BigMartSales

Problem Statement

The data scientists at BigMart have collected 2013 sales data for 1559 products across 10 stores in different cities. Also, certain attributes of each product and store have been defined. The aim is to build a predictive model and find out the sales of each product at a particular store. Using this model, BigMart will try to understand the properties of products and stores which play a key role in increasing sales.

Please note that the data may have missing values as some stores might not report all the data due to technical glitches. Hence, it will be required to treat them accordingly.

Data

We have train (8523) and test (5681) data set, train data set has both input and output variable(s). You need to predict the sales for test data set. Variable Description Item_Identifier Unique product ID Item_Weight Weight of product Item_Fat_Content Whether the product is low fat or not Item_Visibility The % of total display area of all products in a store allocated to the particular product Item_Type The category to which the product belongs Item_MRP Maximum Retail Price (list price) of the product Outlet_Identifier Unique store ID Outlet_Establishment_Year The year in which store was established Outlet_Size The size of the store in terms of ground area covered Outlet_Location_Type The type of city in which the store is located Outlet_Type Whether the outlet is just a grocery store or some sort of supermarket Item_Outlet_Sales Sales of the product in the particulat store. This is the outcome variable to be predicted.

Evaluation Metric: Your model performance will be evaluated on the basis of your prediction of the sales for the test data (test.csv), which contains similar data-points as train except for the sales to be predicted. Your submission needs to be in the format as shown in "SampleSubmission.csv". We at our end, have the actual sales for the test dataset, against which your predictions will be evaluated. We will use the Root Mean Square Error value to judge your response.

RoadMap

#

Data Summary: Exploration, Visalization, Data Imputation

Preprocessing / Feature Engineering: Deriving the column, Transfomation, FEature selection

Dividing our data interms of trainig and testing

Building the model: linear regression, Ensemble regressor methods

In [1]:

```
import matplotlib.pyplot as plt
%matplotlib inline
```

In [4]:

```
import seaborn as sns
```

In [4]:

```
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
#Read CSV

train = pd.read_csv('Train_UWu5bXk.csv')
```

```
train = pd.read_csv('Train_UWu5bXk.csv')
test = pd.read_csv('Test_u94Q5KV.csv')
```

In [5]:

```
train.head()
```

Out[5]:

	Item_Identifier	Item_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_MRP	Outlet_Identifier	Outlet_Establishi
0	FDA15	9.30	Low Fat	0.016047	Dairy	249.8092	OUT049	1999
1	DRC01	5.92	Regular	0.019278	Soft Drinks	48.2692	OUT018	2009
2	FDN15	17.50	Low Fat	0.016760	Meat	141.6180	OUT049	1999
3	FDX07	19.20	Regular	0.000000	Fruits and Vegetables	182.0950	OUT010	1998
4	NCD19	8.93	Low Fat	0.000000	Household	53.8614	OUT013	1987

In [2]:

```
#creates a new column 'source' with values as 'train' for all train data and 'test' for all test d
ata
train['source']='train'
test['source']='test'

data=pd.concat([train,test],ignore_index=True)
print train.shape,test.shape,data.shape

#data.apply(lambda x:sum(x.isnull()))

data.isnull().sum()
```

```
(8523, 13) (5681, 12) (14204, 13)
```

Out[2]:

```
Item_Fat_Content                0
Item_Identifier                 0
Item_MRP                        0
Item_Outlet_Sales            5681
Item_Type                       0
Item_Visibility                 0
Item_Weight                  2439
Outlet_Establishment_Year       0
Outlet_Identifier               0
Outlet_Location_Type            0
Outlet_Size                  4016
Outlet_Type                     0
source                          0
dtype: int64
```

In [3]:

```
data.describe()
```

Out[3]:

	Item_MRP	Item_Outlet_Sales	Item_Visibility	Item_Weight	Outlet_Establishment_Year
count	14204.000000	8523.000000	14204.000000	11765.000000	14204.000000
mean	141.004977	2181.288914	0.065953	12.792854	1997.830681
std	62.086938	1706.499616	0.051459	4.652502	8.371664

	Item_MRP	Item_Outlet_Sales	Item_Visibility	Item_Weight	Outlet_Establishment_Year
min	31.290000	33.290000	0.000000	4.555000	1985.000000
25%	94.012000	834.247400	0.027036	8.710000	1987.000000
50%	142.247000	1794.331000	0.054021	12.600000	1999.000000
75%	185.855600	3101.296400	0.094037	16.750000	2004.000000
max	266.888400	13086.964800	0.328391	21.350000	2009.000000

In [4]:

```
data.apply(lambda x: len(x.unique()))
```

Out[4]:

```
Item_Fat_Content                 5
Item_Identifier               1559
Item_MRP                      8052
Item_Outlet_Sales             3494
Item_Type                       16
Item_Visibility              13006
Item_Weight                    416
Outlet_Establishment_Year        9
Outlet_Identifier               10
Outlet_Location_Type             3
Outlet_Size                      4
Outlet_Type                      4
source                           2
dtype: int64
```

In [5]:

```
#Filter categorical variables and exclude Item_Identifier etc
categorical_columns=[x for x in data.dtypes.index if data.dtypes[x]== 'object']
categorical_columns=[x for x in categorical_columns if x not in
['Item_Identifier','Outlet_Identifier','source']]

for col in categorical_columns:
    print "\nFrequency of categories for variable %s"%col
    print data[col].value_counts()
```

```
Frequency of categories for variable Item_Fat_Content
Low Fat    8485
Regular    4824
LF          522
reg         195
low fat     178
dtype: int64

Frequency of categories for variable Item_Type
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
dtype: int64

Frequency of categories for variable Outlet_Location_Type
Tier 3    5583
Tier 2    4641
Tier 1    3980
dtype: int64

Frequency of categories for variable Outlet_Size
```

```
Frequency of categories for variable Outlet_Size
Medium    4655
Small     3980
High      1553
dtype: int64

Frequency of categories for variable Outlet_Type
Supermarket Type1    9294
Grocery Store        1805
Supermarket Type3    1559
Supermarket Type2    1546
dtype: int64
```

In [6]:

```
item_avg_wt=data.pivot_table(values='Item_Weight',index='Item_Identifier')
print item_avg_wt

miss_bool=data['Item_Weight'].isnull()
# print "hi", sum(miss_bool)
print miss_bool

data.loc[miss_bool,'Item_Weight']=data.loc[miss_bool,'Item_Identifier'].apply(lambda x : item_avg_w
t[x])
print sum(data['Item_Weight'].isnull())
```

```
Item_Identifier
DRA12             11.600
DRA24             19.350
DRA59              8.270
DRB01              7.390
DRB13              6.115
DRB24              8.785
DRB25             12.300
DRB48             16.750
DRC01              5.920
DRC12             17.850
DRC13              8.260
DRC24             17.850
DRC25              5.730
DRC27             13.800
DRC36             13.000
...
NCY30             20.250
NCY41             16.750
NCY42              6.380
NCY53             20.000
NCY54              8.430
NCZ05              8.485
NCZ06             19.600
NCZ17             12.150
NCZ18              7.825
NCZ29             15.000
NCZ30              6.590
NCZ41             19.850
NCZ42             10.500
NCZ53              9.600
NCZ54             14.650
Name: Item_Weight, Length: 1559, dtype: float64
0      False
1      False
2      False
3      False
4      False
5      False
6      False
7       True
8      False
9      False
10     False
11     False
12     False
13     False
14     False
...
14189    False
```

```
14190    False
14191    False
14192     True
14193    False
14194    False
14195    False
14196    False
14197    False
14198    False
14199    False
14200    False
14201    False
14202    False
14203    False
Name: Item_Weight, Length: 14204, dtype: bool
0
```

In [7]:

```
visibility_avg=data.pivot_table(values='Item_Visibility',index='Item_Identifier')
miss_bool=(data['Item_Visibility']==0)

print 'Number of zeros initially %d'%sum(miss_bool)
data.loc[miss_bool,'Item_Visibility']=data.loc[miss_bool,"Item_Identifier"].apply(lambda
x:visibility_avg[x])
print 'Number of zeros after imputing %d'%sum(data['Item_Visibility']==0)
```

```
Number of zeros initially 879
Number of zeros after imputing 0
```

In [8]:

```
# determine another feature
data['Item_Visibility_MeanRatio']=data.apply(lambda x: x['Item_Visibility']/visibility_avg[x['Item_
Identifier']],axis=1)
print data['Item_Visibility_MeanRatio'].describe()
print visibility_avg[[0,10]]#[data[1]['Item_Identifier']]
```

```
count    14204.000000
mean         1.061884
std          0.235907
min          0.844563
25%          0.925131
50%          0.999070
75%          1.042007
max          3.010094
Name: Item_Visibility_MeanRatio, dtype: float64
Item_Identifier
DRA12              0.034938
DRC13              0.028408
Name: Item_Visibility, dtype: float64
```

In [9]:

```
#capturing initial two characters of string and separating the data
data['Item_Type_Combined']=data['Item_Identifier'].apply(lambda x:x[0:2])
#Renaming them to more intuitive categories.
data['Item_Type_Combined']=data['Item_Type_Combined'].map({'FD':'Food',
                                                            'NC':'Non-Consumable',
                                                            'DR':'Drinks'})

data['Item_Type_Combined'].value_counts()
```

Out[9]:

```
Food              10201
Non-Consumable     2686
Drinks             1317
dtype: int64
```

In [10]:

```
data['Outlet_Years']=2013-data['Outlet_Establishment_Year']
data['Outlet_Years'].describe()
```

Out[10]:

```
count    14204.000000
mean        15.169319
std          8.371664
min          4.000000
25%          9.000000
50%         14.000000
75%         26.000000
max         28.000000
Name: Outlet_Years, dtype: float64
```

In [11]:

```
print 'Original Categories :'
print data['Item_Fat_Content'].value_counts()

print '\n Modified Categories :'
data['Item_Fat_Content']=data['Item_Fat_Content'].replace({'LF': 'Low Fat',
                                                           'reg':'Regular',
                                                           'low fat':'Low Fat'})
data['Item_Fat_Content'].value_counts()
```

```
Original Categories :
Low Fat    8485
Regular    4824
LF          522
reg         195
low fat     178
dtype: int64

 Modified Categories :
```

Out[11]:

```
Low Fat    9185
Regular    5019
dtype: int64
```

In [12]:

```
#Mark non-consumables as separate category in low_fat
data.loc[data['Item_Type_Combined']=='Non-Consumable','Item_Fat_Content']='Non-Edible'
data['Item_Fat_Content'].value_counts()
```

Out[12]:

```
Low Fat       6499
Regular       5019
Non-Edible    2686
dtype: int64
```

In [13]:

```
#Outlet Identifier is the store number /name so changed it also to numeric
from sklearn.preprocessing import LabelEncoder
le=LabelEncoder()
data['Outlet']=le.fit_transform(data['Outlet_Identifier'])
var_mod=['Item_Fat_Content','Outlet_Location_Type','Outlet_Size','Item_Type_Combined','Outlet_Type'
,'Outlet']
for i in var_mod:
    data[i]=le.fit_transform(data[i])

data=pd.get_dummies(data,columns=['Item_Fat_Content','Outlet_Location_Type','Outlet_Size','Item_Typ
e_Combined','Outlet_Type','Outlet'])
```

In [14]:

```
data.dtypes#['Item_Fat_Content']
```

```
data.dtypes#['Item_Fat_Content']
```

Out[14]:

```
Item_Identifier              object
Item_MRP                    float64
Item_Outlet_Sales           float64
Item_Type                    object
Item_Visibility             float64
Item_Weight                 float64
Outlet_Establishment_Year     int64
Outlet_Identifier            object
source                       object
Item_Visibility_MeanRatio   float64
Outlet_Years                  int64
Item_Fat_Content_0          float64
Item_Fat_Content_1          float64
Item_Fat_Content_2          float64
Outlet_Location_Type_0      float64
Outlet_Location_Type_1      float64
Outlet_Location_Type_2      float64
Outlet_Size_0               float64
Outlet_Size_1               float64
Outlet_Size_2               float64
Outlet_Size_3               float64
Item_Type_Combined_0        float64
Item_Type_Combined_1        float64
Item_Type_Combined_2        float64
Outlet_Type_0               float64
Outlet_Type_1               float64
Outlet_Type_2               float64
Outlet_Type_3               float64
Outlet_0                    float64
Outlet_1                    float64
Outlet_2                    float64
Outlet_3                    float64
Outlet_4                    float64
Outlet_5                    float64
Outlet_6                    float64
Outlet_7                    float64
Outlet_8                    float64
Outlet_9                    float64
dtype: object
```

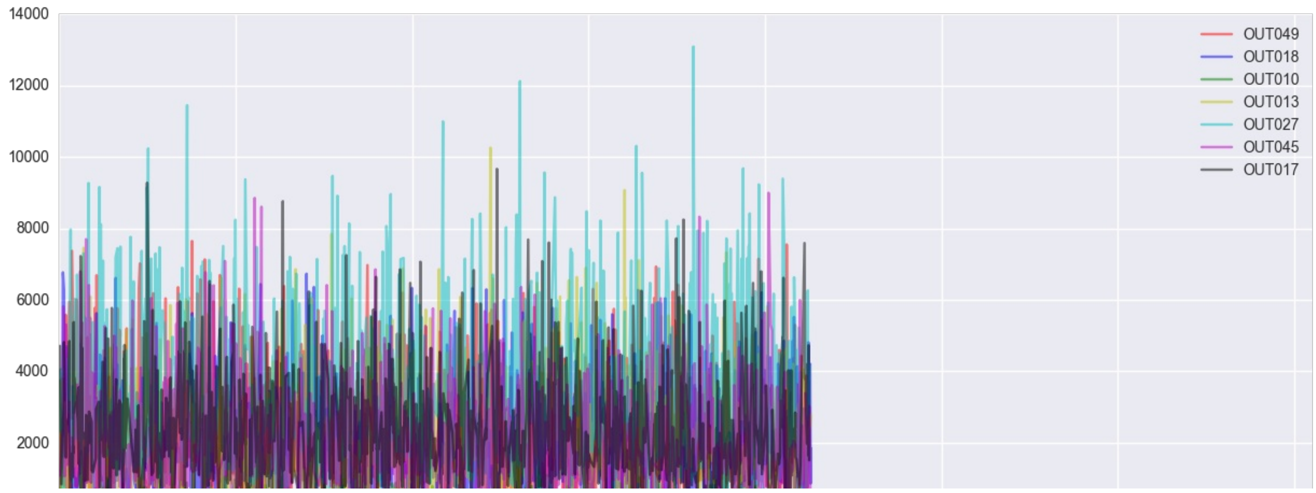
Sales across different outlets

In [15]:

```python
colors = ['r', 'b', 'g', 'y', 'c', 'm', 'k']

for i, s in enumerate(data.Outlet_Identifier.unique()[:7]):
    data[data.Outlet_Identifier == s].Item_Outlet_Sales.plot(c=colors[i], figsize=(15, 6), label=s,
alpha=.5)

plt.legend(loc='best');
```



Stores have varying sales

In [16]:

```
data.Outlet_Identifier.unique()
```

Out[16]:

```
array(['OUT049', 'OUT018', 'OUT010', 'OUT013', 'OUT027', 'OUT045',
       'OUT017', 'OUT046', 'OUT035', 'OUT019'], dtype=object)
```

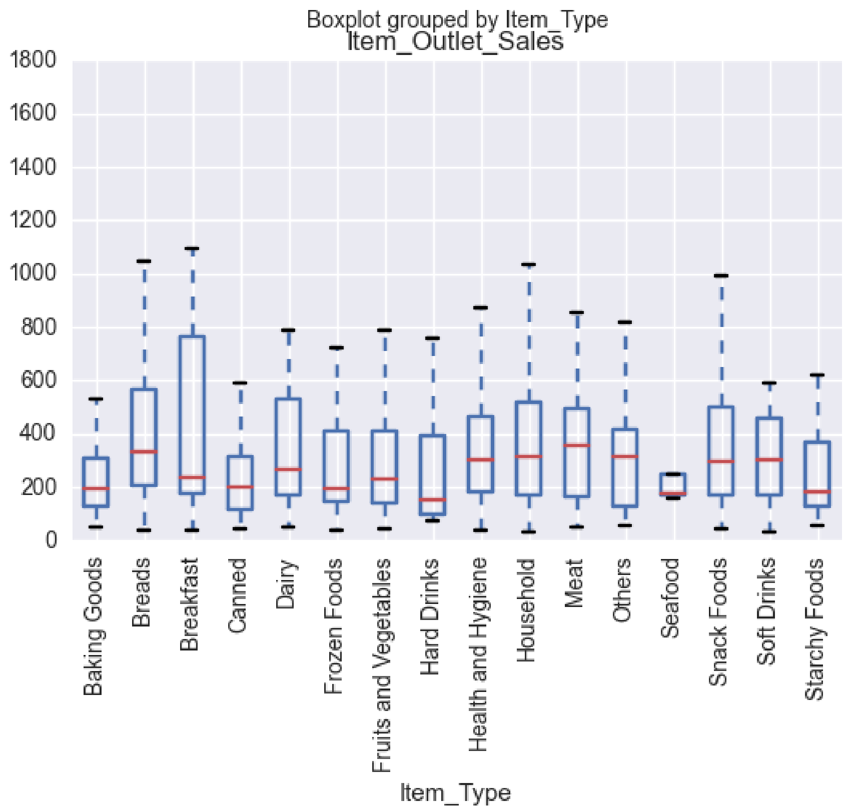
In [17]:

```
data_OUT049 = data[data.Outlet_Identifier == 'OUT049']
data_OUT018 = data[data.Outlet_Identifier == 'OUT018']
data_OUT010 = data[data.Outlet_Identifier == 'OUT010']
data_OUT013 = data[data.Outlet_Identifier == 'OUT013']
data_OUT027 = data[data.Outlet_Identifier == 'OUT027']
data_OUT045 = data[data.Outlet_Identifier == 'OUT045']
data_OUT017 = data[data.Outlet_Identifier == 'OUT017']
data_OUT035 = data[data.Outlet_Identifier == 'OUT035']
data_OUT019 = data[data.Outlet_Identifier == 'OUT019']
data_OUT046 = data[data.Outlet_Identifier == 'OUT046']
```

Correlation between item type and sales for a particular store

In [18]:

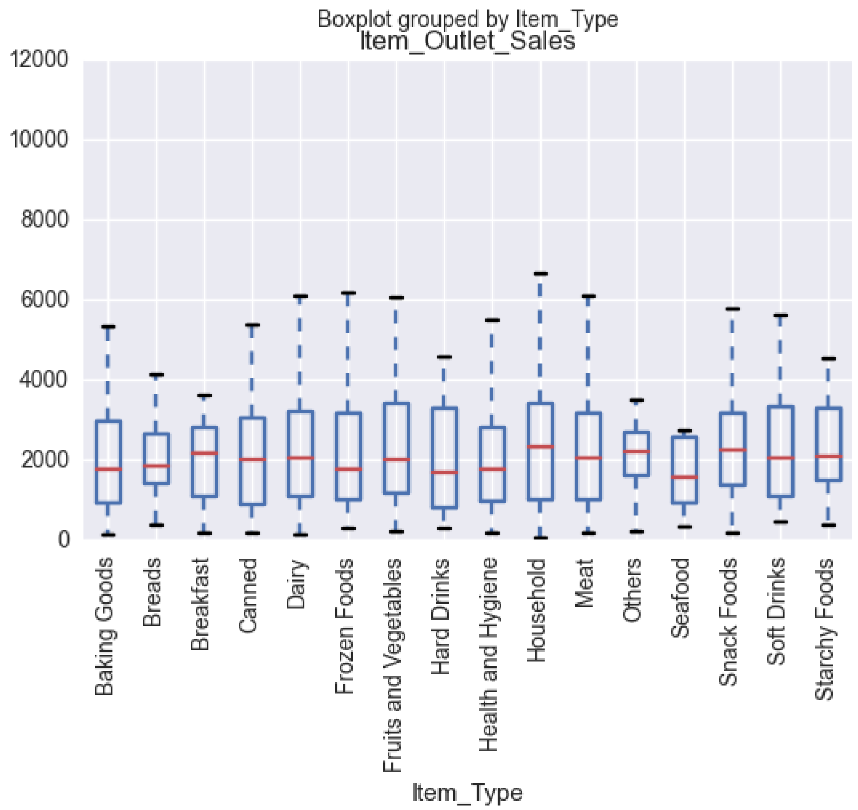
```
data_OUT010.boxplot(column='Item_Outlet_Sales', by='Item_Type')
plt.xticks(rotation=90);
```



In [19]:

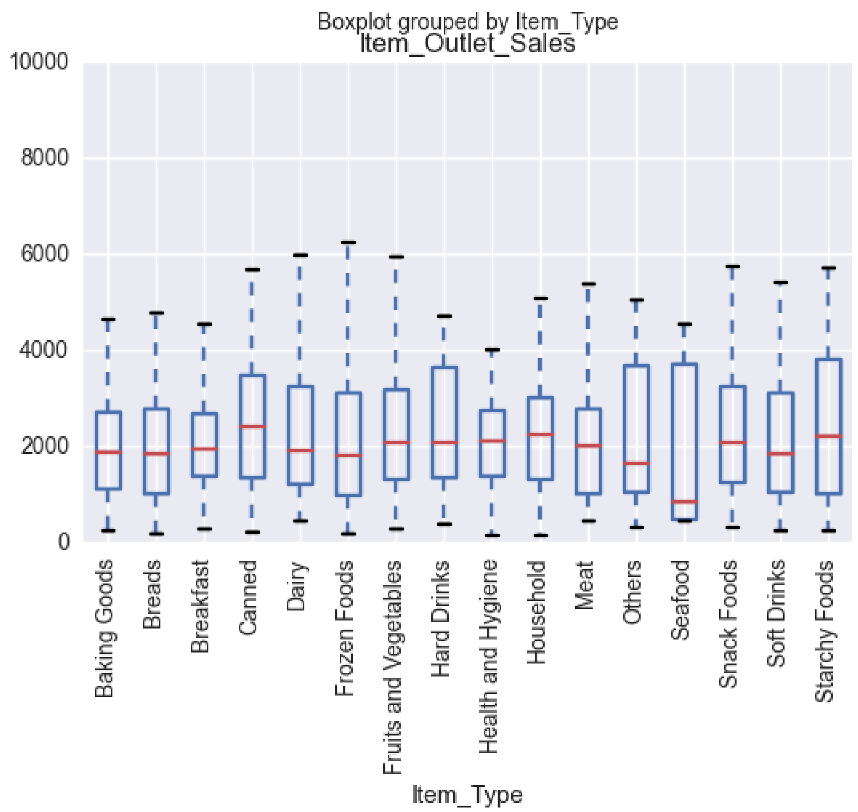
```
data_OUT013.boxplot(column='Item_Outlet_Sales', by='Item_Type')
```

```
plt.xticks(rotation=90);
```



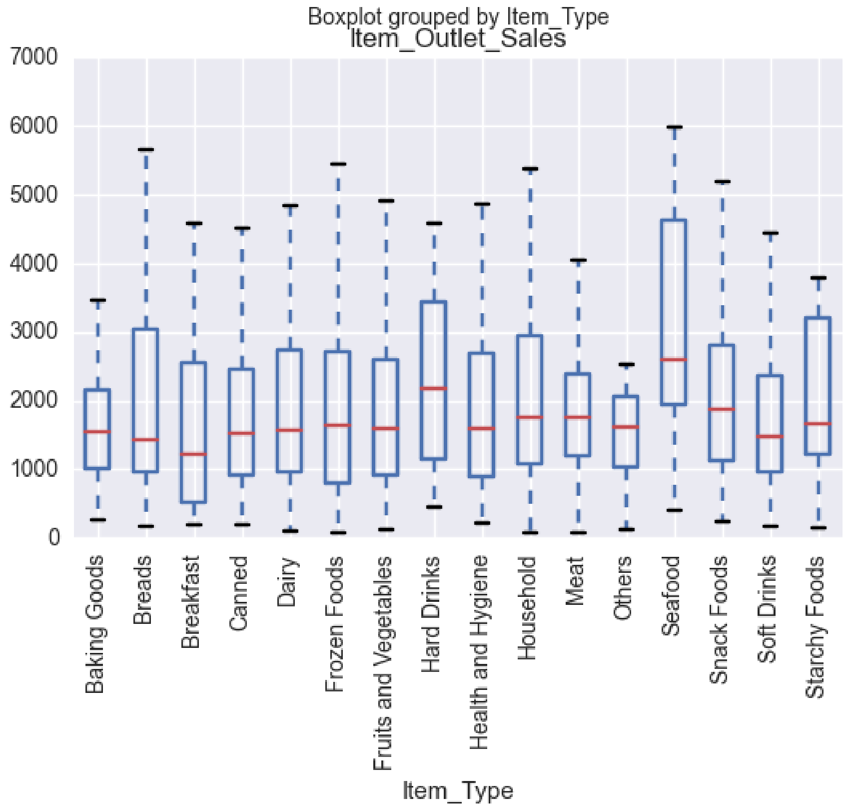
In [20]:

```
data_OUT017.boxplot(column='Item_Outlet_Sales', by='Item_Type')
plt.xticks(rotation=90);
```



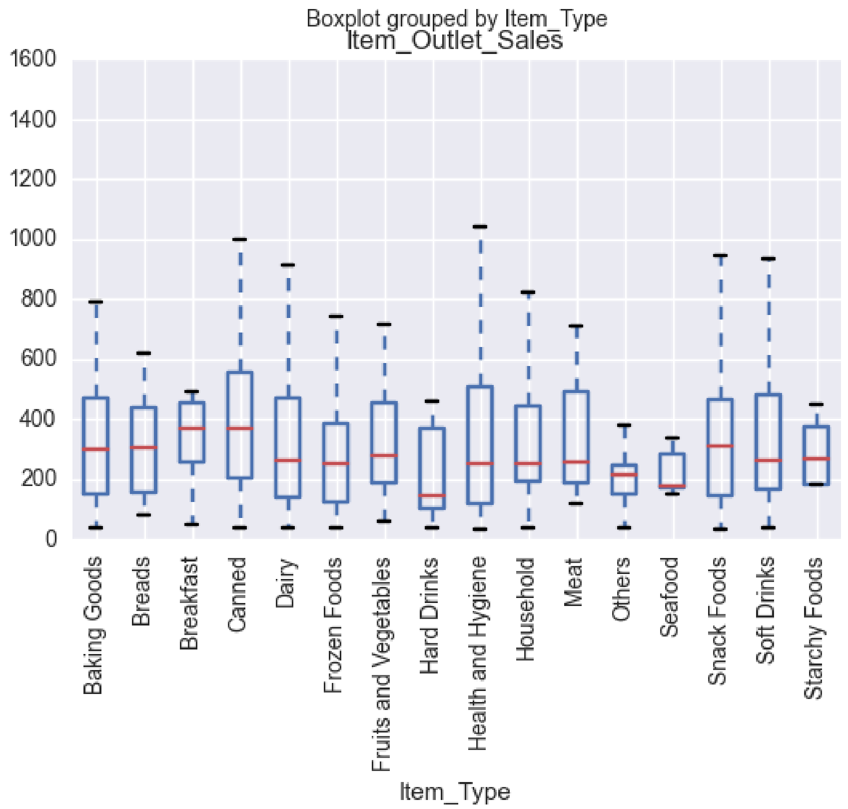
In [21]:

```
data_OUT018.boxplot(column='Item_Outlet_Sales', by='Item_Type')
plt.xticks(rotation=90);
```



In [22]:

```
data_OUT019.boxplot(column='Item_Outlet_Sales', by='Item_Type')
plt.xticks(rotation=90);
```



In [23]:

```
data_OUT027.boxplot(column='Item_Outlet_Sales', by='Item_Type')
plt.xticks(rdata:image/png;base64,iVBORw0KGgoAAAANSUhEUgAAAiIAAAIECAYAAAAkQUUBAAAABHNCSVQICAgIfAhki
AAlwSFlzAAAPYQAAD2EBqD+naQAAIABJREFUeJzs3XmcHHWd//HXHMlMZpIJE64EgoHw45JKCJiwjCuqwK67ym/lioso14
```

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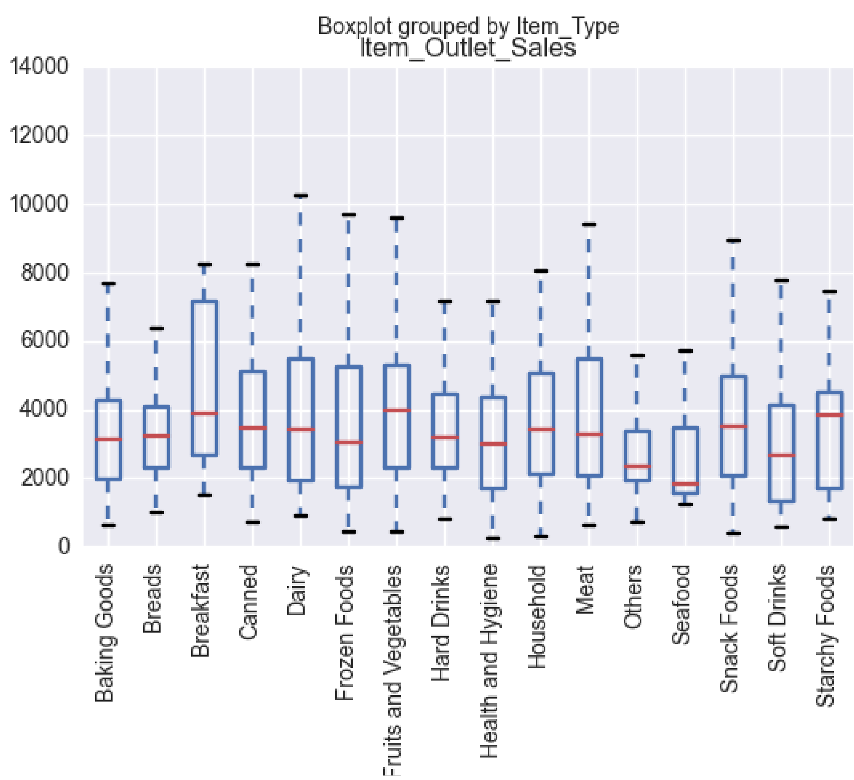
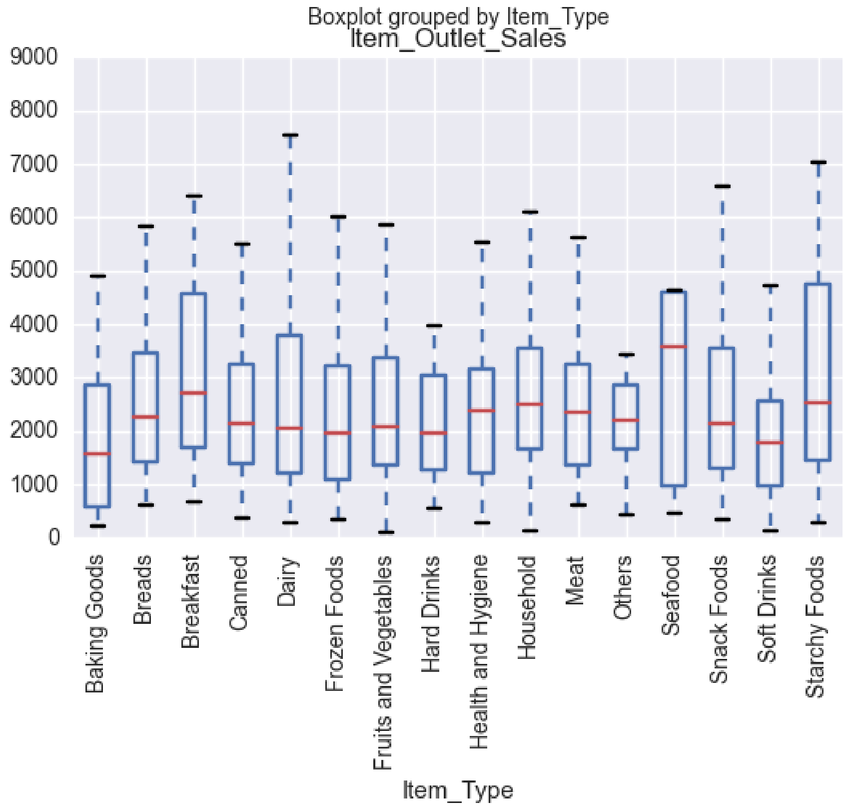


Item_Type

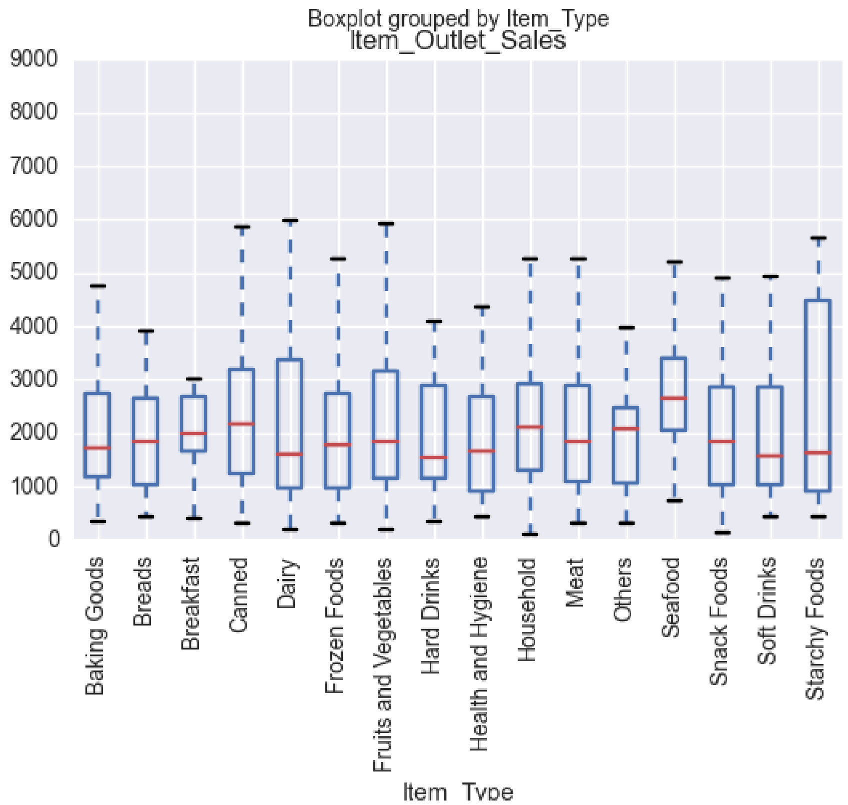
In [24]:

```
data_OUT035.boxplot(column='Item_Outlet_Sales', by='Item_Type')
plt.xticks(rotation=90);
```



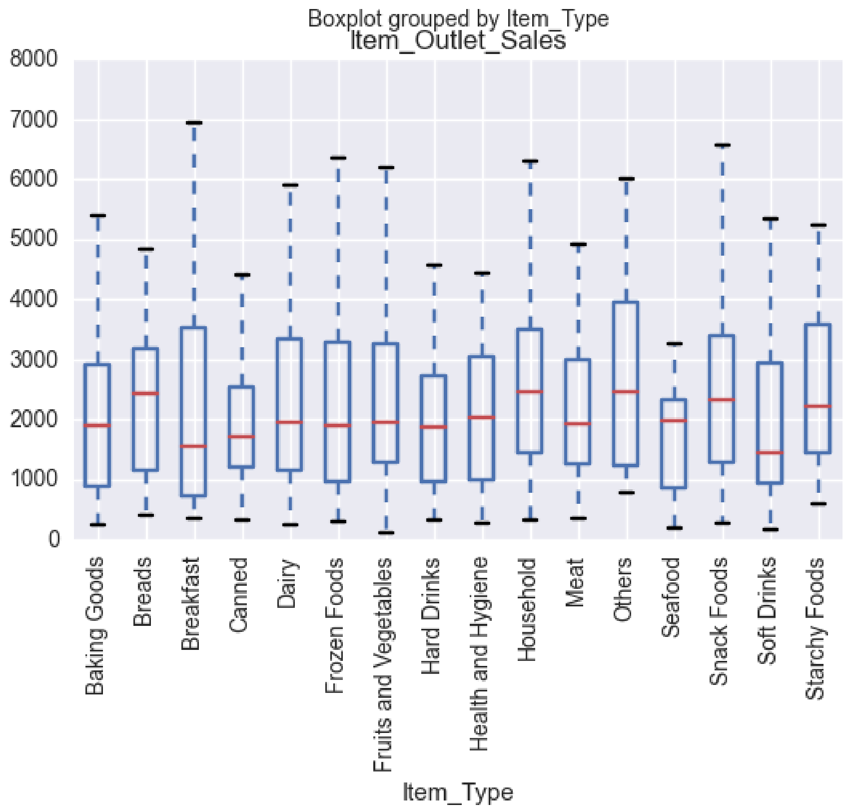
In [25]:

```
data_OUT045.boxplot(column='Item_Outlet_Sales', by='Item_Type')
plt.xticks(rotation=90);
```



In [26]:

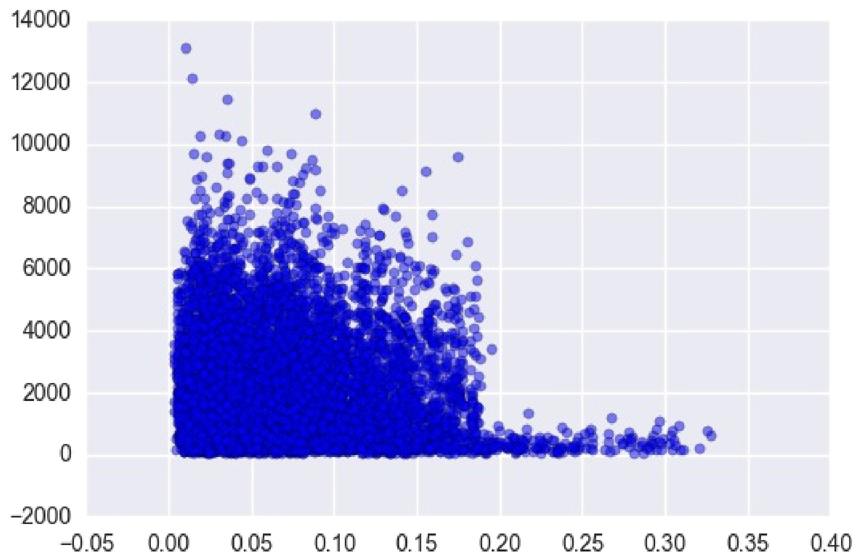
```
data_OUT049.boxplot(column='Item_Outlet_Sales', by='Item_Type')
plt.xticks(rotation=90);
```



Analysis of item visibility with item outlet sales

In [27]:

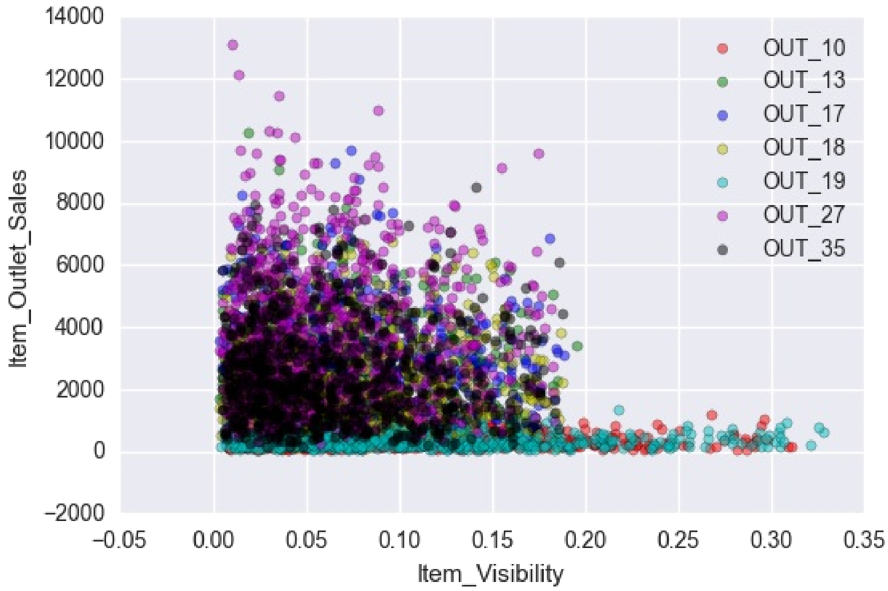
```
plt.scatter(data.Item_Visibility, data.Item_Outlet_Sales, alpha=.5);
```



In [28]:

```
ax = data_OUT010.plot(kind='scatter', x = 'Item_Visibility', y = 'Item_Outlet_Sales', c='r', alpha=
0.5, label='OUT_10')
data_OUT013.plot(kind='scatter', x = 'Item_Visibility', y = 'Item_Outlet_Sales', c='g', ax=ax, alph
```

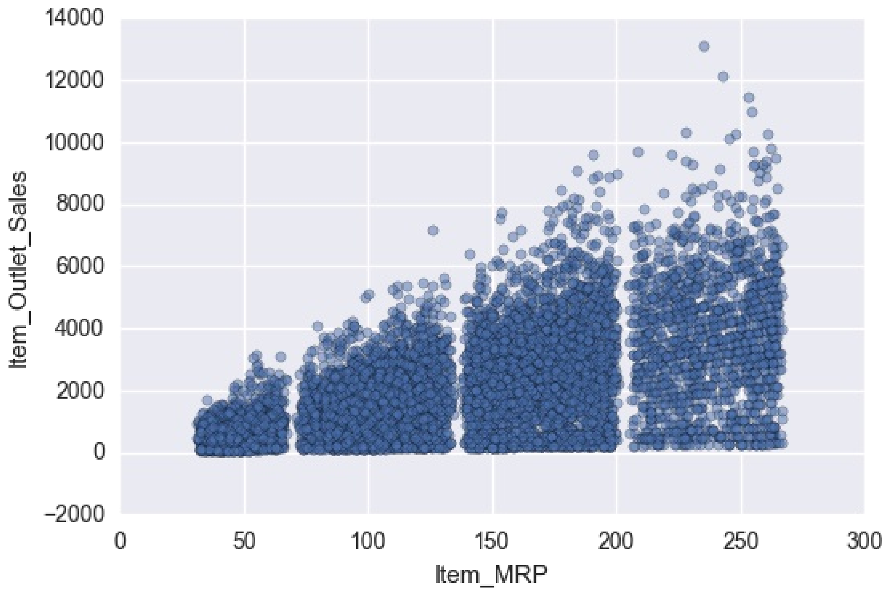
```
a=0.5, label='OUT_13')
data_OUT017.plot(kind='scatter', x = 'Item_Visibility', y = 'Item_Outlet_Sales', c='b', ax=ax, alph
a=0.5, label='OUT_17')
data_OUT018.plot(kind='scatter', x = 'Item_Visibility', y = 'Item_Outlet_Sales', c='y', ax=ax, alph
a=0.5, label='OUT_18')
data_OUT019.plot(kind='scatter', x = 'Item_Visibility', y = 'Item_Outlet_Sales', c='c', ax=ax, alph
a=0.5, label='OUT_19')
data_OUT027.plot(kind='scatter', x = 'Item_Visibility', y = 'Item_Outlet_Sales', c='m', ax=ax, alph
a=0.5, label='OUT_27')
data_OUT035.plot(kind='scatter', x = 'Item_Visibility', y = 'Item_Outlet_Sales', c='k', ax=ax, alph
a=0.5, label='OUT_35')
plt.legend(loc='best');
```



Correlation between item prices and sales

In [29]:

```
data.plot(kind='scatter', x = 'Item_MRP', y = 'Item_Outlet_Sales', alpha=.5);
```

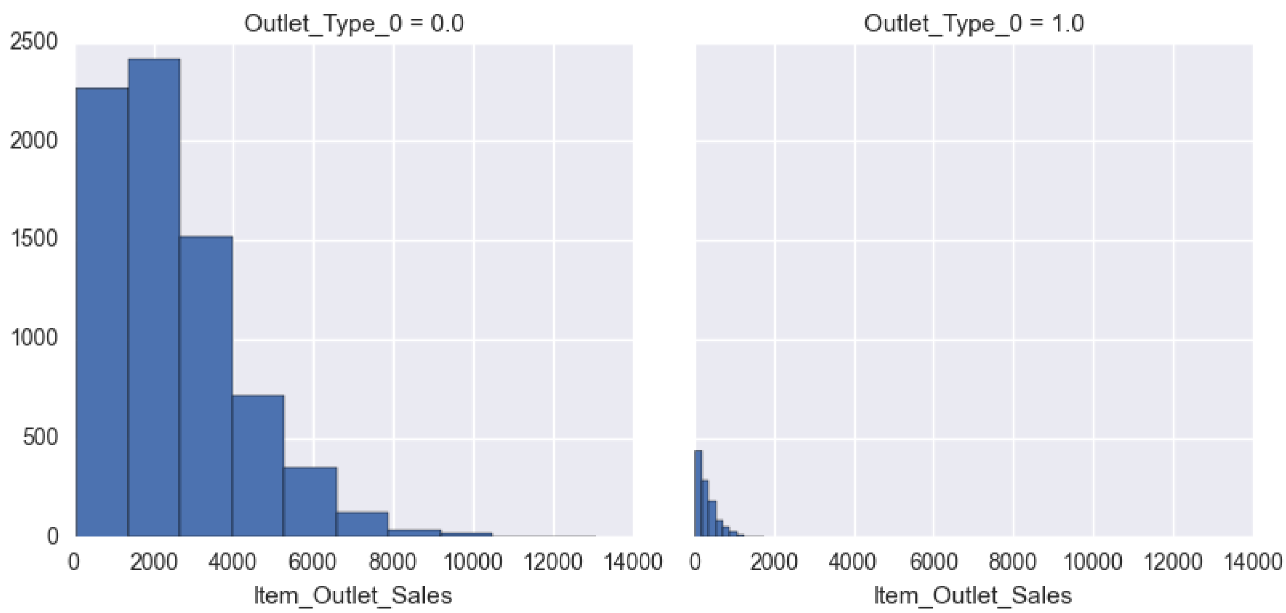


In [30]:

```
sns.FacetGrid(data, col='Item_Type', size=4, col_wrap=5) \
    .map(plt.hist, 'Item_Outlet_Sales') \
    .add_legend();
```

In [31]:

```
sns.FacetGrid(data, col='Outlet_Type_0', size=4) \
    .map(plt.hist, 'Item_Outlet_Sales') \
    .add_legend();
```



In [ ]:

```
Numerical:

    1 column:
```

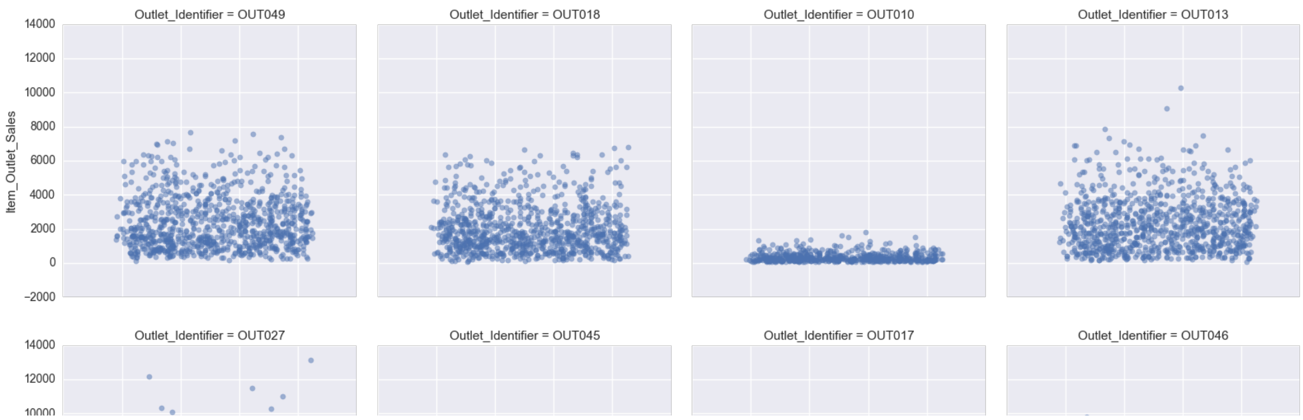
```
    1-column:
          histgram, density plot, gaussion plot

             multivariate analysis: Scatter, Histogram


Categorical:
    1- Bar,Factor plot, Pie chart,
```

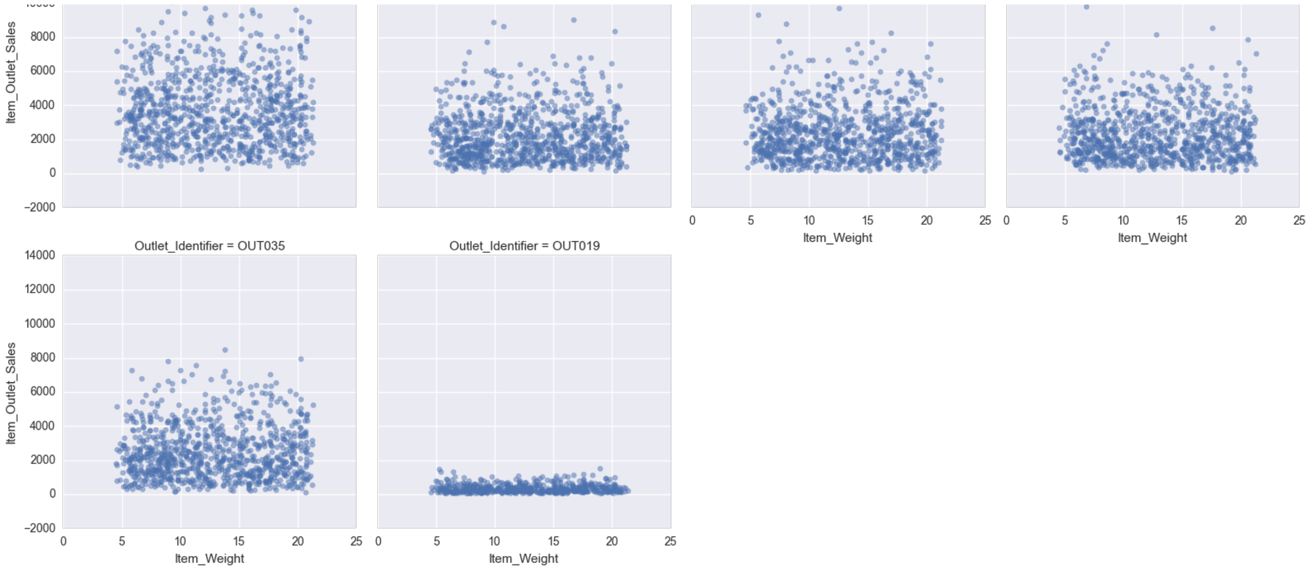
In [32]:

```
sns.FacetGrid(data, col='Outlet_Identifier', col_wrap=4, size=4) \
    .map(plt.scatter, 'Item_MRP', 'Item_Outlet_Sales', c='b', alpha=0.5) \
    .add_legend();
```

In [33]:

```
sns.FacetGrid(data, col='Outlet_Identifier', col_wrap=4, size=4) \
    .map(plt.scatter, 'Item_Weight', 'Item_Outlet_Sales', c='b', alpha=0.5) \
    .add_legend();
```





In [34]:

```
#drop the columns whose data types are converted.  Item type which is of
#16 categories has been reduced to 3 categories and instead of the establishment year
#we consider age of the stores for the analysis.

data = data.drop('Item_Type' , axis = 1)
```

In [35]:

```
data.head()
```

Out[35]:

	Item_Identifier	Item_MRP	Item_Outlet_Sales	Item_Visibility	Item_Weight	Outlet_Establishment_Year	Outlet_Identifier
0	FDA15	249.8092	3735.1380	0.016047	9.30	1999	OUT049
1	DRC01	48.2692	443.4228	0.019278	5.92	2009	OUT018
2	FDN15	141.6180	2097.2700	0.016760	17.50	1999	OUT049
3	FDX07	182.0950	732.3800	0.017834	19.20	1998	OUT010
4	NCD19	53.8614	994.7052	0.009780	8.93	1987	OUT013

5 rows × 37 columns

In [36]:

```
data.head()
```

Out[36]:

	Item_Identifier	Item_MRP	Item_Outlet_Sales	Item_Visibility	Item_Weight	Outlet_Establishment_Year	Outlet_Identifier
0	FDA15	249.8092	3735.1380	0.016047	9.30	1999	OUT049
1	DRC01	48.2692	443.4228	0.019278	5.92	2009	OUT018
2	FDN15	141.6180	2097.2700	0.016760	17.50	1999	OUT049
3	FDX07	182.0950	732.3800	0.017834	19.20	1998	OUT010
4	NCD19	53.8614	994.7052	0.009780	8.93	1987	OUT013

5 rows × 37 columns

In [37]:

```
#Divide the data set back to train and test
train=data.loc[data['source']=='train']
```

```
test=data.loc[data['source']=='test']
train.head
#Drop unnecessary columns
test.drop(['source','Item_Outlet_Sales'],axis=1,inplace=True)
train.drop(['source'],axis=1,inplace=True)
```

In [38]:

```
#Creating a baseline model
mean_sales=train['Item_Outlet_Sales'].mean()

#Define a dataframe with IDs for submission
base1=test[['Item_Identifier','Outlet_Identifier']]
base1['Item_Outlet_Sales']=mean_sales
```

In [39]:

```
base1['Item_Outlet_Sales']=base1['Outlet_Identifier'].apply(lambda x: train.loc[train['Outlet_Ident
ifier']==x]
                                                                        ['Item_Outlet_Sales'].mean())
```

In [ ]:

```
y = ax+ b
```

In [40]:

```
#function to create submission file
#define target and ID Columns for submission
target = 'Item_Outlet_Sales'
IDCol = ['Item_Identifier','Outlet_Identifier']
from sklearn import cross_validation, metrics
```

In [41]:

```
# Linear Regression
from sklearn.linear_model import LinearRegression, Lasso, Ridge
from sklearn.ensemble import AdaBoostRegressor
%matplotlib inline

predictors = [x for x in train.columns if x not in [target]+IDCol]
#print predictors
alg1= LinearRegression(normalize=True)
```

In [42]:

```
#fit the algorithm on the data
alg1.fit(train[predictors],train[target])
```

Out[42]:

```
LinearRegression(copy_X=True, fit_intercept=True, normalize=True)
```

In [43]:

```
#predict training data set
train_predictions = alg1.predict(train[predictors])
```

In [44]:

```
#performs cross validation
cv_score =
cross_validation.cross_val_score(alg1,train[predictors],train[target],cv=20,scoring='mean_squared_e
rror')
cv_score=np.sqrt(np.abs(cv_score))
```

In [45]:

```
#Print model report
print "\nModel Report :"
print "RMSE : %.4g" % np.sqrt(metrics.mean_squared_error(train[target].values,train_predictions))
print "CV Score : Mean - %.4g | Std - %.4g | Min - %.4g | Max - %.4g"%(np.mean(cv_score),np.std(cv
_score),np.min(cv_score),np.max(cv_score))
```

```
Model Report :
RMSE : 1127
CV Score : Mean - 1132 | Std - 45.02 | Min - 1075 | Max - 1209
```

In [46]:

```
#Predict on testing data
test[target]=alg1.predict(test[predictors])
```

In [47]:

```
#Ridge Regression
predictors = [x for x in train.columns if x not in [target]+IDCol]
alg2=Ridge(alpha=0.05,normalize=True)

#fit the algorithm on the data
alg2.fit(train[predictors],train[target])
```

Out[47]:

```
Ridge(alpha=0.05, copy_X=True, fit_intercept=True, max_iter=None,
   normalize=True, solver='auto', tol=0.001)
```

In [48]:

```
#predict training data set
train_predictions = alg2.predict(train[predictors])

#Predict on testing data
test[target]=alg2.predict(test[predictors])
```

In [49]:

```
#performs cross validation
cv_score =
cross_validation.cross_val_score(alg2,train[predictors],train[target],cv=20,scoring='mean_squared_e
rror')
cv_score=np.sqrt(np.abs(cv_score))
#Print model report
print "\nModel Report :"
print "RMSE : %.4g" % np.sqrt(metrics.mean_squared_error(train[target].values,train_predictions))
print "CV Score : Mean - %.4g | Std - %.4g | Min - %.4g | Max - %.4g"%(np.mean(cv_score),np.std(cv
_score),np.min(cv_score),np.max(cv_score))
```

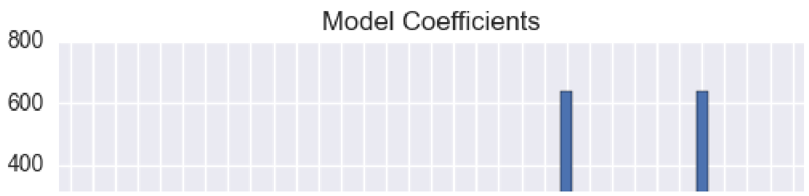
```
Model Report :
RMSE : 1129
CV Score : Mean - 1130 | Std - 44.63 | Min - 1076 | Max - 1217
```

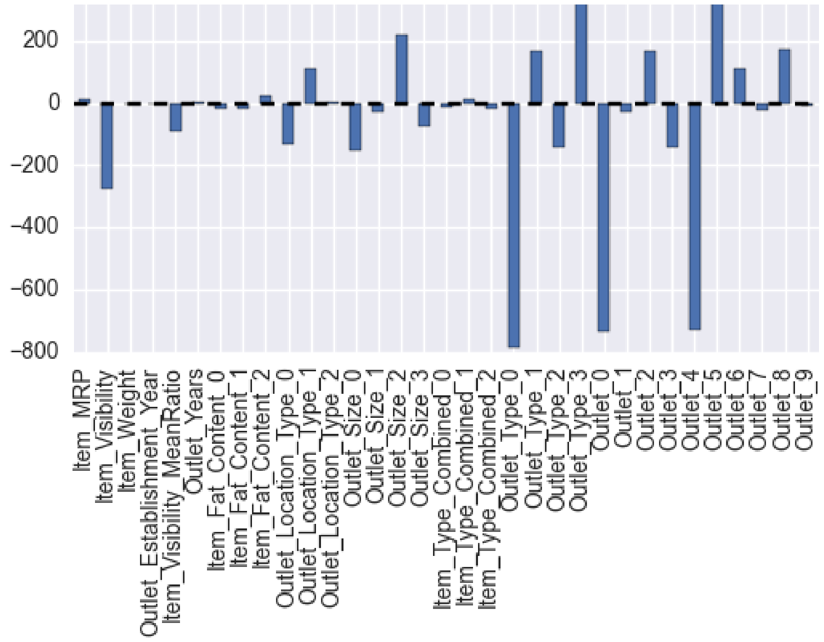
In [50]:

```
coef2 = pd.Series(alg2.coef_,predictors)
coef2.plot(kind='bar',title = 'Model Coefficients')
```

Out[50]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1f25f908>
```





In [51]:

```
ada1=AdaBoostRegressor(base_estimator=alg1,learning_rate=0.9)
#fit the algorithm on the data
ada1.fit(train[predictors],train[target])
```

Out[51]:

```
AdaBoostRegressor(base_estimator=LinearRegression(copy_X=True, fit_intercept=True,
normalize=True),
         learning_rate=0.9, loss='linear', n_estimators=50,
         random_state=None)
```

In [52]:

```
#predict training data set
train_predictions = ada1.predict(train[predictors])

#Predict on testing data
test[target]=ada1.predict(test[predictors])
```

In [53]:

```
cv_score =
cross_validation.cross_val_score(ada1,train[predictors],train[target],cv=20,scoring='mean_squared_e
rror')
cv_score=np.sqrt(np.abs(cv_score))
#Print model report
print "\nModel Report :"
print "RMSE : %.4g" % np.sqrt(metrics.mean_squared_error(train[target].values,train_predictions))
print "CV Score : Mean - %.4g | Std - %.4g | Min - %.4g | Max - %.4g"%(np.mean(cv_score),np.std(cv
_score),np.min(cv_score),np.max(cv_score))
```

```
Model Report :
RMSE : 1127
CV Score : Mean - 1157 | Std - 40.8 | Min - 1076 | Max - 1224
```

In [54]:

```
#DecisionTree Model
from sklearn.tree import DecisionTreeRegressor
predictors=[x for x in train.columns if x not in [target]+IDCol]
alg3=DecisionTreeRegressor(max_depth=15,min_samples_leaf=100)
ada2=AdaBoostRegressor(base_estimator=alg3)#,learning_rate=0.9)


ada2.fit(train[predictors],train[target])
```

Out[54]:

```
AdaBoostRegressor(base_estimator=DecisionTreeRegressor(compute_importances=None, criterion='mse',
max_depth=15,
           max_features=None, max_leaf_nodes=None, min_density=None,
           min_samples_leaf=100, min_samples_split=2, random_state=None,
           splitter='best'),
         learning_rate=1.0, loss='linear', n_estimators=50,
         random_state=None)
```

In [55]:

```
alg3=DecisionTreeRegressor(max_depth=15,min_samples_leaf=100)
alg3.fit(train[predictors],train[target])
```

Out[55]:

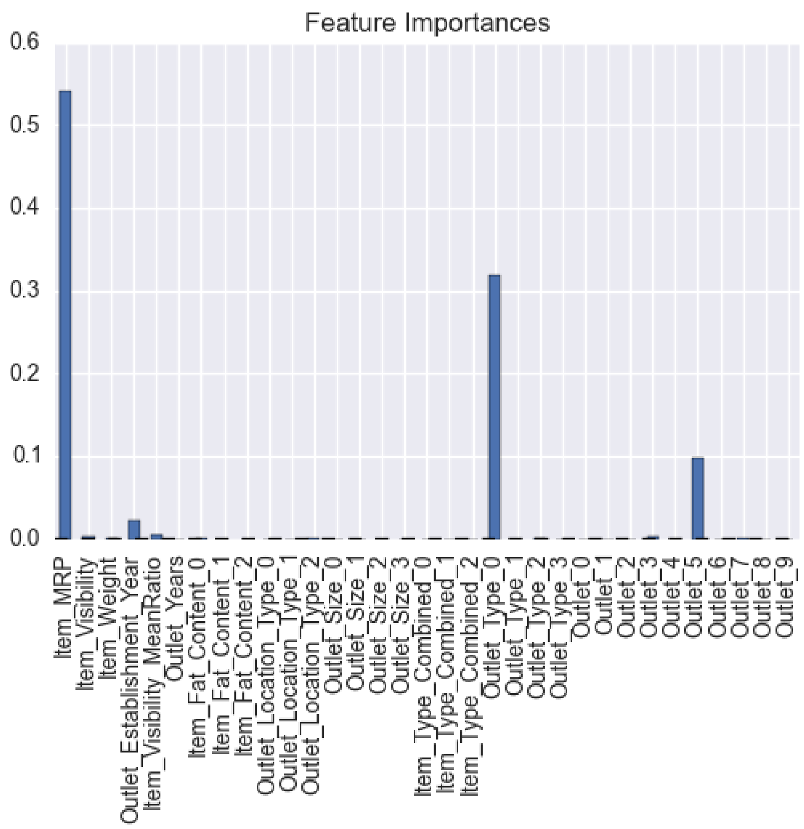
```
DecisionTreeRegressor(compute_importances=None, criterion='mse', max_depth=15,
           max_features=None, max_leaf_nodes=None, min_density=None,
           min_samples_leaf=100, min_samples_split=2, random_state=None,
           splitter='best')
```

In [56]:

```
coef5=pd.Series(alg3.feature_importances_,predictors)
coef5.plot(kind='bar',title='Feature Importances')
```

Out[56]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1ad5fcc0>
```



In [57]:

```
cv_score =
cross_validation.cross_val_score(ada2,train[predictors],train[target],cv=20,scoring='mean_squared_e
rror')
cv_score=np.sqrt(np.abs(cv_score))
#Print model report
print "\nModel Report :"
print "RMSE : %.4g" % np.sqrt(metrics.mean_squared_error(train[target].values,train_predictions))
print "CV Score : Mean - %.4g | Std - %.4g | Min - %.4g | Max - %.4g"%(np.mean(cv_score),np.std(cv
```

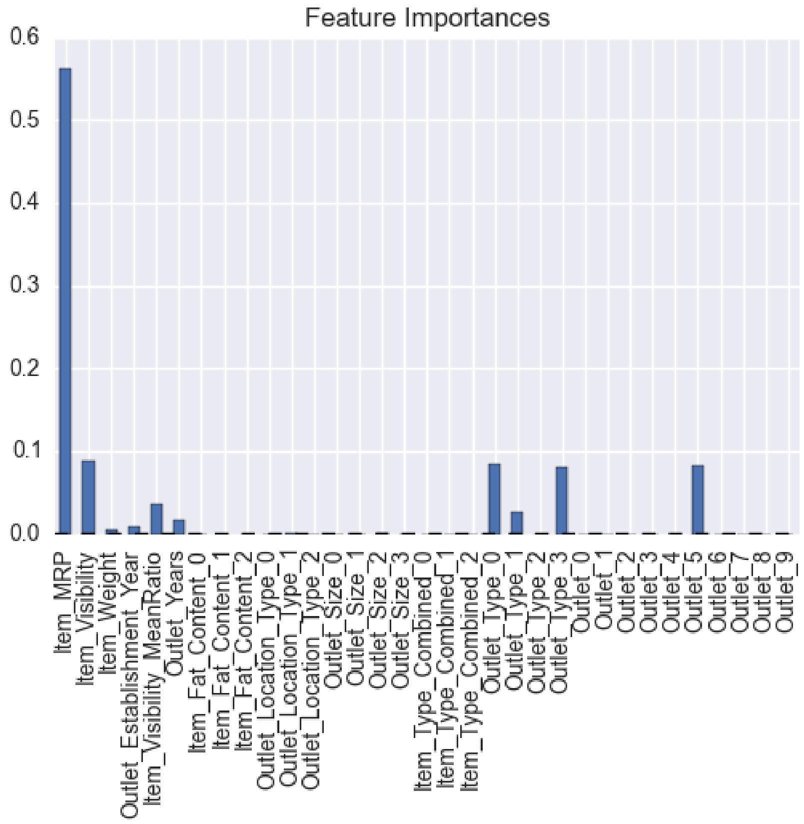
```
_score),np.min(cv_score),np.max(cv_score))
```

```
Model Report :
RMSE : 1127
CV Score : Mean - 1250 | Std - 39.42 | Min - 1180 | Max - 1340
```

In [58]:

```
#RandomForestRegressor
from sklearn.ensemble import RandomForestRegressor
predictors=[x for x in train.columns if x not in [target]+IDCol]
alg5=RandomForestRegressor(n_estimators=200,max_depth=3,min_samples_leaf=300,n_jobs=4)
ada2=AdaBoostRegressor(base_estimator=alg5)#,learning_rate=0.9)
#fit the algorithm on the data
ada2.fit(train[predictors],train[target])
coef5=pd.Series(ada2.feature_importances_,predictors)
coef5.plot(kind='bar',title='Feature Importances')
#Print model report
print "\nModel Report :"
print "RMSE : %.4g" % np.sqrt(metrics.mean_squared_error(train[target].values,train_predictions))
print "CV Score : Mean - %.4g | Std - %.4g | Min - %.4g | Max - %.4g"%(np.mean(cv_score),np.std(cv
_score),np.min(cv_score),np.max(cv_score))
```

```
Model Report :
RMSE : 1127
CV Score : Mean - 1250 | Std - 39.42 | Min - 1180 | Max - 1340
```

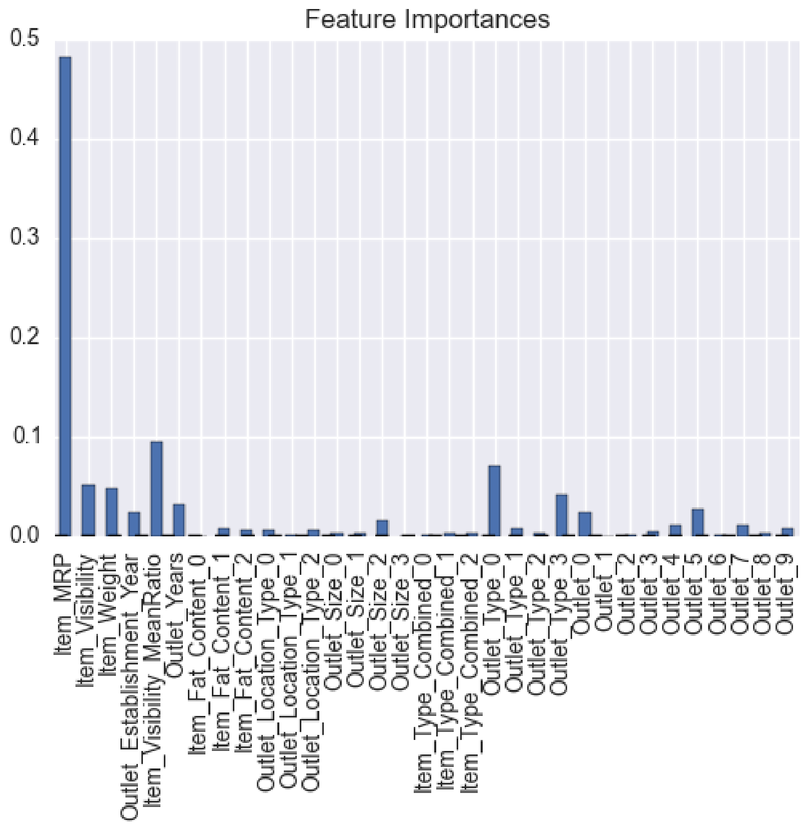


In [ ]:

```
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.grid_search import GridSearchCV

predictors=[x for x in train.columns if x not in [target]+IDCol]
alg1= LinearRegression(normalize=True)
alg7=GradientBoostingRegressor(learning_rate=0.1,max_depth=5,random_state=10,
                              n_estimators=70,min_samples_split=1000,min_samples_leaf=50,
                               max_leaf_nodes=7,max_features='sqrt')#,init=alg1)#loss='huber'
alg7.fit(train[predictors],train[target])
# param_test1 = {'n_estimators':range(20,81,10)}
# gsearch1 = GridSearchCV(estimator = GradientBoostingRegressor(learning_rate=0.1,
```

```
min_samples_split=500,min_samples_leaf=50,max_depth=8,max_features='sqrt',subsample=0.8,random_sta
),
# param_grid = param_test1, scoring='mean_squared_error',n_jobs=4,iid=False, cv=5)
# gsearch1.fit(train[predictors],train[target])

coef5=pd.Series(alg7.feature_importances_,predictors)
coef5.plot(kind='bar',title='Feature Importances')
#Print model report
print "\nModel Report :"
print "RMSE : %.4g" % np.sqrt(metrics.mean_squared_error(train[target].values,train_predictions))
print "CV Score : Mean - %.4g | Std - %.4g | Min - %.4g | Max - %.4g"%(np.mean(cv_score),np.std(cv
_score),np.min(cv_score),np.max(cv_score))
```

```
Model Report :
RMSE : 1127
CV Score : Mean - 1250 | Std - 39.42 | Min - 1180 | Max - 1340
```



In [ ]:

```
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.grid_search import GridSearchCV

param_test2 = {'max_depth':range(5,16,2), 'min_samples_split':range(200,1001,200)}
gsearch2 = GridSearchCV(estimator = GradientBoostingRegressor(learning_rate=0.1, n_estimators=70, m
ax_features='sqrt', subsample=0.8, random_state=10),
param_grid = param_test2, scoring='mean_squared_error',n_jobs=4,iid=False, cv=5)
gsearch2.fit(train[predictors],train[target])
gsearch2.grid_scores_, gsearch2.best_params_, gsearch2.best_score_
#Print model report
print "\nModel Report :"
print "RMSE : %.4g" % np.sqrt(metrics.mean_squared_error(train[target].values,train_predictions))
print "CV Score : Mean - %.4g | Std - %.4g | Min - %.4g | Max - %.4g"%(np.mean(cv_score),np.std(cv
_score),np.min(cv_score),np.max(cv_score))
```

In [ ]:

```
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.grid_search import GridSearchCV

param_test3 = {'min_samples_split':range(1000,2100,200), 'min_samples_leaf':range(30,71,10)}
gsearch3 = GridSearchCV(estimator = GradientBoostingRegressor(learning_rate=0.1,
```

```
n_estimators=70,max_depth=5,max_features='sqrt', subsample=0.8, random_state=10),
param_grid = param_test3, scoring='mean_squared_error',n_jobs=4,iid=False, cv=5)
gsearch3.fit(train[predictors],train[target])
gsearch3.grid_scores_, gsearch3.best_params_, gsearch3.best_score_
```

In [ ]:

```
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.grid_search import GridSearchCV

param_test4 = {'max_features':range(2,20,2)}
gsearch4 = GridSearchCV(estimator = GradientBoostingRegressor(learning_rate=0.1,
n_estimators=70,max_depth=5, min_samples_split=1000, min_samples_leaf=50, subsample=0.8,
random_state=10),
param_grid = param_test4, scoring='mean_squared_error',n_jobs=4,iid=False, cv=5)
gsearch4.fit(train[predictors],train[target])
gsearch4.grid_scores_, gsearch4.best_params_, gsearch4.best_score_
```

In [ ]:

```
 7+ Models === the less rmse we be chosen for depoyment
```

In [ ]:

```
#Export submission file
filename= "Submission.csv"
IDCol.append(target)
submission = pd.DataFrame({x : test[x] for x in IDCol})
submission.to_csv("C:/Users/vamsi/Bigmartsales/"+filename,index=False)
```