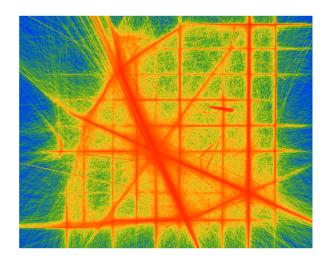


## New opportunities through big mobility data analytics



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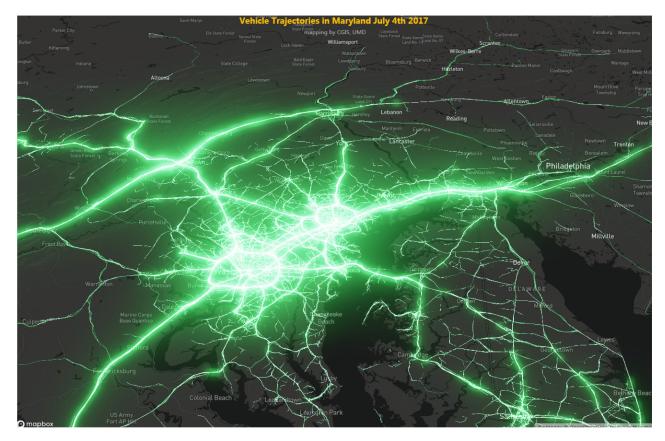
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Location Powers: Data Science Summit, November 13, 2019



### The opportunities: Vehicle travel patterns

50,282 trips for the 4th of July, 2015



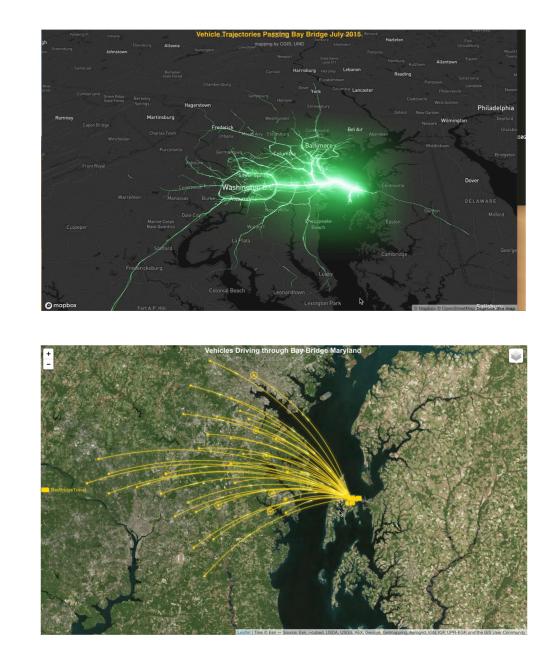




Especially useful for critical or significant locations such as a key bridge at a key time (July 4<sup>th</sup>...)

Exposes different travel patterns over space and time

These 2 visualization tell different stories...





# Space-time patterns are important...

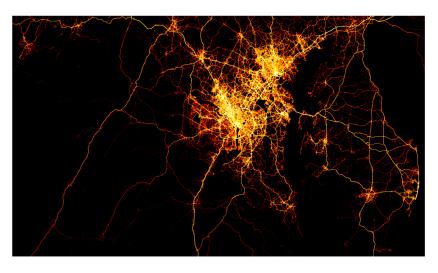
Data that give rise to such patterns are available from different data sources... GPS waypoint data, cell phone data, location-based app data, as well as other sensors (fitness trackers).....

Here we see **big trajectory data** (GPS waypoints transformed into trajectories) useful for highlighting travel behaviors of different groups

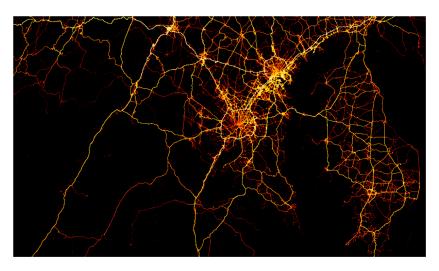
We want to expose different dynamic behaviors over space and time

Important for:

- understanding urban/rural differences
- risk exposure
- Evacuation
- Multi-scale



Passenger vehicle trajectories, Maryland, 2015



Truck fleet trajectories GPS data from in-vehicle sensors, Maryland, 2015 100 million waypoints, 5 million trajectories



# However, big GPS trajectory data comes with its own challenges...

- Hundreds of millions of GPS trajectory data have to be matched back to the underlying road network in order to determine the traffic volume pattern on different segments of the road network
- Irregular GPS sampling intervals and gaps exist for vehicles travelling on the road network derived perhaps from the fixed sampling intervals that can vary between devices

b4ba00bd9748981fc74c19afe5bacfc0,0,2015-06-0110:53:00	000Z,40.1307,-77.0202,,
b4ba00bd9748981fc74c19afe5bacfc0,1,2015-06-0110:56:00	000Z,40.1172,-77.0374,,
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b4ba00bd9748981fc74c19afe5bacfc0,3,2015-06-01 11:01:12	000Z,40.0731,-77.0555,,
b4ba00bd9748981fc74c19afe5bacfc0,4,2015-06-0111:06:00	000Z,40.0111,-77.1013,,
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b4ba00bd9748981fc74c19afe5bacfc0,9,2015-06-0111:29:04	000Z,39.7181,-77.3079,,



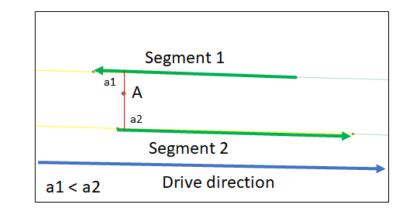
### **Requires trajectory reconstruction algorithms**

#### Snap way-points of a trip to road segments

- Find the K-nearest neighbors (k=10, and distance within 100 meters) as the candidates
- Select the candidate with largest cosine

#### Fill segment gaps by heuristic algorithms

- Due to large time interval between two waypoints (1~2mins or longer), intermediate segments may be missing
- Use road network topology
- Need to use a [shortest path] algorithm to fill the gaps between two segments
  - This assumes that drivers take the shortest path between the two recorded waypoints...



Due to the uncertainty of GPS positioning, we cannot always employ the nearest segment to snap the waypoint

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# Mobility data now comes from numerous different data sources....



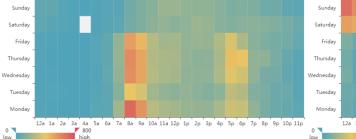
Cell phone data – ~23,775 sample points, ~14,000 devices

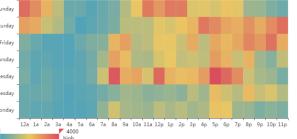


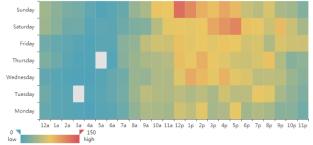
LBS data – ~240,000 sample points from ~7,300 devices



Geo-tagged tweets – ~7,000 sample points from ~2,600 individuals, 2017



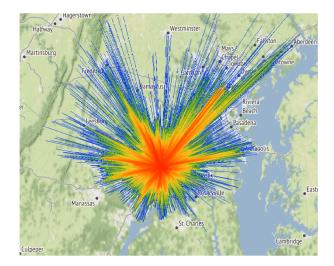




### Dupont Circle, Washington, DC

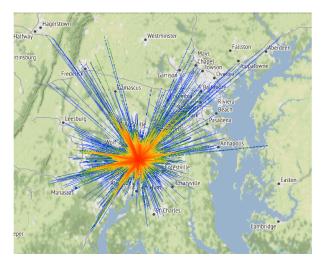


#### Trips originating from Dupont Circle (origin-destination analysis)



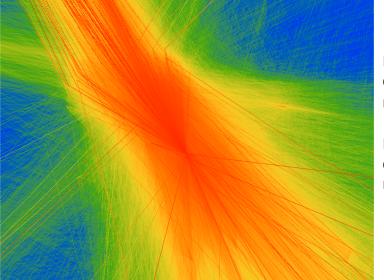
Cell phone data trips

More than 2,400,000 individuals



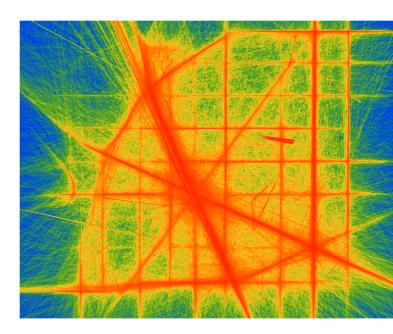
LBS data trips

More than 300,000 individuals



Median trip duration 28 mins

Median trip distance 1.8 mile

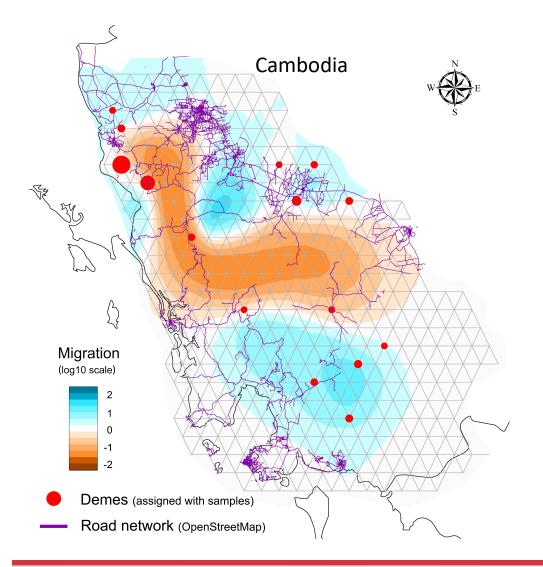


Median trip duration 2 mins

Median trip distance 0.2 mile



### Other new sources of data, e.g., genomic data also bring important opportunities to understanding mobility in new ways



## Malaria elimination in the Greater Mekong Subregion

Use big data techniques to simulate and estimate patterns of **parasite gene flow** with a **human mobility travel network** 

Y. Li



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