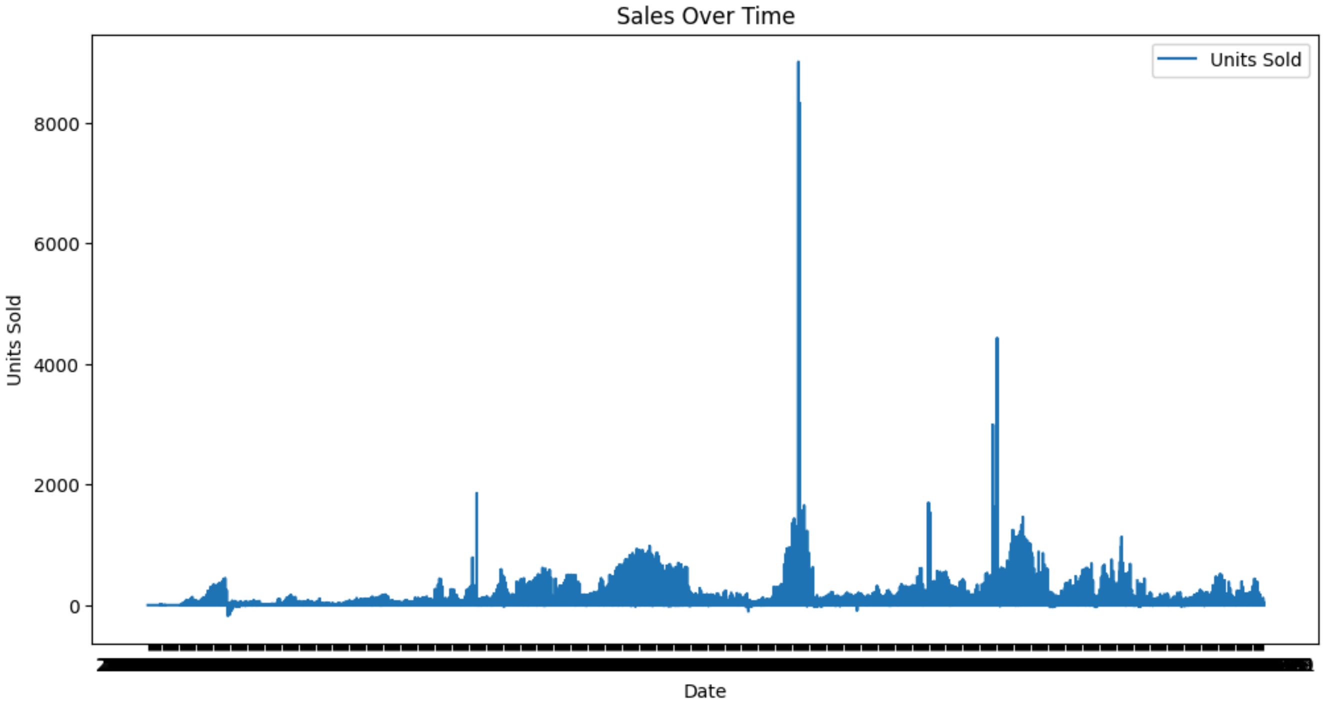
```
import pandas as pd
import matplotlib.pyplot as plt

# Load dataset
data = pd.read_csv('train.csv')

# Data overview
print(data.info())

# Plotting sales data
plt.figure(figsize=(12, 6))
plt.plot(data['date'], data['units'], label='Units Sold')
plt.xlabel('Date')
plt.ylabel('Units Sold')
plt.title('Sales Over Time')
plt.legend()
plt.show()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 101490 entries, 0 to 101489
Data columns (total 8 columns):
 #   Column      Non-Null Count   Dtype
---  ------      --------------   -----
 0   ID          101490 non-null  object
 1   date        101490 non-null  object
 2   Item Id     101488 non-null  object
 3   Item Name   99658 non-null   object
 4   ad_spend    77303 non-null   float64
 5   anarix_id   101490 non-null  object
 6   units       83592 non-null   float64
 7   unit_price  101490 non-null  float64
dtypes: float64(3), object(5)
memory usage: 6.2+ MB
None
```



```
data.shape
```

```
(101490, 8)
```

```
data.dtypes
```

```
                   0
ID            object
date          object
Item Id       object
Item Name     object
ad_spend     float64
anarix_id     object
units        float64
unit_price   float64

dtype: object
```

```
data.isnull().sum()
```

```
                 0
ID               0
date             0
Item Id          2
Item Name     1832
ad_spend     24187
anarix_id        0
units        17898
unit_price       0

dtype: int64
```

```
import pandas as pd
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.impute import SimpleImputer

# Load data
data = pd.read_csv('train.csv')

# Get the actual column names with missing values
columns_with_missing = data.columns[data.isnull().any()].tolist()

# Separate numerical and categorical columns with missing values
numerical_missing = [col for col in columns_with_missing if data[col].dtype != 'object']
categorical_missing = [col for col in columns_with_missing if data[col].dtype == 'object']

# Handle missing values for numerical columns
imputer_numerical = SimpleImputer(strategy='mean')
for column in numerical_missing:
    data[column] = imputer_numerical.fit_transform(data[[column]])

# Handle missing values for categorical columns
# (Replace 'most_frequent' with a suitable strategy if needed)
imputer_categorical = SimpleImputer(strategy='most_frequent')
for column in categorical_missing:
    # Reshape the imputed data to be 1D
    data[column] = imputer_categorical.fit_transform(data[[column]]).ravel()
```

```
!pip install category_encoders

import pandas as pd
import category_encoders as ce

# Sample data
# Pass column names as a list to the 'columns' argument
data = pd.read_csv('train.csv')

# Initialize BinaryEncoder
binary_encoder = ce.BinaryEncoder(cols=['ID', 'date', 'Item Id', 'Item Name', 'anarix_id'])

# Fit and transform the data
data_encoded = binary_encoder.fit_transform(data)

print(data_encoded)
```

```
Requirement already satisfied: category_encoders in /usr/local/lib/python3.10/dist-packages (2.6.3)
Requirement already satisfied: numpy>=1.14.0 in /usr/local/lib/python3.10/dist-packages (from category_encoders)
Requirement already satisfied: scikit-learn>=0.20.0 in /usr/local/lib/python3.10/dist-packages (from category_enc
Requirement already satisfied: scipy>=1.0.0 in /usr/local/lib/python3.10/dist-packages (from category_encoders) (
Requirement already satisfied: statsmodels>=0.9.0 in /usr/local/lib/python3.10/dist-packages (from category_encod
Requirement already satisfied: pandas>=1.0.5 in /usr/local/lib/python3.10/dist-packages (from category_encoders)
Requirement already satisfied: patsy>=0.5.1 in /usr/local/lib/python3.10/dist-packages (from category_encoders) (
Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/python3.10/dist-packages (from pandas>=1.
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (from pandas>=1.0.5->categ
Requirement already satisfied: tzdata>=2022.1 in /usr/local/lib/python3.10/dist-packages (from pandas>=1.0.5->cat
Requirement already satisfied: six in /usr/local/lib/python3.10/dist-packages (from patsy>=0.5.1->category_encode
Requirement already satisfied: joblib>=1.1.1 in /usr/local/lib/python3.10/dist-packages (from scikit-learn>=0.20.
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn
Requirement already satisfied: packaging>=21.3 in /usr/local/lib/python3.10/dist-packages (from statsmodels>=0.9.
        ID_0  ID_1  ID_2  ID_3  ID_4  ID_5  ID_6  ID_7  ID_8  ID_9  ...  \
0          0     0     0     0     0     0     0     0     0     0  ...
1          0     0     0     0     0     0     0     0     0     0  ...
2          0     0     0     0     0     0     0     0     0     0  ...
3          0     0     0     0     0     0     0     0     0     0  ...
4          0     0     0     0     0     0     0     0     0     0  ...
...      ...   ...   ...   ...   ...   ...   ...   ...   ...   ...  ...
101485     1     1     0     0     0     1     1     0     0     0  ...
101486     1     1     0     0     0     1     1     0     0     0  ...
101487     1     1     0     0     0     1     1     0     0     0  ...
101488     1     1     0     0     0     1     1     0     0     0  ...
101489     1     1     0     0     0     1     1     0     0     0  ...

        Item Name_2  Item Name_3  Item Name_4  Item Name_5  Item Name_6  \
0                 0            0            0            0            0
1                 0            0            0            0            1
2                 0            0            0            0            1
3                 0            0            0            1            0
4                 0            0            0            1            0
...             ...          ...          ...          ...          ...
101485            0            0            1            0            0
101486            0            0            1            0            0
101487            0            0            1            0            0
101488            0            0            1            0            0
101489            0            0            1            0            0

        Item Name_7  ad_spend  anarix_id_0  units  unit_price
0                 1       NaN            1    0.0        0.00
1                 0       NaN            1    0.0        0.00
2                 1       NaN            1    0.0        0.00
3                 0       NaN            1    0.0        0.00
4                 1       NaN            1    0.0        0.00
...             ...       ...          ...    ...         ...
101485            0    604.73            1    NaN        0.00
101486            0    261.21            1    2.0      225.32
101487            0      0.00            1    NaN        0.00
101488            0      0.00            1    NaN        0.00
101489            0      0.00            1    NaN        0.00

[101490 rows x 47 columns]
```

```
data = pd.concat([data, data_encoded], axis=1).drop(['ID', 'date', 'Item Id', 'Item Name', 'anarix_id'], axis=1)
```

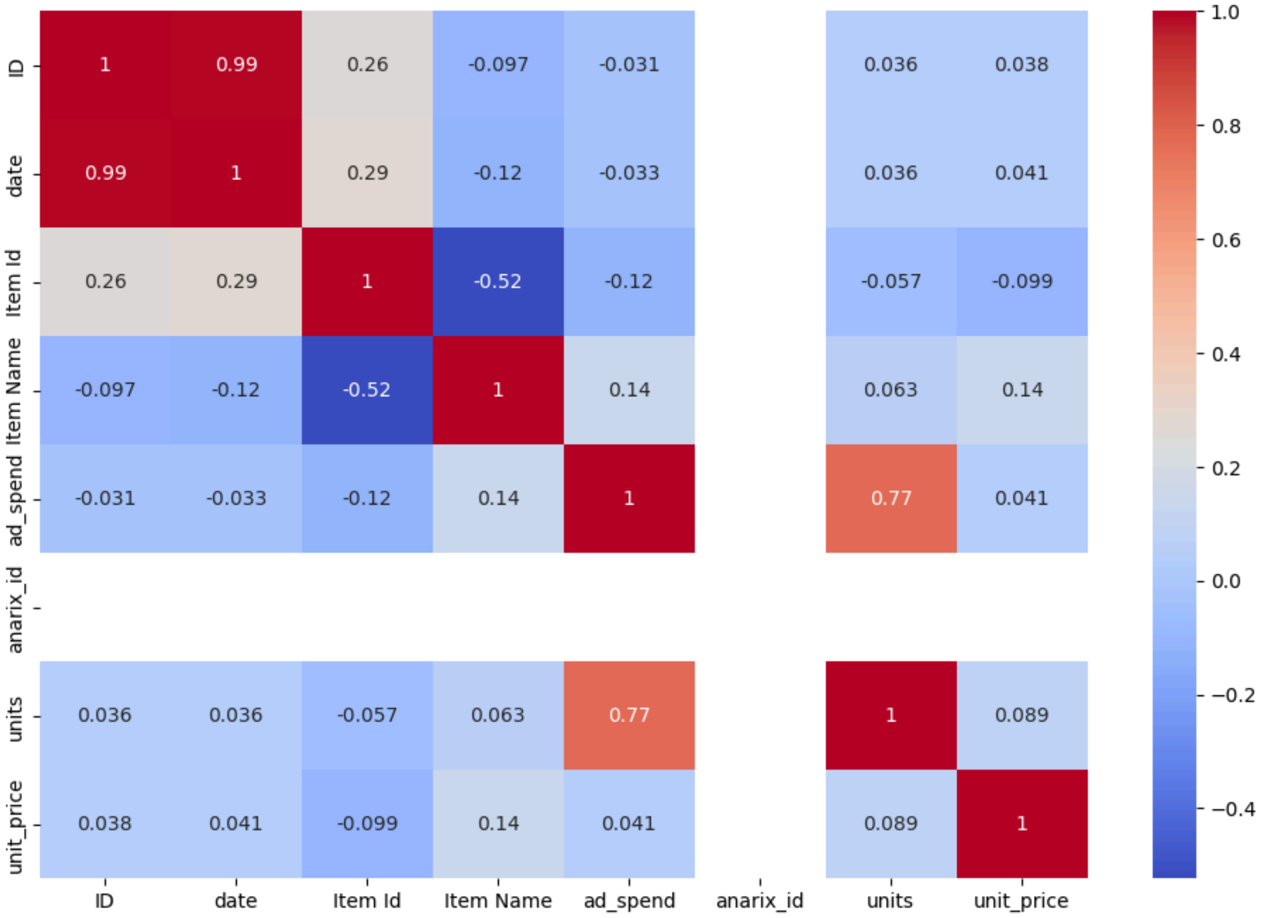
```
# Normalize numerical features
data = pd.read_csv('train.csv')
scaler = StandardScaler()
data[['ad_spend', 'units', 'unit_price']] = scaler.fit_transform(data[['ad_spend', 'units', 'unit_price']])
```

```
import pandas as pd
from sklearn.preprocessing import LabelEncoder
```

```
data = pd.read_csv('train.csv')

# Initialize LabelEncoder
label_encoder = LabelEncoder()

# Columns to encode - use a list
columns_to_encode = ['ID', 'date', 'Item Id', 'Item Name', 'anarix_id']

# Loop through columns and apply label encoding
for col in columns_to_encode:
    data[col] = label_encoder.fit_transform(data[col])

print(data)
```

```
            ID  date  Item Id  Item Name  ad_spend  anarix_id  units  \
0            0     0        9        146       NaN          0    0.0   
1            9     0       25         30       NaN          0    0.0   
2            2     0       17        158       NaN          0    0.0   
3            3     0       18        153       NaN          0    0.0   
4            4     0       19        154       NaN          0    0.0   
...        ...   ...      ...        ...       ...        ...    ...   
101485  101483   780      210        199    604.73          0    NaN   
101486  101482   780      209        199    261.21          0    2.0   
101487  101481   780      208        199      0.00          0    NaN   
101488  101480   780      207        199      0.00          0    NaN   
101489  101484   780      211        199      0.00          0    NaN   

        unit_price  
0             0.00  
1             0.00  
2             0.00  
3             0.00  
4             0.00  
...            ...  
101485        0.00  
101486      225.32  
101487        0.00  
101488        0.00  
101489        0.00  

[101490 rows x 8 columns]
```

```
import seaborn as sns
import matplotlib.pyplot as plt

plt.figure(figsize=(12,8))
sns.heatmap(data.corr(),annot=True, cmap='coolwarm')
plt.show()
```

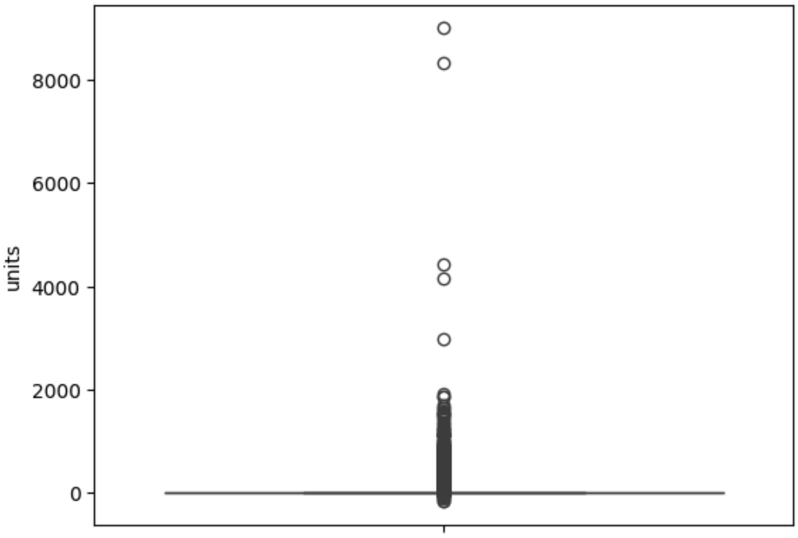


	ID	date	Item Id	Item Name	ad_spend	anarix_id	units	unit_price
ID	1	0.99	0.26	-0.097	-0.031		0.036	0.038
date	0.99	1	0.29	-0.12	-0.033		0.036	0.041
Item Id	0.26	0.29	1	-0.52	-0.12		-0.057	-0.099
Item Name	-0.097	-0.12	-0.52	1	0.14		0.063	0.14
ad_spend	-0.031	-0.033	-0.12	0.14	1		0.77	0.041
anarix_id								
units	0.036	0.036	-0.057	0.063	0.77		1	0.089
unit_price	0.038	0.041	-0.099	0.14	0.041		0.089	1

```
import pandas as pd
from scipy import stats

# Sample data
data = pd.read_csv('train.csv')

# Print the column names to check if 'Values' exists
print(data.columns)

# Assuming the column you want to analyze is named 'units' (based on previous code)
# Compute Z-scores for the 'units' column
z_scores = stats.zscore(data['units'])

# Identify outliers in the 'units' column
outliers = data['units'][abs(z_scores) > 3]
print(outliers)
```

```
Index(['ID', 'date', 'Item Id', 'Item Name', 'ad_spend', 'anarix_id', 'units',
       'unit_price'],
      dtype='object')
Series([], Name: units, dtype: float64)
```

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

# Sample data
data = pd.read_csv('train.csv')

# Create a box plot
sns.boxplot(data=data['units'])
plt.show()
```



```
data = pd.read_csv('train.csv')

# Extracting date features
data['date'] = pd.to_datetime(data['date'])
data['day_of_week'] = data['date'].dt.dayofweek
data['month'] = data['date'].dt.month

# Creating lag features
data['lag_1'] = data['units'].shift(1)
data['rolling_mean_7'] = data['units'].rolling(window=7).mean()

# Dropping NaN values created by lagging
data.dropna(inplace=True)
```

```
from statsmodels.tsa.statespace.sarimax import SARIMAX

# SARIMA model fitting
model = SARIMAX(data['units'], order=(1, 1, 1), seasonal_order=(1, 1, 1, 12))
results = model.fit()

# Model summary
print(results.summary())
```

```
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473: ValueWarning: An unsupported index
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473: ValueWarning: An unsupported index
  self._init_dates(dates, freq)
                                      SARIMAX Results                                       
==========================================================================================
Dep. Variable:                              units   No. Observations:                35746
Model:             SARIMAX(1, 1, 1)x(1, 1, 1, 12)   Log Likelihood             -212836.949
Date:                            Fri, 02 Aug 2024   AIC                         425683.899
Time:                                    10:36:38   BIC                         425726.318
Sample:                                         0   HQIC                        425697.397
                                          - 35746                                         
Covariance Type:                              opg                                         
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          0.0849      0.001    104.884      0.000       0.083       0.087
ma.L1         -0.9993   8.16e-05  -1.22e+04      0.000      -0.999      -0.999
ar.S.L12       0.0017      0.009      0.180      0.857      -0.016       0.020
ma.S.L12      -0.9998      0.001   -708.611      0.000      -1.003      -0.997
sigma2      8638.0026      9.186    940.309      0.000    8619.998    8656.008
===================================================================================
Ljung-Box (L1) (Q):                   0.00   Jarque-Bera (JB):       27520075261.31
Prob(Q):                              0.95   Prob(JB):                         0.00
Heteroskedasticity (H):               3.93   Skew:                            51.37
Prob(H) (two-sided):                  0.00   Kurtosis:                      4301.05
===================================================================================

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

```
from sklearn.model_selection import TimeSeriesSplit
import itertools

# Hyperparameter grid
p = d = q = range(0, 2)
pdq = list(itertools.product(p, d, q))
seasonal_pdq = [(x[0], x[1], x[2], 12) for x in pdq]

# Grid search
best_aic = float("inf")
best_params = None

for param in pdq:
    for param_seasonal in seasonal_pdq:
        try:
            model = SARIMAX(data['units'], order=param, seasonal_order=param_seasonal)
            results = model.fit()
            if results.aic < best_aic:
                best_aic = results.aic
                best_params = (param, param_seasonal)
        except:
            continue

print(f'Best SARIMA params: {best_params}')
```

```
    arams: ((1, 1, 1), (0, 0, 0, 12))

import pandas as pd
import numpy as np
from statsmodels.tsa.statespace.sarimax import SARIMAX
from sklearn.metrics import mean_squared_error
import matplotlib.pyplot as plt
```

Resources KeyError ✕ •••

You

Please explain the error:

```
KeyError: 'The `start` argument could not be matched to a location related to the index of the data.'
```

Gemini

Hypothesis

The error message "KeyError: 'The `start` argument could not be matched to a location related to the index of the data.'" indicates that the `start` date you're providing to the `model_fit.predict` function does not exist in the index of your training data.

This is likely due to a mismatch between the last date in your training data and the first date you want to predict for. The code calculates `start` as the day after the last day in the training data, but if this date is not present in the test data's index, the prediction will fail.

Suggested Changes

```
# Forecasting the test set period
# Ensure the start date is present in the test data's index
start = test.index[0]
end = test.index[-1]

# Make predictions
predictions = model_fit.predict(start=start, end=end, dynamic=False)

# Convert predictions to a DataFrame
predictions = pd.DataFrame(predictions, index=pd.date_range(start=start, end=end), columns=['predicted_units'])  # Explicitly s

# Merge actual and predicted values for comparison
results = pd.concat([test['units'], predictions], axis=1)
results.columns = ['actual_units', 'predicted_units']
```

Use code with caution

By setting the `start` date to the first date in the test data's index (`test.index[0]`), you ensure that the prediction starts from a valid point within your data.

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