soc2

July 22, 2024

1 Final Project - Dhairya Kantawala

First after seeing the data and reading the problem statement carefully I understood the following: * 5 years of store-item sales data * asked to predict 3 months of sales for 50 different items at 10 different stores * Should stores be modeled separately or Pool together? * Does deep learning work better than ARIMA here? * Can either beat xgboost? — I think the best way to go by this is try different methods and see which gives the best result.

1.1 Let's first organize our data and also visulize it (EDA)

[ ]:
```
from google.colab import drive
drive.mount('/content/drive')

import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

train = pd.read_csv('/content/drive/My Drive/final soc project/
 ↪demand-forecasting-kernels-only/train.csv', parse_dates=['date'])
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call
drive.mount("/content/drive", force_remount=True).
```

[ ]:
```
print(train.info())
print(train.describe())
print(train.head())
# Just quick check on the data
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 913000 entries, 0 to 912999
Data columns (total 4 columns):
 #   Column  Non-Null Count   Dtype
---  ------  --------------   -----
 0   date    913000 non-null  datetime64[ns]
 1   store   913000 non-null  int64
 2   item    913000 non-null  int64
 3   sales   913000 non-null  int64
dtypes: datetime64[ns](1), int64(3)
memory usage: 27.9 MB
```

```
None
                                 date           store            item  \
count                          913000  913000.000000  913000.000000
mean    2015-07-02 11:59:59.999999744       5.500000      25.500000
min               2013-01-01 00:00:00       1.000000       1.000000
25%               2014-04-02 00:00:00       3.000000      13.000000
50%               2015-07-02 12:00:00       5.500000      25.500000
75%               2016-10-01 00:00:00       8.000000      38.000000
max               2017-12-31 00:00:00      10.000000      50.000000
std                               NaN       2.872283      14.430878

               sales
count  913000.000000
mean       52.250287
min         0.000000
25%        30.000000
50%        47.000000
75%        70.000000
max       231.000000
std        28.801144
        date  store  item  sales
0 2013-01-01      1     1     13
1 2013-01-02      1     1     11
2 2013-01-03      1     1     14
3 2013-01-04      1     1     13
4 2013-01-05      1     1     10
```

[ ]:
```
print(train.isnull().sum())
# No missing value, I like this :)
```

```
date     0
store    0
item     0
sales    0
dtype: int64
```

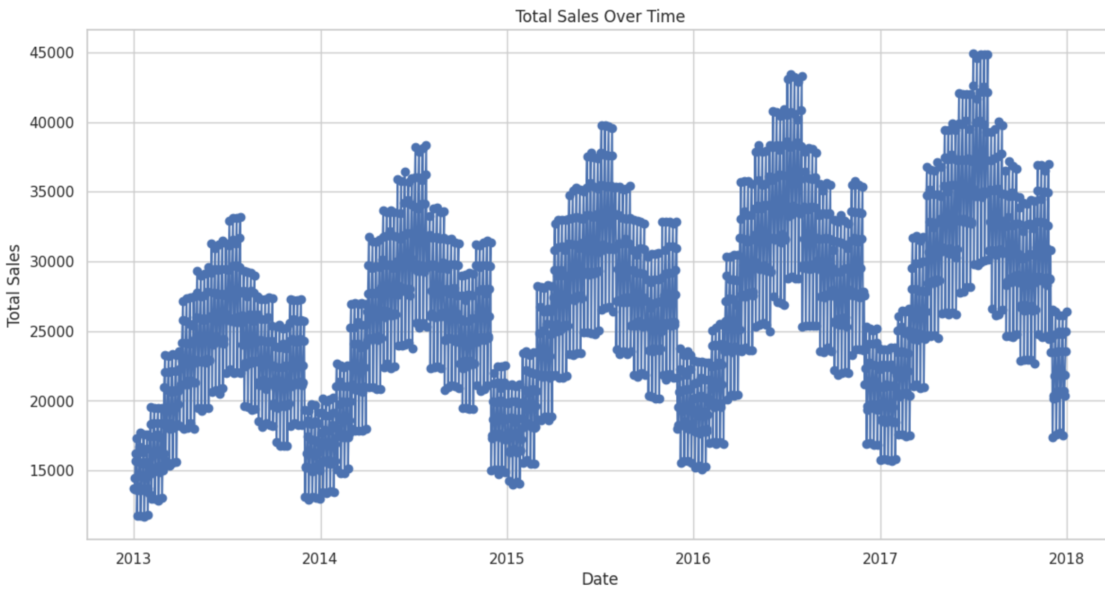
[ ]:
```
# For beautiful plottings
sns.set(style="whitegrid")
plt.figure(figsize=(12, 6))
```

[ ]: <Figure size 1200x600 with 0 Axes>

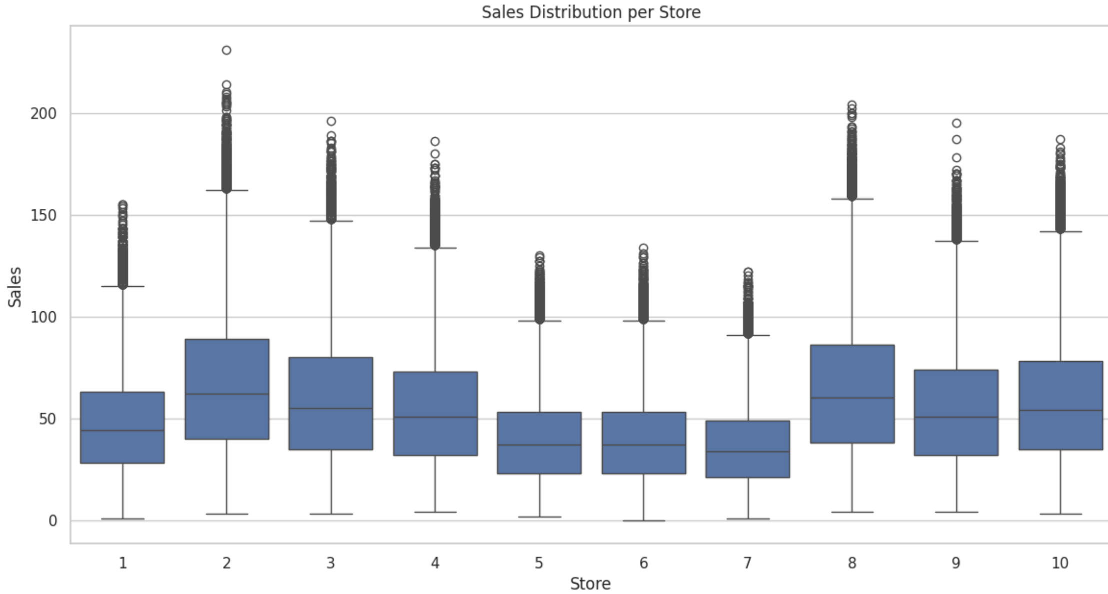
<Figure size 1200x600 with 0 Axes>

[ ]:
```
# Plot of total sales over time
total_sales = train.groupby('date').agg({'sales': 'sum'}).reset_index()
plt.figure(figsize=(14, 7))
plt.plot(total_sales['date'], total_sales['sales'], marker='o')
plt.title('Total Sales Over Time')
```

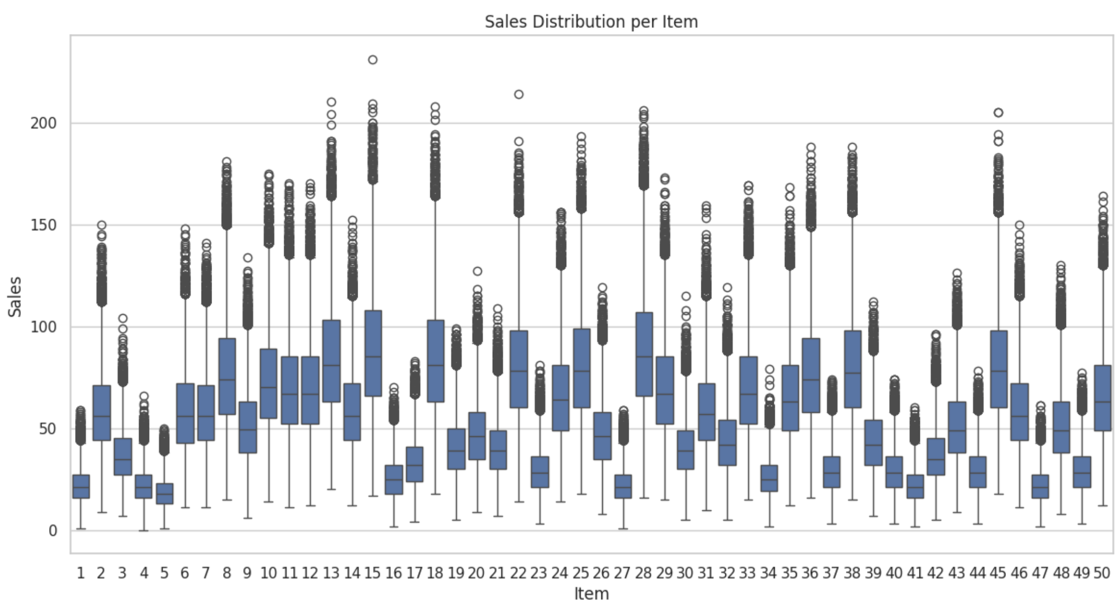
```python
plt.xlabel('Date')
plt.ylabel('Total Sales')
plt.grid(True)
plt.show()

# from the first graph itself we can see a nice seasonality pattern and also␣
↪that is common for all 10 stores which is nice for us.
```



[ ]:
```python
# Sales distribution per store
plt.figure(figsize=(14, 7))
sns.boxplot(x='store', y='sales', data=train)
plt.title('Sales Distribution per Store')
plt.xlabel('Store')
plt.ylabel('Sales')
plt.show()

# Did not gave me much insight.
```

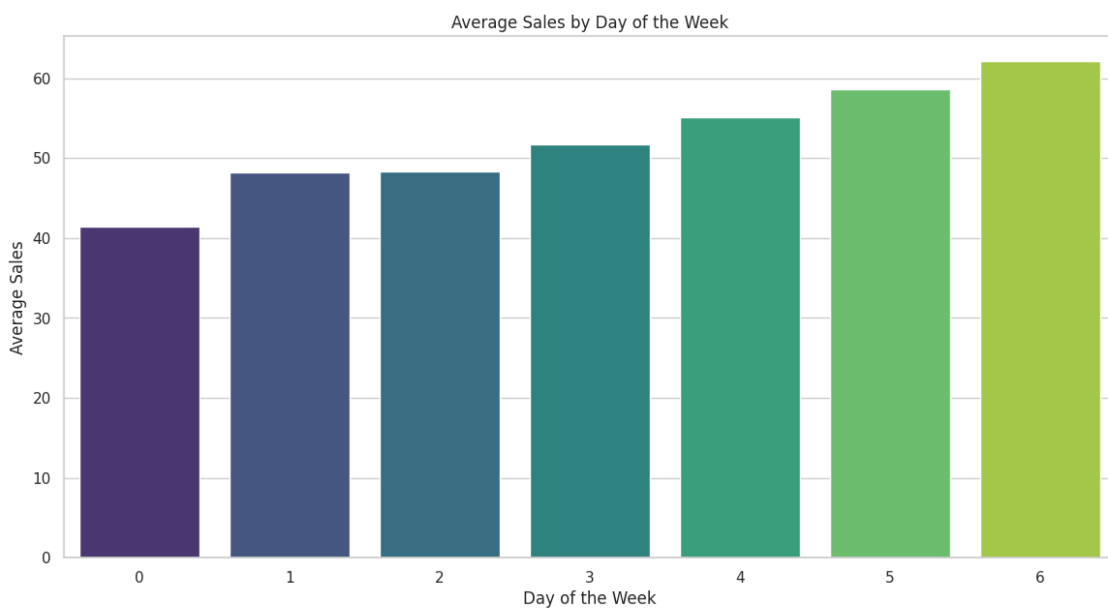



```
[ ]: # Sales distribution per item
plt.figure(figsize=(14, 7))
sns.boxplot(x='item', y='sales', data=train)
plt.title('Sales Distribution per Item')
plt.xlabel('Item')
plt.ylabel('Sales')
plt.show()

# Again not a big insight, will help in knowing some famous items
```



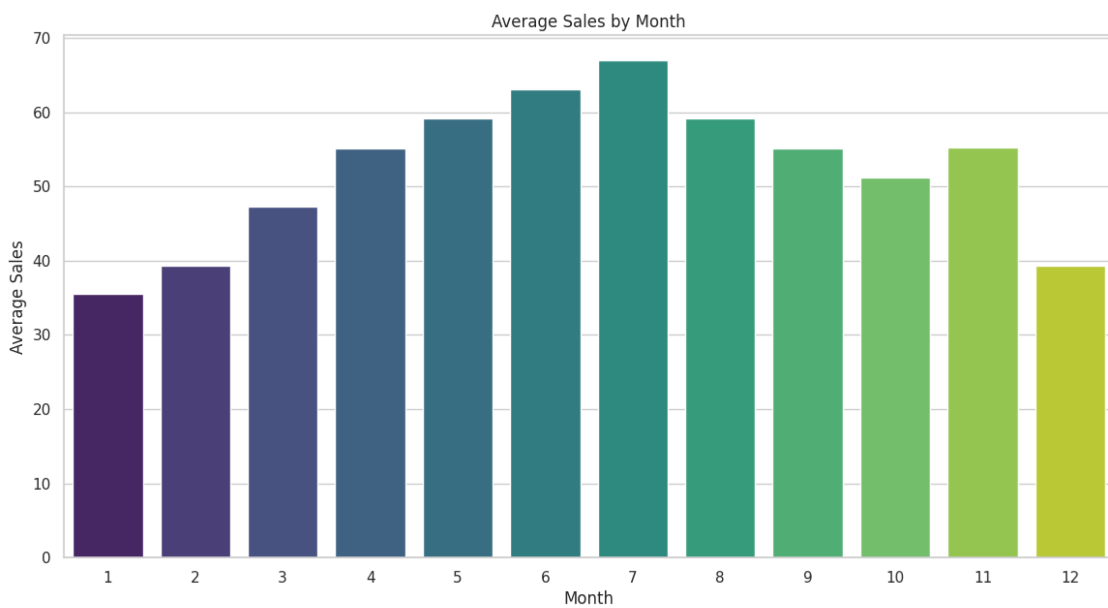
[ ]:
```python
# Average sales by day of the week
train['day_of_week'] = train['date'].dt.dayofweek
average_sales_by_dow = train.groupby('day_of_week').agg({'sales': 'mean'}).
 ↪reset_index()
plt.figure(figsize=(14, 7))
sns.barplot(x='day_of_week', y='sales', data=average_sales_by_dow,␣
 ↪palette='viridis')
plt.title('Average Sales by Day of the Week')
plt.xlabel('Day of the Week')
plt.ylabel('Average Sales')
plt.show()

# This is a nice insight, this just means as the week goes by the sales␣
 ↪gradually increase with the most over the weekend.
```

```
<ipython-input-59-ef62d5e22106>:5: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.barplot(x='day_of_week', y='sales', data=average_sales_by_dow,
palette='viridis')
```



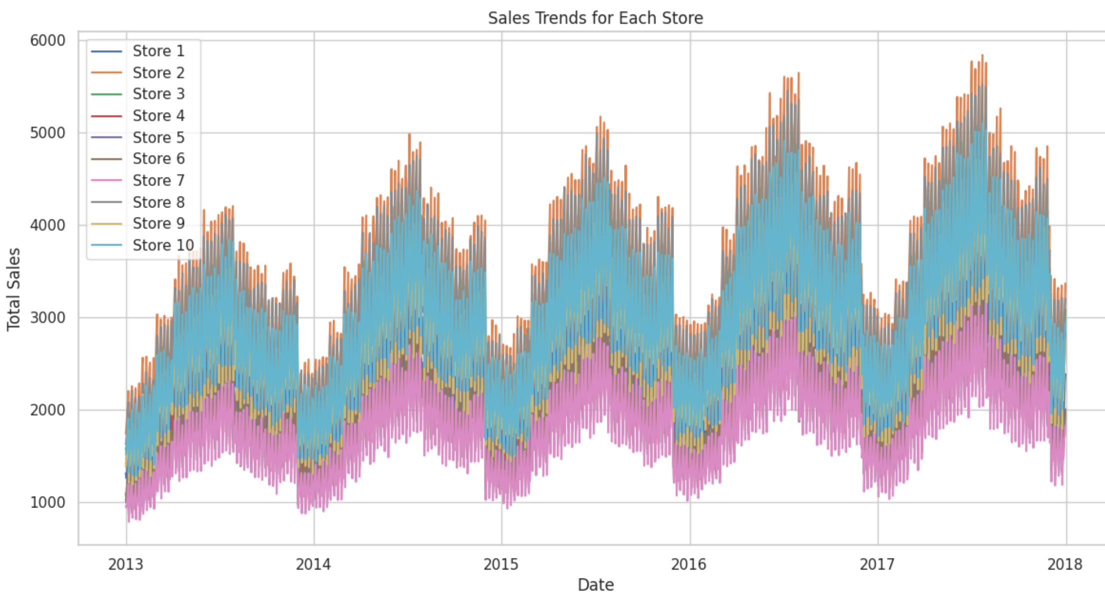
[ ]:
```python
# Average sales by month
train['month'] = train['date'].dt.month
average_sales_by_month = train.groupby('month').agg({'sales': 'mean'}).
    ↪reset_index()
plt.figure(figsize=(14, 7))
sns.barplot(x='month', y='sales', data=average_sales_by_month,␣
    ↪palette='viridis')
plt.title('Average Sales by Month')
plt.xlabel('Month')
plt.ylabel('Average Sales')
plt.show()

# This is also very insigtful, this tells me that there is a nice pattern of␣
    ↪sales which increases and then drops again, exclude month 11.
```

```
<ipython-input-60-7f7b87d19766>:5: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.barplot(x='month', y='sales', data=average_sales_by_month,
palette='viridis')
```



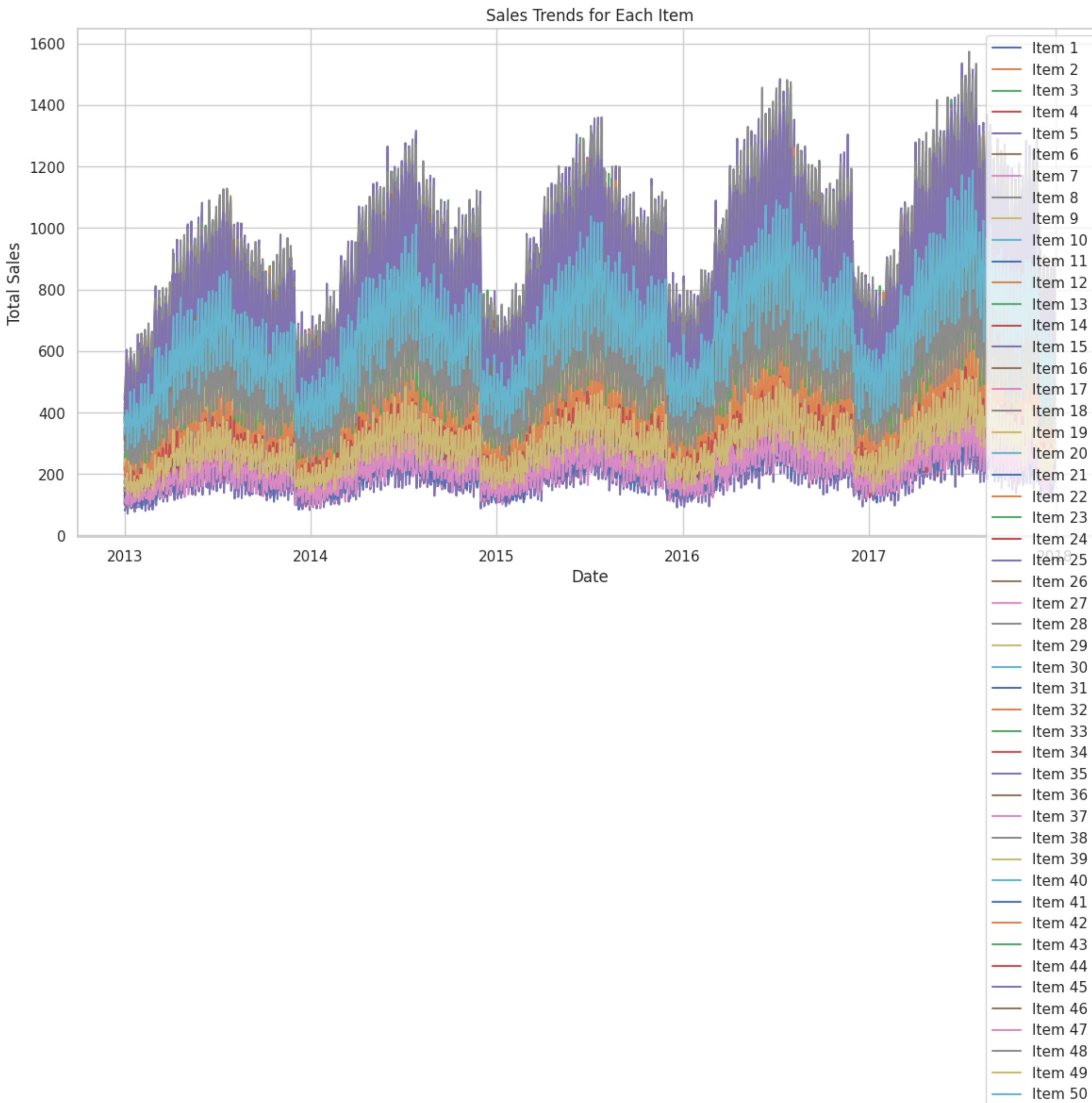
[ ]:
```python
# Sales trends for each store
plt.figure(figsize=(14, 7))
for store_id in train['store'].unique():
```

```
    store_sales = train[train['store'] == store_id].groupby('date').
 ↪agg({'sales': 'sum'}).reset_index()
    plt.plot(store_sales['date'], store_sales['sales'], label=f'Store␣
 ↪{store_id}')
plt.title('Sales Trends for Each Store')
plt.xlabel('Date')
plt.ylabel('Total Sales')
plt.legend()
plt.show()

# This is very similar to the first graph and shows a very nice seasonality␣
 ↪data. We can also see that the month vise sales are also seasonal in every␣
 ↪store.
```



[ ]:
```
# Sales trends for each item
plt.figure(figsize=(14, 7))
for item_id in train['item'].unique():
    item_sales = train[train['item'] == item_id].groupby('date').agg({'sales':␣
 ↪'sum'}).reset_index()
    plt.plot(item_sales['date'], item_sales['sales'], label=f'Item {item_id}')
plt.title('Sales Trends for Each Item')
plt.xlabel('Date')
plt.ylabel('Total Sales')
plt.legend()
plt.show()
```

```
# here also there is a nice seasonality, with this we can see that the most
common items and least common has a very similar pattern.
```



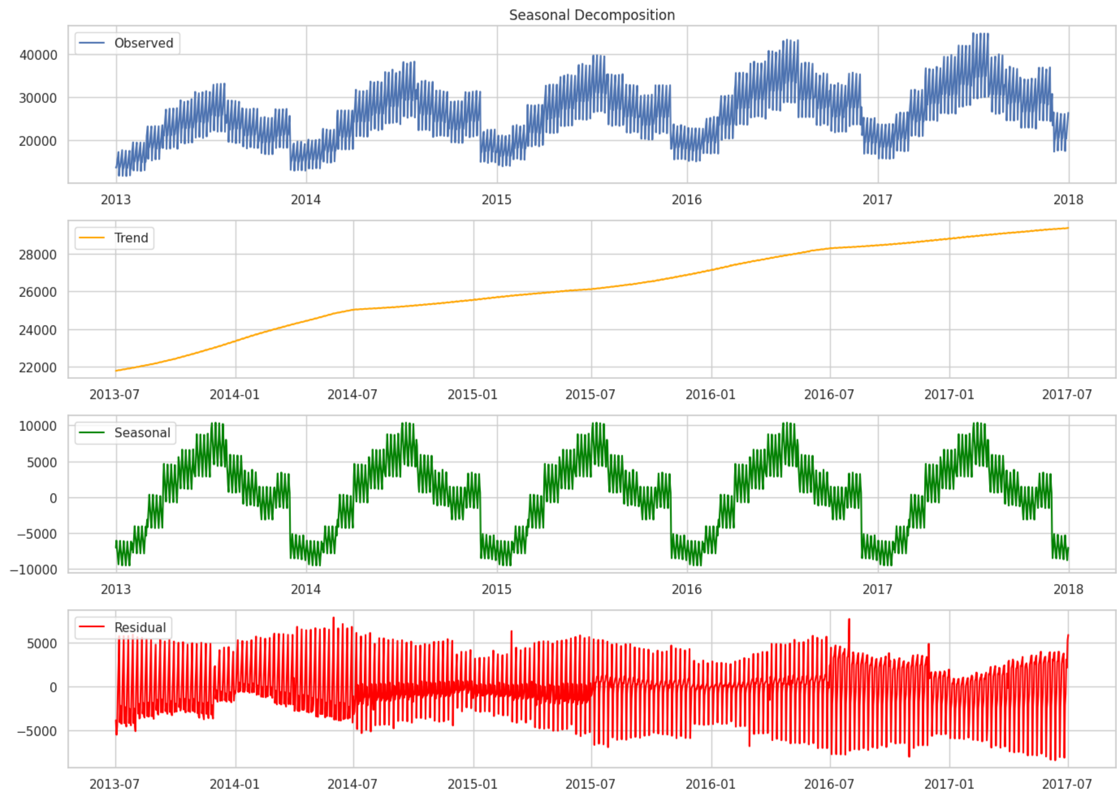
1.2 Now after EDA, let's try seasonal decomposition

[ ]:
```
import pandas as pd
import matplotlib.pyplot as plt
from statsmodels.tsa.seasonal import seasonal_decompose

# Aggregating data to daily total sales
total_sales_daily = train.groupby('date').agg({'sales': 'sum'}).reset_index()
```

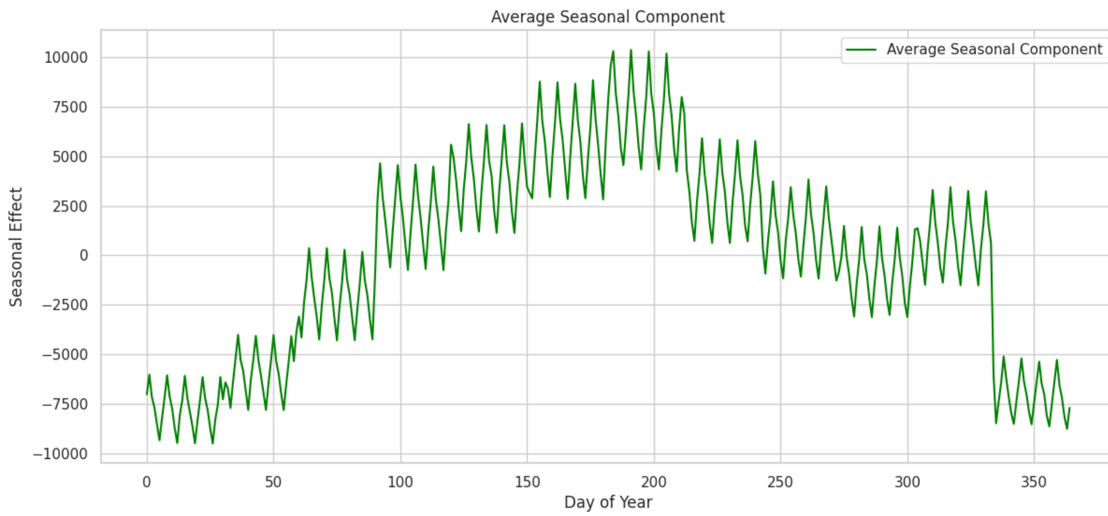
```
# Assuming daily data with yearly seasonality (period=365)
result = seasonal_decompose(total_sales_daily['sales'], model='additive',␣
 ↪period=365)
```

[ ]:

```
# Plot of original series
plt.figure(figsize=(14, 10))
plt.subplot(411)
plt.plot(total_sales_daily['date'], result.observed, label='Observed')
plt.legend(loc='upper left')
plt.title('Seasonal Decomposition')

# Plot of trend component
plt.subplot(412)
plt.plot(total_sales_daily['date'], result.trend, label='Trend', color='orange')
plt.legend(loc='upper left')

# Plot of seasonal component
plt.subplot(413)
plt.plot(total_sales_daily['date'], result.seasonal, label='Seasonal',␣
 ↪color='green')
plt.legend(loc='upper left')

# Plot of residual component
plt.subplot(414)
plt.plot(total_sales_daily['date'], result.resid, label='Residual', color='red')
plt.legend(loc='upper left')


plt.tight_layout()
plt.show()
```




```
[ ]: # Additional insights
     # Average seasonal component over the years, doing this as there is clearly a␣
      ↪pattern ever year
     seasonal_mean = result.seasonal.groupby(result.seasonal.index % 365).mean()
     plt.figure(figsize=(14, 6))
     plt.plot(seasonal_mean, label='Average Seasonal Component', color='green')
     plt.title('Average Seasonal Component')
     plt.xlabel('Day of Year')
     plt.ylabel('Seasonal Effect')
     plt.legend()
     plt.show()
```



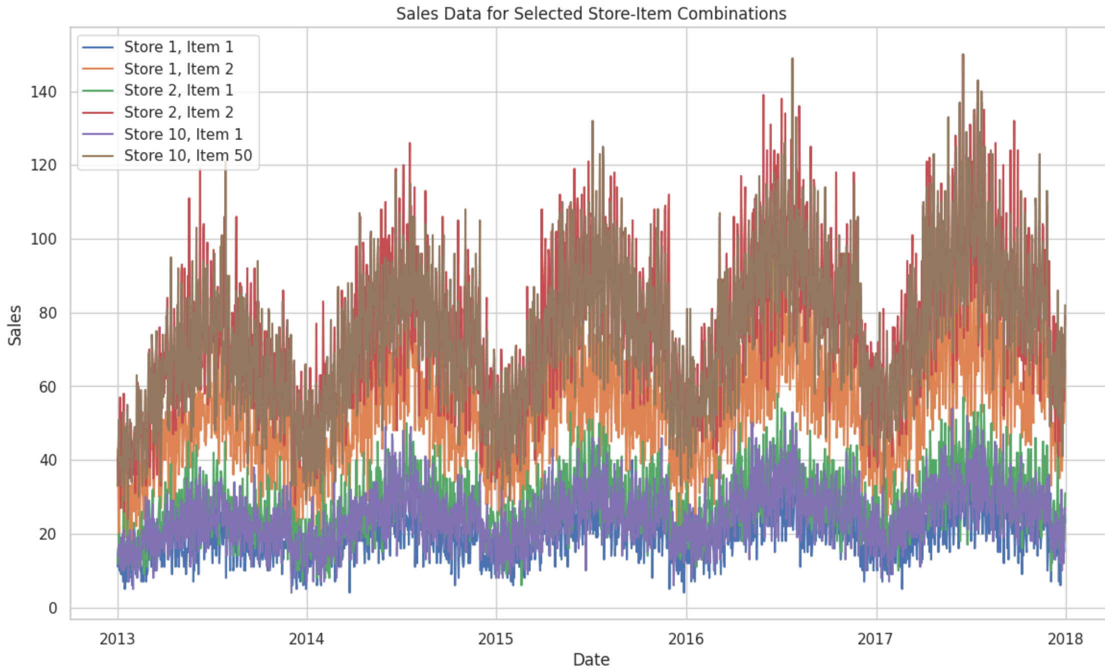
1.3 Let's start with (store, item) SAIRMA modeling

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

#lets see first:
print("Train Data:")
print(train.head())

# then we convert to datetime
train['date'] = pd.to_datetime(train['date'])

# just checking once again
print("\nData Types After Date Conversion:")
print(train.dtypes)

# Pivot the data
train_pivot = train.pivot_table(index='date', columns=['store', 'item'],␣
↪values='sales')

# Print the first few rows of the pivoted data
print("\nPivoted Train Data:")
print(train_pivot.head())

# Visualize the data for a few store-item combinations
store_item_combinations = [(1, 1), (1, 2), (2, 1), (2, 2), (10, 1), (10, 50)]

plt.figure(figsize=(14, 8))
for store, item in store_item_combinations:
```

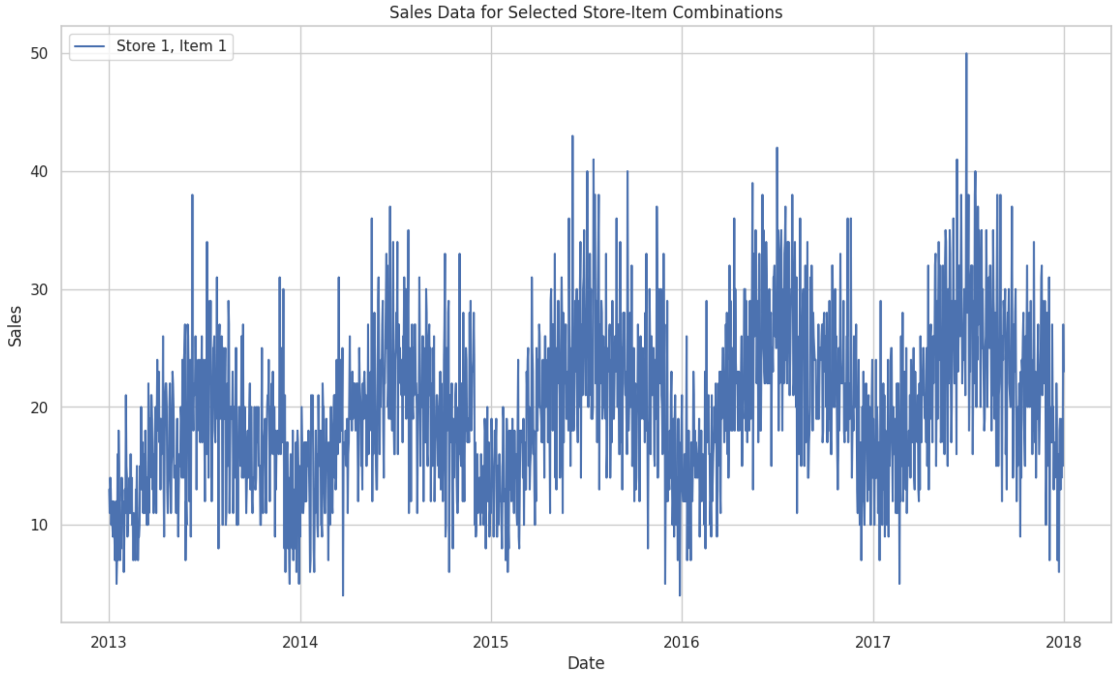
```
    plt.plot(train_pivot.index, train_pivot[(store, item)], label=f'Store␣
  ↪{store}, Item {item}')

plt.xlabel('Date')
plt.ylabel('Sales')
plt.title('Sales Data for Selected Store-Item Combinations')
plt.legend()
plt.show()


# okay so much better visulisation, and we can see that the seasonality is␣
  ↪continued, so far so good.
```

```
Train Data:
        date  store  item  sales  day_of_week  month
0 2013-01-01      1     1     13            1      1
1 2013-01-02      1     1     11            2      1
2 2013-01-03      1     1     14            3      1
3 2013-01-04      1     1     13            4      1
4 2013-01-05      1     1     10            5      1

Data Types After Date Conversion:
date           datetime64[ns]
store                   int64
item                    int64
sales                   int64
day_of_week             int32
month                   int32
dtype: object

Pivoted Train Data:
store        1                                      …  10                  \
item         1   2   3   4   5   6   7   8   9   10 …  41  42  43  44  45
date                                                …
2013-01-01  13  33  15  10  11  31  25  33  18  37  …  12  20  24  17  45
2013-01-02  11  43  30  11   6  36  23  37  23  34  …  10  22  29  10  45
2013-01-03  14  23  14   8   8  18  34  38  25  32  …  17  27  43  20  56
2013-01-04  13  18  10  19   9  19  36  54  22  45  …  13  24  27  12  50
2013-01-05  10  34  23  12   8  31  38  51  29  35  …  14  25  31  25  62

store
item        46  47  48  49  50
date
2013-01-01  37  11  25  17  33
2013-01-02  33  13  24  13  37
2013-01-03  28  16  29  19  46
2013-01-04  44  11  39  23  51
2013-01-05  45  16  34  22  41
```

```
[5 rows x 500 columns]
```



[ ]:
```
# Visualize the data for a store-item combinations
store_item_combinations = [(1, 1)]

plt.figure(figsize=(14, 8))
for store, item in store_item_combinations:
    plt.plot(train_pivot.index, train_pivot[(store, item)], label=f'Store␣
↪{store}, Item {item}')

plt.xlabel('Date')
plt.ylabel('Sales')
plt.title('Sales Data for Selected Store-Item Combinations')
plt.legend()
plt.show()


dataset_1_1 = pd.DataFrame({
    'sales': train_pivot[(1, 1)]
})

print("\nDataset for Store 1, Item 1:")
print(dataset_1_1.head())
```



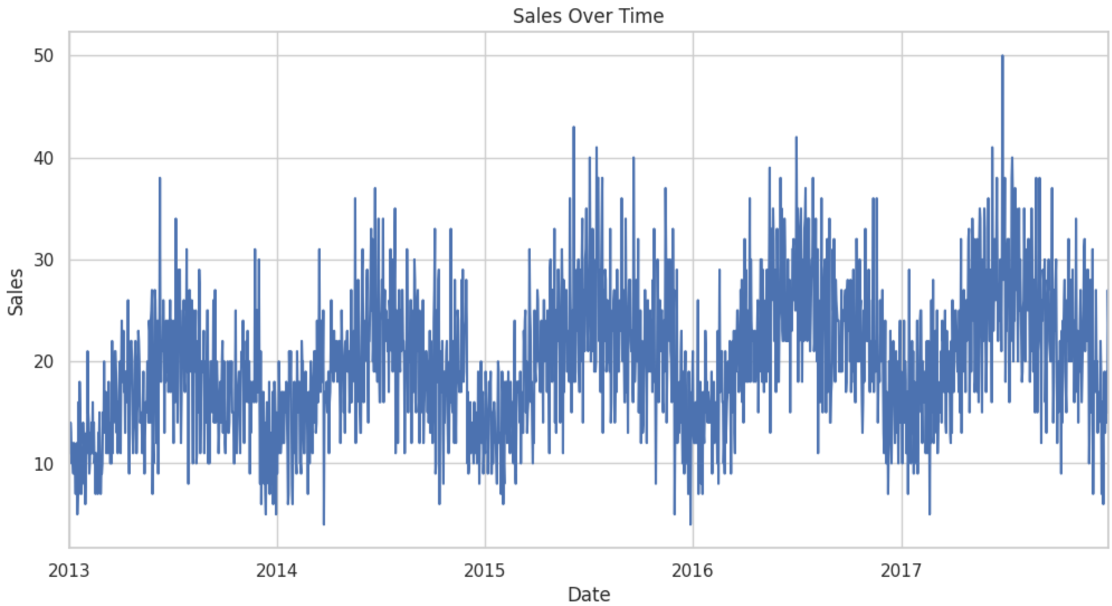

```
Dataset for Store 1, Item 1:
            sales
date
2013-01-01     13
2013-01-02     11
2013-01-03     14
2013-01-04     13
2013-01-05     10
```

[ ]:
```
df = dataset_1_1
#here I am trying to do SARMA on only one then will do for every.
```

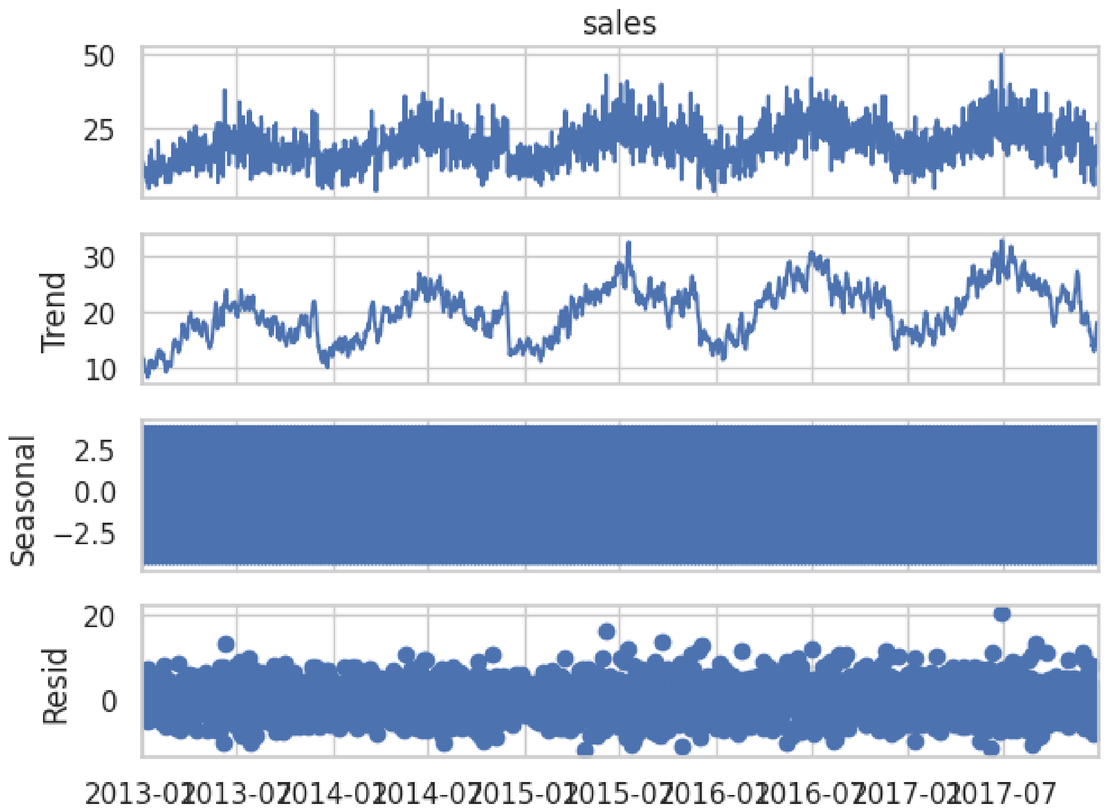
[ ]:
```
import pandas as pd

# Assuming your data is in a DataFrame called `df`
df['date'] = pd.to_datetime(df.index)
df.set_index('date', inplace=True)
```

[ ]:
```
import matplotlib.pyplot as plt

df['sales'].plot(figsize=(12, 6))
plt.title('Sales Over Time')
plt.xlabel('Date')
plt.ylabel('Sales')
```

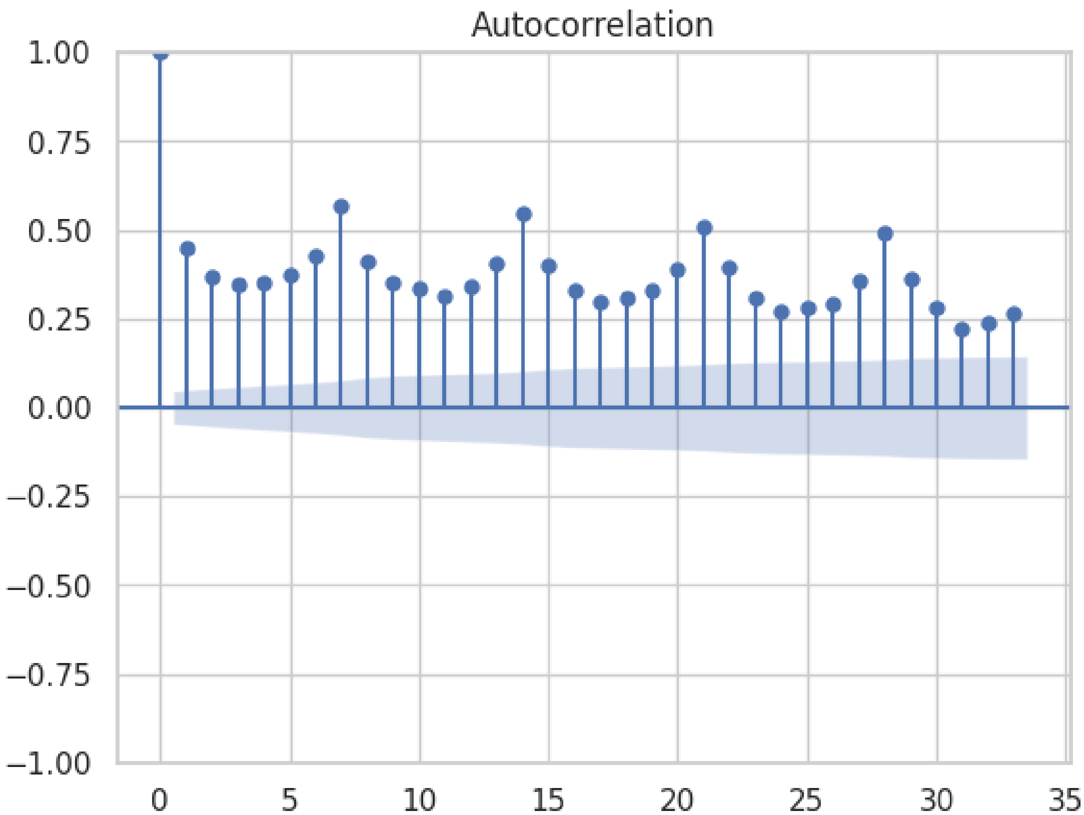
```
plt.show()
```

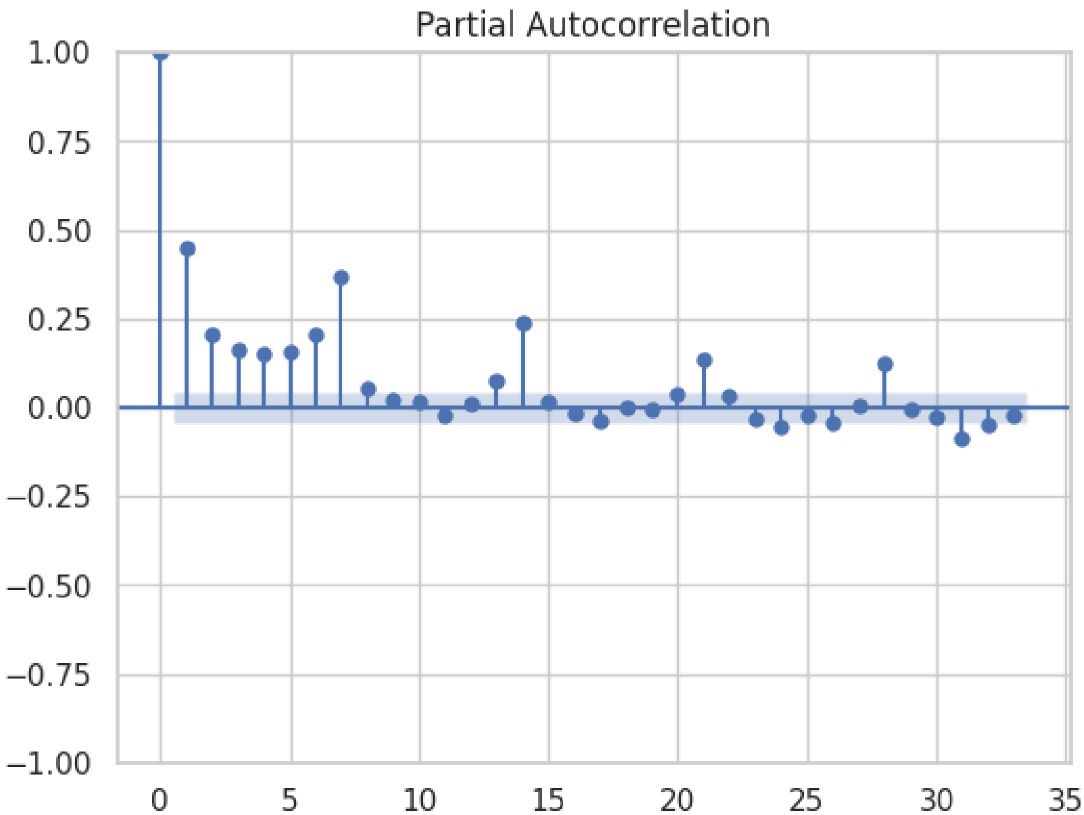


[ ]:
```
from statsmodels.tsa.seasonal import seasonal_decompose

result = seasonal_decompose(df['sales'], model='additive')
result.plot()
plt.show()
```



[ ]:
```
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf

# ACF and PACF plots
plot_acf(df['sales'])
plot_pacf(df['sales'])
plt.show()

from statsmodels.tsa.stattools import adfuller

result = adfuller(df['sales'])
print('ADF Statistic:', result[0])
print('p-value:', result[1])
```


Autocorrelation
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
5
10
15
20
25
30
35




```
ADF Statistic: -3.1576705563328042
p-value: 0.02256938062657153
```

[ ]:
```
#okay so if we want like accurate model with SAIRMA we have to have a lot of␣
↪paitence, sadly I don't have it
```

1.4 Let's get (1,1) using xgboost

[ ]:
```
df['date'] = pd.to_datetime(df.index)
df
```

[ ]:
```
            sales        date
date
2013-01-01     13  2013-01-01
2013-01-02     11  2013-01-02
2013-01-03     14  2013-01-03
2013-01-04     13  2013-01-04
2013-01-05     10  2013-01-05
…             …          …
2017-12-27     14  2017-12-27
2017-12-28     19  2017-12-28
```

```
2017-12-29     15 2017-12-29
2017-12-30     27 2017-12-30
2017-12-31     23 2017-12-31

[1826 rows x 2 columns]
```

[ ]:
```
import pandas as pd
from sklearn.model_selection import train_test_split
```

[ ]:
```
train_size = int(len(df) * 0.8)
train_df = df[:train_size]
test_df = df[train_size:]

train_df.head()
```

[ ]:
```
            sales       date
date
2013-01-01     13 2013-01-01
2013-01-02     11 2013-01-02
2013-01-03     14 2013-01-03
2013-01-04     13 2013-01-04
2013-01-05     10 2013-01-05
```

[ ]:
```
import pandas as pd
from sklearn.model_selection import train_test_split
import xgboost as xgb
from sklearn.metrics import mean_squared_error
import matplotlib.pyplot as plt



# Feature engineering
def create_features(df):
    df.loc[:, 'year'] = df['date'].dt.year
    df.loc[:, 'month'] = df['date'].dt.month
    df.loc[:, 'day'] = df['date'].dt.day
    df.loc[:, 'day_of_week'] = df['date'].dt.dayofweek
    df.loc[:, 'day_of_year'] = df['date'].dt.dayofyear
    df.loc[:, 'week_of_year'] = df['date'].dt.isocalendar().week.astype(int)
    return df

train_df = create_features(train_df)
test_df = create_features(test_df)

# Separate features and target
X_train = train_df.drop(['date', 'sales'], axis=1)
y_train = train_df['sales']
```

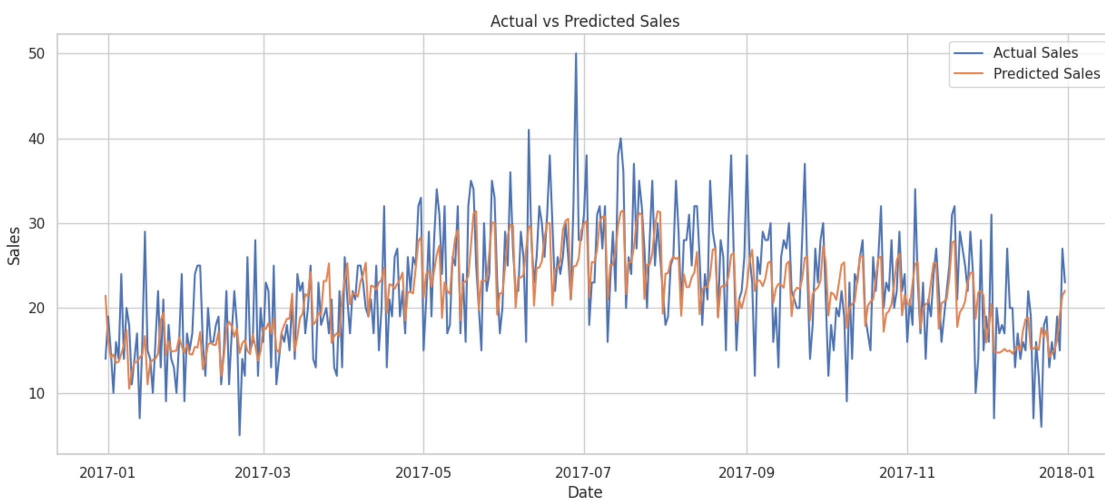
```python
X_test = test_df.drop(['date', 'sales'], axis=1)
y_test = test_df['sales']

model = xgb.XGBRegressor(objective='reg:squarederror', n_estimators=10000,␣
 ↪learning_rate=0.01)
model.fit(X_train, y_train, eval_set=[(X_test, y_test)],␣
 ↪early_stopping_rounds=50, verbose=False)

y_pred = model.predict(X_test)

rmse = mean_squared_error(y_test, y_pred, squared=False)
print(f'RMSE: {rmse:.2f}')

plt.figure(figsize=(15, 6))
plt.plot(test_df['date'], y_test, label='Actual Sales')
plt.plot(test_df['date'], y_pred, label='Predicted Sales')
plt.xlabel('Date')
plt.ylabel('Sales')
plt.title('Actual vs Predicted Sales')
plt.legend()
plt.show()
```

```
<ipython-input-77-3d691a977a27>:11: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df.loc[:, 'year'] = df['date'].dt.year
<ipython-input-77-3d691a977a27>:12: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df.loc[:, 'month'] = df['date'].dt.month
<ipython-input-77-3d691a977a27>:13: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df.loc[:, 'day'] = df['date'].dt.day
<ipython-input-77-3d691a977a27>:14: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
```

```
See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df.loc[:, 'day_of_week'] = df['date'].dt.dayofweek
<ipython-input-77-3d691a977a27>:15: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df.loc[:, 'day_of_year'] = df['date'].dt.dayofyear
<ipython-input-77-3d691a977a27>:16: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df.loc[:, 'week_of_year'] = df['date'].dt.isocalendar().week.astype(int)
<ipython-input-77-3d691a977a27>:11: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df.loc[:, 'year'] = df['date'].dt.year
<ipython-input-77-3d691a977a27>:12: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df.loc[:, 'month'] = df['date'].dt.month
<ipython-input-77-3d691a977a27>:13: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df.loc[:, 'day'] = df['date'].dt.day
<ipython-input-77-3d691a977a27>:14: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df.loc[:, 'day_of_week'] = df['date'].dt.dayofweek
<ipython-input-77-3d691a977a27>:15: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
```

```
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df.loc[:, 'day_of_year'] = df['date'].dt.dayofyear
<ipython-input-77-3d691a977a27>:16: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df.loc[:, 'week_of_year'] = df['date'].dt.isocalendar().week.astype(int)
/usr/local/lib/python3.10/dist-packages/xgboost/sklearn.py:889: UserWarning:
`early_stopping_rounds` in `fit` method is deprecated for better compatibility
with scikit-learn, use `early_stopping_rounds` in constructor or`set_params`
instead.
  warnings.warn(
```

```
RMSE: 4.99
```



[ ]:
```
import numpy as np

def calculate_smape(y_true, y_pred):
    epsilon = 1e-10
    return np.mean(np.abs(y_true - y_pred) / (np.abs(y_true) + np.abs(y_pred) +
 ↪epsilon)) * 100

smape = calculate_smape(y_test, y_pred)
print(f'SMAPE: {smape:.2f}%')
```

```
SMAPE: 9.47%
```

1.5 Let's get (1,1) using LightGBM

[ ]:
```
df = df.drop(columns='date')
```

[ ]:
```
df
```

[ ]:
```
            sales
date
2013-01-01     13
2013-01-02     11
2013-01-03     14
2013-01-04     13
2013-01-05     10
…             …
2017-12-27     14
2017-12-28     19
2017-12-29     15
2017-12-30     27
2017-12-31     23

[1826 rows x 1 columns]
```

[ ]:
```
import pandas as pd
from sklearn.model_selection import train_test_split


df['day'] = df.index.day
df['month'] = df.index.month
df['year'] = df.index.year
```

[ ]:
```
df
```

[ ]:
```
            sales  day  month  year
date
2013-01-01     13    1      1  2013
2013-01-02     11    2      1  2013
2013-01-03     14    3      1  2013
2013-01-04     13    4      1  2013
2013-01-05     10    5      1  2013
…             …  …    …    …
2017-12-27     14   27     12  2017
2017-12-28     19   28     12  2017
2017-12-29     15   29     12  2017
2017-12-30     27   30     12  2017
2017-12-31     23   31     12  2017

[1826 rows x 4 columns]
```

[ ]:
```
X = df[['day', 'month', 'year']]
y = df['sales']
```

[ ]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪shuffle=False)
```

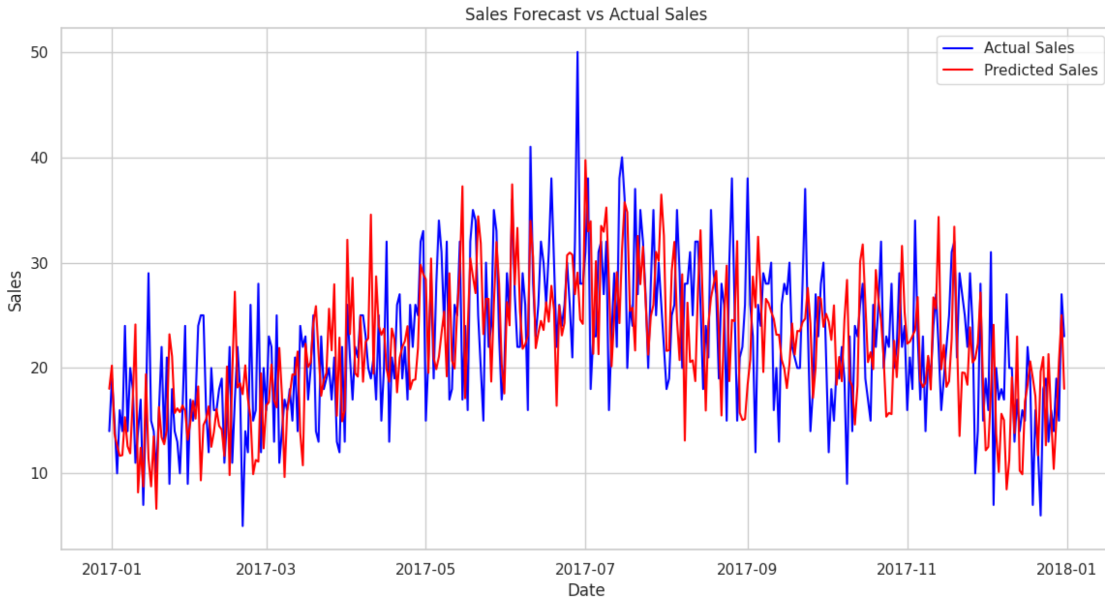
[ ]:
```
import lightgbm as lgb

train_data = lgb.Dataset(X_train, label=y_train)
test_data = lgb.Dataset(X_test, label=y_test, reference=train_data)

params = {
    'objective': 'regression',
    'metric': 'rmse',
    'boosting_type': 'gbdt'
}

model = lgb.train(
    params,
    train_data, num_boost_round=10000,
    valid_sets=[test_data]
)
```

```
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of
testing was 0.000032 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 50
[LightGBM] [Info] Number of data points in the train set: 1460, number of used
features: 3
[LightGBM] [Info] Start training from score 19.422603
```

[ ]:
```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.metrics import mean_squared_error

y_pred = model.predict(X_test, num_iteration=model.best_iteration)

rmse = np.sqrt(mean_squared_error(y_test, y_pred))
print(f'Root Mean Squared Error: {rmse}')

plt.figure(figsize=(14, 7))
plt.plot(y_test.index, y_test, label='Actual Sales', color='blue')
plt.plot(y_test.index, y_pred, label='Predicted Sales', color='red')
plt.xlabel('Date')
plt.ylabel('Sales')
plt.title('Sales Forecast vs Actual Sales')
plt.legend()
```

```
plt.show()
```

```
Root Mean Squared Error: 7.159668530790061
```



[ ]:
```
import numpy as np

def calculate_smape(y_true, y_pred):
    epsilon = 1e-10
    return np.mean(np.abs(y_true - y_pred) / (np.abs(y_true) + np.abs(y_pred) +
 ↪epsilon)) * 100

smape = calculate_smape(y_test, y_pred)
print(f'SMAPE: {smape:.2f}%')
```

```
SMAPE: 13.61%
```

1.6 Let's get (1,1) using prophet

[ ]:
```
df = df.drop(columns='day')
```

[ ]:
```
df = df.drop(columns='month')
```

[ ]:
```
df = df.drop(columns='year')
```

[ ]:
```
df['date'] = pd.to_datetime(df.index)
df
```

[ ]:
```
            sales       date
date
2013-01-01     13 2013-01-01
2013-01-02     11 2013-01-02
2013-01-03     14 2013-01-03
2013-01-04     13 2013-01-04
2013-01-05     10 2013-01-05
…             …          …
2017-12-27     14 2017-12-27
2017-12-28     19 2017-12-28
2017-12-29     15 2017-12-29
2017-12-30     27 2017-12-30
2017-12-31     23 2017-12-31

[1826 rows x 2 columns]
```

[ ]:
```
import pandas as pd
from prophet import Prophet

df.columns = ['y', 'ds']
df['ds'] = pd.to_datetime(df['ds'])
```

[ ]:
```
split_date = '2017-01-01'
train = df[df['ds'] < split_date]
test = df[df['ds'] >= split_date]
```

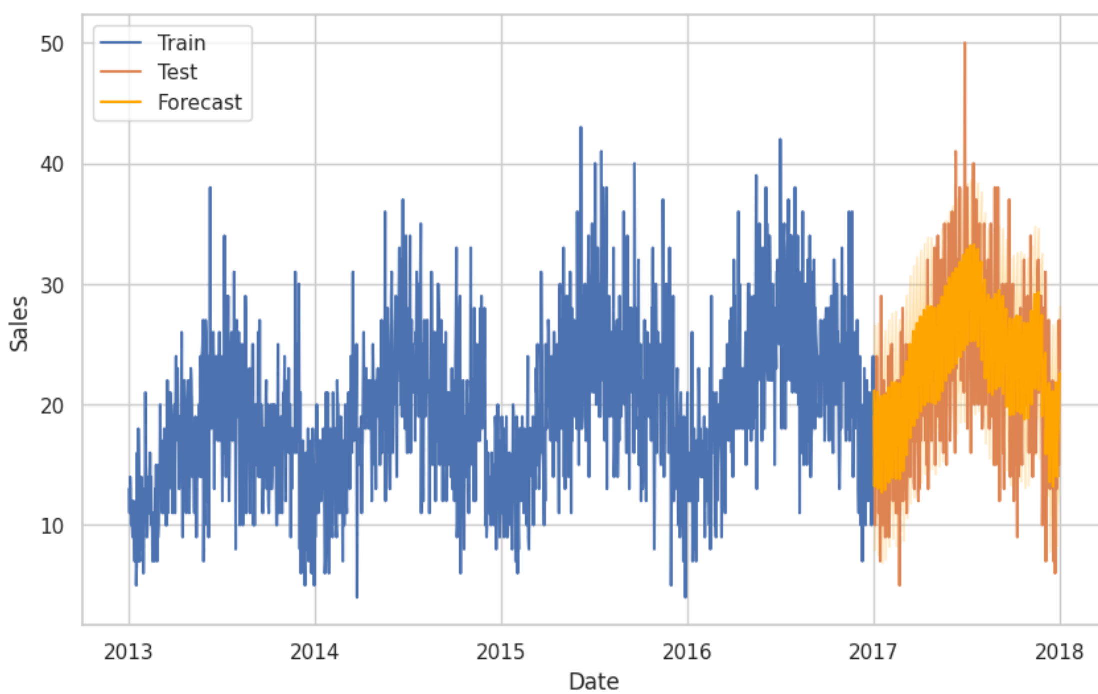
[ ]:
```
model = Prophet()
model.fit(train)
```

```
INFO:prophet:Disabling daily seasonality. Run prophet with
daily_seasonality=True to override this.
DEBUG:cmdstanpy:input tempfile: /tmp/tmppu_qmmjm/tu7yn6mp.json
DEBUG:cmdstanpy:input tempfile: /tmp/tmppu_qmmjm/x3bq_ld3.json
DEBUG:cmdstanpy:idx 0
DEBUG:cmdstanpy:running CmdStan, num_threads: None
DEBUG:cmdstanpy:CmdStan args: ['/usr/local/lib/python3.10/dist-
packages/prophet/stan_model/prophet_model.bin', 'random', 'seed=21383', 'data',
'file=/tmp/tmppu_qmmjm/tu7yn6mp.json', 'init=/tmp/tmppu_qmmjm/x3bq_ld3.json',
'output',
'file=/tmp/tmppu_qmmjm/prophet_modelelgt6dde/prophet_model-20240722082532.csv',
'method=optimize', 'algorithm=lbfgs', 'iter=10000']
08:25:32 - cmdstanpy - INFO - Chain [1] start processing
INFO:cmdstanpy:Chain [1] start processing
08:25:32 - cmdstanpy - INFO - Chain [1] done processing
INFO:cmdstanpy:Chain [1] done processing
```

[ ]:
```
<prophet.forecaster.Prophet at 0x7bc3c07d99c0>
```

[ ]:
```python
future = model.make_future_dataframe(periods=len(test))
forecast = model.predict(future)

forecast = forecast[['ds', 'yhat', 'yhat_lower', 'yhat_upper']]
result = pd.merge(test, forecast, on='ds')
```

[ ]:
```python
import matplotlib.pyplot as plt

plt.figure(figsize=(10, 6))
plt.plot(train['ds'], train['y'], label='Train')
plt.plot(test['ds'], test['y'], label='Test')
plt.plot(result['ds'], result['yhat'], label='Forecast', color='orange')
plt.fill_between(result['ds'], result['yhat_lower'], result['yhat_upper'],␣
 ↪color='orange', alpha=0.2)
plt.xlabel('Date')
plt.ylabel('Sales')
plt.legend()
plt.show()
```



[ ]:
```python
import numpy as np

rmse = np.sqrt(np.mean((result['y'] - result['yhat'])**2))
```

```
smape = 100 * np.mean(np.abs(result['y'] - result['yhat']) / ((np.
↪abs(result['y']) + np.abs(result['yhat'])) / 2))

print(f'RMSE: {rmse}')
print(f'sMAPE: {smape}')
```

```
RMSE: 4.967927662978357
sMAPE: 19.175684276137304
```

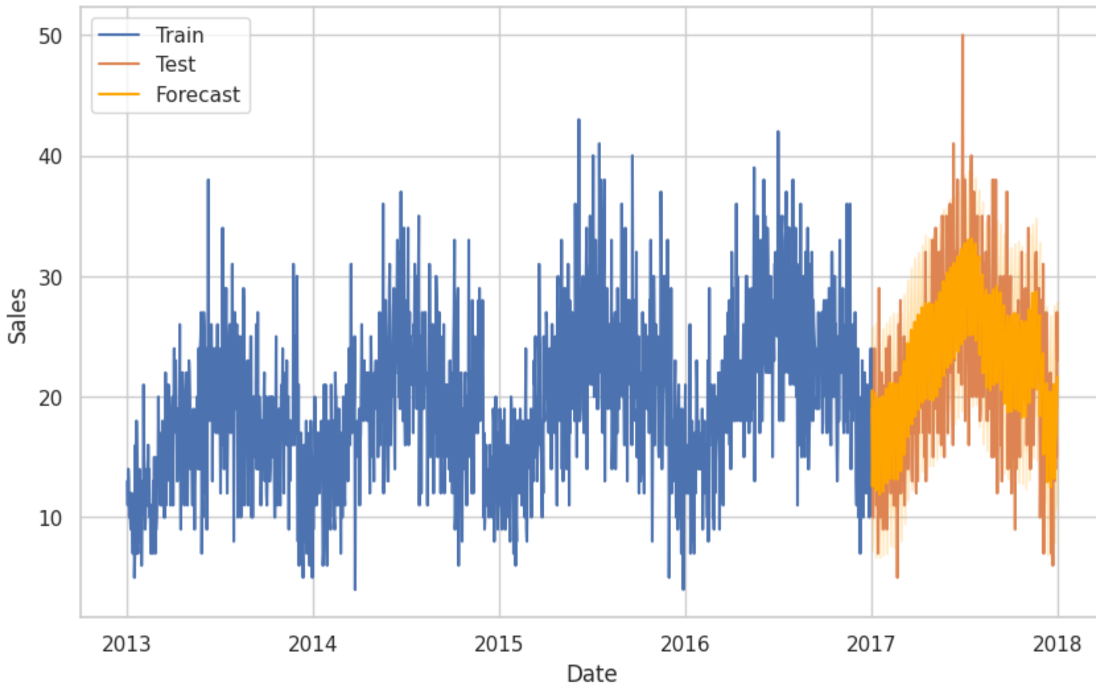
[ ]:
```
df
```

[ ]:
```
             y          ds
date
2013-01-01  13  2013-01-01
2013-01-02  11  2013-01-02
2013-01-03  14  2013-01-03
2013-01-04  13  2013-01-04
2013-01-05  10  2013-01-05
…           ..         …
2017-12-27  14  2017-12-27
2017-12-28  19  2017-12-28
2017-12-29  15  2017-12-29
2017-12-30  27  2017-12-30
2017-12-31  23  2017-12-31

[1826 rows x 2 columns]
```

[ ]:
```
import pandas as pd
from prophet import Prophet
import matplotlib.pyplot as plt
import numpy as np

split_date = '2017-01-01'
train = df[df['ds'] < split_date]
test = df[df['ds'] >= split_date]

model = Prophet(
    yearly_seasonality=True,
    weekly_seasonality=True,
    changepoint_prior_scale=0.5,
    seasonality_prior_scale=10.0
)
model.fit(train)

future = model.make_future_dataframe(periods=len(test))
forecast = model.predict(future)
```

```python
result = pd.merge(test, forecast[['ds', 'yhat', 'yhat_lower', 'yhat_upper']],␣
    ↪on='ds')

plt.figure(figsize=(10, 6))
plt.plot(train['ds'], train['y'], label='Train')
plt.plot(test['ds'], test['y'], label='Test')
plt.plot(result['ds'], result['yhat'], label='Forecast', color='orange')
plt.fill_between(result['ds'], result['yhat_lower'], result['yhat_upper'],␣
    ↪color='orange', alpha=0.2)
plt.xlabel('Date')
plt.ylabel('Sales')
plt.legend()
plt.show()

rmse = np.sqrt(np.mean((result['y'] - result['yhat'])**2))
smape = 100 * np.mean(np.abs(result['y'] - result['yhat']) / ((np.
    ↪abs(result['y']) + np.abs(result['yhat'])) / 2))

print(f'RMSE: {rmse}')
print(f'sMAPE: {smape}')
```

```
INFO:prophet:Disabling daily seasonality. Run prophet with
daily_seasonality=True to override this.
DEBUG:cmdstanpy:input tempfile: /tmp/tmppu_qmmjm/mnseqv4x.json
DEBUG:cmdstanpy:input tempfile: /tmp/tmppu_qmmjm/m9ah3xwo.json
DEBUG:cmdstanpy:idx 0
DEBUG:cmdstanpy:running CmdStan, num_threads: None
DEBUG:cmdstanpy:CmdStan args: ['/usr/local/lib/python3.10/dist-
packages/prophet/stan_model/prophet_model.bin', 'random', 'seed=21798', 'data',
'file=/tmp/tmppu_qmmjm/mnseqv4x.json', 'init=/tmp/tmppu_qmmjm/m9ah3xwo.json',
'output',
'file=/tmp/tmppu_qmmjm/prophet_modeliw__pdxp/prophet_model-20240722082731.csv',
'method=optimize', 'algorithm=lbfgs', 'iter=10000']
08:27:31 - cmdstanpy - INFO - Chain [1] start processing
INFO:cmdstanpy:Chain [1] start processing
08:27:31 - cmdstanpy - INFO - Chain [1] done processing
INFO:cmdstanpy:Chain [1] done processing
```




```
RMSE: 4.860181490857254
sMAPE: 18.71643431424785
```

1.7 Let's get (1,1) using LSTM

I mean I can use it but they have asked to predict next 3 months, this will be very inacurate

1.8 conclusion

So here after using a lot of models, it turns out that making (store, item) df and then using xgboost gives us the best result (here: 9.47%)

```
[ ]:
```