Table of Contents

Restaurant Sales Forecasting

Data Analysis

Load the csv files

In [1]:
```
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 [2]:
```
len(items_data.id)
items_data.sort_values(by='id').head()
```

Out[2]:

	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 [3]:
```
restaurants_data
```

Out[3]:

	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 [4]:
```
sales_data.head(5)
```

Out[4]:

	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 [5]:
```
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 [6]:
```
sales_data.isna().sum()
```

Out[6]:

	0
date	0
item_id	0
price	0
item_count	0

dtype: int64

In [7]:

```
sales_data.describe()
```

Out[7]:

	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

Though item_count column has no null values, its ,in, 25 , 50 an 75% are 0. This means the majority of item_count column values are zero. in this dataset, median and mode make no sense. So we will replace all 0 values with mean

In [8]:

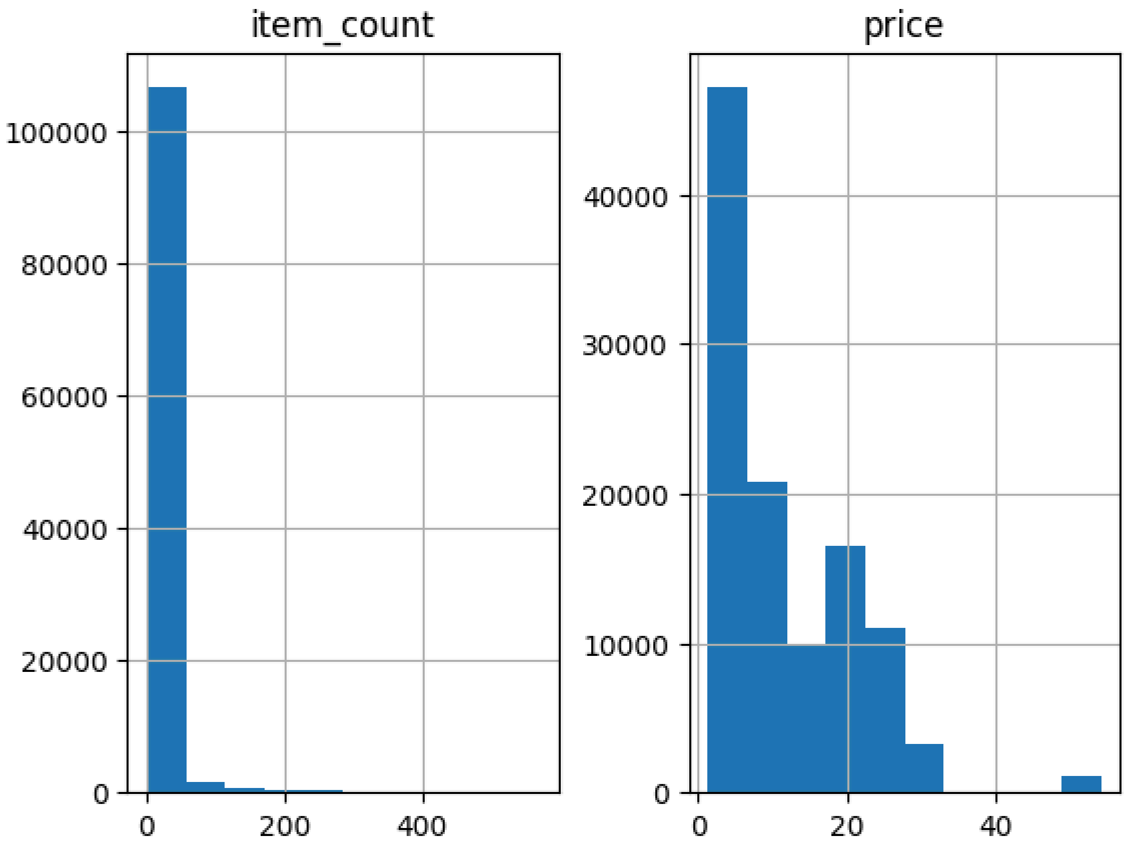
```
mean = round(np.mean(sales_data['item_count']))
sales_data['item_count'] = sales_data['item_count'].replace(0, mean)
sales_data.describe()
```

Out[8]:

	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 [10]:

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



In [94]:
```
# import numpy as np

# def detect_outliers_iqr(data):
#     data = sorted(data)
#     q1 = np.percentile(data, 25)
#     q3 = np.percentile(data, 75)
#     IQR = q3 - q1
#     lwr_bound = q1 - (1.5 * IQR)
#     upr_bound = q3 + (1.5 * IQR)
#     # print(f'iqr {IQR}, lower bound {lwr_bound}, upper bound {upr_bound}')
#     outliers = []
#     for i in data:
#         if i < lwr_bound or i > upr_bound:
#             outliers.append(i)
```

```
#     return outliers


# def remove_outliers(data, outlier_columns):

#   for column in outlier_columns:
#       print('imputing values for column ',column)
#       array = data[column]
#       outliers = detect_outliers_iqr(array)
#       value = np.median(array)
#       for i in outliers:
#           # for every i(outlier) in array , replace it by value else retain the same array element
#           array = np.where(array == i, value, array)
#           data[column] = np.asarray(array)

#   return data


# # Remove outliers
# sales_data = remove_outliers(sales_data, ['item_count','price'])
# sales_data[['item_count','price']].hist()
```

I deliberatley avoided outlier treatment of item_count(which has only outliers as over 86000 records have 0 value.) and price. The 0s have been replaced with mean, but any IQR range used for outlier treatment will result in all item numbers to bahe the same value. This can result in wrong forecasting results.

item and stores data with sales data

Merge all dataframes to one

In [11]:
```
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.sample(5)
print(sales_data.shape)
sales_data.sample(5)
```

```
(109600, 8)
```

Out[11]:

	date	item_id	price	item_count	item_calories	item_name	store_id	rest_name
43702	2020-03-13	12	4.87	11.0	478	Fantastic Sweet Cola	1	Bob's Diner
50504	2020-05-20	16	3.21	222.0	284	Frozen Milky Smoothy	1	Bob's Diner
67485	2020-11-05	84	19.77	6.0	855	BBQ Pork Steak	5	Corner Cafe
21732	2019-08-06	20	7.95	6.0	645	Fruity Milky Soft Drink	5	Corner Cafe
4745	2019-02-17	34	27.47	6.0	721	Sweet Savory Cake	4	Fou Cher

In [12]:

```
sales_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 109600 entries, 0 to 109599
Data columns (total 8 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
dtypes: datetime64[ns](1), float64(2), int64(3), object(2)
memory usage: 6.7+ MB
```

Add a column for total sale amount

In [13]:
```python
sales_data['sale_amount'] = sales_data['item_count'] * sales_data['price']
sales_data.head(5)
```

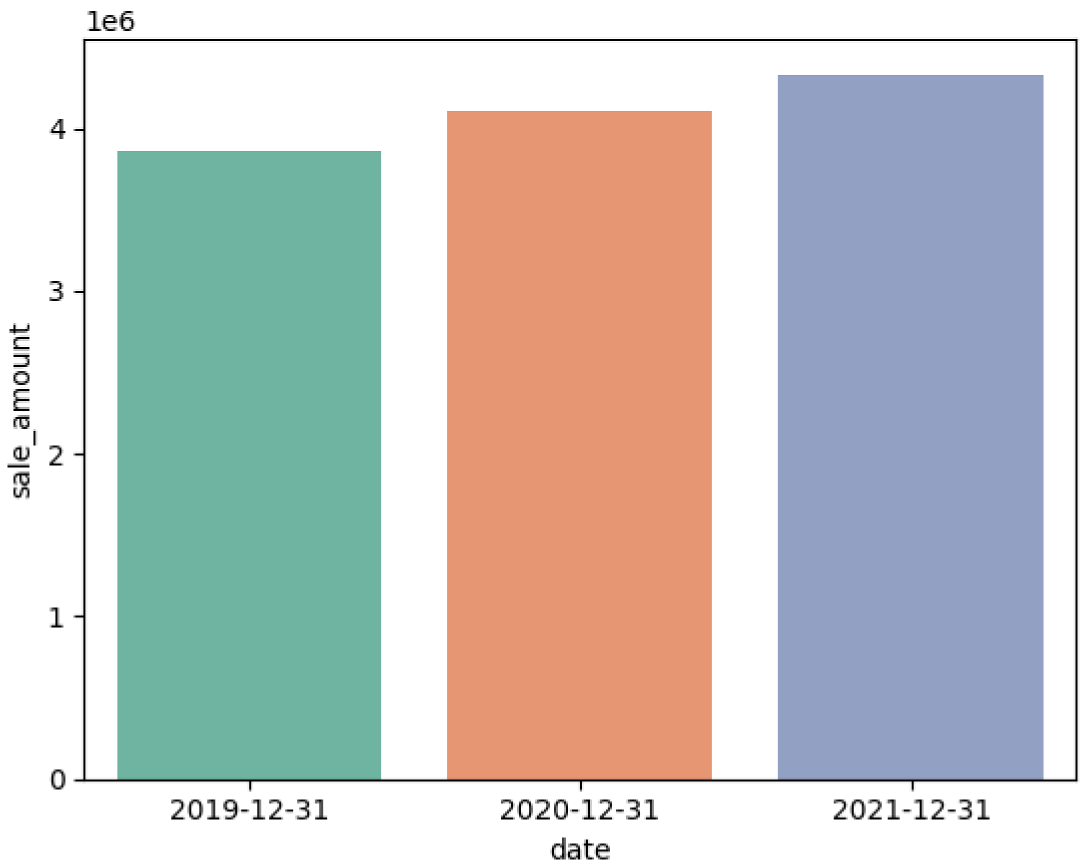
Out[13]:

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

In [14]:
```python
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'))
```

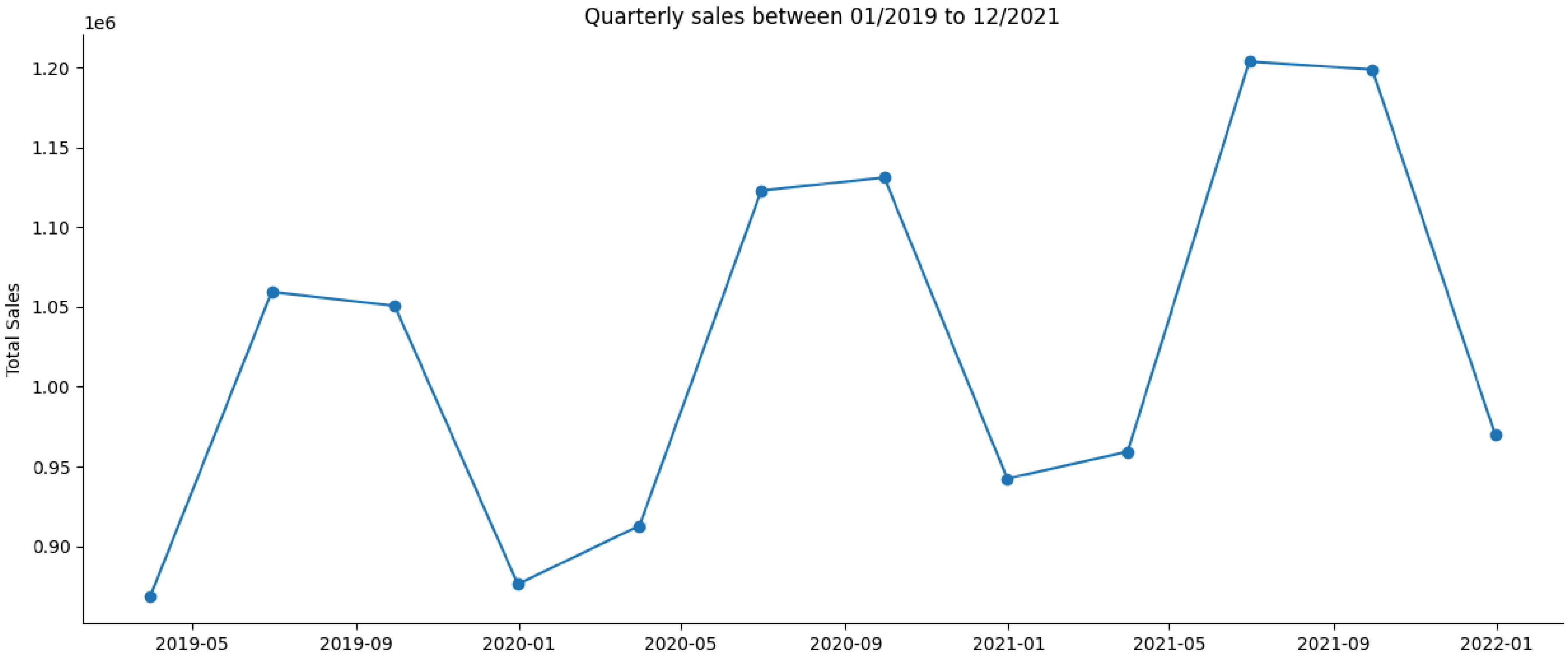
```
         date  sale_amount
0 2019-12-31   3854481.45
1 2020-12-31   4109139.62
2 2021-12-31   4331492.00
```



Quarterly sales data for 3 years

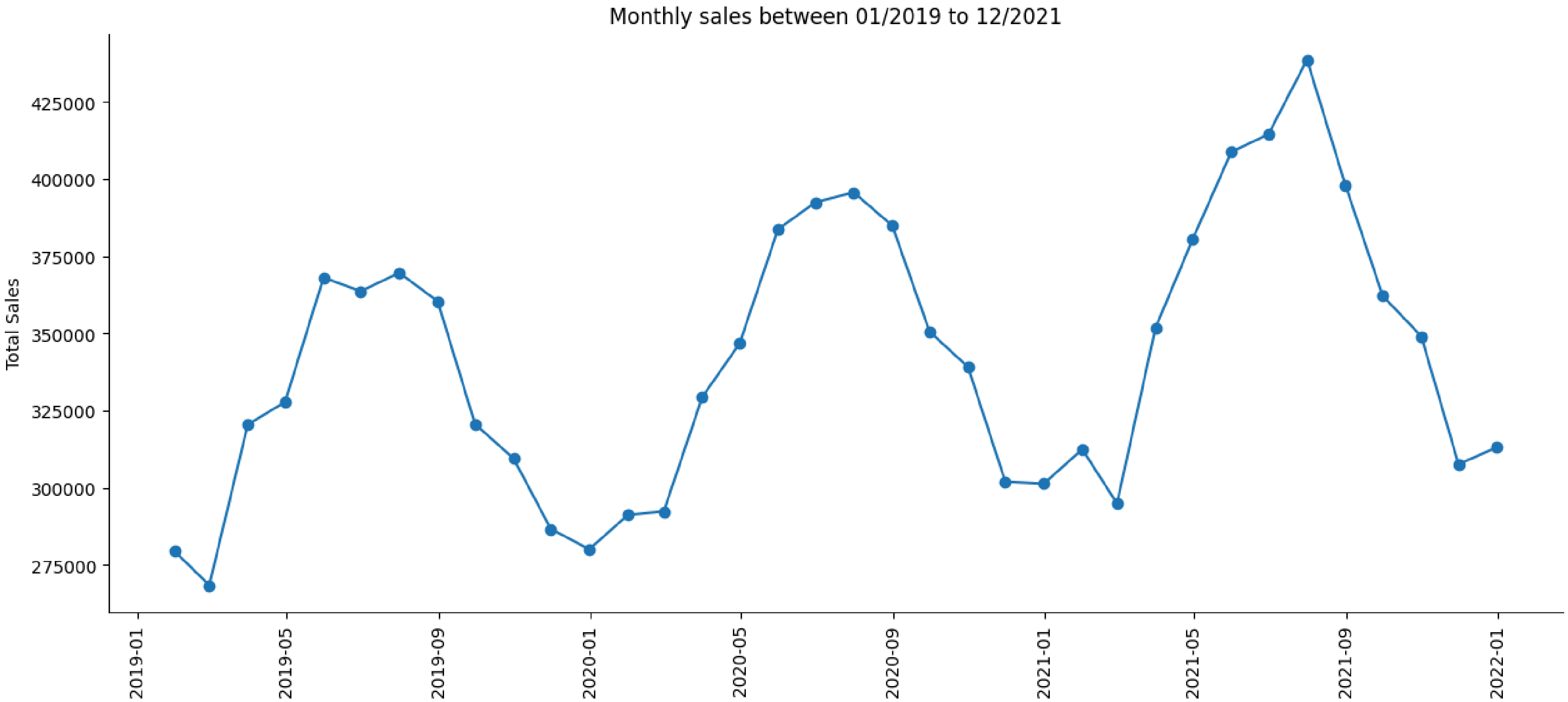
In [15]:
```
quarterly_sales_19_21 = pd.DataFrame(sales_data.groupby(pd.Grouper(key='date', axis=0, freq='QE')).sale_amount.sum()).reset_in
plt.figure(figsize=(15,6))
print(quarterly_sales_19_21)
_=plt.plot(quarterly_sales_19_21['date'], quarterly_sales_19_21['sale_amount'], marker='o', linestyle='-')
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 [16]: 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 )
```

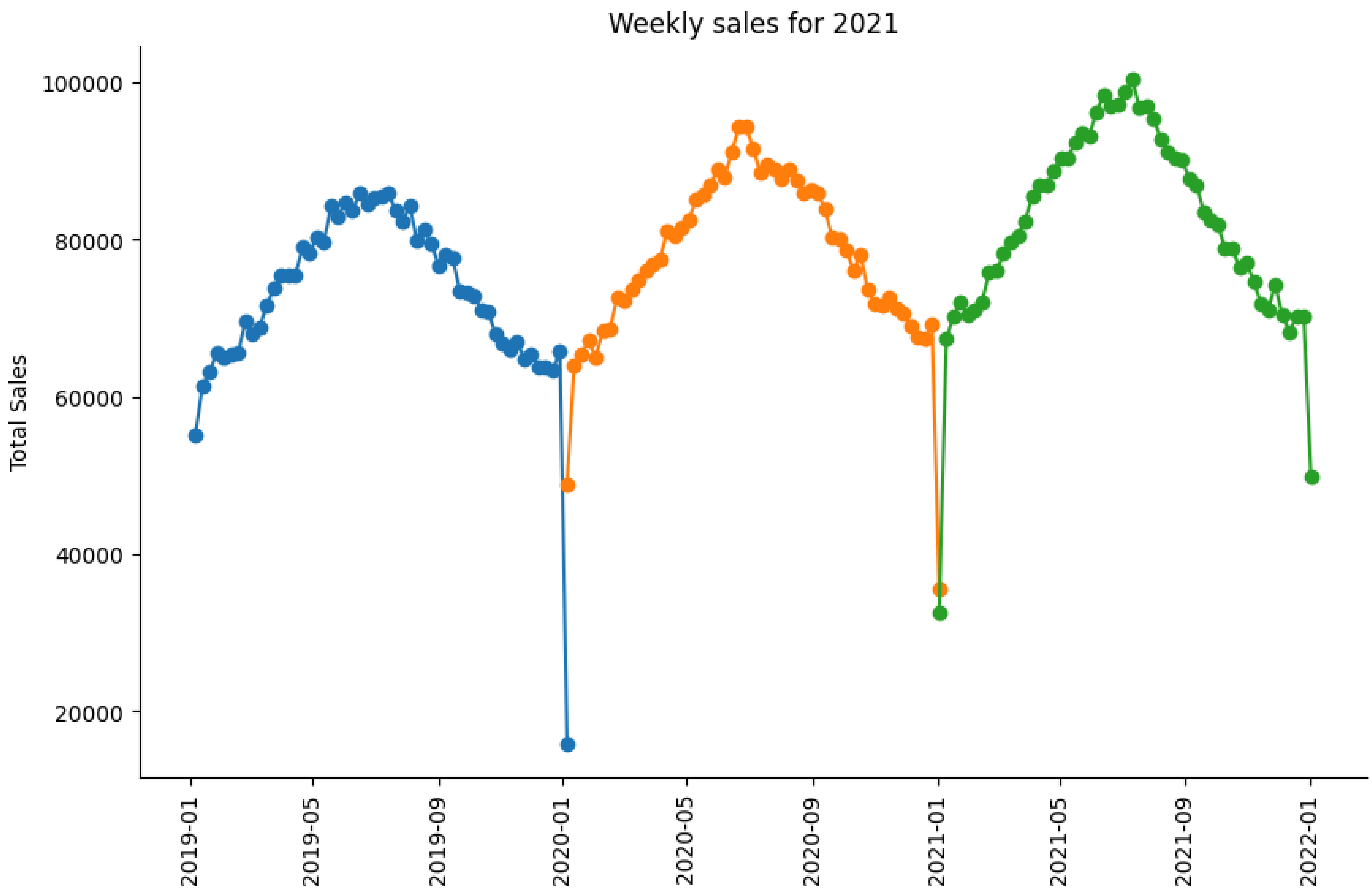


Weekly Sales for 3 years

```
In [17]: 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))
```

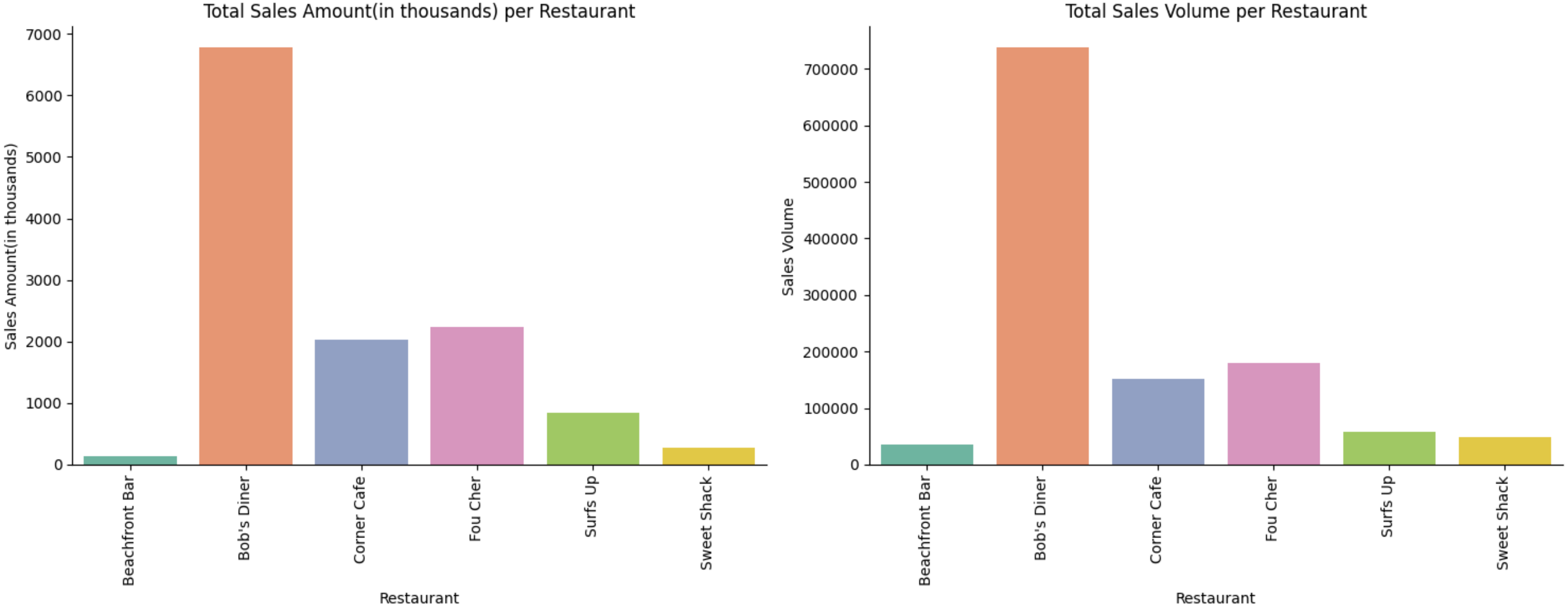
```
for i,year in enumerate(years):
  sales = sales_data[sales_data['date'].dt.year == year]
  weekly_sales = pd.DataFrame(sales.groupby(pd.Grouper(key='date', axis=0, freq='W')).sale_amount.sum()).reset_index()
  plt.plot(weekly_sales['date'], weekly_sales['sale_amount'], marker='o', linestyle='-')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



Sales Revenue vs Sales Volume

In [18]:
```
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))
```

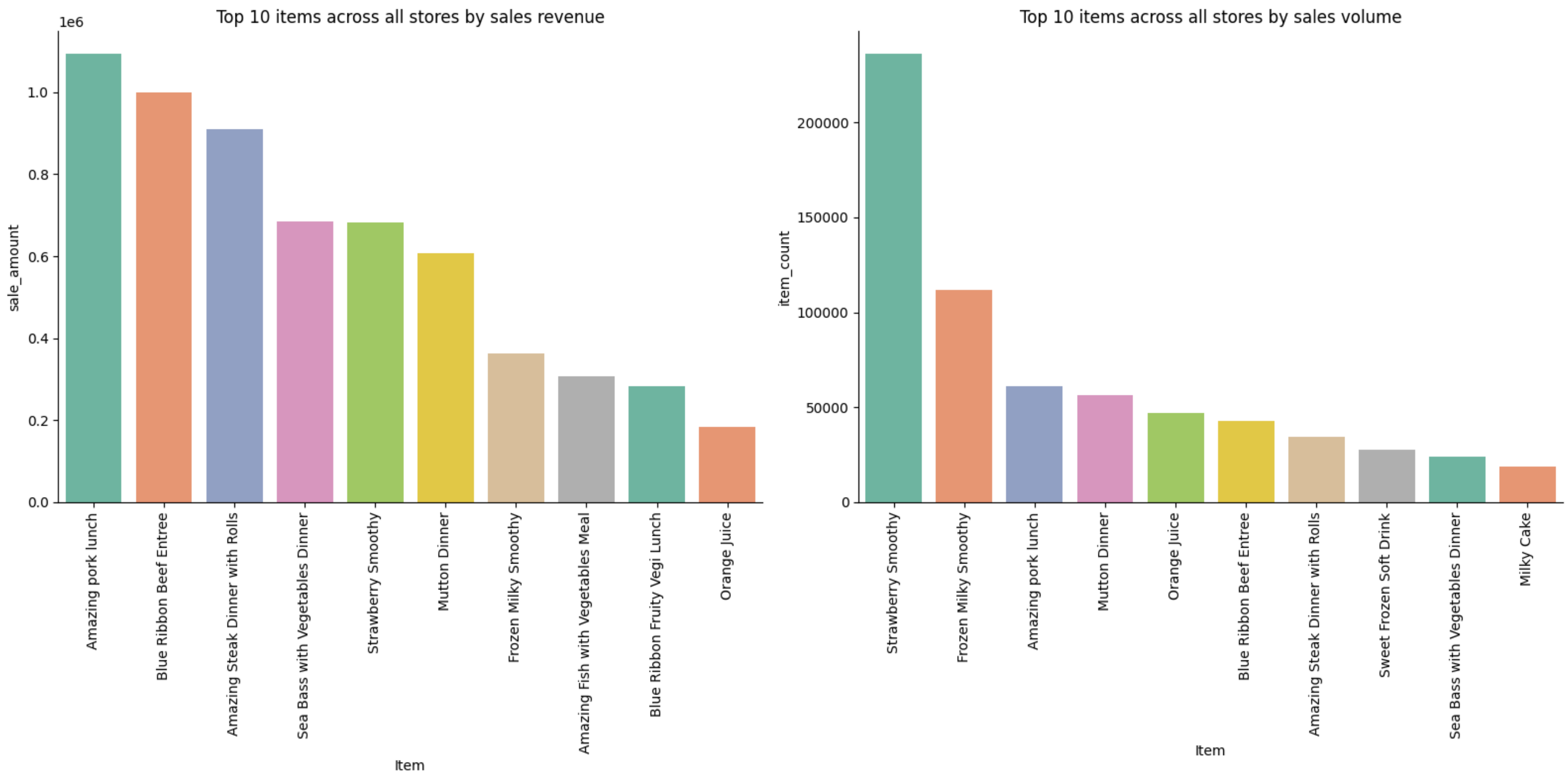
```python
sales = [sales_by_restaurant,volume_by_restaurant]
cols = ['sale_amount','item_count']
col_map = {cols[0]: 'Sales Amount(in thousands)',cols[1]:"Sales Volume"}
for i,item in enumerate(sales):
  plt.subplot(1,2,i+1)
  sns.barplot(x='rest_name', y=cols[i], data=item, palette = sns.color_palette('Set2'))
  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()
```



The restaurant with higher revenue also has higher volume

In [19]:
```python
# 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

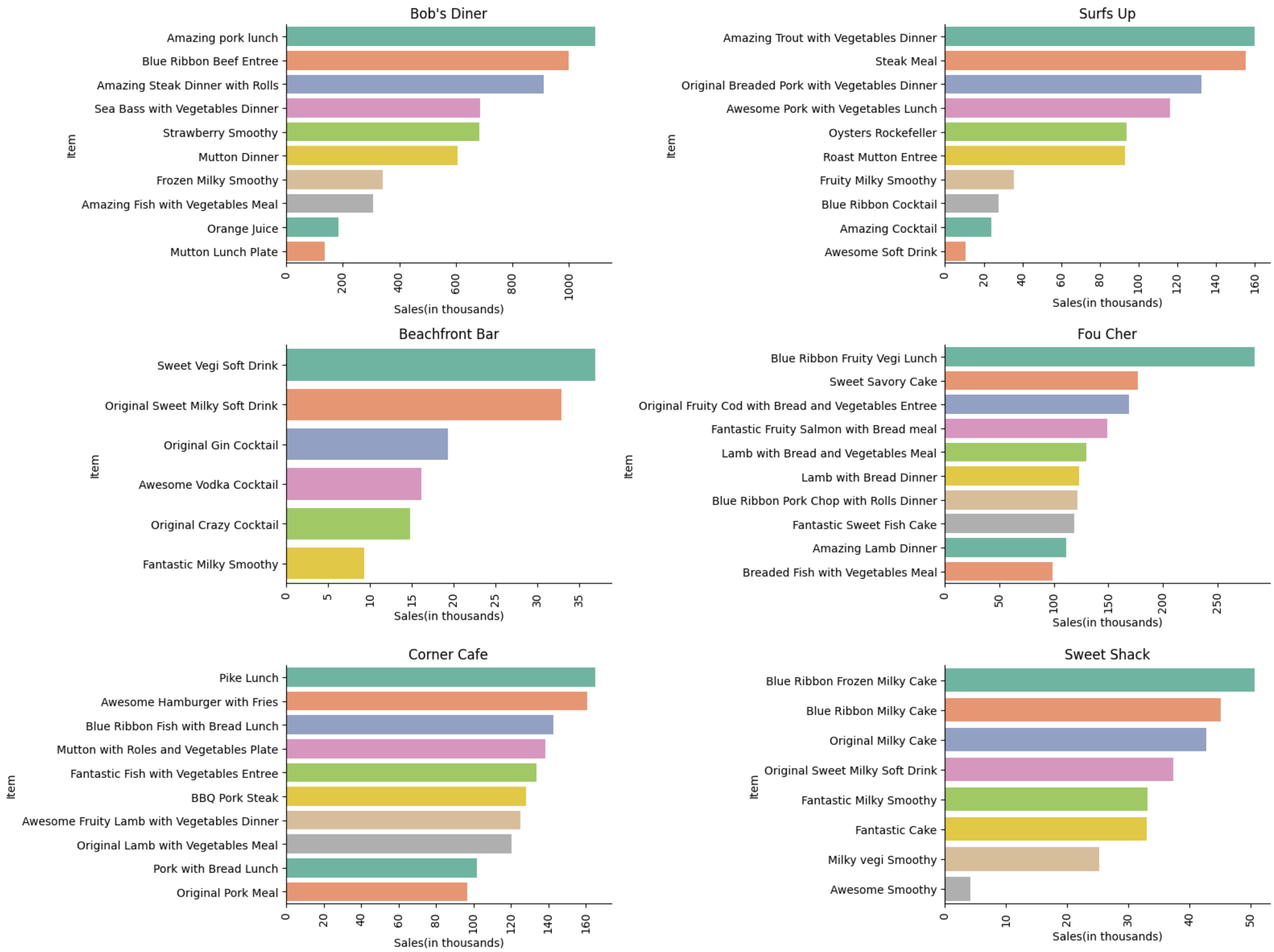
Top 10 items sold by restaurant

In [21]:
```
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()
```

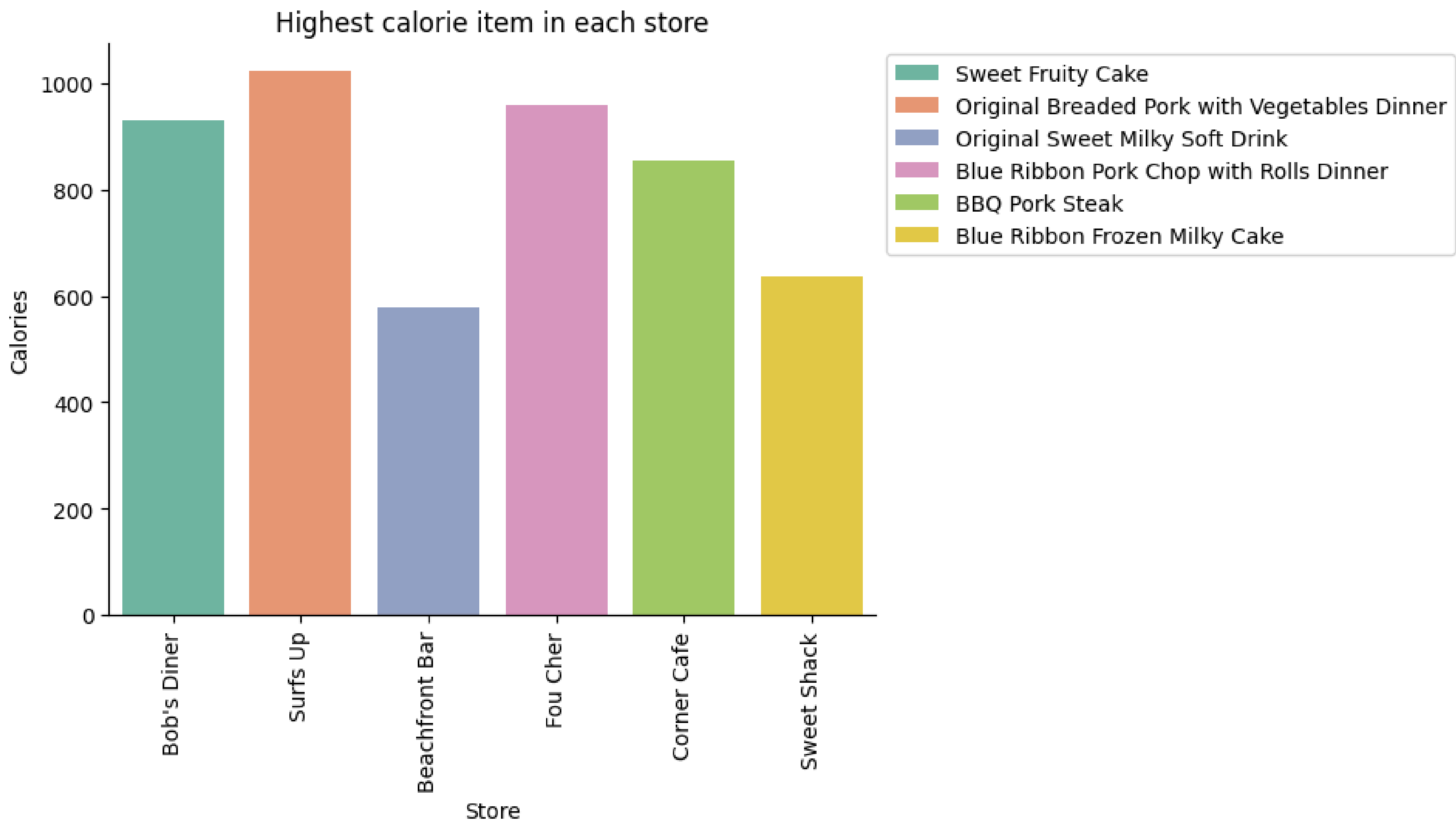


Bob's Diner
Amazing pork lunch
Blue Ribbon Beef Entree
Amazing Steak Dinner with Rolls
Sea Bass with Vegetables Dinner
Strawberry Smoothy
Mutton Dinner
Frozen Milky Smoothy
Amazing Fish with Vegetables Meal
Orange Juice
Mutton Lunch Plate
Item
0 200 400 600 800 1000
Sales(in thousands)
Surfs Up
Amazing 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 [22]:
```
#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()
```



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 [23]:
```
stores = sales_data.rest_name.unique()
print(stores)
```

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

Gridsearch function

In [24]:
```
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
```

```python
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 [25]:
```
# 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 [29]:
```
# 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: -130.06373421839166
Train Root Mean Squared Error for model LinearRegression: 130.0442
Test Root Mean Squared Error for model LinearRegression: 130.6058

Hyperparameter tuning for XGBRegressor starting...

Fitting 3 folds for each of 243 candidates, totalling 729 fits
Best parameters: {'colsample_bytree': 0.8, 'learning_rate': 0.1, 'max_depth': 5, 'n_estimators': 200, 'subsample': 0.9}
Best negative MSE: -13.980782084038713
Train Root Mean Squared Error for model XGBRegressor: 13.9386
Test Root Mean Squared Error for model XGBRegressor: 13.2699

Hyperparameter tuning for RandomForestRegressor starting...

Fitting 3 folds for each of 162 candidates, totalling 486 fits
Best parameters: {'max_depth': 10, 'max_features': 'sqrt', 'min_samples_leaf': 1, 'min_samples_split': 2, 'n_estimators': 200}
Best negative MSE: -2.921526488303614
Train Root Mean Squared Error for model RandomForestRegressor: 2.0369
Test Root Mean Squared Error for model RandomForestRegressor: 2.2270
Best model is RandomForestRegressor
```

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

In [26]:

```
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 [27]:

```
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 3.5802
```

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

In [28]:

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

Out[28]:

	item_id	price	item_count	item_calories	store_id	Sale Amount Actual	Sale Amount Predicted
91200	4	26.42	53.0	763	1	1400.26	1403.107723
91201	9	3.91	136.0	135	1	531.76	529.350959
91202	11	19.48	1.0	787	4	19.48	20.013394
91203	12	4.87	6.0	478	1	29.22	31.625130
91204	13	4.18	63.0	490	1	263.34	251.601674

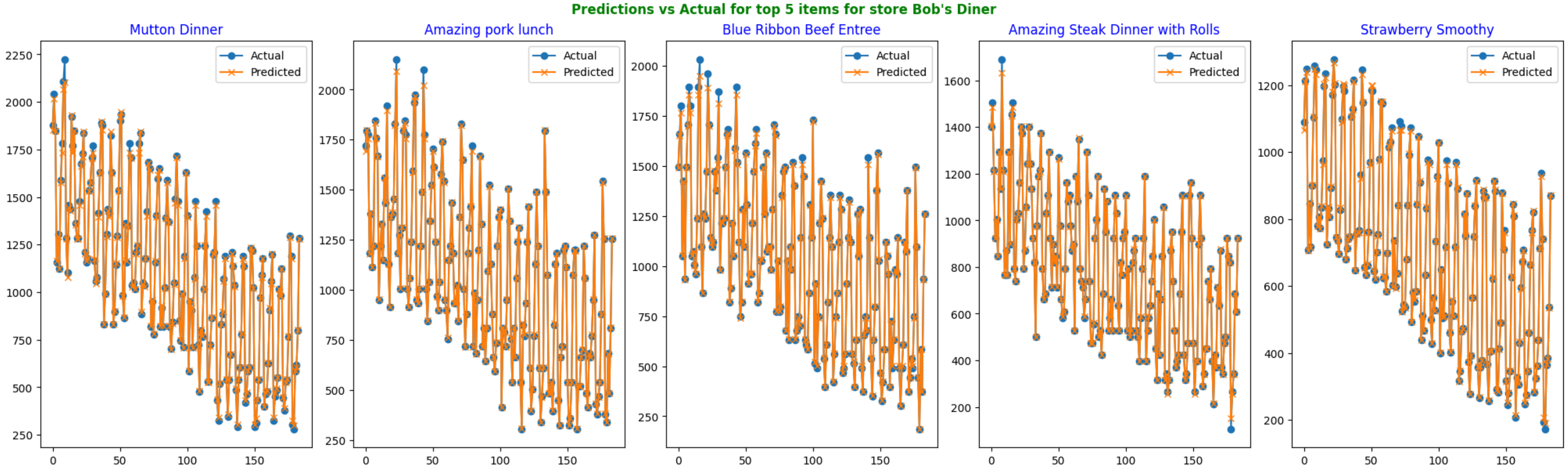
In [29]:

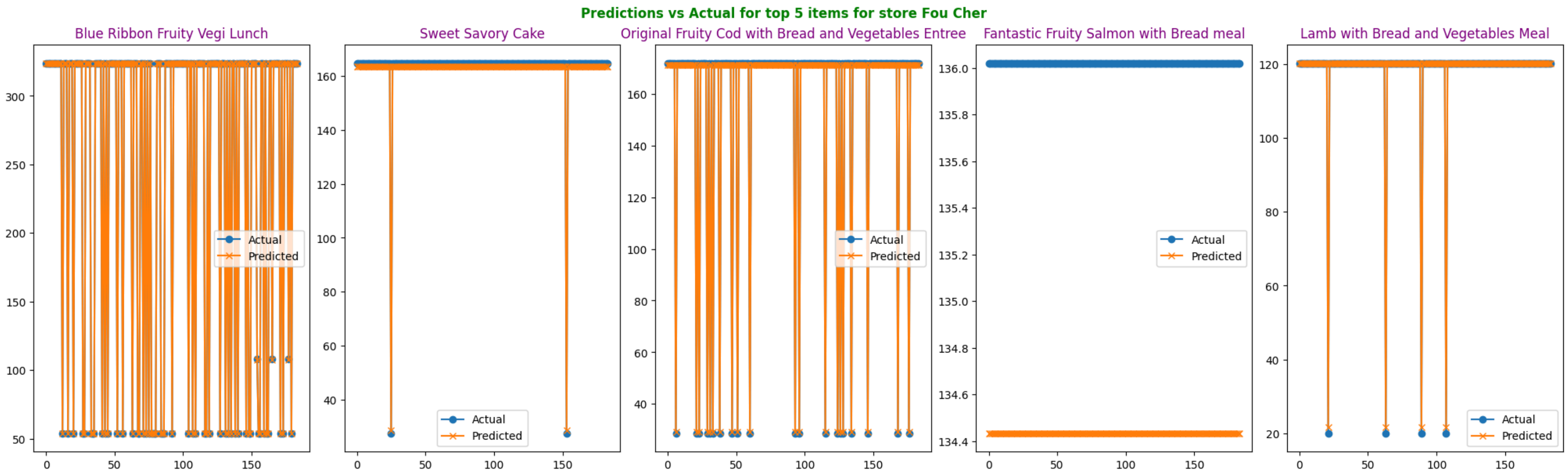
```
store_ids = X_test_data['store_id'].unique().tolist()
top_5_items = {}
for store_id in store_ids:
   data = X_test_data[X_test_data['store_id'] == store_id]
   data_item = pd.DataFrame(data.groupby(['item_id'])['Sale Amount Actual'].sum()).reset_index().sort_values(by='Sale Amount A
   top_5 = data_item['item_id'].to_list()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

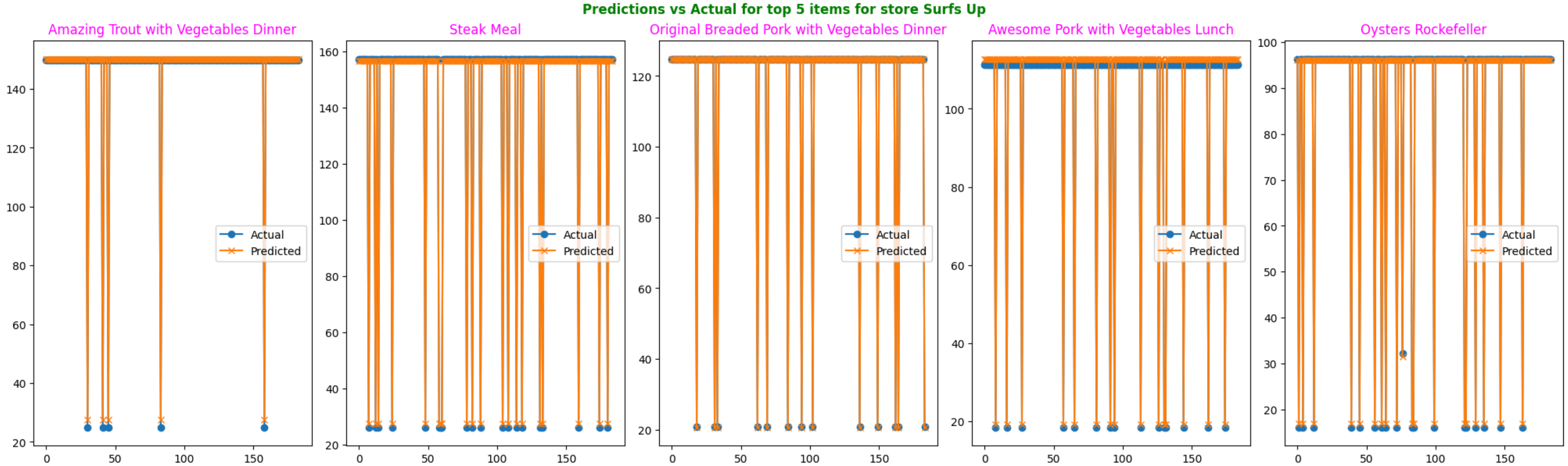
```
{1: [38, 76, 59, 4, 19], 4: [80, 34, 97, 40, 65], 6: [8, 27, 33, 61, 88], 2: [62, 98, 78, 100, 29], 3: [77, 46, 86, 52, 81], 5:
[50, 69, 96, 10, 36]}
```

In [37]:

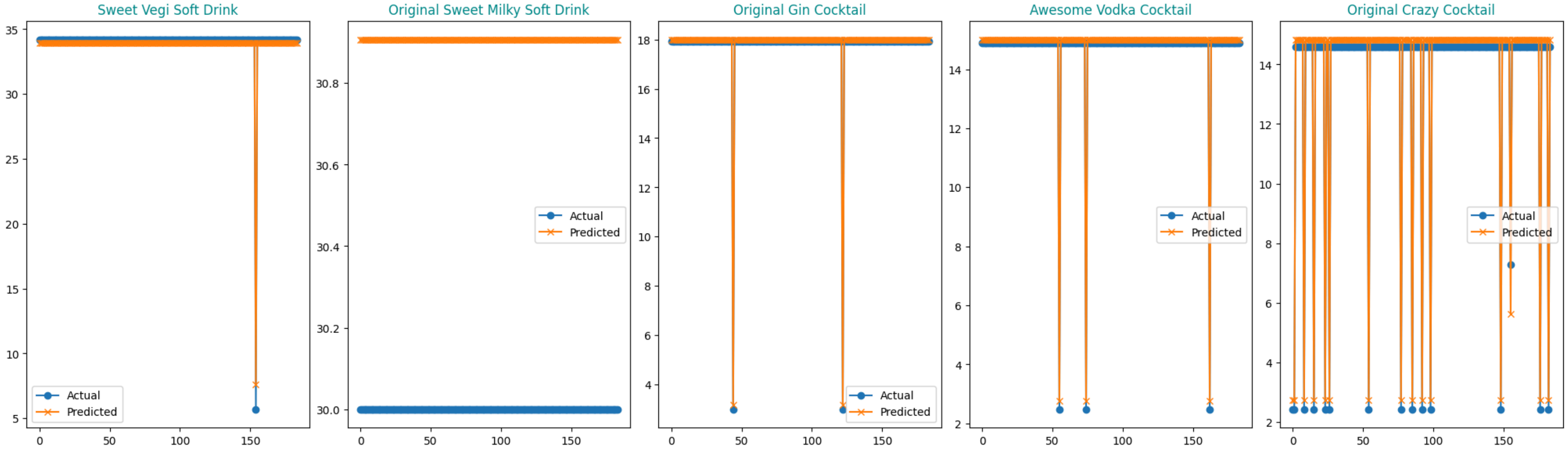
```
colors = ['blue', 'purple','magenta','darkcyan','red','indigo']
for i,(store_id,item_id) in enumerate(top_5_items.items()):
    fig,axes = plt.subplots(1,5,figsize=(20,6), layout='constrained')
    data = X_test_data[X_test_data['store_id'] == store_id]
    for j,id in enumerate(item_id):
      item_data = data[data['item_id'] == id ].reset_index()
      actual = item_data['Sale Amount Actual']
      predicted =  item_data['Sale Amount Predicted']
      axes[j].plot(actual, label='Actual', marker='o')
      axes[j].plot(predicted, label='Predicted', marker='x')
      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()
```



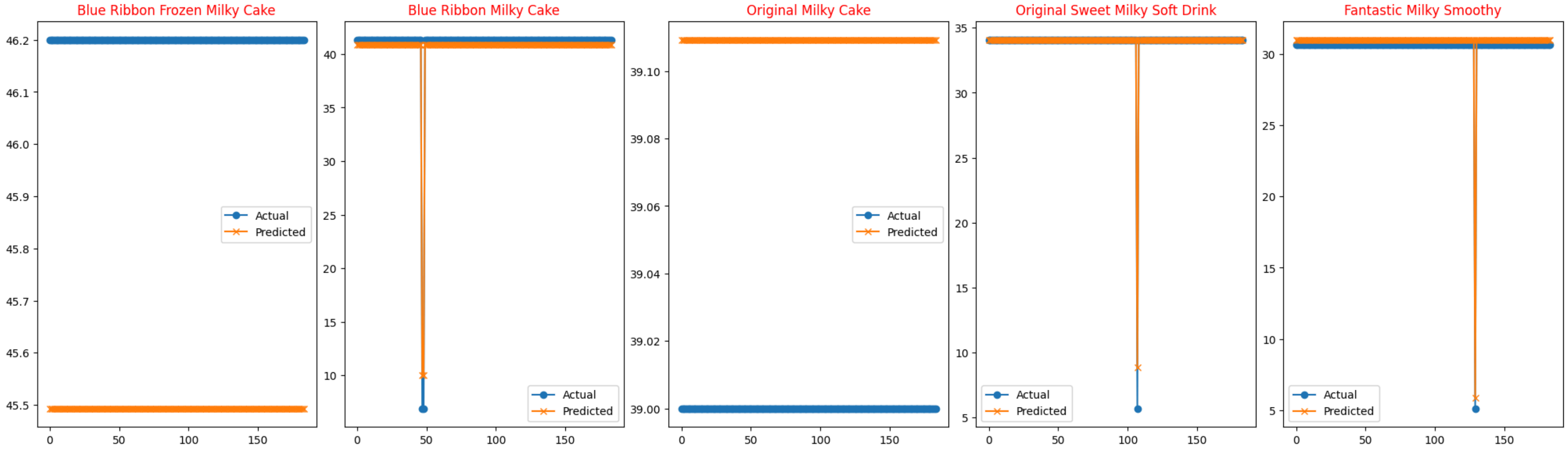

Predictions vs Actual for top 5 items for store Fou Cher
Blue Ribbon Fruity Vegi Lunch
Sweet Savory Cake
Original Fruity Cod with Bread and Vegetables Entree
Fantastic Fruity Salmon with Bread meal
Lamb with Bread and Vegetables Meal
Actual
Predicted

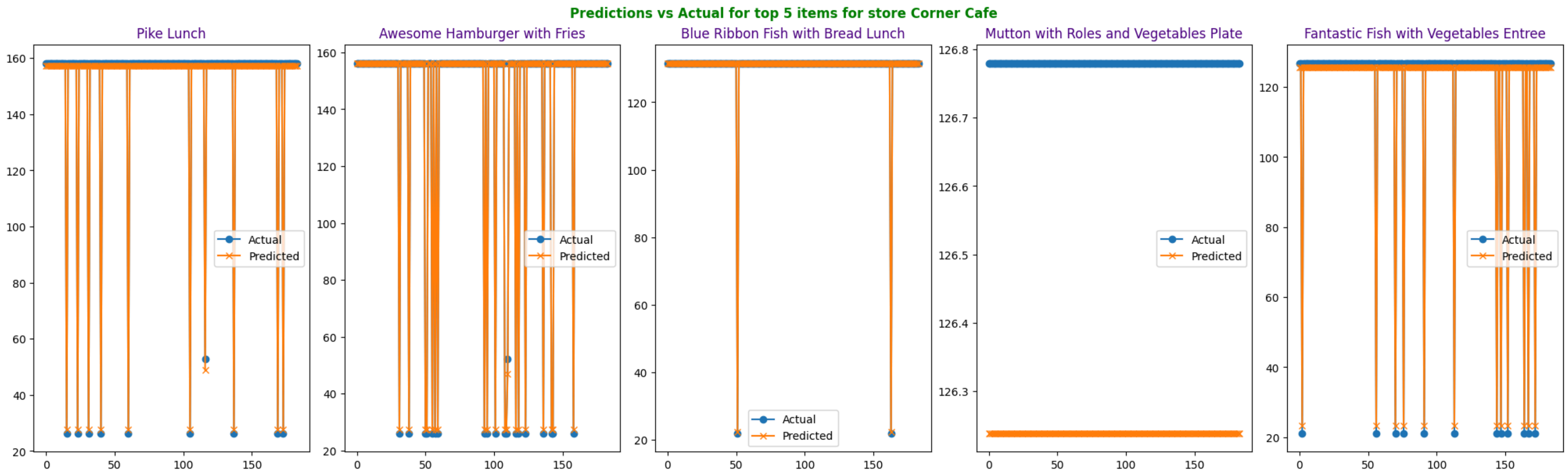

Predictions vs Actual for top 5 items for store Surfs Up
Amazing Trout with Vegetables Dinner
Steak Meal
Original Breaded Pork with Vegetables Dinner
Awesome Pork with Vegetables Lunch
Oysters Rockefeller
Actual
Predicted

Predictions vs Actual for top 5 items for store Beachfront Bar



Predictions vs Actual for top 5 items for store Sweet Shack




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
Actual
Predicted