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Mathematical Models in Marketing

**INTERNET RECOMMENDATION SYSTEMS**

**Motivation:**

A recommendation system is a type of mass customization that recommends products based on available data of the other customers’ preferences. It offers great benefits to both customers and firms. For customers, it decreases the search effort while its advantages for firms are higher customer loyalty, sales and targeted promotions.

Current recommendation systems are either based on collaborative filtering (recommendations based on the preferences of the other customers) or content filtering (recommendations based on the preference for product attributes). The former would have problem recommending a new movie while the latter would fail to make recommendations for a new customer.

Typically, there are five types of information that can be incorporated while making a recommendation:

* A person’s expressed preferences
* Preferences of other customers
* Expert judgements
* Preference for product attributes
* Individual characteristics

A good recommendation system should use all of the information and improve the accuracy of its recommendations with more data.

**Proposed Model:**

The proposed model uses

1. hierarchical Bayesian approach
2. unobserved customer heterogeneity in customer preferences
3. unobserved product heterogeneity on preferences

*The fixed effect on the observed movie j attributes, customer i characteristics and their interactions*

*Error term*

rij = xij’μ + ziγj + wjλi+ eij  ∀i=1:I, j∈Mi

*The rating of movie j by customer i*

*Product heterogeneity:*

*Customer i’s characteristics and unobserved movie j attributes*

*Customer heterogeneity:*

*Movie j’s attributes and unobserved customer i characteristics*

**Empirical study:**

Data is obtained from EachMovie database, which is a recommendation system for movies. Database contains 75000 customers and 1628 movies. Data regarding only 228 movies, 986 customers and 10,344 ratings are used.

Customers and movies can be an existing one or new. If the customer is new, we only know the demographics. In case of a new movie, we only know the genre and expert ratings. Performance of the model is measured by the predictability of the holdout data.

**Results:**

1. The model with movie and customer heterogeneity and both genre and expert attributes outperform the others. Even though the complexity is high, it provides a better fit.
2. Accounting for only customer heterogeneity gives better predictions than accounting for only movie attributes.
3. Customers differ in use of the rating scale and movies equity differs across movies in the sample.
4. Customers have different tastes of genre. There is no significant effect, but action and thriller genres seem to be preferred while horror is disliked.
5. Expert ratings have a positive effect but their degrees of effectiveness vary across customers.
6. Age affects customer ratings.
7. Movie appeal based on unobserved attributes differs across different demographic groups.
8. Perfect predictions of the model are not very strong. Usually the greatest errors are in the neighborhood of the prediction
9. The model performs better at the extreme values.
10. The chances of the model giving a bad recommendation or not giving a good recommendation are very low.
11. The model makes conservative predictions in case of less information (new movie, new customer)

**Contribution and Discussion:**

Their work is significant in the sense that they incorporated both the customer and product heterogeneity in the recommendation systems model. They also show that this model outperforms others though a series of empirical results. Its strength comes from making better recommendations for new customers and/or of new movies than collaborative and content filtering systems. Due to more accurate recommendations, customer acquisition, customer retention and increase in wallet share might be obtained.

Given this model, the next step could be devising an effective rating system. The current rating system (0-5 scale) might not be effective. It has been shown that customers differ in use of the rating scale. A generous evaluator would have ratings between 3-5 while a more critical person would use 0-4 scale and rarely award a 5. Moreover, an explanation of slightly worse performance in-between values might be due to people rating when they either love or hate the movie. In this case, a Tinder system (swipe right or left) can be more effective.

Apart from the rating system, we could study the ways to uncover the unobserved movie attributes or customer characteristics. For instance, there could be a few random explanatory questions such as “would you recommend others to see this movie by themselves, with a significant other or with family/friends?”.