国际人工智能会议
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Out-of-Town Recommendation with Travel Intention Modeling

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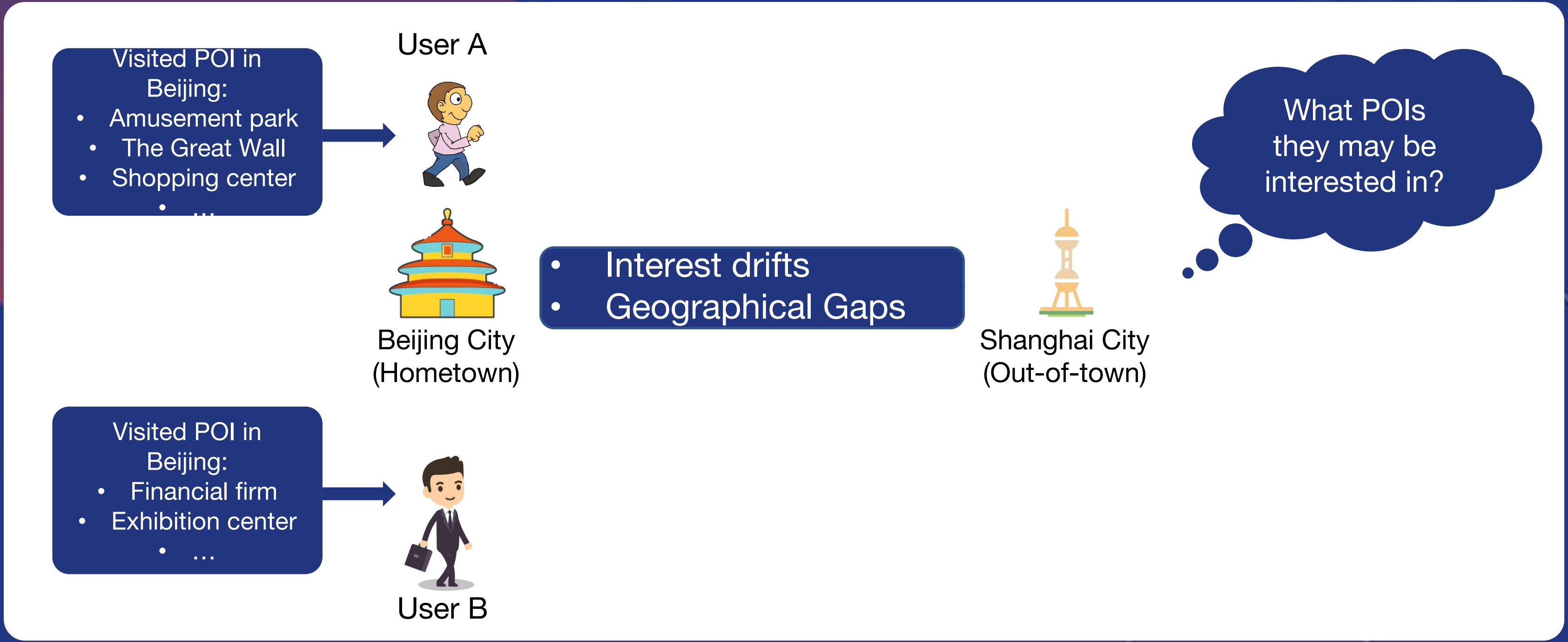
Outline

- Background & Motivation
- Problem Formulation
- Framework Overview
- The Proposed Approach
- Experiments
- Conclusion

Background & Motivation

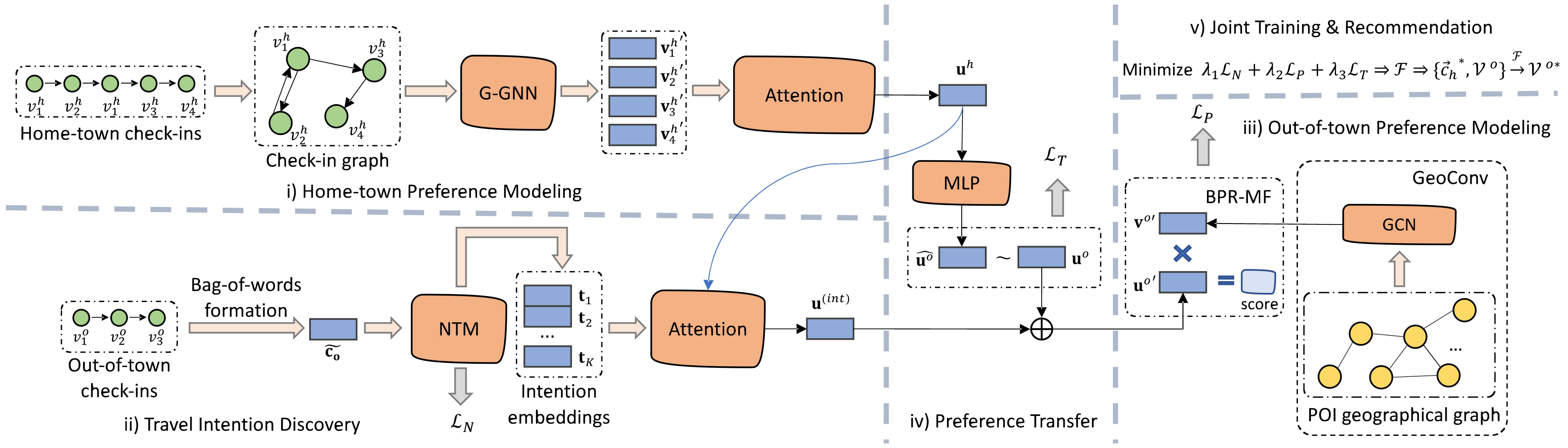
- POI: Point-of-Interest



Problem Formulation

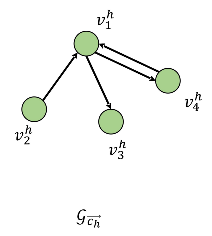
- User set $\mathcal{U}$, out-of-town POI set $\mathcal{V}$
- home-town region r, target region r_o, check-in activities c
- Travel behavior set $\mathfrak{T} = \{\tau | \tau = (u, c_h, c_o, r_u, r_o)\}$
- Learn an out-of-town recommender $\mathcal{F}(\cdot)$ by exploring $\mathfrak{T}$ and $\mathcal{V}$
- For a new coming user $u^* \notin \mathcal{U}$, $\{c_h, \mathcal{V}\} \xrightarrow{\mathcal{F}} \mathcal{V}^* \ (\mathcal{V}^* \subset \mathcal{V})$

Framework Overview of TRAINOR



Home-town Preference Modeling

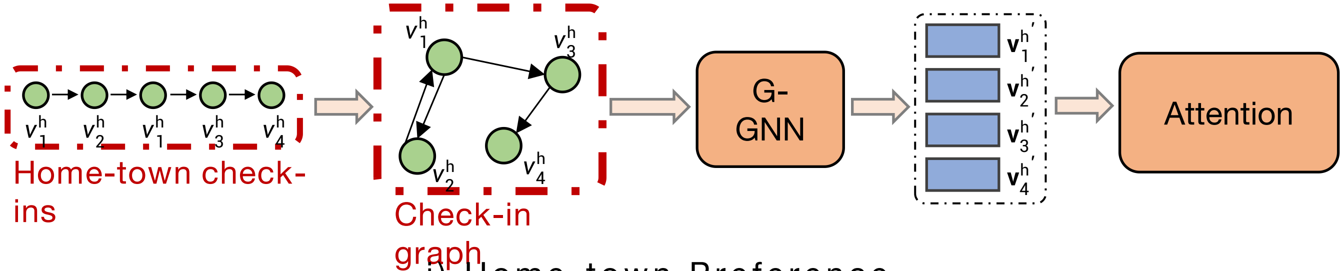
- Home-town check-in graph construction
  - a directed graph $\mathcal{G}_{c_h}$ for each user
  - The adjacent matrix $\mathbf{A}_{c_h}$



	1	2	3	4	1	2	3	4
1	0	0	1/2	1/2	0	1/2	0	1/2
2	1	0	0	0	0	0	0	0
3	0	0	0	0	1	0	0	0
4	0	0	0	1	1	0	0	0

Outgoing edges (columns 1–4, first group); Incoming edges (columns 1–4, second group)

$$\mathbf{A}_{\overrightarrow{c_h}} = [\mathbf{A}^{(out)}, \mathbf{A}^{(in)}]$$



i) Home-town Preference Modeling

Home-town Preference Modeling

- Home-town POI representation learning with Gated GNN (G-GNN)
  - GRU-like updating steps
  - Obtaining POI representations the user visited

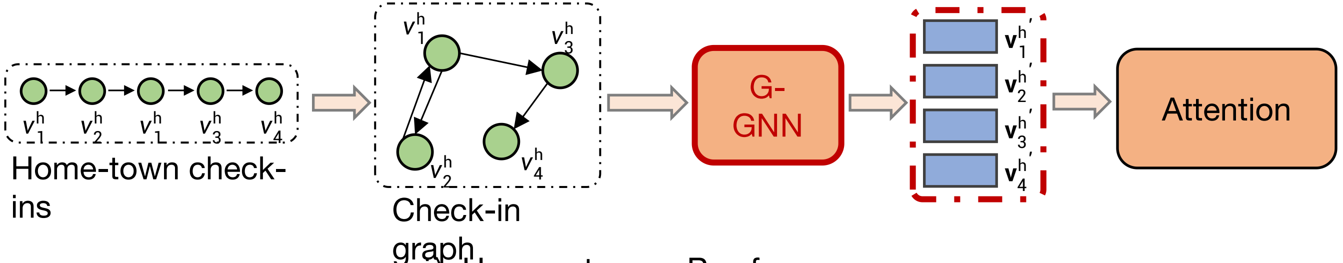
$$\mathbf{a}_v^{(t)} = \mathbf{A}_{v:}^{\mathrm{T}} \left[\mathbf{v}_1^{h\,(t-1)}, \mathbf{v}_2^{h\,(t-1)}, \cdots, \mathbf{v}_{D_1}^{h\,(t-1)}\right]^{\mathrm{T}} + \boldsymbol{b}^g, \quad (1)$$

$$\mathbf{z}_v^{(t)} = \zeta\left(\mathbf{W}^z \mathbf{a}_v^{(t)} + \mathbf{U}^z \mathbf{v}_v^{h\,(t-1)}\right), \quad (2)$$

$$\mathbf{r}_v^{(t)} = \zeta\left(\mathbf{W}^r \mathbf{a}_v^{(t)} + \mathbf{U}^r \mathbf{v}_v^{h\,(t-1)}\right), \quad (3)$$

$$\widetilde{\mathbf{v}_v^{h\,(t)}} = \tanh\left[\overline{\mathbf{W}}\,\mathbf{a}_v^{(t)} + \overline{\mathbf{U}}\left(\mathbf{r}_v^{(t)} \odot \mathbf{v}_v^{h\,(t-1)}\right)\right], \quad (4)$$

$$\mathbf{v}_v^{h\,(t)} = (1 - \mathbf{z}_v^{(t)}) \odot \mathbf{v}_v^{h\,(t-1)} + \mathbf{z}_v^{(t)} \odot \widetilde{\mathbf{v}_v^{h\,(t)}}, \quad (5)$$



i) Home-town Preference Modeling

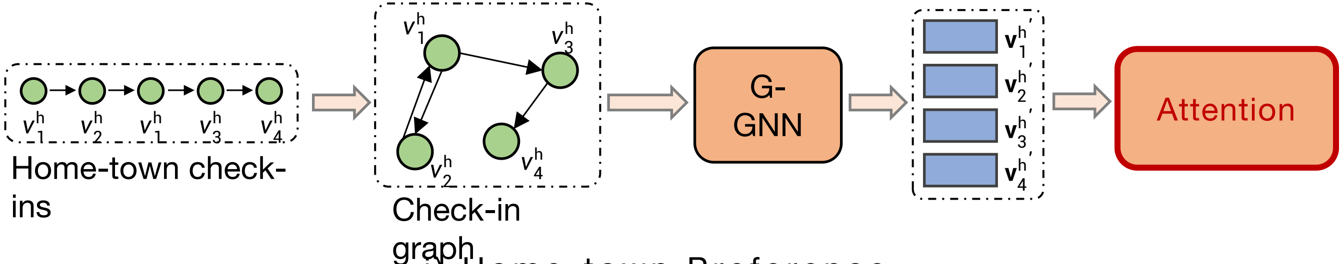
Home-town Preference Modeling

- Home-town preference summarizing
  - Attention network
  - $\mathbf{u}^h$ as the user's home-town preference embedding.

$$\mathbf{V}^{h\prime} = \left[\mathbf{v}_1^{h\prime}, \mathbf{v}_2^{h\prime}, \cdots, \mathbf{v}_{D_1}^{h\ \prime}\right]$$

$$\alpha_i = \mathbf{q}^{\mathrm{T}} \zeta\left(\mathbf{W}^p \mathbf{v}_i^{h\prime} + \boldsymbol{b}^p\right)$$

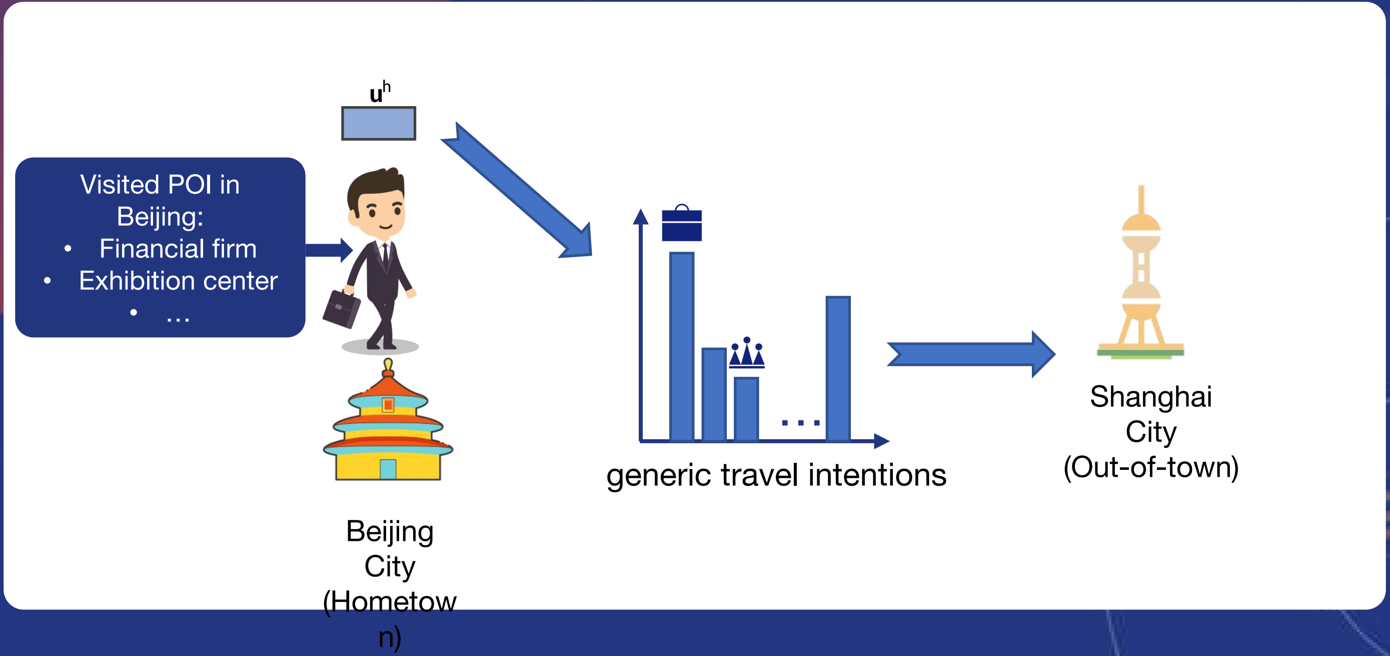
$$\mathbf{u}^h = \sum_{i=1}^{D_1} \alpha_i \mathbf{v}_i^{h\prime}$$



i) Home-town Preference Modeling

Travel Intention Discovery

- Understanding travel intentions is very important in out-of-town rec.



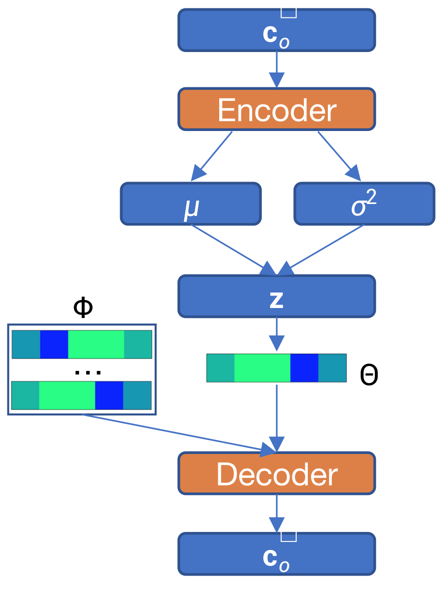
Travel Intention Discovery

- Generic travel intentions uncovering with Neural Topic Model (NTM)
  - K inherent travel intentions
  - Out-of-town POI-intention distribution Φ

$$\Phi_i = \text{softmax}\left(\mathbf{E}\mathbf{t}_i\right)$$

  - User's intention distribution Θ by Gaussian Softmax constructi

- Draw a latent variable $\mathbf{z}$ from a standard Gaussian distribution: $\mathbf{z} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$.
- Generate the out-of-town intention distribution Θ : $\Theta = \text{softmax}\left(F_\Theta(\mathbf{z})\right)$, where F_Θ is a fully connected layer.
- For the i-th POI in $\tilde{\mathbf{c}}_o$, draw a POI $v_i \sim \Phi^{\mathrm{T}}\Theta$.



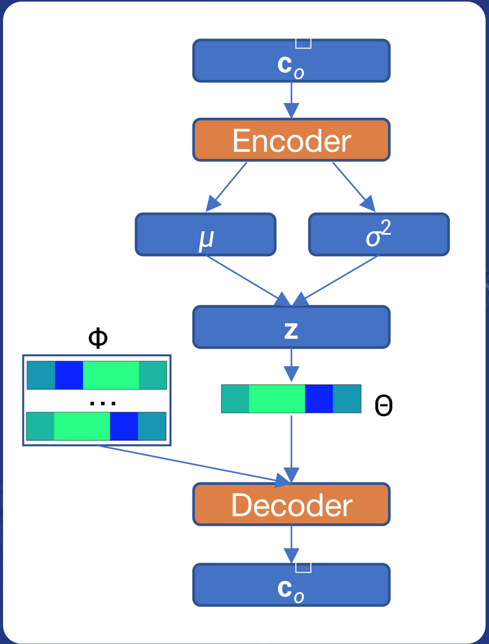
Travel Intention Discovery

- Generic travel intentions uncovering with Neural Topic Model (NTM)
  - Variational posterior distribution

$$
\begin{aligned}
q(\mathbf{z}|\widetilde{\mathbf{c}_o}) &= \mathcal{N}\left(\boldsymbol{\mu}, \boldsymbol{\sigma}^2\right) \\
\boldsymbol{\mu} &= F_{\mu}\left(F_{enc}\left(\widetilde{\mathbf{c}_o}\right)\right) \\
\boldsymbol{\sigma}^2 &= F_{\sigma}\left(F_{enc}\left(\widetilde{\mathbf{c}_o}\right)\right)
\end{aligned}
$$

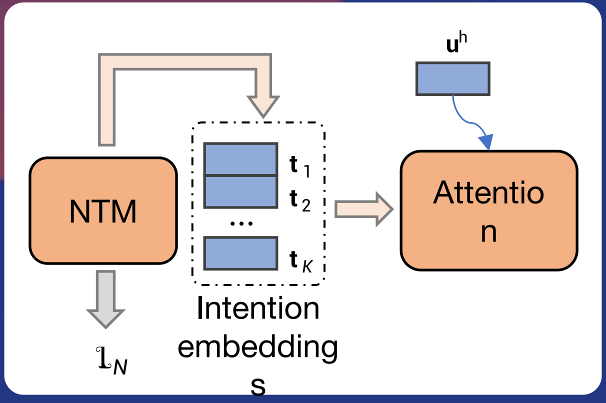
  - Variational lower bound

$$
\begin{aligned}
\mathcal{L}_N = - \sum_{u \in \mathcal{U}} \Big[& \mathbb{E}_{q(\mathbf{z}|\widetilde{\mathbf{c}_o})} \left(\widetilde{\mathbf{c}_o}^{\mathrm{T}} \log\left(\Phi^{\mathrm{T}} \Theta\right) \right) \\
& + \mathbb{D}_{\mathrm{KL}}\left(q\left(\mathbf{z}|\widetilde{\mathbf{c}_o}\right) || p\left(\mathbf{z}\right)\right) \Big]
\end{aligned}
$$



Travel Intention Discovery

- User-specific travel intention summarizing
  - Different users pay different attentions to these inherent travel intentions.
  - Taking advantage of generic out-of-town intention knowledge.

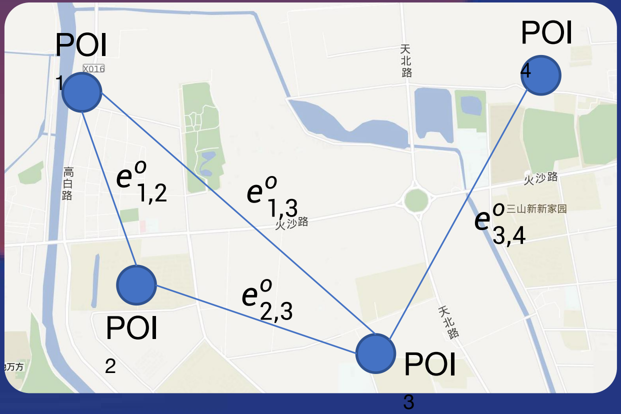


$$\beta_i = \mathrm{softmax}\left(\mathbf{t}_i^{\mathrm{T}} \mathbf{W}^t \mathbf{u}^h\right)$$

$$\mathbf{u}^{(int)} = \sum_{i=1}^{K} \beta_i \mathbf{t}_i$$

Out-of-town Preference Modeling

- GeoConv
  - Mining geographical influence underlying out-of-town POIs



$$\mathcal{G}_{geo} = (\mathcal{V}^o, \mathcal{E}^o)$$

$$e^o_{i,j} = \exp(-dist(i,j))$$

$$\mathbf{V}^{o\prime} = \mathrm{ReLU}\left(\mathbf{A}_{geo}\mathbf{V}^o\mathbf{W}^c + \boldsymbol{b}^c\right)$$

- Out-of-town representation learning
  - Aggregating preference & intention

    $$\mathbf{u}^{o\prime} = \mathrm{ReLU}\left(\mathbf{W}^f \mathrm{concat}\left(\mathbf{u}^o, \mathbf{u}^{(int)}\right) + \boldsymbol{b}^f\right)$$

  - $$s(i,j) = \left(\mathbf{u}_i^{o\prime}\right)^{\mathrm{T}} \mathbf{v}_j^{o\prime}$$

  - $$\mathcal{L}_P = -\sum_{u\in\mathcal{U}}\sum_{j\in\vec{c}_o}\sum_{k\notin\vec{c}_o} \log\zeta\left(s(i,j) - s(i,k)\right)$$

Preference Transfer

- Issues to address
  - Interest drifts
  - Cold-start Problem
- MLP-based non-linear mapping & preference transfer

$$\mathcal{L}_T = \sum_{i \in \mathcal{U}} ||F_{tr}\left(\mathbf{u}_i^h\right) - \mathbf{u}_i^o||^2$$

(F_{tr} is the MLP-based mapping function)

Joint Training & Recommendation

- Joint training
  - Intention inference loss
  - Preference loss
  - Transfer loss

$$\mathcal{L} = \lambda_1 \mathcal{L}_N + \lambda_2 \mathcal{L}_P + \lambda_3 \mathcal{L}_T$$

- Recommendation

$$\widehat{\mathbf{u}_*^o} = F_{tr}(\mathbf{u}_*^h)$$

$$\widehat{\mathbf{u}_*^{o\prime}} = \mathrm{ReLU}\left(\mathbf{W}^f \mathrm{concat}\left(\widehat{\mathbf{u}_*^o}, \mathbf{u}_*^{(int)}\right) + \boldsymbol{b}^f\right)$$

$$\widehat{s(*, j)} = \left(\widehat{\mathbf{u}_*^{o\prime}}\right)^{\mathrm{T}} \mathbf{v}_j^{o\prime}$$

Experiments

- Settings
  - We chose three real-world travel behavior datasets including BJ→SH, SH→HZ and GZ→FS, to evaluate our approach.

Dataset		# Users	# POIs	# Check-ins
BJ→SH	Beijing	10,776	2,111	127,528
	Shanghai		1,140	70,794
SH→HZ	Shanghai	19,997	3,415	263,158
	Hangzhou		1,203	116,475
GZ→FS	Guangzhou	12,788	4,228	220,006
	Foshan		1,225	57,229

- Baselines
  - TOP, UCF, BPR-MF, GRU4Rec, SR-GNN, LA-LDA, EMCDR
  - Variants of ours: TRAINOR-I, TRAINOR-C, TRAINOR-IC
- Evaluation metrics
  - Recall@k (Rec@k) and Mean Average Precision (MAP)

Experiments

- Recommendation Performance

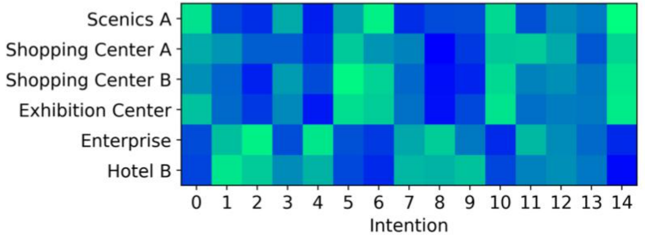
Methods	BJ→SH				SH→HZ				GZ→FS			
	Rec@10	Rec@20	Rec@30	MAP	Rec@10	Rec@20	Rec@30	MAP	Rec@10	Rec@20	Rec@30	MAP
LA-LDA	0.0160	0.0335	0.0417	0.0151	0.0008	0.0021	0.0028	0.0019	0.0020	0.0036	0.0057	0.0021
UCF	0.0443	0.0700	0.0935	0.1133	0.0628	0.0874	0.0981	0.2577	0.0386	0.0661	0.0800	0.1071
SR-GNN	0.1168	0.1807	0.2627	0.1071	0.2287	0.4550	0.5661	0.2013	0.0933	0.1670	0.2541	0.0566
BPR-MF	0.1768	0.2379	0.2844	0.0901	0.2812	0.3588	0.4116	0.1910	0.1642	0.2545	0.3173	0.0947
TOP	0.2062	0.3103	0.3818	0.1494	0.3713	0.4620	0.5176	0.2896	0.1964	0.2838	0.3483	0.1202
GRU4Rec	0.2091	0.3011	0.3763	0.1438	0.3619	0.4650	0.5150	0.2807	0.1789	0.2742	0.3422	0.1034
EMCDR	0.2163	0.3008	0.3649	**0.1553**	0.3772	0.4358	0.4732	**0.3260**	0.1928	0.2770	0.3368	0.1246
TRAINOR-IC	0.2029	0.2880	0.3513	0.1497	0.3679	0.4406	0.4963	0.3020	0.1937	0.2609	0.3178	0.1245
TRAINOR-I	0.2177	0.3084	0.3825	0.1543	0.3825	0.4624	0.5177	0.3016	0.2028	0.2841	0.3449	**0.1266**
TRAINOR-C	**0.2233**	0.3194	**0.3955**	0.1538	**0.3914**	0.4757	**0.5300**	0.2950	0.2032	0.2918	**0.3569**	0.1246
TRAINOR	0.2226	**0.3198**	0.3938	0.1541	**0.3914**	**0.4768**	0.5295	0.2955	**0.2039**	**0.2922**	0.3551	0.1246

Experiments

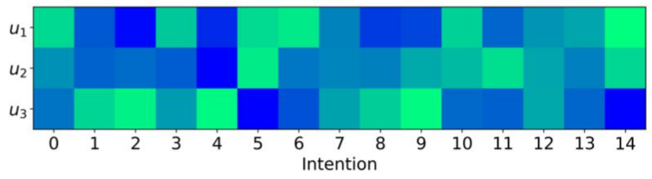
- Case study
  - 3 cases with promising Rec@30 from BJ→SH dataset.

User	Out-of-town check-ins
u_1	Scenics A, Scenics B, Art Gallery, Shopping Center A
u_2	Shopping Center B, Exhibition Center, Life Plaza, Shopping Center C, Hotel A
u_3	Enterprise, Hotel B, Hotel C

- Visualization



reps. POIs over generic intentions.



weights of generic intentions for user-specific intentions.

Conclusion

- Study the out-of-town recommendation problem by modeling user's complex travel intention.
- Propose a novel T_{RAIN}OR framework for out-of-town recommendation.
- Validate the effectiveness quantitatively.
- A case study further validate qualitatively.

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THANKS

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