Sales Forecasting

Problem Statement:

Fresh Analytics aims to forecast the demand for various items across multiple restaurants. Accurate sales predictions enable better decision-making around staffing, inventory, and pricing strategies.

Datasets Used:

1. **restaurants.csv**: Details about restaurants (id, name)
2. **items.csv**: Details about items (id, name, kcal, cost, store_id)
3. **sales.csv**: Sales data (date, item, price, item_count)

Project Tasks:

1. Preliminary Analysis

- Load and inspect datasets.
- Handle missing values and outliers.
- Merge all datasets to a single DataFrame.

2. Exploratory Data Analysis (EDA)

- Analyze overall and time-based sales patterns.
- Weekday, monthly, and quarterly trends.
- Restaurant-wise and item-wise comparisons.
- High-performing restaurants and items.
- Caloric and cost analysis of top items.

3. Feature Engineering

- Extract temporal features: year, month, day, weekday, quarter
- Aggregate sales on different levels.

4. Model Building and Forecasting

- Models: Linear Regression, Random Forest, XGBoost.
- Train on historical data, test on the last 6 months.
- Evaluate using RMSE.

- Forecast for next year using the best model.

Insights:

- Identified top-selling items and restaurants.
- Analyzed temporal patterns in demand.
- Predicted future sales using ML algorithms.

Source Code:

```
# 1. Import Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from datetime import datetime

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

from sklearn.metrics import mean_squared_error
from sklearn.model_selection import train_test_split

# 2. Load Datasets
df_rest = pd.read_csv("resturants.csv")
df_items = pd.read_csv("items.csv")
df_sales = pd.read_csv("sales.csv")

# 3. Rename columns to avoid conflicts
df_items.rename(columns={'name': 'item_name'}, inplace=True)
```

```python
df_rest.rename(columns={'name': 'store_name'}, inplace=True)
df_sales.rename(columns={'name': 'item_name'}, inplace=True)

# Optional: View column names
print("Sales Columns:", df_sales.columns)
print("Items Columns:", df_items.columns)
print("Restaurants Columns:", df_rest.columns)

# 4. Merge Datasets
df = df_sales.merge(df_items, on='item_name', how='left') \
        .merge(df_rest, left_on="store_id", right_on="id", suffixes=('_item', '_store'))

# 5. Convert 'date' and drop missing
df['date'] = pd.to_datetime(df['date'])
df.dropna(inplace=True)

# 6. Feature Engineering
df['year'] = df['date'].dt.year
df['month'] = df['date'].dt.month
df['day'] = df['date'].dt.day
df['weekday'] = df['date'].dt.dayofweek
df['quarter'] = df['date'].dt.quarter

# 7. EDA

# Overall sales trend
plt.figure(figsize=(12,5))
df.groupby('date')['item_count'].sum().plot(title="Daily Sales Trend")
```

```
plt.xlabel("Date")

plt.ylabel("Total Items Sold")

plt.tight_layout()

plt.show()


# Sales by weekday

plt.figure(figsize=(8,4))

sns.barplot(data=df, x='weekday', y='item_count', estimator=sum)

plt.title("Sales by Weekday")

plt.xlabel("Day of Week (0=Monday)")

plt.ylabel("Total Items Sold")

plt.tight_layout()

plt.show()


# Top 10 items

top_items =
df.groupby('item_name')['item_count'].sum().sort_values(ascending=False).head(10)

print("Top 10 Items Sold:\n", top_items)


# Most profitable store

df['revenue'] = df['item_count'] * df['Price']

top_store = df.groupby('store_name')['revenue'].sum().sort_values(ascending=False)

print("Most Profitable Stores:\n", top_store)


# Most expensive item per store

expensive_items = df.groupby('store_name').apply(lambda x: x.sort_values('cost',
ascending=False).iloc[0])

print("Most Expensive Item per Store:\n", expensive_items[['item_name', 'cost', 'kcal']])
```

```
# 8. Modeling and Forecasting

# Aggregate daily sales
daily_sales = df.groupby('date')['item_count'].sum().reset_index()
daily_sales['year'] = daily_sales['date'].dt.year
daily_sales['month'] = daily_sales['date'].dt.month
daily_sales['day'] = daily_sales['date'].dt.day
daily_sales['weekday'] = daily_sales['date'].dt.dayofweek
daily_sales['quarter'] = daily_sales['date'].dt.quarter

# Train/Test Split: Last 6 months as test
cutoff = daily_sales['date'].max() - pd.DateOffset(months=6)
train = daily_sales[daily_sales['date'] <= cutoff]
test = daily_sales[daily_sales['date'] > cutoff]

features = ['year', 'month', 'day', 'weekday', 'quarter']
X_train = train[features]
y_train = train['item_count']
X_test = test[features]
y_test = test['item_count']

# Models
models = {
    "Linear Regression": LinearRegression(),
    "Random Forest": RandomForestRegressor(n_estimators=100, random_state=42),
    "XGBoost": XGBRegressor(n_estimators=100, random_state=42)
}
```

```
print("\nModel Evaluation (RMSE):")

for name, model in models.items():

    model.fit(X_train, y_train)

    preds = model.predict(X_test)

    rmse = mean_squared_error(y_test, preds, squared=False)

    print(f"{name}: RMSE = {rmse:.2f}")


# Use best model (assume Random Forest)

best_model = RandomForestRegressor(n_estimators=100, random_state=42)

best_model.fit(X_train, y_train)


# Forecast next 365 days

future_dates = pd.date_range(start=daily_sales['date'].max() + pd.Timedelta(days=1),
periods=365)

future_df = pd.DataFrame({'date': future_dates})

future_df['year'] = future_df['date'].dt.year

future_df['month'] = future_df['date'].dt.month

future_df['day'] = future_df['date'].dt.day

future_df['weekday'] = future_df['date'].dt.dayofweek

future_df['quarter'] = future_df['date'].dt.quarter


# Predict

future_df['predicted_sales'] = best_model.predict(future_df[features])


# Plot historical + future forecast

plt.figure(figsize=(14,6))

plt.plot(daily_sales['date'], daily_sales['item_count'], label="Historical Sales")

plt.plot(future_df['date'], future_df['predicted_sales'], label="Forecasted Sales", linestyle='--
')
```

```
plt.title("Sales Forecast for Next Year")

plt.xlabel("Date")

plt.ylabel("Items Sold")

plt.legend()

plt.tight_layout()

plt.show()
```

Screenshots:

```
[38] import pandas as pd
     import numpy as np
     import matplotlib.pyplot as plt
     import seaborn as sns
     from datetime import datetime

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

     from sklearn.metrics import mean_squared_error
     from sklearn.model_selection import train_test_split
```

```
[39] df_rest = pd.read_csv("resturants.csv")
     df_items = pd.read_csv("items.csv")
     df_sales = pd.read_csv("sales.csv")
```

```
[40] df_items.rename(columns={'name': 'item_name'}, inplace=True)
     df_rest.rename(columns={'name': 'store_name'}, inplace=True)
     # df_sales.rename(columns={'name': 'item_name'}, inplace=True) # This line caused the error as df_sales does not have a 'name' column
```

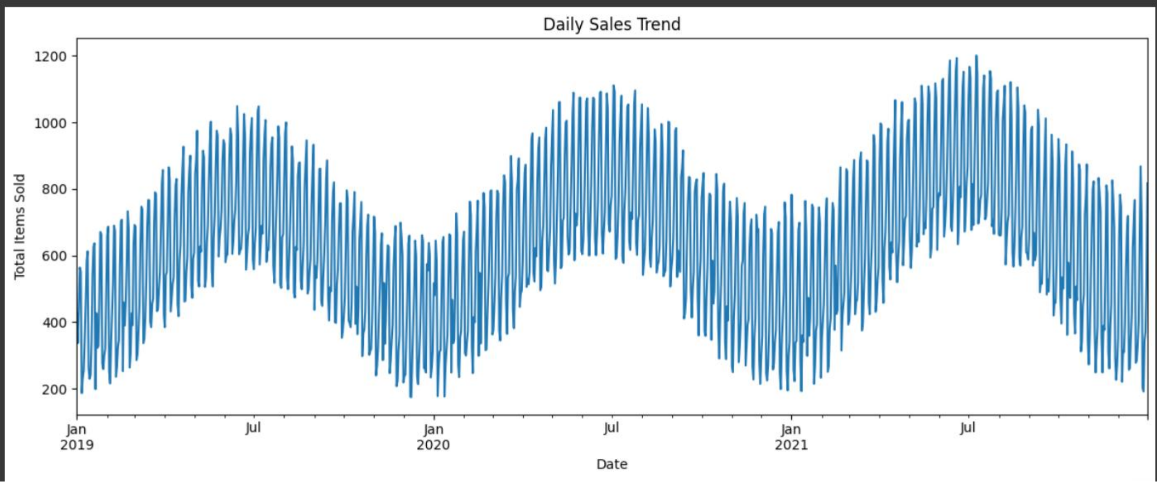
```
[41] print("Sales Columns:", df_sales.columns)
     print("Items Columns:", df_items.columns)
     print("Restaurants Columns:", df_rest.columns)

Sales Columns: Index(['date', 'item_id', 'price', 'item_count'], dtype='object')
Items Columns: Index(['id', 'store_id', 'item_name', 'kcal', 'cost'], dtype='object')
Restaurants Columns: Index(['id', 'store_name'], dtype='object')
```

```
[42] df = df_sales.merge(df_items, left_on='item_id', right_on='id', how='left') \
                  .merge(df_rest, left_on="store_id", right_on="id", suffixes=('_item', '_store'))
```

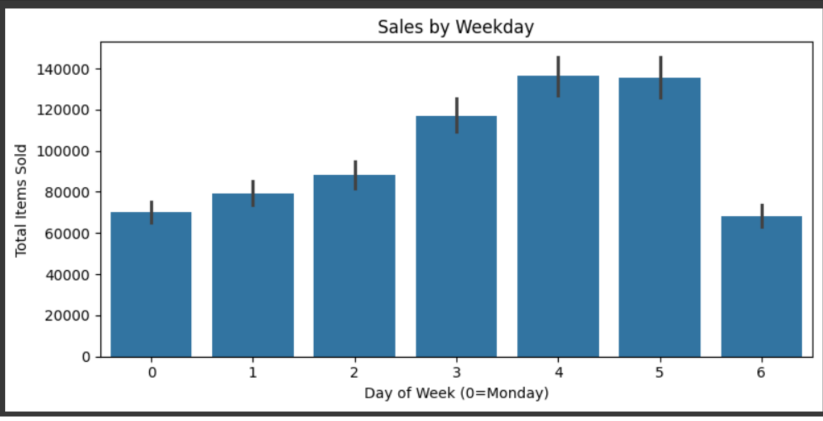
```
[43] df['date'] = pd.to_datetime(df['date'])
     df.dropna(inplace=True)
```

```
[44] df['year'] = df['date'].dt.year
     df['month'] = df['date'].dt.month
     df['day'] = df['date'].dt.day
     df['weekday'] = df['date'].dt.dayofweek
     df['quarter'] = df['date'].dt.quarter
```

[45]
```
plt.figure(figsize=(12,5))
df.groupby('date')['item_count'].sum().plot(title="Daily Sales Trend")
plt.xlabel("Date")
plt.ylabel("Total Items Sold")
plt.tight_layout()
plt.show()
```




```
plt.figure(figsize=(8,4))
sns.barplot(data=df, x='weekday', y='item_count', estimator=sum)
plt.title("Sales by Weekday")
plt.xlabel("Day of Week (0=Monday)")
plt.ylabel("Total Items Sold")
plt.tight_layout()
plt.show()
```



[47]
```
top_items = df.groupby('item_name')['item_count'].sum().sort_values(ascending=False).head(10)
print("Top 10 Items Sold:\n", top_items)
```

```
Top 10 Items Sold:
 item_name
Strawberry Smoothy              236337.0
Frozen Milky Smoothy            103263.0
Amazing pork lunch               61043.0
Mutton Dinner                    52772.0
Orange Juice                     43874.0
Blue Ribbon Beef Entree          42774.0
Amazing Steak Dinner with Rolls  34439.0
Sweet Frozen Soft Drink          27490.0
Sea Bass with Vegetables Dinner  23839.0
Sweet Lamb Cake                  18764.0
Name: item_count, dtype: float64
```

```
# Most profitable store
df['revenue'] = df['item_count'] * df['price']
top_store = df.groupby('store_name')['revenue'].sum().sort_values(ascending=False)
print("Most Profitable Stores:\n", top_store)
```

```
Most Profitable Stores:
 store_name
Bob's Diner       6337275.69
Fou Cher            27885.37
Corner Cafe         16551.43
Surfs Up            15651.49
Beachfront Bar       3796.20
Sweet Shack          2578.27
Name: revenue, dtype: float64
```

```
[49] # Most expensive item per store
expensive_items = df.groupby('store_name').apply(lambda x: x.sort_values('cost', ascending=False).iloc[0])
print("Most Expensive Item per Store:\n", expensive_items[['item_name', 'cost', 'kcal']])
```

```
Most Expensive Item per Store:
                                  item_name   cost  kcal
store_name
Beachfront Bar          Sweet Vegi Soft Drink   5.70   538
Bob's Diner                 Sweet Fruity Cake  29.22   931
Corner Cafe                        Pike Lunch  26.37   653
Fou Cher        Blue Ribbon Fruity Vegi Lunch  53.98   881
Surfs Up                           Steak Meal  26.21   607
Sweet Shack     Blue Ribbon Frozen Milky Cake   7.70   636
/tmp/ipython-input-49-3444379855.py:2: DeprecationWarning: DataFrameGroupBy.apply operated on the grouping columns. This behavior is deprecated,
  expensive_items = df.groupby('store_name').apply(lambda x: x.sort_values('cost', ascending=False).iloc[0])
```

```
[50] # 8. Modeling and Forecasting

# Aggregate daily sales
daily_sales = df.groupby('date')['item_count'].sum().reset_index()
daily_sales['year'] = daily_sales['date'].dt.year
daily_sales['month'] = daily_sales['date'].dt.month
daily_sales['day'] = daily_sales['date'].dt.day
daily_sales['weekday'] = daily_sales['date'].dt.dayofweek
daily_sales['quarter'] = daily_sales['date'].dt.quarter
```

```
# Train/Test Split: Last 6 months as test
cutoff = daily_sales['date'].max() - pd.DateOffset(months=6)
train = daily_sales[daily_sales['date'] <= cutoff]
test = daily_sales[daily_sales['date'] > cutoff]

features = ['year', 'month', 'day', 'weekday', 'quarter']
X_train = train[features]
y_train = train['item_count']
X_test = test[features]
y_test = test['item_count']
```

```
[52] # Models
models = {
    "Linear Regression": LinearRegression(),
    "Random Forest": RandomForestRegressor(n_estimators=100, random_state=42),
    "XGBoost": XGBRegressor(n_estimators=100, random_state=42)
}

print("\nModel Evaluation (RMSE):")
for name, model in models.items():
    model.fit(X_train, y_train)
    preds = model.predict(X_test)
    rmse = np.sqrt(mean_squared_error(y_test, preds))
    print(f"{name}: RMSE = {rmse:.2f}")
```

```
Model Evaluation (RMSE):
Linear Regression: RMSE = 246.54
Random Forest: RMSE = 62.16
XGBoost: RMSE = 61.24
```

```
[53] # Use best model (assume Random Forest)
     best_model = RandomForestRegressor(n_estimators=100, random_state=42)
     best_model.fit(X_train, y_train)
```

```
RandomForestRegressor
RandomForestRegressor(random_state=42)
```

```
[54] # Forecast next 365 days
     future_dates = pd.date_range(start=daily_sales['date'].max() + pd.Timedelta(days=1), periods=365)
     future_df = pd.DataFrame({'date': future_dates})
     future_df['year'] = future_df['date'].dt.year
     future_df['month'] = future_df['date'].dt.month
     future_df['day'] = future_df['date'].dt.day
     future_df['weekday'] = future_df['date'].dt.dayofweek
     future_df['quarter'] = future_df['date'].dt.quarter
```

```
[55] # Predict
     future_df['predicted_sales'] = best_model.predict(future_df[features])
```

```
[56] # Plot historical + future forecast
     plt.figure(figsize=(14,6))
     plt.plot(daily_sales['date'], daily_sales['item_count'], label="Historical Sales")
     plt.plot(future_df['date'], future_df['predicted_sales'], label="Forecasted Sales", linestyle='--')
     plt.title("Sales Forecast for Next Year")
     plt.xlabel("Date")
     plt.ylabel("Items Sold")
     plt.legend()
     plt.tight_layout()
     plt.show()
```