2014 Russell Ackoff Doctoral Student Fellowships

The Impact of Recommender Systems on Consumers: Study of Sales Volume and Diversity

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Previous Ackoff Funded Project Update

I would like to thank the Wharton Risk Management and Decision Processes Center and Russell Ackoff fund for funding my previous research. The paper is completed and is uploaded on SSRN (ssrn.com/abstract=2290802) with full acknowledgement to Ackoff fund and the Risk Center. It's currently under review and is a working paper!

Project Description

Recommender systems (e.g., Amazon's "customers who bought this item also bought") have taken a firm place in people's daily lives, transforming the everyday shopping and web surfing experience. Consumers use recommendation systems for discovering a wide range of products including books, movies, music, electronics, and even personal items such as clothes and are becoming increasingly reliant on these algorithms. In fact, today, it is hard to find online retail or web services that do not utilize some form of recommendation algorithm, however basic. According to a 2013 study by the Accenture Interactive, 73% of consumers prefer buying from companies that use information about them to deliver a more efficient shopping experience. Furthermore, a 2013 study by Econsultancy shows that 94% of companies agree that "personalization is critical to current and future success" Essentially, recommendation system usage is growing and will continue to grow faster than ever due to the exponential growth of personal and usage data online aptly called "THE BIG DATA". *While recommender algorithms constantly guide our decisions online, not much is known about how and what types of recommenders influence us under what circumstances*. *This study aims to change that via field experiment followed by a series of lab experiments.*

Both retailers and academics are just beginning to study the impact of recommendation algorithms. The above-mentioned Econsultancy study also shows that 72% of firms agree that they "understand importance of personalization, but don't know how to do it". While the algorithms and statistical models used to operate recommender systems and filtering have flourished and have been well researched, there is a lack of studies on the actual impact of recommender systems other than on revenues and profits. In fact, the 1990s marked the rise of recommendation systems in e-commerce while in the 2000s retailers and academics studied the first order impact of the recommendation systems such as the effects on revenues and profitability (e.g., Amazon.com and Netflix). These studies have shown that recommendation systems can increase sales and firm's performance (Thompson 2008, Das et al. 2007, Lamere & Green 2008). *Now in 2010s, researchers are beginning to focus on the second order effects such as recommender systems' impact on consumer behavior and product sales concentration*, which has a big influence on competition strategies in addition to immediate operational impact such as product assortment. Both positive and negative impacts of recommenders are beginning to be studied. We dig deeper into this topic with a series of field experiments on several top retailers in the U.S. We believe that this is the first of its kind.

There are many recommendation algorithms and each has different effects. For example, The New York Times offers a list of articles that are "most emailed" and "personalized for you". Similarly, e-tailers (e-commerce retailers) often recommend most popular items in addition to many different personalized recommendations (e.g., "customers who viewed also viewed", "based on your purchase history"). A recent scientific article has shown that positive popularity information can positively bias the opinion of consumers (Muchnik et al 2013). However, what are the different effects of these popularity-based recommendations VS the personalized recommendations? How about the differences within personalized algorithms such as collaborative filtering (e.g., “customers who viewed this item also viewed”), content-based, recently viewed, etc.? In addition, which of these algorithms work best to influence consumers, for what products, and why? There is a severe lack of academic and industry-level analysis papers in this topic.

This topic is now even more relevant since critics of the recommendation system have emerged, arguing that recommendation systems may be harmful. Most notably, Pariser has argued that various forms of personalization algorithms such as search engine filtering and retail recommendation systems, restrict consumers’ choice set and significantly affect consumers’ consumption patterns. Specifically, he argues that recommendation systems can fragment and confine each consumer into a “filter bubble”, or an invisible, personal universe of information, which limits commonality in consumption. Furthermore, critics have argued that these recommendation systems and filtering algorithms are harmful for society when applied to news, political information, and sharing of general ideas. However, this may not be true when applied to e-tailers. In fact, e-tailers may want either outcome (increasing commonality or decreasing commonality of purchased products) under different circumstances. In contrast to offline stores, online stores have a lower cost of stock management and can benefit from selling niche items (Anderson 2006, Brynjolfsson et al. 2006). In this case, limiting the commonality in consumption is not an issue. In other cases, e-tailers may want to get rid of certain stock where commonality in purchases is indeed the goal. Therefore, the study of how and what recommenders influence consumers is an important question with social impact (e.g., how we consume information as a society due to news recommenders) in addition to implications for business.

In essence, different recommendation algorithms are required for different circumstances and we propose studies to equip retailers and any web service providers with the right insights to utilize recommendation systems aptly. In particular, we propose a series of studies to deepen our understanding of how different recommendation system algorithms affect retailers in the following sense (and more):

1. Consumer Purchase Behavior
    a. Average Wallet Size (will some recommendation algorithm cause more purchase?)
    b. Filter Bubble Investigation: fragmentation or cross-over of categories (e.g., will comedy movie buyer start buying action genre due to recommendation systems?)
    c. What recommender works in what circumstances? Are there any moderators that moderate consumers’ susceptibility to recommenders?
2. Firm Sales Concentration
    a. Gini coefficient of products sold by genre or categories (will the best-sellers become more popular or will niche items flourish?)
3. How are these effects moderated by industry or product?

I already have field experiment data from 4 companies including a top 2 retailers in the North American region. Data analysis is in progress and AMT lab experiments need to be run.

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Current Budget and Request

Other budget from department: I’ve already spent all department travel budgets ($800) and previous ackoff funds for research and conference overseas.

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Cost
The only cost will be from utilizing Amazon Mechanical Turk to post process data and to run lab experiments on.

Using AMT for data processing:
Specifically, we need to categorize product ids to pre-defined categories according to context.
For example, one unit of study will only involve movies (dvd and Blu-ray purchases) on Company 1. We have the product IDs but not the movie names or genres – these need to be manually obtained per product ID. Other series of studies will involve different product categories in Company 1 site and another unit of study will involve clothing categories for the company 2 data. And so on. Turkers will search for given product ID on Google, find the product, and then categorize based on context we specify.

Unique # of Products to be Processed

Company 1: 14863	Company 2: 25945	Company 3: 9678	Company 4: 1039

We have a total of 51525 items to tag. We need to get inputs from at least 3 Turkers to ensure the robustness even for this simple task. Based on pilot study, it takes the Turkers about 2-3 minutes on average. Standard AMT wage is at least $1 per hour and so I need to pay at least 4 cents per tags.

0.044 (including 10% AMT fee) * 3 (3 turkers per item) * 51525 = $6801.3

Using AMT to run lab experiments:
I will be running several AMT experiments to see how different recommender signals may influence users. This will be a survey format probably taking around 5-10 minutes to complete. I expect about $2000 for testing 5-7 different recommenders on 10-15 products and getting at least 30 inputs for each recommender x product combination.

I'll be on a job market starting on Sept 2014:
I absolutely need to travel to at least 2 conferences this year to present this research and since I'll be on the job market, 1 is required for recruitment interview. I am requesting budget for only 1 conference. The biggest and required (for job market) conference for my field (ICIS -International Conference on Information Systems) will be in New Zealand in 2015 Dec and the round trip ticket during Dec runs around ~$2000. Including hotel (~$700) and registration fees (more than $700), I need at least $3000 for travel.

Total Budget Request for Research and Travel
$6801.30 (AMT data processing) + $2000 (AMT experiment) + $3000 (required conference) = Total: $11801
So I am requesting the maximum allowed fund of $4000. More if possible.

If possible – fifth year funding
In addition, I need 5th year funding and am actively searching for funding sources. I was told that I need to find at least $18,000 for the fifth year. Any support for this funding would be appreciated and will be used for my dissertation – If funded (any amount), Risk Center will be acknowledged in all my research (3 distinct topics on consumer behavior in retail). My dissertation will be on the impact of recommendation systems on consumer behavior and social/mobile advertising.

Update on Previously Funded Project

I would like to thank the Risk Center and the Ackoff Fund for supporting and selecting my previous research. The Ackoff funding was instrumental for my project "The Effect of Advertising Content on Consumer Engagement: Evidence from Facebook." Although, the project went a little bit over the budget, we successfully finished the paper and currently a working paper**. Full paper can be downloaded at SSRN http://ssrn.com/abstract=2290802. It includes full acknowledgement for the Risk Center and the Ackoff Fund! This paper has been now presented at *4 conferences* (International Symposium of Information Systems, Statistical Challenges in E-commerce conference, International Conference of Information Systems, and Mack institute conference) as well as at *4 universities* (presented by my advisor Professor Kartik Hosanagar at CMU, Michigan, UC Davis, UT-Austin).**

About 1500 dollars were used for traveling to the biggest conference in information systems management at Italy in Dec 2013. Rest was used for Amazon Mechanical Turk prepaid credit to collect data on my large-scale text data.

Thank you and I look forward to producing excellent research papers in this topic I proposed above!