# Where am I going today -Trajectory Prediction Based on GPS Data

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#### **Problem Statement -- Initiative**

- GPS data is critical in analyzing movements of individuals or groups of people in a certain area
- The prevalence of cellphone makes it easier to collect personal GPS data (many apps ask for access to your location when you're using it)
- Decide to make use of the GPS data for predictions
- Due to the privacy concerns, I would start with my personal GPS data

#### **Problem Statement -- Goal**

- Based my historical GPS data with time (longitude, latitude, and time when I'm at the location), build a machine learning model that will predict my future movements (trajectories).
- Assess how the model can be improved in order to apply to a dataset with a large number of agents.

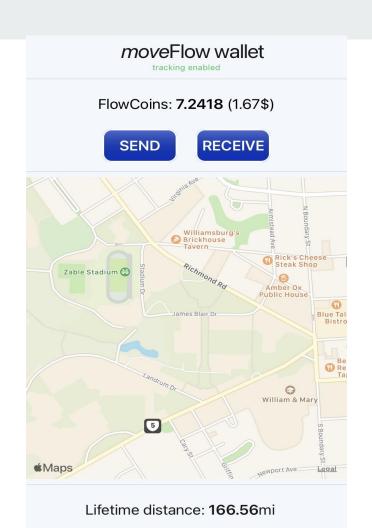
## **Problem Statement -- Significance**

- At individual level, getting people's trajectory enables us to create personalized recommendations for that individual.
  - o if we predict that a person will travel from suburban area to city center, then we can advertise apartments for lease.
- At group level, the ability to predict people's future trajectory is even more significant.
  - Urban planning: building a new shopping mall based on where people frequently go
  - Public health: predict the spread of a disease

**Central Question:** 

How to predict my future movement trajectory based on my movement records?

- The Moveflow App developed by Mr.
   Gregor Laemmel and Dr. Tyler Frazier.
- Collect the user's location data while giving user flowcoins (a cryptocurrency) back as reimbursement
- Receive the data compiled by Mr. Gregor in two files, one gpx file, one jsonl file.



**GPX file**: contains 4

columns: longitude,

latitude, altitude and time

stamp.

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```

**Jsonl file:** contains 3 more columns: speed, activity and course.

```
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```

Although the jsonl file contains information that might be useful in the future (activity), I decide to use the gpx file since it's time format is more readable and can be fit into the model

gpx file time format:

<time>2021-05-12T20:17:25.554570Z</time>

jsonl file time format:

"time\_stamp": 1620851171.640408

Eventually, I retrieve a pandas dataframe from the gpx file, the size of which is 5008 rows by 3 columns. The three columns are: X for longitude, Y for latitude, and time.

	x	Υ	time
0	-76.720370	37.294231	2021/05/12 20:17:25
1	-76.720343	37.294192	2021/05/12 20:20:39
2	-76.720327	37.294208	2021/05/12 20:26:02
3	-76.720327	37.294208	2021/05/12 20:26:11
4	-76.719192	37.292013	2021/05/12 20:27:05
			100
5003	-76.720338	37.294193	2021/05/14 21:57:33
5004	-76.720332	37.294189	2021/05/14 22:24:08
5005	-76.720333	37.294195	2021/05/14 22:24:12
5006	-76.720327	37.294192	2021/05/14 22:24:14
5007	-76.719268	37.292129	2021/05/14 22:32:10

5008 rows x 3 columns

## Model and Results -- Model Description

We use the **scikit-mobility** package in Python. This package is able to

- Process mobility data of various forms, including GPS data
- Extract mobility metrics and patterns from data
- Generate synthetic individual trajectories and move flows

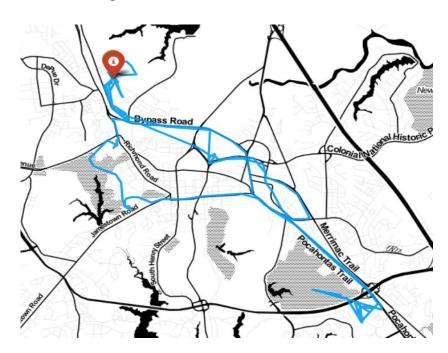
The majority of the codes used to generate the model come from the scikit-mobility github repository.

# Model and Results-- Trajectory Data Frame

```
import skmob

# Create a TrajDataFrame
tdf = skmob.TrajDataFrame(track_points)
tdf.columns = ['lng','lat','datetime']
tdf['uid'] = 1
tdf

tdf.plot_trajectory(zoom=12, weight=3,
opacity=0.9, tiles='Stamen Toner')
```



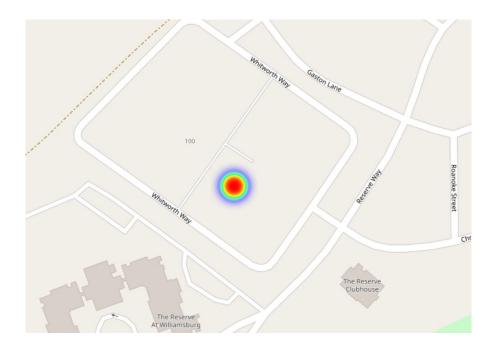
# **Model and Results -- Estimating Stops**

```
from skmob.preprocessing import filtering
ftdf = filtering. filter(tdf,
max speed kmh = 500.)
n deleted points = len(tdf) - len(ftdf)
from skmob.preprocessing import detection
stdf = detection.stops(tdf,
stop radius factor= 0.5,
minutes_for_a_stop= 20.0, spatial_radius_km= 0.2,
leaving time=True)
m = stdf.plot trajectory(max users= 1,
start end markers=False)
stdf.plot_stops(max_users= 1, map_f=m)
```



# **Model and Results-- Estimating Home**

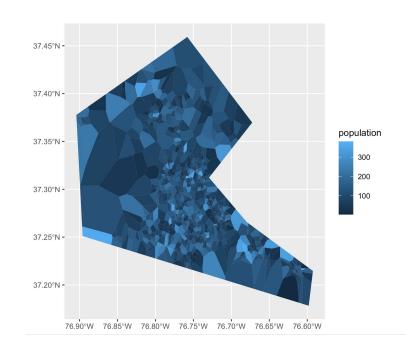
```
from skmob.measures.individual import
jump lengths, radius of gyration,
home location
rg df = radius of gyration(tdf)
jl df =
jump_lengths(tdf.sort_values(by= 'datetime'))
hl df = home location(tdf)
import folium
from folium.plugins import HeatMap
m = folium.Map(tiles = 'openstreetmap',
zoom start=12, control scale= True)
HeatMap(hl_df[[ 'lat',
'lng']].values).add to(m)
```



#### Model and Results -- Individual Generative Model

We have the basic models that predicts the stops and home location based on my historical GPS data. The next step is to generate agents based on the data and predict their trajectories in a certain time interval. To Achieve that ,we first need a tessellation -- an object that marks the subdivisions of a certain area, and in my case, James City County.

With the help of Dr. Frazier, I retrieve the shapefiles for James City.



#### Model and Results -- Individual Generative Model

```
from skmob.models.epr import DensityEPR
tessellation =
gpd.read file('jamescity.shp')
start time = pd.to datetime( '2021/05/19
09:00:00')
end_time = pd.to_datetime( '2021/05/23
23:00:00')
depr = DensityEPR()
tdf = depr.generate(start time,
end time, tessellation,
relevance column= 'population',
n agents=20)
tdf.plot trajectory(zoom= 12, weight= 3,
opacity=0.9, tiles='Stamen Toner')
```



## **Moving Forward -- Individual Generative Model**

However, the individual generative model created before is solely based on the James City tessellation, and it does not incorporate my personal mobility records.

Therefore, the following step for me is to find another function that incorporates my records into the data. So it will predict based on my records

#### Moving Forward -- Collective Generative Model

After finished at the individual level, I would consider moving to forward to collective generative models, such as the Gravity model or the Radiation models. These models can predict the trajectories of a large number of agents and estimate their movements within a certain area.

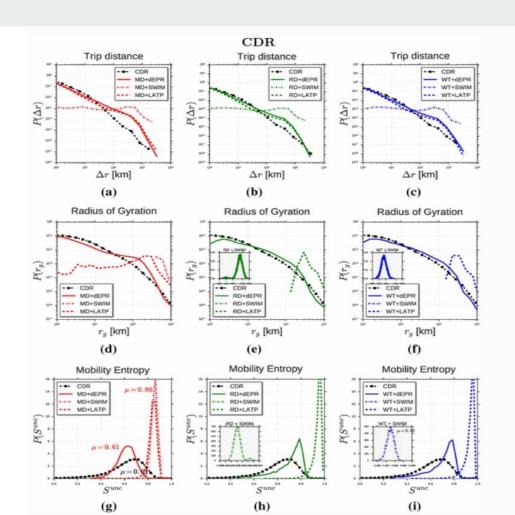
However, to run such models, not only do I need data from more agents, but I also need to convert their location data to flow data. Instead of long and lat, we need origin and destination.

## **Moving Forward -- Alternative Approach**

- Diary-Based Trajectory Generator from the article Data-driven generation of spatio-temporal routines in human mobility
  - Generate a mobility diary (contains long, lat, time stamp) using MD, a
     Markov model that captures routines and out-of-routine behaviors
  - Pass the diary to a trajectory generator, d-EPR, consider new locations and visited locations, as well as urban structures and population density

## Moving Forward -- Desired Result

- Map objects generated from the model
- Validation methods
  - Trip distance
  - Radius of gy
  - Entropy
- Real data source
  - o CDR
  - o GPS



#### References

- Pappalardo, L., Simini, F. Data-driven generation of spatio-temporal routines in human mobility. *Data Min Knowl Disc* 32, 787–829 (2018).
  - https://doi.org/10.1007/s10618-017-0548-4
- Scikit-mobility repository.
  - https://github.com/scikit-mobility/scikit-mobility#collaborate

# Thanks for watching