Forecasting bus ridership with trip planner usage data

a machine learning application

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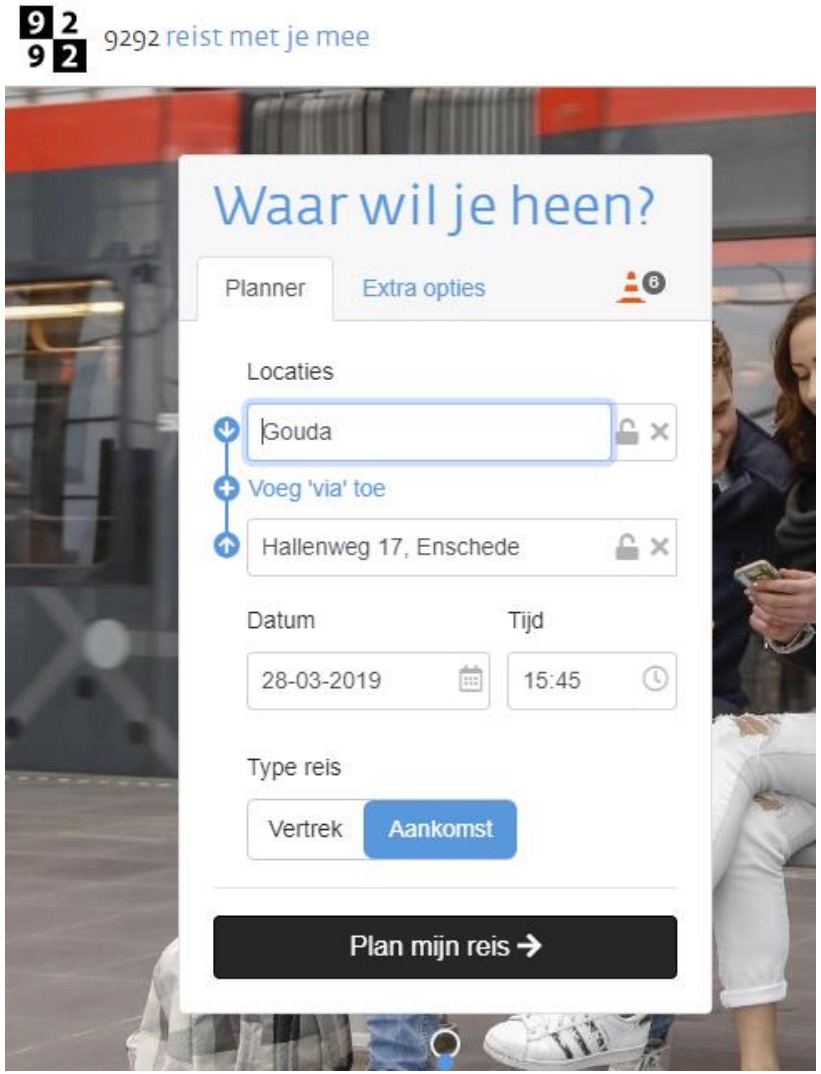
9292 Trip planner



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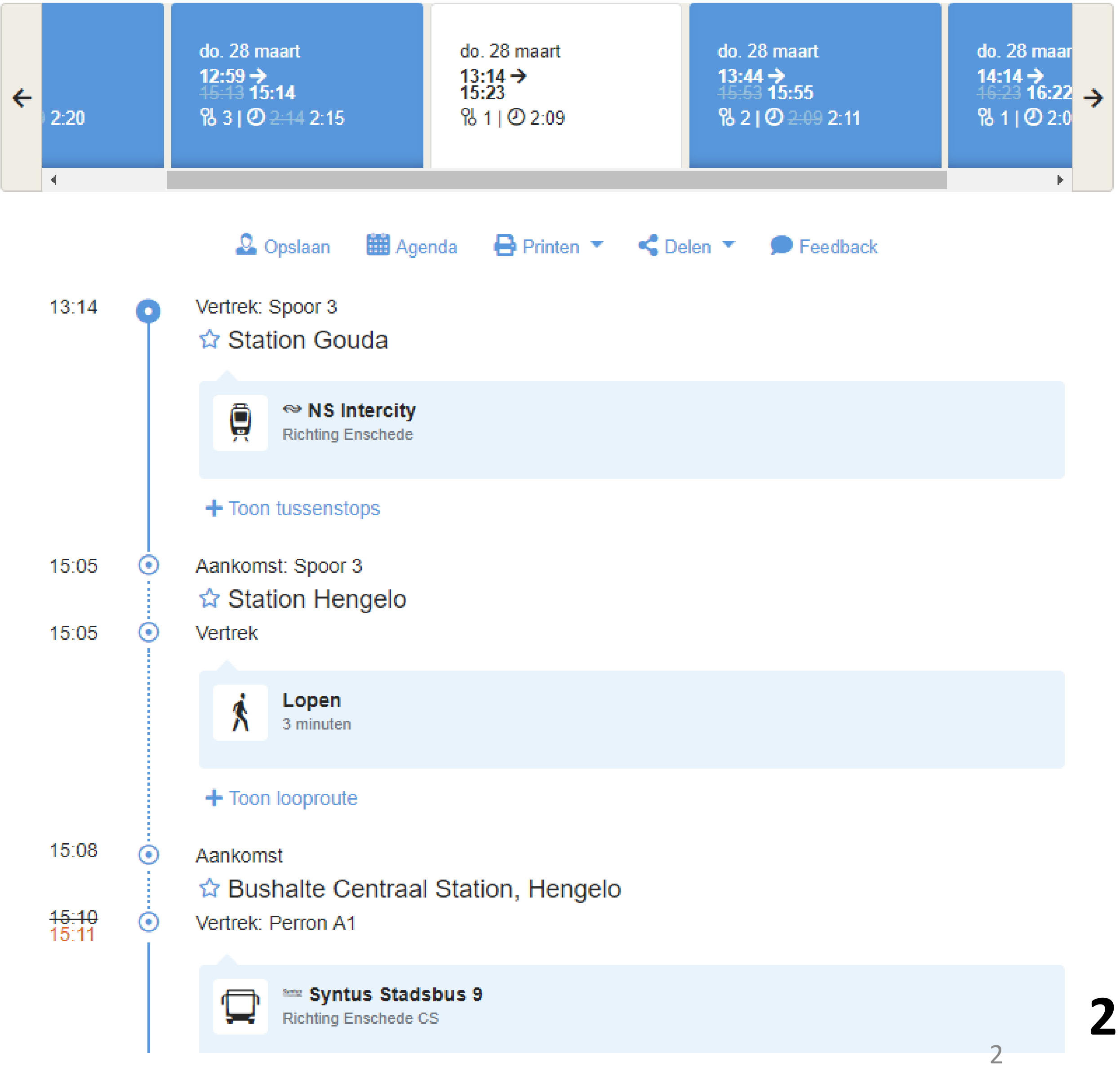

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Introduction

Objective

- Construct a forecasting model
- Determine the accuracy of the models
- Investigate predictive power of trip planner usage data
- Determine valuable features

Methodology

Models

- $Passenger_{stop} = Passenger_{stop-1} + Boarding_{stop} - Alighting_{stop}$ = $\sum_{i=0}^{s} B_i \; - \sum_{i=0}^{s} A_i$

Machine learning

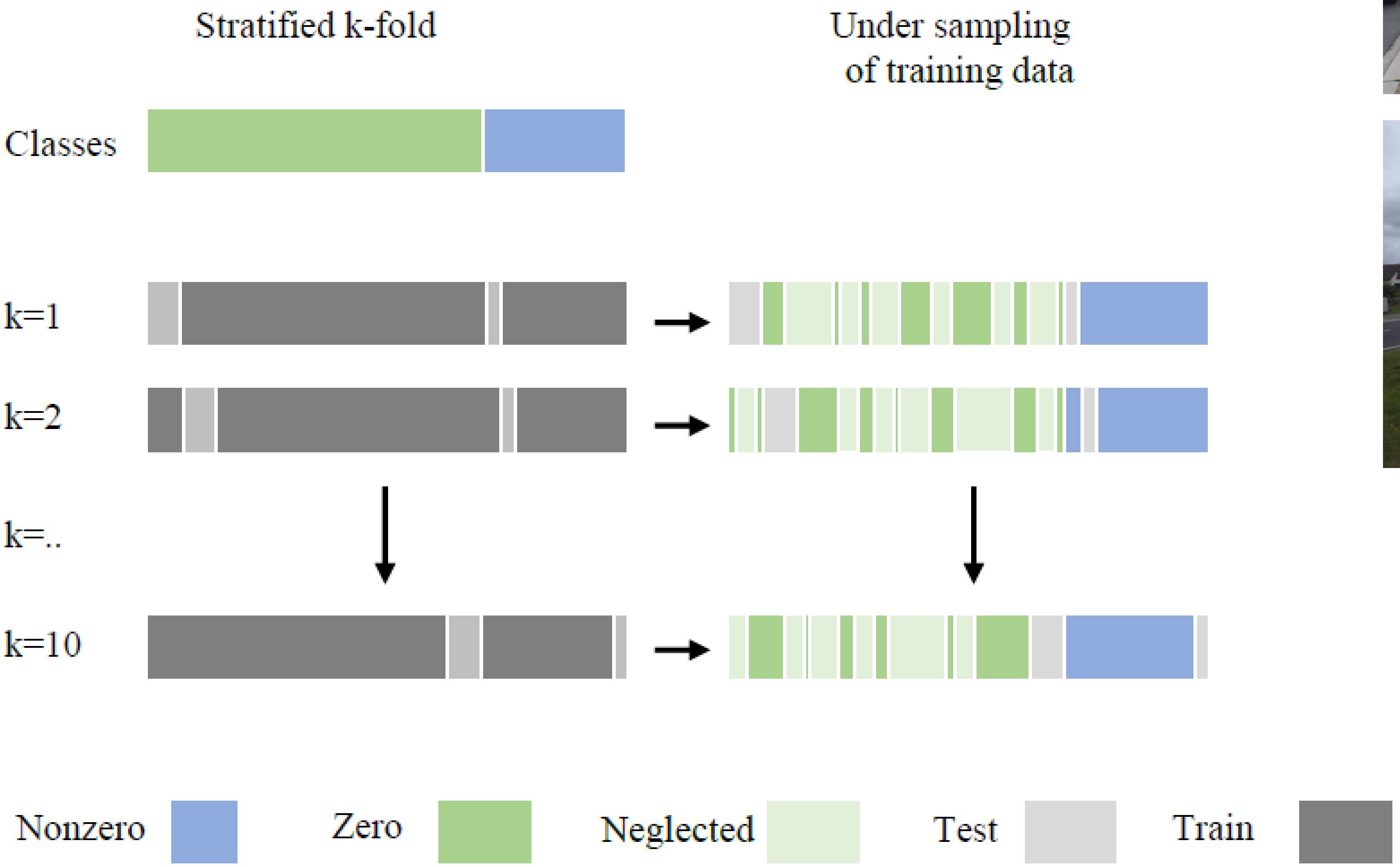
- Multiple linear regression
- Decision tree - decision tree regressor
- Random forests
- Support vector regression with radial basis kernel
- Artificial Neural Networks - Multi-layer Perceptron regressor

Comparison with simple rules

1. Predicted number equals number last week
2. Predicted number equals historical average

Methodology

Undersampling using stratified K-fold



Methodology

Performance metrics

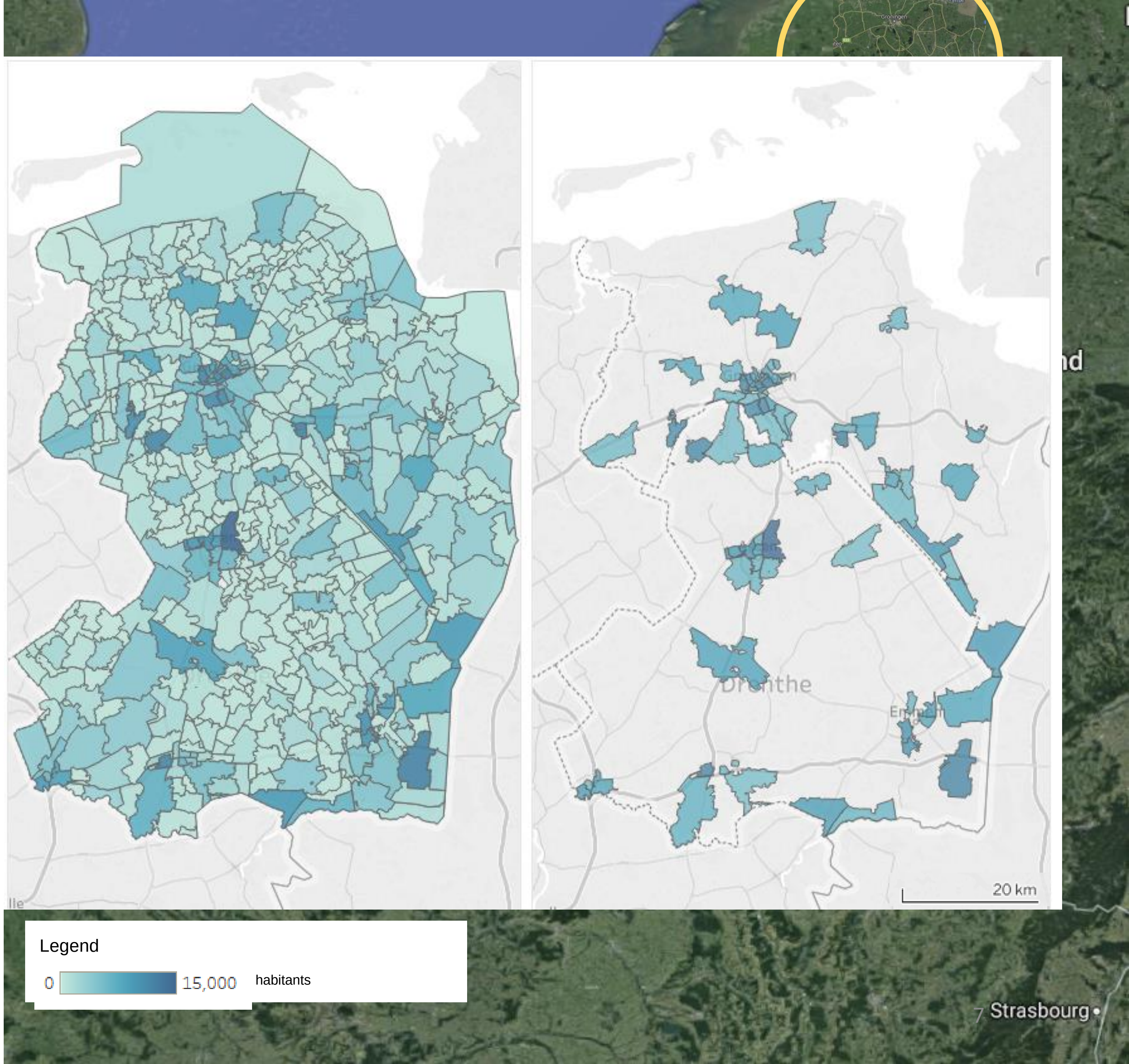
- $RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$
- $R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y}_i)^2}$
- % of passenger count predictions correct
- % of maximum passenger count predictions correct

- Python, Scikit-learn

Case study

Scope

- Data from Groningen and Drenthe
- 4,972 km^2 Land area
- ± 1.1 mil Habitants
- ± 0.2 mil Habitants Groningen City
- January to March 2017
- Time period contains two smaller holidays



Data

Structure

Trip planner

11,694,849

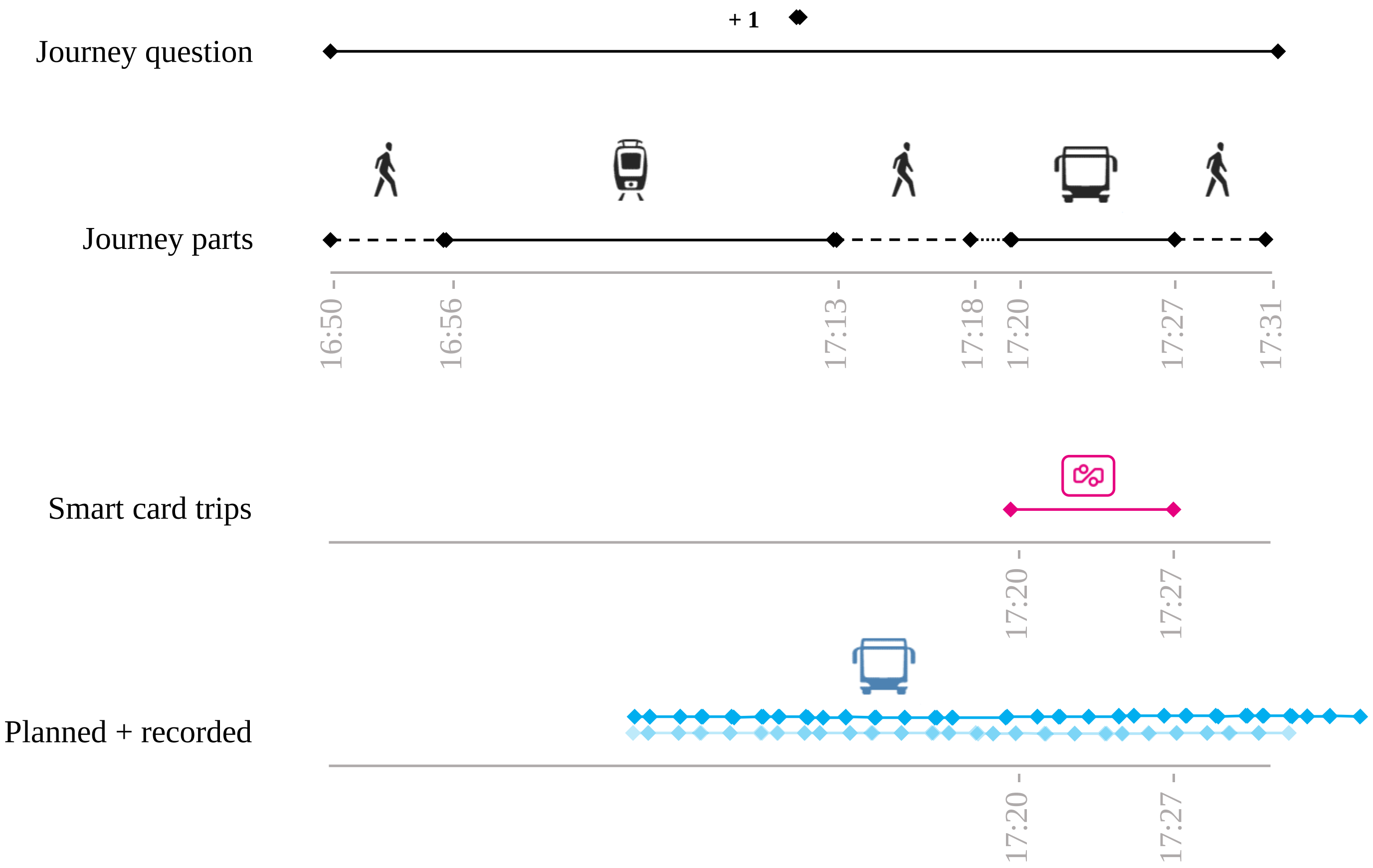
Smart card

6,814,907

4,946 stops

AVL data

11,447,562



All on vehicle level

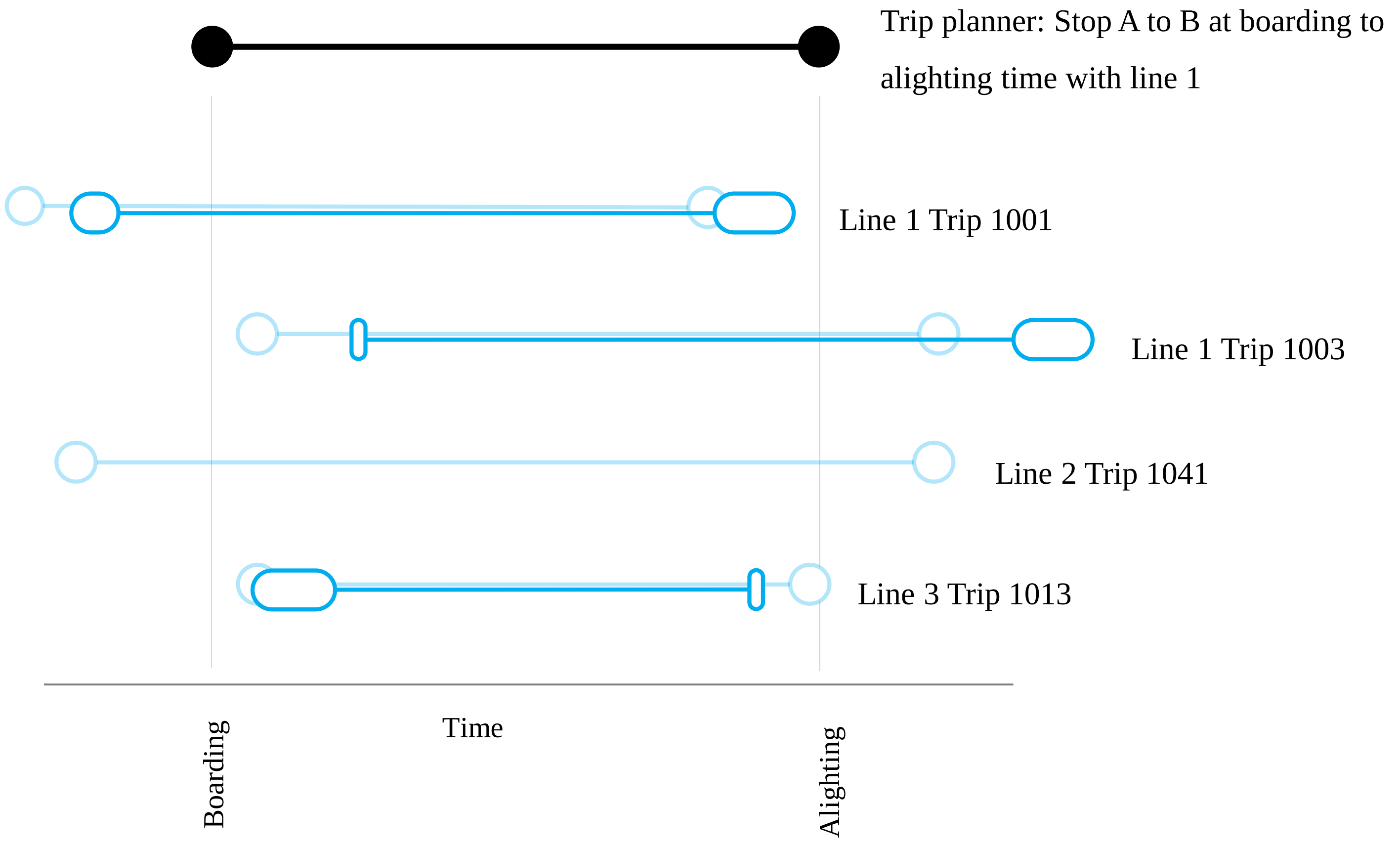
Data

Merging trip planner with bus data

- 6 – dimensional problem
- Almost no exact matches!

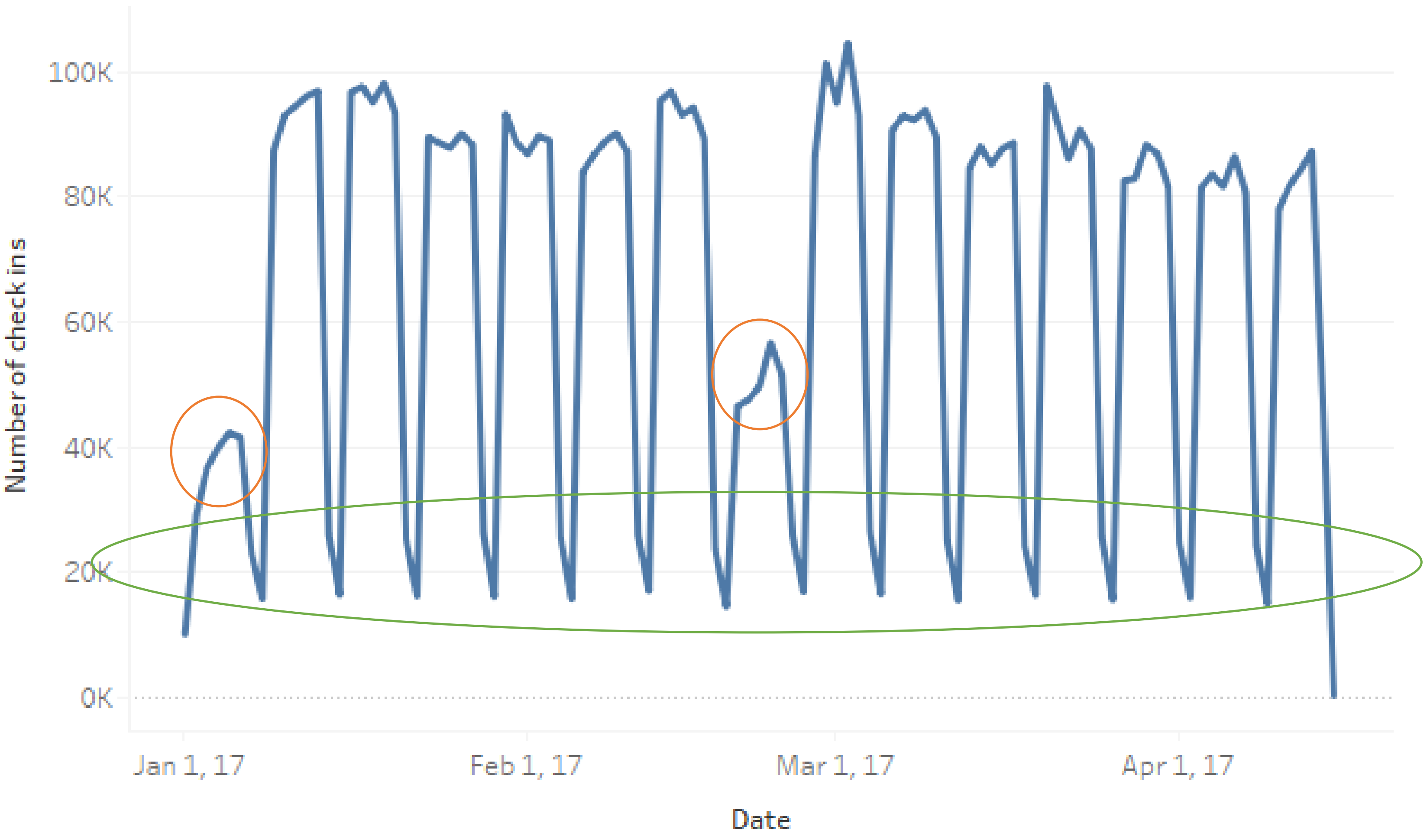
Metric:

Difference boarding times + difference alighting times



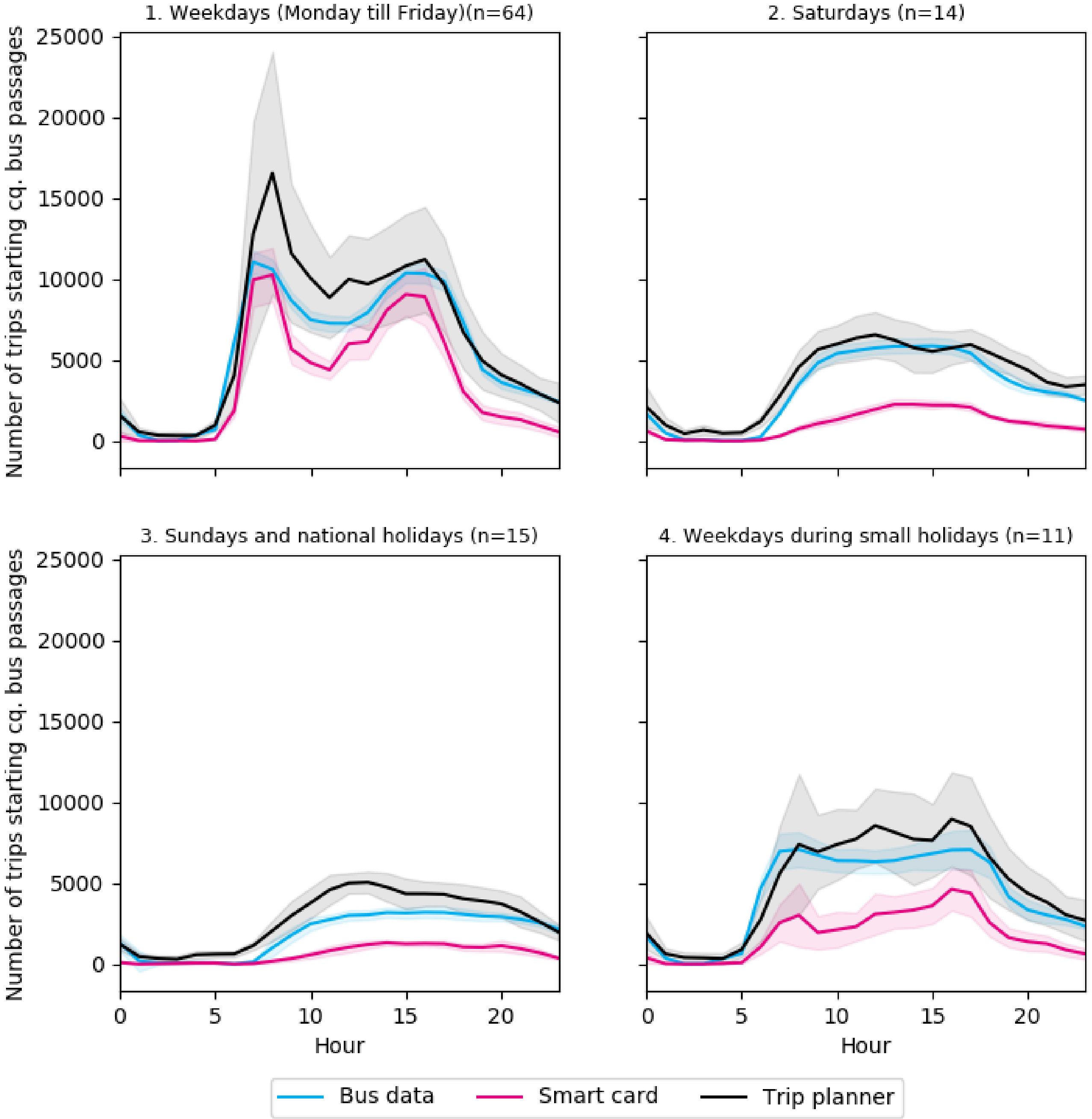
Data

Exploratory data analysis



Data

Exploratory data analysis



Data

Data selection

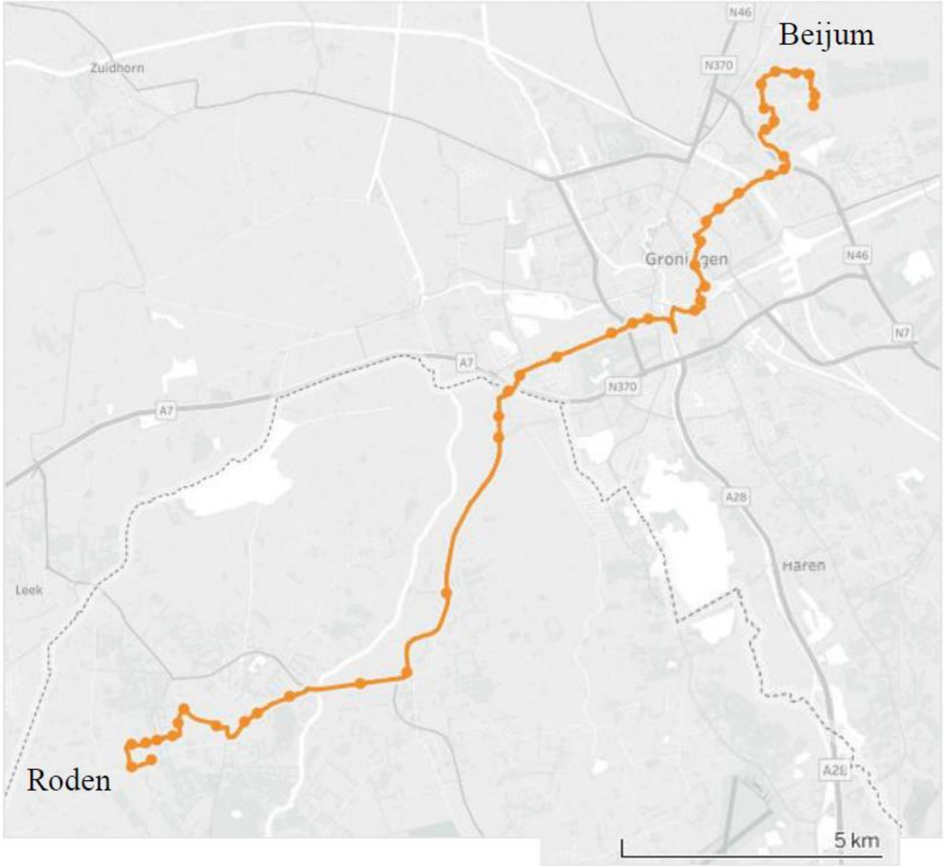
Forecasting demand for trips of line configuration g554-1-0 on workdays around 8 AM

1. 20 lines on workdays around 8 AM
   (56 line configurations, 4173 trips and 138,694 records)
2. 20 lines configurations for the total workday
   (83 line configuration, 51,471 trips and 1,523,115 records)
3. line configuration g554-1-0 for the total workday
   (1 line configuration, 2275 trips and 97,825 records)
4. line configuration g554-1-0 on workdays around 8 AM
   (1 line configuration, 239 trips and 10,277 records)

Data

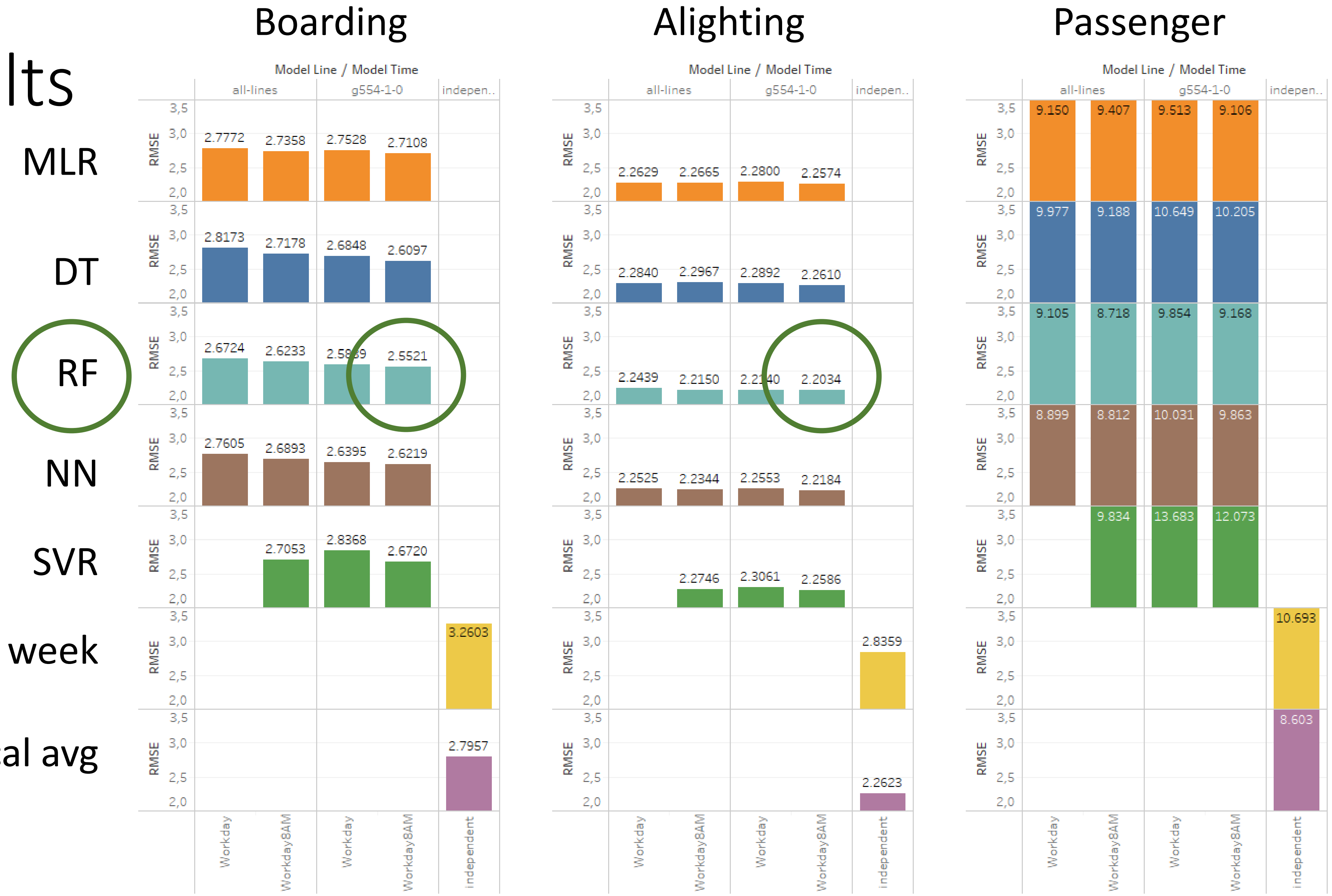
Line configuration g554-1-0

- From Roden via P+R and Groningen central Station to Hospital
- 43 stops
- 631 m average stop spacing
- 26 km total route (partly own lane)
- 61 minutes from begin to end
- 6-2 busses an hour



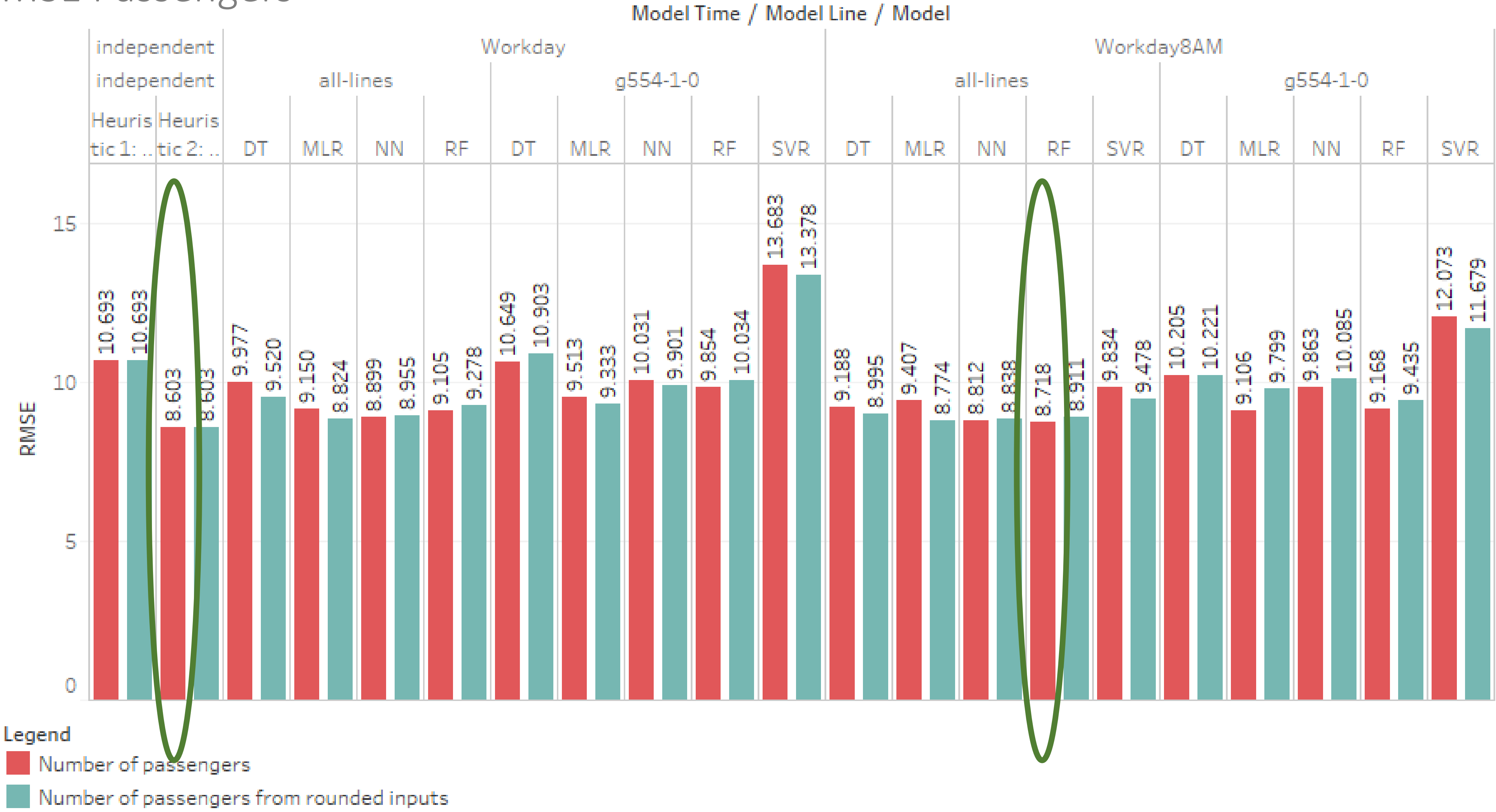
Results

RMSE



Results

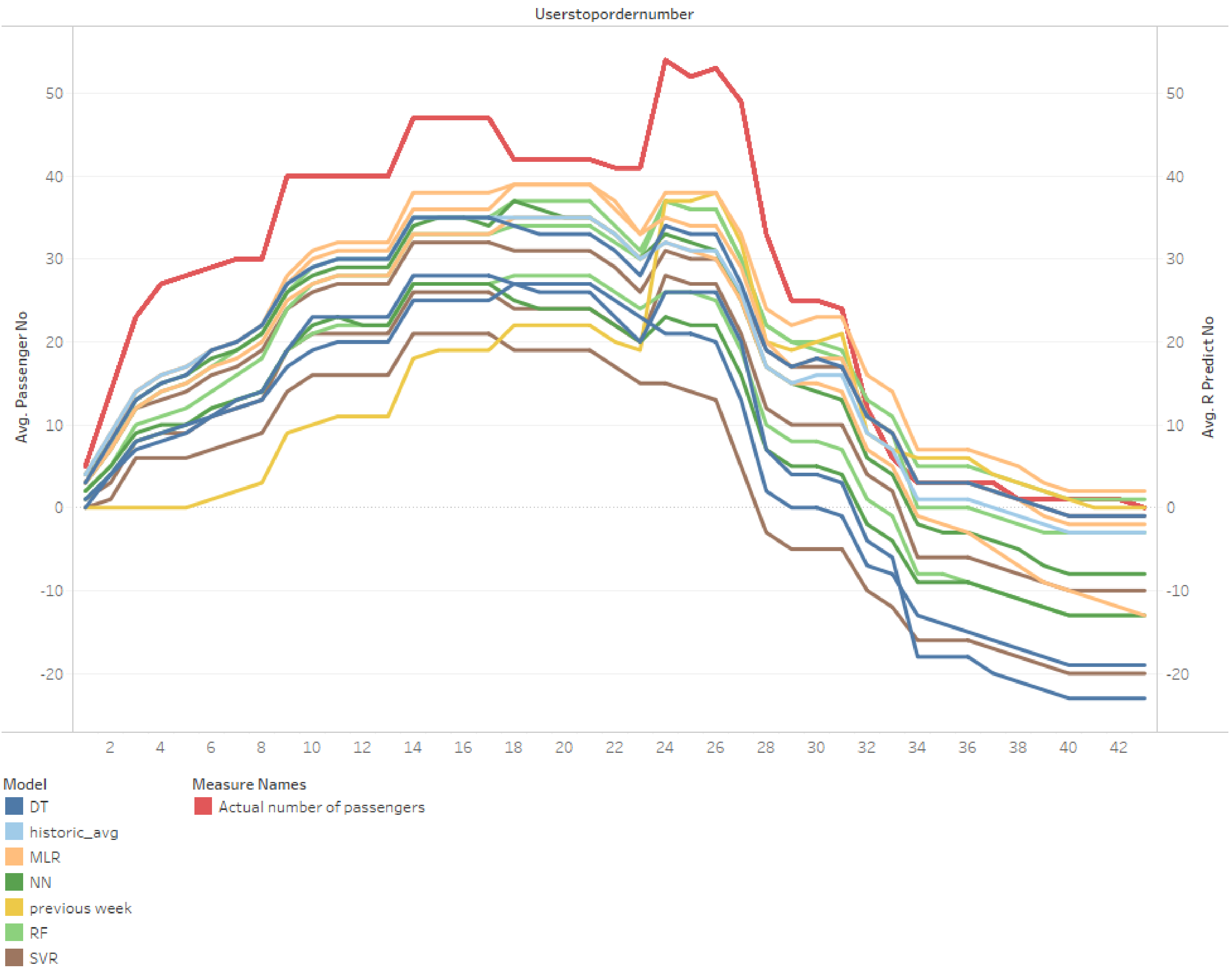
RMSE Passengers



Results

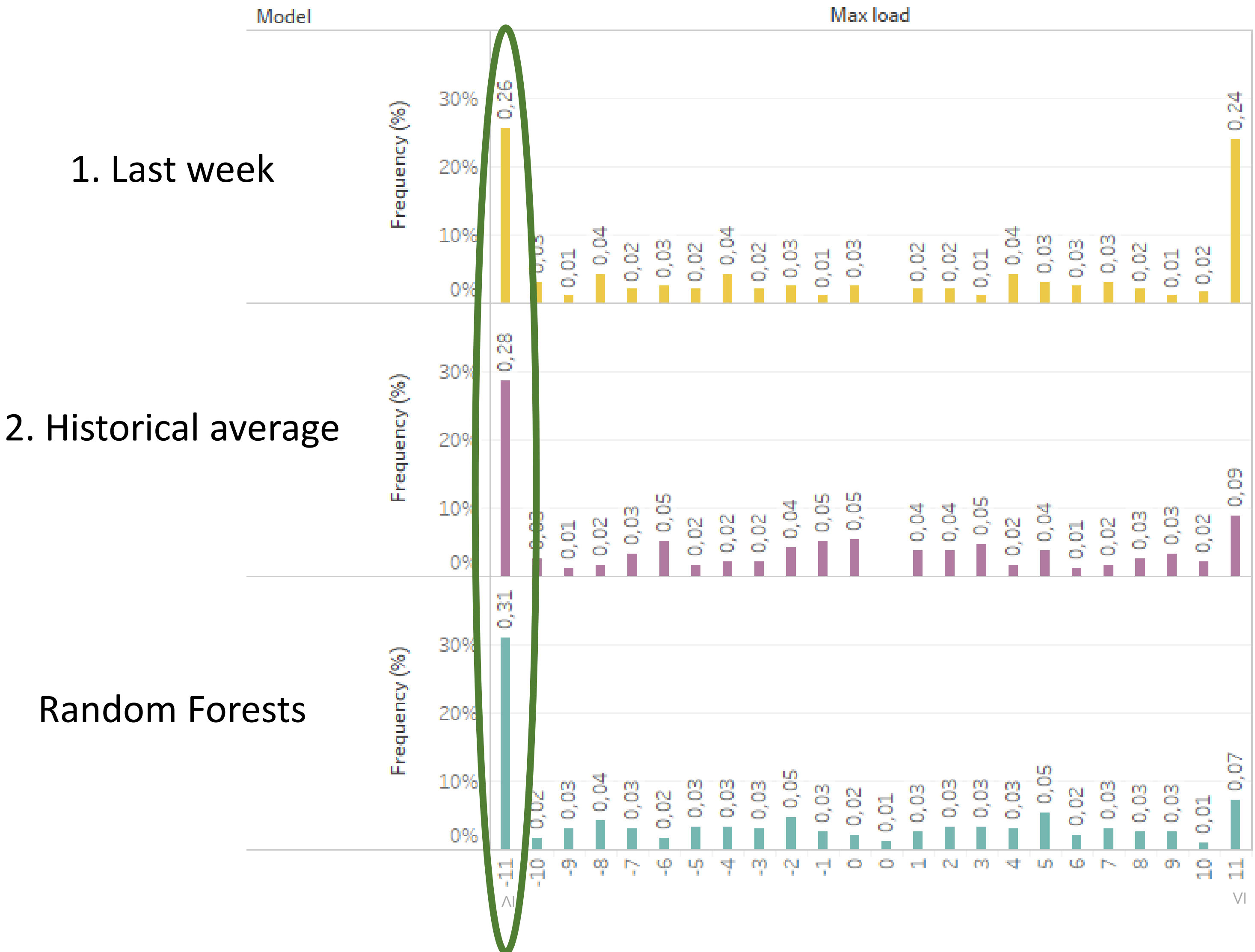
Passenger prediction example

- g554-1-0
- Trip 1018
- February 15, 2017
- Wednesday
- 07:22 – 08:26



Results

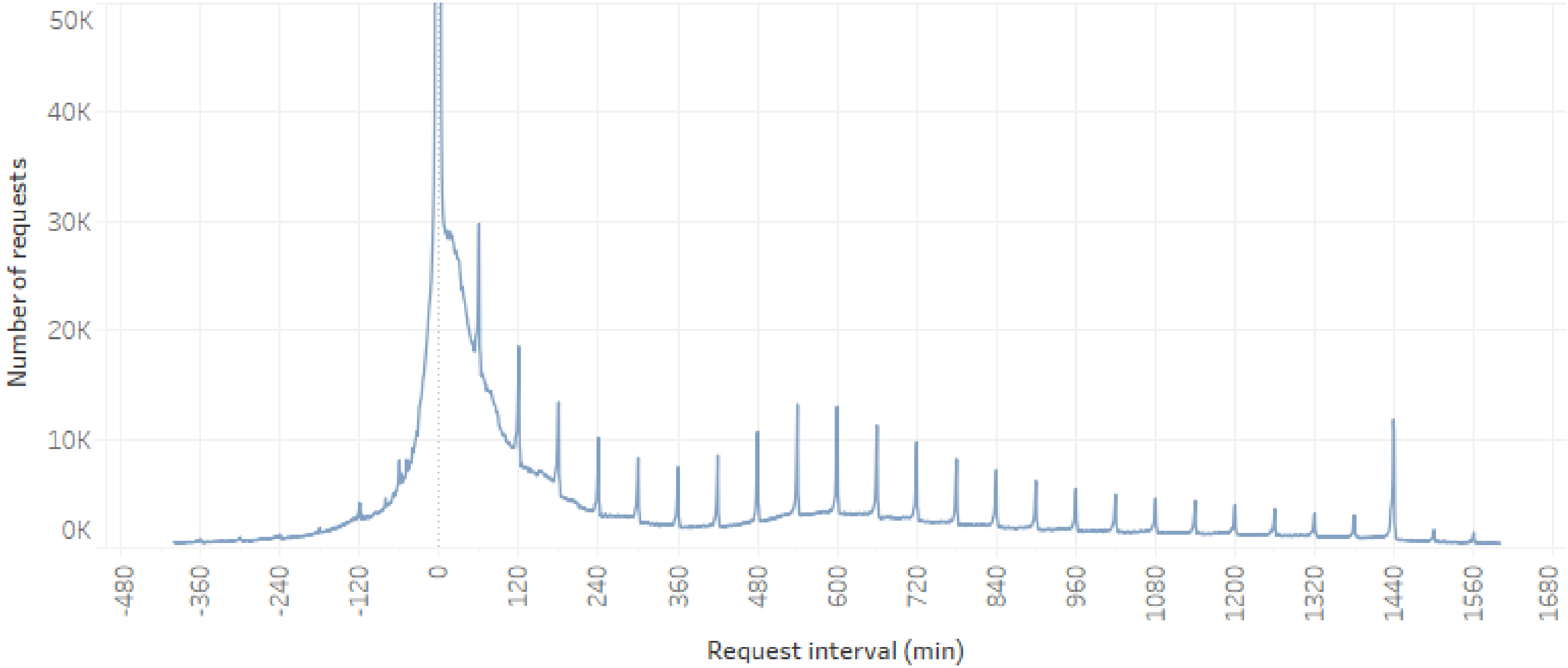
Percentage correct maximum passenger count predictions



Discussion

Limitations

- One trip planner, no session id
- Only smart card



Conclusion

Research question

Can one forecast short-term ridership of buses
using data containing the consulted travel advices
from a widely used trip planner for public transport
and what accuracy can one achieve in different scenarios?

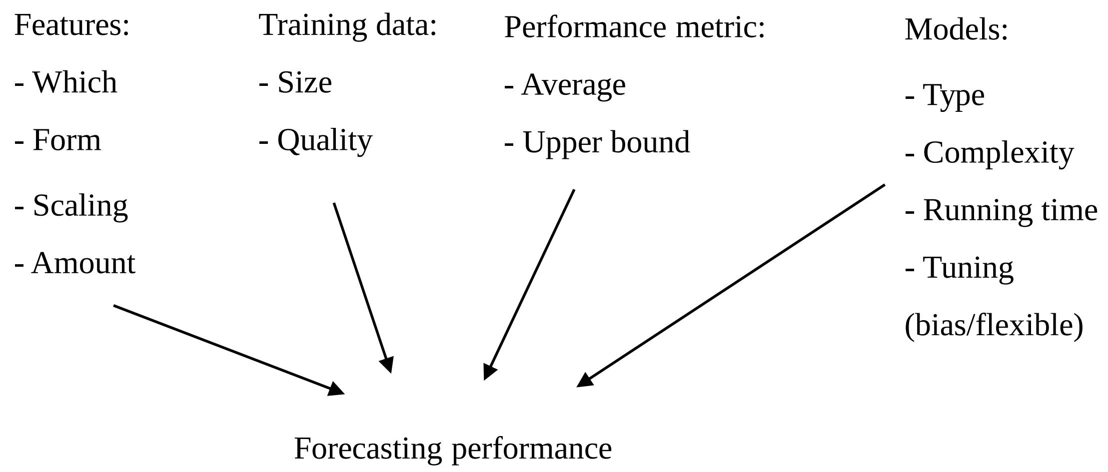
Conclusion

Recommendations

Practice

- Adapt data structure for data analysis
  - Include bus trip number, line number, operation date and stop
  - Include session ID
  - Trip level
  - Use same set of stops
- Models

Research

- Forecasting structure
- 

Thanks for your attention

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