In [145…

```python
# Imports
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import random
import xgboost as xgb
import wandb
import pickle

from sklearn.model_selection import train_test_split
from statsmodels.tsa.arima.model import ARIMA
from sklearn.model_selection import train_test_split
from statsmodels.graphics.tsaplots import plot_pacf
from pmdarima import auto_arima
from statsmodels.tsa.statespace.sarimax import SARIMAX
from sklearn.metrics import mean_squared_error
from wandb.xgboost import wandb_callback
```

In [3]:

```python
# Import all the datasets provided from Kaggle
holiday_events_data = pd.read_csv("kaggle_data/holidays_events.csv", parse_date
oil_data = pd.read_csv("kaggle_data/oil.csv", parse_dates=["date"])
stores_data = pd.read_csv("kaggle_data/stores.csv")
transactions_data = pd.read_csv("kaggle_data/transactions.csv")

# For predictions/Machine Learning problem
train_data = pd.read_csv("kaggle_data/train.csv")
test_data = pd.read_csv("kaggle_data/test.csv")
sample_submission_data = pd.read_csv("kaggle_data/sample_submission.csv")
```

In [264…

```python
holiday_events_data.head()
```

Out[264]:

	date	type	locale	locale_name	description	transferred
0	2012-03-02	Holiday	Local	Manta	Fundacion de Manta	False
1	2012-04-01	Holiday	Regional	Cotopaxi	Provincializacion de Cotopaxi	False
2	2012-04-12	Holiday	Local	Cuenca	Fundacion de Cuenca	False
3	2012-04-14	Holiday	Local	Libertad	Cantonizacion de Libertad	False
4	2012-04-21	Holiday	Local	Riobamba	Cantonizacion de Riobamba	False

In [5]:

```python
# dcoilwtico column is the Daily oil price. Includes values during both the tra
oil_data.head()
```

Out[5]:

	date	dcoilwtico
0	2013-01-01	NaN
1	2013-01-02	93.14
2	2013-01-03	92.97
3	2013-01-04	93.12
4	2013-01-07	93.20

In [6]:
```
# Type is the grocery store chain potentially where A Megamaxi, B Gran Aki, C S
# Cluster is a grouping of similar stores
stores_data.head()
```

Out[6]:

	store_nbr	city	state	type	cluster
0	1	Quito	Pichincha	D	13
1	2	Quito	Pichincha	D	13
2	3	Quito	Pichincha	D	8
3	4	Quito	Pichincha	D	9
4	5	Santo Domingo	Santo Domingo de los Tsachilas	D	4

In [7]:
```
stores_data["city"].value_counts()
```

Out[7]:
```
Quito            18
Guayaquil         8
Cuenca            3
Santo Domingo     3
Manta             2
Latacunga         2
Machala           2
Ambato            2
Quevedo           1
Esmeraldas        1
Loja              1
Libertad          1
Playas            1
Daule             1
Babahoyo          1
Salinas           1
Puyo              1
Guaranda          1
Ibarra            1
Riobamba          1
Cayambe           1
El Carmen         1
Name: city, dtype: int64
```

In [8]:
```
stores_data.shape
```

Out[8]:
```
(54, 5)
```

In [9]:
```
transactions_data.head()
```

Out[9]:

	date	store_nbr	transactions
0	2013-01-01	25	770
1	2013-01-02	1	2111
2	2013-01-02	2	2358
3	2013-01-02	3	3487
4	2013-01-02	4	1922

In [10]:
```
transactions_data["date"].min()
```

Out[10]:
```
'2013-01-01'
```

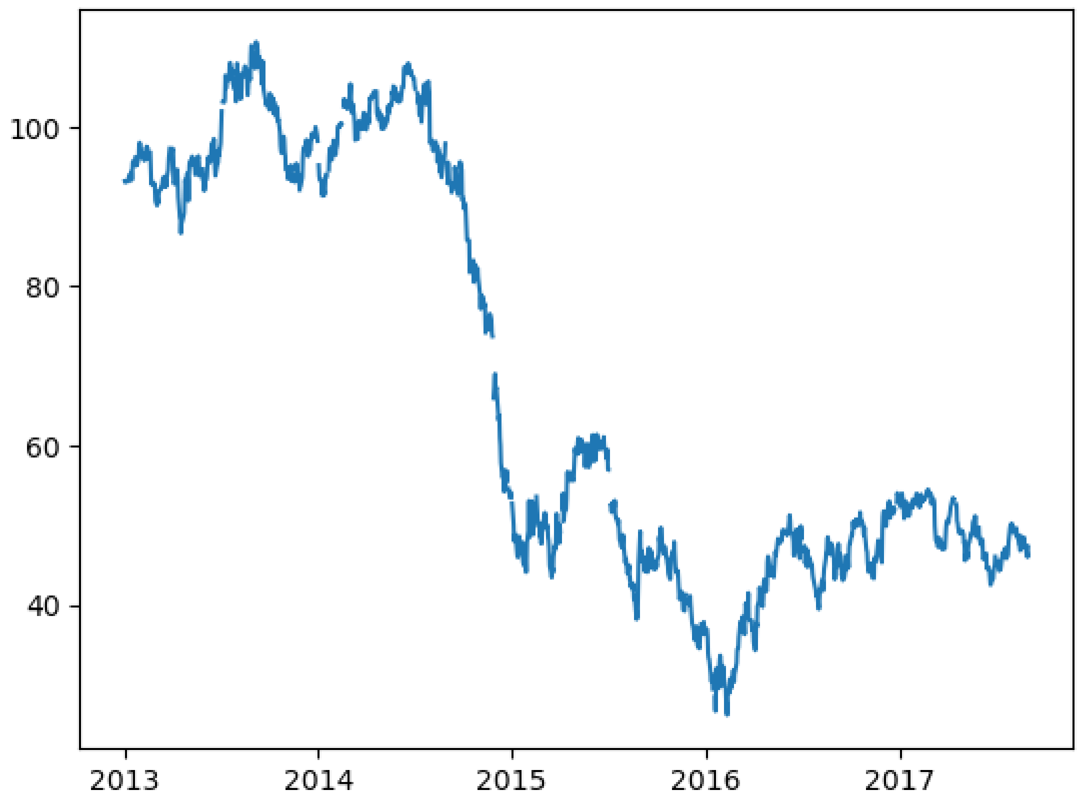
In [11]:
```
transactions_data["date"].max()
```

Out[11]:
```
'2017-08-15'
```

Now lets look into the data.

In [12]:
```
# The problem states that Ecuador is an oil-dependent country and it's economic
# So, we should look into the relationship between oil and transactions to con

plt.plot(oil_data["date"], oil_data["dcoilwtico"])
```

Out[12]:
```
[<matplotlib.lines.Line2D at 0x7f7ec01aa520>]
```



In [13]:
```
# Transactions data has a lot of rows for each store. If we want to find the re
# would be to take the average transactions of all the stores to see if it had
transactions_sum_data = transactions_data.groupby("date")["transactions"].mean(

# We need to do an inner join and only the transaction sums with
transactions_sum_data
```

Out[13]:
```
date
2013-01-01      770.000000
2013-01-02     2026.413043
2013-01-03     1706.608696
2013-01-04     1706.391304
2013-01-05     2034.195652
                  ...
2017-08-11     1658.351852
2017-08-12     1665.314815
2017-08-13     1592.462963
2017-08-14     1582.370370
2017-08-15     1602.981481
Name: transactions, Length: 1682, dtype: float64
```

In [14]:
```
# Ask to use Tableou for data analysis, python isn't the best
```

In [15]:
```
train_data.head()
```

Out[15]:

	id	date	store_nbr	family	sales	onpromotion
0	0	2013-01-01	1	AUTOMOTIVE	0.0	0
1	1	2013-01-01	1	BABY CARE	0.0	0
2	2	2013-01-01	1	BEAUTY	0.0	0
3	3	2013-01-01	1	BEVERAGES	0.0	0
4	4	2013-01-01	1	BOOKS	0.0	0

In [16]:
```
test_data.head()
```

Out[16]:

	id	date	store_nbr	family	onpromotion
0	3000888	2017-08-16	1	AUTOMOTIVE	0
1	3000889	2017-08-16	1	BABY CARE	0
2	3000890	2017-08-16	1	BEAUTY	2
3	3000891	2017-08-16	1	BEVERAGES	20
4	3000892	2017-08-16	1	BOOKS	0

In [17]:
```
# Lets find the list of outlier holidays--holidays that impacted average sales.
```

In [18]:
```
avg_sales = train_data.groupby("date")["sales"].mean()
```

In [19]:
```
def find_outliers_IQR(df):
   q1 = df.quantile(0.25)
   q3 = df.quantile(0.75)
   IQR=q3-q1
   outliers = df[((df<(q1-1.5*IQR)) | (df>(q3+1.5*IQR)))]
   return outliers
```

In [20]:
```
outliers = find_outliers_IQR(avg_sales)
outliers.index
# Bad
```

Out[20]:
```
Index(['2016-04-18', '2017-01-02', '2017-04-01', '2017-05-01', '2017-06-04'],
dtype='object', name='date')
```

In [21]:
```
def find_outliers(data, window, z_thresh):
    # Calculate the rolling mean and standard deviation
    roll_mean = data.rolling(window).mean()
    roll_std = data.rolling(window).std()

    outliers = (np.abs(data - roll_mean) > z_thresh * roll_std)

    return data.index[outliers]

outliers = find_outliers(avg_sales, window=30, z_thresh=2.5)
print(avg_sales[outliers].head())
```

```
date
2013-06-02    357.855497
2013-09-01    359.374984
2013-12-01    391.816571
2014-01-01      4.827197
2014-03-01    511.425509
Name: sales, dtype: float64
```

In [22]:
```
avg_sales.rolling(5).std()
```

Out[22]:
```
date
2013-01-01           NaN
2013-01-02           NaN
2013-01-03           NaN
2013-01-04           NaN
2013-01-05    111.453791
                 ...
2017-08-11     38.672092
2017-08-12     38.175788
2017-08-13     47.043375
2017-08-14     45.716734
2017-08-15     25.042929
Name: sales, Length: 1684, dtype: float64
```

In [23]:
```
from datetime import datetime

dates = []
for i in holiday_events_data["date"]:
    dates.append(str(i.date()))

outlier_inds = []
outlier_dates = []
for i in outliers:
    if i in dates:
        outlier_inds.append(dates.index(i))
        outlier_dates.append(i)

print(outliers)
```

```
Index(['2013-06-02', '2013-09-01', '2013-12-01', '2014-01-01', '2014-03-01',
       '2014-06-01', '2014-07-01', '2014-07-02', '2014-07-06', '2014-09-01',
       '2014-09-06', '2014-09-07', '2015-01-01', '2015-03-01', '2015-05-31',
       '2015-09-06', '2016-01-01', '2016-04-02', '2016-04-03', '2016-04-17',
       '2016-04-18', '2016-09-03', '2016-09-04', '2017-01-01', '2017-04-01',
       '2017-05-01', '2017-06-04'],
      dtype='object', name='date')
```

In [24]:

```
holiday_outliers = holiday_events_data.loc[outlier_inds]
holiday_outliers = holiday_outliers.assign(avg_sales = list(avg_sales[outlier_c
holiday_outliers
```

Out[24]:

	date	type	locale	locale_name	description	transferred	avg_sales
92	2014-01-01	Holiday	National	Ecuador	Primer dia del ano	False	4.827197
117	2014-07-01	Event	National	Ecuador	Mundial de futbol Brasil: Octavos de Final	False	404.310110
159	2015-01-01	Holiday	National	Ecuador	Primer dia del ano	False	7.168135
211	2016-01-01	Holiday	National	Ecuador	Primer dia del ano	False	9.221882
220	2016-04-17	Event	National	Ecuador	Terremoto Manabi+1	False	713.711414
221	2016-04-18	Event	National	Ecuador	Terremoto Manabi+2	False	755.286535
297	2017-01-01	Holiday	National	Ecuador	Primer dia del ano	True	6.780304
302	2017-04-01	Holiday	Regional	Cotopaxi	Provincializacion de Cotopaxi	False	821.034771
308	2017-05-01	Holiday	National	Ecuador	Dia del Trabajo	False	733.276861

In [25]:

```
local_holidays = holiday_events_data[holiday_events_data['locale'] == 'Local']
local_holidays
```

Out[25]:

	date	type	locale	locale_name	description	transferred
0	2012-03-02	Holiday	Local	Manta	Fundacion de Manta	False
2	2012-04-12	Holiday	Local	Cuenca	Fundacion de Cuenca	False
3	2012-04-14	Holiday	Local	Libertad	Cantonizacion de Libertad	False
4	2012-04-21	Holiday	Local	Riobamba	Cantonizacion de Riobamba	False
5	2012-05-12	Holiday	Local	Puyo	Cantonizacion del Puyo	False
...	...	...	...	...	...	...
339	2017-12-05	Additional	Local	Quito	Fundacion de Quito-1	False
340	2017-12-06	Holiday	Local	Quito	Fundacion de Quito	True
341	2017-12-08	Holiday	Local	Loja	Fundacion de Loja	False
342	2017-12-08	Transfer	Local	Quito	Traslado Fundacion de Quito	False
344	2017-12-22	Holiday	Local	Salinas	Cantonizacion de Salinas	False

152 rows × 6 columns

Machine Learning:

In this competition, you will predict sales for the thousands of product families sold at Favorita stores located in Ecuador. Favorita stores is a large Ecuadorian-based grocery retailer.

In [26]:
```
# Feature engineering: colunn for is local holidays, another column for is_regi
```

In [27]:
```
train_data.head()
```

Out[27]:

	id	date	store_nbr	family	sales	onpromotion
0	0	2013-01-01	1	AUTOMOTIVE	0.0	0
1	1	2013-01-01	1	BABY CARE	0.0	0
2	2	2013-01-01	1	BEAUTY	0.0	0
3	3	2013-01-01	1	BEVERAGES	0.0	0
4	4	2013-01-01	1	BOOKS	0.0	0

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

Out[28]:

	id	date	store_nbr	family	onpromotion
0	3000888	2017-08-16	1	AUTOMOTIVE	0
1	3000889	2017-08-16	1	BABY CARE	0
2	3000890	2017-08-16	1	BEAUTY	2
3	3000891	2017-08-16	1	BEVERAGES	20
4	3000892	2017-08-16	1	BOOKS	0

In [29]:
```python
# Next, we need to map train data to stores_data to get the city, from the city

local_holidays = holiday_events_data[holiday_events_data['locale'] == 'Local']
train_data_with_city = pd.merge(train_data, stores_data[['store_nbr', 'city']],
train_data_with_city['date'] = pd.to_datetime(train_data_with_city['date'])
local_holidays['date'] = pd.to_datetime(local_holidays['date'])

temp = local_holidays.drop(["locale", "type", "description", "transferred"], ax
temp["local_holiday"] = 1
local_holidays = temp

sales_with_holidays = pd.merge(train_data_with_city, local_holidays, left_on=['
sales_with_holidays = sales_with_holidays.drop(["locale_name"], axis = 1)
sales_with_holidays["local_holiday"] = sales_with_holidays["local_holiday"].fil

non_local_holidays = holiday_events_data[holiday_events_data['locale'] != 'Loca
non_local_holidays['date'] = pd.to_datetime(non_local_holidays['date'])

temp_2 = non_local_holidays.drop(["locale", "type", "description", "transferred
temp_2["non_local_holiday"] = 1
non_local_holidays = temp_2

sales_with_holidays = pd.merge(sales_with_holidays, non_local_holidays, left_on
sales_with_holidays = sales_with_holidays.drop(["locale_name"], axis = 1)
sales_with_holidays["non_local_holiday"] = sales_with_holidays["non_local_holid
```

```
/var/folders/3f/8w_4h_hj2915c7c2mpbt70sr0000gn/T/ipykernel_4604/3690293686.py:
6: 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/st
able/user_guide/indexing.html#returning-a-view-versus-a-copy
  local_holidays['date'] = pd.to_datetime(local_holidays['date'])
/var/folders/3f/8w_4h_hj2915c7c2mpbt70sr0000gn/T/ipykernel_4604/3690293686.py:
17: 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/st
able/user_guide/indexing.html#returning-a-view-versus-a-copy
  non_local_holidays['date'] = pd.to_datetime(non_local_holidays['date'])
```

In [30]:
```python
sales_with_holidays["non_local_holiday"].value_counts()
```

Out[30]:
```
0.0    2716032
1.0     294030
Name: non_local_holiday, dtype: int64
```

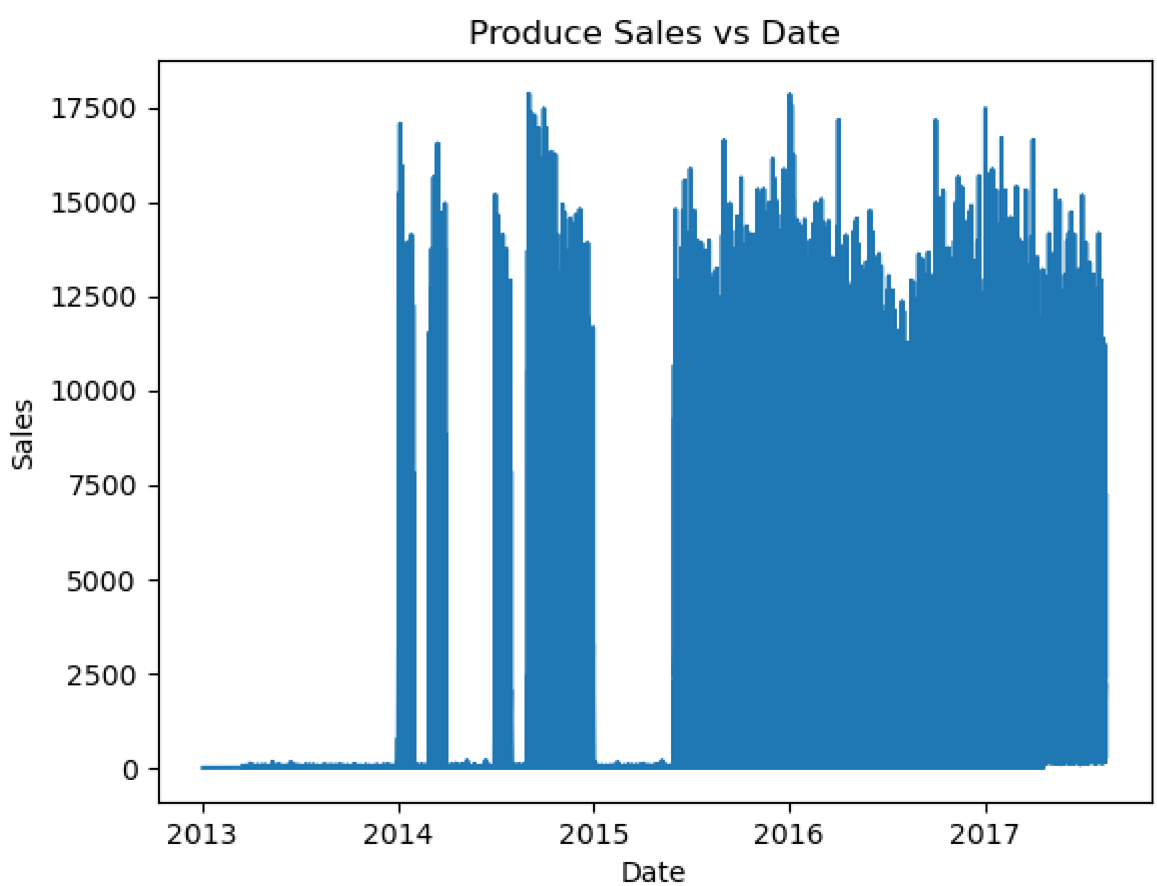
In [31]:
```python
sales_with_holidays.head()
```

Out[31]:

	id	date	store_nbr	family	sales	onpromotion	city	local_holiday	non_local_holid
0	0	2013-01-01	1	AUTOMOTIVE	0.0	0	Quito	0.0	
1	1	2013-01-01	1	BABY CARE	0.0	0	Quito	0.0	
2	2	2013-01-01	1	BEAUTY	0.0	0	Quito	0.0	
3	3	2013-01-01	1	BEVERAGES	0.0	0	Quito	0.0	
4	4	2013-01-01	1	BOOKS	0.0	0	Quito	0.0	

In [152…

```
plt.plot(sales_with_holidays[sales_with_holidays["family"] == "PRODUCE"]["date'
plt.xlabel('Date')
plt.ylabel('Sales')
plt.title('Produce Sales vs Date')
plt.show()
```



In [33]:

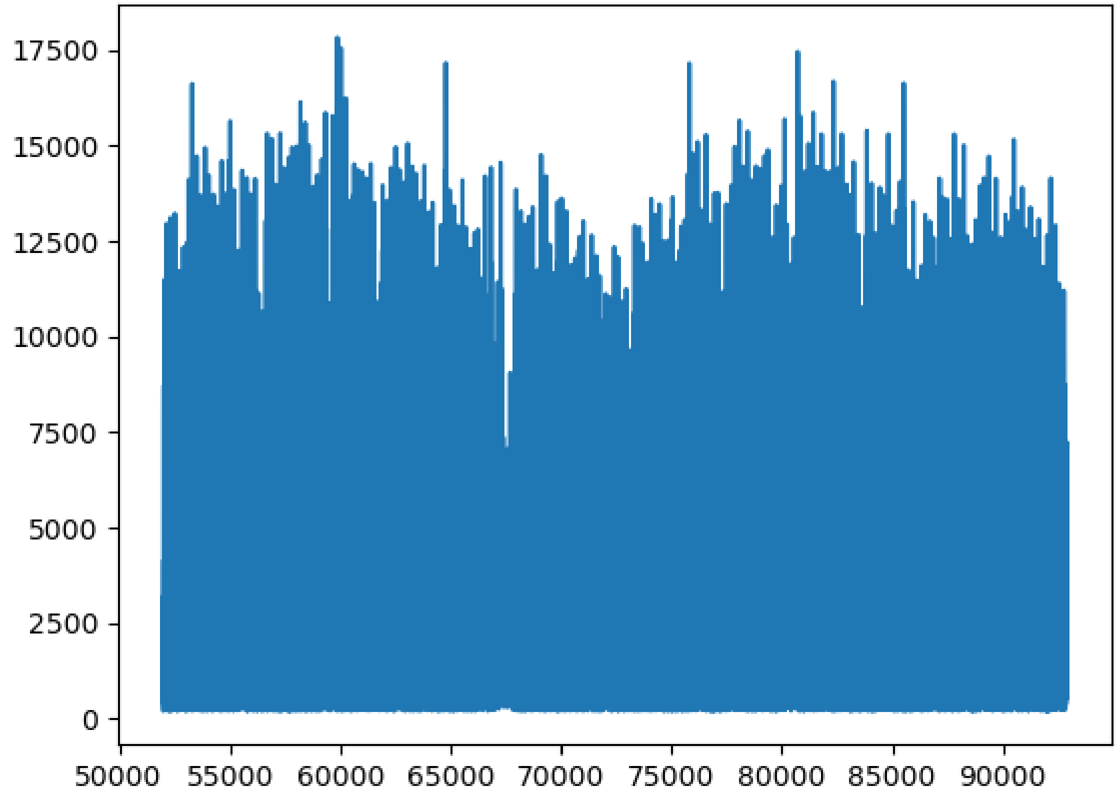
```
from statsmodels.graphics.tsaplots import plot_acf
from statsmodels.tsa.stattools import adfuller
```

In [183…

```
# lets check the ACF plots to find a method to impute the rows using more accu
x_part = sales_with_holidays[sales_with_holidays["family"] == "PRODUCE"]["date'
y_part = sales_with_holidays[sales_with_holidays["family"] == "PRODUCE"]["sales
```

```
y_part = y_part.reset_index(drop = True)[52000:]

plt.plot(y_part)
```

Out[183]: [<matplotlib.lines.Line2D at 0x7f7ef35d31c0>]



In [184…

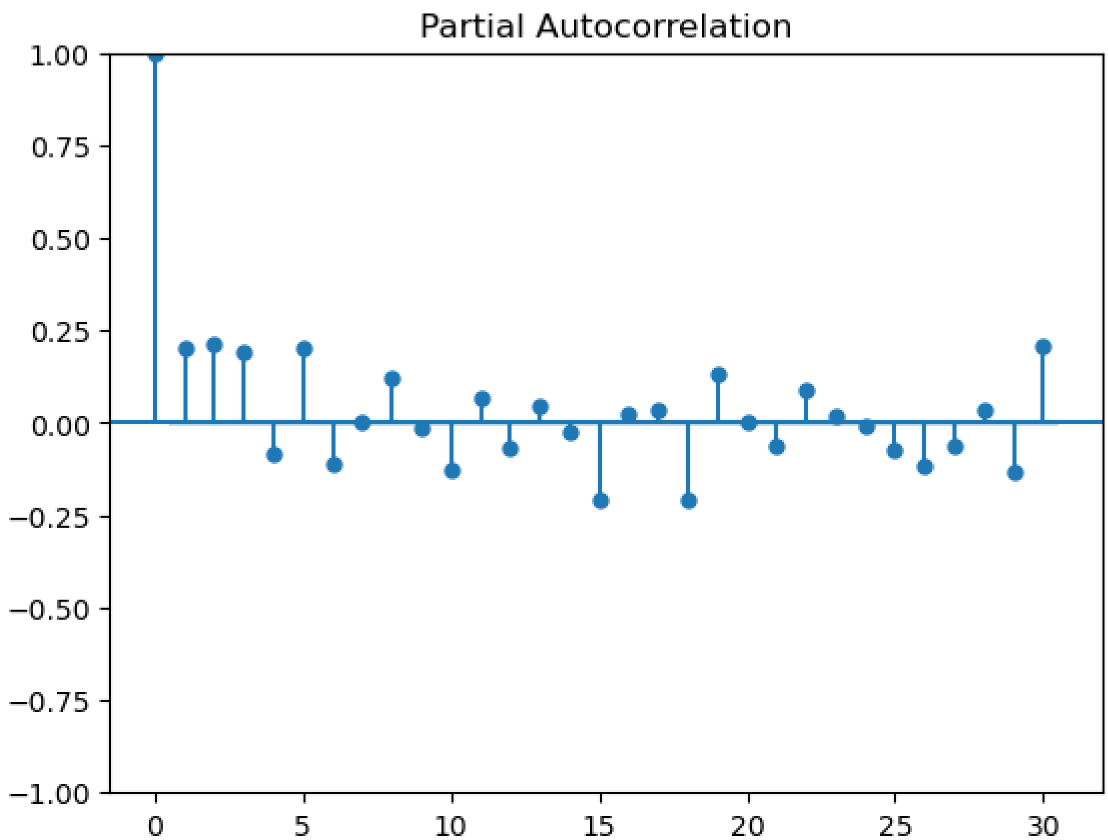
```
# Since the p-value is < 0.05 we can assume the time-series is stationary

# Hypothesis test
result = adfuller(y_part)
print('ADF Statistic: %f' % result[0])
print('p-value: %f' % result[1])
print('Critical Values:')
for key, value in result[4].items():
    print('\t%s: %.3f' % (key, value))
```

```
ADF Statistic: -11.286070
p-value: 0.000000
Critical Values:
	1%: -3.431
	5%: -2.862
	10%: -2.567
```

In [182…

```
# Showing the PACF for fun
plot_pacf(y_part, lags=30)
plt.show()
```

```
/Users/chrisapton/opt/anaconda3/lib/python3.8/site-packages/statsmodels/graphi
cs/tsaplots.py:348: FutureWarning: The default method 'yw' can produce PACF va
lues outside of the [-1,1] interval. After 0.13, the default will change touna
djusted Yule-Walker ('ywm'). You can use this method now by setting method='yw
m'.
  warnings.warn(
```



In [48]:

```
# sampling the produce rows to fill the data

produce_rows = sales_with_holidays[sales_with_holidays["family"] == "PRODUCE"]
good_rows = produce_rows[produce_rows["sales"] >= 200]
bad_rows = produce_rows[produce_rows["sales"] < 200]
```

In [149…

```
# Used auto arima to find better parameters for the arima model
#model = auto_arima(train, trace=True, error_action='ignore', suppress_warnings
# best is 5, 0, 5
print(5, 0, 5)
```

```
5 0 5
```

In [148…

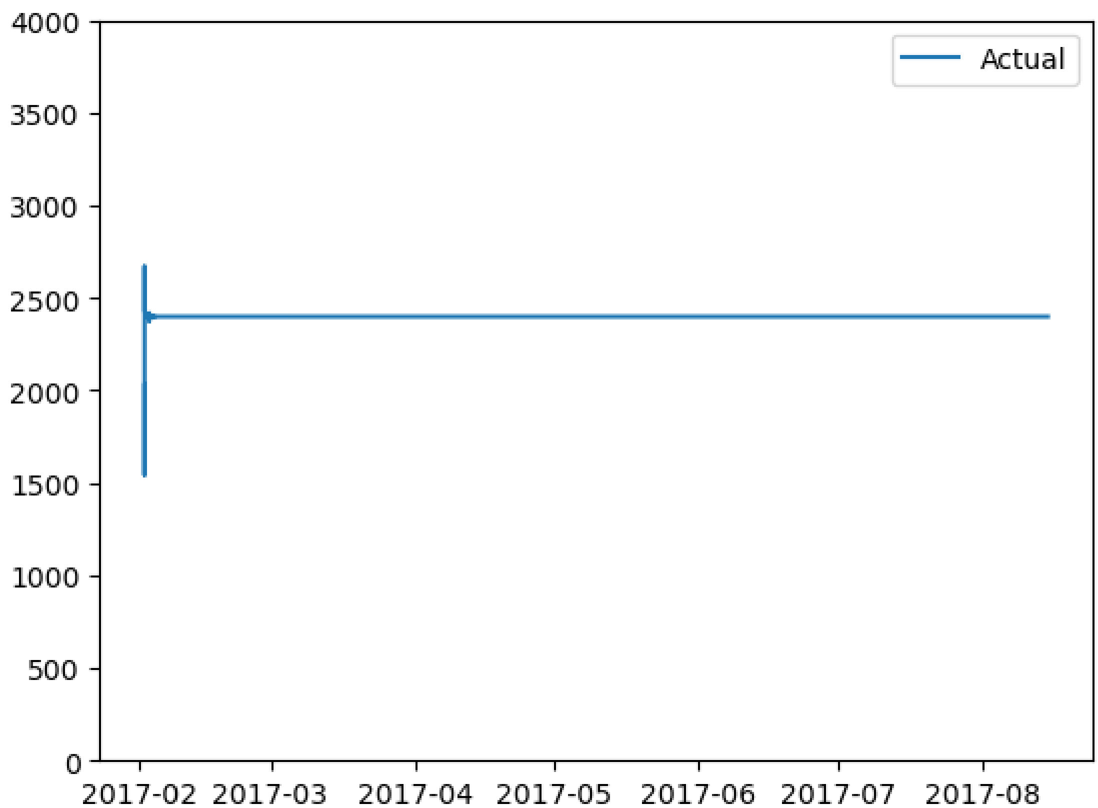
```
df = pd.DataFrame(data={'Time': good_rows["date"].values, 'Value': good_rows["s

train_size = int(len(df) * 0.80)  # 80% for training
train, test = df[0:train_size], df[train_size:len(df)]

# Auto arima to find the best parameters



model = ARIMA(train, order=(5, 0, 5))
model_fit = model.fit()
predictions = model_fit.predict(start=len(train), end=len(train)+len(test)-1, t
predictions_df = pd.DataFrame(predictions.values, index=test.index, columns=['I
```

```
/Users/chrisapton/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/ba
se/tsa_model.py:471: ValueWarning: A date index has been provided, but it has
no associated frequency information and so will be ignored when e.g. forecasti
ng.
  self._init_dates(dates, freq)
/Users/chrisapton/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/ba
se/tsa_model.py:471: ValueWarning: A date index has been provided, but it has
no associated frequency information and so will be ignored when e.g. forecasti
ng.
  self._init_dates(dates, freq)
/Users/chrisapton/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/ba
se/tsa_model.py:471: ValueWarning: A date index has been provided, but it has
no associated frequency information and so will be ignored when e.g. forecasti
ng.
  self._init_dates(dates, freq)
/Users/chrisapton/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/ba
se/tsa_model.py:834: ValueWarning: No supported index is available. Prediction
results will be given with an integer index beginning at `start`.
  return get_prediction_index(
```

It turned out, the arima model didn't really do much better than just taking the mean of the data. So, just to make things easier, I'll just impute the data using the mean.

In [151…

```
# Plot the ARIMA model predictions to show it's unusefulness
plt.plot(predictions_df["Prediction"].index, predictions_df["Prediction"].value
plt.legend(loc='best')
plt.ylim(0, 4000)
plt.show()
```



In [178…

```
# Comparing the line to the mean of the data the ARIMA model was trained from.
print(np.mean(good_rows["sales"]))
```

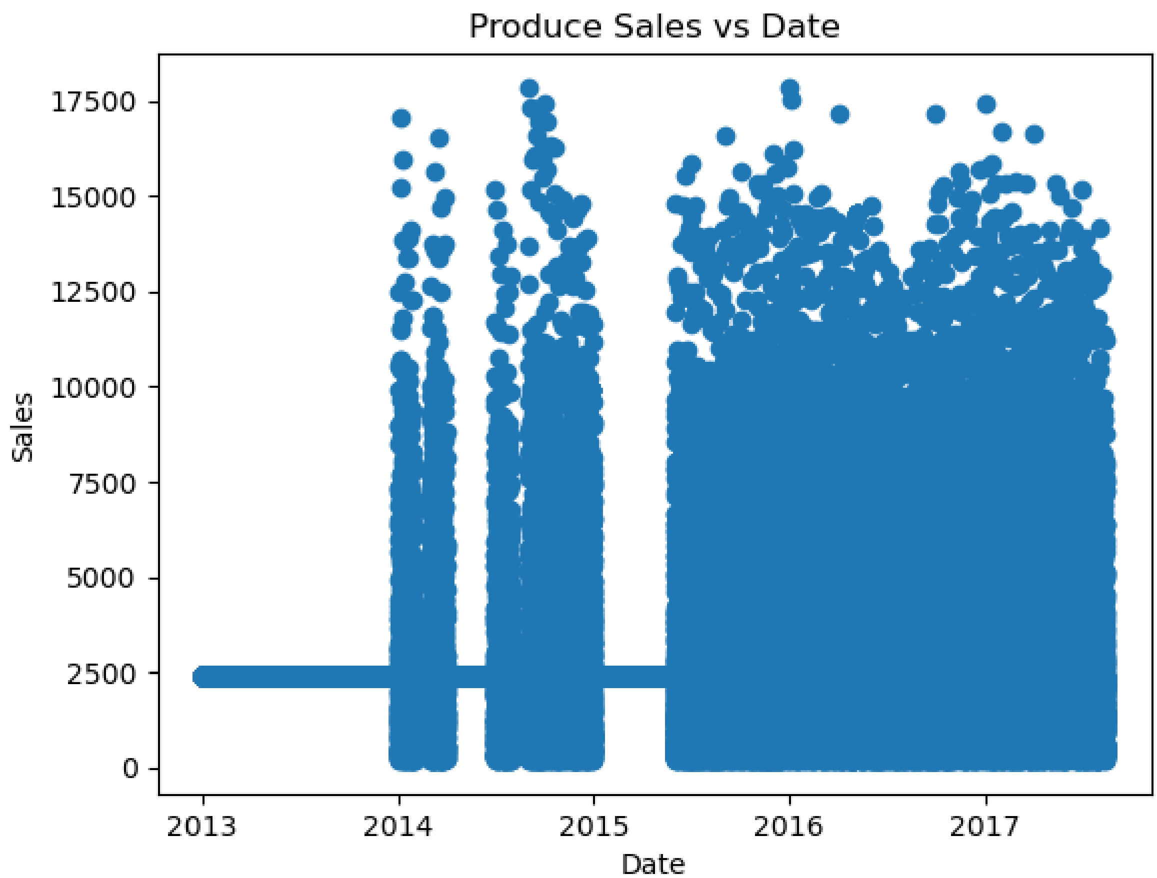
Out[178]: 2409.716470790755

In [185…
```
# Can ignore, testing code

#temp = model_fit.predict(start=len(train), end=len(train) + len(bad_rows["sale
#counter = 0
#for i in list(bad_rows["sales"].index):
#    bad_rows["sales"][i] = temp.values[counter]
#    counter += 1
```

In [180…
```
# I'll just impute by mean
for i in list(bad_rows["sales"].index):
    bad_rows["sales"][i] = np.mean(good_rows["sales"])

updated_produce = pd.concat([good_rows, bad_rows])
updated_produce = updated_produce.drop(["date", "store_nbr", "family", "onpromo

df_merged = pd.merge(sales_with_holidays, updated_produce, left_on=['id'], righ
df_merged['sales'] = df_merged['sales_y'].where(df_merged['sales_y'].notna(), c
df_merged = df_merged.drop(['sales_x', 'sales_y'], axis=1)
sales_with_holidays = df_merged
data = sales_with_holidays
```

```
/var/folders/3f/8w_4h_hj2915c7c2mpbt70sr0000gn/T/ipykernel_4604/3025343523.py:
6: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/st
able/user_guide/indexing.html#returning-a-view-versus-a-copy
  bad_rows["sales"][i] = np.mean(good_rows["sales"])
```

In [186…
```
plt.plot(sales_with_holidays[sales_with_holidays["family"] == "PRODUCE"]["date'
plt.xlabel('Date')
plt.ylabel('Sales')
plt.title('Produce Sales vs Date')
plt.show()
```



In [187…

```
def fill_na_with_avg(series):
    for idx, value in series[series.isnull()].iteritems():
        # get indices of non-NaN neighbors
        idx_before = series.loc[:idx].last_valid_index()
        idx_after = series.loc[idx:].first_valid_index()

        if pd.isnull(idx_before) and pd.isnull(idx_after):  # if no non-NaN nei
            continue
        elif pd.isnull(idx_before):  # if no non-NaN before
            series[idx] = series[idx_after]
        elif pd.isnull(idx_after):  # if no non-NaN after
            series[idx] = series[idx_before]
        else:  # if non-NaN neighbors exist before and after
            series[idx] = (series[idx_before] + series[idx_after]) / 2
    return series
```

In [188…

```
# Next, lets add oil price
# First, we need to remove the NaN values in the oil-data by taking the average
oil_data["dcoilwtico"] = fill_na_with_avg(oil_data["dcoilwtico"])
print(sum(oil_data["dcoilwtico"].isnull()))

sales_with_holidays = pd.merge(sales_with_holidays, oil_data, left_on=['date'],
sales_with_holidays = sales_with_holidays.rename(columns={'dcoilwtico': 'oil_pr
sales_with_holidays.head()
```

```
/var/folders/3f/8w_4h_hj2915c7c2mpbt70sr0000gn/T/ipykernel_4604/2859325137.py:
10: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/st
able/user_guide/indexing.html#returning-a-view-versus-a-copy
  series[idx] = series[idx_after]
/var/folders/3f/8w_4h_hj2915c7c2mpbt70sr0000gn/T/ipykernel_4604/2859325137.py:
14: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/st
able/user_guide/indexing.html#returning-a-view-versus-a-copy
  series[idx] = (series[idx_before] + series[idx_after]) / 2
```

0

Out[188]:

	id	date	store_nbr	family	onpromotion	city	local_holiday	non_local_holiday	sa
0	0	2013-01-01	1	AUTOMOTIVE	0	Quito	0.0	1.0	
1	1	2013-01-01	1	BABY CARE	0	Quito	0.0	1.0	
2	2	2013-01-01	1	BEAUTY	0	Quito	0.0	1.0	
3	3	2013-01-01	1	BEVERAGES	0	Quito	0.0	1.0	
4	4	2013-01-01	1	BOOKS	0	Quito	0.0	1.0	

In [347…

```
# sales_with_holidays
```

In [348…

```
# Thing I realized, trying to use these other datasets into the train data wont
# Train data originally and scrap the work above. The only cleaning so far wil
```

In [349…

```
# I can still use stores_data to add the city, type and cluster to the data
```

In [189…

```
data = data.drop(["id", "local_holiday", "non_local_holiday", "city"], axis = 1
data
```

Out[189]:

	date	store_nbr	family	onpromotion	sales
0	2013-01-01	1	AUTOMOTIVE	0	0.000
1	2013-01-01	1	BABY CARE	0	0.000
2	2013-01-01	1	BEAUTY	0	0.000
3	2013-01-01	1	BEVERAGES	0	0.000
4	2013-01-01	1	BOOKS	0	0.000
...	...	...	...	...	...
3011725	2017-08-15	9	POULTRY	0	438.133
3011726	2017-08-15	9	PREPARED FOODS	1	154.553
3011727	2017-08-15	9	PRODUCE	148	2419.729
3011728	2017-08-15	9	SCHOOL AND OFFICE SUPPLIES	8	121.000
3011729	2017-08-15	9	SEAFOOD	0	16.000

3011730 rows × 5 columns

In [190…

```
# Cleaning function
def clean_data(data):
    temp = pd.merge(data, stores_data, left_on=['store_nbr'], right_on=['store_
    temp['year'] = temp['date'].dt.year
    temp['month'] = temp['date'].dt.month
    temp['day'] = temp['date'].dt.day
    temp['dayofweek'] = temp['date'].dt.dayofweek
    temp['date'] = temp['date'].astype(int) / 10**9
    temp = pd.get_dummies(temp, columns=['store_nbr', 'family', 'city', 'state'
    return temp
```

In [191…

```
train_data = clean_data(data)
train_data.head()
```

Out[191]:

	date	onpromotion	sales	year	month	day	dayofweek	store_nbr_1	store_nbr_2
0	1.356998e+09	0	0.0	2013	1	1	1	1	0
1	1.356998e+09	0	0.0	2013	1	1	1	1	0
2	1.356998e+09	0	0.0	2013	1	1	1	1	0
3	1.356998e+09	0	0.0	2013	1	1	1	1	0
4	1.356998e+09	0	0.0	2013	1	1	1	1	0

5 rows × 154 columns

In [247…

```
# Can ignore, just for fun
# Start off with simple linear regression
#from sklearn.linear_model import LinearRegression
#reg = LinearRegression().fit(X, y)
```

Out[247]: 0.5892504542876198

In [201…

```
# ARIMAX code here

df = train_data[0:100]

# Selecting endogenous and exogenous variables
y = df["sales"]
X = df.drop(["sales"], axis = 1)


# Splitting into train and test (example: 80% for train, 20% for test)
train_size = int(len(df) * 0.8)
train_endog, test_endog = y[:train_size], y[train_size:]
train_exog, test_exog = X[:train_size], X[train_size:]

model = SARIMAX(train_endog, order=(1, 1, 1), seasonal_order=(1, 1, 1, 12), exo
model_fit = model.fit(disp=False)

predictions = model_fit.predict(start=len(train_exog), end=len(train_exog) + le
```

In [219…

```
start = len(train)
end = start + len(X_test) + len(test_exog) - 1 - (643078 - 602346)
model_fit.predict(start, end, exog=X_test)
```

Out[219]:

```
40792     4.173944e+05
40793     4.173613e+05
40794     4.177396e+05
40795     4.173448e+05
40796     4.173771e+05
              ...
602421    6.171017e+06
602422    6.170884e+06
602423    6.170761e+06
602424    6.171259e+06
602425    6.170462e+06
Name: predicted_mean, Length: 561634, dtype: float64
```

In [ ]:

```
y = train_data["sales"]
X = train_data.drop(["sales"], axis = 1)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random
```

In [228…

```
model = xgb.XGBRegressor()
model.fit(X_train,y_train)
```

Out[228]:

```
XGBRegressor(base_score=0.5, booster='gbtree', callbacks=None,
             colsample_bylevel=1, colsample_bynode=1, colsample_bytree=1,
             early_stopping_rounds=None, enable_categorical=False,
             eval_metric=None, gamma=0, gpu_id=-1, grow_policy='depthwise',
             importance_type=None, interaction_constraints='',
             learning_rate=0.300000012, max_bin=256, max_cat_to_onehot=4,
             max_delta_step=0, max_depth=6, max_leaves=0, min_child_weight=1,
             missing=nan, monotone_constraints='()', n_estimators=100, n_jobs=
0,
             num_parallel_tree=1, predictor='auto', random_state=0, reg_alpha=
0,
             reg_lambda=1, ...)
```

In [263…

```
preds = model.predict(X_test)
rmse = np.sqrt(mean_squared_error(y_test, preds))
print("RMSE: %f" % (rmse))
```

```
RMSE: 262.566972
```

In [262…

```
print(model.score(X_train, y_train))
print(model.score(X_test, y_test))
```

```
0.9989728848404914
0.9467731620600427
```

In [231…

```
# cleaning test data
test_data = pd.read_csv("kaggle_data/test.csv")
test_data['date'] = pd.to_datetime(test_data['date'])
ids = test_data["id"]
test_data = test_data.drop(["id"], axis = 1)
test_data = clean_data(test_data)
test_data.head()
```

Out[231]:

	date	onpromotion	year	month	day	dayofweek	store_nbr_1	store_nbr_2	store_
0	1.502842e+09	0	2017	8	16	2	1	0	
1	1.502842e+09	0	2017	8	16	2	1	0	
2	1.502842e+09	2	2017	8	16	2	1	0	
3	1.502842e+09	20	2017	8	16	2	1	0	
4	1.502842e+09	0	2017	8	16	2	1	0	

5 rows × 153 columns

In [259…

```
X_pred = test_data
y_pred = model.predict(X_pred)
```

In [265…

```
y_pred[0:10]
```

Out[265]:

```
array([5.05133152e+00, 4.53193426e-01, 5.93075895e+00, 2.78621167e+03,
       5.79575479e-01, 2.54842499e+02, 1.30977373e+01, 1.00554034e+03,
       7.96895386e+02, 1.42761551e+02], dtype=float32)
```

In [261…

```
# Saving Kaggle Submission
y_pred_series = pd.Series(y_pred)
result = pd.concat([ids, y_pred_series], axis=1)
result.columns = ["id", "sales"]
result.to_csv('submission.csv', index=False)
```

In [245…

```
result.head()
```

Out[245]:

	id	sales
0	3000888	-17.826202
1	3000889	-21.600533
2	3000890	-43.882450
3	3000891	2500.635986
4	3000892	-28.627560

In [251…

```
# configuration for the sweep
sweep_config = {
    'method': 'random', #grid, random
    'metric': {
      'name': 'rmse',
      'goal': 'minimize'
    },
    'parameters': {
        'max_depth': {
            'values': [3, 6, 9, 12]
        },
        'eta': {
            'values': [0.001, 0.01, 0.1]
        },
        'subsample': {
            'values': [0.5, 0.7, 1]
        },
        'colsample_bytree': {
            'values': [0.5, 0.7, 1]
        },
    }
}

# initialize a new sweep
sweep_id = wandb.sweep(sweep_config, project="XGBoost_sweeps")
```

```
wandb: ERROR Error while calling W&B API: An internal error occurred. Please c
ontact support. (<Response [500]>)
Create sweep with ID: avviue94
Sweep URL: https://wandb.ai/chrisapton/XGBoost_sweeps/sweeps/avviue94
```

In [ ]:

```
from xgboost.callback import TrainingCallback

class WandbCallback(TrainingCallback):
    def after_iteration(self, model, epoch, evals_log):
        for data, metric in evals_log.items():
            for metric_name, log in metric.items():
                wandb.log({f"{data}-{metric_name}": log[-1]})
        return False

def train():
    with wandb.init() as run:
        params = {
            'max_depth': run.config.max_depth,
            'eta': run.config.eta,
            'subsample': run.config.subsample,
            'colsample_bytree': run.config.colsample_bytree,
            'objective': 'reg:squarederror',
```

```
            'eval_metric': 'rmse'
        }

        dtrain = xgb.DMatrix(X_train, label=y_train)
        dtest = xgb.DMatrix(X_test, label=y_test)

        bst = xgb.train(params, dtrain, evals=[(dtest, "test")], callbacks=[Wan

wandb.agent(sweep_id, train)
```

In [257…

```
# optimal hyperparameters
optimal_max_depth = 30
optimal_eta = 0.05
optimal_subsample = 1
optimal_colsample_bytree = 1

model = xgb.XGBRegressor(eta = optimal_eta, max_depth = optimal_max_depth, subs
model.fit(X_train,y_train)
```

Out[257]:

```
XGBRegressor(base_score=0.5, booster='gbtree', callbacks=None,
             colsample_bylevel=1, colsample_bynode=1, colsample_bytree=1,
             early_stopping_rounds=None, enable_categorical=False, eta=0.05,
             eval_metric=None, gamma=0, gpu_id=-1, grow_policy='depthwise',
             importance_type=None, interaction_constraints='',
             learning_rate=0.0500000007, max_bin=256, max_cat_to_onehot=4,
             max_delta_step=0, max_depth=30, max_leaves=0, min_child_weight=1,
             missing=nan, monotone_constraints='()', n_estimators=100, n_jobs=
0,
             num_parallel_tree=1, predictor='auto', random_state=0, reg_alpha=
0, ...)
```

In [258…

```
# Save the model
with open('best_model.pkl', 'wb') as f:
    pickle.dump(model, f)
```

In [ ]:

```
# Load the model
with open('best_model.pkl', 'rb') as f:
    best_model = pickle.load(f)
```