Case Study I

May 24, 2020

1 Mercari Price Suggestion Challenge

1.1 Problem Statement

This is a Kaggle Competition where we need to predict the sale price of a listing based on information a user provides for this listing.

1.2 Source/Useful Links

Since the User needs to choose the price of the item listed, the item may not get sold if the price is too high or the user incurs loss if the price is too low. Hence in this Kaggle Competition, we need to predict the price of an item based on the Information provided by the user. https://www.kaggle.com/c/mercari-price-suggestion-challenge

1.2.1 Mapping the problem into Regression Problem

Given details about a product like product category name, brand name, and item condition we need to develop an algorithm to predict the right Product Price * Some Reference Kernel/Links: - https://towardsdatascience.com/mercari-price-recommendation-for-online-retail-sellers-979c4d07f45c

- https://www.kaggle.com/lopuhin/mercari-golf-0-3875-cv-in-75-loc-1900-s
- https://www.youtube.com/watch?v=QFR0IHbzA30
- https://medium.com/unstructured/how-i-lost-a-silver-medal-in-kaggles-mercari-price-suggestion-challenge-using-cnns-and-tensorflow-4013660fcded

1.2.2 Evaluation Metric (RMSLE):

RMSLE stands for Root Mean Squared Logarithm Error.

[5]:
```
from IPython.display import Image
Image(filename="/content/drive/My Drive/Case Study I/RMSLE.png")
```

[5]:

$$\mathrm{RMSLE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\log(y_i+1)-\log(\hat{y}_i+1)\right)^2} =$$
$$= RMSE\left(\log(y_i+1), \log(\hat{y}_i+1)\right) =$$
$$= \sqrt{MSE\left(\log(y_i+1), \log(\hat{y}_i+1)\right)}$$

1.2.3 Business Objective and Constraints :

- Latency should be low as we need to predict the price within a minute and not in hours.
- Difference between predicted price and actual price should be low

[0]:

```

```

[0]:

```
import warnings
warnings.filterwarnings('ignore')
import pandas as pd
import numpy as np
import os
import seaborn as sns
import matplotlib.pyplot as plt
from collections import Counter
from nltk.corpus import stopwords
from tqdm import tqdm
import re
from sklearn.preprocessing import StandardScaler, MinMaxScaler
import math
from nltk.sentiment.vader import SentimentIntensityAnalyzer
from nltk.corpus import stopwords
```

[0]:

```
os.chdir('/content/drive/My Drive/Case Study I')
```

[4]:

```
data = pd.read_csv('train.tsv',sep='\t')
print("Data Shape : ", data.shape)
data.head()
```

```
Data Shape :  (1482535, 8)
```

[4]:
```
   train_id  …                                   item_description
0         0  …                                 No description yet
1         1  …  This keyboard is in great condition and works …
2         2  …  Adorable top with a hint of lace and a key hol…
3         3  …  New with tags. Leather horses. Retail for [rm]…
4         4  …          Complete with certificate of authenticity

[5 rows x 8 columns]
```

So we have around 1.48 Million Training Data points where each data point is made up of * train_id : Unique Id to identify a Data Point * name : Name of the Product in short * Category_Name : The Category under which the Product falls into. * Brand Name : Name of the Brand the Product belongs to * Price : The Price of the Product * Shipping : A boolean variable indicating whether the Shipping price will be paid by seller or buyer * Item Description : A text summary describing the product in much detail.

[5]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1482535 entries, 0 to 1482534
Data columns (total 8 columns):
 #   Column             Non-Null Count    Dtype
---  ------             --------------    -----
 0   train_id           1482535 non-null  int64
 1   name               1482535 non-null  object
 2   item_condition_id  1482535 non-null  int64
 3   category_name      1476208 non-null  object
 4   brand_name         849853 non-null   object
 5   price              1482535 non-null  float64
 6   shipping           1482535 non-null  int64
 7   item_description   1482531 non-null  object
dtypes: float64(1), int64(3), object(4)
memory usage: 90.5+ MB
```

From the Above Information we can see that the number of Null Entries in Columns are * Brand = 632682 * Category Name = 6327 * Item Description = 4

The Important thing to note is that our Predictor Column ``Price'' does not contain any Null values

1.3 EDA on Price

[6]:
```
data['price'].describe().apply(lambda x: format(x, 'f'))
```

[6]:
```
count    1482535.000000
mean          26.737516
std           38.586066
```

```
min            0.000000
25%           10.000000
50%           17.000000
75%           29.000000
max         2009.000000
Name: price, dtype: object
```

As we can see that 75% of the Price falls are less than or equal to 29 while the maximum Price is 2009, so there is huge disparity in the distribution of Price column

[7]:
```
# Reference : https://stackoverflow.com/questions/31594549/
 ↪how-do-i-change-the-figure-size-for-a-seaborn-plot
sns.set(rc={'figure.figsize':(9,6)})
sns.distplot(data.price, kde_kws = {"color" : "red"})
plt.title('Price Distribution')
plt.show()
```

Observation : We can see that the Price Distribution is left skewed in Nature and Majority of Values are less than 100.

[0]:
```
prices = data.price.values # Saving the Price Values in a Numpy array
prices.sort()
```

[9]:
```
for i in range(1,11):
  percentile_value = np.percentile(prices,i*10)
  print(i*10," th Percentile Value : ", percentile_value)
```

```
10  th Percentile Value :  7.0
20  th Percentile Value :  10.0
30  th Percentile Value :  12.0
40  th Percentile Value :  14.0
50  th Percentile Value :  17.0
60  th Percentile Value :  20.0
70  th Percentile Value :  26.0
80  th Percentile Value :  34.0
90  th Percentile Value :  51.0
100  th Percentile Value :  2009.0
```

[10]:
```
for i in range(1,10):
  percentile_value = np.percentile(prices,90 + i)
  print(90 + i," th Percentile Value : ", percentile_value)
```

```
91  th Percentile Value :  55.0
92  th Percentile Value :  58.0
93  th Percentile Value :  62.0
94  th Percentile Value :  67.0
95  th Percentile Value :  75.0
96  th Percentile Value :  85.0
97  th Percentile Value :  99.0
98  th Percentile Value :  122.0
99  th Percentile Value :  170.0
```

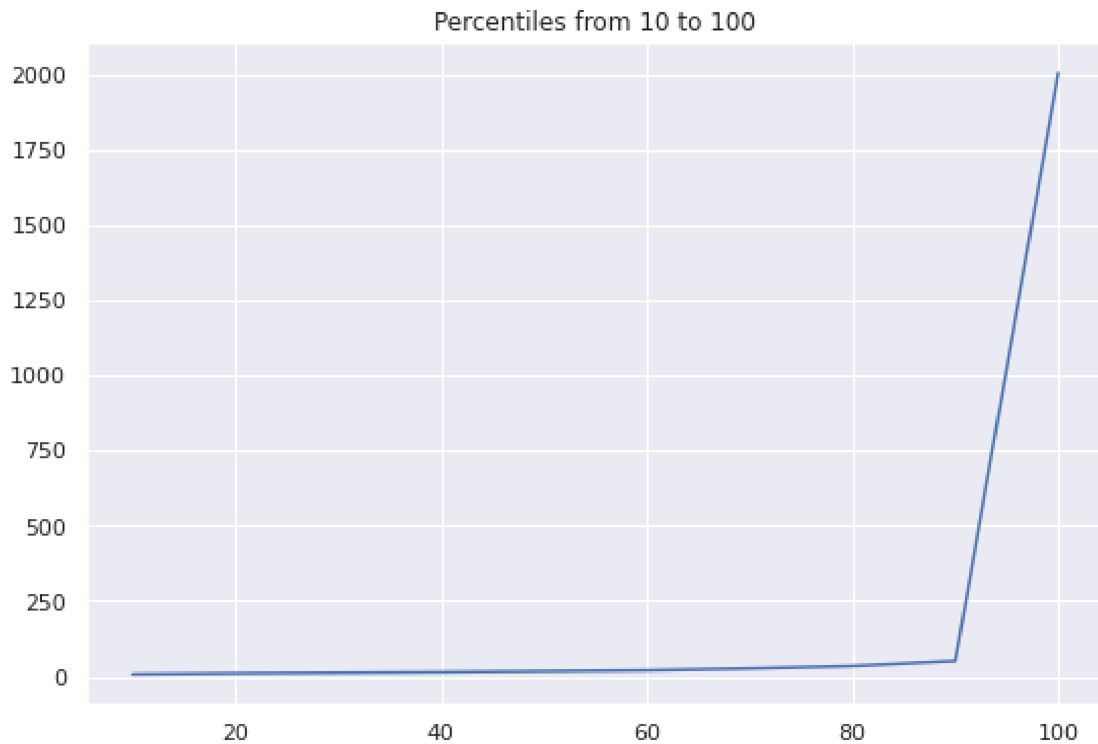
[11]:
```
for i in range(1,11):
  percentile_value = np.percentile(prices,99 + i*0.1)
  print(99 + i*0.1," th Percentile Value : ", percentile_value)
```

```
99.1  th Percentile Value :  180.0
99.2  th Percentile Value :  189.0
99.3  th Percentile Value :  200.0
99.4  th Percentile Value :  210.0
99.5  th Percentile Value :  230.3300000000745
99.6  th Percentile Value :  256.0
99.7  th Percentile Value :  286.0
99.8  th Percentile Value :  340.0
99.9  th Percentile Value :  450.0
100.0  th Percentile Value :  2009.0
```

From the above three Cells we can see that upto 99.3% of the Price value are less than or equal to 200 which could be our inflection point, while the Maximum Price is 2009.

[12]:

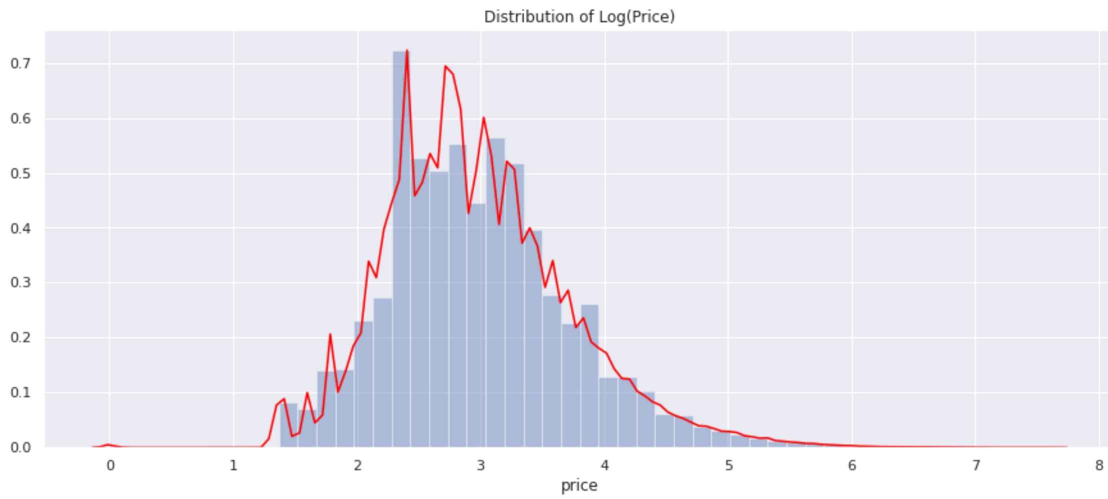
```
y_axis = []
x_axis = []
for i in range(1,11):
  percentile_value = np.percentile(prices,i*10)
  y_axis.append(percentile_value)
  x_axis.append(i*10)

plt.plot(x_axis,y_axis)
plt.title("Percentiles from 10 to 100")
plt.show()
```



Same is being shown through Plot, where 90% of the Price value is less than 200.

[13]:

```
sns.set(rc={'figure.figsize':(15,6)})
sns.distplot(np.log1p(data.price), kde_kws = {"color" : "red"})
plt.title('Distribution of Log(Price)')
plt.show()
```



The Log values of Price Results in somewhat close to Normal Distribution which can help us in future.

1.3.1 Check for Rows having Invalid Price values

[14]:
```
negative_price = len(data[data.price<=0])
print("Number of Rows having Price less than or equal to 0 are : ",␣
↪negative_price)
```

```
Number of Rows having Price less than or equal to 0 are :  874
```

[15]:
```
# As Price cannot be negative, Hence Removing them
data = data[data.price > 0].reset_index(drop=True)
print(data.shape)
```

```
(1481661, 8)
```

1.3.2 EDA on Shipping

Shipping is a boolean value where * value = 0 means shipping price is paid by buyer * value = 1 means shipping price is paid by seller

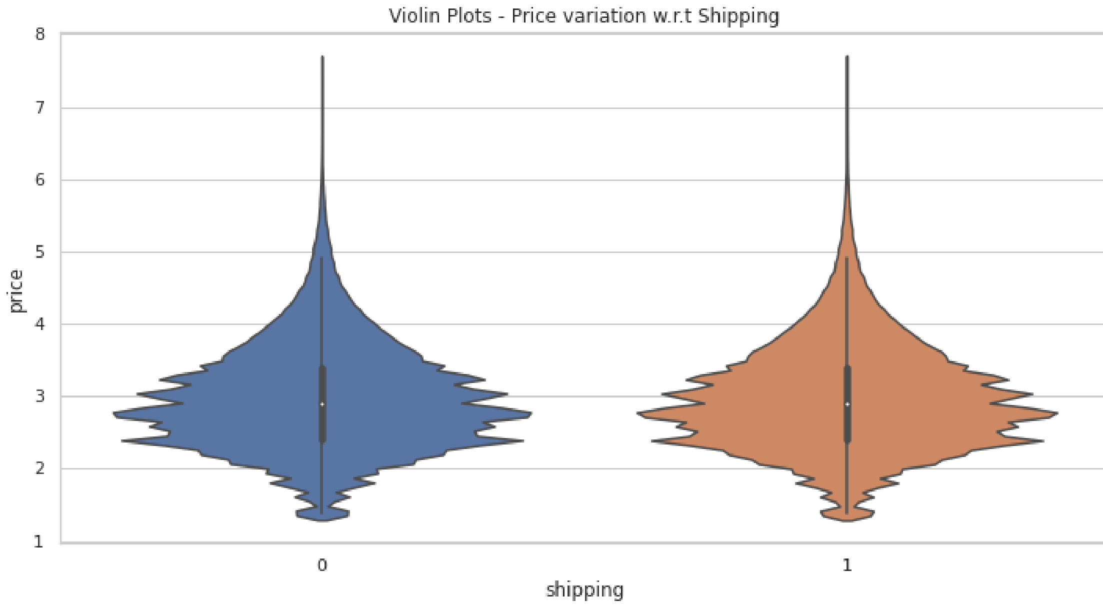
[16]:
```
data.groupby('shipping')['price'].describe()
```

[16]:

shipping	count	mean	std	min	25%	50%	75%	max
0	818961.0	26.759558	38.382572	3.0	10.0	17.0	29.0	2009.0
1	662700.0	26.745540	38.849231	3.0	10.0	17.0	29.0	2006.0

There is not much difference around the mean price irespective of what value the shipping column has. To conclude it further let's try violin-plot to confirm it.

[17]:
```
sns.set(style='whitegrid')
plt.figure(figsize=(12,6))
sns.violinplot(x=data.shipping, y=np.log1p(data.price))
plt.title('Violin Plots - Price variation w.r.t Shipping')
plt.show()
```



Here since there is huge disparity in the Price values I have taken log values of the Price Column and we can see that 25,50 and 75th percentiles of Log(Price) values is almost equal when shipping is taken into consideration

1.3.3 EDA on Item Condition

[18]:
```
data.groupby('item_condition_id')['price'].describe()
```

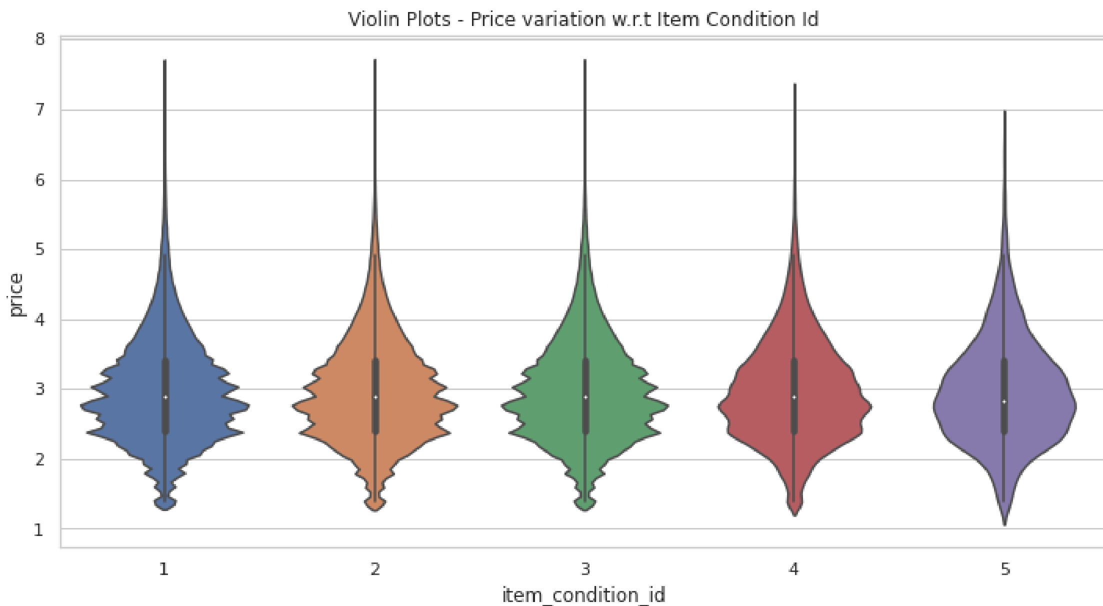
[18]:

item_condition_id	count	mean	std	…	50%	75%	max
1	640149.0	26.769953	38.599212	…	17.0	29.0	2009.0
2	375274.0	26.746050	38.934424	…	17.0	29.0	2004.0
3	431911.0	26.746554	38.373124	…	17.0	29.0	2006.0
4	31945.0	26.575677	37.176963	…	17.0	29.0	1315.0
5	2382.0	27.018052	40.629001	…	16.0	29.0	784.0

[5 rows x 8 columns]

From the Description we can see that Item_condition_id is Categorical Column having 5 values with value = 1 being the most occured one while value = 5 having the least occurence.

[19]:
```
sns.set(style='whitegrid')
plt.figure(figsize=(12,6))
sns.violinplot(x=data.item_condition_id, y=np.log1p(data.price))
plt.title('Violin Plots - Price variation w.r.t Item Condition Id')
plt.show()
```



From the above Violin Plot the 25th,50th and 75th Percentile of the Log(Price) is almost same when Item condition is taken into consideration. The minor difference is the Max value of Price when Item_Condition_id = 5 is much less when compared with the Price value for other Item_condition_Id's.

1.3.4 EDA on Brand

[20]:
```
null_values = data.brand_name.isnull().sum()
percentage_value = np.round(null_values/data.shape[0],4) * 100
print("Percentage of Data out of Total Data having Null/Missing Value in Brand␣
↪Column ", percentage_value, "%")
```

Percentage of Data out of Total Data having Null/Missing Value in Brand Column
42.68 %

[21]:
```
# Table of Brand Name along with the Average Price Per Brand and their Total␣
↪Occurence
```

```
brands_df = pd.DataFrame(data.groupby('brand_name', as_index=False).
↪agg({'price': 'mean','shipping' : 'count'}))
brands_df.columns = ['brand_name','avg_price','count']
brands_df = brands_df.sort_values(by=['count'],ascending = False)

print(brands_df.shape)
brands_df.head(10)
```

```
(4809, 3)
```

[21]:

	brand_name	avg_price	count
3221	PINK	26.717185	54060
3057	Nike	26.692024	54009
4504	Victoria's Secret	26.519090	48010
2604	LuLaRoe	26.875149	31013
267	Apple	26.925849	17316
1510	FOREVER 21	26.894439	15176
3067	Nintendo	26.104400	15000
2626	Lululemon	26.822670	14552
2841	Michael Kors	26.690625	13920
213	American Eagle	26.572561	13251

[22]:
```
# Filling all the Missing/NUll values in brand_name with value "missing"
data['brand_name'] = data['brand_name'].fillna('missing').astype('category')
print(data.brand_name.isnull().sum())
```

```
0
```

1.3.5 EDA on Item Description

[23]:
```
print("Number of Missing Values in Item Description : ", data.item_description.
↪isnull().sum())
```

```
Number of Missing Values in Item Description :  4
```

[24]:
```
# Filling all the Missing/Null Values with "No Description" value
data["item_description"].fillna("No Description", inplace=True)
print("Number of Missing Values in Item Description : ", data.item_description.
↪isnull().sum())
```

```
Number of Missing Values in Item Description :  0
```

[25]:
```
import nltk
nltk.download("stopwords")
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data…
[nltk_data]   Unzipping corpora/stopwords.zip.
```

[25]: True

[0]:
```
# Reference : Applied AI Course
def decontracted(phrase):
    # specific
    phrase = re.sub(r"won't", "will not", phrase)
    phrase = re.sub(r"can\'t", "can not", phrase)

    # general
    phrase = re.sub(r"n\'t", " not", phrase)
    phrase = re.sub(r"\'re", " are", phrase)
    phrase = re.sub(r"\'s", " is", phrase)
    phrase = re.sub(r"\'d", " would", phrase)
    phrase = re.sub(r"\'ll", " will", phrase)
    phrase = re.sub(r"\'t", " not", phrase)
    phrase = re.sub(r"\'ve", " have", phrase)
    phrase = re.sub(r"\'m", " am", phrase)
    return phrase
```

[0]:
```
stop_words = stopwords.words('english')
def preprocessing_desc(description):
  preprocessed_desc = []
  for sentence in tqdm(description.values):
        sentence = decontracted(sentence)
        sent = sentence.replace('\\r', ' ')
        sent = sent.replace('\\"', ' ')
        sent = sent.replace('\\n', ' ')
        sent = re.sub('[^A-Za-z0-9]+', ' ', sent)
        sent = ' '.join(e for e in sent.split() if e not in stop_words)
        preprocessed_desc.append(sent.lower().strip())
  return preprocessed_desc
```

[29]:
```
data["preprocessed_desc"] = preprocessing_desc(data["item_description"])
```

100%| | 1481661/1481661 [01:45<00:00, 14089.39it/s]

Since Item Description is a Textual Column, we can use WordCloud to find the occurence strength of the words present in the Description

[30]:
```
from wordcloud import WordCloud
wordcloud = WordCloud(width = 800, height = 800,background_color = 'black',
                      min_font_size = 10).generate(" ".join(data.
 ↪preprocessed_desc.astype(str)))
plt.figure(figsize = (16, 8), facecolor = None)
plt.imshow(wordcloud)
plt.axis("off")
plt.tight_layout(pad = 0)
plt.show()
```

From the WordCloud we can see that majority of the words either talks about the condition of the Product or shipping condition or some other key details w.r.t to Products which I think are major factors while deciding the Price of the Product

1.3.6 EDA on Name

[32]:
```
# Checking for Missing Name Value
print("Number of Missing Values in Name : ", data.name.isnull().sum())
```

```
Number of Missing Values in Name :  0
```

[33]:
```
data["preprocessed_name"] = preprocessing_desc(data["name"])
```

```
100%|          | 1481661/1481661 [00:34<00:00, 43235.96it/s]
```

[34]:
```python
wordcloud = WordCloud(width = 800, height = 800,background_color = 'black',
                      min_font_size = 10).generate(" ".join(data.
 ↪preprocessed_name.astype(str)))
plt.figure(figsize = (16, 8), facecolor = None)
plt.imshow(wordcloud)
plt.axis("off")
plt.tight_layout(pad = 0)
plt.show()
```

From the WordCloud we can see that the name column mostly contains information related the Brand to which the Product belongs to.

1.3.7 EDA on Category Name

[35]:
```python
# Checking for Missing Value in Brand
print("Number of Missing Values in Category Name : ", data.category_name.
 ↪isnull().sum())
```

```
Number of Missing Values in Category Name :  6324
```

[36]:
```python
# Filling all the Missing/Null Values with "missing" value
data["category_name"].fillna("missing", inplace=True)
print("Number of Missing Values in Category Name : ", data.category_name.
 ↪isnull().sum())
```

```
Number of Missing Values in Category Name :  0
```

[37]:
```python
# Printing some Values from the Category Name Column
data.category_name.values
```

[37]:
```
array(['Electronics/Video Games & Consoles/Games',
       'Women/Athletic Apparel/Pants, Tights, Leggings',
       'Vintage & Collectibles/Antique/Book', …,
       'Sports & Outdoors/Exercise/Fitness accessories',
       'Home/Home Décor/Home Décor Accents',
       "Women/Women's Accessories/Wallets"], dtype=object)
```

As from the above output we can see that Category Name has multiple values in a cell, so we split it into multiple sub-categroies and perform EDA on them individually. Here I have divided them into 3 sub-categories namely gencat_name,subcat1_name and subcat2_name.

[38]:
```python
# Reference = https://stackoverflow.com/questions/14745022/
 ↪how-to-split-a-column-into-two-columns

data['gencat_name'],data['subcat1_name'],data['subcat2_name'] =␣
 ↪data['category_name'].str.split('/', 2).str

print(data.shape)
data.head()
```

```
(1481661, 13)
```

[38]:

	train_id	…	subcat2_name
0	874	…	Games
1	875	…	Pants, Tights, Leggings
2	876	…	Book
3	877	…	Pumps
4	878	…	Shoulder Bag

```
[5 rows x 13 columns]
```

[39]:

```
print("Number of Missing Values in Sub-Category 1 : ", data.subcat1_name.
 ↪isnull().sum())
```

```
Number of Missing Values in Sub-Category 1 :  6324
```

[40]:

```
print("Number of Missing Values in Sub-Category 2 : ", data.subcat2_name.
 ↪isnull().sum())
```

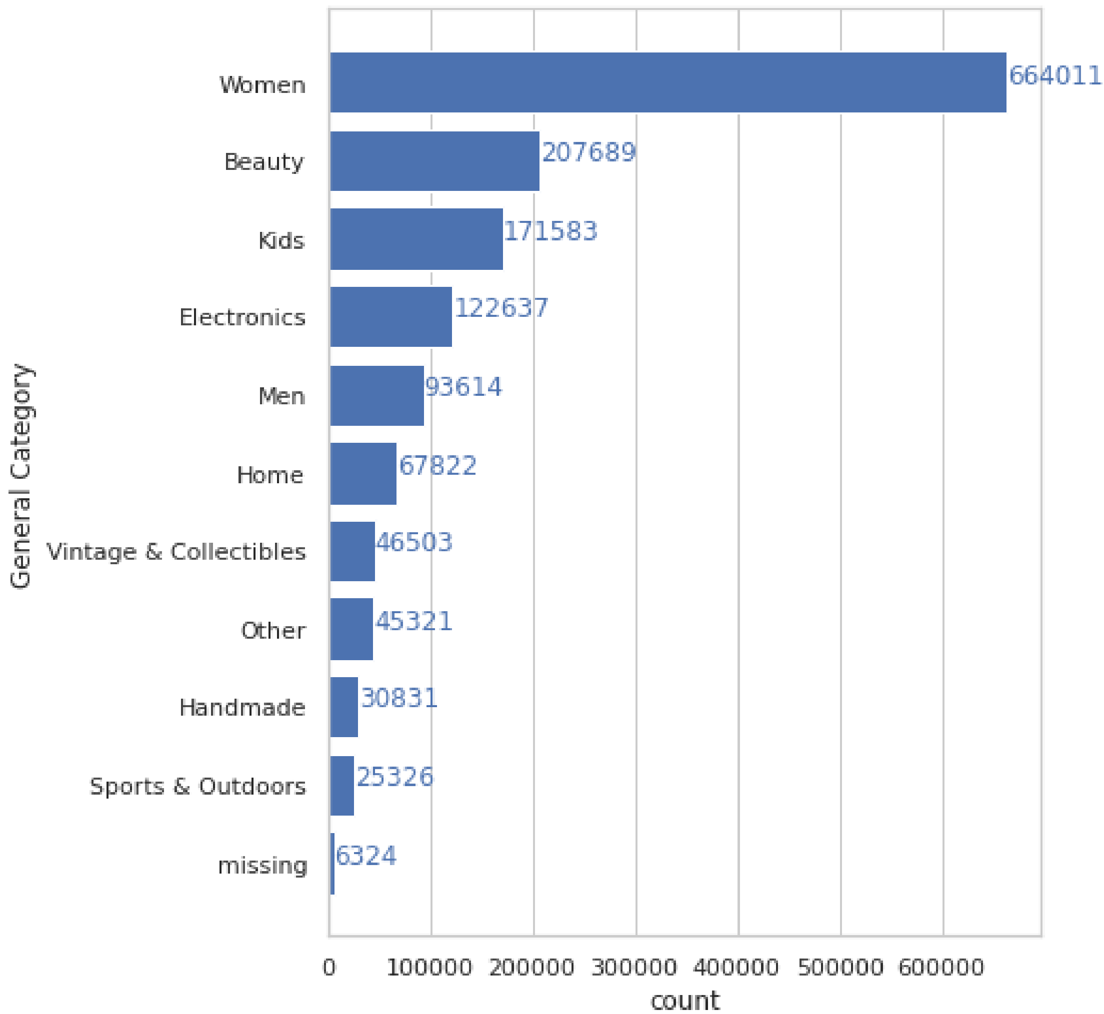
```
Number of Missing Values in Sub-Category 2 :  6324
```

[0]:

```
# Filling all the Missing/Null Values with "missing" value
data["subcat1_name"].fillna("missing", inplace=True)
data["subcat2_name"].fillna("missing", inplace=True)
```

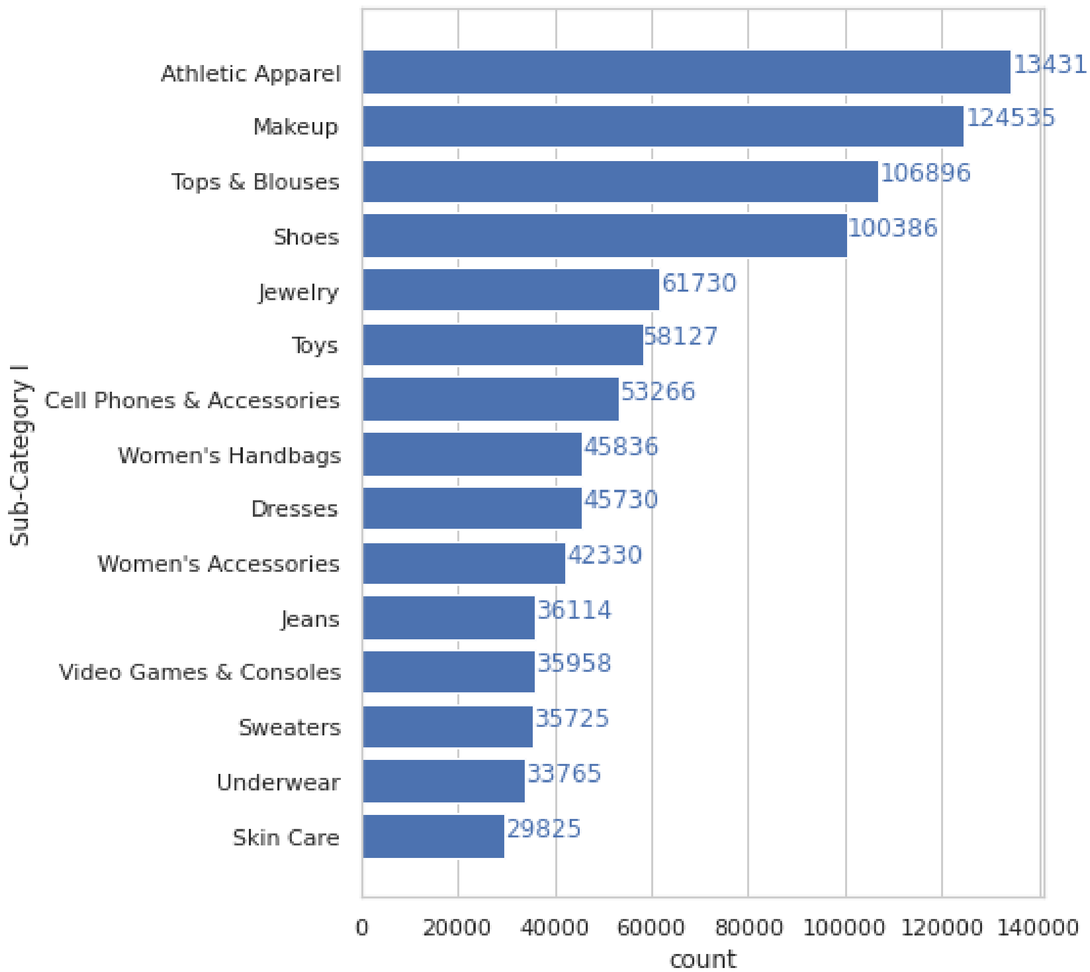
[42]:

```
# Reference : https://towardsdatascience.com/
 ↪mercari-price-suggestion-97ff15840dbd
gencat_count = Counter(list(data.gencat_name.values))
x, y = zip(*gencat_count.most_common(15))
plt.figure(figsize=[6,8])
plt.barh(x, y)
for i, val in enumerate(y):
           plt.annotate(val, (y[i], x[i]), color='b')
plt.gca().invert_yaxis()
plt.ylabel('General Category')
plt.xlabel('count')
plt.grid(False, axis='y')
plt.show()
```



We can see that out of top 15 most General Category ``Women'' category has highest Number of Products.

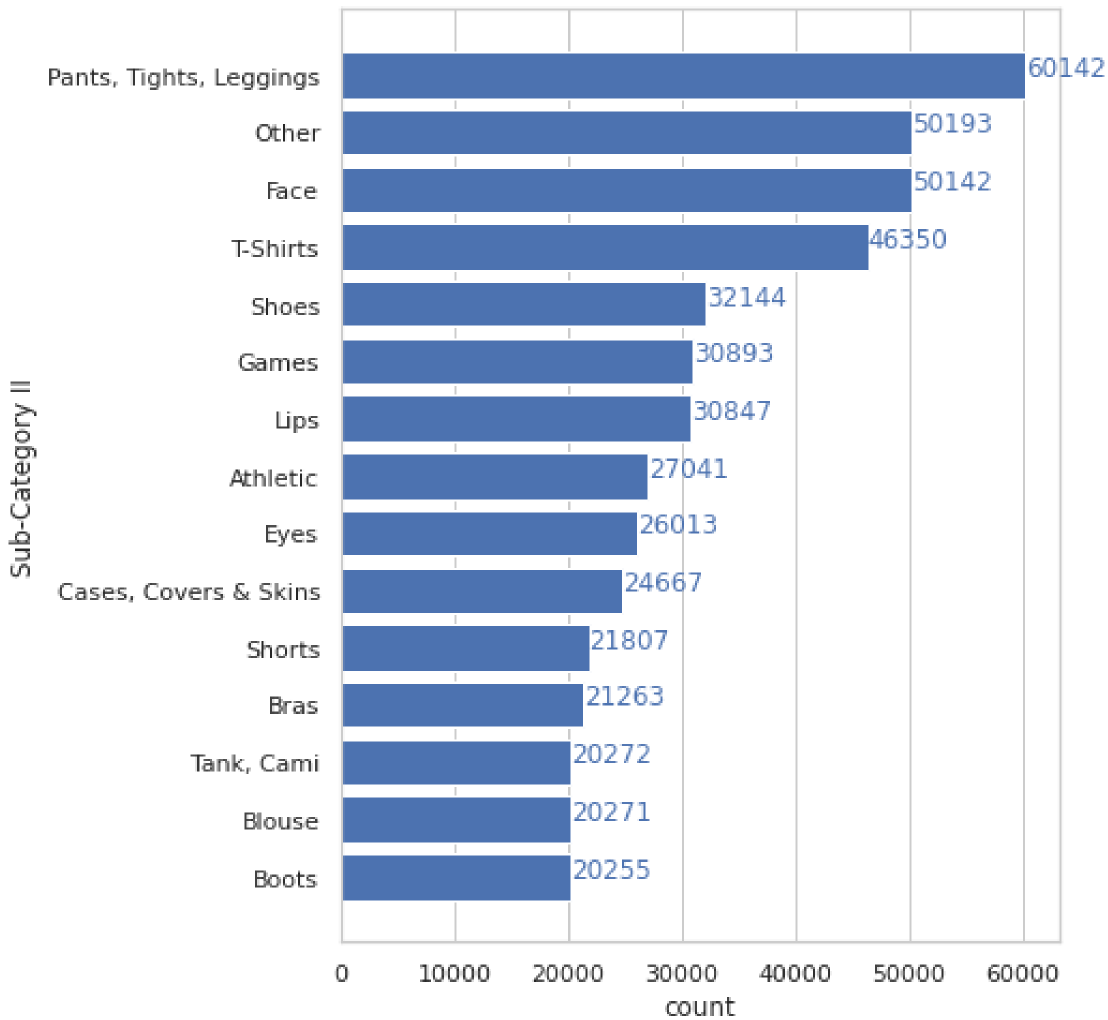
[43]:
```
subcat1_count = Counter(list(data.subcat1_name.values))
x, y = zip(*subcat1_count.most_common(15))
plt.figure(figsize=[6,8])
plt.barh(x, y)
for i, val in enumerate(y):
            plt.annotate(val, (y[i], x[i]), color='b')
plt.gca().invert_yaxis()
plt.ylabel('Sub-Category I')
plt.xlabel('count')
plt.grid(False, axis='y')
plt.show()
```



There is a good Distribution among Sub-categories I categories where Atletic Apparel is the most occuring sub-category1

[44]:

```
subcat2_count = Counter(list(data.subcat2_name.values))
x, y = zip(*subcat2_count.most_common(15))
plt.figure(figsize=[6,8])
plt.barh(x, y)
for i, val in enumerate(y):
           plt.annotate(val, (y[i], x[i]), color='b')
plt.gca().invert_yaxis()
plt.ylabel('Sub-Category II')
plt.xlabel('count')
plt.grid(False, axis='y')
plt.show()
```



There is a good Distribution among Sub-categories II categories where Pants,Tights,Leggings is the most occuring sub-category II

[46]:
```
data.groupby('gencat_name')['price'].describe()
```

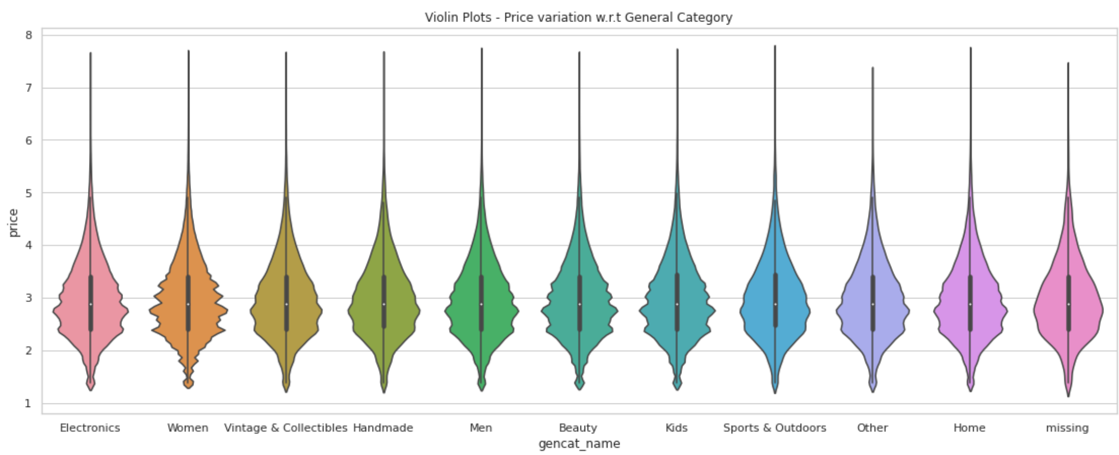
[46]:

	count	mean	std	…	50%	75%	max
gencat_name				…			
Beauty	207689.0	26.756956	39.223420	…	17.0	29.0	1900.0
Electronics	122637.0	26.811986	38.982350	…	17.0	29.0	1850.0
Handmade	30831.0	26.451672	35.491681	…	17.0	29.0	1800.0
Home	67822.0	26.763617	41.003440	…	17.0	29.0	2006.0
Kids	171583.0	26.763482	37.572725	…	17.0	30.0	2000.0
Men	93614.0	26.609978	38.157129	…	17.0	29.0	2000.0
Other	45321.0	26.587498	37.001968	…	17.0	29.0	1354.0
Sports & Outdoors	25326.0	27.358169	45.399650	…	17.0	30.0	2004.0

```
Vintage & Collectibles    46503.0  26.926220  41.036280  …  17.0  29.0  1808.0
Women                    664011.0  26.748621  38.149515  …  17.0  29.0  2009.0
missing                    6324.0  26.683191  40.685330  …  17.0  29.0  1359.0

[11 rows x 8 columns]
```

[47]:

```
sns.set(style='whitegrid')
plt.figure(figsize=(19,7))
sns.violinplot(x=data.gencat_name, y=np.log1p(data.price))
plt.title('Violin Plots - Price variation w.r.t General Category')
plt.show()
```



From the above two Notebook Cells we can see that there is not much variation in Price with Respect to General Category taken under consideration.All the General Category have similar Mean Prices.

[0]:

```
# Referencence Applied AI Course
def clean_categories(category):
  clean_value = []
  cat = list(category)
  for i in tqdm(cat):
    i = re.sub('[^A-Za-z0-9]+', ' ', i)
    i = i.replace(' ','')
    i = i.replace('&','_')
    clean_value.append(i.strip())

  return clean_value
```

[49]:

```
# Cleaning up the Category Name sub-columns
data['gencat_name'] = clean_categories(data['gencat_name'].values)
data['subcat1_name'] = clean_categories(data['subcat1_name'].values)
data['subcat2_name'] = clean_categories(data['subcat2_name'].values)
```

```
100%|      | 1481661/1481661 [00:02<00:00, 573563.04it/s]
100%|      | 1481661/1481661 [00:03<00:00, 478319.85it/s]
100%|      | 1481661/1481661 [00:03<00:00, 479480.50it/s]
```

[50]:
```
data.columns
```

[50]:
```
Index(['train_id', 'name', 'item_condition_id', 'category_name', 'brand_name',
       'price', 'shipping', 'item_description', 'preprocessed_desc',
       'preprocessed_name', 'gencat_name', 'subcat1_name', 'subcat2_name'],
      dtype='object')
```

[0]:
```
# Dropping off Columns not required
data.drop('train_id',axis = 1, inplace = True)
data.drop('name', axis = 1,inplace = True)
data.drop('category_name', axis = 1, inplace = True)
data.drop('item_description', axis = 1, inplace = True)
```

[52]:
```
data.columns
```

[52]:
```
Index(['item_condition_id', 'brand_name', 'price', 'shipping',
       'preprocessed_desc', 'preprocessed_name', 'gencat_name', 'subcat1_name',
       'subcat2_name'],
      dtype='object')
```

[0]:
```

```

[0]:
```

```

2 Feature Engineering

[53]:
```
from sklearn.model_selection import train_test_split

train_data,test_data = train_test_split(data,test_size = 0.25)

print("Train Data Shape : ", train_data.shape)
print("Test Data Shape : ", test_data.shape)
```

```
Train Data Shape :  (1111245, 9)
Test Data Shape :  (370416, 9)
```

Since Mercari App doesn't allow any price to be lower than 3 or greater than 2000 removing such data points from training data

[54]:
```
# Reference : https://www.kaggle.com/valkling/
 ↪mercari-rnn-2ridge-models-with-notes-0-42755
train_data = train_data[(train_data.price >= 3) & (train_data.price <= 2000)]
```

```
print(train_data.shape)
```

```
(1111242, 9)
```

2.0.1 Transforming Price Column into Log Values

[0]:
```
# Transforming Price to Log Values so as the distribution of Log values
# become somewhat Normal making it easy for ML models to predict

train_data['log_price'] = np.log1p(train_data['price'])
test_data['log_price'] = np.log1p(test_data['price'])
```

2.0.2 Generating 7 new features based on Item Description

[56]:
```
# Reference : https://www.kaggle.com/gspmoreira/
↪cnn-glove-single-model-private-lb-0-41117-35th

# The above kernel Item Description into consideration and generate 7 new␣
↪features like
# for each description words lengths, like percentage of upper-case words,␣
↪hashtags, etc
# This was that the 3rd Reference I passed in the Google Docs

print('Generating features with statistics for item description textual␣
↪content')

acronyms_regex = re.compile('([A-Z\-0-9]{2,})')
hashtag_regex = re.compile(r'(#[a-z]{2,})')

#Extracts statistics for each description, words lengths, like percentage of␣
↪upper-case words, hashtags, etc
def extract_counts(text):
    text_size_words_counts = len(text.split(' '))
    text_size_words_log_counts = math.log1p(text_size_words_counts)
    full_uppercase_perc = len(acronyms_regex.findall(text)) /␣
↪float(text_size_words_counts)
    exclamation_log_count = math.log1p(text.count('!'))
    star_log_count = math.log1p(text.count('*'))
    percentage_log_count = math.log1p(text.count('%'))
    price_removed_marker_log_count = math.log1p(text.count('[rm]'))
    hashtag_log_count = math.log1p(len(hashtag_regex.findall(text)))
    return [text_size_words_log_counts,
            full_uppercase_perc,
            exclamation_log_count,
```

```
             star_log_count,
             percentage_log_count,
             price_removed_marker_log_count,
             hashtag_log_count]
```

Generating features with statistics for item description textual content

[57]:
```
# On Training Data
item_descr_counts = np.vstack(train_data['preprocessed_desc'].astype(str).
 ↪apply(extract_counts).values)
item_descr_counts_scaler = StandardScaler(copy=True)
train_desc_feats = item_descr_counts_scaler.fit_transform(item_descr_counts)
print(train_desc_feats.shape)
```

(1111242, 7)

[58]:
```
# On Test Data
item_descr_counts = np.vstack(test_data['preprocessed_desc'].astype(str).
 ↪apply(extract_counts).values)
item_descr_counts_scaler = StandardScaler(copy=True)
test_desc_feats = item_descr_counts_scaler.fit_transform(item_descr_counts)
print(test_desc_feats.shape)
```

(370416, 7)

2.0.3 Sentiment Score on Textual Columns

[0]:
```
# Ref : https://towardsdatascience.com/
 ↪mercari-price-recommendation-for-online-retail-sellers-979c4d07f45c
# This blog suggests to calculate Sentiment Scores from textual columns like␣
 ↪Name and Description
# because better the sentiment score higher are the chances of buyers buying␣
 ↪them.
# Ref : https://stackoverflow.com/questions/60122247/
 ↪how-can-we-do-a-sentiment-analysis-and-create-a-sentiment-record-next-to-each

def sentiment_score(text_values):
  sid = SentimentIntensityAnalyzer()
  scores = []
  for sentence in tqdm(text_values):
    score = sid.polarity_scores(sentence)
    scores.append(score['compound'])

  return scores
```

[60]:
```
nltk.download('vader_lexicon')
nltk.download('punkt')
```

```
[nltk_data] Downloading package vader_lexicon to /root/nltk_data…
[nltk_data] Downloading package punkt to /root/nltk_data…
[nltk_data]   Unzipping tokenizers/punkt.zip.
```

[60]:
```
True
```

[61]:
```
# On Name Column
train_sentiment_name = sentiment_score(train_data['preprocessed_name'])
train_data['sentiment_score_name'] = train_sentiment_name

test_sentiment_name = sentiment_score(test_data['preprocessed_name'])
test_data['sentiment_score_name'] = test_sentiment_name
```

```
100%|      | 1111242/1111242 [01:25<00:00, 13045.50it/s]
100%|      | 370416/370416 [00:28<00:00, 12896.27it/s]
```

[62]:
```
#On Description Column
train_sentiment_desc = sentiment_score(train_data['preprocessed_desc'])
train_data['sentiment_score_desc'] = train_sentiment_desc

test_sentiment_desc = sentiment_score(test_data['preprocessed_desc'])
test_data['sentiment_score_desc'] = test_sentiment_desc
```

```
100%|      | 1111242/1111242 [05:28<00:00, 3381.68it/s]
100%|      | 370416/370416 [01:47<00:00, 3447.69it/s]
```

[63]:
```
"""
On Grouping Category Name, Brand Name and Shipping we will create 8 new features
with respect to Price like Price_Mean, Price_Median, Price_Std_Deviation,␣
↪Minimum and
Maximum Price per group
"""
# Reference : https://www.kaggle.com/gspmoreira/
↪cnn-glove-single-model-private-lb-0-41117-35th
```

[63]:
```
'\nOn Grouping Category Name, Brand Name and Shipping we will create 8 new
features\nwith respect to Price like Price_Mean, Price_Median,
Price_Std_Deviation, Minimum and\nMaximum Price per group\n'
```

[0]:
```
# Reference : https://www.kaggle.com/gspmoreira/
↪cnn-glove-single-model-private-lb-0-41117-35th
def generate_cbs_stats(train,test):
    df_group = train.groupby('cat_brand_ship',as_index = False).agg({"shipping"␣
↪: len,
```

```
                                                    "log_price" : [np.
↪median, np.mean, np.std,np.min,np.max]})
    df_group.columns =␣
↪['cat_brand_ship','cbs_count','cbs_log_price_median','cbs_log_price_mean','cbs_log_price_std',
                    'cbs_log_price_min','cbs_log_price_max']

    df_group['cbs_log_price_std'] = df_group['cbs_log_price_std'].fillna(0)
    df_group['cbs_log_price_conf_variance'] = df_group['cbs_log_price_std'] /␣
↪df_group['cbs_log_price_mean']
    df_group['cbs_log_count'] = np.log1p(df_group['cbs_count'])
    df_group['cbs_min_expected_log_price'] = (df_group['cbs_log_price_mean'] -␣
↪(df_group['cbs_log_price_std']*2)).clip(lower=1.0)
    df_group['cbs_max_expected_log_price'] = (df_group['cbs_log_price_mean'] +␣
↪(df_group['cbs_log_price_std']*2))

    df_group_stats = test.merge(df_group.reset_index(),
                                how = 'left',
                                on = 'cat_brand_ship')[['cbs_log_count',
                                                        ␣
↪'cbs_log_price_mean',
                                                        ␣
↪'cbs_log_price_std',
                                                        ␣
↪'cbs_log_price_conf_variance',
                                                        ␣
↪'cbs_min_expected_log_price',
                                                        ␣
↪'cbs_max_expected_log_price',
                                                        ␣
↪'cbs_log_price_min',
                                                        ␣
↪'cbs_log_price_max']].fillna(0).values

    scaler = StandardScaler(copy=True)
    cbs_feats_scaled = scaler.fit_transform(df_group_stats)
    return cbs_feats_scaled
```

[0]:
```
train_data['cat_brand_ship'] = (train_data['gencat_name'].astype(str) + "/" +
                                train_data['subcat1_name'].astype(str) + "/" +
                                train_data['subcat2_name'].astype(str) + "_" +
                                train_data['brand_name'].astype(str) + "_" +
                                train_data['shipping'].astype(str))
test_data['cat_brand_ship'] = (test_data['gencat_name'].astype(str) + "/" +
                               test_data['subcat1_name'].astype(str) + "/" +
                               test_data['subcat2_name'].astype(str) + "_" +
                             test_data['brand_name'].astype(str) + "_" +
```

```
                              test_data['shipping'].astype(str))
```

[66]:
```
train_cbs_features = generate_cbs_stats(train_data,train_data)
test_cbs_features = generate_cbs_stats(train_data,test_data)
print("New Train CBS Features Shape : ", train_cbs_features.shape)
print("New Test CBS Features Shape : ", test_cbs_features.shape)
```

```
New Train CBS Features Shape :  (1111242, 8)
New Test CBS Features Shape :  (370416, 8)
```

2.0.4 Concatenating all the above 17 features along with Log Price to see the correleation values

[0]:
```
new_df = pd.concat([pd.DataFrame(train_desc_feats,
                                  columns =␣
 ↪['text_size_words_log_counts','full_uppercase_perc','exclamation_log_count',
                                                                  ␣
 ↪'star_log_count','percentage_log_count','price_removed_marker_log_count',
                                     'hashtag_log_count']),
                    pd.DataFrame(generate_cbs_stats(train_data,train_data),
                                  columns =␣
 ↪['cbs_log_count','cbs_log_price_mean','cbs_log_price_std',
                                                                  ␣
 ↪'cbs_log_price_conf_variance','cbs_min_expected_log_price',
                                                                  ␣
 ↪'cbs_max_expected_log_price','cbs_log_price_min','cbs_log_price_max']),
                    train_data[['sentiment_score_name','sentiment_score_desc']].
 ↪reset_index(drop = True),
                    train_data['log_price'].reset_index(drop = True)],axis = 1)
```

[68]:
```
new_df.head()
```

[68]:
```
   text_size_words_log_counts  …  log_price
0                   -0.443376  …   2.302585
1                   -1.665864  …   2.484907
2                    0.551226  …   2.197225
3                    1.216473  …   3.610918
4                    0.779112  …   2.564949

[5 rows x 18 columns]
```

[69]:
```
# First Create a Corrleation Matrix using corr method
# Reference : https://datatofish.com/correlation-matrix-pandas/

correlation_matrix = new_df.corr()
plt.figure(figsize = (18,9))
```

```python
sns.heatmap(correlation_matrix, annot=True)
plt.show()
```

2.1 Observation:

On seeing the Last column we can see that the columns * cbs_log_price_mean *cbs_min_expected_log_price* cbs_max_expected_log_price have higher correlation with the Log Price(Target) column Hence we can use this 3 columns in our Models for Predicting Price.

[0]:
```python

```

[0]:
```python
# Reference : https://www.kaggle.com/gspmoreira/
↪cnn-glove-single-model-private-lb-0-41117-35th
def final_cbs_stats(train,test):
    df_group = train.groupby('cat_brand_ship',as_index = False).agg({"shipping"␣
↪: len,
                                                                   "log_price" : [np.
↪median, np.mean, np.std,np.min,np.max]})
    df_group.columns =␣
↪['cat_brand_ship','cbs_count','cbs_log_price_median','cbs_log_price_mean','cbs_log_price_st
                     'cbs_log_price_min','cbs_log_price_max']
```

```
    df_group['cbs_log_price_std'] = df_group['cbs_log_price_std'].fillna(0)
    df_group['cbs_log_price_conf_variance'] = df_group['cbs_log_price_std'] /␣
↪df_group['cbs_log_price_mean']
    df_group['cbs_log_count'] = np.log1p(df_group['cbs_count'])
    df_group['cbs_min_expected_log_price'] = (df_group['cbs_log_price_mean'] -␣
↪(df_group['cbs_log_price_std']*2)).clip(lower=1.0)
    df_group['cbs_max_expected_log_price'] = (df_group['cbs_log_price_mean'] +␣
↪(df_group['cbs_log_price_std']*2))

    df_group_stats = test.merge(df_group.reset_index(),
                                  how = 'left',
                                  on =␣
↪'cat_brand_ship')[['cbs_log_price_mean',
                                                                          ␣
↪'cbs_min_expected_log_price',
                                                                          ␣
↪'cbs_max_expected_log_price']].fillna(0).values

    scaler = StandardScaler(copy=True)
    cbs_feats_scaled = scaler.fit_transform(df_group_stats)
    return cbs_feats_scaled
```

[71]:
```
train_cbs_features = final_cbs_stats(train_data,train_data)
test_cbs_features = final_cbs_stats(train_data,test_data)
print("New Train CBS Features Shape : ", train_cbs_features.shape)
print("New Test CBS Features Shape : ", test_cbs_features.shape)
```

```
New Train CBS Features Shape :  (1111242, 3)
New Test CBS Features Shape :  (370416, 3)
```

So here in both Training and Testing we have two sets of Data * Initial data given like Name,Description,Shipping etc * Newly choosen 3 features from the above Heatmap

So we will now concatenate these two sets of Data into one set and save them in a pickle file for further processing.

[72]:
```
train_data.columns
```

[72]:
```
Index(['item_condition_id', 'brand_name', 'price', 'shipping',
       'preprocessed_desc', 'preprocessed_name', 'gencat_name', 'subcat1_name',
       'subcat2_name', 'log_price', 'sentiment_score_name',
       'sentiment_score_desc', 'cat_brand_ship'],
      dtype='object')
```

[0]:
```
# Dropping cat_brand_ship column from training and test data
train_data.drop('cat_brand_ship',axis = 1, inplace = True)
test_data.drop('cat_brand_ship',axis = 1, inplace = True)
```

[74]:
```
print("Train Data Shape : ", train_data.shape)
print("Test Data Shape : ", test_data.shape)
print("Original Data Columns : ", train_data.columns)
```

```
Train Data Shape :  (1111242, 12)
Test Data Shape :  (370416, 12)
Original Data Columns :  Index(['item_condition_id', 'brand_name', 'price',
'shipping',
       'preprocessed_desc', 'preprocessed_name', 'gencat_name', 'subcat1_name',
       'subcat2_name', 'log_price', 'sentiment_score_name',
       'sentiment_score_desc'],
      dtype='object')
```

[0]:
```
# Converting Numpy array into a Dataframe
train_cbs_features = pd.DataFrame(train_cbs_features,columns =␣
↪['cbs_log_price_mean','cbs_min_expected_log_price','cbs_max_expected_log_price'])
test_cbs_features = pd.DataFrame(test_cbs_features,columns =␣
↪['cbs_log_price_mean','cbs_min_expected_log_price','cbs_max_expected_log_price'])
```

[0]:
```
# Merging/Concatenating two datasets into One Dataset(for Training)
train_data['cbs_log_price_mean'] = train_cbs_features.cbs_log_price_mean.values
train_data['cbs_min_expected_log_price'] = train_cbs_features.
↪cbs_min_expected_log_price.values
train_data['cbs_max_expected_log_price'] = train_cbs_features.
↪cbs_max_expected_log_price.values
```

[0]:
```
# Merging/Concatenating two datasets into One Dataset(for Testing)
test_data['cbs_log_price_mean'] = test_cbs_features.cbs_log_price_mean.values
test_data['cbs_min_expected_log_price'] = test_cbs_features.
↪cbs_min_expected_log_price.values
test_data['cbs_max_expected_log_price'] = test_cbs_features.
↪cbs_max_expected_log_price.values
```

[78]:
```
print("Final Training Data with Price Column Shape : ", train_data.shape)
print("Final Testing Data with Price Column Shape : ", test_data.shape)
```

```
Final Training Data with Price Column Shape :  (1111242, 15)
Final Testing Data with Price Column Shape :  (370416, 15)
```

[79]:
```
print("Few Training Data Points : ")
train_data.head()
```

```
Few Training Data Points :
```

[79]:

	item_condition_id	…	cbs_max_expected_log_price
251708	1	…	-5.856094
387038	3	…	0.123082

```
153430                      3  ...             0.336782
1222628                     1  ...            -0.028349
429107                      2  ...             0.301645

[5 rows x 15 columns]
```

[80]:
```
print("Few Testing Data Points : ")
test_data.head()
```

```
Few Testing Data Points :
```

[80]:
```
         item_condition_id  ... cbs_max_expected_log_price
1314403                  3  ...                  -0.231460
1207474                  2  ...                   0.360503
281142                   3  ...                  -0.108843
416922                   3  ...                   0.361658
101224                   1  ...                   0.104954

[5 rows x 15 columns]
```

[0]:
```
# Saving them in a Pickle File
import pickle

file = open("train_data","wb")
pickle.dump(train_data,file)
file.close

file = open("test_data","wb")
pickle.dump(test_data,file)
file.close
```

[0]: <function BufferedWriter.close>

[0]: