EDA

In [1]:
```
import numpy as np
import pandas as pd
import scipy.stats as stats
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
# Loading the data from csv files.
train = pd.read_csv('train.csv')
features = pd.read_csv('features.csv')
stores = pd.read_csv('stores.csv')
```

In [3]:
```
print(train.info())
print(features.info())
print(stores.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 421570 entries, 0 to 421569
Data columns (total 5 columns):
 #   Column        Non-Null Count   Dtype  
---  ------        --------------   -----  
 0   Store         421570 non-null  int64  
 1   Dept          421570 non-null  int64  
 2   Date          421570 non-null  object 
 3   Weekly_Sales  421570 non-null  float64
 4   IsHoliday     421570 non-null  bool   
dtypes: bool(1), float64(1), int64(2), object(1)
memory usage: 13.3+ MB
None
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8190 entries, 0 to 8189
Data columns (total 12 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   Store         8190 non-null   int64  
 1   Date          8190 non-null   object 
 2   Temperature   8190 non-null   float64
 3   Fuel_Price    8190 non-null   float64
 4   MarkDown1     4032 non-null   float64
 5   MarkDown2     2921 non-null   float64
 6   MarkDown3     3613 non-null   float64
 7   MarkDown4     3464 non-null   float64
 8   MarkDown5     4050 non-null   float64
 9   CPI           7605 non-null   float64
 10  Unemployment  7605 non-null   float64
 11  IsHoliday     8190 non-null   bool   
dtypes: bool(1), float64(9), int64(1), object(1)
memory usage: 712.0+ KB
None
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45 entries, 0 to 44
Data columns (total 3 columns):
 #   Column  Non-Null Count  Dtype 
---  ------  --------------  ----- 
 0   Store   45 non-null     int64 
 1   Type    45 non-null     object
 2   Size    45 non-null     int64 
dtypes: int64(2), object(1)
memory usage: 1.2+ KB
None
```

In [4]:
```
#Since we have been given three distinct files we joined theses and formed new data file as data.

data = train.merge(features, on=['Store', 'Date'], how='inner').merge(stores, on=['Store'], how='inner')
print(data.info())
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 421570 entries, 0 to 421569
Data columns (total 17 columns):
 #   Column        Non-Null Count   Dtype  
---  ------        --------------   -----  
 0   Store         421570 non-null  int64  
 1   Dept          421570 non-null  int64  
 2   Date          421570 non-null  object 
 3   Weekly_Sales  421570 non-null  float64
 4   IsHoliday_x   421570 non-null  bool   
 5   Temperature   421570 non-null  float64
 6   Fuel_Price    421570 non-null  float64
 7   MarkDown1     150681 non-null  float64
 8   MarkDown2     111248 non-null  float64
 9   MarkDown3     137091 non-null  float64
 10  MarkDown4     134967 non-null  float64
 11  MarkDown5     151432 non-null  float64
 12  CPI           421570 non-null  float64
 13  Unemployment  421570 non-null  float64
 14  IsHoliday_y   421570 non-null  bool   
 15  Type          421570 non-null  object 
 16  Size          421570 non-null  int64  
dtypes: bool(2), float64(10), int64(3), object(2)
memory usage: 52.3+ MB
None
```

In [5]:
```
#drop the dublicate of IsHoliday column
data = data.drop(columns=['IsHoliday_y'])
data = data.rename(columns={'IsHoliday_x': 'IsHoliday'})
```

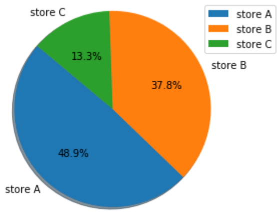
In [6]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 421570 entries, 0 to 421569
Data columns (total 16 columns):
 #   Column        Non-Null Count   Dtype  
---  ------        --------------   -----  
 0   Store         421570 non-null  int64  
 1   Dept          421570 non-null  int64  
 2   Date          421570 non-null  object 
 3   Weekly_Sales  421570 non-null  float64
 4   IsHoliday     421570 non-null  bool   
 5   Temperature   421570 non-null  float64
 6   Fuel_Price    421570 non-null  float64
 7   MarkDown1     150681 non-null  float64
 8   MarkDown2     111248 non-null  float64
 9   MarkDown3     137091 non-null  float64
 10  MarkDown4     134967 non-null  float64
 11  MarkDown5     151432 non-null  float64
 12  CPI           421570 non-null  float64
 13  Unemployment  421570 non-null  float64
 14  Type          421570 non-null  object 
 15  Size          421570 non-null  int64  
dtypes: bool(1), float64(10), int64(3), object(2)
memory usage: 51.9+ MB
```

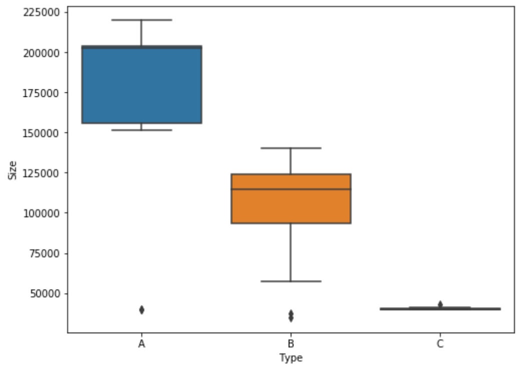
In [13]:
```python
# Pie-chart for the visual representation of store types

# Data to plot
labels = 'store A','store B','store C'
sizes = [(22/(45))*100,(17/(45))*100,(6/(45))*100]
colors = ['gold', 'yellowgreen', 'lightcoral']
explode = (0.1, 0, 0)  # explode 1st slice

# Plot
plt.pie(sizes, labels=labels,autopct='%1.1f%%', shadow=True, startangle=140)
plt.legend(labels, loc="best")
plt.axis('equal')
plt.show()
```

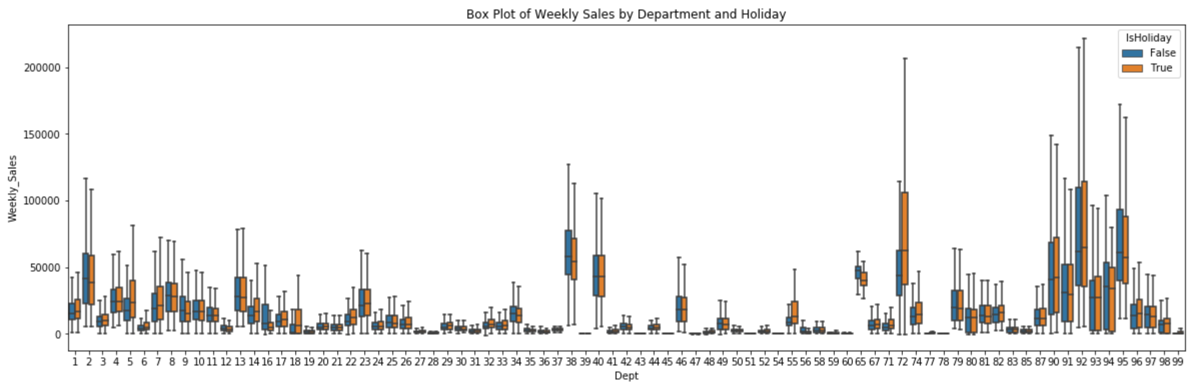


In [7]:
```python
# boxplot for sizes of types of stores
store_type = pd.concat([stores['Type'], stores['Size']], axis=1)
f, ax = plt.subplots(figsize=(8, 6))
fig = sns.boxplot(x='Type', y='Size', data=store_type)
```



There are 45 stores in total. There are a total of 3 types of stores: Type A, B, and C. By boxplot and piechart, we can say that type A store is the largest store and C is the smallest There is no overlapped area in size among A, B, and C

In [8]:
```python
data_11= pd.concat([data['Dept'], data['Weekly_Sales'], data['IsHoliday']], axis=1)
plt.figure(figsize=(20,6))
plt.title('Box Plot of Weekly Sales by Department and Holiday')
fig = sns.boxplot(x='Dept', y='Weekly_Sales', data=data_11, showfliers=False, hue="IsHoliday")
```



Sales on holiday is a little bit more than sales in not-holiday From this plot, we notice the Department with the highest sales lies between Dept 60 and 80 Total we have 421570 values for training and 115064 for testing as part of the competition. But we will work only on 421570 data as we have labels to test the performance and accuracy of models

In [20]:
```python
print(data.describe().T)
```

```
                 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
```

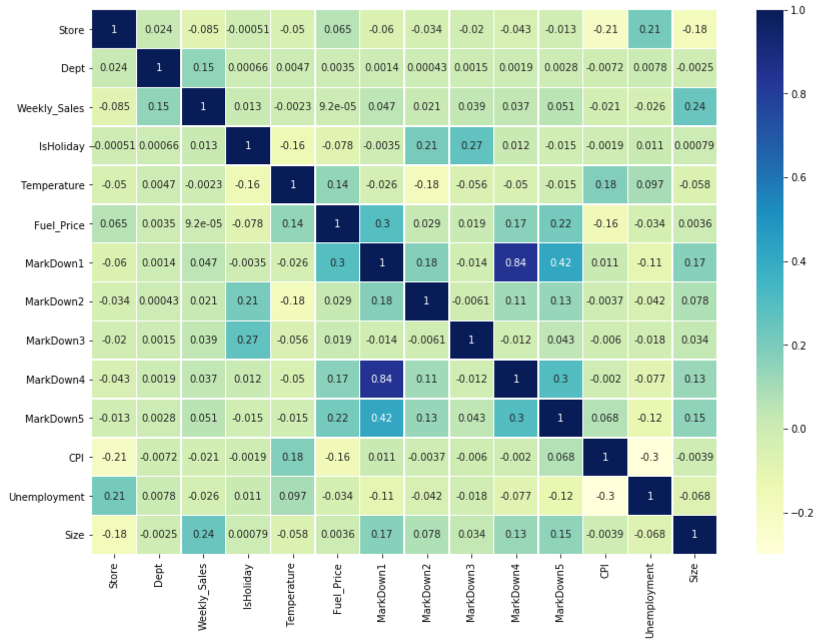
Replaced null values with zeros. Also,looking at the statistics of the dataframe we come to know that there are some rows for which Weekly sales have negative values. Since sales values can't be negative, we skipped those rows having negative weekly sales.

```
In [22]: data=data.fillna(0)
         data = data[data['Weekly_Sales'] >= 0]
```

```
Out[22]: Store           0
         Dept            0
         Date            0
         Weekly_Sales    0
         IsHoliday       0
         Temperature     0
         Fuel_Price      0
         MarkDown1       0
         MarkDown2       0
         MarkDown3       0
         MarkDown4       0
         MarkDown5       0
         CPI             0
         Unemployment    0
         Type            0
         Size            0
         dtype: int64
```

```
In [35]: fig, ax = plt.subplots(figsize=(14,10))         # Sample figsize in inches
         print(sns.heatmap(data.corr(),cmap="YlGnBu", annot=True, linewidths=.5, ax=ax))
```

```
AxesSubplot(0.125,0.125;0.62x0.755)
```



Correlation is a bivariate analysis that measures the strength of association between two variables and the direction of the relationship. In terms of the strength of the relationship, the value of the correlation coefficient varies between +1 and -1.

```
In [38]: test = pd.read_csv('test.csv')
         print(test.shape)
```

```
(115064, 4)
```

Some data preprocceing might be needed. Data is now ready for Machine learning model.However, I filled missing markdown data with zeroes. another impi=utation method such as median or the mean can tested after evaluating the model performance.

Total we have 421570 values for training and 115064 for testing as part of the competition. But we will work only on 421570 data as we have labels to test the performance and accuracy of models.