Problem Statement

The data scientists at BigMart have collected sales data for 1559 products across 10 stores in different cities for the year 2013. Now each product has certain attributes that sets it apart from other products. Same is the case with each store.

The aim is to build a predictive model to find out the sales of each product at a particular store so that it would help the decision makers at BigMart to find out the properties of any product or store, which play a key role in increasing the overall sales.

Importing libraries and data

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

In [2]:
```
train=pd.read_csv("Train.csv")
test =pd.read_csv("Test.csv")
train_original=train.copy()
test_original=test.copy()
```

Understanding the data

In [3]:
```
train.shape , test.shape
```

Out[3]:
```
((8523, 12), (5681, 11))
```

train dataset has 8523 rows and 12 features and test has 5681 rows and 11 columns. train has 1 extra column which is the target variable. We will predict this target variable for the test dataset later in this project.

In [4]:
```
list(train.columns)
```

Out[4]:
```
['Item_Identifier',
 'Item_Weight',
 'Item_Fat_Content',
 'Item_Visibility',
 'Item_Type',
 'Item_MRP',
 'Outlet_Identifier',
 'Outlet_Establishment_Year',
 'Outlet_Size',
 'Outlet_Location_Type',
 'Outlet_Type',
 'Item_Outlet_Sales']
```

In [5]:
```
list(test.columns)
```

Out[5]:
```
['Item_Identifier',
 'Item_Weight',
 'Item_Fat_Content',
 'Item_Visibility',
 'Item_Type',
 'Item_MRP',
 'Outlet_Identifier',
 'Outlet_Establishment_Year',
 'Outlet_Size',
 'Outlet_Location_Type',
 'Outlet_Type']
```

Item_Outlet_Sales is present in train but not in test dataset because this is the target variable that we have to predict

In [6]:
```
test.dtypes
```

Out[6]:
```
Item_Identifier               object
Item_Weight                  float64
Item_Fat_Content              object
Item_Visibility              float64
Item_Type                     object
Item_MRP                     float64
Outlet_Identifier             object
Outlet_Establishment_Year      int64
Outlet_Size                   object
Outlet_Location_Type          object
Outlet_Type                   object
dtype: object
```

As we can see, there are 4 numeric and 7 categorical variables

Continuous variable : Item_Outlet_Sale Item_weight Item_Visibility Item_MRP

Categorical Variables : Item_Fat_Content Item_Type Outlet_Identifier Outlet_Size Outlet_Establishment_Year Outlet_Type Outlet_Location_Type

In [7]:
```
# Combine train and test data.

test['Item_Outlet_Sales']=0
combined=train.append(pd.DataFrame(data=test),ignore_index=True)
combined.shape
```

Out[7]:
```
(14204, 12)
```

In [8]:
```
null_columns=combined.columns[combined.isnull().any()]
combined[null_columns].isnull().sum()

#combined.isnull().sum()
```

Out[8]:
```
Item_Weight    2439
Outlet_Size    4016
dtype: int64
```

In [9]:
```
combined[combined['Outlet_Size'].isnull()]
```

Out[9]:

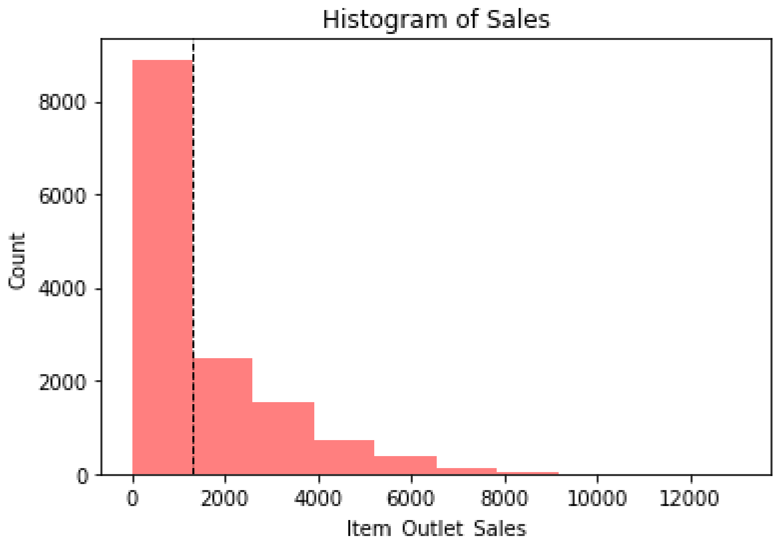
	Item_Identifier	Item_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_MRP	Outl
3	FDX07	19.200	Regular	0.000000	Fruits and Vegetables	182.0950	
8	FDH17	16.200	Regular	0.016687	Frozen Foods	96.9726	
9	FDU28	19.200	Regular	0.094450	Frozen Foods	187.8214	
25	NCD06	13.000	Low Fat	0.099887	Household	45.9060	
28	FDE51	5.925	Regular	0.161467	Dairy	45.5086	
...	...	...	...	...	...	...	
14191	FDC44	15.600	Low Fat	0.288892	Fruits and Vegetables	115.1518	
14193	FDO03	10.395	Regular	0.037092	Meat	229.4352	
14201	NCO17	10.000	Low Fat	0.073529	Health and Hygiene	118.7440	
14202	FDJ26	15.300	Regular	0.000000	Canned	214.6218	
14203	FDU37	9.500	Regular	0.104720	Canned	79.7960	

4016 rows × 12 columns

Module 1 : Extrapolatory Data Analysis

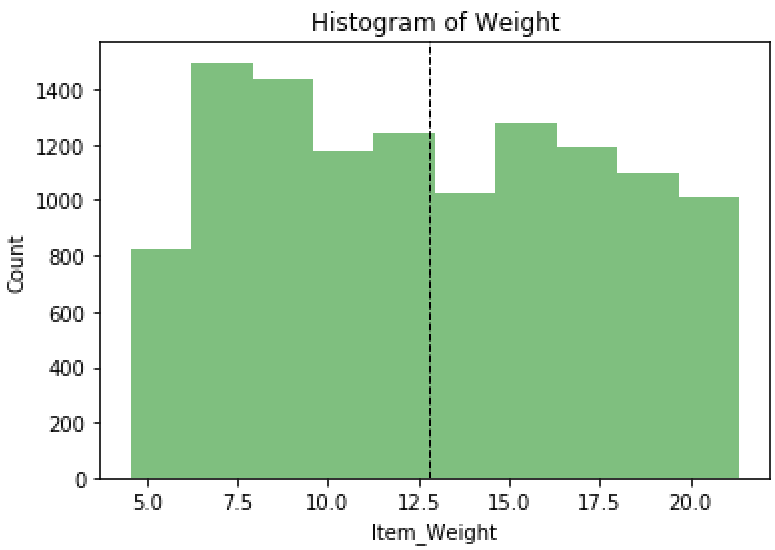
Univariate Analysis : Continuous Variables

In [10]:
```
# Item_Outlet_Sales

combined['Item_Outlet_Sales'].plot.hist(color="r",alpha=0.5)
plt.xlabel('Item_Outlet_Sales')
plt.ylabel('Count')
plt.title('Histogram of Sales')
plt.axvline(combined['Item_Outlet_Sales'].mean(), color='k', linestyle='dashe
d', linewidth=1)
plt.show()
```



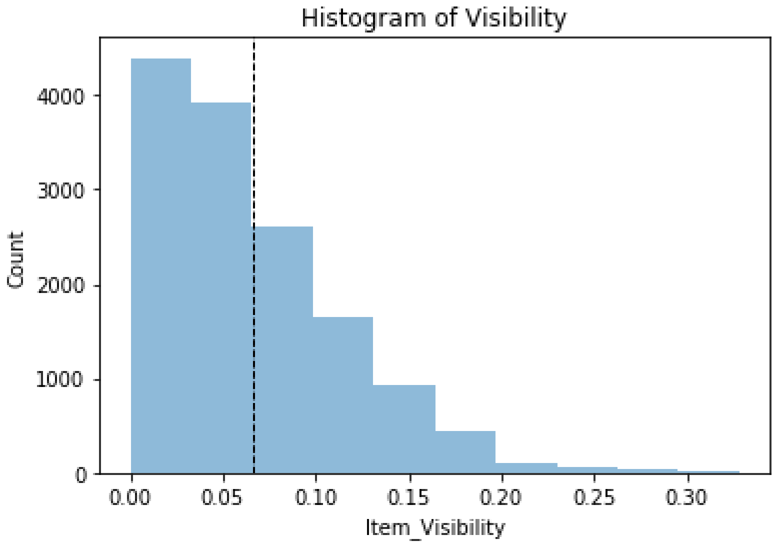
As you can see, it is a right skewd variable and would need some data transformation to treat its skewness.

In [11]:
```
# Item_Weight

combined['Item_Weight'].plot.hist(color='g',alpha=0.5)
plt.xlabel('Item_Weight')
plt.ylabel('Count')
plt.title('Histogram of Weight')
plt.axvline(combined['Item_Weight'].mean(), color='black', linestyle='dashed',
linewidth=1)
plt.show()
```



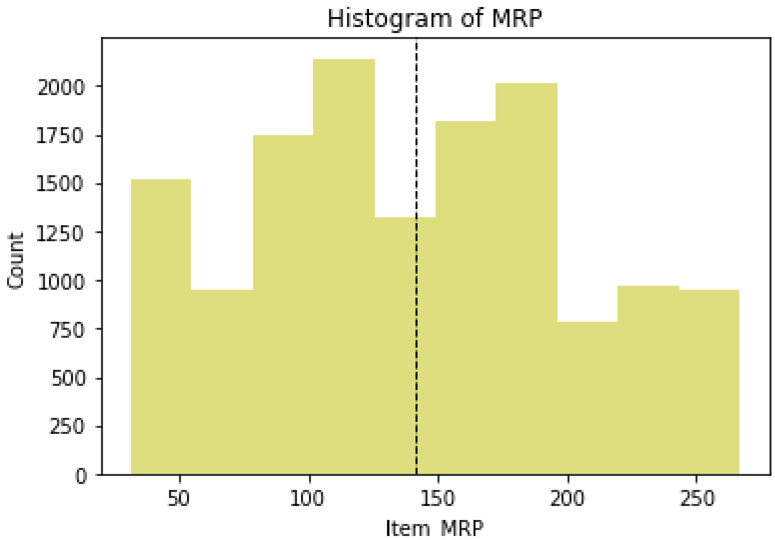
There seems to be no clear-cut pattern in Item_Weight.

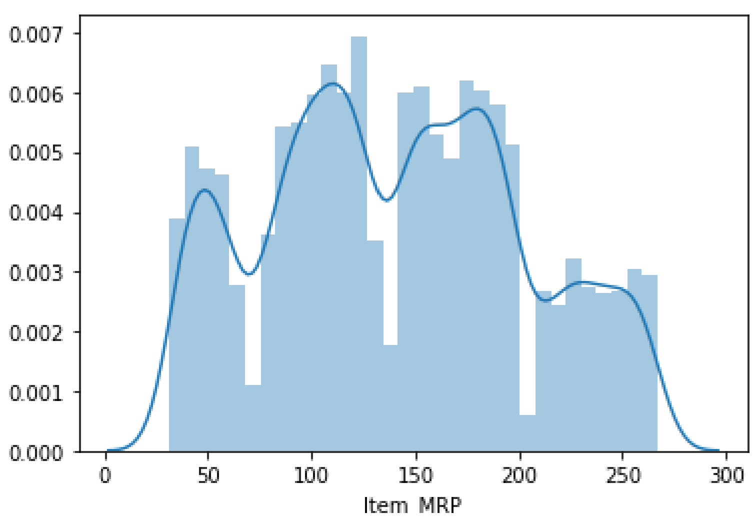
In [12]:
```
# Item_Visibility

combined['Item_Visibility'].plot.hist(alpha=0.5)
plt.xlabel('Item_Visibility')
plt.ylabel('Count')
plt.title('Histogram of Visibility')
plt.axvline(combined['Item_Visibility'].mean(),color='black',linestyle='dashe
d',linewidth=1)
plt.show()
```



Item_Visibility is right-skewed and should be transformed to curb its skewness

In [13]:
```
# Item_MRP

combined['Item_MRP'].plot.hist(color='y',alpha=0.5)
plt.xlabel('Item_MRP')
plt.ylabel('Count')
plt.title('Histogram of MRP')
plt.axvline(combined['Item_MRP'].mean(),color='k',linestyle='dashed',linewidth
=1)
plt.show()
sns.distplot(combined['Item_MRP'])
plt.show()
```

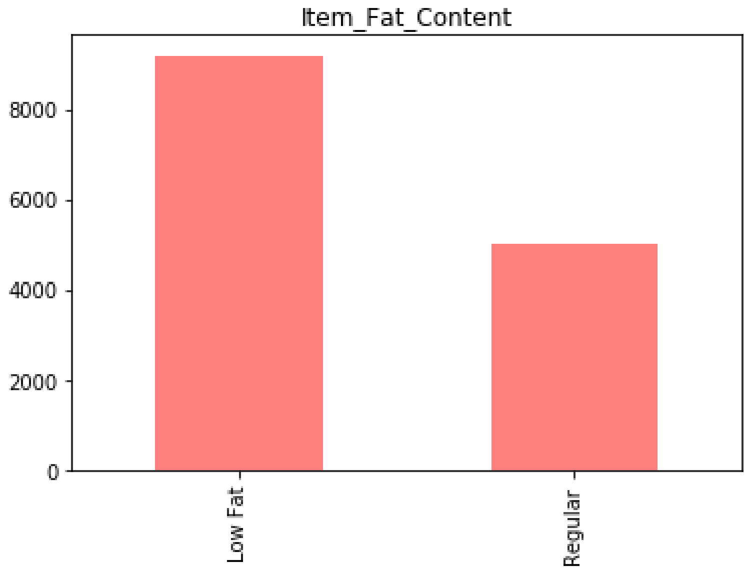




There seems to be no clear-cut pattern in Item_Weight

Univariate Analysis : Categorical Variables

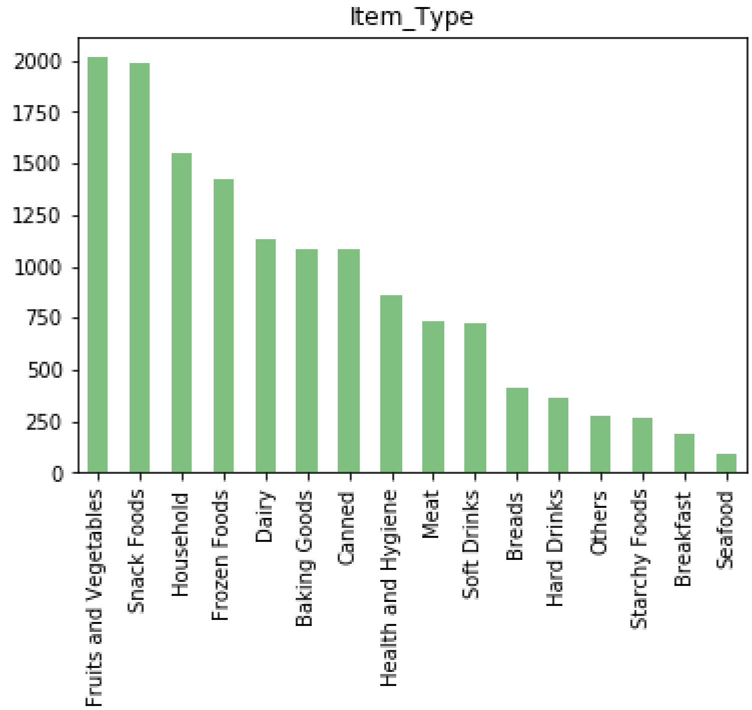
In [14]:
```
# Item_Fat_Content

combined['Item_Fat_Content'].replace(('LF','low fat'),'Low Fat',inplace=True)
combined['Item_Fat_Content'].replace('reg','Regular',inplace=True)
combined['Item_Fat_Content'].value_counts().plot.bar(title='Item_Fat_Content',
color='r',alpha=0.5)
plt.show()
combined['Item_Fat_Content'].value_counts()
```



Out[14]:
```
Low Fat    9185
Regular    5019
Name: Item_Fat_Content, dtype: int64
```

Sales of Low Fat products is higher than the products with Regular amount of Fat.

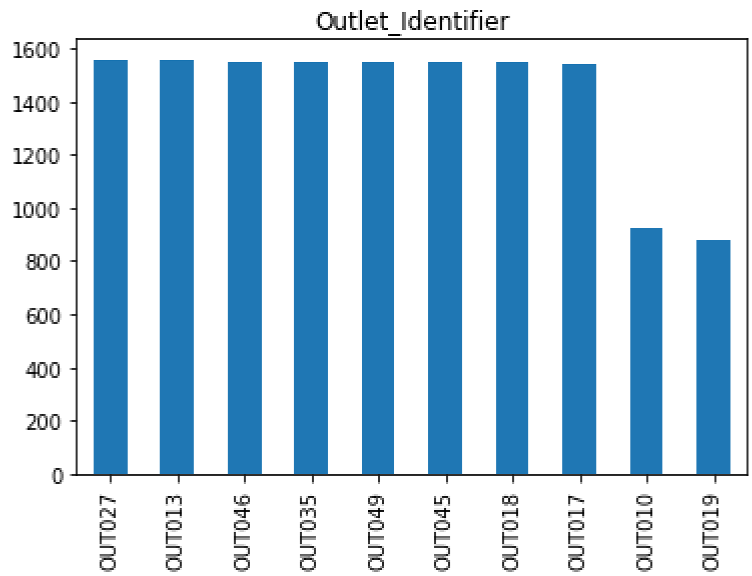
In [15]:
```
# Item_Type

combined['Item_Type'].value_counts().plot.bar(color='g',alpha=0.5)
plt.title('Item_Type')
plt.show()
combined['Item_Type'].value_counts()
```



Out[15]:
```
Fruits and Vegetables    2013
Snack Foods              1989
Household                1548
Frozen Foods             1426
Dairy                    1136
Baking Goods             1086
Canned                   1084
Health and Hygiene        858
Meat                      736
Soft Drinks               726
Breads                    416
Hard Drinks               362
Others                    280
Starchy Foods             269
Breakfast                 186
Seafood                    89
Name: Item_Type, dtype: int64
```

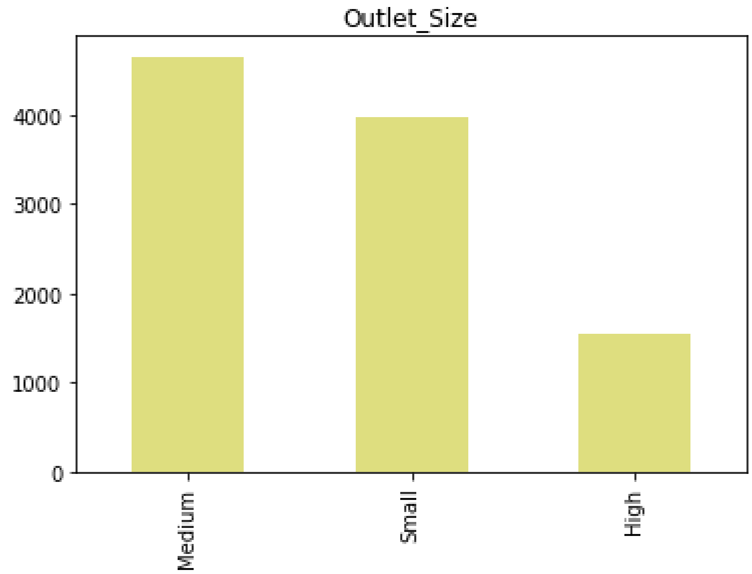
"Fruits & Vegetables" and "Snack food" are the two most selling product category.

In [16]:
```
# Outlet_Identifier

combined['Outlet_Identifier'].value_counts().plot.bar()
plt.title('Outlet_Identifier')
plt.show()
combined['Outlet_Identifier'].value_counts()
```



Out[16]:
```
OUT027    1559
OUT013    1553
OUT046    1550
OUT035    1550
OUT049    1550
OUT045    1548
OUT018    1546
OUT017    1543
OUT010     925
OUT019     880
Name: Outlet_Identifier, dtype: int64
```

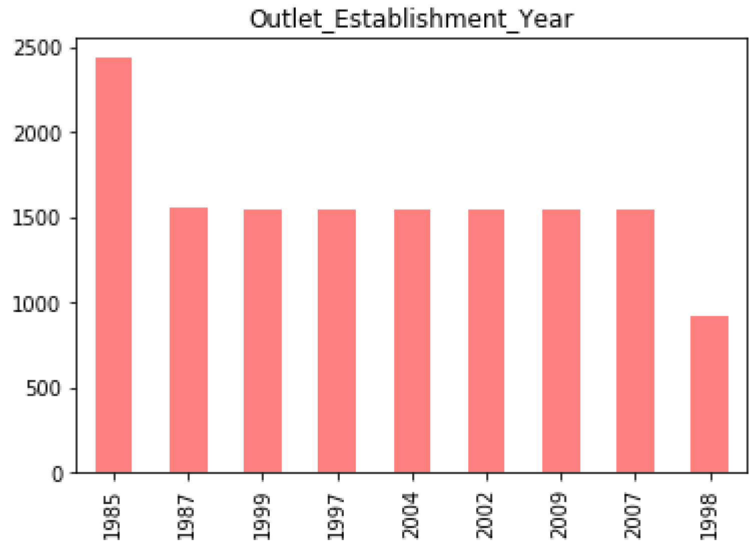
In [17]:
```
# Outlet_Size

combined['Outlet_Size'].value_counts().plot.bar(color='y',alpha=0.5)
plt.title('Outlet_Size')
plt.show()
combined['Outlet_Size'].value_counts()
```



Out[17]:
```
Medium    4655
Small     3980
High      1553
Name: Outlet_Size, dtype: int64
```

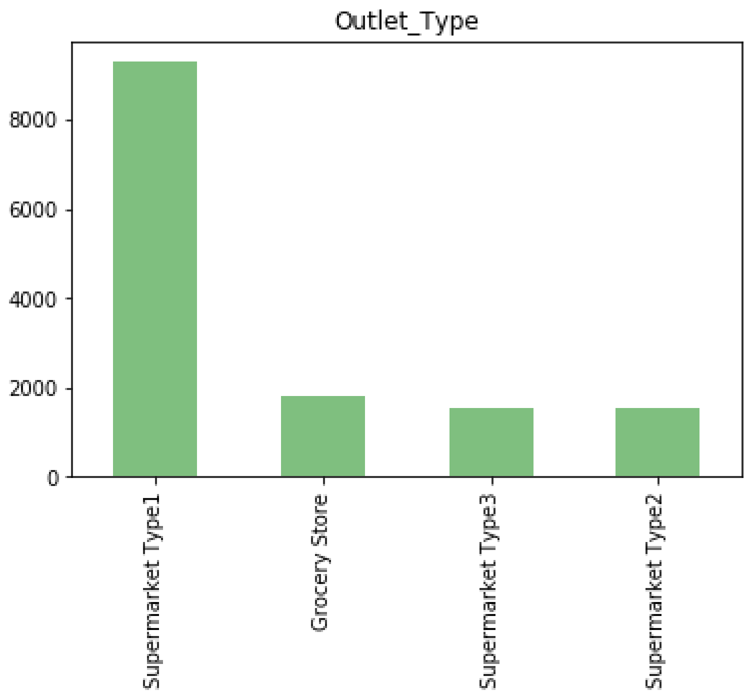
In Outlet_Size's plot, for 4016 observations, Outlet_Size is blank or missing.We will check for this in the bivariate analysis to substitute the missing values in the Outlet_Size.

In [18]:
```
# Outlet_Establishment_Year

combined['Outlet_Establishment_Year'].value_counts().plot.bar(color='r',alpha=
0.5)
plt.title('Outlet_Establishment_Year')
plt.show()
combined['Outlet_Establishment_Year'].value_counts()
```



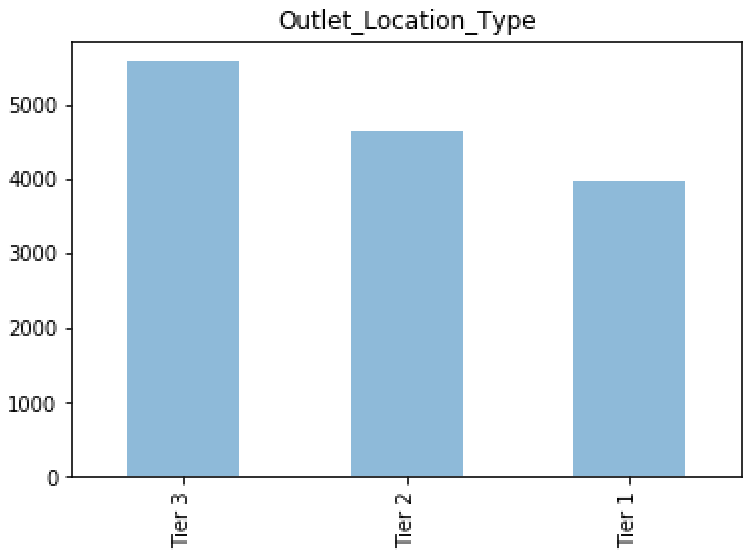
Out[18]:
```
1985    2439
1987    1553
1999    1550
1997    1550
2004    1550
2002    1548
2009    1546
2007    1543
1998     925
Name: Outlet_Establishment_Year, dtype: int64
```

In [19]:
```
# Outlet_Type

combined['Outlet_Type'].value_counts().plot.bar(color='g',alpha=0.5)
plt.title('Outlet_Type')
plt.show()
combined['Outlet_Type'].value_counts()
```



Out[19]:
```
Supermarket Type1    9294
Grocery Store        1805
Supermarket Type3    1559
Supermarket Type2    1546
Name: Outlet_Type, dtype: int64
```

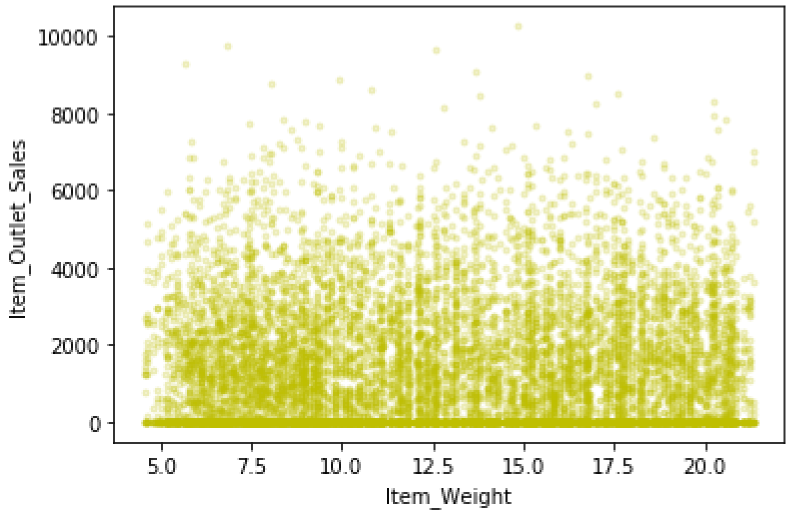
In [20]:
```
# Outlet_Location_Type

combined['Outlet_Location_Type'].value_counts().plot.bar(alpha=0.5)
plt.title('Outlet_Location_Type')
plt.show()
```



Maximum number of products are purchased in Tier 3 location type.

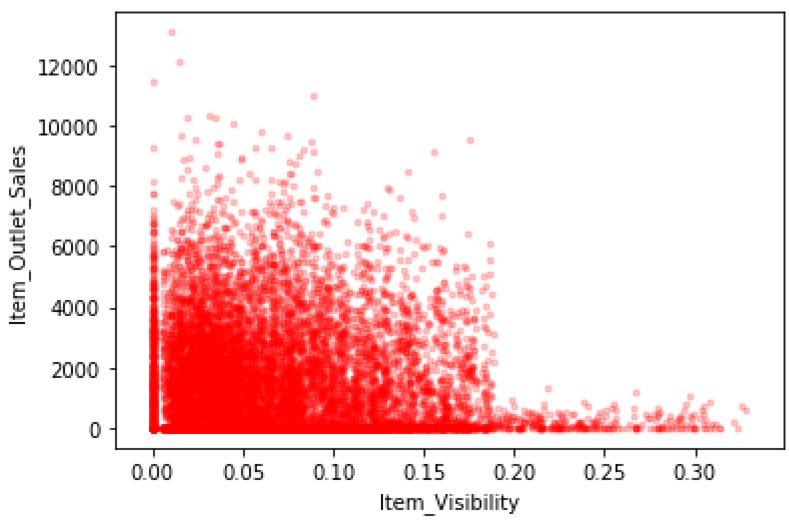
Bivariate Analysis : Target Variable vs Independent Continuous Variables

In [21]:
```
# Item_Weight vs Item_Outlet_Sales

plt.scatter(combined['Item_Weight'],combined['Item_Outlet_Sales'],marker ='.',
alpha=0.2,color='y')
plt.xlabel('Item_Weight')
plt.ylabel('Item_Outlet_Sales')
plt.show()
```



Item_Outlet_Sales is spread well across the entire range of the Item_Weight without any obvious pattern.

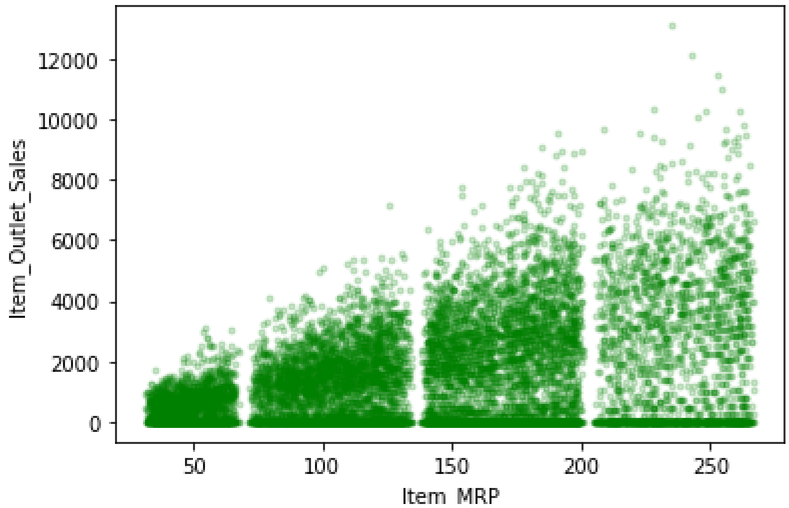
In [22]:
```
# Item_Visibility vs Item_Outlet_Sales

plt.scatter(combined['Item_Visibility'],combined['Item_Outlet_Sales'],marker=
'.',color='r',alpha=0.2)
plt.xlabel('Item_Visibility')
plt.ylabel('Item_Outlet_Sales')
plt.show()
combined[combined['Item_Visibility']==0].shape
```



Out[22]: (879, 12)

There is a string of points at Item_Visibility = 0.0 which seems strange as item visibility cannot be completely zero. We will take note of this issue and deal with it in the later stages.

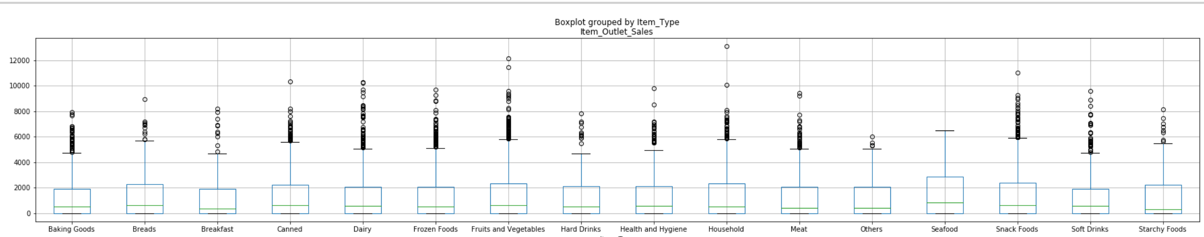
In [23]:
```
# Item_MRP vs Item_Outlet_Sales

plt.scatter(combined['Item_MRP'],combined['Item_Outlet_Sales'],marker='.',colo
r='g',alpha=0.2)
plt.xlabel('Item_MRP')
plt.ylabel('Item_Outlet_Sales')
plt.show()
```



In the this plot of Item_MRP vs Item_Outlet_Sales, we can clearly see 4 segments of prices that can be used in feature engineering to create a new variable.

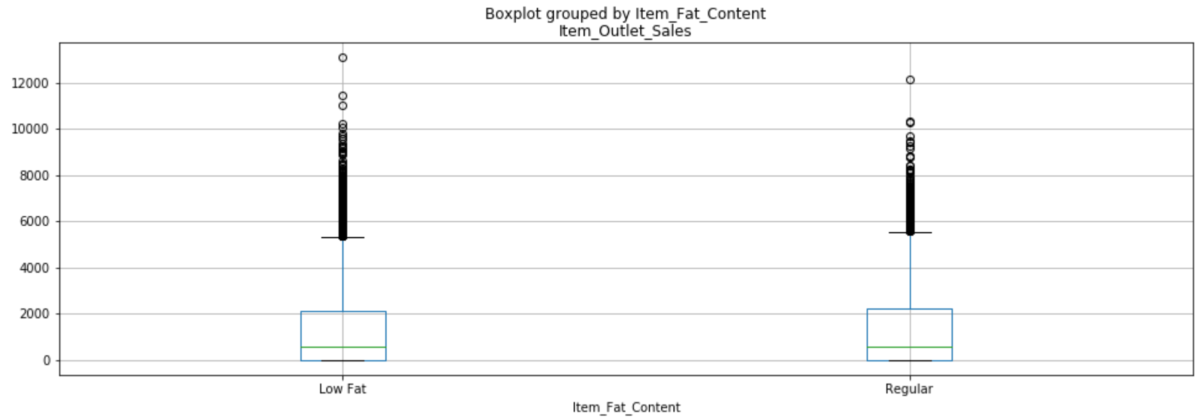
Bivariate Analysis : Target Variable vs Independent Categorical Variables

In [24]:
```
# Item_Outlet_Sales vs Item_Type

combined.boxplot(column='Item_Outlet_Sales',by='Item_Type',figsize=(30,5))
plt.show()
```



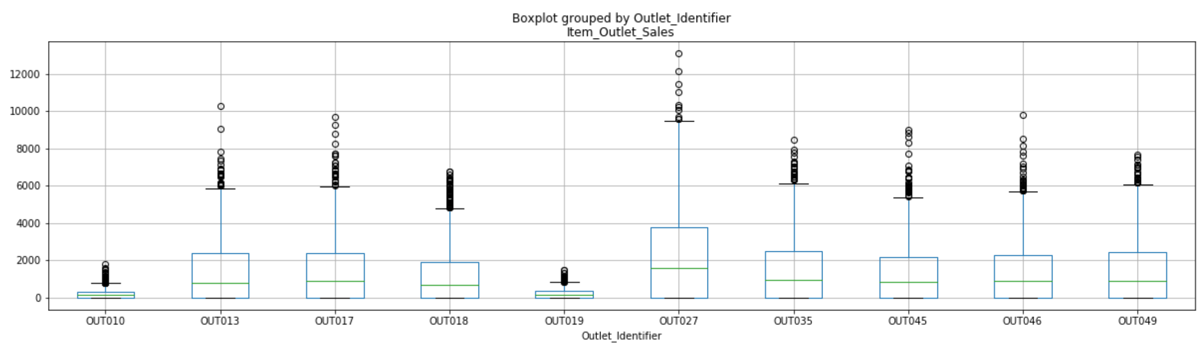
Distribution of Item_Outlet_Sales across the categories of Item_Type is not very distinct.

In [25]:
```
# Item_Outlet_Sales vs Item_Fat_Content

combined.boxplot(column="Item_Outlet_Sales",by='Item_Fat_Content',figsize=(16,
5))
plt.show()
```



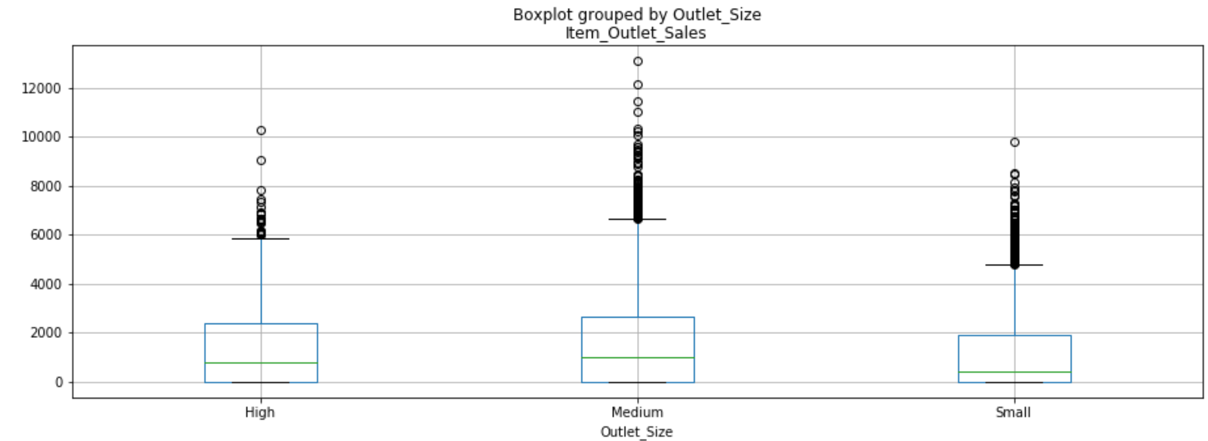
Distribution of Item_Outlet_Sales across the categories of Item_Fat_Content is also not very distinct.

In [26]:
```
# Item_Outlet_Sales vs Outlet_Identifier

combined.boxplot(column='Item_Outlet_Sales',by='Outlet_Identifier',figsize=(20
,5))
plt.show()
```



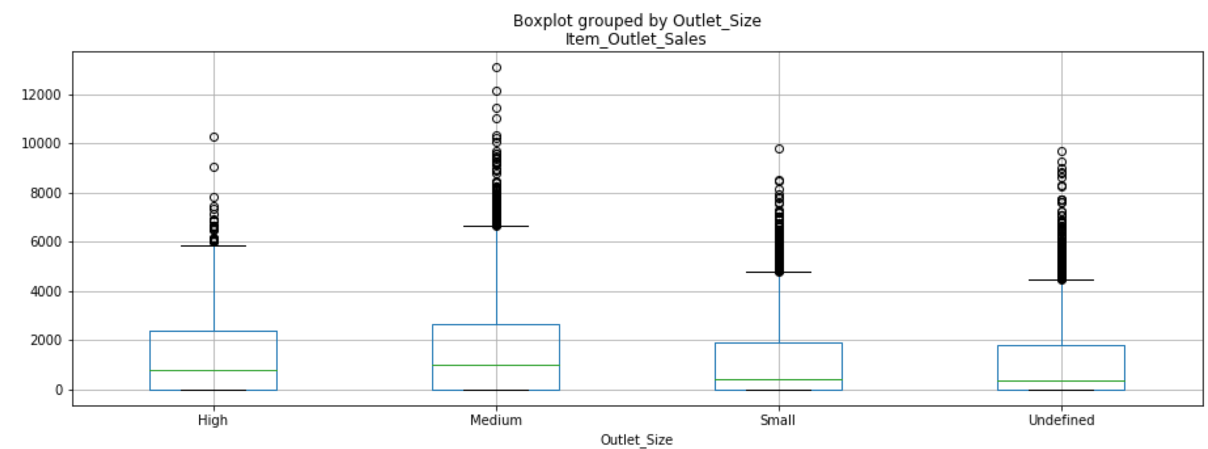
The distribution for OUT010 and OUT019 categories of Outlet_Identifier are quite similar and very much different from the rest of the categories of Outlet_Identifier.

In [27]:
```
# Item_Outlet_Sales vs Outlet_Size

combined.boxplot(column='Item_Outlet_Sales',by='Outlet_Size',figsize=(15,5))
plt.show()
combined['Outlet_Size'].value_counts()
```



Out[27]:
```
Medium    4655
Small     3980
High      1553
Name: Outlet_Size, dtype: int64
```

In [28]:
```
combined['Outlet_Size'].fillna('Undefined',inplace=True)
combined.boxplot(column='Item_Outlet_Sales',by='Outlet_Size',figsize=(15,5))
plt.show()
```

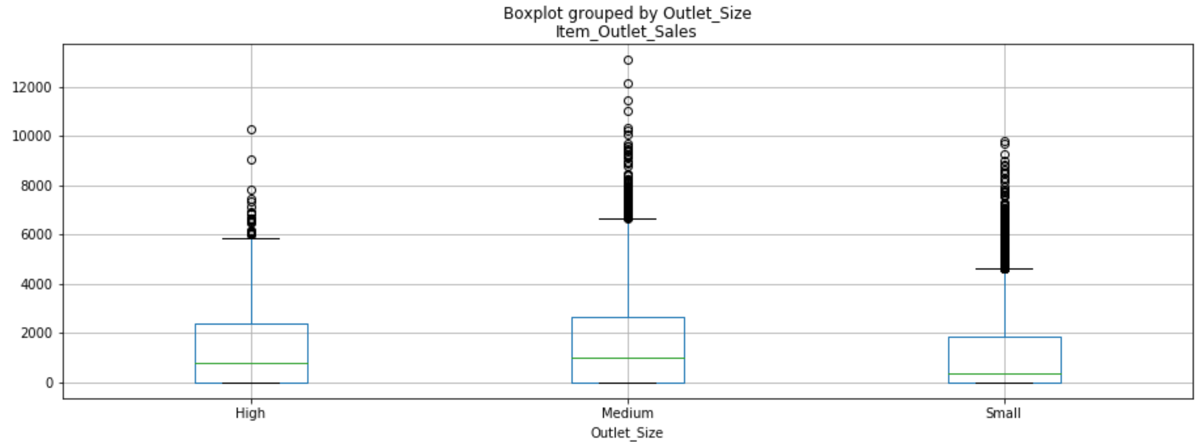


The distribution of ‘Small’ Outlet_Size is almost identical to the distribution of the "undefined" category of Outlet_Size. So, we can substitute the undefined in Outlet_Size with ‘Small’.

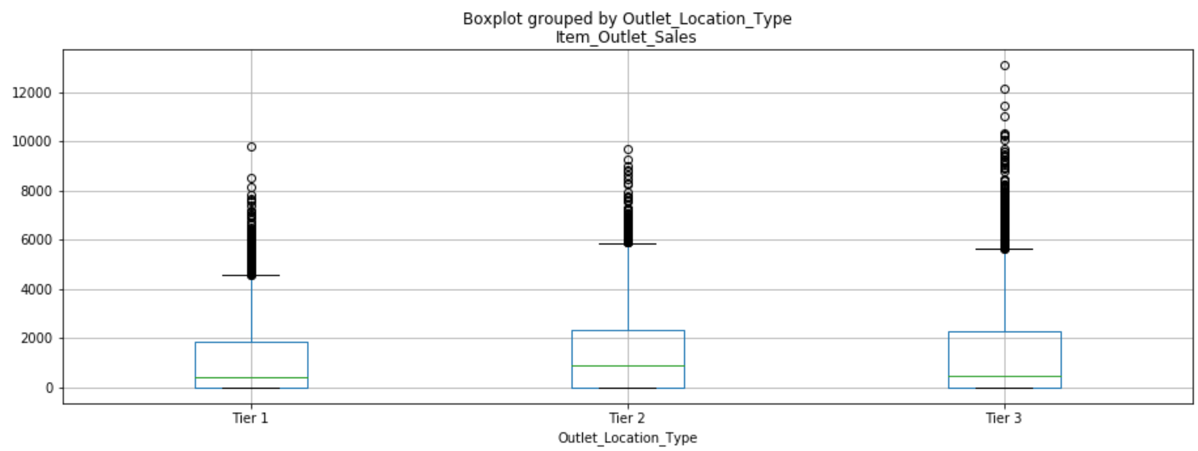
In [29]:
```
combined['Outlet_Size'].replace('Undefined','Small',inplace=True)
combined['Outlet_Size'].value_counts()
```

Out[29]:
```
Small     7996
Medium    4655
High      1553
Name: Outlet_Size, dtype: int64
```

In [30]:
```
combined.boxplot(column='Item_Outlet_Sales',by='Outlet_Size',figsize=(15,5))
plt.show()
```

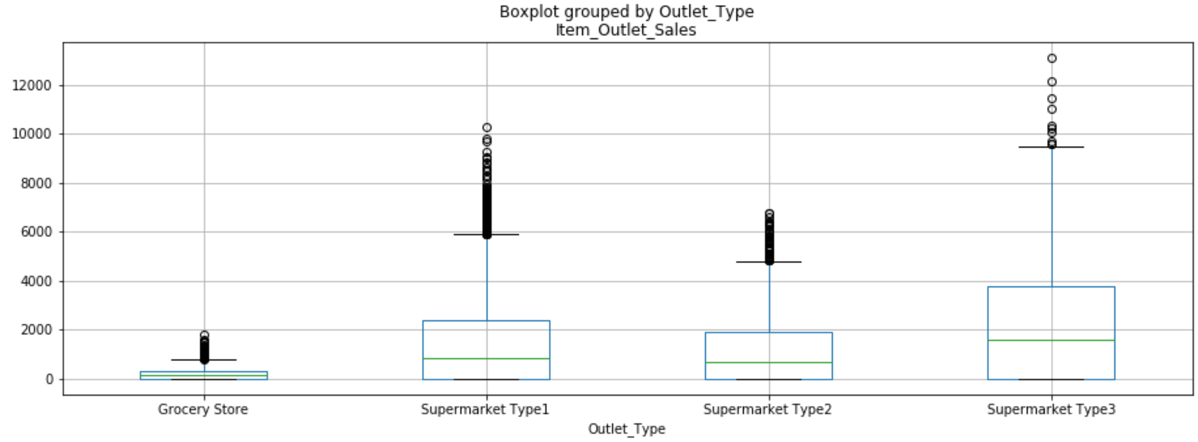


In [31]:
```
# Item_Outlet_Sales vs Outlet_Location_Type

combined.boxplot(column='Item_Outlet_Sales',by='Outlet_Location_Type',figsize=
(15,5))
plt.show()
```



Tier 1 and Tier 3 locations of Outlet_Location_Type look similar.

In [32]:
```
# Item_Outlet_Sales vs Outlet_Type

combined.boxplot(column='Item_Outlet_Sales',by='Outlet_Type',figsize=(15,5))
plt.show()
```



In the Outlet_Type plot, Grocery Store has most of its data points around the lower sales values as compared to the other categories.

Imputing Missing Values

In [33]:
```
#missing_index = np.where(data['Item_Weight'].isnull())
#for i in missing_index :
#   item=data['Item_Identifier'][i]
#   data['Item_Weight'][i]=data['Item_Weight'][data['Item_Identifier']==item].
mean()
```

In [34]:
```
# Imputing Missing Value of Item_Weight

combined['Item_Weight'] = combined.apply(
    lambda row: combined[(combined.Item_Weight.isnull() == False) & (combined.
Item_Identifier == row['Item_Identifier'])].iloc[0].Item_Weight
    if pd.isna(row['Item_Weight']) else row['Item_Weight'],
    axis=1
)
combined['Item_Weight'].isnull().value_counts()
```

Out[34]:
```
False    14204
Name: Item_Weight, dtype: int64
```

In [35]:
```
# Replacing 0's in Item_Visibility variable

combined['Item_Visibility'].replace(0.0,np.nan,inplace=True)
combined['Item_Visibility']= combined.apply(
    lambda row : combined[(combined['Item_Visibility'].isnull()==False) & (com
bined["Item_Identifier"]==row['Item_Identifier'])].iloc[0].Item_Visibility
    if pd.isna(row['Item_Visibility']) else row['Item_Visibility'],
    axis=1
)
combined['Item_Visibility'].isnull().sum()
```

Out[35]: 0