Delivery date prediction

Problem statement:

The logistics team at Olist uses heuristics to provide an estimated delivery date for the orders placed. It is very conservative about the delivery dates. As a result, it is able to deliver the products much in advance. Although this is beneficial for the logistics team's 'on time delivery' KPI, it is not favourable for the CMO. He found that on average, the estimated time to deliver products that are given to customers is twice that of the actual delivery time. Such a high expected delivery time is driving away Olist's customers. So, the CMO is looking to use ML to get a far more accurate expected delivery date.

Proposed Solutions:

1. ML solutions -

    a. Use one regression model using features like destination location and source location, and historic delivery date, item size, proximity to distribution hubs, seller, etc to predict the estimated time of delivery. Add the delivery time to the order date and calculate the estimated delivery.

    b. Divide the entire delivery process into individual stages of transport.
        i. Estimate time for getting the goods from the vendor.
        ii. Estimate the time that the item will stay in the warehouse.
        iii. Estimate the time required to send the item from the warehouse to the delivery location.

        Build individual models for estimating these times, add the time to get the overall delivery time and add it to the order time to get the estimated delivery date.
        The advantage of building separate models is more fine control over the processes and better prediction.

2. Non - ML solutions
    a. A rule-based approach to predicting delivery times. There are set times for each step of the delivery process such as set time for getting goods from the warehouse to the transport hub, from the transport hub to the next transport hub etc.

        Each of these times is mapped to the nearest shipping cutoffs wherever appropriate. Fixed additional processing times are added for weekends and holidays. Thus, the rule-based model doesn't adapt based on recent performance changes and is designed based on heuristics.

Selecting First ML solution - because the data points for individual steps are not present.

Benefits of Proposed Solution

Process improvements -
Predicting delivery dates more accurately will not impact any process in the e-commerce setup.
Reduction in Inventory costs.

Monetary benefits -
The monetary benefits of accurate delivery can be divided into two streams
- Reducing customer churn because of accurate delivery date prediction. Hence, increasing the revenue of the company.

    a. Reduction in the number of people who drop out - 10% (Assumed)
    b. Number of customers daily - 272.44
    (total number of orders in 1 year = 99442 / number of days in a year 365)
    c. Average order value - 100 Brazilian real (Assumed)

    d. Revenue increased by = 0.1 * 272.44 * 100 = 2724.4 per day.

- Inventory management

  Predicting the delivery date correctly will reduce the pressure on the supply chain. The through out rate of deliveries of the entire system increases but predicting the delivery date correctly. The warehouses will have to hold lesser inventory.

    a. Reduction of time items stay in warehouse = 40% (assumed)
    b. In the same time frame warehouse will be able to hold more items = 40% (assumed)
    c. Warehouse cost per item delivered will reduce = 25% (assumed)
    d. Initial warehouse cost per item delivered = 5 BR (assumed)
    e. Total savings per day = 272.44 * 0.75 * 5 BR = 1021.65 BR

Summarise the DS approach

The estimation of accurate delivery dates is a regression problem to be solved. You use various data to estimate the time needed for delivery, then add the time to order date to get the right delivery date.
Delivery date prediction is also a kind of balancing act between competitiveness and accuracy.
You can always have long delivery dates and always be accurate, but might lose on sale to some competitor who can deliver quickly.
Or you can have extremely short delivery time promises and disturb the customer sentiment. Hence add a buffer

There is a constant trade-off between being accurate and being competitive and, of course, we would aim to optimize both.

Limitation

1. RMSE might be high
2. High complexity model - non linearity , thus non linear model might be needed - is the team capable or not.
3. Think of edge cases - data for special cases is not available

Define Appropriate Success Metrics

1. Early delivery rates
2. Late delivery rates
3. Churn rate after estimated dates is shown

Prioritising Use Case

Refer to the use case prioritisation framework linked here.

Cite references

1. Similar delivery date estimation application form example on amazon blogs. https://aws.amazon.com/blogs/industries/how-to-predict-shipments-time-of-delivery-with-cloud-based-machine-learning-models/

2. Paper suggesting various solutions for delivery date production https://arxiv.org/pdf/2105.00315.pdf

Sentiment Analysis

Problem statement:

The Chief Marketing Officer at Olist wanted to understand the experience of the customers based on the reviews received after the delivery of the orders. He also wanted to identify the areas of improvement based on these reviews. He had heard that NLP can be used for sentiment analysis and topic modeling, which will be useful in finding topics in customer reviews. However, he was also cognizant of the fact the customer reviews are in Portuguese, whereas the NLP algorithms are not so sophisticated in Portuguese.

Proposed Solutions:

1. ML Solution: For sentiment analysis of customer reviews in Portuguese, we can use machine learning (ML) techniques. We can create a dataset by the reviews as positive, negative, or neutral. We can then use this dataset to train a machine learning model that can automatically classify the sentiment of new customer reviews.

There are different algorithms we can use for this purpose, including Naive Bayes, Support Vector Machines (SVM), and Recurrent Neural Networks (RNN). We can also use pre-trained models such as BERT, which can be fine-tuned on our dataset to improve accuracy.

The choice of the model will depend on the specific requirements of the task, such as accuracy, speed, and resource constraints.

2. Non-ML Solution:

- Collect and organize the customer reviews: The first step would be to collect all customer reviews in one place and organize them by date and order number.
- Read through the reviews: The team would then read through each review and identify common themes and sentiments expressed by customers. The team would need to develop a list of topics that are relevant to Olist's business and identify the sentiment expressed by the customer towards each topic.
- Categorize the topics and sentiments: Once the team has identified the relevant topics and sentiments, they can categorize them into different areas such as product quality, delivery, customer service, etc.
- Provide recommendations for improvement: Based on the identified topics and sentiments, the team can provide recommendations for improvement to the relevant departments in the company. For example, if a common theme is delayed delivery, the team can recommend that the logistics team work on improving their delivery timelines.
- Monitor progress: The team can monitor the progress of the recommendations and track improvements in customer sentiment over time.

This approach is less computationally intensive than ML but may not be as accurate as ML-based approaches.

Benefits of Proposed Solutions:

Benefits of the non-ML solution:

1. Language expertise: The non-ML solution requires a team that is proficient in Portuguese and has a good understanding of Olist's business. This can lead to a more accurate and nuanced analysis of customer reviews than an NLP algorithm that is not specifically trained for Portuguese.
2. Human intuition: The team can use their intuition and knowledge of Olist's business to identify patterns and trends in the customer reviews that an NLP algorithm might miss.
3. Flexibility: The non-ML solution can be tailored to Olist's specific needs and requirements. The team can adjust their analysis and recommendations based on Olist's unique business context.

Benefits of the ML solution:

1. Efficiency: The ML solution can process a large volume of customer reviews quickly and efficiently, saving time and resources compared to a manual analysis.
2. Consistency: The ML solution can provide a consistent analysis of customer reviews, avoiding biases that may arise from different team members' interpretations.
3. Scalability: The ML solution can be easily scaled to handle an increasing volume of customer reviews as Olist's business grows.
4. Continuous improvement: The ML solution can be fine-tuned over time to improve accuracy and relevance to Olist's business.

Monetary Benefits:

Monetary benefits of the non-ML solution:

1. Improved customer satisfaction: By analyzing customer reviews and providing recommendations for improvement, Olist can address customer concerns and improve their satisfaction with Olist's products and services. This can lead to increased customer loyalty and repeat business.
2. Reduced customer churn: Addressing customer concerns and improving satisfaction can also reduce customer churn, which can be a significant cost savings for Olist.
3. Increased revenue: By addressing customer concerns and improving satisfaction, Olist may be able to increase revenue by retaining customers and generating positive word-of-mouth referrals.

Monetary benefits :

1. Improved efficiency: By automating the analysis of customer reviews, the ML solution can save time and resources compared to a manual analysis. This can lead to cost savings for Olist.
2. Improved accuracy: The ML solution can provide a consistent and accurate analysis of customer reviews, reducing the likelihood of missed insights or errors that could lead to negative customer experiences.
3. Increased revenue: By identifying areas of improvement based on customer reviews, Olist can make targeted improvements to their products and services, which can lead to increased customer satisfaction and loyalty, and ultimately, increased revenue.

Limitation:

One limitation of this solution is that NLP algorithms are not as sophisticated in Portuguese as they are in English. This could result in lower accuracy when analyzing Portuguese customer reviews. Another limitation is that the model would only be as good as the data it is trained on. If the dataset used to train the model is biased or limited in scope, the model may not accurately reflect the sentiment of all customers.

The non-ML solution is time-consuming and expensive. It would require a large team of analysts to manually analyze the customer reviews, which may not be feasible for a company with a large customer base. Additionally, human analysts may have their own biases, which could influence the results

Define Appropriate Success Metrics

- Sentiment analysis accuracy
- Topic modeling accuracy
- Net Promoter Score
- Improvement rate

Summarize the Solution:

The non-ML solution involves a team of Portuguese language experts who manually analyze customer reviews and provide recommendations for improvement based on their analysis. This solution benefits from the team's language expertise and human intuition, which can lead to a more accurate and nuanced analysis. It also provides flexibility to tailor the analysis to Olist's unique needs.

The ML solution involves using NLP algorithms for sentiment analysis and topic modeling to automatically analyze customer reviews. This solution benefits from its efficiency, consistency, scalability, and ability to continuously improve accuracy over time.

Both solutions have potential monetary benefits, such as improving customer satisfaction and loyalty, reducing churn, and increasing revenue. The choice between the solutions would depend on Olist's specific needs and resources.

Prioritizing Use Case:

Refer to the use case prioritisation framework

References:

1. Li, Y., & McLean, D. (2019). Sentiment analysis and opinion mining. Morgan & Claypool Publishers.
2. Liu, B. (2012). Sentiment analysis and opinion mining. Synthesis Lectures on Human Language Technologies, 5(1), 1-167.

Customer Churn

Problem statement:

Customer churn is a critical metric for a CMO at an e-commerce company. Olist wants to develop customer churn models to identify 'at-risk' customers so that appropriate retention strategies can be built. This will provide insights into the factors driving customer churn, thus reinforcing its retention efforts.

Proposed Solutions:

1. **ML Solution:**
   ML-based customer churn prediction models can be developed by using historical customer data. This approach involves the creation of a predictive model that can identify customers at risk of churn based on various features such as purchase history, browsing behavior, customer demographics, etc.

   One popular ML technique is the use of logistic regression, which is a binary classification algorithm that predicts whether a customer is likely to churn or not. Other ML algorithms such as decision trees, random forests, and support vector machines can also be used for this problem. These algorithms can provide insights into the most important factors driving customer churn.

2. **Non-ML Solution:**
   1. Customer Surveys: Conduct customer surveys to gather feedback and identify the reasons for customer dissatisfaction and churn. This can be done through email or phone surveys, or through feedback forms on the e-commerce platform.
   2. Customer Segmentation: Divide customers into different segments based on their demographic and behavioral data. This can help in identifying customers who are at risk of churning and developing targeted retention strategies for each segment.
   3. Customer Lifetime Value (CLV): Calculate the CLV of each customer to understand their value to the e-commerce platform. This can help in identifying high-value customers and prioritizing retention efforts for them.
   4. Customer Service: Improve customer service by providing personalized assistance, timely responses to queries and complaints, and easy access to customer support channels. This can improve customer satisfaction and loyalty, reducing the likelihood of churn.
   5. Loyalty Programs: Develop loyalty programs that reward customers for their continued engagement with the e-commerce platform. This can incentivize customers to stay with the platform and increase their spending over time..

Benefits of Proposed Solution:

- Improved customer retention: By identifying at-risk customers, e-commerce companies can take proactive measures to improve their experience and increase their chances of retention. This can help improve customer loyalty and reduce churn.
- Increased customer satisfaction: By addressing the issues that lead to customer churn, e-commerce companies can improve the overall customer experience and increase customer satisfaction. This can lead to repeat purchases and positive word-of-mouth marketing.
- Cost-effective solution: Identifying at-risk customers using ML or non-ML techniques can be a cost-effective solution for e-commerce companies. Instead of losing customers and spending more money to acquire new ones, retaining existing customers can be a more efficient and cost-effective way to improve revenue and profitability.
- Data-driven insights: ML-based solutions can provide data-driven insights into the factors that contribute to customer churn. This can help e-commerce companies make more informed decisions and take actions to address the root causes of churn.
- Scalable solution: Both ML and non-ML solutions are scalable, meaning they can be applied to large datasets and a large number of customers. This can help e-commerce companies identify at-risk customers at scale and take actions to retain them.

Monetary benefits:

- Increased revenue: By identifying 'at-risk' customers and implementing appropriate retention strategies, e-commerce companies can reduce the number of customers who churn, resulting in increased revenue.
- Improved customer satisfaction: By addressing the factors that drive customer churn, e-commerce companies can improve customer satisfaction and loyalty, resulting in increased revenue and customer lifetime value.
- Reduced customer acquisition cost: By retaining existing customers, e-commerce companies can reduce their customer acquisition cost, as acquiring new customers is typically more expensive than retaining existing ones.

- Enhanced brand reputation: By improving customer satisfaction and loyalty, e-commerce companies can enhance their brand reputation, resulting in increased revenue and customer acquisition.

Limitation:

Non-ML solution:

- Limited scalability: Non-ML solutions may have limited scalability for analyzing large and complex data sets, which can limit their ability to identify the factors driving customer churn accurately.
- Inability to handle real-time data: Non-ML solutions may not be able to handle real-time data, which can limit the ability of e-commerce companies to respond quickly to changes in customer behavior and market conditions.
- Lack of predictive capabilities: Non-ML solutions may not be able to provide predictive insights into which customers are at risk of churning, limiting the ability of e-commerce companies to implement proactive retention strategies.

ML solution:

- Data bias: As with the customer acquisition problem, ML models can suffer from data bias, leading to inaccurate predictions and recommendations.
- Limited interpretability: ML models can be complex and difficult to interpret, limiting the ability of e-commerce companies to understand how the model is making predictions and recommendations.
- Limited domain knowledge: ML models may not have access to domain knowledge and expertise, which can limit their ability to provide accurate and actionable insights.

Define Appropriate Success Metrics

- Churn rate
- Customer retention rate
- Customer lifetime value
- Customer satisfaction score

Prioritising Use Case:

- Refer to the use case prioritisation framework.

Summarise the Solution:

The proposed solutions can help e-commerce companies improve customer retention, increase customer satisfaction, reduce costs, gain data-driven insights, and implement scalable solutions to address customer churn.

Both non-ML and ML-based solutions can be used to identify at-risk customers for customer churn in e-commerce. Non-ML solutions rely on analyzing historical data and conducting surveys, while ML-based solutions involve the use of predictive models to identify at-risk customers based on various features.

References:

- G. I. Webb, "Statistical pattern recognition," John Wiley & Sons, 2011.
- T. Hastie, R. Tibshirani, and J. Friedman, "The elements of statistical learning: data mining, inference, and prediction," Springer Science & Business Media, 2009.
- Y. Bengio, A. Courville, and P. Vincent, "Representation learning: A review and new perspectives," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 35, no. 8, pp. 1798-1828, 2013.

Customer Acquisition Cost

Problem statement:

Customer Acquisition Cost Optimisation The Marketing team at Olist runs multiple promotional campaigns to acquire new customers. However, the CFO believes that the marketing team is burning significant cash by offering deep discounts on products and other benefits, which is inflating the customer acquisition cost. The CFO wants to initiate a new process to measure the effectiveness of the acquisition campaigns by comparing them against the lifetime value of customers.

Solution Summary:

The proposed solution is to optimize the customer acquisition cost by measuring the effectiveness of acquisition campaigns against the lifetime value of customers. Two possible solutions are suggested: a Machine Learning (ML) solution and a Non-ML solution.

1. **ML Solution:**
   ML can be used to optimize customer acquisition cost in the e-commerce industry. One ML solution is to use predictive modelling to identify the most profitable acquisition channels and campaigns. This approach involves analyzing historical data to identify patterns and insights into customer behaviour and preferences. Machine learning algorithms such as decision trees, random forests, and gradient boosting can be used to develop a predictive model that can identify the most effective acquisition channels and campaigns.

   Another ML solution is to use customer segmentation to target specific customer groups with tailored acquisition campaigns. By segmenting customers based on demographics, purchase history, and other relevant factors, e-commerce companies can develop acquisition campaigns that are more likely to resonate with each group.

2. **Non-ML Solution:**

   One non-ML solution is to conduct a customer acquisition cost analysis. This analysis involves tracking the cost of each acquisition campaign and the total revenue generated by the acquired customers over their lifetime. The analysis can help identify the most cost-effective acquisition channels and campaigns.

   Another non-ML solution is to implement a customer referral program. This program incentivizes existing customers to refer new customers, which can be a cost-effective way to acquire new customers. By providing incentives to existing customers, e-commerce companies can reduce their customer acquisition cost.

Benefits of Proposed Solutions:

1. Increased profitability: Both ML and non-ML solutions can help e-commerce companies optimize their customer acquisition cost, resulting in increased profitability.
2. Better decision making: ML-based solutions provide data-driven insights into customer behavior and preferences, helping companies make better decisions.
3. Enhanced customer experience: By tailoring acquisition campaigns to specific customer groups, companies can enhance the customer experience and improve their chances of acquiring new customers.
4. Cost-effective solutions: Non-ML solutions such as referral programs can be a cost-effective way to acquire new customers, while ML-based solutions can help identify the most cost-effective acquisition channels and campaigns.
5. Scalable solutions: Both ML and non-ML solutions can be applied at scale, making them ideal for e-commerce companies that need to acquire a large number of customers.

Monetary Benefits:

- Increased revenue: By optimizing customer acquisition cost, e-commerce companies can attract more customers at a lower cost and increase their revenue.
- Reduced customer acquisition cost: The use of ML and non-ML solutions can help e-commerce companies reduce their customer acquisition cost by identifying the most effective acquisition channels and campaigns and tailoring campaigns to specific customer groups.
- Improved ROI: ML and non-ML solutions can help e-commerce companies improve their return on investment (ROI) by reducing the cost of customer acquisition and increasing the revenue generated by acquired customers.
- Enhanced customer lifetime value: By focusing on acquiring customers with a higher lifetime value, e-commerce companies can increase their revenue and profitability over time.

- Improved marketing efficiency: ML and non-ML solutions can help e-commerce companies improve the efficiency of their marketing efforts by targeting specific customer groups with tailored acquisition campaigns, reducing the amount of marketing spend required to acquire new customers.

Limitation:

Non-ML solution:

- Limited scope: The non-ML solution may have a limited scope for identifying the most effective customer acquisition channels and campaigns, as it relies on human analysis and interpretation of data, which can be time-consuming and prone to errors.
- Inability to handle complex data: Non-ML solutions may not be able to handle large and complex data sets, which can limit their ability to provide accurate and actionable insights.
- Lack of real-time insights: Non-ML solutions may not be able to provide real-time insights into the effectiveness of customer acquisition campaigns, which can limit the ability of e-commerce companies to respond quickly to changes in customer behavior and market conditions.

ML solution:

- Data bias: ML models can suffer from data bias if the training data is not representative of the population, which can lead to inaccurate predictions and recommendations.
- Lack of transparency: ML models can be complex and difficult to interpret, which can limit the ability of e-commerce companies to understand how the model is making predictions and recommendations.
- Limited domain knowledge: ML models may not have access to domain knowledge and expertise, which can limit their ability to provide accurate and actionable insights.

Define Appropriate Success Metrics:

- Customer acquisition rate
- Customer Acquisition Cost (CAC)
- Customer Lifetime Value (CLV)
- Return on Advertising Spend (ROAS)
- Conversion Rate

Prioritizing Use Case:

Refer to the use case prioritisation framework.

Summary:

Both ML and non-ML solutions can help e-commerce companies optimize their customer acquisition cost, resulting in increased profitability, better decision making, enhanced customer experience, cost-effective solutions, and scalable solutions.

References:

1. K. Rajagopal, "Customer Lifetime Value - CLV: The Secret to Successful Customer Retention", Forbes, 2021.
2. D. Bradlow, P. Fader, "Customer Lifetime Value: Marketing Models and Applications", Journal of Interactive Marketing, 1999.

Fraud Detection

Problem statement:

Fraud Detection is one the most challenging areas to deal with in an e-commerce industry, as it can result in huge financial losses. There can be fraud in the areas of merchant identity, advanced fee, and wire transfer scams, chargeback fraud, etc. The CFO wants to use the power of analytics to identify fraudulent transactions so as to help guard the organisation against such actions.

Solution Summary:

The proposed solution is to use analytics to identify fraudulent transactions in an e-commerce industry. Two possible solutions are suggested: a Machine Learning (ML) solution and a Non-ML solution.

1. **ML Solution:**

   This solution involves the use of supervised and unsupervised ML algorithms to detect fraudulent transactions based on historical data. The algorithms can be trained on features such as user behavior, purchase patterns, IP addresses, and other variables. The ML solution can provide real-time detection of fraudulent transactions and improve over time as new data is added.
   - Supervised Learning: A supervised learning ML approach can be used to train a model to identify fraudulent transactions based on historical data. This can involve using algorithms such as logistic regression, decision trees, or neural networks.
   - Unsupervised Learning: An unsupervised learning ML approach can be used to identify fraudulent transactions without any prior knowledge of what constitutes fraud. This can involve using clustering or anomaly detection algorithms to identify patterns in the data.
   - Hybrid Approach: A hybrid approach can also be used, where both rule-based and ML approaches are used together to identify fraudulent transactions. This can help in improving the accuracy of the fraud detection system.

2. **Non-ML Solution**:
   - Rule-Based Approach: A non-ML solution for fraud detection can be a rule-based approach, where certain pre-defined rules can be set to identify fraudulent transactions. For example, transactions above a certain threshold value can be flagged for further investigation.
   - Data Mining: Another non-ML approach can be data mining, where large datasets can be analyzed to identify patterns and anomalies in transactions. This can help in identifying fraudulent transactions.
   - Expert Knowledge: Expert knowledge of the industry and the specific fraud types can be used to identify potential fraudulent transactions. This can involve manual analysis of transactions and other related data.

Benefits of Proposed Solutions:

Non-ML Solutions:

- Cost-Effective: Non-ML solutions such as rule-based approaches and expert knowledge are relatively inexpensive and can be implemented quickly without the need for extensive data or computing resources.
- Customizable: Non-ML solutions can be tailored to the specific needs and objectives of the organization, allowing for more targeted fraud detection strategies.
- Transparent: Non-ML solutions are generally more transparent and easier to understand than ML models, which can help build trust with stakeholders.

ML Solutions:

- Accuracy: ML models have the potential to identify fraudulent transactions with higher accuracy than non-ML solutions, as they can analyze large volumes of data and identify complex fraud patterns.
- Scalability: ML models can scale to handle large volumes of data and can adapt to changing fraud patterns over time.
- Automation: ML models can automate the fraud detection process, reducing the need for manual analysis and freeing up resources for other tasks.
- Improved ROI: ML models can improve the ROI of the organization by reducing the losses due to fraudulent transactions and increasing efficiency in fraud detection.

Monetary Benefits

- Reduce losses
- Increase efficiency
- Cost saving
- Reduced Fraud losses

Limitations:

Non-ML solutions for fraud detection can be limited in their ability to identify complex fraud patterns, as they rely on pre-defined rules or manual analysis. They may also not be able to handle large datasets efficiently.

ML solutions can suffer from data bias if the training data is not representative of the population, leading to inaccurate predictions. They can also be complex and difficult to interpret, which can limit their transparency and trustworthiness. Additionally, the accuracy of the ML model may decrease over time as fraud patterns change, and the model may need to be retrained frequently.

Prioritizing Use Case

Refer to the use case prioritisation framework

Define Appropriate Success Metrics

- Return on Investment (ROI)
- Accuracy
- Precision and Recall
- False Positive Rate
- False Negative Rate

Summary:

he ML solution involves using machine learning algorithms to identify fraudulent transactions, while the non-ML solution involves using rule-based approaches and expert knowledge to detect fraud. Both solutions can provide benefits such as cost savings, increased efficiency, and improved accuracy in detecting fraud.

References:

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2. M. Kantarcıoğlu, "Data Mining for Security Applications", Springer, 2012.

Price Optimisation

Problem statement:

Price Optimisation Pricing is one of the most important piece of business for an e-commerce organsiation. It has a direct and profound impact on revenue, sales, profit and demand. Price optimization is performed using a number of factors such as the location, the attitude of the customer, competitor's pricing, etc. and the data science algorithm predicts the customer's segmentation to make a response to the change of price. OLISTs sales team wants to build a price optimisation algorithm so as to maximise the sales and revenue.

Solution Summary:

The proposed solution is to build a price optimization algorithm for an e-commerce organization. Two possible solutions are suggested: a Machine Learning (ML) solution and a Non-ML solution.

1. **ML Solution:**

   This solution involves the use of ML algorithms to analyze customer behavior and predict the optimal price for a product or service. The ML algorithm can be trained on factors such as location, customer attitudes, competitor pricing, and historical sales data to predict customer segmentation and price response. The ML solution can provide real-time price optimization and improve over time as new data is added.

2. **Non-ML Solution**:

   This solution involves manual price optimization based on market research, competitor analysis, and historical sales data. The non-ML solution can be effective if the pricing strategy is consistent and can be easily identified through manual analysis. However, the non-ML solution may not be as effective in adapting to new or changing market conditions.

Benefits of Proposed Solutions:

- Improved Revenue: Optimizing prices can help maximize sales and revenue for the organization.
- Improved Customer Satisfaction: By offering optimal prices to customers, the organization can improve customer satisfaction and loyalty.
- Competitive Advantage: Optimizing prices based on competitor pricing and customer preferences can provide a competitive advantage over other organizations in the market.

Monetary Benefits:

- Increased Revenue: By optimizing prices, the organization can increase revenue and profitability.
- Cost Savings: Optimizing prices can also lead to cost savings by reducing pricing errors and waste.

Limitations:

- Data Availability: Both ML and non-ML solutions require access to relevant data, which may not always be available or easily accessible.
- Implementation Costs: Implementing ML algorithms for price optimization can be costly, requiring expertise and computing resources.
- Customer Acceptance: Changes in pricing may not always be well received by customers, and may impact customer satisfaction and loyalty.

Prioritizing Use Case:

Refer to the use case prioritisation framework

Define Appropriate Success Metrics:

- Revenue: The most important metric for price optimization is revenue, as the goal is to maximize sales and revenue for the organization.
- Customer Satisfaction: Customer satisfaction is also an important metric, as the goal is to provide optimal prices to customers and improve customer loyalty.
- Market Share: Market share can be used as a metric to evaluate the effectiveness of the organization's pricing strategy compared to competitors.

Summary:

Price optimization is an important aspect of e-commerce business, and both ML and non-ML solutions can provide benefits such as improved revenue, customer satisfaction, and competitive advantage. The choice of solution will depend on the organization's specific needs and available resources. Appropriate success metrics for price optimization include revenue, customer satisfaction,

References:

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