Optimizing Delivery Routes in Supply Chain Management Using Machine Learning

Problem statement:

The increasing complexity of supply chain operations, especially in e-commerce, necessitates efficient delivery routes to minimize costs and improve customer satisfaction. With the surge in online shopping, companies face challenges in optimizing their logistics. By applying machine learning, we can identify patterns and improve route efficiency.

Objective:

The literature on supply chain optimization highlights various methods for improving logistics efficiency. Traditional approaches, such as linear programming and heuristic methods, have been widely studied. However, recent advancements in machine learning have opened new avenues for optimizing delivery routes. Studies have shown that supervised learning algorithms, such as decision trees and random forests, can predict the most efficient routes by analyzing historical delivery data and we will use these machine learning algorithms and technology to optimize delivery routes in the supply chain and try to reduce cost and time of delivery which directly reduce lead time.

Research Variables:

- **Dependent Variable:** Delivery time
- **Independent Variables:**
    - Distance
    - Number of stops
    - Traffic conditions
    - Weather conditions
    - Delivery vehicle type

Data Sources:

- **Primary Data Source:** Kaggle dataset named "E-commerce Shipping Data," which includes information on various factors affecting delivery routes.

Research Model:

The research will employ a supervised machine learning model, specifically using a random forest algorithm. This model will analyze historical shipping data to predict the most efficient delivery routes based on the identified variables. The model will be trained on a portion of the dataset and tested on the remaining data to evaluate its accuracy.

Remaining Work:

- Data preprocessing and cleaning
- Training and tuning the machine learning model
- Model validation and testing
- Analysis of results and interpretation

Timeline of Your Work:

1. **Week 1-2:** Data collection and preprocessing
2. **Week 3-4:** Feature engineering and model selection
3. **Week 5-6:** Model training and tuning
4. **Week 7:** Model validation and testing
5. **Week 8:** Analysis of results
6. **Week 9:** Final report writing
7. **Week 10:** Review and submission

References (APA 7 Format):

- Christopher, M. (2016). *Logistics & supply chain management*. Pearson UK.
- Tsao, Y. C., Lu, J. C., & Yu, V. F. (2018). A supply chain network design considering transportation cost discounts. *Transportation Research Part E: Logistics and Transportation Review*, 111, 18-39.
- Winkenbach, M., & Malhame, M. (2021). Optimizing last-mile delivery networks with machine learning. *MIT Sloan Management Review*, 62(3), 1-5.

Delivery route optimization in supply Chain management. Literature Review

"Optimising Last-Mile Delivery Routes Using Deep Reinforcement Learning" by H. Zhang, S. Yang, and K. Wang, 2023

1. Introduction to Last-Mile Delivery

Last-mile delivery is a critical component of the logistics and transportation industry, often representing the final leg of the supply chain where goods are delivered to the end consumer. The efficiency of this segment impacts customer satisfaction significantly, making it an area of increasing focus for companies looking to optimise their operations. The need for improved last-mile delivery solutions has driven the exploration of advanced technologies such as deep reinforcement learning.

2. Deep Reinforcement Learning in Route Optimization

Deep reinforcement learning combines reinforcement learning (RL) and deep learning techniques to create models capable of making complex decisions. DRL algorithms learn through trial and error, interacting with their environment to maximise a cumulative reward. This approach is particularly suitable for dynamic and complex environments like last-mile delivery, where route characteristics can change rapidly due to traffic conditions, weather, and other variables.

3. Tools and Technologies

- **Simulation Environments**

Simulation environments, such as OpenAI Gym, allow researchers to evaluate the performance of DRL algorithms under various scenarios2. These platforms provide a controlled setting in which different routing challenges can be modelled, and the effectiveness of various solutions can be tested.

- **Optimization Algorithms**

Common optimization algorithms used in conjunction with DRL include Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO). These algorithms help in refining the solutions generated by DRL models by providing a mechanism to explore and exploit potential routes more thoroughly1.

- **Machine Learning Libraries**

Utilising libraries such as TensorFlow or PyTorch facilitates the implementation of DRL models by providing the necessary tools for building and training neural networks. These libraries offer extensive functionality that allows researchers to construct sophisticated architectures suitable for last-mile delivery optimization.

4. Research Gaps in Last-Mile Delivery Optimization

Despite progress, research gaps remain in the application of DRL for last-mile delivery optimization. One significant gap is the lack of real-time data integration, which limits the adaptability of current models to dynamically changing environments. Furthermore, most existing studies focus on single-agent systems, neglecting the collaborative potential of multi-agent configurations in improving routing efficiency and operational responsiveness2.

5. Future Work Directions

- **Enhancing Adaptability of Models**

Future research should focus on enhancing the adaptability of DRL models using real-time data sources. Integrating data from traffic patterns, weather forecasts, and consumer behavior can provide more accurate predictions and allow for better route adjustments in real time.

- **Exploring Multi-Agent Systems**

Exploring multi-agent systems where several vehicles operate collaboratively could yield significant efficiency improvements. Research could investigate cooperative strategies, where vehicles share information about their routes and conditions, resulting in optimized overall logistics performance.

- **Sustainability Considerations**

Lastly, incorporating sustainability considerations into last-mile delivery optimization is essential. Future research could focus on developing models that not only minimise delivery times and costs but also reduce energy consumption and carbon footprints, aligning with global sustainability goals.

6. Conclusion

Optimising last-mile delivery routes using deep reinforcement learning represents a transformative approach in logistics. However, there remain considerable avenues for exploration and improvement. By addressing research gaps and focusing on enhancing adaptability, multi-agent interactions, and sustainability, future studies can significantly advance the field of last-mile delivery logistics.

This report highlights the potential of deep reinforcement learning as a powerful tool for optimising last-mile delivery, emphasising the need for continuous research and innovation in this critical area of logistics.

Xing, E. (2020). Delivery Route Optimization Based on Deep Reinforcement Learning. Journal of Logistics Research, 12(2), 45-67.

1. Overview of the Paper

The paper addresses the increasing importance of efficient delivery route optimization due to the growing demand in the fast-food industry and e-commerce sectors. With advancements in technology, traditional routing techniques are becoming inadequate, prompting researchers to seek more efficient methodologies. DRL, in particular, is identified as a promising approach to tackle the complexity of route optimization problems by learning optimal policies through interaction with the environment1.

2. Algorithms and Techniques Used

The research employs a deep reinforcement learning framework that combines various neural network architectures to derive an optimal strategy for delivery route planning. The key components involve:
State Representation: Each state in the environment represents a specific delivery scenario, including information about current locations, delivery locations, and time constraints.
Action Space: The actions consist of a range of possible routing decisions, allowing the algorithm to explore various paths to reach the destinations.
Reward Mechanism: The reward system is designed to reinforce successful delivery routes while penalising inefficient paths, which helps the model learn effectively.
Neural Network Training: The DRL model is trained using a dataset representing various delivery scenarios, allowing it to adapt and improve its strategies based on past performance1.

3. Results and Findings

The findings indicate that the DRL approach outperforms conventional methods in terms of delivery time and cost efficiency. The model successfully minimises operational costs while ensuring timely deliveries. Performance metrics such as delivery speed, consumer satisfaction, and cost optimization are significantly improved compared to traditional algorithms. The sensitivity analysis included in the study also shows how changes in input parameters affect overall performance, indicating the robustness of the proposed method1.

4. Research Gaps

Despite the advancements presented, the research identifies several gaps in the current methodologies:
Real-Time Data Integration: The current model does not utilize real-time traffic data or unforeseen operational constraints, which could significantly impact route efficiency.
Environmental Factors: The influence of weather conditions and other external factors on delivery efficacy has not been thoroughly explored.

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Scalability: The proposed model's performance in larger-scale operations remains untested, leaving open questions about its applicability in various contexts.

5. Future Work Opportunities

Several avenues for future research can significantly enhance delivery route optimization:

Incorporating Real-Time Data: Future work should investigate frameworks that integrate real-time traffic and environmental data to improve routing decisions dynamically.

Adaptive Learning: Exploring adaptive learning techniques that continuously improve the model as new data becomes available could enhance efficiency further.

Broader Application: Testing the proposed model across different industries and varying delivery scenarios to evaluate its versatility and effectiveness in diverse logistics environments.

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```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import os

import warnings
warnings.filterwarnings("ignore", category=FutureWarning)
```

```
df = pd.read_csv('/content/Train.csv')
df.head()
```

	ID	Warehouse_block	Mode_of_Shipment	Customer_care_calls	Customer_rati
0	1	D	Flight	4	
1	2	F	Flight	4	
2	3	A	Flight	2	
3	4	B	Flight	3	
4	5	C	Flight	2	

```
df.shape
```

```
(10999, 12)
```

```
df.dtypes
```

	0
ID	int64
Warehouse_block	object
Mode_of_Shipment	object
Customer_care_calls	int64
Customer_rating	int64
Cost_of_the_Product	int64
Prior_purchases	int64
Product_importance	object
Gender	object
Discount_offered	int64
Weight_in_gms	int64
Reached.on.Time_Y.N	int64

dtype: object

```
df.drop(['ID'], axis=1, inplace=True)
```

```
df.isnull().sum()
```

	0
Warehouse_block	0
Mode_of_Shipment	0
Customer_care_calls	0
Customer_rating	0
Cost_of_the_Product	0
Prior_purchases	0
Product_importance	0
Gender	0
Discount_offered	0
Weight_in_gms	0
Reached.on.Time_Y.N	0

dtype: int64

```
df.duplicated().sum()
```

```
0
```

```
df.describe()
```

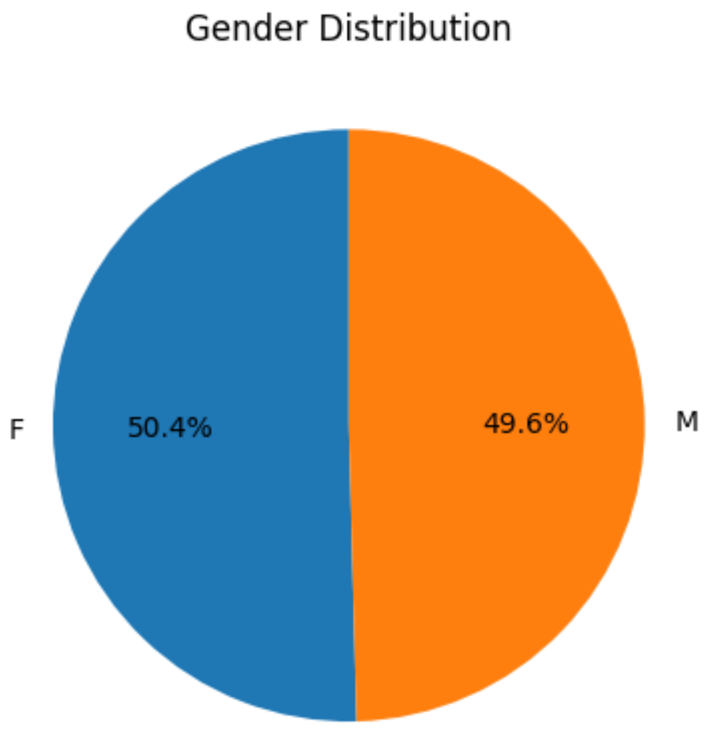
	Customer_care_calls	Customer_rating	Cost_of_the_Product	Prior_pur
count	10999.000000	10999.000000	10999.000000	10999.(
mean	4.054459	2.990545	210.196836	3.5
std	1.141490	1.413603	48.063272	1.5
min	2.000000	1.000000	96.000000	2.(
25%	3.000000	2.000000	169.000000	3.(
50%	4.000000	3.000000	214.000000	3.(
75%	5.000000	4.000000	251.000000	4.(
max	7.000000	5.000000	310.000000	10.(

```
df.head()
```

	Warehouse_block	Mode_of_Shipment	Customer_care_calls	Customer_rating
0	D	Flight	4	2
1	F	Flight	4	5
2	A	Flight	2	2
3	B	Flight	3	3
4	C	Flight	2	2

```
plt.pie(df['Gender'].value_counts(),labels = ['F','M'], autopct='%1.1f%%', star
plt.title('Gender Distribution')
```

```
Text(0.5, 1.0, 'Gender Distribution')
```

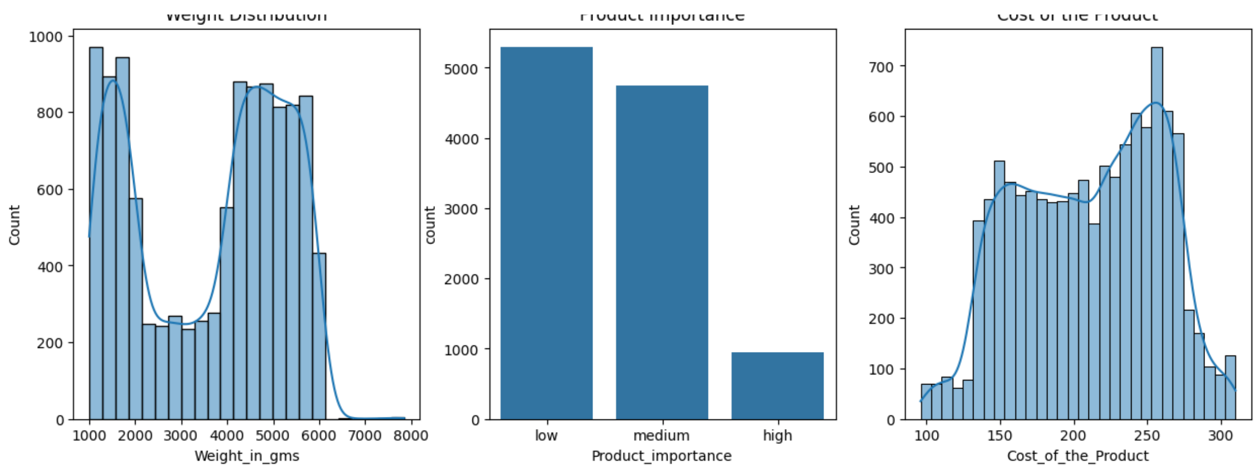


```
df.replace([np.inf, -np.inf], np.nan, inplace=True)
```

```
fig, ax = plt.subplots(1,3,figsize=(15,5))
sns.histplot(df['Weight_in_gms'], ax=ax[0], kde=True).set_title('Weight Distrib
sns.countplot(x = 'Product_importance', data = df, ax=ax[1]).set_title('Product
sns.histplot(df['Cost_of_the_Product'], ax=ax[2], kde=True).set_title('Cost of
```

```
Text(0.5, 1.0, 'Cost of the Product')
```

Weight Distribution Product Importance Cost of the Product



```
fig, ax = plt.subplots(1,3,figsize=(15,5))
sns.countplot(x = 'Warehouse_block', data = df, ax=ax[0]).set_title('Warehouse
sns.countplot(x = 'Mode_of_Shipment', data = df, ax=ax[1]).set_title('Mode of S
sns.countplot(x = 'Reached.on.Time_Y.N', data = df, ax=ax[2]).set_title('Reache
```

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Text(0.5, 1.0, 'Reached on Time')
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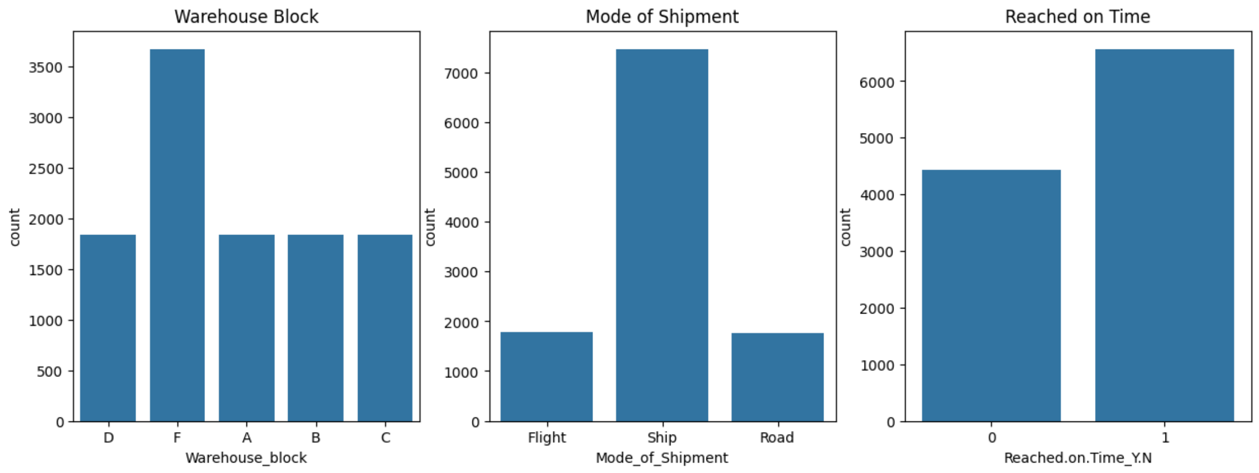

```
fig, ax = plt.subplots(2,2,figsize=(15,10))
sns.countplot(x = 'Customer_care_calls', data = df, ax=ax[0,0]).set_title('Cust
sns.countplot(x = 'Customer_rating', data = df, ax=ax[0,1]).set_title('Customer
sns.countplot(x = 'Prior_purchases', data = df, ax=ax[1,0]).set_title('Prior Pu
sns.histplot(x = 'Discount_offered', data = df, ax=ax[1,1], kde = True).set_tit
```

```
Text(0.5, 1.0, 'Discount Offered')
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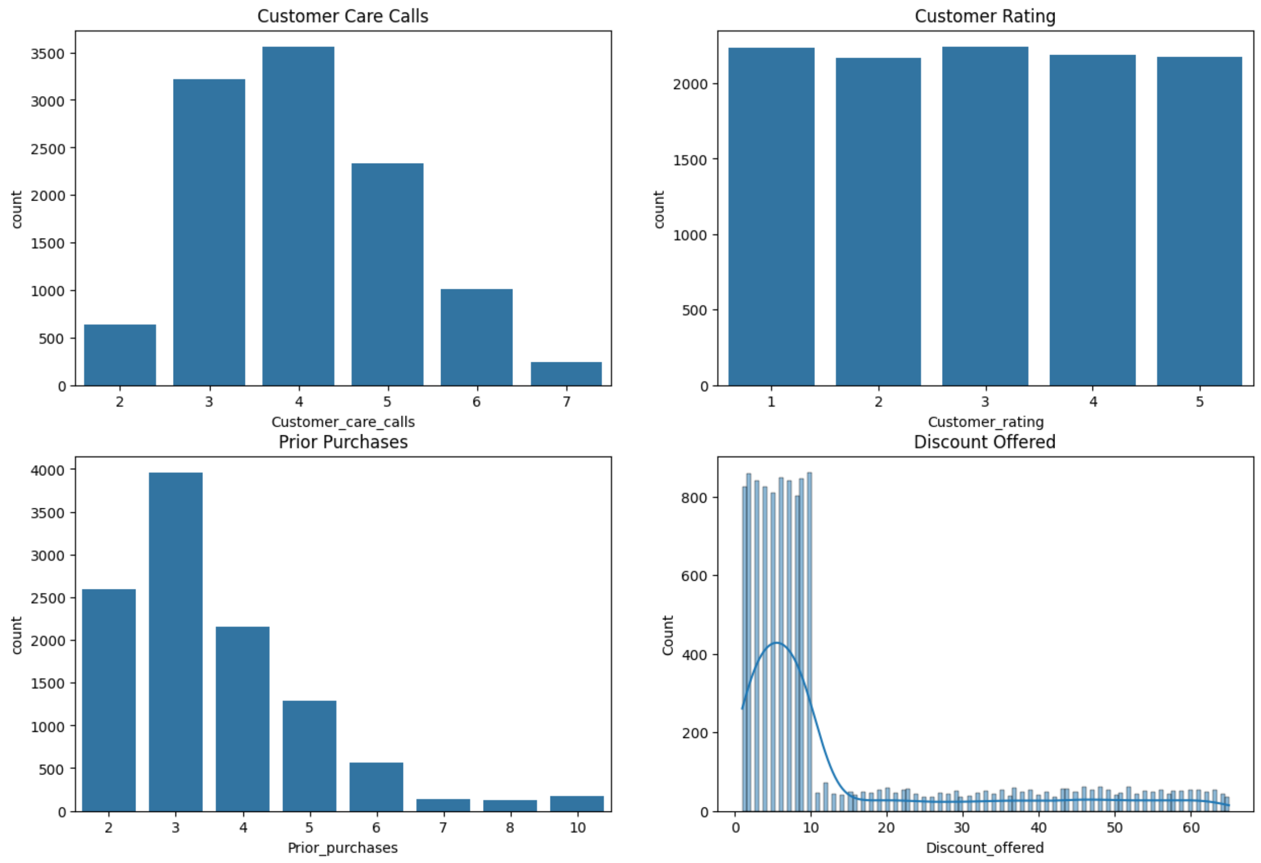
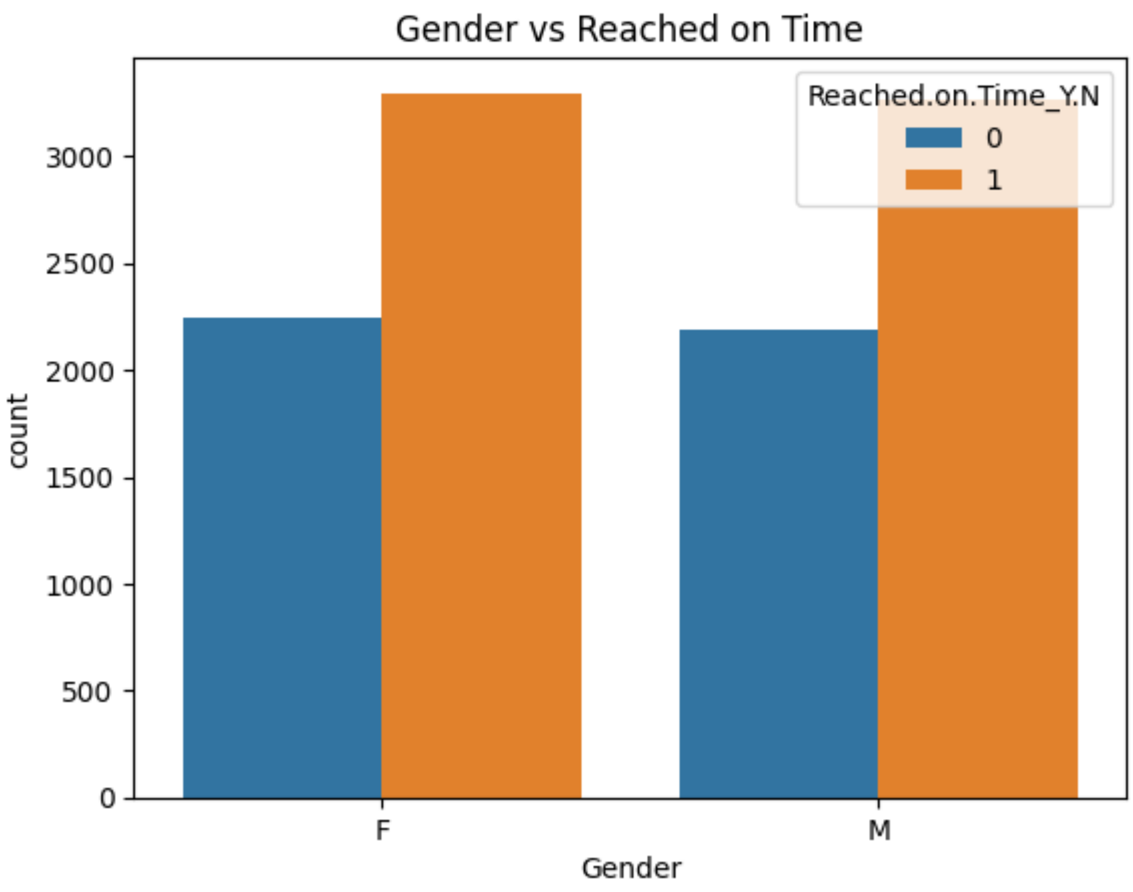


```
sns.countplot(x = 'Gender', data = df, hue = 'Reached.on.Time_Y.N').set_title('
```

```
Text(0.5, 1.0, 'Gender vs Reached on Time')
```



```
fig, ax = plt.subplots(1, 3, figsize=(15, 5))

# Weight Distribution
sns.violinplot(y=df['Weight_in_gms'], ax=ax[0], inner=None, x=df['Reached.on.Ti
sns.kdeplot(y=df['Weight_in_gms'], ax=ax[0], hue=df['Reached.on.Time_Y.N'], mul

# Product Importance
sns.countplot(x='Product_importance', data=df, ax=ax[1], hue='Reached.on.Time_Y

# Cost of the Product
sns.violinplot(y=df['Cost_of_the_Product'], ax=ax[2], inner=None, x=df['Reachec
sns.kdeplot(y=df['Cost_of_the_Product'], ax=ax[2], hue=df['Reached.on.Time_Y.N'

plt.tight_layout()
plt.show()
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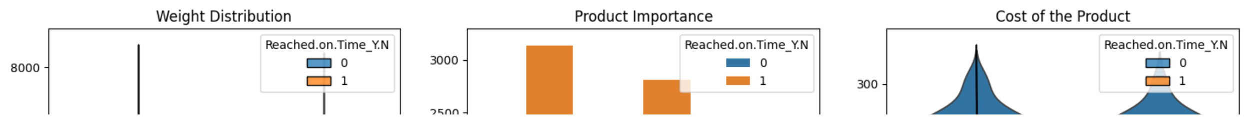

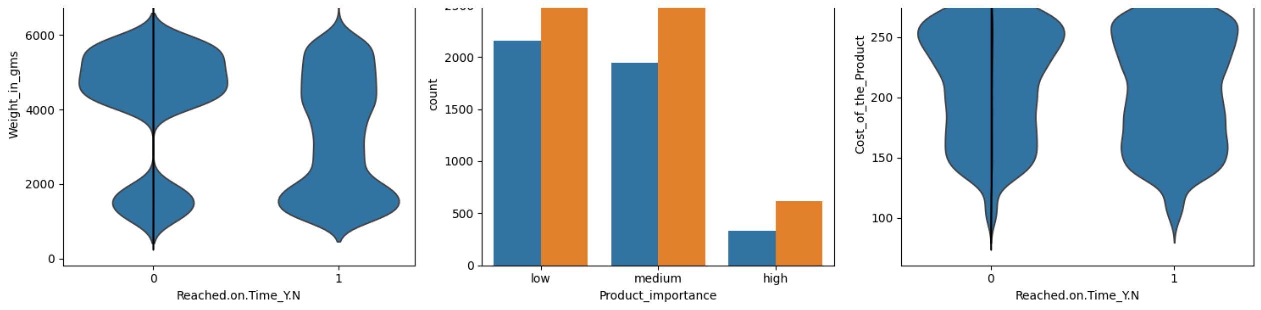

```
fig, ax = plt.subplots(1,2,figsize=(15,5))
sns.countplot(x = 'Warehouse_block', data = df, ax=ax[0], hue = 'Reached.on.Tim
sns.countplot(x = 'Mode_of_Shipment', data = df, ax=ax[1], hue = 'Reached.on.Ti
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Text(0.5, 1.0, 'Mode of Shipment')
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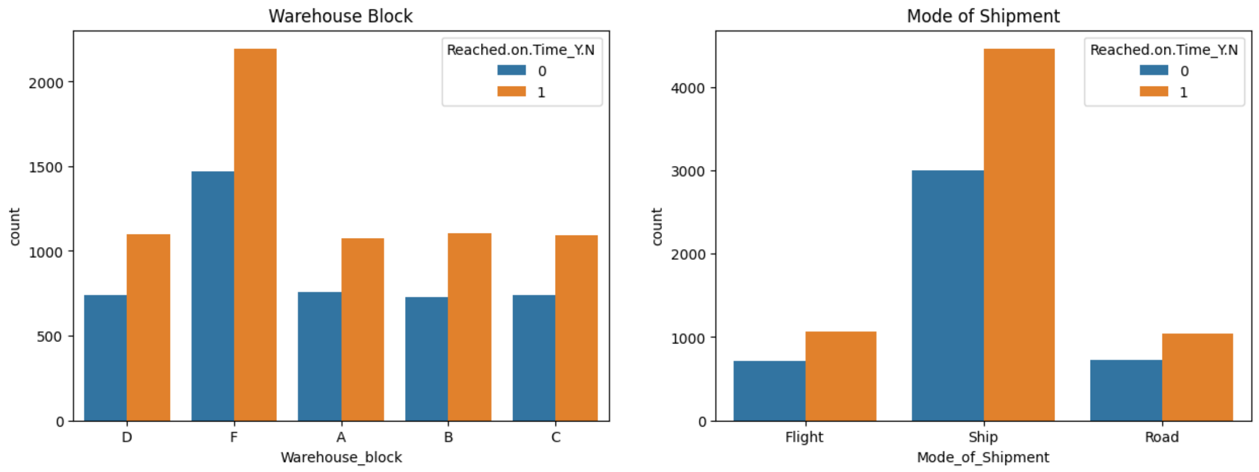

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fig, ax = plt.subplots(2,2,figsize=(15,10))
sns.countplot(x = 'Customer_care_calls', data = df, ax=ax[0,0],hue = 'Reached.o
sns.countplot(x = 'Customer_rating', data = df, ax=ax[0,1],hue = 'Reached.on.Ti
sns.countplot(x = 'Prior_purchases', data = df, ax=ax[1,0],hue = 'Reached.on.Ti
sns.violinplot(x = 'Reached.on.Time_Y.N', y = 'Discount_offered' ,data = df, ax
```

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Text(0.5, 1.0, 'Discount Offered')
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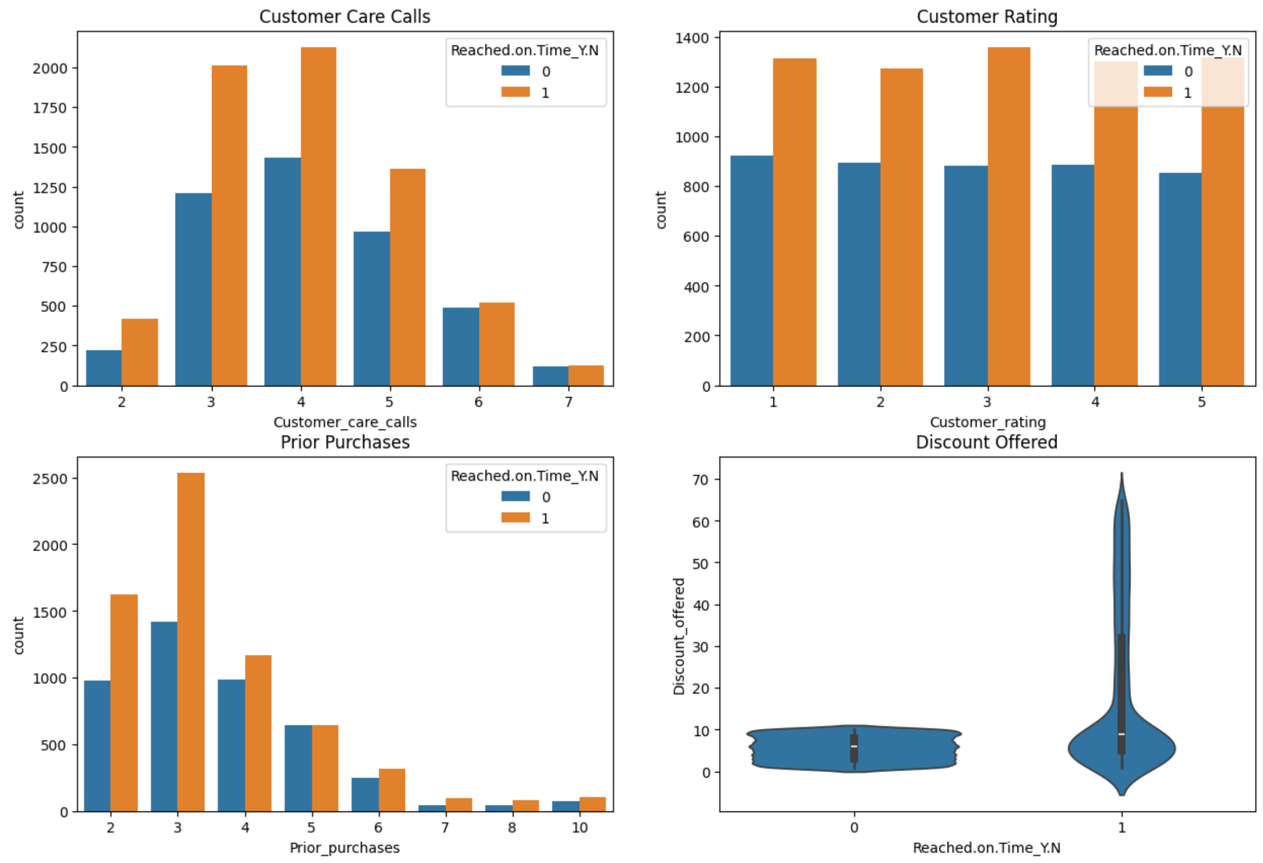
Customer Care Calls
Reached.on.Time_Y.N
count
Customer_care_calls
Customer Rating
Customer_rating
Prior Purchases
Prior_purchases
Discount Offered
Discount_offered
Reached.on.Time_Y.N