LARS: A Location-Aware Recommendation System

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Contents

Introduction / Motivation

- Previous Methods:

  Collaborative filtering(CF) to suggest personalized items

  Community opinions (user, rating, item)

- New form of SNS such as Foursquare and Facebook Places started gaining popularity in 2012

- Why not use location data? (location-based ratings)

Why would Location data be useful?

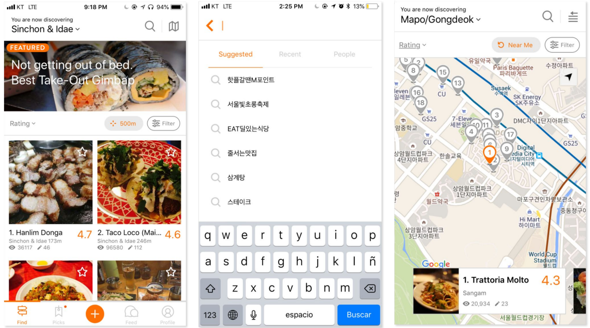
Preference Locality

South Korea	Nov 6, 2014	$12,412,781	$68,974,677
United Kingdom	Nov 7, 2014	$8,534,697	$34,452,006

- users from a spatial region prefer certain items

Travel Locality

- The closer it is, the better



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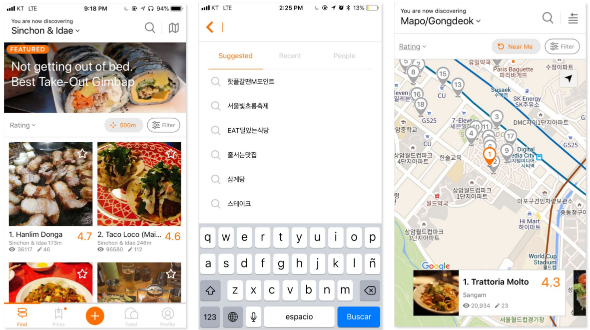

Contribution

- Produce location-aware recommendations using each of the three types of location-based rating within a single classification framework
    - Spatial ratings for non-spatial items
    - non spatial ratings for spatial items
    - Spatial ratings for spatial items

LARS Overview

- Query Model
  - User id U
  - Numeric limit K
  - Location L
  - K recommended Items

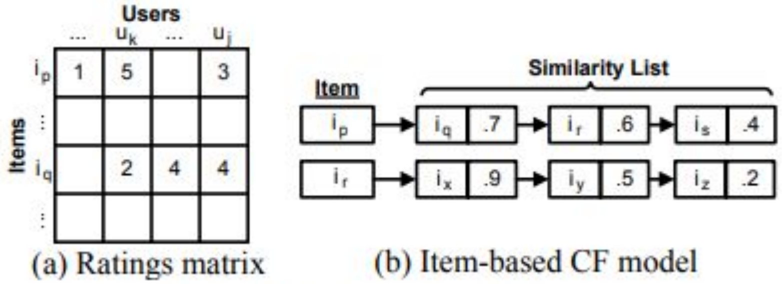

Fig. 2. Item-based CF model generation.

- Item-Based Collaborative Filtering
  - Similarity Score for each object -> similarity list
  - Similarity : Cosine Similarity

$$P_{(u,i)} = \frac{\sum_{l \in \mathcal{L}} sim(i,l) * r_{u,l}}{\sum_{l \in \mathcal{L}} |sim(i,l)|}$$

$$sim(i_p, i_q) = \frac{\vec{i_p} \cdot \vec{i_q}}{\|\vec{i_p}\| \|\vec{i_q}\|}$$

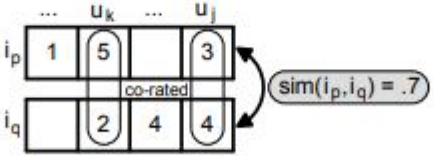

Fig. 3. Item-based similarity calculation.

Spatial User Ratings for Non-Spatial Items

(user, user_location, rating, item)

Preference Locality - User opinions are spatially unique

(1) Locality: recommendations should be influenced by those ratings with user locations spatially close to the querying user location

(2) Scalability: recommendation structure should scale up to large number of users

(3) Influence: users should be able to control the size of the spatial neighborhood that influences their recommendation

Spatial User Ratings for Non-Spatial Items

User Partitioning

- Divide users into separate spatial neighborhoods then carry on with CF over the 3 attributes

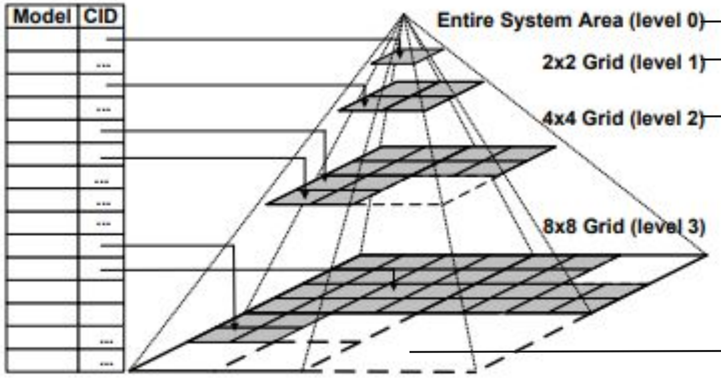

Fig. 4. Partial pyramid data structure.

Korea (Non spatial item based CF)

Seoul, Busan, Daegu, Gyeonggi

Gangnam, Seocho

Split or merge based on trade-offs of locality and scalability

Spatial User Ratings for Non-Spatial Items

Maintenance

- Regard for new users!
- Rebuild CF model
- Merge / Split (scalability gain vs locality loss)
    -

Query Processing

- (user, user_location, rating, item)

1. Use user_location to find its cell location in the pyramid (if cell does not exist due to merging or splitting, return the nearest maintained ancestor cell)
2. item-based CF technique using the model stored at its cell
3. For the *influence* factor let the user choose which level to process the recommendation

Non-Spatial User Ratings For Spatial Items

(user, rating, item, item_location)

travel locality - the closer, the better

- single system-wide item-based collaborative filtering model to generate the top-k recommendations

$$RecScore(u,i) = P(u,i) - TravelPenalty(u,i)$$

Query Processing

- User id: U, location: L, limit: K, R: list of top-K items
- k-nearest-neighbor algorithm to populate list R with K items