Real-time Consumer preference based Recommendation to reduce Choice Overload and Decision Fatigue

Isha Gupta
Columbia University
414 W 121 Street
Apt No. 64
(646) 201 8804
isha.gupta@columbia.edu

1. INTRODUCTION

In this era of rapid globalization and advancement, human beings are inundated with the need to make decisions every day. Right from deciding breakfast meal, mails to send, people to meet, social media platform to use, restaurant to dine, the dish to eat – to – partner to marry, companies to invest in, career to pursue – thousands of decisions have to be taken. As per a study [5], humans beings make 35000 decisions in a day, on average. It turns out that the quality of our decisions begins to erode during the course of a typical day, as our fixed amount of willpower is used up. This causes decision fatigue due to choice overload, depleting the brain's energy and decision's productivity [2]. As per a study [1], the online shopping cart abandonment rate is 74.58%, as of 1st quarter 2018. Beyond eCommerce, it is applicable to almost every industry such as media entertainment, career decisions, life decisions and so on. This paper proposes a solution to this problem through a recommendation engine that uses session-based sequential sampling and comparison based ranking to provide lesser but closer and better alternatives to choose from.

2. PROBLEM AND MOTIVATION

Existing recommendation engines are based on two major assumptions that – 1) Users tend to like similar kinds of products and 2) Similar users tend to stay similar. However, with the glut of information, a consumer is exposed to every day, her/his preferences can change drastically within a short period as short as weeks or even days. Also, recommendation engines showing filtered but the vast volume of likable products causes decision fatigue due to choice overload which sometimes even deter customers from completing the transaction [2].

This paper merges the sequential session-based recommendation with comparison based ranking to deal with choice overload rather than rating based ranking. Overchoice usually leads to unhappiness, decision fatigue, going with default option or choice deferral. While all affect the quality and efficacy of life of the decision-maker, the latter affects the eCommerce companies the most, despite creating and bettering recommendation algorithms. This paper, hence, goes beyond the conventional rating based ranking as the rating is likely to be less reliable, more prone to change within and among individuals and relative in nature. Performing comparison based ranking by sampling the dataset sequentially and asking the customer to choose between 'just' 2 variants of a product in a sequential manner is hypothesized to produce stronger and better recommendation rankings. The 'further' filtering that the human brain has to do while choosing among the recommended products, will now be done by the algorithm – making purchases less fatiguing, faster, more frequent and more productive. Choose one among two is far easier and simpler than choosing one among thirty products. Producing these 2 choices sequentially from sequential sampling as per the choices made before will recommend less and better.

3. RELATED WORK

Despite various researches in the areas of session-based & session-aware recommender systems using Cosine similarity, Recurrent Neural Networks or Reinforcement Learning, none of these truly account for customers' rapidly changing preferences and hence the current ones along with reducing the recommendations with more confidence.

4. APPROACH AND UNIQUENESS

This paper works on adding comparison based ranking on top of sequential session-based algorithms and after modifying, evaluates the most relevant of these models in the domains of Music, Ecommerce and Career decision proving significant improvement.

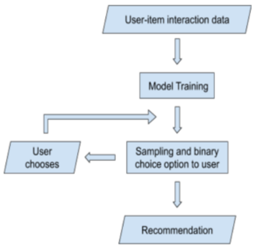

Figure 1 Flowchart to showcase novelty introduced

Rating based ranking is quite prominent, however, there is no comparison based ranking. No, the current recommendation engine incorporates the user's real-time preference and hence, ignoring the possibility that the user might change his/her type of preferences, which is in fact quite common. Furthermore, producing lesser and more confident recommendations, in the end, to make decision making faster for the end consumer.

Comparison based ranking is better than the rating based ranking in 4 ways:

- Ignores flawed assumption of conventional (rating-based) recommendation engines that users' preferences, similarity won't change and user is not a first time visitor
- Comparison is more reliable and absolute than rating which is relative in nature
- Incorporates user's latest preferences in easy binary choice format – which is easiest kind of choice for human beings
- Huge time-saving for user/consumer and higher conversion rates for online sellers/retailers

Domains and models

Music: 210000 latest songs were scraped from Spotify API to build real-time mood based music recommendation. A song was featured on 2 kind of attributes – technical (loudness, tempo, energy, valence etc) and psychological (sentiments and emotional). Former were obtained from Spotify and latter were determined by applying sentiment analysis to the scraped lyrics from web. The more similar any 2 songs are, the more likely they are to be forming same impression for person. Since, perceived similarity maay differ from person to person due to varying tastes and past listening experience, taking user's current mood and preference into account, recommends in a personalized fashion. Two similarity metrics were compared -K-nearest neighbours and cosine similarity - to be used on top *n* most frequent and recent songs from user's play history. At any given time of the day, user is first asked to choose one song among two least similar songs from the set and then sequentially sample dataset into half with songs closest to the choice selected. At the end, giving user 5-8 songs most relevant to her/his current mood. It was tested with students in Columbia University and feedback was recorded.

E-Commerce: RSC15 – E-Commerce dataset is used from the ACM RecSys 2015 Challenge which was also used by [8]. User sessions were modeled using *RNN (Recurrent Neural Network) with Gated Recurrent Units* to predict conditional probability of next items given a set of items in the current session. Presently, network architecture, loss function and parallel mini batches of sessions are used to evaluate and compare.

Career: Data is being collected in Columbia University through surveys on students' careers, past experience and personalities to recommend 'next career move' – be it the most relevant job, higher studies or a new MOOC to upskill as per the person's career interests.

Figure 2 (Only 13% masters students at Columbia are sure of their career interests)

Session-based Matrix Factorization [4] is to be used by hyper tuning the optimal time window to be used as session and then student features, personalities, skillset and preferences as the items. In the end recommend mentors, courses and jobs/internships on the basis of output. As it deals with the cold-start problem, this algorithm would be able to recommend a new student as well. Items predicted will be transformed into relevant mentorship, MOOCs, job/internship posting, etc and a score will be generated for a session when a candidate is browsing based on the weighted sum of session preferences and sequential dynamics.

We wish to solicit constructive feedback on this idea from experts at GHC 2020. As per our hypothesis, it should work due to the following reasons:

1) **Time and energy-saving :** With the glut of information all around and choice overload, human brains tend to get confused to take a decision. It aids, speeds up and improves decision making in choosing – which song to listen, which item to buy or how to grow in career
2) **Latest preferences accounted :** For excessive exposure to social media, celebrities' comments, news, online connectivity – consumers' preferences change at a rapid pace. This method makes a recommendation on the basis of the user's latest interests.
3) **Better Recommendations :** Despite serving the 2 most important reasons above, sequential session-based recommendation algorithms are shown to

be better. Adding another layer of asking user - comparisons rather than baselining on ratings will incorporate both personalization as well as artificial intelligence.

5. ANALYSIS AND RESULTS

Mood based Music Recommender:

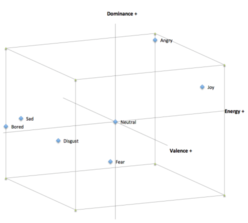

Figure 3 Music mood and emotions dimensions

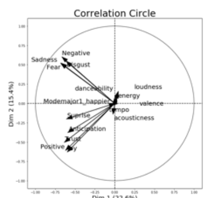

Figure 4 Correlation circle of song features

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Enter how many most frequent songs listened by users we should pick?90
 90
How many steps closer to your mood? (How many comparisons, max 3-4?) 3
 3
How many closest recommendations, you think we should offer?6
(90, 18)
Chose among songs:   Selah   &   Bad Bad Bad .
Which one do you feel like listening?
 Sela

You most likely feel like listening:
0                 Enemies
1         Beautiful People
2                   Lover
3                  On God
4                Somebody
5                 ROXANNE
6           Nice To Meet Ya
7                Graveyard
8                   Selah
9      HIGHEST IN THE ROOM
10             The London
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Recommended product list-length analysis for efficient online shopping:

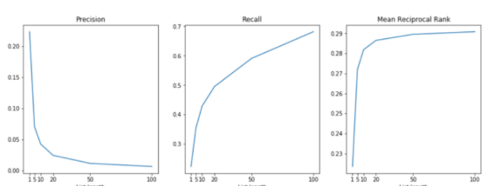

Figure 5 Precision, Recall and Mean Reciprocal Rank v/s length of recommendation list

Table 1. Precision, Recall and MRR for different Recommendation list

Length of list	Precision	Recall	Mean Reciprocal Rank
1	0.224	0.224	0.224
5	0.071	0.355	0.071
10	0.043	0.429	0.043
20	0.025	0.495	0.025
50	0.012	0.591	0.012
100	0.007	0.682	0.007

Session-based matrix factorization for career growth recommender:

The data for this algorithm is being collected from the masters' students in Columbia and the alumni to capture their personalities, past skillset, and preferences through this form https://zerotonext.typeform.com/to/kIh5JR. The platform in real-time based on a person's choices – will recommend the top 2-3 MOOCs, most relevant job openings, and closest matching mentors for mentorship. The algorithm was tested on dummy data created but the real test will be obtained only on survey data collected. This is the major part of the poster, I will be honored to be seeking valuable guidance and suggestions from the experts at GHC to make it a true career enabler.

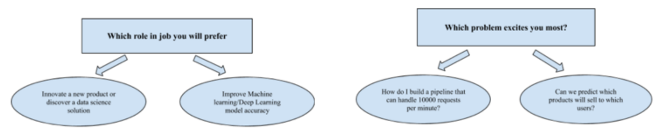

Figure 5 Intuitive comparison-questions for better candidate understanding and recommendation

6. REFERENCES

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