



Introduction to Next Generation Business Intelligence with Automated Analytics Mode in SAP Predictive Analytics Case Study

Product

SAP Predictive Analytics

Level

Undergraduate Graduate Intermediate

Focus

Business Analytics

Authors

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Version

1.1 for UWM Workshop

Updated by Nancy Jones and Hossam Ali-Hassan for the SAP UA Analytics Summer Workshop 2016 @ UWM.

Motivation

This case study provides an introduction into four different use cases of Automated Analytics in SAP Predictive Analytics to demonstrate how business users can develop predictive models that can be published to target specific customers, assess risks or predict what products are of interest to which customers.

Prerequisites

A basic understanding of predictive analytics is recommended. Students should be familiar with classification, correlation and regression concepts.

To complete these exercises you will require SAP Predictive Analytics and the accompanying data files which should be installed in the \07 Predictive Analytics Automated folder.

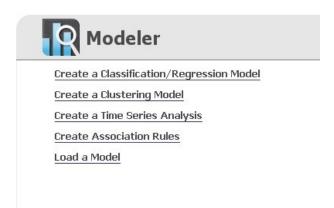
Exercise 1: Auto Insurance Risk Analysis with SAP Predictive Analytics

In this exercise, an analyst of an Insurance company notices the number of accident claims has increased. He decides that it would be better to analyze the key factors that lead to claim and use them to evaluate the risk of claim for new contracts in the future. The analyst uses SAP Predictive Analytics to statistically analyze what factors lead to a claim. Using the pattern developed using past data, she is able to predict the risk of claim for new contracts considering the profile of the subscriber and the car insured.

Start SAP Predictive Analytics by following the menu **Start > All Programs > SAP Business Intelligence > SAP Predictive Analytics Desktop > SAP Predictive Analytics**

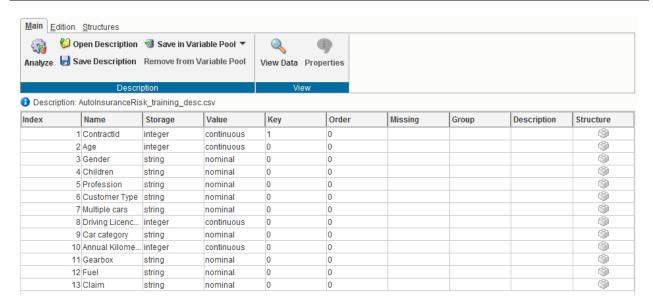


Click on the option Modeler.



Field Label	Value	Description
		Click on the option Create a Classification / Regression Model .
Data Type	Text files	

Field Label	Value	Description
Folder	.\07 Predictive Analytics Automated	Click Browse for the Data Set option.
		Select the file AutoInsuranceRisk_training.csv.
		Click OK.
		Click Next.
		Click Open Description.
		Main
		Click Browse for the Description .
		Select the file AutoInsuranceRisk_training_desc.csv.
		Click OK.
		Click OK.

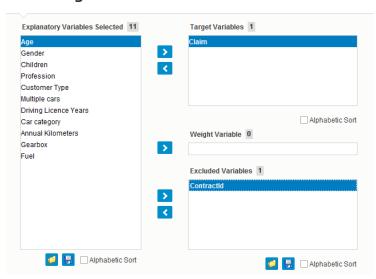


Click **View Data** to see the actual records.

Take some time to understand what data you have available by looking at the actual records. It is important to understand the business problem and the data to make the right decisions based on using these tools.

Field Label	Value	Description
		Click Close to close the sample data.
		Click Next.

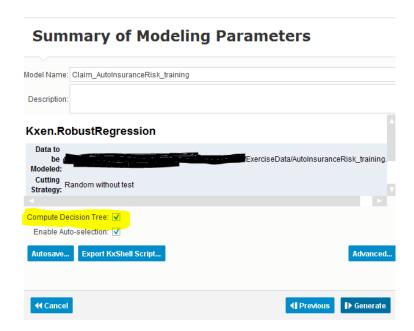
Selecting Variables



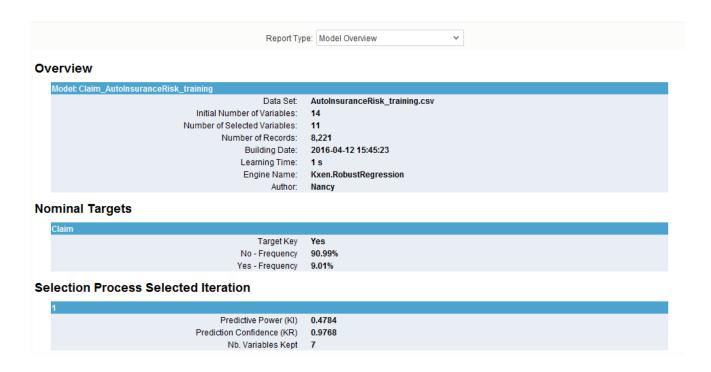
The model identifies a pattern in how one, few or all of the explanatory variables lead to a claim.

Note: The target variable is the phenomena we would like to explain, in this case the fact that the contract led to an accident claim. The explanatory variables are the potential variables that could explain the phenomena. Here we think that the driver age, its gender, the car category, etc. can potentially have an impact on the risk of accident. SAP Predictive Analytics is going to identify the most significant variables that contribute to explain the risk of accident. Note that the Contract Id will be excluded, as it may not have any impact on the risk of accident.

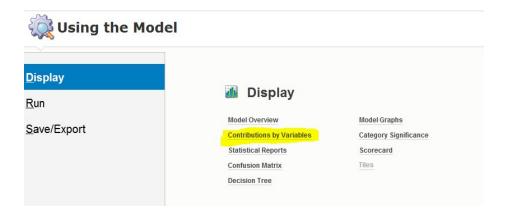
Check that the column **Contract ID** is in the list of the **Excluded Variables**. Click **Next**.



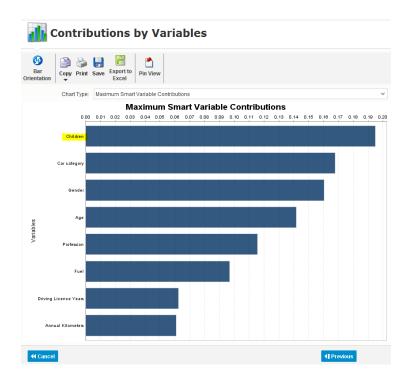
Activate the option Compute Decision Tree. Click Generate.



At the bottom you can see that SAP Predictive Analytics found 7 variables that are influencing the claims. Click **Next**.



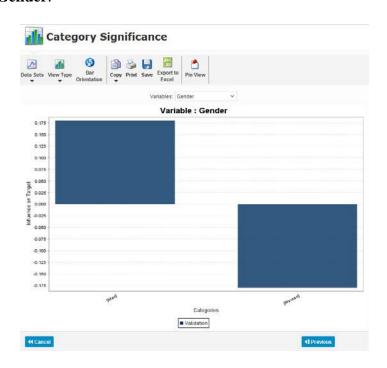
Click on **Contributions by Variables**. – You can change the direction of the Bars by clicking on the Bar **Orientation** Button on the top left.



As you can see the number of children is the most important factor. Double-click on the bar for **Children**.



You can see now that customers without children have a much higher propensity to have an accident compared to customers with 4 or more children. Another way to see this is that positive numbers for Influence on Target means that having no children has a greater likelihood of accidents, while the negative numbers for Influence on Target means that having 4 or more children has a smaller likelihood of claiming an automobile accident. Click on **Previous**. Double-click on the bar for **Gender**.

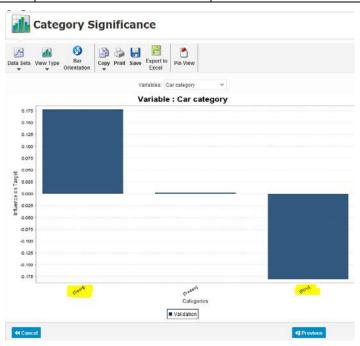


You see that Gender makes a difference.

Q1: Is a Man or Woman likely to have an accident?

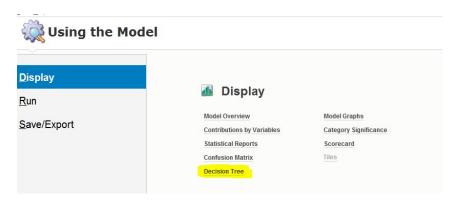
Field Label	Value	Description
		Click on Previous .
		Double-click on the bar for Car Category.

1 mark

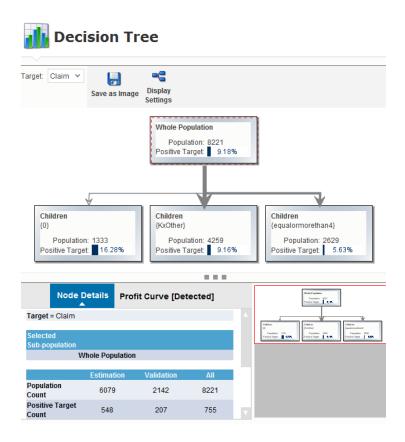


So a man in a sports car is a much higher risk than a woman in a SUV.

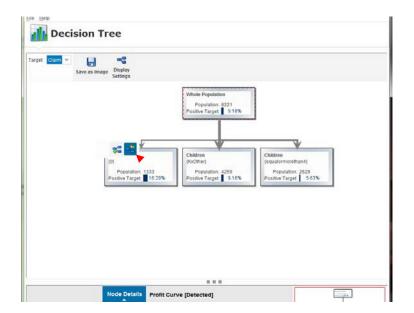
Field Label	Value	Description
		Click Previous.
		Click Previous.



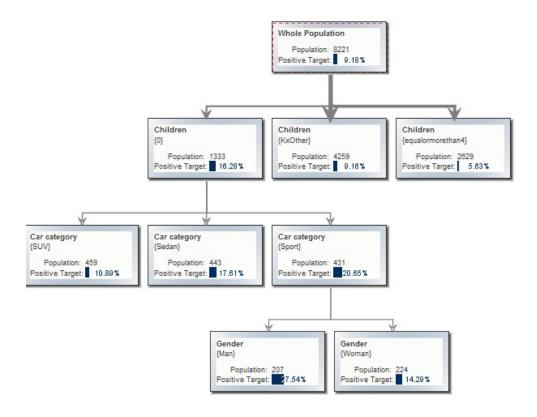
Click on **Decision Tree**.



The decision tree accompanied the model shows that comparing to overall claim rate of 9.18%, the customers who don't have children had a claim rate of 16.28%. On the contrary, those who have 4 children and more only had a claim rate of 5.63%.



Move the mouse cursor on top of the node of 0 **Children** and **expand the node**. Repeat this and expand the node for the **Car Category Sport**. (you may have to play about with one of the other boxes to view this)



So we can see that Man without Children driving Sport cars have a claim rate of 27.54% - a very high risk group.

Q2. What is the claim rate for women without children driving sports cars? 1 - Mark

Below the node, you can examine the details for Males without Children in Sport cars.

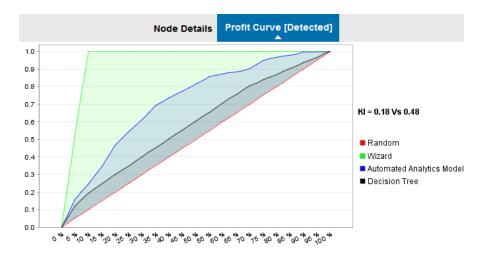
	Node Details	rofit Curve [Detected]	
Target = Claim			
Selected Sub-population			
	Children is in {0}		
AND	Car category is in {S	port}	
AND	Gender is in {Man}		
	Estimation	Validation	All
Population Count	146	61	207
Positive Target Count	41	16	57
Positive Target Ratio	28.08%	26.23%	27.54%
Negative Target Count	105	45	150
Negative Target Ratio	71.92%	73.77%	72.46%
Variance	0	0	
Weighted Population	146.0	61.0	

Here you can see how accurate the model is at predicting claims based on a cutting strategy of estimating using 146 drivers and validating with 61 drivers.

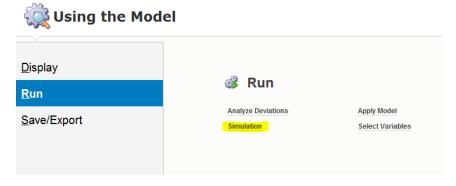
Click on **Profit Curve [Detected]** to view the ROC (Receiver operating characteristic Curve) for the Predictive Analytics model compared to the Decision Tree and a Random selection.

The Red line would be the performance if we used no model.

The Green line would be the model performance if we created a theoretically perfect model. The Blue line is how well our current model performed.



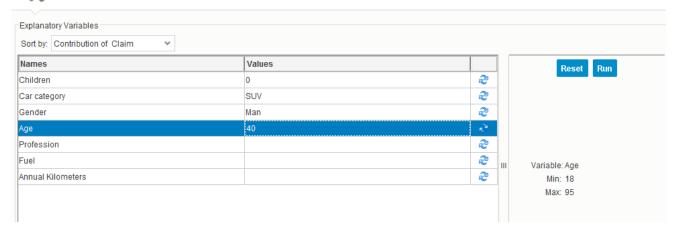
Field Label	Value	Description
		Click Previous.
		Select the option Run .



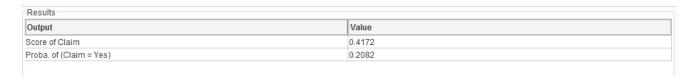
Select the option **Simulation**. Enter the following values:

Field Label	Value	Description
Children	0	
Car Category	SUV	
Gender	Man	
Age	40	

Simulating the Model



Click Run.



The probability for a claim of our 40 year old man driving a SUV without any children is 20.82%.

Note: this means the probability that this driver belongs to the group "Claim=Yes" is 20.82%, which is a subtle difference from saying that this driver has a 20.82% chance of having an accident. For the purposes of pricing Insurance premiums this subtlety is not a problem because one deals with aggregated customer groups who collectively will have 20.82% of their members having claims, which allows insurers to calculate the cost of insuring those customers.

Q. 3 Enter the following and Run:

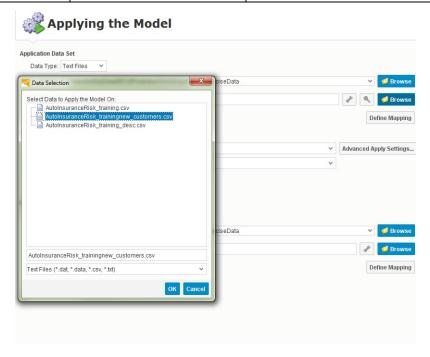
What is the probability for a claim in this instance? 1 - Mark

Field Label	Value	Description
Children	4	
Car Category	SUV	
Gender	Man	
Age	55	

Field Label	Value	Description
		Click Previous.
		Click Apply Model.

Now we are going to load a set of new customers and apply the probabilistic model to predict their risk. For this we load a data file with no claim information, apply the model and then output a new data file with the calculated risk scores. In a real-time business, one would have the model applied as new customer information is entered to generate an instant risk score instead of the process we are doing here.

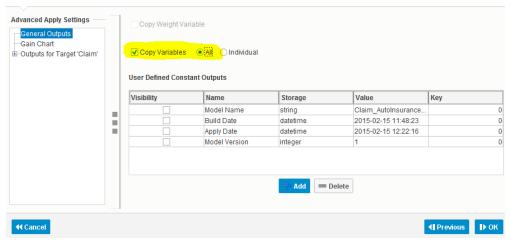
Field Label	Value	Description
		Click Previous.
		Click Apply Model.



Click on Browse for the Data and select the file AutoInsuranceRisk_trainingnew_customers.csv.

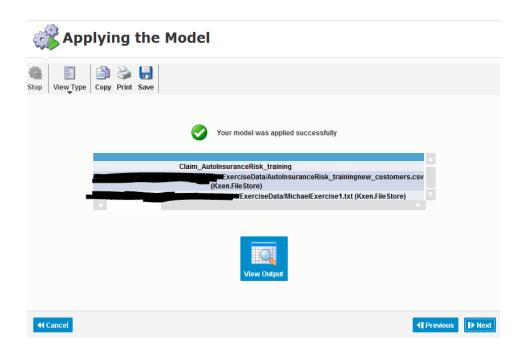
Field Label	Value	Description
		Click OK.
		Click on Advanced Apply Settings.

Model Advanced Apply Settings

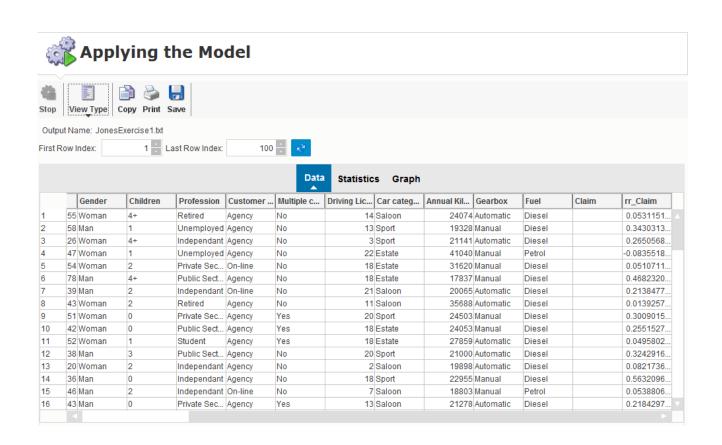


Field Label	Value	Description
		Activate the option Copy Variables.
		Activate the option All.
		Click OK.
		Click on Browse for the Folder in the Results Generated by the Model area.
		Check that the folder /07 Predictive Analytics Automated is set as location to store the file.
		Enter YourNameExercise1.txt for the field Data.
		Click Apply.

Be careful when entering Directory and filenames



Click View Output.



If you look at the rightmost column, you can see the prediction that was added by applying the model to the dataset. The first row is a 55 year old Woman in a Saloon (=Sedan in American English) with 4+ Children, while the second one is a 58 year old Man with one Child in a Sport car, who is clearly a higher insurance risk!

Q4. Which Contract id has the highest Insurance Risk? (1 Mark)

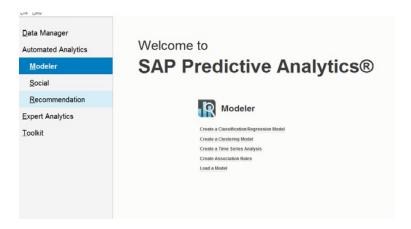
Exercise 2: Long-Term Customer Relationships with SAP Predictive Analytics

In an ever-competitive market, banks face challenges to keep customers, especially when they are highly profitable. One of many KPIs regularly monitored in the retail bank is customer attrition. When a highly profitable customer leaves, it hurts the bottom line. Giving near real-time visibility to attrition helps executives to develop proactive strategies.

The head of sales for retail banking sees that the attrition numbers are rising. He is made aware of high-value customers at risk of attrition through his dashboard and then can get a 360-degree view of the customer, including suggested offers to entice the customers to stay. A comprehensive customer view means finding insights that only come from a complete picture.

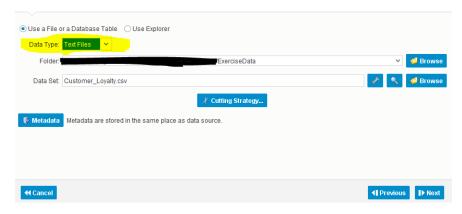
Mary, an analyst at BestRun Bank, has been tasked to find the factors that contributed to customer leave.

Start SAP Predictive Analytics by following the menu **Start > All Programs > SAP Business Intelligence > SAP Predictive Analytics Desktop > SAP Predictive Analytics**



Click on the option **Modeler**, then **Create a Classification / Regression Model**. Ensure the option **Data Type** is set to **Text Files**. Enter the following to the option Folder: \\07 Predictive Analytics Automated.

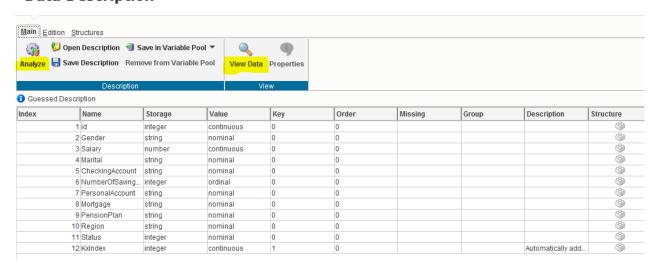
Select a Data Source



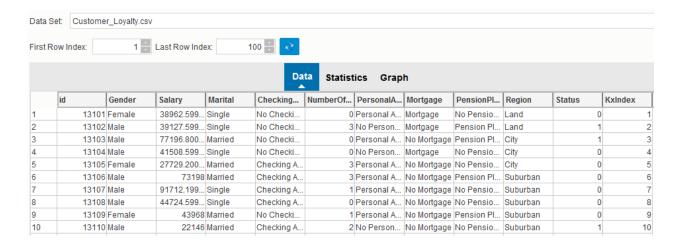
Field Label	Value	Description
		Click Browse for the Data Set option.
		Select the file Customer_Loyalty.csv.
		Click OK.
		Click Next.
		Click Analyze.

Here the data is automatically described. We could edit and save these definitions if we wanted to here. Have a look to understand what values we will use in the model.

Data Description

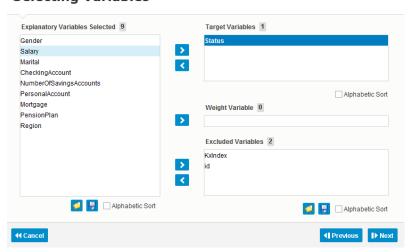


Click View Data to examine and understand what we are working with.



Field Label	Value	Description
		Click Close.
		Click Next.
Explanatory Variables Selected		Move the column ID to the Excluded Variables.
		Ensure the column Status is set in Target Variables .

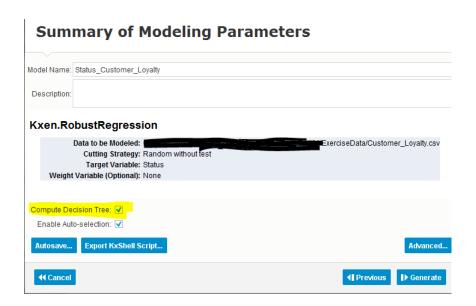
Selecting Variables



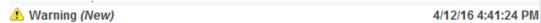
Note: The target variable is the phenomena the user would like to explain, in this case the status of a customer (whether they have left or not). The explanatory variables are the potential variables that could explain the phenomena. Here customer's gender, marital status, region are included because they can potentially impact the risk to leave.

SAP Predictive Analytics is going to identify the most significant variables that contribute to explaining the leave. Note that the Id is excluded, as it may not have any impact on the risk of leave. In this dataset, positive target corresponds with records that have '0' value, which is customers who stay.

Field Label	Value	Description
		Click Next.

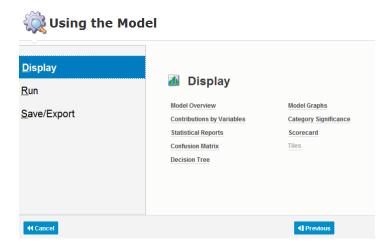


Field Label	Value	Description
Compute Decision Tree		Set checkbox.
		Click Generate.
		Click Next.



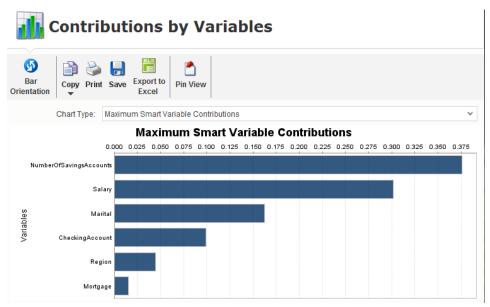
Found significant deviation on data set Validation: model will be suspicious. The following variables have deviations: Gender. Consider changing the cutting strategy or excluding these variables from the model.

Close the error message and click Next.

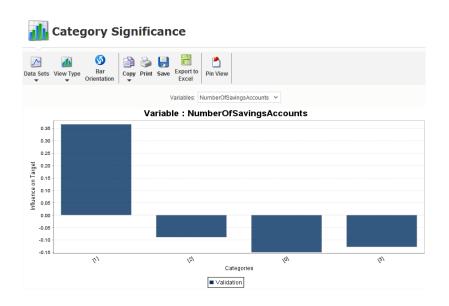


Field Label	Value	Description
		Click on Contributions by Variables
		Click on Bar Orientation

Now you should see the bars and text horizontally which is easier to read.



Double-Click on the bar for the **Number of Saving Accounts**.



Customers with no savings account or more than 1 saving accounts have a higher propensity to leave the bank than customers who have just 1 savings account.

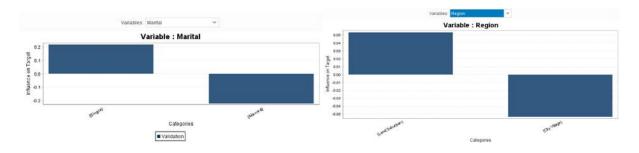
Field Label	Value	Description
		Click Previous.
		Double-click on the bar for Salary .



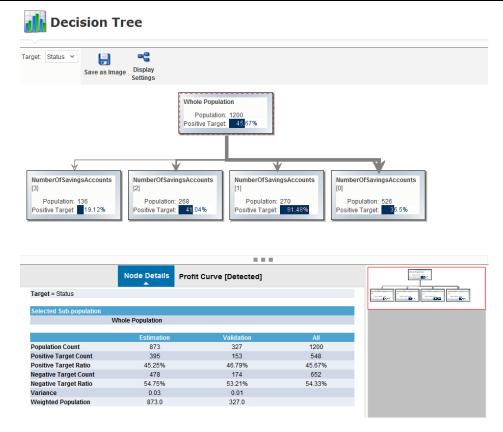
Customers with a lower income have a higher propensity to leave. Click **Previous**. Take a look at the details for the variables Marital and Region. You will notice:

• Married customers have a higher propensity to leave the bank.

• Customer from the city or from a village have a higher propensity.



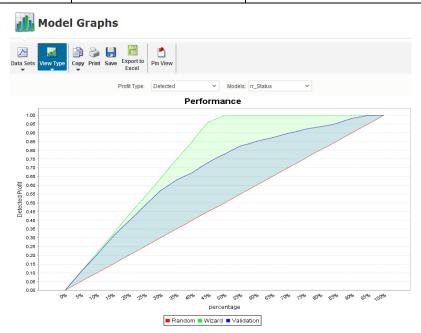
Field Label	Value	Description
		Click Previous.
		Click Previous.
		Click on Decision Tree .



We can see that 45.67 % of the population is not about to leave our bank. The population statistics also show that SAP Predictive Analytics used a cutting strategy with 873 customers to create the model and 327 to validate it.

By expanding the decision tree we can see that the percentage value of loyal customers goes up to 81 % for customers with 1 Savings account. Means we should focus on customers with more than 1 saving account or 0 saving account.

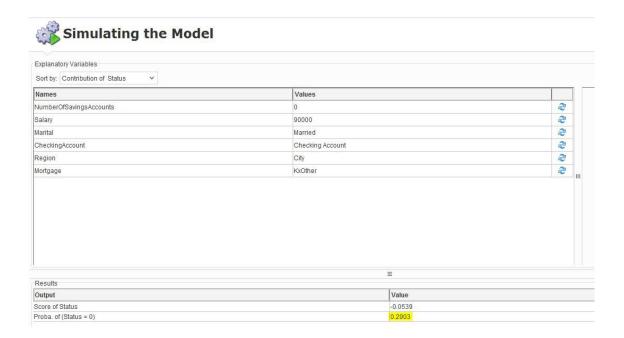
Field Label	Value	Description
		Click Previous.
		Click Model Graphs.



Ensure the **Profit Type is set to Detected** and the **Models option is set to the value rr_Status**. The Red line would be the performance if we used no model. The Green line would be the model performance if we created a theoretically perfect model. The Blue line is how well our current model performed. Click **Previous**. Navigate to the **Run** area. Select the option **Simulation**.

Field Label	Value	Description
Salary value	90000	
Marital value	Married	Click Run.

The results of the simulation will appear in the Results section. You will obtain the Predicted value (score) of the observation described in the table of Explanatory variables, as well as the probability that this observation belongs to the target category of the target variable.



The probability of our customers – Married with 90,000 \$ income – staying is 29%. Note that certain variables of the table of Explanatory variables were automatically completed upon execution of the simulation. In fact, the model automatically completed certain missing values that were essential to the simulation. In our example the model assumed 0 Savings Accounts, 1 Checking Account, and in the Region City.

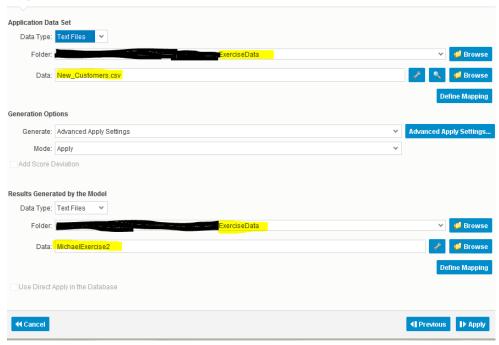
Change the **NumberOfSavingsAccounts** to 1 and **Run** the simulation again. This time the probability that the customer is will be loyal jumped to 87%. Click **Previous**, then **Apply Model**.

Q5. What is the probability of customers with an income of \$106,000, a mortgage, checking account, married, region city and one saving account? 1 – Mark

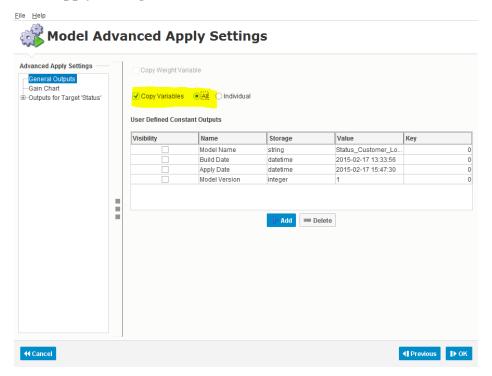
We will apply the model to a new data file of customers to now predict their probability of leaving. For this we will load New_Customers.csv which contains a list of 20 new customers.

Field Label	Value	Description
		Click Browse and select file New_Customers.csv.
		Click OK.





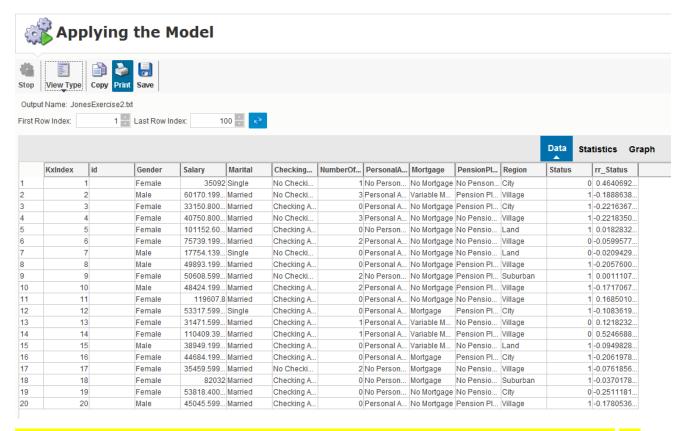
Click on Advanced Apply Settings.



Field Label	Value	Description
Copy Variables		Set checkbox.
All		Set this option.
		Click OK.
		Click Browse

For the Folder option of Results Generated by the Model select the folder \\07 Predictive Analytics Automated if not automatically. For the Results Generated by the model enter a file name YourNameExercise2 to store the output.

Field Label	Value	Description
		Click Apply.
		Click View Output.



Q6. Here you can see the scores for the new 20 customers. Which one is most likely to leave? 1 - Mark

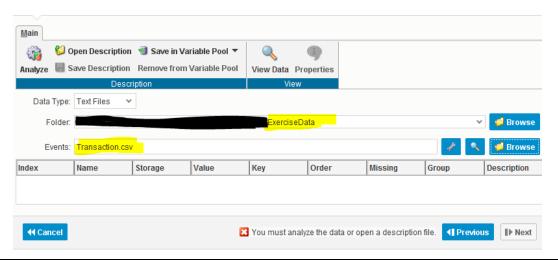
Click on the **rr_Status** column to sort to see the smallest likelihood of being a loyal customer. This should make sense, given what we learned about our customers. The least likely customer to stay is Married, has a lower salary of 53,818, no Savings Accounts, and from a Region "City". Click **Next**.

Navigate back to the Home Panel of SAP Predictive Analytics (using Previous or Cancel). Click **Recommendation**.



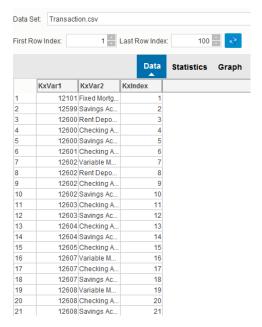
Click **Create a New Recommender**. Here we will load a file that contains events which trigger a recommendation.

Transaction Data



Field Label	Value	Description
Data Type	Text Files	
Folder	. \07 Predictive Analytics Automated	Click Browse for the Events option. Select the file Transaction.csv .
		Click OK.
		Click Analyze.

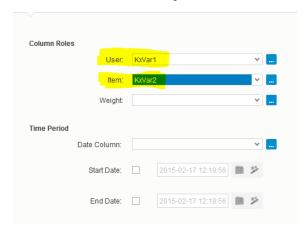
Field Label	Value	Description
		Click View Data to inspect what kind of data we are working with.



As you can see here we have a customer number and a transaction related to a specific bank product. So when a customer opens a new Checking Account, we will predict what else that customer might be interested in purchasing.

Field Label	Value	Description
		Click Close.
		Click Next.

Transactions Description

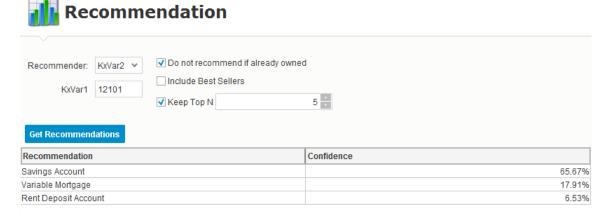


Field Label	Value	Description
User	KxVar1	
Item	KxVar2	Click Next.
		Click Next.
		Click Generate.
		Click Next.
		Click on Recommendation in the Display area .



You can now enter a customer ID number – for example 12101 – into the field KxVar1.

Click on **Get Recommendations** to receive the recommendations.



For the customer 12101, three products are recommended - savings account is the number one product that should be recommended to this customer based on the Transaction of her getting a Fixed Mortgage, which you can see in the transaction table from step 64.

If you look in the raw data excel file Customer_Loyalty.csv you will see what her profile looks like.

200	13299 Male	29423.6 Married	Checking	0 No Persor Variable N No Penso City	1
201	13300 Male	53343.2 Single	No Checki	0 Personal / Variable N Pension P Village	0
202	12101 Female	35092 Single	No Checki	1 No Persor No Mortga No Pensol City	0
203	12102 Male	60170.2 Married	No Checki	3 Personal / Variable N Pension P Village	1
204	12103 Female	33150 8 Married	Checking	0 Personal / No Mortg: Pension P City	1

Q7. What is the recommendation for customer 12605? Only has Checking Account currently – 1 Mark

<mark>7 - Marks</mark>