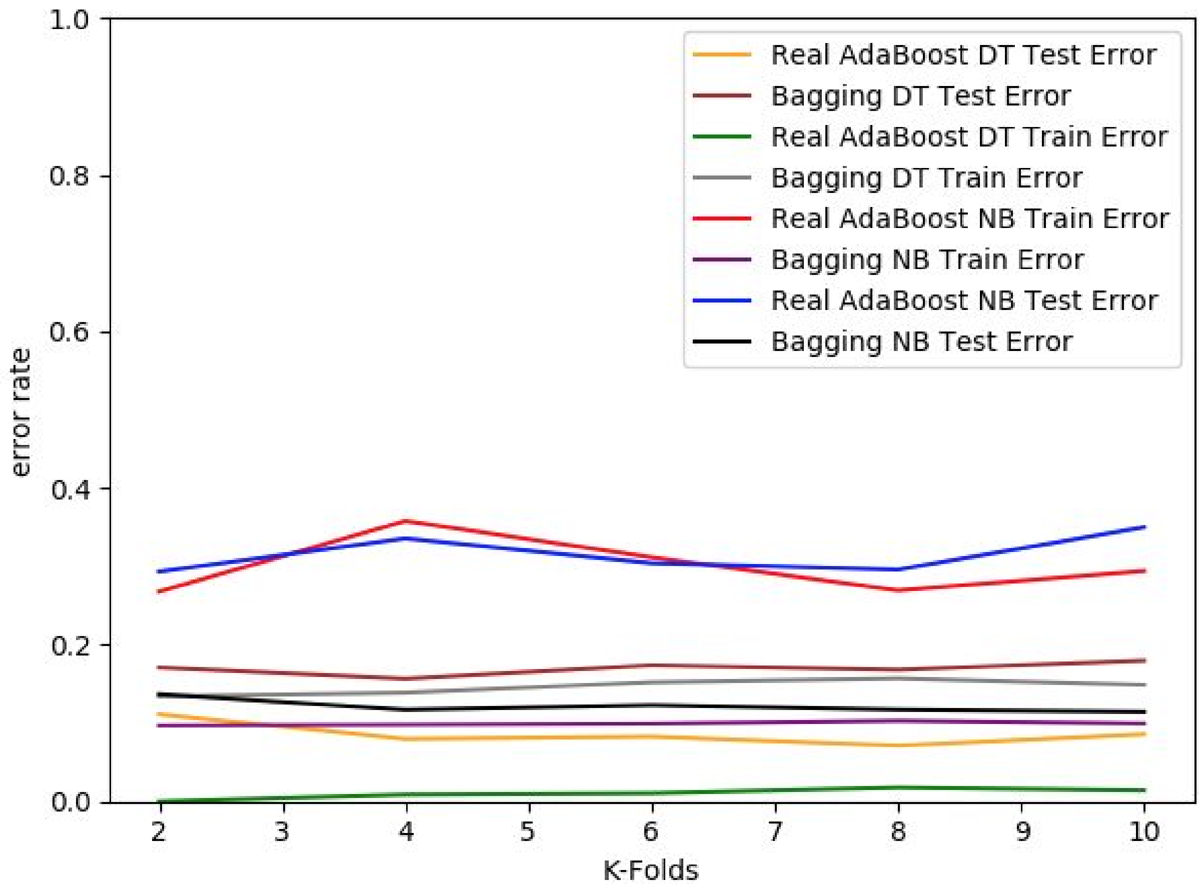
d)



As we can see on the graph, for boosting method on Decision tree stamp for K = 10 we notice a little overfitting, because error rate on training set start to decrease and test set error on the same time starts to increase. Same situation we can observe and for Bagging method on decision tree. Overall, AdaBoost ensemble method shows better results for Decision Tree.

Bagging ensemble method works best for Naive Bayes classifier and increasing K in K-Fold doesn't produce overfitting.

e) Boosting can cause sophisticated model to overfit, because on every iteration it will increase weight of wrong classified examples causing decision boundary to change accordingly around this examples.

Bagging, may lead to underfitting, because for each bootstrap data we may choose majority of not important features, what will lead model to poor performance on test data.

f)

Boosting is sequential method, we cannot run it in parallel, Bagging, on the other hand, we can run in parallel. If the single model gets low performance, bagging may not help to get a better bias, on the over hand boosting helps to reduce errors.
If single model suffers with overfitting, bagging is the best option, because boosting faces sometimes the same issue itself.

g) Random forest ensemble learning is a method what creates many decision trees and adds additional randomness to the model, while growing the trees. Instead of choosing the most important feature among all features while splitting the node, Random forest chooses the best feature among the random subset of features. It leads to wide diversity between trees and reduces correlation between them.