question-1

March 9, 2024

1 Question 1 codes and answers

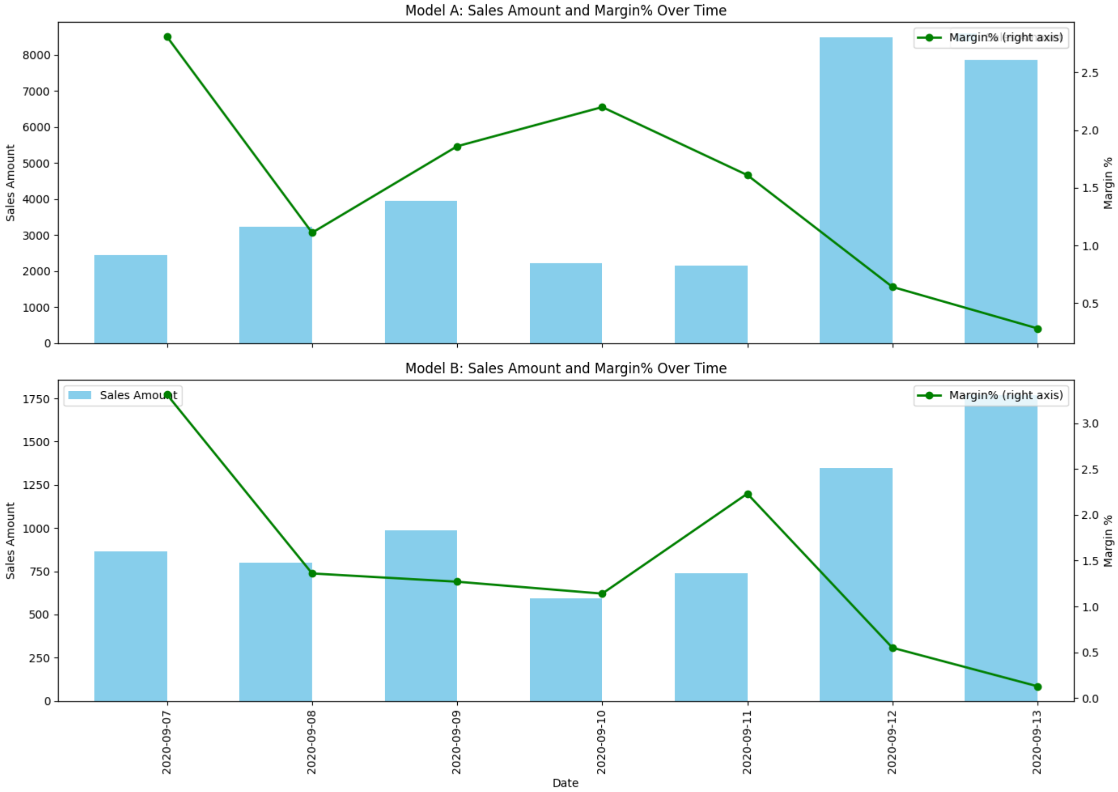
[1]:

```
import pandas as pd

# Load the model comparison data
model_compare_df = pd.read_csv('model_compare.csv')
model_compare_df['Margin%'] = model_compare_df['Margin%'].str.replace('%', '').
  ↪astype(float)
```

[3]:

```
import matplotlib.pyplot as plt

# Separate the data for Model A and Model B
model_a_df = model_compare_df[model_compare_df['By'] == 'Model A']
model_b_df = model_compare_df[model_compare_df['By'] == 'Model B']

# Create subplots for Model A and Model B
fig, axes = plt.subplots(nrows=2, ncols=1, figsize=(14, 10), sharex=True)

# Function to plot the charts
def plot_model_data(ax, df, title):
    ax2 = ax.twinx()

    # Bar chart for Sales Amount
    df.plot(kind='bar', x='Date', y='Sales_Amount', ax=ax, color='skyblue',␣
  ↪position=1, label='Sales Amount')

    # Line chart for Margin%
    df.plot(kind='line', x='Date', y='Margin%', marker='o', ax=ax2,␣
  ↪color='green', linewidth=2, label='Margin% (right axis)')

    # Setting the labels and title
    ax.set_ylabel('Sales Amount')
    ax2.set_ylabel('Margin %')
    ax.set_title(title)

# Plot the data for Model A
```

```
plot_model_data(axes[0], model_a_df, 'Model A: Sales Amount and Margin% Over␣
  ↪Time')

# Plot the data for Model B
plot_model_data(axes[1], model_b_df, 'Model B: Sales Amount and Margin% Over␣
  ↪Time')

# Set the x-axis label
axes[1].set_xlabel('Date')

# Show plot
plt.tight_layout()
plt.show()
```



There's a visible trend where the sales amount increases on certain days, which correspond to weekends, while the margin percentage tends to decrease on those days. This could indicate that while more sales are made on weekends, these sales are less profitable.

```
[4]: # Add the Sales_Per_Customer column to the original dataframe
model_compare_df['Sales_Per_Customer'] = model_compare_df['Sales_Amount'] /␣
  ↪model_compare_df['Customer_Count']
```

```
# Show the updated dataframe with the new column
model_compare_df[['Date', 'By', 'Customer_Count', 'Sales_Amount', 'Net_amount',␣
 ↪'Sales_Per_Customer']]
```

[4]:

```
          Date       By  Customer_Count  Sales_Amount  Net_amount  \
0   2020-09-07  Model A              74          2448       68.80
1   2020-09-08  Model A              92          3232       35.72
2   2020-09-09  Model A             120          3948       73.29
3   2020-09-10  Model A              63          2207       48.45
4   2020-09-11  Model A              64          2155       34.68
5   2020-09-12  Model A             265          8484       54.29
6   2020-09-13  Model A             241          7857       22.37
7   2020-09-07  Model B              29           863       28.54
8   2020-09-08  Model B              25           800       10.88
9   2020-09-09  Model B              29           986       12.56
10  2020-09-10  Model B              19           593        6.79
11  2020-09-11  Model B              22           739       16.44
12  2020-09-12  Model B              42          1348        7.37
13  2020-09-13  Model B              53          1768        2.30

    Sales_Per_Customer
0            33.081081
1            35.130435
2            32.900000
3            35.031746
4            33.671875
5            32.015094
6            32.601660
7            29.758621
8            32.000000
9            34.000000
10           31.210526
11           33.590909
12           32.095238
13           33.358491
```

Both models display a relatively stable `Sales_Per_Customer` metric throughout the week, with the numbers varying within a narrow range for each model, suggesting consistency in the sales generated per customer for both Model A and Model B.

[5]:

```
# Calculate the average margin for each model
average_margin = model_compare_df.groupby('By')['Margin%'].mean()

# Correcting column names for total sales and net amount calculations
total_sales = model_compare_df.groupby('By')['Sales_Amount'].sum()
total_net_amount = model_compare_df.groupby('By')['Net_amount'].sum()
```

```python
# Calculate the total customer count for each model
total_customers = model_compare_df.groupby('By')['Customer_Count'].sum()

# Combine all the calculated metrics into a summary dataframe
summary_df = pd.DataFrame({
    'Average Margin (%)': average_margin,
    'Total Sales Amount': total_sales,
    'Total Net Amount': total_net_amount,
    'Total Customers': total_customers
})

# Calculate the variance of the margin for each model to see which one has more␣
 ↪consistent performance.
margin_variance = model_compare_df.groupby('By')['Margin%'].var()
summary_df['Margin Variance'] = margin_variance

summary_df
```

[5]:

```
         Average Margin (%)  Total Sales Amount  Total Net Amount  \
By
Model A            1.501429               30331            337.60
Model B            1.427143                7097             84.88

         Total Customers  Margin Variance
By
Model A              919         0.787981
Model B              219         1.125557
```

[6]:

```python
# Create a pivot table with dates as rows and models as columns for the margin.
pivot_margins = model_compare_df.pivot(index='Date', columns='By',␣
 ↪values='Margin%')

# Calculate the correlation between Model A and Model B's daily margins
correlation_between_models = pivot_margins.corr()

# Since we only have two models, the result will be a 2x2 matrix, we are␣
 ↪interested in the off-diagonal value.
correlation_between_models_value = correlation_between_models.iloc[0, 1]

correlation_between_models_value
```

[6]:

```
0.8247525232172935
```

1.1 Model A vs Model B Performance Summary

1.1.1 Overview

- **Model A** has demonstrated a higher engagement and revenue generation compared to Model B within the testing period:
  - Average Margin: **1.50%**
  - Total Sales Amount: **30,331**
  - Total Net Amount: **337.60**
  - Total Customers: **919**
- **Model B** has shown a slightly lower average margin but not significantly different from Model A:
  - Average Margin: **1.43%**
  - Total Sales Amount: **7,097**
  - Total Net Amount: **84.88**
  - Total Customers: **219**

1.1.2 Consistency and Variability

- Model A has a lower margin variance (**0.788%**) indicating more consistent performance.
- Model B has a higher margin variance (**1.126%**) suggesting greater variability in its performance.

1.1.3 Correlation Analysis

- There is a strong positive correlation between the daily margins of Model A and Model B (~**0.825**), suggesting that both models tend to perform similarly across the tested dates, responding to market conditions or customer behaviors in a comparable manner.

1.1.4 Conclusion

Given the above analysis, **Model A** is the preferred choice due to: - Higher overall sales and net amounts indicating a broader appeal or effectiveness. - A larger customer base, which could be indicative of better market penetration. - More consistent performance with lower variability in margins. - A strong correlation in performance with Model B suggests that choosing Model A does not forgo the benefits observed in Model B, especially given Model A's higher engagement metrics.

1.1.5 Decision Factors

The choice to recommend Model A is supported by its robust performance across multiple metrics. However, it's worth considering operational factors such as costs, scalability, and implementation ease before finalizing the decision. As external factors influence both models similarly, the priority would be to ensure that Model A aligns with the strategic goals and operational capabilities of the business.