Linear_Regression_from_Scratch_Walmart_Store_Level_Weekly_Sales_Fo

December 11, 2019

1 Forecasting total weekly Walmart sales with Linear Regression from Scratch

The purpose of this notebook is to predict Walmart sales using linear regression models generated using numpy only (no ready-made Linear Regression models used). This is in order to more fully understand Linear Regression, how Linear Regression models are built, trained and used to generate predications.

The Walmart historical sales data is found on Kaggle here: https://www.kaggle.com/c/walmart-recruiting-store-sales-forecasting/data

Using the historical sales data for 45 Walmart stores located in different regions, this project will involve building a Linear Regression model from scratch to predict weekly total sales for stores.

The data from Kaggle includes:

`stores.csv`: This contains anonymised information about the 45 stores, indicating the type and size of store.

`train.csv`: This is the historical training data, which covers from 2010-02-05 to 2012-11-01. Within this file are the following fields:

```
Store - the store number
Dept - the department number
Date - the week
Weekly_Sales -  sales for the given department in the given store
IsHoliday - whether the week is a special holiday week
```

`features.csv`: This contains additional data related to the store, department, and regional activity for the given dates. It contains the following fields:

```
Store - the store number
Date - the week
Temperature - average temperature in the region
Fuel_Price - cost of fuel in the region
MarkDown1-5 - anonymized data related to promotional markdowns that Walmart is running. MarkDow
CPI - the consumer price index
Unemployment - the unemployment rate
IsHoliday - whether the week is a special holiday week
```

[1]:
```python
import warnings
warnings.filterwarnings("ignore")

import numpy as np
import pandas as pd
import scipy.stats as stats
import matplotlib.pyplot as plt
import sklearn
from sklearn import linear_model
from sklearn import metrics
import seaborn as sns
sns.set_style("whitegrid")
from sklearn.model_selection import train_test_split
```

1.1 Data preparation

[2]:
```python
train = pd.read_csv('train.csv')
stores = pd.read_csv('stores.csv')
features = pd.read_csv('features.csv')
```

[3]:
```python
train.head()
```

[3]:

	Store	Dept	Date	Weekly_Sales	IsHoliday
0	1	1	2010-02-05	24924.50	False
1	1	1	2010-02-12	46039.49	True
2	1	1	2010-02-19	41595.55	False
3	1	1	2010-02-26	19403.54	False
4	1	1	2010-03-05	21827.90	False

[4]:
```python
features.tail()
```

[4]:

	Store	Date	Temperature	Fuel_Price	MarkDown1	MarkDown2	\
8185	45	2013-06-28	76.05	3.639	4842.29	975.03	
8186	45	2013-07-05	77.50	3.614	9090.48	2268.58	
8187	45	2013-07-12	79.37	3.614	3789.94	1827.31	
8188	45	2013-07-19	82.84	3.737	2961.49	1047.07	
8189	45	2013-07-26	76.06	3.804	212.02	851.73	

	MarkDown3	MarkDown4	MarkDown5	CPI	Unemployment	IsHoliday
8185	3.00	2449.97	3169.69	NaN	NaN	False
8186	582.74	5797.47	1514.93	NaN	NaN	False
8187	85.72	744.84	2150.36	NaN	NaN	False
8188	204.19	363.00	1059.46	NaN	NaN	False
8189	2.06	10.88	1864.57	NaN	NaN	False

[5]:
```python
stores.head()
```

[5]:
```
   Store Type    Size
0      1    A  151315
1      2    A  202307
2      3    B   37392
3      4    A  205863
4      5    B   34875
```

[6]:
```
#merge train and feature dfs on store and date and is holiday
df_merged = pd.merge(train, features, on=['Store','Date','IsHoliday'],␣
↪how='inner')
```

[7]:
```
#merge merged and stores dfs on store
df_merged = pd.merge(df_merged, stores, on=['Store'], how='inner')
```

[8]:
```
df_merged.head()
```

[8]:
```
   Store  Dept        Date  Weekly_Sales  IsHoliday  Temperature  Fuel_Price  \
0      1     1  2010-02-05      24924.50      False        42.31       2.572
1      1     2  2010-02-05      50605.27      False        42.31       2.572
2      1     3  2010-02-05      13740.12      False        42.31       2.572
3      1     4  2010-02-05      39954.04      False        42.31       2.572
4      1     5  2010-02-05      32229.38      False        42.31       2.572

   MarkDown1  MarkDown2  MarkDown3  MarkDown4  MarkDown5         CPI  \
0        NaN        NaN        NaN        NaN        NaN  211.096358
1        NaN        NaN        NaN        NaN        NaN  211.096358
2        NaN        NaN        NaN        NaN        NaN  211.096358
3        NaN        NaN        NaN        NaN        NaN  211.096358
4        NaN        NaN        NaN        NaN        NaN  211.096358

   Unemployment Type    Size
0         8.106    A  151315
1         8.106    A  151315
2         8.106    A  151315
3         8.106    A  151315
4         8.106    A  151315
```

[9]:
```
df_merged.Dept.nunique()
```

[9]: 81

[10]:
```
df_merged.describe().transpose()
```

[10]:
```
                 count          mean           std       min          25%  \
Store         421570.0     22.200546     12.785297     1.000    11.000000
Dept          421570.0     44.260317     30.492054     1.000    18.000000
Weekly_Sales  421570.0  15981.258123  22711.183519 -4988.940  2079.650000
```

```
Temperature   421570.0      60.090059     18.447931     -2.060      46.680000
Fuel_Price    421570.0       3.361027      0.458515      2.472       2.933000
MarkDown1     150681.0    7246.420196   8291.221345      0.270    2240.270000
MarkDown2     111248.0    3334.628621   9475.357325   -265.760      41.600000
MarkDown3     137091.0    1439.421384   9623.078290    -29.100       5.080000
MarkDown4     134967.0    3383.168256   6292.384031      0.220     504.220000
MarkDown5     151432.0    4628.975079   5962.887455    135.160    1878.440000
CPI           421570.0     171.201947     39.159276    126.064     132.022667
Unemployment  421570.0       7.960289      1.863296      3.879       6.891000
Size          421570.0  136727.915739  60980.583328  34875.000   93638.000000

                    50%            75%            max
Store          22.00000      33.000000      45.000000
Dept           37.00000      74.000000      99.000000
Weekly_Sales 7612.03000   20205.852500  693099.360000
Temperature    62.09000      74.280000     100.140000
Fuel_Price      3.45200       3.738000       4.468000
MarkDown1    5347.45000    9210.900000   88646.760000
MarkDown2     192.00000    1926.940000  104519.540000
MarkDown3      24.60000     103.990000  141630.610000
MarkDown4    1481.31000    3595.040000   67474.850000
MarkDown5    3359.45000    5563.800000  108519.280000
CPI           182.31878     212.416993     227.232807
Unemployment    7.86600       8.572000      14.313000
Size       140167.00000  202505.000000  219622.000000
```

[11]:
```
df_merged.dtypes
```

[11]:
```
Store             int64
Dept              int64
Date             object
Weekly_Sales    float64
IsHoliday          bool
Temperature     float64
Fuel_Price      float64
MarkDown1       float64
MarkDown2       float64
MarkDown3       float64
MarkDown4       float64
MarkDown5       float64
CPI             float64
Unemployment    float64
Type             object
Size              int64
dtype: object
```

[12]:
```
#create column where date converted into datetime object
from datetime import datetime as dt
```

[13]:
```
df_merged['DateTime']=[dt.strptime(x,'%Y-%m-%d') for x in␣
↪list(df_merged['Date'])]
df_merged['DateTime'].head()
```

[13]:
```
0   2010-02-05
1   2010-02-05
2   2010-02-05
3   2010-02-05
4   2010-02-05
Name: DateTime, dtype: datetime64[ns]
```

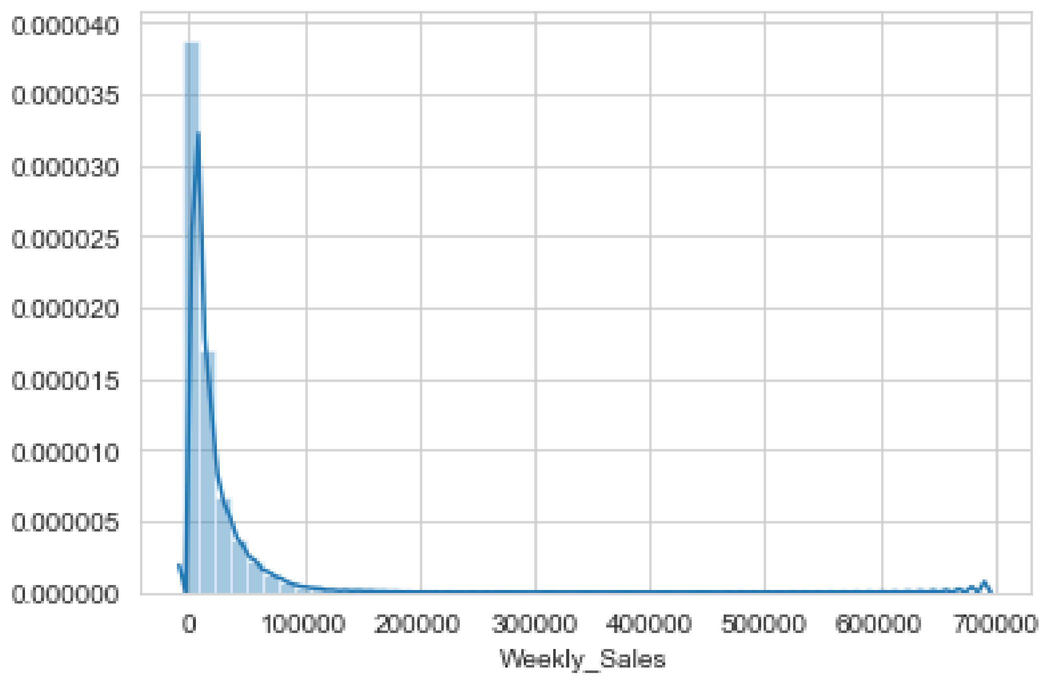
[14]:
```
df_merged.head()
```

[14]:
```
   Store  Dept        Date  Weekly_Sales  IsHoliday  Temperature  Fuel_Price  \
0      1     1  2010-02-05      24924.50      False        42.31       2.572
1      1     2  2010-02-05      50605.27      False        42.31       2.572
2      1     3  2010-02-05      13740.12      False        42.31       2.572
3      1     4  2010-02-05      39954.04      False        42.31       2.572
4      1     5  2010-02-05      32229.38      False        42.31       2.572

   MarkDown1  MarkDown2  MarkDown3  MarkDown4  MarkDown5         CPI  \
0        NaN        NaN        NaN        NaN        NaN  211.096358
1        NaN        NaN        NaN        NaN        NaN  211.096358
2        NaN        NaN        NaN        NaN        NaN  211.096358
3        NaN        NaN        NaN        NaN        NaN  211.096358
4        NaN        NaN        NaN        NaN        NaN  211.096358

   Unemployment Type    Size    DateTime
0         8.106    A  151315  2010-02-05
1         8.106    A  151315  2010-02-05
2         8.106    A  151315  2010-02-05
3         8.106    A  151315  2010-02-05
4         8.106    A  151315  2010-02-05
```

1.2 Data Exploration and Pre-Processing

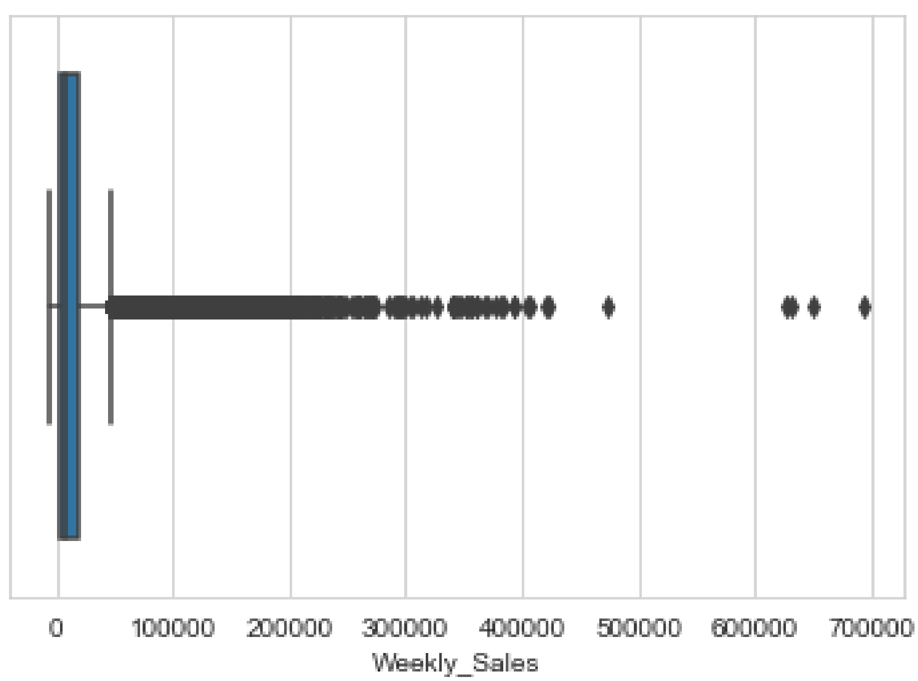
[15]:
```
sns.distplot(df_merged['Weekly_Sales'])
```

[15]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fc9d9aa01d0>
```



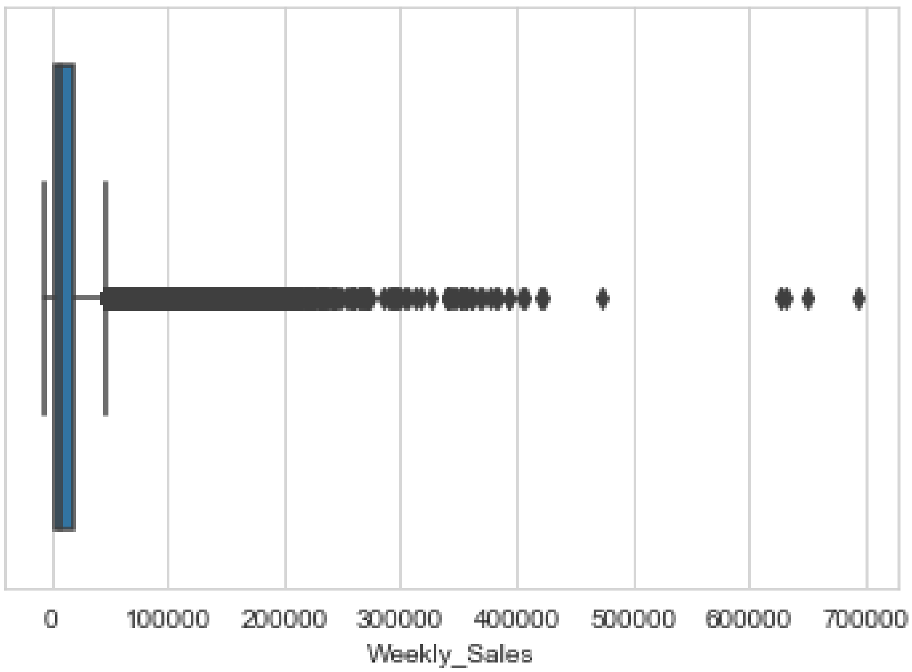
[16]:
```
sns.boxplot(df_merged['Weekly_Sales'])
```

[16]: <matplotlib.axes._subplots.AxesSubplot at 0x7fc9c884ae80>



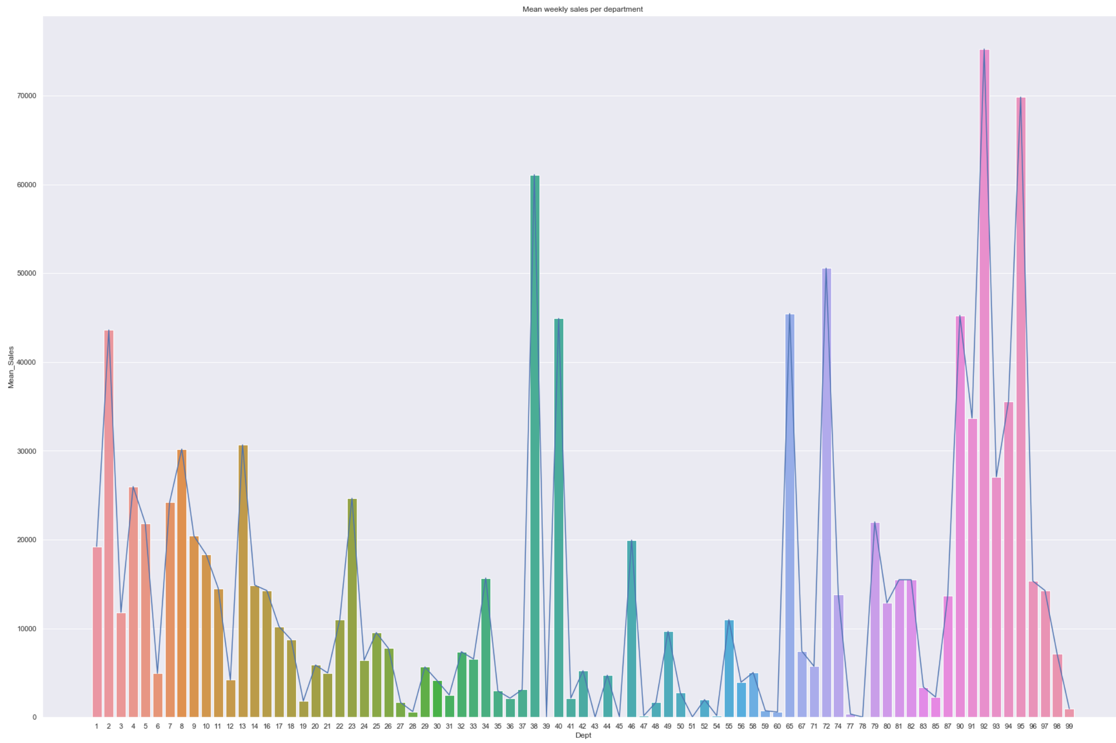
[17]:
```
sns.boxplot(df_merged['Weekly_Sales'])
```

[17]: <matplotlib.axes._subplots.AxesSubplot at 0x7fc9b8b925f8>

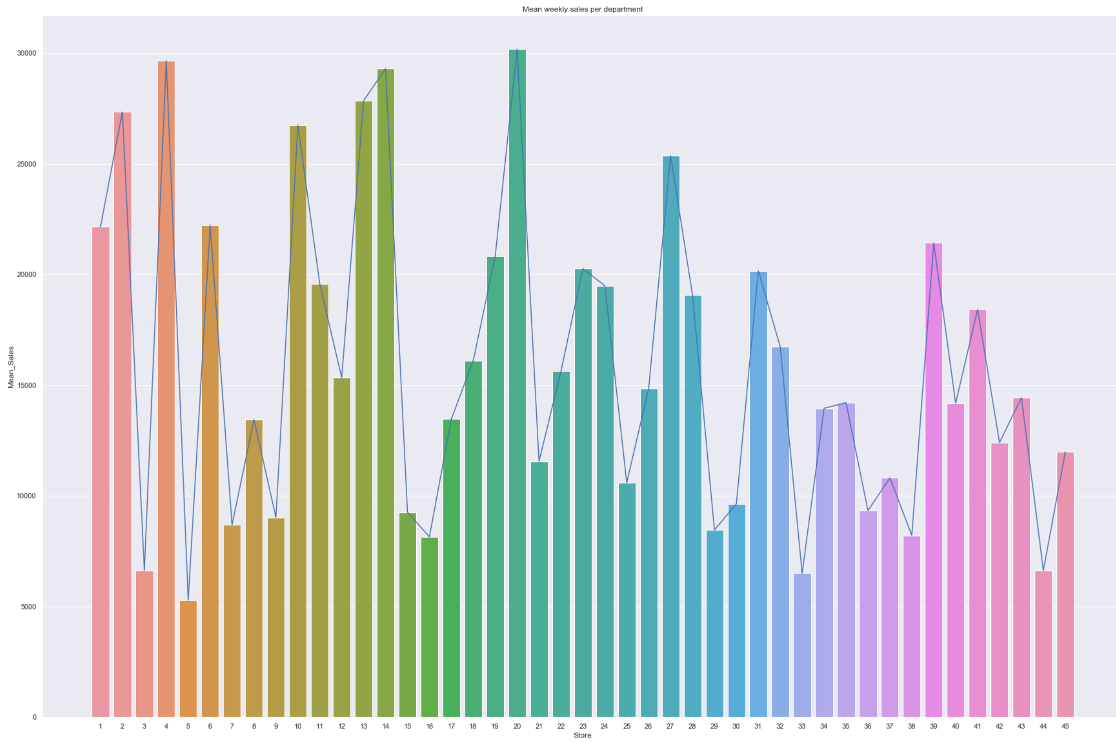


[18]:
```
#clip weekly sales 0, 400,000
df_merged['Weekly_Sales'] = df_merged['Weekly_Sales'].clip(0,400000)
```

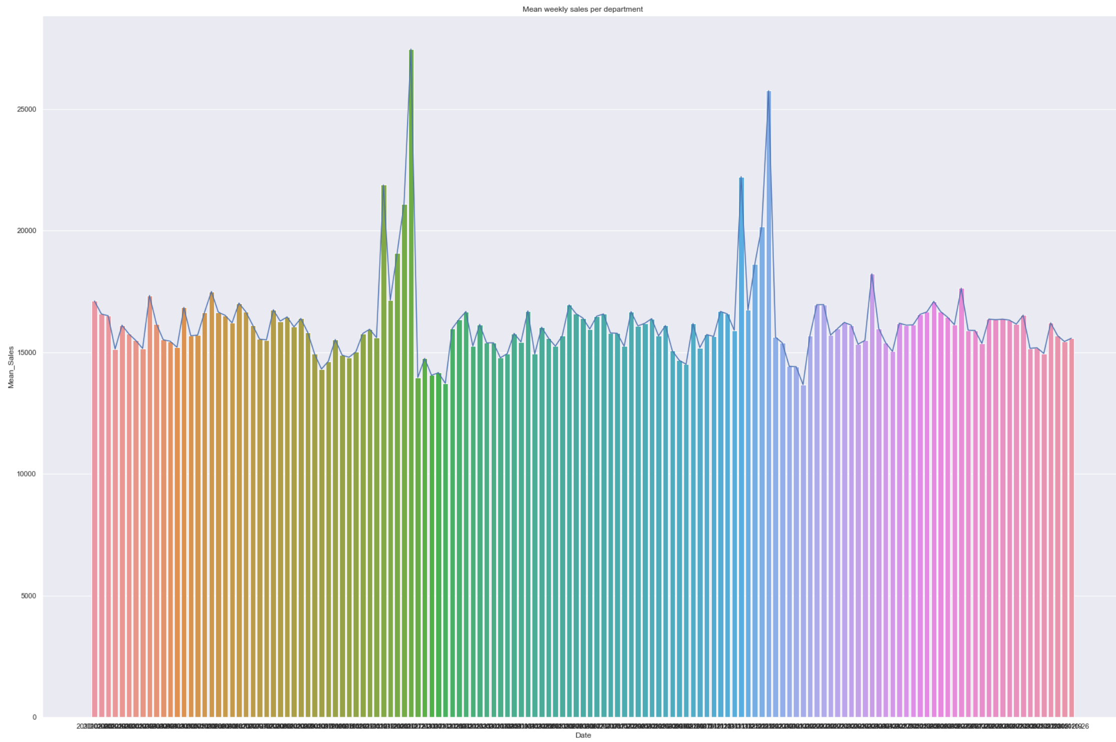
[19]:
```
#mean weekly sales per dept
sns.set(rc={'figure.figsize':(30, 20)})
dept_df = pd.DataFrame(df_merged[['Dept','Weekly_Sales']].drop_duplicates().
 ↪groupby('Dept').mean()).reset_index()
dept_df.columns = ['Dept', 'Mean_Sales']
sns.barplot(x ='Dept', y='Mean_Sales', data=dept_df);
plt.plot(dept_df['Mean_Sales']);
plt.title('Mean weekly sales per department')
del dept_df
```



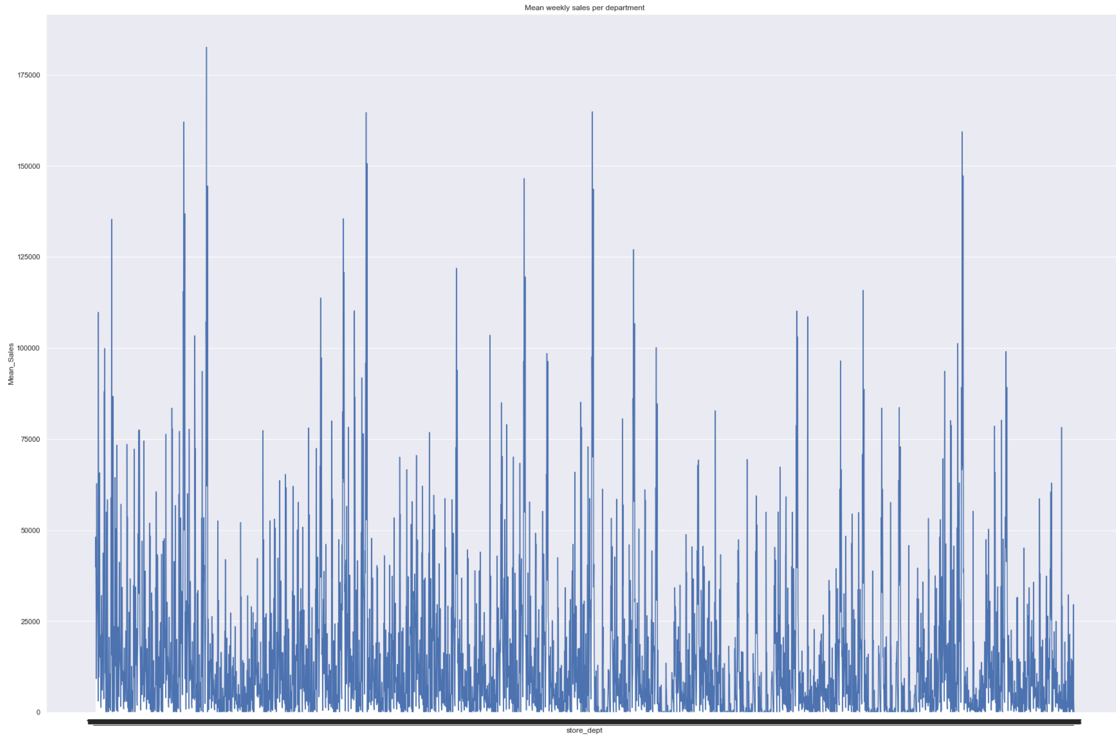
[20]:
```
#mean weekly sales per store
sns.set(rc={'figure.figsize':(30, 20)})
store_df = pd.DataFrame(df_merged[['Store','Weekly_Sales']].drop_duplicates().
 ↪groupby('Store').mean()).reset_index()
store_df.columns = ['Store', 'Mean_Sales']
sns.barplot(x ='Store', y='Mean_Sales', data=store_df);
plt.plot(store_df['Mean_Sales']);
plt.title('Mean weekly sales per department')
del store_df
```



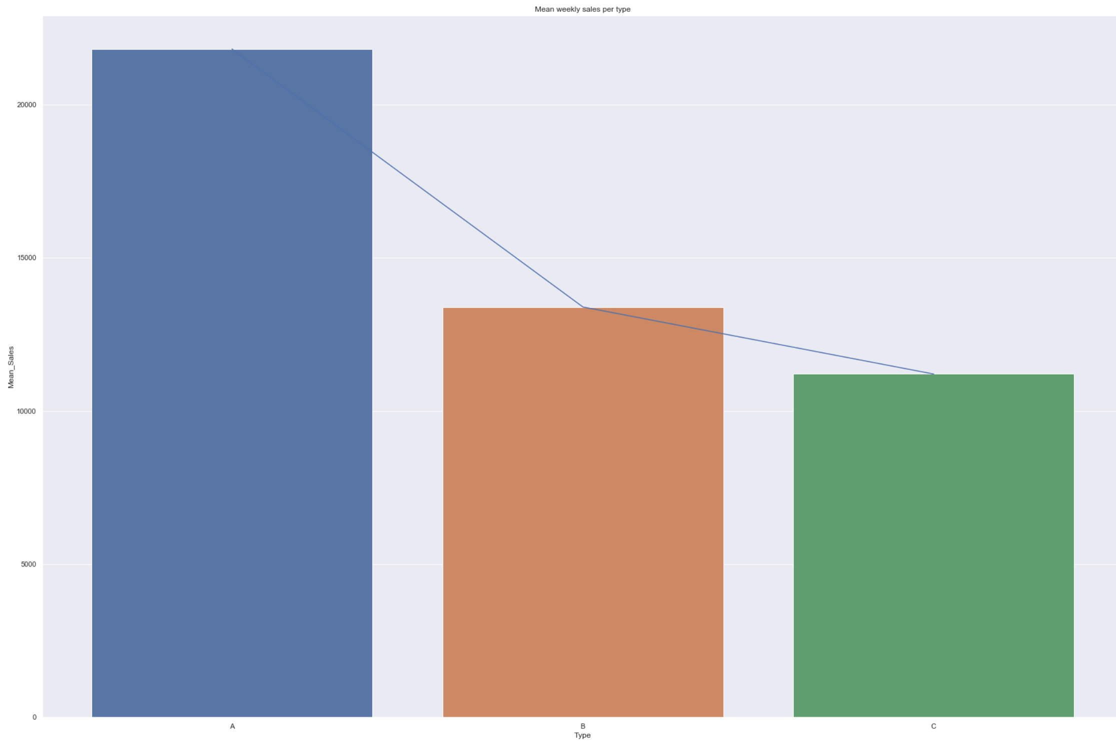
[21]:
```
#mean weekly sales
sns.set(rc={'figure.figsize':(30, 20)})
date_df = pd.DataFrame(df_merged[['Date','Weekly_Sales']].drop_duplicates().
 ↪groupby('Date').mean()).reset_index()
date_df.columns = ['Date', 'Mean_Sales']
sns.barplot(x ='Date', y='Mean_Sales', data=date_df);
plt.plot(date_df['Mean_Sales']);
plt.title('Mean weekly sales per department')
del date_df
```



[22]:
```
#mean weekly sales per store-dept
sns.set(rc={'figure.figsize':(30, 20)})
date_df = pd.DataFrame(df_merged[['Store','Dept','Weekly_Sales']].
    ↪drop_duplicates())
date_df['store_dept'] = date_df['Store'].astype(str) + "_" + date_df['Dept'].
    ↪astype(str)
date_df = date_df.drop(['Store','Dept'], axis=1)
date_df = date_df.groupby('store_dept').mean().reset_index()
date_df.columns = ['store_dept', 'Mean_Sales']
sns.barplot(x ='store_dept', y='Mean_Sales', data=date_df);
plt.plot(date_df['Mean_Sales']);
plt.title('Mean weekly sales per department')
del date_df
```

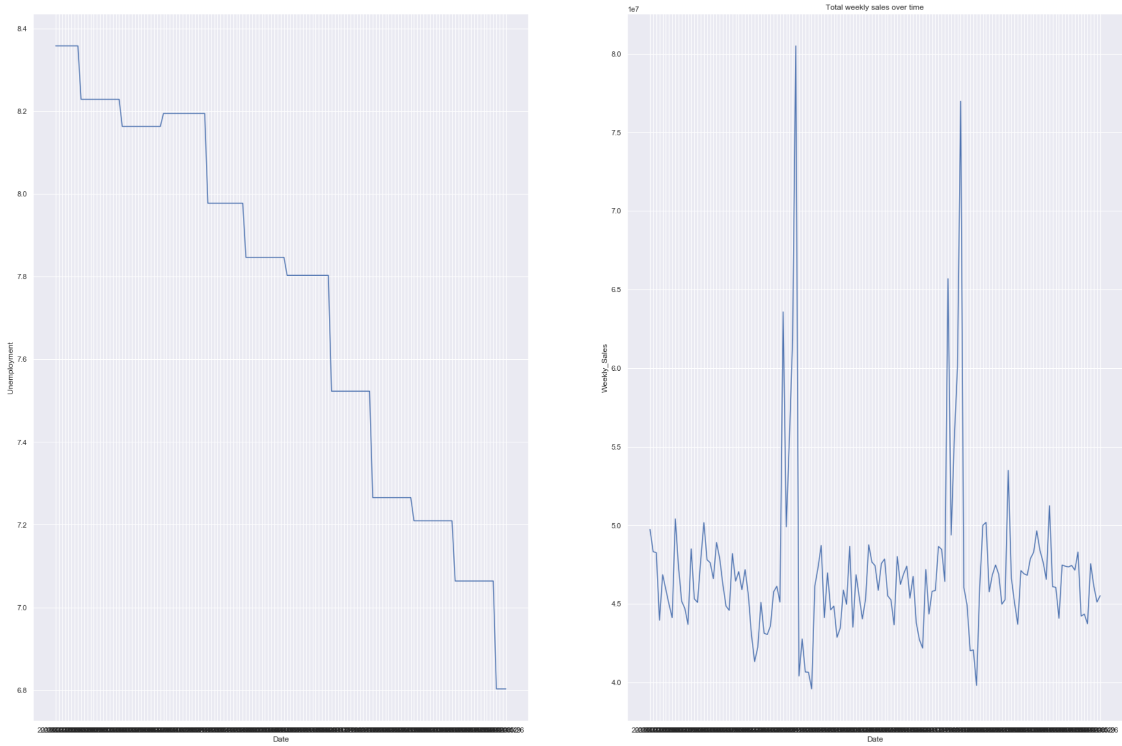



```
[23]: #mean weekly sales by type
sns.set(rc={'figure.figsize':(30, 20)})
type_df = pd.DataFrame(df_merged[['Type','Weekly_Sales']].drop_duplicates().
 ↪groupby('Type').mean()).reset_index()
type_df.columns = ['Type', 'Mean_Sales']
sns.barplot(x ='Type', y='Mean_Sales', data=type_df);
plt.plot(type_df['Mean_Sales']);
plt.title('Mean weekly sales per type')
del type_df
```



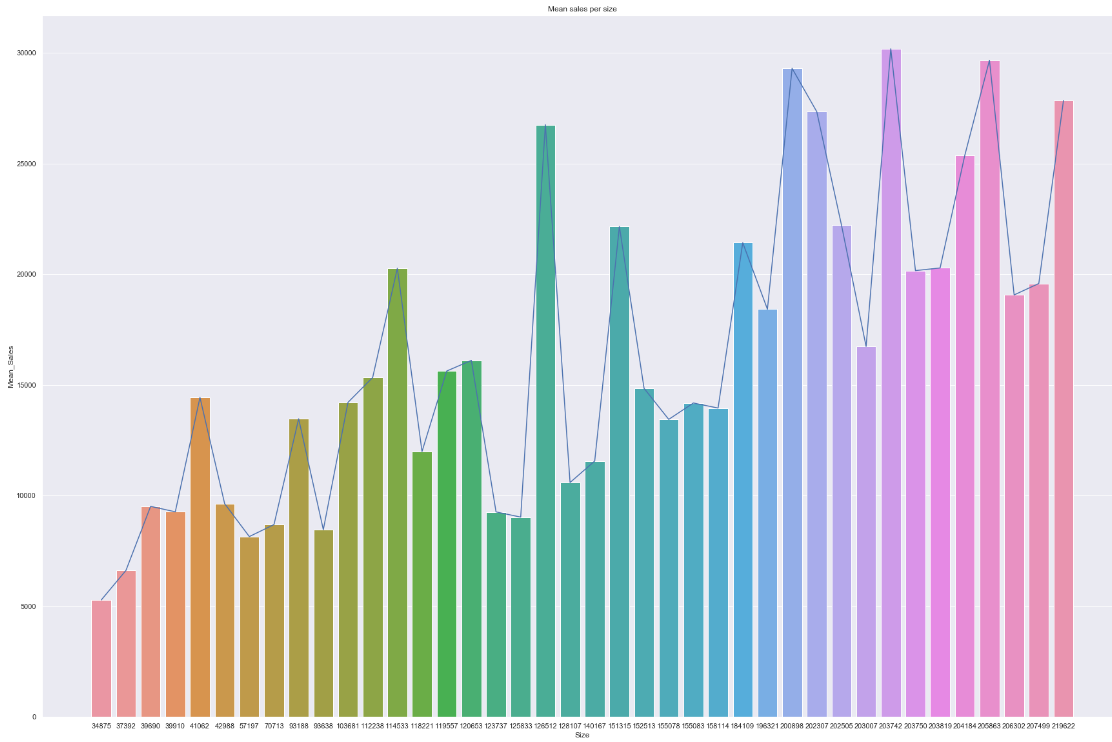
There appears to be a relationship between store type and sales.

[24]:
```
#mean weekly sales by type
sns.set(rc={'figure.figsize':(30, 20)})
unemp_df = pd.DataFrame(df_merged[['Date','Unemployment']].drop_duplicates().
 ↪groupby('Date').mean()).reset_index()
unemp_df.columns = ['Date', 'Unemployment']
sales_df = pd.DataFrame(df_merged[['Date','Weekly_Sales']].drop_duplicates().
 ↪groupby('Date').sum()).reset_index()
sales_df.columns = ['Date', 'Weekly_Sales']

f, axes = plt.subplots(1, 2)
sns.lineplot(x ='Date', y='Unemployment', data=unemp_df, ax=axes[0]);
plt.title('Mean unemployment over time')
sns.lineplot(x ='Date', y='Weekly_Sales', data=sales_df, ax=axes[1]);
plt.title('Total weekly sales over time')
del unemp_df, sales_df
```



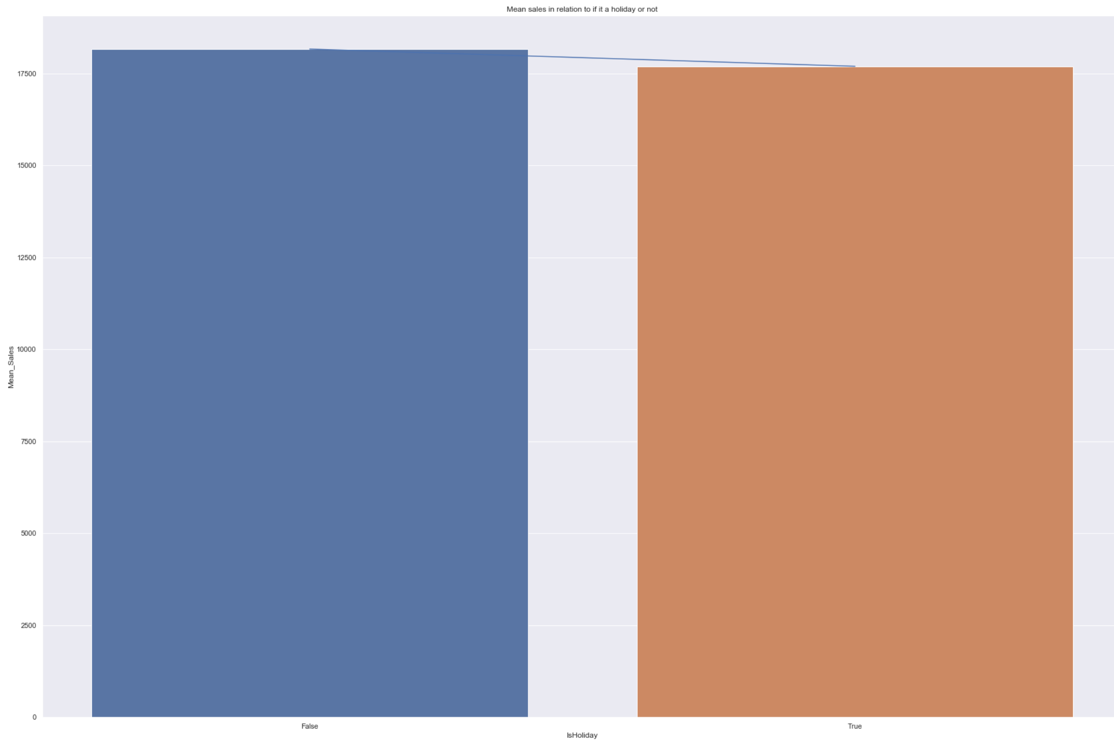
There does not appear to be any link between unemployment and weekly sales.

[25]:
```
#mean weekly sales by type
sns.set(rc={'figure.figsize':(30, 20)})
size_df = pd.DataFrame(df_merged[['Size','Weekly_Sales']].drop_duplicates().
 ↪groupby('Size').mean()).reset_index()
size_df.columns = ['Size', 'Mean_Sales']
sns.barplot(x ='Size', y='Mean_Sales', data=size_df);
plt.plot(size_df['Mean_Sales']);
plt.title('Mean sales per size')
del size_df
```



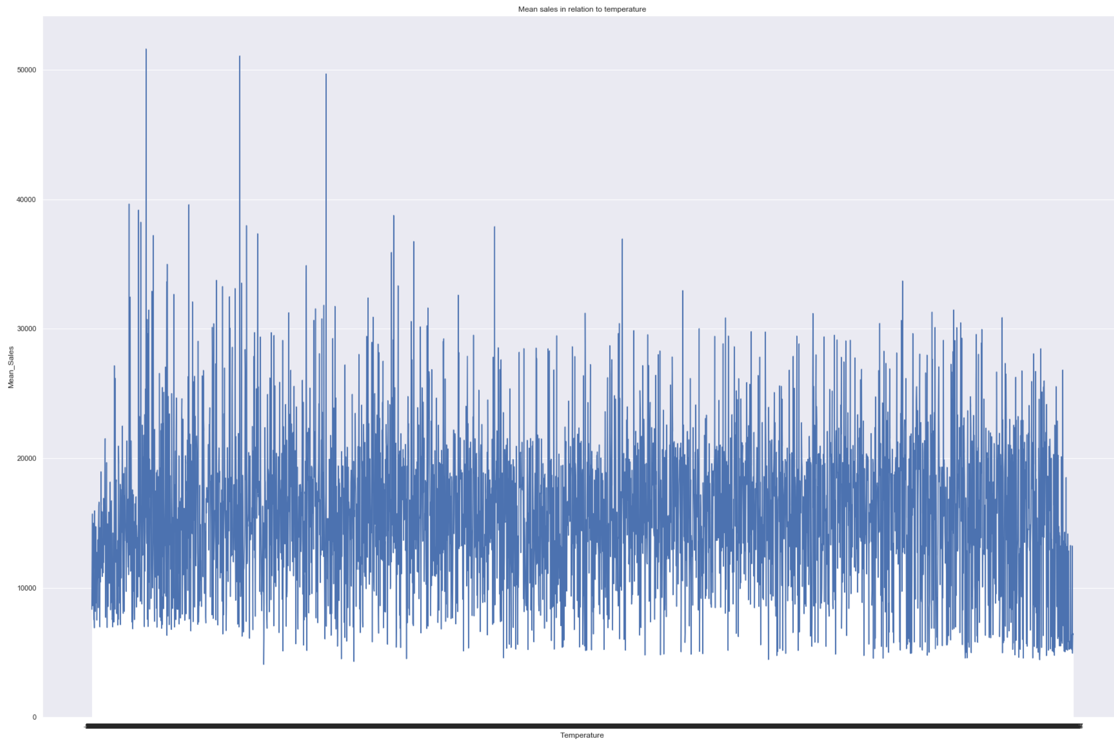
Size does appear to be associated with different levels of sales.

[26]:
```
#mean weekly sales by type
sns.set(rc={'figure.figsize':(30, 20)})
hol_df = pd.DataFrame(df_merged[['IsHoliday','Weekly_Sales']].drop_duplicates().
 ↪groupby('IsHoliday').mean()).reset_index()
hol_df.columns = ['IsHoliday', 'Mean_Sales']
sns.barplot(x ='IsHoliday', y='Mean_Sales', data=hol_df);
plt.plot(hol_df['Mean_Sales']);
plt.title('Mean sales in relation to if it a holiday or not')
del hol_df
```



Whether it is a holiday or not appears to have a minimal impact on sales.

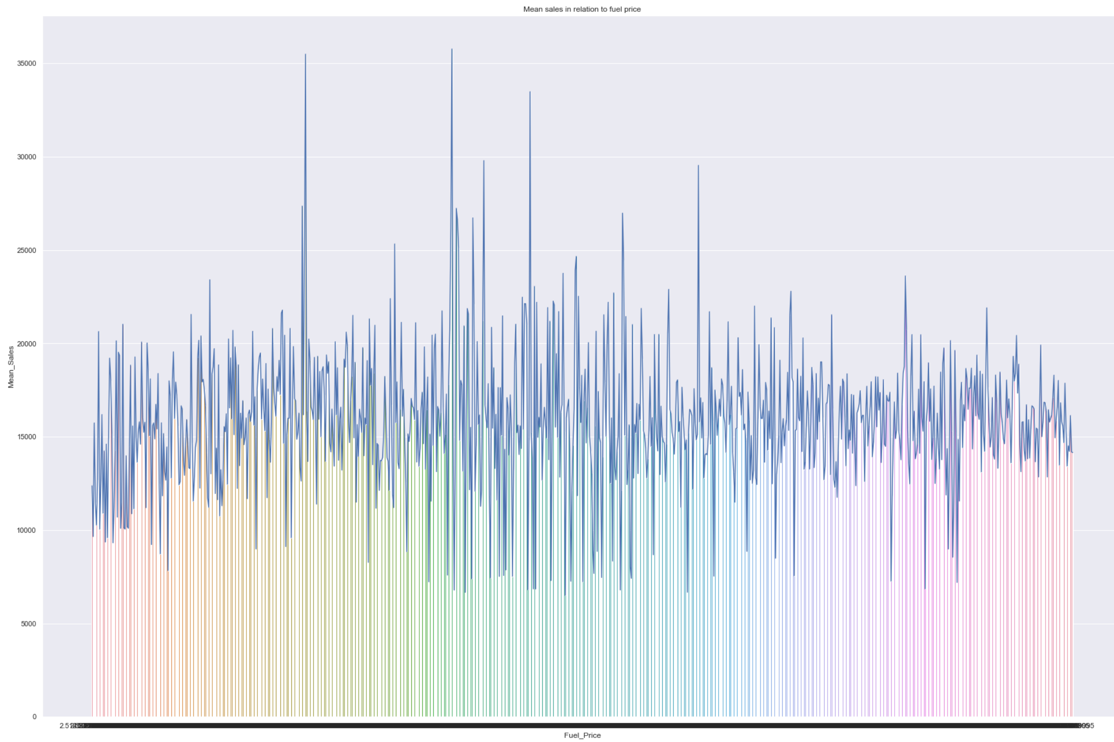
[27]:
```
#mean weekly sales by type
sns.set(rc={'figure.figsize':(30, 20)})
temp_df = pd.DataFrame(df_merged[['Temperature','Weekly_Sales']].
 ↪drop_duplicates().groupby('Temperature').mean()).reset_index()
temp_df.columns = ['Temperature', 'Mean_Sales']
sns.barplot(x ='Temperature', y='Mean_Sales', data=temp_df);
plt.plot(temp_df['Mean_Sales']);
plt.title('Mean sales in relation to temperature')
del temp_df
```



Temperature appears to have a minimal effect on sales, but mainly at the lower temperatures.

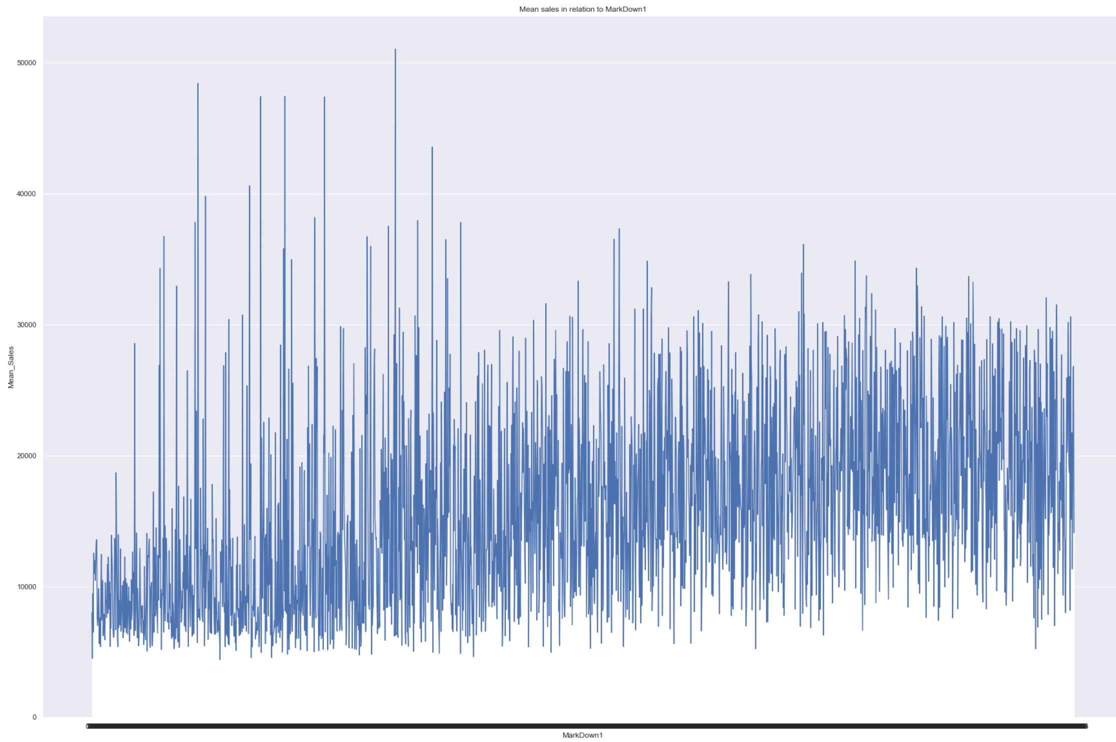
[28]:

```
#mean weekly sales by type
sns.set(rc={'figure.figsize':(30, 20)})
fuel_df = pd.DataFrame(df_merged[['Fuel_Price','Weekly_Sales']].
 ↪drop_duplicates().groupby('Fuel_Price').mean()).reset_index()
fuel_df.columns = ['Fuel_Price', 'Mean_Sales']
sns.barplot(x ='Fuel_Price', y='Mean_Sales', data=fuel_df);
plt.plot(fuel_df['Mean_Sales']);
plt.title('Mean sales in relation to fuel price')
del fuel_df
```

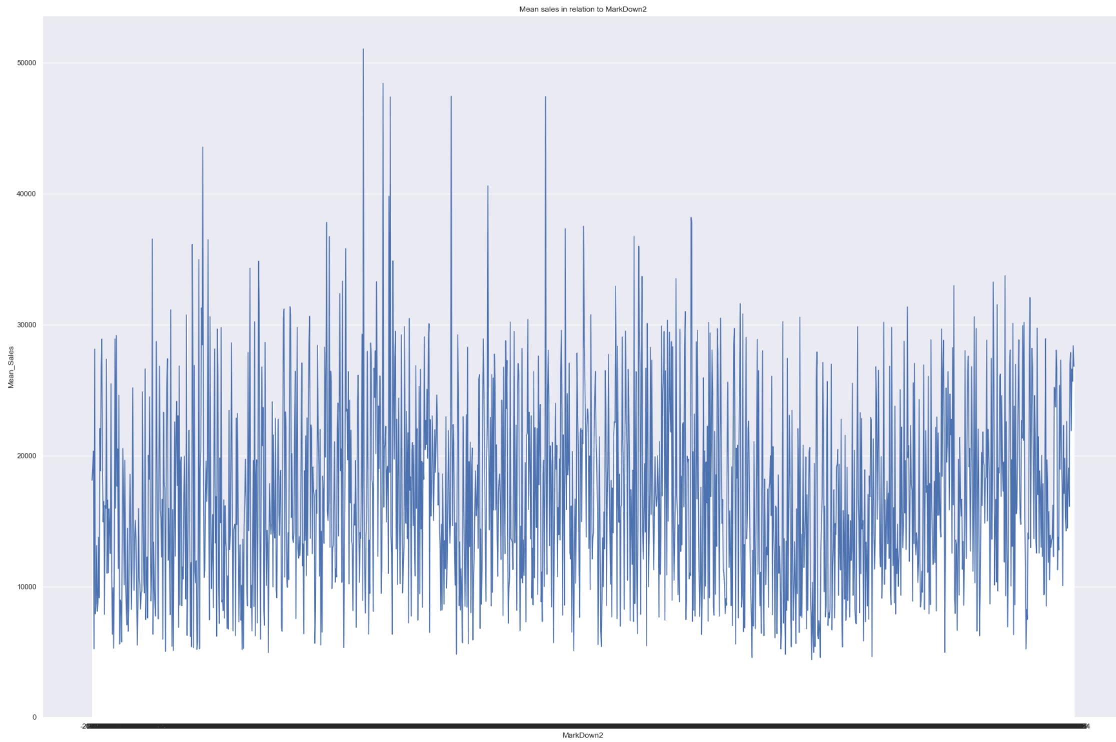


Fuel price appears to have a minimal effect on sales, mainly around the the mid-price range.

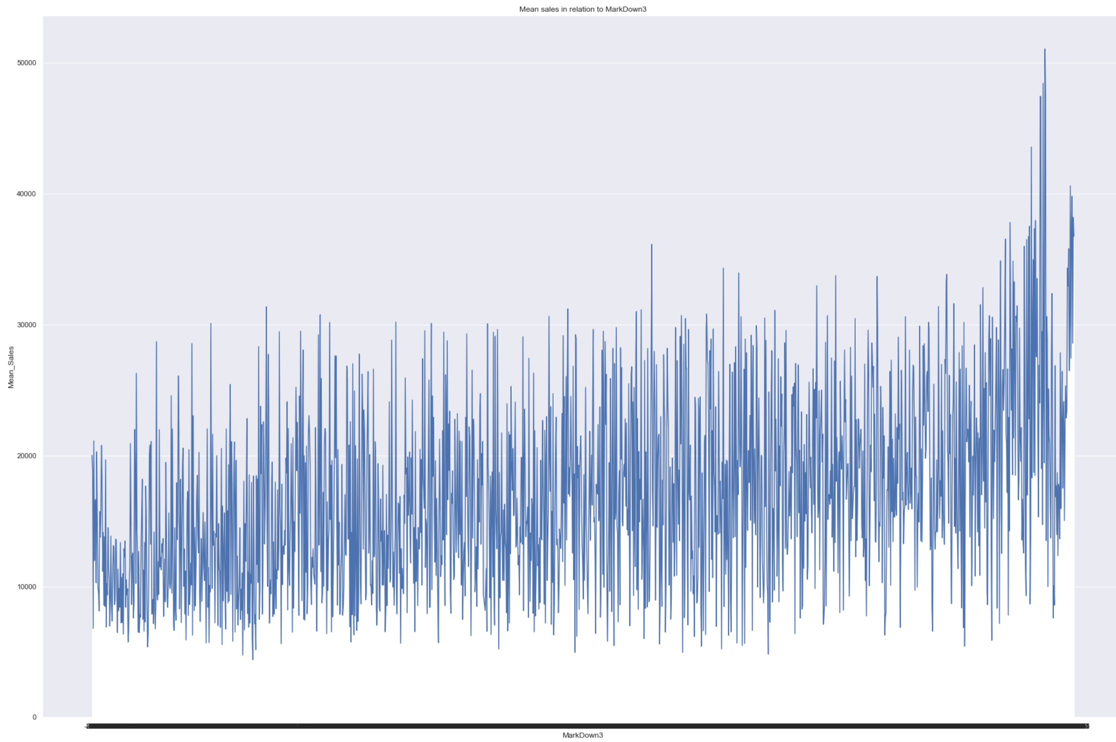
[29]:
```
#mean weekly sales by type
sns.set(rc={'figure.figsize':(30, 20)})
MarkDown1_df = pd.DataFrame(df_merged[['MarkDown1','Weekly_Sales']].
 ↪drop_duplicates().groupby('MarkDown1').mean()).reset_index()
MarkDown1_df.columns = ['MarkDown1', 'Mean_Sales']
sns.barplot(x ='MarkDown1', y='Mean_Sales', data=MarkDown1_df);
plt.plot(MarkDown1_df['Mean_Sales']);
plt.title('Mean sales in relation to MarkDown1')
del MarkDown1_df
```



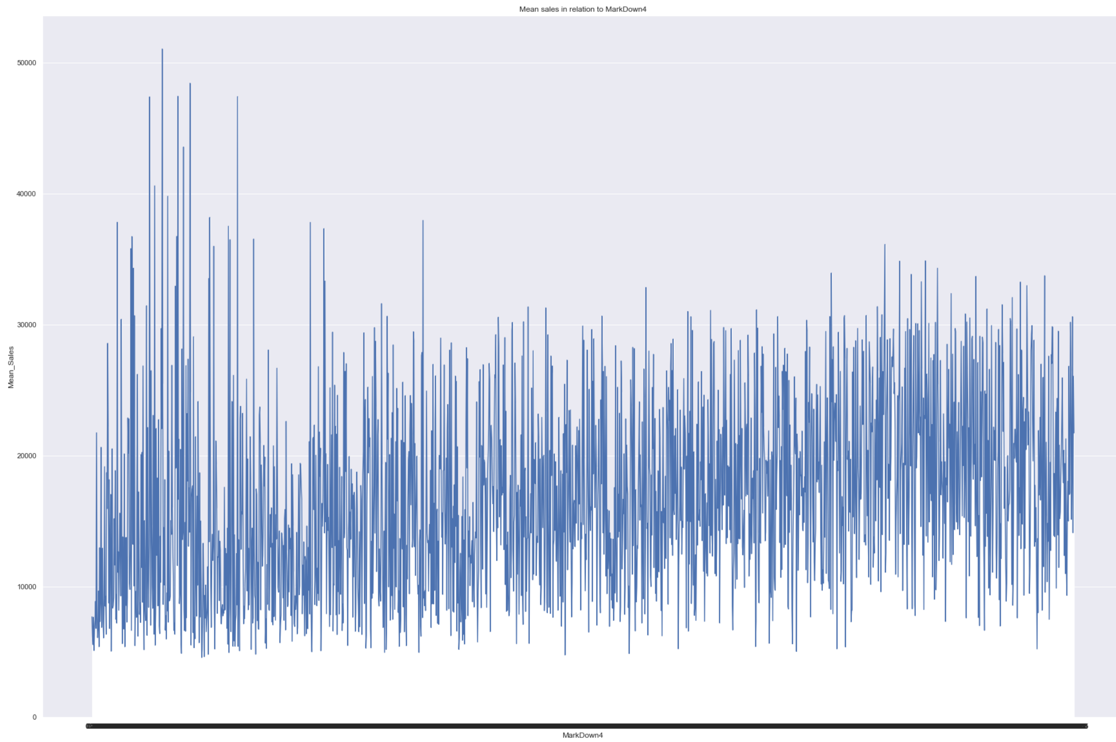
[30]:
```
#mean weekly sales by type
sns.set(rc={'figure.figsize':(30, 20)})
MarkDown2_df = pd.DataFrame(df_merged[['MarkDown2','Weekly_Sales']].
 ↪drop_duplicates().groupby('MarkDown2').mean()).reset_index()
MarkDown2_df.columns = ['MarkDown2', 'Mean_Sales']
sns.barplot(x ='MarkDown2', y='Mean_Sales', data=MarkDown2_df);
plt.plot(MarkDown2_df['Mean_Sales']);
plt.title('Mean sales in relation to MarkDown2')
del MarkDown2_df
```



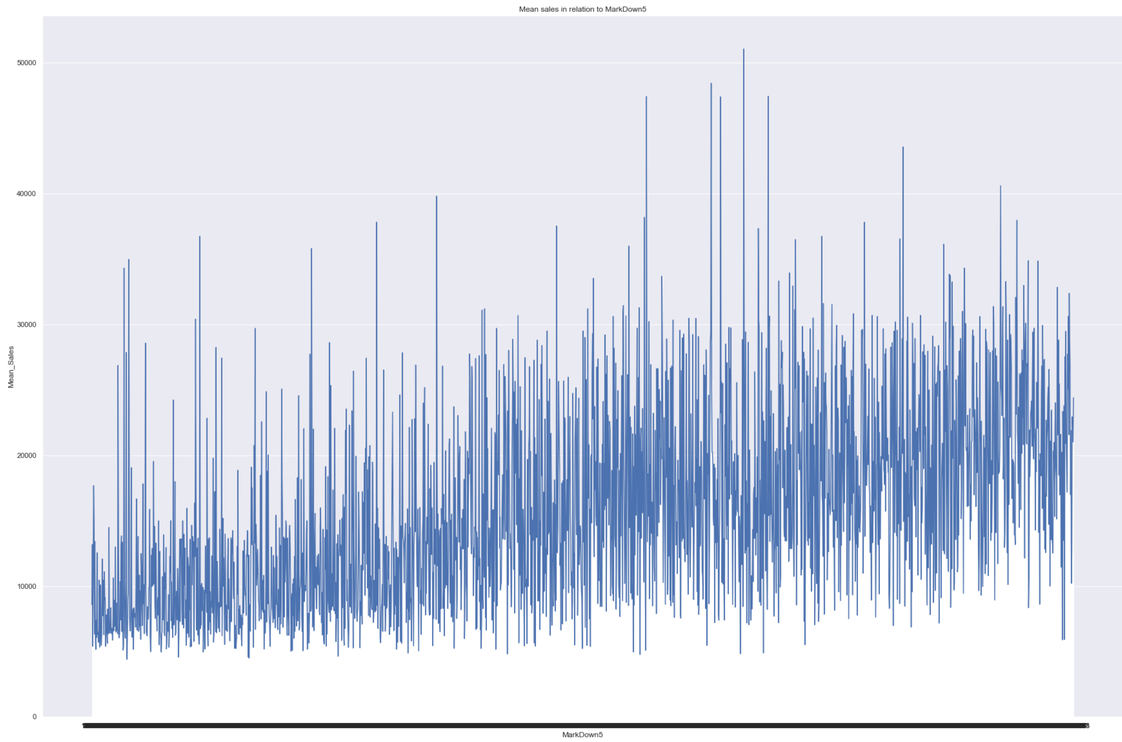

```
[31]: #mean weekly sales by type
sns.set(rc={'figure.figsize':(30, 20)})
MarkDown3_df = pd.DataFrame(df_merged[['MarkDown3','Weekly_Sales']].
 ↪drop_duplicates().groupby('MarkDown3').mean()).reset_index()
MarkDown3_df.columns = ['MarkDown3', 'Mean_Sales']
sns.barplot(x ='MarkDown3', y='Mean_Sales', data=MarkDown3_df);
plt.plot(MarkDown3_df['Mean_Sales']);
plt.title('Mean sales in relation to MarkDown3')
del MarkDown3_df
```




```
[32]: #mean weekly sales by type
sns.set(rc={'figure.figsize':(30, 20)})
MarkDown4_df = pd.DataFrame(df_merged[['MarkDown4','Weekly_Sales']].
 ↪drop_duplicates().groupby('MarkDown4').mean()).reset_index()
MarkDown4_df.columns = ['MarkDown4', 'Mean_Sales']
sns.barplot(x ='MarkDown4', y='Mean_Sales', data=MarkDown4_df);
plt.plot(MarkDown4_df['Mean_Sales']);
plt.title('Mean sales in relation to MarkDown4')
del MarkDown4_df
```



[33]:
```
#mean weekly sales by type
sns.set(rc={'figure.figsize':(30, 20)})
MarkDown5_df = pd.DataFrame(df_merged[['MarkDown5','Weekly_Sales']].
 ↪drop_duplicates().groupby('MarkDown5').mean()).reset_index()
MarkDown5_df.columns = ['MarkDown5', 'Mean_Sales']
sns.barplot(x ='MarkDown5', y='Mean_Sales', data=MarkDown5_df);
plt.plot(MarkDown5_df['Mean_Sales']);
plt.title('Mean sales in relation to MarkDown5')
del MarkDown5_df
```



In terms of all MarkDown features, there does appear to be variation in sales along with varying MarkDown.

1.3 Drop unwanted features

[34]:
```
df_merged = df_merged.drop(['Unemployment','IsHoliday'], axis=1)
```

1.4 Feature engineering

1.4.1 Create week number feature

[35]:
```
df_merged['Week_num'] = df_merged['DateTime'].dt.week
df_merged['Year'] = df_merged['DateTime'].dt.year
df_merged.head()
```

[35]:
```
   Store  Dept        Date  Weekly_Sales  Temperature  Fuel_Price  MarkDown1  \
0      1     1  2010-02-05      24924.50        42.31       2.572        NaN
1      1     2  2010-02-05      50605.27        42.31       2.572        NaN
2      1     3  2010-02-05      13740.12        42.31       2.572        NaN
3      1     4  2010-02-05      39954.04        42.31       2.572        NaN
4      1     5  2010-02-05      32229.38        42.31       2.572        NaN

   MarkDown2  MarkDown3  MarkDown4  MarkDown5         CPI Type    Size  \
0        NaN        NaN        NaN        NaN  211.096358    A  151315
```

```
1         NaN         NaN         NaN         NaN  211.096358    A  151315
2         NaN         NaN         NaN         NaN  211.096358    A  151315
3         NaN         NaN         NaN         NaN  211.096358    A  151315
4         NaN         NaN         NaN         NaN  211.096358    A  151315

    DateTime  Week_num  Year
0 2010-02-05         5  2010
1 2010-02-05         5  2010
2 2010-02-05         5  2010
3 2010-02-05         5  2010
4 2010-02-05         5  2010
```

[36]:
```
df_merged.Week_num.nunique()
```

[36]:
```
52
```

[37]:
```
df_merged.Year.unique()
```

[37]:
```
array([2010, 2011, 2012])
```

1.4.2 Convert IsHoliday into Numerical Feature

[38]:
```
#as shown in the plot above, spikes in sales at certain points in year around␣
 ↪holidays
#convert holiday from boolean to numerical value so it can be quantified and␣
 ↪utilised in the model
#df_merged['IsHolidayInt'] = [int(x) for x in list(df_merged.IsHoliday)]
```

[39]:
```
#df_merged.head()
```

1.4.3 Mean encode categorical features

[40]:
```
mean_encoded_col = ['Store','Dept','Type','Week_num']

from tqdm import tqdm
from sklearn.model_selection import KFold

Target = 'Weekly_Sales'
global_mean = df_merged[Target].mean()
y_tr = df_merged[Target].values

for col in tqdm(mean_encoded_col):
    col_tr = df_merged[[col] + [Target]]
    corrcoefs = pd.DataFrame(columns = ['Cor'])

    # 3.1.1 Mean encodings - KFold scheme
```

```
    kf = KFold(n_splits = 5, shuffle = False, random_state = 0)
    col_tr[col + '_sales_week_mean_Kfold'] = global_mean

    for tr_ind, val_ind in kf.split(col_tr):
        X_tr, X_val = col_tr.iloc[tr_ind], col_tr.iloc[val_ind]
        means = X_val[col].map(X_tr.groupby(col)[Target].mean())
        X_val[col + '_sales_week_mean_Kfold'] = means
        col_tr.iloc[val_ind] = X_val

    col_tr.fillna(global_mean, inplace = True)
    corrcoefs.loc[col + '_sales_week_mean_Kfold'] = np.corrcoef(y_tr,␣
↪col_tr[col + '_sales_week_mean_Kfold'])[0][1]


     # 3.1.2 Mean encodings - Leave-one-out scheme
    item_id_target_sum = col_tr.groupby(col)[Target].sum()
    item_id_target_count = col_tr.groupby(col)[Target].count()
    col_tr[col + '_sales_week_sum'] = col_tr[col].map(item_id_target_sum)
    col_tr[col + '_sales_week_count'] = col_tr[col].map(item_id_target_count)
    col_tr[col + '_target_mean_LOO'] = (col_tr[col + '_sales_week_sum'] -␣
↪col_tr[Target]) / (col_tr[col + '_sales_week_count'] - 1)
    col_tr.fillna(global_mean, inplace = True)
    corrcoefs.loc[col + '_target_mean_LOO'] = np.corrcoef(y_tr, col_tr[col +␣
↪'_target_mean_LOO'])[0][1]


     # 3.1.3 Mean encodings - Smoothing
    item_id_target_mean = col_tr.groupby(col)[Target].mean()
    item_id_target_count = col_tr.groupby(col)[Target].count()
    col_tr[col + '_sales_week_mean'] = col_tr[col].map(item_id_target_mean)
    col_tr[col + '_sales_week_count'] = col_tr[col].map(item_id_target_count)
    alpha = 100
    col_tr[col + '_sales_week_mean_Smooth'] = (col_tr[col + '_sales_week_mean']␣
↪*  col_tr[col + '_sales_week_count'] + global_mean * alpha) / (alpha +␣
↪col_tr[col + '_sales_week_count'])
    col_tr[col + '_sales_week_mean_Smooth'].fillna(global_mean, inplace=True)
    corrcoefs.loc[col + '_sales_week_mean_Smooth'] = np.corrcoef(y_tr,␣
↪col_tr[col + '_sales_week_mean_Smooth'])[0][1]


    # 3.1.4 Mean encodings - Expanding mean scheme
    cumsum = col_tr.groupby(col)[Target].cumsum() - col_tr[Target]
    sumcnt = col_tr.groupby(col).cumcount()
    col_tr[col + '_sales_week_mean_Expanding'] = cumsum / sumcnt
    col_tr[col + '_sales_week_mean_Expanding'].fillna(global_mean, inplace=True)
    corrcoefs.loc[col + '_sales_week_mean_Expanding'] = np.corrcoef(y_tr,␣
↪col_tr[col + '_sales_week_mean_Expanding'])[0][1]
```

```
df_merged = pd.concat([df_merged, col_tr[corrcoefs['Cor'].idxmax()]], axis␣
↪= 1)
print(corrcoefs.sort_values('Cor'))
```

```
 25%|          | 1/4 [00:00<00:00,  3.08it/s]

                                   Cor
Store_sales_week_mean_Kfold      0.048446
Store_sales_week_mean_Expanding  0.304708
Store_target_mean_LOO            0.305705
Store_sales_week_mean_Smooth     0.306006

 50%|          | 2/4 [00:00<00:00,  3.18it/s]

                                  Cor
Dept_sales_week_mean_Kfold      0.716156
Dept_sales_week_mean_Smooth     0.734195
Dept_target_mean_LOO            0.734228
Dept_sales_week_mean_Expanding  0.747110

 75%|          | 3/4 [00:01<00:00,  2.70it/s]

                                  Cor
Type_sales_week_mean_Kfold      0.162263
Type_target_mean_LOO            0.189030
Type_sales_week_mean_Smooth     0.189060
Type_sales_week_mean_Expanding  0.205713

100%|          | 4/4 [00:01<00:00,  2.77it/s]

                                      Cor
Week_num_sales_week_mean_Kfold      0.049599
Week_num_target_mean_LOO            0.075060
Week_num_sales_week_mean_Smooth     0.076696
Week_num_sales_week_mean_Expanding  0.100752
```

[41]:
```
df_merged.head()
```

[41]:
```
   Store  Dept        Date  Weekly_Sales  Temperature  Fuel_Price  MarkDown1  \
0      1     1  2010-02-05      24924.50        42.31       2.572        NaN
1      1     2  2010-02-05      50605.27        42.31       2.572        NaN
2      1     3  2010-02-05      13740.12        42.31       2.572        NaN
3      1     4  2010-02-05      39954.04        42.31       2.572        NaN
4      1     5  2010-02-05      32229.38        42.31       2.572        NaN

   MarkDown2  MarkDown3  MarkDown4  …         CPI  Type    Size   DateTime  \
```

```
0        NaN        NaN        NaN  ...  211.096358     A  151315 2010-02-05
1        NaN        NaN        NaN  ...  211.096358     A  151315 2010-02-05
2        NaN        NaN        NaN  ...  211.096358     A  151315 2010-02-05
3        NaN        NaN        NaN  ...  211.096358     A  151315 2010-02-05
4        NaN        NaN        NaN  ...  211.096358     A  151315 2010-02-05

  Week_num  Year  Store_sales_week_mean_Smooth  \
0        5  2010                  21655.514828
1        5  2010                  21655.514828
2        5  2010                  21655.514828
3        5  2010                  21655.514828
4        5  2010                  21655.514828

   Dept_sales_week_mean_Expanding  Type_sales_week_mean_Expanding  \
0                     15978.78611                     15978.78611
1                     15978.78611                     24924.50000
2                     15978.78611                     37764.88500
3                     15978.78611                     29756.63000
4                     15978.78611                     32305.98250

   Week_num_sales_week_mean_Expanding
0                         15978.78611
1                         24924.50000
2                         37764.88500
3                         29756.63000
4                         32305.98250

[5 rows x 21 columns]
```

[42]:
```
df_merged.Week_num.unique()
```

[42]:
```
array([ 5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21,
       22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38,
       39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52,  1,  2,  3,
        4])
```

[43]:
```
df_merged.to_pickle('data.pickle.gzde', compression='gzip')
```

1.4.4 Create 12-month weekly sales lagged feature (based on week number)

As on the Kaggle test dataset, predictions are for weekly sales up to 7 months in advance. In addition, given the similar annual sales patterns shown in the plots above, lags will be for 12 months previous.

[44]:
```
df = pd.read_pickle('data.pickle.gzde', compression='gzip')
```

[45]:
```
#function to create time lags
def lag_feature(df, lags, col):
    tmp = df[['Year','Week_num','Store','Dept',col]]
    for i in lags:
        shifted = tmp.copy()
        shifted.columns = ['Year','Week_num','Store','Dept', col+'_lag_'+str(i)]
        shifted['Year'] += i
        df = pd.merge(df, shifted, on=['Year','Week_num','Store','Dept'],␣
 ↪how='left')
    return df
```

[46]:
```
cols = ['Weekly_Sales', 'Store_sales_week_mean_Smooth',
        'Dept_sales_week_mean_Expanding', 'Type_sales_week_mean_Expanding',
        'Week_num_sales_week_mean_Expanding']

for col in cols:
    df = lag_feature(df, [1], col)

df.head()
```

[46]:
```
   Store  Dept        Date  Weekly_Sales  Temperature  Fuel_Price  MarkDown1  \
0      1     1  2010-02-05      24924.50        42.31       2.572        NaN
1      1     2  2010-02-05      50605.27        42.31       2.572        NaN
2      1     3  2010-02-05      13740.12        42.31       2.572        NaN
3      1     4  2010-02-05      39954.04        42.31       2.572        NaN
4      1     5  2010-02-05      32229.38        42.31       2.572        NaN

   MarkDown2  MarkDown3  MarkDown4  …  Year  Store_sales_week_mean_Smooth  \
0        NaN        NaN        NaN  …  2010                  21655.514828
1        NaN        NaN        NaN  …  2010                  21655.514828
2        NaN        NaN        NaN  …  2010                  21655.514828
3        NaN        NaN        NaN  …  2010                  21655.514828
4        NaN        NaN        NaN  …  2010                  21655.514828

  Dept_sales_week_mean_Expanding  Type_sales_week_mean_Expanding  \
0                    15978.78611                     15978.78611
1                    15978.78611                     24924.50000
2                    15978.78611                     37764.88500
3                    15978.78611                     29756.63000
4                    15978.78611                     32305.98250

  Week_num_sales_week_mean_Expanding  Weekly_Sales_lag_1  \
0                        15978.78611                 NaN
1                        24924.50000                 NaN
2                        37764.88500                 NaN
3                        29756.63000                 NaN
4                        32305.98250                 NaN
```

```
   Store_sales_week_mean_Smooth_lag_1  Dept_sales_week_mean_Expanding_lag_1  \
0                                 NaN                                   NaN
1                                 NaN                                   NaN
2                                 NaN                                   NaN
3                                 NaN                                   NaN
4                                 NaN                                   NaN

   Type_sales_week_mean_Expanding_lag_1  \
0                                   NaN
1                                   NaN
2                                   NaN
3                                   NaN
4                                   NaN

   Week_num_sales_week_mean_Expanding_lag_1
0                                       NaN
1                                       NaN
2                                       NaN
3                                       NaN
4                                       NaN

[5 rows x 26 columns]
```

[47]:
```
features_to_drop =␣
↪['Store_sales_week_mean_Smooth','Dept_sales_week_mean_Expanding',
                    'Type_sales_week_mean_Expanding',
                    'Week_num_sales_week_mean_Expanding','Type']

df = df.drop(features_to_drop, axis=1)
```

1.4.5 Drop the first 12 months (due to NaNs created through lag values)

[48]:
```
mask1 = df['Year'] > 2010
```

[49]:
```
df = df[mask1]
```

[50]:
```
# delete all rows with column 'Year' has value 2011 and 'Week_num' <5
index = df[ (df['Year'] == 2011) & (df['Week_num'] < 5) ].index
df.drop(index, inplace=True)
```

[51]:
```
df.head()
```

[51]:
```
      Store  Dept        Date  Weekly_Sales  Temperature  Fuel_Price  \
3729      1     1  2011-02-04      21665.76        42.27       2.989
3730      1     2  2011-02-04      46829.12        42.27       2.989
```

```
3731      1     3  2011-02-04      11012.52        42.27       2.989
3732      1     4  2011-02-04      35870.49        42.27       2.989
3733      1     5  2011-02-04      31280.62        42.27       2.989

      MarkDown1  MarkDown2  MarkDown3  MarkDown4  …         CPI    Size  \
3729        NaN        NaN        NaN        NaN  …  212.566881  151315
3730        NaN        NaN        NaN        NaN  …  212.566881  151315
3731        NaN        NaN        NaN        NaN  …  212.566881  151315
3732        NaN        NaN        NaN        NaN  …  212.566881  151315
3733        NaN        NaN        NaN        NaN  …  212.566881  151315

       DateTime Week_num  Year  Weekly_Sales_lag_1  \
3729 2011-02-04        5  2011            24924.50
3730 2011-02-04        5  2011            50605.27
3731 2011-02-04        5  2011            13740.12
3732 2011-02-04        5  2011            39954.04
3733 2011-02-04        5  2011            32229.38

      Store_sales_week_mean_Smooth_lag_1  \
3729                        21655.514828
3730                        21655.514828
3731                        21655.514828
3732                        21655.514828
3733                        21655.514828

      Dept_sales_week_mean_Expanding_lag_1  \
3729                           15978.78611
3730                           15978.78611
3731                           15978.78611
3732                           15978.78611
3733                           15978.78611

      Type_sales_week_mean_Expanding_lag_1  \
3729                           15978.78611
3730                           24924.50000
3731                           37764.88500
3732                           29756.63000
3733                           32305.98250

      Week_num_sales_week_mean_Expanding_lag_1
3729                               15978.78611
3730                               24924.50000
3731                               37764.88500
3732                               29756.63000
3733                               32305.98250

[5 rows x 21 columns]
```

[52]:
```
#replace nans with 0
df = df.replace(np.nan, 0)
```

1.4.6 One-Hot Encode Store and Dept features

[53]:
```
#as shown by the above plots, single stores weekly sales differ from each other
#store categorical data will be converted to dummy variables so stores can be␣
↪quantified,
#compared and utilised by the model to predict weekly sales

dept_num_dummies = pd.get_dummies(df.Dept, prefix='Dept')
df = pd.concat([dept_num_dummies, df], axis=1)
```

[54]:
```
store_num_dummies = pd.get_dummies(df.Store, prefix='Store')
df = pd.concat([store_num_dummies, df], axis=1)
```

[55]:
```
df.head()
```

[55]:
```
      Store_1  Store_2  Store_3  Store_4  Store_5  Store_6  Store_7  Store_8  \
3729        1        0        0        0        0        0        0        0
3730        1        0        0        0        0        0        0        0
3731        1        0        0        0        0        0        0        0
3732        1        0        0        0        0        0        0        0
3733        1        0        0        0        0        0        0        0

      Store_9  Store_10  …         CPI    Size   DateTime  Week_num  Year  \
3729        0         0  …  212.566881  151315 2011-02-04         5  2011
3730        0         0  …  212.566881  151315 2011-02-04         5  2011
3731        0         0  …  212.566881  151315 2011-02-04         5  2011
3732        0         0  …  212.566881  151315 2011-02-04         5  2011
3733        0         0  …  212.566881  151315 2011-02-04         5  2011

      Weekly_Sales_lag_1  Store_sales_week_mean_Smooth_lag_1  \
3729            24924.50                        21655.514828
3730            50605.27                        21655.514828
3731            13740.12                        21655.514828
3732            39954.04                        21655.514828
3733            32229.38                        21655.514828

      Dept_sales_week_mean_Expanding_lag_1  \
3729                           15978.78611
3730                           15978.78611
3731                           15978.78611
3732                           15978.78611
3733                           15978.78611

      Type_sales_week_mean_Expanding_lag_1  \
```

```
3729                        15978.78611
3730                        24924.50000
3731                        37764.88500
3732                        29756.63000
3733                        32305.98250

      Week_num_sales_week_mean_Expanding_lag_1
3729                               15978.78611
3730                               24924.50000
3731                               37764.88500
3732                               29756.63000
3733                               32305.98250

[5 rows x 147 columns]
```

1.4.7 Encode week number (cyclical)

[56]:
```
def encode(data, col, max_val):
    data[col + '_sin'] = np.sin(2 * np.pi * data[col]/max_val)
    data[col + '_cos'] = np.cos(2 * np.pi * data[col]/max_val)
    return data
```

[57]:
```
df = encode(df, 'Week_num', 52)
```

[58]:
```
df.head()
```

[58]:
```
      Store_1  Store_2  Store_3  Store_4  Store_5  Store_6  Store_7  Store_8  \
3729        1        0        0        0        0        0        0        0
3730        1        0        0        0        0        0        0        0
3731        1        0        0        0        0        0        0        0
3732        1        0        0        0        0        0        0        0
3733        1        0        0        0        0        0        0        0

      Store_9  Store_10  …   DateTime  Week_num  Year  Weekly_Sales_lag_1  \
3729        0         0  … 2011-02-04         5  2011            24924.50
3730        0         0  … 2011-02-04         5  2011            50605.27
3731        0         0  … 2011-02-04         5  2011            13740.12
3732        0         0  … 2011-02-04         5  2011            39954.04
3733        0         0  … 2011-02-04         5  2011            32229.38

      Store_sales_week_mean_Smooth_lag_1  \
3729                        21655.514828
3730                        21655.514828
3731                        21655.514828
3732                        21655.514828
3733                        21655.514828
```

```
      Dept_sales_week_mean_Expanding_lag_1  \
3729                               15978.78611
3730                               15978.78611
3731                               15978.78611
3732                               15978.78611
3733                               15978.78611

      Type_sales_week_mean_Expanding_lag_1  \
3729                               15978.78611
3730                               24924.50000
3731                               37764.88500
3732                               29756.63000
3733                               32305.98250

      Week_num_sales_week_mean_Expanding_lag_1  Week_num_sin  Week_num_cos
3729                                   15978.78611      0.568065      0.822984
3730                                   24924.50000      0.568065      0.822984
3731                                   37764.88500      0.568065      0.822984
3732                                   29756.63000      0.568065      0.822984
3733                                   32305.98250      0.568065      0.822984

[5 rows x 149 columns]
```

[59]:
```
df = df.drop(['Store','Dept','Year','DateTime','Week_num','Date'], axis=1)
```

[60]:
```
df.to_pickle('data2.pickle.gzde', compression='gzip')
```

1.5 Splitting the data into train and test

[61]:
```
df2 = pd.read_pickle('data2.pickle.gzde', compression='gzip')
```

[62]:
```
train_set, test_set = train_test_split(df2, test_size=0.3,random_state=42)
```

[63]:
```
train_set.shape, test_set.shape
```

[63]:
```
((188437, 143), (80759, 143))
```

2 Building the models

2.1 Linear Regression

[64]:
```
train_linear = train_set.copy()
test_linear = test_set.copy()
```

[65]:
```
X_train = train_linear.drop(['Weekly_Sales'], axis=1)
X_train = np.matrix((X_train).values)
```

```
y_train = np.matrix((train_linear['Weekly_Sales']).values)
```

[66]:
```
y_train = y_train.T
X_train.shape, y_train.shape
```

[66]: ((188437, 142), (188437, 1))

[67]:
```
def featureNormalize(X):
    X_norm = X
    mu = np.zeros((1, X.shape[1]))
    sigma = np.zeros((1, X.shape[1]))
    for i in range(X.shape[1]):
        mu[:,i] = np.mean(X[:,i])
        sigma[:,i] = np.std(X[:,i], dtype=np.float64)
        X_norm[:,i] = (X[:,i] - float(mu[:,i]))/float(sigma[:,i])
    return X_norm, mu, sigma
```

[68]:
```
print('Normalising features...')

X_norm, mu, sigma = featureNormalize(X_train)
```

Normalising features…

[69]:
```
#add intercept term to X
m = len(y_train)
X_padded = np.column_stack((np.ones((m,1)),X_norm)) #add column of ones to x
theta = np.zeros((X_padded.shape[1],1))
```

[70]:
```
# Initialize learning rate  .
alpha = 0.15

# Check the dimensions of the matrices.
X_padded.shape, y_train.shape, theta.shape
```

[70]: ((188437, 143), (188437, 1), (143, 1))

[71]:
```
# Create a function to compute cost.
def computeCost(x, y, theta):
    """
    Compute the cost function.
    Args:
        x: a m by n+1 matrix
        y: a m by 1 vector
        theta: a n+1 by 1 vector
    Returns:
        cost: float
    """
```

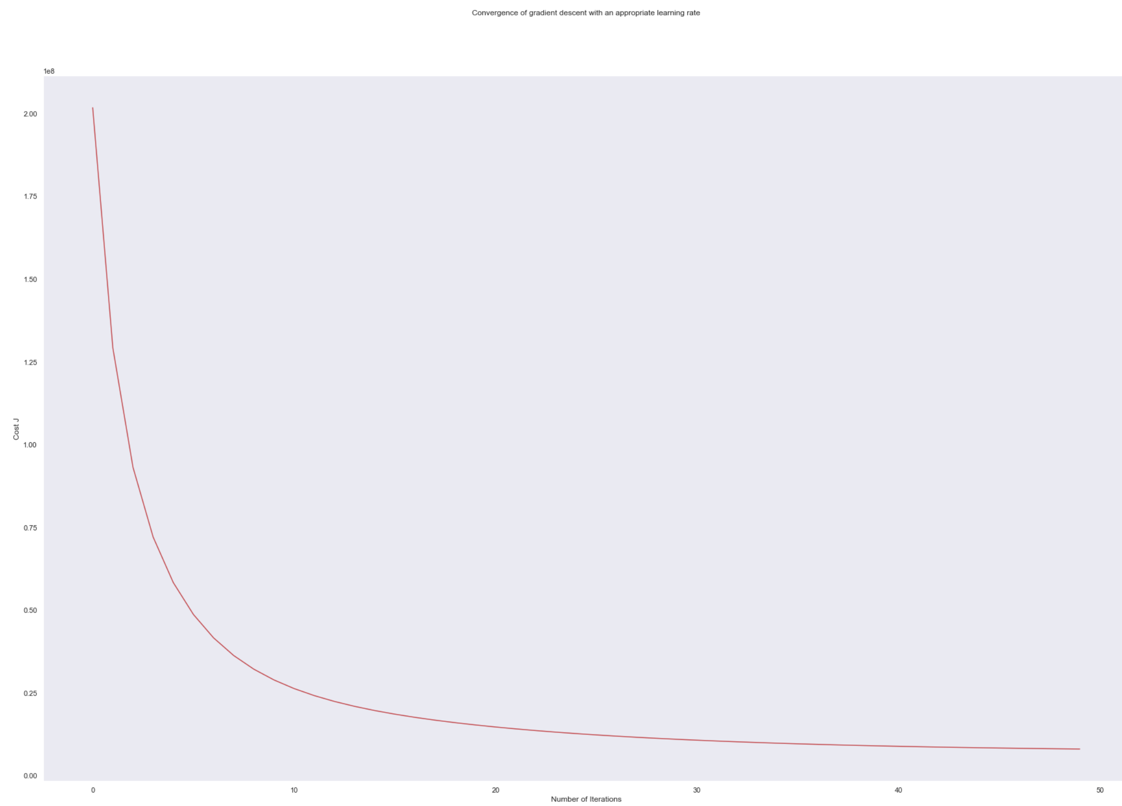
```
    m = len(x)
    cost = np.sum(np.square((x * theta) - y)) / (2 * m)
    return cost
```

[72]:
```
# Create a function to implement gradient descent.
def gradientDescent(x,y, theta, iterations):
    """
    Implement gradient descent.
    Args:
        x: a m by n+1 matrix
        theta: a n+1 by 1 vector
    Return:
        theta: a n+1 by 1 vector
        J_vals: a #iterations by 1 vector
    """
    m = len(x)
    J_vals = []

    for i in range(iterations):
        error = (x * theta) - y
        for j in range(len(theta.flat)):
            theta.T[0, j] = theta.T[0, j] - (alpha/m) * np.sum(np.
 ↪multiply(error, x[:, j]))
        J_vals.append(computeCost(x, y, theta))
    return (theta, J_vals)
```

[73]:
```
theta, J_vals = gradientDescent(X_padded, y_train, theta, iterations=50)
```

[74]:
```
plt.xlabel('Number of Iterations')
plt.ylabel('Cost J')
plt.title('Convergence of gradient descent with an appropriate learning rate',␣
 ↪y=1.08)
plt.grid()
plt.plot(range(50), J_vals, 'r')
```

[74]:
```
[<matplotlib.lines.Line2D at 0x7fc9d9c229e8>]
```



2.1.1 Testing the model

[75]:
```
X_test = test_linear.drop(['Weekly_Sales'], axis=1)
X_test = np.matrix((X_test).values)
y_test = np.matrix((test_linear['Weekly_Sales']).values)
y_test = y_test.T
```

[76]:
```
X_test.shape, y_test.shape
```

[76]: ((80759, 142), (80759, 1))

[77]:
```
def featureNormalizeTest(X, mu, sigma):
    X_norm_test = X
    for i in range(X.shape[1]):
        X_norm_test[:,i] = (X[:,i] - float(mu[:,i]))/float(sigma[:,i])
    return X_norm_test
```

[78]:
```
print('Normalising features...')

X_norm_test = featureNormalizeTest(X_test, mu, sigma)
```

Normalising features…

[79]:
```
#add intercept term to X
m = len(y_test)

X_padded_test = np.column_stack((np.ones((m,1)),X_norm_test)) #add column of ones to x
```

[80]:
```
X_padded_test.shape, y_test.shape, theta.shape
```

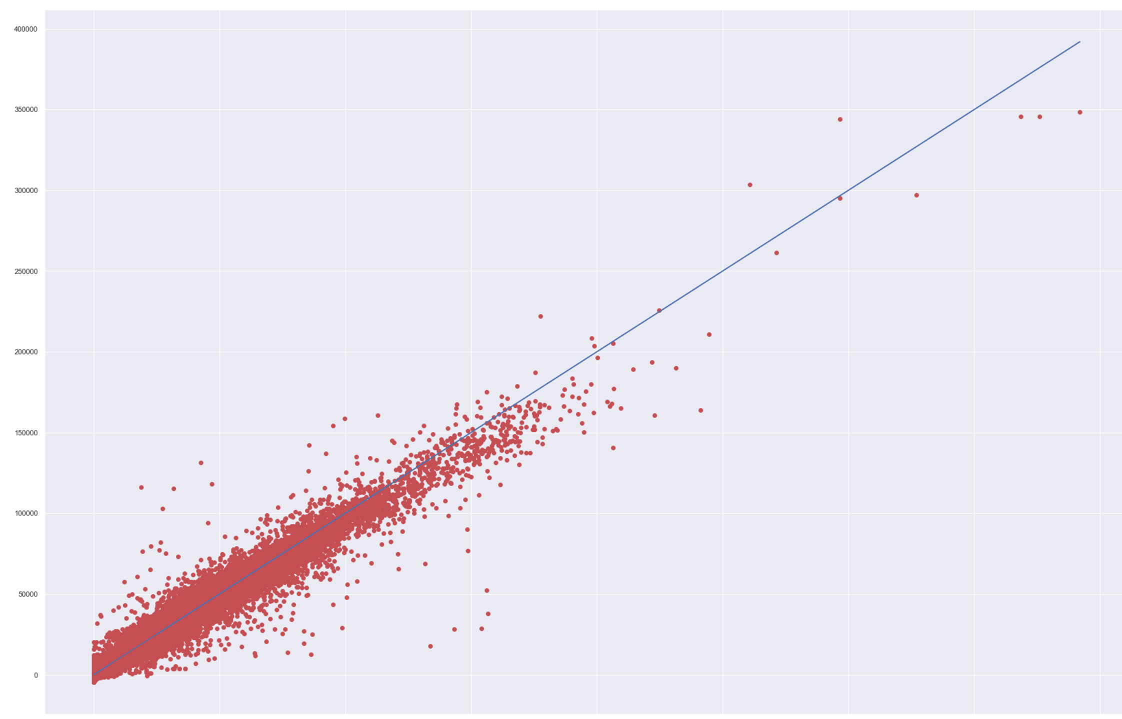
[80]:
```
((80759, 143), (80759, 1), (143, 1))
```

[81]:
```
y_predict = X_padded_test * theta
```

2.1.2 Evaluating the model

[82]:
```
from sklearn import metrics
```

[83]:
```
plt.plot(y_test, y_predict,'ro')
plt.plot(y_test, y_test,'b-')
plt.show()
```



[84]:
```
y_vals = pd.DataFrame(y_predict, columns=['Predictions'])
y_vals['Actual'] = y_test
y_vals.head().round(0)
```

[84]:
	Predictions	Actual
0	8562.0	7576.0
1	3954.0	4204.0
2	40860.0	41856.0
3	6027.0	5069.0
4	48323.0	44752.0

[85]:
```
# mean squared error
mse = np.sum((y_vals.Predictions - y_vals.Actual)**2)

# root mean squared error
# m is the number of training examples
rmse = np.sqrt(mse/m)
```

[86]:
```
# sum of square of residuals
ssr = np.sum((y_vals.Predictions - y_vals.Actual)**2)

#  total sum of squares
sst = np.sum((y_vals.Actual - np.mean(y_vals.Actual))**2)

# R2 score
r2_score = 1 - (ssr/sst)
```

[87]:
```
print(rmse)
print(r2_score)
```

```
4137.387476481783
0.9659868878659682
```

The R-squared score indicates that the percentage variable variation (total store weekly sales) that is explained by the model is approximately 96.6%.

2.2 Linear Regression SKLearn implementation

[88]:
```
train_linear = train_set.copy()
test_linear = test_set.copy()
```

[89]:
```
X_train = train_linear.drop(['Weekly_Sales'], axis=1)
X_train = np.matrix((X_train).values)
y_train = np.matrix((train_linear['Weekly_Sales']).values)
```

[90]:
```
y_train = y_train.T
X_train.shape, y_train.shape
```

[90]: ((188437, 142), (188437, 1))

[91]:
```
X_test = test_linear.drop(['Weekly_Sales'], axis=1)
X_test = np.matrix((X_test).values)
y_test = np.matrix((test_linear['Weekly_Sales']).values)
y_test = y_test.T
```

[92]:
```
linear_sk = linear_model.LinearRegression()
linear_sk.fit(X_train, y_train)
```

[92]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
         normalize=False)
```

[93]:
```
prediction_linear_sk = linear_sk.predict(X_test)
```

[94]:
```
linear_RMSE = np.sqrt(metrics.mean_squared_error(y_test, prediction_linear_sk))
linear_r2 = metrics.r2_score(y_test, prediction_linear_sk)

print(linear_RMSE)
print(linear_r2)
```

```
3925.9266709888047
0.9693748413758706
```

2.3 Ridge Regression

This involves the introduction of L2 regularisation in the cost function.

[95]:
```
train_ridge = train_set.copy()
test_ridge = test_set.copy()
```

[96]:
```
X_train_ridge = train_ridge.drop(['Weekly_Sales'], axis=1)
X_train_ridge = np.matrix((X_train_ridge).values)
y_train_ridge = np.matrix((train_ridge['Weekly_Sales']).values)
```

[97]:
```
y_train_ridge = y_train_ridge.T
X_train_ridge.shape, y_train_ridge.shape
```

[97]:
```
((188437, 142), (188437, 1))
```

[98]:
```
print('Normalising features...')

X_norm_ridge, mu, sigma = featureNormalize(X_train_ridge)
```

```
Normalising features…
```

[99]:
```
#add intercept term to X
m = len(y_train_ridge)
X_padded_ridge = np.column_stack((np.ones((m,1)),X_norm_ridge)) #add column of␣
 ↪ones to x
```

```
theta_ridge = np.zeros((X_padded_ridge.shape[1],1))
```

[100]:
```
# Initialize learning rate  .
alpha = 0.15

# Check the dimensions of the matrices.
X_padded_ridge.shape, y_train_ridge.shape, theta_ridge.shape
```

[100]: ((188437, 143), (188437, 1), (143, 1))

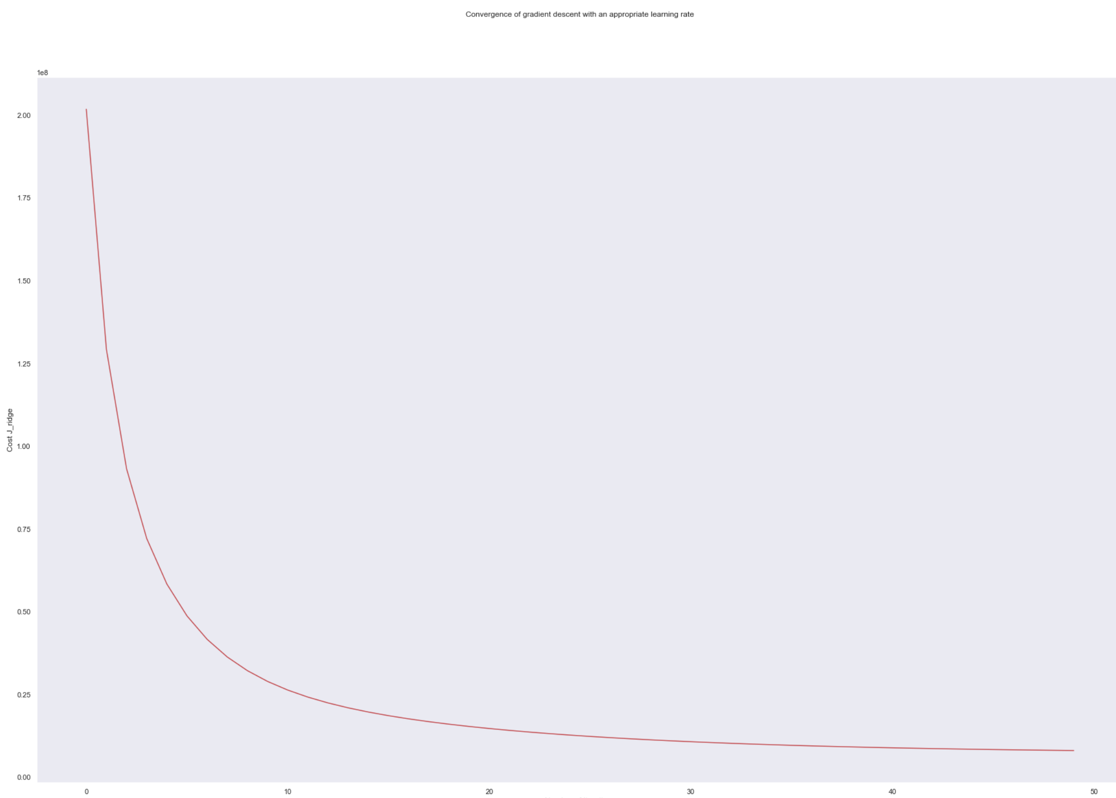
[101]:
```
# Create a function to compute cost.
def computeCostRidge(x, y, theta, lamda_coef):
    """
    Compute the cost function.
    Args:
        x: a m by n+1 matrix
        y: a m by 1 vector
        theta: a n+1 by 1 vector
    Returns:
        cost: float
    """
    m = len(x)
    l2_reg = (lamda_coef / (2*m)) * np.sum(np.square(theta[1:len(theta)]))
    cost = (np.sum(np.square((x * theta) - y)) / (2 * m)) + l2_reg
    return cost
```

[102]:
```
# Create a function to implement gradient descent.
def gradientDescentRidge(x,y, theta, lamda_coef, iterations):
    """
    Implement gradient descent.
    Args:
        x: a m by n+1 matrix
        theta: a n+1 by 1 vector
    Return:
        theta: a n+1 by 1 vector
        J_vals: a #iterations by 1 vector
    """
    m = len(x)
    J_vals = []

    for i in range(iterations):
        error = (x * theta) - y
        for j in range(len(theta.flat)):
            theta.T[0, j] = theta.T[0, j] - (alpha/m) * np.sum(np.
 ↪multiply(error, x[:, j]))
        J_vals.append(computeCostRidge(x, y, theta, lamda_coef))
    return (theta, J_vals)
```

[103]:
```
lamda_coef = 1
theta_ridge, J_vals_ridge = gradientDescentRidge(X_padded_ridge, y_train_ridge,␣
↪theta_ridge, lamda_coef, iterations=50)
```

[104]:
```
plt.xlabel('Number of Iterations')
plt.ylabel('Cost J_ridge')
plt.title('Convergence of gradient descent with an appropriate learning rate',␣
↪y=1.08)
plt.grid()
plt.plot(range(50), J_vals_ridge, 'r')
```

[104]: [<matplotlib.lines.Line2D at 0x7fc9fa41acc0>]



2.3.1 Testing the model

[105]:
```
X_test_ridge = test_ridge.drop(['Weekly_Sales'], axis=1)
X_test_ridge = np.matrix((X_test_ridge).values)
y_test_ridge = np.matrix((test_ridge['Weekly_Sales']).values)
y_test_ridge = y_test_ridge.T
```

[106]:
```
X_test_ridge.shape, y_test_ridge.shape
```

[106]: ((80759, 142), (80759, 1))

[107]:
```
print('Normalising features...')

X_norm_test_ridge = featureNormalizeTest(X_test_ridge, mu, sigma)
```

Normalising features…

[108]:
```
X_norm_test_ridge.shape, y_test_ridge.shape
```

[108]: ((80759, 142), (80759, 1))

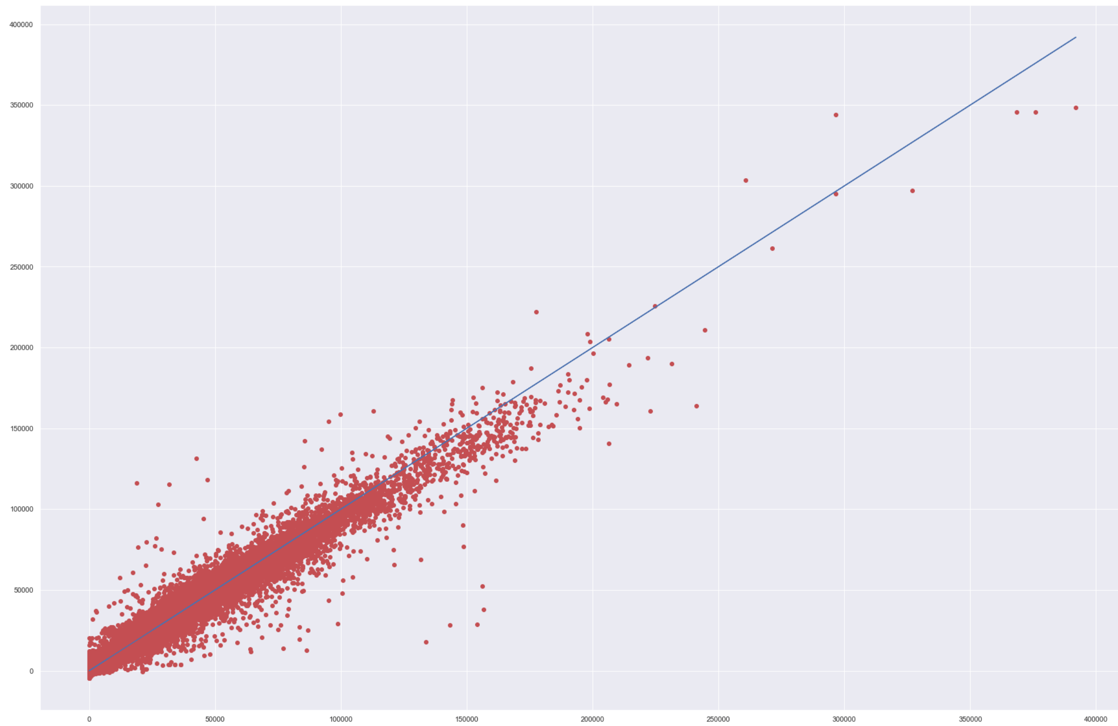
[109]:
```
#add intercept term to X
m = len(y_test_ridge)

X_padded_test_ridge = np.column_stack((np.ones((m,1)),X_norm_test_ridge)) #add␣
↪column of ones to x
```

[110]:
```
X_padded_test_ridge.shape, y_test_ridge.shape, theta_ridge.shape
```

[110]: ((80759, 143), (80759, 1), (143, 1))

[111]:
```
y_predict_ridge = X_padded_test_ridge * theta_ridge
```

[112]:
```
plt.plot(y_test_ridge, y_predict_ridge,'ro')
plt.plot(y_test_ridge, y_test_ridge,'b-')
plt.show()
```



[113]:
```
y_vals_ridge = pd.DataFrame(y_predict_ridge, columns=['Predictions'])
y_vals_ridge['Actual'] = y_test_ridge
y_vals_ridge.head().round(0)
```

[113]:

	Predictions	Actual
0	8562.0	7576.0
1	3954.0	4204.0
2	40860.0	41856.0
3	6027.0	5069.0
4	48323.0	44752.0

[114]:
```
# mean squared error
mse_ridge = np.sum((y_vals_ridge.Predictions - y_vals_ridge.Actual)**2)

# root mean squared error
# m is the number of training examples
rmse_ridge = np.sqrt(mse_ridge/m)
```

[115]:
```
# sum of square of residuals
ssr_ridge = np.sum((y_vals_ridge.Predictions - y_vals_ridge.Actual)**2)

#  total sum of squares
sst_ridge = np.sum((y_vals_ridge.Actual - np.mean(y_vals_ridge.Actual))**2)
```

```
# R2 score
r2_score_ridge = 1 - (ssr_ridge/sst_ridge)
```

[116]:
```
print(rmse_ridge)
print(r2_score_ridge)
```

```
4137.387476481783
0.9659868878659682
```

2.4 Ridge Regression SKLearn implementation

[117]:
```
train_ridge = train_set.copy()
test_ridge = test_set.copy()
```

[118]:
```
X_train_ridge = train_ridge.drop(['Weekly_Sales'], axis=1)
X_train_ridge = np.matrix((X_train_ridge).values)
y_train_ridge = np.matrix((train_ridge['Weekly_Sales']).values)
```

[119]:
```
y_train_ridge = y_train_ridge.T
X_train_ridge.shape, y_train_ridge.shape
```

[119]:
```
((188437, 142), (188437, 1))
```

[120]:
```
X_test_ridge = test_ridge.drop(['Weekly_Sales'], axis=1)
X_test_ridge = np.matrix((X_test_ridge).values)
y_test_ridge = np.matrix((test_ridge['Weekly_Sales']).values)
y_test_ridge = y_test_ridge.T
```

[121]:
```
ridge_sk = linear_model.Ridge()
ridge_sk.fit(X_train_ridge, y_train_ridge)
```

[121]:
```
Ridge(alpha=1.0, copy_X=True, fit_intercept=True, max_iter=None,
   normalize=False, random_state=None, solver='auto', tol=0.001)
```

[122]:
```
prediction_ridge_sk = ridge_sk.predict(X_test_ridge)
```

[123]:
```
ridge_RMSE = np.sqrt(metrics.mean_squared_error(y_test_ridge,␣
 ↪prediction_ridge_sk))
ridge_r2 = metrics.r2_score(y_test_ridge, prediction_ridge_sk)

print(ridge_RMSE)
print(ridge_r2)
```

```
3925.9799648298417
0.9693740099067423
```

3 Lasso

3.1 From scratch

[124]:
```
train_lasso = train_set.copy()
test_lasso = test_set.copy()
```

[125]:
```
X_train_lasso = train_lasso.drop(['Weekly_Sales'], axis=1)
X_train_lasso = np.matrix((X_train_lasso).values)
y_train_lasso = np.matrix((train_lasso['Weekly_Sales']).values)
```

[126]:
```
y_train_lasso = y_train_lasso.T
X_train_lasso.shape, y_train_lasso.shape
```

[126]: ((188437, 142), (188437, 1))

[127]:
```
print('Normalising features...')

X_norm_lasso, mu, sigma = featureNormalize(X_train_lasso)
```

Normalising features…

[128]:
```
#add intercept term to X
m = len(y_train_lasso)
X_padded_lasso = np.column_stack((np.ones((m,1)),X_norm_lasso)) #add column of␣
 ↪ones to x
theta_lasso = np.zeros((X_padded_lasso.shape[1],1))
```

[129]:
```
# Initialize learning rate  .
alpha = 0.15

# Check the dimensions of the matrices.
X_padded_lasso.shape, y_train_lasso.shape, theta_lasso.shape
```

[129]: ((188437, 143), (188437, 1), (143, 1))

[130]:
```
# Create a function to compute cost.
def computeCostLasso(x, y, theta, lamda_coef):
    """
    Compute the cost function.
    Args:
        x: a m by n+1 matrix
        y: a m by 1 vector
        theta: a n+1 by 1 vector
    Returns:
        cost: float
    """
    m = len(x)
```

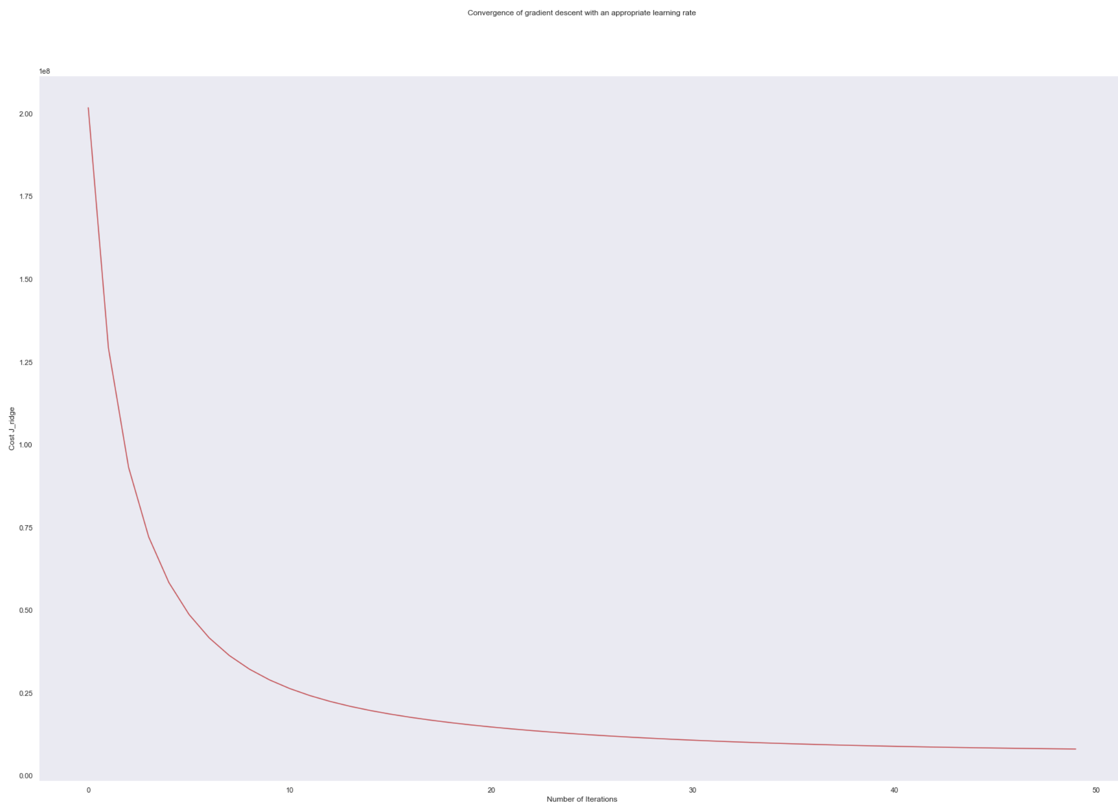
```
    l1_reg = (lamda_coef / (2*m)) * np.sum(np.absolute(theta[1:len(theta)]))
    cost = (np.sum(np.square((x * theta) - y)) / (2 * m)) + l1_reg
    return cost
```

[131]:
```
# Create a function to implement gradient descent.
def gradientDescentLasso(x,y, theta, lamda_coef, iterations):
    """
    Implement gradient descent.
    Args:
        x: a m by n+1 matrix
        theta: a n+1 by 1 vector
    Return:
        theta: a n+1 by 1 vector
        J_vals: a #iterations by 1 vector
    """
    m = len(x)
    J_vals = []

    for i in range(iterations):
        error = (x * theta) - y
        for j in range(len(theta.flat)):
            theta.T[0, j] = theta.T[0, j] - (alpha/m) * np.sum(np.
 ↪multiply(error, x[:, j]))
        J_vals.append(computeCostLasso(x, y, theta, lamda_coef))
    return (theta, J_vals)
```

[132]:
```
lamda_coef = 1
theta_lasso, J_vals_lasso = gradientDescentLasso(X_padded_lasso, y_train_lasso,␣
 ↪theta_lasso, lamda_coef, iterations=50)
```

[133]:
```
plt.xlabel('Number of Iterations')
plt.ylabel('Cost J_ridge')
plt.title('Convergence of gradient descent with an appropriate learning rate',␣
 ↪y=1.08)
plt.grid()
plt.plot(range(50), J_vals_lasso, 'r')
```

[133]:
```
[<matplotlib.lines.Line2D at 0x7fc9c8564048>]
```



3.1.1 Testing the model

[134]:
```
X_test_lasso = test_lasso.drop(['Weekly_Sales'], axis=1)
X_test_lasso = np.matrix((X_test_lasso).values)
y_test_lasso = np.matrix((test_lasso['Weekly_Sales']).values)
y_test_lasso = y_test_lasso.T
```

[135]:
```
X_test_lasso.shape, y_test_lasso.shape
```

[135]:
```
((80759, 142), (80759, 1))
```

[136]:
```
print('Normalising features...')

X_norm_test_lasso = featureNormalizeTest(X_test_lasso, mu, sigma)
```

```
Normalising features…
```

[137]:
```
X_norm_test_lasso.shape, y_test_lasso.shape
```

[137]:
```
((80759, 142), (80759, 1))
```

[138]:
```
#add intercept term to X
m = len(y_test_lasso)

X_padded_test_lasso = np.column_stack((np.ones((m,1)),X_norm_test_lasso)) #add␣
↪column of ones to x
```

[139]:
```
X_padded_test_lasso.shape, y_test_lasso.shape, theta_lasso.shape
```

[139]:
```
((80759, 143), (80759, 1), (143, 1))
```

[140]:
```
y_predict_lasso = X_padded_test_lasso * theta_lasso
```

[141]:
```
plt.plot(y_test_lasso, y_predict_lasso,'ro')
plt.plot(y_test_lasso, y_test_lasso,'b-')
plt.show()
```

[142]:
```
y_vals_lasso = pd.DataFrame(y_predict_lasso, columns=['Predictions'])
y_vals_lasso['Actual'] = y_test_lasso
y_vals_lasso.head().round(0)
```

[142]:

	Predictions	Actual
0	8562.0	7576.0
1	3954.0	4204.0
2	40860.0	41856.0

```
3       6027.0   5069.0
4      48323.0  44752.0
```

[143]:
```
# mean squared error
mse_lasso = np.sum((y_vals_lasso.Predictions - y_vals_lasso.Actual)**2)

# root mean squared error
# m is the number of training examples
rmse_lasso = np.sqrt(mse_lasso/m)
```

[144]:
```
# sum of square of residuals
ssr_lasso = np.sum((y_vals_lasso.Predictions - y_vals_lasso.Actual)**2)

#  total sum of squares
sst_lasso = np.sum((y_vals_lasso.Actual - np.mean(y_vals_lasso.Actual))**2)

# R2 score
r2_score_lasso = 1 - (ssr_lasso/sst_lasso)
```

[145]:
```
print(rmse_lasso)
print(r2_score_lasso)
```

```
4137.387476481783
0.9659868878659682
```

3.2 Lasso SKLearn implementation

[146]:
```
train_lasso = train_set.copy()
test_lasso = test_set.copy()
```

[147]:
```
X_train_lasso = train_lasso.drop(['Weekly_Sales'], axis=1)
X_train_lasso = np.matrix((X_train_lasso).values)
y_train_lasso = np.matrix((train_lasso['Weekly_Sales']).values)
```

[148]:
```
y_train_lasso = y_train_lasso.T
X_train_lasso.shape, y_train_lasso.shape
```

[148]:
```
((188437, 142), (188437, 1))
```

[149]:
```
X_test_lasso = test_lasso.drop(['Weekly_Sales'], axis=1)
X_test_lasso = np.matrix((X_test_lasso).values)
y_test_lasso = np.matrix((test_lasso['Weekly_Sales']).values)
y_test_lasso = y_test_lasso.T
```

[150]:
```
lasso_sk = linear_model.Lasso(alpha=0.1)
lasso_sk.fit(X_train_lasso, y_train_lasso)
```

```
[150]: Lasso(alpha=0.1, copy_X=True, fit_intercept=True, max_iter=1000,
          normalize=False, positive=False, precompute=False, random_state=None,
          selection='cyclic', tol=0.0001, warm_start=False)
```

```
[151]: predictions_lasso_sk = lasso_sk.predict(X_test_lasso)
```

```
[152]: lasso_RMSE = np.sqrt(metrics.mean_squared_error(y_test_lasso,␣
        ↪predictions_lasso_sk))
       lasso_r2 = metrics.r2_score(y_test_lasso, predictions_lasso_sk)

       print(lasso_RMSE)
       print(lasso_r2)
```

```
3926.977635332551
0.9693584425684058
```

3.3 Elastic Net

Combination of L1 and L2 regularisation

```
[153]: train_elastic = train_set.copy()
       test_elastic = test_set.copy()
```

```
[154]: X_train_elastic = train_elastic.drop(['Weekly_Sales'], axis=1)
       X_train_elastic = np.matrix((X_train_elastic).values)
       y_train_elastic = np.matrix((train_elastic['Weekly_Sales']).values)
```

```
[155]: y_train_elastic = y_train_elastic.T
       X_train_elastic.shape, y_train_elastic.shape
```

```
[155]: ((188437, 142), (188437, 1))
```

```
[156]: print('Normalising features...')

       X_norm_elastic, mu, sigma = featureNormalize(X_train_elastic)
```

```
Normalising features…
```

```
[157]: #add intercept term to X
       m = len(y_train_elastic)
       X_padded_elastic = np.column_stack((np.ones((m,1)),X_norm_elastic)) #add column␣
        ↪of ones to x
       theta_elastic = np.zeros((X_padded_elastic.shape[1],1))
```

```
[158]: # Create a function to compute cost.
       def computeCostElastic(x, y, theta, alpha, lamda_coef):
           """
           Compute the cost function.
```

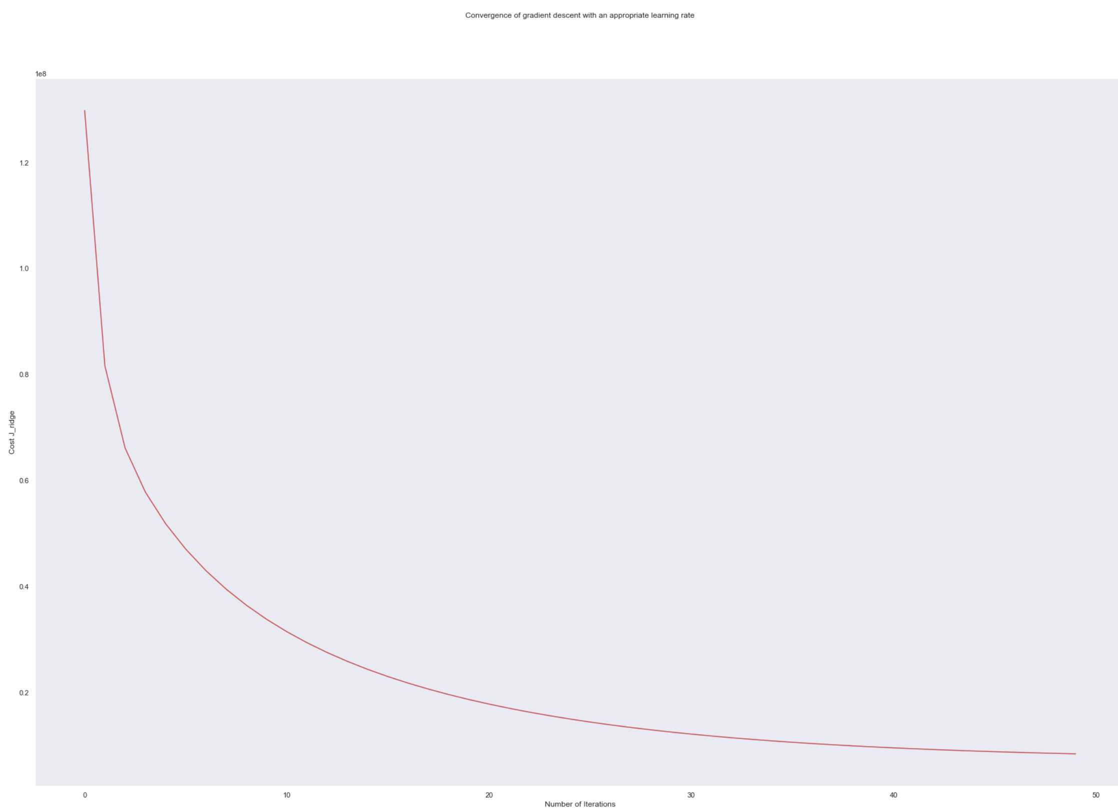
```
    Args:
        x: a m by n+1 matrix
        y: a m by 1 vector
        theta: a n+1 by 1 vector
    Returns:
        cost: float
    """
    m = len(x)
    l1_reg = alpha * np.sum(np.absolute(theta[1:len(theta)]))
    l2_reg = ((1 - alpha)/2) * np.sum(np.square(theta[1:len(theta)]))
    tot_reg = (lamda_coef / (2*m)) * (l2_reg + l1_reg)
    cost = (np.sum(np.square((x * theta) - y)) / (2 * m)) + tot_reg
    return cost
```

[159]:
```
# Create a function to implement gradient descent.
def gradientDescentElastic(x,y, theta, alpha, lamda_coef, iterations):
    """
    Implement gradient descent.
    Args:
        x: a m by n+1 matrix
        theta: a n+1 by 1 vector
    Return:
        theta: a n+1 by 1 vector
        J_vals: a #iterations by 1 vector
    """
    m = len(x)
    J_vals = []

    for i in range(iterations):
        error = (x * theta) - y
        for j in range(len(theta.flat)):
            theta.T[0, j] = theta.T[0, j] - (alpha/m) * np.sum(np.
 ↪multiply(error, x[:, j]))
        J_vals.append(computeCostElastic(x, y, theta, alpha, lamda_coef))
    return (theta, J_vals)
```

[160]:
```
lamda_coef = 1
alpha = 0.5
theta_elastic, J_vals_elastic = gradientDescentElastic(X_padded_elastic,␣
 ↪y_train_elastic, theta_elastic, alpha, lamda_coef, iterations=50)
```

[161]:
```
plt.xlabel('Number of Iterations')
plt.ylabel('Cost J_ridge')
plt.title('Convergence of gradient descent with an appropriate learning rate',␣
 ↪y=1.08)
plt.grid()
plt.plot(range(50), J_vals_elastic, 'r')
```

[161]: [<matplotlib.lines.Line2D at 0x7fc9c84e2198>]



3.3.1 Testing the model

[162]:
```
X_test_elastic = test_elastic.drop(['Weekly_Sales'], axis=1)
X_test_elastic = np.matrix((X_test_elastic).values)
y_test_elastic = np.matrix((test_elastic['Weekly_Sales']).values)
y_test_elastic = y_test_elastic.T
```

[163]:
```
X_test_elastic.shape, y_test_elastic.shape
```

[163]: ((80759, 142), (80759, 1))

[164]:
```
print('Normalising features...')

X_norm_test_elastic = featureNormalizeTest(X_test_elastic, mu, sigma)
```

Normalising features…

[165]:
```
X_norm_test_elastic.shape, y_test_elastic.shape
```

[165]: ((80759, 142), (80759, 1))

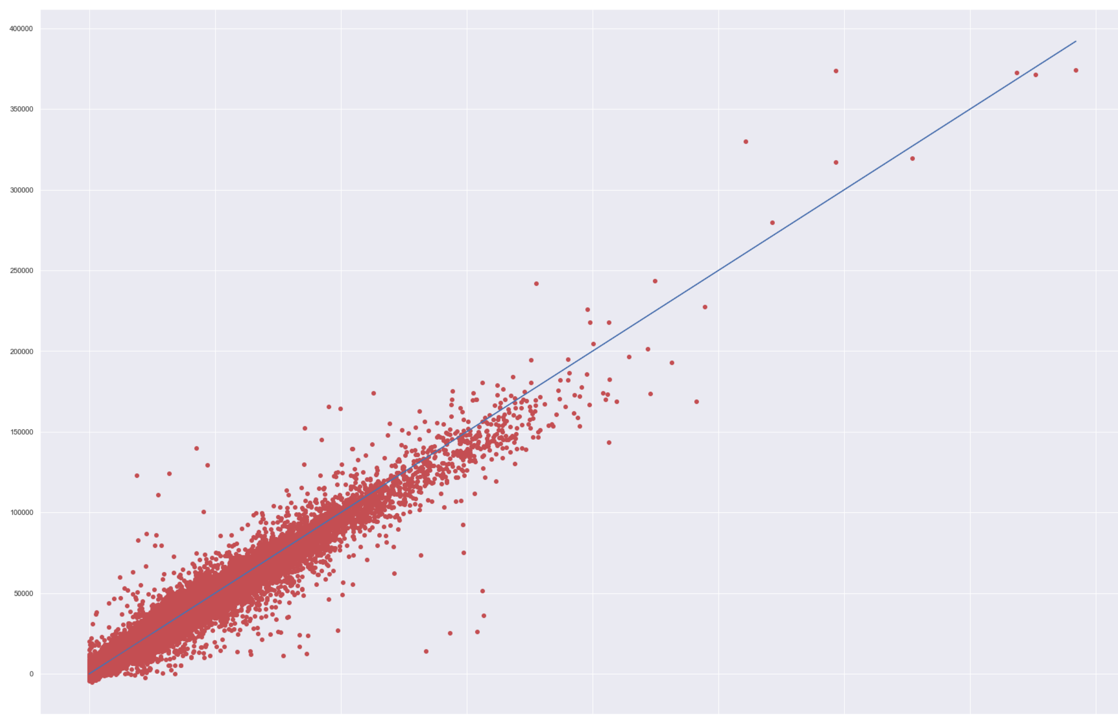
[166]:
```
#add intercept term to X
m = len(y_test_elastic)

X_padded_test_elastic = np.column_stack((np.ones((m,1)),X_norm_test_elastic))␣
↪#add column of ones to x
```

[167]:
```
X_padded_test_elastic.shape, y_test_elastic.shape, theta_elastic.shape
```

[167]: ((80759, 143), (80759, 1), (143, 1))

[168]:
```
y_predict_elastic = X_padded_test_elastic * theta_elastic
```

[169]:
```
plt.plot(y_test_elastic, y_predict_elastic,'ro')
plt.plot(y_test_elastic, y_test_elastic,'b-')
plt.show()
```



[170]:
```
y_vals_elastic = pd.DataFrame(y_predict_elastic, columns=['Predictions'])
y_vals_elastic['Actual'] = y_test_elastic
y_vals_elastic.head().round(0)
```

[170]:

	Predictions	Actual
0	8097.0	7576.0
1	3127.0	4204.0
2	39994.0	41856.0

```
3       3679.0   5069.0
4      49217.0  44752.0
```

[171]:
```
# mean squared error
mse_elastic = np.sum((y_vals_elastic.Predictions - y_vals_elastic.Actual)**2)

# root mean squared error
# m is the number of training examples
rmse_elastic = np.sqrt(mse_elastic/m)
```

[172]:
```
# sum of square of residuals
ssr_elastic = np.sum((y_vals_elastic.Predictions - y_vals_elastic.Actual)**2)

#  total sum of squares
sst_elastic = np.sum((y_vals_elastic.Actual - np.mean(y_vals_elastic.
 ↪Actual))**2)

# R2 score
r2_score_elastic = 1 - (ssr_elastic/sst_elastic)
```

[173]:
```
print(rmse_elastic)
print(r2_score_elastic)
```

```
4215.770766124629
0.9646859151912964
```

3.4 Elastic Net SKLearn implementation

[174]:
```
train_elastic = train_set.copy()
test_elastic = test_set.copy()
```

[175]:
```
X_train_elastic = train_elastic.drop(['Weekly_Sales'], axis=1)
X_train_elastic = np.matrix((X_train_elastic).values)
y_train_elastic = np.matrix((train_elastic['Weekly_Sales']).values)
```

[176]:
```
y_train_elastic = y_train_elastic.T
X_train_elastic.shape, y_train_elastic.shape
```

[176]:
```
((188437, 142), (188437, 1))
```

[177]:
```
X_test_elastic = test_elastic.drop(['Weekly_Sales'], axis=1)
X_test_elastic = np.matrix((X_test_elastic).values)
y_test_elastic = np.matrix((test_elastic['Weekly_Sales']).values)
y_test_elastic = y_test_elastic.T
```

[178]:
```
elastic_sk = linear_model.ElasticNet(alpha=0.001)
elastic_sk.fit(X_train_elastic, y_train_elastic)
```

[178]:
```
ElasticNet(alpha=0.001, copy_X=True, fit_intercept=True, l1_ratio=0.5,
           max_iter=1000, normalize=False, positive=False, precompute=False,
           random_state=None, selection='cyclic', tol=0.0001, warm_start=False)
```

[179]:
```
predictions_elastic_sk = elastic_sk.predict(X_test_elastic)
```

[180]:
```
elastic_RMSE = np.sqrt(metrics.mean_squared_error(y_test_elastic,␣
 ↪predictions_elastic_sk))
elastic_r2 = metrics.r2_score(y_test_elastic, predictions_elastic_sk)

print(elastic_RMSE)
print(elastic_r2)
```

```
3928.15051636024
0.9693401362414069
```

These scores can definitely be improved. However, the purpose of this notebook was only to demonstrate Linear Regression algorithms from scratch.

[ ]:
```

```