Walmart_Sales_Prediction

December 25, 2020

0.1 Walmart Sales Forecasting

This project predicted daily sales for food categories at Walmart stores in California with the input data (06/19/2015-06/19/2016) covered item ids, item sales, item prices, departments, product categories, store ids and holiday/special events. * Clean and merge data * Investigate holiday impacts * Explore Trends by State/Category/Stores * Train Models

[3]:
```
#import libraries
import warnings
import gc

import pandas as pd
from pandas.plotting import register_matplotlib_converters
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import mean_squared_error
from sklearn.preprocessing import LabelEncoder
from statsmodels.tsa.stattools import adfuller
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
import statsmodels.api as sm
from statsmodels.tsa.arima_model import ARIMA
from sklearn.pipeline import make_pipeline
from sklearn.model_selection import KFold, cross_val_score, train_test_split,␣
↪GridSearchCV
from sklearn.metrics import mean_absolute_error
from sklearn.preprocessing import RobustScaler
from sklearn.ensemble import RandomForestRegressor
from sklearn.tree import DecisionTreeRegressor
import lightgbm as lgb
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics.scorer import make_scorer

warnings.filterwarnings("ignore")
pd.set_option("display.max_columns", 500)
pd.set_option("display.max_rows", 500)
register_matplotlib_converters()
sns.set()
```

0.1.1 Clean and Merge Data

In this section, I cleaned three datasets (calendar, sales and prices) with reduced memory usage, combined them together and saved a copy of csv file with the most recent 366 days for future use.

[1]:
```
#define a helper function to reduce memory sizes as the original datasets are␣
↪large
def reduce_mem_usage(df, verbose=False):
    start_mem = df.memory_usage().sum() / 1024 ** 2
    int_columns = df.select_dtypes(include=["int"]).columns
    float_columns = df.select_dtypes(include=["float"]).columns

    for col in int_columns:
        df[col] = pd.to_numeric(df[col], downcast="integer")

    for col in float_columns:
        df[col] = pd.to_numeric(df[col], downcast="float")

    end_mem = df.memory_usage().sum() / 1024 ** 2
    if verbose:
        print(
            "Mem. usage decreased to {:5.2f} Mb ({:.1f}% reduction)".format(
                end_mem, 100 * (start_mem - end_mem) / start_mem
            )
        )
    return df
```

[25]:
```
#read in data and reduce memory size
calendar = pd.read_csv("/Users/qingchuanlyu/Documents/Application/Projects/
↪time-series-analysis/calendar.csv").pipe(reduce_mem_usage)
prices = pd.read_csv("/Users/qingchuanlyu/Documents/Application/Projects/
↪time-series-analysis/sell_prices.csv").pipe(reduce_mem_usage)
sales = pd.read_csv("/Users/qingchuanlyu/Documents/Application/Projects/
↪time-series-analysis/sales_train_evaluation.csv",).pipe(reduce_mem_usage)
```

[26]:
```
calendar['date'] = pd.to_datetime(calendar['date'])
```

[27]:
```
calendar.dtypes
```

[27]:
```
date              datetime64[ns]
wm_yr_wk                   int16
weekday                   object
wday                        int8
month                       int8
year                       int16
d                         object
event_name_1              object
```

```
event_type_1            object
event_name_2            object
event_type_2            object
snap_CA                   int8
snap_TX                   int8
snap_WI                   int8
dtype: object
```

[28]:
```
#select sales records in the most recent year
#1581 = 1947-366, where 1947 is the total number of columns
#first six columns are item and store info
sales_1yr = sales.iloc[:, np.r_[0:6, 1581:1947]]
sales_1yr.to_csv('sales_1yr.csv', index = False)
```

[29]:
```
#1574 = 1940-366, where index 1940 corresponds to d_1941, the last day in sales␣
↪dataset
calendar_1yr = calendar.iloc[1574:1941, :]
calendar_1yr.to_csv('calendar_1yr.csv', index = False)
```

[30]:
```
#change sales data from wide to long, preparing for merging with calendar data␣
↪on "d"
id_columns = ["id", "item_id", "dept_id", "cat_id", "store_id", "state_id"]
sales_1yr = sales_1yr.melt(id_vars=id_columns, var_name="d",␣
↪value_name="demand")
```

[31]:
```
#merge with calendar and price datasets
sales_1yr = sales_1yr.merge(calendar_1yr[['wm_yr_wk', 'd', 'event_name_1',␣
↪'event_name_2']], how="left", on="d")
sales_1yr = sales_1yr.merge(prices, how="left", on=["store_id", "item_id",␣
↪"wm_yr_wk"])
```

[32]:
```
sales_1yr.head(5)
```

[32]:
```
                              id        item_id    dept_id   cat_id store_id  \
0  HOBBIES_1_001_CA_1_evaluation  HOBBIES_1_001  HOBBIES_1  HOBBIES     CA_1
1  HOBBIES_1_002_CA_1_evaluation  HOBBIES_1_002  HOBBIES_1  HOBBIES     CA_1
2  HOBBIES_1_003_CA_1_evaluation  HOBBIES_1_003  HOBBIES_1  HOBBIES     CA_1
3  HOBBIES_1_004_CA_1_evaluation  HOBBIES_1_004  HOBBIES_1  HOBBIES     CA_1
4  HOBBIES_1_005_CA_1_evaluation  HOBBIES_1_005  HOBBIES_1  HOBBIES     CA_1

  state_id       d  demand  wm_yr_wk event_name_1 event_name_2  sell_price
0       CA  d_1576       0     11517          NaN          NaN        8.26
1       CA  d_1576       0     11517          NaN          NaN        3.97
2       CA  d_1576       1     11517          NaN          NaN        2.97
3       CA  d_1576       4     11517          NaN          NaN        4.64
4       CA  d_1576       0     11517          NaN          NaN        2.88
```

[34]:
```python
#define a helper function to extract digits from date variables
def extract_num(ser):
    return ser.str.extract(r"(\d+)").astype(np.int16)
```

[35]:
```python
#only keep digit parts of time variables
sales_1yr["d"] = extract_num(sales_1yr["d"])
#reduce memory usage
sales_1yr = reduce_mem_usage(sales_1yr)
```

[36]:
```python
sales_1yr.to_csv('input_1yr.csv', index = False)
```

0.1.2 Investigate holiday impacts

In this section, I investigated the impact of holidays on daily sales of Hobbies_1 department at a California store (CA_1). Then, zoomed into the item daily sales of Hobbies_1_001 at the same location. My conclusion is daily sale at the department level doesn't change with holidays with a fixed pattern, sometimes local maxima, sometimes local minima; however, daily sale at the item level is even more intractable–sometimes there's no change in item daily sales at all during holidays.

[4]:
```python
#read in most recent (1 year) data
input_data = pd.read_csv("/Users/qingchuanlyu/Documents/Application/Projects/
↪time-series-analysis/input_1yr.csv").pipe(reduce_mem_usage)
```

[ ]:
```python
input_data.shape
```

[39]:
```python
input_data.head(2)
```

[39]:
```
                              id        item_id    dept_id   cat_id store_id  \
0  HOBBIES_1_001_CA_1_evaluation  HOBBIES_1_001  HOBBIES_1  HOBBIES     CA_1
1  HOBBIES_1_002_CA_1_evaluation  HOBBIES_1_002  HOBBIES_1  HOBBIES     CA_1

  state_id     d  demand  wm_yr_wk event_name_1  event_name_2  sell_price
0       CA  1576       0     11517          NaN           NaN        8.26
1       CA  1576       0     11517          NaN           NaN        3.97
```

[67]:
```python
#use a dummy variable to indicate if there's a holiday (event1 or event 2)
input_data['holiday'] = np.where(input_data.event_name_1.isnull() & input_data.
↪event_name_2.isnull(), 0, 1)
```

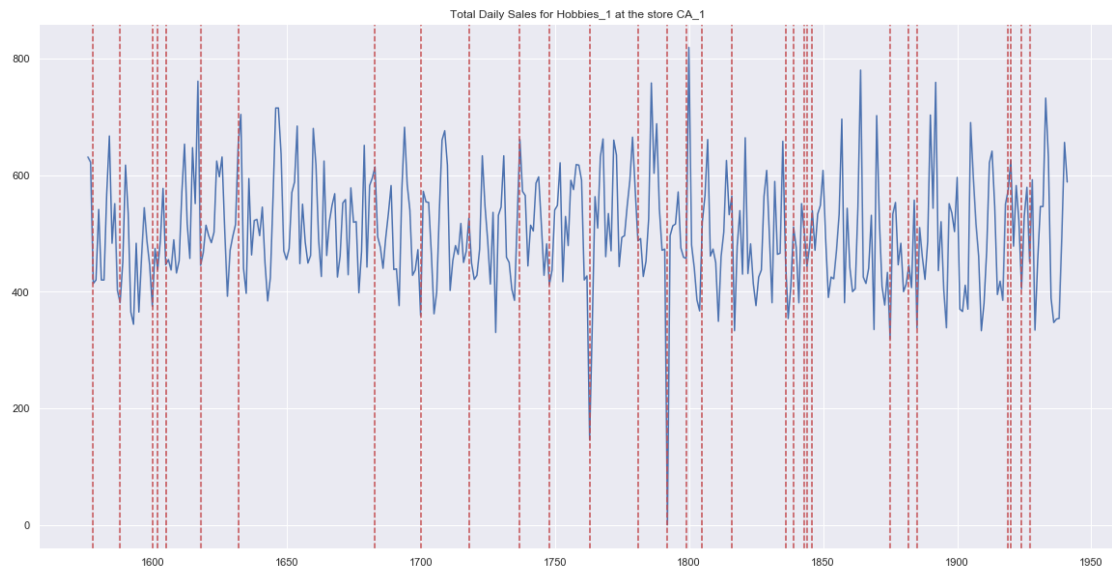
[70]:
```python
#for store CA_1 and department Hobbies_1, summarize total demand (sales) per␣
↪day for a year
sales_ca1_hb1 = input_data.loc[(input_data.dept_id == "HOBBIES_1") &␣
↪(input_data.store_id == "CA_1")]\
                              .fillna("None")\
                              .groupby(['d', 'holiday']).agg(daily_sales =␣
↪('demand', 'sum')).reset_index()
```

[75]:
```
#extract day indices with a holiday
days_holiday = input_data.loc[input_data.holiday==1].d.unique()
```

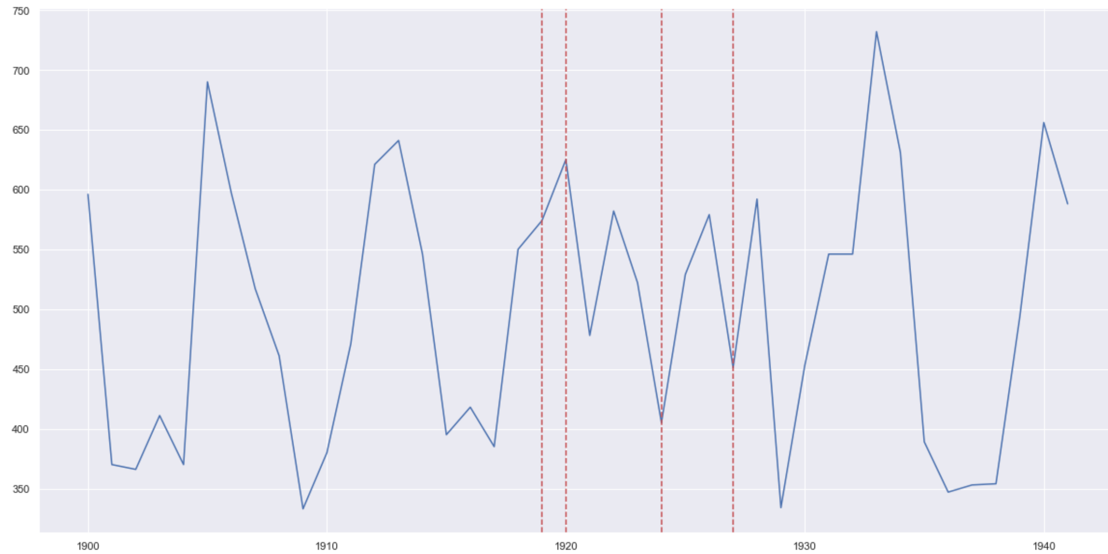
[76]:
```
days_holiday
```

[76]:
```
array([1578, 1588, 1600, 1602, 1605, 1618, 1632, 1683, 1700, 1718, 1737,
       1748, 1763, 1781, 1792, 1799, 1805, 1816, 1836, 1839, 1843, 1844,
       1846, 1875, 1882, 1885, 1919, 1920, 1924, 1927], dtype=int16)
```

[88]:
```
#plot daily sales of hobbies_1 at CA_1 store. red lines indicate a holiday
fig, ax = plt.subplots(figsize=(20,10))
ax.plot(sales_ca1_hb1['d'], sales_ca1_hb1['daily_sales'])
ax.set(title='Total Daily Sales for Hobbies_1 at the store CA_1')
for xc in days_holiday:
    ax.axvline(x=xc, color='r', linestyle='--')
```

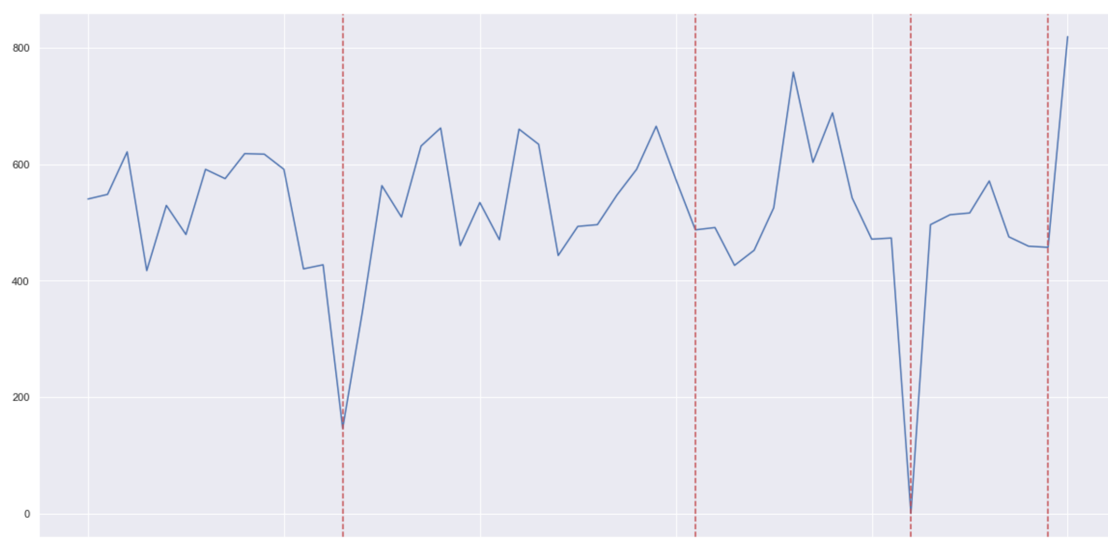


[81]:
```
#zoom in the last part
fig, ax = plt.subplots(figsize=(20,10))
ax.plot(sales_ca1_hb1.loc[sales_ca1_hb1.d>=1900]['d'], sales_ca1_hb1.
 ↪loc[sales_ca1_hb1.d>=1900]['daily_sales'])
for xc in days_holiday:
    if xc >= 1900:
        ax.axvline(x=xc, color='r', linestyle='--')
```



[85]:

```
#zoom in the middle part
fig, ax = plt.subplots(figsize=(20,10))
ax.plot(sales_ca1_hb1.loc[(sales_ca1_hb1.d>=1750) & (sales_ca1_hb1.d<=1800)]['d'], sales_ca1_hb1.loc[(sales_ca1_hb1.d>=1750) & (sales_ca1_hb1.d<=1800)]['daily_sales'])
for xc in days_holiday:
    if xc >= 1750 and xc<= 1800:
        ax.axvline(x=xc, color='r', linestyle='--')
```

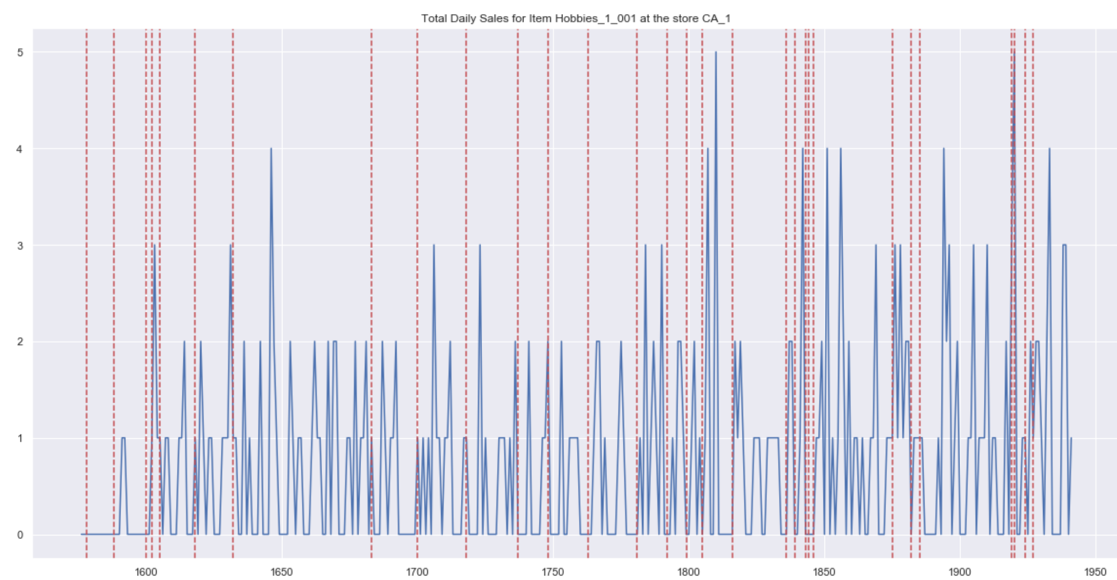


Two cases of total daily sales at a store when there's a holiday, according to the plot: * Local maxima/minima on holidays * Close to local maxima/minima when two holidays were very close

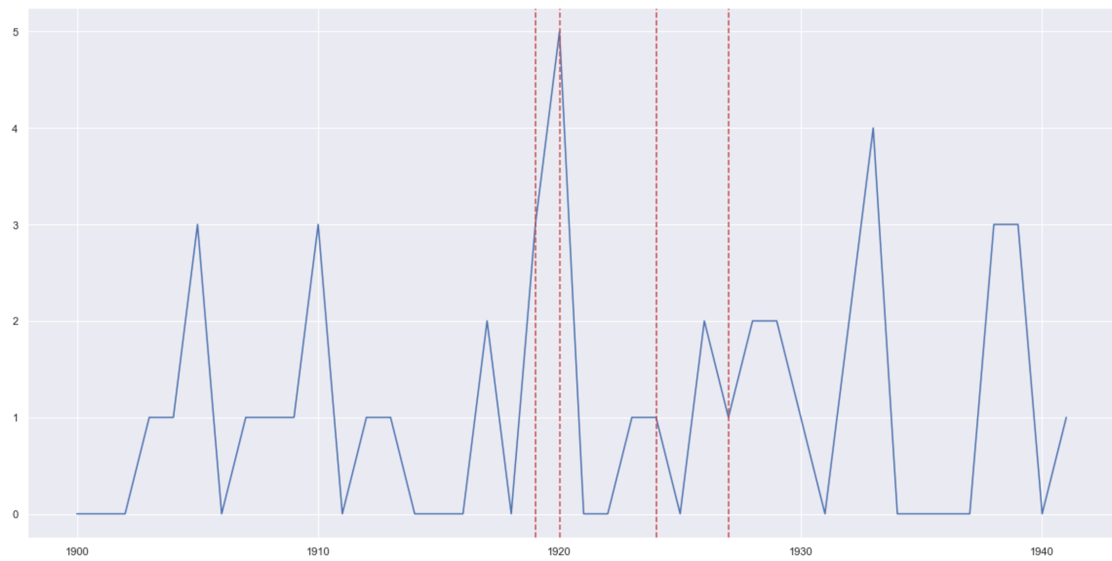
Conclusion: there's no need to view a few days before or after a holiday also as days with speical events

[89]:
```
#for the item HOBBIES_1_001 at store CA_1 and department Hobbies_1, summarize␣
↪total demand (sales) per day for a year
sales_ca1_hb1_001 = input_data.loc[(input_data.item_id=='HOBBIES_1_001') &␣
↪(input_data.dept_id == "HOBBIES_1") & (input_data.store_id == "CA_1")]\
                              .fillna("None")\
                              .groupby(['d', 'holiday']).agg(daily_sales =␣
↪('demand', 'sum')).reset_index()
```

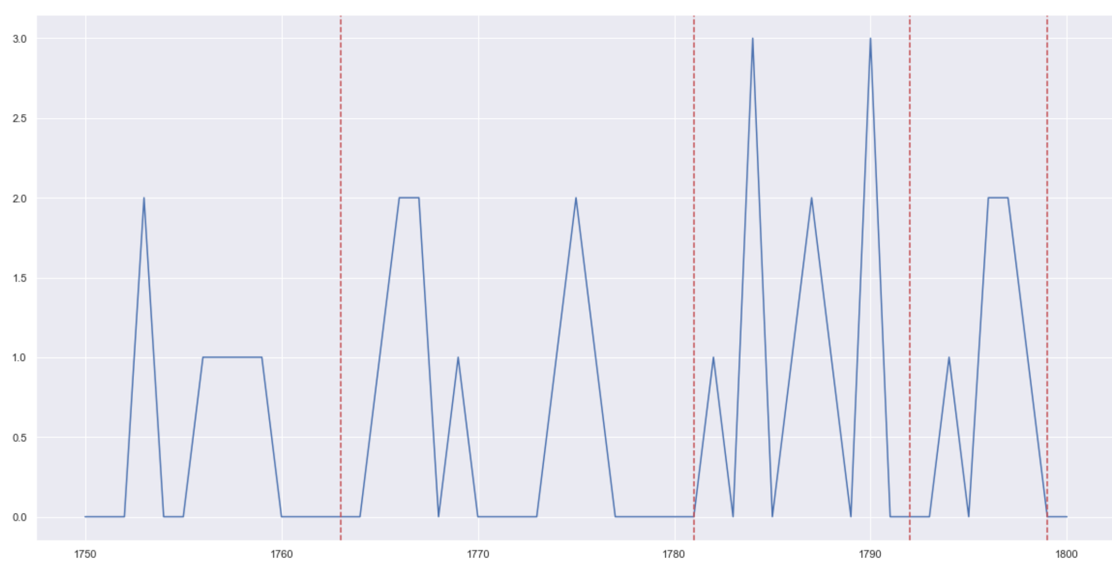
[91]:
```
#plot daily sales of item hobbies_1_001 at CA_1 store. red lines indicate a␣
↪holiday
fig, ax = plt.subplots(figsize=(20,10))
ax.plot(sales_ca1_hb1_001['d'], sales_ca1_hb1_001['daily_sales'])
ax.set(title='Total Daily Sales for Item Hobbies_1_001 at the store CA_1')
for xc in days_holiday:
    ax.axvline(x=xc, color='r', linestyle='--')
```



[92]:
```
#zoom in the last part
fig, ax = plt.subplots(figsize=(20,10))
ax.plot(sales_ca1_hb1_001.loc[sales_ca1_hb1_001.d>=1900]['d'],␣
↪sales_ca1_hb1_001.loc[sales_ca1_hb1_001.d>=1900]['daily_sales'])
for xc in days_holiday:
    if xc >= 1900:
        ax.axvline(x=xc, color='r', linestyle='--')
```



[95]:
```
#zoom in the middle part
fig, ax = plt.subplots(figsize=(20,10))
ax.plot(sales_ca1_hb1_001.loc[(sales_ca1_hb1_001.d>=1750) & (sales_ca1_hb1_001.
 ↪d <=1800)]['d'], sales_ca1_hb1_001.loc[(sales_ca1_hb1.d>=1750) &␣
 ↪(sales_ca1_hb1.d <=1800)]['daily_sales'])
for xc in days_holiday:
    if xc >= 1750 and xc<= 1800:
        ax.axvline(x=xc, color='r', linestyle='--')
```



Three cases of item daily sales at a store when there's a holiday, according to the plot: * Local maxima/minima on holidays * Close to local maxima/minima when two holidays were very close * Increased from zero or decreased to zero. This happens to non-holiday days also * Stayed zero

Conclusion: * There's no need to view a few days before or after a holiday also as days with speical events * Holidays don't always make an impact on item sales

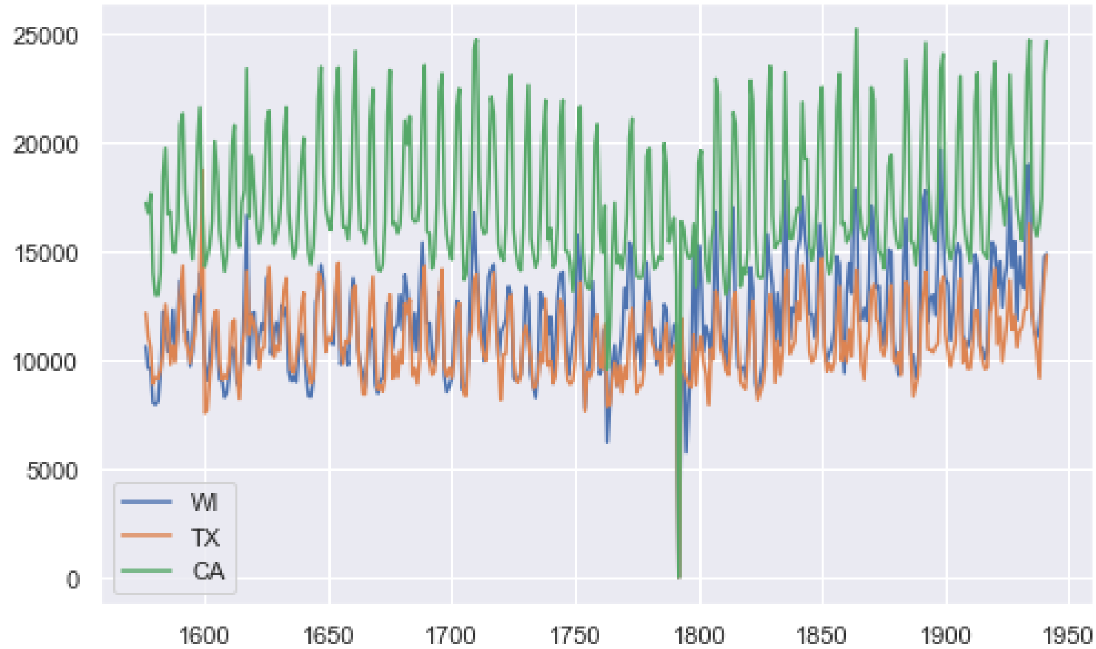
0.1.3 Explore Trends by State/Category/Stores

In this section, I plotted the trend of daily total sales at state, category and store-level and chose a level to build models. The category-level was chosen, because each trend of three categories was clearly separable from one another and had obvious seasonality. * Trend by State

[96]:
```
input_data.head(5)
```

[96]:
```
                             id        item_id    dept_id   cat_id store_id  \
0  HOBBIES_1_001_CA_1_evaluation  HOBBIES_1_001  HOBBIES_1  HOBBIES     CA_1
1  HOBBIES_1_002_CA_1_evaluation  HOBBIES_1_002  HOBBIES_1  HOBBIES     CA_1
2  HOBBIES_1_003_CA_1_evaluation  HOBBIES_1_003  HOBBIES_1  HOBBIES     CA_1
3  HOBBIES_1_004_CA_1_evaluation  HOBBIES_1_004  HOBBIES_1  HOBBIES     CA_1
4  HOBBIES_1_005_CA_1_evaluation  HOBBIES_1_005  HOBBIES_1  HOBBIES     CA_1

  state_id     d  demand  wm_yr_wk event_name_1  event_name_2  sell_price  \
0       CA  1576       0     11517          NaN           NaN        8.26
1       CA  1576       0     11517          NaN           NaN        3.97
2       CA  1576       1     11517          NaN           NaN        2.97
3       CA  1576       4     11517          NaN           NaN        4.64
4       CA  1576       0     11517          NaN           NaN        2.88

   holiday
0        0
1        0
2        0
3        0
4        0
```

[102]:
```
#check if the trend of sales is different across three states: WI, CA and TX
state = ['WI', 'TX', "CA"]
fig, ax = plt.subplots(figsize=(8,5))
for s in state:
    temp = input_data.loc[(input_data.state_id == s)]\
            .groupby('d').agg(daily_sales = ('demand', 'sum')).reset_index()
    ax.plot(temp['d'], temp['daily_sales'])
    ax.legend(state)
```



CA's trend is much higher than WI and TX. For WI and TX, WI's trend was slightly below TX's trend in the second half of 2015, then slightly it in the first half of 2016. These observations suggest a state-level model. * Trend by Category

[120]:
```
Cat = input_data['cat_id'].unique()
fig, ax = plt.subplots(figsize=(8,5))
for c in Cat:
    temp = input_data.loc[(input_data.cat_id == c)]\
               .groupby('d').agg(daily_sales = ('demand', 'sum')).reset_index()
    ax.plot(temp['d'], temp['daily_sales'])
    ax.legend(Cat)
for xc in days_holiday:
    if xc >= 1750 and xc<= 1800:
        ax.axvline(x=xc, color='b', linestyle='--')
ax.set(title = 'Total daily sales for each category')
ax.set_xlabel('Day Identifiers')
ax.set_ylabel('Sales')
```

[120]:
```
Text(0, 0.5, 'Sales')
```

[ ]:
```
Cat = input_data['cat_id'].unique()
fig, ax = plt.subplots(figsize=(8,5))
for c in Cat:
    temp = input_data.loc[(input_data.cat_id == c) & (input_data.
↪state_id=='CA')]\
               .groupby('d').agg(daily_sales = ('demand', 'sum')).reset_index()
    ax.plot(temp['d'], temp['daily_sales'])
    ax.legend(Cat)
for xc in days_holiday:
    if xc >= 1750 and xc<= 1800:
        ax.axvline(x=xc, color='b', linestyle='--')
ax.set(title = 'Total daily sales for each category in CA')
ax.set_xlabel('Day Identifiers')
ax.set_ylabel('Sales')
```

[ ]:
```
del temp
gc.collect()
```

[111]:
```
input_data.loc[input_data.d==1792]
```

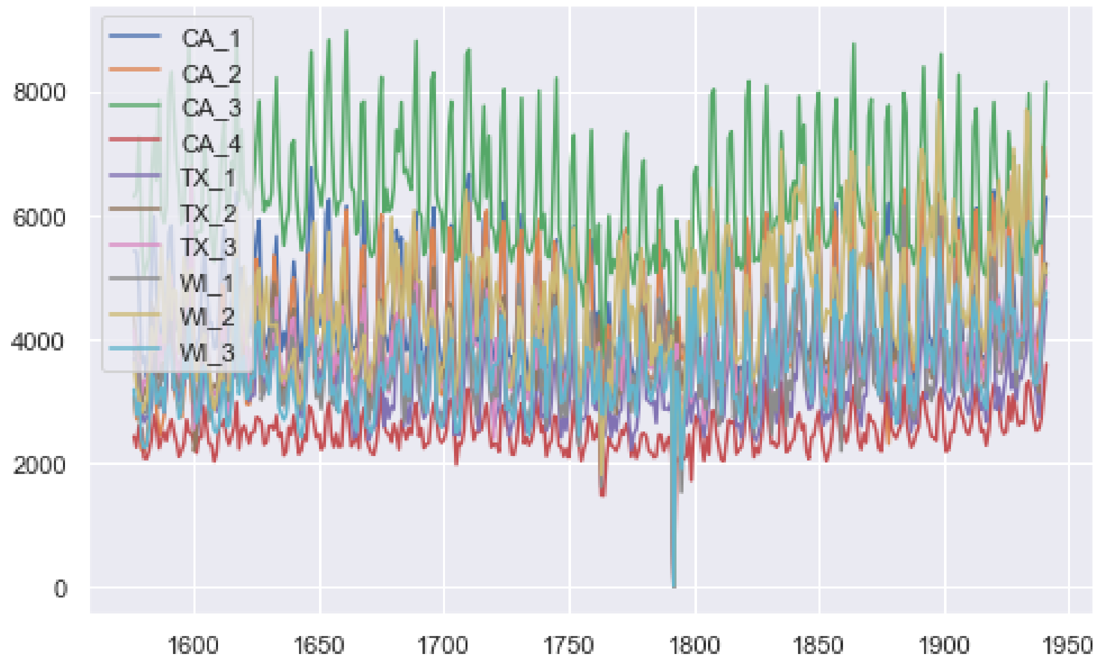
[111]:
```
                                    id       item_id    dept_id   cat_id  \
6585840  HOBBIES_1_001_CA_1_evaluation  HOBBIES_1_001  HOBBIES_1  HOBBIES
6585841  HOBBIES_1_002_CA_1_evaluation  HOBBIES_1_002  HOBBIES_1  HOBBIES
6585842  HOBBIES_1_003_CA_1_evaluation  HOBBIES_1_003  HOBBIES_1  HOBBIES
```

```
6585843  HOBBIES_1_004_CA_1_evaluation  HOBBIES_1_004  HOBBIES_1  HOBBIES
6585844  HOBBIES_1_005_CA_1_evaluation  HOBBIES_1_005  HOBBIES_1  HOBBIES
…                                    …              …          …        …
6616325    FOODS_3_823_WI_3_evaluation    FOODS_3_823    FOODS_3    FOODS
6616326    FOODS_3_824_WI_3_evaluation    FOODS_3_824    FOODS_3    FOODS
6616327    FOODS_3_825_WI_3_evaluation    FOODS_3_825    FOODS_3    FOODS
6616328    FOODS_3_826_WI_3_evaluation    FOODS_3_826    FOODS_3    FOODS
6616329    FOODS_3_827_WI_3_evaluation    FOODS_3_827    FOODS_3    FOODS

        store_id state_id     d  demand  wm_yr_wk event_name_1  event_name_2  \
6585840     CA_1       CA  1792       0     11547    Christmas           NaN
6585841     CA_1       CA  1792       0     11547    Christmas           NaN
6585842     CA_1       CA  1792       0     11547    Christmas           NaN
6585843     CA_1       CA  1792       0     11547    Christmas           NaN
6585844     CA_1       CA  1792       0     11547    Christmas           NaN
…            …      …    …     …       …        …           …
6616325     WI_3       WI  1792       0     11547    Christmas           NaN
6616326     WI_3       WI  1792       0     11547    Christmas           NaN
6616327     WI_3       WI  1792       0     11547    Christmas           NaN
6616328     WI_3       WI  1792       0     11547    Christmas           NaN
6616329     WI_3       WI  1792       0     11547    Christmas           NaN

         sell_price  holiday
6585840        8.26        1
6585841        3.97        1
6585842        2.97        1
6585843        4.64        1
6585844        2.88        1
…               …        …
6616325        2.50        1
6616326        2.00        1
6616327        3.98        1
6616328        1.28        1
6616329        1.00        1

[30490 rows x 13 columns]
```

Category-level daily total sales are pretty separable. Household and food categories were pretty stable and presented strong seasonality. The significant downfall of the sales of Food Category was due to the Christmas of 2015. * Trend by Stores

[112]:
```
Stores = input_data['store_id'].unique()
fig, ax = plt.subplots(figsize=(8,5))
for st in Stores:
    temp = input_data.loc[(input_data.store_id == st)]\
            .groupby('d').agg(daily_sales = ('demand', 'sum')).reset_index()
    ax.plot(temp['d'], temp['daily_sales'])
```

```
    ax.legend(Stores)
```



The overall trend at store-level is very similar to the trend at category-level, with lots of overlaps among stores. I decided to build cateogry-level models.

0.1.4 Train Models

In this section, I trained ARIMA, Decision Tree, Random Forest and Light GBM. Then, compared results. * ARIMA

[ ]:
```
#Augmented Dickey-Fuller Test to check integration order
#Ho: not stationary
#H1: stationary
#Cat = input_data['cat_id'].unique()
#for c in Cat:
input_ca = input_data.loc[input_data.state_id == 'CA']
input_ca.to_csv('input_ca.csv', index = False)
```

[9]:
```
del input_data
gc.collect()
```

[9]: 158

[11]:
```
input_ca_cat = input_ca.groupby(['cat_id','d']).agg(daily_sales = ('demand',␣
↪'sum')).reset_index()
```

[12]:
```
del input_ca
gc.collect()
```

[12]: 52

[17]:
```
test_res = {}
Cat = input_ca_cat['cat_id'].unique()
for c in Cat:
    test_res[c]=adfuller(input_ca_cat.loc[input_ca_cat.
↪cat_id==c]['daily_sales'])
test_res
```

[17]:
```
{'FOODS': (-2.581480837668372,
  0.09688552631219105,
  14,
  351,
  {'1%': -3.44911857009962,
   '5%': -2.8698097654570507,
   '10%': -2.5711757061225153},
  5884.603369242338),
 'HOBBIES': (-3.4326177018702304,
  0.009895937408940472,
  13,
  352,
  {'1%': -3.4490648539347544,
   '5%': -2.8697861692116478,
   '10%': -2.5711631253228306},
  4793.473520162877),
 'HOUSEHOLD': (-1.9991674911663337,
  0.2869382445422097,
  15,
  350,
  {'1%': -3.4491725955218655,
   '5%': -2.8698334971428574,
   '10%': -2.5711883591836733},
  5245.101338942865)}
```

Only p-value of Hobbies (0.0099) is less than 0.05. I rejected the null hypothesis of daily sales being non-stationary for Hobbies category. Foods and household categories, however, need to be differenced.

[35]:
```
input_ca_foods = input_ca_cat.loc[input_ca_cat.cat_id=='FOODS']
input_ca_hs = input_ca_cat.loc[input_ca_cat.cat_id=='HOUSEHOLD']
input_ca_hobbies = input_ca_cat.loc[input_ca_cat.cat_id=='HOBBIES']
```

[28]:
```python
input_ca_foods['first_diff'] = input_ca_foods['daily_sales'] -␣
↪input_ca_foods['daily_sales'].shift(1)
input_ca_hs['first_diff'] = input_ca_hs['daily_sales'] -␣
↪input_ca_hs['daily_sales'].shift(1)
```

[20]:
```python
input_ca_foods.head(5)
```

[20]:
```
  cat_id     d  daily_sales  first_diff
0  FOODS  1576        10182         NaN
1  FOODS  1577        10184         2.0
2  FOODS  1578        10710       526.0
3  FOODS  1579         8215     -2495.0
4  FOODS  1580         7864      -351.0
```

[23]:
```python
adfuller(input_ca_foods['first_diff'].dropna())
```

[23]:
```
(-7.4928273110853025,
 4.458805020075203e-11,
 13,
 351,
 {'1%': -3.44911857009962,
  '5%': -2.8698097654570507,
  '10%': -2.5711757061225153},
 5872.775908746674)
```

[29]:
```python
adfuller(input_ca_hs['first_diff'].dropna())
```

[29]:
```
(-7.4577597293483455,
 5.455025041587284e-11,
 14,
 350,
 {'1%': -3.4491725955218655,
  '5%': -2.8698334971428574,
  '10%': -2.5711883591836733},
 5233.300853765576)
```

[30]:
```python
#p-value is smaller, but still not siginificant. Need to differentiate again␣
↪(2nd diff)
input_ca_foods['second_diff'] = input_ca_foods['first_diff'] -␣
↪input_ca_foods['first_diff'].shift(1)
input_ca_hs['second_diff'] = input_ca_hs['first_diff'] -␣
↪input_ca_hs['first_diff'].shift(1)
input_ca_foods.head(5)
```

[30]:
```
  cat_id     d  daily_sales  first_diff  second_diff
0  FOODS  1576        10182         NaN          NaN
1  FOODS  1577        10184         2.0          NaN
```

```
2  FOODS  1578        10710       526.0        524.0
3  FOODS  1579         8215     -2495.0      -3021.0
4  FOODS  1580         7864      -351.0       2144.0
```

[24]:
```
adfuller(input_ca_foods['second_diff'].dropna())
```

[24]:
```
(-9.684320684841467,
 1.181669110391987e-16,
 16,
 347,
 {'1%': -3.449336554273722,
  '5%': -2.8699055166063085,
  '10%': -2.571226758215748},
 5898.38873008727)
```

[31]:
```
adfuller(input_ca_hs['second_diff'].dropna())
```

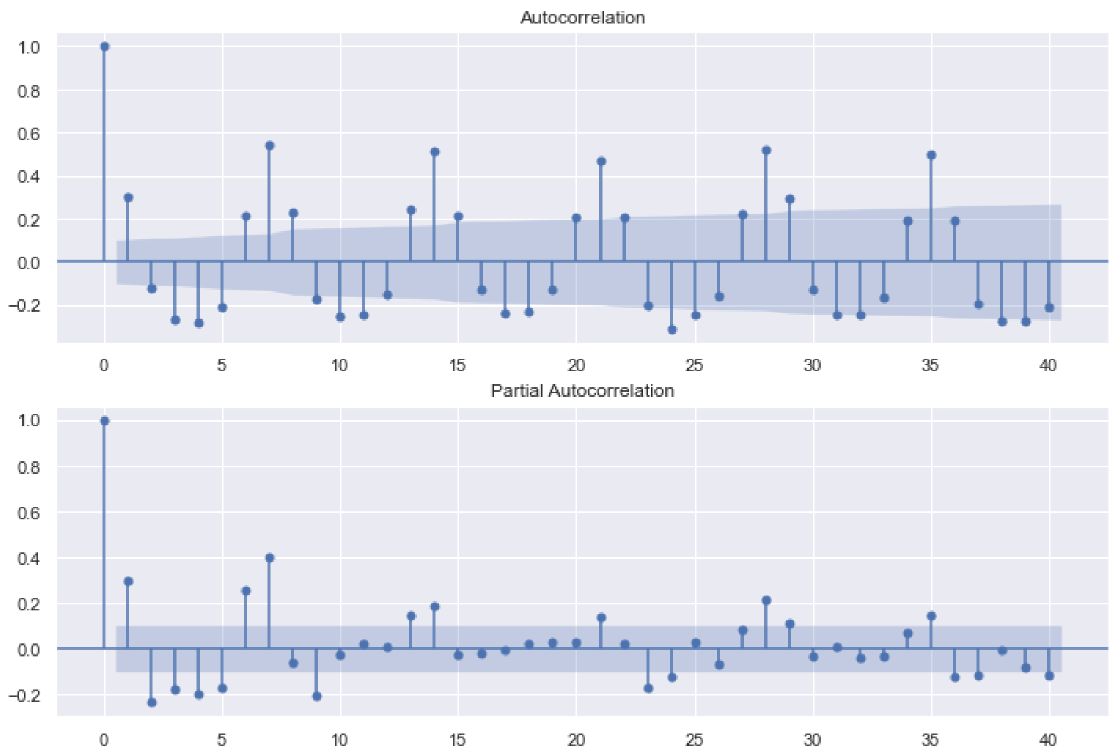
[31]:
```
(-10.486685066825105,
 1.1754251284033695e-18,
 16,
 347,
 {'1%': -3.449336554273722,
  '5%': -2.8699055166063085,
  '10%': -2.571226758215748},
 5263.075007383312)
```

[33]:
```
input_ca_foods['third_diff'] = input_ca_foods['second_diff'] -␣
 ↪input_ca_foods['second_diff'].shift(1)
input_ca_hs['third_diff'] = input_ca_hs['second_diff'] -␣
 ↪input_ca_hs['second_diff'].shift(1)
adfuller(input_ca_foods['third_diff'].dropna())
adfuller(input_ca_hs['third_diff'].dropna())
```

[33]:
```
(-13.006496351161248,
 2.6211366077118204e-24,
 17,
 345,
 {'1%': -3.4494474563375737,
  '5%': -2.8699542285903887,
  '10%': -2.5712527305187987},
 5316.258968096278)
```

As integrated orders go up, p-values within Dickey-Fuller tests jump up and down for Foods and Household categories. I'll stop here for FOODS and HOUSEHOLDS instead of running into a rabbit hole. Below is training ARIMA for HOBBIES category.

[40]:
```
fig = plt.figure(figsize = (12, 8))
ax1 = fig.add_subplot(211)
fig = sm.graphics.tsa.plot_acf(input_ca_hobbies['daily_sales'], lags = 40, ax =␣
 ↪ax1)
ax2 = fig.add_subplot(212)
fig = sm.graphics.tsa.plot_pacf(input_ca_hobbies['daily_sales'], lags = 40, ax=␣
 ↪ax2)
```



[82]:
```
#train ARIMA model accordingly
ARMA_model = ARIMA(input_ca_hobbies['daily_sales'], order = (2, 0 , 1))
model_fit = ARMA_model.fit()
model_fit.summary()
```

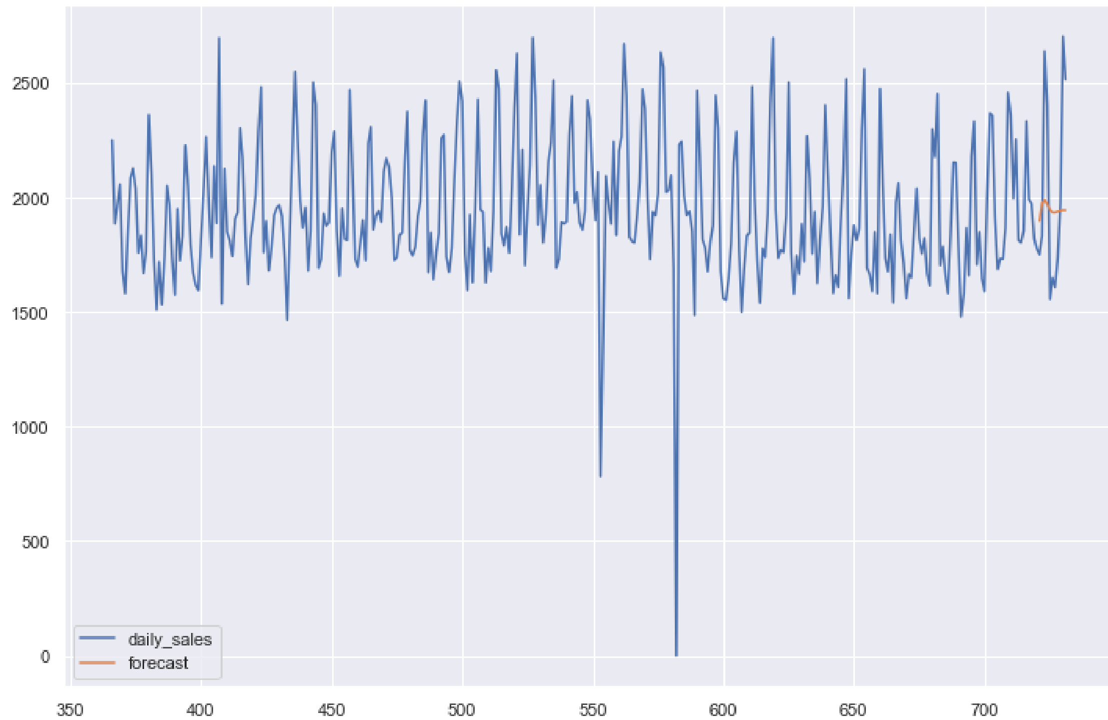
[82]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                              ARMA Model Results
==============================================================================
Dep. Variable:            daily_sales   No. Observations:                  366
Model:                     ARMA(2, 1)   Log Likelihood               -2576.650
Method:                       css-mle   S.D. of innovations            276.059
Date:                Wed, 23 Dec 2020   AIC                           5163.300
Time:                        16:58:22   BIC                           5182.813
Sample:                             0   HQIC                          5171.054
```

```
==============================================================================
=====
                          coef    std err          z      P>|z|      [0.025
0.975]
------------------------------------------------------------------------------
-----
const              1942.0694     12.122    160.214      0.000    1918.311
1965.828
ar.L1.daily_sales     0.8649      0.080     10.824      0.000       0.708
1.022
ar.L2.daily_sales    -0.4185      0.048     -8.665      0.000      -0.513
-0.324
ma.L1.daily_sales    -0.5365      0.075     -7.108      0.000      -0.684
-0.389
                                    Roots
=============================================================================
                  Real          Imaginary           Modulus         Frequency
-----------------------------------------------------------------------------
AR.1            1.0334           -1.1496j            1.5458           -0.1335
AR.2            1.0334           +1.1496j            1.5458            0.1335
MA.1            1.8640           +0.0000j            1.8640            0.0000
-----------------------------------------------------------------------------
"""
```

[83]:

```
input_ca_hobbies['forecast'] = model_fit.predict(start=355, end = 365, dynamic␣
↪= True)
input_ca_hobbies[['daily_sales', 'forecast']].plot(figsize = (12, 8))
```

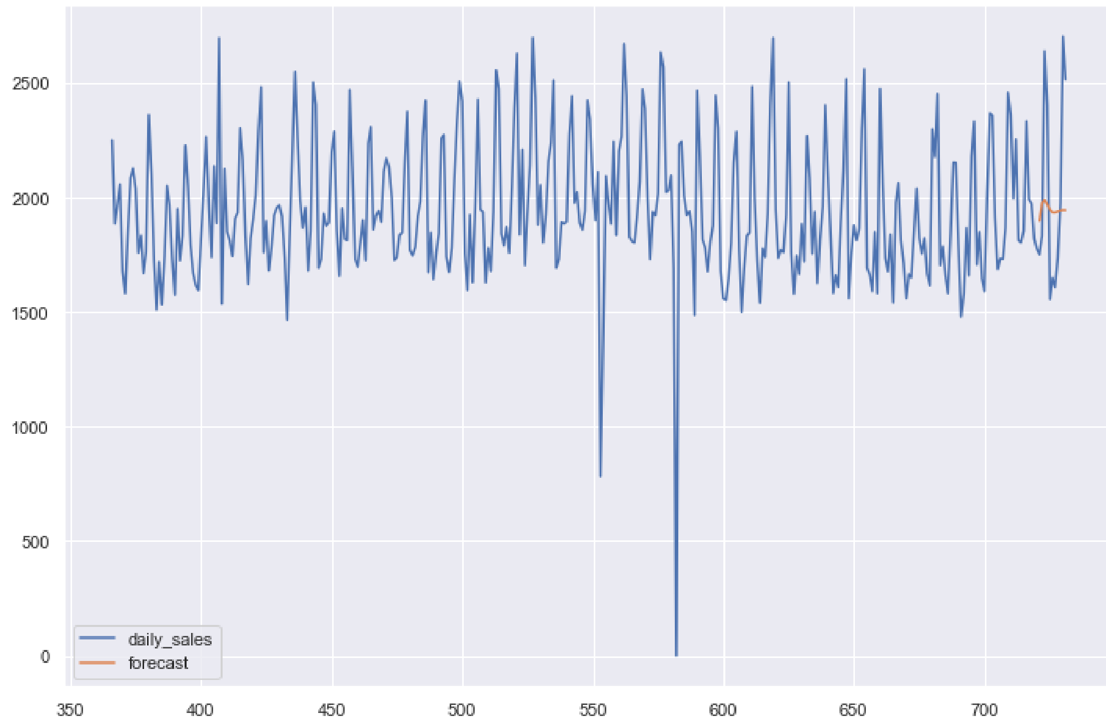
[83]: <AxesSubplot:>



[87]:
```
#the prediction is not as good as desire
#use SARIMA to incoporate seasonality
sarima_model = sm.tsa.statespace.SARIMAX(input_ca_hobbies['daily_sales'], order
↪= (2, 0, 1), seasonal_order = (2, 0, 1, 3))
sarima_results = sarima_model.fit()
```

[88]:
```
input_ca_hobbies['forecast'] = model_fit.predict(start=355, end = 365, dynamic
↪= True)
input_ca_hobbies[['daily_sales', 'forecast']].plot(figsize = (12, 8))
```

[88]: <AxesSubplot:>



The results from ARIMA and SARIMA are both not as desired, probably because these models are too simple and don't use extra information, such as holidays and prices. * Decision Tree, Random Forest and Gradient Boosting Tree

[91]:
```
input_data.head(4)
```

[91]:
```
                                id        item_id    dept_id   cat_id store_id  \
0  HOBBIES_1_001_CA_1_evaluation  HOBBIES_1_001  HOBBIES_1  HOBBIES     CA_1
1  HOBBIES_1_002_CA_1_evaluation  HOBBIES_1_002  HOBBIES_1  HOBBIES     CA_1
2  HOBBIES_1_003_CA_1_evaluation  HOBBIES_1_003  HOBBIES_1  HOBBIES     CA_1
3  HOBBIES_1_004_CA_1_evaluation  HOBBIES_1_004  HOBBIES_1  HOBBIES     CA_1

  state_id     d  demand  wm_yr_wk event_name_1  event_name_2  sell_price
0       CA  1576       0     11517          NaN           NaN        8.26
1       CA  1576       0     11517          NaN           NaN        3.97
2       CA  1576       1     11517          NaN           NaN        2.97
3       CA  1576       4     11517          NaN           NaN        4.64
```

[5]:
```
#use a dummy variable to indicate if there's a holiday (event1 or event 2)
input_data['holiday'] = np.where(input_data.event_name_1.isnull() & input_data.
 ↪event_name_2.isnull(), 0, 1)
input_ca_cat = input_data.loc[input_data.state_id == 'CA'].
 ↪groupby(['cat_id','holiday','d']).agg(daily_sales = ('demand', 'sum')).
 ↪reset_index()
```

[6]:
```python
input_ca_cat['lag1'] = input_ca_cat['daily_sales'].shift(1)
input_ca_cat['lag2'] = input_ca_cat['daily_sales'].shift(2)
```

[7]:
```python
#label encoder for categories
lbl = LabelEncoder()
lbl.fit(list(input_ca_cat['cat_id'].values))
input_ca_cat['cat_id'] = lbl.transform(list(input_ca_cat['cat_id'].values))
```

[8]:
```python
input_ca_cat.dropna(inplace=True)
train = input_ca_cat.loc[input_ca_cat.cat_id == 0][['cat_id', 'holiday', 'd',␣
↪'lag1', 'lag2']]
y_train = input_ca_cat.loc[input_ca_cat.cat_id == 0]['daily_sales']
```

[12]:
```python
input_ca_cat
```

[12]:
```
      cat_id  holiday     d  daily_sales     lag1     lag2
2          0        0  1579         8215  10184.0  10182.0
3          0        0  1580         7864   8215.0  10184.0
4          0        0  1581         7919   7864.0   8215.0
5          0        0  1582         8405   7919.0   7864.0
6          0        0  1583        11209   8405.0   7919.0
…        …       …    …          …        …        …
1093       2        1  1885         5280   3553.0   3367.0
1094       2        1  1919         5634   5280.0   3553.0
1095       2        1  1920         5888   5634.0   5280.0
1096       2        1  1924         3753   5888.0   5634.0
1097       2        1  1927         4731   3753.0   5888.0

[1096 rows x 6 columns]
```

[ ]:
```python
train.shape, y_train.shape
```

[9]:
```python
def mean_absolute_percentage_error(y_true, y_pred):
    y_true, y_pred = np.array(y_true), np.array(y_pred)
    return np.median(np.abs((y_true - y_pred) / y_true))
```

[10]:
```python
cost_scorer = make_scorer(mean_absolute_percentage_error,␣
↪greater_is_better=False)
```

[16]:
```python
dt = make_pipeline(RobustScaler(), DecisionTreeRegressor(max_depth=40,␣
↪min_samples_split=10, random_state=1))
param_grid={
            'max_depth': range(2,50)
        }
search = GridSearchCV(DecisionTreeRegressor(), param_grid, cv=10,␣
↪scoring=cost_scorer, n_jobs=-1)
search.fit(train, y_train)
```

```
best_params_tree = search.best_params_
print(f"{search.best_params_}")
print(f"{np.sqrt(-search.best_score_):.4}")
```

```
{'max_depth': 4}
0.2715
```

[17]:
```
#random forest
rdf = make_pipeline(RobustScaler(), RandomForestRegressor(max_depth=4,␣
 ↪n_estimators=50, random_state=1))
param_grid={
            'max_depth': range(2,50),
            'n_estimators': (50, 100)
        }
search = GridSearchCV(RandomForestRegressor(), param_grid, cv=10,␣
 ↪scoring=cost_scorer, n_jobs=-1)
search.fit(train, y_train)
best_params_forest = search.best_params_
print(f"{search.best_params_}")
print(f"{np.sqrt(-search.best_score_):.4}")
```

```
{'max_depth': 25, 'n_estimators': 50}
0.2532
```

[13]:
```
#Lightgbm
rdf = make_pipeline(RobustScaler(), lgb.LGBMRegressor(boosting_type='gbdt',␣
 ↪objective='regression', num_leaves=10,
                                                  learning_rate=0.12,␣
 ↪n_estimators=50, max_depth=4,
                                                  random_state=1))
param_grid={'num_leaves': [10, 20],
            'learning_rate': np.linspace(0.01, 0.2, 20),
            'max_depth': range(2,50),
            'n_estimators': (50, 100)
        }
search = GridSearchCV(lgb.LGBMRegressor(), param_grid, cv=10,␣
 ↪scoring=cost_scorer, n_jobs=-1)
search.fit(train, y_train)
best_params_forest = search.best_params_
print(f"{search.best_params_}")
print(f"{np.sqrt(-search.best_score_):.4}")
```

```
{'learning_rate': 0.09999999999999999, 'max_depth': 5, 'n_estimators': 50,
'num_leaves': 20}
0.2555
```