Predicting crime rates using taxi rides in NYC

Carlos Petricioli   Varsha Muralidharan   Valerie Angulo

New York University
{cpa253,vm1370,vaa238}@nyu.edu

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Analytics Project

Predicting crime rates using taxi rides in NYC

Team

- Carlos Petricioli (cpa253)
- Varsha Muralidharan (vm1370)
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Abstract

- Our study looks at the relationship between crime rates and taxi usage in New York City.
- Our hypothesis is that people are less likely to walk in areas subjectively deemed more dangerous and will instead opt to use more reliable and immediate transportation such as designated taxis.
- WE FOUND THAT _____.

Motivation

Typical users of this application

The scientific community, law enforcement, those in public transportation

Beneficiaries of this application

Members of the community and tourists, law enforcement

Importance of this analytic

- This analytic can help law enforcement predict areas of crime based on New Yorkers transportation habits. Law enforcement officials may be able to predict which areas will have a higher rate of crime in the future.
- People who live in an area are aware of the safety of their surroundings and this awareness can be represented by how comfortable residents may be in walking or taking the subway versus taking more immediate, more expensive, modes of transportation such as taxis.
- This analytic can benefit the community and tourists by influencing their current and future transportation behaviors

Data Sources

Taxi rides data from TLC (*Link*)

- It covers years from 2009 to June 2017.
- The yellow taxi trip records include:
    - pick-up and drop-off dates/times,
    - pick-up and drop-off locations,
    - trip distance,
    - itemized fares,
    - rate types,
    - payment type,
    - passenger counts.
- *Data Size*: 250 GB

**NYPD Complaint Data (*Link 1, Link 2*)**

- This dataset includes all valid felony, misdemeanor, and violation crimes reported to the New York City Police Department (NYPD) from 2006 to year to date data.
- *Data Size*: 1.5 GB

NOAA Weather stations data *(Link)*

The *Integrated Surface Database (ISD)* consists of global hourly ansynoptic observations compiled from numerous sources into a single common ASCII format and common data model.

- ISD's complete history of hour-by-hour readings for one user-specified weather stations
- We selected:
  - Central Park
  - JFK
  - Laguardia
- *Data Size*: 165 MB

Design Diagram
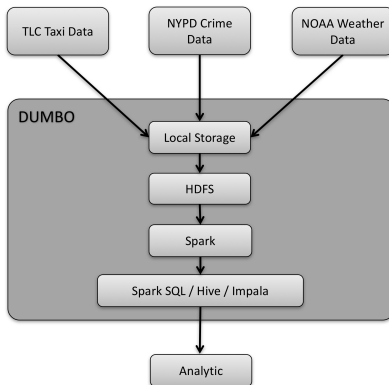
Platform:

- NYU HPC cluster (Dumbo)

Obstacles

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- Dates needed to be cleaned. (**24:00:00 vs 00:00:00**)
- Meaningful interpretations of other dates could not be made for certain records and these records had to be filtered.

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- Negative, but consistent values for amounts.
- Weird trip distances, like greater than 1000 miles.
- Exorbitant total amounts (which might not be a problem because most were negotiated fares)

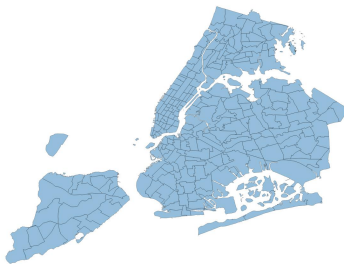## Cleaning the data: Taxis

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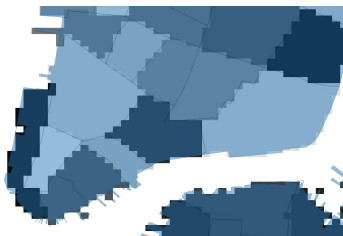- About 1.2 billion x 14 thousand $\approx$ 16,800 $\approx$ 2 1.6x10^ 13 distances computed (just for pick-up)

(a) Shape   **(b)** Raster

Figure 1: NYC Taxi zones file formats

(a) Both

Figure 2: NYC Taxi zones file formats

Cleaning the data: Crime

- Crime data was reasonably clean.
- The most challenging factor here was that we had a lot of missing values for some columns so we needed to setup a schema that accepted this fact.

Cleaning the data: Weather

- Weather data was the most decent.
- We basically just needed made sure that the data was clean which was the case.
- The only major issue was to figure out a way to assign weather data to the taxis.

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- So, we estimated the centroids on the pick-up zones and then computed the min distance to the weather stations.
- Finally taxis were joined to crime by using time periods of one hour.

Goodness

Consistent data

- One of our main concerns was that the data
  Some of the taxi and crime data records had incorrectly entered/ambigious
  date/time columns. We tried to identify the correct dates and times for most
  of them so that we wouldn't have to throw away those records
- We had to make sure that the three data sets were related by zone

model testing

we made sure that –

Results

3 results, insights, observations, outcomes

1. Result 1
2. Result 2
3. Result 3

Summary

- We collected NYC taxi trip data, NYC crime data and weather data from Central Park, JFK and LaGuardia
- We joined together the data sets through taxi zones (taxi_zone_id) and hourly_data
- Our main questions revolve around whether taxi usage depends on crime rate in a specific zone, how much weather plays a part in the relationship between taxi usage and crime and how the distance of the trip affects taxi usage in relationship to crime
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Acknowledgements

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Thank you!