Toronto Parking Tickets

Where shouldn't you park?

Emily Warman

Project Goals:

There are approximately 2.8 million parking tickets given in Toronto every year. Details about every ticket given in the last 8 years is available here:
http://www1.toronto.ca/wps/portal/contentonly?vgnextoid=ca20256c54ea4310VgnVCM1000003dd60f89RCRD

My project was an exploration of this data. My goals were to identify the worst places to park in the city and to learn if the demographics of neighborhoods are an indicator of the number of parking tickets given.

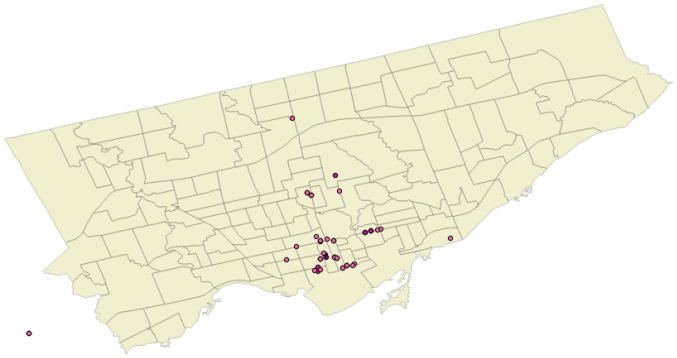
Approach:

The first thing I did was some general exploration of the data – basic numbers about the distribution of infraction types, fees, and the number of addresses with no duplicates. When I had an idea of what was going on, I started to geocode the addresses. The API I ended up using was Mapzen – it has a rate limit of 30,000 calls per day. To finish the project, I collapsed the number of addresses by rounding the street addresses. After some experimentation, 100 proved to be the number that collapsed the data the most while still being fine grained enough for good analysis. After collapsing, ~75,000 addresses remained. Downloading a Nominatim instance from Docker and using a .pbf of Toronto would be a way to geocode without collapsing. I stored the geocoded addresses in a MongoDB collection.

After geocoding, I was able to create maps in QGIS. I found a map of Toronto census tracts and picked out a few interesting demographic features from the census. The features I chose were population of census tract, percent Canadian residents, and median household income.

I tried to map the geocoded addresses to the census tract they fell into and calculate the number of tickets given in each area, but I couldn't get part this working. My plan was to create a logistic regression model using these features to see if demographic factors influenced the number of tickets given in an area. Instead, I took a closer look at some of the worst places to park and created some metrics and graphs for understanding what's happening.

Results:



The 25 worst places to park in Toronto (summarized)

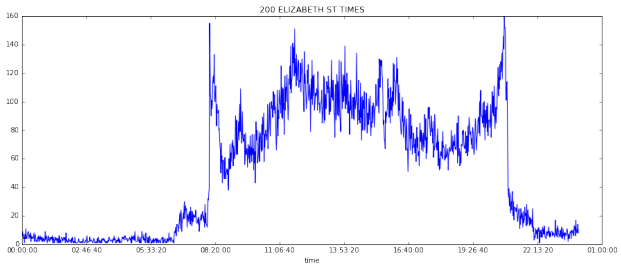
1. Urban Hospitals
    1. 200 Elizabeth Street – Toronto General Hospital
    2. 100 Elm Street – Hospital For Sick Children
    21. 200 Elm Street – Mt. Sinai Hospital

2. Urban shopping areas – not malls!

(19 locations)

3. Downtown Universities (Ryerson and U of T)
    16. 100 Bond Street – Ryerson University
    18. 300 Victoria Street – Ryerson University
    20. 100 College Street – University of Toronto

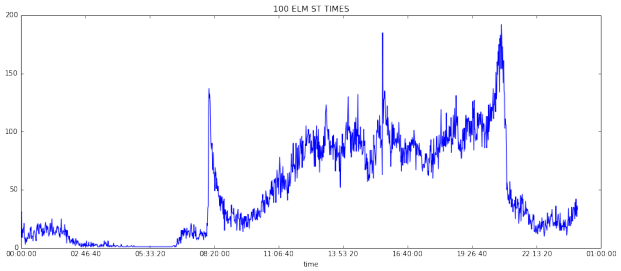
Hospitals Analysis:
The graphs on the left plot the number of tickets given at a collapsed address at every second of the day.



200 ELIZABETH ST:
Most Common Infractions Associated:

```
('PARK FAIL TO DEP. FEE MACHINE', '30')
('STOP HWY PROHIBITED TIME/DAY', '60')
('PARK HWY PROHIBED TIME/DAY', '30')
('PARK FAIL TO DISPLAY RECEIPT', '30')
```

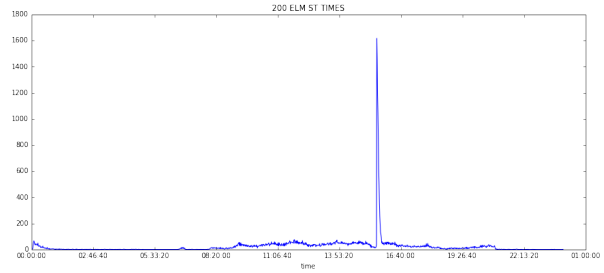
Tickets Given Per Day: 25.4
Daily Revenue: $1140.08
Number of Parking Spots: 9



100 ELM ST:
Most Common Infractions Associated:

```
('PARK FAIL TO DEP. FEE MACHINE', '30')
('PARK HWY PROHIBED TIME/DAY', '30')
('PARK FAIL TO DISPLAY RECEIPT', '30')
('STAND SIGN HWY PRO TIMES/DAYS', '60')
```

Tickets Given Per Day: 23.8
Daily Revenue: $1002.95
Number of Parking Spots: 14

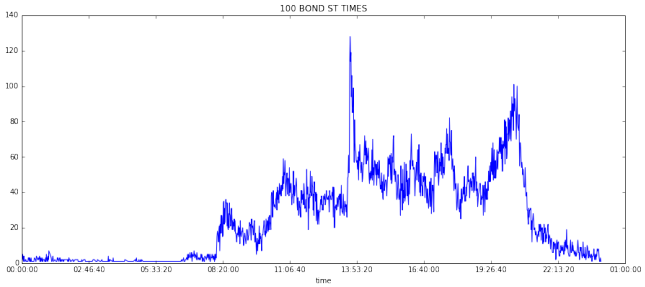


200 ELM ST:
Most Common Infractions Associated:

```
('PARK HWY PROHIBED TIME/DAY', '30')
('PARK FAIL TO DEP. FEE MACHINE', '30')
('PARK FAIL TO DISPLAY RECEIPT', '30')
('STOP HWY PROHIBITED TIME/DAY', '60')
```

Tickets Given Per Day: 11.6
Daily Revenue: $564.98
Number of Parking Spots: 5

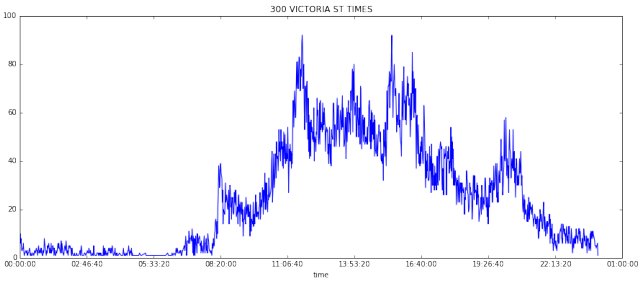
Universities:



100 BOND ST:
Most Common Infractions Associated:

```
('PARK HWY PROHIBED TIME/DAY', '30')
('PARK FAIL TO DEP. FEE MACHINE', '30')
('PARK FAIL TO DISPLAY RECEIPT', '30')
('STOP HWY PROHIBITED TIME/DAY', '60')
```

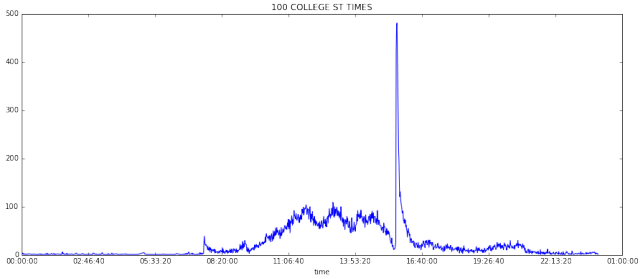
Tickets Given Per Day: 12.4
Daily Revenue: $470.58
Number of Parking Spots: 5



300 VICTORIA ST:
Most Common Infractions Associated:

```
('STAND SIGN HWY PRO TIMES/DAYS', '60')
('PARK FAIL TO DISPLAY RECEIPT', '30')
('STOP HWY PROHIBITED TIME/DAY', '60')
('PARK FAIL TO DEP. FEE MACHINE', '30')
```

Tickets Given Per Day: 12.1
Daily Revenue: $581.35
Number of Parking Spots: 11



100 COLLEGE ST:
Most Common Infractions Associated:

```
('PARK FAIL TO DISPLAY RECEIPT', '30')
('PARK HWY PROHIBED TIME/DAY', '30')
('PARK FAIL TO DEP. FEE MACHINE', '30')
('STOP HWY PROHIBITED TIME/DAY', '60')
```

Tickets Given Per Day: 11.6
Daily Revenue: $523.61
Number of Parking Spots: 9

Interesting Observations:

-Most common ways to get a ticket are not paying and not observing signage about appropriate times to park.
-Parking police must visit areas multiple times a day – these 6 addresses had at least twice the number of tickets given per day as there were "places to park" (this was determined by looking at the frequencies of parking tickets given per day). Assuming that everyone parked illegally, the police would have to come at least twice a day to give that many tickets in these locations.
-Police definitely like to visit certain spots at certain times. At 200 Elm Street, more tickets were given from 3:36 to 3:46PM than any other time combined.
-Police seem to like giving tickets at end of the day rather than the beginning – particularly after 5pm.
-Police don't give too many tickets before 8am.

Future plans:

I was bummed that I couldn't get the model working – I ran code for 8 hours to try to assign all collapsed addresses to census tracts. Definitely made some mistakes (I think my shape file included multiple cities in Ontario) and ran out of time to fix them. The analytics part was really interesting. I think it would cool to enter an address that you want to park at and see the time graph and some of the information that I calculated above. It could help people make much more informed decisions when parking.
I was tremendously busy this semester and didn't put as much time into this project as I would have liked. If I continue working on it, I will definitely let you know. I'd love to look at more addresses and get the model working.