



UNIVERSITY OF PISA

Process Mining and Intelligence

Year 2021/22

Sea Container inspection

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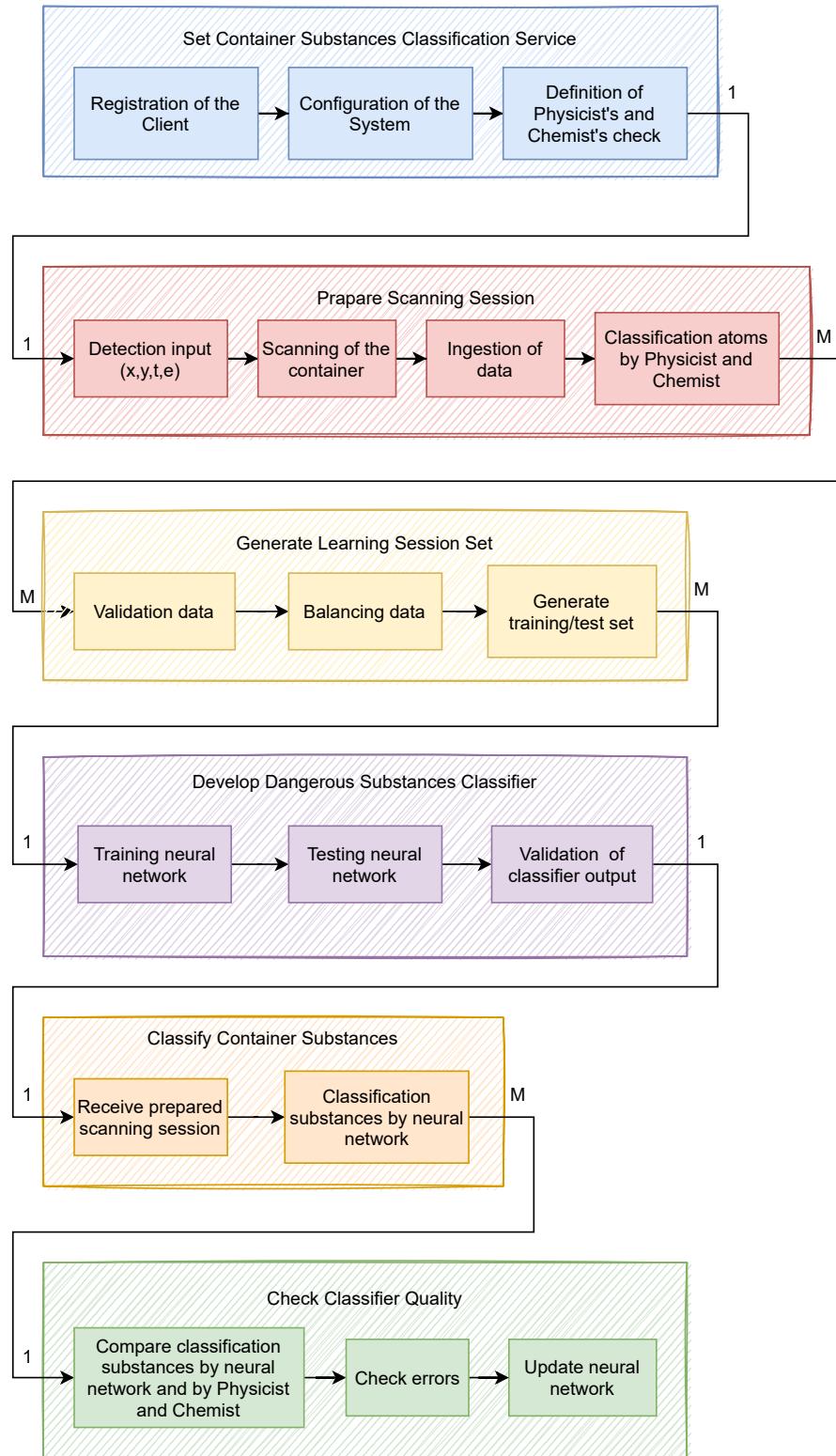
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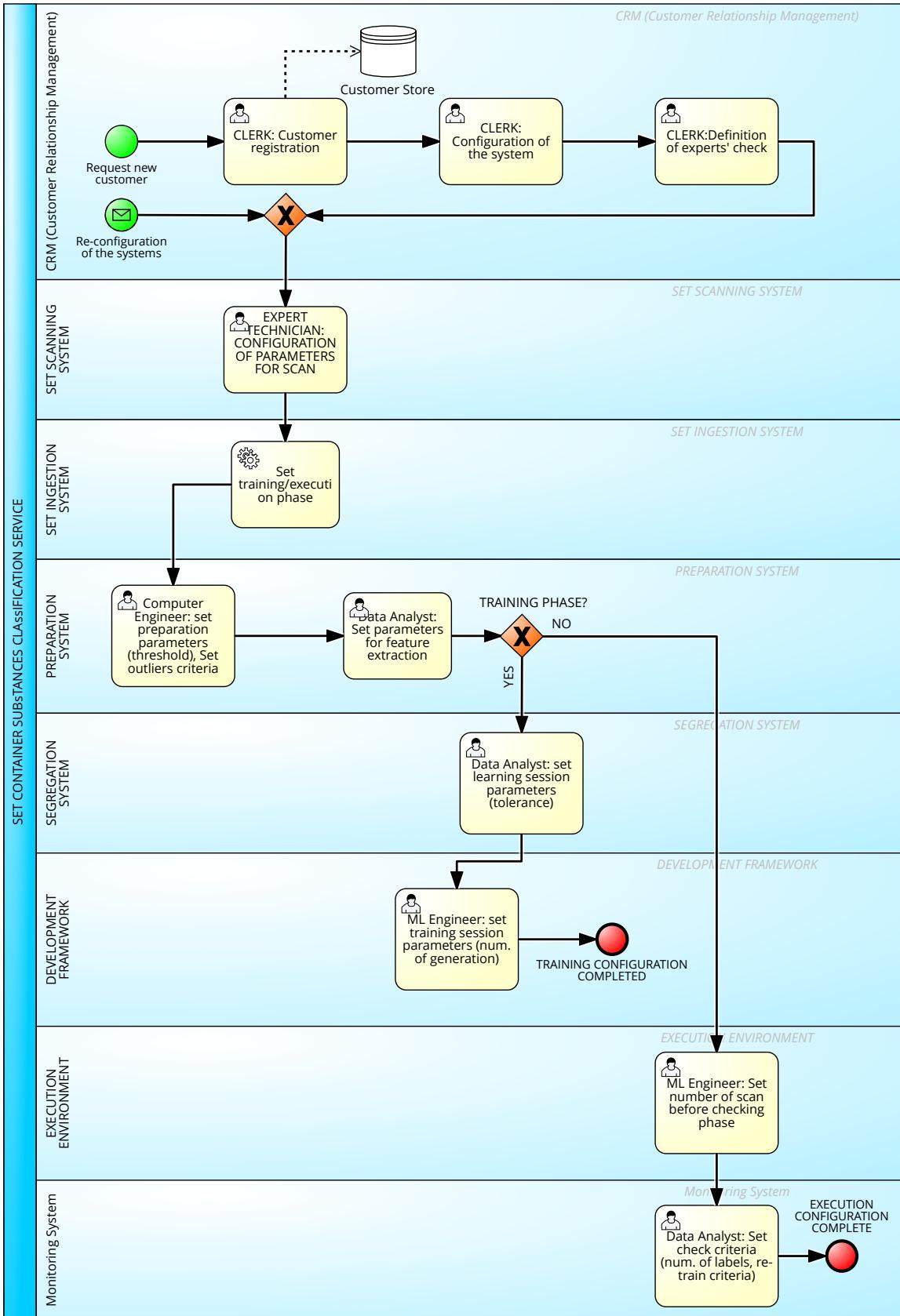
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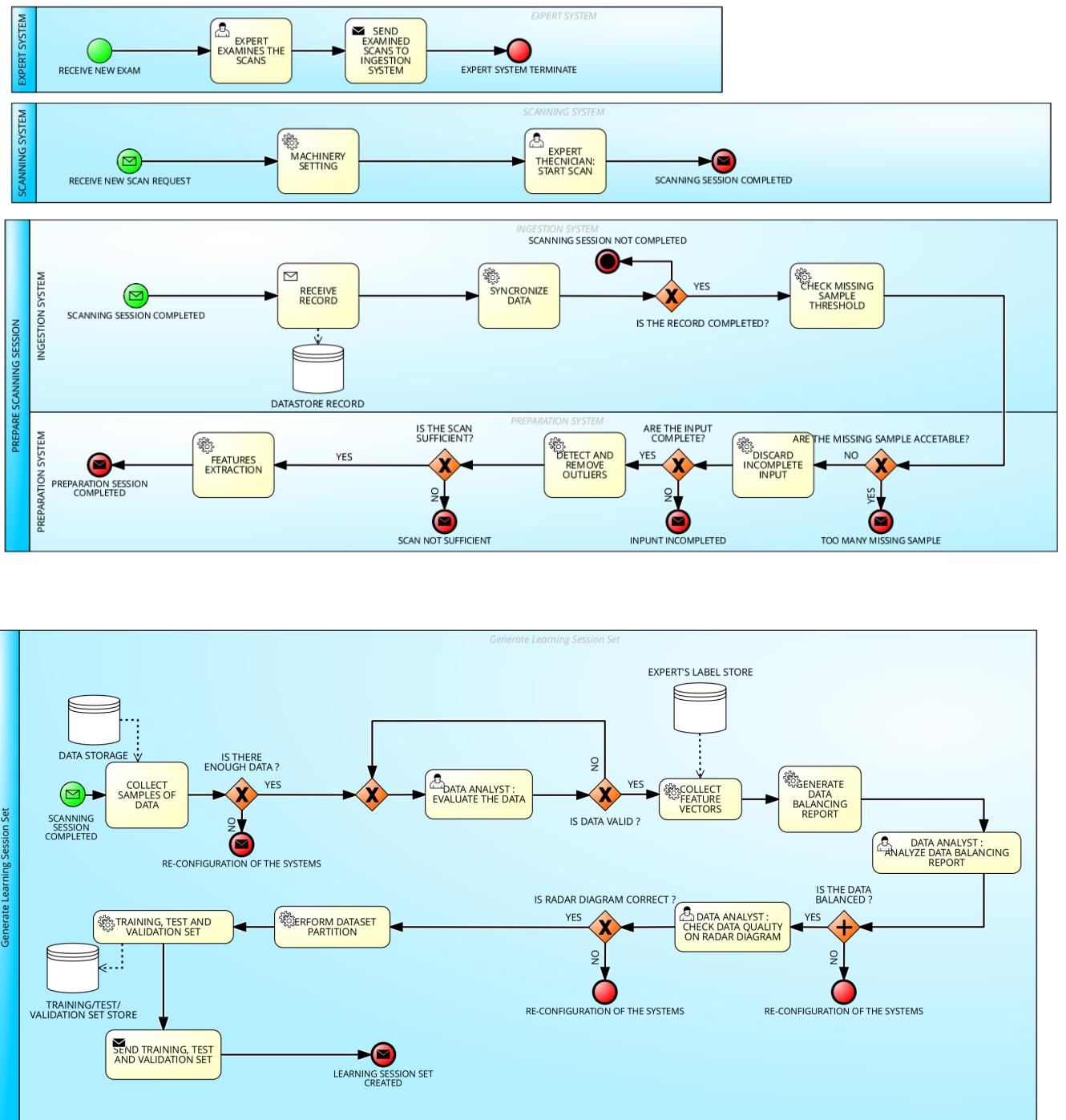
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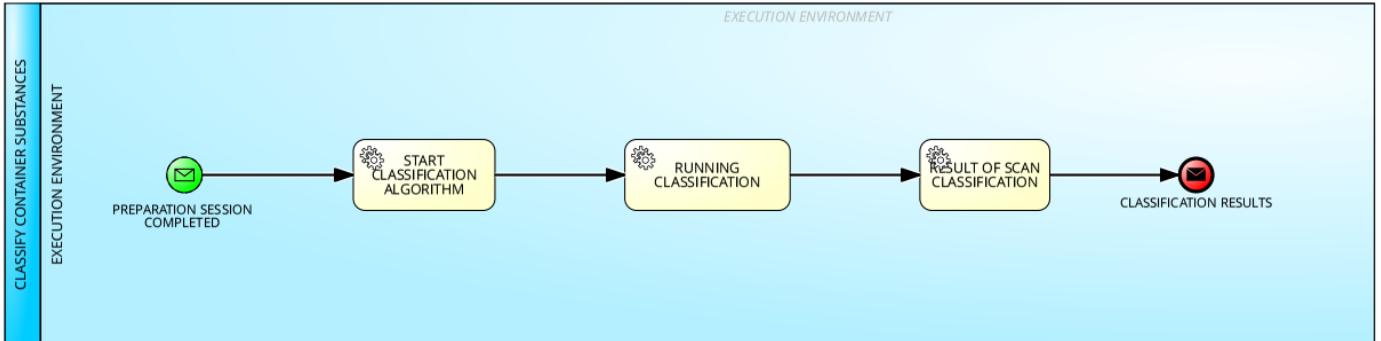
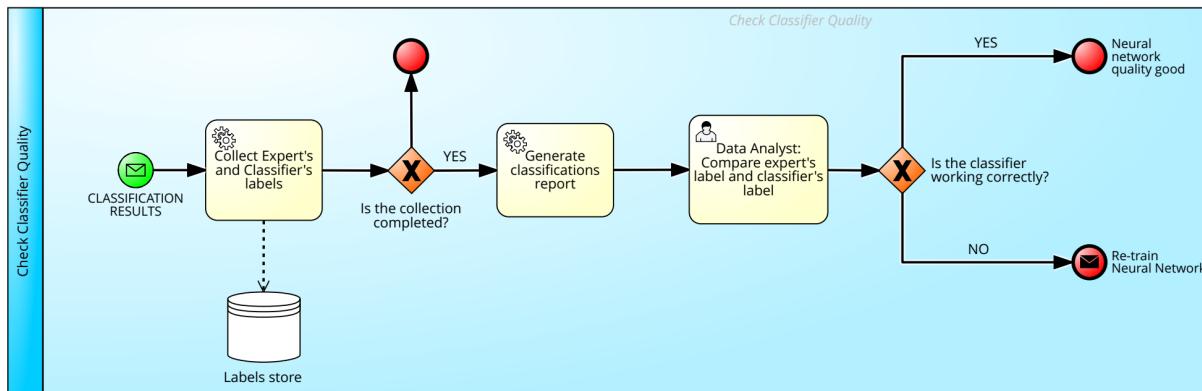
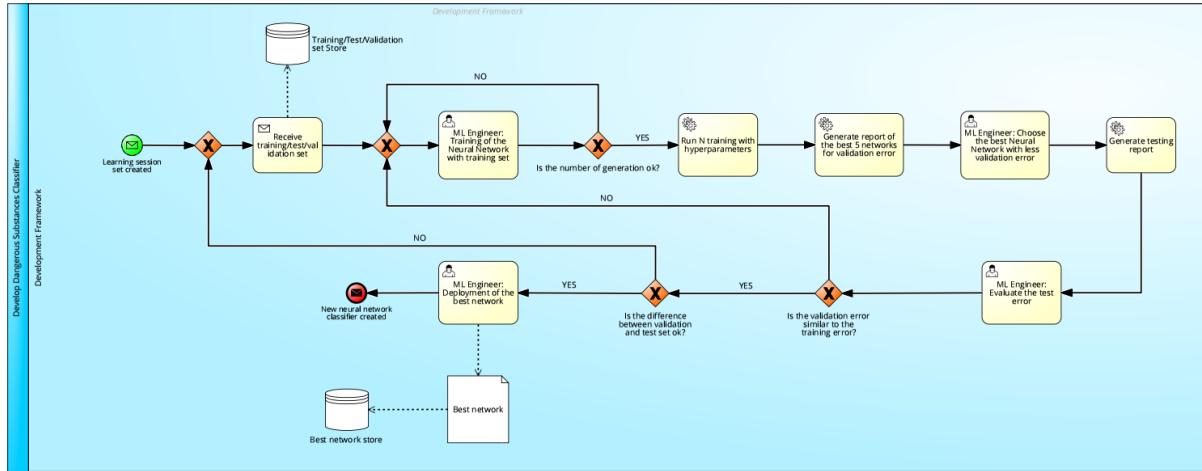
1. PROCESS LANDSCAPE



2. BPMN DIAGRAMS







3. COGNITIVE COST EVALUATION

3.1. SALARIES PROPORTION

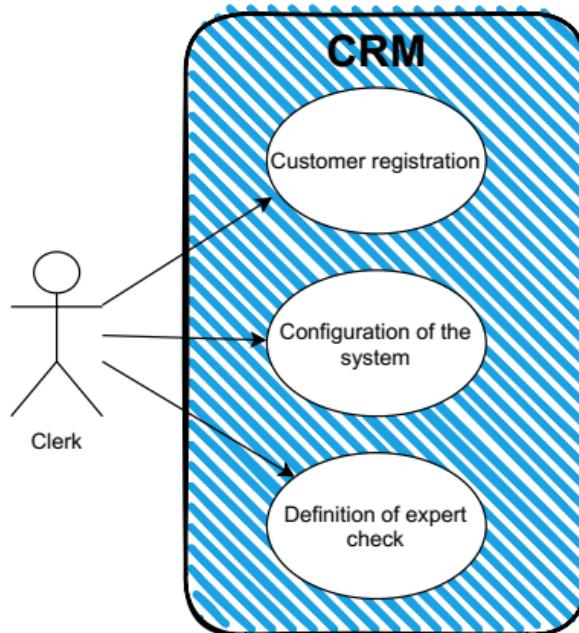
ACTOR	LINK	COST (HOUR)	NORMALIZED COST
Machine Learning Enginner	https://www.salary.com/research/salary/posting/machine-learning-engineer-hourly-wages#:~:text=The%20average%20hourly%20wage%20for,falls%20between%20%2453%20and%20%2465	46 €	3,07
Data Analyst	https://www.salary.com/research/salary/benchmark/business-data-analyst-i-hourly-wages	23 €	1,53
Computer Enginner	https://www.salary.com/research/salary/listing/computer-engineer-hourly-wages#:~:text=How%20much%20does%20a%20Computer,falls%20between%20%2438%20and%20%2447.	33 €	2,20
Clerk	https://www.ziprecruiter.co.uk/?utm_source=zr-go-redirect	15 €	1
System Administrator	https://www.ziprecruiter.co.uk/?utm_source=zr-go-redirect	17 €	1,13
Technician	https://www.payscale.com/research/US/Job=Field_Service_Technician/Hourly_Rate	19,17 €	1,28
Expert	https://it.talent.com/salary	20€	1,33

Salaries are computed using the following algorithm:

1. Take the salary per hour
2. Divide it by Clerk's salary (minor salary)

4. USE CASES

4.1. SET CONTAINER SUBSTANCES CLASSIFICATION SERVICE



CLERK: CUSTOMER REGISTRATION

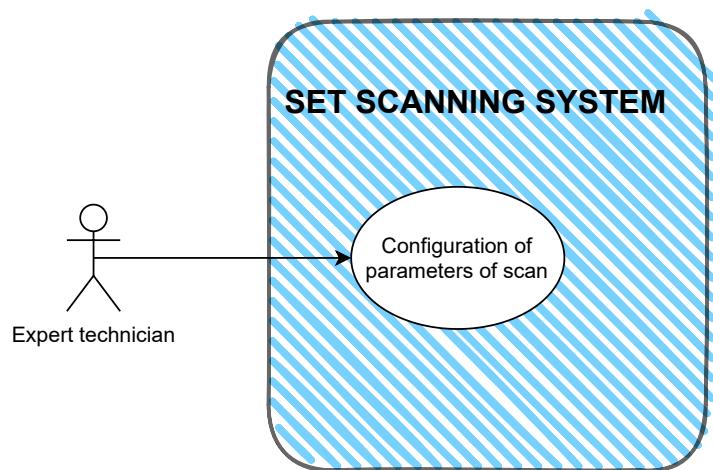
1. Clerk open customer registration interface
2. **System** shows new customer registration interface
3. Clerk choose 'add new customer'
4. **System** shows new customer registration module
5. Clerk insert new costumer data
6. **System** adds new customer to DB

CLERK: CONFIGURATION OF THE SYSTEM

1. Clerk opens configuration of the system interface
2. **System** shows new system configuration window
3. Clerk configures the system
4. **System** show 'system configured'

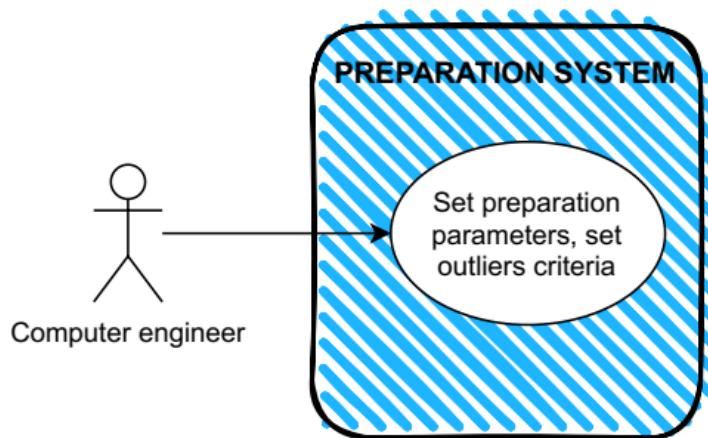
CLERK: DEFINITION OF EXPERT CHECK

1. Clerk opens list of expert interface
2. **System** shows list of experts
3. Clerk chooses experts
4. **System** set the expert 'not available'



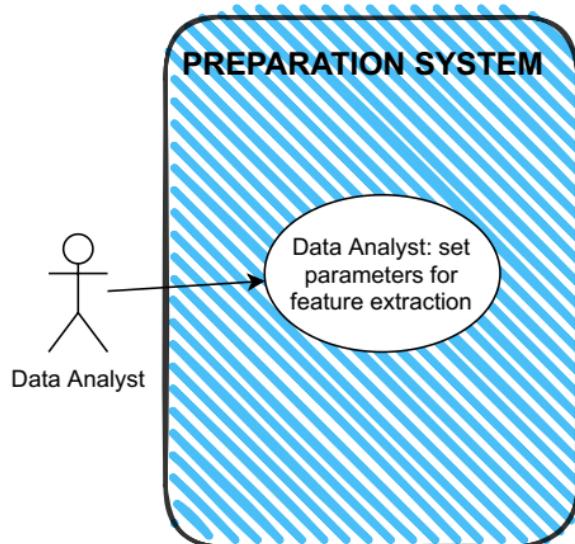
EXPERT TECHNICIAN: CONFIGURATION OF PARAMETERS FOR SCAN

1. Expert Technician opens scanner parameters setup interface
2. **System:** shows 4 input to set
3. Expert Technician inserts inputs
4. **System:** shows the message "ready to scan"



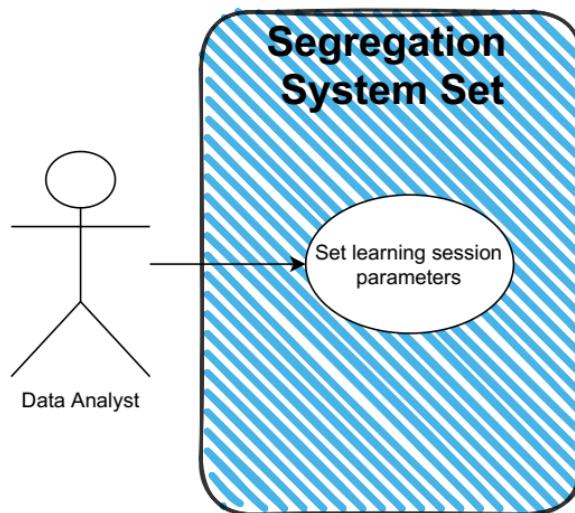
COMPUTER ENGINEER: SET PREPARATION PARAMETERS, SET OUTLIERS CRITERIA

1. Computer Engineer opens setup parameters interface
2. **System:** show 'missing sample' set
3. Computer Engineer setup the percentage of missing sample
4. **System:** show 'incomplete output parameters' set
5. Computer Engineer setup the percentage of incomplete output
6. **System:** show 'outliers'
7. Computer Engineer setup the percentage of outliers
8. **System:** shows preparation system ready



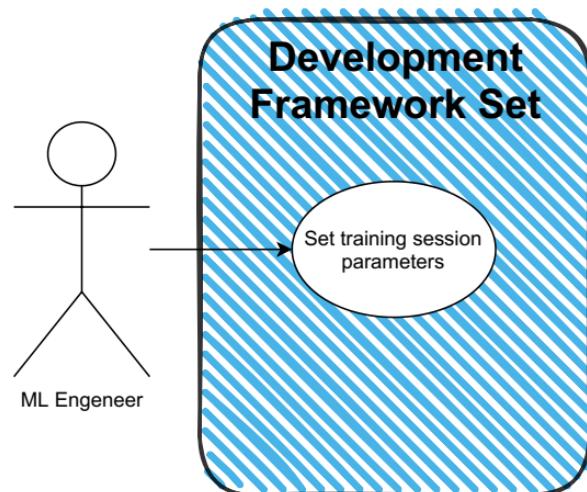
DATA ANALYST: SET PARAMETERS FOR FEATURE EXTRACTION

1. Data Analyst opens feature extraction interface
2. **System:** shows different parameters to set
3. Data Analyst set parameters



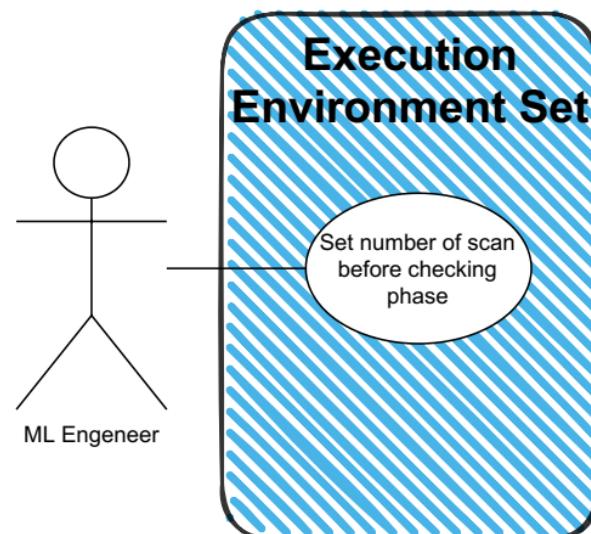
DATA ANALYST: SET LEARNING SESSION PARAMETERS

1. Data Analyst open Learning Interface
2. **System:** show Learning Interface
3. Data Analyst set the tolerance value
4. **System:** show "OK" message



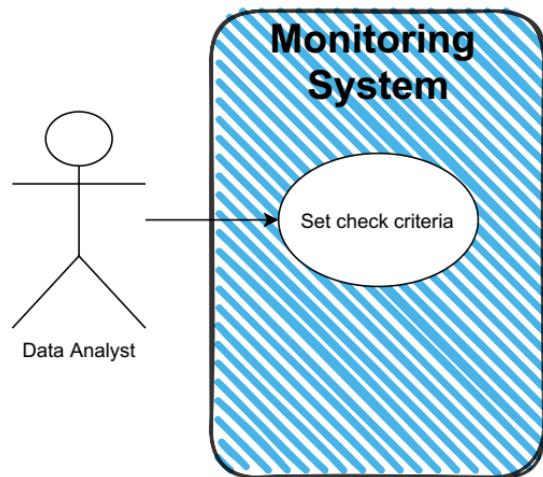
ML ENGINEER: SET TRAINING SESSION PARAMETERS

1. ML Engineer open the Training Neural Network interface
2. **System:** show the Training Neural Network interface.
3. ML Engineer set the desired number of generations



ML ENGINEER: SET NUMBER OF SCAN BEFORE CHECKING PHASE

1. ML Engineer open the Neural Network Classifier Interface (NNCI)
2. **System:** show the NNCI
3. ML Engineer set the number of scans after which send some scans to the Monitoring System from the last sent
4. ML Engineer set the number of scans to send to the Monitoring System



DATA ANALYST: SET CHECK CRITERIA (NUM. OF LABELS, RE-TRAIN CRITERIA)

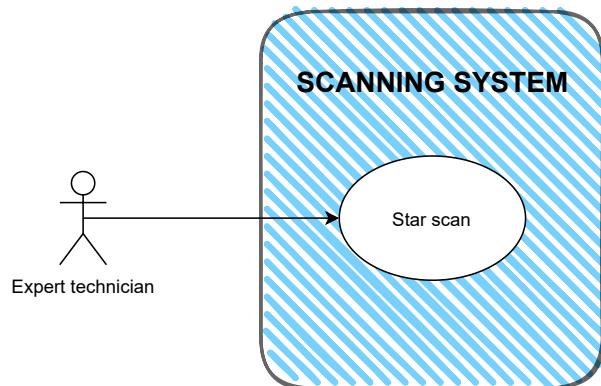
1. Data Analyst open Monitoring System Interface
2. **System:** show Monitoring System Interface
3. Data Analyst Set the check criteria between sequential or total error
4. **System:** show “OK” message

Use Case	Step	Actor	Cognitive Effort	Execution Probability	Total cost
CLERK: CUSTOMER REGISTRATION	Clerk opens customer registration interface	Clerk	Remember (1)	1	$1*1*1=1$
	Clerk choose ‘add new customer’	Clerk	Remember (1)	1	$1*1*1=1$
	Clerk inserts new costumer data	Clerk	Understand (2)	1	$1*1*2=2$
				TOTAL COST	4

CLERK: CONFIGURATION OF THE SYSTEM	Clerk opens configuration of the system interface	Clerk	Remember (1)	1	$1*1*1=1$
	Clerk configures the system	Clerk	Understand (2)	1	$1*1*2=2$
				TOTAL COST	3
CLERK: DEFINITION OF EXPERT CHECK	Clerk opens list of expert interface	Clerk	Remember (1)	1	$1*1*1=1$
	Clerk chooses experts	Clerk	Understand (2)	1	$1*1*2=2$
				TOTAL COST	3
EXPERT TECHNICIAN: CONFIGURATION OF PARAMETERS FOR SCAN	Expert Technician inserts inputs	Expert Technician	Understand (2)	1	$1*1.28*2=2.56$
SET PREPARATION PARAMETERS, SET OUTLIERS CRITERIA	setup the percentage of missing sample	Computer Enginner	Understand (2)	1	$1*2.20*2=4.40$
	setup the percentage of incomplete output	Computer Enginner	Understand (2)	1	$1*2.20*2=4.40$
	setup the percentage of outliers	Computer Enginner	Understand (2)	1	$1*2.20*2=4.40$
				TOTAL COST	13.2
SET PARAMETERS FOR FEATURE EXTRACTION	Evaluate ad labels the scans	Data Analyst	Analyze(4)	1	$1*4*1.53=6,12$
SET LEARNING SESSION PARAMETERS	Set tolerance value	Data Analyst	Understand (2)	1	$2*1*1.53 = 3.06$

SET TRAINING SESSION PARAMETERS	Set the desired number of generations	Machine Learning Enginner	Understand (2)	1	$2*1*3.07 = 6.14$
SET NUMBER OF SCAN BEFORE CHECKING PHASE	Set the number of scans after which send some scans to the Monitoring System from the last sent	Machine Learning Enginner	Understand (2)	1	$2*1*3.07 = 6.14$
	set the number of scans to send to the Monitoring System	Machine Learning Enginner	Understand (2)	1	$2*1*3.07 = 6.14$
				TOTAL COST	12.28
SET CHECK CRITERIA	Set check criteria between sequential and total error	Data Analyst	Understand (2)	1	$2*1*1.53 = 3.06$

4.2. SCANNING SYSTEM

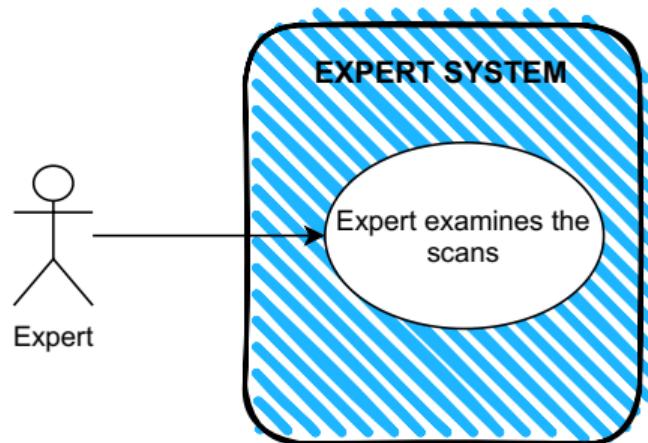


EXPERT THECNICIAN: START SCAN

1. Expert Technicians opens scanning system interface
2. ET stars scan
3. **System:** Scanning
4. **IF** scans terminate System:
 - 4.1 send message 'scanning session completed' to **INGESTION SYSTEM**

Use Case	Step	Actor	Cognitive Effort	Execution Probability	Total cost
EXPERT THECNICIAN: START SCAN	Start Scan	Expert Technician	Remember (1)	1	$1 * 1.28 * 1 = 1.28$

4.3. EXPERT SYSTEM

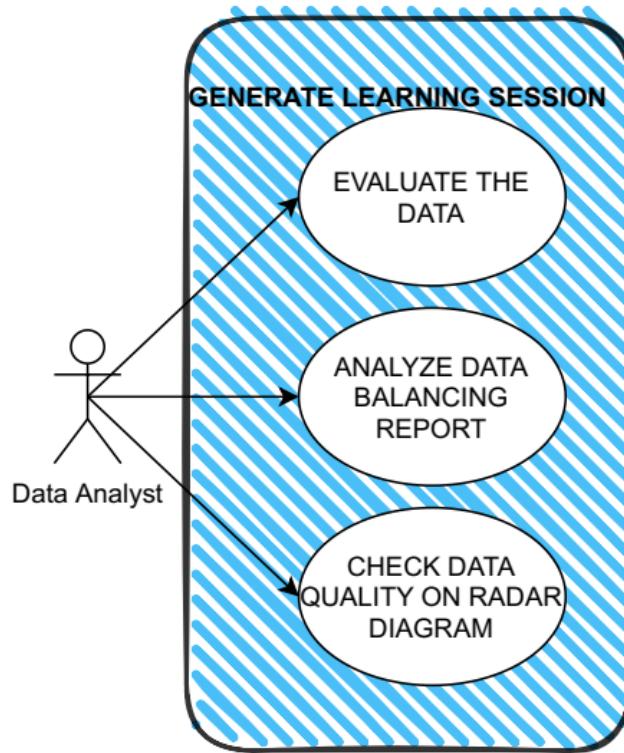


EXPERT EXAMINES THE SCANS

1. Expert open result scans interface
2. **System** shows the result of the scans
3. Evaluate ad labels the scans

Use Case	Step	Actor	Cognitive Effort	Execution Probability	Total cost
EXPERT EXAMINES THE SCANS	Evaluate ad labels the scans	Expert	Analyze(4)	1	$1 * 1,33 * 4 = 5,32$

4.4. GENERATE LEARNING SESSION



DATA ANALYST: EVALUATE THE DATA

1. Data analyst opens 1000 samples of the data
2. **System:** shows 1000 samples of the data
3. Data analyst examines if the data are acceptable by experience
4. **IF** data is acceptable
 - 4.1. **GOTO** -> Communicate that Data is acceptable
5. **ELSE**
 - 5.1. **GOTO** -> 3

DATA ANALYST: ANALYZE DATA BALANCING REPORT

1. Data analyst opens Data Balancing report
2. **System:** show Data Balancing Report
3. Data analyst categorizes the balancing report
4. **IF** data is not balanced
 - 4.1 **GOTO** -> Communicates that is NOT balanced
5. **ELSE** (Data is balanced)
 - 5.1 **GOTO** -> Communicates that data IS balanced

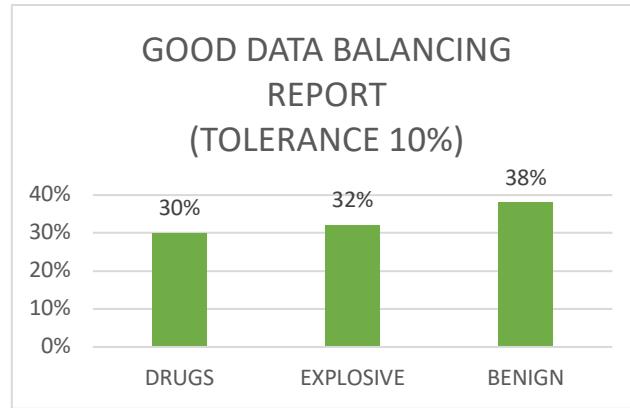


Figura 1 Good data balancing report

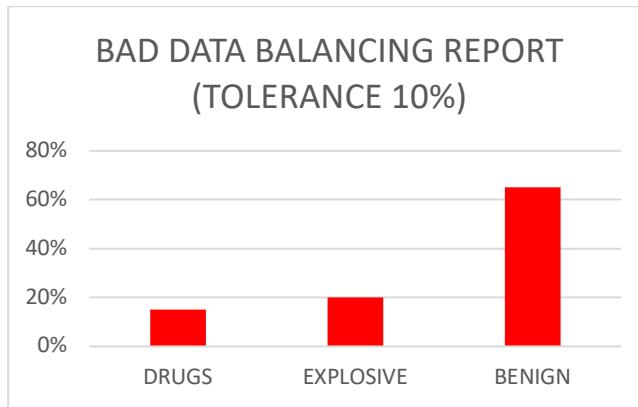


Figura 2 Bad data balancing report

DATA ANALYST: CHECK DATA QUALITY ON RADAR DIAGRAM

1. Data Analyst open the Radar Diagram
2. **System:** shows Radar Diagram
3. Data analyst check quality of the radar diagram
4. Data Analyst check if there are some areas where there is a lack of data.
5. **IF** there are zone
 - 5.1. DA check if zones are "physiological"
 - 5.2. IF are "physiological"
 - 5.2.1. **DA PRESS** "correct radar diagram" button
 - 5.3. ELSE
 - 5.3.1. **DA PRESS** "RE-CONFIGURATION" button
6. DA PRESS "correct radar diagram" button

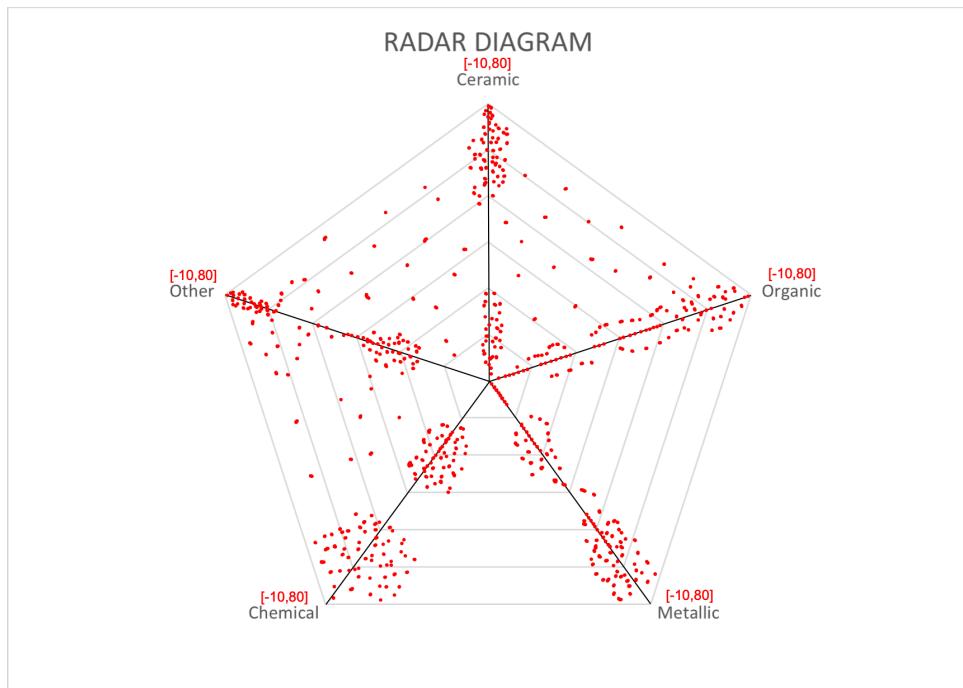
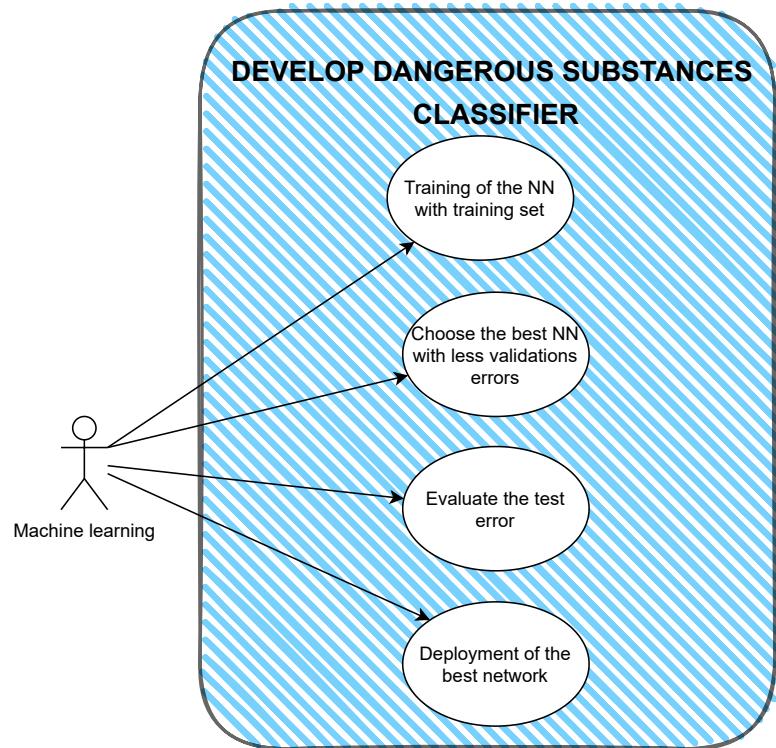


Figura 3 Radar diagram

Use Case	Step	Actor	Cognitive Effort	Execution Probability	Total cost
EVALUATE THE DATA	Data analyst examines if the data are acceptable	Data analyst	Analyze (4)	1	$1*1,53*4= 6,12$
ANALYZE DATA BALANCING REPORT	Data analyst checks if the data is balanced	Data analyst	Understand (2)	1	$1*1,53*2= 3,06$
CHECK DATA QUALITY ON RADAR DIAGRAM	Check quality of the radar diagram	Data analyst	Understand (2)	1	$1*1,53*4= 6,12$
	Data Analyst check if there are some areas where there is a lack of data.	Data analyst	Apply (3)	1	$1*1,53*3= 4,59$
	DA check if they are "physiological"	Data analyst	Analyze (4)	1	$1*1,53*4= 6,12$
				TOTAL COST	16,83

4.5. DEVELOP DANGEROUS SUBSTANCES CLASSIFIER



ML ENGINEER: TRAINING OF THE NEURAL NETWORK WITH TRAINING SET

1. **System** receives training/test/validation set
2. ML Engineer Train the Neural Network with training set

IF number of generations is not sufficient:

- 2.1. ML Engineer Go to step 2

ELSE

3. **System** Run N training set

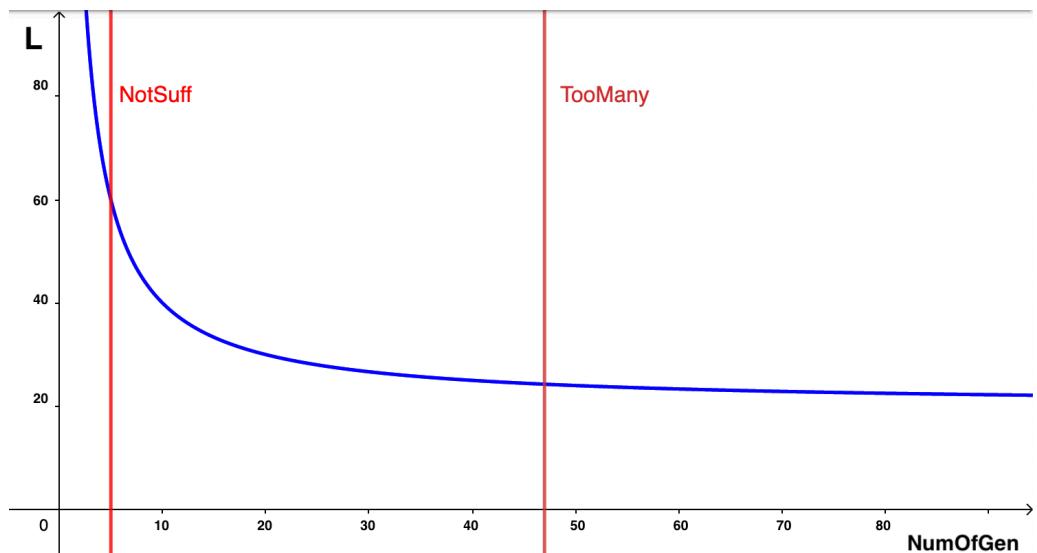


Figura 4 Training plot

ML ENGINEER: CHOOSE THE BEST NEURAL NETWORK WITH LESS VALIDATION ERROR

1. ML Engineer press the button to generate the validation report
2. **System** generate report for validation error of the best 5 networks
3. ML Engineer analyze validation report

Neural Network	Validation Error	Training Error	Network Complexity	
			Neuron	Levels
NN_1	3.45%	0.010	10	2
NN_2	2.87%	0.029	12	3
NN_3	11.62%	0.019	16	4
NN_4	4.82%	0.047	9	3
NN_5	7.35%	0.032	11	5

Figura 5 Report validation set

ML ENGINEER: EVALUATE THE TEST ERROR

1. ML Engineer press the button to generate the testing report
2. **System** generate report for testing error
3. ML Engineer compare validation and training error

IF validation error is not similar to training error

- 3.1. ML Engineer Train the Neural Network with training set

ELSE

- 3.1.1. ML Engineer Test the Neural Network

ML ENGINEER: DEPLOYMENT OF THE BEST NETWORK

1. **System** Run N training set
2. ML Engineer Compare validation and test set

IF Difference between validation and test set is not ok

- 2.1. ML Engineer Ask for training/validation/test set

ELSE

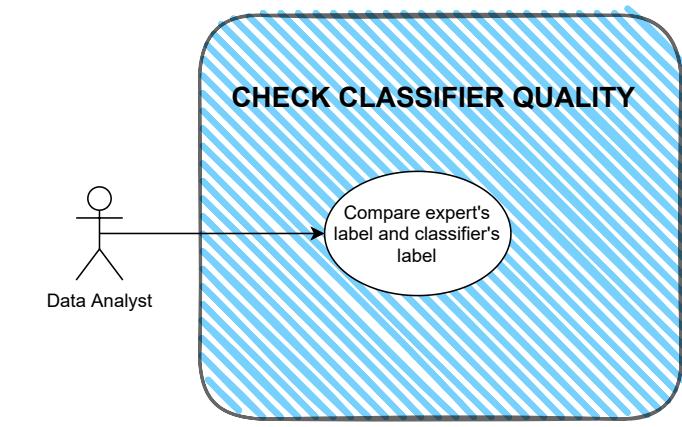
3. ML Engineer Choose best Neural Network

Neural Network	Validation Error	Training Error	Test Error	Network Complexity	
				Neuron	Levels
NN_1	3.45%	0.010	2.1%	10	2
NN_2	2.87%	0.029	0.5%	12	3
NN_3	11.62%	0.019	5.7%	16	4
NN_4	4.82%	0.047	3.8%	9	3
NN_5	7.35%	0.032	4.2%	11	5

Figura 6 Report test set

Use Case	Step	Actor	Cognitive Effort	Execution Probability	Total cost
ML ENGINEER: TRAINING OF THE NEURAL NETWORK WITH TRAINING SET	Train the Neural Network with training set	Machine Learning Enginner	Analyze (4)	1	$1*3.07*4=12.28$
ML ENGINEER: CHOOSE THE BEST NEURAL NETWORK WITH LESS VALIDATION ERROR	Analyze validation report	Machine Learning Enginner	Apply (3)	1	$1*3.07*3=.21$
ML ENGINEER: EVALUATE THE TEST ERROR	Compare validation and training error	Machine Learning Enginner	Apply (3)	1	$1*3.07*3=.21$
	Train the Neural Network with training set	Machine Learning Enginner	Apply (3)	0.3	$0.3*3.07*3=2.76$
	Test the Neural Network	Machine Learning Enginner	Apply (3)	0.7	$0.7*3.07*3=6.45$
				TOTAL COST	18,42
ML ENGINEER: DEPLOYMENT OF THE BEST NETWORK	Compare validation and test set	Machine Learning Enginner	Apply (3)	1	$1*3.07*3=.21$
	Ask for training/validation/test set	Machine Learning Enginner	Remember (1)	0.2	$0.2*3.07*1=.61$
	Choose best Neural Network	Machine Learning Enginner	Apply(3)	0.8	$0.8*3.07*3=7.37$
				TOTAL COST	17.19

4.6. CHECK CLASSIFIER QUALITY



DATA ANALYST: COMPARE EXPERT LABELS AND CLASSIFIER LABELS

1. Data Analyst open the classifier interface.
2. **System:** show the classifier interface.
3. Data Analyst open the label collection from the interface.
4. **System:** show the label collection of the last n classifications.
5. Data Analyst select a raw.
6. Data Analyst read the experts label for the selected raw.
7. Data Analyst read the classifier label for the selected raw.
8. Data Analyst compare the two labels and generate a result for the raw.
9. IF comparation result is negative
 - 9.1. IF the check criteria is “sequential error”
 - 9.1.1. Data Analyst increase the sequential errors count (SEC).
 - 9.1.2. IF SEC >= (sequential threshold)
 - 9.1.2.1. **GO TO -> 13**
 - 9.2. ELSE IF the check criteria is “total error”
 - 9.2.1. Data Analyst increase the total errors count (TEC).
 - 9.2.2. IF TEC >= (total threshold)
 - 9.2.2.1. **GO TO -> 13**
10. ELSE IF the result is positive
 - 10.1. Data Analyst reset the sequential errors count
11. IF there other raws to
 - 11.1. **GO TO -> 5**
12. Data Analyst push button “Check quality OK”
13. Data Analyst push button “Re-train classifier”

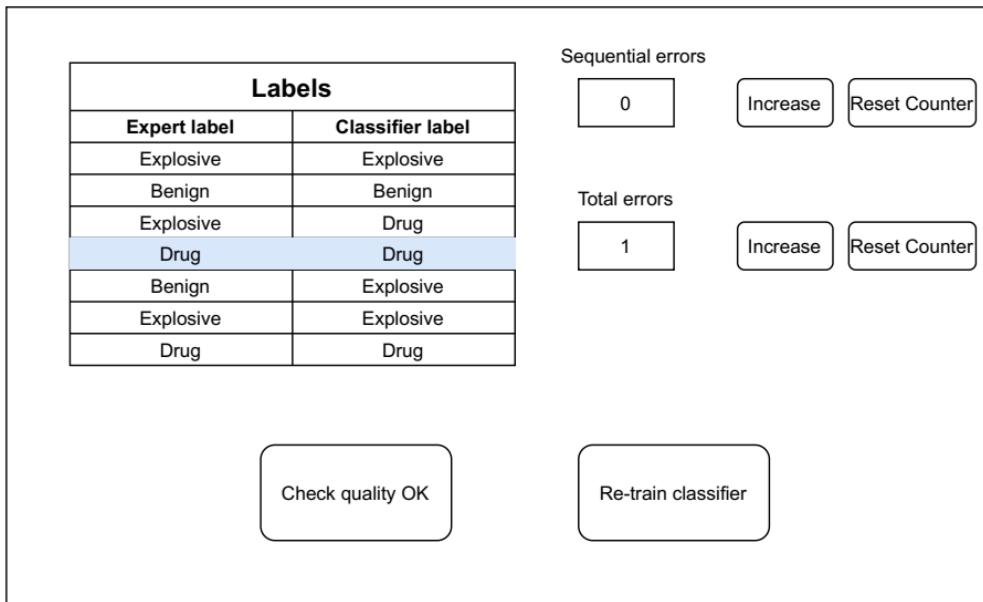


Figura 7 Example of interface

Use Case	Step	Actor	Cognitive Effort	Execution Probability	Total cost
COMPARE EXPERT LABELS AND CLASSIFIER LABELS	Compare the two labels	Data Analyst	Understand(2)	1	$2*1*1.53 = 3.06$
	Increase sequential error count	Data Analyst	Remember(1)	0.05	$1*0.05*1.53 = 0.0765$
	Increase the total error count	Data Analyst	Remember(1)	0.05	$1*0.05*1.53 = 0.0765$
	Reset sequential error count	Data Analyst	Remember(1)	0.9	$1*0.9*1.53 = 1.377$
	Push button "Check quality OK"	Data Analyst	Remember(1)	0.5	$1*0.5*1.53 = 0.765$
	Push button "Re-train classifier"	Data Analyst	Remember(1)	0.5	$1*0.5*1.53 = 0.765$
				TOTAL COST	6.12

5. SIMULATION

5.1. AS IS

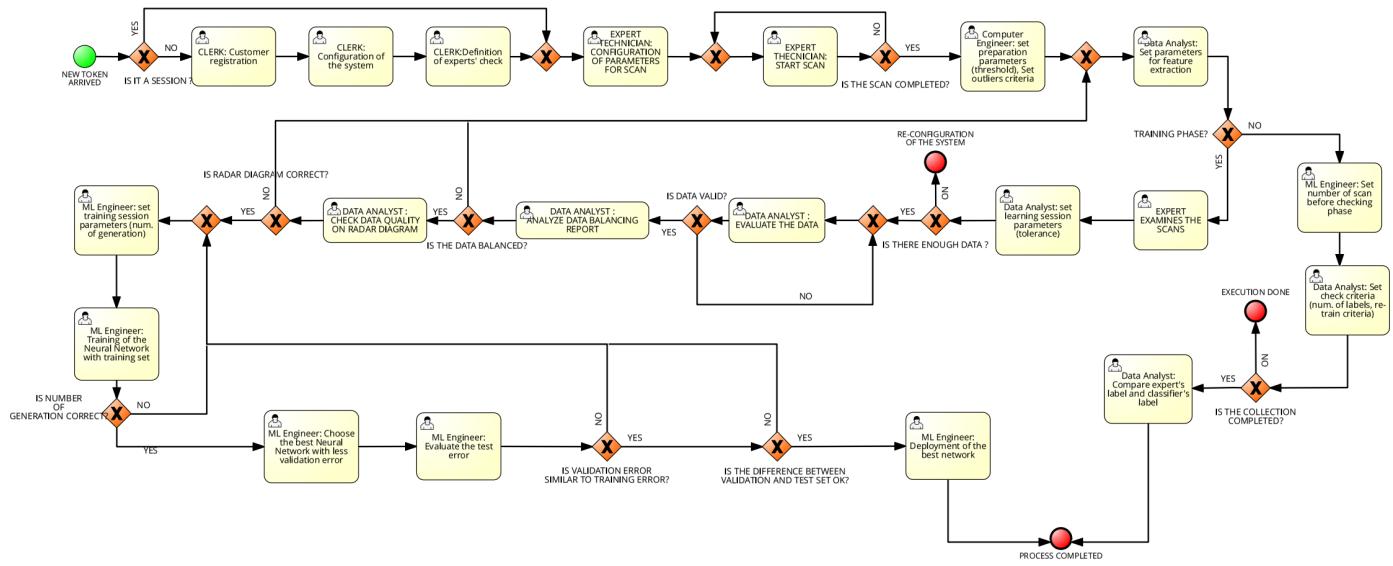


Figura 8 As Is Model

5.2. TO BE

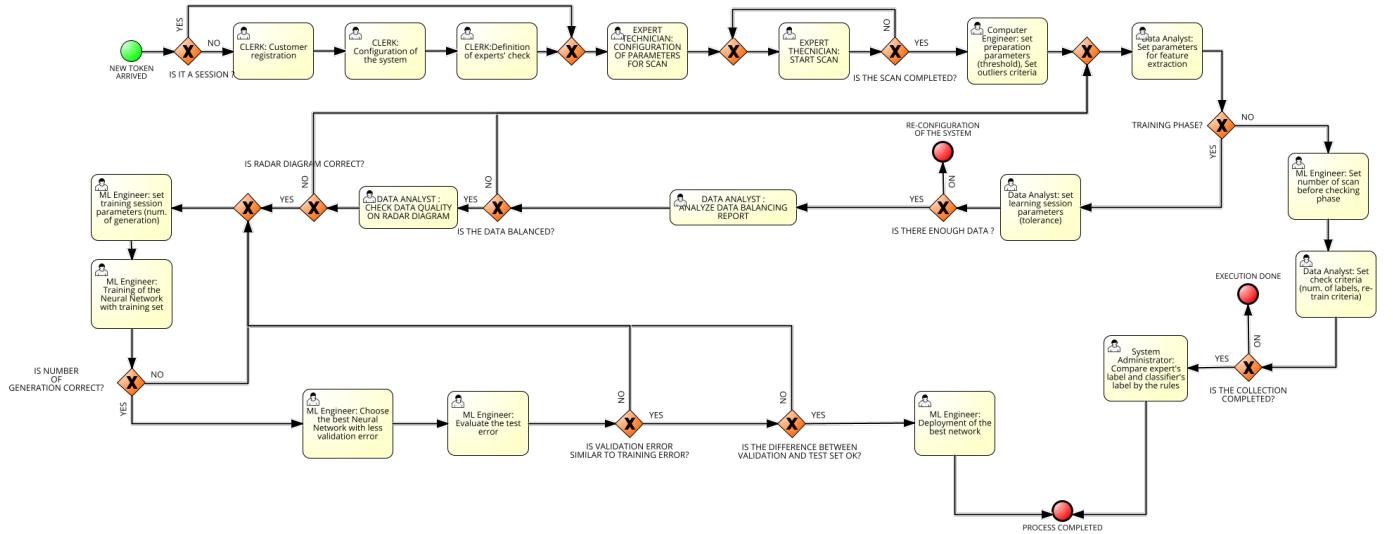


Figura 9 To Be Model

5.3. COSTS EXPLANATION

This subsection contains the explanation of the costs used in the simulation phase.

TASKS

Clerk customer registration: 4.

Clerk configuration of the system: 3.

Clerk definition of experts' check ("AS IS"): 3.

Clerk definition of experts' check ("TO BE"): 1. *The cost for the task Clerk definition of experts' check is fixed to 1 according to the evaluation explained in the next paragraph.*

Expert technician configuration of parameters for scan: 2,56.

Expert technicians start scan: 1,28.

Expert examines the scans ("AS IS"): 5,32.

Computer Engineer Set preparation parameters, set outliers criteria: 13,2.

Data analyst Set parameters for feature extraction: 6,12.

Data analyst Set learning session parameters: 3,06.

ML Engineer Set training session parameters: 6,14.

ML Engineer Set number of scans before checking phase: 12,28.

Data Analyst Set check criteria: 3,06.

Data Analyst Evaluate the data: 6,12.

Data Analyst Analyze data balancing report: 3,06.

Data Analyst Check data quality on radar diagram: 16,83.

ML engineer training of the neural network with training set: 12,28.

ML engineer: choose the best neural network with less validation error: 9,21.

ML engineer: evaluate the test error ("AS IS"): 18,42.

ML engineer: evaluate the test error ("TO BE"): 15. *The cost for the task evaluate the test error is fixed to 15 according to the evaluation explained in the next paragraph.*

ML engineer: deployment of the best network ("AS IS"): 17,19.

ML engineer: deployment of the best network ("TO BE"): 14. *The cost for the task deployment of the best network is fixed to 14 according to the evaluation explained in the next paragraph.*

Data Analyst: Compare expert labels and classifier labels ("AS IS"): 6,12.

System administrator: compare experts' labels and classifier's labels by the rules ("TO BE"): 3. *The cost for the task compare experts' labels and classifier's labels by the rules is fixed to 3 according to the evaluation explained in the next paragraph.*

GATEWAYS

“Is it a session?” (“As Is”): 99% → yes, 1% → no.

Is it a session in the 99 percent of the time, the remaining it is going to be a new costumer

“Is the scan completed?” (“As Is”): 60% → yes, 40% → no.

We assumed that on average the scan is completed 6 time out of 10.

“Is the scan completed?” (“To Be”): 70% → yes, 30% → no.

We estimate that in the To be model the percentage was improved by 10%.

“Training phase?” (“As Is”): 30% → yes, 70% → no.

Initially the training phase is higher in percentage than in the To be model.

“Training phase?” (“To Be”): 20% → yes, 80% → no.

We estimate that the model was already trained, so we can lower the percentage at 20%

“Is there enough data?” (“As Is”): 40% → yes, 60% → no.

The data are enough only in 40% of the cause, because we store them in a database, and we decided that enough is considered to be at least 10000 scans

“Is there enough data?” (“To Be”): 40% → yes, 60% → no.

The data are enough only in 40% of the cause, because we store them in a database, and we decided that enough is considered to be at least 10000 scans

“Is data valid?”: 90% → yes, 10% → no.

The data is correct in 90% of the cases, since we have various check through the BPMN

“Is the data balanced?” (“As Is”): 75% → yes, 25% → no.

Data are balanced in 75% of cases, and the system provide us with a colored graph that already tell the operator if they are balanced or not

“Is the data balanced?” (“To Be”): 85% → yes, 15% → no.

Data are balanced in 85% of cases, and the system provide us with a colored graph that already tell the operator if they are balanced or not

“Is radar diagram correct?” (“As Is”): 90% → yes, 10% → no.

The radar diagram is correct in 90% of the cases, the remaining 10 it goes back to ‘Set parameters for feature extraction’

“Is radar diagram correct?” (“To Be”): 95% → yes, 5% → no.

We supposed that in the “To be” model the percentage was improved by 5%.

“Is number of generations correct?” (“As Is”): 80% → yes, 20% → no.

We estimate that on average the number of generations is correct 8 times out of 10.

“Is number of generations correct?” (“To Be”): 85% → yes, 15% → no.

We supposed that in the “To be” model the percentage was improved by 5%.

“Is validation error similar to training error?” (“As Is”): 94% → yes, 6% → no.

We estimate that out of 100 loops only 6 must be re-run from set training session parameters.

“Is validation error similar to training error?” (“To Be”): 98% → yes, 2% → no.

We supposed that in the “To be” model the percentage was improved by 4%.

“Is the difference between validation and test set ok?” (“As Is”): 94% → yes, 6% → no.

We have estimated that out of 100 trainings only 6 must be re-run set training session parameters.

“Is the difference between validation and test set ok?” (“To Be”): 98% → yes, 2% → no.

We supposed that in the “To be” model the percentage was improved by 4%.

“Is the collection completed?” (“As Is”): 5% → yes, 95% → no.

The collection is completed in 5% of the cases, the remaining 95 it goes to execution done.

“Is the classifier working correctly?” (“To Be”): 3% → yes, 97% → no.

We supposed that in the “To be” model the percentage was improved by 2%.

5.4. DIFFERENCES IN AS IS AND TO BE

1. Categorize port by substances, we can configure the threshold etc., lowering the costs (system administrator for maintenance instead of data analyst)
Data Analyst: Compare expert labels and classifier labels à System administrator: compare experts' labels and classifier's labels by the rules
2. Data not balanced, if I have a port from same category, I take the data from it,
 We remove the expert from "Expert examines the scans"
3. For the examination of the training plot will lower our cognitive effort from 4 to 3 inserting patience interval in "ML Engineer: Training of the neural network with training set"
4. The ML engineer instead of analyzing the similarity between training error and the validation error, the ML engineer will set a percentage that will lower the cognitive effort from 3 to 2 in TO BE of the task "ML engineer: evaluate the test error".
5. The ML engineer instead of analyzing the similarity between test set and the validation set, the ML engineer will set a percentage that will lower the cognitive effort from 3 to 2 in TO BE of the task "ML engineer: deployment of the best network".
6. We removed "Data Analyst: Evaluate the data" because we can used previously examined data that are stored in the database.
7. "Clerk definition of experts' check", we change the probability from 1 to 0,2 because we will have an expert who examines the scans when we will need to retrain the neural network.

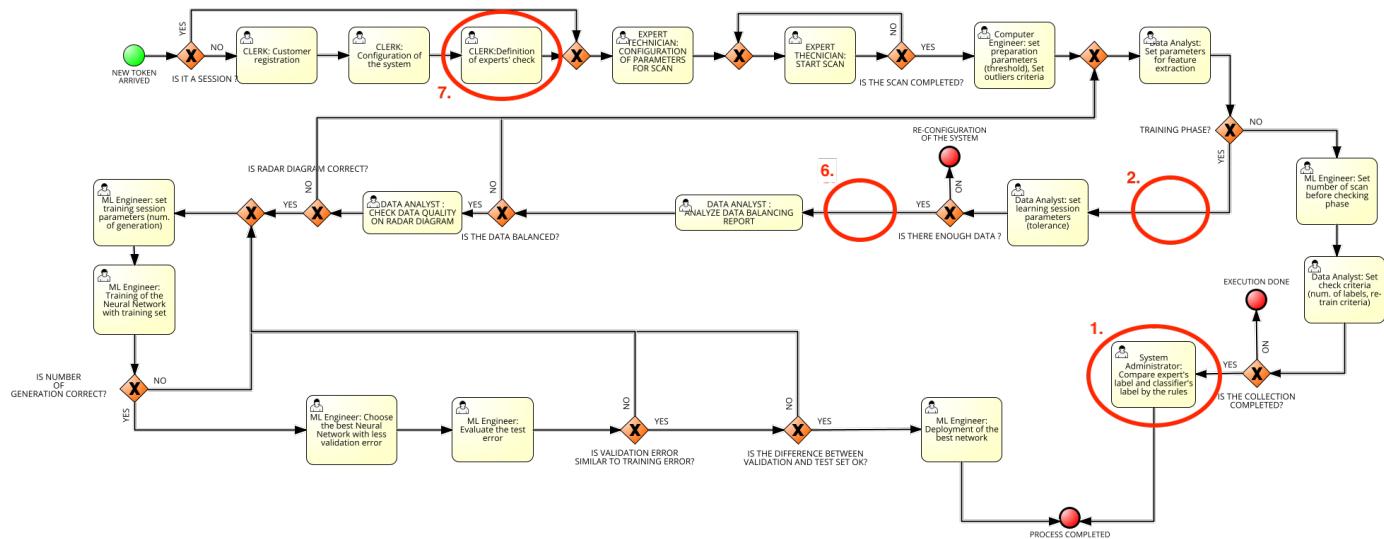
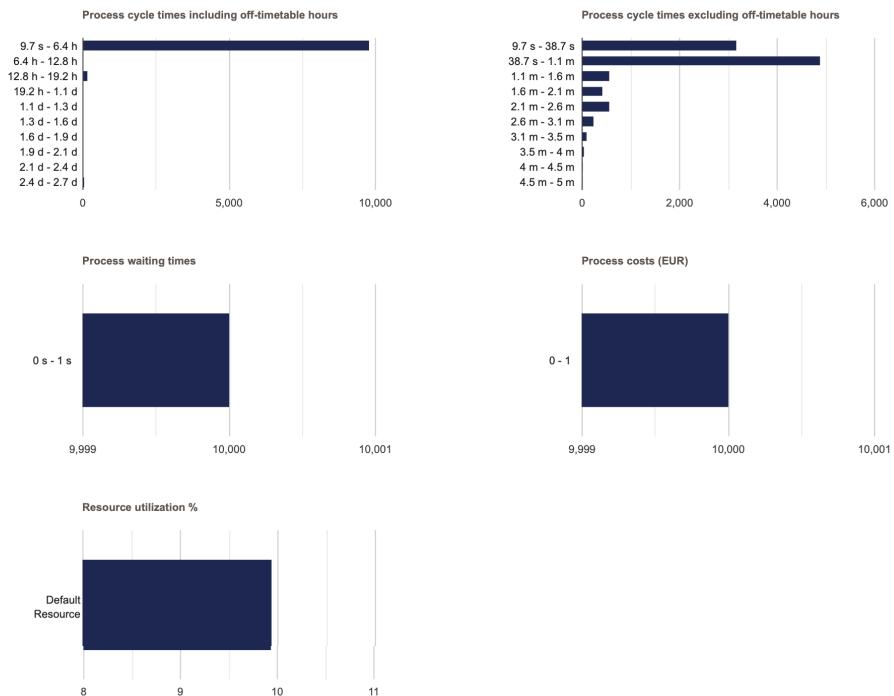


Figura 10 Difference between As Is and To Be

5.5. STATISTICS AS IS

Total simulation time 41.4 weeks

Charts



Scenario Statistics

	Minimum	Maximum	Average
Process instance cycle times including off-timetable hours	9.7 seconds	2.7 days	32.8 minutes
Process instance cycle times excluding off-timetable hours	9.7 seconds	5 minutes	59.6 seconds
Process instance costs	0 EUR	0 EUR	0 EUR

Activity Durations, Costs, Waiting times, Deviations from Thresholds

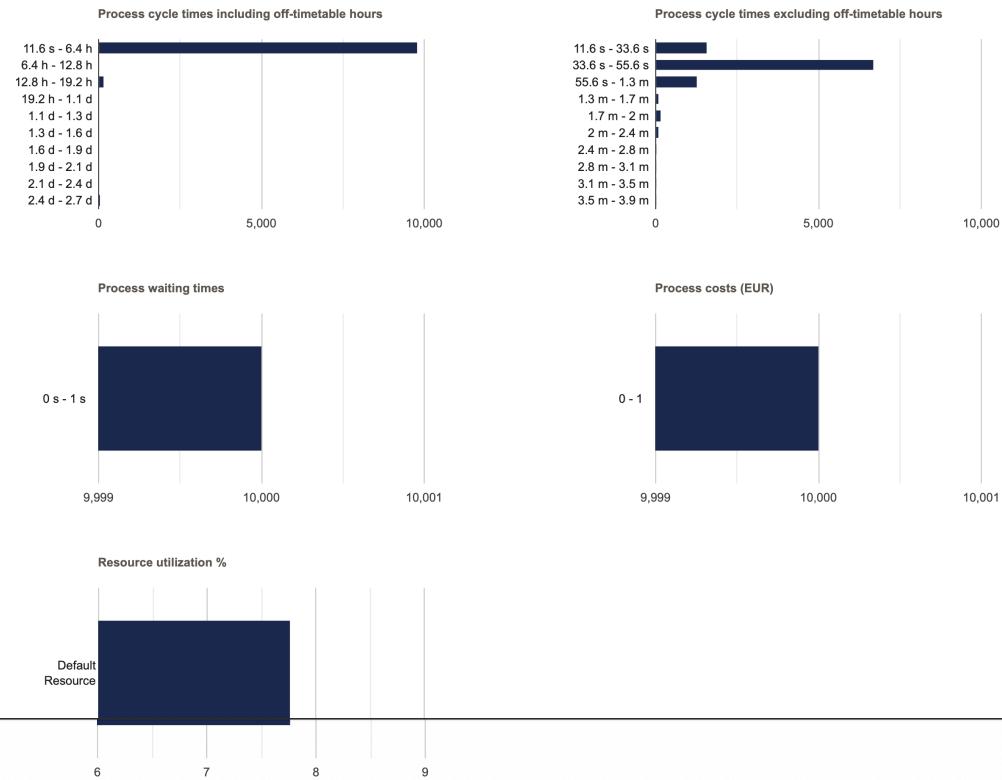
Name	Waiting time				Duration				Duration over threshold			Cost			Cost over threshold		
	Count	Min	Avg	Max	Min	Avg	Max	Min	Avg	Max	Min	Avg	Max	Min	Avg	Max	
CLERK: Customer registration	105	0 s	0 s	0 s	0 s	5.7 s	14.4 s	0 s	0 s	0 s	0	0	0	0	0	0	
CLERK: Configuration of the system	105	0 s	0 s	0 s	0.1 s	4.6 s	15 s	0 s	0 s	0 s	0	0	0	0	0	0	
CLERK: Definition of experts' check	105	0 s	0 s	0 s	0 s	4.8 s	19.4 s	0 s	0 s	0 s	0	0	0	0	0	0	
Computer Engineer: set preparation	10000	0 s	0 s	0 s	0 s	13.2 s	31.1 s	0 s	0 s	0 s	0	0	0	0	0	0	

Figura 11 Statistic As Is

5.6. STATISTICS TO BE

Total simulation time 41.4 weeks

Charts



Scenario Statistics

	Minimum	Maximum	Average
Process instance cycle times including off-timetable hours	11.6 seconds	2.7 days	32.6 minutes
Process instance cycle times excluding off-timetable hours	11.6 seconds	3.7 minutes	46.6 seconds
Process instance costs	0 EUR	0 EUR	0 EUR

Activity Durations, Costs, Waiting times, Deviations from Thresholds

Name	Waiting time				Duration				Duration over threshold			Cost			Cost over threshold		
	Count	Min	Avg	Max	Min	Avg	Max	Min	Avg	Max	Min	Avg	Max	Min	Avg	Max	
CLERK: Customer registration	121	0 s	0 s	0 s	0.2 s	5.7 s	17.5 s	0 s	0 s	0 s	0	0	0	0	0	0	
CLERK:Configuration of the system	121	0 s	0 s	0 s	0 s	5.3 s	16.5 s	0 s	0 s	0 s	0	0	0	0	0	0	
CLERK:Definition of experts' check	121	0 s	0 s	0 s	0.1 s	4.4 s	15.9 s	0 s	0 s	0 s	0	0	0	0	0	0	
Computer Engineer: set preparation	10000	0 s	0 s	0 s	0 s	13 s	34.8 s	0 s	0 s	0 s	0	0	0	0	0	0	

Figura 12 Statistic To Be

5.7. HEATMAP AS IS

COUNT

Heatmap

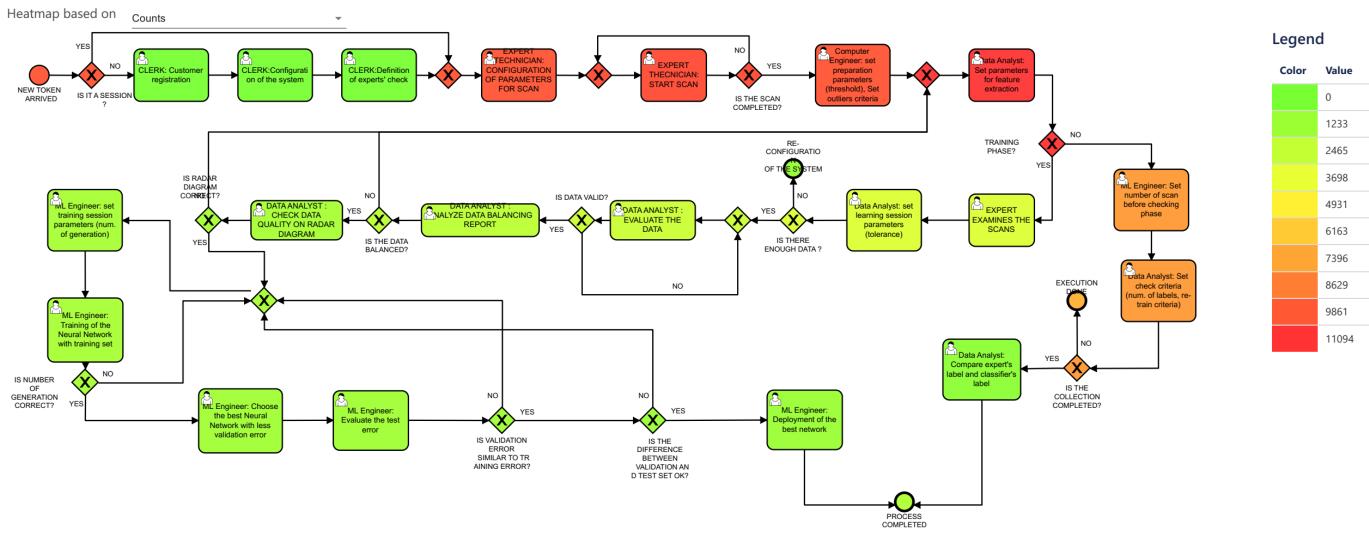


Figura 13 Heat Map As Is - Count

DURATION

Heatmap

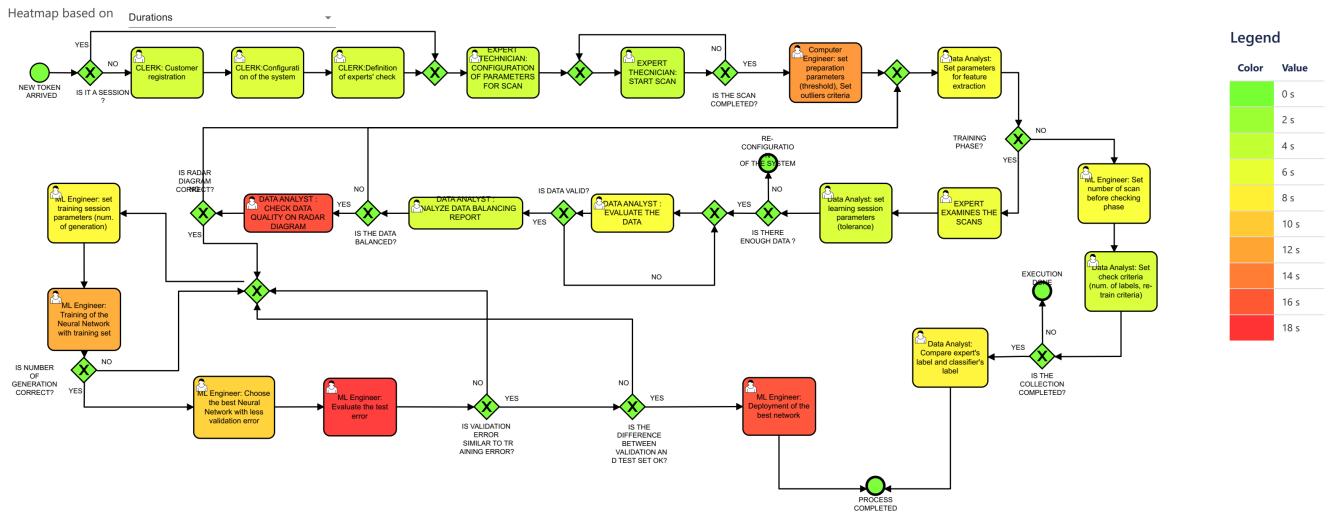


Figura 14 Heat Map As Is - Duration

5.8. HEATMAP TO BE

COUNT

Heatmap

Heatmap based on

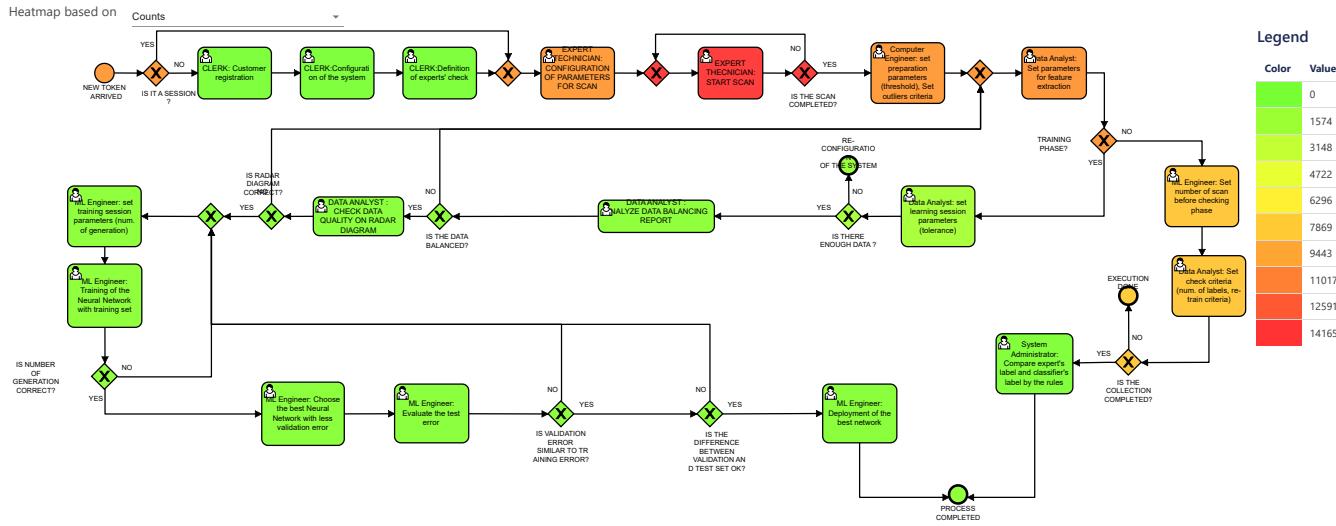


Figura 15 Heat Map To Be - Count

	Count
CLERK: Customer registration	74
CLERK: Configuration of the system	74
CLERK: Definition of experts' check	74

ML Engineer:
Training of the
Neural Network
with training set

ML Engineer: Choose the best Neural Network with less validation error

ML Engineer: Deployment of the best network

ML Engineer: Evaluate the test error

ML Engineer: Set number of scan before checking phase

ML Engineer: set training session parameters (num. of generation)

System Administrator: Compare expert's label and classifier's label by the rules

DURATION

Heatmap

Heatmap based on

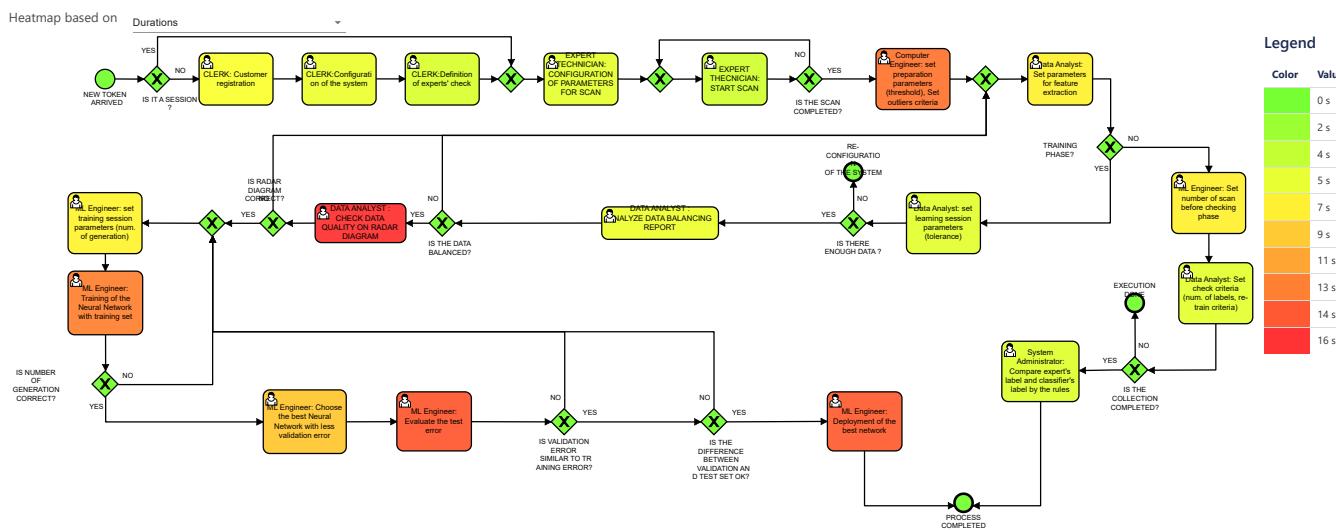


Figura 16 Heat Map To Be - Duration

6. PROCESS MINING

6.1. NORMATIVE MODEL (50/50 AS IS BPMN)

In order to obtain the original log, normative model is simulated using BIMP considering 100 tokens and 50% as probability for each gateway. Task cost is set to 1€, and task duration is set to 1s for each task.

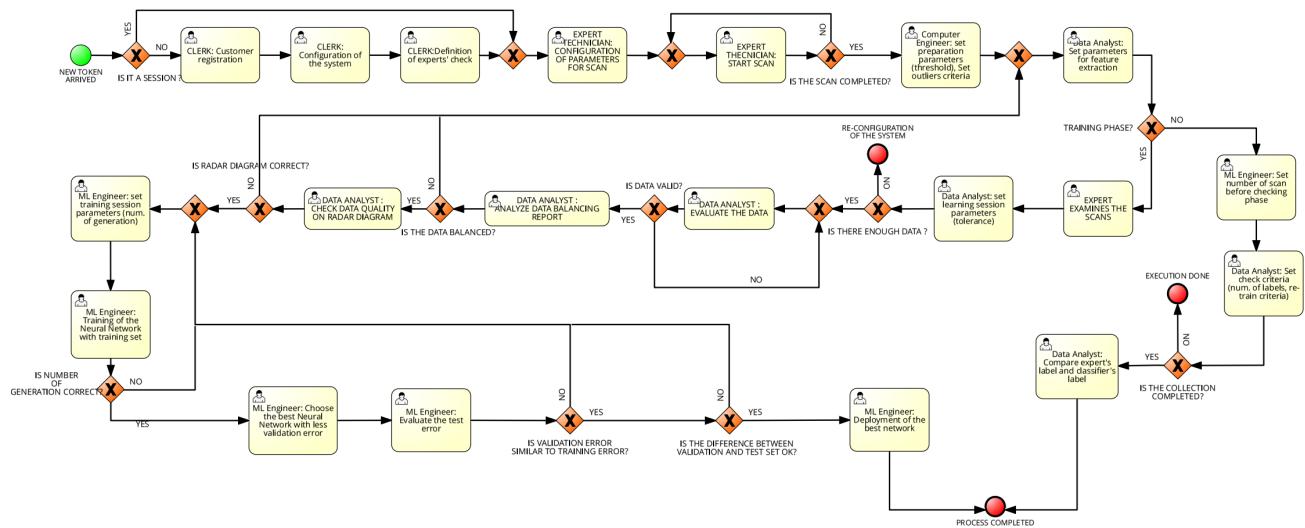


Figura 17 Normative Model

6.2. COMPARISON NORMATIVE MODEL TRANSITION MAP DISCO AND TRANSITION MAP APROMORE

The two model are the same as we can see from the two graphs.

TRANSITION MAP GENERATED FROM ORIGINAL LOG USING DISCO

Normative model obtained using disco after adding a single end event manually on signavio.

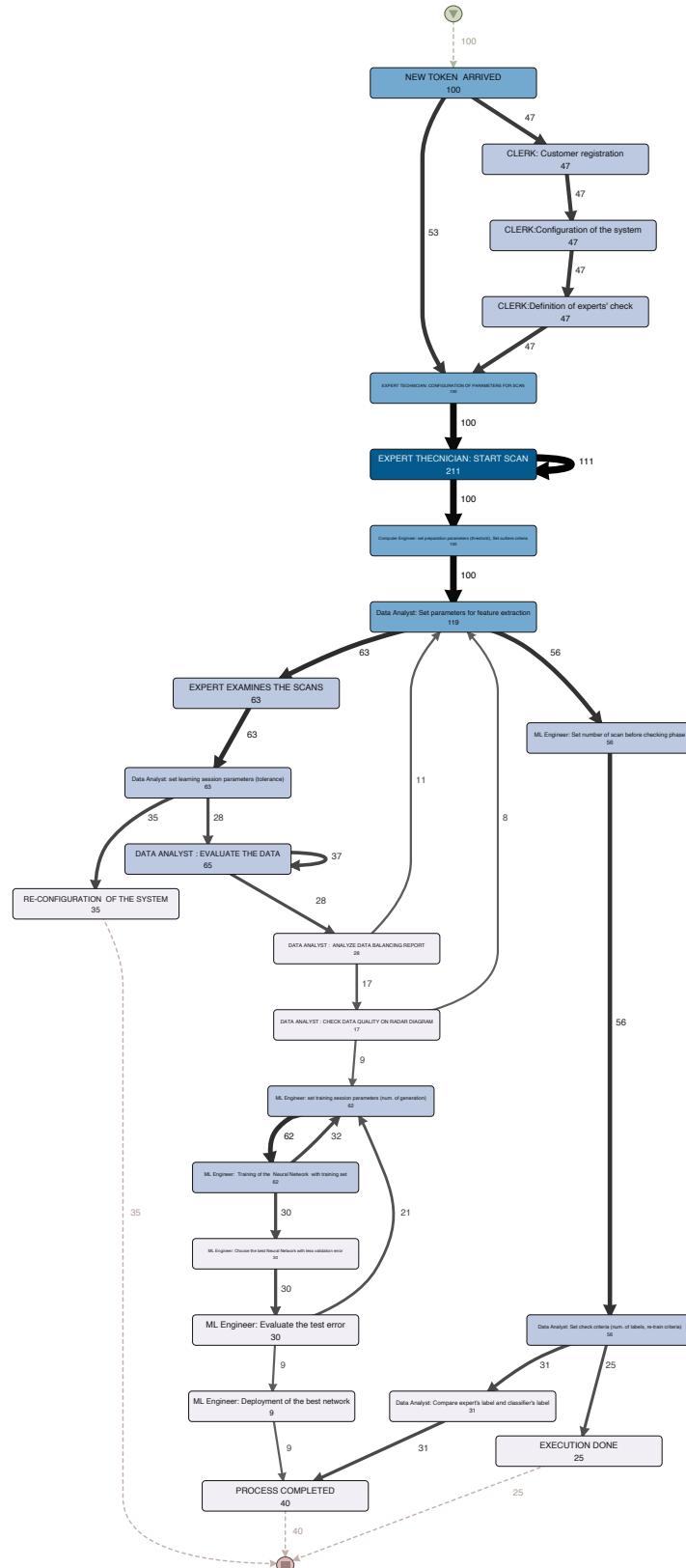


Figura 18 Transition Map Normative model - DISCO

TRANSITION MAP GENERATED FROM ORIGINAL LOG USING APROMORE

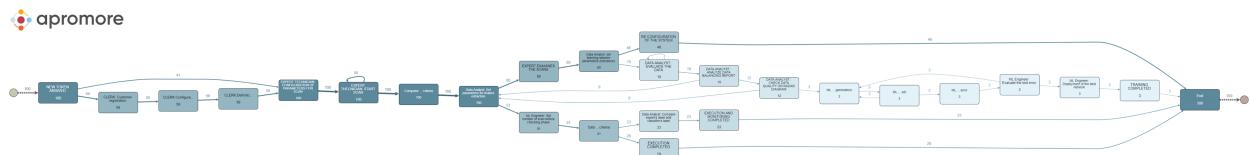


Figura 19 Transition Map Normative Model - APRMORE

6.3. COMPARISON BETWEEN BPMN NORMATIVE MODEL AND BPMN ORIGINAL LOG USING PROM

BPMN MODEL GENERATED FROM ORIGINAL LOG USING PROM

In order to obtain the model, we took the simulated MXML log from Bimp.

The MXML log generated by BIMP contains additional start/end events separated from the process, which cause issues for conformance;

To solve the issues we imported the MXML in Disco, exported it as CSV adding an end point, imported the CSV in ProM and converted it in XES on ProM by selecting only the time of process end.

Then, we took the resulting XES and we used it as a log in ProM.

To generate the mined model then, we select the LOG and apply the filter ‘BPMN miner’. Then we select the ‘Inductive miner’ and obtained the BPMN model.

The BPMN model is obtained using *ProM*, and in particular Inductive Miner algorithm.

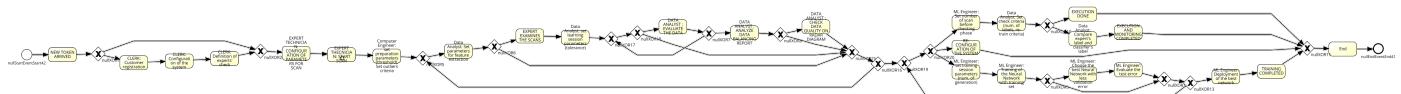


Figura 20 BPMN Model Original log - PROM

Difference between BPMN NORMATIVE MODEL and BPMN ORIGINAL LOG PROM:

1. In ProM “Expert Technician: Start scan” is a loop without gateway and it is devided into 3 subtasks “Expert Technician: Start scan start”, “Expert Technician: Start scan repeat”, “Expert Technician: Start scan complete”.
 2. Gateway 6 -> 12 -> 13 -> 14 -> 15 paths for execution phase
 3. End Event for Re-configuration of the system gateway 18 -> 19 -> 12 -> 13 -> 14 -> 15 -> Re-configuration of the system
 4. Is the data balanced -> No. gateways 8 -> 12 -> 13 -> 5
 5. Is the radar diagram correct -> No. gateway 12 -> 13 -> 5
 6. Gateway 14, 15 were not there before
 7. To continue training phase gateway 12 -> 13 -> 14 -> 15 -> ML set training parameters number of generations
 8. Is number of generations correct -> No. gateway 9 -> 16 -> 17 -> 14
 9. Is validation error similar to training error -> No. gateway 17 -> 14



HOW TO OBTAIN INSPECTOR GRAPH

Upload on ProM of the bpmn mined model from modified log and original ones.

After that, “Select BPMN Diagram” on BPMN to generate BPMN diagram; by selecting resource ‘BPMNDiagram generated’, we applied “Convert BPMN Diagram to Petri Net (Control-flow)”, generating the Petri Net. Finally we apply to the Petri Net and to the original Log the filter “Replay a log on Petri Net for conformance analysis” (set the resources to None except the ones with t_act, t_end e t_start).

Fitness obtained considering original log and mined model from *ProM* is shown in the following figure. It is equal to 0.90600 because the original log does not fit perfectly the mined model because of the differences mentioned before.



Figura 21 Inspector graph - PROM

Precision and **Generalization** values, computed through the specific plugin, are 0,63596 and 0,99788 respectively. This means that the model is not so precise, allowing a bit much extra behavior. Generalization is high, meaning that it does not restrict behavior just to the log. **Simplicity**, computed as the sum of the number of gateways, sequence flows and activities, is equal to 96 (17 gateways, 54 sequence flows, 25 activities).

6.4. COMPARISON BETWEEN BPMN NORMATIVE MODEL AND BPMN ORIGINAL LOG USING APROMORE

BPMN MODEL GENERATED FROM ORIGINAL LOG USING APROMORE



Figura 22 BPMN Original Log - APROMORE

BPMN model generated considering original log using *Apromore* is identical to the normative one, the only exception is the management of the ending events (green circle) and it put together the two gateways “is validation error similar to training error?” and “is the difference validation and test set ok?” (red circle). As a matter of fact, *Apromore* generates a gateway for the merge of the final events.

Fitness obtained considering the original log and the model mined through *Apromore* is shown in the following figure.



Figura 23 Inspector Graph - APROMORE

Fitness obtained considering original log and mined model from *Apromore* is shown in the following figure. It is equal to 1 because the original log perfectly fits the mined model. **Precision** and **Generalization** values, computed through the specific plugin, are 0,76451 and 0,99788 respectively. This means that the model is not so precise, allowing a bit much extra behavior. Generalization is high, meaning that it does not restrict behavior just to the log. **Simplicity**, computed as the sum of the number of gateways, sequence flows and activities, is equal to 77 (16 gateways, 35 sequence flows, 26 activities).

7. SUMMARY TABLE OF EXPERIMENTS WITH ORIGINAL LOG

Model	Fitness	Simplicity(g,sf,a,e)	Precision	Generalization
Original Log + ProM	0.90600	$17 + 54 (-5?) + 25(-5) = 96$	0,63596	0,99788
Original Log + Apmomore	1	$16 + 35 + 26(-6) = 77$	0,76451	0,99788

8. MODIFIED LOG EXPERIMENTS

8.1. VIOLATIONS LIST

The list of violations considered for this experiment are listed below.

- “**Expert examines the scan**” skipped (**Case 1**): under the assumption that we have a new customer that is similar to a port already classified in our database. After an initial evaluation phase and categorization of the type of port, we saved the parameters related to that specific port due to a future use for a new port with similar category.
The task “Expert examines the scan” is deleted from logs 0, 11, 15, 16 and 69.
- “**Data Analyst: evaluate the data**” skipped (**Case 2**): we skipped this task because after an evaluation of data by the data analyst, if it would ever be necessary getting new data, the experts’ evaluation will not be necessary anymore. We can confront the new data with the stored ones without the experts’ involvement.
The task “Evaluate the data” is deleted from logs 2, 3, 14, 31 and 78.
- “**ML Engineer: set training session parameters (num. of generation)**” skipped (**Case 3**): under the assumption that we have similar conditions for which the neural network training can be the same, we use the same hyperparameters used in the previous network to train the new one. The task “Set training session parameters (num. of generation)” is deleted from logs 3, 51, 58, 65, and 76.

8.2. FITNESS OF VIOLATIONS

To perform conformance checking, the modified log and the normative model. The model is converted in Petri Net using *Normative Model*, and then the latter is used to perform conformance checking with the modified log. **Fitness** that we calculate is equal to 1.

8.3. BPMN MODEL GENERATED FROM MODIFIED LOG USING PROM

The BPMN model represented in figure is obtained by applying Inductive Miner on the modified log. As shown, there are some differences with the BPMN model obtained from the original log. In particular, the task “Expert examines the scan” can be skipped according to *Case 1*. The fact that the task “Data Analyst: evaluate the data” is skipped is highlighted with the second circle in red (*Case 2*). At the end, the fact that the task “ML Engineer: set training session parameters (num. of generation)” can be skipped is highlighted by the red cycle named *Case 3*.

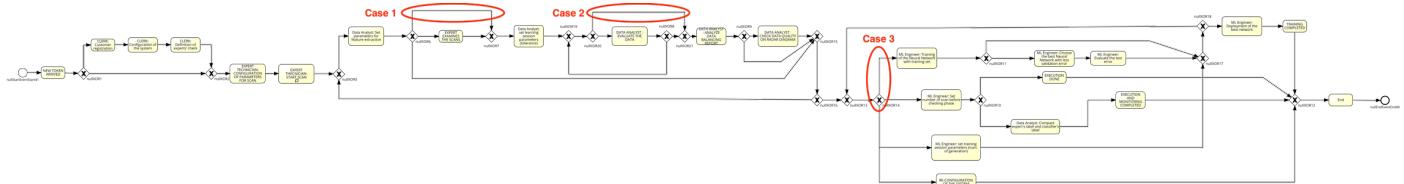


Figura 24 BPMN Modified Log - PROM

Fitness value is shown in the following figure. The value is not perfect (0.9217) because ProM divides the task “Expert tachnichan: start scan” into three different subtask due to the loop, so every time ProM does three tasks instead of one.

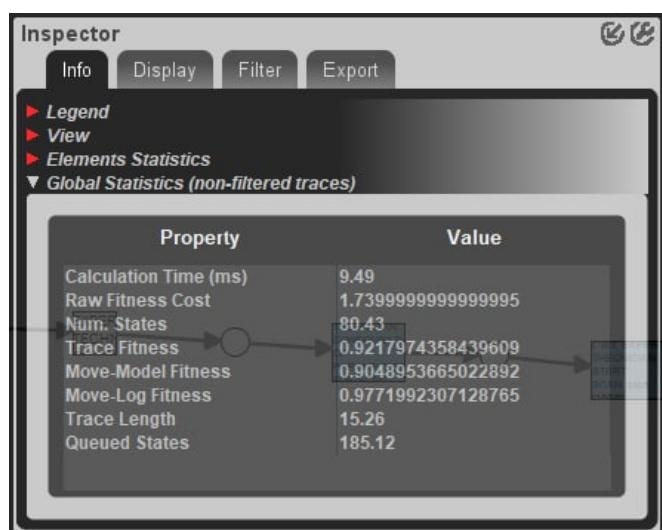


Figura 25 Inspector Graph Modified Log - PROM

Precision and **Generalization**, computed with the specific plugin, are 0,57650 and 0,99671 respectively. This means that the model permits a bit much of extra behavior and has a satisfying capability to generalize. Generalization is high because the model does not restrict the behavior just to the log. **Simplicity**, computed as the sum of the number of gateways, sequence flows and activities, is equal to 106 (18 gateways, 62 sequence flows, 26 activities).

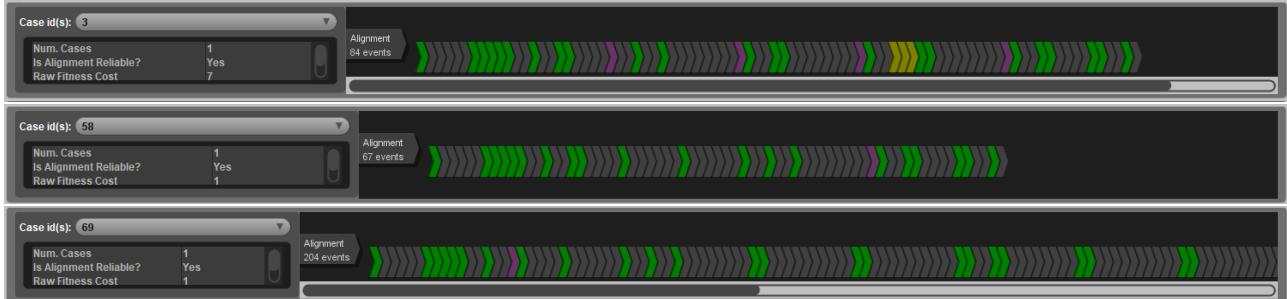


Figura 26 Project alignment case 3, 58, 69 Modified Log - PROM

In case 3 we can observe that the purple task corresponds to “Data Analyst: evaluate the data” as expected. The latter purple tasks are: “ML Engineer: Set learning session parameters”.

The tasks “ML Engineer training with training set” are yellow because they are present in the log and not in the bpmn model.

In case 58 purple tasks correspond to “ML Engineer: Set learning session parameters” as expected.

In case 69 we can observe that the purple task corresponds “Expert examines the scans” as expected.

8.4. TRANSITION MAP GENERATED FROM MODIFIED LOG USING APROMORE

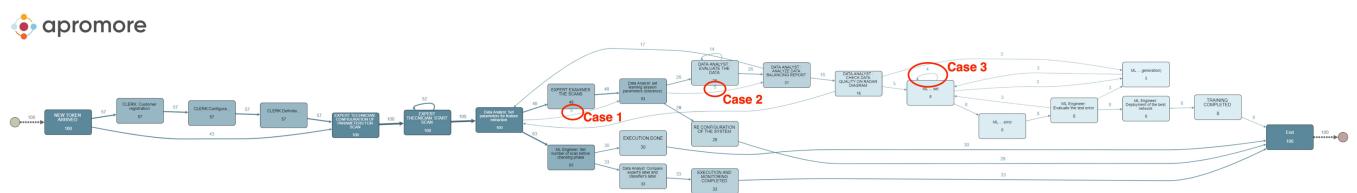


Figura 27 Transition Map Modified Log - APROMORE

8.5. BPMN MODEL GENERATED FROM MODIFIED LOG USING APROMORE

BPMN model generated from modified log using *Apromore* is shown in the following figure. As shown, there are some differences with the BPMN model obtained from the original log. In particular, the task “Expert examines the scan” can be skipped according to *Case 1*. The fact that the task “Data Analyst: evaluate the data” is skipped is highlighted with the second circle in red (*Case 2*). At the end, the fact that the task “ML Engineer: set training session parameters (num. of generation)” can be skipped is highlighted by the red cycle named *Case 3*.



Figura 28 BPMN Modified Log - APROMORE

Fitness is shown in the following figure. As expected, it is equal to 1.



Figura 29 Inspector graph Modified Log - APROMORE

Precision and **Generalization**, computed with the specific plugin, are 0, 62030 and 0, 99746 respectively. This means that the model permits a bit much of extra behavior and has a satisfying capability to generalize. Generalization is high because the model does not restrict the behavior just to the log. **Simplicity**, computed as the sum of the number of gateways, sequence flows and activities, is equal to 81 (19 gateways, 38 sequence flows, 24 activities).

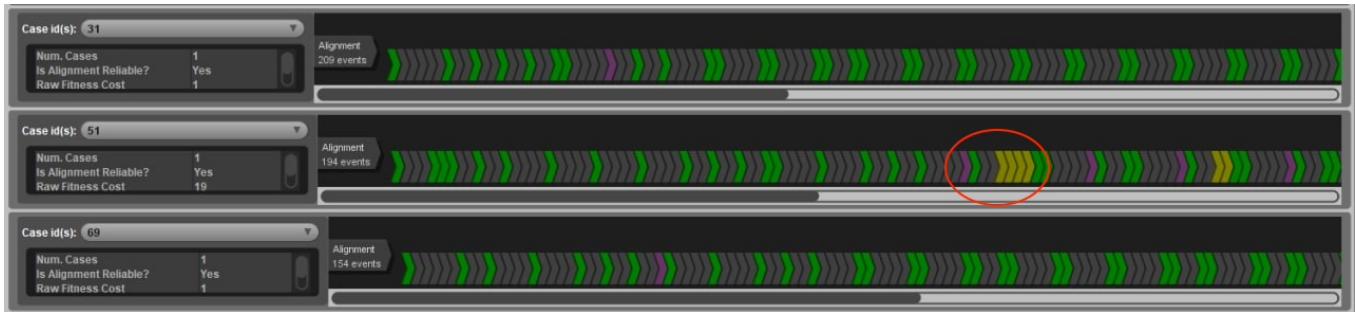


Figura 30 Project alignment case 31, 51, 69 Modified Log - APROMORE

In case 31 we can observe that the purple task corresponds to “Data Analyst: evaluate the data” as expected

In case 51 purple tasks corresponds to “ML Engineer: Set learning session parameters” as expected. Yellow tasks, instead, correspond to “ML Engineer training with training set” that it is present in the log and not in the bpmn model.

In particular, in the section highlighted, the purple tasks is in the bpmn model and not in the log because we eliminate it. The next one is green because it is present in both and then there are four yellow arrows because the loop is present only in the log and not in the bpmn model.

In case 69, we can see that purple tasks correspond to “Expert examines the scans” as expected.

9. FINAL CONSIDERATIONS

Model	Fitness	Simplicity(g,sf,a,e)	Precision	Generalization
Original Log + Normative Model	1	$16 + 33 + 24 = 73$	0,76451	0,99788
Original Log + ProM Inductive Miner Model	0.90600	$17 + 54 + 25 = 96$	0,63596	0,99788
Original Log + Apromore Model	1	$16 + 35 + 26 = 77$	0,76451	0,99788
Modified Log + ProM Inductive Miner Model	0.921797	$18 + 62 + 26 = 106$	0,57650	0,99671
Modified Log + Apromore Model	1	$19 + 38 + 24 = 81$	0,62030	0,99746

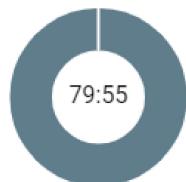
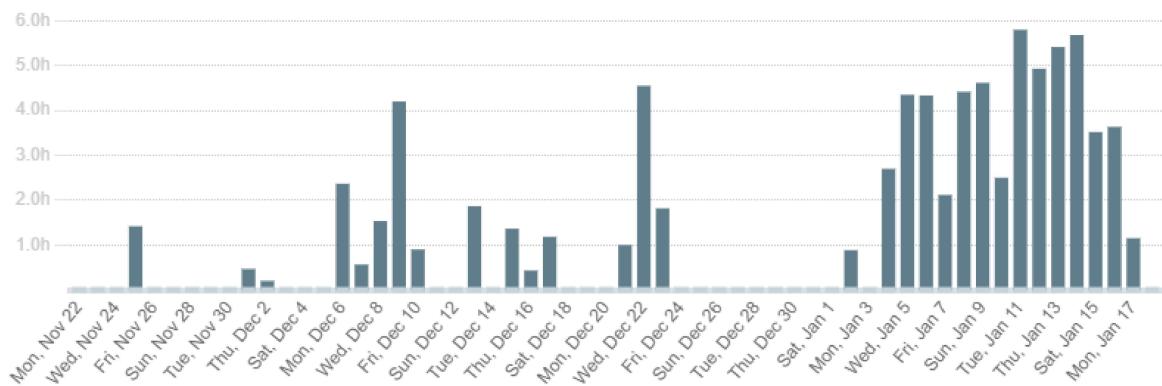
In the summary table above, the various results obtained are reported. As you can see from the 4 qualities calculated, considering the **original log**, the best result is the BPMN generated by *Apromore*, in fact the fitness is 1 and the generalization and precision values are better than the one generated by *ProM*. The bpmn generated by *ProM* still has a fitness very close to 1 (0.90), but it has more modifications in the BPMN than the original one and in fact precision and generalization are lower. Simplicity, in both cases, is higher compared to the normative model because of a different management of starting/ending activities, and the adding of gateways.

Comparing the various models from the business perspective, we can assume that the modified model adds alternative paths that generate a lower cost for the company (**internal prospective**). More in details, we skip the task “Expert examines the scan” (case 1) because every time there is a training phase, it is not necessary to involve an expert to examine the scans. This is an advantage in term of costs because the company must pay the expert for a minor number of hours. Another advantage is the increase of the velocity of the process due to the elimination of the waiting time for the labeling because task 1 and the next one are asynchronous. In the same way, for “Data Analyst: evaluate the data” (case 2) and “ML Engineer: set training session parameters (num. of generation)” (case 3), the process becomes faster because data and parameters are taken from a previous trained network thanks to the categorization of ports.

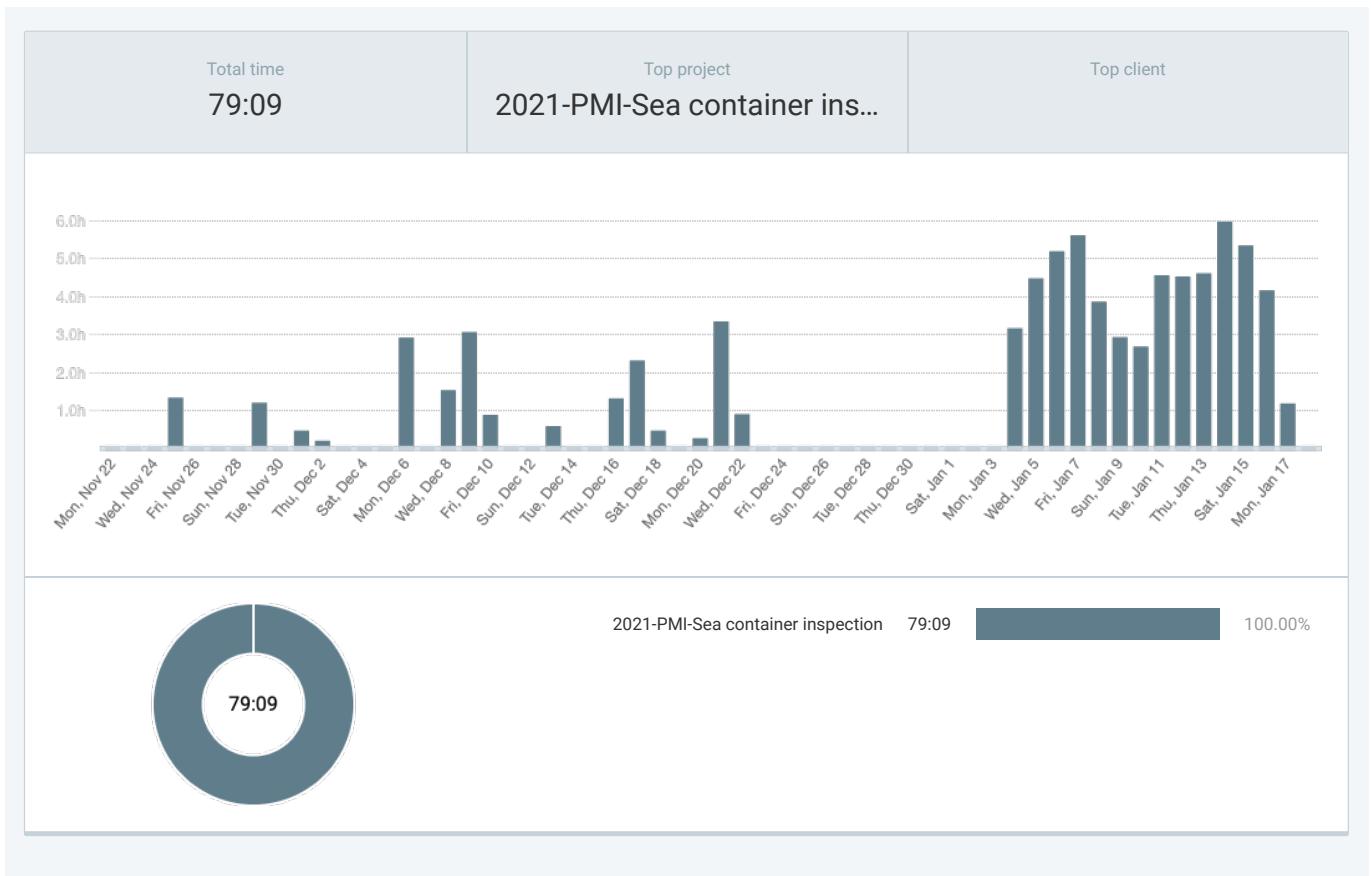
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DASHBOARD Clockify: Rossella DE DOMINICIS

Total time 79:55	Top project 2021-PMI-Sea contain...	Top client
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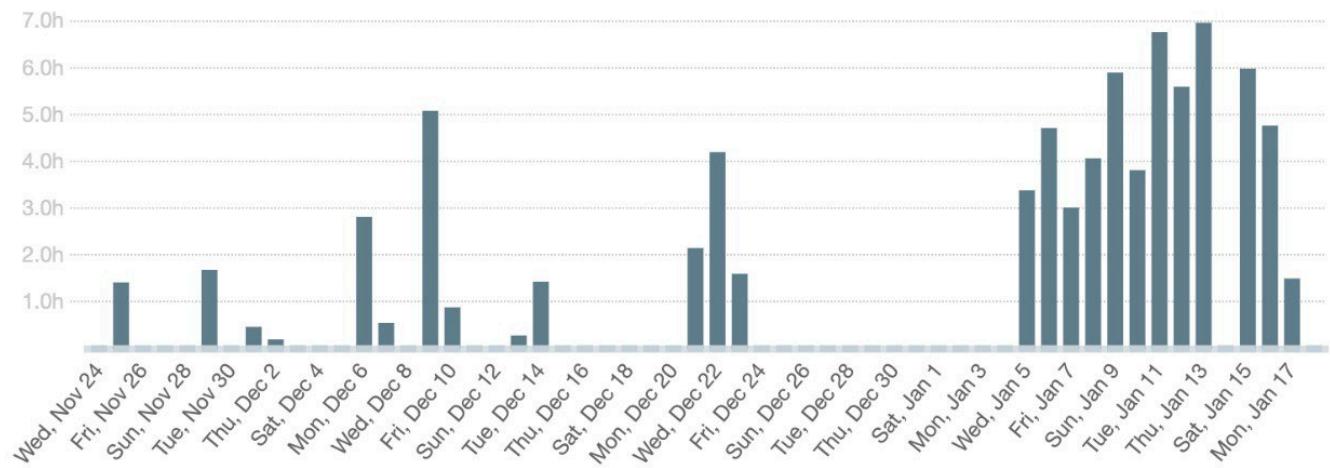


DASHBOARD Clockify: Veronica GAVAGNA



DASHBOARD Clockify: Giacomo PIACENTINI

Total time	Top project	Top client
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2021-PMI-Sea container inspe...

79:15



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DASHBOARD Clockify: Gaetano Niccolò TERRANOVA

