WOLT DATA SCIENTIST INTERN (2024) APPLICATION ASSIGNMENT

ENRICO SANTORO
ENRICO.SANTORO.N2@GMAIL.COM

Exploring Data and **Forecasting Delays** in Deliveries





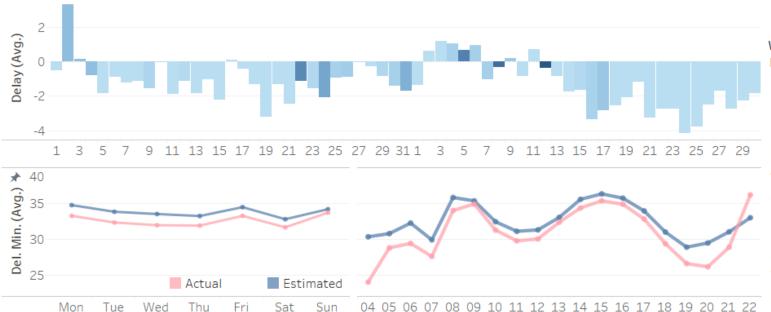
EDA PART 1



We can observe periodic patterns, due to the regular increase of orders during weekends.

Daily Delays (Actual - Estimated Delivery Minutes)

and how they're affected by weather, weekday, hour.



Are more orders linked with delays?
What other factors are delays affected from?

Weather Condition Rain (mm)

0 3.288

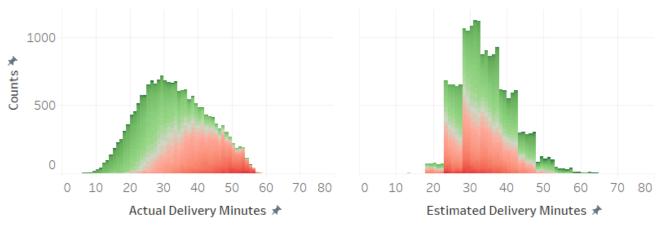
On average, Estimated Delivery time is lower than the Actual one. The first one is correctly adjusted during busy hours.

Delivery time doesn't seem to be strongly influenced by weather or weekday.

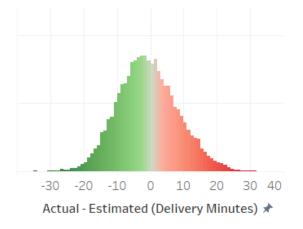
Interactive Dashboard at this link

A Survey in Delays

Looking at Actual Delivery Minutes and Estimated Delivery Minutes distributions



EDA PART 2

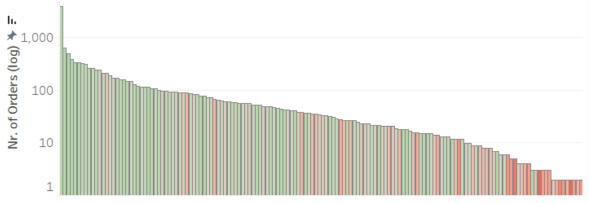


Distribution (number of occurrences) for delivery minutes (Actual, Estimated and their difference).

Actual - Es.. -35

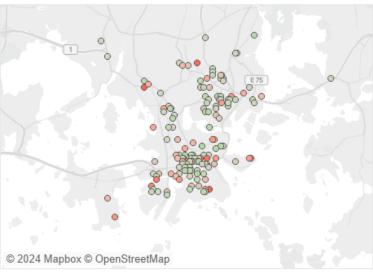
Ranking Venues

According to the **Avg. Difference** between Actual and Estimated Delivery Time. **Are delays linked to Position/Popularity of Venues?**



Most popular venues (higher number of orders) show shorter average delays.

No obvious correlation between delays and Venue Position.



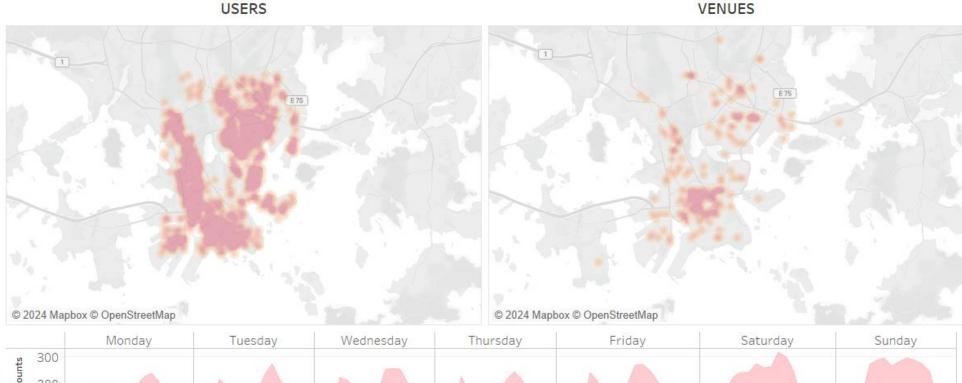
Top N Venues (Actual - Estimated Del. Min.) 150

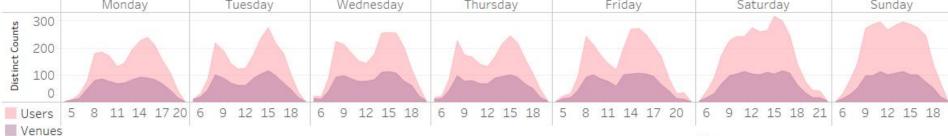
Interactive Dashboard at this link

HeatMap

EDA PART 3

Positions of Users and Venues





Is the **location** of ordering users influenced by hour or weekday? Is there a **shift** of *hot* regions?

How do the numbers of users and venues **change over time**?

Hour

11

Weekday All

Interactive Dashboard at this link

MAKING PREDICTIONS BASED ON DATA

The EDA showed interesting trends but didn't suggest any surprising phenomenon.

To yield quantitative predicitons, making the most of the data, we stick to a well defined, interpretable variable.

We forecast:

Delays (Act. – Est. Del. Min.)

time (hourly avg. delay)

considering their dependence

from:

weekday

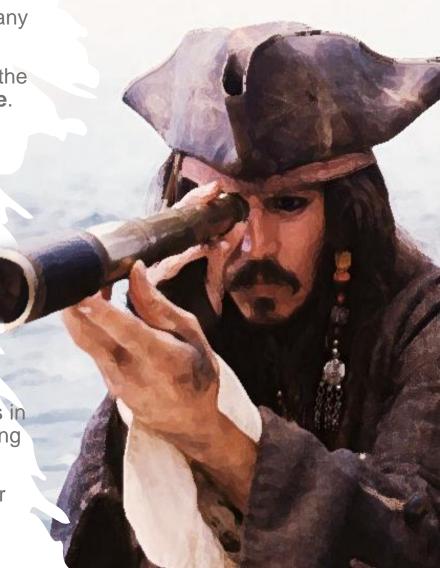
hour of the day

rain

WHY?

The company could favor a higher number of couriers in those hours where more delays are expected, countering the latter by properly distributing deliveries.

❖ The app could estimate higher delivery times, in order not to disappoint users, making them 'conscious' of the longer waiting times.



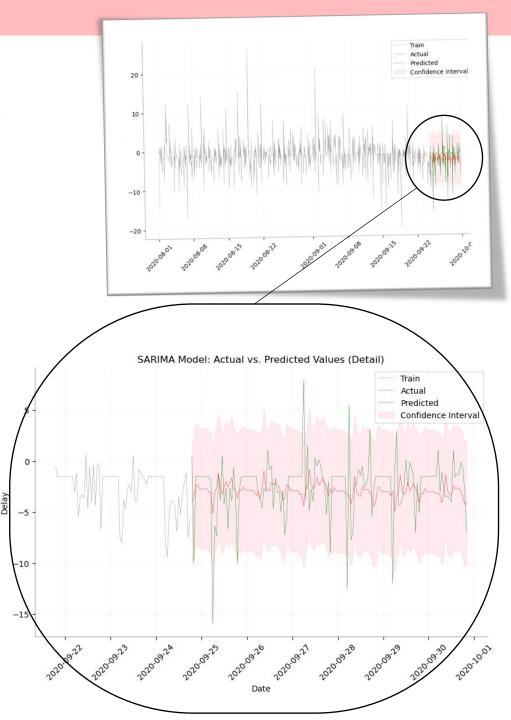
FORECASTING WITH SARIMAX

Details in the notebook

- Seasonal AutoRegressive Integrated Moving Average with HeXogenous features
- Consider the series global trends (MA) and the autocorrelation (AR), for stationary and seasonal component.
- We used correlograms to identify the order parameters (p, d, q) for the ARIMA part and (P, D, Q, s) for the SARIMA part

Results:

- The model captures global behaviours and patterns
- High values for hourly delay fail to be predicted, sometimes even trespassing outside of the 95% confidence band (pink).
- RMSE is about 2.9 (minutes)



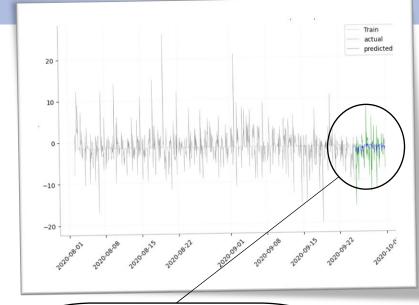
FORECASTING WITH LSTMs

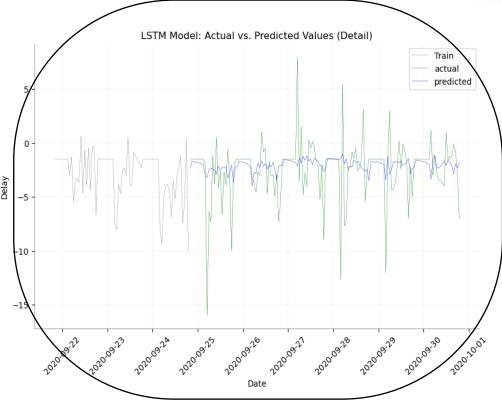
Details in the notebook

- Long Short-Term Memory Recurrent Neural Networks.
- Ability to remember long-term dependencies and handle variable-length sequences.
- We build two basic architectures and set a 24 hours lookback window.

Results:

- The model captures global behaviours and patterns, but not better than SARIMAX.
- High values for hourly delay fail to be predicted. The predicted values tend to lay around the mean.
- RMSE is about 2.8 (minutes)





CONCLUSIONS AND FURTHER DEVELOPMENTS

- Forecasting daily delays rather than hourly ones would be reasonable, and likely yield better results. More data is needed in order to do that.
- SARIMAX and LSTM models should be optimized by tuning parameters and modifying architectures.
- Anomaly detection could be employed to predict spikes in the delivery time.
- More advanced models should be considered. LSTMs could be replaced by Transformers.

