assignment-1

August 15, 2023

1 1. Importing Libraries

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

[2]:
```
data=pd.read_excel("daily_offers.xlsx",parse_dates=['delivery date'])
```

[3]:
```
df=data.copy()
```

2 2. Exploring the dataset

[4]:
```
df.head()
```

[4]:
```
                                     id   item_date quantity tons    customer  \
0  EC06F063-9DF0-440C-8764-0B0C05A4F6AE  20210401.0     54.151139  30156308.0
1  4E5F4B3D-DDDF-499D-AFDE-A3227EC49425  20210401.0    768.024839  30202938.0
2  E140FF1B-2407-4C02-A0DD-780A093B1158  20210401.0    386.127949  30153963.0
3  F8D507A0-9C62-4EFE-831E-33E1DA53BB50  20210401.0    202.411065  30349574.0
4  4E1C4E78-152B-430A-8094-ADD889C9D0AD  20210401.0    785.526262  30211560.0

   country status item type  application  thickness   width  \
0     28.0    Won         W         10.0       2.00  1500.0
1     25.0    Won         W         41.0       0.80  1210.0
2     30.0    Won        WI         28.0       0.38   952.0
3     32.0    Won         S         59.0       2.30  1317.0
4     28.0    Won         W         10.0       4.00  2000.0

                           material_ref  product_ref delivery date  \
0                           DEQ1 S460MC   1670798778      20210701
1  0000000000000000000000000000000104991   1668701718      20210401
2                              S0380700       628377      20210101
3                 DX51D+ZM310MAO 2.3X1317   1668701718      20210101
4                       2_S275JR+AR-CL1       640665      20210301
```

```
   selling_price
0         854.00
1        1047.00
2         644.33
3         768.00
4         577.00
```

[5]:
```
df.shape
```

[5]:
```
(181673, 14)
```

[6]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 181673 entries, 0 to 181672
Data columns (total 14 columns):
 #   Column         Non-Null Count   Dtype
---  ------         --------------   -----
 0   id             181671 non-null  object
 1   item_date      181672 non-null  float64
 2   quantity tons  181673 non-null  object
 3   customer       181672 non-null  float64
 4   country        181645 non-null  float64
 5   status         181671 non-null  object
 6   item type      181673 non-null  object
 7   application    181649 non-null  float64
 8   thickness      181672 non-null  float64
 9   width          181673 non-null  float64
 10  material_ref   103754 non-null  object
 11  product_ref    181673 non-null  int64
 12  delivery date  181672 non-null  object
 13  selling_price  181672 non-null  float64
dtypes: float64(7), int64(1), object(6)
memory usage: 19.4+ MB
```

[7]:
```
df.corr()
```

[7]:
```
               item_date  customer   country  application  thickness  \
item_date       1.000000 -0.008821 -0.015801    -0.015962   0.003075
customer       -0.008821  1.000000  0.083560     0.000882   0.009589
country        -0.015801  0.083560  1.000000    -0.019350  -0.019580
application    -0.015962  0.000882 -0.019350     1.000000  -0.059472
thickness       0.003075  0.009589 -0.019580    -0.059472   1.000000
width           0.020480  0.009203  0.055295    -0.204430   0.161714
product_ref     0.037441 -0.007716 -0.147389    -0.131843   0.038082
selling_price   0.004467 -0.000053  0.002993     0.001462  -0.001130
```

	width	product_ref	selling_price
item_date	0.020480	0.037441	0.004467
customer	0.009203	-0.007716	-0.000053
country	0.055295	-0.147389	0.002993
application	-0.204430	-0.131843	0.001462
thickness	0.161714	0.038082	-0.001130
width	1.000000	-0.034460	0.000583
product_ref	-0.034460	1.000000	0.002118
selling_price	0.000583	0.002118	1.000000

[8]:
```
df.describe()
```

[8]:

	item_date	customer	country	application
count	1.816720e+05	1.816720e+05	181645.000000	181649.000000
mean	2.020459e+07	3.051221e+07	44.893022	25.615809
std	4.551119e+03	2.433382e+07	24.404214	17.754175
min	1.995000e+07	1.245800e+04	25.000000	2.000000
25%	2.020093e+07	3.019688e+07	26.000000	10.000000
50%	2.020113e+07	3.020524e+07	30.000000	15.000000
75%	2.021020e+07	3.028042e+07	78.000000	41.000000
max	2.021040e+07	2.147484e+09	113.000000	99.000000

	thickness	width	product_ref	selling_price
count	181672.000000	181673.000000	1.816730e+05	1.816720e+05
mean	2.564827	1295.286724	4.739679e+08	1.918036e+03
std	6.572321	261.631754	7.175101e+08	3.317956e+05
min	0.180000	1.000000	6.117280e+05	-1.160000e+03
25%	0.700000	1180.000000	6.119930e+05	6.690000e+02
50%	1.500000	1250.000000	6.406650e+05	8.120000e+02
75%	3.000000	1500.000000	1.332077e+09	9.530000e+02
max	2500.000000	2990.000000	1.722208e+09	1.000010e+08

3 3. Data Cleaning

3.1 3.1 Dropping Irrelevant Columns

[9]:
```
df=df.drop(columns=['id','item_date','material_ref','product_ref'],axis=1)
```

[10]:
```
df.head(1)
```

[10]:

	quantity tons	customer	country	status	item type	application	thickness
0	54.151139	30156308.0	28.0	Won	W	10.0	2.0

	width	delivery date	selling_price
0	1500.0	20210701	854.0

3.2 3.2 Handling Missing Values

[11]:
```
df.isnull().sum()
```

[11]:
```
quantity tons     0
customer          1
country          28
status            2
item type         0
application      24
thickness         1
width             0
delivery date     1
selling_price     1
dtype: int64
```

[12]:
```
for x in df.columns:
    null=df[x].isnull().sum()
    percentage=(null/len(df))*100
    print(x,' :',"%.3f"%percentage,'%')
```

```
quantity tons  : 0.000 %
customer  : 0.001 %
country  : 0.015 %
status  : 0.001 %
item type  : 0.000 %
application  : 0.013 %
thickness  : 0.001 %
width  : 0.000 %
delivery date  : 0.001 %
selling_price  : 0.001 %
```

4 Filling missing values

To fill the nan values we find the which entity have maximum frequecy in each column to find frequency we calculate the mode

[13]:
```
df['country'].fillna(df['country'].mode()[0],inplace=True)
df['application'].fillna(df.application.mode()[0],inplace=True)
df['customer'].fillna(df['customer'].mode()[0],inplace=True)
df['thickness'].fillna(df['thickness'].mean(),inplace=True)
df['selling_price'].fillna(df['selling_price'].mean(),inplace=True)
df['delivery date'].fillna(df['delivery date'].mode()[0],inplace=True)
df['status'].fillna(df['status'].mode()[0],inplace=True)
```

[14]:
```
df.isna().sum()
```

[14]:
```
quantity tons    0
customer         0
country          0
status           0
item type        0
application      0
thickness        0
width            0
delivery date    0
selling_price    0
dtype: int64
```

[15]:
```
df.dropna(inplace=True)
df.isna().sum()
```

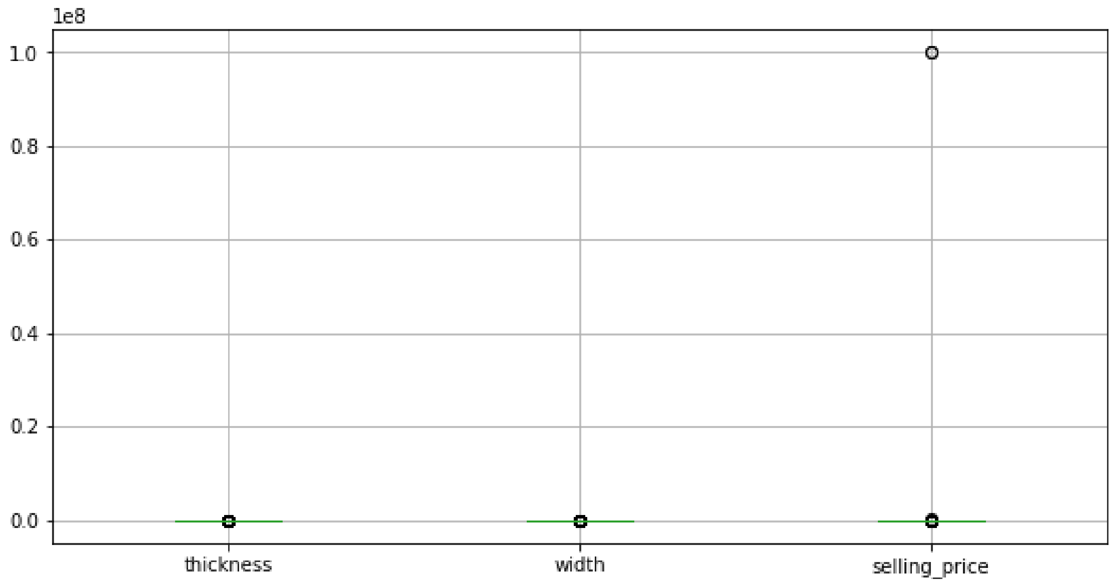
[15]:
```
quantity tons    0
customer         0
country          0
status           0
item type        0
application      0
thickness        0
width            0
delivery date    0
selling_price    0
dtype: int64
```

[16]:
```
df.drop(df[df['quantity tons']=='e'].index,inplace=True) # dataset had a record␣
↪with id='e'
```

4.1 3.3 Handling Outliers

[17]:
```
plt.figure(figsize = (10,5))
df.boxplot(column=['thickness','width','selling_price'])
```

[17]: <AxesSubplot:>



[18]:
```
df['zscore']=(df['selling_price']-df['selling_price'].mean())/
 ↪df['selling_price'].std()
df
```

[18]:
```
       quantity tons    customer  country status item type  application  \
0          54.151139  30156308.0     28.0    Won         W         10.0
1         768.024839  30202938.0     25.0    Won         W         41.0
2         386.127949  30153963.0     30.0    Won        WI         28.0
3         202.411065  30349574.0     32.0    Won         S         59.0
4         785.526262  30211560.0     28.0    Won         W         10.0
…                …           …        …      …       …          …
181668    102.482422  30200854.0     25.0    Won         W         41.0
181669    208.086469  30200854.0     25.0    Won         W         41.0
181670      4.235594  30200854.0     25.0    Won         W         41.0
181671         -2000  30200854.0     25.0    Won         W         41.0
181672    406.686538  30200854.0     25.0    Won         W         41.0

        thickness   width delivery date  selling_price    zscore
0            2.00  1500.0      20210701         854.00 -0.003207
1            0.80  1210.0      20210401        1047.00 -0.002625
2            0.38   952.0      20210101         644.33 -0.003839
3            2.30  1317.0      20210101         768.00 -0.003466
4            4.00  2000.0      20210301         577.00 -0.004042
…             …       …              …              …         …
181668       0.96  1220.0      20200701         591.00 -0.004000
181669       0.95  1500.0      20200701         589.00 -0.004006
181670       0.71  1250.0      20200701         619.00 -0.003915
```

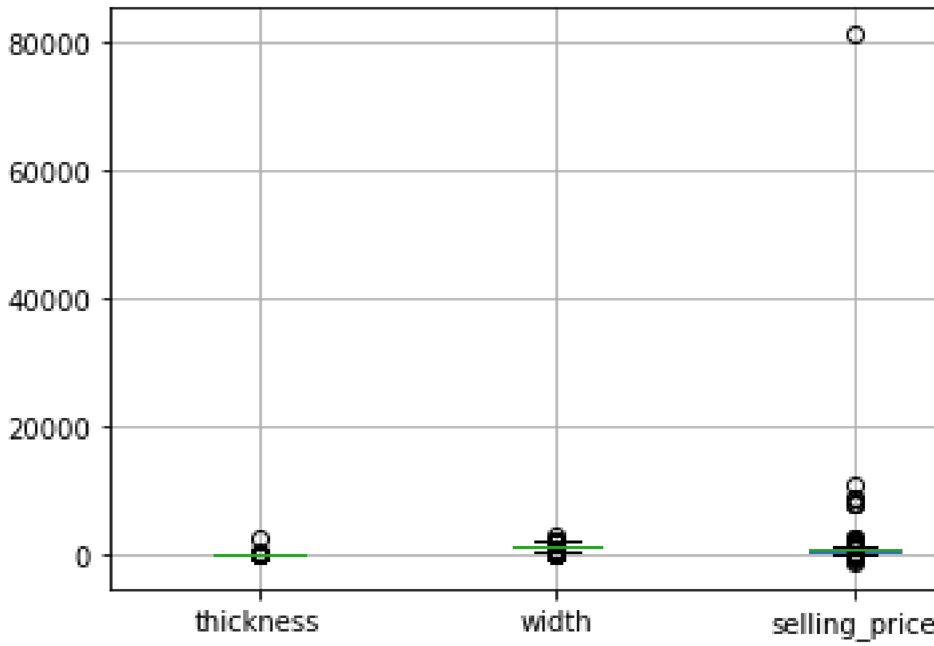
```
181671        0.85  1250.0      20200701         601.00 -0.003969
181672        0.71  1240.0      20200701         607.00 -0.003951

[181672 rows x 11 columns]
```

[19]:
```
df=(df[(df['zscore']>=-3) & (df['zscore']<=3)])
```

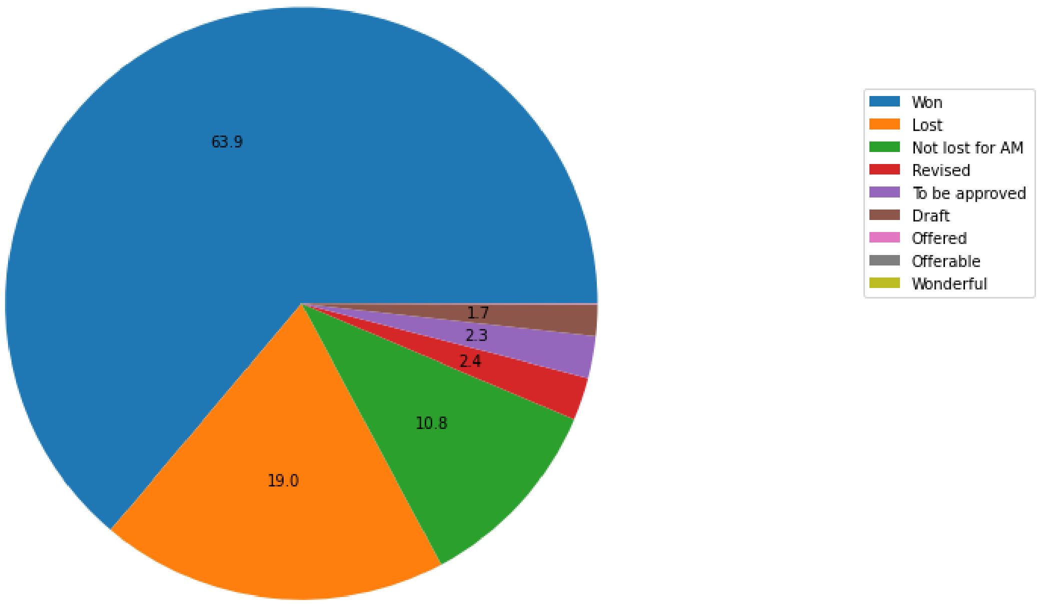
[20]:
```
df.boxplot(column=['thickness','width','selling_price'])
```

[20]: <AxesSubplot:>



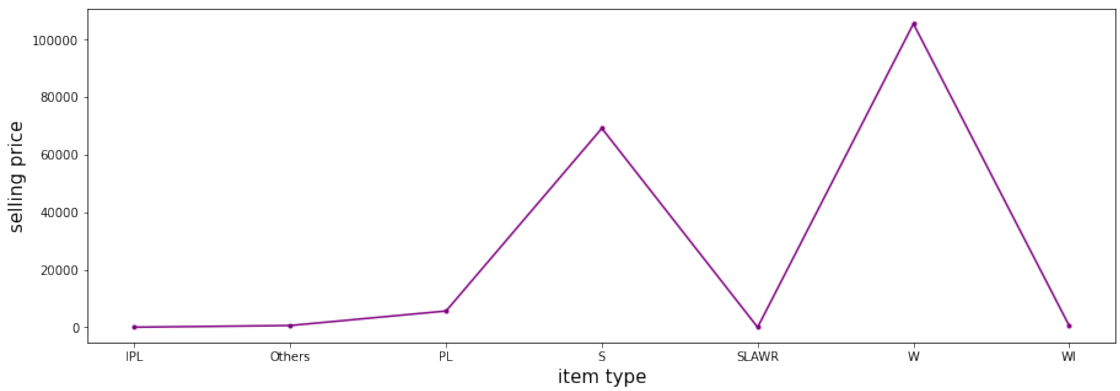
[21]:
```
c=df.value_counts(df['status'])
def autopct(pct):
    return('%.1f'%pct) if pct>1 else ''
label=['Won','Lost','Not lost for AM ','Revised','To be␣
 ↪approved','Draft','Offered','Offerable','Wonderful']
plt.figure(figsize = (9,9))
plt.pie(c,autopct=autopct)
plt.legend(label,loc='best',bbox_to_anchor=(1.5, 0.8))
```

[21]: <matplotlib.legend.Legend at 0x282d47c5220>



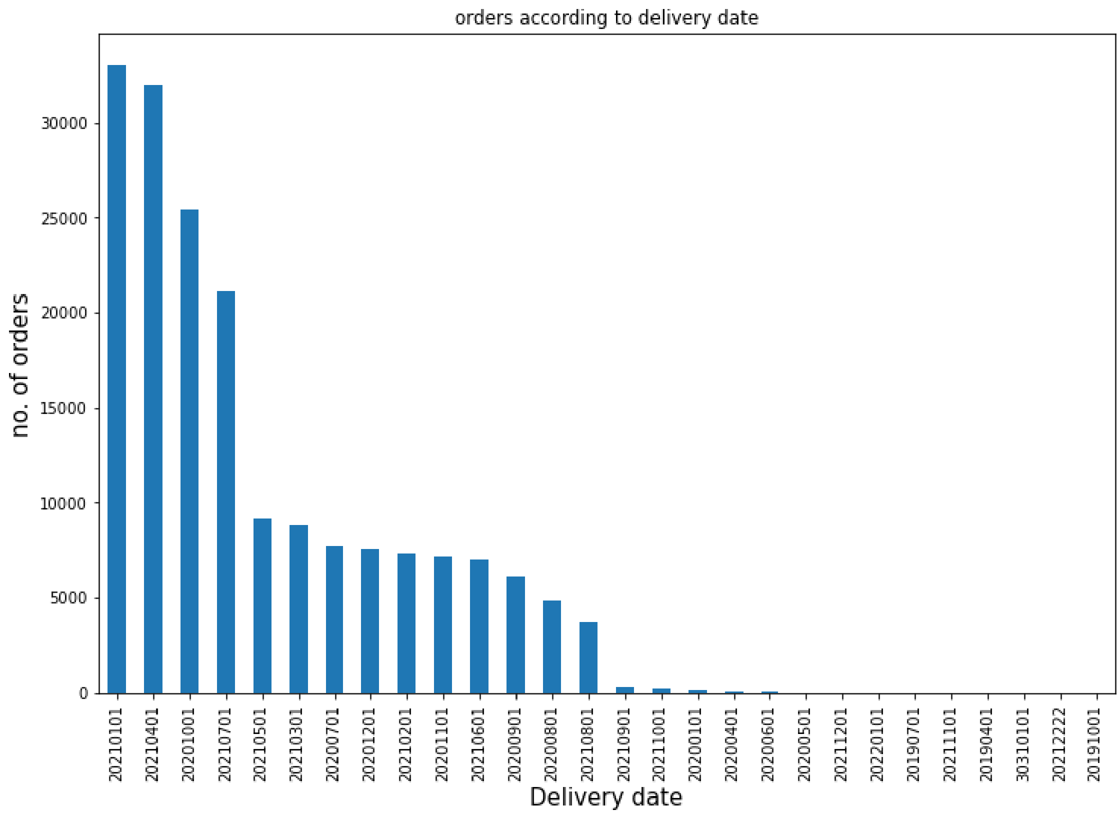
[22]:
```
x=df['selling_price'].groupby(df['item type']).value_counts().unstack('item type').sum(axis=0)
plt.figure(figsize = (15,5))
plt.plot(x,marker='.',color='purple')
plt.xlabel('item type',fontsize=15)
plt.ylabel('selling price',fontsize=15)
```

[22]: Text(0, 0.5, 'selling price')



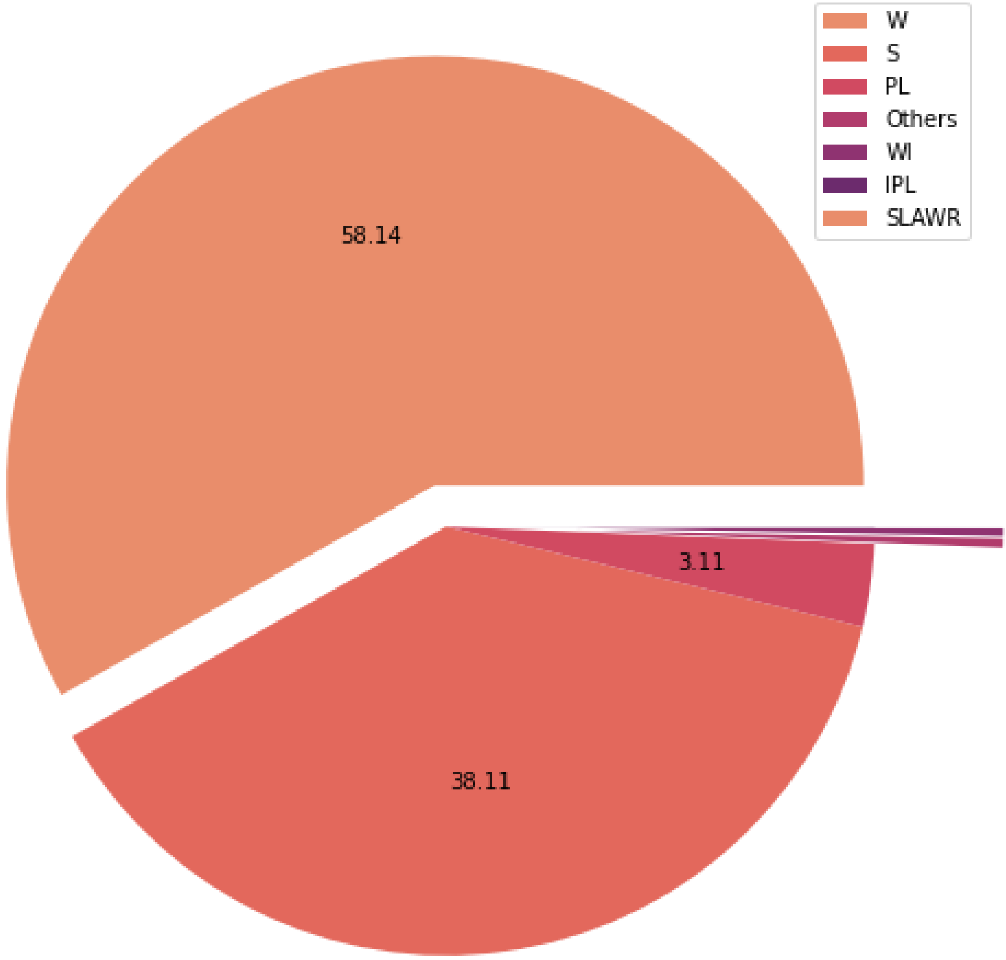
[23]:
```python
x=df['delivery date'].value_counts()
ax=x.plot(kind='bar',ylabel='orders',title='orders according to delivery␣
↪date',figsize = (12,8))
ax.set_xlabel('Delivery date',fontsize=15)
ax.set_ylabel('no. of orders',fontsize=15)
```

[23]:
```
Text(0, 0.5, 'no. of orders')
```



[24]:
```python
k=df['item type'].value_counts()
def autopct(pct):
    return ('%.2f' %pct) if pct > 1 else ''
plt.figure(figsize = (9,9))
plt.pie(k,explode=[0.1,0,0,0.3,0.3,0,0],autopct=autopct,colors=sns.
↪color_palette('flare'))
plt.legend(k.index)
```

[24]:
```
<matplotlib.legend.Legend at 0x282d6300670>
```




```
[25]: df_model=df[['quantity tons','country','status','item␣
        ↪type','application','thickness','width','selling_price']]
```

```
[26]: for x in df_model.columns:
          print(x," has ",len(df[x].unique())," categories")
```

```
quantity tons  has  181670  categories
country  has  17  categories
status  has  9  categories
item type  has  7  categories
application  has  30  categories
thickness  has  595  categories
width  has  1386  categories
selling_price  has  9794  categories
```

[27]:
```
top10=[x for x in df_model['country'].value_counts().
 ↪sort_values(ascending=False).head(15).index]
for x in top10:
    df_model[x]=np.where(df_model['country']==x,1,0)
```

```
C:\Users\pulki\AppData\Local\Temp\ipykernel_10032\3970385872.py:3:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_model[x]=np.where(df_model['country']==x,1,0)
C:\Users\pulki\AppData\Local\Temp\ipykernel_10032\3970385872.py:3:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_model[x]=np.where(df_model['country']==x,1,0)
```

[28]:
```
top10=[x for x in df_model['status'].value_counts().
 ↪sort_values(ascending=False).head(6).index]
def onehot(df,variable,top_labels):

    for label in top_labels:
        df_model[label]=np.where(df_model[variable]==label,1,0)

onehot(df_model,'status',top10)
```

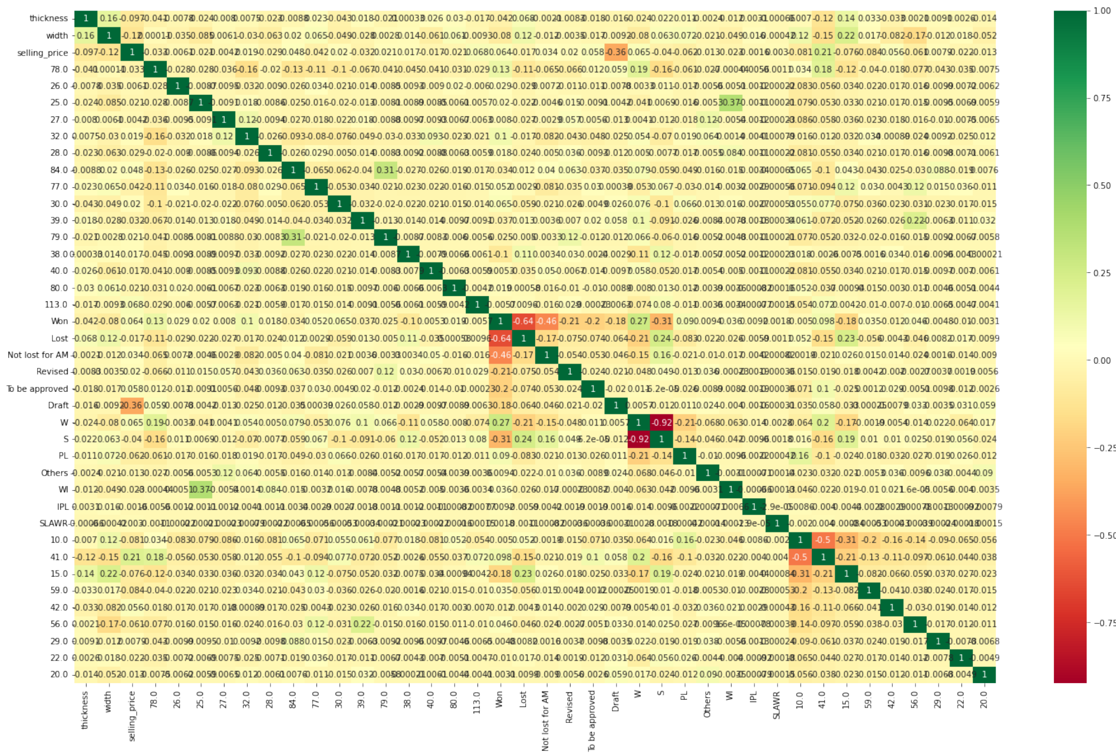
[29]:
```
top10=[x for x in df_model['item type'].value_counts().
 ↪sort_values(ascending=False).head(7).index]
for x in top10:
    df_model[x]=np.where(df_model['item type']==x,1,0)
```

[30]:
```
top10=[x for x in df_model['application'].value_counts().
 ↪sort_values(ascending=False).head(15).index]
for x in top10:
    df_model[x]=np.where(df_model['application']==x,1,0)
```

[31]:
```
df_model.drop(['country','status','item␣
 ↪type','application'],axis=1,inplace=True)
```

[32]:
```
plt.figure(figsize=(25,15))
sns.heatmap(df_model.corr(),annot=True,cmap="RdYlGn",cbar=True)
```

[32]: <AxesSubplot:>



[33]:
```python
# Independent and dependent features
X=df_model.drop("selling_price",axis=1)
Y=df_model.selling_price
```

[34]:
```python
# train test spilt
from sklearn.model_selection import train_test_split
X_train,X_test,Y_train,Y_test=train_test_split(X,Y,test_size=0.
↪1,random_state=10)
```

[35]:
```python
## standardising dataset
from sklearn.preprocessing import StandardScaler
scaler=StandardScaler()
```

[36]:
```python
X_train=scaler.fit_transform(X_train)
```

```
C:\Users\pulki\anaconda3\lib\site-packages\sklearn\utils\validation.py:1688:
FutureWarning: Feature names only support names that are all strings. Got
feature names with dtypes: ['float', 'str']. An error will be raised in 1.2.
  warnings.warn(
C:\Users\pulki\anaconda3\lib\site-packages\sklearn\utils\validation.py:1688:
FutureWarning: Feature names only support names that are all strings. Got
```

```
feature names with dtypes: ['float', 'str']. An error will be raised in 1.2.
  warnings.warn(
```

[37]:
```python
X_test=scaler.transform(X_test)
```

```
C:\Users\pulki\anaconda3\lib\site-packages\sklearn\utils\validation.py:1688:
FutureWarning: Feature names only support names that are all strings. Got
feature names with dtypes: ['float', 'str']. An error will be raised in 1.2.
  warnings.warn(
```

4.1.1 Model 1: Linear Regression

[38]:
```python
from sklearn.linear_model import LinearRegression
regression=LinearRegression()
```

[39]:
```python
regression.fit(X_train,Y_train)
```

[39]:
```
LinearRegression()
```

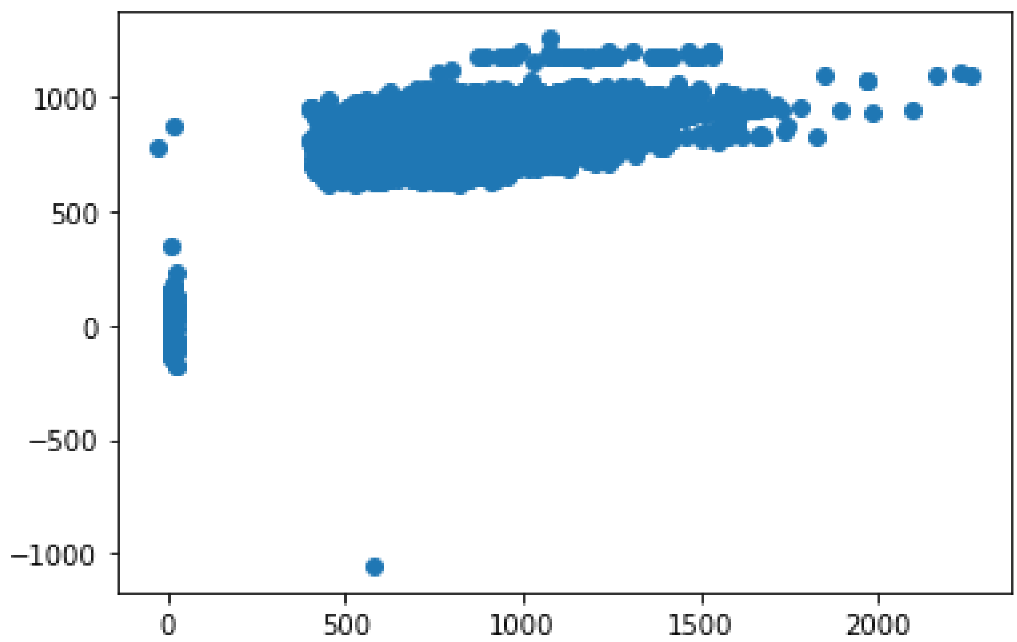
[40]:
```python
reg_pred=regression.predict(X_test)
```

[41]:
```python
print("coefficient: ",regression.coef_)
```

```
coefficient:  [-2.32672102e-01 -1.62186773e+01 -2.53134941e+01 -1.62463257e+01
 -7.74571319e-02 -3.75626623e+00  5.43705972e-01  3.59723804e+00
 -7.73219377e+00  1.25464816e+01 -1.28449933e+00  5.69921797e-01
  1.27372860e+00  2.91647142e+00  4.06125890e+00 -5.07593388e+00
 -3.29474824e+00  1.47935036e+01 -7.43696323e+01 -5.95753202e+01
 -4.15045321e+01 -2.04294660e+01 -1.44457259e+01 -1.27583167e+02
 -5.88441147e+13 -5.79300202e+13 -2.07318321e+13 -6.89344364e+12
 -6.35159796e+12 -1.41451754e+12 -2.94967141e+11  5.40022430e+00
  6.34479696e+01 -6.04193636e+00 -1.53455089e+01  1.87666388e+01
 -1.30293093e+01  3.82073744e+00  7.18635847e-01  3.01577521e+00]
```

[42]:
```python
plt.scatter(Y_test,reg_pred)
```

[42]:
```
<matplotlib.collections.PathCollection at 0x282d71762e0>
```



[43]:
```
from sklearn.metrics import mean_squared_error
print(mean_squared_error(Y_test,reg_pred))
```

```
32212.770174482248
```

4.1.2 Model 2: Random Forest Regression

[44]:
```
from sklearn.ensemble import RandomForestRegressor
rf=RandomForestRegressor(n_estimators=100,random_state=42)
```

[ ]:
```
rf.fit(X_train,Y_train)
```

[ ]:
```
rf_pred=rf.predict(X_test)
```

[ ]:
```
print(mean_squared_error(Y_test,rf_pred))
```

[ ]:
```
plt.scatter(Y_test,rf_pred)
```

4.1.3 Model 3: Lasso Regression

[ ]:
```
from sklearn.linear_model import Lasso
lm=Lasso(alpha=0.1)
lm.fit(X_train,Y_train)
lm_pred=lm.predict(X_test)
```

```
[ ]: print(mean_squared_error(Y_test,lm_pred))
```

```
[ ]: plt.scatter(Y_test,lm_pred)
```

4.1.4 Model 4: Ridge Regression

```
[ ]: from sklearn.linear_model import Ridge
     rm=Ridge(alpha=0.1)
     rm.fit(X_train,Y_train)
```

```
[ ]: rm_pred=rm.predict(X_test)
```

```
[ ]: print(mean_squared_error(Y_test,lm_pred))
```

```
[ ]: plt.scatter(Y_test,rm_pred)
```

```
[ ]: from sklearn.ensemble import RandomForestRegressor
     rf_random=RandomForestRegressor()
```

```
[ ]: from sklearn.metrics import r2_score
     score=r2_score(Y_test, rf_pred)
```

```
[ ]: predictions=rf_random.predict(X_test)
```

```
[ ]: #Hyperparameter Tuning Randomforest

     # Randomised search CV
     #Number of trees in random forest
     n_estimators=[int(x) for x in np.linspace(start=100,stop=1200,num=12)]
     #no. of features to consider at every split
     max_features=['auto','sqrt']
     #max no. of levels in tree
     max_depth=[int(x) for x in np.linspace(5,30,num=6)]
     # Min no. of samples required to split a node
     min_samples_split=[2,5,10,15,100]
     min_samples_leaf=[1,2,5,10]
```

```
[ ]: from sklearn.model_selection import RandomizedSearchCV
     random_grid = {'n_estimators': n_estimators,
                    'max_features': max_features,
                    'max_depth': max_depth,
                    'min_samples_split': min_samples_split,
                    'min_samples_leaf': min_samples_leaf}

     print(random_grid)
```

[ ]:
```
rf_random = RandomizedSearchCV(estimator = rf, param_distributions =␣
↪random_grid,scoring='neg_mean_squared_error', n_iter = 10, cv = 5,␣
↪verbose=2, random_state=42,n_jobs=1)
```

[ ]:
```
plt.scatter(Y_test,predictions)
```

[ ]:
```
sns.distplot(Y_test-predictions)
```

[ ]:
```
rf_random.fit(X_train,Y_train)
```