Lab 4 - Student Notebook

Overview

In this lab, you will prepare a dataset for creating a forecast by using Amazon Forecast.

This lab includes two Jupyter notebooks:

1. This notebook contains the steps that you will follow to prepare the dataset and evaluate the forecast.
2. The `forecast-autorun.ipynb` notebook contains the steps to create the forecast by using Amazon Forecast. This notebook is run in the background when the lab starts, and it can take between 1–2 hours to complete. You will refer to this notebook during the lab steps, but you won't need to run any cells.

About the dataset

This Online Retail II dataset contains all transactions that occurred between January 12, 2009 and September 12, 2011 for a non-store, online retail organization that's registered and based in the United Kingdom. The company mainly sells unique all-occasion giftware. Many customers of the company are wholesalers.

Attribute information

- **InvoiceNo** – Invoice number. Nominal. A 6-digit integral number that's uniquely assigned to each transaction. If this code starts with the letter *c*, it indicates a cancelation.
- **StockCode** – Product (item) code. Nominal. A 5-digit integral number that's uniquely assigned to each distinct product.
- **Description** – Product (item) name. Nominal.
- **Quantity** – The quantities of each product (item) per transaction. Numeric.
- **InvoiceDate** – Invoice date and time. Numeric. The day and time when a transaction was generated.
- **UnitPrice** – Unit price. Numeric. Product price per unit in pounds sterling (£).
- **CustomerID** – Customer number. Nominal. A 5-digit integral number that's uniquely assigned to each customer.
- **Country** – Country name. Nominal. The name of the country where a customer resides.

Dataset attributions

This dataset was obtained from: Dua, D. and Graff, C. (2019). UCI Machine Learning Repository (http://archive.ics.uci.edu/ml). Irvine, CA: University of California, School of

Information and Computer Science.

Lab instructions

To complete this lab, read and run the cells below.

Task 1: Importing Python packages

Start by importing the Python packages that you need.

In the following code:

- *boto3* represents the AWS SDK for Python (Boto3), which is the Python library for AWS
- *pandas* provides DataFrames for manipulating time series data
- *matplotlib* provides plotting functions
- *sagemaker* represents the API that's needed to work with Amazon SageMaker
- *time*, *sys*, *os*, *io*, and *json* provide helper functions

In [13]:
```
import warnings
warnings.filterwarnings('ignore')
bucket_name='c100915a2303024l5531726t1w839105429-forecastbucket-ruehrdwq8umk'

import boto3
import pandas as pd
import matplotlib
import matplotlib.pyplot as plt
import sagemaker
import time, sys, os, io, json
import xlrd
!pip3 install pandas==1.5.3
```

```
Requirement already satisfied: pandas==1.5.3 in /home/ec2-user/anaconda3/envs/p
ython3/lib/python3.10/site-packages (1.5.3)
Requirement already satisfied: python-dateutil>=2.8.1 in /home/ec2-user/anacond
a3/envs/python3/lib/python3.10/site-packages (from pandas==1.5.3) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in /home/ec2-user/anaconda3/envs/py
thon3/lib/python3.10/site-packages (from pandas==1.5.3) (2023.3.post1)
Requirement already satisfied: numpy>=1.21.0 in /home/ec2-user/anaconda3/envs/p
ython3/lib/python3.10/site-packages (from pandas==1.5.3) (1.22.4)
Requirement already satisfied: six>=1.5 in /home/ec2-user/anaconda3/envs/python
3/lib/python3.10/site-packages (from python-dateutil>=2.8.1->pandas==1.5.3) (1.
16.0)
```

Task 2: Exploring the data

The data is in the *Microsoft Excel* format. pandas can read Excel files.

Note: This data might take 1–2 minutes to load

In [14]:
```
retail = pd.read_excel('online_retail_II.xlsx',engine='openpyxl')
```

According to the description for the dataset, some values are missing. To keep things simple, you will remove anything wtih a missing value.

In [15]:
```
retail = retail.dropna()
```

Start by examining the data.

How many rows and columns are in the dataset?

In [16]:
```
retail.shape
```

Out[16]:
```
(417534, 8)
```

What are the data types?

In [17]:
```
retail.dtypes
```

Out[17]:
```
Invoice                object
StockCode              object
Description            object
Quantity                int64
InvoiceDate    datetime64[ns]
Price                 float64
Customer ID           float64
Country                object
dtype: object
```

What does the data look like?

In [18]:
```
retail.head(20)
```

Out[18]:

	Invoice	StockCode	Description	Quantity	InvoiceDate	Price	Customer ID	Country
0	489434	85048	15CM CHRISTMAS GLASS BALL 20 LIGHTS	12	2009-12-01 07:45:00	6.95	13085.0	United Kingdom
1	489434	79323P	PINK CHERRY LIGHTS	12	2009-12-01 07:45:00	6.75	13085.0	United Kingdom
2	489434	79323W	WHITE CHERRY LIGHTS	12	2009-12-01 07:45:00	6.75	13085.0	United Kingdom
3	489434	22041	RECORD FRAME 7" SINGLE SIZE	48	2009-12-01 07:45:00	2.10	13085.0	United Kingdom
4	489434	21232	STRAWBERRY CERAMIC TRINKET BOX	24	2009-12-01 07:45:00	1.25	13085.0	United Kingdom
5	489434	22064	PINK DOUGHNUT TRINKET POT	24	2009-12-01 07:45:00	1.65	13085.0	United Kingdom
6	489434	21871	SAVE THE PLANET MUG	24	2009-12-01 07:45:00	1.25	13085.0	United Kingdom
7	489434	21523	FANCY FONT HOME SWEET HOME DOORMAT	10	2009-12-01 07:45:00	5.95	13085.0	United Kingdom
8	489435	22350	CAT BOWL	12	2009-12-01 07:46:00	2.55	13085.0	United Kingdom
9	489435	22349	DOG BOWL , CHASING BALL DESIGN	12	2009-12-01 07:46:00	3.75	13085.0	United Kingdom
10	489435	22195	HEART MEASURING SPOONS LARGE	24	2009-12-01 07:46:00	1.65	13085.0	United Kingdom
11	489435	22353	LUNCHBOX WITH CUTLERY FAIRY CAKES	12	2009-12-01 07:46:00	2.55	13085.0	United Kingdom
12	489436	48173C	DOOR MAT BLACK FLOCK	10	2009-12-01 09:06:00	5.95	13078.0	United Kingdom
13	489436	21755	LOVE BUILDING BLOCK WORD	18	2009-12-01 09:06:00	5.45	13078.0	United Kingdom
14	489436	21754	HOME BUILDING BLOCK WORD	3	2009-12-01 09:06:00	5.95	13078.0	United Kingdom
15	489436	84879	ASSORTED COLOUR BIRD ORNAMENT	16	2009-12-01 09:06:00	1.69	13078.0	United Kingdom
16	489436	22119	PEACE WOODEN	3	2009-12-01 09:06:00	6.95	13078.0	United Kingdom

	Invoice	StockCode	Description	Quantity	InvoiceDate	Price	Customer ID	Country
			BLOCK LETTERS					
17	489436	22142	CHRISTMAS CRAFT WHITE FAIRY	12	2009-12-01 09:06:00	1.45	13078.0	United Kingdom
18	489436	22296	HEART IVORY TRELLIS LARGE	12	2009-12-01 09:06:00	1.65	13078.0	United Kingdom
19	489436	22295	HEART FILIGREE DOVE LARGE	12	2009-12-01 09:06:00	1.65	13078.0	United Kingdom

Amazon Forecast has schemas for domains such as retail. Review the schema information at RETAIL Domain in the AWS Documentation.

The target time series is the historical time series data for each item or product that's sold by the retail organization. The following fields are required:

- **item_id** (string) – A unique identifier for the item or product that you want to predict the demand for.
- **timestamp** (timestamp)
- **demand** (float) – The number of sales for that item at the timestamp. It's also the target field that Amazon Forecast generates a forecast for.

If you examine the previous data, there are certain columns that you don't need for your investigation. You can drop these columns. The columns you can drop are **Invoice**, **Description**, and **Customer ID**.

Note: It's possible that items in the same order (as shown by the **Invoice** column) could have a correlation that impacts the model. For this lab, you will ignore this possibility.

Drop the columns that you don't need.

In [19]:
```
retail = retail[['StockCode','Quantity','Price','Country','InvoiceDate']]
```

The **InvoiceDate** column is your datetime data. You can inform pandas of this by using the `to_datetime` function. You can explore the data by time by setting the index of the DataFrame to the **InvoiceDate** column.

In [20]:
```
retail['InvoiceDate'] = pd.to_datetime(retail.InvoiceDate)
retail = retail.set_index('InvoiceDate')
```

You will now examine the updated DataFrame.

The number of rows and columns are:

In [21]:
```
retail.shape
```

Out[21]:
```
(417534, 4)
```

The new data looks like this example:

In [22]:
```
retail.head()
```

Out[22]:

InvoiceDate	StockCode	Quantity	Price	Country
2009-12-01 07:45:00	85048	12	6.95	United Kingdom
2009-12-01 07:45:00	79323P	12	6.75	United Kingdom
2009-12-01 07:45:00	79323W	12	6.75	United Kingdom
2009-12-01 07:45:00	22041	48	2.10	United Kingdom
2009-12-01 07:45:00	21232	24	1.25	United Kingdom

Note that **InvoiceDate** is the index, and it's shown in the first column.

Because you set the index to your datetime data, you can use it to select data.

To select all the rows from a specific date, use the date in the index.

In [23]:
```
retail['2010-01-04']
```

Out[23]:

InvoiceDate	StockCode	Quantity	Price	Country
2010-01-04 09:24:00	TEST001	5	4.50	United Kingdom
2010-01-04 09:43:00	21539	-1	4.25	United Kingdom
2010-01-04 09:53:00	TEST001	5	4.50	United Kingdom
2010-01-04 10:28:00	21844	36	2.55	United Kingdom
2010-01-04 10:28:00	21533	12	4.25	United Kingdom
...	...	...	...	...
2010-01-04 17:39:00	90214G	1	1.25	United Kingdom
2010-01-04 17:39:00	90214N	1	1.25	United Kingdom
2010-01-04 17:39:00	90214N	1	1.25	United Kingdom
2010-01-04 17:39:00	90214C	1	1.25	United Kingdom
2010-01-04 17:39:00	21690	2	3.75	United Kingdom

633 rows × 4 columns

You can use parts of a date, and date ranges. To view the **Jan** and **Feb** rows:

In [24]:
```
retail['2010-01':'2010-02']
```

Out[24]:

	StockCode	Quantity	Price	Country
InvoiceDate				
2010-01-04 09:24:00	TEST001	5	4.50	United Kingdom
2010-01-04 09:43:00	21539	-1	4.25	United Kingdom
2010-01-04 09:53:00	TEST001	5	4.50	United Kingdom
2010-01-04 10:28:00	21844	36	2.55	United Kingdom
2010-01-04 10:28:00	21533	12	4.25	United Kingdom
...	...	...	...	...
2010-02-28 16:14:00	84279B	1	3.75	United Kingdom
2010-02-28 16:14:00	84882	1	3.75	United Kingdom
2010-02-28 16:14:00	84882	1	3.75	United Kingdom
2010-02-28 16:14:00	44242B	5	1.25	United Kingdom
2010-02-28 16:16:00	10133	40	0.85	United Kingdom

46345 rows × 4 columns

The date range starts at:

In [25]:
```
retail.index.min()
```

Out[25]:
```
Timestamp('2009-12-01 07:45:00')
```

The date range ends at:

In [26]:
```
retail.index.max()
```

Out[26]:
```
Timestamp('2010-12-09 20:01:00')
```

With pandas, you can extract date information easily. You might extract date information to explore the data further and look for time-related trends.

Extract the year, month, and day of the week.

In [27]:
```
retail['Year'] = retail.index.year
retail['Month'] = retail.index.month
retail['weekday_name'] = retail.index.day_name()
```

In [28]:
```
retail.head()
```

Out[28]:

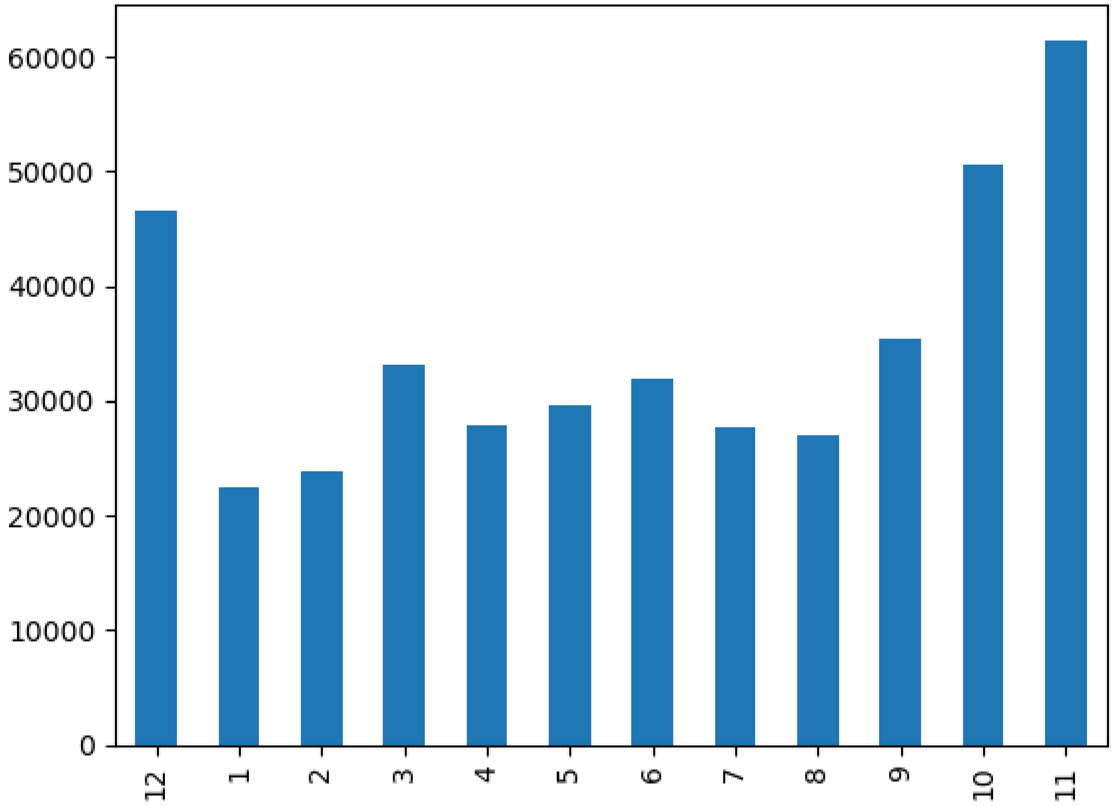
	StockCode	Quantity	Price	Country	Year	Month	weekday_name
InvoiceDate							
2009-12-01 07:45:00	85048	12	6.95	United Kingdom	2009	12	Tuesday
2009-12-01 07:45:00	79323P	12	6.75	United Kingdom	2009	12	Tuesday
2009-12-01 07:45:00	79323W	12	6.75	United Kingdom	2009	12	Tuesday
2009-12-01 07:45:00	22041	48	2.10	United Kingdom	2009	12	Tuesday
2009-12-01 07:45:00	21232	24	1.25	United Kingdom	2009	12	Tuesday

The dataset that you now have includes purchases made between December 2009 and December 2010. It's reasonable to assume there would be some seasonality in this data. You will now investigate whether there is seasonality.

In [29]:

```
retail.Month.value_counts(sort=False).plot(kind='bar')
```

Out[29]: <Axes: >



From the chart, you could deduce some seasonality:

1. November and December seem to be higher than the rest of the year.
2. Q4 seems to be higher than other quarters.

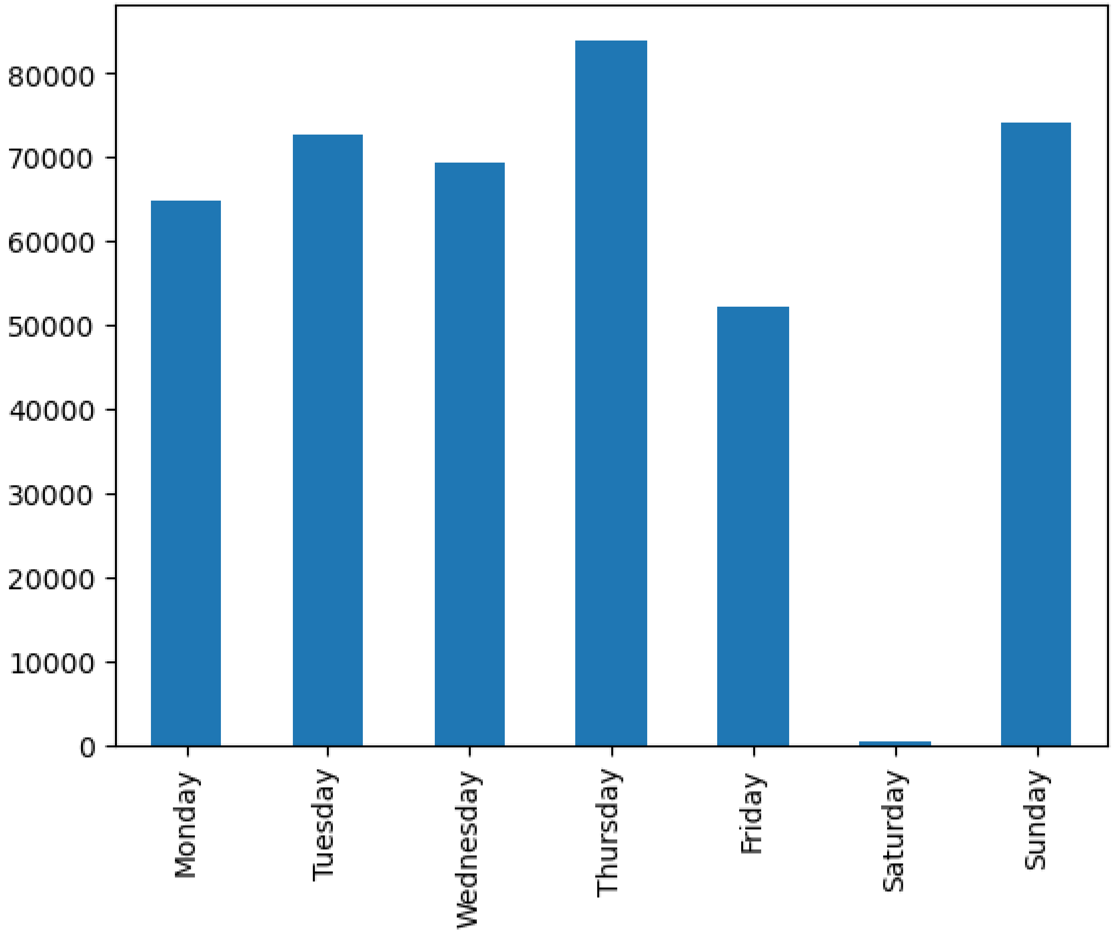
3. For Q1, Q2, and Q3: The last month of the quarter (months 3, 6, and 9) seem to have spikes.

Do you notice any other seasonal patterns?

Now, investigate whether there is any seasonality during the week.

In [30]:
```
day_order = ["Monday", "Tuesday", "Wednesday", "Thursday", "Friday", "Saturday",
retail.weekday_name.value_counts(sort=False).loc[day_order].plot(kind='bar')
```

Out[30]: <Axes: >



Saturday shows very few orders. Why might this be the case?

Task 3: Cleaning and reducing the size of the data

In this task, you will reduce the size of the data. You will also remove any anomalies, such as negative prices, outliers, and country data.

Reducing the countries

Examine the **Country** data.

In [31]:
```
retail.Country.unique()
```

Out[31]:
```
array(['United Kingdom', 'France', 'USA', 'Belgium', 'Australia', 'EIRE',
       'Germany', 'Portugal', 'Japan', 'Denmark', 'Netherlands', 'Poland',
       'Spain', 'Channel Islands', 'Italy', 'Cyprus', 'Greece', 'Norway',
       'Austria', 'Sweden', 'United Arab Emirates', 'Finland',
       'Switzerland', 'Unspecified', 'Nigeria', 'Malta', 'RSA',
       'Singapore', 'Bahrain', 'Thailand', 'Israel', 'Lithuania',
       'West Indies', 'Korea', 'Brazil', 'Canada', 'Iceland'],
      dtype=object)
```

In [32]:
```
retail.Country.value_counts()
```

Out[32]:
```
United Kingdom          379423
EIRE                      8710
Germany                   8129
France                    5710
Netherlands               2769
Spain                     1278
Switzerland               1187
Belgium                   1054
Portugal                  1024
Channel Islands            906
Sweden                     883
Italy                      731
Australia                  654
Cyprus                     554
Austria                    537
Greece                     517
Denmark                    428
Norway                     369
Finland                    354
United Arab Emirates       318
Unspecified                280
USA                        244
Japan                      224
Poland                     194
Malta                      172
Lithuania                  154
Singapore                  117
Canada                      77
Thailand                    76
Israel                      74
Iceland                     71
RSA                         65
Korea                       63
Brazil                      62
West Indies                 54
Bahrain                     42
Nigeria                     30
Name: Country, dtype: int64
```

Most of the data seems to be for the United Kingdom. To make your job easier, filter the data by *United Kingdom*.

In [33]:
```
country_filter = ['United Kingdom']
retail = retail[retail.Country.isin(country_filter)]
```

Because the **Country** column only contains the same value, you can drop it.

In [34]:
```
retail = retail[['StockCode','Quantity','Price']]
```

In [35]:
```
retail.head()
```

Out[35]:

InvoiceDate	StockCode	Quantity	Price
2009-12-01 07:45:00	85048	12	6.95
2009-12-01 07:45:00	79323P	12	6.75
2009-12-01 07:45:00	79323W	12	6.75
2009-12-01 07:45:00	22041	48	2.10
2009-12-01 07:45:00	21232	24	1.25

Examining StockCode and removing anomalies

Examine the distribution of the **StockCode** column:

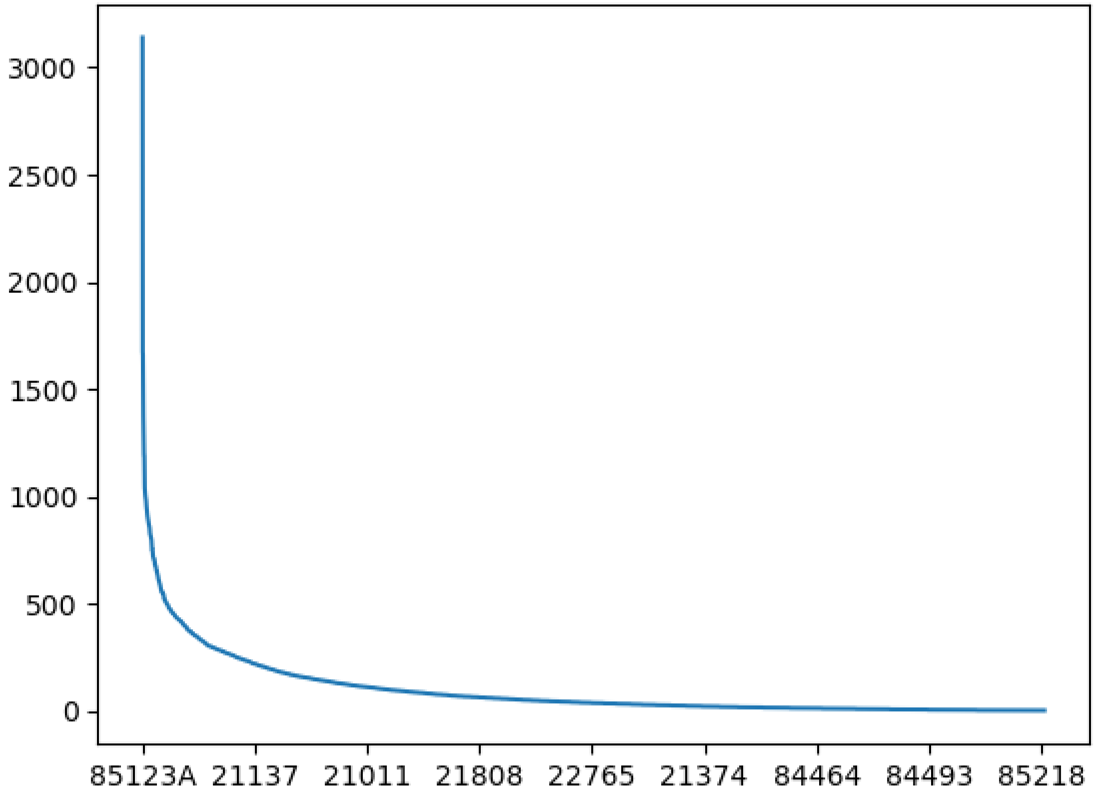
In [36]:
```
retail.StockCode.describe()
```

Out[36]:
```
count     379423
unique      4015
top       85123A
freq        3140
Name: StockCode, dtype: object
```

There are 4,015 unique values for **StockCode**. A quick plot of the counts might give you some insight into how the values are distributed.

In [37]:
```
retail.StockCode.value_counts().plot()
```

Out[37]:
```
<Axes: >
```



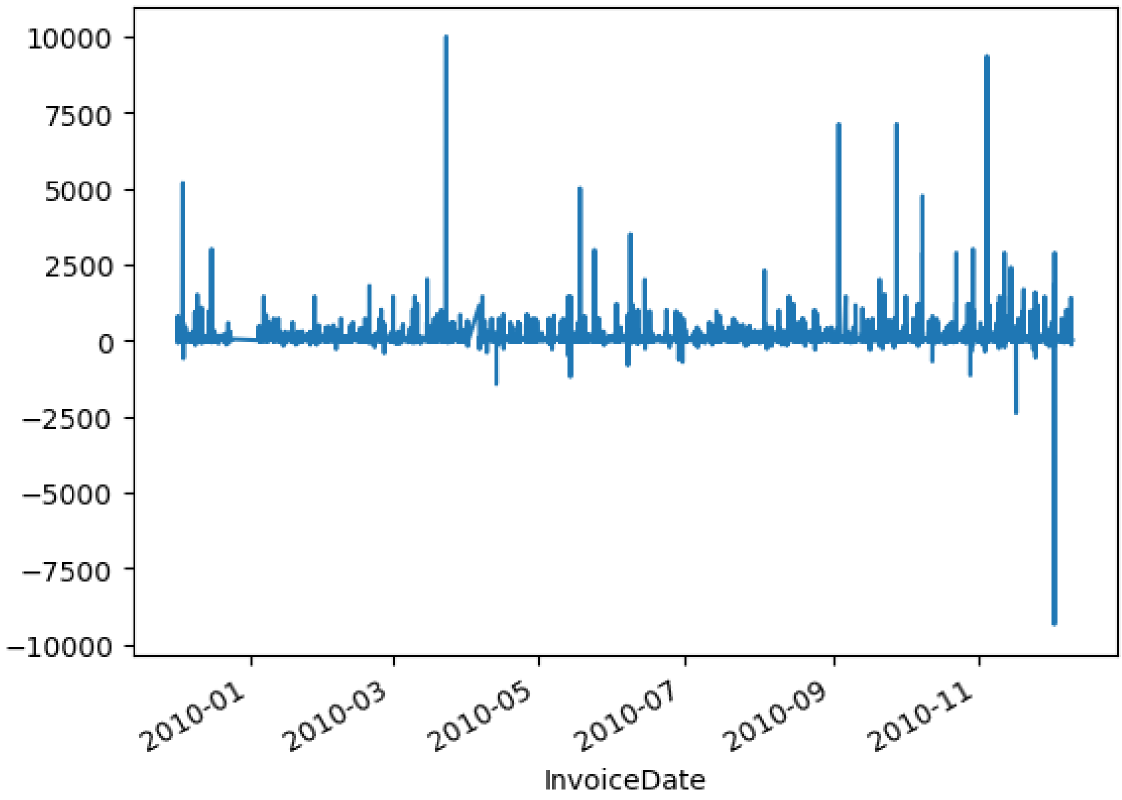
It seems that there are a few high-selling products, with a long tail behind them. You could investigate this situation further. However, for now, examine **Quantity**.

In [38]:
```
retail.Quantity.describe()
```

Out[38]:
```
count    379423.000000
mean         11.451517
std          68.943709
min       -9360.000000
25%           2.000000
50%           4.000000
75%          12.000000
max       10000.000000
Name: Quantity, dtype: float64
```

In [39]:
```
retail.Quantity.plot()
```

Out[39]:
```
<Axes: xlabel='InvoiceDate'>
```



From the initial plot, notice a couple of interesting aspects.

1. There appear to be negative quantities.

2. There are very large spikes throughout the year.

Negative and zero quantities could impact the forecast if you don't know why these values exist. To make things easier for now, you will remove negative and zero quantities

In [40]:
```
retail = retail[retail.Quantity>0]
```

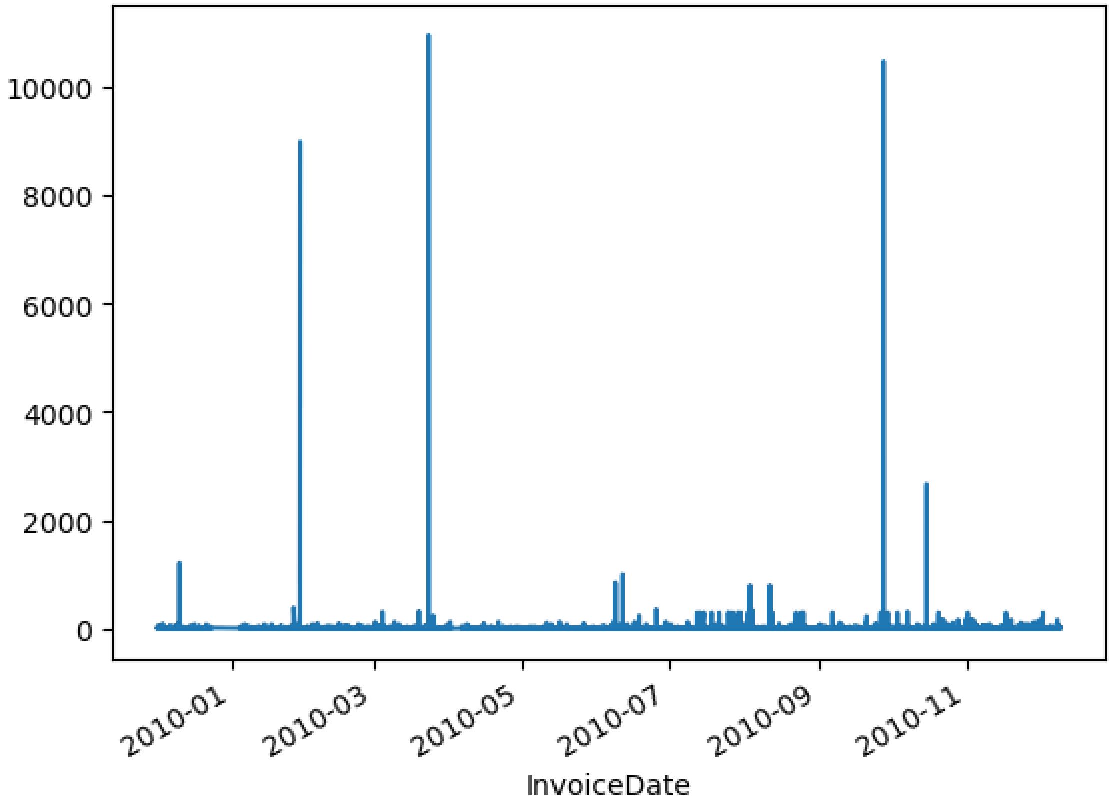
Now, examine **Price**.

In [41]:
```
retail.Price.describe()
```

Out[41]:
```
count    370951.000000
mean          3.145220
std          30.551482
min           0.000000
25%           1.250000
50%           1.950000
75%           3.750000
max       10953.500000
Name: Price, dtype: float64
```

In [42]:
```
retail.Price.plot()
```

Out[42]: <Axes: xlabel='InvoiceDate'>



The plot shows some clear price spikes. You will now try to find out why these spikes exist.

In [43]:
```
retail[retail.Price>500].head()
```

Out[43]:

InvoiceDate	StockCode	Quantity	Price
2009-12-10 11:50:00	M	1	1213.02
2010-01-29 11:04:00	M	1	8985.60
2010-03-23 15:22:00	M	1	10953.50
2010-06-08 16:39:00	M	1	849.45
2010-06-11 15:54:00	M	1	1000.63

The **StockCode** value of *M* looks unusual. If you had access to a domain expert, you could learn about the importance of *M*. Because you can't ask a domain expert for this lab, you will drop everything that has a **StockCode** value of *M*.

In [44]:
```
retail = retail[retail.StockCode!='M']
```

In [45]:
```
retail.Price.describe()
```

Out[45]:
```
count    370576.000000
mean          3.009463
std           4.576951
min           0.000000
25%           1.250000
50%           1.950000
75%           3.750000
max         387.540000
Name: Price, dtype: float64
```

This result is better, but the **max** value is still high. You will now investigate this situation further.

In [46]:
```
retail[retail.Price>300].head(20)
```

Out[46]:

InvoiceDate	StockCode	Quantity	Price
2010-01-26 16:29:00	ADJUST	1	342.80
2010-01-26 17:28:00	ADJUST	1	387.54
2010-06-25 14:15:00	ADJUST2	1	300.13
2010-06-25 14:15:00	ADJUST2	1	358.47
2010-08-04 11:38:00	POST	1	334.88

It seems that some adjustments occurred. You will also drop any data that shows these adjustments.

In [47]:
```
stockcodes = ['ADJUST', 'ADJUST2', 'POST']
retail = retail[~retail.StockCode.isin(stockcodes)]
```

In [48]:
```
retail.Price.describe()
```

Out[48]:
```
count    370554.000000
mean          3.002500
std           4.363688
min           0.000000
25%           1.250000
50%           1.950000
75%           3.750000
max         295.000000
Name: Price, dtype: float64
```

You will now examine zero-priced items.

In [49]:
```
retail[retail.Price==0].count
```

Out[49]:
```
<bound method DataFrame.count of                     StockCode  Quantity  Price
InvoiceDate
2009-12-02 13:34:00     22076        12    0.0
2009-12-03 11:19:00     48185         2    0.0
2009-12-08 15:25:00     22065         1    0.0
2009-12-08 15:25:00     22142        12    0.0
2009-12-15 13:49:00     85042         8    0.0
2009-12-18 14:22:00     21143        12    0.0
2010-01-06 14:54:00     79320        24    0.0
2010-01-15 12:43:00     21533        12    0.0
2010-02-12 14:58:00   TEST001         5    0.0
2010-02-12 15:47:00   TEST001         5    0.0
2010-03-04 11:44:00     21662         1    0.0
2010-04-01 17:13:00     22459         8    0.0
2010-04-01 17:13:00     22458         8    0.0
2010-06-11 11:12:00     21765         1    0.0
2010-06-17 10:12:00     20914         2    0.0
2010-06-24 12:34:00     22423         5    0.0
2010-07-19 13:13:00     22690         6    0.0
2010-09-27 16:59:00    46000M       648    0.0
2010-09-30 12:19:00     22218         2    0.0
2010-10-18 15:13:00     22121         1    0.0
2010-11-07 14:26:00     21843         2    0.0>
```

There aren't many values in these results, so you can drop zero-priced items.

In [50]:
```
retail = retail[retail.Price>0]
```

Splitting the data

The timeseries data that you need to create a forecast requires a *timestamp*, an *itemId*, and a *demand*. These features will map to the **InvoiceDate**, **StockCode**, and **Quantity** columns.

The related timeseries data needs a *timestamp*, an *itemId*, and a *price*. These features will map to the **InvoiceDate**, **StockCode**, and **Price** columns.

Create the two DataFrames:

In [52]:
```
df_time_series = retail[['StockCode','Quantity']]
df_related_time_series = retail[['StockCode','Price']]
```

Downsampling

You will now examine a single item.

In [53]:
```
df_time_series[df_time_series.StockCode==21232]['2009-12-01']
```

Out[53]:

InvoiceDate	StockCode	Quantity
2009-12-01 07:45:00	21232	24
2009-12-01 10:49:00	21232	48
2009-12-01 12:13:00	21232	3
2009-12-01 12:14:00	21232	20
2009-12-01 13:31:00	21232	4
2009-12-01 13:37:00	21232	12
2009-12-01 13:43:00	21232	24
2009-12-01 14:19:00	21232	12
2009-12-01 15:26:00	21232	12
2009-12-01 16:18:00	21232	12

You can see multiple orders for each day. You want to create a forecast that predicts demand at a daily level.

You must *downsample* the data from the individual orders into a daily total.

The orders for each day can be summed, because the total demand for the day is the value that you will forecast.

pandas provides the `resample` function for this purpose. `sum` will sum the **Quantity** column. You will also reset the index based on the **InvoiceDate** value. However, this time, it will be a date without the time portion.

Note: It might take up to 1 minute for this process to complete.

In [54]:
```
df_time_series = df_time_series.groupby('StockCode').resample('D').sum().reset_i
```

In [55]:
```
df_time_series['InvoiceDate'] = pd.to_datetime(df_time_series.InvoiceDate)
df_time_series = df_time_series.set_index('InvoiceDate')
df_time_series.head()
```

Out[55]:

InvoiceDate	StockCode	Quantity
2009-12-01	10002	12
2009-12-02	10002	0
2009-12-03	10002	7
2009-12-04	10002	25
2009-12-05	10002	0

In [56]:
```
df_time_series = df_time_series.groupby('StockCode').resample('D').sum().reset_i
```

Examine the new DataFrame.

In [57]:
```
df_time_series[df_time_series.StockCode==21232]
```

Out[57]:

InvoiceDate	StockCode	Quantity
2009-12-01	21232	171
2009-12-02	21232	164
2009-12-03	21232	192
2009-12-04	21232	264
2009-12-05	21232	36
...	...	...
2010-12-04	21232	0
2010-12-05	21232	4
2010-12-06	21232	12
2010-12-07	21232	28
2010-12-08	21232	61

373 rows × 2 columns

The order now has a single entry for each day.

Repeat this process with the related time series data.

In [58]:
```
df_related_time_series.head()
```

Out[58]:

InvoiceDate	StockCode	Price
2009-12-01 07:45:00	85048	6.95
2009-12-01 07:45:00	79323P	6.75
2009-12-01 07:45:00	79323W	6.75
2009-12-01 07:45:00	22041	2.10
2009-12-01 07:45:00	21232	1.25

In [59]:
```
df_related_time_series2 = df_related_time_series.groupby('StockCode').resample('
```

In [60]:
```
df_related_time_series2.head(20)
```

Out[60]:

InvoiceDate	StockCode	Price
2009-12-01	**10002**	0.85
2009-12-02	**10002**	NaN
2009-12-03	**10002**	0.85
2009-12-04	**10002**	0.85
2009-12-05	**10002**	NaN
2009-12-06	**10002**	0.85
2009-12-07	**10002**	0.85
2009-12-08	**10002**	NaN
2009-12-09	**10002**	NaN
2009-12-10	**10002**	NaN
2009-12-11	**10002**	0.85
2009-12-12	**10002**	NaN
2009-12-13	**10002**	NaN
2009-12-14	**10002**	0.85
2009-12-15	**10002**	NaN
2009-12-16	**10002**	NaN
2009-12-17	**10002**	NaN
2009-12-18	**10002**	NaN
2009-12-19	**10002**	NaN
2009-12-20	**10002**	NaN

Question: Why are some of the previous values showing as *NaN*?

Answer: That product had no orders for those days, and thus it has no price. Should you fill these NaN values with a numerical value?

In [61]:

```
retail[retail.StockCode == 10002]['2009-12']
```

Out[61]:

	StockCode	Quantity	Price
InvoiceDate			
2009-12-01 09:08:00	10002	12	0.85
2009-12-03 13:49:00	10002	1	0.85
2009-12-03 13:49:00	10002	1	0.85
2009-12-03 19:13:00	10002	1	0.85
2009-12-03 20:03:00	10002	4	0.85
2009-12-04 08:46:00	10002	12	0.85
2009-12-04 12:20:00	10002	12	0.85
2009-12-04 17:31:00	10002	1	0.85
2009-12-06 15:24:00	10002	1	0.85
2009-12-07 16:40:00	10002	2	0.85
2009-12-11 12:21:00	10002	9	0.85
2009-12-14 12:02:00	10002	12	0.85
2009-12-14 14:12:00	10002	24	0.85
2009-12-21 13:29:00	10002	12	0.85
2009-12-23 12:07:00	10002	1	0.85

You can use `pad` to forward-fill the price. The previous value will be used to fill the gap for each missing value.

In [62]:
```
df_related_time_series3 = df_related_time_series2.groupby('StockCode').pad()
```

In [63]:
```
df_related_time_series3.head(20)
```

Out[63]:

InvoiceDate	StockCode	Price
2009-12-01	10002	0.85
2009-12-02	10002	0.85
2009-12-03	10002	0.85
2009-12-04	10002	0.85
2009-12-05	10002	0.85
2009-12-06	10002	0.85
2009-12-07	10002	0.85
2009-12-08	10002	0.85
2009-12-09	10002	0.85
2009-12-10	10002	0.85
2009-12-11	10002	0.85
2009-12-12	10002	0.85
2009-12-13	10002	0.85
2009-12-14	10002	0.85
2009-12-15	10002	0.85
2009-12-16	10002	0.85
2009-12-17	10002	0.85
2009-12-18	10002	0.85
2009-12-19	10002	0.85
2009-12-20	10002	0.85

Task 4: Reviewing the creation of the forecast

The following cells are Markdown. They demonstrate the API calls that are needed to create a forecast based on the data that you have been working with. Creating a forecast with Amazon Forecast involves three stages:

1. Creating the datasets and importing the data. This process typically takes 5–10 minutes.
2. Creating the predictor. This process trains a model by using the data that you provided. It takes 30–60 minutes to complete.
3. Creating the forecast. This process generates a forecast for a particular item by using the predictor. It also takes 30–60 minutes to complete.

To save time, when this lab was started, the `forecast-autorun.ipynb` was also ran in the background. The notebook will be updated with the results after running completes. It takes about 65 minutes to run, but it might take a little longer. By the time you review this cell, the forecast creation should in process. While it's finishing, you will review the code.

Note: Feel free to review the actual `forecast-autorun.ipynb` notebook if you want some more detail. However, make sure that you don't run any cells!

Creating the datasets and importing the data

The first step is to create a Forecast Dataset Group:

```
session = boto3.Session()
forecast = session.client(service_name='forecast')
create_dataset_group_response =
forecast.create_dataset_group(DatasetGroupName=dataset_group_name,
Domain="RETAIL")
dataset_group_arn = create_dataset_group_response['DatasetGroupArn']
```

The `create_dataset` function requires a few parameters:

- **DOMAIN** – This parameter specifies the domain, such as *retail*, that the forecast should use.
- **DatasetType** – For the time series data, this parameter will be set to *TARGET_TIME_SERIES*.
- **DatasetName** – This parameter specifies the name of the dataset.
- **DataFrequency** – This parameter specifices the frequency. For the daily dataset, it will be *D*.
- **Schema** – This parameter specifies the schema of the dataset.

The dataset schema for the time series data is:

```
schema ={
   "Attributes":[
      {
         "AttributeName":"timestamp",
         "AttributeType":"timestamp"
      },
      {
         "AttributeName":"item_id",
         "AttributeType":"string"
      },
      {
         "AttributeName":"demand",
         "AttributeType":"float"
      }
   ]
}
```

The code to create the dataset is:

```
time_series_response=forecast.create_dataset(
                    Domain="RETAIL",
                    DatasetType='TARGET_TIME_SERIES',
                    DatasetName='retail_time_series_data',
                    DataFrequency='D',
                    Schema = schema
```

```
)
dataset_arn = time_series_response['DatasetArn']
```

Now that the dataset is defined, a job is needed to import the data:

```
ds_import_job_response=forecast.create_dataset_import_job(DatasetImportJobl

DatasetArn=dataset_arn,
                                                          DataSource=
data_source,

TimestampFormat=timestamp_format
                                                         )
```

Note that the *data_source* is a path to the data that's stored in Amazon Simple Storage Service (Amazon S3).

The final step is to add the dataset to the dataset group:

```
forecast.update_dataset_group(DatasetGroupArn=dataset_group_arn,
DatasetArns=[dataset_arn])
```

The process of adding the related data or metadata is done in the same way: by changing the names, schema, and dataset type. Although you have prepared this data, you won't use it in the predictor because the model wasn't impacted by the additional data.

Creating the predictor

The next step is to create the predictor. The `create_predictor` command needs a few parameters:

- **PredictorName** – This parameter specifies the name that you want to give the predictor.

  ```
  predictor_name= prefix+'_deeparp_algo'
  ```
- **AlgorithmArn** – This parameter is the path to the algorithm that you want to use. In this example, you will use DeepAR+.

  ```
  algorithm_arn = 'arn:aws:forecast:::algorithm/Deep_AR_Plus
  ```
- **EvaluationParameters** – This parameter enables you to specify the number and size of the back test windows. Recall from the module that this parameter controls the size and number of testing windows that are created from the data.

  ```
  evaluation_parameters= {"NumberOfBacktestWindows": 1,
  "BackTestWindowOffset": 30}
  ```
- **ForecastHorizon** – How many units to forecast (in this case, the units are days).

  ```
  forecast_horizon = 30
  ```
- **InputDataConfig** – This parameter specifies the data, along with optional vacation days.

  ```
  input_data_config = {"DatasetGroupArn": dataset_group_arn,
  "SupplementaryFeatures": [ {"Name": "holiday","Value": "UK"} ]}
  ```

- **FeaturizationConfig** – This parameter sets the frequency, but it can also be used to specify filling methods for data.

  ```
  featurization_config= {"ForecastFrequency": dataset_frequency }
  ```

The code to create the predictor is:

```
create_predictor_response=forecast.create_predictor(PredictorName = predictor_name,
      AlgorithmArn = algorithm_arn,
      ForecastHorizon = forecast_horizon,
      PerformAutoML = False,
      PerformHPO = False,
      EvaluationParameters= evaluation_parameters,
      InputDataConfig = input_data_config,
      FeaturizationConfig = featurization_config
     )
```

After the predictor is created, you can create a forecast.

Creating the forecast

To create the forecast, use the `create_forecast` method:

```
predictor_arn = create_predictor_response['PredictorArn']

create_forecast_response=forecast.create_forecast(ForecastName=forecast_Na

PredictorArn=predictor_arn)
```

After the forecast is generated, the results can be queried by using the `query_forecast` method:

```
forecast_response = forecast_query.query_forecast(
    ForecastArn=forecast_arn,
    Filters={"item_id":"22423"}
)
```

Task 5: Waiting for the forecast creation to complete

The forecast should now be created. You can investigate to see whether the forecast creation is complete.

First, create a helper method to show the status.

In [64]:
```
import sys

class StatusIndicator:

    def __init__(self):
        self.previous_status = None
        self.need_newline = False
```

```
    def update( self, status ):
        if self.previous_status != status:
            if self.need_newline:
                sys.stdout.write("\n")
            sys.stdout.write( status + " ")
            self.need_newline = True
            self.previous_status = status
        else:
            # sys.stdout.write(".")
            print('.',end='')
            self.need_newline = True
        sys.stdout.flush()

    def end(self):
        if self.need_newline:
            sys.stdout.write("\n")
```

Next, create instances of the forecast and the forecast query objects.

In [65]:
```
bucket='mlf-lab4-forecastbucket-12sb9sjex9iv'

session = boto3.Session()
forecast = session.client(service_name='forecast')
forecast_query = session.client(service_name='forecastquery')
```

You will read the variables from the store, and check whether the forecast was defined. After the forecast is defined, you will wait until its status becomes active.

In [66]:
```
print('Waiting for the predictor arn to be available')
while True:
    %store -r
    is_local = "forecast_arn" in locals()
    if is_local: break
    print('.',end='')
    time.sleep(10)

print('Waiting for the predictor to be available')
status_indicator_predictor = StatusIndicator()
while True:
    status = forecast.describe_predictor(PredictorArn=predictor_arn)['Status']
    status_indicator_predictor.update(status)
    if status in ('ACTIVE', 'CREATE_FAILED'): break
    time.sleep(10)

status_indicator_predictor.end()

print('Waiting for forecast to be available')
status_indicator = StatusIndicator()
while True:
    status = forecast.describe_forecast(ForecastArn=forecast_arn)['Status']
    status_indicator.update(status)
    if status in ('ACTIVE', 'CREATE_FAILED'): break
    time.sleep(10)

status_indicator.end()
```

```
Waiting for the predictor arn to be available
................................................................................
Waiting for the predictor to be available
ACTIVE
Waiting for forecast to be available
CREATE_IN_PROGRESS .............................................................
ACTIVE
```

Task 6: Using the forecast

At this point, there should be a forecast that's ready to be queried.

Check that you get data for the following test stock code: *21232*

In [67]:
```
print()
forecast_response = forecast_query.query_forecast(
    ForecastArn=forecast_arn,
    Filters={"item_id":"21232"}
)
print(forecast_response)
```

{'Forecast': {'Predictions': {'p10': [{'Timestamp': '2010-11-01T00:00:00', 'Value': -11.5225353241}, {'Timestamp': '2010-11-02T00:00:00', 'Value': 28.4542007446}, {'Timestamp': '2010-11-03T00:00:00', 'Value': 0.6409492493}, {'Timestamp': '2010-11-04T00:00:00', 'Value': 22.9499511719}, {'Timestamp': '2010-11-05T00:00:00', 'Value': 12.8035917282}, {'Timestamp': '2010-11-06T00:00:00', 'Value': -9.7075366974}, {'Timestamp': '2010-11-07T00:00:00', 'Value': 10.6902999878}, {'Timestamp': '2010-11-08T00:00:00', 'Value': -2.03698349}, {'Timestamp': '2010-11-09T00:00:00', 'Value': 0.6015701294}, {'Timestamp': '2010-11-10T00:00:00', 'Value': -7.4712715149}, {'Timestamp': '2010-11-11T00:00:00', 'Value': -24.835559845}, {'Timestamp': '2010-11-12T00:00:00', 'Value': -17.5017166138}, {'Timestamp': '2010-11-13T00:00:00', 'Value': -30.1197967529}, {'Timestamp': '2010-11-14T00:00:00', 'Value': -2.4642601013}, {'Timestamp': '2010-11-15T00:00:00', 'Value': 28.218744278}, {'Timestamp': '2010-11-16T00:00:00', 'Value': -47.3824996948}, {'Timestamp': '2010-11-17T00:00:00', 'Value': -32.1527442932}, {'Timestamp': '2010-11-18T00:00:00', 'Value': 15.8644695282}, {'Timestamp': '2010-11-19T00:00:00', 'Value': 14.4303426743}, {'Timestamp': '2010-11-20T00:00:00', 'Value': -8.0414609909}, {'Timestamp': '2010-11-21T00:00:00', 'Value': 12.9835548401}, {'Timestamp': '2010-11-22T00:00:00', 'Value': 21.7709445953}, {'Timestamp': '2010-11-23T00:00:00', 'Value': 21.7110137939}, {'Timestamp': '2010-11-24T00:00:00', 'Value': 5.607875824}, {'Timestamp': '2010-11-25T00:00:00', 'Value': 14.6439571381}, {'Timestamp': '2010-11-26T00:00:00', 'Value': 9.5583028793}, {'Timestamp': '2010-11-27T00:00:00', 'Value': -4.4880018234}, {'Timestamp': '2010-11-28T00:00:00', 'Value': 16.6695823669}, {'Timestamp': '2010-11-29T00:00:00', 'Value': 9.8039693832}, {'Timestamp': '2010-11-30T00:00:00', 'Value': 59.981338501}], 'p50': [{'Timestamp': '2010-11-01T00:00:00', 'Value': -7.8252024651}, {'Timestamp': '2010-11-02T00:00:00', 'Value': 42.2838554382}, {'Timestamp': '2010-11-03T00:00:00', 'Value': 19.9369106293}, {'Timestamp': '2010-11-04T00:00:00', 'Value': 35.9277305603}, {'Timestamp': '2010-11-05T00:00:00', 'Value': 23.8865871429}, {'Timestamp': '2010-11-06T00:00:00', 'Value': -0.4412196279}, {'Timestamp': '2010-11-07T00:00:00', 'Value': 36.6791992188}, {'Timestamp': '2010-11-08T00:00:00', 'Value': 69.2811126709}, {'Timestamp': '2010-11-09T00:00:00', 'Value': 71.7817382812}, {'Timestamp': '2010-11-10T00:00:00', 'Value': 49.5807914734}, {'Timestamp': '2010-11-11T00:00:00', 'Value': 24.5932483673}, {'Timestamp': '2010-11-12T00:00:00', 'Value': 31.5766201019}, {'Timestamp': '2010-11-13T00:00:00', 'Value': -14.126996994}, {'Timestamp': '2010-11-14T00:00:00', 'Value': 36.6376190186}, {'Timestamp': '2010-11-15T00:00:00', 'Value': 63.5094604492}, {'Timestamp': '2010-11-16T00:00:00', 'Value': 68.3955612183}, {'Timestamp': '2010-11-17T00:00:00', 'Value': 37.393737793}, {'Timestamp': '2010-11-18T00:00:00', 'Value': 37.2220306396}, {'Timestamp': '2010-11-19T00:00:00', 'Value': 26.2264251709}, {'Timestamp': '2010-11-20T00:00:00', 'Value': 2.7028605938}, {'Timestamp': '2010-11-21T00:00:00', 'Value': 37.9927864075}, {'Timestamp': '2010-11-22T00:00:00', 'Value': 39.2493362427}, {'Timestamp': '2010-11-23T00:00:00', 'Value': 70.4927978516}, {'Timestamp': '2010-11-24T00:00:00', 'Value': 46.2303581238}, {'Timestamp': '2010-11-25T00:00:00', 'Value': 32.3256149292}, {'Timestamp': '2010-11-26T00:00:00', 'Value': 23.550567627}, {'Timestamp': '2010-11-27T00:00:00', 'Value': 7.3469939232}, {'Timestamp': '2010-11-28T00:00:00', 'Value': 44.541469574}, {'Timestamp': '2010-11-29T00:00:00', 'Value': 41.4398155212}, {'Timestamp': '2010-11-30T00:00:00', 'Value': 83.3426132202}], 'p90': [{'Timestamp': '2010-11-01T00:00:00', 'Value': -4.7509727478}, {'Timestamp': '2010-11-02T00:00:00', 'Value': 52.8470420837}, {'Timestamp': '2010-11-03T00:00:00', 'Value': 37.1509094238}, {'Timestamp': '2010-11-04T00:00:00', 'Value': 48.7191467285}, {'Timestamp': '2010-11-05T00:00:00', 'Value': 32.908996582}, {'Timestamp': '2010-11-06T00:00:00', 'Value': 10.8257637024}, {'Timestamp': '2010-11-07T00:00:00', 'Value': 63.4393806458}, {'Timestamp': '2010-11-08T00:00:00', 'Value': 139.5895233154}, {'Timestamp': '2010-11-09T00:00:00', 'Value': 148.5250549316}, {'Timestamp': '2010-11-10T00:00:00', 'Value': 142.5830383301}, {'Timestamp': '2010-11-11T00:00:00', 'Value': 88.3896636963}, {'Timestamp': '2010-11-12T00:00:00', 'Value': 66.7280883789}, {'Timestamp': '2010-11-13T00:00:00', 'Value': 0.8954854012}, {'Timestamp': '2010-11-14T00:00:00', 'Value': 90.3079528809}, {'Timestamp': '2010-11-15T00:00:00', 'Value': 175.5196228027}, {'Timestamp': '2010-11

-16T00:00:00', 'Value': 222.234375}, {'Timestamp': '2010-11-17T00:00:00', 'Value': 93.5000228882}, {'Timestamp': '2010-11-18T00:00:00', 'Value': 71.3357391357}, {'Timestamp': '2010-11-19T00:00:00', 'Value': 48.6339187622}, {'Timestamp': '2010-11-20T00:00:00', 'Value': 30.949174881}, {'Timestamp': '2010-11-21T00:00:00', 'Value': 68.7886505127}, {'Timestamp': '2010-11-22T00:00:00', 'Value': 64.649269104}, {'Timestamp': '2010-11-23T00:00:00', 'Value': 142.3708343506}, {'Timestamp': '2010-11-24T00:00:00', 'Value': 93.399017334}, {'Timestamp': '2010-11-25T00:00:00', 'Value': 70.5572128296}, {'Timestamp': '2010-11-26T00:00:00', 'Value': 58.9060745239}, {'Timestamp': '2010-11-27T00:00:00', 'Value': 28.0365486145}, {'Timestamp': '2010-11-28T00:00:00', 'Value': 85.4194946289}, {'Timestamp': '2010-11-29T00:00:00', 'Value': 90.4818344116}, {'Timestamp': '2010-11-30T00:00:00', 'Value': 106.892829895}]}}, 'ResponseMetadata': {'RequestId': 'a8503395-393b-4105-93ca-a5399710e94d', 'HTTPStatusCode': 200, 'HTTPHeaders': {'date': 'Sun, 31 Dec 2023 07:31:19 GMT', 'content-type': 'application/x-amz-json-1.1', 'content-length': '5261', 'connection': 'keep-alive', 'x-amzn-requestid': 'a8503395-393b-4105-93ca-a5399710e94d'}, 'RetryAttempts': 0}}

Plotting the actual results

Earlier, you split the data and held back the *November* and *December* values. You will plot these values against the predicted values for the same time period.

You will start by reading the test values back into a DataFrame.

In [68]:
```
actual_df = pd.read_csv(test, names=['InvoiceDate','StockCode','Quantity'])
actual_df['InvoiceDate'] = pd.to_datetime(actual_df.InvoiceDate)
actual_df = actual_df.set_index('InvoiceDate')
actual_df.head()
```

Out[68]:

	StockCode	Quantity
InvoiceDate		
2010-11-01	21232	0
2010-11-02	21232	60
2010-11-03	21232	130
2010-11-04	21232	255
2010-11-05	21232	24

Check that you only have data for the *21232* stock code.

In [76]:
```
stockcode_filter = ['21232']
actual_df = actual_df[actual_df['StockCode'].isin(stockcode_filter)]
```

In [77]:
```
actual_df.head()
```

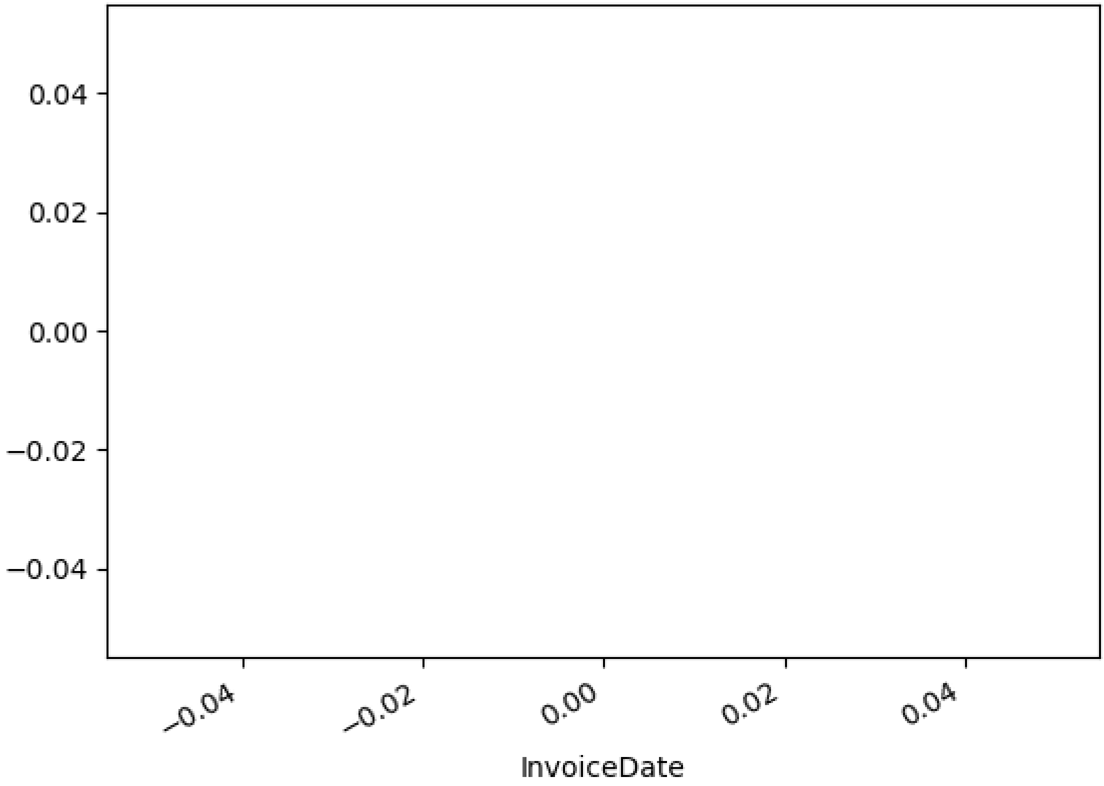
Out[77]:

	StockCode	Quantity
InvoiceDate		

You can do a quick plot of the data. Remember that this data is test data, so the actual values are plotted. In the next step, you will plot the predicted values.

In [71]:
```
actual_df.Quantity.plot()
```

Out[71]: <Axes: xlabel='InvoiceDate'>



Plotting the prediction

Next, you must convert the JSON response from the predictor to a DataFrame that you can plot.

Start by getting the P10 predictions.

In [72]:
```
# Generate DF
prediction_df_p10 = pd.DataFrame.from_dict(forecast_response['Forecast']['Predic
prediction_df_p10.head()
```

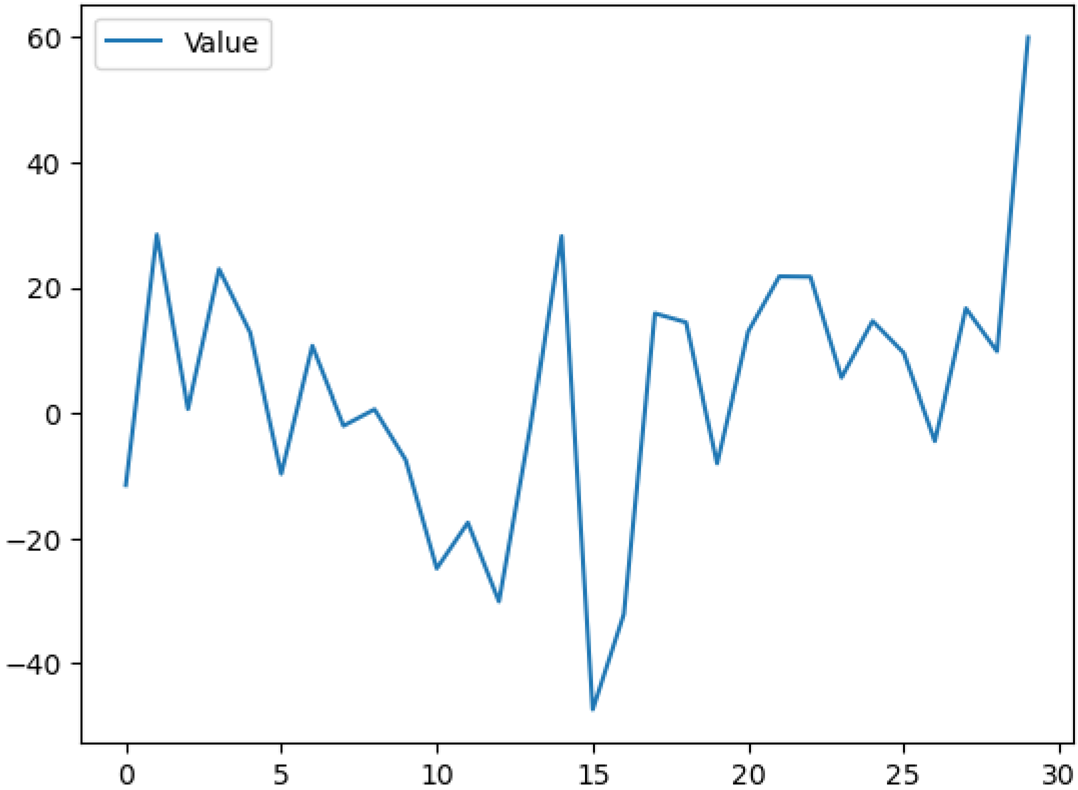
Out[72]:

	Timestamp	Value
0	2010-11-01T00:00:00	-11.522535
1	2010-11-02T00:00:00	28.454201
2	2010-11-03T00:00:00	0.640949
3	2010-11-04T00:00:00	22.949951
4	2010-11-05T00:00:00	12.803592

Next, plot the P10 predictions.

In [73]:
```
# Plot
prediction_df_p10.plot()
```

Out[73]: <Axes: >



The previous code only retrieved the P10 values and put them in a DataFrame. Now, complete the same process for the P50 and P90 values.

In [74]:
```
prediction_df_p50 = pd.DataFrame.from_dict(forecast_response['Forecast']['Predic
prediction_df_p90 = pd.DataFrame.from_dict(forecast_response['Forecast']['Predic
```

Comparing the prediction to actual results

After you obtain the DataFrames, the next task is to plot them together to determine the best fit.

In [75]:
```
# Start by creating a DataFrame to house the content. Here, Source will be which
results_df = pd.DataFrame(columns=['timestamp','value','Source'])

results_df.head()
```

Out[75]:

timestamp	value	Source

Import the observed values into the DataFrame:

In [78]:
```
import dateutil.parser
for index, row in actual_df.iterrows():
    #clean_timestamp = dateutil.parser.parse(index)
    results_df = results_df.append({'timestamp' : index , 'value' : row['Quantit
```

In [79]:
```
# To show the new DataFrame
results_df.head()
```

Out[79]:

timestamp	value	Source

In [80]:
```
# Now add the P10, P50, and P90 Values
for index, row in prediction_df_p10.iterrows():
    clean_timestamp = dateutil.parser.parse(row['Timestamp'])
    results_df = results_df.append({'timestamp' : clean_timestamp , 'value' : ro
for index, row in prediction_df_p50.iterrows():
    clean_timestamp = dateutil.parser.parse(row['Timestamp'])
    results_df = results_df.append({'timestamp' : clean_timestamp , 'value' : ro
for index, row in prediction_df_p90.iterrows():
    clean_timestamp = dateutil.parser.parse(row['Timestamp'])
    results_df = results_df.append({'timestamp' : clean_timestamp , 'value' : ro
```

By creating a pivot on the data, you can compare the actual P10, P50, and P90 values.

In [81]:
```
pivot_df = results_df.pivot(columns='Source', values='value', index="timestamp")
pivot_df
```

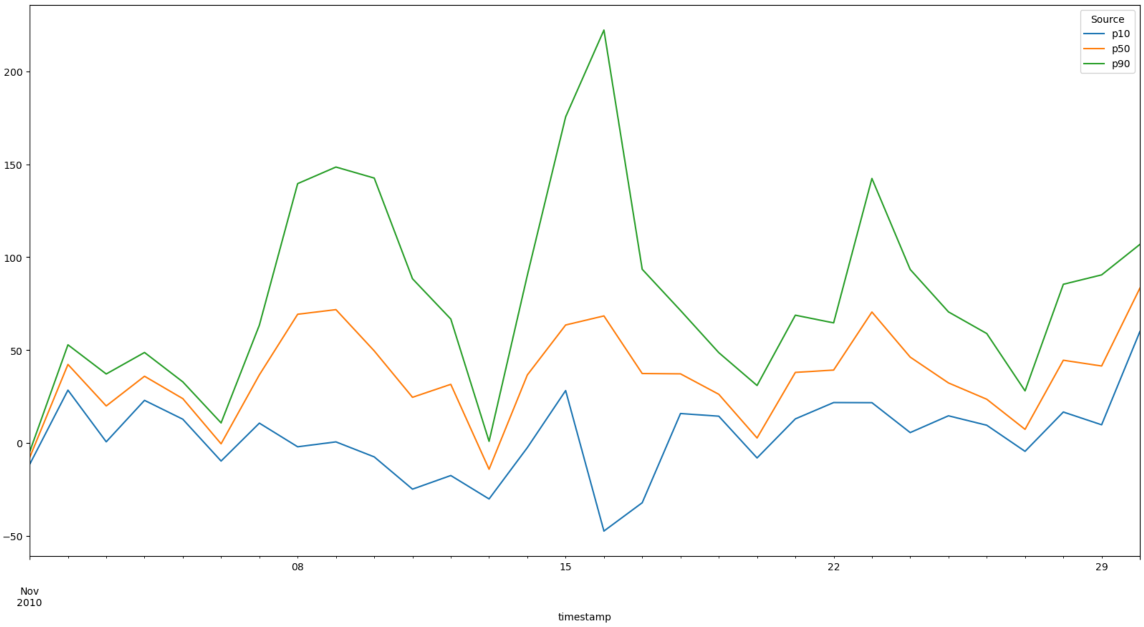
Out[81]:

Source	p10	p50	p90
timestamp			
2010-11-01	-11.522535	-7.825202	-4.750973
2010-11-02	28.454201	42.283855	52.847042
2010-11-03	0.640949	19.936911	37.150909
2010-11-04	22.949951	35.927731	48.719147
2010-11-05	12.803592	23.886587	32.908997
2010-11-06	-9.707537	-0.441220	10.825764
2010-11-07	10.690300	36.679199	63.439381
2010-11-08	-2.036983	69.281113	139.589523
2010-11-09	0.601570	71.781738	148.525055
2010-11-10	-7.471272	49.580791	142.583038
2010-11-11	-24.835560	24.593248	88.389664
2010-11-12	-17.501717	31.576620	66.728088
2010-11-13	-30.119797	-14.126997	0.895485
2010-11-14	-2.464260	36.637619	90.307953
2010-11-15	28.218744	63.509460	175.519623
2010-11-16	-47.382500	68.395561	222.234375
2010-11-17	-32.152744	37.393738	93.500023
2010-11-18	15.864470	37.222031	71.335739
2010-11-19	14.430343	26.226425	48.633919
2010-11-20	-8.041461	2.702861	30.949175
2010-11-21	12.983555	37.992786	68.788651
2010-11-22	21.770945	39.249336	64.649269
2010-11-23	21.711014	70.492798	142.370834
2010-11-24	5.607876	46.230358	93.399017
2010-11-25	14.643957	32.325615	70.557213
2010-11-26	9.558303	23.550568	58.906075
2010-11-27	-4.488002	7.346994	28.036549
2010-11-28	16.669582	44.541470	85.419495
2010-11-29	9.803969	41.439816	90.481834
2010-11-30	59.981339	83.342613	106.892830

Charts can be easier to analyze than the raw values.

In [82]:
```
pivot_df.plot(figsize=(20,10))
```

Out[82]:
```
<Axes: xlabel='timestamp'>
```



Examining the results

Hopefully, in the previous chart, you will see at least some correlation between the predicted values and the actual values. The correlation might not be good, and there could be several reasons for this outcome:

- The sales are mostly wholesale, but they do include some smaller orders.
- You held back data, which meant that an entire season wasn't included in the training data.
- You might have been missing useful category or sales promotion data.

Like all machine learning models, the results are as good as the data you use to train the model. As noted previously, the model could be improved with more data.

Task 7: Cleaning up

The following cells will clean up the resources that were created during the lab.

In [83]:
```
%store -r
```

In [84]:
```
print(forecast_arn)
```

```
arn:aws:forecast:us-east-1:839105429622:forecast/lab_4_deeparp_algo_forecast
```

In [85]:
```
forecast.delete_forecast(ForecastArn=forecast_arn)
time.sleep(60)
```

In [86]:
```
forecast.delete_predictor(PredictorArn=predictor_arn)
time.sleep(60)
```

In [87]:
```
forecast.delete_dataset_import_job(DatasetImportJobArn=ds_related_import_job_arn
```

```
---------------------------------------------------------------------------
ResourceInUseException                    Traceback (most recent call last)
Cell In[87], line 1
----> 1 forecast.delete_dataset_import_job(DatasetImportJobArn=ds_related_impor
t_job_arn)

File ~/anaconda3/envs/python3/lib/python3.10/site-packages/botocore/client.py:5
53, in ClientCreator._create_api_method.<locals>._api_call(self, *args, **kwarg
s)
    549     raise TypeError(
    550         f"{py_operation_name}() only accepts keyword arguments."
    551     )
    552 # The "self" in this scope is referring to the BaseClient.
--> 553 return self._make_api_call(operation_name, kwargs)

File ~/anaconda3/envs/python3/lib/python3.10/site-packages/botocore/client.py:1
009, in BaseClient._make_api_call(self, operation_name, api_params)
   1005     error_code = error_info.get("QueryErrorCode") or error_info.get(
   1006         "Code"
   1007     )
   1008     error_class = self.exceptions.from_code(error_code)
-> 1009     raise error_class(parsed_response, operation_name)
   1010 else:
   1011     return parsed_response

ResourceInUseException: An error occurred (ResourceInUseException) when calling
the DeleteDatasetImportJob operation: Operation not allowed when the resource a
rn:aws:forecast:us-east-1:839105429622:dataset-import-job/lab_4_rds/EP_DSIMPORT
_JOB_TARGET_RELATED is being referenced by these resources : [ arn:aws:forecas
t:us-east-1:839105429622:predictor/lab_4_deeparp_algo ]
```

In [ ]:
```
forecast.delete_dataset_import_job(DatasetImportJobArn=ds_import_job_arn)
```

In [ ]:
```
time.sleep(60)
```

In [ ]:
```
forecast.delete_dataset(DatasetArn=related_dataset_arn)
```

In [ ]:
```
forecast.delete_dataset(DatasetArn=dataset_arn)
```

In [ ]:
```
time.sleep(60)
```

In [ ]:
```
forecast.delete_dataset_group(DatasetGroupArn=dataset_group_arn)
```

In [ ]: