Taxi Travel Time Prediction

Assignment 1 - Outcome Lecture

Sebastian Caldas and Nicholay Topin

This lecture has 3 objectives:

Socialize the students' solutions to the assignment

Understand how the assignment relates to the **course's goals** Provide the appropriate **context for the next assignment**

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lfigeneia Apostolopoulou



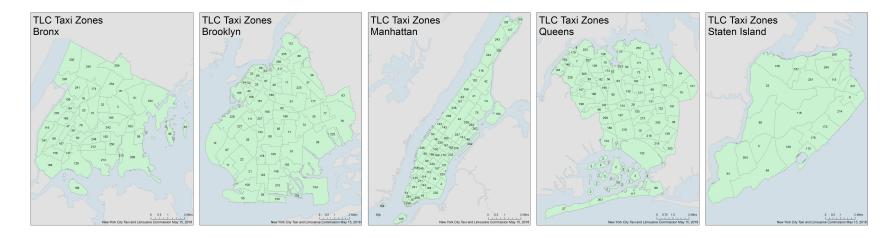
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Global summary

- > 67 million samples
- 7 features
 - Vendor ID {1,2}
 - Tpep_pickup_datetime (date-time format)
 - Tpep_dropoff_datetime (date-time format)
 - Passenger count [1,9]
 - PULocationID [1,265]
 - DOLocationID[1,265]
 - Payment_type [1,5]

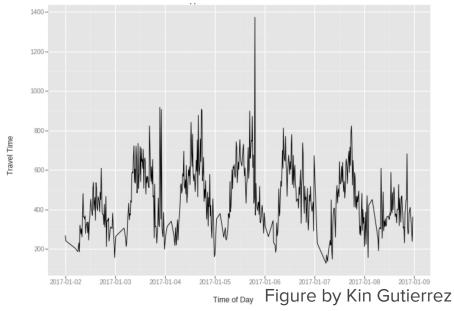
• Locations:

- Most trips start in Manhattan (61m), Queens (4m), Unknown (1m), and Brooklyn (1m)
- Most trips end in Manhattan (59m), Queens (3m), Brooklyn (3m), and Unknown (1m)
- 20 most common locations are in Manhattan (all except LaGuardia and JFK Airport)

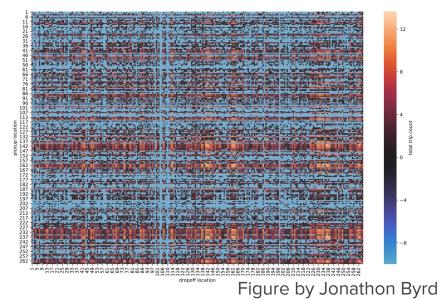


- Data is given only for certain months (Jan-July) of 2017
 - Any data from another year or month should be removed
- Outliers:
 - Trips with time less than 0 (some students suggested trips under X minutes were outliers)
 - Trips with time more than 60 or 120 or 720 minutes (no trip across NYC is more than 6h)
 - \circ $\,$ Trips before 2017 / Trips outside of expected month range
 - Trips with 0 passengers (maybe trips with >7 passengers)

• Students found that trip time correlated with features such as day of the week, pick up hour and (to a lesser extent) passenger count.



• 99.95% of trips are between a pair of zones which has at least 5 occurrences.



Any other interesting findings?



"Formulate a machine learning problem that will help the domain expert achieve their goal"

- Regression problem
 - MSE
 - $\circ \quad \mbox{Root Mean Squared Log Error}$
 - Avoids large travel times having too large an impact
 - Penalizes underestimates more than overestimates
 - \circ $\hfill \hfill \hf$
 - MAE, MAPE
 - Huber loss
 - Discretized accuracy (e.g., % within some 'd' of actual time)
- To avoid over-penalizing some samples, we can cap the loss.

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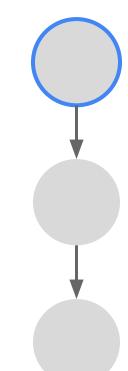
- Dealing with the dataset's size:
 - Subsample plus ensembling
 - Divide into distinct tasks (e.g., split 6am-10am predictions into own task, task per pick up location)
 - Use methods with low overhead (data + method fit in memory)
 - Use online methods (e.g., gradient descent)
- External factors:
 - Add external information about weather and holidays
- Train/Val/Test splits:
 - Strangely, people suggested random splits
 - Some suggested withholding last part only (correct!)

Any comments?



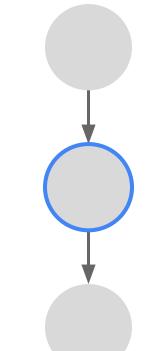
"Propose a detailed analytical pipeline to solve the machine learning problem"

- 1. Preprocessing
 - Remove outliers
 - Extract travel time from "datetime" columns
- 2. Feature engineering
 - Distance between locations
 - Split "datetime" columns into day of week and hour of day.
 - Treat "vendor ID" and "payment type" columns as categorical
 - Treat "passenger count" as continuous
 - Remove "payment type" and "vendor ID"



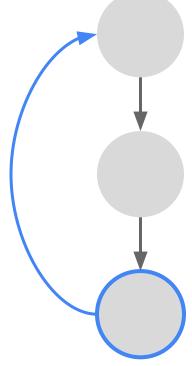
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- 3. Split into train/val/test sets
 - Normalize within each set
- 4. Potential methods:
 - Linear regression / polynomial regression
 - LASSO
 - Random forests
 - Gradient boosting
 - Nearest neighbor matching
 - Shallow feed-forward neural network
 - ARIMA
 - Bayesian regression (assume log-normal distribution)



"Propose a detailed analytical pipeline to solve the machine learning problem"

- 5. Evaluate
- 6. Diagnose
 - For which locations does your pipeline work well?
 - Use different stratifications
- 7. Iterate!



Any comments?



"Design an experiment to evaluate the effectiveness of your approach"

- Baselines:
 - Most previous methods need finer location information
 - The baselines should be run on the same data
 - A common suggested approach was to use the average trip duration for each pair of pick up and drop off destinations
 - Use a global average for pairs with too little data
- Ultimately, a practitioner will have a real business need that needs to be addressed and should evaluate how the overall solution addresses these needs

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Typical Steps of Applied Data Analysis

Steps

Overview of research Some research questions the data might answer Description of data Data checks / transfer Return to questions and translating them Present to collaborators

Simple methods to give preliminary answers Present to collaborators

Do better / Iterate Present to collaborators

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Assignment 2 will focus on the implementation of a preliminary pipeline

- We will provide you with a preprocessed version of the data
- We will not impose any restrictions on which pipeline you decide to implement but **you can only use the given data**
 - \circ $\hfill Any engineered features must come from this data$
 - You should not use any external data (e.g., from other years)

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- We will provide a baseline which you should beat



Assignment 2 will have two deadlines

- By the first deadline, you should have a Kaggle submission that beats our proposed baseline
 - Failing to do so will impact your grade
- By the second deadline, you should improve your model and write your report
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- The first deadline will be one week before the second
- The Kaggle competition is meant to incentivize you
 - Your grade will not be negatively affected based on your ranking
 - The only exception is failing to beat the given baseline

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- For the students that didn't do so well on Assignment 1:
 - Look at the sample submissions and come to office hours
- For the students that did well:
 - Keep up the good work!

Any questions?

