# Understanding what drives prices of ride-hailing services

November 2023 Antonio Montilla



#### Database

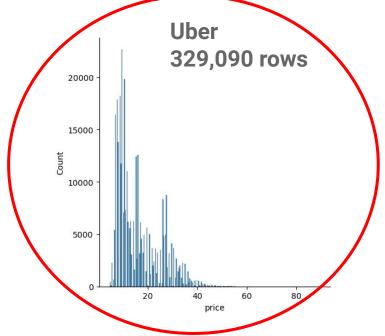
- Dataset: Kaggle challenge (see Kaggle)
  - 693,000 request trips using Uber & Lyft APIs
  - 12 districts of the city of Boston
  - During the last week of November 2018

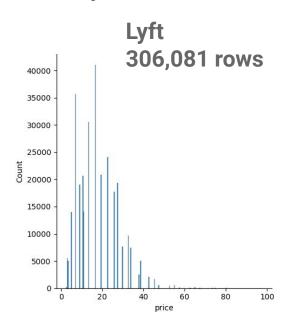
#### Main columns:

- Price (target variable)
- Distance
- Time: hour of the day, day of the week
- Location: destination & source
- Cab type
- Weather: rain, temperature, wind

#### Database: downshifting the problem

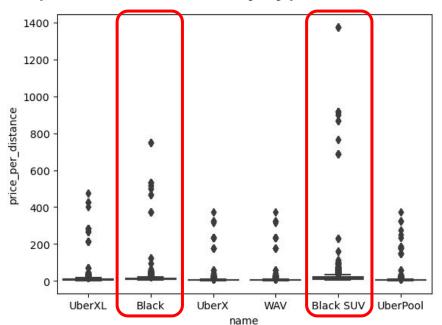
- Price histograms of rides from Uber vs. Lyft





#### Database: downshifting the problem

- Price per mile of Uber by type of service



#### **Decision:**

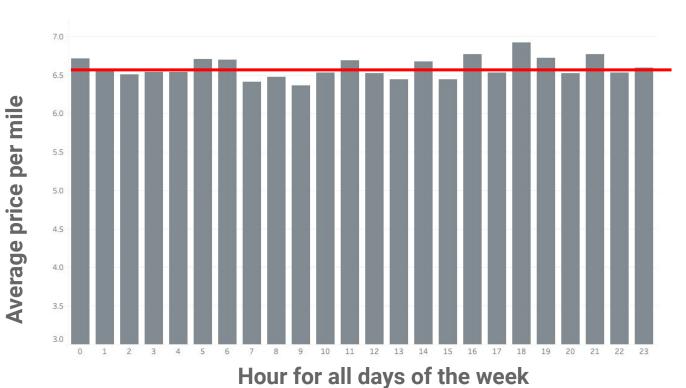
- Exclude Black SUV
- Exclude Black

Final rows: 219,407

# First: ¿how average prices change per day?

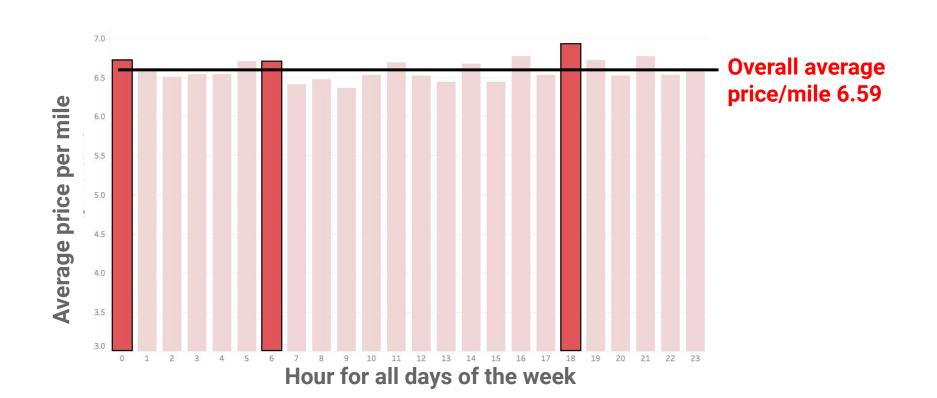


# ¿What about by hour of the day?



**Overall average** price/mile 6.59

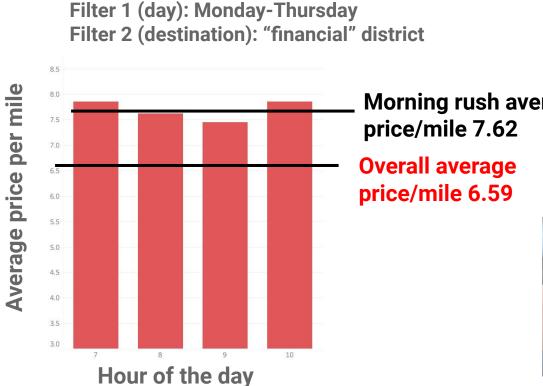
# ¿What about by hour of the day?



## ¿What about by the destination of the ride?



#### Hyp. 1: prices are higher in morning rush hours?



Morning rush average price/mile 7.62

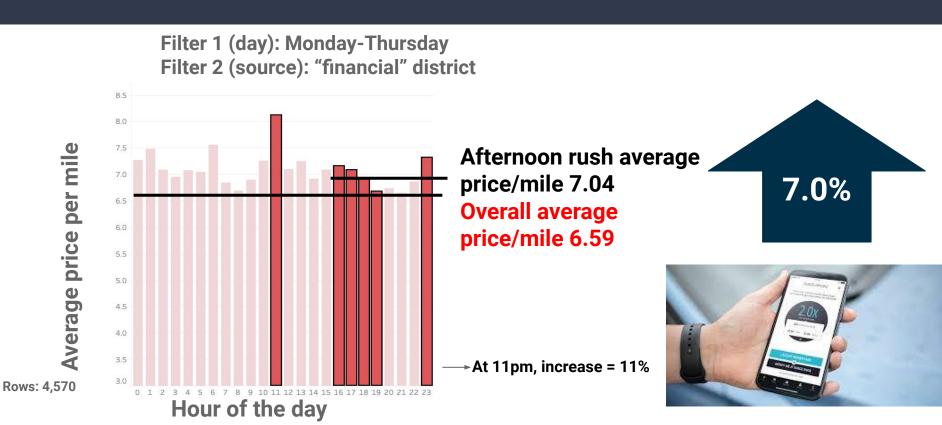
Overall average

Price / mile 6.50



Rows: 3,424

#### Hyp. 2: prices are higher in afternoon rush hours?



#### Hyp. 3: prices are higher in weekend rush hours?

Filter 1 (day): Friday-Saturday Filter 2 (destination): "entertainment" & "commercial" districts

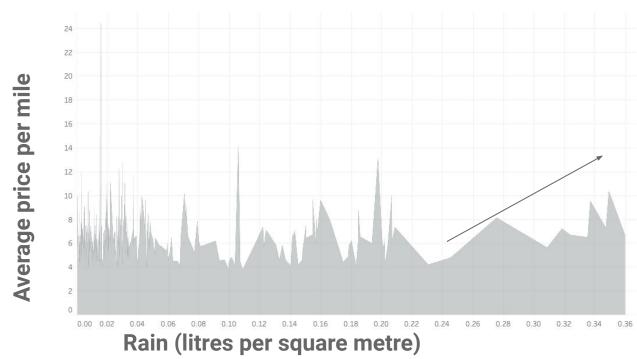


At 12am

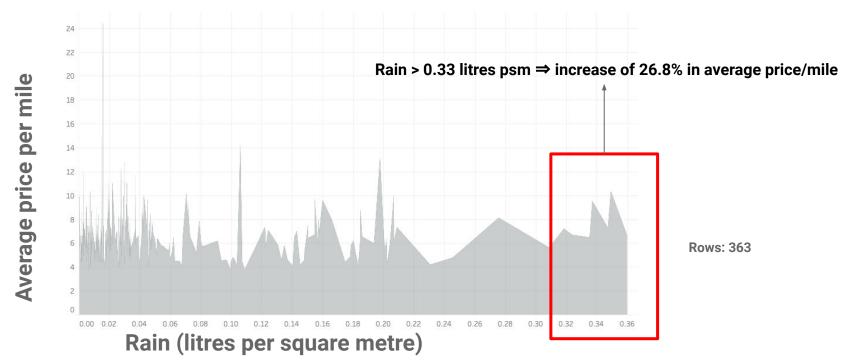
5.5%



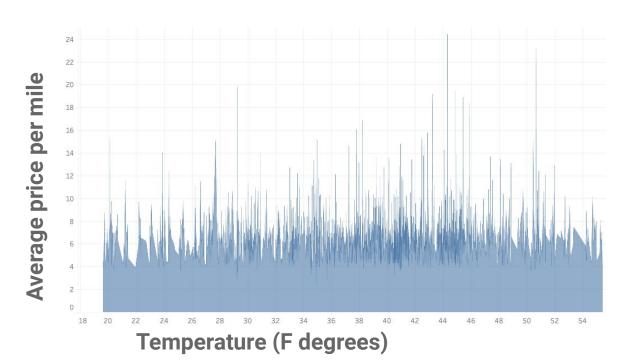
Average price/mile per hour versus rain (litres per square metre)



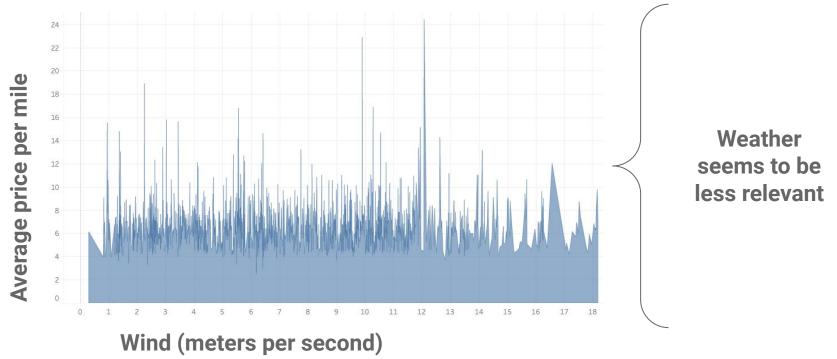
Average price/mile per hour versus rain (litres per square metre)



Average price/mile per hour versus temperature (F degrees)

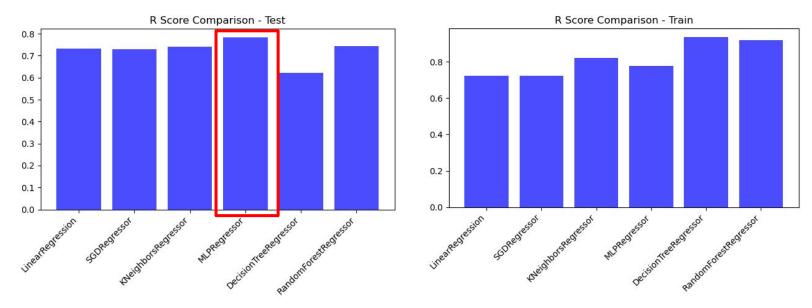


Average price/mile per hour versus wind (meters per second)

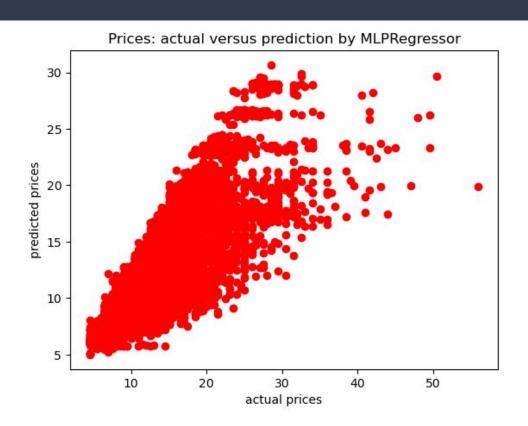


#### Objective 2: a ML regression model to predict prices

- Construct ML regression models to see effect of X variables in explaining prices
- Data wrangling, data transformations, X-Y split, etc...
- ...testing different models:

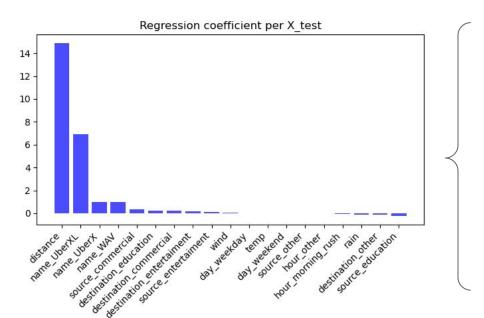


## MLP Regressor: Y\_pred versus Y\_test



#### BUT: which factors are more relevant for prices?

 Results based on a Linear Regression model, as MLPRegressor does not allow to see coefficients for each X\_train columns.



- No surprise: distance explains most of the variability in prices.
- **Other factors**: type of Uber, e.g. if XL or if WAV.
- Other columns seem very irrelevant in explaining prices.
- In fact, a separate model only with 'distance' and cab type delivers same R\_score

## Final thoughts, caveats

- Distance is by far the most single factor influencing the price set by ride-hailing firms.
- Other factors that have some relevance in prices are also the **type of service** chosen in the App.
- But, **dynamic pricing is at play** (e.g. morning rush hours, late nights, extreme weather conditions)...
- ...only that for a **small share of the rides** (less than 10%).
- The **main caveats** for these insights are the specification of the data:
  - Timing: 1 week in late-November 2018
  - Location: only 12 districts of Boston.
  - User: same requests.