

Next Wave Challenge 2019: My Approach

Presentation: France final

EY

Ulrich GOUE

ENS Paris Saclay (MVA)

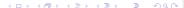
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Ensae ParisTech (3A-DS)



Plan

- Stylized facts
- 2 Feature Engineering
- 3 Earlier experiments
- 4 Best Regression
- Best Classification
- 6 Conclusions & Perspectives



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- our target average by hour tends to confirm the existence of specific hour effect

Stylized facts

Feature Engineering

Earlier experiment

Best Regression

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Classification

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Based on what has been said in the *stylized facts* we proceeded as follows in the feature engineering.

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 - we also extract trip departure hour and trip arrival.



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- compute associate synthetic speed based on both distances.

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$$(w*, y*) = \arg \min |x - x'| + |y - y'|$$
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- the file makedata.py performs the feature engineering while getfeatures.py adds the lags and pads the devices recording few trips for our RNN.

Number of features = 24

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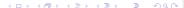
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 - Intuituion 1: the target is generated by the tests $x_{min} \le x' \le x_{max}, y_{min} \le y' \le y_{max}$ is tree of depth 4
 - Intuition 2: using the tree in the second step will correct at some extent some systematic errors madse by the first step MLP regressor.



Model with lags (up to 4)

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experiment:



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• Tree: It scored ≈ 0.882



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- If we reduce MSE by 50% from $\approx 8.10^{-4}$ to $\approx 3.5 \times 10^{-4}$, the F1-score remains ≈ 0.865



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- It scored ≈ 0.894



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 - speed data are obviously more important for long trips.
 Unfortunately we dropped it because we didn't know how to properly impute them.
 - When we tried a specific model for long trips, we lost power since we surrender 66% of the sample while neural networks require large samples to learn.

THANKYOU FOR YOUR ATTENTION!!!