

Dibyamshu Shrestha, Hemanya Tyagi, Mohinder Pal Goyal, Robin Jindal, Matthew A. Lanham
 Purdue University Krannert School of Management
 dshresth@purdue.edu; tyagih@purdue.edu; goyal62@purdue.edu; rjindal@purdue.edu; lanhamm@purdue.edu

ABSTRACT

This study provides frameworks to incorporate real-time search data into a resort recommendation system for a timeshare exchange company. Previous models leveraged the search data up to the last day to provide recommendations to the user. However, this approach doesn't work out well as it does not account for the current context. We developed two models to leverage real-time search data for recommendations and significantly improved bookings and henceforth revenue.

INTRODUCTION

Real-Time personalized recommendations in today's world :

#1 Driver of consumer purchase decisions
35% Customer Purchases on Amazon
\$1 Billion Per year cost saving for Netflix
44% Travel bookings on TripAdvisor

Cost of Deploying Recommendation System << Profit from Recommendation System = ROI

Having a robust, relevant, and diverse recommendation system leads to cost savings and enriched customer experiences. Thus, incorporating the current user context becomes crucial to provide accurate and appropriate recommendations.

RESEARCH QUESTIONS

- How to convert search activity into features and incorporate this info into learning algorithm and produce recommendations within 5 seconds?
- How much does incorporating the search activity improve the recommendation system compared to baseline?

LITERATURE REVIEW

| Author, Year | Collaborative Filtering | Cosine Similarity | Rankboost Algorithm | Neural Network | Gradient Boosting | Latent Factor |
|-----------------|-------------------------|-------------------|---------------------|----------------|-------------------|---------------|
| Our study, 2020 | ✓ | ✓ | | | | |
| Y Zhou, 2017 | ✓ | | | ✓ | | |
| M Arruza, 2016 | | ✓ | | | ✓ | |
| G Huming, 2010 | ✓ | | ✓ | | | |
| Y Hu, 2008 | ✓ | | | | | ✓ |

Table 1: Literature review summary by method used

After discussing and evaluating various modeling approached, we went ahead with Collaborative Filtering & Cosine Similarity as it suited our field.

METHODOLOGY

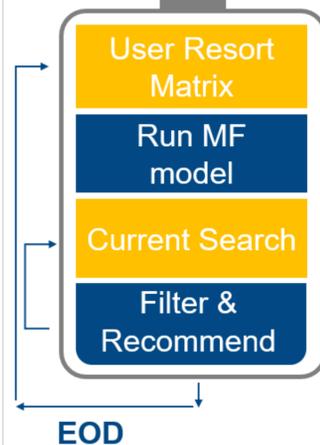
The data used for this study was provided by the company. In this dataset we have details of around 2.5 Million members, confirmation data of past 5 years, search data of past 1 year and 350 amenities details of 4345 resorts.

MATRIX FACTORIZATION

$$\text{Weight Factor} = (\text{Surge Factor}) * \left\{ \frac{x}{y} \right\} * \frac{(a^x - a^{-x})}{(a^x + a^{-x})}$$

Equation 1: Update Factor for MF model

- x is Current Search Count
- y is Average Search Count
- $SF_{\text{Booking}} > SF_{\text{Recent Search}} > SF_{\text{Past Search}}$
- $a_{\text{Resort Search}} > a_{\text{City Search}} > a_{\text{Region Search}}$



EOD

Figure 1: Process Flow of MF model

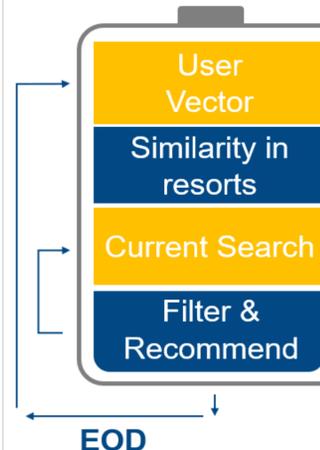


Figure 2: Recommendation Distribution of MF model

3 BUSINESS FACTORS

- More granular search has more weightage
- More recent search has more weightage
- Bookings have more weightage than search

COSINE SIMILARITY



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Figure 3: Process Flow of CS model

| FACTOR | COEFFICIENT | SIGNIFICANCE |
|-----------------------|---------------------|--------------------|
| Popularity Factor | 1 | Cold-Start Problem |
| Cosine Similarity | # of bookings | Similar Resorts |
| Search Factor | # of past searches | Decay Factor |
| Current Search Factor | # of searches today | Recency Effect |

Table 2: Update Factor for CS model

Based on cosine score which is the sum product of mentioned factors, top 8 resorts in the current search's region are recommended to the user.

RESULTS

| | Matrix Factorization | Cosine Similarity |
|-----------------|--|---|
| 1. ACCURACY | 50% of the times resorts booked were recommended within 17 days | 60% of the times resorts booked were recommended within 17 days |
| 2. AVG RUN TIME | 1.5 seconds | 1.13 seconds |
| 3. PROS | <ul style="list-style-type: none"> • Diversification • Works well with sparse data | <ul style="list-style-type: none"> • User-Amenities relationships • Quick Results |
| 4. CONS | Time consuming | Not good for sparse data |

Although Cosine Similarity is more accurate and fast we recommended our industry partner Matrix Factorization because of diverse recommendations. The problem of time consuming nature can be resolved by deploying parallel processing and GPUs.

20%* Expected increase in bookings in 1st year
+5% # of customers due to synergy effect
> \$24 M Expected increase in revenue in 1st year

* : Based on an online survey of 136 people

CONCLUSIONS

- The recommendation system significantly improves the bookings and expectedly would increase click-through rate
- Educates resorts about amenities which specific customers are targeting.
- Solved the cold-start problem by offering recommendations based on most popular resorts in the area.
- Our method is an AI-based model, and its accuracy will increase with time as the model would learn more with increasing amount of data

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