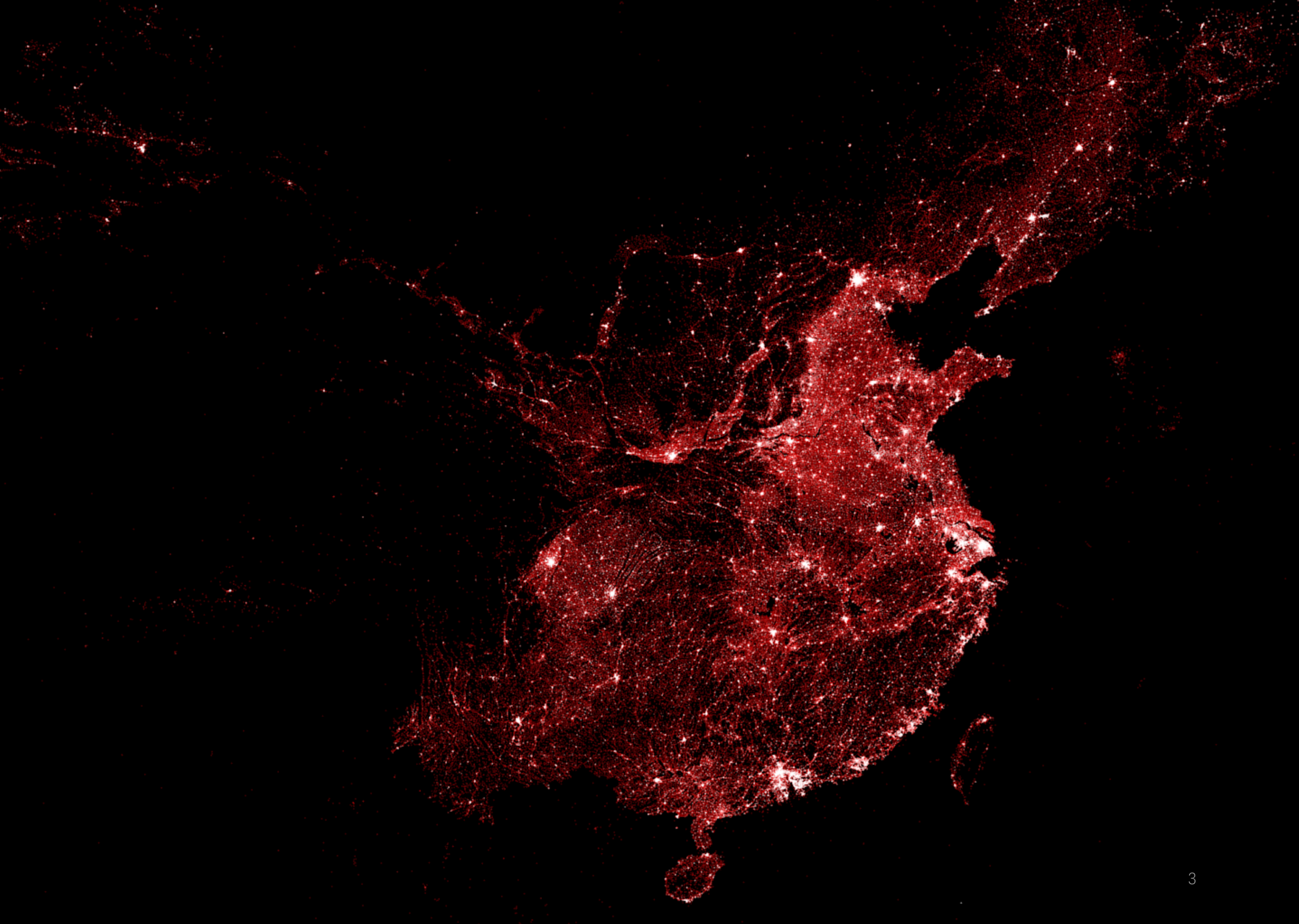
POI知识图谱：构建及应用

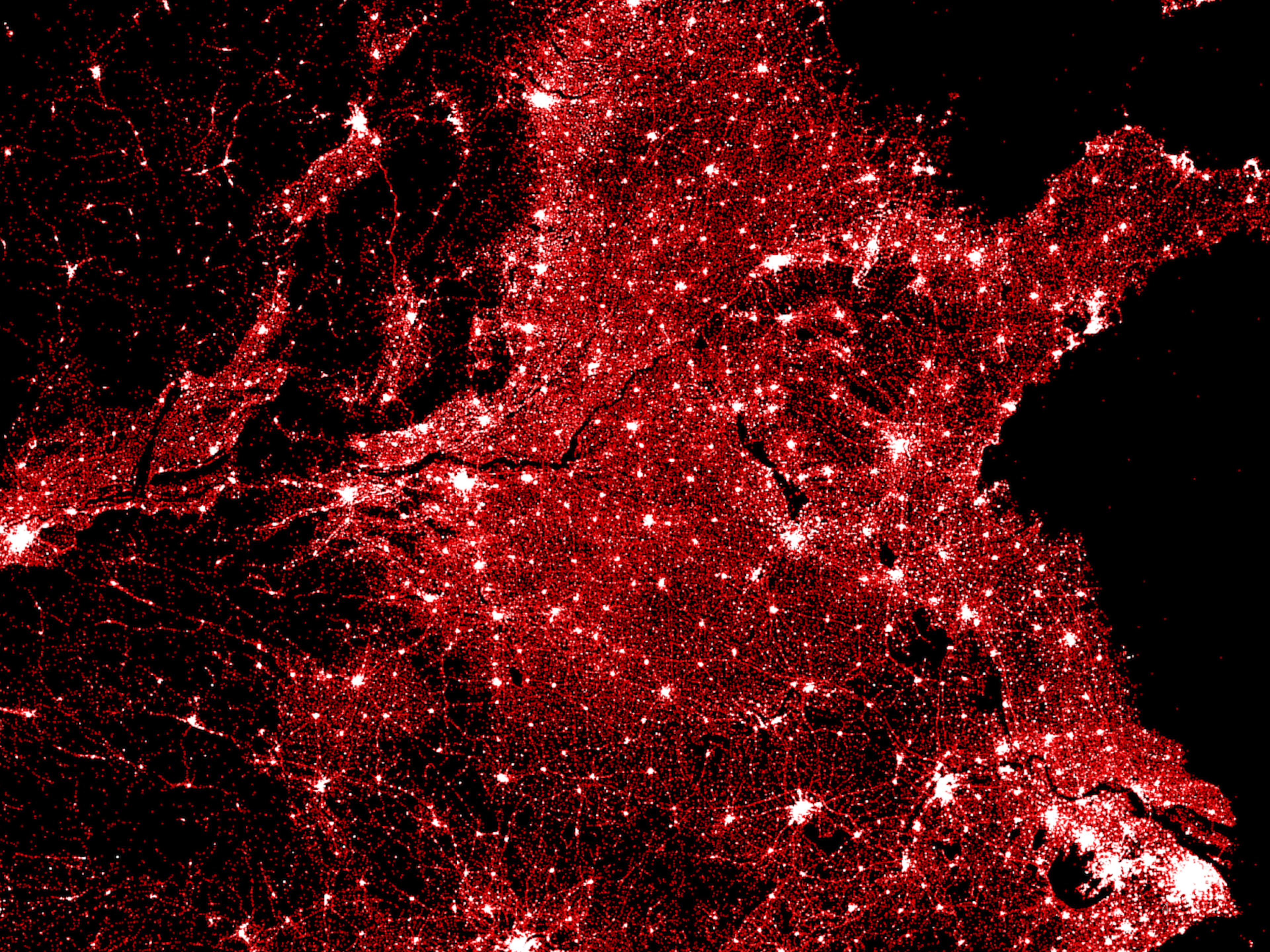
2020年11月

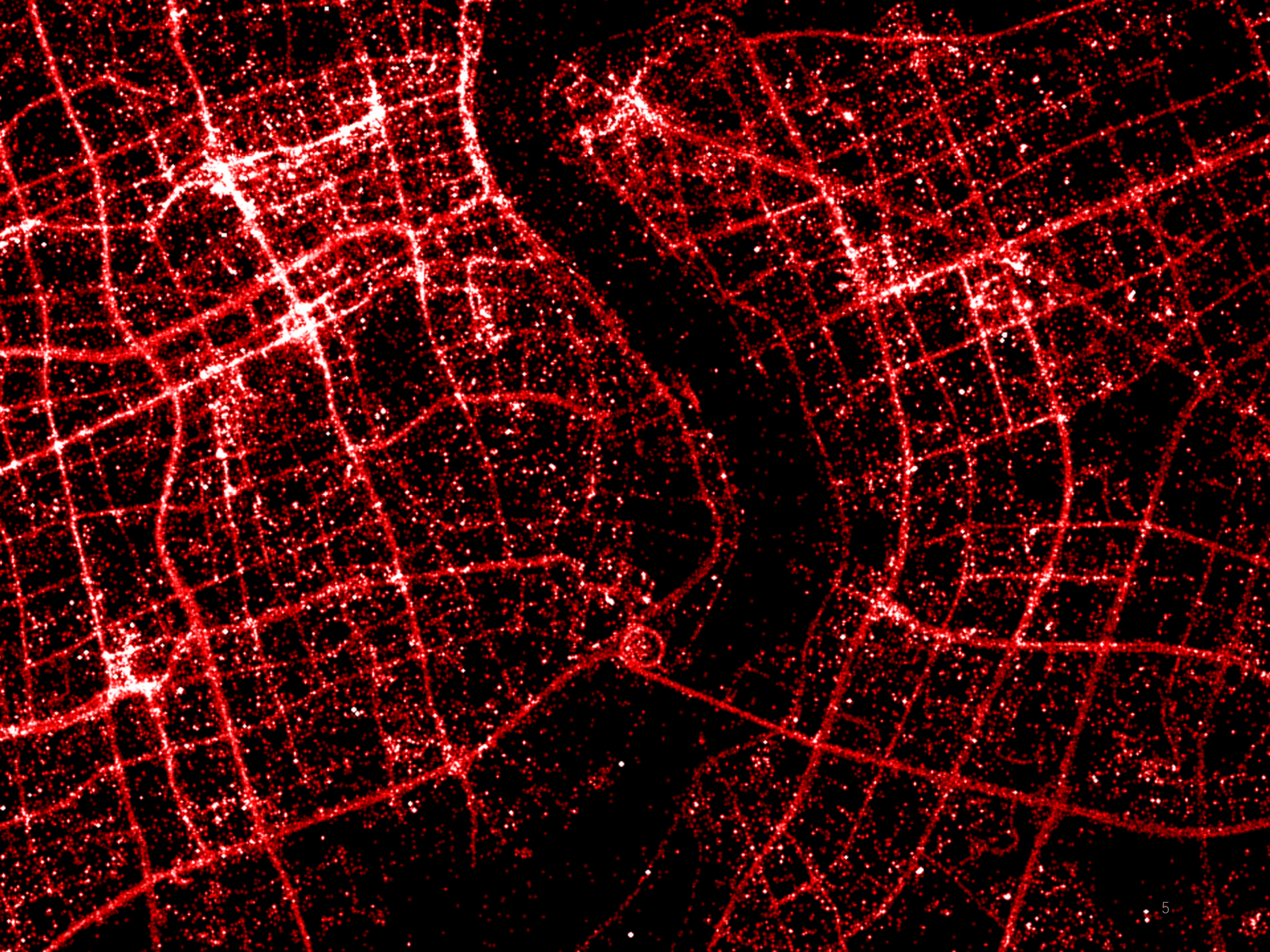
Outline

- Introduction
- POI Knowledge Graph Construction
  - Tag refinement
  - Competitive relationship
- POI-KG application
  - Geodemographic Influence Maximization
  - Multi-level POI recommendation
  - Joint Intent Detection and Entity Linking
  - Multi-Modal Transportation Recommendation

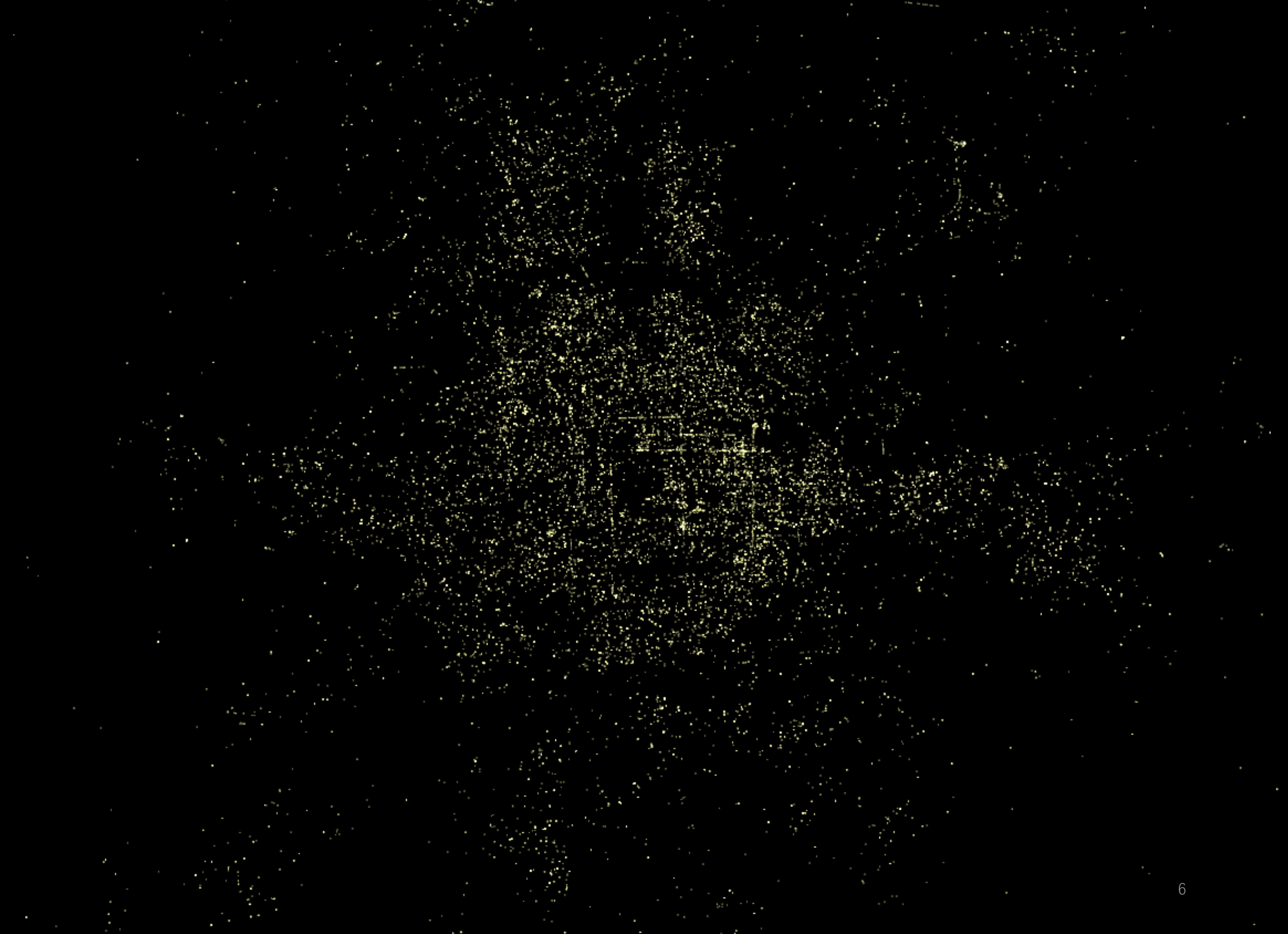
Baidu lights China

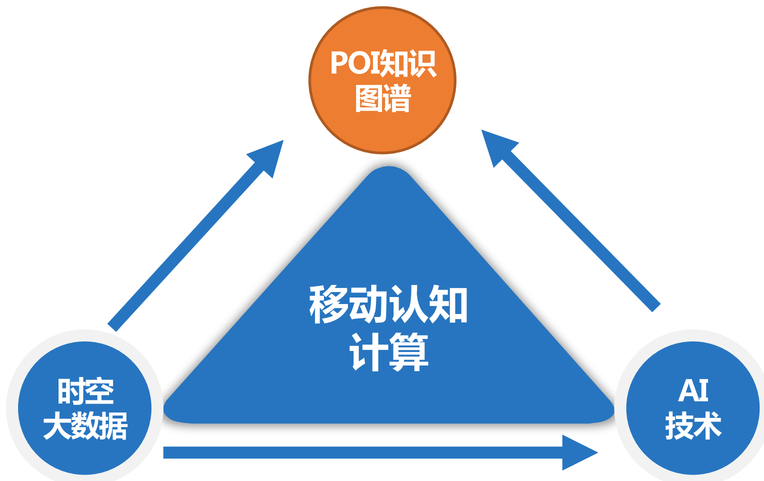






北京的一天





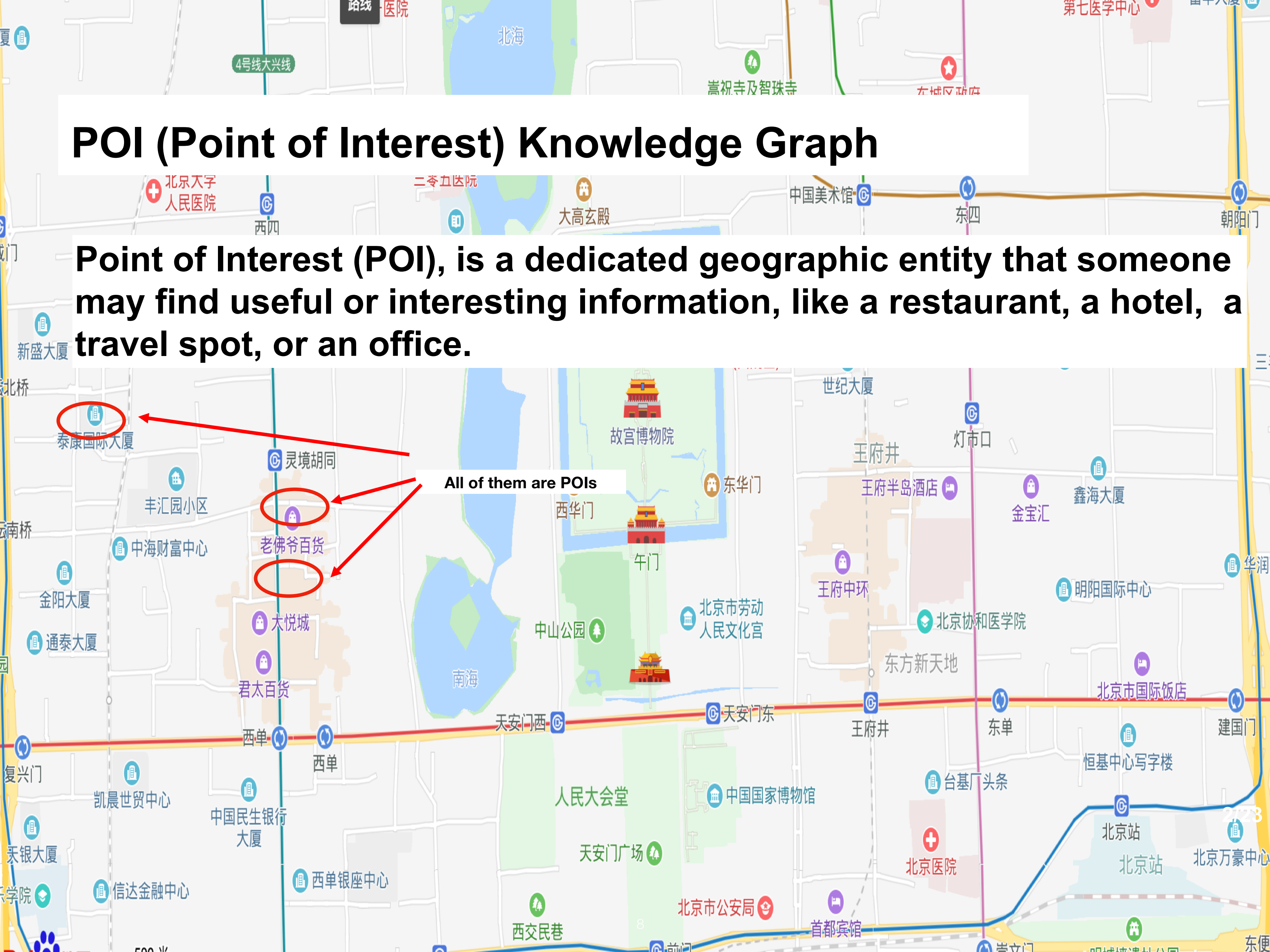
每天数亿次的地图搜索,每天导航**6亿**公里

百度App每天活跃用户**2亿+**

每天**1200亿**次的定位

POI (Point of Interest) Knowledge Graph

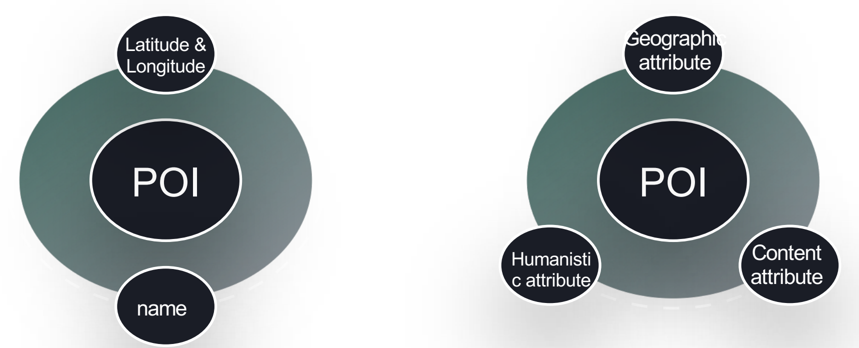
Point of Interest (POI), is a dedicated geographic entity that someone may find useful or interesting information, like a restaurant, a hotel, a travel spot, or an office.



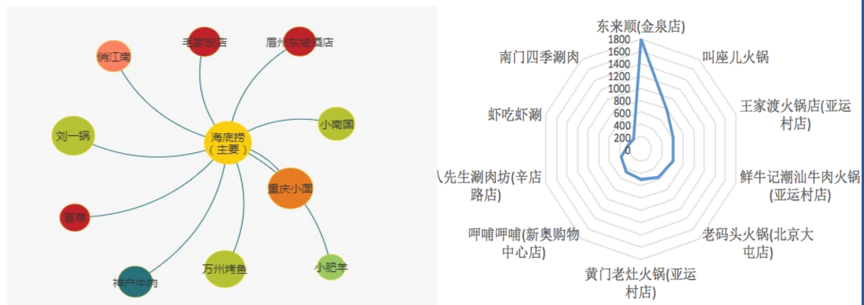
POI Knowledge Graph

POI knowledge graph: From POI profiling to POI semantics

- Enrich tags/attributes to POI
- Build relations among POIs



From single view data to multi-view location information



Competitive relationship among POIs

POI Knowledge Graph

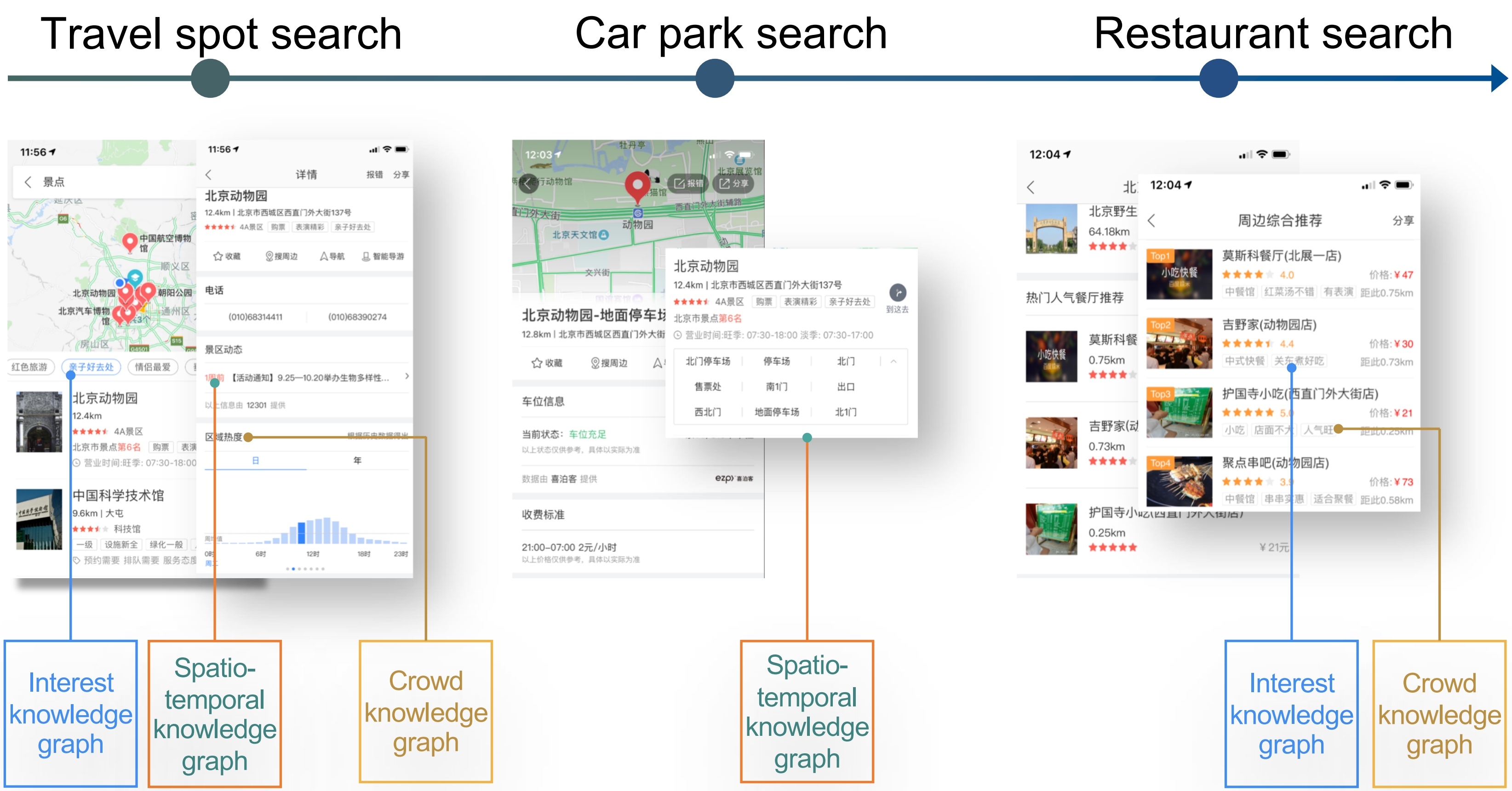
POI knowledge graph: Applications on Baidu Maps

Spatio-temporal
knowledge graph

Interest
knowledge graph

Crowd
knowledge graph

POI Knowledge Graph



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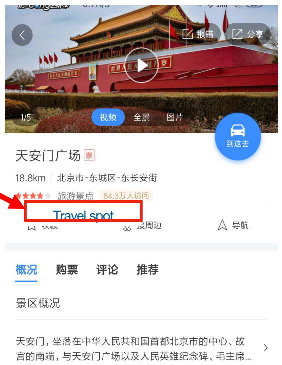
POI Knowledge Graph – Tag Refinement (KDD 2019)

- Tags are an important element for online maps
  - Describe the features of POIs.
  - Mined from text or annotated by users

- Tags of POIs are usually incomplete or imprecise
  - Incomplete: do not have enough users to generate tags
  - Imprecise: errors by users or models

POI: Tiananmen

Tag



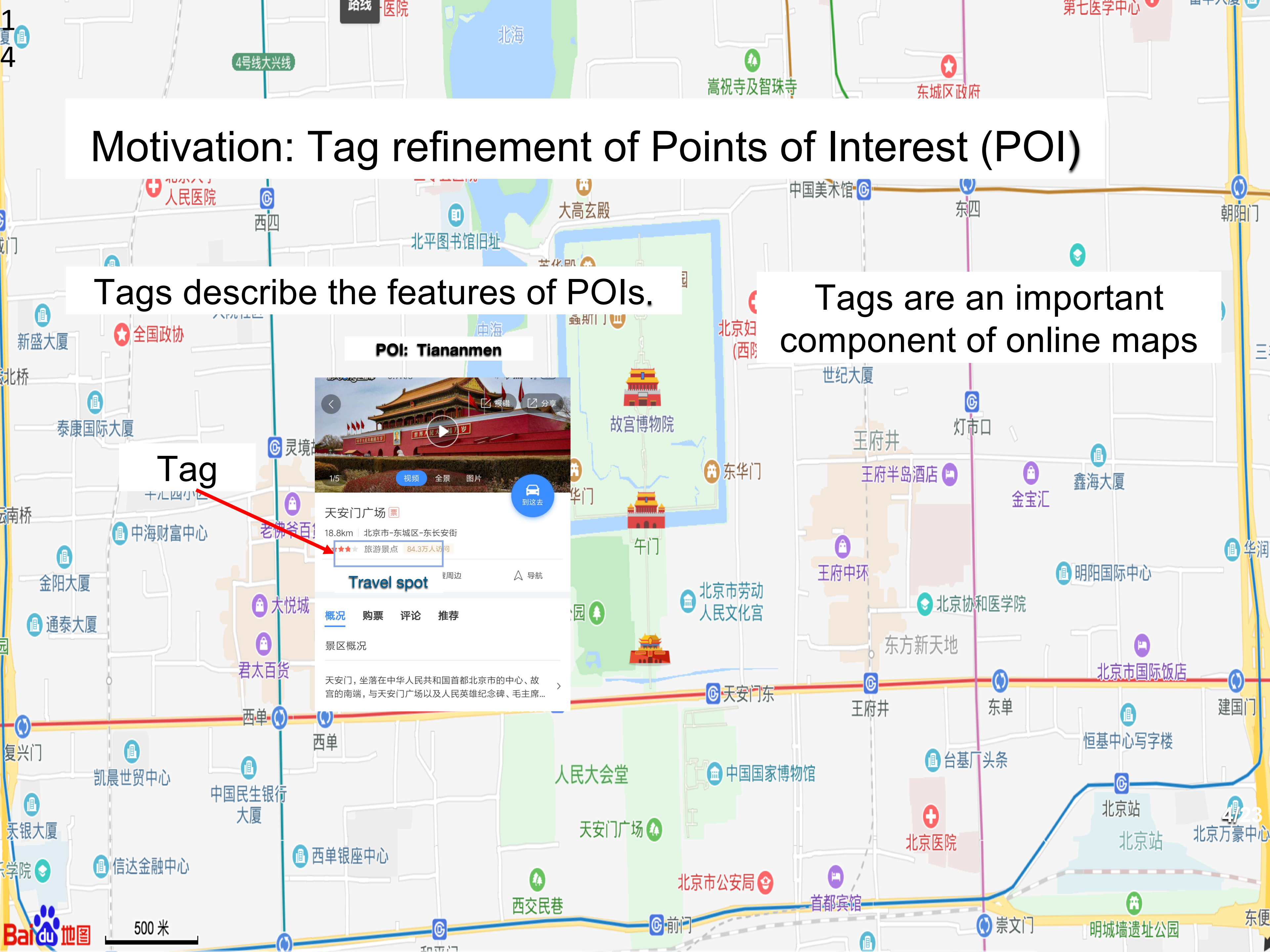
Motivation:
- Use machine learning method to refine the tags of POIs

A Collaborative Learning Framework to Tag Refinement for Points of Interest; in ***KDD 2019***

Motivation: Tag refinement of Points of Interest (POI)

Tags describe the features of POIs.

Tags are an important component of online maps

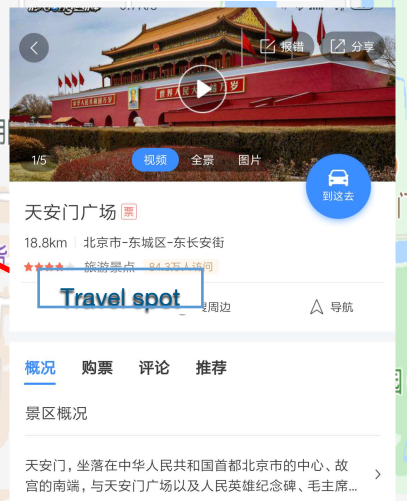


Motivation: Tag refinement of Points of Interest (POI)

How can we get tags of POIs?

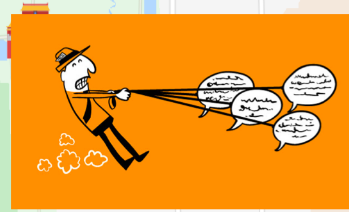
Usually, tags are mined from text

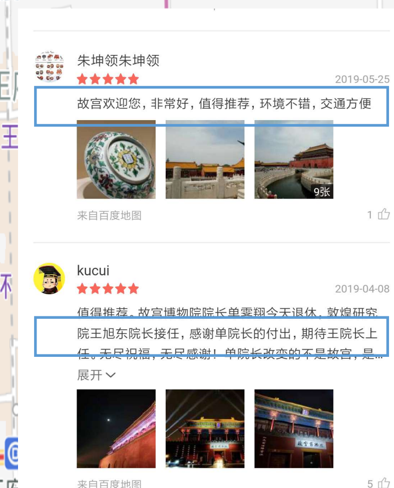
POI: Tiananmen



Tag

Travel spot





Motivation: Tag refinement of Points of Interest (POI)

How can we get tags of POIs?

POI: Tiananmen

Tag

Usually, tags are mined from text
or
annotated by users

Motivation: Tag refinement of Points of Interest (POI)

The problem of our paper:

Tag refinement of POIs

POI: Tiananmen

Tag

Tags of POIs are incomplete or imprecise

Incomplete:
donot have enough users to generate tags

Imprecise:
Errors by users or models

POI Knowledge Graph – Tag Refinement (KDD 2019)

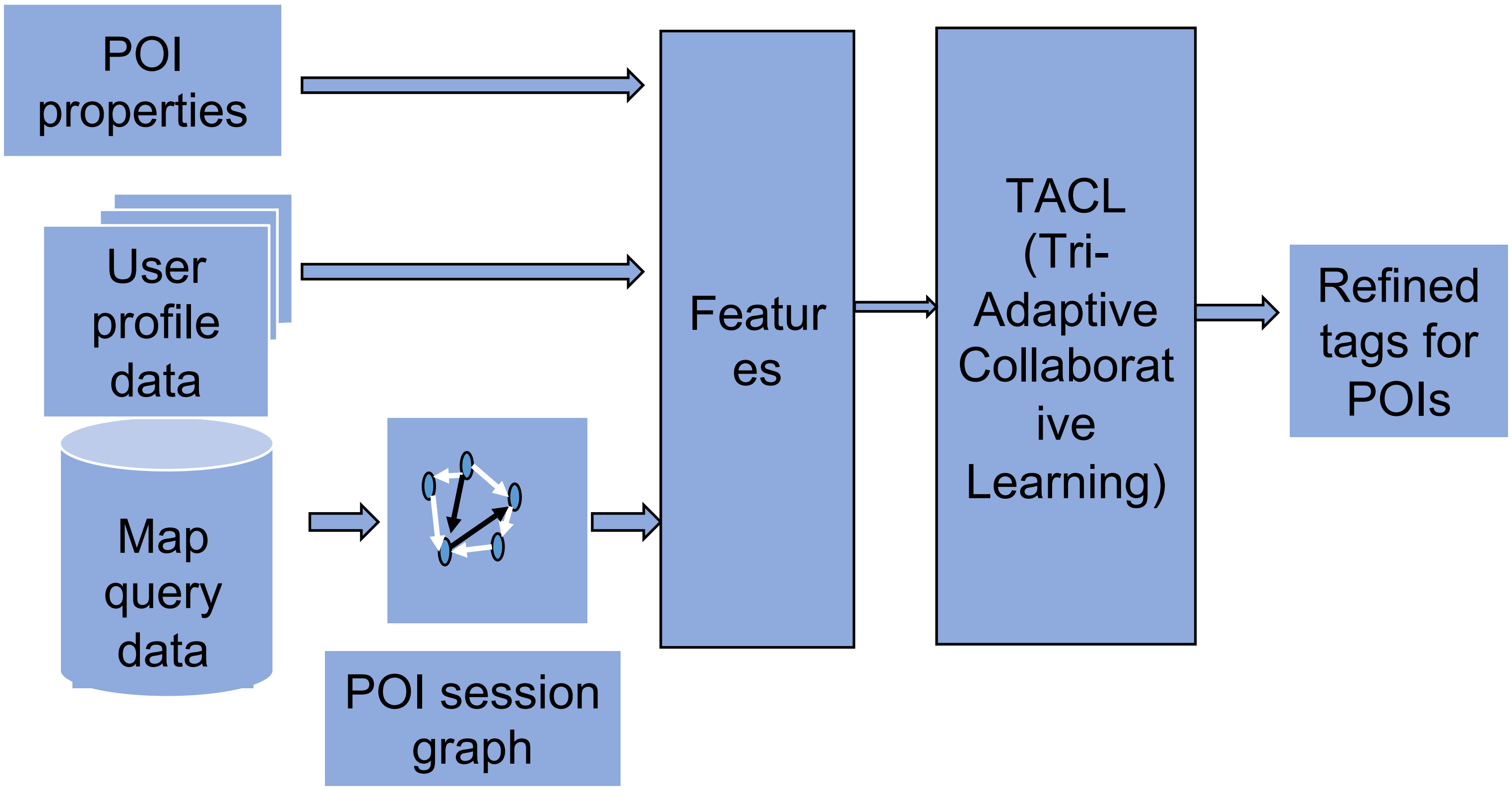
- From annotated POI-tag matrix to optimal POI-tag matrix

	POI 1	POI 2	POI 3	POI 4	POI 5	…	POI n
TAG 1	1	1	0	1	1	…	0
TAG 2	0	0	1	1	1	…	0
TAG 3	1	0	1	0	0	…	0
TAG 4	1	1	0	0	1	…	1
TAG 5	1	1	1	0	0	…	1
…	…	…	…	…	…	…	…
TAG m	0	0	0	0	1	…	1

→ Optimal POI-tag matrix

POI Knowledge Graph – Tag Refinement (KDD 2019)

- Framework overview

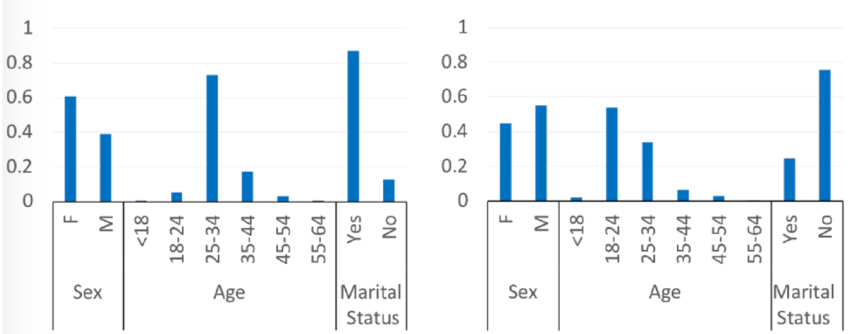


POI Knowledge Graph – Tag Refinement (KDD 2019)

- Feature Engineering

- POI property data:
  - Text description of POI: name, address, alias etc.
  - Using word embedding trained on the Chinese corpus from Baidu Baike
  - Average all the vectors to form property features

- POI profile features
  - "Users" of a POI as people who have searched the POI on Baidu Maps
  - POI profile feature vector is the histogram statistics of user profile distribution

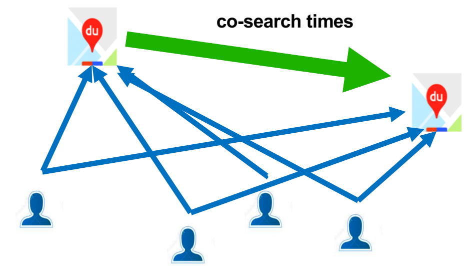


(a) Qiaohu Happy Island (b) Element Bar

POI Knowledge Graph – Tag Refinement (KDD 2019)

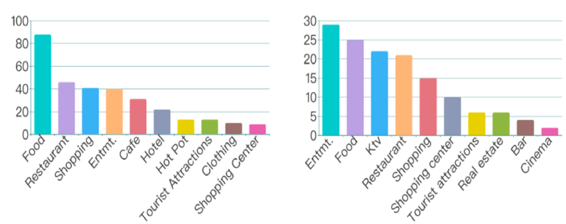
Features from mobility data

- POI session graph
  - if there are many users interacting with two POIs in a short time session, there exists an edge between these two POIs.
  - Calculate the tag distribution of its neighbors in the POI session graph.



User behavior on POI data

- Tag features is aggregated from the POI features



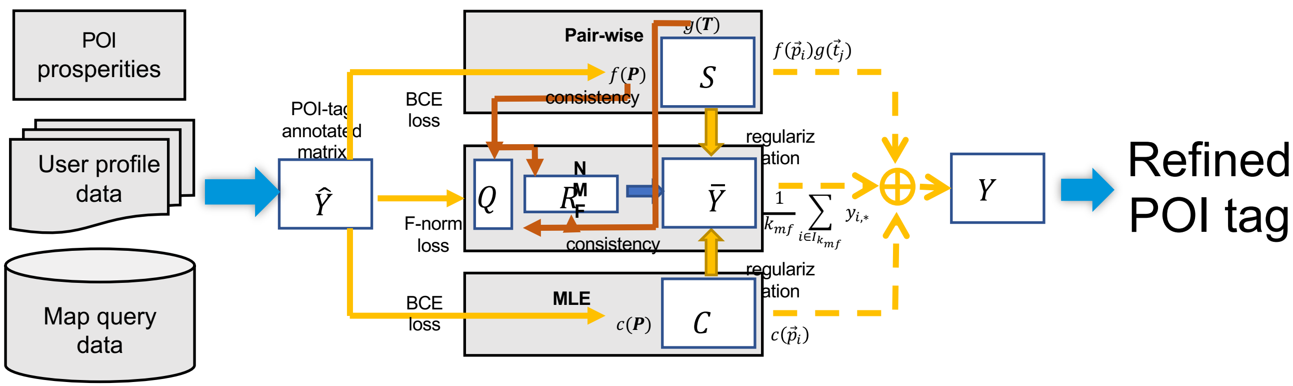
Examples of features from POI session graph

(a) Starbucks (b) Windsor KTV

Examples of nodes and edges in POI session graph

POI Knowledge Graph – Tag Refinement (KDD 2019)

Propose a tri-adaptive collaborative learning framework to tag refinement for POI in Baidu Maps



Tri-adaptive collaborative framework for POI tag refinement

The number of POIs with "parent-kids" tag is increased by 55.6%, and the total click volume of the POIs having "parent-kids" tag is increased by 38.0%.

Case study

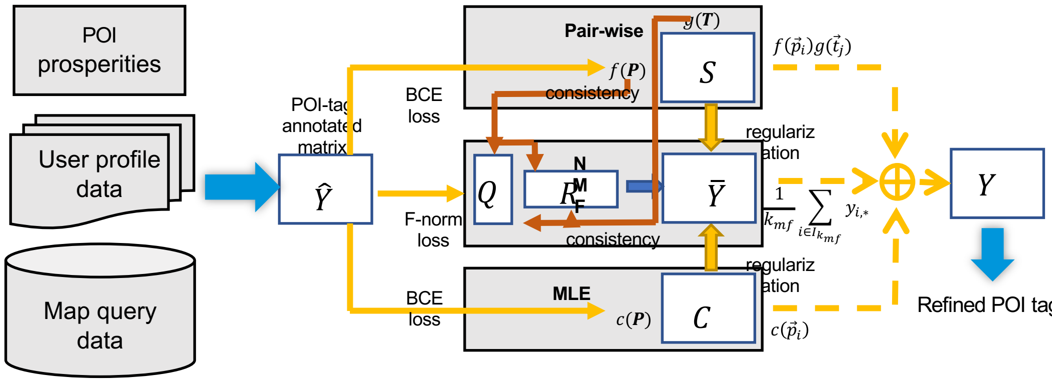
POI Knowledge Graph – Tag Refinement (KDD 2019)

- Tri-Adaptive Collaborative Learning framework (TACL) to tag refinement for POIs in Baidu Maps

- Multi-view learning with three components:
  - NMF
  - Pair-wise
  - MLE

- Regularization & consistency for multi-view learning

- Prediction with ensemble



Tri-adaptive collaborative framework for POI tag refinement

Tag Refinement Framework

- Tri-Adaptive Collaborative Learning framework (TACL) to tag refinement for POIs in Baidu Maps

- Three components:
  - **NMF**: non-negative matrix factorization

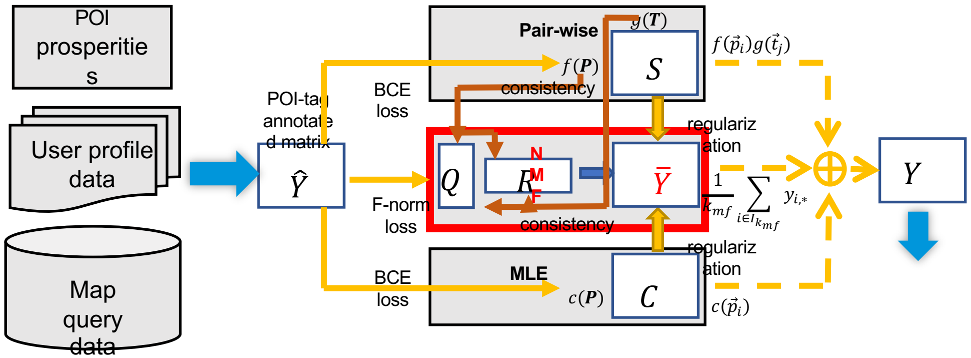
Suppose POI-tag annotated matrix is $\hat{Y}$

NMF is to find Q and R (with nonnegative entries) such that

$$\hat{Y} \approx \mathrm{QR}$$

With optimization by with the Frobenius norm:

$$\mathcal{L}_{\boldsymbol{mf}} = \| \hat{Y} - \mathrm{QR} \|_F^2 \;\; \boldsymbol{with}\; \mathrm{Q} \geq 0, \mathrm{R} \geq 0$$



Tri-adaptive collaborative framework for POI tag refinement

POI Knowledge Graph – Tag Refinement (KDD 2019)

Tag Refinement Framework

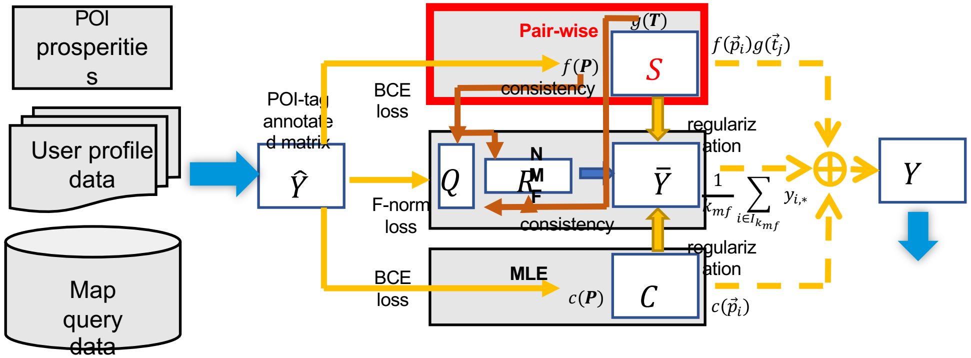
- Tri-Adaptive Collaborative Learning framework (TACL) to tag refinement for POIs in Baidu Maps

- Three components:

  - Pair-wise: matching similarity between POIs and tags based on their features

$$S = f(P)g(T)^T$$
$$f(P) = [f(\vec{p}_1), \dots, f(\vec{p}_n)]^T$$
$$g(T) = [g(\vec{t}_1), \dots, g(\vec{t}_n)]^T$$

$f(P)$ *and* $g(T)^T$ are Siamese networks with two multilayer perceptron (MLP) network to process the POI and tag in parallel, just like Siamese network for Question Answering.



Tri-adaptive collaborative framework for POI tag refinement

POI Knowledge Graph – Tag Refinement (KDD 2019)

Tag Refinement Framework

- Tri-Adaptive Collaborative Learning framework (TACL) to tag refinement for POIs in Baidu Maps

- Three components:
  - Pair-wise: $\boldsymbol{S = f(P)g(T)^T}$

    $\boldsymbol{f(P)}$ **and** $\boldsymbol{g(T)^T}$ **are MLP network.**

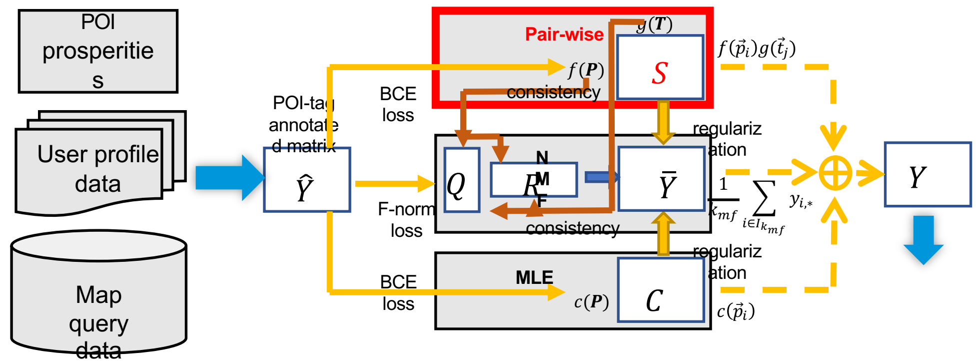
Optimization function:

1) Minimize the loss between the pairwise similarity and the annotated POI-tag matrix $\hat{Y}$

$$\mathcal{L}_{ps1} = -\sum_{\substack{1\le i\le n \\ 1\le j\le m}} (\hat{y}_{ij} \log(f(\vec{p}_i)g(\vec{t}_j)) + (1-\hat{y}_{ij})\log(1-f(\vec{p}_i)g(\vec{t}_j)))$$

2) regularize the difference between the pairwise similarity matrix and low-rank recovered matrix QR

$$\mathcal{L}_{ps2} = \| f(P)g(T)^T - \mathrm{QR} \|_2$$



Tri-adaptive collaborative framework for POI tag refinement

POI Knowledge Graph – Tag Refinement (KDD 2019)

Tag Refinement Framework

- Tri-Adaptive Collaborative Learning framework (TACL) to tag refinement for POIs in Baidu Maps

- Three components:
  - Pair-wise: $\boldsymbol{S} = \boldsymbol{f}(\boldsymbol{P})\boldsymbol{g}(\boldsymbol{T})^{\boldsymbol{T}}$

    $\boldsymbol{f}(\boldsymbol{P})$ ***and*** $\boldsymbol{g}(\boldsymbol{T})^{\boldsymbol{T}}$ **are MLP network.**

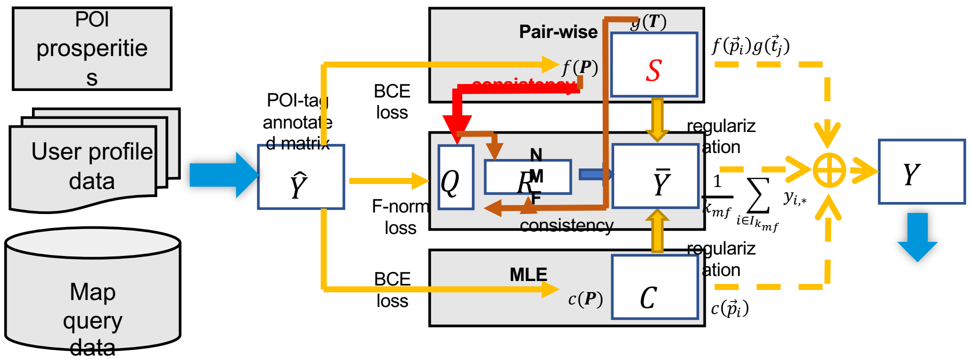
Regularization with consistency:

1) Ensure the consistency between the POI similarity defined by POI-tag matrix and the MLP network $\boldsymbol{f}(\cdot)$

$$\mathcal{L}_{\boldsymbol{pp}} = \| \boldsymbol{f}(\boldsymbol{P})\boldsymbol{f}(\boldsymbol{P})^{\boldsymbol{T}} - \mathrm{QR}(QR)^T \|_2$$

2) Ensure the consistency between the tag similarity defined by POI-tag matrix and the MLP network $\mathrm{g}(\cdot)$

$$\mathcal{L}_{\boldsymbol{tt}} = \| \boldsymbol{g}(\boldsymbol{T})\boldsymbol{g}(\boldsymbol{T})^{\boldsymbol{T}} - (QR)^T QR \|_2$$



Tri-adaptive collaborative framework for POI tag refinement

Tag Refinement Framework

- Tri-Adaptive Collaborative Learning framework (TACL) to tag refinement for POIs in Baidu Maps
- Three components:

  - MLE: multi-label classification, using an MLP model to predict the tags of a POI.

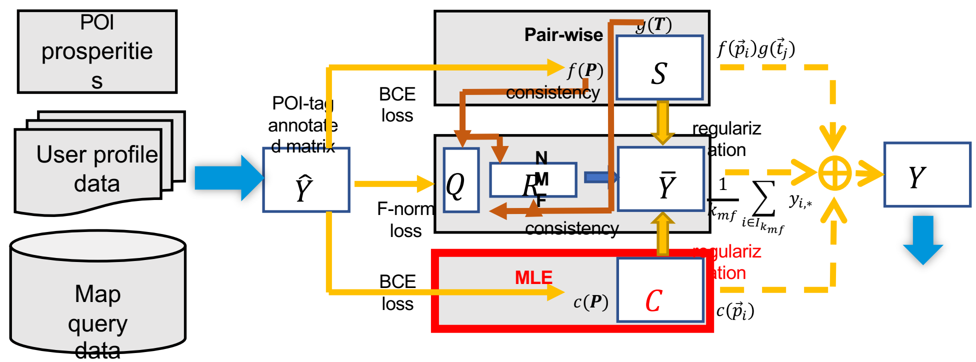
Optimization function:

1) Minimize the loss between predicted tags and the observed POI-tag matrix $\hat{Y}$

$$\mathcal{L}_{c1} = -\sum_{\substack{1\le i\le n \\ 1\le j\le m}} (\hat{\boldsymbol{y}}_{ij}\boldsymbol{log}(\boldsymbol{c}(\vec{\boldsymbol{p}}_i)) + (\mathbf{1}-\hat{\boldsymbol{y}}_{ij})\boldsymbol{log}(\mathbf{1}-\boldsymbol{c}(\vec{\boldsymbol{p}}_i))$$

2) regularize the difference between the predicted score and matrix QR

$$\mathcal{L}_{c2} = \| \boldsymbol{c}(\boldsymbol{P}) - \mathrm{QR} \|_2$$



Tri-adaptive collaborative framework for POI tag refinement

POI Knowledge Graph – Tag Refinement (KDD 2019)

- Optimization
  - Alternating optimization strategy
  - Optimize QR with sequentially quadratic optimization
  - Optimize other parameters by gradient descent with adaptive momentum (ADAM) optimizer

- Prediction

For a candidate POI p_0, the predicted scores are:

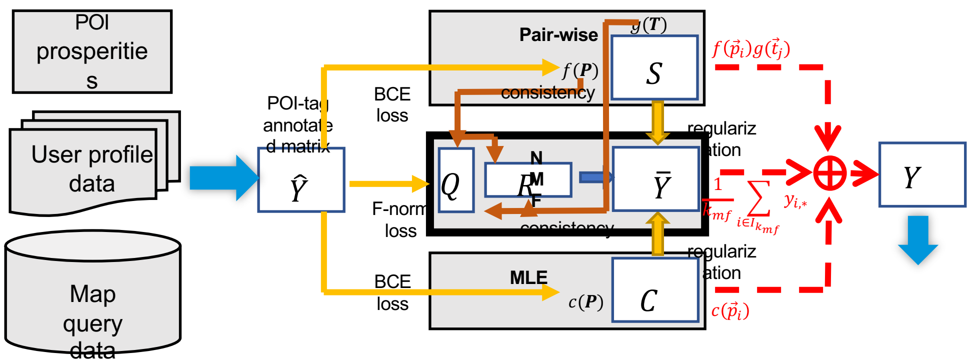
Pair-wise: $\boldsymbol{y_{0,*}^{ps}} = \boldsymbol{f(\vec{p}_0)g(\vec{T})}$

NMF: retrieve top k_{mf} POI from dataset by similarity defined by function $f(\cdot)$, then

$$\boldsymbol{y_{0,*}^{mf}} = \frac{\mathbf{1}}{k_{mf}} \boldsymbol{\sum_i I_{k_{mf}} (QR)_{i,*}}$$

MLE: $\boldsymbol{y_{0,*}^{c}} = \boldsymbol{c(\vec{p}_0)}$

Result: $y_{0,*} = (1-\alpha-\beta)\ \boldsymbol{y_{0,*}^{mf}} + \alpha \boldsymbol{y_{0,*}^{ps}} + \beta \boldsymbol{y_{0,*}^{c}}$



Tri-adaptive collaborative framework for POI tag refinement

POI Knowledge Graph – Tag Refinement (KDD 2019)

Experiments

- Datasets
  - POI data of two cities in China : Beijing and Chengdu

Table 1: Statistics of map query data and POIs

Dataset	# of map queries	# of POIs	Avg. # of tag
Beijing	50.6M	306K	2.43
Chengdu	21.0M	234K	2.15

- Baselines:
  - TransE (Translating Embeddings in KG)
  - PPE (Predictive Place Embedding for POI tag annotation)
  - TMC (Tag Completion Algorithm from an image processing method)
  - NMF (Non-negative Matrix Factorization)
  - MLP (Multilayer Perceptron)

POI Knowledge Graph – Tag Refinement (KDD 2019)

Experiments

- Performance evaluation on original data

Dataset		Beijing						Chengdu					
Model		TransE	PPE	TMC	NMF	MLP	TACL	TransE	PPE	TMC	NMF	MLP	TACL
AP@N	1	11.32	23.49	62.50	80.67	83.25	**87.83**	12.54	31.30	63.06	80.81	84.19	**88.42**
	3	8.42	27.33	40.87	49.25	60.06	**64.03**	8.41	22.97	36.82	45.42	55.50	**58.67**
	5	7.29	26.73	29.13	33.19	40.60	**42.82**	7.12	17.91	25.97	30.27	37.16	**38.79**
AR@N	1	11.05	4.36	28.34	37.72	38.76	**41.10**	12.37	19.33	37.09	46.08	47.73	**49.98**
	3	21.25	16.42	52.52	63.18	76.94	**81.60**	21.53	33.33	57.42	67.70	81.08	**84.92**
	5	29.26	25.56	61.62	70.16	84.96	**89.10**	29.52	42.12	65.08	73.83	88.06	**91.16**
C@N	1	11.32	23.49	62.50	80.67	83.25	**87.83**	12.54	31.30	63.06	80.81	84.19	**88.42**
	3	25.23	19.71	77.63	87.68	91.45	**93.35**	25.20	55.43	81.89	87.58	93.20	**94.68**
	5	34.56	52.57	83.85	91.25	94.42	**95.93**	33.96	65.85	86.43	90.66	95.74	**96.75**
MAP@N	1	11.32	23.49	62.50	80.67	83.25	**87.83**	12.54	31.30	63.06	80.81	84.19	**88.42**
	3	16.67	31.21	68.18	82.89	86.14	**89.40**	17.50	44.24	70.62	83.18	87.58	**90.56**
	5	18.96	38.29	67.52	81.61	85.20	**88.62**	19.63	46.80	70.36	82.09	86.85	**89.91**
	Total	20.77	31.21	54.65	67.58	80.84	**85.72**	22.05	35.39	57.24	70.98	83.39	**87.41**

TACL and baselines on original data

POI Knowledge Graph – Tag Refinement (KDD 2019)

Experiment

Dataset		Beijing						Chengdu					
Model		TransE	PPE	TMC	NMF	MLP	TACL	TransE	PPE	TMC	NMF	MLP	TACL
N=3	AP@N	8.12	18.63	40.55	47.56	56.95	**61.46**	10.91	22.94	38.14	44.48	52.84	**57.37**
	AR@N	21.62	20.51	52.09	61.18	73.29	**78.32**	28.28	33.39	58.76	66.62	77.71	**83.36**
	C@N	24.32	41.26	77.78	87.12	91.11	**92.54**	32.71	55.71	82.95	87.41	92.53	**94.78**
	MAP@N	16.87	30.02	68.75	82.31	85.20	**88.25**	20.89	44.01	71.99	82.72	86.26	**90.42**
MAP@Total		21.12	23.87	54.49	65.30	77.08	**82.24**	24.92	35.20	58.59	69.87	79.83	**85.74**

Performance(%) evaluation with adding noisy tags to 50% of POIs

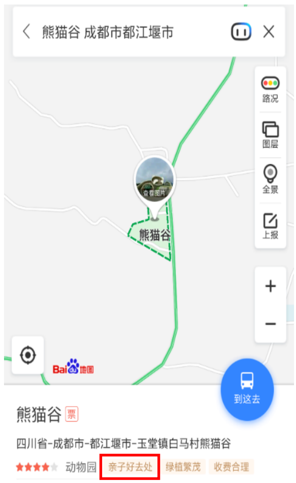
Dataset		Beijing						Chengdu					
Model		TransE	PPE	TMC	NMF	MLP	TACL	TransE	PPE	TMC	NMF	MLP	TACL
N=3	AP@N	1.35	17.45	34.83	48.40	57.97	**63.24**	4.60	21.99	34.50	44.11	53.07	**58.08**
	AR@N	3.84	21.58	45.73	62.54	74.47	**80.66**	11.75	32.57	54.52	66.26	78.08	**84.28**
	C@N	4.06	51.80	78.50	89.07	92.00	**93.70**	13.81	55.68	80.26	87.15	92.89	**94.90**
	MAP@N	1.52	35.84	67.50	83.19	85.44	**88.89**	8.42	38.55	69.68	82.02	85.39	**89.66**
MAP@Total		5.78	23.27	46.87	66.35	78.35	**84.34**	15.23	30.52	53.78	69.09	79.61	**86.12**

Performance(%) evaluation with randomly removing a half of tags of 50% of POIs

POI Knowledge Graph – Tag Refinement (KDD 2019)

Case study

- A deployed case for tag refinement on Baidu Maps - “parent-kids” tag completion



The number of POIs with “parent-kids” tag is increased by 55.6%, and the total click volume of the POIs having “parent-kids” tag is increased by 38.0%.

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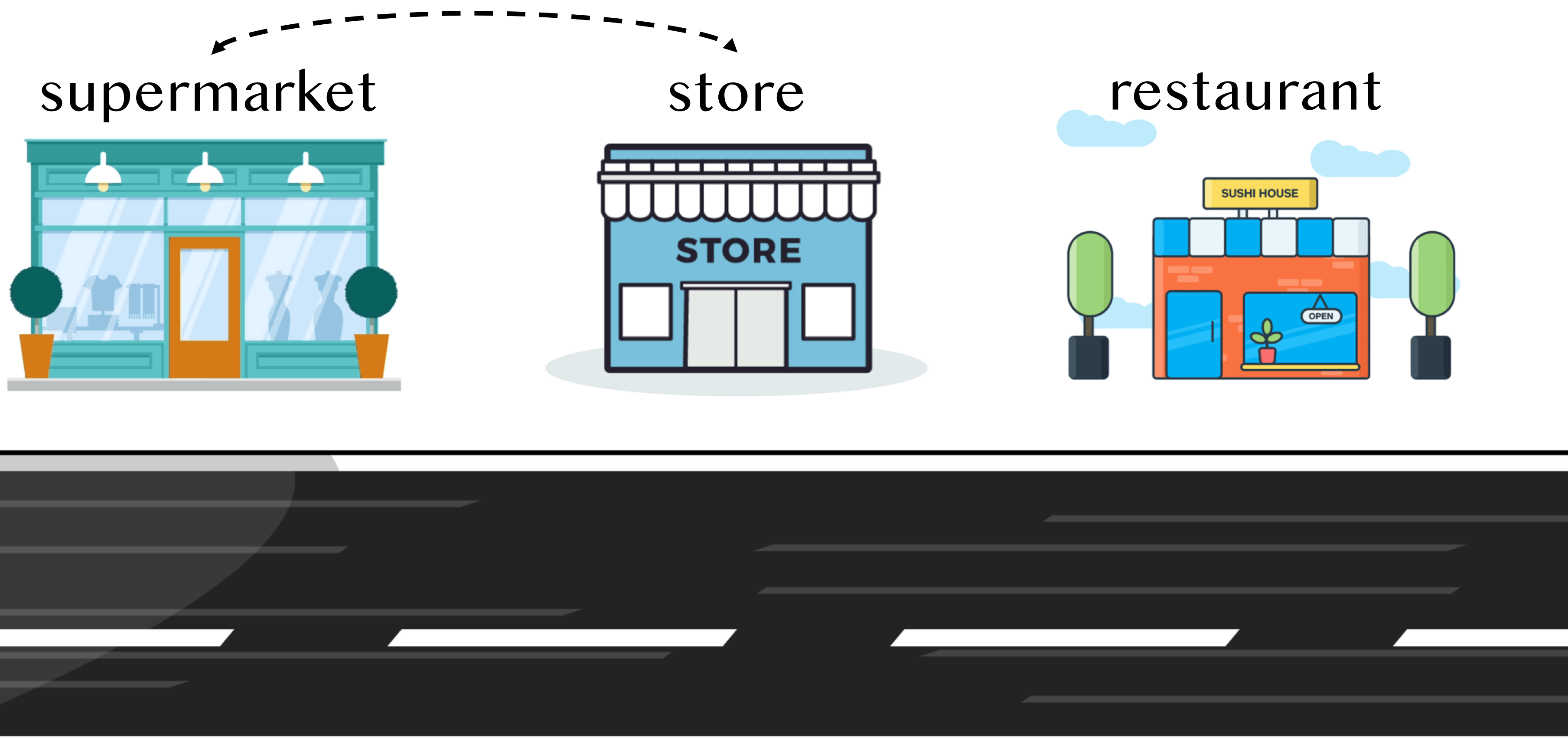
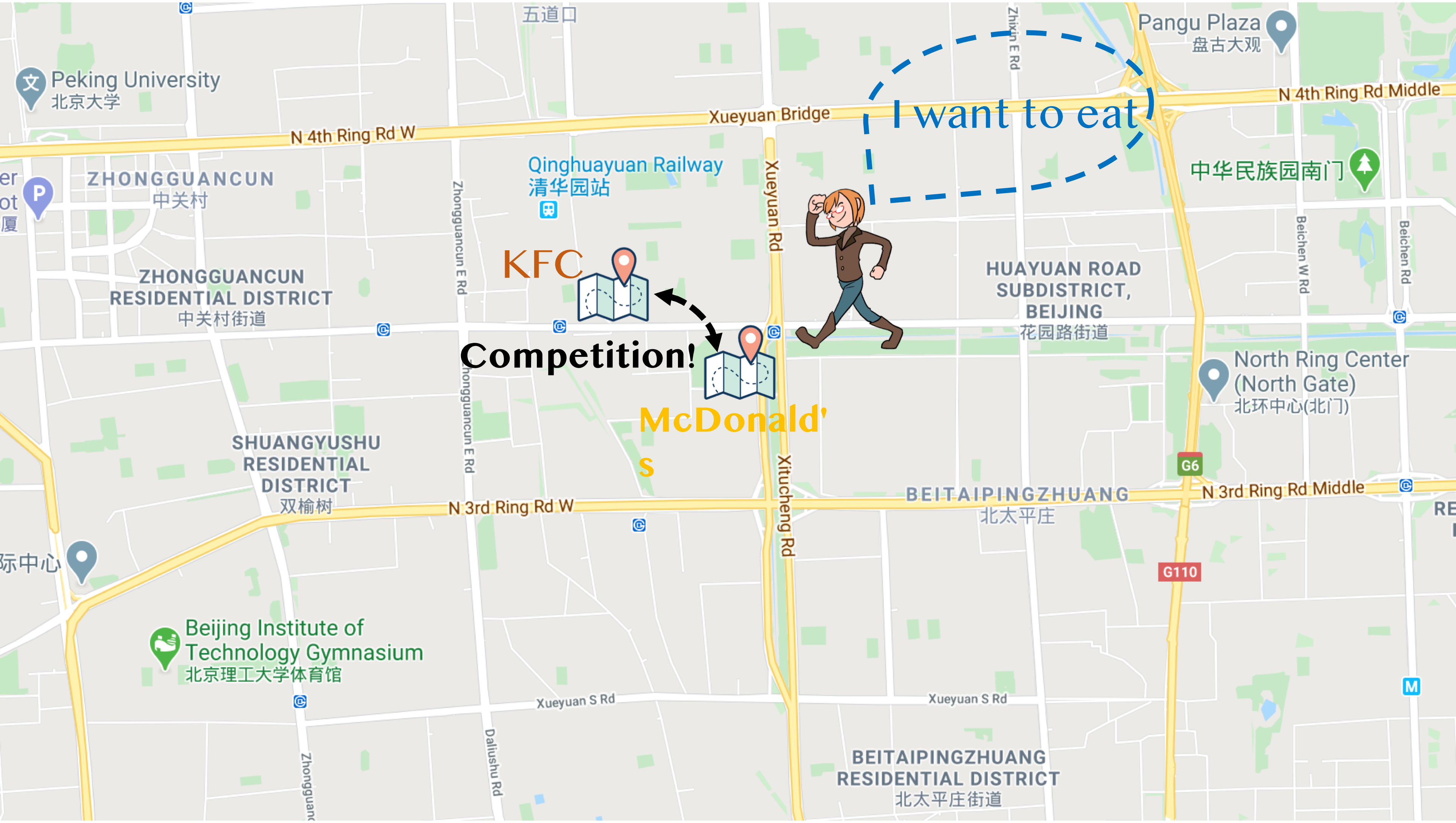
competitive relationship




I want to eat
KFC
Competition!
McDonald's
Peking University
北京大学
N 4th Ring Rd W
Xueyuan Bridge
N 4th Ring Rd Middle
Pangu Plaza
盘古大观
五道口
ZHONGGUANCUN
中关村
Qinghuayuan Railway
清华园站
中华民族园南门
ZHONGGUANCUN RESIDENTIAL DISTRICT
中关村街道
HUAYUAN ROAD SUBDISTRICT, BEIJING
花园路街道
North Ring Center (North Gate)
北环中心(北门)
SHUANGYUSHU RESIDENTIAL DISTRICT
双榆树
N 3rd Ring Rd W
BEITAIPINGZHUANG
北太平庄
N 3rd Ring Rd Middle
Beijing Institute of Technology Gymnasium
北京理工大学体育馆
Xueyuan S Rd
BEITAIPINGZHUANG RESIDENTIAL DISTRICT
北太平庄街道
Xueyuan Rd
Xitucheng Rd
Zhongguancun E Rd
Dalushu Rd
G6
G110

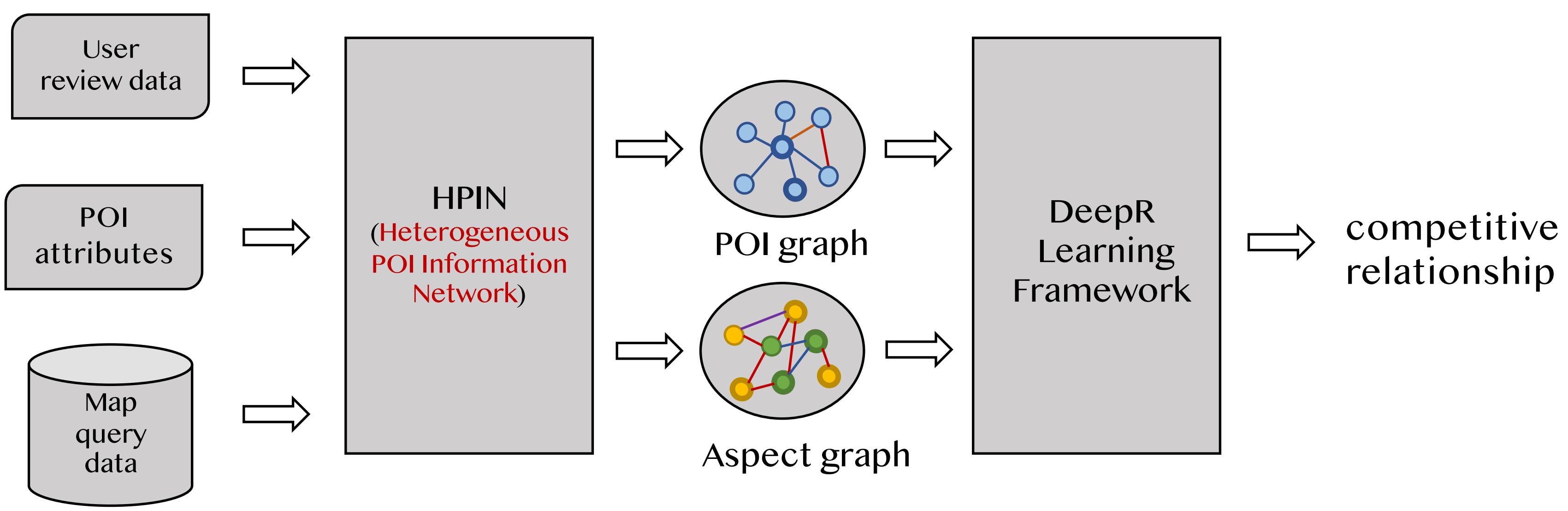
Motivation

- Help to make a reasonable price level
- For Location-based services: POI recommendation, advertising …
- We introduce an approach for POI competitive analysis

How to predict and analyze the competitive relationship of POIs…

Framework Overview

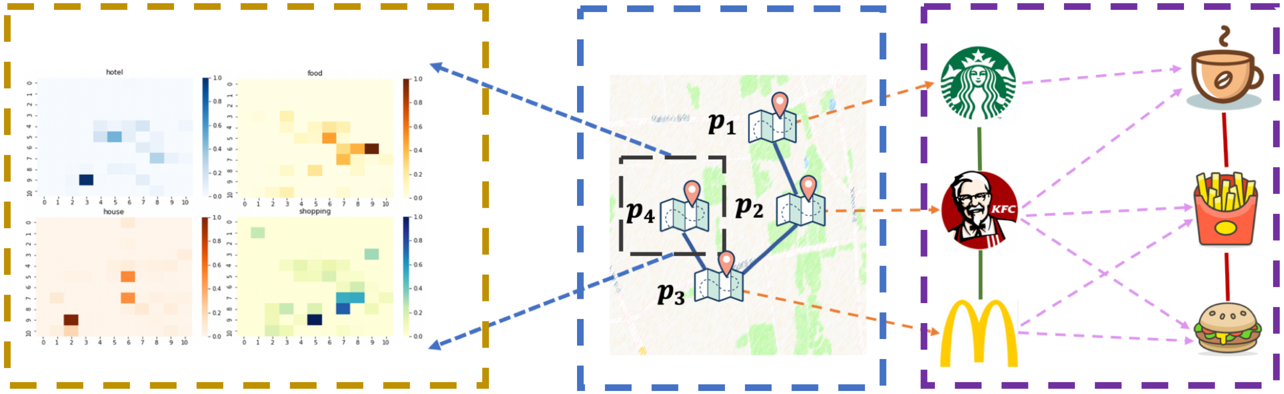
- The POI competitive relationship analysis process



HPIN Construction

- Competitive Relationship Prediction for POI
  - $G = (\mathcal{P} \cup \mathcal{B} \cup \mathcal{A} \cup \mathcal{M}, \mathcal{E}_{pp} \cup \mathcal{E}_{pb} \cup \mathcal{E}_{bb} \cup \mathcal{E}_{ba} \cup \mathcal{E}_{aa})$
  - $\mathcal{P} = \{p_1, ..., p_{n_p}\} \quad \mathcal{A} = \{a_1, ..., a_{n_a}\}$

    $\mathcal{B} = \{b_1, ..., b_{n_b}\} \quad \mathcal{M} = \{M_1, ..., M_{n_M}\}$



Spatial heat map

POI graph & aspect graph

*Competitive Analysis for Points of Interest; in **KDD 2020***

HPIN Construction

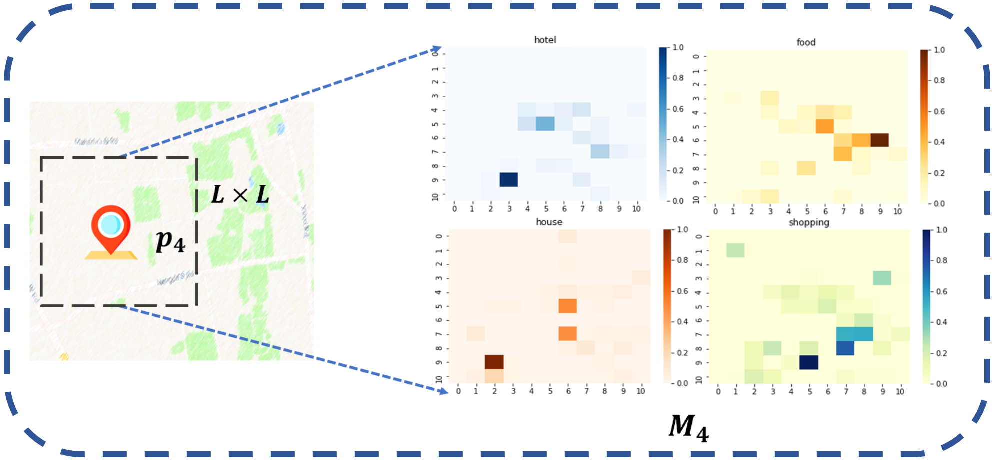
- POI Attribute: spatial heat map
  - Treat POI with its surrounding neighborhood as $L \times L$ image

$$\mathbf{v}_k^c = \mathbf{max}_{\forall p_t \in S_k} \left\{ f_{hot}(p_t) \mid \mathrm{tag}(p_t) = c, 1 \le c \le C \right\}$$

All POIs in the grid Sk

returns the hot value of p

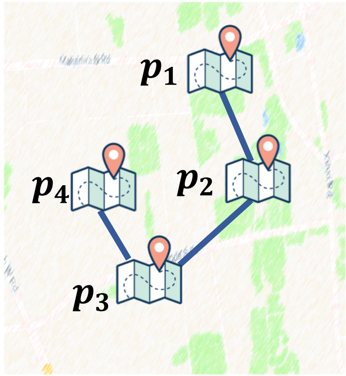
limits p has a category of c



HPIN Construction

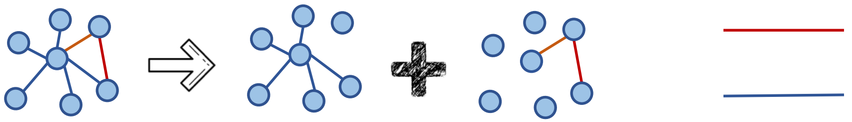
- POI-POI Relation: co-query
  - Co-query edges based on map query data

$$cod_u(i,j) = \begin{cases} 1 & \text{if } \ 0 < |t_i - t_j| \leqslant \Delta T, \\ 0 & \text{otherwise} \ . \end{cases} \qquad \omega_{ij} = \sum_{u \in U} cod_u(i,j)$$



POI graph

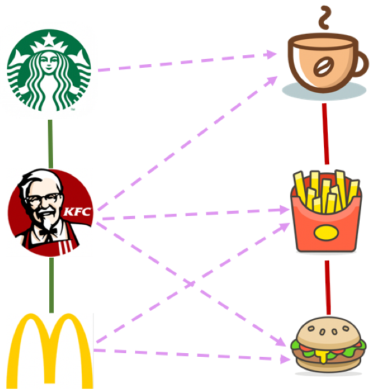
- Divide POI graph into two sub-graphs
  - Diffusion graph
  - Affinity graph



HPIN Construction

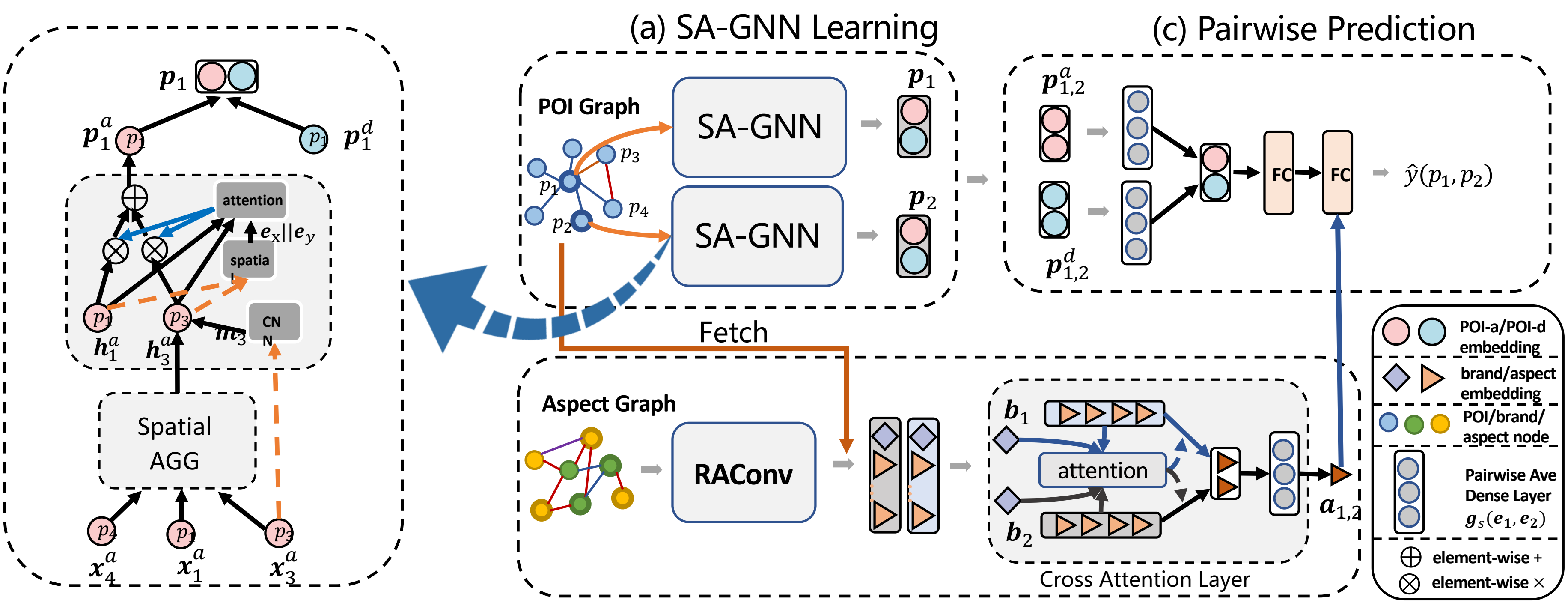
- Aspect extraction: select top k aspects sorted by TF-IDF
- Relation of brand-aspect: TF-IDF weight
- Relation of aspect-aspect: PMI
- Relation of brand-brand: meta-path
  - Define meta-path: $b_i \xrightarrow{R_{pb}^{-1}} p_k \xrightarrow{R_{pp}} p_l \xrightarrow{R_{pb}} b_j$
  - PathSim for weight:

$$s(b_i, b_j) = s(b_j, b_i) = \frac{\left|\{\boldsymbol{p}_{b_i \rightsquigarrow b_j} : \boldsymbol{p}_{b_i \rightsquigarrow b_j} \models \Phi\}\right|}{\sqrt{\left|\mathcal{N}_i^{(pb)}\right|} \cdot \sqrt{\left|\mathcal{N}_j^{(pb)}\right|}}$$



aspect graph

Our Proposed Model

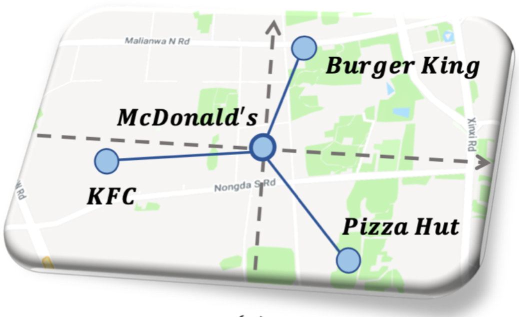


(d) SA-GNN Layer

(b) Pairwise POI Knowledge Extraction

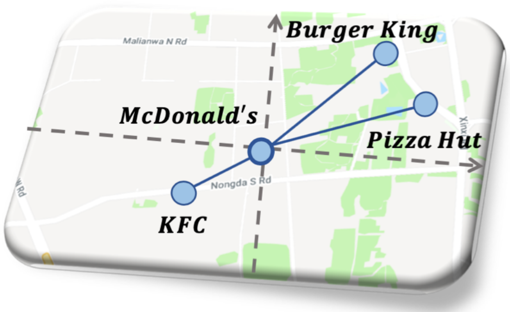
Spatial Adaptive Graph Neural Network

- Limitations of classical message-passing neural networks (MPNNs)
  - lose the spatial information of POIs
  - lack of the ability to capture distant-range spatial location



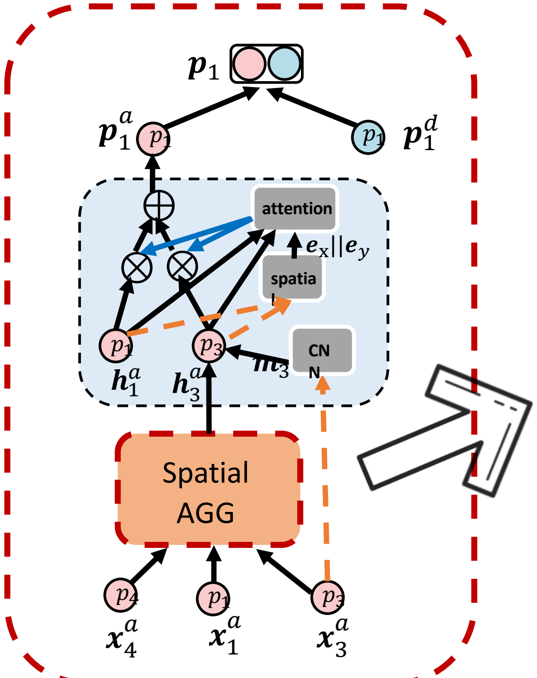
(a)

different!

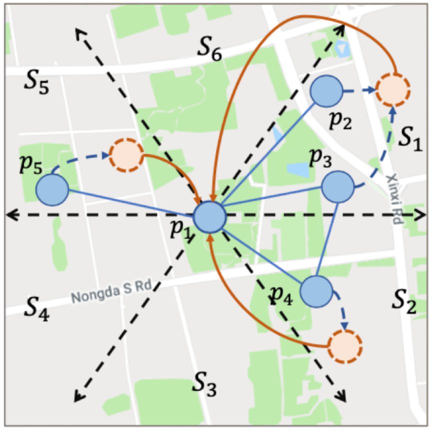


(b)

Spatial Adaptive Graph Neural Network



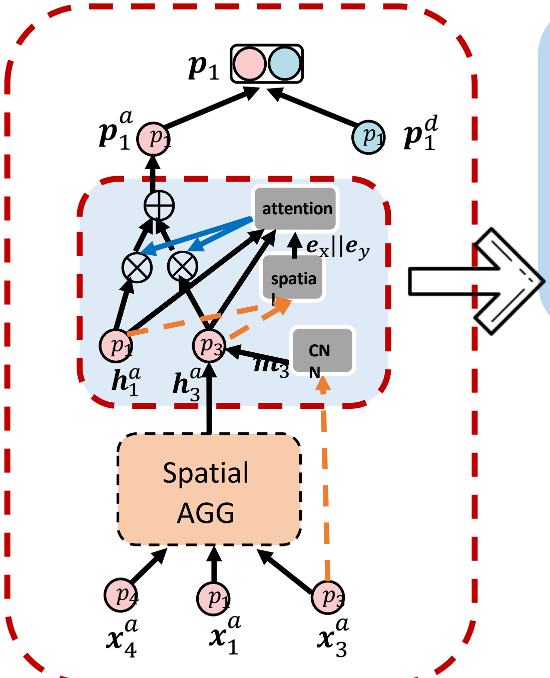
- evenly divide the neighbors of each POI node p into several sectors
- use the same graph convolutional rule based on symmetric normalized Laplacian as GCN



- Local oriented aggregation: $s_i^k = \sum_{p_j \in \mathcal{N}_k(p_i)} (\deg(p_i)\deg(p_j))^{-\frac{1}{2}} \boldsymbol{x}_j$
- Global oriented aggregation: $q_i = \sigma(\mathbf{W}_q \cdot \Vert_{k=0}^{n} \, s_i^k)$

Competitive Analysis for Points of Interest; in ***KDD 2020***

Spatial Adaptive Graph Neural Network



- Use heat map convolution layer to model the surrounding environment
- Use location-aware attentive propagation layer to process the relative spatial positions between POIs

$$\boldsymbol{p}_i = \Big\Vert_{k=1}^{K} \sigma\left(\sum_{j \in \mathcal{N}_i} attn_s^k(p_i, p_j, \boldsymbol{r}_s)\boldsymbol{W}_p^k \cdot \mathrm{CONV}(p_j)\right)$$

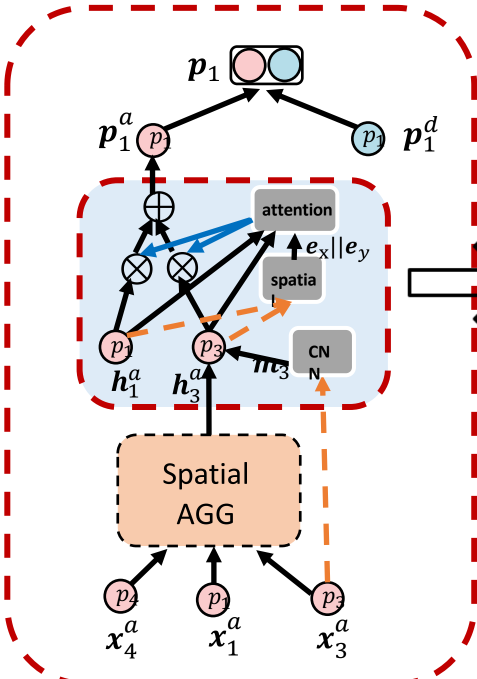
1. CNN for spatial heat map

$$\boldsymbol{m}_i = f_{CNN}\left(\boldsymbol{M}_i; \boldsymbol{w}_h\right)$$

2. concatenate $\boldsymbol{m}_i$ and $\boldsymbol{q}_i$

$$\boldsymbol{h}_i = \mathrm{CONV}(p_i) = \sigma\left(\boldsymbol{q}_i \oplus \boldsymbol{m}_i\right)$$

Spatial Adaptive Graph Neural Network



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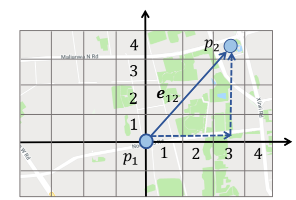


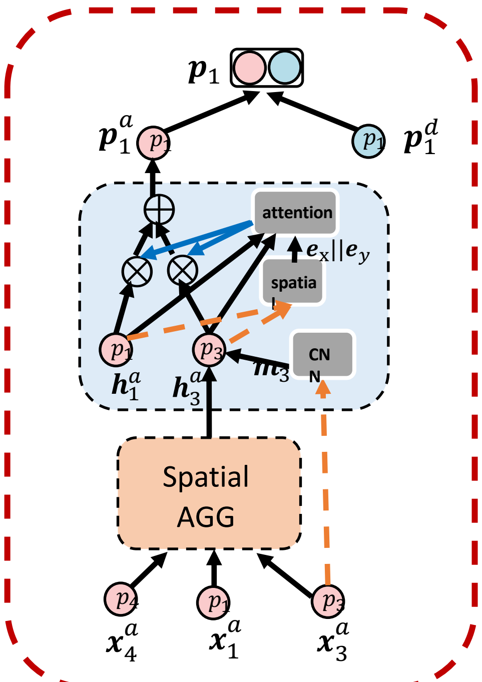
1. Location encoder

$$\boldsymbol{r}_s = \boldsymbol{W}_s \cdot \left(\boldsymbol{e}_x(i, j) \oplus \boldsymbol{e}_y(i, j)\right)$$

2. Attention weight

$$attn_s(p_i, p_j, \boldsymbol{r}_s) = \sigma\left(\boldsymbol{a}^T \cdot (\boldsymbol{W}_t \boldsymbol{h}_i \oplus \boldsymbol{W}_t \boldsymbol{h}_j \oplus \boldsymbol{r}_s)\right)$$

Spatial Adaptive Graph Neural Network



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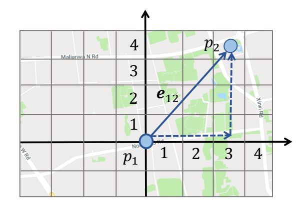

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2. Attention weight $\quad attn_s(p_i, p_j, \boldsymbol{r}_s) = \sigma\big(\boldsymbol{a}^T \cdot (\boldsymbol{W}_t\, \boldsymbol{h}_i \oplus \boldsymbol{W}_t\, \boldsymbol{h}_j \oplus \boldsymbol{r}_s)\big)$

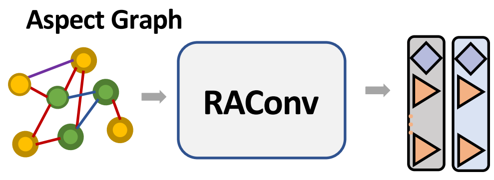
- Apply SA-GNN on the two sub-graphs $\boldsymbol{p}_i = \boldsymbol{p}_i^d \oplus \boldsymbol{p}_i^a$

Pairwise POI Knowledge Extraction

- Relation-aware convolution (RAConv)
  - learn representations for brand and aspect

$$AGG(\boldsymbol{a}_i^{(l)}) = \sum_{j \in \mathcal{N}_i^a} (\hat{\mathrm{A}}_a)_{ij} \boldsymbol{W}_a \boldsymbol{a}_j^{(l-1)} + \sum_{j \in \mathcal{N}_i^t} (\hat{\mathrm{A}}_t)_{ij} \boldsymbol{W}_t \boldsymbol{b}_j^{(l-1)}$$

$$\boldsymbol{a}_i^{(l)} = \sigma\left(\boldsymbol{W} \boldsymbol{a}_i^{(l-1)} + AGG(\boldsymbol{a}_i^{(l)})\right)$$

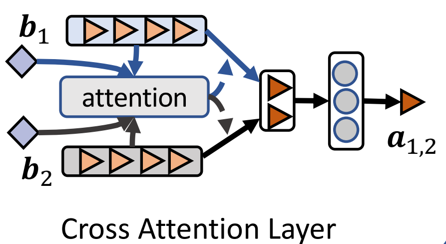


- Cross Attention
  - Calculate the similarity
  - Weighted sum

$$\boldsymbol{\pi}(b_i, a_l^j) = \frac{\boldsymbol{b}_i \cdot \boldsymbol{a}_l^j}{\|\boldsymbol{b}_i\| \cdot \|\boldsymbol{a}_l^j\|}, l \in [1, n]$$

$$\beta_k = \frac{\exp(\boldsymbol{\pi}(b_j, a_k^i))}{\sum_{t=1}^m \exp(\boldsymbol{\pi}(b_j, a_t^i))}$$

$$\boldsymbol{a}_i = \sum_{k=1}^m \beta_k \boldsymbol{a}_k^i \quad \boldsymbol{a}_{i,j} = \boldsymbol{g}_s(\boldsymbol{a}_i, \boldsymbol{a}_j)$$



Experiments

- Settings
  - Experiments are conducted on two real-world POIs datasets in Beijing and Chengdu.

Dataset	#POIs	#Co-query Edges	#Pairs	#Heat Maps
Beijing	96,972	1,113,962	18,731	19,841
Chengdu	32,449	256,954	7,514	9,624

- Baselines
  - Rule-based methods

    DIST, EW
  - Feature-based methods

    MLP, XGboost
  - Graph embedding methods

    DeepaWalk, Node2Vec
  - GNN-based methods

    GCN, GAT, SEAL, Geom-GCN, HAN

Competitive Analysis for Points of Interest; in ***KDD 2020***

Experiments

- Overall Comparison

	Beijing					Chengdu				
	Acc	AUC	F1	Prec	Rec	Acc	AUC	F1	Prec	Rec
EW	0.5765	0.6225	/	/	/	0.5667	0.6133	/	/	/
DIST	0.6442	0.7131	/	/	/	0.6257	0.6963	/	/	/
MLP	0.7221	0.8102	0.7389	0.6968	0.7863	0.6883	0.7476	0.7117	0.6621	0.7694
XGboost	0.7814	0.8641	0.7915	0.7566	0.8298	0.7300	0.8090	0.7353	0.7211	0.7500
Deepwalk	0.7732	0.8511	0.7811	0.7549	0.8511	0.7397	0.8158	0.7485	0.7241	0.7745
Node2vec	0.7784	0.8527	0.7866	0.7586	0.8167	0.7411	0.8151	0.7518	0.7291	0.7759
GCN	0.8061	0.8790	0.8139	0.7826	**0.8477**	0.7534	0.8394	0.7569	0.7463	0.7677
GAT	0.8069	0.8828	0.8077	0.8046	0.8108	0.7581	0.8281	0.7542	0.7669	0.7418
Geom-GCN	0.8091	0.8835	0.8045	0.8071	0.802	0.7527	0.8309	0.7447	0.7697	0.7213
SEAL	0.8023	0.8813	0.8094	0.7814	0.8396	0.7489	0.8418	0.7505	0.7455	0.7557
HAN	0.8145	0.8893	0.8175	0.8046	0.8308	0.7633	0.8424	0.7656	0.7556	0.7758
DeepR	**0.8516**	**0.9129**	**0.8509**	**0.8546**	0.8472	**0.7876**	**0.8566**	**0.7884**	**0.7857**	**0.7911**

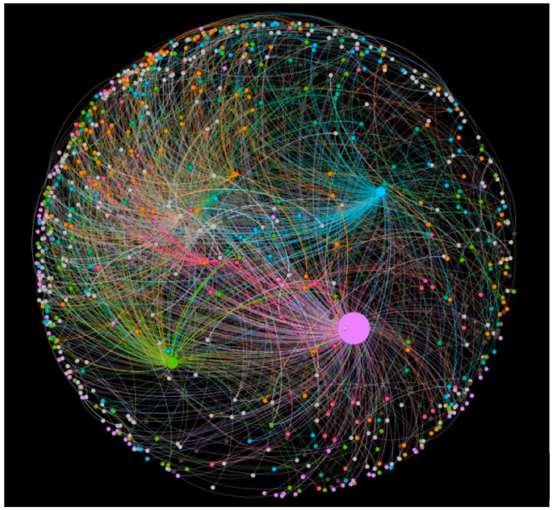
- Our proposed model DeepR achieves the best performance

Outline

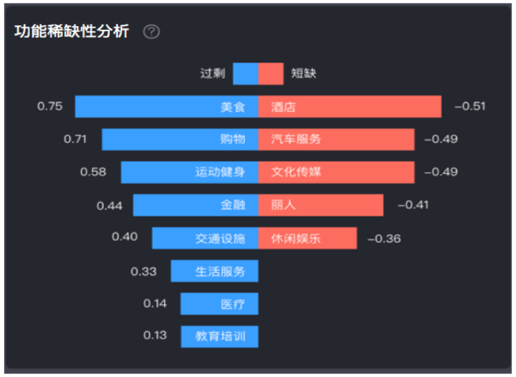
- Introduction
- POI Knowledge Graph Construction
  - Tag refinement
  - Competitive relationship
- POI-KG application
  - Geodemographic Influence Maximization
  - Multi-level POI recommendation
  - Joint Intent Detection and Entity Linking
  - Multi-Modal Transportation Recommendation

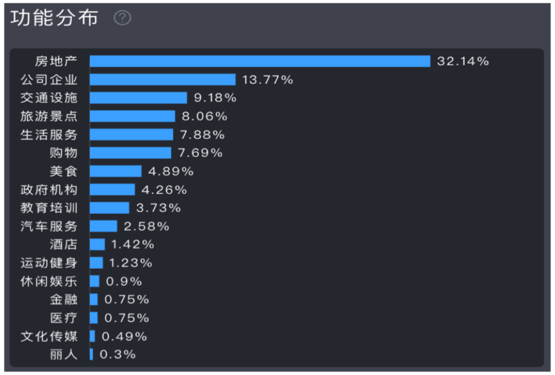
POI Knowledge Graph

- POI知识图谱，建模物理空间的人-地-物关系
  - ➢ 完善空间知识建模和感知，使用复杂网络分析理解城市城市生态
  - ➢ 推导空间需求分布，合理规划资源分布



构建人-地-物关系图谱，进行复杂网络分析





基于知识图谱的区域功能分析，助力城市规划与建设

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Geodemographic Influence Maximization

Problem definition

Outdoor advertising in the form of printed posters and billboards, as well as their digital counterparts, is gaining appeal due to its proven effectiveness; its revenue is in the order of 30 billion dollars in the US alone.

Geodemographic Influence Maximization

Given a set of locations in a city, on which ones should we place ads on so as to reach as many people as possible within a limited budget?

Key points:

1. How to deal with influence overlap
2. Data should be easily obtained
3. Efficiency to real-world large-scale data

Geodemographic Influence Maximization

Our model is based on the probability graph, G=(V,E,cost,coord,spec).

Then a spector who stand on node u and will move k steps will be influenced by the selected nodes set S by the probability:

$$f(u,k,S)=\begin{cases}1, & u\in S\\ 0, & k=0\wedge u\notin S\\ \sum\limits_{(u,v,p)\in E} p\cdot f(v,k-1,S), & k>0\end{cases}$$

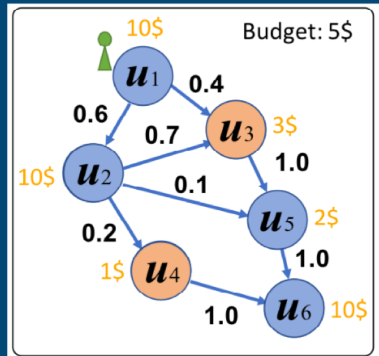
GIM problem is to find

$$\underset{S\subseteq V,\, cost(S)\le L}{\arg\max}\ \{F(S)\}$$

where

$$F(S)=\sum_{u\in V}\sum_{k=0}^{K} spec(u,k)\cdot f(u,k,S)$$

We show that GIM is NP-hard but F is monotone and submodular.



(a)POI network model

k	Moves	Contribution
1	u_1u_2	~~0.6~~
	$u_1\mathbf{u}_3$	0.4
2	$u_1u_2\mathbf{u}_3$	0.6*0.7=0.42
	$u_1u_2\mathbf{u}_4$	0.6*0.2=0.12
	$u_1u_2u_5$	~~0.6*0.1=0.06~~
	$u_1\mathbf{u}_3u_5$	0.4*1.0=0.40

(b)The contribution of each move when a person is to make k steps from u_1

A simple case of GIM. Each row in the table calculates the probability of a path of k steps between node u_1 (where a member of population stands) and any location, for k = 1 and k = 2. To maximize the aggregate probability, contributed by all selected locations, of hitting such a path under a budget of 5\$, it suffices to chose locations u_3 and u_4, with total probability 0.42 + 0.12 + 0.40 = 0.94. As paths u_1u_2 and $u_1u_2u_5$ are not affected by the solution, we strip a line over them.

Geodemographic Influence Maximization; in ***KDD 2020***

Geodemographic Influence Maximization

Algorithm 1: GREEDY(G, L)

Function Comp_F(V^*, E^*, S)
    for $k = 0$ **to** K **do**
        foreach $u \in V^*$ **do**
            if $u \in S$ **then** $\phi[u, k] \leftarrow 1$;
            else if $k = 0$ **then** $\phi[u, k] \leftarrow 0$;
            else
                $\phi[u, k] \leftarrow 0$;
                foreach $(u, v, p) \in E^*$ **do**
                    $\phi[u, k] \leftarrow \phi[u, k] + \phi[v, k-1] \times p$;
    $result = \sum_{u \in V} \sum_{k=0}^{K} \phi[u, k] \times spec(u, k)$;
    return $result$
Initialize a matrix ϕ;
$S \leftarrow \emptyset$;
$N \leftarrow V$;
while $N \neq \emptyset$ **do**
    $x^* \leftarrow \arg\max_{x \in N} \frac{F_S(x)}{cost(x)}$;
    // $F_S(x) =$ Comp_F$(V, E, S \cup \{x\})$ - Comp_F(V, E, S)
    if $cost(S) + cost(x^*) \leq L$ **then**
        $S \leftarrow S \cup \{x^*\}$;
    $N \leftarrow N \setminus \{x^*\}$;
$v^* \leftarrow \arg\max_{v \in V, cost(v) \leq L} F(\{v\})$;
return $\arg\max\{F(S), F(\{v^*\})\}$

A basic greedy algorithm:

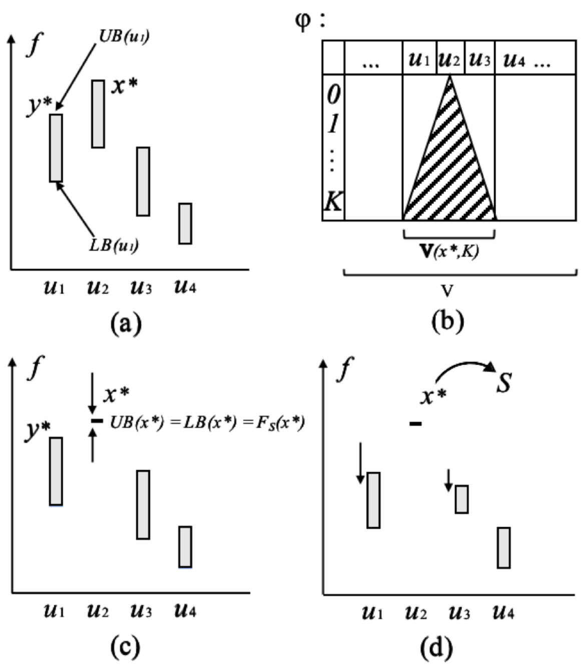
In each iteration, we add to S the vertex u that maximizes the unit marginal influence, $\frac{F_S(x)}{cost(x)}$,unless adding u violates the budget, where $F_S(x) = \mathcal{F}(S \cup u) - \mathcal{F}(S)$. Its time complexity is $O(K|V|^2(|V| + |E|))$, where K is a given threshold.

Locality property:

People check-in at a few places within each trip. It follows that each network location may be influenced by, or exercise influence upon, nearby locations only.

Geodemographic Influence Maximization; in ***KDD 2020***

Geodemographic Influence Maximization



Lazy-Sower:
Marginal Influence Improvement boosts the computation of $F_S(x)$.

LazyTag reduces the number of nodes to check in each iteration by maintaining tight bounds of marginal influence for each nodes.

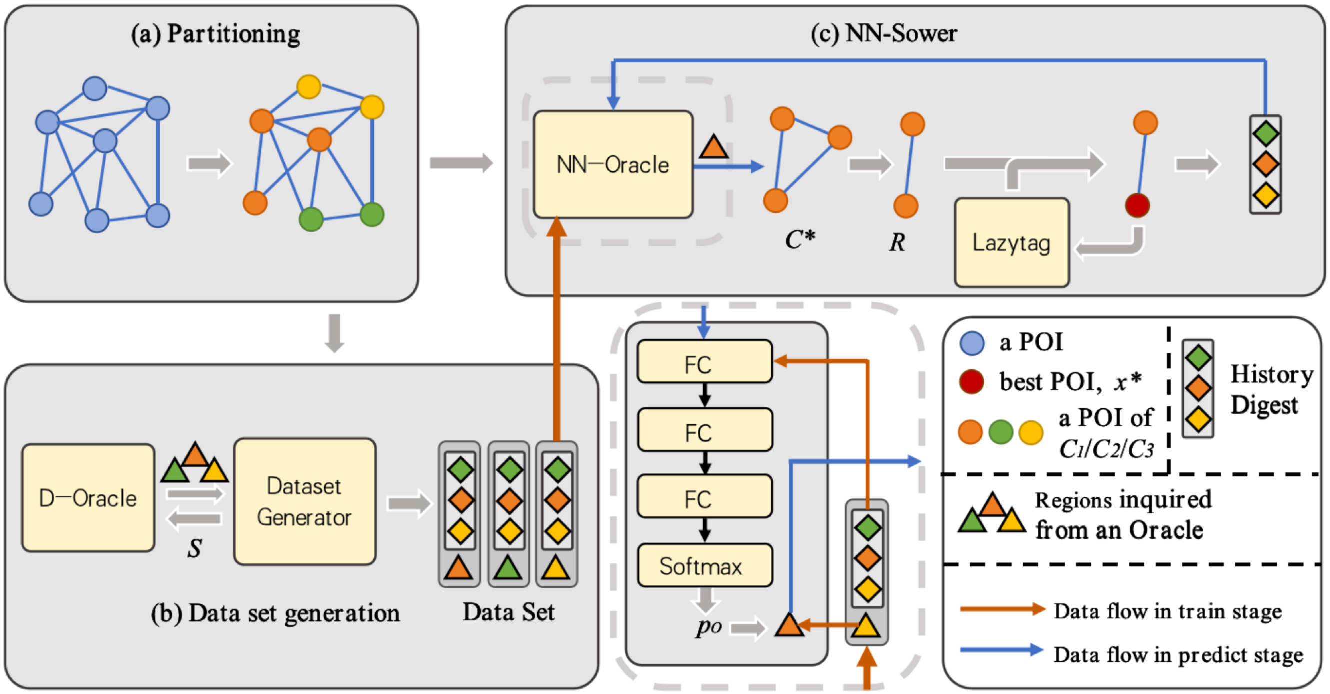
Its time complexity is $O(K|V|$|V(x,K)| · (|V(x,K)| + |E(x,K)|)),
For K = 5 in Beijing data, the average of |V(x, K)| and |E(x, K)| is respectively 1/2997 and 1/2429 of $|V|$ and $|E|$.

*Geodemographic Influence Maximization; in **KDD 2020***

Geodemographic Influence Maximization

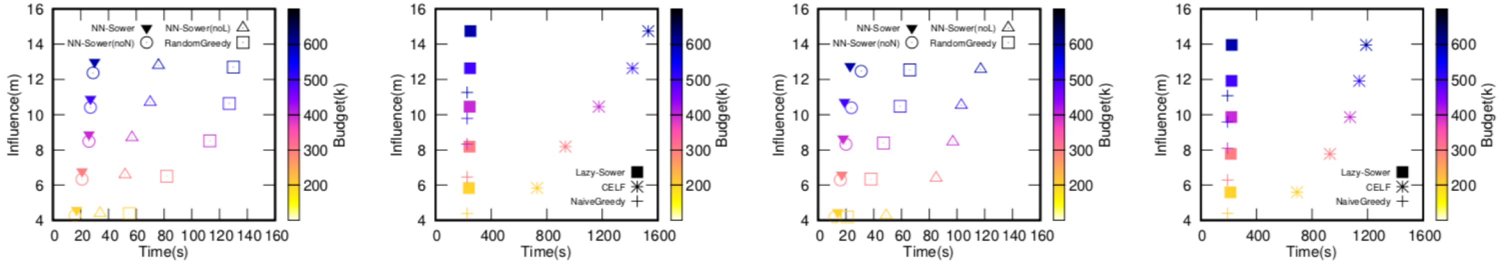
NN-Sower:
This variant trains a neural network (NN) model to choose network regions likely to yield good candidates.

In each iteration, it chooses a region using the NN,
randomly generates a subset of candidate nodes therein,
and returns the one that maximizes unit marginal influence.



Geodemographic Influence Maximization; in ***KDD 2020***

Geodemographic Influence Maximization



(a) **Non-Deterministic Algs, Beijing** (b) **deterministic Algs, Beijing** (c) **Non-Deterministic Algs, Chengdu** (d) **deterministic Algs, Chengdu**

Figure 4: Effect of varying Budget L; best viewed in color — each color stands for a certain budget.

Our method: Lazy-Sower & NN-Sower   Baseline: CELF(state-of-the-art)

Lazy-Sower: Same influnce and 20% runtime as CELF
NN-Sower: 91% influence and 2% runtime as CELF

Geodemographic Influence Maximization; in ***KDD 2020***

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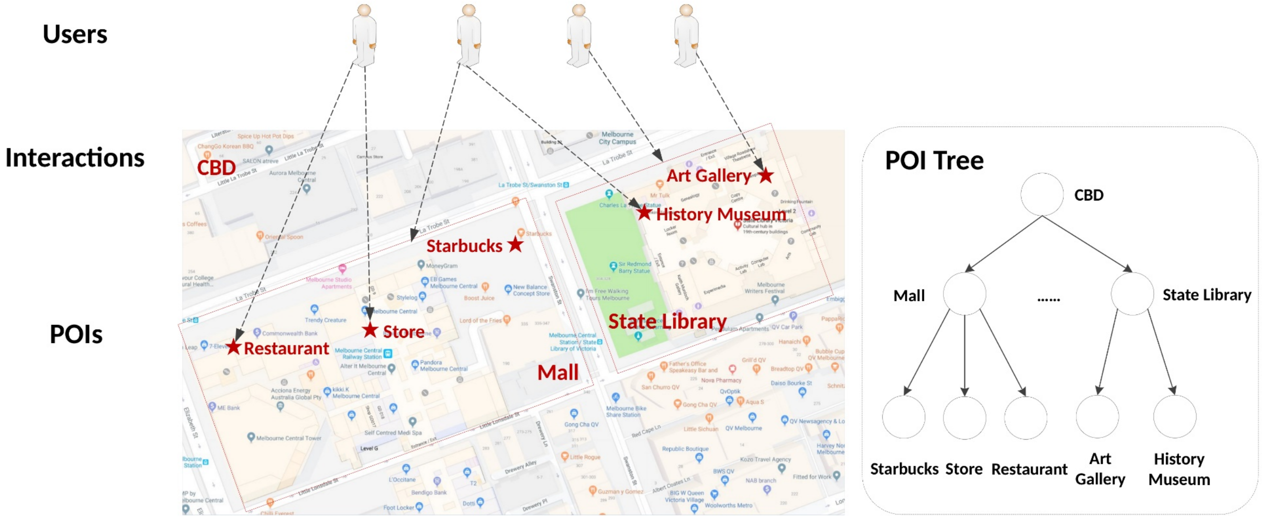
Problem Definition

- Multi-level POI Recommendation
  - Given a user, a historical interaction pattern Q, and a parameter *k*, we aim to return the top-*k* most relevant POIs at varying levels of granularity covered by the POI tree T .



Spatial Object Recommendation with Hints: When Spatial Granularity Matters; in ***SIGIR 2020***

Approach

- A straightforward solution
  - Build a separate recommendation model for each level of spatial granularity
  - Apply an existing POI recommendation algorithm directly
- Drawback
  - It may not fully leverage mutual information among POIs at different spatial granularity levels.
  - For example, a user may prefer to visit an area because of the POIs contained in that area.

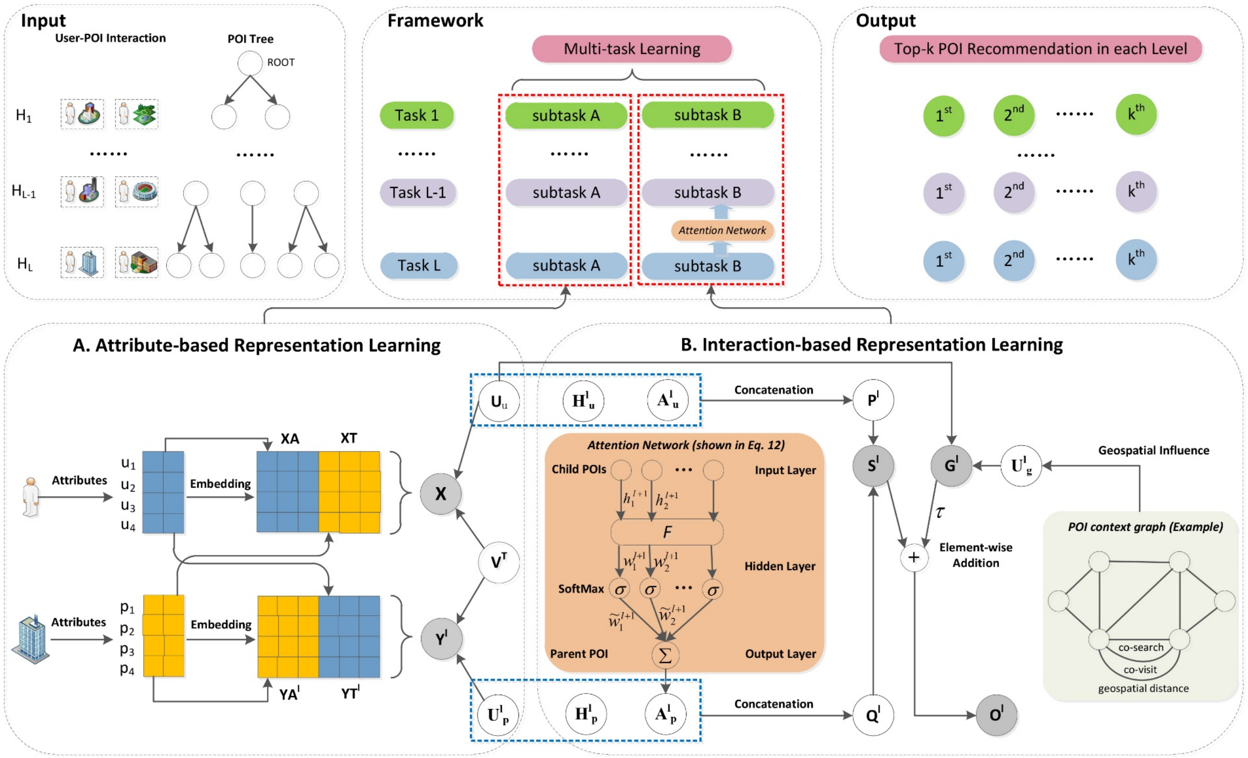
Challenge

How can we achieve a one-size-fits-all model to make effective recommendations at every level of spatial granularity?

Spatial Object Recommendation with Hints: When Spatial Granularity Matters; in ***SIGIR 2020***

Approach

- MPR Model



Spatial Object Recommendation with Hints: When Spatial Granularity Matters; in ***SIGIR 2020***

Experiment

- Datasets
  - Baidu Maps: two city-level datasets (*Beijing* and *Chengdu*)

TABLE II
STATISTICS OF DATASETS.

Datasets	#users	#POIs			#check-ins	Period
	m	n_1	n_2	n_3	(raw)	
Beijing	41,498	576	33,845	45,343	522,213	May 27-Aug 27, 2018
Chengdu	13,839	61	20,500	25,807	140,148	Feb 1-May 31, 2019

- Baselines
  - WRMF [7]: weighted regularized matrix factorization
  - BPRMF [8]: bayesian personalized ranking
  - PACE [9]: preference and context embedding
  - SAE-NAD [10]: self-attentive autoencoders with neighbor-aware influence
- Evaluation Metrics
  - precision (P@k)
  - normalized discounted cumulative gain (NDCG@k)

Experiment

- Q1：Our MPR model vs the state-of-the-art methods

Table 2: Model performance comparisons on the *Beijing* and *Chengdu* dataset. Entries marked $^{\vartriangle}$ and $^{\blacktriangle}$ correspond to statistical significance using a paired t-test with Bonferroni correction at 95% and 99.9% confidence intervals respectively. Comparisons are relative to PACE.

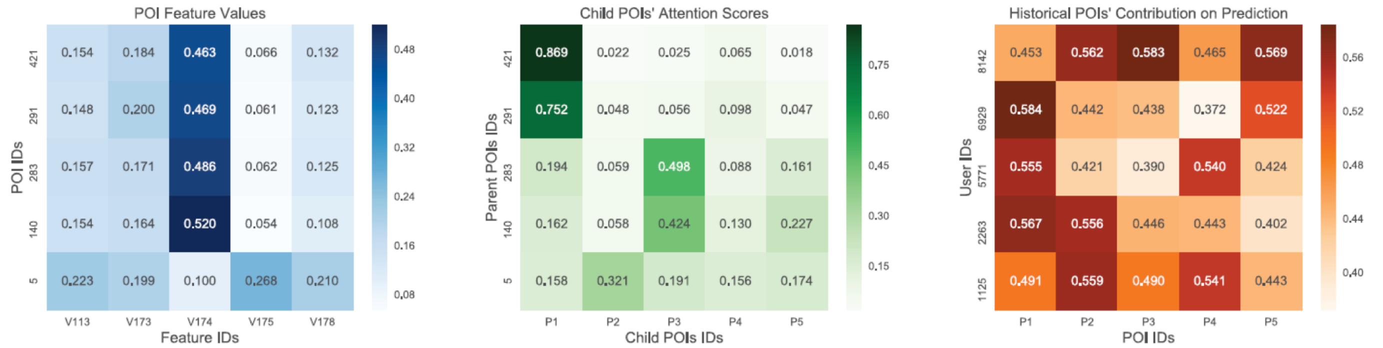
Level	Model	*Beijing*						*Chengdu*					
		P@5	NDCG@5	P@10	NDCG@10	P@20	NDCG@20	P@5	NDCG@5	P@10	NDCG@10	P@20	NDCG@20
H_1	WRMF	0.056$^{\blacktriangledown}$	0.096$^{\blacktriangledown}$	0.047$^{\blacktriangledown}$	0.121$^{\blacktriangledown}$	0.037$^{\blacktriangledown}$	0.151$^{\blacktriangledown}$	0.063$^{\blacktriangledown}$	0.079$^{\blacktriangledown}$	0.051$^{\blacktriangledown}$	0.098$^{\blacktriangledown}$	0.041$^{\blacktriangledown}$	0.127$^{\blacktriangledown}$
	BPRMF	0.079$^{\blacktriangle}$	0.123$^{\blacktriangle}$	0.064$^{\blacktriangle}$	0.150$^{\blacktriangle}$	0.050$^{\blacktriangle}$	0.187$^{\blacktriangle}$	0.110$^{\blacktriangle}$	0.142$^{\blacktriangle}$	0.086$^{\blacktriangle}$	0.170$^{\blacktriangle}$	0.061$^{\blacktriangle}$	0.202$^{\blacktriangle}$
	PACE	0.067	0.104	0.053	0.124	0.043	0.156	0.087	0.117	0.074	0.152	0.054	0.181
	SAE-NAD	0.078$^{\blacktriangle}$	0.125$^{\blacktriangle}$	0.064$^{\blacktriangle}$	0.155$^{\blacktriangle}$	0.051$^{\blacktriangle}$	0.194$^{\blacktriangle}$	0.100$^{\blacktriangle}$	0.128$^{\blacktriangle}$	0.081$^{\blacktriangle}$	0.155$^{\blacktriangle}$	0.057$^{\blacktriangle}$	0.185$^{\blacktriangle}$
	MPR	**0.084**$^{\blacktriangle}$	**0.133**$^{\blacktriangle}$	**0.067**$^{\blacktriangle}$	**0.162**$^{\blacktriangle}$	**0.053**$^{\blacktriangle}$	**0.203**$^{\blacktriangle}$	**0.119**$^{\vartriangle}$	**0.159**$^{\vartriangle}$	**0.094**$^{\blacktriangle}$	**0.190**$^{\blacktriangle}$	**0.064**$^{\blacktriangle}$	**0.222**$^{\blacktriangle}$
H_2	WRMF	0.009	0.017	0.007	0.022	0.005	0.026$^{\blacktriangle}$	0.022	0.027	0.018$^{\triangledown}$	0.034	0.013	0.040
	BPRMF	0.007	0.014$^{\blacktriangle}$	0.007	0.020$^{\blacktriangle}$	0.005	0.026$^{\blacktriangle}$	0.027	0.037	0.022	0.047	0.017	0.058
	PACE	0.007	0.013	0.007	0.019	0.005	0.024	0.022	0.031	0.022	0.039	0.013	0.046
	SAE-NAD	0.007	0.014$^{\blacktriangle}$	0.006$^{\blacktriangledown}$	0.018$^{\blacktriangledown}$	0.005	0.024	**0.033**	0.043	0.019	0.049	0.017	0.059
	MPR	**0.010**$^{\blacktriangle}$	**0.018**$^{\blacktriangle}$	**0.008**$^{\blacktriangle}$	**0.023**$^{\blacktriangle}$	**0.007**$^{\blacktriangle}$	**0.030**$^{\blacktriangle}$	**0.033**$^{\blacktriangle}$	**0.044**$^{\blacktriangle}$	**0.026**$^{\vartriangle}$	**0.054**$^{\blacktriangle}$	**0.020**$^{\blacktriangle}$	**0.067**$^{\blacktriangle}$
H_3	WRMF	0.008$^{\blacktriangle}$	0.015$^{\blacktriangle}$	0.006$^{\blacktriangle}$	0.018$^{\blacktriangle}$	0.004	0.022$^{\blacktriangle}$	0.021$^{\vartriangle}$	0.027$^{\vartriangle}$	0.017	0.033	0.013	0.041
	BPRMF	0.006$^{\blacktriangledown}$	0.012$^{\blacktriangle}$	0.005	0.015$^{\blacktriangle}$	0.004	0.019$^{\blacktriangle}$	0.021$^{\vartriangle}$	0.029	0.017	0.036	0.013$^{\vartriangle}$	0.043$^{\blacktriangle}$
	PACE	0.007	0.008	0.005	0.009	0.004	0.010	0.016	0.023	0.016	0.032	0.009	0.035
	SAE-NAD	0.008$^{\blacktriangle}$	0.015$^{\blacktriangle}$	0.007$^{\blacktriangle}$	0.020$^{\blacktriangle}$	0.005$^{\blacktriangle}$	**0.026**$^{\blacktriangle}$	0.020$^{\blacktriangle}$	0.027$^{\blacktriangle}$	0.020$^{\vartriangle}$	0.038$^{\blacktriangle}$	0.016$^{\blacktriangle}$	0.047$^{\blacktriangle}$
	MPR	**0.009**$^{\blacktriangle}$	**0.015**$^{\blacktriangle}$	**0.007**$^{\blacktriangle}$	**0.021**$^{\blacktriangle}$	**0.006**$^{\blacktriangle}$	**0.026**$^{\blacktriangle}$	**0.032**$^{\blacktriangle}$	**0.042**$^{\blacktriangle}$	**0.021**$^{\blacktriangle}$	**0.046**$^{\blacktriangle}$	**0.016**$^{\blacktriangle}$	**0.056**$^{\blacktriangle}$

- Q2：Our MPR model under varying hyper-parameter settings
  - Impact of matrix tradeoff parameter τ
  - Impact of embedding size r_l

Table 3: Impact of Parameters τ and r_l on *Beijing* dataset

Level	Metric	τ			r_l		
		0.6	1	1.4	50	150	250
H_1	P@10	0.067	0.067	**0.068**	0.065	0.067	**0.068**
	NDCG@10	0.161	**0.162**	0.162	0.153	**0.162**	0.162
H_2	P@10	0.007	**0.008**	0.008	0.008	**0.008**	0.008
	NDCG@10	0.021	**0.023**	0.023	0.021	**0.023**	0.023
H_3	P@10	0.007	**0.007**	0.007	0.006	**0.007**	0.007
	NDCG@10	0.018	**0.021**	0.019	0.018	**0.021**	0.020

- Q3：Recommendation hints derived from our MPR model



(a) User-apsect hint (b) POI-aspect hint (c) Interaction-aspect hint

Figure 4: Visualization heat maps of three recommendation hints on the *Beijing* dataset. The larger a value is, the darker color its corresponding cell has.

Outline

- Introduction
- POI Knowledge Graph Construction
  - Tag refinement
  - Competitive relationship
- POI-KG application
  - Geodemographic Influence Maximization
  - Multi-level POI recommendation
  - Joint Intent Detection and Entity Linking
  - Multi-Modal Transportation Recommendation

Intent Detection and Entity Linking

- Motivation: Language Understanding (LU) for spatial domain queries
  - Voice assistants on smart speakers and mobile devices.
  - E.g. recommending restaurants, providing route planning

- Problem: intent detection and entity linking
  - Challenge1: lexical-similar but diverse intents, e.g.
    - “从这到北京体育馆有多远？ VS 从这到北京的体育馆有多远？
  - Entities is diverse and ambiguous.
    - 黄焖鸡米饭：food name and brand name

Joint Intent Detection and Entity Linking on Spatial Domain Queries, Findings of ***EMNLP 2020***

Intent Detection and Entity Linking

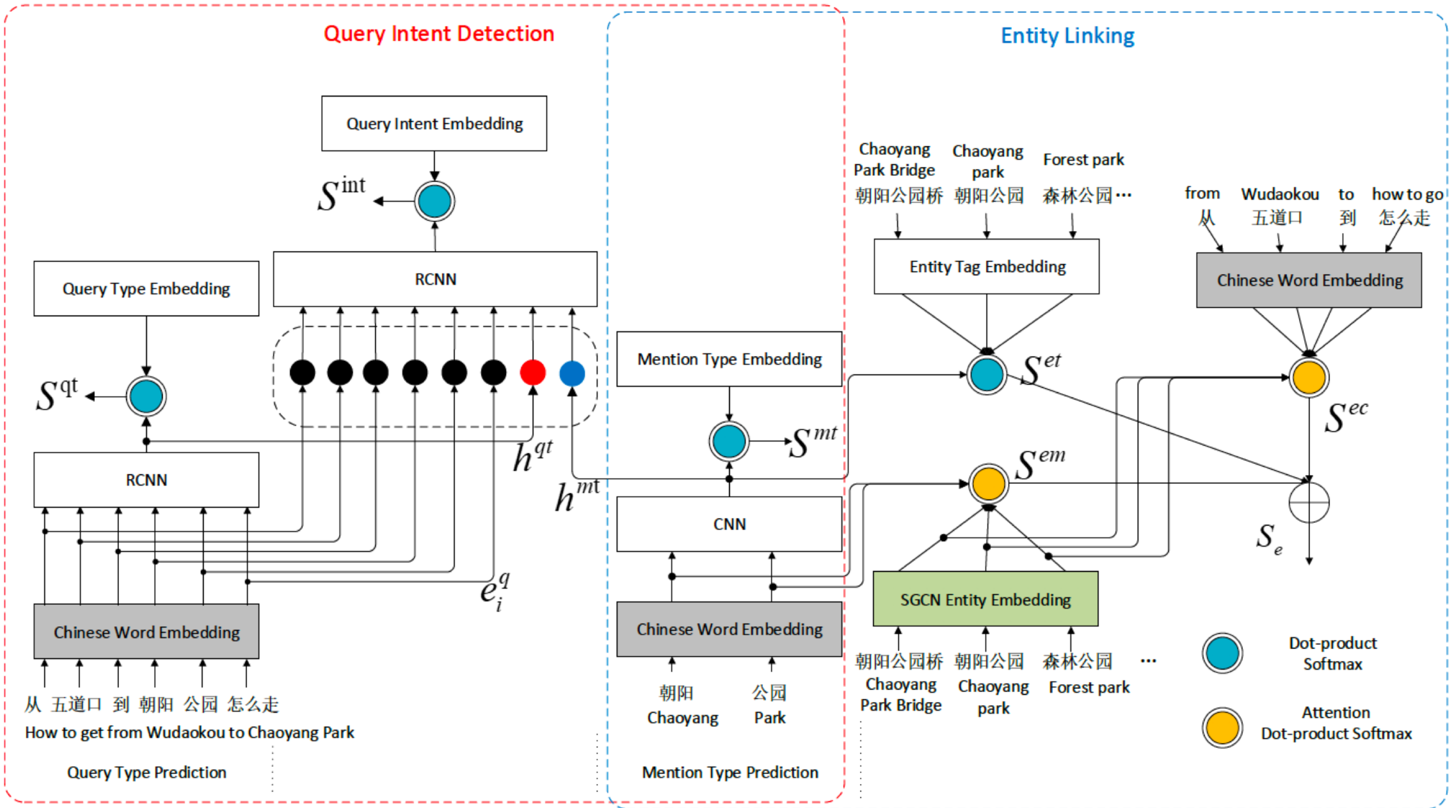


Figure 3: The architecture of the proposed multi-task framework MELIP. It consists of two main tasks(query intent detection and entity linking) and tow auxiliary tasks(query type prediction and mention type prediction).

*Joint Intent Detection and Entity Linking on Spatial Domain Queries, Findings of **EMNLP 2020***

Intent Detection and Entity Linking

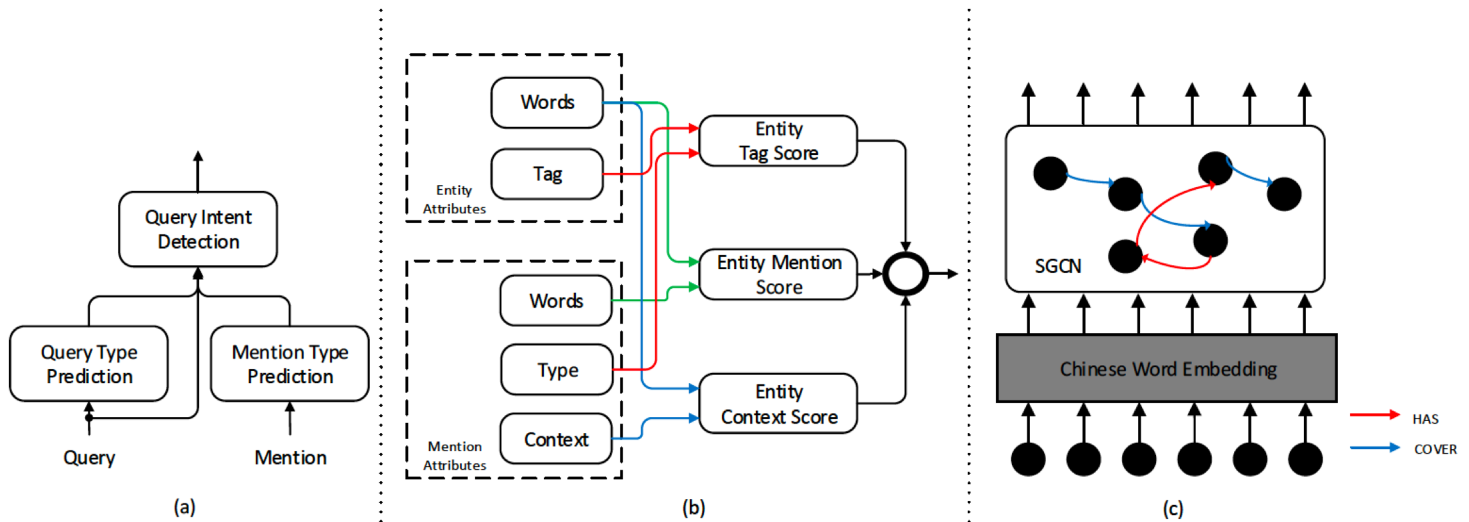


Figure 4: (a): The hierarchical intent detection structure. (b): The triple-scoring mechanism for entity linking. (c): The spatial GCN-based model for pre-training entity embedding.

*Joint Intent Detection and Entity Linking on Spatial Domain Queries, Findings of **EMNLP 2020***

Experiment

- Dataset- SMQ
  - 44,000 for training,
  - 5,500 for validation,
  - 5,500 for testing

- Baseline
  - FastText
  - CNN
  - BERT
  - Slot-Gated Atten
  - Stack-Propagation

Type index	Query Type	Example
0	Ask for the distance information between two places	从上海到北京多少公里
1	Ask for the information between two places except distance and time	从上海到北京最近线路
2	Ask for the time information between two places	从上海到北京要多长时间
3	Ask for the location information of one place	上海市的准确位置在哪里
4	Ask for the information of one place except location	上海的土地面积
5	Ask for a recommendation	上海有哪些景点
6	Only one entity	上海迪士尼酒店

Table 2: The defined seven query types and their examples.

Task	Model	Accuracy(%)
Query Intent detection	FastText	50
	CNN	76.38
	RCNN	77.33
	BERT	80.47
	BERT+RCNN	81.88
	Slot-Gated Atten	70.76
	Stack-Propagation	78.47
	MELIP	**83.20**
Entity Linking	MLR	67.75
	DCA	76.30
	MELIP	**89.37**
Mention Type Prediction	Fasttext	67.8
	CNN	80.63
	RCNN	80.47
	MELIP	**92.27**
Query Type Prediction	Fasttext	94
	CNN	95
	RCNN	95.6
	MELIP	**96.4**

Table 4: The Results on *SMQ* of different models.

*Joint Intent Detection and Entity Linking on Spatial Domain Queries, Findings of **EMNLP 2020***

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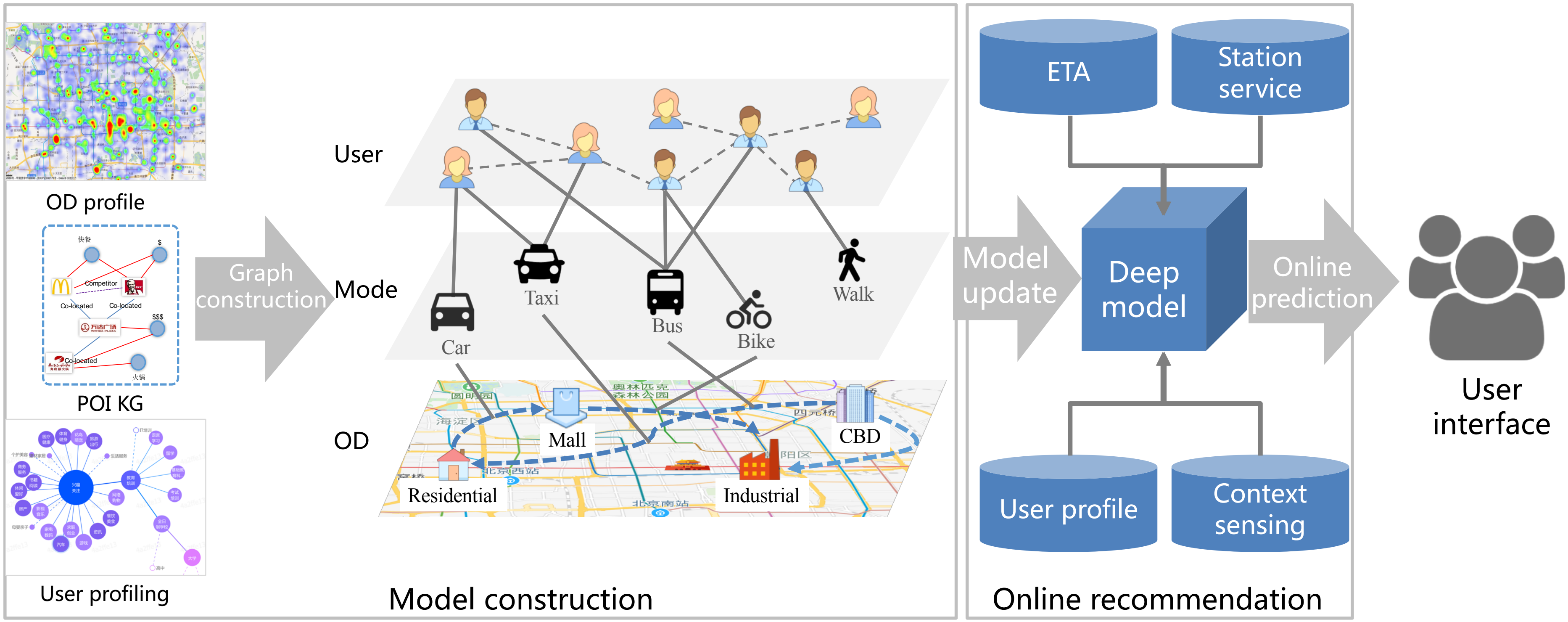
多模态混合出行方案推荐

路径推荐系统



多模态混合出行方案推荐

20%

Faster than bus & drive

50%

Cheaper than taxi

Conclusion

- **POI knowledge graph**
  - Enrich the information of POI
  - Multiple views and attributes of POI
  - Build semantic structure of POI

- **Applications**
  - A new way to investigate the POI from knowledge graph view
  - Enhance the AI-based Maps.

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Reference

- Jingbo Zhou, Shan Gou, Renjun Hu, Dongxiang Zhang， Jin Xu, Airong Jiang, Ying Li， Hui Xiong; "A Collaborative Learning Framework to Tag Refinement for Points of Interest"; KDD 2019.
- Shuangli Li, Jingbo Zhou, Tong Xu, Xinjiang Lu, Hao Liu and Hui Xiong, Competitive Analysis for Points of Interest, KDD 2020
- Kaichen Zhang, Jingbo Zhou, Donglai Tao, Panagiotis Karras, Qing Li, Hui Xiong, Geodemographic Influence Maximization; in KDD 2020
- Hui Luo, Jingbo Zhou, Zhifeng Bao, Shangli Li, J.Shane Culpepper, Haochao Ying, Hao Liu, Hui Xiong; "Spatial Object Recommendation with Hints-When Spatial Granularity Matters.“; SIGIR 2020.
- Lei Zhang, Runze Wang, Jingbo Zhou, Jingsong Yu, Zhenhua Ling, Hui Xiong, Joint Intent Detection and Entity Linking on Spatial Domain Queries, Findings of EMNLP 2020
- Hao Liu, Jindong Han, Yanjie Fu, Jingbo Zhou, Xinjiang Lu and Hui Xiong. Multi-Modal Transportation Recommendation with Unified Route Representation Learning, VLDB 2021.

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Q&A

Thanks!

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