Towards the Next Generation of Mobile Recommender Systems

Professor Hui Xiong

Rutgers, the State University of New Jersey
Definition of Recommender Systems

Background

- Information Explosion
- Personalization

Which book should I read?

Recommendation from Friends

Auto Recommendation
Definition of Recommender Systems

Definition

**Recommend** the *right content* and products (items) to the *right user* at the *right time* so as to archive the most *relevant experience*.

Dependence

- **Most Popular**
  - “What’s most engaging overall?”

- **Personalized Recommendation**
  - “What’s most relevant to me based on my interests and attributes?”

- **Related items**
  - Behavioral Affinity: People who did X, did Y
  - Similarity: Based on metadata
Definition of Recommender Systems

A Case Study

These recommendations are based on: your most recently viewed items.

<table>
<thead>
<tr>
<th>#</th>
<th>Product</th>
<th>Author</th>
<th>Release Date</th>
<th>Customer Review</th>
<th>List Price</th>
<th>Price</th>
<th>Status</th>
<th>Add to cart</th>
<th>Add to Wish List</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>The Time Paradox (Artemis Fowl, Book 6)</td>
<td>Eoin Colfer</td>
<td>Jul 15, 2008</td>
<td>4.5</td>
<td>$47.99</td>
<td>$10.79</td>
<td>In Stock</td>
<td><img src="#" alt="Add to cart" /></td>
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<tr>
<td></td>
<td>Foul</td>
<td></td>
<td></td>
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<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>Inkdeath (Inkheart)</td>
<td>Cornelia Funke</td>
<td>Sep 26, 2008</td>
<td>4.5</td>
<td>$94.99</td>
<td>$14.99</td>
<td>In Stock</td>
<td><img src="#" alt="Add to cart" /></td>
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### Problem Formalization

#### With Rating

<table>
<thead>
<tr>
<th></th>
<th>Item-1</th>
<th>Item-2</th>
<th>Item-3</th>
<th>Item-4</th>
<th>Item-5</th>
</tr>
</thead>
<tbody>
<tr>
<td>User-1</td>
<td>4</td>
<td>?</td>
<td>2</td>
<td>5</td>
<td>?</td>
</tr>
<tr>
<td>User-2</td>
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<td>2</td>
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<td>?</td>
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<tr>
<td>User-3</td>
<td>?</td>
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<td>?</td>
<td>3</td>
<td>?</td>
</tr>
<tr>
<td>User-4</td>
<td>?</td>
<td>3</td>
<td>3</td>
<td>5</td>
<td>4</td>
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</tbody>
</table>

#### Without Rating

<table>
<thead>
<tr>
<th></th>
<th>Item-1</th>
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<th>Item-4</th>
<th>Item-5</th>
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<td>1</td>
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<td>1</td>
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</tbody>
</table>
Classification of Algorithms

Content-based Method

- Thinking In C++
- Hello world
- Java Hello world
- Sequence pattern mining
- Social network mining
- Data mining
- Web mining
- Text mining
- Text classify
- Machine learning
- NLP
- NLU
- Writing Good papers
- Search papers
- Linux
- Unix
- Windows
- Hello world
- Thinking In C++
Classification of Algorithms

Collaborative Filtering Method

User-based CF
Classification of Algorithms

Collaborative Filtering Method

Item-based CF
Hybrid Method

- implementing collaborative and content-based methods separately and combining their predictions
- incorporating some content-based characteristics into a collaborative approach
- incorporating some collaborative characteristics into a content-based approach
- constructing a general unifying model that incorporates both content-based and collaborative characteristics.
Motivation

Challenges for Mobile Recommendation

The Characteristics of Mobile Data

Two Case Studies
  • Location traces by taxi drivers
  • The tourism data
Motivation

Background

Revolution in Mobile Devices
- GPS
- WiFi
- Mobile phone

The Urgent Demand for Better Service
- Driving route suggestion
- Mobile tourist guides

Definition

Mobile Pervasive Recommendation is Promised to Provide Mobile Users Access to Personalized Recommendations Anytime, Anywhere.
Motivation

Traditional Recommender Systems don’t Work

- The complexity of spatial data and intrinsic spatio-temporal relationships
- The unclear roles of context-aware information
- The lack of user rating information
- The diversified location-sensitive recommendation tasks
Challenges for Mobile Recommendation (I)

- **Complexity of the Mobile Data**
  - Heterogeneous
    - The spatio-temporal data
  - Noisy

- **The Validation Problem**
  - No Ratings

- **The Transplantation Problem**
  - Difficult to apply traditional Recommendation techniques for mobile recommendation
Challenges for Mobile Recommendation (II)

- The Generality Problem
  - Different application domains with different recommendation techniques

- The Cost Constraints
  - Time
  - Price

- The Life Cycle Problem
Mobile Recommender Systems

The Characteristics of Mobile Data

Two Cases

- Case 1. Location trace by taxi drivers
- Case 2. The tourism data

Why?

- A good coverage of unique characteristics of mobile data
- Can be naturally exploited for developing mobile recommender systems
- They are the real-world data
The Characteristics of Mobile Data

Case 1. Location trace by taxi drivers

Data Description

- GPS traces
  - Location information (Longitude, Latitude), timestamp
  - The operation status (with or without passengers)

- Experienced drivers can usually have more driving hours and high occupancy rates
- Inexperienced drivers tend to have less driving hours and low occupancy rates
The Characteristics of Mobile Data

Case 1. Location trace by taxi drivers

Driving pattern comparison

- The experienced drivers have a wider operation area.
- The experienced drivers know the roads as well the traffic patterns better.
The Characteristics of Mobile Data

Case 1. Location trace by taxi drivers

What can we do?

• Develop a mobile recommender system
  - Users ~ Taxi drivers
  - Items ~ Potential pick-up points

What did we learn?

• The difference between Mobile RS and traditional RS
  - The items are application-dependent
  - There is some cost to extract items
  - The items are not i.i.d while spatial auto correlation

An Illustration of Pick-up Points.
The Characteristics of Mobile Data

Case 2. The tourism data

Data Description

- Expense records
  - Tourists: ID, travel time
  - Package: ID, name, landscapes, price, travel days
  - Duration: 2000–2010

Recommender System

- Users ~ Tourists
- Items ~ Packages
The Characteristics of Mobile Data

Case 2. The tourism data

Characteristics of Tourism Data (I)

- Spatial auto correlation of packages
  - For example, the 1-day Niagara Falls Tour
- The Sparseness
  - Much sparser than the Netflix data set.

A comparison of the data sparseness between the movie data and the tourism data. (a) The percentage of users/tourists whose co-rating movies/co-traveling packages with their nearest neighbors are no more than 20, (30, 40 for the movie users)/(2, 3, 4 for the tourists). (b) The percentage of users/tourists whose rated movies are more than 100, 150, 200 in all movie users/whose traveling logs are 10, 15, 20 in all tourists, respectively.
The Characteristics of Mobile Data

Case 2. The tourism data

Characteristics of Tourism Data (II)

- The time dependence
  - Packages and tourists have seasonal tendency
  - Packages have a life cycle
  - Short-period packages are more popular

The illustration of the time-dependence of the tourism data. (a) The distribution of cumulative percentages of packages/tourists by the number of their active months in a year; (b) The percentage of remaining packages in the following several years after they have been introduced; (c) The percentage of different packages and tourist logs according to their travel days.
Introduction

Research Motivation

Traditional recommender system
- Prediction performance (MSE/RMSE)
- Implicit/Explicit rating

Mobile recommender systems
- Business success metrics
- Location-based recommendation
An Energy-Efficient Mobile Recommender System

Mobile Sequential Recommendation

Problem Formalization

The MSR Problem
Given: A set of potential pick-up points \( \mathcal{C} \) with \( |\mathcal{C}| = N \), a probability set \( \mathcal{P} = \{ P(C_1), P(C_2), \ldots, P(C_N) \} \), a directed sequence set \( \mathcal{R} \) with \( |\mathcal{R}| = M \) and the current position (PoCab) of a cab driver, who needs the service.

Objective: Recommending an optimal driving route \( \mathcal{R} \) (\( \mathcal{R} \in \mathcal{R} \)). The goal is to minimize the PTD:

\[
\min_{\mathcal{R}_i \in \mathcal{R}} \mathcal{F}(PoCab, \mathcal{R}_i, \mathcal{P}_{\mathcal{R}_i}) \tag{1}
\]

\( \mathcal{P}_{\mathcal{R}_i} \): all probabilities of all pick-up points contained in

\( \text{PTD: Potential travel distance} \)
An Energy-Efficient Mobile Recommender System

Mobile Sequential Recommendation

An Example

An Illustration Example.

PoCab -> C1 -> C4 or PoCab -> C4 -> C3 -> C2?
Summary

- Definition of Recommender Systems
- Traditional Recommender Systems
- Mobile Recommender Systems
- A Case Study for Mobile RS
  ---An Energy-Efficient Mobile Recommender System
Thank you!

Yong Ge