Sales Forecasting Models

June 14, 2024

0.0.1 1. Data Processing

[1]:
```
import pandas as pd
import numpy as np
```

[2]:
```
#Load Data
df=pd.read_excel(r"C:\Users\USER\Documents\Data Portfolio Projects\Retail\Sales␣
↪Forecasting\refined_sales_forecasting_dataset.xlsx")
df.head()
```

[2]:

	Date	Langa_Fresh Produce	Langa_Dairy	Langa_Canned Goods	\
0	2021-01-01	NaN	NaN	NaN	
1	2021-01-02	15.0	20.0	21.0	
2	2021-01-03	21.0	28.0	20.0	
3	2021-01-04	25.0	22.0	16.0	
4	2021-01-05	15.0	17.0	17.0	

	Langa_Bakery	Langa_Frozen Foods	Nyanga_Fresh Produce	Nyanga_Dairy	\
0	NaN	NaN	NaN	NaN	
1	9.0	29.0	16.0	18.0	
2	17.0	20.0	17.0	18.0	
3	20.0	22.0	29.0	21.0	
4	26.0	17.0	16.0	11.0	

	Nyanga_Canned Goods	Nyanga_Bakery	…	Pinelands_Bakery	\
0	NaN	NaN	…	NaN	
1	18.0	21.0	…	17.0	
2	17.0	20.0	…	17.0	
3	17.0	20.0	…	18.0	
4	27.0	22.0	…	22.0	

	Pinelands_Frozen Foods	Thornton_Fresh Produce	Thornton_Dairy	\
0	NaN	NaN	NaN	
1	26.0	18.0	11.0	
2	25.0	26.0	18.0	
3	33.0	18.0	20.0	
4	23.0	22.0	30.0	

```
   Thornton_Canned Goods  Thornton_Bakery  Thornton_Frozen Foods  \
0                    NaN              NaN                    NaN
1                   20.0             20.0                   16.0
2                   25.0             16.0                   23.0
3                   18.0             17.0                   14.0
4                   23.0             23.0                   26.0

   Economic_Indicator  Holiday_Indicator  Promotion_Indicator
0           88.728706                  0                    0
1          115.513937                  0                    0
2           87.385129                  0                    0
3          114.177901                  0                    0
4           96.823213                  0                    0

[5 rows x 29 columns]
```

[3]:
```
# Handle missing values by imputing with the median
df.fillna(df.median(), inplace=True)
```

```
C:\Users\USER\AppData\Local\Temp\ipykernel_13268\32931963.py:2: FutureWarning:
DataFrame.mean and DataFrame.median with numeric_only=None will include
datetime64 and datetime64tz columns in a future version.
  df.fillna(df.median(), inplace=True)
```

[4]:
```
#Create additional features that may help in forecasting, such as day of the week, month, and year

df['Day_of_Week'] = df['Date'].apply(lambda x: pd.Timestamp(x).dayofweek)
df['Month'] = df['Date'].apply(lambda x: pd.Timestamp(x).month)
df['Year'] = df['Date'].apply(lambda x: pd.Timestamp(x).year)
```

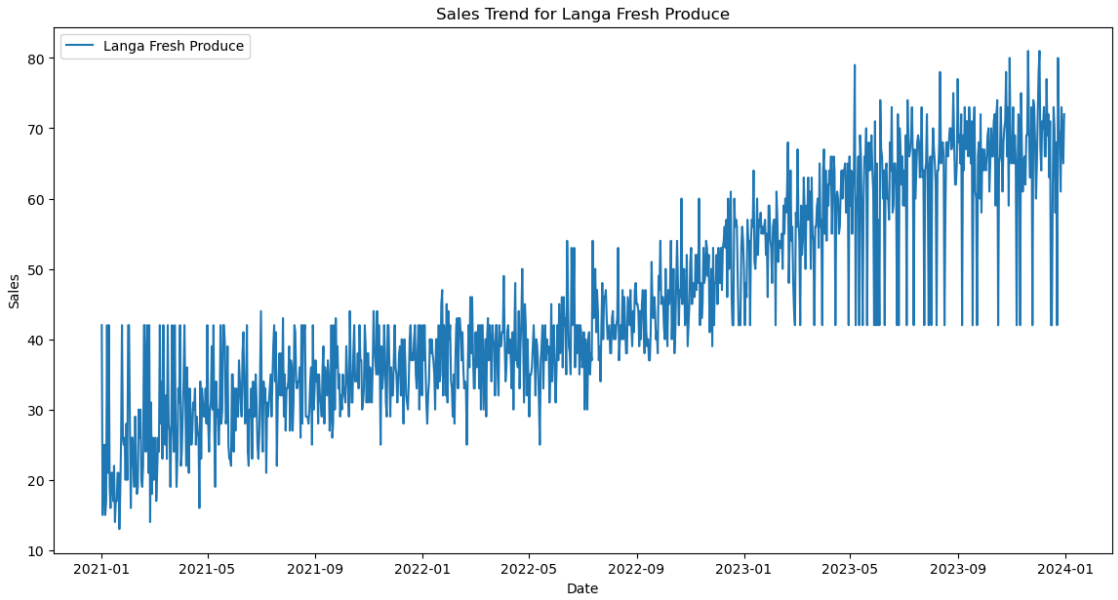
[ ]:
```

```

0.0.2 Exploratory Data Analysis

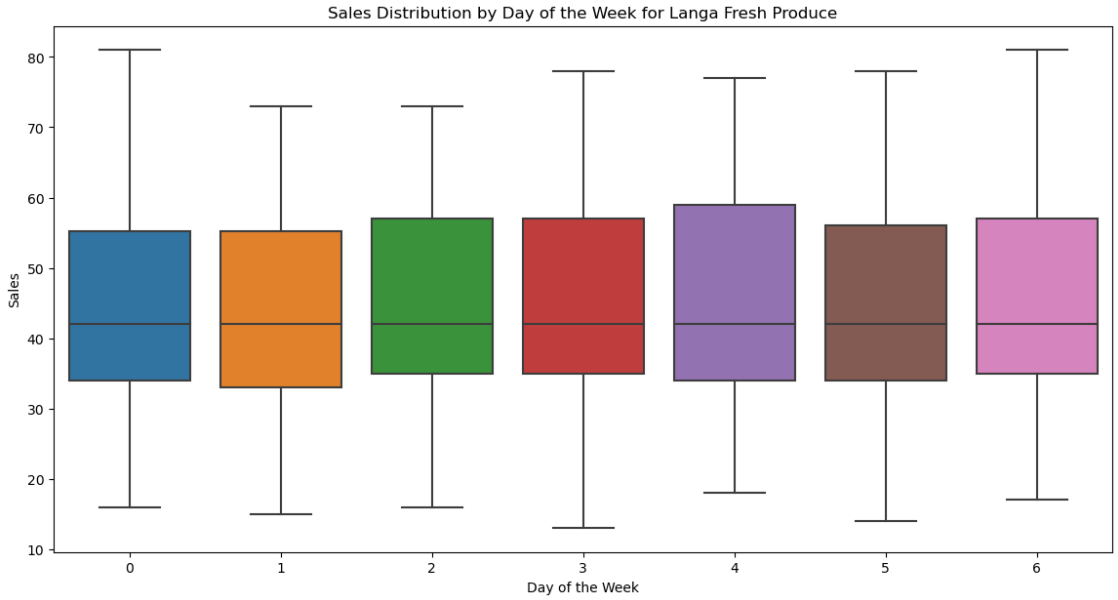
Data will be visualized to identify trends, seasonality, and relationships between variables.

[5]:
```
import matplotlib.pyplot as plt
import seaborn as sns
```

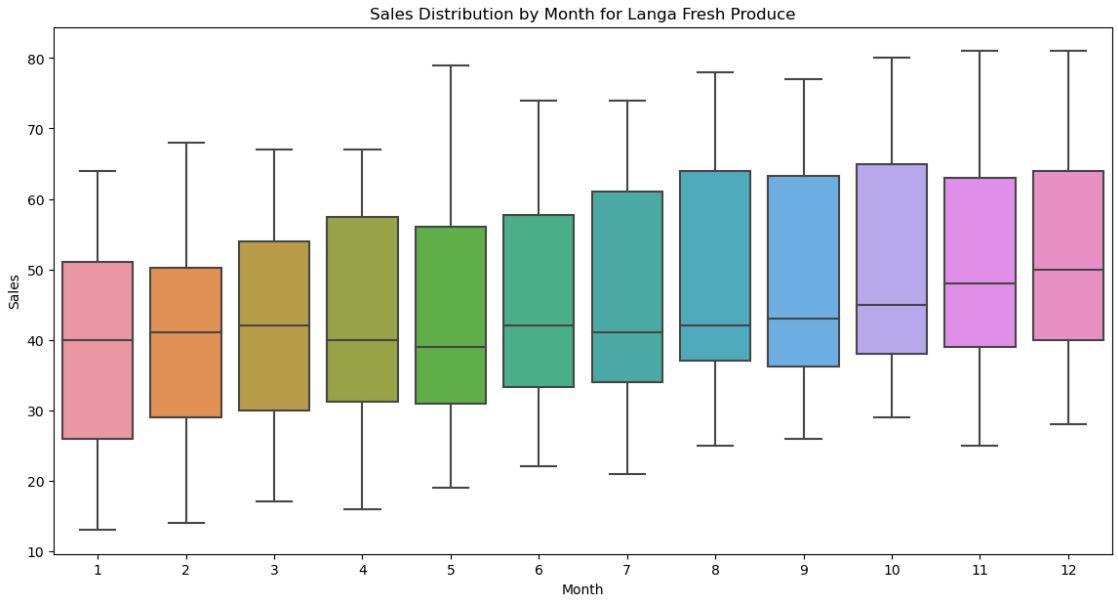
[6]:
```
# Plot of the sales trends for the Langa Store and the Fresh Produce category
plt.figure(figsize=(14, 7))
plt.plot(df['Date'], df['Langa_Fresh Produce'], label='Langa Fresh Produce')
plt.xlabel('Date')
plt.ylabel('Sales')
plt.title('Sales Trend for Langa Fresh Produce')
plt.legend()
plt.show()
```



[7]:
```
# Sales by day of the week
plt.figure(figsize=(14, 7))
sns.boxplot(x='Day_of_Week', y='Langa_Fresh Produce', data=df)
plt.xlabel('Day of the Week')
plt.ylabel('Sales')
plt.title('Sales Distribution by Day of the Week for Langa Fresh Produce')
plt.show()
```



[8]:
```
# Sales by month
plt.figure(figsize=(14, 7))
sns.boxplot(x='Month', y='Langa_Fresh Produce', data=df)
plt.xlabel('Month')
plt.ylabel('Sales')
plt.title('Sales Distribution by Month for Langa Fresh Produce')
plt.show()
```



[ ]:
```
```

0.0.3 Model Selection and Training

We'll use a simple ARIMA model for time series forecasting. We'll start by preparing the data for the ARIMA model and then train the model.

Preparing the Data

[9]:
```
from statsmodels.tsa.arima.model import ARIMA
```

[10]:
```
# Convert the date column to datetime
df['Date'] = pd.to_datetime(df['Date'])
```

[11]:
```
# Set the date column as the index
df.set_index('Date', inplace=True)
```

[12]:
```
# Select the time series for the Langa store and Fresh Produce category
series = df['Langa_Fresh Produce']
```

[13]:
```
# Split the data into training and testing sets
train_size = int(len(series) * 0.8)
train, test = series[:train_size], series[train_size:]
```

[ ]:

Train the ARIMA Model

[14]:
```
# Train the ARIMA model
model = ARIMA(train, order=(5, 1, 0))
model_fit = model.fit()

# Print the summary of the model
print(model_fit.summary())
```

```
C:\Users\USER\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473:
ValueWarning: No frequency information was provided, so inferred frequency D
will be used.
  self._init_dates(dates, freq)
C:\Users\USER\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473:
ValueWarning: No frequency information was provided, so inferred frequency D
will be used.
  self._init_dates(dates, freq)
C:\Users\USER\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473:
ValueWarning: No frequency information was provided, so inferred frequency D
will be used.
  self._init_dates(dates, freq)
```

SARIMAX Results

Dep. Variable:	Langa_Fresh Produce	No. Observations:	876
Model:	ARIMA(5, 1, 0)	Log Likelihood	-2836.816
Date:	Mon, 10 Jun 2024	AIC	5685.632
Time:	17:00:34	BIC	5714.278
Sample:	01-01-2021	HQIC	5696.590
	- 05-26-2023		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	-0.8381	0.031	-26.893	0.000	-0.899	-0.777
ar.L2	-0.6752	0.040	-16.746	0.000	-0.754	-0.596
ar.L3	-0.5233	0.042	-12.553	0.000	-0.605	-0.442
ar.L4	-0.3285	0.039	-8.496	0.000	-0.404	-0.253
ar.L5	-0.1719	0.030	-5.682	0.000	-0.231	-0.113
sigma2	38.2859	1.620	23.640	0.000	35.112	41.460

Ljung-Box (L1) (Q):	0.09	Jarque-Bera (JB):	

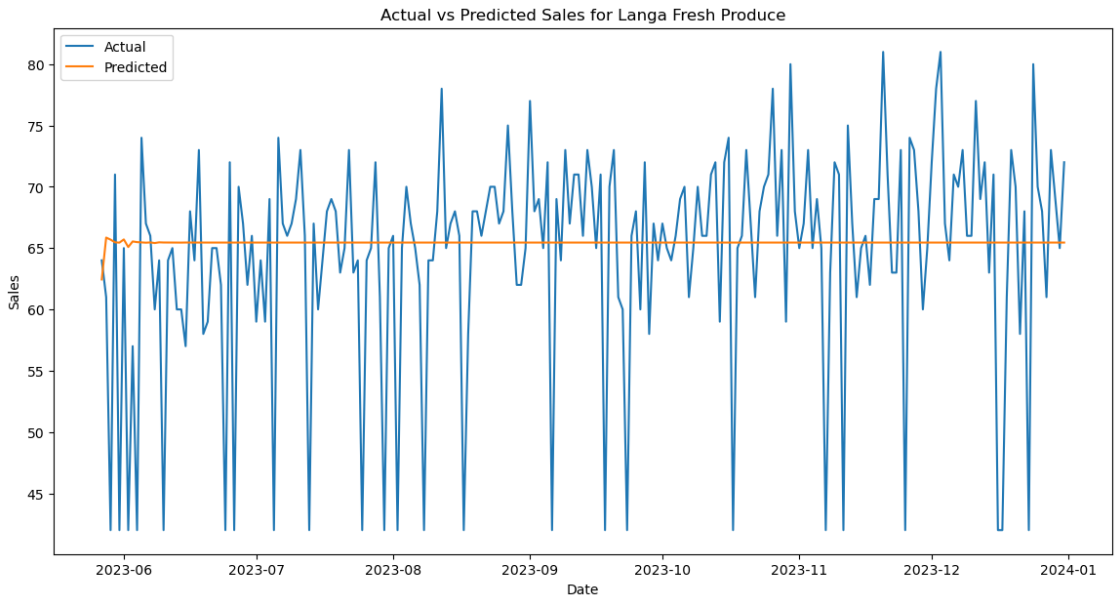
```
16.45
Prob(Q):                              0.76   Prob(JB):
0.00
Heteroskedasticity (H):               0.81   Skew:
-0.03
Prob(H) (two-sided):                  0.07   Kurtosis:
3.67
================================================================================
===

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-
step).
```

[ ]:

0.0.4 Model Evaluation

[15]:
```
# Make predictions
predictions = model_fit.forecast(steps=len(test))
```

[16]:
```
# Plot the actual vs predicted values
plt.figure(figsize=(14, 7))
plt.plot(test.index, test, label='Actual')
plt.plot(test.index, predictions, label='Predicted')
plt.xlabel('Date')
plt.ylabel('Sales')
plt.title('Actual vs Predicted Sales for Langa Fresh Produce')
plt.legend()
plt.show()
```



[17]:
```
# Calculate evaluation metrics
from sklearn.metrics import mean_squared_error

mse = mean_squared_error(test, predictions)
rmse = np.sqrt(mse)
print(f'RMSE: {rmse}')
```

```
RMSE: 9.184774172849416
```

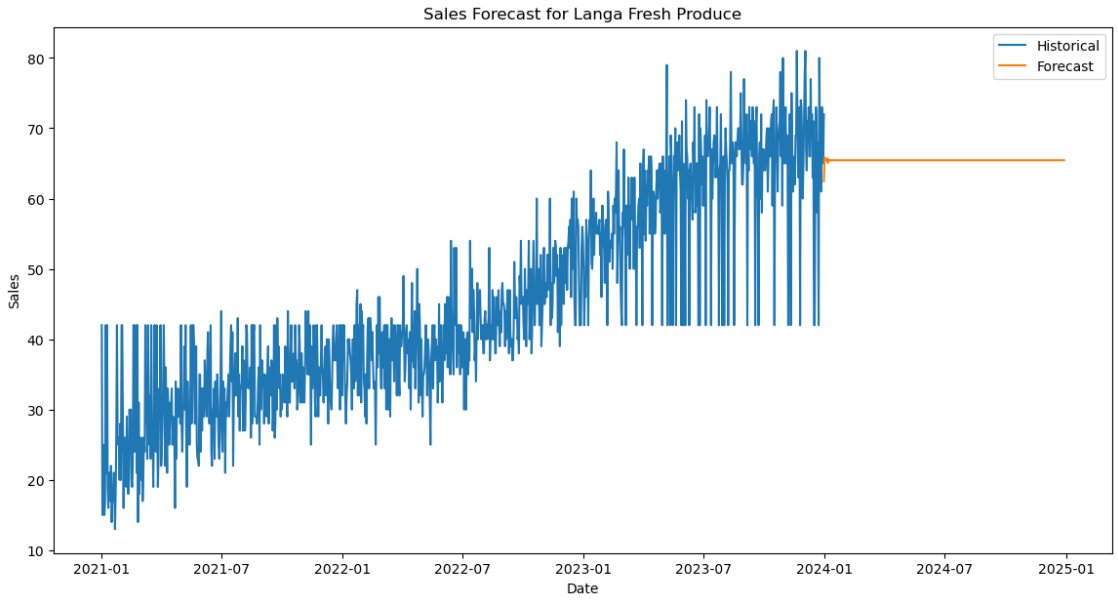
[ ]:
```

```

0.0.5 Forecasting

Finally, we'll generate forecasts for different time horizons (weekly, monthly, quarterly, annual) and visualize the results

[18]:
```
# Generate forecasts for the next year
future_steps = 365
forecast = model_fit.forecast(steps=future_steps)
```

[19]:
```
# Plot the forecast
plt.figure(figsize=(14, 7))
plt.plot(series.index, series, label='Historical')
plt.plot(pd.date_range(start=series.index[-1], periods=future_steps, freq='D'),␣
 ↪forecast, label='Forecast')
plt.xlabel('Date')
plt.ylabel('Sales')
plt.title('Sales Forecast for Langa Fresh Produce')
plt.legend()
plt.show()
```


Sales Forecast for Langa Fresh Produce
Historical
Forecast
Sales
Date
10
20
30
40
50
60
70
80
2021-01
2021-07
2022-01
2022-07
2023-01
2023-07
2024-01
2024-07
2025-01

[ ]: