



# Capstone Project

## Explaining and predicting customer churn for ClientCo

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# Agenda

## 1. Introduction

- Churn Impact
- Actual Problem

## 2. Solution Overview

- Expected Outcome

## 3. Models

- Churn
- Demand Prediction

## 4. Business Impact

## 5. Call to Action



# Introduction



ClientCo is an international construction and renovation products distributor. Its core business consists of buying products from suppliers and reselling them through a network of point distributions dedicated to B2B Channels.

## Churn Impact on ClientCo

- Limited digital engagement
- Increasing debt costs
- Environmental and regulatory pressures
- Supply chain inefficiently
- Improper handling of customer relationship



## Actual Problem's

- **30%** of the customer base of ClientCo has **not** purchased in the **last 6 months**.
  - **53%** of the customers that have not purchased come from sales at **the store**, **43%** from sales **by phone** and the rest from the other channels.
- Based on the Average **CLV \$109,826.08** and the **50,772 customers that have not purchased in the last 6 months**; there is a **financial impact of \$5.5 billion**.

# Financial analysis

## Balance sheet

- Rise in goodwill and inventories
- Exponential growth of long term assets in 2006

## Cashflow Statement

- Lack of significant dividends in 2011 and 2012 indicates a business reinvestment
- Regular increases in long term debit

## Income Statement

- Gross profit shows stable growth year over year

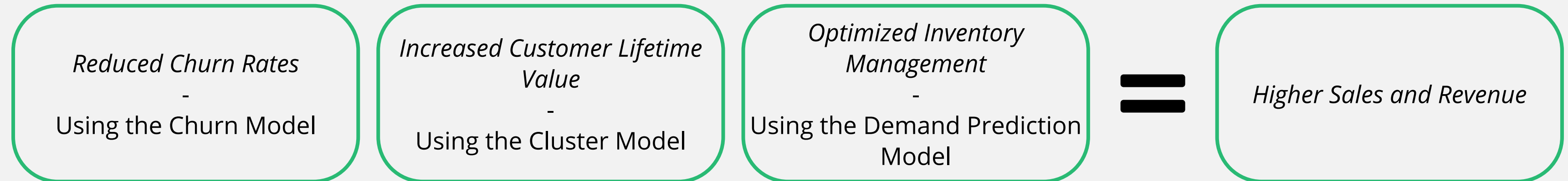


# Solution Approach

Use our insights to personalize customer interactions, enhancing our marketing and loyalty programs. Personalized interactions are more effective, so we'll target at-risk customers with customized marketing depending of their most use channel.

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## Expected Outcomes



# Models Development

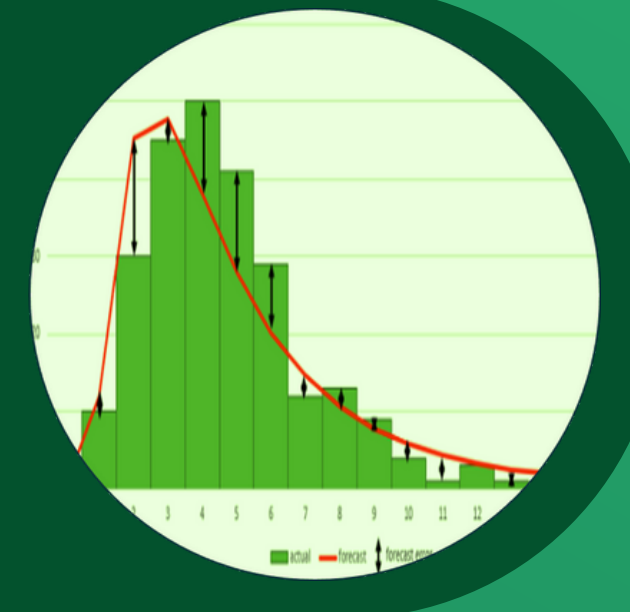
## Churn Prediction Model

Targeting the customers that are going to churn so that we would be able to take measures and keep them.



## Demand Prediction Model

Predicting the demand during a certain month and help the company reduce storage cost.



# Models Development

## Churn Prediction Model

### Churn Labeling

#### Exploration

- Threshold for recency
- Confidence interval
- K-means
- K-means + confidence interval
- K-means + 3 \* purchase interval

#### Result

- Windows of whether the customer has purchased or not (2 months prediction)

window	0	1	2	3	4	5	6	7	8	9	10	11	12
client_id													
6	1	1	0	1	1	0	0	3	3	0	0	3	0
7	0	0	0	0	0	1	0	1	0	0	0	0	0
14	27	42	42	42	42	43	39	46	40	43	41	45	1
18	12	26	24	25	22	26	24	26	21	27	20	32	1
25	0	0	0	0	0	0	1	0	0	0	0	0	0

# Models Development

## Churn Prediction Model

### Model - XGBoost

Evaluation - *F1 Score: 0.84*

### Model evolution

	window	f1_score	roc_auc	accuracy
0	3	0.787780	0.847353	0.785684
1	4	0.790483	0.853984	0.792009
2	5	0.800059	0.850398	0.777489
3	6	0.797245	0.858937	0.790989
4	7	0.797146	0.860591	0.787853
5	8	0.788965	0.870457	0.795831
6	9	0.796392	0.876691	0.798744
7	10	0.795682	0.880946	0.801283
8	11	0.837898	0.891110	0.811055
9	12	0.745712	0.890776	0.828201

Window 3: Positive ratio = 0.51  
Window 4: Positive ratio = 0.51  
Window 5: Positive ratio = 0.56  
Window 6: Positive ratio = 0.53  
Window 7: Positive ratio = 0.53  
Window 8: Positive ratio = 0.50  
Window 9: Positive ratio = 0.51  
Window 10: Positive ratio = 0.51  
Window 11: Positive ratio = 0.56  
Window 12: Positive ratio = 0.35

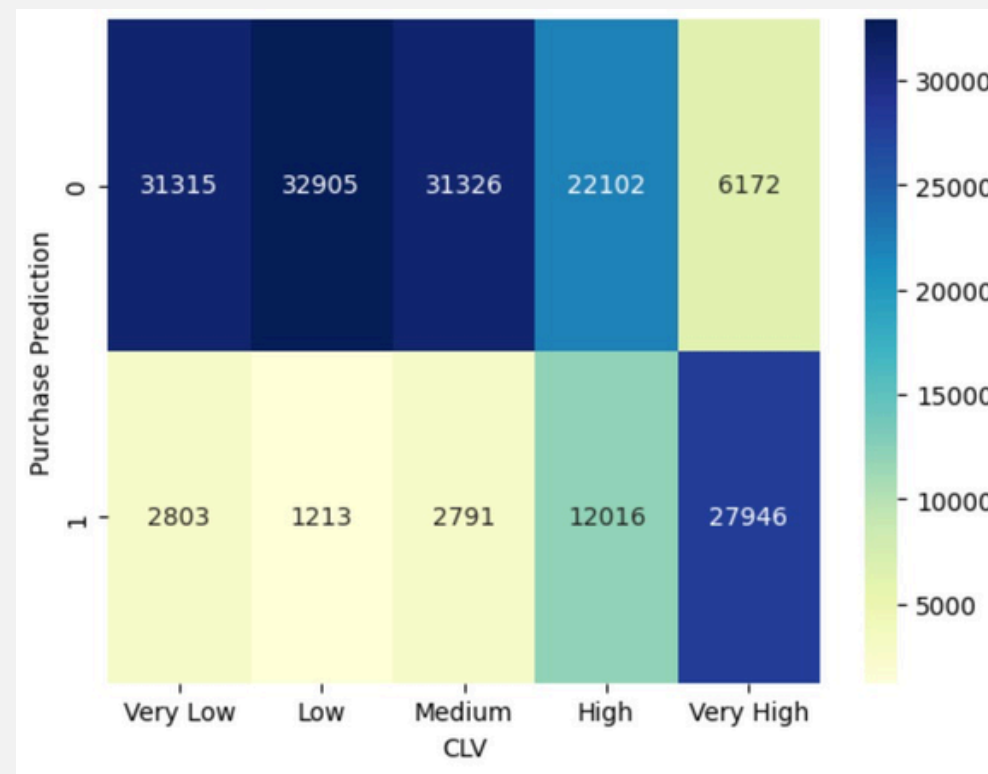


# Models Development

## Churn Prediction Model

### Use Case I

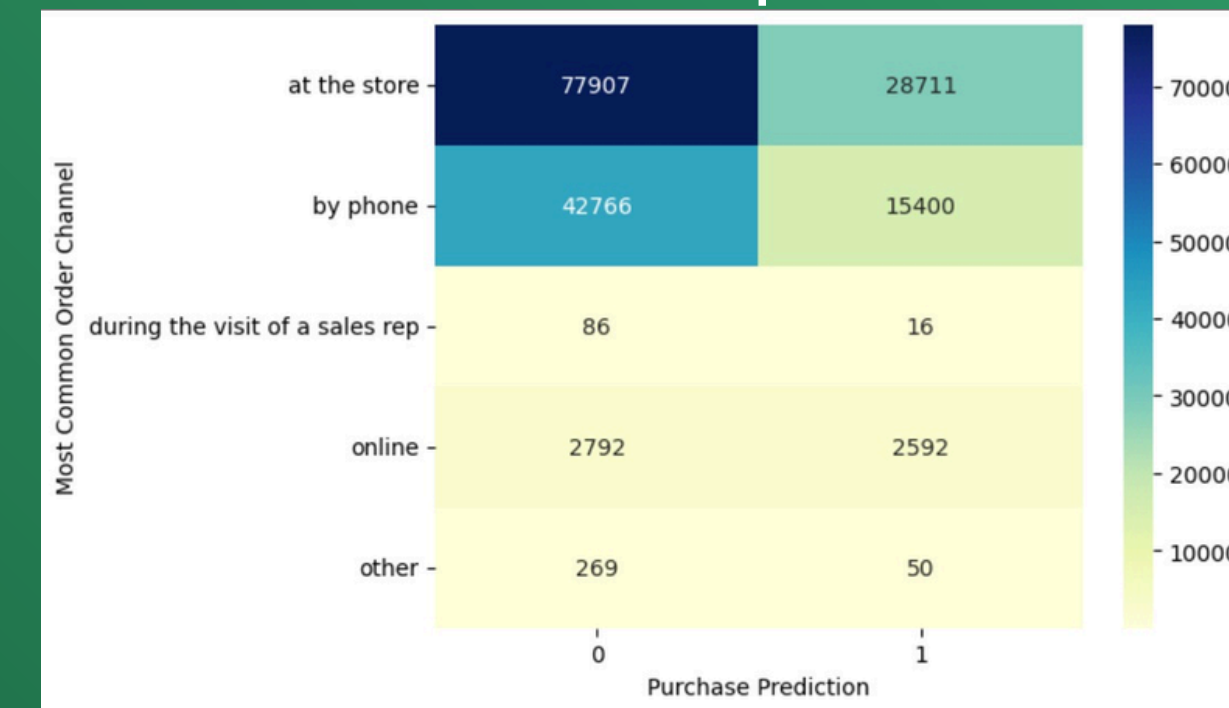
Targeting the high value customer that are churning



client_id	most_common_order_channel	most_common_branch	product_id	purchase_prediction
6	by phone	8470	169851	0
7	at the store	7453	121848	0
14	by phone	10319	2512504	1
18	at the store	6654	3000784	1
25	at the store	2876	91564	0

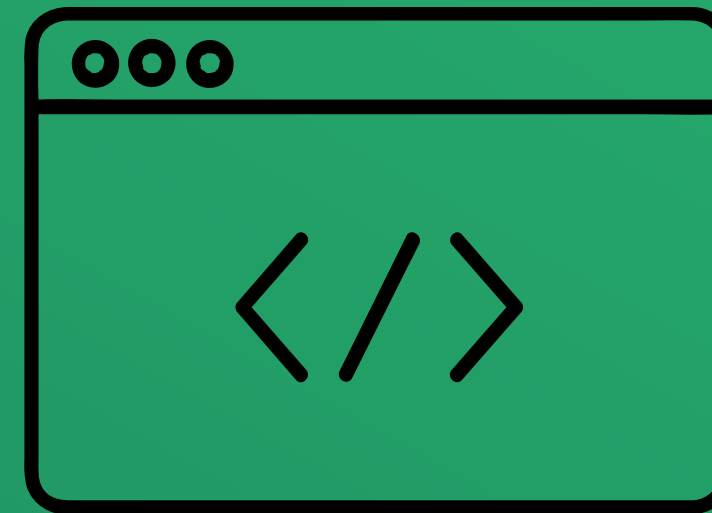
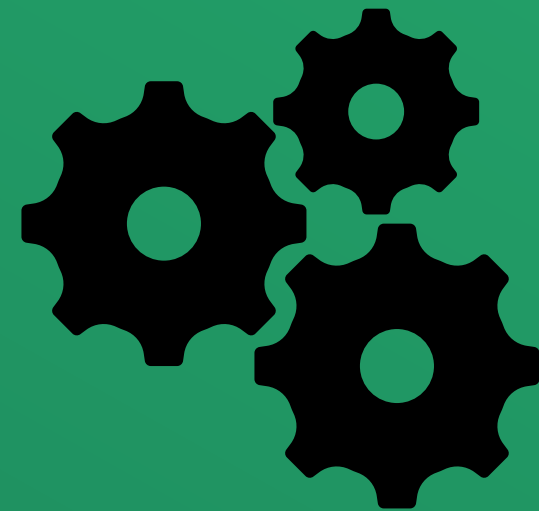
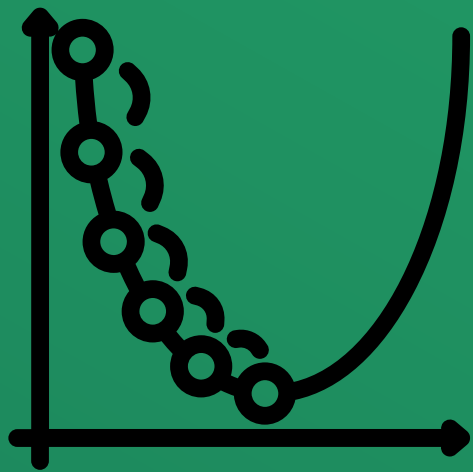
### Use Case II

Encourage customers that are purchasing mostly by phone to transition to online purchases



# Models Development

Demand Prediction



Model - XGBoost

Explanatory Variables

- *Client*
- *Product*
- *Branch*
- *Order Channel*
- *Purchase Month*

Target Variable

- *Quantity*

Evaluation

- MAPE 1.26
- MAE 49.86

Supply Chain Ops Support



# Business Impact

- Improved Customer Retention
- Increased Customer Lifetime Value
- Better Demand Forecasting and Inventory Management
- Enhanced Sales and Revenue
- Data-Driven Decision Making

# Financial Impact (Churn Predictive Model)

## Customer Base and Purchase Behavior

- Customer Base: 170.589 unique customers
- Customers not purchasing in the last two months: 78.565 customers (46%)

## Model Performance Metrics

- F1-Score of the Model: 0.84
- Average Customer Lifetime Value (CLV): \$109,826.08

## Financial Impact Estimation

- Total Revenue Saved = True Positives × Average CLV
- Total Revenue Saved = 7.252.747.760,60

# Call to Action

## Enhance Online Channel Presence

- Transition phone customers to online purchases with incentives.
- Develop a user-friendly e-commerce platform with personalized recommendations.

## Address Customer Churn

- Reactivate high CLV customers not expected to purchase soon through personalized outreach.





# Call to Action

## Demand Forecasting

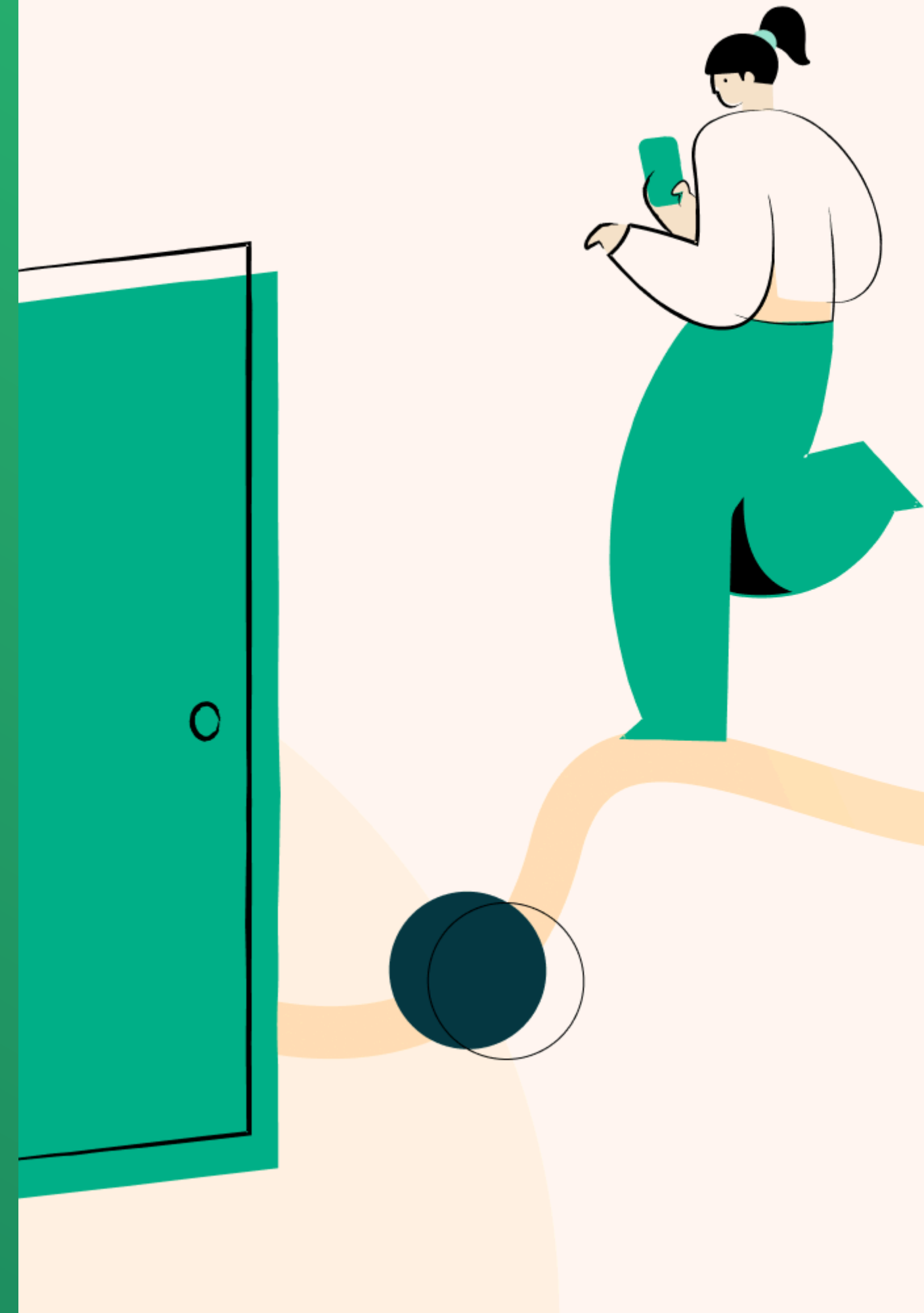
- Utilize the demand prediction model to align inventory with forecasted demand, reducing stockouts and excess costs.

## Branch Performance Improvement

- Share best practices from high-performing branches and provide targeted support to underperforming ones.

## Monitoring for Data Drift

- Regularly retrain models with new data or use data drift detection techniques to determine the optimal retraining period.





# Q&A

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