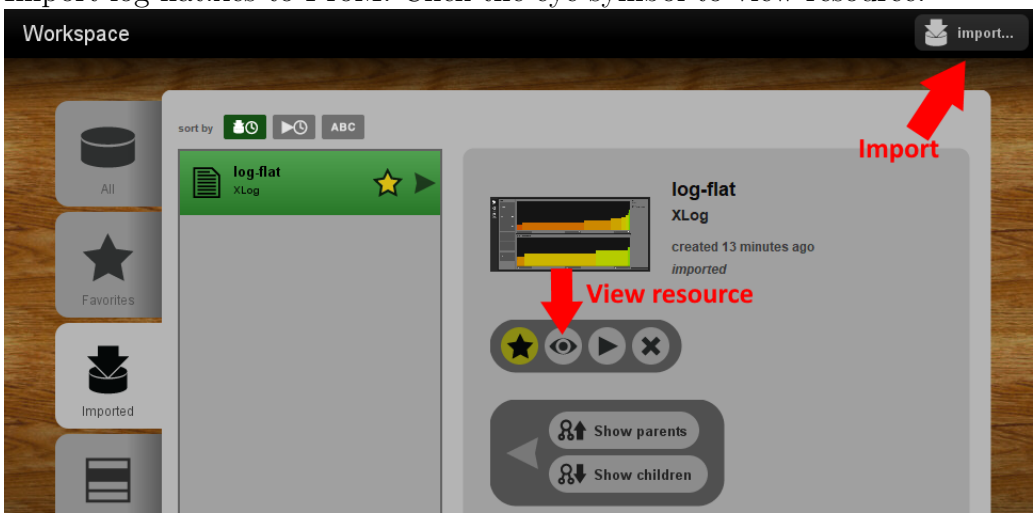
Question 1

(a)

Import log-flat.xes to ProM. Click the eye symbol to view resource.

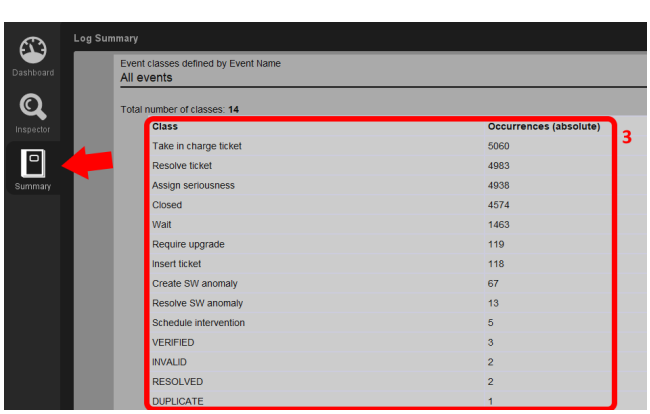


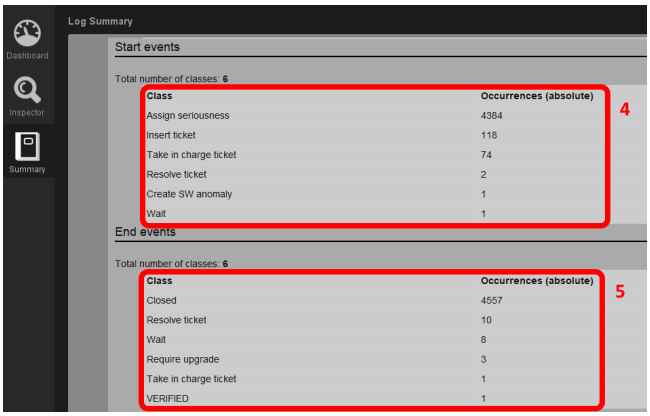
This results in the following view:

From it we can read

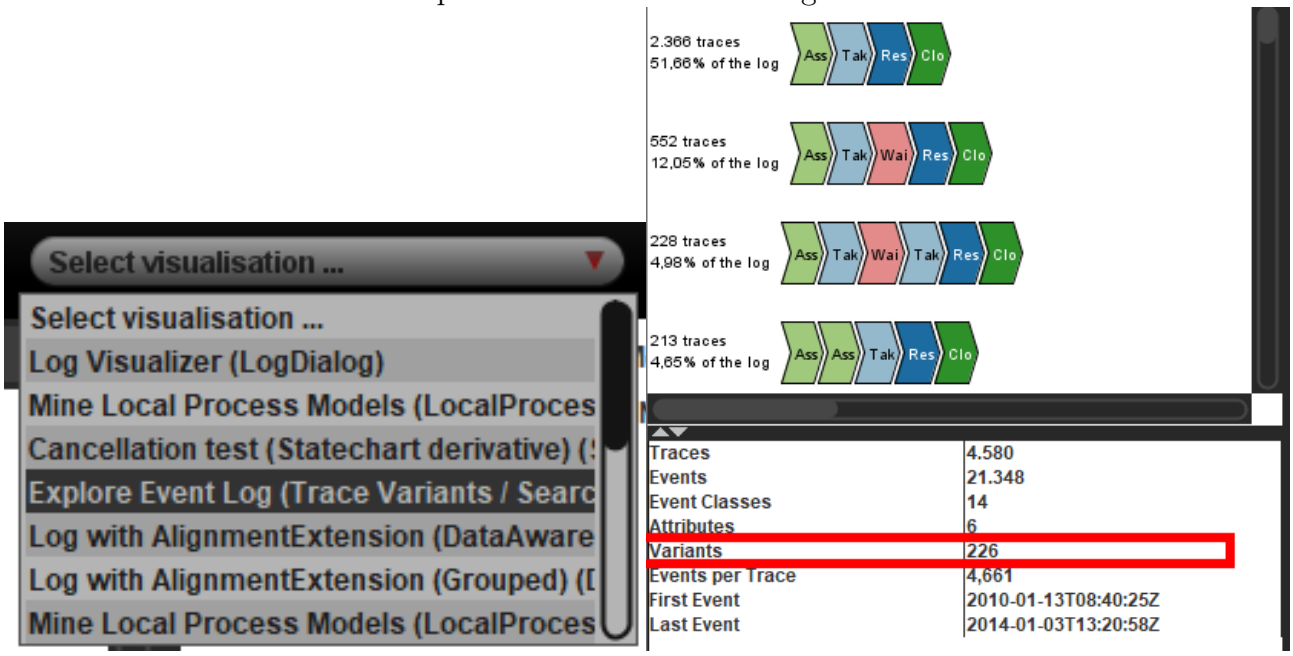
- the time period (1) covered by the event log, which is from 13.01.2010 to 03.01.2014
- the number of cases, events and activities of the log (2), being 4580, 21348 and 14 respectively (note that activities appear in ProM as event classes)

To gain more information on the activities we click the summary tab in the left which results in the following view:





From (3) we get a table of occurence frequencies for each activity. From (4) we get a table of occurence frequencies for each start activity. From (5) we get a table of occurence frequencies for each end activity.
To determine the number of unique trace variants we click on 'Select visualization' and select 'Explore Event Log'
Under this view all trace variants are listed and some further information is given. From this we learn that there are 226 unique variants in the event log.

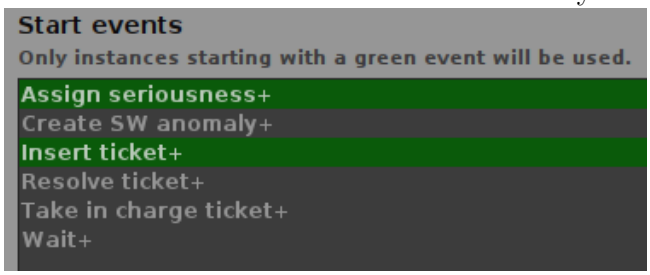


98% of tickets taken in charge are resolved ($\frac{4983}{5060}$) The variants seem to be quite diverse ($\tilde{1}$:20 ratio of cases to variants, although distributed very unevenly).
From (4) we also observe that a quite high number of cases start with "illegal" activities (so not 'Assign seriousness' or 'Insert ticket'). It strikes out, that people managed in 74 cases to start their tickets with the "illegal" activity 'Take in charge ticket', while in comparison only 118 cases begin with the activity 'Insert ticket'.

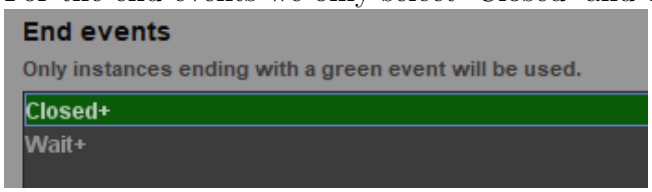
(b)

From the introduction we learned that every trace has to start with 'Insert ticket' or 'Assign seriousness' and ends with 'Closed'. Therefore every trace that does not begin/end with these events must have started/ended outside of our observed time period, making it incomplete.
To filter out incomplete traces we go on the 'Actions' tab, select 'Filter Log using Simple Heuristics' and press 'Start'. In the first dialogue we just click 'Next'. In the next dialogue

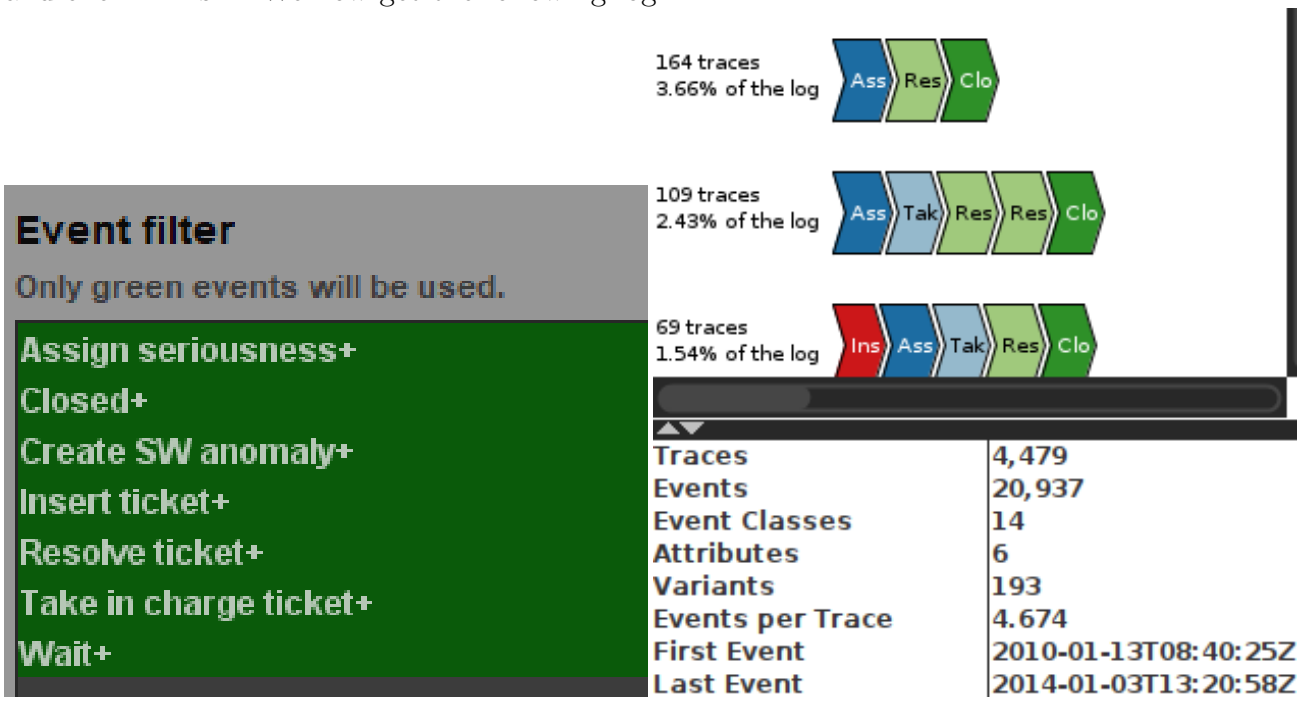
window we select 'Insert ticket' as our only start event and click 'Next'.



For the end events we only select 'Closed' and click 'Next'.

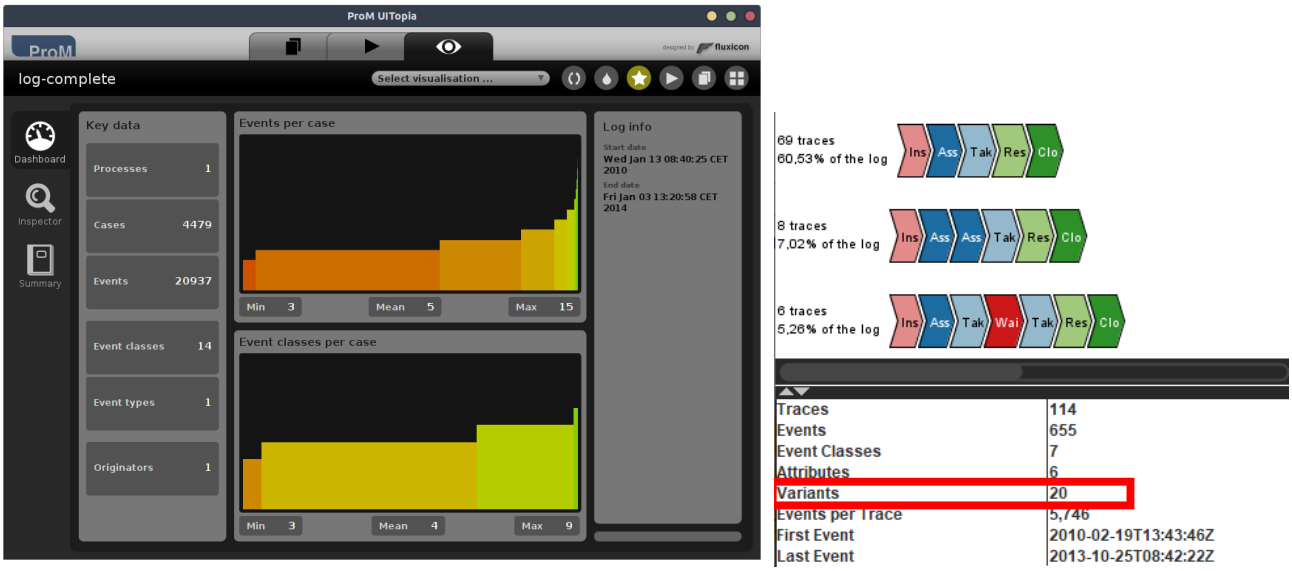


Since we do not want to filter out any other events we select 100% of events in Event Filter and click 'Finish'. We now get the following log:

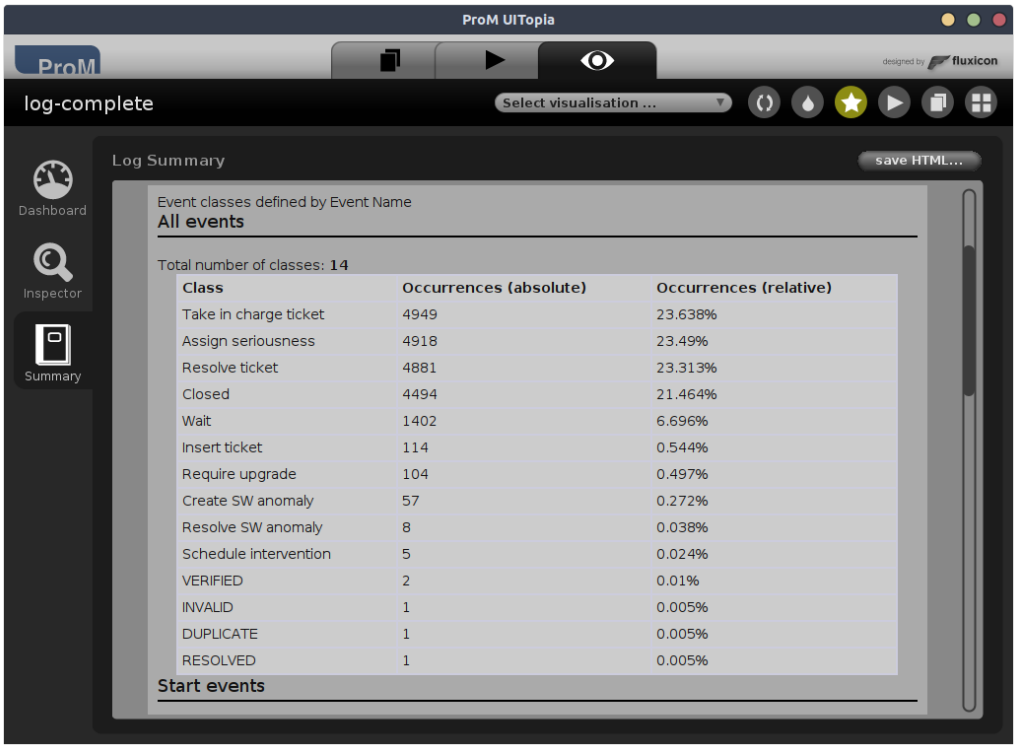


(c)

1. As in (a) we inspect the overview of *log-complete* to find 114 cases, 655 events and 7 activities. Also just like in (a) we select the visualization 'Explore Event Log' to find out there are 20 unique trace variants.

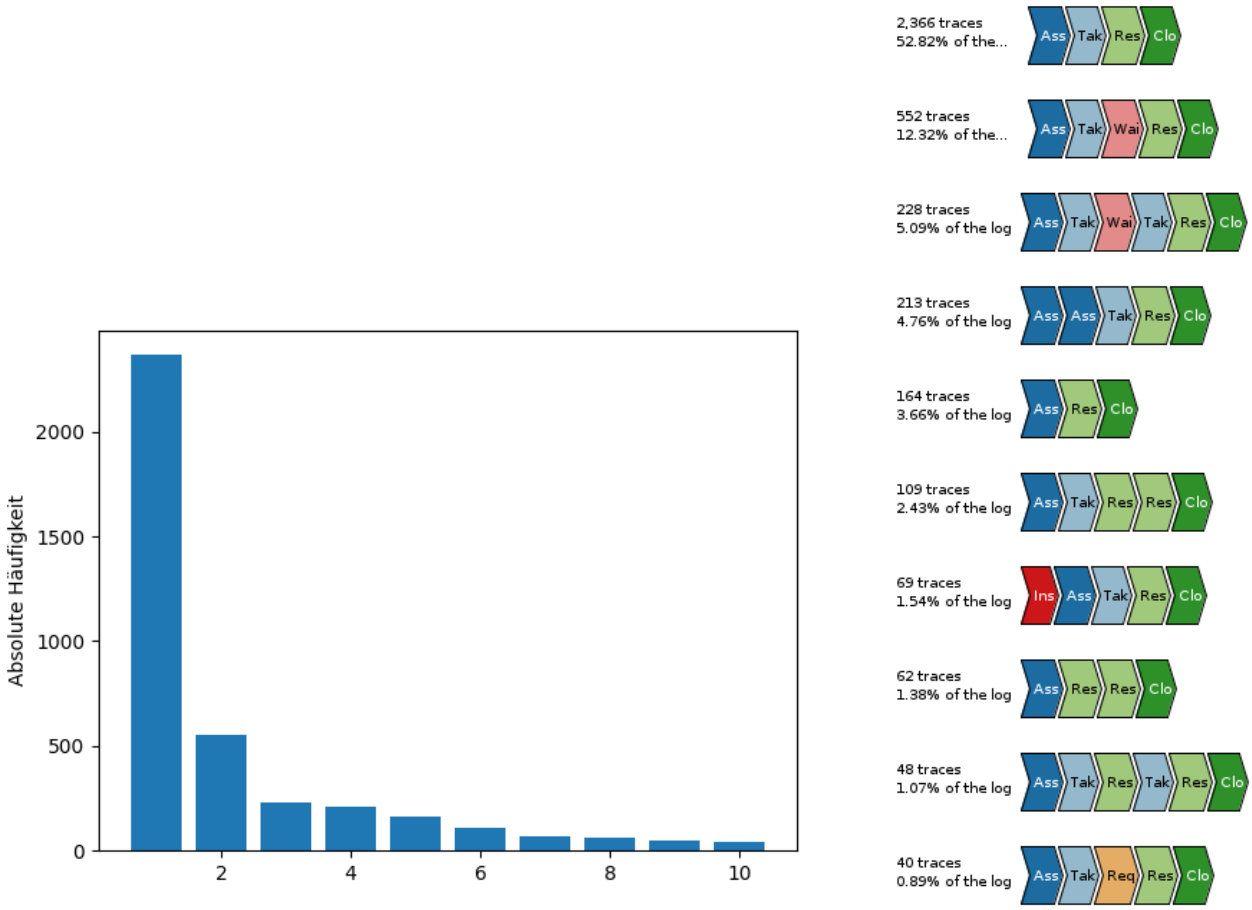


2. Just like in (a) we look at 'Summary' to find a table of activities along with their frequency of occurrence:



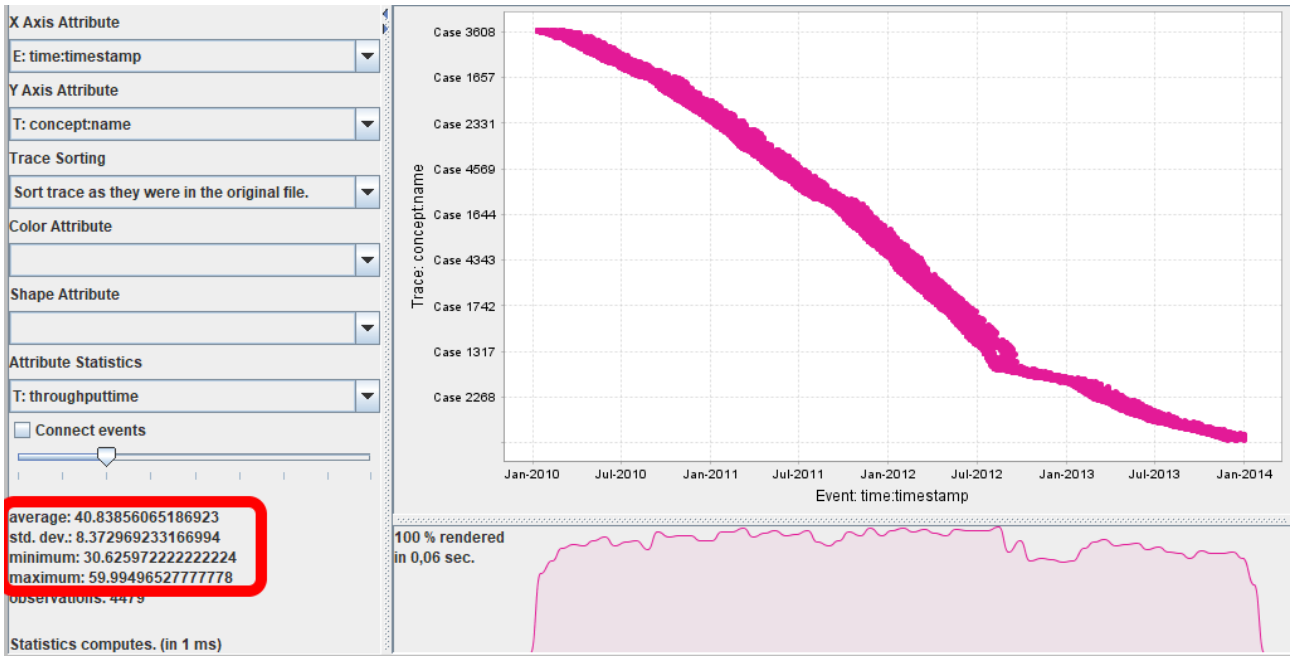
Class	Occurrences (absolute)	Occurrences (relative)
Take in charge ticket	4949	23.638%
Assign seriousness	4918	23.49%
Resolve ticket	4881	23.313%
Closed	4494	21.464%
Wait	1402	6.696%
Insert ticket	114	0.544%
Require upgrade	104	0.497%
Create SW anomaly	57	0.272%
Resolve SW anomaly	8	0.038%
Schedule intervention	5	0.024%
VERIFIED	2	0.01%
INVALID	1	0.005%
DUPLICATE	1	0.005%
RESOLVED	1	0.005%

3. We read the counts of the top 10 traces from the Event Log Explorer in RapidMiner, and the plugged those values into a short python script to create the following bar chart.

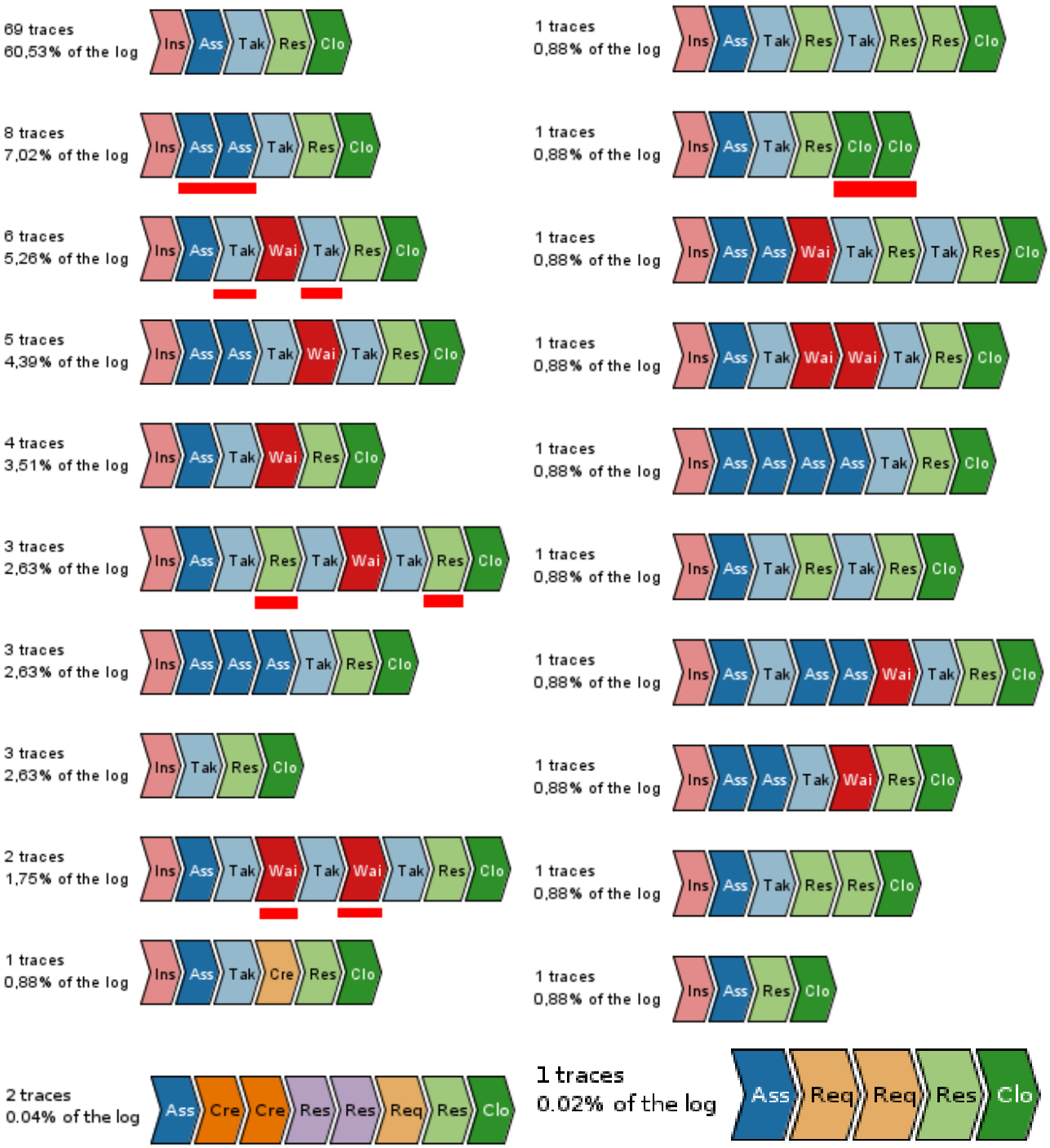


4. We apply the 'Add Throughput Time as Trace Attribute (In place)' plugin to *log-complete* and select 'DAYS' as the resolution to be used for the elapsed time. We then select the visualization 'Dotted Chart' on the result. To retrieve minimum, maximum and average trace durations we select 'T: throughputtime' as Attribute Statistics and get the following rounded result:

- minimum trace duration: 31 days
- maximum trace duration: 60 days
- average trace duration: 41 days



5. To find out which activities appear more than once in at least one trace we again take a look at the 'Explore Event Log' visualization:



The tasks that appear more than once (as marked in the visualization) are

- Ass: Assign seriousness
- Tak: Take in charge ticket
- Res: Resolve ticket
- Wai: Wait
- Clo: Closed
- Cre: Create SW Anomaly
- Req: Require Update

(d)

1. We choose Pie Charts for these visualization. For *Ticket type* distribution we choose `TICKET TYPE` as dimension:

```
"case_table_csv"."TICKET TYPE"
```

and `COUNT(TICKET TYPE)` as KPI:

```
COUNT("case_table_csv"."TICKET TYPE")
```

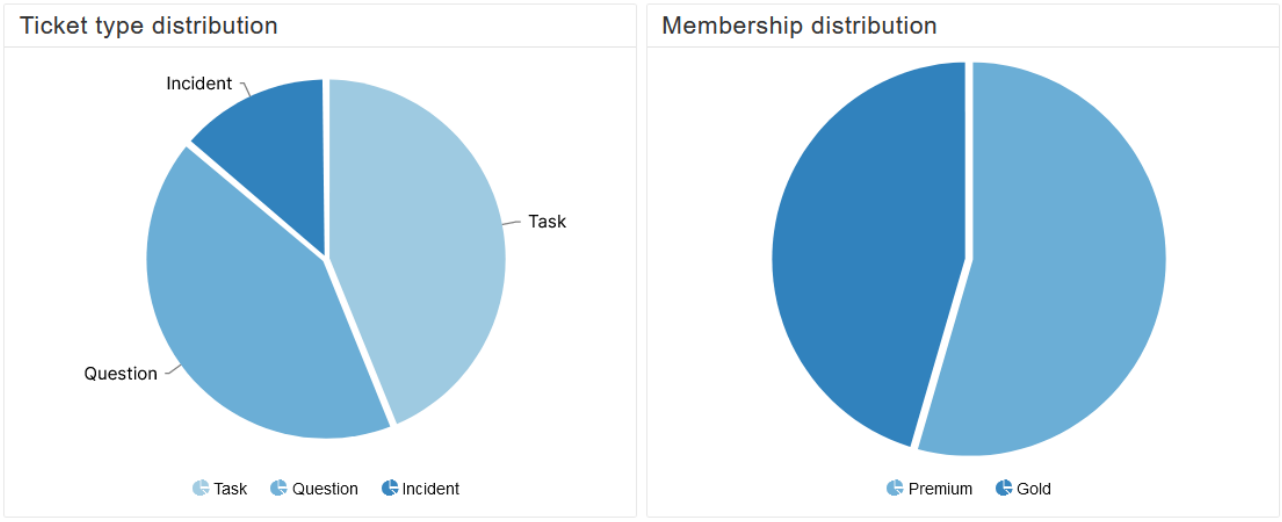
For *Membership* distribution we choose `MEMBERSHIP` as dimension:

```
"case_table_csv"."MEMBERSHIP"
```

and `COUNT(MEMBERSHIP)` as KPI:

```
COUNT("case_table_csv"."MEMBERSHIP")
```

The resulting distribution visualization can be seen below.



2. We obtained the column chart titeled 'Total workload per ressource' by using

```
"event_table_csv"."RESOURCE"
```

as dimension and

```
COUNT("event_table_csv"."ACTIVITY")
```

as KPI. The x-Axis shows the resources 1-8 in ascending order, the y-Axis shows the summed number of activities handeled by the given resource.

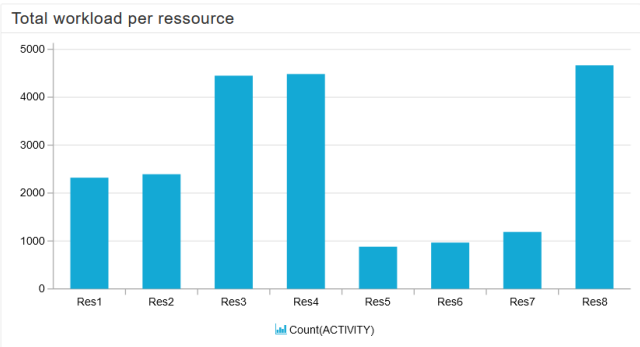
3. We created the column chart named 'Throughput times distribution' by selecting the total throughput time in days as our dimension:

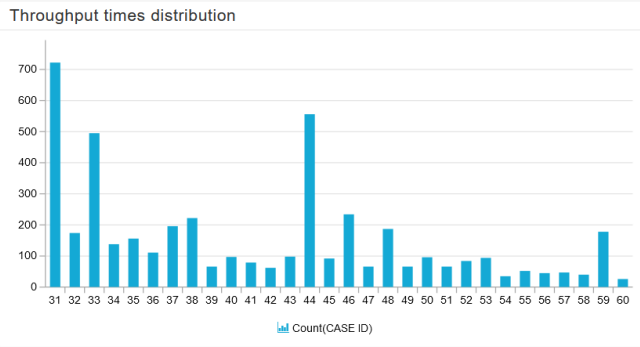
```
CALC_THROUGHPUT(ALL_OCCURRENCE['Process Start'] TO ALL_OCCURRENCE['Process End'], REMAP_
```

and selecting

```
COUNT("case_table_csv"."CASE ID")
```

as our KPI. The x-Axis shows the throughput time in days and the y-Axis shows the number of cases with a given throughput time.

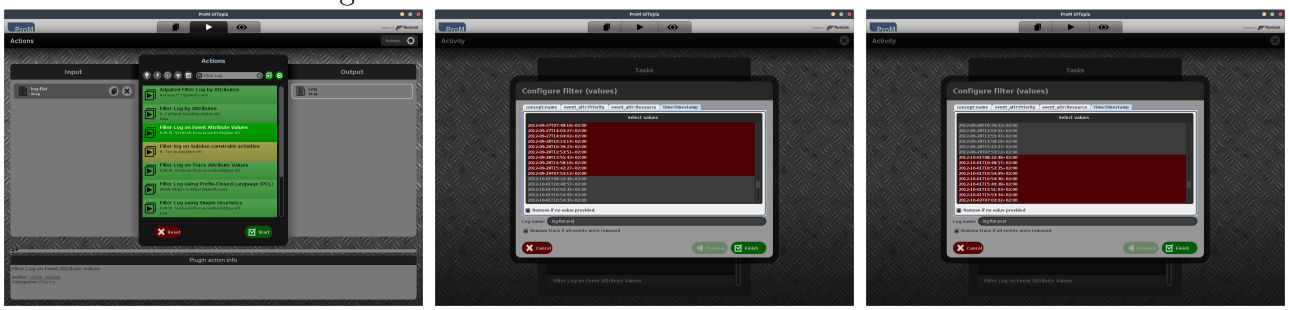




Question 2

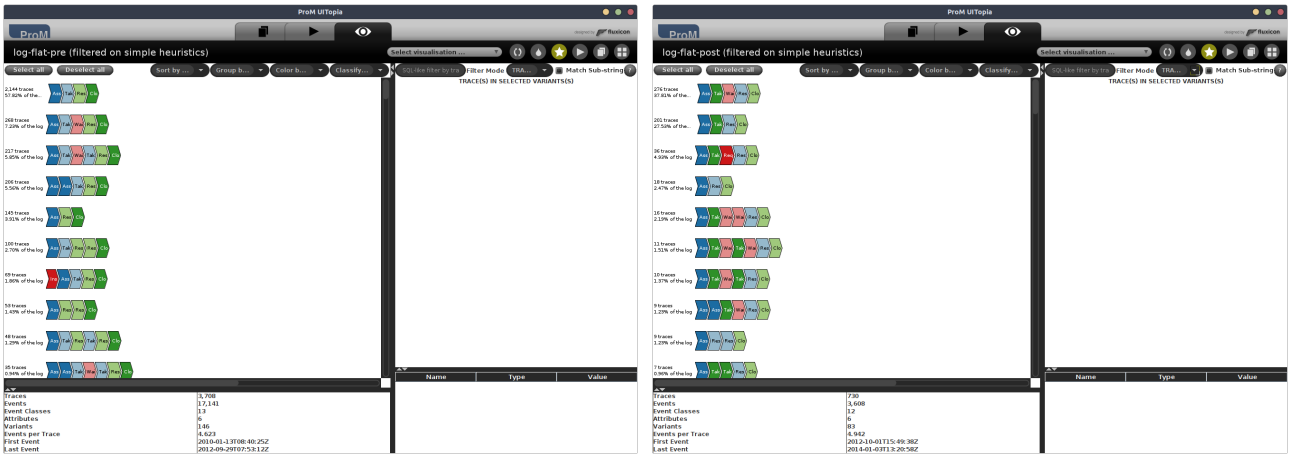
(a)

We can split the event log into two event logs using the plugin 'Filter Log on Event Attribute Values' with the following selections:



Afterwards, we can apply our filtering to only allow valid traces, as seen before.

For the event log pre 01.10.2012 we get 13 unique activities across 3708 cases, as a whole consisting of 6 variants.
For the event log post (including) 01.10.2012 we get 12 unique activities across 730 cases, as a whole consisting of 6 variants.



(b)

1. We apply the following workflow both for *log-pre-complete* and *log-post-complete*:
    1. Apply plugin 'Interactive Data-aware Heuristic Miner (iDHM)'

2. Set 'Options & Thresholds' to
   All tasks connected: True

	i) (*log-pre-complete*)	ii) (*log-pre-complete*)	iii) (*log-post-complete*)	iv) (*log-post-comple*
Frequency	0.1	0	0.1	0
Dependency	0.9	0.9	0.9	0.9
Bindings	0.1	0.1	0.1	0.1
Conditions	0.5	0.5	0.5	0.5

3. Select 'Petri net' as 'Output: Process Model' and click 'Export model'
4. Use the log and the newly created Petri net as input for the 'Multi-perspective Process Miner' plugin

This results in the following Models:

As we can see all these models exceed our fitness threshold of 90% and contain all activities occuring in their respective logs (*log-pre-complete* doesn't contain the activity DUPLICATE and *log-post.complete* doesn't contain the activities INVALID and RESOLVED).

(c)

(d)

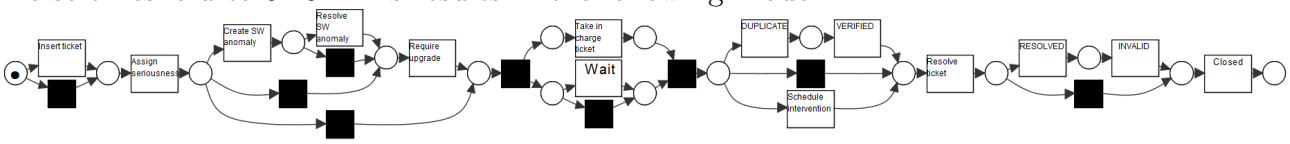
Question 3

(a)

We use the Plugin 'Use Trace Attribute Values' to only select Tickets of type 'Task'. As visualization we then choose 'Explore Event Log'. This gives us the table below:

Traces	2.018
Events	10.283
Event Classes	14
Attributes	6
Variants	201
Events per Trace	5,096
First Event	2010-01-13T12:30:37Z
Last Event	2014-01-03T13:20:58Z

From it we can take that there are 2018 traces, 201 trace variants and 10283 events. We then apply the plugin 'Mine Petri net with Inductive Miner' on this filtered log and make sure we choose 'Inductive Miner - Infrequent (IMf)' as our variant and set it to 20% by assigning the Noise threshold to 0.20. This results in the following Model:



(b)

We use the plugin 'Multi-perspective Process Explorer' on our Petri net from (a). This gives us the following information on fitness and precision:

Avg fitness	92,3%
% Violations	14,2%
% Event Violations	14,2%
% Data Violations	0%
# Correct Events	8.966
# Wrong Events	1.317
# Missing Events	166

Avg activity precision	82,9%
# Moves Observed	33.237
# Moves Possible	40.096
Avg fitness	92,3%
% Violations	14,2%
% Event Violations	14,2%
% Data Violations	0%
# Correct Events	8.966
# Wrong Events	1.317
# Missing Events	166

We obtain the percentage of fitting traces by calculating 100% minus the percentage of violations (100% - 14.2%), resulting in 85,8% fitting traces. Alignment-based fitness (92.3%) and precision (82.9%) can be read from the tables above.
By using the inductive miner again and adjusting the infrequency parameter to 10% we obtain a process model with better fitness, precision and more perfectly fitting traces than before. The stats of the new model can be seen below:

Avg activity precision	83,6%
# Moves Observed	35.324
# Moves Possible	42.242
Avg fitness	92,4%
% Violations	14%
% Event Violations	14%
% Data Violations	0%
# Correct Events	8.985
# Wrong Events	1.298
# Missing Events	169

(c)

Question 4

(a)

We created the following OLAP Table:

CASE ID	TICKET TYPE	MEMBERSHIP	PRIORITY	RESOURCE OF STARTING ...	NUMBER OF ACTIVE CASE...	Decision
Case 1	Question	Gold	Normal	Res4	18	False/No-Wait
Case 10	Task	Premium	Normal	Res4	18	False/No-Wait
Case 100	Task	Premium	Normal	Res3	18	False/No-Wait
Case 1000	Incident	Gold	Urgent	Res8	18	False/No-Wait
Case 1001	Task	Premium	Normal	Res4	18	False/No-Wait
Case 1002	Task	Gold	High	Res3	18	False/No-Wait
Case 1003	Task	Premium	Normal	Res4	18	False/No-Wait
Case 1004	Incident	Premium	Normal	Res4	18	False/No-Wait
Case 1005	Task	Premium	Normal	Res3	18	False/No-Wait
Case 1006	Question	Gold	High	Res4	18	False/No-Wait
Case 1007	Task	Premium	Normal	Res3	18	False/No-Wait
Case 1008	Task	Gold	High	Res8	18	False/No-Wait
Case 1009	Task	Premium	High	Res8	18	True/Wait
Case 101	Question	Premium	Normal	Res3	18	False/No-Wait
Case 1010	Task	Premium	Normal	Res4	18	False/No-Wait
Case 1011	Question	Gold	Normal	Res8	18	False/No-Wait
Case 1012	Incident	Premium	Normal	Res8	18	False/No-Wait
Case 1013	Question	Premium	Normal	Res4	18	False/No-Wait
Case 1014	Task	Premium	Normal	Res4	18	True/Wait
Case 1015	Incident	Gold	Normal	Res8	18	False/No-Wait
Case 1016	Question	Gold	High	Res8	18	False/No-Wait
Case 1017	Task	Premium	Normal	Res4	18	True/Wait
Case 1018	Task	Premium	Normal	Res4	18	False/No-Wait
Case 1019	Task	Premium	Normal	Res8	18	True/Wait
Case 102	Question	Gold	Normal	Res3	18	False/No-Wait
Case 1020	Task	Premium	Normal	Res4	18	True/Wait
Case 1021	Question	Premium	Normal	Res3	18	False/No-Wait
Case 1022	Question	Premium	Normal	Res8	18	False/No-Wait
Case 1023	Task	Premium	Normal	Res3	18	False/No-Wait
Case 1024	Task	Gold	High	Res4	18	False/No-Wait
Case 1025	Task	Premium	Normal	Res4	18	True/Wait
Case 1026	Task	Premium	Normal	Res8	18	False/No-Wait
Case 1027	Task	Premium	Normal	Res3	18	True/Wait
Case 1028	Task	Gold	High	Res4	18	False/No-Wait
Case 1029	Question	Gold	Normal	Res3	18	False/No-Wait
Case 103	Task	Premium	Normal	Res4	18	True/Wait

For this, we used the following PQL Queries in the order of columns in the image left to right:

```
"case_table_csv"."CASE ID"
```

```
"case_table_csv"."MEMBERSHIP"
```

```
"case_table_csv"."TICKET TYPE"
```

```
"event_table_csv"."PRIORITY"
```

```
PU_FIRST ( "case_table_csv", "event_table_csv"."RESOURCE")
```

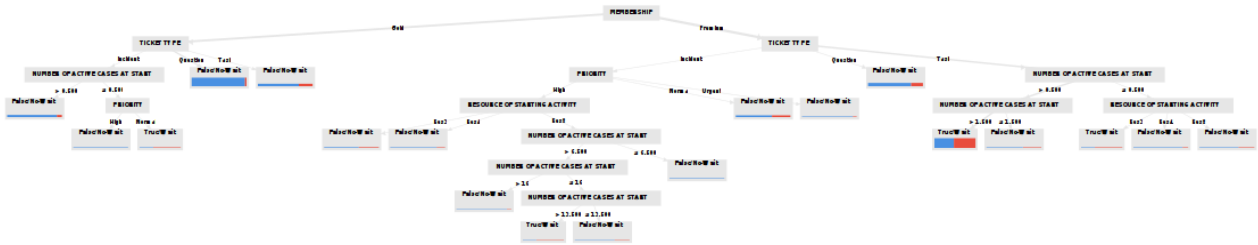
```
RUNNING_SUM (
  CASE WHEN MATCH_PROCESS_REGEX("event_table_csv"."ACTIVITY", 'Closed'$) = 1 THEN 0
  ELSE 1
  END
)
```

```
CASE WHEN
MATCH_PROCESS_REGEX ( "event_table_csv"."ACTIVITY", 'Wait' ) = 1 THEN 'True/Wait'
ELSE 'False/No-Wait'
END
```

(b)

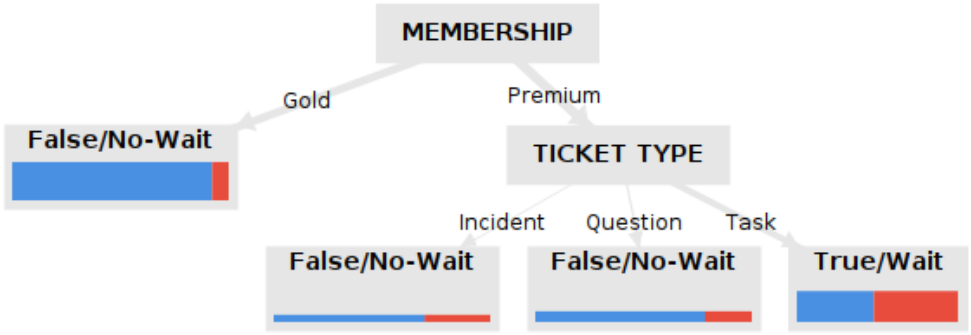
First, we export the OLAP Table and import it into RapidMiner as described in Instruction 2. The resulting decision tree is evidently too large to fit into a PDF, thus we have added the

description in the Appendix:



We found that some tasks using Resource 3 would wait, even if they were the only task running at creation. From the tree we can also observe that some high priority incidents (using Resource 3 or 8) would have to wait depending on the number of active cases at start, although there does not seem to be any connection to the prior predictor variables.

After removing the attribute 'number of active cases at start', we get a much more simplified, but comprehensible Decision Tree:



Here we see that about half the Premium Tasks will have to wait, while for all other tickets waiting is less likely.

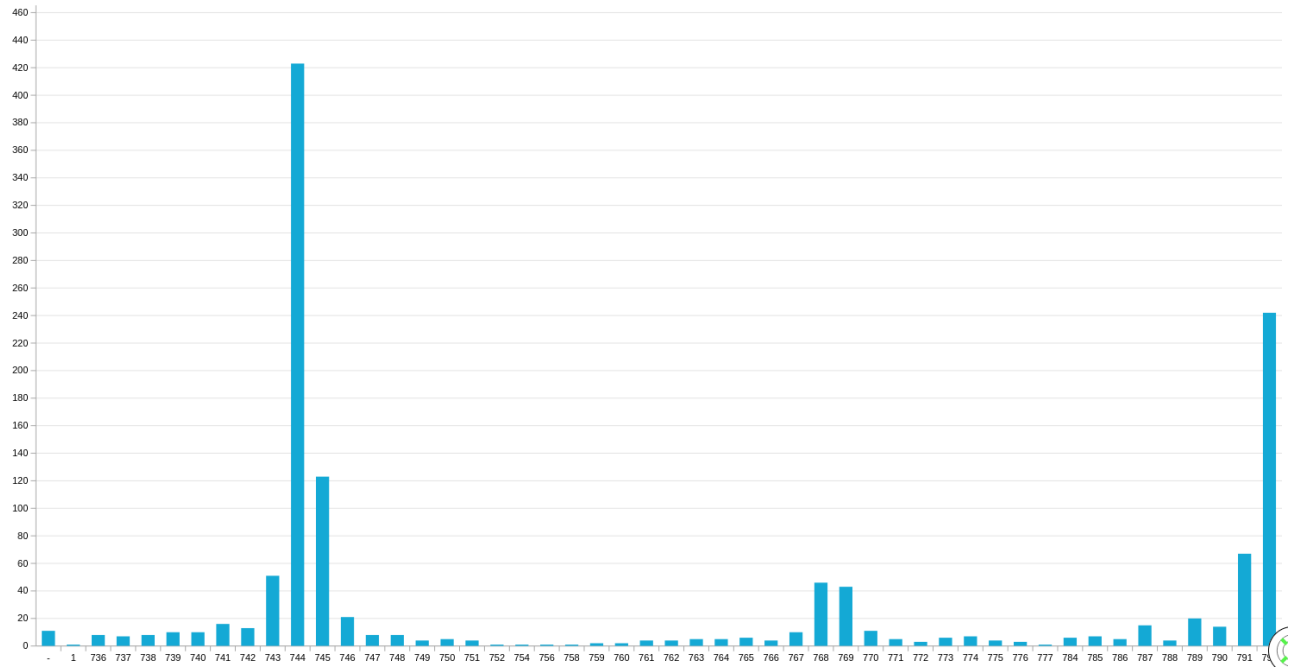
Question 5

(a)

Similarly to 1d), we created a new column chart. Here, we used the following Dimension:

```
CASE WHEN MATCH_PROCESS_REGEX("event_table_csv"."ACTIVITY", 'Closed'$) = 1
THEN CALC_THROUGHPUT(
CASE_START TO CASE_END,
REMAP_TIMESTAMPS("event_table_csv"."TIMESTAMP",HOURS)
)
ELSE CALC_THROUGHPUT(
CASE_START TO LAST_OCCURRENCE['Resolve ticket'],
REMAP_TIMESTAMPS("event_table_csv"."TIMESTAMP",HOURS)
)
END
```

Using the Case Count as a Dimension, we got the following chart. Note that this is just a tiny section of the entire chart. There are cases with throughput times up to 1440h:



(b)

We applied the `Quantile` function on the real throughput times (see above) for 0.3 and 0.7, respectively (here for 0.3):

```
QUANTILE(CASE WHEN MATCH_PROCESS_REGEX("event_table_csv"."ACTIVITY", 'Closed'$) = 1
THEN CALC_THROUGHPUT(
CASE_START TO CASE_END,
REMAP_TIMESTAMPS("event_table_csv"."TIMESTAMP",HOURS)
)
ELSE CALC_THROUGHPUT(
CASE_START TO LAST_OCCURRENCE['Resolve ticket'],
REMAP_TIMESTAMPS("event_table_csv"."TIMESTAMP",HOURS)
)
END, 0.3)
```

For the 0.3-quantile we got 795h, for the 0.7-quantile 1079h.

(c)

Approach equivalent to Question 4a). We used the following PQL queries:

```
"case_table_csv"."CASE ID"
```

```
"case_table_csv"."TICKET TYPE"
```

```
"case_table_csv"."MEMBERSHIP"
```

```
"event_table_csv"."PRIORITY"
```

```
CASE

WHEN (CASE WHEN MATCH_PROCESS_REGEX("event_table_csv"."ACTIVITY", 'Closed'$) = 1
THEN CALC_THROUGHPUT(
CASE_START TO CASE_END,
```

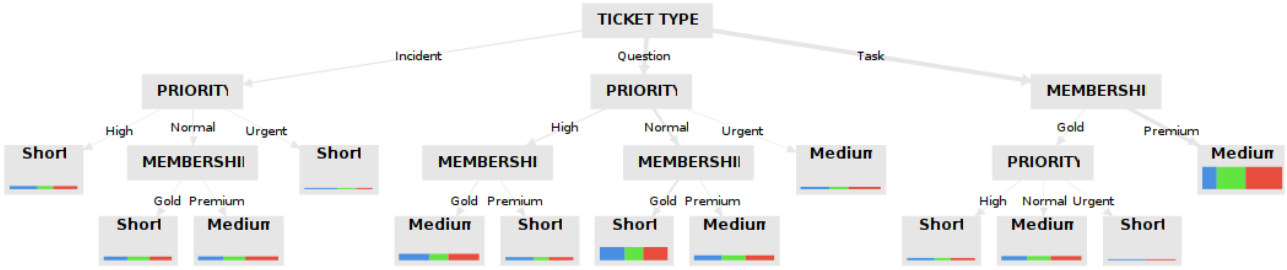
```
REMAP_TIMESTAMPS("event_table_csv"."TIMESTAMP",HOURS)
)
ELSE CALC_THROUGHPUT(
CASE_START TO LAST_OCCURRENCE['Resolve ticket'],
REMAP_TIMESTAMPS("event_table_csv"."TIMESTAMP",HOURS)
)
END) < 795 THEN 'Short'

WHEN (CASE WHEN MATCH_PROCESS_REGEX("event_table_csv"."ACTIVITY", 'Closed'$) = 1
THEN CALC_THROUGHPUT(
CASE_START TO CASE_END,
REMAP_TIMESTAMPS("event_table_csv"."TIMESTAMP",HOURS)
)
ELSE CALC_THROUGHPUT(
CASE_START TO LAST_OCCURRENCE['Resolve ticket'],
REMAP_TIMESTAMPS("event_table_csv"."TIMESTAMP",HOURS)
)
END) < 1079 THEN 'Medium'

ELSE 'Long'

END
```

CASE ID	TICKET TYPE	MEMBERSHIP	PRIORITY	Performance class
Case 1	Question	Gold	Normal	Short
Case 10	Task	Premium	Normal	Long
Case 100	Task	Premium	Normal	Long
Case 1000	Incident	Gold	Urgent	Medium
Case 1001	Task	Premium	Normal	Medium
Case 1002	Task	Gold	High	Short
Case 1003	Task	Premium	Normal	Medium
Case 1004	Incident	Premium	Normal	Short
Case 1005	Task	Premium	Normal	Long
Case 1006	Question	Gold	High	Long
Case 1007	Task	Premium	Normal	Long
Case 1008	Task	Gold	High	Medium
Case 1009	Task	Premium	High	Medium
Case 101	Question	Premium	Normal	Long
Case 1010	Task	Premium	Normal	Medium
Case 1011	Question	Gold	Normal	Long
Case 1012	Incident	Premium	Normal	Short
Case 1013	Question	Premium	Normal	Medium
Case 1014	Task	Premium	Normal	Short
Case 1015	Incident	Gold	Normal	Short
Case 1016	Question	Gold	High	Long
Case 1017	Task	Premium	Normal	Medium
Case 1018	Task	Premium	Normal	Long
Case 1019	Task	Premium	Normal	Short
Case 102	Question	Gold	Normal	Long
Case 1020	Task	Premium	Normal	Long
Case 1021	Question	Premium	Normal	Medium
Case 1022	Question	Premium	Normal	Short
Case 1023	Task	Premium	Normal	Short
Case 1024	Task	Gold	High	Medium
Case 1025	Task	Premium	Normal	Long
Case 1026	Task	Premium	Normal	Medium
Case 1027	Task	Premium	Normal	Medium
Case 1028	Task	Gold	High	Short
Case 1029	Question	Gold	Normal	Short
Case 103	Task	Premium	Normal	Medium

(d)

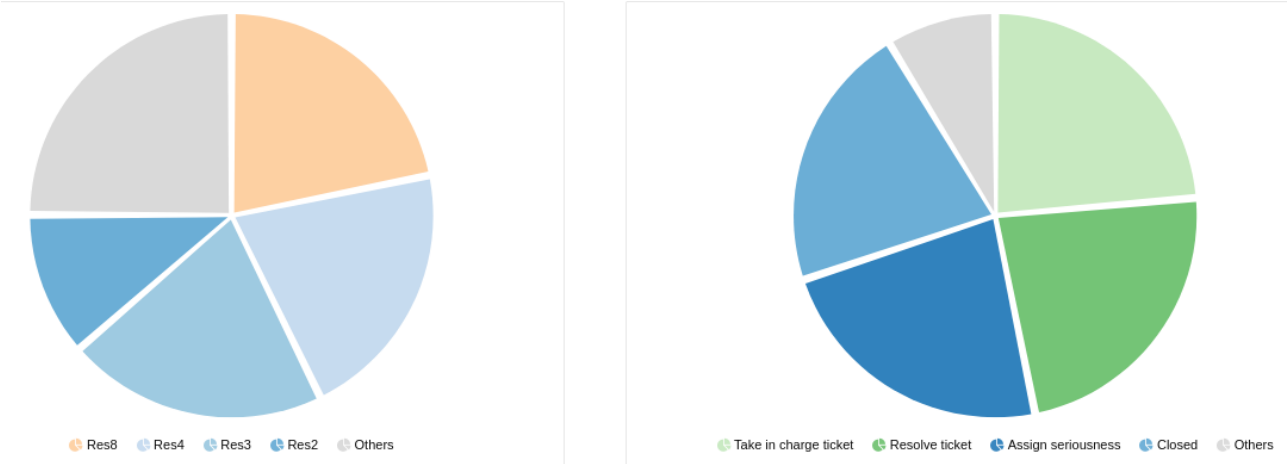
First, we export the OLAP Table and import it into RapidMiner as described in Instruction 2. Even after setting the parameters of the Decision Tree algorithm to extreme values (minimal gain at 1.0E-6), we could not find any clear variable that predicts the outcome of the performance class in any way. Thus, we conclude that the performance class (and thus the real

throughput time) has no strong correlation with neither Priority nor Ticket Type. The only thing noticeable was, that close to half the Tasks stemming from Premium Memberships were Medium rated in real throughput time.



Question 6

(a)



For the left Pie Chart we used `"event_table_csv"."RESOURCE"` as the Dimension and `COUNT("event_tabl` as the KPI.
For the right Pie Chart we used `"event_table_csv"."ACTIVITY"` as the Dimension and `COUNT("event_table_csv"."RESOURCE")` as the KPI.

(b)

Appendix

Question 4b) Decision Tree description:

```
MEMBERSHIP = Gold
|   TICKET TYPE = Incident
|   |   NUMBER OF ACTIVE CASES AT START > 0.500: False/No-Wait {False/No-Wait=266, True/Wait=27}
|   |   NUMBER OF ACTIVE CASES AT START <= 0.500
|   |   |   PRIORITY = High: False/No-Wait {False/No-Wait=2, True/Wait=0}
|   |   |   PRIORITY = Normal: True/Wait {False/No-Wait=1, True/Wait=2}
|   TICKET TYPE = Question: False/No-Wait {False/No-Wait=1391, True/Wait=41}
|   TICKET TYPE = Task: False/No-Wait {False/No-Wait=262, True/Wait=89}
MEMBERSHIP = Premium
|   TICKET TYPE = Incident
```

```
|   |   PRIORITY = High
|   |   |   RESOURCE OF STARTING ACTIVITY = Res3: False/No-Wait {False/No-Wait=19, True/Wait=11}
|   |   |   RESOURCE OF STARTING ACTIVITY = Res4: False/No-Wait {False/No-Wait=22, True/Wait=4}
|   |   |   RESOURCE OF STARTING ACTIVITY = Res8
|   |   |   |   NUMBER OF ACTIVE CASES AT START > 6.500
|   |   |   |   |   NUMBER OF ACTIVE CASES AT START > 16: False/No-Wait {False/No-Wait=11, True/Wait=1}
|   |   |   |   |   NUMBER OF ACTIVE CASES AT START <= 16
|   |   |   |   |   |   NUMBER OF ACTIVE CASES AT START > 13.500: True/Wait {False/No-Wait=1, True/Wait=2}
|   |   |   |   |   |   NUMBER OF ACTIVE CASES AT START <= 13.500: False/No-Wait {False/No-Wait=8, True/Wait=3}
|   |   |   |   NUMBER OF ACTIVE CASES AT START <= 6.500: False/No-Wait {False/No-Wait=3, True/Wait=0}
|   |   PRIORITY = Normal: False/No-Wait {False/No-Wait=147, True/Wait=75}
|   |   PRIORITY = Urgent: False/No-Wait {False/No-Wait=13, True/Wait=1}
|   TICKET TYPE = Question: False/No-Wait {False/No-Wait=401, True/Wait=110}
|   TICKET TYPE = Task
|   |   NUMBER OF ACTIVE CASES AT START > 0.500
|   |   |   NUMBER OF ACTIVE CASES AT START > 1.500: True/Wait {False/No-Wait=777, True/Wait=861}
|   |   |   NUMBER OF ACTIVE CASES AT START <= 1.500: False/No-Wait {False/No-Wait=4, True/Wait=2}
|   |   NUMBER OF ACTIVE CASES AT START <= 0.500
|   |   |   RESOURCE OF STARTING ACTIVITY = Res3: True/Wait {False/No-Wait=2, True/Wait=4}
|   |   |   RESOURCE OF STARTING ACTIVITY = Res4: False/No-Wait {False/No-Wait=9, True/Wait=1}
|   |   |   RESOURCE OF STARTING ACTIVITY = Res8: False/No-Wait {False/No-Wait=5, True/Wait=2}
```