Learning Latent Factor Models of Human Travel

Presented By:

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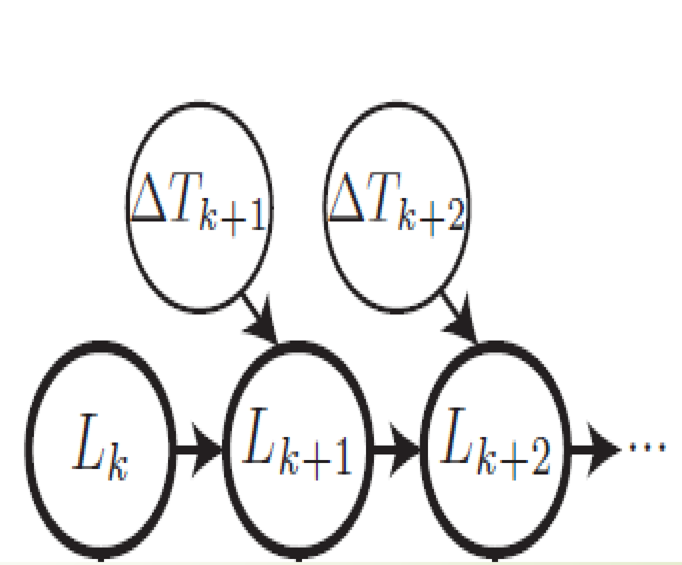
Goal

- **Goal**: Estimate the likelihood of traveling to a destination

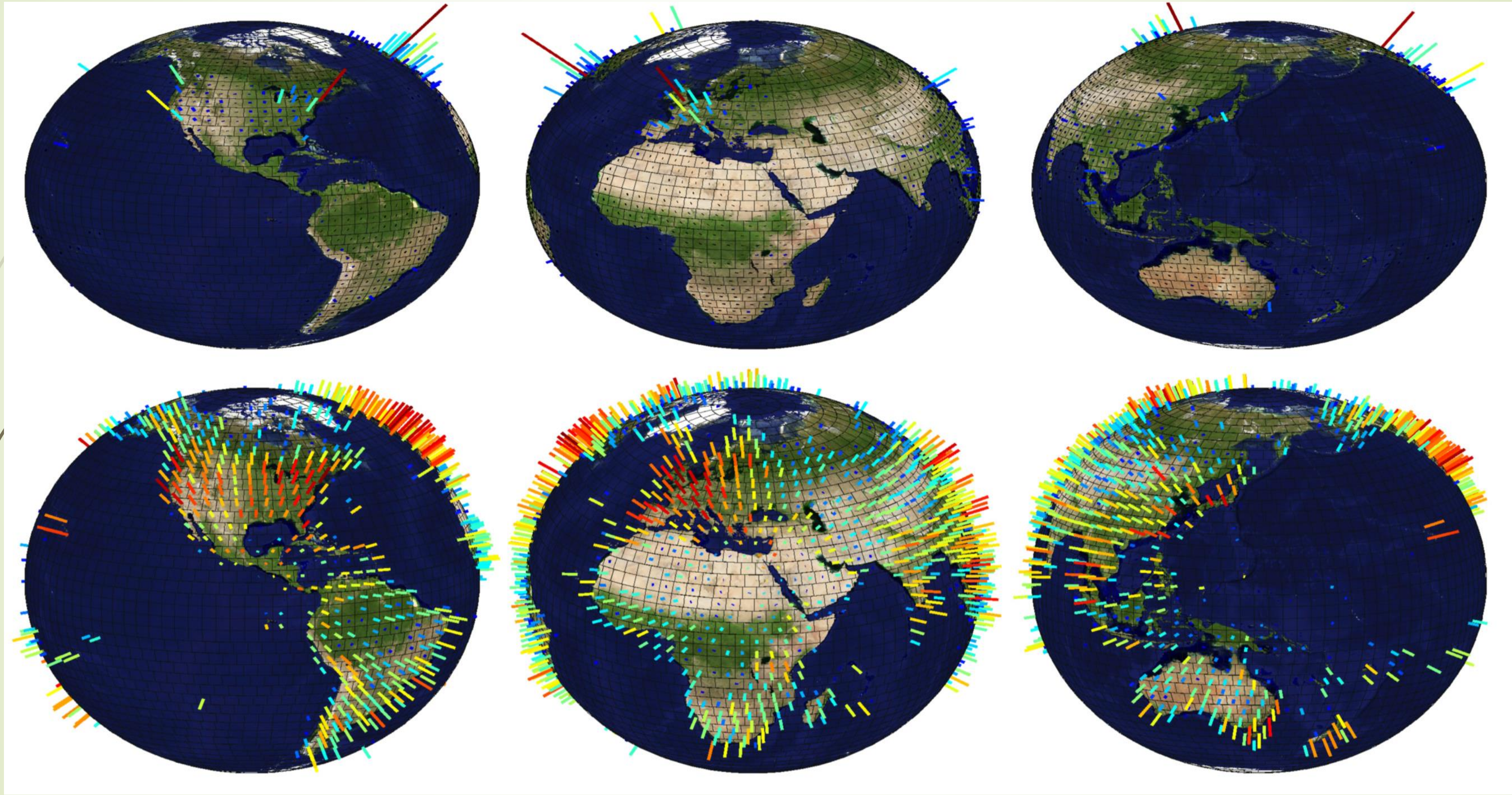


- Predict the probability of travelling from bin L_k to L_{k+1} in Time Period ΔT

Dataset

- Metadata of 6,341,877 Geo tagged Flickr images comprising of 75,248 individuals
- Mid pts of 3186 bins of 400*400 sq. km. spanning Earth
- Mapping of each photograph to a bin
- Distance 'intervals' between consecutive photographs
- Time intervals between consecutive photographs

Distribution of Data



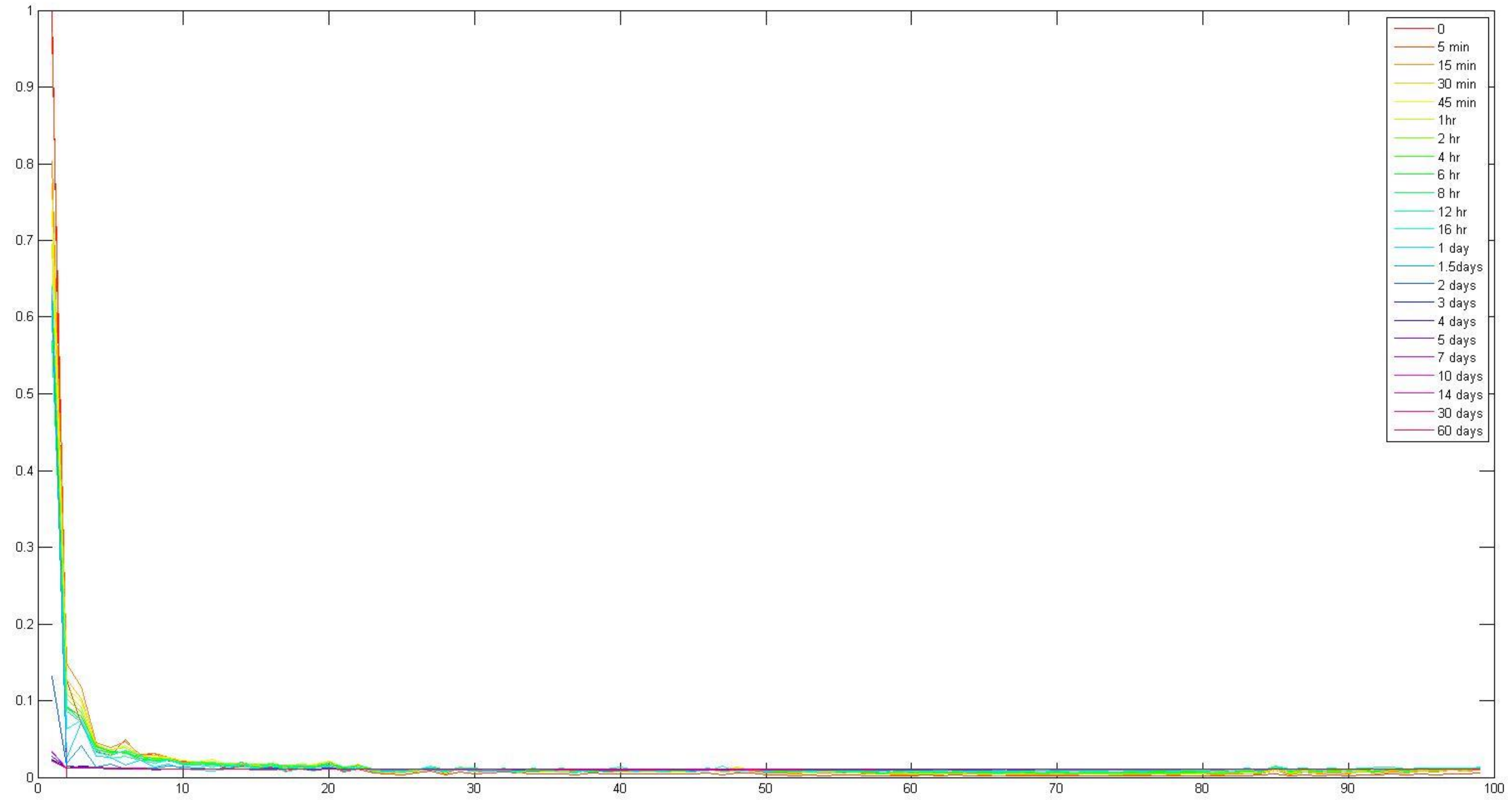
Basic Model

- **Hypothesis**
  - Some destinations are more desirable than others
  - Long Distance travel is rare but not surprising
- **Multiplicative Model**
  - $P_{ij\tau} = \frac{\exp(\rho(d(i,j),\tau)+\alpha_j)}{\sum_\ell \exp(\rho(d(i,\ell),\tau) + \alpha_\ell)}$
  - $\rho(d,\tau)$ captures dependence of travel on the distance
  - α represents the desirability of a destination
  - No of parameters= 5486 parameters (3186 bins + 100 distances * 23 time differences)

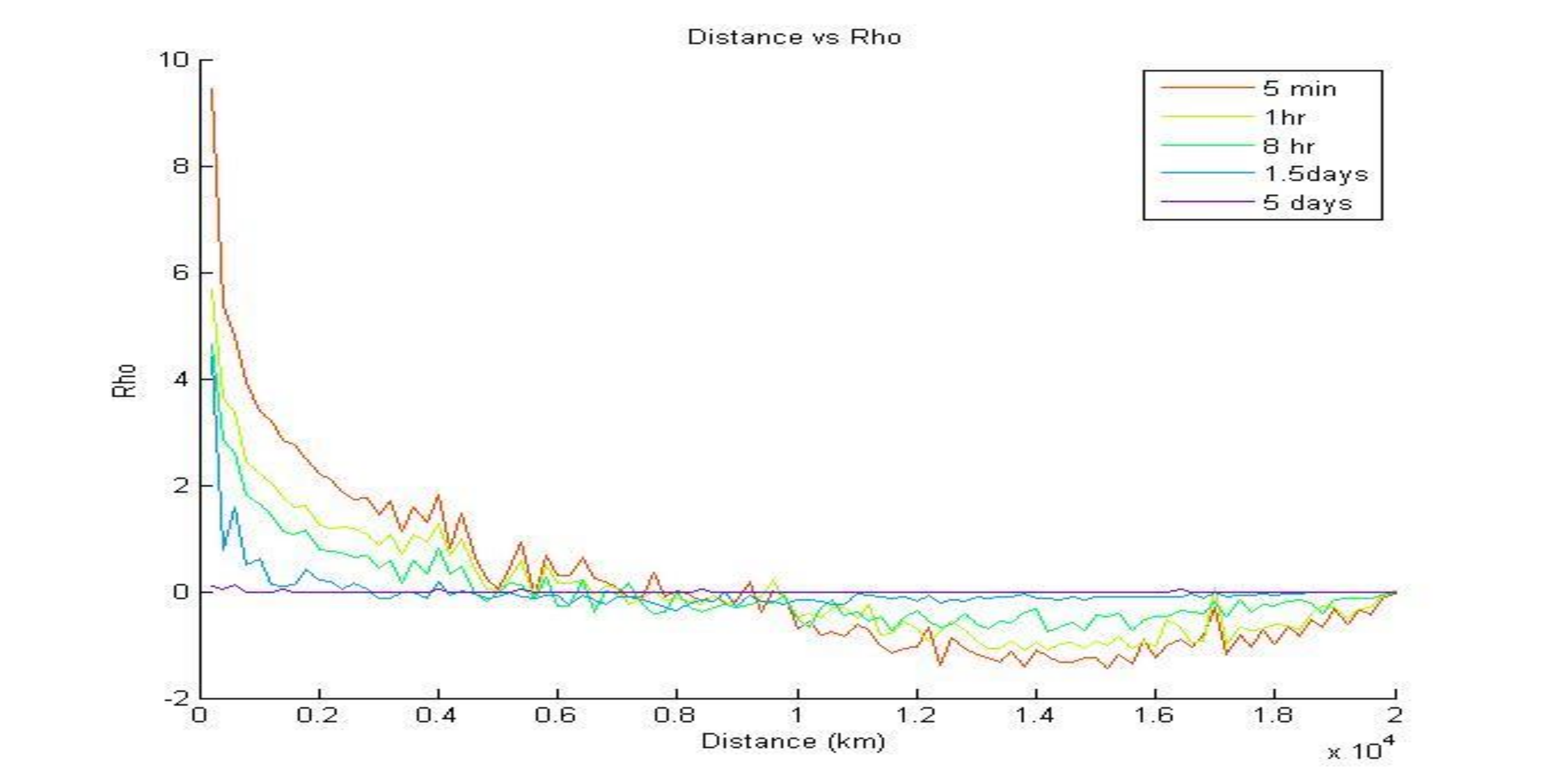
Learning using Batch Gradient

- **Objective Function**
  - NLL = $-\sum_{ij\tau} N_{ij\tau} \ln P_{ij\tau}$
- **Derivative of alpha**
  - $\frac{\partial NLL}{\partial \propto_j} = -N_j + \sum_{i\tau} N_{i\tau} \frac{\exp(\rho(d_{ij},\tau)+\propto_j)}{\sum_\iota \exp(\rho(d_{i\iota},\tau)+\propto_\iota)} = -N_j + \sum_{i\tau} N_{i\tau}\, P_{ij\tau}$
- **Derivative of rho**
  - $\frac{\partial NLL}{\partial \rho_{\tau d}} = -N_{\tau d} + \sum_{ij} N_{ij\tau} \frac{\sum_{\iota:d_{i\iota}=d} \exp(\rho(d_{i\iota},\tau)+\propto_\iota)}{\sum_\iota \exp(\rho(d_{i\iota},\tau)+\propto_\iota)} = -N_{\tau d} + \sum_i N_{i\tau}\, P_{i\tau d}$
- **Issues:**
  - ~2 minutes for each iteration on KillDevil even after considerable optimization
  - Matlab doesn't allow global variables in parallel constructs
  - Large Step size: Pijt goes out of range
  - Local Minima
  - Non Linear Conjugate Gradient: not enough time!

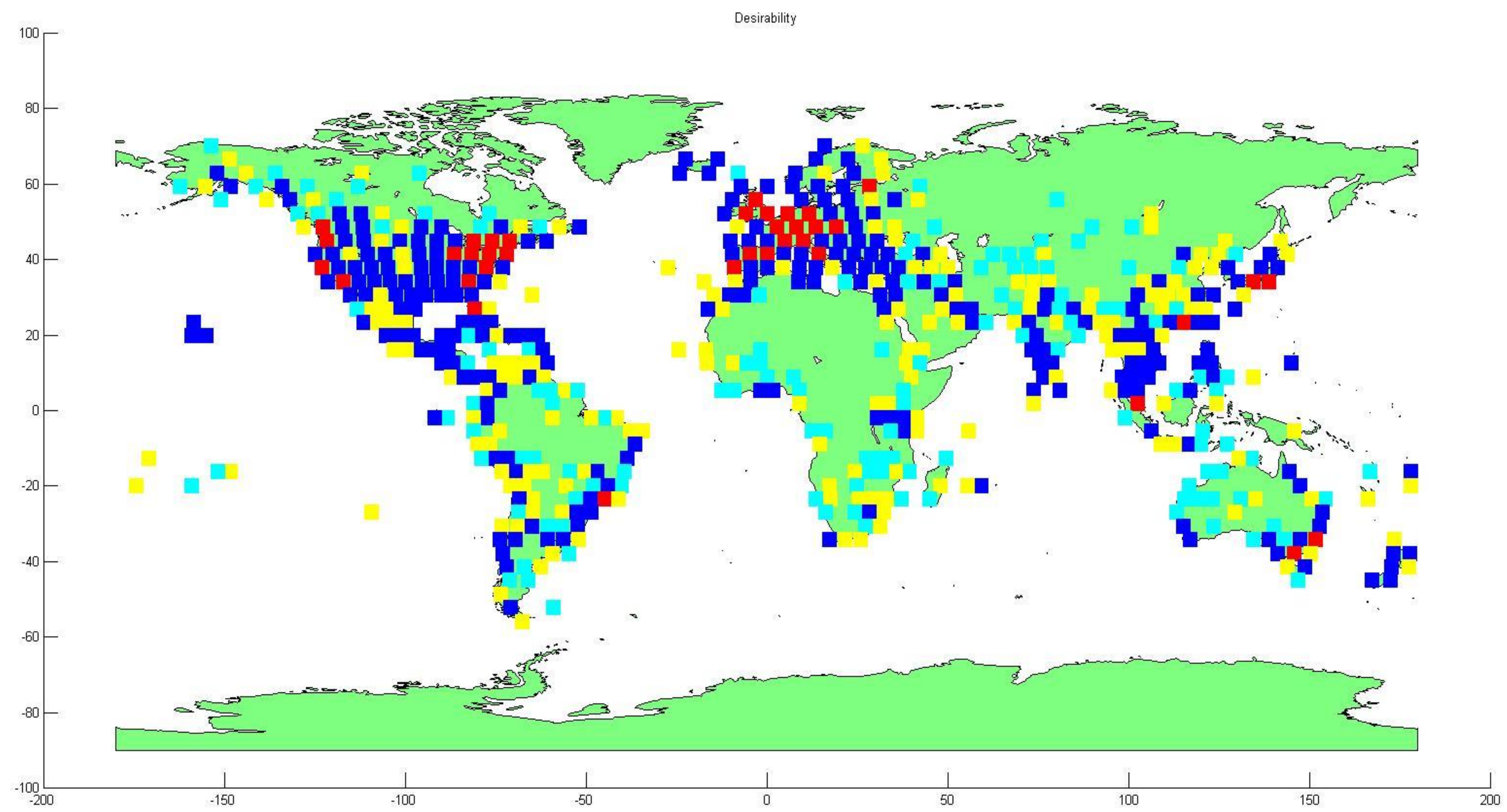
Travel Model $P_{ij\tau}$ (Source London)



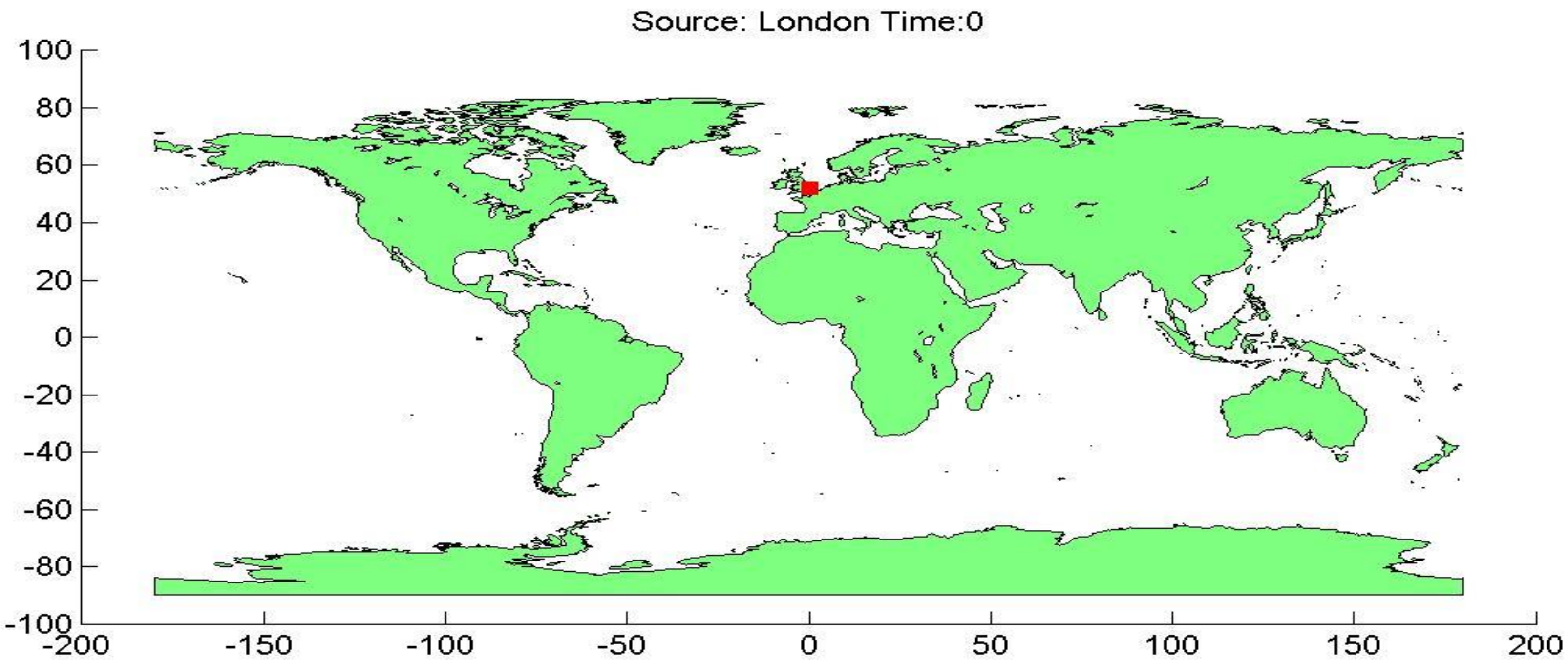
Distance Factor (ρ)

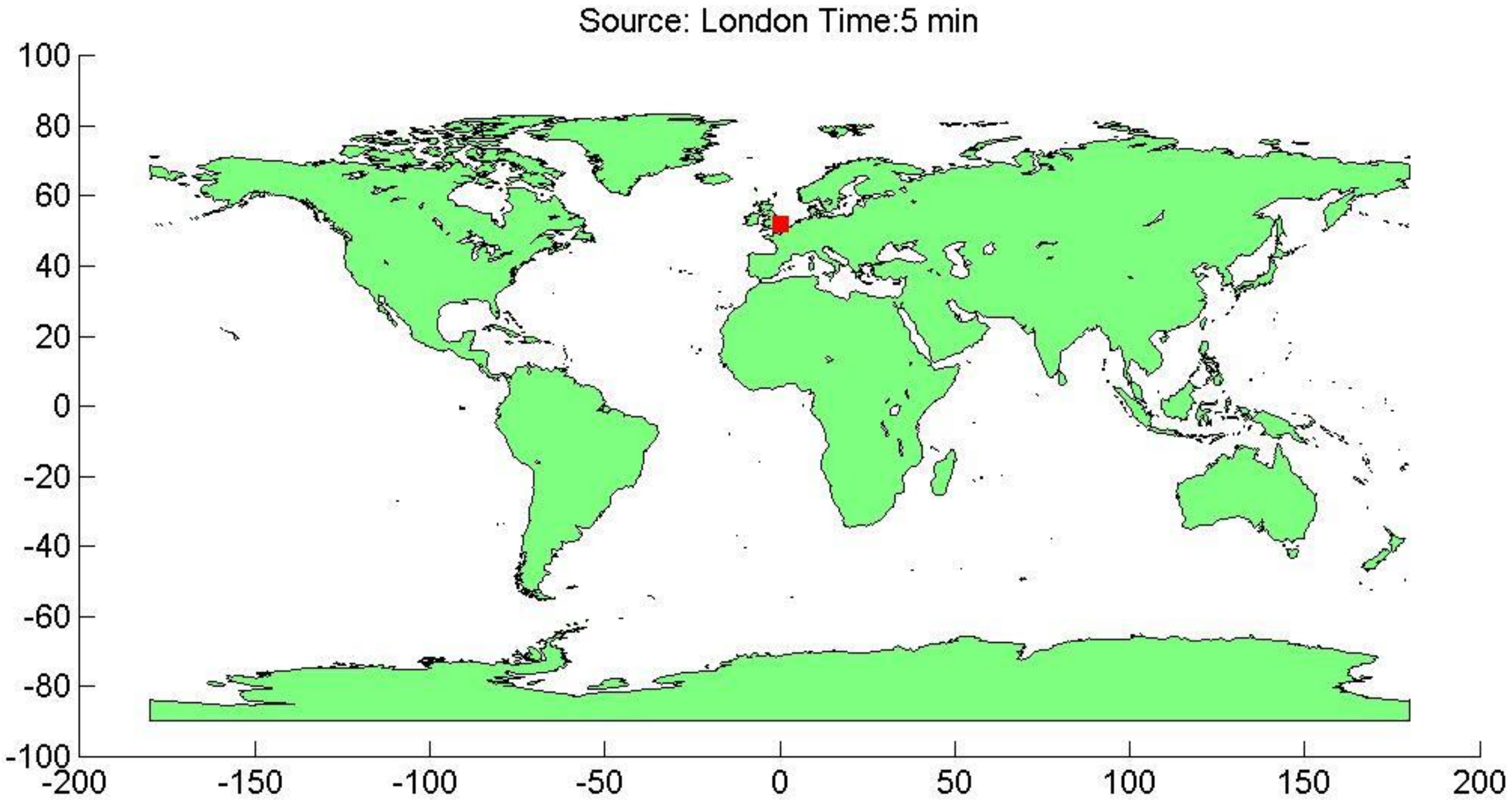


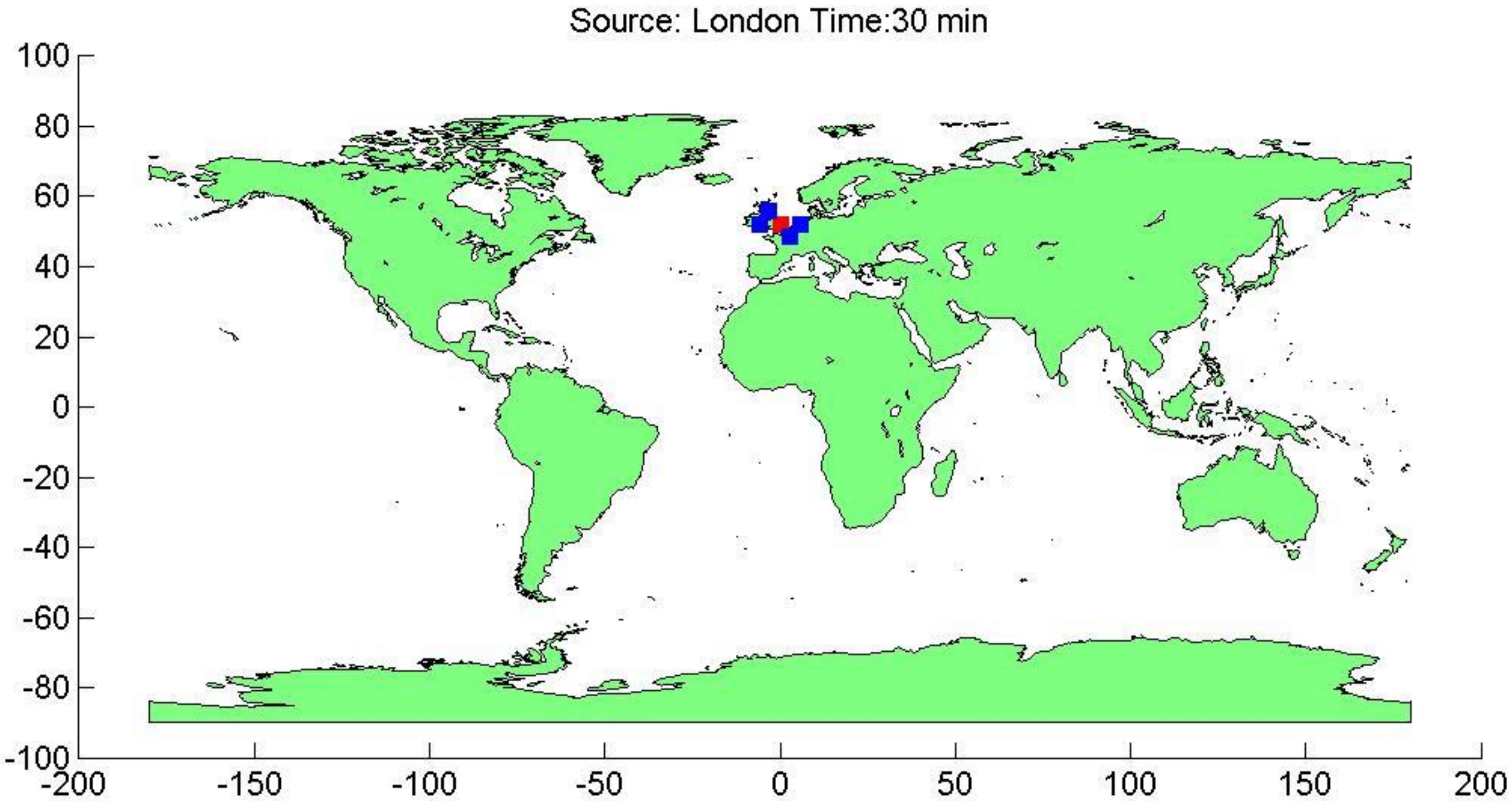
Desirability Factor (α)

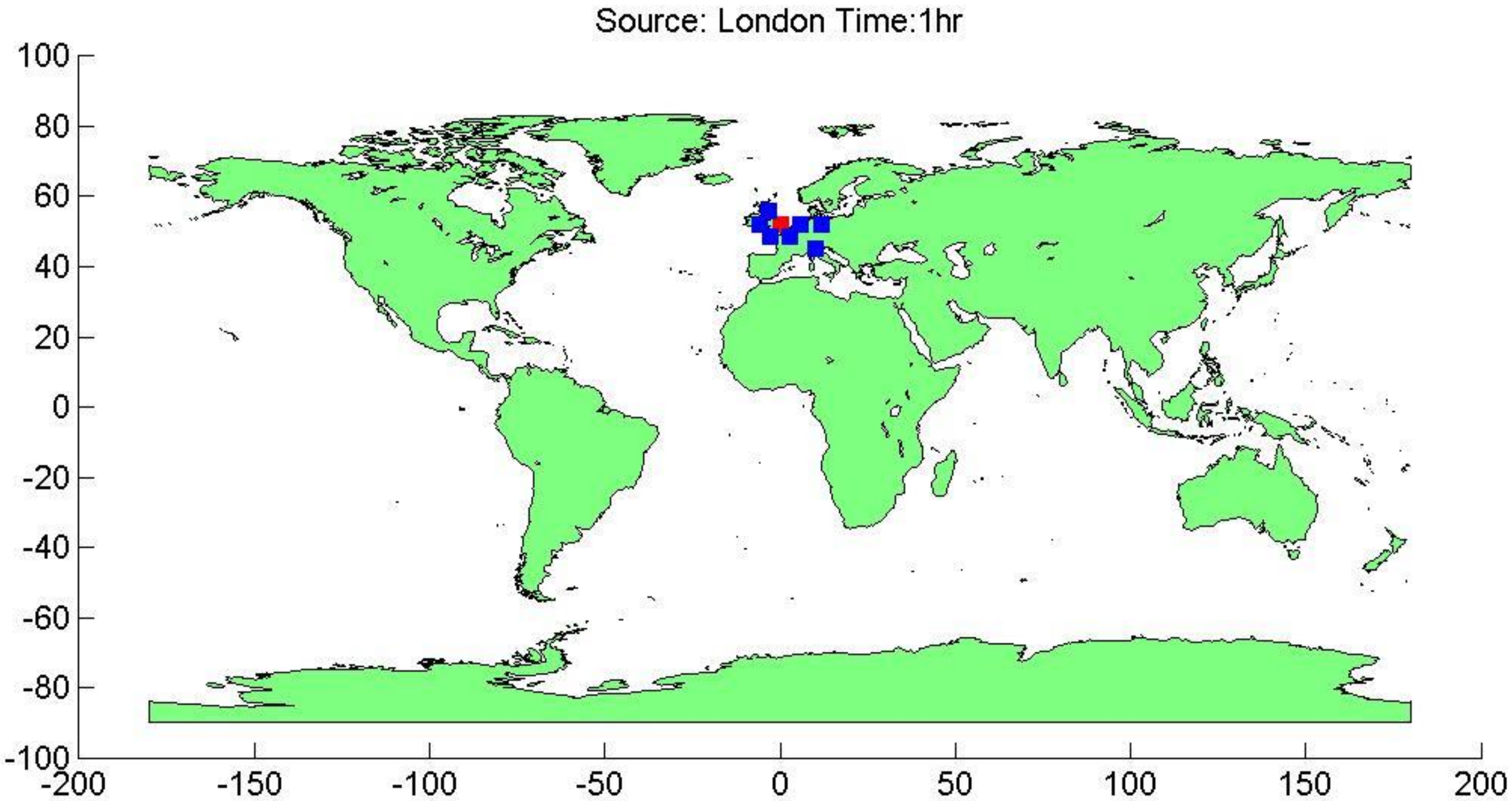


Travel Probabilities

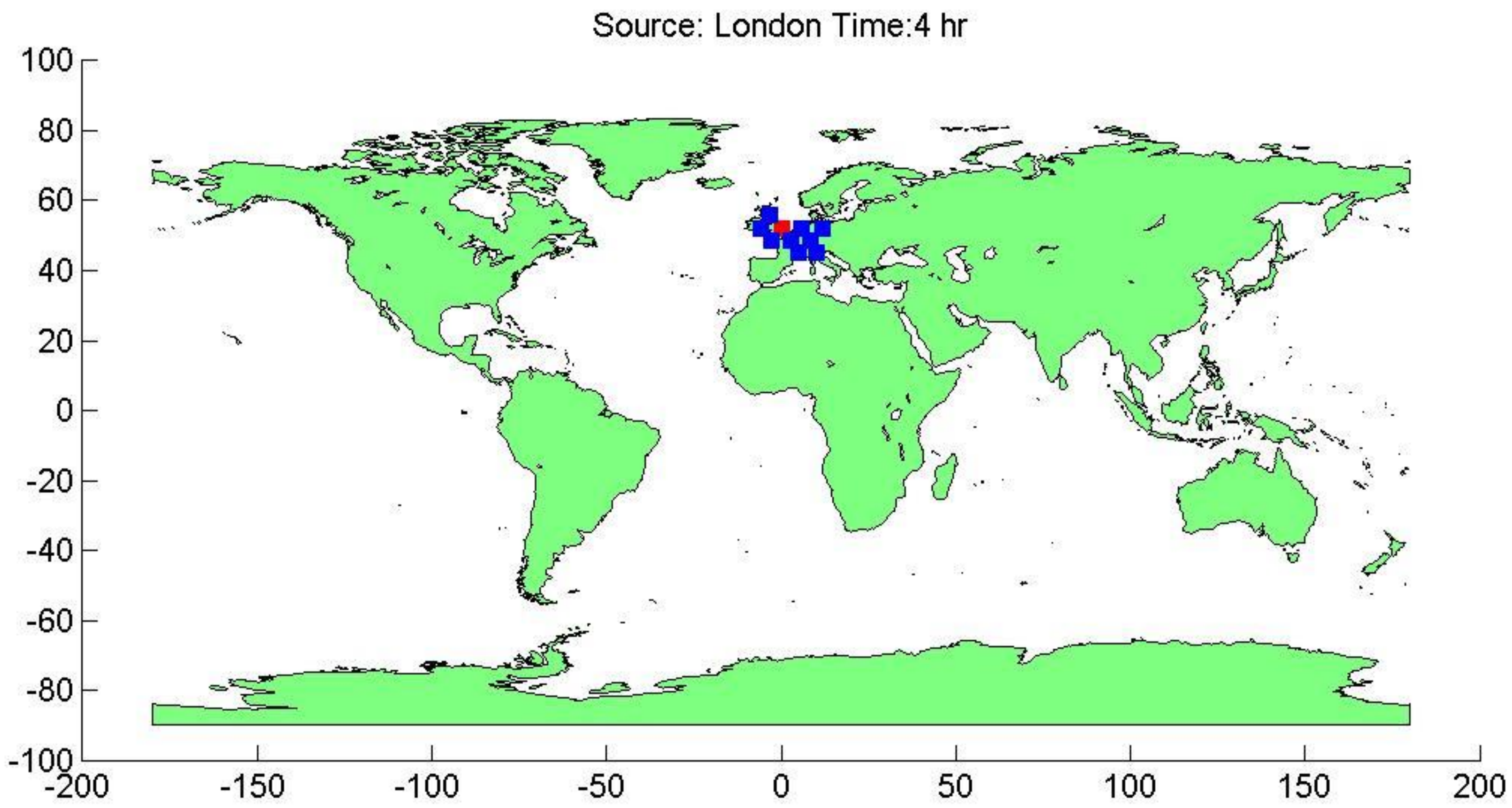


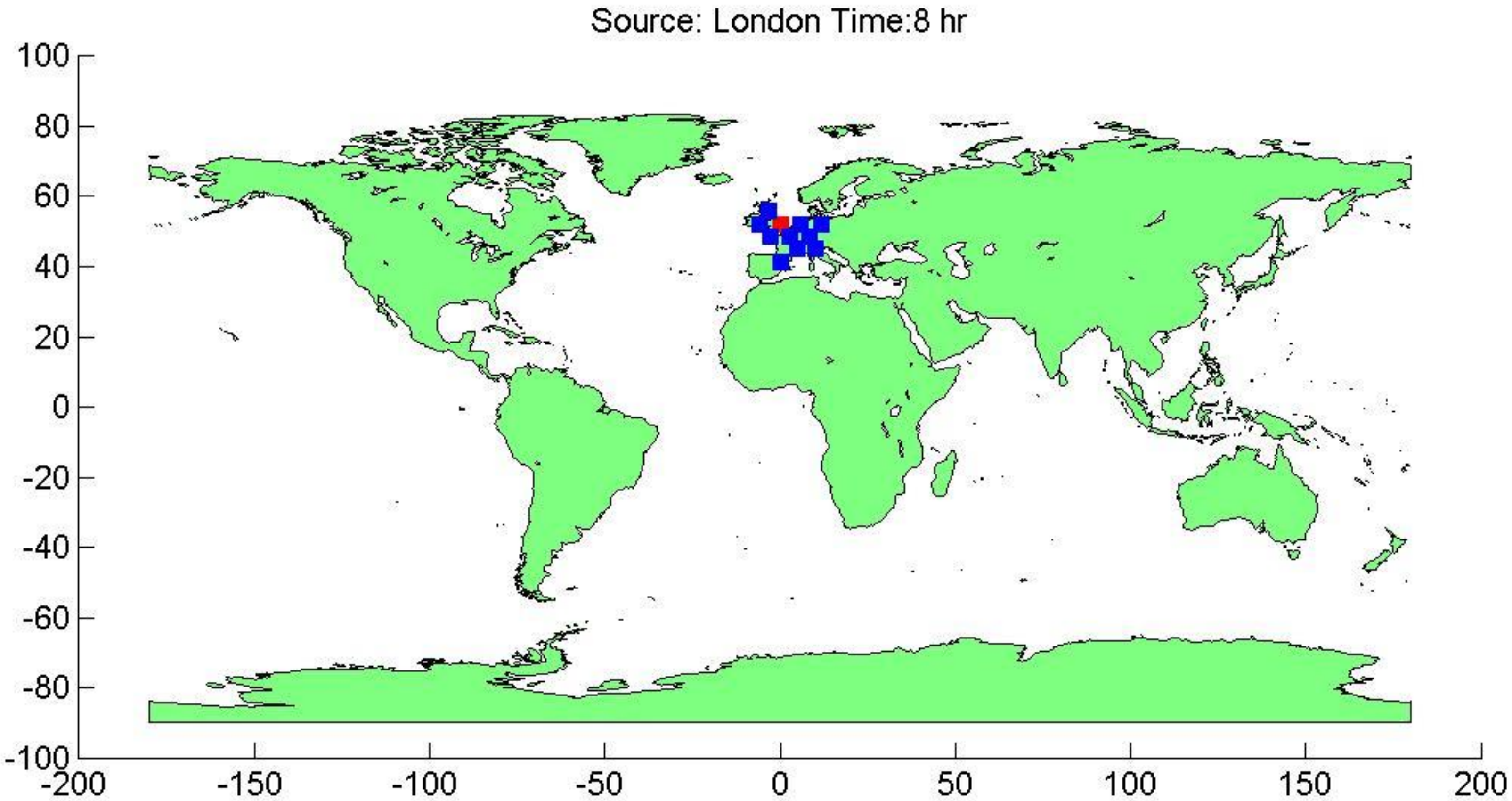

Source: London Time:5 min
100
80
60
40
20
0
-20
-40
-60
-80
-100
-200
-150
-100
-50
0
50
100
150
200

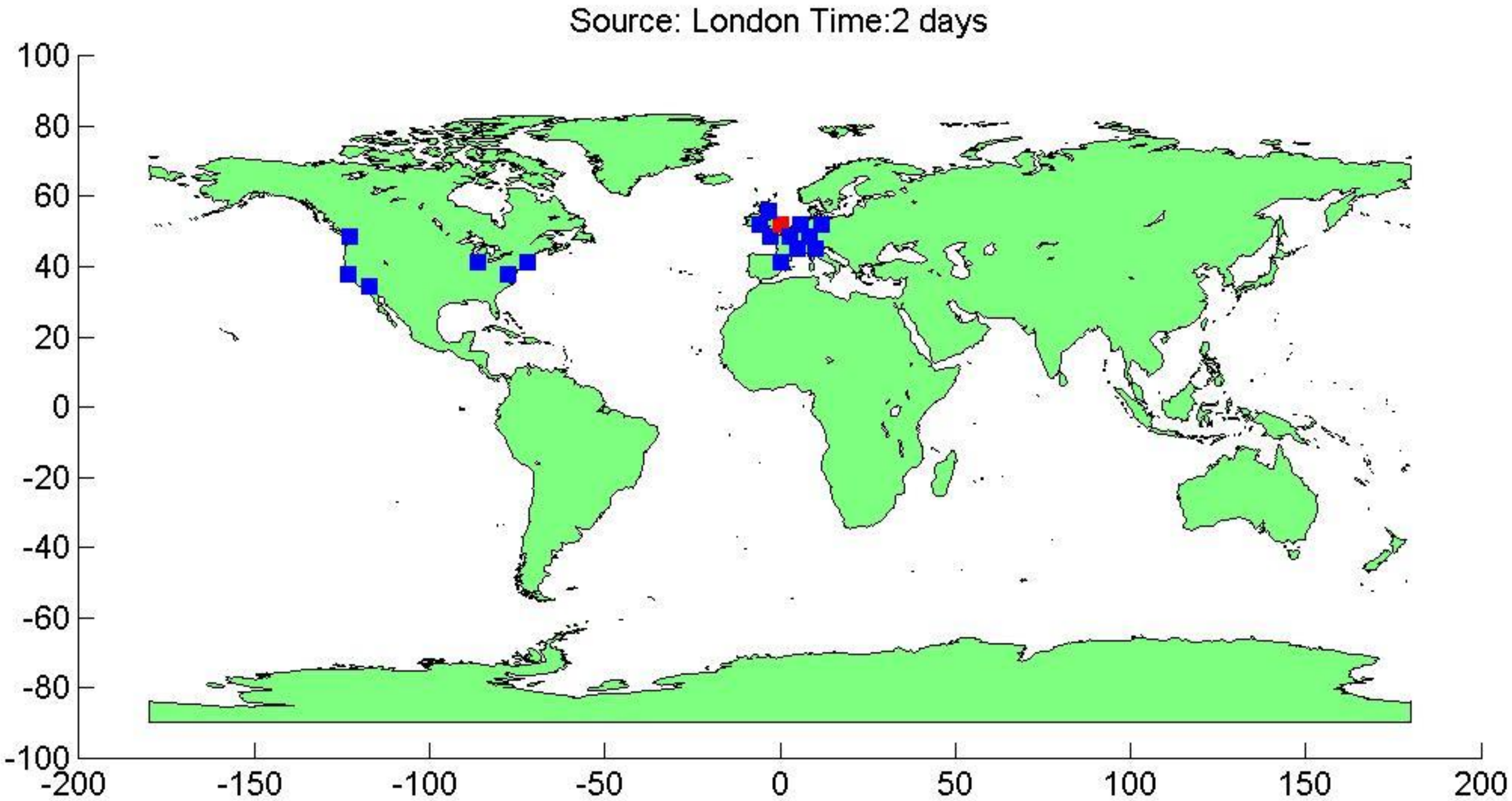

Source: London Time:30 min
100
80
60
40
20
0
-20
-40
-60
-80
-100
-200
-150
-100
-50
0
50
100
150
200

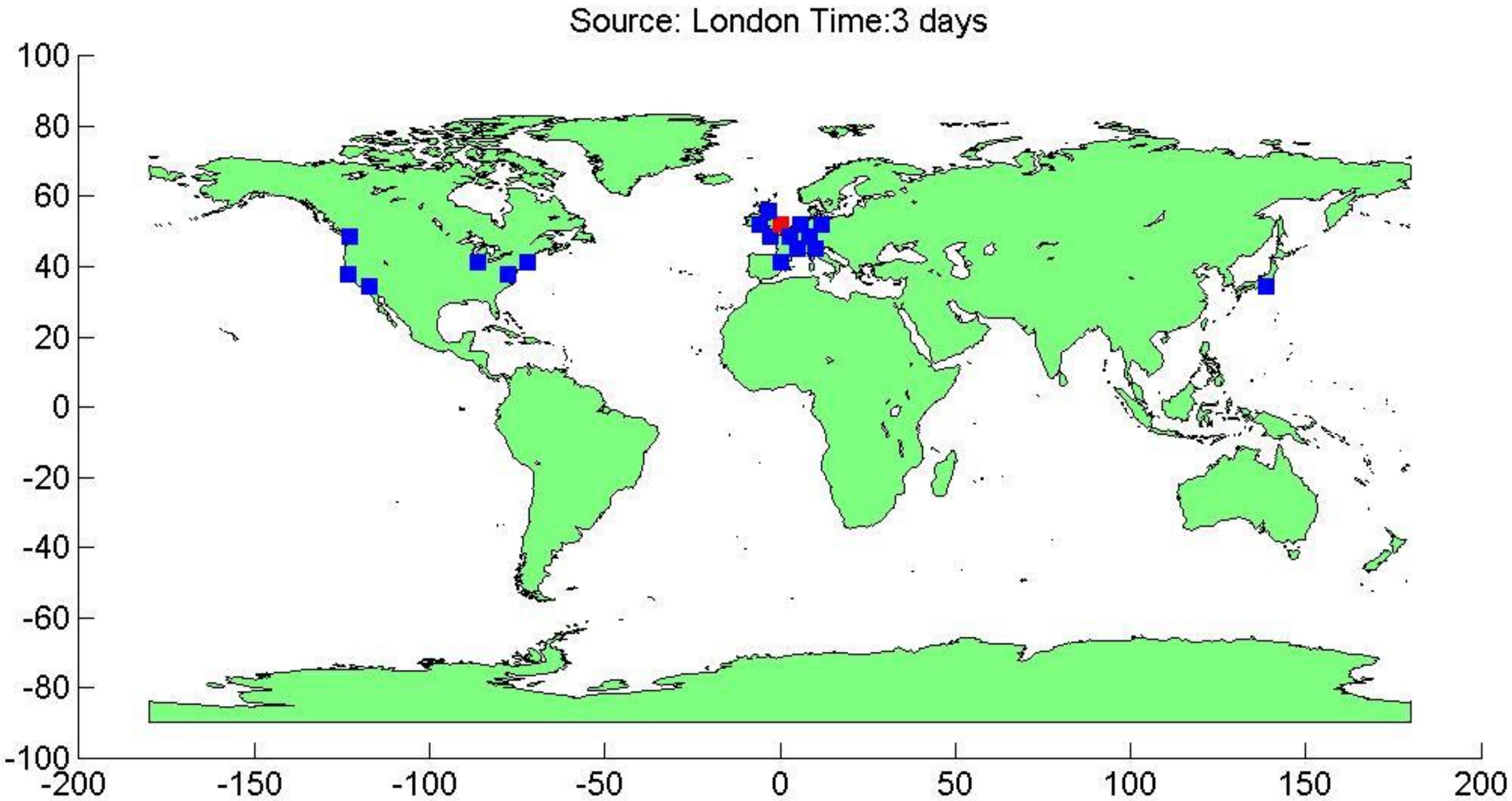


Source: London Time:1hr
100
80
60
40
20
0
-20
-40
-60
-80
-100
-200
-150
-100
-50
0
50
100
150
200


Source: London Time:4 hr
100
80
60
40
20
0
-20
-40
-60
-80
-100
-200
-150
-100
-50
0
50
100
150
200


Source: London Time:8 hr
100
80
60
40
20
0
-20
-40
-60
-80
-100
-200
-150
-100
-50
0
50
100
150
200


Source: London Time:2 days
100
80
60
40
20
0
-20
-40
-60
-80
-100
-200
-150
-100
-50
0
50
100
150
200



Source: London Time:3 days
100
80
60
40
20
0
-20
-40
-60
-80
-100
-200
-150
-100
-50
0
50
100
150
200

Popularity vs Desirability

Popular Destination (Actual)

London, GB
New York, US
San Francisco/San Jose, US
Paris, FR
Milan, IT
Washington DC/Baltimore, US
Vancouver, CA
Chicago, US
Los Angeles, US
Brussels, BE
Berlin, DE
Tokyo, JP
Rome, IT
Glasgow, GB
Frankfurt, DE
Barcelona, ES

Desirable Destinations [1]

London, GB
New York, US
Brussels, BE
San Francisco/San Jose, US
Paris, FR
Frankfurt, DE
Sydney, AU
Melbourne, AU
Tokyo, JP
Dublin, IE
Shanghai, CN
Washington DC/Baltimore, US
Berlin, DE
Toronto, CA
Hilo, US
Marseille, FR

Desirable Destination (Our)

New York
London
San Francisco
Seattle
Washington D.C.
Vancouver
Los Angeles
Chicago
Milan
Glasgow
Berlin
Tokyo
Naples
Barcelona
Amsterdam
Paris
Sydney

Conclusion

- ‘Decent’ predictive power
- Parametric Models are Efficient
- Can generalize (outperforms empirical model)
- Learn ‘Meaningful’ Concepts

Future Work

- Implement Conjugate Gradient
- Include affinity between destinations
- Implement Clustered Model i.e. cluster individuals based on previous travel
- Take into account the “season” of travel (i.e. time of year travel occurred)

References

- M. Guerzhoy and A. Hertzmann. Learning latent factor models of human travel. In *NIPS Workshop on Social Network and Social Media Analysis: Methods, Models and Applications*, 2012.
- E. Kalogerakis, O. Vesselova, J. Hays, A. Efros, and A. Hertzmann. Image Sequence Geolocation with Human Travel Priors. In Proc. ICCV, 2009.
- T. Kurashima, T. Iwata, G. Irie, and K. Fujimura. Travel route recommendation using geotags in photo sharing sites. In Proc. CIKM, 2010.

Questions ???

Iteration vs Cost