TÉCNICO LISBOA

DS 2025

Data Science Project

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CLASSIFICATION

1 DATA PROFILING

Data Dimensionality

Regarding the Missing Values analysis, the completeness metric for Dataset 1 was adjusted to treat 'UNKNOWN' occurrences as missing values.

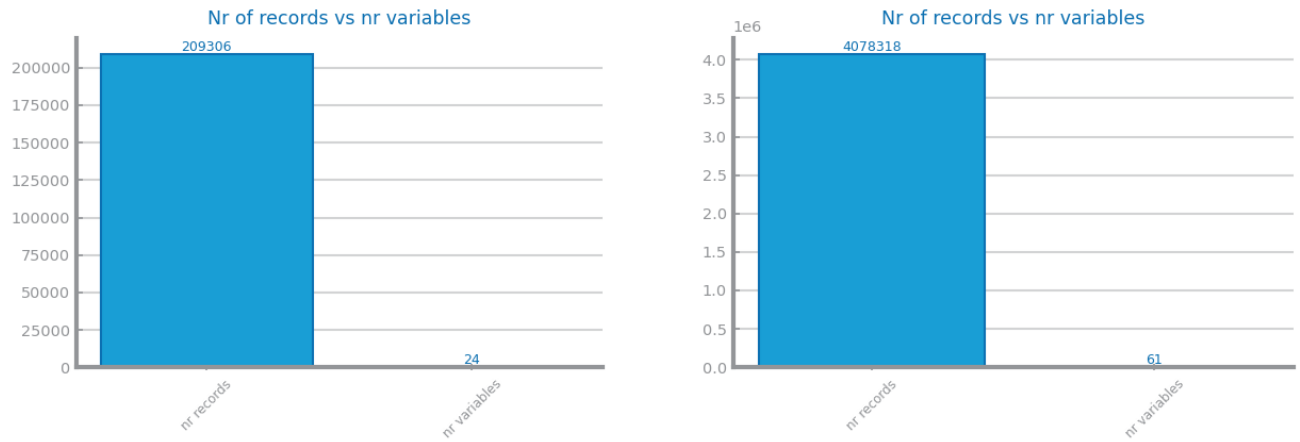


Figure 1: Nr Records x Nr variables for dataset 1 (left) and dataset 2 (right)

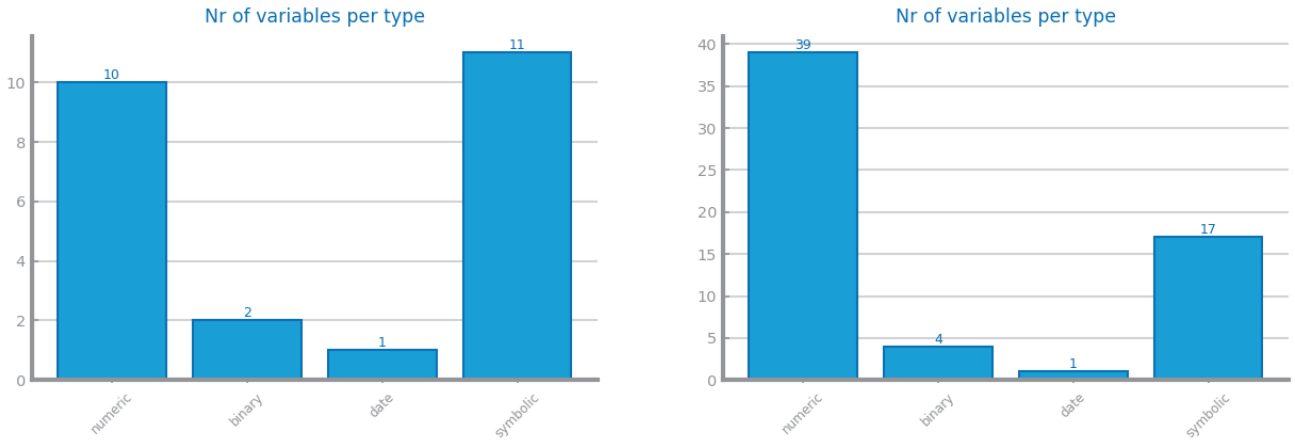


Figure 2: Nr variables per type for dataset 1 (left) and dataset 2 (right)

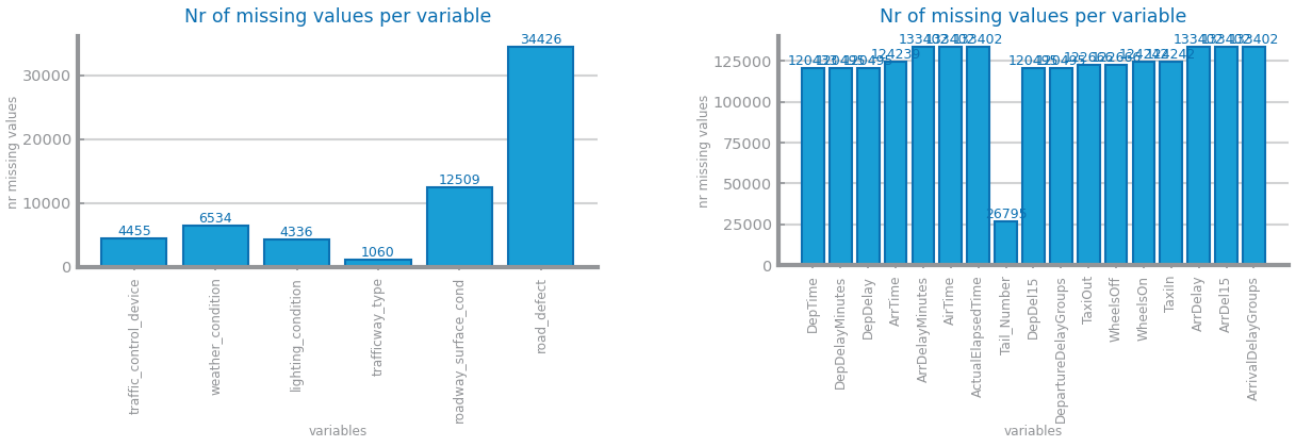


Figure 3: Nr missing values for dataset 1 (left) and dataset 2 (right)

Data Distribution

The distribution analysis reveals that the raw data is significantly dispersed, exhibiting high variance across several features. Certain variables show a clear lack of balance, with distributions heavily skewed toward specific classes or ranges and presence of evident outliers.

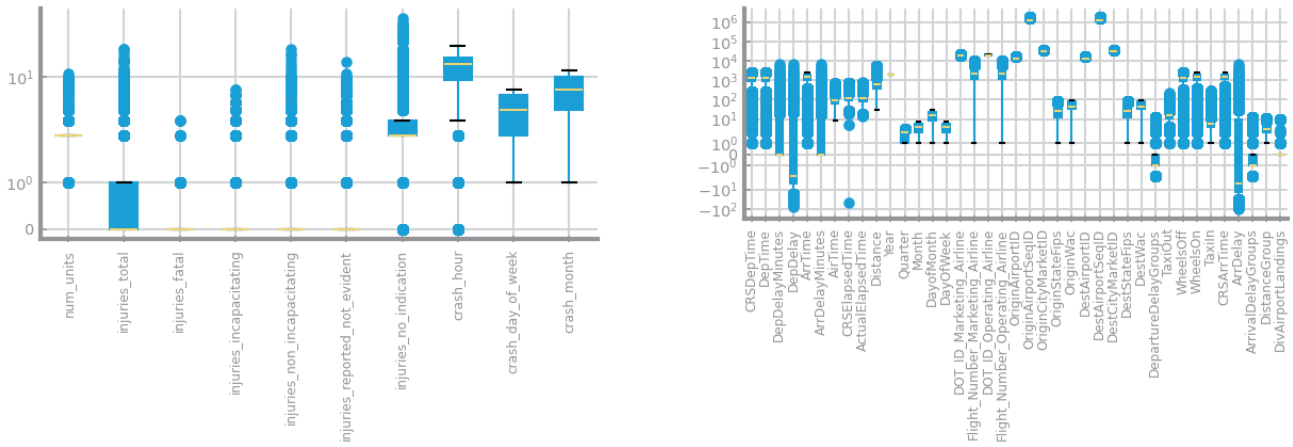


Figure 4: Global boxplots dataset 1 (left) and dataset 2 (right)

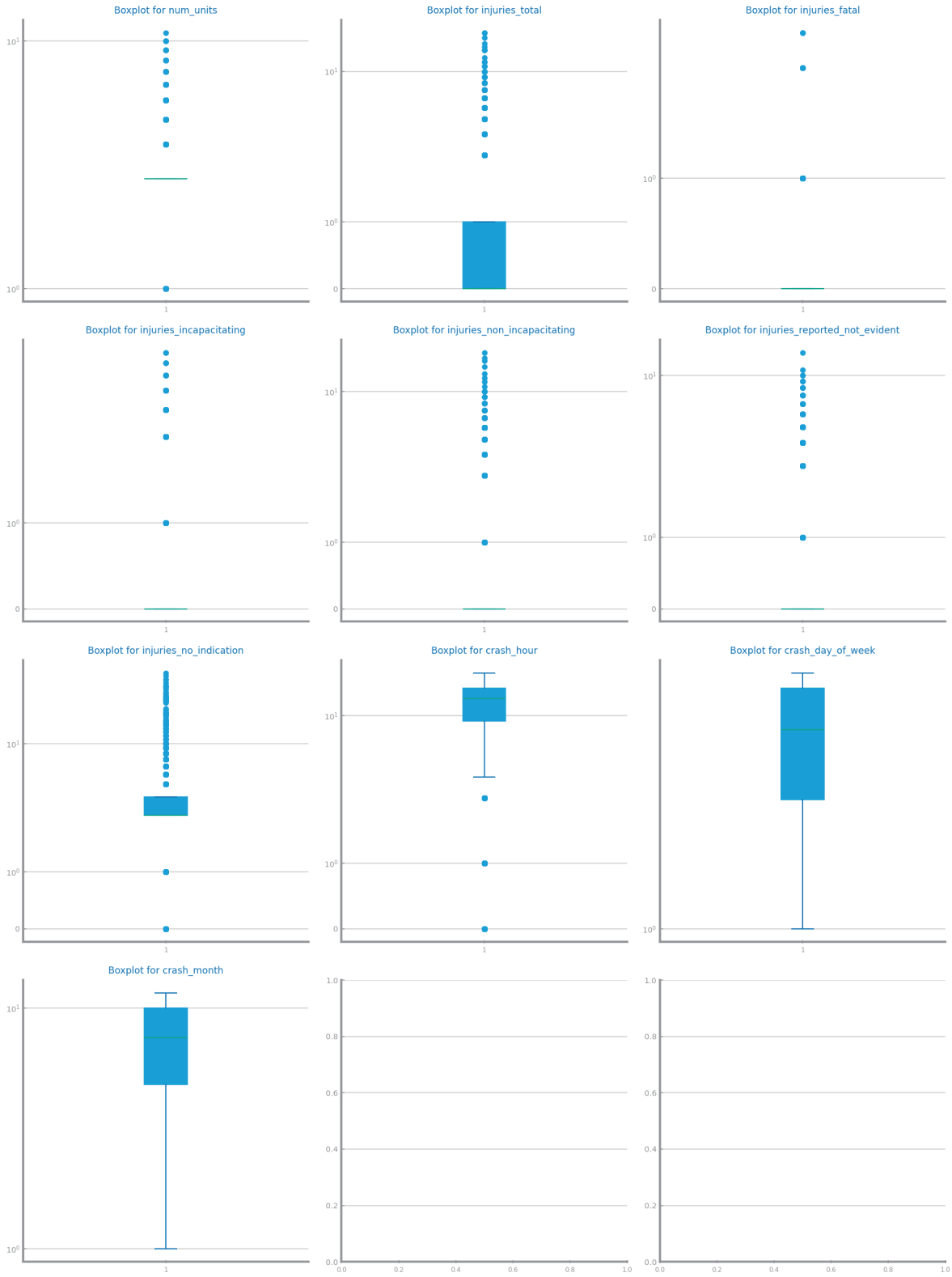


Figure 5: Single variables boxplots for dataset 1

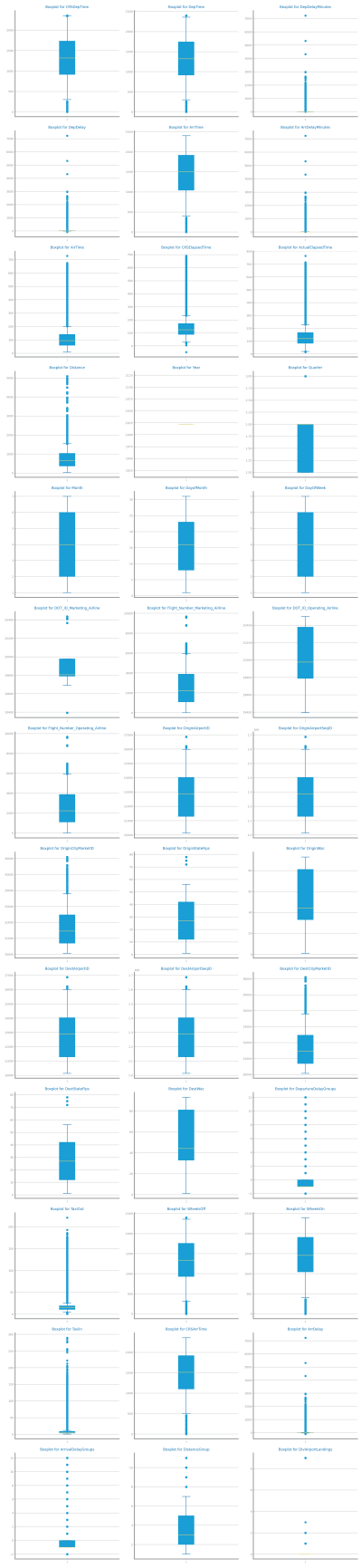


Figure 6: Single variables boxplots for dataset 2

Figure 7: Histograms for dataset 1

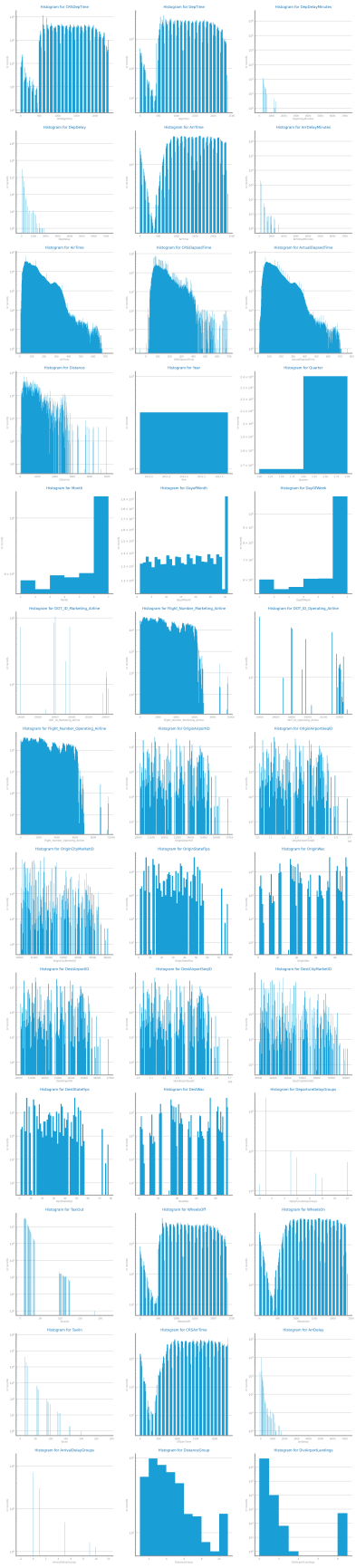


Figure 8: Histograms for dataset 2

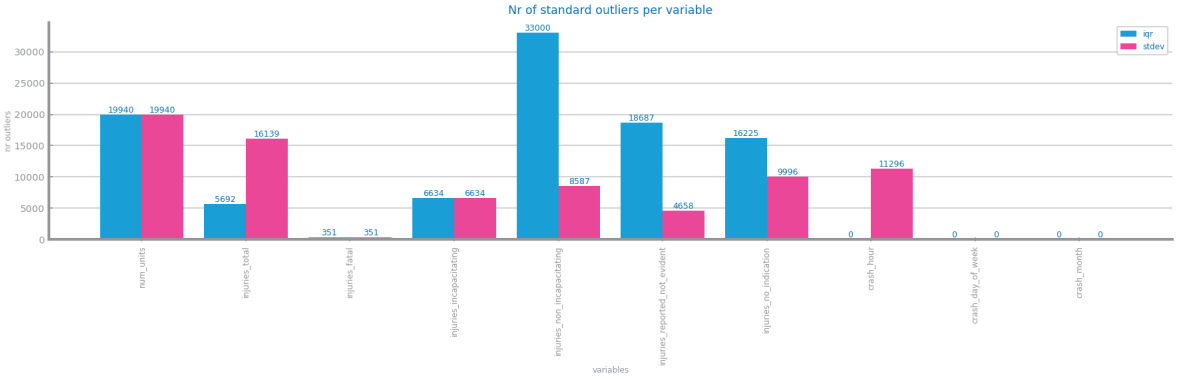


Figure 9: Outliers study dataset 1

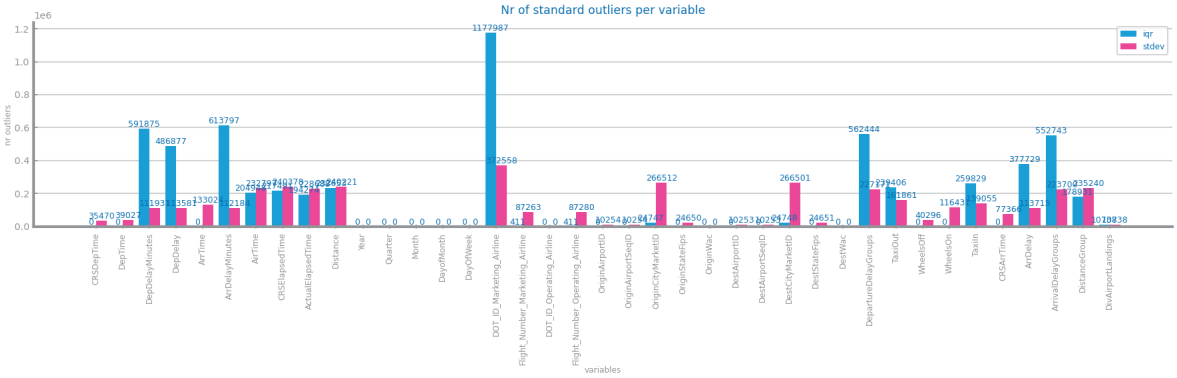


Figure 10: Outliers study dataset 2

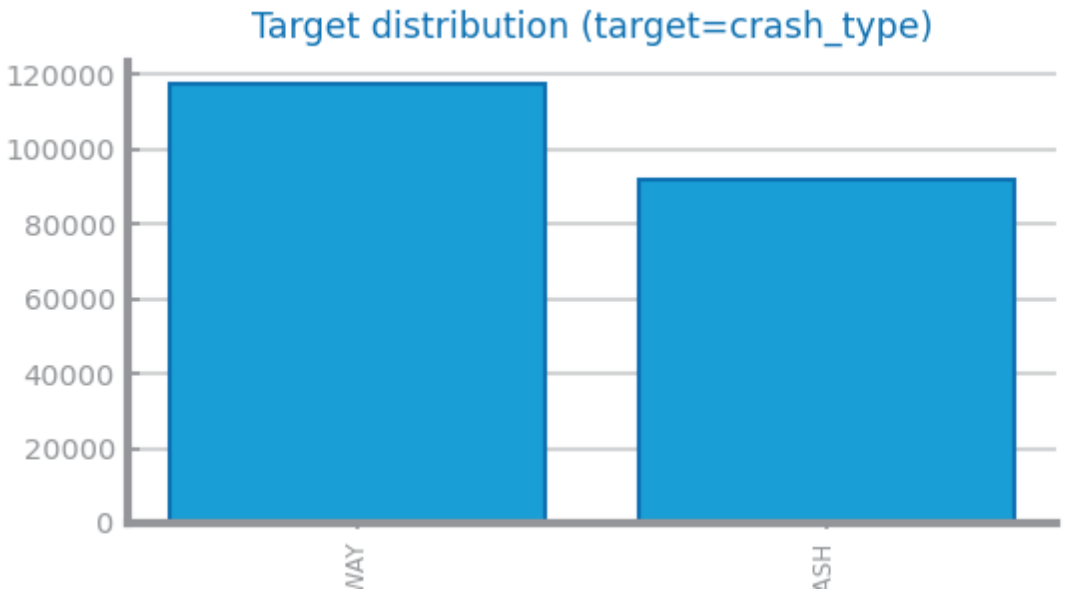


Figure 11: Class distribution for dataset 1

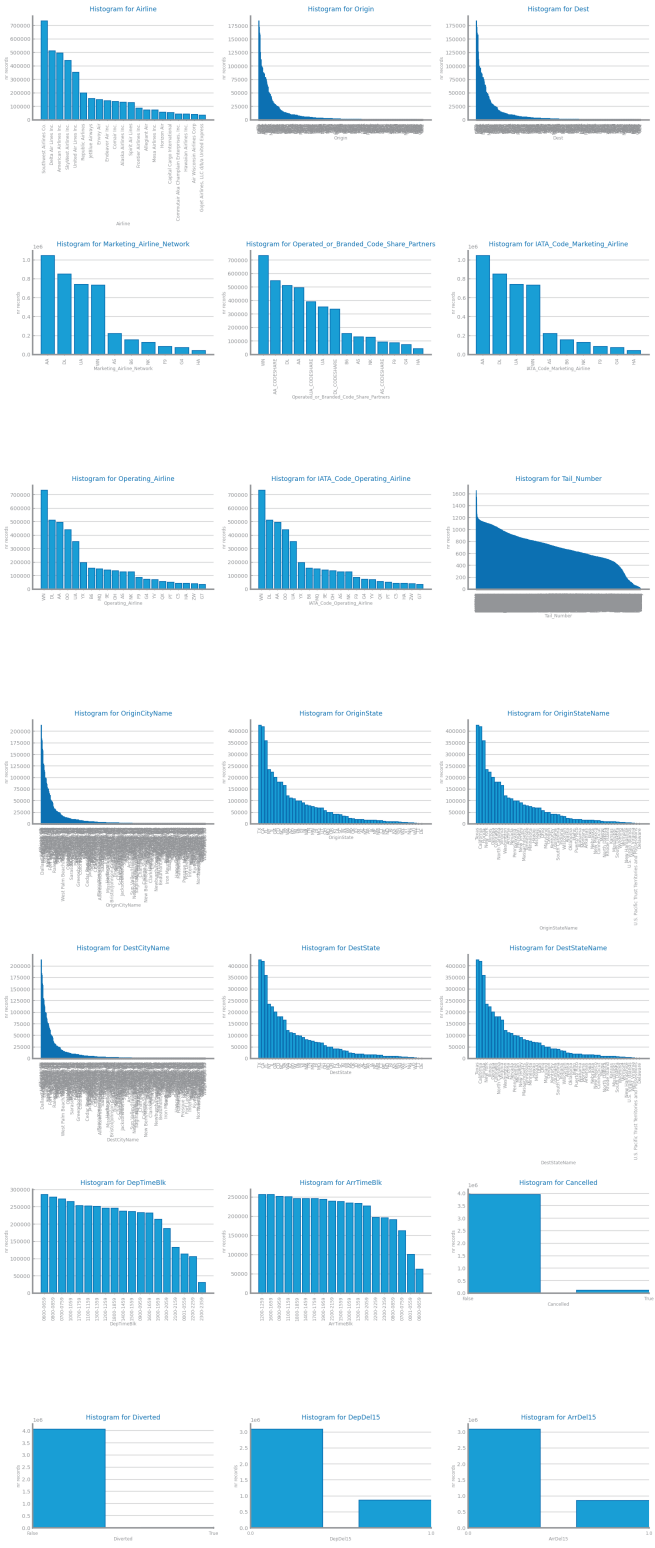
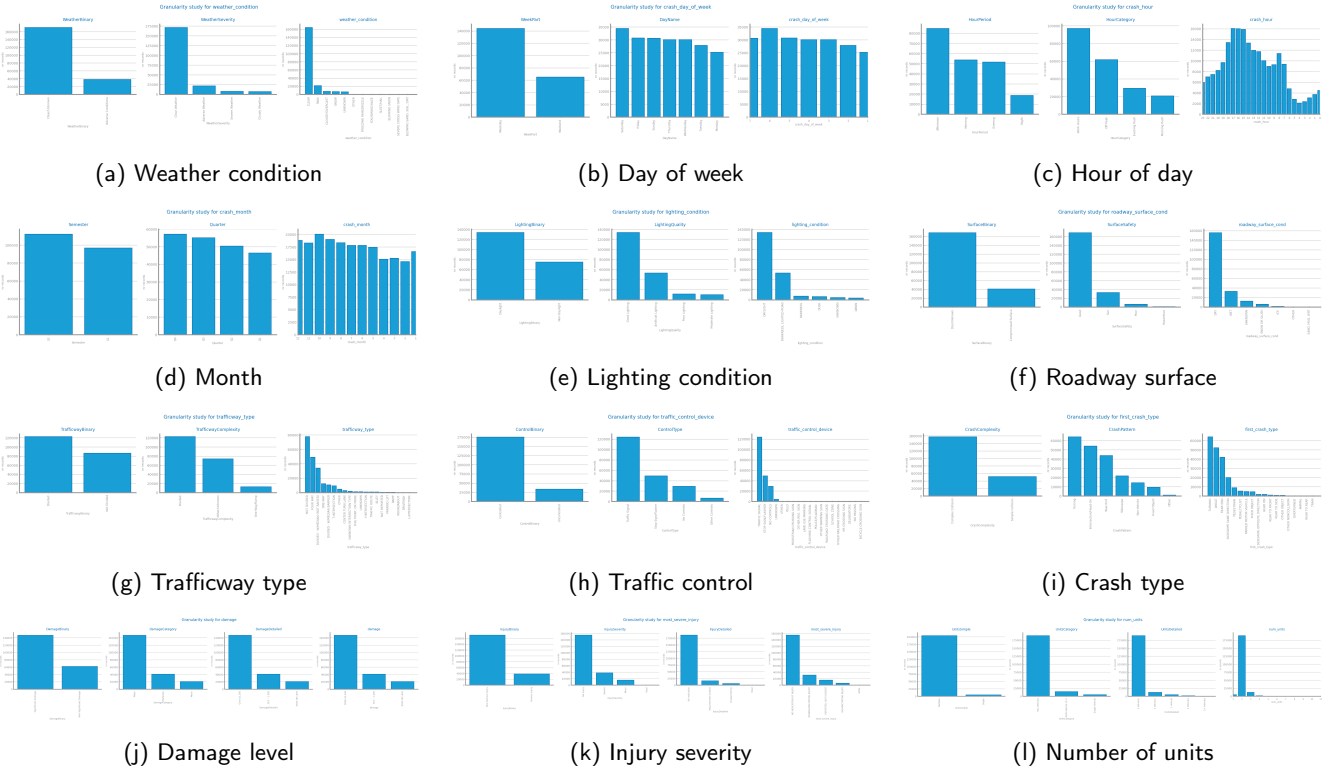


Figure 12: Class distribution for dataset 2

Data Granularity

The granularity analysis highlights significant variability across variables in both datasets. Categorical features such as weather, lighting conditions, airline, and airport present low to medium granularity, while temporal and numerical variables (hour, delays, distance) show higher granularity and dispersion. These differences suggest the need for appropriate grouping or discretization strategies to avoid sparsity and improve downstream analysis and modeling.



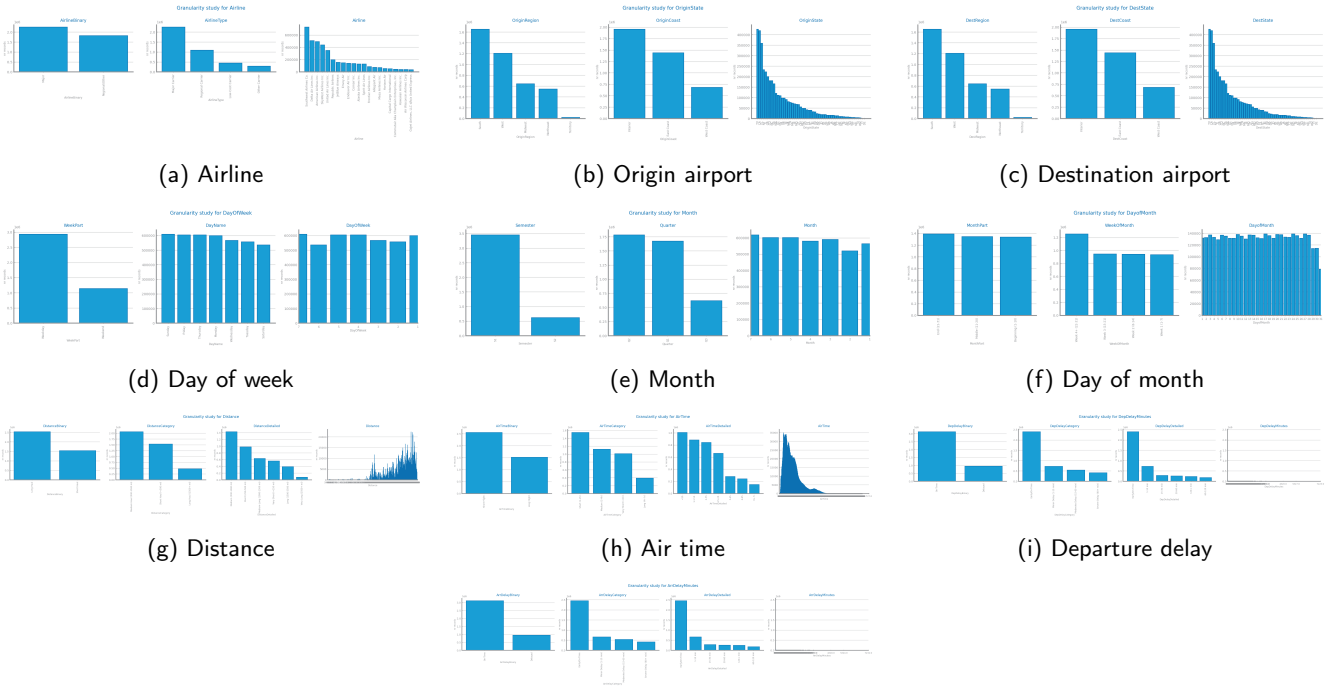
(a) Weather condition (b) Day of week (c) Hour of day

(d) Month (e) Lighting condition (f) Roadway surface

(g) Trafficway type (h) Traffic control (i) Crash type

(j) Damage level (k) Injury severity (l) Number of units

Figure 13: Granularity analysis for dataset 1



(a) Airline (b) Origin airport (c) Destination airport

(d) Day of week (e) Month (f) Day of month

(g) Distance (h) Air time (i) Departure delay

(j) Arrival delay

Figure 14: Granularity analysis for dataset 2

Data Sparsity

The sparsity analysis reveals uneven domain coverage across variables, with several categorical features dominated by a small number of frequent values and many rare ones. Correlation analysis shows limited strong dependencies between most variables, indicating sparse relationships in the feature space.

Figure 15: Sparsity analysis for dataset 1

Figure 16: Sparsity analysis for dataset 2 - View on Google Drive

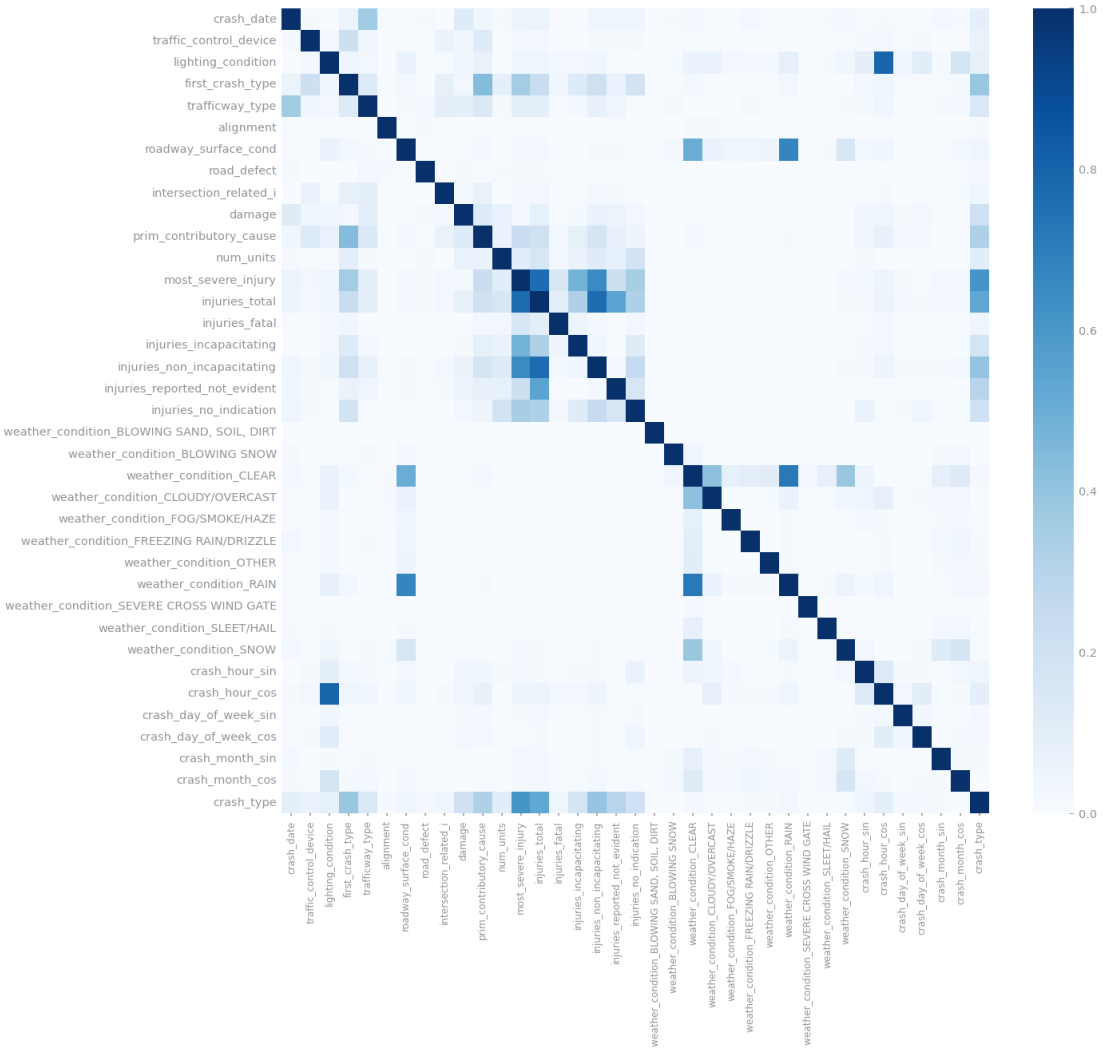


Figure 17: Correlation analysis for dataset 1

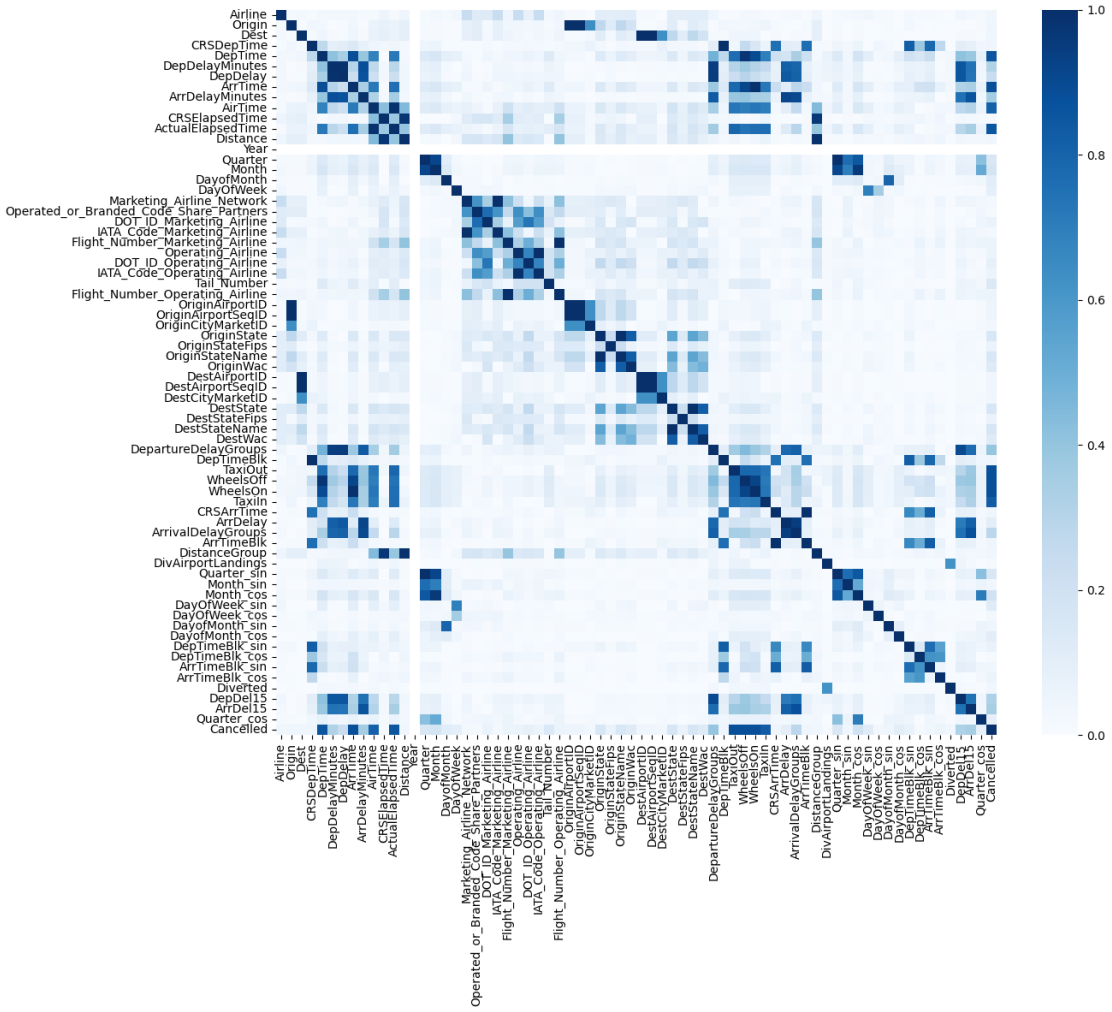


Figure 18: Correlation analysis for dataset 2

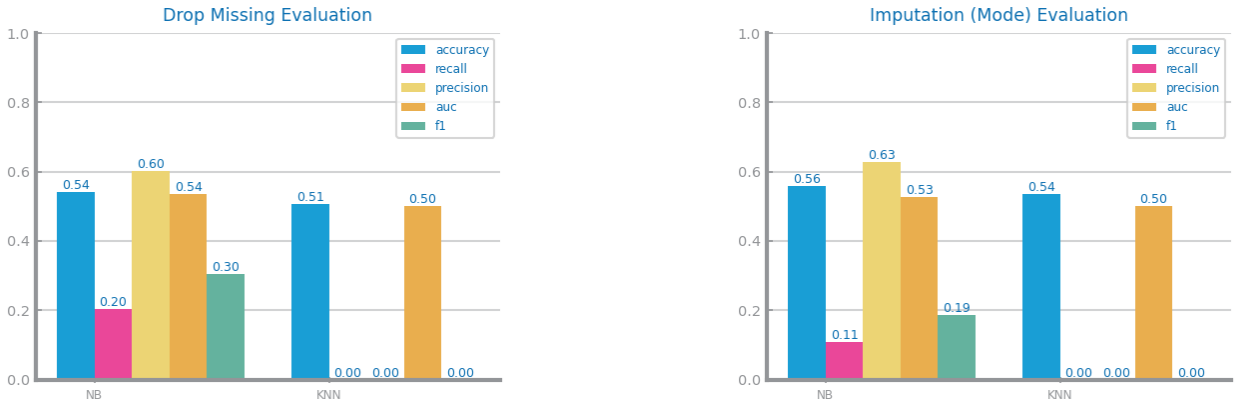
2 DATA PREPARATION

Variables Encoding

In Dataset 2, airline categories were ordinal-encoded according to market relevance. Time-block fields were converted to ordinal values (0–18). Cyclic variables (e.g., Quarter) were transformed using sin/cos encoding and the original columns removed. Numeric fields were kept unchanged, and redundant or leakage-prone columns had been removed earlier.

Missing Value Imputation

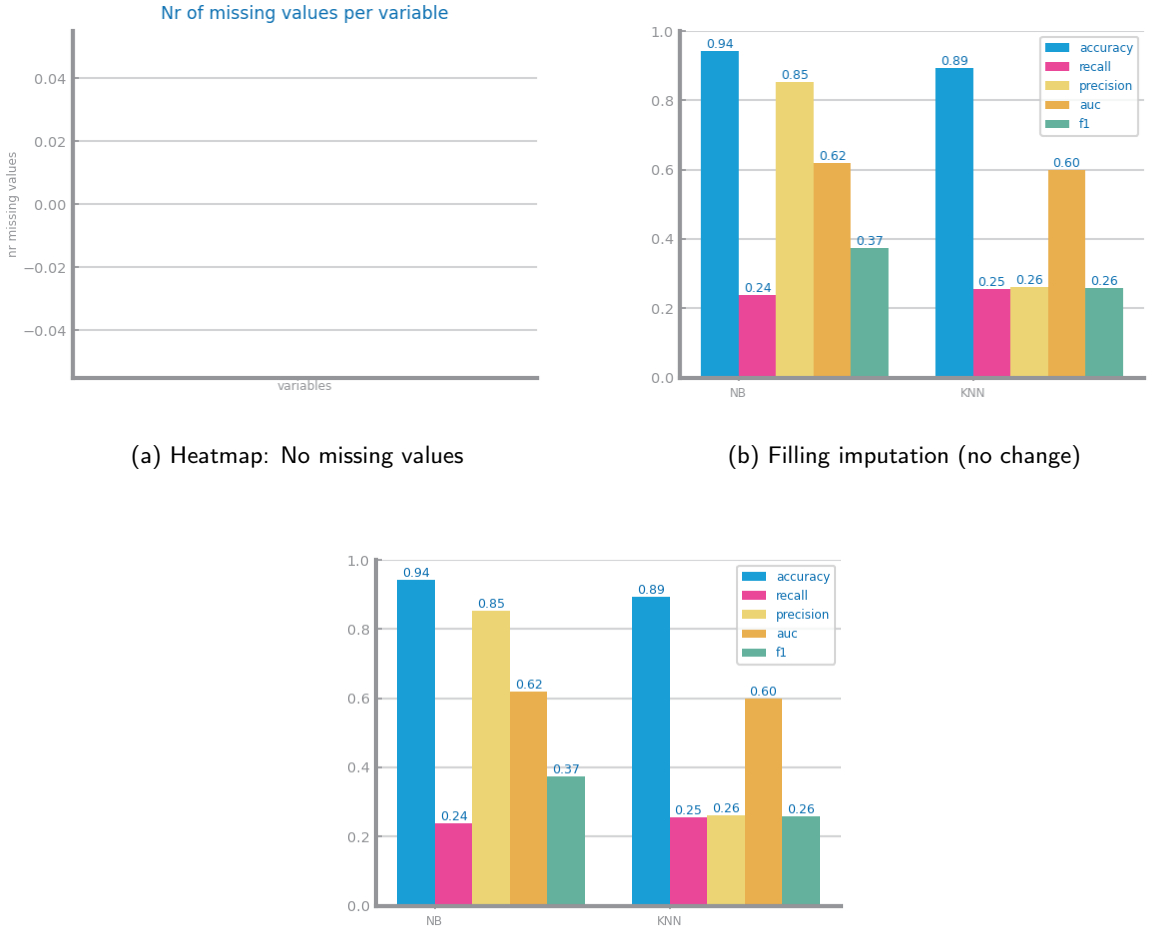
For the dataset 1, dropping records was compared with mode imputation. Imputation yielded higher performance , improving KNN accuracy from 0.51 (drop) to 0.54 (impute). Thus, mode imputation was selected to prevent data loss. In Dataset 2, after removing leakage-prone columns, no missing values were found in the remaining variables. Therefore, imputation was not required and no method (filling or dropping) had any effect on the dataset.



(a) Drop

(b) Impute

Figure 19: Missing values imputation results with different approaches for dataset 1



(a) Heatmap: No missing values

(b) Filling imputation (no change)

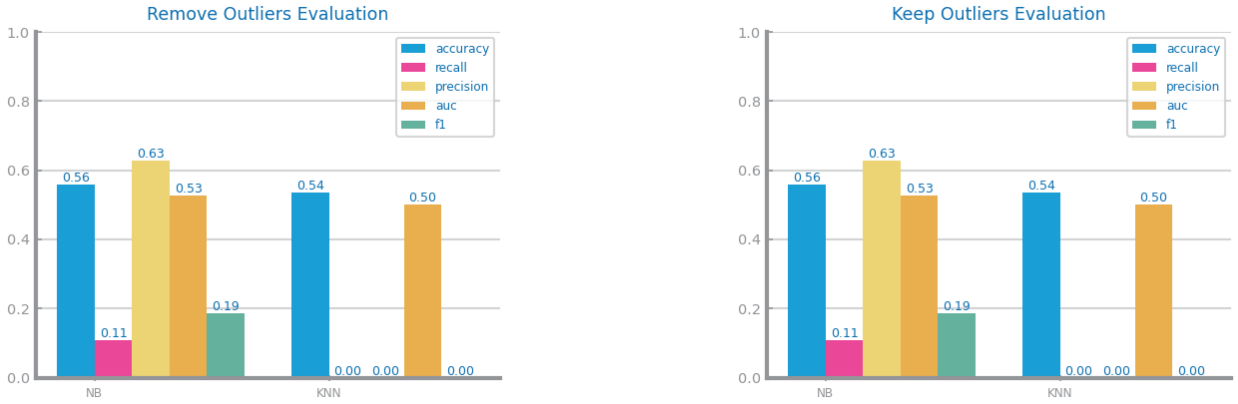
(c) Dropping rows (no change)

Figure 20: Missing values analysis and imputation attempts for dataset 2 (no missings detected)

Outliers Treatment

For Dataset 1, two approaches were tested: "Keep Outliers" and "Remove Outliers (Z-Score and Isolation Forest)". "Keep Outliers" yielded better accuracy (NB: 0.56, KNN: 0.54) compared to removal strategies (Z-Score: 0.55, Isolation Forest: 0.55). Thus, no outliers were removed.

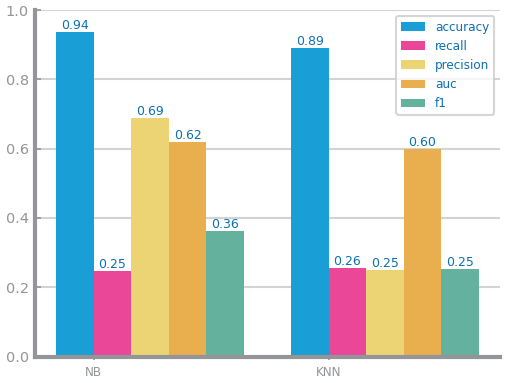
For Dataset 2, outliers in CRSElapsedTime, Distance and airline codes were treated by dropping, median replacement, and truncation. Dropping was chosen as it delivered the best results (NB acc. 0.94, KNN 0.89)



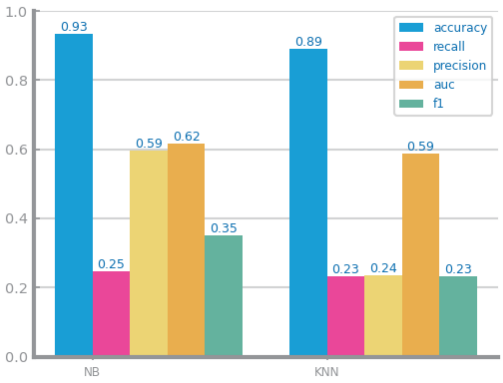
(a) Drop outliers

(b) Keep outliers

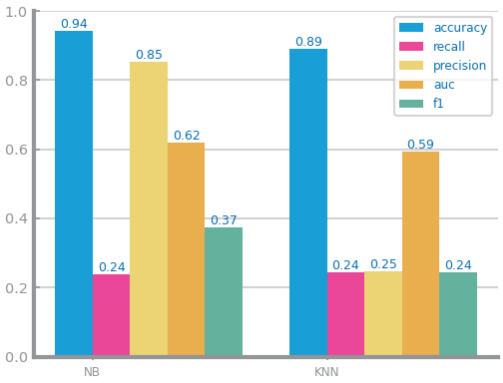
Figure 21: Outliers imputation results with different approaches for dataset 1



(a) Drop outliers (selected)



(b) Replace with median



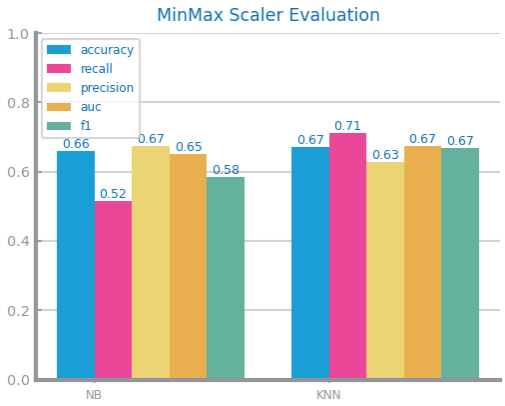
(c) Truncate

Figure 22: Impact of different outlier treatments on NB and KNN performance for dataset 2

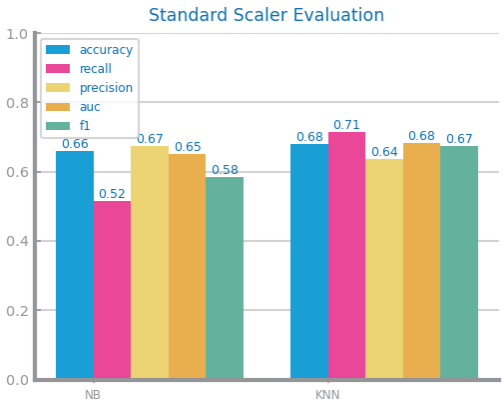
Scaling

For Dataset 1 StandardScaler outperformed MinMaxScaler as it improved KNN auc to 0.68 compared to 0.67. Flights: MinMaxScaler outperformed ABSScaler with the best performance - NB acc. 0.94, KNN 0.89.

The Dataset 2 numeric variables were scaled using ABSScaler, MinMaxScaler. MinMaxScaler was selected as it yielded the best model performance (NB acc. 0.94, KNN 0.89).

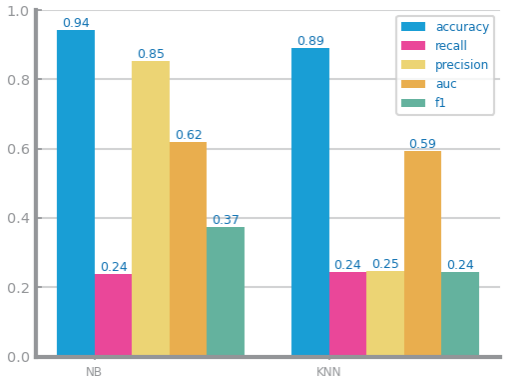


(a) MinMaxScaler

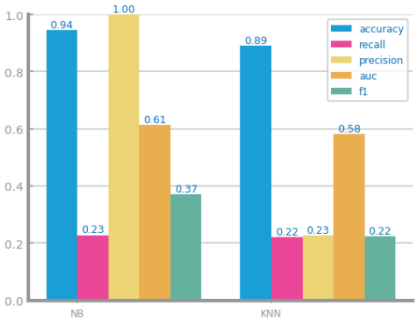


(b) StandardScaler

Figure 23: Scaling results with different approaches for dataset 1



(a) MinMaxScaler (selected)



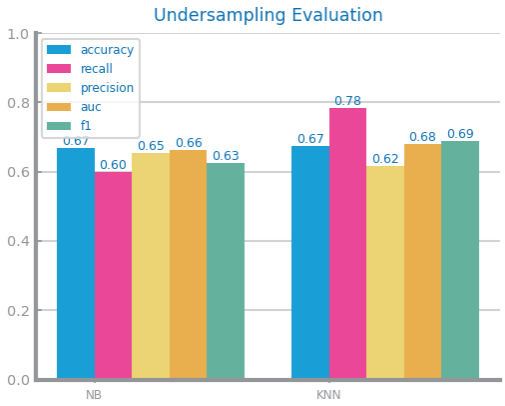
(b) ABSScaler

Figure 24: Scaling results with different approaches (NB and KNN performance) for dataset 2

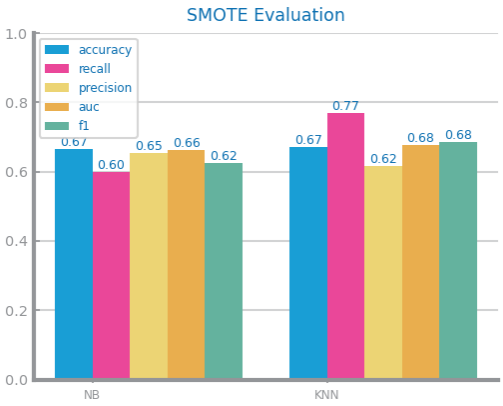
Balancing

For Dataset 1, Random Undersampling and SMOTE were evaluated. Undersampling was selected (KNN acc 0.67) as it achieved a slightly higher recall (0.78) compared to SMOTE (recall 0.77).

The Dataset 2 was balanced using Random Undersampling, Random Oversampling, and SMOTE. Random Undersampling was chosen as it provided the best model performance (NB acc. 0.62, KNN 0.73).

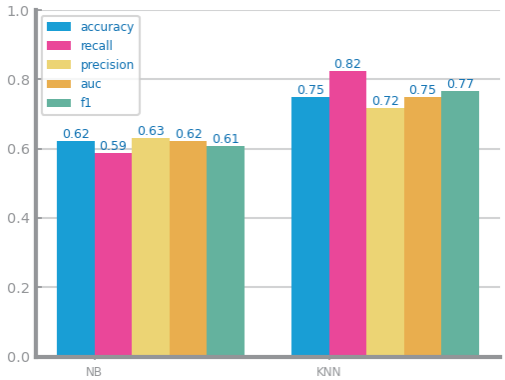


(a) Random Undersampling

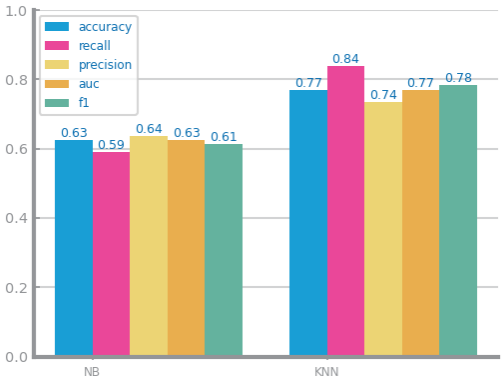


(b) SMOTE

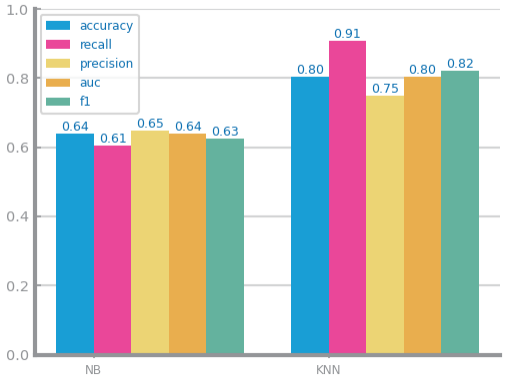
Figure 25: Balancing results with different approaches for dataset 1



(a) Random Undersampling (selected)



(b) Random Oversampling



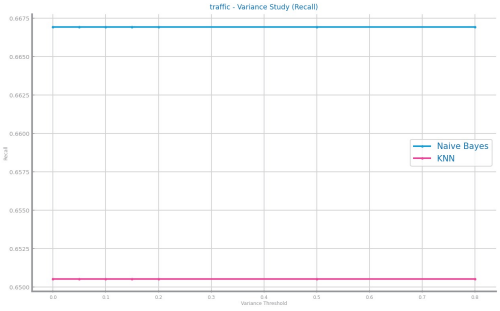
(c) SMOTE

Figure 26: Balancing results with different approaches (NB and KNN performance) for dataset 2

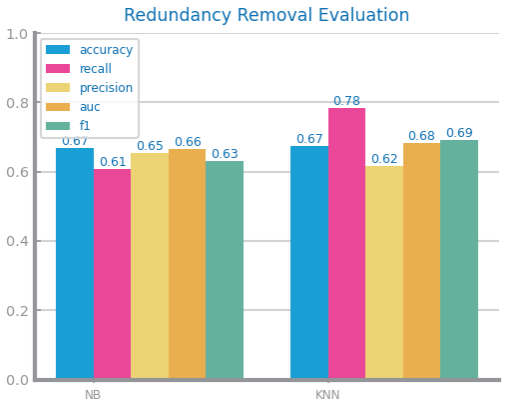
Feature Selection

For Dataset 1, the Variance filter (threshold 0.8) retained all features due to standardization. The Redundancy filter (correlation > 0.75) was selected as it effectively reduced dimensionality, achieving the best trade-off with KNN Recall 0.78 and Accuracy 0.67.

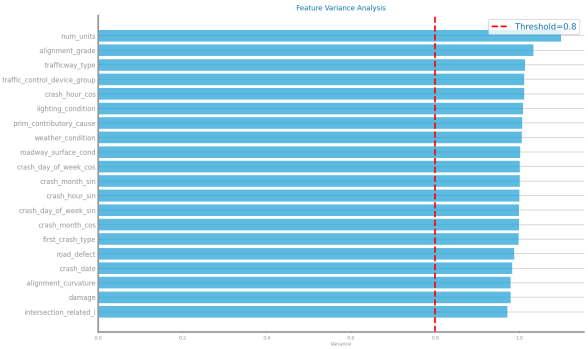
For Dataset 2, feature selection was performed using redundant and relevant variable analysis. Redundant variables were identified via correlation analysis and removed. Relevant variables were selected based on variance thresholds. The final feature set improved model performance (NB acc. 0.62, KNN 0.68).



(a) Redundant variables removal

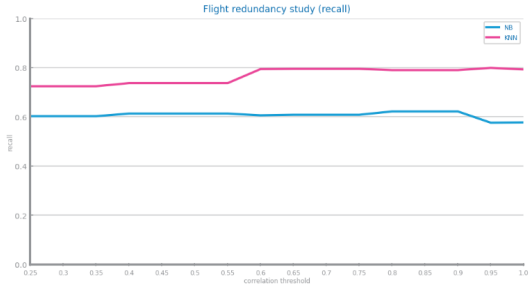


(b) Variance Evaluation(variance threshold study)

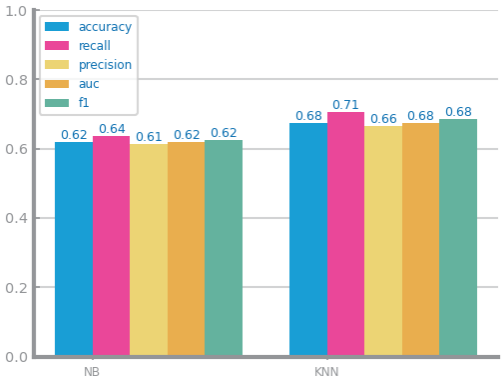


(c) Variance Evaluation plot

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

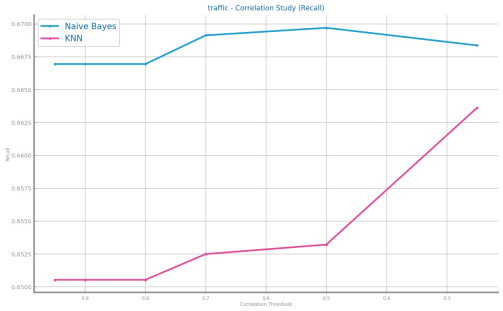


(a) Redundant variables removal (correlation matrix/threshold)

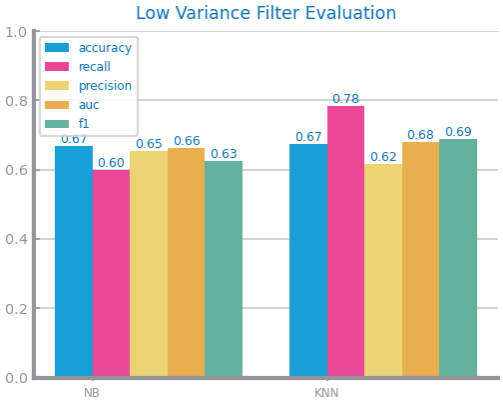


(b) Relevant variables selection (variance threshold study)

Figure 28: Feature selection results for redundant and low-variance variables in dataset 2

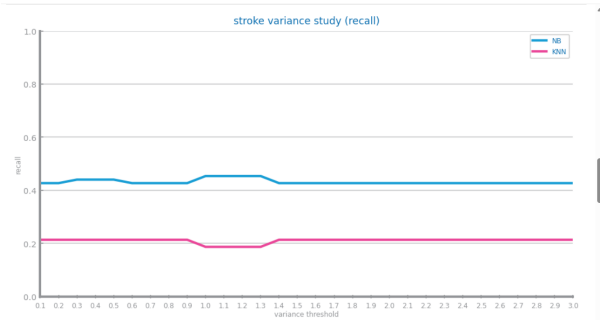


(a) Redundant variables removal

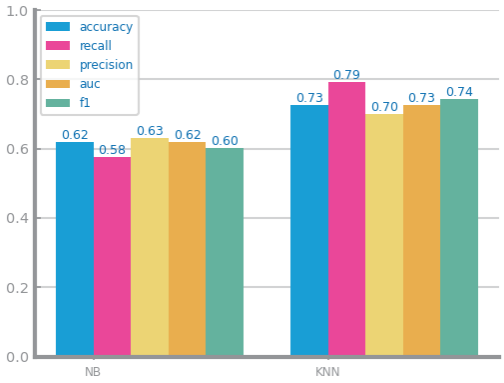


(b) Variance Evaluation(variance threshold study)

Figure 29: Feature selection of relevant variables results with different parameters for dataset 1 (variance study)



(a) Redundant variables removal (correlation matrix/threshold)



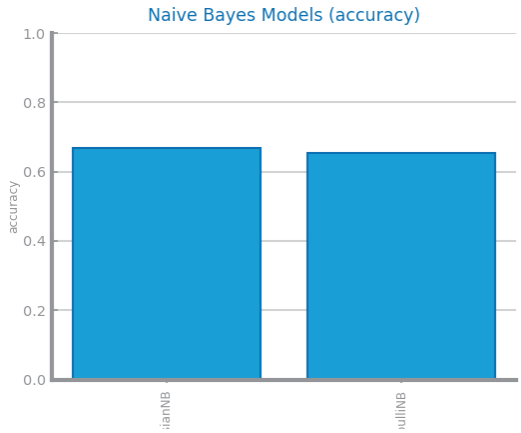
(b) Relevant variables selection (variance threshold study)

Figure 30: Feature selection of relevant variables results with different parameters for dataset 2 (variance study)

3 MODELS' EVALUATION

Naïve Bayes

The Naïve Bayes variants show similar accuracy, with BernoulliNB achieving the best results on both datasets due to better alignment with binary feature representations. The best model was evaluated using accuracy, precision, recall, F1-score, and confusion matrices.



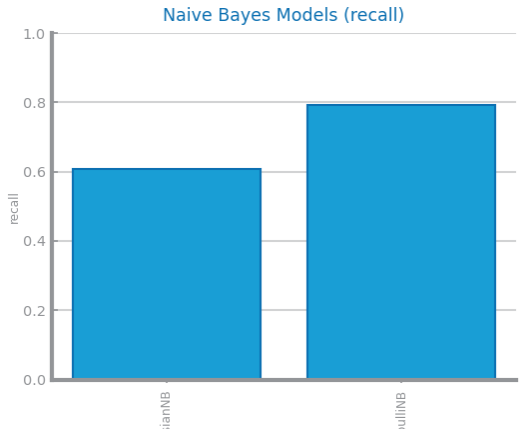


Figure 31: Naïve Bayes alternatives comparison for dataset 1

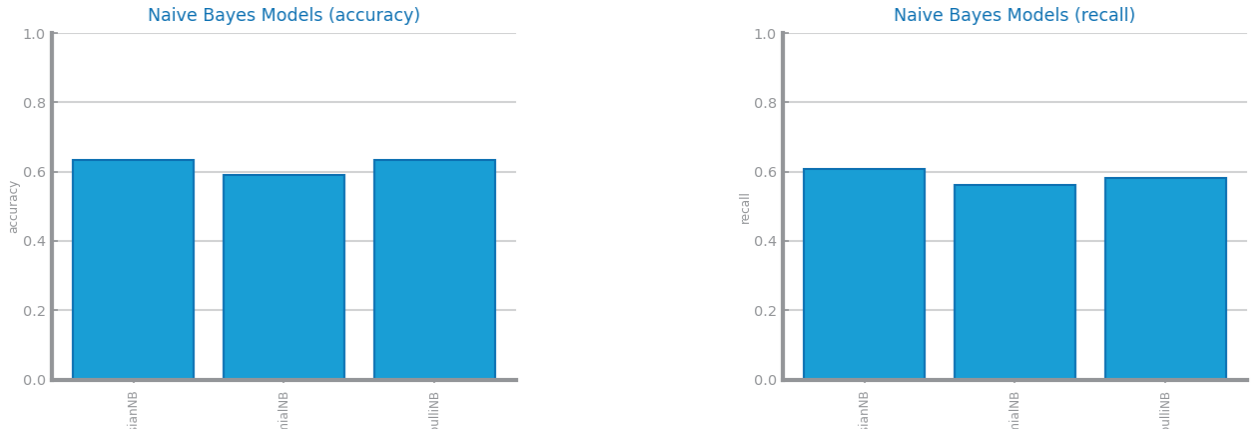


Figure 32: Naïve Bayes alternatives comparison for dataset 2

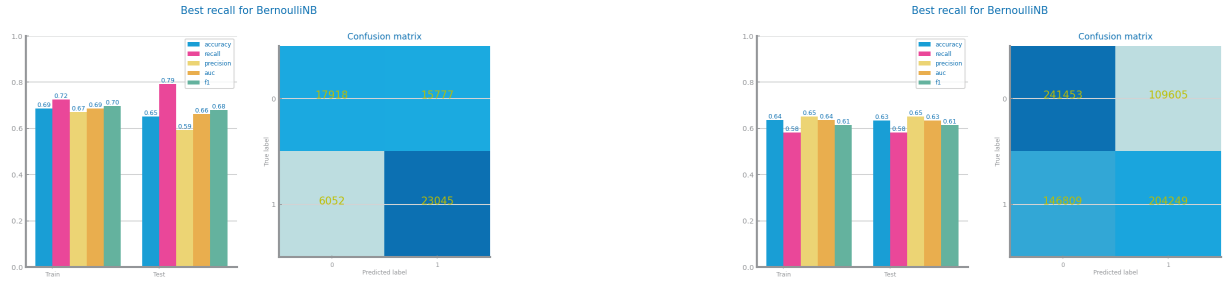


Figure 33: Naïve Bayes best model results for dataset 1 (left) and dataset 2 (right)

KNN

KNN favors Manhattan distance in both datasets, likely due to better handling of high-dimensional sparsity. In Dataset 1, accuracy improves with k, mitigating overfitting; the best model (k=17, Manhattan) achieves 0.66 accuracy with balanced predictions. Conversely, Dataset 2 shows declining accuracy as k increases. The best model (k=1, Manhattan) yields 0.71 accuracy but suffers from severe overfitting and class imbalance, predicting mostly Class 0 (low recall).

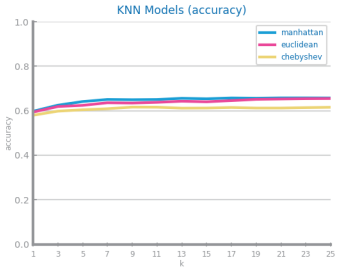


Figure 34: KNN different parameterisations comparison for dataset 1

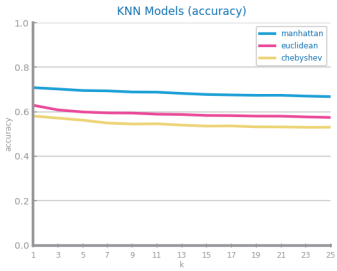


Figure 35: KNN different parameterisations comparison for dataset 2

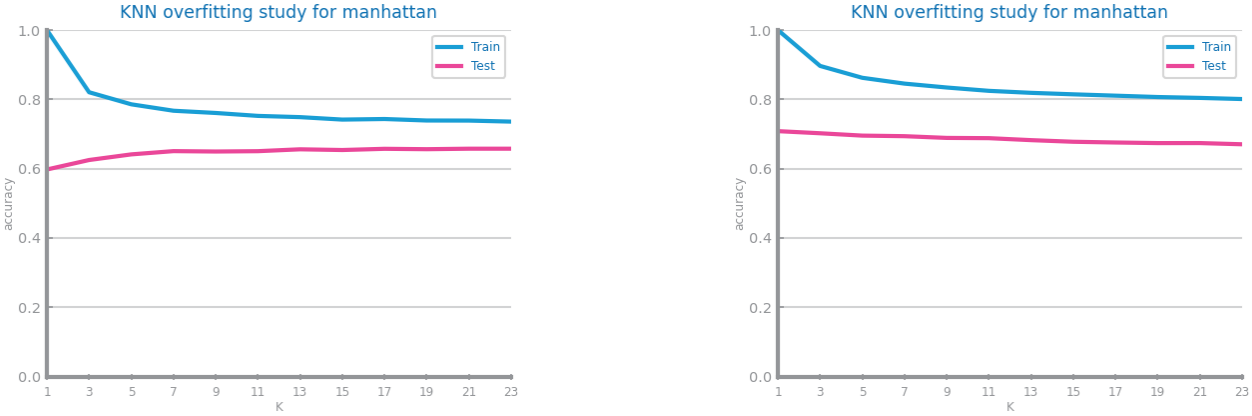


Figure 36: KNN overfitting analysis for dataset 1 (left) and dataset 2 (right)

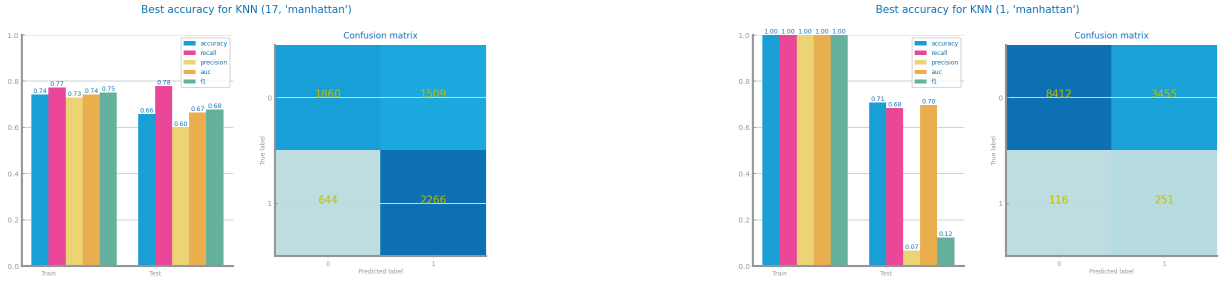


Figure 37: KNN best model results for dataset 1 (left) and dataset 2 (right)

Logistic Regression

Logistic Regression proves robust to parameter changes, showing flat accuracy across iterations for both regularizers. In Dataset 1, mild overfitting occurs (Train>Test). The best model (l1, 500 iter) achieves 0.65 accuracy, driven primarily by first_crash_type and damage.

In Dataset 2, the model biases heavily toward the majority class, achieving 0.70 accuracy but failing to capture Class 1 (poor recall). Distance and CRSElapsedTime are the top predictors.

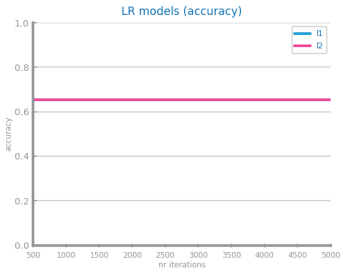


Figure 38: Logistic Regression different parameterisations comparison for dataset 1

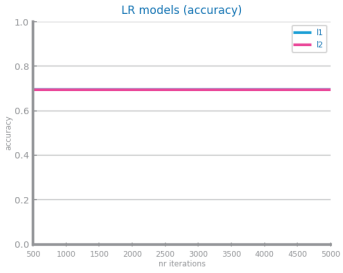


Figure 39: Logistic Regression different parameterisations comparison for dataset 2

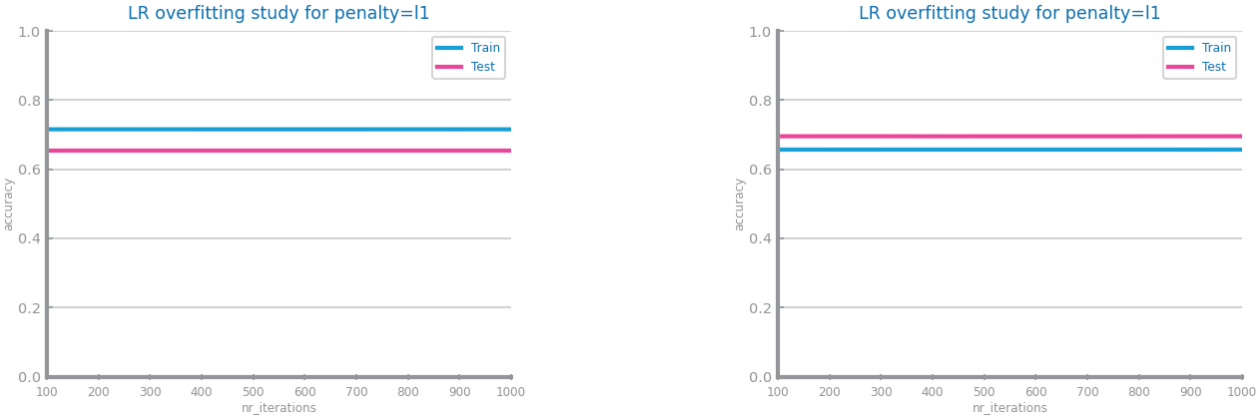


Figure 40: Logistic Regression overfitting analysis for dataset 1 (left) and dataset 2 (right)

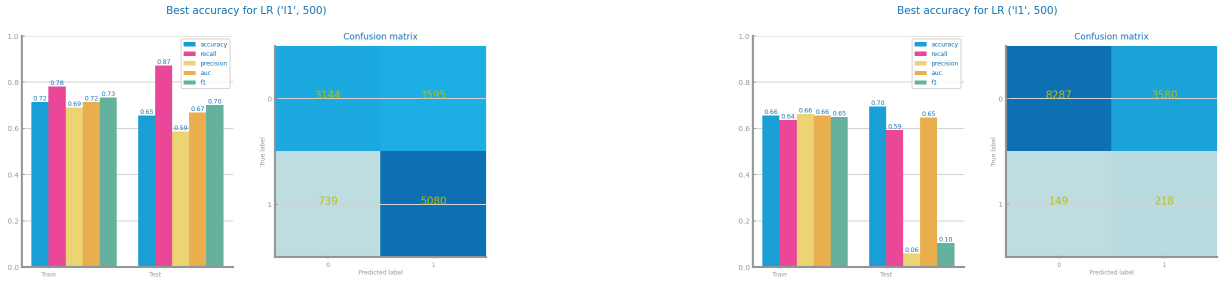


Figure 41: Logistic Regression best model results for dataset 1 (left) and dataset 2 (right)

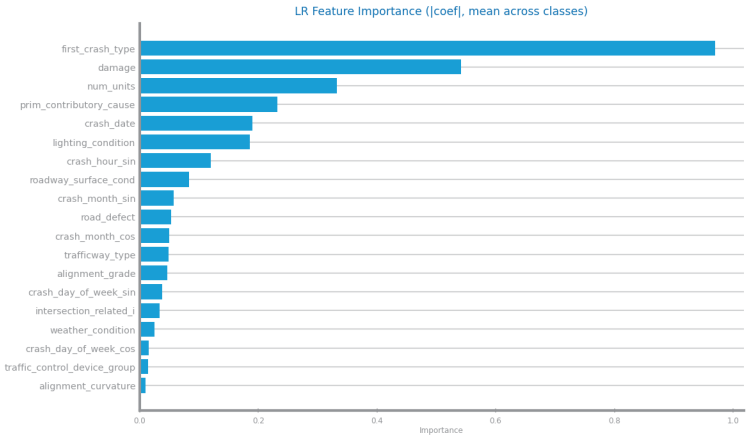


Figure 42: Logistic Regression feature importance for dataset 1

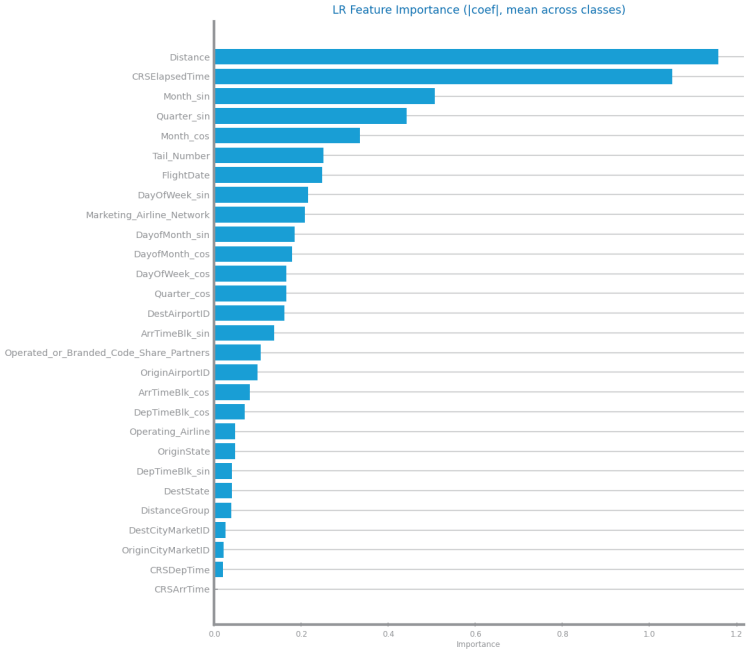


Figure 43: Logistic Regression feature importance for dataset 2

Decision Trees

Decision trees behave differently across the two datasets.In Dataset 1, accuracy peaks early (depth 6-8, 0.75) then slightly declines, showing mild overfitting.The best model (entropy, depth 6) reaches 0.74 accuracy with balanced precision and recall; key features include *crash_type*, *damage*, *dry_cause*, *num_units*, and *ash_date*. In Dataset 2, entropy slightly outperforms gini, although deep trees overfit.The best model (gini, depth 16) achieves 0.81 test accuracy.

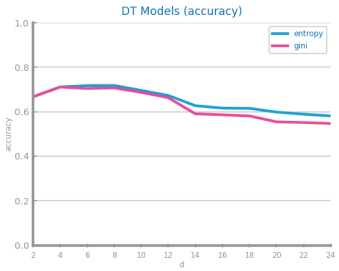


Figure 44: Decision Trees different parameterisations comparison for dataset 1

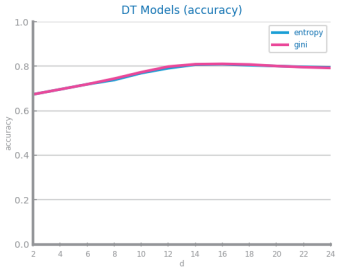


Figure 45: Decision Trees different parameterisations comparison for dataset 2

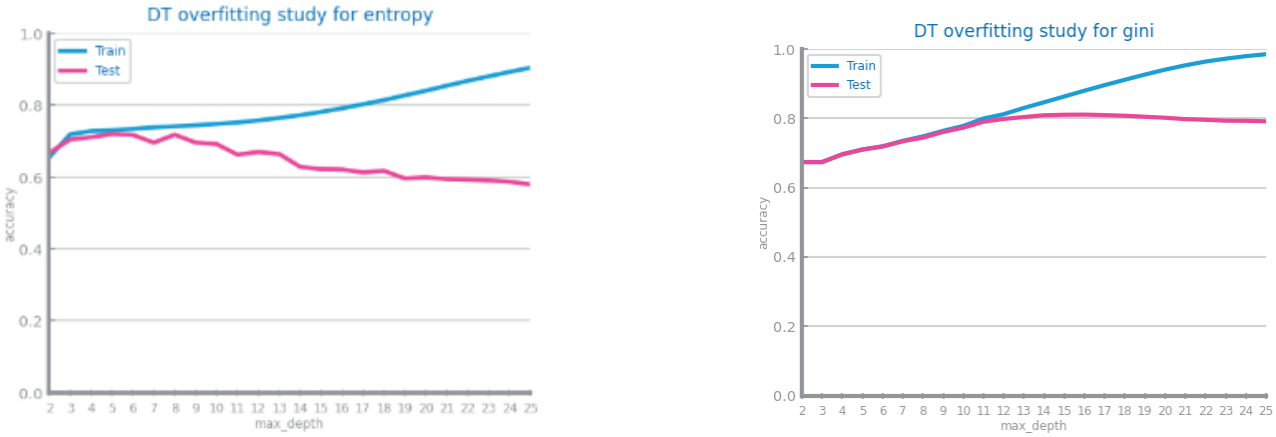


Figure 46: Decision Trees overfitting analysis for dataset 1 (left) and dataset 2 (right)

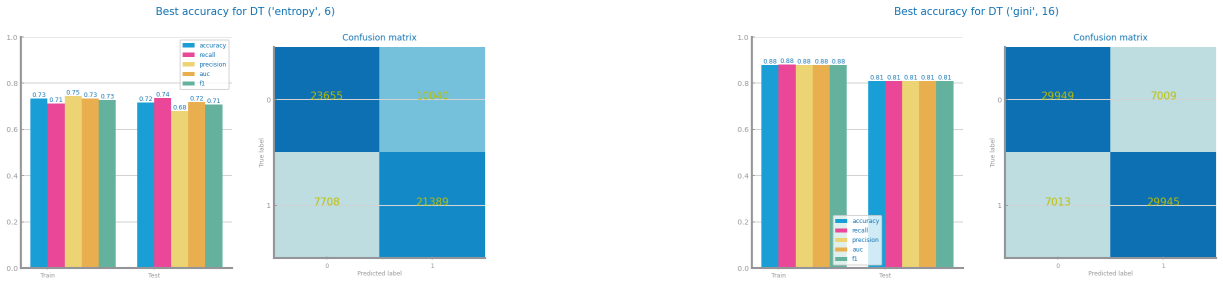


Figure 47: Decision trees best model results for dataset 1 (left) and dataset 2 (right)

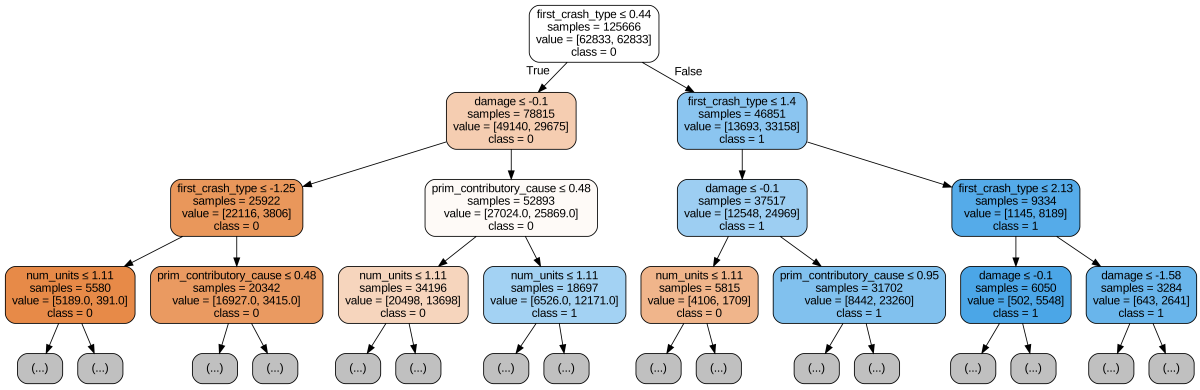


Figure 48: Best tree for dataset 1

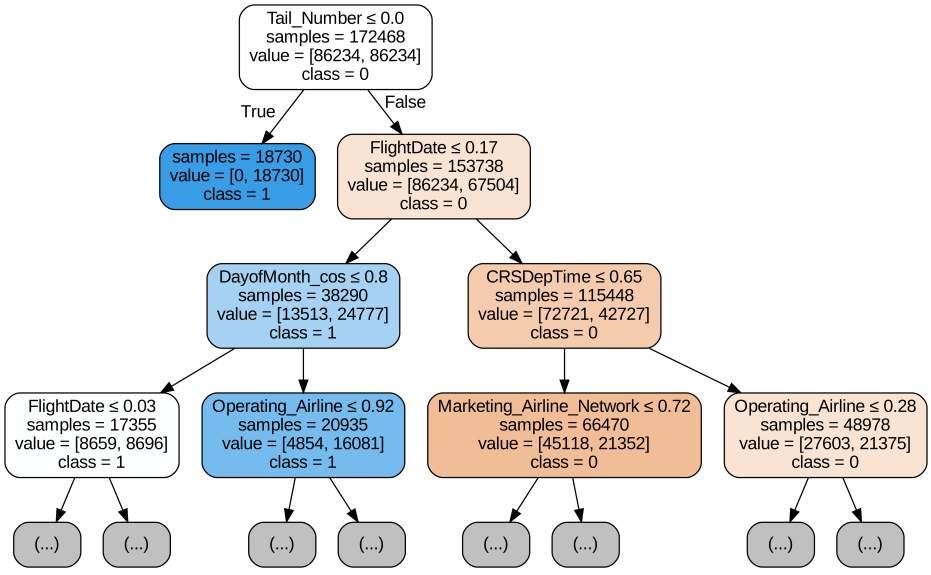


Figure 49: Best tree for dataset 2

Random Forests

Random forests improve steadily in both datasets.In Dataset 1, accuracy increases quickly and stabilizes. The best model (depth 5, feature fraction 0.5, 750 trees) reaches 0.72 test accuracy with balanced metrics.In Dataset 2, performance

remains stable across configurations.The best configuration (max depth 7, feature fraction 0.7, 500 trees) achieves 0.75 test accuracy, with strong precision (0.86) but lower recall (0.60).

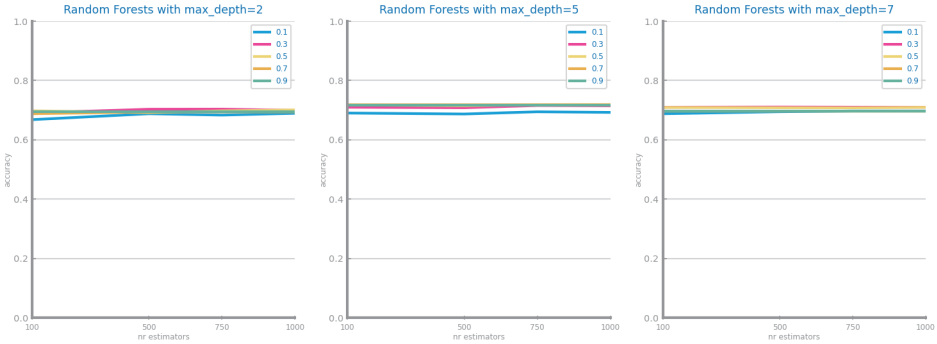


Figure 50: Random Forests different parameterisations comparison for dataset 1

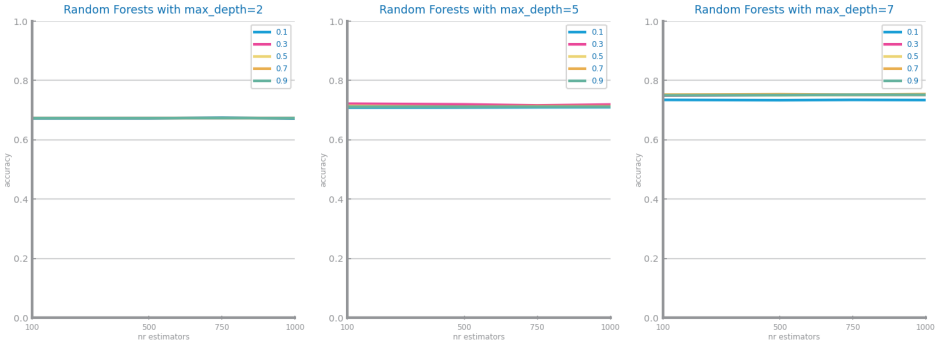


Figure 51: Random Forests different parameterisations comparison for dataset 2

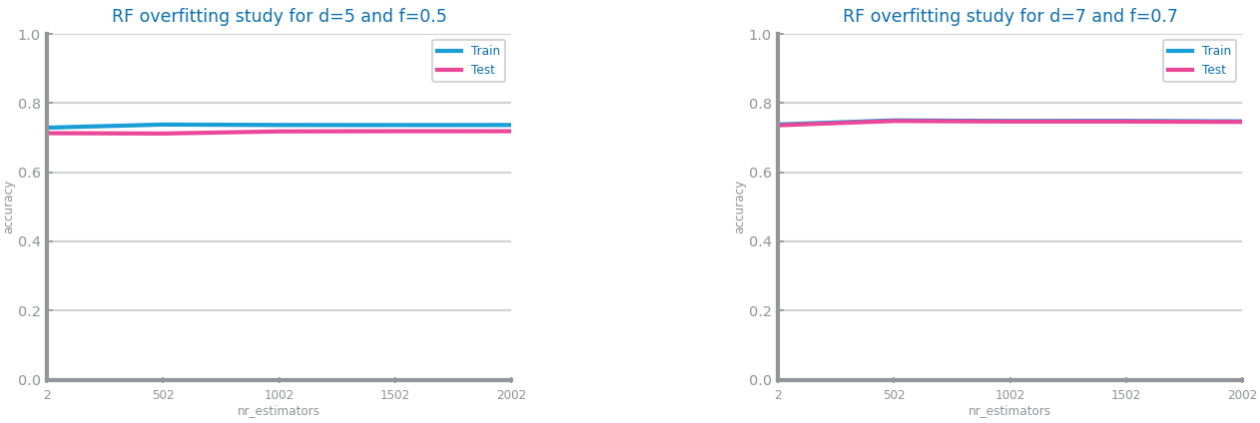


Figure 52: Random Forests overfitting analysis for dataset 1 (left) and dataset 2 (right)

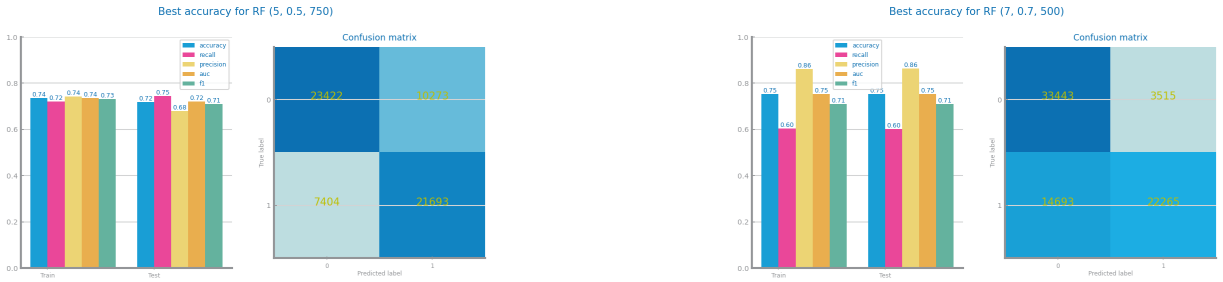


Figure 53: Random Forests best model results for dataset 1 (left) and dataset 2 (right)

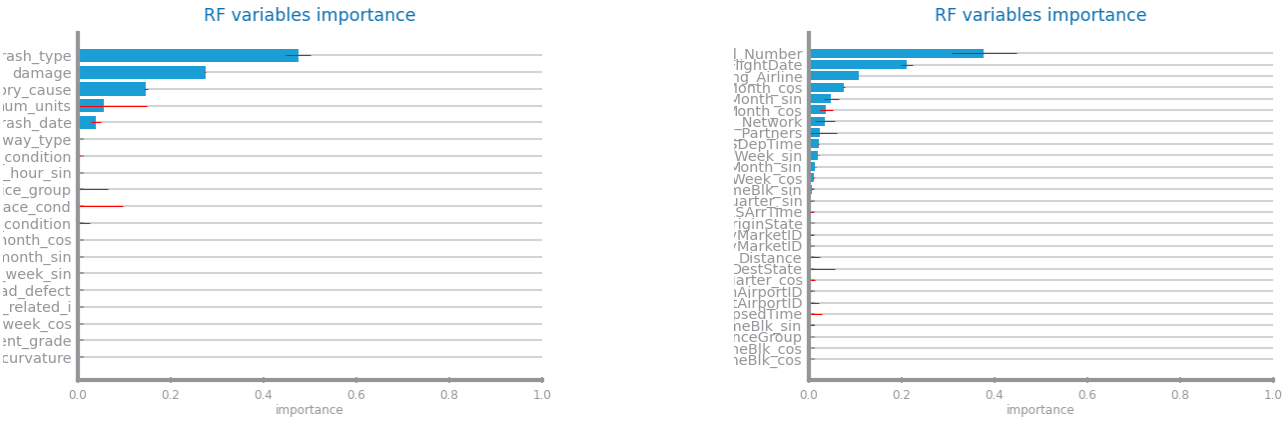


Figure 54: Random Forests variables importance for dataset 1 (left) and dataset 2 (right)

Gradient Boosting

In Dataset 1, overfitting appears early; Test F1 peaks at depth 3 and 50 estimators, then declines as complexity increases. The best model achieves 0.70 accuracy with high Recall (0.82) but low Precision (0.64). Conversely, Dataset 2 benefits from increased complexity, showing no overfitting as depth and estimators rise. However, the model suffers from severe class imbalance, achieving near-perfect Precision (0.99) but poor Recall (0.20), failing to identify most cancellations.

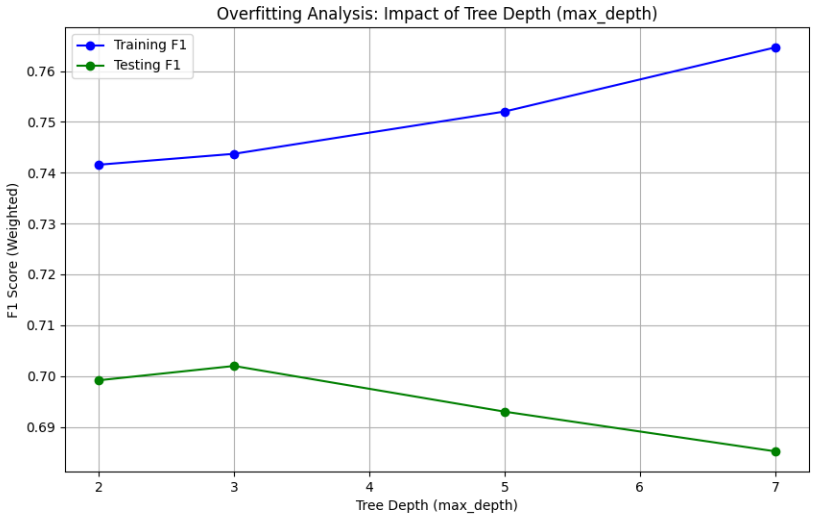


Figure 55: Gradient boosting different parameterisations comparison for dataset 1

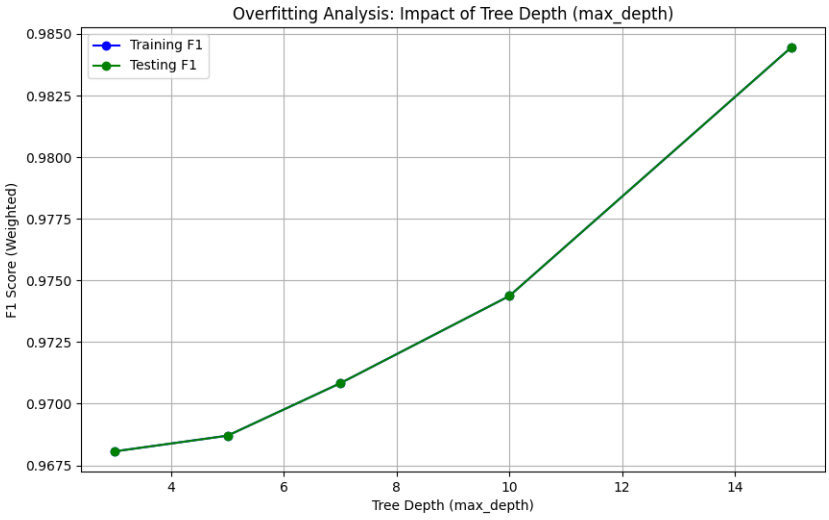


Figure 56: Gradient boosting different parameterisations comparison for dataset 2

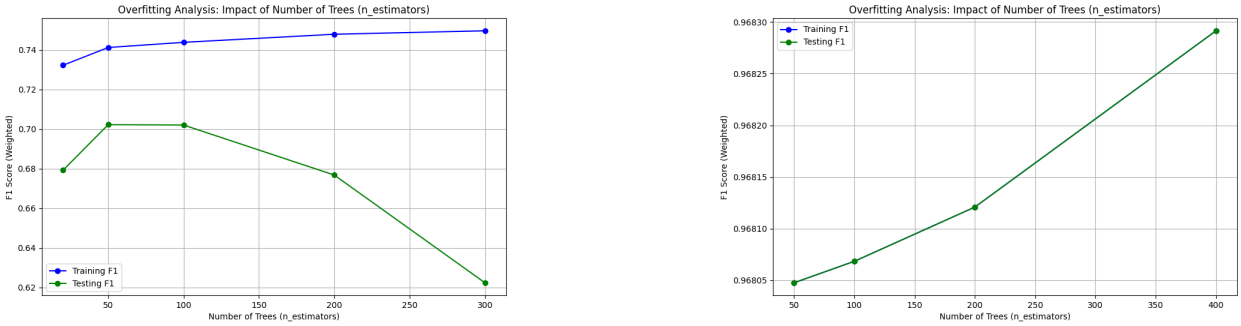


Figure 57: Gradient boosting overfitting analysis for dataset 1 (left) and dataset 2 (right)

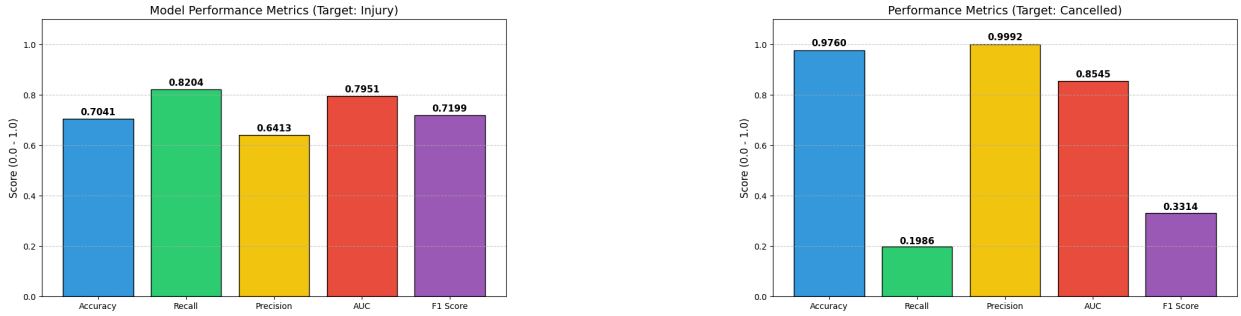


Figure 58: Gradient boosting best model results for dataset 1 (left) and dataset 2 (right)

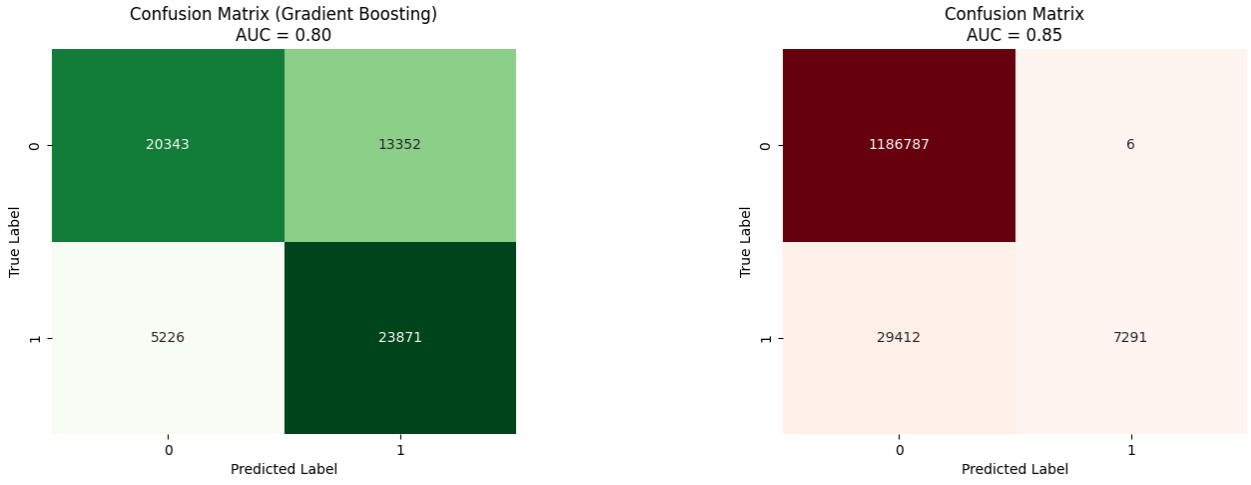


Figure 59: Gradient boosting variables importance for dataset 1 (left) and dataset 2 (right)

Multi-Layer Perceptrons

In Dataset 1, 'constant' and 'adaptive' schedules stabilize quickly, while 'invscaling' struggles. Mild overfitting is evident as training accuracy exceeds testing. The best model (constant, lr=0.5) achieves 0.71 accuracy; however, the loss curve

plateaus early, resulting in high Recall (0.75) but lower Precision due to False Positives. Dataset 2 converges smoothly with minimal overfitting. The best model (constant, lr=0.5, 3000 iter) reaches 0.79 accuracy, showing balanced metrics and a healthy, convex loss curve.

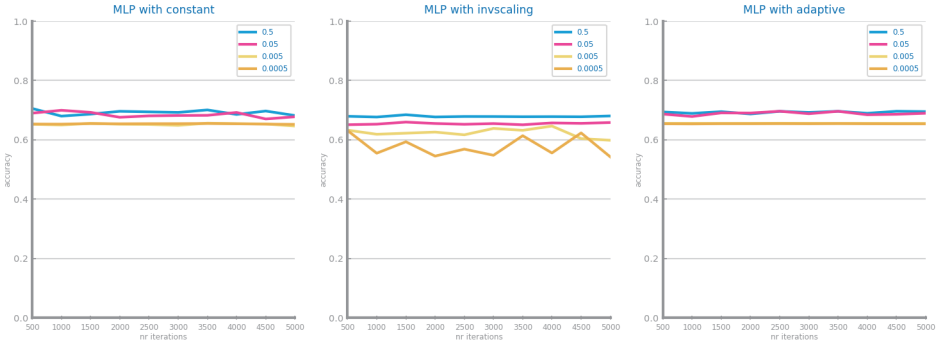


Figure 60: MLP different parameterisations comparison for dataset 1

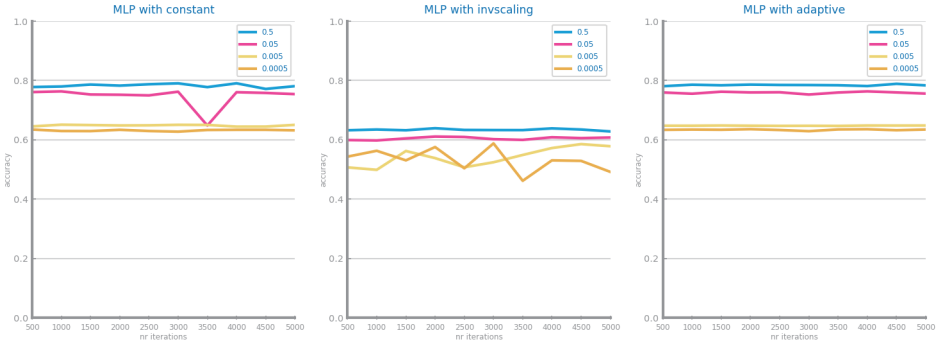


Figure 61: MLP different parameterisations comparison for dataset 2

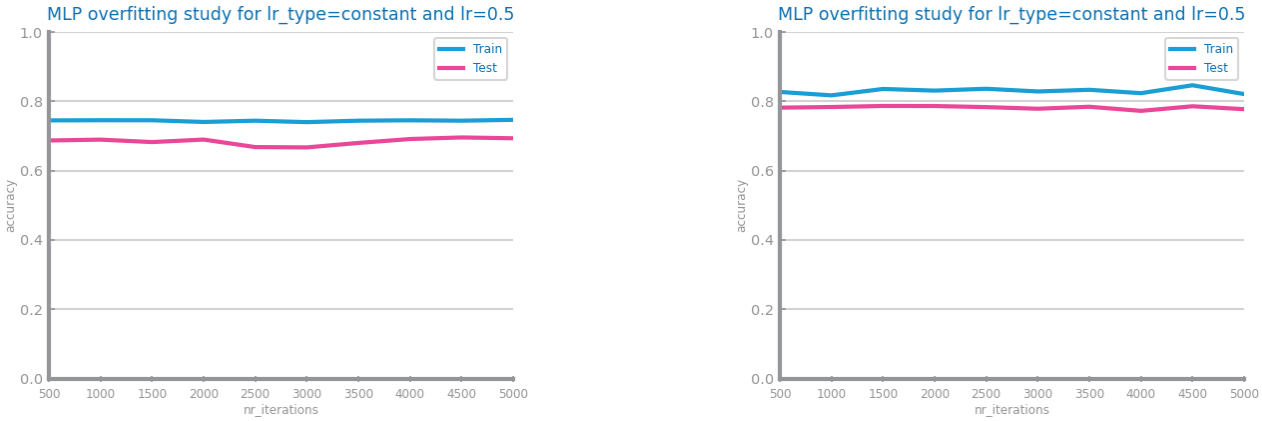


Figure 62: MLP overfitting analysis for dataset 1 (left) and dataset 2 (right)

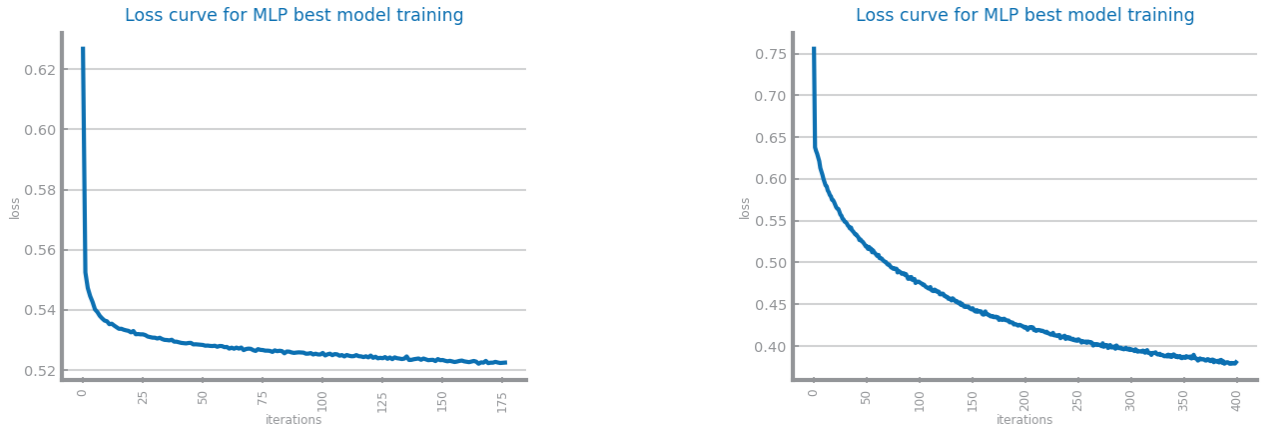


Figure 63: Loss curve analysis for dataset 1 (left) and dataset 2 (right)

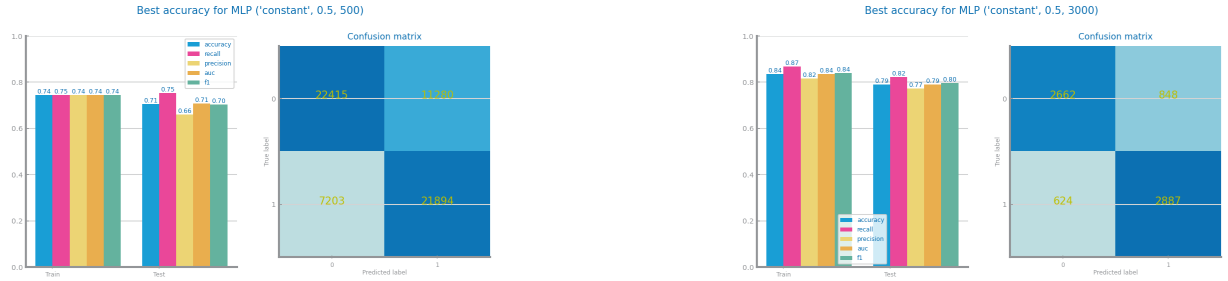


Figure 64: MLP best model results for dataset 1 (left) and dataset 2 (right)

4 CRITICAL ANALYSIS

The modeling phase revealed distinct performance patterns across both datasets. In Dataset 1 (Traffic Accidents), the Decision Tree (0.74) and Random Forest (0.72) models emerged as the most balanced, while Naïve Bayes and Logistic Regression struggled with accuracies near 0.65. Key variables like crash_type and damage were consistently identified as primary predictors across multiple classifiers.

In Dataset 2 (Flight Cancellations), metrics were generally higher but skewed. While Gradient Boosting achieved a remarkable 0.97 accuracy, and the Decision Tree reached 0.81, these figures are deceptive. A cross-analysis shows a recurring failure across KNN, Logistic Regression, and Gradient Boosting to achieve high Recall for Class 1. These models biased toward the majority class (Class 0), resulting in high precision but failing to identify actual cancellations. The MLP (0.79) and Random Forest (0.75) provided the most reliable generalization with smoother convergence.

Preparation tasks had a moderate impact on performance. The alignment of BernoulliNB with binary features and the success of Manhattan distance in KNN suggest that the initial feature encoding was beneficial for high-dimensional sparsity. However, the persistent class imbalance in Dataset 2 significantly hindered the predictive power of distance-based and linear models, suggesting that more aggressive resampling or synthetic data generation (SMOTE) could have improved the results further.

The models developed for Dataset 1 are promising, showing balanced Precision and Recall, though they may require further feature engineering to break the 0.75 accuracy ceiling. For Dataset 2, despite high accuracy scores (up to 0.97),

the models are currently not sufficient for real-world application due to poor Recall on the minority class. While the MLP shows the healthiest learning curve, the overall framework requires better handling of class imbalance before it can be considered a robust solution for flight cancellation forecasting.

TIME SERIES ANALYSIS

5 DATA PROFILING

Data Dimensionality and Granularity

The time series was analyzed at three temporal granularities: 15-minute intervals (most atomic), daily aggregation, and weekly aggregation. The most granular level captures short-term variability and peaks, while daily and weekly granularities smooth fluctuations and highlight medium- and long-term trends.

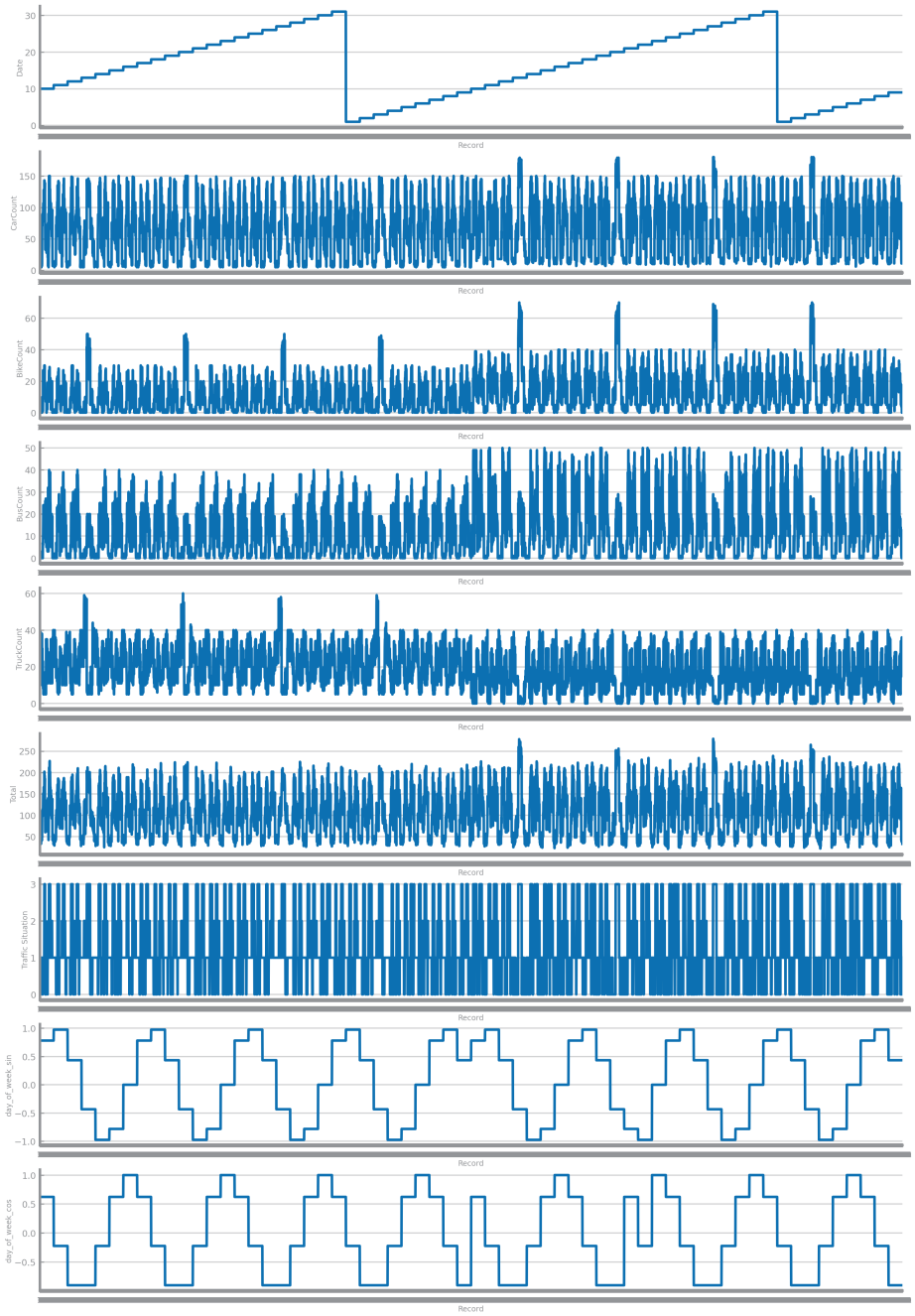


Figure 65: Time series 1 at the most granular detail

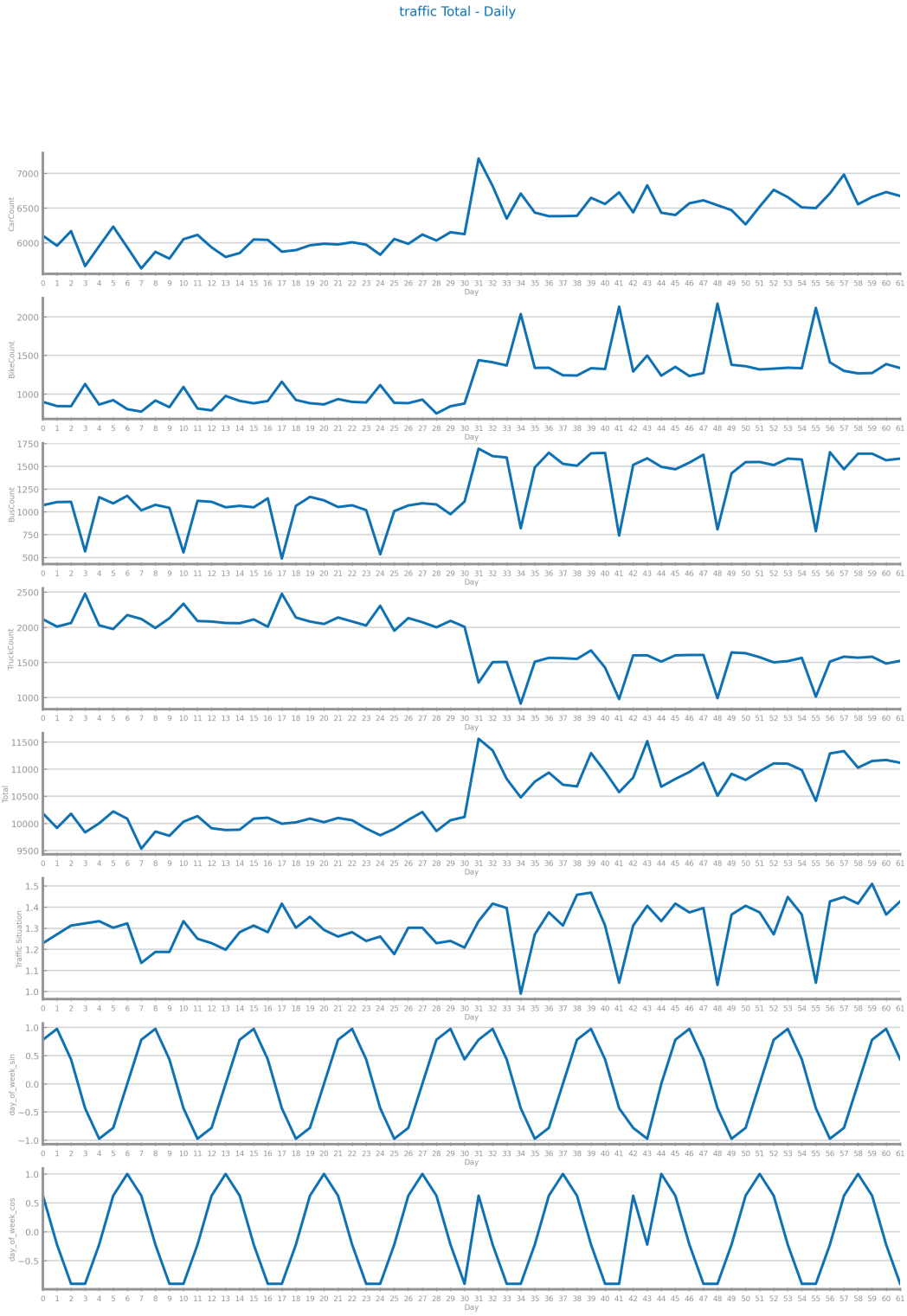


Figure 66: Time series 1 at the second chosen granularity

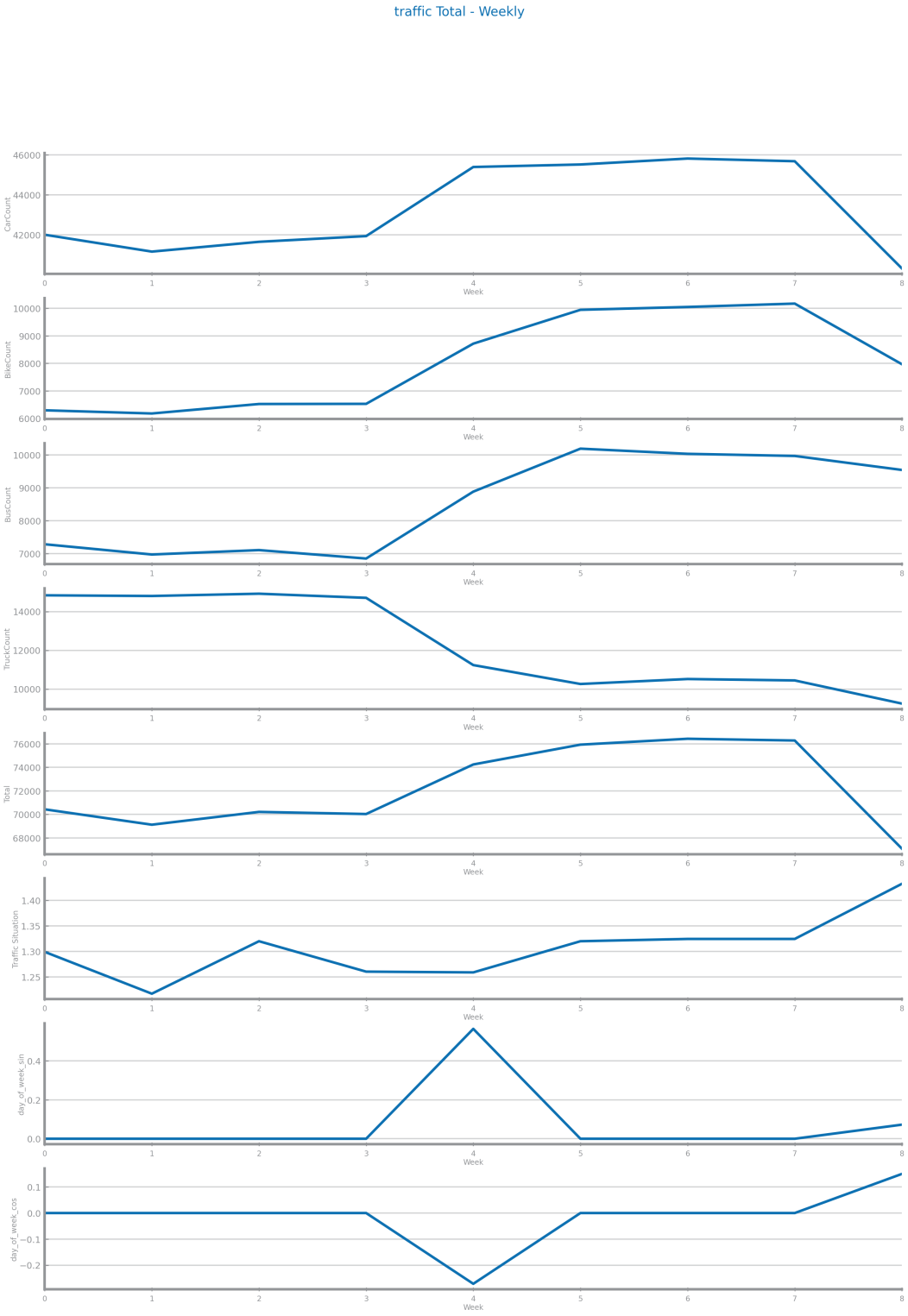
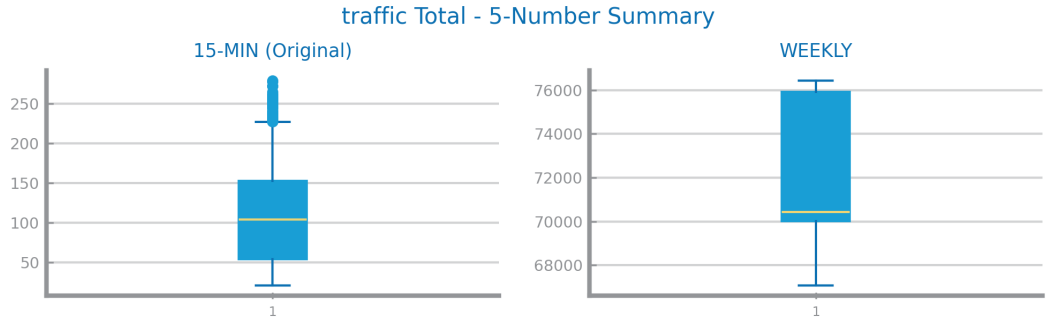


Figure 67: Time series 1 at the third chosen granularity

Data Distribution

The distribution analysis across granularities shows that aggregation reduces variability and outliers. The 15-minute series presents higher dispersion and skewness, while hourly and daily series exhibit smoother distributions.



	15-MIN (Original)	WEEKLY
count	5952.000000	9.000000
mean	109.161458	72192.111111
std	55.996312	3536.807580
min	21.000000	67082.000000
25%	54.000000	70026.000000
50%	104.000000	70427.000000
75%	153.000000	75926.000000
max	279.000000	76427.000000

Name: Total, dtype: float64 Name: Total, dtype: float64

Figure 68: Boxplot(s) for time series 1

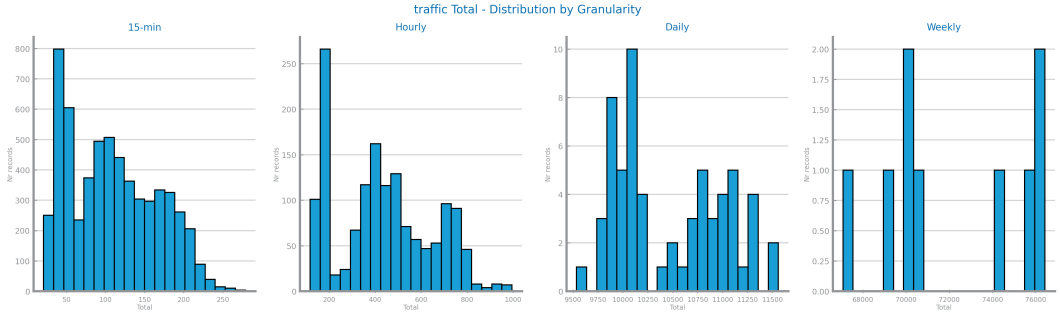


Figure 69: Histogram(s) for time series 1

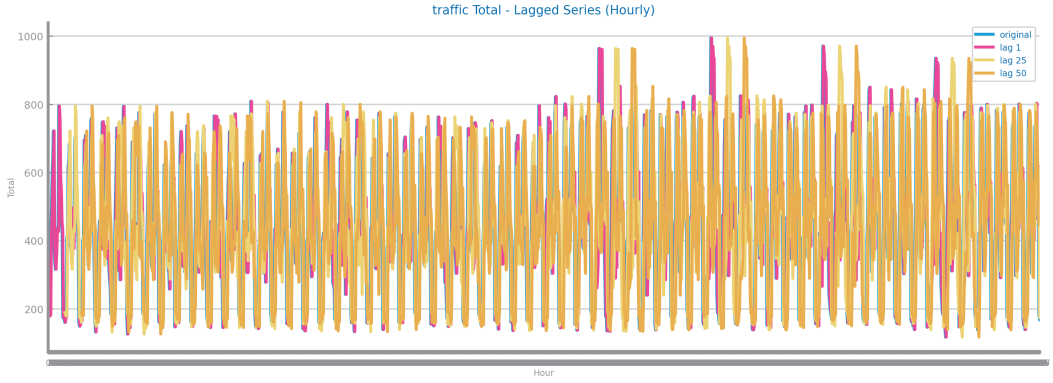


Figure 70: Autocorrelation lag-plots for original time series 1

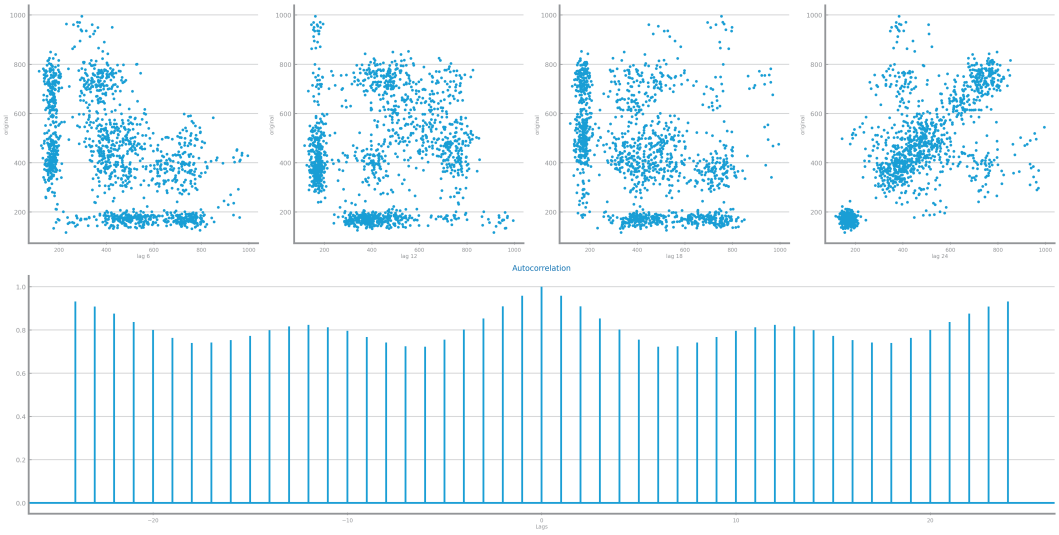


Figure 71: Autocorrelation correlogram for original time series 1

Data Stationarity

Stationarity analysis shows that the series is stationary at finer granularities but loses stationarity when aggregated daily. Augmented Dickey-Fuller Test confirm that trend components become more pronounced at coarser granularities, indicating the need for detrending or differencing when modeling aggregated series.

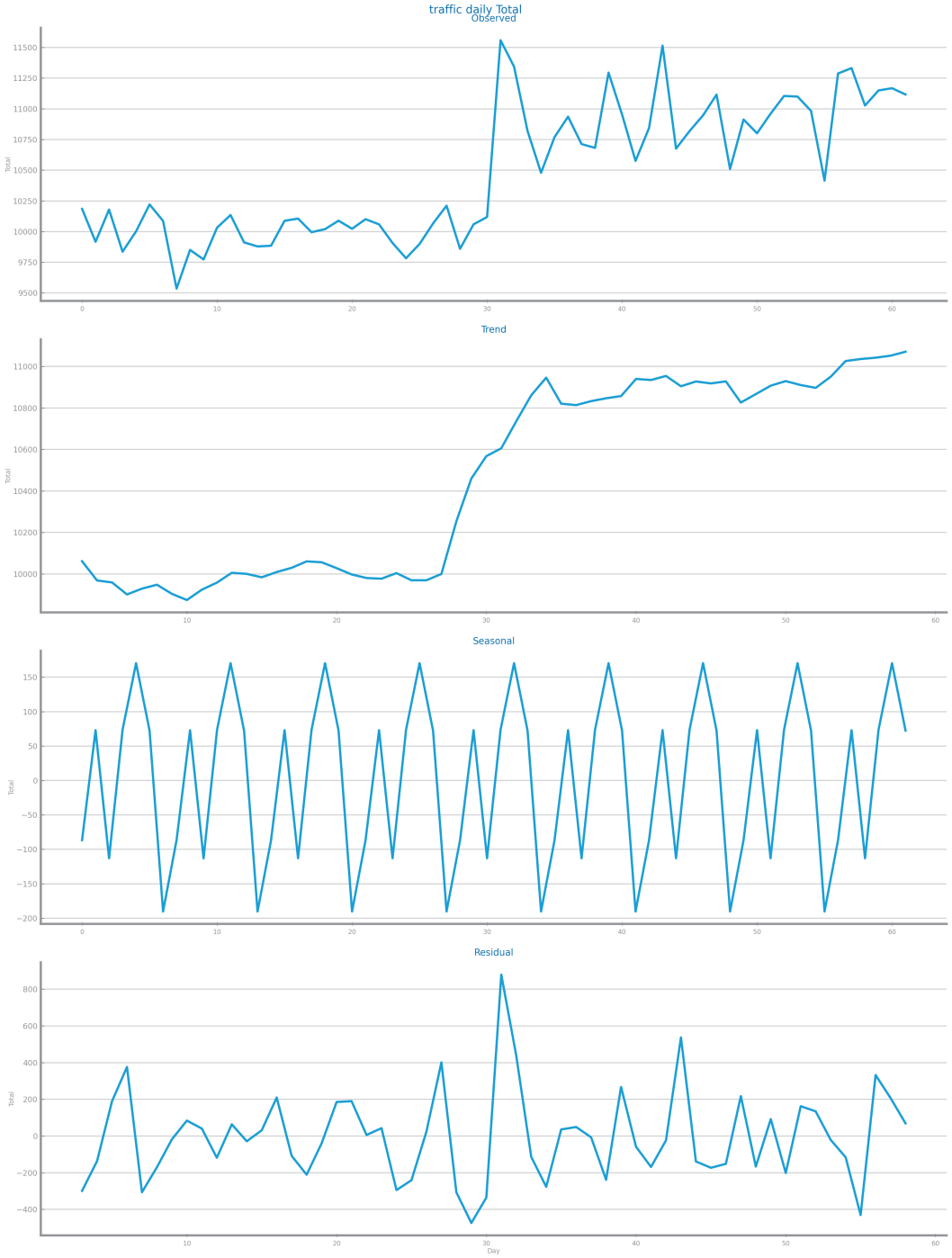


Figure 72: Components study for time series 1

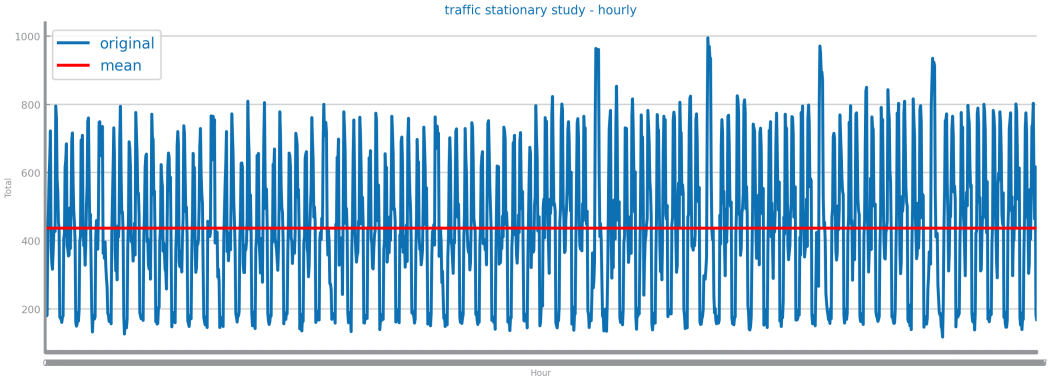


Figure 73: Stationarity study for time series 1

Augmented Dickey-Fuller Test Results:

Original (15-min):

- ADF Statistic: -14.441
- p-value: 0.000
- Critical Values: 1%: -3.431, 5%: -2.862, 10%: -2.567
- **The series IS stationary**

Hourly:

- ADF Statistic: -8.903
- p-value: 0.000
- Critical Values: 1%: -3.435, 5%: -2.864, 10%: -2.568
- **The series IS stationary**

Daily:

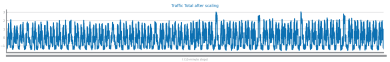
- ADF Statistic: -0.826
- p-value: 0.811
- Critical Values: 1%: -3.548, 5%: -2.913, 10%: -2.594
- **The series IS NOT stationary**

6 DATA TRANSFORMATION

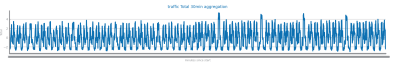
Aggregation

We tested 30-minute, hourly, daily, and weekly aggregations to see how each level reduces noise and how much detail is lost.The plots (see Figures 75, 76, and 77) reveal that no aggregation keeps high-frequency noise, while daily and weekly

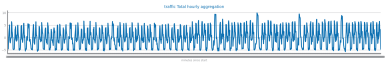
levels smooth the data too much.On the test set, linear regression produced constant predictions with R^2 close to 0, signaling a poor fit to the data.Meanwhile, the optimistic persistence model performed better, and the 30-minute level gave the best R^2 (0.67), so we chose it.



(a) No Aggregation (original after scaling)

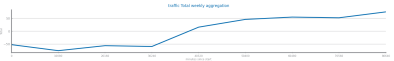


(b) 30min Aggregation



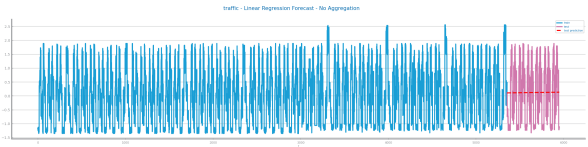
(c) Hourly Aggregation

(a) Daily Aggregation

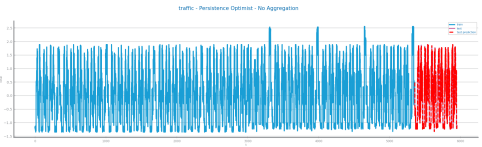


(b) Weekly Aggregation

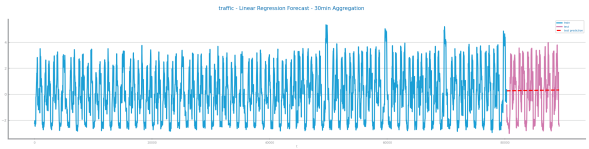
Figure 75: Time series plots after different levels of aggregation



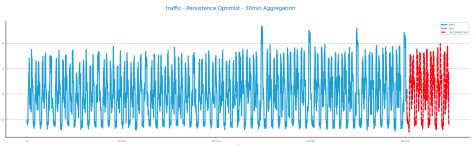
(a) Linear Regression – No Aggregation



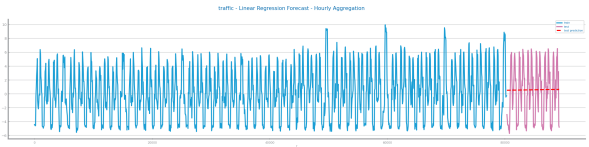
(b) Persistence Optim – No Aggregation



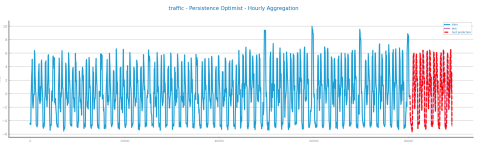
(c) Linear Regression – 30min Aggregation



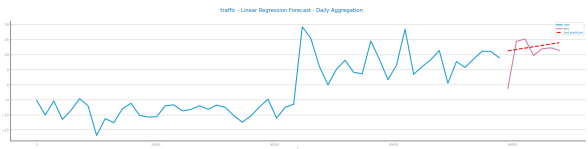
(d) Persistence Optim – 30min Aggregation



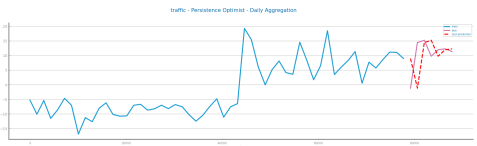
(e) Linear Regression – Hourly Aggregation



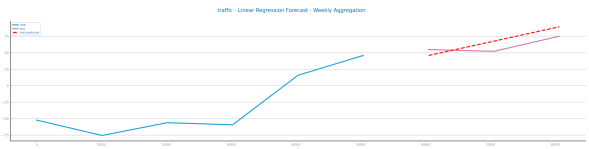
(f) Persistence Optim – Hourly Aggregation



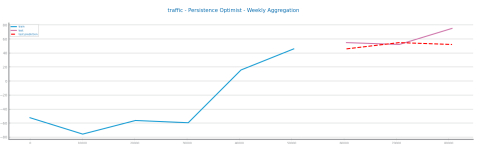
(g) Linear Regression – Daily Aggregation



(h) Persistence Optim – Daily Aggregation



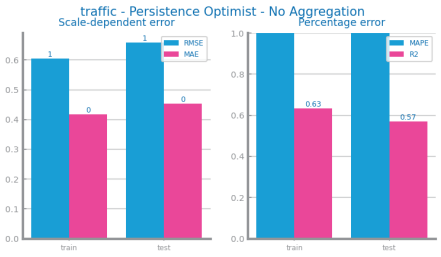
(i) Linear Regression – Weekly Aggregation



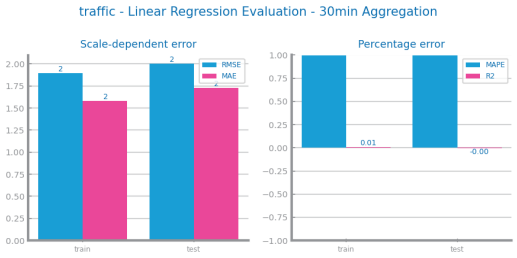
(j) Persistence Optim – Weekly Aggregation

Figure 76: Forecasting plots for Linear Regression and Persistence Optim after different aggregations

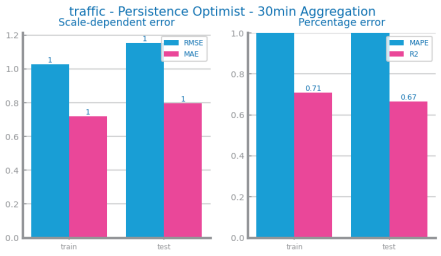
(a) Linear Regression Evaluation – No Aggregation



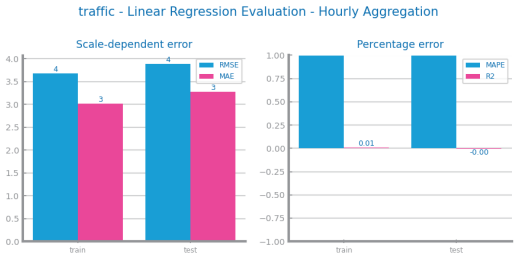
(b) Persistence Optim Evaluation – No Aggregation



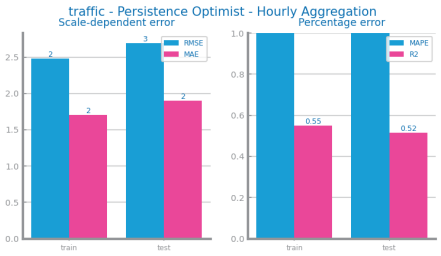
(c) Linear Regression Evaluation – 30min Aggregation



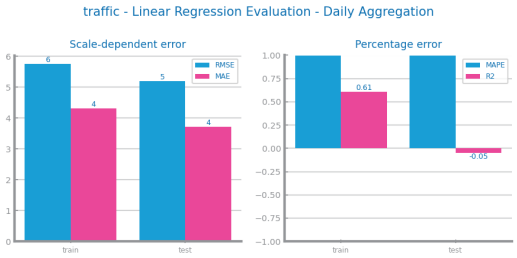
(d) Persistence Optim Evaluation – 30min Aggregation



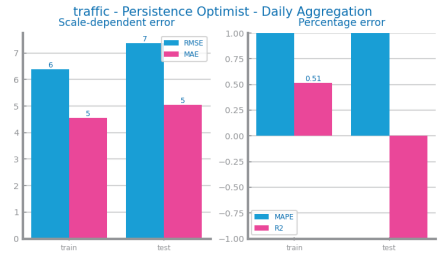
(e) Linear Regression Evaluation – Hourly Aggregation



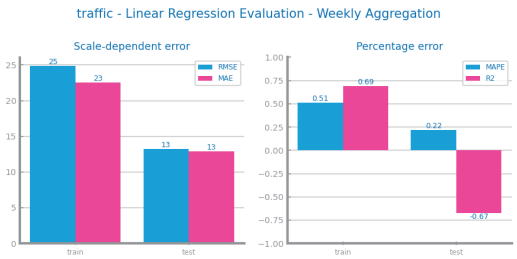
(f) Persistence Optim Evaluation – Hourly Aggregation



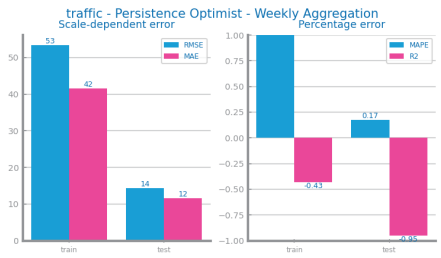
(g) Linear Regression Evaluation – Daily Aggregation



(h) Persistence Optim Evaluation – Daily Aggregation



(i) Linear Regression Evaluation – Weekly Aggregation

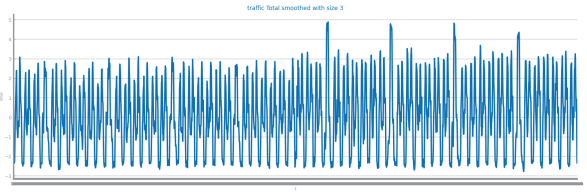


(j) Persistence Optim Evaluation – Weekly Aggregation

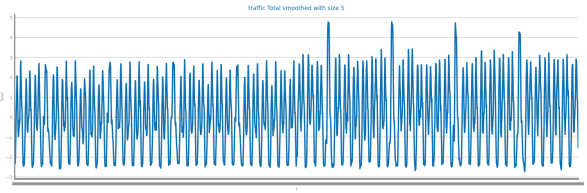
Figure 77: Evaluation results for Linear Regression and Persistence Optim after different aggregations

Smoothing

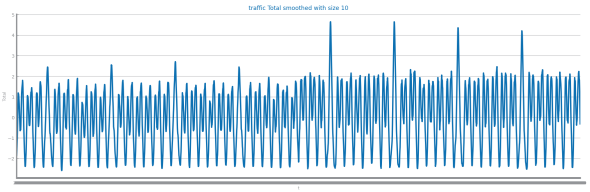
We tested moving-average smoothing with window sizes of 3, 5, 10, and 15 to see how noise reduction affects forecasting without distorting the data.Smaller windows kept more noise, while larger ones over-smoothed.The window of 15 worked best, giving RMSE 0.3, MAE 0.25, and R^2 0.96 in the optimistic persistence model.Linear regression stayed flat with low R^2, so we chose size 15.



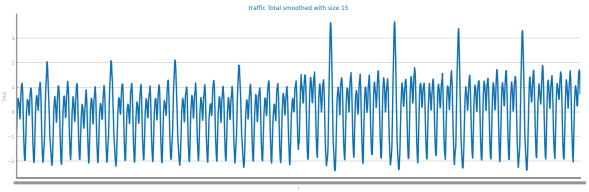
(a) Smoothing Size 3



(b) Smoothing Size 5

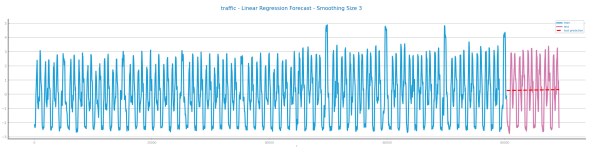


(c) Smoothing Size 10

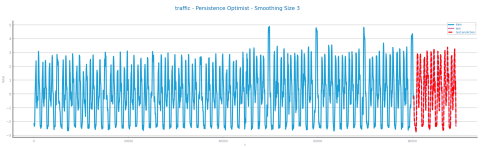


(d) Smoothing Size 15

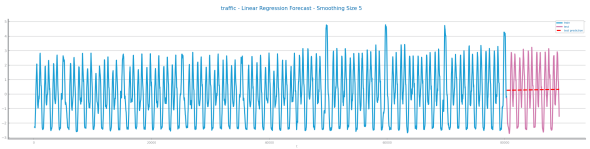
Figure 78: Time series plots after applying moving average smoothing with different window sizes



(a) Linear Regression – Size 3

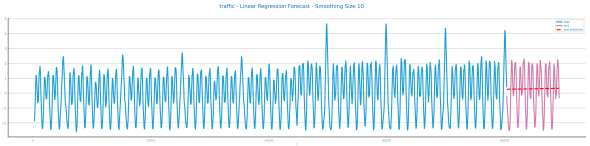


(b) Persistence Optim – Size 3



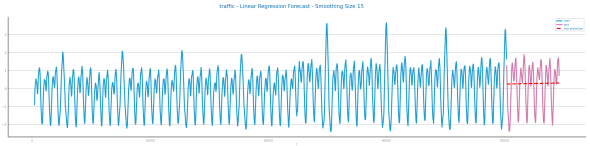
(c) Linear Regression – Size 5

(d) Persistence Optim – Size 5

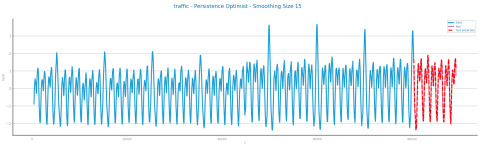


(e) Linear Regression – Size 10

(f) Persistence Optim – Size 10

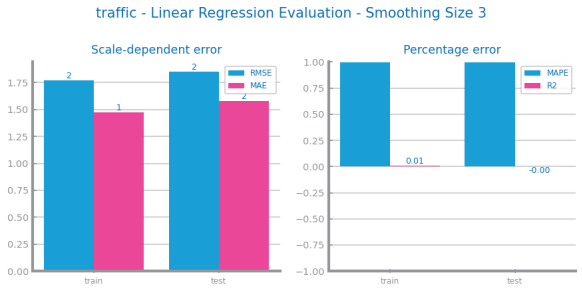


(g) Linear Regression – Size 15

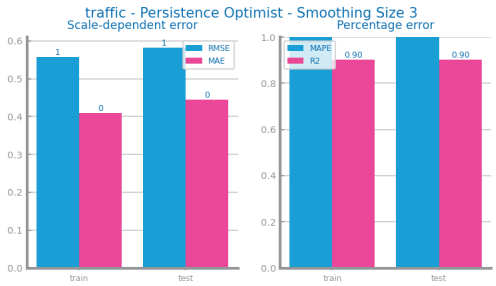


(h) Persistence Optim – Size 15

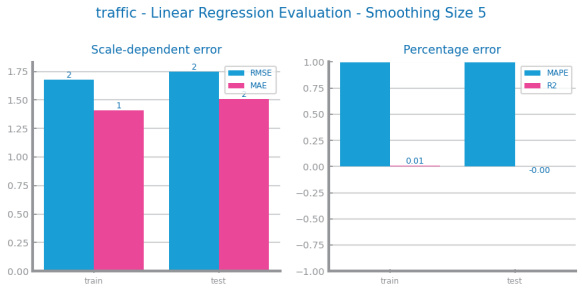
Figure 79: Forecasting plots for Linear Regression and Persistence Optim after different smoothing window sizes



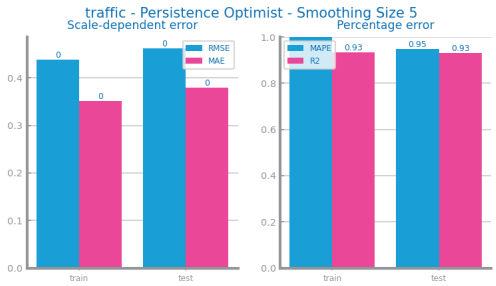
(a) Linear Regression Evaluation – Size 3



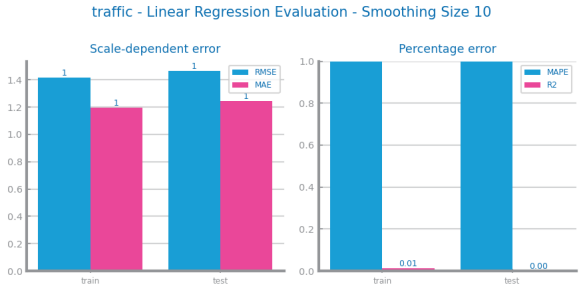
(b) Persistence Optim Evaluation – Size 3



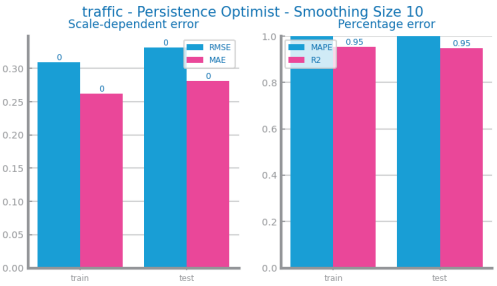
(c) Linear Regression Evaluation – Size 5



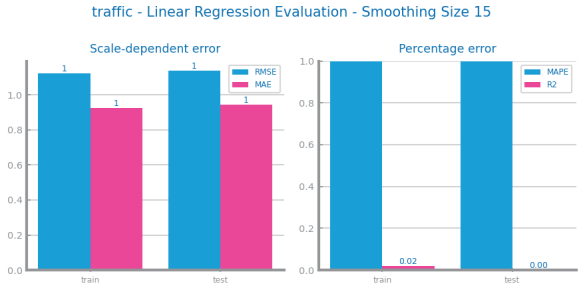
(d) Persistence Optim Evaluation – Size 5



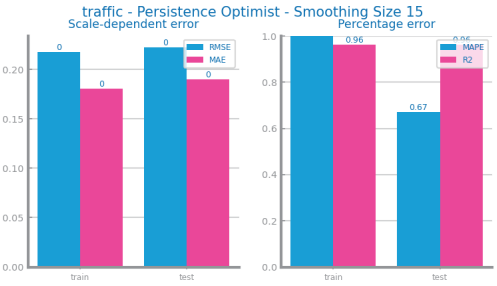
(e) Linear Regression Evaluation – Size 10



(f) Persistence Optim Evaluation – Size 10



(g) Linear Regression Evaluation – Size 15



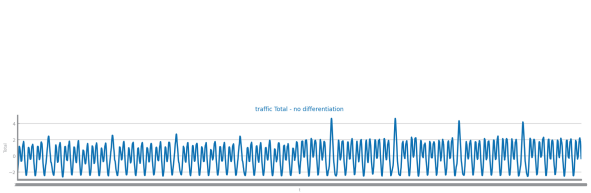
(h) Persistence Optim Evaluation – Size 15

Figure 80: Evaluation results for Linear Regression and Persistence Optim after different smoothing window sizes

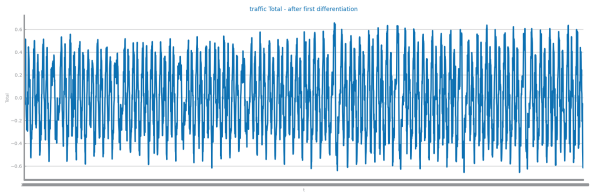
Differentiation

To handle possible non-stationarity, we tested no differencing, first-order, and second-order differencing.No differencing kept the trend, first-order removed linear trends and centered the data, and second-order added noise without helping.The

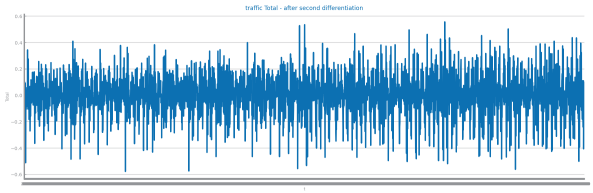
optimistic persistence model performed best with no differencing, reaching R^2 0.95.Linear regression improved only slightly, so we chose no differencing.



(a) No Differentiation

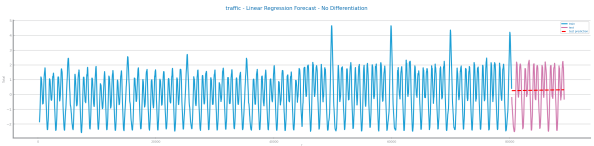


(b) First Differentiation

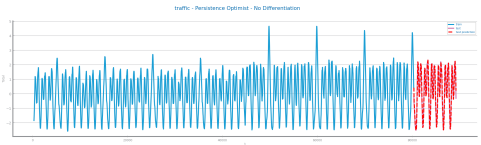


(c) Second Differentiation

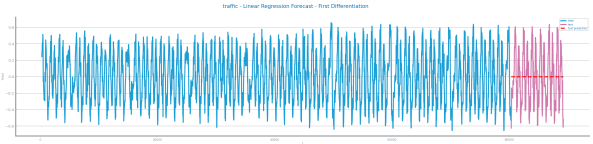
Figure 81: Time series plots without and after applying first, and second differentiation



(a) Linear Regression – No Differentiation

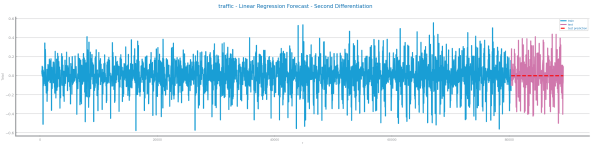


(b) Persistence Optim – No Differentiation

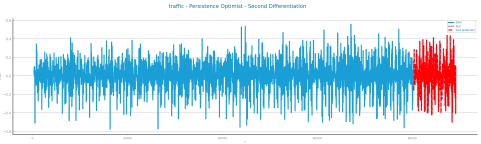


(c) Linear Regression – First Differentiation

(d) Persistence Optim – First Differentiation

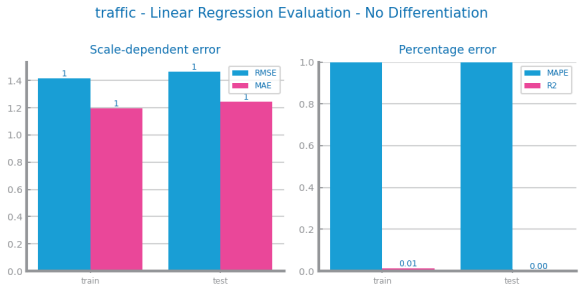


(e) Linear Regression – Second Differentiation

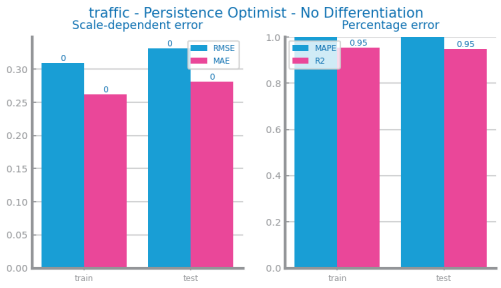


(f) Persistence Optim – Second Differentiation

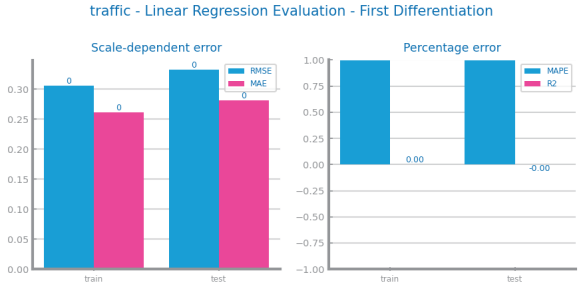
Figure 82: Forecasting plots for Linear Regression and Persistence Optim after different levels of differentiation



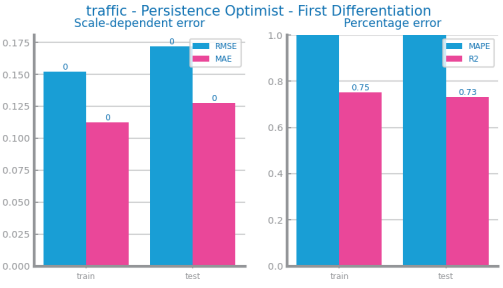
(a) Linear Regression Evaluation – No Differentiation



(b) Persistence Optim Evaluation – No Differentiation

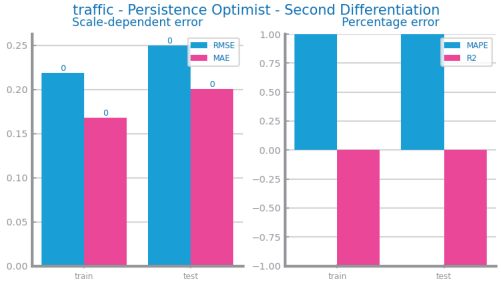


(c) Linear Regression Evaluation – First Differentiation



(d) Persistence Optim Evaluation – First Differentiation

(e) Linear Regression Evaluation – Second Differentiation

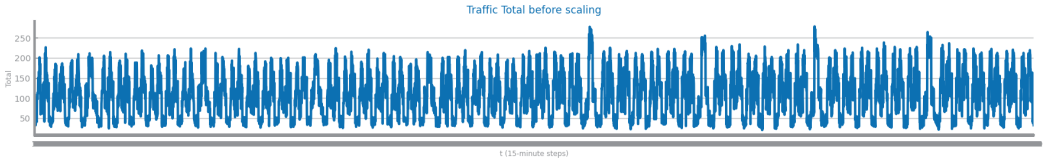


(f) Persistence Optim Evaluation – Second Differentiation

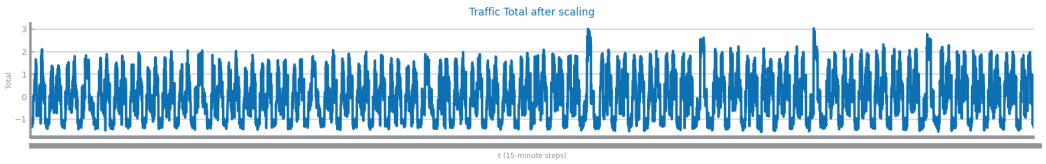
Figure 83: Evaluation results for Linear Regression and Persistence Optim after different levels of differentiation

Scaling

We used StandardScaler to normalize the data, converting it to a mean of 0 and a standard deviation of 1.Before scaling, the values ranged from about 25 to 250 with high variance; after scaling, they fell roughly between –1 and 3.This improved model stability,and sped up convergence as shown in the before-and-after plots.We did not test other scaling methods because StandardScaler solved the scale issues without adding complexity.The final preparation pipeline for the traffic dataset is: 30-minute aggregation, smoothing with window size 15, no differencing, and scaling with StandardScaler.



(a) Before scaling



(b) After StandardScaler()

Figure 84: Effect of StandardScaler on the original 15-minute time series

7 MODELS' EVALUATION

Exponential Smoothing Model

We applied simple exponential smoothing and tuned alpha from 0.1 to 0.9. The hyperparameter study (Figure 85) shows R^2 starts near 0.0 at alpha = 0.1 and drops sharply to −1.0 by alpha = 0.3, indicating the model overreacts to recent changes.

The forecast (Figure 86) follows the overall trend but smooths out sharp variations. The evaluation (Figure 87) shows poor test performance: RMSE ≈ 0.24, MAE ≈ 0.20, MAPE ≈ 100%, R^2 ≈ −0.01, revealing weak accuracy and poor generalization.

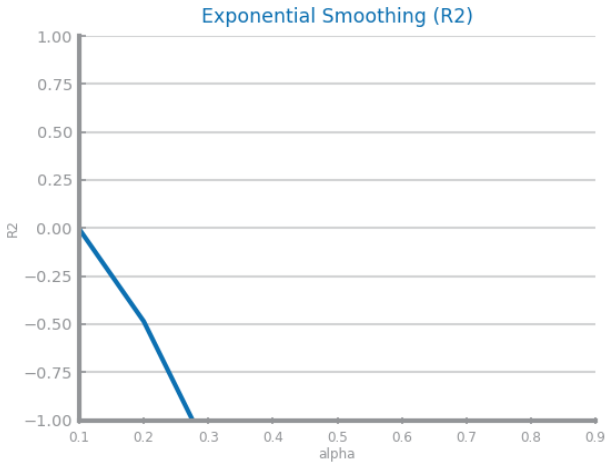


Figure 85: Hyperparameter study: R^2 as a function of alpha for Exponential Smoothing

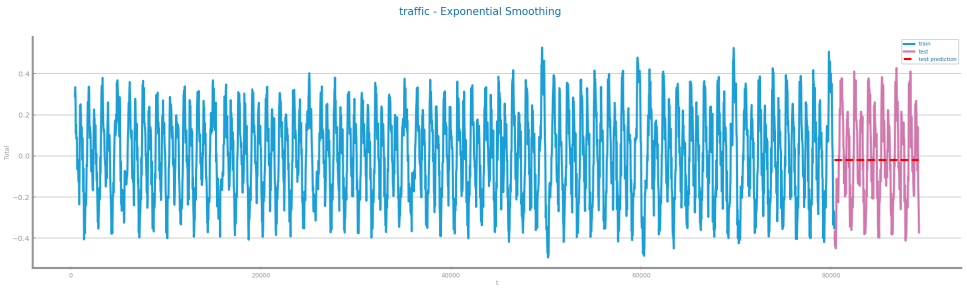


Figure 86: Forecasting plots obtained with the best Exponential Smoothing model (predictions in red vs actual test data in pink)

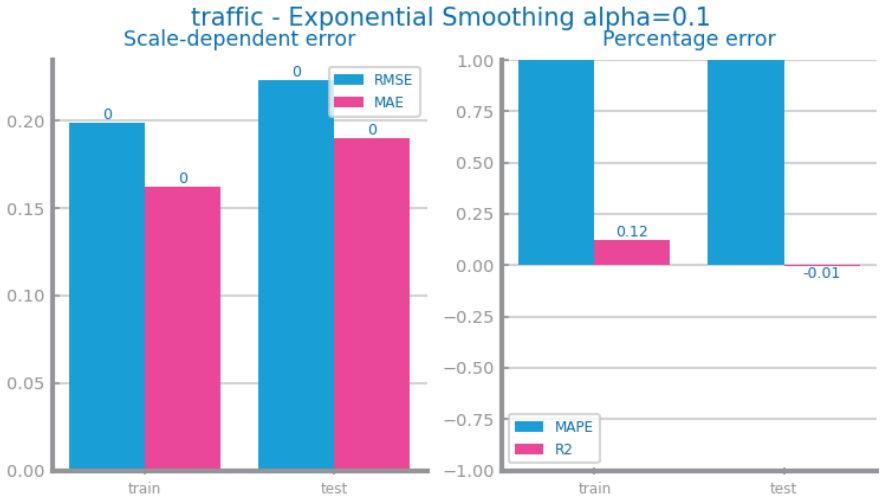


Figure 87: Performance metrics of the best Exponential Smoothing model (RMSE, MAE, MAPE, R^2)

Multi-layer Perceptrons Model

For the MLP model, we explored various hidden layer architectures, including single layers with 50 or 100 neurons, and multi-layers such as (50, 50) and (100, 50), trained with the Adam optimizer and MSE loss.The best setup was (50, 50), reaching test $R^2 \approx 0.86$ after $\sim$800 epochs with stable training and no overfitting.The forecasting plot (Figure 89) closely matched the test data, capturing nonlinear patterns better than simpler models.Performance metrics (Figure 90) show RMSE ≈ 0.25, MAE ≈ 0.20, MAPE $\approx 18\%$, and $R^2 \approx 0.86$, confirming solid medium-term performance despite higher computational cost.

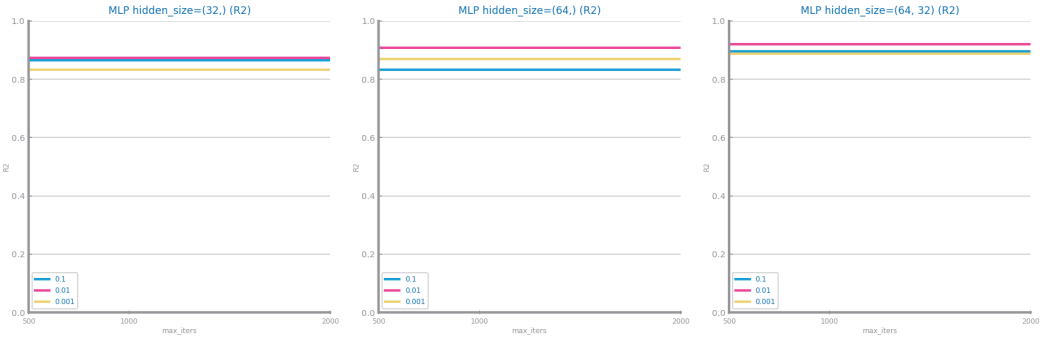


Figure 88: Hyperparameter study: R^2 convergence for different MLP hidden layer configurations

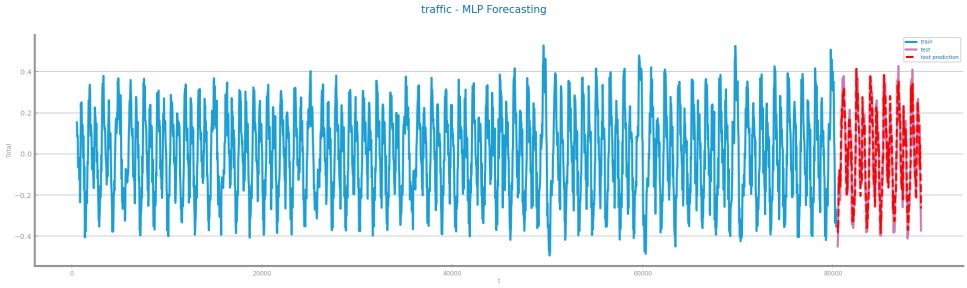


Figure 89: Forecasting plots obtained with the best MLP model (predictions in red vs actual test data in pink)

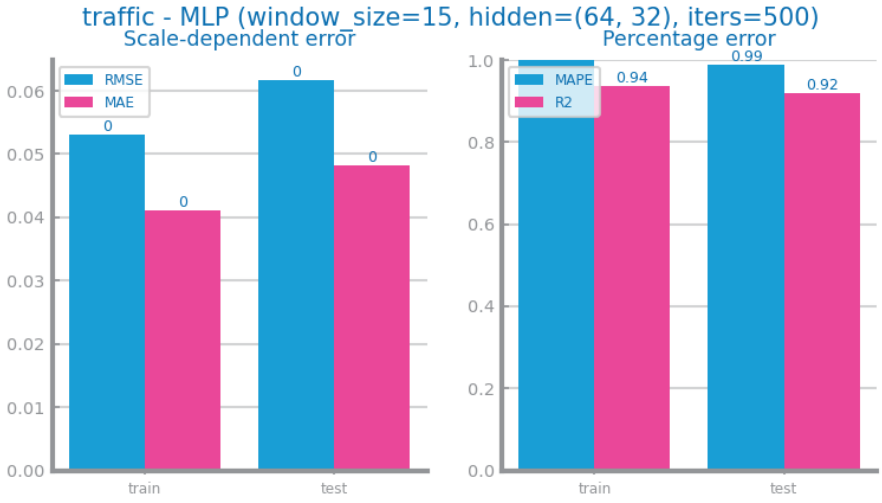


Figure 90: Performance metrics of the best MLP model (RMSE, MAE, MAPE, R^2)

ARIMA Model

We ran a grid search for ARIMA with p and q from 0 to 8 and d from 0 to 2.The study (Figure 91) highlights the optimal univariate configuration as p=5, d=1, q=7.ARIMA fit training data well ($R^2 \approx 0.85$) but dropped on test ($R^2 \approx 0.08$), with RMSE rising from 0.08 to 0.21 (Figure 93). VAR with lag=4 showed more stable training ($R^2 \approx 0.82$) but also weak

test performance ($R^2 \approx 0.06$) (Figure 96).Both models captured trends but failed on sharp changes, with high MAPE (100%) and limited generalization. (Figure 92)

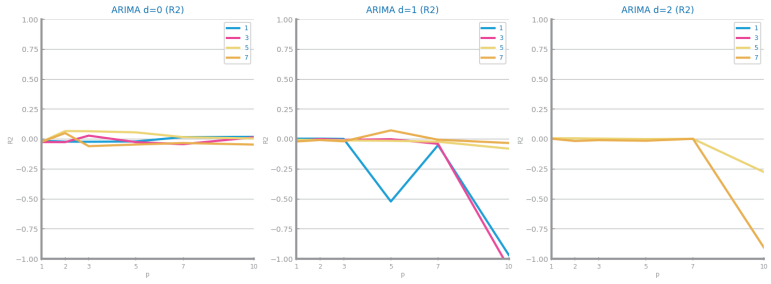


Figure 91: Hyperparameter study: best ARIMA configuration (p=5, d=1, q=7) – univariate

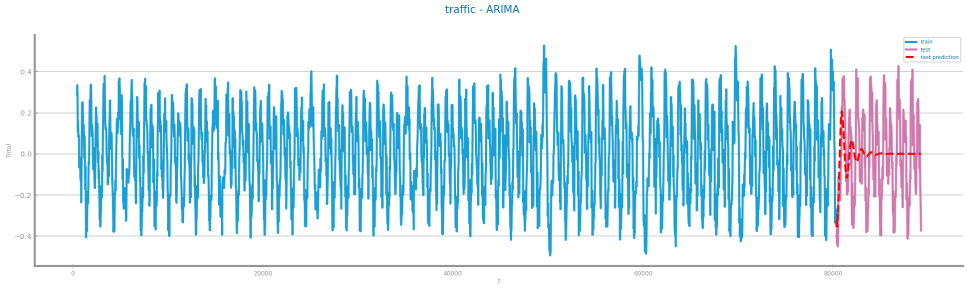


Figure 92: Forecasting plots obtained with the best ARIMA model (predictions in red vs actual test data in pink) – univariate

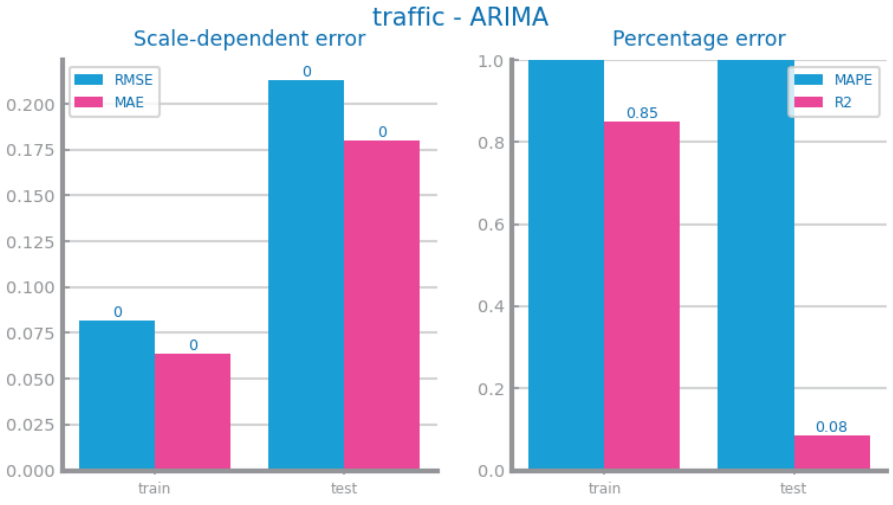


Figure 93: Performance metrics of the best ARIMA model (RMSE, MAE, MAPE, R^2) – univariate

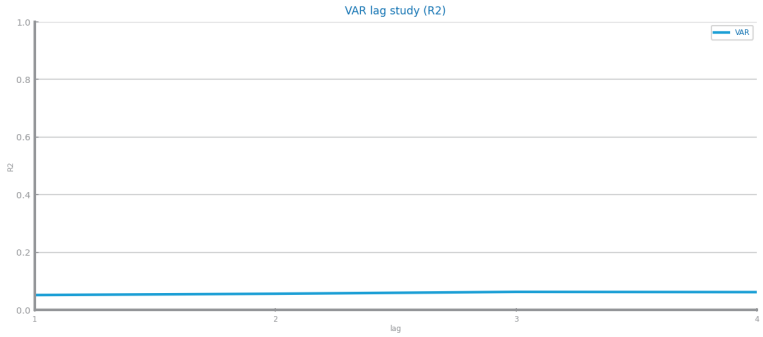


Figure 94: Hyperparameter study: best VAR configuration (lag=4) – multivariate

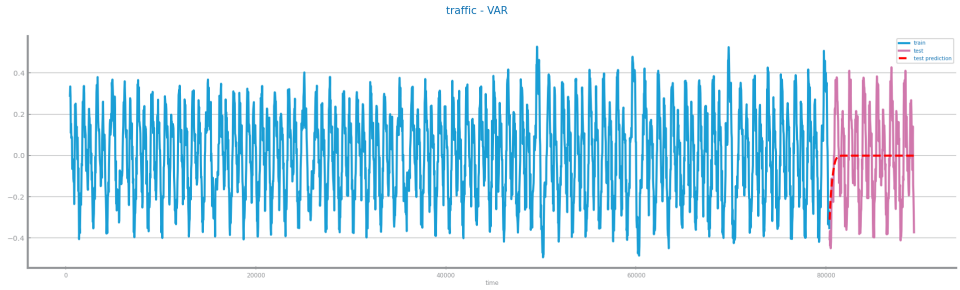


Figure 95: Forecasting plots obtained with the best VAR model (predictions in red vs actual test data in pink) – multivariate

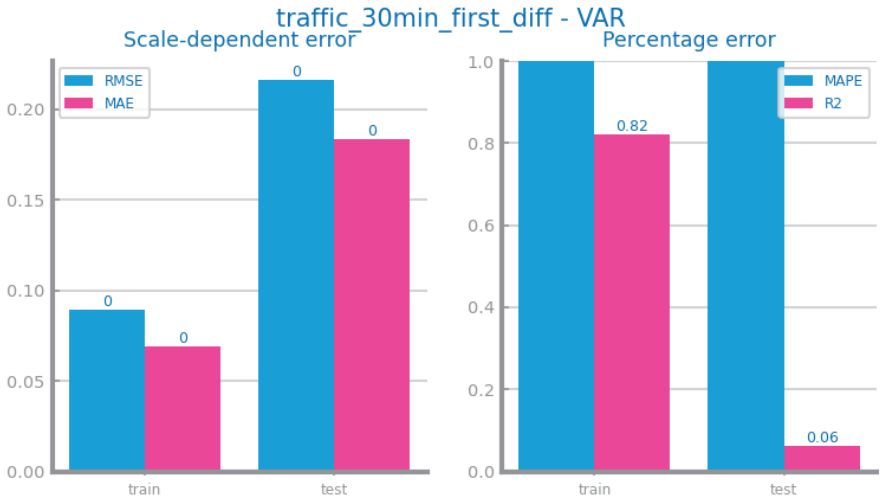


Figure 96: Performance metrics of the best VAR model (RMSE, MAE, MAPE, R^2) – multivariate

LSTMs Model

We tuned LSTM with sequence lengths 3-6, hidden units 20-50, and up to 2500 epochs using Adam and MSE. The study (Figure 97) identifies the best univariate setup was seq=4, hidden=25, epochs=2100, reaching test R^2 0.91.The

forecasting plot (Figure 98) closely matched test data, capturing trends and irregularities.Metrics (Figure 99) report test RMSE 0.20, MAE 0.15, MAPE 13%, R^2 0.84.In the multivariate case, similar tuning led to stable R^2 0.87 and better generalization across variables.

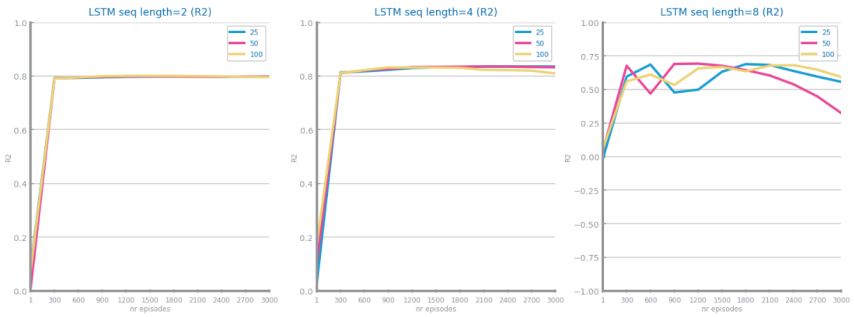


Figure 97: Hyperparameter study: best LSTM configuration (sequence length=4, hidden=25, epochs=2100) – univariate

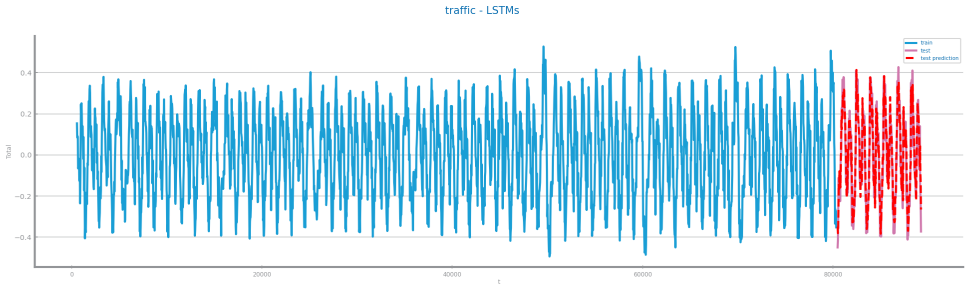


Figure 98: Forecasting plots obtained with the best LSTM model (predictions in red vs actual test data in pink) – univariate

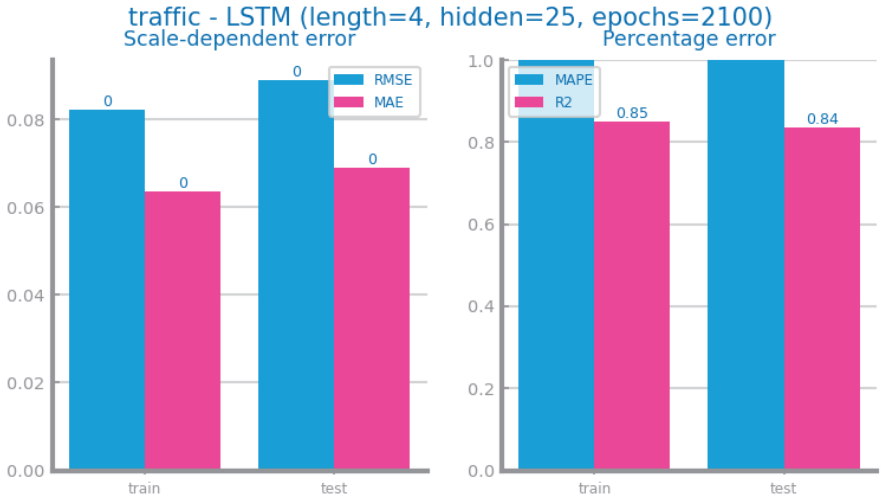


Figure 99: Performance metrics of the best LSTM model (RMSE, MAE, MAPE, R^2) – univariate

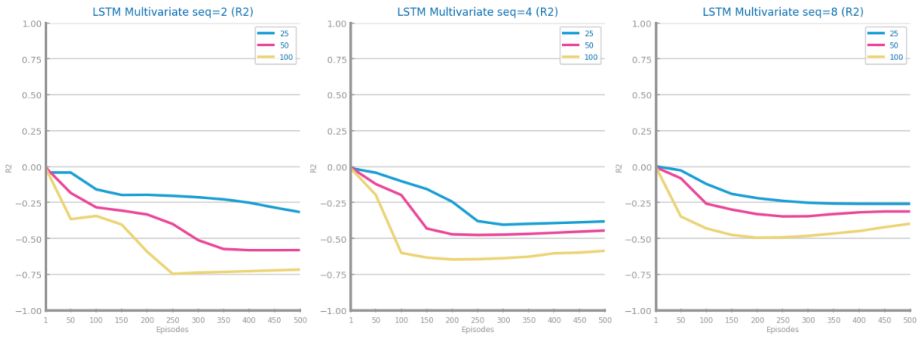


Figure 100: Hyperparameter study: best LSTM configuration – multivariate

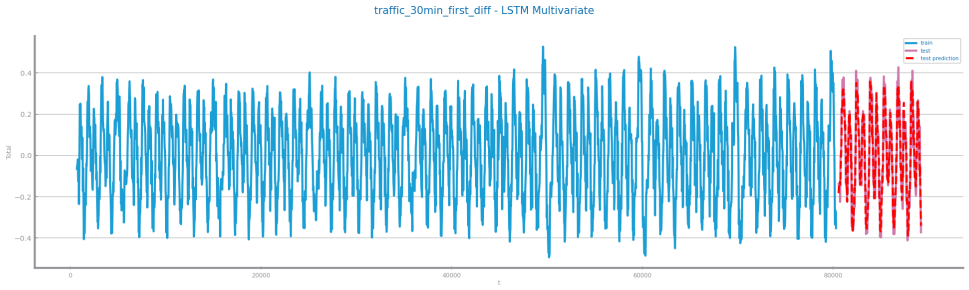


Figure 101: Forecasting plots obtained with the best LSTM model (predictions in red vs actual test data in pink) – multivariate

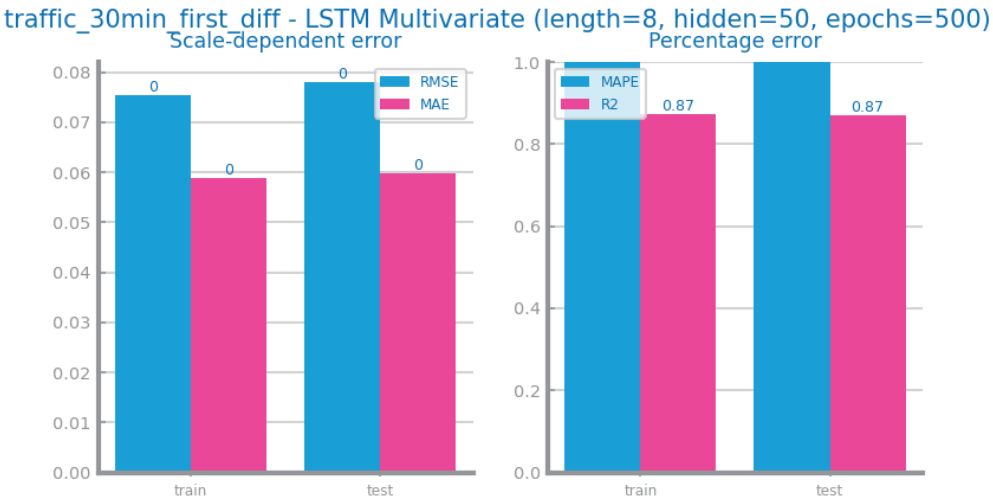


Figure 102: Performance metrics of the best LSTM model (RMSE, MAE, MAPE, R^2) – multivariate

8 CRITICAL ANALYSIS

The forecasting models showed distinct performance differences on the processed traffic data. Exponential smoothing performed the worst, with test R^2 near zero, very high MAPE, and poor ability to follow variability, making it unsuitable

for this task.ARIMA and VAR fit the training data well but generalized poorly, with low test R^2 ($\approx$ 0.08 and 0.06). Both models captured overall trends but failed on sharp fluctuations due to their linear assumptions and limited flexibility.MLP delivered stronger results, reaching $R^2 \approx 0.86$ and capturing nonlinear patterns more effectively, though at a higher computational cost. LSTM clearly outperformed all other models.The univariate version reached $R^2 \approx 0.84$, while the multivariate version achieved ≈ 0.87, with lower RMSE and MAPE.LSTM handled sequential dependencies, irregularities, and local variations better than statistical models and even better than MLP, making it the most reliable option for medium-term traffic forecasting. Aggregating the data into 30-minute intervals reduced high-frequency noise and exposed clearer temporal patterns. Smoothing with a window of 15 further stabilized the series without removing essential structure.Avoiding differencing prevented unnecessary noise amplification, since the aggregated and smoothed series was already close to stationary.Scaling was essential for neural models, ensuring stable gradients and faster convergence.Together, these steps transformed noisy raw data into a predictable signal that models could learn effectively.