quantium-2

January 7, 2025

[2]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

[3]:
```
df = pd.read_csv('final_df.csv')
df.head()
```

[3]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	TOT_SALES	LIFESTAGE	PREMIUM_CUSTOMER	PACK_SIZE	BRAND	MONTH
0	2018-10-17	1	1000	1	5	Natural Chip Compny SeaSalt175g	2	6.0	YOUNG SINGLES/COUPLES	Premium	175	Natural	10
1	2019-05-14	1	1307	348	66	CCs Nacho Cheese 175g	3	6.3	MIDAGE SINGLES/COUPLES	Budget	175	CCs	5
2	2019-05-20	1	1343	383	61	Smiths Crinkle Cut Chips Chicken 170g	2	2.9	MIDAGE SINGLES/COUPLES	Budget	170	Smiths	5
3	2018-08-17	2	2373	974	69	Smiths Chip Thinly S/Cream&Onion 175g	5	15.0	MIDAGE SINGLES/COUPLES	Budget	175	Smiths	8
4	2018-08-18	2	2426	1038	108	Kettle Tortilla ChpsHny&Jlpno Chili 150g	3	13.8	MIDAGE SINGLES/COUPLES	Budget	150	Kettle	8

[4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 264833 entries, 0 to 264832
Data columns (total 13 columns):
 #   Column            Non-Null Count   Dtype
---  ------            --------------   -----
 0   DATE              264833 non-null  object
 1   STORE_NBR         264833 non-null  int64
 2   LYLTY_CARD_NBR    264833 non-null  int64
```

```
 3   TXN_ID            264833 non-null  int64
 4   PROD_NBR          264833 non-null  int64
 5   PROD_NAME         264833 non-null  object
 6   PROD_QTY          264833 non-null  int64
 7   TOT_SALES         264833 non-null  float64
 8   LIFESTAGE         264833 non-null  object
 9   PREMIUM_CUSTOMER  264833 non-null  object
 10  PACK_SIZE         264833 non-null  int64
 11  BRAND             264833 non-null  object
 12  MONTH             264833 non-null  int64
dtypes: float64(1), int64(7), object(5)
memory usage: 26.3+ MB
```

[5]:
```
# Now we need to filter for stores that have transactions in every month of the␣
 ↪experiment's 12 month
# Group by store number and count unique months for each store
monthly_counts = df.groupby('STORE_NBR')['MONTH'].nunique()
valid_stores = monthly_counts == 12
# Map this boolean series back to the original dataframe
df['valid_control_store'] = df['STORE_NBR'].map(valid_stores)
valid_control_stores = df.loc[df['valid_control_store']==True]['STORE_NBR'].
 ↪unique()
```

[6]:
```
trial_stores = df.loc[df['STORE_NBR'].isin([77, 86, 88])]
control_stores = df.loc[(df['STORE_NBR'].isin(valid_control_stores)) &␣
 ↪(~df['STORE_NBR'].isin([77, 86, 88]))]
trial_stores_before_feb = trial_stores.loc[trial_stores['DATE'] < '2019-02-01']
control_stores_before_feb = control_stores.loc[control_stores['DATE'] <␣
 ↪'2019-02-01']
df_before_feb = df.loc[df['DATE'] < '2019-02-01']
trial_stores_trial_period = trial_stores.loc[(trial_stores['DATE'] >=␣
 ↪'2019-02-01') & (trial_stores['DATE'] < '2019-04-01')]
control_stores_trial_period = control_stores.loc[(control_stores['DATE'] >=␣
 ↪'2019-02-01') & (control_stores['DATE'] < '2019-04-01')]
df_trial_period = df.loc[(df['DATE'] >= '2019-02-01') & (df['DATE'] <␣
 ↪'2019-04-01')]
```

[7]:
```
# Metrics to compare store performances
def make_pivot_table(df):

    pivot_table = pd.pivot_table(
        df,
        index=['MONTH', 'STORE_NBR'],
        values=['TOT_SALES', 'LYLTY_CARD_NBR', 'TXN_ID'],
        aggfunc={
            'TOT_SALES': 'sum',                    # Monthly overall sales␣
 ↪revenue
```

```
            'LYLTY_CARD_NBR': pd.Series.nunique,  # Monthly number of customers
            'TXN_ID': 'count'                     # Monthly number of␣
↪transactions
        }
    )

    # Calculate the monthly number of transactions per customer
    pivot_table['Avg_Transactions_Per_Customer'] = pivot_table['TXN_ID'] /␣
↪pivot_table['LYLTY_CARD_NBR']

    # Rename the columns for clarity
    pivot_table.rename(columns={
        'TOT_SALES': 'Monthly_Sales_Revenue',
        'LYLTY_CARD_NBR': 'Monthly_Customers',
        'TXN_ID': 'Monthly_Transactions'
    }, inplace=True)

    # Reset index to make it easier to read
    pivot_table.reset_index(inplace=True)
    return pivot_table
```

[8]:
```
# Creating pivot tables to match similarity
pre_feb_df_metrics = make_pivot_table(df_before_feb)
trial_period_metrcis = make_pivot_table(df_trial_period)
```

[9]:
```
# then find the hieghest correlated control store with each trial store
pre_feb_df_metrics.head()
```

[9]:

	MONTH	STORE_NBR	Monthly_Customers	Monthly_Sales_Revenue	Monthly_Transactions	Avg_Transactions_Per_Customer
0	1	1	35	154.8	36	1.028571
1	1	2	43	162.8	45	1.046512
2	1	3	102	1051.7	121	1.186275
3	1	4	134	1525.0	168	1.253731
4	1	5	92	838.0	118	1.282609

[10]:
```
# from sklearn.preprocessing import StandardScaler
# from dtaidistance import dtw

# # Standardize the data
# scaler = StandardScaler()
```

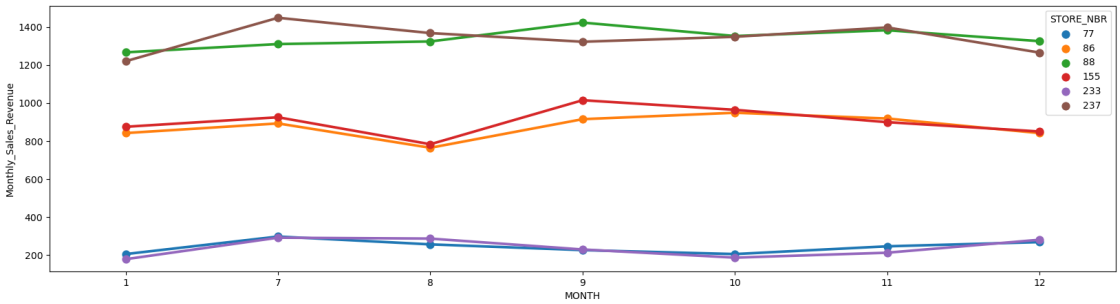
```
# pre_feb_trial_metrics[['Monthly_Customers', 'Monthly_Sales_Revenue',␣
 ↪'Monthly_Transactions']] = scaler.
 ↪fit_transform(pre_feb_trial_metrics[['Monthly_Customers',␣
 ↪'Monthly_Sales_Revenue', 'Monthly_Transactions']])
# pre_feb_control_metrics[['Monthly_Customers', 'Monthly_Sales_Revenue',␣
 ↪'Monthly_Transactions']] = scaler.
 ↪fit_transform(pre_feb_control_metrics[['Monthly_Customers',␣
 ↪'Monthly_Sales_Revenue', 'Monthly_Transactions']])

# # Function to calculate DTW distance
# def calculate_dtw(trial_store, control_store):
#     distances = []
#     for feature in ['Monthly_Customers', 'Monthly_Sales_Revenue',␣
 ↪'Monthly_Transactions']:
#         distance = dtw.distance(trial_store[feature].values,␣
 ↪control_store[feature].values)
#         distances.append(distance)
#     return sum(distances)

# # Find the closest control store for each trial store
# closest_stores = {}
# for trial_id in pre_feb_trial_metrics['STORE_NBR'].unique():
#     trial_store_data =␣
 ↪pre_feb_trial_metrics[pre_feb_trial_metrics['STORE_NBR'] == trial_id]
#     min_distance = float('inf')
#     closest_store = None
#     for control_id in pre_feb_control_metrics['STORE_NBR'].unique():
#         control_store_data =␣
 ↪pre_feb_control_metrics[pre_feb_control_metrics['STORE_NBR'] == control_id]
#         distance = calculate_dtw(trial_store_data, control_store_data)
#         if distance < min_distance:
#             min_distance = distance
#             closest_store = control_id
#     closest_stores[trial_id] = closest_store

# print("Closest Store Pairs:", closest_stores)
```

[11]:
```
# import numpy as np

# def calculate_magnitude_distance(input_table, metric_col, store_comparison):
#     calc_dist_table = pd.DataFrame(columns=['Store1', 'Store2', 'YEARMONTH',␣
 ↪'measure'])
#     store_numbers = input_table['STORE_NBR'].unique()

#     for i in store_numbers:
#         if i != store_comparison:
```

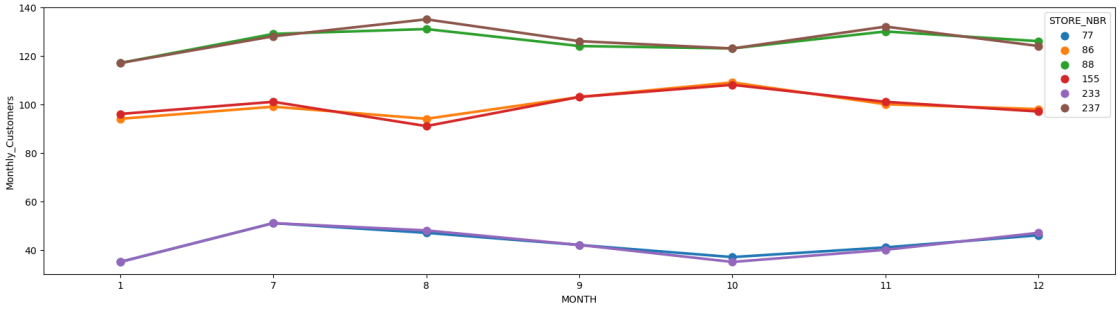
```
#             calculated_measure = pd.DataFrame({
#                 'Store1': [store_comparison] *␣
 ↪len(input_table[input_table['STORE_NBR'] == store_comparison]),
#                 'Store2': [i] * len(input_table[input_table['STORE_NBR'] ==␣
 ↪store_comparison]),
#                 'YEARMONTH': input_table[input_table['STORE_NBR'] ==␣
 ↪store_comparison]['MONTH'].values,
#                 'measure': np.abs(
#                     input_table[input_table['STORE_NBR'] ==␣
 ↪store_comparison][metric_col].values -
#                     input_table[input_table['STORE_NBR'] == i][metric_col].
 ↪values
#                 )
#             })
#             calc_dist_table = pd.concat([calc_dist_table,␣
 ↪calculated_measure], ignore_index=True)

#     # Standardize the magnitude distance so that the measure ranges from 0 to␣
 ↪1
#     min_max_dist = calc_dist_table.groupby(['Store1',␣
 ↪'YEARMONTH'])['measure'].agg(['min', 'max']).reset_index()
#     min_max_dist.columns = ['Store1', 'YEARMONTH', 'minDist', 'maxDist']
#     dist_table = pd.merge(calc_dist_table, min_max_dist, on=['Store1',␣
 ↪'YEARMONTH'])
#     dist_table['magnitudeMeasure'] = 1 - (dist_table['measure'] -␣
 ↪dist_table['minDist']) / (dist_table['maxDist'] - dist_table['minDist'])

#     final_dist_table = dist_table.groupby(['Store1',␣
 ↪'Store2'])['magnitudeMeasure'].mean().reset_index()
#     final_dist_table.columns = ['Store1', 'Store2', 'mag_measure']

#     return final_dist_table

# corr_df = calculate_magnitude_distance(pre_feb_df_metrics,␣
 ↪'Monthly_Sales_Revenue', 77)
```

0.0.1 Now that we have selected our control stores, let's compare pairwise performance during the pre-trial period

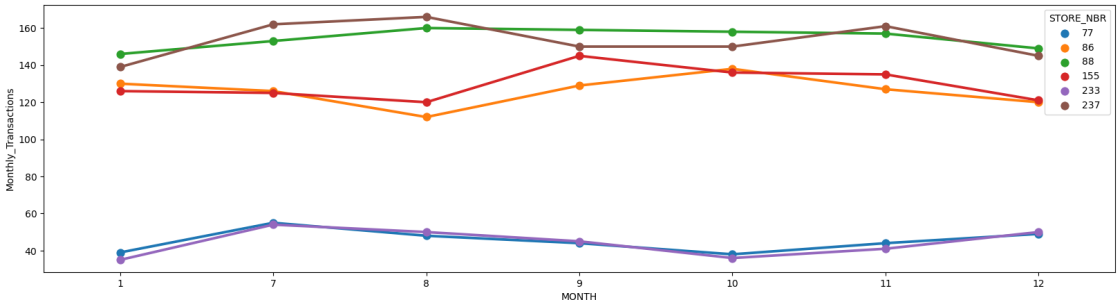
[12]:
```
exp_stores = [77, 86, 88, 233, 155, 237]
plt.figure(figsize=(20, 5))
sns.pointplot(x='MONTH', y='Monthly_Sales_Revenue',␣
 ↪data=pre_feb_df_metrics[pre_feb_df_metrics['STORE_NBR'].isin(exp_stores)],␣
 ↪estimator=sum, errorbar=None, hue='STORE_NBR')
plt.show()
```



[13]:
```
plt.figure(figsize=(20, 5))
sns.pointplot(x='MONTH', y='Monthly_Customers',␣
 ↪data=pre_feb_df_metrics[pre_feb_df_metrics['STORE_NBR'].isin(exp_stores)],␣
 ↪estimator=sum, errorbar=None, hue='STORE_NBR')
plt.show()
```



[14]:
```
plt.figure(figsize=(20, 5))
sns.pointplot(x='MONTH', y='Monthly_Transactions',␣
 ↪data=pre_feb_df_metrics[pre_feb_df_metrics['STORE_NBR'].isin(exp_stores)],␣
 ↪estimator=sum, errorbar=None, hue='STORE_NBR')
plt.show()
```



0.0.2 We can see that the control stores are indeed performing very similarly to the selected trial tores

[26]:
```
# Now let's visually check the effect of the new layout on the performance
sns.lineplot(x='MONTH', y='Monthly_Sales_Revenue',␣
 ↪data=trial_period_metrcis[trial_period_metrcis['STORE_NBR'].
 ↪isin(exp_stores)], hue='STORE_NBR', palette='tab10', estimator=sum)
plt.show()

# from the graph, it appears there's a noticable difference in performace after␣
 ↪applying
# the new product layout in stores 86, 88 but an insignificant diffrence in␣
 ↪store 77
```