TÉCNICO LISBOA

DS 2023

Data Science Project

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	Student 2 : Francisco Abreu	**IST nr:** 110946
	Student 3 : João Ferreira	**IST nr:** 110954
	Student 4 : Rúben Nobre	**IST nr:** 99321

CLASSIFICATION

1 DATA PROFILING

DS1

Imbalanced target: No 70% vs Yes 30%

BMI = weight (kg) / [height (m)]^2

DS2

Remove & check input errors like

Narrow age from 0 to 120 in *Transformation*

Unusual values *Interest Rate* above 150%

Data Dimensionality

No dimensionality curse in both datasets.

DS1

Most variables are binary

No date variables

Max % of missing values is 9.1, not that relevant in the context of this Dataset

DS2

Most variables are **numeric**

10 out of 27 are **symbolic**, can cause difficulties when trying to convert them to ordinal later

CreditMix has 20% of MV which must me dealt with later on in the Preparation Step

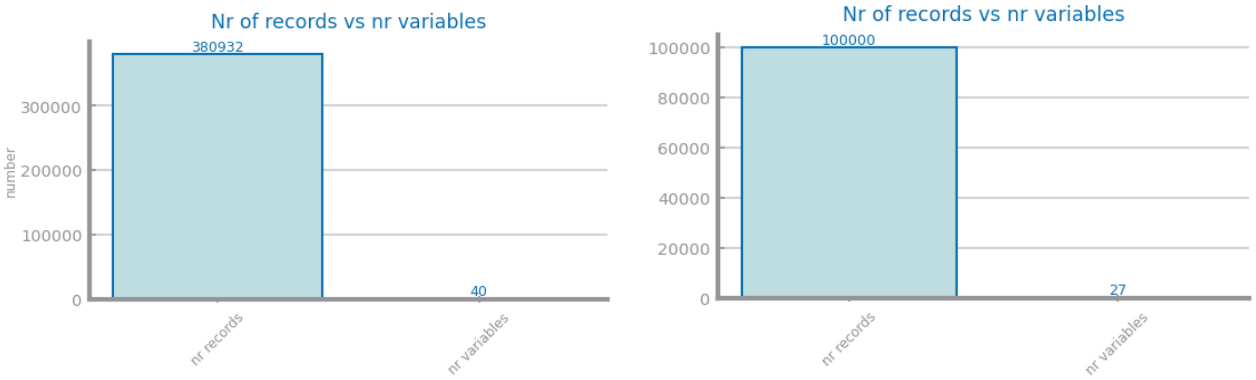


Figure 1 Nr Records x Nr variables for dataset 1 (left) and dataset 2 (right)

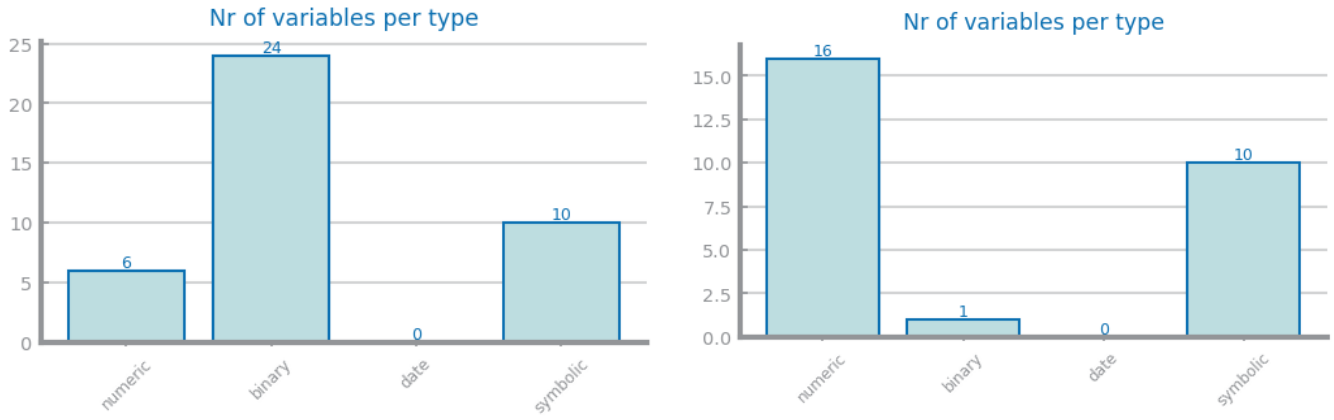


Figure 2 Nr variables per type for dataset 1 (left) and dataset 2 (right)

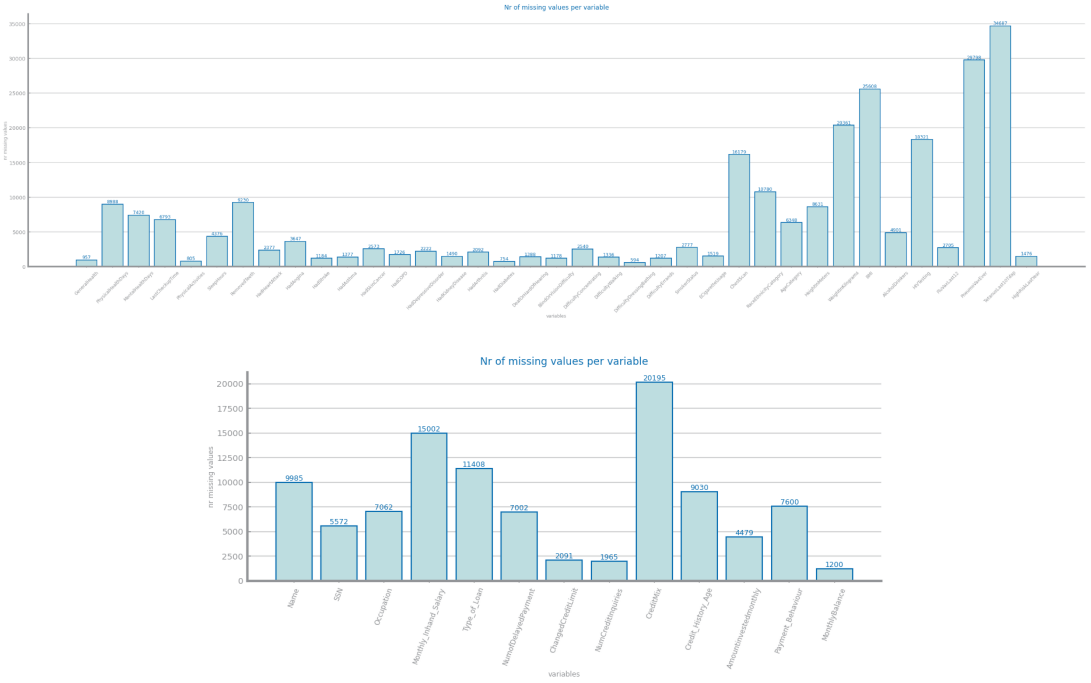


Figure 3 Nr missing values for dataset 1 (top) and dataset 2 (bottom)

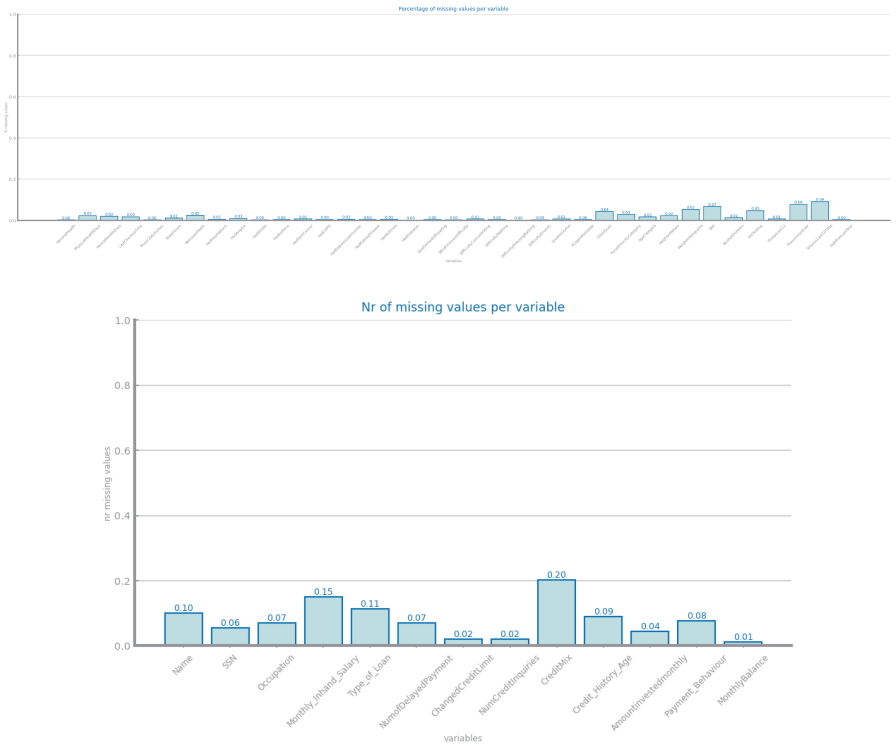


Figure 3.1 Nr missing values for dataset 1 (top) and dataset 2 (bottom) percentages (%)

Data Distribution

DS1

No clearly visible outliers on boxplots

Many 0s on physical and mental health days, possible MV. Other numeric vars show near-normal distribution

Unbalanced target, majority=No (70/30)

DS2

In Fig4&6, outliers skew scales

Remove not meaningful ID's - ID , CustomerID, SSN & Name

Remove Extreme Outlier in *MonthlyBalance* 9*Recs* = -3.3333E+26 *not in the context of the problem*

Neg Input Errors

Credit_History_Age treat as **numeric**

Unbalanced *Target* 0.41:1, majority is Good Credit Score

Most **Log-n** distributions

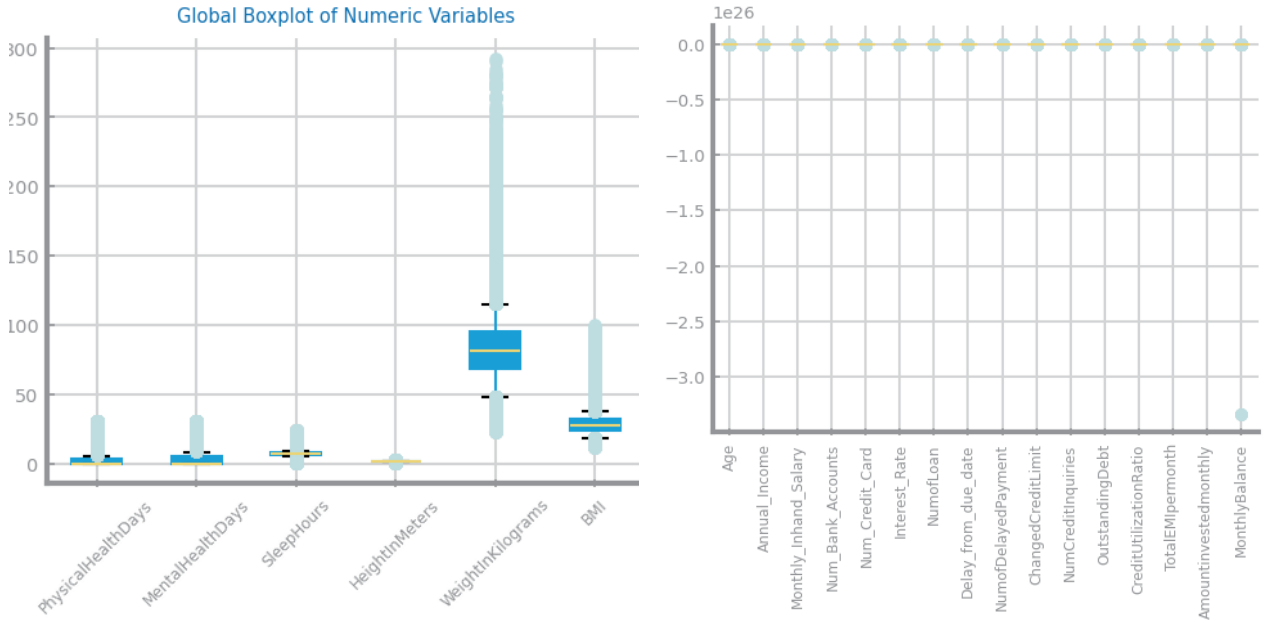


Figure 4 Global boxplots dataset 1 (left) and dataset 2 (right)

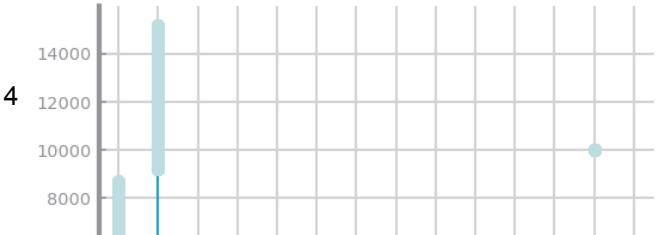


Figure 4.1 Global boxplots dataset 2 (without specific vars)

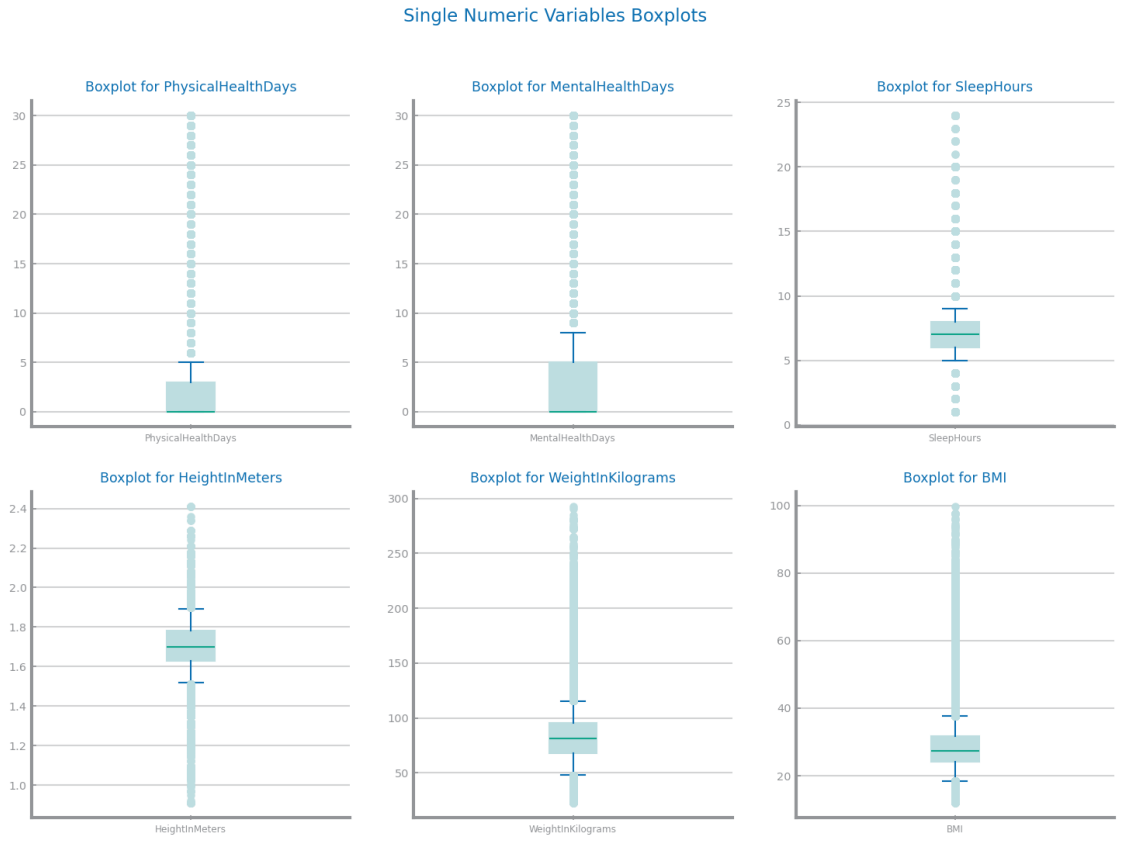


Figure 5 Single variable boxplots for dataset 1

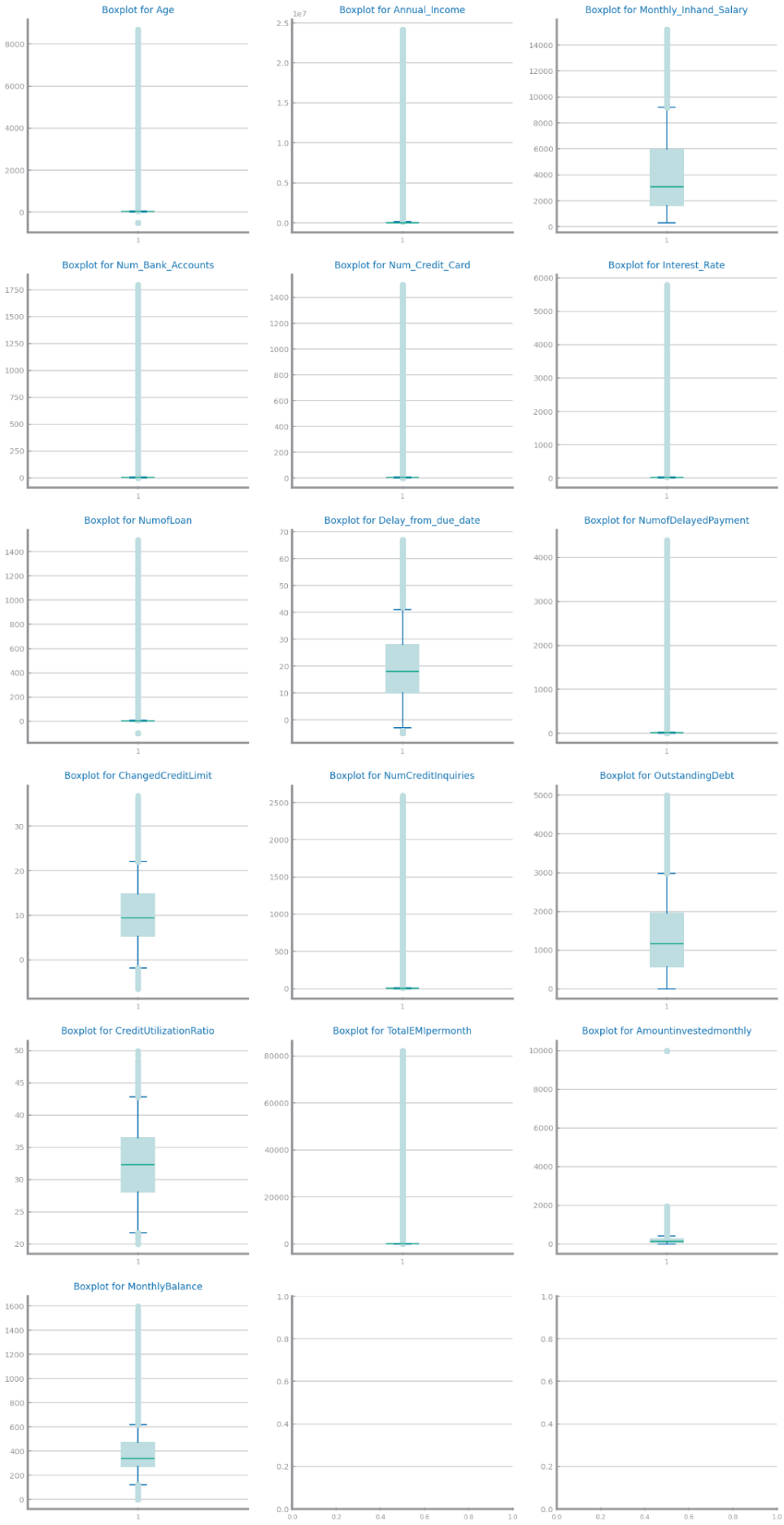


Figure 6 Single variable boxplots for dataset 2

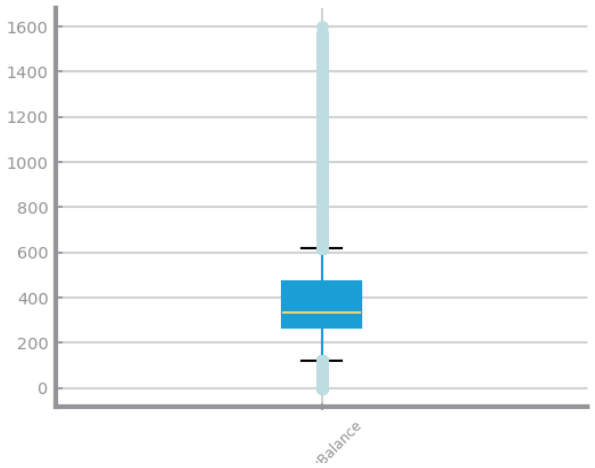


Figure 6.1 Single variable boxplot for Monthly_Balance dataset 2

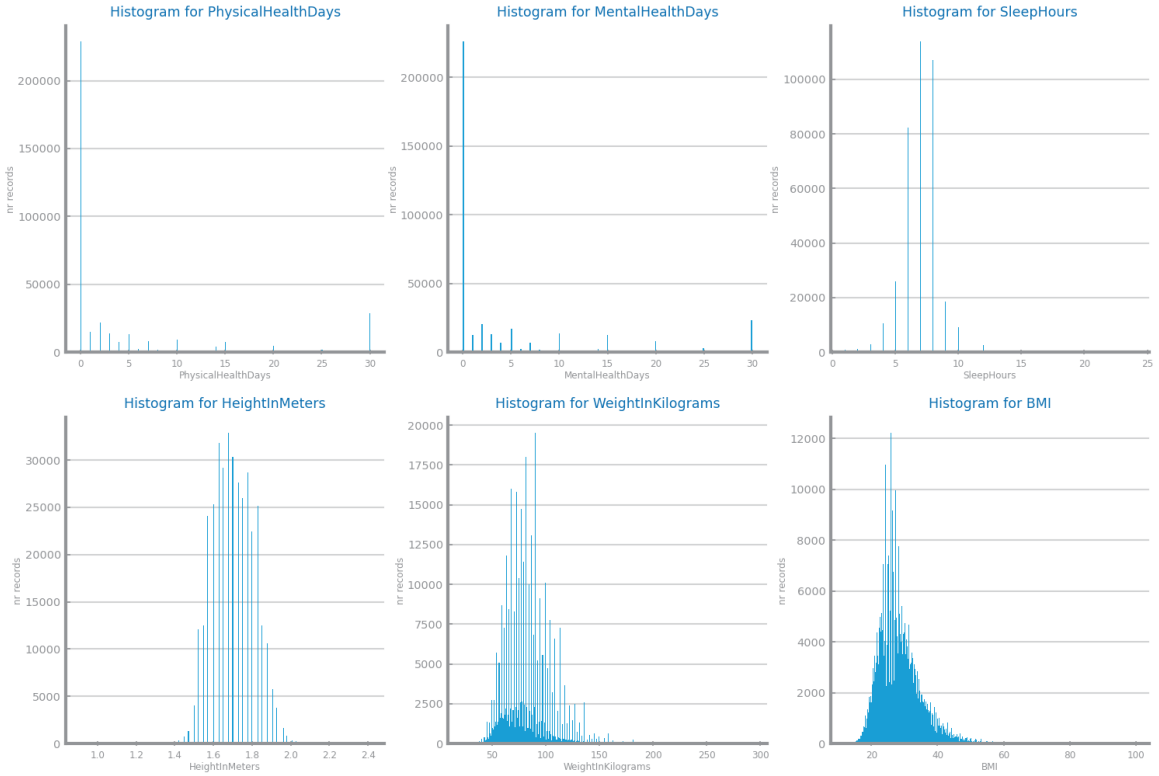


Figure 7 Numeric Histograms for dataset 1

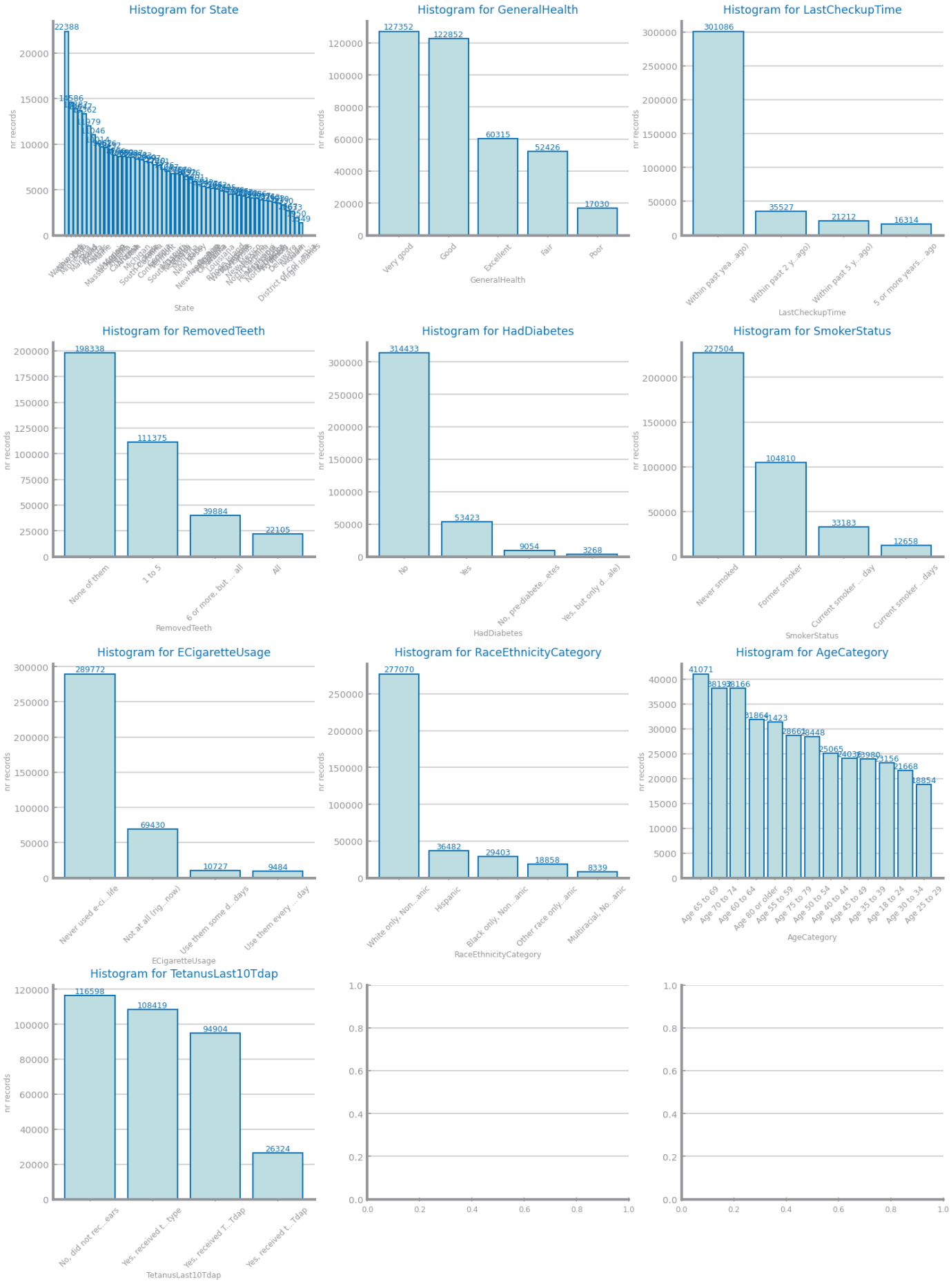


Figure 7.1 Symbolic Histograms for dataset 1

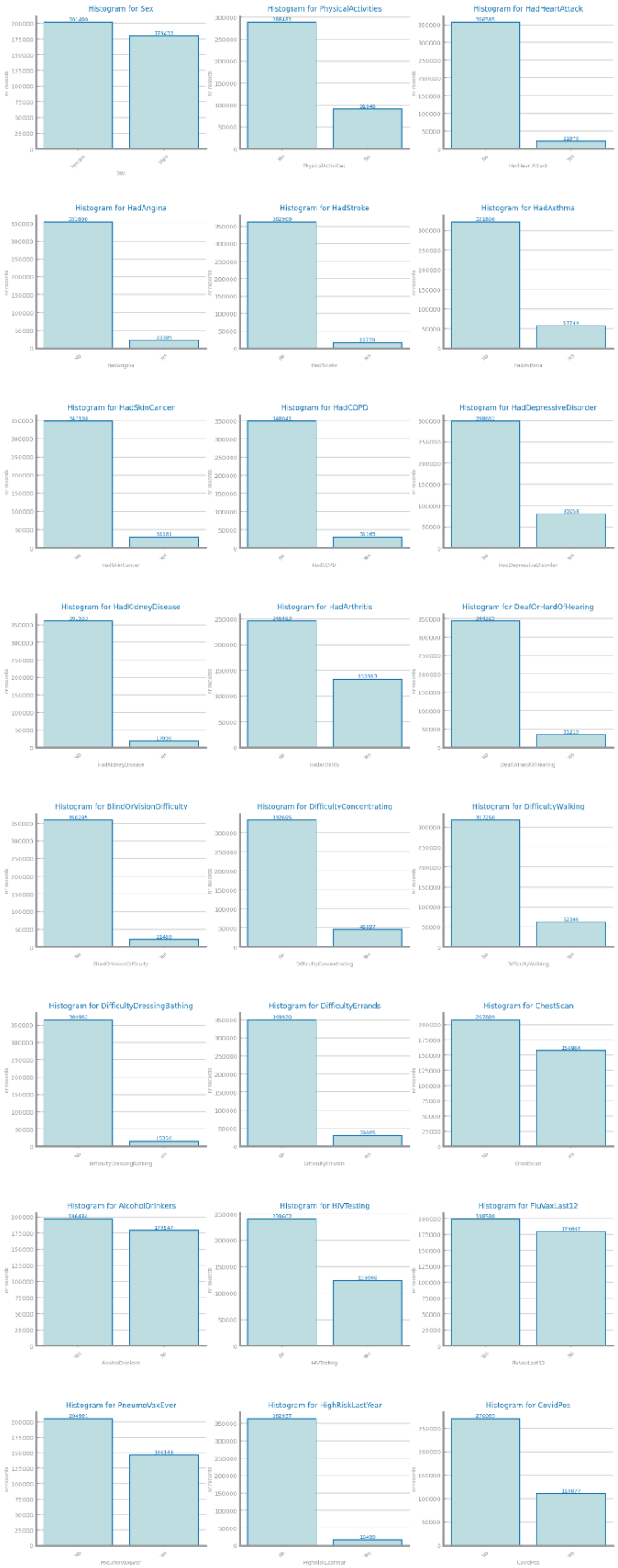
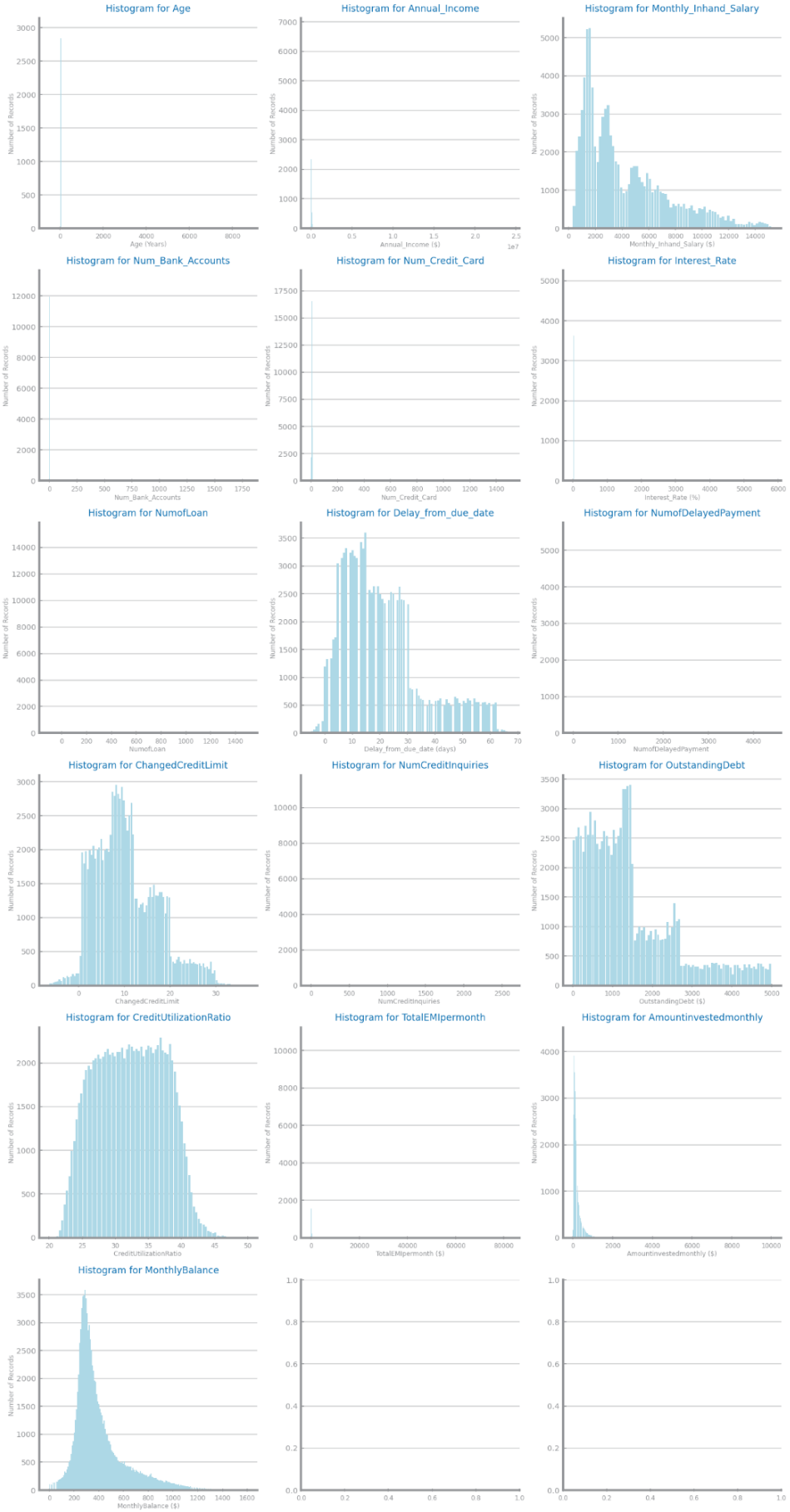


Figure 7.2 Binary Histograms for dataset 1


Histogram for Age
Number of Records
Age (Years)
Histogram for Annual_Income
Number of Records
Annual_Income ($)
1e7
Histogram for Monthly_Inhand_Salary
Number of Records
Monthly_Inhand_Salary ($)
Histogram for Num_Bank_Accounts
Number of Records
Num_Bank_Accounts
Histogram for Num_Credit_Card
Number of Records
Num_Credit_Card
Histogram for Interest_Rate
Number of Records
Interest_Rate (%)
Histogram for NumofLoan
Number of Records
NumofLoan
Histogram for Delay_from_due_date
Number of Records
Delay_from_due_date (days)
Histogram for NumofDelayedPayment
Number of Records
NumofDelayedPayment
Histogram for ChangedCreditLimit
Number of Records
ChangedCreditLimit
Histogram for NumCreditInquiries
Number of Records
NumCreditInquiries
Histogram for OutstandingDebt
Number of Records
OutstandingDebt ($)
Histogram for CreditUtilizationRatio
Number of Records
CreditUtilizationRatio
Histogram for TotalEMIpermonth
Number of Records
TotalEMIpermonth ($)
Histogram for Amountinvestedmonthly
Number of Records
Amountinvestedmonthly ($)
Histogram for MonthlyBalance
Number of Records
MonthlyBalance ($)

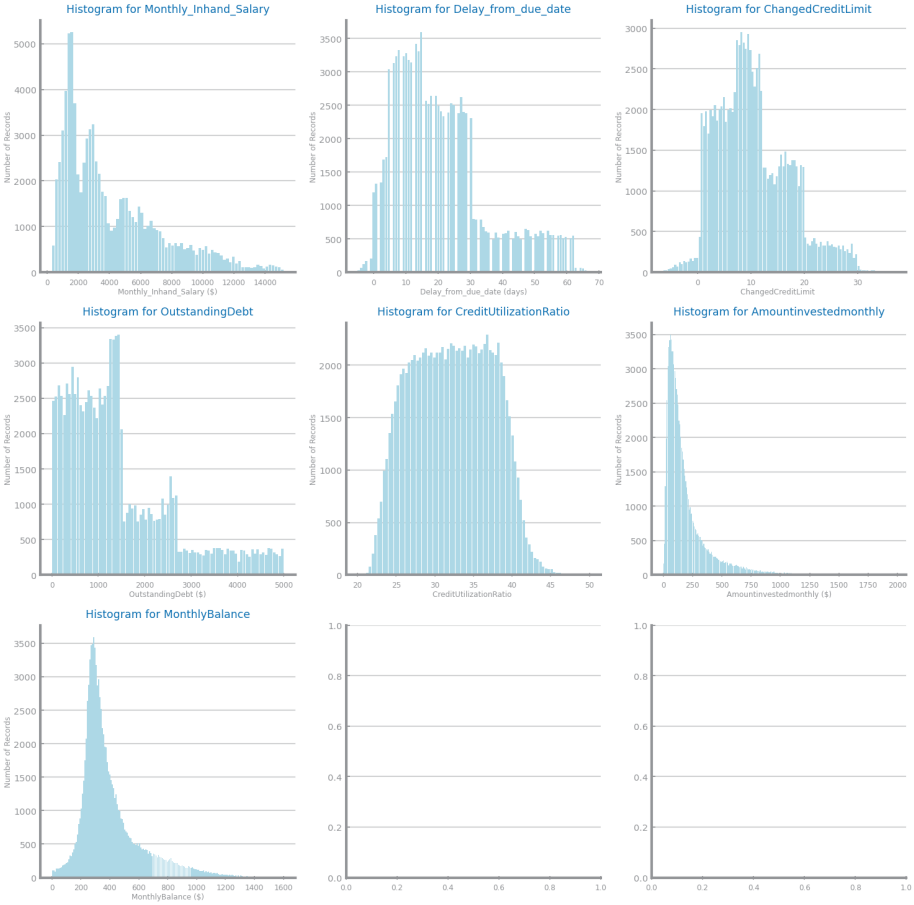


Figure 8 Numeric Histograms for dataset 2

Figure 8.1 Symbolic Histograms for dataset 2 (with distributions is enough)

Figure 8.2 Relevant Symbolic Histograms for dataset 2

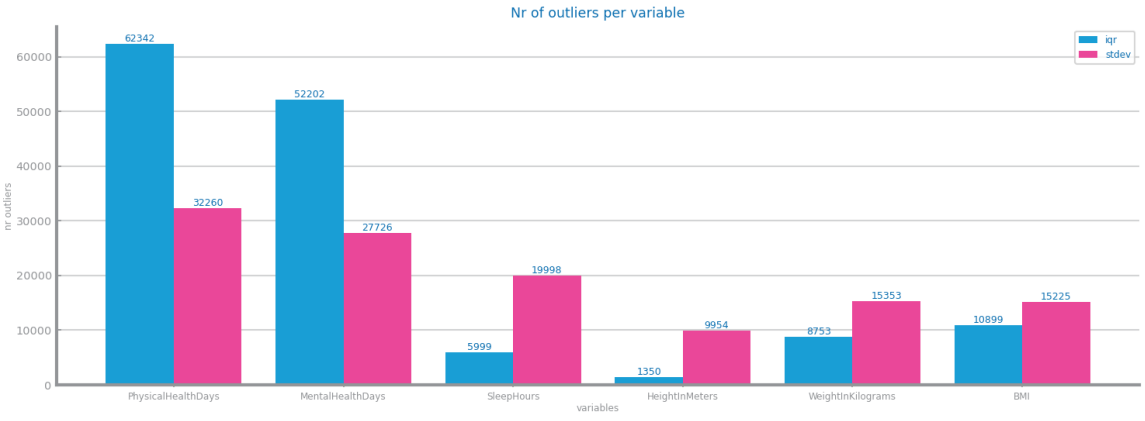


Figure 9 Outliers study dataset 1

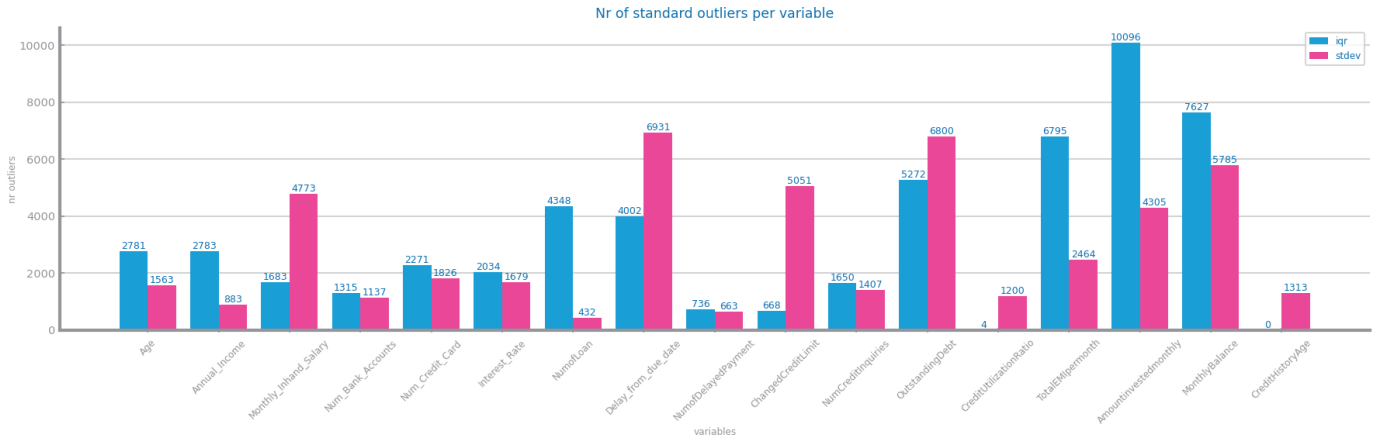


Figure 10 Outliers study for dataset 2

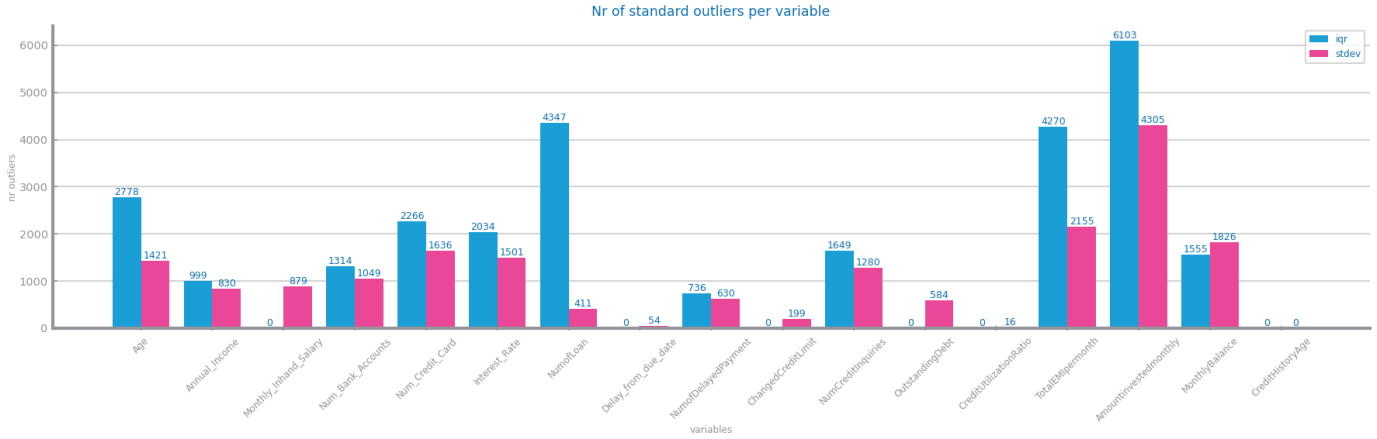


Figure 10.1 Outliers study for dataset 2

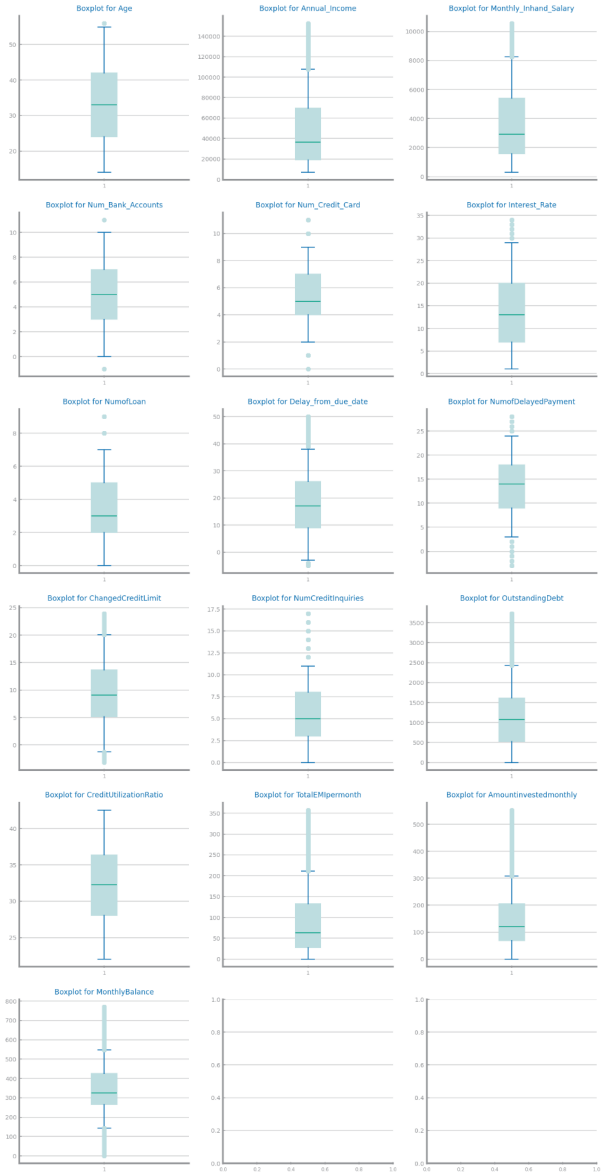


Figure 10.2 Boxplots without Outliers

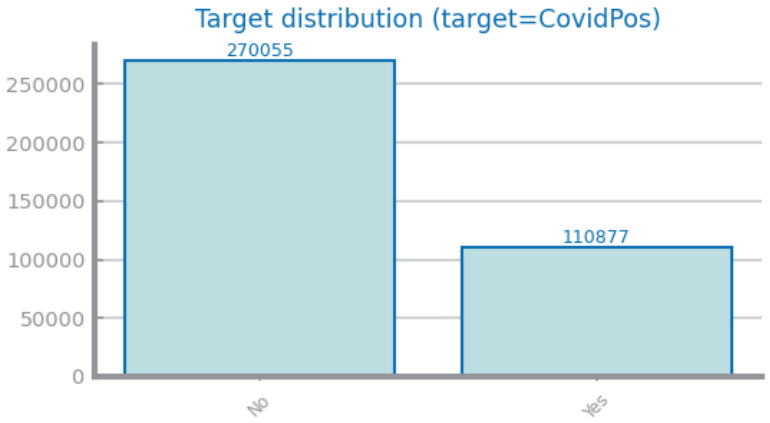


Figure 11 Class distribution for dataset 1

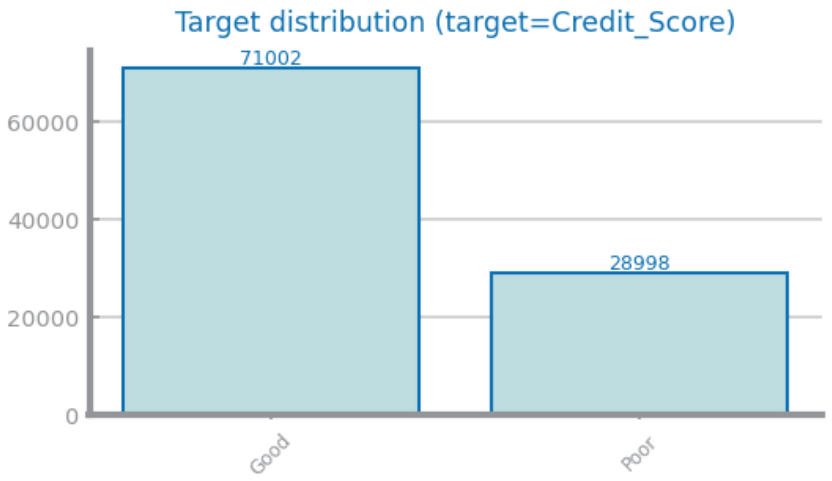


Figure 12 Class distribution for dataset 2

Data Granularity

DS1
The age ranges have been categorized and segmented into groups.
Figure 13.3 displays the aggregated data of the 'state' variable, categorized by region.
DS2
Taxonomies -> 1. Occupation - divided in different sectors, Loan Risk - from Low to High , Loan Type - from real world experience
Confirm majority has *Log-n* distribution

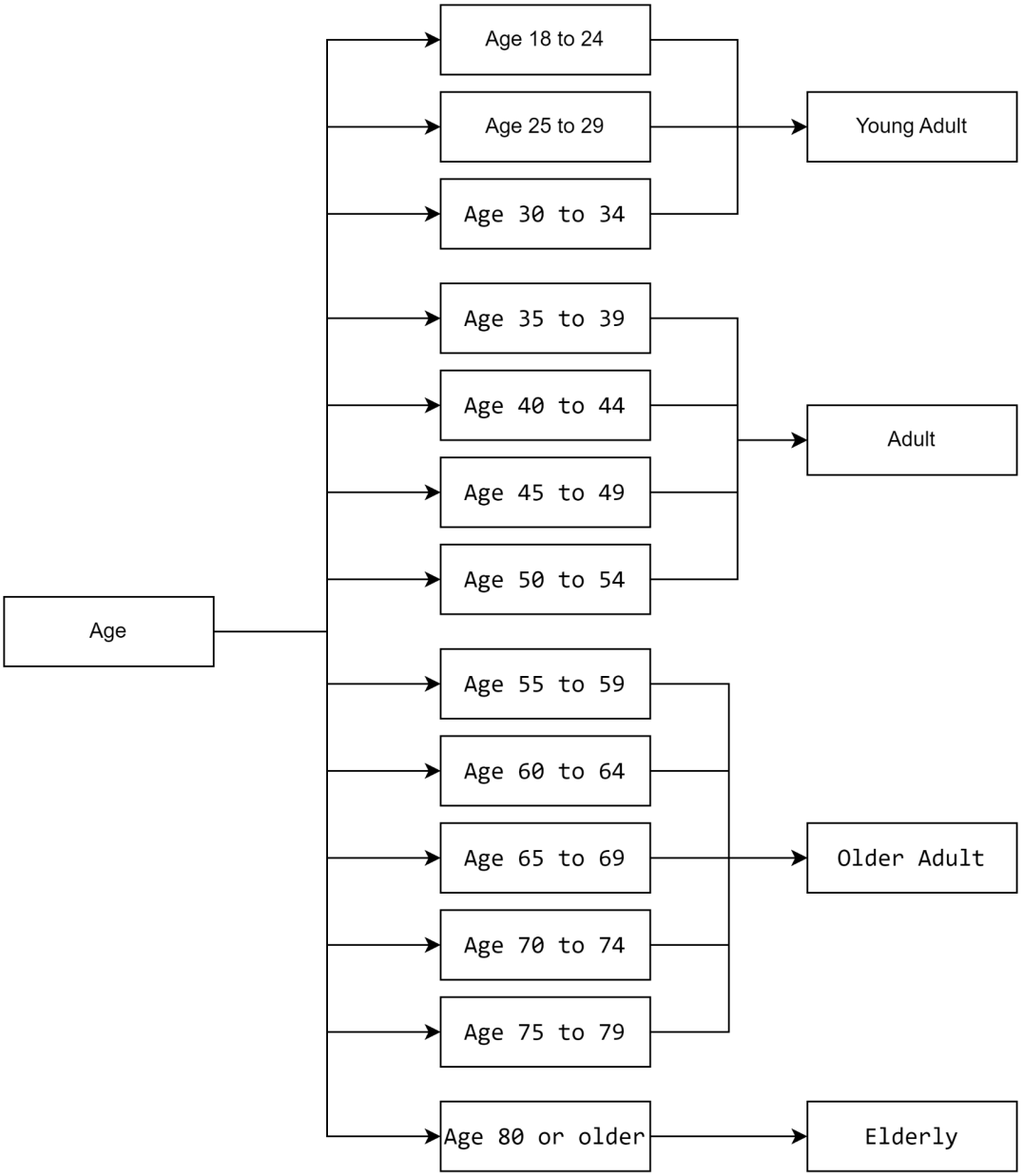


Figure 13.1 Granularity analysis for dataset 1 (Age)

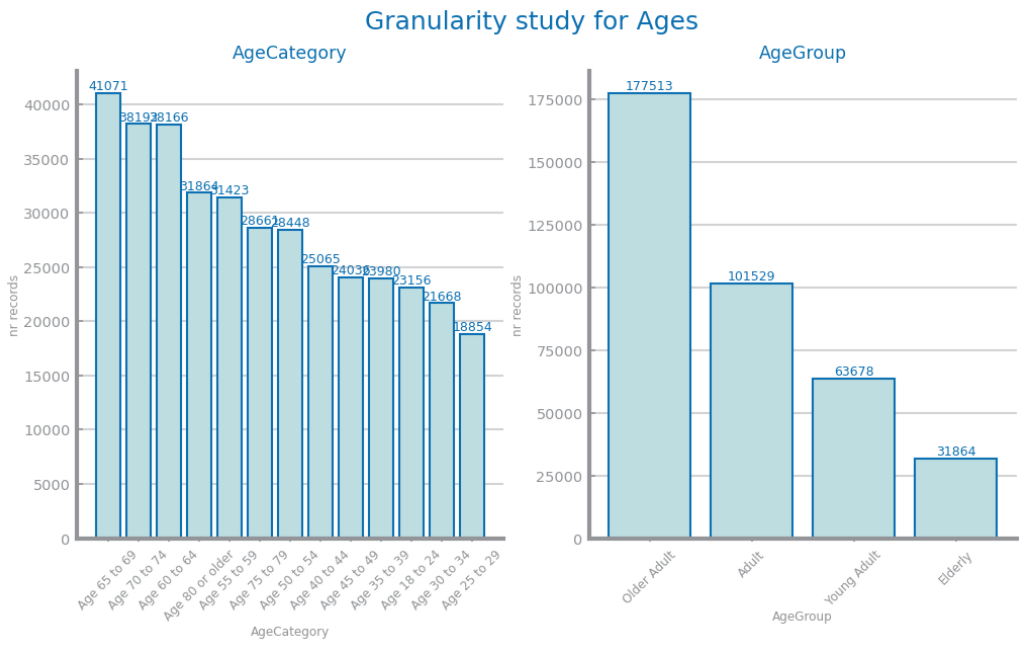
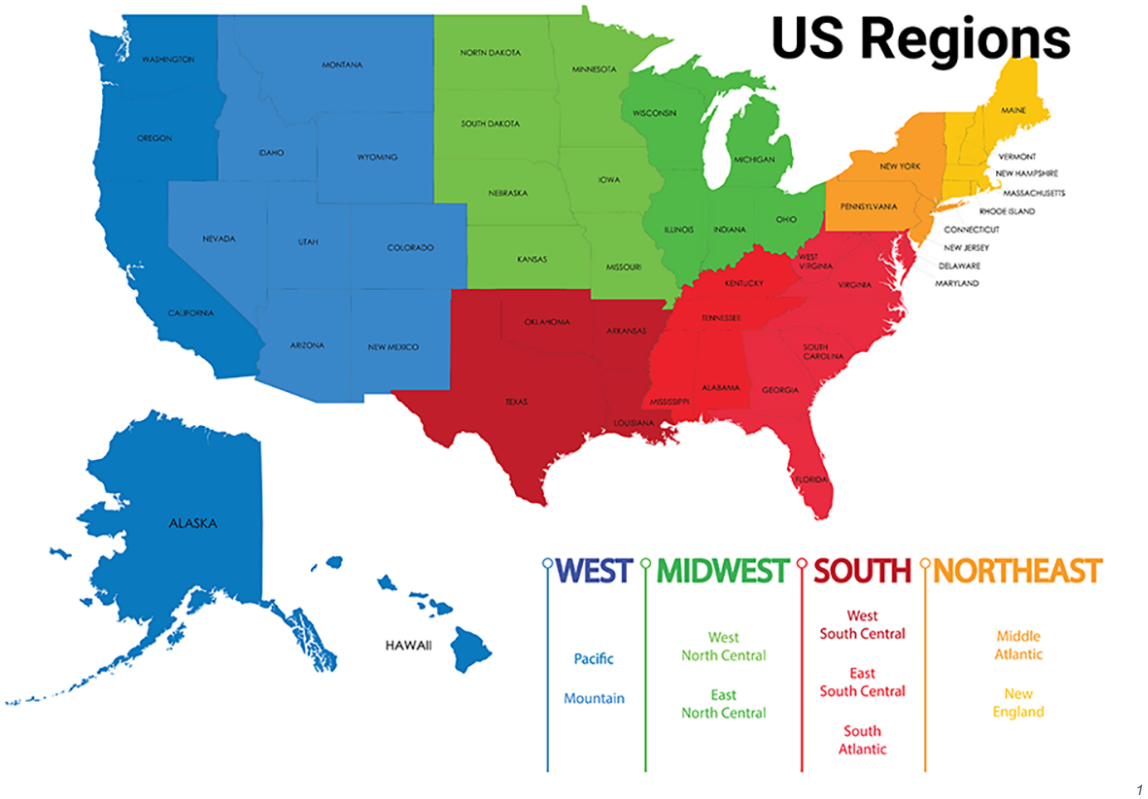


Figure 13.2 Granularity study for dataset 1 (Age)



[1]

Figure 13.3 Granularity analysis for dataset 1 (State)

[1] https://www.50states.com/city/regions.htm

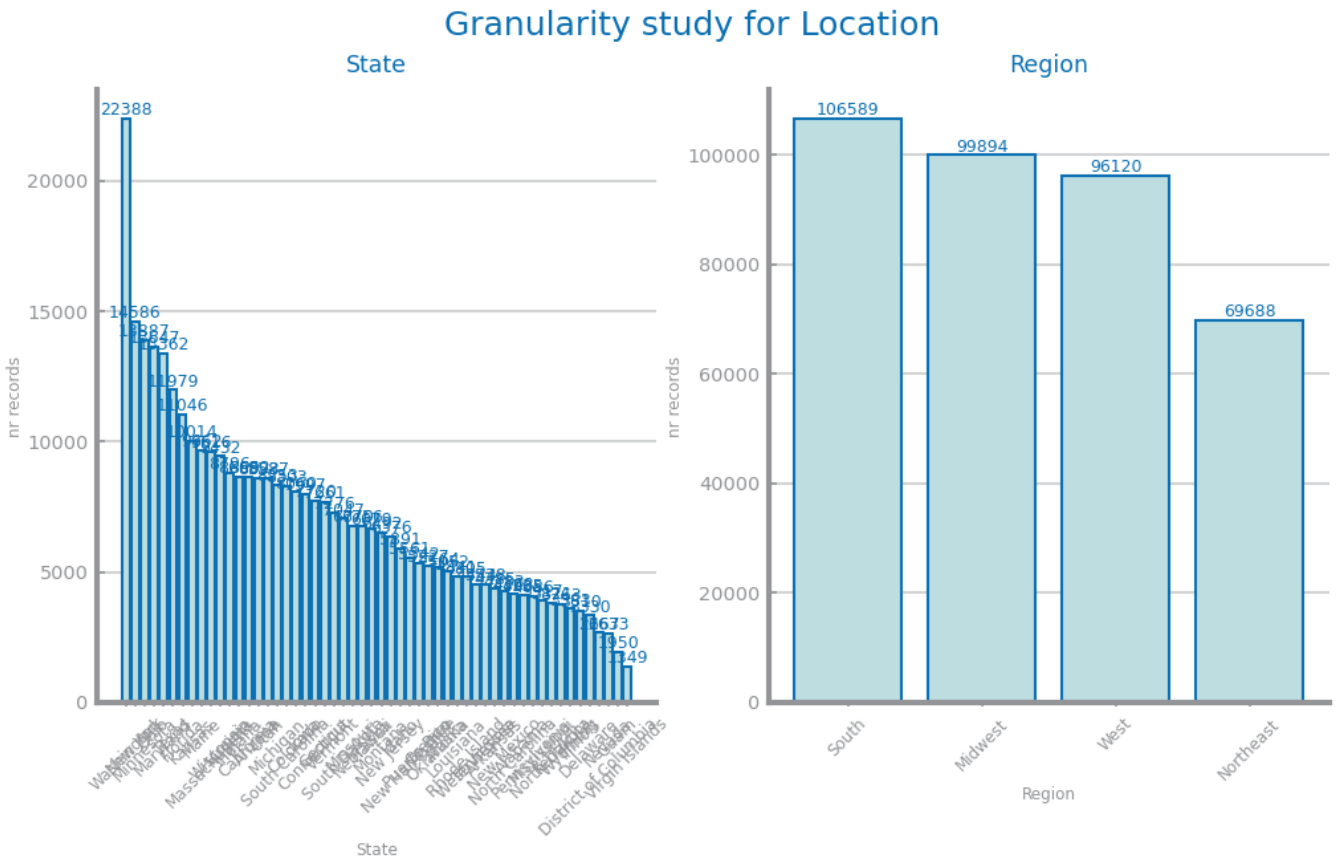
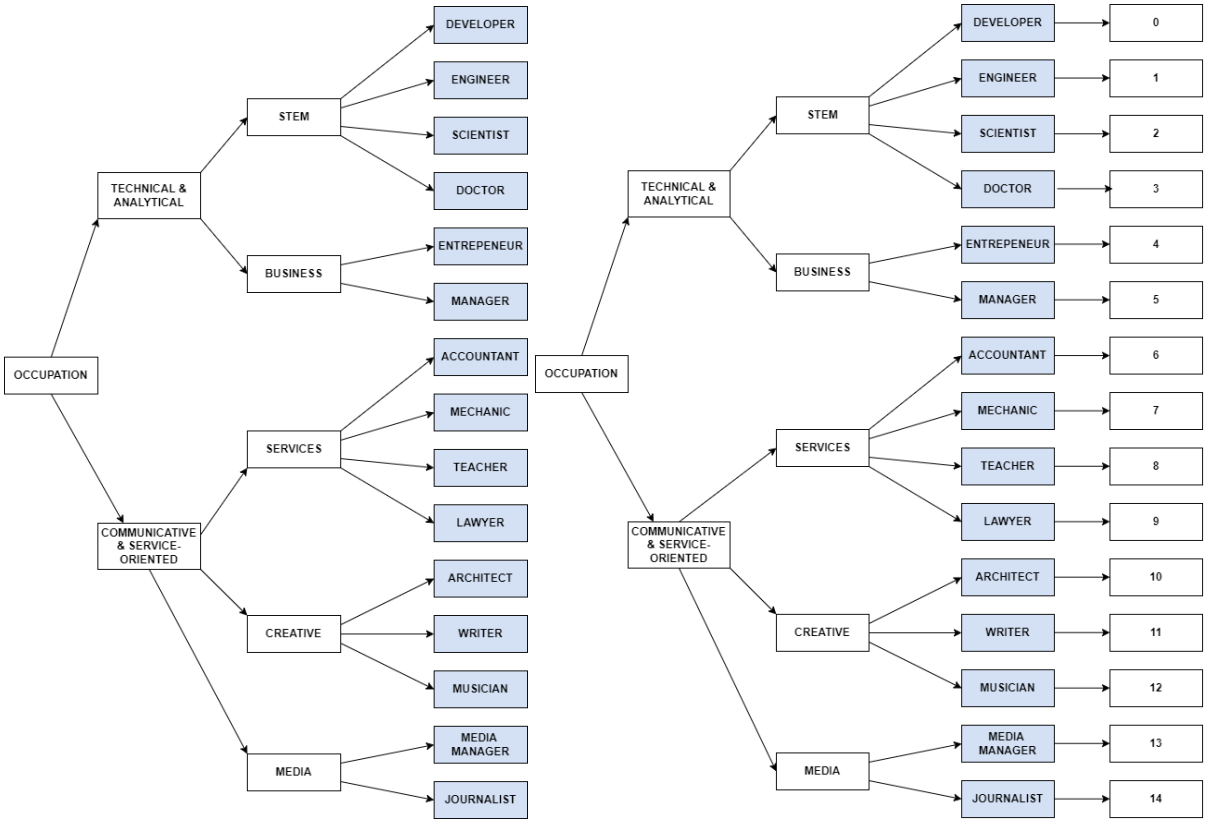
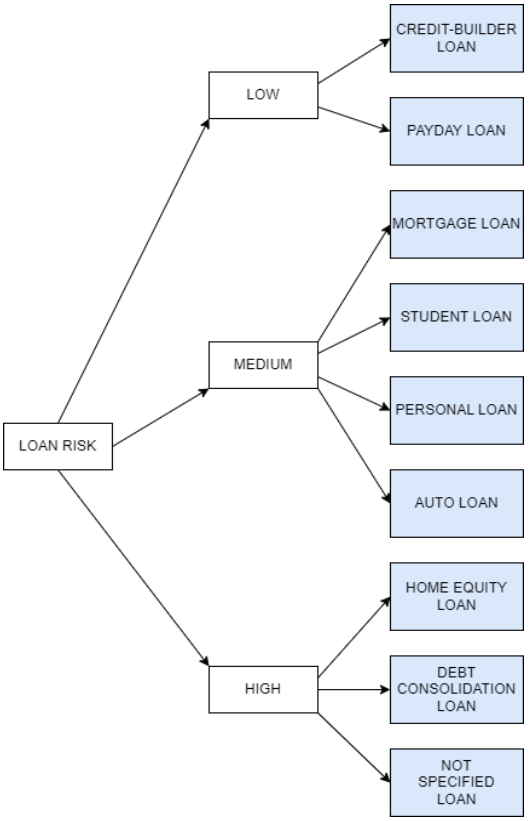


Figure 13.3 Granularity study for dataset 1 (State)

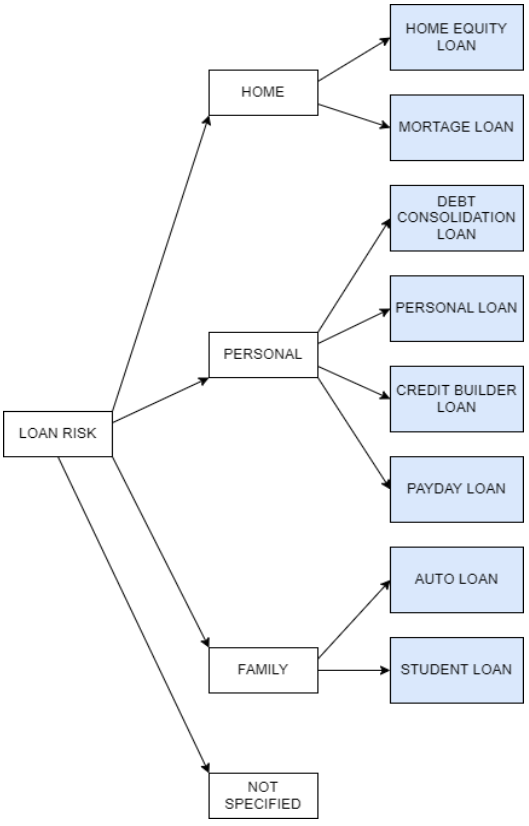
Below are our chosen taxonomies for dataset 2: Occupation, Loan Risk and Loan Type.



Explicar Taxonomia feita e valores para ordinal taxonomy encoding

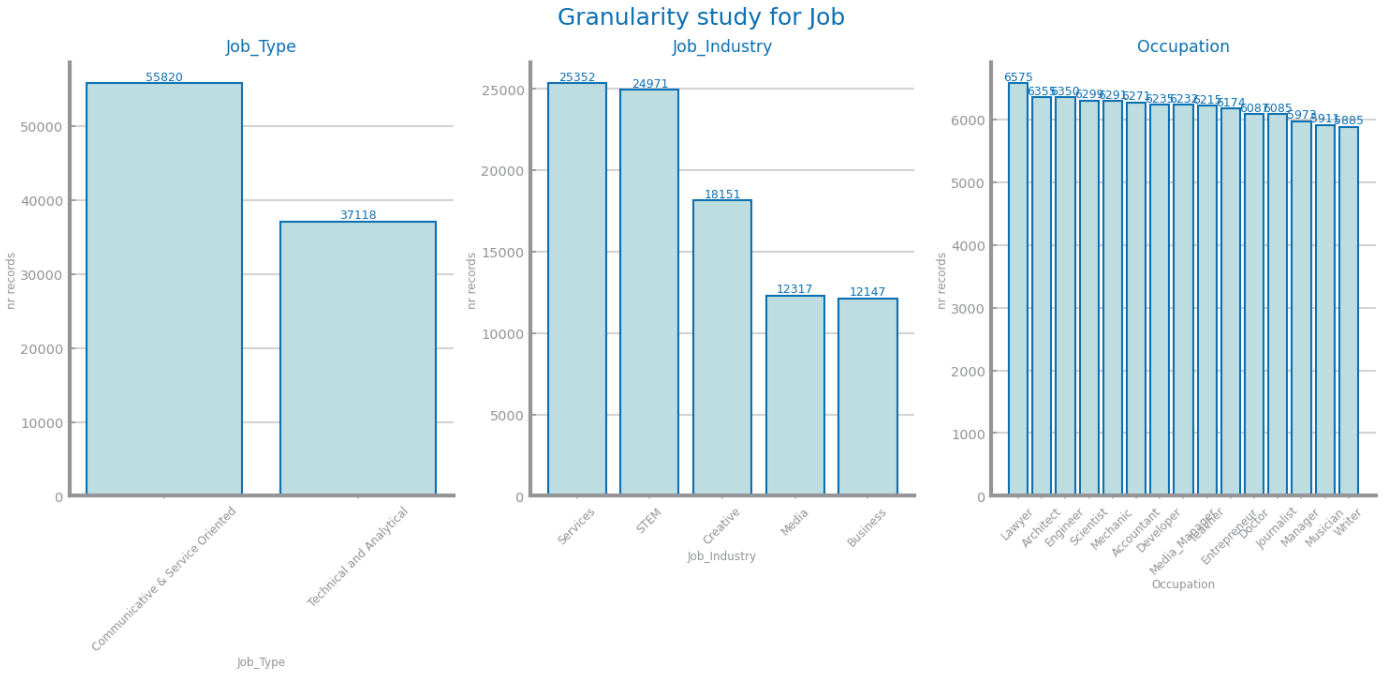


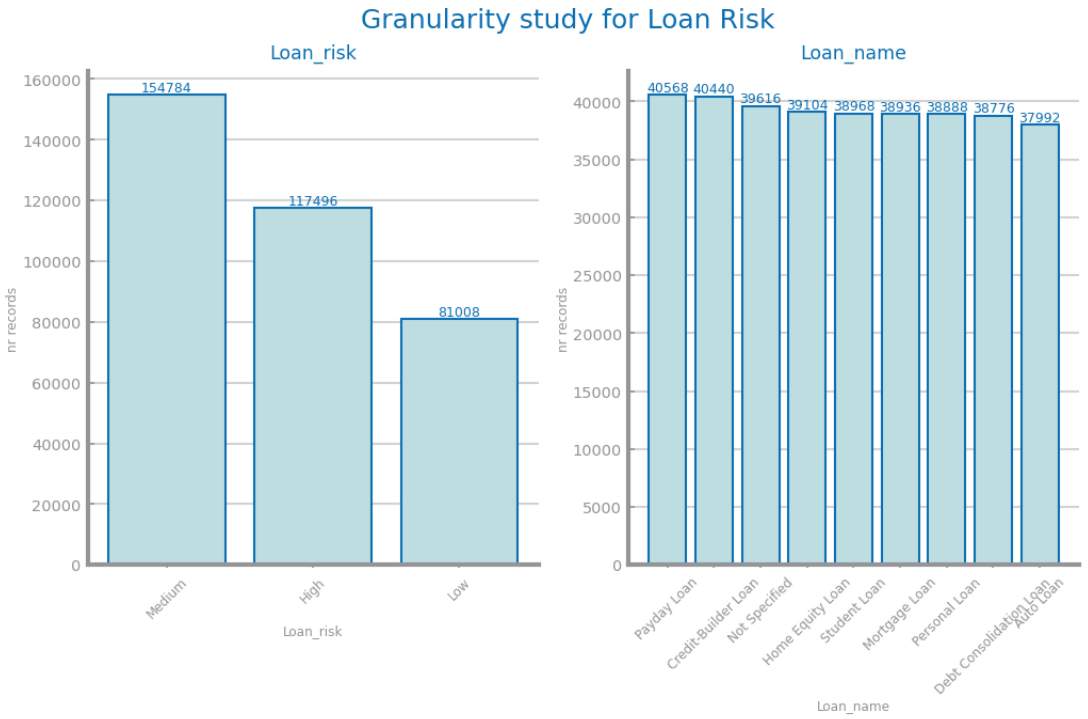
Explicar Taxonomia feita e valores para ordinal taxonomy encoding



Explicar Taxonomia feita e valores para ordinal taxonomy encoding

And the corresponding granularity analysis:


Granularity study for Job
Job_Type
55820
37118
nr records
Communicative & Service Oriented
Technical and Analytical
Job_Type
Job_Industry
25352
24971
18151
12317
12147
Services
STEM
Creative
Media
Business
Job_Industry
Occupation
6575
6355
6350
6298
6291
6271
6235
6232
6215
6174
6087
6085
5973
5911
5885
Lawyer
Architect
Engineer
Scientist
Mechanic
Accountant
Developer
Media_Manager
Banker
Entrepreneur
Doctor
Journalist
Manager
Musician
Writer
Occupation


Granularity study for Loan Risk
Loan_risk
154784
117496
81008
nr records
Medium
High
Low
Loan_risk
Loan_name
40568
40440
39616
39104
38968
38936
38888
38776
37992
Payday Loan
Credit-Builder Loan
Not Specified
Home Equity Loan
Student Loan
Mortgage Loan
Personal Loan
Debt Consolidation Loan
Auto Loan
Loan_name

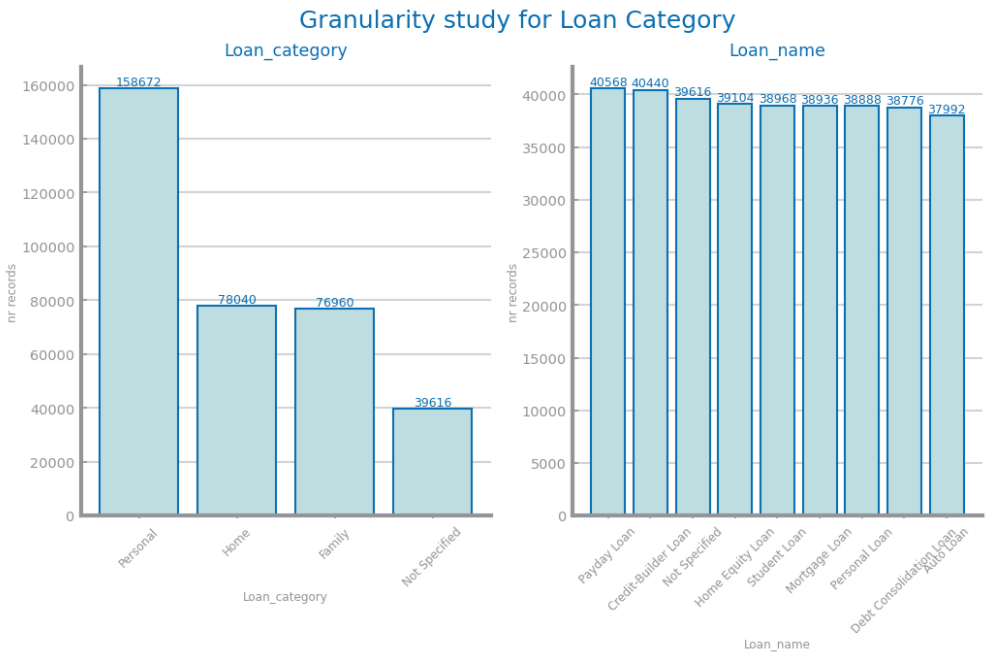


Figure 14 Granularity analysis for dataset 2

Data Sparsity

DS1
Challenges w/ scatter plots w/ many qualitative vars
High *BMI* correlation with *weight & height* (fig15 row5 plot1)
DS2
Data well covered *(**Good Sparsity**)*; issues due w/ outliers & incorrect entries
Many qualitative features
HeatMap shows good correlations *OutstandingDebt & Delay_From_due_date, Credit_History_Age & OutStandingDebt*, *Payment_of_Min_Amount & Credit_History_Age*, *Credit_History_Age & Delay_From_due_date*
Considering *Naive Bayes* assumption of independence, **reduction of features is advised**

Figure 15 Sparsity analysis for dataset 1

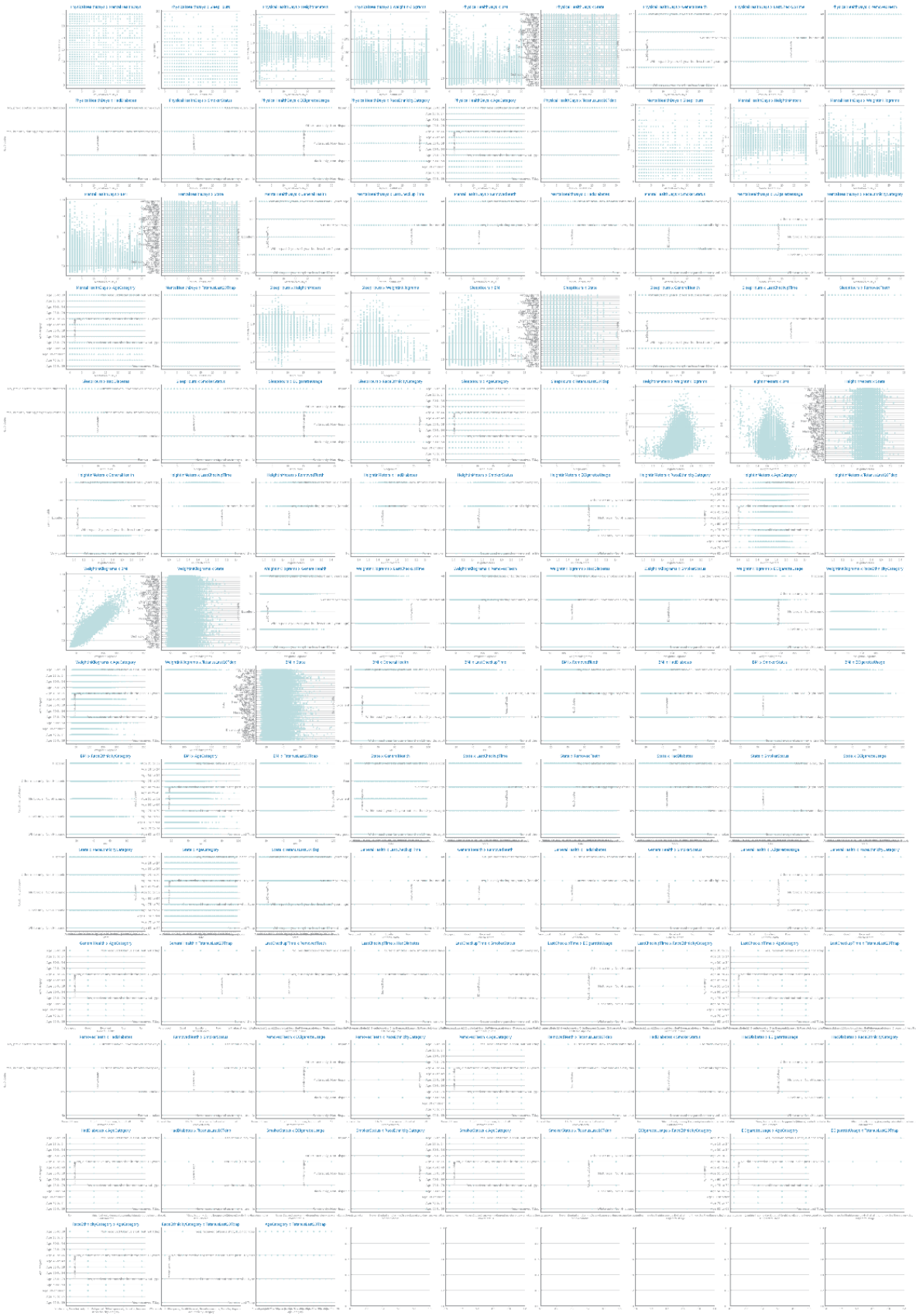


Figure 15.1 Sparsity analysis for dataset 1 without empty plots

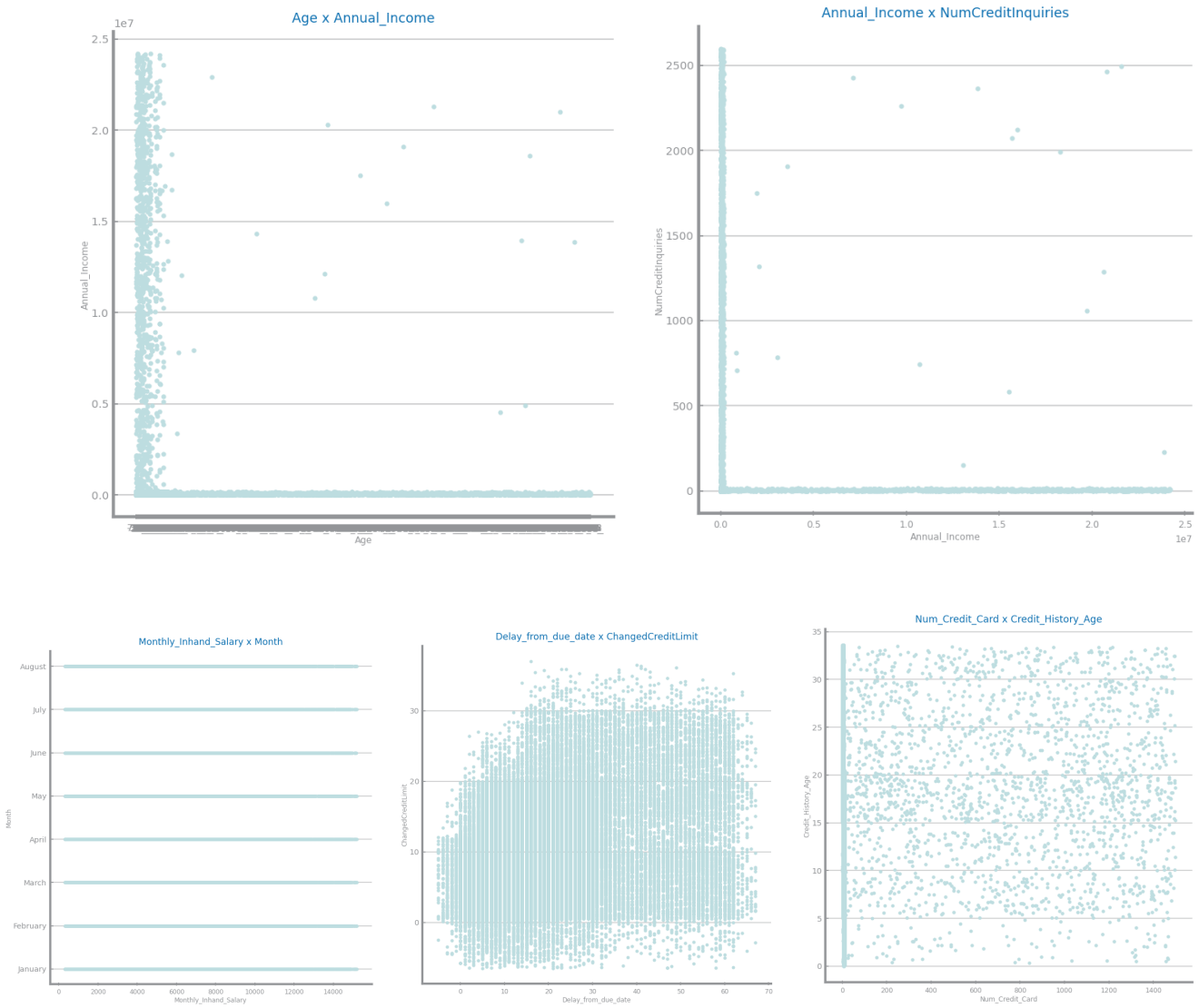


Figure 16 Sparsity analysis for dataset 2

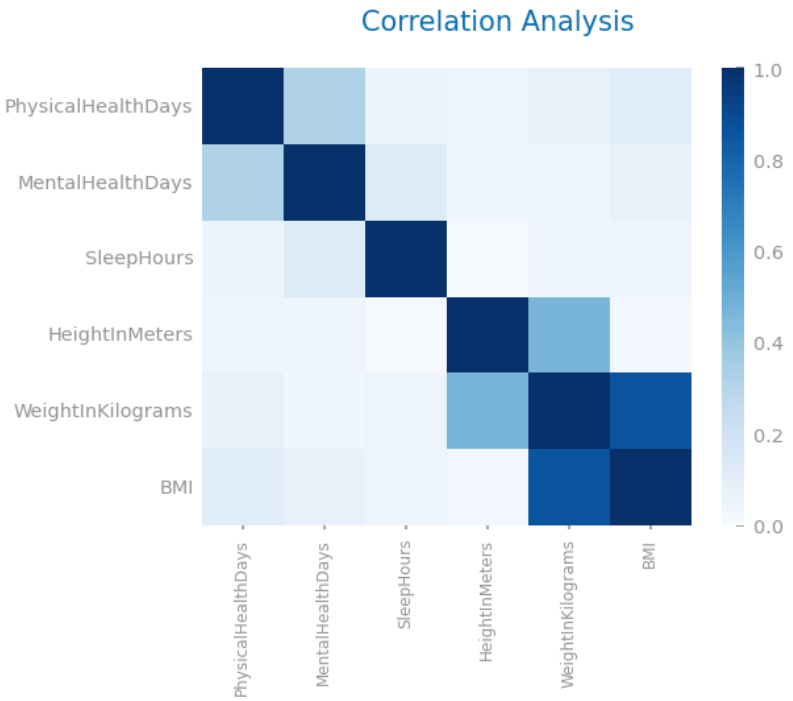


Figure 17 Correlation analysis for dataset 1

Figure 18 Correlation analysis for dataset 2

2 Data Preparation

Variables Encoding

DS1

State: replaced states with latitude and longitude values.

Ordinal Linear: GeneralHealth, LastCheckupTime, RemovedTeeth, HadDiabetes, SmokerStatus, ECigaretteUsage, RaceEthnicityCategory, AgeCategory, TetanusLast10Tdap, AgeGroup

Ordinal Linear (from taxonomy)**:** AgeCategory, Regions

DS2

ID used as **PK**

Drop *identifying columns (check & clean)* - Customer_ID, SSN, Name

Ordinal Linear Credit_Score *(binary),* CreditMix, Payment_of_Min_Amount

Ordinal Taxonomy Payment_Behaviour, Occupation *(Granularity Section)*

Transform to numeric Credit_History_Age

Cyclic Month, Credit_History_Age

Other Type_of_Loan - Mix One-hot & Ordinal Taxonomy, Each *type* gets a column. Counter increment according to *Taxonomy* rules specified in *Granularity Section*, aiding in separate frequency and trait analysis.

Missing Value Imputation

DS1- Continue w/ knn mean

Very small changes but we used knn mean due to better results

DS2 - Continue w/ Approach 1

Invalid ‘Age’, ‘Num_Bak_Accounts’, ‘NumofLoan’ values set as MV

Fig3.1 shows most MV under 15%, except ‘CreditMix’

Alternatives:

1º Eliminate columns above certain *Threshold*

- Columns > 15%, Rows > 16%

- Fill MV *Mean Numerics*, *Most Freq Symbolic*

2º *Fill MV Median & Most Freq*

3º Don’t eliminate col/row *KNN Imputer*

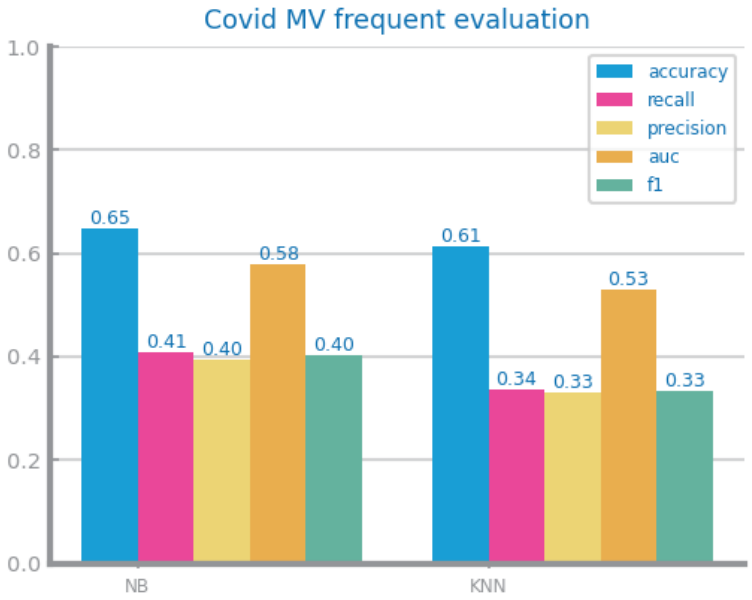


Figure 19.1 Missing values imputation results with the most frequent approach for dataset 1

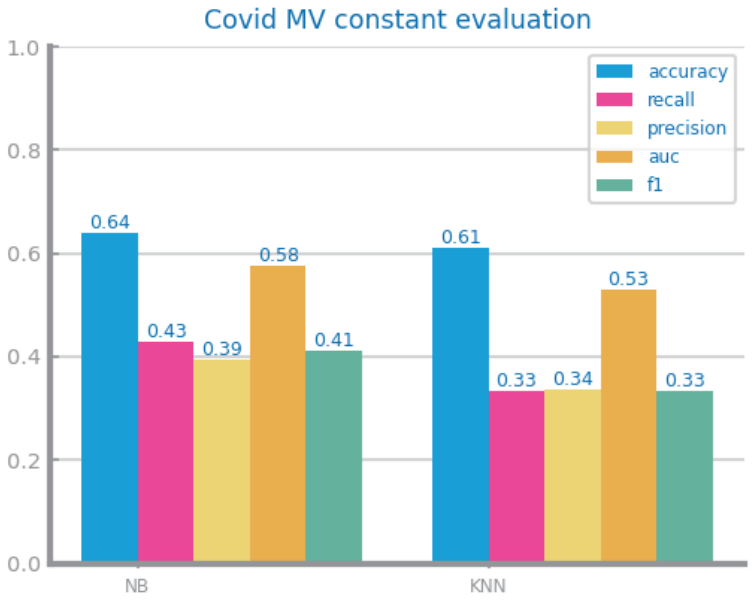


Figure 19.2 Missing values imputation results with the constant approach for dataset 1

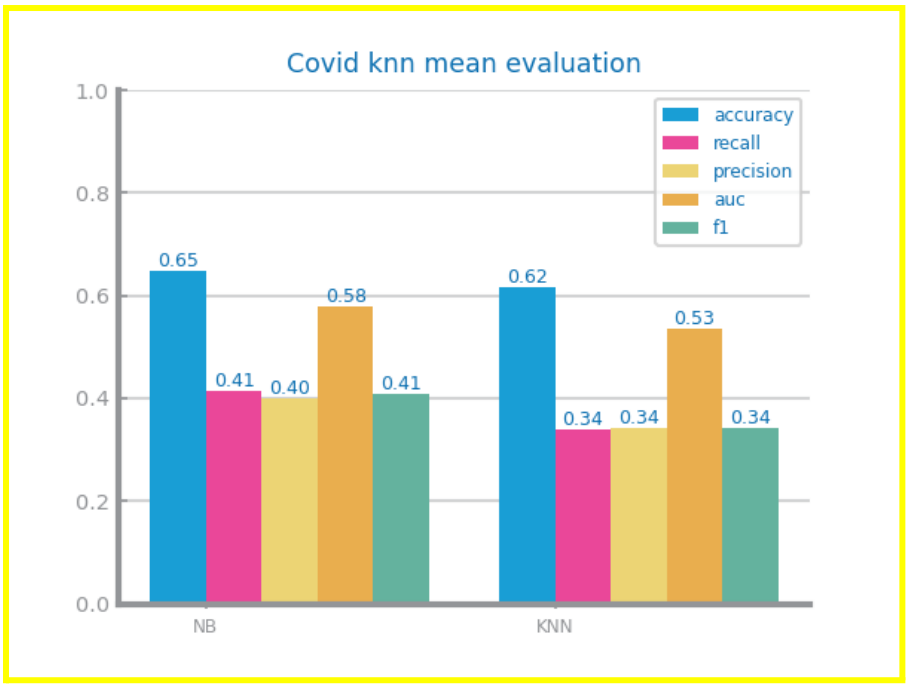


Figure 19.3 Missing values imputation results with KNN mean approach for dataset 1

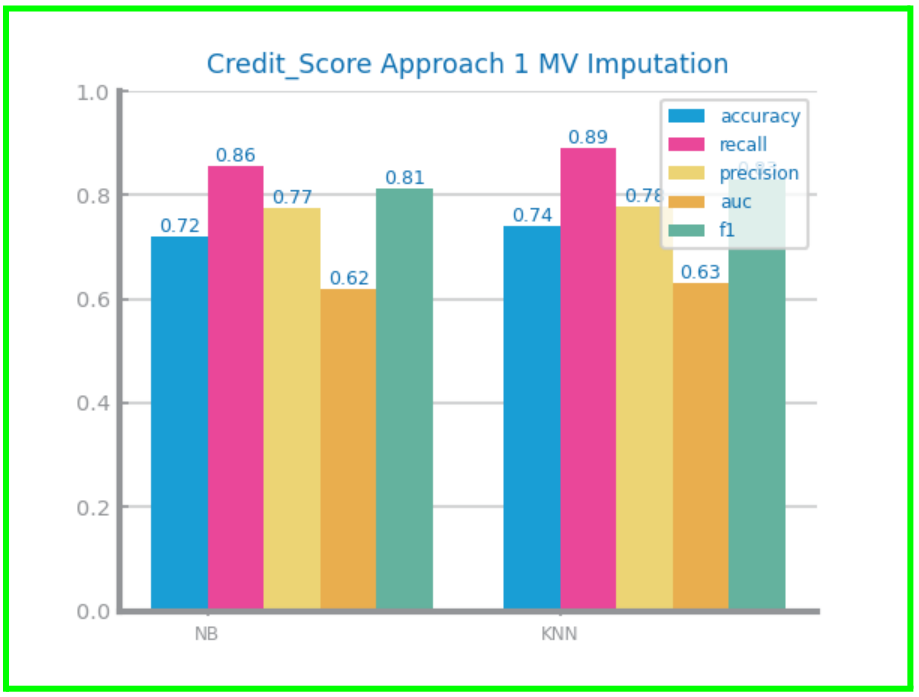


Figure 20 Missing values imputation results with approach 1 for dataset 2

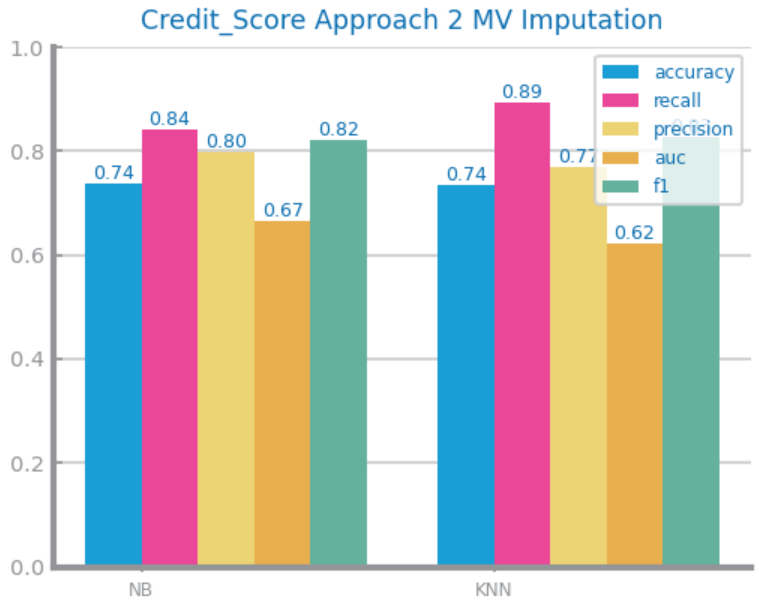


Figure 20.1 Missing values imputation results with approach 2 for dataset 2

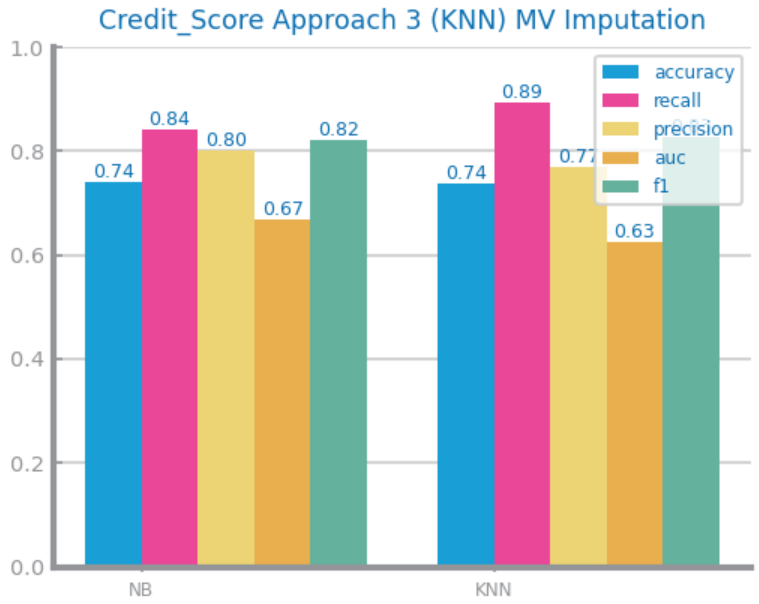


Figure 20.2 Missing values imputation results with approach 3 for dataset 2

Outliers Treatment

DS1
drop outliers (dropped 168324 records) was the chosen one because of the better results. The best of the replaces was the mean(fig 21.2)
DS2 - <u>Continue w/ Approach 2 (mode)</u>
Alternatives *(values and other statistics are adjusted depending on the **strategy**)*:
1º Drop - dropped out **13543** records. *too many*

2º Replaced w/ fixed value 3º Truncate

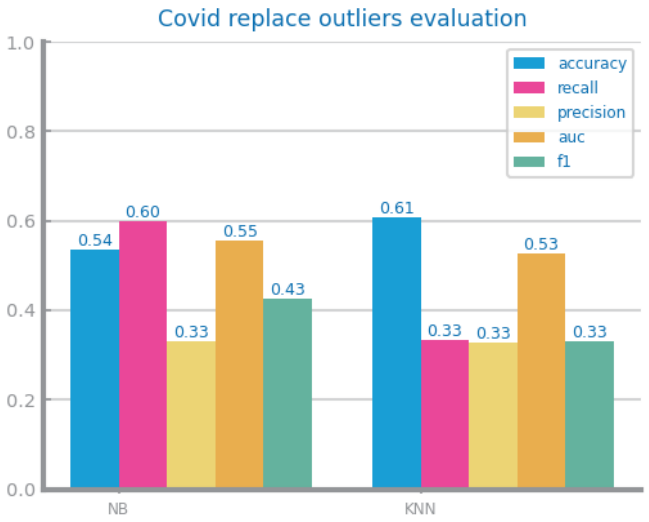


Figure 21.1 Outliers imputation results with replace with median approach for dataset 1

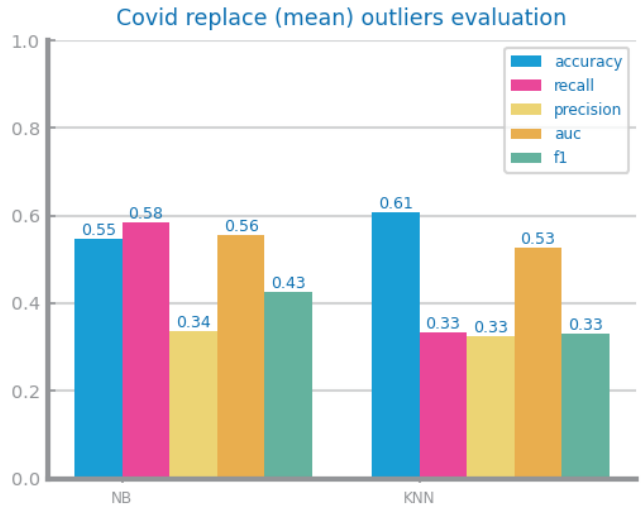


Figure 21.2 Outliers imputation results with replace with mean approach for dataset 1

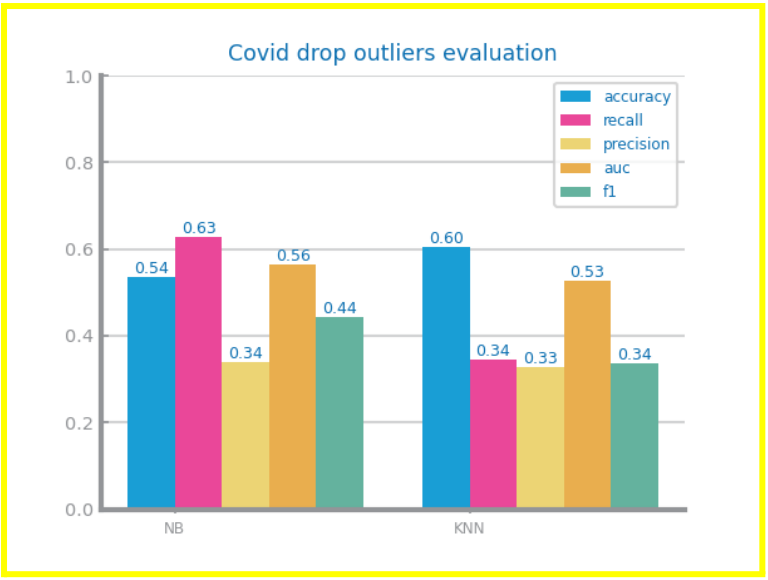


Figure 21.2 Outliers imputation results with drop approach for dataset 1

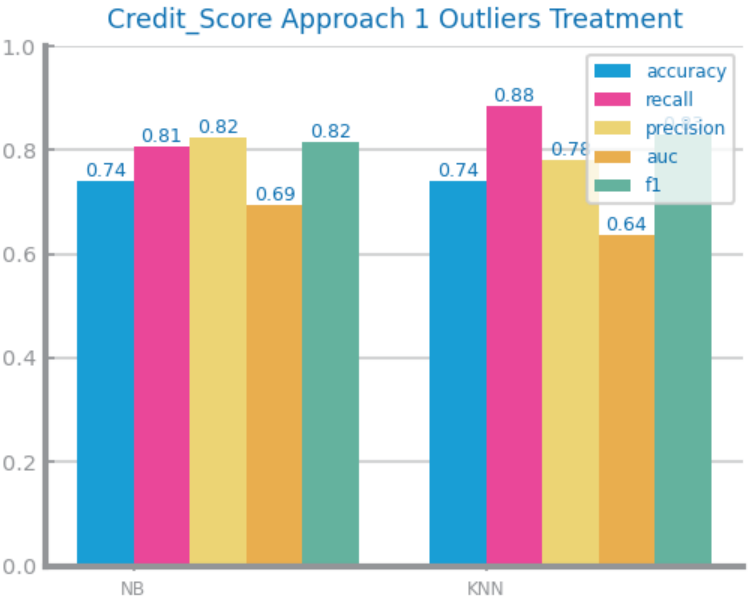
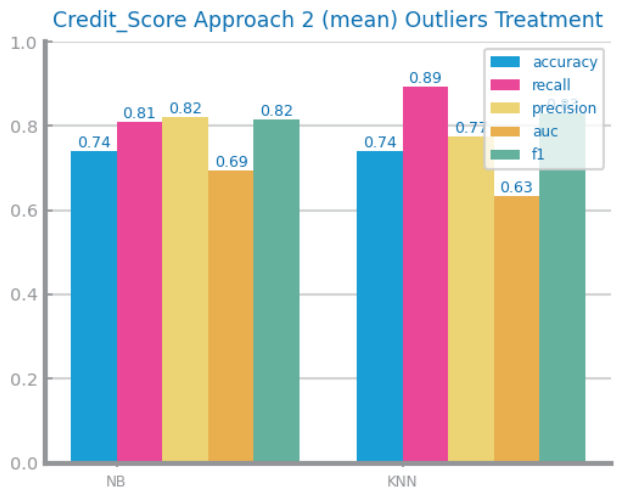
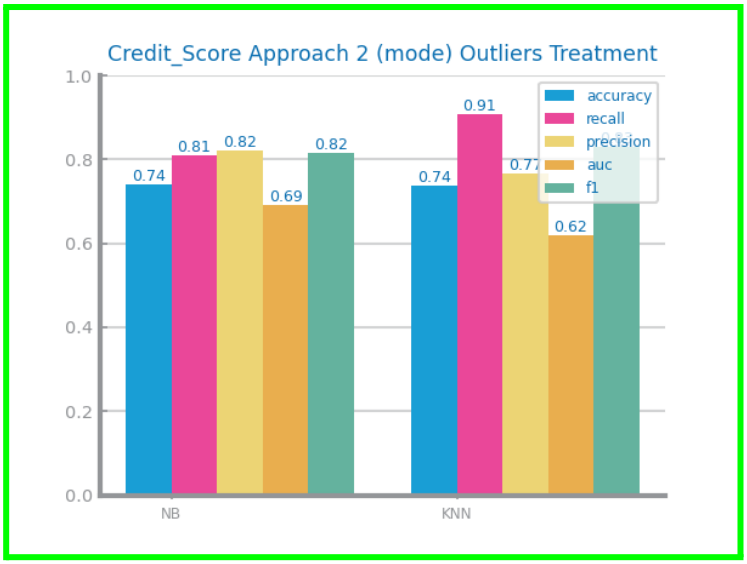


Figure 22 Outliers imputation results with approach 1 (DROP) for dataset 2





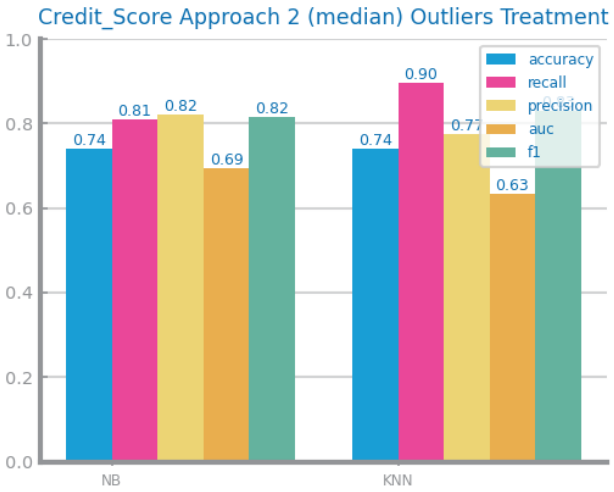


Figure 22.1 Outliers imputation results with approach 2 (FILL) for dataset 2

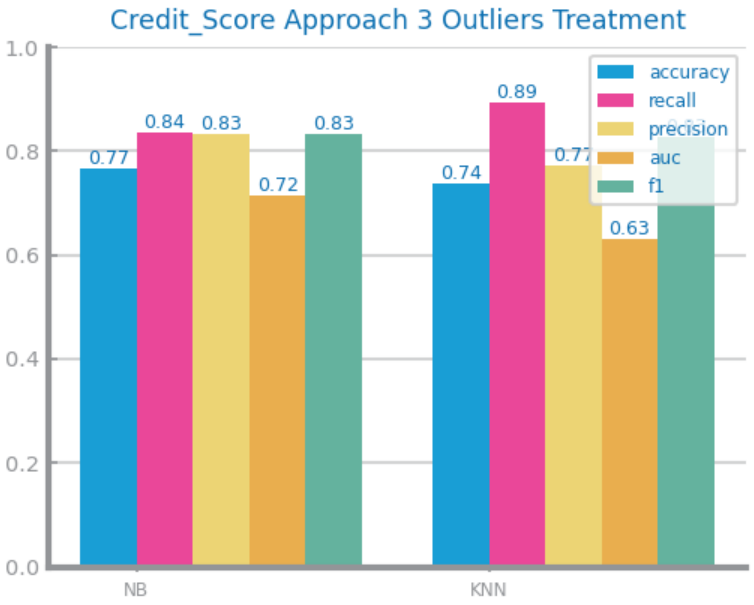


Figure 22.2 Outliers imputation results with approach 3 (TRUNCATE) for dataset 2

Scaling

DS1

Results on NB should be identical, discrepancy prob due to numbers being too small & data structures not prepared

Analyzing knn we opted by not using scaling

DS2 - Continue w/ Approach 1

Outliers far from the main clusters

Alternatives:

1º Standard Scaler - for *Gaussian*

2º MinMax - *used for Neural Networks*; reduce the impact of outliers

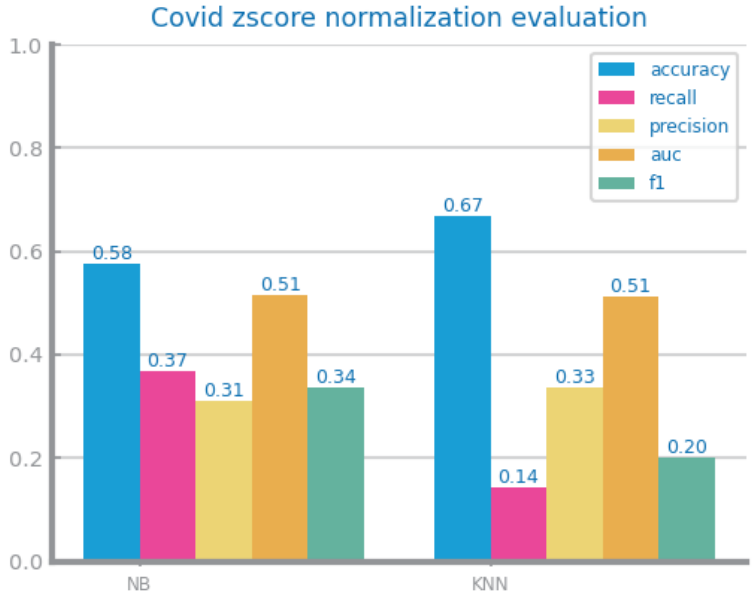


Figure 23.1 Scaling results with (Z-SCORE) normalization approach for dataset 1

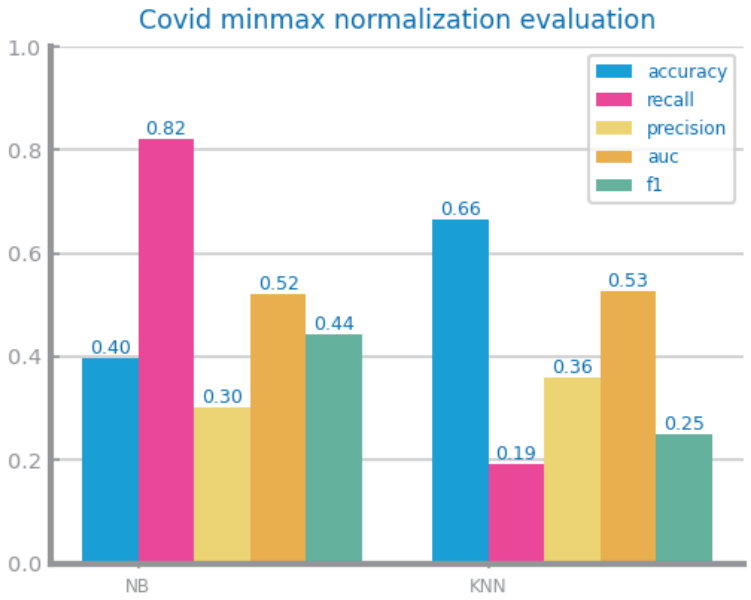


Figure 23.2 Scaling results with (MINMAX) normalization approach for dataset 1

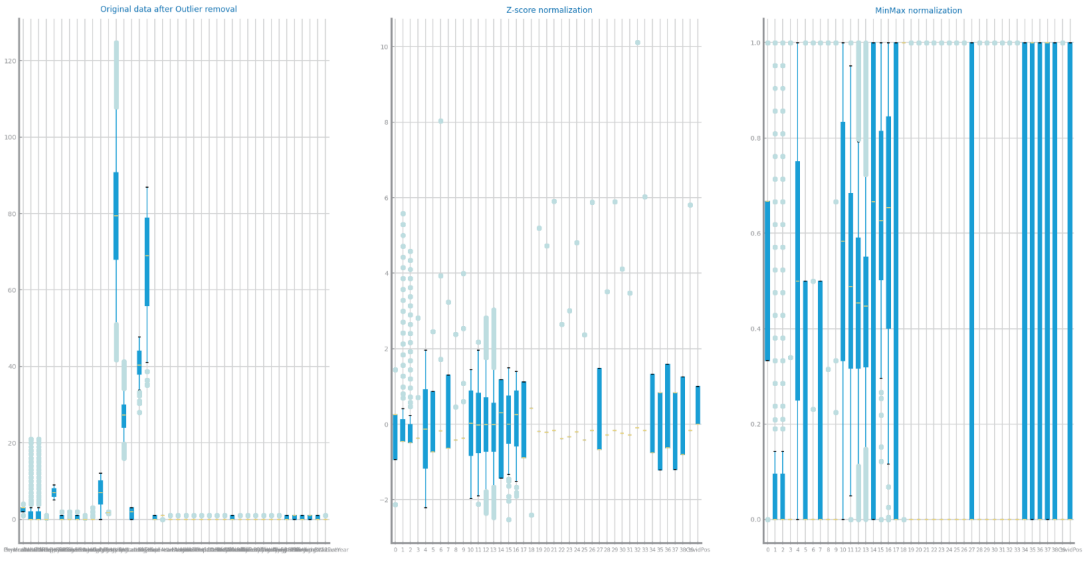


Figure 23.3 Scaling Boxplots for dataset 1

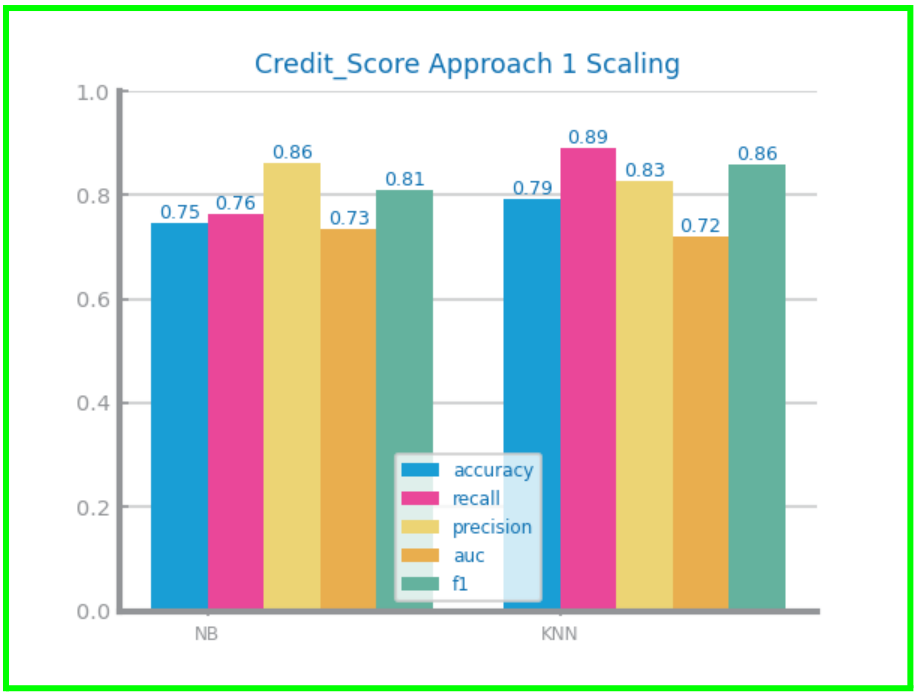


Figure 24 Scaling results with approach 1 (Z-SCORE) for dataset 2

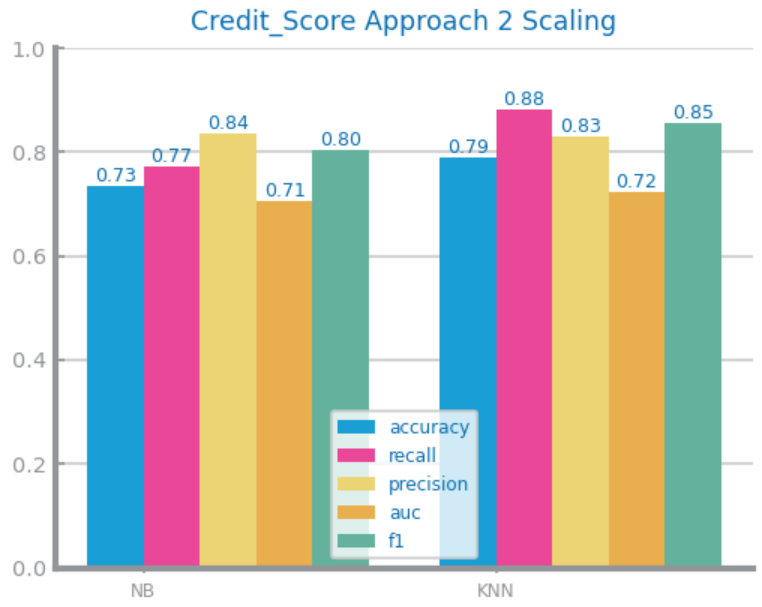


Figure 24.1 Scaling results with approach 2 (MINMAX) for dataset 2

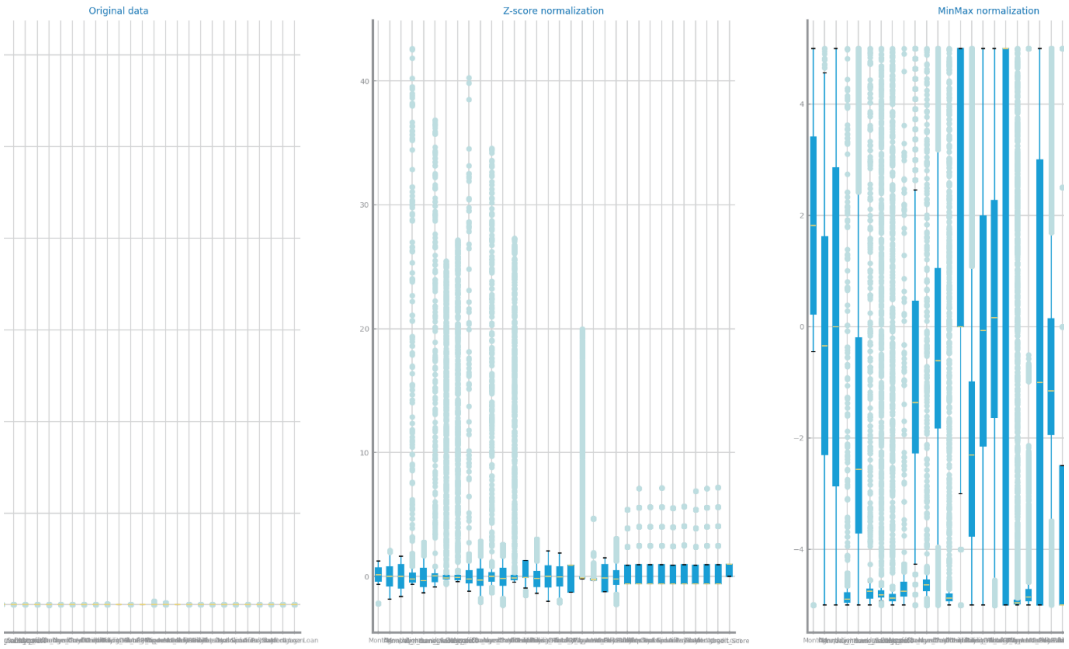


Figure 24.2 Scaling Boxplots for dataset 2

Balancing

BALANCE TRAINING SET ONLY

DS1- Continue w/ SMOTE

Big imbalance (fig25)

over&under- recall is better because minority class has more importance

SMOTE-best accuracy due to more diverse samples in minority class

DS2 - Continue w/ Approach 2

Fig12 reveals significant class imbalance, causing models to neglect minority class.

Alternatives:

1º Under - Loses major class info

2º Over - Viable, but larger & costly dataset

3º SMOTE - creates synthetic minority instance for better generalization

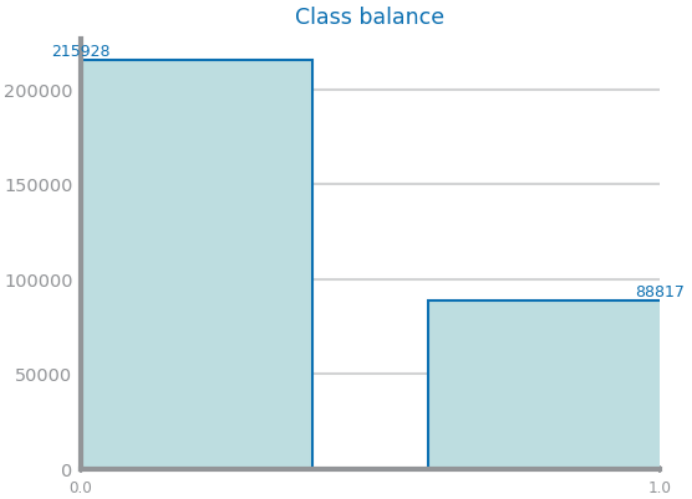


Figure 25 Class distribution before balancing for dataset 1

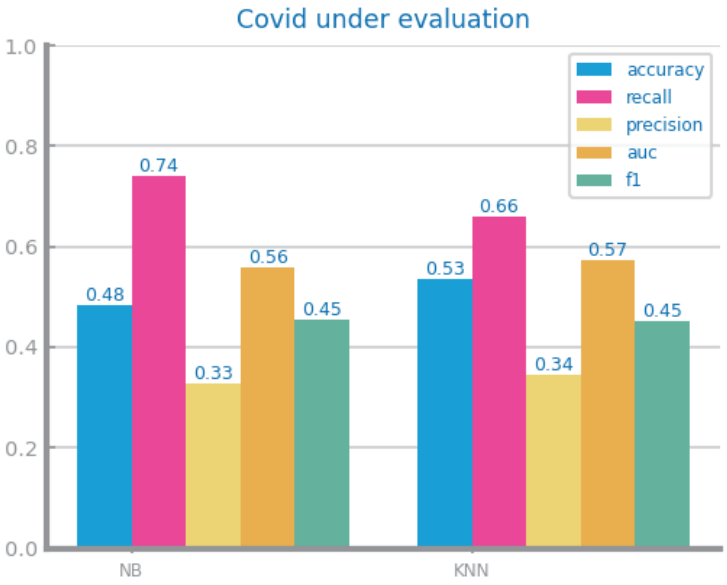


Figure 25.1 Balancing results with under approach for dataset 1

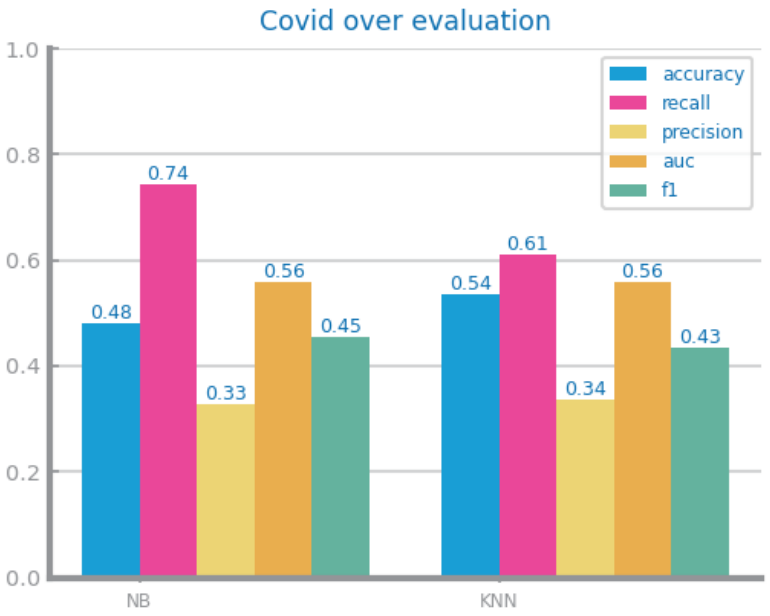


Figure 25.2 Balancing results with over approach for dataset 1

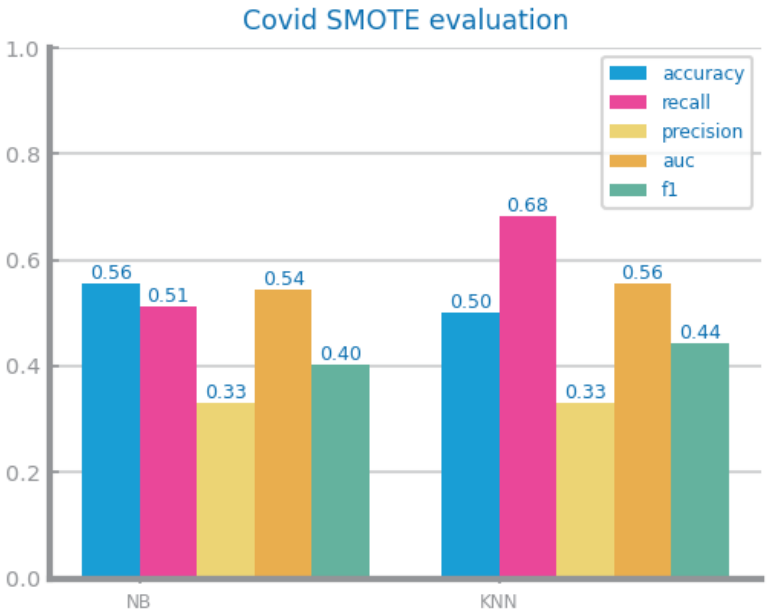


Figure 25.2 Balancing results with SMOTE approach for dataset 1

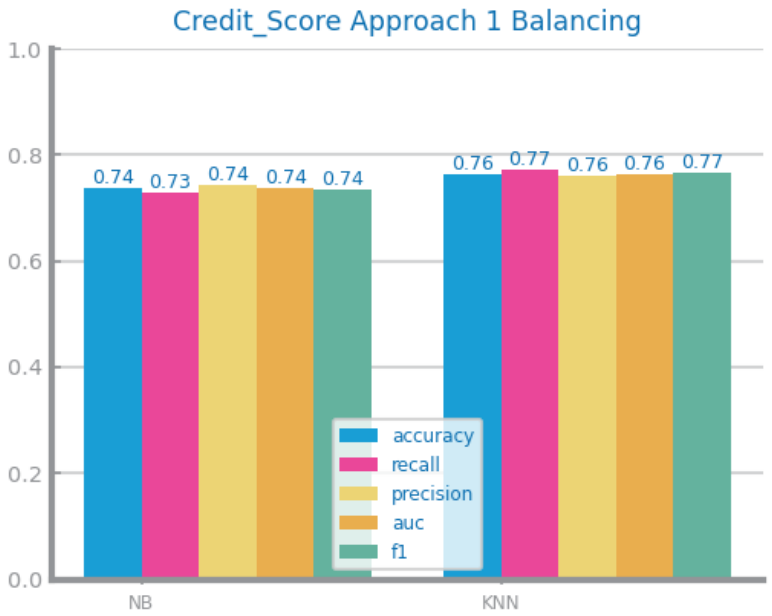


Figure 26 Balancing results with approach 1 (UNDER) for dataset 2

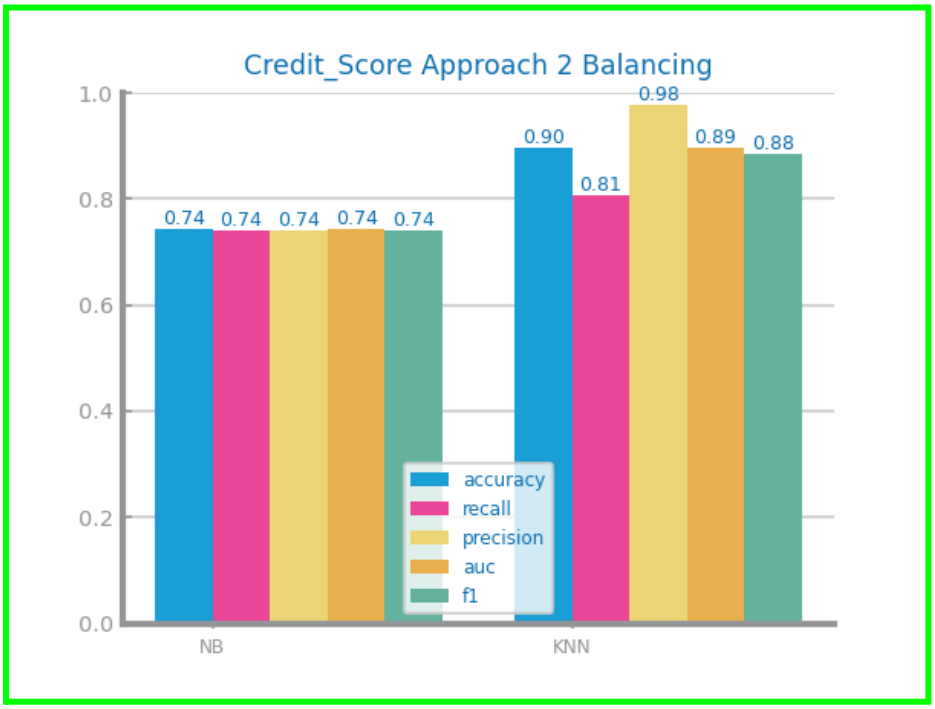


Figure 26.1 Balancing results with approach 2 (OVER) for dataset 2

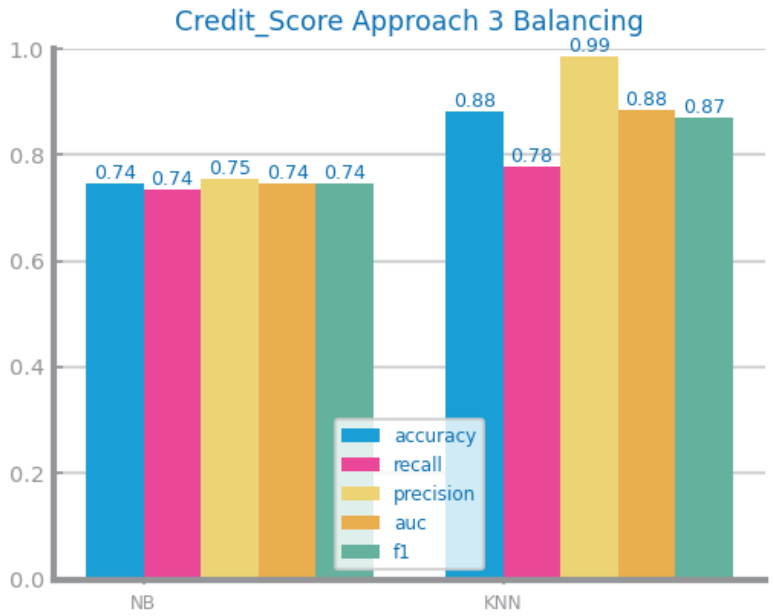


Figure 26.2 Balancing results with approach 3 (SMOTE) for dataset 2

Feature Selection

DS1

The redundant feature selection improved the KNN and didn't have a significant impact on the NB, while the relevant approach only dropped the accuracy score so we proceeded with the redundant selection approach on the dataset.

DS2 - Continue w/ Approach 2

Applied after Balancing

Alternatives:

1st Select relevant variables, inconclusive

2nd Drop redundant variables, good

3rd Recursive Feature Elimination, best approach, dropped 6 columns

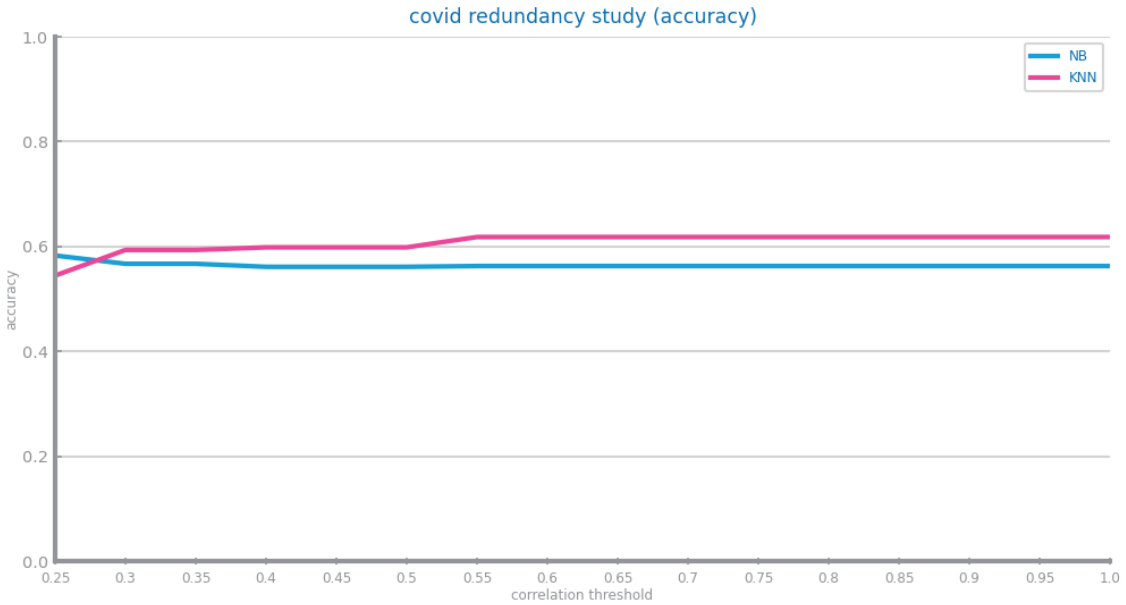


Figure 27 Feature selection of redundant variables results with different parameters for dataset 1

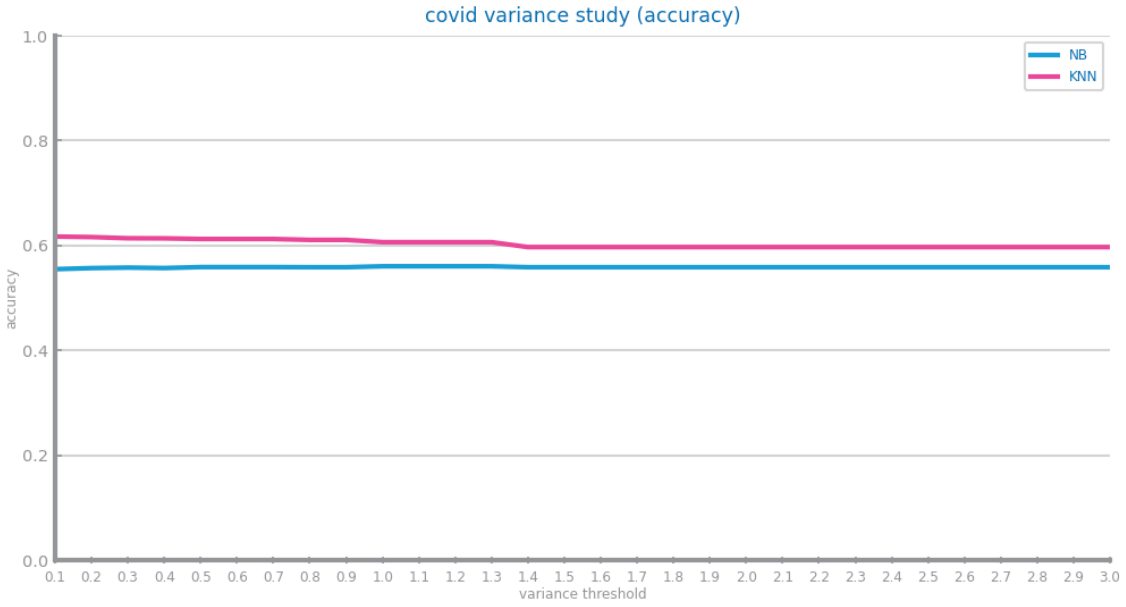
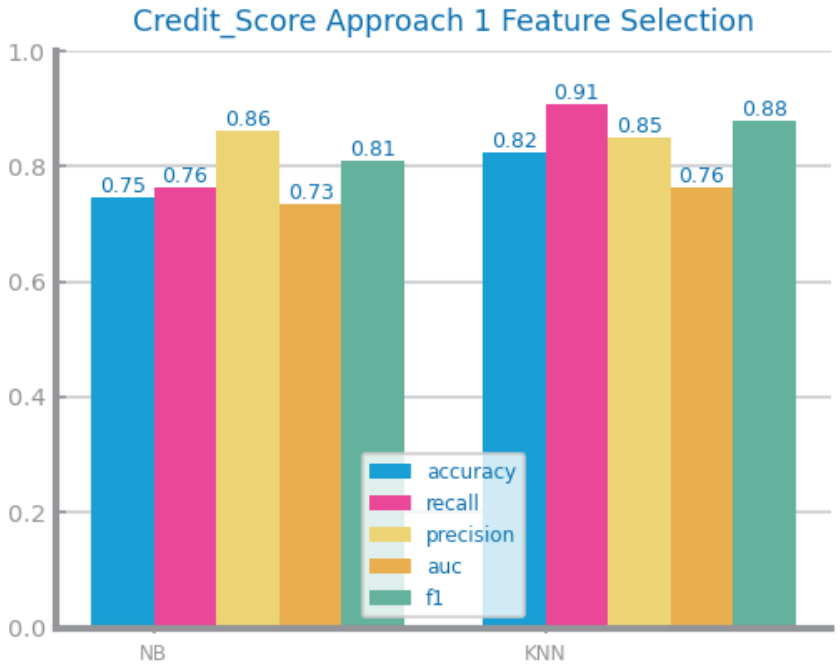
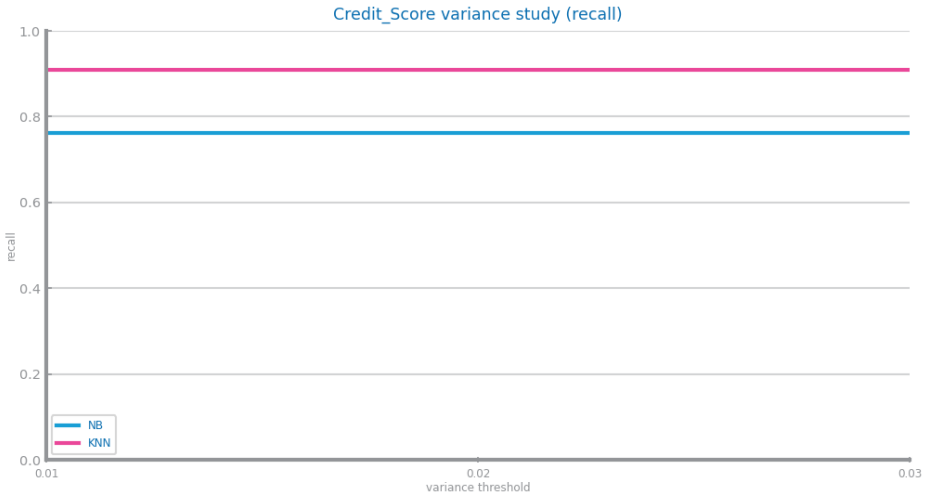


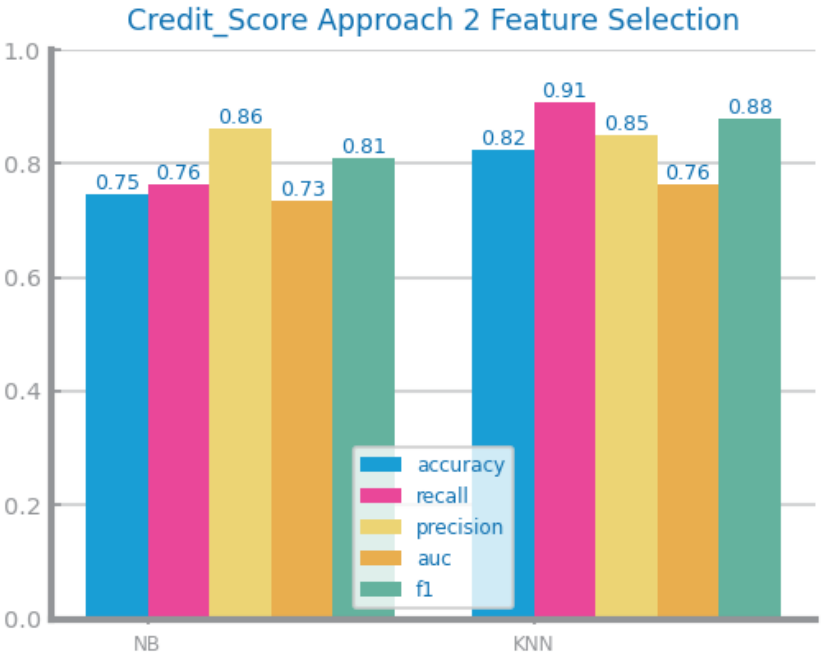
Figure 27 Feature selection of relevant variables results with different parameters for dataset 1 (variance study)

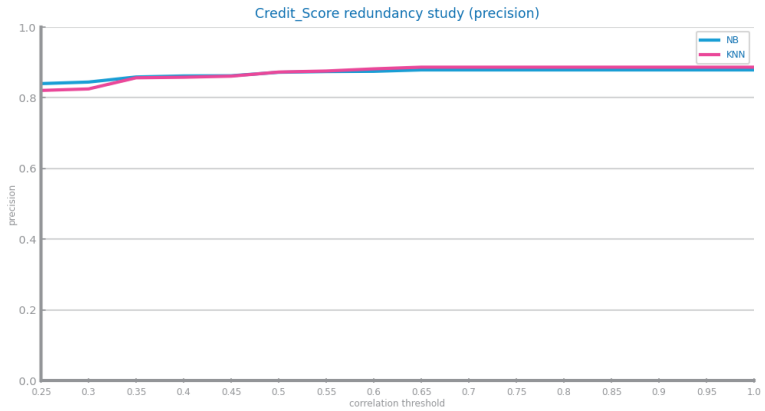


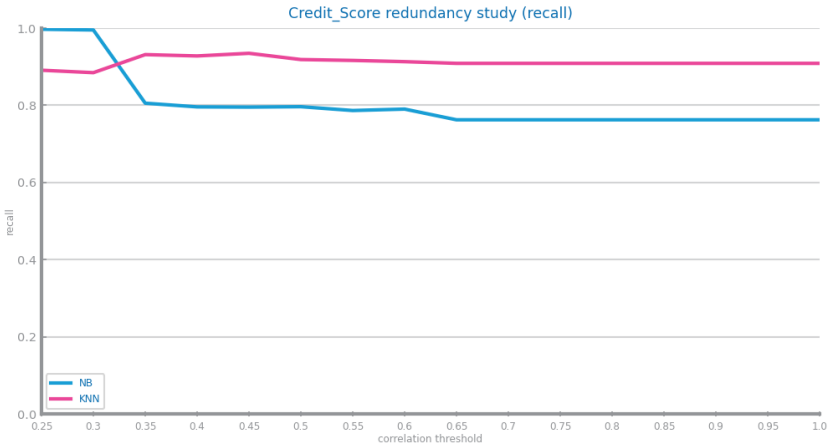


Figures 27 Feature selection of relevant variables results with different parameters for dataset 2 (variance study)

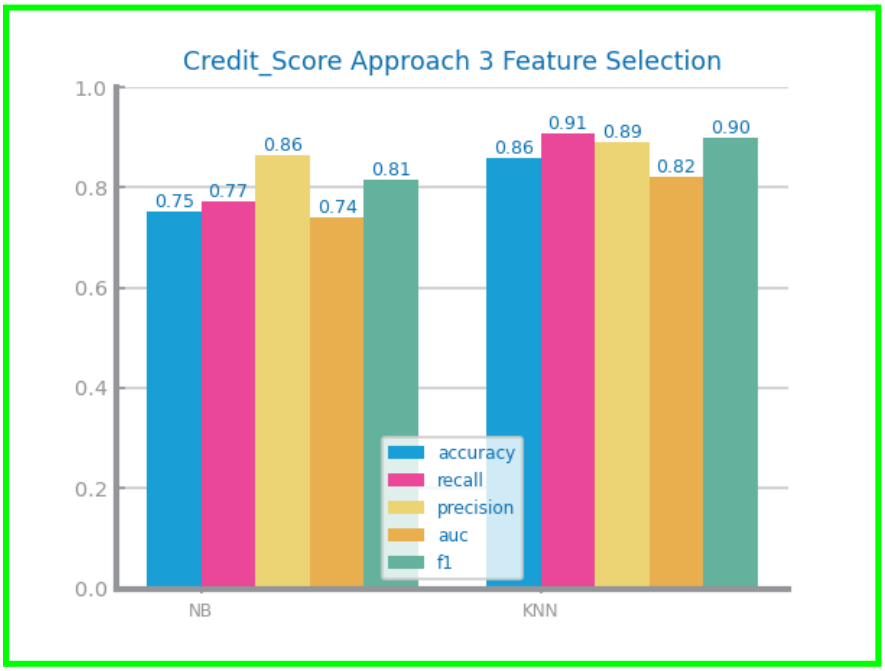
(the results are inconclusive because all variables have variance of 1 (z-scaling scaling method)







Figures 28 Feature selection of redundant variables results with different parameters for dataset 2



Additional Feature Generation (optional)

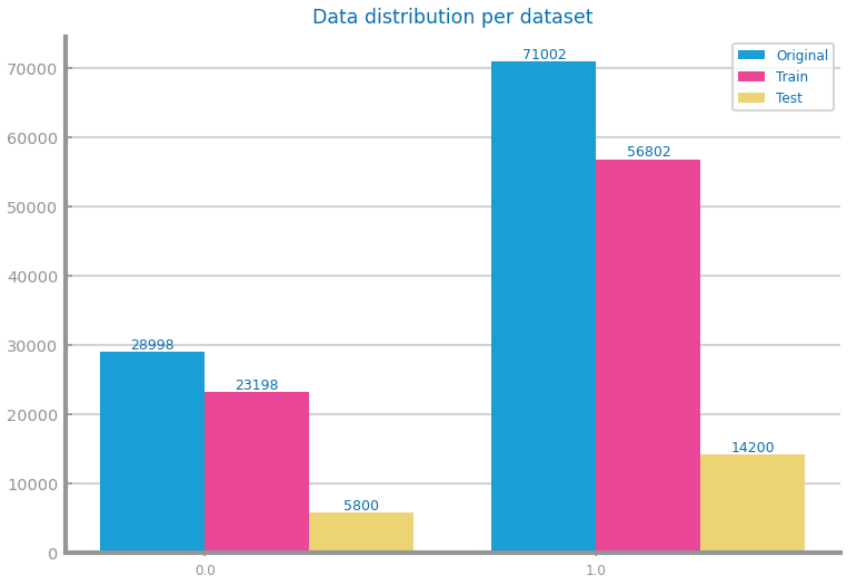
DS	Feature(s)	Description	Formula	Modelling Impact
2	“Name”_Loan	Loan Type Count	n * a (0 <= n <= max_n)	Loan diversity insight

Figure 31 Feature generation results for dataset 1

Figure 32 Feature generation results for dataset 2

3 Models' Evaluation

DS1
Hold-out strategy (same data used to compare parameters and models)
Prioritize accuracy (no class is more important)
DS2
Train strat Hold-out for speed, lower cost, size
Balance *FP* & *FN* but prioritize **Precision** *(Willing to accept FN in order to reduce FP)*
Maximize **Precision** & **Recall**, but try to prioritize **Precision**.
(Cost of a **bad loan** *FP is very high*, so minimize risk of default, even if it means missing out a good customer)



Naïve Bayes

DS1
Multinomial & bernoulli similar & better for accuracy (gaussian more for continuous data)
not good performance: auc=0.57 (similar to random)

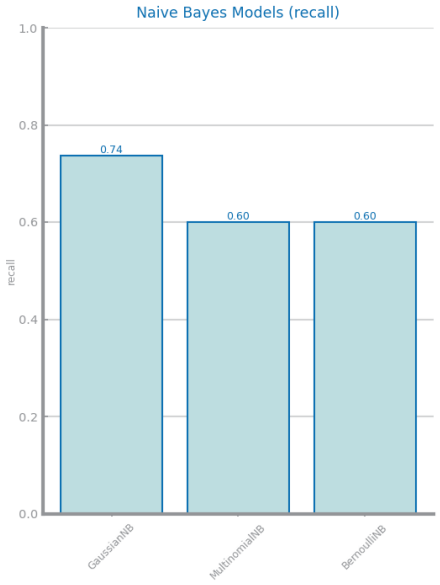
DS2

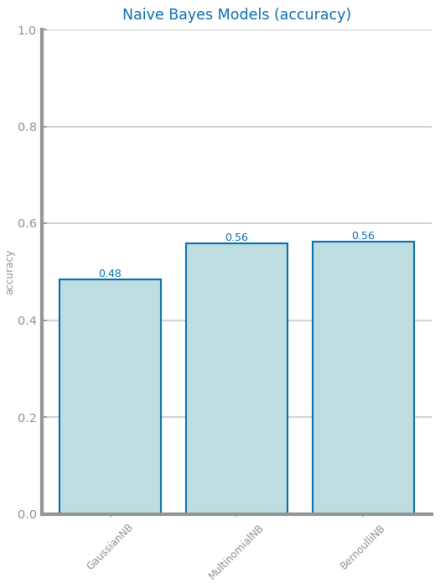
Comparison baseline

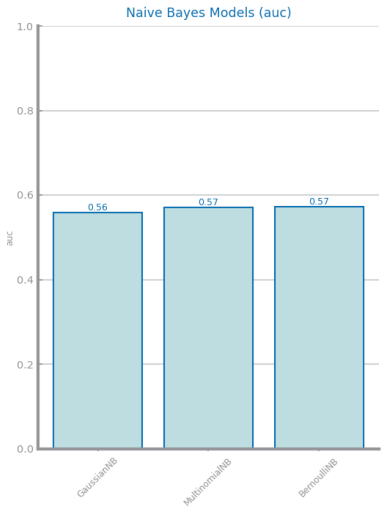
Bernoulli best

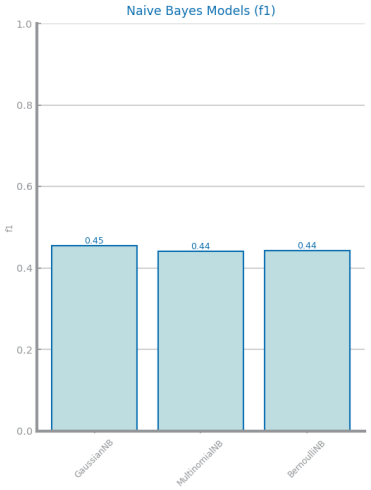
Naive Bayes ignores correlation between variables presented in the correlation matrix

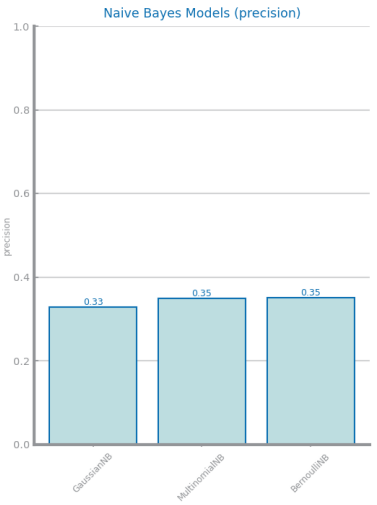
Bad due to simplicity & complex nature of data











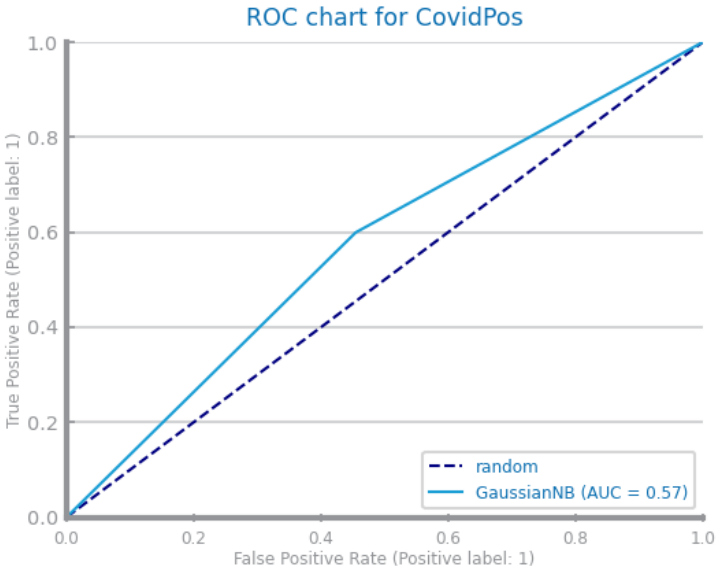
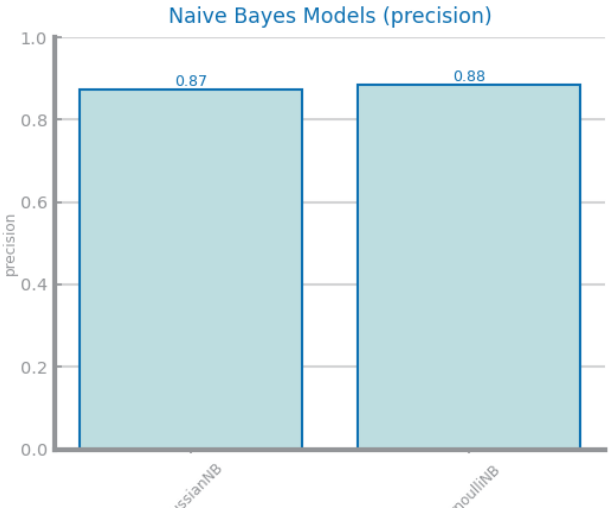
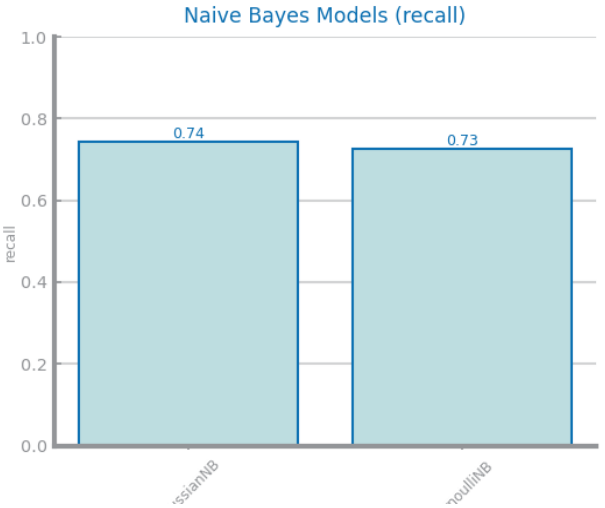


Figure 33 Naïve Bayes alternatives comparison for dataset 1





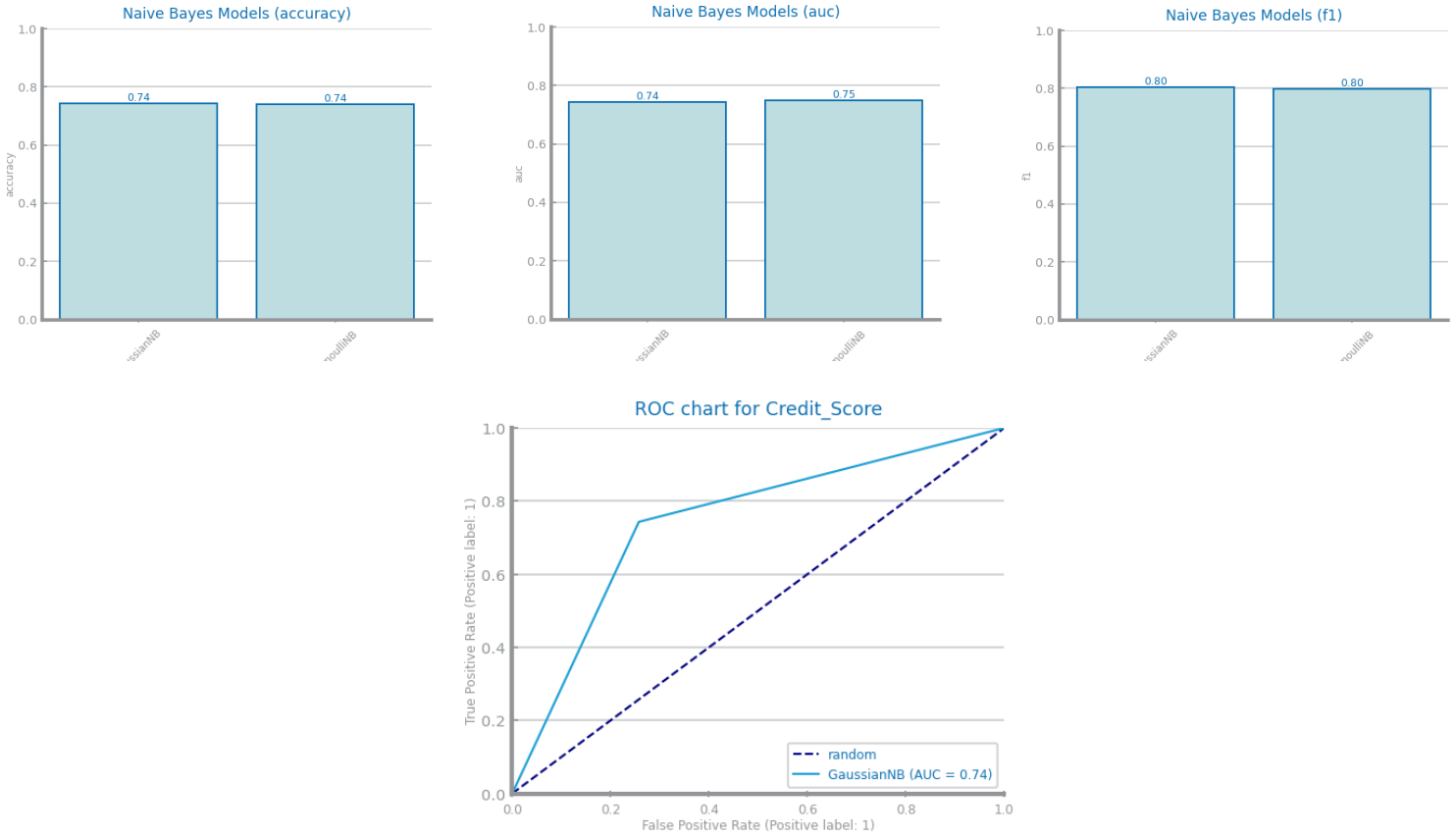


Figure 34 Naïve Bayes alternative comparison for dataset 2

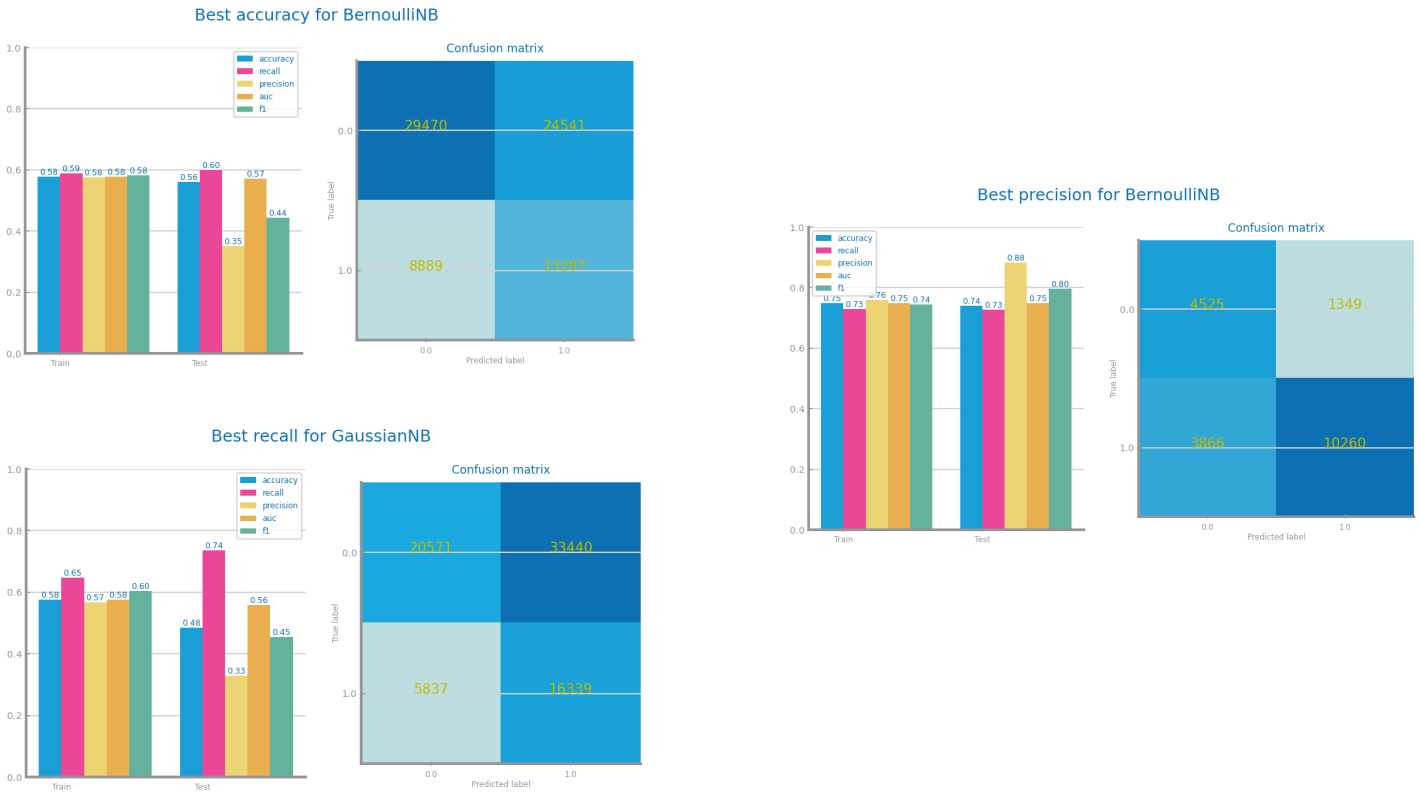


Figure 35 Naïve Bayes best model results for dataset 1 (left) and dataset 2 (right)

KNN

DS1
Manhattan & euclidean - best parameters
There is overfitting w/ k=1, however it was the best considered model
DS2
Test K values from 1 to 1000 (larger range)
KNN best w/ k=5
Manhattan best measure for **all** metrics
For k=1, there is overfitting - train and test have different trends when maximizing *Precision*;
Model conservative about predicting the positive class; more balanced and generalizable, less likely to overfit
Small neighbors number, so model could be over-specialized

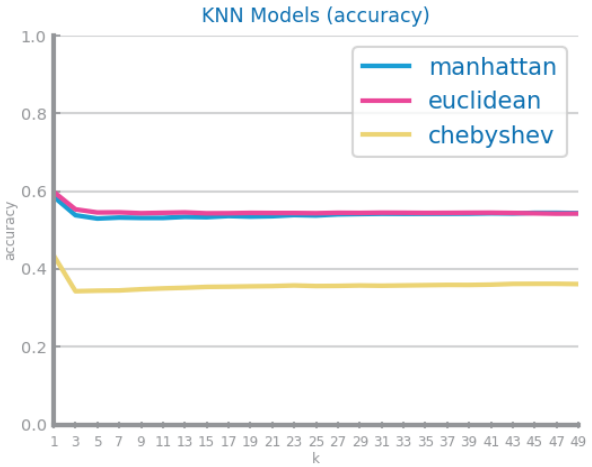


Figure 36 KNN different parameterisations comparison for dataset 1

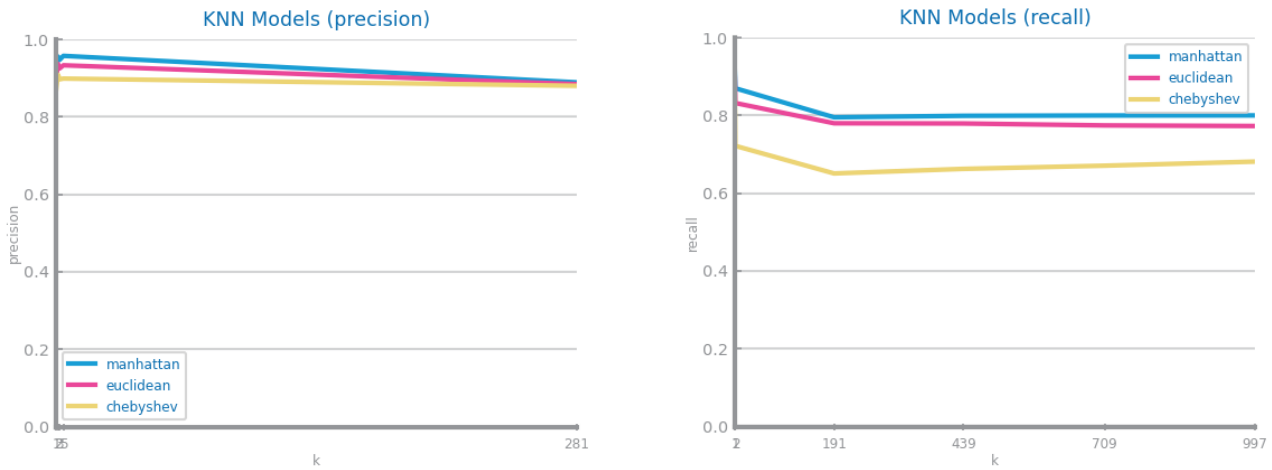
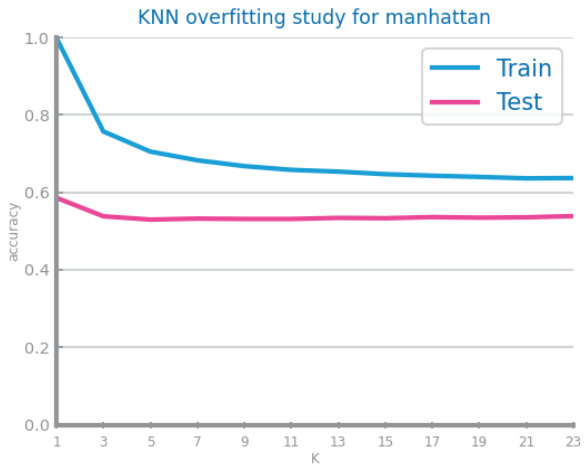
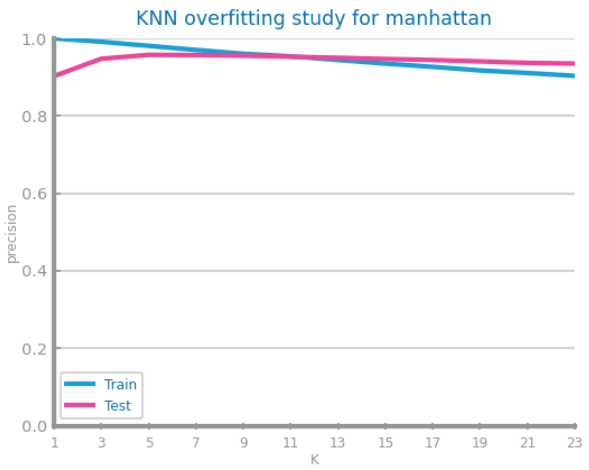
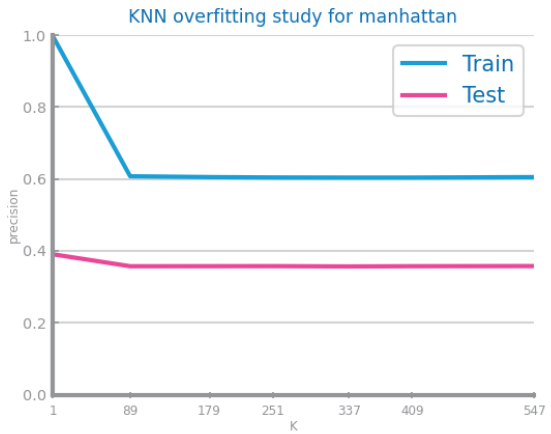


Figure 37 KNN different parameterisations comparison for dataset 2







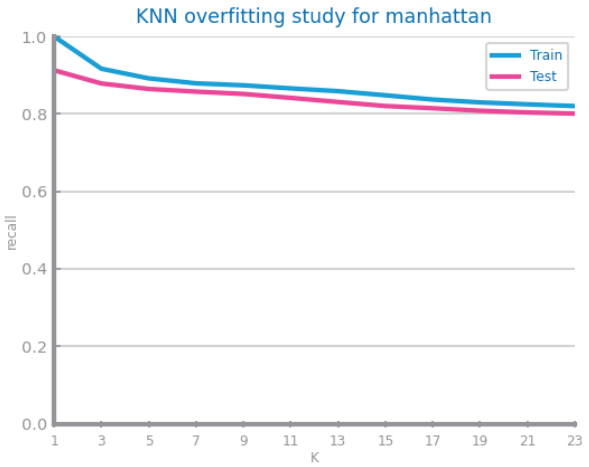
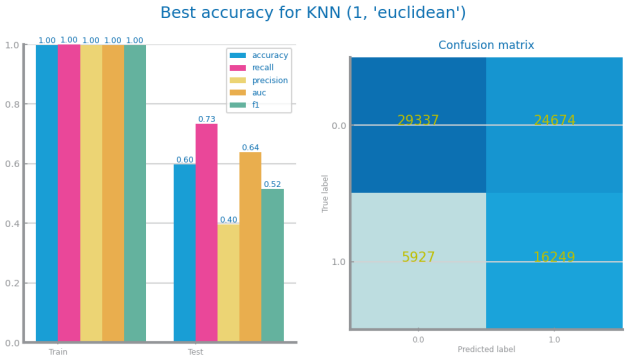


Figure 38 KN N overfitting analysis for dataset 1 (left) and dataset 2 (right)



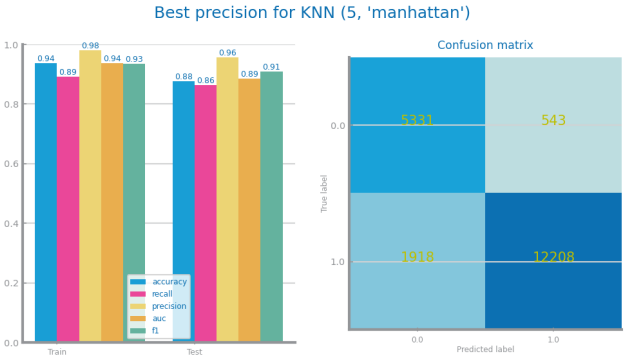


Figure 39 KNN best model results for dataset 1 (left) and dataset 2 (right)

Decision Trees

DS1

Model starts overfit in depth=46

Best model .entropy, **depth=40**

after depth 30 model doesn't improve

DS2

DT best with **gini** and **depth**=18

after +-26 **depth** model doesn't improve

Overfitting after **max_depth** of 6 or 7 where test precision stagnates; this is the value of highest **optimal depth**, gives a trade-off & helps choose the right complexity of the model

OutstandingDebt by far & *CreditMix* are most important; have the first as root so its most important discriminator between classes

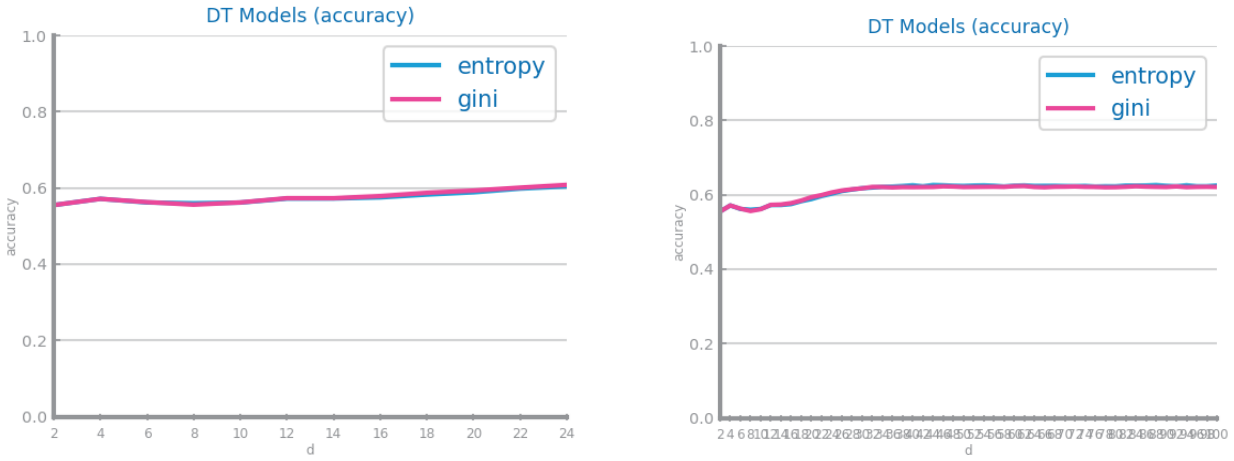


Figure 40 Decision Trees different parameterisations comparison for dataset 1

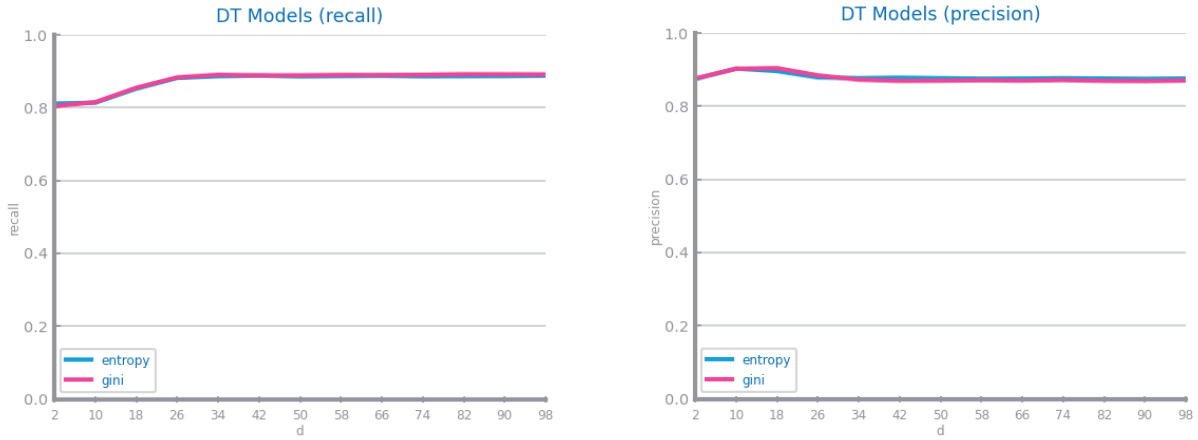


Figure 41 Decision Trees different parameterisations comparison for dataset 2

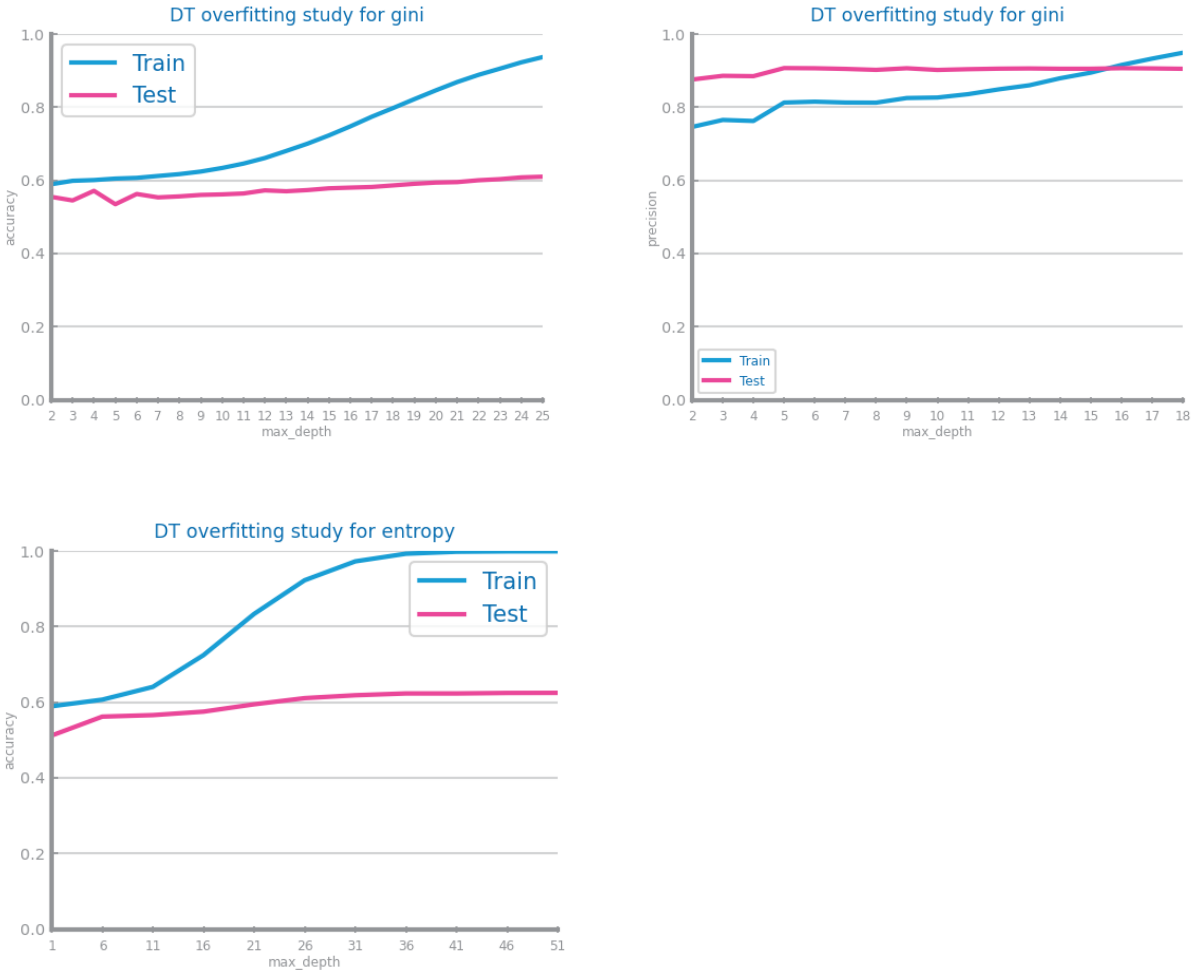


Figure 42 Decision Trees overfitting analysis for dataset 1 (left) and dataset 2 (right)

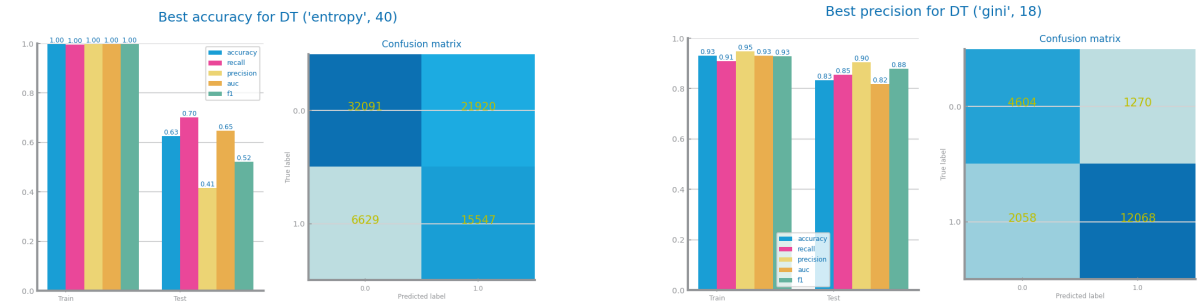


Figure 43 Decision trees best model results for dataset 1 (left) and dataset 2 (right)

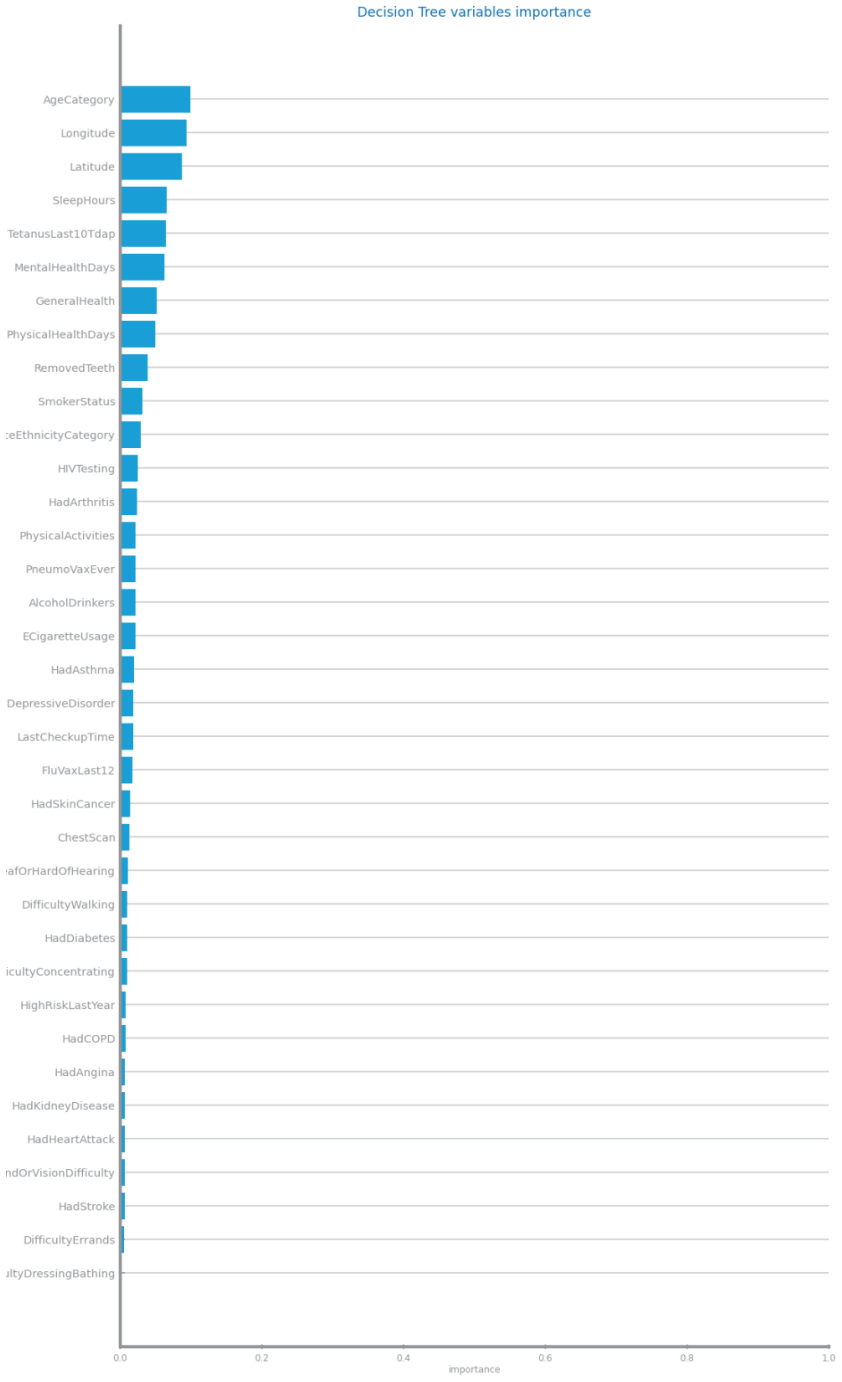


Figure 44.1 Variables importance for dataset 1

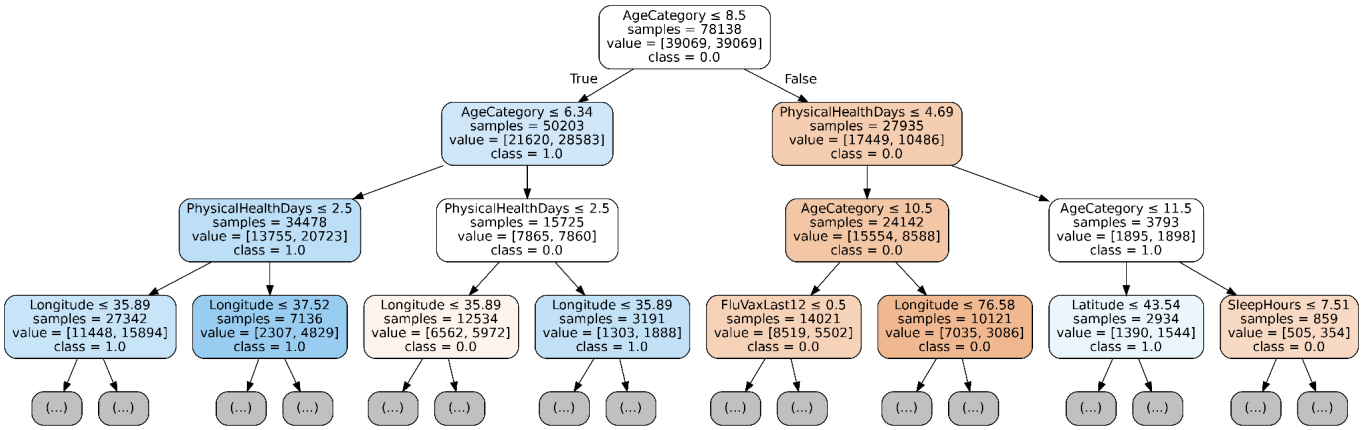


Figure 44.2 Best tree for dataset 1

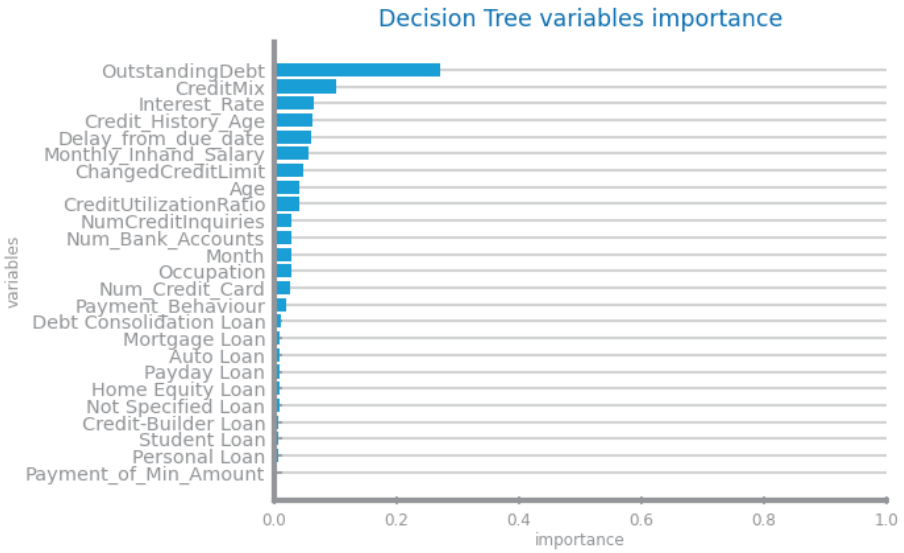


Figure 45.1 Variables importance for dataset 2

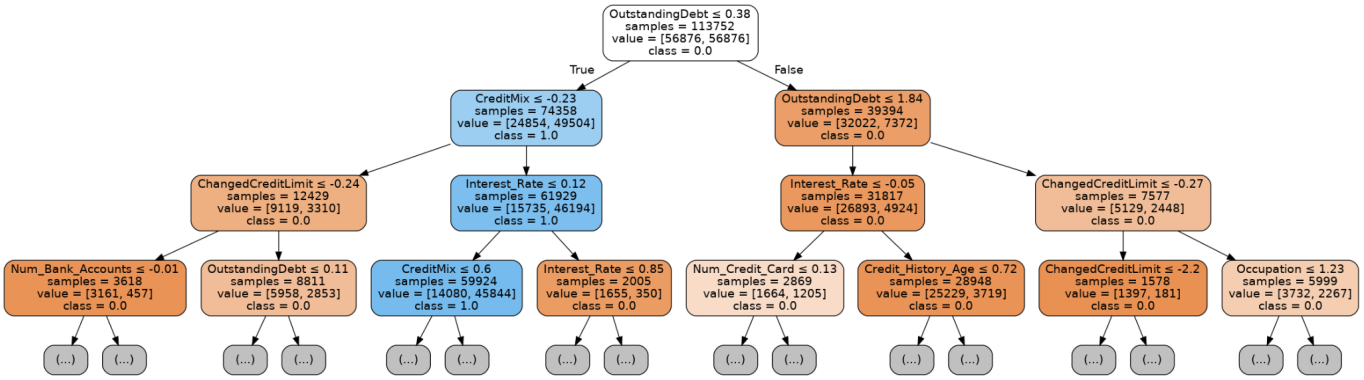


Figure 45.1 Best trees for dataset 2

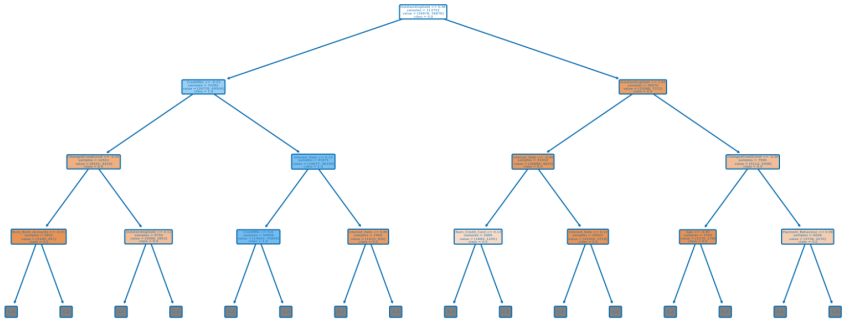


Figure 45.2 Best trees simplified for dataset 2

Random Forests

DS1

No big differences in the parameters(fig46) & No overfitting observed

Most important var AgeCategory

DS2

RF best with 100 trees (d=7, f=0.3)

Key variables in model *OutstandingDebt*, *Interest_Rate* & *CreditMix*; small stdev means the importance of these features are consistent across different trees; some variables have more variability

Precision shows less variance in vars ranking compared to recall

There is no overfitting, since the *Precision* over both datasets almost doesn't change (expected)

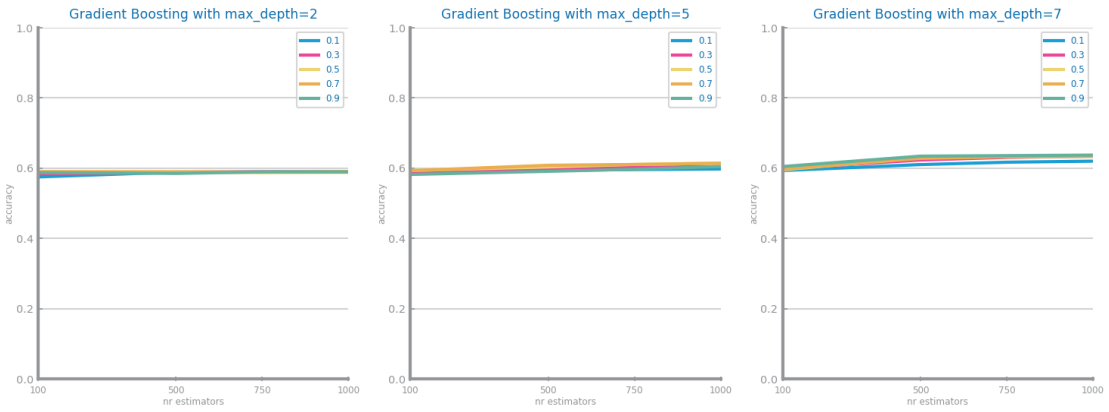


Figure 46 Random Forests different parameterisations comparison for dataset 1

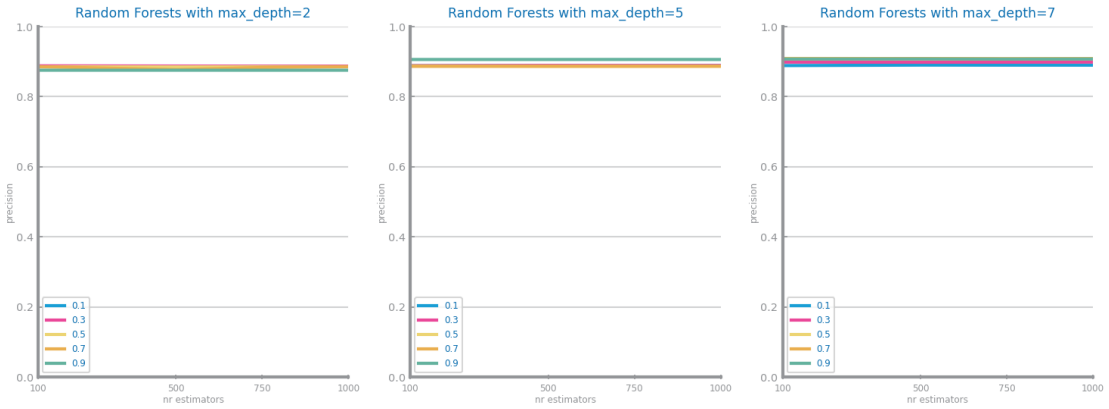


Figure 47 Random Forests different parameterisations comparison for dataset 2

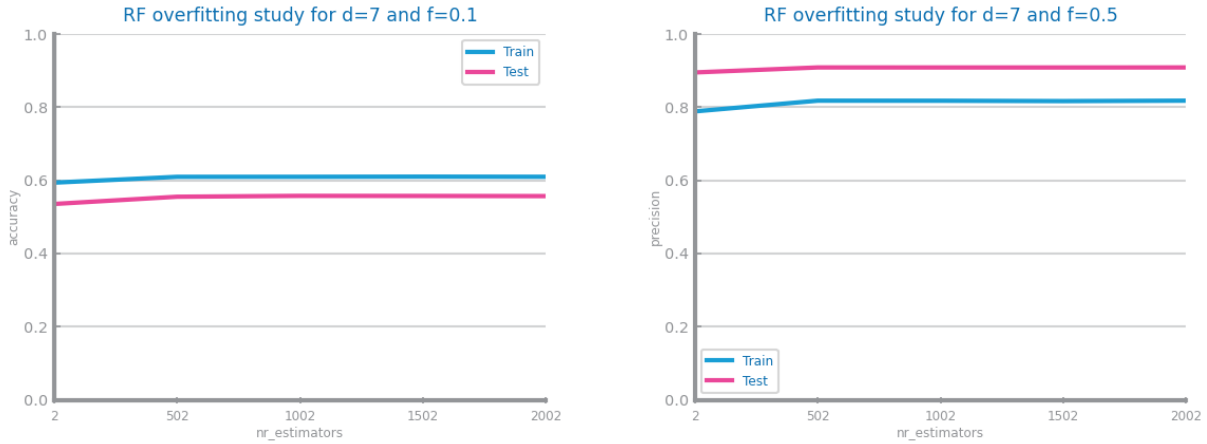


Figure 48 Random Forests overfitting analysis for dataset 1 (left) and dataset 2 (right)

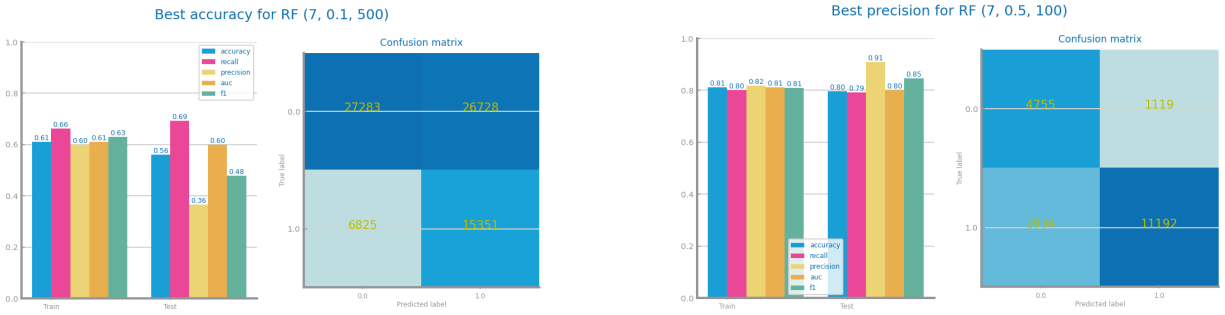


Figure 49 Random Forests best model results for dataset 1 (left) and dataset 2 (right)

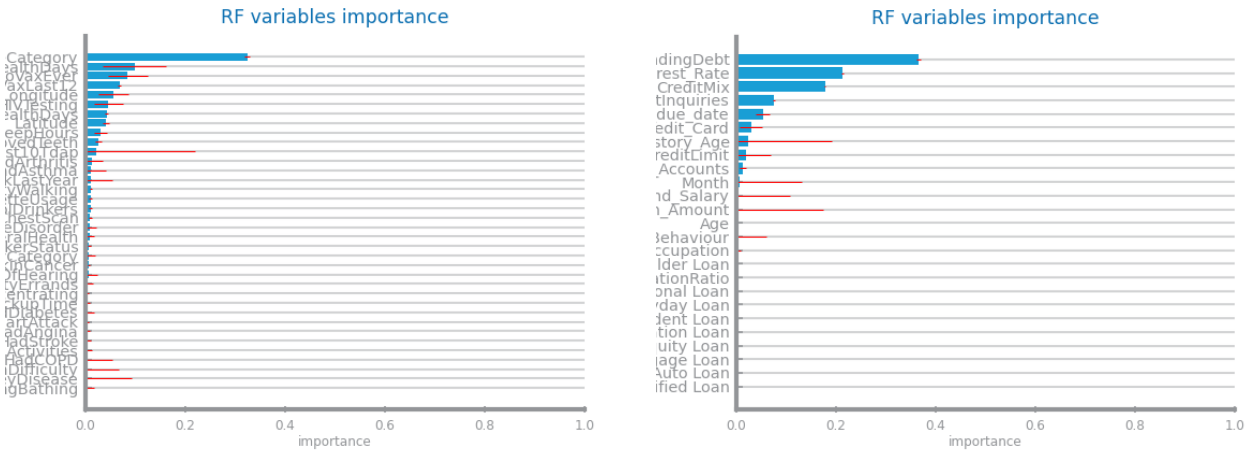


Figure 50 Random Forests variables importance for dataset 1 (left) and dataset 2 (right)

Gradient Boosting

DS1

From 502 estimators the model is overfitting (fig55)

Most important vars AgeCategory, Lat & long

DS2

GB best with 1000 trees (d=7, lr=0.3). Precision is consistent across depths and learning rates. Recall improves with depth and rate, while some overfitting is detected. Key variables: OutstandingDebt, CreditMix, Delay_from_due_date, with the latter showing inconsistent importance.

Figure 51 Gradient boosting different parameterisations comparison for dataset 1

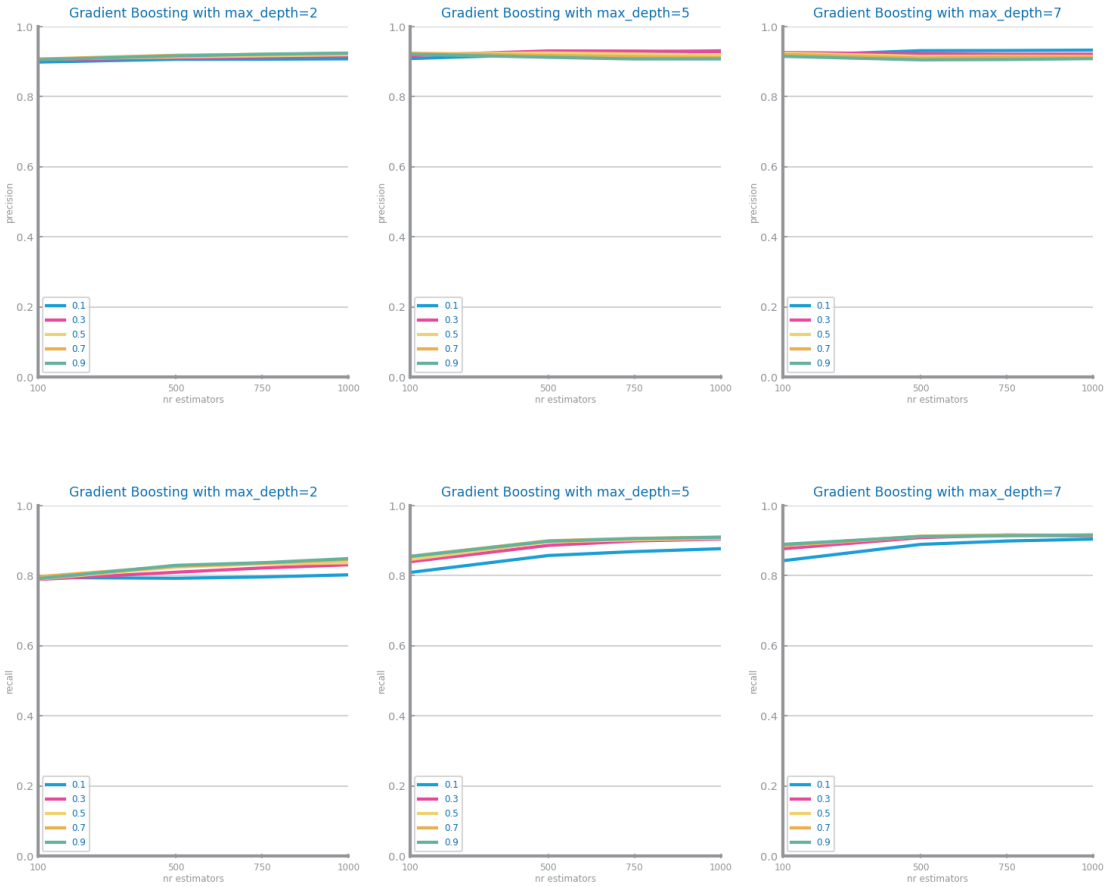


Figure 52 Gradient boosting different parameterisations comparison for dataset 2

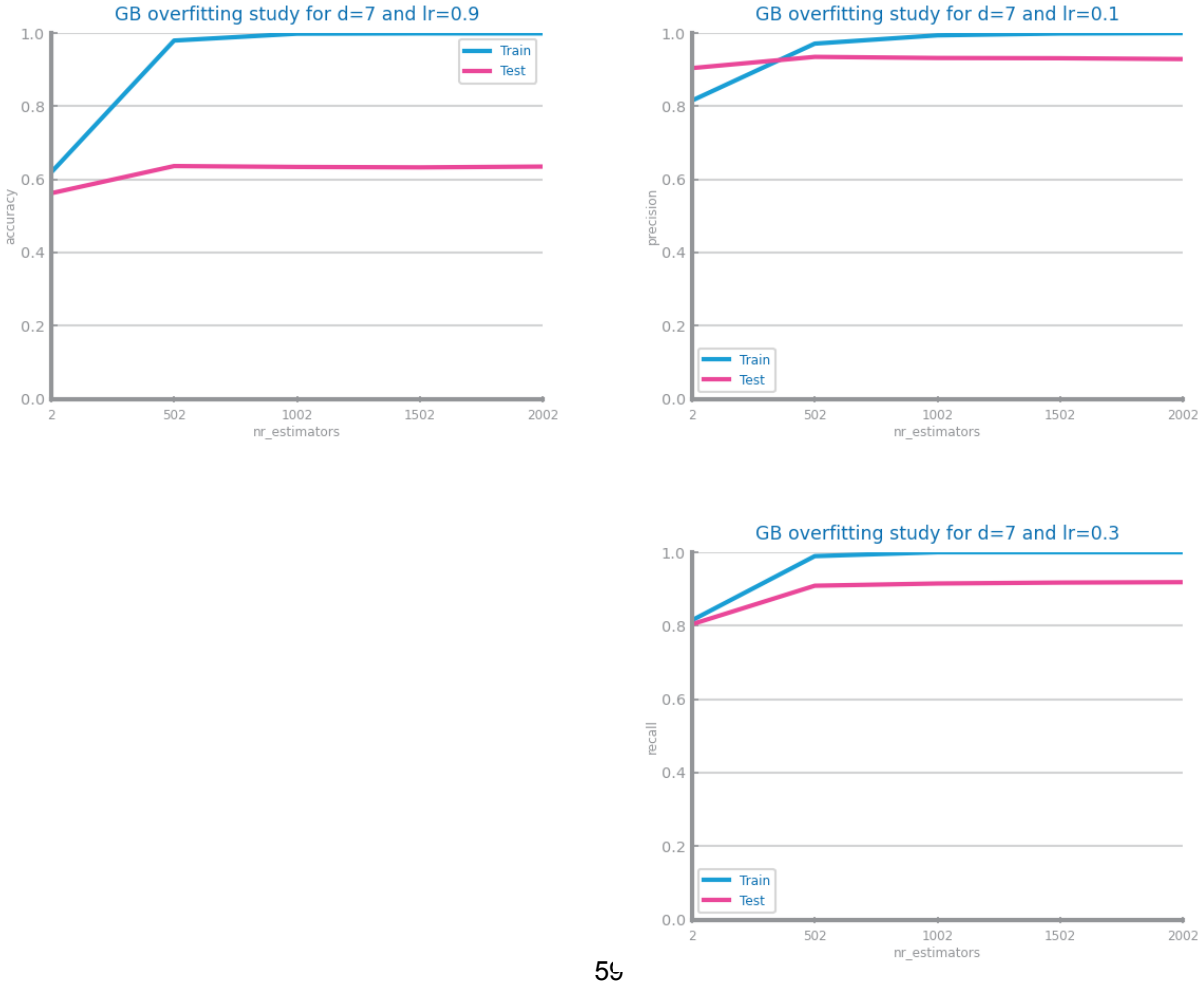


Figure 53 Gradient boosting overfitting analysis for dataset 1 (left) and dataset 2 (right)

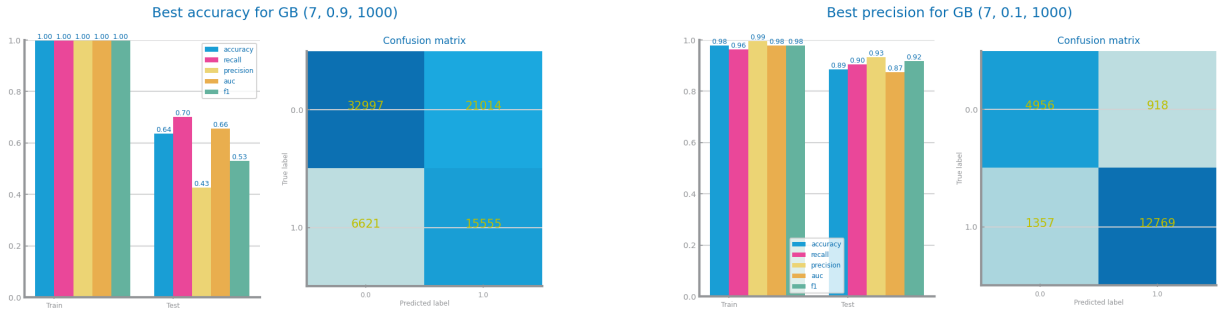


Figure 54 Gradient boosting best model results for dataset 1 (left) and dataset 2 (right)

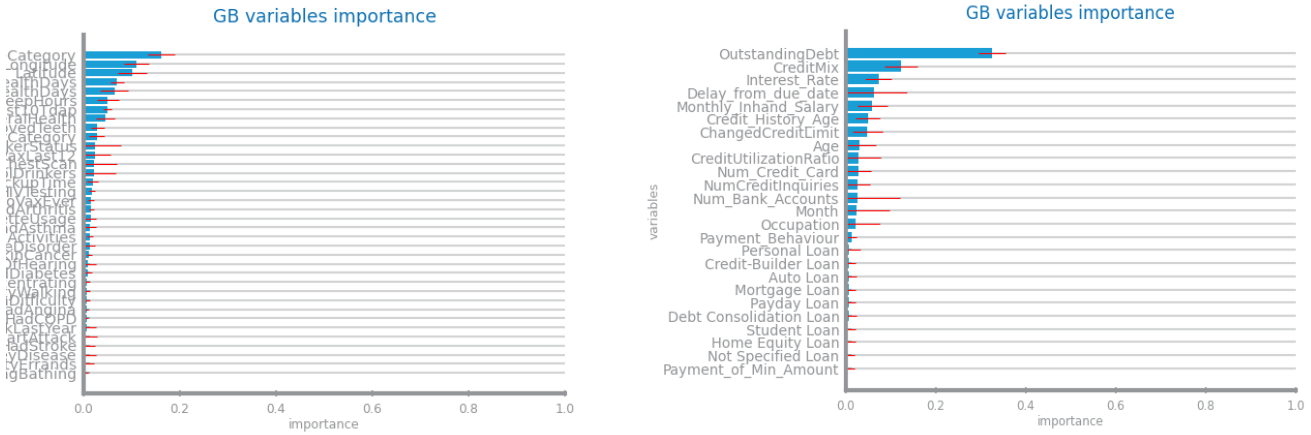


Figure 55 Gradient boosting variables importance for dataset 1 (left) and dataset 2 (right)

Multi-Layer Perceptrons

DS1

Irregular overfitting char due to randomness of the training of MLP (fig58)

Accuracy isn't the best measure to optimize in MLP. Everything is considered negative (fig59)

DS2

Model's robustness is evident with a consistent 0.9 precision across all learning rate types. Adaptive parameterization ensures stable recall, avoiding overfitting and local minimums. No overfitting is detected from the corresponding study.

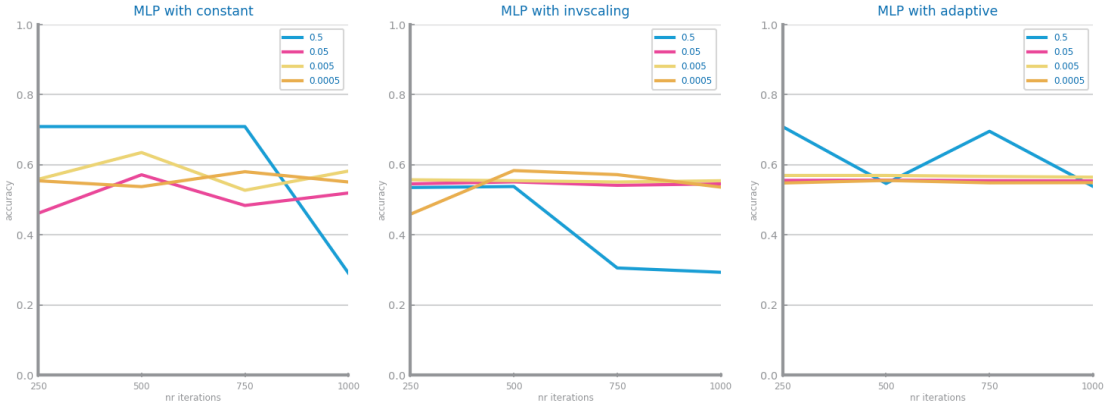


Figure 56 MLP different parameterisations comparison for dataset 1

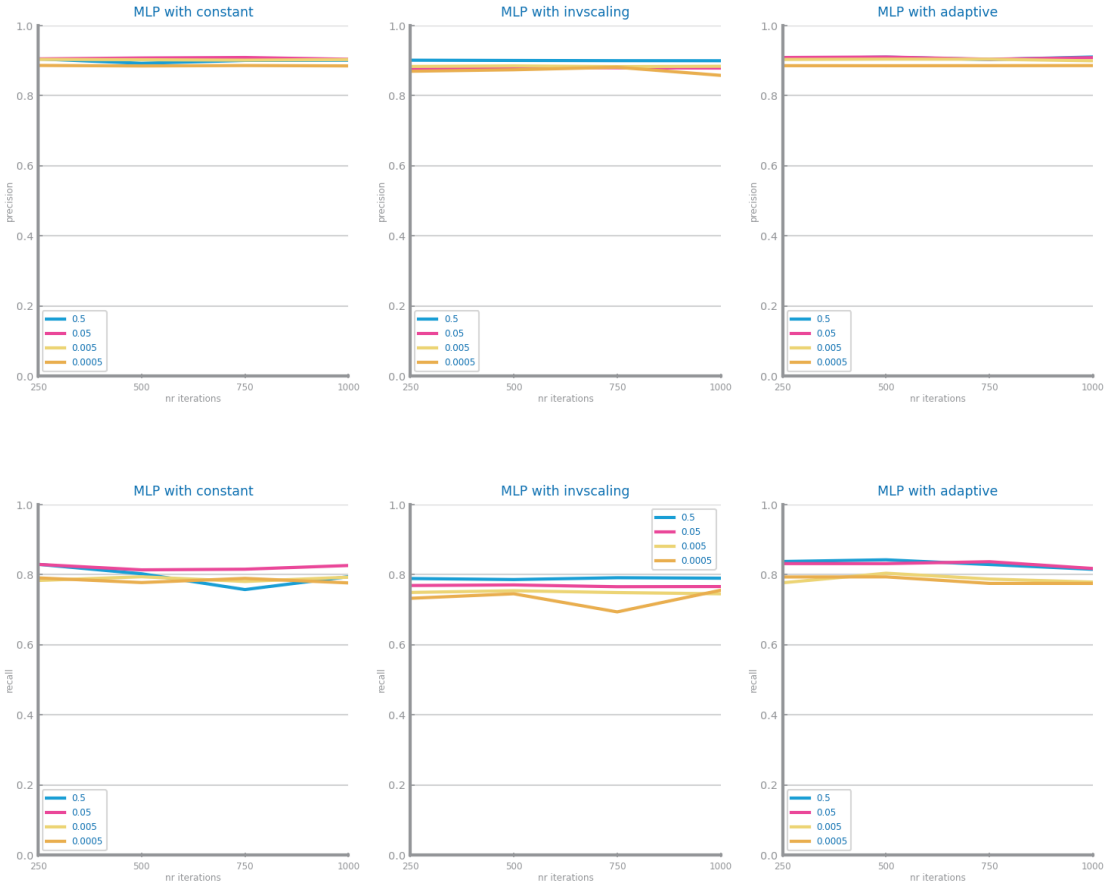


Figure 57 MLP different parameterisations comparison for dataset 2

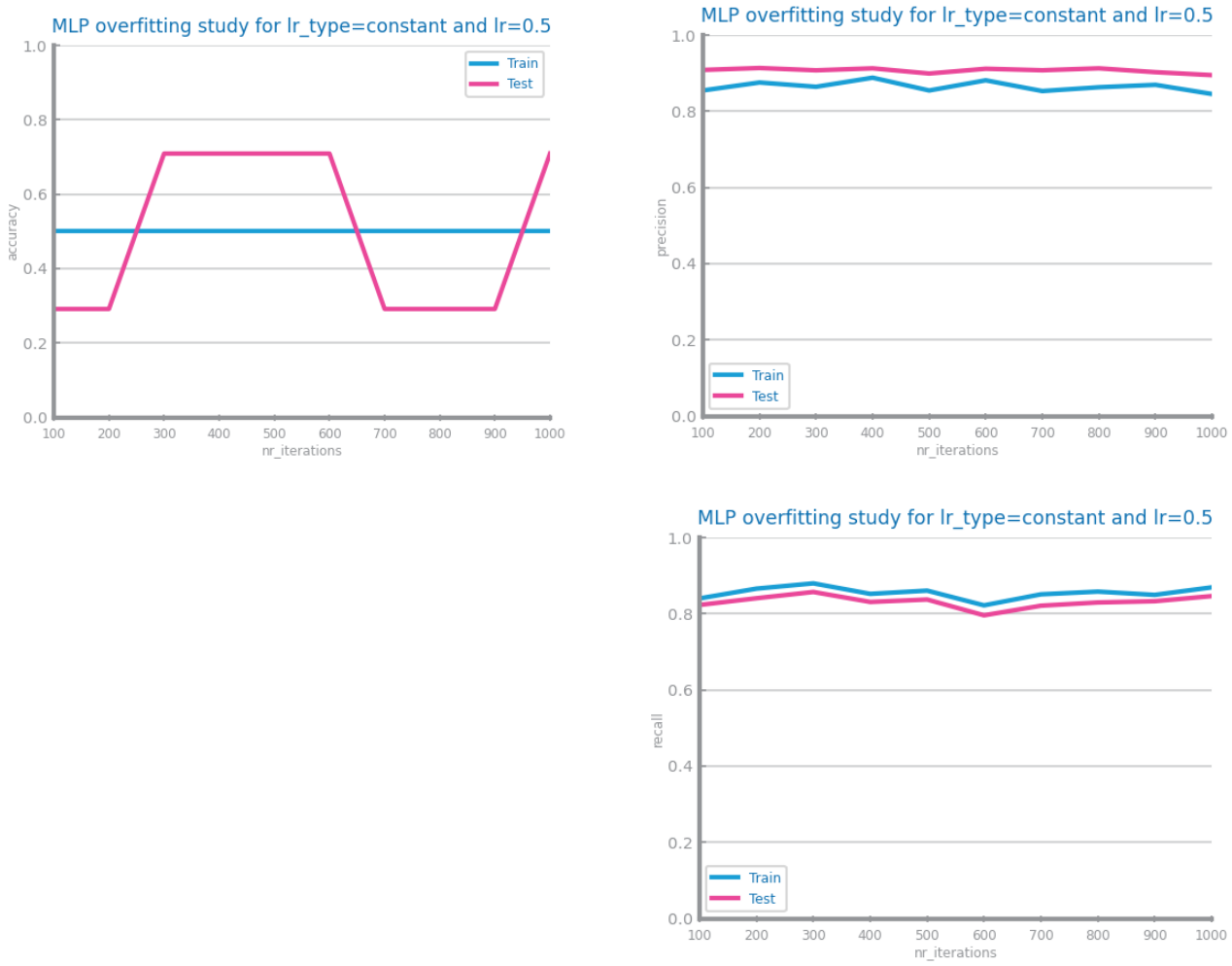


Figure 58 MLP overfitting analysis for dataset 1 (left) and dataset 2 (right)

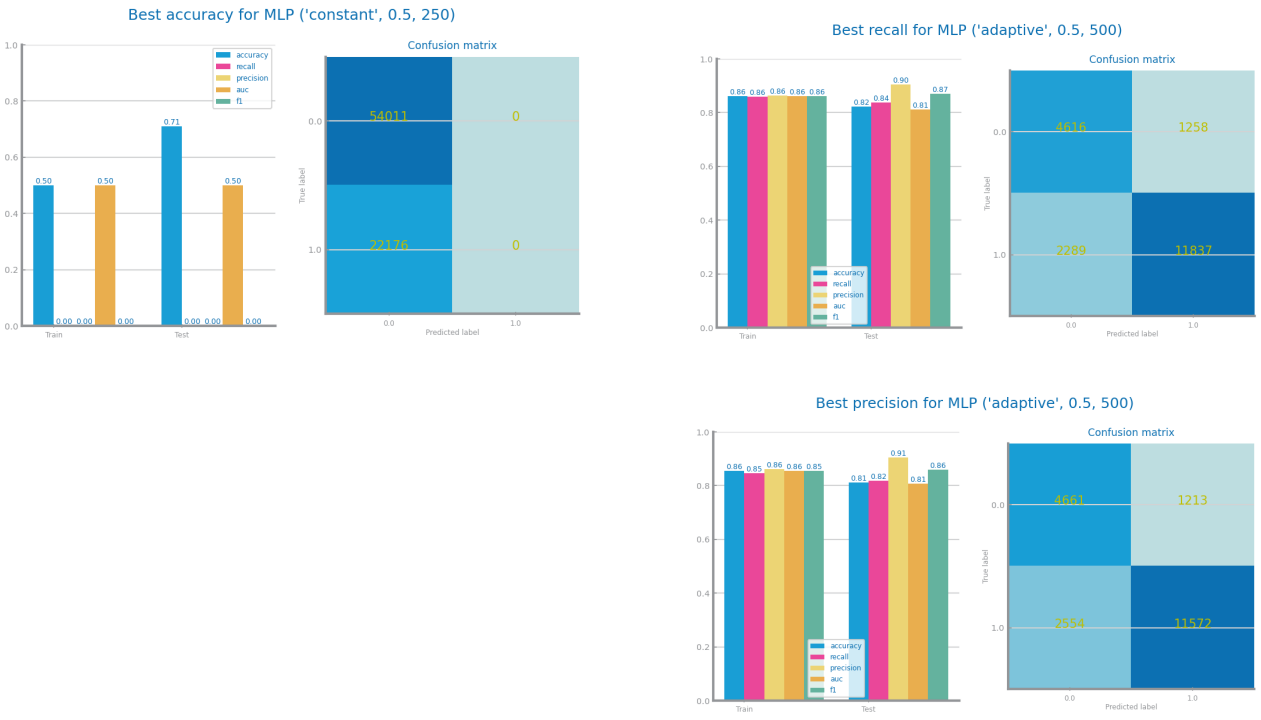


Figure 59 MLP best model results for dataset 1 (left) and dataset 2 (right)

4 Critical Analysis

DS1

AgeCategory turned out to be the most important var followed by latitude and longitude for most models. Would probably be interesting to have more granularity like the exact ages and cities, to understand if it is possible to get better results.

Lots of models entered overfitting, to solve this we could try to use less data on training set, changing training strategy to cross-validation or even try to better fit hyperparameters.

With the results obtained tree models seemed a better choice.

DS2

Primarily aiming for accurate credit classification, we decided to maximize the precision of our models to reduce the number of False Negatives (which equates to giving a loan to someone with a bad credit score). During the encoding step, we encoded diverse loan types so the models could better distinguish between these. Scaling played a vital role in ensuring equitable feature impact across all models (MLP, DT, RF), preventing dominance of a singular feature. Outlier treatment was critical for MLP due to sensitivity, and had limited impact on DT, while RF's stability relied on ensemble averaging. Balancing classes significantly improved fairness in predictions for MLP and DT, maintaining robustness. These steps collectively optimized models for higher precision and recall, effectively reducing overfitting in the credit score classification process.

We consider MLP and Random Forests among the best models for credit scoring. MLP's structure enables learning intricate, nonlinear patterns via backpropagation and nonlinear activations, ideal for capturing complex data relationships. Simultaneously, Random Forests' ensemble nature offers robustness, reducing overfitting by aggregating decisions from multiple trees, ensuring more reliable predictions in credit scoring tasks.

5 DATA PROFILING

Data Dimensionality and Granularity

DS1

Atomic is weekly.

There is an upward trend and it's cumulative.

DS2

Goal give insights for planning & congestion management

Atomic granularity 15-min intervals

Other granularities, Hourly & 4Hours

"Sum" aggregation function

No Trend, stable over the months

Daily Seasonality - morning & evening rush *(affected by time of the day - fixed & known period)*

Weekly Cycle - Peak intervals suggesting regular weekend increases and from $1st$ to $2nd$ Peak an occasional 10-days gap *(reflects **anomaly** or **special event**)*

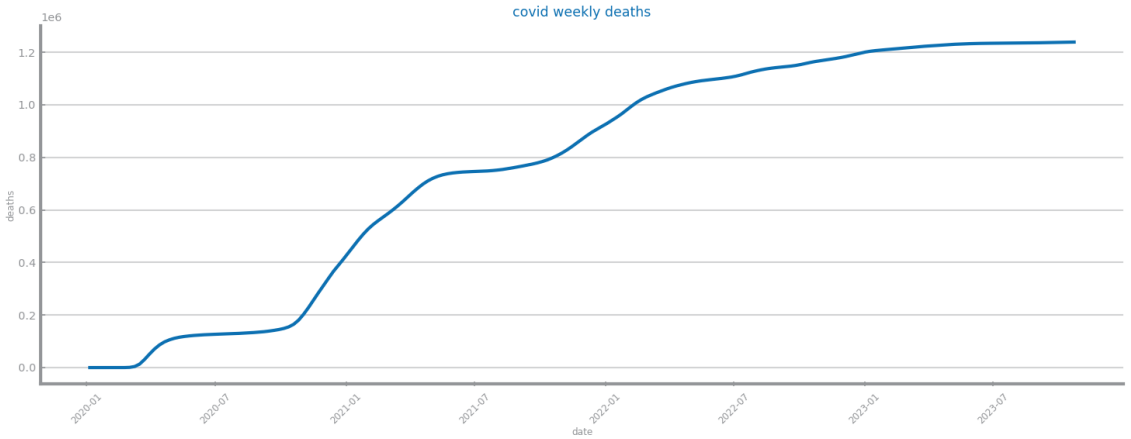


Figure 60 Time series 1 at the most granular detail

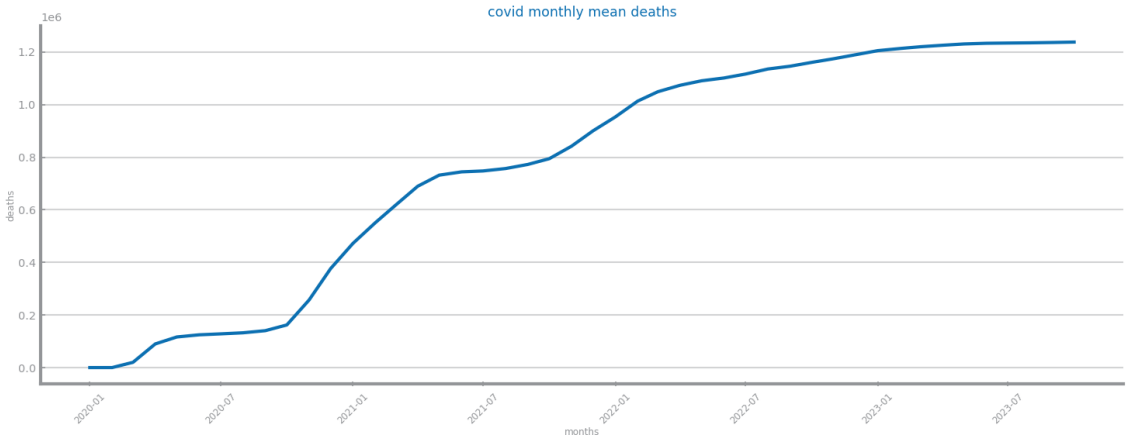


Figure 61 Time series 1 at the second chosen granularity

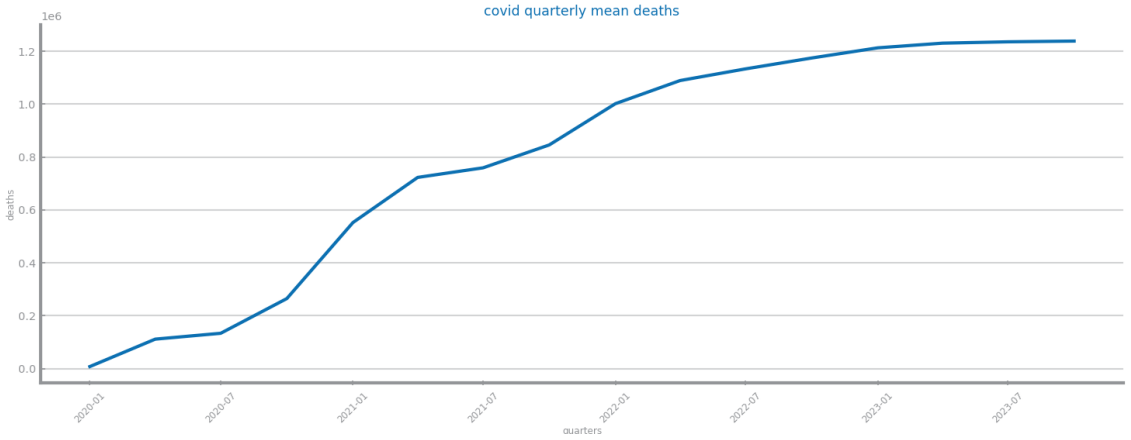


Figure 62 Time series 1 at the third chosen granularity

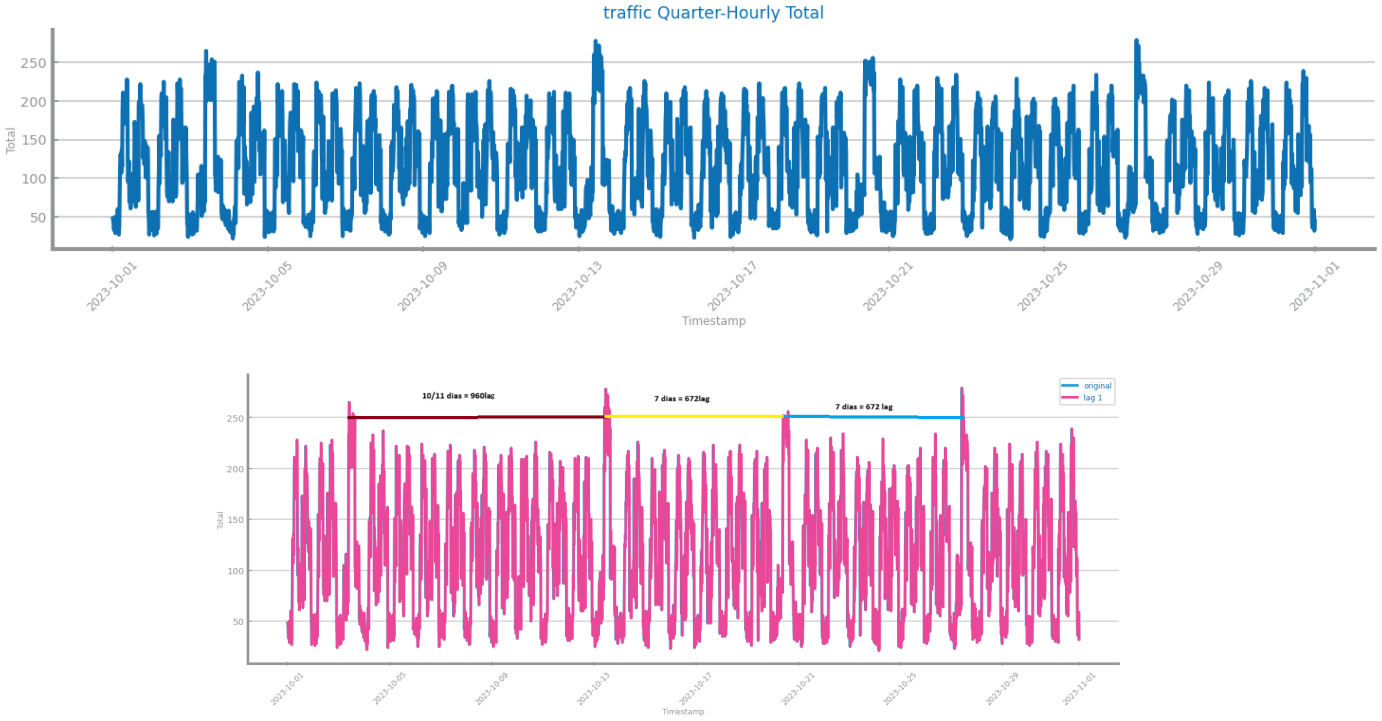


Figure 63 Time series 2 at the most granular detail

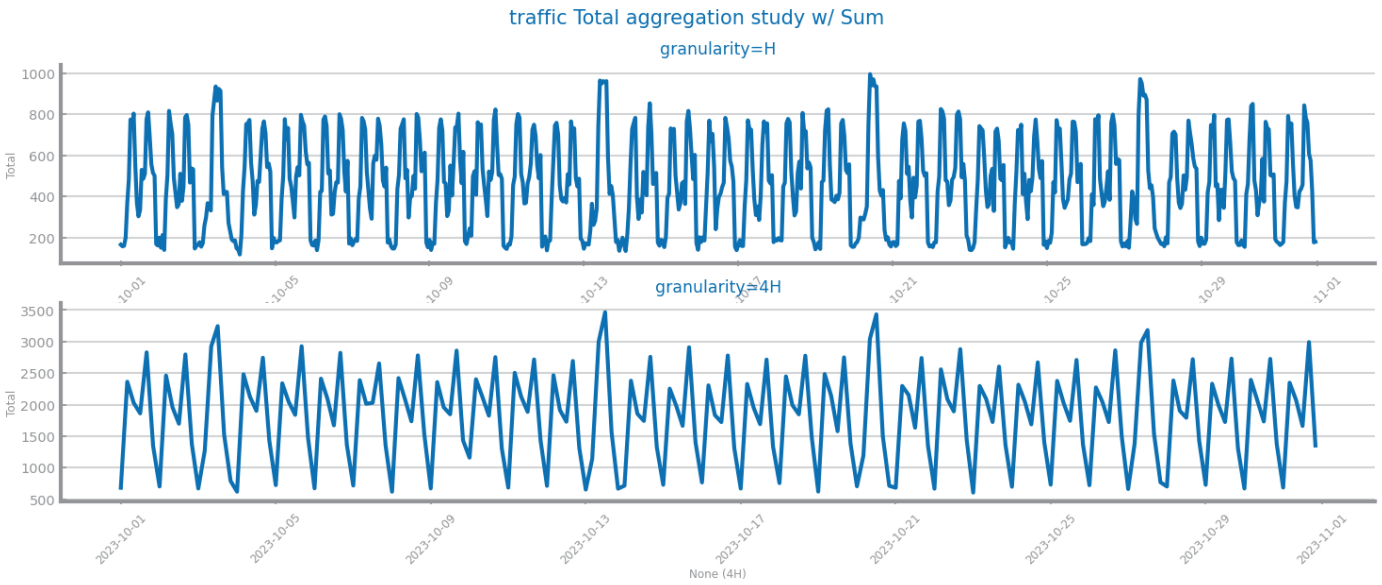


Figure 64 & 65 Time series 2 at the second and third chosen granularity

Data Distribution

DS1

The distributions don't vary in any meaningful way from one granularity to another

DS2

Lag **96** corresponds to **One Day**

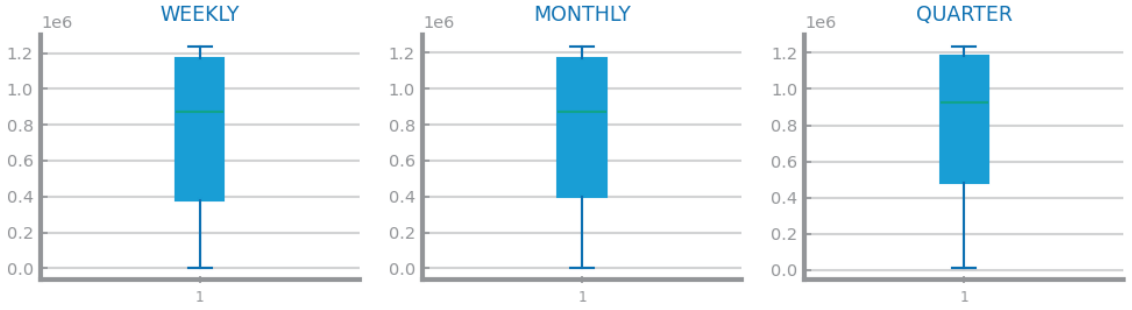
May have a trend, *autocorrelation* high and positive for small lags, and *ac* decreases as lag increases

3 *outliers* in 4-Hourly Boxplot

Autocorrelation is larger for **seasonal lags** *(multiple of seasonal - 7,14, 192, etc.)*

Highest Peaks tend to be **one week** apart, smaller ones two times a day

No White Noise



count	1.990000e+02
mean	7.743876e+05
std	4.356312e+05
min	0.000000e+00
25%	3.775975e+05
50%	8.691990e+05
75%	1.172049e+06
max	1.238650e+06

Name: deaths, dtype: float64

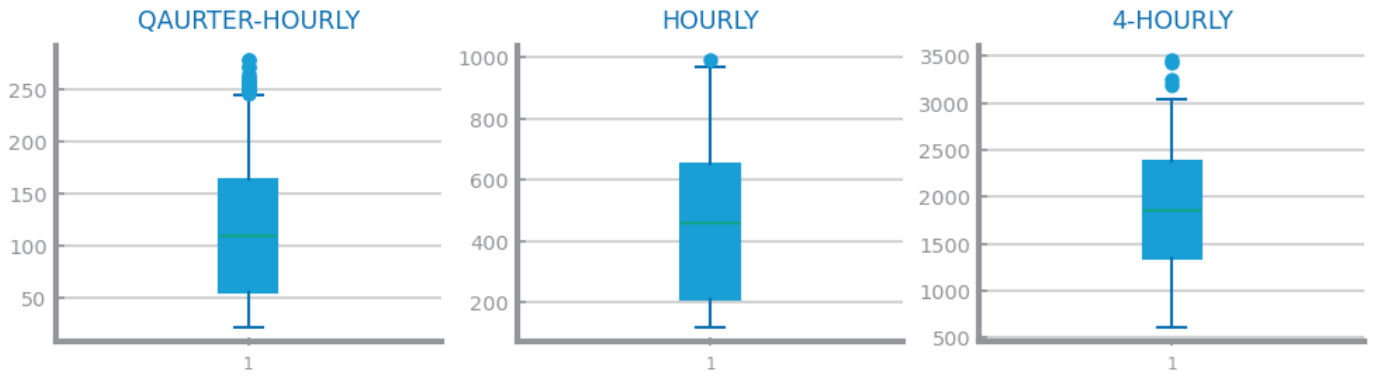
count	4.600000e+01
mean	7.750457e+05
std	4.398647e+05
min	2.500000e-01
25%	4.007008e+05
50%	8.714809e+05
75%	1.171477e+06
max	1.238175e+06

Name: deaths, dtype: float64

count	1.600000e+01
mean	7.944554e+05
std	4.483506e+05
min	7.682846e+03
25%	4.803667e+05
50%	9.235195e+05
75%	1.183809e+06
max	1.238175e+06

Name: deaths, dtype: float64

Figure 66 Boxplot(s) for time series 1



count 2976.000000
mean 114.218414
std 60.190627
min 21.000000
25% 55.000000
50% 109.000000
75% 164.000000
max 279.000000
Name: Total, dtype: float64

count 744.000000
mean 456.873656
std 224.577031
min 117.000000
25% 210.750000
50% 459.500000
75% 650.750000
max 995.000000
Name: Total, dtype: float64

count 186.000000
mean 1827.494624
std 736.869773
min 603.000000
25% 1351.000000
50% 1850.000000
75% 2385.750000
max 3466.000000
dtype: float64

Figure 67 Boxplot(s) for time series 2

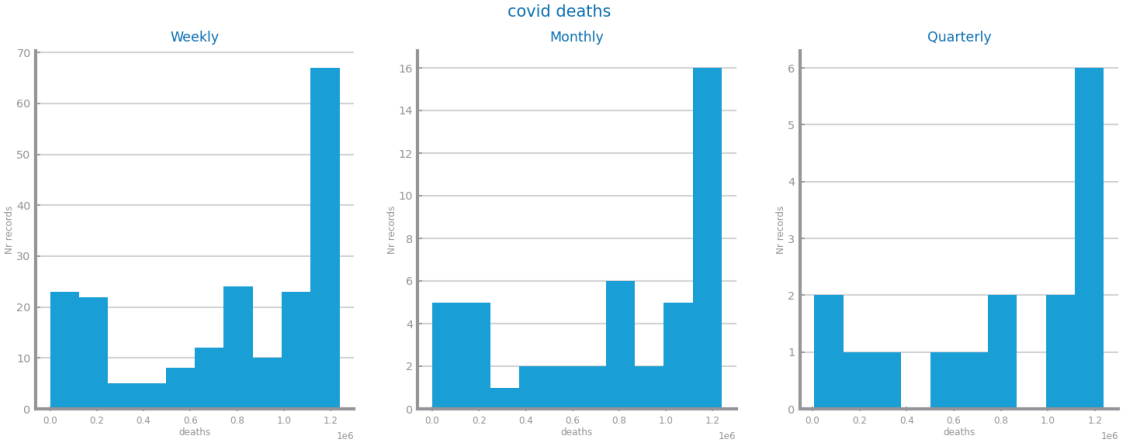


Figure 68 Histogram(s) for time series 1

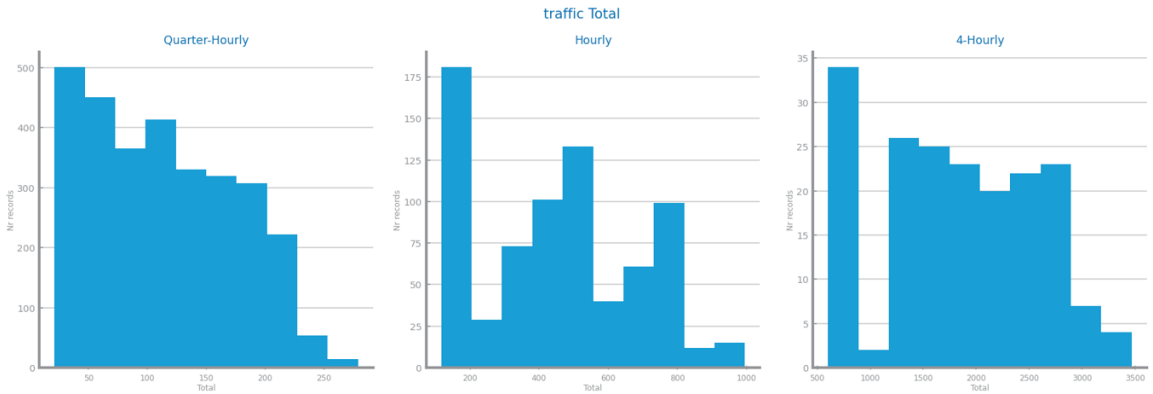


Figure 69 Histogram(s) for time series 2

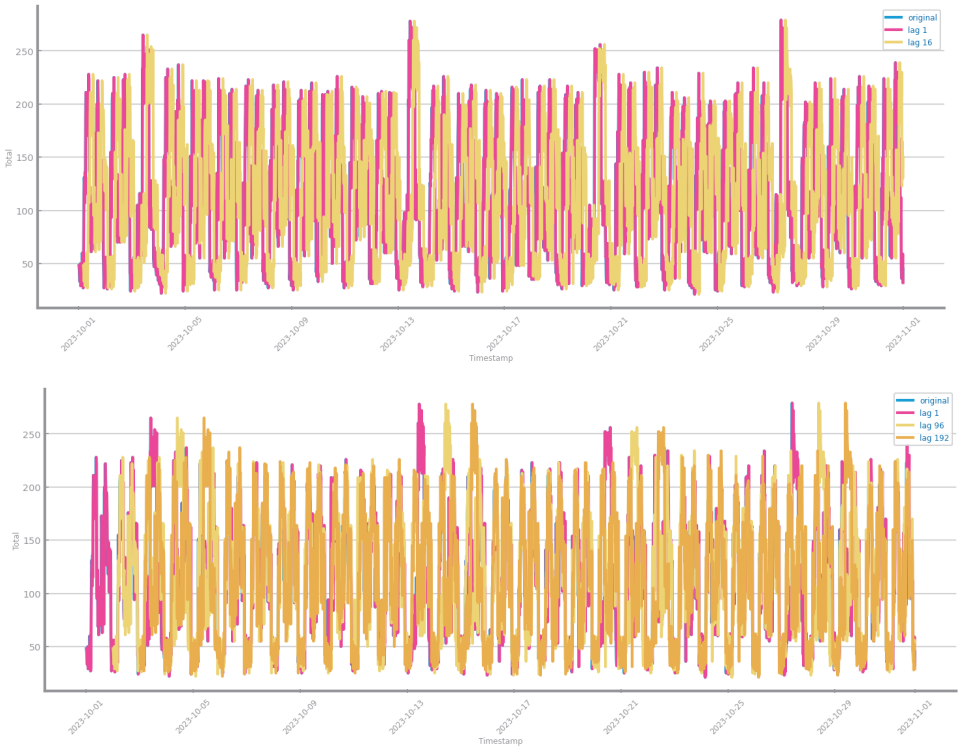


Figure xx Autocorrelation lag-plots (24,16) && (192,96) for time series 2

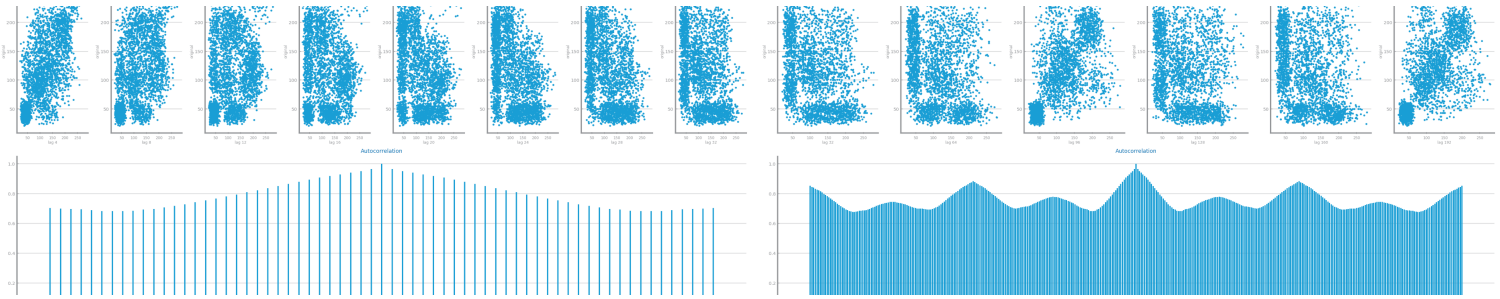


Figure xx Autocorrelation correlogram (32,4) && (192,32) for time series 2

DS2

Left fig - **lag 0** *(highest - correlated w/ itself)*. Decreases when we increase the lag. In **lag 26**, we see it starts to increase again. *"observations nearby in time are also nearby in value" - Hyndman*

Right fig - show some peaks which may be due a **seasonal pattern** in the data. Peaks appear in **lag 96**, and then again in **lag 192**.

There seems to be a combination of seasonality with trend (despite in *Fig 62*, there seems to be **no trend**)

Data Stationarity

DS1

The data is not stationary and it has an upward trend that tapers off.

DS2

Fig72 - ***STL*** *& Additive Decomposition.* No strong up/down trend. It shows no **Seasonal patterns** or **Cycles**

Fig73 - mean line flat and constant over time, suggests the average traffic volume **not have a strong up or downward trend**.

Constant Variance.

Show some regular fluctuations within each day, and suggest a *daily pattern*.

Fig73.2 - p = 0.00 ***Stationary*** means the series is not defined by a trend, and does not depend on time.

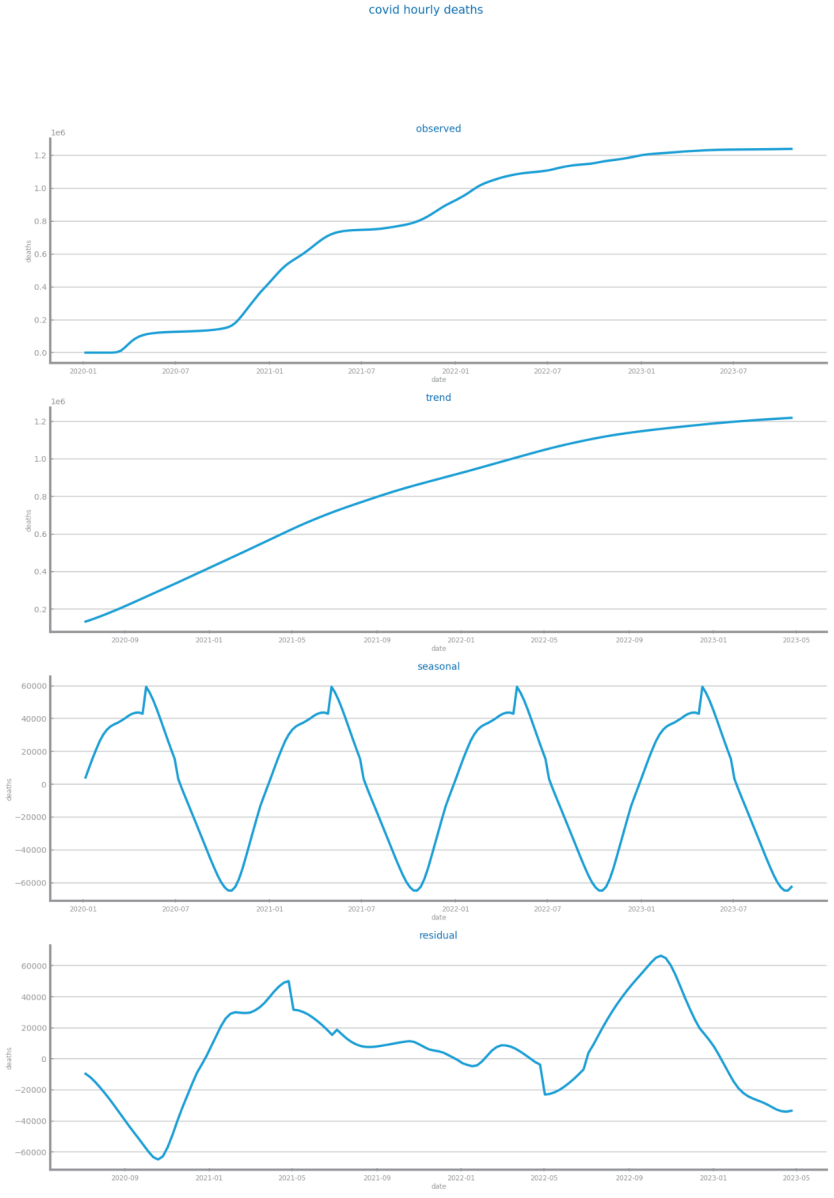


Figure 70 Components study for time series 1

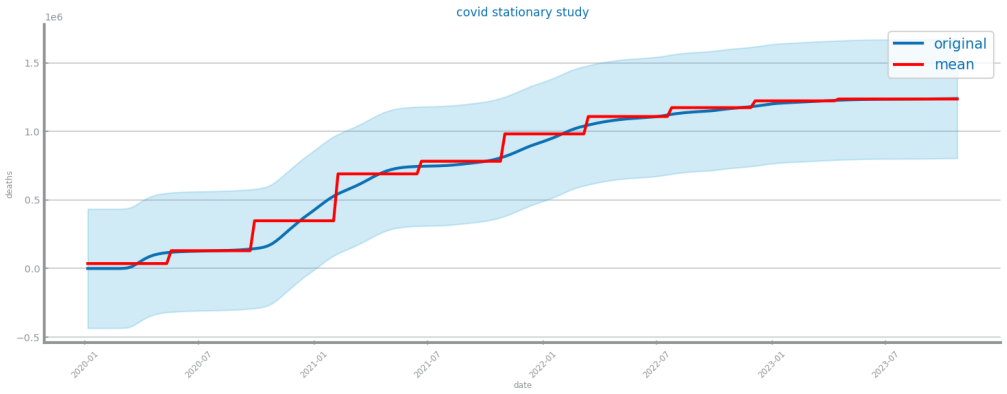


Figure 71 Stationarity study for time series 1

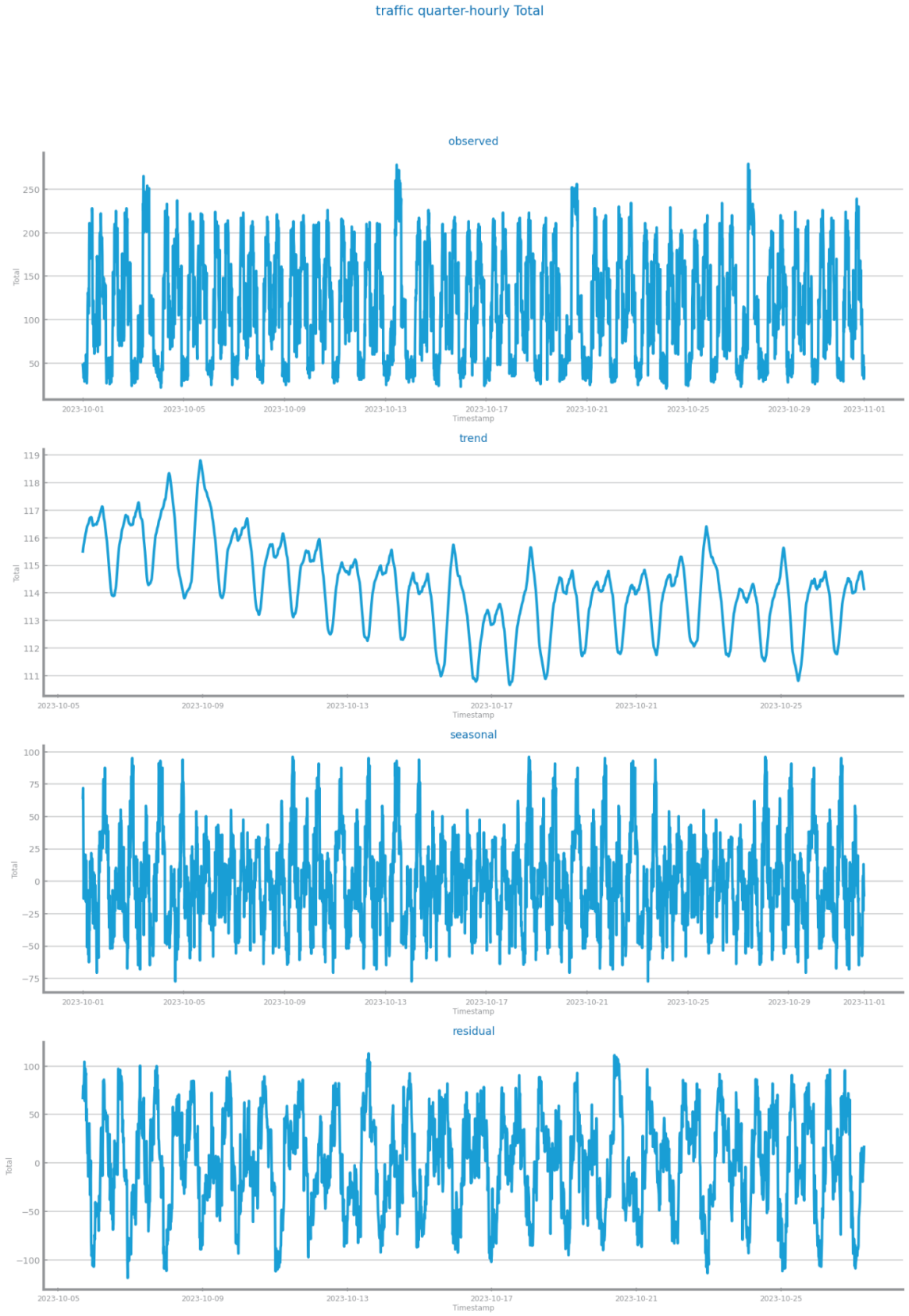


Figure 72 Components study for time series 2

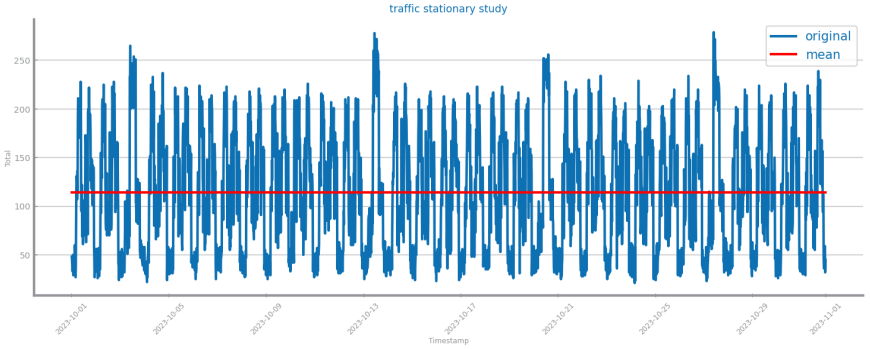


Figure 73 Stationarity study - no bins - for time series 2

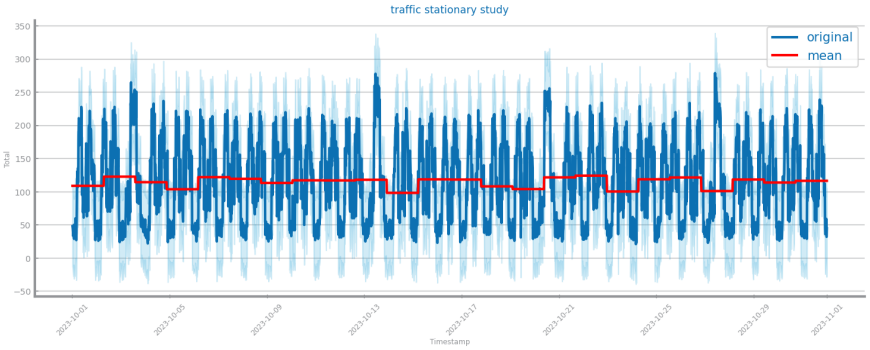


Figure 73.1 Stationarity study - 24 bins - for time series 2

```
ADF Statistic: -14.436
p-value: 0.000
Critical Values:
        1%: -3.439
        5%: -2.866
        10%: -2.569
The series is stationary
```

Figure 73.2 Stationarity study - Augmented Dickey-Fuller test - for time series 2

6 Data Transformation

Aggregation

DS1

Chose atomic aggregation due to no significant improvements and data retention preference.

DS2

Atomic, **Hourly** *(second)* and **4-Hourly** *(third)* from Profiling. Aggregation function *"sum"* (retains total volume & introduces less error)

Opted for **Atomic** as plot shows pattern/info loss w/ other aggregations

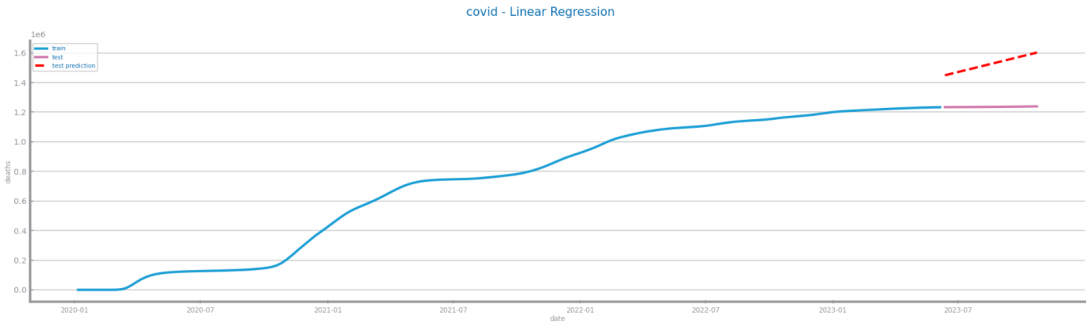


Figure 74.1 Forecasting plots after different aggregations on time series 1 (Weekly)

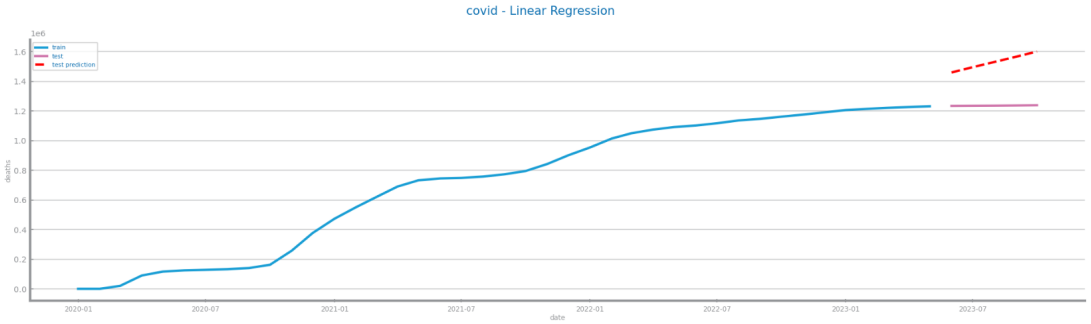


Figure 74.2 Forecasting plots after different aggregations on time series 1 (Monthly)

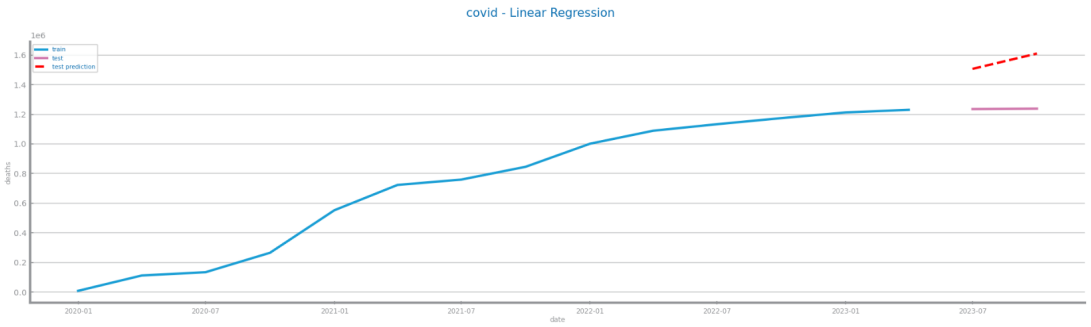


Figure 74.3 Forecasting plots after different aggregations on time series 1 (Quarterly)

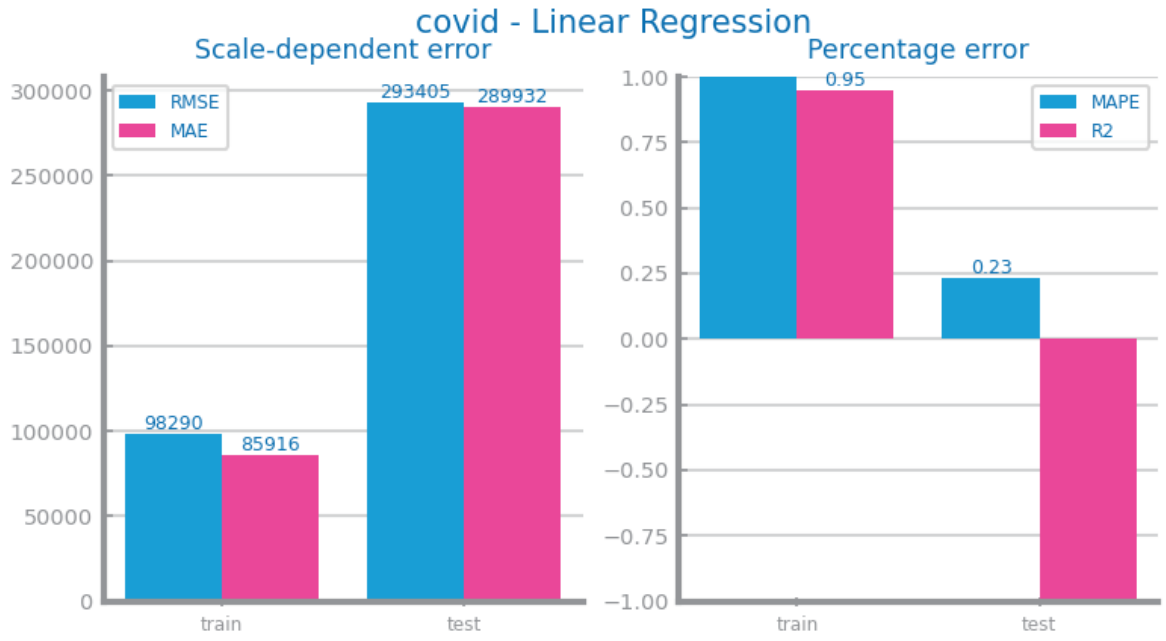


Figure 75.1 Forecasting results after different aggregations on time series 1 (Weekly)

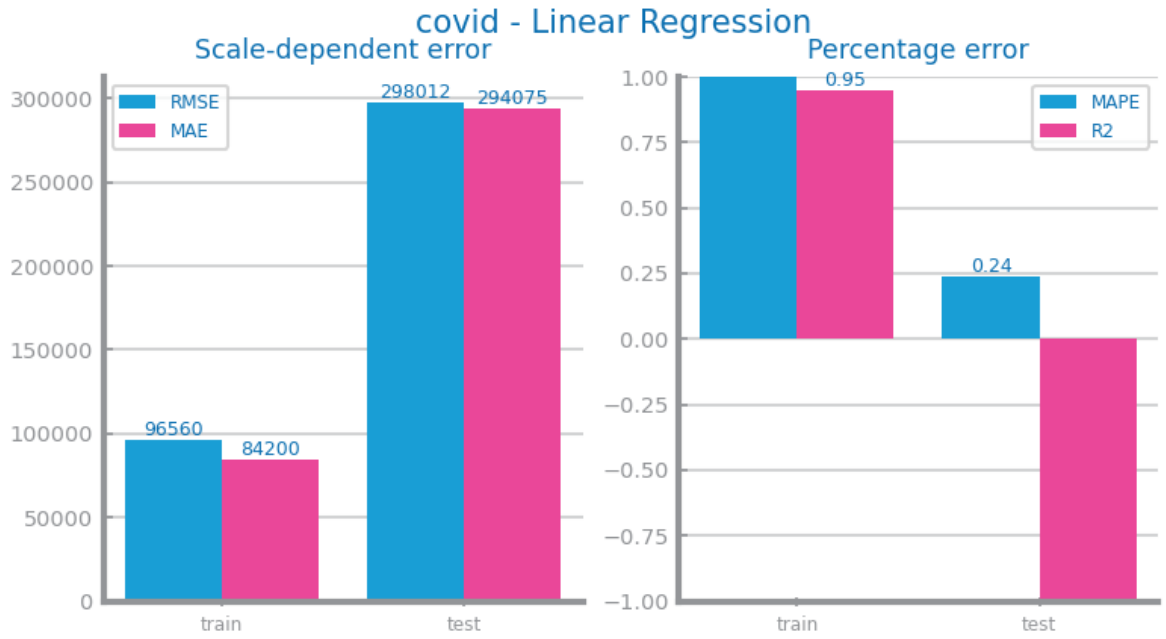


Figure 75.2 Forecasting results after different aggregations on time series 1 (Monthly)

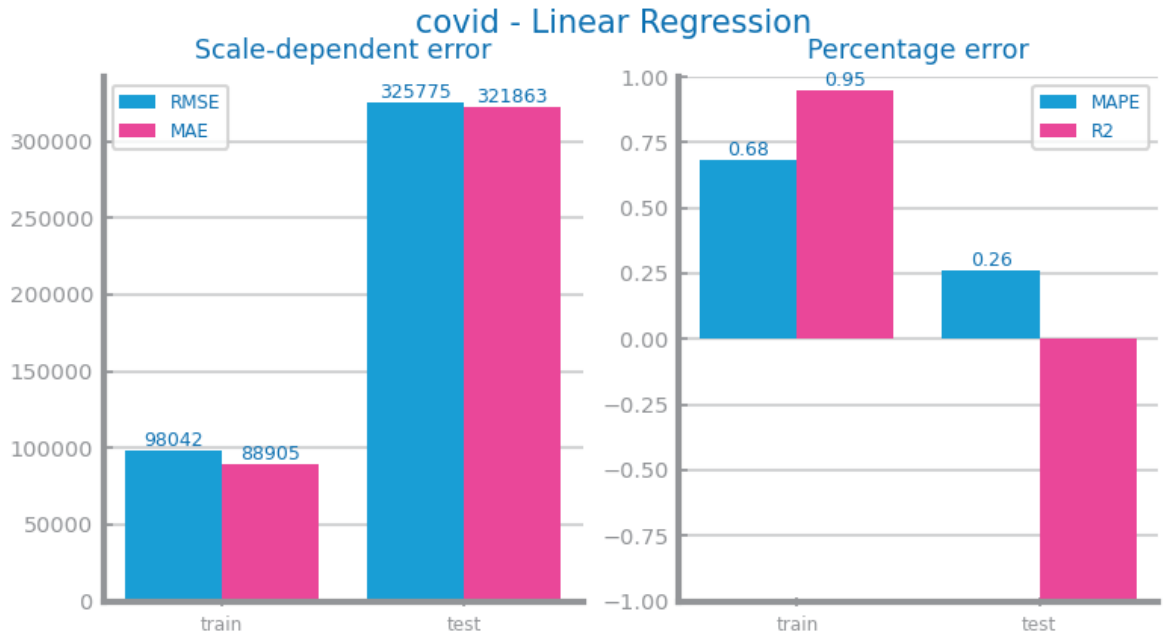


Figure 75.3 Forecasting results after different aggregations on time series 1 (Quarterly)

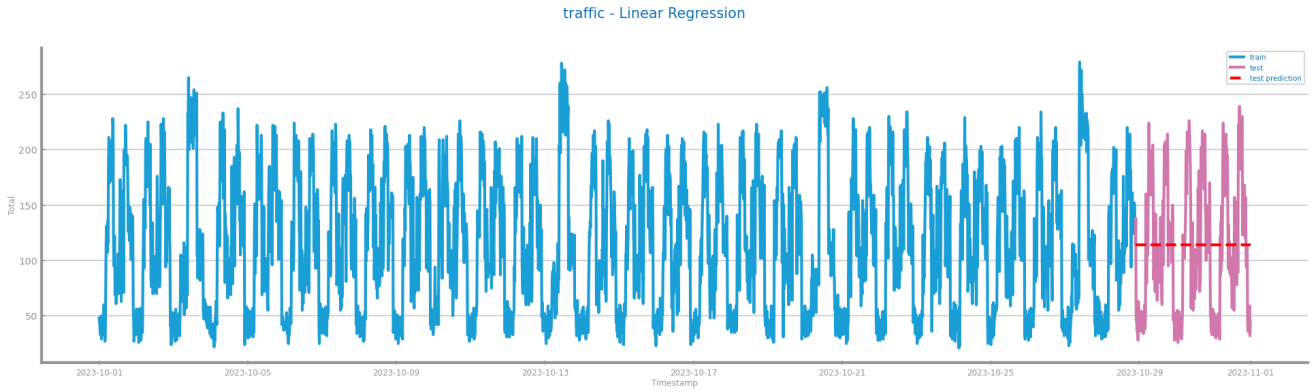


Figure 76 Forecasting plots after different aggregations - ATOMIC - on time series 2

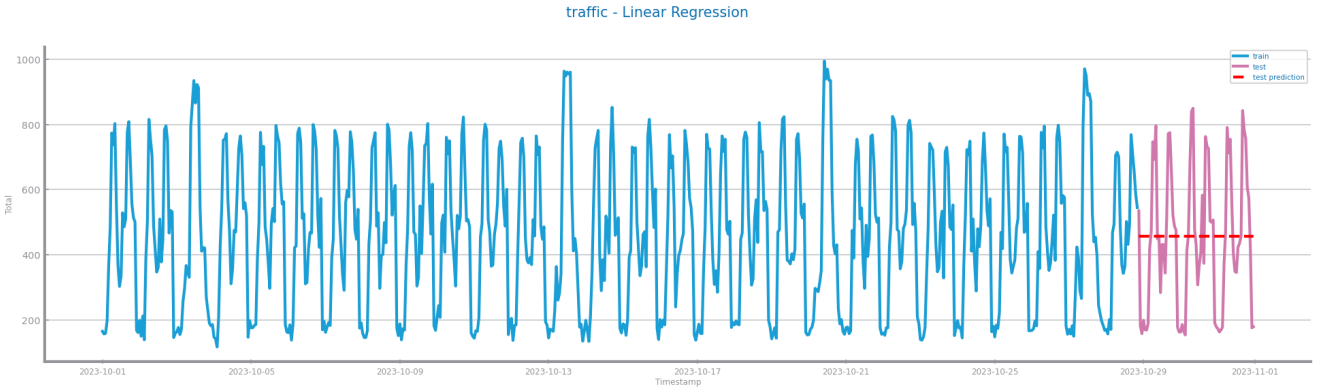


Figure 76 Forecasting plots after different aggregations - SECOND - on time series 2

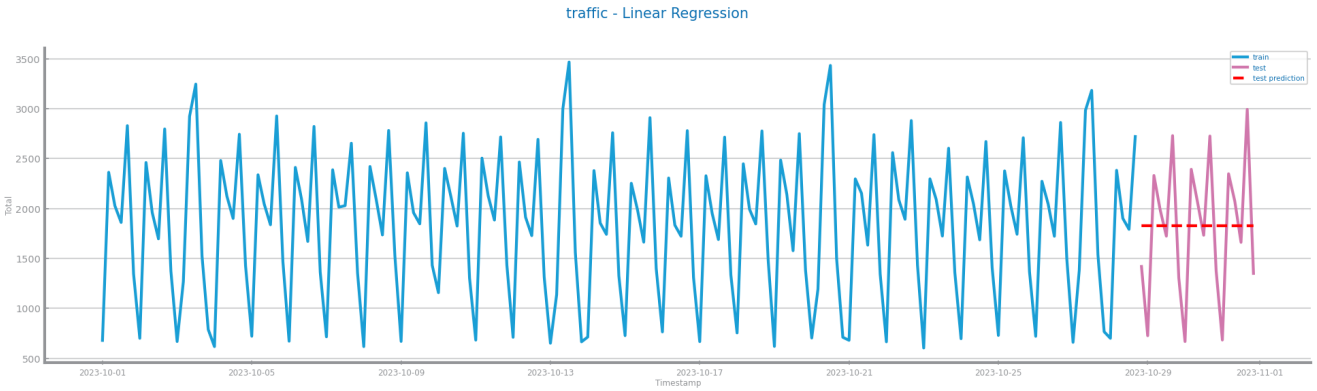


Figure 76 Forecasting plots after different aggregations - THIRD - on time series 2

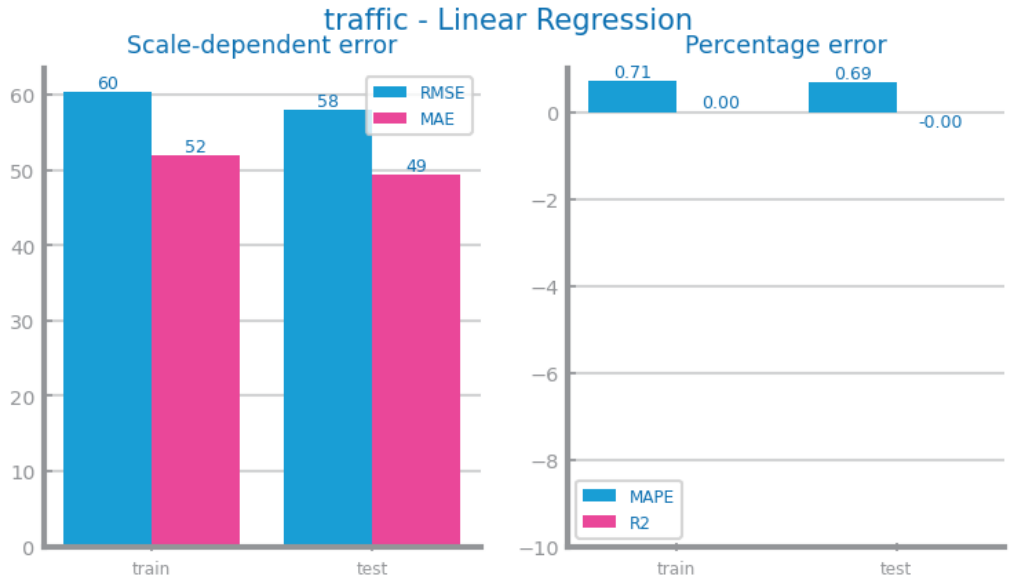


Figure 77 Forecasting results after different aggregations - ATOMIC - on time series 2

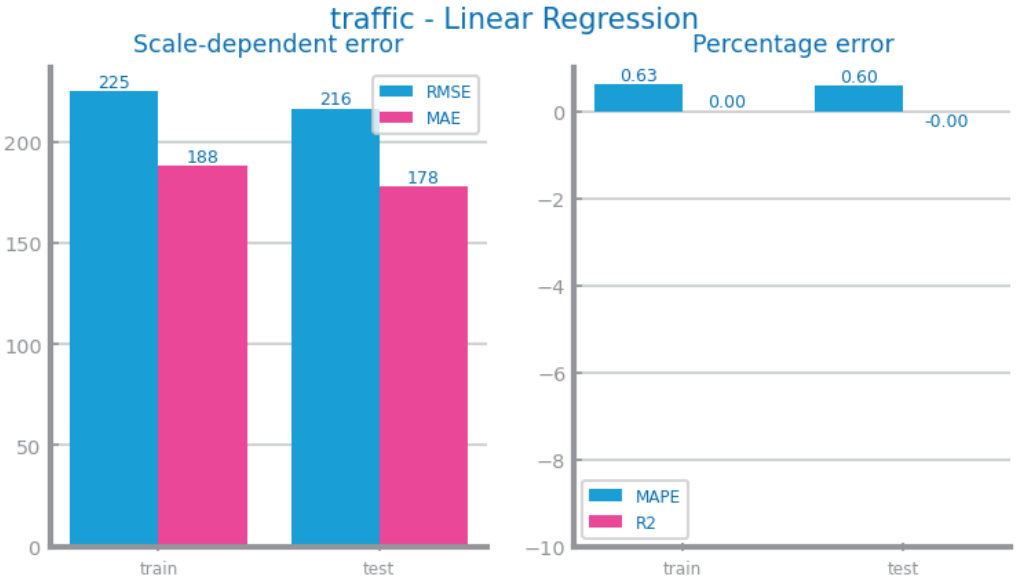


Figure 77 Forecasting results after different aggregations - SECOND - on time series 2

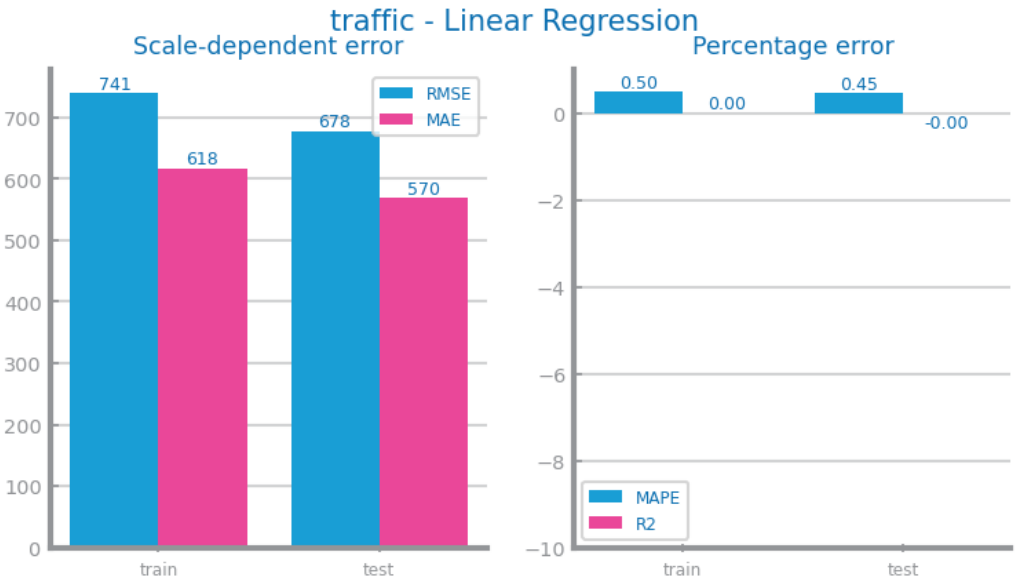


Figure 77 Forecasting results after different aggregations - THIRD - on time series 2

Smoothing

Only done in the Training Set
Used Backward Fill to impute MV in both
DS1
Retained *Original* as window didn't improve results; data is cumulative
DS2
Applied short-window moving average
WIN_SIZE=16 *same as 4 Hours*
Fig72 showed lots of noise & variance
Smooth short-term fluctuations & clarified weekly patterns

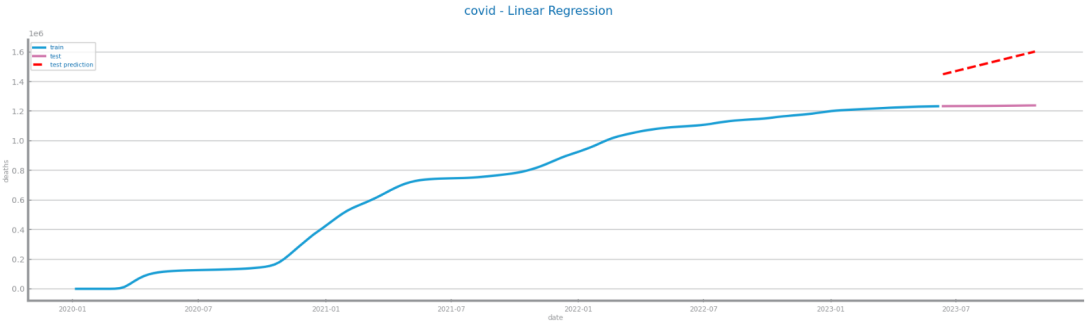


Figure 78 Forecasting plots after different smoothing parameterisations on time series 1

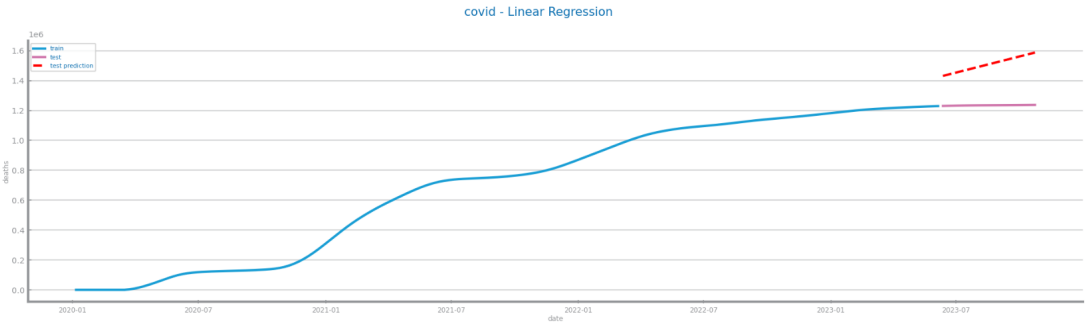


Figure 78 Forecasting plots after different smoothing parameterisations on time series 1

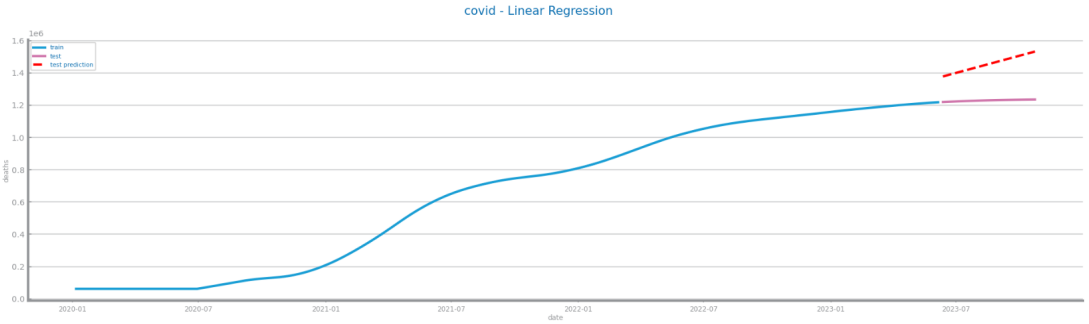


Figure 78 Forecasting plots after different smoothing parameterisations on time series 1

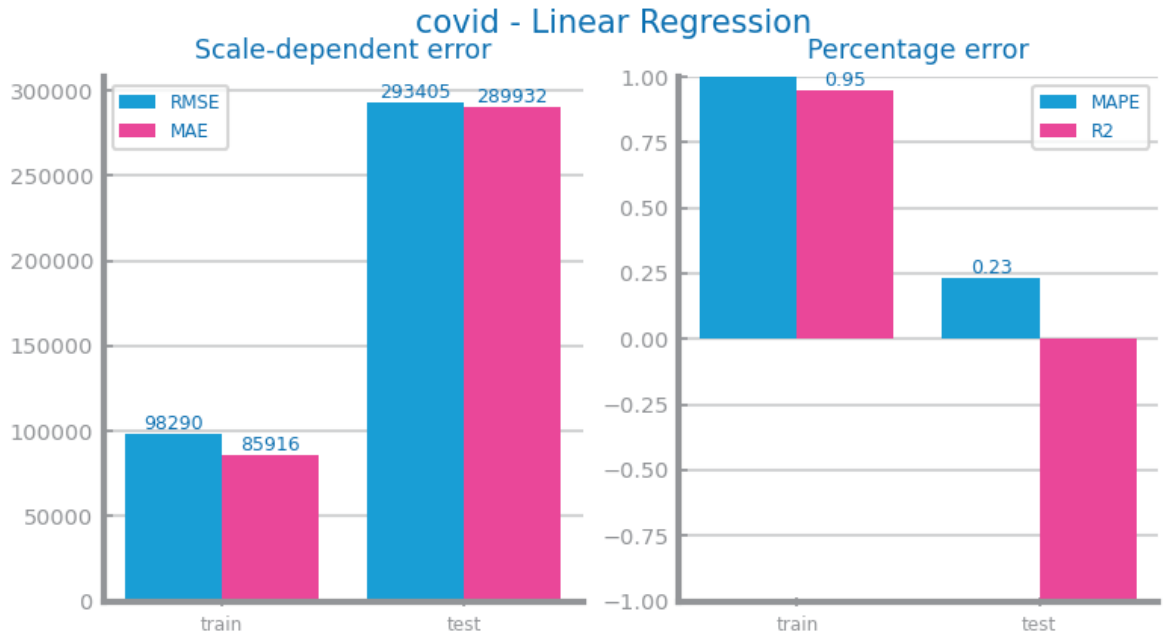


Figure 79 Forecasting results after different smoothing parameterisations on time series 1

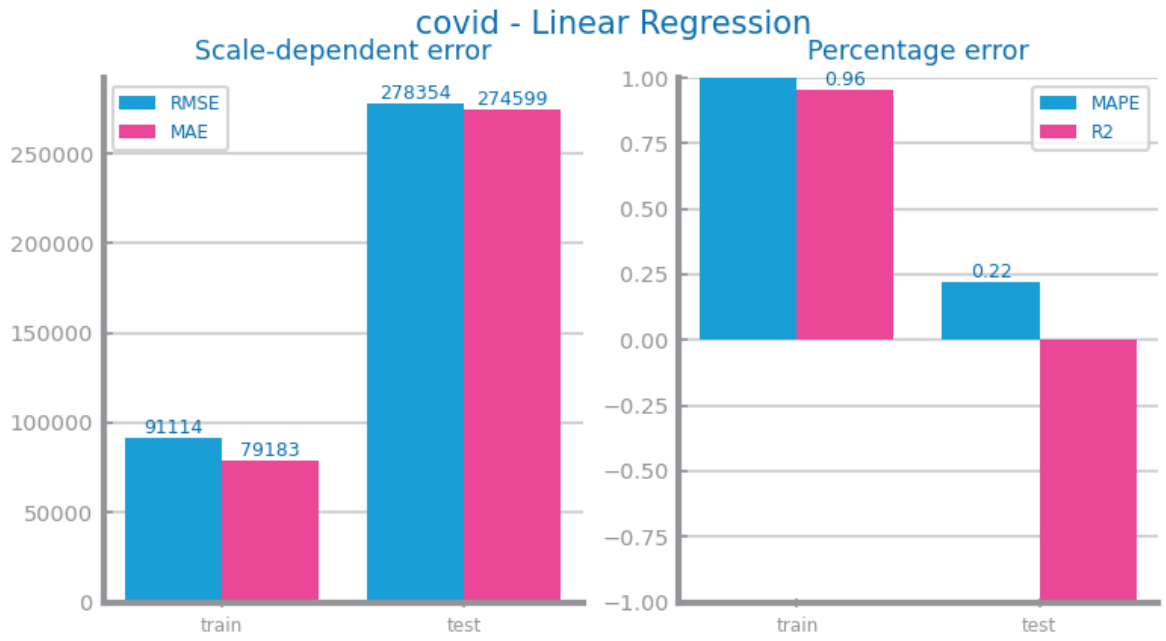


Figure 79 Forecasting results after different smoothing parameterisations on time series 1

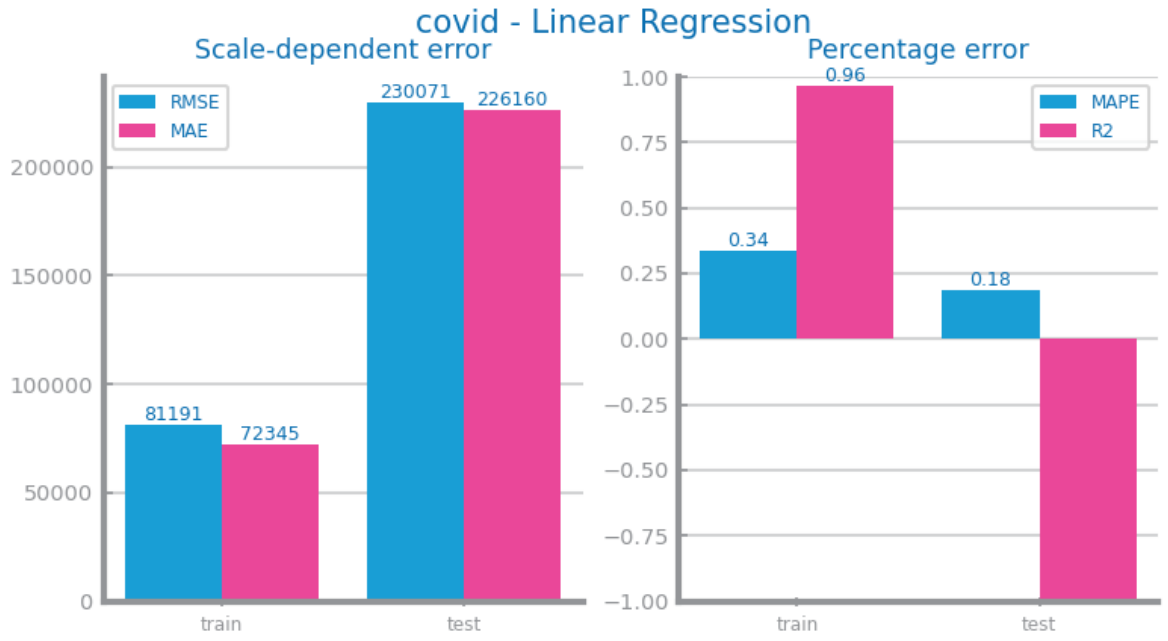


Figure 79 Forecasting results after different smoothing parameterisations on time series 1

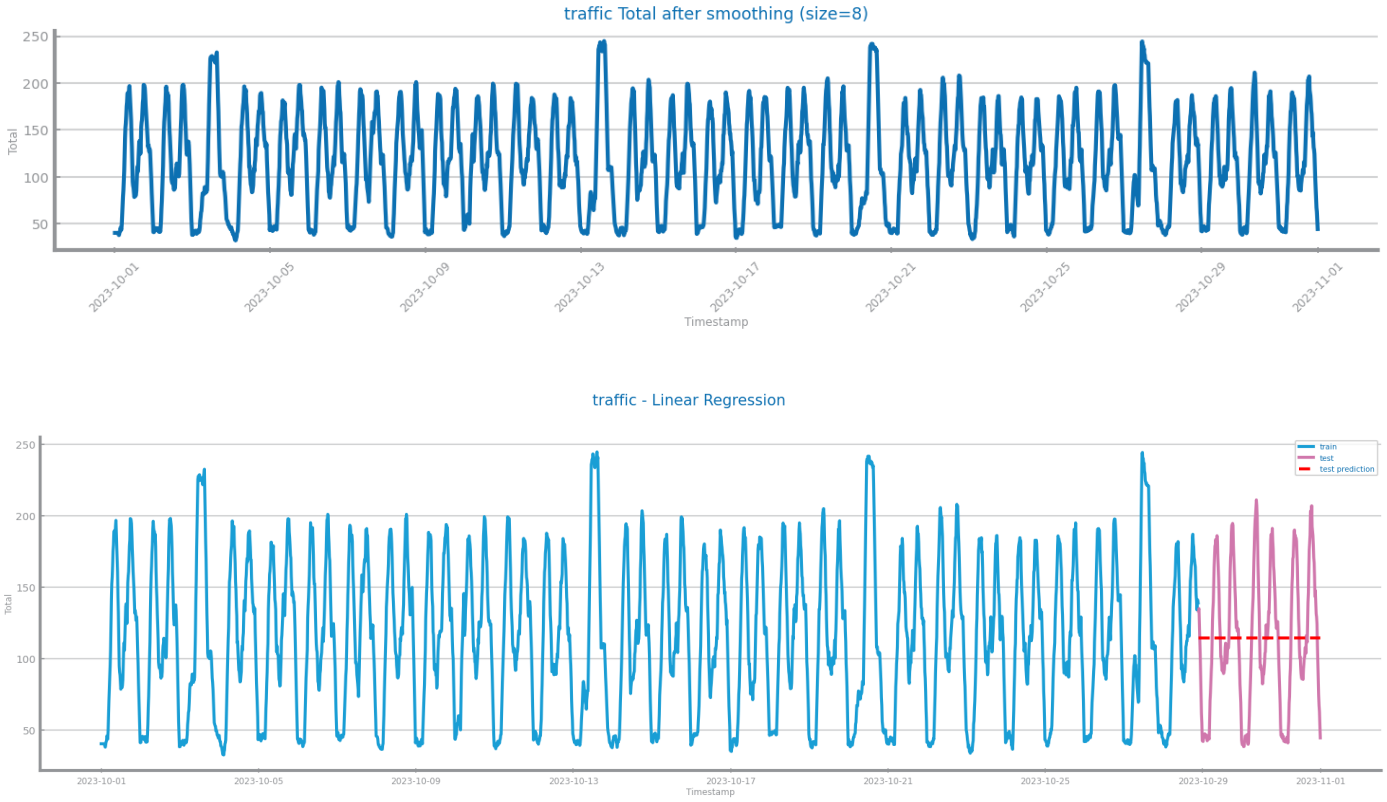


Figure 80 Forecasting plots after different smoothing parameterisations - WIN_SIZE (8) - on time series 2

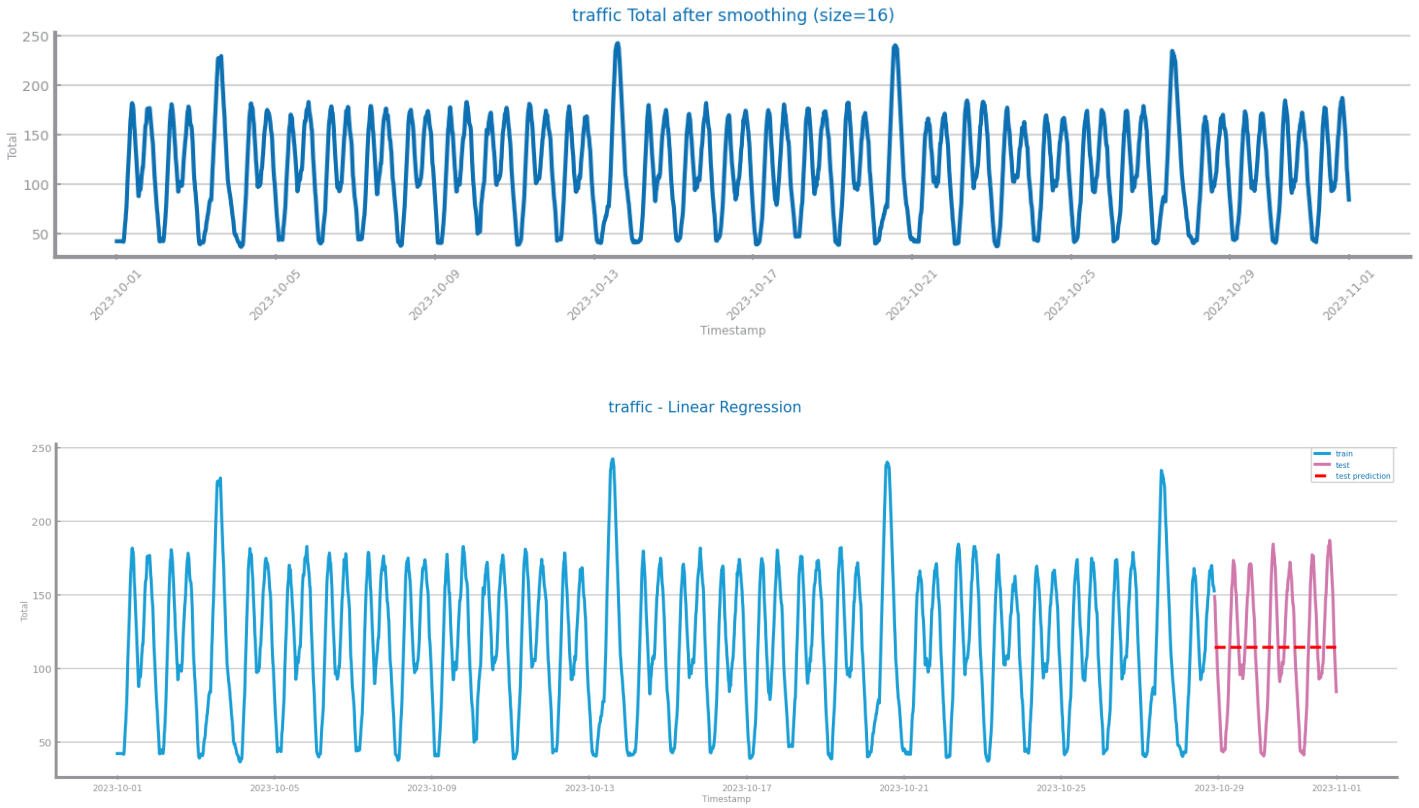


Figure 80.1 Forecasting plots after different smoothing parameterisations - WIN_SIZE (16) - on time series 2

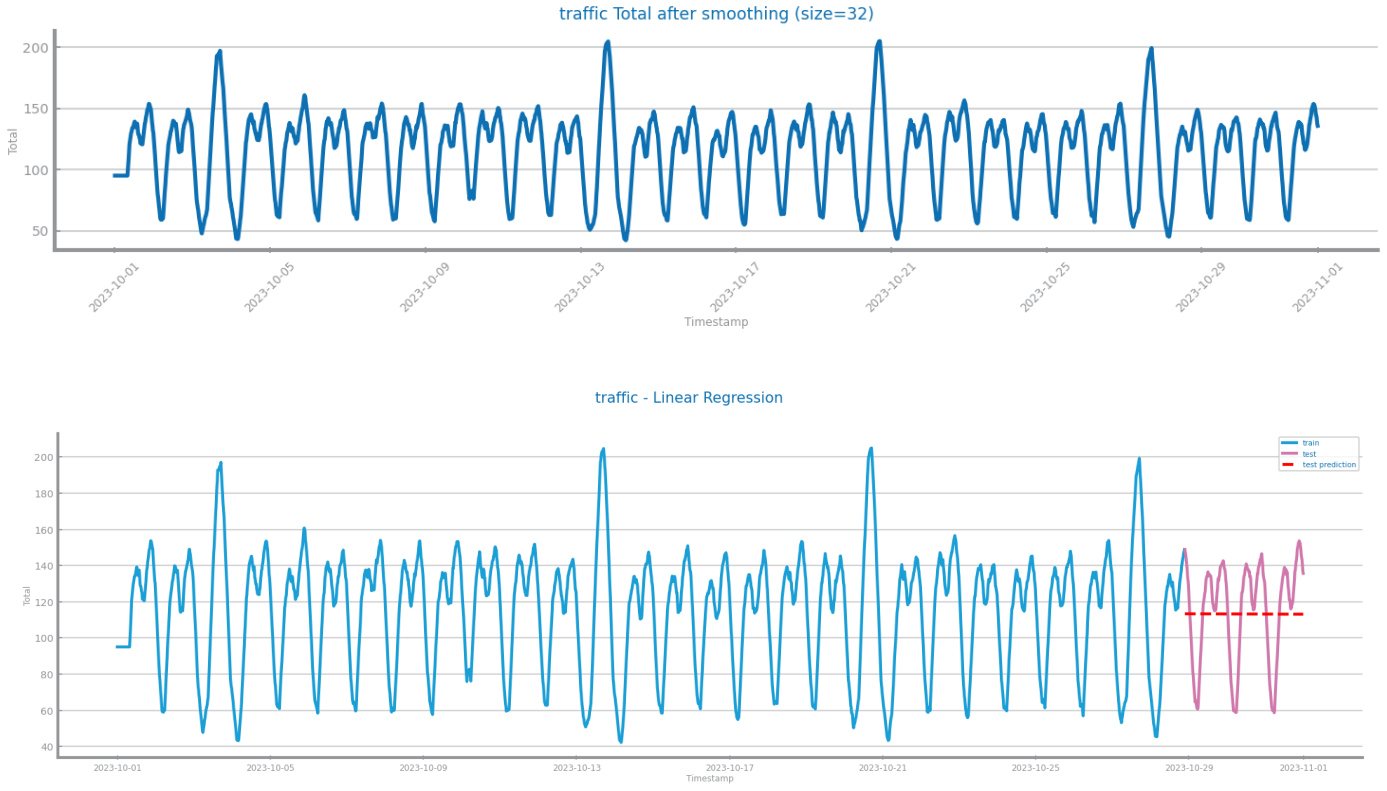


Figure 80.2 Forecasting plots after different smoothing parameterisations - WIN_SIZE (32) - on time series 2

Figure 81 Forecasting results after different smoothing parameterisations - WIN_SIZE (8) - on time series 2

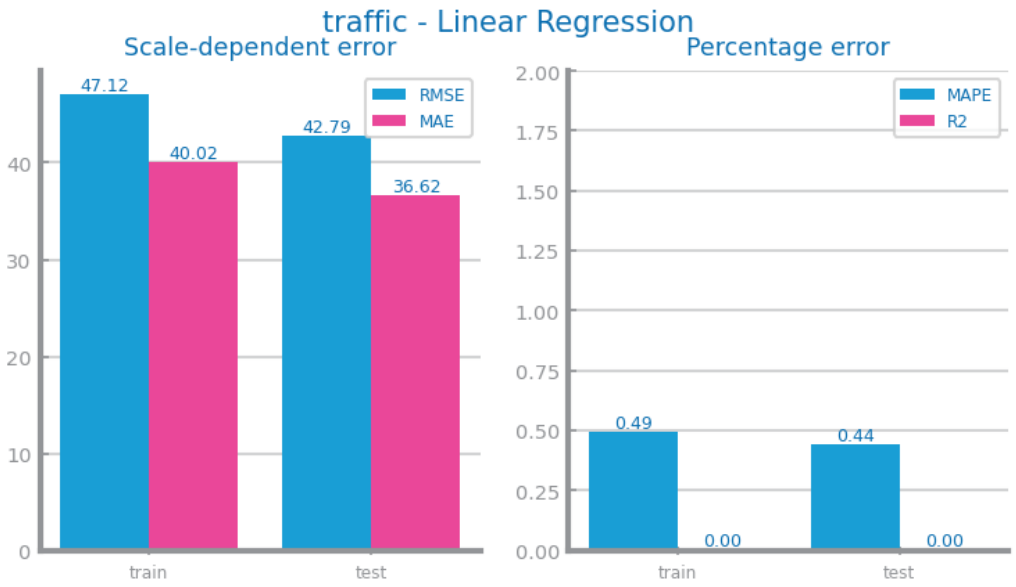


Figure 81.1 Forecasting results after different smoothing parameterisations - WIN_SIZE (16) - on time series 2

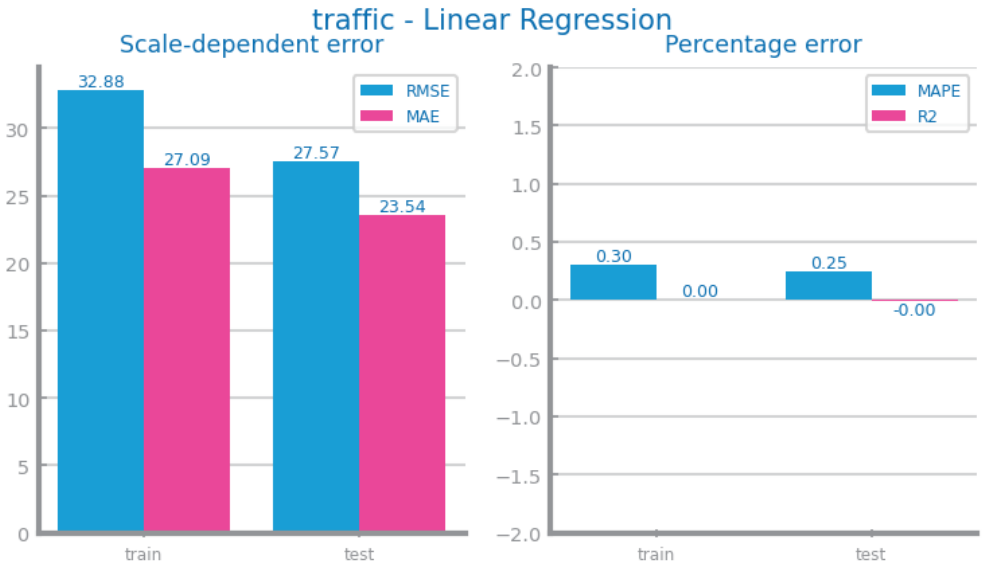


Figure 81.2 Forecasting results after different smoothing parameterisations - WIN_SIZE (32) - on time series 2

Differentiation

DS1
Used to remove the *Series* dependence on time
Second differentiation was adopted
DS2
Not applied
Scale-dependent error decreased, MAPE has non-viable values; due to the granularity we chose to proceed the transformation
The plot gives no information, introduces noise
Proceed w/ the result from *Smoothing*

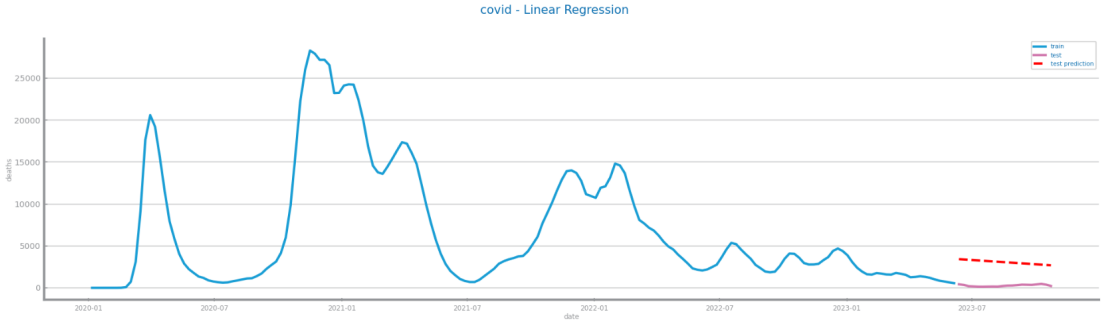


Figure 82.1 Forecasting plots after first differentiation of time series 1

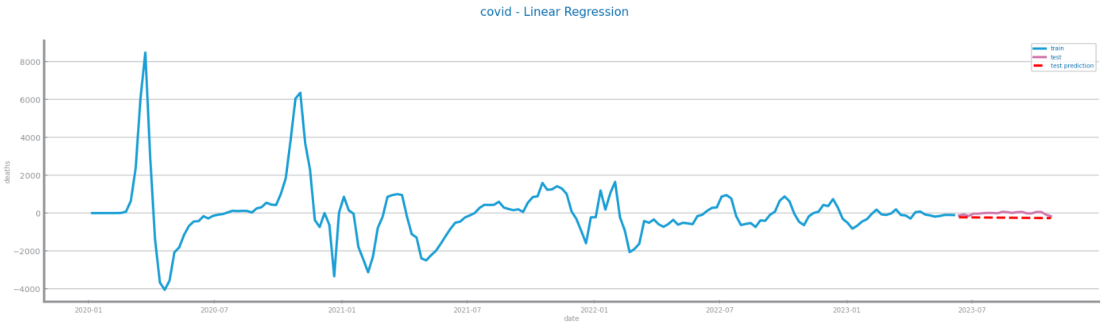


Figure 82.2 Forecasting plots after second differentiation of time series 1

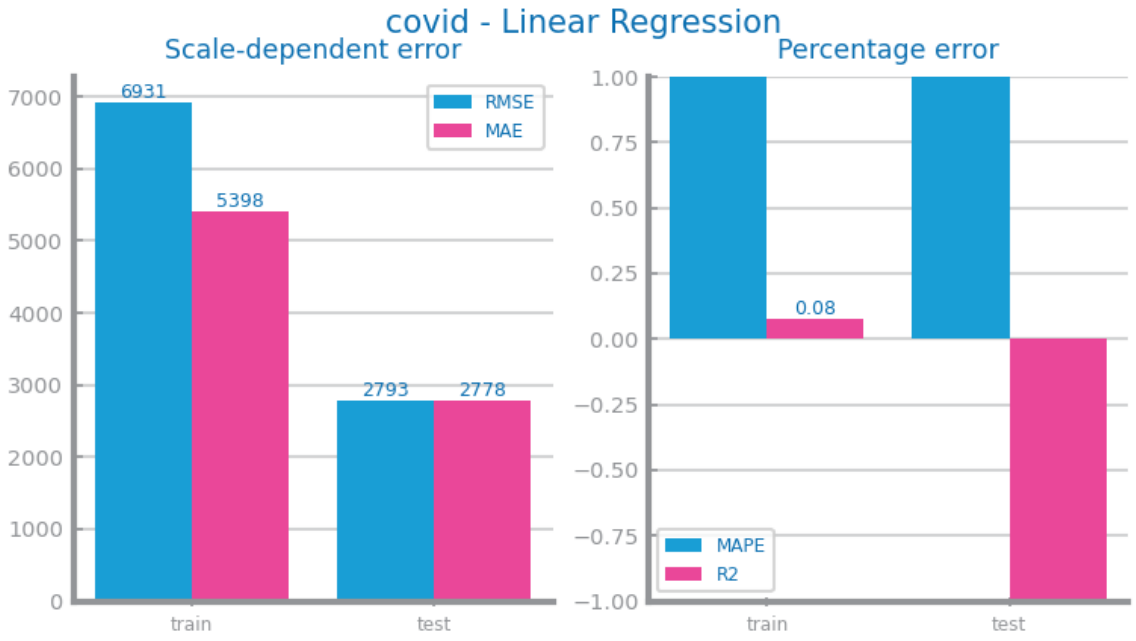


Figure 83.1 Forecasting results after first and second differentiation of time series 1

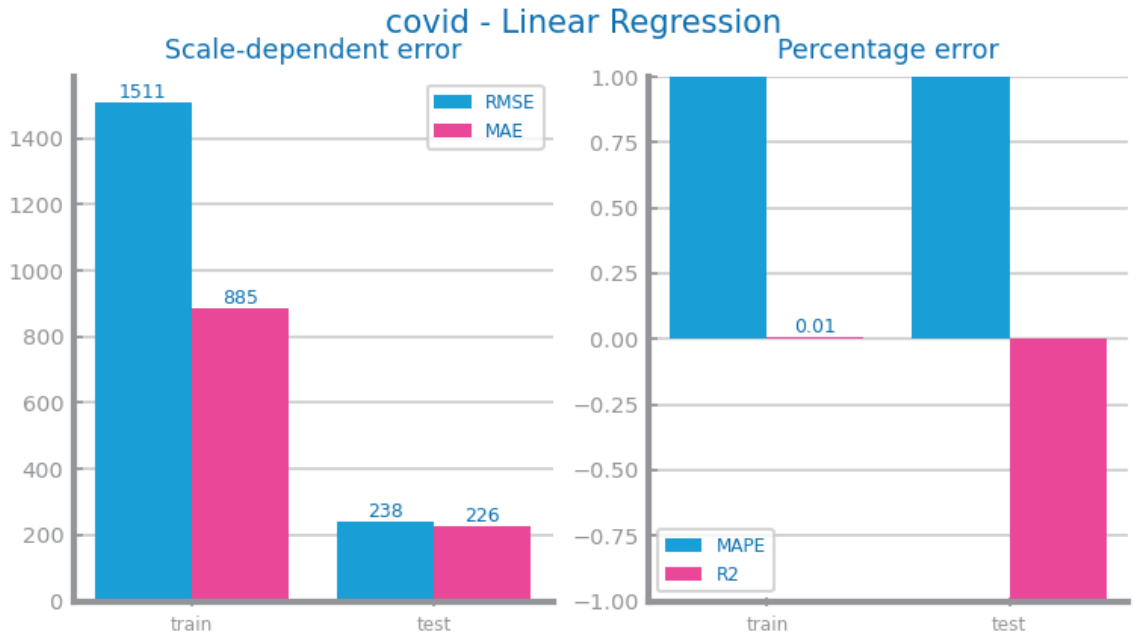


Figure 83.2 Forecasting results after first and second differentiation of time series 1

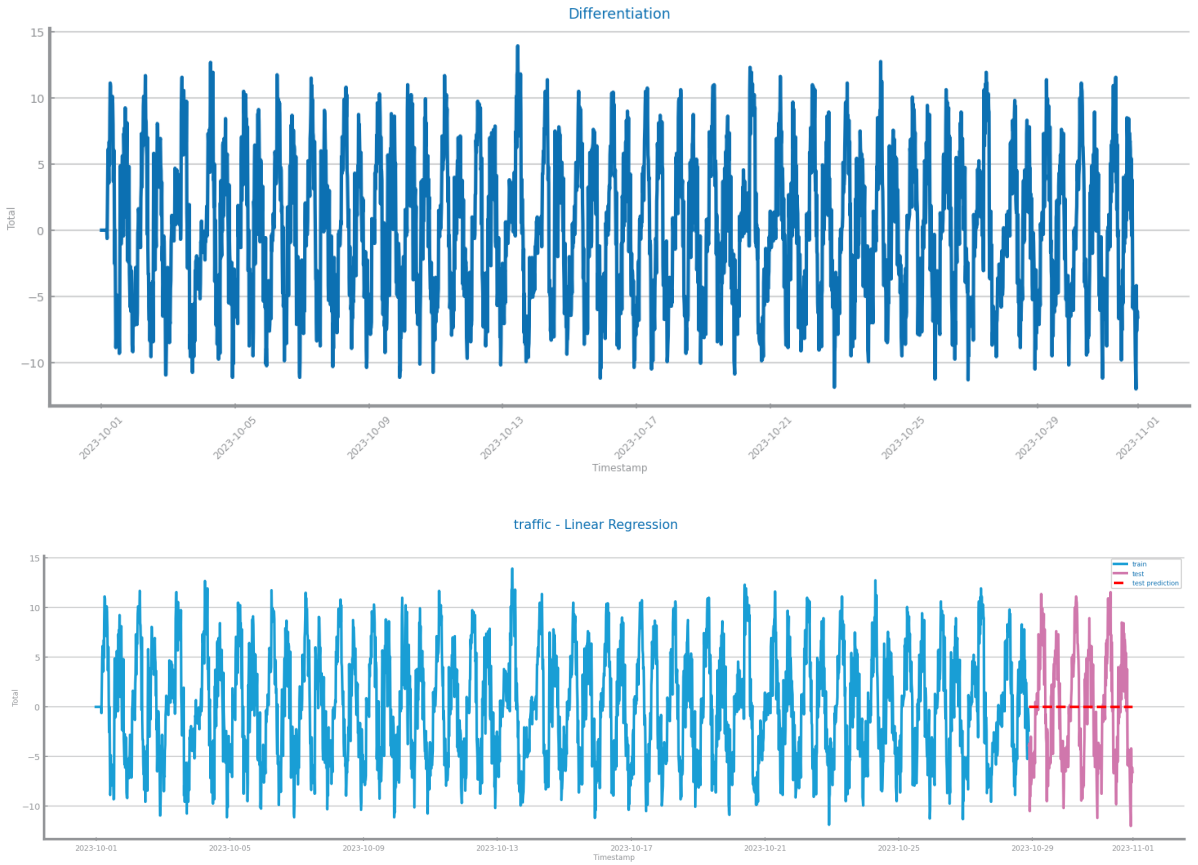


Figure 84 Forecasting plots after first differentiation of time series 2

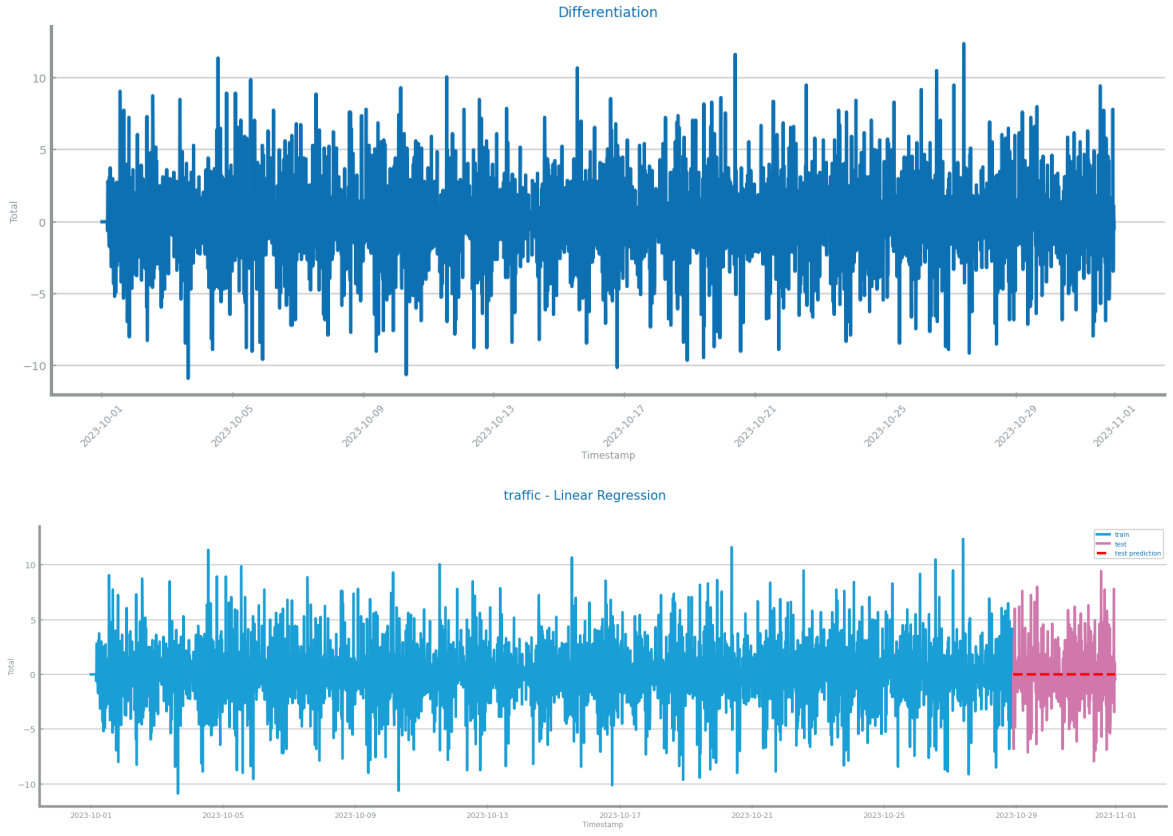
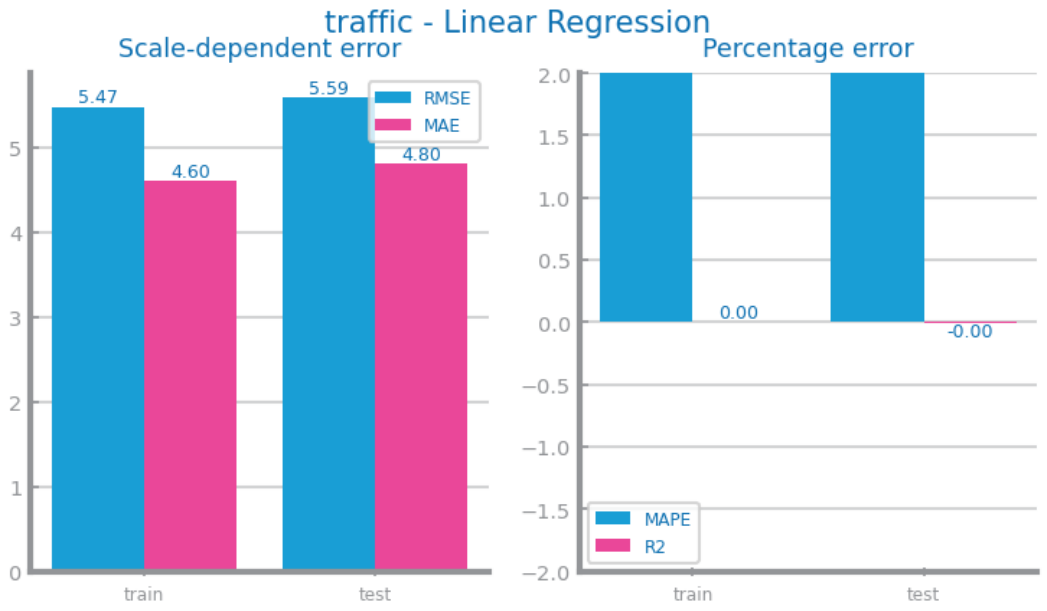


Figure 84.1 Forecasting plots after second differentiation of time series 2




```
{'RMSE': [5.474, 5.591], 'MAE': [4.595, 4.803]} {'MAPE': [2888839254183.7, 53230202313.469], 'R2': [1.53400e-05, -0.00168]}
```

Figure 85 Forecasting results after first differentiation of time series 2


```
{'RMSE': [3.033, 2.998], 'MAE': [2.267, 2.283]} {'MAPE': [99057114225.309, 357566406282.854], 'R2': [2.74627e-07, -9.4198e-06]}
```

Figure 85.1 Forecasting results after second differentiation of time series 2

Other transformations (Scaling)

No Missing Values in both (not applied)
Used for LSTM suitability; by speeding learning process & better convergence
DS1
Minor result changes; Used for LSTM
DS2
LSTM benefits from *Log transformation*
ARIMA can stabilize the variance, which we can benefit from
Greatly improved MAPE and scale-dependent error

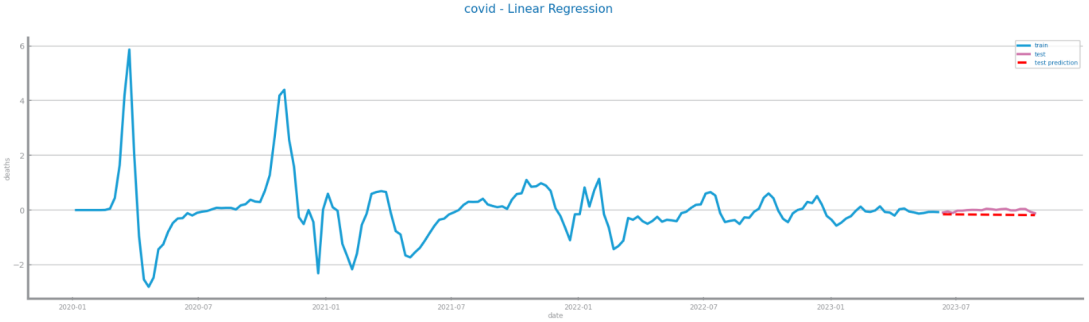


Figure 82 Forecasting plots after applying other transformations over time series 1

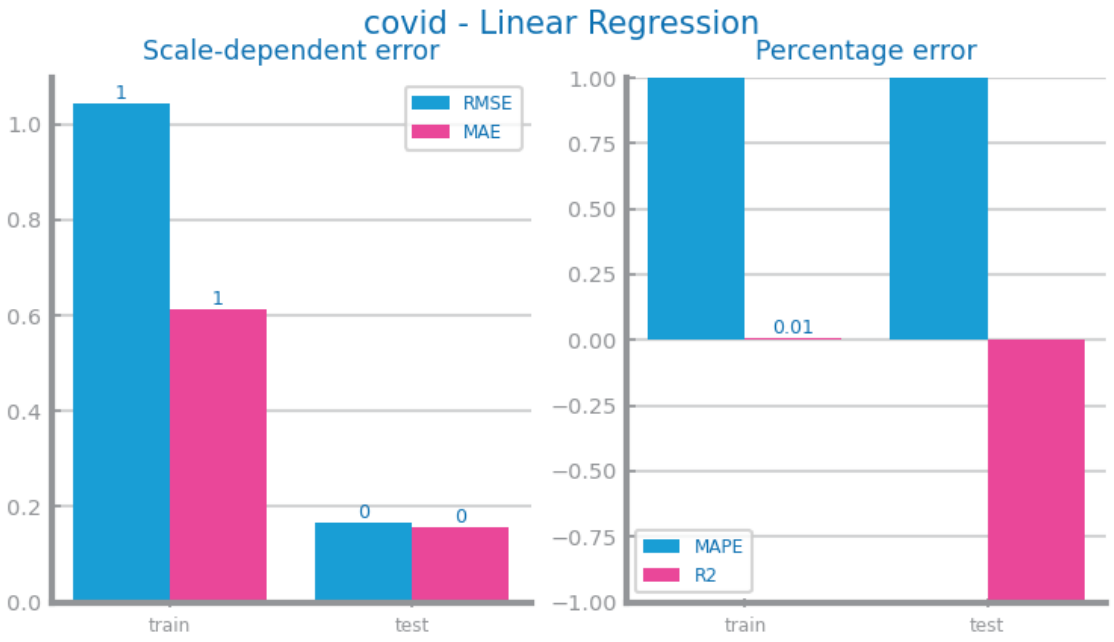


Figure 83 Forecasting results after applying other transformations over time series 1

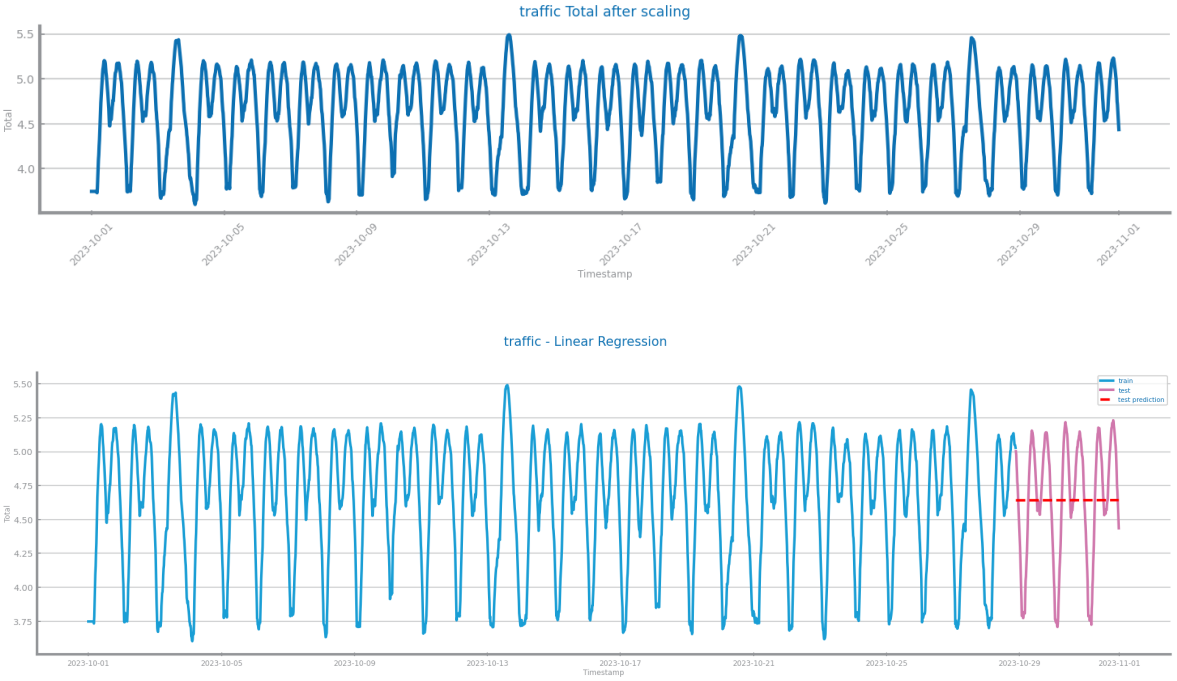


Figure 84 Forecasting plots after applying other transformations over time series 2

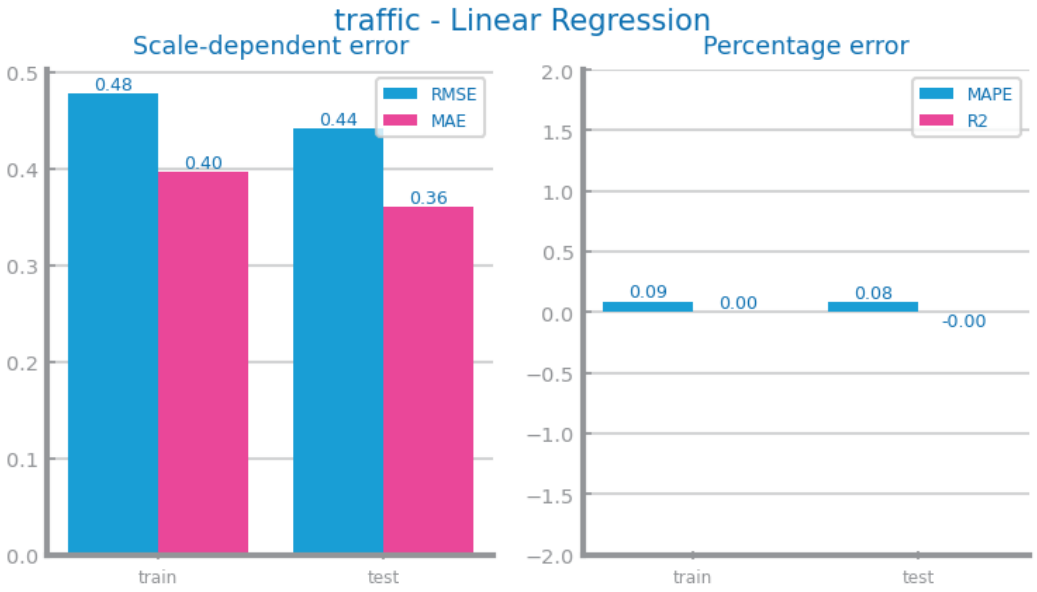


Figure 85 Forecasting results after applying other transformations over time series 2

7 Models' Evaluation

DS1

We only used the second derivative and scaling for transformations, and we measured our models accuracy by the R2.

DS2

Didn't based in Scale-dependent error most of the time

MAPE guides is through the *Transformation*

Maximize R2 from now on

Linear Regression didn't capture patterns/relationships in the data effectively, was practically **0**, as expected. Not the appropriate model to base our decision over which operation leads to better results in *Transformation*

Simple Average Model

DS1

Expected results due lack of parameters

DS2

Ignore trends, seasonality, and cycles; low R2

Unsuitable due to the **high variability** around the mean, as shown *Profiling* Fig73

It doesn't perform well

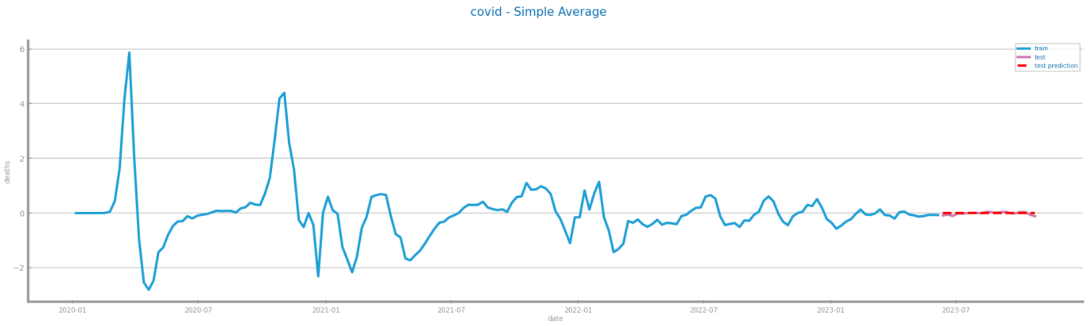


Figure 86 Forecasting plots obtained with Simple Average model over time series 1

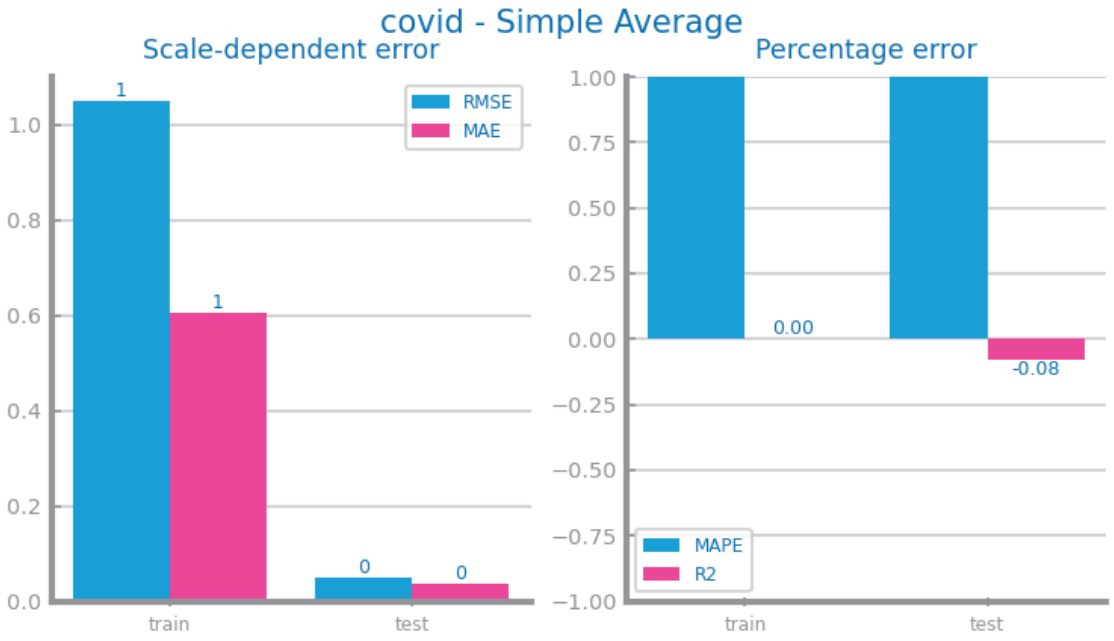


Figure 86 Forecasting results obtained with Simple Average model over time series 1

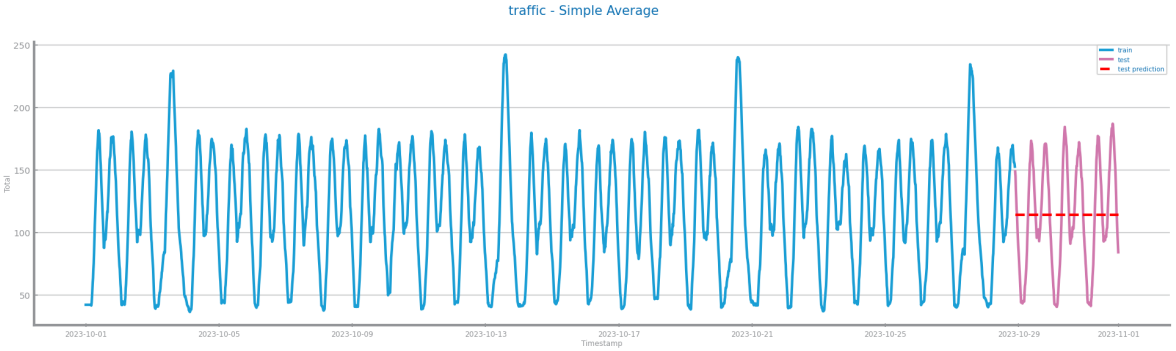


Figure 87 Forecasting plots obtained with Simple Average model over time series 2

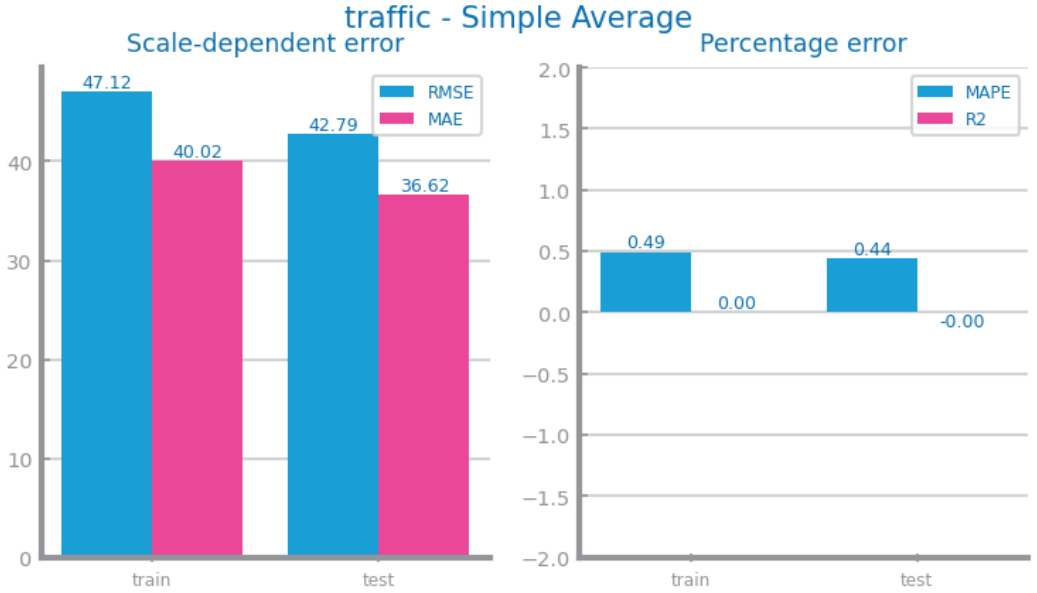


Figure 86 Forecasting results obtained with Simple Average model over time series 2

Persistence Model

DS1

The optimistic model showed better results than the realistic, so the data follows a one-set-behind model closer than a long term one.

DS2

As expected really good results *R2* for the optimistic model (low MAPE error and almost perfect R2)

Assumes the future will be the same as the present

(The optimistic persistence model showed way better results than the realistic one and we can see that the realistic one only predicted a line)

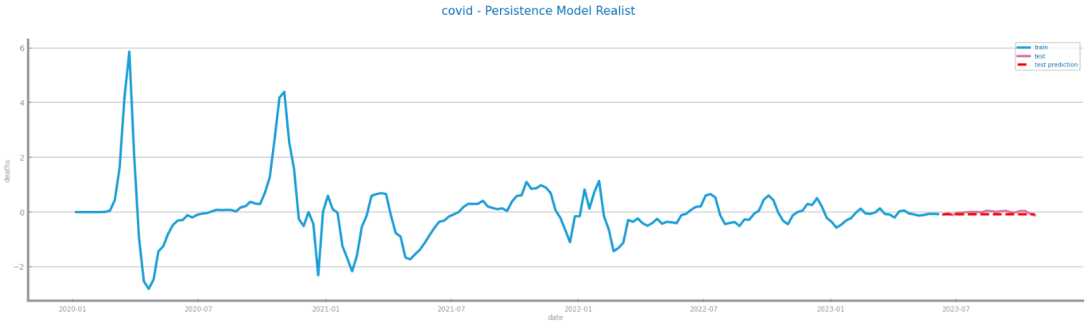


Figure 88 Forecasting plots obtained with Persistence model (long term) over time series 1

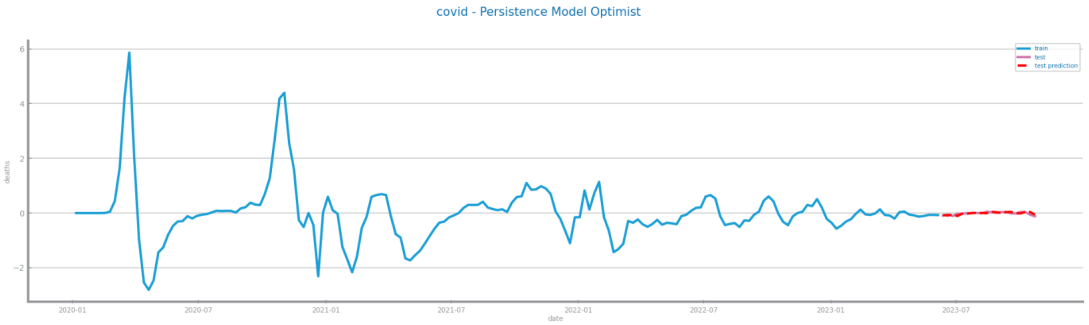


Figure 89 Forecasting plots obtained with Persistence model (one-set-behind) over time series 1

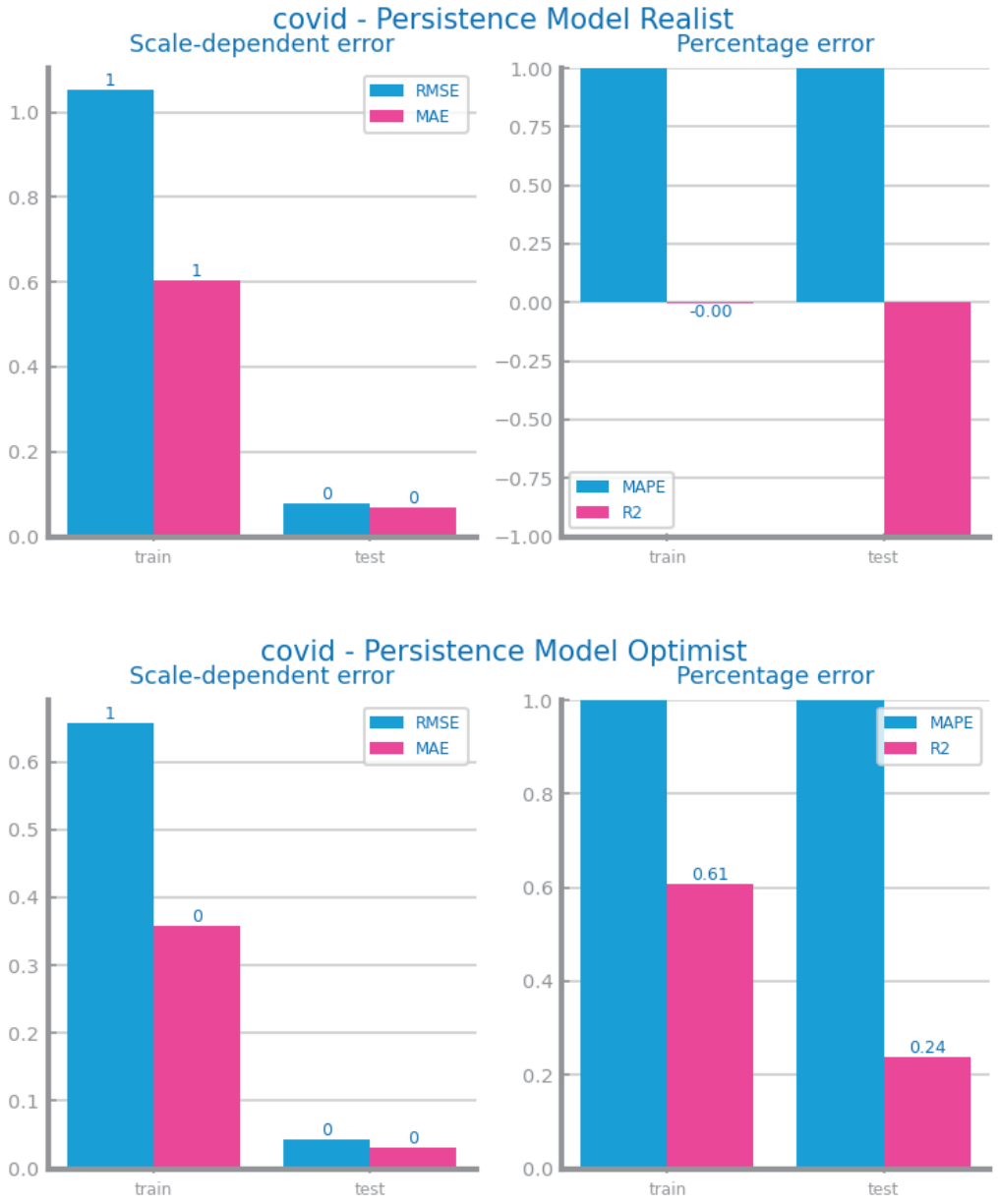


Figure 86 Forecasting results obtained with Persistence model in both situations over time series 1

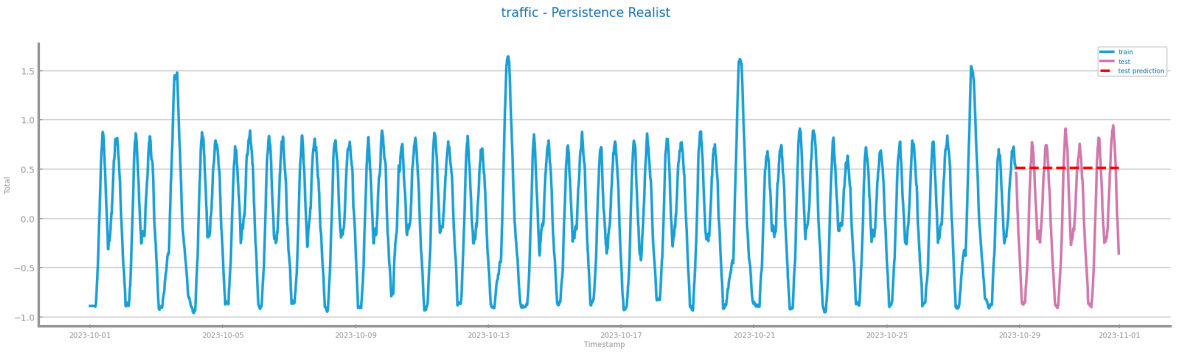


Figure 88 Forecasting plots obtained with Persistence model (long term) over time series 2

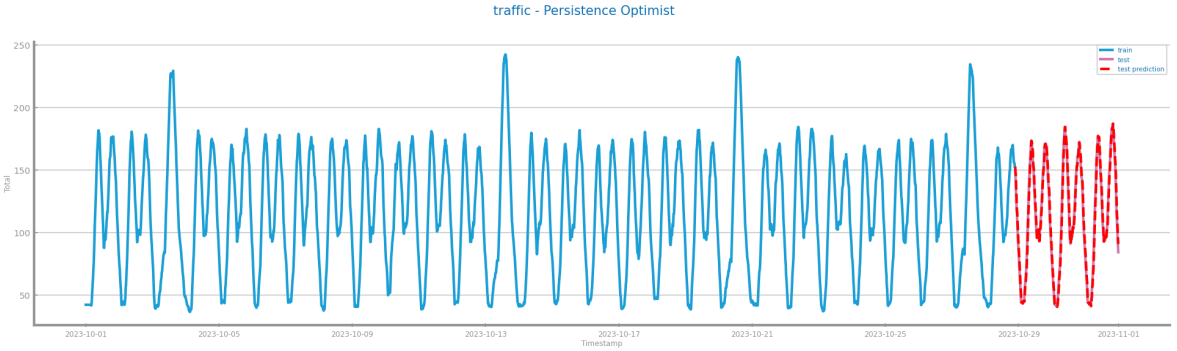


Figure 89 Forecasting plots obtained with Persistence model (one-set-behind) over time series 2

Figure 86 Forecasting results obtained with Persistence model in both situation over time series 2

Rolling Mean Model

DS1
WIN-SIZE from 1 to 179
Displayed a cyclic pattern in *R2* values, overall performance was not optimal
DS2
Adjustable parameter WIN_SIZE
81 as best; diff sizes were tests; start with upward pattern and then stabilize for *R2*
Despite low *MAPE* suggesting high predictive accuracy, *R2* of **0** indicates the model failed to account variability in the data
Mean-based approaches are unsuitable here, as the technique compute its mean value for predicting the next one

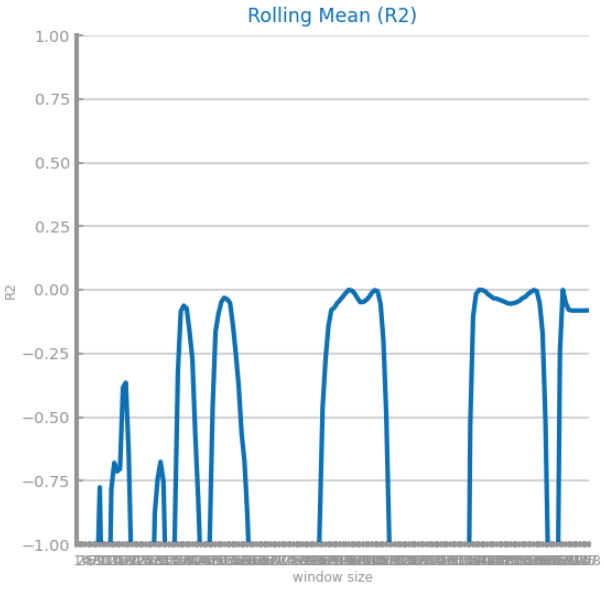


Figure 90 Forecasting study over different parameterisations of the rolling mean algorithm over time series 1

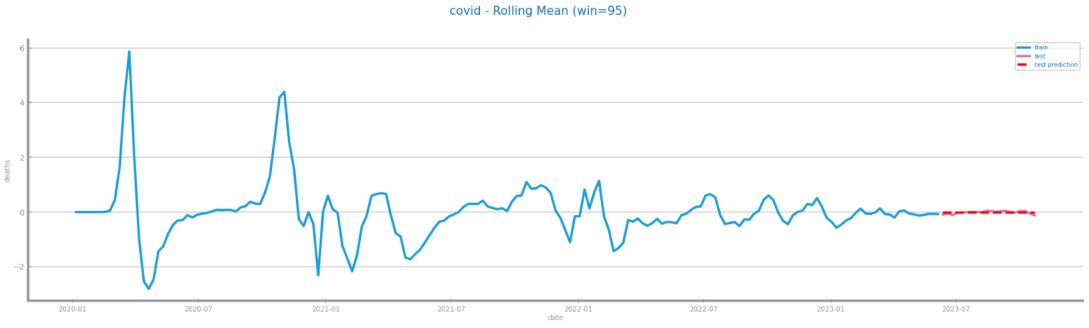


Figure 91 Forecasting plots obtained with the best parameterisation of rolling mean algorithm, over time series 1

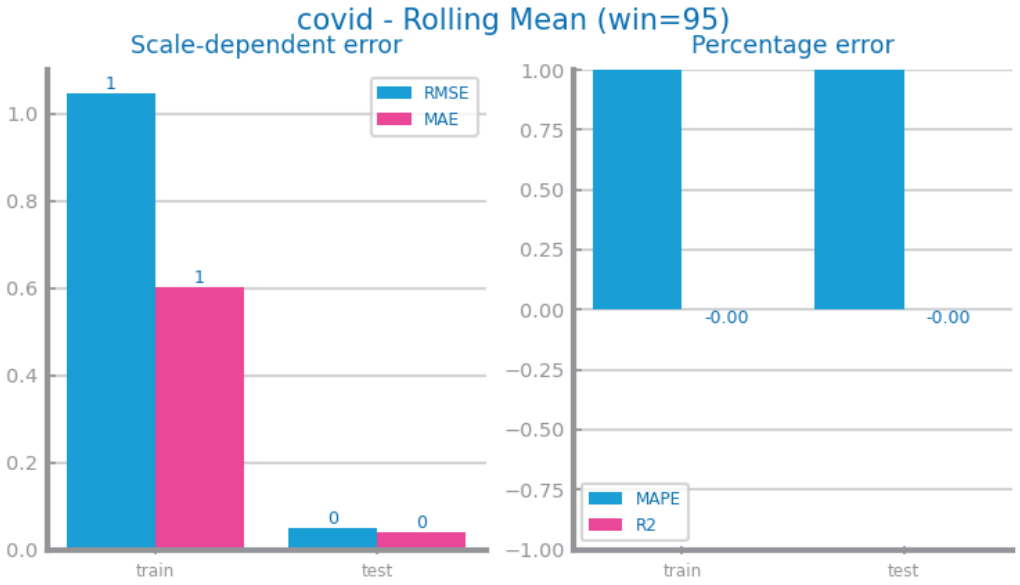
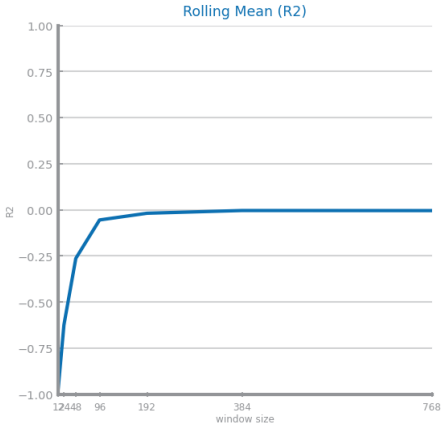
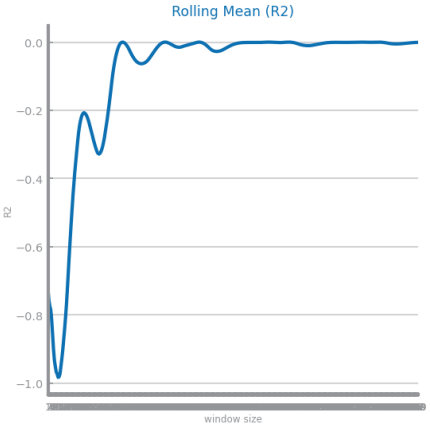


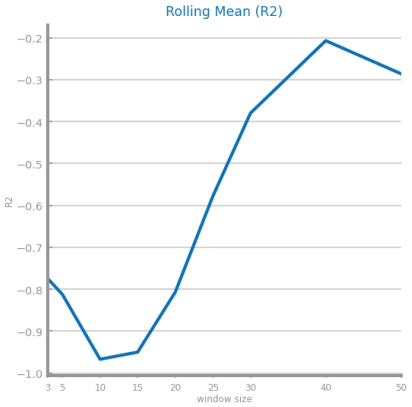
Figure 92 Forecasting results obtained with the best parameterisation of rolling mean algorithm, over time series 1



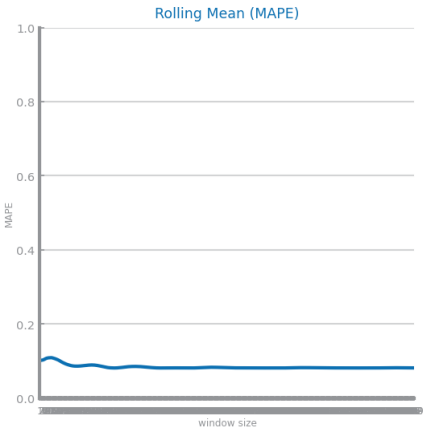
Rolling Mean best = 384 -> R2=-0.0042



Rolling Mean best = 81 -> R2=-0.0001561

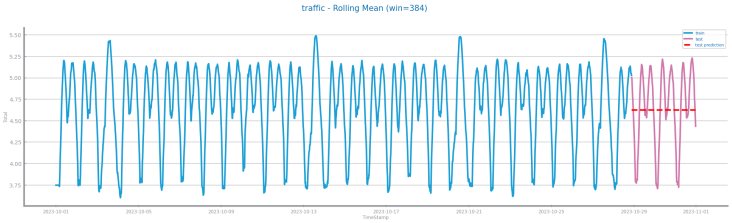


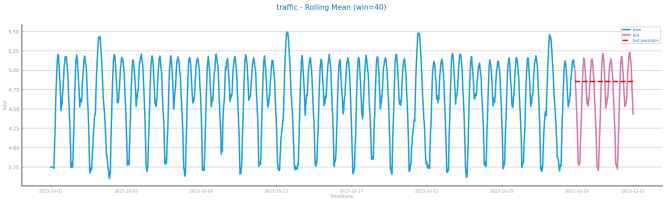
Rolling Mean best = 40 -> R2=-0.20691

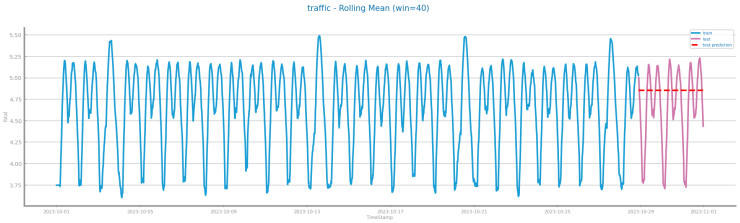


Rolling Mean best = 81 -> MAPE=0.081251648215

Figure 93 Forecasting study over different parameterisations of the rolling mean algorithm over time series 2

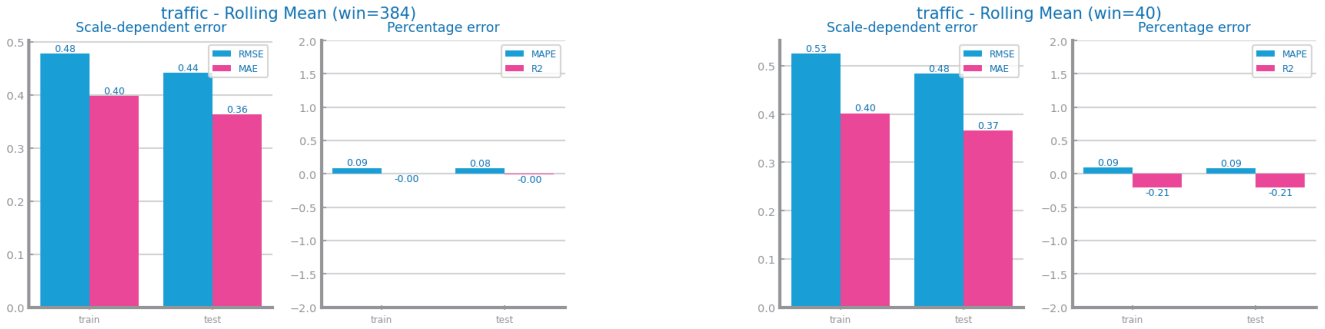






384 *81* *40*

Figure 94 Forecasting plots obtained with the best parameterisation of rolling mean algorithm, over time series 2



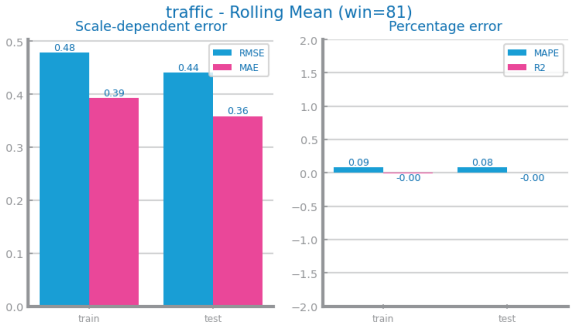


Figure 95 Forecasting results obtained with the best parameterisation of rolling mean algorithm, over time series 2

ARIMA Model

DS1

Best parameters w/ low d values indicate stationarity: d [0,1,2], p [1,2,3,5,7,10], q [1,3,5,7]

DS2

Study *(2,8,4)*:

Std residuals have no pattern, structure is well captured *assumptions are good*

Q-Q plot, almost all points in reference line, residuals normal distributed

no White Noise, correlations present

Despite study good feedback, **best model (2,0,7)** was short, perfect *R2* train but significant *MAPE* error & low *R2* test; Expected better due to Stationary

Plot test prediction doesn't follow the test

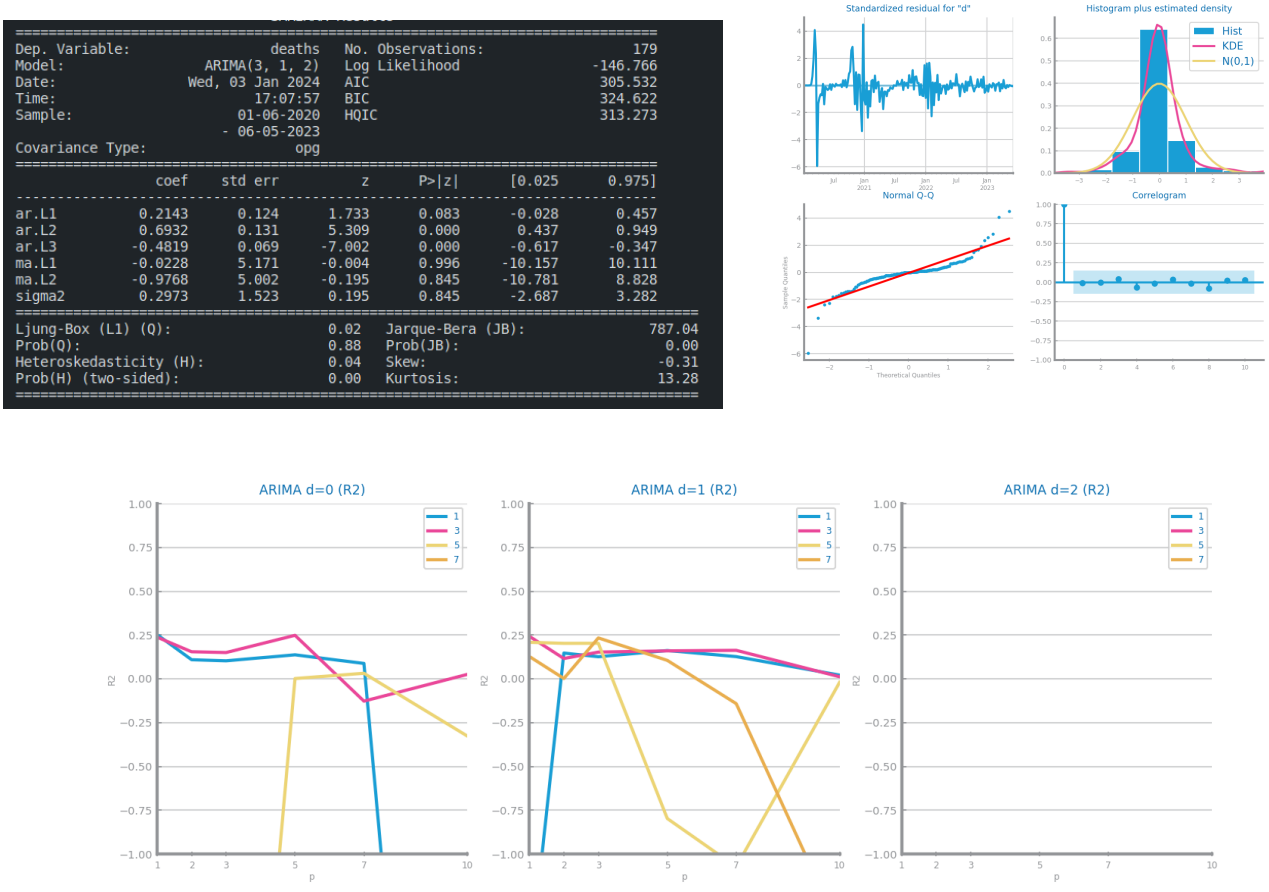


Figure 96 Forecasting study over different parameterisations of the ARIMA algorithm over time series 1

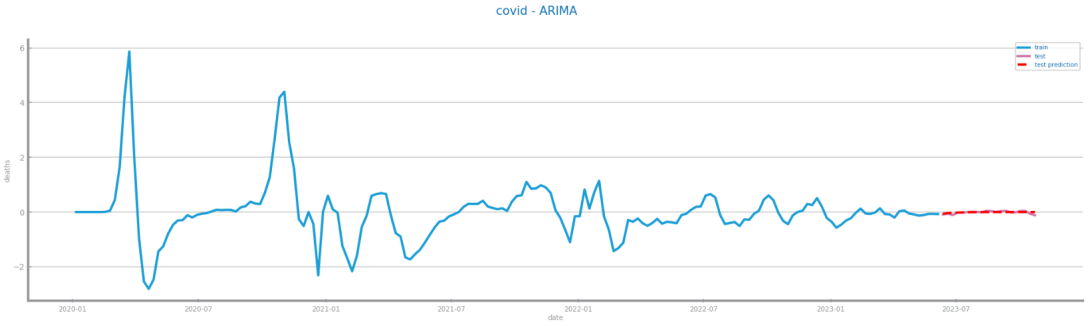


Figure 97 Forecasting plots obtained with the best parameterisation of ARIMA algorithm, over time series 1

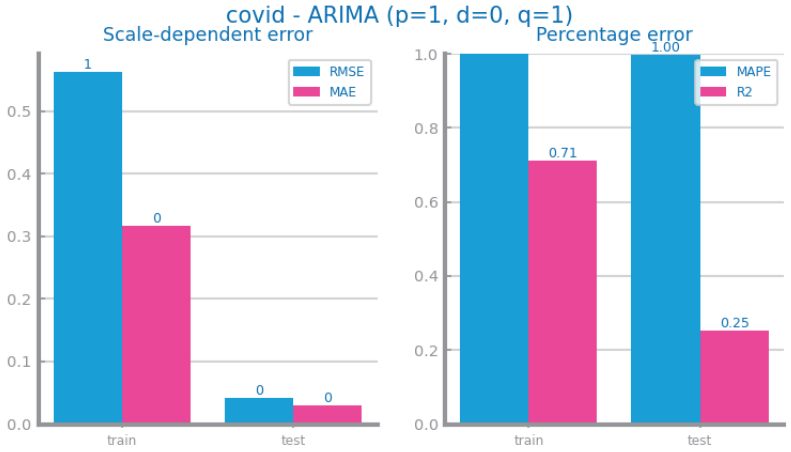


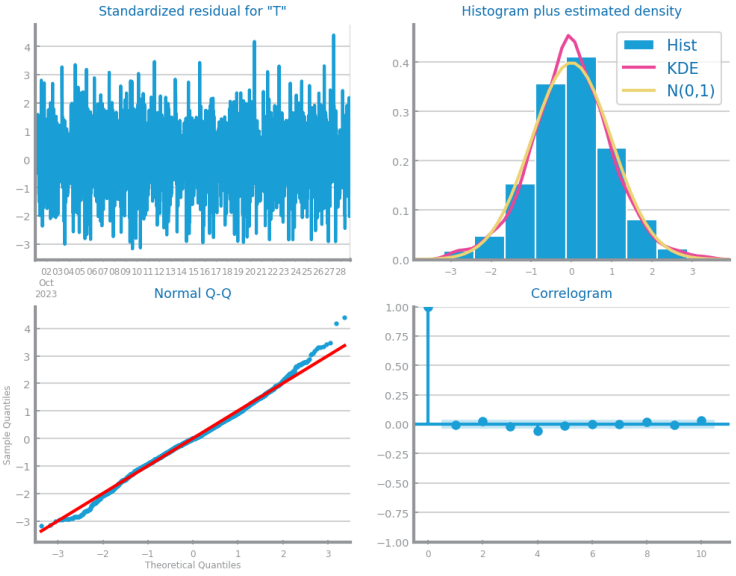
Figure 98 Forecasting results obtained with the best parameterisation of ARIMA algorithm, over time series 1

SARIMAX Results

Dep. Variable:	Total	No. Observations:	2678
Model:	ARIMA(3, 1, 2)	Log Likelihood	-6429.193
Date:	Thu, 28 Dec 2023	AIC	12870.386
Time:	14:18:04	BIC	12905.741
Sample:	10-01-2023 - 10-28-2023	HQIC	12883.177
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	2.2490	0.028	78.937	0.000	2.193	2.305
ar.L2	-1.5599	0.055	-28.246	0.000	-1.668	-1.452
ar.L3	0.2971	0.027	10.858	0.000	0.243	0.351
ma.L1	-1.7335	0.020	-87.316	0.000	-1.772	-1.695
ma.L2	0.7929	0.020	39.980	0.000	0.754	0.832
sigma2	7.1313	0.175	40.672	0.000	6.788	7.475

Ljung-Box (L1) (Q):	0.03	Jarque-Bera (JB):	54.78
Prob(Q):	0.87	Prob(JB):	0.00
Heteroskedasticity (H):	0.97	Skew:	0.07
Prob(H) (two-sided):	0.61	Kurtosis:	3.68

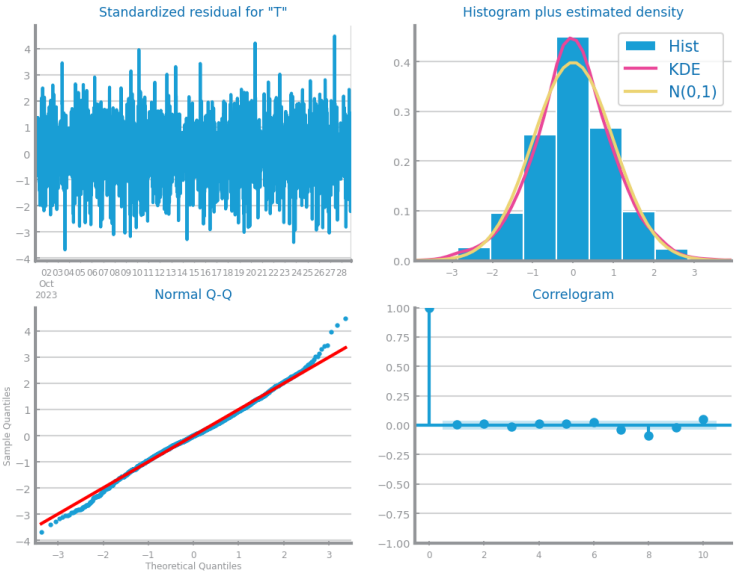


SARIMAX Results

Dep. Variable:	Total	No. Observations:	2678
Model:	ARIMA(4, 1, 9)	Log Likelihood	-6330.456
Date:	Sat, 30 Dec 2023	AIC	12688.911
Time:	12:32:15	BIC	12771.405
Sample:	10-01-2023 - 10-28-2023	HQIC	12718.756
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	0.9561	0.045	21.252	0.000	0.868	1.044
ar.L2	-0.3674	0.042	-8.733	0.000	-0.450	-0.285
ar.L3	0.8198	0.036	22.742	0.000	0.749	0.890
ar.L4	-0.5619	0.026	-21.905	0.000	-0.612	-0.512
ma.L1	-0.4335	0.049	-8.759	0.000	-0.531	-0.337
ma.L2	0.3149	0.036	8.729	0.000	0.244	0.386
ma.L3	-0.7145	0.033	-21.874	0.000	-0.779	-0.651
ma.L4	0.3102	0.029	10.812	0.000	0.254	0.366
ma.L5	0.1866	0.026	7.255	0.000	0.136	0.237
ma.L6	0.0764	0.027	2.839	0.005	0.024	0.129
ma.L7	0.1986	0.027	7.244	0.000	0.145	0.252
ma.L8	0.2098	0.027	7.789	0.000	0.157	0.263
ma.L9	0.0320	0.034	0.954	0.340	-0.034	0.098

...



SARIMAX Results

Dep. Variable:	Total	No. Observations:	2678
Model:	ARIMA(2, 8, 4)	Log Likelihood	-9906.263
Date:	Sat, 30 Dec 2023	AIC	19826.525
Time:	12:33:35	BIC	19867.754
Sample:	10-01-2023 - 10-28-2023	HQIC	19841.443
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	-1.7628	0.012	-149.432	0.000	-1.786	-1.740
ar.L2	-0.7981	0.012	-67.738	0.000	-0.821	-0.775
ma.L1	-1.9970	7.991	-0.250	0.803	-17.660	13.666
ma.L2	-0.0011	8.000	-0.000	1.000	-15.681	15.679
ma.L3	1.9970	7.998	0.250	0.803	-13.679	17.673
ma.L4	-0.9989	7.989	-0.125	0.900	-16.656	14.659
sigma2	96.3951	771.000	0.125	0.901	-1414.736	1607.526

Ljung-Box (L1) (Q):	652.69	Jarque-Bera (JB):	27.71
Prob(Q):	0.00	Prob(JB):	0.00
Heteroskedasticity (H):	1.05	Skew:	-0.01
Prob(H) (two-sided):	0.46	Kurtosis:	3.50

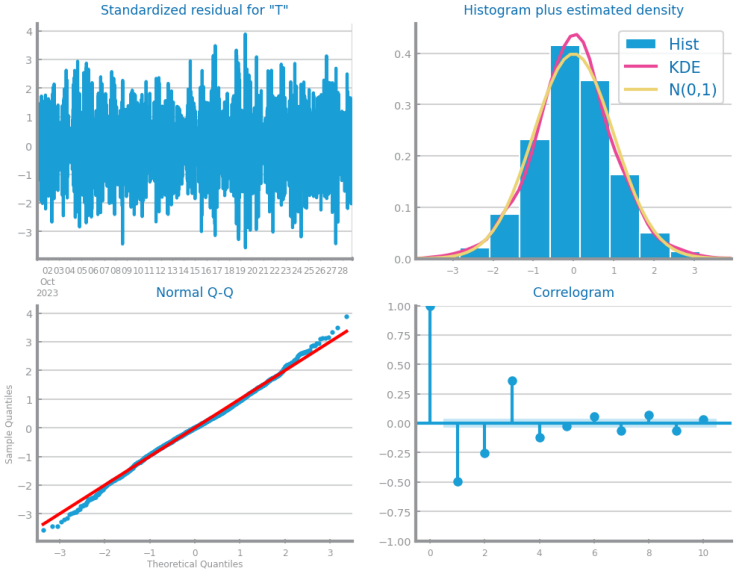
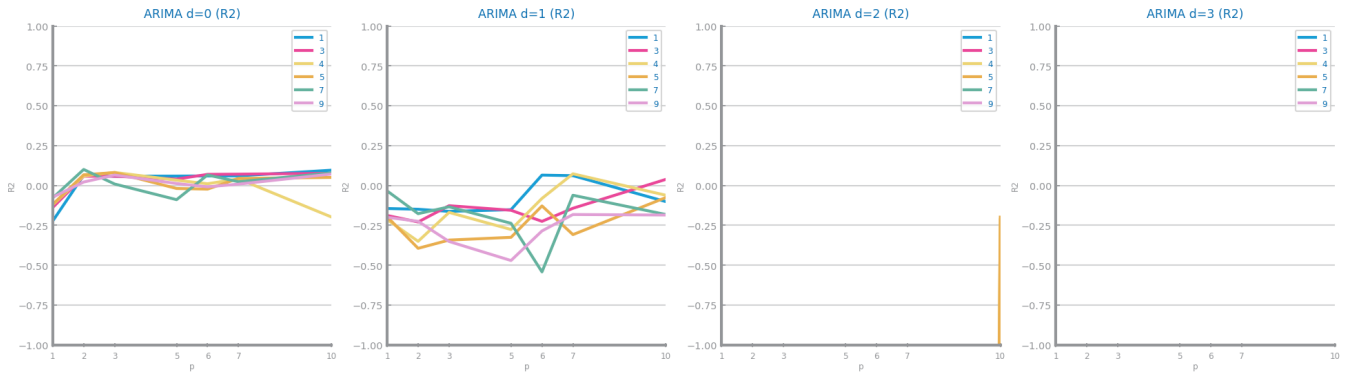


Figure 99 Forecasting study over different parameterisations of the ARIMA algorithm over time series 2




```
ARIMA best results achieved with (p,d,q)=(2, 0, 7) ==> measure=0.10
```

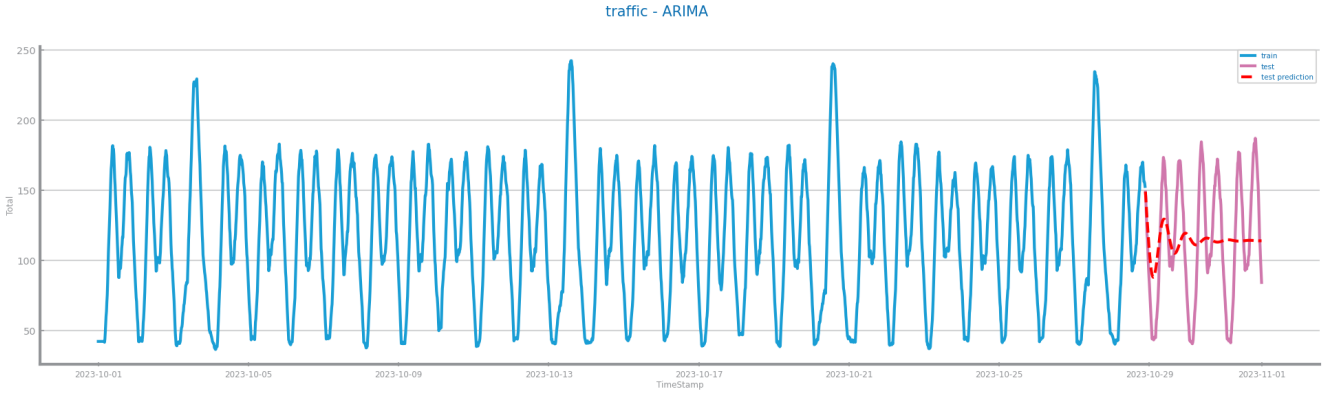


Figure 100 Forecasting plots obtained with the best parameterisation of ARIMA algorithm, over time series 2

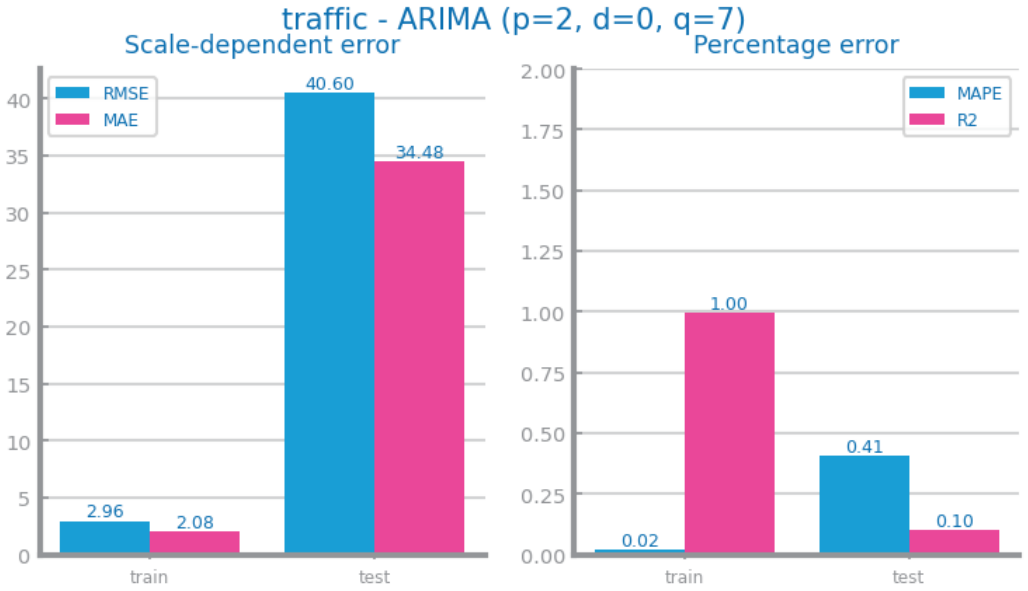


Figure 101 Forecasting results obtained with the best parameterisation of ARIMA algorithm, over time series 2

LSTMs Model

DS1

Use values in Fig102 for LSTM; Perform better in small sequence lengths due to data tapering off

DS2

Best result w/ sequence **<8**, consistent *R2* by capturing variability

Best model ***(4, 25, 300);*** Perfect R2 & low MAPE error in train & test; Scale-dependent errors practically **0**

Test predictions near 0 in plot, indicating it does not reflect pattern capture *(problem in Transformation or w/ the dataset)*

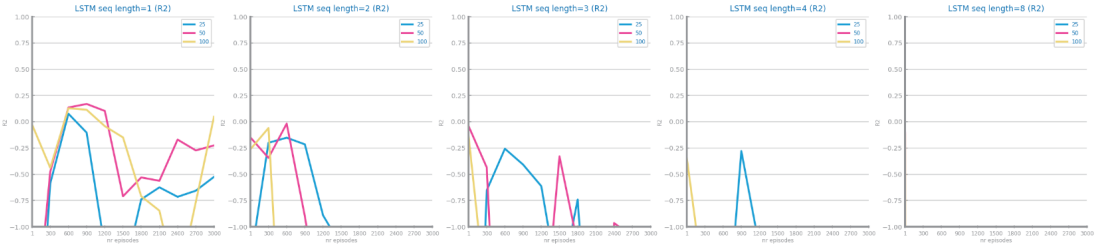


Figure 102 Forecasting study over different parameterisations of LSTMs over time series 1

Figure 103 Forecasting plots obtained with the best parameterisation of LSTMs, over time series 1

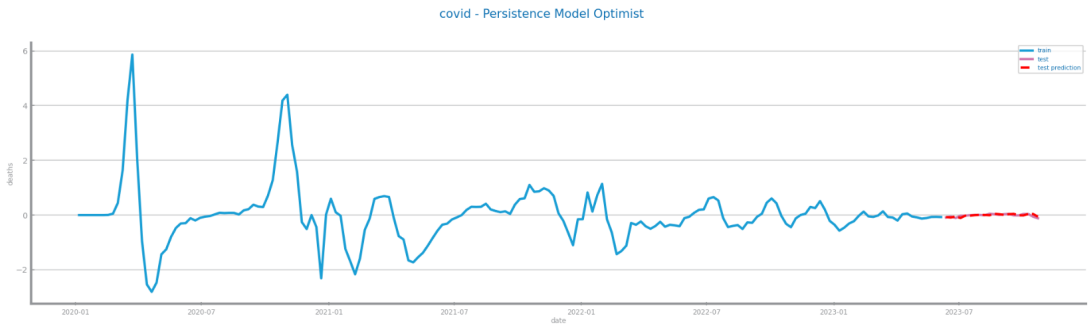


Figure 104 Forecasting results obtained with the best parameterisation of LSTMs, over time series 1

```
tensor(18.4214, grad_fn=<MseLossBackward0>)

LSTM best results achieved with length=4 hidden_units=25 and nr_episodes=300) ==> measure=1.00
```

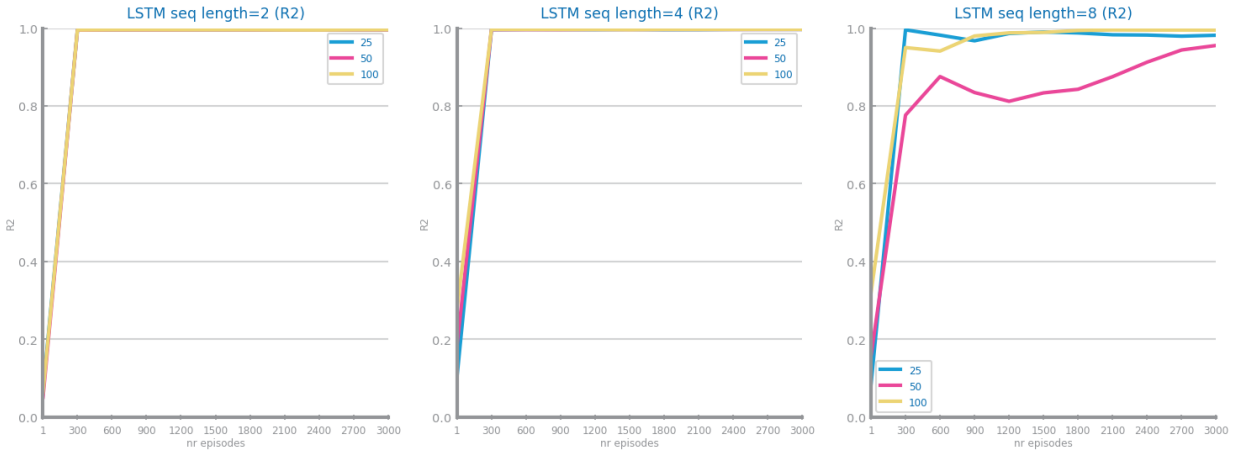


Figure 105 Forecasting study over different parameterisations - length, hidden_units, nr_episodes - of the LSTMs over time series 2

Figure 106 Forecasting plots obtained with the best parameterisation of LSTMs, over time series 2

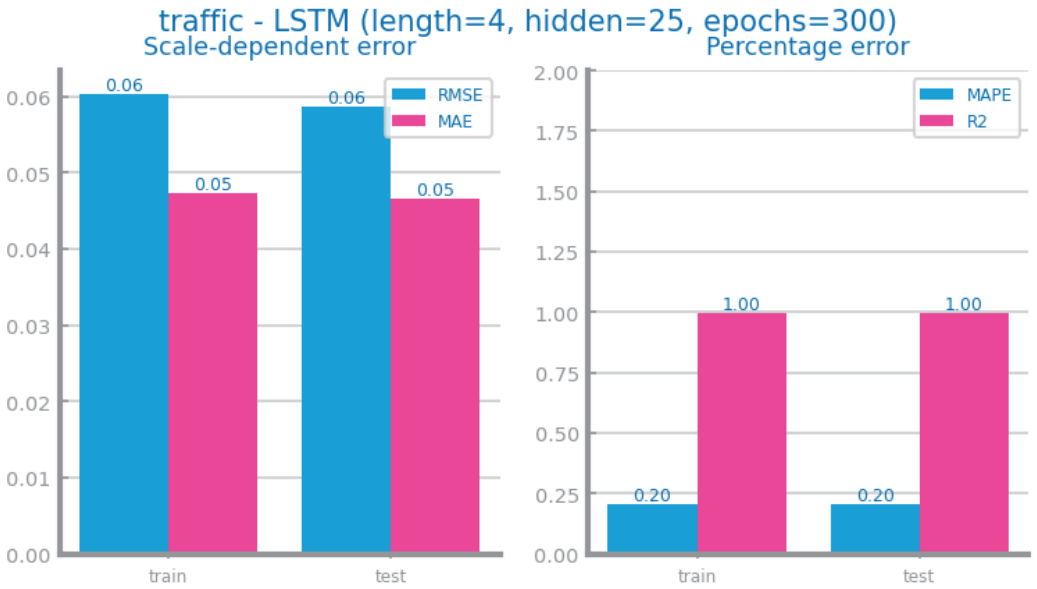
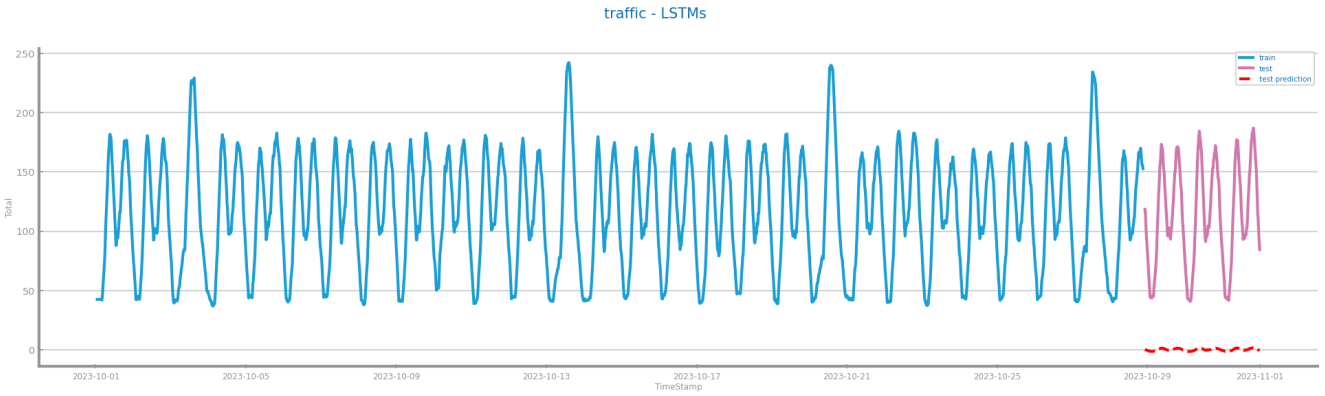


Figure 107 Forecasting results obtained with the best parameterisation of LSTMs, over time series 2


traffic - LSTMs
train
test
test prediction
250
200
150
100
50
0
Total
2023-10-01
2023-10-05
2023-10-09
2023-10-13
2023-10-17
2023-10-21
2023-10-25
2023-10-29
2023-11-01
TimeStamp

8 Critical Analysis

DS1

From the data profiling done on this data set we can infer that the data isn't stationary however its upwards trend its really fast in the first points of the data and then slows down considerably, we also inferred this by the differentiation done on the transformation section where wither the first or the second derivative had really intense activity on the first half of the series, and settles down in the later portion. This drop off in the death-rates (first derivative) and transmission-rate(second derivative*some mortality function) could be justified by the vaccination of the population reaching a point of herd immunity, but there wouldn't be any way to predict this with a univariate time series, like the one we have, and that explains the poor performance of our models since the series takes such an unpredictable turn this is further corroborated by the fact that the best LSTMs, ARIMA and persistence models were the ones where they had a small seasonality/memory function.

DS2

From *Profiling*, it's possible to conclude the Series is **Stationary**, w/ a constant mean & high variability

More granular approach would mean the lost of info

SAM & *Linear Regression* were not suited, due the high **variability** around the mean & the patterns *not capture nuances*, so none performed well

The *Persistence Model* excelled *Optimistic* projections, accurately predicting stable values, but faltered in *Realistic*, **due to instability** & exhibits day/weekly patterns, not perform well for long-term forecasts

Rolling Mean (mean-based problem), due to complexity, given **the mean was constant** *predict almost the same values* & difficult size to match the cyclicity, resulted in a poor prediction and evaluation

Despite modest test outcomes, *ARIMA* stands as a robust option with minimal *MAPE* error, indicating reliable performance. Capable of capturing the *Trend & Seasonality*.

Conversely, while *LSTM* demonstrates promising results, it encounters issues in prediction testing, warranting further investigation