Predicting response times of the Paris Fire Brigade vehicles

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Contents

I. Introduction

II. Data Analysis

III. Feature engineering

IV. Model

V. Conclusion

Introduction

Quick briefing

- Response time: turnout + travel

- Besides the IDs, 3 groups of features:
  - Vehicle features
  - Intervention features
  - Spatial-temporal features

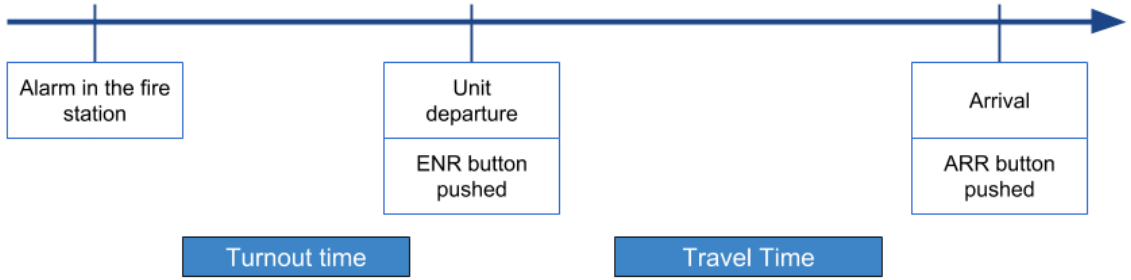


Figure 1. Definition of the response time.

Data Analysis

Response time distribution

- After cleaning, we notice both the turnout and travel times seem to follow a Rayleigh distribution
- Average turnout time: 2:18 min
- Average travel time: 5:48 min

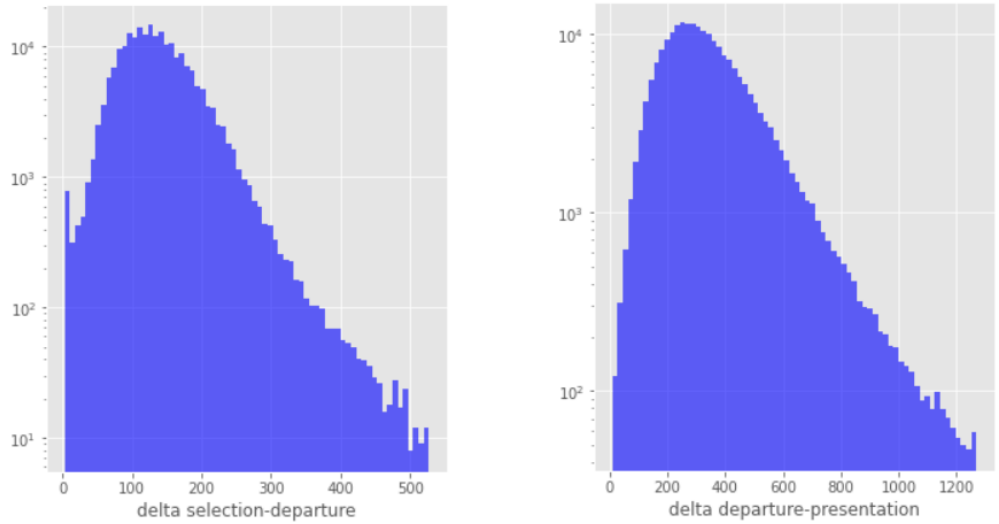


Figure 2. Distribution of the response time.

Vehicle features

- Emergency vehicle type (category)
- Status preceding selection (boolean)
- Departed from its rescue center (boolean)

Vehicle features

- 70 types of vehicle
- Can we distinguish slow and fast vehicles?

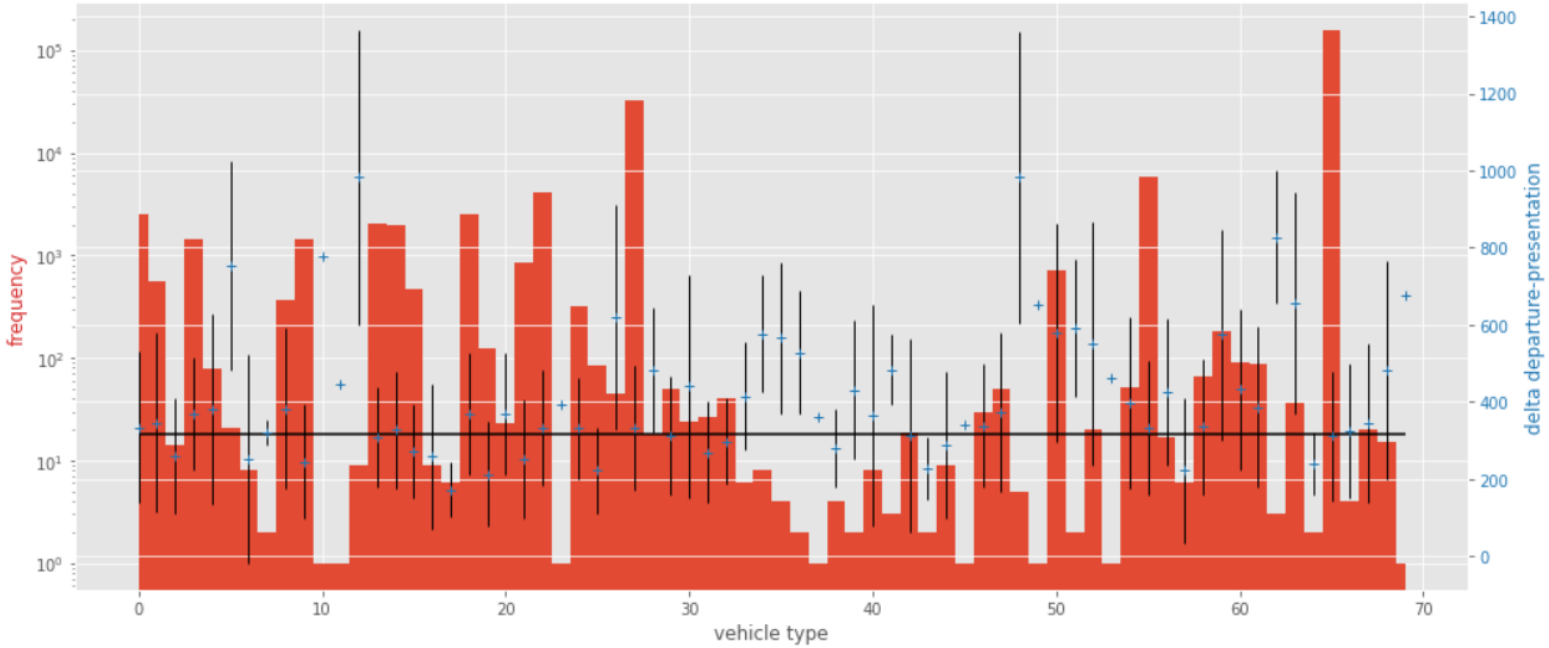


Figure 3. Travel time depending on the vehicle type.

Vehicle features

- Reduce to 50 types when using the first word
- Still issues with some types...
- When reducing to 30, 20 or 10 types, the problem remains

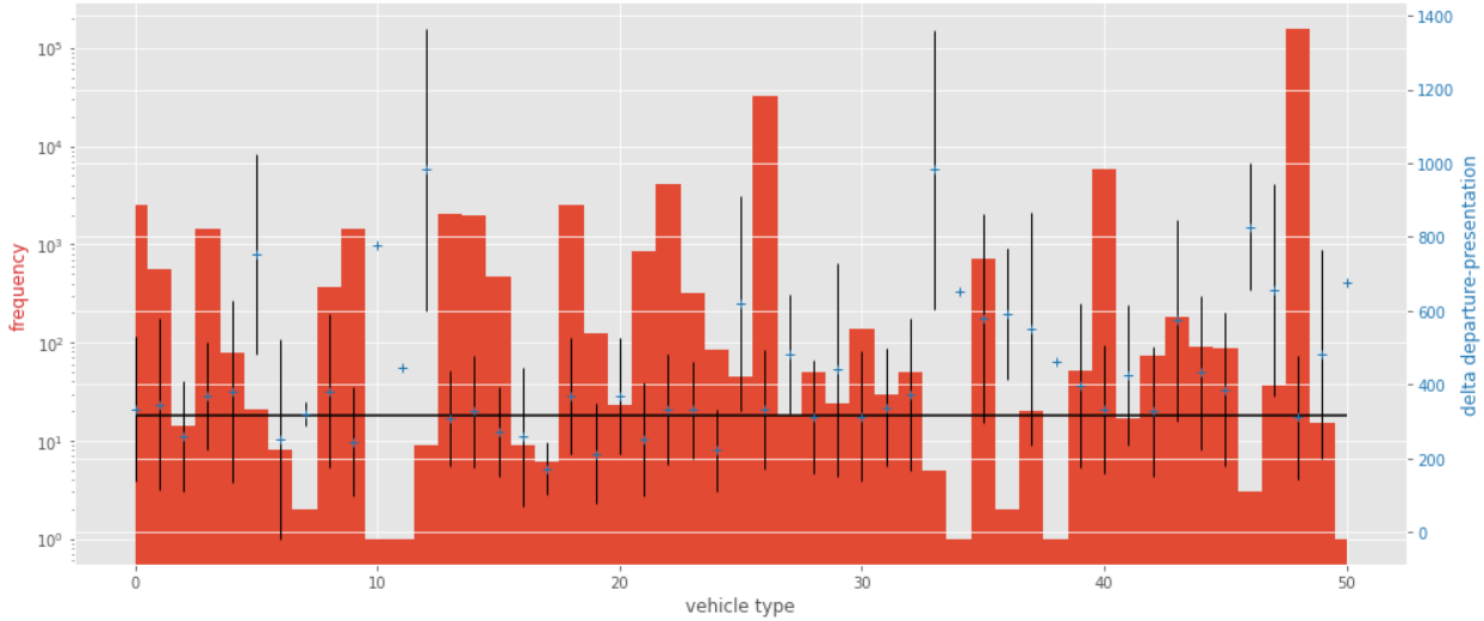
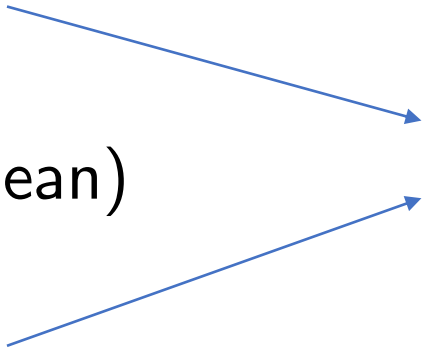


Figure 4. Travel time depending on the vehicle type after grouping.

Intervention features

- Alert reason (category)
- Alert reason category (category)
- Intervention on public roads (boolean)
- Location of the event (category)
- Floor (int)



Too much values to be useful...

Intervention features

- We notice a difference between the 9 categories of the alert reason feature

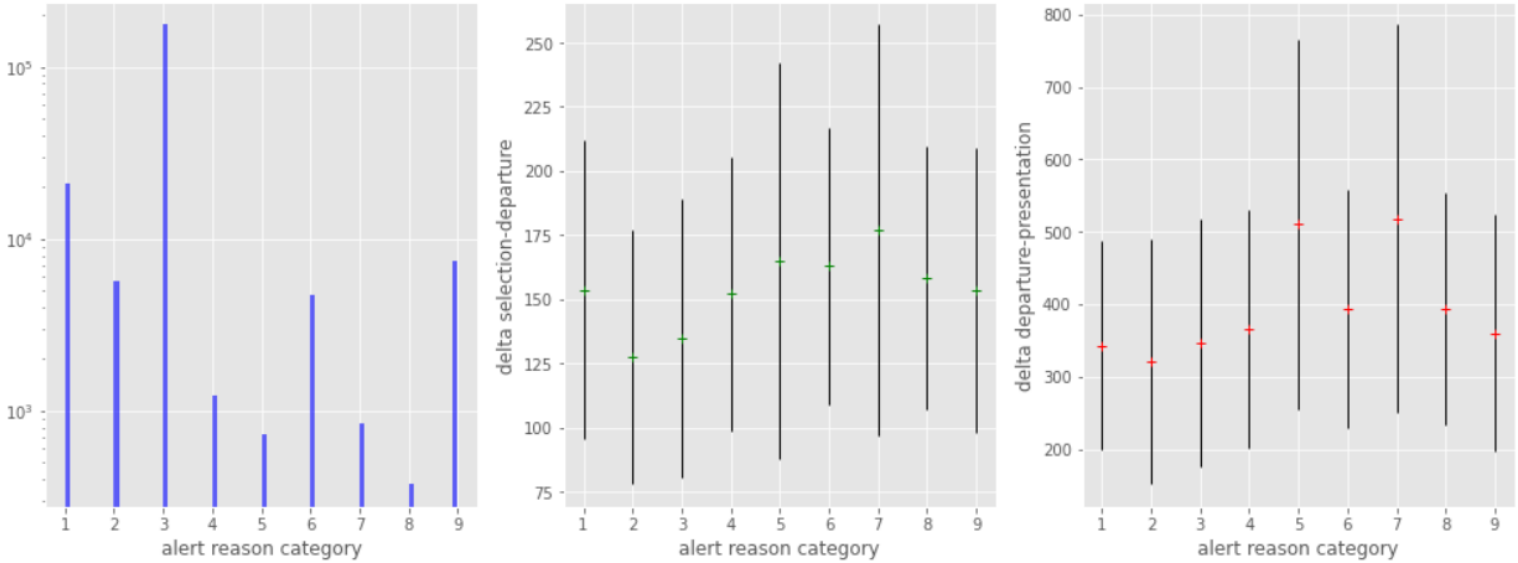


Figure 5. Times depending on the alert reason category.

Spatial-temporal features

- Longitudes/latitudes (float)
- GPS tracks (list of positions or dates)
- OSRM response (estimation of distance and duration)

Spatial-temporal features

- The interventions span most of the region Ile-de-France
- Centers are well distributed
- The vehicle selected is not always in the closest center

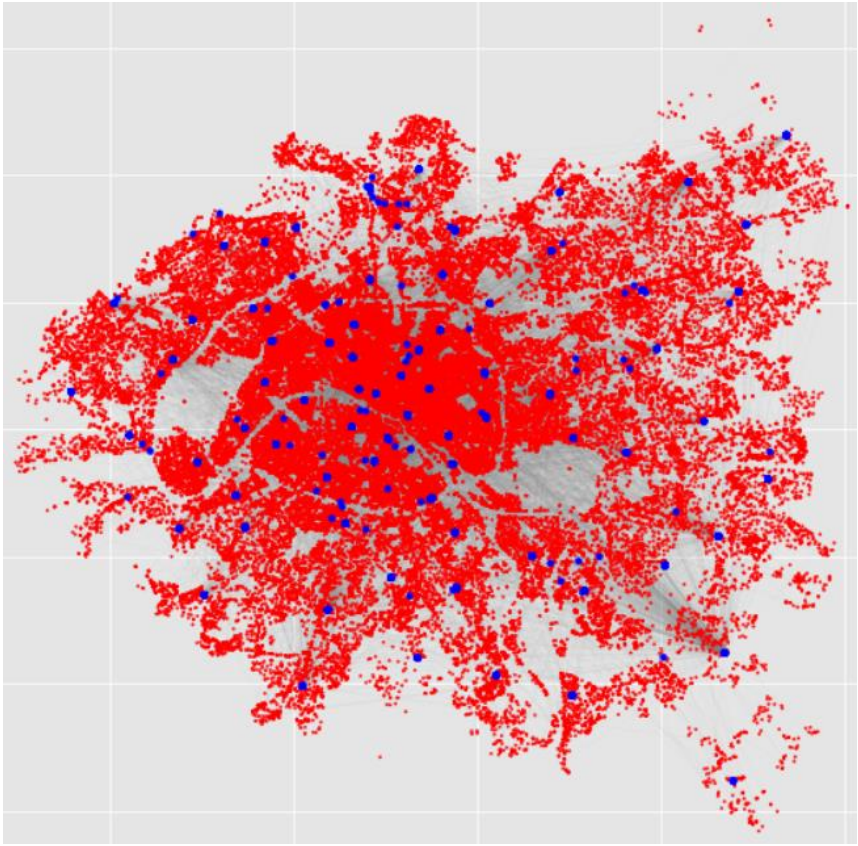


Figure 6. Repartition of the interventions and the rescue centers.

Spatial-temporal features

- The OSRM estimations are very useful but not always accurate
- Additional data can be used (see next section)
- GPS tracks can be used (see next section)

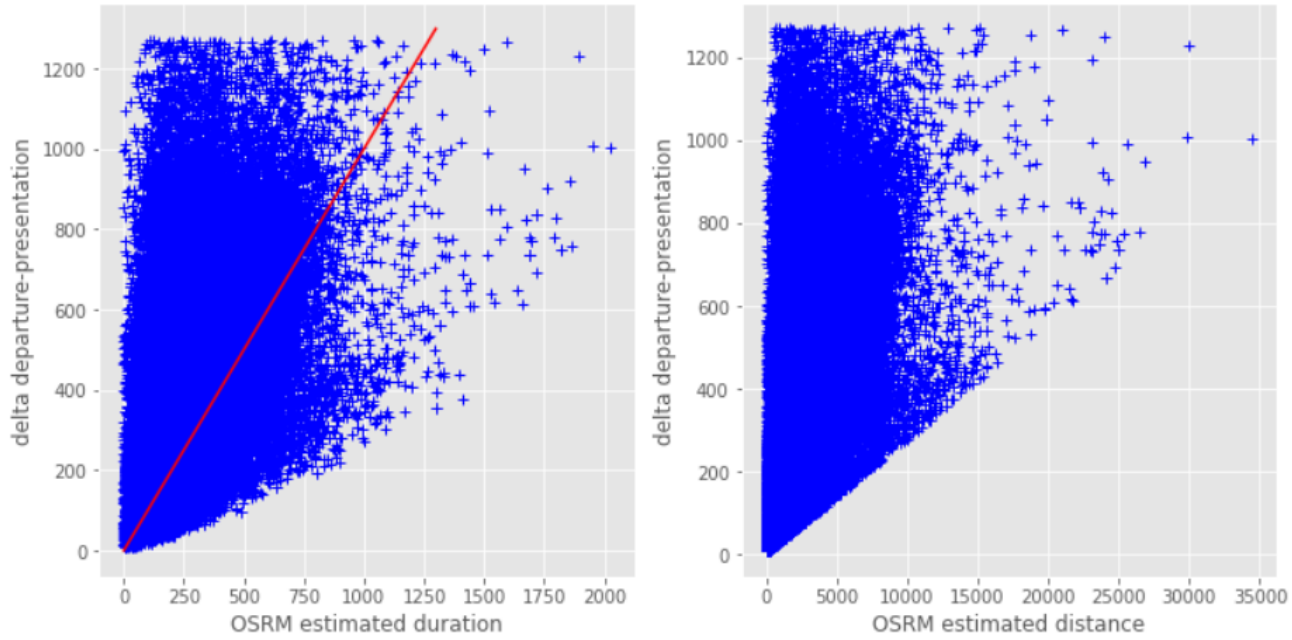


Figure 7. Travel time as a function of the OSRM estimates.

Feature engineering

Seasonality

- Retrieve the hour, the day and the month of the intervention
- Working hours
- Weekend or not
- Hollidays or not

Figure 8. Travel time depending on the hour, day or month, respectively.

Meteorological data

- Weather influences both times
- Scrapped the data for 2018

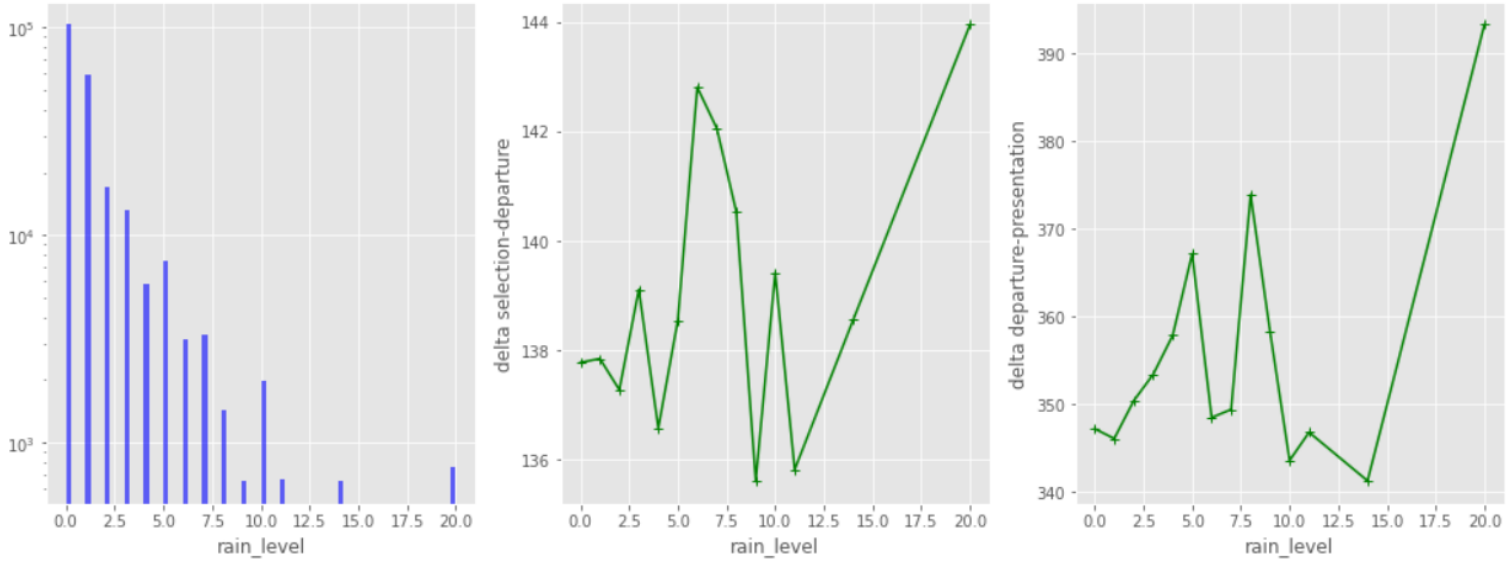


Figure 9. Travel time depending on the rain level.

Using longitudes and latitudes

- Compute Haversine and Manhattan distances
- Compute the direction
- Compute the average speed
- Cluster to find neighborhoods

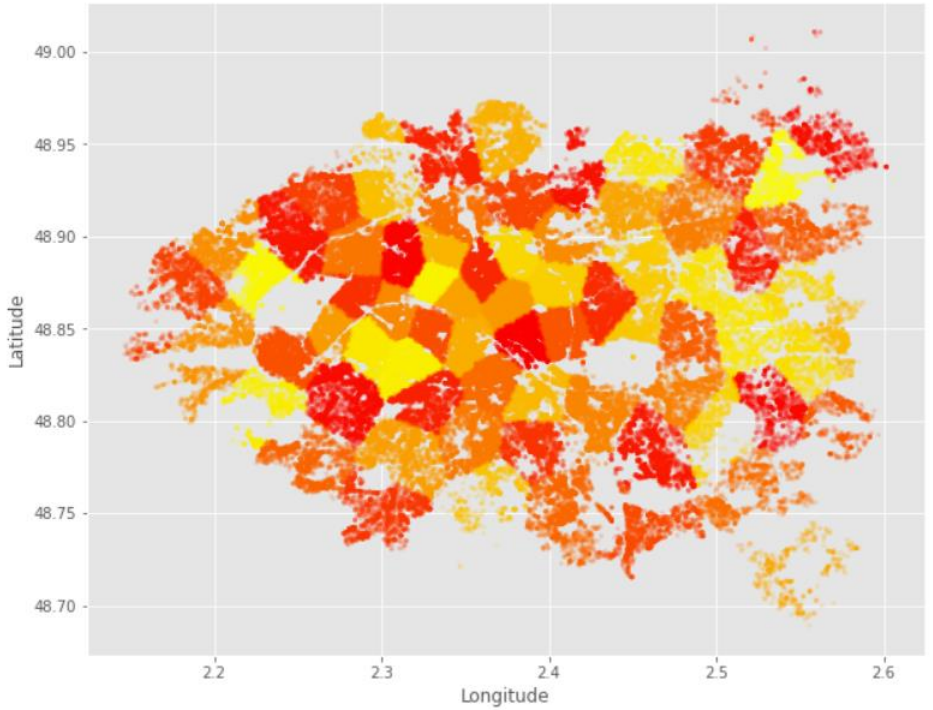


Figure 10. Kmeans on the longitudes/latitudes.

Refine OSRM estimation

- Use the additional data available for 30% of the dataset to update the OSRM estimation
- Use the GPS tracks to compute an estimation of the travel time for 30% of the dataset

Refine OSRM estimation

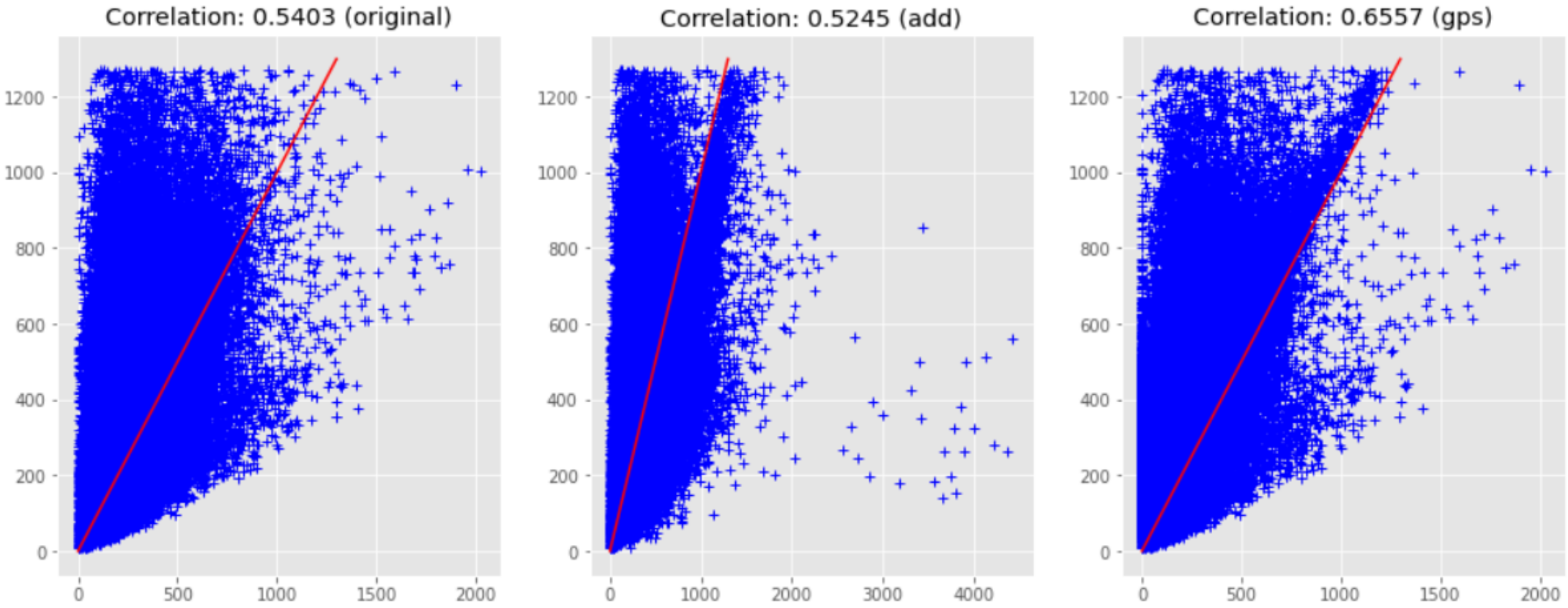
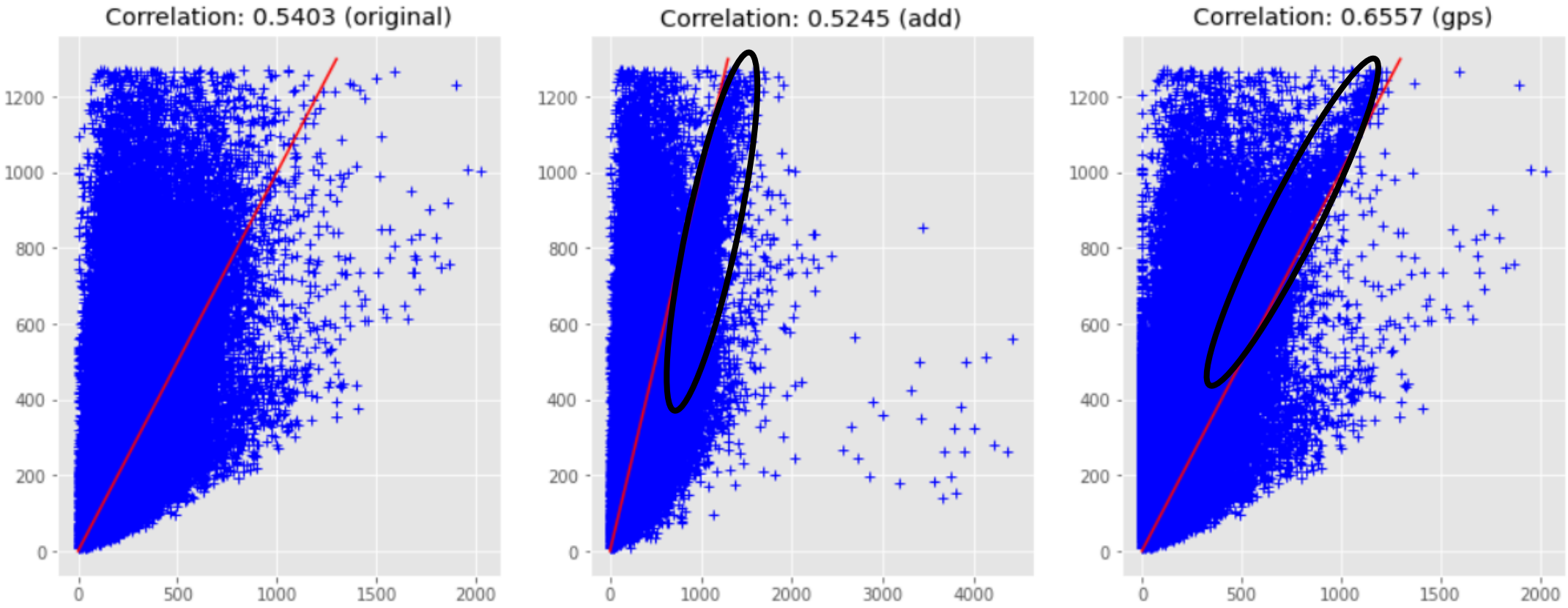


Figure 11. OSRM time estimations. Original, with the additional data or with the GPS tracks, respectively.

Refine OSRM estimation



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Refine OSRM estimation

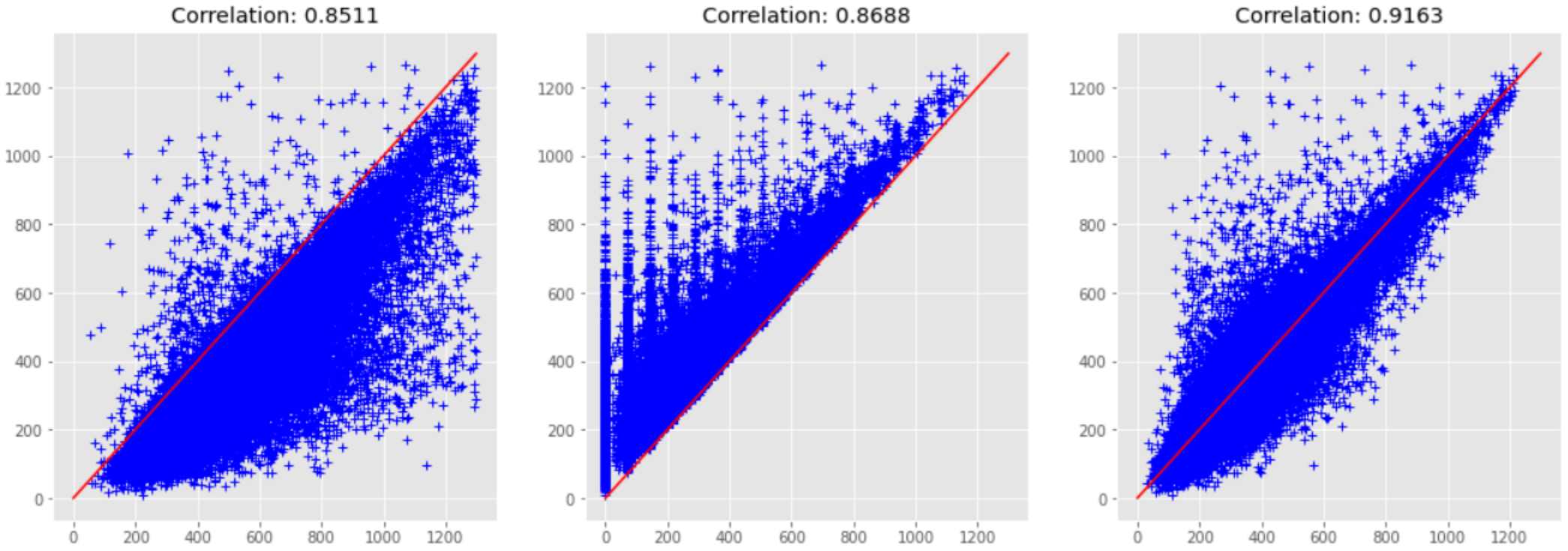

Figure 12. OSRM time estimations. With the additional data, with the GPS tracks, or both, respectively.

Model

Models considered

- Linear regression with L1 or L2 regularization (i.e. Ridge or LASSO), polynomial regression
- Issue: there are a lot of categorical features
- Solution: use decision trees and boosting (XGBoost)
- Neural networks are likely to overfit

Models considered

- Fine-tuned the maximum depth, regularization parameters etc.
- Plot the importance of each feature

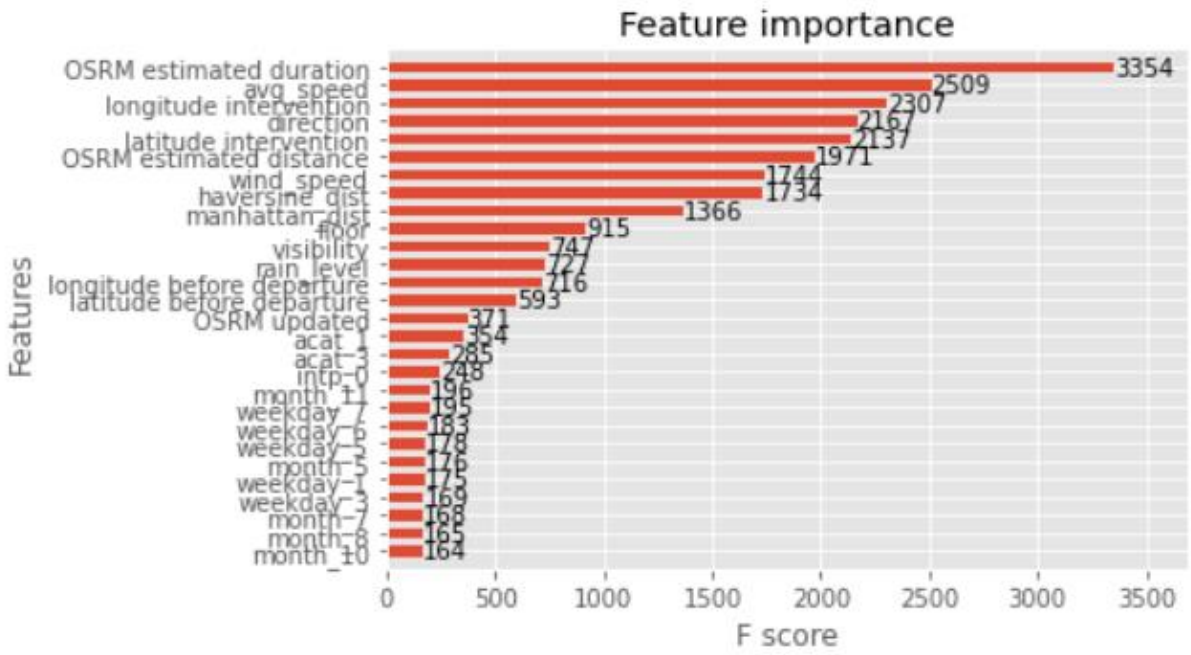

Figure 13. Feature importance of the XGBoost.

Conclusion

Thank you!