User Model Enrichment for Venue Recommendation

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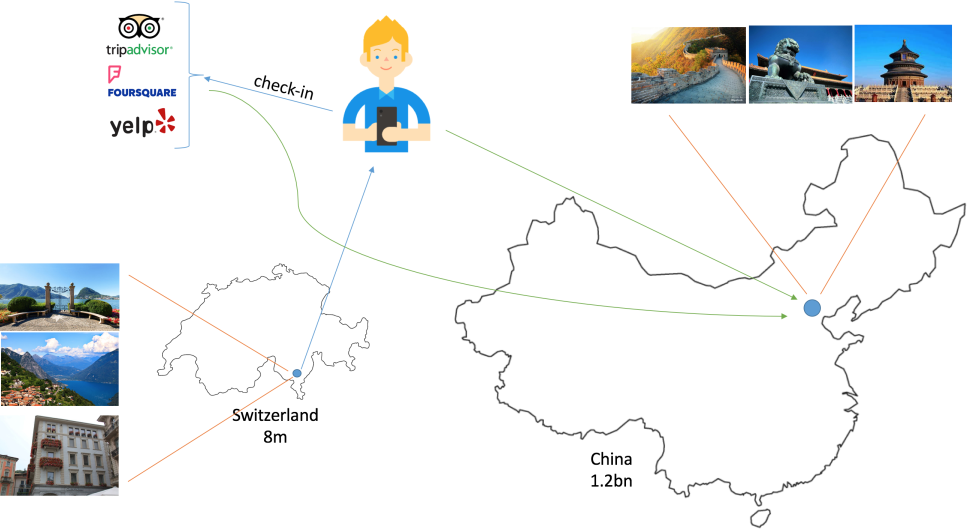
Venue Recommendation

Asia Information Retrieval Societies



Motivation

Challenges

- To model a user based on her history of preferences
- Different ratings for similar venues
- No reviews from the users, only ratings

Our Goal

- To model the user based on venue content
- To mine the reasons a user gave a specific rating to a venue

Approach

- A combination of multimodal scores from multiple sources
- Sources: Yelp, Foursquare, and TripAdvisor
- Types of information: categories, venue taste keywords, reviews
- Two types of scores:
  - Content based
  - Review based

Content-based Scores

- To have a better idea of the user's taste and interest we need to take into account their liked/disliked categories
- It is not clear exactly which category or subcategory a user likes/dislikes.
- In this example, we see the corresponding categories to three attractions a user likes:
  - Pizzeria - Italian - Takeaway - **Pizza**
  - Restaurant - Pasta - **Pizza** - Sandwich
  - Restaurant - American - **Pizza** - Burger
- The user likes **Pizza**, since it is the only category in common
- We introduce a score to model user interest

Content-based Scores (cont.)

for all $v_i \in V$ **do**
  for all $c_j \in C(v_i)$ **do**
    if $c_j \notin \mathrm{CM}_{pos}$ **then**
      $\mathrm{CM}_{pos} \leftarrow \mathrm{CM}_{pos} \cup c_j$
      $\mathrm{count}(c_j) = \sum_{v_s \in V} \sum_{c_k \in C(v_s)} \delta(c_j, c_k)$
      $N = \sum_{v_s \in V} \sum_{c_k \in C(v_s)} 1$
      $\mathrm{cf}_{pos}(c_j) = \mathrm{count}(c_j)/N$
    end if
  end for
end for

Content-based Scores (cont.)

Given a user u and a venue v, the category-based similarity score $S_{CM}(u, v)$ is:

$$S_{CM}(u, v) = \sum_{c_i \in C(v)} \mathrm{cf}_{pos}(c_i) - \mathrm{cf}_{neg}(c_i)$$

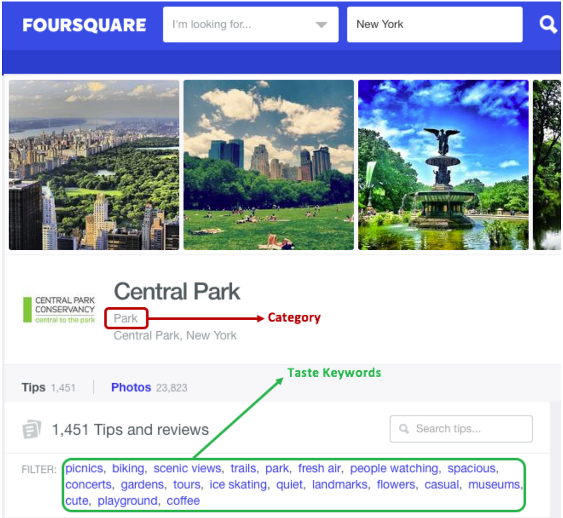
where cf_{pos} and cf_{neg} are respectively the positive and negative categories' frequencies.

Content-based Scores (cont.)

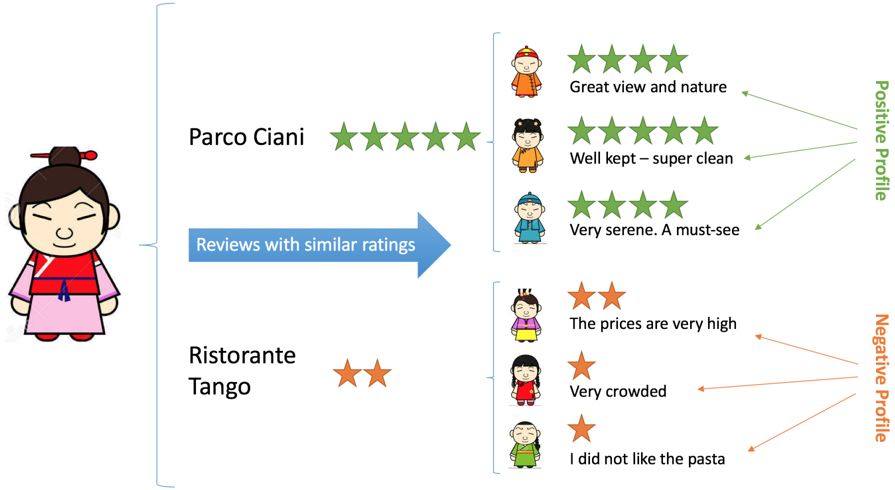
We calculate three frequency-based scores using different types and sources of information:

- Categories from Yelp: S_{CM}^{Yelp}
- Categories from TripAdvisor: $S_{CM}^{TAdvisor}$
- Venue taste keywords from Foursquare: S_{TM}

Venue Taste Keywords



Review-based Score



Review-based Score (cont.)

- We assume that user likes what others like about a place and vice versa
- Find reviews with similar rating:
  - **Positive Profile:** Reviews with rating 3 or 4 corresponding to places that user gave a similar rating
  - **Negative Profile:** Reviews with rating 0 or 1 corresponding to places that user gave a similar rating
- Train a classifier for each user: SVM and Naïve Bayes
- Features: TF-IDF score of each term
- Score: decision function $\rightarrow S_{BM}$

Suggestion Ranking

- We rank the venues based on their similarity with the user
- Given user *u* and venue *v*, we calculate the similarity score as follows:

$$SIM(u,v) = \alpha \times S_{CM}^{Yelp}(u,v) + \beta \times S_{CM}^{TAdvisor}(u,v) + \eta \times S_{TM}(u,v) + \gamma \times S_{BM}(u,v)$$

TREC CS Track

- TREC 2015
  - *Contextual Suggestion Track* deals with complex information needs which are highly dependent on context and user interests.
- What do we have?
  - 211 users
  - User context
  - User history: 60 rated venues in two cities
- What should we do?
  - Rank the candidate list: 30 venues in a new city
- Evaluation: P@5 and MRR

Context

- A city the user is located in, which consists of:
  - An ID
  - A city - The name of the city
  - A state - The name of the US state the city is in
  - A latitude and longitude - These are available for convenience and do not represent the exact user location but are analogous to the city name.
- A trip type (optionally), which is one of:
  - Business
  - Holiday
  - Other

Context (cont.)

- A trip duration (optionally), which is one of:
  - Night out
  - Day trip
  - Weekend trip
  - Longer
- The type of group the person is traveling with (optionally), which is one of:
  - Traveling alone (Alone)
  - Traveling with a group of friends (Friends)
  - Traveling with family (Family)
  - Traveling with an other group (Other)
- The season the trip will occur in (optionally)

User History

- Profiles consist of a list of attractions the user has previously rated. For each attraction the profile will include a rating as follows:
  - 4: Strongly interested
  - 3: Interested
  - 2: Neither interested or uninterested
  - 1: Uninterested
  - 0: Strongly uninterested
  - -1: No rating given
- Additionally the user may annotate the attraction with tags that indicate why the user likes the particular attraction:
  - Art Galleries, Family Friendly, Fine Art Museums, etc.
- The user's age and gender (optionally).

Dataset

What was provided by the organizers?

- An attraction ID
- A city ID which indicates which city this attraction is in
- A URL with more information about the attraction
- A title

What did we collect?

- Crawl venues from Location-based Social Networks (LBSNs):
  - Foursquare
  - Yelp
  - TripAdvisor

Dataset (cont.)

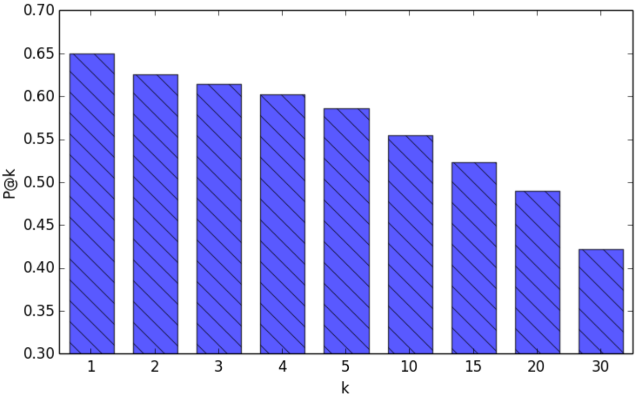
	Y	T	F
# of crawled venues	6290	4633	5534
Distribution of categories over venues			
Median	2	2	1
Mean	2.80	1.94	1.63
Variance	1.98	1.23	0.63
Distribution of reviews over venues			
Median	17	89	-
Mean	117.34	446.42	-
Maximum	6060	57365	-
Distribution of taste tags over venues			
Median	-	-	7
Mean	-	-	8.73
Variance	-	-	7.22

Results

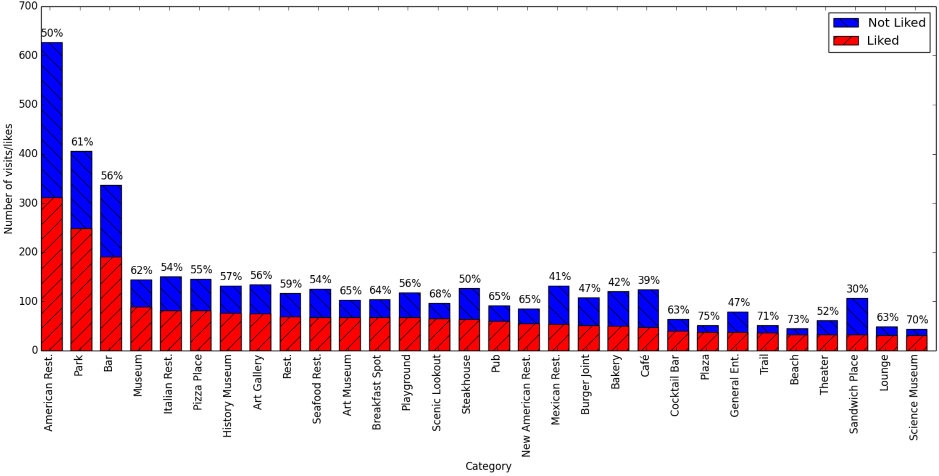
Approach	P@5 Rank	P@5	MRR
CatRev-SVM	**1**	**0.5858**	**0.7404**
CatRev-NB	7	0.5450	0.6991
BASE1	2	0.5706	0.7190
BASE2	3	0.5583	0.6815
TREC Median		0.5090	0.6716

- 17 teams - 30 runs

Analysis



Analysis (cont.)



Conclusion

- We proposed content-based and review-based scores
- We combined multimodal scores from multiple LBSNs
- Official results of TREC 2015 proves the effectiveness of our approach

- Context-aware venue recommendation
- Mapping user tags into venue content to have a more precise user model

Thanks

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Thanks for your attention
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