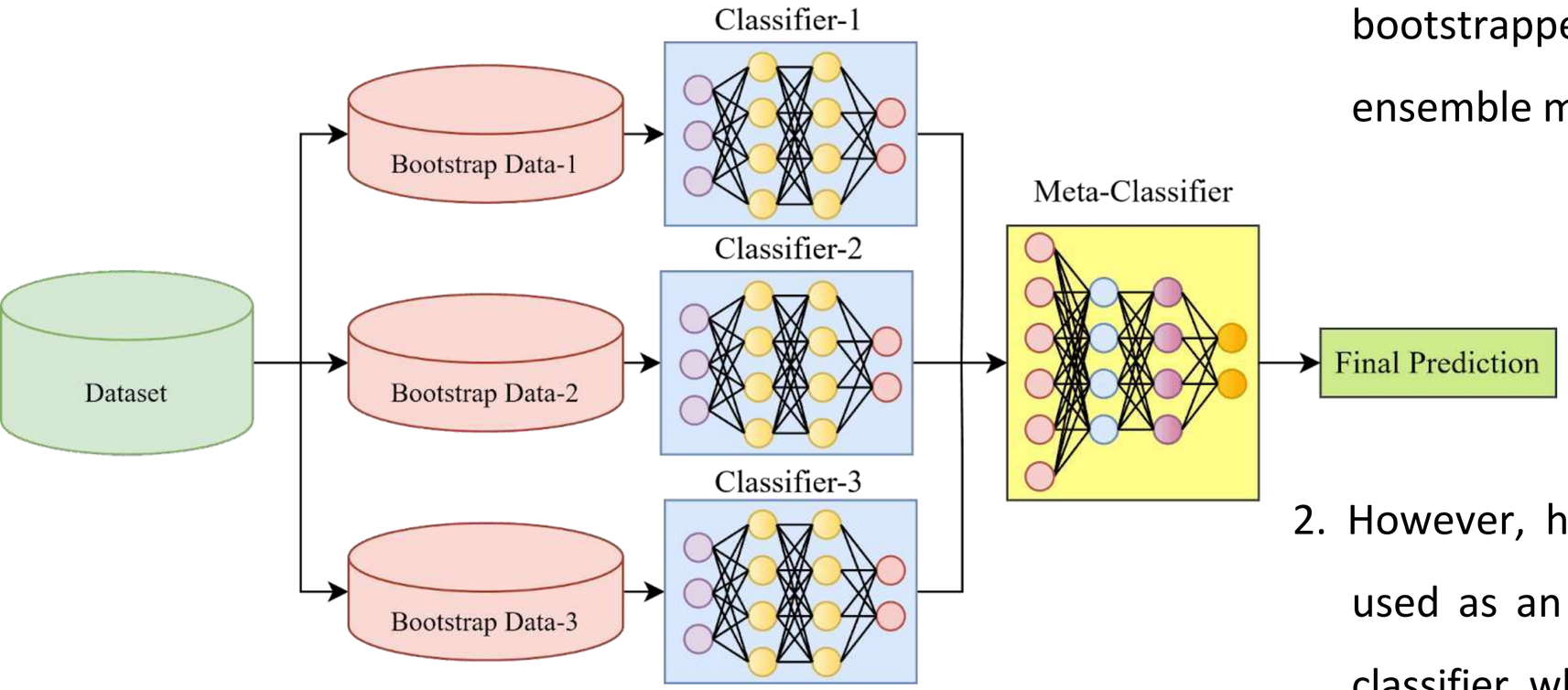



Boosting trains a learner on some initial dataset, *d*. The resultant learner is typically weak, misclassifying many samples in the dataset.

Boosting then samples instances from the initial dataset to create a new dataset ($d_2$)

Boosting prioritizes misclassified data instances from the first model or learner. A new learner is trained on this new dataset $d_2$.

# Ensemble Learning Methods - Stacking




1. The stacking ensemble method also involves creating bootstrapped data subsets, like the bagging ensemble mechanism for training multiple models.

2. However, here, the outputs of all such models are used as an input to another classifier, called meta-classifier, which finally predicts the samples.