

Dissecting Urban Noises from Heterogeneous Geo-Social Media and Sensor Data



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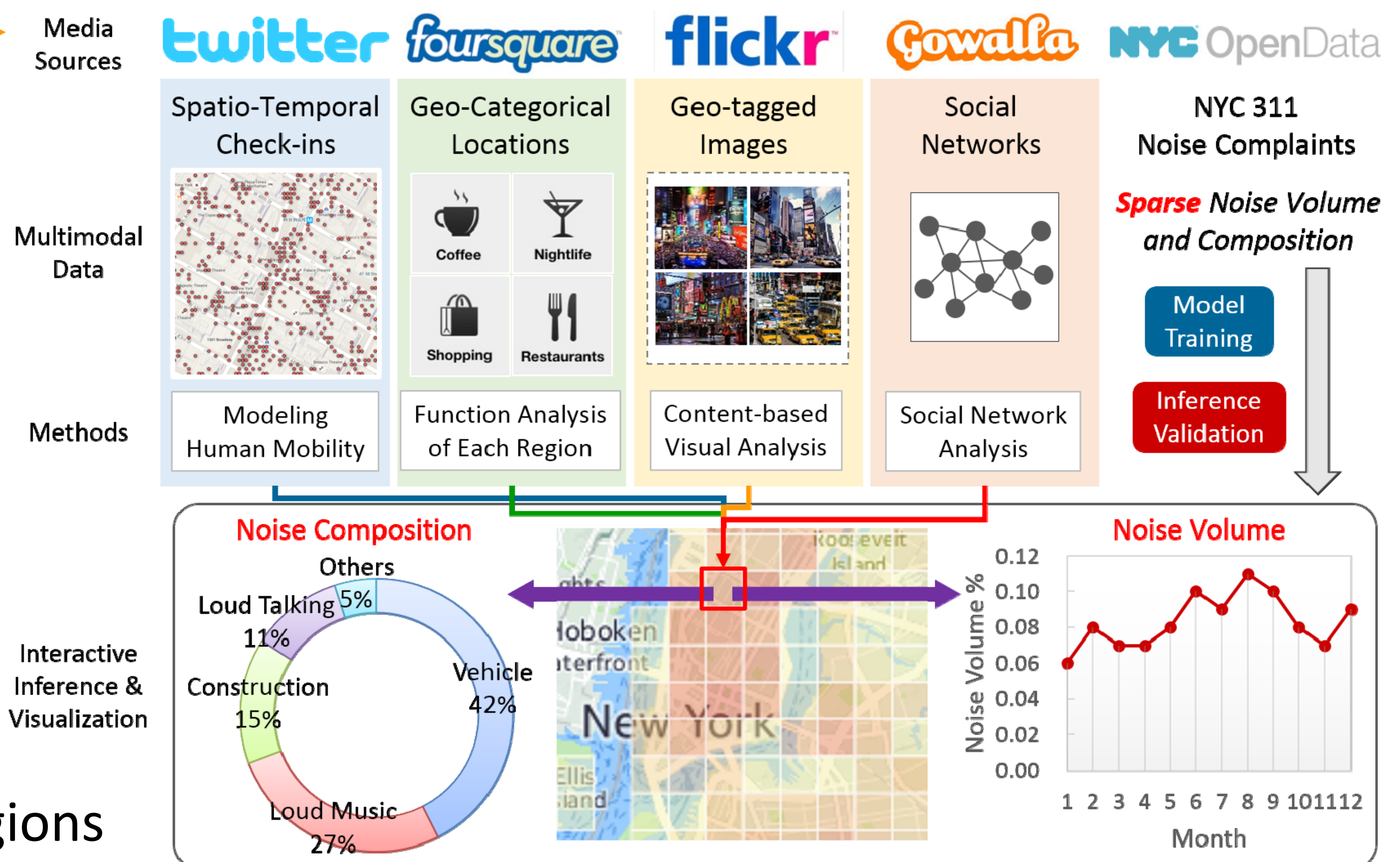
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Motivation

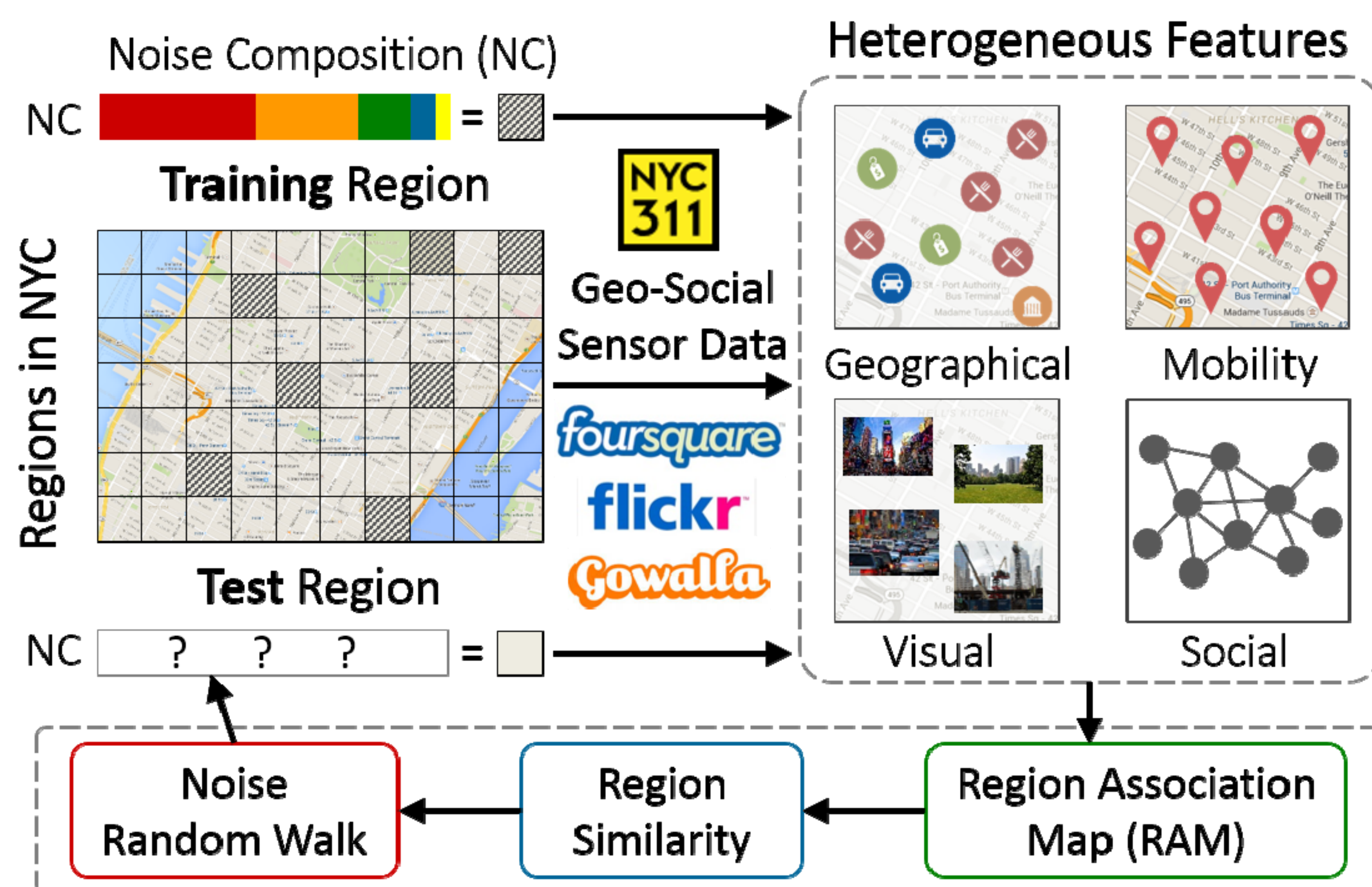
- Geo-social media** can be considered as a kind of sensors that monitor urban human activities.
- Urban noise pollution damages the mental health (e.g. work efficiency and sleep quality).
- We need to first understand the elements and causes that produce the noise. E.g. @TimeSquare "in evening rush hour, 60% noise come from vehicle traffic, 30% from loud music of stores, and 10% from people' talking"

Problem Statement

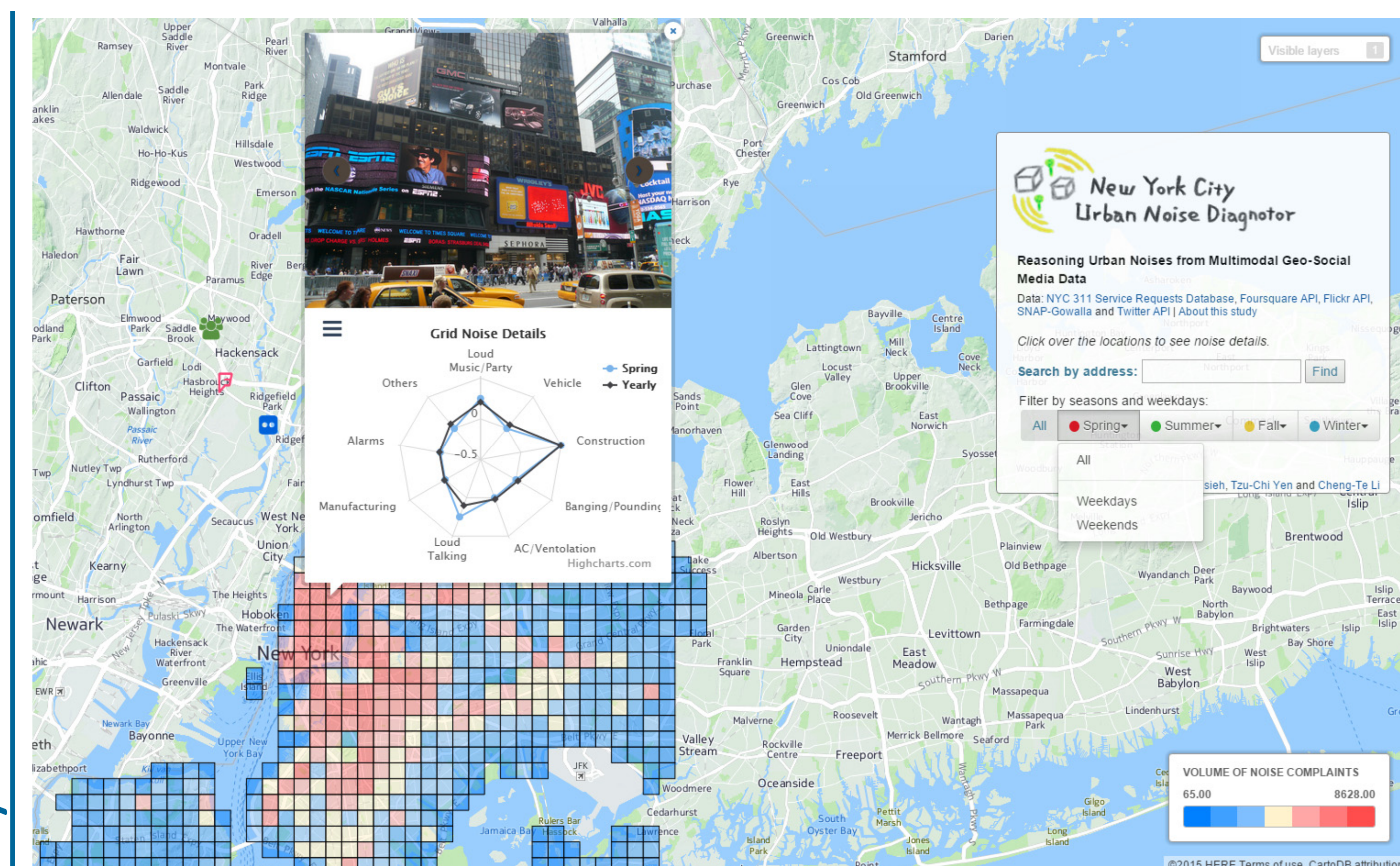
- Given a few NYC regions whose noise info are known, infer the noise composition of other regions



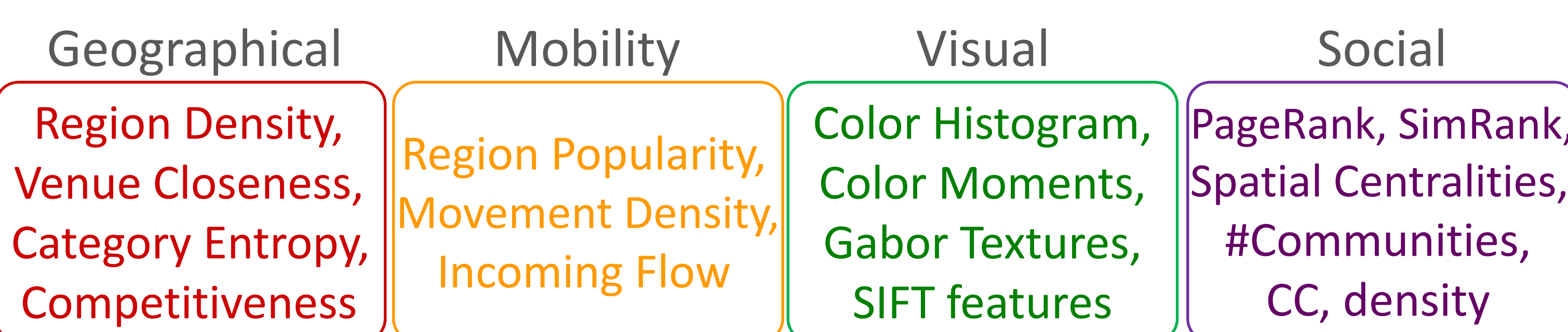
Approach Overview



System Demonstration

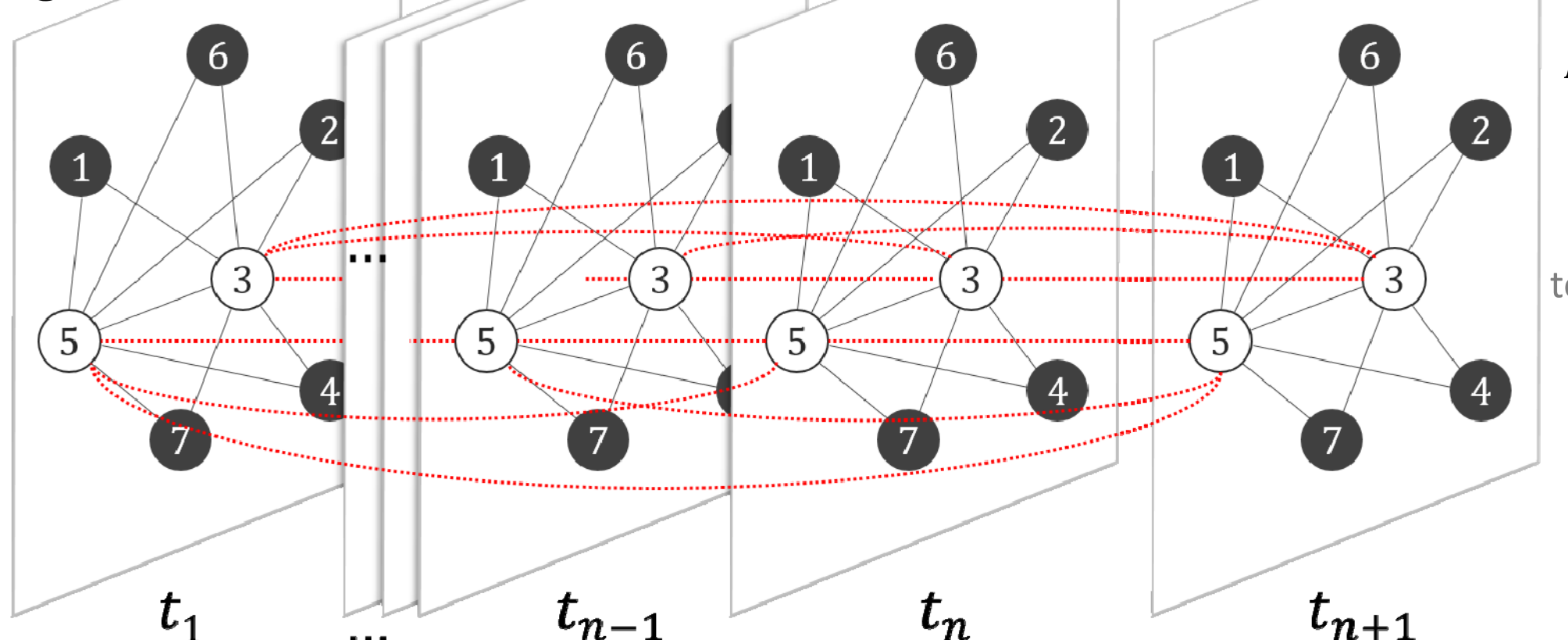


Step 1 Extracting Geo-Social Features



Step 2 Region Association Map

A region is a node. Edges are constructed based on geo-closeness, time, and labeled data.



Region Similarity

$$\text{EdgeWeight}(u, v) = \text{RegSim}(u, v) = \exp\left(-\sum_{k=1}^m \pi_k \times \|f_k(u) - f_k(v)\|\right)$$

totally k features

Feature Weights Learned from validation set!

Feature Vector of feature k for node v

Step 4 Noise Random Walk in RAM

- Iteratively update each unlabeled node based on the noise composition of its neighbors

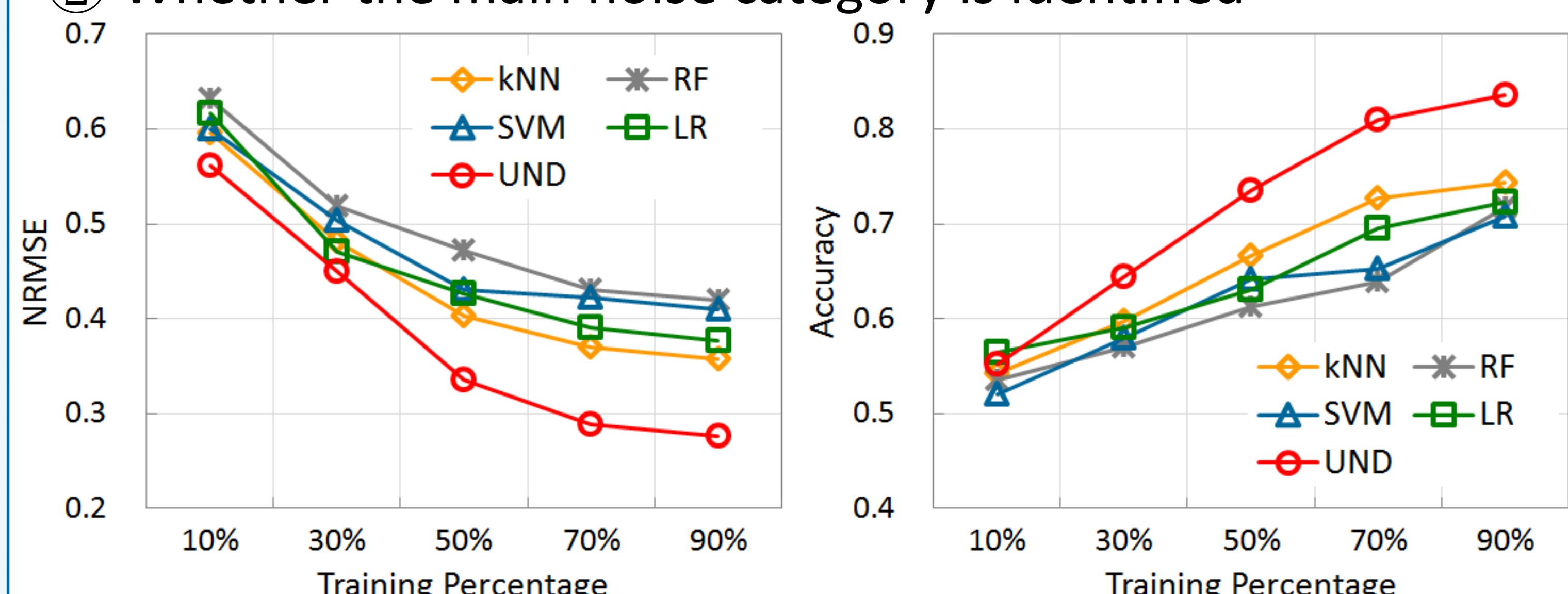
$$n_c(v) \leftarrow \sum_{u \in \mathcal{N}(v)} w_{v,u} \times n_c(u)$$

Neighbor nodes of v

Experimental Results

560 regions in NYC

- NYC 311 Noise Compliant Data e.g. Loud Music/Party, Construction, Loud Talking, Vehicle – 14 noise categories
- 47,581 venues, 196,591 users, 6,442,890 check-ins
- ① Measure the error between the ground-truth and the inferred noise values 5% data used for tuning parameters
- ② Whether the main noise category is identified



	Days		Hour Intervals					
	Weekday	Weekend	00-03	04-07	08-11	12-15	16-19	20-23
RMSE	0.118	0.159	0.167	0.061	0.081	0.075	0.106	0.219
Accuracy	0.909	0.858	0.853	0.923	0.904	0.911	0.895	0.836