



A filtering algorithm to GPS probe vehicles

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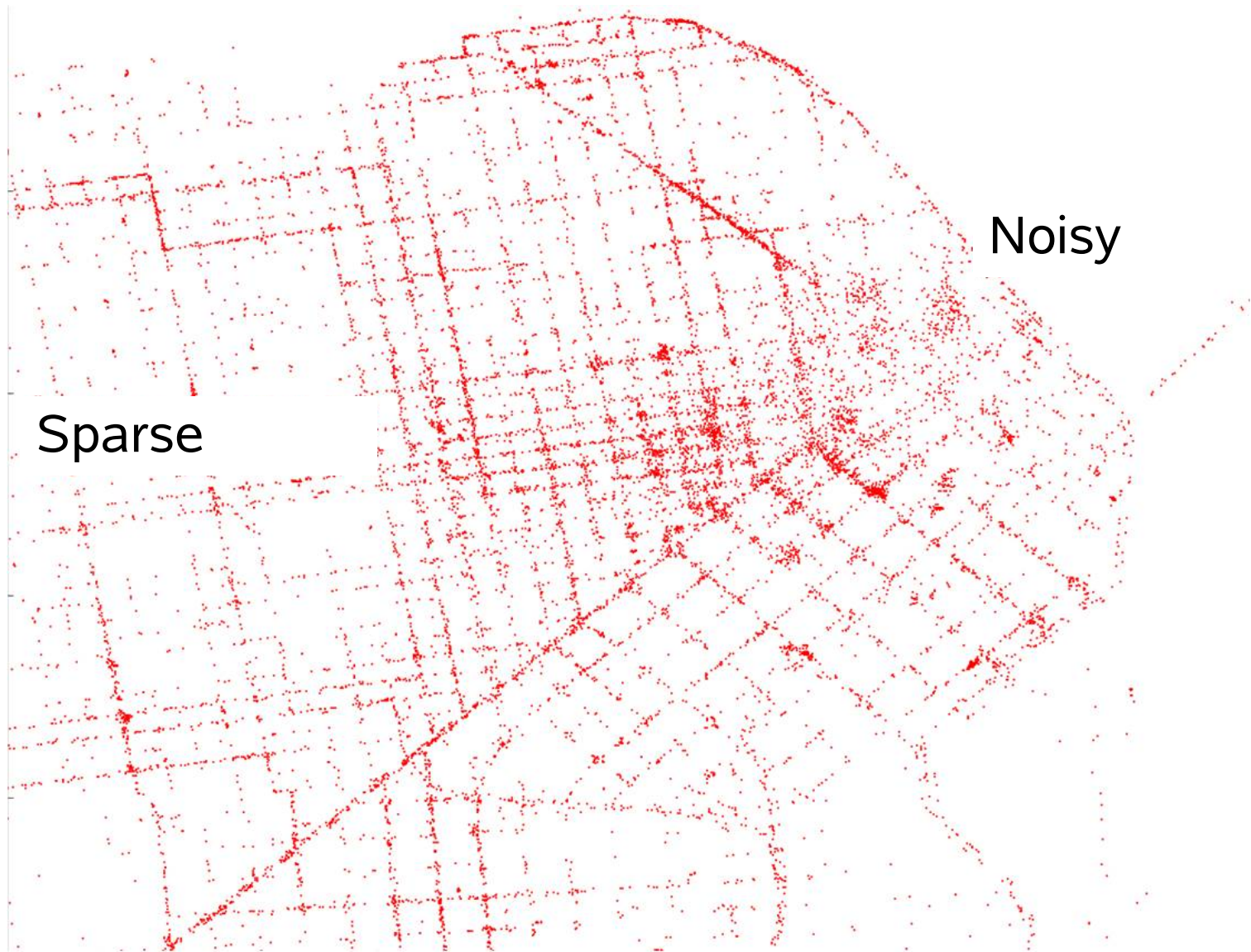
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Our data source for traffic estimation

- 630 taxis for the bay area
- About 600k points per day
- each taxi sends its position every minute



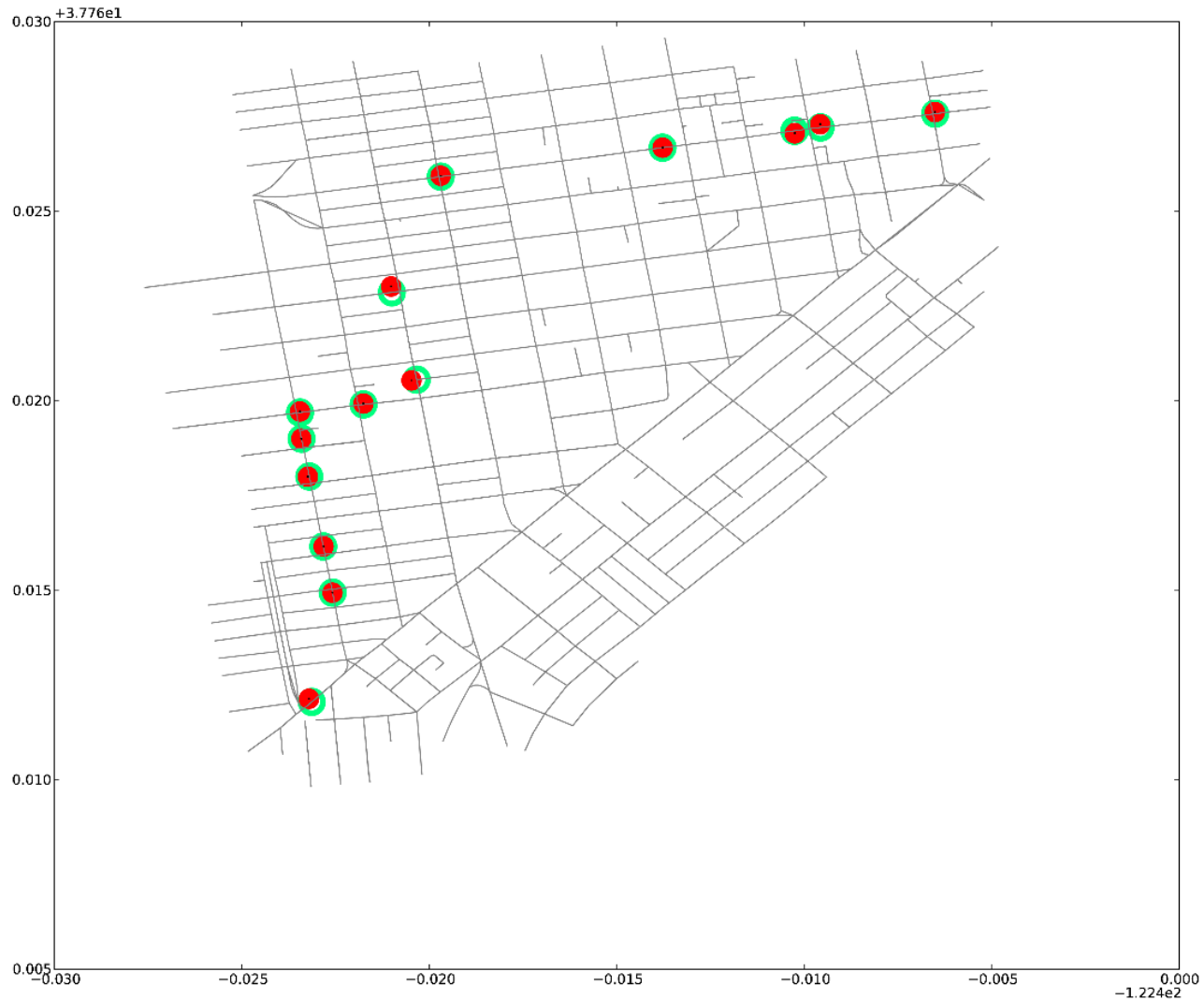
Data source for traffic estimation



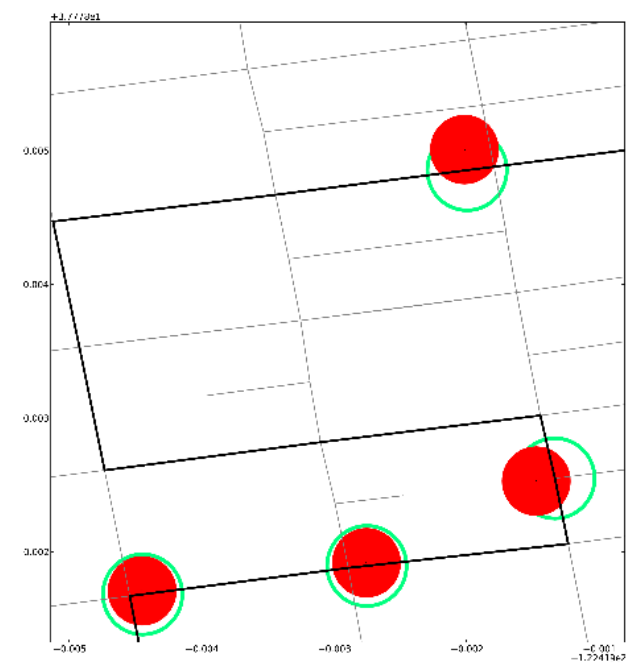
General workflow



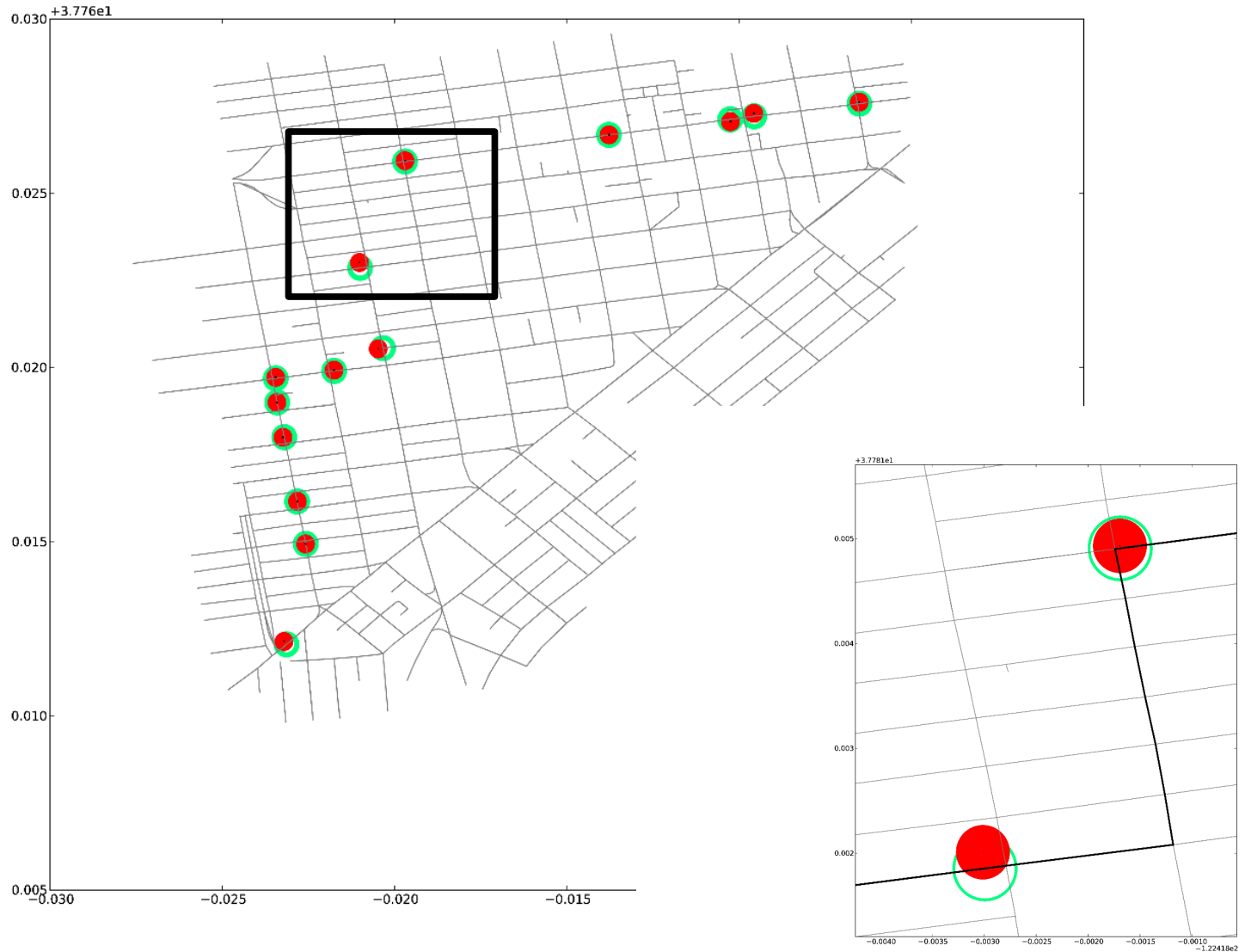
General workflow – projection, shortest path



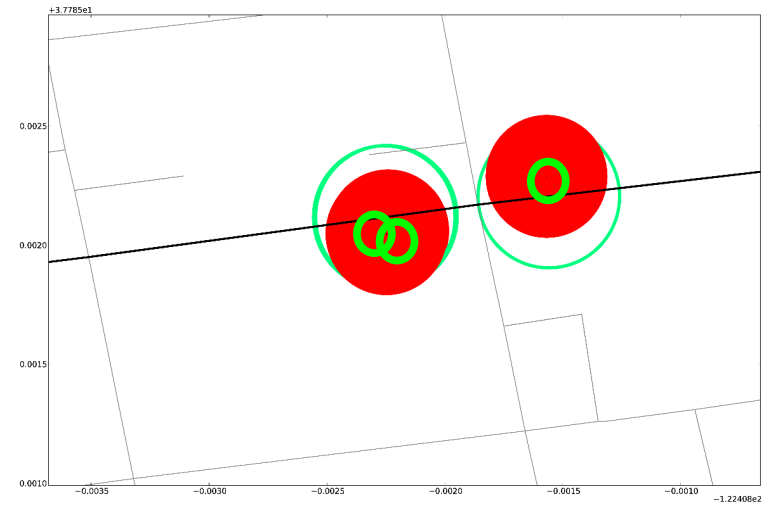
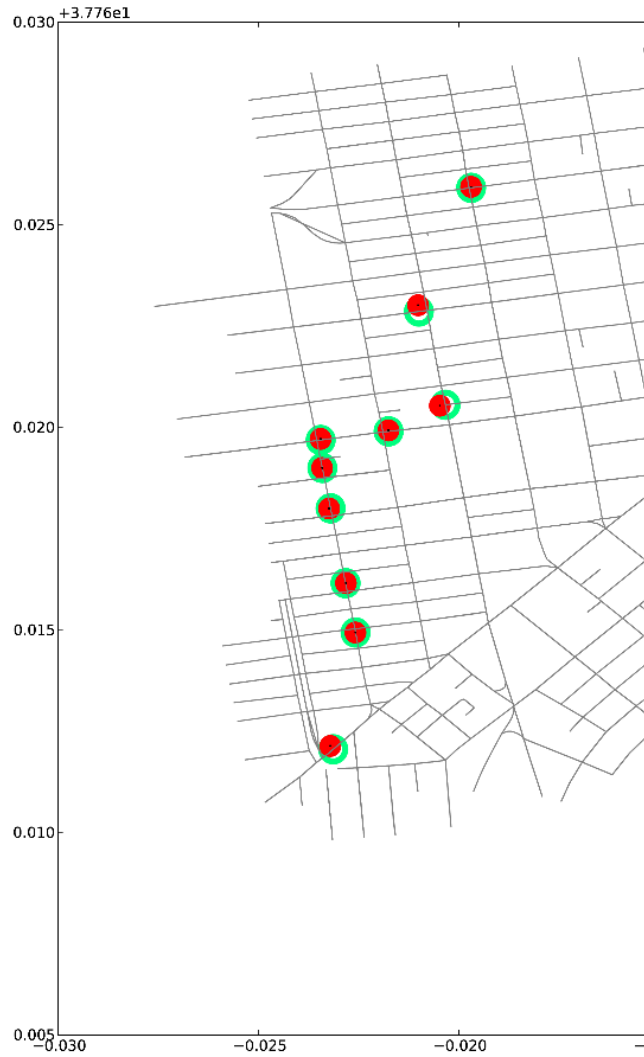
Issues with projection



Issues – path uncertainty



Issues – noisy GPS data





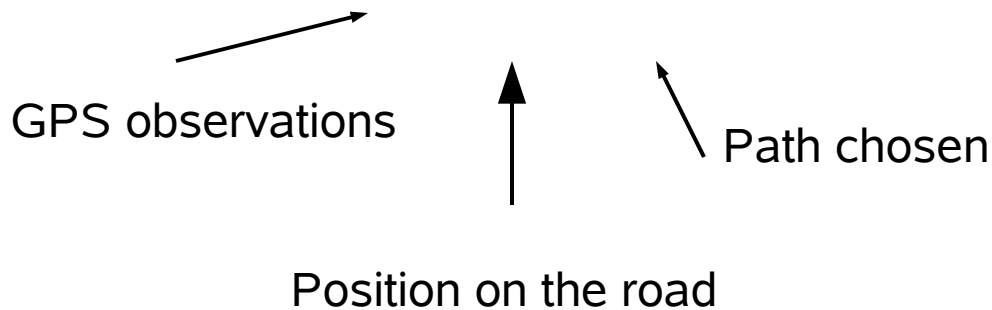
Hidden Markov Model

- Taxi chooses its path according to some preferences
- Taxi follows road
- We make a noisy measurement of the position at some time

Hidden Markov Model

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- Model:

$$p(G, x, p) = p(G^{1:T}, x^{1:T}, p^{1:T-1})$$



Hidden Markov Model



$$p(G, x, p) = \prod_{t=1}^T p(G^t / x^t) \prod_{t=1}^{T-1} p(p^t / x^t) p(x^{t+1} / p^t)$$

$p(G^t / x^t)$ is the *observation model* (Gaussian)

$p(p^t / x^t)$ is the *transition model*. Exponential shape:

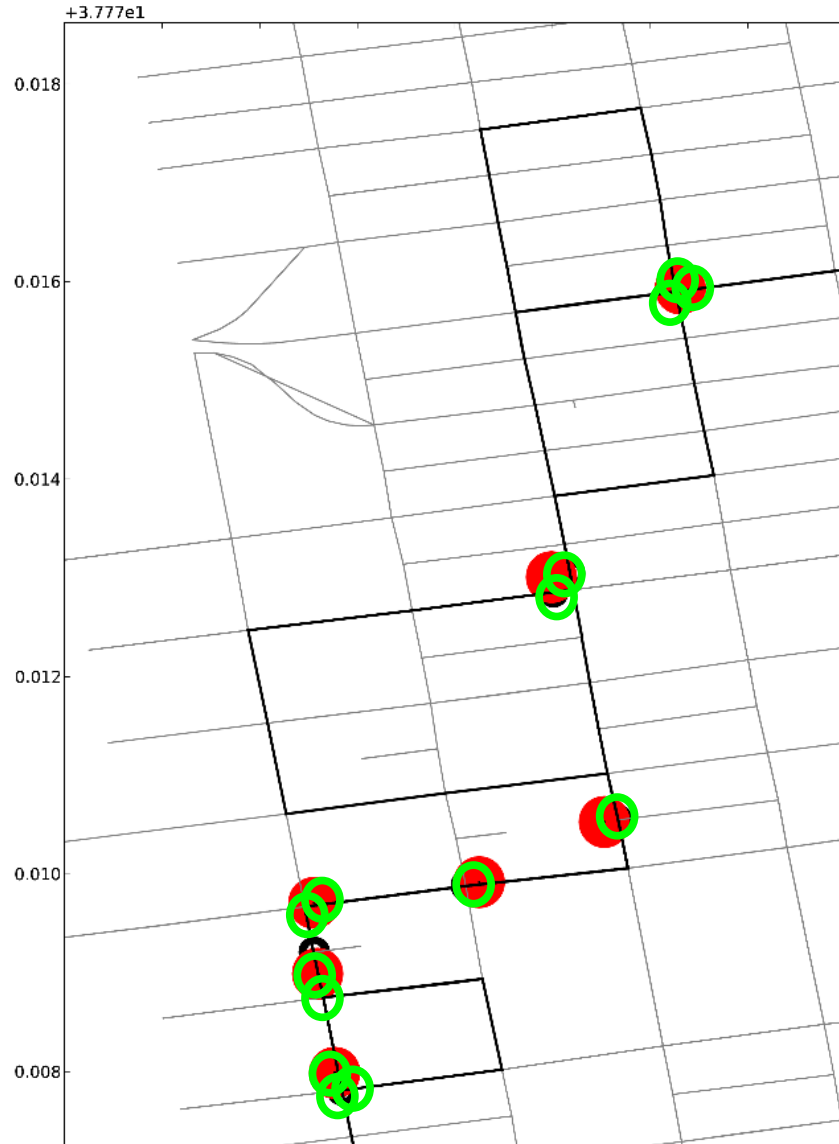
$$p(p^t / x^t) = \frac{\exp(\mu^T \phi(p^t, x^t) - A(\mu))}{Z}$$

What we want to learn

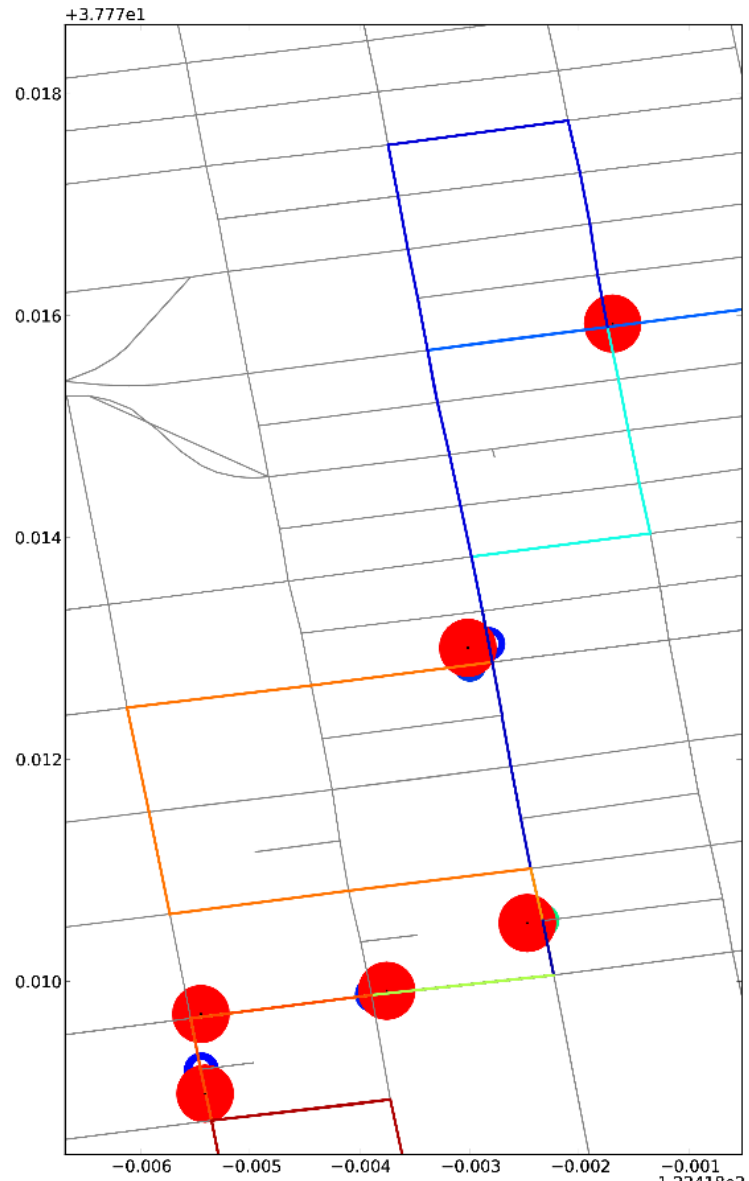
Some vector of features

Normalization constant

Multiple paths and projections



Assigning probabilities



Filtering – final output



Conclusion



- Presented an algorithm for filtering sparse, noisy observations from GPS probe vehicles
- Can be used to build more complex traffic models
- Works reasonably well with some simple features
- Need to test with more features and validate against test data