Utilizing Marginal Net Utility for Recommendation in E-commerce

Jian Wang & Yi Zhang
Information Retrieval and Knowledge Management Lab
University of California, Santa Cruz
Recommendation based on Predicted Rating is Not Good for Consumers

- Will you like it?
  - Traditional recommender systems recommend item with the highest predicted rating

- Will you purchase it?
  - Diminishing of return
  - A rational user will purchase the product with the highest marginal net utility
Total Utility, Marginal Utility
Total Utility, Marginal Utility

Jian Wang & Yi Zhang Utilizing Marginal Net Utility for Recommendation in E-commerce
Total Utility, Marginal Utility

Jian Wang & Yi Zhang Utilizing Marginal Net Utility for Recommendation in E-commerce
Total Utility, Marginal Utility

Total Utility

Marginal Utility

Purchase Quantity

Wang & Yi Zhang Utilizing Marginal Net Utility for Recommendation in E-commerce
Marginal Net Utility

Marginal Net Utility

= Marginal Utility - Price
Making Consumers Happier

1. Model the consumer behavior based on marginal net utility

2. Make recommendations to maximize the marginal net utility for each user
Outline

• Motivation

• Algorithm
  – Basic economics: two existing utility functions studied by economists
  – Problem setting
  – Propose a new utility function tailored for recommender systems

• Experimental Results

• Conclusion
Basic Economics: Linear Utility Function

\[ U(X) = \sum_j \alpha_j x_j \]

\[ \Delta U(X,i) = U(X,i) - U(X) = \alpha_i \]

- does not capture diminishing return characteristic
- most existing algorithms are implicitly based on this utility function

| \( U(X) \) | • Total utility |
| \( X \) | • purchase history |
| \( \alpha_i \) | • product \( p_i \)'s basic utility |
| \( x_i \) | • purchase quantity of product \( p_i \) in \( X \) |
| \( \Delta U(X,i) \) | • marginal utility for the addition purchase of \( p_i \) |
Basic Economics: Cobb-Douglas Utility

\[ U(X) = \sum_j \alpha_j \log(x_j) \]

\[ \Delta U(X, i) = \alpha_i (\log(x_i + 1) - \log(x_i)) \]

- diminishing of return rate is fixed \( \log(x_i + 1) - \log(x_i) \)
- basic utility \( \alpha_i \) is not personalized

<table>
<thead>
<tr>
<th>( U(X) )</th>
<th>Total utility</th>
</tr>
</thead>
<tbody>
<tr>
<td>( X )</td>
<td>purchase history</td>
</tr>
<tr>
<td>( \alpha_i )</td>
<td>product ( p_i )’s basic utility</td>
</tr>
<tr>
<td>( x_i )</td>
<td>purchase quantity of product ( p_i ) in ( X )</td>
</tr>
<tr>
<td>( \Delta U(X,i) )</td>
<td>marginal utility for the addition purchase of ( p_i )</td>
</tr>
</tbody>
</table>
Making Consumers Happier: Recommendation based on Marginal Net Utility

- **Design**: Design the utility functional form
- **Learn**: Learn the utility function parameters from user history
- **Predict**: Predict the marginal net utility of a product for a user using the function learned and user history
- **Rank**: Rank products based on predicted marginal net utility
Problem Setting

\[ u = 1, \ldots, M \]

\[ i \text{ or } j = 1, \ldots, N \]

\[ c_i \]

day 1
day 3
day 7
day 10

Time \( t \)

Jian Wang & Yi Zhang Utilizing Marginal Net Utility for Recommendation in E-commerce
Design the Utility Functional Form

\[ \Delta U(X, i) = \alpha_i \log(x_i + 1) - \log(x_i) \]

New

\[ \Delta U_{u,t}(X, i) = \alpha_{u,t}(x_{u,i,t} + 1) - x_{u,i,t} \]

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>( U(X) )</td>
<td>• Total utility</td>
</tr>
<tr>
<td>( X )</td>
<td>• purchase history</td>
</tr>
<tr>
<td>( \alpha_i )</td>
<td>• product ( p_i )’s basic utility</td>
</tr>
<tr>
<td>( x_i )</td>
<td>• purchase quantity of product ( p_i ) in ( X )</td>
</tr>
<tr>
<td>( \Delta U(X,i) )</td>
<td>• marginal utility for the addition purchase of ( p_i )</td>
</tr>
</tbody>
</table>
Design the Utility Functional Form

\[ \Delta U_{u,t}(X, i) = \alpha_{u,i} \left( (x_{u,i,t} + 1)^{\gamma_i} - (x_{u,i,t})^{\gamma_i} \right) \]

\[ x_{u,i,t} = \sum_{j: \text{sim}(i,j) \geq \theta} C_{u,j,t} \times \text{sim}(i, j) \]

\[ \theta = 1 \quad \text{• only same product will influence the marginal utility} \]

New framework to revamp existing recommendation algorithms
Revamp Existing Algorithms

Marginal net utility

\[ \nu_{u,i,t} = f(u,i)\left[ (x_{u,i,t}+1)^{y_i} - (x_{u,i,t})^{y_i} \right] - c_i \]

Take Singular Value Decomposition (SVD) as an example

\[ P_{u,i} = q_i^T P_u \]

\[ \nu_{u,i,t} = q_i^T P_u [ (x_{u,i,t}+1)^{y_i} - (x_{u,i,t})^{y_i} ] - c_i \]
Learn the Utility Function Parameters

Maximum A Posteriori Estimation

\[(p_u, q_i, \gamma_i) = \arg \min [-\log L]\]

Joint Likelihood

\[L = \prod_u P(p_u) \prod_i P(q_i) \prod_i P(\gamma_i) \prod_{u,i,t} P(\gamma_{u,i,t} | v_{u,i,t})\]

Purchase Likelihood Conditional on the marginal net utility

\[P(purchase | v_{u,i,t}) = \frac{1}{1 + e^{-v_{u,i,t}}}\]
Outline

• Motivation
• Algorithm
• Experimental Results
• Conclusion
Experiment Dataset

- More than 5-years purchase history from – 2004-01-01 to 2009-03-08

- 10,399 users, 65,551 products, and 102,915 unique (user, product) pairs

- 80% training, 10% validation, and 10% testing
Experiment Design

• Methods to compare
  - Top Popular
  - $\text{SVD}_{\text{matrix}}$
  - $\text{SVD}_{\text{util}}$ with $\theta = 1$ same product
  - $\text{SVD}_{\text{util}}$ with $\theta = 0.7$ similar product

$$x_{u,i,t} = \sum_{j: \text{sim}(i,j) \geq \theta} C_{u,j,t} \times \text{sim}(i, j)$$

• Evaluation Metric

conversion rate@$K = 1$ \( |S_{\text{purchased}} \cap S_{K, \text{recommended}} | \neq \emptyset \)
General Analysis

The conversion rate at different values of $K$ is shown in the graph. The highest conversion rate is observed at $K = 5$, with a rate of 87.39%. The rates are compared for different methods: Top Popular, $\text{SVD}_{\text{matrix}}$, $\text{SVD}_{\text{util with } \theta = 1}$, and $\text{SVD}_{\text{util with } \theta = 0.7}$. The $y$-axis represents the conversion rate, and the $x$-axis represents the values of $K$. The graph visually demonstrates the effectiveness of utilizing marginal net utility for recommendation in e-commerce.
Further Analysis

• Consider all products
  – 13.79% repurchase
  – 90.64% new purchase

• Evaluate orders with the specific purchase type (repurchase or new purchase)
Further Analysis

• The new utility function achieves significantly better performance in both tasks

• Examples of Repurchases
  – diaper, pet food, etc.
  – Tend to be consumable products

• Examples of New purchases
  – computer, cell phone, bed frame, etc
  – Tend to be durable product
  – law of diminishing marginal utility
Outline

• Motivation
• Algorithm
• Experimental Results
• Conclusion
Conclusion

• Introduce a new framework for recommender system in e-commerce sites

• Recommend products with the highest marginal net utility

• Take SVD as an example to revamp

• Achieve significant improvement in the conversion rate
Utilizing Marginal Net Utility for Recommendation in E-commerce

Jian Wang & Yi Zhang
Information Retrieval and Knowledge Management Lab
University of California, Santa Cruz