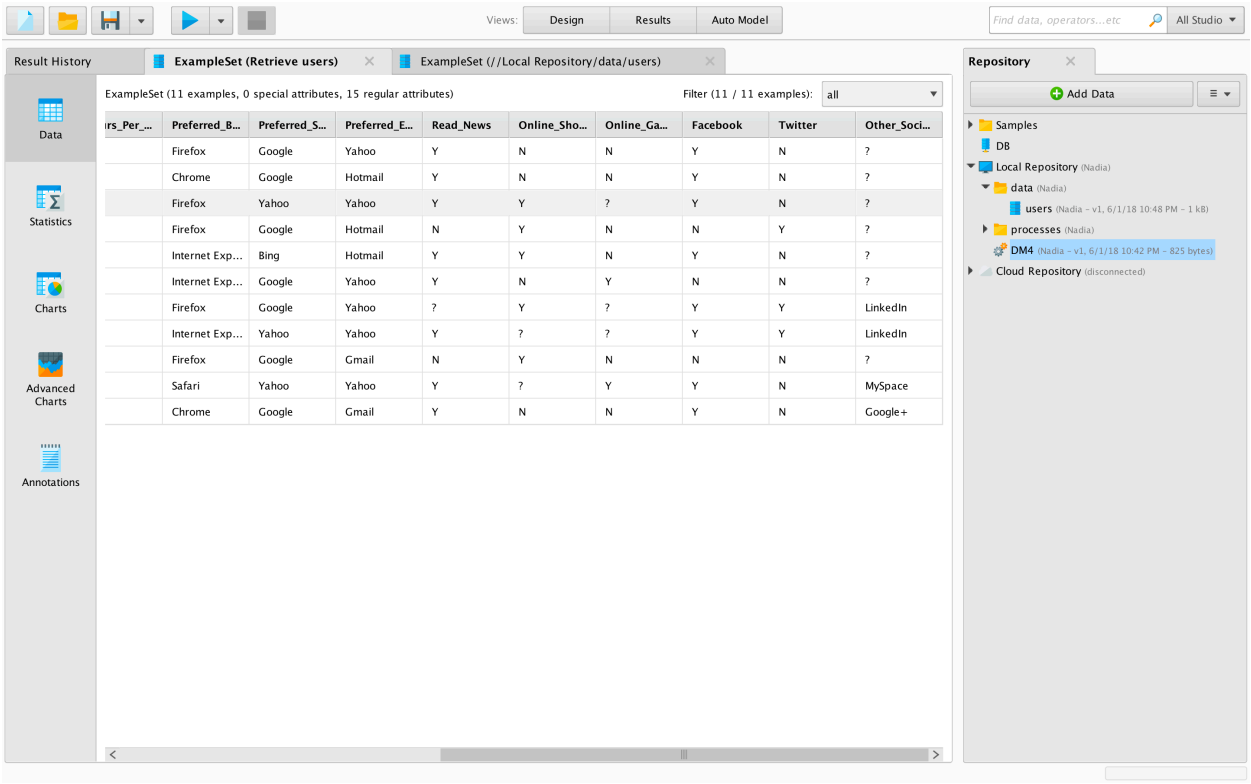
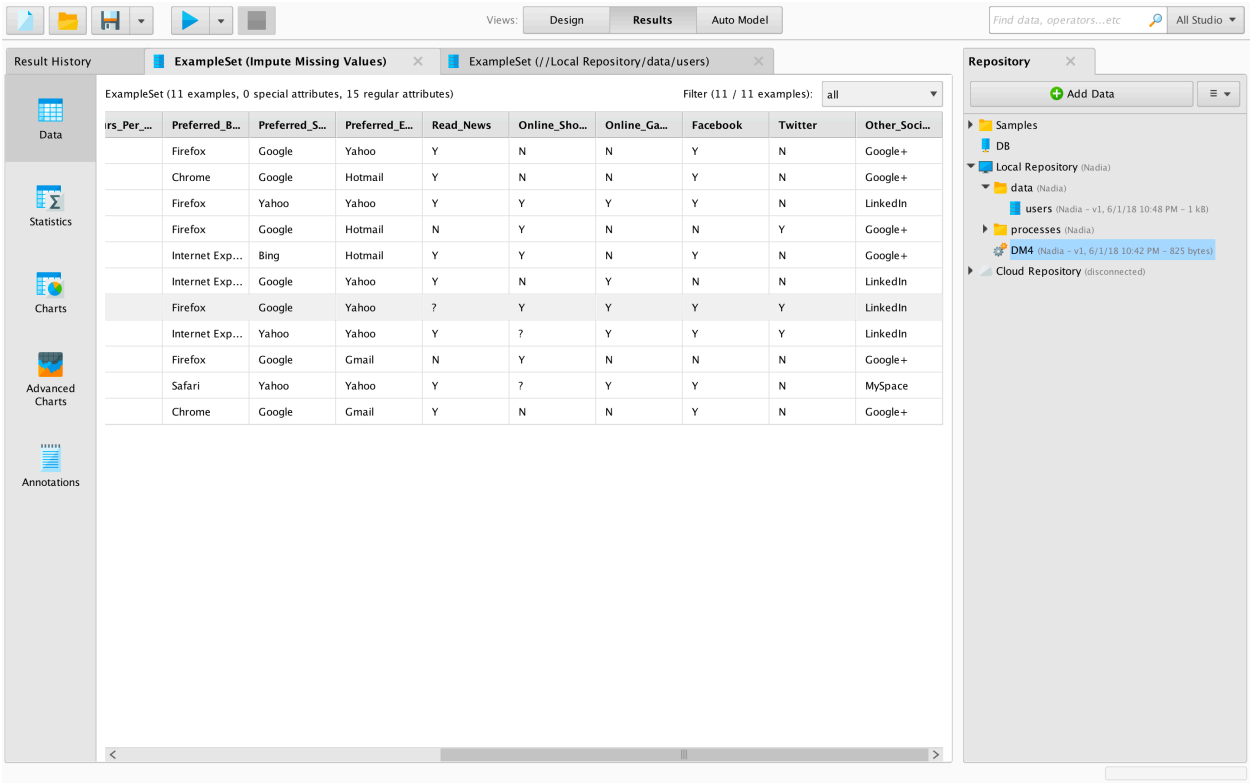
Retrieving users results in :



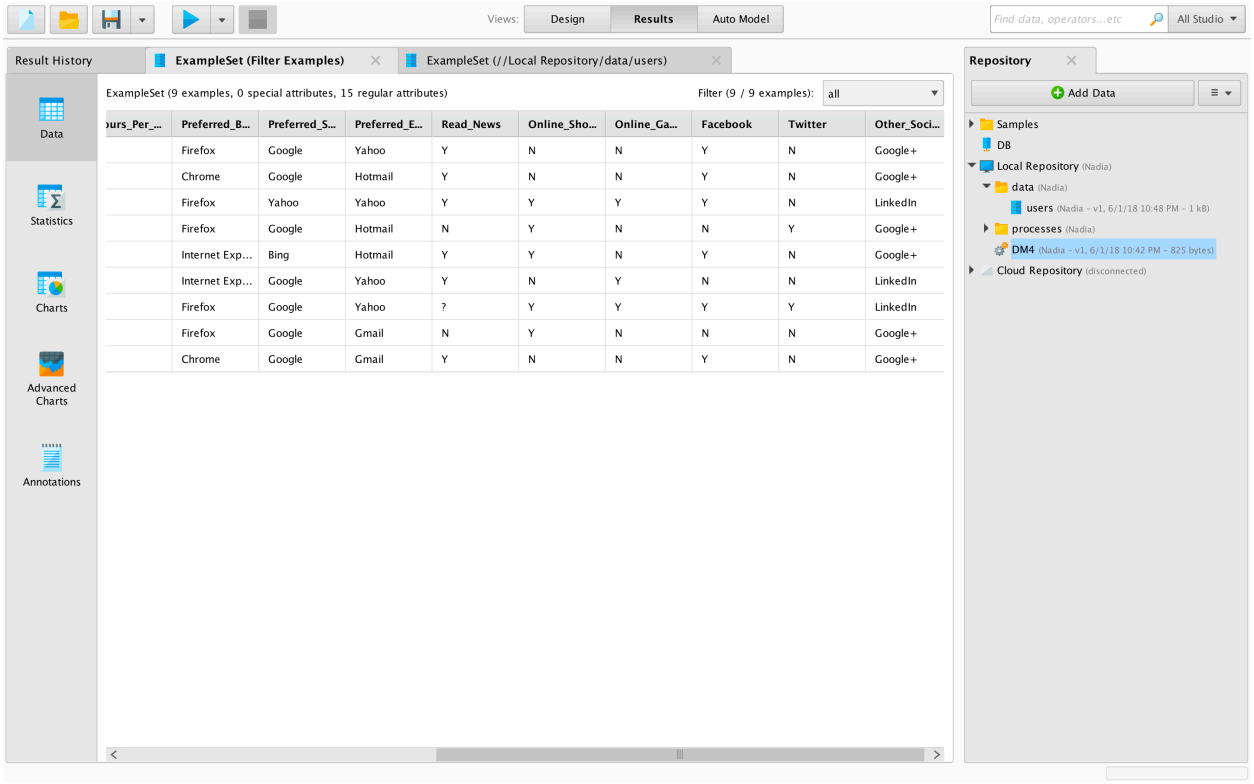
rs_Per_...	Preferred_B...	Preferred_S...	Preferred_E...	Read_News	Online_Sho...	Online_Ga...	Facebook	Twitter	Other_Soci...
	Firefox	Google	Yahoo	Y	N	N	Y	N	?
	Chrome	Google	Hotmail	Y	N	N	Y	N	?
	Firefox	Yahoo	Yahoo	Y	Y	?	Y	N	?
	Firefox	Google	Hotmail	N	Y	N	N	Y	?
	Internet Exp...	Bing	Hotmail	Y	Y	N	Y	N	?
	Internet Exp...	Google	Yahoo	Y	N	Y	N	N	?
	Firefox	Google	Yahoo	?	Y	?	Y	Y	LinkedIn
	Internet Exp...	Yahoo	Yahoo	Y	?	?	Y	Y	LinkedIn
	Firefox	Google	Gmail	N	Y	N	N	N	?
	Safari	Yahoo	Yahoo	Y	?	Y	Y	N	MySpace
	Chrome	Google	Gmail	Y	N	N	Y	N	Google+

we see missing values in online shopping, online Gaming and the social network column.

then missing values in online gaming and social network column would be filled by KNN.

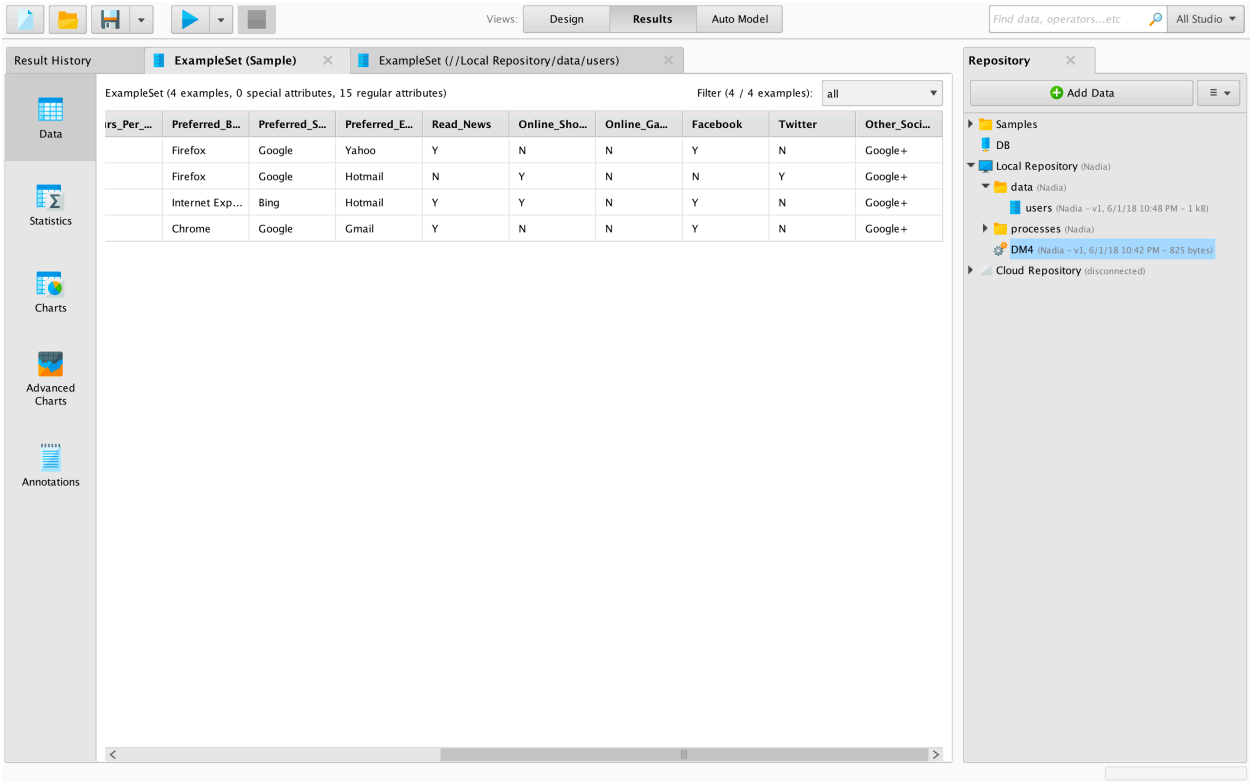


Filtering examples by Online_Shopping=. causes removing missing online shopping rows.



...urs_Per_...	Preferred_B...	Preferred_S...	Preferred_E...	Read_News	Online_Sho...	Online_Ga...	Facebook	Twitter	Other_Soci...
	Firefox	Google	Yahoo	Y	N	N	Y	N	Google+
	Chrome	Google	Hotmail	Y	N	N	Y	N	Google+
	Firefox	Yahoo	Yahoo	Y	Y	Y	Y	N	LinkedIn
	Firefox	Google	Hotmail	N	Y	N	N	Y	Google+
	Internet Exp...	Bing	Hotmail	Y	Y	N	Y	N	Google+
	Internet Exp...	Google	Yahoo	Y	N	Y	N	N	LinkedIn
	Firefox	Google	Yahoo	?	Y	Y	Y	Y	LinkedIn
	Firefox	Google	Gmail	N	Y	N	N	N	Google+
	Chrome	Google	Gmail	Y	N	N	Y	N	Google+

results data for Sampling 50% of data examples using sample operator in relative mode and sample ratio =0.5 are shown below :

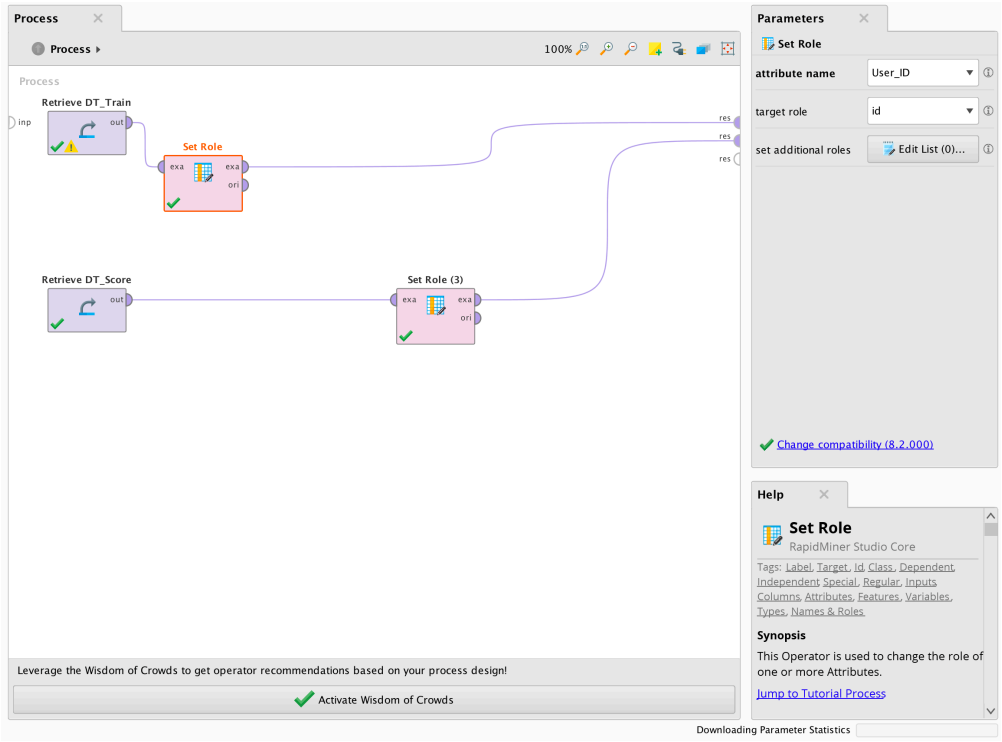


rs_Per_...	Preferred_B...	Preferred_S...	Preferred_E...	Read_News	Online_Sho...	Online_Ga...	Facebook	Twitter	Other_Soci...
	Firefox	Google	Yahoo	Y	N	N	Y	N	Google+
	Firefox	Google	Hotmail	N	Y	N	N	Y	Google+
	Internet Exp...	Bing	Hotmail	Y	Y	N	Y	N	Google+
	Chrome	Google	Gmail	Y	N	N	Y	N	Google+

we had 9 items before and 50% sampling results in choose 4 of them.

Decision tree

adding set_Role to both DT_Train and DT_Test results in:



the user_ID column has shown as a special attribute in blue color. set_Role identifies user_ID as ID so decision tree doesn't determine this column.

Views: Design Results Auto Model

ExampleSet (Set Role (3)) ExampleSet (Set Role)

ExampleSet (661 examples, 1 special attribute, 10 regular attributes) Filter (661 / 661 examples): all

Row No.	User_ID	Gender	Age	Marital_Sta...	Website_Ac...	Browsed_El...	Bought_Ele...	Bought_Di...
1	9552	M	61	M	Seldom	Yes	Yes	Yes
2	6757	M	27	M	Regular	Yes	No	Yes
3	3599	F	29	M	Seldom	Yes	Yes	Yes
4	6811	M	49	M	Seldom	Yes	Yes	Yes
5	4104	M	29	S	Seldom	Yes	Yes	Yes
6	7226	M	60	S	Seldom	No	Yes	Yes
7	7814	F	53	S	Regular	Yes	No	Yes
8	4693	F	63	S	Seldom	Yes	Yes	Yes
9	7266	M	46	M	Regular	Yes	Yes	Yes
10	5259	F	25	S	Seldom	Yes	Yes	Yes
11	7417	F	40	M	Regular	Yes	Yes	No
12	6795	M	29	S	Seldom	Yes	Yes	Yes
13	8669	F	49	S	Seldom	Yes	Yes	Yes
14	9888	M	41	M	Regular	Yes	Yes	Yes

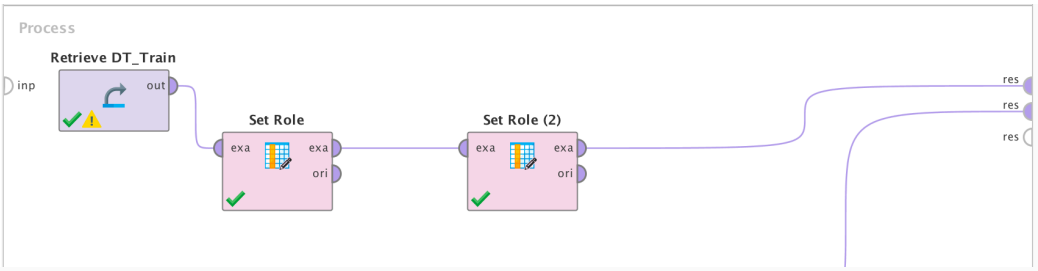
Views: Design Results Auto Model

ExampleSet (Set Role (3)) ExampleSet (Set Role)

ExampleSet (473 examples, 1 special attribute, 9 regular attributes) Filter (473 / 473 examples): all

Row No.	User_ID	Gender	Age	Marital_Sta...	Website_Ac...	Browsed_El...	Bought_Ele...	Bought_Di...
1	56031	M	57	S	Regular	Yes	Yes	Yes
2	25913	F	51	M	Regular	Yes	Yes	No
3	19396	M	41	M	Seldom	Yes	Yes	Yes
4	93666	M	66	S	Regular	Yes	Yes	Yes
5	72282	F	31	S	Seldom	Yes	No	Yes
6	64466	M	68	M	Regular	Yes	Yes	Yes
7	76655	F	51	S	Seldom	Yes	No	No
8	48465	F	36	S	Frequent	Yes	No	Yes
9	19889	M	29	M	Regular	Yes	Yes	Yes
10	63570	M	61	M	Frequent	Yes	No	Yes
11	63239	M	47	S	Regular	Yes	No	Yes
12	67603	F	62	S	Regular	Yes	Yes	Yes
13	65685	M	32	M	Regular	Yes	No	Yes
14	77373	M	17	M	Seldom	Yes	No	Yes

then we add another set_Role to identify eReader_Adoption as label so we can then classify data by decision tree.

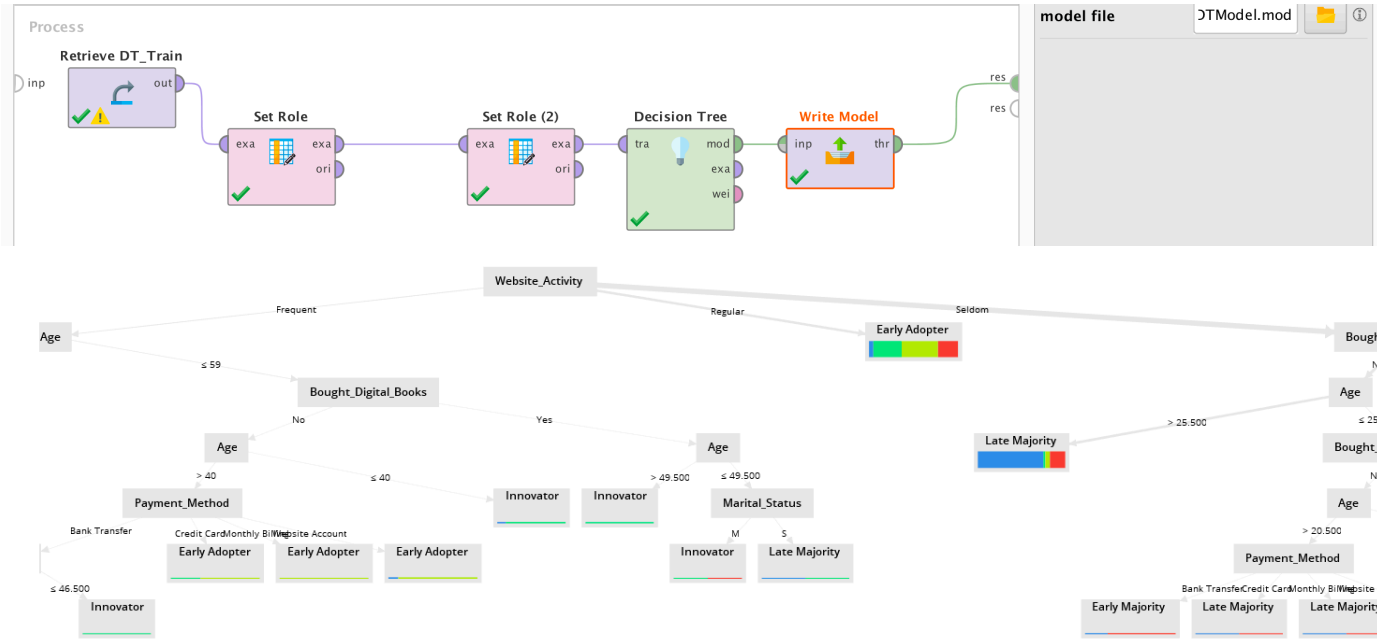


ExampleSet (Set Role (3)) | ExampleSet (Set Role (2))

ExampleSet (661 examples, 2 special attributes, 9 regular attributes) Filter (661 / 661 examples): all

Row No.	User_ID	eReader_A...	Gender	Age	Marital_Sta...	Website_Ac...	Browsed_El...	Bought_Ele...
1	9552	Late Majority	M	61	M	Seldom	Yes	Yes
2	6757	Innovator	M	27	M	Regular	Yes	No
3	3599	Early Adopter	F	29	M	Seldom	Yes	Yes
4	6811	Early Adopter	M	49	M	Seldom	Yes	Yes
5	4104	Late Majority	M	29	S	Seldom	Yes	Yes
6	7226	Early Majority	M	60	S	Seldom	No	Yes
7	7814	Early Adopter	F	53	S	Regular	Yes	No
8	4693	Late Majority	F	63	S	Seldom	Yes	Yes
9	7266	Innovator	M	46	M	Regular	Yes	Yes
10	5259	Early Majority	F	25	S	Seldom	Yes	Yes
11	7417	Innovator	F	40	M	Regular	Yes	Yes
12	6795	Early Adopter	M	29	S	Seldom	Yes	Yes
13	8669	Late Majority	F	49	S	Seldom	Yes	Yes
14	9888	Innovator	M	41	M	Regular	Yes	Yes
15	9181	Innovator	F	47	S	Regular	Yes	No
16	2792	Late Majority	F	43	M	Seldom	Yes	Yes
17	5174	Early Adopter	M	63	M	Seldom	Yes	Yes
18	8702	Early Adopter	F	37	M	Regular	No	Yes
19	4318	Early Majority	M	32	S	Seldom	Yes	Yes
20	6091	Late Majority	M	48	M	Seldom	No	No
21	8380	Early Adopter	F	57	M	Seldom	Yes	No
22	6892	Early Majority	M	36	M	Seldom	Yes	Yes
23	7976	Late Majority	F	55	S	Seldom	Yes	No

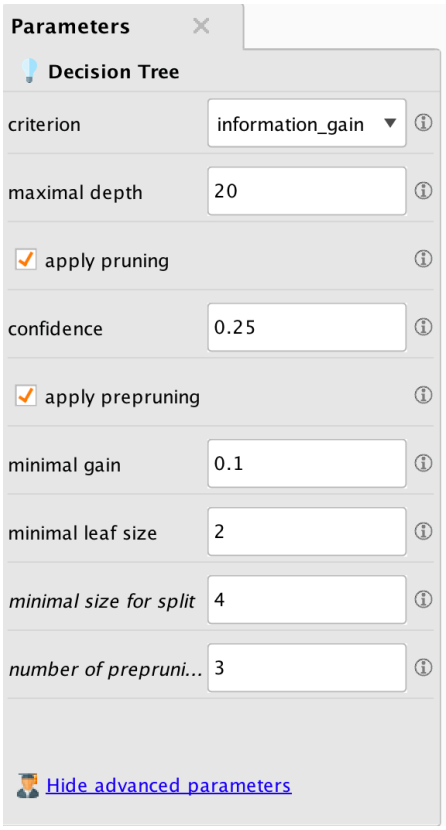
next step we should train a model using Decision tree and save it. Results shown below.



Tree

```
Website_Activity = Frequent
|   Age > 59
|   |   Age > 63.500: Innovator {Late Majority=1, Innovator=2, Early Adopter=0, Early Majority=0}
|   |   Age ≤ 63.500
|   |   |   Browsed_Electronics_12Mo = No: Early Majority {Late Majority=0, Innovator=1, Early Adopter=0, Early Maj
|   |   |   Browsed_Electronics_12Mo = Yes
|   |   |   |   Bought_Electronics_12Mo = No
|   |   |   |   |   Gender = F
|   |   |   |   |   |   Age > 61.500: Early Majority {Late Majority=0, Innovator=0, Early Adopter=0, Early Majority=
|   |   |   |   |   |   Age ≤ 61.500: Early Adopter {Late Majority=0, Innovator=0, Early Adopter=2, Early Majority=
|   |   |   |   |   Gender = M: Early Majority {Late Majority=0, Innovator=0, Early Adopter=0, Early Majority=2}
|   |   |   |   Bought_Electronics_12Mo = Yes: Early Adopter {Late Majority=0, Innovator=0, Early Adopter=2, Early
|   Age ≤ 59
|   |   Bought_Digital_Books = No
|   |   |   Age > 40
|   |   |   |   Payment_Method = Bank Transfer
|   |   |   |   |   Age > 46.500
|   |   |   |   |   |   Gender = F: Early Adopter {Late Majority=0, Innovator=0, Early Adopter=2, Early Majority=0}
|   |   |   |   |   |   Gender = M: Innovator {Late Majority=0, Innovator=2, Early Adopter=1, Early Majority=0}
|   |   |   |   |   Age ≤ 46.500: Innovator {Late Majority=0, Innovator=2, Early Adopter=0, Early Majority=0}
|   |   |   |   Payment_Method = Credit Card: Early Adopter {Late Majority=0, Innovator=1, Early Adopter=2, Early Ma
|   |   |   |   Payment_Method = Monthly Billing: Early Adopter {Late Majority=0, Innovator=0, Early Adopter=2, Ear
|   |   |   |   Payment_Method = Website Account: Early Adopter {Late Majority=1, Innovator=0, Early Adopter=8, Ear
|   |   |   Age ≤ 40: Innovator {Late Majority=1, Innovator=7, Early Adopter=0, Early Majority=0}
|   |   Bought_Digital_Books = Yes
|   |   |   Age > 49.500: Innovator {Late Majority=0, Innovator=6, Early Adopter=0, Early Majority=0}
|   |   |   Age ≤ 49.500
|   |   |   |   Marital_Status = M: Innovator {Late Majority=0, Innovator=1, Early Adopter=0, Early Majority=1}
|   |   |   |   Marital_Status = S: Late Majority {Late Majority=1, Innovator=1, Early Adopter=0, Early Majority=0}
Website_Activity = Regular: Early Adopter {Late Majority=9, Innovator=58, Early Adopter=75, Early Majority=41}
Website_Activity = Seldom
|   Bought_Digital_Books = No
|   |   Age > 25.500: Late Majority {Late Majority=142, Innovator=4, Early Adopter=10, Early Majority=33}
|   |   Age ≤ 25.500
|   |   |   Bought_Electronics_12Mo = No
|   |   |   |   Age > 20.500
|   |   |   |   |   Payment_Method = Bank Transfer: Early Majority {Late Majority=1, Innovator=0, Early Adopter=0,
|   |   |   |   |   Payment_Method = Credit Card: Late Majority {Late Majority=1, Innovator=0, Early Adopter=0, Ear
```

decision tree has several parameters such as max-depth, minimum_leaf_size, ...



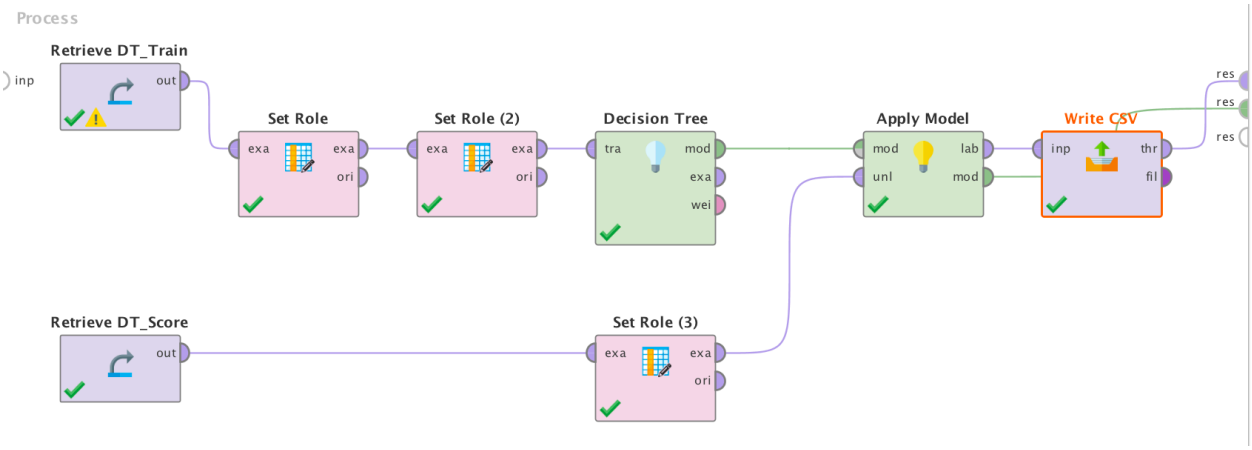
criterion is the method which decision tree decides about nodes arrangement based on it. we can try different methods like information_gain, gain_ratio, ...

maximal depth is used to restrict the depth of the decision tree.

apply pruning: The decision tree model can be pruned after generation. If checked, some branches are replaced by leaves according to the confidence parameter

confidence: This parameter specifies the confidence level used for the pessimistic error calculation of pruning.

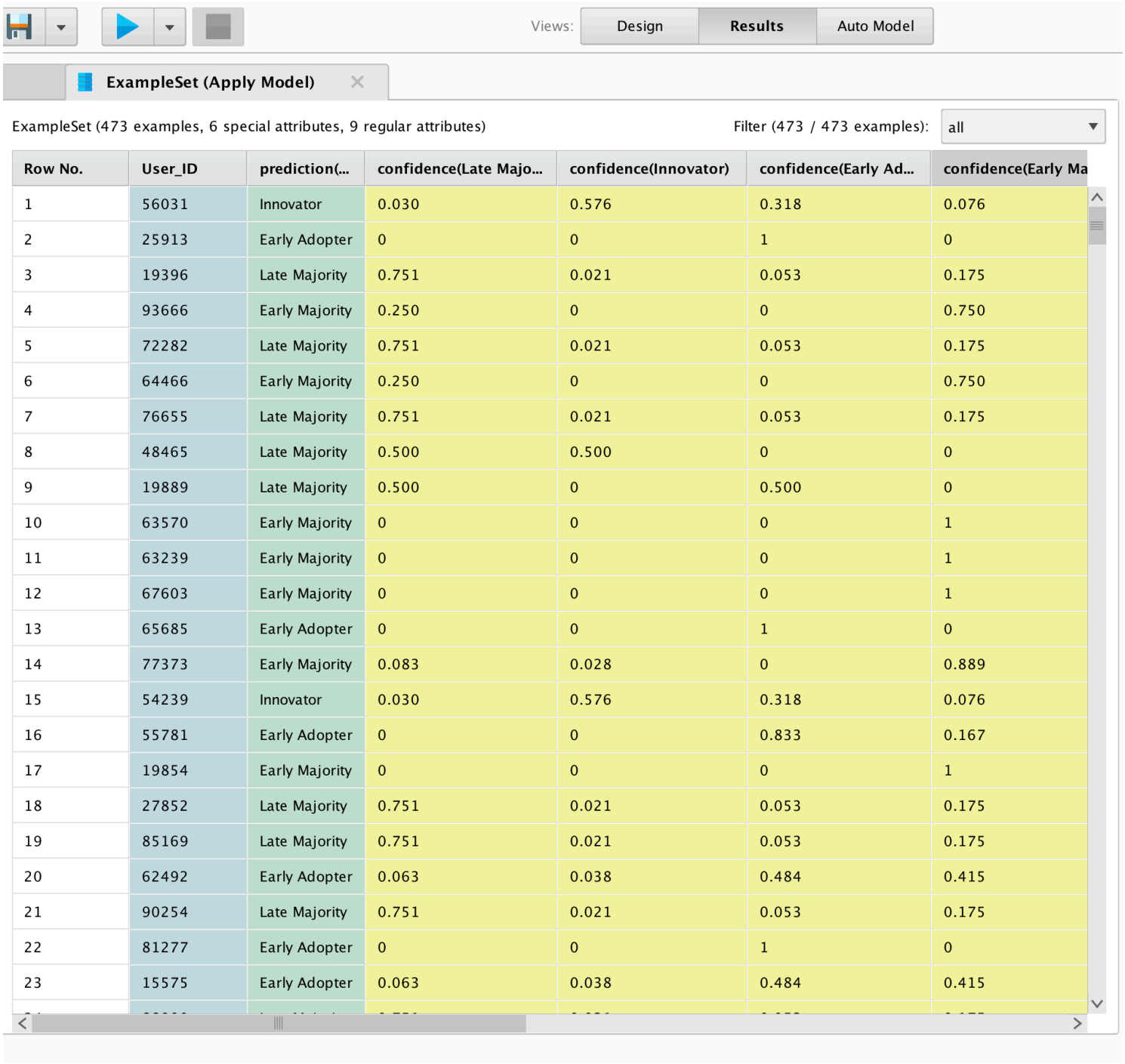
then by using apply_model operation eReader_Adoption is predicted for test samples.



it calculates confidence for each attribute and then predicts eReader_Adoption with attribute which has the most confidence. for example confidence of early majority in 10th row is 1 while other values are zero so we could be sure eReader_Adoption is early_majority there.

Row No.	User_ID	prediction(...	confidence(Late Maj...	confidence(Innovat...	confidence(Early Ad...	confidence(Early Majori
1	56031	Early Adopter	0.049	0.317	0.410	0.224
2	25913	Early Adopter	0.049	0.317	0.410	0.224
3	19396	Late Majority	0.751	0.021	0.053	0.175
4	93666	Early Adopter	0.049	0.317	0.410	0.224
5	72282	Late Majority	0.751	0.021	0.053	0.175
6	64466	Early Adopter	0.049	0.317	0.410	0.224
7	76655	Late Majority	0.751	0.021	0.053	0.175
8	48465	Innovator	0.125	0.875	0	0
9	19889	Early Adopter	0.049	0.317	0.410	0.224
10	63570	Early Majority	0	0	0	1
11	63239	Early Adopter	0.049	0.317	0.410	0.224
12	67603	Early Adopter	0.049	0.317	0.410	0.224
13	65685	Early Adopter	0.049	0.317	0.410	0.224
14	77373	Early Majority	0	0	0	1
15	54239	Early Adopter	0.049	0.317	0.410	0.224
16	55781	Early Adopter	0.049	0.317	0.410	0.224
17	19854	Early Adopter	0.049	0.317	0.410	0.224
18	27852	Late Majority	0.751	0.021	0.053	0.175
19	85169	Late Majority	0.751	0.021	0.053	0.175
20	62492	Early Adopter	0.070	0.060	0.508	0.362

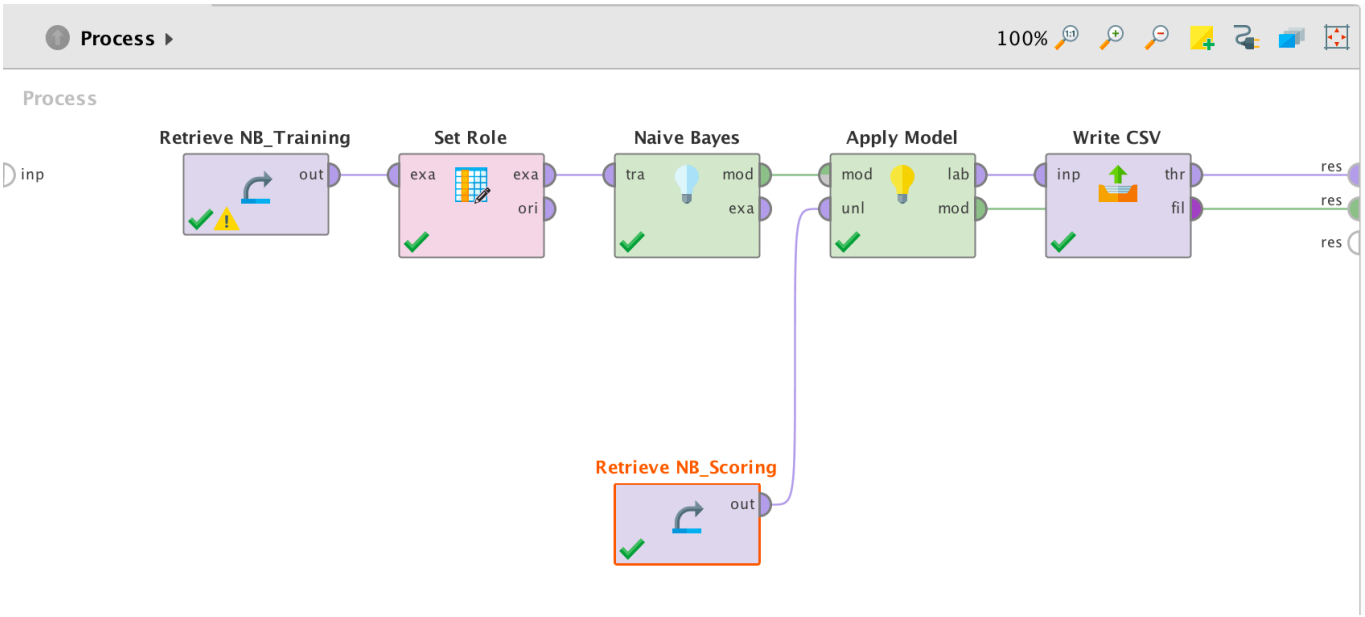
if we choose gain_ratio for criterion it will separate classes better so we'll get better results as we see in the following :



Row No.	User_ID	prediction(...	confidence(Late Majo...	confidence(Innovator)	confidence(Early Ad...	confidence(Early Ma
1	56031	Innovator	0.030	0.576	0.318	0.076
2	25913	Early Adopter	0	0	1	0
3	19396	Late Majority	0.751	0.021	0.053	0.175
4	93666	Early Majority	0.250	0	0	0.750
5	72282	Late Majority	0.751	0.021	0.053	0.175
6	64466	Early Majority	0.250	0	0	0.750
7	76655	Late Majority	0.751	0.021	0.053	0.175
8	48465	Late Majority	0.500	0.500	0	0
9	19889	Late Majority	0.500	0	0.500	0
10	63570	Early Majority	0	0	0	1
11	63239	Early Majority	0	0	0	1
12	67603	Early Majority	0	0	0	1
13	65685	Early Adopter	0	0	1	0
14	77373	Early Majority	0.083	0.028	0	0.889
15	54239	Innovator	0.030	0.576	0.318	0.076
16	55781	Early Adopter	0	0	0.833	0.167
17	19854	Early Majority	0	0	0	1
18	27852	Late Majority	0.751	0.021	0.053	0.175
19	85169	Late Majority	0.751	0.021	0.053	0.175
20	62492	Early Adopter	0.063	0.038	0.484	0.415
21	90254	Late Majority	0.751	0.021	0.053	0.175
22	81277	Early Adopter	0	0	1	0
23	15575	Early Adopter	0.063	0.038	0.484	0.415

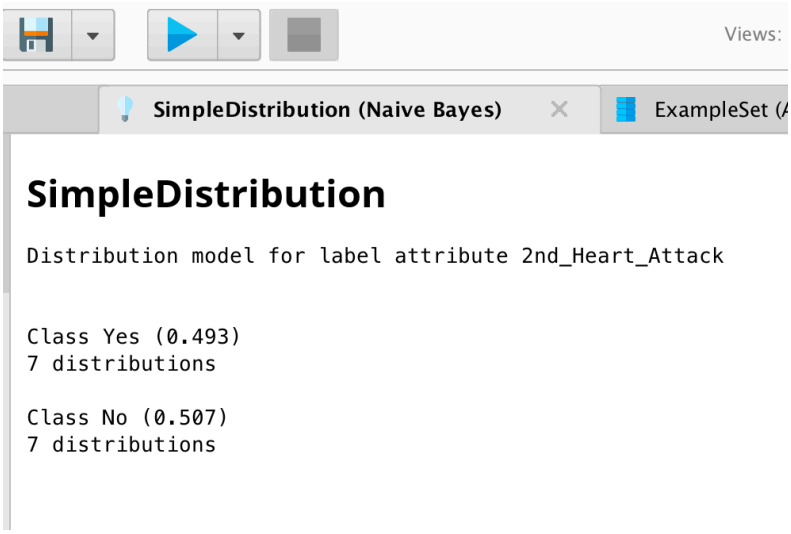
Naive Bayes

we applied this process to NB dataset :



set Role determines 2nd_Heart_Attack as label and it will predicted for NB_Scoring dataset.

predicted results by NaiveBayes are shown below:

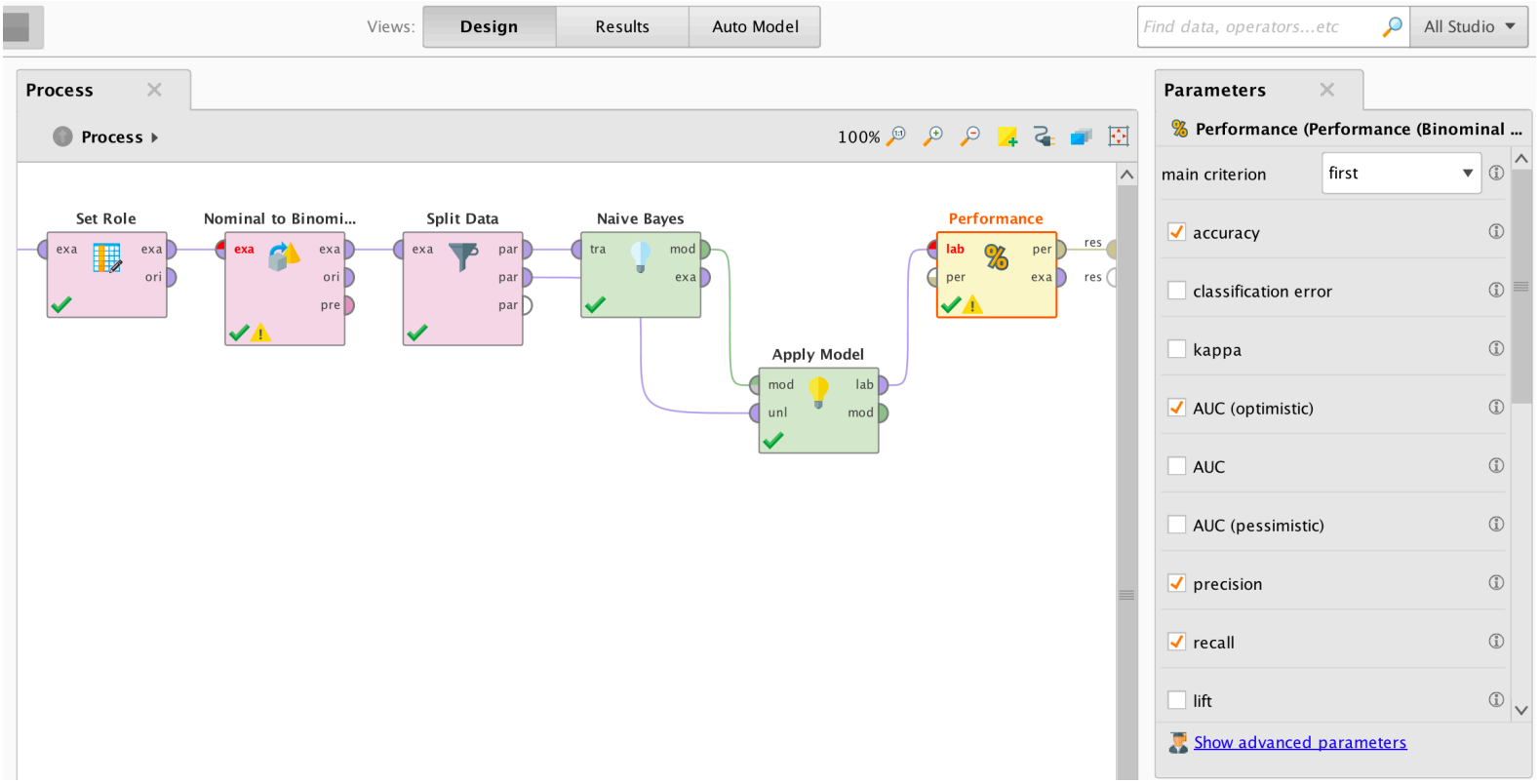


SimpleDistribution (Naive Bayes) | ExampleSet (Apply Model)

ExampleSet (690 examples, 3 special attributes, 7 regular attributes) Filter (690 / 690 examples): all

Row No.	prediction(...	confidence(Yes)	confidence(No)	Age	Marital_Sta...	Gender	Weight_Cat...	Cholester
1	No	0.000	1.000	61	0	1	1	139
2	Yes	0.963	0.037	55	2	1	2	163
3	No	0.163	0.837	53	1	1	1	172
4	Yes	0.999	0.001	58	1	1	2	206
5	No	0.139	0.861	62	2	1	1	148
6	No	0.020	0.980	70	1	0	0	172
7	No	0.000	1.000	52	1	0	0	171
8	No	0.109	0.891	50	1	1	1	172
9	Yes	0.954	0.046	67	2	1	1	172
10	No	0.040	0.960	62	1	1	1	166
11	Yes	1.000	0.000	66	2	1	2	220
12	No	0.007	0.993	56	2	1	0	141
13	Yes	1.000	0.000	77	2	1	2	181
14	Yes	0.931	0.069	64	2	1	1	174

we can use performance operator for classification results analysis. I have implemented it for the naive bayes algorithm on NB_training dataset. we should split it to train and test to measure accuracy of it so I used Split Data operator too.

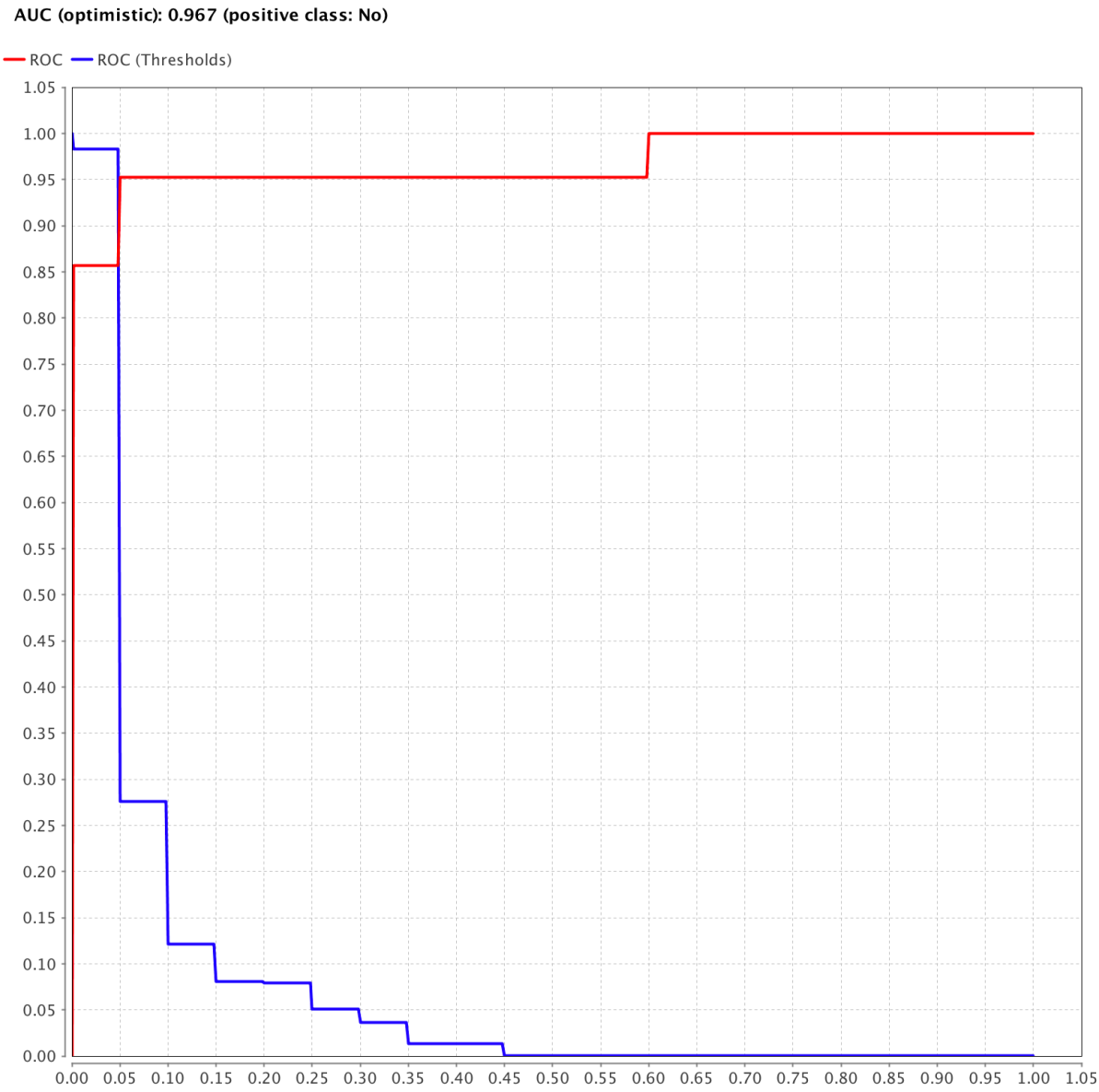


Results shown below :

accuracy: 92.68%

	true Yes	true No	class precision
pred. Yes	19	2	90.48%
pred. No	1	19	95.00%
class recall	95.00%	90.48%	

we can measure AUC too. It has been reported 0.967 :



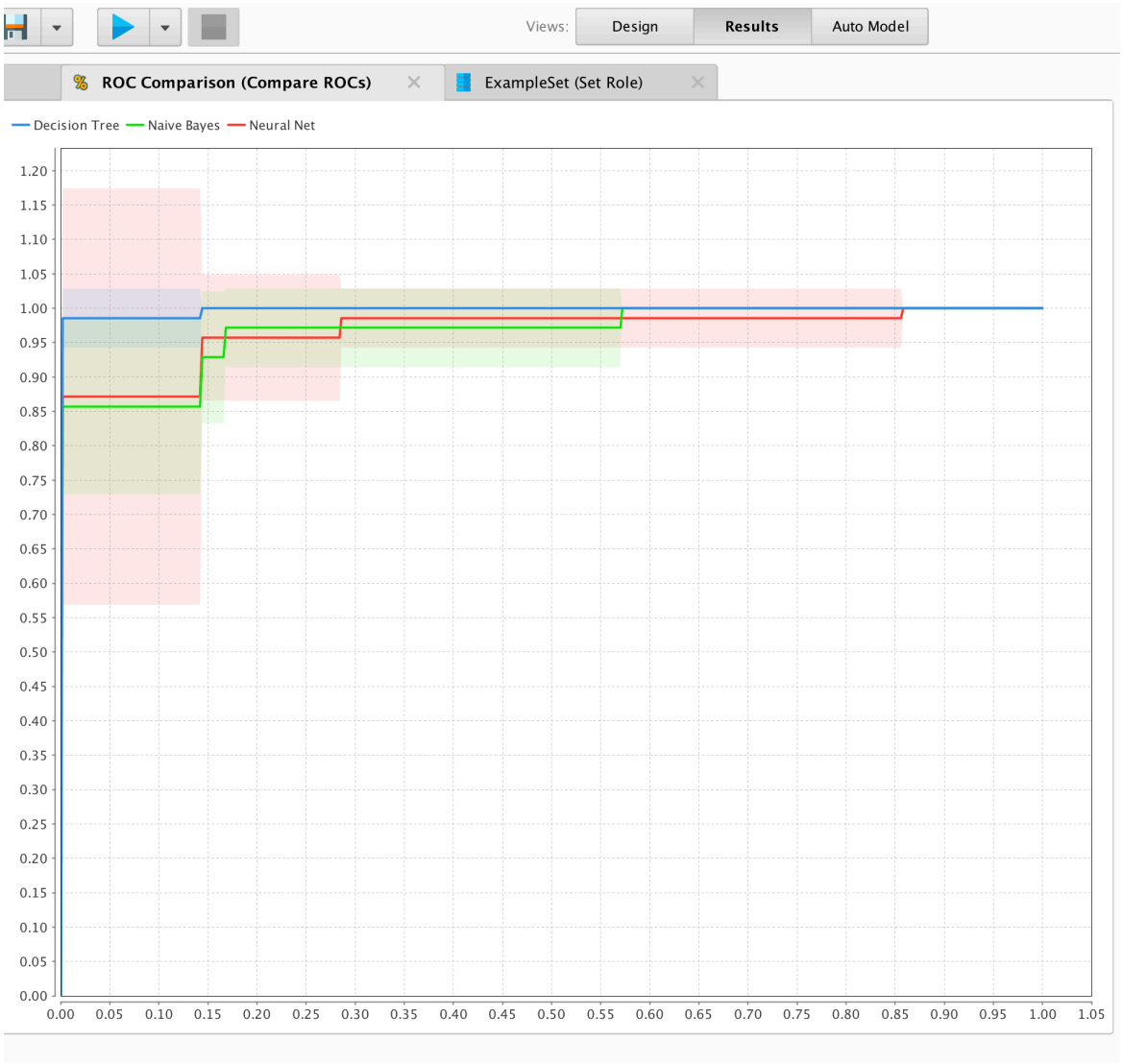
then I replaced naive bayes with decision tree and the accuracy is 95.12 which is more than Naive bayes accuracy (92.68):

accuracy: 95.12%

	true Yes	true No	class precision
pred. Yes	19	1	95.00%
pred. No	1	20	95.24%
class recall	95.00%	95.24%	

ROC

An ROC curve plots sensitivity or TPR(True Positive Rate) vs. FPR(False Positive Rate) at different classification thresholds. For a perfect classifier the ROC curve will go straight up the Y axis and then along the X axis. A classifier with no power will sit on the diagonal, whilst most classifiers fall somewhere in between.



we see that Decision Tree is better for this problem.

the Confidence column in Naive Bayes shows how sure predicted value is true. for example 0.9 for true shows that it's 90 percent true positive. The ROC curve plots TPR vs FPR at different confidences so

AUC measures the entire two-dimensional area underneath the entire ROC curve. One way of interpreting AUC is as the probability that the model ranks a random positive example more highly than a random negative example. more AUC represents a better classification method. for example in upper image Decision Tree has more AUC so it's a better method for classification.

Compare ROC operator has many parameters like number of folds, split ratio, sampling Type, ... it uses k-fold cross validation and we can adjust k by number of folds parameter.
Several types of sampling can be used for building the subsets. for example Linear sampling simply divides the ExampleSet into partitions without changing the order of the examples but Shuffled sampling builds random subsets of the ExampleSet. in this problem shuffle sampling result is better.