ACM SIGSPATIAL 2017

City-wide Traffic Volume Inference with Loop Detector Data and Taxi Trajectories

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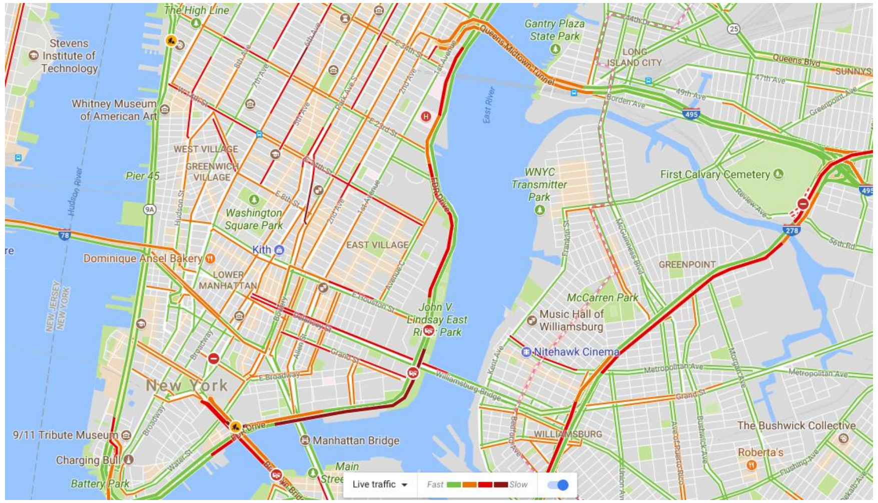
Urban Transportation Challenges

Traffic Volume

- Definition
  - Total number of vehicles traversing by a road segment during a time window
- A unique traffic condition metric
  - Most common measurement is Travel Speed
  - The volume reveals detailed condition information besides average speed
- Applications



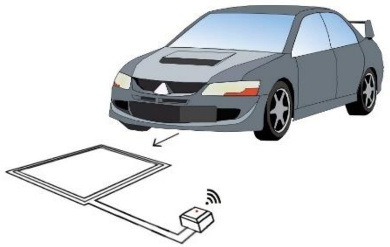
Speed-based Traffic Conditions

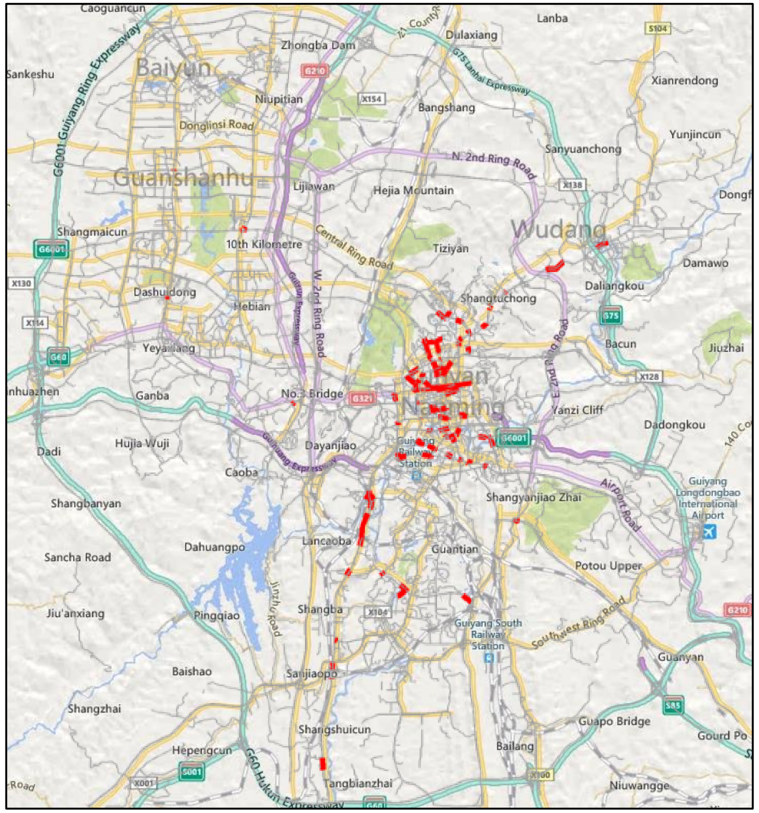
Traffic Control

Pollution Emission

Loop Detectors

- Loop Detectors
  - Sensors buried under the pavements, can detect vehicles passing by

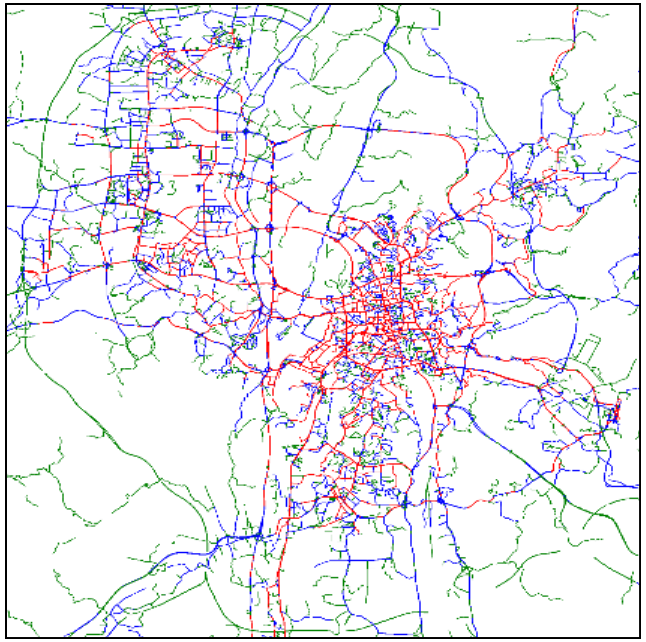




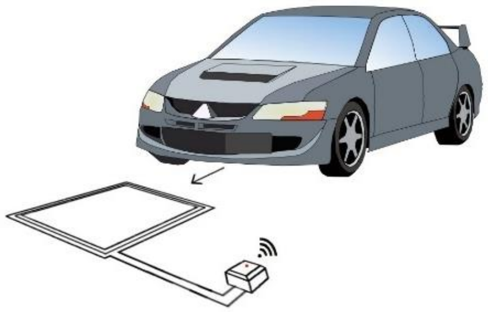
- Pro
  - Accurate
- Con
  - Expensive & not scalable
  - Extreme sparsity (155/19165 in Guiyang)

Taxi Trajectories

- GPS Trajectory
  - A sequence of time-ordered spatial points
- Pro
  - High coverage
- Con
  - Only a biased sample of all vehicles
  - no direct information about total volume



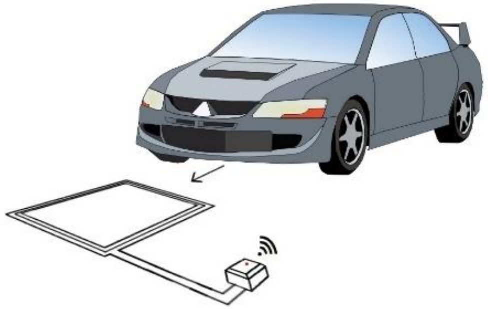
Loop Detectors & Taxi Trajectories



- High Accuracy
- Low Coverage

- High Coverage
- Low Accuracy

Loop Detectors & Taxi Trajectories

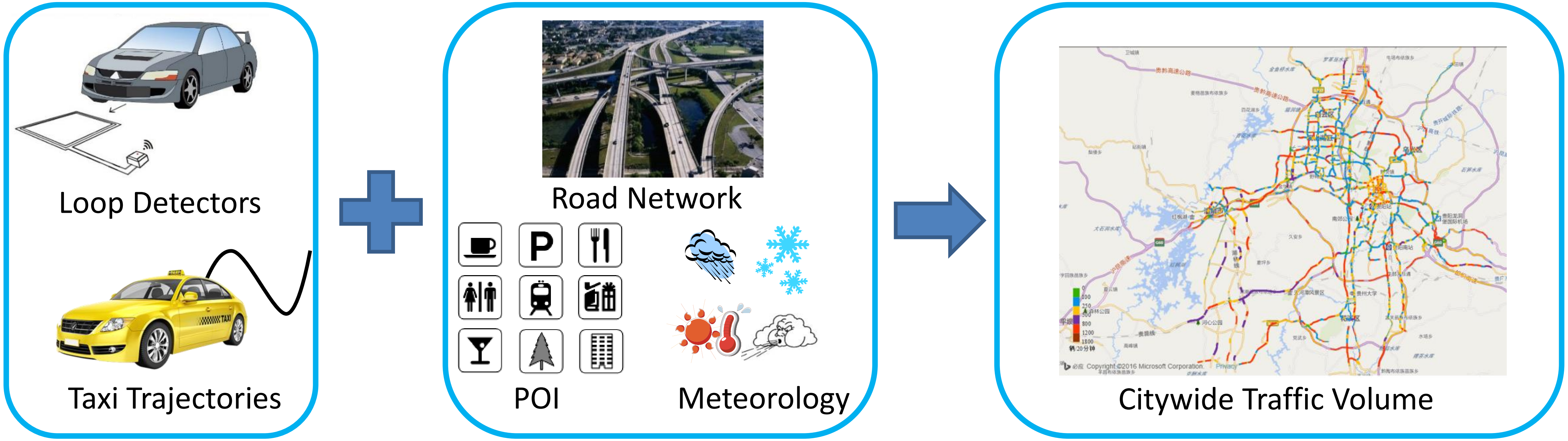


- High Accuracy
- Low Coverage

- High Coverage
- Low Accuracy

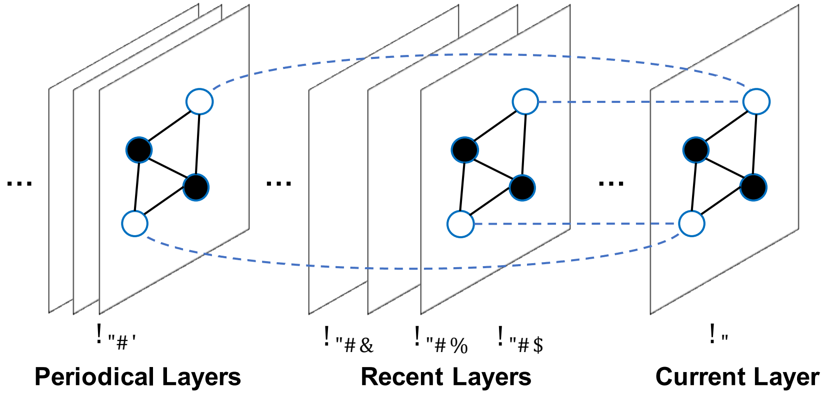
Goal

- Infer city-wide traffic volume on each road segment based on
  - **Loop detector data**
  - **Taxi trajectories**
  - **Urban context**



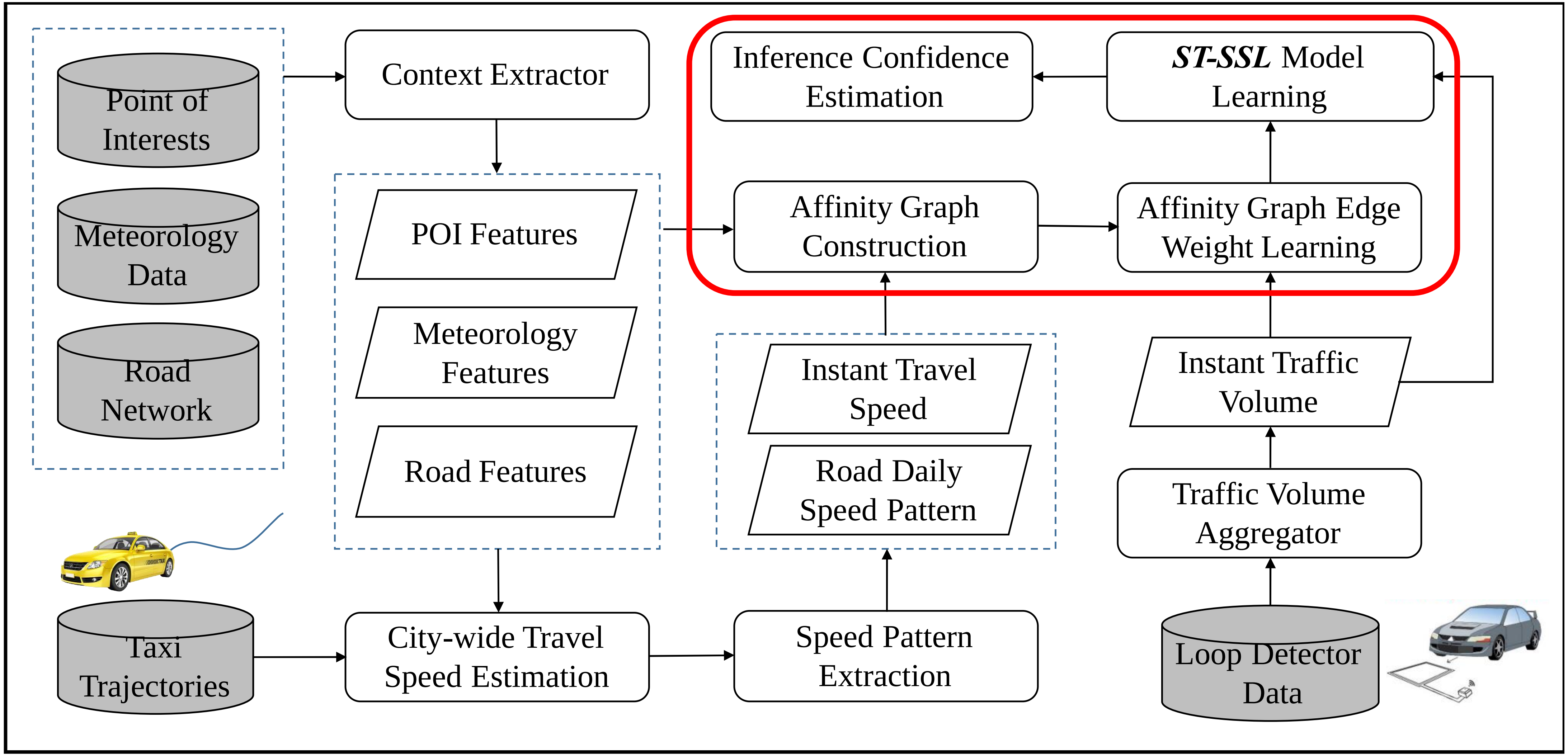
Main Idea

- Graph-based Semi-supervised learning
  - Take advantage of the benefits of both data sources
  - Construct traffic affinity graph with taxi trajectories
  - Estimate city-wide traffic volume with loop detector data
  - **High coverage & High Accuracy**



- Incorporate spatio-temporal properties of traffic volume
  - Constructing the road affinity graph
  - Inference on the semi-supervised learning model

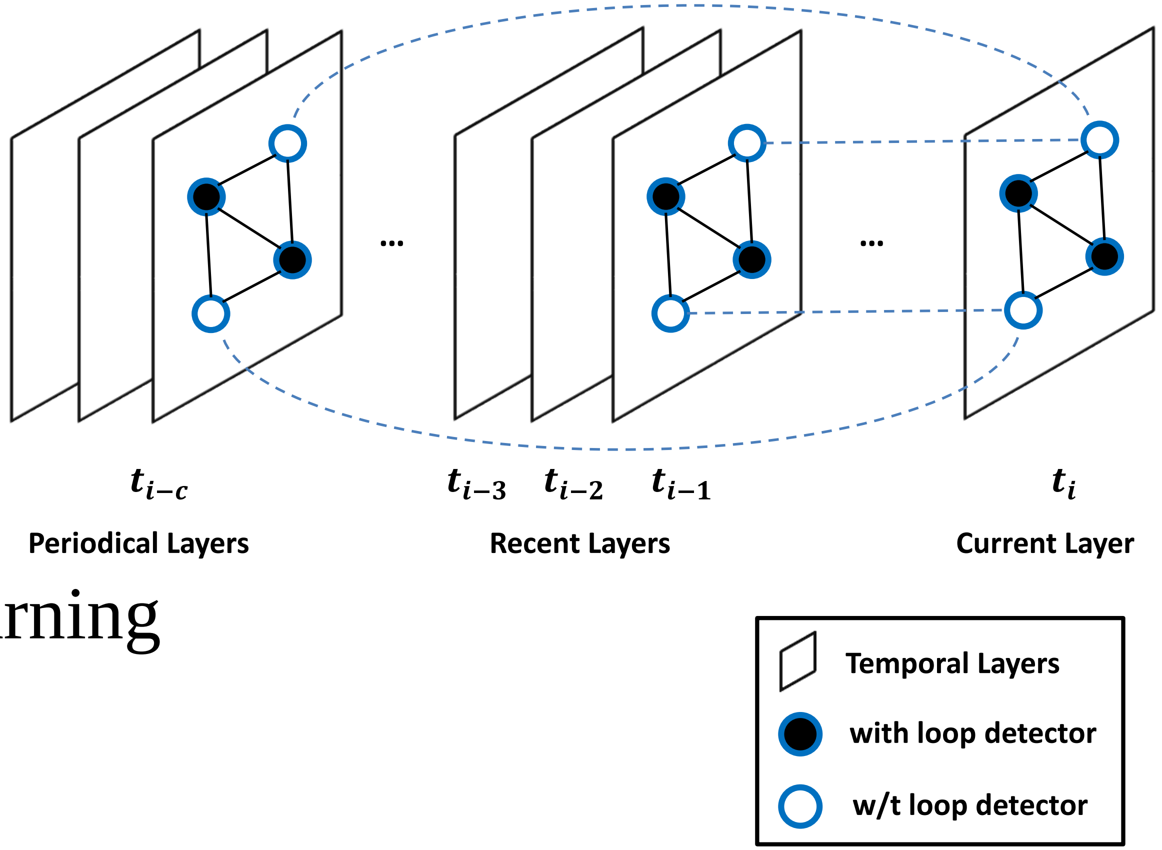
Framework



Point of Interests
Meteorology Data
Road Network
Context Extractor
POI Features
Meteorology Features
Road Features
Inference Confidence Estimation
ST-SSL Model Learning
Affinity Graph Construction
Affinity Graph Edge Weight Learning
Instant Travel Speed
Road Daily Speed Pattern
Instant Traffic Volume
Traffic Volume Aggregator
Taxi Trajectories
City-wide Travel Speed Estimation
Speed Pattern Extraction
Loop Detector Data

Main Procedures

- Affinity Graph Construction
  - Determine the graph structure
- Graph Edge Weight Learning
  - Learn the correlations with urban context
- Spatio-temporal Semi-supervised Learning
  - Estimate traffic volume of every road segment



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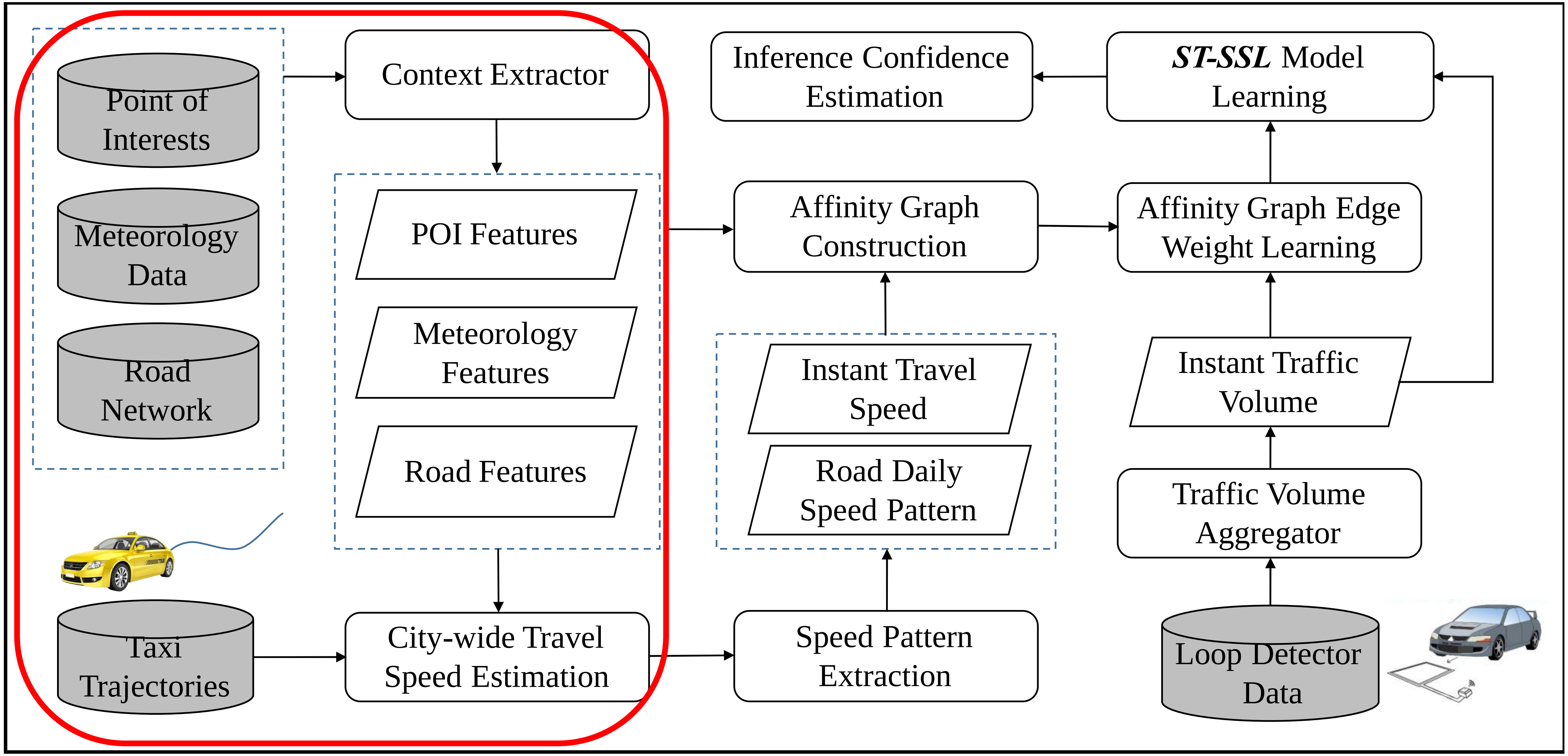

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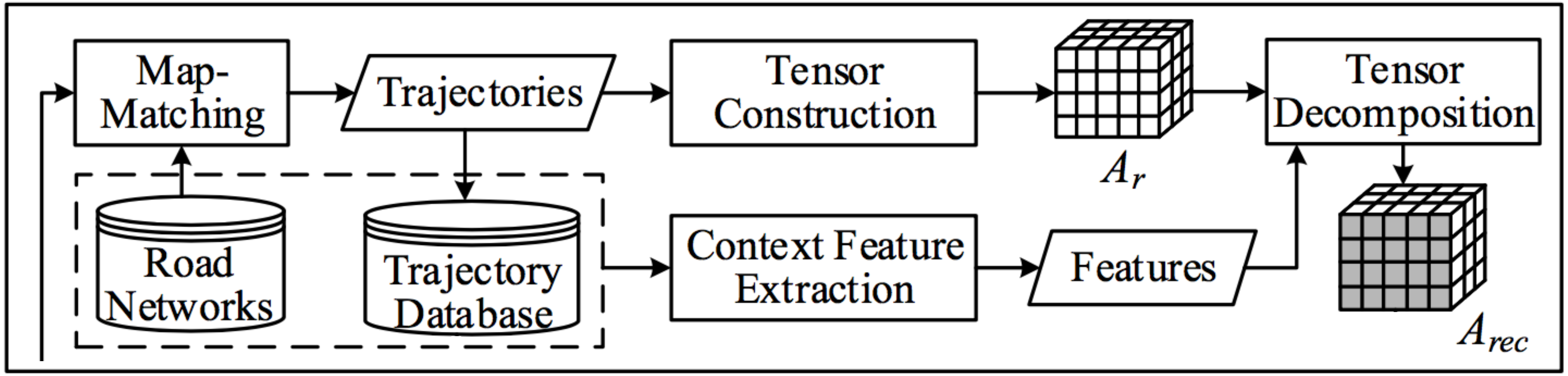
Preliminary: City-wide Travel Speed Estimation

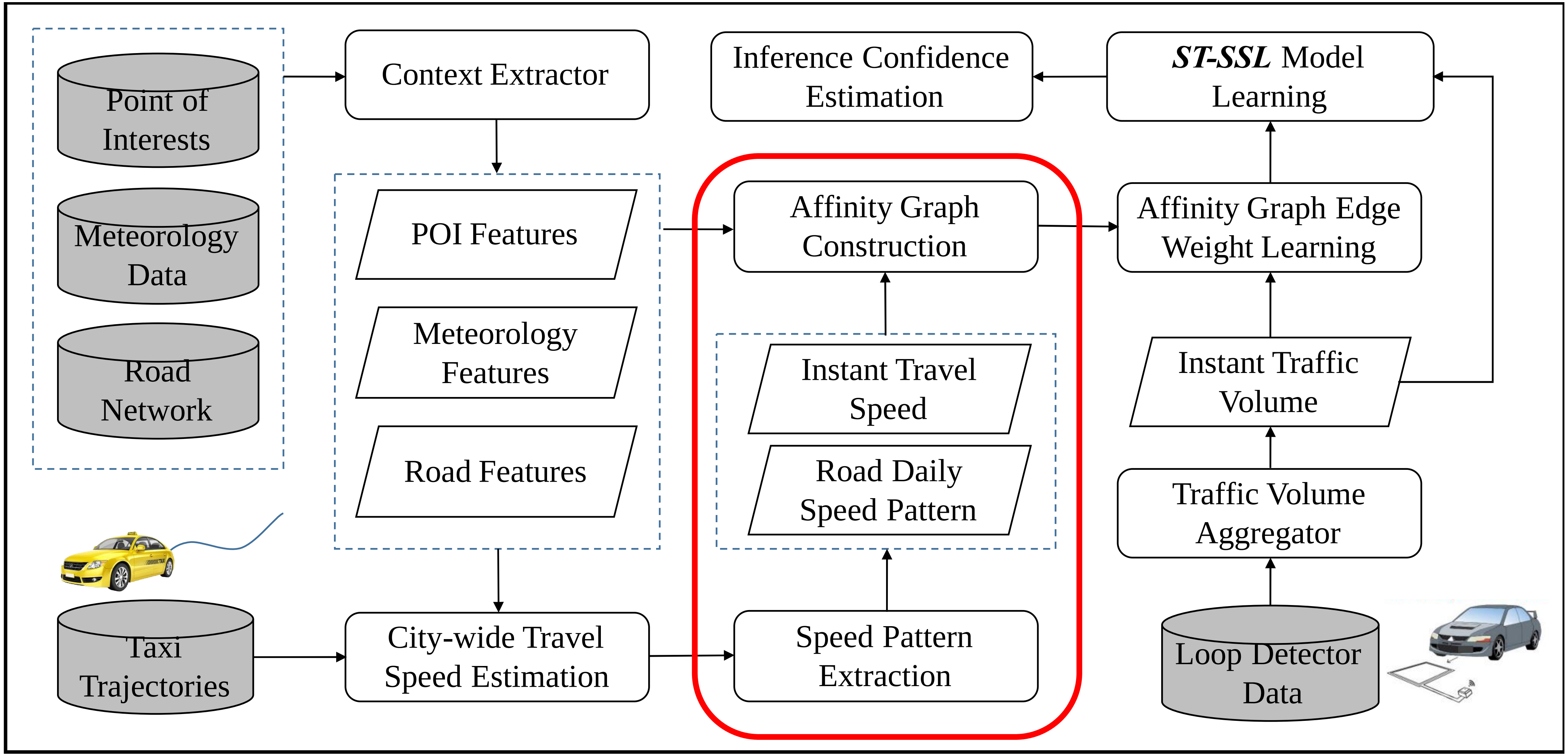
- Context-Aware Tensor Decomposition* (**CATD**)



- Output: travel speed on *every* road segment

* Wang, Yilun, Yu Zheng, and Yexiang Xue. "Travel time estimation of a path using sparse trajectories." *Proceedings of the 20th ACM SIGKDD international conference on Knowledge discovery and data mining*. ACM, 2014.

Framework



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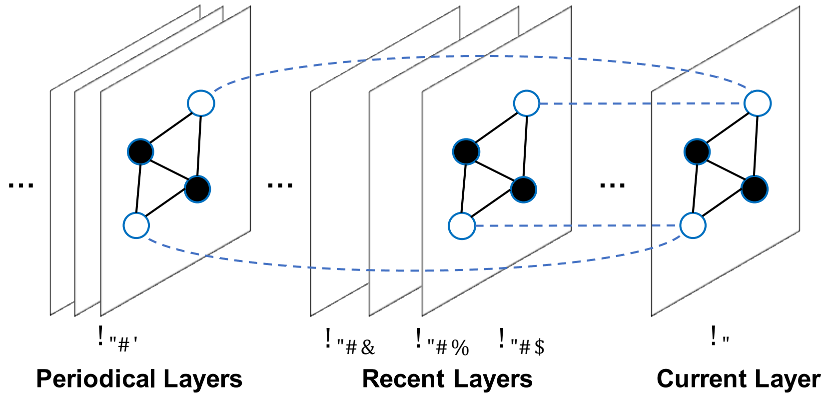
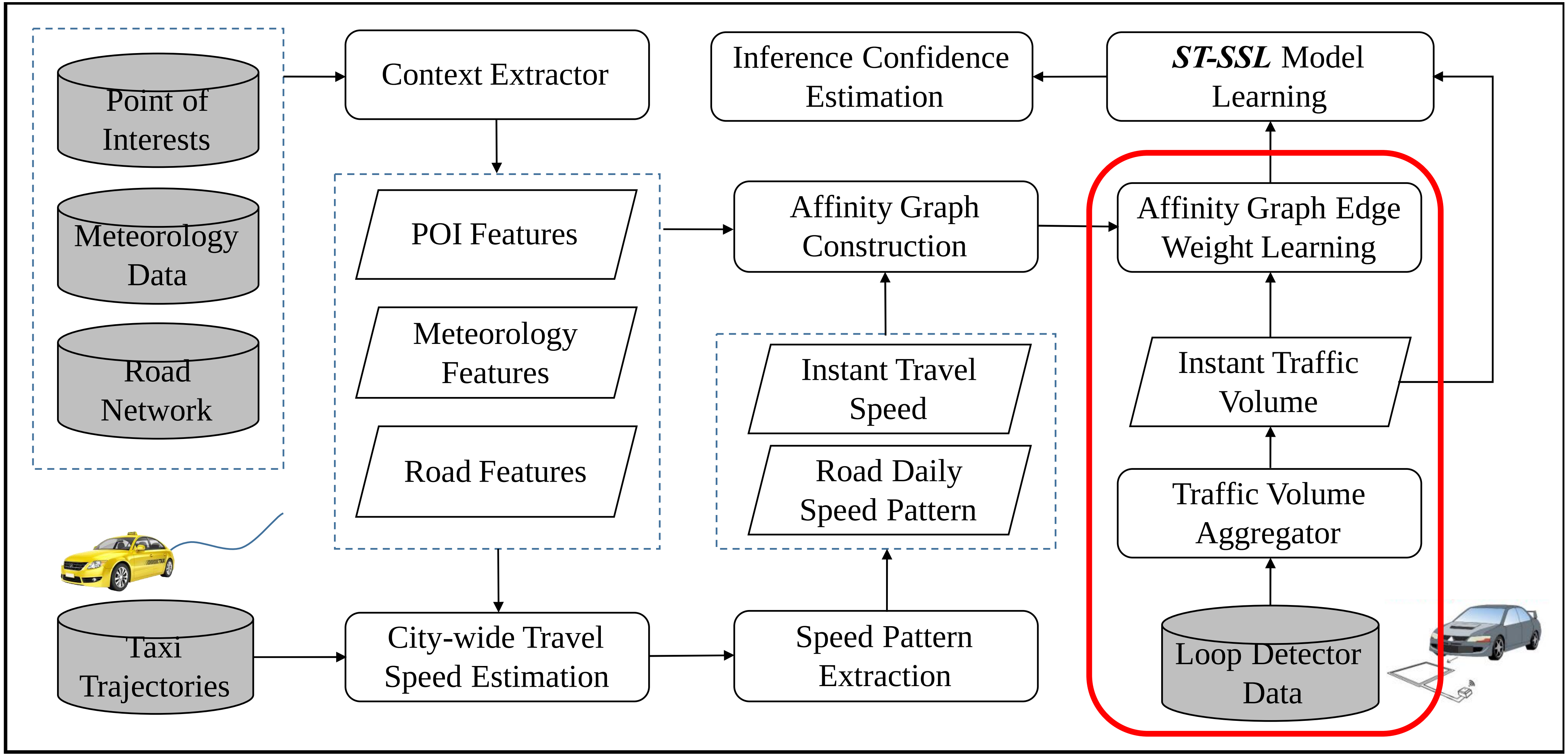
Traffic Affinity Graph Construction



- Affinity Graph
  - Node: per-lane volume on a road at one time slot
  - Edge: traffic condition similarity between two nodes
- Edge Construction with spatio-temporal knowledge
  - **Spatial**: connect to segments with similar traffic patterns
    - within a radius (e.g., 200m)
    - within several hops in the road network
    - with several similar roads equipped loop detectors
    - satisfies: 1) have similar average speed, 2) have similar daily speed patterns (characterized by Pearson correlations)
  - **Temporal**: connect to correlated temporal layers
    - connect to recent temporal layers
    - connect to periodical temporal layers (day/week)

Framework



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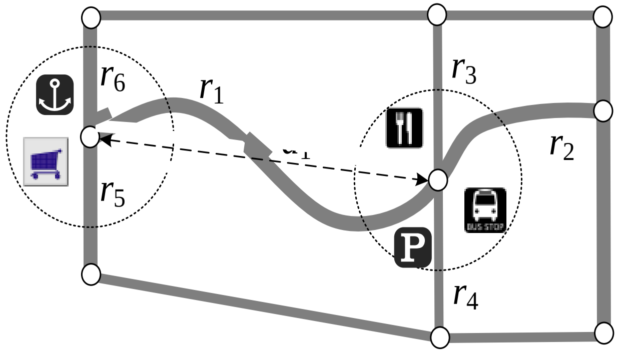
Graph Edge Weight Learning

- Motivation
  - Edge weight denotes the traffic condition similarities among road segments
  - Roads are associated with many urban context features, e.g., POIs, road network.
  - Representative features should co-evolves with the volume change

- Edge weight learning
  - Step 1: Normalize $|\Delta f_i|$ for all urban features i
  - Step 2: Calculate Pearson Correlation $corr_{f_i}$ between $|\Delta f_i|$ and $|\Delta Vol|$
  - Step 3: Define weight between two nodes u and v

$$a_{u,v} = \exp(-\sum_i corr_{f_i} \times |f_i(u) - f_i(v)|)$$



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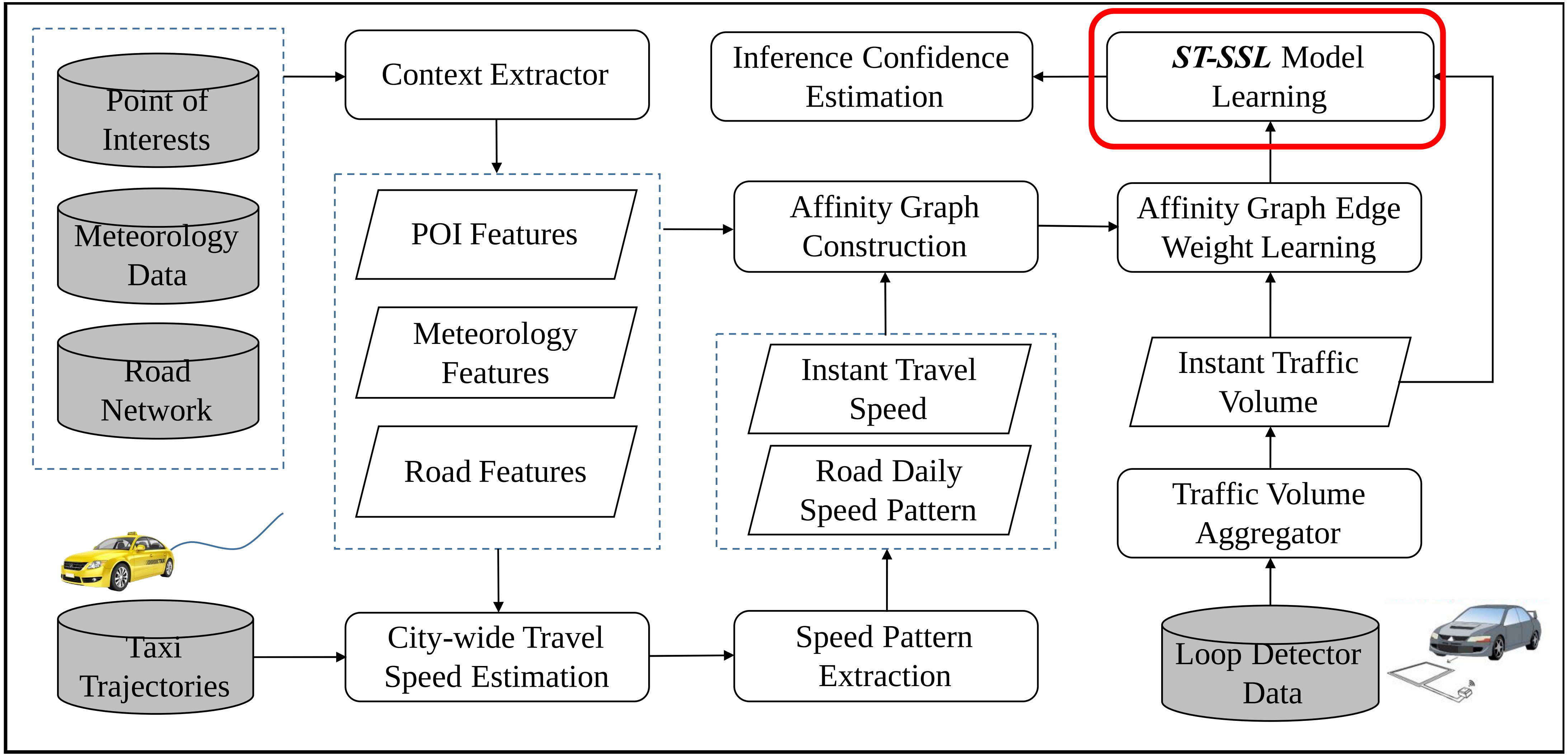

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Spatio-temporal Semi-supervised Learning

- Insights
  - Spatial property: volume changing rates are similar among roads nearby
  - Temporal property: volume on recent and periodical time slots should be similar

- Spatial change rate similarity

$$L_s = \sum_{t \in T} \sum_{(u,v) \in E} a_{u,v} \left(\frac{\Delta x_u(t)}{x_u(t-1)} - \frac{\Delta x_v(t)}{x_v(t-1)} \right)^2$$

- Temporal value similarity

$$L_t = \alpha_1 \sum_{t \in T} \sum_{v \in V} \big(x_v(t) - \underbrace{x_v(t-1)}_{\text{Recent time}}\big)^2 + \alpha_2 \sum_{t \in T} \sum_{v \in V} \big(x_v(t) - \underbrace{x_v(t-P)}_{\text{Periodical time}}\big)^2$$

Spatio-temporal Semi-supervised Learning

- Loss function

$$
\begin{aligned}
\mathcal{L}_{STSSL} &= \mathcal{L}_s + \mathcal{L}_t \\
&= \sum_{t \in T} \sum_{(u,v) \in E} a_{u,v} \left(\frac{\Delta x_u(t)}{x_u(t-1)} - \frac{\Delta x_v(t)}{x_v(t-1)} \right)^2 \\
&\quad + \alpha \sum_{t \in T} \sum_{c \in corr(t)} \sum_{u \in U} (x_u(t) - x_u(c))^2
\end{aligned}
$$

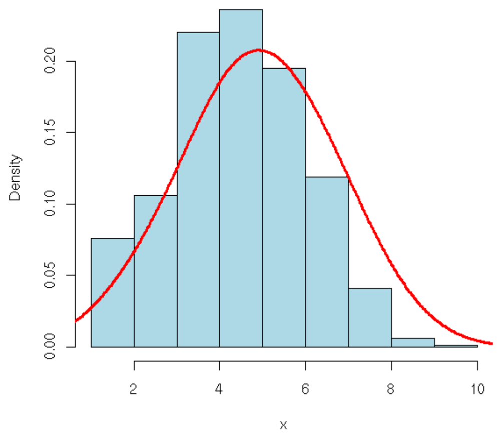
- Solution

$$X = \arg\min_{X} \mathcal{L}_{STSSL}$$

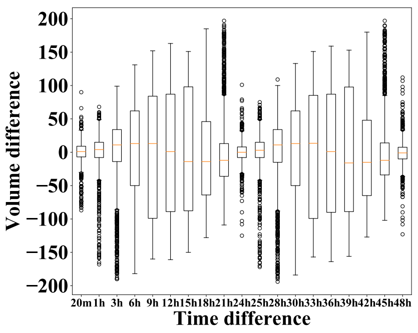
$$x_v(t) = \frac{\sum_{u \in N(v)} \frac{a_{u,v} x_u(t)}{x_u(t-1) x_v(t-1)} + \alpha \sum_{c \in corr(t)} x_v(t+c)}{\sum_{u \in N(v)} \frac{a_{u,v}}{x_v^2(t-1)} + \alpha C}$$

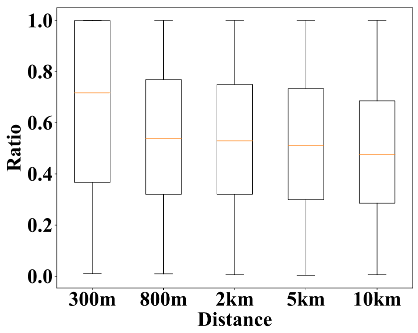
Inference Confidence Estimation

- Motivation
  - inferred value should be statistically significant compared with its spatial & temporal neighbors



- **Spatio-temporal Smoothness Confidence**
  - volume should not change dramatically over both temporal and spatial dimensions
- **Graph Structure Confidence**
  - nodes connected to labelled data with higher weights should receive more confidence

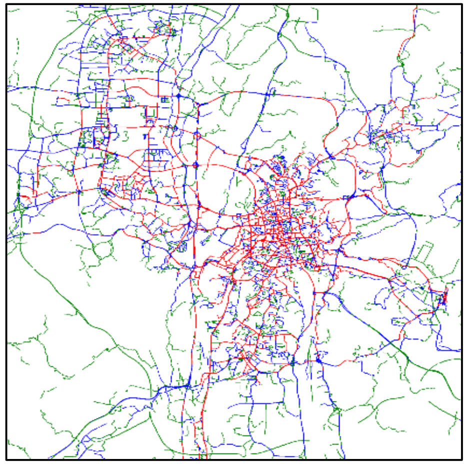




Experiment Data Sets

- Loop Detectors
  - Time span: **2016.3.16 -- 4.1 @Guiyang**
  - Data sparsity: **155/19165**
- Taxi Trajectories
  - Time span: **2016.3.16 -- 4.1 @Guiyang**
  - **6918** taxis with 37.6s sample rate
- Road network features
  - Length, level, direction, #lanes, #connections, speed limit, etc.
- POIs features
  - Distribution and total numbers of POI categories

Loop Detectors



Taxi Trajectories

Baselines

ST-SSL is compared with the following baseline methods:

- **LR**: Linear regression.
- **ANN:** Artificial neural network.
- **RF:** Random forest regression.
- **Basic-SSL** [30]:
  - A classical semi-supervised learning model
  - Do not consider the spatio-temporal properties

Performance Measurements

- MSPE (Root **M**ean **S**quare **P**ercentage **E**rrors)
- MAPE (**M**ean **A**bsolute **P**ercentage **E**rrors)

Volume Inference Performance

Table 1: Volume Inference Accuracy

Method	Undetected Road Inference				Missing Observation Recovery			
	MSPE	***MAPE***	Var_{MSPE}	Var_{MAPE}	***MSPE***	***MAPE***	Var_{MSPE}	Var_{MAPE}
LR	5.951	2.068	0.306	0.079	6.124	1.695	0.053	**0.000**
RF	2.542	1.116	0.169	0.043	1.054	0.357	0.007	**0.000**
ANN	7.887	2.356	0.407	0.608	2.058	0.646	0.174	0.003
Basic-SSL	3.215	1.342	0.257	0.044	0.759	0.288	**0.002**	**0.000**
ST-SSL	**0.952**	**0.915**	**0.001**	**0.000**	**0.503**	**0.179**	0.004	**0.000**

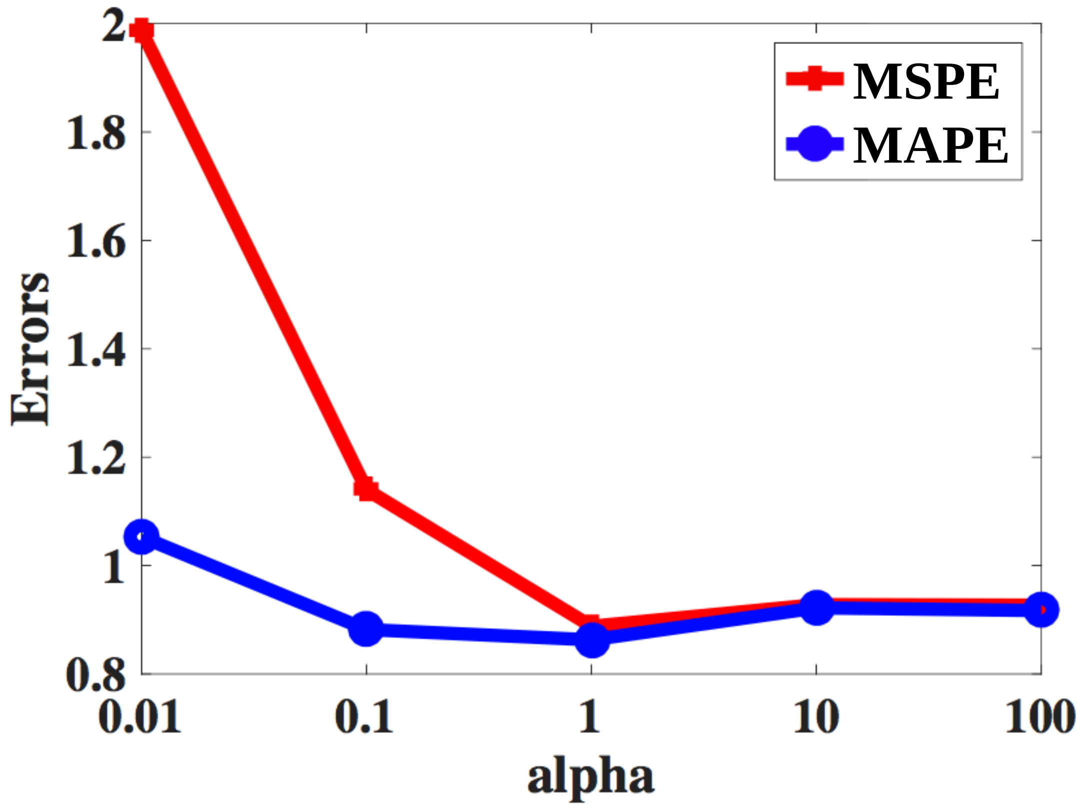
Varying Spatial Neighbors

Table 2: Performance Varying # Spatial Neighbors

Method	# Spatial Neighbors				
	10	20	30	40	50
Basic-SSL	3.131	2.523	1.853	1.959	1.3988
ST-SSL	**0.895**	**0.940**	**0.886**	**0.906**	**0.887**

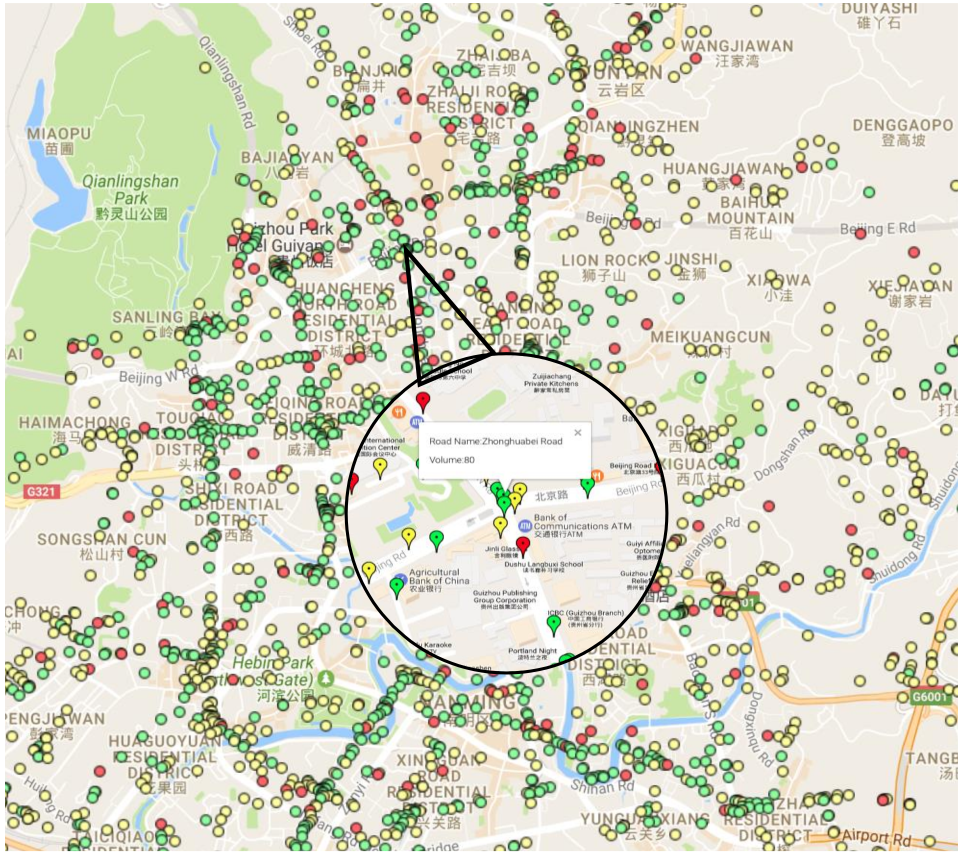
- Performance of Basic-SSL gets better when the graph has more spatial neighbors in the affinity graph
- Proposed Spatio-temporal semi-supervised learning requires less information passed through the graph, because it genuinely incorporates those prior knowledge

Vary Spatio-temporal Factor α



- hyper-parameter α is a factor that gives different weights on the spatial and temporal terms
- this factor is application dependent

Visualization of Inference Confidence



Conclusions

- We propose a Spatio-Temporal Semi-Supervised Learning model to tackle the challenges associated with loop detectors and taxi trajectories.

- The knowledge from two different domains are fused in this framework to infer a city-wide volume information.

- We conduct extensive experiments on real-world data. The results demonstrate the advantages of the proposed framework on correctly inferring the city-wide traffic volume.