Venue Appropriateness Prediction for Contextual Suggestion

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Introduction

- What is the track?
  - *Contextual Suggestion Track* deals with complex information needs which are highly dependent on context and user interests.
- What do we have?
  - User context
  - User history or *profile*
- What should we do?
  - Rank the candidate list: Phase 1 and Phase 2
- Evaluation: nDCG@5, P@5, and MRR
- Fifth year

Collection

- What is provided by the organizers?
  - An attraction ID
  - A context (city) ID which indicates which city this attraction is in
  - A URL with more information about the attraction
  - A title
  - A crawled collection of the URLs in the collection
- What should we collect?
  - Crawl venues from Location-based Social Networks (LBSNs):
    - Foursquare
    - Yelp

Collection
(cont.)

- Phase 1:
  - Virtually 600K venues crawled on Foursquare
- Phase 2:
  - 13,704 venues crawled on Foursquare
  - 13,604 venues crawled on Yelp

Approach

- A combination of multimodal scores from multiple sources
- Sources: Foursquare and Yelp
- Types of information: categories, venue taste keywords, reviews, user context
- Context appropriateness prediction
- Two types of scores:
  - Frequency based
  - Machine-learning based

Frequency-based Scores

- To have a better idea of the user's taste and behavior we need to take into account their liked/disliked categories
- We have already extracted the categories and subcategories for each place using Yelp, Foursquare
- It is not clear exactly which category or subcategory is liked/disliked:
  - Italian - Takeaway - Pizza
  - Italian - Pasta - Seafood - Pizza
  - American - Good for Families - Pizza
- It is quite obvious that he/she likes *Pizza*
- We calculate a frequency-based score to model users

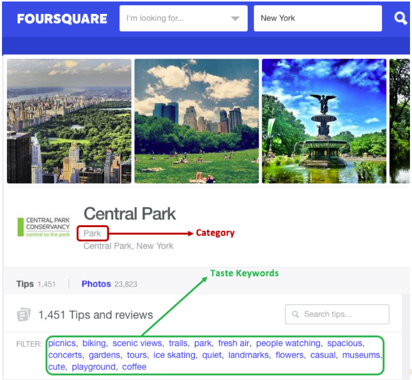
Frequency-based Scores (cont.)

- To calculate the frequency-based scores, we followed these steps to create frequency-based profiles:
    1. For each category/subcategory for a place with positive rating
    2. Add the category/subcategory to *positive* profile (cf^+)
    3. If the category/subcategory already exists in model, add one to its count
    4. Normalize the counts
    5. Do the same for places with negative rating to build *negative* profile (cf^-)
- A new venue's categories is compared to the profile and the scores are summed up:

$$S_{cat}(u, v) = \sum_{c_i \in C(v)} \mathrm{cf}^+(c_i) - \mathrm{cf}^-(c_i).$$

Frequency-based Scores (cont.)

- Calculate the frequency-based score with following types of information:
  - Foursquare Categories → S^{F}_{cat}
  - Yelp Categories → S^{Y}_{cat}
  - Foursquare Venue Taste Keywords → S^{F}_{key}



Machine-learning-based Scores

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

Contextual Appropriateness

- We need to predict the appropriateness of a venue given a context
- Some are objective and easy to predict:
  - Is a *Nightlife Spot* appropriate for a *Family*? No
  - Is a *Pizza Place* appropriate to go with *Friends*? Yes
- Some are very subjective:
  - Is a *Pharmacy* appropriate to go on a *Business* trip?
  - Is a *University* appropriate to go on a *Day trip*?
- We asked crowd workers on CrowdFlower to judge it.

Contextual Appropriateness (cont.)

- We asked the crowd workers to judge if a *Context* is appropriate for a *Category*?
- We did for almost all category-context pairs, 5 assessments per pair
- Examples:

Venue Type	Trip Descriptor	Answer
Pizza Place	Trip Type: Holiday	**YES**
Pizza Place	Trip Type: Business	**NO** *Tip: A Pizza Place is not the best place for inviting business partners*
Sushi Bar	Trip Duration: Weekend trip	**YES**
Pub	Trip Duration: Night out	**YES**
Museum	Trip Duration: Night out	**NO** *Tip: A Museum is not the best place to visit late at night.*

Contextual Appropriateness (cont.)

- Sample output:

id	is_the_venue_appropriate_...	is_the_ven...	category	context
10312740...	yes	1	Business Service	Group type: Alone
10312721...	no	0.9219	Park	Trip type: Business
10312721...	yes	0.9216	Food	Group type: Alone
10312721...	yes	0.9216	Outdoors & Recreation	Group type: Other
10312721...	yes	0.8734	Bar	Group type: Family
10312721...	yes	0.8734	Shop & Service	Group type: Family
10312721...	yes	0.8571	Food	Group type: Other
10312721...	yes	0.8571	American Restaurant	Trip duration: Longer
10312721...	yes	0.8571	American Restaurant	Group type: Other
10312721...	yes	0.8571	Bar	Trip type: Holiday
10312721...	yes	0.8571	Museum	Trip type: Holiday
10312721...	yes	0.8568	Outdoors & Recreation	Trip duration: Weekend trip
10312721...	yes	0.8568	Shop & Service	Trip type: Holiday
10312721...	yes	0.8556	Arts & Entertainment	Trip duration: Longer

Appropriateness Prediction

- Given all pairs of context-category assessments, we need to decide if a venue is appropriate for a context
- A trip is described with multiple contextual dimensions: Trip Type, Group Type, Trip Duration
- A venue is described with multiple categories: Restaurant, Pizza Place, Pasta
- Given the full description of the trip, we predict the appropriateness for each category:
  - For training data: we asked crowd workers to label 10% of the data
  - We gave them the full description, and asked 3 workers to assess the appropriateness

Appropriateness Prediction (cont.)

- Examples:

Venue	Keywords	Answer
Pizza Place	Holiday, Family, Weekend trip	**YES**
Pizza Place	Business, Alone, Weekend trip	**NO** *Tip: A Pizzeria is not the best place for inviting business partners*
Sushi Bar	Business, Other group, Weekend trip	**YES**
Pub	Holiday, Friends, Night out	**YES**

Appropriateness Prediction (cont.)

- Examples:

id	is_the_venue_appropriate...	is_the_ven...	category	keywords
10313264...	yes	1	Food	Holiday, Family, Weekend trip
10313264...	yes	0.5143	Playground	Business, Friends, Weekend trip
10313264...	yes	1	Wings Joint	Holiday, Alone, Night out
10313264...	yes	0.6667	Buffet	Holiday, Family, Longer trip
10313265...	no	0.7419	Miscellaneous Shop	Business, Friends, Weekend trip
10313265...	yes	0.6585	Pizza Place	Holiday, Other group, Day trip
10313265...	no	0.6585	Clothing Store	Holiday, Friends, Day trip
10313265...	yes	0.6667	Convenience Store	Holiday, Family, Longer trip
10313265...	yes	0.6702	Furniture / Home Store	Holiday, Other group, Day trip
10313265...	yes	1	Karaoke Bar	Holiday, Friends, Longer trip
10313265...	yes	0.5018	Residential Building (Apartmen...	Holiday, Family, Day trip
10313265...	no	0.68	Hospital	Holiday, Family, Weekend trip
10313265...	no	0.6923	College Residence Hall	Holiday, Friends, Weekend trip
10313265...	no	1	Grocery Store	Business, Alone, Day trip

Appropriateness Prediction (cont.)

- We trained a SVM classifier using the training set
- We predicted the appropriateness score for each category associated with a venue
- The overall appropriateness for a venue is the minimum score (S^{F}_{cxt})
- Example:
  - Assume the scores for a context given the categories:
  - Restaurant: 1
  - Asian Restaurant: 0.8
  - Sushi: **0.1**

Ranking

- Our approach:
  We perform a linear combination on the scores:
  - S^F_{cat} = Frequency-based category score from Foursquare (Phase 1 & 2)
  - S^Y_{cat} = Frequency-based category score from Yelp (Phase 2)
  - S^F_{key} = Frequency-based venue taste keyword score from Foursquare (Phase 1 & 2)
  - S^Y_{rev} = Machine-learning-based review score from Yelp (Phase 2)
  - S^F_{cxt} = Machine-learning-based context appropriateness score from Foursquare (Phase 2)
- 5-fold cross-validation

Results

- We submitted 5 runs: 2 for Phase 1 and 3 for Phase 2
- Phase 1:
  - **USI1**: S^F_{cat}
  - **USI2**: S^F_{cat} and S^F_{key}
- Phase 2:
  - **USI3**: Fielded Factorization Machines to combine: categories and reviews
  - **USI4**: S^F_{cat}, S^Y_{cat}, S^F_{key}, and S^Y_{rev}
  - **USI5**: S^F_{cat}, S^Y_{cat}, S^F_{key}, S^Y_{rev}, and S^F_{cxt}

Results

		nDCG@5	P@5	MRR
Phase 1	USI1	0.2578	0.3934	0.6139
	USI2	**0.2826**	**0.4295**	**0.6150**
	Median	0.2133	0.3508	0.5041
Phase 2	USI3	0.2470	0.4259	0.6231
	USI4	0.3234	0.4828	**0.6854**
	USI5	**0.3265**	**0.5069**	0.6796
	Median	0.2562	0.3931	0.6015

Conclusion and Future Work

- We presented a set of multimodal scores from multiple LBSNs
- We created two datasets which can be used to predict contextually appropriate venues
- We showed how we can use those datasets to suggest appropriate venues

- Explore other methods to incorporate contextual information in the basic model

Questions

Thank you for your attention