PARATRANSIT OPERATIONS:

Impact of driver behavior and demand forecast

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PROBLEM STATEMENT

The RIDE is MBTA's door-to-door shared-ride paratransit service managing **large complex operations**

- **$115M** Annual budget in 2019
- **1.65M** Number of trips in 2019
- **1238** Number of drivers trained by **4 providers**

Objectives: Quantify and include driver behavior in the RIDE's operations management schemes and reduce demand and supply mismatch

DATA SOURCES

Transportation and scheduling data sources requiring **massive** data computing

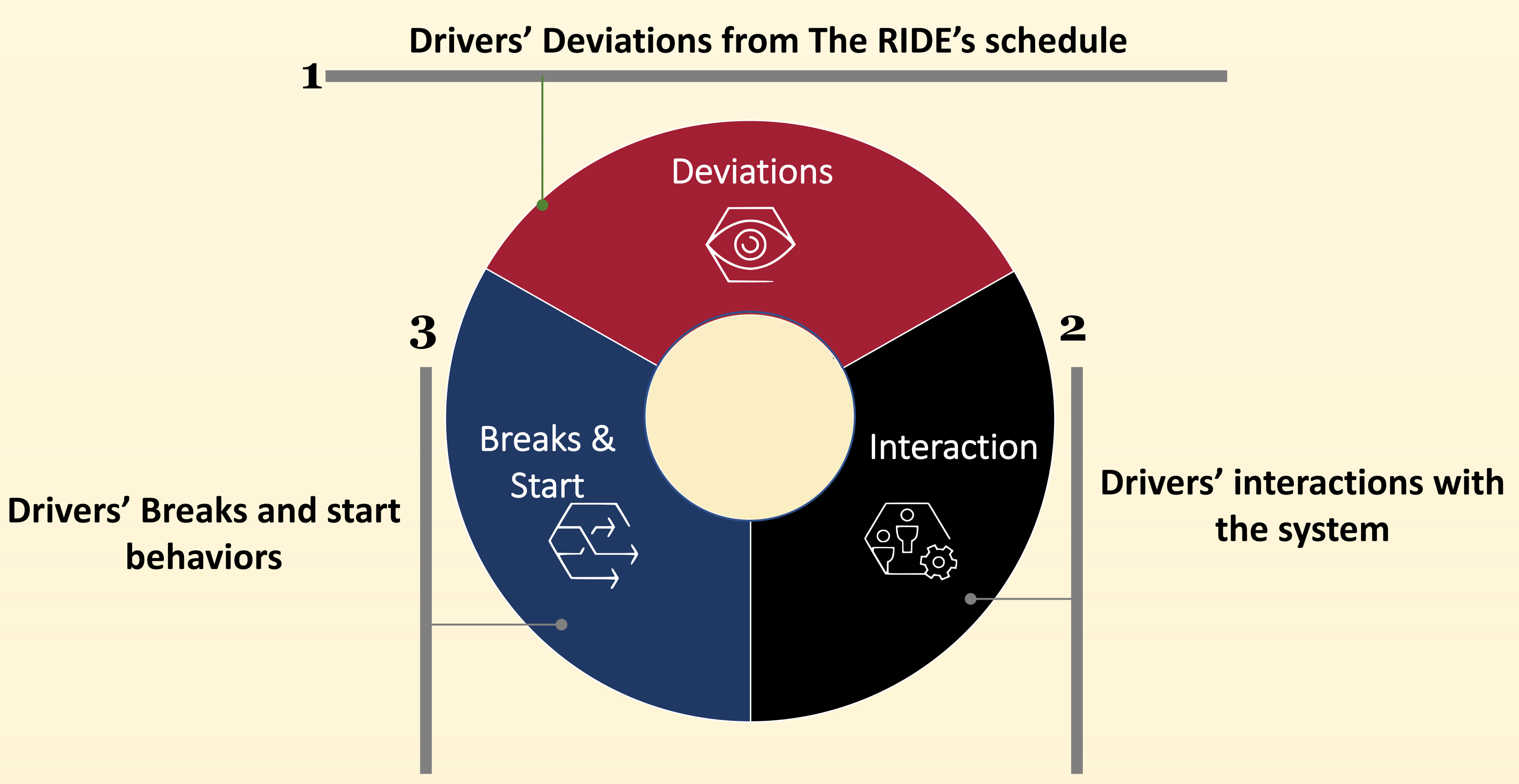
- **90M** GPS points every 2 minutes indicating driver's **position**, **speed** and **system interaction**
- **2M** Trips data on scheduled trips, their timings and associated driver
- **200K** Routes data on the **overall system schedule**
- Quarterly run-structure: **supplied driving hours** in the overall network

Problem definition *February-March* → ***Feature analysis and engineering*** *April-May* → ***Driver score design and delivery*** *June* → ***Demand forecasting model*** *July*

DRIVER BEHAVIOR

Quantifying behaviors

Our exploration analysis on the GPS data lead to three comprehensive categories of driver behaviors:



Driver score definition

Two goals were defined for a driver score: **Capture the most important behaviors** and **differentiate drivers based on their performance.** A survey conducted with the RIDE's managers assessed the importance of each feature. Hence, for driver j on day d we get the following score:

Variability — Importance

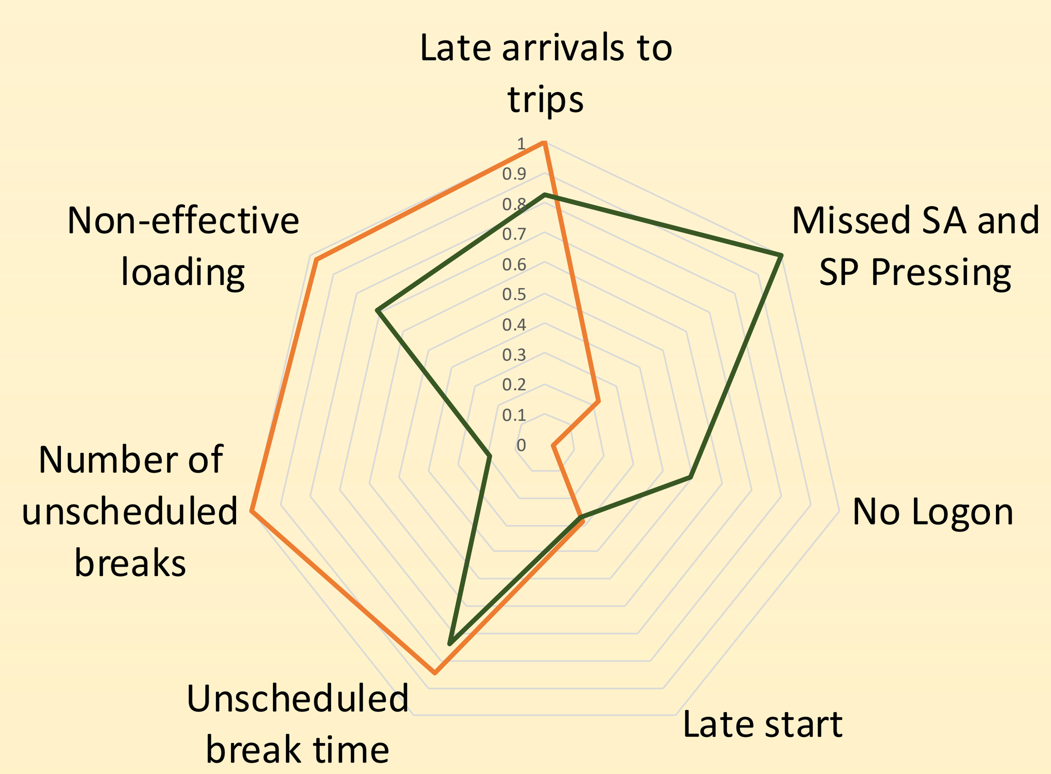
$$score_{j,d} = 1 - \frac{\sum_i Behavior_{i,j,d}(\lambda\sigma_i + \beta w_i)}{\sum_i(\lambda\sigma_i + \beta w_i)}$$

Higher score for better drivers

71% Consistency with **correlation** of bi-weekly scores

Case study

Driver score catches the overall behavior and enable comparison while each provider has its own **distinctive behavioral patterns**



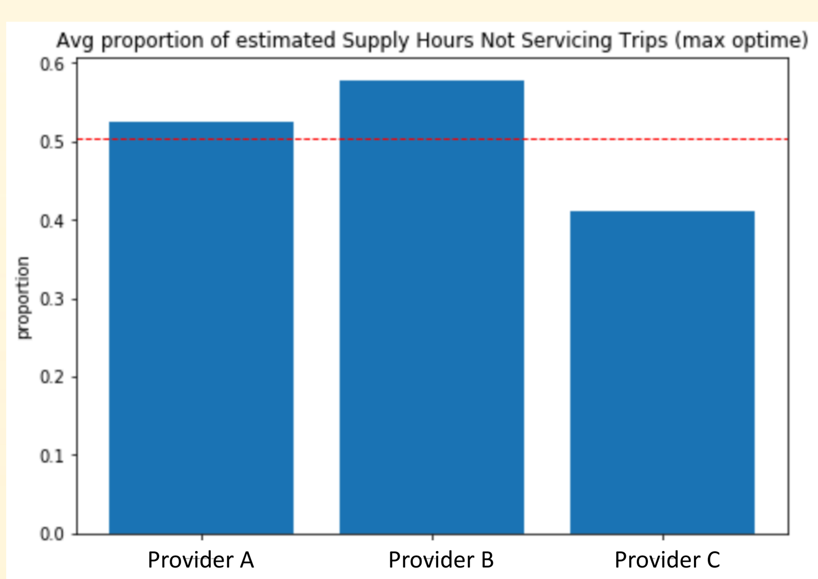
DEMAND FORECAST

Identifying non-revenue time

In the overall network, we identified that **50% of the supply** time is spent without any client interaction

The supply is defined by hour, by provider, by route lead to the idea of a **geographic approach**

Time with no client interaction per provider



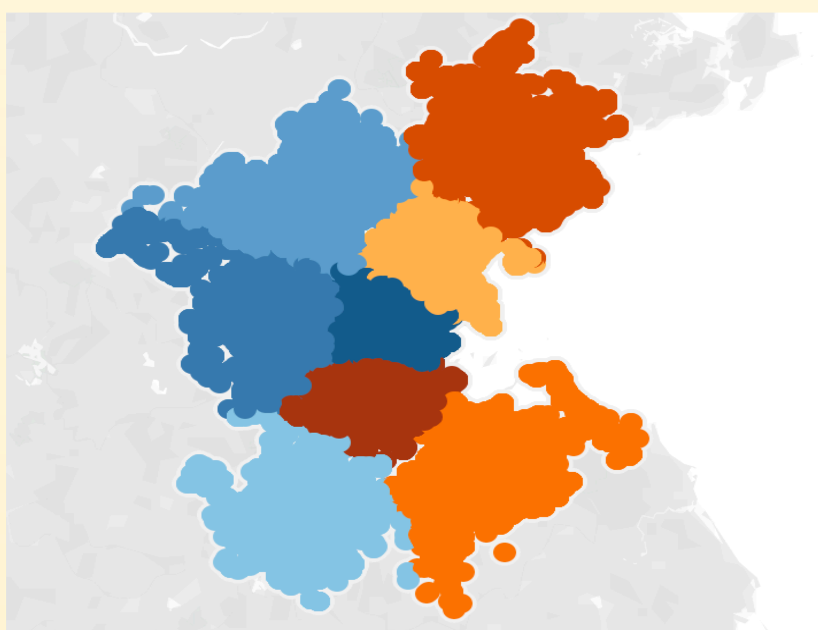
Geographic clustering

K-means clustering helped us identify 8 stable geographical clusters for trip pick-ups and departures

Granularity

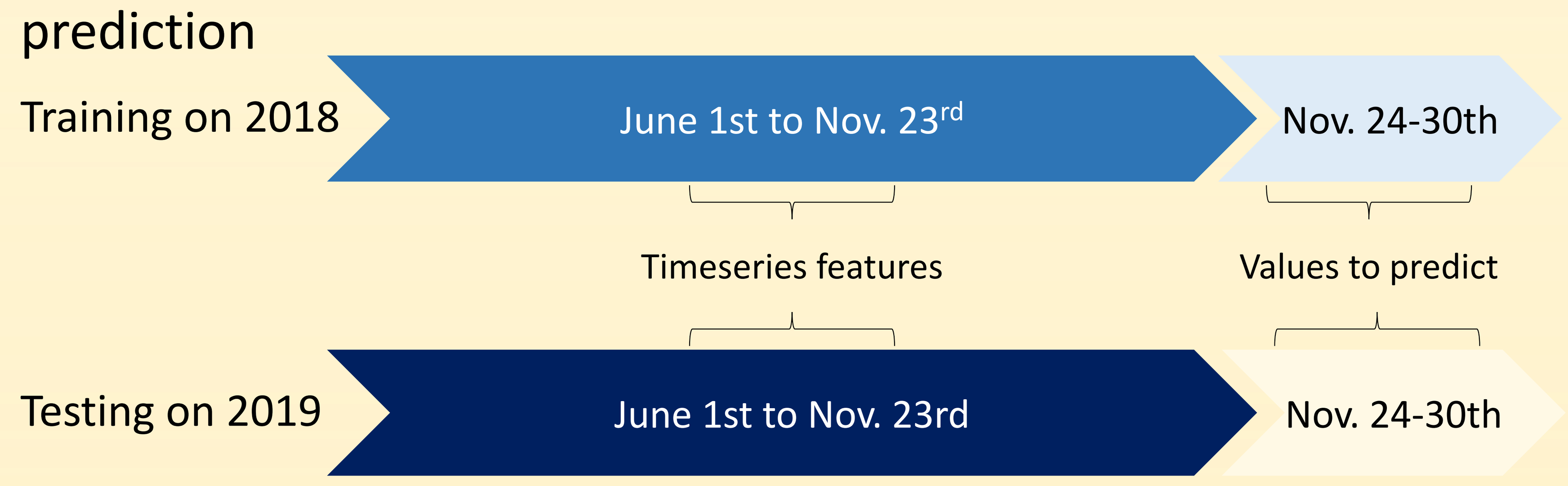
DAY OF THE WEEK | TIME-BIN | TRAJECTORY

Greater Boston clusters



Model building

Timeseries' analysis with **tsfresh** and **gradient boosting model** for prediction



Results

Maintaining **high-resolution prediction with only one month of prior observations**

Out-of-sample R^2

Prior data period	Six months	One month
Operating time	70.1%	69.1%
Number of trips	79.5%	78.8%

BUSINESS IMPACT

- Identify **personalized key areas of improvement** for drivers and providers
- Assess performance to **define incentives** for providers and drivers
- Provide an **assessment methodology** to quantify the efficiency of The Ride's discussions with providers
- Link with the garage location for drivers depending on geographical demand
- **New design of the run-structure** precisely identifying which areas are served at each time-bin
- Moving from a scheduling system based on optimizing only to a system based on **prediction-prescription methods**