## DA C3

## November 3, 2020

```
[1]: import numpy as np
     import pandas as pd
     import matplotlib.pyplot as plt
     import seaborn as sns
     from sklearn.preprocessing import LabelEncoder
     from sklearn.model_selection import train_test_split
     from sklearn.linear_model import LinearRegression
     from sklearn import metrics
     # import lightqbm as lqb
     pd.set_option('display.max_columns',15)
     pd.set_option('display.max_rows', 500)
     pd.set_option('display.width', 1000)
[6]: df_train = pd.read_csv('Train.csv')
     df_test = pd.read_csv('Test.csv')
[8]: df_train.head()
[8]:
       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
     0
                FDA15
                                             Low Fat
                               9.30
                                                             0.016047
```

Dairy 249.8092 **0UT049** 1999 Medium Tier 1 Supermarket Type1 3735.1380 DRC01 5.92 Regular 0.019278 Soft Drinks 48.2692 OUT018 2009 Medium 443,4228 Tier 3 Supermarket Type2 2 FDN15 17.50 Low Fat 0.016760 Meat 141.6180 **OUT049** 1999 Medium Tier 1 Supermarket Type1 2097.2700 FDX07 19.20 Regular 0.000000 Fruits and OUT010 Vegetables 182.0950 1998 NaNTier 3 Grocery Store 732.3800 NCD19 8.93 Low Fat 0.000000

994.7052 Tier 3 Supermarket Type1 [9]: df\_test.head() Item\_Identifier Item\_Weight Item\_Fat\_Content Item\_Visibility [9]: Item\_Type Item\_MRP Outlet\_Identifier Outlet\_Establishment\_Year Outlet\_Size Outlet\_Location\_Type Outlet\_Type FDW58 20.750 0.007565 Snack Foods Low Fat 107.8622 OUT049 1999 Medium Tier 1 Supermarket Type1 FDW14 8.300 0.038428 Dairy reg 87.3198 **OUT017** 2007 NaNTier 2 Supermarket Type1 NCN55 14.600 Low Fat 0.099575 Others 241.7538 **OUT010** 1998 NaNTier 3 Grocery Store FDQ58 7.315 Low Fat 0.015388 Snack Foods 155.0340 **OUT017** NaN 2007 Tier 2 Supermarket Type1 FDY38 NaNRegular 0.118599 Dairy 234.2300 **0UT027** Medium 1985 Tier 3 Supermarket Type3 [10]: df\_train.shape, df\_test.shape [10]: ((8523, 12), (5681, 11)) [12]: df\_train.isnull().sum() 0 [12]: Item\_Identifier Item\_Weight 1463 Item\_Fat\_Content 0 Item\_Visibility 0 Item Type 0 Item MRP 0 Outlet Identifier 0 Outlet\_Establishment\_Year 0 Outlet\_Size 2410 Outlet\_Location\_Type 0 Outlet\_Type 0 Item\_Outlet\_Sales 0 dtype: int64 [13]: df\_test.isnull().sum()

OUT013

1987

High

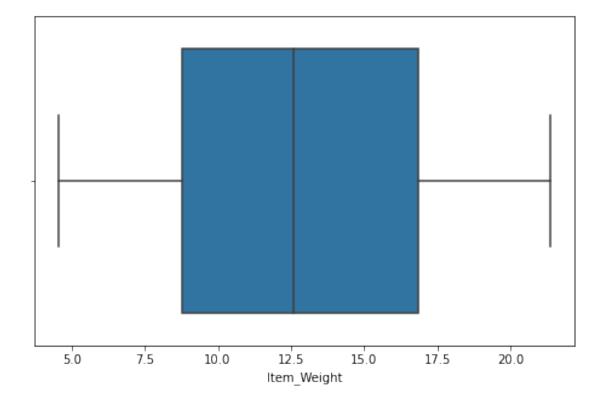
Household

53.8614

```
[13]: Item_Identifier
                                       0
      Item_Weight
                                     976
      Item_Fat_Content
                                       0
      Item_Visibility
                                       0
      Item_Type
                                       0
      Item_MRP
                                       0
                                       0
      Outlet_Identifier
      Outlet_Establishment_Year
                                       0
      Outlet_Size
                                    1606
      Outlet_Location_Type
                                       0
      Outlet_Type
                                       0
      dtype: int64
```

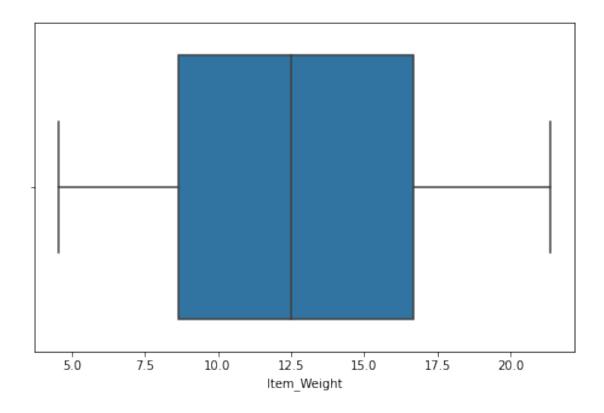
```
[20]: plt.figure(figsize=(8,5))
sns.boxplot('Item_Weight',data=df_train)
```

[20]: <AxesSubplot:xlabel='Item\_Weight'>



```
[21]: plt.figure(figsize=(8,5))
sns.boxplot('Item_Weight',data=df_test)
```

[21]: <AxesSubplot:xlabel='Item\_Weight'>



```
[22]: df_train['Item_Weight'] = df_train['Item_Weight'].
       →fillna(df_train['Item_Weight'].mean())
      df_test['Item_Weight'] = df_test['Item_Weight'].fillna(df_test['Item_Weight'].
       \rightarrowmean())
[25]: df_train['Item_Weight'].isnull().sum(), df_test['Item_Weight'].isnull().sum()
[25]: (0, 0)
[28]: df_train['Outlet_Size'].value_counts(), df_test['Outlet_Size'].value_counts()
[28]: (Medium
                 2793
       Small
                 2388
                  932
       High
       Name: Outlet_Size, dtype: int64,
       Medium
                 1862
       Small
                 1592
                  621
       High
       Name: Outlet_Size, dtype: int64)
[29]: df_train['Outlet_Size'] = df_train['Outlet_Size'].
       →fillna(df_train['Outlet_Size'].mode()[0])
```

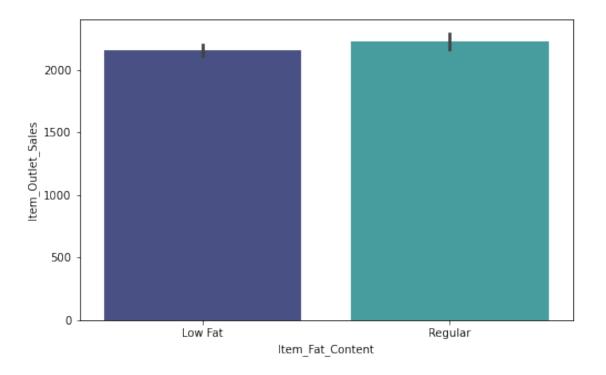
```
df_test['Outlet_Size'] = df_test['Outlet_Size'].fillna(df_test['Outlet_Size'].
       \rightarrowmode()[0])
[30]: df train['Outlet Size'].isnull().sum(), df test['Outlet Size'].isnull().sum()
[30]: (0, 0)
[32]: df_train['Item_Fat_Content'].value_counts(), df_test['Item_Fat_Content'].
       →value_counts()
[32]: (Low Fat
                  5089
       Regular
                  2889
       LF
                   316
       reg
                   117
       low fat
                   112
       Name: Item_Fat_Content, dtype: int64,
       Low Fat
                  3396
       Regular
                  1935
       LF
                   206
                    78
       reg
       low fat
                    66
       Name: Item_Fat_Content, dtype: int64)
[33]: df_train['Item_Fat_Content'].replace(['low fat','LF','reg'],['Low Fat','Low_
       →Fat','Regular'],inplace = True)
      df_test['Item_Fat_Content'].replace(['low fat','LF','reg'],['Low Fat','Low_
       →Fat','Regular'],inplace = True)
[34]: df_train['Item_Fat_Content'].value_counts(), df_test['Item_Fat_Content'].
       →value counts()
[34]: (Low Fat
                  5517
                  3006
       Regular
       Name: Item_Fat_Content, dtype: int64,
       Low Fat
                  3668
       Regular
                  2013
       Name: Item_Fat_Content, dtype: int64)
[35]: df train['Years Established'] = df train['Outlet Establishment Year'].
       \rightarrowapply(lambda x: 2020 - x)
      df_test['Years_Established'] = df_test['Outlet_Establishment_Year'].
       →apply(lambda x: 2020 - x)
[36]: df_train.head()
[36]:
        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 Years_Established
                                         Low Fat
                                                          0.016047
            FDA15
                           9.30
Dairy 249.8092
                            0UT049
                                                          1999
                                                                    Medium
                                    3735.1380
Tier 1
        Supermarket Type1
                                                               21
            DRC01
                           5.92
                                         Regular
                                                          0.019278
                                                                               Soft
         48.2692
                             OUT018
                                                           2009
Drinks
                                                                     Medium
Tier 3 Supermarket Type2
                                     443.4228
                                                               11
            FDN15
                                                          0.016760
2
                          17.50
                                         Low Fat
                           0UT049
Meat 141.6180
                                                         1999
                                                                   Medium
Tier 1
       Supermarket Type1
                                    2097.2700
                                                               21
            FDX07
                                                          0.000000 Fruits and
                          19.20
                                         Regular
Vegetables
            182.0950
                                 OUT010
                                                               1998
                                                                          Medium
Tier 3
            Grocery Store
                                     732.3800
                                                               22
            NCD19
                           8.93
                                         Low Fat
                                                          0.000000
            53.8614
                                OUT013
                                                              1987
Household
                                                                           High
Tier 3 Supermarket Type1
                                     994.7052
                                                               33
```

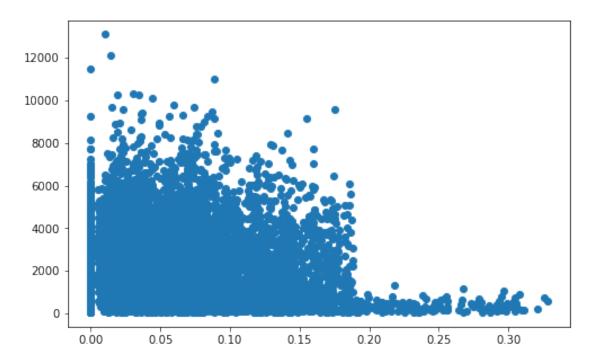
```
[37]: df_train['Item_Fat_Content'] = df_train['Item_Fat_Content'].astype(str)
```

[39]: <AxesSubplot:xlabel='Item\_Fat\_Content', ylabel='Item\_Outlet\_Sales'>



```
[40]: plt.figure(figsize=(8,5)) plt.scatter('Item_Visibility','Item_Outlet_Sales',data=df_train)
```

[40]: <matplotlib.collections.PathCollection at 0x7f74a588ef70>



```
[41]: df_train['Item_Visibility'] = df_train['Item_Visibility'].

→replace(0,df_train['Item_Visibility'].mean())

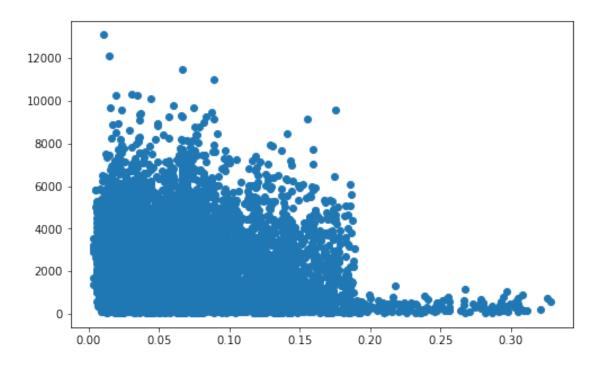
df_test['Item_Visibility'] = df_test['Item_Visibility'].

→replace(0,df_test['Item_Visibility'].mean())

[42]: plt.figure(figsize=(8,5))
```

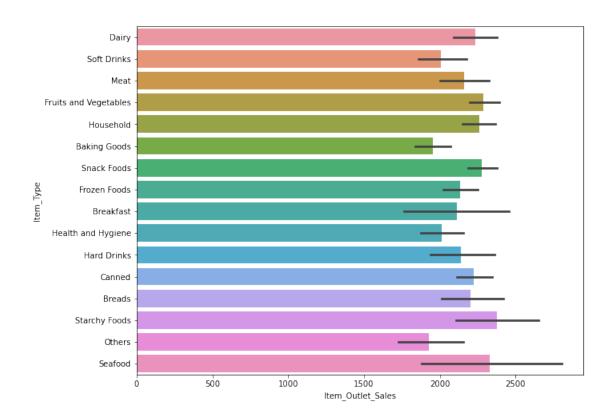
plt.scatter('Item\_Visibility','Item\_Outlet\_Sales',data=df\_train)

[42]: <matplotlib.collections.PathCollection at 0x7f74a57fc100>



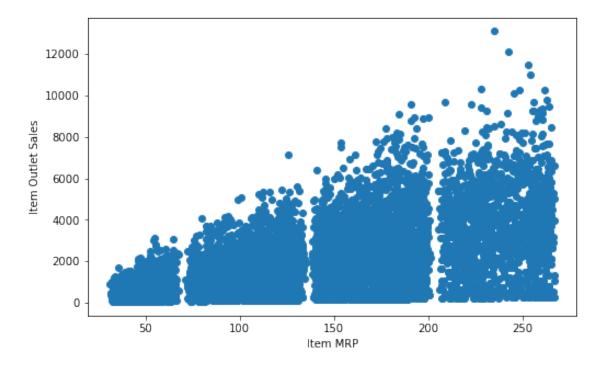
```
[44]: plt.figure(figsize=(10,8)) sns.barplot(y='Item_Type',x='Item_Outlet_Sales',data=df_train)
```

[44]: <AxesSubplot:xlabel='Item\_Outlet\_Sales', ylabel='Item\_Type'>



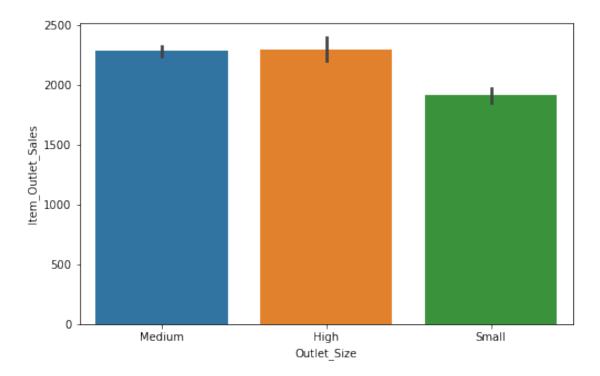
```
[45]: plt.figure(figsize=(8,5))
   plt.scatter(y='Item_Outlet_Sales',x='Item_MRP',data=df_train)
   plt.xlabel('Item_MRP')
   plt.ylabel('Item_Outlet_Sales')
```

[45]: Text(0, 0.5, 'Item Outlet Sales')



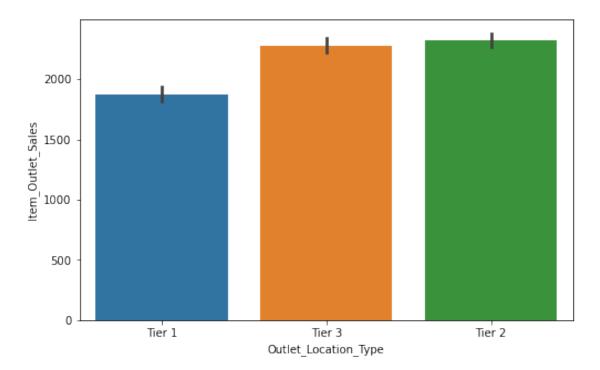
```
[47]: plt.figure(figsize=(8,5))
sns.barplot(x='Outlet_Size',y='Item_Outlet_Sales',data=df_train)
```

[47]: <AxesSubplot:xlabel='Outlet\_Size', ylabel='Item\_Outlet\_Sales'>



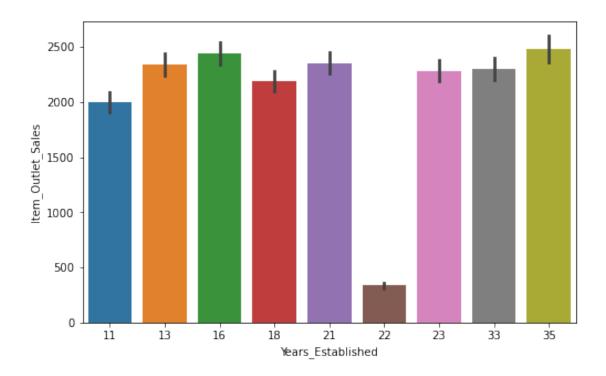
```
[48]: plt.figure(figsize=(8,5)) sns.barplot(x='Outlet_Location_Type',y='Item_Outlet_Sales',data=df_train)
```

[48]: <AxesSubplot:xlabel='Outlet\_Location\_Type', ylabel='Item\_Outlet\_Sales'>

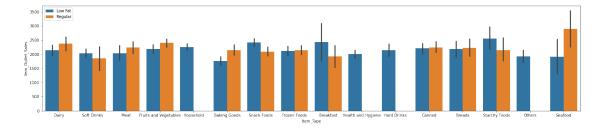


```
[49]: plt.figure(figsize=(8,5)) sns.barplot(x='Years_Established',y='Item_Outlet_Sales',data=df_train)
```

[49]: <AxesSubplot:xlabel='Years\_Established', ylabel='Item\_Outlet\_Sales'>



[50]: <matplotlib.legend.Legend at 0x7f74a5396df0>



```
for i in var_mod:
          df_test[i] = le.fit_transform(df_test[i])
[53]: df train[:10]
[53]:
        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 Years_Established
                            9.300000
                                                               0.016047
                  FDA15
                                                                                  4
      249.8092
                          OUT049
                                                       1999
      0
                                                        21
                   1
                              3735.1380
      1
                  DRC01
                            5.920000
                                                                0.019278
                                                                                 14
      48.2692
                         OUT018
                                                      2009
      2
                   2
                               443.4228
                                                        11
      2
                  FDN15
                           17.500000
                                                                0.016760
                                                                                 10
      141.6180
                          OUT049
                                                       1999
```

0

3

4

2

5

2

6

2

7

2

8

9

182.0950

53.8614

51.4008

57.6588

107.7622

96.9726

187.8214

1

0

1

2

1

3

1

FDX07

NCD19

FDP36

FD010

FDP10

FDH17

FDU28

2097.2700

732.3800

994.7052

556.6088

343.5528

4022.7636

1076.5986

19.200000

8.930000

10.395000

13.650000

12.857645

16.200000

19.200000

OUT010

OUT013

OUT018

OUT013

0UT027

0UT045

**OUTO17** 

1

0

1

0

1

1

6

9

0

13

13

5

5

0.066132

0.066132

0.066132

0.012741

0.127470

0.016687

0.094450

21

1998

22

1987

2009

1987

33

1985

35

2002

18

2007

1

1

11

1

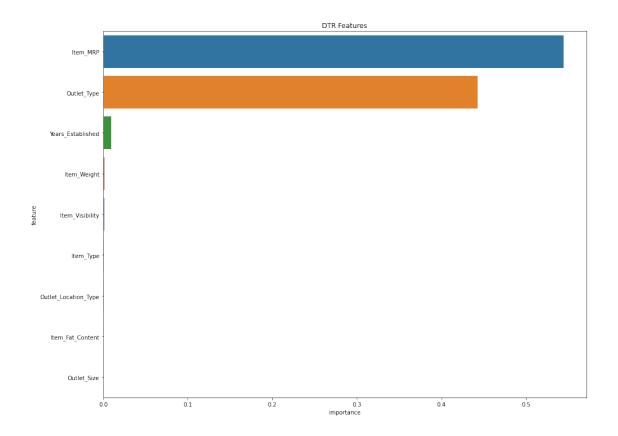
33

1 1 4710.5350 13 [55]: df train = df train. ¬drop(['Item\_Identifier','Outlet\_Identifier','Outlet\_Establishment\_Year'],axis=1) df\_test= df\_test. →drop(['Item\_Identifier','Outlet\_Identifier','Outlet\_Establishment\_Year'],axis=1)

[58]: df train[:10]

```
[58]:
          Item_Weight Item_Fat_Content Item_Visibility Item_Type Item_MRP
       Outlet_Size Outlet_Location_Type Outlet_Type Item_Outlet_Sales
       Years Established
             9.300000
                                                  0.016047
                                                                     4 249.8092
       1
                              0
                                            1
                                                       3735.1380
                                                                                   21
       1
             5.920000
                                                  0.019278
                                                                         48.2692
                                        1
                                                                    14
       1
                              2
                                            2
                                                        443.4228
                                                                                   11
       2
            17.500000
                                                  0.016760
                                                                    10
                                                                        141.6180
       1
                              0
                                            1
                                                       2097.2700
                                                                                   21
       3
            19.200000
                                        1
                                                  0.066132
                                                                       182.0950
       1
                                            0
                                                                                   22
                              2
                                                        732.3800
       4
             8.930000
                                                  0.066132
                                                                         53.8614
                                       0
                              2
                                                                                   33
       0
                                            1
                                                        994.7052
       5
            10.395000
                                                  0.066132
                                                                         51.4008
                                        1
       1
                                                         556.6088
                                                                                   11
       6
            13.650000
                                                  0.012741
                                                                    13
                                                                         57.6588
                                        1
       0
                              2
                                            1
                                                        343.5528
                                                                                   33
       7
            12.857645
                                        0
                                                  0.127470
                                                                    13 107.7622
       1
                              2
                                                       4022.7636
                                                                                   35
       8
            16.200000
                                        1
                                                  0.016687
                                                                         96.9726
       1
                              1
                                            1
                                                       1076.5986
                                                                                   18
       9
            19.200000
                                                  0.094450
                                                                        187.8214
                                        1
       1
                              1
                                            1
                                                       4710.5350
                                                                                   13
[59]: df_test.shape[0]
[59]: 5681
[152]: from sklearn.tree import DecisionTreeRegressor
       from sklearn.ensemble import AdaBoostRegressor
       Y = df_train['Item_Outlet_Sales']
       feats = ___
        →['Item_Weight','Item_Fat_Content','Item_Visibility','Item_Type','Item_MRP','Outlet_Size','O
       X = df_train[feats]
[176]: # sub preds = np.zeros(df test.shape[0])
       trn_x, val_x, trn_y, val_y = train_test_split(X, Y, test_size=0.1,_
       →random_state=42)
       feature_importance_df = pd.DataFrame()
       dtr = DecisionTreeRegressor(max depth=9,min_samples leaf=150, random_state=22)
       # clf = LGBMClassifier(n estimators=10000, learning rate=0.
        \rightarrow 10, num_leaves=30, subsample=.9, max_depth=7, req_alpha=.1, req_lambda=.
        →1, min split qain=.01, min child weight=2, silent=-1, verbose=-1,)
```

```
dtr.fit(trn_x,trn_y)
       sub_preds = dtr.predict(val_x)
       fold_importance_df = pd.DataFrame()
       fold_importance_df["feature"] = feats
       fold_importance_df["importance"] = dtr.feature_importances_
       feature_importance_df = pd.concat([feature_importance_df, fold_importance_df],__
        ⇒axis=0)
[177]: dtr.score(val_x,val_y)
[177]: 0.6155057880241049
[178]: cols = feature_importance_df[["feature", "importance"]].groupby("feature").
        →mean().sort_values(by="importance", ascending=False)[:50].index
       best_features = feature_importance_df.loc[feature_importance_df.feature.
       →isin(cols)]
       plt.figure(figsize=(14,10))
       sns.barplot(x="importance", y="feature", data=best_features.
       ⇔sort_values(by="importance", ascending=False))
       plt.title('DTR Features')
       plt.tight_layout()
```



```
[236]: from sklearn.model_selection import cross_val_score
    def cross_val(model_name,model,X,y,cv):
        scores = cross_val_score(model, X, y, cv=cv)
        print(f'{model_name} Scores:')
        for i in scores:
            print(round(i,2))
        print(f'Average {model_name} score: {round(scores.mean(),2)}')
[241]: cross_val(dtr,DecisionTreeRegressor(),X,Y,5)
```

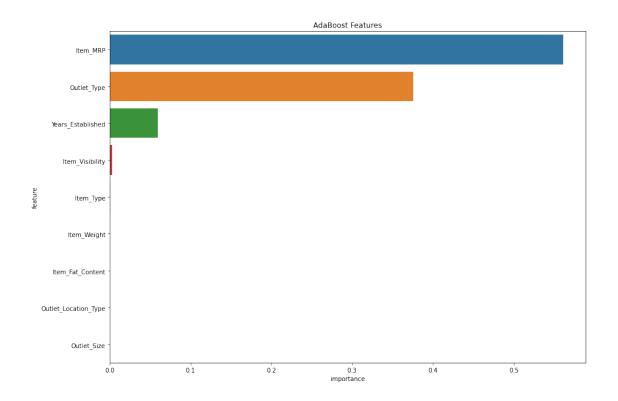
DecisionTreeRegressor(max\_depth=9, min\_samples\_leaf=150, random\_state=22)
Scores:

- 0.23
- 0.13
- 0.07
- 0.17
- 0.18

Average DecisionTreeRegressor(max\_depth=9, min\_samples\_leaf=150, random\_state=22) score: 0.15

```
[204]: | ada = AdaBoostRegressor(DecisionTreeRegressor(max_depth=5),n_estimators=500,__
       →learning_rate=0.001, random_state=22)
       ada.fit(trn x,trn y)
       sub preds1 = ada.predict(val x)
       feature_importance_df1 = pd.DataFrame()
       fold_importance_df1 = pd.DataFrame()
       fold_importance_df1["feature"] = feats
       fold_importance_df1["importance"] = ada.feature_importances_
       feature_importance_df1 = pd.concat([feature_importance_df1,__
        →fold_importance_df1], axis=0)
[205]: ada.score(val_x,val_y)
[205]: 0.6171924629651433
[207]: cols = feature importance_df1[["feature", "importance"]].groupby("feature").
       →mean().sort_values(by="importance", ascending=False)[:50].index
       best_features = feature_importance_df1.loc[feature_importance_df1.feature.
       →isin(cols)]
       plt.figure(figsize=(14,10))
       sns.barplot(x="importance", y="feature", data=best_features.
       →sort_values(by="importance", ascending=False))
       plt.title('AdaBoost Features')
```

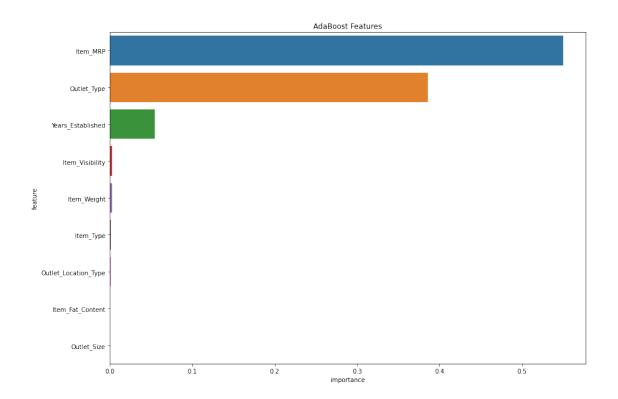
[207]: Text(0.5, 1.0, 'AdaBoost Features')



```
[242]: cross_val(ada,AdaBoostRegressor(),X,Y,10)
      AdaBoostRegressor(base_estimator=DecisionTreeRegressor(max_depth=5),
                        learning_rate=0.001, n_estimators=500, random_state=22)
      Scores:
      0.5
      0.49
      0.45
      0.51
      0.43
      0.5
      0.56
      0.52
      0.55
      Average AdaBoostRegressor(base_estimator=DecisionTreeRegressor(max_depth=5),
                        learning_rate=0.001, n_estimators=500, random_state=22) score:
      0.5
[224]: from sklearn.ensemble import RandomForestRegressor
       RF= RandomForestRegressor(n_estimators=300,max_depth=10,__
        →min_samples_leaf=100,n_jobs=4,random_state=22, verbose=-1)
       RF.fit(trn_x,trn_y)
```

```
sub_preds2 = RF.predict(val_x)
       feature_importance_df2 = pd.DataFrame()
       fold_importance_df2 = pd.DataFrame()
       fold_importance_df2["feature"] = feats
       fold_importance_df2["importance"] = RF.feature_importances_
       feature_importance_df2 = pd.concat([feature_importance_df2,__
        →fold_importance_df2], axis=0)
      [Parallel(n_jobs=4)]: Using backend ThreadingBackend with 4 concurrent workers.
      [Parallel(n_jobs=4)]: Done 64 tasks
                                                 | elapsed:
                                                               0.1s
      [Parallel(n_jobs=4)]: Done 280 tasks
                                                 | elapsed:
                                                               0.6s
      [Parallel(n_jobs=4)]: Done 300 out of 300 | elapsed:
                                                               0.7s finished
      [Parallel(n jobs=4)]: Using backend ThreadingBackend with 4 concurrent workers.
      [Parallel(n_jobs=4)]: Done 64 tasks
                                                 | elapsed:
                                                               0.0s
      [Parallel(n_jobs=4)]: Done 280 tasks
                                                               0.0s
                                                | elapsed:
      [Parallel(n_jobs=4)]: Done 300 out of 300 | elapsed:
                                                               0.0s finished
[225]: RF.score(val_x,val_y)
      [Parallel(n jobs=4)]: Using backend ThreadingBackend with 4 concurrent workers.
      [Parallel(n_jobs=4)]: Done 64 tasks
                                                | elapsed:
                                                               0.0s
      [Parallel(n_jobs=4)]: Done 280 tasks
                                                 | elapsed:
                                                               0.1s
      [Parallel(n_jobs=4)]: Done 300 out of 300 | elapsed:
                                                               0.1s finished
[225]: 0.6253330302688165
[226]: cols = feature importance_df2[["feature", "importance"]].groupby("feature").
        →mean().sort_values(by="importance", ascending=False)[:50].index
       best_features = feature_importance_df2.loc[feature_importance_df2.feature.
       →isin(cols)]
       plt.figure(figsize=(14,10))
       sns.barplot(x="importance", y="feature", data=best features.
       →sort_values(by="importance", ascending=False))
       plt.title('AdaBoost Features')
[226]: Text(0.5, 1.0, 'AdaBoost Features')
```

. .



```
[244]: cross_val(RF,RandomForestRegressor(),X,Y,5)
      RandomForestRegressor(max_depth=10, min_samples_leaf=100, n_estimators=300,
                            n_jobs=4, random_state=22, verbose=-1) Scores:
      0.57
      0.52
      0.52
      0.55
      0.57
      Average RandomForestRegressor(max_depth=10, min_samples_leaf=100,
      n estimators=300,
                            n_jobs=4, random_state=22, verbose=-1) score: 0.55
[231]: LR = LinearRegression(normalize=True)
       LR.fit(trn_x,trn_y)
       sub_preds3 = LR.predict(val_x)
       feature_importance_df3 = pd.DataFrame()
       fold_importance_df3 = pd.DataFrame()
       fold_importance_df3["feature"] = feats
       fold_importance_df3["importance"] = RF.feature_importances_
       feature_importance_df3 = pd.concat([feature_importance_df3,__
        →fold_importance_df3], axis=0)
```

[233]: LR.score(val\_x,val\_y)

## [233]: 0.5309791442288767

```
[246]: cross_val(LR,LinearRegression(),X,Y,5)
      LinearRegression(normalize=True) Scores:
      0.53
      0.5
```

0.49

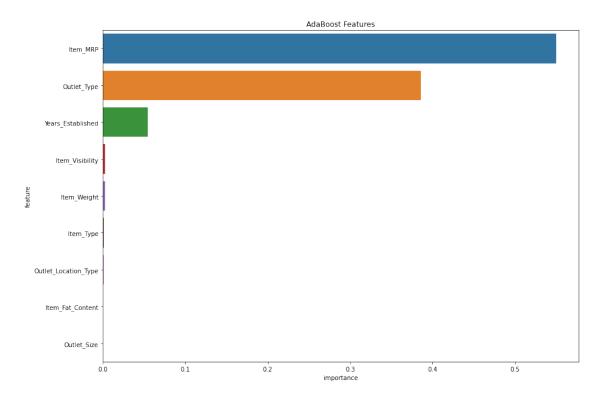
0.51

0.51

Average LinearRegression(normalize=True) score: 0.51

```
[248]: cols = feature_importance_df3[["feature", "importance"]].groupby("feature").
       →mean().sort_values(by="importance", ascending=False)[:50].index
       best_features = feature_importance_df3.loc[feature_importance_df3.feature.
       →isin(cols)]
       plt.figure(figsize=(14,10))
       sns.barplot(x="importance", y="feature", data=best_features.
       →sort_values(by="importance", ascending=False))
       plt.title('AdaBoost Features')
```

## [248]: Text(0.5, 1.0, 'AdaBoost Features')



[]:[