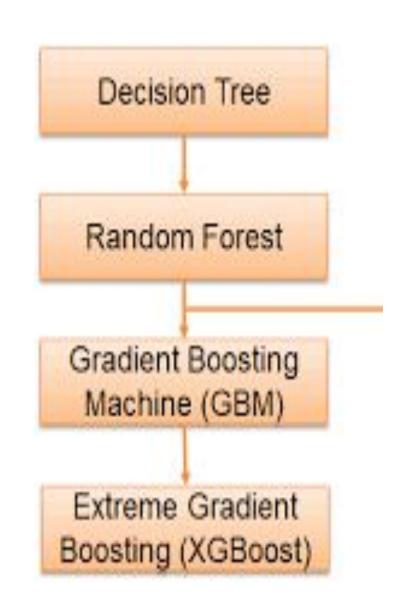
# Car Price Prediction Using Machine Learning

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## Names of Algorithums

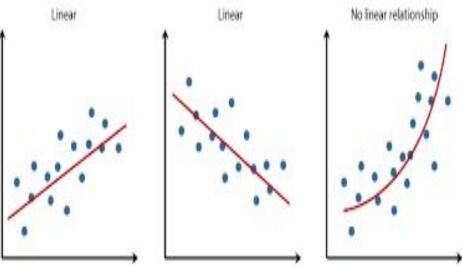
- •1-Linear Regression
- •2-Random Forest Regressor
- •3-Gradient Boosting Regressor
- 4-XGBoost Regressor
- •5-Decision tree



## 1-Linear Regression

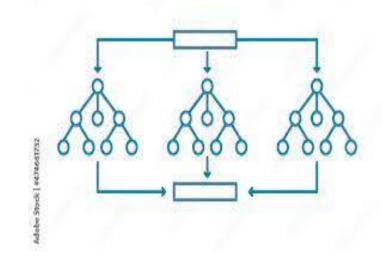
- Linear regression is a simple and interpretable regression algorithm that models the relationship between the input features and the target variable as a linear equation.
- How it works: It assumes a linear relationship between the input features and the target variable and tries to find the best-fitting line through the data points.

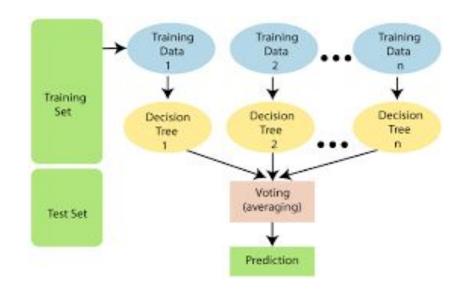




## 2-Random Forest Regressor

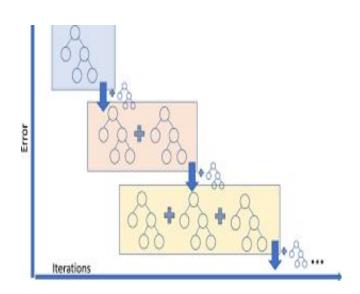
- Random Forest is an ensemble learning method that constructs multiple decision trees during training and outputs the average prediction of the individual trees for regression tasks.
- How it works: It builds a collection of decision trees and combines their predictions to improve overall accuracy and generalization.

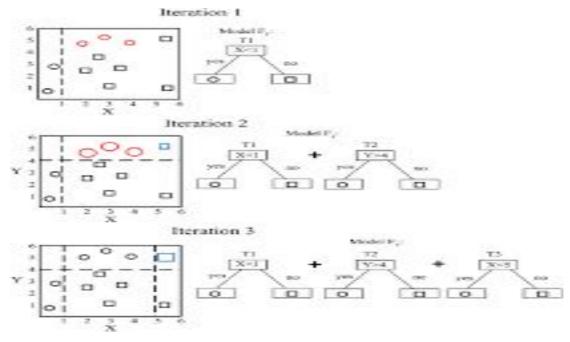




## **3-Gradient Boosting Regressor**

- Gradient Boosting is another ensemble learning technique that builds a series of weak learners (usually decision trees) sequentially, with each tree trying to correct the errors of the previous one.
- How it works: It iteratively fits new trees to the residuals (errors) of the existing model, gradually improving the overall model's performance.

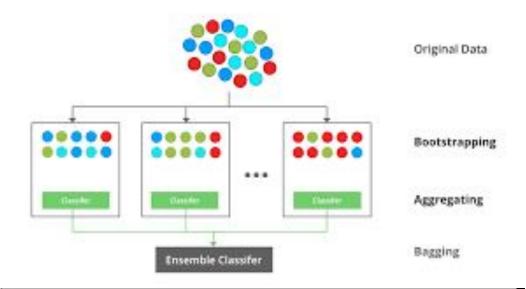




### **4-XGBoost Regressor**

XGBoost (Extreme Gradient Boosting) is a scalable and efficient implementation of gradient boosting. It is known for its speed and performance.

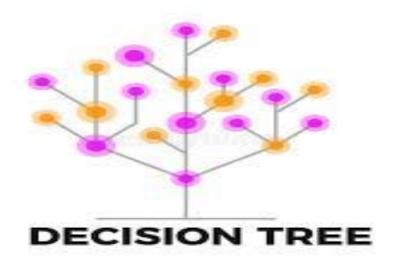
How it works: Similar to traditional gradient boosting, XGBoost builds a series of decision trees sequentially, optimizing a regularized objective function to improve both accuracy and prevent overfitting.

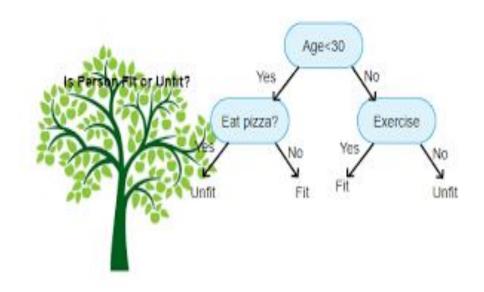




#### 5-Decision tree

- •A decision tree model is a predictive algorithm that uses a tree-like structure to make decisions based on input features.
- How it works: It recursively splits data into subsets, making binary decisions at each node, and assigns outcomes or predictions at the tree's leaves. The model is interpretable and widely used for classification and regression tasks in machine learning.





## Steps

- Display The Dataset
- Shape of Our Dataset
- Get Information About Our Dataset .
- Check Null Values In The Dataset
- Get Overall Statistics About The Dataset
- Data Preprocessing
- Outlier Removal
- Encoding the Categorical Columns

- Store Feature Matrix In X and Response(Target) In Vector Y
- Splitting The Dataset
- Import The models
- Training the dataset
- Tunning hyper parameters
- Prediction on Test Data
- Evaluating the Algorithm
- Error analysis

#### **Dataset**

## Display the dataset Shape of Our Dataset

#### 1. Display Top 5 Rows of The Dataset

lat	ta.head()								
	Car_Name	Year	Selling_Price	Present_Price	Kms_Driven	Fuel_Type	Seller_Type	Transmission	Owner
0	ritz	2014	3.35	5.59	27000	Petrol	Dealer	Manual	0
1	sx4	2013	4.75	9.54	43000	Diesel	Dealer	Manual	0
2	ciaz	2017	7.25	9.85	6900	Petrol	Dealer	Manual	0
3	wagon r	2011	2.85	4.15	5200	Petrol	Dealer	Manual	0
4	swift	2014	4.60	6.87	42450	Diesel	Dealer	Manual	0

#### **Get Information About Our Dataset**

```
data.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 301 entries, 0 to 300
Data columns (total 9 columns):
    Column
                  Non-Null Count
                                Dtype
    Car_Name 301 non-null
                                object
              301 non-null
    Year
                                 int64
    Selling Price 301 non-null
                                float64
    Present Price 301 non-null
                                float64
    Kms Driven 301 non-null
                                int64
    Fuel_Type 301 non-null
                                object
    Seller Type 301 non-null
                                 object
    Transmission 301 non-null
                                 object
                  301 non-null
    Owner
                                 int64
dtypes: float64(2), int64(3), object(4)
memory usage: 21.3+ KB
```

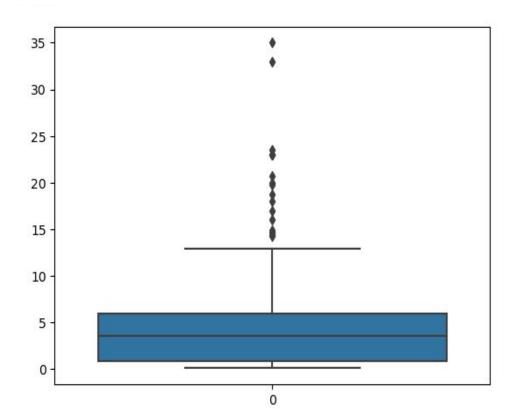
#### **Dataset**

- •Check Null Values In The Dataset
- •Get Overall Statistics About The Dataset
- Data Preprocessing

data.describe()		

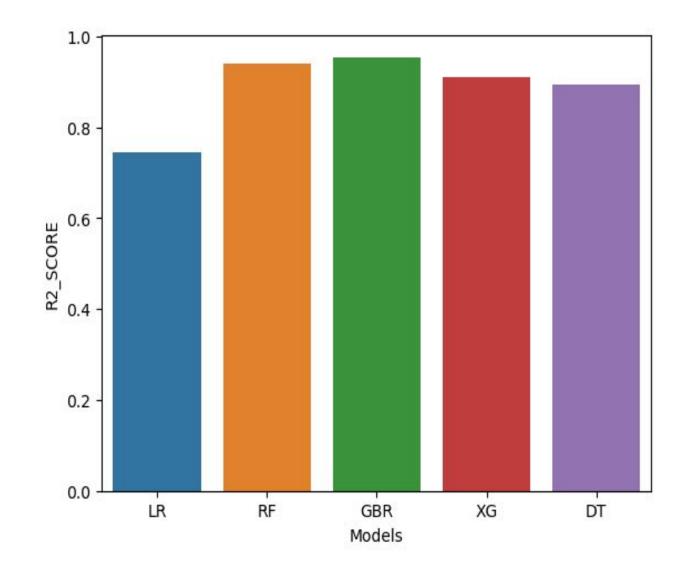
Year	Selling_Price	Present_Price	Kms_Driven	Owner	
301.000000	301.000000	301.000000	301.000000	301.000000	
2013.627907	4.661296	7.628472	36947.205980	0.043189	
2.891554	5.082812	8.644115	38886.883882	0.247915	
2003.000000	0.100000	0.320000	500.000000	0.000000	
2012.000000	0.900000	1.200000	15000.000000	0.000000	
2014.000000	3.600000	6.400000	32000.000000	0.000000	
2016.000000	6.000000	9.900000	48767.000000	0.000000	
2018.000000	35.000000	92.600000	500000.000000	3.000000	
	301.000000 2013.627907 2.891554 2003.000000 2012.000000 2014.000000 2016.000000	301.000000 301.000000 2013.627907 4.661296 2.891554 5.082812 2003.000000 0.100000 2012.000000 0.900000 2014.000000 3.600000 2016.000000 6.000000	301.000000       301.000000       301.000000         2013.627907       4.661296       7.628472         2.891554       5.082812       8.644115         2003.000000       0.100000       0.320000         2012.000000       0.900000       1.200000         2014.000000       3.600000       6.400000         2016.000000       6.000000       9.900000	301.000000         301.000000         301.000000         301.000000           2013.627907         4.661296         7.628472         36947.205980           2.891554         5.082812         8.644115         38886.883882           2003.000000         0.100000         0.320000         500.000000           2012.000000         0.900000         1.200000         15000.00000           2014.000000         3.600000         6.400000         32000.00000           2016.000000         6.000000         9.900000         48767.000000	

- Outlier Removal
- •Encoding the Categorical Columns
- •Store Feature Matrix In X and Response(Target) In Vector Y



#### **Dataset**

- Splitting The Dataset
- Import The models
- Training the dataset
- Tunning hyper parameters
- Prediction on Test Data
- Evaluating the Algorithm



#### Results

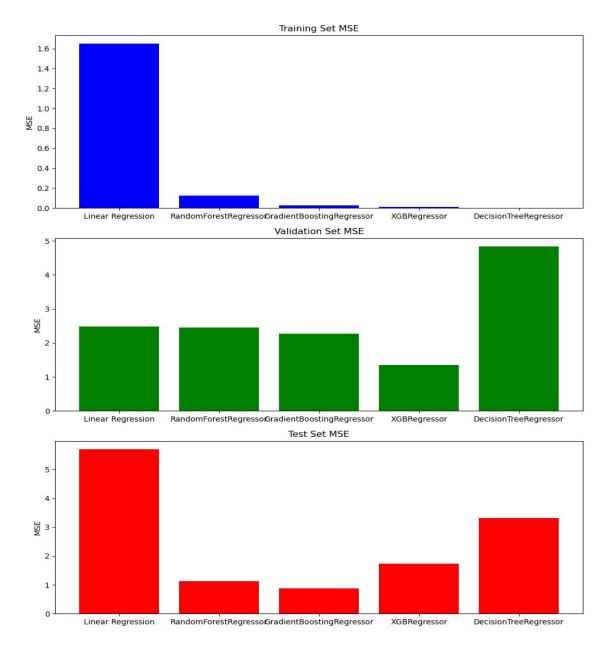
```
Linear Regression MSE on Training Set: 1.6474
Linear Regression MSE on Validation Set: 2.4866
Linear Regression MSE on Test Set: 5.6974
```

RandomForestRegressor MSE on Training Set: 0.1247 RandomForestRegressor MSE on Validation Set: 2.4474 RandomForestRegressor MSE on Test Set: 1.1347

GradientBoostingRegressor MSE on Training Set: 0.0250 GradientBoostingRegressor MSE on Validation Set: 2.2705 GradientBoostingRegressor MSE on Test Set: 0.8843

XGBRegressor MSE on Training Set: 0.0108
XGBRegressor MSE on Validation Set: 1.3471
XGBRegressor MSE on Test Set: 1.7333

DecisionTreeRegressor MSE on Training Set: 0.0000 DecisionTreeRegressor MSE on Validation Set: 4.8327 DecisionTreeRegressor MSE on Test Set: 3.3231



## **Error analysis**

- Linear Regression: High training set MSE compared to validation and test sets suggests potential overfitting or complexity insufficient to capture the underlying patterns.
- RandomForestRegressor:Low training set MSE, but higher validation and test set MSE indicate some overfitting. However, it's not as severe as in linear regression.
- **GradientBoostingRegressor:**Low training, validation, and test set MSE indicate good generalization. This model seems well-tuned and balanced.
- XGBRegressor: Similar to GradientBoostingRegressor, XGBRegressor shows low MSE across all sets, indicating good generalization.
- **DecisionTreeRegressor:**MSE of 0 on the training set suggests overfitting. The high MSE on the validation and test sets indicates poor generalization.

#### **Recommendations:**

- The RandomForestRegressor, GradientBoostingRegressor, and XGBRegressor seem to perform well without significant signs of overfitting or underfitting.
- For the DecisionTreeRegressor, reducing its complexity or using techniques like pruning may help mitigate overfitting.
- Fine-tuning hyperparameters or using more advanced models could improve the performance of Linear Regression.
- It's essential to strike a balance between model complexity and generalization for optimal performance on unseen data. Cross-validation and hyperparameter tuning are common techniques to address overfitting and underfitting.

## Thanks