Enabling Machine Learning Prediction of Consumer Stalling in Checkout Process

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ABSTRACT

At the eCommerce company I interned for in 2022, customers would sometimes stall at certain points in the process of checking out. The solution my team proposed was to develop a machine learning model to predict how likely a customer is to stall at a phase of the checkout process. My role in this project was to develop the microservice, or backend architecture, that links the frontend to the customer stalling ML model. I used the framework Flask and the language Python in order to develop the microservice. In the development of this project, I implemented the following mechanisms: processing of the front-end request, API calls to retrieve relevant data, feature engineering of retrieved data into model input form, an API call to the ML model, and processing prediction output data for delivery to the front-end. Essentially, my work transformed the prediction data into a readable format for the front-end and returned the prediction to the front-end for use. Upon completion of my project and internship, my team integrated the microservice I developed into the checkout process nudging system. In follow up with this project, the microservice could be improved to be able to handle large volumes of front-end requests or work in faster time as it is meant to deliver predictive analytics in real-time.

1. INTRODUCTION

In eCommerce, the issue of customers abandoning the checkout process presents a difficult obstacle for maximizing conversion rates. Conversion rates in eCommerce are a crucial metric for businesses that reflects the effectiveness of their online platforms in turning visitors into customers. However, the persistent issue of customer stalling during the checkout process poses a significant challenge to optimizing a company's conversion rates. When customers abandon their carts or hesitate at certain stages of the purchasing process, it directly impacts the overall conversion rate, hampering revenue potential. Understanding and addressing the factors that contribute to customer stalling are important in enhancing conversion rates and maximizing the value of a company's online presence.

The eCommerce company I interned with struggled with regular customer abandonment of the checkout process. Reducing checkout abandonment requires a comprehensive understanding of the factors that may indicate that a customer may stall. This need highlights the value of predictive analytics solutions to preemptively identify and address potential points of friction. Leveraging machine learning models offers an avenue for achieving this goal by gathering vast data to discern patterns indicative of stalling behavior. By predicting the likelihood of such occurrences at different stages of checkout, the eCommerce company can strategically intervene to mitigate abandonment and augment purchases.

2. RELATED WORKS

The integration of machine learning models and predictive analytics has become instrumental in predicting and mitigating customer abandonment during the checkout process. Research published in the 2022 Conference on Computer Science and Intelligence Systems leveraged advanced algorithms to forecast the likelihood of a customer proceeding to checkout based on their browsing behavior and engagement patterns. This robust machine learning (ML) model "helped online merchants in business growth and effective stock management" (Rifat, et. al, 2022). This ML model not only provided real-time insights into potential checkout abandonment, but also offers merchants an opportunity to encourage customers to complete checkout. With these predictions, online retailers can tailor their strategies to mitigate abandonment rates. By proactively predicting customer stalling, businesses can enhance conversion rates, bolster sales, and foster growth in a competitive eCommerce landscape.

The implementation of these predictive models enables companies to identify when a customer is likely to stall and enact tailored strategies to re-engage and convert them into paying customers. Through personalized interventions such as individual chat pop-ups, exclusive coupons, or time-sensitive discounts, businesses can dynamically respond to customer hesitations during the checkout process (Casteel, 2021). This is the strategy my team undertook to manage consumer checkout abandonment. By strategically deploying personalized tactics such as nudges, a company may alleviate immediate abandonment issues and foster customer relationships. Furthermore, intervening in real-time enables an eCommerce to ensure maximum effectiveness in capturing potential sales opportunities. As a result, using machine learning and predictive analytics in eCommerce not only improves conversion rates but also creates a more seamless consumer shopping experience, which in turn leads to business profitability.

3. PROJECT DESIGN

In the project design phase, the goal was to address checkout process stalling by developing a microservice to integrate predictive analytics in the checkout process. My role was to create a microservice facilitating coordination between the frontend and the ML model.

3.1 Requirements

At my eCommerce company, a persistent issue involved customers stalling at certain points in the check-out process. The solution my team proposed was to develop a machine learning model to predict how likely a customer is to stall at a phase of the checkout process. This customer stalling prediction integration adds onto the company's existing online purchasing process. The frontend team responsible for checkout will use this prediction to deliver a personalized nudge to the customer, urging them to perform certain actions depending on what phase they are likely to stall at. For example, if the ML model predicts that the customer will pause at the "Finances" stage in the process, the user interface will prompt the user to ensure that the selected vehicle meets their budget.

In a more holistic view of the implementation, the process would go as follows: As the customer selects "Proceed to Checkout" on the eCommerce website, the prediction from the ML model will be retrieved in real time, and the customer may be nudged with an appropriate prompt. The team I worked with foresees that this new feature will help facilitate the checkout process for the high rate of stalling that occurs when the checkout process is entered. My role in this project was to develop the microservice, or backend architecture, that provides the frontend with the prediction from the customer stalling ML model upon request.

3.2 Specifications

The specifications for the project dictate the development of the microservice using Flask and Python to ensure compatibility with the existing systems of the team. The microservice was required to accept requests from the frontend, extracting essential customer and purchase item data from these requests. This data retrieval process involves interfacing with external data providers to gather the necessary information for input into the checkout scorer ML model. Subsequently, the microservice must call the ML model with the collected data and retrieve the predicted output. The output must then be formatted appropriately according to predefined standards before being returned to the frontend. Compatibility with the team's systems and adherence to specified data exchange and formatting requirements are essential aspects of the project.

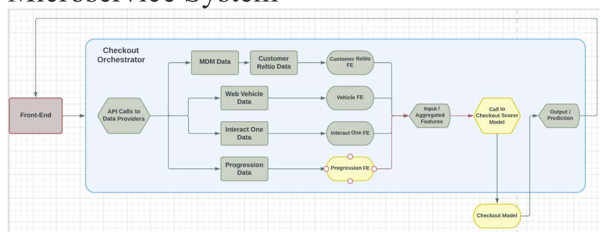
3.3 Challenges

Throughout the project, I encountered challenges. First, I had to tackle the implementation of the microservice functionalities autonomously, without prior experience in such development tasks. This demanded a steep learning curve as I familiarized myself with Flask, Python, and integrating external data providers. Second, the evolving nature of the project posed a significant challenge. As different teams, including data providers and frontend developers, made adjustments to their services, I had to continually adapt the microservice's input and output variables and formats to maintain compatibility. Last, a critical challenge was optimizing the microservice's performance to reduce latency so that it could operate in real-time. This required fine-tuning the code and employing efficient algorithms to enhance runtime efficiency without compromising accuracy.

3.4 Solution

In the development of this project, I implemented the following mechanisms: processing of the front-end request, API calls to retrieve relevant data, feature engineering of retrieved data into model input form, an API call to the ML model, and processing prediction output data for delivery to the front-end, as shown in Figure 1 below:

Figure 1. Diagram of Checkout Scorer Microservice System



When the front-end requires a model prediction, it makes a request to my service. The first functionality I implemented was the service's ability to accept a request from the front-end and store the customer data that the front-end sends. I then parsed the customer data to construct appropriate inputs to the required data provider APIs. The machine learning model required additional data from these data providers in order to make a prediction. In making the API calls to data providers, I had to use proper authentication credentials in order to access private customer data from the company's internal databases.

In order to reduce the latency of my microservice, I implemented the API calls concurrently because running them sequentially was the most time-costly part of the system. After retrieving the response from the APIs, I serialized the data to prepare for the feature engineering stage. Feature engineering involved the extraction of features, or appropriate model input data, from the raw data provided by the APIs. Finally, in the last stage of development, I inputted the extracted features in a call to the ML model to retrieve the prediction. I transformed the prediction data into a readable format for the front-end and returned the prediction to the front-end for use.

4. ANTICIPATED RESULTS

Upon the conclusion of my project and internship, the microservice I developed was integrated into the checkout process nudging system by my team. While I was not present to witness the final stages of integration, the impact of my work on the eCommerce company's conversion rates was clear. The successful deployment of the microservice added to the company's efforts to enhance the efficiency and effectiveness of its online purchasing experience. My team was able to work with the frontend checkout interface team and other teams working on data providers to deploy the microservice for use in a customer’s checkout experience.

Moreover, the significance of my contribution was evidenced through prior data analysis, which showed that missed sales opportunities due to customers dropping out of the checkout process was approximately 25% of complete sales made. By addressing the persistent issue of checkout stalling, the implementation of my microservice had the potential to increase sales by up to 25%, although the true value may not have been that high. My team’s system mitigated the obstacles hindering successful transactions by leveraging predictive analytics to anticipate customer behavior and provide personalized nudges. In turn, the overall results of my project optimized sales conversion rates.

5. CONCLUSION

The development and integration of the checkout scorer microservice represents an advancement in addressing the persistent challenge of customer abandonment during the checkout process in eCommerce. By leveraging machine learning, this project aimed to preemptively identify potential points of friction and provide personalized interventions to mitigate abandonment rates. My role in developing the backend architecture helped to facilitate the seamless integration of predictive analytics into the checkout process. The successful deployment of the microservice, integrated into the checkout process nudging system, was expected to demonstrate tangible improvements in conversion rates and sales potential. Through prior data analysis, it was evident that missed sales opportunities due to checkout abandonment could be significantly reduced, potentially increasing sales by up to 25%. Moreover, my project enabled consumers to have a more seamless checkout process with nudges that would assist in the completion of the process. Ultimately, my project highlights the impact of predictive analytics in optimizing the online purchasing experience and driving business profitability in eCommerce business.

6. FUTURE WORK

Moving forward, there are several opportunities for future work and enhancement of the checkout scorer microservice. First, the scalability and efficiency of the microservice could be improved so it could handle larger volumes of front-end requests and deliver predictive analytics in faster real-time. This could involve efficiencies such as optimizing the code or implementing parallel processing techniques. Additionally, the machine learning model used to predict customer stalling could be further refined to enhance its accuracy and effectiveness. Furthermore, the scope of the microservice could be expanded to offer more personalized interventions beyond nudges. This may include tailored product recommendations that could further improve the checkout experience. Overall, the future work on the checkout scorer microservice involves many opportunities to continually refine solutions to customer stalling.

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