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# Feature Learning from Massive Spatial Trajectories: A Case Study of Map Matching

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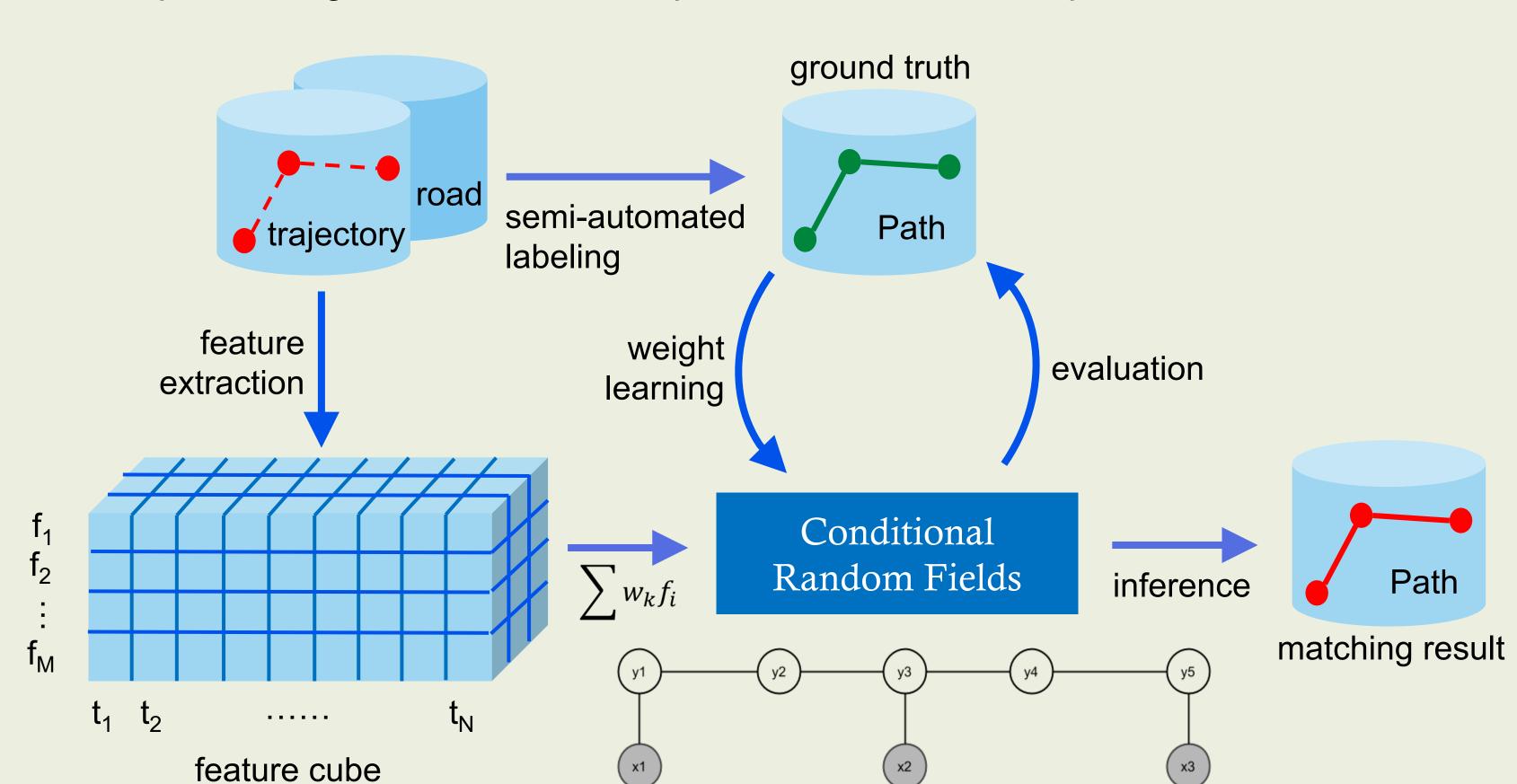
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Introduction

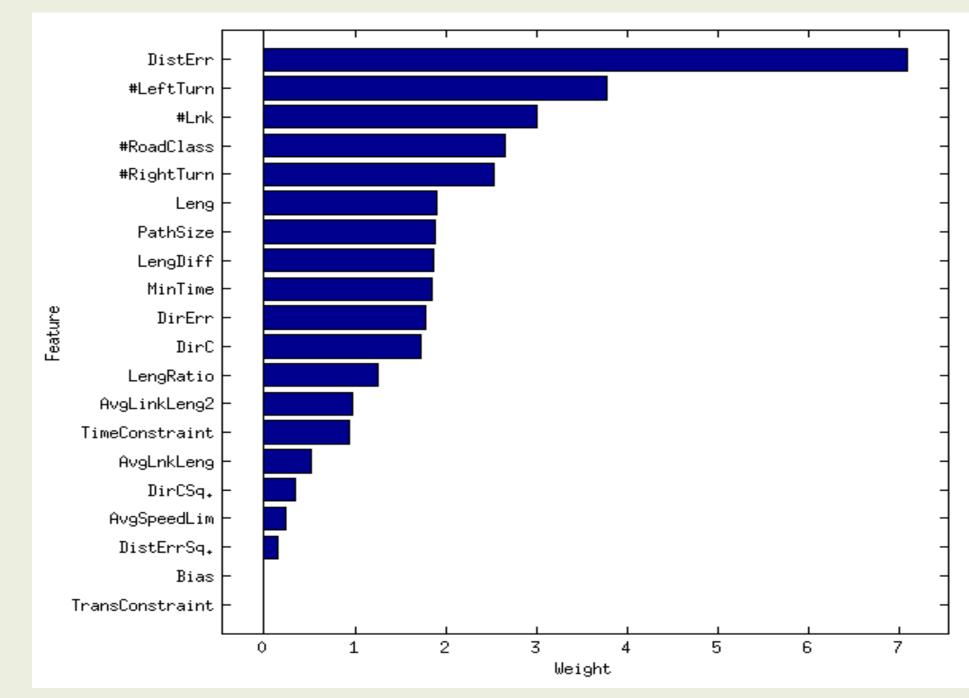
Mining spatial trajectories aims to extract non-explicit information from spatial trajectory data that can be organized as temporally ordered locations, such as taxi GPS logs, twitter check-ins. The field has been revolutionizing the traditional means of collecting and processing geo-spatial information for mapping and many other realworld applications. One of the mining tasks requires the labeling of individual points in trajectories with states in query such that the physical measurements can be better interpreted. For example, by means of map matching, each data point in the location sequence is assigned to the road segment on which the moving object travelled, while methods of location-based activity recognition are used to identify the most probable activities (e.g., at home, at work, at bar) associated with each location in the trajectory data. These labeling tasks impose challenges on label assignments especially when the measurements are noisy and when there are nonexclusive semantic correspondences between data points and labels.

## **Study Case – Map Matching via Feature Learning**

Map Matching: Given location sequences, recover travel paths in road network



## **Results – Learned Features** DistErr



Features learned for map matching of low sampling rate GPS data. The weights' magnitudes indicate the relevance degree of the feature to the task. Among all the features, distance error (DistErr), number of left turn (#LeftTurn), number of the link in the path (#Lnk) and number of different road classes in the path (#RoadClass) are the most relevant ones. (Yang, 2016)

### Results – ground truths vs. recovered paths





Recovered paths between GPS data points with sampling rate of 120s. Green paths are ground truths and red ones are results generated by our map matching method. The comparisons illustrate the cases when fastest paths ate less preferred by the taxi drivers: (a) path with fewer turns, (b)-(c) path skipping traffic crossing, (d)-(e) paths with smooth transitions, (f) path with fewer lane transitions.

#### Conclusions

Based on this extensive study, a number of conclusions incl. our new insight can be drawn: 1) The quality of labeled data has a significant impact on the feature learning results and the performance of the probabilistic models; 2) The interpretation of learned features should be carefully used to understand routing preference.

#### References

Yang, J. . (2016). Labeling Spatial Trajectories in Road Network Using Probabilistic Graphical Models. Technischen Universität München. Yang, J, & Meng, L. (2015). Feature Selection in Conditional Random Fields for Map Matching of GPS Trajectories. In G. Gartner & H. Huang (Eds.), Progress in Location-Based Services 2014, Lecture Notes in Geoinformation and Cartography (pp. 121–135). Springer International Publishing. http://doi.org/10.1007/978-3-319-11879-6 9