Retail_exploratory.pynb

March 9, 2018

Let's do some exploratory analysis on store sales data. Let's load and combine the data first.

```
In [8]: import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        %matplotlib inline
        from datetime import datetime
        from pandas import Series, DataFrame, concat
```

```
In [9]: def build_dataset():
            #LOAD DATA
            features_data = pd.read_csv('~/Projects/Store_sales/Features_data_set.csv').fillna
            sales_data = pd.read_csv('~/Projects/Store_sales/sales_data_set.csv').fillna('VK')
            stores_data = pd.read_csv('~/Projects/Store_sales/stores_data_set.csv').fillna('VK

            #MERGE DATA INTO A SINGLE DATA SET
            features_data.drop('IsHoliday', axis = 1, inplace = True)
            data = pd.merge(sales_data, stores_data, on='Store')
            data = pd.merge(data, features_data, on=['Store', 'Date'])
            del(features_data, sales_data, stores_data)

            #REPLACE DATE STRING WITH DATETIME
            data['Date'] = pd.Series([datetime.strptime(d, '%d/%m/%Y') for d in data['Date']])

            #ADD YEAR, MONTH AND WEEK COLUMNS
            data['Year'] = pd.Series([t.year for t in data['Date']])
            data['Month'] = pd.Series([t.month for t in data['Date']])
            '''there is a slight inconsistency here because of a leap year and the
            defnintion of the sales week depending on what week day the year starts;
            however given the dates are all fridays the datetime week function does
            a good job assigning week numbers'''
            data['Week'] = pd.Series([t.week for t in data['Date']])

            return data
```

```
In [3]: data = build_dataset()
```

Let's take a look now what this data set contains.

```
In [4]: data.describe(include = 'all')
```

```
Out[4]:            Store           Dept                 Date   Weekly_Sales  \
count   421570.000000  421570.000000               421570  421570.000000
unique            NaN            NaN                  143            NaN
top               NaN            NaN  2011-12-23 00:00:00            NaN
freq              NaN            NaN                 3027            NaN
first             NaN            NaN  2010-02-05 00:00:00            NaN
last              NaN            NaN  2012-10-26 00:00:00            NaN
mean        22.200546      44.260317                  NaN   15981.258123
std         12.785297      30.492054                  NaN   22711.183519
min          1.000000       1.000000                  NaN   -4988.940000
25%         11.000000      18.000000                  NaN    2079.650000
50%         22.000000      37.000000                  NaN    7612.030000
75%         33.000000      74.000000                  NaN   20205.852500
max         45.000000      99.000000                  NaN  693099.360000

       IsHoliday    Type           Size    Temperature     Fuel_Price  \
count     421570  421570  421570.000000  421570.000000  421570.000000
unique         2       3            NaN            NaN            NaN
top        False       A            NaN            NaN            NaN
freq      391909  215478            NaN            NaN            NaN
first        NaN     NaN            NaN            NaN            NaN
last         NaN     NaN            NaN            NaN            NaN
mean         NaN     NaN  136727.915739      60.090059       3.361027
std          NaN     NaN   60980.583328      18.447931       0.458515
min          NaN     NaN   34875.000000      -2.060000       2.472000
25%          NaN     NaN   93638.000000      46.680000       2.933000
50%          NaN     NaN  140167.000000      62.090000       3.452000
75%          NaN     NaN  202505.000000      74.280000       3.738000
max          NaN     NaN  219622.000000     100.140000       4.468000

       MarkDown1 MarkDown2 MarkDown3 MarkDown4 MarkDown5            CPI  \
count     421570    421570    421570    421570    421570  421570.000000
unique      2278      1500      1663      1945      2294    2145.000000
top           VK        VK        VK        VK        VK     129.855533
freq      270889    310322    284479    286603    270138     711.000000
first        NaN       NaN       NaN       NaN       NaN            NaN
last         NaN       NaN       NaN       NaN       NaN            NaN
mean         NaN       NaN       NaN       NaN       NaN            NaN
std          NaN       NaN       NaN       NaN       NaN            NaN
min          NaN       NaN       NaN       NaN       NaN            NaN
25%          NaN       NaN       NaN       NaN       NaN            NaN
50%          NaN       NaN       NaN       NaN       NaN            NaN
75%          NaN       NaN       NaN       NaN       NaN            NaN
max          NaN       NaN       NaN       NaN       NaN            NaN

        Unemployment           Year          Month           Week
```

```
count     421570.000  421570.000000  421570.000000  421570.000000
unique       349.000            NaN            NaN            NaN
top            8.099            NaN            NaN            NaN
freq        5152.000            NaN            NaN            NaN
first            NaN            NaN            NaN            NaN
last             NaN            NaN            NaN            NaN
mean             NaN    2010.968591       6.449510      25.826762
std              NaN       0.796876       3.243217      14.151887
min              NaN    2010.000000       1.000000       1.000000
25%              NaN    2010.000000       4.000000      14.000000
50%              NaN    2011.000000       6.000000      26.000000
75%              NaN    2012.000000       9.000000      38.000000
max              NaN    2012.000000      12.000000      52.000000
```

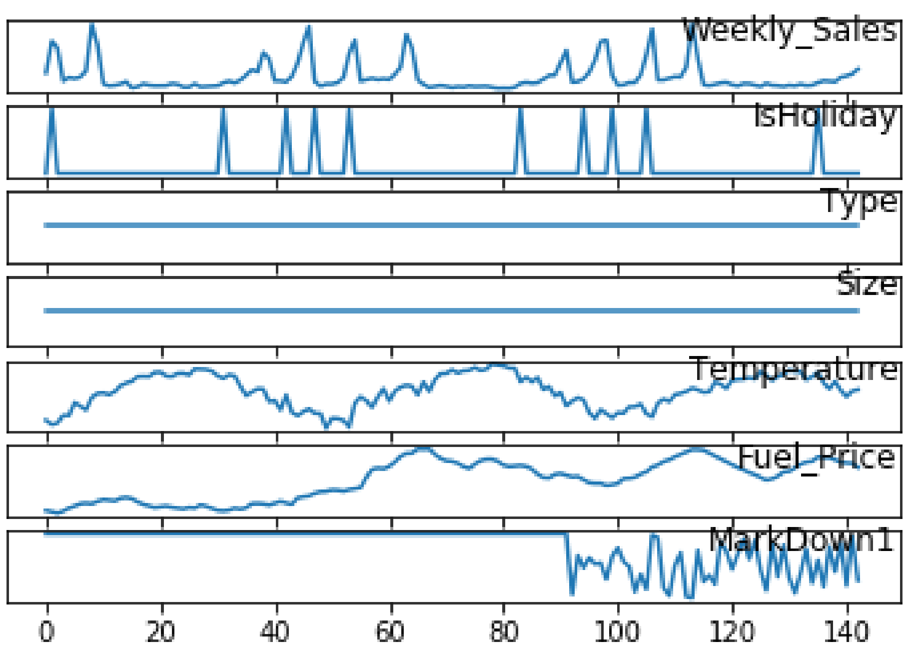
```
In [5]: data.dtypes
```

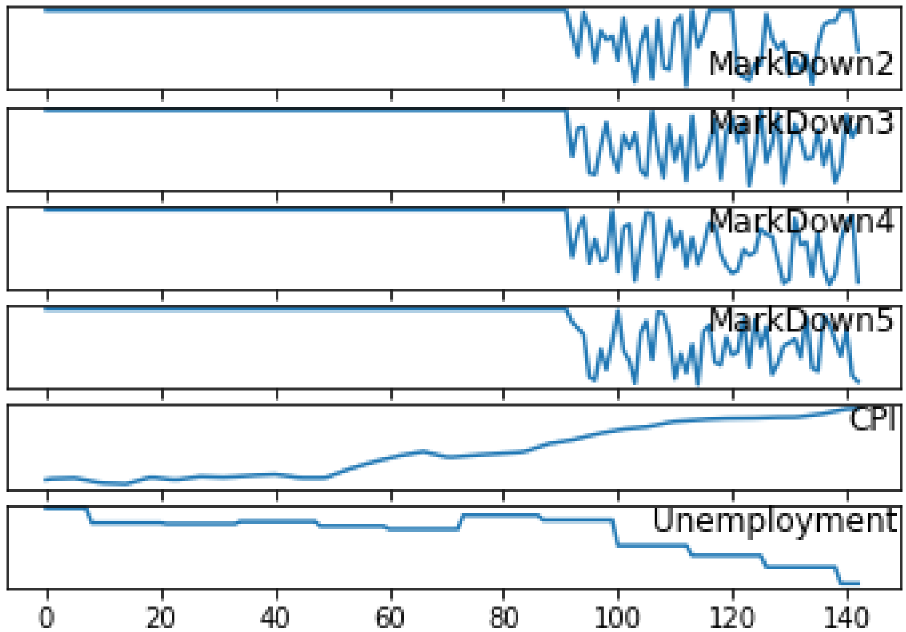
```
Out[5]: Store                      int64
        Dept                       int64
        Date              datetime64[ns]
        Weekly_Sales             float64
        IsHoliday                   bool
        Type                      object
        Size                       int64
        Temperature              float64
        Fuel_Price               float64
        MarkDown1                 object
        MarkDown2                 object
        MarkDown3                 object
        MarkDown4                 object
        MarkDown5                 object
        CPI                       object
        Unemployment              object
        Year                       int64
        Month                      int64
        Week                       int64
        dtype: object
```

Now it would be interesting to take a look at an individual store just to make sense we are clear as to what the building block of the data set represents. Let's select store 1 and see what we got. We will show two separate graphs just to keep the spatial presentation under control:

```
In [11]: select_store = 1
         select_dept = 1
         data_df = data.loc[(data['Store'] == select_store) & (data['Dept'] == select_dept)]

         #PLOT SELECTED COLUMNS FOR THE SELECTED STORE - FIRST GROUP
         values = data_df.values
         to_plot = [ 3, 4, 5, 6, 7, 8, 9]
         i = 1
```

```python
plt.figure()
for item in to_plot:
    plt.subplot(len(to_plot), 1, i)
    plt.plot(values[:, item])
    plt.yticks([])
    plt.title(data_df.columns[item], y=0.5, loc='right')
    i += 1
plt.show()

#AND THEN SECOND GROUP
to_plot = [10, 11, 12, 13, 14, 15]
i = 1
# plot each column
plt.figure()
for item in to_plot:
    plt.subplot(len(to_plot), 1, i)
    plt.plot(values[:, item])
    plt.yticks([])
    plt.title(data.columns[item], y=0.5, loc='right')
    i += 1
plt.show()
```





I think it gives some good idea as to what should be useful here - weekly sales for sure, IsHoliday factor perhaps, and maybe some other values for hygene (e.g. CPI, unemployment, etc.) but perhaps these won't really swing the results. I don't quite understand the nature of MarkDowns and what they represent and I don't think I will use them in the analysis anyway for this reason, and because they are only only available for 1/3 of the time series.

I also think that given the seasonal nature of the data, it would be important to add number of the week to the data set. Sales spikes occur in week 47 and 51 and we should be able to capture this.

Now let's look at some other useful things.

```
In [19]: #THE NUMBER OF UNIQUE STORES
         print('The number of unique stores:')
         data['Store'].nunique()
```

```
The number of unique stores:
```

```
Out[19]: 45
```

```
In [20]: #PLOT STORES VS NUMBER OF DEPARTMENTS FOR EACH STORE
         def store_plot():

             x = data['Store'].unique()
             y = []
             for i in range(len(x)):
                 temp_df = data.loc[data['Store'] == i+1]
                 y.append(temp_df['Dept'].nunique())
```

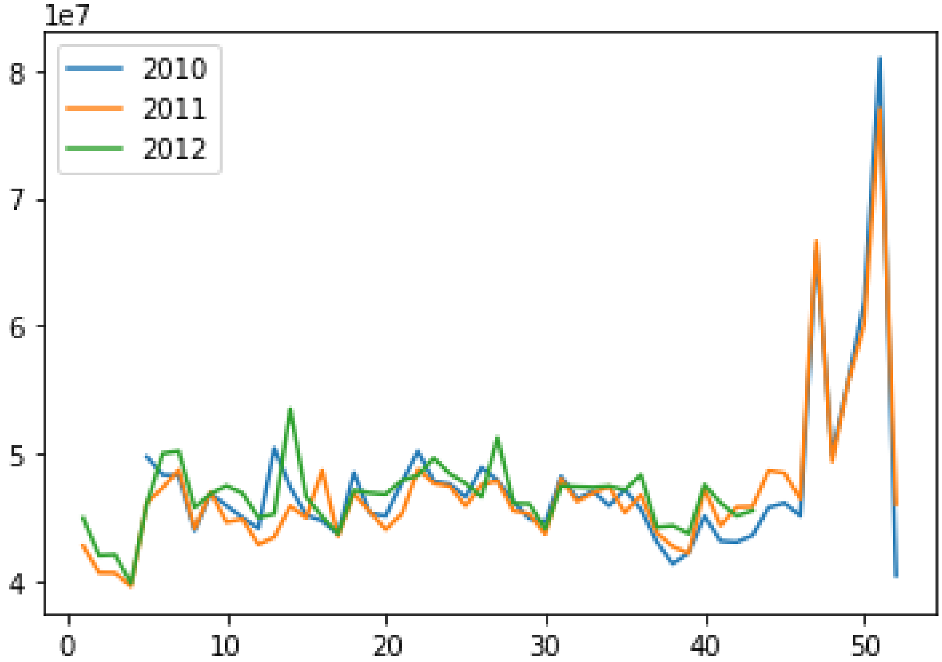
```
            i += 1


        plt.figure()
        plt.scatter(x, y, alpha=0.5)
        plt.xlabel('stores')
        plt.ylabel('departments')
        plt.show()
```

In [21]:
```
#ANNUAL SALES PER STORE

df_2010 = data[data['Date'].isin(pd.date_range("2010-01-01", "2010-12-31"))]
df_2011 = data[data['Date'].isin(pd.date_range("2011-01-01", "2011-12-31"))]
df_2012 = data[data['Date'].isin(pd.date_range("2012-01-01", "2012-12-31"))]

x = data['Week'].unique()
x = df_2010['Week'].unique()
y = df_2010.groupby('Week')['Weekly_Sales'].sum()
```

In [22]:
```
#build table aggregating sales by year and week
annual_sales_df = pd.concat([df_2010.groupby('Week')['Weekly_Sales'].sum(), df_2011.g
annual_sales_df = pd.concat([annual_sales_df, df_2012.groupby('Week')['Weekly_Sales']
annual_sales_df.columns = ['2010', '2011', '2012']
```

And now let's take a look at the plot showing all aggregated sales by week of the year.

In [24]:
```
plt.figure()
plt.plot(annual_sales_df['2010'])
plt.plot(annual_sales_df['2011'])
plt.plot(annual_sales_df['2012'])
plt.legend(loc='upper left')
plt.show()
```



It would be helpful at this stage to also look separately at each year aggregate sales, 2010, 2011 and 2012:

```
In [25]: df_2010.groupby(['Week', 'Store']).sum()['Weekly_Sales'].unstack().plot(legend = None)
         plt.title('Weekly sales by store in 2010')
         plt.xlim(1,52)

Out[25]: (1, 52)
```


```
In [26]: df_2011.groupby(['Week', 'Store']).sum()['Weekly_Sales'].unstack().plot(legend = None)
         plt.title('Weekly sales by store in 2011')
         plt.xlim(1,52)

Out[26]: (1, 52)
```


```
In [27]: df_2012.groupby(['Week', 'Store']).sum()['Weekly_Sales'].unstack().plot(legend = None)
         plt.title('Weekly sales by store in 2012')
         plt.xlim(1,52)

Out[27]: (1, 52)
```

I think these graphs give a pretty complete picture of the data: we have incomplete year 2010 (a few weeks in the beginning) and 2012 (~7 weeks at the end, including all of the holiday season). Now it would be interesting to see if a model can be built that predicts the usual seasonal fluctuation based on the observations from 2010 and 2011.

I am not going to bother with building a train/test split this time, butinstead will use the full data set as for training. It's pretty clear what we can expect to see in that gap at the end of 2012 graph.

The purpose here is only to set up a model that would correctly infer the typical sales patterns surrounding the holiday season. LSTM is an ovious model candidate. Given LSTM choice, it would be intresting to:

- make a series of predictions in one go, i.e. make one prediction of several weeks, as opposed to a week by week prediction
- experiment with adding different independent variables and their effect on the model performance

This is exactly what I will try next.