Incorporating Semantic Similarity with Geographic Correlation for Query-POI Relevance Learning

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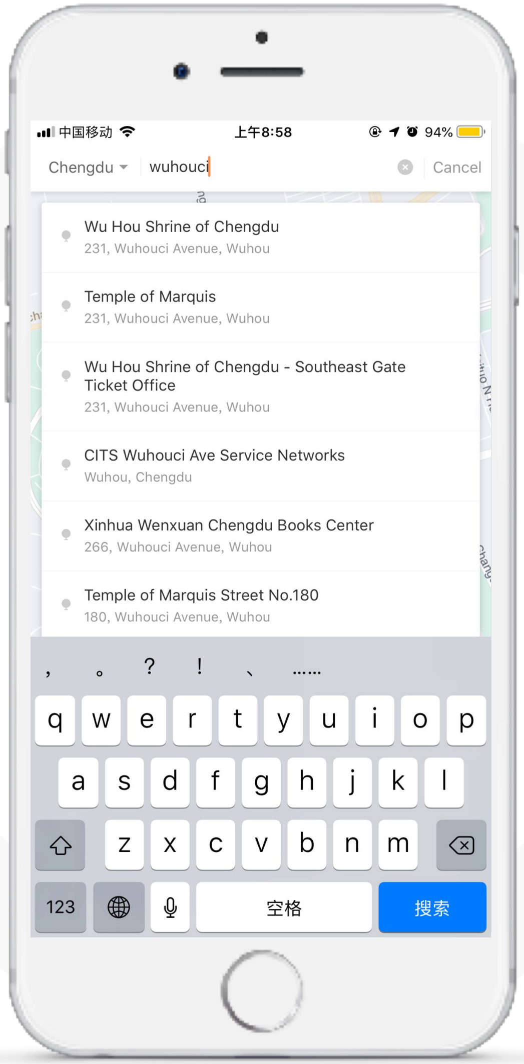
DiDi Chuxing

MORE THAN A JOURNEY

DiDi

POI Retrieval on ride-hailing App



Important: Critical Steps to Service Delivery

- Finding destination is **first** and key step of rides
- Affecting billion customer search experience
- **Extendable** to other Location-Based Service
- eg. Hotel&Travel, Food Delivery, Package Delivery

Challenging

- Gap between User intent and POI information
- **Short text learning**: incomplete and various order of Query
- **Multi-text fusion and representing**: POI matching based on multi-field textual attributes
- Geographic **location correlation** of User and POI

Problem Definition

INPUT

User Intent

Query: NJ caref

Location: (116.2900, 40.0433)

POI Collection

POI_1

Name: Carrefour (Haiguang Shop)

Addr: 302, NanJing Rd, Nankai

Location: (116.6461, 40.1480)

POI_2

Name: CAREFREE KIDS

Addr: Near Jiangtai Rd

Location: (114.4169, 38.0418)

……

OUTPUT

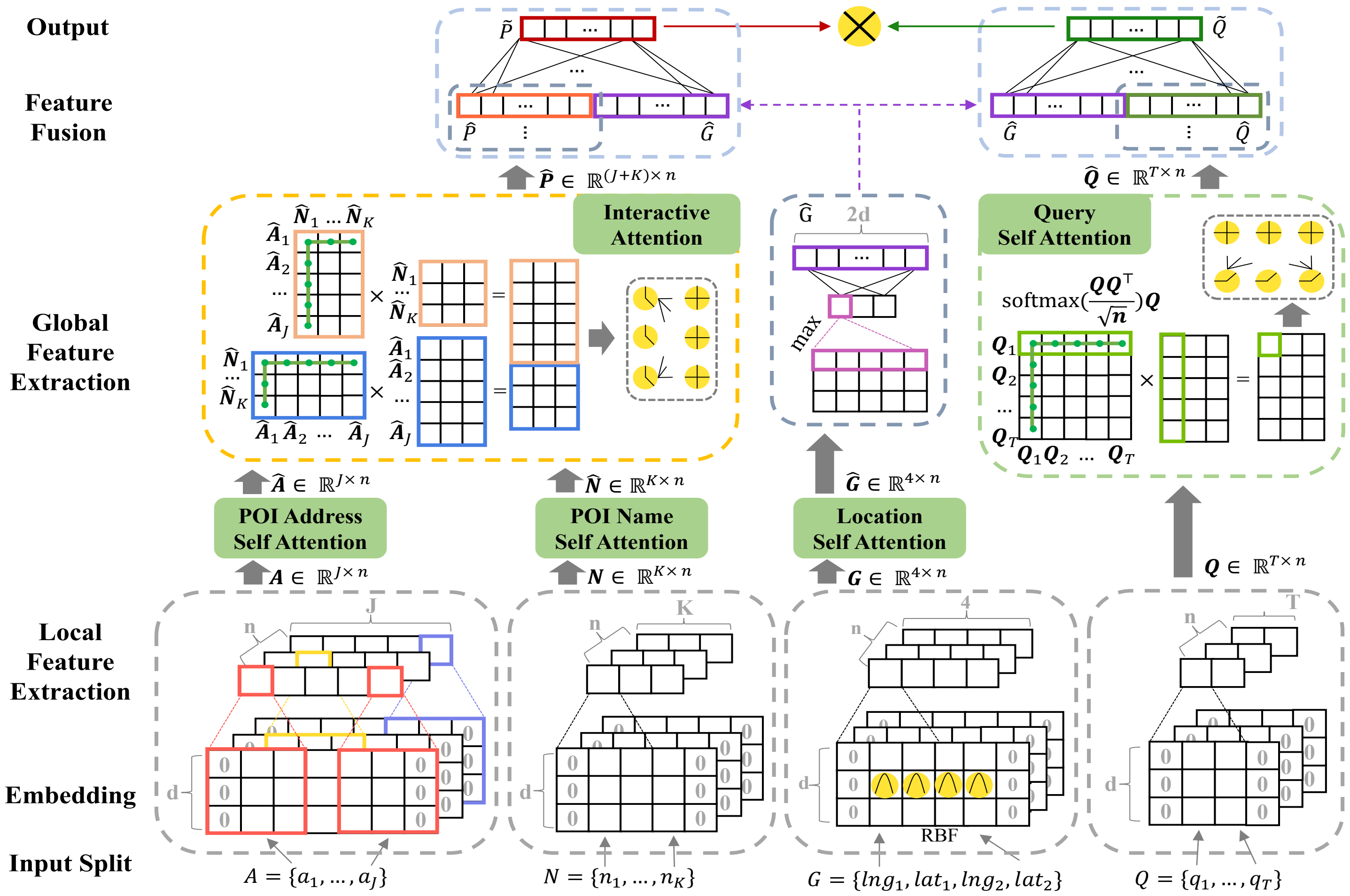
Relevance $\mathcal{F}(User, POI_i)$

- $\mathcal{F}(User, POI_1) = 0.83$
- $\mathcal{F}(User, POI_2) = 0.79$
- …

How to learn the Relevance function?

POI : Point-Of-Interest

POI Attention Location Model+(PALM+)



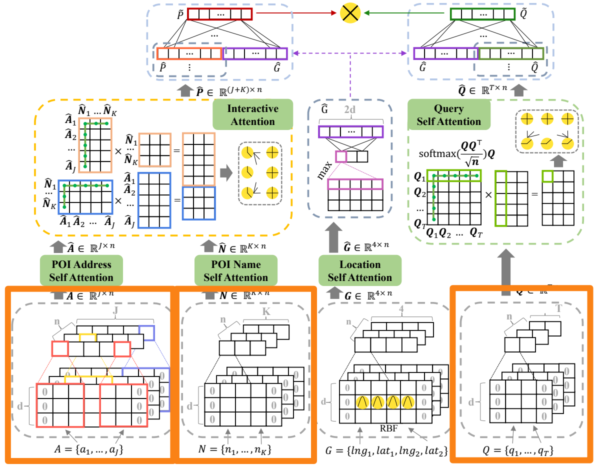
Semantic Similarity

- Multi-field texts
- Local & Global features

Geographic Correlation

- Location embedding
- Geographic features

Semantic Representation - I



Multi-field Textual Attributes

POI Address + POI Name + Query

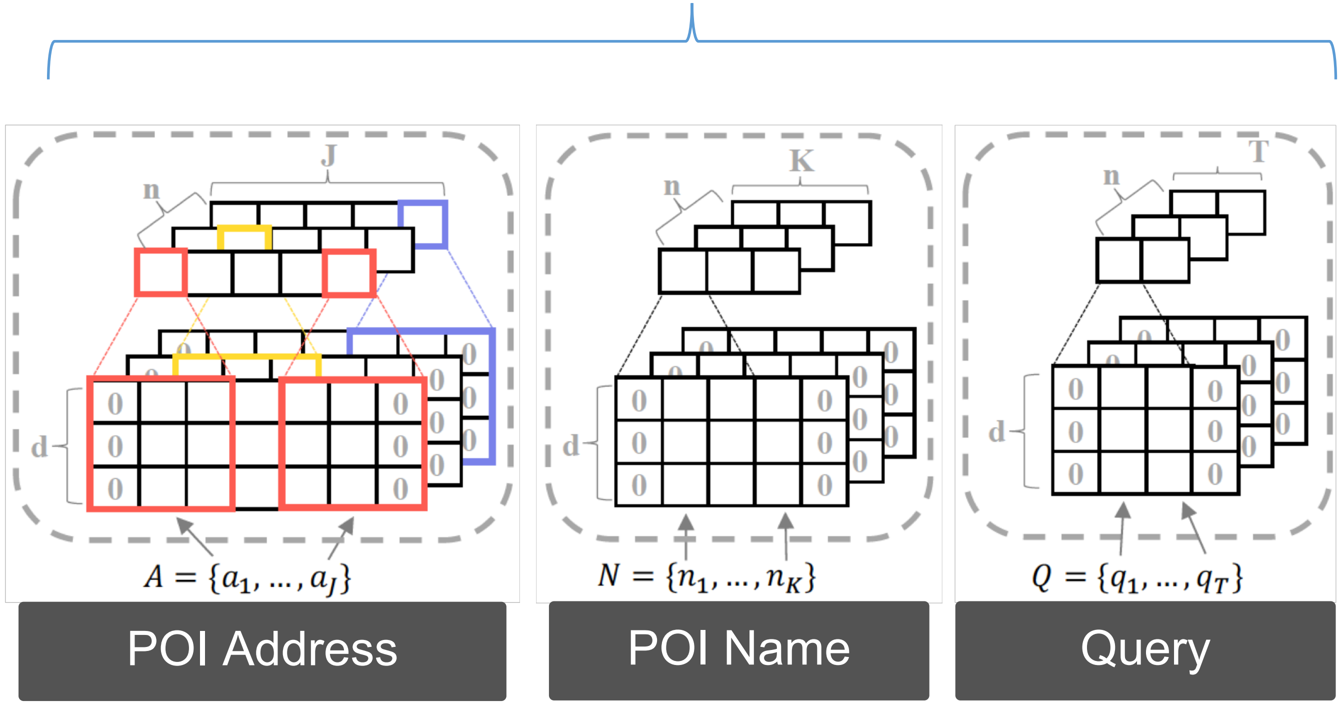
Multi-granularity Embeddings

Letter + Word

	Chinese	English
letter	中	a
word	中国	apple

Convolution

Capture the local semantic feature



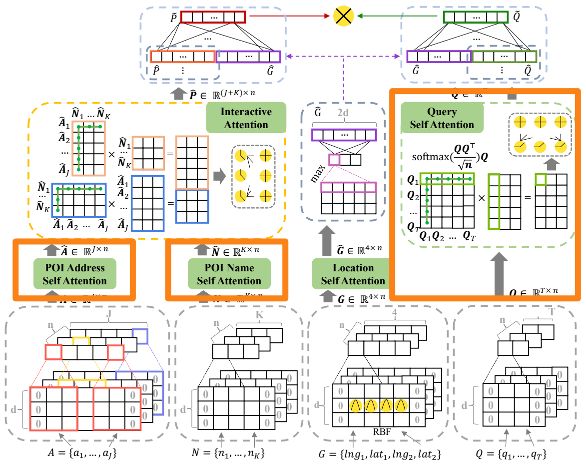
Semantic Representation - II

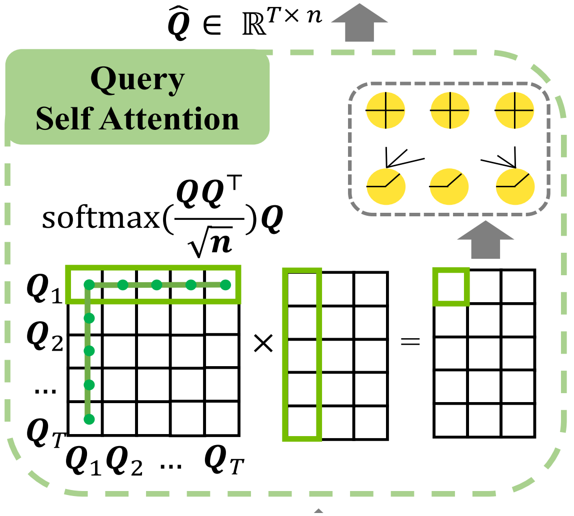
Self-Attention mechanism

- Distinguish the key information from the whole
- Intra-dependency within the texts

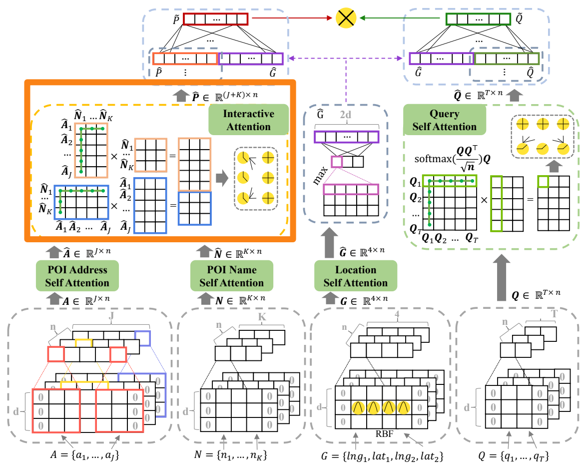
$$X_q = softmax\left(\frac{QQ^T}{\sqrt{n}}\right)Q$$

$$\hat{Q} = \max(0, X_q \times W_{q1} + B_{q1}) \times W_{q2} + B_{q2}$$





Semantic Representation - III

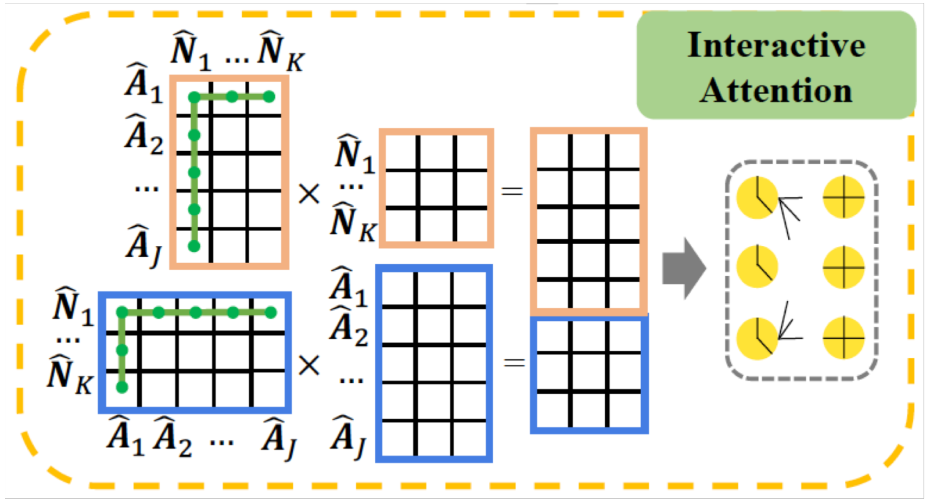


Interactive Attention mechanism

- Fusion information from multi-field source
- Highlights mapping between Address and Name

$$\widehat{N2A} = softmax\left(\frac{\hat{A}\hat{N}^T}{\sqrt{n}}\right)\hat{N}$$

$$\widehat{A2N} = softmax\left(\frac{\hat{N}\hat{A}^T}{\sqrt{n}}\right)\hat{A}$$



Example: Interactive Attention

Strengthen semantic expression by highlighting keywords according to another field

- Example:

Query: joy city

POI Name: Hutaoli Music Restaurant & Bar (Joy City)

POI Address: Dayue Rd No. 518, Joy City, 1F-**J01**

	Hutaoli	Music	Rest-aurant	Bar	Joy City
Dayue Rd	0.35	0.42	0.07	0.03	0.10
No. 518	0.66	0.06	0.01	0.00	0.25
Joy City	0.56	0.12	0.03	0.00	0.26
1F	0.73	0.00	0.00	0.00	0.25
J01	0.65	0.09	0.04	0.01	0.18

(a) Interactive attention: Name2Addr

	Dayue Rd	No. 518	Joy City	1F	J01
Hutaoli	0.28	0.02	0.11	0.03	0.55
Music	0.76	0.00	0.05	0.00	0.17
Restaurant	0.57	0.00	0.07	0.00	0.34
Bar	0.61	0.00	0.03	0.00	0.34
Joy City	0.27	0.02	0.16	0.03	0.49

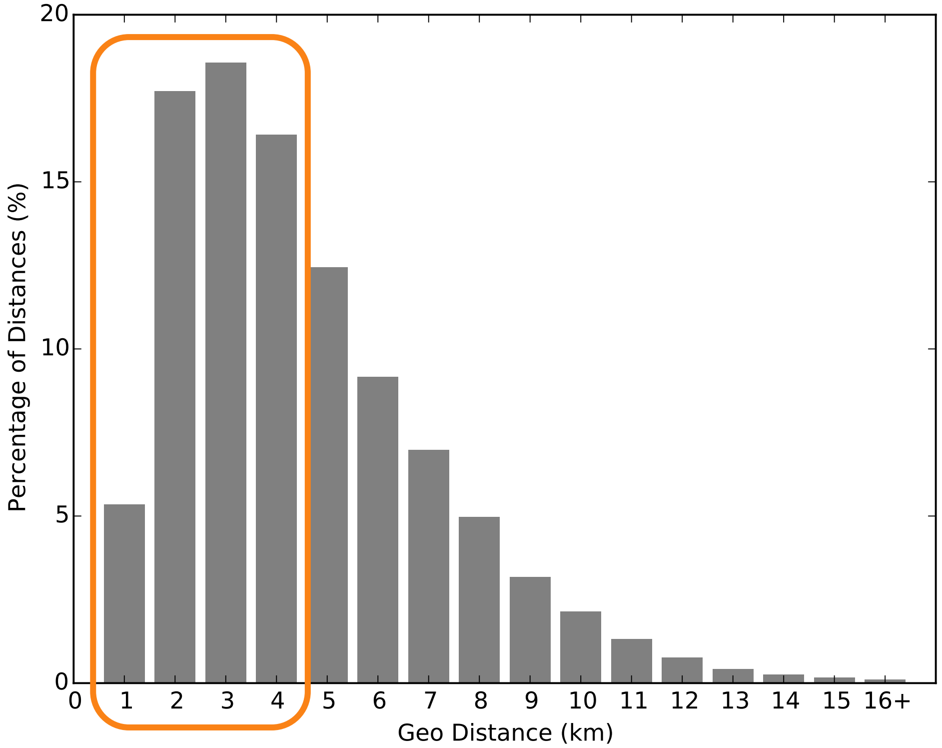
(b) Interactive attention: Addr2Name

Geographic Correlation - I

Users are highly sensitive to Origin-Destination distances

Hidden correlation of clicked Query-POI pairs

- Over 50% O-D distances are less than 4km



Geographic Correlation - II

Split Coordinates to reduce embedding size

Location Embeddings

- ~~One-hot Vector~~
- Coordinate Embedding
- Kernel Embedding to avoid Boundary Effect

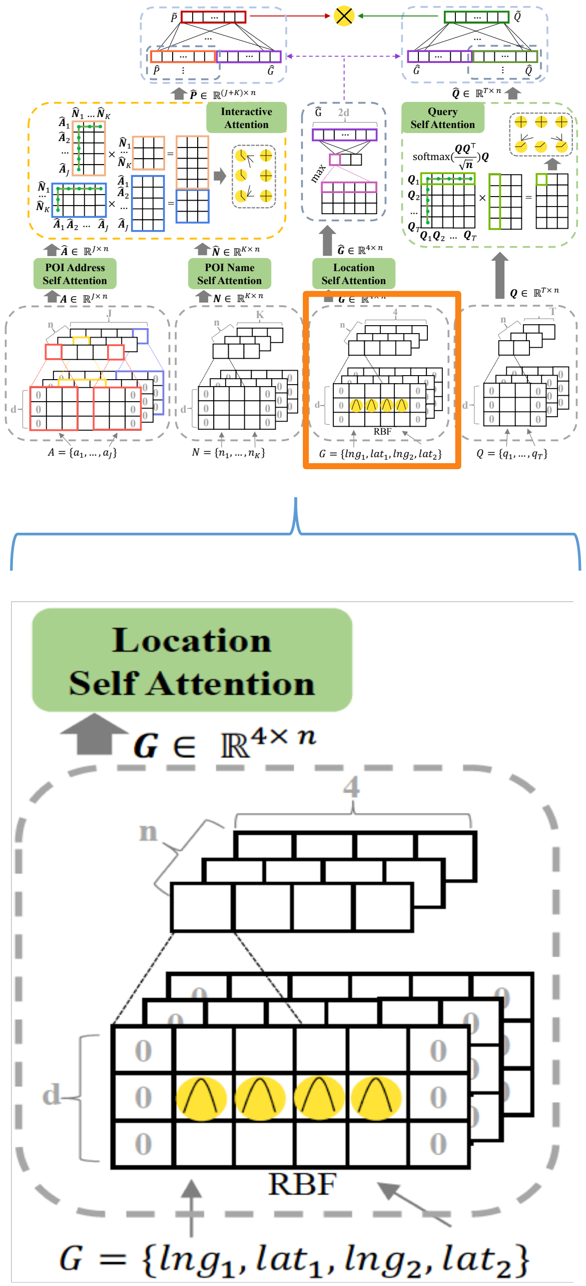
$$Latitude:\ \widehat{\Phi}_i = w_{i-1}\widehat{\Phi}_{i-1} + w_i\widehat{\Phi}_i + w_{i+1}\widehat{\Phi}_{i+1}$$

$$Longitude:\ \widehat{\Psi}_j = w_{j-1}\widehat{\Psi}_{j-1} + w_j\widehat{\Psi}_j + w_{j+1}\widehat{\Psi}_{j+1}$$

$$RBF:\ w = \frac{(dis-\mu)^2}{\sigma^2}, \mu = 0, \sigma^2 = 0.3$$

Geographic Feature

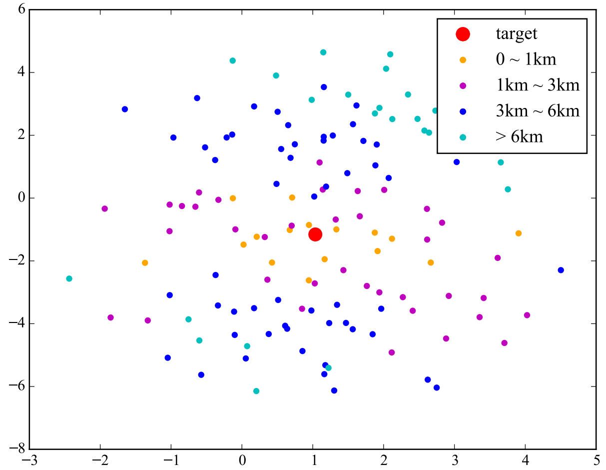
- Convolution +Self-Attention



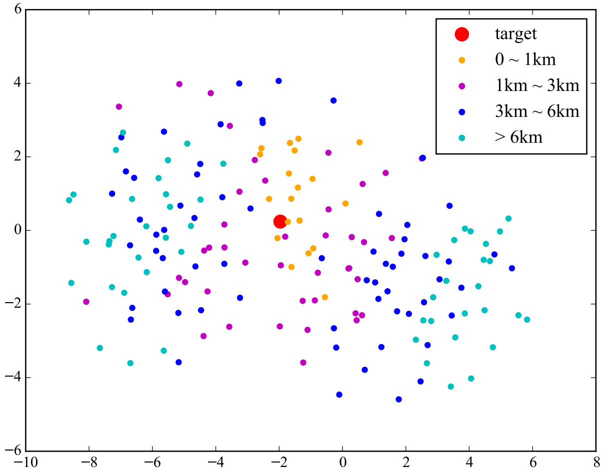
Example: Location Embedding

Scalable + faithfully preserve the physical relation

- **PALM**

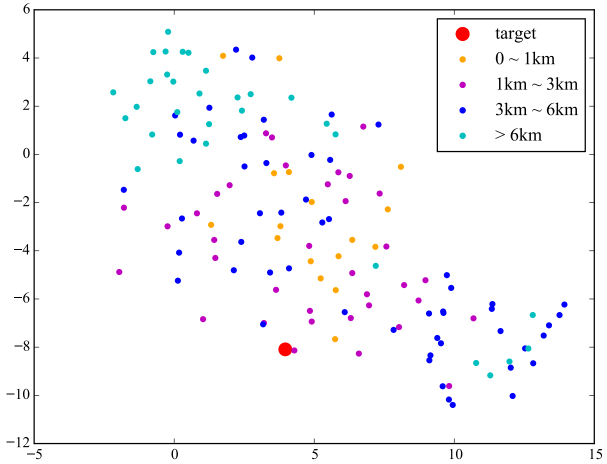


(a) PALM lat embedding

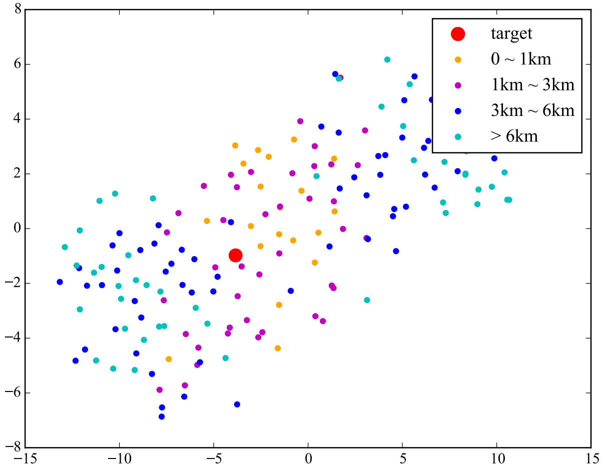


(b)PALM lng embedding

- **Deep Walk**



(c) DeepWalk lat embedding



(d) DeepWalk lng embedding

Dataset

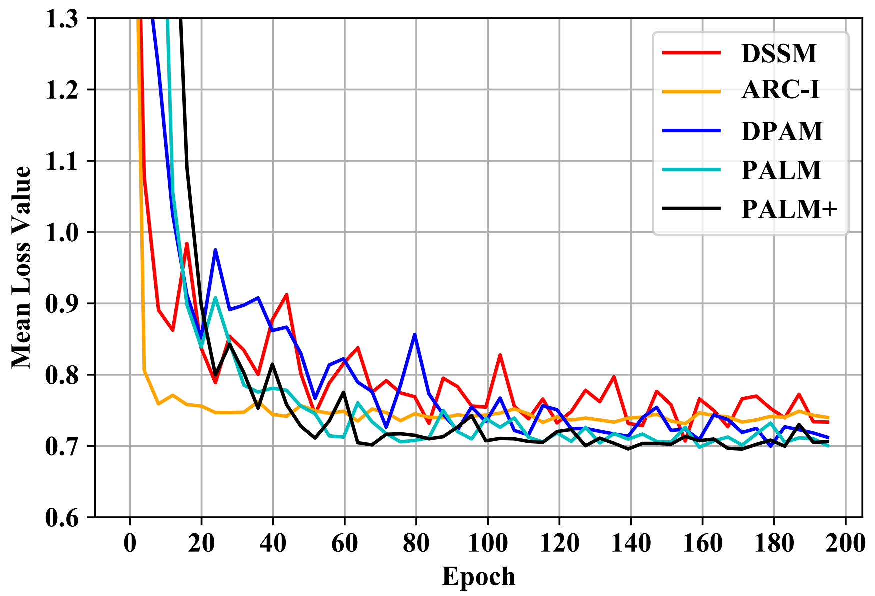
POI retrieval data and click behavior collected by DiDi APP for one month

Dataset A is publicly available to the academic community as part of GAIA Initiative:
https://outreach.didichuxing.com/appEn-vue/POI?id=11

	Dataset A (Chengdu)		Dataset B (Nationwide)	
	Training	Testing	Training	Testing
Total Num of Query	115,724	15,261	1,476,645	112,747
Total Num of POIs	711,824	95,369	12,654,847	947,878
Avg Num of Recalls	6.15	6.24	8.57	8.41
Avg Len of Query	4.61	4.65	3.21	3.24
Avg Len of POI Addr	19.04	19.05	18.93	18.89
Avg Len of POI Name	9.38	9.42	7.87	7.96
Avg P-Q Distance (km)	4.05	4.04	7.28	8.53

Experiments: Results

	Dataset A (Chengdu)		Dataset B (Nationwide)	
	NDCG@3	NDCG@10	NDCG@3	NDCG@10
DSSM	0.8246	0.8989	0.7617	0.8810
ARC-I	0.8298	0.9024	0.7558	0.8788
DPAM	0.8383	0.9058	0.7822	0.8907
PALM	0.8407	0.9050	0.8116	0.9022
PALM+	**0.8465**	**0.9110**	**0.8124**	**0.9027**



DSSM: DNN, semantic + word hashing

ARC-I: CNN, semantic + pre-trained Word2Vec

DPAM: CNN, semantic + attention mechanisms + text embedding

PALM: DPAM + geographic + coordinate embedding

PALM+: PALM + kernel embedding

Summary

A novel Query-POI relevance model for effective POI retrieval

- Enriched semantic similarity
  - via attention mechanism
- Integrated geographic correlation
  - with location kernel embedding
- Extensive experiments
  - achieve 5pp NDCG@3 improvement on real-world large-scale click-through datasets
- Open dataset
  - dataset is publicly available to the academic community

THANKS

Q & A

DiDi