Vehicular Mobility in San Francisco

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1 Motivation

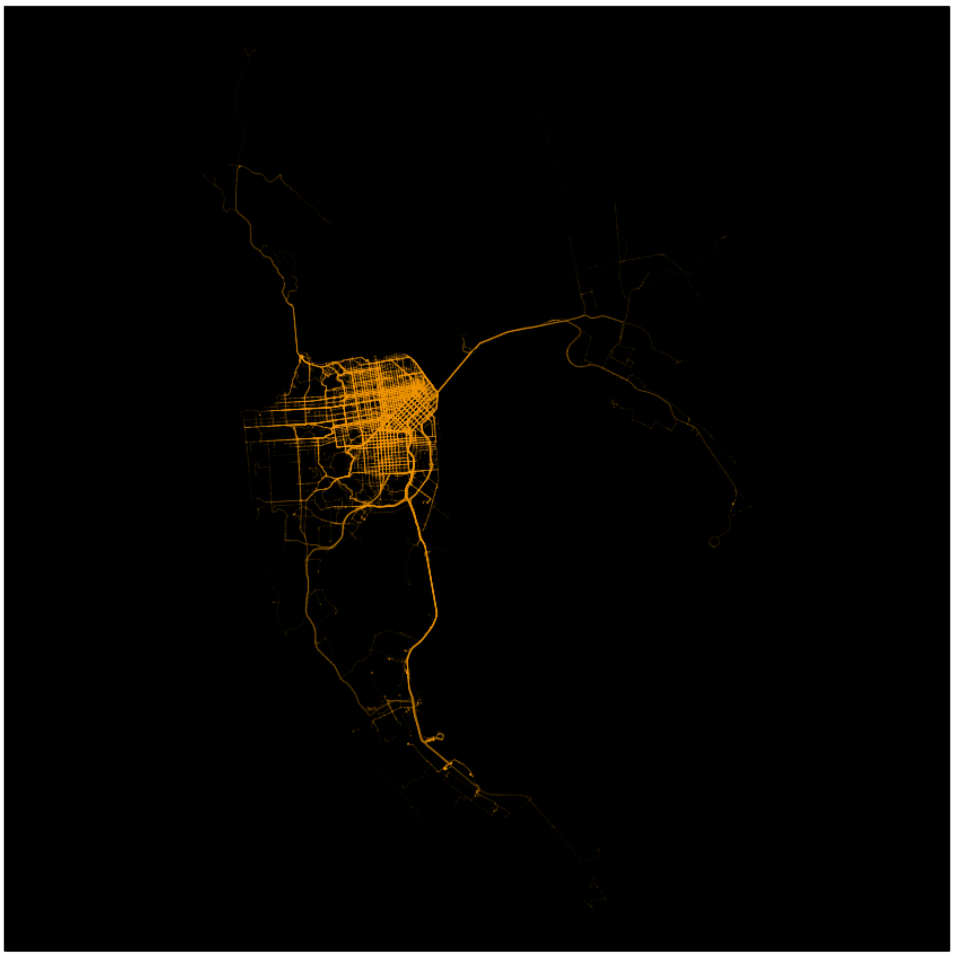
As urbanization, vehicular dependence, and fuel consumption continue to grow into the future, mobility within cities becomes an increasingly relevant dilemma. Large metropolitan areas like Los Angeles, New York City, and Washington, D.C. are notorious for terrible traffic conditions. Los Angeles conditions are particularly problematic as many carpool lanes are in effect 24/7, as opposed to the typical rush hour period in most cities. Traffic has direct impacts on commute times, road safety, energy consumption and dependence, etc., not to mention countless intangible impacts. This project is aimed at evaluating the traffic problem from a mobility perspective.

2 Introduction

In my preliminary work, I have found a dataset which contains archived anonymized GPS traces from Uber – time of day, day of week, latitude, and longitude of 25,000 trips in San Francisco, logged every four seconds. The data has been anonymized by truncating the beginning and end of every trip and removing the actual dates of the trips.

From this dataset, my goal is to obtain a better understanding of different driving behaviors in San Francisco, and how they may affect fuel economy and travel times. I plan to characterize driving behaviors in the city of San Francisco as a function of day of week, time of day, and location. Additionally, I would like to develop a model to predict fuel consumption. To achieve these goals, I will need to derive several intermediary variables from those provided in the data sets:

Figure 1: An overlay of Uber GPS traces in San Francisco.



- traffic: create a model of standard traffic for all roads given weekday/weekend and hour of the day using Uber and SFMTA data
- Driver velocity: time derivative of position, using central differences method
- Driver acceleration: second time derivative of position

3 Data Project

With the above variables established, I propose three projects, each compounding upon the previous.

1. **Project 1**: First, I will use *k*-means and/or hierarchical clustering to categorize driver behavior. Clustering will be based on features engineered out of the variables listed above (*e.g.*, maximum velocity, median velocity, maximum acceleration, maximum deceleration, etc.). In order to normalize out traffic conditions, perhaps the time series will be modified by the standard traffic model, mentioned above. Alternatively, this can be performed separately for rush-hour and non-rush-hour times. I will also create a rudimentary model for fuel consumption, which will be approximately proportional to an integral of positive accelerations. Alternatively, for electrified vehicles, electricity consumption may also be computed by subtracting some integral of negative accelerations to model regenerative braking. It may also be influenced by topography (*e.g.*, accelerating uphill, regenerating downhill, etc.). This will allow me to find the relationship (if any) between categorized driving behaviors and fuel economy.

2. **Project 2**: I will build a routing algorithm, given starting location, destination, day of week, time of day, and driving behavior. The base algorithm will use Dijkstra's algorithm, however it will be modified to present multiple route options, *e.g.*, fastest route, most direct, best fuel economy, least congestion, etc.

3. **Project 3**: I will build a mobility map of San Francisco. The tool will take as inputs starting location, day of week, time of day, travel time, and driving behavior (based on the clustering in Project 1). As output, it will present a highlighted area of all potential destinations that are reachable in the given travel time. Versions of this have already been implemented, *i.e.*, Isoscope and Trulia. However, Isoscope is limited to 10 minute trips, Trulia

has no time dependence feature (presumably limited to commute hours), and neither factor in driving behavior. Additionally, my tool will report (via color) the fuel/electricity consumed for all destinations at the boundary. To find the potential destinations, I will use some modified form of Dijkstra's algorithm. Cumulative travel time and consumed fuel will be tracked as the algorithm proceeds.

4 Preliminary Work

From the Uber dataset, I have derived velocity and acceleration time series for each driver using a central differences method. An example of one extracted time series can be found here (top to bottom: position, speed, acceleration time series).

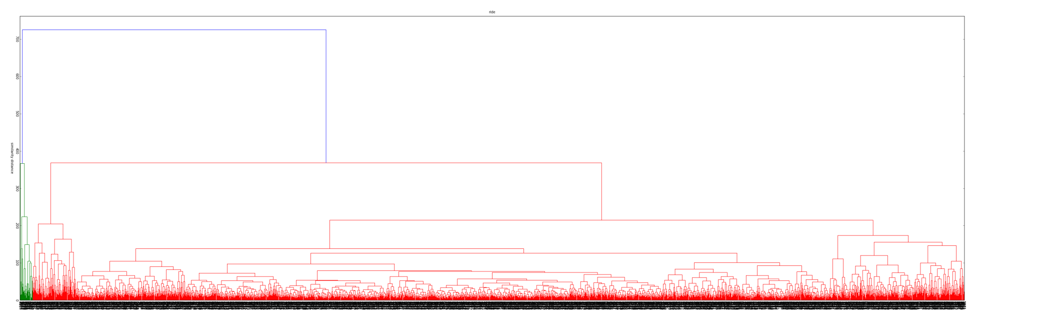
Further, simple features have been extracted from these time series, such as maximum velocity, median velocity, mean velocity, maximum acceleration, median acceleration, mean acceleration, maximum deceleration, median deceleration, mean deceleration, and mean free path. The mean free path is a metric crudely approximated by averaging the duration of driving between successive pauses in a route (*i.e.*, the time between zero-velocity and zero-velocity).

Figure 2: An overview of preliminary features.

	max_speed	avg_speed	med_speed	max_accel	avg_accel	med_accel	max_decel	avg_decel	med_decel	mfp
count	2697.000000	2697.000000	2697.000000	2697.000000	2697.000000	2697.000000	2697.000000	2697.000000	2697.000000	2697.000000
mean	41.618813	19.011738	19.533524	1.928635	0.510623	0.383884	-2.488529	-0.664388	-0.499092	51.638858
std	12.088831	6.855878	8.017118	0.761572	0.141083	0.140602	1.082216	0.211776	0.221064	14.102453
min	17.680185	3.850620	1.511980	0.378706	0.092040	0.030783	-9.692428	-1.923282	-2.378872	38.000000
25%	33.020428	15.284668	15.299468	1.444731	0.414730	0.292993	-2.696939	-0.746880	-0.591734	42.000000
50%	38.491886	17.957420	18.703114	1.690133	0.493462	0.367529	-2.157267	-0.632940	-0.474697	47.000000
75%	47.186523	21.135661	22.449465	2.128796	0.587524	0.458673	-1.844707	-0.540524	-0.367485	56.000000
max	99.904385	73.088352	75.345888	4.497397	1.351528	1.170839	-0.807755	-0.173247	-0.046000	140.000000

These ten simple features have been used to build a hierarchical clustering dendrogram. Due to some noisy data, a large majority of rides had to be removed for this preliminary study. The resulting dendrogram shows four clusters of slightly varying radii.

Figure 3: Preliminary dendrogram.



5 Challenges Ahead

Here are four initial foreseeable challenges and my approach to addressing them:

1. **Extract Dendrogram Clusters**: Since the dendrogram clusters are potentially of varying size, it is somewhat difficult to inspect the clusters. If scipy does not provide a feasible way to do this, one solution is to switch to k-means. Alternatively, I could implement my own hierarchical clustering, which will have the required functionality to inspect variable-sized clusters.

2. **Noisy Data**: I have two solutions for this which could be used unison. The first is a Kalman Filter, which should smooth out the positional data. The second is mapping GPS coordinates onto streets. This will require building a graph of intersections (nodes) and streets (edges) of San Francisco, using SF street lines shape files. Mapping might be done through a process of voting, where successive time series points will vote on the street.

3. **Normalize Out Traffic**: This will require the graph/mapping solution from the previous challenge. With the time series mapped onto streets, I can find average time series per edge per time window (perhaps every one hour window). Normalizing would then be some comparison between individual time series per edge to average time series per edge. I will consider subtraction, division, Z-scoring, and maybe others.

4. **Fuel Economy**: I need to build a model for fuel usage. This will be a function of integrating positive accelerations. For now, the model will not

be based on concrete data since vehicle performance is unknown.

6 Alternate Project

As a backup project, I might use data from my previous research in molecular simulations of supercapacitors. I have tens of thousands of atom trajectories over millions of timesteps for multiple combinations of parameters (*i.e.*, surface charge density, atomic constituents, surface substrate material, etc.). Atomic and molecular arrangement and orientation turn out to be key to determining a system's capacitance, but are highly susceptible to the substrate lattice. I can use the data to build a model for predicting substrate, given a subset of ionic and solvent locations. If possible, it will be a generative model which will be able to generate atom locations given a particular substrate and surface charge density.