



THE UNIVERSITY OF TEXAS AT DALLAS

# Driving pattern analysis of Emergency Vehicle (EV)

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# Background Introduction

➤ Response time?



- Successful Incident  
As long as one EV arrives within eight minutes.
- Unsuccessful Incident  
All dispatched EVs fail to arrive within eight minutes.

Research Purpose: What causes the delay of emergency vehicles

## Data

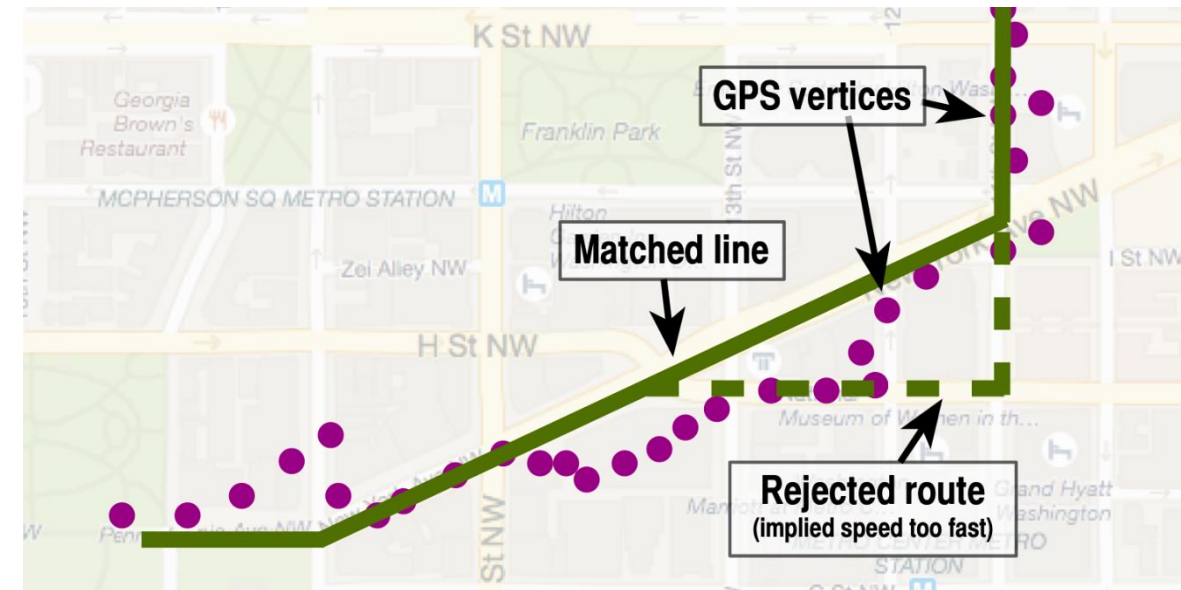
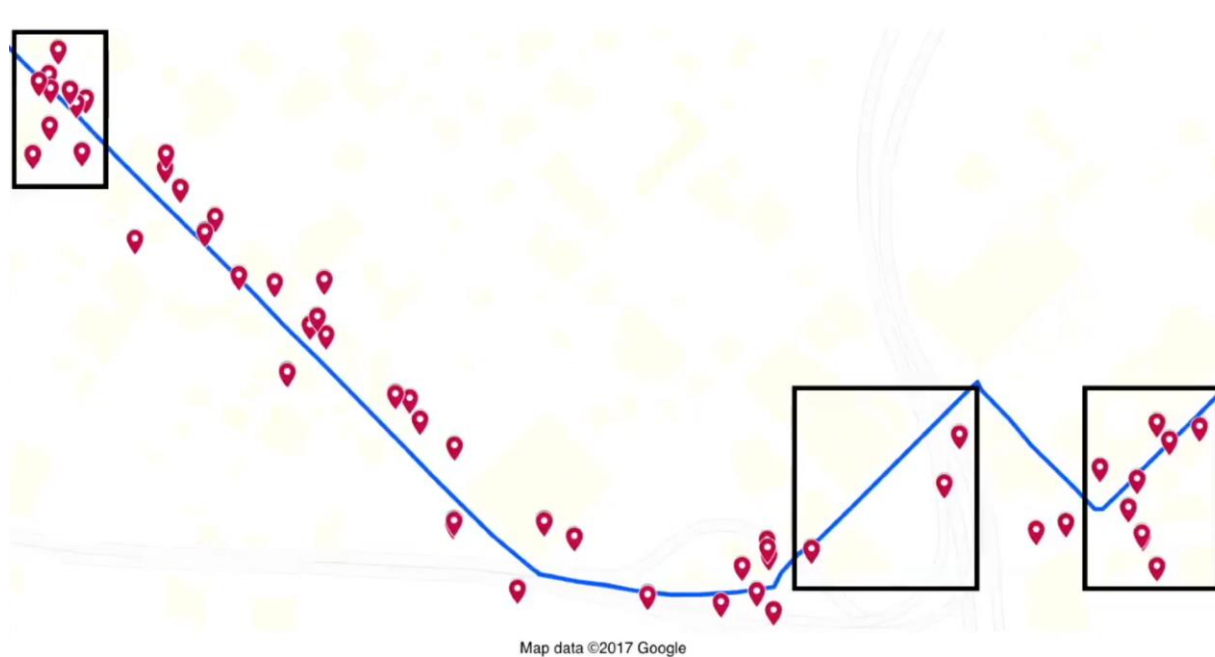
- From October 2015 to November 2017
- 2,325,360 GPS Records From Emergency Vehicles
- 887,825 Emergency Runs.
- 532,653 Incidents.

### Research Question:

1. What information we can get from these records?
2. How can we achieve a better response strategy?

## Step1: Restore trajectories from GPS records (Map-Matching)

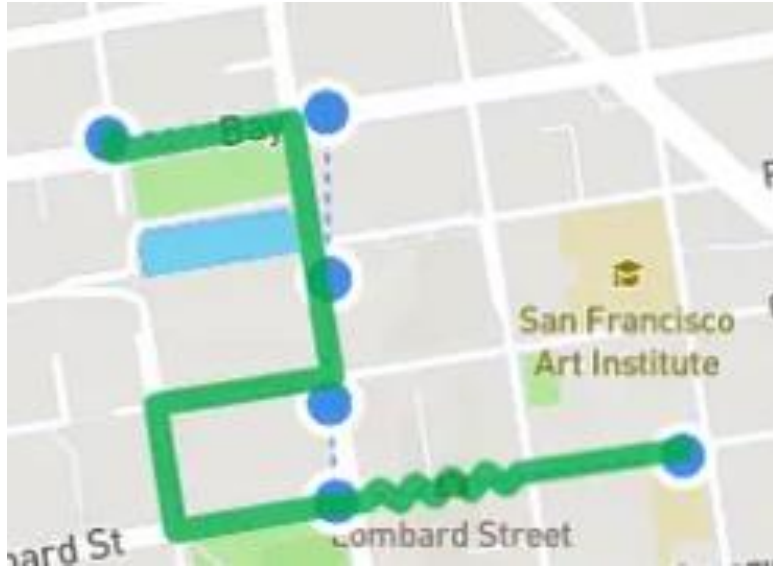
- Given a sequence of GPS signals, find the most probable sequence of road segments
  - Noise (Random effects)
  - Sparseness (Signal of Cross Positioning)
  - Physical Constrain (Speed / Road Property, etc.)



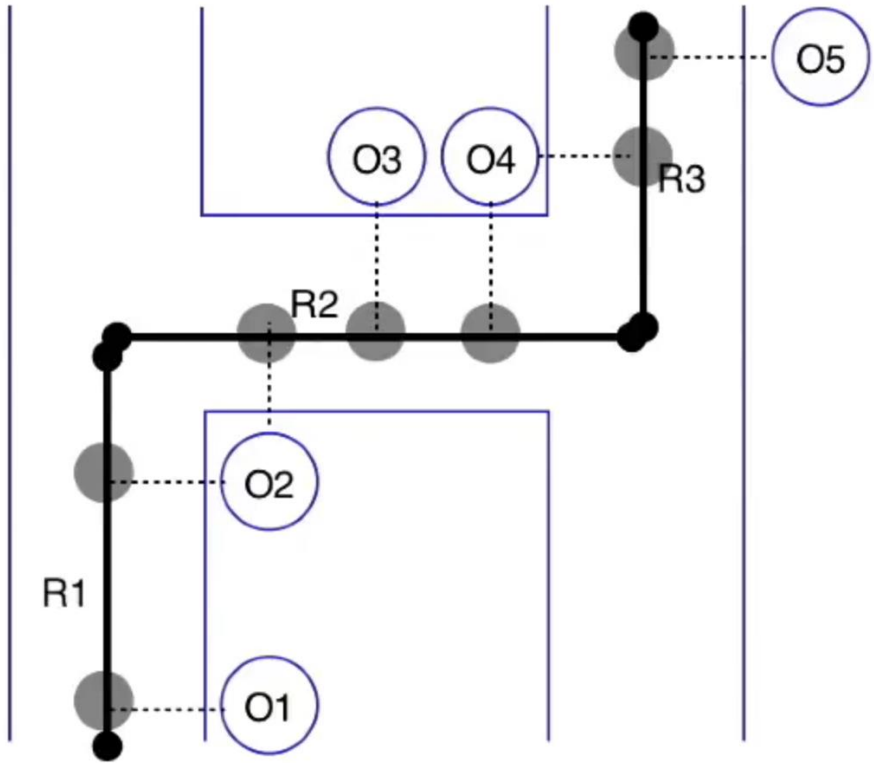
Naïve way:

1. Snap(Project) GPS Points to the closest road with a distance threshold

1. Wired Path generated on a nested road network

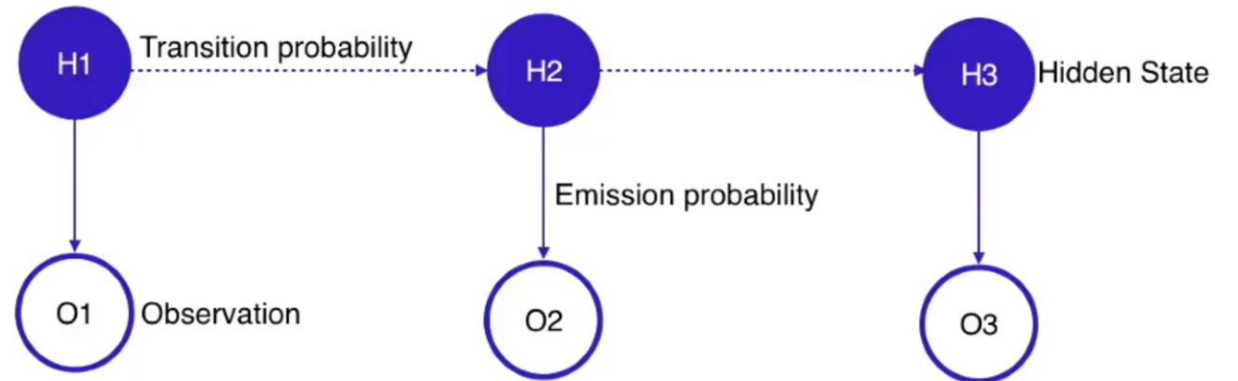


# Map-Matching using the Hidden Markov Model (Presented by Uber, 2017)



## Hidden Markov Models (HMM)

- Markov process + unobservable state
- Observations, which depend only on the current state, are visible



Observe States: GPS points

Hidden States: Points on Roads (Projected Points)

Emission Probability

Gaussian distribution of distance

$z_t$ : GPS signal

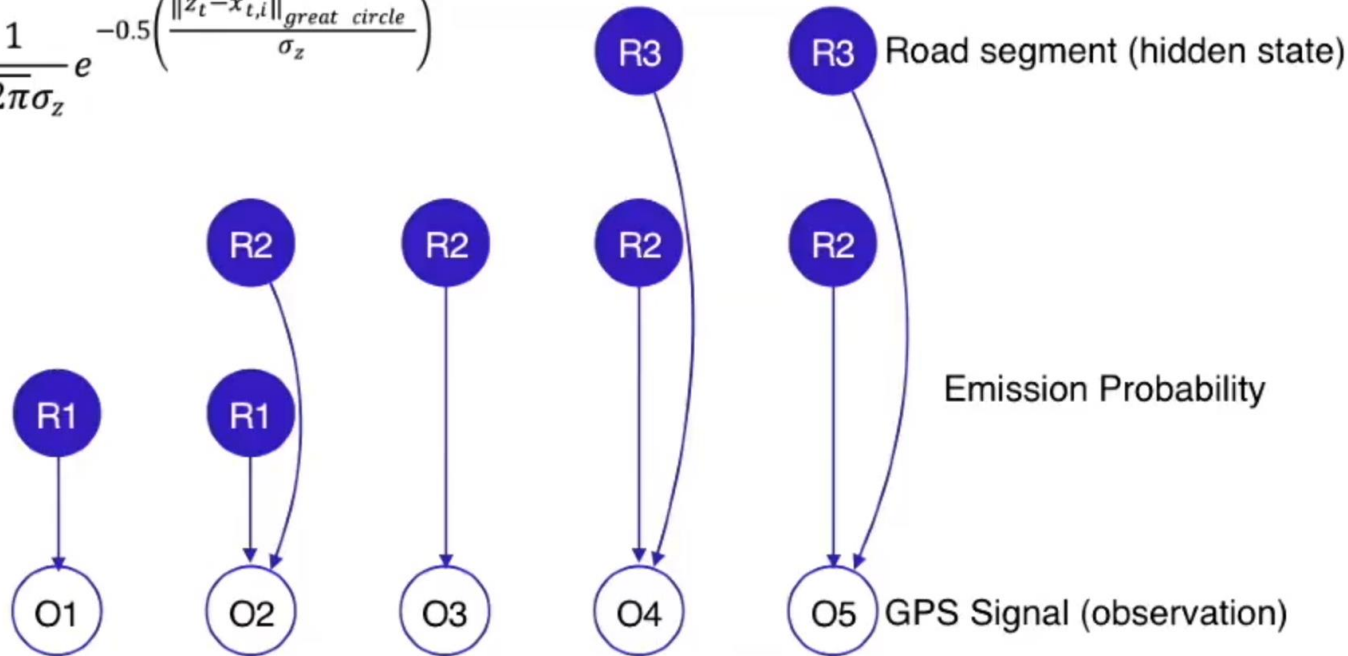
$x_t$ : projected point on the road

Only consider within 200 meters

$$\sigma_z = 1.4826 \operatorname{median}_t \left( \|z_t - x_{t,i^*}\|_{\text{great circle}} \right) \quad (5)$$

For our test data, this value was  $\sigma_z = 4.07$  meters, which is a reasonable value for GPS noise.

$$p(z_t | r_i) = \frac{1}{\sqrt{2\pi}\sigma_z} e^{-0.5 \left( \frac{\|z_t - x_{t,i}\|_{\text{great circle}}}{\sigma_z} \right)^2}$$



# Transition Probability

Inverse Exponential distribution of distance difference of two consecutive points

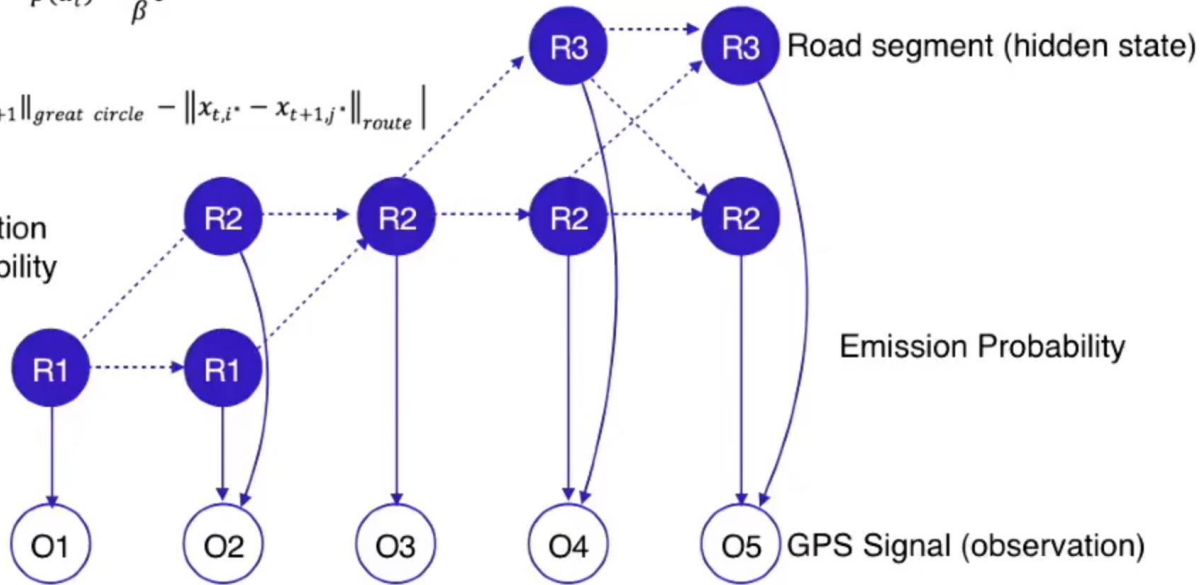
$$p(d_t) = \frac{1}{\beta} e^{-d_t/\beta}$$

Here

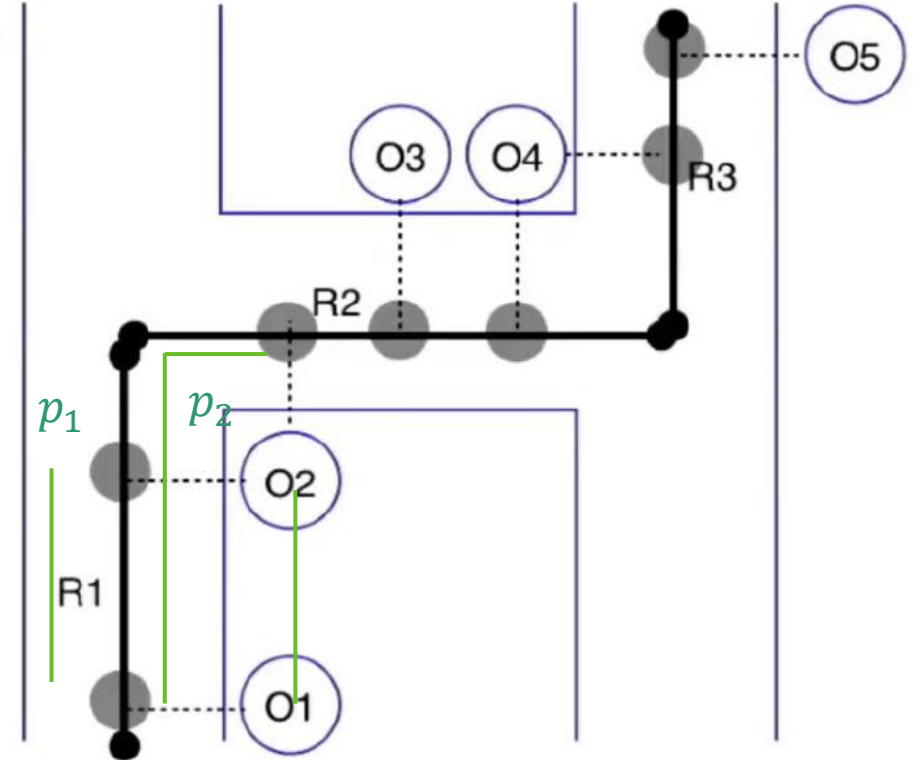
$$d_t = \left| \|z_t - z_{t+1}\|_{great\ circle} - \|x_{t,i^*} - x_{t+1,j^*}\|_{route} \right|$$

Transition Probability

Emission Probability



$$\beta = \frac{1}{\ln(2)} \text{median}_t \left( \left| \|z_t - z_{t+1}\|_{great\ circle} - \|x_{t,i^*} - x_{t+1,j^*}\|_{route} \right| \right)$$





# Implement

## Snap

```
# Find the road segment with the closest point
closest_road_idx = np.argmin([shortest_distance, ...])

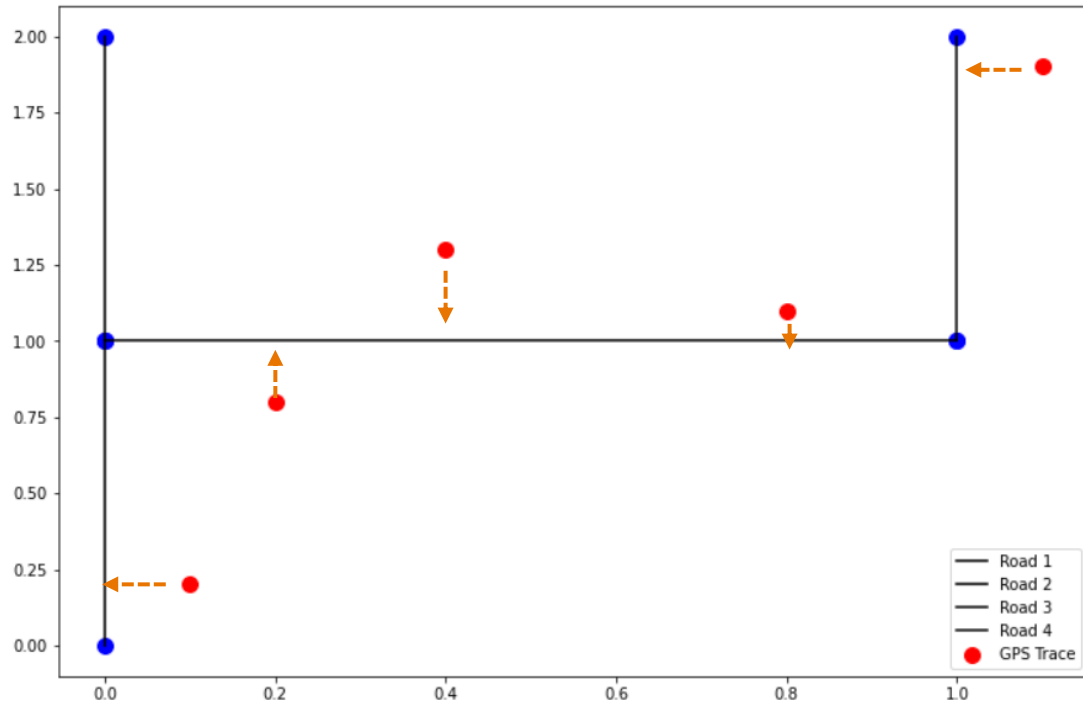
# Add the closest road segment to the path
path.append(closest_road_idx)

return path

# Run map matching algorithm
path = map_matching_close_distance(gps_trace, [road1, ...])

# Print the path
print("Most likely path: ", path)
```

Most likely path: [0, 1, 1, 1, 3]



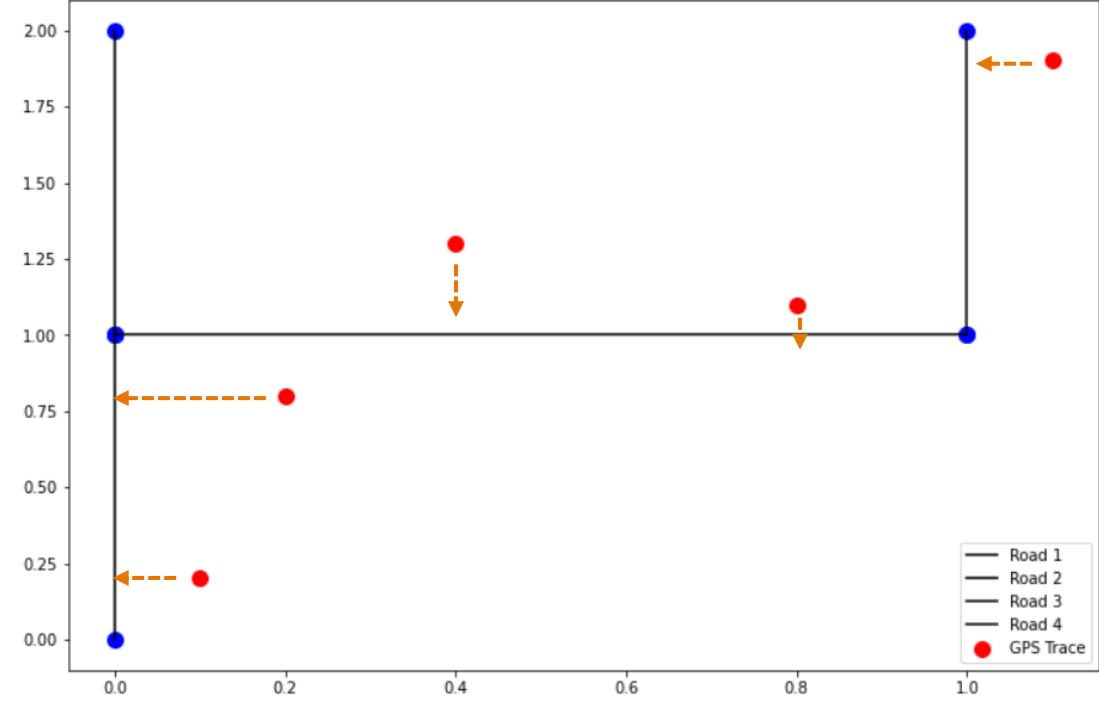
## HMM

```
for j in range(4):
    temp = np.zeros(4)
    for k in range(4):
        temp[k] = viterbi_mat[i-1,k] * trans_mat[i-1,k,j]
    viterbi_mat[i,j] = np.max(temp)
    backpointers[i-1,j] = np.argmax(temp)

# Find most likely sequence of hidden states
path = [np.argmax(viterbi_mat[-1])]
for i in range(len(gps_trace)-2, -1, -1):
    path.append(backpointers[i, path[-1]])
path.reverse()

# Print results
print("Most likely sequence of road segments: ", path)
```

Most likely sequence of road segments: [0, 0, 1, 1, 3]



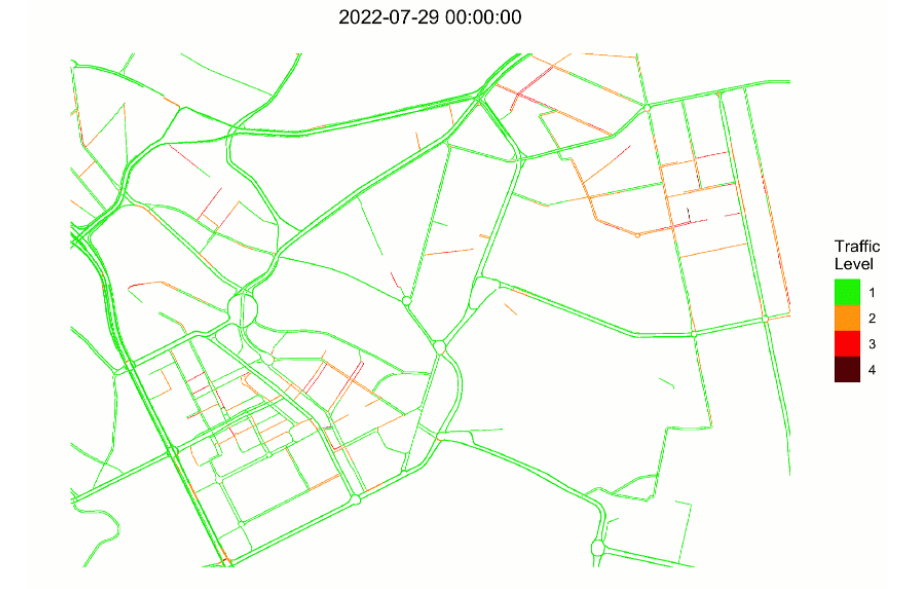


Still have breaks



## Future Work

1. Fix the break problem to restore the true path
2. Find the shortest distance path and shortest driving time path from  $s \rightarrow t$
3. Propose an index to measure the difference between the True path and the suggested path  
(shortest driving time path), figure out the reason behind it



# Thank you! Questions?



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