USI at the TREC 2015 Contextual Suggestion Track

Università
della
Svizzera
italiana

Faculty
of Informatics

Mohammad Aliannejadi
Seyed Ali Bahrainian
Fabio Crestani

University of Lugano

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Outline

Introduction

- Task: Provide travel suggestions in new cities for visitors based on their personal interests in venues that they have visited
- Two experiments:
  - Live Experiment
  - Batch Experiment
- Our attempt: Batch experiment
- 211 user profiles
- 60 attractions the user has previously rated
- 30 candidate suggestions to rank

Overview

Our attempt for this track is done in four steps:

1. Useful information gathering
2. Profile modeling
3. Profile enrichment
4. Suggestion ranking

Useful Information Gathering

- Analyze the URL collection: almost 9,000 URLs
- Approximately half of the URLs are from known sources of information: Yelp, Foursquare, TripAdvisor
- What to do with the other half?!
  - Fetch URL and use its content to represent the place → not a good idea ✗
  - Locate the place in known sources of information → good idea ✓
- Try to make the information homogeneous: All from Yelp
- Try to combine it with other sources of information: Foursquare and TripAdvisor

Useful Information Gathering

(cont.)

Steps for useful information gathering:

1. Fetch all given Yelp URLs
2. Locate Yelp profiles for all other attractions
3. Fetch located Yelp URLs
4. Use information on Yelp profiles to locate Foursquare and TripAdvisor profiles for each attraction
5. Scrape all fetched pages

Data Layout

- Yelp
  - Name
  - Yelp URL
  - Overall rating
  - Categories
  - Subcategories
  - Reviews
    - Rating
    - Comment
    - Date
    - ...
  - ...

Data Layout

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    - ...
  - ...
- Foursquare
  - ...
  - Tips
  - Visits
  - Visitors
  - ...
- TripAdvisor
  - ...
  - Dining options
  - Rating summary
  - Attraction ranking
  - ...

Profile Modeling

- 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
- Features: Tf-idf score of each term

Profile Enrichment

- 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 metric to model user interest

Profile Enrichment

(cont.)

- To model the user taste, we followed these steps:
  1. For each category/subcategory for a place with positive rating
  2. Add the category/subcategory to *positive* taste model
  3. Compute its normalized frequency:
     $cf(category, user) = \frac{count(category, user)}{\sum_c count(c, user)}$
  4. Do the same for places with negative rating to build *negative* taste model
- Each category item in the *positive* or *negative* taste profile will have a score between 0 and 1
- A category may be in both *positive* and *negative* taste profiles

Lack of Information

- There are some cases for which the system is unable to build positive/negative user profile $\rightarrow$ we adapt the scores
- For example: How can we build a *negative* profile when there is no such review?
- In such cases, we redefine positive and negative places and reviews
- There is no negative reviews (0 or 1)
  Positive profile will be reviews with rating 4
  Negative profile will be reviews with rating 3
- Doing so, we are still differentiating between places the user liked more and less.

Ranking

- Our approach:
  To combine scores from user profile, user taste profile and other information:
  - UP = Extract all the reviews and classify using the user profile classifier: Support Vector Machines (SVM) and Naïve Bayes
  - UT = Assign a taste score to place by adding positive scores of all categories subtracted by all negative scores
  - $U4$ = Score given to the place based on Foursquare tips classifier
  - UTA = Score given to the place based on TripAdvisor taste model
  - $Sc = \omega_1 UP + \omega_2 UT + \omega_3 U4 + \omega_4 UTA$

Results

- We assigned weights ω_1 to ω_4 by doing cross-validation on UDel dataset:

$$\omega_1 = 1, \omega_2 = 1, \omega_3 = 0.3, \omega_4 = 0.3$$

- We submitted two runs: one using SVM classifier named *11* and one Naïve Bayes classifier named *22*:

Runs	P@5	MRR
11	**0.5858**	**0.7404**
22	0.5450	0.6991
TREC Median	0.5090	0.6716

Discussion

- Parameters are tuned based on cross-validation on another dataset
- It is not the optimal parameter set, but hopefully performs better than a random assignment.
- User profile (UP) is the richest information source; thus, it has the highest weight (ω_1).
- Due to lack of reviews in some cases, user taste profile (UT) plays a significant role to achieve a better ranking. Therefore, it has the highest weight as well.
- The other two terms are not as comprehensive as the first ones. Therefore, assigning high weights to them may have reverse result on overall performance.

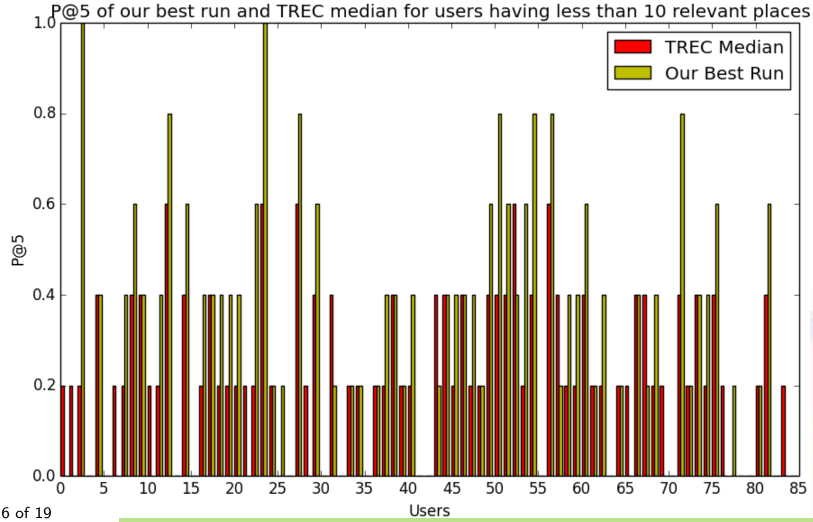
Discussion

(cont.)

- Dataset in comprehensive and homogeneous: information plays a significant role.
- The run with SVM classifier as user profile performed better.
- Why?
  - High dimensions
  - Weighted features
  - Sparse document vectors
  - Text is usually linearly separable
- Lack of reviews is compensated for by profile enrichment.

Discussion

(cont.)



Discussion

(cont.)

- The plot shows the performance for the users who liked less than 10 places.
- These users are considered to be *more* difficult to model.

- When we are unable to build user profile, profile enrichment will be the decision maker.
- The plot shows that in such cases, profile enrichment benefited our system comparing to TREC median.

Future work

- Look into ways to find relation between the context and the candidate places.
- Try to form a relation between the user tags and profiles to make user profile even richer.
- Look more deeply into users with imbalanced distribution of reviews and try to find a solution for them.
- Retune weights and add more information sources to the scoring algorithm using the real data.

Questions

Thanks for your attention

Mohammad Aliannejadi
mohammad.alian.nejadi@usi.ch
@maliannejadi