Business Process Intelligence (BPI) course

Data Mining Decision Trees, Clustering, Association Rule

Harry Beyel

BPI-Instruction2





Pen-and-paper Exercises



Decision Tree **Exercise 1**

- Consider the following training dataset. Suppose *Outcome* is our response variable.
- Provide a decision tree that predicts the outcome. Use the information gain criterion for splitting.

District	Income	Previous Customer	Outcome
Suburban	High	No	Not responded
Suburban	High	Yes	Not responded
Rural	High	No	Responded
Urban	High	No	Responded
Urban	Low	No	Responded
Urban	Low	Yes	Not responded
Rural	Low	Yes	Responded
Suburban	High	Yes	Not responded
Suburban	Low	No	Responded
Urban	Low	No	Responded
Suburban	Low	Yes	Responded
Rural	High	Yes	Responded
Rural	Low	No	Responded
Urban	High	Yes	Not responded

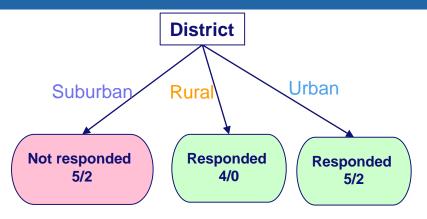


Compute the entropy for the whole data

$$E = -\sum_{i=1}^{2} p_i log_2(pi) = -\frac{9}{14} log_2\left(\frac{9}{14}\right) - \frac{5}{14} log_2\left(\frac{5}{14}\right)$$
$$= 0.41 + 0.53 = 0.94$$

District	Income	Previous	Outcome
		Customer	
Suburban	High	No	Not responded
Suburban	High	Yes	Not responded
Rural	High	No	Responded
Urban	High	No	Responded
Urban	Low	No	Responded
Urban	Low	Yes	Not responded
Rural	Low	Yes	Responded
Suburban	High	Yes	Not responded
Suburban	Low	No	Responded
Urban	Low	No	Responded
Suburban	Low	Yes	Responded
Rural	High	Yes	Responded
Rural	Low	No	Responded
Urban	High	Yes	Not responded





$$E_1 = -\sum_{i=1}^{2} p_i log_2(pi) = -\frac{2}{5} log_2(\frac{2}{5}) - \frac{3}{5} log_2(\frac{3}{5}) = 0.97$$

$$E_2 = 0$$

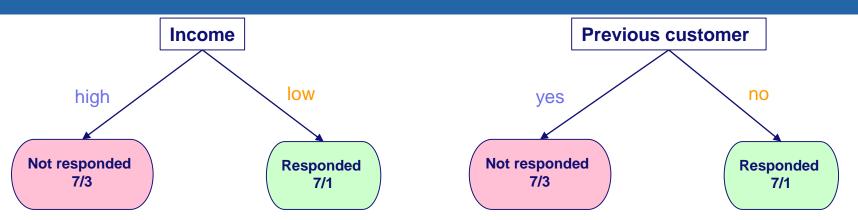
$$E_3 = -\sum_{i=1}^{2} p_i log_2(pi) = -\frac{3}{5} log_2\left(\frac{3}{5}\right) - \frac{2}{5} log_2\left(\frac{2}{5}\right) = 0.97$$

$$E_{District} = \frac{5}{14} \times 0.97 + \frac{4}{14} \times 0 + \frac{5}{14} \times 0.97 = 0.69$$

Information gain = 0.94 - 0.69 = 0.25

District	Income	Previous Customer	Outcome
Suburban	High	No	Not responded
Suburban	High	Yes	Not responded
Rural	High	No	Responded
Urban	High	No	Responded
Urban	Low	No	Responded
Urban	Low	Yes	Not responded
Rural	Low	Yes	Responded
Suburban	High	Yes	Not responded
Suburban	Low	No	Responded
Urban	Low	No	Responded
Suburban	Low	Yes	Responded
Rural	High	Yes	Responded
Rural	Low	No	Responded
Urban	High	Yes	Not responded





Calculate the information gain for all the attributes:

$$E - E_{District} = 0.25$$

$$E - E_{Income} = 0.15$$

$$E - E_{Previous-Customer} = 0.15$$

Which attribute should be selected? Why?



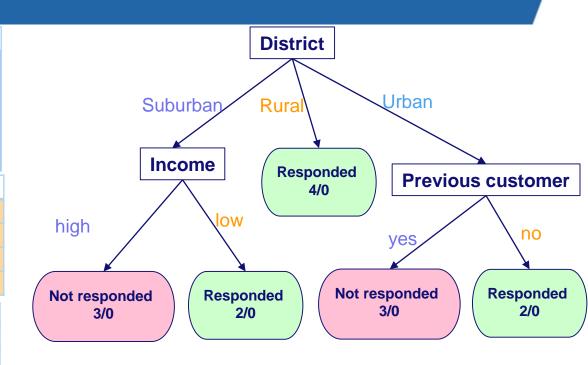
District	Income	Previous Customer	Outcome
Suburban	High	No	Not responded
Suburban	High	Yes	Not responded
Suburban	High	Yes	Not responded
Suburban	Low	No	Responded
Suburban	Low	Yes	Responded

Diotriot		i iotiodo odolomoi	Gutoomo
Rural	High	No	Responded
Rural	Low	Yes	Responded
Rural	High	Yes	Responded
Rural	Low	No	Responded

Previous Customer

Outcome

District	Income	Previous Customer	Outcome
Urban	High	No	Responded
Urban	Low	No	Responded
Urban	Low	Yes	Not responded
Urban	Low	No	Responded
Urban	High	Yes	Not responded





District

Clustering Exercise 2

	att_1	att ₂
1	2	10
2	2	5
3	8	4
4	5	8
5	7	5
6	6	4
7	1	2
8	4	9

Provide three clusters for the data instances on the left side. The distance function is Euclidean distance. Suppose initially we assign (2,10), (5,8), and (1,2) as the center of each cluster, respectively. Use the *K-means* algorithm to find the clusters.



Clustering Exercise 2

Algorithm: *k*-means. The *k*-means algorithm for partitioning, where each cluster's center is represented by the mean value of the objects in the cluster.

Input:

- \blacksquare k: the number of clusters,
- \blacksquare *D*: a data set containing *n* objects.

Output: A set of *k* clusters.

$$d(i,j) = \sqrt{(x_{i1} - x_{j1})^2 + (x_{i2} - x_{j2})^2 + \dots + (x_{ip} - x_{jp})^2}$$

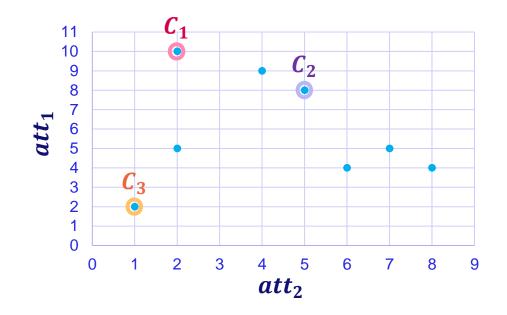
$$d(i,j) = |x_{i1} - x_{j1}| + |x_{i2} - x_{j2}| + \dots + |x_{ip} - x_{jp}|$$

Method:

- (1) arbitrarily choose k objects from D as the initial cluster centers;
- (2) repeat
- (3) (re)assign each object to the cluster to which the object is the most similar, based on the mean value of the objects in the cluster;
- (4) update the cluster means, that is, calculate the mean value of the objects for each cluster;
- (5) **until** no change;



	att_1	att ₂
1	2	10
2	2	5
3	8	4
4	5	8
5	7	5
6	6	4
7	1	2
8	4	9



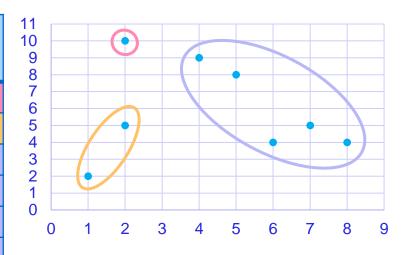


	att ₁	att ₂	Distance from (2,10)	Distance from (5,8)	Distance from (1,2)
1	2	10	0		
2	2	5	5	4.24	3.16
3	8	4	8.49	5	7.28
4	5	8		0	
5	7	5	7.07	3.61	6.71
6	6	4	7.21	4.12	5.39
7	1	2			0
8	4	9	2.24	1.41	7.62

Assign instances to the nearest cluster.



	att ₁	att ₂	Distance from (2,10)	Distance from (5,8)	Distance from (1,2)
1	2	10	0		
2	2	5	5	4.24	3.16
3	8	4	8.49	5	7.28
4	5	8		0	
5	7	5	7.07	3.61	6.71
6	6	4	7.21	4.12	5.39
7	1	2			0
8	4	9	2.24	1.41	7.62



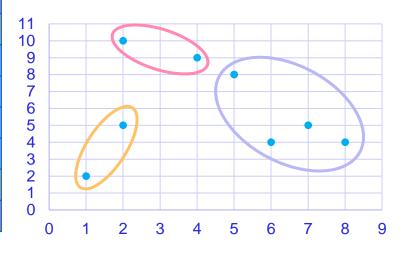
Update cluster means.

New centroids: $C_1 = (2, 10), C_2 = (6, 6), C_3 = (1.5, 3.5)$



	att ₁	att ₂	Distance from (2,10)	Distance from (6,6)	Distance from (1.5,3.5)
1	2	10	0	5.66	6.52
2	2	5	5	4.12	1.58
3	8	4	8.49	2.83	6.52
4	5	8	3.61	2.24	5.7
5	7	5	7.07	1.41	5.7
6	6	4	7.21	2	4.53
7	1	2	8.06	6.40	1.58
8	4	9	2.24	3.61	6.04

Assign instances to the nearest cluster, update cluster means.

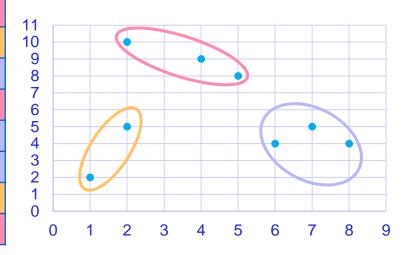


New centroids: $C_1 = (3, 9.5), C_2 = (6.5, 5.25), C_3 = (1.5, 3.5)$



	att ₁	att ₂	Distance from (3,9.5)	Distance from (6.5,5.25)	Distance from (1.5,3.5)
1	2	10	1.11	6.54	6.52
2	2	5	4.61	4.51	1.58
3	8	4	7.43	1.95	6.52
4	5	8	2.5	3.13	5.7
5	7	5	6.02	0.56	5.7
6	6	4	6.26	1.35	4.53
7	1	2	7.76	6.39	1.58
8	4	9	1.12	4.51	6.04

Assign instances to the nearest cluster, update cluster means.

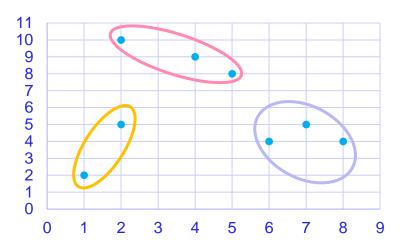


New centroids: $C_1 = (3.67, 9), C_2 = (7, 4.33), C_3 = (1.5, 3.5)$



	att ₁	att ₂	Distance from (3.67,9)	Distance from (7,4.33)	Distance from (1.5,3.5)
1	2	10	1.95	7.56	6.52
2	2	5	4.33	5.04	1.58
3	8	4	6.61	1.06	6.52
4	5	8	1.66	4.17	5.7
5	7	5	5.2	0.66	5.7
6	6	4	5.52	1.06	4.53
7	1	2	7.49	6.44	1.58
8	4	9	0.33	5.54	6.04

No change!





Association rules Exercise 3

Consider the following dataset:

$$D = [\{A\}^{50}, \{A, B\}^{30}, \{A, B, C\}^{20}, \{A, D\}^{20}, \{A, F, C\}^{5}]$$

- Consider $minimum\ support\ count = 22$. Draw the FP-tree after removing the infrequent items.
- Find the frequent itemsets (without calculating the conditional FP-trees)



Association rules Solution 3

$$D = [\{A\}^{50}, \{A, B\}^{30}, \{A, B, C\}^{20}, \{A, D\}^{20}, \{A, F, C\}^{5}]$$

minimum support count = 22

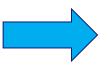
A: 125

B: 50

C: 25

D: 20

F: 5

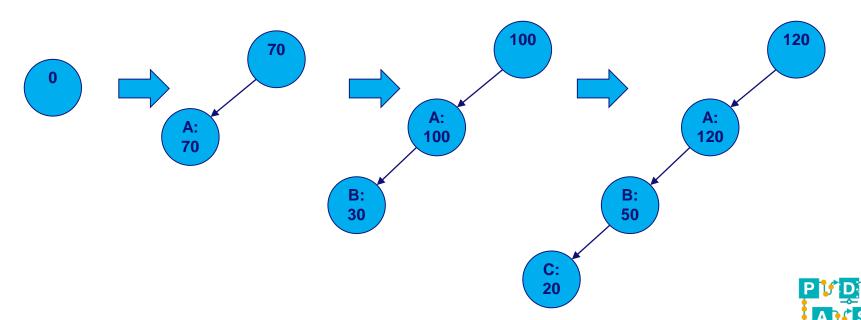


$$D' = [\{A\}^{50}, \{A, B\}^{30}, \{A, B, C\}^{20}, \{A\}^{20}, \{A, C\}^{5}]$$
$$= [\{A\}^{70}, \{A, B\}^{30}, \{A, B, C\}^{20}, \{A, C\}^{5}]$$

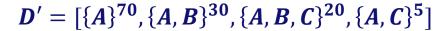


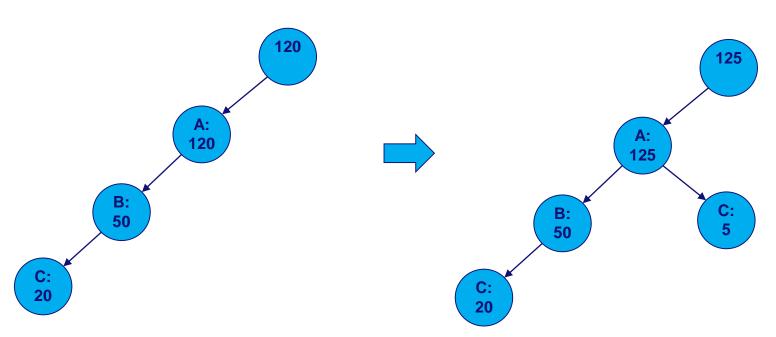
Association rules Solution 3

$$D' = [\{A\}^{70}, \{A, B\}^{30}, \{A, B, C\}^{20}, \{A, C\}^{5}]$$



Association rules Solution 3

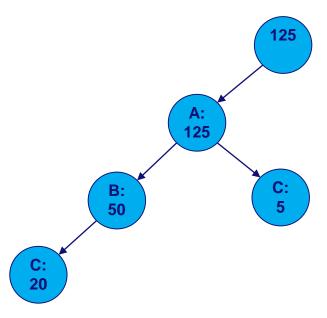






Association rules Solution 3

$$D' = [\{A\}^{70}, \{A, B\}^{30}, \{A, B, C\}^{20}, \{A, C\}^{5}]$$



Itemsets: **Frequent Itemsets: {A} {A}: support 125 {B}: support 50 {B} {C}**: support 25 **{C}** {A,B} **{A,B}: support 50** {A,C} **{A,C}:** support 25 {B,C}: support 20 **{A,B,C}: support 20**

minimum support count = 22



Association rules Exercise 4

1. Compute *support*, *confidence* and *lift* for the following rules:

- $\{A,B\} \Rightarrow \{E\}$
- $\{A\} \Rightarrow \{C\}$

2. Which of the following rules satisfies the following conditions:

- $Support \geq 0.5$
- $Confidence \ge 0.8$
- 0.9 < *lift* < 1.1

TID	Data items	frequency
1	A,B,E	10
2	C,A,D	25
3	C,B,D	15
4	C,A,B,E	20



Association rules Solution 4

• Support
$$(\{A, B\} \Rightarrow \{E\}) = \frac{30}{70} = 0.43$$

• Confidence
$$(\{A, B\} \Rightarrow \{E\}) = \frac{30}{30} = 1$$

• Lift
$$(\{A, B\} \Rightarrow \{E\}) = \frac{30 \times 70}{30 \times 30} = 2.3$$

• Support
$$(\{A\} \Rightarrow \{C\}) = \frac{45}{70} = 0.64$$

• Confidence
$$(\{A\} \Rightarrow \{C\}) = \frac{45}{55} = 0.81$$

• Lift
$$(\{A\} \Rightarrow \{C\}) = \frac{45 \times 70}{55 \times 60} = 0.95$$

TID	Data items	frequency
1	A,B,E	10
2	C,A,D	25
3	C,B,D	15
4	C,A,B,E	20

 ${A, B} \Rightarrow {E}$ does not satisfy our conditions,

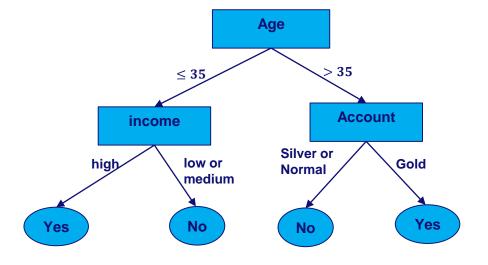
 $\{A\} \Rightarrow \{C\}$, does satify the conditions



Evaluation Exercise 5 – part 1

Create the confusion matrix for the following classifier model using the test data in the table:

ID	Age	Account type	Income	Accepted (actual class)
1	35	Silver	high	Yes
2	63	Gold	high	No
3	42	Normal	high	No
4	30	Normal	medium	No
5	35	Gold	low	Yes
6	56	Gold	high	Yes
7	23	Normal	low	No
8	48	Gold	medium	No





Evaluation Exercise 5 – part 1

Confusion Matrix and performance measures

		predicted		
		yes	no	
target	yes	TP	FN	P
tar	no	FP	TN	N
		P'	N'	P + N

Measure	Formula
accuracy	TP + TN
	$\overline{TP + TN + FP + FN}$
misclassification	1-accuracy
recall	TP
	$\overline{TP + FN}$
precision	TP
	$\overline{TP + FP}$
F1 – measure	$precision \times recall$
	$2 \times \frac{r}{precision + recall}$



Evaluation Solution 5 – part 1

ID	Age	Account type	Income	Accepted (actual class)	predicted class	type
1	25	Silver	high	Yes	Yes	TP
2	63	Gold	high	No	Yes	FP
3	42	Normal	high	No	No	TN
4	30	Normal	medium	No	No	TN
5	35	Gold	low	Yes	No	FN
6	56	Gold	high	Yes	Yes	TP
7	23	Normal	low	No	No	TN
8	48	Gold	medium	No	Yes	FP

		predic		
		yes	no	
get	yes	2	1	3
yes no		2	3	5
		4	4	8



Evaluation Exercise 5 – part 2

Calculate precision, recall, accuracy and F1 - measure based on the confusion matrix.



Evaluation Solution 5 – part 2

		predicted		
	yes no			
target	yes	2	1	3
tar	no	2	3	5
		4	4	8

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN} = \frac{5}{8} = 0.63$$

$$precision = \frac{TP}{TP + FP} = \frac{2}{4} = 0.5$$

$$recall = \frac{TP}{TP + FN} = \frac{2}{3} = 0.67$$

$$F1-measure = 2 \times \frac{precision \times recall}{precision + recall} = 0.57$$



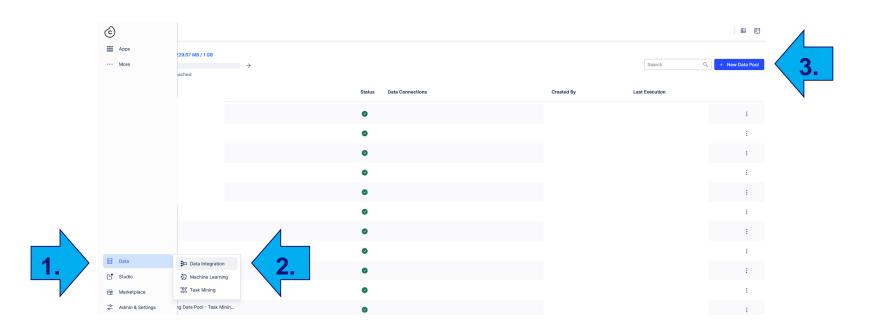


Creating Case-Situation Tables in Celonis





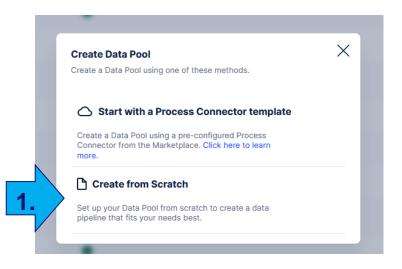
Create a Data Pool







Create a Data Pool



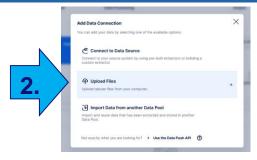






File Upload











File Upload

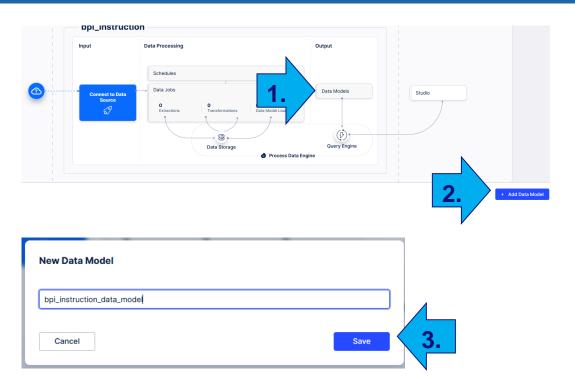
Files



2.) Return to overview

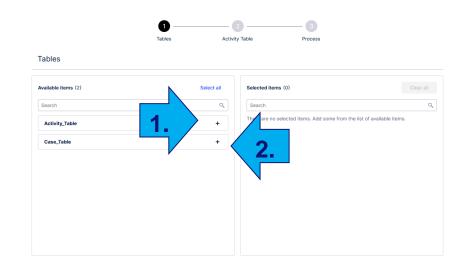










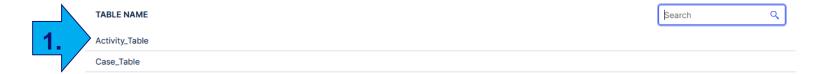






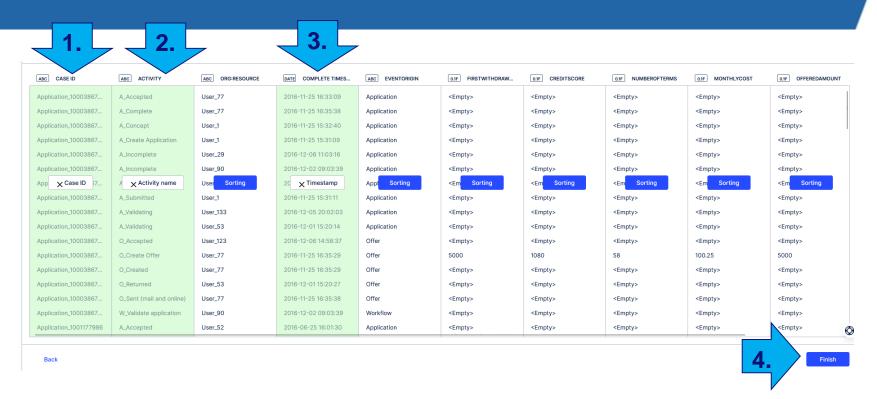
Activity Table

This table contains all information about the activities of your event log (activity name column, case ID column, timestamp column and optionally a sorting and end timestamp column).





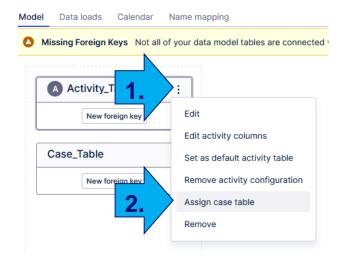








Data Model



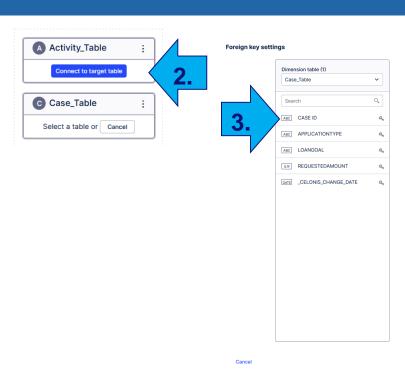


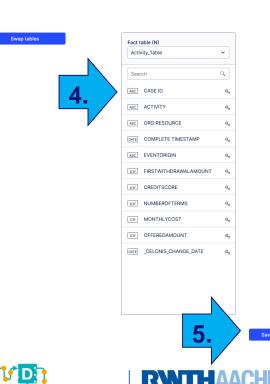




Data Model

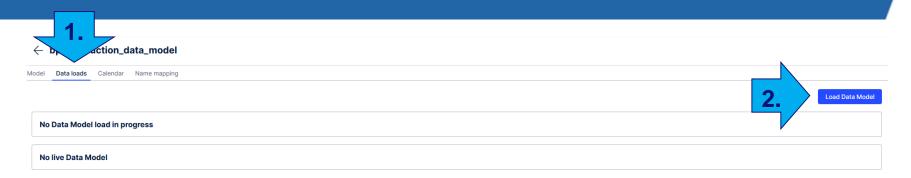






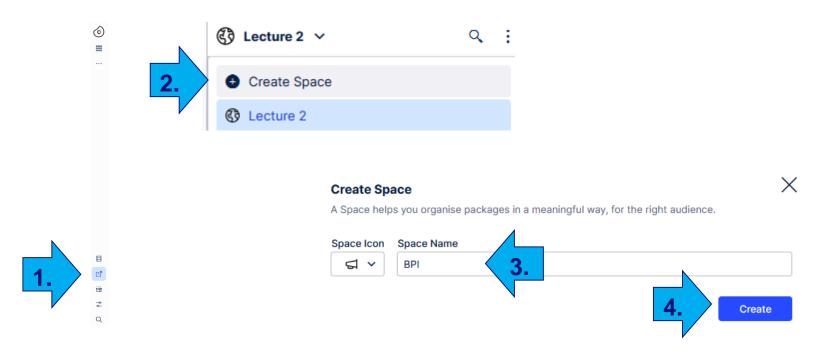
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Data Model



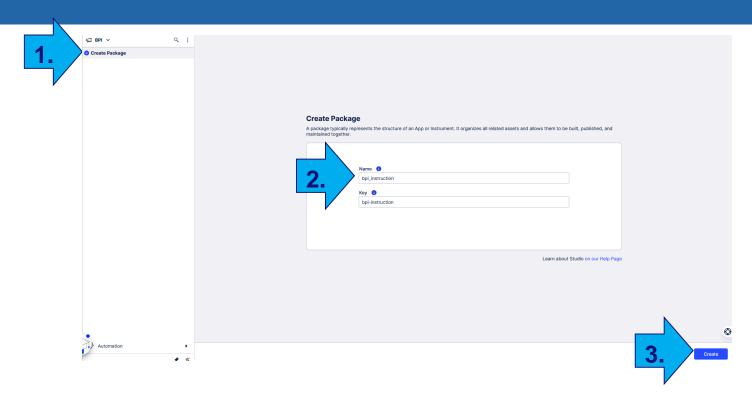






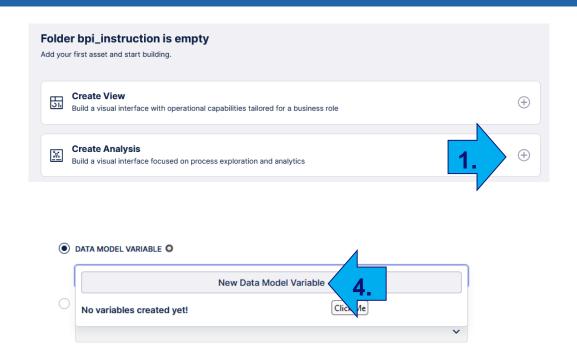


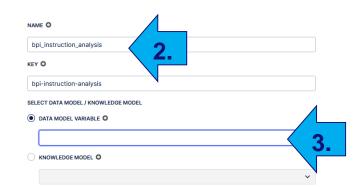




























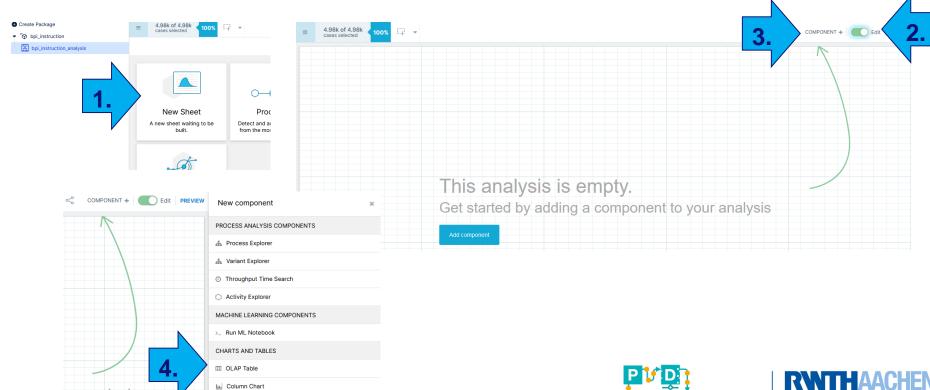
Create New Analysis 0

NA	AME O	
t	bpi_instruction_analysis	
KE	EY O	
t	bpi-instruction-analysis	
SE	ELECT DATA MODEL / KNOWLEDGE MODEL	
•	DATA MODEL VARIABLE O	
	bpi_instruction_data_model	~
	KNOWLEDGE MODEL O	
		~

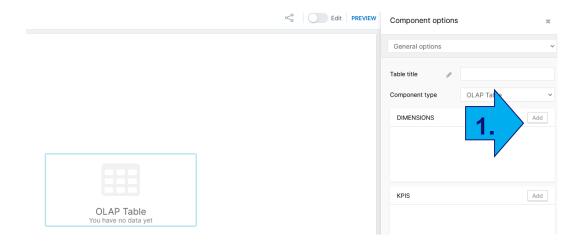






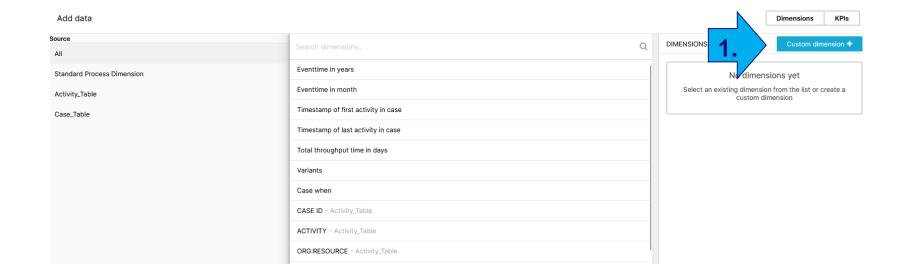






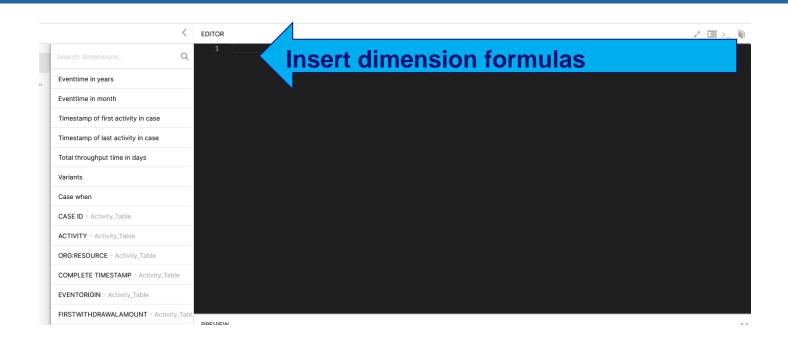
















Accessing Columns in Table

 For later formulas, you need to refer to the columns of your table

You refer to columns with YourTable.YourColumn





Pull Up Aggregation

- Pull-Up-functions are used to achieve nested aggregations and filters on aggregations
- The formula always consists of "PU_X (target_table, source_table.column ...)"
- A 1:N relationship between the target table and the table of the specified source column is required.
 - Therefore, your case table is, most of the time, the target table, your activity table the source table





Function Name	General Formula
Case When	Case When Then Else End
COUNT	Count([Distinct] Column)
CALC_REWORK	CALC_REWORK(Condition, Column)
PU_AGGREGATION	PU_FIRST(/LAST) (Group, Column, Condition, Order)
CALC_THROUGHPUTTIME	CALC_THROUGHPUTTIME(Trace Crop, Transformed Timestamp to Integer)
DAYS_BETWEEN	DAYS_BETWEEN (Column, Column)
MATCH_ACTIVITIES	MATCH_ACTIVITIES(Column, STARTING[], NODE[], EXCLUDING[], ENDING [some Activities])

PVD Chair of Process and Data Science



Function Name	Role in Creating the Situation Table's Variables
Case When	Creating conditional structures in other functions
COUNT/COUNT Distinct	Extracting trace features based on the times certain activities occur in the trace/ or checks just the existence of these activities in the trace
CALC_REWORK	Extracting trace features based on the times certain activities occur in the trace
PU_FIRST, PU_LAST	Extracting trace attributes based on the first/last trace's event attribute
CALC_THROUGHPUTTIME	Extracting the throughput time feature of a trace(between start and end events or any other pairs of the trace)
DAYS_BETWEEN	Extracting a time feature of a trace between a pair of its events (in days)
MATCH_ACTIVITIES	Extracting a binary trace attribute whether it starts/ ends with certain activities or includes /excludes these activities

More formulas and explanations: https://docs.celonis.com/en/pql-function-library.html





Dimension Name	Dimension Formula				
Case ID	"Case_Table"."CASE ID"				
Application Type	"Case_Table"."APPLICATIONTYPE"				
Loan Goal	"Case_Table"."LOANGOAL"				
Requested Amount	"Case_Table"."REQUESTEDAMOUNT"				
First Credit Score	PU_FIRST ("Case_Table", "Activity_Table"."CREDITSCORE")				
Last Credit Score	PU_LAST ("Case_Table", "Activity_Table"."CREDITSCORE")				





Dimension Name	Dimension Formula
Having Call to Complete Application	COUNT(DISTINCT CASE WHEN "Activity_Table"."ACTIVITY"='W_Call incomplete files' THEN 1 END) Or alternatively: CASE WHEN MATCH_ACTIVITIES("Activity_Table"."ACTIVITY", NODE ['W_Call incomplete files'])=1 THEN 1 ELSE 0 END





Dimension Name	Dimension Formula
Number of Offers	COUNT(CASE WHEN "Activity_Table"."ACTIVITY"='O_Create Offer' THEN "Activity_Table"."ACTIVITY" END) Or alternatively: CALC_REWORK ("Activity_Table"."ACTIVITY"='O_Create Offer',"Activity_Table"."ACTIVITY")





Dimension Name	Dimension Formula			
First Offer	PU_FIRST ("Case_Table", "Activity_Table"."OFFEREDAMOUNT")			
Last Offer	PU_LAST ("Case_Table", "Activity_Table"."OFFEREDAMOUNT")			
First Offers' Monthly Cost	PU_FIRST ("Case_Table","Activity_Table"."MONTHLYCOST")			
Last Offers' Monthly Cost	PU_LAST ("Case_Table","Activity_Table"."MONTHLYCOST")			





Dimension Name	Dimension Formula
Throughput Times	DAYS_BETWEEN (MIN("Activity_Table"."COMPLETE TIMESTAMP"), MAX("Activity_Table"."COMPLETE TIMESTAMP")) Or alternatively: CALC_THROUGHPUT (CASE_START TO CASE_END, REMAP_TIMESTAMPS("Activity_Table"."COMPL ETE TIMESTAMP", DAYS))

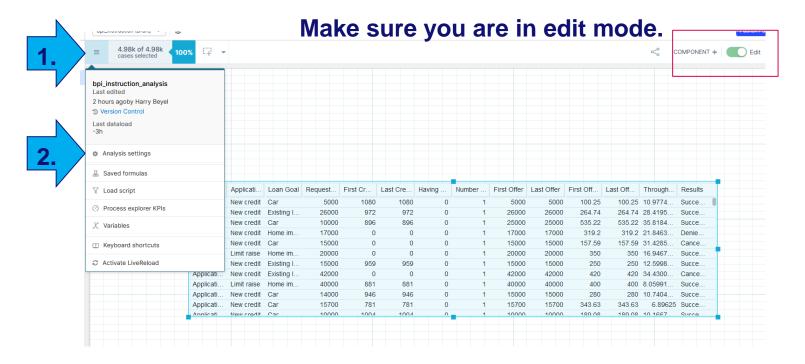




Dimension Name	Dimension Formula
Results	CASE WHEN MATCH_ACTIVITIES ("Activity_Table"."ACTIVITY", NODE ['A_Cancelled']) = 1 THEN 'Cancelled by client' WHEN MATCH_ACTIVITIES ("Activity_Table"."ACTIVITY", NODE ['A_Denied']) = 1 THEN 'Denied by the bank' WHEN MATCH_ACTIVITIES ("Activity_Table"."ACTIVITY", NODE ['A_Pending']) = 1 THEN 'Successful completion' END

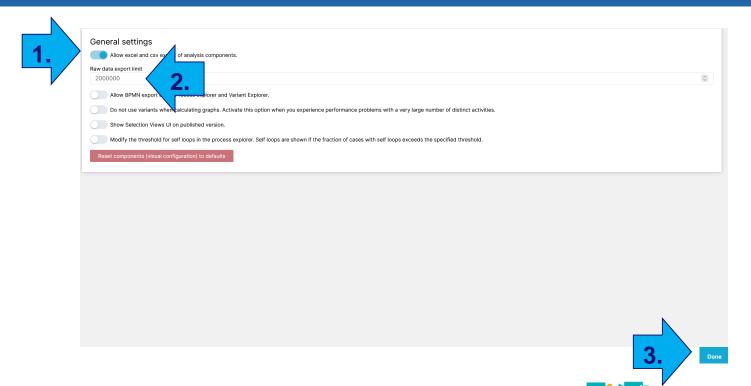














3	SE ID	Applicati	Loan Goal	Request	First Cr	Last Cre	Having	Number F
1. Right-click	in tal	ble dit	Settings		1080 972	1080 972	0	1
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You can find your CSV-file in your download folder.







Working with Situation Tables from Celonis







About the data

- 1. CASE ID: The unique identifier assigned to each loan application
- 2. Application Type: The type of each loan application
- 3. Loan Goal: The goal of each loan application
- 4. Requested Amount The amount each loan application asks to be paid
- 5. First Credit Score: The first recorded credit of the application
- 6. Last Credit Score: The last recorded credit of the application
- 7. Having Call to Complete Application: Indicates if the loan application process includes the activity "W_Call incomplete files" which means the bank calls the applicant to provide further data/documents.
- 8. Number Of Offers: The number of times the bank offers a loan to an application. These offers are logged when the event's activity is "O Create Offer".
- 9. First Offer: The amount of the first offer the bank provides to an application.
- 10. Last Offer: The amount of the last offer the bank provides to an application.
- 11. First Offer's Monthly Cost: The monthly cost of the first offer the bank provides to an application.
- 12. Last Offer's Monthly Cost: The monthly cost of the last offer the bank provides to an application.
- 13. Throughput Time: The time spent on each application from its first event to the last
- 14. Results: The outcome of each application. This could be one of the following:
 - i. Successful completion: the application includes the "A_Pending" activity. This activity describes a situation in which all documents have been received and the assessment is positive. The loan is confirmed and signed to be paid to the customer.
 - ii. Denied by the bank: the application includes "A_Denied" activity. This activity describes a situation in which the application doesn't match the acceptance criteria.
 - iii. Cancelled by client: the application includes the "A_Cancelled" activity. This activity describes a situation in which the applicant does not get back to the bank after an offer was sent out



Import the data

Import the data in RapidMiner

No date format needed





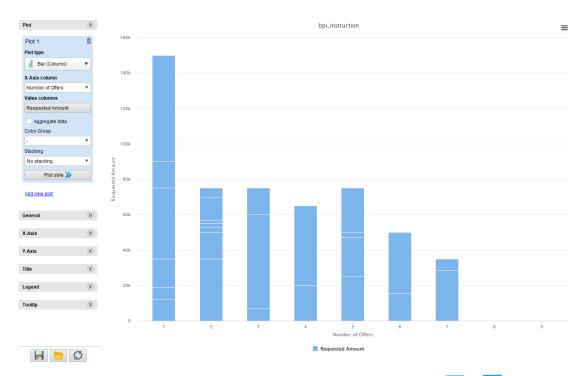
Visualization

- Click on Visualization and create a bar graph (column), with an x-axis showing *Numbers of Offers*, and *Requested Amount* as value column
- What are your observations?





Solution







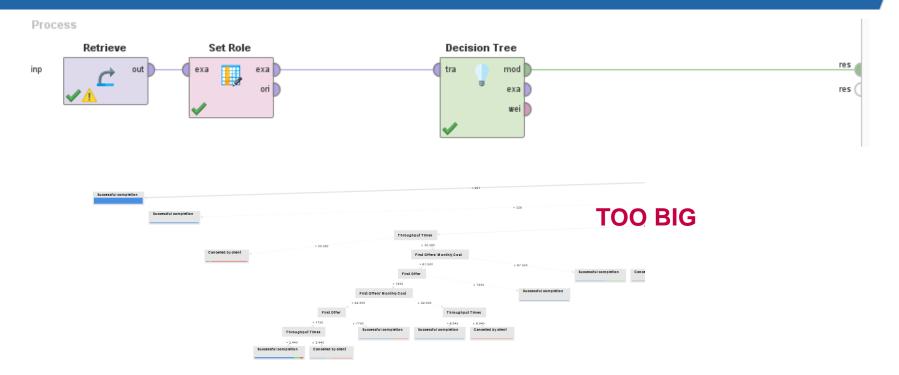
Decision Tree

- We want to predict Result. Therefore, we have to set the role.
- As the target role, select label.
- Connect the *Decision Tree* with the *Set Role* module and run the process.





Solution







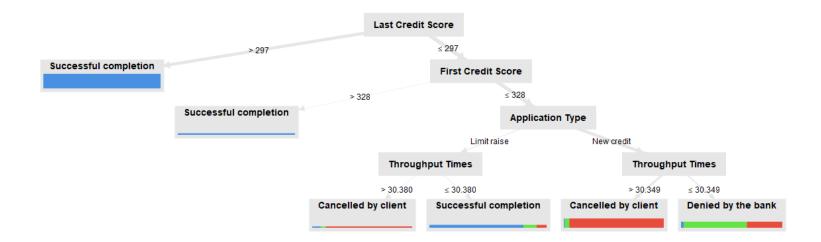
Decision Tree – Parameters

- For most modules, you can set different parameters.
- For now, set the maximal depth to 5
- Rerun the process





Solution





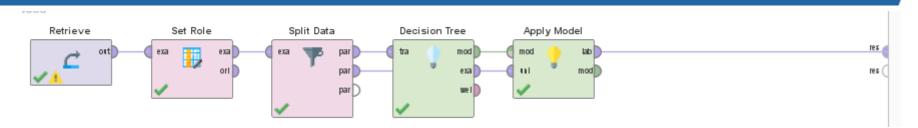


Decision Tree – Check results

- To evaluate your results, you need to split the data.
 Otherwise, you will evaluate on data your model knows.
- To split data, use the Split Data module. Specify as partitions 0.8 and 0.2
- Next, apply the decision tree to the unseen data, using Apply Model
- Run the process







Row No. ↑	Results	prediction(Results)	confidence(Successful completion)	confidence(Denied by the bank)	confidence(Cancelled by client)
1	Successful completion	Successful completion	0.806	0.118	0.075
2	Successful completion	Successful completion	0.806	0.118	0.075
3	Successful completion	Successful completion	1	0	0
4	Successful completion	Successful completion	1	0	0
5	Successful completion	Successful completion	1	0	0
6	Successful completion	Successful completion	1	0	0
7	Denied by the bank	Cancelled by client	0.014	0.266	0.720
8	Cancelled by client	Cancelled by client	0.014	0.266	0.720
9	Successful completion	Cancelled by client	0.014	0.266	0.720



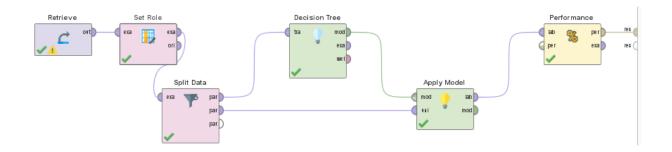


Decision Tree – Evaluating

- Checking every data instance by hand is impossible.
- Use the Performance module and link it with the labeled data from the Apply Model module
- Rerun the process.







accuracy: 85.46%

	true Successful completion	true Denied by the bank	true Cancelled by client	class precision	
pred. Successful completion	524	7	11	96.68%	
pred. Denied by the bank	0	0	0	0.00%	
pred. Cancelled by client	8	119	328	72.09%	
class recall	98.50%	0.00%	96.76%		



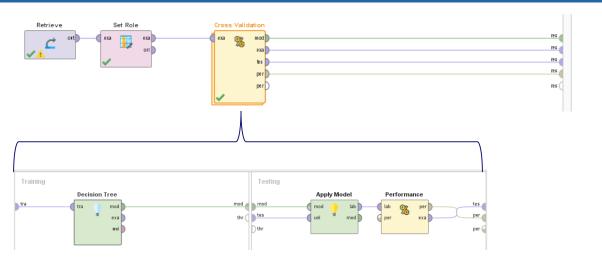


Decision Tree – Cross Validation

- Instead of doing the previous steps, you can also use the Cross Validation operator
- You only have three modules on the "main" process page: Retrieve, Set Role, and Cross Validation. Link the first four outputs of the operator to the process output
- By double-clicking on Cross Validation, you can see the operator's subprocess
- For training, use the prev. decision tree, for testing, the operators Apply Model and Performance
- Rerun the process







accuracy: 90.04% +/- 2.08% (micro average: 90.04%)

	true Successful completion	true Denied by the bank	true Cancelled by client	class precision
pred. Successful completion	2612	40	31	97.35%
pred. Denied by the bank	21	474	263	62.53%
pred. Cancelled by client	25	116	1400	90.85%
class recall	98.27%	75.24%	82.64%	



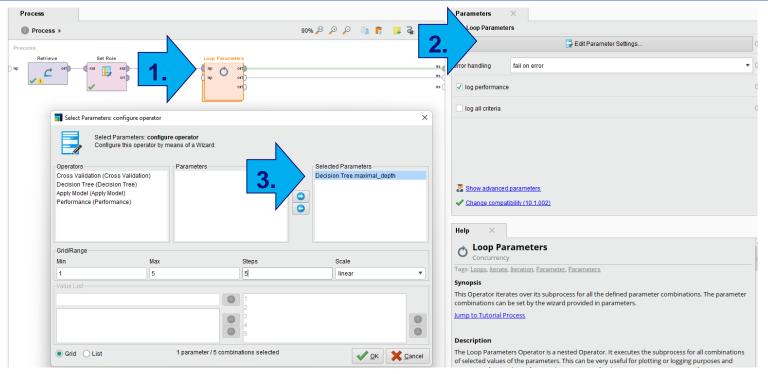


Decision Tree – Play with Parameters

- As seen earlier, we can change multiple parameters.
- Instead of changing parameters one by one and rerunning the process, we can do that with an operator: Loop parameters
- Drag Cross Validation into Loop Parameters
- Setting for Loop Parameters: Selected parameter is maximal depth, min=1, max=5, in 5 steps
- Input for Loop Parameters: Set Role
- Output for Cross Validation: Model and performance

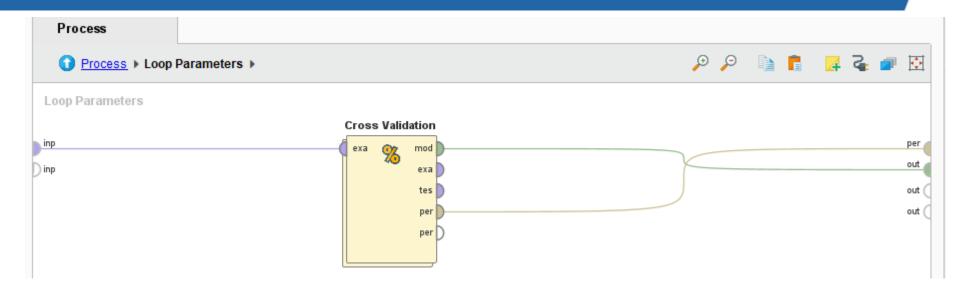








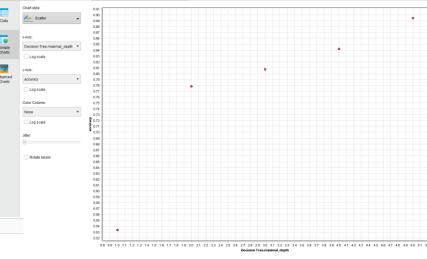




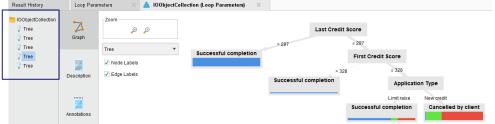




iteration	Decision Tree.maximal_depth	accuracy ↑
1	1	0.534
2	2	0.778
3	3	0.807
4	4	0.842
5	5	0.895



Inspect different trees:





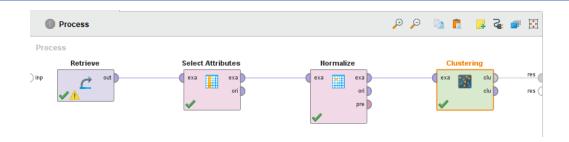


Clustering – Getting Started

- Using Select Attributes, select the attributes Numbers of Offers, Requested Amount, Throughput Times
- Normalize the values using Z-transformation (advanced parameters)
- Let's cluster similar instances. To group them, we use the operator *Clustering (k-Means)*, with 4 centroids
- Run the process







Attribute	cluster_0	ster_0 cluster_1 cluster_2		cluster_3
Requested Amount	1.975	-0.281	-0.351	0.077
Number of Offers	-0.151	-0.128	-0.249	3.025
Throughput Times	0.016	0.923	-0.772	0.675



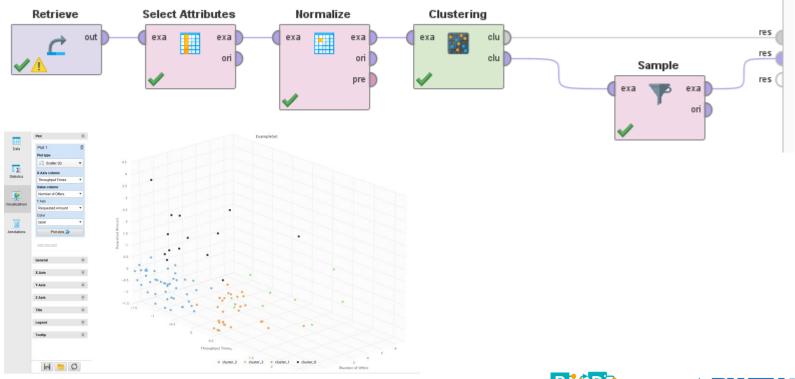


Clustering – Visualize Clusters

- If we want to visualize the clusters, we cannot display every instance → Sampling is needed
- Connect the output clustered set with Sample operator. Set the sample size to 100 and the local random seed to 2023 (advanced parameter).
- Create a 3D-visualization of the clustered samples.





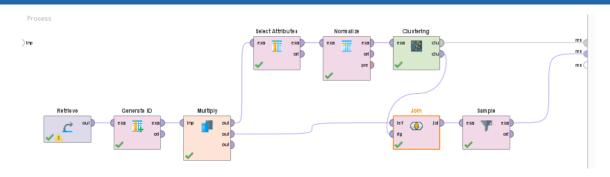


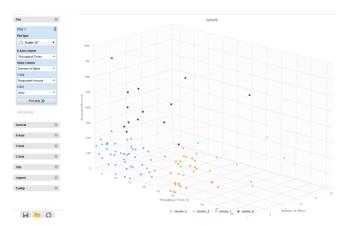
Clustering – Drawing Conclusions

- To draw conclusions related to unnormalized, or even original data, we have to join the clustered data with the original one
- To join data, we generate ids. Then we use the Multiply operator to multiply the original data with ids.
- Then, we run the process.
- Create a 3D-Visualization as before.











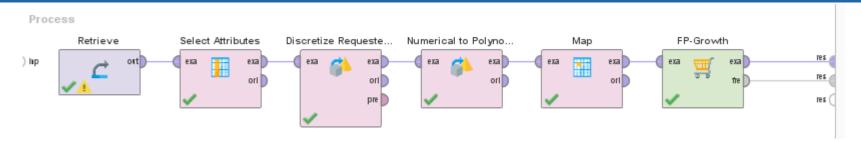


Frequent Itemsets

- We want to know which of the following variable values appear together: Requested Amount, Having a Call to Complete Application, Results
- In this process, we discretize the variables:
 - Requested amount:
 - Upper limit 9000: low request
 - Upper limit 20,000: medium request
 - Upper limit Infinity: High request
 - Having a Call to Complete Application:
 - Two operators are needed: *Numerical to Polynomial, Map*
 - If there was a call, denote it with "called," otherwise with "not called"
- Use the module FP-Growth, by setting the frequency to 100







Size	Support ↓	Item 1	Item 2	Item 3
1	0.915	Not called		
1	0.534	Successful completion		
2	0.474	Not called	Successful completion	
1	0.377	medium request		
1	0.362	low request		
2	0.348	Not called	medium request	
1	0.340	Cancelled by client		



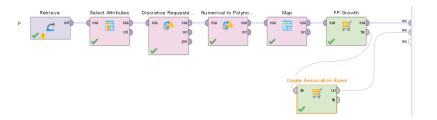


Association Rules

- Add to your former process the module Create
 Association Rules
- Set the minimum confidence to 0.8
- Connect the frequent set output with this module and run the process







No.	Premises	Conclusion	Support	Confiden ↓	LaPlace	Gain	p-s	Lift	Convicti
15	low request, Denied by the bank	Not called	0.047	0.967	0.998	-0.050	0.003	1.056	2.562
14	medium request, Cancelled by client	Not called	0.118	0.956	0.995	-0.129	0.005	1.045	1.929
13	Cancelled by client	Not called	0.322	0.948	0.987	-0.358	0.011	1.036	1.631
12	low request, Cancelled by client	Not called	0.124	0.945	0.994	-0.138	0.004	1.032	1.539



