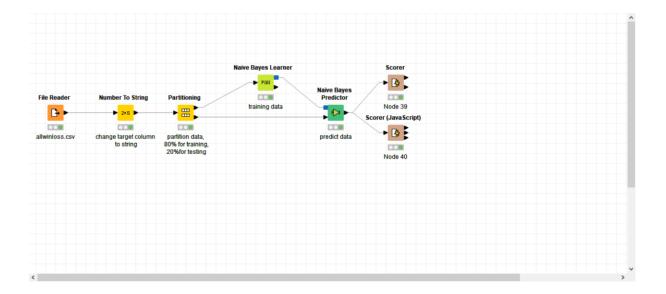
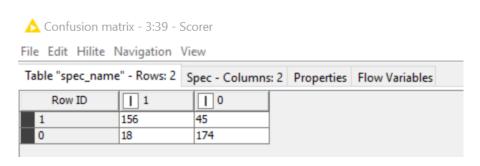
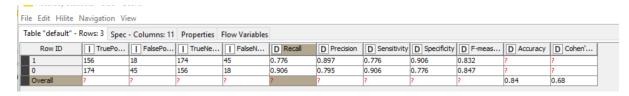
#### Overall workflow:



I read the allwinloss.csv file since we are doing classification for Naïve Bayes. Naïve Bayes needs the classification column as string type, so I used number to string node to change target column from number to string. Then, I select 80% as training data and 20% as testing data. In class, it says 1/3 of them should be testing data. I will have a try for it then make comparison. I am training the data by Naïve Bayes learner node and predict by predictor. There are 2 nodes that is useful for scoring methods, including classification accuracy, confusion matrix, F-value, and summaries.



### confusion matrix



Accuracy statistics, including data for true positive, false positive, true negative, false negative, accuracy, F-measurement.

#### Scorer View

Confusion Matrix	nfusion Matrix						
Rows Number : 393	0 (Predicted)	1 (Predicted)					
0 (Actual)	174	18	90.63%				
1 (Actual)	45	156	77.61%				
	79.45%	89.66%					

Class Statistics									
Class	True Positives	False Positives	True Negatives	False Negatives	Recall	Precision	Sensitivity	Specificity	F-measure
0	174	45	156	18	90.63%	79.45%	90.63%	77.61%	84.67%
1	156	18	174	45	77.61%	89.66%	77.61%	90.63%	83.20%

Overall Statistics	overall Statistics								
Overall Accuracy	Overall Error	Cohen's kappa (к)	Correctly Classified	Incorrectly Classified					
83.97%	16.03%	0.680	330	63					

A better view for the report, including confusion matrix, F-measure, summary for overall statistics includes accuracy, error, number of correct and incorrect classifications.

File Edit Hilite Navigation View

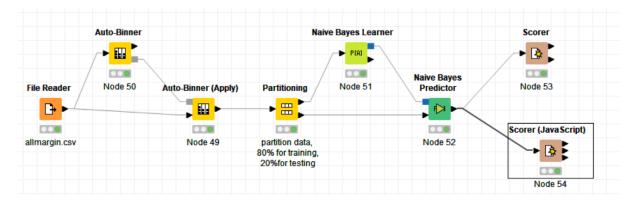
Table "default" - Rows: 1 Spec - Columns: 5 Properties Flow Variables

Row ID D Overall Accuracy D Overall Error D Cohen's kappa I Correctly Classified

Overall 0.84 0.16 0.68 330 63

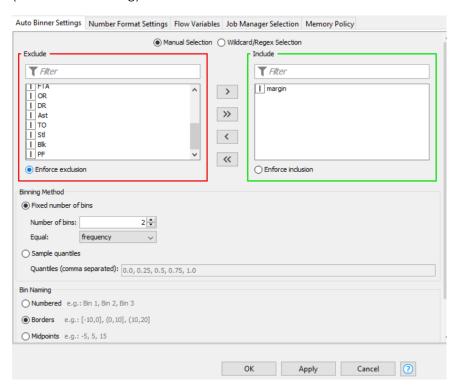
An overall summary for the result.

For the other dataset with numeric result, I am binning the target column into 5 groups, then do the similar thing as above. Here is the workflow:

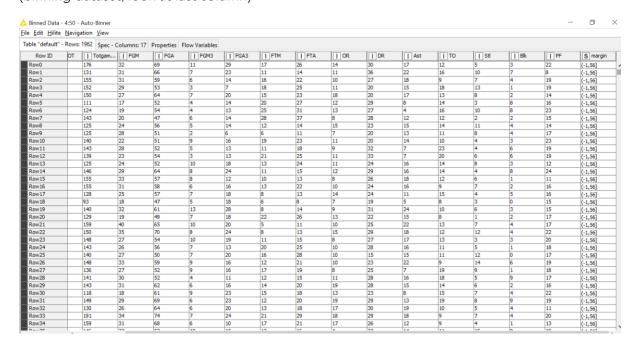


I used auto-binner for binning the target column into 2 bins, since we need to compare with win/loss classifier. Then I set the binning by frequency, naming them by border. Later we can change the naming by win / loss (suppose larger margin group is win, lower is loss). Then apply auto-binner into the dataset.

### (auto binner setting)



# (binning dataset, look at last column)

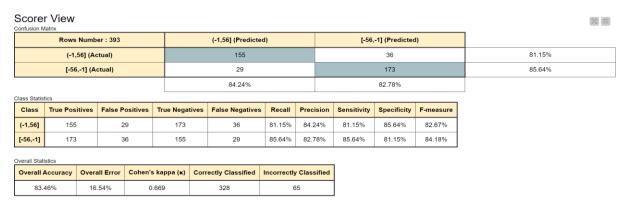


Then, I select 80% as training data and 20% as testing data. I am training the data by Naïve Bayes learner node and predict by predictor. Then I scored them by classification accuracy, confusion matrix, F-value, and summaries. They are the same steps as win/loss.

#### Confusion matrix



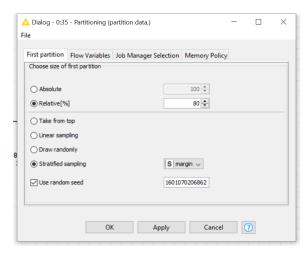
Better view for confusion matrix, class statistics, overall statistics.



# Compare with win/loss:

By the steps above, if I run the same setting of model again, it will give me different result, since I partition data randomly. So, at the step of partition, I need to make sure these two model's data partitions to be the same. (since I am comparing them)

So, for comparison, when partition data, I choose 'Stratified sampling' instead of draw randomly, and use the same random seed, to make sure these two model's data partitions are the same.



Now, other things are equal, but difference with target column, do the following comparison:

Result for margin model (with grouping by width):

# Scorer View

	Confusion Matrix				
	Rows Number : 393	(0,56] (Predicted)	[-56,0] (Predicted)		
(0,56] (Actual)		145	51	73.98%	
	[-56,0] (Actual)	21	176	89.34%	
		87.35%	77.53%		

Class Stati	stics								
Class	True Positives	False Positives	True Negatives	False Negatives	Recall	Precision	Sensitivity	Specificity	F-measure
(0,56]	145	21	176	51	73.98%	87.35%	73.98%	89.34%	80.11%
[-56,0]	176	51	145	21	89.34%	77.53%	89.34%	73.98%	83.02%

Overall Statistics									
Overall Accuracy	Overall Error	rror Cohen's kappa (κ) Correctly Classified Inco		Incorrectly Classified					
81.68%	18.32%	0.633	321	72					

Result for margin model (with grouping by frequency):

# Scorer View

Co	nfusion Matrix			
	Rows Number : 393	(-1,56] (Predicted)	[-56,-1] (Predicted)	
(-1,56] (Actual)		145	51	73.98%
	[-56,-1] (Actual)	21	176	89.34%
		87.35%	77.53%	

Class Statis	tics								
Class	True Positives	False Positives	True Negatives	False Negatives	Recall	Precision	Sensitivity	Specificity	F-measure
(-1,56]	145	21	176	51	73.98%	87.35%	73.98%	89.34%	80.11%
[-56,-1]	176	51	145	21	89.34%	77.53%	89.34%	73.98%	83.02%

Overall Statistics									
Overall Accuracy	Overall Error Cohen's kappa (κ		Correctly Classified	Incorrectly Classified					
81.68%	18.32%	0.633	321	72					

We can see binning is a little bit different, but the result is the same. Also, same result when binning by percentiles (0,0.5,1).

#### Result for win/loss model

Scorer View Confusion Matrix								
Rows Number : 393								
0 (Actual)	176	21	89.34%					
1 (Actual)	51	145	73.98%					
	77.53%	87.35%						
Class Statistics								

Class	True Positives	False Positives	True Negatives	False Negatives	Recall	Precision	Sensitivity	Specificity	F-measure
0	176	51	145	21	89.34%	77.53%	89.34%	73.98%	83.02%
1	145	21	176	51	73.98%	87.35%	73.98%	89.34%	80.11%

Overall Statistics								
Overall Accuracy	Overall Error	Cohen's kappa (κ)	Correctly Classified	Incorrectly Classified				
81.68%	18.32%	0.633	321	72				

So, we can see the prediction is the same, between directly using model by dataset with win/loss or binning continuous target columns into two groups by dataset with margin.

Though from the steps above, they did the same things, but binning continuous target can tell

us more information if we divide it within more groups. For example, we can divide margin into 4 groups, by descending sequence, with win absolutely, just win several points, just loss several points, loss absolutely, according to 4 intervals.

Also, sometimes the accuracy between binning continuous target and categorical variable is different (other things are equal), since this example is evenly distributed, 50% percent of them are loss, 50% of them are win. When it is win, data is above 0. So, in this example, it should be like this (the predictions are the same). In the real life, most datasets are not like this.