# Predicting Shared Dockless Vehicle Time to Activation

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#### Why dockless micromobility?

- → New transportation mode that has been both popular and controversial
- → Human-scaled electric transportation suited to urban environments
- → Potential to address first- and last-mile problem for neighborhoods poorly served by transit and traditional bikeshare
- Research suggests it provides more equitable access than traditional, dock-based bikeshare
- → It's a fun and convenient way to get around



#### The problem

{ will be familiar to anyone who's ever arrived at their favorite neighborhood Indego dock only to find it empty }

Because anyone can take a vehicle at any time, there's no guarantee it'll still be there when you need it

What are the chances that a bike or scooter listed as "available" in an app will be taken before I can get to it?

## How can I model how long an inactive bike or scooter will remain idle between trips?

### Bike & scooter location data

- → Clean datasets not publicly available
- → Real-time API publishes coordinates for all inactive vehicles
- → Standardized format:
  General Bikeshare Feed
  Specification (GBFS)



#### Micromobility in Washington, D.C.

- → D.C. Department of Transportation (DDOT) requires all dockless micromobility operators to publish real-time vehicle data
- → Includes city bikeshare system
  (Capital Bikeshare, operated by Lyft)
  and five private companies (Bird,
  Helbiz, Lime, Lyft, Spin)
- → Initially scraped data from Capital Bikeshare only; later expanded to all six providers

#### capital bikeshare











#### From last time:

#### Two issues with the bikeshare data

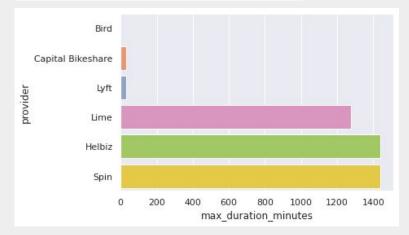
- → Same bike, different IDs: Bicycle IDs reset every 30 minutes
- → Same ID, different instance: One ID can represent more than one period of inactivity (if someone activates a bike, rides it, and deactivates it again)

bike_id	is_reserved	is_disabled	type	lon	lat	timestamp
002604d3123025e6e2fa8384ee72d2a6	0	0	electric_bike	-76.974229	38.932343	09:30:07
002604d3123025e6e2fa8384ee72d2a6	0	0	electric_bike	-76.974219	38.932373	09:31:09
002604d3123025e6e2fa8384ee72d2a6	0	0	electric_bike	-76.974228	38.932403	09:32:11
002604d3123025e6e2fa8384ee72d2a6	0	0	electric_bike	-76.974228	38.932403	09:33:13
002604d3123025e6e2fa8384ee72d2a6	0	0	electric_bike	-76.974240	38.932374	09:34:14

#### Can I finally get out from under my data issues?

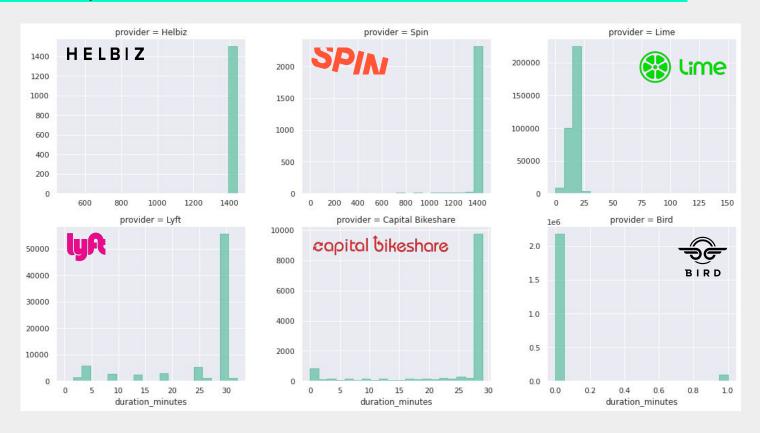
even in an ostensibly standardized format, data varies substantially between providers

	provider	max_duration	max_duration_minutes
0	Bird	0 days 00:01:00	1
1	Capital Bikeshare	0 days 00:29:00	29
2	Lyft	0 days 00:30:00	30
3	Lime	0 days 21:16:00	1276
4	Helbiz	0 days 23:59:00	1439
5	Spin	0 days 23:59:00	1439



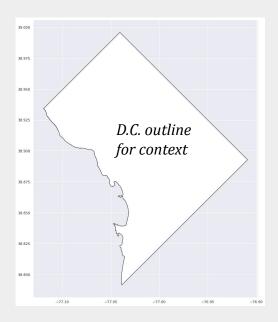
#### Time each ID is present in the data, by provider

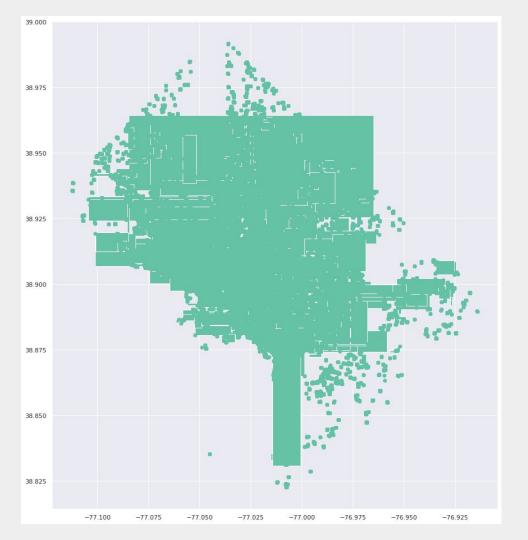
(This has implications for which is easiest to model)



#### Still, nothing is ever easy

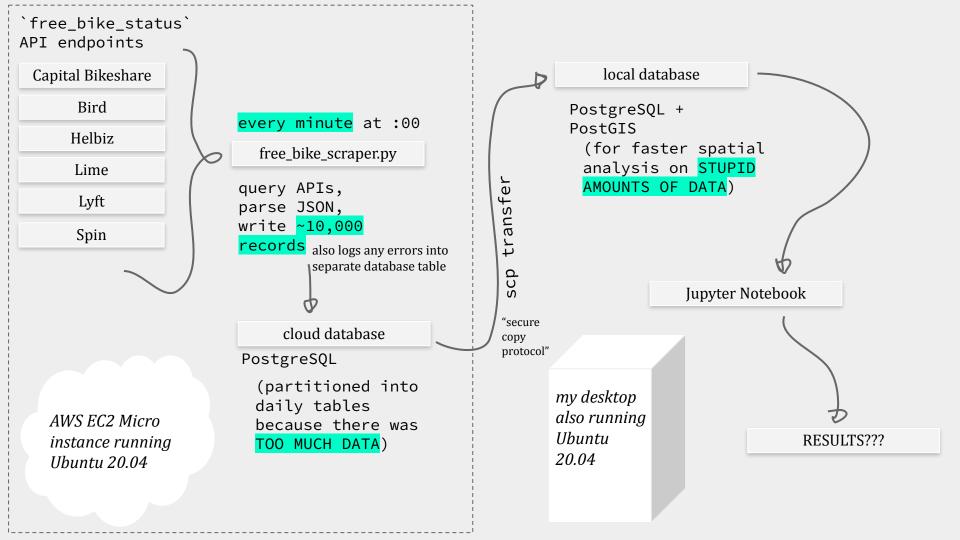
(spatial bounding boxes
for each Lime scooter ID)





#### Data pipeline and infrastructure

this turned into most of the project, to be honest



#### things I had never done before this project

- → scraped anything on a recurring basis
- → written a stand-alone Python script
- used a scheduler to run something repeatedly
- → worked with data in the millions of records, never mind tens of millions
- → used SQL really at all
- → set up a Postgres database (or several)
- → partitioned a database table
- → written Python error handling
- → used AWS or any other cloud instance
- → used PostGIS for spatial analysis

- → accidentally deleted my entire database (with 60 million irreplaceable records)
   because I made a typo in the terminal
- → ...and many more things I don't remember

```
Scrapes General Bikeshare Feed Specification (GBFS)
                                                                           scrape dockless vehicles (provider,
free bike status API endpoints for all current Washington, D.C.
                                                                time scraped=time scraped)
dockless vehicle providers as of 2022-04-16. Saves data to a
PostgreSQL database. Logs any errors to a separate table.
                                                                       except:
11 11 11
                                                                           time failed =
                                                                datetime.now().astimezone().isoformat(timespec='seconds', sep='
import traceback
                                                                ')
import time
                                                                           traceback text = traceback.format exc()
                     Questions?
import requests
                                                                           with psycopg.connect("dbname=capstone-aws
import psycopg
                                                                user=ubuntu") as conn:
import schedule
                                                                               with conn.cursor() as cur:
from datetime import datetime
                                                                                   cur.execute("""
                                                                                       INSERT INTO errors (time scraped,
                                                                provider, time failed, traceback)
def main():
                                                                                       VALUES (%s, %s, %s, %s)
   """Schedules scraper to run once every minute."""
                                                                                       """, (time scraped, provider, time failed,
                                                                traceback text))
   schedule.every().minute.at(':00').do(scrape all)
                                                                                   conn.commit()
   while True:
```

try:

"""Scrapes D.C. dockless vehicle locations every minute.