Restaurant Sales Forecasting

Data Analysis

Load the csv files

In [ ]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
items = 'https://raw.githubusercontent.com/tksundar/sales_forecasting/refs/heads/master/items.csv'
restaurants = 'https://raw.githubusercontent.com/tksundar/sales_forecasting/refs/heads/master/resturants.csv'
sales = 'https://raw.githubusercontent.com/tksundar/sales_forecasting/refs/heads/master/sales.csv'
items_data = pd.read_csv(items)
restaurants_data = pd.read_csv(restaurants)
sales_data = pd.read_csv(sales)
```

In [ ]:
```
len(items_data.id)
items_data.sort_values(by='id').head()
```

Out[ ]:

	id	store_id	name	kcal	cost
0	1	4	Chocolate Cake	554	6.71
1	2	4	Breaded Fish with Vegetables Meal	772	15.09
2	3	1	Sweet Fruity Cake	931	29.22
3	4	1	Amazing Steak Dinner with Rolls	763	26.42
4	5	5	Milk Cake	583	6.07

In [ ]:
```
restaurants_data
```

Out[ ]:

	id	name
0	1	Bob's Diner
1	2	Beachfront Bar
2	3	Sweet Shack
3	4	Fou Cher
4	5	Corner Cafe
5	6	Surfs Up

In [ ]:
```
sales_data.head(5)
```

Out[ ]:

	date	item_id	price	item_count
0	2019-01-01	3	29.22	2.0
1	2019-01-01	4	26.42	22.0
2	2019-01-01	12	4.87	7.0
3	2019-01-01	13	4.18	12.0
4	2019-01-01	16	3.21	136.0

The `cost` in items data and `price` in sales data are the same

In [ ]:
```
sales_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 109600 entries, 0 to 109599
Data columns (total 4 columns):
 #   Column      Non-Null Count   Dtype  
---  ------      --------------   -----  
 0   date        109600 non-null  object 
 1   item_id     109600 non-null  int64  
 2   price       109600 non-null  float64
 3   item_count  109600 non-null  float64
dtypes: float64(2), int64(1), object(1)
memory usage: 3.3+ MB
```

In [ ]:
```
sales_data.isna().sum()
```

Out[ ]:

	0
date	0
item_id	0
price	0
item_count	0

dtype: int64

In [ ]:
```
sales_data.describe()
```

Out[ ]:

	item_id	price	item_count
count	109600.000000	109600.000000	109600.000000
mean	50.500000	11.763700	6.339297
std	28.866202	8.946225	30.003728
min	1.000000	1.390000	0.000000
25%	25.750000	5.280000	0.000000
50%	50.500000	7.625000	0.000000
75%	75.250000	18.790000	0.000000
max	100.000000	53.980000	570.000000

THis is a peculiar scenario. Thare are no missing values per se. But a majority of values for the item_count column is zero. This as good as a missing value. But we can nt drop this column because dropping this column will prevent any further analysis(we can not find sales per item based on which we can make predictions). So the best option is to replace the zero with mean.

In [ ]:

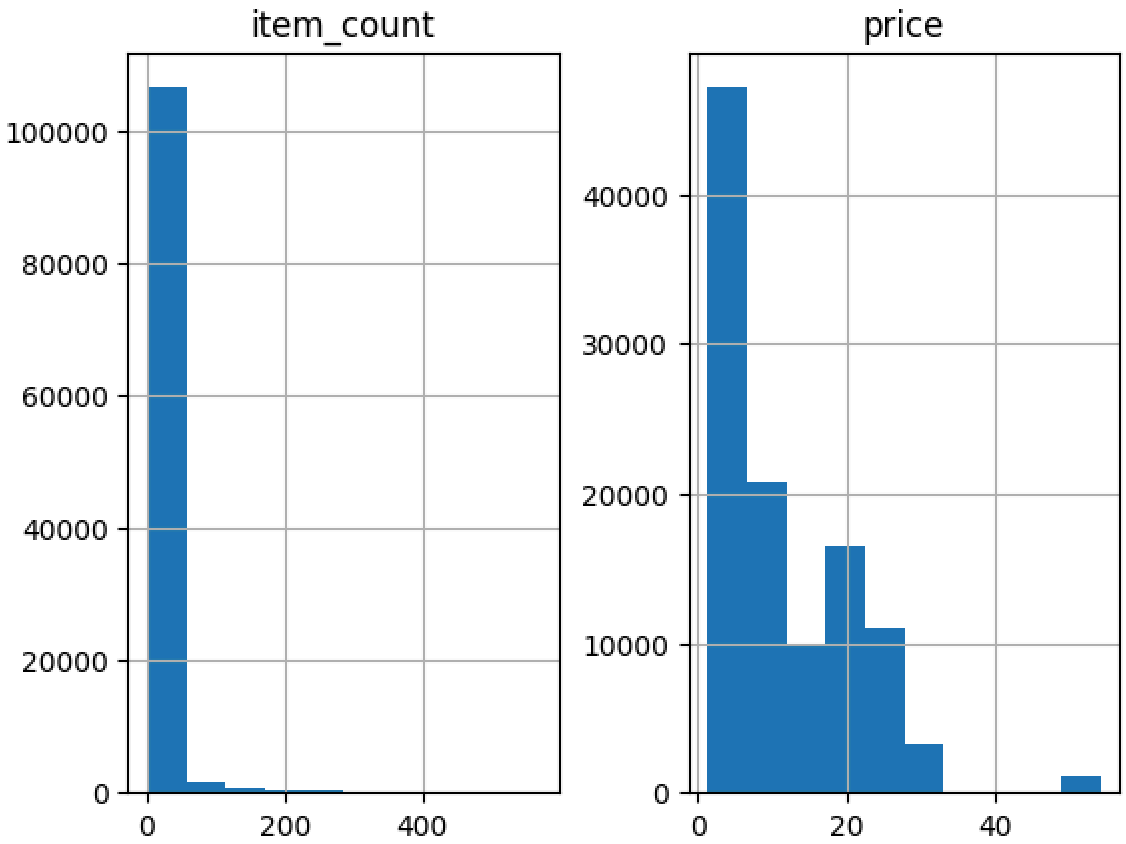
```
mean = round(np.mean(sales_data['item_count']))
sales_data['item_count'] = sales_data['item_count'].replace(0, mean)
sales_data.describe()
```

Out[ ]:

	item_id	price	item_count
count	109600.000000	109600.000000	109600.000000
mean	50.500000	11.763700	11.053677
std	28.866202	8.946225	29.094886
min	1.000000	1.390000	1.000000
25%	25.750000	5.280000	6.000000
50%	50.500000	7.625000	6.000000
75%	75.250000	18.790000	6.000000
max	100.000000	53.980000	570.000000

In [ ]:

```
_=sales_data[['item_count','price']].hist()
```



Merge all dataframes to one

```
In [ ]: id_name_dict = dict(zip(items_data.id, items_data.name))
id_storeid_dict = dict(zip(items_data.id, items_data.store_id))
rest_id_name_dict = dict(zip(restaurants_data.id, restaurants_data.name))
item_id_kcal_dict = dict(zip(items_data.id, items_data.kcal))
sales_data['item_calories'] = sales_data['item_id'].map(item_id_kcal_dict)
sales_data['item_name'] = sales_data['item_id'].map(id_name_dict)
sales_data['store_id'] = sales_data['item_id'].map(id_storeid_dict)
sales_data['rest_name'] = sales_data['store_id'].map(rest_id_name_dict)
sales_data['date'] = pd.to_datetime(sales_data['date'])
sales_data['day_of_the_week'] = sales_data.date.dt.day_of_week
```

```
print(sales_data.shape)
sales_data.sample(5)
```

(109600, 9)

Out[ ]:

	date	item_id	price	item_count	item_calories	item_name	store_id	rest_name	day_of_the_week
4458	2019-02-14	52	5.68	6.0	535	Original Sweet Milky Soft Drink	3	Sweet Shack	3
13983	2019-05-20	84	19.77	6.0	855	BBQ Pork Steak	5	Corner Cafe	0
77493	2021-02-13	94	5.71	6.0	331	Fruity Milky Smoothy	6	Surfs Up	5
22115	2019-08-10	68	8.70	1.0	652	Blue Ribbon Fruity Milky Cake	1	Bob's Diner	5
76693	2021-02-05	94	5.71	6.0	331	Fruity Milky Smoothy	6	Surfs Up	4

In [ ]:

```
sales_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 109600 entries, 0 to 109599
Data columns (total 9 columns):
 #   Column           Non-Null Count   Dtype
---  ------           --------------   -----
 0   date             109600 non-null  datetime64[ns]
 1   item_id          109600 non-null  int64
 2   price            109600 non-null  float64
 3   item_count       109600 non-null  float64
 4   item_calories    109600 non-null  int64
 5   item_name        109600 non-null  object
 6   store_id         109600 non-null  int64
 7   rest_name        109600 non-null  object
 8   day_of_the_week  109600 non-null  int32
dtypes: datetime64[ns](1), float64(2), int32(1), int64(3), object(2)
memory usage: 7.1+ MB
```

Add a column for total sale amount

In [ ]:

```
sales_data['sale_amount'] = sales_data['item_count'] * sales_data['price']
sales_data.head(5)
```

Out[ ]:

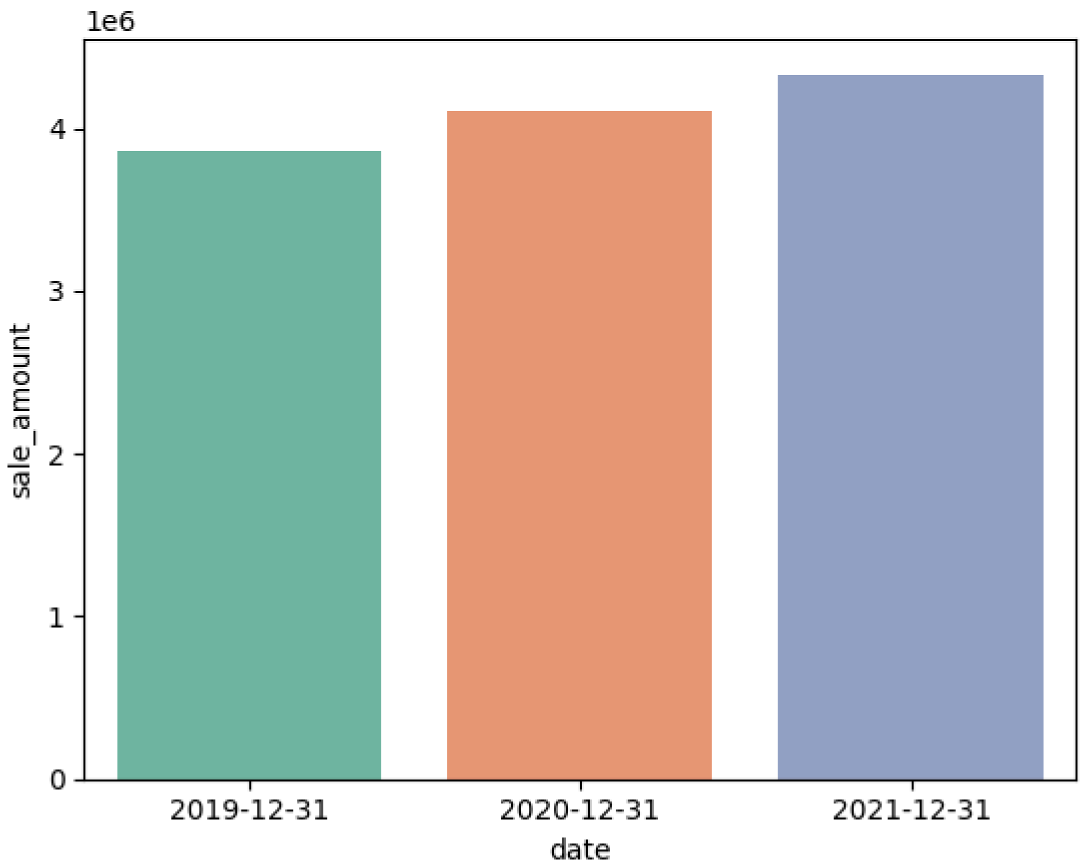
	date	item_id	price	item_count	item_calories	item_name	store_id	rest_name	day_of_the_week	sale_amount
0	2019-01-01	3	29.22	2.0	931	Sweet Fruity Cake	1	Bob's Diner	1	58.44
1	2019-01-01	4	26.42	22.0	763	Amazing Steak Dinner with Rolls	1	Bob's Diner	1	581.24
2	2019-01-01	12	4.87	7.0	478	Fantastic Sweet Cola	1	Bob's Diner	1	34.09
3	2019-01-01	13	4.18	12.0	490	Sweet Frozen Soft Drink	1	Bob's Diner	1	50.16
4	2019-01-01	16	3.21	136.0	284	Frozen Milky Smoothy	1	Bob's Diner	1	436.56

In [ ]:

```
import warnings
warnings.filterwarnings('ignore')

yearly_sales_data = pd.DataFrame(sales_data.groupby(pd.Grouper(key='date', axis=0, freq='YE')).sale_amount.sum()).reset_index(
print(yearly_sales_data)
_=sns.barplot(data=yearly_sales_data, x='date', y='sale_amount', palette = sns.mpl_palette('Set2'))
```

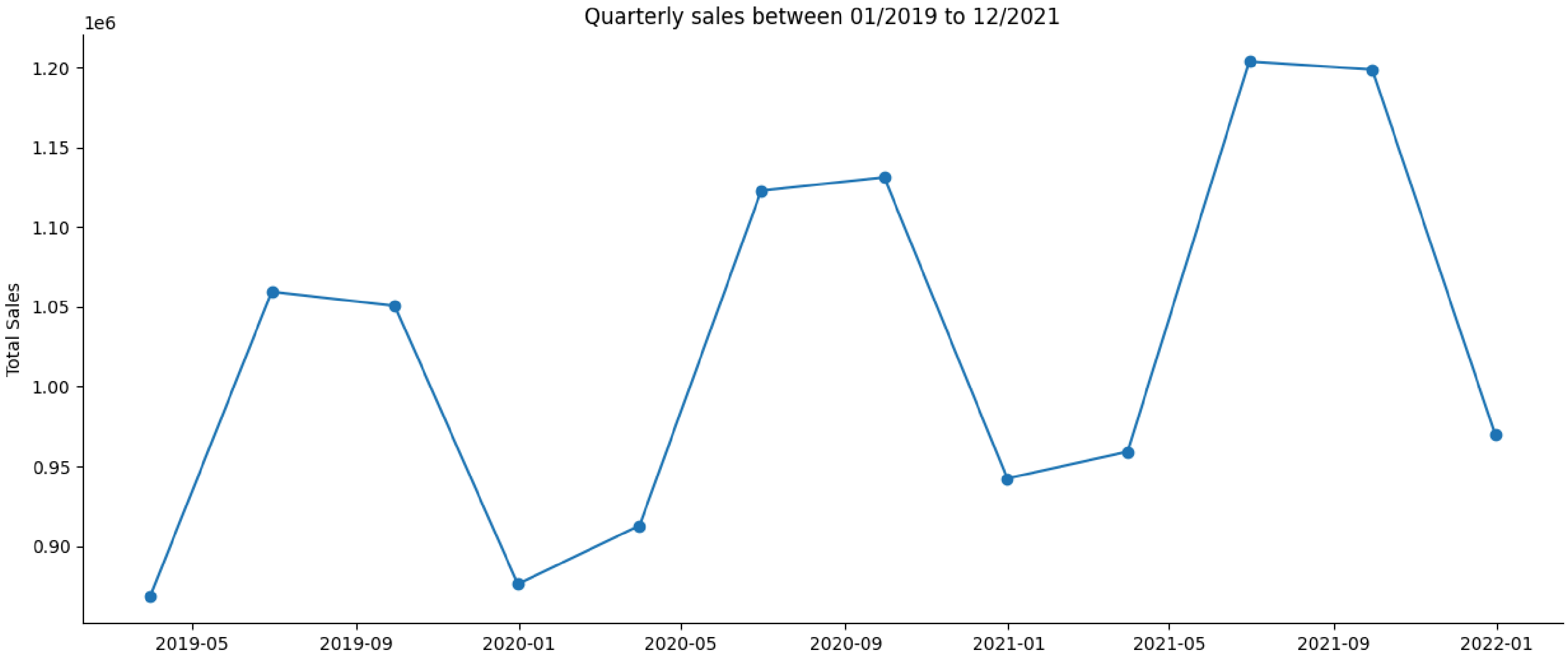
```
        date  sale_amount
0 2019-12-31   3854481.45
1 2020-12-31   4109139.62
2 2021-12-31   4331492.00
```



Quarterly sales data for 3 years

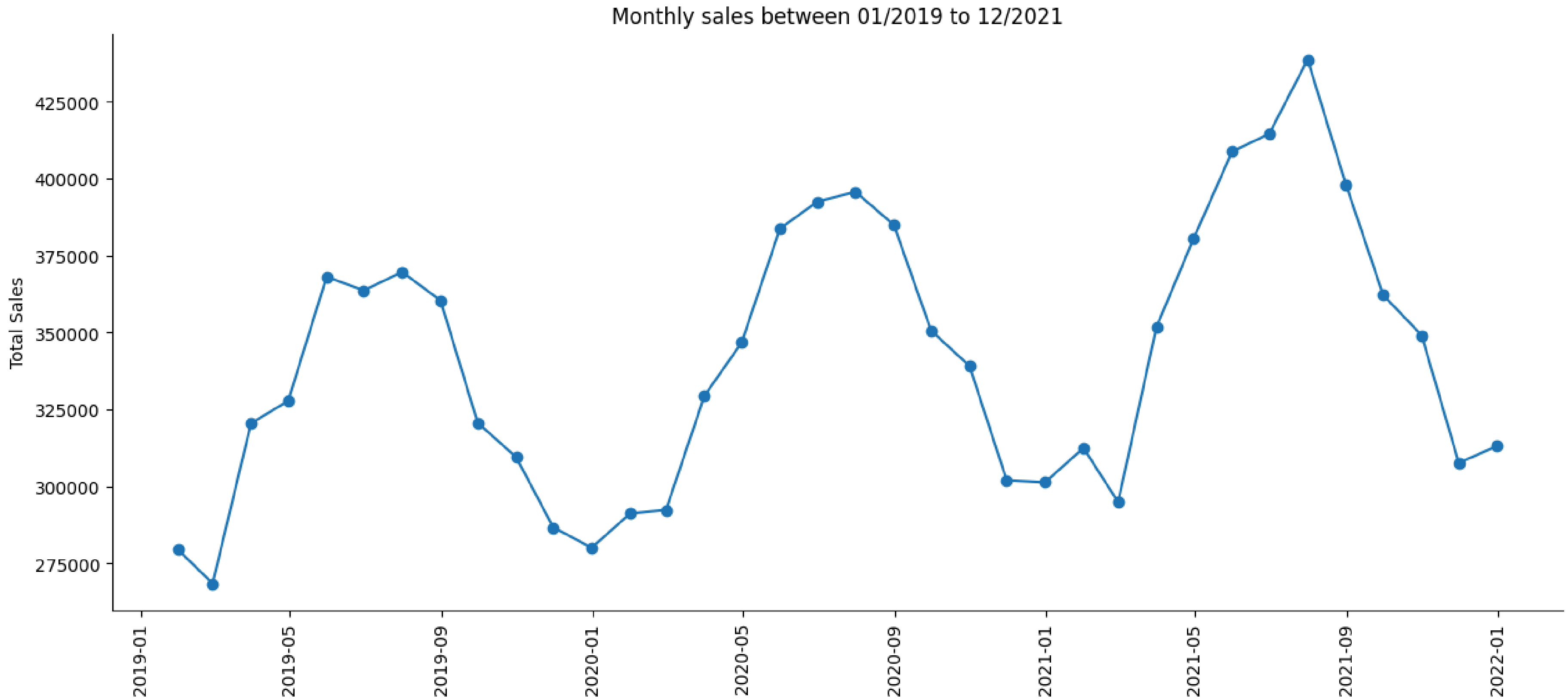
In [ ]:
```
quarterly_sales_19_21 = pd.DataFrame(sales_data.groupby(pd.Grouper(key='date', axis=0, freq='QE')).sale_amount.sum()).reset_in
plt.figure(figsize=(15,6))
print(quarterly_sales_19_21)
_=plt.plot(quarterly_sales_19_21['date'], quarterly_sales_19_21['sale_amount'], marker='o', linestyle='-')
plt.ylabel('Total Sales')
plt.title("Quarterly sales between 01/2019 to 12/2021" )
plt.gca().spines[['top', 'right',]].set_visible(False )
```

```
         date  sale_amount
0  2019-03-31    868277.48
1  2019-06-30   1059445.94
2  2019-09-30   1050594.53
3  2019-12-31    876163.50
4  2020-03-31    912813.58
5  2020-06-30   1122807.33
6  2020-09-30   1131167.76
7  2020-12-31    942350.95
8  2021-03-31    959148.15
9  2021-06-30   1203849.99
10 2021-09-30   1198713.82
11 2021-12-31    969780.04
```



Monthly Sales for 3 years

```
In [ ]: monthly_sales_19_21 = pd.DataFrame(sales_data.groupby(pd.Grouper(key='date', axis=0, freq='ME')).sale_amount.sum()).reset_inde
        plt.figure(figsize=(15,6))
        plt.plot(monthly_sales_19_21['date'], monthly_sales_19_21['sale_amount'], marker='o', linestyle='-')
        plt.ylabel('Total Sales')
        plt.xticks(rotation = 90)
        plt.title("Monthly sales between 01/2019 to 12/2021" )
        plt.gca().spines[['top', 'right',]].set_visible(False )
```

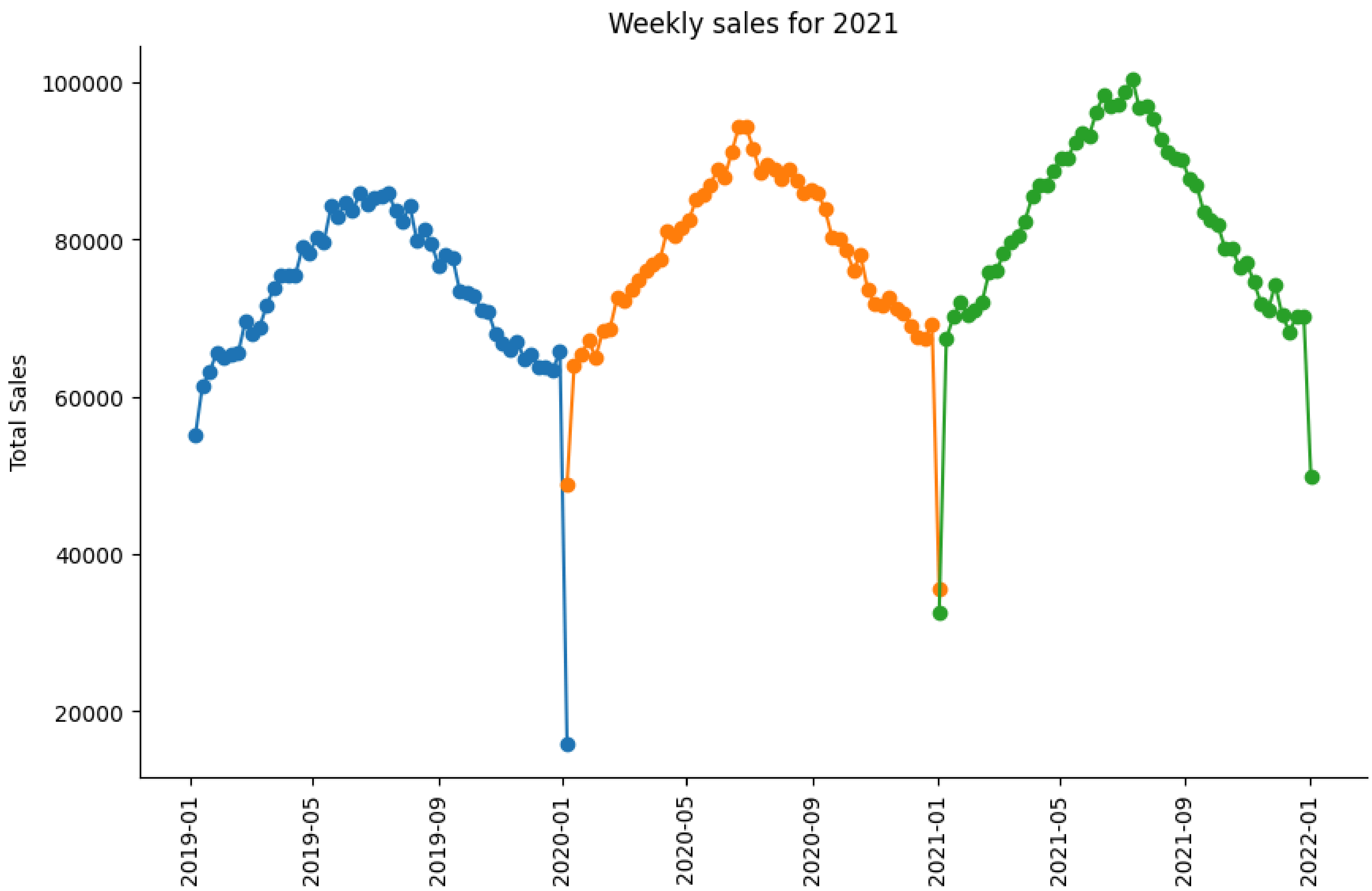


Weekly Sales for 3 years

```
In [ ]: weekly_sales_19_21 = pd.DataFrame(sales_data.groupby(pd.Grouper(key='date', axis=0, freq='W')).sale_amount.sum()).reset_index(

        years = [2019,2020,2021]
        plt.figure(figsize=(10,6))
```

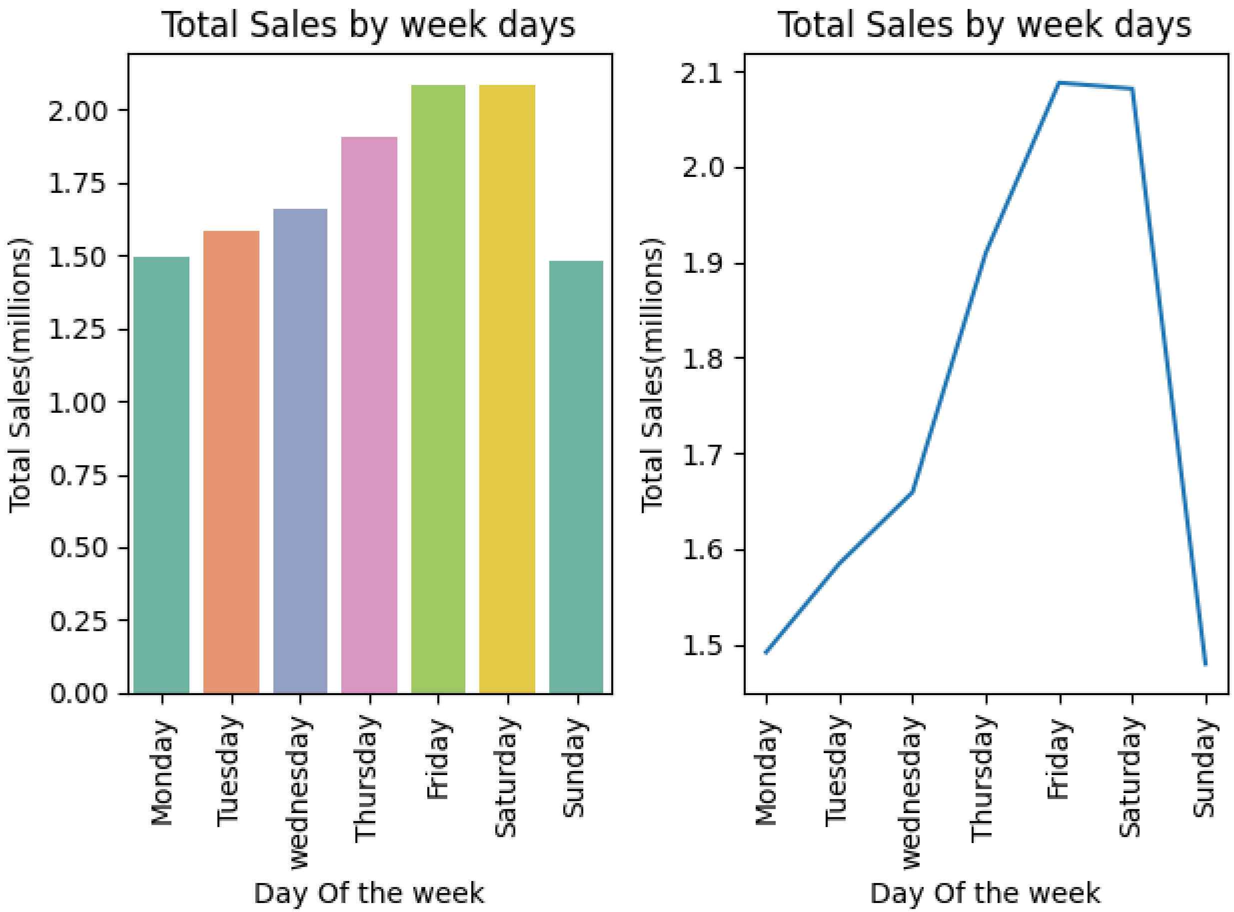
```
for i,year in enumerate(years):
  sales = sales_data[sales_data['date'].dt.year == year]
  weekly_sales = pd.DataFrame(sales.groupby(pd.Grouper(key='date', axis=0, freq='W')).sale_amount.sum()).reset_index()
  plt.plot(weekly_sales['date'], weekly_sales['sale_amount'], marker='o', linestyle='-')
  plt.ylabel('Total Sales')
  plt.xticks(rotation=90)
  plt.title(f"Weekly sales for {year}" )
  plt.gca().spines[['top', 'right',]].set_visible(False )
```



Total Sales by week day

In [ ]:
```
week_days = {
    0: 'Monday',
    1: 'Tuesday',
```

```
    2: 'wednesday',
    3: 'Thursday',
    4: 'Friday',
    5: 'Saturday',
    6: 'Sunday'
}
million = 1000000
df = pd.DataFrame(sales_data.groupby('day_of_the_week')['sale_amount'].sum()/million).reset_index()
df['day_of_the_week'] = df.day_of_the_week.map(week_days)
plt.subplot(1,2,1)
sns.barplot(data = df , x='day_of_the_week', y='sale_amount', palette=sns.mpl_palette('Set2'))
plt.xticks(rotation = 90)
plt.xlabel('Day Of the week')
plt.ylabel('Total Sales(millions)')
plt.title('Total Sales by week days')
plt.subplot(1,2,2)
sns.lineplot(data=df, x='day_of_the_week', y='sale_amount')
plt.xlabel('Day Of the week')
plt.ylabel('Total Sales(millions)')
plt.title('Total Sales by week days')
plt.xticks(rotation = 90)
plt.tight_layout()
plt.show()
df
```


Total Sales by week days
Total Sales(millions)
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
Monday
Tuesday
wednesday
Thursday
Friday
Saturday
Sunday
Day Of the week
Total Sales by week days
Total Sales(millions)
1.5
1.6
1.7
1.8
1.9
2.0
2.1
Monday
Tuesday
wednesday
Thursday
Friday
Saturday
Sunday
Day Of the week

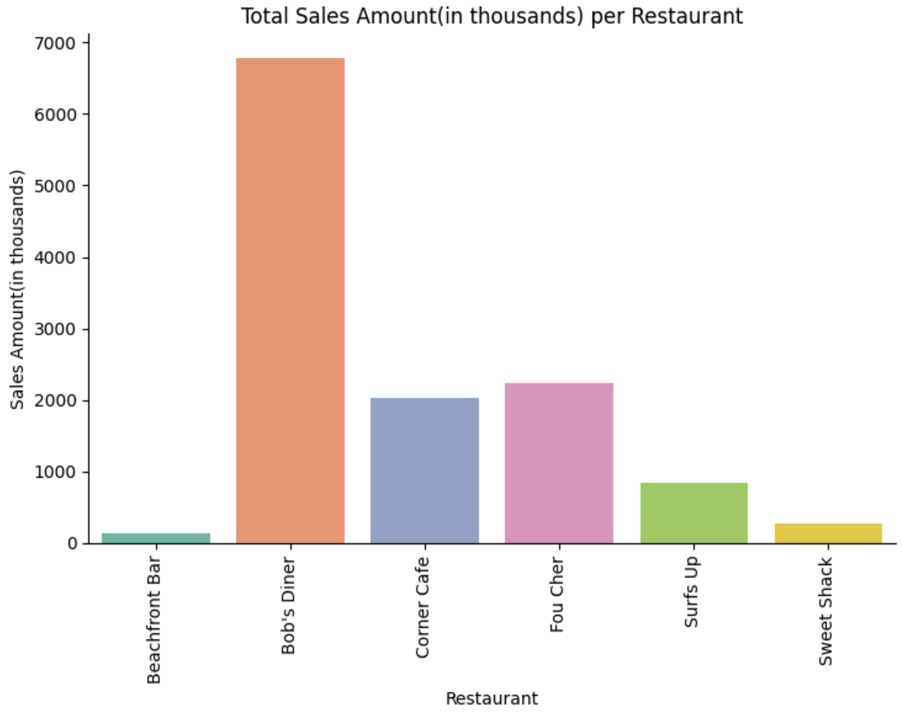
Out[ ]:

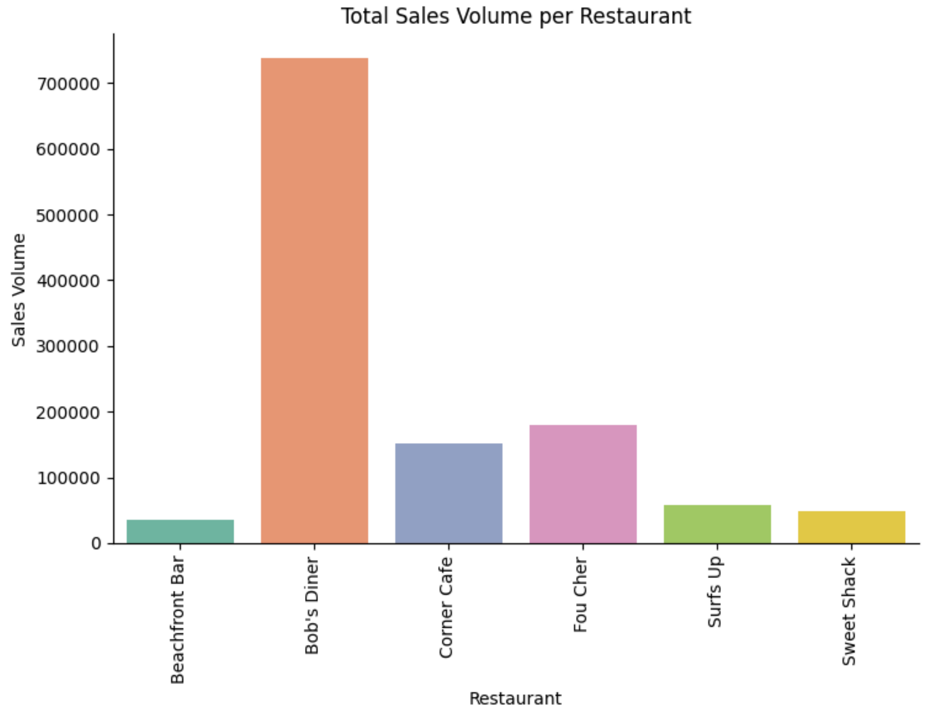
	day_of_the_week	sale_amount
0	Monday	1.491830
1	Tuesday	1.584728
2	wednesday	1.659573
3	Thursday	1.909694
4	Friday	2.087893
5	Saturday	2.081594
6	Sunday	1.479801

Sales Revenue vs Sales Volume

In [ ]:

```
import warnings
warnings.filterwarnings('ignore')
sales_by_restaurant = pd.DataFrame(sales_data.groupby('rest_name').sale_amount.sum()/1000).reset_index()
volume_by_restaurant = pd.DataFrame(sales_data.groupby('rest_name').item_count.sum()).reset_index()
plt.figure(figsize=(15,6))
sales = [sales_by_restaurant,volume_by_restaurant]
cols = ['sale_amount','item_count']
col_map = {cols[0]: 'Sales Amount(in thousands)',cols[1]:"Sales Volume"}
for i,item in enumerate(sales):
  plt.subplot(1,2,i+1)
  sns.barplot(x='rest_name', y=cols[i], data=item, palette = sns.color_palette('Set2'))
  plt.xlabel('Restaurant')
  plt.xticks(rotation=90)
  plt.ylabel(f'{col_map[cols[i]]}')
  plt.title(f'Total {col_map[cols[i]]} per Restaurant')
  plt.gca().spines[['top', 'right',]].set_visible(False)
plt.tight_layout()
plt.show()
sales_by_restaurant
```





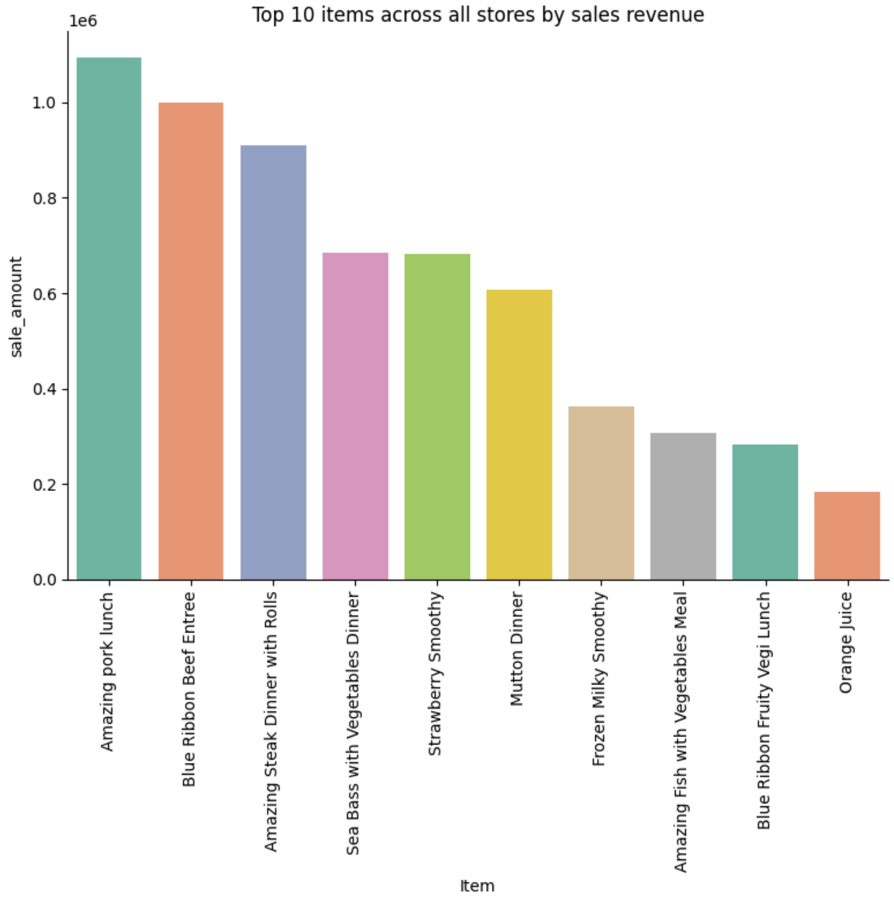
Out[ ]:

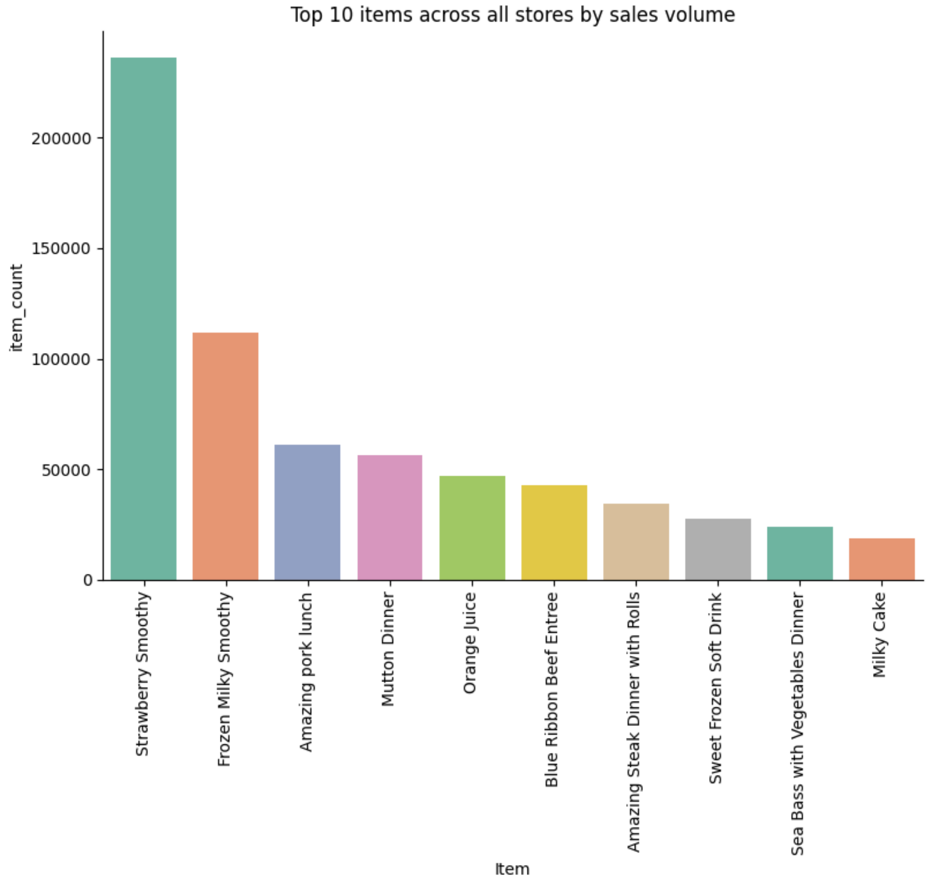
	rest_name	sale_amount
0	Beachfront Bar	129.35394
1	Bob's Diner	6780.94365
2	Corner Cafe	2031.71563
3	Fou Cher	2232.64087
4	Surfs Up	849.02197
5	Sweet Shack	271.43701

We will be tempted to leave out Bobs diner as an outlier. I feel this is wrong. Just because Bob's diner has roughly three times the revenue of the next rstaurant doesnt mean it is an outlier. If for arguments sake we drop Bob's diner, then Fou Cher has almost 20 times revenue as Beachfront bar. So we should drop Beachfront bar too as an outlier. This is illogical. Such cases exist in real life too.In any case it will not skew out data analysis or forecasting as we will see.

The restaurant with higher revenue also has higher volume

```
In [ ]: # most popular items
top_10_by_sales = pd.DataFrame(sales_data.groupby('item_name').sale_amount.sum()).reset_index().sort_values(by='sale_amount',a
top_10_by_item_count = pd.DataFrame(sales_data.groupby('item_name').item_count.sum()).reset_index().sort_values(by='item_count
top_10 = [top_10_by_sales,top_10_by_item_count]
cols = ['sale_amount','item_count']
title = {cols[0]: 'sales revenue',cols[1]:'sales volume'}
plt.figure(figsize=(16,8))
for i,item in enumerate(top_10):
  plt.subplot(1,2,i+1)
  sns.barplot(x='item_name', y=cols[i], data=item, palette = sns.color_palette('Set2'))
  plt.ylabel(f'{cols[i]}')
  plt.xticks(rotation=90)
  plt.xlabel('Item')
  plt.title(f'Total {cols[i]} per Item')
  plt.gca().spines[['top', 'right',]].set_visible(False)
  plt.title(f'Top 10 items across all stores by {title[cols[i]]}')
plt.tight_layout()
plt.show()
```





Most of the items figure in both lists

Top 10 items sold by restaurant

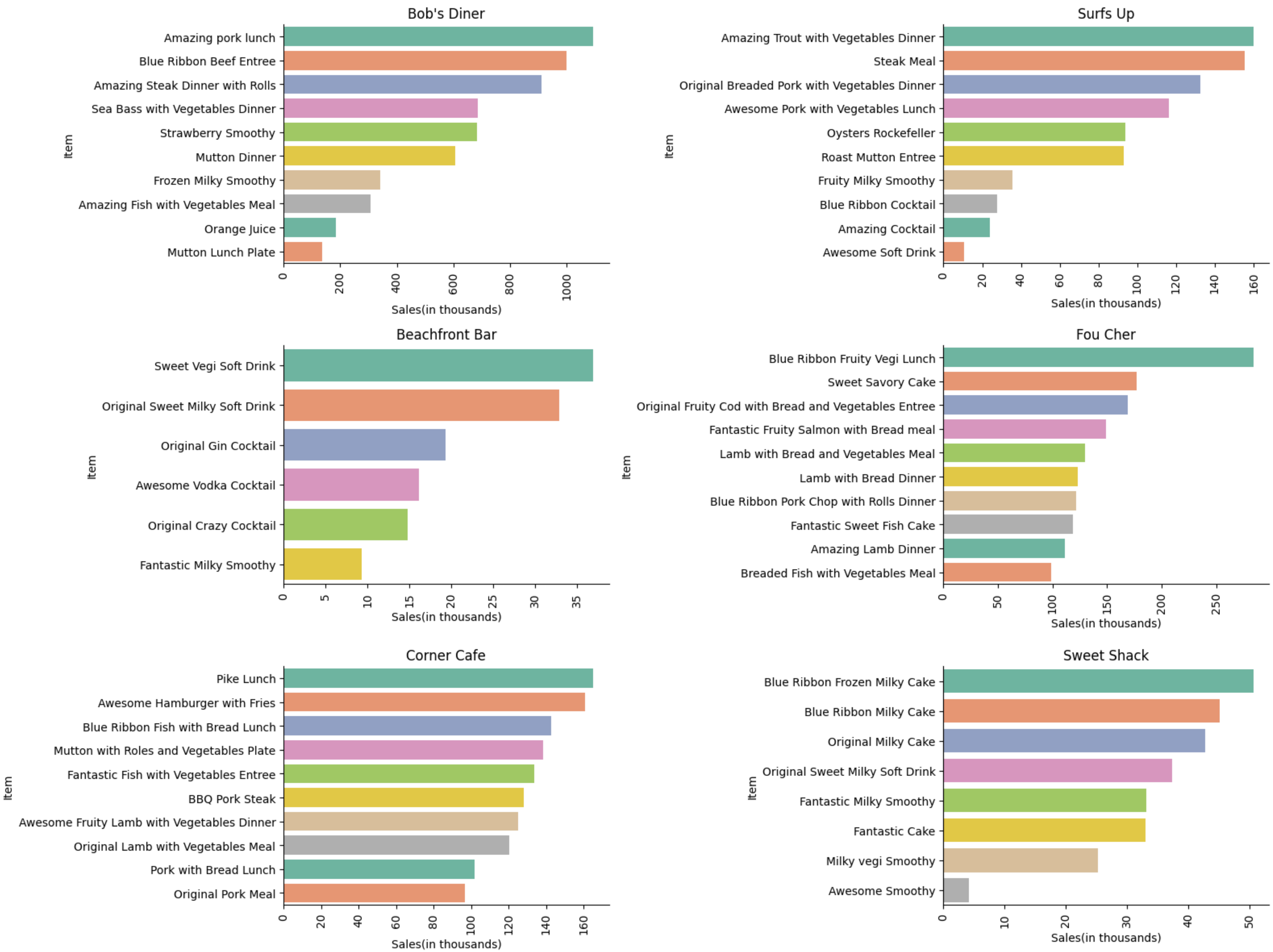
In [ ]:

```
stores = sales_data['rest_name'].unique()
plt.figure(figsize=(16,12))
for i,store in enumerate(stores):
  plt.subplot(3,2,i+1)
  store_data = sales_data[sales_data['rest_name'] == store]
  store_sales_by_item = pd.DataFrame(store_data.groupby('item_name').sale_amount.sum()/1000).reset_index().sort_values(by='sal
  ax = sns.barplot(y='item_name', x='sale_amount', data=store_sales_by_item, palette = sns.color_palette('Set2'))
```

```
    plt.title(store)
    plt.xticks(rotation=90)
    plt.xlabel('Sales(in thousands)')
    plt.ylabel('Item')

    plt.gca().spines[['top', 'right',]].set_visible(False)
plt.tight_layout()

plt.show()
```

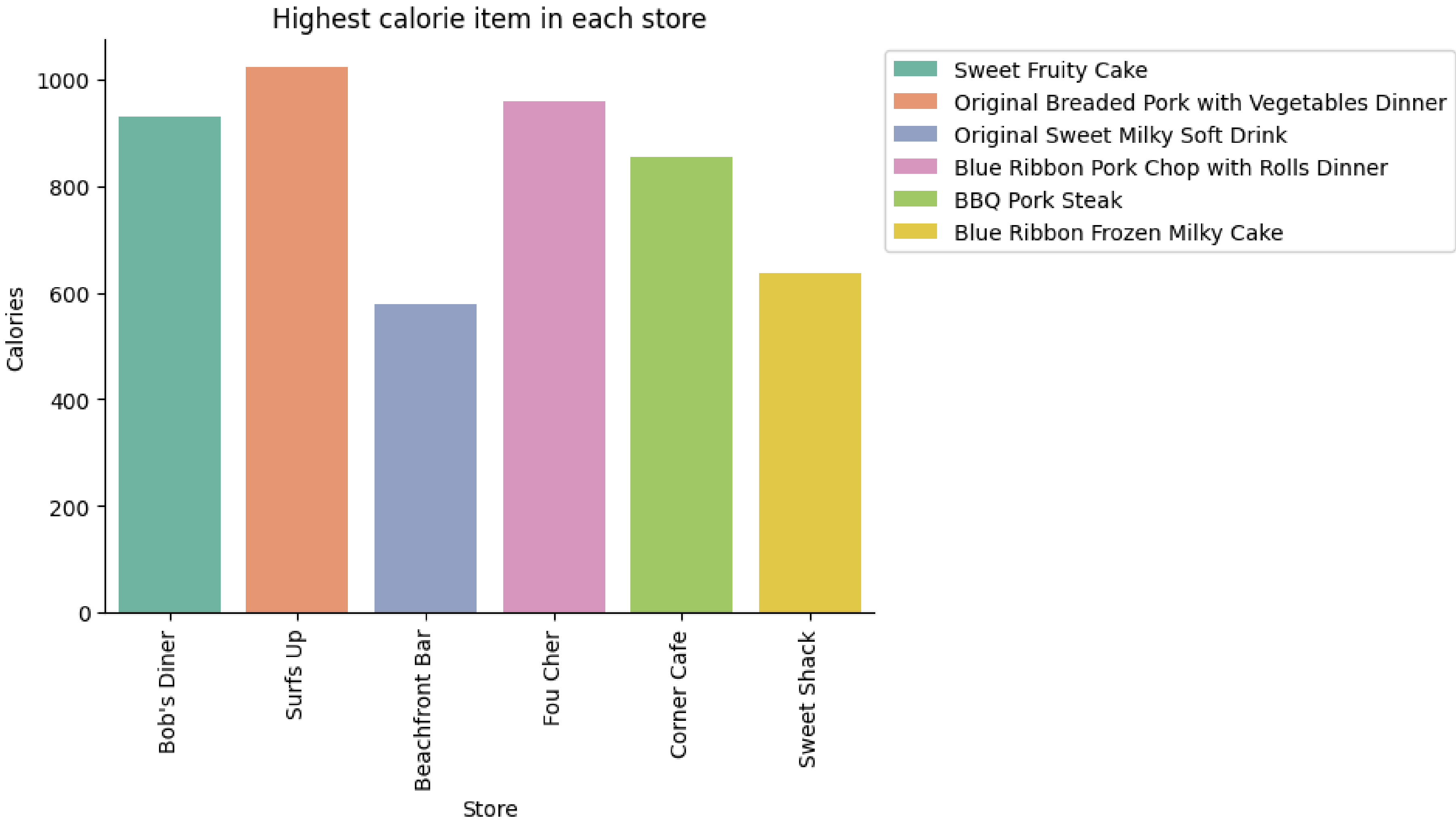

Bob's Diner
Amazing pork lunch
Blue Ribbon Beef Entree
Amazing Steak Dinner with Rolls
Sea Bass with Vegetables Dinner
Strawberry Smoothy
Mutton Dinner
Frozen Milky Smoothy
Amazing Fish with Vegetables Meal
Orange Juice
Mutton Lunch Plate
Item
0 200 400 600 800 1000
Sales(in thousands)
Surfs Up
Amazing Trout with Vegetables Dinner
Steak Meal
Original Breaded Pork with Vegetables Dinner
Awesome Pork with Vegetables Lunch
Oysters Rockefeller
Roast Mutton Entree
Fruity Milky Smoothy
Blue Ribbon Cocktail
Amazing Cocktail
Awesome Soft Drink
Item
0 20 40 60 80 100 120 140 160
Sales(in thousands)
Beachfront Bar
Sweet Vegi Soft Drink
Original Sweet Milky Soft Drink
Original Gin Cocktail
Awesome Vodka Cocktail
Original Crazy Cocktail
Fantastic Milky Smoothy
Item
0 5 10 15 20 25 30 35
Sales(in thousands)
Fou Cher
Blue Ribbon Fruity Vegi Lunch
Sweet Savory Cake
Original Fruity Cod with Bread and Vegetables Entree
Fantastic Fruity Salmon with Bread meal
Lamb with Bread and Vegetables Meal
Lamb with Bread Dinner
Blue Ribbon Pork Chop with Rolls Dinner
Fantastic Sweet Fish Cake
Amazing Lamb Dinner
Breaded Fish with Vegetables Meal
Item
0 50 100 150 200 250
Sales(in thousands)
Corner Cafe
Pike Lunch
Awesome Hamburger with Fries
Blue Ribbon Fish with Bread Lunch
Mutton with Roles and Vegetables Plate
Fantastic Fish with Vegetables Entree
BBQ Pork Steak
Awesome Fruity Lamb with Vegetables Dinner
Original Lamb with Vegetables Meal
Pork with Bread Lunch
Original Pork Meal
Item
0 20 40 60 80 100 120 140 160
Sales(in thousands)
Sweet Shack
Blue Ribbon Frozen Milky Cake
Blue Ribbon Milky Cake
Original Milky Cake
Original Sweet Milky Soft Drink
Fantastic Milky Smoothy
Fantastic Cake
Milky vegi Smoothy
Awesome Smoothy
Item
0 10 20 30 40 50
Sales(in thousands)

Highest calorie item sold by each restaurant

In [ ]:

```
#Most expensive item per restaurant with caolorie count
stores = sales_data.rest_name.unique()
items = []
calories = []
for store in stores:
    store_data = sales_data[sales_data.rest_name == store].sort_values(by='item_calories', ascending=False).head(1)
    max_cals = store_data.item_calories.max()
    max_cal_item = store_data.item_name.values[0]
    items.append(max_cal_item)
    calories.append(max_cals)

d = {
    'Store' : stores,
    'Item' : items,
    'Calories' : calories
}
df = pd.DataFrame(d)
sns.barplot(data=df, x='Store', y='Calories',hue='Item',palette = sns.color_palette('Set2'))
plt.legend(loc='upper left', bbox_to_anchor=(1, 1))
plt.gca().spines[['top', 'right',]].set_visible(False)
plt.xticks(rotation=90)
plt.title('Highest calorie item in each store')
plt.show()
```



In [ ]:

```
sales_data.groupby('day_of_the_week')['sale_amount'].mean()
```

Out[ ]:

day_of_the_week	sale_amount
0	95.630143
1	100.938060
2	105.705318
3	121.636540
4	132.986839
5	133.435497
6	94.859038

dtype: float64

Forecasting

The problem statement doesnt specify a target feature for prediction. I have added a `sale_amount` column to capture the sales for each item. I will use this column as the target. That is , the model will predict the sales of top 5 menu items for each resturant in the last 6 months. Model performance will be evaluated based on the root mean square error metric

In [ ]:

```
stores = sales_data.rest_name.unique()
print(stores)
```

```
["Bob's Diner" 'Surfs Up' 'Beachfront Bar' 'Fou Cher' 'Corner Cafe'
 'Sweet Shack']
```

Gridsearch function

In [ ]:

```
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split,GridSearchCV
from sklearn.metrics import root_mean_squared_error
```

```
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from xgboost import XGBRegressor

param_grid_xgb = {
    'n_estimators': [50, 100, 200],
    'learning_rate': [0.01, 0.05, 0.1],
    'max_depth': [3, 4, 5],
    'subsample': [0.7, 0.8, 0.9],
    'colsample_bytree': [0.7, 0.8, 0.9]
}

param_grid_rf =  {
    'n_estimators': [50, 100, 200],
    'max_depth': [2, 5, 10],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 3, 5],
    'max_features': ['sqrt', 0.5]
}

param_grid_lr = {
    'n_jobs' : [-1]
}

params_grid = {'RF': param_grid_rf, 'XG' : param_grid_xgb,'LR': param_grid_lr }

models = {'LR' : LinearRegression(n_jobs= -1),'RF':RandomForestRegressor(n_jobs = -1,random_state=42),'XG' : XGBRegressor(n_jc

estimators = {}

BOLD_START = '\033[1m'
END = '\033[0m'
UNDERLINE = '\033[4m'
DARKCYAN = '\033[36m'

def grid_search_cv(model_key,X_train,y_train,X_test,y_test):
  print(f'\n{DARKCYAN}Hyperparameter tuning for {type(models[model_key]).__name__} starting...{END}\n')
  grid_search = GridSearchCV(estimator=models[model_key],
                             param_grid=params_grid[model_key],
                             scoring='neg_root_mean_squared_error',
                             cv=3,
```

```
                            verbose=1,
                            n_jobs=-1)

  # Fit GridSearchCV to the training data
  grid_search.fit(X_train, y_train)

  # Get the best parameters and the best score
  best_params = grid_search.best_params_
  best_score = grid_search.best_score_

  print(f"Best parameters: {best_params}")
  print(f"Best negative MSE: {best_score}")

  # Use the best model for predictions
  best_model = grid_search.best_estimator_
  y_pred_tuned_test = best_model.predict(X_test)
  y_pred_tuned_train = best_model.predict(X_train)
  estimators[model_key] = best_model

  # # rsme for testing
  rmse_tuned_test = root_mean_squared_error(y_test, y_pred_tuned_test)
  # rsme for training
  rmse_tuned_train = root_mean_squared_error(y_train, y_pred_tuned_train)

  print(f'Train Root Mean Squared Error for model {type(models[model_key]).__name__}: {rmse_tuned_train:.4f}')
  print(f'Test Root Mean Squared Error for model {type(models[model_key]).__name__}: {rmse_tuned_test:.4f}')
  return rmse_tuned_test
```

Create train, validation and test data

In [ ]:
```
# extract rows up to the end of June 2021
train_data = sales_data[sales_data['date'] <= '2021-06-30' ]
test_data = sales_data[sales_data['date'] > '2021-06-30']
print(f'train data {train_data.shape[0]} rows, test data {test_data.shape[0]} rows')

# drop the categorical columns and the date column
train_data.drop(['date','item_name','rest_name'],inplace = True,axis=1)
test_data.drop(['date','item_name','rest_name'],inplace = True,axis=1)
```

```
X = train_data.drop('sale_amount',axis=1)
y = train_data['sale_amount']

X_train,X_test,y_train,y_test = train_test_split(X,y,train_size=0.8,random_state=42)
scaler = MinMaxScaler()
scaler.fit_transform(X_train)
_=scaler.transform(X_test)

# define a filename for saving the model
filename = 'random_forest_model.joblib'
```

```
train data 91200 rows, test data 18400 rows
```

Evaluate models with hyperparameter tuning

In [ ]:

```
# Performing grid serach for XGBoost and RandomForest regressors
import joblib
rmses = {}
rmses['LR'] = grid_search_cv('LR',X_train, y_train,X_test,y_test)
rmses['XG'] = grid_search_cv('XG',X_train,y_train,X_test,y_test)
rmses['RF'] = grid_search_cv('RF',X_train,y_train,X_test,y_test)

best_model_key = 'XG' if rmses['XG'] <=  rmses['RF'] else 'RF'

best_model = estimators[best_model_key]
print(f'Best model is {type(best_model).__name__}')
# save the model
joblib.dump(best_model, filename)
print(f"{type(best_model).__name__} model saved to {filename} using joblib")
```

```
Hyperparameter tuning for LinearRegression starting...

Fitting 3 folds for each of 1 candidates, totalling 3 fits
Best parameters: {'n_jobs': -1}
Best negative MSE: -130.5126438165997
Train Root Mean Squared Error for model LinearRegression: 130.4880
Test Root Mean Squared Error for model LinearRegression: 128.6056

Hyperparameter tuning for XGBRegressor starting...

Fitting 3 folds for each of 243 candidates, totalling 729 fits
Best parameters: {'colsample_bytree': 0.9, 'learning_rate': 0.1, 'max_depth': 5, 'n_estimators': 200, 'subsample': 0.7}
Best negative MSE: -13.968043304746061
Train Root Mean Squared Error for model XGBRegressor: 13.0841
Test Root Mean Squared Error for model XGBRegressor: 13.9018

Hyperparameter tuning for RandomForestRegressor starting...

Fitting 3 folds for each of 162 candidates, totalling 486 fits
Best parameters: {'max_depth': 10, 'max_features': 0.5, 'min_samples_leaf': 1, 'min_samples_split': 2, 'n_estimators': 200}
Best negative MSE: -6.542046572008746
Train Root Mean Squared Error for model RandomForestRegressor: 5.2508
Test Root Mean Squared Error for model RandomForestRegressor: 5.6138
Best model is RandomForestRegressor
RandomForestRegressor model saved to random_forest_model.joblib using joblib
```

Load the model file. This is useful if we have a saved model and we do not want execute gridsearch on session restart

In [ ]:

```
import joblib
import os

if os.path.exists(filename):
  best_model = joblib.load(filename)
```

Using the best model to predict on test_data for last 6 months

In [ ]:

```
X_test_data = test_data.drop('sale_amount',axis = 1)
y_test_data = test_data['sale_amount']
```

```
scaler.transform(X_test_data)
y_pred_test_data = best_model.predict(X_test_data)
rsme = root_mean_squared_error(y_test_data,y_pred_test_data)
print(f'root mean squared error is {rsme:.4f}')
```

```
root mean squared error is 8.0566
```

Plots of precited and actual values for top 5 items for each store

In [ ]:
```
X_test_data['Sale Amount Actual'] = y_test_data
X_test_data['Sale Amount Predicted'] = y_pred_test_data
X_test_data.head()
```

Out[ ]:

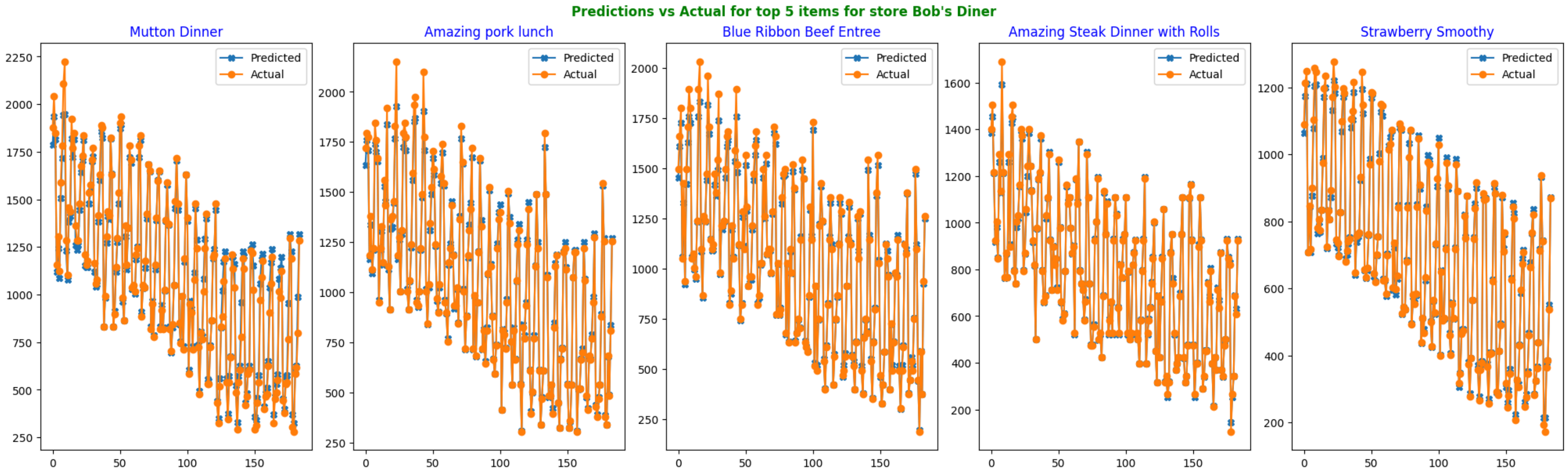
	item_id	price	item_count	item_calories	store_id	day_of_the_week	Sale Amount Actual	Sale Amount Predicted
91200	4	26.42	53.0	763	1	3	1400.26	1384.103274
91201	9	3.91	136.0	135	1	3	531.76	516.622294
91202	11	19.48	1.0	787	4	3	19.48	20.892953
91203	12	4.87	6.0	478	1	3	29.22	32.200253
91204	13	4.18	63.0	490	1	3	263.34	244.196727

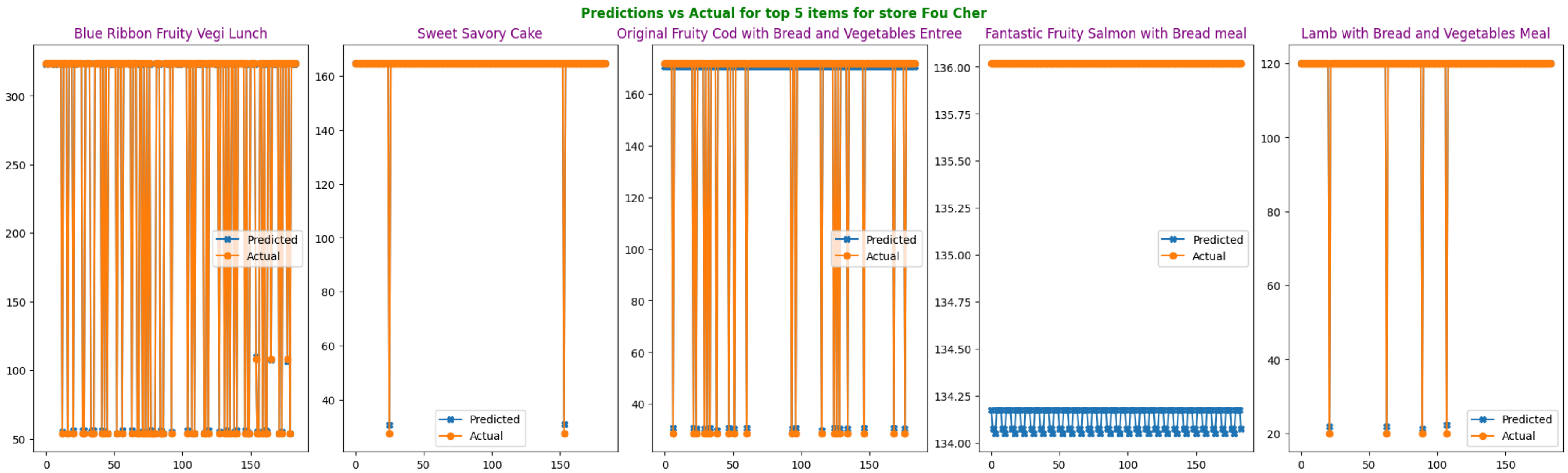
In [ ]:
```
store_ids = X_test_data['store_id'].unique().tolist()
top_5_items = {}
for store_id in store_ids:
   data = X_test_data[X_test_data['store_id'] == store_id]
   data_item = pd.DataFrame(data.groupby(['item_id'])['Sale Amount Actual'].sum()).reset_index().sort_values(by='Sale Amount A
   top_5 = data_item['item_id'].to_list()
   top_5_items[store_id] = top_5
print(top_5_items)
```

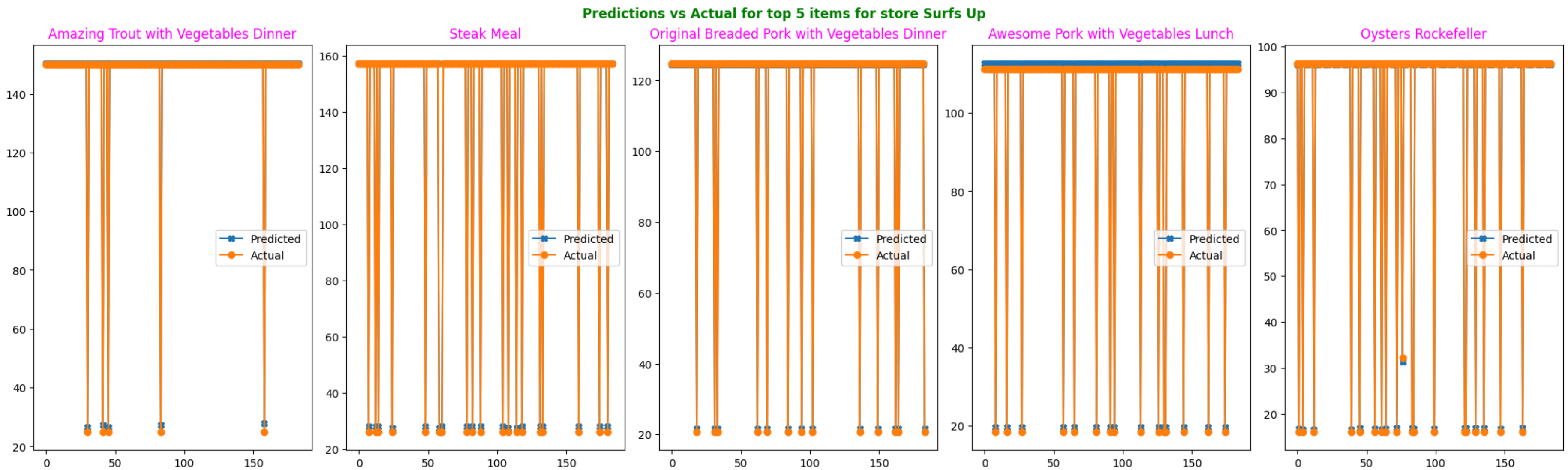
```
{1: [38, 76, 59, 4, 19], 4: [80, 34, 97, 40, 65], 6: [8, 27, 33, 61, 88], 2: [62, 98, 78, 100, 29], 3: [77, 46, 86, 52, 81], 5:
[50, 69, 96, 10, 36]}
```

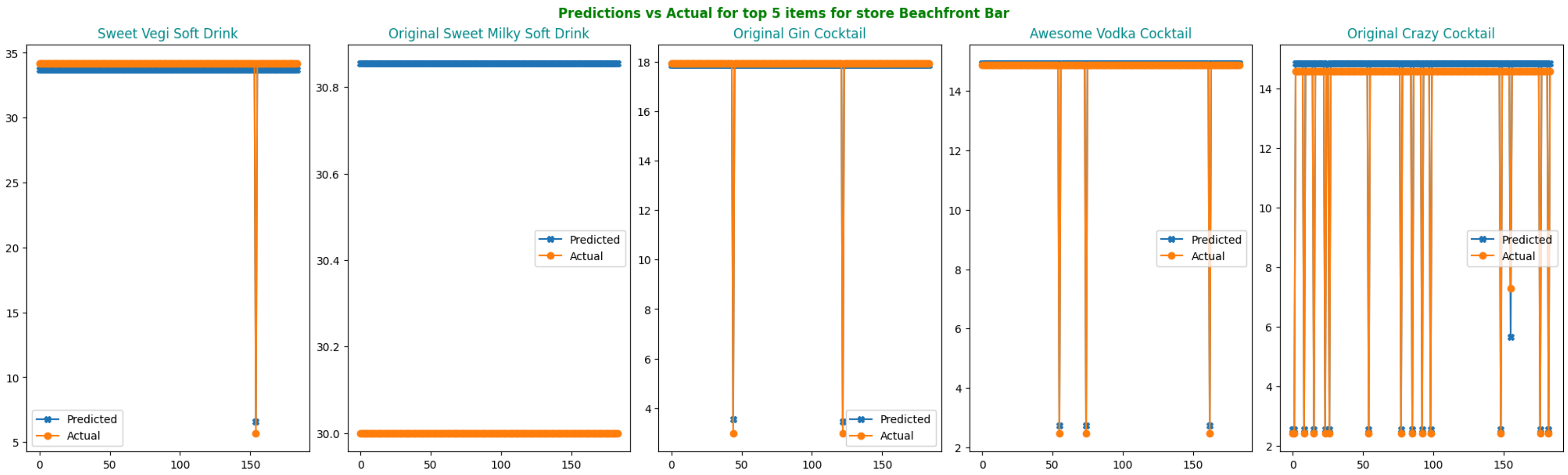
In [ ]:
```
colors = ['blue', 'purple','magenta','darkcyan','red','indigo']
for i,(store_id,item_id) in enumerate(top_5_items.items()):
```

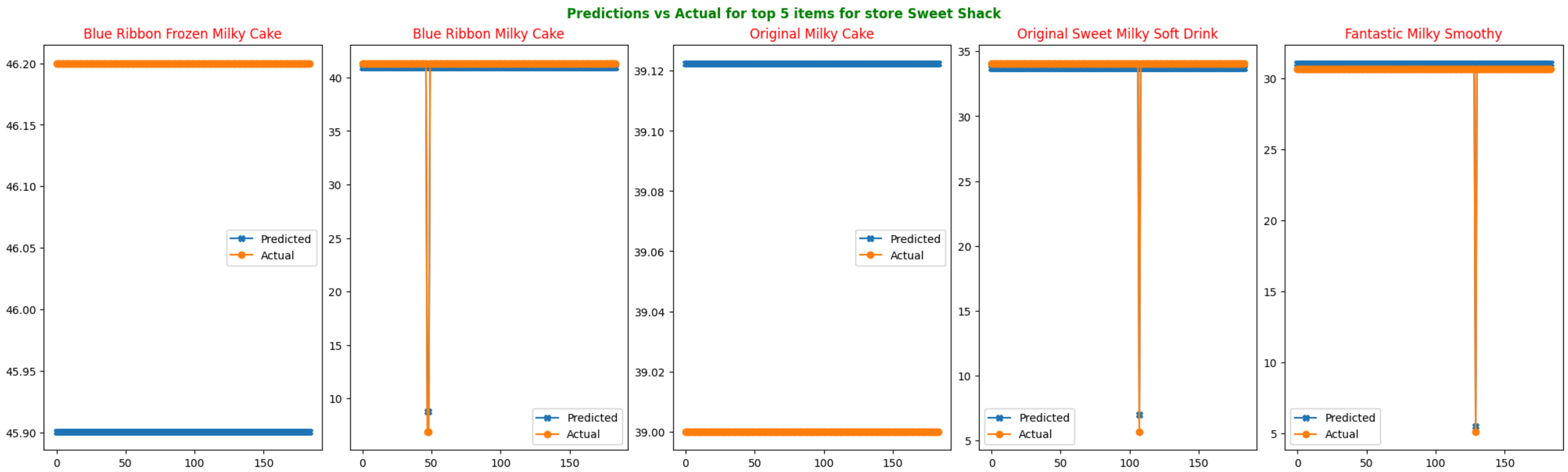
```
    fig,axes = plt.subplots(1,5,figsize=(20,6), layout='constrained')
    data = X_test_data[X_test_data['store_id'] == store_id]
    for j,id in enumerate(item_id):
      item_data = data[data['item_id'] == id ].reset_index()
      actual = item_data['Sale Amount Actual']
      predicted =  item_data['Sale Amount Predicted']
      axes[j].plot(predicted, label='Predicted', marker='X')
      axes[j].plot(actual, label='Actual', marker='o')
      axes[j].set_title(f'{id_name_dict[id]}', color = colors[i])
      axes[j].legend(loc='best')
    plt.suptitle(f'Predictions vs Actual for top 5 items for store {rest_id_name_dict[store_id]}', color = 'green',fontweight
plt.show()
```

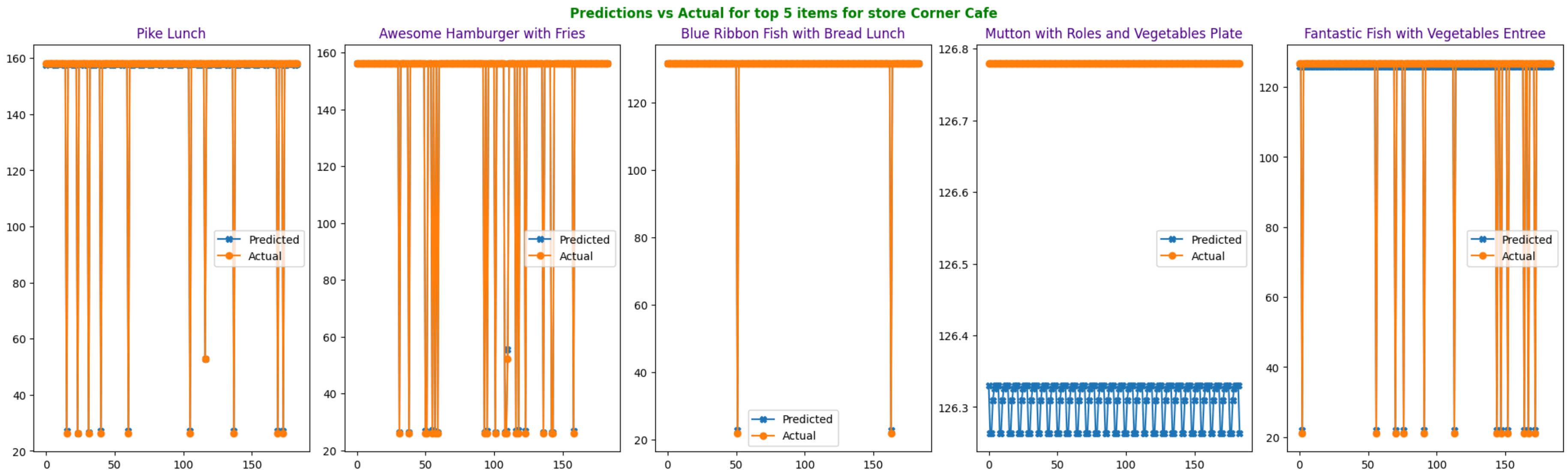



Predictions vs Actual for top 5 items for store Fou Cher
Blue Ribbon Fruity Vegi Lunch
Sweet Savory Cake
Original Fruity Cod with Bread and Vegetables Entree
Fantastic Fruity Salmon with Bread meal
Lamb with Bread and Vegetables Meal
Predicted
Actual


Predictions vs Actual for top 5 items for store Surfs Up
Amazing Trout with Vegetables Dinner
Steak Meal
Original Breaded Pork with Vegetables Dinner
Awesome Pork with Vegetables Lunch
Oysters Rockefeller
Predicted
Actual


Predictions vs Actual for top 5 items for store Beachfront Bar
Sweet Vegi Soft Drink
Original Sweet Milky Soft Drink
Original Gin Cocktail
Awesome Vodka Cocktail
Original Crazy Cocktail
Predicted
Actual


Predictions vs Actual for top 5 items for store Sweet Shack
Blue Ribbon Frozen Milky Cake
Blue Ribbon Milky Cake
Original Milky Cake
Original Sweet Milky Soft Drink
Fantastic Milky Smoothy
Predicted
Actual


Predictions vs Actual for top 5 items for store Corner Cafe
Pike Lunch
Awesome Hamburger with Fries
Blue Ribbon Fish with Bread Lunch
Mutton with Roles and Vegetables Plate
Fantastic Fish with Vegetables Entree
Predicted
Actual