ML Algorithm	Algorithm Comparison
k-NN	**Type**: Supervised Classification, Non-Parametric, lazy learner, discriminative. **Feature Data:** For majority of the scenario, Numeric/Quantitative sometimes categorical. **Target Variable:** Categorical **Noisy Data:** Is sensitive to noisy data and outliers are liable to get misclassified. **Missing Data:** k-NN cannot train on missing values therefore some reasonable imputation has to be performed or NA records must be deleted. **Correlated Data:** Does not affect the classification. **Hyperparameters**: K: number of neighbors, D: distance function like Euclidean, Cosine, Manhattan for numeric feature space and Hamming for categorical feature space. **Evaluation Measures:** Confusion Matrix, Specificity, Sensitivity etc. **Package Implementation:** class, caret.
Naïve Bayes'	**Type:** Supervised Classification, Parametric, eager learner, generative. **Feature Data:** For majority of the scenario Categorical **Target Variable:** Categorical **Noisy Data:** Averages out the noisy therefore not sensitive to noisy data. Its performance degrades more slowly as compared to other algorithms. **Missing Data :** The specific record is ignored for the frequency count. The R package implementation can also determine whether to ignore the example/record or the feature. **Correlated Data:** Does not work optimally due to class conditional independence assumption. **Hyperparameters:** Maximum Likelihood Estimation, Bayesian Estimation, optimization of loss criterion. **Evaluation Measures**: Confusion Matrix ,Sensitivity, Specificity. **Package Implementation**: e1071,naïve bayes, caret
Classification Trees	**Type:** Supervised Classification and Prediction(Dual), Non-Parametric, eager learner, discriminative, greedy learner, top down divide and conquer, bottom up pruning, recursive partitioning **Feature Data:** Numeric/Quantitative or Categorical **Target Variable:** Categorical or Numeric. **Noisy Data:** Decision trees are very sensitive to the noise in the data and even a small change in the data can throw the classification/prediction off therefore an ensemble of tree is better than just one tree. **Missing Data :** Is handled as per the package implementation for instance CART provides the functionality of assigning the missing data examples to the partition which has maximum examples already assigned to it. **Correlated Data**: Typically, it will not be affected by correlated variables and the split will occur as per the best feature in terms of info gain.

	Hyperparameters: Gini index, information gain, chi square ,pre pruning ,post pruning, assigning levels of trees **Evaluation Measures:** Confusion Matrix ,Sensitivity, Specificity, R squared, MSE. **Package Implementation:** CART,C5.0,ID 3
Classification Rules	**Type:** Supervised Classification , Non-Parametric, eager learner, discriminative, greedy learner, bottom up separate and conquer. **Feature Data:** In most scenarios Categorical. **Target Variable:** Mostly Categorical . **Noisy Data:** Decision rules are very sensitive to the noise in the data and even a small change in the data can throw the classification/prediction off . **Missing Data :** Is handled as per the package implementation for instance CART provides the functionality of assigning the missing data examples to the partition which has maximum examples already assigned to it. **Correlated Data**: Typically, it will not be affected by correlated variables and the split will occur as per the best feature in terms of info gain. **Hyperparameters**: Gini index, information gain, chi square ,pre pruning ,post pruning, assigning levels of trees **Evaluation Measures:** Confusion Matrix ,Sensitivity, Specificity **Package Implementation:** CART,C5.0,ID 3