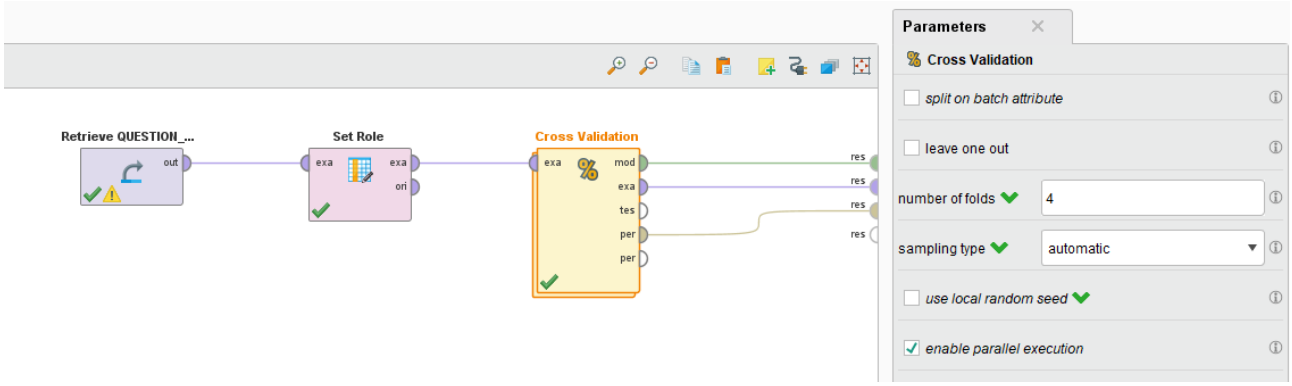
Question 1

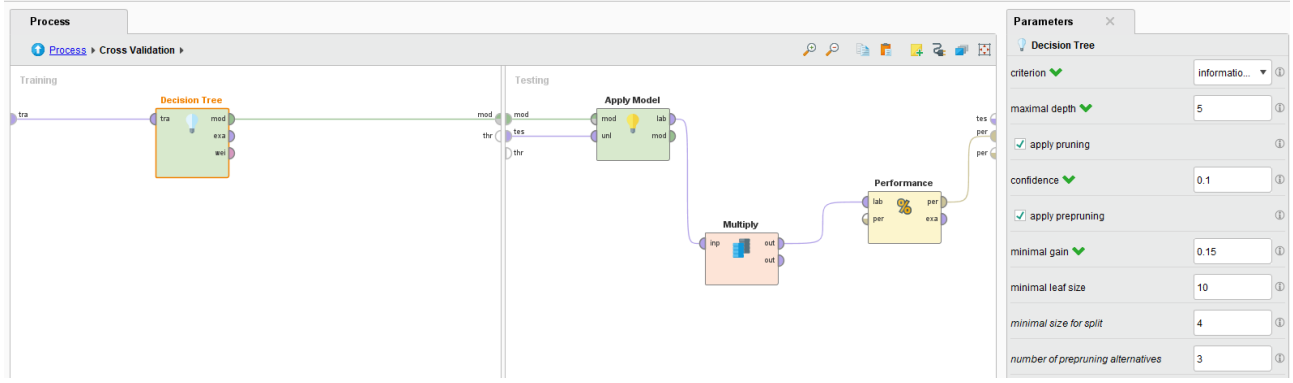
Question 2

(a)

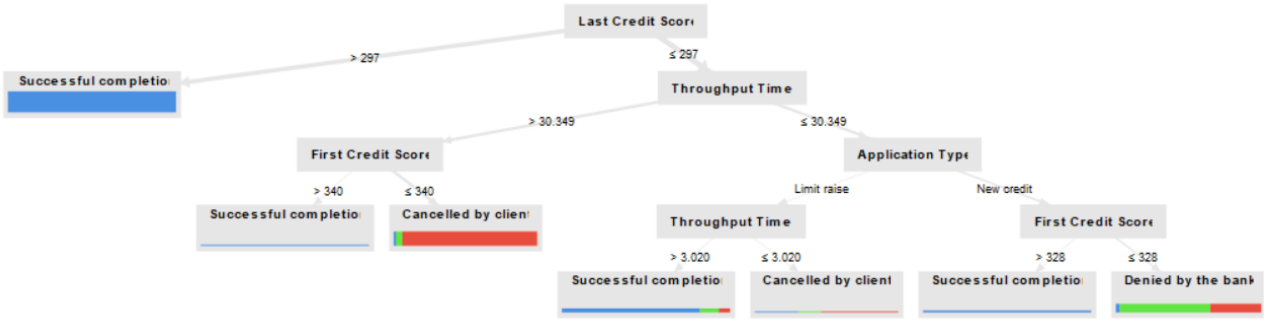
After importing the situation table from Celonis into RapidMiner we can design the decision tree learning process using the cross validation operator after setting the class variable:



We construct the training section of the cross validation using the decision tree operator in RapidMiner and also specifying the given parameters. In the testing section we simply apply the current test set to the given model and run a performance check upon it.



This process results in the following decision tree:



Here we can see that for all applications, where the applicants last credit score was above 297, the application was successfully completed.

We can also observe, that the very few applicants for new credits, those credit scores dropped significantly (First Credit Score > 329 and Last Credit Score ≤ 297) within a time less or equal to 30.349 days, all completed their application successfully.

Using the cross validation operator, we could also observe the following performance metrics:

Table View Plot View

accuracy: 90.16% +/- 0.80% (micro average: 90.16%)

	true Successful completion	true Denied by the bank	true Cancelled by client	class precision
pred. Successful completion	2600	40	30	97.38%
pred. Denied by the bank	23	524	296	62.16%
pred. Cancelled by client	35	66	1368	93.12%
class recall	97.82%	83.17%	80.76%	

From this table we can take that the accuracy of the model is $90.16\% \pm 0.8\%$. Predictions of successful completions are 97.38% precise, real successful completions are predicted correct 97.82% of the time (recall).
Predictions of Denials by the bank are 62.16% precise. Recall of 'Denied by the bank' cases is 83.17%.
Predictions of Cancellations by the client are 93.12% precise. Recall of this outcome class is 80.76%.

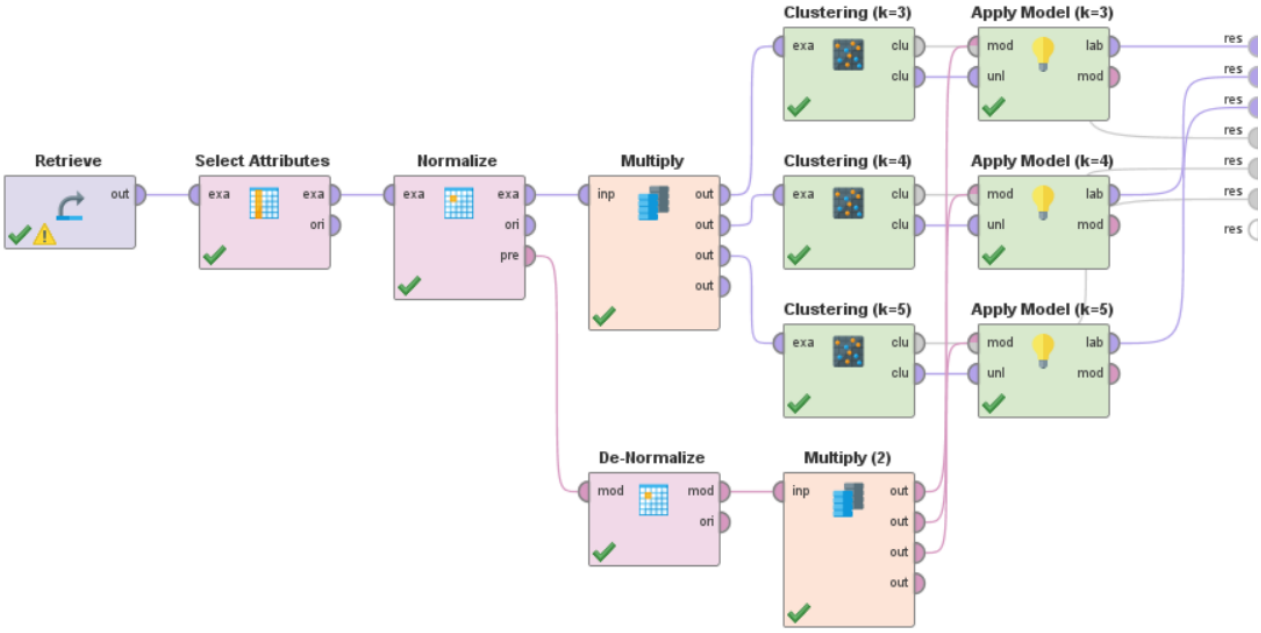
(b)

1. Most applicants with a last credit score of at most 297 cancelled their own application when it was already roughly over a month's time in progress. Perhaps the current application process needs to be revised to minimize throughput times.
2. 62% of applications, that was roughly under a months time in progress, by applicants with a last credit score of at most 297 for a new credit were rejected by the bank, if their first credit score was at most 328. If the bank seeks for more successful application completions, perhaps they should adjust their rejection criteria.

Question 3

(a)

After selecting the three specified attributes, normalization by Z-transformation is done. The result is multiplied so it can be fed to all k-means clusterers at once. For each clustering we set the necessary 'k' and 'max runs' and select the 'add as label' checkbox so the cluster labels are added as a new column. To use the unscaled dataset as a model we first reverse the Z-transformation by De-Normalizing and then apply it to the clustered data.



The following graphics show the clustering results for the Requested Amount on the x-Axis mapped against the Throughput times on the y-Axis (with high Jitter for better visualization of regions). Additionally, Number of Offers was chosen to determine the size of each dot on the scatter plot to visualize all 3 dimensions at once. Over all $k \in \{3, 4, 5\}$ there are a few similar clusters:

- One that is characterized best by its high Requested Amounts (mostly $> 20k$) and Throughput times of mostly under 40 days.
- One that is characterized by its generally lower Requested Amounts of mostly $< 40k$ and Throughput times of mostly over 20 days. It also includes mostly larger Numbers of Offers. There is a little ambiguity however, for example because k=3 doesn't have a great resolution and clusters together more generously. For higher case the opposite is true, so some cases from this cluster fall to a new cluster.
- Then there are clusters that are generally $< 40k$ in Requested Amounts and with Throughput Times of mostly under 40 days. These clusters change the most for different k and also frequently intersect with other clusters in the x and y dimension, especially for lower k.

Marc Ludevid-Wulf
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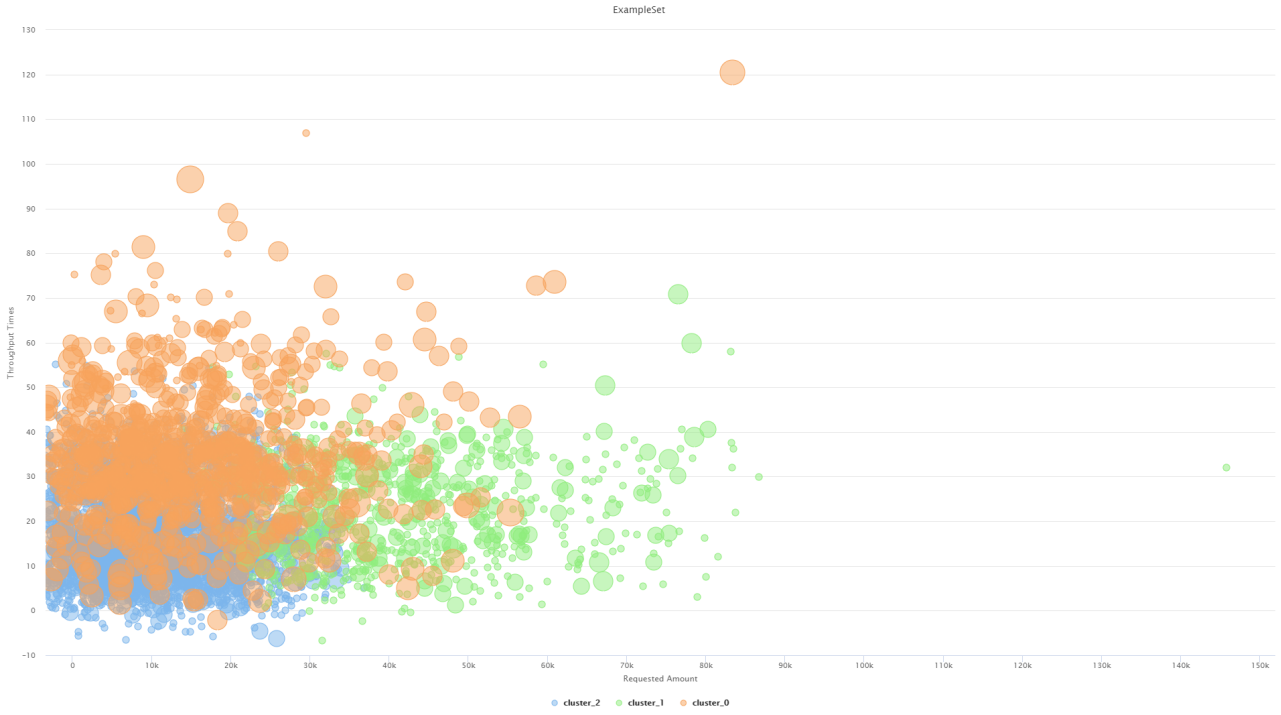
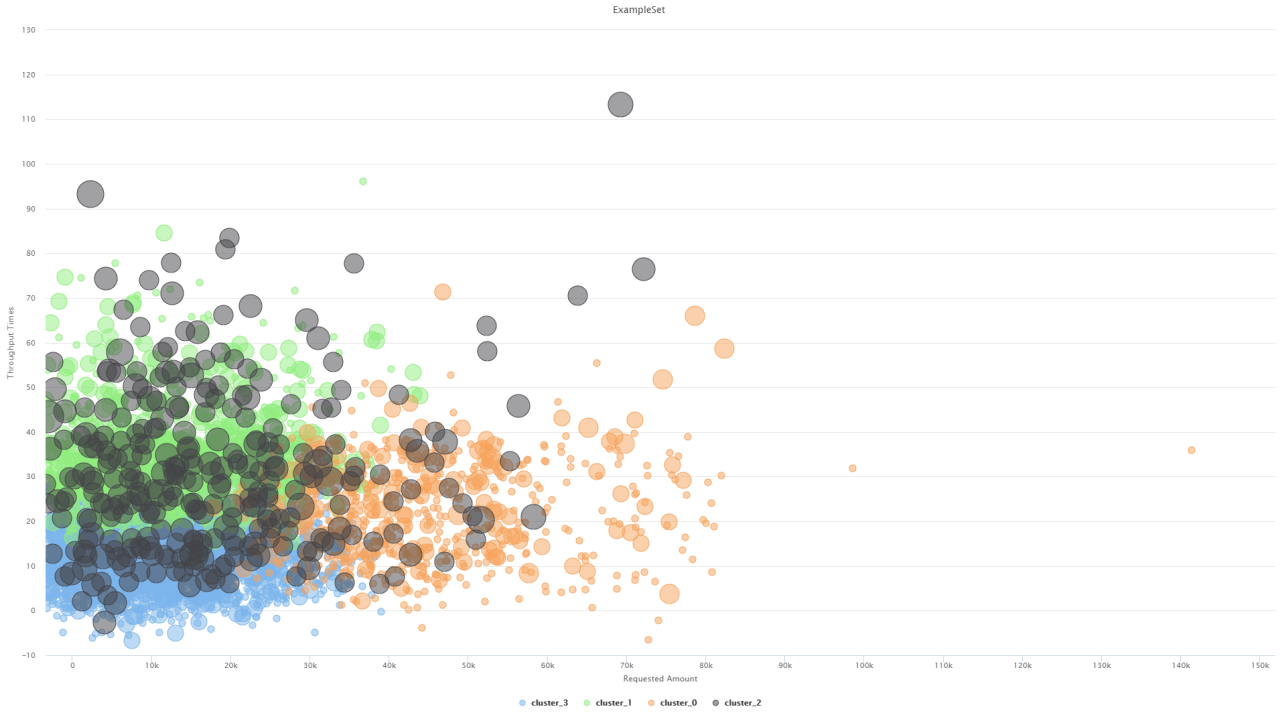
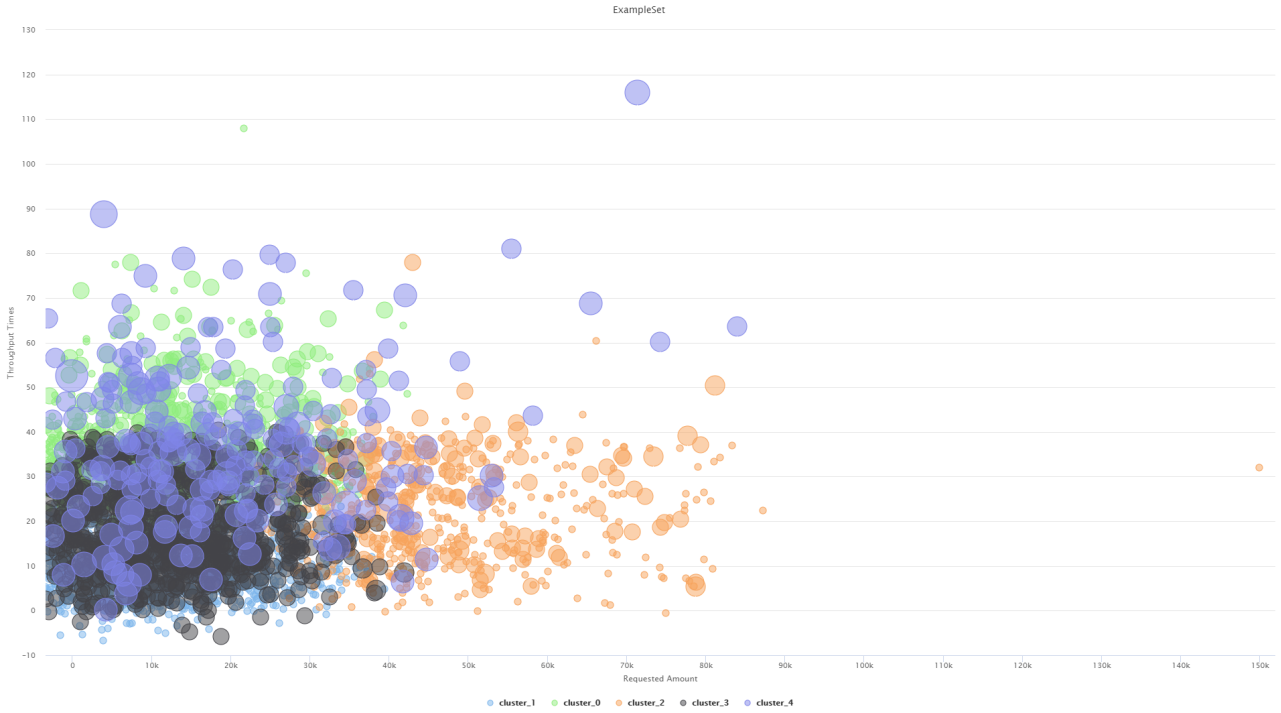






As mentioned above, k=3 has a very low 'resolution' which makes it hard to differentiate between clusters. For this reason k=4 or k=5 are more suitable to distinguish clusters. Especially for k=5 it is easy to see which traits define a cluster and therefore an intuitive discription of what applications belong to it become easier. Even visually these applications are very distinguishable because they are always very similar in at least 2 parameters.
One could argue that a lower amount of clusters is advantageous because there aren't so many different types of loan applications to consider in management ($\Rightarrow$ maybe less bureaucracy), however we cannot judge this well with our knowledge and because k=5 is not that large of a number we choose it as the most suitable one.

The value of cluster centroids are displayed in the 3 tables below:

Attribute	cluster_0	cluster_1	cluster_2
Requested Amount	-0.082	1.688	-0.407
Number of Offers	1.622	-0.240	-0.330
Throughput Times	1.028	0.101	-0.273

Attribute	cluster_0	cluster_1	cluster_2	cluster_3
Requested Amount	1.971	-0.282	0.077	-0.351
Number of Offers	-0.150	-0.128	3.025	-0.249
Throughput Times	0.018	0.924	0.675	-0.772

Attribute	cluster_0	cluster_1	cluster_2	cluster_3	cluster_4
Requested Amount	-0.281	-0.342	2.063	-0.244	0.200
Number of Offers	-0.344	-0.508	-0.189	1.046	3.285
Throughput Times	0.989	-0.776	0.035	-0.203	1.142

The number of applications in each cluster is displayed below:

Cluster Model

```
Cluster 0: 803 items
Cluster 1: 843 items
Cluster 2: 3336 items
Total number of items: 4982
```

Cluster Model

```
Cluster 0: 648 items
Cluster 1: 1713 items
Cluster 2: 296 items
Cluster 3: 2325 items
Total number of items: 4982
```

Cluster Model

```
Cluster 0: 1415 items
Cluster 1: 1929 items
Cluster 2: 590 items
Cluster 3: 832 items
Cluster 4: 216 items
Total number of items: 4982
```

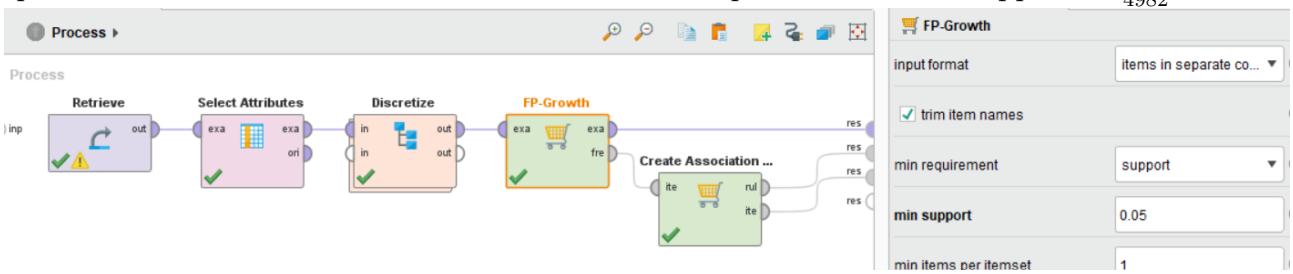
(b)

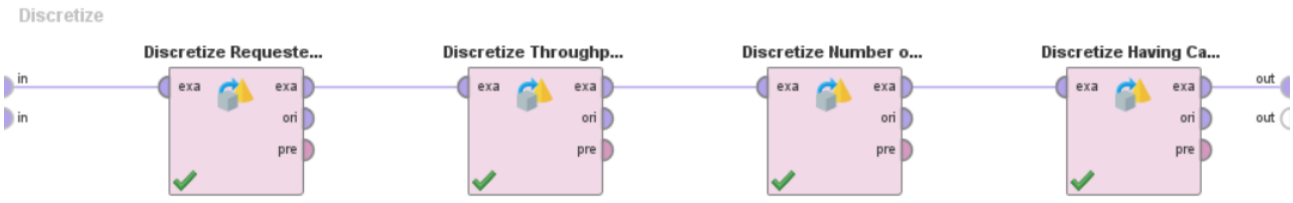
1. 1929 of our 4982 applications (38.7%) were for amounts of less than 40k and were handled within a month with just one offer.
2. Our large amount applications ($> 30k$) were mostly handled within a month.
3. The applications with longer throughput times generally had larger numbers of offers

Question 4

(a)

The following screenshots show the process used for 4a). A minimum support count of 250 was specified in the task. At a dataset size of 4982 this equals a minimum support of $\frac{250}{4982} = 0.05$





158 association rules were found at a minimum confidence of 0.8, the top 10 in confidence can be seen below:

No.	Premises	Conclusion	Support	Confiden...	LaPlace	Gain	p-s	Lift
158	one offer, med duration, Cancelled by client, Car	not called	0.063	0.991	0.999	-0.064	0.005	1.082
157	one offer, med duration, med request, Cancelled b...	not called	0.071	0.983	0.999	-0.074	0.005	1.074
156	med duration, Cancelled by client, Home improve...	not called	0.058	0.983	0.999	-0.060	0.004	1.074
155	one offer, med duration, low request, Cancelled by...	not called	0.079	0.983	0.999	-0.082	0.005	1.074
154	med duration, med request, Cancelled by client	not called	0.089	0.982	0.999	-0.093	0.006	1.073
153	med duration, Cancelled by client, Car	not called	0.078	0.982	0.999	-0.081	0.005	1.073
152	one offer, med duration, Cancelled by client	not called	0.200	0.981	0.997	-0.208	0.013	1.072
151	med duration, Cancelled by client	not called	0.249	0.976	0.995	-0.261	0.015	1.066
150	med duration, Cancelled by client, high request	not called	0.063	0.972	0.998	-0.067	0.004	1.062
149	med duration, low request, Cancelled by client	not called	0.096	0.972	0.997	-0.102	0.006	1.062

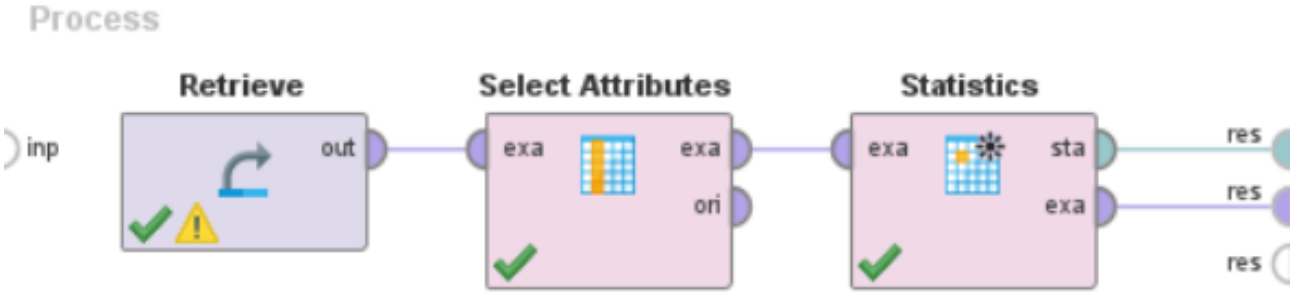
(b)

The conclusion with the highest confidence (0.991) states that if there is a car loan with one offer and a medium throughput time that gets cancelled by the client, the client likely doesn't call to complete the application. However this association rule is not very interesting to the bank manager due to its low support of just $\sim 6\%$
The conclusion with the lowest confidence in our analysis (0.8) states that if an application had a medium duration and was cancelled by the client there was likely just one offer. This rule has a fairly good support of 20% and lift larger than one, therefore it might theoretically be interesting to the bank manager. However it does not state any useful new facts besides that when an application is cancelled by the client after a medium time there usually aren't many offers to be made.

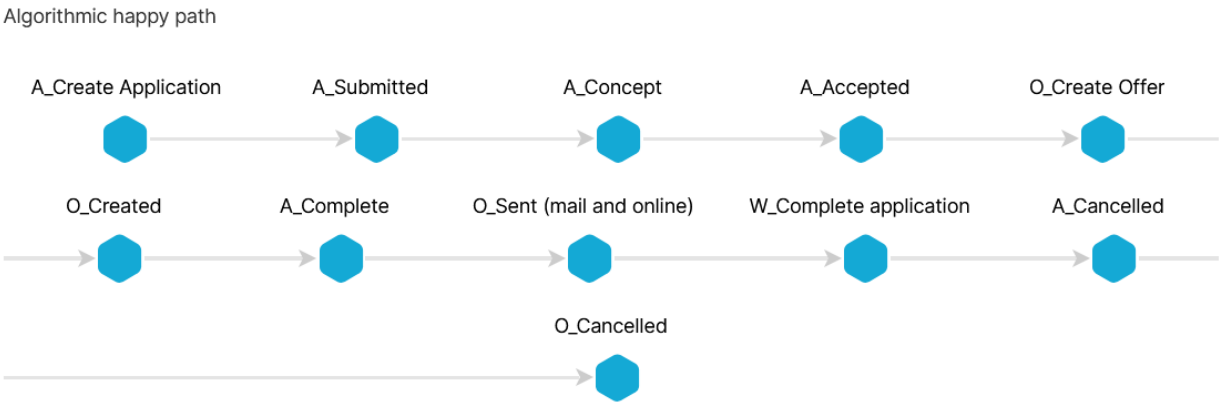
Question 5

(a)

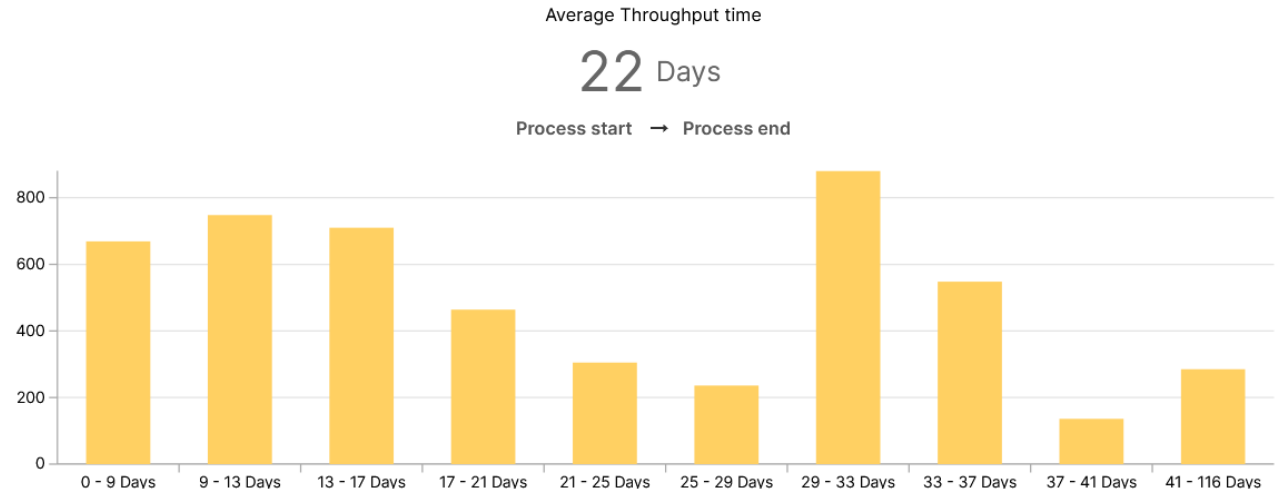
There are 4982 Applications with an average throughput time of 21.904 as determined using the following Process:



Using Celonis Process AI on our Dataset we learn that the most frequent variant (happy path) happens 320 times. This variant can be seen below.

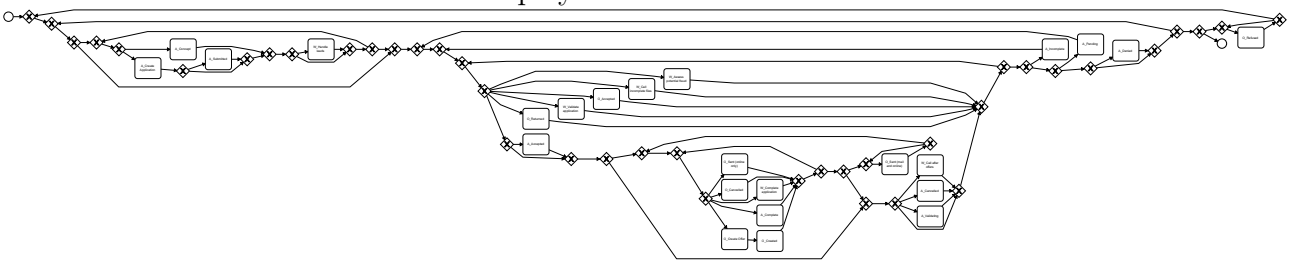


The following graph shows the frequency distribution of the throughput times. As one can see they are initially quite high and eventually deteriorate in frequency until the 29-33 Day, where they spike again and after that deteriorate quickly again. The reason for the spike at 29-33 Days is probably that a new month begins/ends at this time. Therefore many applications will likely be terminated at this time for administrative reasons.

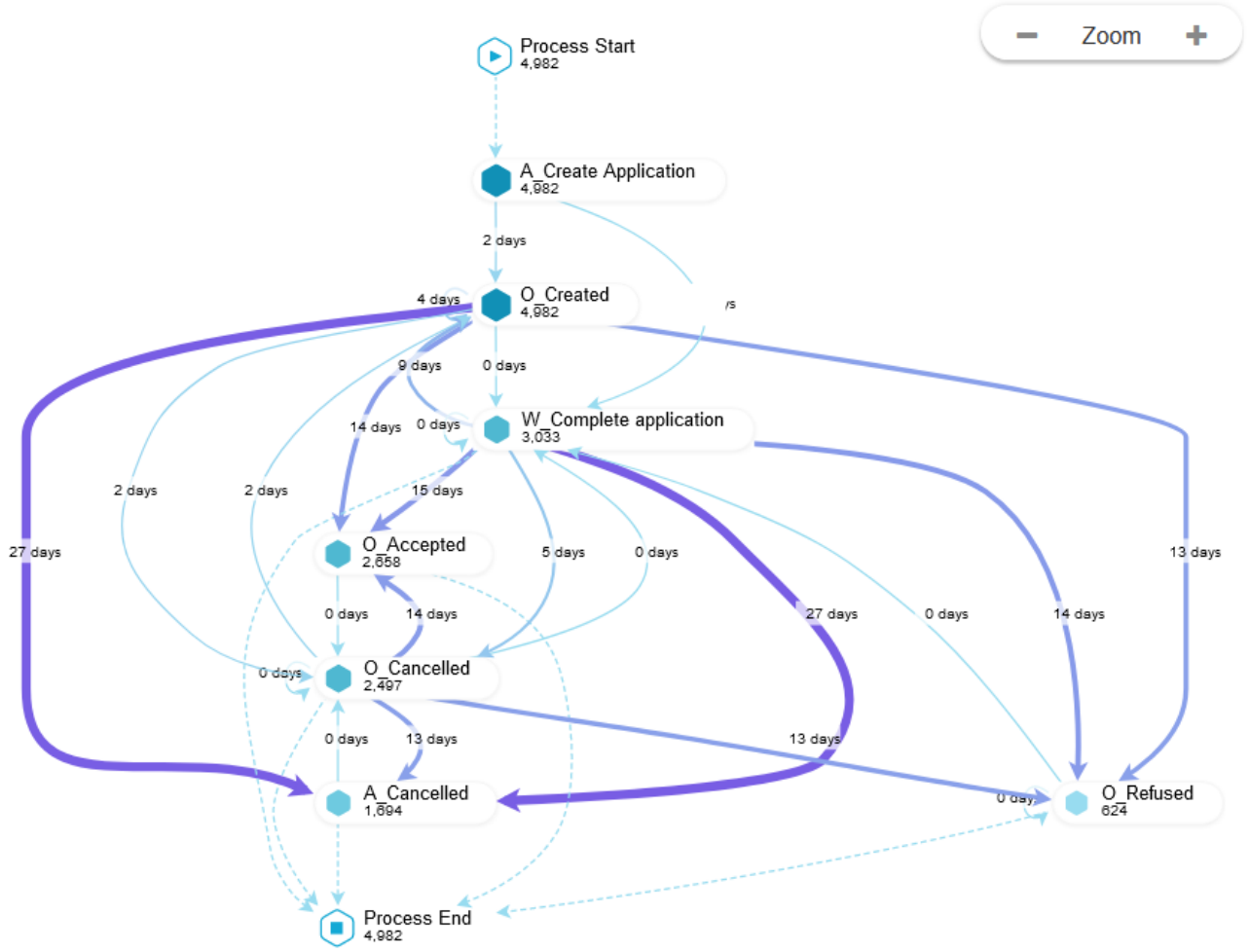


(b)

The BPMN model for cases running under 30 days can be seen below (zoom in to inspect in detail). We created it by starting a new Analysis and opening a new *conformance* sheet. Then we clicked *Mine process model* and in the next window added a new selection for Throughput time under 30. Then we clicked *select all* and *Launch analysis*. We then clicked *View process model* where the model below was displayed and downloadable.



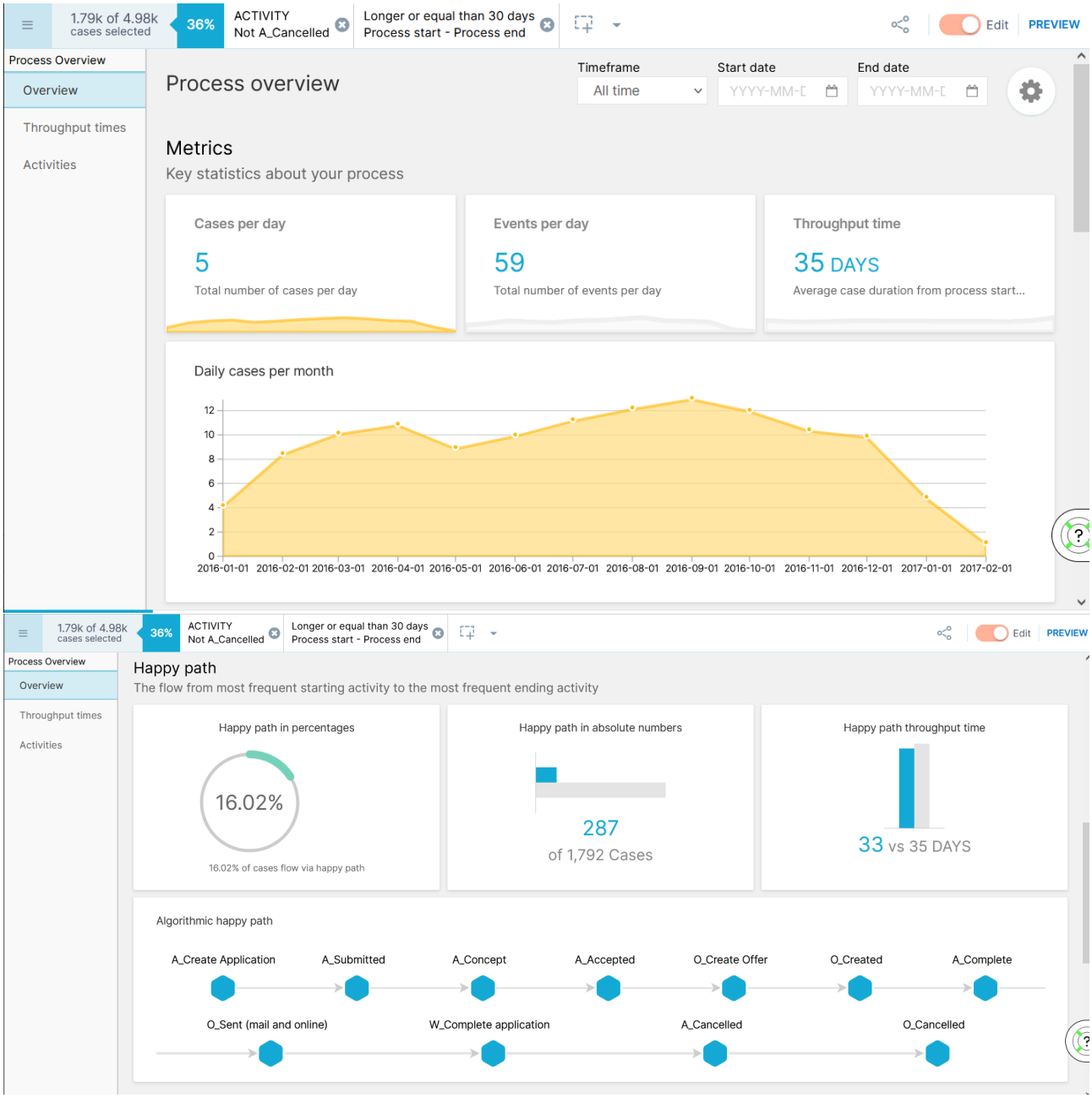
The DFG below was created by opening a new process explorer and only selecting the following activities to display: A_Create _Application, O_Created, W_Complete_Application, O_Accepted, O_Refused, O_Cancelled and A_Cancelled. 100% of activities and connections are being displayed. To see which edges are especially long lasting we selected throughput time as our edge lable.



This way we can see that there are two very long lasting edges (`O_Created`→`A_Cancelled` and `W_Complete_application`→`A_Cancelled`) with a throughput time of 27 days. There is also a number of medium long lasting edges with throughput times of 13-15 days

(c)

We open a new Process Overview for our Process in Celonis just like we did in a). To exclude all cancelled applications we add a new selection of type *Attribute selection*. Since per definition cancelled applications are those that contain the activity *A_cancelled* we exclude all the applications containing it by selecting `Activity_table_csv > ACTIVITY > A_Cancelled` and click *Invert selection*. We also create a new throughput time selection for applications with a throughput time between 30 and infinity to only see long running cases. The resulting Process Overview can be seen below.



From it we learn that there are 1792 long running applications that weren't cancelled.

(d)