

1. SVM, Random Forest and Boosting Models

Code:

```
Train.data=read.csv("WineData.csv",header=T)
Test.data=read.csv("WineHoldoutData.csv",header=T)

summary(Train.data)

## fixed_acidity    volatile_acidity    citric_acid    residual_sugar
## Min.      : 3.800    Min.      :0.0800    Min.      :0.0000    Min.      : 0.60
## 1st Qu.: 6.400    1st Qu.:0.2300    1st Qu.:0.2500    1st Qu.: 1.80
## Median : 7.000    Median :0.2900    Median :0.3100    Median : 3.00
## Mean   : 7.212    Mean   :0.3418    Mean   :0.3184    Mean   : 5.43
## 3rd Qu.: 7.700    3rd Qu.:0.4100    3rd Qu.:0.3900    3rd Qu.: 8.10
## Max.   :15.900    Max.   :1.3300    Max.   :1.6600    Max.   :65.80
## chlorides        free_sulfur_dioxide    total_sulfur_dioxide    dens
ity
## Min.      :0.00900    Min.      : 1.0      Min.      : 6.0      Min.
:0.9871
## 1st Qu.:0.03800    1st Qu.: 17.0      1st Qu.: 78.0      1st Qu.
:0.9924
## Median :0.04700    Median : 29.0      Median :118.0      Median
:0.9949
## Mean   :0.05619    Mean   : 30.4      Mean   :115.3      Mean
:0.9947
## 3rd Qu.:0.06600    3rd Qu.: 41.0      3rd Qu.:155.0      3rd Qu.
:0.9969
## Max.   :0.61000    Max.   :289.0      Max.   :440.0      Max.
:1.0390
## pH              sulphates          alcohol          quality
## Min.      :2.74    Min.      :0.220    Min.      : 8.0    Min.      :3.000
## 1st Qu.:3.11    1st Qu.:0.430    1st Qu.: 9.5    1st Qu.:5.000
## Median :3.21    Median :0.510    Median :10.3    Median :6.000
## Mean   :3.22    Mean   :0.531    Mean   :10.5    Mean   :5.812
## 3rd Qu.:3.32    3rd Qu.:0.600    3rd Qu.:11.3    3rd Qu.:6.000
## Max.   :4.01    Max.   :2.000    Max.   :14.9    Max.   :9.000
## style
## Length:5198
## Class :character
## Mode  :character
##
##
##

summary(Test.data)
```

```
## fixed_acidity    volatile_acidity    citric_acid    residual_sugar
## Min.      : 4.200    Min.      :0.100    Min.      :0.0000    Min.      : 0.800
## 1st Qu.: 6.400    1st Qu.:0.230    1st Qu.:0.2500    1st Qu.: 1.800
## Median : 7.000    Median :0.290    Median :0.3100    Median : 3.000
## Mean      : 7.229    Mean      :0.331    Mean      :0.3195    Mean      : 5.496
## 3rd Qu.: 7.700    3rd Qu.:0.390    3rd Qu.:0.3900    3rd Qu.: 8.200
## Max.      :15.600    Max.      :1.580    Max.      :1.2300    Max.      :20.800
## chlorides      free_sulfur_dioxide    total_sulfur_dioxide    dens
ity
## Min.      :0.01200    Min.      : 3.00      Min.      : 8.0      Min.
:0.9874
## 1st Qu.:0.03800    1st Qu.: 17.00      1st Qu.: 76.0      1st Qu.
:0.9922
## Median :0.04700    Median : 29.00      Median :119.0      Median
:0.9950
## Mean      :0.05543    Mean      : 31.01      Mean      :117.5      Mean
:0.9947
## 3rd Qu.:0.06100    3rd Qu.: 43.00      3rd Qu.:159.0      3rd Qu.
:0.9971
## Max.      :0.61100    Max.      :118.50      Max.      :366.5      Max.
:1.0037
## pH            sulphates            alcohol            quality
## Min.      :2.720    Min.      :0.2700    Min.      : 8.40    Min.      :3.000
## 1st Qu.:3.100    1st Qu.:0.4300    1st Qu.: 9.50    1st Qu.:5.000
## Median :3.200    Median :0.5100    Median :10.20    Median :6.000
## Mean      :3.214    Mean      :0.5323    Mean      :10.46    Mean      :5.843
## 3rd Qu.:3.320    3rd Qu.:0.6000    3rd Qu.:11.30    3rd Qu.:6.000
## Max.      :3.800    Max.      :1.9500    Max.      :14.05    Max.      :8.000
## style
## Length:1299
## Class :character
## Mode :character
##
##
##
```

#Checking correlation between predictors

```
df=data.frame(Train.data[,c(1:12)])
cor(df)
```

```
##              fixed_acidity    volatile_acidity    citric_acid re
sidual_sugar
## fixed_acidity              1.000000000          0.21599868    0.316851216
-0.11599079
## volatile_acidity          0.21599868          1.000000000   -0.383379676
-0.19143517
```

## citric_acid 0.14382003	0.31685122	-0.38337968	1.000000000
## residual_sugar 1.00000000	-0.11599079	-0.19143517	0.143820029
## chlorides -0.12957070	0.29904393	0.38098335	0.040924485
## free_sulfur_dioxide 0.39439450	-0.28158153	-0.35139672	0.134708918
## total_sulfur_dioxide 0.49149983	-0.33439763	-0.41453324	0.196411471
## density 0.55323017	0.45499336	0.27477397	0.090671339
## pH -0.25667780	-0.25613859	0.26688742	-0.327915413
## sulphates -0.18573401	0.29903244	0.22864088	0.051192324
## alcohol -0.35437668	-0.09043771	-0.04036961	-0.003289993
## quality -0.03042104	-0.07735971	-0.26501969	0.091516750
##	chlorides	free_sulfur_dioxide	total_sulfur_d
ioxide			
## fixed_acidity 439763	0.29904393	-0.28158153	-0.33
## volatile_acidity 453324	0.38098335	-0.35139672	-0.41
## citric_acid 641147	0.04092449	0.13470892	0.19
## residual_sugar 149983	-0.12957070	0.39439450	0.49
## chlorides 116864	1.00000000	-0.20126300	-0.28
## free_sulfur_dioxide 192584	-0.20126300	1.00000000	0.72
## total_sulfur_dioxide 000000	-0.28116864	0.72192584	1.00
## density 432206	0.36307630	0.01281186	0.02
## pH 854277	0.04450119	-0.14912465	-0.23
## sulphates 157204	0.39161142	-0.19028761	-0.28
## alcohol 347313	-0.25560197	-0.16981465	-0.26
## quality 099676	-0.20197733	0.05365606	-0.04

##	density	pH	sulphates	alcohol
## fixed_acidity	0.45499336	-0.25613859	0.2990324398	-0.0904377083
## volatile_acidity	0.27477397	0.26688742	0.2286408812	-0.0403696144
## citric_acid	0.09067134	-0.32791541	0.0511923244	-0.0032899935
## residual_sugar	0.55323017	-0.25667780	-0.1857340053	-0.3543766776
## chlorides	0.36307630	0.04450119	0.3916114213	-0.2556019733
## free_sulfur_dioxide	0.01281186	-0.14912465	-0.1902876070	-0.1698146470
## total_sulfur_dioxide	0.02432206	-0.23854277	-0.2815720444	-0.2634731329
## density	1.00000000	0.02023940	0.2590991926	-0.6815074023
## pH	0.02023940	1.00000000	0.1940256211	0.114718896
## sulphates	0.25909919	0.19402562	1.0000000000	-0.0009596393
## alcohol	-0.68150740	0.11471189	-0.0009596393	1.0000000000
## quality	-0.30437481	0.02247475	0.0383116145	0.4503066020
##	quality			
## fixed_acidity	-0.07735971			
## volatile_acidity	-0.26501969			
## citric_acid	0.09151675			
## residual_sugar	-0.03042104			
## chlorides	-0.20197733			
## free_sulfur_dioxide	0.05365606			
## total_sulfur_dioxide	-0.04099676			
## density	-0.30437481			
## pH	0.02247475			
## sulphates	0.03831161			
## alcohol	0.45030660			
## quality	1.00000000			

#Max correlation is between free sulphur dioxide and total sulphur dioxide =0.72

Explanation:

From the summary of training and test data, it can be seen that there are no missing entries or any absurd values. Correlation matrix shows that all the predictors (except free sulfur dioxide and total sulfur dioxide) are linearly independent. Free sulfur dioxide and total sulfur dioxide have a maximum correlation of 0.72, but they are not removed from the dataset, since Boosting, Random Forest and SVM are not affected by collinearity like linear regression.

Boosting code:

```
#Boosting-----

library(caret)

boost.caretGrid=expand.grid(interaction.depth=c(3,5),n.trees=seq(from=
100,to=1000,by=50),
                           shrinkage=c(0.001,0.01,0.05,0.1),n.minobsi
nnode=c(100,200))
metric="RMSE"
trainControl=trainControl(method="cv",number=10)
set.seed(1)
gbm.caret=train(quality~., data=Train.data,method="gbm",
               trControl=trainControl, verbose=FALSE,
               tuneGrid=boost.caretGrid, metric=metric)

print(gbm.caret)

## Stochastic Gradient Boosting
##
## 5198 samples
## 12 predictor
##
## No pre-processing
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 4678, 4679, 4678, 4679, 4678, 4678, ...
## Resampling results across tuning parameters:
##
## shrinkage interaction.depth n.minobsinnode n.trees RMSE Rsquared
## 0.001 3 100 100 0.8581667 0.2537761
## 0.001 3 100 150 0.8497450 0.2556744
## 0.001 3 100 200 0.8419646 0.2575327
## 0.001 3 100 250 0.8347567 0.2594653
## 0.001 3 100 300 0.8281291 0.2609338
## 0.001 3 100 350 0.8219986 0.2622104
## 0.001 3 100 400 0.8163367 0.2636886
## 0.001 3 100 450 0.8110510 0.2654652
## 0.001 3 100 500 0.8061354 0.2672129
## 0.001 3 100 550 0.8015682 0.2686750
## 0.001 3 100 600 0.7973308 0.2702253
## 0.001 3 100 650 0.7933790 0.2716898
## 0.001 3 100 700 0.7897003 0.2731013
## 0.001 3 100 750 0.7862677 0.2744495
```

##	0.001	3	100	800	0.7830713	0.2758017
##	0.001	3	100	850	0.7800848	0.2771151
##	0.001	3	100	900	0.7772735	0.2784129
##	0.001	3	100	950	0.7746352	0.2796267
##	0.001	3	100	1000	0.7722121	0.2806798
##	0.001	3	200	100	0.8581065	0.2527020
##	0.001	3	200	150	0.8496727	0.2546334
##	0.001	3	200	200	0.8418884	0.2564503
##	0.001	3	200	250	0.8346913	0.2579255
##	0.001	3	200	300	0.8280128	0.2597249
##	0.001	3	200	350	0.8218724	0.2612960
##	0.001	3	200	400	0.8161900	0.2628651
##	0.001	3	200	450	0.8109393	0.2642958
##	0.001	3	200	500	0.8060584	0.2658225
##	0.001	3	200	550	0.8015324	0.2670740
##	0.001	3	200	600	0.7973493	0.2684179
##	0.001	3	200	650	0.7934608	0.2697804
##	0.001	3	200	700	0.7898422	0.2709634
##	0.001	3	200	750	0.7864460	0.2722831
##	0.001	3	200	800	0.7832784	0.2736226
##	0.001	3	200	850	0.7803403	0.2748136
##	0.001	3	200	900	0.7775956	0.2760282
##	0.001	3	200	950	0.7750152	0.2772896
##	0.001	3	200	1000	0.7725780	0.2785035
##	0.001	5	100	100	0.8563690	0.2762736
##	0.001	5	100	150	0.8471725	0.2769489
##	0.001	5	100	200	0.8386787	0.2780040
##	0.001	5	100	250	0.8308041	0.2794375
##	0.001	5	100	300	0.8236117	0.2803962
##	0.001	5	100	350	0.8169135	0.2817434
##	0.001	5	100	400	0.8107420	0.2830053
##	0.001	5	100	450	0.8050240	0.2844224
##	0.001	5	100	500	0.7997346	0.2856655
##	0.001	5	100	550	0.7948243	0.2870395
##	0.001	5	100	600	0.7903028	0.2882434
##	0.001	5	100	650	0.7860821	0.2895431
##	0.001	5	100	700	0.7821528	0.2908775
##	0.001	5	100	750	0.7784869	0.2923607
##	0.001	5	100	800	0.7750240	0.2938434
##	0.001	5	100	850	0.7717922	0.2952983
##	0.001	5	100	900	0.7687864	0.2967845
##	0.001	5	100	950	0.7659472	0.2982348
##	0.001	5	100	1000	0.7632618	0.2997585
##	0.001	5	200	100	0.8565232	0.2717616
##	0.001	5	200	150	0.8473701	0.2723373
##	0.001	5	200	200	0.8389763	0.2734746
##	0.001	5	200	250	0.8311861	0.2747451
##	0.001	5	200	300	0.8240343	0.2758255
##	0.001	5	200	350	0.8174219	0.2769859
##	0.001	5	200	400	0.8113172	0.2781582
##	0.001	5	200	450	0.8056867	0.2793905
##	0.001	5	200	500	0.8004818	0.2806165
##	0.001	5	200	550	0.7956782	0.2818344
##	0.001	5	200	600	0.7912230	0.2830327
##	0.001	5	200	650	0.7870826	0.2843421

##	0.001	5	200	700	0.7832260	0.2857349
##	0.001	5	200	750	0.7796175	0.2872939
##	0.001	5	200	800	0.7762538	0.2886603
##	0.001	5	200	850	0.7731349	0.2899592
##	0.001	5	200	900	0.7701682	0.2914777
##	0.001	5	200	950	0.7673981	0.2928497
##	0.001	5	200	1000	0.7648069	0.2942007
##	0.010	3	100	100	0.7722378	0.2802282
##	0.010	3	100	150	0.7541883	0.2918763
##	0.010	3	100	200	0.7425068	0.3042441
##	0.010	3	100	250	0.7339057	0.3154309
##	0.010	3	100	300	0.7272511	0.3249672
##	0.010	3	100	350	0.7222227	0.3322135
##	0.010	3	100	400	0.7180833	0.3381343
##	0.010	3	100	450	0.7147625	0.3430463
##	0.010	3	100	500	0.7120017	0.3471731
##	0.010	3	100	550	0.7095649	0.3509618
##	0.010	3	100	600	0.7074002	0.3543133
##	0.010	3	100	650	0.7056832	0.3569313
##	0.010	3	100	700	0.7042933	0.3590240
##	0.010	3	100	750	0.7030962	0.3609112
##	0.010	3	100	800	0.7019227	0.3628360
##	0.010	3	100	850	0.7008768	0.3645304
##	0.010	3	100	900	0.6997609	0.3664986
##	0.010	3	100	950	0.6988078	0.3681127
##	0.010	3	100	1000	0.6979486	0.3695984
##	0.010	3	200	100	0.7723865	0.2786929
##	0.010	3	200	150	0.7545306	0.2898955
##	0.010	3	200	200	0.7431223	0.3015987
##	0.010	3	200	250	0.7348233	0.3123707
##	0.010	3	200	300	0.7284737	0.3213351
##	0.010	3	200	350	0.7233869	0.3289113
##	0.010	3	200	400	0.7193678	0.3349121
##	0.010	3	200	450	0.7162793	0.3393454
##	0.010	3	200	500	0.7136847	0.3431829
##	0.010	3	200	550	0.7115183	0.3464700
##	0.010	3	200	600	0.7096751	0.3492797
##	0.010	3	200	650	0.7081327	0.3516874
##	0.010	3	200	700	0.7067797	0.3538644
##	0.010	3	200	750	0.7056313	0.3557704
##	0.010	3	200	800	0.7045060	0.3576930
##	0.010	3	200	850	0.7035810	0.3592744
##	0.010	3	200	900	0.7027199	0.3607779
##	0.010	3	200	950	0.7019360	0.3620964
##	0.010	3	200	1000	0.7011430	0.3634842
##	0.010	5	100	100	0.7629906	0.3001882
##	0.010	5	100	150	0.7427265	0.3147969
##	0.010	5	100	200	0.7301406	0.3269330
##	0.010	5	100	250	0.7209294	0.3382731
##	0.010	5	100	300	0.7141570	0.3472246
##	0.010	5	100	350	0.7093497	0.3537683
##	0.010	5	100	400	0.7056485	0.3589093
##	0.010	5	100	450	0.7026952	0.3631873
##	0.010	5	100	500	0.7002330	0.3668612
##	0.010	5	100	550	0.6982362	0.3699180

##	0.010	5	100	600	0.6965224	0.3727231
##	0.010	5	100	650	0.6951790	0.3748942
##	0.010	5	100	700	0.6938305	0.3771220
##	0.010	5	100	750	0.6926858	0.3790920
##	0.010	5	100	800	0.6916729	0.3808392
##	0.010	5	100	850	0.6908287	0.3823110
##	0.010	5	100	900	0.6899242	0.3838980
##	0.010	5	100	950	0.6891843	0.3851572
##	0.010	5	100	1000	0.6885080	0.3863287
##	0.010	5	200	100	0.7645890	0.2942197
##	0.010	5	200	150	0.7452152	0.3074191
##	0.010	5	200	200	0.7329850	0.3197250
##	0.010	5	200	250	0.7241137	0.3305374
##	0.010	5	200	300	0.7178349	0.3388740
##	0.010	5	200	350	0.7129638	0.3457343
##	0.010	5	200	400	0.7093664	0.3508879
##	0.010	5	200	450	0.7065778	0.3551221
##	0.010	5	200	500	0.7042671	0.3587447
##	0.010	5	200	550	0.7025109	0.3616282
##	0.010	5	200	600	0.7008780	0.3643663
##	0.010	5	200	650	0.6995014	0.3667289
##	0.010	5	200	700	0.6985470	0.3684168
##	0.010	5	200	750	0.6975834	0.3700856
##	0.010	5	200	800	0.6966868	0.3716917
##	0.010	5	200	850	0.6957899	0.3732799
##	0.010	5	200	900	0.6949960	0.3746784
##	0.010	5	200	950	0.6942340	0.3760739
##	0.010	5	200	1000	0.6936515	0.3771210
##	0.050	3	100	100	0.7122997	0.3463652
##	0.050	3	100	150	0.7030925	0.3607060
##	0.050	3	100	200	0.6981429	0.3692634
##	0.050	3	100	250	0.6946954	0.3753321
##	0.050	3	100	300	0.6920731	0.3800363
##	0.050	3	100	350	0.6906194	0.3824908
##	0.050	3	100	400	0.6894312	0.3845999
##	0.050	3	100	450	0.6876389	0.3876743
##	0.050	3	100	500	0.6867382	0.3893886
##	0.050	3	100	550	0.6856102	0.3913427
##	0.050	3	100	600	0.6847189	0.3929588
##	0.050	3	100	650	0.6837825	0.3946673
##	0.050	3	100	700	0.6833197	0.3954656
##	0.050	3	100	750	0.6829821	0.3960868
##	0.050	3	100	800	0.6822524	0.3974018
##	0.050	3	100	850	0.6814674	0.3987348
##	0.050	3	100	900	0.6809360	0.3998020
##	0.050	3	100	950	0.6803608	0.4006761
##	0.050	3	100	1000	0.6800436	0.4012639
##	0.050	3	200	100	0.7143470	0.3416080
##	0.050	3	200	150	0.7067469	0.3535745
##	0.050	3	200	200	0.7025793	0.3609238
##	0.050	3	200	250	0.6997932	0.3657855
##	0.050	3	200	300	0.6976194	0.3696308
##	0.050	3	200	350	0.6963190	0.3720808
##	0.050	3	200	400	0.6952079	0.3741005
##	0.050	3	200	450	0.6941559	0.3759835

##	0.050	3	200	500	0.6929360	0.3782144
##	0.050	3	200	550	0.6922306	0.3795495
##	0.050	3	200	600	0.6915904	0.3806939
##	0.050	3	200	650	0.6904945	0.3824822
##	0.050	3	200	700	0.6897224	0.3839647
##	0.050	3	200	750	0.6896039	0.3842461
##	0.050	3	200	800	0.6889760	0.3852737
##	0.050	3	200	850	0.6882345	0.3865871
##	0.050	3	200	900	0.6881165	0.3868132
##	0.050	3	200	950	0.6874075	0.3881610
##	0.050	3	200	1000	0.6869976	0.3889328
##	0.050	5	100	100	0.7012347	0.3646711
##	0.050	5	100	150	0.6944334	0.3758453
##	0.050	5	100	200	0.6905381	0.3827920
##	0.050	5	100	250	0.6873113	0.3884733
##	0.050	5	100	300	0.6854727	0.3917212
##	0.050	5	100	350	0.6833814	0.3954141
##	0.050	5	100	400	0.6819470	0.3978457
##	0.050	5	100	450	0.6801365	0.4011938
##	0.050	5	100	500	0.6795695	0.4021190
##	0.050	5	100	550	0.6788439	0.4035914
##	0.050	5	100	600	0.6772096	0.4064277
##	0.050	5	100	650	0.6766611	0.4073065
##	0.050	5	100	700	0.6754907	0.4093836
##	0.050	5	100	750	0.6745935	0.4109534
##	0.050	5	100	800	0.6737978	0.4123566
##	0.050	5	100	850	0.6729002	0.4138626
##	0.050	5	100	900	0.6724639	0.4147275
##	0.050	5	100	950	0.6718121	0.4157630
##	0.050	5	100	1000	0.6712200	0.4168549
##	0.050	5	200	100	0.7041734	0.3587231
##	0.050	5	200	150	0.6979078	0.3694969
##	0.050	5	200	200	0.6932760	0.3777859
##	0.050	5	200	250	0.6908678	0.3821928
##	0.050	5	200	300	0.6888490	0.3858865
##	0.050	5	200	350	0.6870920	0.3889154
##	0.050	5	200	400	0.6860994	0.3906776
##	0.050	5	200	450	0.6843188	0.3939007
##	0.050	5	200	500	0.6830105	0.3961346
##	0.050	5	200	550	0.6827148	0.3966903
##	0.050	5	200	600	0.6818150	0.3981789
##	0.050	5	200	650	0.6814667	0.3988585
##	0.050	5	200	700	0.6807369	0.4001349
##	0.050	5	200	750	0.6801798	0.4010136
##	0.050	5	200	800	0.6794995	0.4021241
##	0.050	5	200	850	0.6793208	0.4027386
##	0.050	5	200	900	0.6785405	0.4040740
##	0.050	5	200	950	0.6781668	0.4047304
##	0.050	5	200	1000	0.6781442	0.4049031
##	0.100	3	100	100	0.6991857	0.3668671
##	0.100	3	100	150	0.6937574	0.3767540
##	0.100	3	100	200	0.6904313	0.3830016
##	0.100	3	100	250	0.6887795	0.3857501
##	0.100	3	100	300	0.6868803	0.3892108
##	0.100	3	100	350	0.6851442	0.3924489

##	0.100	3	100	400	0.6854112	0.3919858
##	0.100	3	100	450	0.6842333	0.3939950
##	0.100	3	100	500	0.6836957	0.3951078
##	0.100	3	100	550	0.6827659	0.3967498
##	0.100	3	100	600	0.6822958	0.3976817
##	0.100	3	100	650	0.6821849	0.3979155
##	0.100	3	100	700	0.6812463	0.3997226
##	0.100	3	100	750	0.6809889	0.3999880
##	0.100	3	100	800	0.6800760	0.4018395
##	0.100	3	100	850	0.6790940	0.4035487
##	0.100	3	100	900	0.6792632	0.4035284
##	0.100	3	100	950	0.6785498	0.4045025
##	0.100	3	100	1000	0.6787313	0.4045442
##	0.100	3	200	100	0.7033274	0.3595979
##	0.100	3	200	150	0.6982301	0.3687036
##	0.100	3	200	200	0.6950898	0.3744513
##	0.100	3	200	250	0.6934043	0.3773381
##	0.100	3	200	300	0.6917798	0.3802137
##	0.100	3	200	350	0.6905947	0.3822889
##	0.100	3	200	400	0.6891199	0.3849831
##	0.100	3	200	450	0.6885200	0.3861144
##	0.100	3	200	500	0.6884279	0.3863255
##	0.100	3	200	550	0.6873095	0.3884965
##	0.100	3	200	600	0.6867638	0.3896127
##	0.100	3	200	650	0.6868129	0.3894328
##	0.100	3	200	700	0.6860070	0.3909083
##	0.100	3	200	750	0.6850943	0.3924902
##	0.100	3	200	800	0.6852033	0.3925008
##	0.100	3	200	850	0.6853986	0.3921536
##	0.100	3	200	900	0.6845150	0.3937575
##	0.100	3	200	950	0.6841177	0.3944737
##	0.100	3	200	1000	0.6832034	0.3959351
##	0.100	5	100	100	0.6904254	0.3829091
##	0.100	5	100	150	0.6855922	0.3915604
##	0.100	5	100	200	0.6826523	0.3969902
##	0.100	5	100	250	0.6809679	0.3999928
##	0.100	5	100	300	0.6798449	0.4018751
##	0.100	5	100	350	0.6784306	0.4046584
##	0.100	5	100	400	0.6761041	0.4085639
##	0.100	5	100	450	0.6754817	0.4098385
##	0.100	5	100	500	0.6744848	0.4116528
##	0.100	5	100	550	0.6735755	0.4133974
##	0.100	5	100	600	0.6728631	0.4147672
##	0.100	5	100	650	0.6720839	0.4162547
##	0.100	5	100	700	0.6715979	0.4172170
##	0.100	5	100	750	0.6717513	0.4170798
##	0.100	5	100	800	0.6715324	0.4174592
##	0.100	5	100	850	0.6710122	0.4184630
##	0.100	5	100	900	0.6701016	0.4200126
##	0.100	5	100	950	0.6698501	0.4207806
##	0.100	5	100	1000	0.6693939	0.4216555
##	0.100	5	200	100	0.6950160	0.3745018
##	0.100	5	200	150	0.6901132	0.3832688
##	0.100	5	200	200	0.6883418	0.3864236
##	0.100	5	200	250	0.6864304	0.3898568

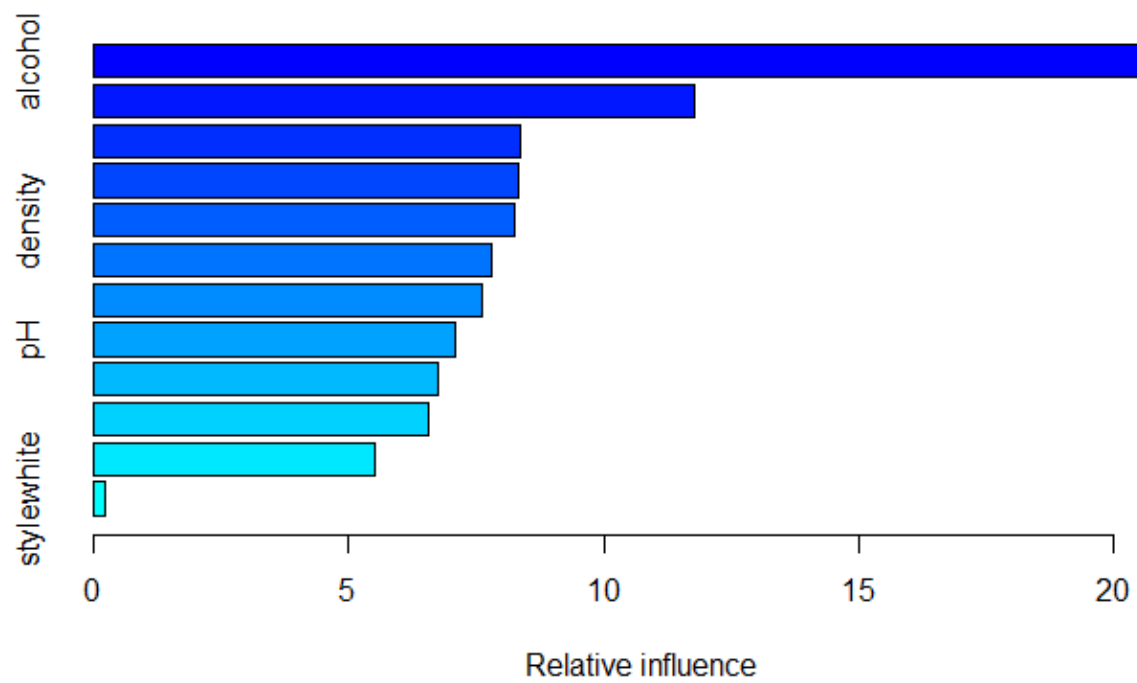
```
## 0.100      5      200      300      0.6853924 0.3919402
## 0.100      5      200      350      0.6841042 0.3940763
## 0.100      5      200      400      0.6827993 0.3963075
## 0.100      5      200      450      0.6826574 0.3968774
## 0.100      5      200      500      0.6821246 0.3979067
## 0.100      5      200      550      0.6811965 0.3995464
## 0.100      5      200      600      0.6804466 0.4010221
## 0.100      5      200      650      0.6803318 0.4013843
## 0.100      5      200      700      0.6802246 0.4015018
## 0.100      5      200      750      0.6789962 0.4037769
## 0.100      5      200      800      0.6785844 0.4046930
## 0.100      5      200      850      0.6782839 0.4053268
## 0.100      5      200      900      0.6773275 0.4071341
## 0.100      5      200      950      0.6764926 0.4085214
## 0.100      5      200     1000      0.6754954 0.4104012
```

```
## RMSE was used to select the optimal model using the smallest value.
## The final values used for the model were n.trees = 1000, interaction.depth =
```

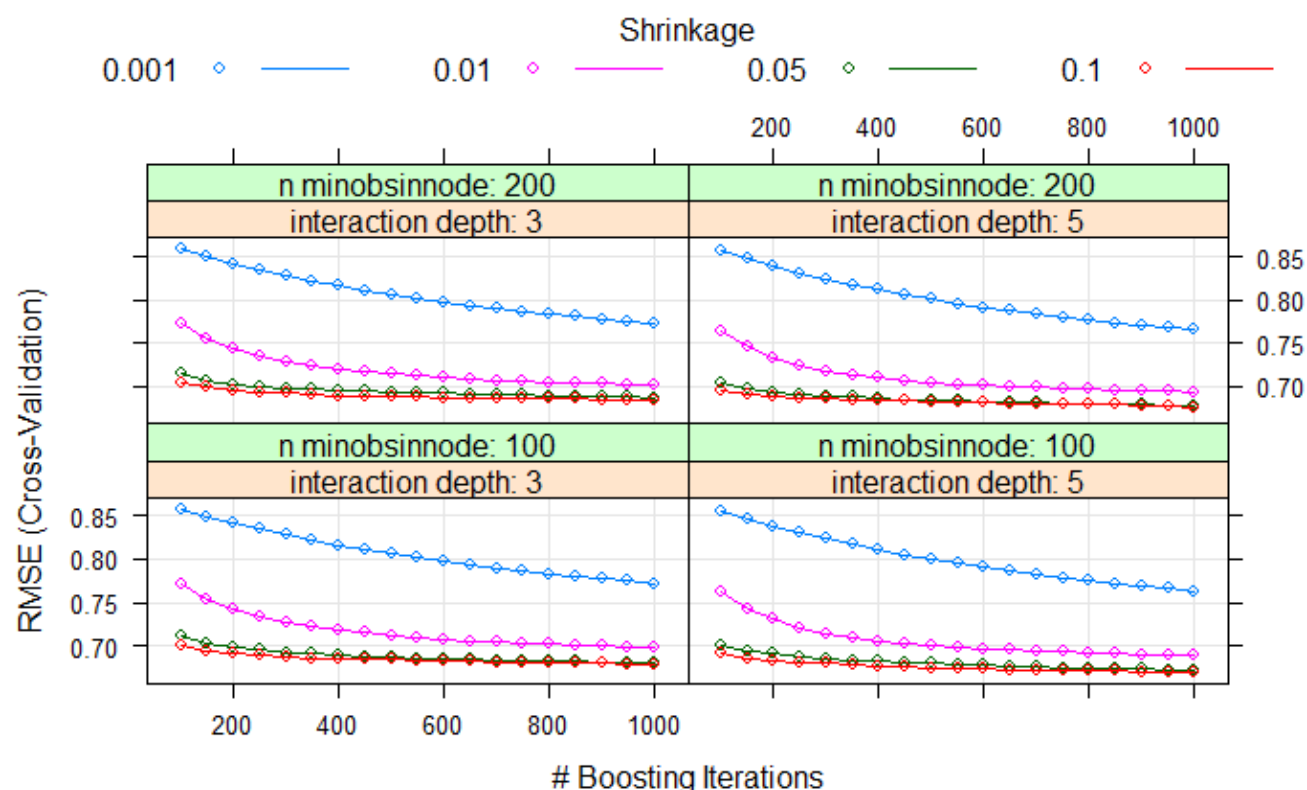
```
## 5, shrinkage = 0.1 and n.minobsinnode = 100.
```

```
> summary(gbm.caret)
```

```
##              var      rel.inf
## alcohol              alcohol 21.7660390
## volatile_acidity    volatile_acidity 11.7731859
## free_sulfur_dioxide  free_sulfur_dioxide 8.3500203
## total_sulfur_dioxide total_sulfur_dioxide 8.3149068
## density              density 8.2468528
## residual_sugar      residual_sugar 7.8071170
## sulphates            sulphates 7.6158444
## pH                  pH 7.0877860
## citric_acid          citric_acid 6.7395801
## chlorides            chlorides 6.5561664
## fixed_acidity        fixed_acidity 5.5230847
## stylewhite           stylewhite 0.2194164
```



```
plot(gbm.caret)
```



Explanation:

For Boosting, caret package was used to tune the parameters. Number of variables tried at each node was varied from 3 and 5, number of trees grown was changed from 100 to 1000 in increments of 50, shrinkage/learning rate was tried from 0.001, 0.01, 0.05 and 0.1. Number of minimum observations at node was set at 100 and 200, which is high enough to prevent overfitting of model to training data. 10-fold cross-validation was used with RMSE as the metric. From the plot, it can be observed that for higher shrinkage rates (0.05 and 0.1), there is no significant decrease in RMSE after around 600 trees, whereas the RMSE keeps decreasing for lower shrinkage (0.001 and 0.01), indicating that more number of trees would be required for lower shrinkage rates.

Random Forest code:

```
#Random Forest-----

rf.caretGrid=expand.grid(mtry=c(4,6,8,10))
metric="RMSE"
trainControl=trainControl(method="cv",number=10)
set.seed(1)
rf.caret=train(quality~., data=Train.data,method="rf",
               trControl=trainControl, verbose=FALSE,
               tuneGrid=rf.caretGrid, metric=metric, ntree=500)
```

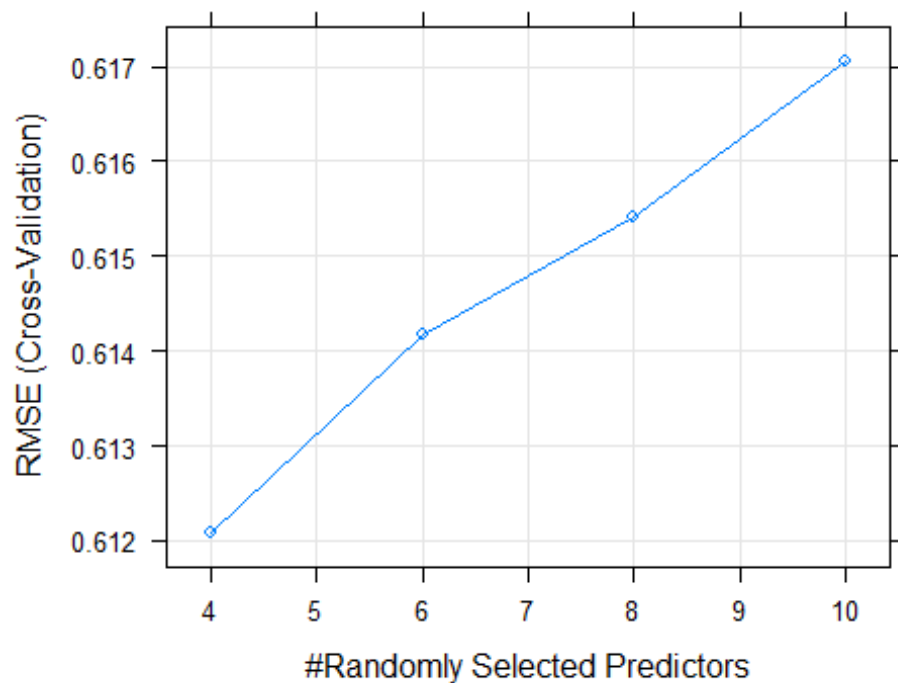
```

print(rf.caret)

## Random Forest
##
## 5198 samples
## 12 predictor
##
## No pre-processing
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 4678, 4679, 4678, 4679, 4678, 4678, ...
## Resampling results across tuning parameters:
##
##  mtry  RMSE      Rsquared  MAE
##    4    0.6120737  0.5212333  0.4459086
##    6    0.6141681  0.5159709  0.4462314
##    8    0.6154171  0.5133363  0.4468721
##   10    0.6170645  0.5098836  0.4468749
##
## RMSE was used to select the optimal model using the smallest value.
## The final value used for the model was mtry = 4.

plot(rf.caret)

```



```
library(randomForest)
```

```

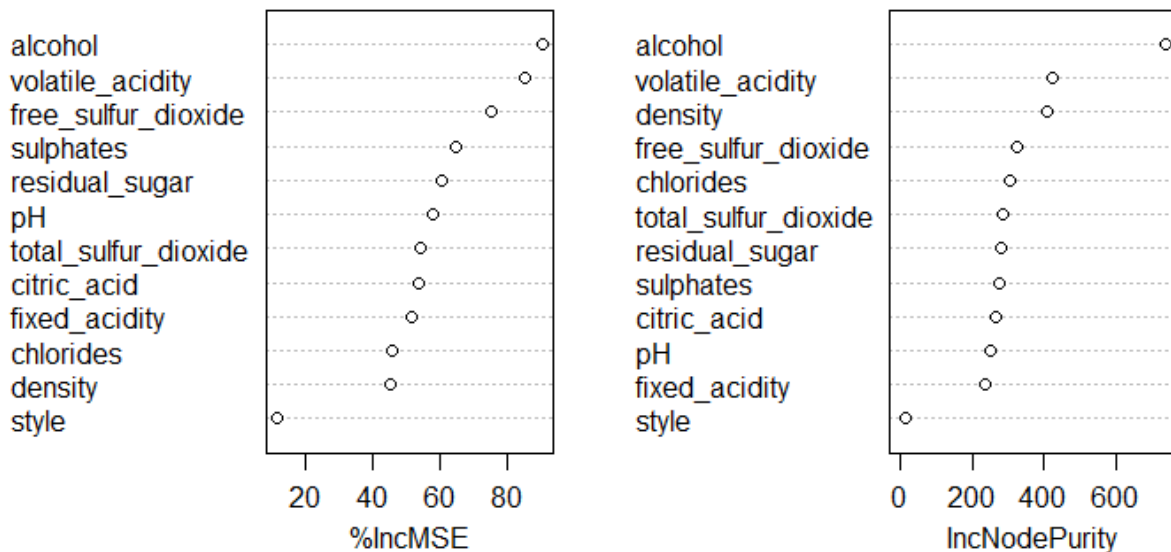
set.seed(1)
rfor=randomForest(quality~.,data=Train.data,mtry=4,ntree=500,importance=TRUE)
varImp(rfor)

##              Overall
## fixed_acidity    52.83715
## volatile_acidity 79.70257
## citric_acid      51.67916
## residual_sugar   53.15982
## chlorides        47.43820
## free_sulfur_dioxide 68.80161
## total_sulfur_dioxide 51.33943
## density          41.47568
## pH              58.65402
## sulphates        62.89265
## alcohol          89.12409
## style           13.39972

varImpPlot(rfor)

```

rfor



Explanation:

For Random Forest, number of predictors tried at each node was varied between 4, 6, 8 and 10. Since there are a total of 12 predictors, the best value of mtry should be 4 as $p/3$, where p is the

number of predictors, is the thumb rule. This is the case, as seen from the graph and the RMSE values as well. As mtry increases, the RMSE increases, for 500 trees. Variable importance was also derived from the random forest model. It is seen that for predicting the wine quality, %alcohol is the most influential predictor, closely followed by volatile_acidity and free_sulfur_dioxide. Wine style (red or white) does not have any effect on its quality.

SVM code:

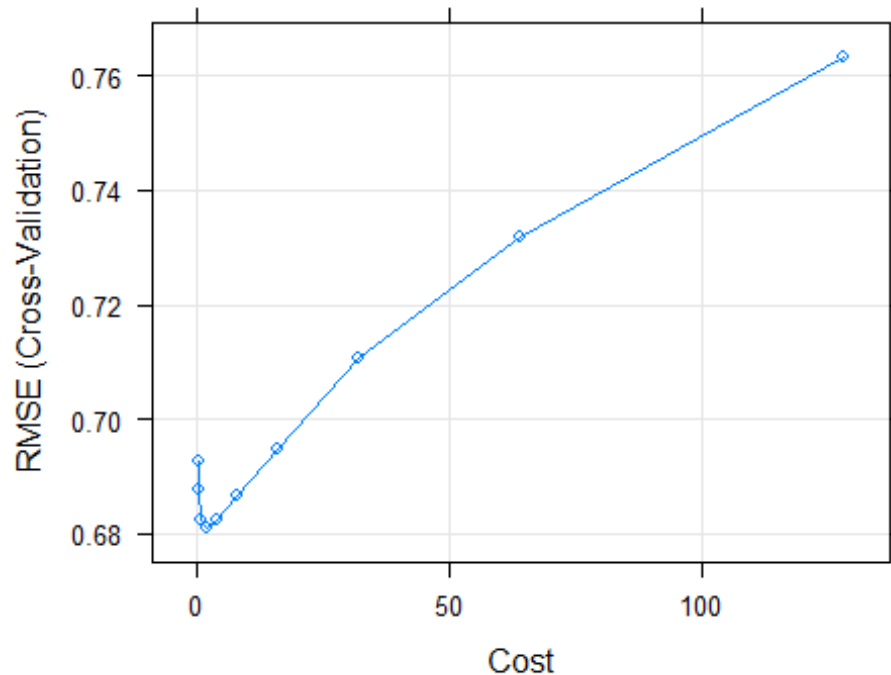
```
#SVM-----

library(e1071)
trainControl=trainControl(method="cv",number=10)

set.seed(1)
svm.caret=train(quality~.,data=Train.data,method="svmRadial",
               preProcess=c("center","scale"),
               tuneLength=10,trControl=trainControl)
svm.caret

## Support Vector Machines with Radial Basis Function Kernel
##
## 5198 samples
## 12 predictor
##
## Pre-processing: centered (12), scaled (12)
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 4678, 4679, 4678, 4679, 4678, 4678, ...
## Resampling results across tuning parameters:
##
##  C          RMSE          Rsquared    MAE
##  0.25  0.6926980  0.3792132  0.5251839
##  0.50  0.6877696  0.3881147  0.5198233
##  1.00  0.6824698  0.3977056  0.5132648
##  2.00  0.6807917  0.4015503  0.5105128
##  4.00  0.6823434  0.4007518  0.5097913
##  8.00  0.6864692  0.3970218  0.5109669
## 16.00  0.6947185  0.3895968  0.5156426
## 32.00  0.7106061  0.3751361  0.5240890
## 64.00  0.7319058  0.3594585  0.5324724
##128.00  0.7634800  0.3387071  0.5454074
##
## Tuning parameter 'sigma' was held constant at a value of 0.09179926
## RMSE was used to select the optimal model using the smallest value.
## The final values used for the model were sigma = 0.09179926 and C =
2.

plot(svm.caret)
```

Explanation:

For Support Vector Machines, radial kernel was used in the caret package, instead of tune command of e1071 library. This is because using caret, the best model is selected based on RMSE values, whereas for e1071, the best model selection is based on MSE values. Since it is essential to compare the three algorithms, a similar metric to select the best model for each algorithm should be used. In caret, tuneLength argument is used, which varies the cost associated with the model, at a constant sigma value. From the graph, it can be seen that RMSE decreases initially with increase in cost and then starts increasing.

The model RMSE values are compared for all three algorithms in the table below:

Algorithm	Training RMSE
Boosting	0.6693
Random Forest	0.6120
SVM (Radial)	0.6807

From the table above, it is seen that Random Forest has the least RMSE on training data

Code for performance on test data:

```
#Performance on holdout data-----

gbm.predict=predict(gbm.caret,Test.data)
mean((gbm.predict-Test.data$quality)^2)

## [1] 0.4161539
```

```
rf.predict=predict(rf.caret,Test.data)
mean((rf.predict-Test.data$quality)^2)

## [1] 0.3368632

svmcaret.predict=predict(svm.caret,Test.data)
mean((svmcaret.predict-Test.data$quality)^2)

## [1] 0.4372144

#RMSE gbm:0.416 rf:0.33 svmrad:0.43
```

Explanation:

The performance of all three algorithms were compared for holdout data using RMSE value. The performance is summarized in the table below:

Algorithm	Test RMSE
Boosting	0.4161
Random Forest	0.3368
SVM (Radial)	0.4372

From the table, it can be seen that Random Forest has the best performance on holdout data.

2. Assumptions made about wine quality data when using a regression model

In a regression model the wine quality data is a numeric value. The underlying assumption is that the data on which wine quality is rated is based on a numeric model. That is, the quality value can be mathematically be derived from the predictor data. It implies that a wine with a score of 8 is twice better than a wine with a quality of 4.

Another assumption about the predicted data is that the wine quality can be a decimal number. This is because the quality data is treated as numeric by the model and the output of the model can be any numeric value, including decimals. This means the wine quality can be 5.5, which is not the case since all the datapoints in training data has an integer value.

This is generally not the case, as the quality cannot be arrived at mathematically. Most of the times, the quality is based on a wine taster's opinion and experience. Therefore, treating the quality as a numerical value is not correct. It should be treated as a class data, and therefore classification should be performed instead of regression.