GROUP RED

TRAINING, TESTING & VALIDATION OF A PREDICTIVE MODEL

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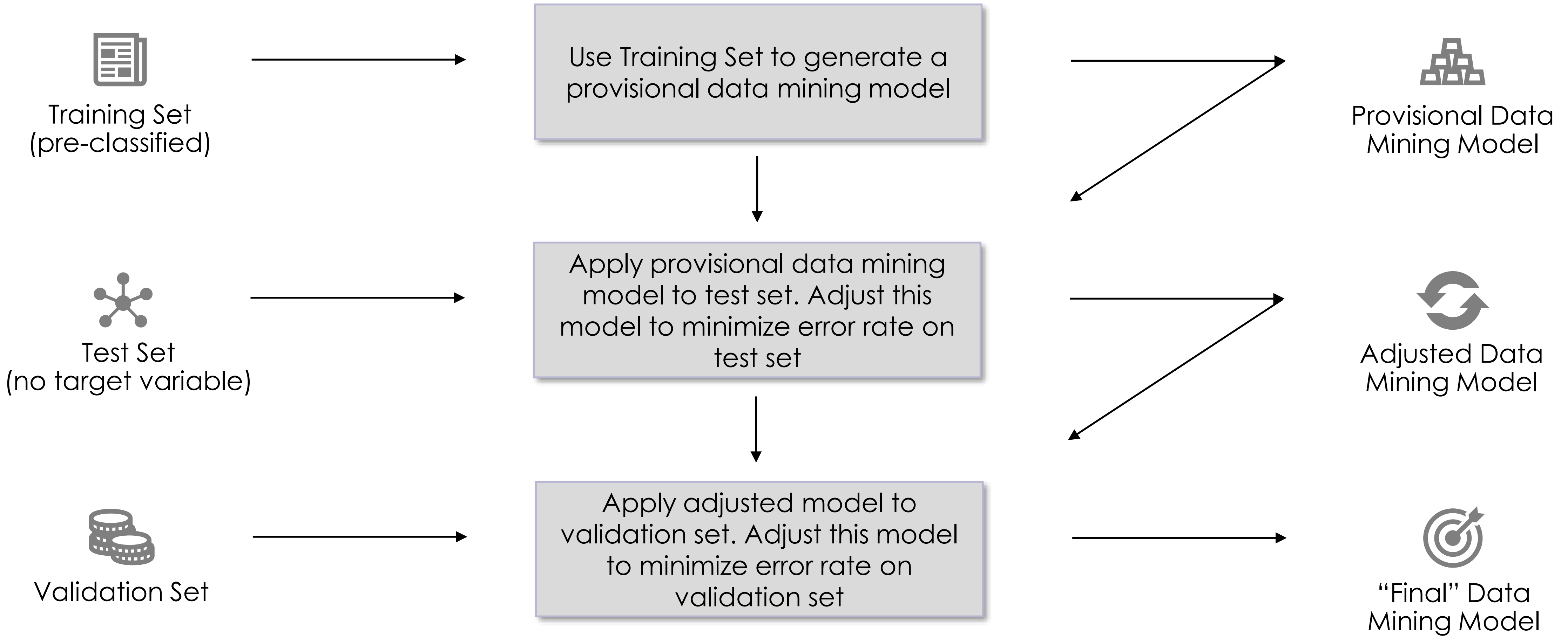
GOAL

To choose a predictive model that can score records as True or False with at least 95% accuracy



DECISION TREE

A popular supervised classification method used in data mining

A decision tree is a collection of decision nodes, connected by branches, extending downward from **root** node to terminating **leaf** nodes

Begins with a root node, attributes are tested at decision nodes, and each possible outcome results in a branch; each branch leads to a decision node or a leaf node

Decision trees learn by ***example***, hence the training set contains records with varied attribute values

Tool used for building the decision tree model: **RapidMiner Studio**

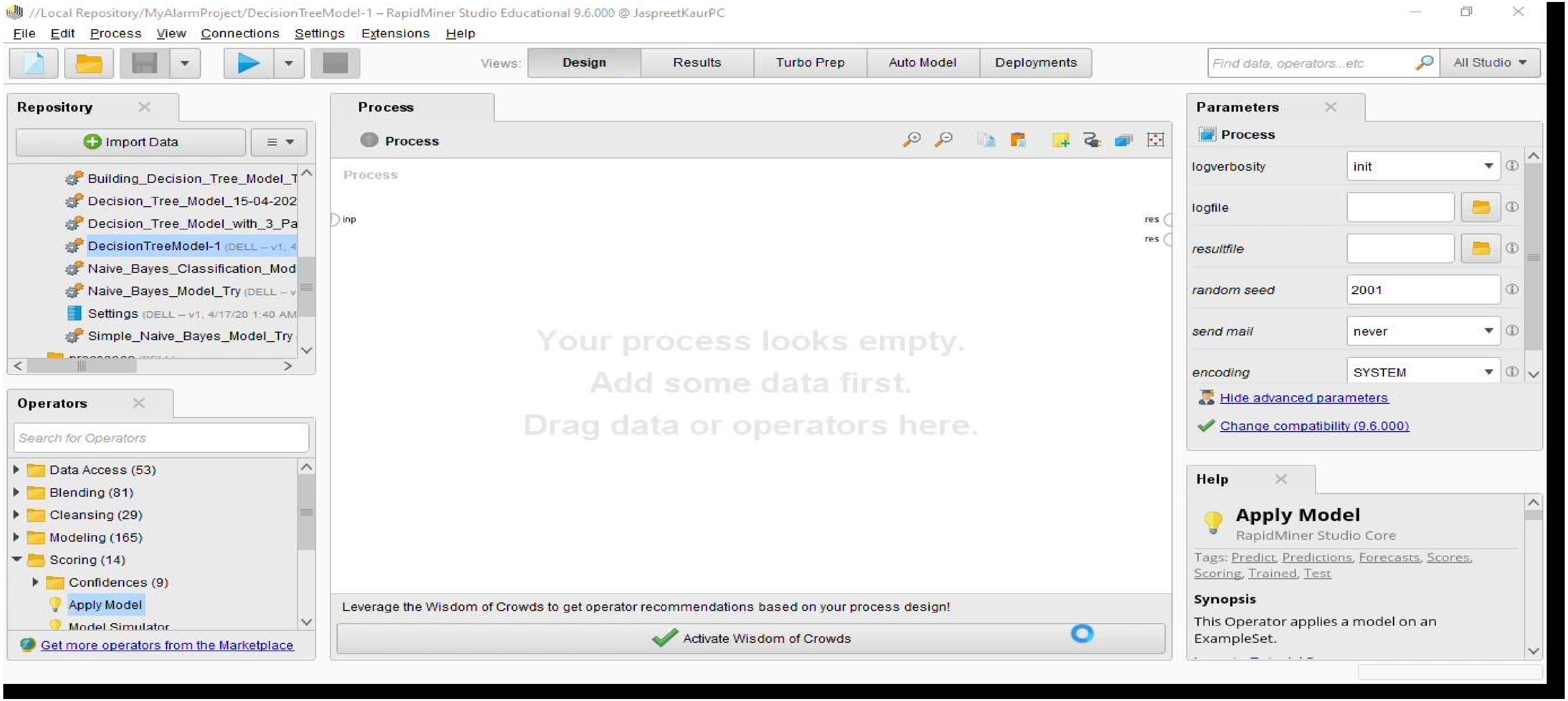
RapidMiner is a very effective data science software platform that unites data prep, machine learning & predictive model deployment

Recommendation in EDA Phase:

….

Looks like it is extremely fast to build and learn and seems to provide an accuracy of 96.8%

DECISION TREE - USING THE TRAINING SET



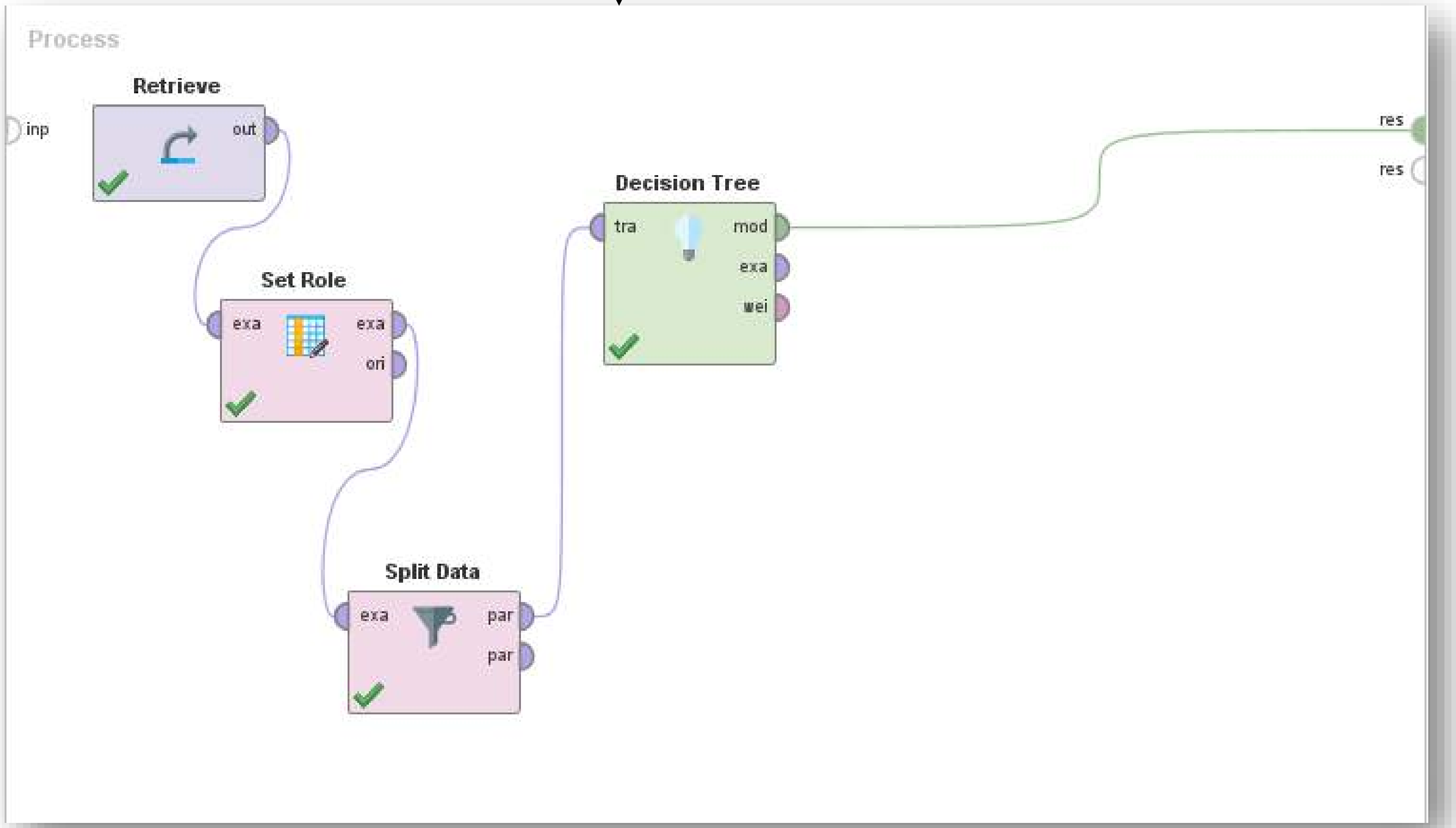
DECISION TREE - USING THE TRAINING SET

Process Editor

The first step is to retrieve the data i.e. Alarm file

'Set Role' operator is used to tell RapidMiner which is our target variable (Alarm)

To partition the data set, we use 'Split Data' operator



Dataset is split into 3 sets: Training, Test & Validation datasets (1/3rd each)

Now, we use 'Decision Tree' operator to build the provisional model

We connect the inputs with their relevant outputs and run the process

DECISION TREE MODEL

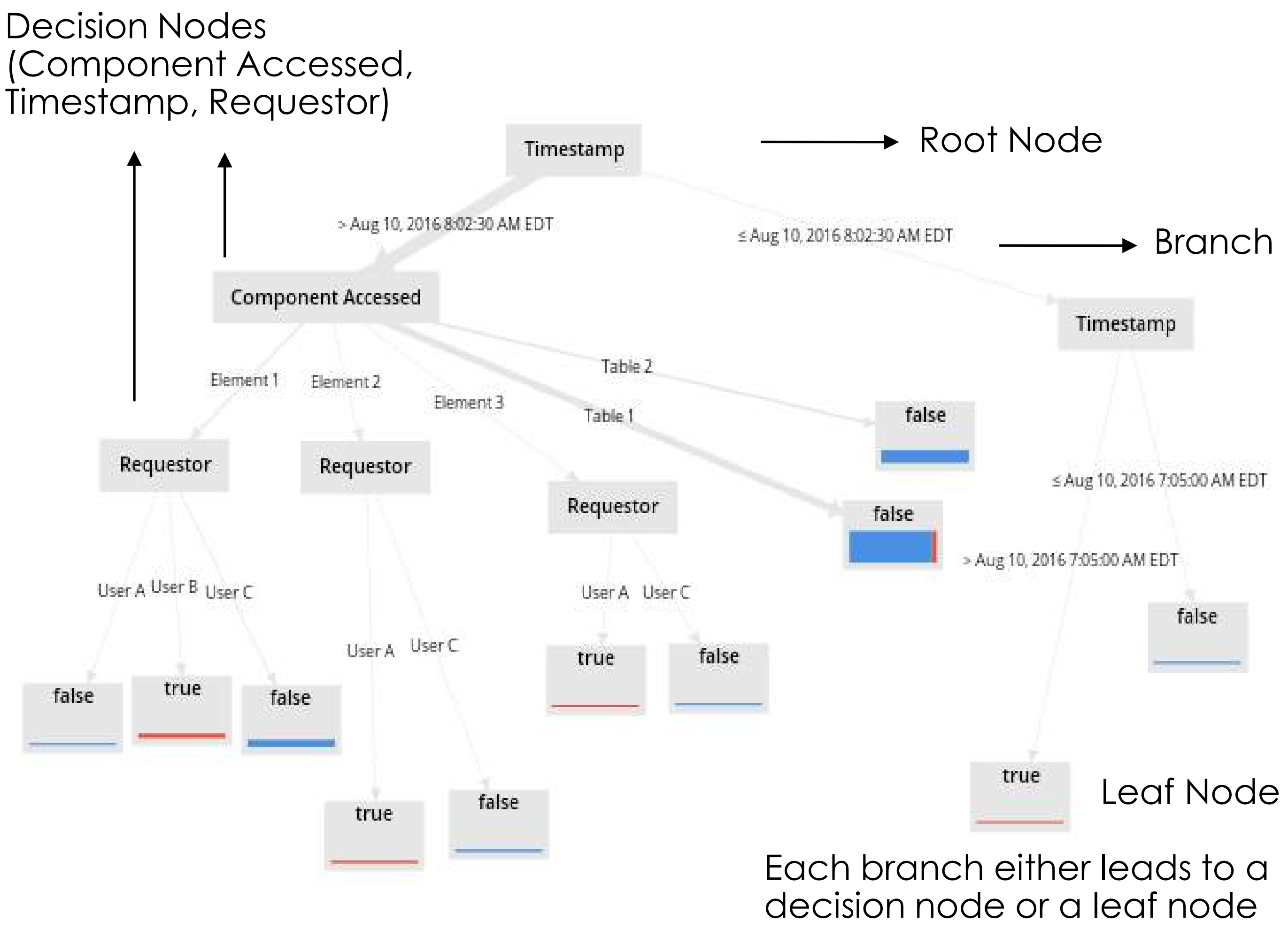


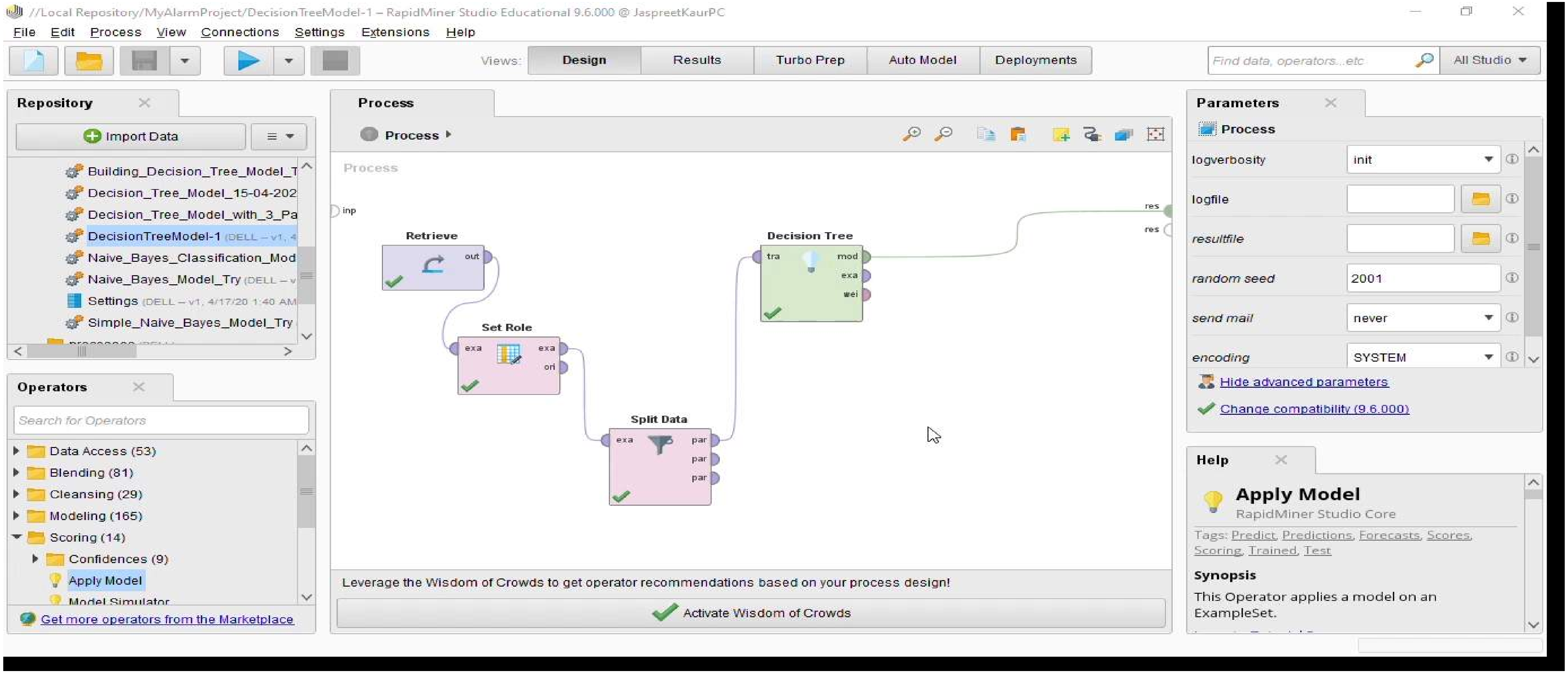
Figure 1.1 Decision Tree Model (provisional)

Tree

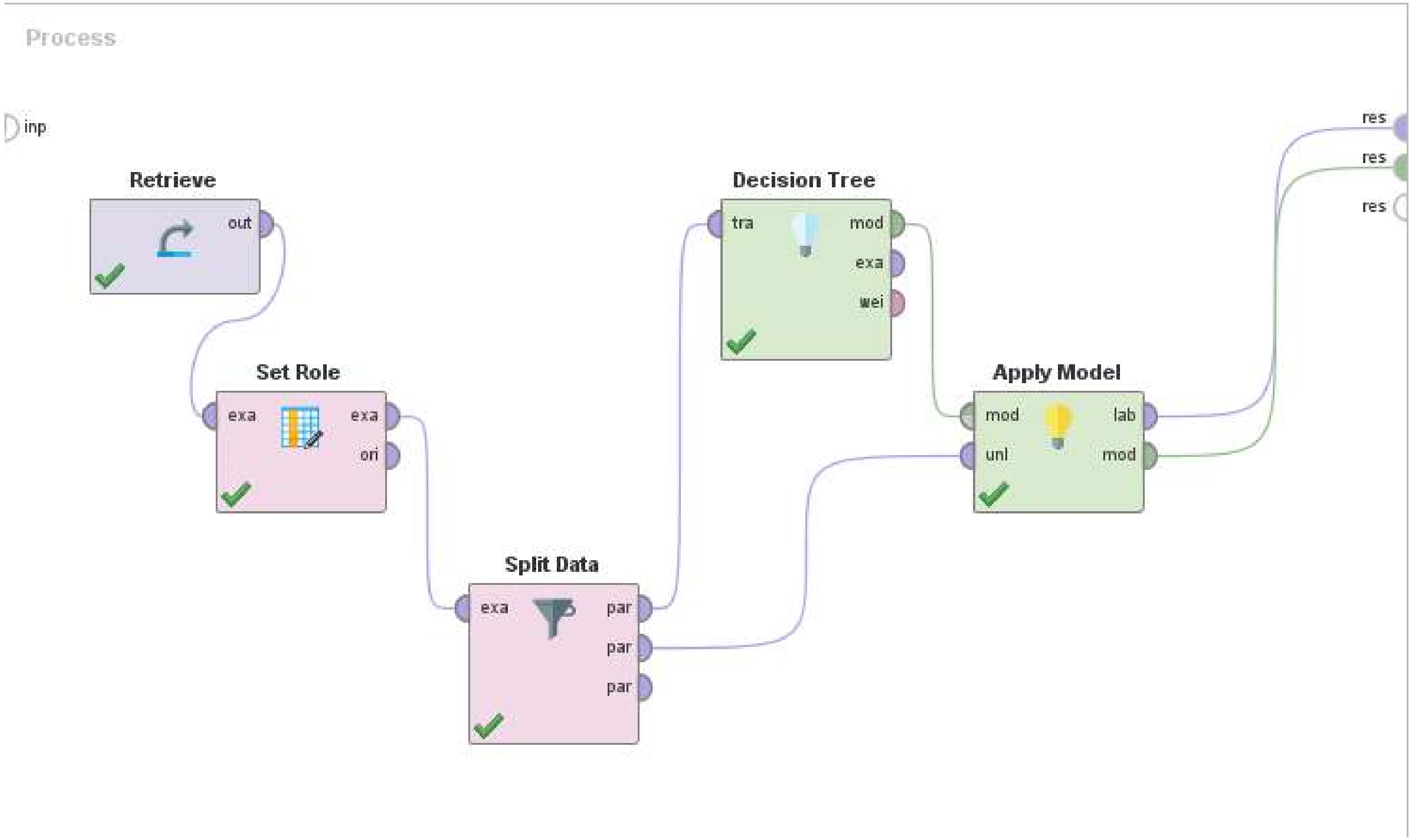
```
Timestamp > Aug 10, 2016 8:02:30 AM EDT
|   Component Accessed = Element 1
|   |   Requestor = User A: false {false=4, true=0}
|   |   Requestor = User B: true {false=0, true=20}
|   |   Requestor = User C: false {false=40, true=0}
|   Component Accessed = Element 2
|   |   Requestor = User A: true {false=0, true=9}
|   |   Requestor = User C: false {false=8, true=0}
|   Component Accessed = Element 3
|   |   Requestor = User A: true {false=0, true=3}
|   |   Requestor = User C: false {false=3, true=0}
|   Component Accessed = Table 1: false {false=207, true=12}
|   Component Accessed = Table 2: false {false=80, true=0}
Timestamp ≤ Aug 10, 2016 8:02:30 AM EDT
|   Timestamp > Aug 10, 2016 7:05:00 AM EDT: true {false=0, true=4}
|   Timestamp ≤ Aug 10, 2016 7:05:00 AM EDT: false {false=4, true=0}
```

Description of the provisional Decision Tree Model

DECISION TREE - USING THE TEST SET



DECISION TREE - USING THE TEST SET



To apply the provisional data mining model to the test set, we use ‘Apply Model’ operator

‘Apply Model’ operator requires two inputs:
i) Model ii) Unlabeled data

The ‘Apply Model’ operator pretends as if 33.33% of the data (which comes from the test set) is unlabeled and applies the model to create the labels (false/true alarms)

And, the model is going to come from the ‘output’ port of the Decision Tree operator

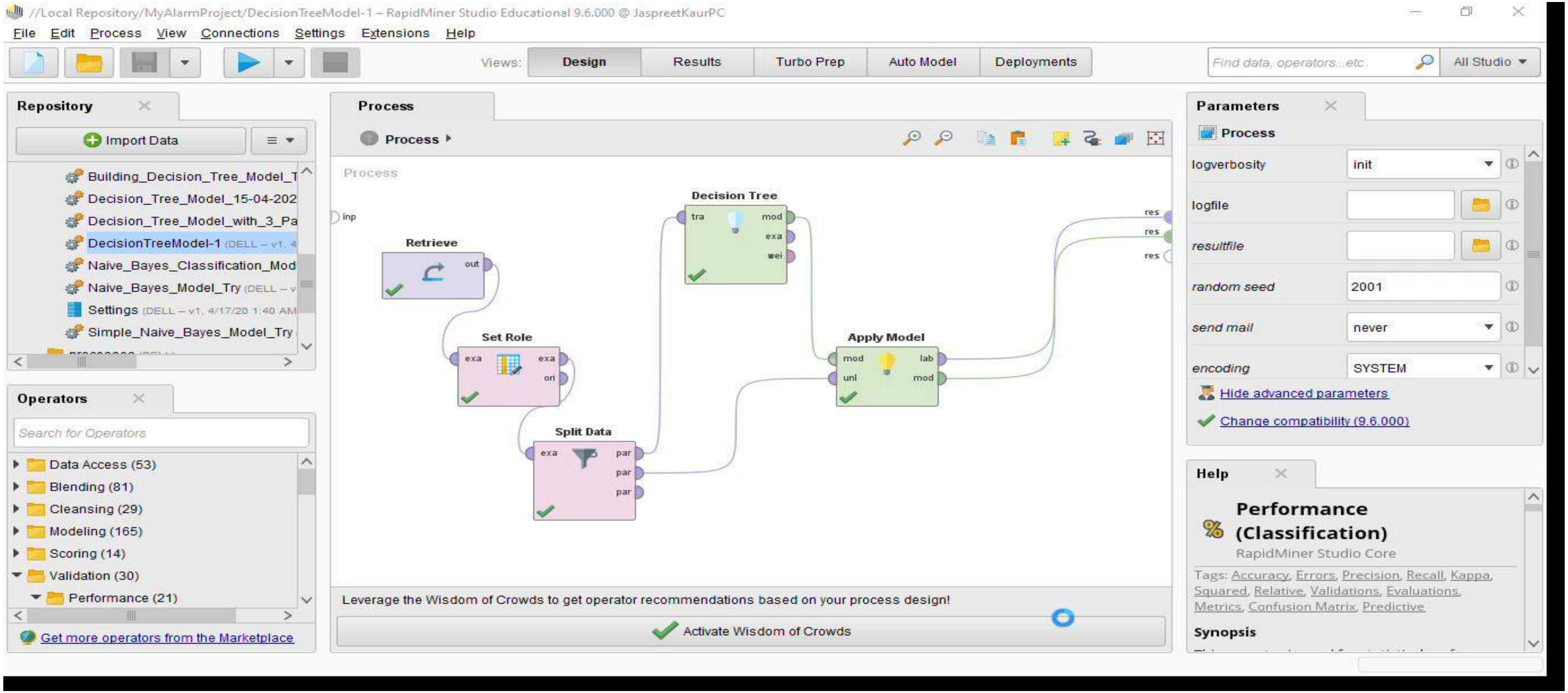
FEEDBACK FROM THE TEST SET

- 12 records show **“No Match”** in the feedback from the test set, out of the 393 records
- The security analysts had stated that the alarms were true (as shown below in yellow) but our model predicts that those alarms were false (as shown below in orange)
- Clearly, the 12 predicted values of Alarm (as shown below) are **“False Negatives”** - *generated by **Business User** (**User B**) on **Table 1** using Select query between August 14, 2016 and August 17, 2016*
- Let’s find out the accuracy of the model!

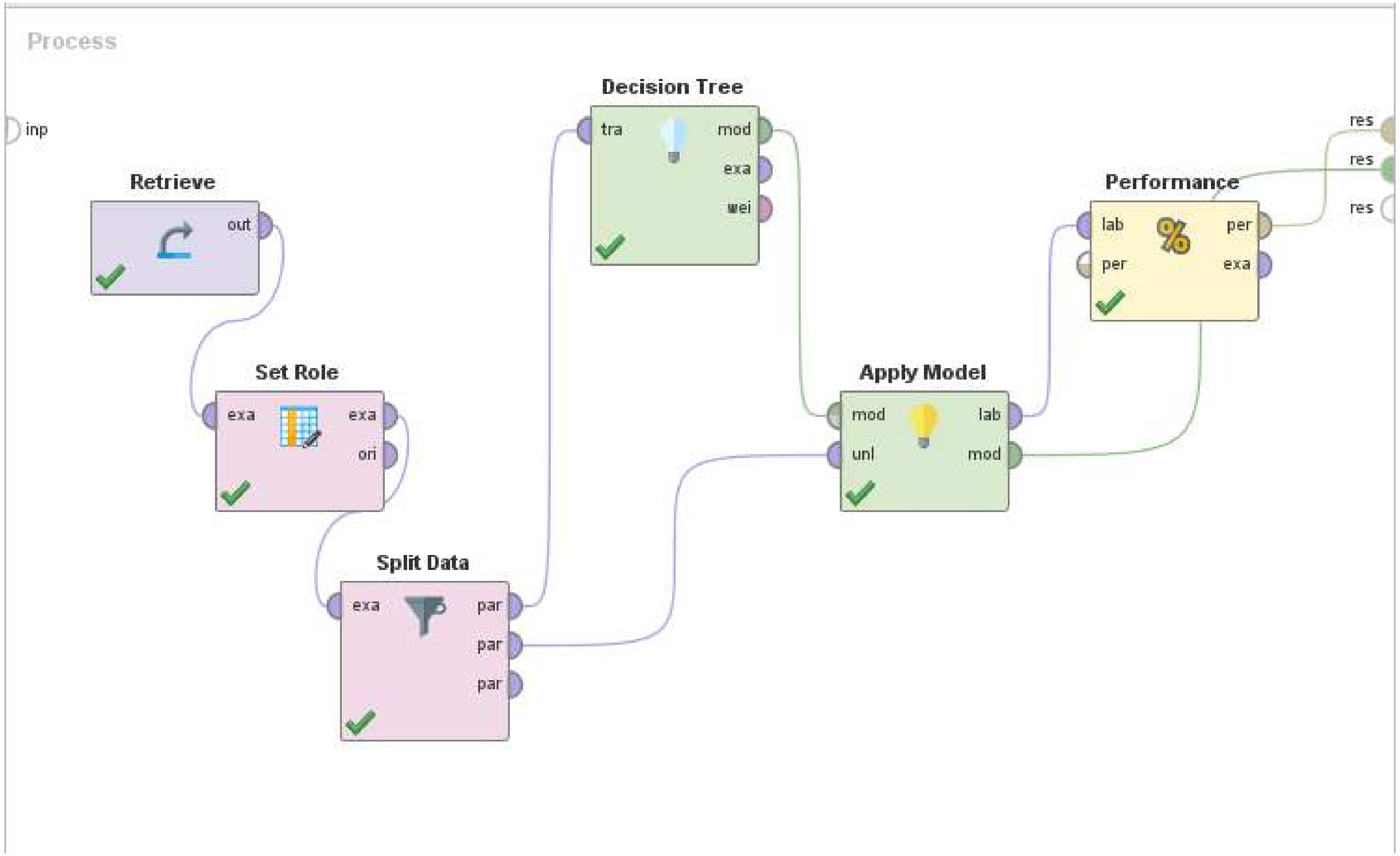
Microsoft Excel Worksheet

Timestamp	Request	Role	Component Accesse	Request ty	Violation type	Alar	confidence(fals	confidence(tru	prediction(Alarr	Match/No matc
2016-08-14 18:29:00	User B	Business user	Table 1	Select	No authorization	true	0.9	0.1	false	No Match
2016-08-14 22:05:00	User B	Business user	Table 1	Select	No authorization	true	0.9	0.1	false	No Match
2016-08-14 22:19:00	User B	Business user	Table 1	Select	No authorization	true	0.9	0.1	false	No Match
2016-08-14 22:34:00	User B	Business user	Table 1	Select	No authorization	true	0.9	0.1	false	No Match
2016-08-15 22:34:00	User B	Business user	Table 1	Select	No authorization	true	0.9	0.1	false	No Match
2016-08-16 02:10:00	User B	Business user	Table 1	Select	No authorization	true	0.9	0.1	false	No Match
2016-08-16 02:24:00	User B	Business user	Table 1	Select	No authorization	true	0.9	0.1	false	No Match
2016-08-16 02:39:00	User B	Business user	Table 1	Select	No authorization	true	0.9	0.1	false	No Match
2016-08-17 02:39:00	User B	Business user	Table 1	Select	No authorization	true	0.9	0.1	false	No Match
2016-08-17 06:15:00	User B	Business user	Table 1	Select	No authorization	true	0.9	0.1	false	No Match
2016-08-17 06:29:00	User B	Business user	Table 1	Select	No authorization	true	0.9	0.1	false	No Match
2016-08-17 06:43:00	User B	Business user	Table 1	Select	No authorization	true	0.9	0.1	false	No Match

DECISION TREE - ACCURACY CHECK



DECISION TREE - ACCURACY CHECK



'Performance (Classification)' Operator is used to evaluate the model that we are building in terms of the model accuracy, classification error etc.

'Performance (Classification) Operator' has one mandatory input: **labeled data** (which comes from the output port of the Apply Model

We get a Performance (Classification) matrix and a decision tree model when we run the process

This table (or matrix) is also called **'Confusion Matrix'** as it describes the performance of a classification model (decision tree in our case) on a set of test data for which the true values are known

HOW GOOD OUR MODEL IS?

Tree (Decision Tree) | PerformanceVector (Performance)

Criterion
- accuracy
- classification error

Table View | Plot View

Actual (or True) Values

accuracy: 96.95%

Predicted Values	true false	true true	class precision
pred. false	348 (TN)	12 (FN) - Type II error	96.67%
pred. true	0 (FP) - Type I error	33 (TP)	100.00%
class recall	100.00%	73.33%	

Here, True Negative (TN) = 348
False Negative (FN) = 12
False Positive (FP) = 0
True Positive (TP) = 33

Hence, **True Positive Rate (TPR)** can be calculated as: TP/(TP + FN) = **73.33%**

True Negative Rate (TNR) can be calculated as: TN/(TN + FP) = **100.00%**

Positive Predictive Value (PPV) can be calculated as: TP/(TP+FP) = **100.00%**

Negative Predictive Value (NPV) can be calculated as: TN/(TN+FN) = **96.67%**

Accuracy can be calculated as: (TP+TN)/(TP+TN+FP+FN) = **96.95%**

Tree (Decision Tree) | PerformanceVector (Performance)

Criterion
- accuracy
- classification error

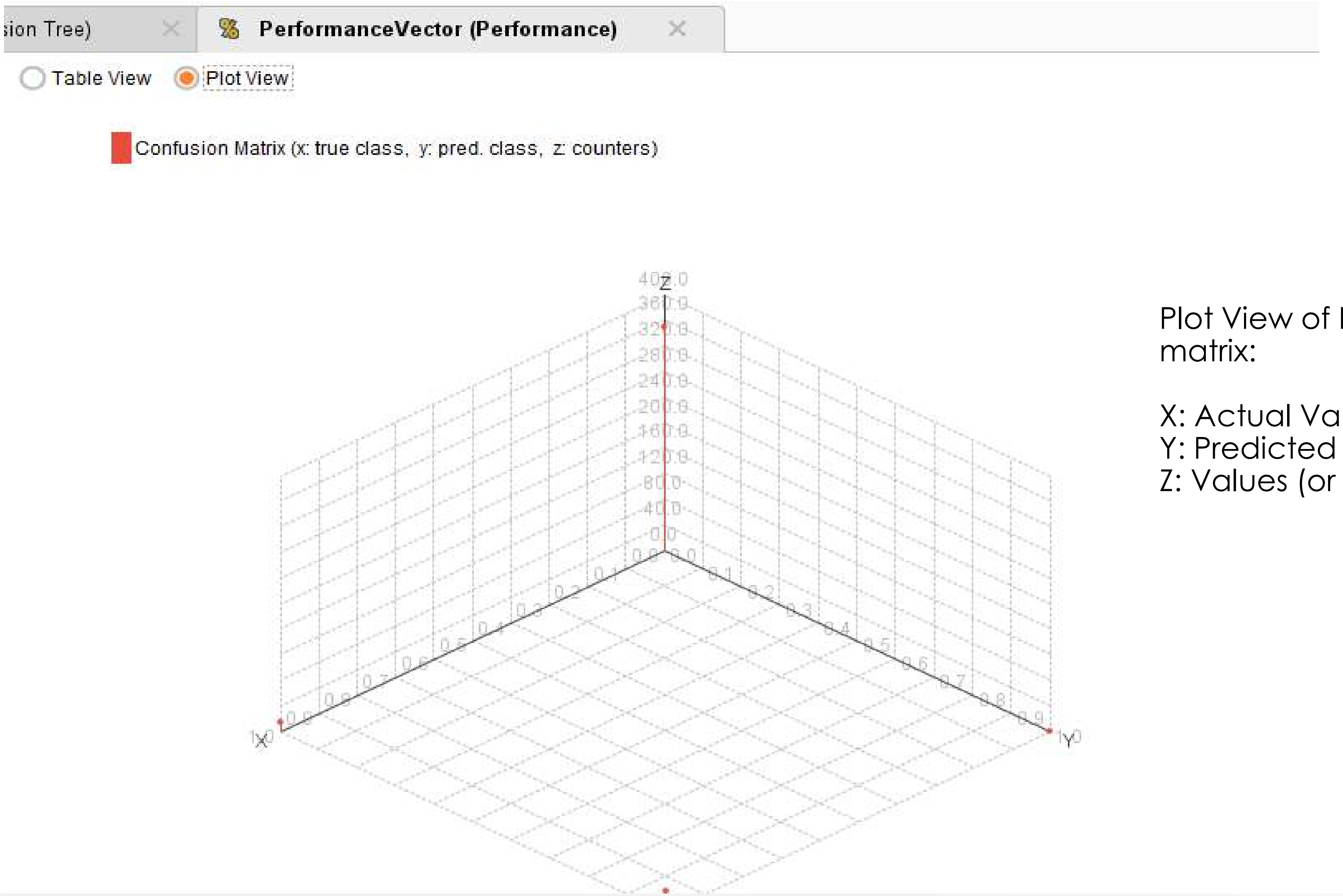
Table View | Plot View

Classification error can be calculated as: (FP+FN)/(TP+TN+FP+FN) = **3.05%**

classification_error: 3.05%

	true false	true true	class precision
pred. false	348	12	96.67%
pred. true	0	33	100.00%
class recall	100.00%	73.33%	

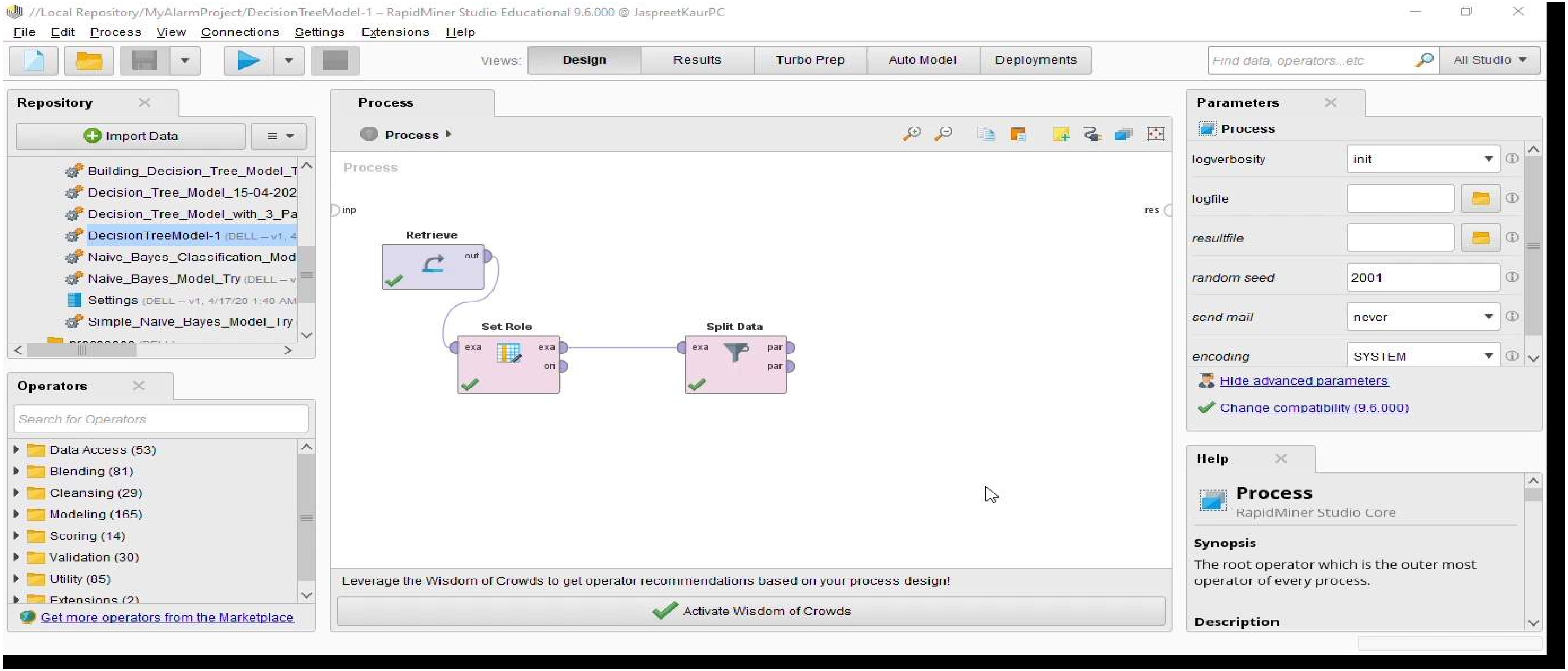
HOW GOOD OUR MODEL IS?



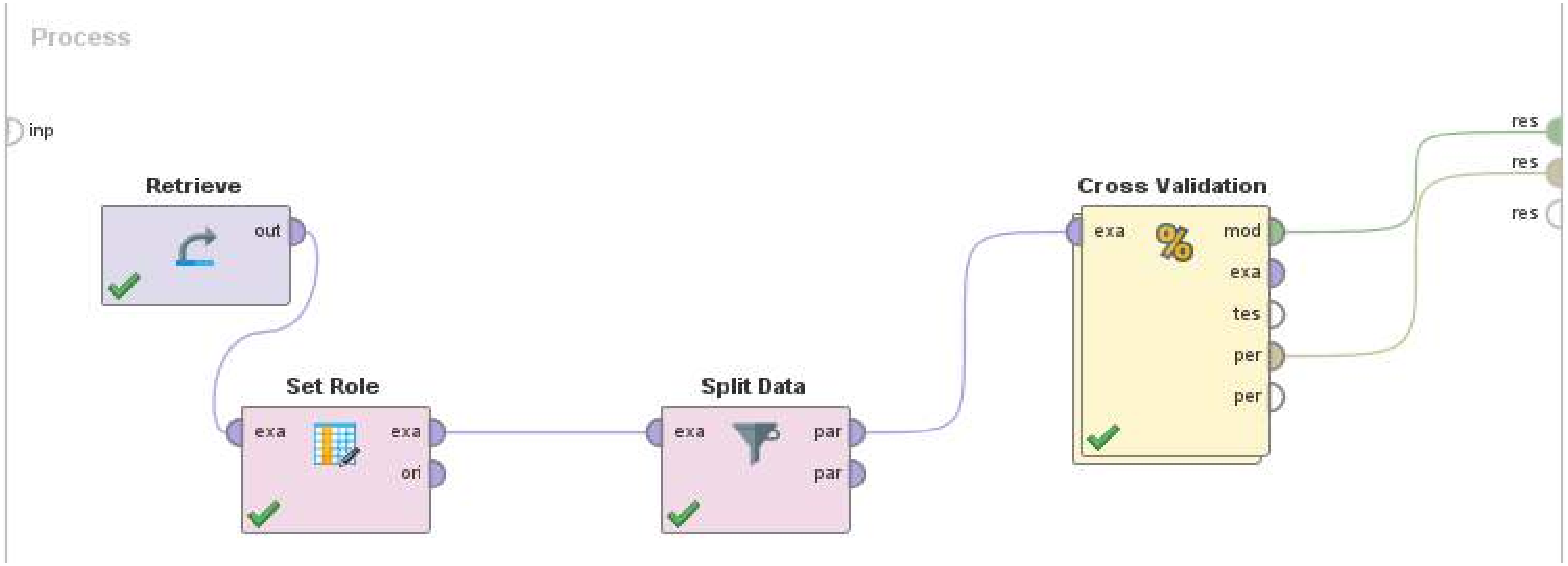
Plot View of Performance (Classification) matrix:

X: Actual Values
Y: Predicted Values
Z: Values (or Counters)

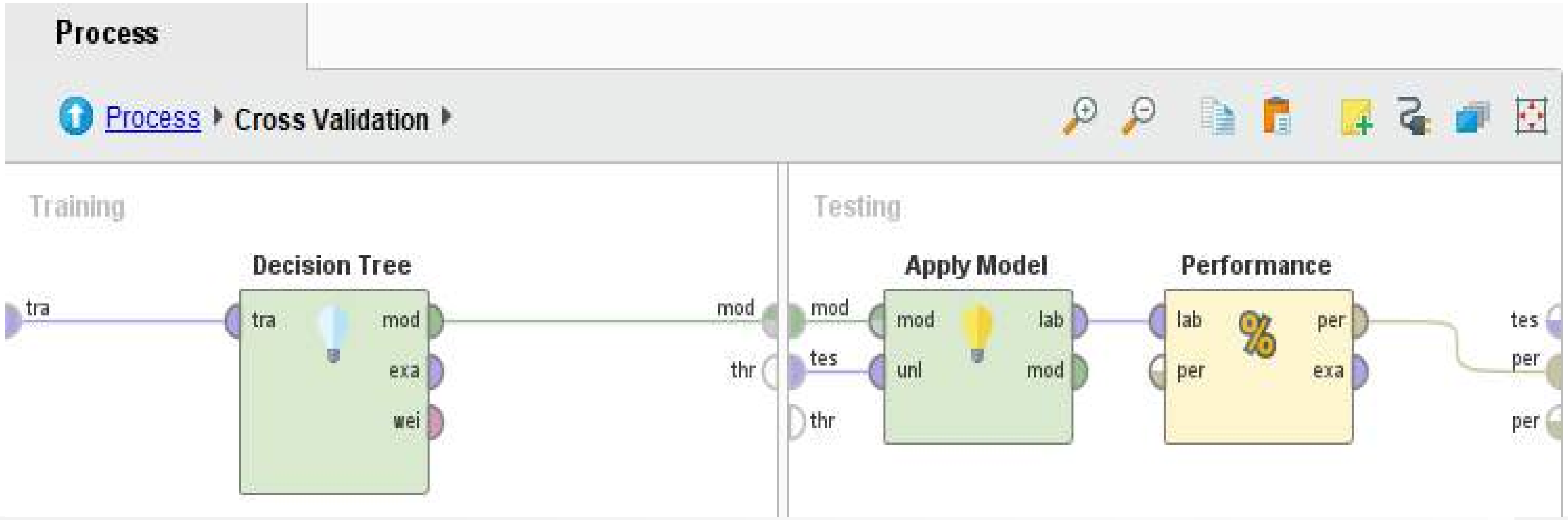
BUT, ARE WE SURE? CHECK FOR OVER-FITTING



USING CROSS VALIDATION



Cross Validation is used to see if the model is over-fitting



ACCURACY RESULT AFTER USING CROSS VALIDATION

Table View Plot View

accuracy: 96.20% +/- 3.40% (micro average: 96.19%)

	true false	true true	class precision
pred. false	343	12	96.62%
pred. true	3	36	92.31%
class recall	99.13%	75.00%	

There is a little difference in the accuracy of the model after using cross validation

The accuracy **before** using cross validation was **96.95%** whereas **now**, it is **96.20% +/- 3.40%** - hence, we can say that the model might be over fitting

Similarly, there is a little difference in the classification error of the model after using cross validation

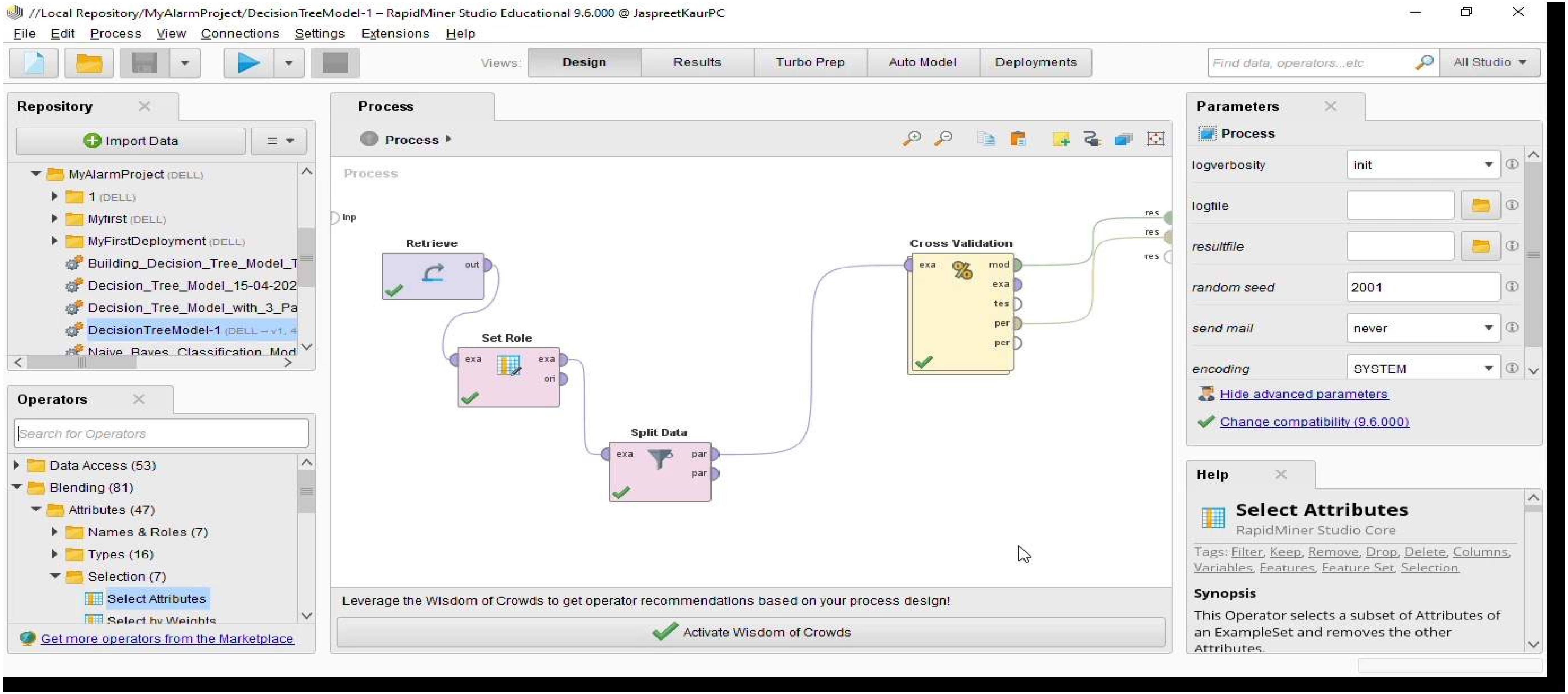
The classification error **before** using cross validation was **3.05%** whereas **now**, it is **3.80% +/- 3.40%** - hence, we can really say that the model might have a tendency to over fit

Table View Plot View

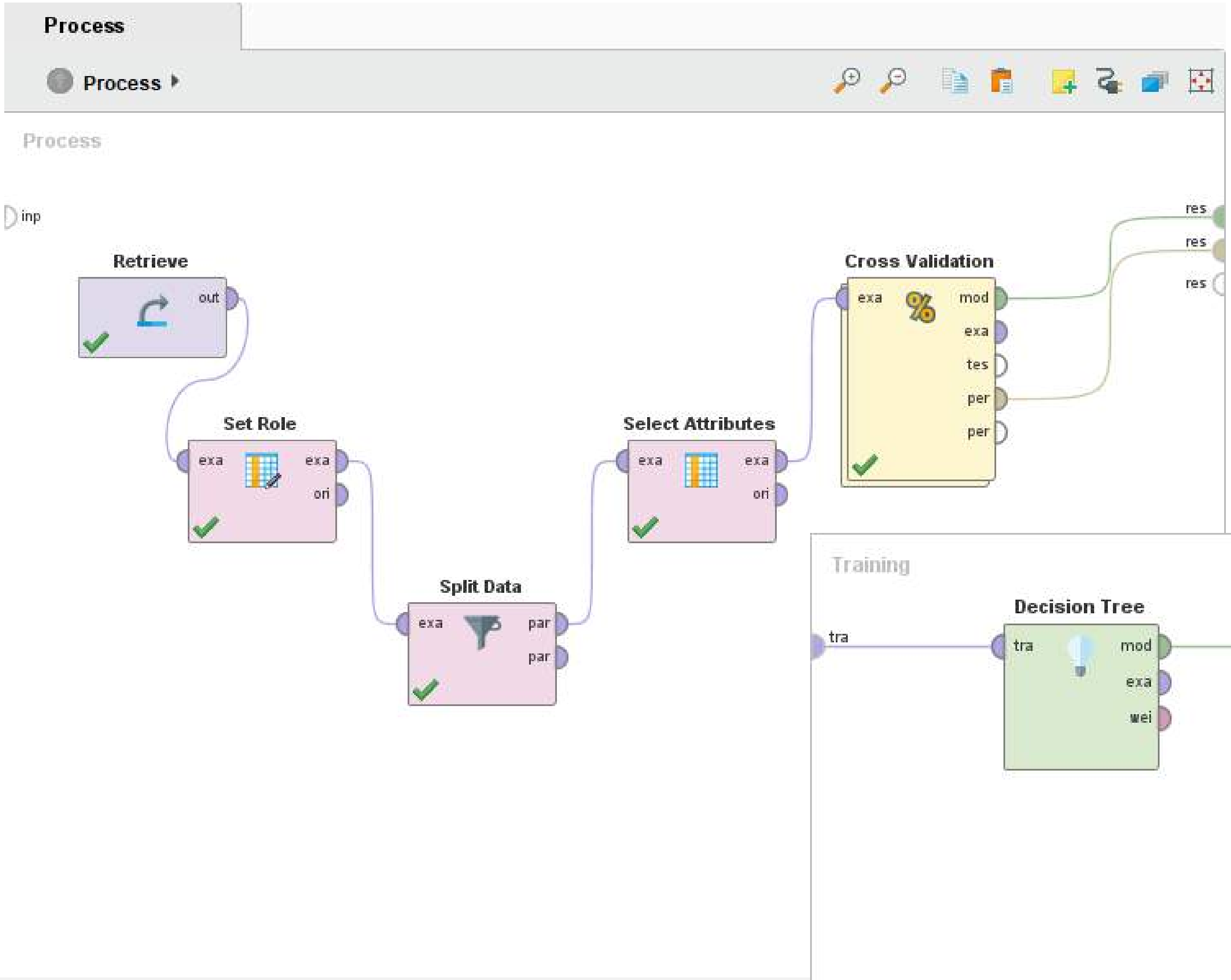
classification_error: 3.80% +/- 3.40% (micro average: 3.81%)

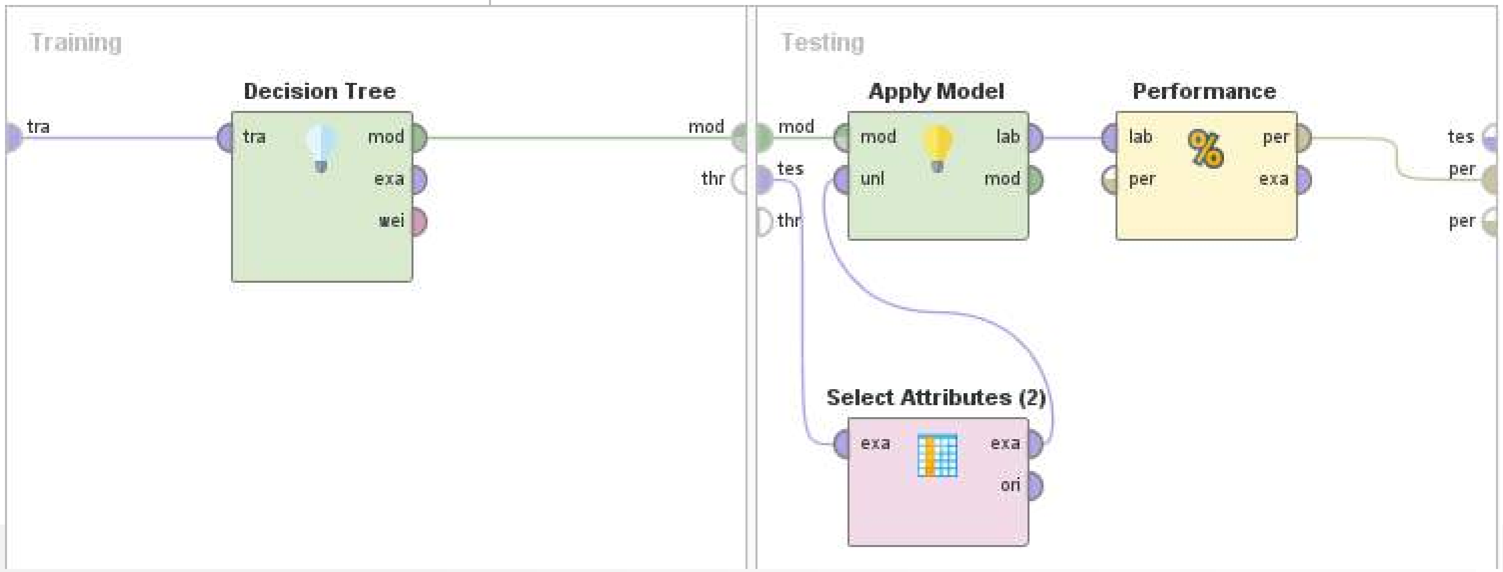
	true false	true true	class precision
pred. false	343	12	96.62%
pred. true	3	36	92.31%
class recall	99.13%	75.00%	

RE-TRAINING THE MODEL



REMOVING TIMESTAMP & VIOLATION TYPE

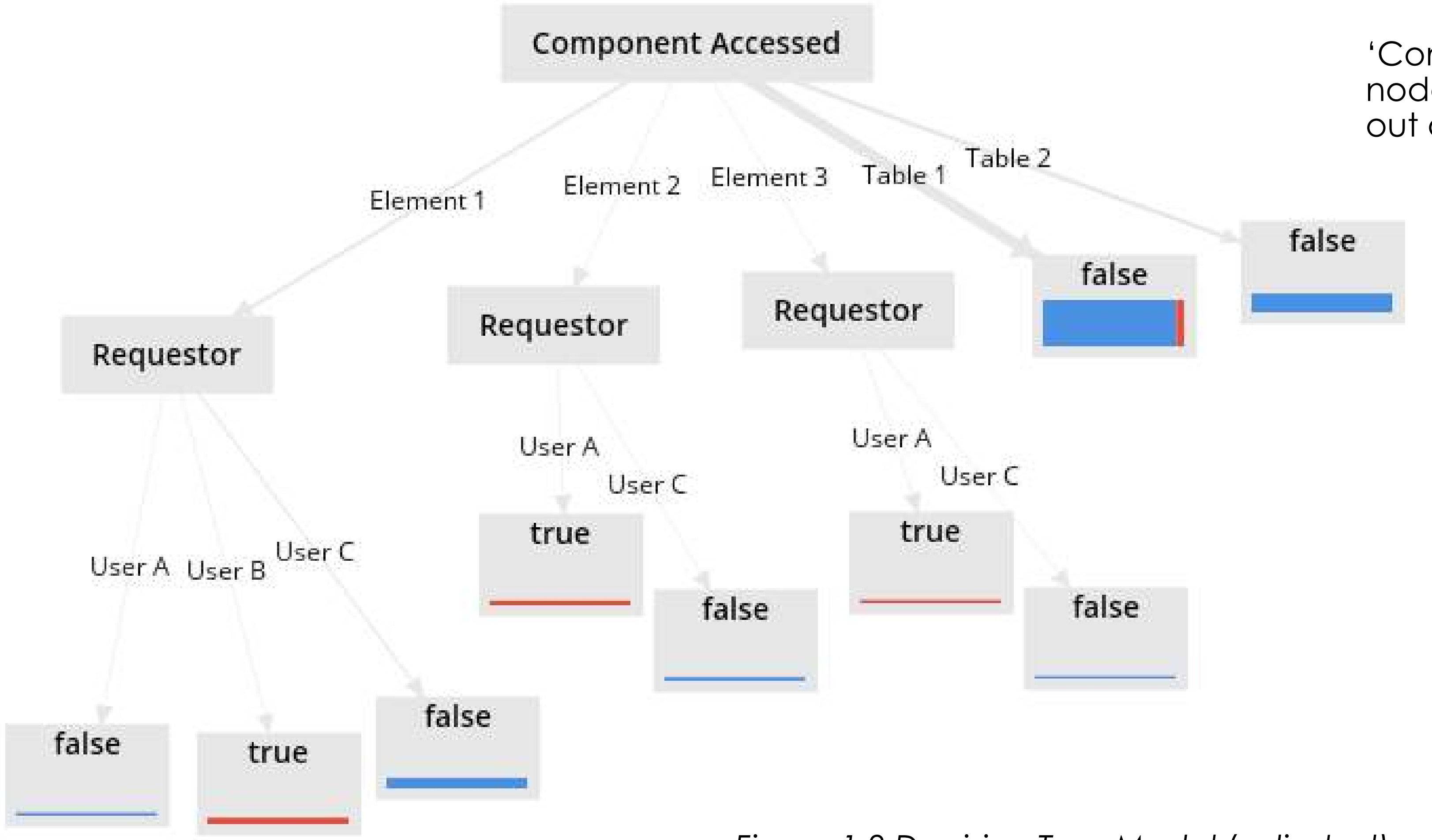




'Select Attributes' operator is used to select which attributes one would like to keep or remove in the dataset

As stated in EDA phase, we removed **Timestamp** (to speed up the model building) and **Violation Type** (since the column is practically constant) predictor variables to check if the model performs even better

DECISION TREE



'Component Accessed' (here, root node) seems to be the best predictor out of all the other predictor variables

Figure 1.2 Decision Tree Model (adjusted)

FEEDBACK - AFTER RE-TRAINING THE MODEL

- 12 records show **“No Match”** in the feedback from the test set, out of the 393 records
- The security analysts had stated that the alarms were true (as shown below in yellow) but our model predicts that those alarms were false (as shown below in orange)
- Clearly, the 12 predicted values of Alarm (as shown below) are **“False Negatives”**
- Let’s find out how much accurate our model is!

Microsoft Excel Worksheet

Request	Role	Component Accesse	Request ty	Alar	confidence(fals	confidence(tru	prediction(Alarr	Match/No Mat
User B	Business user	Table 1	Select	true	0.9	0.1	false	No Match
User B	Business user	Table 1	Select	true	0.9	0.1	false	No Match
User B	Business user	Table 1	Select	true	0.9	0.1	false	No Match
User B	Business user	Table 1	Select	true	0.9	0.1	false	No Match
User B	Business user	Table 1	Select	true	0.9	0.1	false	No Match
User B	Business user	Table 1	Select	true	0.9	0.1	false	No Match
User B	Business user	Table 1	Select	true	0.9	0.1	false	No Match
User B	Business user	Table 1	Select	true	0.9	0.1	false	No Match
User B	Business user	Table 1	Select	true	0.9	0.1	false	No Match
User B	Business user	Table 1	Select	true	0.9	0.1	false	No Match
User B	Business user	Table 1	Select	true	0.9	0.1	false	No Match
User B	Business user	Table 1	Select	true	0.9	0.1	false	No Match

ACCURACY - AFTER RE-TRAINING THE MODEL

Table View Plot View

accuracy: 96.46% +/- 3.38% (micro average: 96.45%)

	true false	true true	class precision
pred. false	344	12	96.63%
pred. true	2	36	94.74%
class recall	99.42%	75.00%	

After removing **Timestamp** and **Violation Type** predictor variables, the accuracy **increased** from **96.19%** to **96.45%** *(if we consider the micro average)*

Since, RapidMiner tells us the range of the accuracy of the model, hence, it might be difficult for us to explicitly say if removing Timestamp & Violation Type variables will improve the accuracy

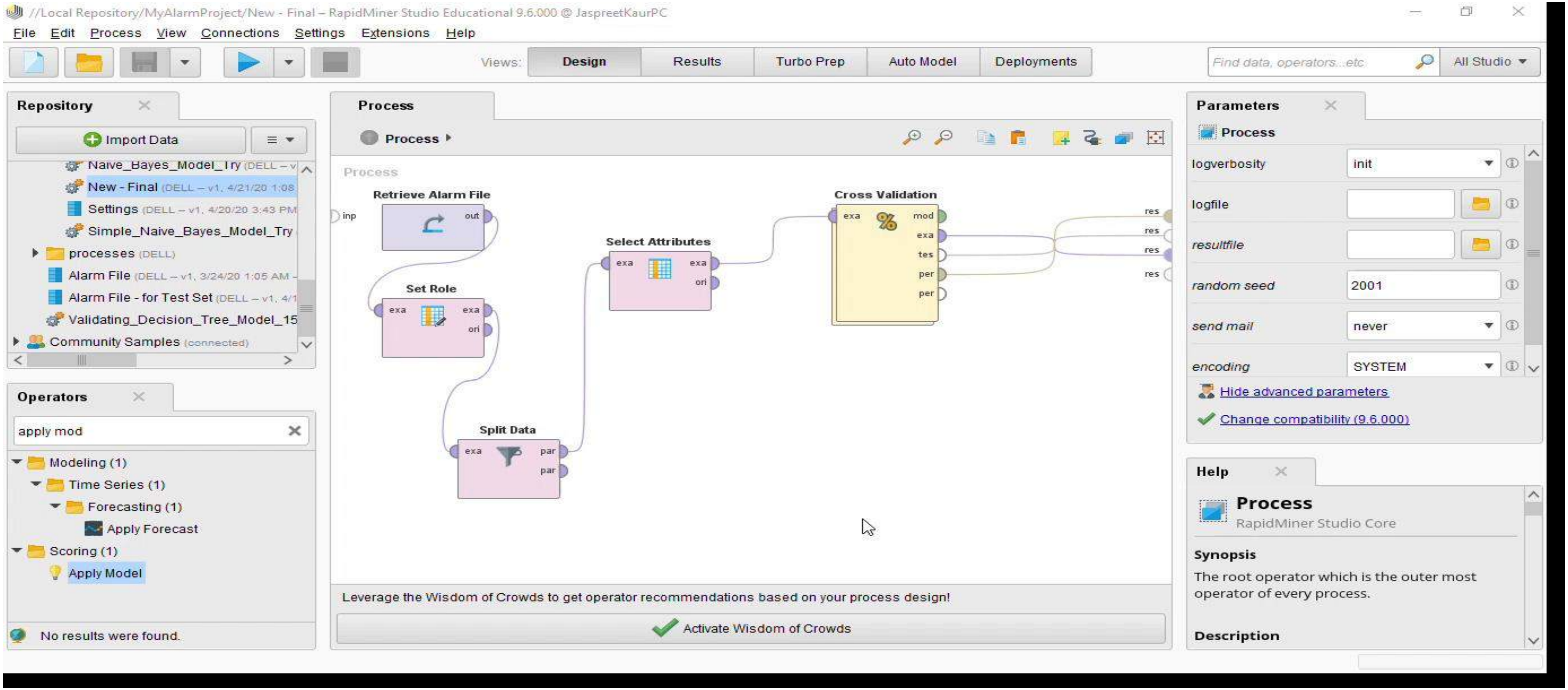
Table View Plot View

classification_error: 3.54% +/- 3.38% (micro average: 3.55%)

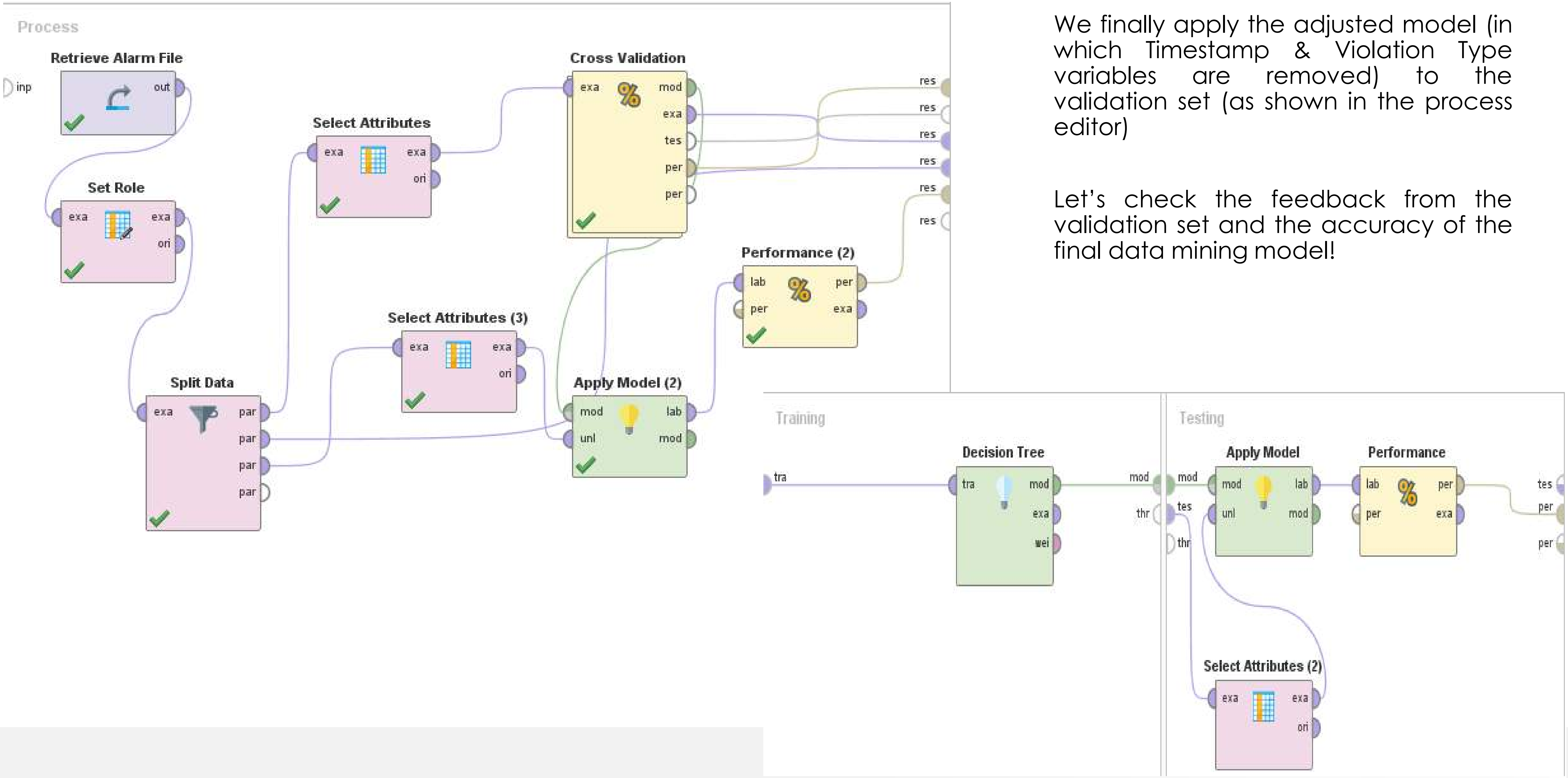
	true false	true true	class precision
pred. false	344	12	96.63%
pred. true	2	36	94.74%
class recall	99.42%	75.00%	

Similarly, the Classification Error after removing **Timestamp** and **Violation Type** variables **reduced** from **3.81%** to **3.55%** - if we consider the micro average method, but this method can sometimes be misleading

APPLYING THE ADJUSTED MODEL ON VALIDATION SET



DECISION TREE - FINAL DATA MINING MODEL



We finally apply the adjusted model (in which Timestamp & Violation Type variables are removed) to the validation set (as shown in the process editor)

Let's check the feedback from the validation set and the accuracy of the final data mining model!

FEEDBACK FROM THE VALIDATION SET

- 16 records show **“No Match”** in the feedback from the validation set, out of the 406 records
- The security analysts had stated that the alarms were true (as shown below in yellow) but our model predicts that those alarms were false (as shown below in orange)
- Clearly, the 16 predicted values of Alarm (as shown below) are **“False Negatives”** - generated by ***Business User*** *(**User B**) on **Table 1** using Select query*
- Let’s find out how much accurate our model is!

Microsoft Excel Worksheet

Request	Role	Component Accesse	Request ty	Alar	confidence(fals	confidence(tru	prediction(Alarr	Match/No Match
User B	Business user	Table 1	Select	true	0.9	0.1	false	No Match
User B	Business user	Table 1	Select	true	0.9	0.1	false	No Match
User B	Business user	Table 1	Select	true	0.9	0.1	false	No Match
User B	Business user	Table 1	Select	true	0.9	0.1	false	No Match
User B	Business user	Table 1	Select	true	0.9	0.1	false	No Match
User B	Business user	Table 1	Select	true	0.9	0.1	false	No Match
User B	Business user	Table 1	Select	true	0.9	0.1	false	No Match
User B	Business user	Table 1	Select	true	0.9	0.1	false	No Match
User B	Business user	Table 1	Select	true	0.9	0.1	false	No Match
User B	Business user	Table 1	Select	true	0.9	0.1	false	No Match
User B	Business user	Table 1	Select	true	0.9	0.1	false	No Match
User B	Business user	Table 1	Select	true	0.9	0.1	false	No Match
User B	Business user	Table 1	Select	true	0.9	0.1	false	No Match
User B	Business user	Table 1	Select	true	0.9	0.1	false	No Match
User B	Business user	Table 1	Select	true	0.9	0.1	false	No Match
User B	Business user	Table 1	Select	true	0.9	0.1	false	No Match

PERFORMANCE CLASSIFICATION MATRIX

◉ Table View ○ Plot View

accuracy: 96.46% +/- 3.38% (micro average: 96.45%)

	true false	true true	class precision
pred. false	344	12	96.63%
pred. true	2	36	94.74%
class recall	99.42%	75.00%	

Test set performance classification **result** shows **96.46% +/- 3.38%** accuracy

Sensitivity or Recall of all positive classes or **True Positive Rate (TPR**) = **75.00%**

◉ Table View ○ Plot View

accuracy: 96.06% classification_error: 3.94%

	true false	true true	class precision
pred. false	359	16	95.73%
pred. true	0	31	100.00%
class recall	100.00%	65.96%	

Validation set performance classification **result** shows **96.06%** accuracy

Sensitivity or Recall of all positive classes or **True Positive Rate (TPR)** = **65.96%**

DECISION TREE - GOOD MODEL OR NOT?

The decision tree model gives us an **overall accuracy** of **96.46% +/- 3.38%** on the **test set** and **96.06%** on the **validation set**

The assumption that alarm inspection team should focus on inspecting the alerts generated by Business User on Table 1 (since the number of True alarms generated by this user or role is the highest), from the EDA phase is **confirmed**

The assumption that CISO should investigate alarm process & system for Administrator role (since the number of False alarms generated by this user or role is the highest), from the EDA phase is **rejected.**

Removing Timestamp definitely increases the execution time of the model (0s execution time)

Removing Violation Type has no impact on the decision tree model, since the column is unary or constant

The model chooses only one variable out of Role and **Requestor**. Here, both the variables are the same and hence, we can say that they are perfectly correlated since one user has only one role and hence, the model omits Role - but in real life, many different users can have one role

Component Accessed has strong correlation with Requestor

Model Accuracy: 93.00% to 96.06%

A good model!

NAÏVE BAYES

- A popular supervised classification method used in data mining, which comes under the Bayesian Classification
- Uses probability for doing predictive analysis
- Works on the assumption that the predictor variables are independent - but is not so naïve!
- A low-variance classifier and works well even on small data sets
- Tool used for building the Naïve Bayes classification model: **RapidMiner**
- RapidMiner is a very effective data science software platform that unites data prep, machine learning & predictive model deployment

Recommendation in EDA Phase:

….

Looks like it is simple to use and seems to provide an accuracy of 96.5%

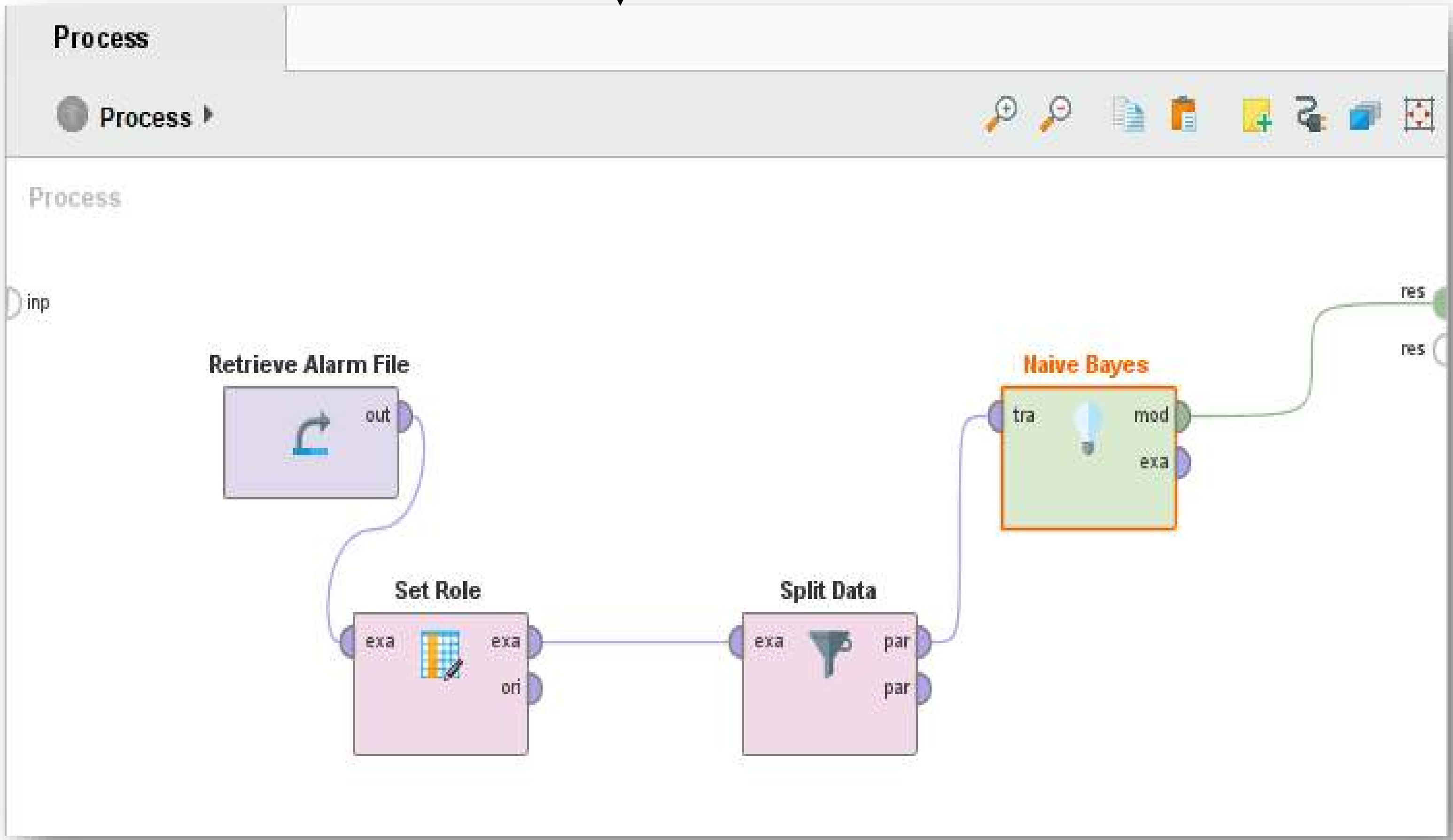
NAÏVE BAYES - USING THE TRAINING SET

Process Editor

The first step is to retrieve the data i.e. Alarm file

'Set Role' operator is used to tell RapidMiner which is our target variable (Alarm)

To partition the data set, we use 'Split Data' operator



Dataset is split into 3 sets: Training, Test & Validation datasets (1/3rd each)

Now, we use 'Naïve Bayes' operator to build the provisional model

We connect the inputs with their relevant outputs and run the process

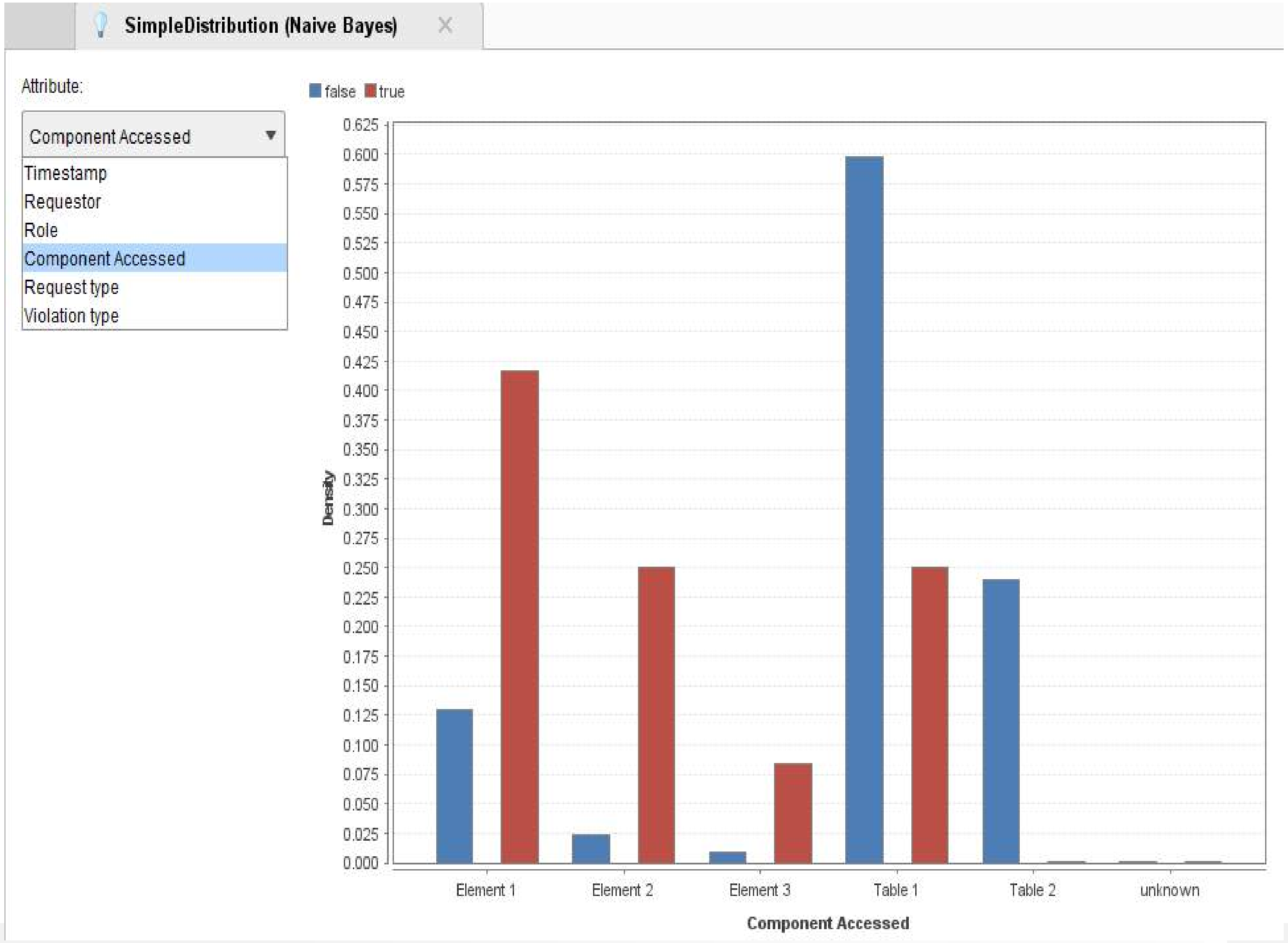
NAÏVE BAYES CLASSIFICATION

SimpleDistribution

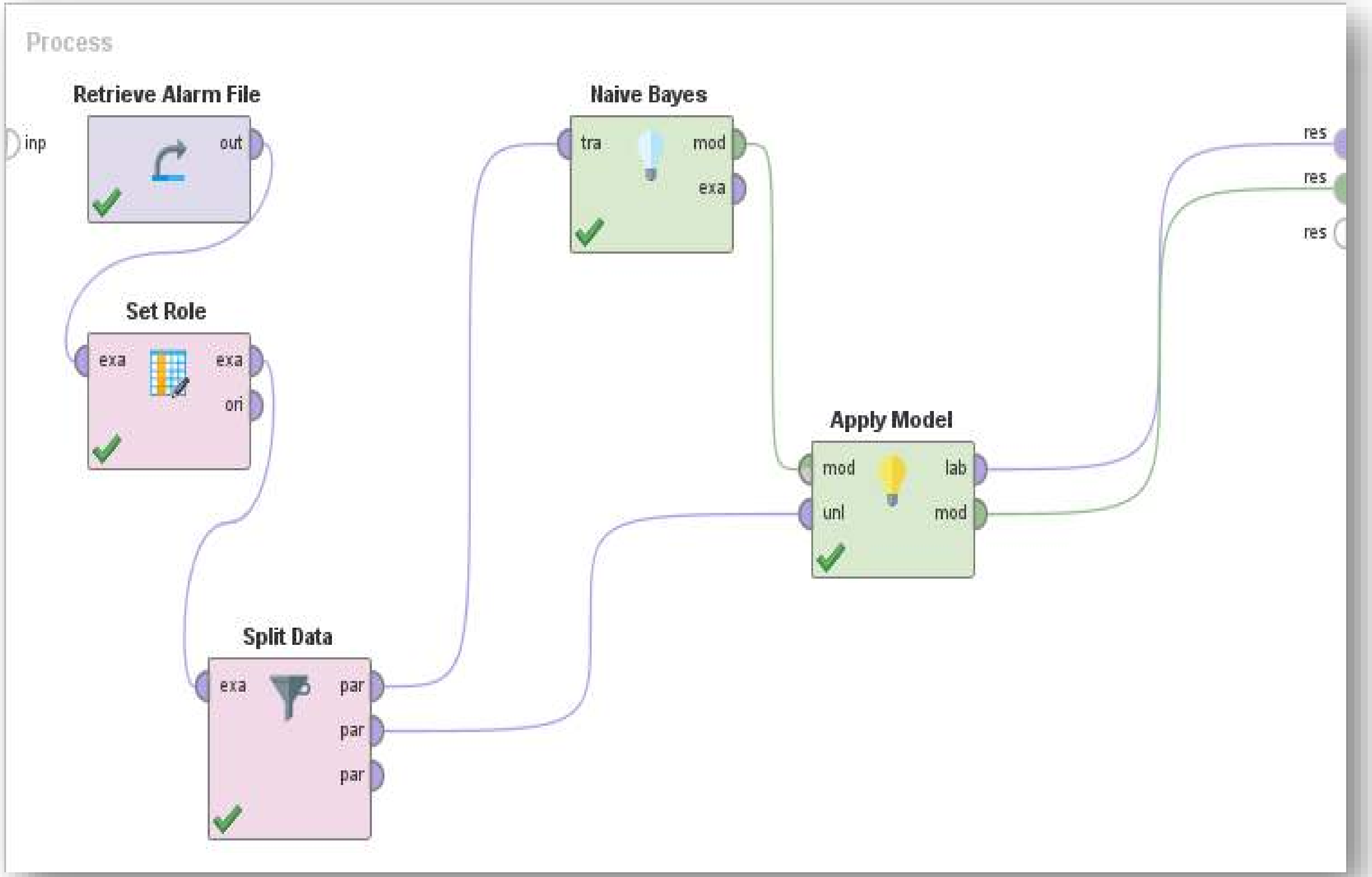
```
Distribution model for label attribute Alarm

Class false (0.878)
6 distributions

Class true (0.122)
6 distributions
```

Naïve Bayes Classification Model gives the overall probability of true and false classes

It also shows the individual probability of true and false classes in each of the predictor variables – as shown in the chart on the right



NAÏVE BAYES - USING THE TEST SET



To apply the provisional data mining model to the test set, we use 'Apply Model' operator

'Apply Model' operator requires two inputs: i) Model ii) Unlabeled data

The 'Apply Model' operator pretends as if 33.33% of the data (which comes from the test set) is unlabeled and applies the model to create the labels (false/true alarms)

And, the model is going to come from the 'output' port of the Naïve Bayes operator

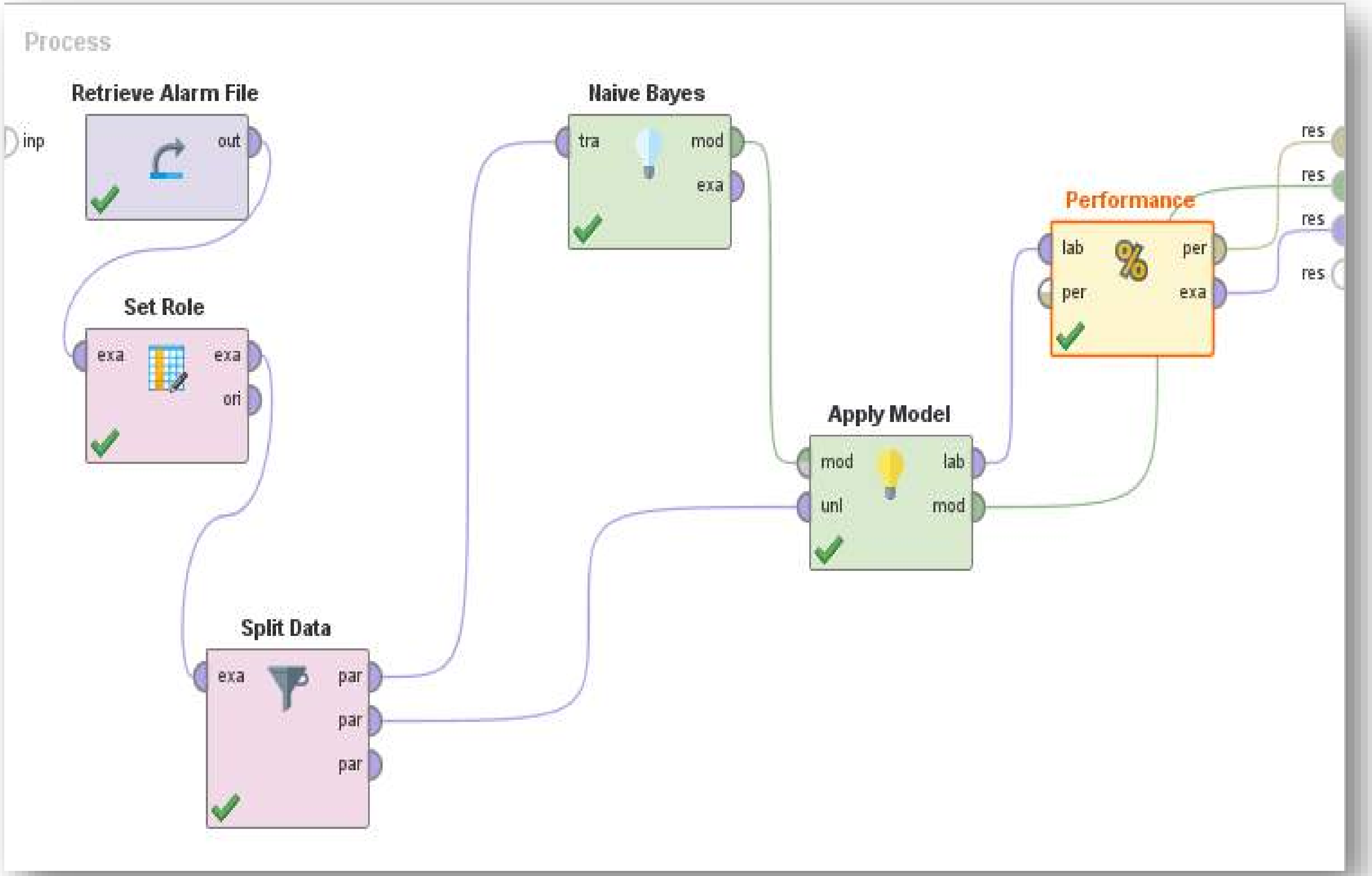
FEEDBACK FROM THE TEST SET

- 17 records show **"No Match"** in the feedback from the test set, out of the 393 records
- The security analysts had stated that the alarms were true (as shown below in yellow) but our model predicts that those alarms were false (as shown below in orange)
- Clearly, the 17 actual values of Alarm (as shown below) are **"False Negatives"** – out of which 8 were generated by Business User (or User B) on Table 1 using Select query and 9 were generated by Analyst (or User A) on Element 2 (using Select) and Element 3 (using Append)
- Let's find out the accuracy of the model!

Microsoft Excel Worksheet

Timestamp	Request	Role	Component Accesse	Request typ	Violation type	Alar	confidence(fals	confidence(tru	prediction(Alarr	Match/No Mat
2016-08-14 18:29:00	User B	Business user	Table 1	Select	No authorization	true	0.6	0.4	false	No Match
2016-08-14 22:05:00	User B	Business user	Table 1	Select	No authorization	true	0.6	0.4	false	No Match
2016-08-14 22:19:00	User B	Business user	Table 1	Select	No authorization	true	0.6	0.4	false	No Match
2016-08-14 22:34:00	User B	Business user	Table 1	Select	No authorization	true	0.6	0.4	false	No Match
2016-08-14 23:31:00	User A	Analyst	Element 2	Select	No authorization	true	0.6	0.4	false	No Match
2016-08-14 23:46:00	User A	Analyst	Element 2	Select	No authorization	true	0.6	0.4	false	No Match
2016-08-15 00:00:00	User A	Analyst	Element 2	Select	No authorization	true	0.6	0.4	false	No Match
2016-08-15 00:15:00	User A	Analyst	Element 3	Append	No authorization	true	0.7	0.3	false	No Match
2016-08-15 22:34:00	User B	Business user	Table 1	Select	No authorization	true	0.5	0.5	false	No Match
2016-08-16 02:10:00	User B	Business user	Table 1	Select	No authorization	true	0.5	0.5	false	No Match
2016-08-16 02:24:00	User B	Business user	Table 1	Select	No authorization	true	0.5	0.5	false	No Match
2016-08-16 02:39:00	User B	Business user	Table 1	Select	No authorization	true	0.5	0.5	false	No Match
2016-08-16 03:36:00	User A	Analyst	Element 2	Select	No authorization	true	0.5	0.5	false	No Match
2016-08-16 03:51:00	User A	Analyst	Element 2	Select	No authorization	true	0.5	0.5	false	No Match
2016-08-16 04:05:00	User A	Analyst	Element 2	Select	No authorization	true	0.5	0.5	false	No Match
2016-08-16 04:19:00	User A	Analyst	Element 3	Append	No authorization	true	0.6	0.4	false	No Match
2016-08-17 08:24:00	User A	Analyst	Element 3	Append	No authorization	true	0.5	0.5	false	No Match

NAÏVE BAYES - ACCURACY CHECK



'Performance (Classification)' Operator is used to evaluate the model that we are building

'Performance (Classification) Operator' has one mandatory input: labeled data (which comes from the output port of the Apply Model

We get a Performance (Classification) matrix and a distribution table showing probabilities, when we run the process

This table (or matrix) is also called 'Confusion Matrix' as it describes the performance of a classification model (naïve bayes in our case) on a set of test data for which the true values are known

HOW GOOD OUR MODEL IS?

95.67% accuracy! The model is not bad!

et (Apply Model) | SimpleDistribution (Naive Bayes) | **PerformanceVector (Performance)**

Table View   Plot View

Actual (or True) Values

accuracy: 95.67%

Predicted Values	true false	true true	class precision
pred. false	348 (TN)	17 (FN) - Type II error	95.34%
pred. true	0 (FP) - Type I error	28 (TP)	100.00%
class recall	100.00%	62.22%	

Here, True Negative (TN) = 348
False Negative (FN) = 17
False Positive (FP) = 0
True Positive (TP) = 28

Hence, **True Positive Rate (TPR)** can be calculated as: TP/(TP + FN) = **62.22%**

True Negative Rate (TNR) can be calculated as: TN/(TN + FP) = **100.00%**

Positive Predictive Value (PPV) can be calculated as: TP/(TP+FP) = **100.00%**

Negative Predictive Value (NPV) can be calculated as: TN/(TN+FN) = **95.34%**

Accuracy can be calculated as: (TP+TN)/(TP+TN+FP+FN) = **95.67%**

t (Apply Model) | SimpleDistribution (Naive Bayes) | **PerformanceVector (Performance)**

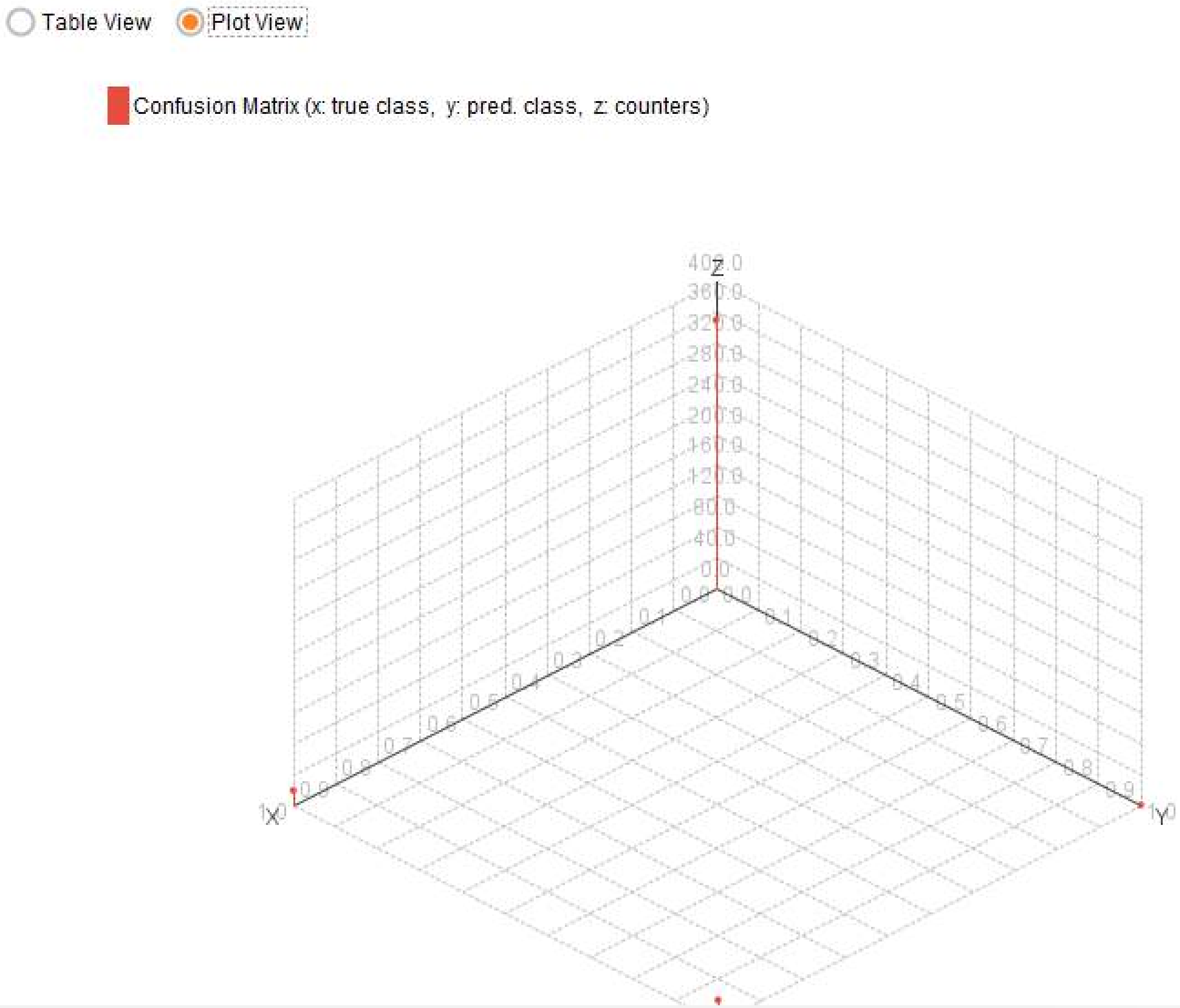
Table View   Plot View

Classification error can be calculated as: (FP+FN)/(TP+TN+FP+FN) = **4.33%**

classification_error: 4.33%

	true false	true true	class precision
pred. false	348	17	95.34%
pred. true	0	28	100.00%
class recall	100.00%	62.22%	

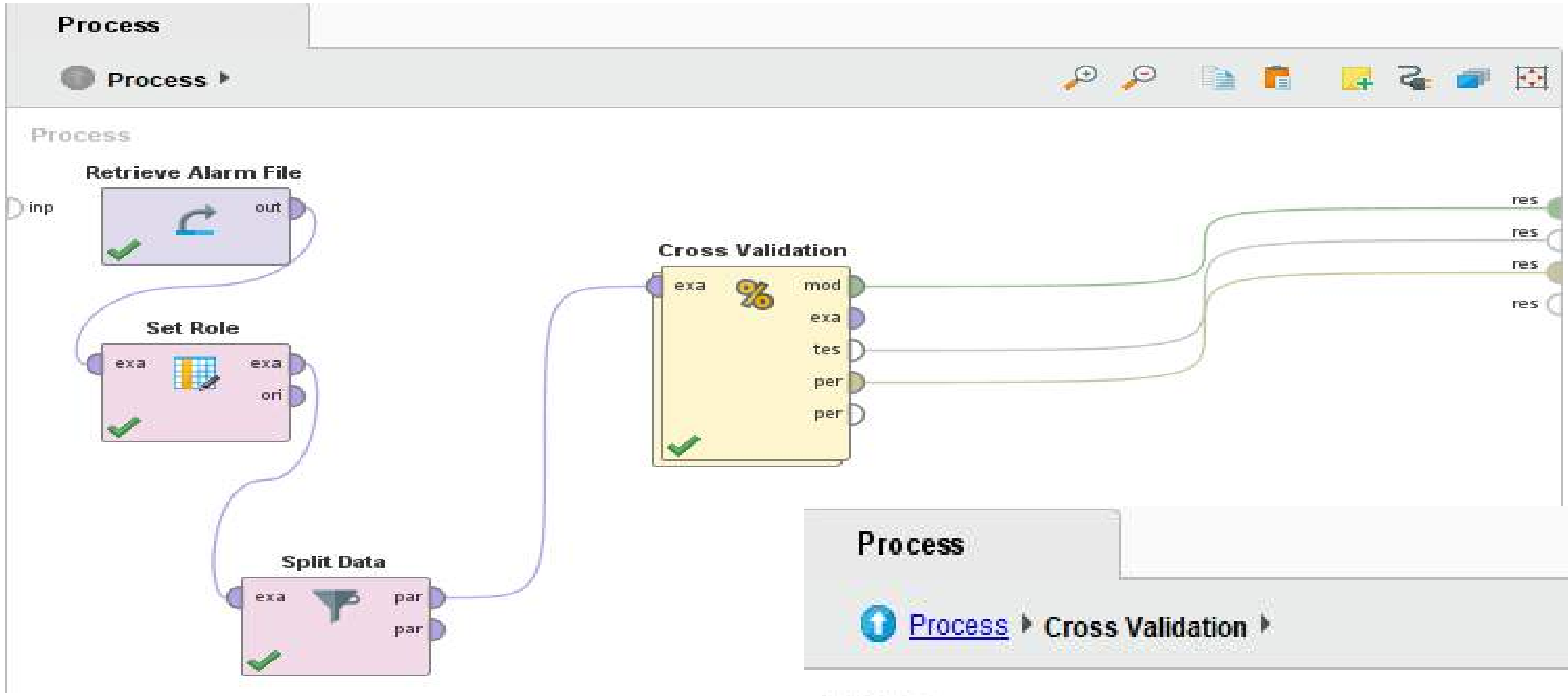
HOW GOOD OUR MODEL IS?

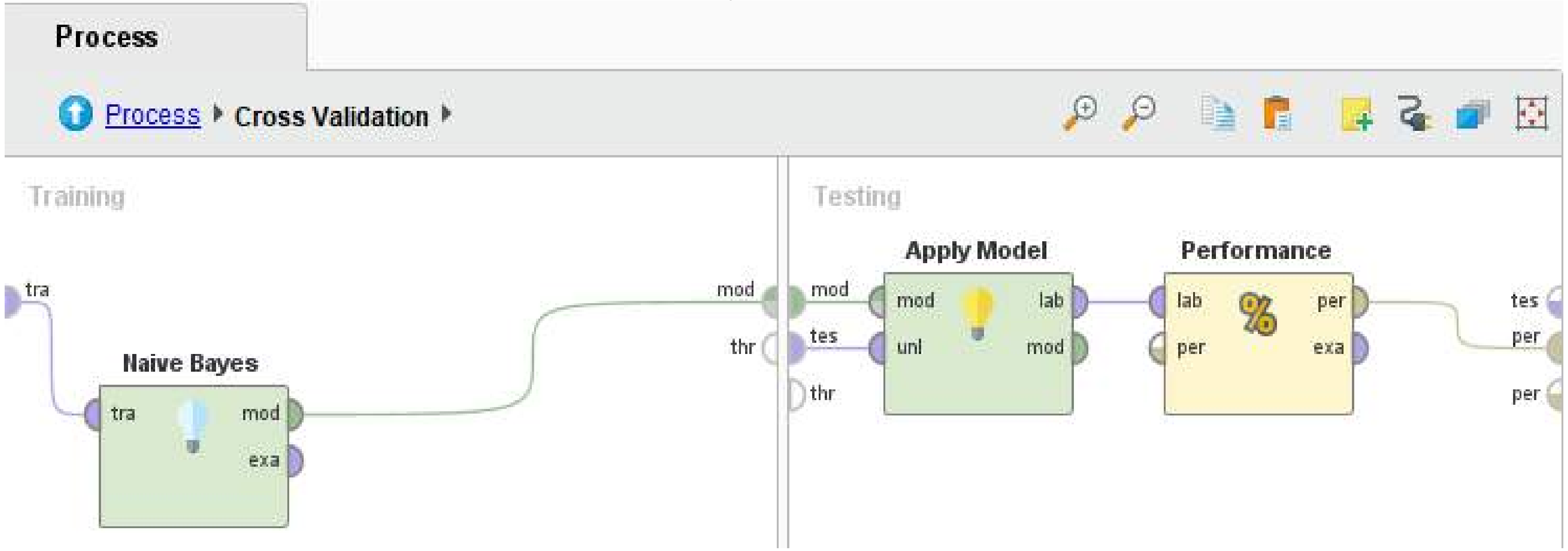


Plot View of Performance (Classification) matrix:

X: Actual Values
Y: Predicted Values
Z: Values (or Counters)

USING CROSS VALIDATION TO CHECK OVER-FITTING





Cross Validation is used to see if the model is over-fitting

FEEDBACK FROM THE TEST SET

Timestamp	Request	Role	Component Accesse	Request ty	Violation type	confidence(fals	Ala	confidence(tru	prediction(Alarr	Match/No Mat
2016-08-11 10:05:00	User B	Business use	Table 1	Select	No authorizatio	0.7	true	0.3	false	No Match
2016-08-12 14:24:00	User B	Business use	Table 1	Select	No authorizatio	0.7	true	0.3	false	No Match
2016-08-13 19:55:00	User A	Analyst	Element 2	Select	No authorizatio	0.7	true	0.3	false	No Match
2016-08-12 15:51:00	User A	Analyst	Element 2	Select	No authorizatio	0.7	true	0.3	false	No Match
2016-08-10 07:41:00	User A	Analyst	Element 2	Select	No authorizatio	0.8	true	0.2	false	No Match
2016-08-11 11:17:00	User A	Analyst	Element 2	Select	No authorizatio	0.8	true	0.2	false	No Match
2016-08-13 19:27:00	User A	Analyst	Element 2	Select	No authorizatio	0.8	true	0.2	false	No Match
2016-08-13 19:41:00	User A	Analyst	Element 2	Select	No authorizatio	0.8	true	0.2	false	No Match
2016-08-10 07:12:00	User A	Analyst	Element 2	Select	No authorizatio	0.7	true	0.3	false	No Match
2016-08-10 07:55:00	User A	Analyst	Element 3	Append	No authorizatio	0.9	true	0.1	false	No Match
2016-08-13 14:24:00	User B	Business use	Table 1	Select	No authorizatio	0.6	true	0.4	false	No Match
2016-08-12 15:22:00	User A	Analyst	Element 2	Select	No authorizatio	0.7	true	0.3	false	No Match
2016-08-12 15:36:00	User A	Analyst	Element 2	Select	No authorizatio	0.7	true	0.3	false	No Match
2016-08-11 10:19:00	User B	Business use	Table 1	Select	No authorizatio	0.7	true	0.3	false	No Match
2016-08-13 20:10:00	User A	Analyst	Element 3	Append	No authorizatio	0.8	true	0.2	false	No Match
2016-08-11 11:46:00	User A	Analyst	Element 2	Select	No authorizatio	0.7	true	0.3	false	No Match
2016-08-11 12:00:00	User A	Analyst	Element 3	Append	No authorizatio	0.9	true	0.1	false	No Match
2016-08-12 13:55:00	User B	Business use	Table 1	Select	No authorizatio	0.7	true	0.3	false	No Match
2016-08-10 07:27:00	User A	Analyst	Element 2	Select	No authorizatio	0.7	true	0.3	false	No Match
2016-08-11 06:15:00	User B	Business use	Table 1	Select	No authorizatio	0.8	true	0.2	false	No Match
2016-08-11 09:51:00	User B	Business use	Table 1	Select	No authorizatio	0.8	true	0.2	false	No Match
2016-08-12 10:19:00	User B	Business use	Table 1	Select	No authorizatio	0.7	true	0.3	false	No Match
2016-08-11 11:31:00	User A	Analyst	Element 2	Select	No authorizatio	0.7	true	0.3	false	No Match
2016-08-12 14:10:00	User B	Business use	Table 1	Select	No authorizatio	0.7	true	0.3	false	No Match
2016-08-12 16:05:00	User A	Analyst	Element 3	Append	No authorizatio	0.8	true	0.2	false	No Match
2016-08-13 18:00:00	User B	Business use	Table 1	Select	No authorizatio	0.7	true	0.3	false	No Match
2016-08-13 18:15:00	User B	Business use	Table 1	Select	No authorizatio	0.7	true	0.3	false	No Match
2016-08-13 18:29:00	User B	Business use	Table 1	Select	No authorizatio	0.7	true	0.3	false	No Match

- 28 records show **"No Match"** in the feedback from the test set after cross validation
- The security analysts had stated that the alarms were true (as shown in yellow) but our model predicts that those alarms were false (as shown in orange)
- Clearly, the 28 predicted values of Alarm (as shown below) are "False Negatives"
- Since, the model over fitted, hence, we now have more records showing "No Match"
- Let's find out how much accurate our model prediction is after using cross validation!

Microsoft Excel Worksheet

ACCURACY RESULT

Table View Plot View

accuracy: 92.90% +/- 2.61% (micro average: 92.89%)

	true false	true true	class precision
pred. false	346	28	92.51%
pred. true	0	20	100.00%
class recall	100.00%	41.67%	

Clearly, there is a lot of difference in the accuracy after doing cross validation

The accuracy before using cross validation was 95.67% whereas now, it is 92.89% - if we consider the micro average method, hence, we can say that the model is over fitting

Table View Plot View

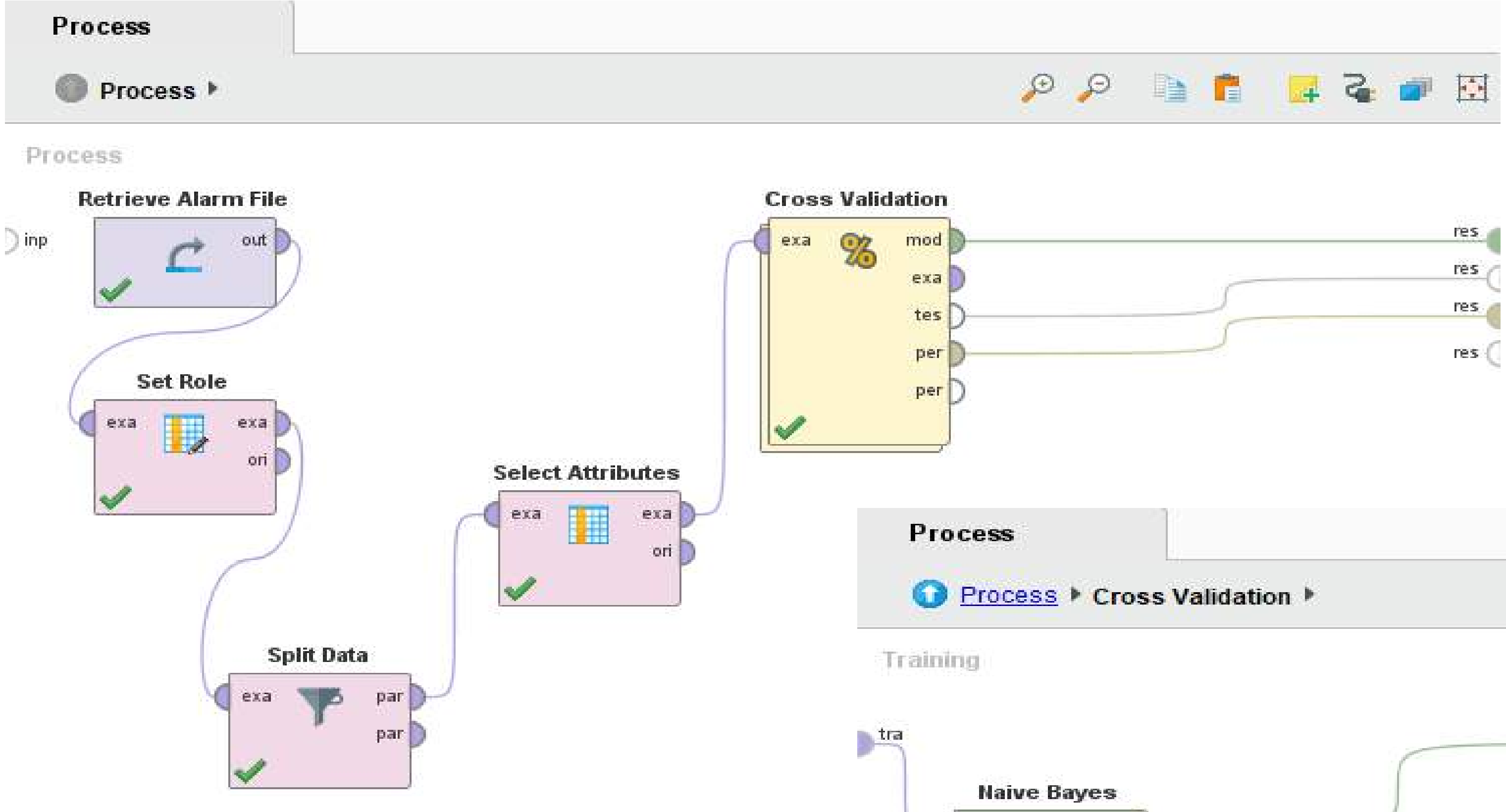
classification_error: 7.10% +/- 2.61% (micro average: 7.11%)

	true false	true true	class precision
pred. false	346	28	92.51%
pred. true	0	20	100.00%
class recall	100.00%	41.67%	

Similarly, there is again a lot of difference in the classification error of the model after using cross validation

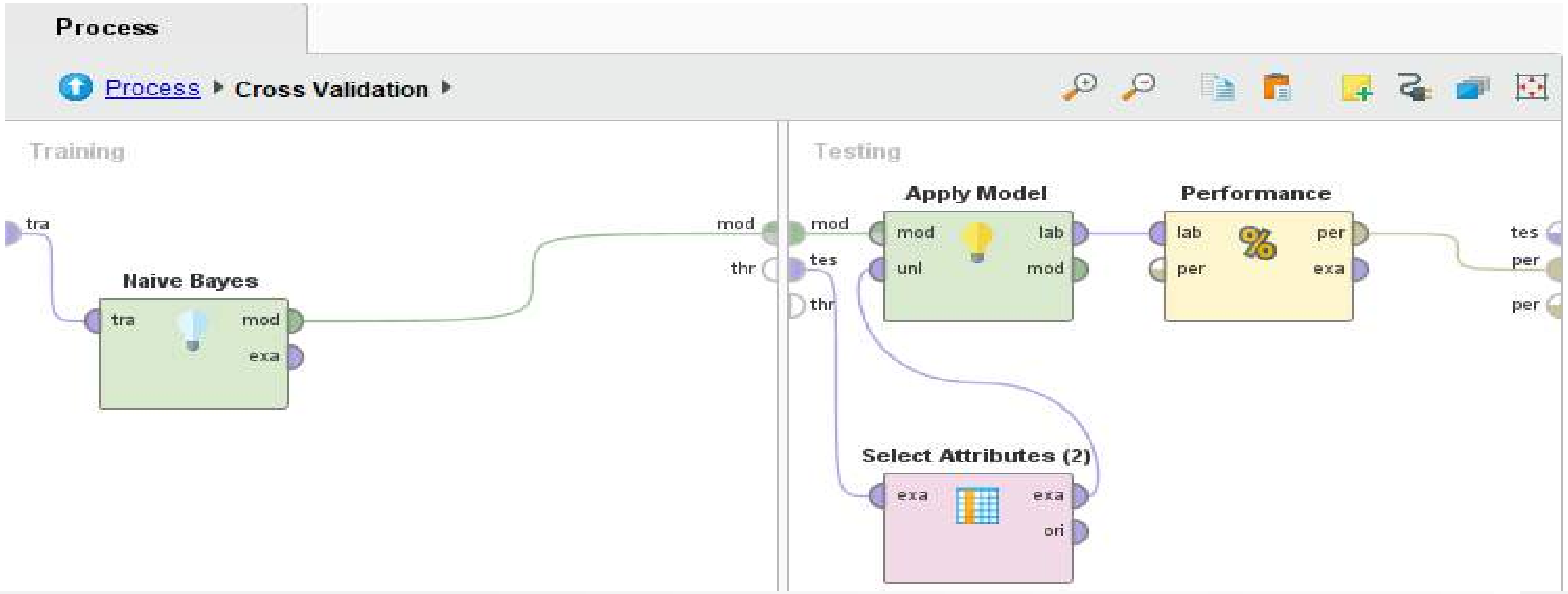
The classification error before using cross validation was 4.33% whereas now, it is 7.11% - if we consider the micro average method, hence, we can say that the model over fits

RE-TRAINING THE MODEL



‘Select Attributes’ operator is used to select which attributes one would like to keep or remove in the dataset

As stated in EDA phase, we removed Timestamp (to speed up the model building) and Violation Type (since the column is practically constant) predictor variables to check if the model performs even better



FEEDBACK FROM THE TEST SET

Request	Role	Component Accesse	Request ty	confidence(tru	confidence(fals	prediction(Aları	Ala	Match/No Mat
User B	Business use	Table 1	Select	0.3	0.7	false	true	No Match
User B	Business use	Table 1	Select	0.3	0.7	false	true	No Match
User A	Analyst	Element 2	Select	0.3	0.7	false	true	No Match
User A	Analyst	Element 2	Select	0.3	0.7	false	true	No Match
User A	Analyst	Element 2	Select	0.2	0.8	false	true	No Match
User A	Analyst	Element 2	Select	0.2	0.8	false	true	No Match
User A	Analyst	Element 2	Select	0.2	0.8	false	true	No Match
User A	Analyst	Element 2	Select	0.2	0.8	false	true	No Match
User A	Analyst	Element 2	Select	0.3	0.7	false	true	No Match
User A	Analyst	Element 3	Append	0.1	0.9	false	true	No Match
User B	Business use	Table 1	Select	0.3	0.7	false	true	No Match
User A	Analyst	Element 2	Select	0.3	0.7	false	true	No Match
User A	Analyst	Element 2	Select	0.3	0.7	false	true	No Match
User B	Business use	Table 1	Select	0.3	0.7	false	true	No Match
User A	Analyst	Element 3	Append	0.1	0.9	false	true	No Match
User A	Analyst	Element 2	Select	0.3	0.7	false	true	No Match
User A	Analyst	Element 3	Append	0.1	0.9	false	true	No Match
User B	Business use	Table 1	Select	0.3	0.7	false	true	No Match
User A	Analyst	Element 2	Select	0.4	0.6	false	true	No Match
User B	Business use	Table 1	Select	0.3	0.7	false	true	No Match
User B	Business use	Table 1	Select	0.3	0.7	false	true	No Match
User B	Business use	Table 1	Select	0.3	0.7	false	true	No Match
User A	Analyst	Element 2	Select	0.3	0.7	false	true	No Match
User B	Business use	Table 1	Select	0.3	0.7	false	true	No Match
User A	Analyst	Element 3	Append	0.2	0.8	false	true	No Match
User B	Business use	Table 1	Select	0.3	0.7	false	true	No Match
User B	Business use	Table 1	Select	0.3	0.7	false	true	No Match
User B	Business use	Table 1	Select	0.3	0.7	false	true	No Match

- 28 records show “No Match” in the feedback from the test set after cross validation
- The security analysts had stated that the alarms were true (as shown in yellow) but our model predicts that those alarms were false (as shown in orange)
- Clearly, the 28 predicted values of Alarm (as shown below) are “False Negatives”
- Let’s find out how much accurate our model prediction is after removing Timestamp & Violation Type variables

Microsoft Excel Worksheet

PERFORMANCE RESULT

Table View Plot View

accuracy: 92.90% +/- 2.61% (micro average: 92.89%)

	true false	true true	class precision
pred. false	346	28	92.51%
pred. true	0	20	100.00%
class recall	100.00%	41.67%	

Clearly, there is no difference in the accuracy of the model even after retraining the provisional model

The accuracy of the model still remains 92.89% - which is quite low and hence, we might want to rethink before considering such a model

Table View Plot View

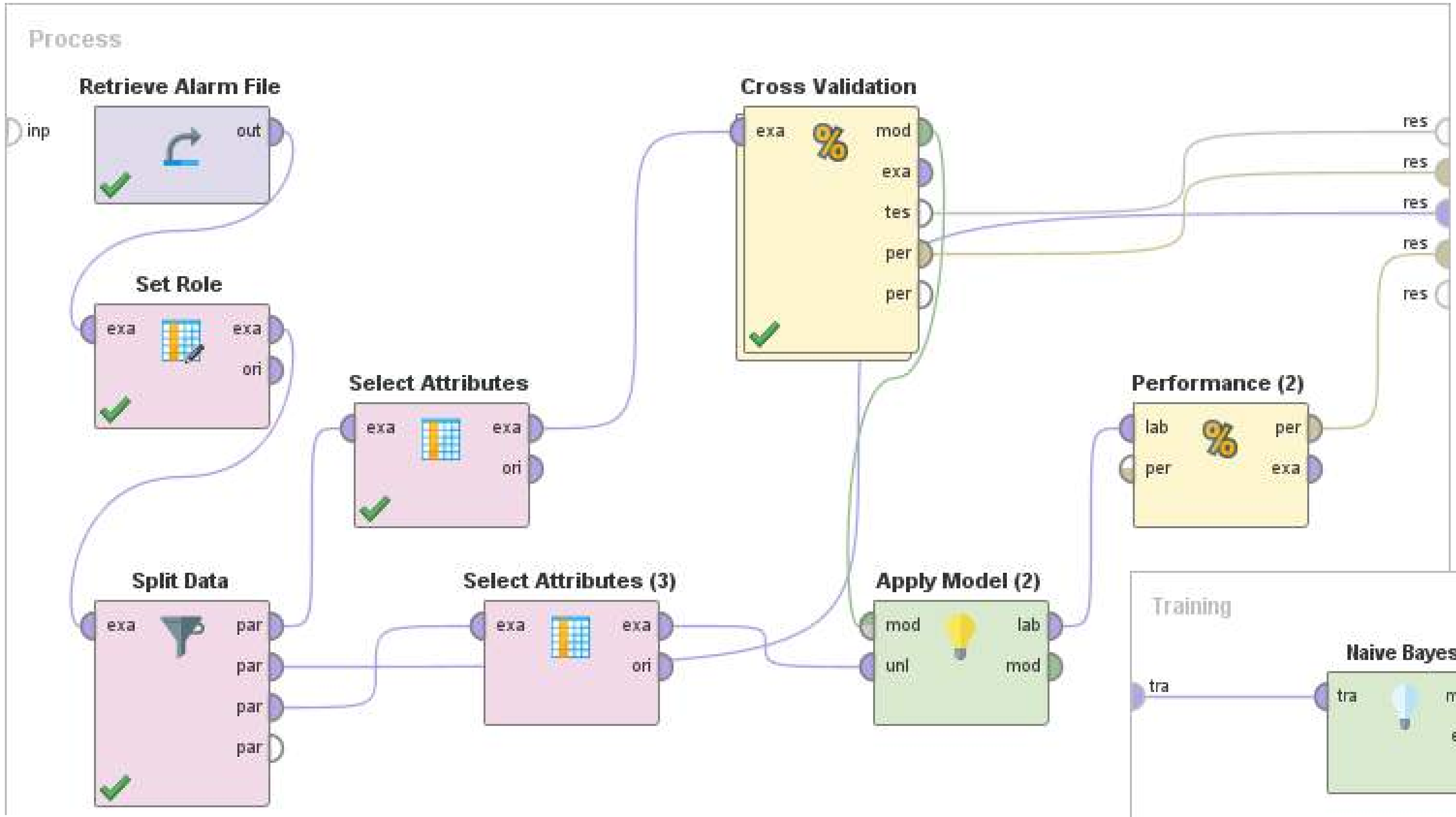
classification_error: 7.10% +/- 2.61% (micro average: 7.11%)

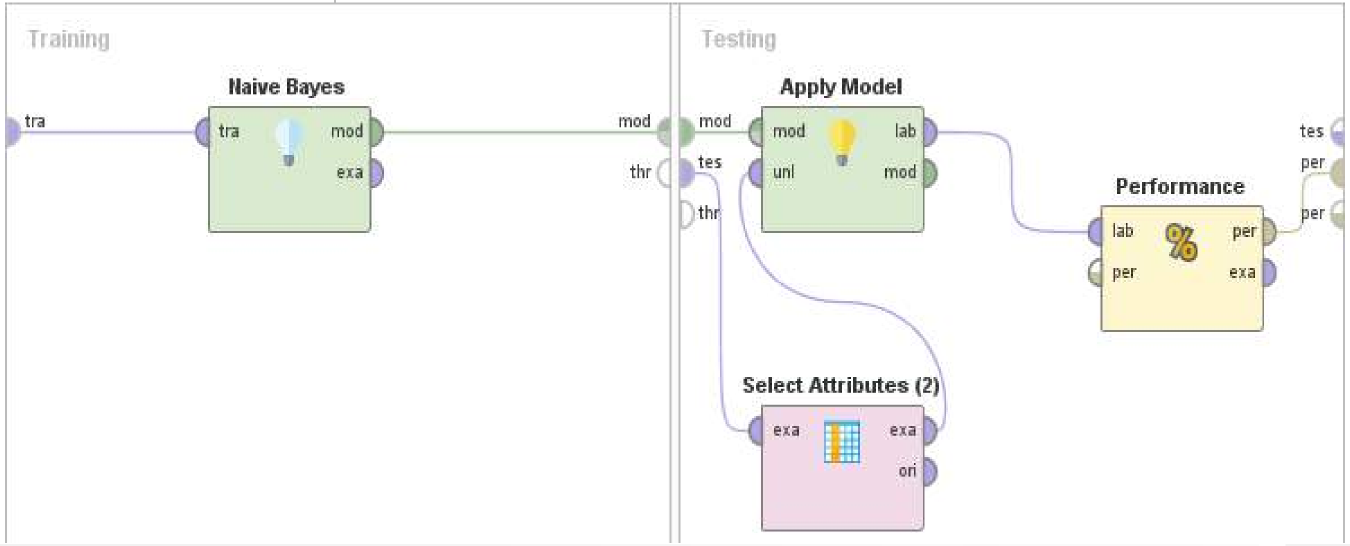
	true false	true true	class precision
pred. false	346	28	92.51%
pred. true	0	20	100.00%
class recall	100.00%	41.67%	

Similarly, there is no difference in the classification error of the model even after retraining the provisional model

The classification error still remains 7.11% - which is quite high and hence, we might want to rethink before considering such a model

APPLYING THE ADJUSTED MODEL ON VALIDATION SET





We finally apply the adjusted model (in which Timestamp & Violation Type variables are removed) to the validation set (as shown in the process editor)

Let's check the feedback from the validation set and the accuracy of the final data mining model!

FEEDBACK FROM THE VALIDATION SET

Request	Role	Component Accesse	Request ty	Ala	confidence(fals	confidence(tru	prediction(Aları	Match/No Mat
User B	Business use	Table 1	Select	true	0.7	0.3	false	No Match
User B	Business use	Table 1	Select	true	0.7	0.3	false	No Match
User B	Business use	Table 1	Select	true	0.7	0.3	false	No Match
User B	Business use	Table 1	Select	true	0.7	0.3	false	No Match
User A	Analyst	Element 2	Select	true	0.7	0.3	false	No Match
User A	Analyst	Element 2	Select	true	0.7	0.3	false	No Match
User A	Analyst	Element 2	Select	true	0.7	0.3	false	No Match
User A	Analyst	Element 3	Append	true	0.8	0.2	false	No Match
User B	Business use	Table 1	Select	true	0.7	0.3	false	No Match
User B	Business use	Table 1	Select	true	0.7	0.3	false	No Match
User B	Business use	Table 1	Select	true	0.7	0.3	false	No Match
User B	Business use	Table 1	Select	true	0.7	0.3	false	No Match
User A	Analyst	Element 2	Select	true	0.7	0.3	false	No Match
User A	Analyst	Element 2	Select	true	0.7	0.3	false	No Match
User A	Analyst	Element 2	Select	true	0.7	0.3	false	No Match
User A	Analyst	Element 3	Append	true	0.8	0.2	false	No Match
User B	Business use	Table 1	Select	true	0.7	0.3	false	No Match
User B	Business use	Table 1	Select	true	0.7	0.3	false	No Match
User B	Business use	Table 1	Select	true	0.7	0.3	false	No Match
User B	Business use	Table 1	Select	true	0.7	0.3	false	No Match
User A	Analyst	Element 2	Select	true	0.7	0.3	false	No Match
User A	Analyst	Element 2	Select	true	0.7	0.3	false	No Match
User A	Analyst	Element 2	Select	true	0.7	0.3	false	No Match
User A	Analyst	Element 3	Append	true	0.8	0.2	false	No Match
User B	Business use	Table 1	Select	true	0.7	0.3	false	No Match
User B	Business use	Table 1	Select	true	0.7	0.3	false	No Match
User B	Business use	Table 1	Select	true	0.7	0.3	false	No Match
User B	Business use	Table 1	Select	true	0.7	0.3	false	No Match

- 28 records show "No Match" in the feedback from the validation set, out of the 406 records
- The security analysts had stated that the alarms were true (as shown below in yellow) but our model predicts that those alarms were false (as shown below in orange)
- Clearly, the 28 predicted values of Alarm (as shown below) are "False Negatives" – some generated by Business User (User B) on Table 1 using Select query and some generated by Analyst (User A) on Element 2 and Element 3
- Let's find out how much accurate our model prediction is!

Microsoft Excel Worksheet

PERFORMANCE CLASSIFICATION MATRIX

Table View Plot View

accuracy: 92.90% +/- 2.61% (micro average: 92.89%)   classification_error: 7.10% +/- 2.61% (micro average: 7.11%)

	true false	true true	class precision
pred. false	346	28	92.51%
pred. true	0	20	100.00%
class recall	100.00%	41.67%	

Test set performance classification result shows 92.90% accuracy

Sensitivity or Recall of all positive classes or True Positive Rate (TPR) = 41.67%

Table View Plot View

Validation set performance classification result shows 93.10% accuracy

Sensitivity or Recall of all positive classes or True Positive Rate (TPR) = 40.43%

accuracy: 93.10%   classification_error: 6.90%

	true false	true true	class precision
pred. false	359	28	92.76%
pred. true	0	19	100.00%
class recall	100.00%	40.43%	

NAÏVE BAYES - GOOD MODEL OR NOT?

The decision tree model gives us an **overall accuracy** of **92.90% +/- 2.61%** on the **test set** and **93.10%** on the **validation set**

Removing Timestamp and Violation Type do not make any difference on the accuracy of the model

Since, the model accuracy is below 95% and the error rate is also high (6.90%), hence, we might want to rethink before considering such a model

Model Accuracy: 90.00% to 93.10%

Not recommended!

LOGISTIC REGRESSION

- A popular go-to supervised classification method used in data mining
- Uses a predictive analysis algorithm which is based on the concept of probability
- Used to assign observations to a discrete set of classes (here, True and False)
- Required polynomial variables to be converted to numerical variables (also called dummy variables)
- Tool used for building the Logistic Regression classification model: **RapidMiner Studio**
- RapidMiner is a very effective data science software platform that unites data prep, machine learning & predictive model deployment

Recommendation in EDA Phase:

….

Seems to give 100.00% accuracy results and seems to be very efficient

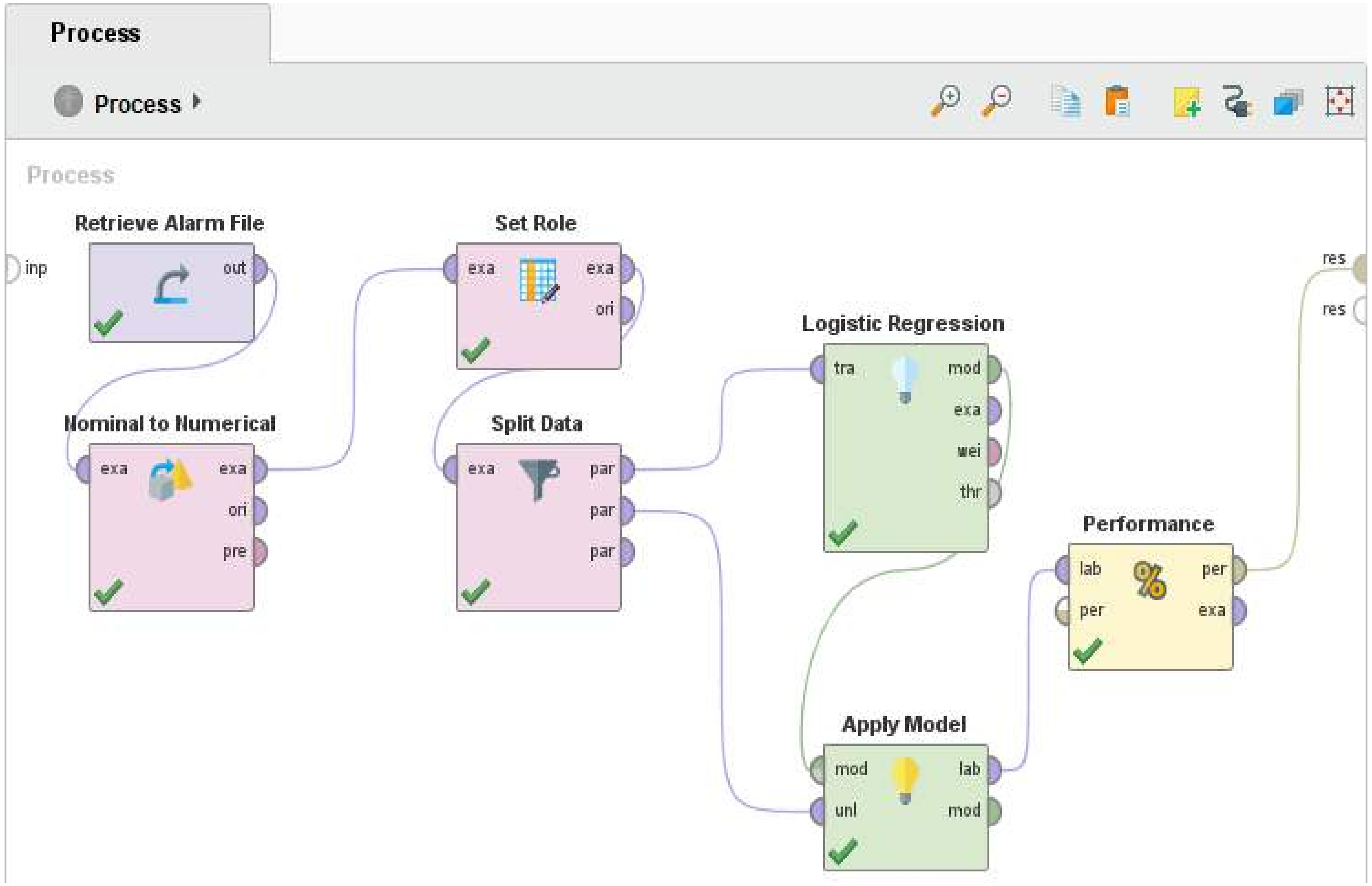
LOGISTIC REGRESSION - USING THE TRAINING AND TEST SET

The first step is to retrieve the data i.e. Alarm file

The second step is to convert polynomial variables into numeric variables by using 'Nominal to Numerical' operator

The 'Nominal to Numerical' operator converts the nominal variables into dummy variables depending on the number of values of the nominal variable

'Set Role' operator is used to tell RapidMiner which is our target variable (Alarm)



Dataset is split into 3 sets: Training, Test & Validation datasets (1/3rd each) using the 'Split Data' operator

Now, we use 'Logistic Regression' operator to build the provisional model

Now, we apply the provisional model to the test set using 'Apply Model' operator

Lastly, 'Performance (Classification)' operator is used to evaluate the model by telling us the accuracy of the model

ACCURACY RESULT

Microsoft Excel Worksheet

100.00% accuracy, The best model so far!

et (Apply Model) | PerformanceVector (Performance)

Table View Plot View

Actual (or True) Values

accuracy: 100.00%

Predicted Values	true false	true true	class precision
pred. false	348	0	100.00%
pred. true	0	46	100.00%
class recall	100.00%	100.00%	

Here, True Negative (TN) = 348
False Negative (FN) = 0
False Positive (FP) = 0
True Positive (TP) = 46

Hence, **True Positive Rate (TPR)** can be calculated as: TP/(TP + FN) = **100.00%**

True Negative Rate (TNR) can be calculated as: TN/(TN + FP) = **100.00%**

Positive Predictive Value (PPV) can be calculated as: TP/(TP+FP) = **100.00%**

Negative Predictive Value (NPV) can be calculated as: TN/(TN+FN) = **100.00%**

Accuracy can be calculated as: (TP+TN)/(TP+TN+FP+FN) = **100.00%**

et (Apply Model) | PerformanceVector (Performance)

Table View Plot View

Classification error can be calculated as: (FP+FN)/(TP+TN+FP+FN) = **0.00%**

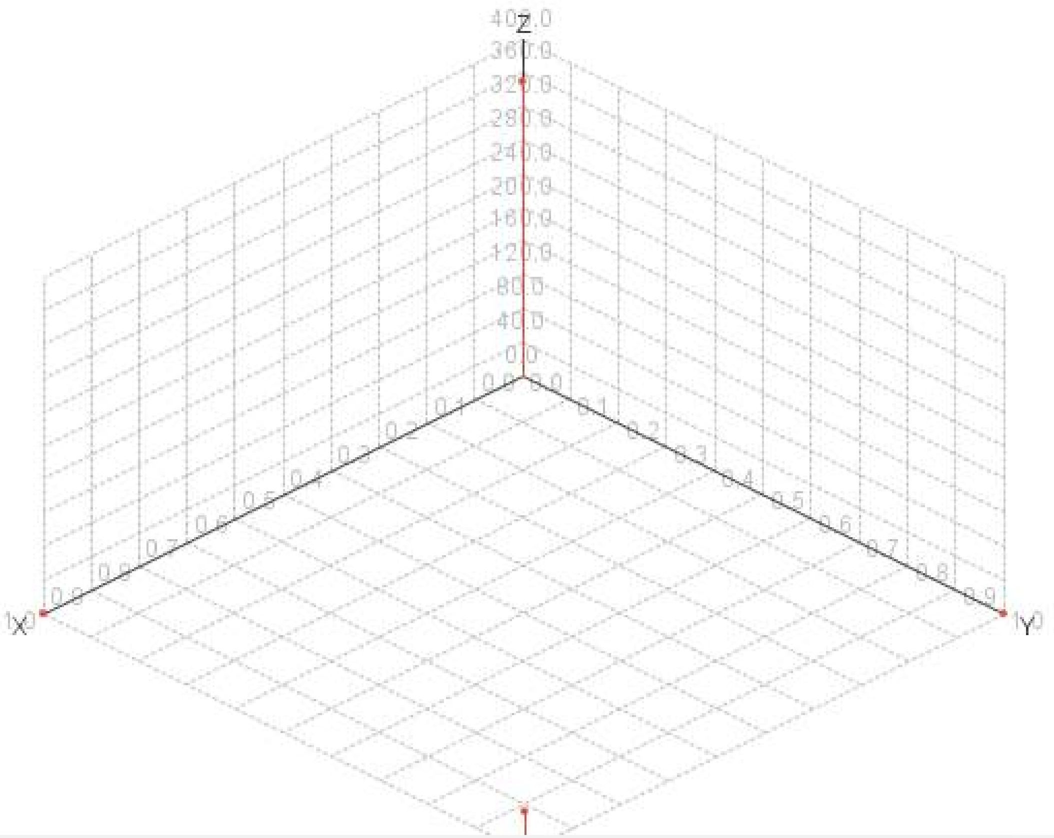
classification_error: 0.00%

	true false	true true	class precision
pred. false	348	0	100.00%
pred. true	0	46	100.00%
class recall	100.00%	100.00%	

ACCURACY RESULT

Table View Plot View

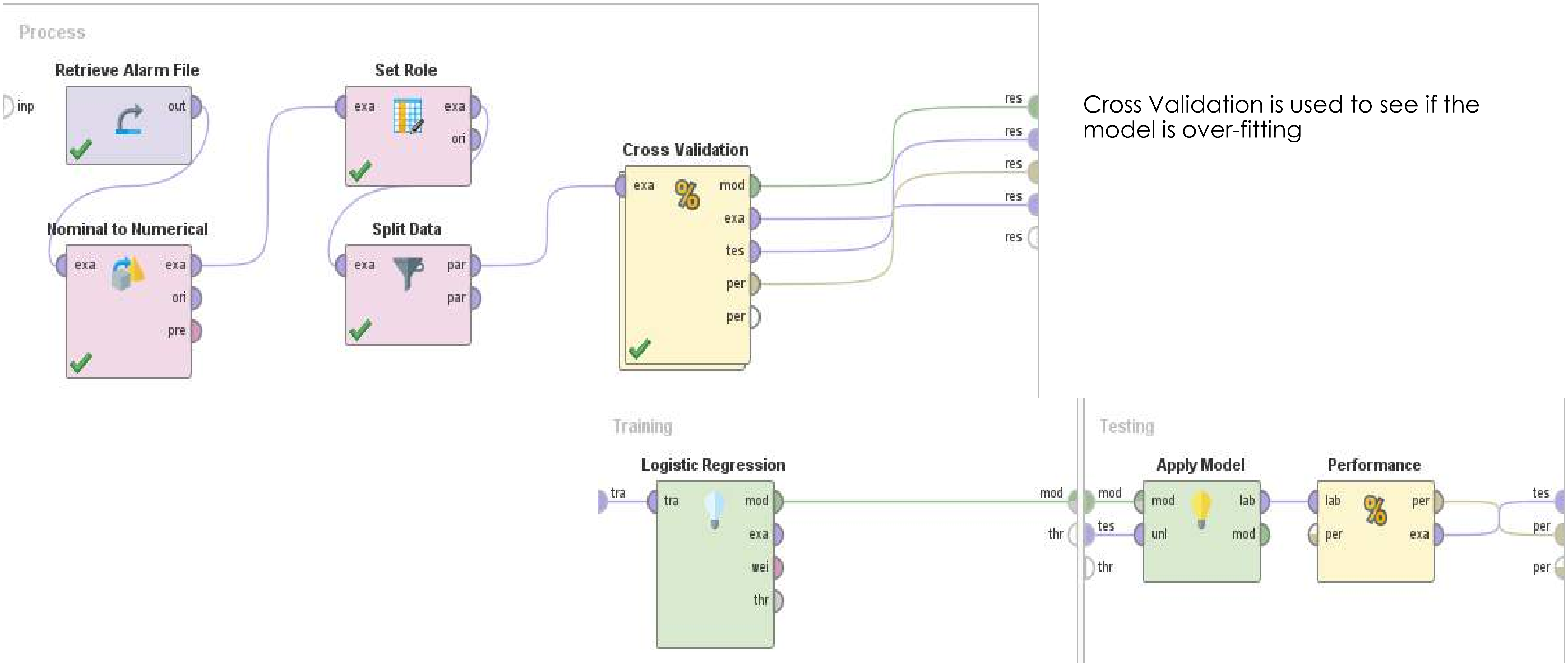
Confusion Matrix (x: true class, y: pred. class, z: counters)



Plot View of Performance (Classification) matrix:

X: Actual Values
Y: Predicted Values
Z: Values (or Counters)

USING CROSS VALIDATION TO CHECK OVER-FITTING



Cross Validation is used to see if the model is over-fitting

FEEDBACK FROM THE TEST SET

Reques	Reques	Reques	Role_B	Role_A	Role_A	Compo	Compo	Compo	Compo	Compo	Reques	Reques	confide	predict	Alarm	confidence(tru	Match/No Mat
0.0	0.0	1.0	0.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0	1.0	0.0	0.0	true	false	1.0	No Match

- Only one record shows ‘No Match’
- Let’s find out how much accurate our model prediction is after using cross validation!

Microsoft Excel Worksheet

ACCURACY RESULT

Table View Plot View

accuracy: 99.75% +/- 0.79% (micro average: 99.75%)

	true false	true true	class precision
pred. false	346	0	100.00%
pred. true	1	46	97.87%
class recall	99.71%	100.00%	

Clearly, there is not much difference between the accuracy of the model before and after using cross validation

The accuracy before using cross validation was 100.00% whereas now, it is 99.75% - hence, we cannot explicitly say if the model over fits

Table View Plot View

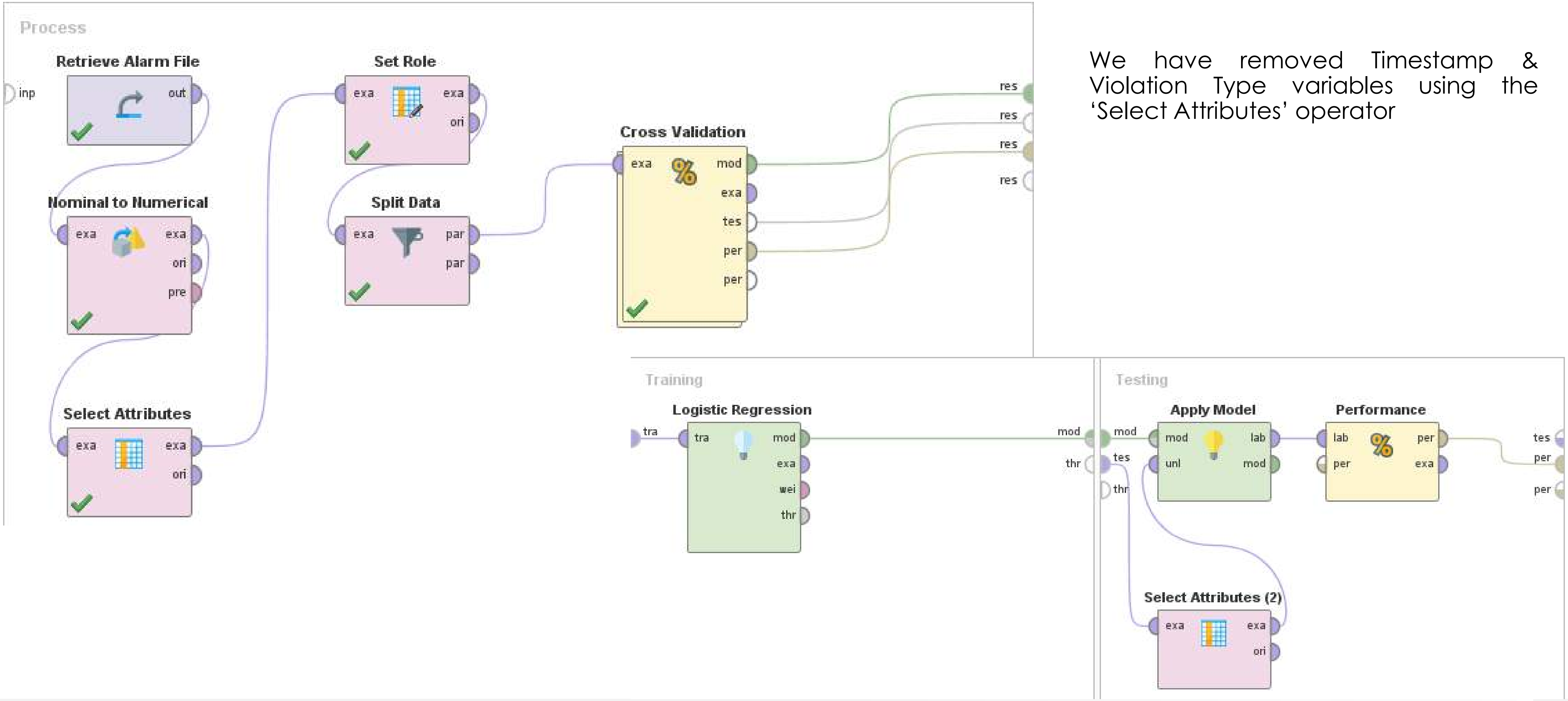
Similarly, there is not much difference in the classification error of the model before and after using cross validation

The classification error before using cross validation was 0.00% whereas now, it is 0.25% - hence, we cannot explicitly say that the model over fits

classification_error: 0.25% +/- 0.79% (micro average: 0.25%)

	true false	true true	class precision
pred. false	346	0	100.00%
pred. true	1	46	97.87%
class recall	99.71%	100.00%	

RE-TRAINING THE MODEL



We have removed Timestamp & Violation Type variables using the ‘Select Attributes’ operator

PERFORMANCE RESULT

Table View Plot View

accuracy: 99.75% +/- 0.79% (micro average: 99.75%)

	true false	true true	class precision
pred. false	346	0	100.00%
pred. true	1	46	97.87%
class recall	99.71%	100.00%	

There is no difference in the accuracy of the model even after removing Timestamp & Violation Type variables

The accuracy still remains 99.75%

Again, there is no difference in the classification error of the model even after removing Timestamp & Violation Type variables

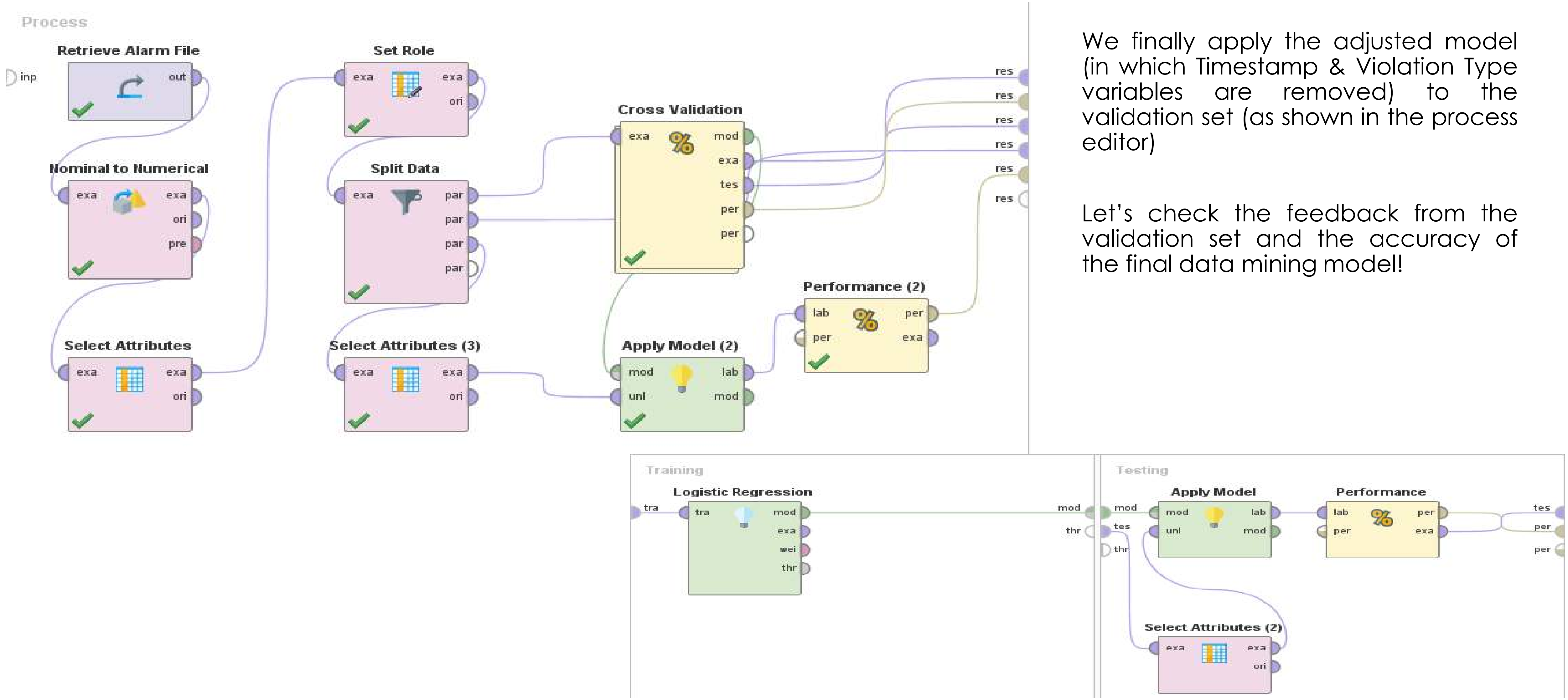
The classification error rate still remains 0.25%

Table View Plot View

classification_error: 0.25% +/- 0.79% (micro average: 0.25%)

	true false	true true	class precision
pred. false	346	0	100.00%
pred. true	1	46	97.87%
class recall	99.71%	100.00%	

APPLYING THE ADJUSTED MODEL ON VALIDATION SET



We finally apply the adjusted model (in which Timestamp & Violation Type variables are removed) to the validation set (as shown in the process editor)

Let's check the feedback from the validation set and the accuracy of the final data mining model!

PERFORMANCE CLASSIFICATION MATRIX

Table View Plot View

accuracy: 99.75% +/- 0.79% (micro average: 99.75%)

	true false	true true	class precision
pred. false	346	0	100.00%
pred. true	1	46	97.87%
class recall	99.71%	100.00%	

Test set performance classification result shows 99.75% accuracy

Sensitivity or Recall of all positive classes or True Positive Rate (TPR) = 100.00%

Table View Plot View

accuracy: 100.00%

	true false	true true	class precision
pred. false	358	0	100.00%
pred. true	0	48	100.00%
class recall	100.00%	100.00%	

Validation set performance classification result shows 100.00% accuracy

Sensitivity or Recall of all positive classes or True Positive Rate (TPR) = 100.00%

LOGISTIC REGRESSION - GOOD MODEL OR NOT?

The decision tree model gives us an **overall accuracy** of **99.75% +/- 0.79%** on the **test set** and **100.00%** on the **validation set**

Removing Timestamp and Violation Type do not make any difference on the accuracy of the model but definitely reduce the execution time of the model building

Since, the model accuracy is above 95% and the error rate is also very low(0.00% to 0.25%), hence, we can definitely think of considering this model as the best one!

Model Accuracy: 98.00% to 99.99%

The best model so far!

SUMMARY AND RECOMMENDATIONS

Based on the percentages calculated, we must consider the following scenarios:

i) **False Positive Rate (FPR):** FPR is equal to the level of significance ($\alpha = 0.05$). Hence, a large False Positive Rate (or Fall-out rate) can present a poor performance of the Data Loss Detection Engine/System

ii) **False Negative Rate (FNR):** A large False Negative Rate (FNR) can make CISO or any other organization an easy target to sabotage since the result is erroneously marked as 'False' alarms

iii) **True Positive Rate (TPR):** A large True Positive Rate (or Sensitivity) can give confidence to CISO or any other organization about the rising number of 'true' alarms and hence, can take appropriate actions at an early stage

iv) **True Negative Rate (TNR):** A large True Negative Rate (or Specificity) may present a higher efficiency of security analysts at work and hence, CISO can improve workforce management

The False Positive Rate (**FPR**) in all the 3 models is: **0.00%** => FP/(FP+TN) - which is good

The False Negative Rate (**FNR**) in all the 3 models is calculated as => FN/(FN+TP)

Decision Tree: 34.04% (rethink)	Naïve Bayes: 59.57% (too high)	Logistic Regression: 0.00% (best to consider)