Introduction to Machine Learning

Class

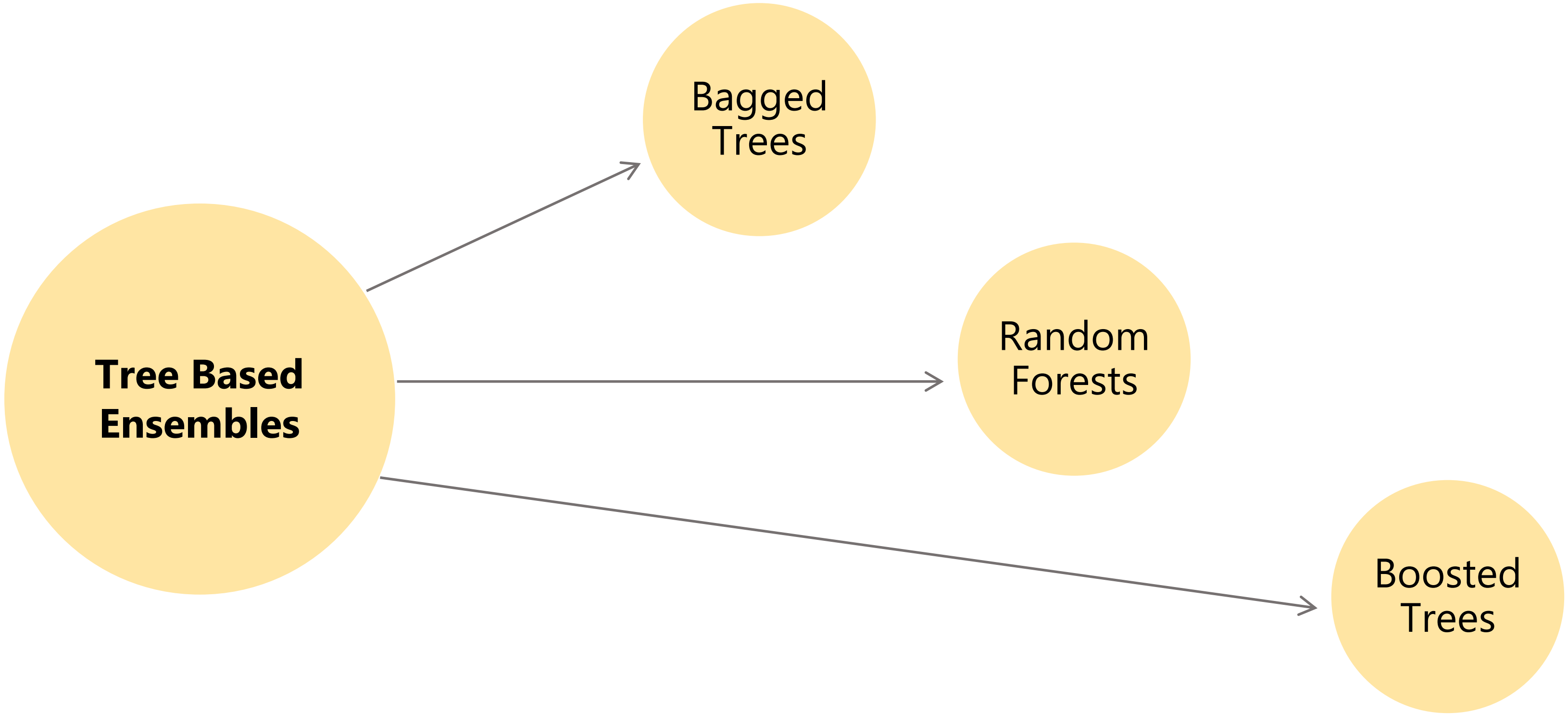
Tree Based Model

Topic

Tree Based Ensembles: Bagged Trees and Random Forests

Agenda

Another category of machine learning models → Ensemble Models



Tree Based Ensembles Overview

Single model

One good single regression model or one good single classification model

Ensemble model

Combine several simple models together to create one single meta model

Powerful models

Regression ensemble

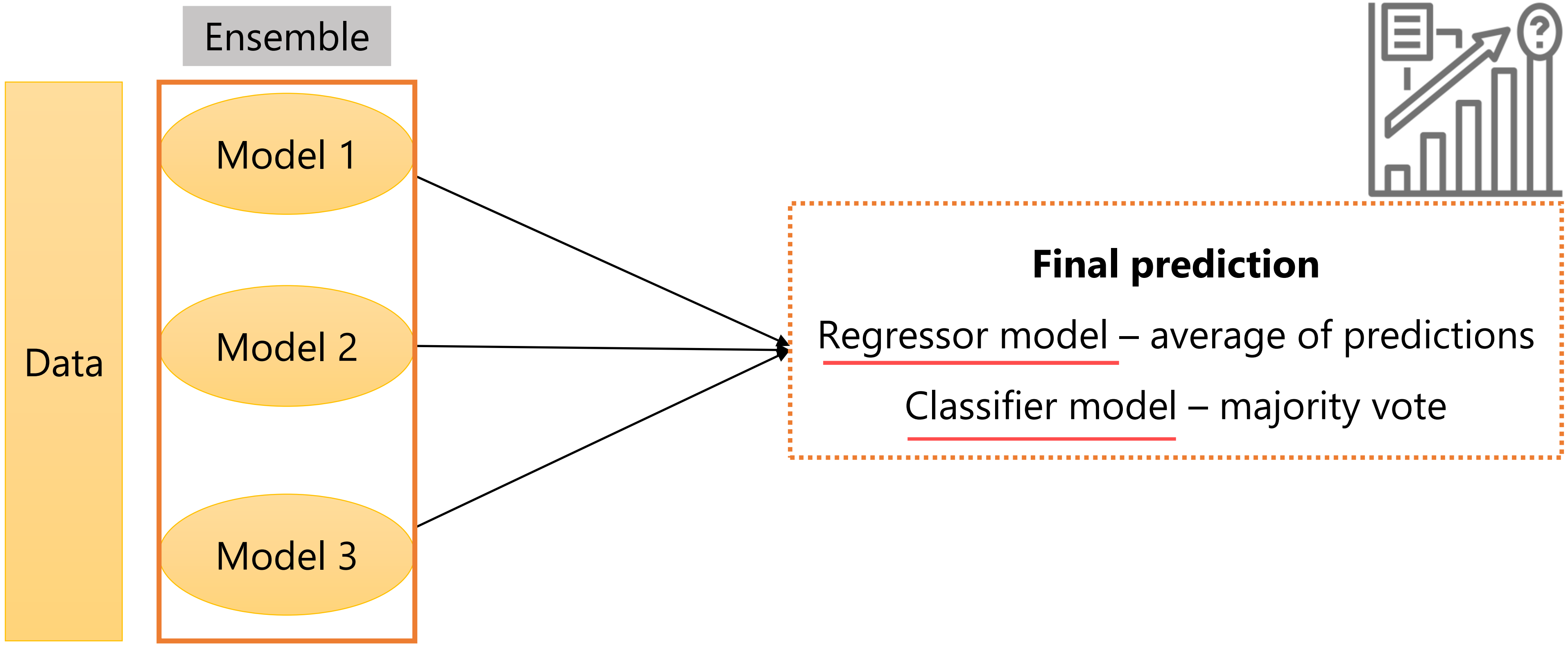
Final prediction is the average predictions from all the simple regression models in the ensemble

Classification ensemble

Final prediction is the majority vote out of all the predictions made by the constituent classifiers that make up this ensemble

Tree Based Ensembles Overview

Schematic working of ensembles



Tree Based Ensembles Overview

Tree based ensemble model

- More popular choice
- Only a subset of total data is used by each base learner

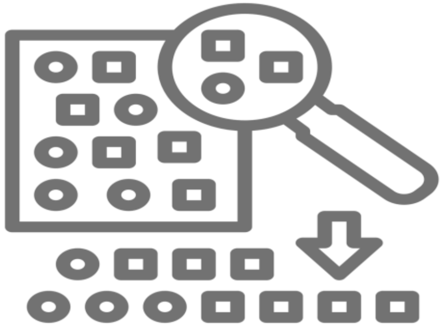
The way this data set is fed into each of the base learners is based on a **data sampling scheme**

Different sampling schemes give rise to different types of tree based ensembles

Tree Based Ensemble Models

- Tree based ensemble model
  - Bagged Tree
  - Random Forests
  - Boosted Trees

Sampling Scheme	Bootstrap Sampling	Bootstrap Sampling + Feature Sampling	Data Reweighing
Base Learner	Tree	Tree	Tree



Bagged Trees

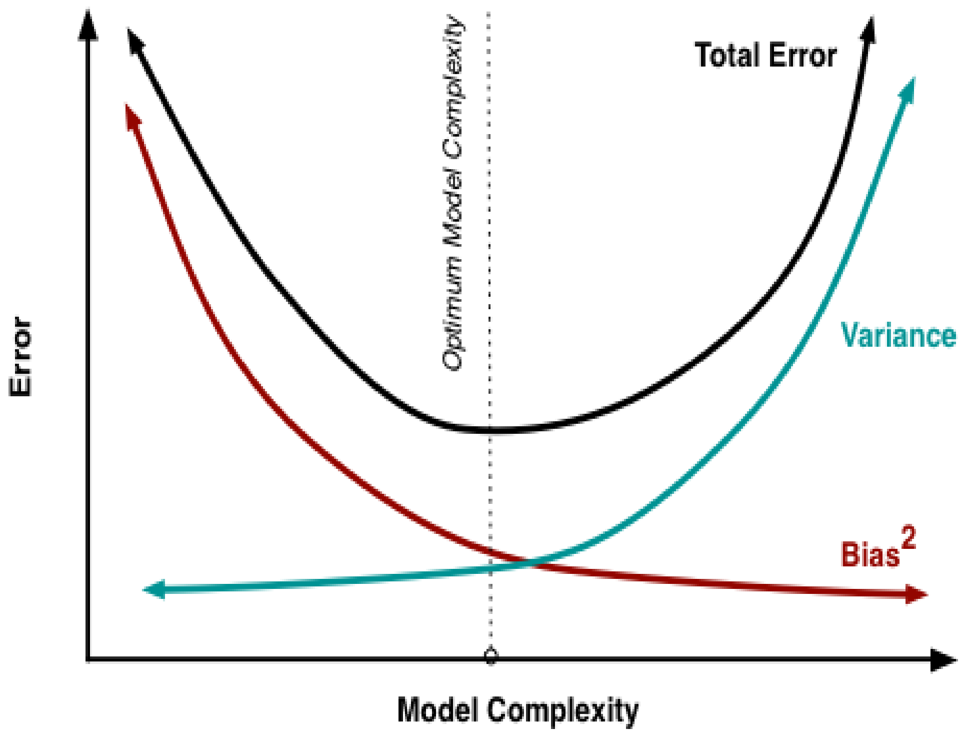
The total error due to any machine learning algorithm = In-sample error + Out-of-sample error

In-sample error → Inability of an ML algorithm to fit the training data well

Out-of-sample error → Inability of a model to generalize well

Good predictions on training data but is unable to do so on unseen data

Bagged Trees



Error = Bias + Variance = In-sample Error + Out-of-sample Error

Trade offs between the model complexity and the error in models

More complicated models have very **low in-sample error but have a high out-of-sample error**

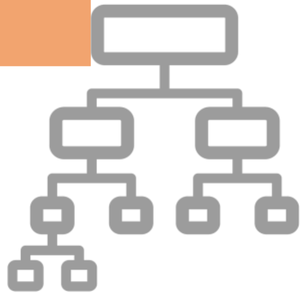
Simpler models have **low out-of-sample error but high in-sample error**

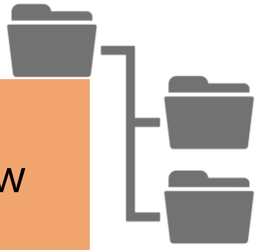
Theoretically, there is a limit to minimum error that can be achieved

Reduce error further by decreasing in-sample error and out-of-sample error simultaneously

Bagged Trees

Use tree based models as base learners to reduce in-sample error



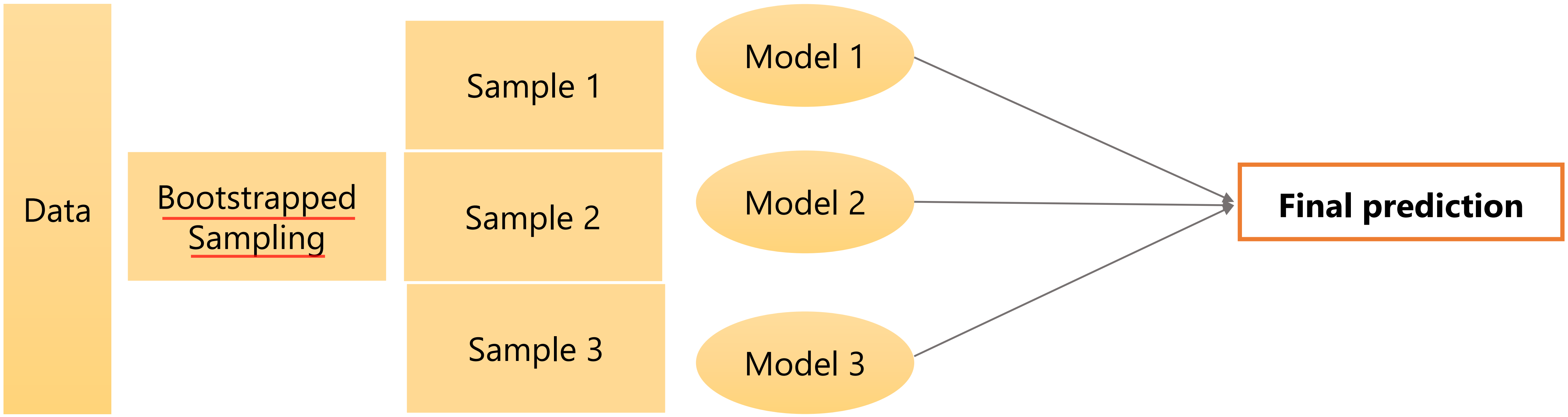


While training a tree based ensemble the constituent tree models are allowed to grow **many levels deep**

The intricacies of training data are captured intimately, thereby reducing the in-sample error

Bagged Trees

In the case of **Bagged trees** each of the unpruned trees are fed bootstrapped samples of original data set



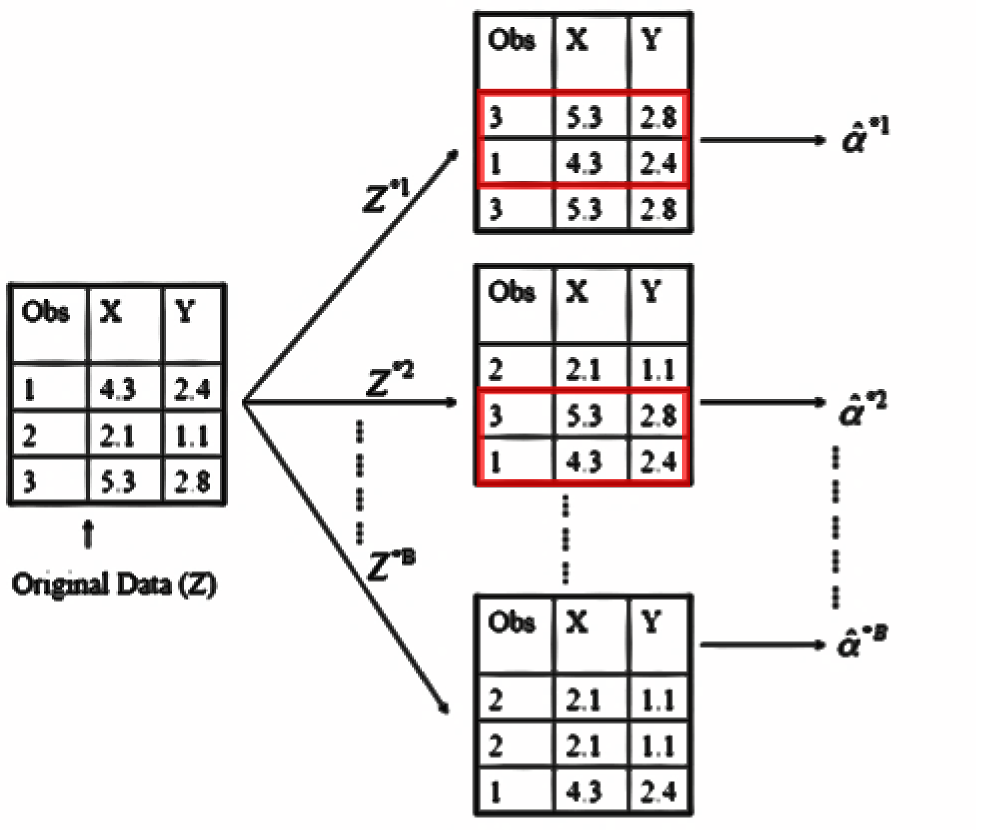
Bootstrapped Sampling

Bootstrapped sampling simply refers to **sampling by replacement**

Blue and red dots are repeated more often in the samples than they are present in the original data

Bootstrapped Sampling

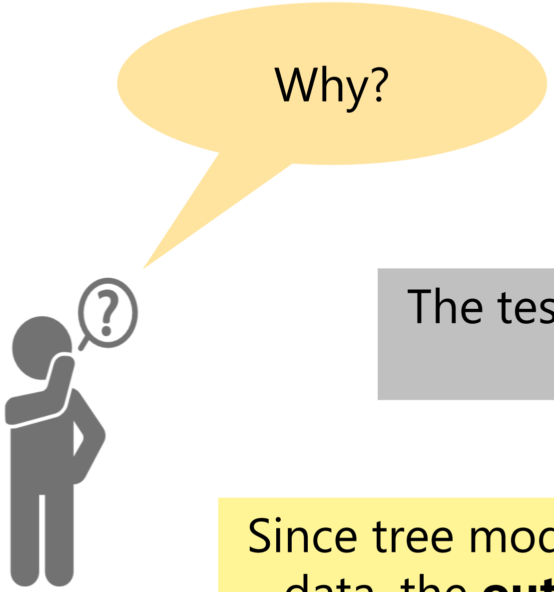
Bootstrapped Sampling at the data level



Bootstrapped Sampling

Bootstrapped Sampling helps in reducing out of sample error

If an unpruned decision tree is fit into any data set then the model will have **very high out-of-sample error**



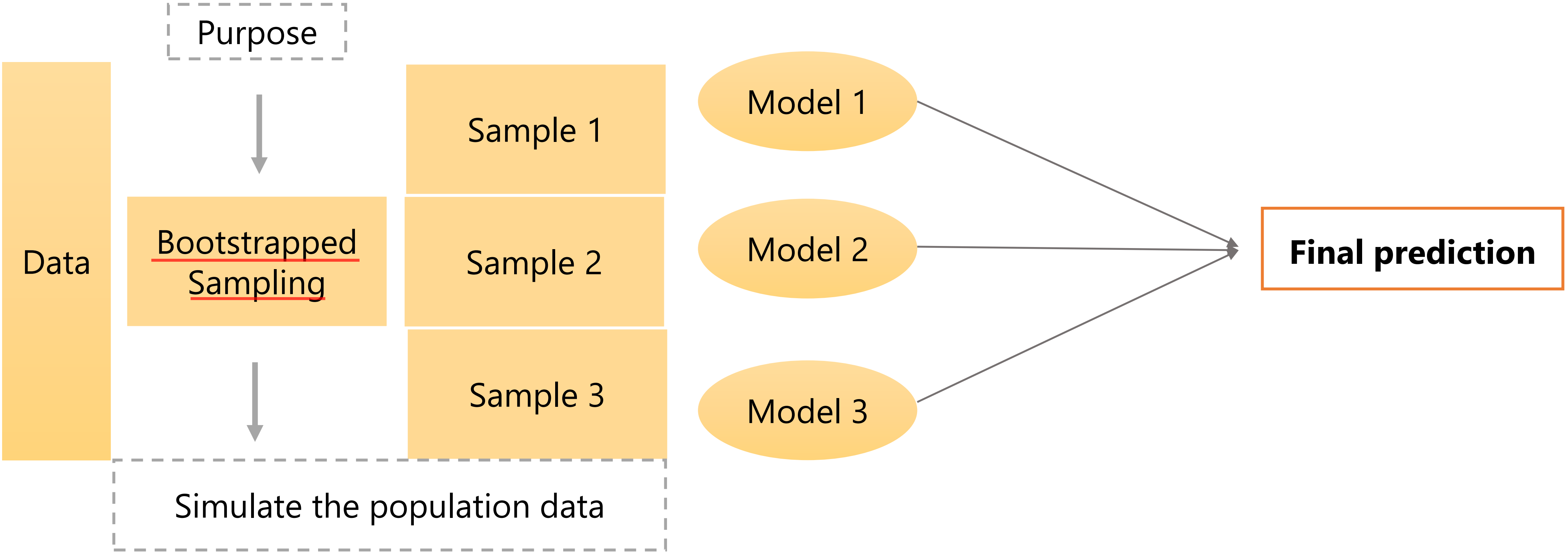
The test data can be very different from training data

Since tree model is being overfitted on training data, the **out-of-sample error will be high**

Hypothetically, if unpruned tree model is being fitted on **total population data** the error will be very low

Low error due to all the variation and variety in data has been already seen by the model as the population data has been used to train the model

Bootstrapped Sampling



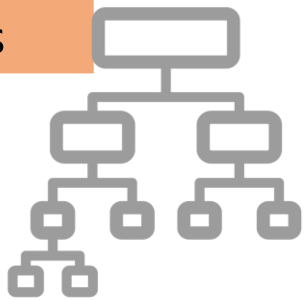
Realistic view of the data generation process

Synthetically generate variation and variety in the training data itself

Bagged Trees

Characteristics of Bagged Model

Using **unpruned decision trees** as base learners

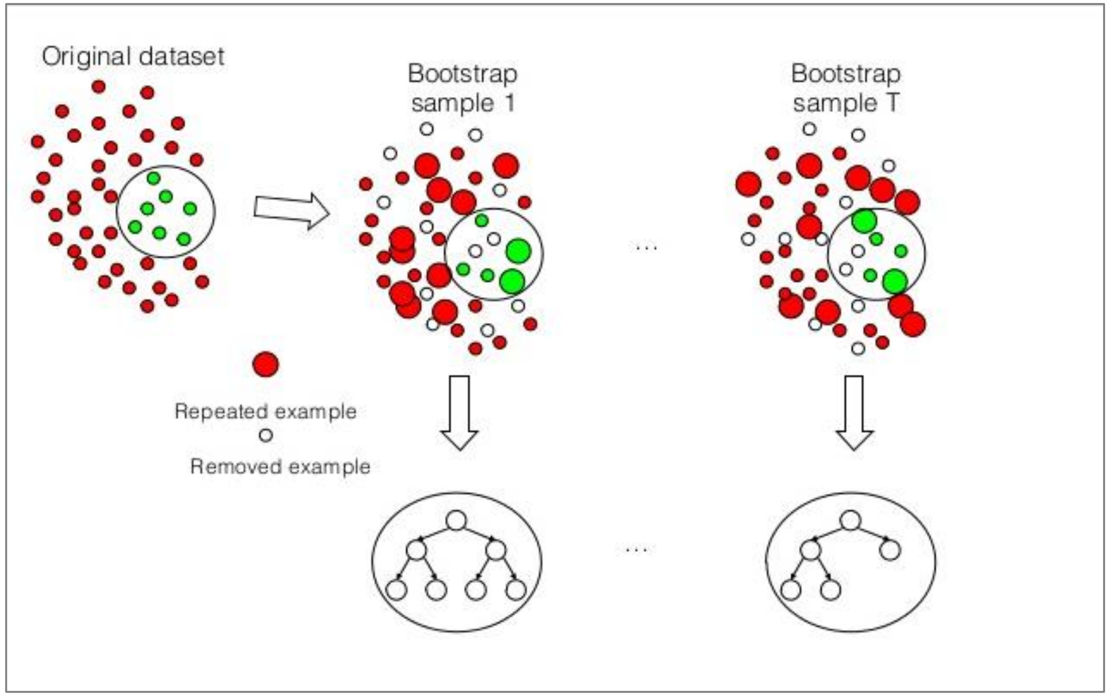


Using **Bootstrapped Sampling** to create samples that are fed to each of the base learners

Peculiarities of Bagged Trees

Bagged tree ensemble is comprised of multiple decision trees

Not interpretable as a linear model or simple decision tree



Qualitative statement on ensemble models

Identify the important predictors by looking at **Variable Importance**

Variable Importance

Variable Importance - Averaging or summing the improvement in **Gini or Entropy for a classification model** and **RSS for a regression model** for all the variables

Bagged tree ensemble model contains many tree models

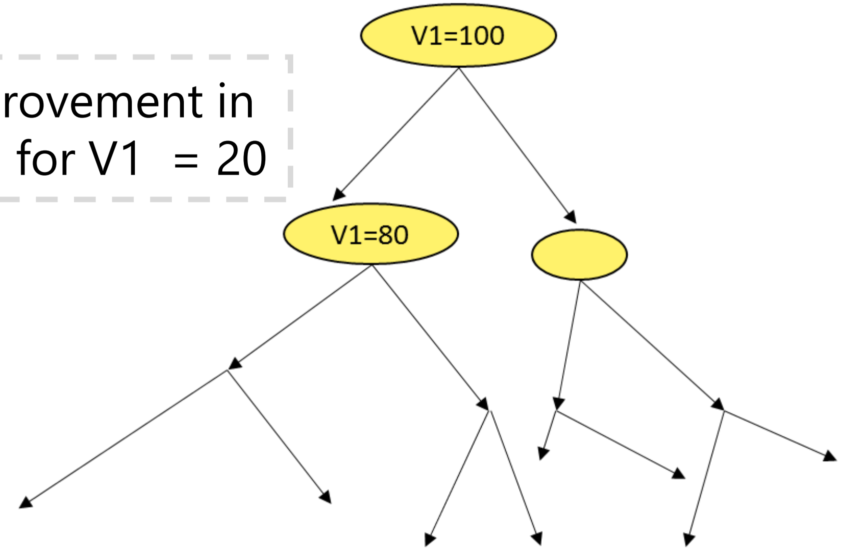
Feature importance of each variable in each of the constituent trees

Tracking the decrease in Gini metric and weighing this decrease appropriately

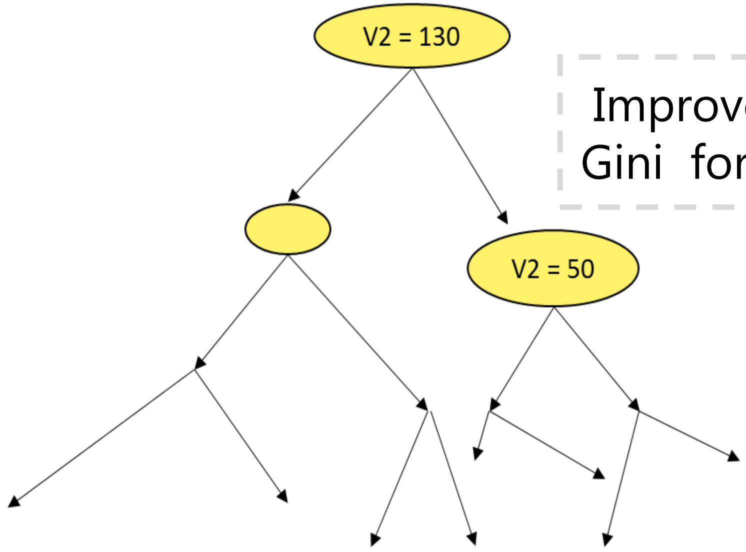
Variable Importance

Example

Improvement in Gini for V1 = 20



Tree 1
Gini Measure for each split



Improvement in Gini for V2 = 80

Tree 2
Gini Measure for each split

Computing variable importance for all the variables used in the split

Variable Importance

Ensemble has N trees

Improvement in Gini/RSS Across Splits

Variable	Tree 1	Tree 2	Tree 3	.....	Tree N
V1	300	30	12	.....	0
V2	600	0	200	.....	150
…	…	…	…	.....	…
V_k	120	450	30	.....	19

Variable	Variable Importance
V1	$\frac{(300+30+12+\cdots+0)}{N}$
V2	$\frac{(600+0+200+\cdots+150)}{N}$
…	….
V_k	$\frac{(120+450+30+\cdots+19)}{N}$

The average values of importance measures per variable will produce a consolidated number

Parameters of Bagged Trees

What could be the user specified parameters while building a bagged tree model?

User specified parameters or **Hyperparameters**

- Number of tree used to build an ensemble
- Depth of the tree
- Number of observations per node of a tree

Parameters of Bagged Trees

User specified parameters have an implication

Different ensemble model depending on different parameters

Which among the three model?

K-Fold CV to get an estimate of out of sample error

Expensive

Out of Bag Error is generally used in most tree based models

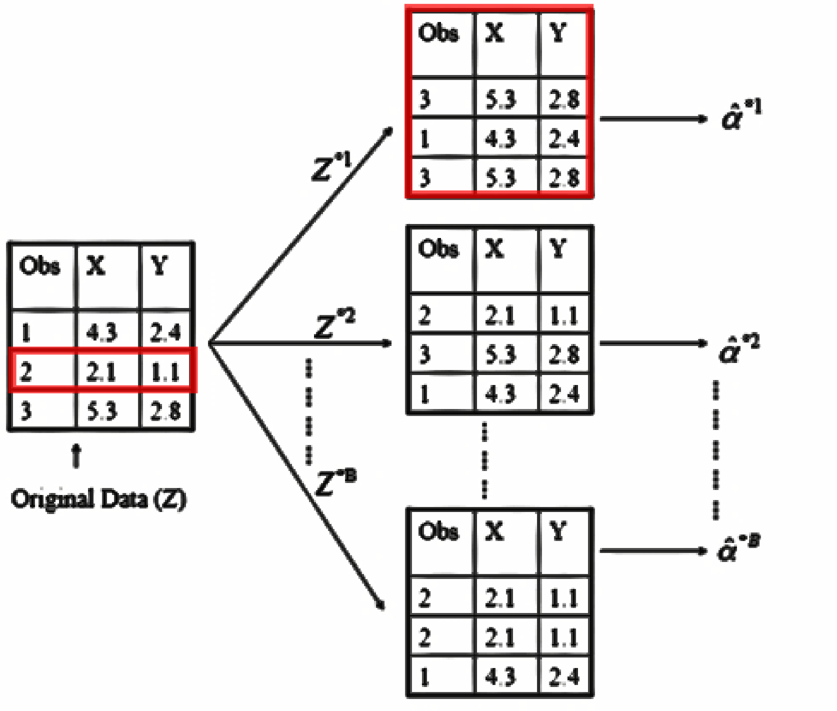
Model 1:
Trees = 100
Depth of Tree = 4

Model 2:
Trees = 150
Depth of Tree = 3

Model 3:
Trees = 500
Depth of Tree = 4

Out Of Bag Error (OOB)

In Bootstrap Sampling, some observation gets left out from the original data



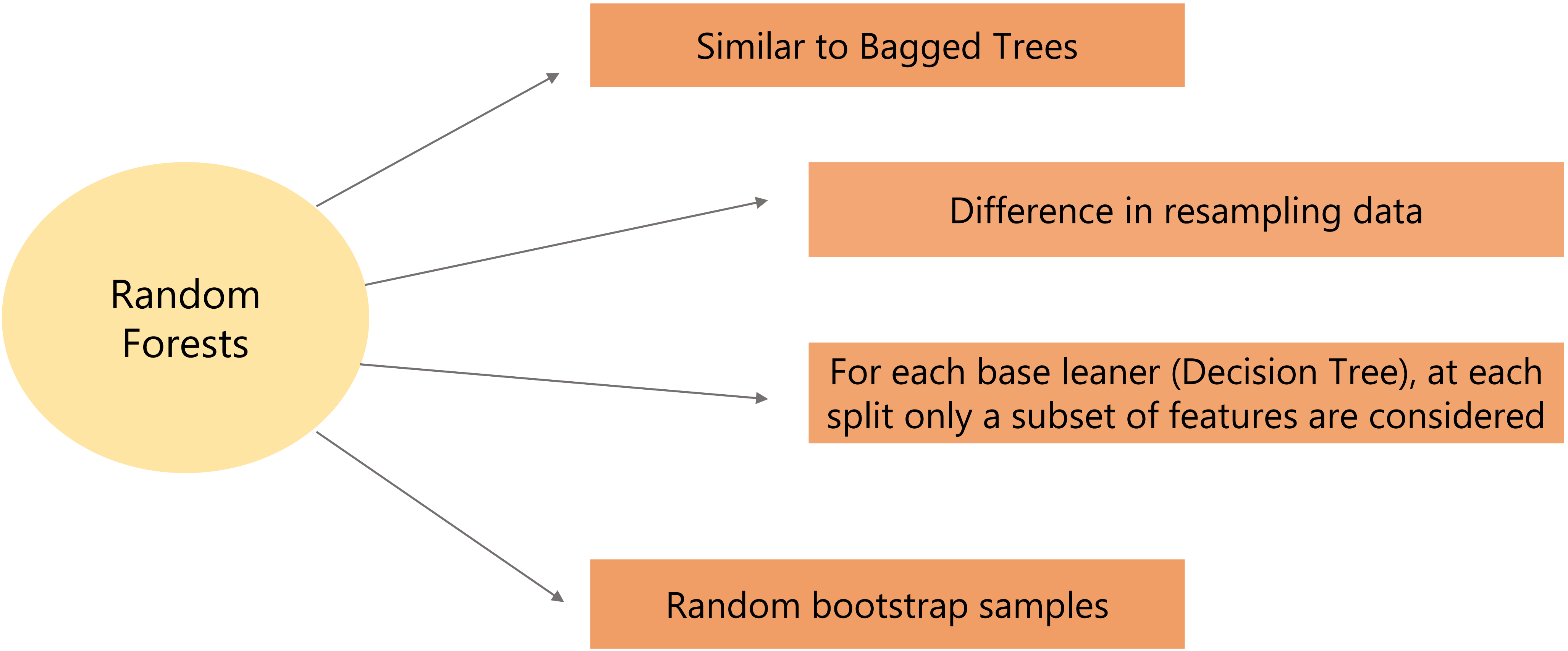
Tree 1 — Row 2 is **out of bag**

Tree 2

Tree B — Row 3 is **out of bag**

Average Out of Bag observations in Bootstrapped Sampling is around **33%**

Random Forests



Random Forests

V1	V2	V3	…	Vn
…	…	…	…	…
…	…	…	…	…

Bootstrapped Sample

Tree 1

{V1, V10, V19} considered for split

{V12, V116, V9} considered for split

Bootstrapped Sample

Tree 2

{V10, V1, V18} considered for split

Number of random sample features for splitting can vary and is usually a **hyperparameter** that the user of the algorithm specifies

Random Forests

Random Forests uses tree models as base learner

Extract **Variable Importance** or compute **Out-of-bag Error** to get an estimate of out of sample model performance for parameter tuning

Parameters of Radom Forests

- Number of features considered for each split
- Number of trees
- Number of observations in root node
- Depth of tree models

Recap

- Tree based ensembles overview
- Tree based ensembles models – Bagged Tree and Random Forests
- Bootstrapped sampling
- Variable importance
- Out of bag error (OOB error)
- Random Forests
- Code Demo