



Tailored Recommender Systems With Implicit Feedback
An Assessment of Analytical Needs

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Executive Summary

G-MM Trgovina is a company that sells construction tools, currently most of its operation is in Slovenia and east Europe, with an annual revenue of more than 6 million euros since 2017 2. In order to expand the business, the top management of the company intends to increase its profit margin through a better sales procedure using automated recommendation through sales representatives using an internal order management system. Therefore, the company contacted us and asked for our help in order to elaborate a data model that recommends products to clients and thus optimizing their operations.

Performing the initial investigation of the data, we realized that the company's customers have a very high churn rate 3, on average the customer turnover changes in 60% already in the second month, causing a great effort of the sales team to acquire new accounts. Furthermore, we could notice that even though the company has more than 15 thousand products available, only 100 products represent 50 percent of all the company's revenue 4, this type of dynamic creates difficulties for the company especially in the optimization of their operational cost and simplification of the sales operations.

With the definition of the problem, we designed a product recommendation system to help the sales team on suggesting products that are of interest to their customers 1, using two tools. The first being the recommender system where it is analyzed at the SKU level using a hybrid system containing a content based and collaborative filtering approach, and secondly a system of association rules by product category to facilitate the choice of complementary items.

The result of the recommender systems model was promising, following the metrics evaluation criteria we achieved an accuracy of 80% and a recall of 50% in our model, this means that 80% of the recommended products were relevant to the user (i.e. consumed by the client) and that 50% of them are products that were already part of the client's top 10 items. Overall the results were very good as it aligns with the customer's buying profile and additionally helps the salesperson to increase product diversity for each account, moreover with the results presented we created a mock-up design to implement the functionality 1.

To achieve these results, we used the ensemble method in the hybrid recommender system, which compiles many results generating the best output possible 2

| Model | R2 | MAE | RSME | Precision@10 | Recall@10 | F1@10 |
|-------|------|------|-------|--------------|-----------|-------|
| 1 | 0.50 | 6.65 | 10.66 | 0.81 | 0.50 | 0.60 |

Table 1: Recommender System Results

As the next steps for the implementation of the project and respecting the objectives defined by the company, we decided that for each recommendation generated by the recommender system and the association of rules we will enhance the result from the following steps: 1) Retrain the association rules model monthly, separate 3 subsets of products containing, products bought in the last months, products not bought in the last months and strategic products to the profit of G-MM. With this methodology, we can increase the diversity of products sold, facilitate the recommended products for the salesperson and provide items that are of interest to the end customer.

As the last recommendation to improve the model, more detail on categories is needed to understand hidden buying relationships, more detail on product descriptions to use other data (size, color, model, etc...), and finally data on products on sale to recommending to customers.

Appendix



Figure 1: Mock-up for implementation

| Recommender | Model 1 | Model 2 | Model 3 |
|-------------------------|--------------|---------------|--------------|
| Collaborative filtering | KNNWithMeans | Co-Clustering | SVD |
| Content-based | Lasso | Random Forest | MLPRegressor |

Table 2: Recommender System Models

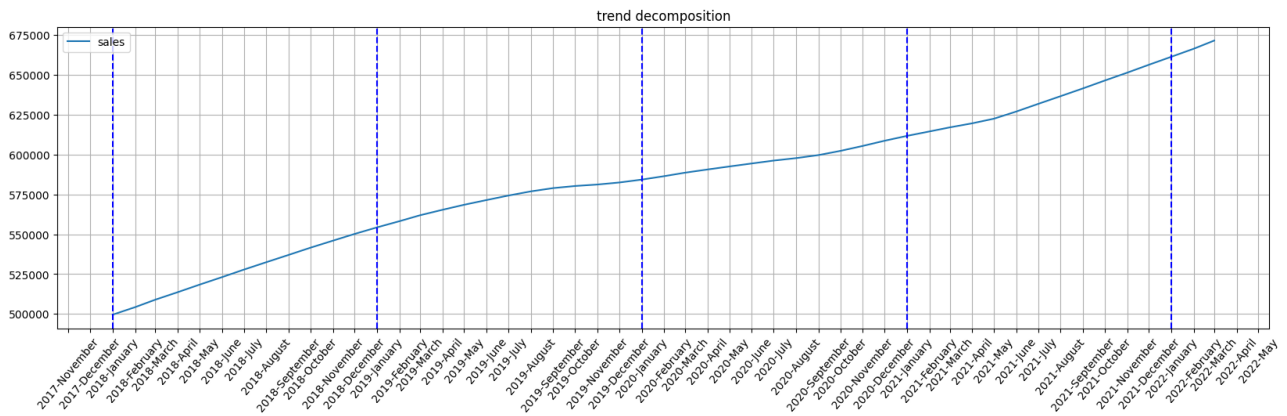


Figure 2: Annual Turnover Decomposition

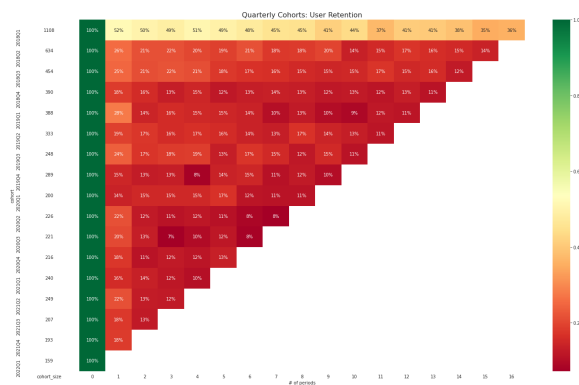


Figure 3: Churn Analysis

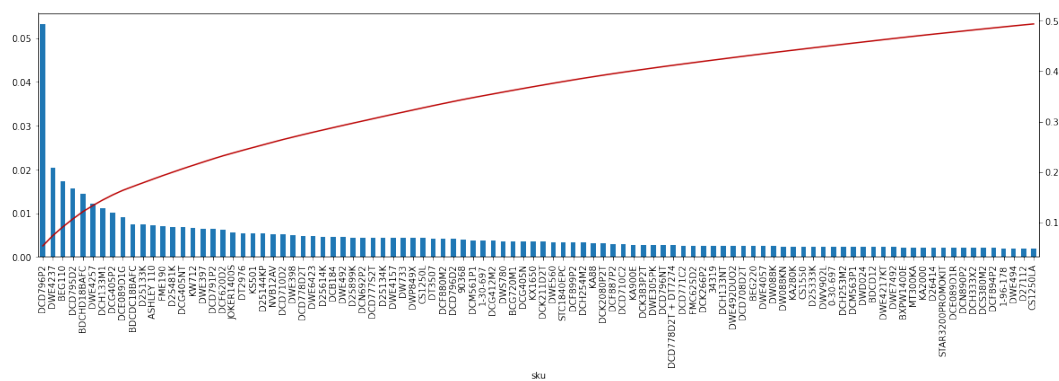


Figure 4: Pareto Analysis