Notebook Information

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Purpose of the Notebook

This Jupyter Notebook was created for the CSE512 course assignment on distributed database management systems. The purpose of this notebook is to demonstrate the use of Python programming language and distributed computing techniques to implement a sales forecasting system for a retail chain.

Notebook Contents

This notebook contains code, explanations, and examples related to the following topics:

- Database design and schema definition
- Data visualization, data transformation
- Model evaluation and predictions
- Sales forecasting algorithms using machine learning techniques

The notebook applies machine learning algorithms to answer the following sales forecasting queries:

1. Forecast the one year sales (Breakdown monthly) for each of the items.
2. Forecast the sales of the stores for the next 30 days.

The notebook also includes examples of how to visualize the forecasted sales using Matplotlib and how to present the results in a user-friendly format.

Instructions for Running the Notebook

To run this notebook, make sure you have Python 3 installed on your system along with the necessary packages such as NumPy, Pandas, Scikit-learn, and Matplotlib. You can install these packages using the following command:

```
pip install numpy pandas scikit-learn matplotlib
```

Once the required packages are installed, you can open the notebook in Jupyter Notebook or JupyterLab and run each cell in sequence to execute the code and see the results.

In [ ]:

Import Packages

In [1]:
```
import pandas as pd
from sklearn.linear_model import LinearRegression
import psycopg2
import psycopg2.extras
import pandas as pd
from tqdm import tqdm
import numpy as np
import pandas as pd
from sqlalchemy import create_engine
from sklearn.linear_model import LinearRegression
from dateutil.relativedelta import relativedelta
import matplotlib.pyplot as plt
import seaborn as sns
from statsmodels.tsa.arima.model import ARIMA
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
```

E-commerce Data Loader Class for PostgreSQL Database

In [2]:
```
class EcommerceDataLoader:
    """
    A class to load E-commerce data from a PostgreSQL database into Pandas DataFrames.
    """

    def __init__(self, host, port, username, password, database):
        """
        Initializes the EcommerceDataLoader class with the database connection paramete
        """
        self.engine = create_engine(f'postgresql://{username}:{password}@{host}:{port}/

    def load_fact_table(self, schema):
        """
        Loads the fact table from the specified schema into a Pandas DataFrame.
        """
        query = f"SELECT * FROM {schema}.fact_table"
        return pd.read_sql_query(query, self.engine)

    def load_item_dim(self, schema):
        """
        Loads the item dimension table from the specified schema into a Pandas DataFrar
        """
        query = f"SELECT * FROM {schema}.item_dim"
        return pd.read_sql_query(query, self.engine)

    def load_time_dim(self, schema):
        """
        Loads the time dimension table from the specified schema into a Pandas DataFrar
        """
        query = f"SELECT * FROM {schema}.time_dim"
        return pd.read_sql_query(query, self.engine)

    def load_store_dim(self, schema):
        """
        Loads the store dimension table from the specified schema into a Pandas DataFra
        """
        query = f"SELECT * FROM {schema}.store_dim"
        return pd.read_sql_query(query, self.engine)


# create an instance of this class and use its methods
ecom_loader = EcommerceDataLoader('localhost', '5434', 'postgres', '1234', 'ecomdb')
fact_table = ecom_loader.load_fact_table('ecom_schema')
item_dim = ecom_loader.load_item_dim('ecom_schema')
time_dim = ecom_loader.load_time_dim('ecom_schema')
store_dim = ecom_loader.load_store_dim('ecom_schema')
```

Function to merge E-commerce tables

In [3]:
```
def merge_tables(fact_table, item_dim, time_dim, store_dim):
    """
    A function to merge the E-commerce tables.
    """
    merged_df = pd.merge(fact_table, item_dim, on='item_key', how='left')
    merged_df = pd.merge(merged_df, time_dim, on='time_key', how='left')
    merged_df = pd.merge(merged_df, store_dim, on='store_key', how='left')
    return merged_df

merged_df = merge_tables(fact_table, item_dim, time_dim, store_dim)
```

Function to split data

In [4]:
```
def split_data(df, train_size):
    """
    A function to split data into training and testing datasets.
    """
    train_size = int(len(df) * train_size)
    train_df = df[:train_size]
    test_df = df[train_size:]
    return train_df, test_df

train_df, test_df = split_data(merged_df, 0.8)
```

SalesForecast: ARIMA Model

ARIMA is a form of regression analysis that indicates the strength of a dependent variable relative to other changing variables. The final objective of the model is to predict future time series movement by examining the differences between values in the series instead of through actual values. However, to answer the question no 1: "Forecast the one year sales (Breakdown monthly) for each of the items", we shall apply the ARIMA model and let's see the outcome.

Forecast the one year sales (Breakdown monthly) for each of the items

In [5]:
```
import warnings
warnings.filterwarnings("ignore")
from tqdm import tqdm

class SalesForecastARIMA:
    def __init__(self, train_df):
        self.train_df = train_df

    def fit(self):
        # Convert the 'date' column to datetime format
        self.train_df['date'] = pd.to_datetime(self.train_df['date'])

        # Define the ARIMA model parameters
        p = 2  # AR term
        d = 1  # I term
        q = 2  # MA term

        # Group the training data by year and month
        train_data = self.train_df.groupby([self.train_df['date'].dt.year.rename('year

        # Create a dictionary to store the forecasts for each item
        forecasts_dict = {}

        # Loop over each item and fit an ARIMA model
        for item in tqdm(train_data['item_key'].unique(), desc='Fitting ARIMA models')
            # Subset the data for the current item
            item_data = train_data[train_data['item_key'] == item]

            # Fit the ARIMA model for the current item
            model = ARIMA(item_data['total_price'], order=(p, d, q)).fit()

            # Use the fitted model to make predictions for the next 12 months
            forecast = model.forecast(steps=12)

            # Add the forecast to the forecasts dictionary, using the item key as the k
            forecasts_dict[item] = forecast

        # Combine the forecasts into a single dataframe
        forecasts_df = pd.DataFrame(forecasts_dict)

        # Add a column for the year and month of each forecast
        forecasts_df['year'] = pd.date_range(start='2022-01-01', periods=12, freq='MS'
        forecasts_df['month'] = pd.date_range(start='2022-01-01', periods=12, freq='MS

        # Reorder the columns to match the original data
        self.forecasts_df = forecasts_df[['year', 'month'] + train_data['item_key'].uni


    def fit_2(self):
        # Convert the 'date' column to datetime format
        self.train_df['date'] = pd.to_datetime(self.train_df['date'])

        # Define the ARIMA model parameters
        p = 2  # AR term
        d = 1  # I term
        q = 2  # MA term

        # Group the training data by year and month
        train_data = self.train_df.groupby([self.train_df['date'].dt.year.rename('year
```

```
        # Create a dictionary to store the forecasts for each item
        forecasts_dict = {}

        # Loop over each item and fit an ARIMA model
        for item in tqdm(train_data['item_key'].unique(), desc='Fitting ARIMA models')
            # Subset the data for the current item
            item_data = train_data[train_data['item_key'] == item]

            # Fit the ARIMA model for the current item
            model = ARIMA(item_data['total_price'], order=(p, d, q)).fit()

            # Use the fitted model to make predictions for the next 30 days
            forecast = model.forecast(steps=30)

            # Add the forecast to the forecasts dictionary, using the item key as the k
            forecasts_dict[item] = forecast

        # Combine the forecasts into a single dataframe
        forecasts_df = pd.DataFrame(forecasts_dict)

        # Add a column for the date of each forecast
        forecasts_df['date'] = pd.date_range(start='2022-01-01', periods=30, freq='D')

        # Reorder the columns to match the original data
        self.forecasts_df2 = forecasts_df[['date'] + train_data['item_key'].unique().to



    def predict(self):
        # Print the forecasts
        #print(self.forecasts_df.to_string(index=False))
        print(self.forecasts_df.head())


    def predict_2(self):

        print(self.forecasts_df2.head())

# Instantiate the model and fit the data
model = SalesForecastARIMA(train_df)
model.fit()

# Generate and print the forecasts
model.predict()
```

```
Fitting ARIMA models: 100%|
| 263/263 [00:35<00:00,  7.37it/s]
```

	year	month	I00001	I00002	I00003	I00004	\
85	2022	1	2414.955529	1456.474529	1402.417480	1433.646680	
86	2022	2	2821.038316	1463.229346	1374.710056	1361.885411	
87	2022	3	2329.700853	1456.710833	1476.664708	1450.874363	
88	2022	4	2777.644484	1460.975293	1395.694300	1415.372701	
89	2022	5	2381.995604	1458.029568	1475.612980	1439.952082	

	I00005	I00006	I00007	I00008	...	I00255	\
85	1657.218743	3436.594815	1294.135702	3053.322384	...	4188.335983	
86	1447.896971	3294.704982	1388.534292	3142.587383	...	4443.488595	
87	1499.544349	3417.051666	1439.409787	3062.646541	...	4206.546217	
88	1466.710754	3407.513326	1468.999209	3120.336707	...	4410.613714	
89	1465.838971	3427.621320	1486.624605	3082.382294	...	4235.048902	

	I00256	I00257	I00258	I00259	I00260	\
85	4256.133100	4518.293361	4299.914901	5183.695108	3477.511779	
86	4049.383021	4667.179180	4228.105376	5588.205955	2958.061886	
87	4144.552491	4566.581368	4144.981911	5255.401440	3632.733164	
88	4146.764071	4667.038099	4133.670015	5504.880398	3109.591102	
89	4158.615969	4571.187871	4144.500784	5318.591202	3590.856258	

	I00261	I00262	I00263	I00264
85	7119.629827	2868.046712	2813.395952	2740.118132
86	6572.285649	3011.526771	2856.751784	3543.351757
87	7119.658953	2911.044431	2727.974112	2831.512979
88	6766.609984	2991.590465	2725.307474	3455.564763
89	7043.738005	2927.164255	2740.266392	2908.523204

[5 rows x 265 columns]

Sales Forecasting for Next 30 Days

In this section, we will use the SalesForecastARIMA class to generate sales forecasts for the next 30 days. The class has already been fitted to the training data, so we can simply call the predict2() method to generate the forecasts. We will then visualize the forecasts using a line chart to see the predicted sales trends for each store.

In [6]:
```
# Instantiate the model and fit the data
model = SalesForecastARIMA(train_df)
model.fit_2()

# Generate and print the forecasts
model.predict_2()
```

```
Fitting ARIMA models: 100%|██████████████████████████████████████████████████████
| 263/263 [00:38<00:00,  6.91it/s]

         date       I00001       I00002       I00003       I00004
85 2022-01-01  2414.955529  1456.474529  1402.417480  1433.646680  \
86 2022-01-02  2821.038316  1463.229346  1374.710056  1361.885411
87 2022-01-03  2329.700853  1456.710833  1476.664708  1450.874363
88 2022-01-04  2777.644484  1460.975293  1395.694300  1415.372701
89 2022-01-05  2381.995604  1458.029568  1475.612980  1439.952082

         I00005       I00006       I00007       I00008       I00009  ...
85  1657.218743  3436.594815  1294.135702  3053.322384  3585.371725  ...  \
86  1447.896971  3294.704982  1388.534292  3142.587383  3245.025704  ...
87  1499.544349  3417.051666  1439.409787  3062.646541  3599.708034  ...
88  1466.710754  3407.513326  1468.999209  3120.336707  3390.239835  ...
89  1465.838971  3427.621320  1486.624605  3082.382294  3530.938341  ...

         I00255       I00256       I00257       I00258       I00259
85  4188.335983  4256.133100  4518.293361  4299.914901  5183.695108  \
86  4443.488595  4049.383021  4667.179180  4228.105376  5588.205955
87  4206.546217  4144.552491  4566.581368  4144.981911  5255.401440
88  4410.613714  4146.764071  4667.038099  4133.670015  5504.880398
89  4235.048902  4158.615969  4571.187871  4144.500784  5318.591202

         I00260       I00261       I00262       I00263       I00264
85  3477.511779  7119.629827  2868.046712  2813.395952  2740.118132
86  2958.061886  6572.285649  3011.526771  2856.751784  3543.351757
87  3632.733164  7119.658953  2911.044431  2727.974112  2831.512979
88  3109.591102  6766.609984  2991.590465  2725.307474  3455.564763
89  3590.856258  7043.738005  2927.164255  2740.266392  2908.523204

[5 rows x 264 columns]
```

SalesForecast: Linear Regression Model

Linear regression is a data analysis technique that predicts the value of unknown data by using another related and known data value. It mathematically models the unknown or dependent variable and the known or independent variable as a linear equation. However, to answer the question no 1: "Forecast the one year sales (Breakdown monthly) for each of the items", we shall apply the Linear Regression model and let's see the outcome.

Forecast the one year sales (Breakdown monthly) for each of the items

In [7]:
```
class SalesForecastLinear:
    def __init__(self, train_df):
        self.train_df = train_df


    def fit_linear(self):
        # Convert the 'date' column to datetime format
        self.train_df['date'] = pd.to_datetime(self.train_df['date'])

        # Group the training data by year and month
        train_data = self.train_df.groupby([self.train_df['date'].dt.year.rename('year

        # Create a dictionary to store the forecasts for each item
        forecasts_dict = {}

        # Loop over each item and fit a Linear Regression model
        for item in tqdm(train_data['item_key'].unique(), desc='Fitting Linear Regress
            # Subset the data for the current item
            item_data = train_data[train_data['item_key'] == item]

            # Create a Linear Regression model for the current item
            model = LinearRegression()

            # Prepare the training data
            X_train = item_data[['year', 'month']]
            y_train = item_data['total_price']

            # Fit the Linear Regression model for the current item
            model.fit(X_train, y_train)

            # Use the fitted model to make predictions for the next 12 months
            X_test = pd.DataFrame({'year': [2022]*12, 'month': range(1,13)})
            forecast = model.predict(X_test)

            # Add the forecast to the forecasts dictionary, using the item key as the k
            forecasts_dict[item] = forecast

        # Combine the forecasts into a single dataframe
        forecasts_df = pd.DataFrame(forecasts_dict)

        # Add a column for the year and month of each forecast
        forecasts_df['year'] = pd.date_range(start='2022-01-01', periods=12, freq='MS'
        forecasts_df['month'] = pd.date_range(start='2022-01-01', periods=12, freq='MS

        # Reorder the columns to match the original data
        self.forecasts_df = forecasts_df[['year', 'month'] + train_data['item_key'].uni

    def fit_linear_2(self):
        # Convert the 'date' column to datetime format
        self.train_df['date'] = pd.to_datetime(self.train_df['date'])

        # Group the training data by year, month, and store
        train_data = self.train_df.groupby([self.train_df['date'].dt.year.rename('year

        # Create a dictionary to store the forecasts for each store
        store_forecasts_dict = {}

        # Loop over each store and fit a Linear Regression model
        for store in tqdm(train_data['store_key'].unique(), desc='Fitting Linear Regres
            # Subset the data for the current store
```

```
            store_data = train_data[train_data['store_key'] == store]

            # Create a linear regression model
            model = LinearRegression()

            # Train the model on the training data
            X = store_data[['year', 'month']]
            y = store_data['total_price']
            model.fit(X, y)

            # Use the trained model to make predictions for the next 30 days
            next_month_year = store_data['year'].max()
            next_month_month = store_data['month'].max() + 1
            if next_month_month > 12:
                next_month_month = 1
                next_month_year += 1
            forecast_dates = pd.DataFrame({'year': [next_month_year], 'month': [next_m
            forecast = model.predict(forecast_dates)

            # Add the forecast to the store_forecasts dictionary, using the store key
            store_forecasts_dict[store] = forecast

        # Combine the forecasts for all stores into a single dataframe
        self.store_forecasts_df = pd.DataFrame(store_forecasts_dict)

        # Add a column for the date of each forecast
        self.store_forecasts_df['date'] = pd.date_range(start='2022-03-01', periods=1,

        # Set the date column as the index of the store_forecasts_df dataframe
        self.store_forecasts_df = self.store_forecasts_df.set_index('date')


    def predict(self):
        # Print the forecasts
        print(self.forecasts_df.head())


    def predict_2(self):
        # Print the forecasts
        #print(self.store_forecasts_df.head())
        print(self.store_forecasts_df.to_string())

# Instantiate the model and fit the data using ARIMA
model = SalesForecastLinear(train_df)

# Fit the linear regression models and generate the forecasts
model.fit_linear()
model.predict()
```

```
Fitting Linear Regression models: 100%|██████████████████████████████████████|
263/263 [00:01<00:00, 145.52it/s]
```

```
   year  month       I00001       I00002       I00003       I00004  \
0  2022      1  2442.460564  1387.201204  1431.333482  1406.176666  \
1  2022      2  2449.416539  1392.014861  1437.956372  1412.348978
2  2022      3  2456.372514  1396.828518  1444.579261  1418.521291
3  2022      4  2463.328490  1401.642175  1451.202151  1424.693603
4  2022      5  2470.284465  1406.455832  1457.825041  1430.865916

        I00005       I00006       I00007       I00008  ...       I00255  \
0  1379.472366  3309.960484  1578.564312  3337.137861  ...  4366.032613  \
1  1402.522847  3345.803412  1573.943218  3349.720306  ...  4410.928826
2  1425.573327  3381.646340  1569.322123  3362.302750  ...  4455.825039
3  1448.623807  3417.489268  1564.701029  3374.885194  ...  4500.721252
4  1471.674287  3453.332197  1560.079935  3387.467639  ...  4545.617465

        I00256       I00257       I00258       I00259       I00260  \
0  3783.309724  4464.678256  4336.361450  5040.260094  3494.014931  \
1  3820.042017  4527.950869  4401.966912  5138.687389  3510.558394
2  3856.774310  4591.223482  4467.572374  5237.114683  3527.101857
3  3893.506603  4654.496094  4533.177836  5335.541978  3543.645319
4  3930.238896  4717.768707  4598.783298  5433.969272  3560.188782

        I00261       I00262       I00263       I00264
0  6014.926110  2518.876681  2864.512815  3009.196128
1  6067.804622  2566.273396  2899.179813  3034.376910
2  6120.683133  2613.670111  2933.846811  3059.557691
3  6173.561645  2661.066826  2968.513808  3084.738473
4  6226.440156  2708.463541  3003.180806  3109.919254

[5 rows x 265 columns]
```

Sales Forecasting for Next 30 Days

In this section, we will use the SalesForecastLinear class to generate sales forecasts for the next 30 days. The class has already been fitted to the training data, so we can simply call the predict_2() method to generate the forecasts. We will then visualize the forecasts using a line chart to see the predicted sales trends for each store.

In [8]:
```
# Instantiate the model and fit the data
model2 = SalesForecastLinear(train_df)
model2.fit_linear_2()
# Generate and print the forecasts
model2.predict_2()
```

```
63       S00164       S00165       S00166       S00167       S00168       S00169
S0017       S00170       S00171       S00172       S00173       S00174       S0017
5       S00176       S00177       S00178       S00179        S0018       S00180
S00181       S00182       S00183       S00184       S00185       S00186       S001
87       S00188       S00189        S0019       S00190       S00191       S00192
S00193       S00194       S00195       S00196       S00197       S00198       S001
99        S0020       S00200       S00201       S00202       S00203       S00204
S00205       S00206       S00207       S00208       S00209        S0021       S002
10       S00211       S00212       S00213       S00214       S00215       S00216
S00217       S00218       S00219       S0022       S00220       S00221       S0022
2       S00223       S00224       S00225       S00226       S00227       S00228
S00229       S0023       S00230       S00231       S00232       S00233       S0023
4      S00235       S00236       S00237       S00238       S00239        S0024
S00240       S00241       S00242       S00243       S00244       S00245       S002
46       S00247       S00248       S00249        S0025      S00250     S00251
S00252       S00253       S00254       S00255       S00256       S00257       S002
58       S00259        S0026       S00260       S00261       S00262       S00263
S00264       S00265       S00266       S00267       S00268       S00269        S00
27       S00270       S00271       S00272       S00273       S00274       S00275
```

In [ ]:

Exploratory Data Analysis (EDA)

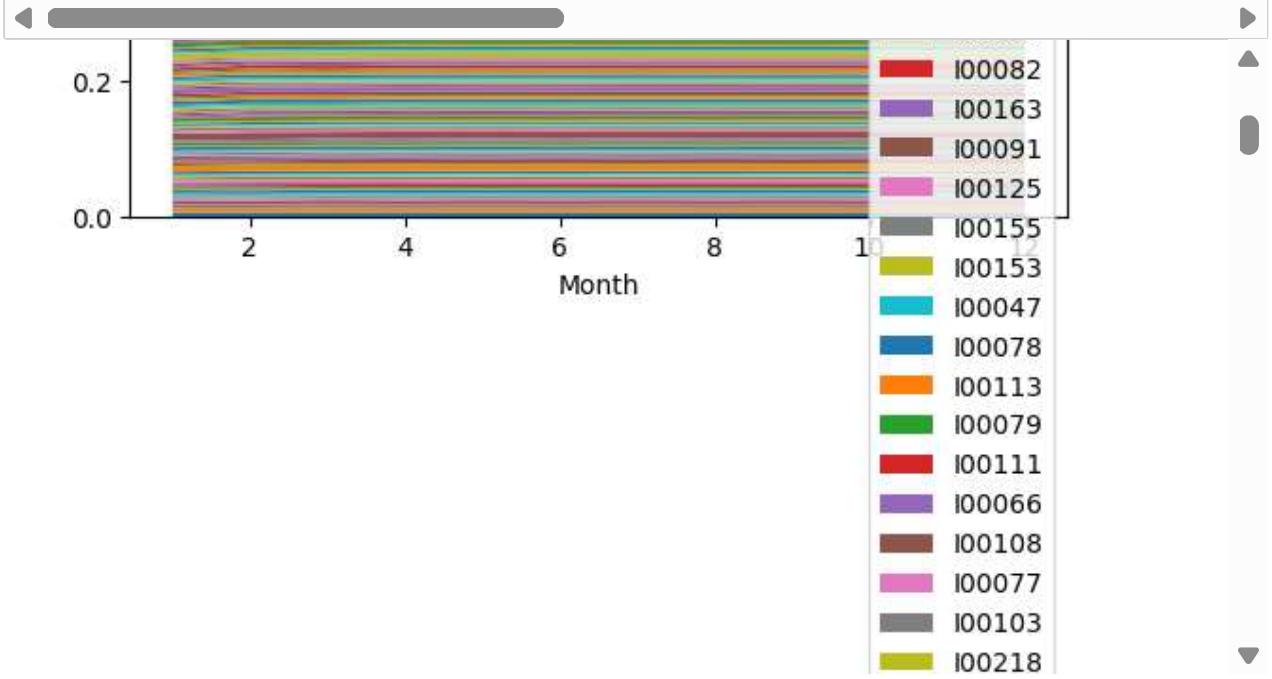
The goal of EDA is to identify patterns, relationships, and insights in the data, and to understand the underlying structure and nature of the variables. EDA typically involves visualizing the data using various graphs and charts, calculating descriptive statistics such as mean, median, and standard deviation, and detecting outliers and missing values. By performing EDA, data analysts and scientists can gain a deeper understanding of the data and make more informed decisions about modeling and analysis techniques.

EDA1—Monthly sales forecast for each item

In [9]:
```
def plot_forecasts(model_instance):
    fig, ax = plt.subplots()

    for item in model_instance.train_df['item_key'].unique():
        ax.plot(model_instance.forecasts_df['month'], model_instance.forecasts_df[item

    ax.set_xlabel('Month')
    ax.set_ylabel('Sales Forecast')
    ax.legend()

    plt.show()

model = SalesForecastARIMA(train_df)
model.fit()

plot_forecasts(model)
```

EDA2— What is the total sales forecast for each month and how each item contributes to it?

In [10]:
```
def plot_forecast_area(model_instance):
    fig, ax = plt.subplots()

    ax.stackplot(model_instance.forecasts_df['month'], model_instance.forecasts_df[tra

    ax.set_xlabel('Month')
    ax.set_ylabel('Sales Forecast')
    ax.legend()

    plt.show()


model = SalesForecastARIMA(train_df)
model.fit()

plot_forecast_area(model)
```

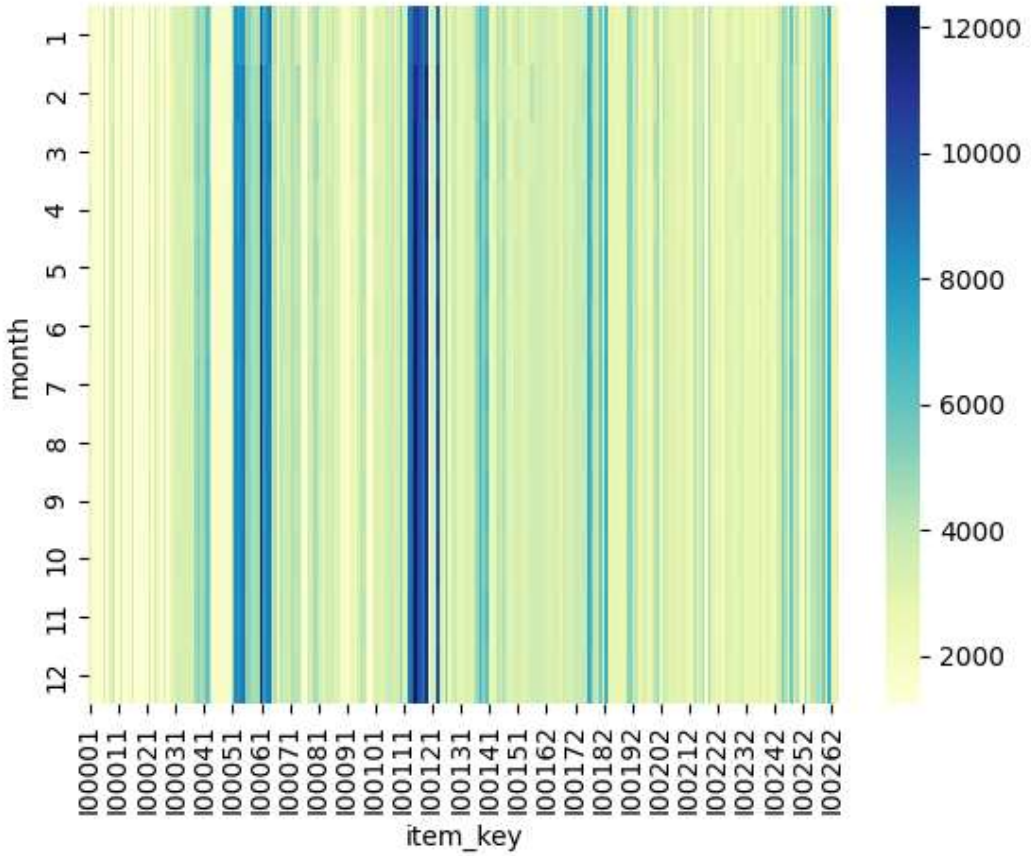


In [ ]:

EDA3—Visualize the monthly sales forecast for each item

In [11]:
```
def visualize_monthly_sales(model_instance):

    item_forecasts_df = model_instance.forecasts_df.melt(id_vars=['year', 'month'], va
    sns.heatmap(item_forecasts_df.pivot(index='month', columns='item_key', values='sal
    plt.show()


model = SalesForecastARIMA(train_df)
model.fit()

visualize_monthly_sales(model)
```

```
Fitting ARIMA models: 100%|
| 263/263 [00:38<00:00,  6.85it/s]
```



EDA4—Forecast sales by item

In [12]:
```
def forecast_sales_by_item(model_instance):

    # Reset the index of the forecasts_df dataframe
    forecasts_df = model_instance.forecasts_df.reset_index()

    # Create a horizontal bar chart of the forecasted sales for each item
    ax = forecasts_df.plot(kind='barh', x='index', figsize=(10, 8))

    # Set the axis labels and title
    ax.set_xlabel('Forecasted Sales')
    ax.set_ylabel('Item')
    ax.set_title('Forecasted Sales by Item')

    # Display the plot
    plt.show()

model = SalesForecastARIMA(train_df)
model.fit()

forecast_sales_by_item(model)
```