A novel approach for venue recommendation using cross-domain techniques

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Outline

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1. Introduction
2. Cross-domain in Venue Recommendation
3. Experiments
4. Conclusions and Future Work

Venue (POI) Recommendation

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- The great development of Location-Based Social Networks (LBSN) has encouraged the research into the venue (POI) recommendation problem
- Some examples of LBSN include Gowalla, Foursquare, or GeoLife, where the users share the locations they have visited

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- POI recommendation has specific details that differ from the traditional recommendation problem (**Liu et al. (2017); Wang et al. (2013)**)

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- Implicit information and repetitions
  - We only know when the user visited a POI (we only have 1s)
  - The users may check-in the same POI more than once (behavior analized in our work in **RecTour2018**)
- External influences
  - Geographical: location of POIs
  - Social: user's friends
  - Categorical: categories of venues (museums, hotels, restaurants)

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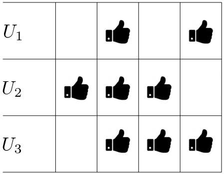
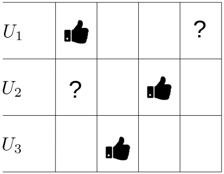
Books



Movies



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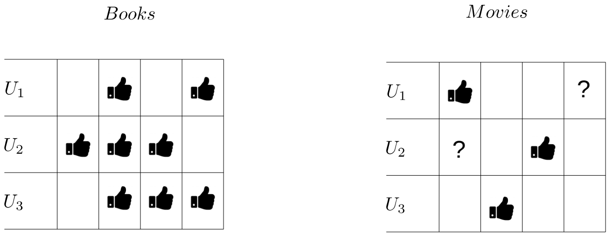

- For a complete analysis of different cross-domain techniques see **Cantador et al. (2015)**

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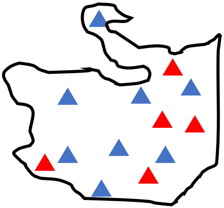
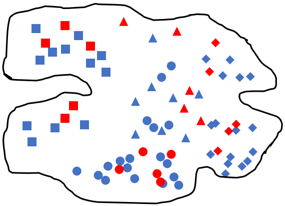
Typical evaluation approaches in POI recommendation

- When conducting experiments in POI recommendation datasets, the most common ways to proceed are:

Training with one city
and test with the same city



Training with many cities
and test with many cities



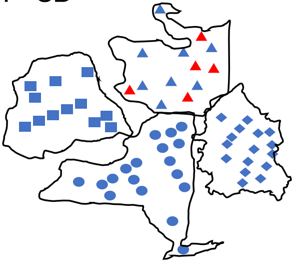
Cross-domain strategies in Venue Recommendation

- In order to perform recommendations over a target city $\mathcal{C}_T$, we can use the check-ins obtained over a set of source cities $\mathcal{C}_S$

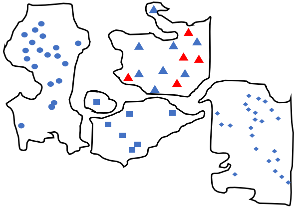
Cross-domain strategies in Venue Recommendation

- In order to perform recommendations over a target city $\mathcal{C}_T$, we can use the check-ins obtained over a set of source cities $\mathcal{C}_S$
- Two analyzed strategies. Use the check-ins of the most popular cities (P-CD) or use the check-ins of the closest cities to the target one (N-CD)

P-CD



N-CD



Goal

- Do cross-domain techniques help us improve the performance of the recommenders?
- Which cross-domain strategy is better?

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Dataset

Checkin period	**U**	**I**	**C**	**Density**	**C/U**	**C/I**
Apr'12-Sep'13	267k	3.6M	33M	0.0034%	123.596	9.16
Training: May-Oct '12	202k	1.1M	4.7M	0.0021%	23.267	4.278
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- Temporal evaluation. All the check-ins in the test set were made after the training set. 6 months for training and 1 month for test
- Selected the 8 most popular cities (we will show the results of 5 of them). Complete results can be found in the paper

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  - HKV (matrix factorization from **Hu et al. (2008)**)
- Personalized venue recommenders
  - IRenMF (matrix factorization from **Liu et al. (2014)**)
  - AvgDis (computes the user midpoint)
  - PGN (hybrid approach combining Popularity, AvgDis, and UB)

Single domain: NDCG@5

City	Rnd	Pop	AvgDis	PGN	UB	IB	HKV	IRenMF
IST	0.000	0.054	0.001	0.067	**0.073**	0.059	0.070	0.069
MEX	0.000	0.041	0.001	0.043	0.044	0.013	**0.047**	0.043
MOS	0.000	0.027	0.002	0.032	0.037	0.017	**0.039**	0.035
SAO	0.000	0.053	0.001	**0.057**	0.049	0.015	0.048	0.043
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- IRenMF although it is competitive, is not the best (we tested again this recommender using repetitions and the performance increased: see our paper in RecTour2018)
- PGN very competitive, beating more complex models

Cross-domain: NDCG@5

City		AvgDis	PGN	UB	IB	HKV	IRenMF
IST	N-CD	0.001	0.068	**0.073**	0.057	0.071	0.059
	Δ(%)	−9.7	1.6	0.3	−3.2	▲2.0	▼−14.8
	P-CD	0.001	0.068	**0.073**	0.059	0.068	0.052
	Δ(%)	−0.1	▲0.9	0.4	0.0	−3.4	▼−24.7
MEX	N-CD	0.001	0.044	0.045	0.013	**0.045**	0.040
	Δ(%)	▲13.3	2.2	1.6	−6.5	−5.0	▼−6.8
	P-CD	0.001	0.044	**0.045**	0.013	0.037	0.037
	Δ(%)	−0.2	▲1.3	1.2	−0.1	▼−22.1	−13.6
MOS	N-CD	0.002	0.033	0.038	0.017	**0.040**	0.034
	Δ(%)	▼−6.9	0.8	2.5	−0.7	▲3.3	−1.1
	P-CD	0.002	0.032	**0.037**	0.018	0.036	0.029
	Δ(%)	−0.6	0.1	0.3	▲1.1	−7.7	▼−17.4
SAO	N-CD	0.001	**0.057**	0.056	0.016	0.056	0.046
	Δ(%)	▼−7.1	0.4	▲15.4	5.5	15.2	7.3
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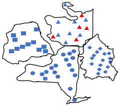
	Δ(%)	−9.2	▲0.5	−0.2	−0.2	−2.1	▼−20.2
TOK	N-CD	0.000	**0.073**	0.073	0.048	0.064	0.071
	Δ(%)	▼−15.6	4.9	5.4	−0.2	▲8.7	4.2
	P-CD	0.001	**0.070**	0.069	0.048	0.064	0.064
	Δ(%)	−0.3	−0.2	−0.2	−0.1	▲8.6	▼−6.1

P-CD



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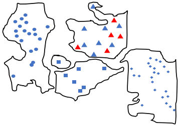

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- N-CD approach obtain better results than P-CD
- Algorithms that use geographical influence lose performance

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- Different cities entail different users patterns

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TOK	N-CD	0.000	**0.073**	0.073	0.048	0.064	0.071
	Δ(%)	▼−15.6	4.9	5.4	−0.2	▲8.7	4.2
	P-CD	0.001	**0.070**	0.069	0.048	0.064	0.064
	Δ(%)	−0.3	−0.2	−0.2	−0.1	▲8.6	▼−6.1

- N-CD approach obtain better results than P-CD
- Algorithms that use geographical influence lose performance
- Different cities entail different users patterns
- PGN still very competitive

Cross-domain: NDCG@5

City		AvgDis	PGN	UB	IB	HKV	IRenMF
IST	N-CD	0.001	0.068	**0.073**	0.057	0.071	0.059
	Δ(%)	−9.7	1.6	0.3	−3.2	▲2.0	▼−14.8
	P-CD	0.001	0.068	**0.073**	0.059	0.068	0.052
	Δ(%)	−0.1	▲0.9	0.4	0.0	−3.4	▼−24.7
MEX	N-CD	0.001	0.044	0.045	0.013	**0.045**	0.040
	Δ(%)	▲13.3	2.2	1.6	−6.5	−5.0	▼−6.8
	P-CD	0.001	0.044	**0.045**	0.013	0.037	0.037
	Δ(%)	−0.2	▲1.3	1.2	−0.1	▼−22.1	−13.6
MOS	N-CD	0.002	0.033	0.038	0.017	**0.040**	0.034
	Δ(%)	▼−6.9	0.8	2.5	−0.7	▲3.3	−1.1
	P-CD	0.002	0.032	**0.037**	0.018	0.036	0.029
	Δ(%)	−0.6	0.1	0.3	▲1.1	−7.7	▼−17.4
SAO	N-CD	0.001	**0.057**	0.056	0.016	0.056	0.046
	Δ(%)	▼−7.1	0.4	▲15.4	5.5	15.2	7.3
	P-CD	0.001	**0.057**	0.049	0.015	0.047	0.034
	Δ(%)	−9.2	▲0.5	−0.2	−0.2	−2.1	▼−20.2
TOK	N-CD	0.000	**0.073**	0.073	0.048	0.064	0.071
	Δ(%)	▼−15.6	4.9	5.4	−0.2	▲8.7	4.2
	P-CD	0.001	**0.070**	0.069	0.048	0.064	0.064
	Δ(%)	−0.3	−0.2	−0.2	−0.1	▲8.6	▼−6.1

- N-CD approach obtain better results than P-CD
- Algorithms that use geographical influence lose performance
- Different cities entail different users patterns
- PGN still very competitive
- HKV and UB benefit the most from N-CD

Conclusions

- Cross-domain techniques could be useful to address some problems of POI recommendation

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- N-CD approach is promising as we are able to obtain better results than the pure single domain approach.
  - "Everything is related to everything else, but near things are more related than distant things" **Miller (2004)**

Conclusions

- Cross-domain techniques could be useful to address some problems of POI recommendation
- N-CD approach is promising as we are able to obtain better results than the pure single domain approach.
  - "Everything is related to everything else, but near things are more related than distant things" **Miller (2004)**
- Important advantage of using cross-domain techniques: we only need to train the recommenders once and we can use them to perform recommendations over all the cities in the source domain

Future Work

- We would like to explore new methods to select the candidate cities. For example, using categorical information or selecting the cities by the same country

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- We would like to explore new methods to select the candidate cities. For example, using categorical information or selecting the cities by the same country
- We aim to use algorithms that take into account the geographical component but that are less negatively affected by cross-domain strategies

A novel approach for venue recommendation using cross-domain techniques

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Thank you

`https://bitbucket.org/PabloSanchezP/TempCDSeqEval`

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