Assignment 02

Analysis of data set 1

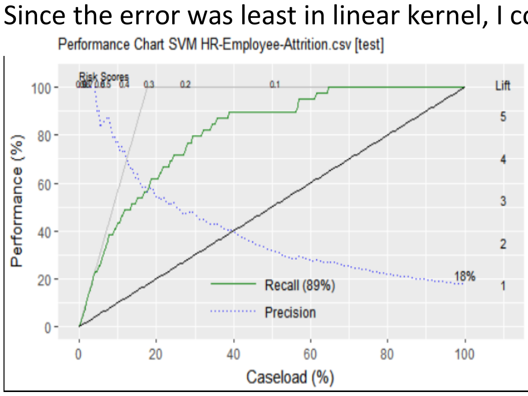
Data Description: The analytic methods can improve Human Resources (HR) management for companies with substantial number of employees. I tried to analyze how can companies benefit from machine learning methods applied to HR. I would like to present how to predict employee attrition with machine learning. For analysis I will use a data set created by IBM data scientists. In this data each sample (row) describes the employee with parameters like: age, department, distance from home, marital status, income, years at company. However, the attrition is unknown and we want to predict (compute) it with our machine learning model.

Algorithm 1: SVM

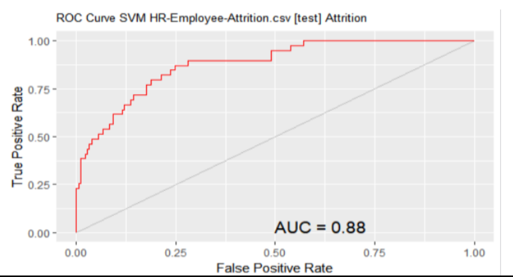
Comparison of the three kernels used:

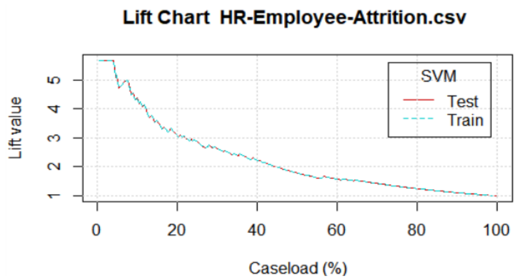
Parameters	Linear Kernel	Radial Kernel	Laplacian Kernel
Confusion matrix using training dataset	Predicted Actual No Yes Error No 82.7 1.5 1.7 Yes 8.7 7.1 55.2	Predicted Actual No Yes Error No 866 0 0.0 Yes 117 46 71.8	Predicted Actual No Yes Error No 866 0 0 Yes 163 0 100
Overall Error	10.2%	11.3%	15.8%
Average Class Error	28.45%	35.9%	50%
Confusion matrix using test dataset	Predicted Actual No Yes Error No 79.6 2.7 3.3 Yes 10.0 7.7 56.4	Predicted Actual No Yes Error No 182 0 0.0 Yes 32 7 82.1	Predicted Actual No Yes Error No 182 0 0 Yes 39 0 100
Overall Error	12.7%	14.4%	17.6%
Average Class Error	29.85%	41.05%	50%

Since the error was least in linear kernel, I considered it for further analysis.



Performance chart shows the tradeoff between the caseload (number of instances) and the performance of the model. It shows that the precision of the model decreases as we increase the caseload. When we use 100% of the test dataset, we can correctly predict 18% of employee's attrition. Whereas recall increases as well increase the caseload. The best recall obtained from this model is 89% i.e. we can identify 89% of employees who are likely to undergo attrition.

	Accuracy of the model is 88%. It identifies 88% of employees' attrition

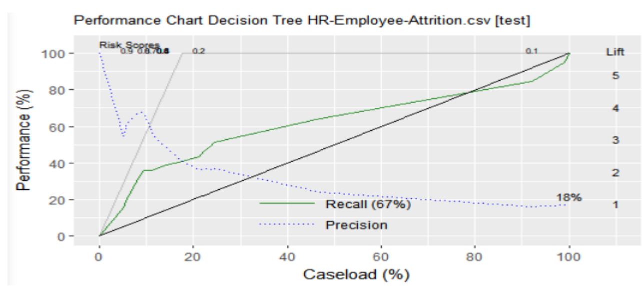
	Through this lift chart we can say that if we consider only on 10% of the employees based on the predictive model we can identify 5 times as many employees that are likely to undergo attrition as if we use no model.

Algorithm 2: Decision Tree:

Comparison of Decision Tree before and after pruning

Parameters	Before pruning	After Pruning
Confusion matrix using training dataset	Predicted Actual No Yes Error No 827 39 4.5 Yes 40 123 24.5	Predicted Actual No Yes Error No 849 17 2.0 Yes 81 82 49.7
Overall Error	7.60%	9.50%
Average Class Error	14.50%	25.85%
Confusion matrix using test dataset	Predicted Actual No Yes Error No 164 18 9.9 Yes 24 15 61.5	Predicted Actual No Yes Error No 171 11 6.0 Yes 25 14 64.1
Overall Error	19.00%	16.30%
Average Class Error	35.70%	35.05%
Complexity Parameter	CP nsplit rel error xerror xstd 1 0.0265849 0 1.00000 1.00000 0.071855 2 0.0214724 6 0.84049 0.98773 0.071495 3 0.0184049 9 0.76687 0.95706 0.070579 4 0.0168712 13 0.69325 0.95706 0.070579 5 0.0122699 17 0.62577 1.00000 0.071855 6 0.0061350 19 0.60123 1.06135 0.073598 7 0.0030675 28 0.54601 1.11043 0.074928 8 0.0023006 33 0.52761 1.16564 0.076359 9 0.0020450 41 0.50920 1.19632 0.077127 10 0.0015337 48 0.49080 1.19632 0.077127 11 0.0000100 52 0.48466 1.21472 0.077578	CP nsplit rel error xerror xstd 0.026585 0 1.00000 1.00000 0.071855 0.021472 6 0.84049 0.98773 0.071495 0.018405 9 0.76687 0.95706 0.070579 0.016871 13 0.69325 0.95706 0.070579 0.012270 17 0.62577 1.00000 0.071855 0.010000 19 0.60123 1.03681 0.072912

From the table above, we can see that decision tree gives better result after pruning as the errors on the test set has reduced. For pruning the tree, I considered Complexity Parameter to be the key value. I pruned the tree till the value of CP reduced and were close for all the buckets. Complexity of the pruned tree is 0.01.

<table>
<tr>
<td>
</td>
<td>When we use 100% of the test dataset, we can correctly predict 18% of employee's attrition. Whereas recall increases as well increase the caseload. The best recall obtained from this model is 67% i.e. we can identify 67% of employees who are likely to undergo attrition. We can see the recall of this model is not good. It even falls below the baseline. So, we should not consider this model for prediction.</td>
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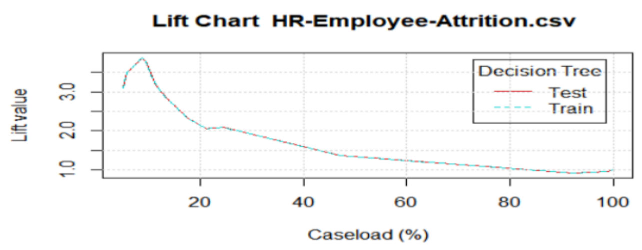
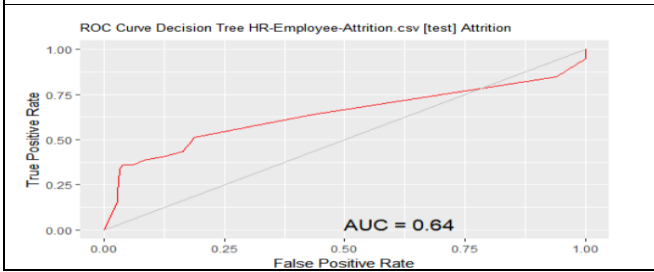
<tr>
<td>
</td>
<td>Through this lift chart we can say that if we can say although only on 10% of the employees based on the predictive model we can identify 4 times as many employees that are likely to undergo attrition as if we use no model, but it falls rapidly as we increase the size of our dataset.</td>
</tr>
<tr>
<td>
</td>
<td>Accuracy of the model is 64%. It identifies 64% of employees' attrition. It also falls below the baseline after 80%.</td>
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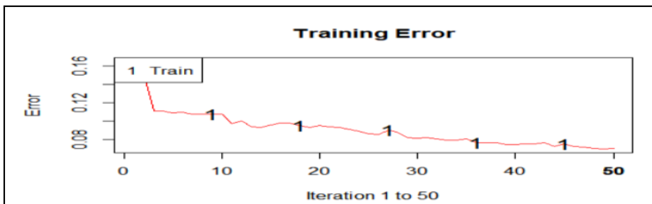
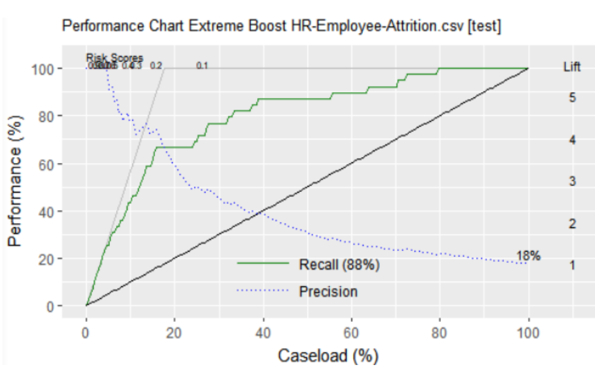
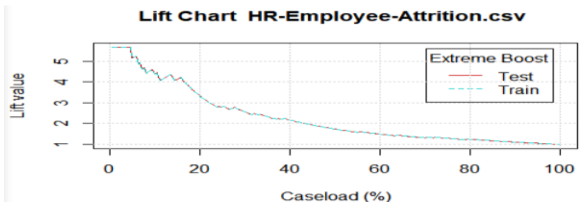
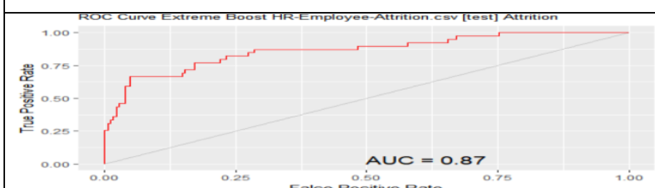
</table>

<u>Algorithm 3: Boosting</u>

<table>
<tr>
<td>
</td>
<td>We can see that training error reduces almost after every iteration. After 50 trees the error reached almost zero. Therefore, I used 50 trees for boosting.</td>
</tr>
</table>

<table>
<tr>
<td>
</td>
<td>Performance chart shows the tradeoff between the caseload (number of instances) and the performance of the model. It shows that the precision of the model decreases as we increase the caseload. When we use 100% of the test dataset, we can correctly predict 18% of employee's attrition. Whereas recall increases as well increase the caseload. The best recall obtained from this model is 88% i.e. we can identify 88% of employees who are likely to undergo attrition.</td>
</tr>
<tr>
<td>
</td>
<td>Through this lift chart we can say that if we can say although only on 5% of the employees based on the predictive model we can identify more than 5 times as many employees that are likely to undergo attrition as if we use no model, but it falls rapidly as we increase the size of our dataset</td>
</tr>
<tr>
<td>
</td>
<td>Accuracy of the model is 87%. It identifies 87% of employees' attrition</td>
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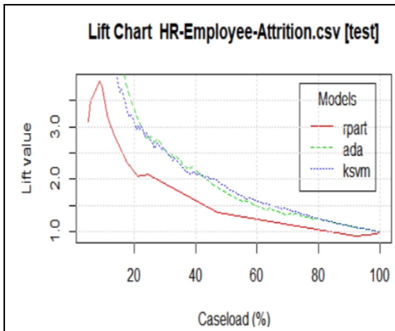
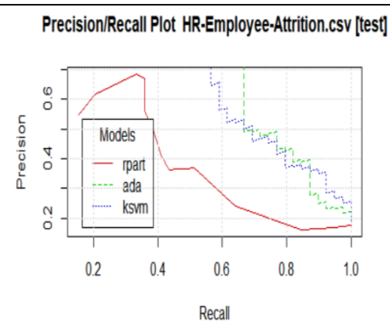
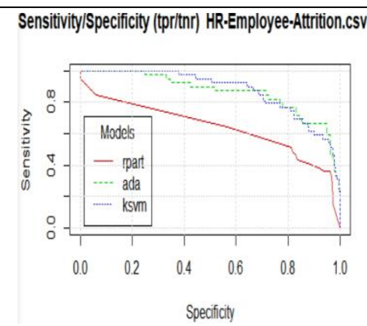
Model Comparison:

<table>
<tr>
<td>
</td>
<td>
</td>
<td>
</td>
</tr>
<tr>
<td>From the lift chart for all the three models we can say that svm and boosting gives comparable result while decision tree is not very good for model generalization as it gives very few correct results</td>
<td>We can say from Precision/ Recall chart that for 80% of data boosting gives the best result while data from 90-100% svm performs better. We should not consider of decision tree in any of the cases.</td>
<td>Looking at Sensitivity/Specificity chart, we can say for 70% of data svm performs better than boosting while after that boosting is slightly better. Decision tree is not good in any case.</td>
</tr>
</table>

Conclusion:

Analyzing all the charts of various graphs we can say for this particular problem we should consider SVM or boosting as it shows the best results. Also, the accuracy of boosting and SVM are 87% and 89% respectively whereas through SVM we get only 64% accuracy.

Analysis of dataset 2

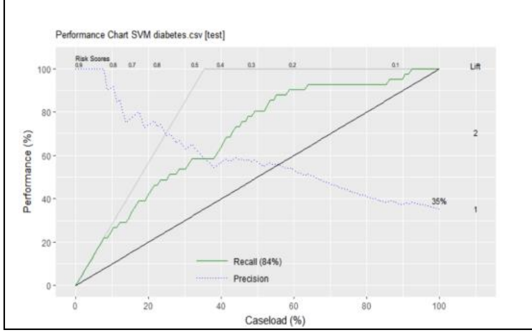
Data Description: Analytics play a huge role in Healthcare industry. Given the physical condition of a person it can be easily identified which disease is that person most likely to suffer. This dataset is originally from the National Institute of Diabetes and Digestive and Kidney Diseases. The objective is to predict based on diagnostic measurements whether a patient has diabetes. It consists of features like number of pregnancies, BMI, Blood Pressure, Skin Thickness and I am trying to predict whether the person is diabetic or not.

Algorithm 1: SVM

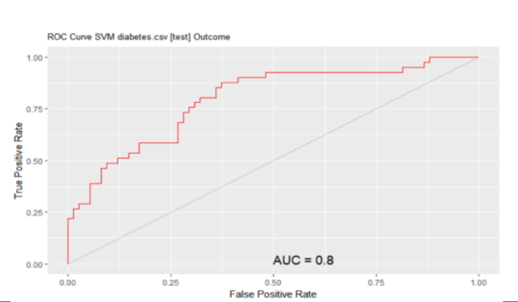
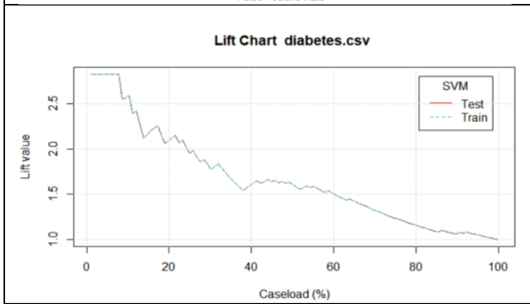
Comparison of the three kernels used:

Parameters	Linear Kernel	Radial Kernel	Laplacian Kernel
Confusion matrix using training dataset	Predicted Actual 0 1 Error 0 313 41 11.6 1 70 113 38.3	Predicted Actual 0 1 Error 0 330 24 6.8 1 57 126 31.1	Predicted Actual 0 1 Error 0 329 25 7.1 1 59 124 32.2
Overall Error	20.7%	15%	15.6%
Average Class Error	24.95%	18.5%	19.65%
Confusion matrix using test dataset	Predicted Actual 0 1 Error 0 62 13 17.3 1 19 22 46.3	Predicted Actual 0 1 Error 0 62 13 17.3 1 17 24 41.5	Predicted Actual 0 1 Error 0 61 14 18.7 1 19 22 46.3
Overall Error	27.6%	25.9%	28.4%
Average Class Error	31.8%	29.4%	32.5%

Since the error was least in radial kernel, I considered it for further analysis.



Performance chart shows the tradeoff between the caseload (number of instances) and the performance of the model. It shows that the precision of the model decreases as we increase the caseload. When we use 100% of the test dataset, we can correctly predict 35% of persons suffering from diabetes. Whereas recall increases as well increase the caseload. The best recall obtained from this model is 84% i.e. we can identify 89% of persons who have diabetes.

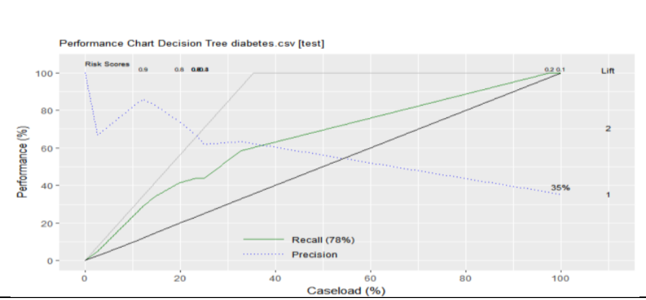
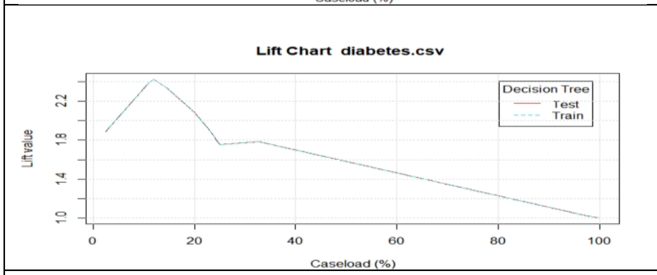
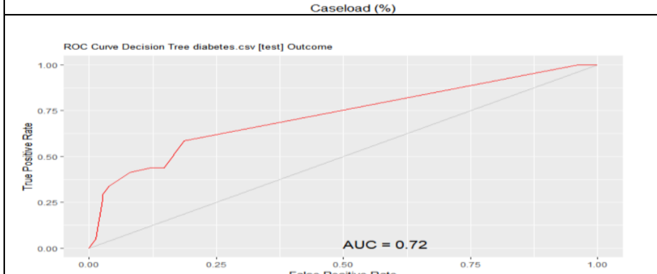
	Accuracy of the model is 80%. It identifies 80% of persons who have diabetes.
	Through this lift chart we can say that if we consider approximately on 10% of the persons based on the predictive model we can identify 3 times as many persons that are likely to have diabetes as if we use no model.

Algorithm 2: Decision Tree:

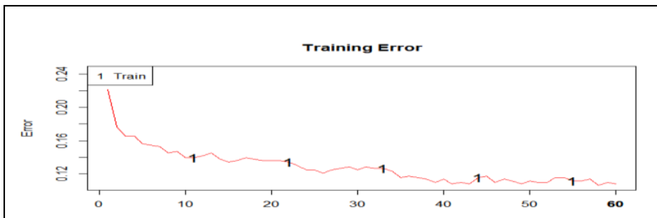
Comparison of Decision Tree before and after pruning

Parameters	Before pruning	After Pruning
Confusion matrix using training dataset	Predicted Actual 0 1 Error 0 330 24 6.8 1 46 137 25.1	Predicted Actual 0 1 Error 0 336 18 5.1 1 68 115 37.2
Overall Error	13%	16%
Average Class Error	15.95%	21.15%
Confusion matrix using test dataset	Predicted Actual 0 1 Error 0 64 11 14.7 1 14 27 34.1	Predicted Actual 0 1 Error 0 69 6 8.0 1 24 17 58.5
Overall Error	21.5%	25.8%
Average Class Error	24.4%	33.25%
Complexity Parameter	CP nsplit rel error xerror xstd 1 0.3060109 0 1.00000 1.00000 0.060019 2 0.1038251 1 0.69399 0.74863 0.055202 3 0.0200364 2 0.59016 0.62295 0.051783 4 0.0136612 5 0.53005 0.66667 0.053060 5 0.0109290 7 0.50273 0.70492 0.054099 6 0.0095628 10 0.46995 0.72678 0.054661 7 0.0091075 14 0.43169 0.72678 0.054661 8 0.0027322 18 0.39344 0.76503 0.055593 9 0.0018215 20 0.38798 0.76503 0.055593 10 0.0000100 23 0.38251 0.76503 0.055593	CP nsplit rel error xerror xstd 1 0.306011 0 1.00000 1.00000 0.060019 2 0.103825 1 0.69399 0.74863 0.055202 3 0.020036 2 0.59016 0.62295 0.051783 4 0.013661 5 0.53005 0.66667 0.053060 5 0.010929 7 0.50273 0.70492 0.054099 6 0.010000 10 0.46995 0.72678 0.054661

From the table above, we can see that decision tree gives better result after pruning as the errors on the test set has reduced. For pruning the tree, I considered Complexity Parameter to be the key value. I pruned the tree till the value of CP reduced and were close for all the buckets. Complexity of the pruned tree is 0.01.

<table>
<tr>
<td>
</td>
<td>When we use 100% of the test dataset, we can correctly predict 35% of people with diabetes. Whereas recall increases as well increase the caseload. The best recall obtained from this model is 78% i.e. we can identify 78% of people who are likely to have diabetes. We can see the recall of this model is not good.</td>
</tr>
<tr>
<td>
</td>
<td>Through this lift chart we can say that if we can say although only on 10% of the employees based on the predictive model we can identify 2.4 times as many people that are likely to have diabetes as if we use no model.</td>
</tr>
<tr>
<td>
</td>
<td>Accuracy of the model is 72%. It identifies 72% of people who are likely to have diabetes.</td>
</tr>
</table>

<u>Algorithm 3: Boosting</u>

<table>
<tr>
<td>
</td>
<td>We can see that training error reduces almost after every iteration. It is a wiggly curve but after 60 iteration the error reached almost zero. Therefore, I used 60 iterations for boosting.</td>
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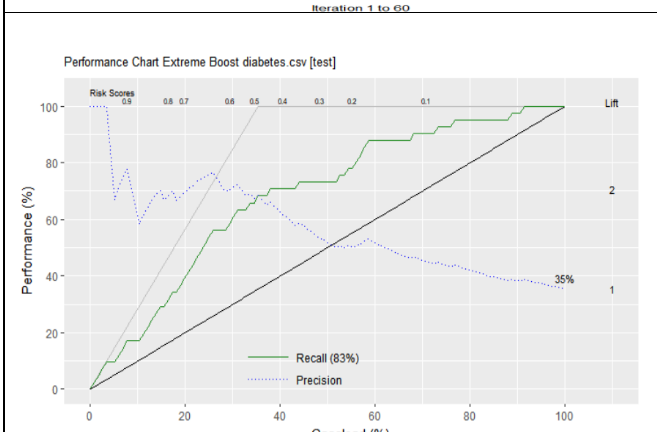
<tr>
<td>
</td>
<td>Performance chart shows the tradeoff between the caseload (number of instances) and the performance of the model. It shows that the precision of the model decreases as we increase the caseload. When we use 100% of the test dataset, we can correctly predict 35% of people who might have diabetes. Whereas recall increases as well increase the caseload. The best recall obtained from this model is 83% i.e. we can identify 83% of people who are likely to have diabetes.</td>
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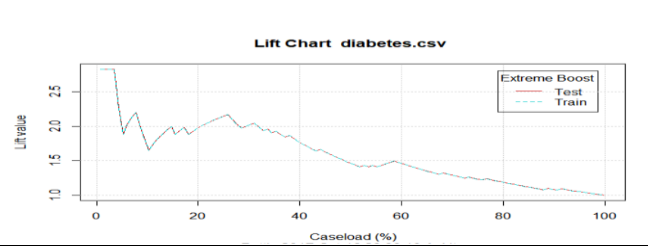
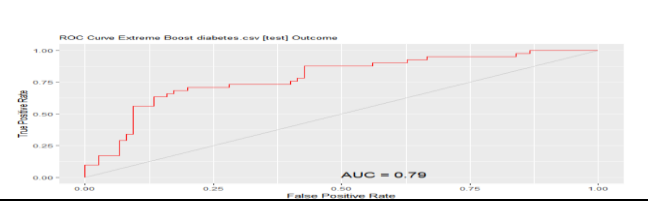
<tr>
<td>
</td>
<td>This lift chart is quite confusing to predict anything. We can assume on 25% of the employees based on the predictive model we can identify more than more than 2 times as many people that are likely to have diabetes as if we use no model, but it falls rapidly as we increase the size of our dataset</td>
</tr>
<tr>
<td>
</td>
<td>Accuracy of the model is 79%. It identifies 79% of people who are likely to have diabetes.</td>
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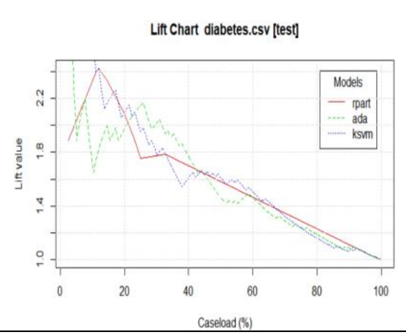
Model Comparison:

<table>
<tr>
<td>
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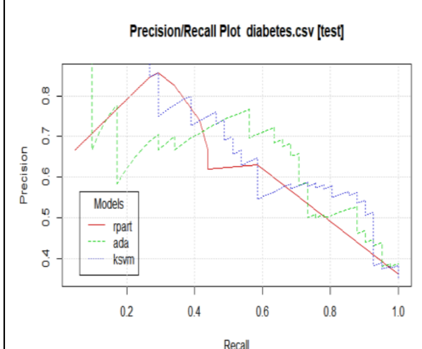
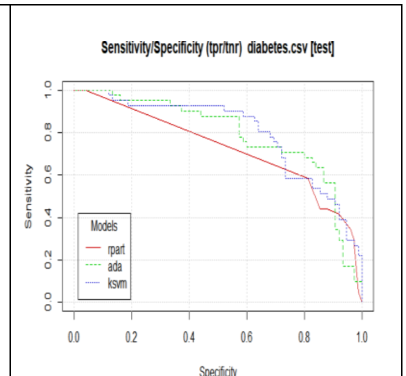
<td>
</td>
<td>
</td>
</tr>
<tr>
<td>From the lift chart for all the three models we can say that svm and boosting gives comparable result while decision tree is not very good for model generalization as it gives very few correct results</td>
<td>We can say from Precision/ Recall chart that for 50% of data svm gives the best result while data from 50-70% boosting performs better. We should not consider of decision tree in any of the cases.</td>
<td>Looking at Sensitivity/Specificity chart, we can say for 70% of data svm performs better than boosting while after that boosting is slightly better. Decision tree is not good in any case.</td>
</tr>
</table>

Conclusion:

Analyzing all the charts of various graphs we can say in order to predict if a person has diabetes on not from this data set, we should consider SVM or boosting as it shows the best results. Also, the accuracy of boosting and SVM are 79% and 80% respectively whereas through SVM we get only 72% accuracy.