

|                       |                   | ALGORITHM                    | DESCRIPTION  | APPLICATIONS  | ADVANTAGES  | DISADVANTAGES  |
|-----------------------|-------------------|------------------------------|--|---|---|--|
| > Supervised Learning | Linear Models     | Linear Regression            | A simple algorithm that models a linear relationship between inputs and a continuous numerical output variable   | USE CASES<br>1. Stock price prediction<br>2. Predicting housing prices<br>3. Predicting customer lifetime value | 1. Explainable method<br>2. Interpretable results by its output coefficients<br>3. Faster to train than other machine learning models                       | 1. Assumes linearity between inputs and output<br>2. Sensitive to outliers<br>3. Can underfit with small, high-dimensional data  |
|                       |                   | Logistic Regression          | A simple algorithm that models a linear relationship between inputs and a categorical output (1 or 0)  | USE CASES<br>1. Credit risk score prediction<br>2. Customer churn prediction                                    | 1. Interpretable and explainable<br>2. Less prone to overfitting when using regularization<br>3. Applicable for multi-class predictions                     | 1. Assumes linearity between inputs and outputs<br>2. Can overfit with small, high-dimensional data                              |
|                       |                   | Ridge Regression             | Part of the regression family — it penalizes features that have low predictive outcomes by shrinking their coefficients closer to zero. Can be used for classification or regression | USE CASES<br>1. Predictive maintenance for automobiles<br>2. Sales revenue prediction                           | 1. Less prone to overfitting<br>2. Best suited where data suffer from multicollinearity<br>3. Explainable & interpretable                                   | 1. All the predictors are kept in the final model<br>2. Doesn't perform feature selection  |
|                       |                   | Lasso Regression             | Part of the regression family — it penalizes features that have low predictive outcomes by shrinking their coefficients to zero. Can be used for classification or regression        | USE CASES<br>1. Predicting housing prices<br>2. Predicting clinical outcomes based on health data               | 1. Less prone to overfitting<br>2. Can handle high-dimensional data<br>3. No need for feature selection   | 1. Can lead to poor interpretability as it can keep highly correlated variables  |
|                       | Tree-Based Models | Decision Tree                | Decision Tree models make decision rules on the features to produce predictions. It can be used for classification or regression   | USE CASES<br>1. Customer churn prediction<br>2. Credit score modeling<br>3. Disease prediction                  | 1. Explainable and interpretable<br>2. Can handle missing values  | 1. Prone to overfitting<br>2. Sensitive to outliers  |
|                       |                   | Random Forests               | An ensemble learning method that combines the output of multiple decision trees  | USE CASES<br>1. Credit score modeling<br>2. Predicting housing prices   | 1. Reduces overfitting<br>2. Higher accuracy compared to other models   | 1. Training complexity can be high<br>2. Not very interpretable  |
|                       |                   | Gradient Boosting Regression | Gradient Boosting Regression employs boosting to make predictive models from an ensemble of weak predictive learners   | USE CASES<br>1. Predicting car emissions<br>2. Predicting ride hailing fare amount                              | 1. Better accuracy compared to other regression models<br>2. It can handle multicollinearity<br>3. It can handle non-linear relationships                   | 1. Sensitive to outliers and can therefore cause overfitting<br>2. Computationally expensive and has high complexity             |
|                       |                   | XGBoost                      | Gradient Boosting algorithm that is efficient & flexible. Can be used for both classification and regression tasks   | USE CASES<br>1. Churn prediction<br>2. Claims processing in insurance   | 1. Provides accurate results<br>2. Captures non linear relationships  | 1. Hyperparameter tuning can be complex<br>2. Does not perform well on sparse datasets   |
|                       |                   | LightGBM Regressor           | A gradient boosting framework that is designed to be more efficient than other implementations   | USE CASES<br>1. Predicting flight time for airlines<br>2. Predicting cholesterol levels based on health data    | 1. Can handle large amounts of data<br>2. Computational efficient & fast training speed<br>3. Low memory usage  | 1. Can overfit due to leaf-wise splitting and high sensitivity<br>2. Hyperparameter tuning can be complex                        |
|                       | Clustering        | K-Means                      | K-Means is the most widely used clustering approach—it determines K clusters based on euclidean distances  | USE CASES<br>1. Customer segmentation<br>2. Recommendation systems  | 1. Scales to large datasets<br>2. Simple to implement and interpret<br>3. Results in tight clusters   | 1. Requires the expected number of clusters from the beginning<br>2. Has troubles with varying cluster sizes and densities       |
|                       |                   | Hierarchical Clustering      | A "bottom-up" approach where each data point is treated as its own cluster—and then the closest two clusters are merged together iteratively   | USE CASES<br>1. Fraud detection<br>2. Document clustering based on similarity                                   | 1. There is no need to specify the number of clusters<br>2. The resulting dendrogram is informative   | 1. Doesn't always result in the best clustering<br>2. Not suitable for large datasets due to high complexity                     |
|                       |                   | Gaussian Mixture Models      | A probabilistic model for modeling normally distributed clusters within a dataset  | USE CASES<br>1. Customer segmentation<br>2. Recommendation systems  | 1. Computes a probability for an observation belonging to a cluster<br>2. Can identify overlapping clusters<br>3. More accurate results compared to K-means | 1. Requires complex tuning<br>2. Requires setting the number of expected mixture components or clusters                          |
|                       | Association       | Apriori algorithm            | Rule based approach that identifies the most frequent itemset in a given dataset where prior knowledge of frequent itemset properties is used  | USE CASES<br>1. Product placements<br>2. Recommendation engines<br>3. Promotion optimization                    | 1. Results are intuitive and Interpretable<br>2. Exhaustive approach as it finds all rules based on the confidence and support                              | 1. Generates many uninteresting itemsets<br>2. Computationally and memory intensive.<br>3. Results in many overlapping item sets |