****

**Implementing and Testing a Machine Learning Recommender System :**

Using Machine Learning to Enhance Customer Engagement in Banking

**By: ELETHU MOLOSE**

**SIYABONGA KHULONG MASHILWANE**

**MODUPI HOPE DLAMINI**

**BENNEDICT MKHONTO**

**30 MAY 2025**

**FNB DataQuest**

**Table of Content**

1.Abstract ......................................................................... 1

2.Table of content ............................................................. 2

3. Abstract …………………………………………………….3

4.Introduction…………………………………………………3

5.Live Testing of the LightFM Model (Content-Based Filtering) .... 4  
  3.1 Objective ............................................................................. 4  
  3.2 Setup ................................................................................... 4  
  3.3 Live Testing Procedure ........................................................ 4  
   3.3.1 Real-Time Input Simulation ........................................... 4  
   3.3.2 Dynamic Interaction Matrix Update ............................... 5  
   3.3.3 Generating Recommendations ..................................... 5  
   3.3.4 Evaluation ..................................................................... 5  
  3.4 Deployment Considerations ...........................................…..5  
  3.5 Example Use Case ............................................................. 5

6.Implementation Plan in Real Life ................................... 6

7.Improvement on User Engagement ............................... 7

8.Conclusion ....................................................................7

**Abstract**

In today’s highly competitive digital marketplace, delivering personalized customer experiences is crucial for driving engagement, satisfaction, and long-term loyalty. This project aims to develop a recommender system that can effectively prioritize and rank personalized offers tailored to individual customer needs, as inferred from a wide range of contextual data points such as browsing behaviour, purchase history, time of interaction, and demographic attributes. The primary question guiding this work is: Which recommender system approach can most effectively recommend relevant and personalized offers for individual customers based on the given dataset, and how efficient is it for both the customer and the business? Through systematic experimentation and evaluation, the project will explore multiple modelling approaches to determine the most suitable technique for generating high-quality, context-aware recommendations. The goal is to enhance customer satisfaction while simultaneously driving business outcomes such as increased conversions and improved customer retention.

**Introduction**

In today’s banking world, personalization isn’t just a buzzword, it’s the ticket to real customer engagement and solid business growth. Banks like FNB are all-in on machine learning, aiming to make their services smarter and more relevant. Recommender systems are at the heart of this shift. These tools sift through customer data to predict and suggest products that actually fit each person’s needs and habits. It’s about smarter offers, happier customers, and, not to sugarcoat it, better business results.

By delivering personalized product offers, this system aims to increase customer conversion rates by providing timely and relevant suggestions, ultimately boosting revenue and improving customer retention for FNB. In a rapidly evolving digital banking environment, personalization offers a key competitive advantage by enhancing customer loyalty and satisfaction. This report zeroes in on building a recommendation system tailored for FNB. We cover the full process: data wrangling, feature selection, model training, and a deep dive into performance. It's not just about getting the correct solution but also whether it delivers real value. We also examine practical deployment issues: can the system scale up, is it compliant with regulations, and does it deliver a smooth user experience? All things considered, the goal is a solution that’s ready for real-world action.

Of course, there are limits. The available data set isn’t perfect, there’s no live user interaction to learn from, and this system isn’t plugged into FNB’s actual operations yet. Even so, the findings here offer a solid foundation for any financial institution looking to up their digital game and keep pace with fast-changing customer expectations. In short: innovate or risk falling behind.

**Body**

**Live Testing of the LightFM Model (Content-Based Filtering)**

1. Objective

The goal of live testing is to evaluate the trained LightFM model's effectiveness in recommending relevant items to users in a production-like environment. This includes testing with unseen user-item interactions and ensuring the system can dynamically provide recommendations based on user behavior such as clicks or checkouts.

2. Setup

- Trained Model: A LightFM model trained using WARP loss on historical user interactions (CLICK and CHECKOUT).  
 - Input Features: User IDs and item IDs encoded as integers, with interactions mapped to weights (CLICK = 1, CHECKOUT = 2).  
 - Evaluation Metric: Precision@K (e.g., k=5) to measure the proportion of relevant items among the top K recommended.

3. Live Testing Procedure

a. Real-Time Input Simulation

Simulate or capture real-time user behavior such as:  
 - A new session where a user clicks on an item  
 - A user completes a checkout  
 - A user browses multiple products  
  
 These actions are logged and transformed into the same format as training data.

b. Dynamic Interaction Matrix Update

Update the interaction matrix with new real-time interactions. Note that LightFM models do not support true online training; for live updates, the model needs to be retrained periodically or warmed up with new data.

c. Generating Recommendations

Use the trained model to generate top-N item recommendations for a specific user based on the current state of interactions. These recommendations reflect the most relevant items given the user's recent behavior.

d. Evaluation

Compare the recommended items with the user's actual next action to calculate key performance metrics:

- Precision@K

- Recall@K  
  
  
 These metrics can be logged or visualized in dashboards for ongoing monitoring and performance tracking.

4. Deployment Considerations

- Cold Start: For new users/items, leverage metadata or content-based features to generate initial recommendations.  
 - Retraining Schedule: Periodically update the model (e.g., daily or weekly) to incorporate the latest data.  
 - Latency: Precompute and cache recommendations for active users to ensure fast response times.

5. Example Use Case

A user logs in and clicks on a product. The system logs this interaction and updates the interaction matrix. The model uses the updated data to generate top 5 product recommendations, which are displayed on the homepage. These recommendations are monitored to assess whether the user engages with them by clicking or checking out.

**Implementation Plan in real life**

The implementation of the recommender system centres around improving the digital product experience by personalizing content for each user. It works by picking up on patterns in how users interact with the platform and then recommending products that they are more likely to find useful or interesting. This kind of personalization not only helps users find what they need faster but also keeps them more engaged and likely to return.

In terms of how this would work in a real business setting, the system could be rolled out in stages. For example, we could start with users who are already very active on the platform and test how well the recommendations perform. Based on that, the system could later be adapted for newer or less active users. The recommendations could be shown in the app or website by changing what products are shown first, or through smart notifications. This kind of step-by-step rollout also makes it easier to track progress and improve the system over time.

Overall, this recommender system has the potential to support different parts of a business, like marketing and product design. It can help improve user satisfaction, encourage more people to interact with products, and even help the company target users more effectively. With a few more steps, this system could be a great tool for making digital platforms more responsive and user friendly.

In conclusion, this recommender system offers a practical and scalable solution for enhancing digital user experiences in a real-world business environment. By combining personalization with smart rollout strategies, it has the potential to create lasting value for both users and the company. With continued refinement and monitoring, it can grow into a key part of a data-driven product strategy.

**Improvement on User Engagement**

Bringing a recommender system into FNB’s digital platforms isn’t just a tech upgrade, it's a strategic move that could seriously boost customer engagement. Instead of the usual random approach, customers would see offers and services actually tailored to how they bank, what they spend on, and what they need next. It’s smarter, more focused, and, honestly, just more helpful. The platform would analyze through transaction history, personal preferences, and then serve up financial products that actually make sense for each user. No more analyzing through irrelevant offers just targeted recommendations that save everyone time and drive real value.

Plus, as customers interact more (and the system keeps learning), recommendations get sharper and more on-point. That not only makes the experience smoother but also strengthens the relationship between customers and the bank. Over time, this sort of personalization can keep people coming back, boosting loyalty and repeat business. It’s a win-win situation where customers feel understood, and FNB gets more meaningful engagement.

**Conclusion** Building this recommender system has shown how machine learning can be used to improve how customers interact with digital platforms. The system looks at user behaviour and uses that information to suggest products that are more relevant to everyone. This kind of personalization means users don’t have to scroll through irrelevant options; they get recommendations that make sense for them. In the long run, this can make the platform feel more user-friendly and useful.

If this system were to be rolled out in the real world, it could start with active users to test how well it works, and then slowly be expanded to other groups like new or semi-active users. These recommendations could appear on different screens of the app or through smart notifications, depending on how users interact. Over time, as the system gets more data, the recommendations would also get better and more accurate. This would help make the experience smoother for users while also helping the business grow.

From a business point of view, this system could support areas like marketing and product strategy. It gives teams better ways to reach the right customers with the right products, without having to guess. It also helps FNB get more value from the data they already have by turning it into insights that are easy to act on. That could lead to better campaigns, more satisfied customers, and stronger loyalty over time.

To sum it all up, this recommender system shows how smart tech can improve both customer experience and business results. It’s flexible enough to grow with the platform and strong enough to make a real difference. While there’s still room to improve and expand, the work done here provides a solid foundation that could be taken even further in a live environment.