

# Inferring Traffic Cascading Patterns

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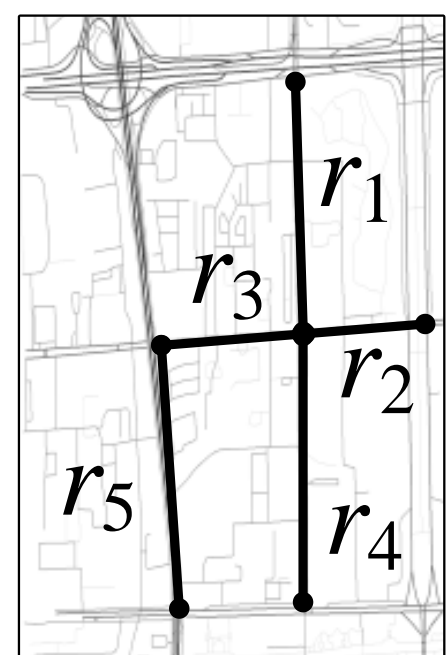
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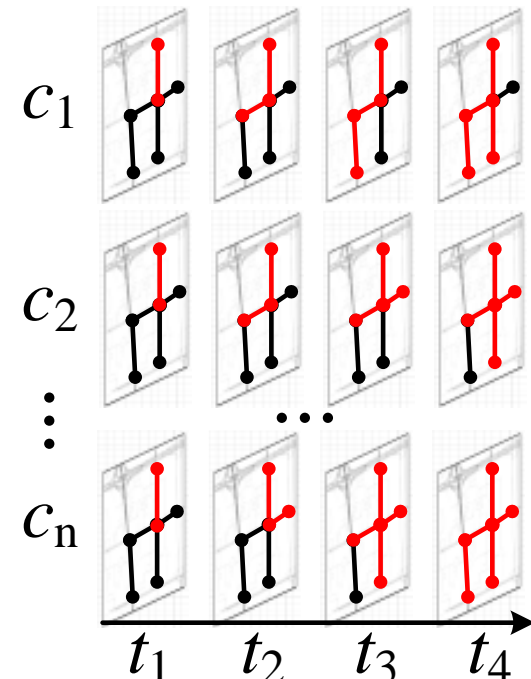


Released Codes & Paper

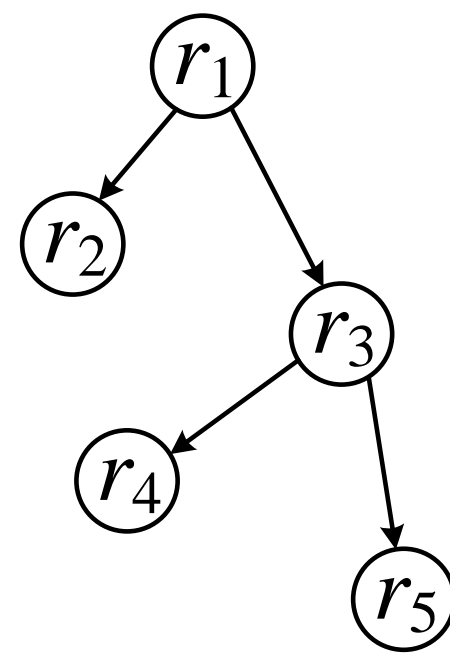
## Introduction



(a) Road Network



(b) Observed Cascades



(c) Cascading Pattern

### Knowing the traffic cascading pattern can help

- predict future traffic conditions
- identify bottlenecks of road networks

### Challenges

- Implicit interaction
- Multiple sources
- Geospatial correlation

### Contribution

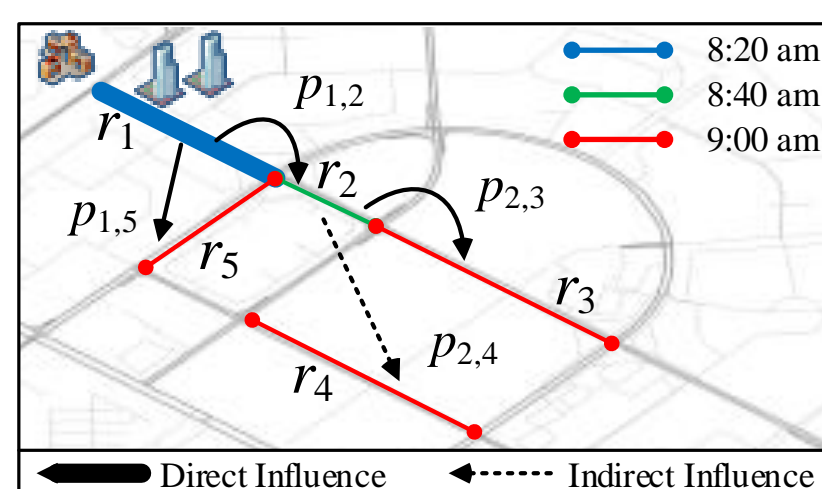
- Modeling three-fold influence
- **Cascading pattern inference**
- Real evaluation

## Insight

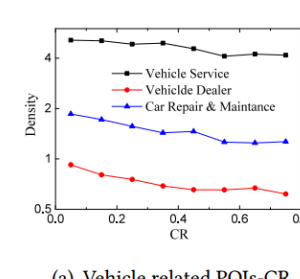
### Three-fold influences

- Direct influence
- Indirect influence

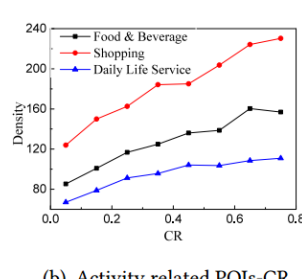
$$f(t_i|t_j; a_{j,i}, \lambda) \propto e^{-a_{j,i}(\Delta_{j,i} + \lambda * d_{i,j})}$$



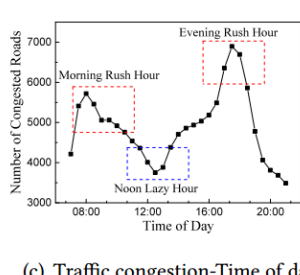
- Environmental influence



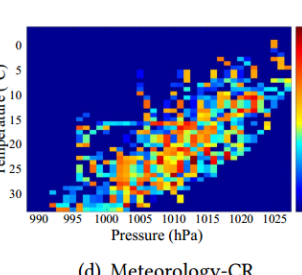
(a) Vehicle related POIs-CR



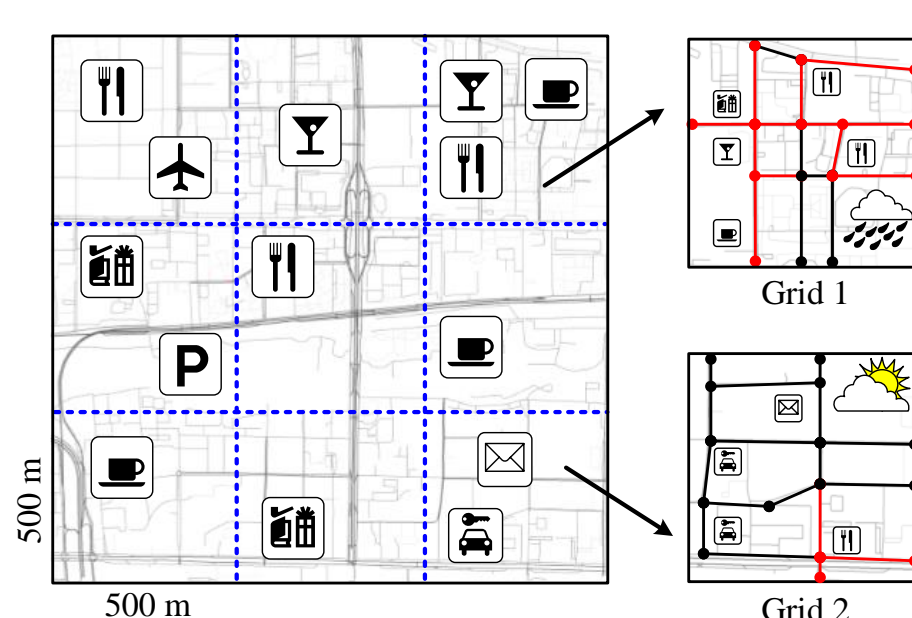
(b) Activity related POIs-CR



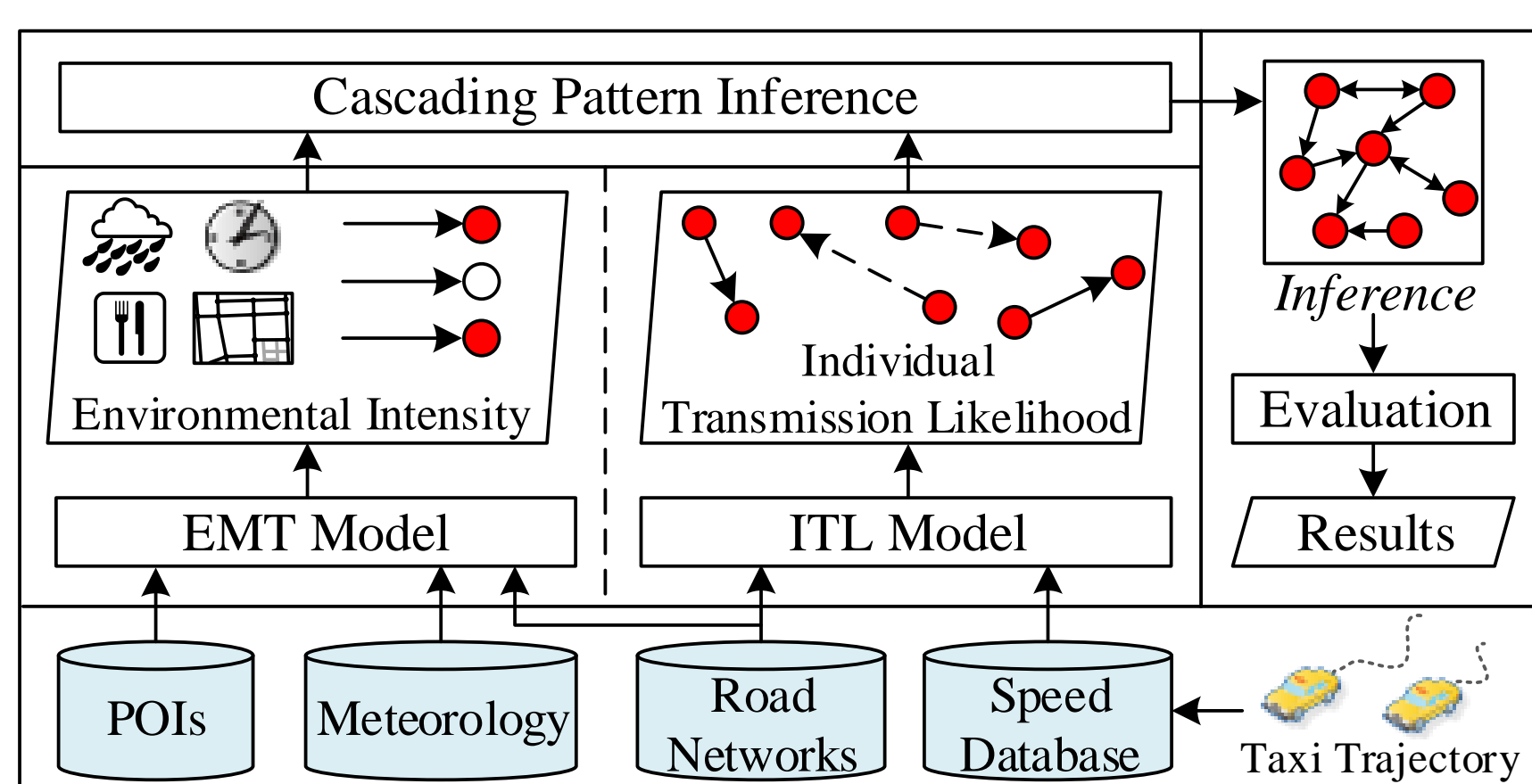
(c) Traffic congestion-Time of day



(d) Meteorology-CR



## Overview



## Methodology

### Cascading Pattern Construction

- Given a **propagation tree**  $T$ , the likelihood of a **cascade**  $c$ :
- Given a **network**  $G$  considering all **possible trees**, the likelihood of a **cascade**  $c$ :
- Conditional independence assumption

$$f(c|T) = \prod_{(j,i) \in E_T} f(t_i|t_j; \alpha, \lambda),$$

$$f(c|G) = \sum_{T \in \mathcal{T}_c(G)} f(c|T)P(T|G),$$

$$f(C|G) = \prod_{c \in C} f(c|G).$$

### Network Inference

$$\hat{G} = \arg \max_{|G| \leq k} f(C|G),$$

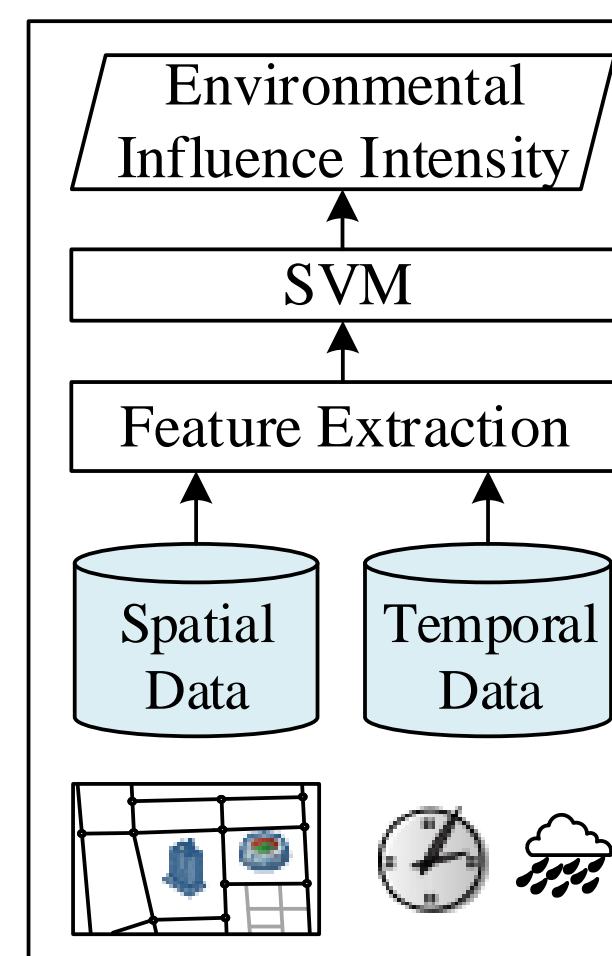
### Alternative Target

$$\hat{G} = \arg \max_{|G| \leq k} F(C|G)$$

$$F(c|G) = \sum_{t_i \in c} \log \sum_{t_j \in C: t_j \leq t_i} w_c(j, i),$$

$$w_c(j, i) = \theta \varepsilon_g^{-1} f(t_i|t_j; a_{j,i}, \lambda)$$

### Environmental Influence Inference



### Approximate Algorithm

Algorithm 1 Approximate algorithm for CasInf

**Input:**  
 $k$ : the number of edges in cascading patterns we infer.  
 $C$ : the set of cascades obtained in a time span.  
 $\mathcal{D}$ : a constant denoting the spatial constraint.

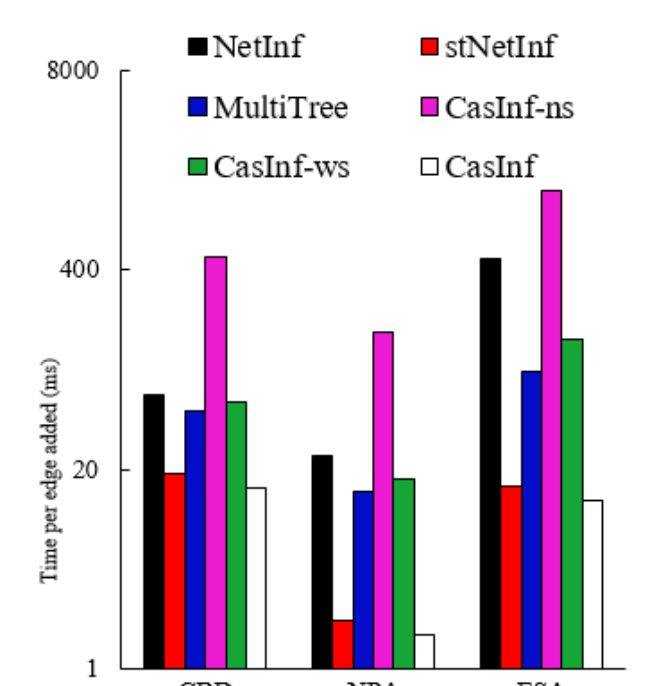
**Output:**  $G$ : the inferred cascading pattern.

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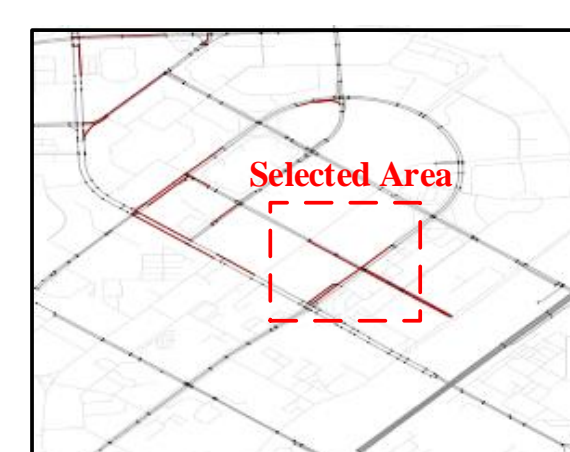
1:  $G \leftarrow \emptyset$ ;
2:  $P \leftarrow$  all pairs  $(j, i): \exists c \in C$  with  $t_j < t_i$  and  $d_{j,i} < \mathcal{D}$ 
3: while  $|G| \leq k$  do
4:   for all  $(j, i) \in P \setminus G$  do
5:      $\delta_{j,i} = 0$ ;
6:     for all  $c: t_j < t_i$  do
7:        $\varepsilon_g \leftarrow$  environmental intensity inference
8:        $w_c(m, n) \leftarrow$  weight of  $(m, n)$  in  $G \cup \{(j, i)\}$ ;
9:       for all  $m: t_m < t_i$  and  $m \neq j$  do
10:         $\delta_{c,j,i} = \delta_{c,j,i} + w_c(m, i)$ ;
11:      end for
12:       $\delta_{j,i} = \delta_{j,i} + \log(\frac{\delta_{c,j,i} + w_c(j, i)}{\delta_{c,j,i}})$ ;
13:    end for
14:  end for
15:   $(j^*, i^*) \leftarrow \arg \max_{(j,i) \in P \setminus G} \delta_{j,i}$ ;
16:   $G \leftarrow G \cup \{(j^*, i^*)\}$ ;
17: end while
    
```

## Evaluation

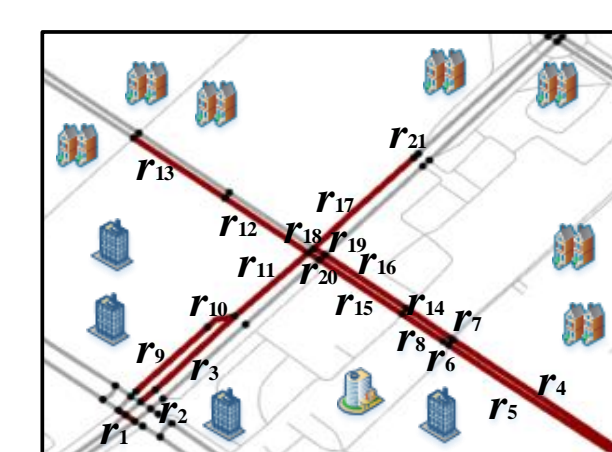
Methods	CBD	NPA	ESA	Overall
NetInf	0.270	0.119	0.116	0.168
stNetInf	0.308	0.201	0.394	0.301
MultiTree	0.311	0.140	0.141	0.197
FBM	0.287	0.193	0.171	0.217
STC-DBN	0.307	0.198	0.225	0.243
CasInf-gd	0.359	0.258	0.488	0.368
CasInf-td	0.336	0.199	0.203	0.246
CasInf-ne	0.363	0.298	0.515	0.392
CasInf-ni	0.197	0.129	0.215	0.180
<b>CasInf</b>	<b>0.384</b>	<b>0.317</b>	<b>0.545</b>	<b>0.415</b>



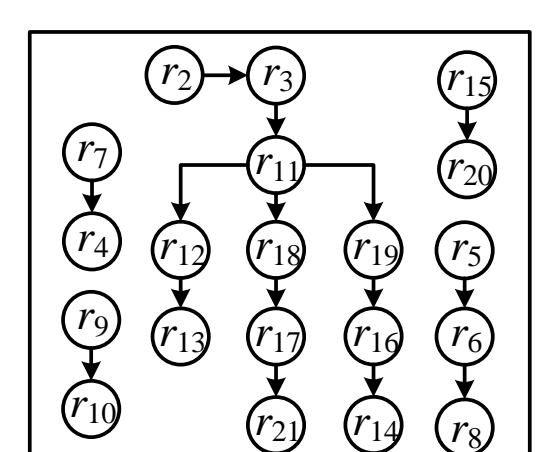
## Case Study



(a) Wangjing district



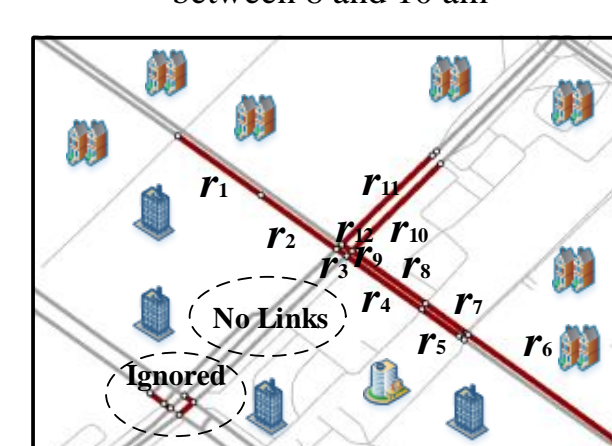
(b) Traffic cascading pattern between 8 and 10 am



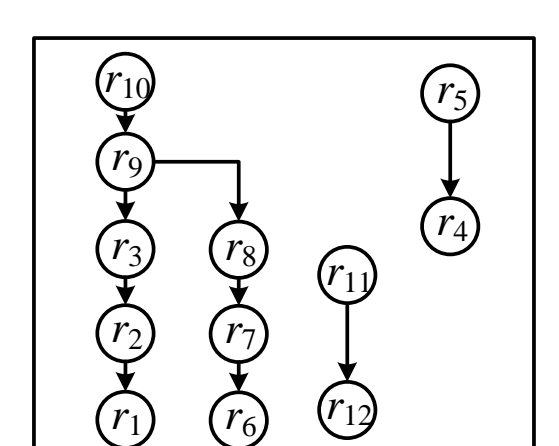
(c) Cascading pattern in (b)



(d) Selected area



(e) Traffic cascading pattern between 7 and 9 pm



(f) Cascading pattern in (e)