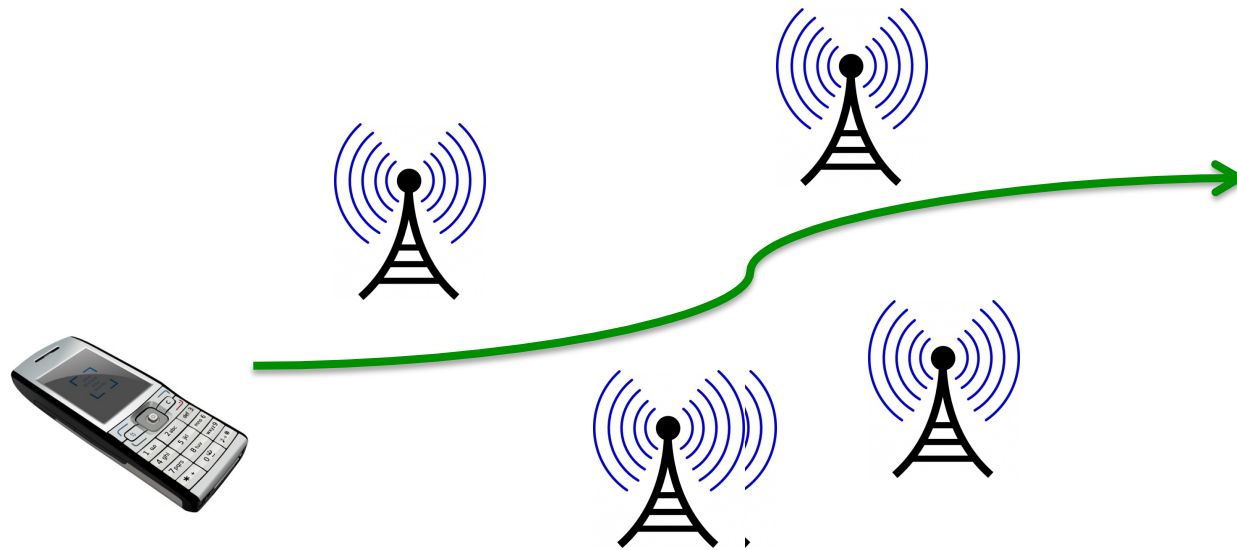


# Accurate, Low Energy Trajectory Mapping For Mobile Phones

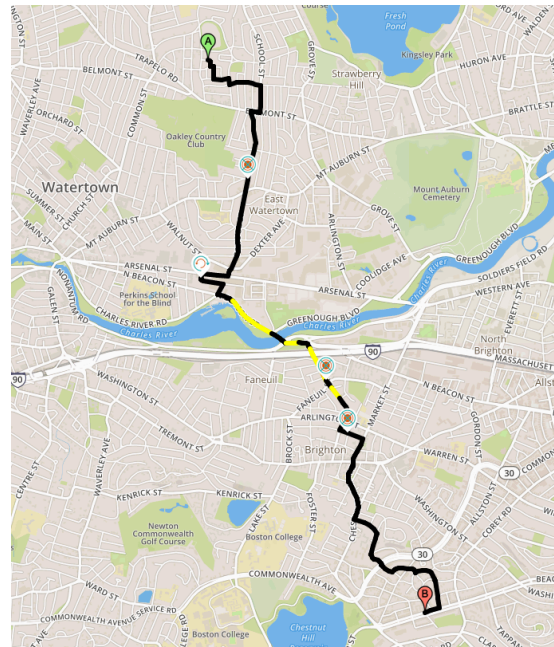


Arvind Thiagarajan, Lenin Ravindranath,  
Hari Balakrishnan, Sam Madden, Lewis Girod

MIT CSAIL

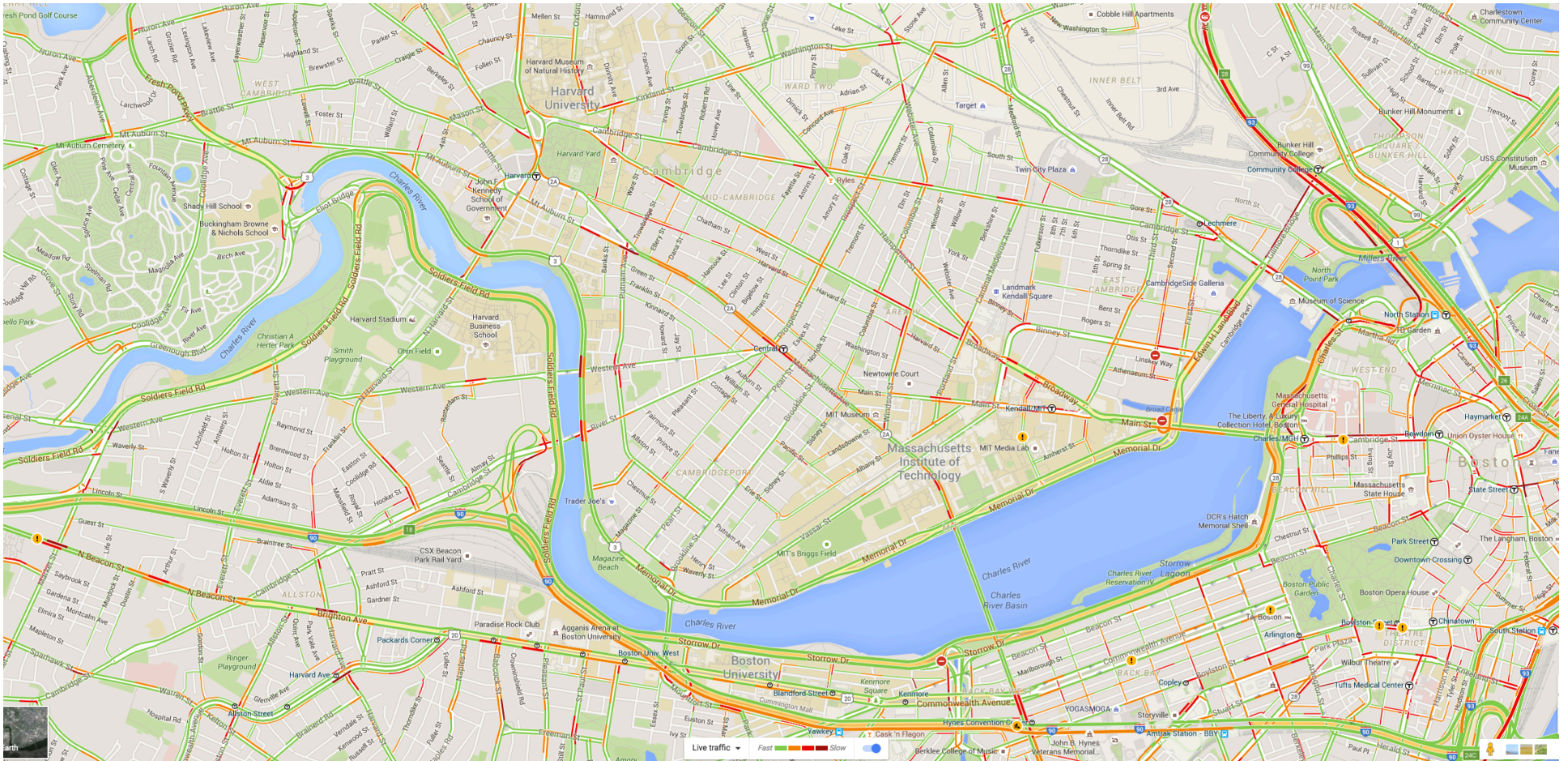
# Goal

- Find the *trajectory* i.e. *sequence of locations* visited by a mobile device



- Applications need to find path both *accurately* and *energy-efficiently*

# Traffic Estimation



# Crowdsourced Traffic Monitoring

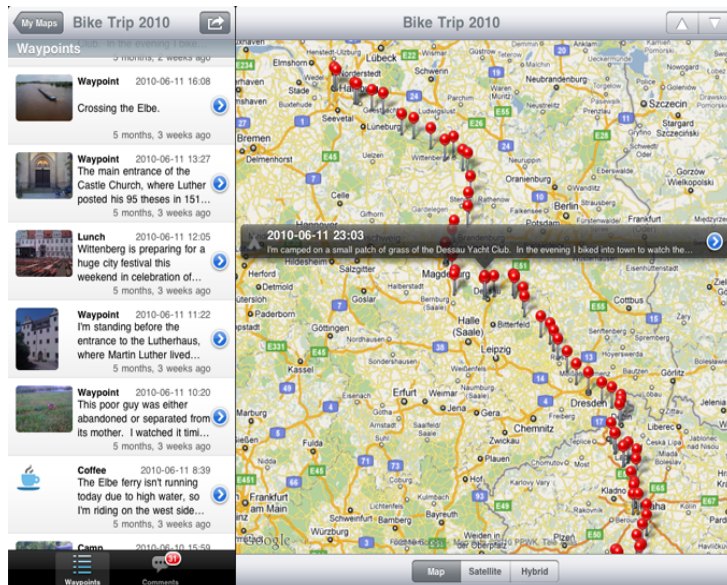


**Battery dies in ~6 hours if monitoring with GPS**

# Bike Routes

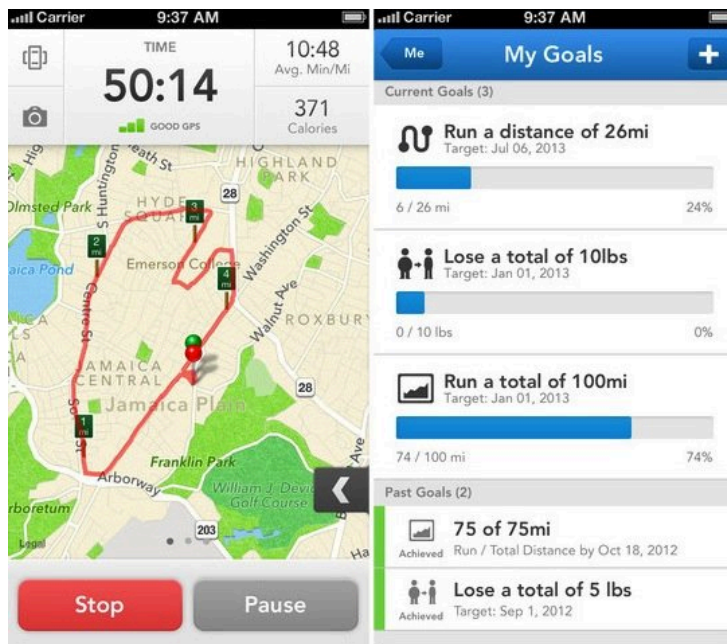


<http://www.jonathanokeeffe.com/strava/multi-ride-mapper/>



## TrackMyTour

Allows users to keep track of their trips and annotate them

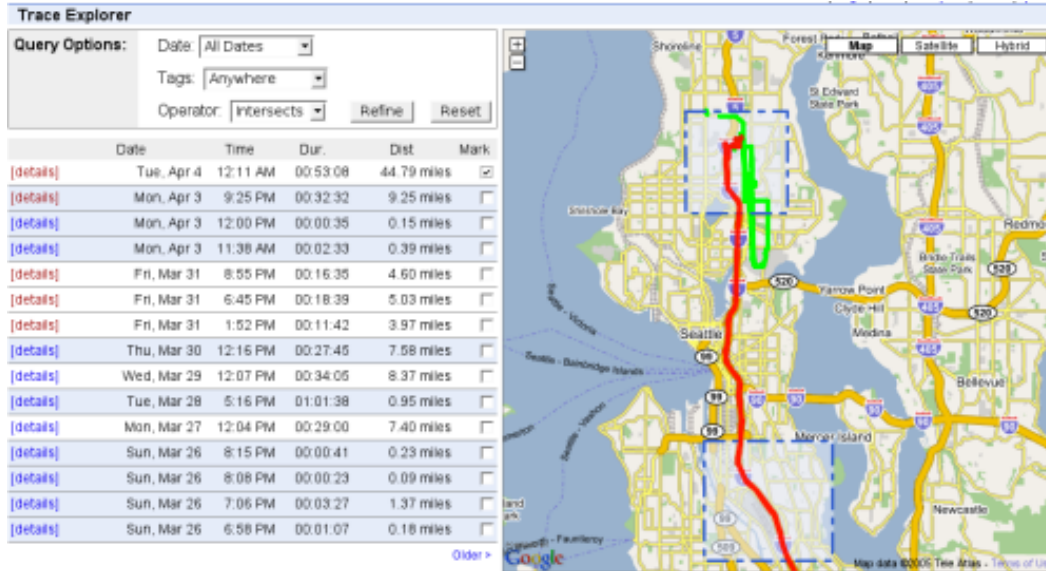
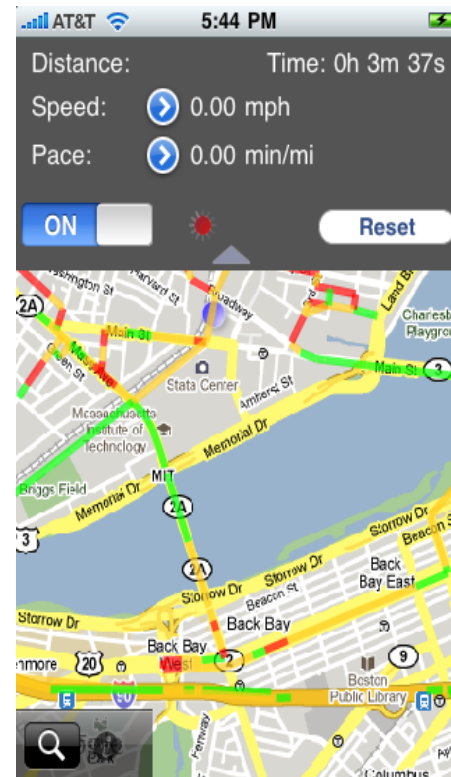
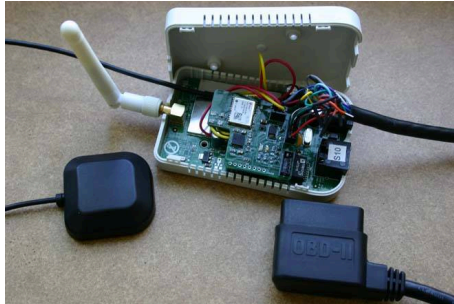


## Running

# Trash Track



# Context: CarTel Project

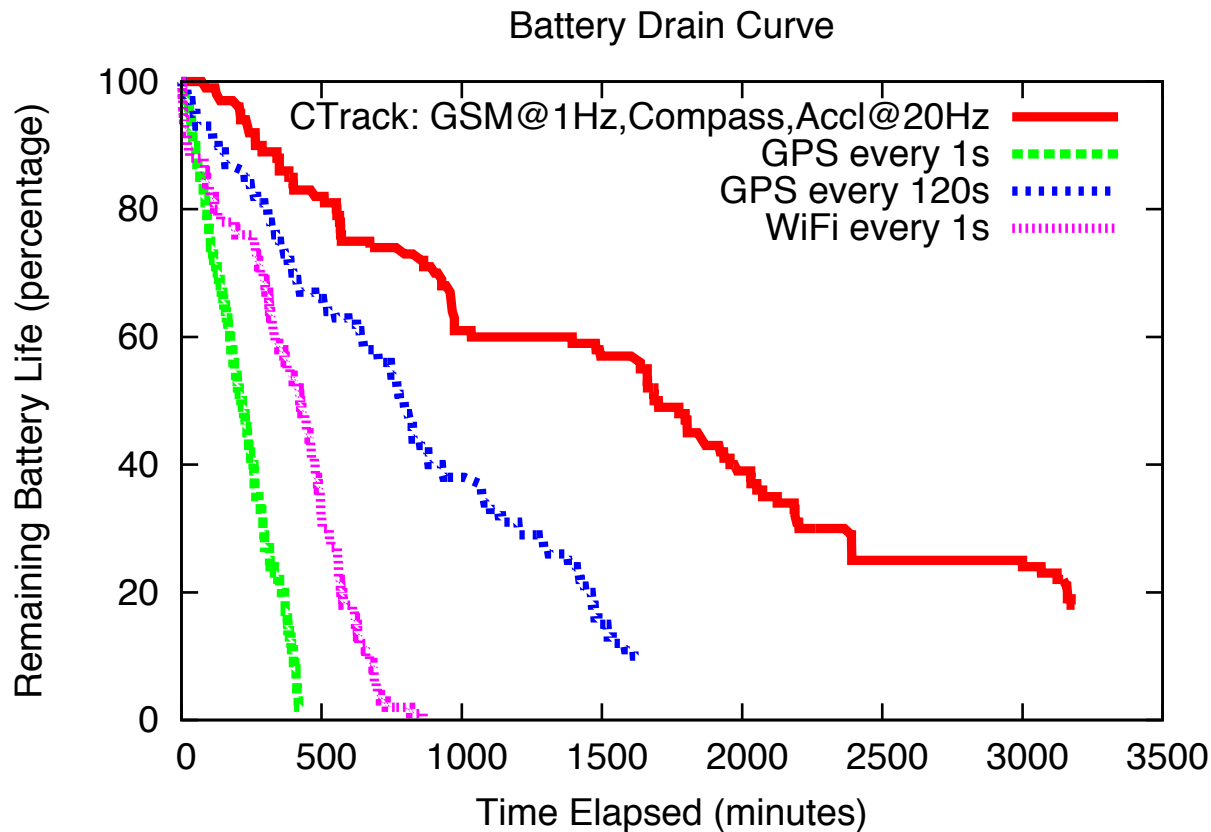


Crowdsource tracks to estimate traffic on road segments



# Limitation of GPS: Energy

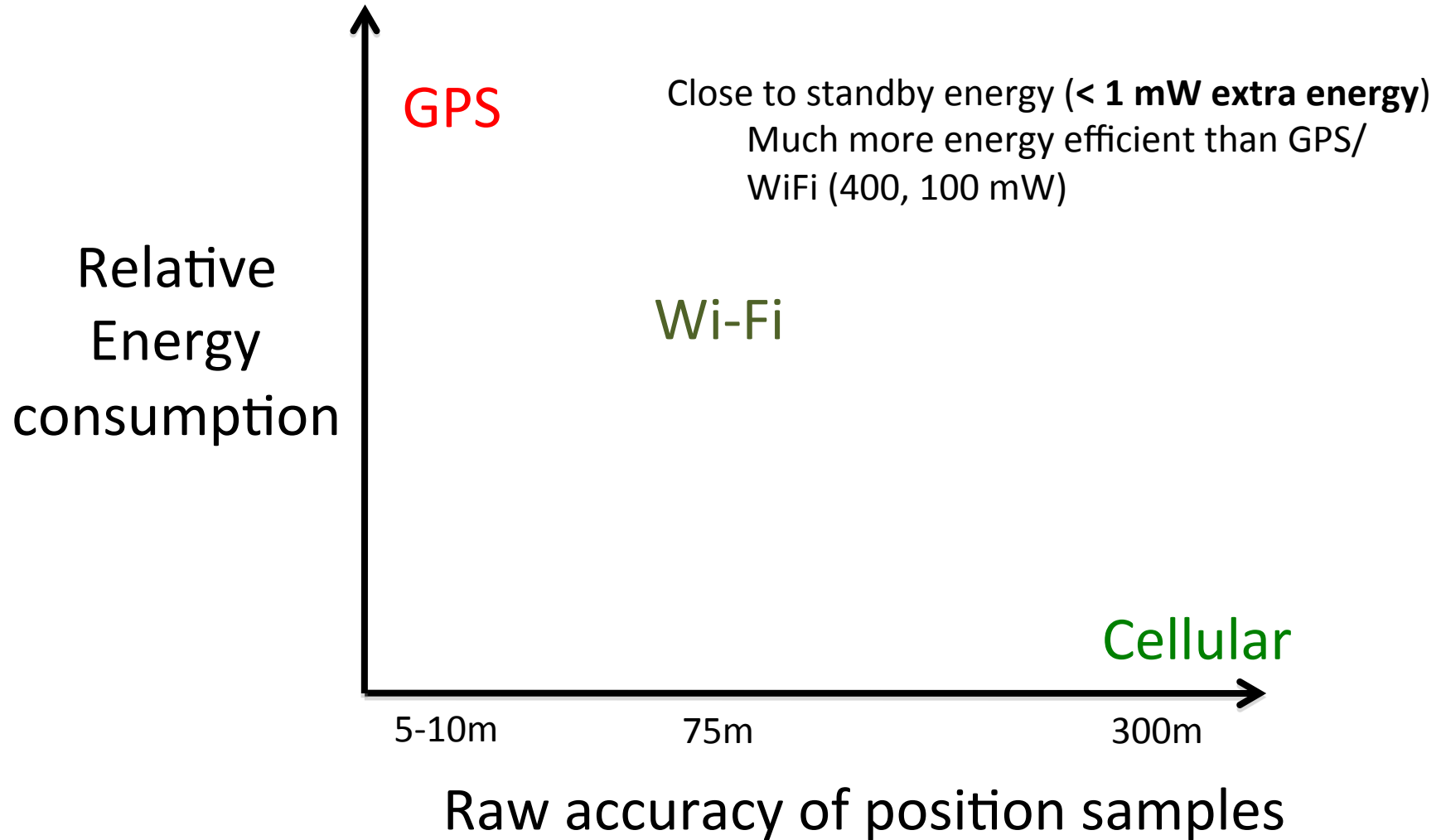
- GPS signals are energy-intensive to acquire & process
- Frequent GPS sampling drains battery fast
- This data is from 2010-11, but the same trends persist today



6 hrs on iPhone 3GS  
vs 18 hrs w/o GPS  
(dim screen)

Android G1 phone: 6-8 hours with 1 Hz GPS

# Approach: Use low-power sensors

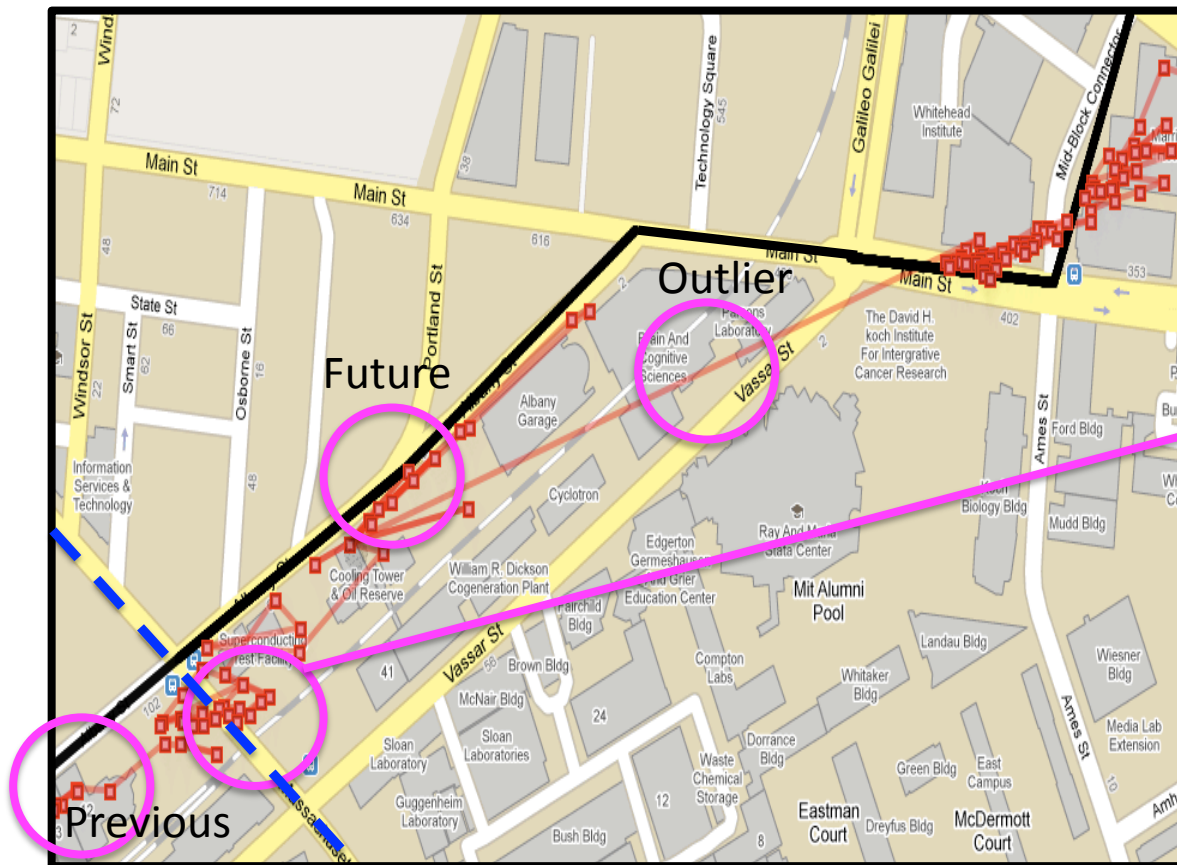


# Outline

- Prior work
  - Intermittent GPS (Microsoft Krumm et al.)
  - Vtrack – uses Wi-Fi data – from same group that did the Ctrack work (CarTel project)
- CTrack paper
  - Cellular fingerprints
  - Better energy
  - Accuracy?

# Background: Vtrack Algorithm

## Noisy Data (Wi-Fi example)

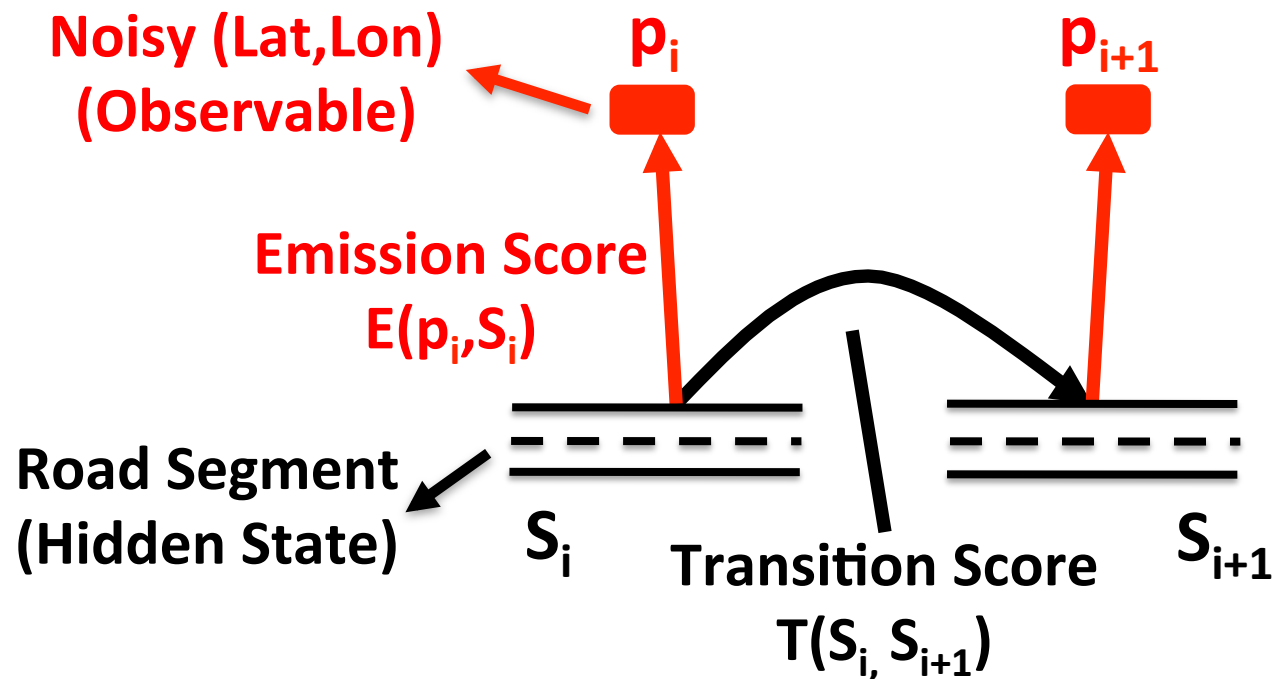


The closest road to a position sample is **not** where it originally came from

- Exploit both previous and future location information
- Don't overly weight *any one* location sample
- Find a *continuous (unbroken) sequence* of roads

# Solution: Hidden Markov Model

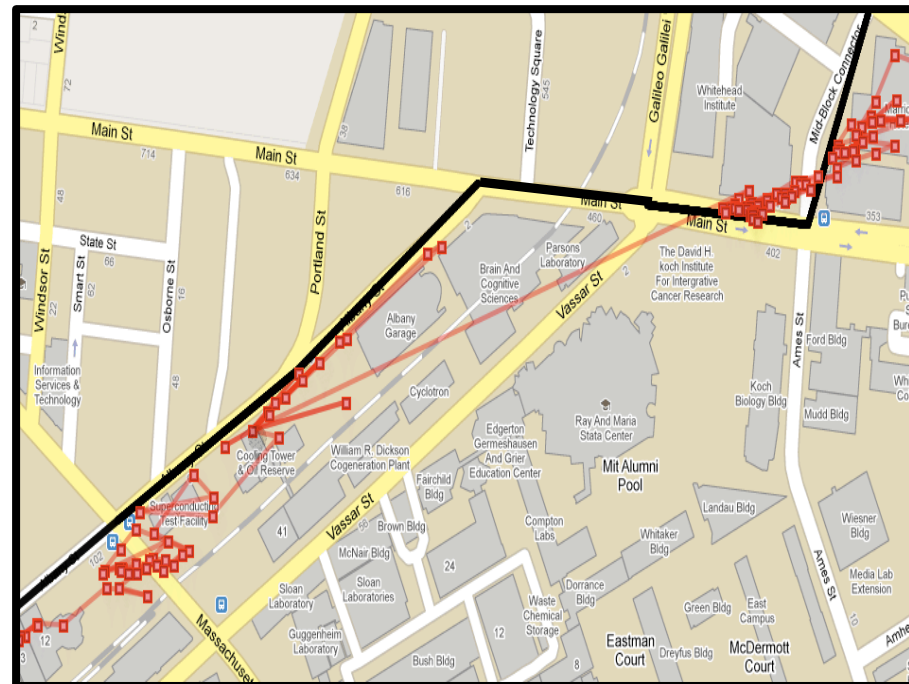
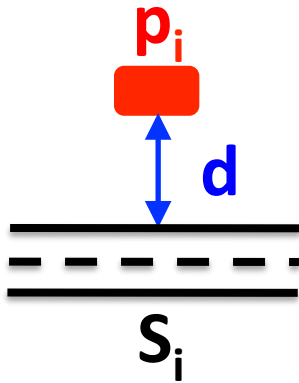
- Maps noisy observations (coordinates) to hidden states (underlying road segments)



Dynamic Program Finds Best State Sequence (cf. Viterbi)  
"Best" => Max Product of Emission and Transition Scores

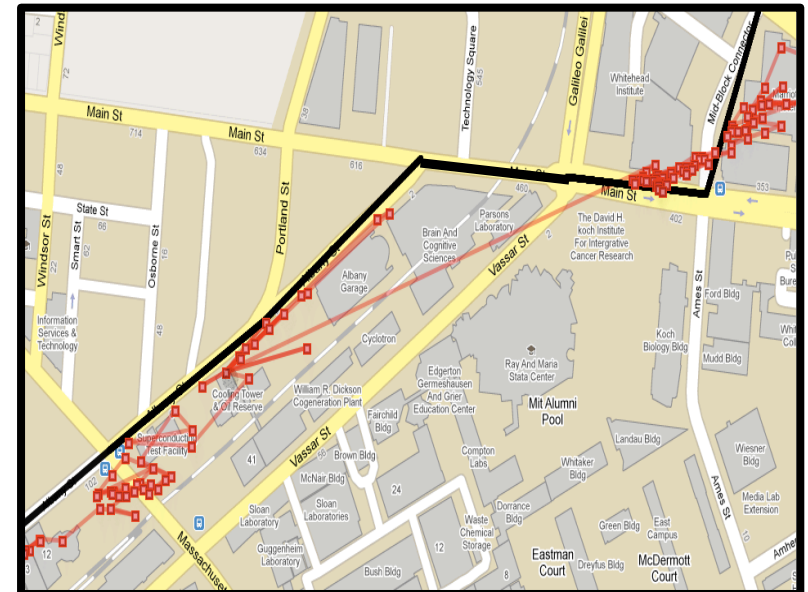
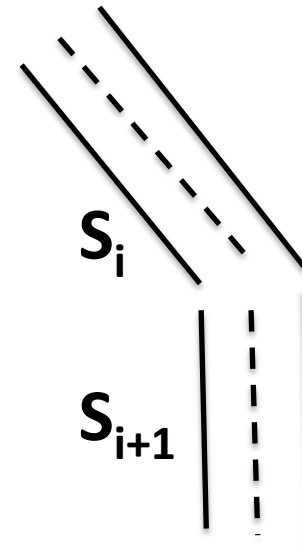
# Emission Score

- Emission Score  $E(p_i, S_i) = e^{-d^2/\sigma^2_{\text{sensor}}}$ 
  - Intuition: pts closer to a segment are more likely to come from it
  - $\sigma_{\text{sensor}}$  depends on GPS/WiFi/Cellular

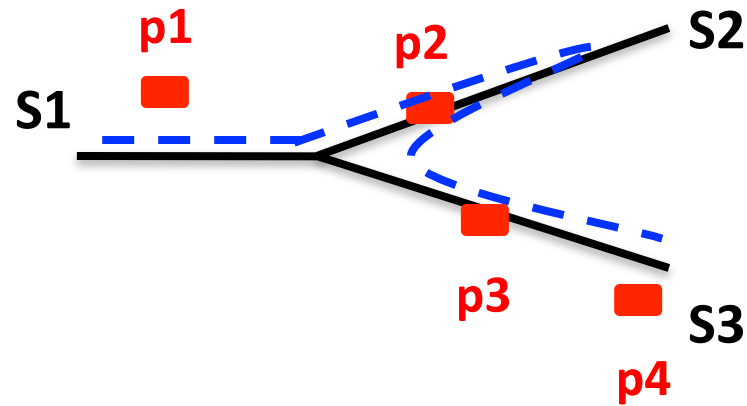


# Transition Score

- Transition Score  $T(S_i, S_{i+1})$ 
  - 0 if segments are not adjacent or not enough time has been spent on  $S_i$
  - 1 if segments are adjacent and enough time has been spent on  $S_i$
- Speed constraint is essential: because algorithm jumps around and follows noise in the input data without it
  - Decreases error significantly

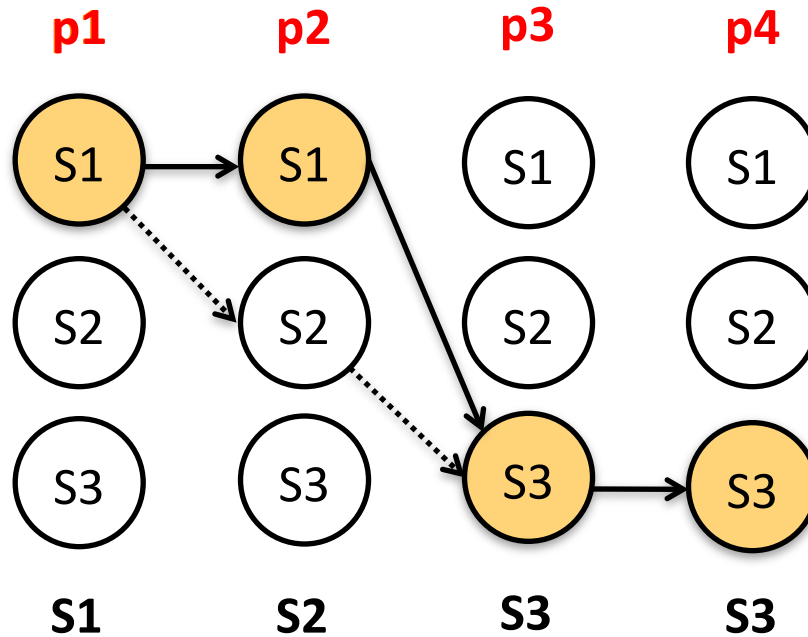


# VTrack In Action



**S1 S1 S3 S3** is  
most likely match

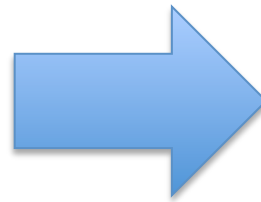
S1 S2 S3 S3 has  
score 0, isn't  
permitted  
(speed constraint)





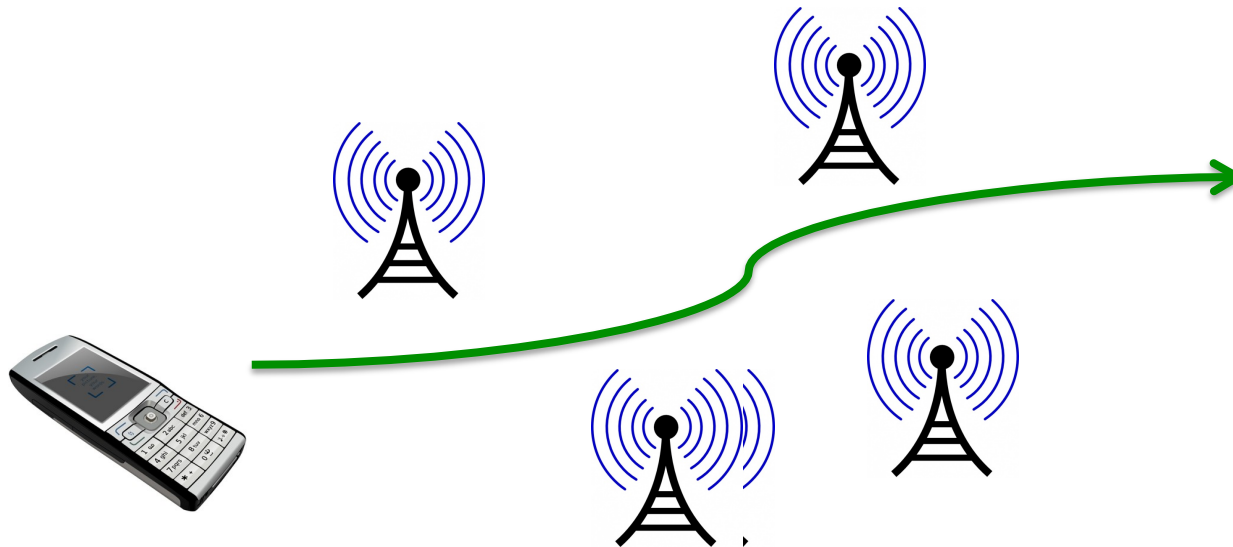
# Handling Gaps: Interpolation

- VTrack's HMM maps input to output samples one-to-one
- We need frequent (1 Hz) input because we want output to be continuous (so we can enforce adjacency constraint)
- Interpolate gaps, *then* run HMM (linear interpolation)



# CTrack Problem Statement

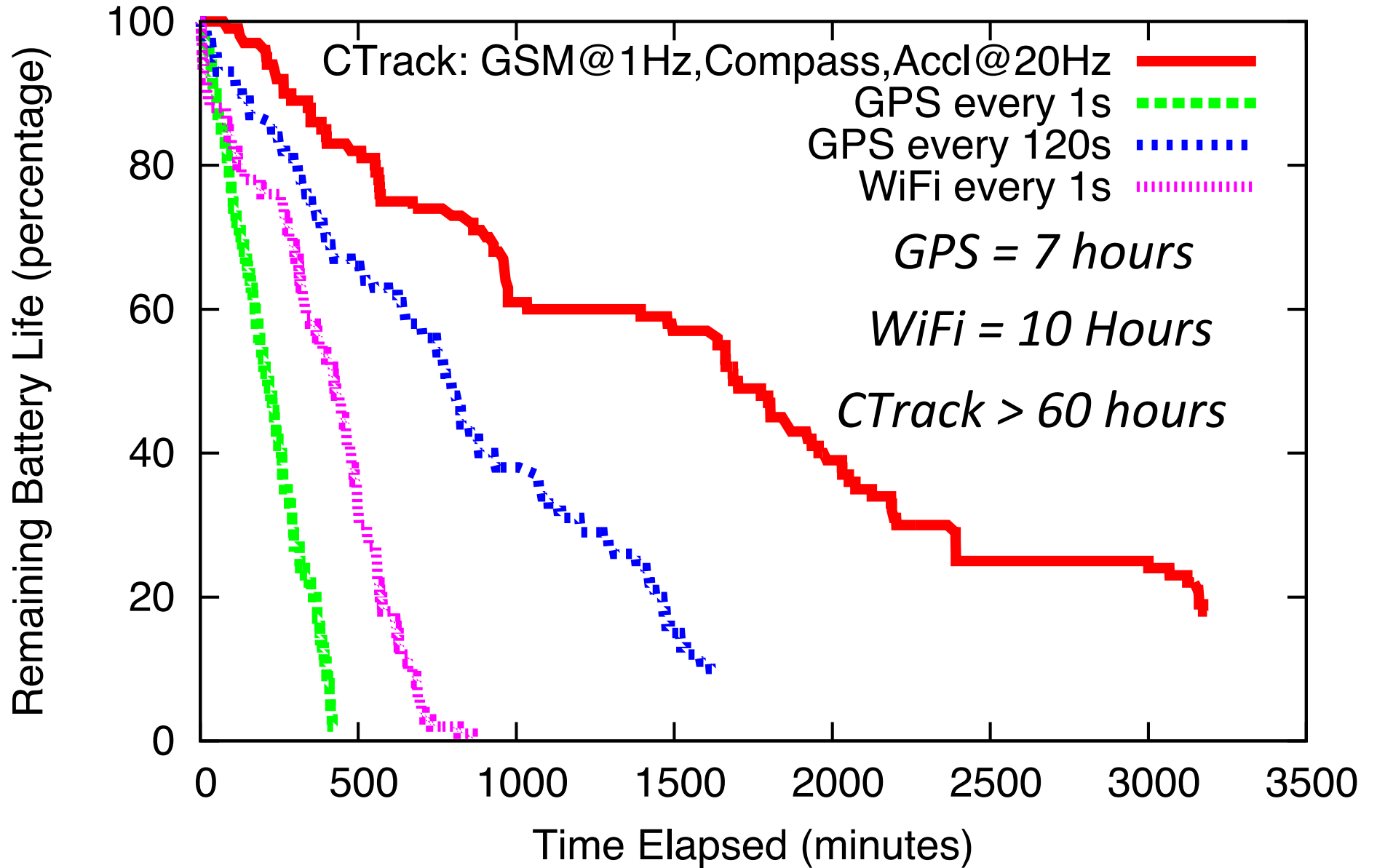
- Can we develop techniques to process cellular signal information to produce accurate trajectories?
- How accurate?



# CTrack: Accurate Trajectory Mapping with Inaccurate Cellular Signals

- Consumes *no* extra energy
- New techniques achieve good enough accuracy for track-based apps
  - “75% as accurate as 1 Hz GPS”
  - “As accurate as GPS every 2 minutes”
  - As energy-efficient as GPS every 4 minutes and much more accurate”
  - Over “3x better” than previous cellular (GSM) systems
  - (I’ll explain what these mean)
- Optionally, augment with low-energy “*sensor hints*”
  - Compass to detect turns (15  $\mu$ W @ 1 Hz)
  - Accelerometer to detect movement (60  $\mu$ W @ 10 Hz)

# Battery Drain Curve



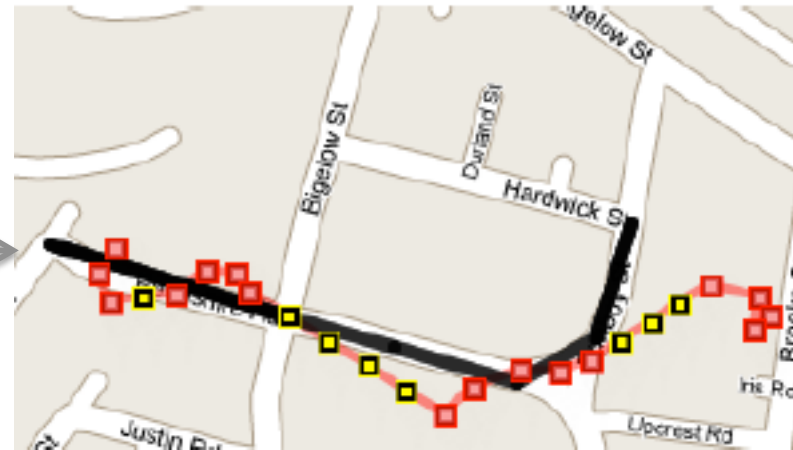
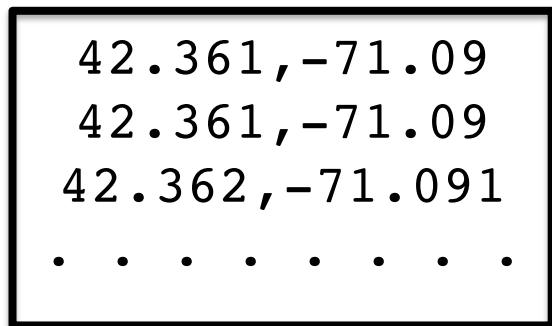
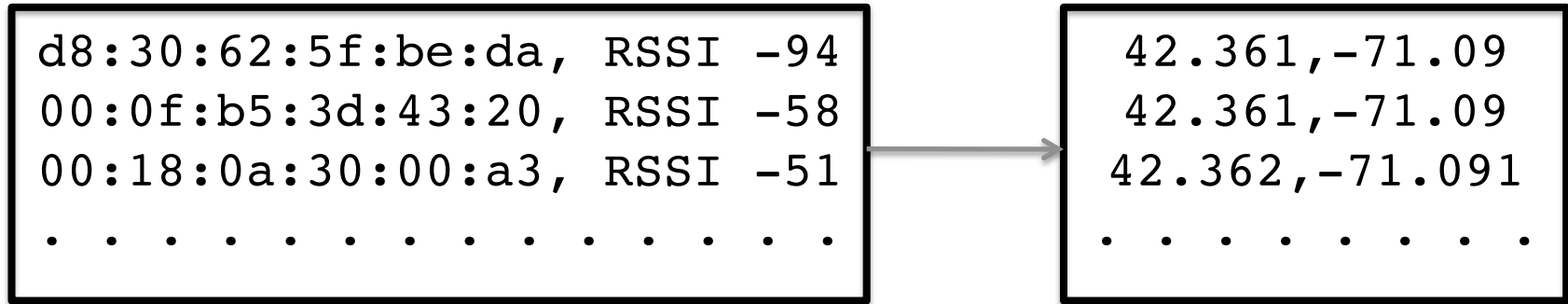
Android G1 phone

# Existing Cellular Location Systems Aren't Good Enough To Find Tracks

- State-of-the-art is “radio fingerprinting” (E.g. PlaceLab)
- OK for best static localization estimate
- But poor at identifying tracks



# Existing Map-Matching Algorithms Perform Poorly w/ Cellular Radios



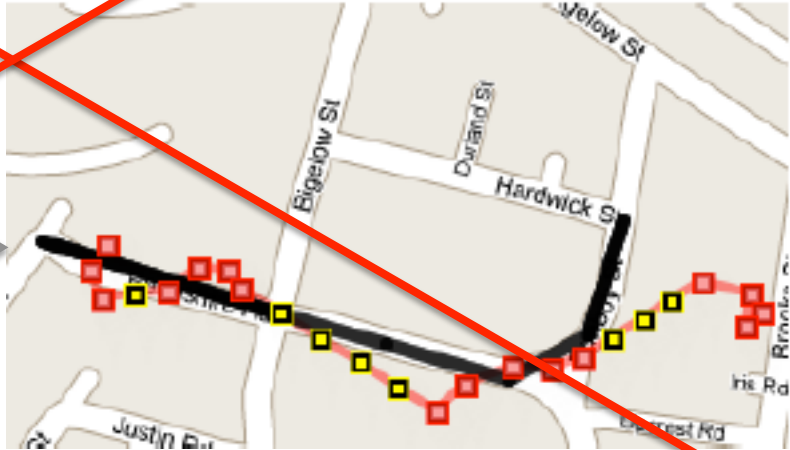
*Krumm et al. (SAE World Congress '07), VTrack (SenSys '09)*

# Existing Map-Matching Algorithms Ok For GPS/WiFi, But Poor For GSM

```
d8:30:62:5f:be:da, RSSI -94  
00:0f:b5:3d:43:20, RSSI -58  
00:18:0a:30:00:a3, RSSI -51  
.....
```

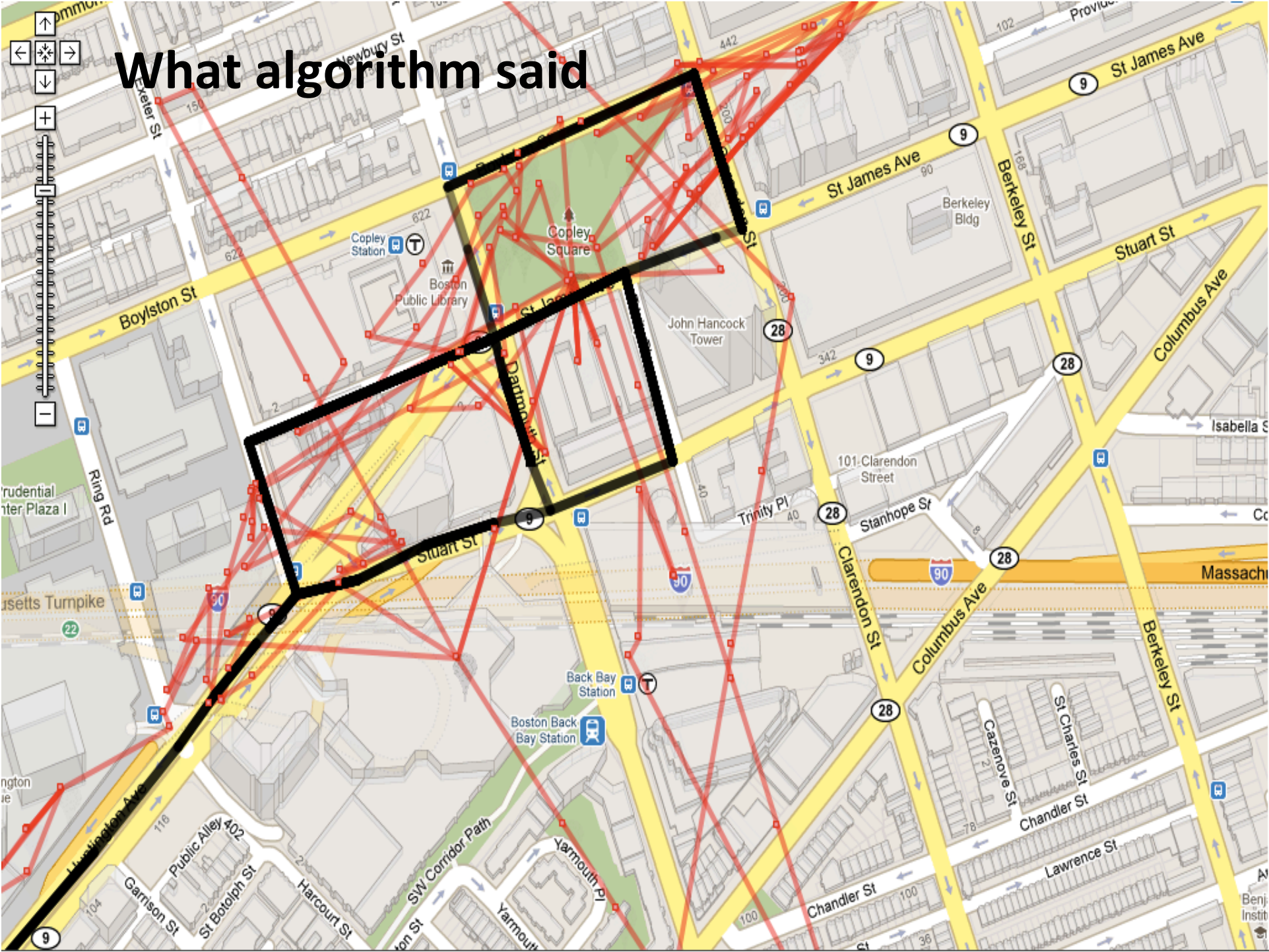
```
42.361, -71.09  
42.361, -71.09  
42.362, -71.091  
.....
```

```
42.361, -71.09  
42.361, -71.09  
42.362, -71.091  
.....
```



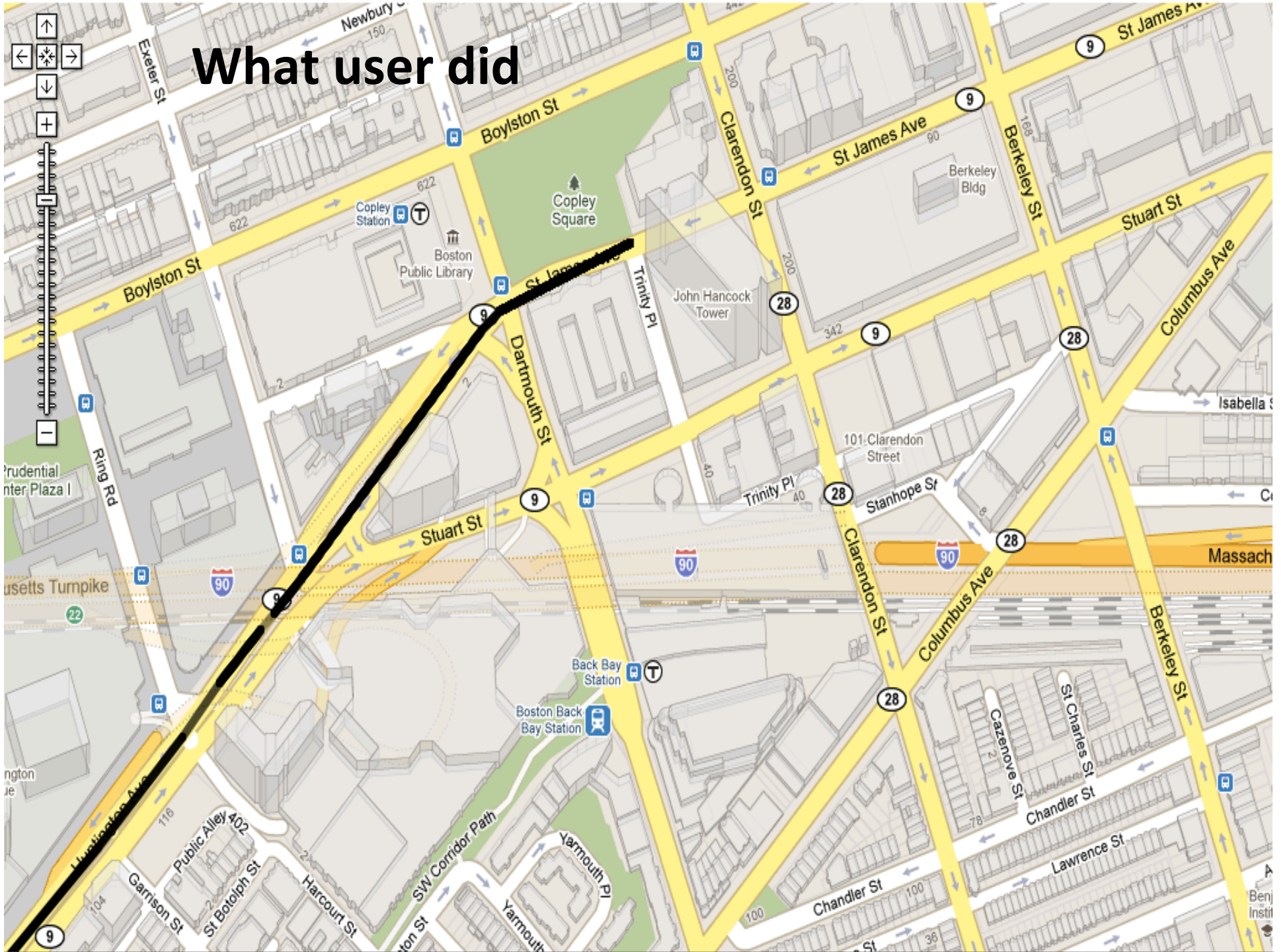
*Krumm et al. (SAE World Congress '07), VTrack (SenSys '09)*

# What algorithm said





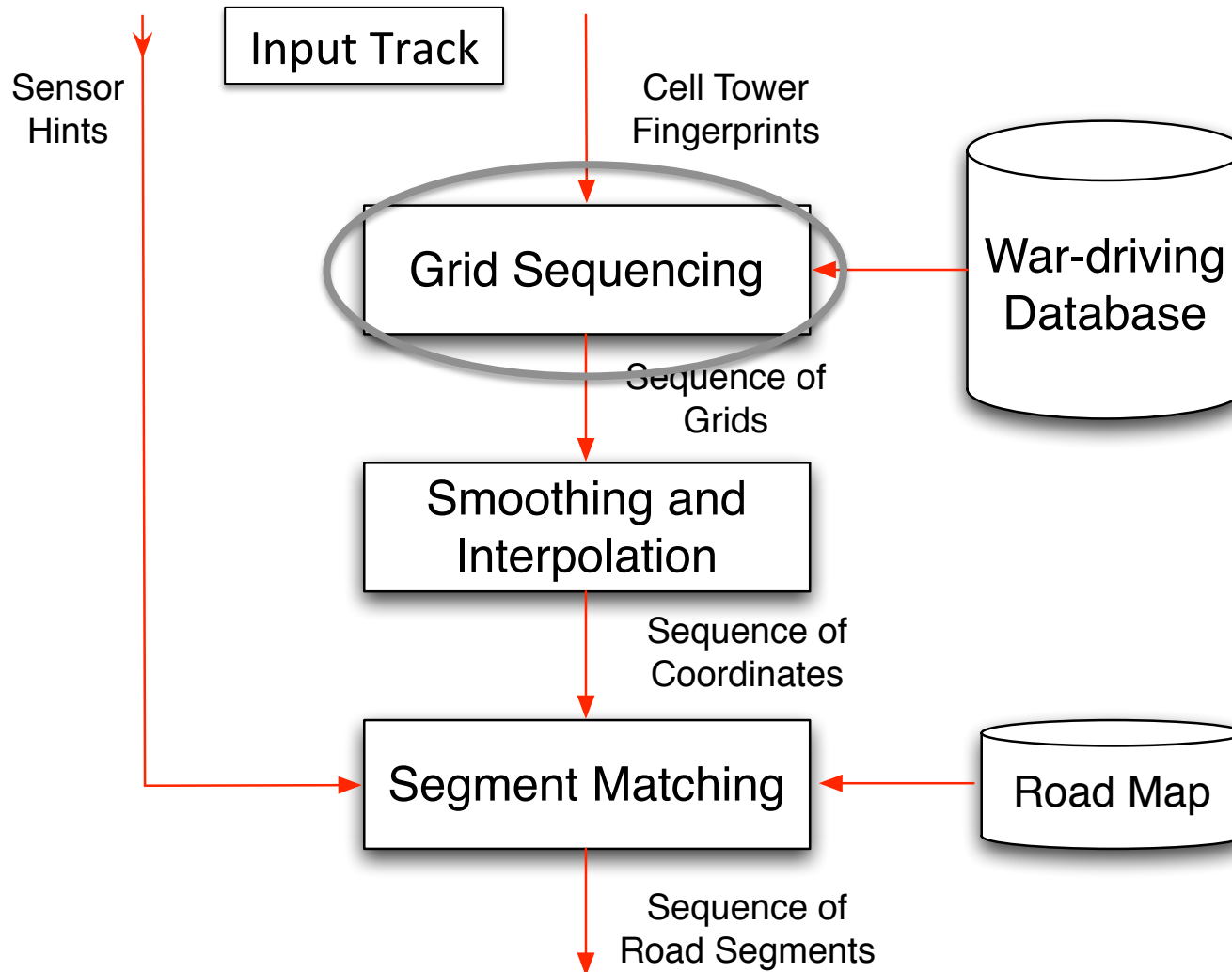
# What user did



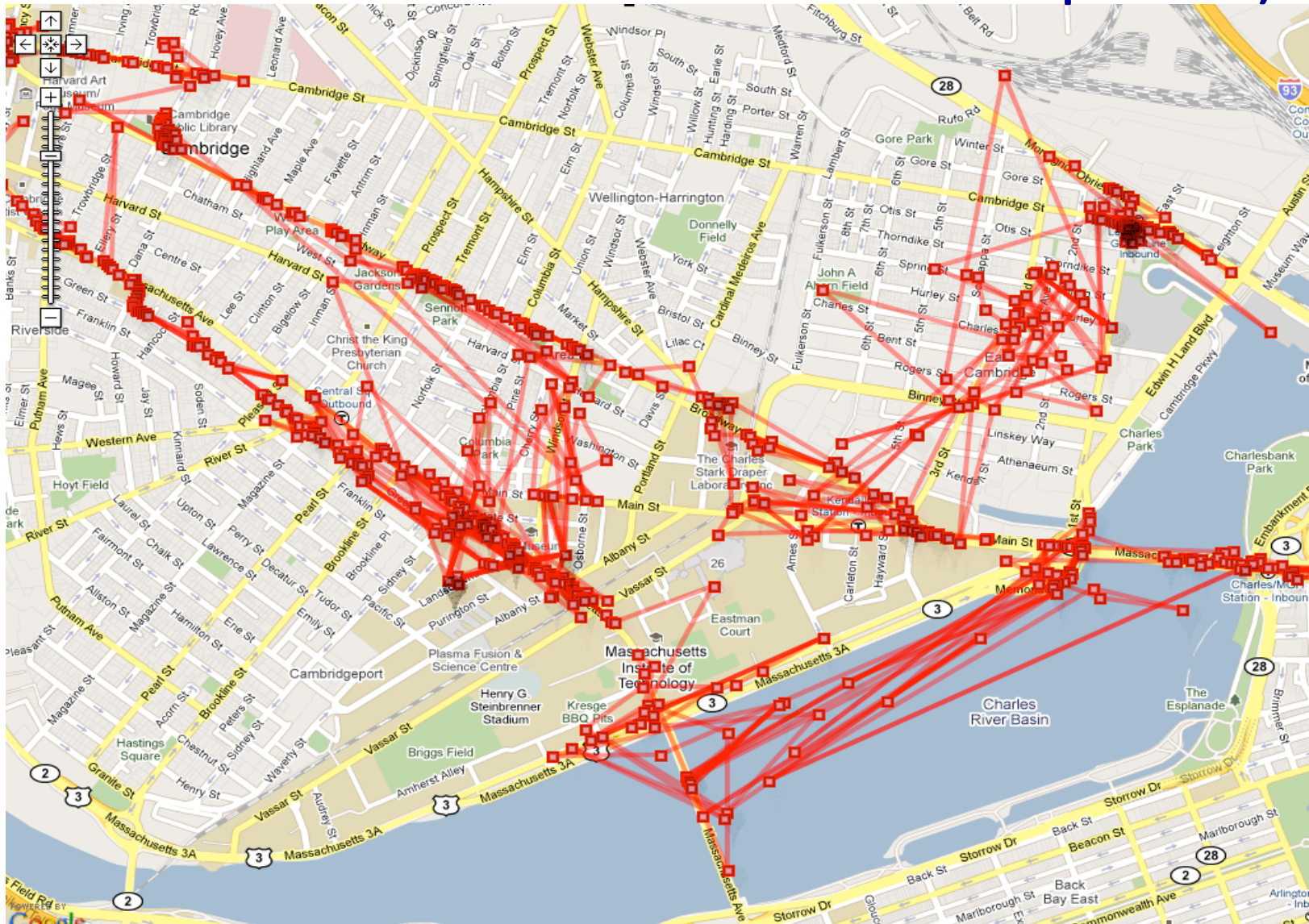
# Key Insight in CTrack

- Do *not* convert radio fingerprints to (lat, lon) coordinates and then sequence them on map
- Instead, first *sequence* GSM fingerprints on a spatial grid
- This insight is crucial: it reduces error by 3x

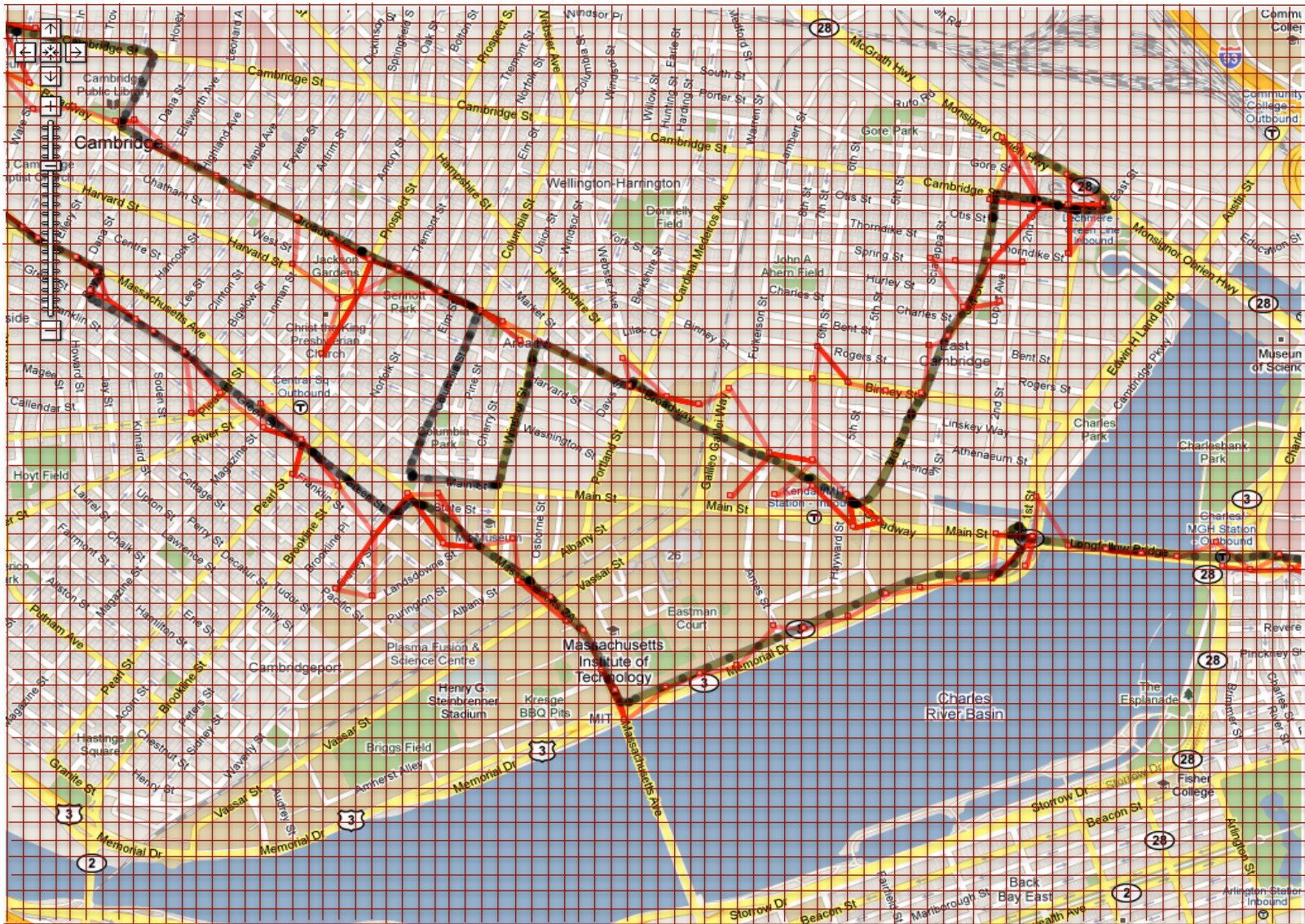
# CTrack FlowChart



# Raw points (using Placelab for illustration – Ctrack does not use these “raw” points)



# Grid Sequence



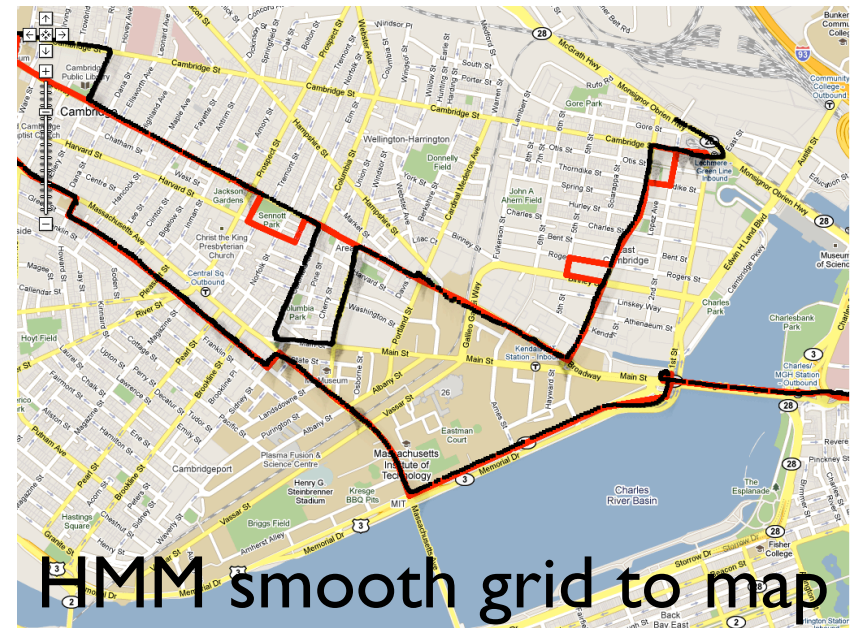
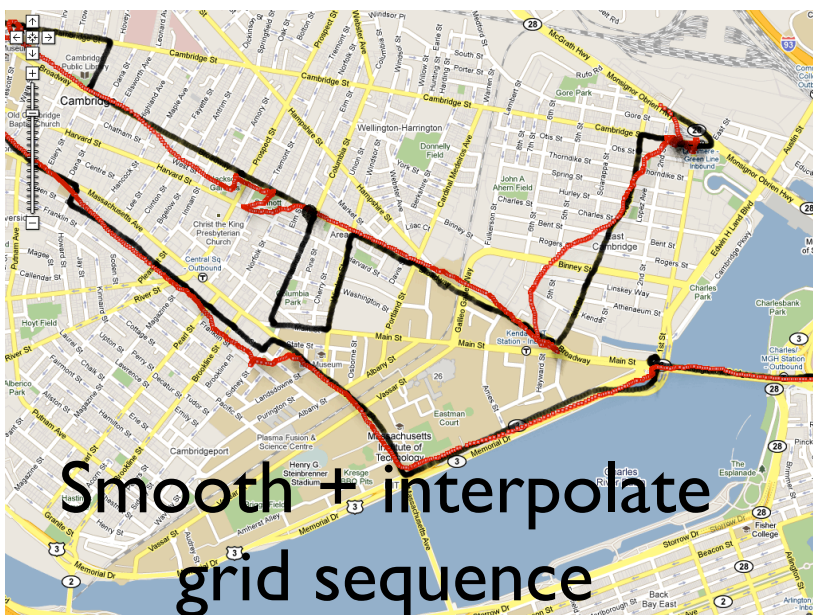
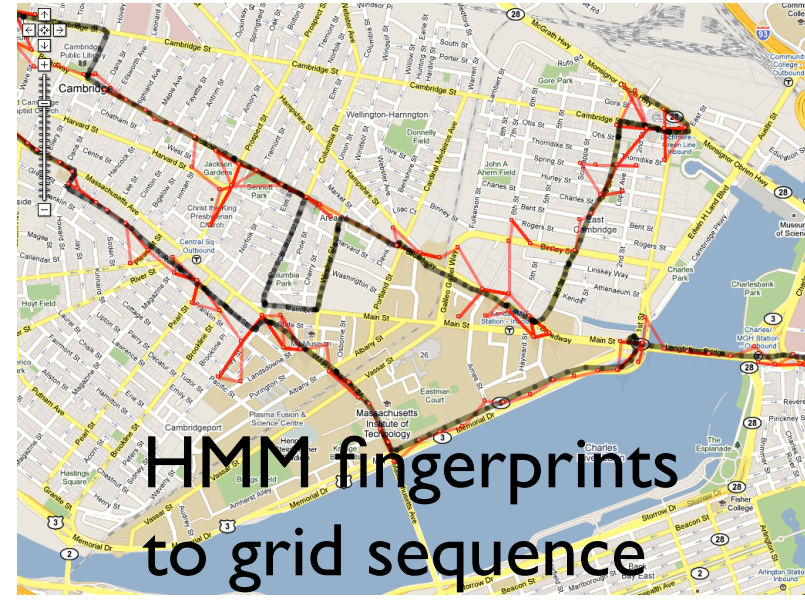
# Smooth + Interpolate Grid Sequence



# Smoothed Grid → Road Segments



# CTrack Steps

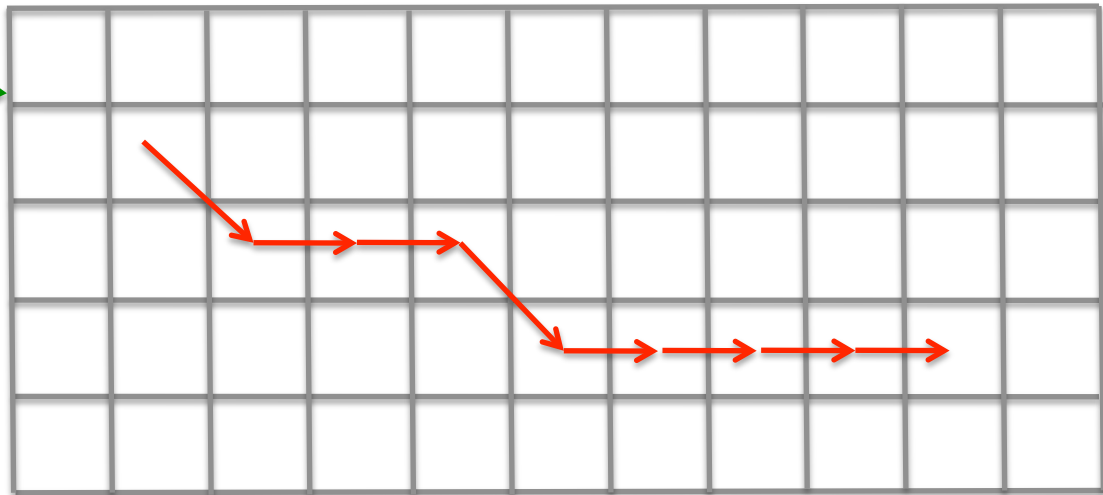




# Grid Sequencing

Time	TowerId	RSSI
18.03	334490560	14
	334478599	12
	337772865	18
	334478600	14
	334470539	12
	334490699	12
19.01	.	.

Size of grid = 125 meters  
Why?



Given a sequence of GSM fingerprints (TowerID, RSSI),  
what is the most likely sequence of grid cells?

# HMM For Grid Sequencing

GSM Signature  
(Towers+ RSSI)  
"Observable"

334490560,14  
334478599,12  
337772865,18

Grid Cell  
("Hidden  
State")

Grid Cell

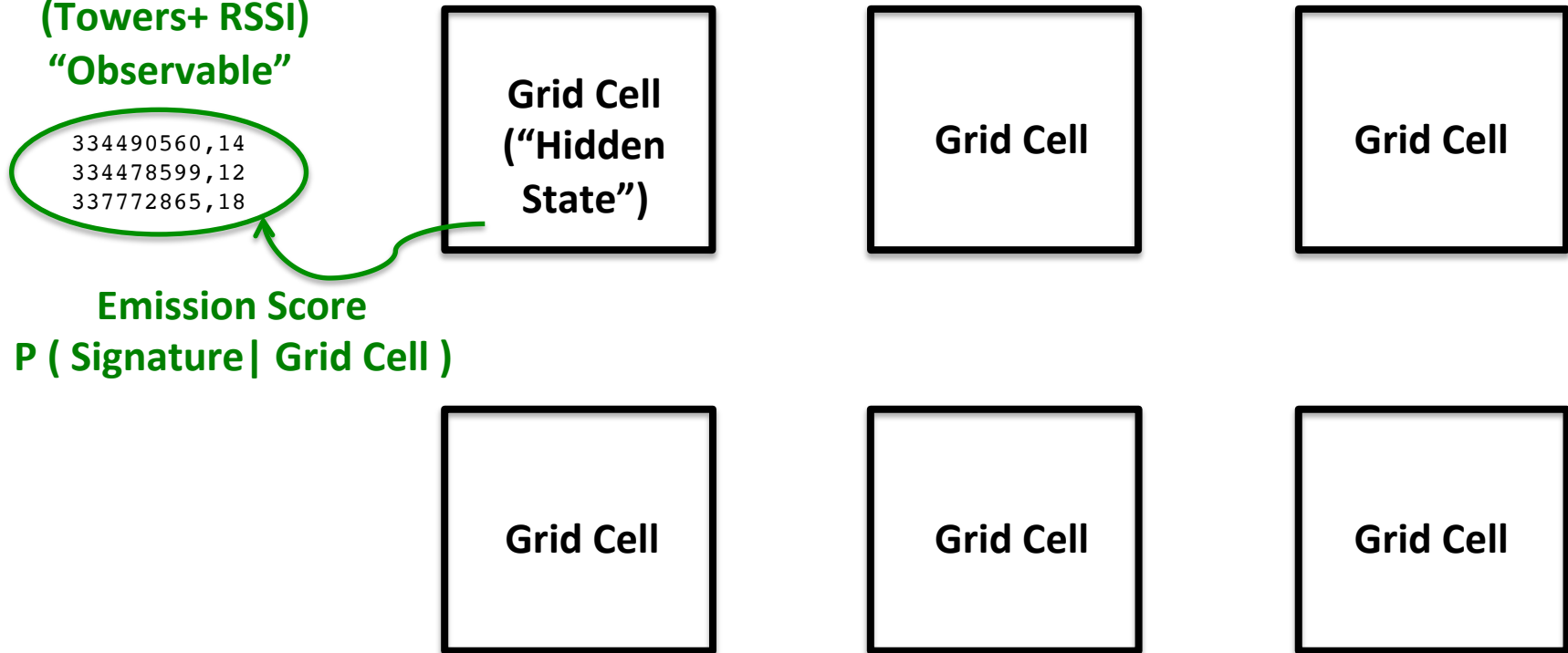
Grid Cell

Emission Score  
 $P(\text{Signature} | \text{Grid Cell})$

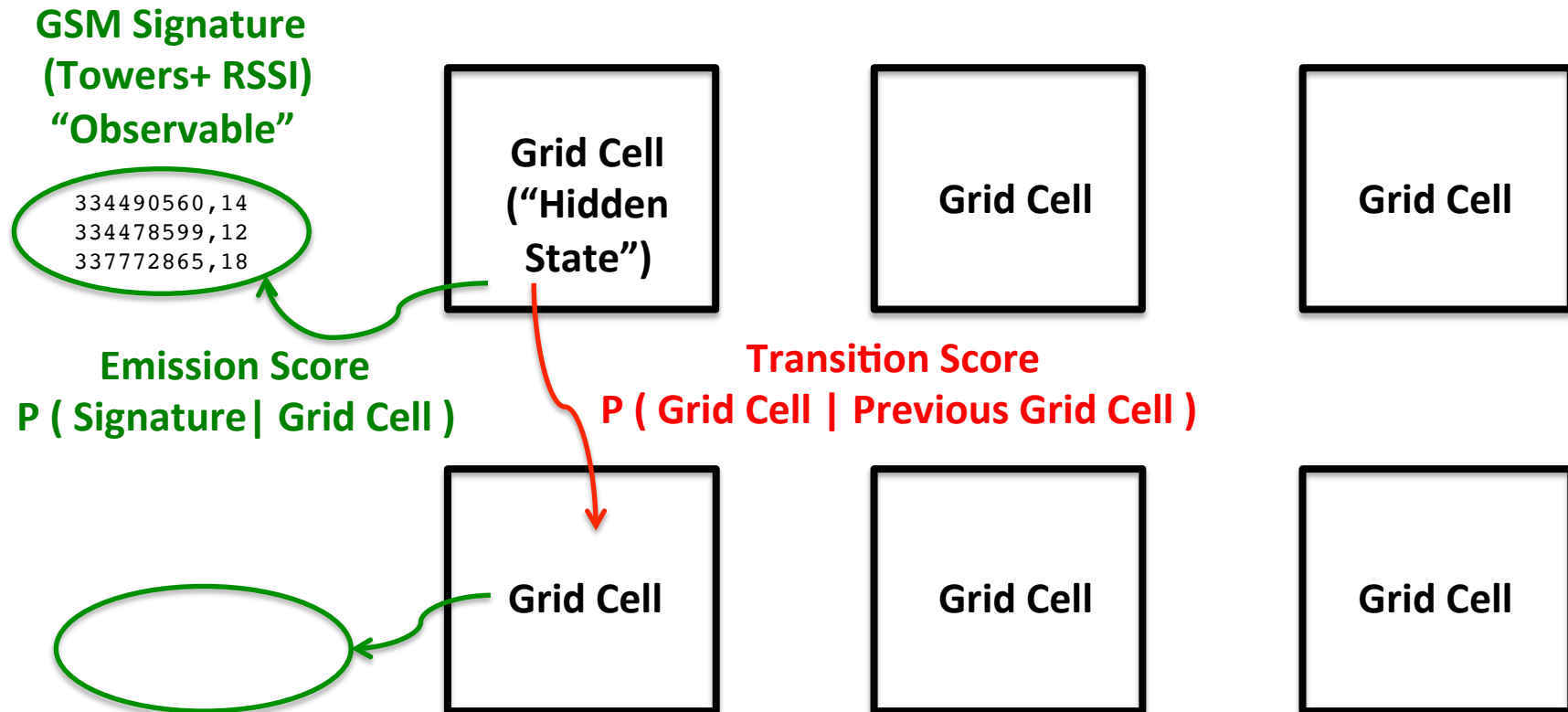
Grid Cell

Grid Cell

Grid Cell



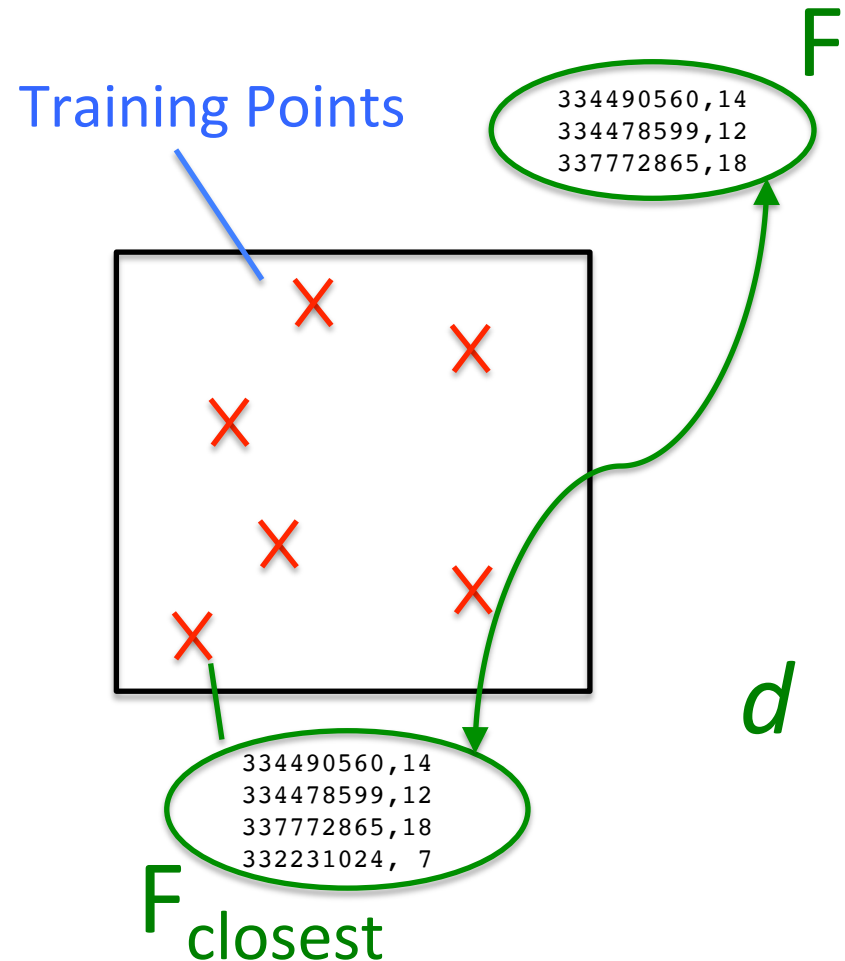
# HMM For Grid Sequencing



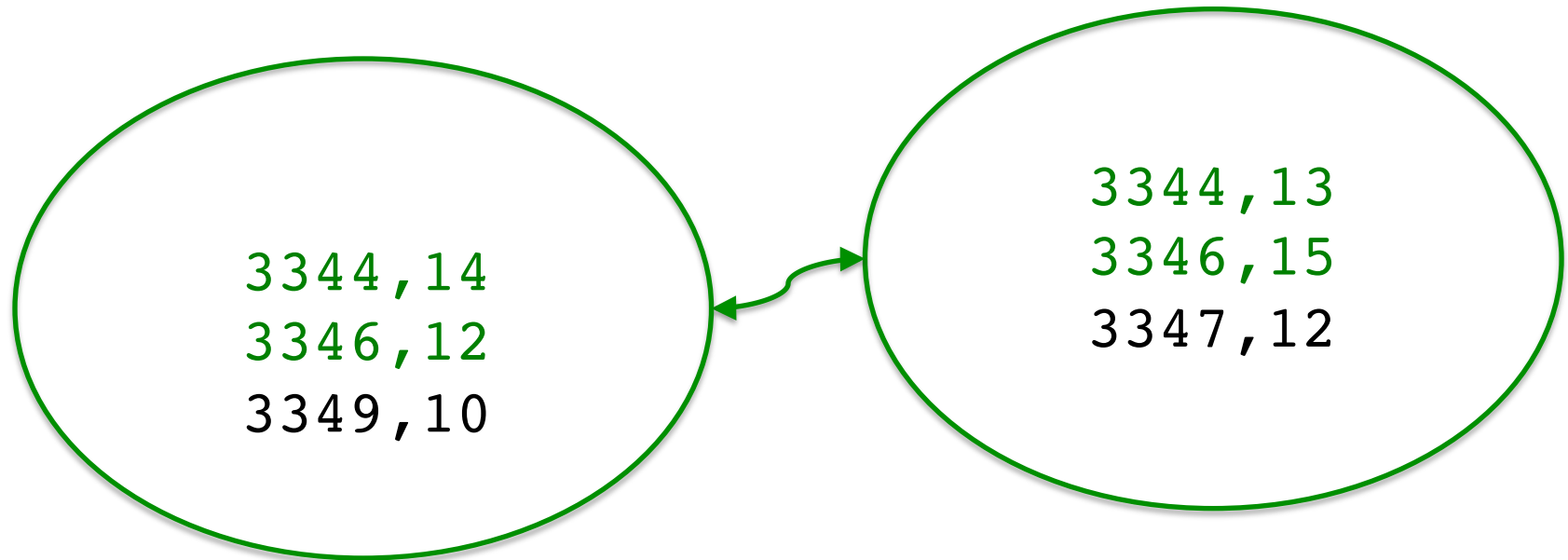
Dynamic Programming Finds Best Grid Sequence (cf. Viterbi)  
"Best" =>  $\text{Max}(\text{Emission Score} * \text{Transition Score})$

# Emission Score (Grid Cell G, Fingerprint F)

- Find *closest* matching fingerprint  $F_{\text{closest}}$  to  $F$  in all training data for grid cell  $G$
- Score is *inversely proportional* to “distance”  $d$  of  $F_{\text{closest}}$  from  $F$  in signal strength space
- Better match  $\Rightarrow$  smaller  $d \Rightarrow$  higher score



# Example



$$d = \lambda * 2 + (d_{\max} - 0.5 * \text{sqrt}((14-13)^2 + (12-15)^2))$$

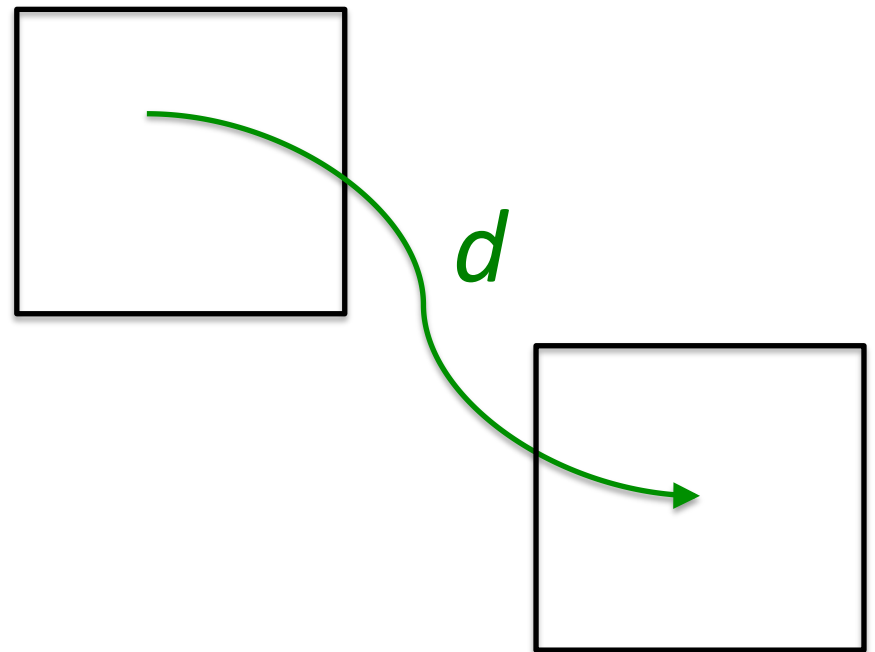
With  $\lambda=3$  and  $d_{\max}=32$ ,

Emission Score =  $38 - \text{sqrt}(10)/2$

Normalize this to (0,1] range

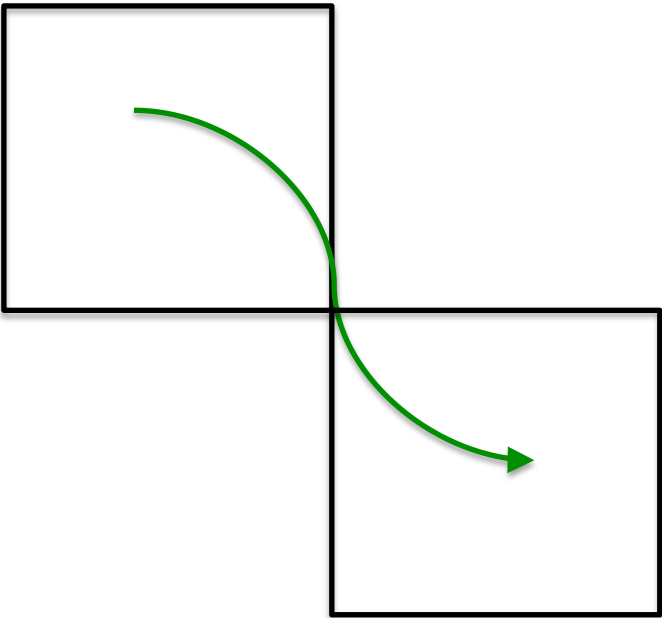
# Tolerant Transition Score

- Inversely proportional to distance between grid cells
- The score is ***very tolerant*** of jumps between non-adjacent grid cells
- Necessary to tolerate large outliers/regions of poor coverage in the GSM data

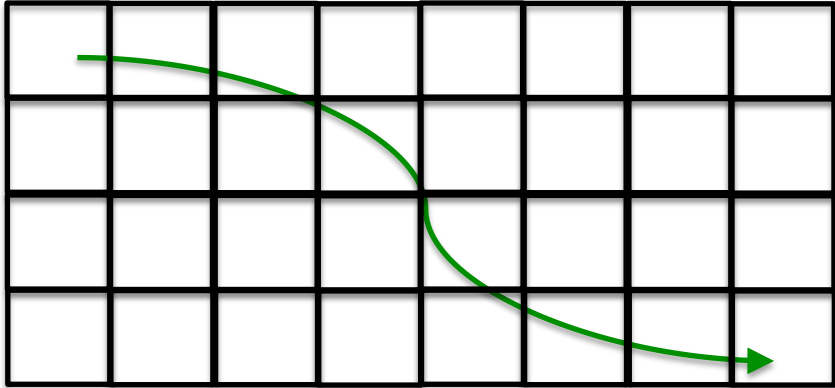


$$\text{Score} = 1/d$$

# Example



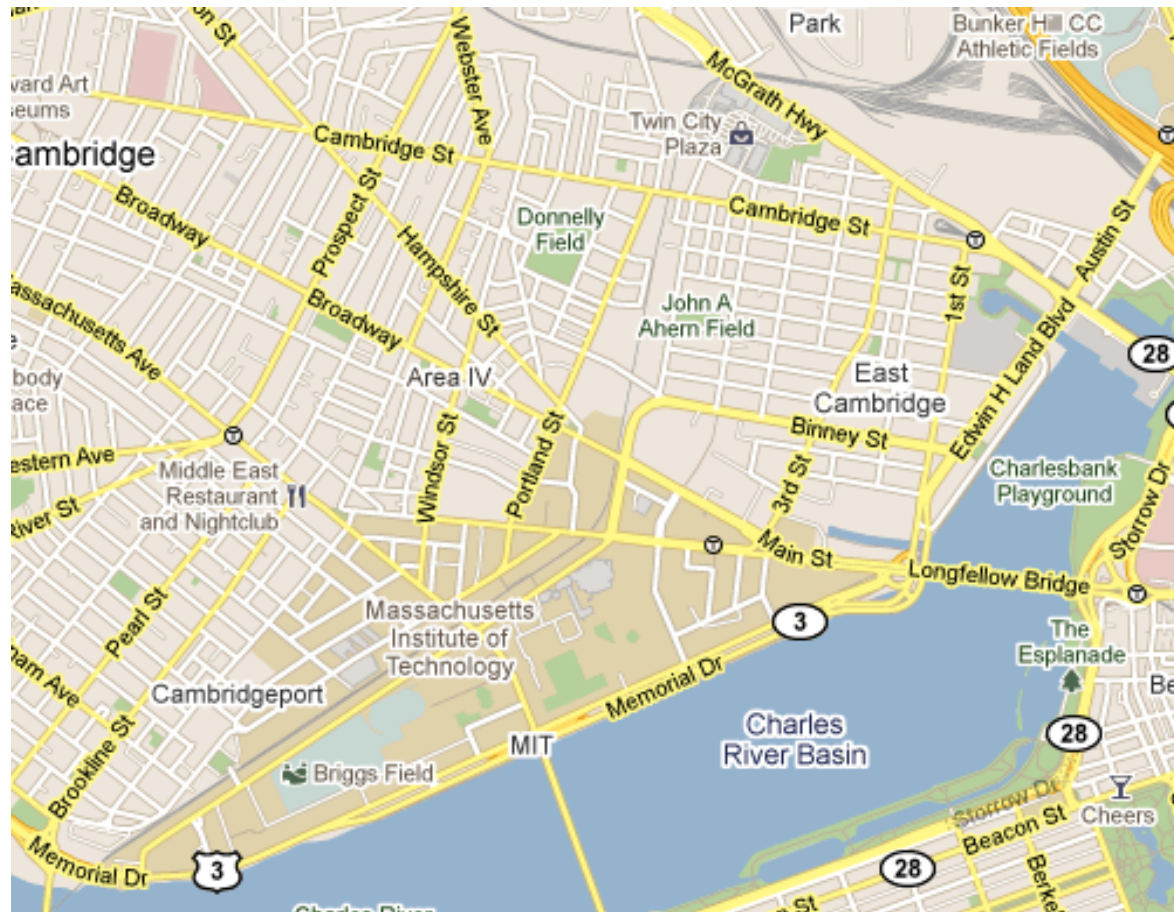
*Transition Score = 1*



$$d = 7$$

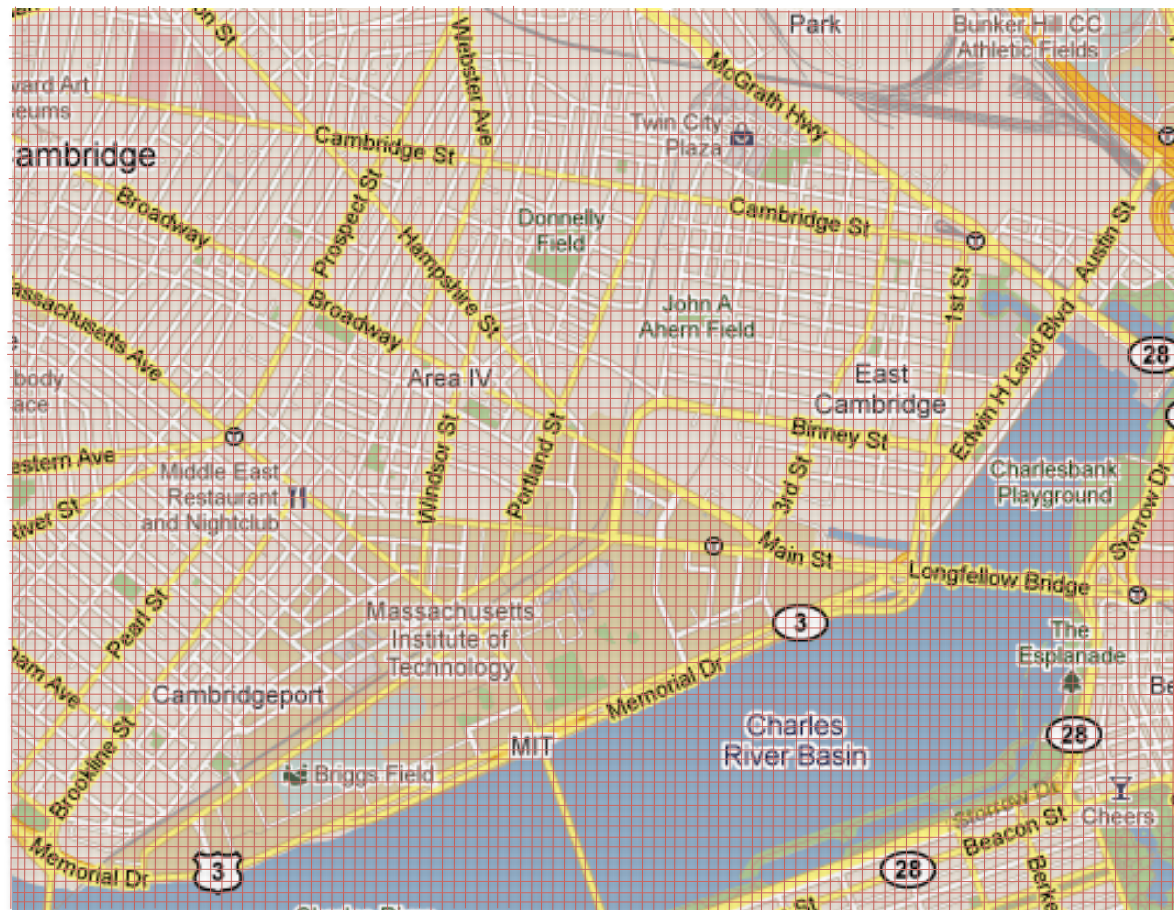
*Transition Score = 1/7*

# Grid Sequencing In Action

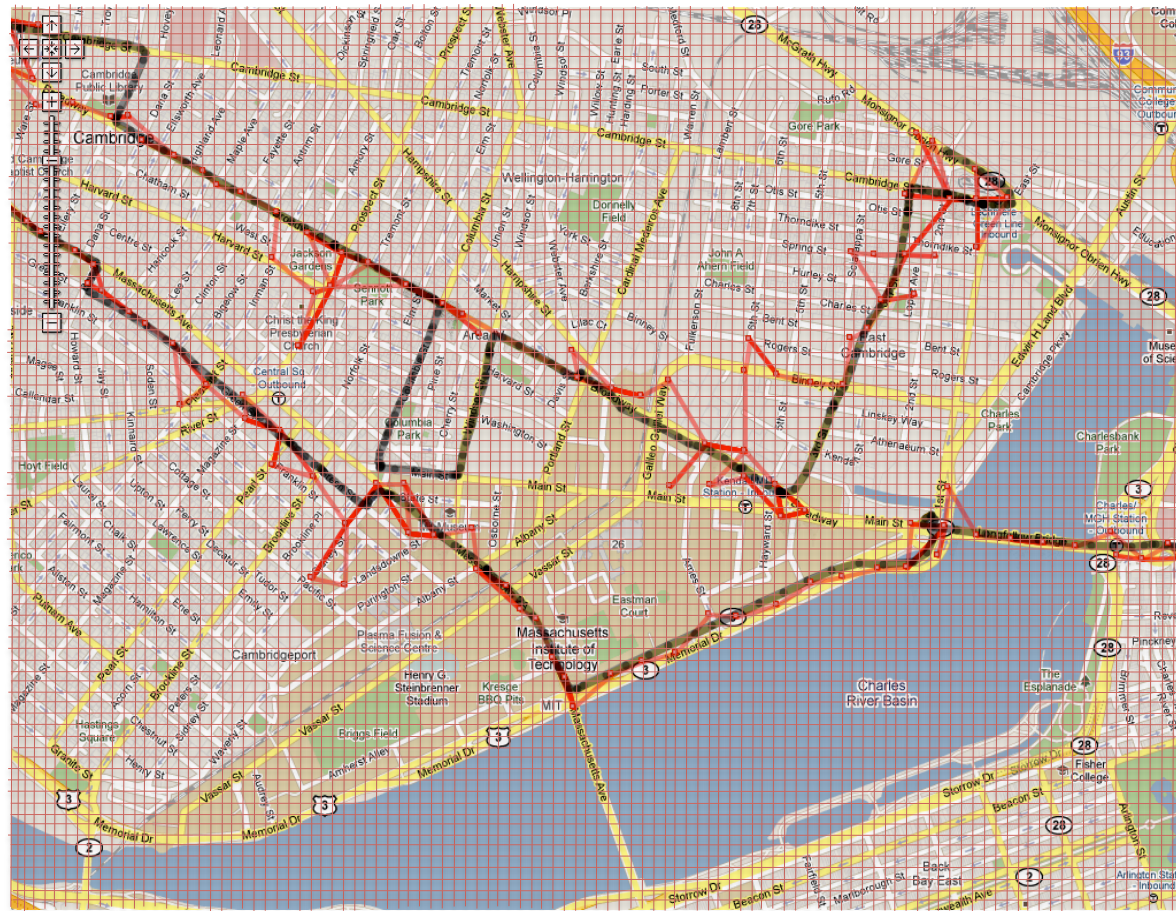


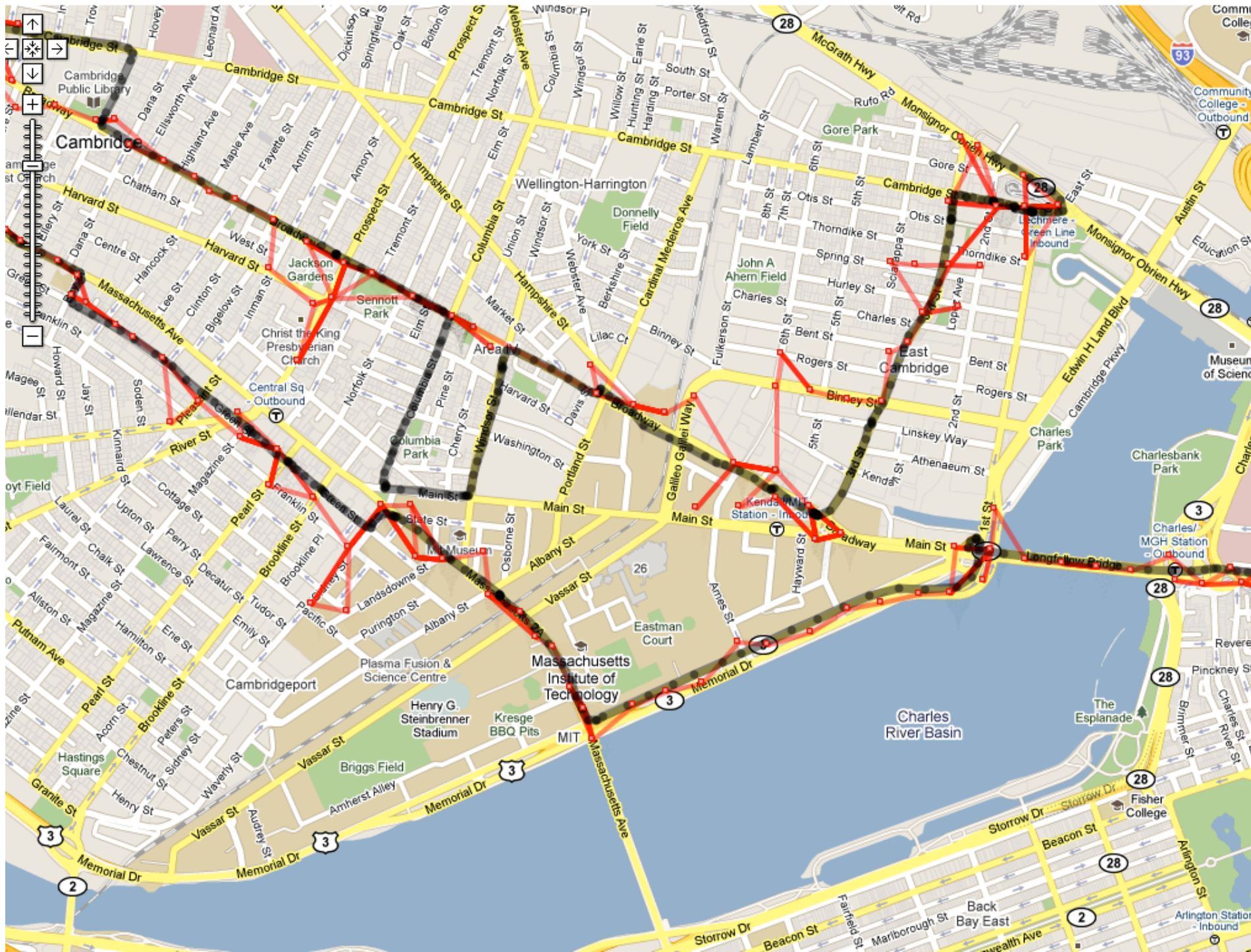


# Grid Sequencing In Action



# Grid Sequencing In Action

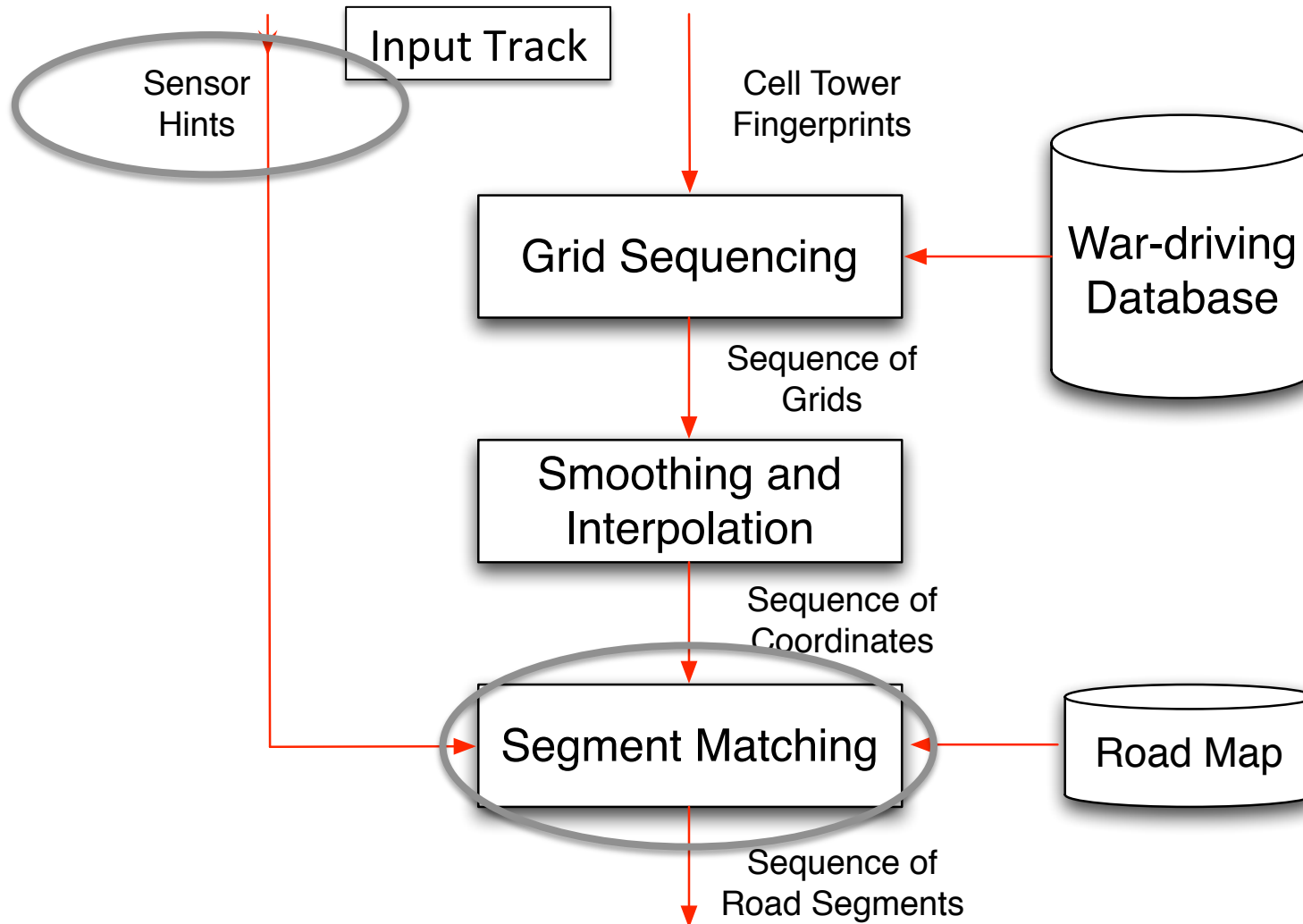




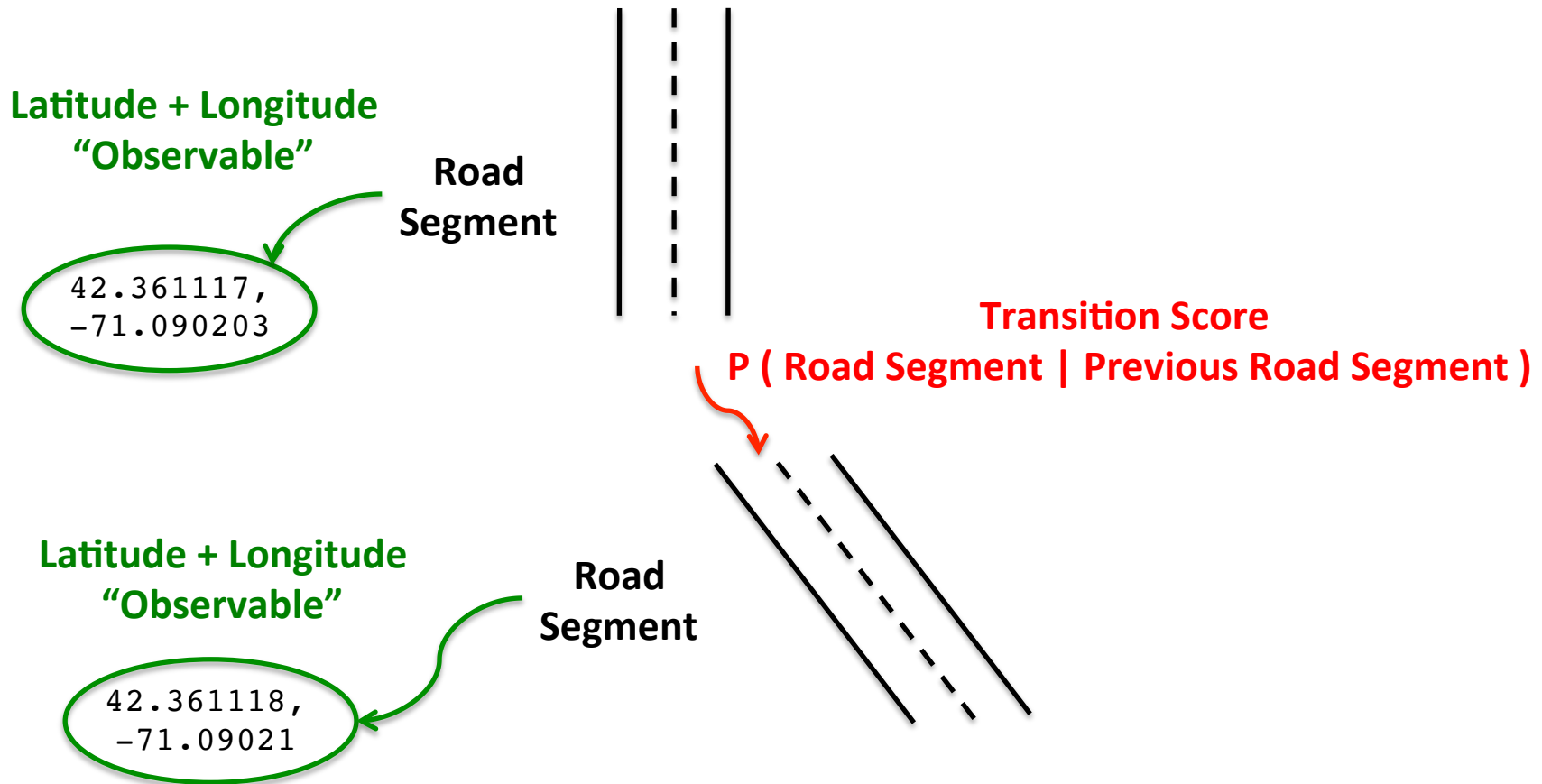
# Smoothing & Interpolation



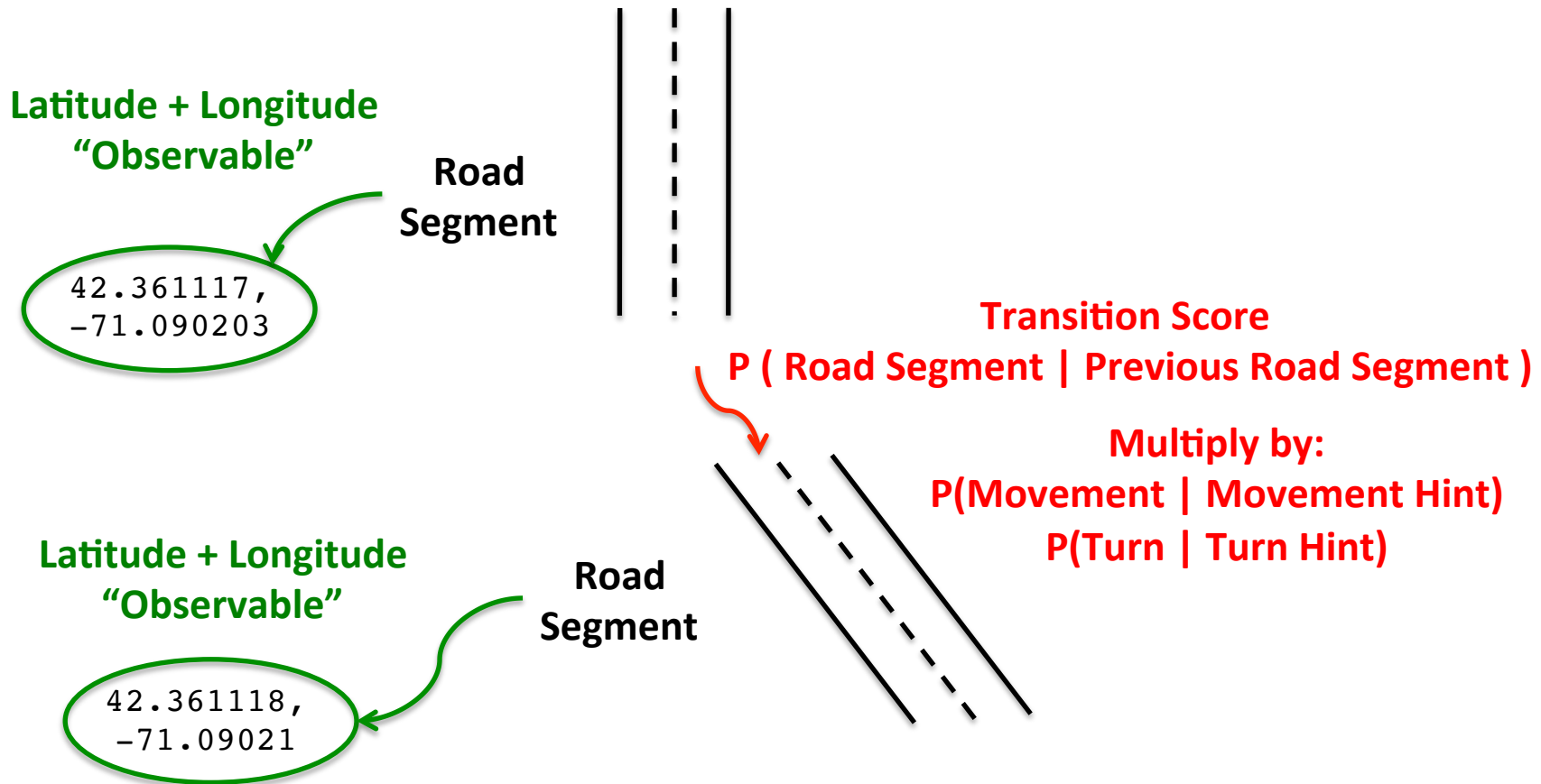
# CTrack FlowChart



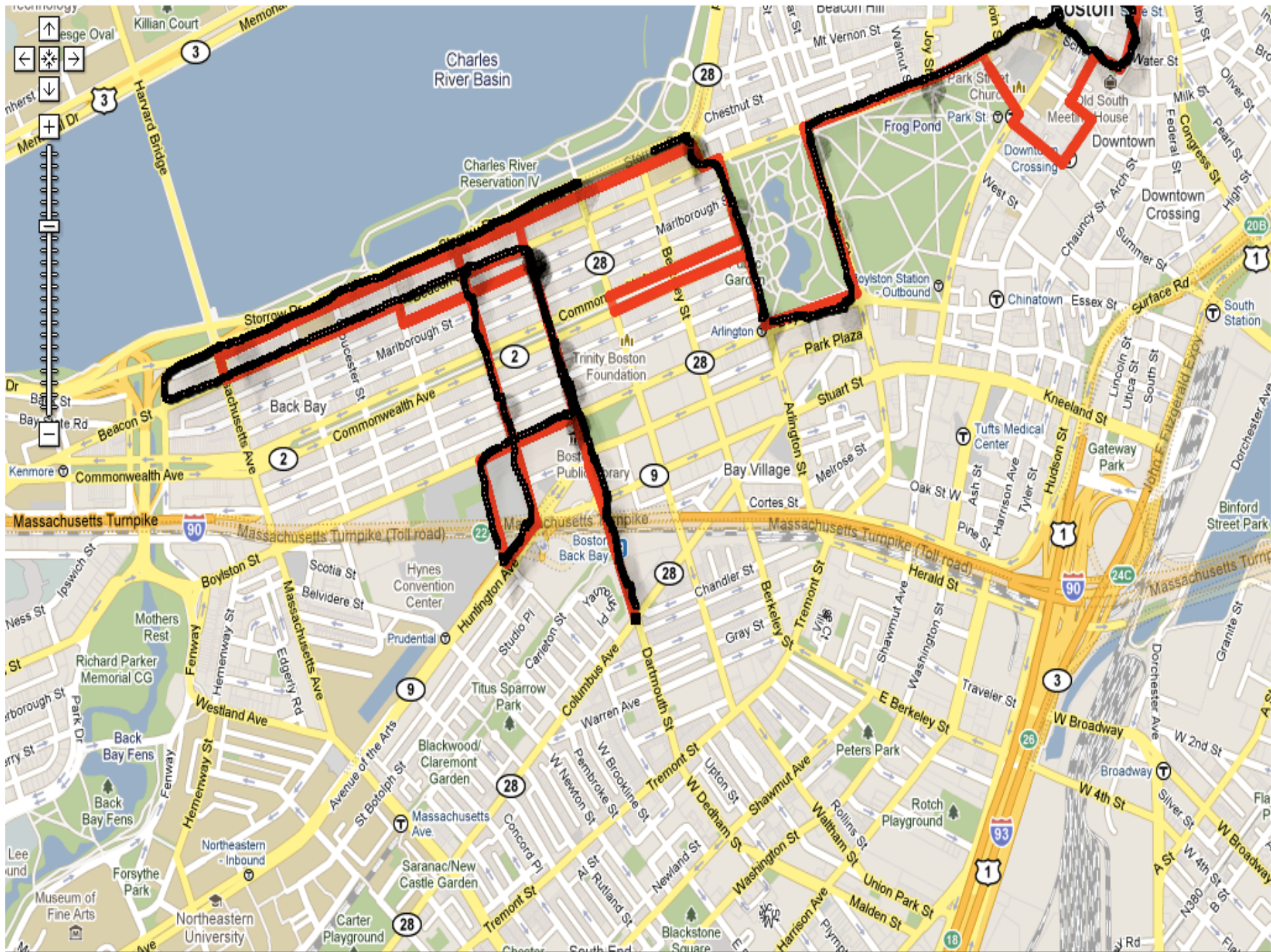
# Matching (Lat, Lon) To Segments



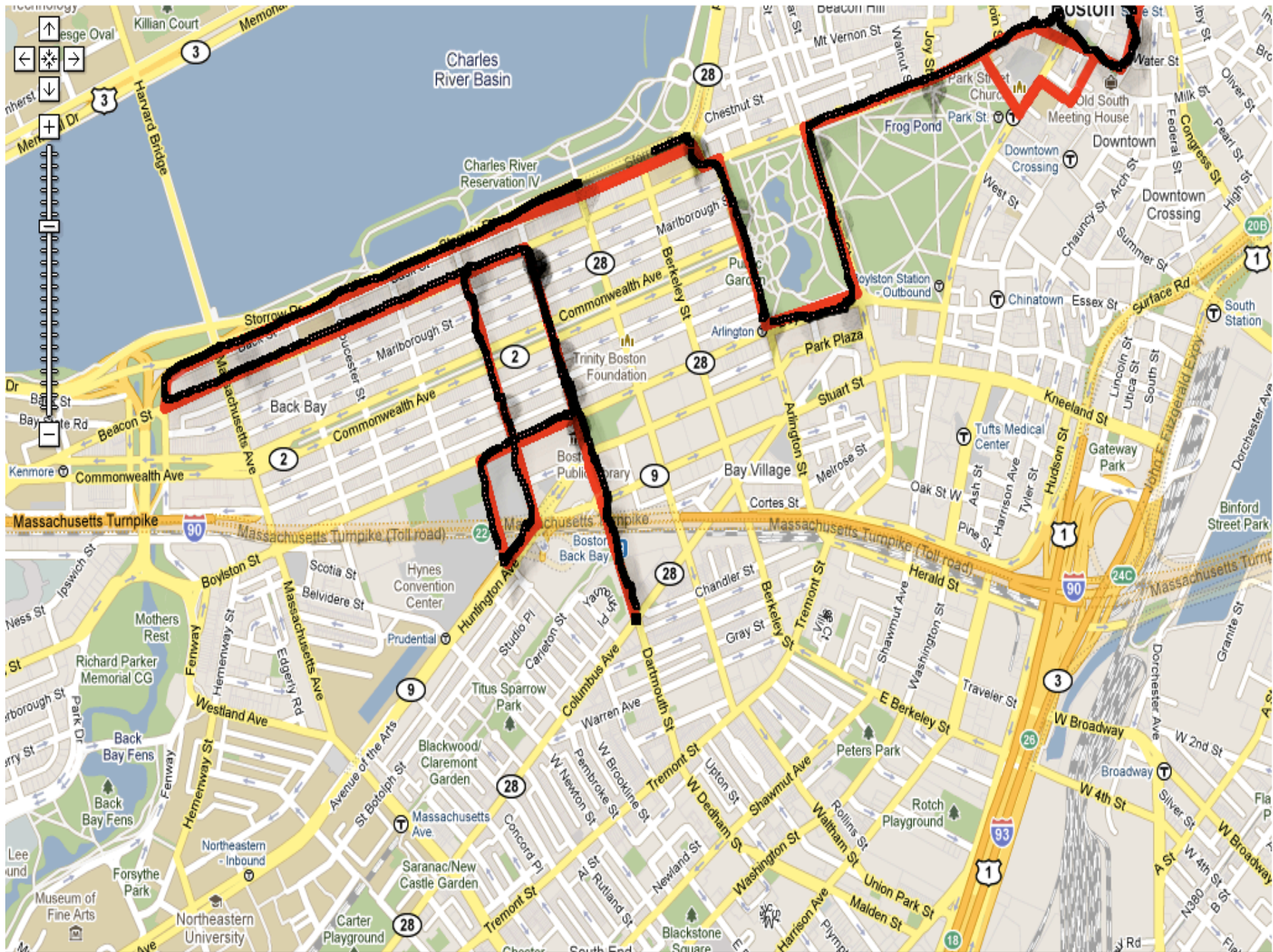
# Matching (Lat, Lon) To Segments



Extract 0/1 (Binary) Movement and Turn Hints For Each Time Slot

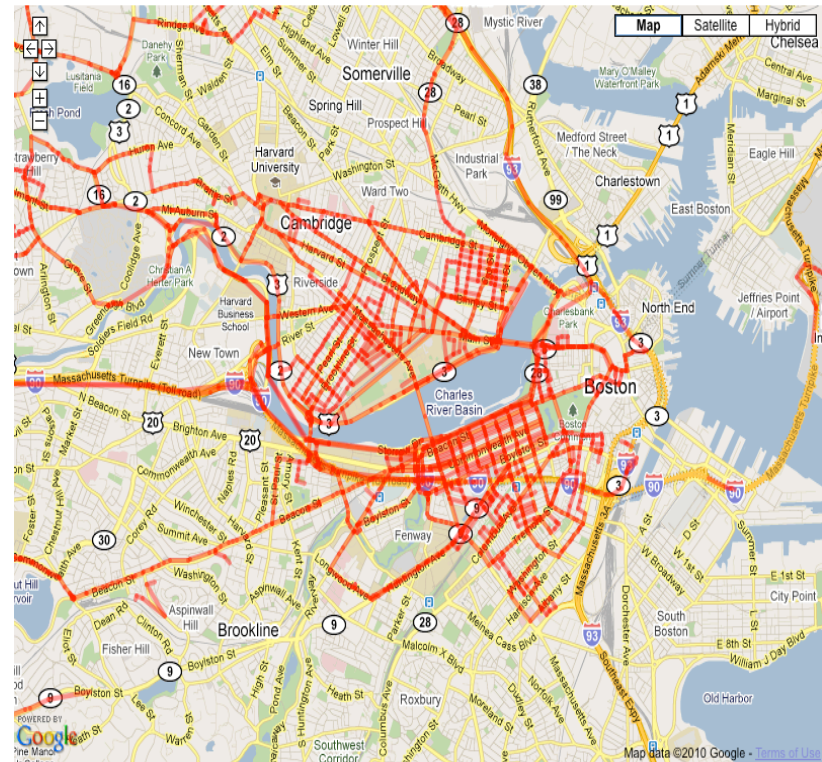






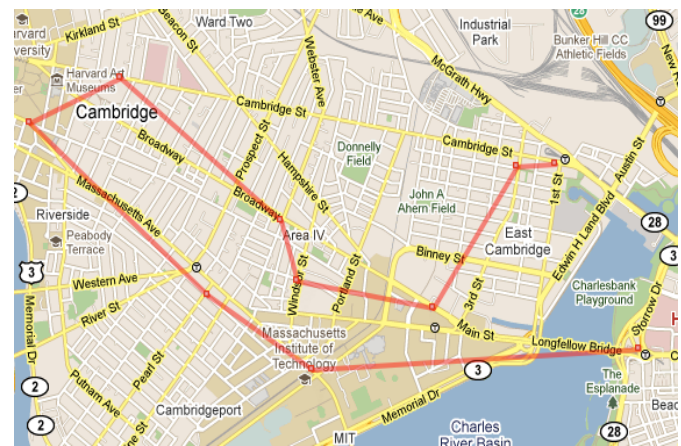
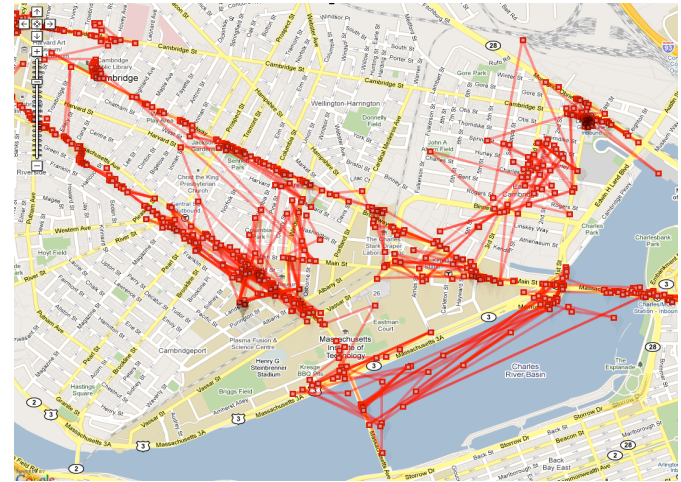
# Evaluation

- 125 Hours (312 “Drives”)
  - From 16 Android phones
  - Logged GPS ground truth, GSM, accel, compass
- Selected subset of 53 drives (28 hours) as “test drives”
  - Tests lie in dense cov. area
  - Tests have good GPS accuracy
  - Mean drive length: 30-35 mins
- Leave-one-out evaluation
  - Train on all but test, evaluate on test drive



# We Compared CTrack To...

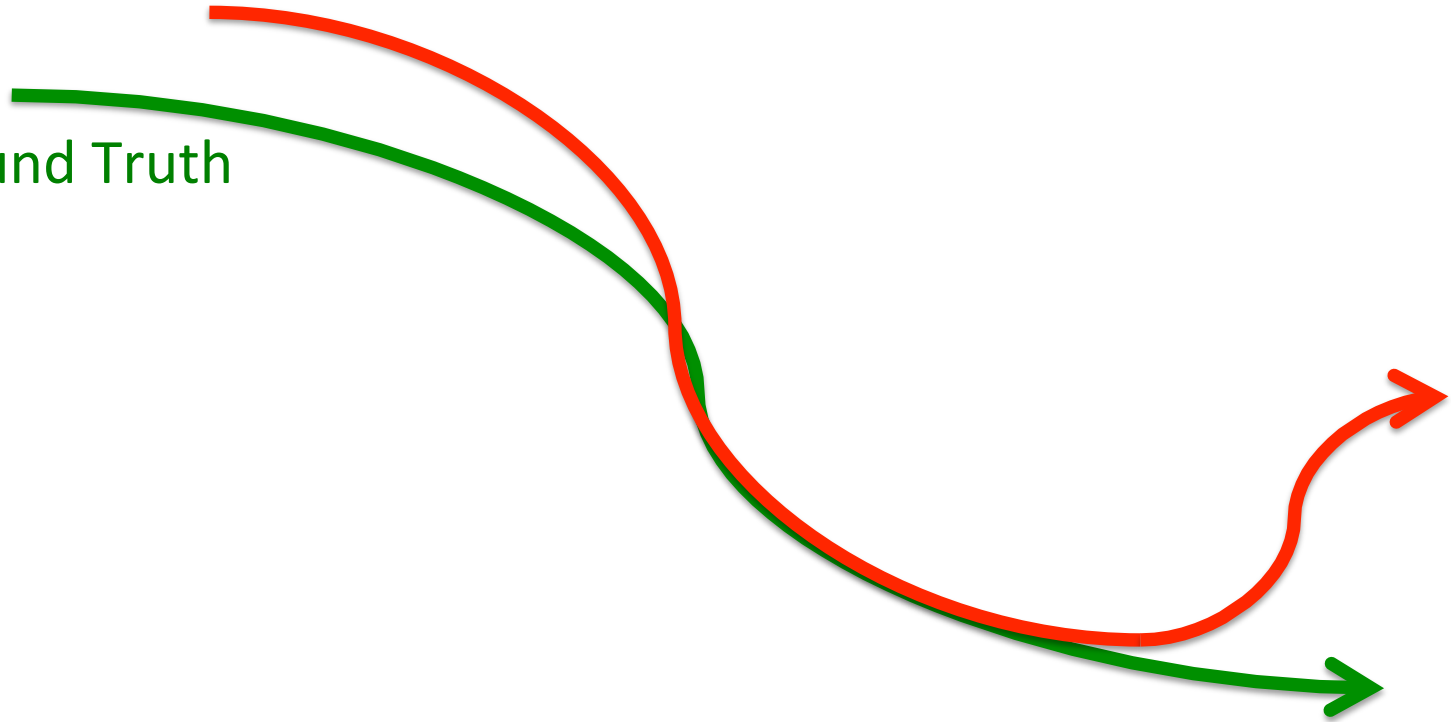
- Placelab + VTrack
  - Look up single best matching GSM fingerprint for each time
  - Match (lat, lon) using VTrack
  
- *GPS k* + VTrack
  - Get a GPS sample every  $k$  secs
  - Match (lat, lon) using VTrack
  - $k = 4$  min is *energy-equivalent* to CTrack



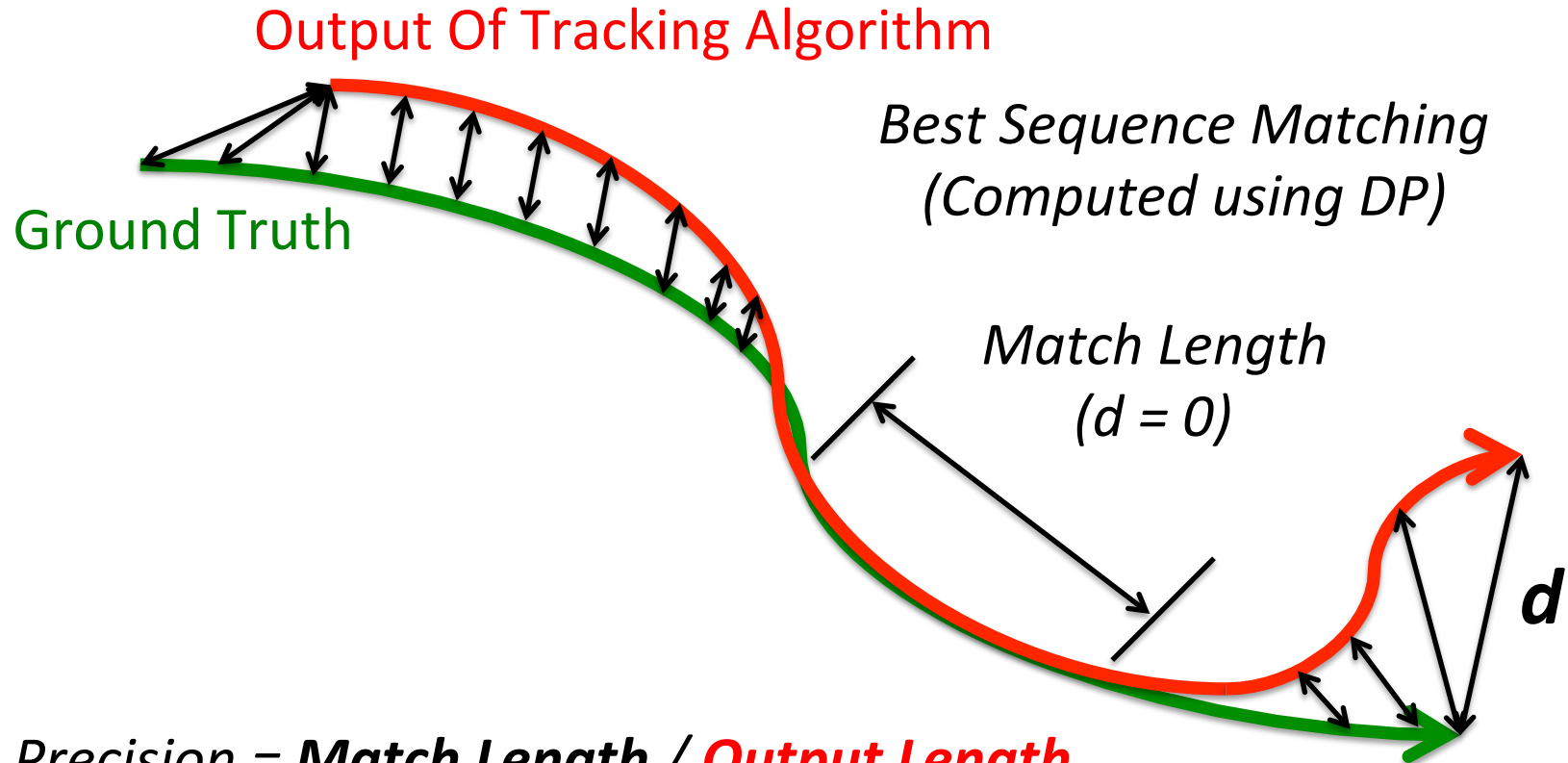
# Evaluation Metrics

Output Of Tracking Algorithm

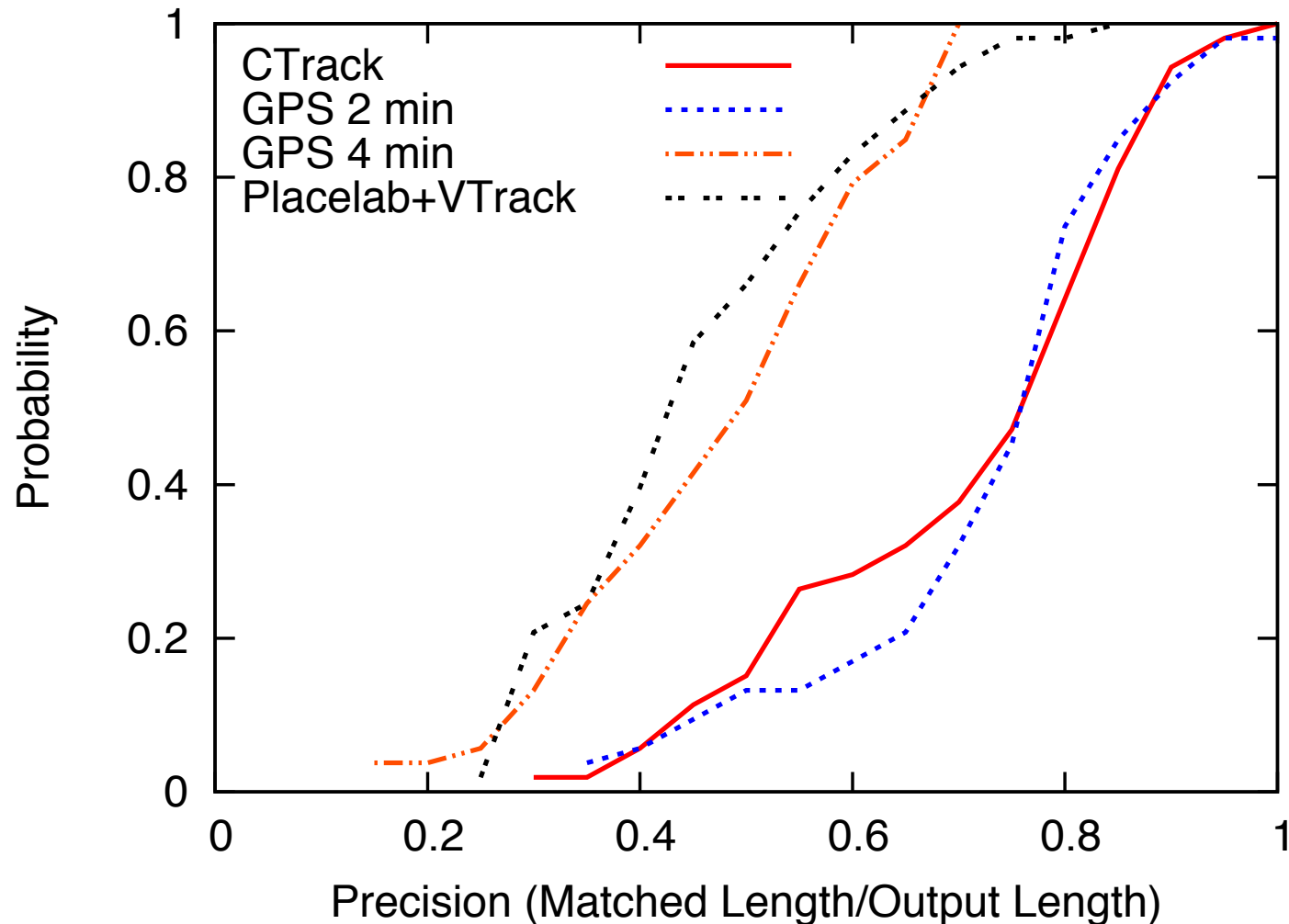
Ground Truth



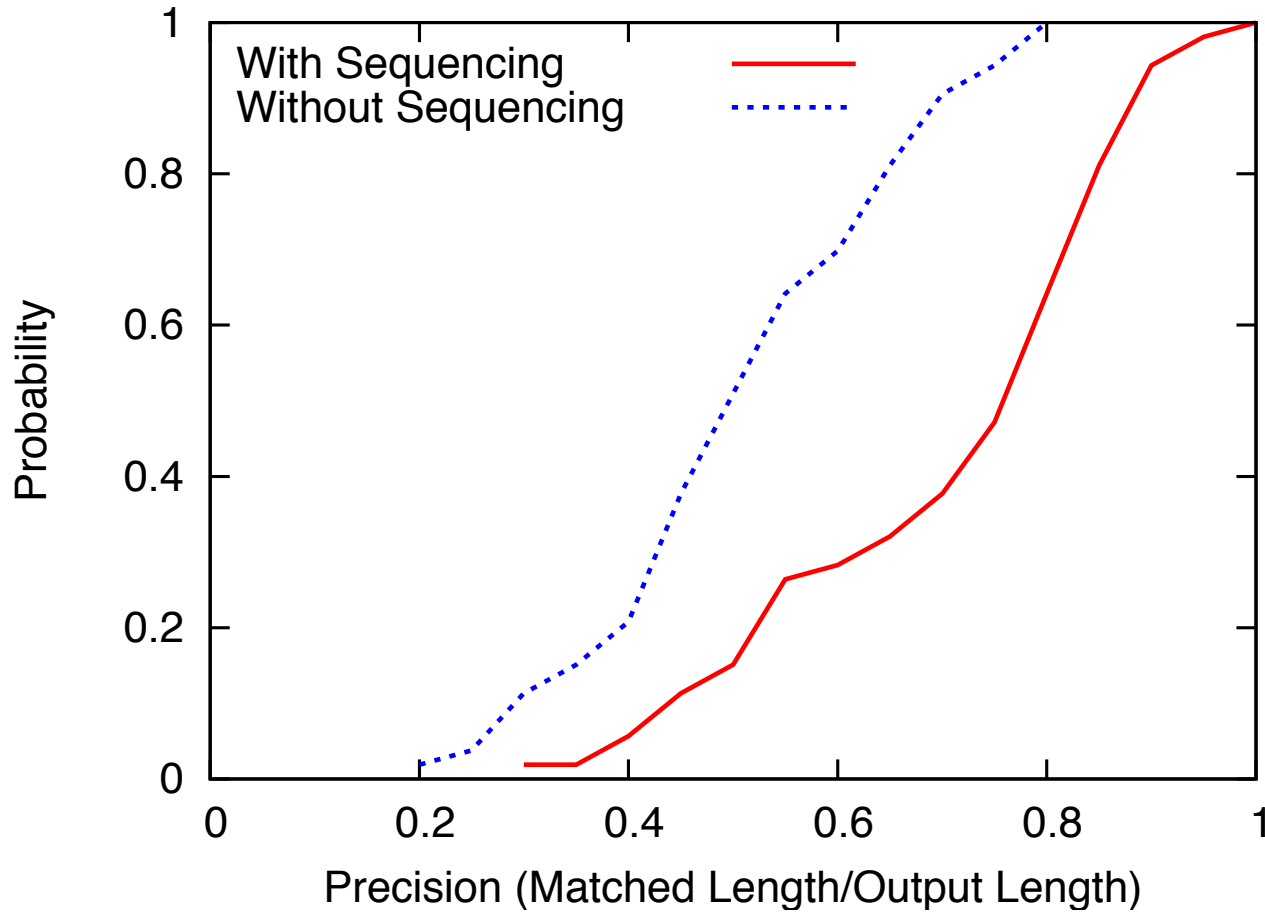
# Evaluation Metrics



# CTrack Has 75% Precision: 3x Less Error Than Placelab+VTrack, GPS k



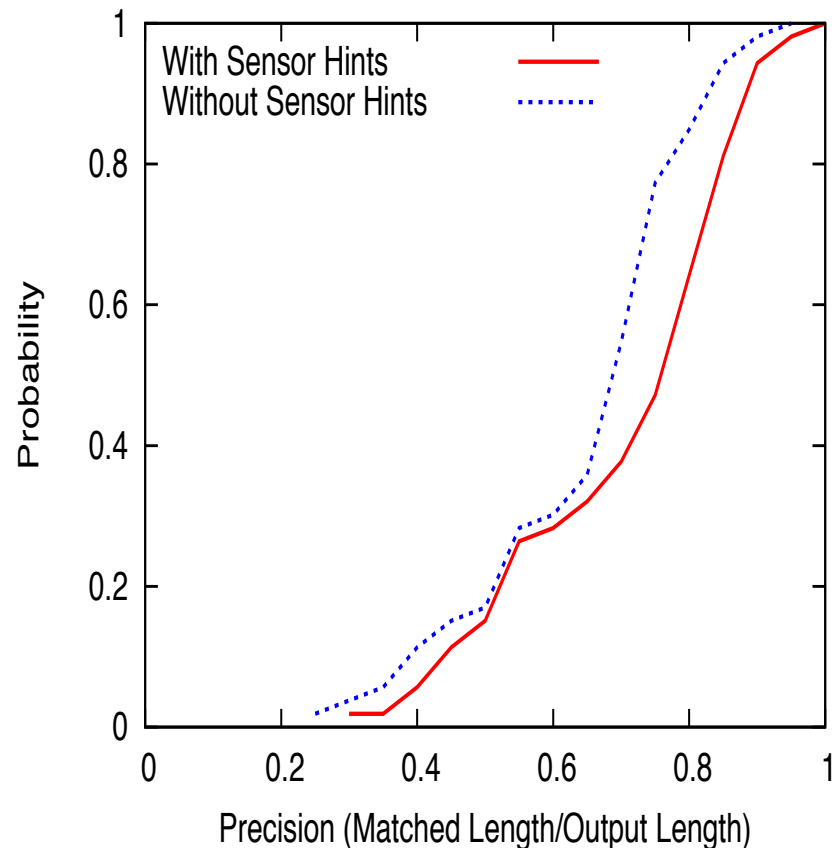
# Grid Sequencing Step is Critical



*Sequencing First Before Converting to (Lat, Lon)  
Coordinates is Critical*

# Impact Of Sensor Hints

- Small in quantitative terms
  - 6% precision, 3% recall
- But help correct some systematic errors
  - Turn hints fix “kinks” in output track
  - Movement hints fix “looping” in GSM signature



*Makes sense to take advantage of hints when available (i.e. on a smartphone) – they are free in terms of energy!*



# Conclusion

- CTrack is a *cellular-only system* that:
  - Can recover over 75% of a user's track
  - Significantly (over 3x) better in energy/accuracy tradeoff than existing approaches
- Broader impact
  - Make large scale deployment of location-based apps feasible without running into energy barriers
  - Enable devices without GPS (was: 85% of phone market) to contribute to and benefit from location-based services
  - Many IoT devices may have cellular or other long-range low-power radios such as LoRaWAN or Sigfox, but no GPS