# Joint Representation Learning for Multi-Modal Transportation Recommendation

Hao Liu[1], Ting Li[2], Renjun Hu[3], Yanjie Fu[4], Jingjing Gu[5], Hui Xiong[1*]

[1]The Business Intelligence Lab, Baidu Research

[2]National University of Defense Technology, Changsha, China

[3]SKLSDE Lab, Beihang University, Beijing, China

[4]Missouri University of Science and Technology, Missouri, USA

[5]Nanjing University of Aeronautics and Astronautics, Nanjing, China

Present by: Dr. Hao Liu

Emerging user requirements

## High route planning decision cost across multiple transportation modes

Increasing
activity radius

Complex
travel context

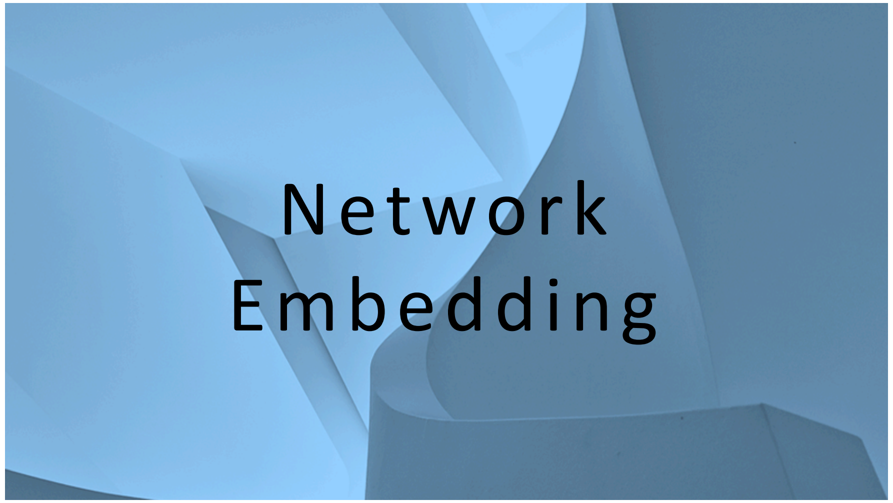
Diversified
transportation choices

**Personalized** and **context-aware** intelligent route planning

Multi-Modal Transportation Recommendation

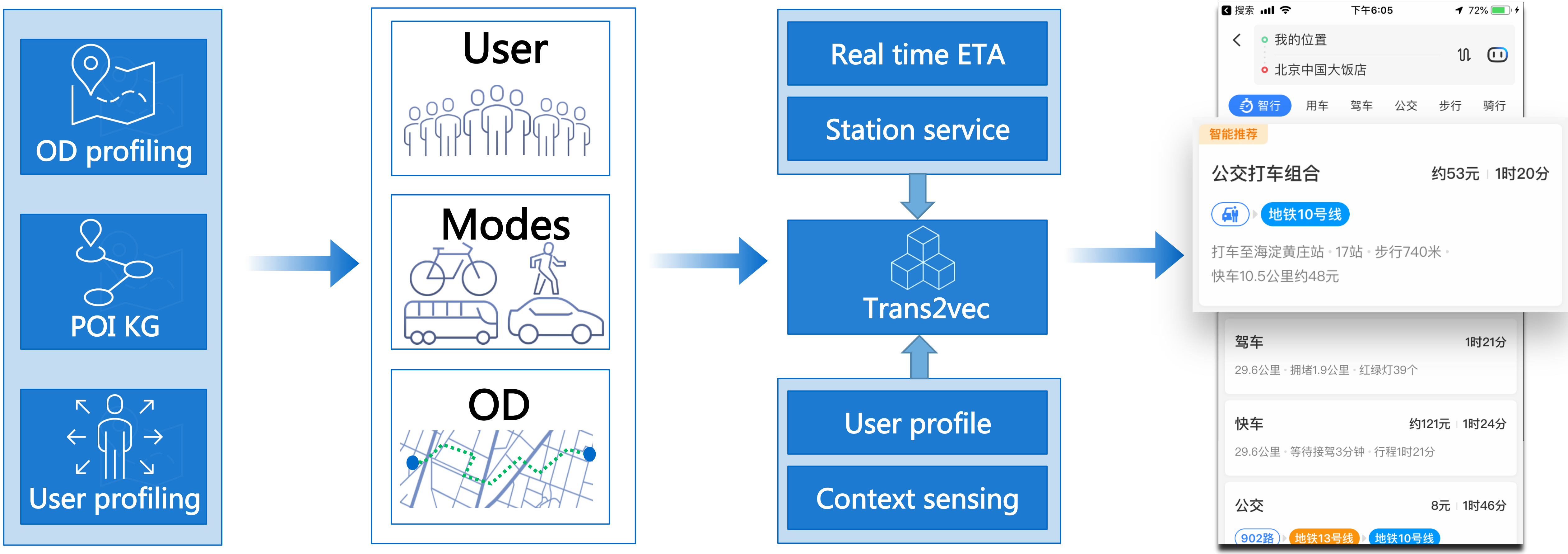
# Related Work


- Liu et al.[1] discussed generating multi-modal shortest routes based on heterogeneous transportation network.
- MPR[2] and TPMFP[3] mines the most popular routes and the most frequent paths from massive trajectories on the road network, respectively.
- Rogers et al.[4] considers personal preference to improve route recommendations quality.




- Metapath2vec[5] studies network embedding in heterogeneous networks.
- Yao et al.[6] and Wang et al.[7] leverages network embedding for region function profiling.
- Feng et al.[8] and Zhao et al.[9] applies network embedding on POI recommendations.

# Trans2vec: Multi-Modal Transportation Recommendation Architecture




Multi-modal data

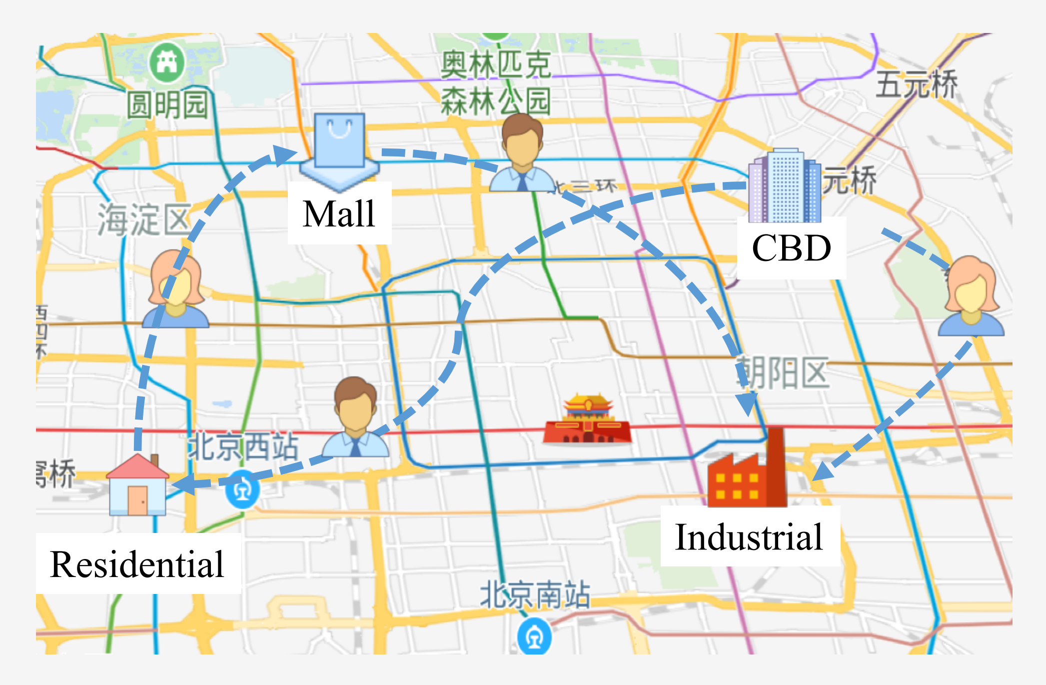
Multi-modal transportation graph construction

Joint representation learning

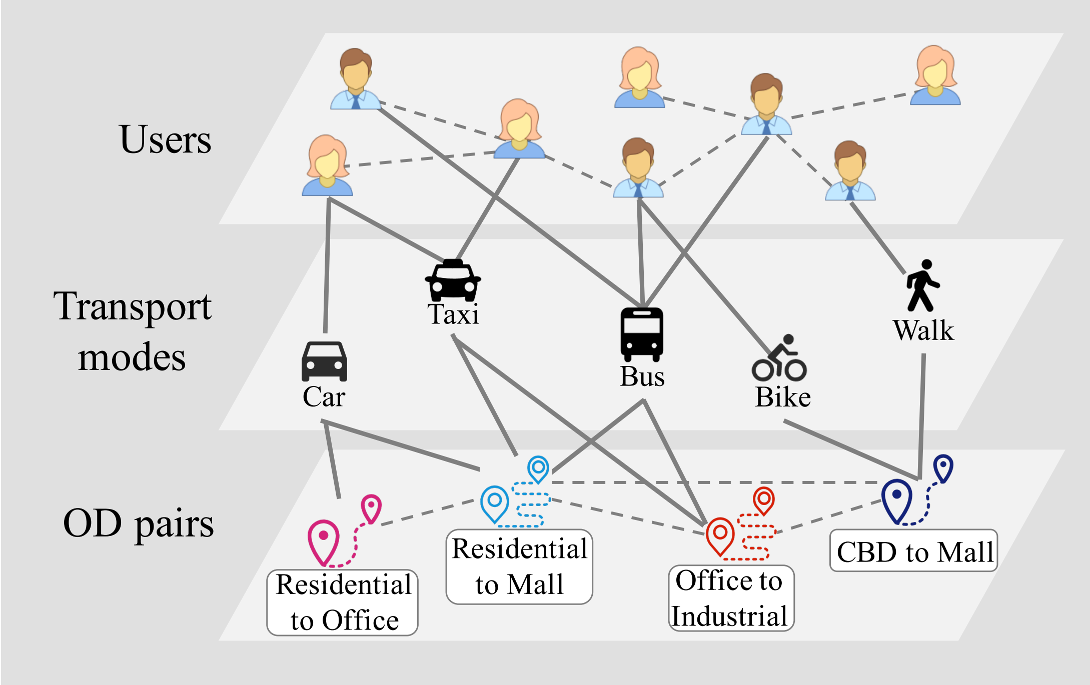
Online recommendations

# Multi-Modal Transportation Graph Construction

- *A multi-modal transportation graph is a heterogeneous undirected weighted graph $G=(V,E)$, where $V=U \cup OD \cup M$ is a set of heterogeneous nodes, and $E=E_{um} \cup E_{odm} \cup E_{uu} \cup E_{odod}$ is a set of heterogeneous edges including user-mode edges $E_{um}$, OD-mode edges $E_{odm}$, user-user edges $E_{uu}$ and OD-OD edges $E_{odod}$.*




Travel events




An illustrative Example of
Multi-modal Transportation Graph

## The Base Model

- Analogize travel events to sentences and random walks, in order to learn low-dimensional representations of users, OD pairs, and transport modes.

sigmoid

Embedding of user — Embedding of mode — Embedding of OD

User-mode-OD embedding:

$$O_0 = \sum_{(u,m)\in\mathcal{E}_{um}} \log \sigma(\mathbf{x}_u^\top \cdot \mathbf{x}_m) + \sum_{(od,m)\in\mathcal{E}_{odm}} \log \sigma(\mathbf{x}_{od}^\top \cdot \mathbf{x}_m)$$

Embedding with Negative sampling:

$$O_0 = \sum_{\substack{(u,m)\in\mathcal{E}_{um}\\ m'\sim U}} \left(\log \sigma(\mathbf{x}_u^\top \cdot \mathbf{x}_m) + \log \sigma(-\mathbf{x}_u^\top \cdot \mathbf{x}_{m'})\right) + \sum_{\substack{(od,m)\in\mathcal{E}_{odm}\\ m'\sim U}} \left(\log \sigma(\mathbf{x}_{od}^\top \cdot \mathbf{x}_m) + \log \sigma(-\mathbf{x}_{od}^\top \cdot \mathbf{x}_{m'})\right).$$

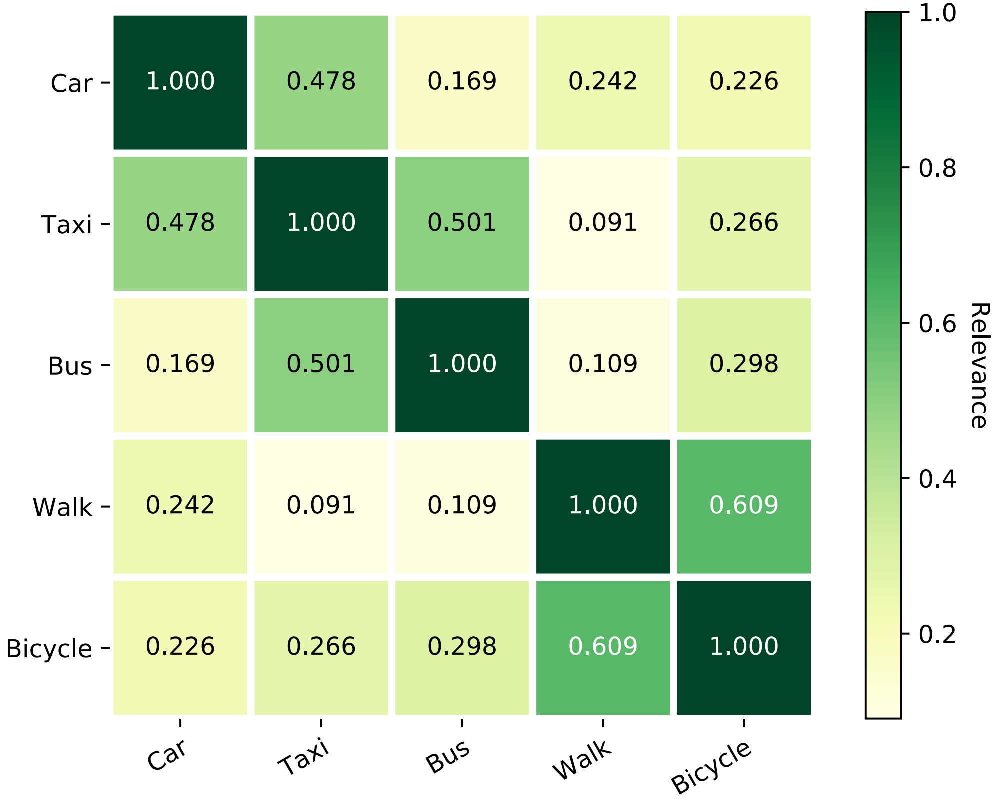
# Anchor Embedding

## Problem

- ➢ there are only several (e.g., 5 in our case) transport mode nodes whereas there are a large number of user nodes and OD nodes.

## Solution

- ✓ each node is assigned a discriminative embedding that reflects its inherent context information.




Pairwise transport mode relevance matrix

# Modeling User Relevance

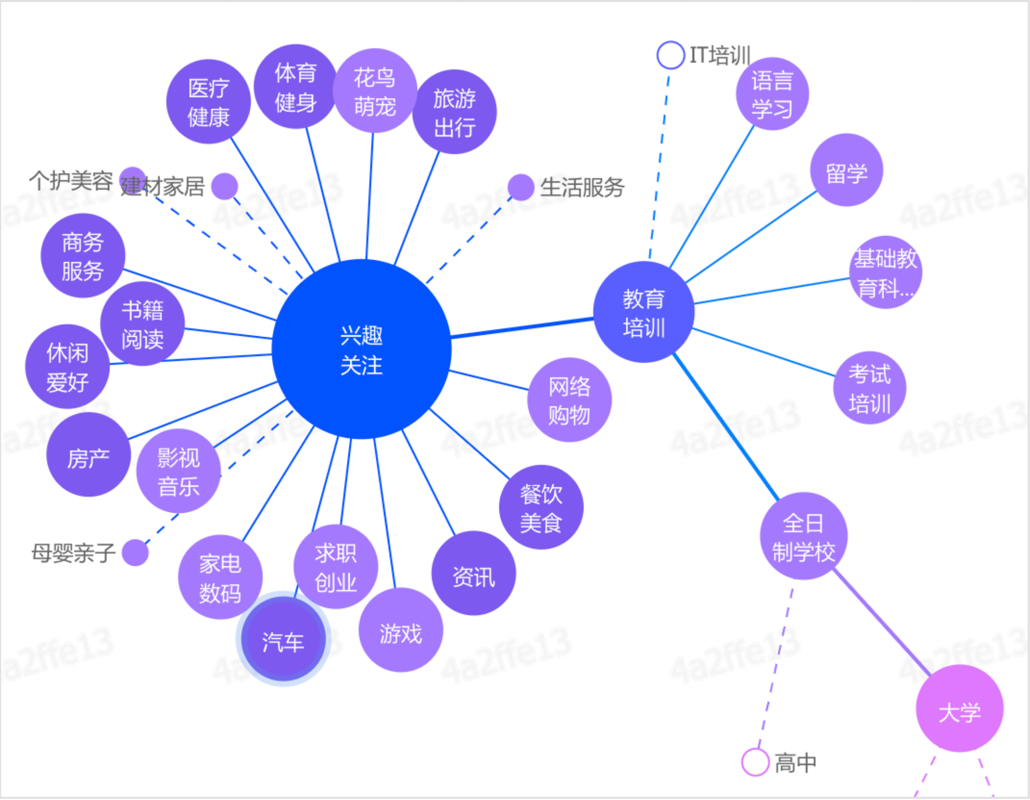
- The choice of transport mode is highly influenced by the characteristics of users
  - e.g., age, sex, martial
- User-user relevance:

User attribute vector

$$rel(u,u') = \sum_i \mathbf{w}_i I(\mathcal{A}(u)_i, \mathcal{A}(u')_i) / \sum_i \mathbf{w}_i$$

- User constraints:

$$O_1 = -\frac{1}{2} \sum_{(u,u') \in \mathcal{E}_{uu}} (\mathbf{x}_u^\top \cdot \mathbf{x}_{u'} - rel(u,u'))^2.$$




Beyond travel preference:
fined-grained user profile at Baidu

Baidu 百度

# Modeling OD Relevance

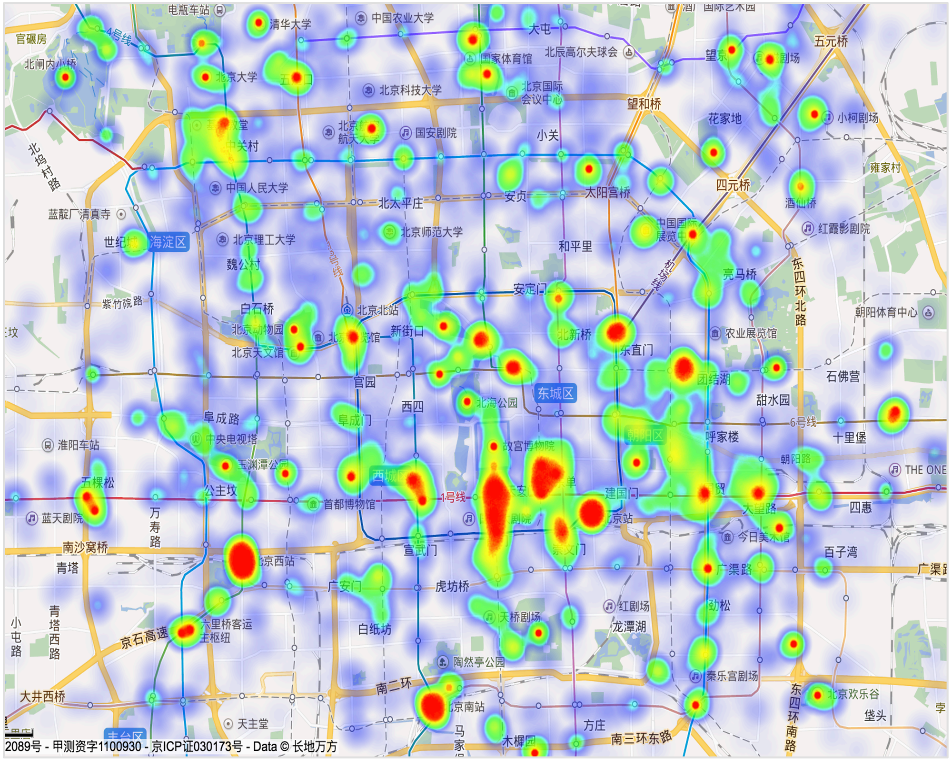
- Distance and travel purpose (e.g., home-work, home-commercial) are among the most influential factors for choosing transport modes
- OD relevence：

$$\mathbf{od} = d_{od} \oplus \mathbf{p}_o \oplus \mathbf{p}_d.$$

$$rel(od, od') = \exp\{-||\mathbf{w} \odot (\mathbf{od} - \mathbf{od}')||\}.$$

- OD constraints:

$$O_2 = -\frac{1}{2} \sum_{(od,od') \in \mathcal{E}_{odod}} \left(\mathbf{x}_{od}^{\top} \cdot \mathbf{x}_{od'} - rel(od, od')\right)^2,$$




OD heat map

# Joint Learning & Online Recommendations

- Overall objective:

$$O = O_0 + \beta_1 O_1 + \beta_2 O_2$$

- The score of each mode is computed by:

$$f(u, od, m) = \gamma \mathbf{x}_u^\top \cdot \mathbf{x}_m + (1-\gamma)\mathbf{x}_{od}^\top \cdot \mathbf{x}_m$$

**Algorithm 1:** Joint learning algorithm of Trans2Vec

**Input:** A multi-modal transportation graph $G$, number $d$ of dimensions, number $K$, learning rate $\alpha$, parameters $\beta_1$ and $\beta_2$;

**Output:** $\mathbf{x}_u/\mathbf{x}_{od}/\mathbf{x}_m$ for $u/od/m \in \mathcal{U}/\mathcal{OD}/\mathcal{M}$;

Initialize entries of $\mathbf{x}_u/\mathbf{x}_{od}/\mathbf{x}_m$ with uniform$[-\frac{1}{2d}, \frac{1}{2d}]$;

Compute user and OD relevance with Eqs. (4) & (7);

$iter \leftarrow 1$;

**repeat**

  **foreach** $(u, u') \in \mathcal{E}_{uu}$ **do**

    $\mathbf{x}_u \leftarrow \mathbf{x}_u - \frac{\alpha\beta_1}{iter}(\mathbf{x}_u^\top \cdot \mathbf{x}_{u'} - rel(u,u'))\mathbf{x}_{u'}$;

    $\mathbf{x}_{u'} \leftarrow \mathbf{x}_{u'} - \frac{\alpha\beta_1}{iter}(\mathbf{x}_u^\top \cdot \mathbf{x}_{u'} - rel(u,u'))\mathbf{x}_u$;

  **foreach** $(od, od') \in \mathcal{E}_{odod}$ **do**

    $\mathbf{x}_{od} \leftarrow \mathbf{x}_{od} - \frac{\alpha\beta_2}{iter}(\mathbf{x}_{od}^\top \cdot \mathbf{x}_{od'} - rel(od,od'))\mathbf{x}_{od'}$;

    $\mathbf{x}_{od'} \leftarrow \mathbf{x}_{od'} - \frac{\alpha\beta_2}{iter}(\mathbf{x}_{od}^\top \cdot \mathbf{x}_{od'} - rel(od,od'))\mathbf{x}_{od}$;

  **foreach** $(u, m) \in \mathcal{E}_{um}$ **do**

    Sample a transport mode $m' \sim U$;

    $\mathbf{x}_u \leftarrow \mathbf{x}_u - \frac{\alpha}{iter}(\sigma(\mathbf{x}_u^\top \cdot \mathbf{x}_m) - 1)\mathbf{x}_m - \frac{\alpha}{iter}\sigma(\mathbf{x}_u^\top \cdot \mathbf{x}_{m'})\mathbf{x}_{m'}$;

  **foreach** $(od, m) \in \mathcal{E}_{odm}$ **do**

    Sample a transport mode $m' \sim U$;

    $\mathbf{x}_{od} \leftarrow \mathbf{x}_{od} - \frac{\alpha}{iter}(\sigma(\mathbf{x}_{od}^\top \cdot \mathbf{x}_m) - 1)\mathbf{x}_m - \frac{\alpha}{iter}\sigma(\mathbf{x}_{od}^\top \cdot \mathbf{x}_{m'})\mathbf{x}_{m'}$;

  $iter \leftarrow iter + 1$;

**until** *converge*;

**return** $\mathbf{x}_u/\mathbf{x}_{od}/\mathbf{x}_m$ for $u/od/m \in \mathcal{U}/\mathcal{OD}/\mathcal{M}$;

# Experiments – Objectives & Data Sets

## Objectives

- The overall performance of Trans2Vec
- The parameter sensitivity
- The transport mode relevance
- The robustness of Trans2Vec

## Data sets

- BEIJING and SHANGHAI
- Produced based on the map queries and user feedbacks on the Baidu Map,
- Time window April 1, 2018 - August 20, 2018.

| Notation | Description | BEIJING | SHANGHAI |
|---|---|---|---|
| $\lvert\mathcal{Q}\rvert$ | # of travel events | 1,137,688 | 1,117,981 |
| $\lvert\mathcal{U}\rvert$ | # of users | 318,879 | 316,060 |
| $\lvert\mathcal{OD}\rvert$ | # of ODs | 375,165 | 350,904 |
| $\lvert\mathcal{M}\rvert$ | # of modes | 5 | 5 |

Table 1. Data Statistics

# Experiments – Overall Results

## Evaluation metrics

- NDCG@5,
- The weighted precision (PREC)
- Recall (REC)
- F1

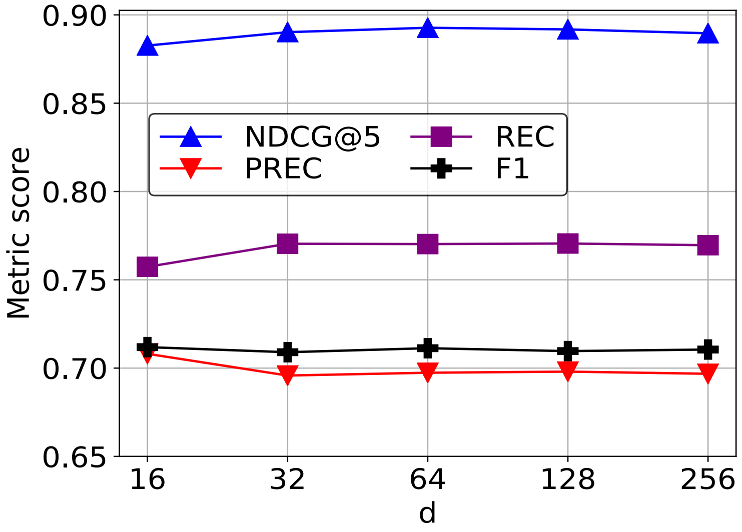
## Baselines

- Logistic regression
- L2R[10]
- PTE[11]
- Metapath2Vec [5]

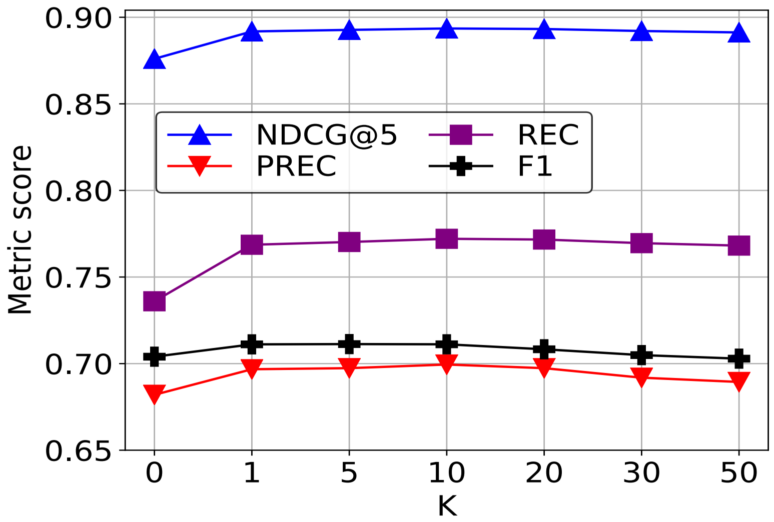
| Algorithm | Beijing | | | | Shanghai | | | |
|---|---|---|---|---|---|---|---|---|
| | NDCG@5 | PREC | REC | F1 | NDCG@5 | PREC | REC | F1 |
| LR | 0.804 | 0.704 | 0.589 | 0.633 | 0.848 | 0.682 | 0.657 | 0.658 |
| LTR | 0.824 | 0.667 | 0.662 | 0.664 | 0.830 | 0.671 | 0.666 | 0.668 |
| PTE | 0.770 | 0.493 | 0.518 | 0.499 | 0.807 | 0.564 | 0.610 | 0.585 |
| Metapath2Vec | 0.731 | **0.718** | 0.439 | 0.515 | 0.736 | **0.728** | 0.451 | 0.528 |
| BTrans2Vec | 0.876 | 0.682 | 0.736 | 0.704 | 0.878 | 0.695 | 0.754 | **0.718** |
| Trans2Vec | **0.893** | 0.700 | **0.770** | **0.711** | **0.891** | 0.708 | **0.778** | **0.719** |

Table 2. Overall performance

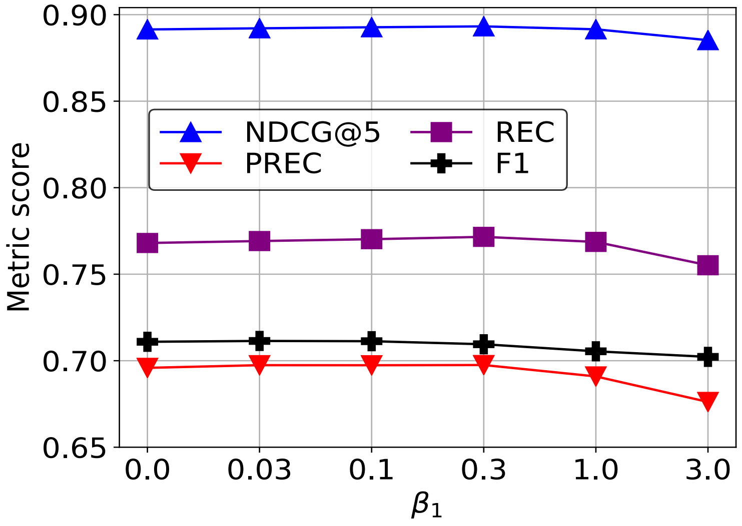
# Experiments – Parameter Sensitivity



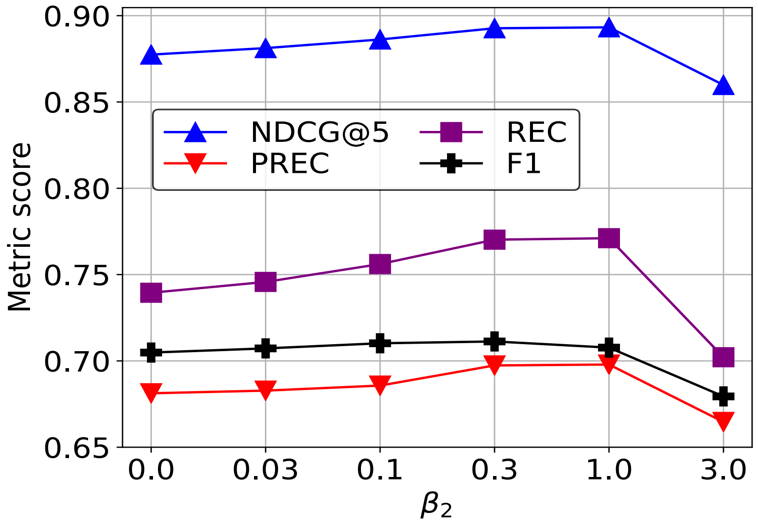

Effect of d on BEIJING




Effect of k on BEIJING



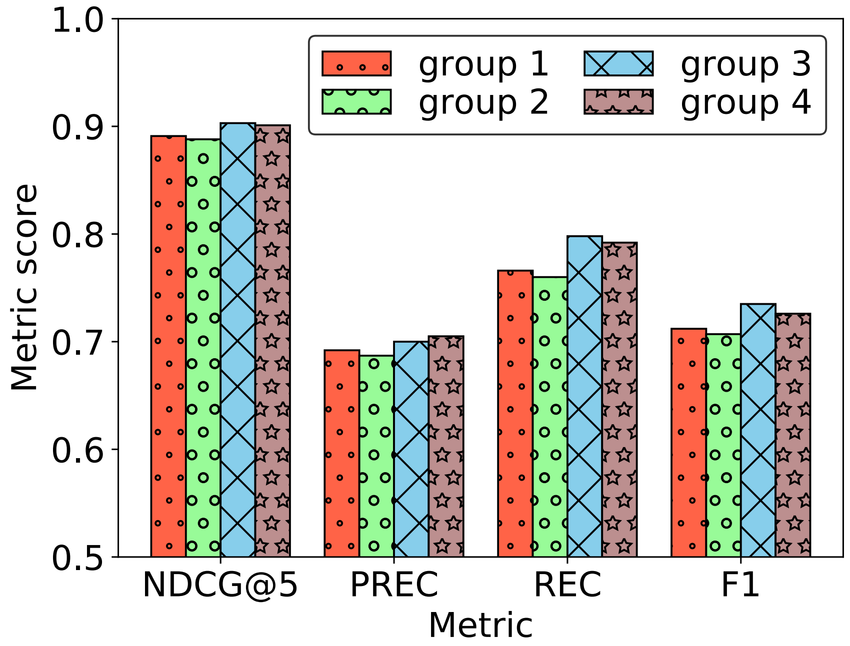

Effect of $\beta_1$ on BEIJING



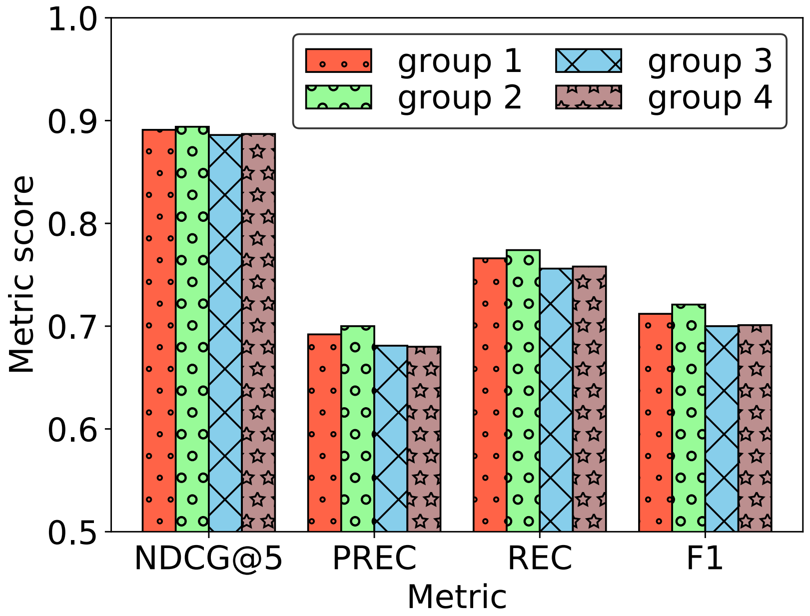

Effect of $\beta_2$ on BEIJING

## Experiments – Robustness Check

- We test the performance on four subgroups of users (resp. OD pairs)
  - Group users (resp. OD pairs) by K-means
- The performance is stable in different groups of users and OD pairs.




Group by users on BEIJING




Group by ods on BEIJING

# Multi-Modal Transportation Recommendation on Baidu Map

20%

Faster than bus & drive


50%

Cheaper than taxi

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Thanks !
Q & A