Mercari Price Suggestion Challenge

1. Business Problem

1.1 Description

- Mercari is a Japanese e-commerce company. Their main product is marketplace app which enables people to easily sell and purchase second-hand items with smartphones.
- The company has over 19 million monthly active users on its platform, the company wants to help the sellers by suggesting the right pricing of the items.
- Suggesting the pricing to its sellers is tough job because the sellers can sell anything, or any bundle of things on Mercari's marketplace.
- Mercari wants us to build an algorithm that automatically suggests the right product prices from the user-inputted text descriptions of their products, including details like product category name, brand name, item condition, etc.

1.2 Source Link

source: https://www.kaggle.com/c/mercari-price-suggestion-challenge

1.3 Real world/Business Objectives and Constraints:

- The goal is to solve the problem of suggesting the appropriate price of products to online sellers.
- Some Latency constraints. It Should finish in few seconds.
- Incorrect suggesting of price could impact customer's experience.

In [ ]:

```
'''

##Mercari Price Suggestion Challenge
####Can you automatically suggest product prices to online sellers?


Problem Statement: Predict the sale price of a listing based on information a user provides for this listing.
'''
```

Exploratory Data Analysis

In [1]:

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

In [2]:

```
!gdown --id 1i_xu5xZwPSvbO6n3xdWFdOnYDis5paCe
```

```
/usr/local/lib/python3.7/dist-packages/gdown/cli.py:131: FutureWarning: Option `--id` was deprecated in versio
n 4.3.1 and will be removed in 5.0. You don't need to pass it anymore to use a file ID.
  category=FutureWarning,
Downloading...
From: https://drive.google.com/uc?id=1i_xu5xZwPSvbO6n3xdWFdOnYDis5paCe
To: /content/test_stg2.tsv.zip
100% 309M/309M [00:02<00:00, 136MB/s]
```

In [ ]:

```
!unzip '/content/test_stg2.tsv.zip'
```

```
Archive:  /content/test_stg2.tsv.zip
  inflating: test_stg2.tsv
```

In [14]:

```
!gdown --id 13pcSpXZIAVm7qGTtxwULheecppLDUcS2
```

```
/usr/local/lib/python3.7/dist-packages/gdown/cli.py:131: FutureWarning: Option `--id` was deprecated in versio
n 4.3.1 and will be removed in 5.0. You don't need to pass it anymore to use a file ID.
  category=FutureWarning,
Downloading...
From: https://drive.google.com/uc?id=13pcSpXZIAVm7qGTtxwULheecppLDUcS2
To: /content/final_test_stg2_pp.zip
100% 771M/771M [00:13<00:00, 58.2MB/s]
```

In [16]:

```
!unzip '/content/final_test_stg2_pp.zip'
```

```
Archive:  /content/final_test_stg2_pp.zip
  inflating: final_test_stg2_pp.pkl
```

In [ ]:

```
!7z e '/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train.tsv.7z'
```

```
7-Zip [64] 16.02 : Copyright (c) 1999-2016 Igor Pavlov : 2016-05-21
p7zip Version 16.02 (locale=en_US.UTF-8,Utf16=on,HugeFiles=on,64 bits,2 CPUs Intel(R) Xeon(R) CPU @ 2.20GHz (4
06F0),ASM,AES-NI)

Scanning the drive for archives:
  0M Scan /content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/
1 file, 77912192 bytes (75 MiB)

Extracting archive: /content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train.tsv.7z
--
Path = /content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train.tsv.7z
Type = 7z
Physical Size = 77912192
Headers Size = 122
Method = LZMA2:24
Solid = -
Blocks = 1

  0%      1%      4% - train.tsv                 8% - train.tsv                 11% - train.tsv
 16% - train.tsv                 19% - train.tsv                 23% - train.tsv                 27% - train.t
sv                 31% - train.tsv                 34% - train.tsv                 38% - train.tsv
 40% - train.tsv                 43% - train.tsv                 45% - train.tsv                 48% - train.t
sv                 50% - train.tsv                 54% - train.tsv                 58% - train.tsv
 62% - train.tsv                 65% - train.tsv                 69% - train.tsv                 73% - train.t
sv                 76% - train.tsv                 80% - train.tsv                 84% - train.tsv
 88% - train.tsv                 91% - train.tsv                 95% - train.tsv                 99% - train.t
sv                 Everything is Ok

Size:       337809843
Compressed: 77912192
```

In [3]:

```
# importing library
import numpy as np
import pandas as pd


import pandas as pd
import matplotlib.pyplot as plt

import pickle
#import cPickle


import regex as re
import nltk
from nltk.stem.porter import PorterStemmer
from nltk.stem import WordNetLemmatizer
nltk.download('wordnet')
!pip install Wordbatch
from wordbatch.models import FTRL, FM_FTRL
!pip install kmodes
from kmodes.kmodes import KModes

from sklearn.linear_model import Ridge
```

```
[nltk_data] Downloading package wordnet to /root/nltk_data...
[nltk_data]   Unzipping corpora/wordnet.zip.
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Collecting Wordbatch
  Downloading Wordbatch-1.4.9.tar.gz (1.2 MB)
     |████████████████████████████████| 1.2 MB 5.2 MB/s
Requirement already satisfied: Cython in /usr/local/lib/python3.7/dist-packages (from Wordbatch) (0.29.30)
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.7/dist-packages (from Wordbatch) (1.0.2)
Collecting python-Levenshtein
  Downloading python-Levenshtein-0.12.2.tar.gz (50 kB)
     |████████████████████████████████| 50 kB 7.5 MB/s
Collecting py-lz4framed
  Downloading py-lz4framed-0.14.0.tar.gz (128 kB)
     |████████████████████████████████| 128 kB 64.3 MB/s
Collecting randomgen>=1.16.6
  Downloading randomgen-1.21.2-cp37-cp37m-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (3.5 MB)
     |████████████████████████████████| 3.5 MB 58.6 MB/s
Requirement already satisfied: numpy in /usr/local/lib/python3.7/dist-packages (from Wordbatch) (1.21.6)
Requirement already satisfied: scipy in /usr/local/lib/python3.7/dist-packages (from Wordbatch) (1.4.1)
Requirement already satisfied: pandas in /usr/local/lib/python3.7/dist-packages (from Wordbatch) (1.3.5)
Requirement already satisfied: wheel>=0.33.4 in /usr/local/lib/python3.7/dist-packages (from Wordbatch) (0.37.
1)
Requirement already satisfied: pytz>=2017.3 in /usr/local/lib/python3.7/dist-packages (from pandas->Wordbatch)
(2022.1)
Requirement already satisfied: python-dateutil>=2.7.3 in /usr/local/lib/python3.7/dist-packages (from pandas->
Wordbatch) (2.8.2)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.7/dist-packages (from python-dateutil>=2.7.3
->pandas->Wordbatch) (1.15.0)
Requirement already satisfied: setuptools in /usr/local/lib/python3.7/dist-packages (from python-Levenshtein->
Wordbatch) (57.4.0)
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.7/dist-packages (from scikit-learn->Word
batch) (1.1.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.7/dist-packages (from scikit-lea
rn->Wordbatch) (3.1.0)
Building wheels for collected packages: Wordbatch, py-lz4framed, python-Levenshtein
  Building wheel for Wordbatch (setup.py) ... done
  Created wheel for Wordbatch: filename=Wordbatch-1.4.9-cp37-cp37m-linux_x86_64.whl size=2768573 sha256=cf3ece
e02af06977262fdc2090fbedabab3ec18f3ab1ce2ffa2a742dc98f80e0
  Stored in directory: /root/.cache/pip/wheels/7c/c6/17/9c8d8c8e37a08ea8a9a3d7e75aaa642ae0e1d2f4079ce11d93
  Building wheel for py-lz4framed (setup.py) ... done
  Created wheel for py-lz4framed: filename=py_lz4framed-0.14.0-cp37-cp37m-linux_x86_64.whl size=346635 sha256=
ac6f09147d06d8edef5c3de41813d4065903c20d6474729b9789efaa9dcfc855
  Stored in directory: /root/.cache/pip/wheels/5c/9c/8e/5d008dfcbb83cfb99763f100d10b6b2d953274f48744b7be81
  Building wheel for python-Levenshtein (setup.py) ... done
  Created wheel for python-Levenshtein: filename=python_Levenshtein-0.12.2-cp37-cp37m-linux_x86_64.whl size=14
9863 sha256=fda5a61b31f5da9f30cac0583c2739ac082c5cb4f277268a2e4571f1e9e6be9e
  Stored in directory: /root/.cache/pip/wheels/05/5f/ca/7c4367734892581bb5ff896f15027a932c551080b2abd3e00d
Successfully built Wordbatch py-lz4framed python-Levenshtein
Installing collected packages: randomgen, python-Levenshtein, py-lz4framed, Wordbatch
Successfully installed Wordbatch-1.4.9 py-lz4framed-0.14.0 python-Levenshtein-0.12.2 randomgen-1.21.2
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Collecting kmodes
  Downloading kmodes-0.12.1-py2.py3-none-any.whl (20 kB)
Requirement already satisfied: scipy>=0.13.3 in /usr/local/lib/python3.7/dist-packages (from kmodes) (1.4.1)
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.7/dist-packages (from kmodes) (1.1.0)
Requirement already satisfied: scikit-learn>=0.22.0 in /usr/local/lib/python3.7/dist-packages (from kmodes) (1
.0.2)
Requirement already satisfied: numpy>=1.10.4 in /usr/local/lib/python3.7/dist-packages (from kmodes) (1.21.6)
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.7/dist-packages (from scikit-lea
rn>=0.22.0->kmodes) (3.1.0)
Installing collected packages: kmodes
Successfully installed kmodes-0.12.1
```

In [4]:

```python
from scipy.sparse import load_npz
from scipy.sparse import hstack
from lightgbm import LGBMRegressor

from sklearn.model_selection import RandomizedSearchCV

from scipy.sparse import load_npz
```

In [ ]:

```python
# Python code to convert .tsv file to .csv file

tsv_file='/content/train.tsv'
```

```
# reading tsv file
data=pd.read_table(tsv_file,sep='\t')

# converting tsv into csv
data.to_csv('GfG.csv',index=False)
```

In [ ]:

```
data.head()
```

Out[ ]:

	train_id	name	item_condition_id	category_name	brand_name	price	shipping	item_description
0	0	MLB Cincinnati Reds T Shirt Size XL	3	Men/Tops/T-shirts	NaN	10.0	1	No description yet
1	1	Razer BlackWidow Chroma Keyboard	3	Electronics/Computers & Tablets/Components & P...	Razer	52.0	0	This keyboard is in great condition and works ...
2	2	AVA-VIV Blouse	1	Women/Tops & Blouses/Blouse	Target	10.0	1	Adorable top with a hint of lace and a key hol...
3	3	Leather Horse Statues	1	Home/Home Décor/Home Décor Accents	NaN	35.0	1	New with tags. Leather horses. Retail for [rm]...
4	4	24K GOLD plated rose	1	Women/Jewelry/Necklaces	NaN	44.0	0	Complete with certificate of authenticity

In [21]:

```
# Python code to convert .tsv file to .csv file

tsv_file='/content/test_stg2.tsv'

# reading tsv file
test_stg_2=pd.read_table(tsv_file,sep='\t')
```

In [ ]:

```
print('Total number of row and columns in dataset:',data.shape)
```

```
Total number of row and columns in dataset: (1482535, 8)
```

In [ ]:

```
data.columns
```

Out[ ]:

```
Index(['train_id', 'name', 'item_condition_id', 'category_name', 'brand_name',
       'price', 'shipping', 'item_description'],
      dtype='object')
```

In [ ]:

```
test_stg_2.head()
```

Out[ ]:

	test_id	name	item_condition_id	category_name	brand_name	shipping	item_description
0	0	Breast cancer "I fight like a girl" ring	1	Women/Jewelry/Rings	NaN	1	Size 7
1	1	25 pcs NEW 7.5"x12" Kraft Bubble Mailers	1	Other/Office supplies/Shipping Supplies	NaN	1	25 pcs NEW 7.5"x12" Kraft Bubble Mailers Lined...
2	2	Coach bag	1	Vintage & Collectibles/Bags and Purses/Handbag	Coach	1	Brand new coach bag. Bought for [rm] at a Coac...
3	3	Floral Kimono	2	Women/Sweaters/Cardigan	NaN	0	-floral kimono -never worn -lightweight and pe...
4	4	Life after Death	3	Other/Books/Religion & Spirituality	NaN	1	Rediscovering life after the loss of a loved o...

In [ ]:

```
test_stg_2.shape
```

Out[ ]:

```
(3460725, 7)
```

Data fields:

- train_id : the id of the listing.
- name - the title of the listing.
- item_condition_id - the condition of the items provided by the seller
- category_name - category of the listing
- brand_name - brand name of the item
- price - the price that the item was sold for.
- shipping - 1 if shipping fee is paid by seller and 0 by buyer
- item_description - the full description of the item.

In [ ]:

```
null_value_count=np.sum(data.isnull(),axis=0)  # this line get us the null value count in each field

from prettytable import PrettyTable

columns = ["columns", "Null value count", "% of Null value count"]

myTable = PrettyTable()

# Add Columns
myTable.add_column(columns[0],data.columns)
myTable.add_column(columns[1],null_value_count)
myTable.add_column(columns[2], list(map(lambda x: round(x/data.shape[0]*100,4),null_value_count)))

print(myTable)
```

```
+-------------------+------------------+-----------------------+
|      columns      | Null value count | % of Null value count |
+-------------------+------------------+-----------------------+
|      train_id     |        0         |          0.0          |
|        name       |        0         |          0.0          |
| item_condition_id |        0         |          0.0          |
|   category_name   |       6327       |         0.4268        |
|     brand_name    |      632682      |        42.6757        |
|       price       |        0         |          0.0          |
|      shipping     |        0         |          0.0          |
|  item_description |        4         |         0.0003        |
+-------------------+------------------+-----------------------+
```

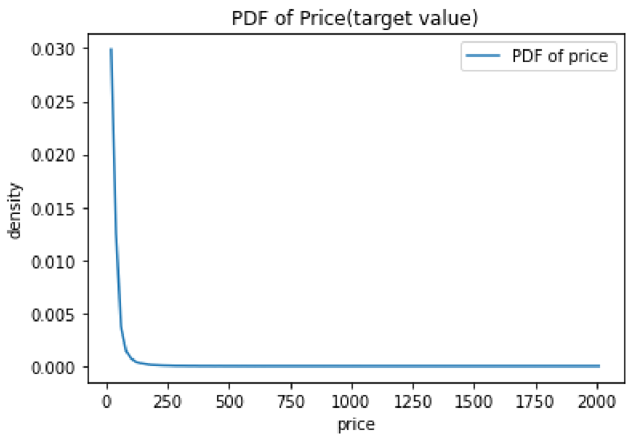
Observation:

- 42.6% of brand name data is missing.This is a significant number.
- 0.42% of category_name field data is missing.
- 0.0003% of data doesn't contain item_description.

Uni-varient analysis of price(target value):

In [ ]:

```
histogram, bins = np.histogram(data['price'].values, bins=100, density=True)
#density = True, the result is the value of the probability density function at the bin

bin_centers = bins[1:]

plt.plot(bin_centers, histogram, label="PDF of price")
plt.xlabel('price')
plt.ylabel('density')
plt.title('PDF of Price(target value)')
plt.legend()
plt.show()
```



Obervation:

- From the above graph it was observed that most of the pricing of items that are sold in mercari's app value lie between 0 to 200.
- Their are only few item whose pricing from 200 to 2000.
- The target value have right skewed distribution. (has a long right tail).

In [ ]:

```
arr = data['price'].values

print("25th percentile of price : ",np.percentile(arr, 25))
print("50th percentile of price : ",np.percentile(arr, 50))
print("75th percentile of price : ",np.percentile(arr, 75))
print("100th percentile of price : ",np.percentile(arr, 100))
```

```
25th percentile of price :  10.0
50th percentile of price :  17.0
75th percentile of price :  29.0
100th percentile of price :  2009.0
```

In [ ]:

```
for i in range(90,101):
  print("{} th percentile of price : {}".format(i,np.percentile(arr,i)))
```

```
90 th percentile of price : 51.0
91 th percentile of price : 55.0
92 th percentile of price : 58.0
93 th percentile of price : 62.0
94 th percentile of price : 67.0
95 th percentile of price : 75.0
96 th percentile of price : 85.0
97 th percentile of price : 99.0
98 th percentile of price : 122.0
99 th percentile of price : 170.0
100 th percentile of price : 2009.0
```

In [ ]:

```
for i in range(1,11):
  j=99+(0.1)*i
  print("{} th percentile of price : {}".format(j,np.percentile(arr,j)))
```

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

Notes:

- If tail is on the right, it is right skewed data. It is also called positive skewed data.

What is problem with skewed distribution data?

- In skewed data, the tail region may act as an outlier for the statistical model and we know that outliers adversely affect the model's performance especially regression-based models.
- So there is a necessity to transform the skewed data to close enough to a Gaussian distribution or Normal distribution.

Reference:-https://towardsdatascience.com/skewed-data-a-problem-to-your-statistical-model-9a6b5bb74e37

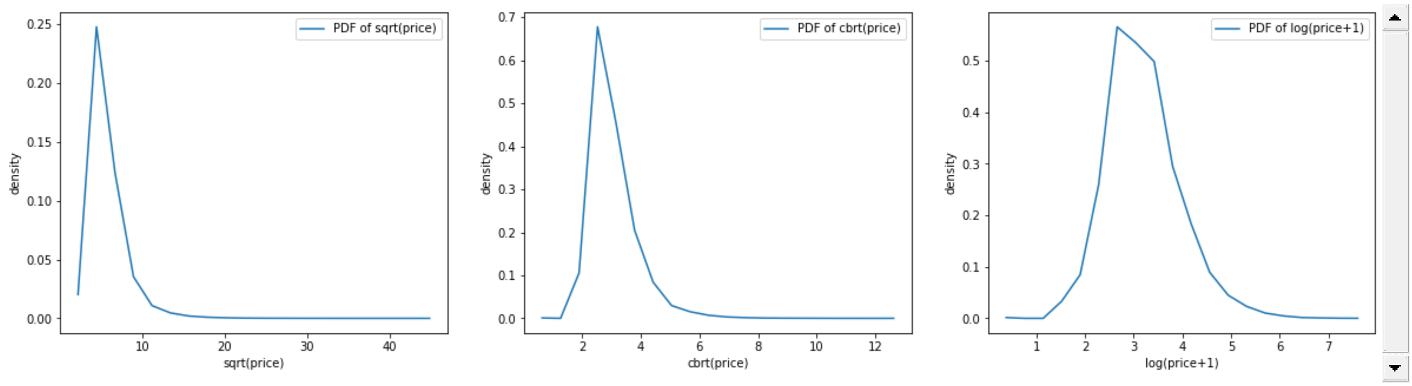
Solution:

- To convert right skewed data to noraml distribution common transformations which are applied on data include square root, cube root, and log.

Reference:-https://medium.com/@TheDataGyan/day-8-data-transformation-skewness-normalization-and-much-more-4c144d370e55

In [ ]:

```
plt.figure(figsize=(20, 5))

histogram, bins = np.histogram(np.sqrt(data['price'].values), bins=20, density=True)
bin_centers = bins[1:]
plt.subplot(1, 3, 1)
plt.plot(bin_centers, histogram, label="PDF of sqrt(price)")
plt.xlabel('sqrt(price)')
plt.ylabel('density')
plt.legend()

histogram, bins = np.histogram(np.cbrt(data['price'].values), bins=20, density=True)
bin_centers = bins[1:]
plt.subplot(1, 3, 2)
plt.plot(bin_centers, histogram, label="PDF of cbrt(price)")
plt.xlabel('cbrt(price)')
plt.ylabel('density')
plt.legend()

histogram, bins = np.histogram(np.log(data['price'].values+1), bins=20, density=True)
bin_centers = bins[1:]
plt.subplot(1, 3, 3)
plt.plot(bin_centers, histogram, label="PDF of log(price+1)")
plt.xlabel('log(price+1)')
plt.ylabel('density')


plt.legend()
plt.show()
```



Observation:

- From the above three plots ,the third plot (log(price+1)) is less skewed compared to other two plots.
- In third plot we are adding 1, to avoid the problem of log(0) which is undefined.

Loss function:

- From the above observations we can use Mean squared logarithmic error (MSLE) (OR) Root Mean Squared Logaritmic Error (RMSLE) as the loss function for the given dataset.
- MSLE and RMSE loss functions are the same, only differ by square root.
- Properties of MSLE:
  - MSLE will treat small differences between small true and predicted values approximately the same as big differences between large true and predicted values.

True value	Predicted value	MSE loss	MSLE loss
30	20	100	0.02861
30000	20000	100 000 000	0.03100
	Comment	big difference	small difference

  - MSLE also penalizes underestimates more than overestimates, introducing an asymmetry in the error curve.

True value	Predicted value	MSE loss	MSLE loss
20	10 (underestimate by 10)	100	0.07886
20	30 (overestimate by 10)	100	0.02861
	Comment	no difference	big difference

  - Reference:-https://peltarion.com/knowledge-center/documentation/modeling-view/build-an-ai-model/loss-functions/mean-squared-logarithmic-error-(msle)
- We choose RMSLE as our loss function because it do have same properties as MSLE and added plus point is square root which is used to remove the effects of the squaring.
- Since our target value (price) have large range from 0 to 2000, it was observed that there are fewer point that lie in higher range, if the predicated value and actual value differ a lot then RMSLE doesn't penalise much.This is added advantage because those few points may be outliers, this doesn't affect the model drastically.

RMSE Formula:

RMSLE= $\sqrt{\frac{1}{n}\sum_{i=1}^{n}(log(p_i+1)-log(y_i+1))^2}$

where,

p_i is the preidicted value

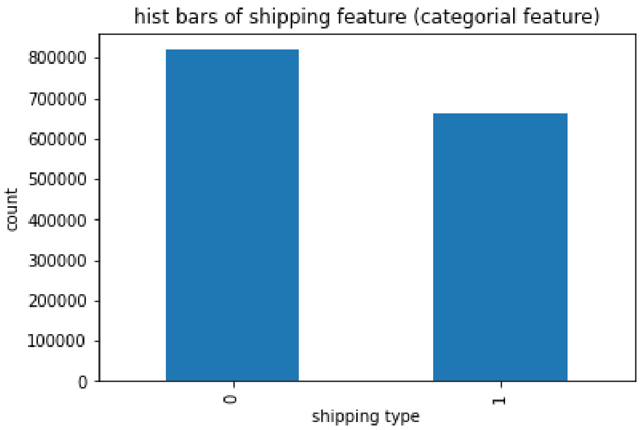
y_i is the actual value

n is total number of observation

Analysis of shipping:

In [ ]:

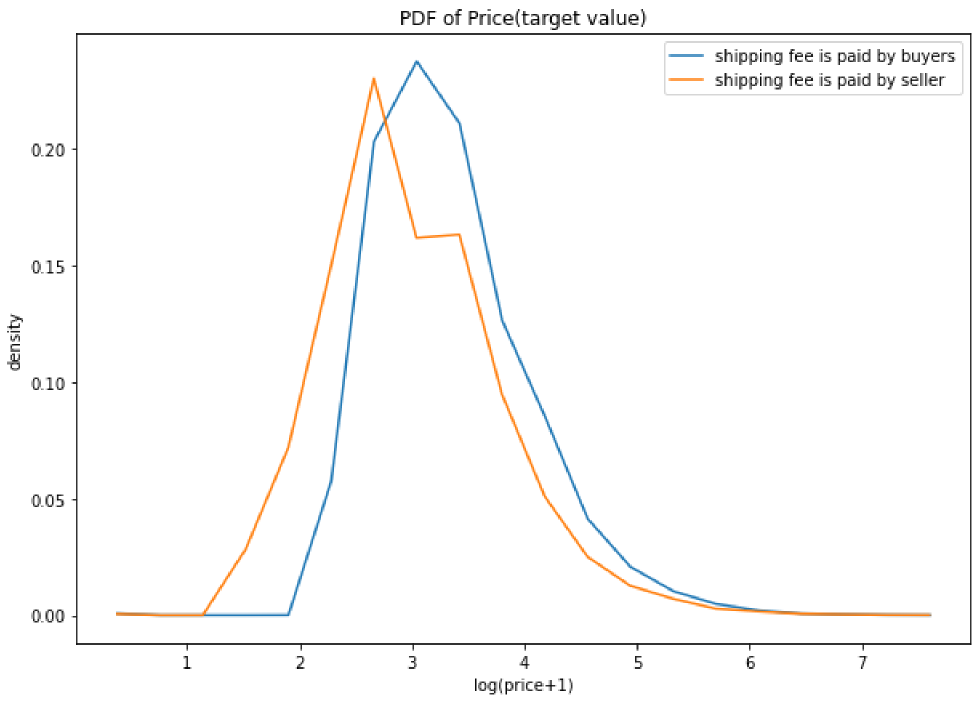
```
# 1 if shipping fee is paid by seller and 0 by buyer
data['shipping'].value_counts().plot(kind='bar')
plt.title('hist bars of shipping feature (categorial feature)')
plt.xlabel('shipping type')
plt.ylabel('count')
plt.show()
x=data['shipping'].value_counts()
print('shipping 0 :'+str(round(x[0]/sum(x)*100,2))+' %')
print('shipping 1 :'+str(round(x[1]/sum(x)*100,2))+' %')
```




```
shipping 0 :55.27 %
shipping 1 :44.73 %
```

In [ ]:

```
data['log_price']=np.log(data['price']+1)
shipping_0_price=data[data['shipping']==0]['log_price'].values
shipping_1_price=data[data['shipping']==1]['log_price'].values

plt.figure(figsize=(10, 7))
histogram, bins = np.histogram(shipping_0_price, bins=20, density=True)
#density = True, the result is the value of the probability density function at the bin
bin_centers = bins[1:]
pdf = histogram / sum(histogram)
plt.plot(bin_centers, pdf, label="shipping fee is paid by buyers")

histogram, bins = np.histogram(shipping_1_price, bins=20, density=True)
bin_centers = bins[1:]
pdf = histogram / sum(histogram)
plt.plot(bin_centers, pdf, label="shipping fee is paid by seller")

plt.xlabel('log(price+1)')
plt.ylabel('density')
plt.title('PDF of Price(target value)')
plt.legend()
plt.show()
```



Observation:

- PDF of log_price when shipping=1 is slightly left centred when compared with PDF of log_price when shipping=0
- From the above plot it is observed that most of the time shipping cost is paid by sellers when pricing of the item is low.
- Another takeaway from above plot is when price is high most of the times Shipping cost is paid by buyers.

Analysis of Item condition feature:

In [ ]:

```
item_cond=data['item_condition_id'].value_counts().to_frame()

item_cond['percentage_of_item_condition']=list(map(lambda x: round(x/data.shape[0]*100,2),item_cond['item_conc
item_cond=item_cond.reset_index()
item_cond.rename(columns={'index': 'item_cond_id', 'item_condition_id': 'cnt'}, inplace=True)
item_cond
```

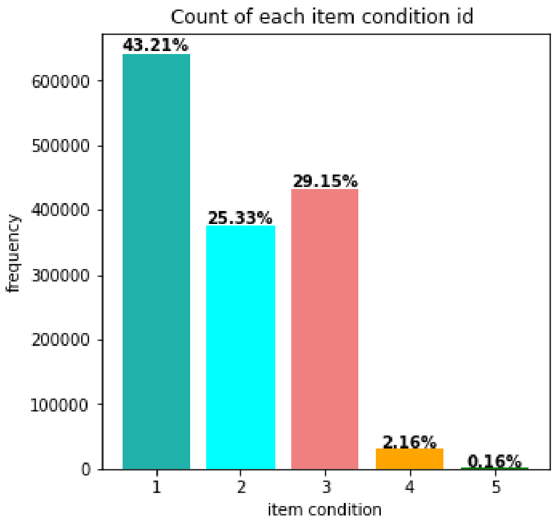
Out[ ]:

	item_cond_id	cnt	percentage_of_item_condition
0	1	640549	43.21
1	3	432161	29.15
2	2	375479	25.33
3	4	31962	2.16
4	5	2384	0.16

In [ ]:

```
#reference: https://www.geeksforgeeks.org/display-percentage-above-bar-chart-in-matplotlib/


plt.figure(figsize=(5, 5))

colors_list = ['#20B2AA','#F08080', '#00FFFF', 'Orange','Green']

graph = plt.bar(item_cond.item_cond_id,item_cond.cnt, color = colors_list)
plt.title('Count of each item condition id ')
plt.xlabel('item condition')
plt.ylabel('frequency')

i = 0
for p in graph:
 width = p.get_width()
 height = p.get_height()
 x, y = p.get_xy()
```

```
    plt.text(x+width/2,
      y+height*1.01,
      str(item_cond.percentage_of_item_condition[i])+'%',
      ha='center',
      weight='bold')
    i+=1
plt.show()
```

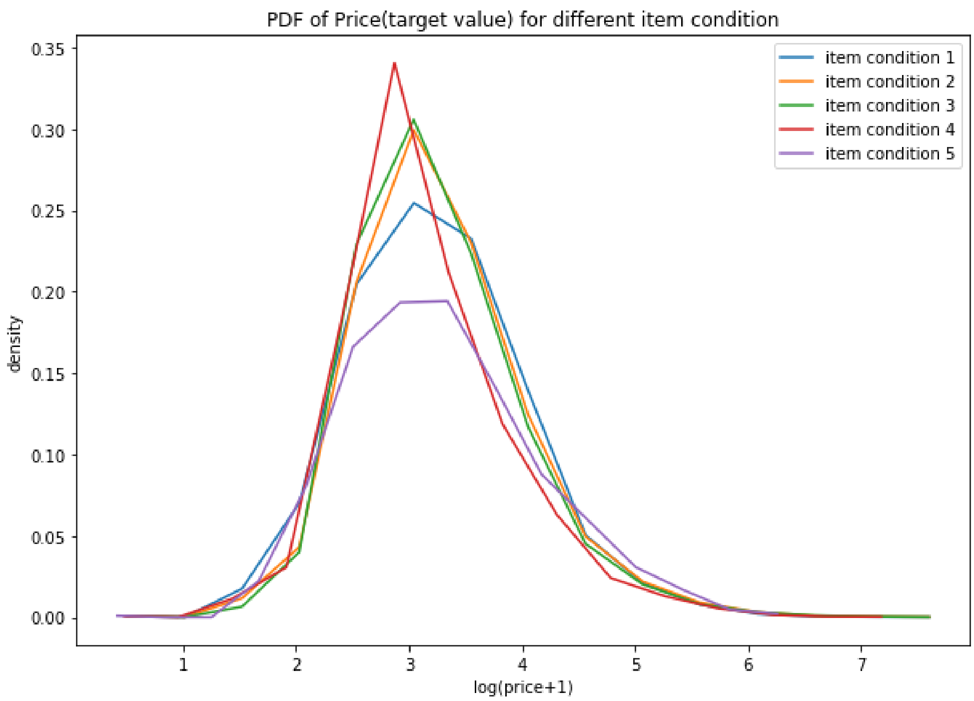


Observation:

- 43.2% of the item have been rated as 1.
- There are fewer item with item condition as 4 and 5.

In [ ]:

```
plt.figure(figsize=(10, 7))

for i in [1,2,3,4,5]:
  histogram, bins = np.histogram(data[data['item_condition_id']==i]['log_price'], bins=15, density=True)
  #density = True, the result is the value of the probability density function at the bin
  bin_centers = bins[1:]
  pdf = histogram / sum(histogram)
  plt.plot(bin_centers, pdf, label='item condition '+str(i))

plt.xlabel('log(price+1)')
plt.ylabel('density')
plt.title('PDF of Price(target value) for different item condition')
plt.legend()
plt.show()
```



Obervation:

- PDF of log(price+1) for different the item condition is ploted above. *These PDF's are overlapping, no conclusion can be drawn from this plot.

Analysis of Brand name feature:

In [ ]:

```
print('Total number of unique Brands :',len(data['brand_name'].unique()))  # including NAN
```

```
Total number of unique Brands : 4810
```

In [ ]:

```
count_of_NAN=sum(data['brand_name'].isnull().values)
print('Total number of missing values in brand field',count_of_NAN)
print('\nPercentage of missing values :',round((count_of_NAN/data.shape[0])*100,2))
```

```
Total number of missing values in brand field 632682

Percentage of missing values : 42.68
```

In [ ]:

```
# filling the missing values with "not known"

data['brand_name'].fillna(value='not known', inplace=True)
```

In [ ]:

```
data['brand_name']=data['brand_name'].str.lower()
brand_df=data['brand_name'].value_counts().to_frame().reset_index()
brand_df.rename(columns={'index': 'Brand', 'brand_name': 'cnt'}, inplace=True)
brand_df['percentage_of_brand']=list(map(lambda x:round(x/data.shape[0]*100,2),brand_df['cnt'].values))
brand_df.head(10)
```

Out[ ]:

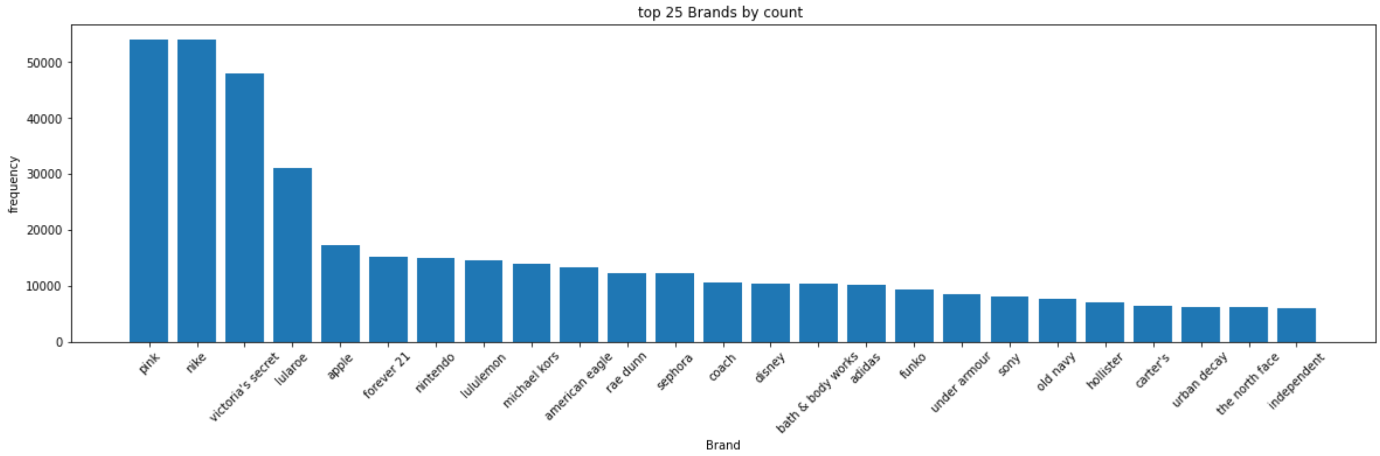
	Brand	cnt	percentage_of_brand
0	not known	632682	42.68
1	pink	54088	3.65
2	nike	54043	3.65
3	victoria's secret	48036	3.24
4	lularoe	31024	2.09
5	apple	17322	1.17
6	forever 21	15186	1.02
7	nintendo	15007	1.01
8	lululemon	14558	0.98
9	michael kors	13928	0.94

In [ ]:

```
plt.figure(figsize=(20, 5))

plt.bar(brand_df.Brand[1:26],brand_df.cnt[1:26]) # ignoring "not known" values
plt.title('top 25 Brands by count ')
plt.xticks(rotation=45)
plt.xlabel('Brand')
plt.ylabel('frequency')
```

Out[ ]:

```
Text(0, 0.5, 'frequency')
```



Observation:

- Top 3 Brands by count are pink,nike and victoria's secret.These 3 Brands cover 10% of over dataset.
- Their are few elctronic brand in top 25 by count like apple, sony.

In [ ]:

```
brand_df=brand_df.merge(data[['brand_name','price']].groupby(by='brand_name').mean(), how='inner', left_on='Br
brand_df.rename(columns={'price': 'mean_price'}, inplace=True)
brand_df=brand_df.merge(data[['brand_name','price']].groupby(by='brand_name').median(), how='inner', left_on=
brand_df.rename(columns={'price': 'median_price'}, inplace=True)
brand_df.head(10)
```

Out[ ]:

	Brand	cnt	percentage_of_brand	mean_price	median_price
0	not known	632682	42.68	21.133453	14.0
1	pink	54088	3.65	26.341314	20.0
2	nike	54043	3.65	30.760265	22.0
3	victoria's secret	48036	3.24	23.214287	19.0
4	lularoe	31024	2.09	33.667967	29.0
5	apple	17322	1.17	73.268618	22.0
6	forever 21	15186	1.02	12.929935	12.0
7	nintendo	15007	1.01	34.672619	20.0
8	lululemon	14558	0.98	47.096717	39.0
9	michael kors	13928	0.94	62.254775	49.0

In [ ]:

```
brand_df=brand_df.merge(data[['brand_name','price']].groupby(by='brand_name').max(), how='inner', left_on='Bra
brand_df.rename(columns={'price': 'max_price'}, inplace=True)
brand_df=brand_df.merge(data[['brand_name','price']].groupby(by='brand_name').min(), how='inner', left_on='Bra
brand_df.rename(columns={'price': 'min_price'}, inplace=True)
brand_df.head(20)
```

Out[ ]:

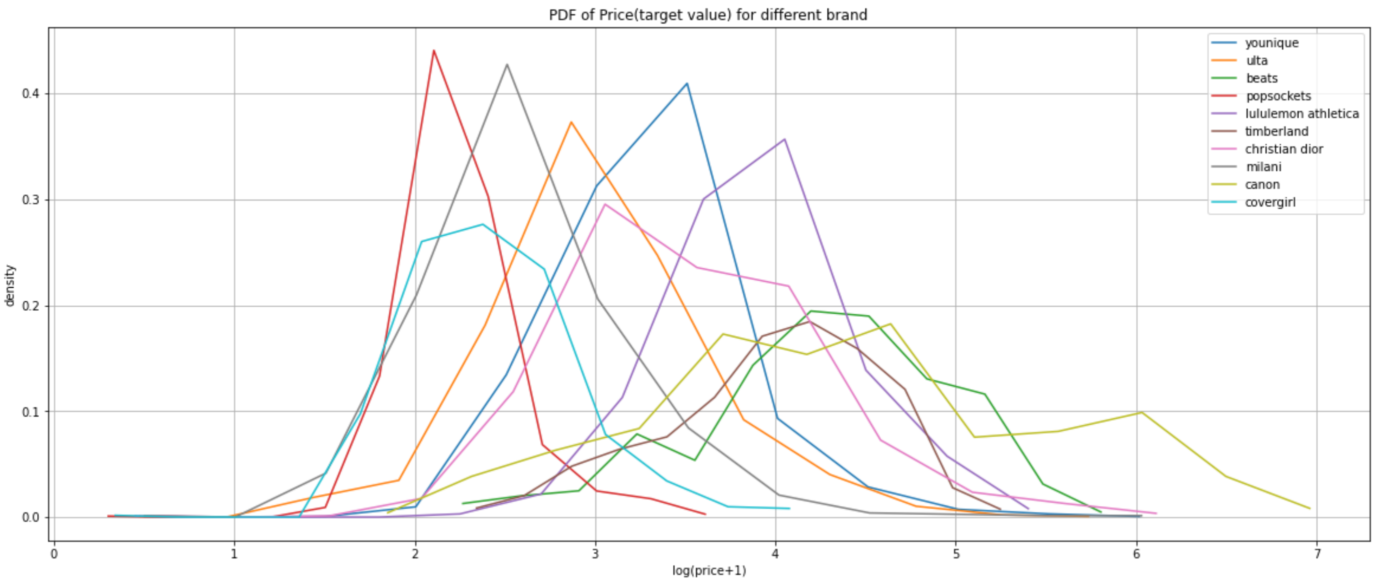
	Brand	cnt	percentage_of_brand	mean_price	median_price	max_price	min_price
0	not known	632682	42.68	21.133453	14.0	2000.0	0.0
1	pink	54088	3.65	26.341314	20.0	798.0	0.0
2	nike	54043	3.65	30.760265	22.0	459.0	0.0
3	victoria's secret	48036	3.24	23.214287	19.0	1400.0	0.0
4	lularoe	31024	2.09	33.667967	29.0	350.0	0.0
5	apple	17322	1.17	73.268618	22.0	1909.0	0.0
6	forever 21	15186	1.02	12.929935	12.0	180.0	0.0
7	nintendo	15007	1.01	34.672619	20.0	600.0	0.0
8	lululemon	14558	0.98	47.096717	39.0	711.0	0.0
9	michael kors	13928	0.94	62.254775	49.0	1770.0	0.0
10	american eagle	13254	0.89	15.960955	14.0	210.0	0.0
11	rae dunn	12305	0.83	37.170581	30.0	490.0	0.0
12	sephora	12172	0.82	21.820613	16.0	613.0	0.0
13	coach	10463	0.71	41.142550	31.0	720.0	0.0
14	disney	10360	0.70	17.146670	13.0	506.0	0.0
15	bath & body works	10354	0.70	17.905737	14.0	565.0	0.0
16	adidas	10202	0.69	43.127328	25.0	950.0	0.0
17	funko	9237	0.62	29.054888	20.0	775.0	0.0
18	under armour	8461	0.57	19.367923	16.0	356.0	0.0
19	sony	7994	0.54	35.466662	19.0	750.0	0.0

Observation:

- From the above table it was observed that there are items in the brands(top 20) which are priced as zero.
- Their are brands whose item pricing fall in large range like victoria's secret, apple, michael kors.

In [ ]:

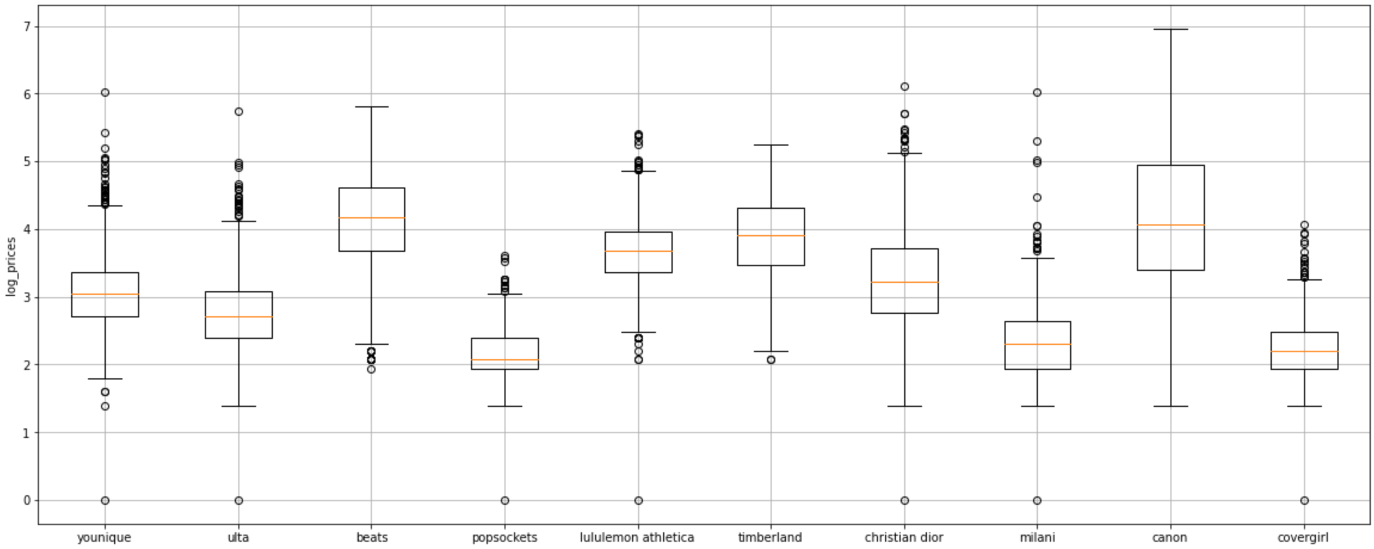
```
plt.figure(figsize=(20, 8))

gf=data[['brand_name','price','log_price']].groupby(by='brand_name',sort=False)

lt_brand=brand_df['Brand'][100:200:10].values #some random brand name

tmp_brand=[]
tmp_brand_price=[]
for i in lt_brand:
  temp=gf.get_group(i)
  #display(i)
  #print(type(temp))
  lg_price=temp['log_price'].values
  histogram, bins = np.histogram(lg_price, bins=12, density=True)
  #density = True, the result is the value of the probability density function at the bin
  bin_centers = bins[1:]
  pdf = histogram / sum(histogram)

  plt.plot(bin_centers, pdf, label=i)
  tmp_brand.append(i)
  tmp_brand_price.append(lg_price)




plt.xlabel('log(price+1)')
plt.ylabel('density')
plt.title('PDF of Price(target value) for different brand')
plt.legend()
plt.grid()
plt.show()
```



In [ ]:

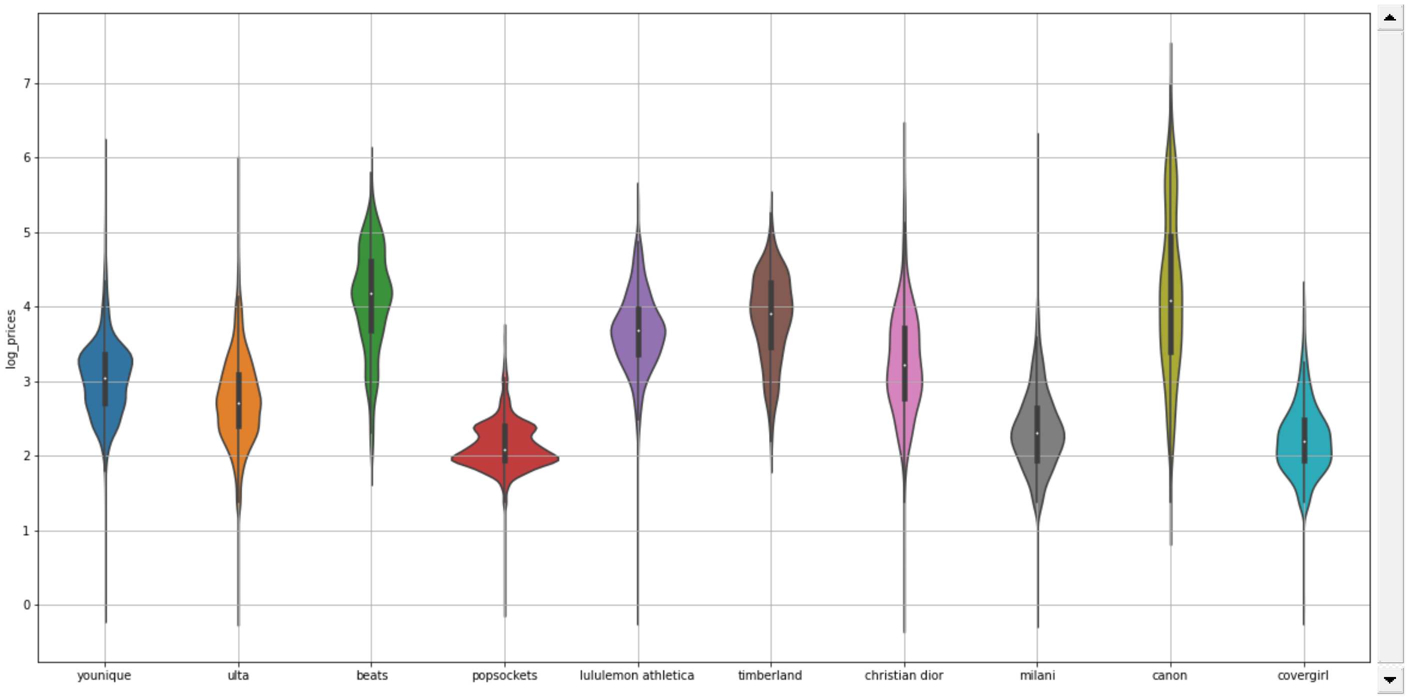
```
plt.figure(figsize=(20, 8))
plt.boxplot(tmp_brand_price)
plt.xticks(list(range(1,len(tmp_brand)+1)),tmp_brand)
plt.ylabel('log_prices')
plt.grid()
plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/matplotlib/cbook/__init__.py:1376: VisibleDeprecationWarning: Creating an ndarray from ragged nested sequences (which is a list-or-tuple of lists-or-tuples-or ndarrays with different lengths or shapes) is deprecated. If you meant to do this, you must specify 'dtype=object' when creating the ndarray.
  X = np.atleast_1d(X.T if isinstance(X, np.ndarray) else np.asarray(X))
```



In [ ]:

```
import seaborn as sns

plt.figure(figsize=(20,10))
sns.violinplot(data=tmp_brand_price)
plt.xticks(list(range(0,len(tmp_brand))),tmp_brand)
plt.ylabel('log_prices')
plt.grid()
plt.show()
```



Observatoin:

- From the above 3 plot, we can say that different brand have different target value distribution.
- There are brand like canon which spread over wide range of pricing.
- Brand name field do contain some important information as target values of different brand have different distribution.

Analysis of category_name feature:

In [ ]:

```
print('Total number of unique category name : ',len(data['category_name'].unique()))
```

```
Total number of unique category name :  1288
```

In [ ]:

```
data['category_name'].value_counts().to_frame()
```

Out[ ]:

	category_name
Women/Athletic Apparel/Pants, Tights, Leggings	60177
Women/Tops & Blouses/T-Shirts	46380
Beauty/Makeup/Face	34335
Beauty/Makeup/Lips	29910
Electronics/Video Games & Consoles/Games	26557
...	...
Handmade/Dolls and Miniatures/Primitive	1
Handmade/Pets/Tag	1
Handmade/Patterns/Accessories	1
Home/Kids' Home Store/Nursery Furniture	1
Handmade/Pets/Blanket	1

1287 rows × 1 columns

In [ ]:

```
data['category_name'].value_counts().to_frame().head(10)
```

Out[ ]:

	category_name
Women/Athletic Apparel/Pants, Tights, Leggings	60177
Women/Tops & Blouses/T-Shirts	46380
Beauty/Makeup/Face	34335
Beauty/Makeup/Lips	29910
Electronics/Video Games & Consoles/Games	26557
Beauty/Makeup/Eyes	25215
Electronics/Cell Phones & Accessories/Cases, Covers & Skins	24676
Women/Underwear/Bras	21274
Women/Tops & Blouses/Blouse	20284
Women/Tops & Blouses/Tank, Cami	20284

Observation:

- Total number of unique category name = 1287
- Most of the categories are related to woman accessories in top 10 by count.
- By looking at the Category name field contain three aspect, which are separeted by '/'.

In [ ]:

```
# splitting the category_name field into 3 fields main_cat_1, sub_cat_2, sub_cat_3
def len_fun(x):
  try:

    return x.split('/',3)
  except:

    return 'no label','no label','no label'

temp_category_name = data['category_name'].apply(lambda x: len_fun(x))

data['main_cat_1'],data['sub_cat_2'],data['sub_cat_3']=zip(*temp_category_name)
```

In [ ]:

```
data.head()
```

Out[ ]:

	train_id	name	item_condition_id	category_name	brand_name	price	shipping	item_description	log_price	main_cat_1	sub_ca
0	0	MLB Cincinnati Reds T Shirt Size XL	3	Men/Tops/T-shirts	not known	10.0	1	No description yet	2.397895	Men	T
1	1	Razer BlackWidow Chroma Keyboard	3	Electronics/Computers & Tablets/Components & P...	razer	52.0	0	This keyboard is in great condition and works ...	3.970292	Electronics	Comput & Tabl
2	2	AVA-VIV Blouse	1	Women/Tops & Blouses/Blouse	target	10.0	1	Adorable top with a hint of lace and a key hol...	2.397895	Women	Top Blou
3	3	Leather Horse Statues	1	Home/Home Décor/Home Décor Accents	not known	35.0	1	New with tags. Leather horses. Retail for [rm]...	3.583519	Home	Ho Dé
4	4	24K GOLD plated rose	1	Women/Jewelry/Necklaces	not known	44.0	0	Complete with certificate of authenticity	3.806662	Women	Jewe

In [ ]:

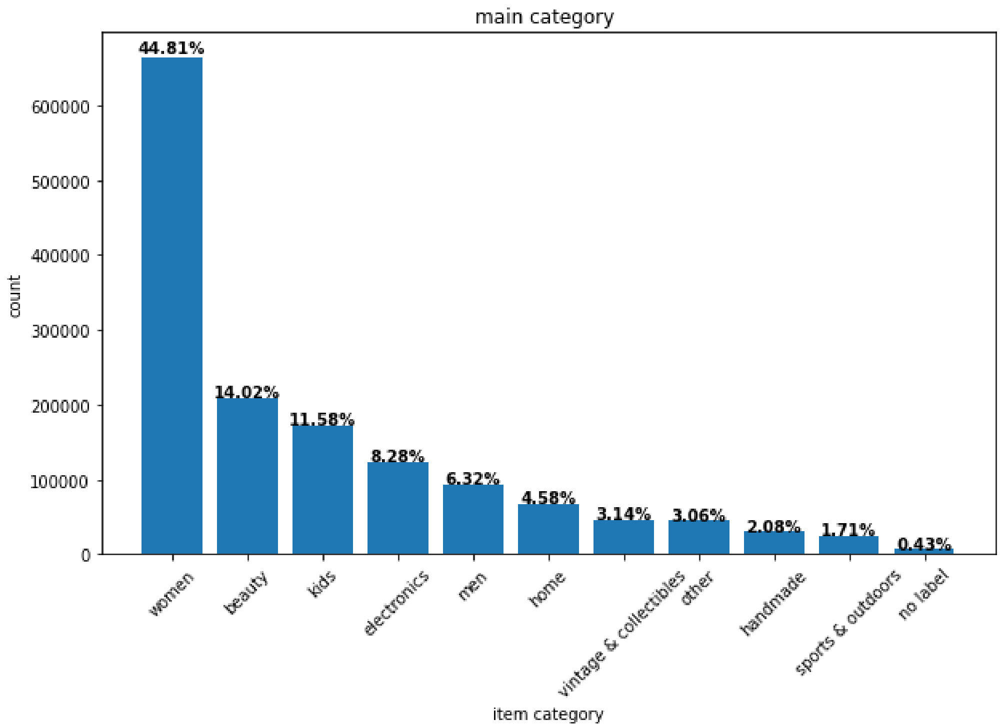
```
data['main_cat_1']=data['main_cat_1'].str.lower()
category_name_df=data['main_cat_1'].value_counts().to_frame().reset_index()
category_name_df.rename(columns={'index': 'main_category_name', 'main_cat_1': 'cnt'}, inplace=True)
category_name_df['percentage_of_category_name']=list(map(lambda x:round(x/data.shape[0]*100,2),category_name_
category_name_df
```

Out[ ]:

	main_category_name	cnt	percentage_of_category_name
0	women	664385	44.81
1	beauty	207828	14.02
2	kids	171689	11.58
3	electronics	122690	8.28
4	men	93680	6.32
5	home	67871	4.58
6	vintage & collectibles	46530	3.14
7	other	45351	3.06
8	handmade	30842	2.08
9	sports & outdoors	25342	1.71
10	no label	6327	0.43

In [ ]:

```
#reference: https://www.geeksforgeeks.org/display-percentage-above-bar-chart-in-matplotlib/

plt.figure(figsize=(10, 6))

graph = plt.bar(category_name_df.main_category_name,category_name_df.cnt)
plt.title('main category ')
plt.xlabel('item category')
plt.ylabel('count')
plt.xticks(rotation=45)
i = 0
for p in graph:
 width = p.get_width()
 height = p.get_height()
 x, y = p.get_xy()
 plt.text(x+width/2,
   y+height*1.01,
   str(category_name_df.percentage_of_category_name[i])+'%',
   ha='center',
   weight='bold')
 i+=1
plt.show()
```

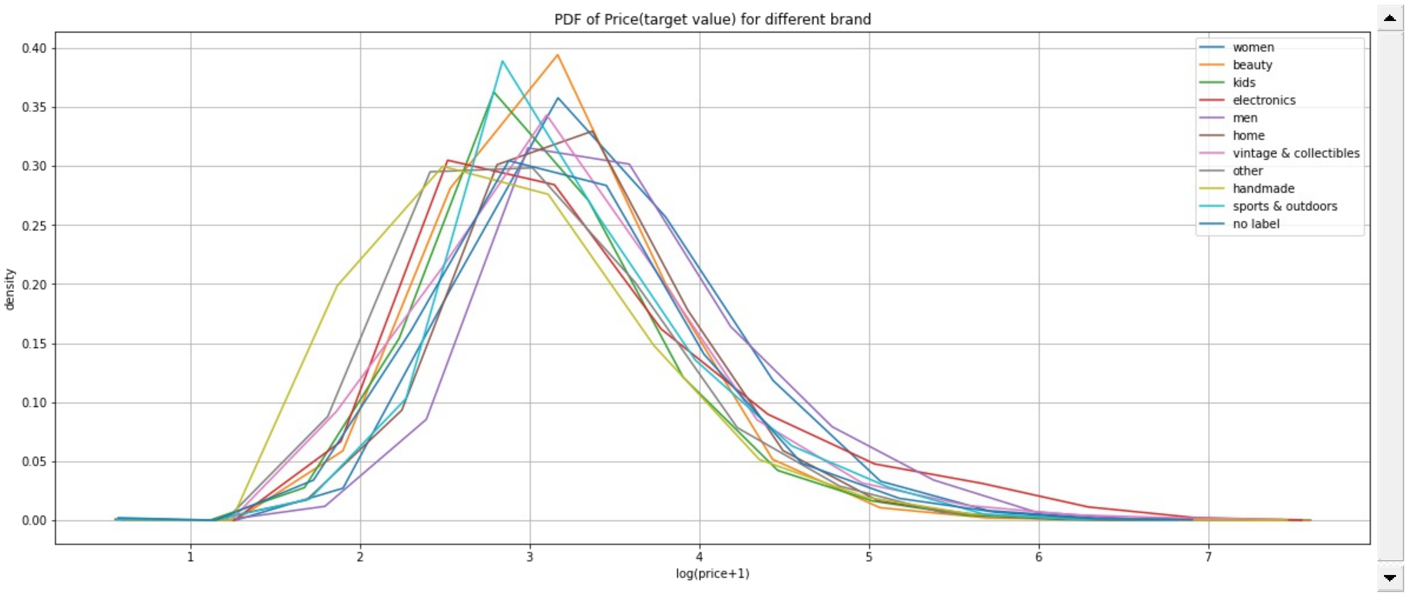


Observation:

- 44.8% of the item in the dataset are related to women.

In [ ]:

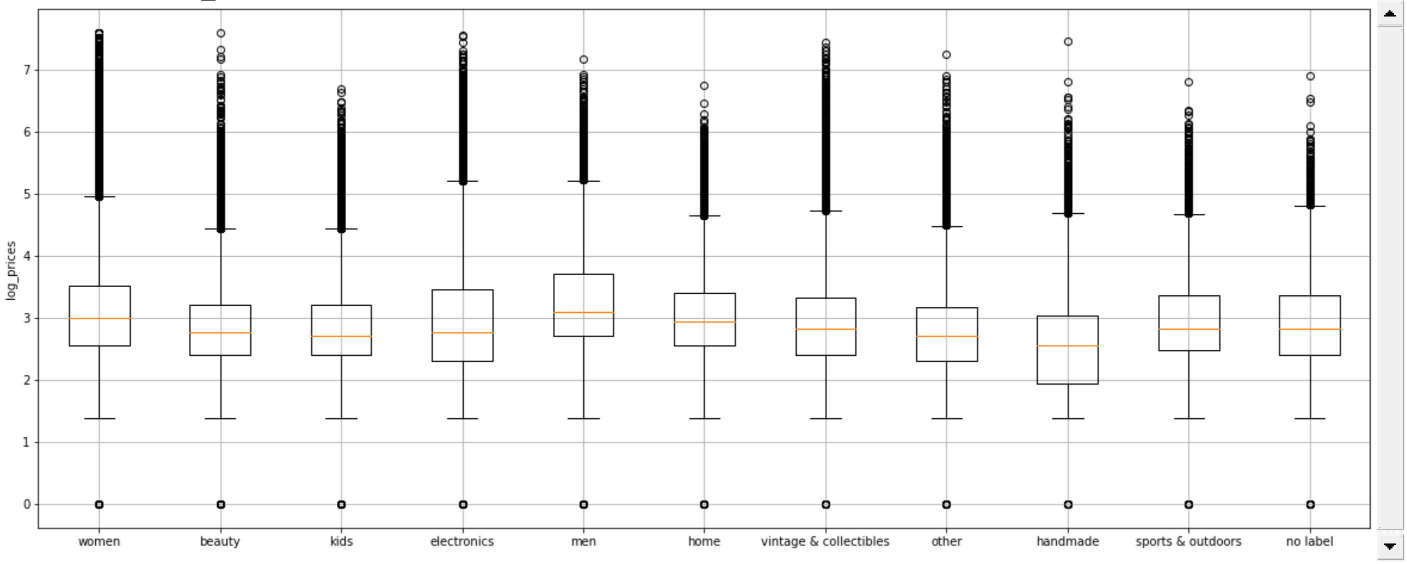
```
plt.figure(figsize=(20, 8))
tmp_cat_name=[]
tmp_cat_price=[]
for i in category_name_df.main_category_name.values:

  lg_price=data[data['main_cat_1']==i]['log_price']

  histogram, bins = np.histogram(lg_price, bins=12, density=True)
  #density = True, the result is the value of the probability density function at the bin
  bin_centers = bins[1:]
  pdf = histogram / sum(histogram)

  plt.plot(bin_centers, pdf, label=i)
  tmp_cat_name.append(i)
  tmp_cat_price.append(lg_price)



plt.xlabel('log(price+1)')
plt.ylabel('density')
plt.title('PDF of Price(target value) for different brand')
plt.legend()
plt.grid()
plt.show()
```



In [ ]:

```
plt.figure(figsize=(20, 8))
plt.boxplot(tmp_cat_price)
plt.xticks(list(range(1,len(tmp_cat_name)+1)),tmp_cat_name)
plt.ylabel('log_prices')
plt.grid()
plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/matplotlib/cbook/__init__.py:1376: VisibleDeprecationWarning: Creating an ndarray from ragged nested sequences (which is a list-or-tuple of lists-or-tuples-or ndarrays with different lengths or shapes) is deprecated. If you meant to do this, you must specify 'dtype=object' when creating the ndarray.
  X = np.atleast_1d(X.T if isinstance(X, np.ndarray) else np.asarray(X))
```



Observation:

- From the above 2 plots, no major takeaway as these distributions are overlapping

In [ ]:

```
data['sub_cat_2']=data['sub_cat_2'].str.lower()
sub_cat_name_df=data['sub_cat_2'].value_counts().to_frame().reset_index()
sub_cat_name_df.rename(columns={'index': 'sub_cat_2', 'sub_cat_2': 'cnt'}, inplace=True)
sub_cat_name_df['percentage_of_sub_category_name']=list(map(lambda x:round(x/data.shape[0]*100,2),sub_cat_name
sub_cat_name_df
```

Out[ ]:

	sub_cat_2	cnt	percentage_of_sub_category_name
0	athletic apparel	134383	9.06
1	makeup	124624	8.41
2	tops & blouses	106960	7.21
3	shoes	100452	6.78
4	jewelry	61763	4.17
...	...	...	...
109	candles	64	0.00
110	ceramics and pottery	57	0.00
111	dolls and miniatures	49	0.00
112	books and zines	46	0.00
113	quilts	31	0.00

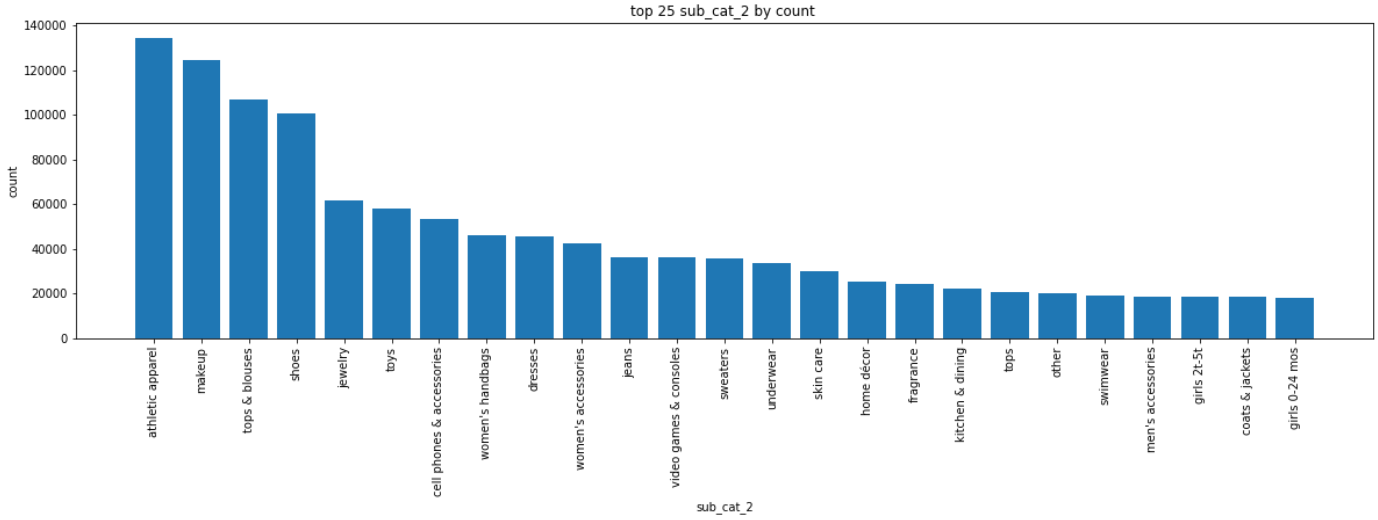
114 rows × 3 columns

In [ ]:

```
plt.figure(figsize=(20, 5))

plt.bar(sub_cat_name_df.sub_cat_2[:25],sub_cat_name_df.cnt[:25])
plt.title('top 25 sub_cat_2 by count ')
plt.xticks(rotation=90)
plt.xlabel('sub_cat_2')
plt.ylabel('count')
```

Out[ ]:

```
Text(0, 0.5, 'count')
```



In [ ]:

```
data['sub_cat_3']=data['sub_cat_3'].str.lower()
sub_cat_name_df=data['sub_cat_3'].value_counts().to_frame().reset_index()
sub_cat_name_df.rename(columns={'index': 'sub_cat_3', 'sub_cat_3': 'cnt'}, inplace=True)
sub_cat_name_df['percentage_of_sub_category_name']=list(map(lambda x:round(x/data.shape[0]*100,2),sub_cat_name
sub_cat_name_df
```

Out[ ]:

	sub_cat_3	cnt	percentage_of_sub_category_name
0	t-shirts	61488	4.15
1	pants, tights, leggings	60177	4.06
2	other	50224	3.39
3	face	50171	3.38
4	shoes	32168	2.17
...	...	...	...
865	st patricks	1	0.00
866	garbage disposals	1	0.00
867	decorating	1	0.00
868	pet food	1	0.00
869	ephemera	1	0.00

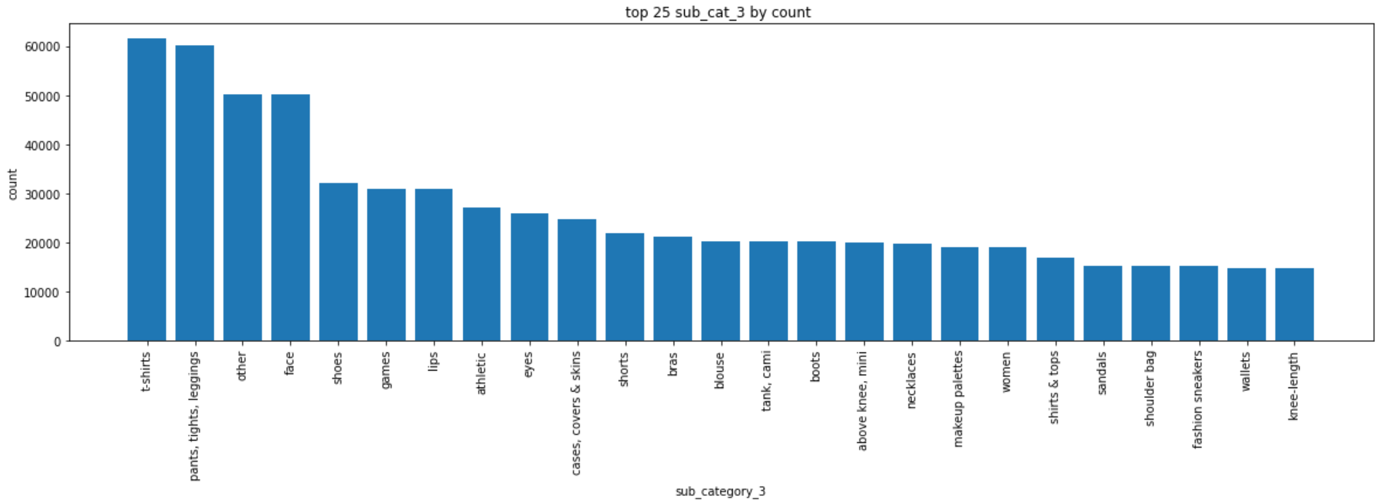
870 rows × 3 columns

In [ ]:

```
plt.figure(figsize=(20, 5))

plt.bar(sub_cat_name_df.sub_cat_3[:25],sub_cat_name_df.cnt[:25])
plt.title('top 25 sub_cat_3 by count ')
plt.xticks(rotation=90)
plt.xlabel('sub_category_3')
plt.ylabel('count')
```

Out[ ]:

```
Text(0, 0.5, 'count')
```



Observation:

- number of Unique categories in sub_category_3 : 870
- Most of the items in top 25 are clothing related items.

Analysis of name field:

In [ ]:

```
# reference https://www.geeksforgeeks.org/generating-word-cloud-python/

from wordcloud import WordCloud

txt=' '.join(data['name'].str.lower().values)

wordcloud = WordCloud(width = 800, height = 800,max_words=500,
                background_color ='white',min_font_size = 10).generate(txt)

# plot the WordCloud image
plt.figure(figsize = (8, 8), facecolor = None)
plt.imshow(wordcloud)
plt.axis("off")
plt.tight_layout(pad = 0)

plt.show()
```

Observation:

- From the above world cloud, we can see few frequent words that sellers are using like "FREE shipping","Brand new" in the name field.
- Brand names like "PINK", "Victoria Secret", "America Eagle","Nike" are most frequently observed in the name field.
- Apple products like "iPhone 5s","iPhone 6s","6s plus" seems to be mostly sold electronic item by the sellers.

In [ ]:

```
no_of_words=data['name'].str.split().apply(len)
temp=no_of_words.value_counts().to_frame().reset_index()
temp.rename(columns={'index': 'no_of_words', 'name': 'cnt'}, inplace=True)
temp
```

Out[ ]:

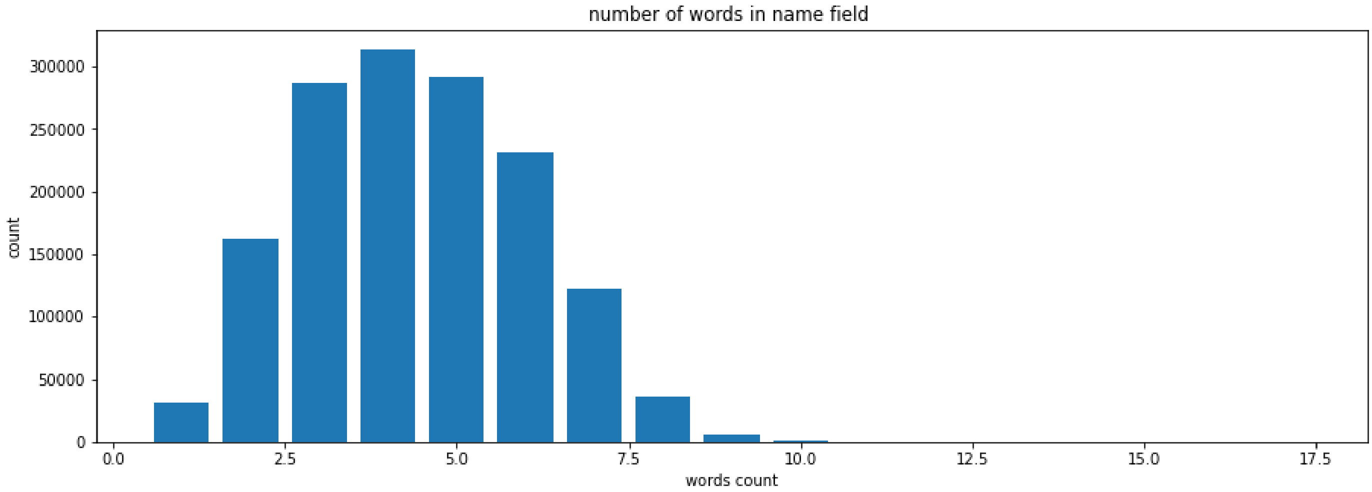
	no_of_words	cnt
0	4	313585
1	5	291636
2	3	287424
3	6	231559
4	2	161912
5	7	121641
6	8	35970
7	1	31620
8	9	6385
9	10	722
10	11	67
11	12	7
12	13	5
13	17	1
14	14	1

In [ ]:

```
plt.figure(figsize=(15, 5))

plt.bar(temp.no_of_words,temp.cnt)
plt.title('number of words in name field ')
#plt.xticks(rotation=90)
plt.xlabel('words count')
plt.ylabel('count')
```

Out[ ]:

```
Text(0, 0.5, 'count')
```



Observation:

- Most of the sellars have used 3 to 6 words in the name field

Analysis of item_description field:

In [ ]:

```
print('Number of null values :',sum(data['item_description'].isnull()))
```

```
Number of null values : 4
```

In [ ]:

```
# filling the null values with no data
data['item_description'].fillna(value='no data',inplace=True)
```

In [ ]:

```
# reference https://www.geeksforgeeks.org/generating-word-cloud-python/

from wordcloud import WordCloud

txt=' '.join(data['item_description'].str.lower().values)

wordcloud = WordCloud(width = 800, height = 800,max_words=500,
                background_color ='white',min_font_size = 10).generate(txt)

# plot the WordCloud image
plt.figure(figsize = (8, 8), facecolor = None)
plt.imshow(wordcloud)
plt.axis("off")
plt.tight_layout(pad = 0)

plt.show()
```

Observation:

- Sellers have used words like "good condition","great condition","perfect condition","never used","never worn","brand new","excellent condition","never opened" to describe the condition of the item.
- "save shipping","free shipping","free home" these words are used by sellers ,this means sellars are willing to pays for shipping

In [ ]:

```
no_of_words=data['item_description'].str.split().apply(len)
temp=no_of_words.value_counts().to_frame().reset_index()
temp.rename(columns={'index': 'no_of_words', 'item_description': 'cnt'}, inplace=True)
temp
```

Out[ ]:

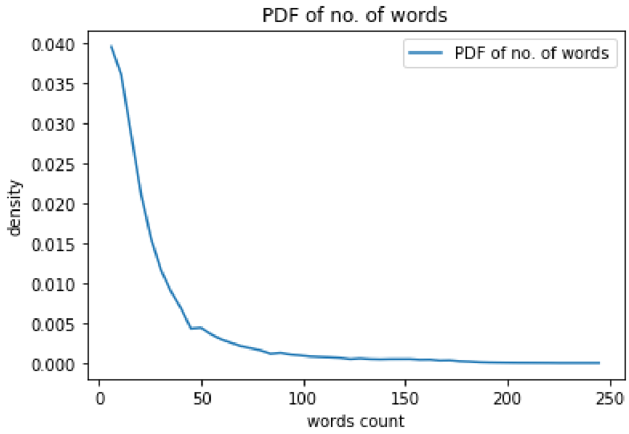
	no_of_words	cnt
0	3	121909
1	6	55542
2	7	53822
3	8	53201
4	4	52640
...	...	...
223	235	1
224	245	1
225	242	1
226	230	1
227	234	1

228 rows × 2 columns

In [ ]:

```
histogram, bins = np.histogram(no_of_words.values, bins=50, density=True)
#density = True, the result is the value of the probability density function at the bin

bin_centers = bins[1:]
```

```
plt.plot(bin_centers, histogram, label="PDF of no. of words")
plt.xlabel('words count')
plt.ylabel('density')
plt.title('PDF of no. of words')
plt.legend()
plt.show()
```

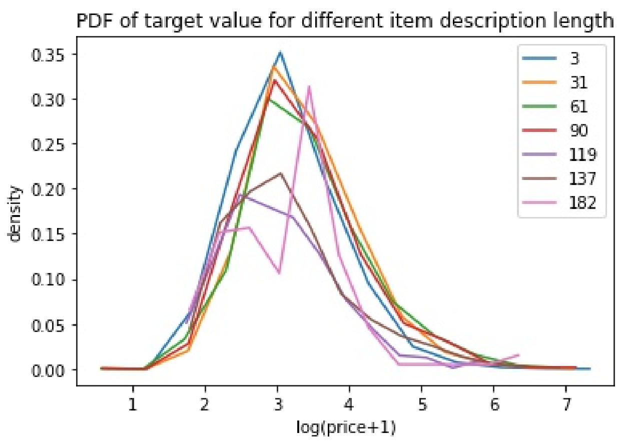


Observation:

- From the above we can say that most of the item description have 3 to 50 words.
- Their are only few item description with 100 to 250 words.

In [ ]:

```
data['no_of_words_in_item_description']=data['item_description'].str.split().apply(len)

for i in temp['no_of_words'].values[:200:30]:

  lg_price = data[data['no_of_words_in_item_description']==i]['log_price'].values
  histogram, bins = np.histogram(lg_price, bins=12, density=True)
  #density = True, the result is the value of the probability density function at the bin
  bin_centers = bins[1:]
  pdf = histogram / sum(histogram)
  plt.plot(bin_centers, pdf, label=i)




plt.xlabel('log(price+1)')
plt.ylabel('density')
plt.title('PDF of target value for different item description length')
plt.legend()
plt.show()
```



Observation:

- The above is the plot of PDF's of target value for different number of words in item description.
- Since the PDF's are overlapping, no takeaway, we need to come up with some feature engineering.

In [ ]:

In [ ]:

```
data.columns
```

Out[ ]:

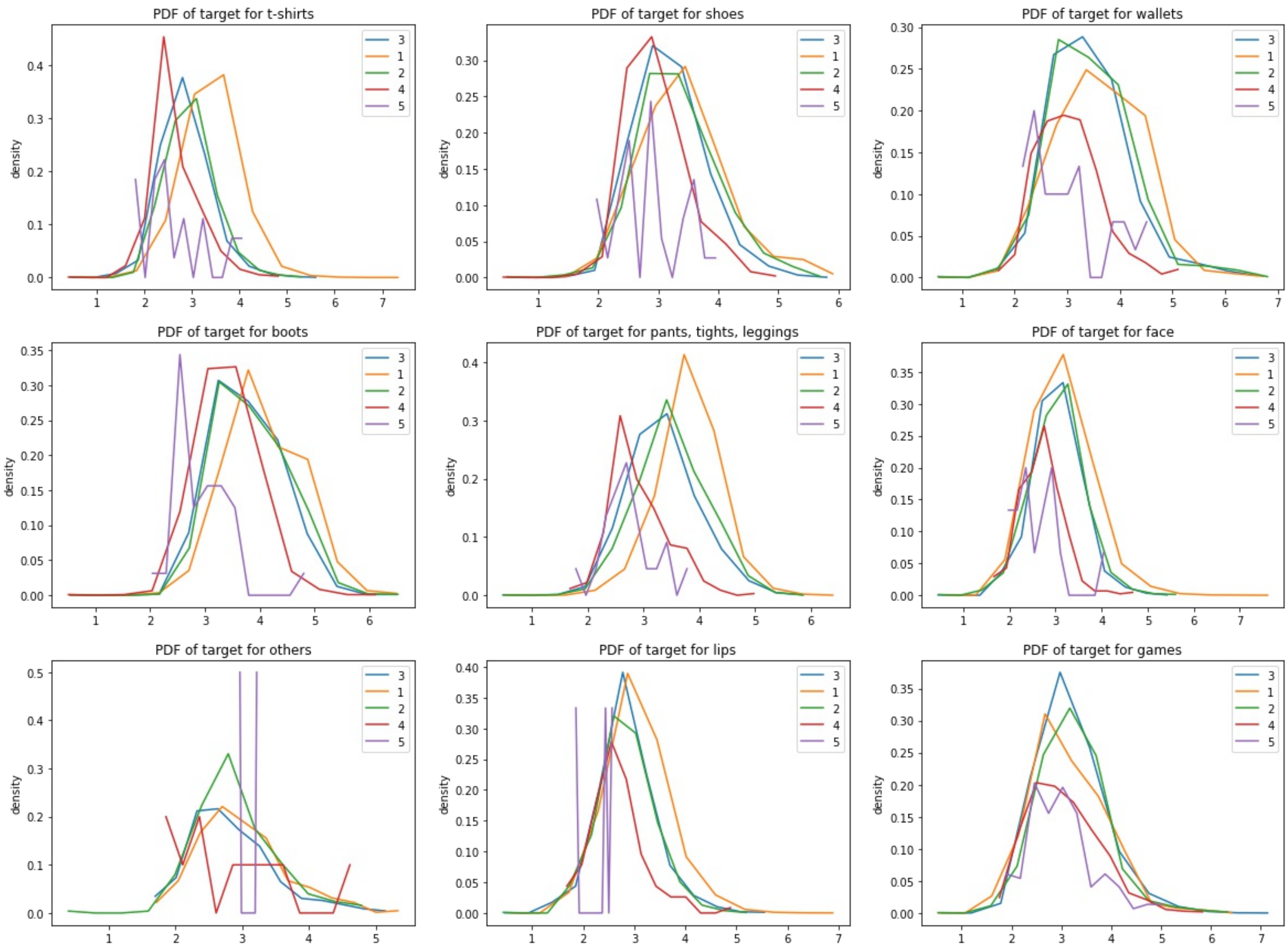
```
Index(['train_id', 'name', 'item_condition_id', 'category_name', 'brand_name',
       'price', 'shipping', 'item_description', 'log_price', 'main_cat_1',
       'sub_cat_2', 'sub_cat_3', 'no_of_words_in_item_description'],
      dtype='object')
```

Interaction features:

item condition & sub category 3

In [ ]:

```
plt.figure(figsize=(20, 15))

for index,j in enumerate(['t-shirts','shoes','wallets','boots','pants, tights, leggings','face','others','lips
  #print(index)
  plt.subplot(3,3,index+1)
  for i in data['item_condition_id'].unique():

    lg_price=data[(data['item_condition_id']==i) & (data['sub_cat_3']==j)]['log_price']
    #lg_price = data[data['no_of_words_in_item_description']==i]['log_price'].values
    histogram, bins = np.histogram(lg_price, bins=12, density=True)
    #density = True, the result is the value of the probability density function at the bin
    bin_centers = bins[1:]
    pdf = histogram / sum(histogram)



    plt.plot(bin_centers, pdf, label=i)

  #plt.xlabel('log(price+1)')
  plt.ylabel('density')
  plt.title('PDF of target for '+str(j))
  plt.legend()
plt.show()
```



Observation:

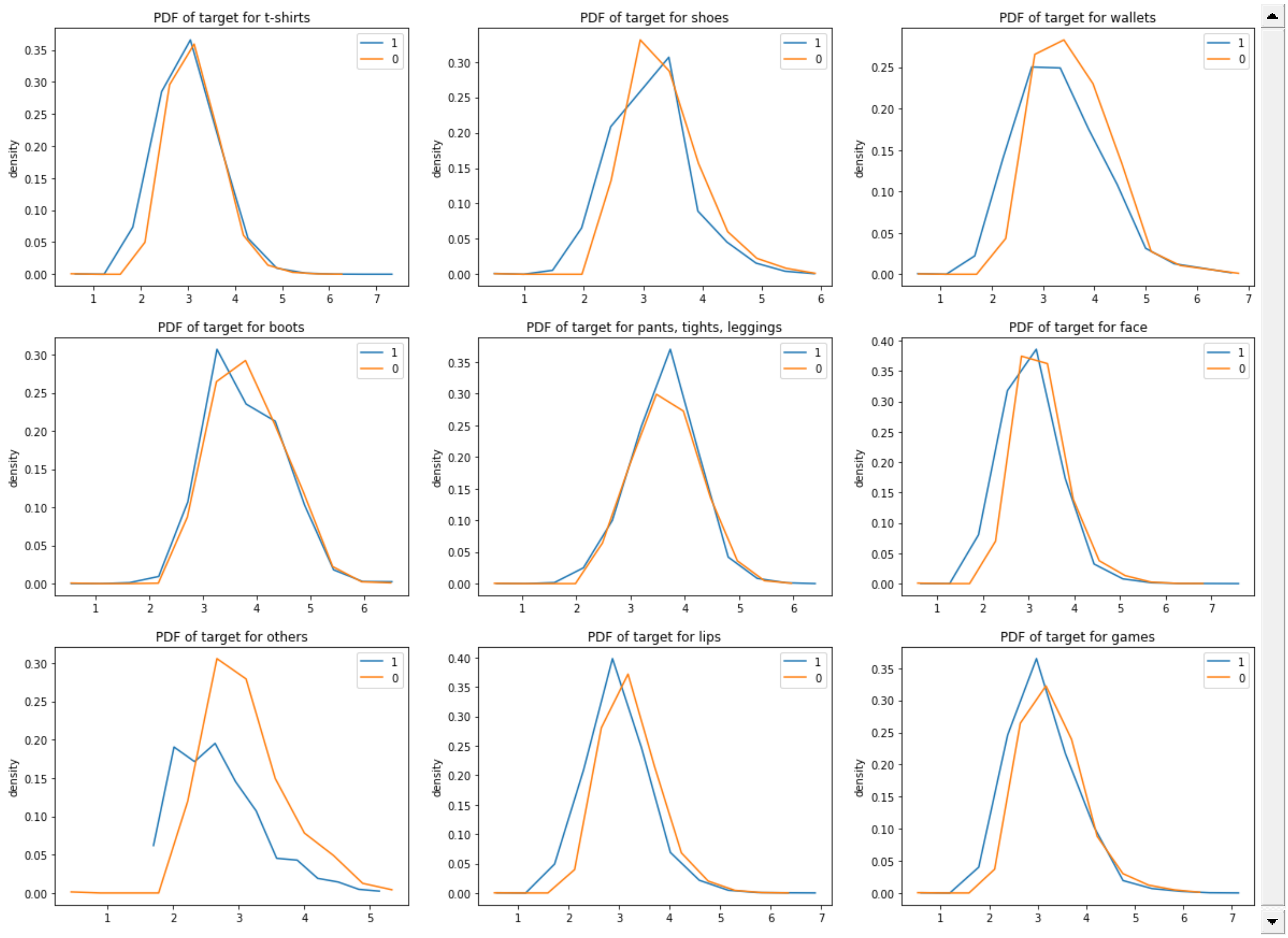
- Above are the plots of PDF's of few sub_category_3 for different item condition id.
- if we observe PDF's of 't-shirts', 'wallets', 'pants,tights,leggings','boots','face' , their is slight shift in pdf's of different item condition.
- item condition id = 1 ,is price higher then item condition id = 5.Which indicates products with item conditoin id=1 are good condition compared to the products with item conditoin id=5.

Interaction feature

shipping and sub category 3

In [ ]:

```
plt.figure(figsize=(20, 15))

for index,j in enumerate(['t-shirts','shoes','wallets','boots','pants, tights, leggings','face','others','lip
  #print(index)
  plt.subplot(3,3,index+1)
  for i in data['shipping'].unique():

    lg_price=data[(data['shipping']==i) & (data['sub_cat_3']==j)]['log_price']
    #lg_price = data[data['no_of_words_in_item_description']==i]['log_price'].values
    histogram, bins = np.histogram(lg_price, bins=12, density=True)
    #density = True, the result is the value of the probability density function at the bin
    bin_centers = bins[1:]
    pdf = histogram / sum(histogram)



    plt.plot(bin_centers, pdf, label=i)

  #plt.xlabel('log(price+1)')
  plt.ylabel('density')
  plt.title('PDF of target for '+str(j))
  plt.legend()
plt.show()
```



Observation:

- if shipping = 1 delivery fee is paid by seller

  if shipping = 0 delivery fee is paid by buyer
- For most of the item when shipping=0 (i.e when delivery fee paid by the buyer) the pricing is the item is slightly higher compared to the item when shipping=1.

Summary of EDR:

- 42.6% of brand name data is missing.So, treated it as a separate category.
- It was observed that most of the pricing of items that are sold in mercari's app value lie between 0 to 200. Their are only few item whose pricing from 200 to 2000.
- The target value(price) have right skewed distribution. (has a long right tail).
- To convert right skewed data to noraml distribution we have used simple transformations on target data like square root, cube root, and log, out-off log tranformation on target value was more like normal distribution.
- We have choosen RMSLE as our loss function because of it's properties.
- It was observed that most of the time shipping cost is paid by sellers when pricing of the item is low and when price is high most of the times Shipping cost is paid by buyers.
- 43.2% of the item/product in the dataset are rated with item condition as 1.
- It was observed that their are items which are priced as zero.
- Their are brands whose item pricing fall in large range like victoria's secret, apple, michael kors.
- can say that different brand have different target value distribution.
- There are brand like canon which spread over wide range of pricing.
- Brand name field do contain some important information as target values of different brand have different distribution.
- 44.8% of the item in the dataset are related to women.
- Sellers have used words like "good condition","great condition","brand new","excellent condition",etc. to describe the condition of the item in item description.
- Most of the item description have 3 to 50 words. Their are only few item description with 100 to 250 words.
- Items with item condition id = 1 ,is price higher then item condition id = 5 for same category products.Which indicates products with item conditoin id=1 are good condition compared to the products with item conditoin id=5.
- For most of the item when shipping=0 (i.e when delivery fee paid by the buyer) the pricing is the item is slightly higher compared to the item when shipping=1.

In [ ]:

In [ ]:

Improvements:

Outlier analysis on price (target feature)

In [ ]:

```
# considering 99.9 percentile of price value as threshold for as outliers
temp_var = np.percentile(data['price'].values,99.9)
print('Total number of data points :',data.shape[0])
temp_cnt=sum(data['price'].values<=temp_var)
print('number of data points whose price is lesser then 99.9 ({}) percentile of price : {}'.format(temp_var,te
print('number of data points whose price is greater then 99.9 ({}) percentile of price : {}'.format(temp_var,d
```

```
Total number of data points : 1482535
number of data points whose price is lesser then 99.9 (450.0) percentile of price : 1481094
number of data points whose price is greater then 99.9 (450.0) percentile of price : 1441
```

Observation:

- If we consider price greater then 450 as outliers, then we have 1441 outliers .

Outlier analysis on word count of item description

In [ ]:

```
# filling the null values with no data
data['item_description'].fillna(value='no data',inplace=True)
```

In [ ]:

```
# considering 99.9 percentile of number of words value as threshold for as outliers
```

```
no_of_words=data['item_description'].str.split().apply(len)
temp=no_of_words.value_counts().to_frame().reset_index()
temp.rename(columns={'index': 'no_of_words', 'item_description': 'cnt'}, inplace=True)
temp
```

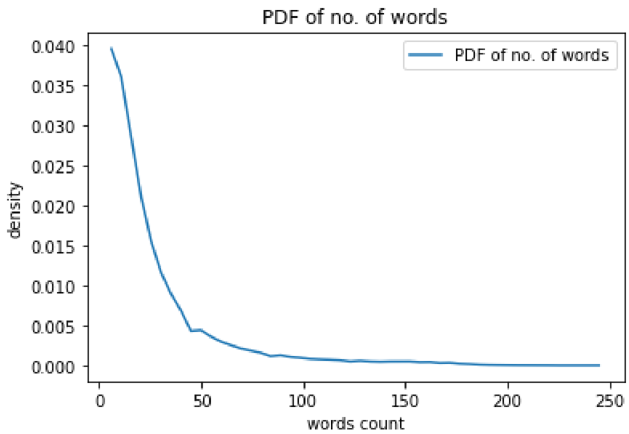
Out[ ]:

	no_of_words	cnt
0	3	121909
1	6	55542
2	7	53822
3	8	53201
4	4	52640
...	...	...
223	235	1
224	245	1
225	242	1
226	230	1
227	234	1

228 rows × 2 columns

In [ ]:

```
histogram, bins = np.histogram(no_of_words.values, bins=50, density=True)
#density = True, the result is the value of the probability density function at the bin

bin_centers = bins[1:]

plt.plot(bin_centers, histogram, label="PDF of no. of words")
plt.xlabel('words count')
plt.ylabel('density')
plt.title('PDF of no. of words')
plt.legend()
plt.show()
```



In [ ]:

```
for i in range(0,101,25):
  print("{} th percentile of price : {}".format(i,np.percentile(no_of_words.values,i)))
```

```
0 th percentile of price : 1.0
25 th percentile of price : 7.0
50 th percentile of price : 15.0
75 th percentile of price : 31.0
100 th percentile of price : 245.0
```

In [ ]:

```
for i in range(90,101,1):
  print("{} th percentile of price : {}".format(i,np.percentile(no_of_words.values,i)))
```

```
90 th percentile of price : 61.0
91 th percentile of price : 65.0
92 th percentile of price : 70.0
93 th percentile of price : 76.0
94 th percentile of price : 83.0
95 th percentile of price : 91.0
96 th percentile of price : 102.0
97 th percentile of price : 115.0
98 th percentile of price : 134.0
99 th percentile of price : 155.0
100 th percentile of price : 245.0
```

In [ ]:

```
for i in range(0,11,1):
  print("{} th percentile of price : {}".format((99+(i/10)),np.percentile(no_of_words.values,(99+(i/10)))))
```

```
99.0 th percentile of price : 155.0
99.1 th percentile of price : 157.0
99.2 th percentile of price : 159.0
99.3 th percentile of price : 162.0
99.4 th percentile of price : 164.0
99.5 th percentile of price : 167.0
99.6 th percentile of price : 170.0
99.7 th percentile of price : 173.0
99.8 th percentile of price : 179.0
99.9 th percentile of price : 189.0
100.0 th percentile of price : 245.0
```

In [ ]:

```
sum(no_of_words.values>189)
```

Out[ ]:

```
1374
```

Observation:

- Max number of words in item description = 245
- If we consider 99.9 percentile (189) as the threshold for outliers, then we end by leaving 1374 data points.

Trying to fill the missing values of brand_name feature using text data

In [ ]:

```
data.head()
```

Out[ ]:

	train_id	name	item_condition_id	category_name	brand_name	price	shipping	item_description
0	0	MLB Cincinnati Reds T Shirt Size XL	3	Men/Tops/T-shirts	NaN	10.0	1	No description yet
1	1	Razer BlackWidow Chroma Keyboard	3	Electronics/Computers & Tablets/Components & P...	Razer	52.0	0	This keyboard is in great condition and works ...
2	2	AVA-VIV Blouse	1	Women/Tops & Blouses/Blouse	Target	10.0	1	Adorable top with a hint of lace and a key hol...
3	3	Leather Horse Statues	1	Home/Home Décor/Home Décor Accents	NaN	35.0	1	New with tags. Leather horses. Retail for [rm]...
4	4	24K GOLD plated rose	1	Women/Jewelry/Necklaces	NaN	44.0	0	Complete with certificate of authenticity

In [ ]:

```
# brand name  count
temp_brand=data['brand_name'].value_counts()
temp=temp_brand.to_frame().reset_index()
temp.rename(columns={'index': 'brand', 'brand_name': 'cnt'}, inplace=True)
temp
```

Out[ ]:

	brand	cnt
0	PINK	54088
1	Nike	54043
2	Victoria's Secret	48036
3	LuLaRoe	31024
4	Apple	17322
...	...	...
4804	The Learning Journey	1
4805	Pampers Baby Fresh	1
4806	Huggies One & Done	1
4807	Classic Media	1
4808	Kids Only	1

4809 rows × 2 columns

In [ ]:

```
temp[:15]
```

Out[ ]:

	brand	cnt
0	PINK	54088
1	Nike	54043
2	Victoria's Secret	48036
3	LuLaRoe	31024
4	Apple	17322
5	FOREVER 21	15186
6	Nintendo	15007
7	Lululemon	14558
8	Michael Kors	13928
9	American Eagle	13254
10	Rae Dunn	12305
11	Sephora	12172
12	Coach	10463
13	Disney	10360
14	Bath & Body Works	10354

Observation:

- For predicating the brand name with high accuracy we should have sufficient data point of each brand, which is not their in our case.
- For the top 12 brands we have more than 12000 points for each brand.
- So, we are considering top 12 brands by count for training, to predict the brand name for missing values.

In [ ]:

```
tp_16_brands = temp[temp['cnt']>12000]['brand'].values
# getting top 12 brand data (which only include name and item description and corresponding brand name)
tp_brand_data = data[data['brand_name'].apply(lambda x: x in tp_16_brands)][['name','item_description','brand_
```

In [ ]:

```
X_tp_brand=tp_brand_data[['name','item_description']]
y_tp_brand=tp_brand_data['brand_name']
```

In [ ]:

```
X_missing_brand_data = data[data['brand_name'].isnull()][['train_id','name','item_description']]
nan_brd_train_id = X_missing_brand_data['train_id']
X_missing_brand_data = X_missing_brand_data[['name','item_description']]
```

text pre-processing for brand predication

In [ ]:

```python
# concatenating strings
X_tp_brand_txt_data       = X_tp_brand['name']+' '+X_tp_brand['item_description']
X_missing_brand_txt_data  = X_missing_brand_data['name']+' '+X_missing_brand_data['item_description']
# converting to lower case
X_tp_brand_txt_data = X_tp_brand_txt_data.str.lower()
X_missing_brand_txt_data= X_missing_brand_txt_data.str.lower()
```

In [ ]:

```python
# removing stopwords from text
import nltk
nltk.download('stopwords')
stopwords = nltk.corpus.stopwords.words('english')

def rm_stp_wds(sentence):
  temp_lst=[]
  for word in sentence.split(' '):
    if word not in stopwords:
      temp_lst.append(word)
  return ' '.join(temp_lst)

X_pre_process_txt = X_tp_brand_txt_data.apply(lambda x : rm_stp_wds(x))
X_nan_brd_pre_process_txt = X_missing_brand_txt_data.apply(lambda x : rm_stp_wds(x))
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

In [ ]:

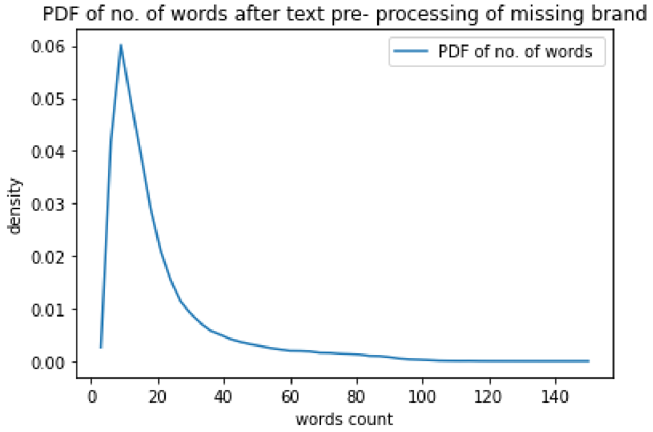
```python
# replacing '_' with space
X_pre_process_txt = X_pre_process_txt.str.replace('_',' ')
X_nan_brd_pre_process_txt = X_nan_brd_pre_process_txt.str.replace('_',' ')
```

In [ ]:

```python
import regex as re
'''
 replace all the words except "A-Za-z_" with space.
'''
def extract_words(input_data=' '):
    '''
    this function replace all the words except "A-Za-z_" with space
    '''
    pattern_17='\s{0,1}[A-Za-z_]+\s{0,1}'
    regex_17 = re.compile(pattern_17)
    xt=input_data.split()
    #print(xt)
    tmp_list=[]
    for i in xt:
        t=regex_17.fullmatch(i.strip())
        if t!=None:
            tmp_list.append(t.group())

    return ' '.join(tmp_list)


X_filtered_txt = X_pre_process_txt.apply(lambda x : extract_words(x))
X_nan_brd_filter_txt = X_nan_brd_pre_process_txt.apply(lambda x : extract_words(x))
```

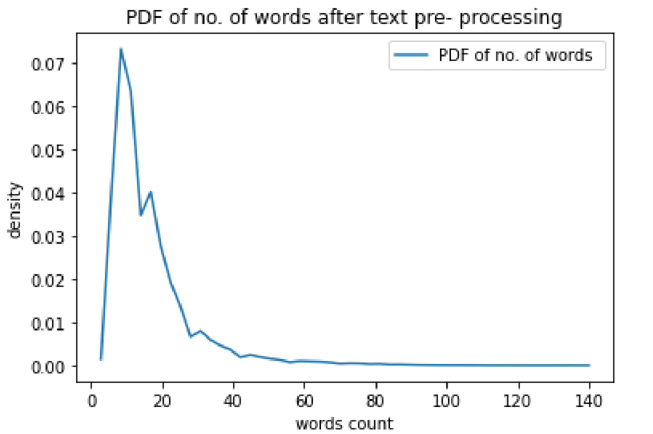
In [ ]:

```python
# plotting pdf of number of words after pre-processing

no_of_words=X_nan_brd_filter_txt.str.split().apply(len)

histogram, bins = np.histogram(no_of_words.values, bins=50, density=True)
#density = True, the result is the value of the probability density function at the bin

bin_centers = bins[1:]

plt.plot(bin_centers, histogram, label="PDF of no. of words ")
plt.xlabel('words count')
plt.ylabel('density')
plt.title('PDF of no. of words after text pre- processing of missing brand')
plt.legend()
plt.show()
```



In [ ]:

```
# plotting pdf of number of words after pre-processing

no_of_words=X_filtered_txt.str.split().apply(len)

histogram, bins = np.histogram(no_of_words.values, bins=50, density=True)
#density = True, the result is the value of the probability density function at the bin

bin_centers = bins[1:]

plt.plot(bin_centers, histogram, label="PDF of no. of words ")
plt.xlabel('words count')
plt.ylabel('density')
plt.title('PDF of no. of words after text pre- processing')
plt.legend()
plt.show()
```



Observation:

- The distribution of above 2 plots are similar.(number of words in top 12 brand and missing brand name)
- The max number of words is reduced to 140 after pre-processing.

In [ ]:

```
# applying  Stemming on text
from nltk.stem.porter import PorterStemmer

porter_stemmer = PorterStemmer()

def stemming(txt):
  stem_txt = [porter_stemmer.stem(word) for word in txt.split(' ')]
  return ' '.join(stem_txt)

X_stm_train  = X_filtered_txt.apply(lambda x: stemming(x))
X_nan_brd_stm_txt = X_nan_brd_filter_txt.apply(lambda x: stemming(x))
```

In [ ]:

```
# applying Lemmatization on text data
from nltk.stem import WordNetLemmatizer
nltk.download('wordnet')

wordnet_lemmatizer = WordNetLemmatizer()
def lemmatizer(txt):
```

```
    lem_txt = [wordnet_lemmatizer.lemmatize(word) for word in txt.split(' ')]
    return ' '.join(lem_txt)

X_train_final = X_stm_train.apply(lambda x:lemmatizer(x))
X_nan_brd_final = X_nan_brd_stm_txt.apply(lambda x:lemmatizer(x))
```

```
[nltk_data] Downloading package wordnet to /root/nltk_data...
[nltk_data]   Package wordnet is already up-to-date!
```

In [ ]:

```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X_train_final,y_tp_brand, test_size=0.20, random_state=42,

for i in [X_train, X_test, y_train, y_test]:
  print(i.shape)
```

```
(240738,)
(60185,)
(240738,)
(60185,)
```

In [ ]:

```
y_train.value_counts()
```

Out[ ]:

```
PINK                 43270
Nike                 43234
Victoria's Secret    38429
LuLaRoe              24819
Apple                13858
FOREVER 21           12149
Nintendo             12006
Lululemon            11646
Michael Kors         11142
American Eagle       10603
Rae Dunn              9844
Sephora               9738
Name: brand_name, dtype: int64
```

In [ ]:

```
y_test.value_counts()
```

Out[ ]:

```
PINK                 10818
Nike                 10809
Victoria's Secret     9607
LuLaRoe               6205
Apple                 3464
FOREVER 21            3037
Nintendo              3001
Lululemon             2912
Michael Kors          2786
American Eagle        2651
Rae Dunn              2461
Sephora               2434
Name: brand_name, dtype: int64
```

In [ ]:

```
# bag of words : converting text to numeric data
from sklearn.feature_extraction.text import CountVectorizer

vectorizer = CountVectorizer(min_df=50)
X_cnt_vect_train = vectorizer.fit_transform(X_train.values)

X_cnt_vect_test = vectorizer.transform(X_test.values)

X_cnt_vect_nan_brd = vectorizer.transform(X_nan_brd_final)
```

In [ ]:

```
#print(vectorizer.get_feature_names())
len(vectorizer.get_feature_names()[:])
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/utils/deprecation.py:87: FutureWarning: Function get_feature_na
mes is deprecated; get_feature_names is deprecated in 1.0 and will be removed in 1.2. Please use get_feature_n
ames_out instead.
  warnings.warn(msg, category=FutureWarning)
```

Out[ ]:

```
3119
```

In [ ]:

```
# target value(beand name) label encoding
from sklearn import preprocessing

label_encoder = preprocessing.LabelEncoder()

y_train_final= label_encoder.fit_transform(y_train)
y_test_final= label_encoder.transform(y_test)

keys = label_encoder.classes_
values = label_encoder.transform(label_encoder.classes_)
dictionary = dict(zip(keys, values))
dictionary
```

Out[ ]:

```
{'American Eagle': 0,
 'Apple': 1,
 'FOREVER 21': 2,
 'LuLaRoe': 3,
 'Lululemon': 4,
 'Michael Kors': 5,
 'Nike': 6,
 'Nintendo': 7,
 'PINK': 8,
 'Rae Dunn': 9,
 'Sephora': 10,
 "Victoria's Secret": 11}
```

In [ ]:

```
# applying Multinomial navie bayes on text data

from sklearn.naive_bayes import MultinomialNB

M_NB  = MultinomialNB(alpha=0.05,class_prior=[0.5]*12)
model_NB = M_NB.fit(X_cnt_vect_train, y_train_final)
model_NB_predictions = model_NB.predict(X_cnt_vect_test)
```

In [ ]:

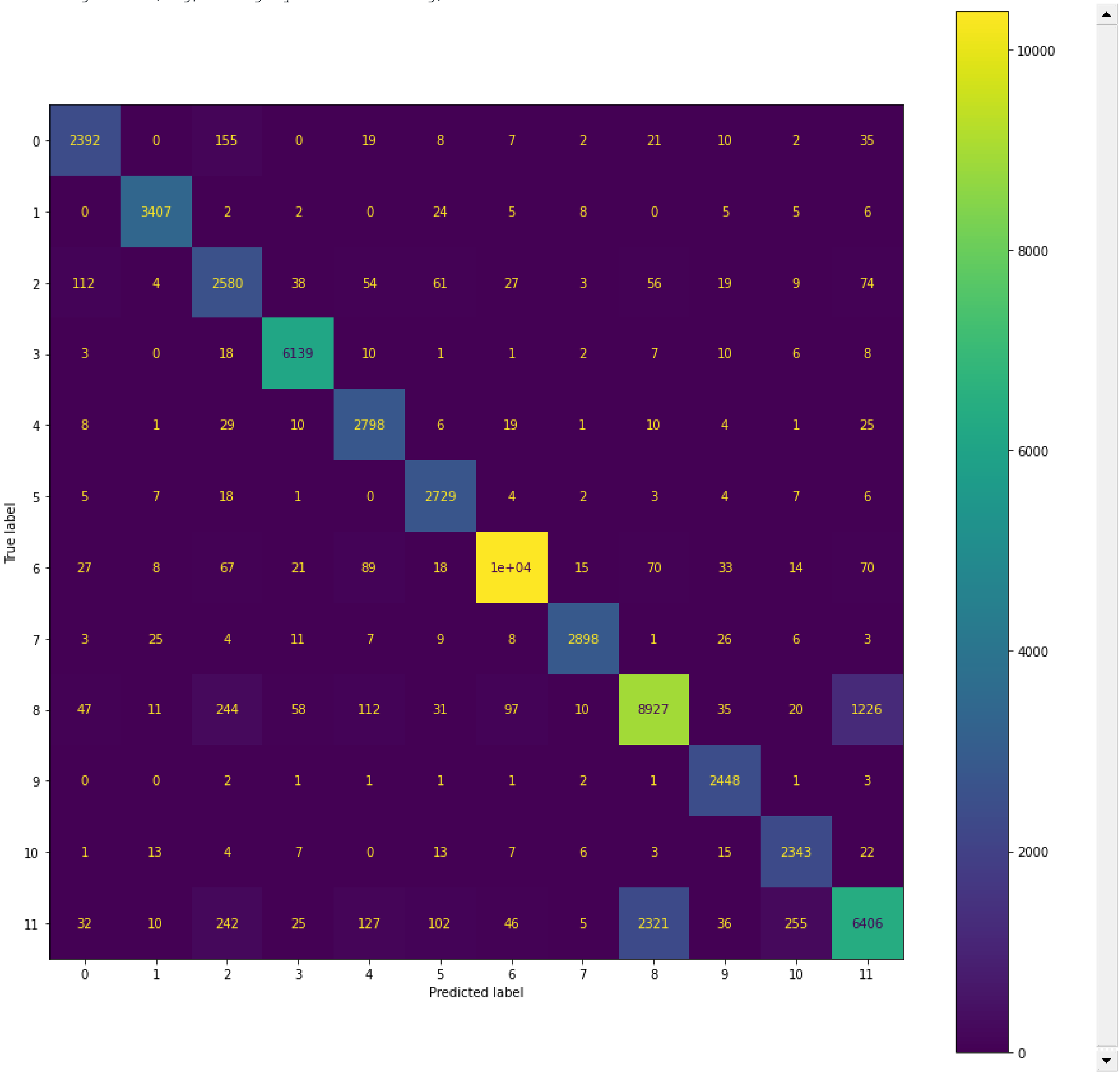
```
print('Accuracy : ',sum(model_NB_predictions==y_test_final)/len(y_test_final))
```

```
Accuracy :  0.8879953476779928
```

In [ ]:

```
import matplotlib.pyplot as plt
from sklearn.metrics import plot_confusion_matrix
fig, ax = plt.subplots(figsize=(15, 15))
plot_confusion_matrix(M_NB, X_cnt_vect_test, y_test_final,ax=ax)

plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/utils/deprecation.py:87: FutureWarning: Function plot_confusion
_matrix is deprecated; Function `plot_confusion_matrix` is deprecated in 1.0 and will be removed in 1.2. Use o
ne of the class methods: ConfusionMatrixDisplay.from_predictions or ConfusionMatrixDisplay.from_estimator.
  warnings.warn(msg, category=FutureWarning)
```



Observations:

- From the above confusion matrix we can say that model is performing pretty good, except for 8 and 11 labels.
- "Having no data is better then having wrong data", thus we want our model to perform at the best. *Below is the code for tweaking threshold probability to improve accuracy of the model.

In [ ]:

```
accuracy_thrd=[]
crt_prd_cnt=[]
wrg_prd_cnt=[]
nt_prd_cnt=[]
prb_thrd_lst=[0.5,0.6,0.7,0.8,0.9,0.95,0.99,0.999,0.9999,0.99999,1]
for prob_threshold in prb_thrd_lst:

  correct_predicated=0
  wrong_predicated=0
  not_predicated=0
  for prob,label in zip(M_NB.predict_proba(X_cnt_vect_test),y_test_final):
    x= prob>= prob_threshold   #returns [False,  True, False, False, False, False, False, False, False, False
    if (any(x)):
      pred_label=x.argmax()
```

```
      if(pred_label==label):
        correct_predicated=correct_predicated+1
      else:
        wrong_predicated=wrong_predicated+1
    else:
      not_predicated=not_predicated+1

  crt_prd_cnt.append(correct_predicated)
  wrg_prd_cnt.append(wrong_predicated)
  nt_prd_cnt.append(not_predicated)
  accuracy_thrd.append(correct_predicated/(wrong_predicated+correct_predicated))
```

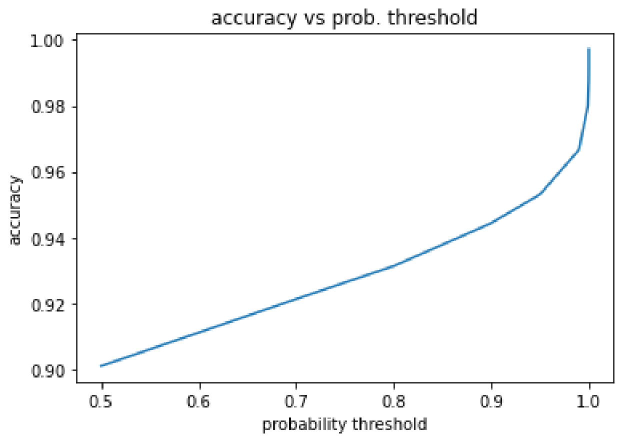
In [ ]:

```
from prettytable import PrettyTable

columns = ["prob. threshold", "correct predicated cnt", "wrong predicated cnt","not predicated","% of correct
           "% of not predicated "]

myTable = PrettyTable()

# Add Columns
myTable.add_column(columns[0],prb_thrd_lst)
myTable.add_column(columns[1],crt_prd_cnt)
myTable.add_column(columns[2],wrg_prd_cnt)
myTable.add_column(columns[3],nt_prd_cnt )
myTable.add_column(columns[4],list(map(lambda x: round(x,4),accuracy_thrd)))
myTable.add_column(columns[5],list(map(lambda x: round(x,4),np.array(nt_prd_cnt)/len(y_test_final))))

print(myTable)
```

```
+-----------------+------------------------+----------------------+----------------+-------------------------
+----------------------+
| prob. threshold | correct predicated cnt | wrong predicated cnt | not predicated | % of correct predicated
| % of not predicated  |
+-----------------+------------------------+----------------------+----------------+-------------------------
+----------------------+
|       0.5       |         53041          |         5829         |      1315      |           0.901
|        0.0218        |
|       0.6       |         52203          |         5093         |      2889      |           0.9111
|        0.048         |
|       0.7       |         51158          |         4369         |      4658      |           0.9213
|        0.0774        |
|       0.8       |         49791          |         3672         |      6722      |           0.9313
|        0.1117        |
|       0.9       |         47551          |         2802         |      9832      |           0.9444
|        0.1634        |
|       0.95      |         45463          |         2238         |     12484      |           0.9531
|        0.2074        |
|       0.99      |         40870          |         1410         |     17905      |           0.9667
|        0.2975        |
|      0.999      |         35426          |         725          |     24034      |           0.9799
|        0.3993        |
|      0.9999     |         30941          |         390          |     28854      |           0.9876
|        0.4794        |
|     0.99999     |         26925          |         231          |     33029      |           0.9915
|        0.5488        |
|        1        |          7775          |          22          |     52388      |           0.9972
|        0.8704        |
+-----------------+------------------------+----------------------+----------------+-------------------------
+----------------------+
```

In [ ]:

```
import matplotlib.pyplot as plt

x = prb_thrd_lst
y = accuracy_thrd
plt.plot(x, y)
plt.xlabel('probability threshold')
plt.ylabel('accuracy')
plt.title('accuracy vs prob. threshold')
plt.show()
```



Observation:

- When probability threshold = 0.99999 ,the accuracy of predicated points = 99.15 % which is a good number.
- The percentage of not predicated points is 54.8%; Its ok to not to predicate when not sure rather then wrong predication.

In [ ]:

```
# predicating the probabilty for missing values
nan_brand_proba_predictions = model_NB.predict_proba(X_cnt_vect_nan_brd)
```

In [ ]:

```
best_prob_threshold=0.99999
nan_brand_labels=[]
predicated_ids=[]
not_predicated=0
for prob,id in zip(nan_brand_proba_predictions,nan_brd_train_id.values):
  x= prob >= best_prob_threshold   #returns [False,  True, False, False, False, False, False, False, False, Fa

  if (any(x)):
    pred_label=x.argmax()
    nan_brand_labels.append(pred_label)
    predicated_ids.append(id)
  else:
    not_predicated=not_predicated+1
```

In [ ]:

```
print('Number of predications : ',len(nan_brand_labels))
print('Number of no predications : ',not_predicated)
print('percentage of values predicated : {:.2f} %'.format((len(nan_brand_labels)/len(nan_brd_train_id.values))
```

```
Number of predications :  158386
Number of no predications :  474296
percentage of values predicated : 25.03 %
```

Observation:

- We are able to predicate brand name for 158386 data points which is 25% of the missing value with 0.99999 as probability threshold.

In [ ]:

```
nan_pred_labels = label_encoder.inverse_transform(nan_brand_labels)
indices = list(data[data['train_id'].isin(predicated_ids)].index)
```

In [ ]:

```
data.loc[indices,['brand_name']]=nan_pred_labels
```

In [ ]:

```
#sum(data['brand_name'].isnull())
#data.to_csv('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/pre_processed_data.csv', header=False,
```

Summuary on improvements:

- By using text data (item_description and name feature) of top 12 brand by count in dataset we are able to fill 25% of the missing values of brand_name feature.
- The 99.9 percent of data points have less then eaual to 189 number of words in item description, if we consider 189 as the threshold for outliers, then we end by leaving 1374 data points.

- The 99.9 percent of data points have less then or eaual to 450 price of the items, if we consider 450 as the threshold for outliers, then we end by leaving 1441 data points.

In [ ]:

Feature *Engineering*

is digit present or not in text data

In [ ]:

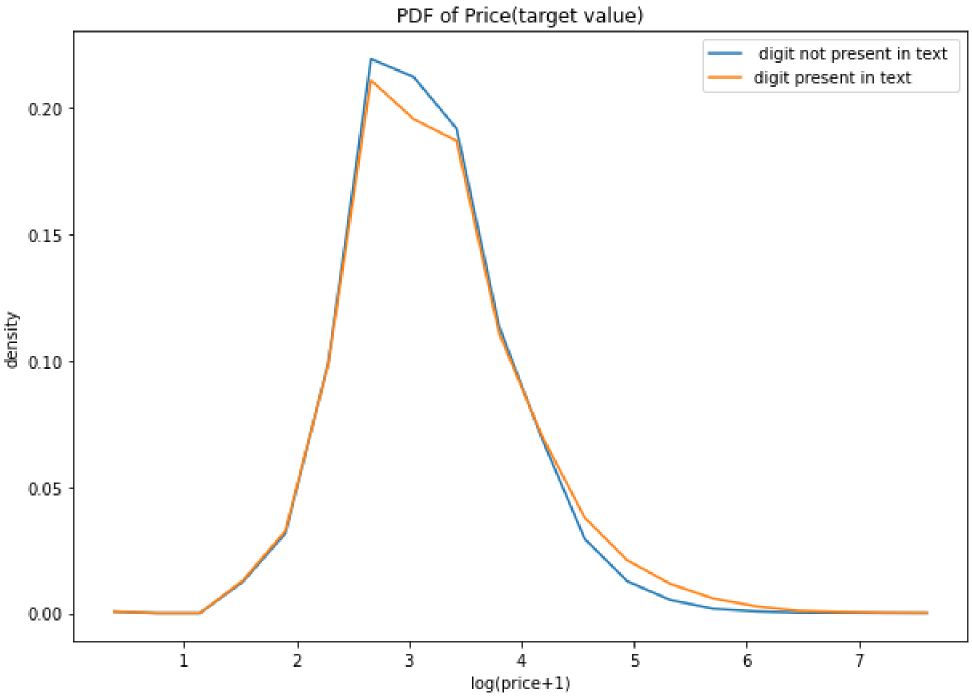
```
data['dup_item_description']=data['item_description']
data['dup_item_description'].fillna(value='no data', inplace=True)
```

In [ ]:

```
import re
def has_digits(txt):
    #print('hello')
    return bool(re.search(r'\d', txt))+0

txt_data =  data['name']+' '+data['dup_item_description']

data['is_digit_present_txt'] =txt_data.apply(lambda x: has_digits(x))
```

In [ ]:

```
data['log_price']=np.log(data['price']+1)
isdigit_present_0_price = data[data['is_digit_present_txt']==0]['log_price'].values
isdigit_present_1_price = data[data['is_digit_present_txt']==1]['log_price'].values

plt.figure(figsize=(10, 7))
histogram, bins = np.histogram(isdigit_present_0_price, bins=20, density=True)
#density = True, the result is the value of the probability density function at the bin
bin_centers = bins[1:]
pdf = histogram / sum(histogram)
plt.plot(bin_centers, pdf, label=" digit not present in text ")

histogram, bins = np.histogram(isdigit_present_1_price, bins=20, density=True)
bin_centers = bins[1:]
pdf = histogram / sum(histogram)
plt.plot(bin_centers, pdf, label="digit present in text ")

plt.xlabel('log(price+1)')
plt.ylabel('density')
plt.title('PDF of Price(target value)')
plt.legend()
plt.show()
```



Observation:

- Is digit present in text data or not. This feature does not seems to be useful feature. As the above pdf plots are overlapping.

K mode clustering on category name :

In [ ]:

```
!pip install kmodes
from kmodes.kmodes import KModes
```

```
Collecting kmodes
  Downloading kmodes-0.12.1-py2.py3-none-any.whl (20 kB)
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.7/dist-packages (from kmodes) (1.1.0)
Requirement already satisfied: numpy>=1.10.4 in /usr/local/lib/python3.7/dist-packages (from kmodes) (1.21.6)
Requirement already satisfied: scikit-learn>=0.22.0 in /usr/local/lib/python3.7/dist-packages (from kmodes) (1
.0.2)
Requirement already satisfied: scipy>=0.13.3 in /usr/local/lib/python3.7/dist-packages (from kmodes) (1.4.1)
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.7/dist-packages (from scikit-lea
rn>=0.22.0->kmodes) (3.1.0)
Installing collected packages: kmodes
Successfully installed kmodes-0.12.1
```

In [ ]:

```
# splitting the category_name field into 3 fields main_cat, sub_cat_1, sub_cat_2
def len_fun(x):
  try:

    return x.split('/',3)
  except:

    return 'no label','no label','no label'

temp_category_name = data['category_name'].apply(lambda x: len_fun(x))

data['main_cat'],data['sub_cat_1'],data['sub_cat_2']=zip(*temp_category_name)
```

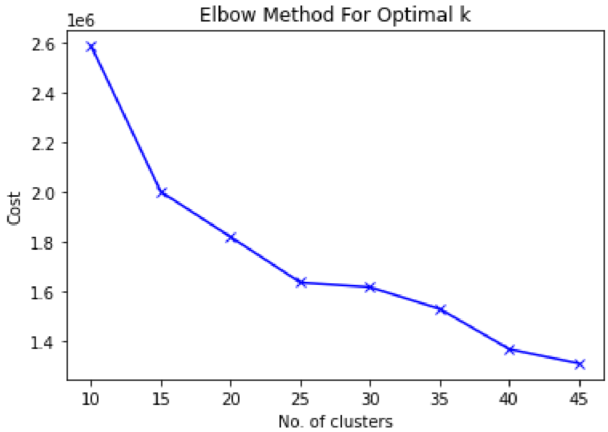
In [ ]:

```
temp_data = data[['main_cat','sub_cat_1','sub_cat_2']]
```

In [ ]:

```
## reference https://www.analyticsvidhya.com/blog/2021/06/kmodes-clustering-algorithm-for-categorical-data/
from kmodes.kmodes import KModes
cost = []
K = range(10,50,5)
for num_clusters in list(K):
    kmode = KModes(n_clusters=num_clusters, init = "random", n_init = 1, verbose=1)
    kmode.fit_predict(temp_data)
    cost.append(kmode.cost_)

plt.plot(K, cost, 'bx-')
plt.xlabel('No. of clusters')
plt.ylabel('Cost')
plt.title('Elbow Method For Optimal k')
plt.show()
```

```
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 125730, cost: 2587766.0
Run 1, iteration: 2/100, moves: 0, cost: 2587766.0
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 209612, cost: 2003026.0
Run 1, iteration: 2/100, moves: 284244, cost: 2003026.0
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 376576, cost: 1821766.0
Run 1, iteration: 2/100, moves: 17286, cost: 1821766.0
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 234002, cost: 1652421.0
Run 1, iteration: 2/100, moves: 14612, cost: 1638464.0
Run 1, iteration: 3/100, moves: 2, cost: 1638464.0
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 86055, cost: 1619765.0
Run 1, iteration: 2/100, moves: 1696, cost: 1619765.0
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 132184, cost: 1532764.0
Run 1, iteration: 2/100, moves: 166, cost: 1532764.0
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 214466, cost: 1370516.0
Run 1, iteration: 2/100, moves: 7099, cost: 1370516.0
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 33072, cost: 1313376.0
Run 1, iteration: 2/100, moves: 0, cost: 1313376.0
```



- Thumb rule to select k for cluster is elbow method

In [ ]:

```
kmode = KModes(n_clusters=25, init = "random", n_init = 1, verbose=1)
clusters = kmode.fit_predict(temp_data)
```

```
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 120324, cost: 1717938.0
Run 1, iteration: 2/100, moves: 13, cost: 1717938.0
```

In [ ]:

```
data.columns
```

Out[ ]:

```
Index(['train_id', 'name', 'item_condition_id', 'category_name', 'brand_name',
       'price', 'shipping', 'item_description', 'main_cat', 'sub_cat_1',
       'sub_cat_2', '25_clusters_'],
      dtype='object')
```

In [ ]:

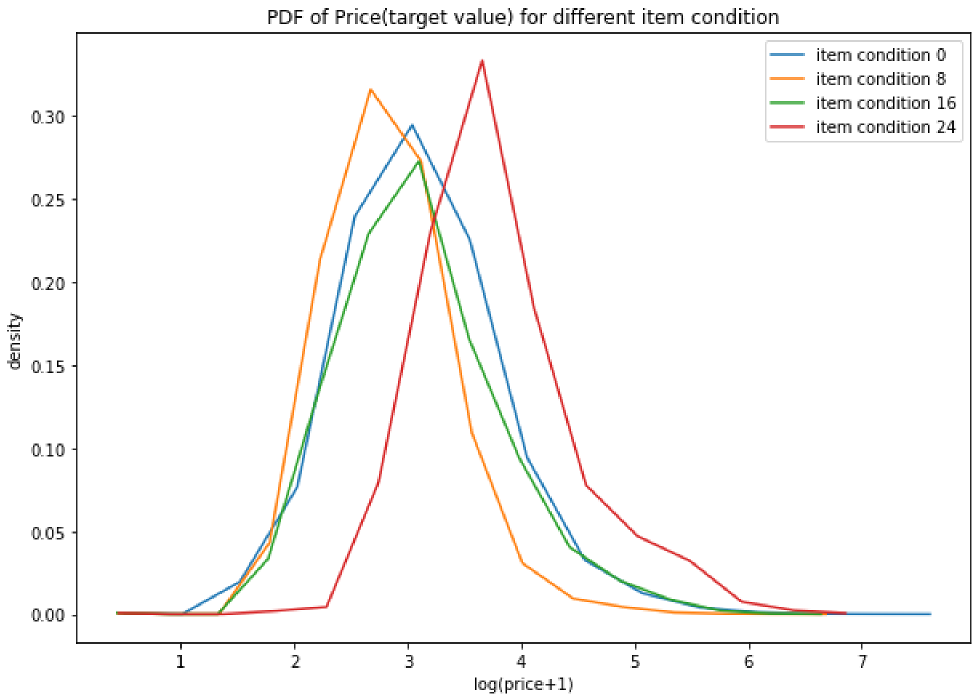
```
data['log_price']=np.log(data['price']+1)
```

In [ ]:

```
data['25_clusters_']=clusters
```

In [ ]:

```
plt.figure(figsize=(10, 7))

for i in list(range(0,26,8)):
  histogram, bins = np.histogram(data[data['25_clusters_']==i]['log_price'], bins=15, density=True)
  #density = True, the result is the value of the probability density function at the bin
  bin_centers = bins[1:]
  pdf = histogram / sum(histogram)
  plt.plot(bin_centers, pdf, label='item condition '+str(i))

plt.xlabel('log(price+1)')
plt.ylabel('density')
plt.title('PDF of Price(target value) for different item condition')
plt.legend()
plt.show()
```



In [ ]:

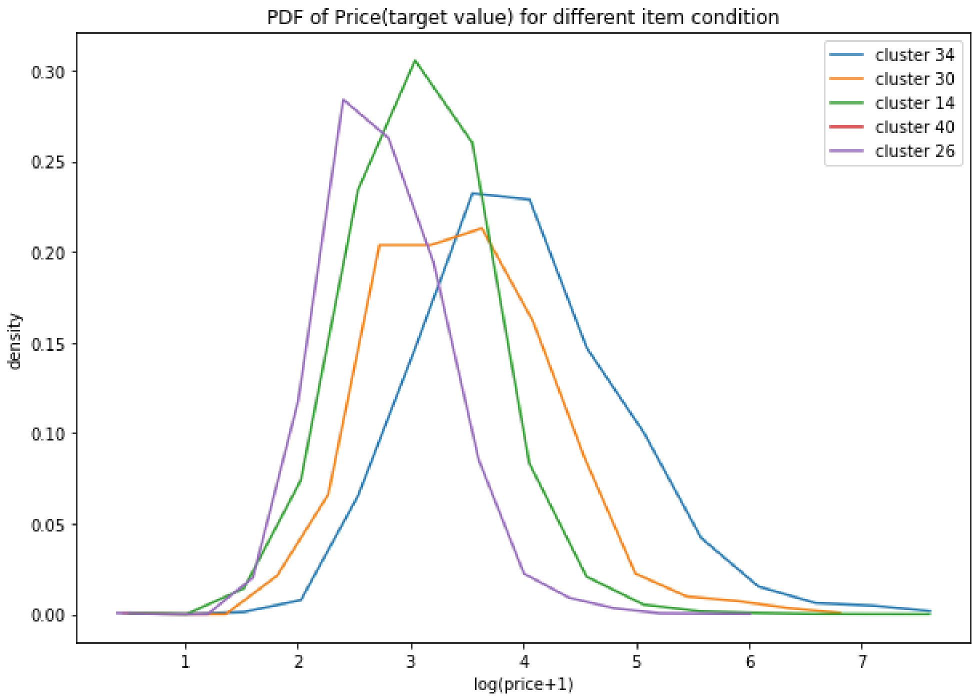
```
kmode = KModes(n_clusters=40, init = "random", n_init = 1, verbose=1)
clusters = kmode.fit_predict(temp_data)
data['40_clusters_']=clusters
```

```
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 140380, cost: 1410963.0
Run 1, iteration: 2/100, moves: 520, cost: 1410963.0
```

In [ ]:

```
import random

plt.figure(figsize=(10, 7))

for i in list(random.sample(range(0, 41), 5)):
  histogram, bins = np.histogram(data[data['40_clusters_']==i]['log_price'], bins=15, density=True)
  #density = True, the result is the value of the probability density function at the bin
  bin_centers = bins[1:]
  pdf = histogram / sum(histogram)
  plt.plot(bin_centers, pdf, label='cluster '+str(i))

plt.xlabel('log(price+1)')
plt.ylabel('density')
plt.title('PDF of Price(target value) for different item condition')
plt.legend()
plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/numpy/lib/histograms.py:906: RuntimeWarning: invalid value encountered in true_divide
  return n/db/n.sum(), bin_edges
```



Observation:

- Above are the plots of pdf of target value for different cluster.
- Features used for Kmode clustering:
    - 'main_cat'
    - 'sub_cat_1'
    - 'sub_cat_2'
- Since central tendency of the above pdf's are different , this feature can be handy for modeling.

In [ ]:

In [ ]:

```
data.columns
```

Out[ ]:

```
Index(['train_id', 'name', 'item_condition_id', 'category_name', 'brand_name',
       'price', 'shipping', 'item_description', 'log_price'],
      dtype='object')
```

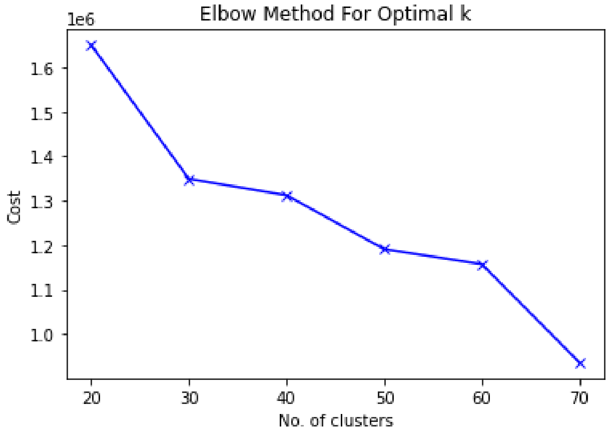
In [ ]:

```
# these are features used for kmode algorithm
temp2_data = data[['item_condition_id','shipping','main_cat','sub_cat_1']]
```

In [ ]:

```
## reference https://www.analyticsvidhya.com/blog/2021/06/kmodes-clustering-algorithm-for-categorical-data/
from kmodes.kmodes import KModes
cost = []
K = range(20,80,10)
for num_clusters in list(K):
    kmode = KModes(n_clusters=num_clusters, init = "random", n_init = 1, verbose=1)
    kmode.fit_predict(temp2_data)
    cost.append(kmode.cost_)

plt.plot(K, cost, 'bx-')
plt.xlabel('No. of clusters')
plt.ylabel('Cost')
plt.title('Elbow Method For Optimal k')
plt.show()
```

```
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 240089, cost: 1649501.0
Run 1, iteration: 2/100, moves: 179, cost: 1649501.0
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 210960, cost: 1349067.0
Run 1, iteration: 2/100, moves: 4, cost: 1349067.0
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 259175, cost: 1312321.0
Run 1, iteration: 2/100, moves: 30519, cost: 1312321.0
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 208654, cost: 1191167.0
Run 1, iteration: 2/100, moves: 1555, cost: 1191167.0
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 235233, cost: 1157330.0
Run 1, iteration: 2/100, moves: 26251, cost: 1157330.0
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 326548, cost: 937233.0
Run 1, iteration: 2/100, moves: 18996, cost: 936591.0
Run 1, iteration: 3/100, moves: 35, cost: 936591.0
```



In [ ]:

In [ ]:

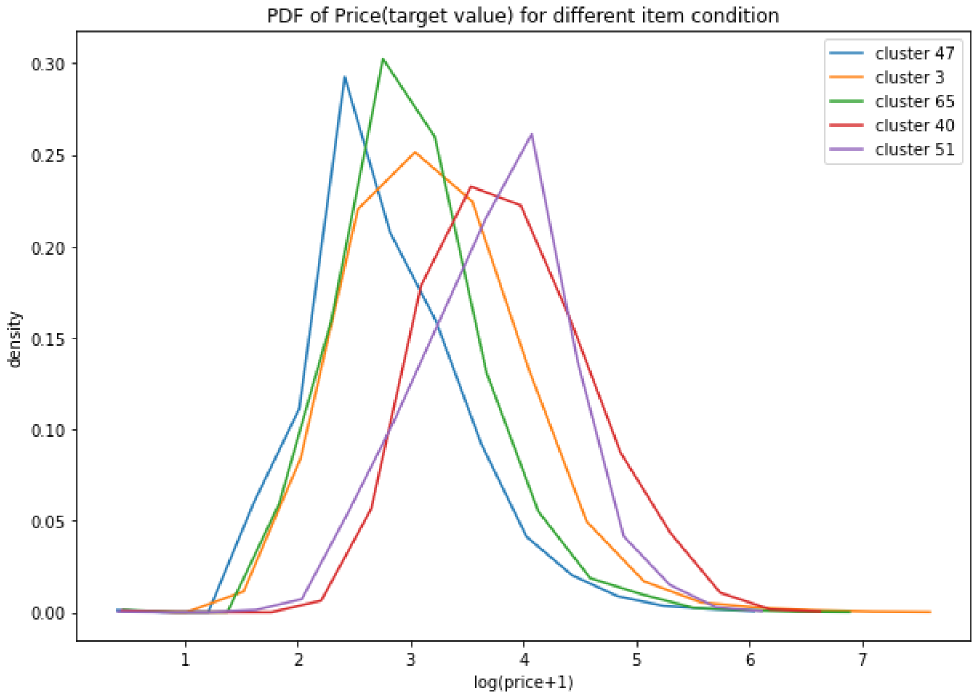
```
kmode = KModes(n_clusters=70, init = "random", n_init = 1, verbose=1)
clusters = kmode.fit_predict(temp2_data)
data['70_clusters_']=clusters
```

```
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 195445, cost: 1084250.0
Run 1, iteration: 2/100, moves: 10, cost: 1084250.0
```

In [ ]:

```
import random

plt.figure(figsize=(10, 7))

for i in list(random.sample(range(0, 70), 5)):
  histogram, bins = np.histogram(data[data['70_clusters_']==i]['log_price'], bins=15, density=True)
  #density = True, the result is the value of the probability density function at the bin
  bin_centers = bins[1:]
  pdf = histogram / sum(histogram)
  plt.plot(bin_centers, pdf, label='cluster '+str(i))

plt.xlabel('log(price+1)')
plt.ylabel('density')
plt.title('PDF of Price(target value) for different item condition')
```

```
plt.legend()
plt.show()
```



Observation:

- Above are the plots of pdf of target value for different cluster.
- Features used for Kmode clustering:
  - 'item_condition_id'
  - 'shipping'
  - 'main_cat'
  - 'sub_cat_1'
- Since central tendency of the above pdf's are different , this feature can be handy for modeling.

In [ ]:

Data Processing and Feature Engineering

- Removing the datapoints whose prices are <=0
- Apply log Transform on target values.
- Handle missing values in brand name
  - By taking missing value as a separate category.
  - By using item description and name feature to predicate brand name using simple model.
- Text (item description + name) len
- Data pre-processing
- Applying Kmodes algorithm on category features which gives us interactive features.
- One-hot encoding of categorial features

In [ ]:

```
data.head()
```

Out[ ]:

	train_id	name	item_condition_id	category_name	brand_name	price	shipping	item_description
0	0	MLB Cincinnati Reds T Shirt Size XL	3	Men/Tops/T-shirts	NaN	10.0	1	No description yet
1	1	Razer BlackWidow Chroma Keyboard	3	Electronics/Computers & Tablets/Components & P...	Razer	52.0	0	This keyboard is in great condition and works ...
2	2	AVA-VIV Blouse	1	Women/Tops & Blouses/Blouse	Target	10.0	1	Adorable top with a hint of lace and a key hol...
3	3	Leather Horse Statues	1	Home/Home Décor/Home Décor Accents	NaN	35.0	1	New with tags. Leather horses. Retail for [rm]...
4	4	24K GOLD plated rose	1	Women/Jewelry/Necklaces	NaN	44.0	0	Complete with certificate of authenticity

In [ ]:

```
data.shape
```

Out[ ]:

```
(1482535, 8)
```

In [ ]:

```
# removing the datapoints whose price is less then equal to zero
train_data = data[data['price']>0].copy()
train_data.shape
```

Out[ ]:

```
(1481661, 8)
```

In [ ]:

```
print('Number of points removed : ', data.shape[0]-train_data.shape[0])
```

```
Number of points removed :  874
```

Price --> log(price)

In [ ]:

```
# as explained earlier why log(price) in EDA
train_data['log_price'] = np.log(train_data['price'].values+1)
```

Train - Validation split

In [ ]:

```
train_data.columns
```

Out[ ]:

```
Index(['train_id', 'name', 'item_condition_id', 'category_name', 'brand_name',
       'price', 'shipping', 'item_description', 'log_price'],
      dtype='object')
```

In [ ]:

```
from sklearn.model_selection import train_test_split

y = train_data['log_price']
X = train_data.drop(['log_price'], axis=1)

X_train, X_validation, y_train, y_validationt = train_test_split(X, y, test_size=0.10, random_state=30)

print('X_train :',X_train.shape)
print('y_train : ',y_train.shape)
print('X_validation : ',X_validation.shape)
print('y_validationt :',y_validationt.shape)
```

category_name

In [ ]:

```
# splitting the category_name field into 3 fields main_category, sub_category_1, sub_category_2

def len_fun(x):
  try:
    return x.split('/',3)
  except:
    return 'no label','no label','no label'

temp_category_name = X_train['category_name'].apply(lambda x: len_fun(x))
```

```
X_train['main_category'],X_train['sub_category_1'],X_train['sub_category_2']=zip(*temp_category_name)
```

```
X_train = X_train.drop(['category_name'], axis=1)
```

```
X_train.head(2)
```

Out[ ]:

	train_id	name	item_condition_id	brand_name	price	shipping	item_description	main_category	sub_category_1	sub_category_2
610488	610488	Hollister Paisley Flowy Top	2	Hollister	10.0	1	Hollister brand | Size: M | Polyester blend | ...	Women	Tops & Blouses	Blouse
565926	565926	Sparkle Styling Kit For Horses	1	American Boy & Girl	26.0	0	New with box. Box is a bit crushed from storing.	Kids	Toys	Dolls & Accessories

brand_name

In [ ]:

```
# filling the missing values
```

```
X_train['brand_name'].fillna(value='not known', inplace=True)
```

```
sum(X_train['brand_name']=='not known')
```

Out[ ]:

```
569539
```

Number of words in text data

In [ ]:

```
# filling the null values with no data
X_train['item_description'].fillna(value='no data',inplace=True)
```

```
X_train['name'].fillna(value='no data',inplace=True)
```

In [ ]:

```
# considering 99.9 percentile of number of words value as threshold for as outliers

txt_data = X_train['name']+' '+X_train['item_description']
X_train['no_of_words_in_txt'] = txt_data.str.split().apply(len)
```

text data pre-processing

In [ ]:

```
txt_data = txt_data.str.lower()
```

In [ ]:

```
# removing stopwords from text
import nltk
nltk.download('stopwords')
stopwords = nltk.corpus.stopwords.words('english')
print(stopwords)
print(len(stopwords))
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
['i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'ourselves', 'you', "you're", "you've", "you'll", "you'd", 'y
our', 'yours', 'yourself', 'yourselves', 'he', 'him', 'his', 'himself', 'she', "she's", 'her', 'hers', 'hersel
f', 'it', "it's", 'its', 'itself', 'they', 'them', 'their', 'theirs', 'themselves', 'what', 'which', 'who', 'w
hom', 'this', 'that', "that'll", 'these', 'those', 'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'h
ave', 'has', 'had', 'having', 'do', 'does', 'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or', 'becau
se', 'as', 'until', 'while', 'of', 'at', 'by', 'for', 'with', 'about', 'against', 'between', 'into', 'through'
, 'during', 'before', 'after', 'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on', 'off', 'over',
'under', 'again', 'further', 'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'all', 'any', 'bo
th', 'each', 'few', 'more', 'most', 'other', 'some', 'such', 'no', 'nor', 'not', 'only', 'own', 'same', 'so',
'than', 'too', 'very', 's', 't', 'can', 'will', 'just', 'don', "don't", 'should', "should've", 'now', 'd', 'll
', 'm', 'o', 're', 've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't", 'didn', "didn't", 'doesn', "doesn
't", 'hadn', "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "isn't", 'ma', 'mightn', "mightn't", 'must
n', "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn', "shouldn't", 'wasn', "wasn't", 'weren', "weren
't", 'won', "won't", 'wouldn', "wouldn't"]
179
```

In [ ]:

```
# removing 'no' and 'not' from stopwords list
if 'no' in stopwords:
  stopwords.remove('no')
if 'not' in stopwords:
  stopwords.remove('not')

print(len(stopwords))
```

177

In [ ]:

```
# saving stopwords for datapipline
pickle.dump(stopwords, open("/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/stopwo

## load pickle
#stopwords = pickle.load(open("/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/stop
```

In [ ]:

```
# removing stopwords from text

def rm_stp_wds(sentence):
  temp_lst=[]
  for word in sentence.split(' '):
    if word not in stopwords:
      temp_lst.append(word)
  return ' '.join(temp_lst)

pre_proc_txt_data = txt_data.apply(lambda x : rm_stp_wds(x))
```

In [ ]:

```
# replacing '_' with space
pre_proc_txt_data = pre_proc_txt_data.str.replace('_',' ')
```

In [ ]:

```
import regex as re
'''
 replace all the words except "A-Za-z_" with space.
'''
def extract_words(input_data=' '):
    '''
    this function replace all the words except "A-Za-z_" with space
    '''
    pattern_17='\s{0,1}[A-Za-z_]+\s{0,1}'
    regex_17 = re.compile(pattern_17)
    xt=input_data.split()
    #print(xt)
    tmp_list=[]
    for i in xt:
        t=regex_17.fullmatch(i.strip())
        if t!=None:
            tmp_list.append(t.group())

    return ' '.join(tmp_list)


pre_proc_txt_data = pre_proc_txt_data.apply(lambda x : extract_words(x))
```

In [ ]:

```
# applying  Stemming on text
from nltk.stem.porter import PorterStemmer

porter_stemmer = PorterStemmer()

def stemming(txt):
  stem_txt = [porter_stemmer.stem(word) for word in txt.split(' ')]
  return ' '.join(stem_txt)

pre_proc_stm_txt_data  = pre_proc_txt_data.apply(lambda x: stemming(x))
```

In [ ]:

```
# applying Lemmatization on text data
from nltk.stem import WordNetLemmatizer
nltk.download('wordnet')

wordnet_lemmatizer = WordNetLemmatizer()
def lemmatizer(txt):
```

```
    lem_txt = [wordnet_lemmatizer.lemmatize(word) for word in txt.split(' ')]
    return ' '.join(lem_txt)

final_txt_data = pre_proc_stm_txt_data.apply(lambda x:lemmatizer(x))
```

```
[nltk_data] Downloading package wordnet to /root/nltk_data...
[nltk_data]   Package wordnet is already up-to-date!
```

In [ ]:

```
X_train['pre_processed_txt'] = final_txt_data
```

number of words after pre - -processing

In [ ]:

```
X_train['no_of_words_after_pre_process']=X_train['pre_processed_txt'].str.split().apply(len)
X_train['no_of_words_after_pre_process'].describe()
```

Out[ ]:

```
count    1.333494e+06
mean     1.673719e+01
std      1.468188e+01
min      0.000000e+00
25%      8.000000e+00
50%      1.200000e+01
75%      2.000000e+01
max      1.500000e+02
Name: no_of_words_after_pre_process, dtype: float64
```

trying to fill the missing brand name values

In [ ]:

```
X_train['imp_brand_name'] = X_train['brand_name'].values
```

In [ ]:

```
# brand name  count
temp_brand=X_train['brand_name'].value_counts()
temp=temp_brand.to_frame().reset_index()
temp.rename(columns={'index': 'brand', 'brand_name': 'cnt'}, inplace=True)
temp[:15]
```

Out[ ]:

	brand	cnt
0	not known	569539
1	PINK	48742
2	Nike	48576
3	Victoria's Secret	43210
4	LuLaRoe	27869
5	Apple	15602
6	FOREVER 21	13660
7	Nintendo	13469
8	Lululemon	13069
9	Michael Kors	12494
10	American Eagle	11937
11	Rae Dunn	11064
12	Sephora	10933
13	Coach	9409
14	Disney	9276

In [ ]:

```
tp_12_brands   =   temp[(temp['cnt']>10000 )& (temp['brand']!='not known') ]['brand'].values

# getting top 12 brand data (which only include name and item description and corresponding brand name)
tp_brand_data   =  X_train[X_train['brand_name'].apply(lambda x: x in tp_12_brands)][['pre_processed_txt','bra

X_train_tp_brand   =  tp_brand_data['pre_processed_txt']
y_train_tp_brand   =  tp_brand_data['brand_name']

X_missing_brand_data   =  X_train[X_train['brand_name']=='not known'][['train_id','pre_processed_txt']]
```

```
nan_brd_train_id       =  X_missing_brand_data['train_id']
X_missing_brand_data   =  X_missing_brand_data['pre_processed_txt']

print('nan_brd_train_id shape   :',nan_brd_train_id.shape)
print('X_missing_brand_data shape :',X_missing_brand_data.shape)
```

```
nan_brd_train_id shape   : (569539,)
X_missing_brand_data shape : (569539,)
```

In [ ]:

```
y_train_tp_brand.shape
```

Out[ ]:

```
(270625,)
```

In [ ]:

```
X_train_tp_brand.values
```

Out[ ]:

```
array(['makeup bundl piec cliniqu makeup bag rimmel spici bronz new benefit highlight travel swatch twice hard candi blush swatch wet n wild eyebrow swatch highbrow loreal infalli eyeshadow etern new maybellin eyeshadow quad mad swatch wet n wild le bronzer everyth swatch covergirl singl eyeshadow brown swatch twice covergirl singl eyeshadow forev rimmel eyeshadow swatch color take good care everyth frequent spray makeup sanit plea ask pay ship fee',
       'v tank top small new tag price firm',
       'nike hoodi kid boy nike size', ...,
       'use worn time nike free flyknit use free flyknit nike chukka size men origin price great condit nike free flyknit chukka wolf green',
       'bless oval new stamp instead rae dunn ship bubbl wrap extrem care plea note rae dunn item uniqu exact item receiv plea zoom one flaw sale not respons item transit purchas agre',
       'v pink ultim sport bra one nwt other gentli use great condit size push ultim sport bra'],
      dtype=object)
```

In [ ]:

```
# bag of words : converting text to numeric data
from sklearn.feature_extraction.text import CountVectorizer

vectorizer = CountVectorizer(min_df=50)
X_cnt_vect_train = vectorizer.fit_transform(X_train_tp_brand.values)

X_cnt_vect_nan_brd = vectorizer.transform(X_missing_brand_data.values)
```

In [ ]:

```
# saving vectorizer for datapipline
pickle.dump(vectorizer, open("/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/missin

## load pickle
#vectorizer = pickle.load(open("/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/miss
```

In [ ]:

```
X_cnt_vect_nan_brd.shape
```

Out[ ]:

```
(569539, 3293)
```

In [ ]:

```
#print(vectorizer.get_feature_names())
len(vectorizer.get_feature_names()[:])
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/utils/deprecation.py:87: FutureWarning: Function get_feature_names is deprecated; get_feature_names is deprecated in 1.0 and will be removed in 1.2. Please use get_feature_names_out instead.
  warnings.warn(msg, category=FutureWarning)
```

Out[ ]:

```
3293
```

In [ ]:

```
# target value(beand name) label encoding
from sklearn import preprocessing

label_encoder = preprocessing.LabelEncoder()

y_train_final= label_encoder.fit_transform(y_train_tp_brand)
#y_test_final= label_encoder.transform(y_test)

keys = label_encoder.classes_
values = label_encoder.transform(label_encoder.classes_)
dictionary = dict(zip(keys, values))
dictionary
```

Out[ ]:

```
{'American Eagle': 0,
 'Apple': 1,
 'FOREVER 21': 2,
 'LuLaRoe': 3,
 'Lululemon': 4,
 'Michael Kors': 5,
 'Nike': 6,
 'Nintendo': 7,
 'PINK': 8,
 'Rae Dunn': 9,
 'Sephora': 10,
 "Victoria's Secret": 11}
```

In [ ]:

```
# saving the encoder for data pipline

pickle.dump(label_encoder, open("/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/lal

# load pickle
#vectorizer = pickle.load(open("/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/labe
```

In [ ]:

In [ ]:

```
# applying Multinomial navie bayes on text data

from sklearn.naive_bayes import MultinomialNB

M_NB  = MultinomialNB(alpha=0.05,class_prior=[0.5]*12)
model_NB = M_NB.fit(X_cnt_vect_train, y_train_final)

model_NB_train_predictions = model_NB.predict(X_cnt_vect_train)
model_NB_nan_predictions = model_NB.predict(X_cnt_vect_nan_brd)
```

In [ ]:

```
# save the classifier for data pipline
with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/brandname_classifier.pkl
    pickle.dump(M_NB, fp)
'''
# load it again
with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/brandname_classifier.pkl
    M_NB = Pickle.load(fid)
'''
```

Out[ ]:

```
"\n# load it again\nwith open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/brand
name_classifier.pkl', 'rb') as fid:\n    M_NB = Pickle.load(fid)\n"
```

In [ ]:

```
print('Train Accuracy : ',sum(model_NB_train_predictions==y_train_final)/len(y_train_final))
```

```
Train Accuracy :  0.891691454965358
```

In [ ]:

```
X_cnt_vect_train.shape
```

Out[ ]:

```
(270625, 3293)
```

In [ ]:

```
X_cnt_vect_nan_brd.shape
```

Out[ ]:

```
(569539, 3293)
```

In [ ]:

```
best_prob_threshold=0.99999
nan_brand_labels=[]
predicated_ids=[]
not_predicated=0
for prob,id in zip(M_NB.predict_proba(X_cnt_vect_nan_brd),nan_brd_train_id.values):
  x= prob >= best_prob_threshold   #returns [False,  True, False, False, False, False, False, False, False, Fa
  #print(x)
  if (any(x)):
    pred_label=x.argmax()
    nan_brand_labels.append(pred_label)
    predicated_ids.append(id)
  else:
    not_predicated=not_predicated+1
```

```
print('total predicated count : ',len(predicated_ids))
print('not predicated count : ',not_predicated)
```

```
total predicated count :  144074
not predicated count :  425465
```

In [ ]:

```
nan_pred_labels = label_encoder.inverse_transform(nan_brand_labels)

X_train = X_train.set_index('train_id')
X_train.loc[predicated_ids,['imp_brand_name']]=nan_pred_labels
```

In [ ]:

In [ ]:

```
'''
indices = list(X_train[X_train['train_id'].isin(predicated_ids)].index)

X_train.loc[indices,['imp_brand_name']]=nan_pred_labels
''
```

In [ ]:

TF-IDF

In [ ]:

```
from sklearn.feature_extraction.text import TfidfVectorizer
tfidf_vectorizer = TfidfVectorizer(ngram_range=(1, 2),min_df=50, max_features=110000)
tfidf_txt_data = tfidf_vectorizer.fit_transform(X_train['pre_processed_txt'].values)
```

In [ ]:

```
tfidf_txt_data.shape
```

Out[ ]:

```
(1333494, 60400)
```

In [ ]:

```
# save the vectorizer for data pipline
with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/tfidf_vectorizer.pkl', 'w
    pickle.dump(tfidf_vectorizer, fp)
'''
# load it again
with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/tfidf_vectorizer.pkl', 'r
    tfidf_vectorizer = Pickle.load(fp)
'''
```

Out[ ]:

```
"\n# load it again\nwith open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/tfidf
_vectorizer.pkl', 'rb') as fp:\n    tfidf_vectorizer = Pickle.load(fp)\n"
```

Kmode

In [ ]:

```
!pip install kmodes
from kmodes.kmodes import KModes
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Requirement already satisfied: kmodes in /usr/local/lib/python3.7/dist-packages (0.12.1)
Requirement already satisfied: numpy>=1.10.4 in /usr/local/lib/python3.7/dist-packages (from kmodes) (1.21.6)
Requirement already satisfied: scipy>=0.13.3 in /usr/local/lib/python3.7/dist-packages (from kmodes) (1.4.1)
Requirement already satisfied: scikit-learn>=0.22.0 in /usr/local/lib/python3.7/dist-packages (from kmodes) (1
.0.2)
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.7/dist-packages (from kmodes) (1.1.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.7/dist-packages (from scikit-lea
rn>=0.22.0->kmodes) (3.1.0)
```

In [ ]:

```
train_data.columns
```

Out[ ]:

```
Index(['train_id', 'name', 'item_condition_id', 'category_name', 'brand_name',
       'price', 'shipping', 'item_description', 'log_price'],
      dtype='object')
```

clustering using below features

- main_category
- sub_category_1
- sub_category_2

In [ ]:

```
temp_data = X_train[['main_category','sub_category_1','sub_category_2']]
```

In [ ]:

```
## reference https://www.analyticsvidhya.com/blog/2021/06/kmodes-clustering-algorithm-for-categorical-data/

kmode_1 = KModes(n_clusters=40, init = "random", n_init = 1, verbose=1)
clusters = kmode_1.fit_predict(temp_data)
```

```
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 130707, cost: 1242138.0
Run 1, iteration: 2/100, moves: 7, cost: 1242138.0
```

In [ ]:

```
X_train['40_clusters_'] = clusters
```

In [ ]:

```
# save the vectorizer for data pipline
with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/kmode_1_category.pkl', 'w
    pickle.dump(kmode_1, fp)
'''
# load it again
with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/kmode_1_category.pkl', 'r
    kmode_1 = Pickle.load(fp)
'''
```

Out[ ]:

```
"\n# load it again\nwith open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/kmode
_1_category.pkl', 'rb') as fp:\n    kmode_1 = Pickle.load(fp)\n"
```

clustering using below features

- item_condition_id
- shipping
- main_category
- sub_category_1

In [ ]:

```
temp2_data = X_train[['item_condition_id','shipping','main_category','sub_category_1']]
```

In [ ]:

```
kmode_2 = KModes(n_clusters=70, init = "random", n_init = 1, verbose=1)
clusters = kmode_2.fit_predict(temp2_data)
X_train['70_clusters_']=clusters
```

```
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 174622, cost: 906985.0
Run 1, iteration: 2/100, moves: 21293, cost: 906985.0
```

In [ ]:

```
# save the vectorizer for data pipline
with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/kmode_2_id_shp_category.p
    pickle.dump(kmode_2, fp)
'''
# load it again
with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/kmode_2_id_shp_category.p
    kmode_2 = Pickle.load(fp)
'''
```

Out[ ]:

```
"\n# load it again\nwith open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/kmode
_2_id_shp_category.pkl', 'rb') as fp:\n    kmode_2 = Pickle.load(fp)\n"
```

one hot encoding

In [ ]:

```
X_train.columns
```

Out[ ]:

```
Index(['name', 'item_condition_id', 'brand_name', 'price', 'shipping',
       'item_description', 'main_category', 'sub_category_1', 'sub_category_2',
       'no_of_words_in_txt', 'pre_processed_txt',
       'no_of_words_after_pre_process', 'imp_brand_name', '40_clusters_',
       '70_clusters_'],
      dtype='object')
```

In [ ]:

```
from sklearn.preprocessing import OneHotEncoder

def one_hot_encoder(dataframe,feature):

  enc = OneHotEncoder(handle_unknown='ignore')
  temp=enc.fit_transform(dataframe[feature].values.reshape(-1,1))

  return enc,temp
```

In [ ]:

```
categorical_features =['item_condition_id', 'main_category', 'sub_category_1', 'sub_category_2', 'brand_name',
                       '40_clusters_','70_clusters_','imp_brand_name']

one_hot_enc_dict=dict()

for feature in categorical_features:
  encoder , one_hot_enc_dict[feature] = one_hot_encoder(X_train,feature)
  with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/one_hot_encode_'+str(fe
    pickle.dump(encoder, fp)
  print(feature,'   : ',one_hot_enc_dict[feature].shape)
```

```
item_condition_id    :  (1333494, 5)
main_category    :  (1333494, 11)
sub_category_1    :  (1333494, 114)
sub_category_2    :  (1333494, 870)
brand_name    :  (1333494, 4670)
40_clusters_    :  (1333494, 35)
70_clusters_    :  (1333494, 66)
imp_brand_name    :  (1333494, 4670)
```

standardization of numeric data

In [ ]:

```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()

std=scaler.fit_transform(X_train[['no_of_words_in_txt','no_of_words_after_pre_process']].values)
```

In [ ]:

```
with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/numeric_std.pkl', 'wb') a
  pickle.dump(scaler, fp)

'''
with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/numeric_std.pkl', 'rb') a
    scaler = pickle.load(fp)

'''
```

Out[ ]:

```
"\nwith open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/numeric_std.pkl', 'rb'
) as fp:\n    scaler = pickle.load(fp)\n\n"
```

In [ ]:

```
'''
with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/X_train.pkl', 'wb') as fp
  pickle.dump(X_train, fp)

with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/y_train.pkl', 'wb') as fp
  pickle.dump(y_train, fp)
'''
```

Final Train data

Total Data 1:

In [ ]:

```
# without thrsholding price and number of words

from scipy.sparse import hstack

final_train_data_1 = hstack((std,one_hot_enc_dict['40_clusters_'],one_hot_enc_dict['70_clusters_'],one_hot_enc
               one_hot_enc_dict['item_condition_id'],one_hot_enc_dict['main_category'],one_hot_enc_dict['sub_c
               one_hot_enc_dict['sub_category_2'],tfidf_txt_data)).tocsr()

print("="*30)
print("Final Train Data matrix:")
print(final_train_data_1.shape)
print("="*30)
```

```
==============================
Final Train Data matrix:
(1333494, 66173)
==============================
```

In [ ]:

```
from scipy import sparse
'''
sparse.save_npz("/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/train_data_1.npz",
'''
```

Total Data with brand_name feature imputed:

In [ ]:

```
#  imputed values

final_train_data_2 = hstack((std,one_hot_enc_dict['40_clusters_'],one_hot_enc_dict['70_clusters_'],one_hot_enc
               one_hot_enc_dict['item_condition_id'],one_hot_enc_dict['main_category'],one_hot_enc_dict['sub_c
               one_hot_enc_dict['sub_category_2'],tfidf_txt_data)).tocsr()

print("="*30)
print("Final Train Data 2 matrix:")
print(final_train_data_2.shape)
print("="*30)
```

```
==============================
Final Train Data 2 matrix:
(1333494, 66173)
==============================
```

In [ ]:

```
sparse.save_npz("/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/train_data_2.npz",
```

Removing the datapoints

> whose price greater then 450 (99.9 percentile) and also the datapoints whose number of words in text greater then 189(99.9 percentile)

In [ ]:

```
'''
tmp = data[['train_id','price']]
X_train = pd.merge(X_train, tmp, on="train_id", how="left")
'''
```

In [ ]:

```
without_outliers_train_data = X_train[(X_train['price']<450) & (X_train['no_of_words_in_txt']<189)]
without_outliers_train_data.shape
```

Out[ ]:

```
(1330151, 15)
```

In [ ]:

```
y_train_without_outliers = np.log(without_outliers_train_data['price'].values+1)
```

standardization of numeric data

In [ ]:

```
from sklearn.preprocessing import StandardScaler

scaler_2 = StandardScaler()

std_2 = scaler_2.fit_transform(without_outliers_train_data[['no_of_words_in_txt','no_of_words_after_pre_proces

with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/std_2_numeric_data.pkl',
```

```
    pickle.dump(scaler_2, fp)
```

vectorization of text data

In [ ]:

```
from sklearn.feature_extraction.text import TfidfVectorizer

vectorizer_without_outliers = TfidfVectorizer(ngram_range=(1, 2),min_df=50, max_features=110000)
tfidf_txt_data_2 = vectorizer_without_outliers.fit_transform(without_outliers_train_data['pre_processed_txt']

with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/vectorizer_without_outlie
    pickle.dump(vectorizer_without_outliers, fp)

tfidf_txt_data_2.shape
```

Out[ ]:

```
(1330151, 59985)
```

trying to fill the missing brand name values for without outliers data

In [ ]:

```
#without_outliers_train_data['train_id'] = without_outliers_train_data.index
```

In [ ]:

```
without_outliers_train_data['imp_brand_name_2'] = without_outliers_train_data['brand_name'].values
# brand name  count
temp_brand=without_outliers_train_data['brand_name'].value_counts()
temp=temp_brand.to_frame().reset_index()
temp.rename(columns={'index': 'brand', 'brand_name': 'cnt'}, inplace=True)
temp[:15]
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:1: 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#re
turning-a-view-versus-a-copy
  """Entry point for launching an IPython kernel.
```

Out[ ]:

	brand	cnt
0	not known	567672
1	PINK	48714
2	Nike	48565
3	Victoria's Secret	43179
4	LuLaRoe	27869
5	Apple	15259
6	FOREVER 21	13658
7	Nintendo	13462
8	Lululemon	13065
9	Michael Kors	12483
10	American Eagle	11935
11	Rae Dunn	11060
12	Sephora	10920
13	Coach	9406
14	Disney	9274

In [ ]:

```
tp_12_brands   =   temp[(temp['cnt']>10000 )& (temp['brand']!='not known') ]['brand'].values

# getting top 12 brand data (which only include name and item description and corresponding brand name)
tp_brand_data   =  without_outliers_train_data[without_outliers_train_data['brand_name'].apply(lambda x: x in

X_train_tp_brand   =  tp_brand_data['pre_processed_txt']
y_train_tp_brand   =  tp_brand_data['brand_name']

X_missing_brand_data   =  without_outliers_train_data[without_outliers_train_data['brand_name']=='not known']
nan_brd_train_id       =  X_missing_brand_data['train_id']
```

```
X_missing_brand_data   =  X_missing_brand_data['pre_processed_txt']

print('nan_brd_train_id shape   :',nan_brd_train_id.shape)
print('X_missing_brand_data shape :',X_missing_brand_data.shape)
```

```
nan_brd_train_id shape   : (567672,)
X_missing_brand_data shape : (567672,)
```

In [ ]:

```
# bag of words : converting text to numeric data
from sklearn.feature_extraction.text import CountVectorizer

vectorizer_2 = CountVectorizer(min_df=50)
X_cnt_vect_train = vectorizer_2.fit_transform(X_train_tp_brand.values)

X_cnt_vect_nan_brd = vectorizer_2.transform(X_missing_brand_data.values)

# saving vectorizer for datapipline
pickle.dump(vectorizer_2, open("/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/mis

X_cnt_vect_nan_brd.shape
```

Out[ ]:

```
(567672, 3285)
```

In [ ]:

```
# target value(beand name) label encoding
from sklearn import preprocessing

label_encoder_2 = preprocessing.LabelEncoder()

y_train_final= label_encoder_2.fit_transform(y_train_tp_brand)
#y_test_final= label_encoder.transform(y_test)

# saving the encoder for data pipline
pickle.dump(label_encoder, open("/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/lab


keys = label_encoder_2.classes_
values = label_encoder_2.transform(label_encoder_2.classes_)
dictionary = dict(zip(keys, values))
dictionary
```

Out[ ]:

```
{'American Eagle': 0,
 'Apple': 1,
 'FOREVER 21': 2,
 'LuLaRoe': 3,
 'Lululemon': 4,
 'Michael Kors': 5,
 'Nike': 6,
 'Nintendo': 7,
 'PINK': 8,
 'Rae Dunn': 9,
 'Sephora': 10,
 "Victoria's Secret": 11}
```

In [ ]:

```
# applying Multinomial navie bayes on text data

from sklearn.naive_bayes import MultinomialNB

M_NB_2  = MultinomialNB(alpha=0.05,class_prior=[0.5]*12)
model_NB = M_NB_2.fit(X_cnt_vect_train, y_train_final)


# save the classifier for data pipline
with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/brandname_classifier_2.pl
    pickle.dump(M_NB_2, fp)

model_NB_train_predictions = model_NB.predict(X_cnt_vect_train)
model_NB_nan_predictions = model_NB.predict(X_cnt_vect_nan_brd)
```

In [ ]:

```
print('Train Accuracy : ',sum(model_NB_train_predictions==y_train_final)/len(y_train_final))
```

```
Train Accuracy :  0.8915123496774241
```

In [ ]:

```
best_prob_threshold=0.99999
```

```
nan_brand_labels=[]
predicated_ids=[]
not_predicated=0
for prob,id in zip(M_NB_2.predict_proba(X_cnt_vect_nan_brd),nan_brd_train_id.values):
  x= prob >= best_prob_threshold   #returns [False,  True, False, False, False, False, False, False, False, Fa
  #print(x)
  if (any(x)):
    pred_label=x.argmax()
    nan_brand_labels.append(pred_label)
    predicated_ids.append(id)
  else:
    not_predicated=not_predicated+1

print('total predicated count : ',len(predicated_ids))
print('not predicated count : ',not_predicated)
```

```
total predicated count :  142856
not predicated count :  424816
```

In [ ]:

```
nan_pred_labels = label_encoder_2.inverse_transform(nan_brand_labels)

without_outliers_train_data = without_outliers_train_data.set_index('train_id')

without_outliers_train_data.loc[predicated_ids,['imp_brand_name']]=nan_pred_labels
```

one hot encoding of categorical data

In [ ]:

```
categorical_features =['item_condition_id', 'main_category', 'sub_category_1', 'sub_category_2', 'brand_name',
                       '40_clusters_','70_clusters_','imp_brand_name']

one_hot_enc_dict_2=dict()

for feature in categorical_features:
  encoder_2 , one_hot_enc_dict_2[feature] = one_hot_encoder(without_outliers_train_data,feature)

  with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/one_hot_encode_WoOutlie
    pickle.dump(encoder_2, fp)

  print(feature,'   : ',one_hot_enc_dict_2[feature].shape)
```

```
item_condition_id    :  (1330151, 5)
main_category    :  (1330151, 11)
sub_category_1    :  (1330151, 114)
sub_category_2    :  (1330151, 870)
brand_name    :  (1330151, 4669)
40_clusters_    :  (1330151, 35)
70_clusters_    :  (1330151, 66)
imp_brand_name    :  (1330151, 4669)
```

In [ ]:

Data without outliers 3:

In [ ]:

```
final_train_data_3 = hstack((std_2,one_hot_enc_dict_2['40_clusters_'],one_hot_enc_dict_2['70_clusters_'],\
                             one_hot_enc_dict_2['brand_name'],one_hot_enc_dict_2['item_condition_id'],\
                             one_hot_enc_dict_2['main_category'],one_hot_enc_dict_2['sub_category_1'],\
                             one_hot_enc_dict_2['sub_category_2'],tfidf_txt_data_2)).tocsr()

print("="*30)
print("Final Data matrix:")
print(final_train_data_3.shape)
print("="*30)
```

```
==============================
Final Data matrix:
(1330151, 65757)
==============================
```

In [ ]:

```
from scipy import sparse

sparse.save_npz("/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/train_data_3.npz",
```

Data without outliers and brand_name feature imputed:

In [ ]:

```
#  imputed values

final_train_data_4 = hstack((std_2,one_hot_enc_dict_2['40_clusters_'],one_hot_enc_dict_2['70_clusters_'],\
                             one_hot_enc_dict_2['imp_brand_name'],one_hot_enc_dict_2['item_condition_id'],\
                             one_hot_enc_dict_2['main_category'],one_hot_enc_dict_2['sub_category_1'],\
                             one_hot_enc_dict_2['sub_category_2'],tfidf_txt_data_2)).tocsr()

print("="*30)
print("Final Data matrix:")
print(final_train_data_4.shape)
print("="*30)
```

```
==============================
Final Data matrix:
(1330151, 65757)
==============================
```

In [ ]:

```
from scipy import sparse

sparse.save_npz("/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/train_data_4.npz",
```

Data Pipline

This tab contain all the required functions for datapipline

In [ ]:

```
# applying  Stemming on text

porter_stemmer = PorterStemmer()

def stemming(txt):
  stem_txt = [porter_stemmer.stem(word) for word in txt.split(' ')]
  return ' '.join(stem_txt)
```

In [ ]:

```
# applying Lemmatization on text data

wordnet_lemmatizer = WordNetLemmatizer()
def lemmatizer(txt):

  lem_txt = [wordnet_lemmatizer.lemmatize(word) for word in txt.split(' ')]
  return ' '.join(lem_txt)
```

In [ ]:

```
def len_fun(x):
  try:
    return x.split('/',3)
  except:
    return 'no label','no label','no label'
```

In [ ]:

```
# removing stopwords from text

def rm_stp_wds(sentence):

  stopwords = pickle.load(open("/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/stop

  temp_lst=[]
  for word in sentence.split(' '):
    if word not in stopwords:
      temp_lst.append(word)
  return ' '.join(temp_lst)
```

In [ ]:

```
def extract_words(input_data=' '):
    '''
    this function replace all the words except A-Za-z_ with space
    '''
    pattern_17='\s{0,1}[A-Za-z_]+\s{0,1}'
```

```
    regex_17 = re.compile(pattern_17)
    xt=input_data.split()
    #print(xt)
    tmp_list=[]
    for i in xt:
        t=regex_17.fullmatch(i.strip())
        if t!=None:
            tmp_list.append(t.group())

    return ' '.join(tmp_list)
```

In [ ]:

```
def fill_missing_brand_name(data_frame , without_outliers_data=False):

  nan_brand_labels=[]
  predicated_ids=[]
  best_prob_threshold=0.99999
  not_predicated=0

  tmp = data_frame[data_frame['brand_name']=='not known'].shape[0]

  if (tmp==0): # no missing values
    return data_frame
  else :
    missing_value_data = data_frame[data_frame['brand_name']=='not known'][['train_id','pre_processed_txt']]
    nan_brd_train_id       =  missing_value_data['train_id']
    X_missing_brand_data   =  missing_value_data['pre_processed_txt']

    if without_outliers_data ==False:
      # import vectorizer
      vectorizer = pickle.load(open("/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files
      # import trained model
      with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/brandname_classifie
        M_NB = pickle.load(fp)

    else:
      vectorizer = pickle.load(open("/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files
      with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/brandname_classifie
        M_NB = pickle.load(fp)


    X_cnt_vect_nan_brd = vectorizer.transform(X_missing_brand_data.values)

    for prob,id in zip(M_NB.predict_proba(X_cnt_vect_nan_brd),nan_brd_train_id.values):
      x= prob >= best_prob_threshold   #returns [False,  True, False, False, False, False, False, False, Fals
      #print(x)
      if (any(x)):
        pred_label=x.argmax()
        nan_brand_labels.append(pred_label)
        predicated_ids.append(id)
      else:
        not_predicated=not_predicated+1


    label_encoder = pickle.load(open("/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_file
    nan_pred_labels = label_encoder.inverse_transform(nan_brand_labels)
    data_frame = data_frame.set_index('train_id')
    data_frame.loc[predicated_ids,['imp_brand_name']]=nan_pred_labels
    '''
    indices = list(data_frame[data_frame['train_id'].isin(predicated_ids)].index)
    data_frame.loc[indices,['imp_brand_name']]=nan_pred_labels
    '''
    return data_frame
```

In [ ]:

```
def vect_txt_data(data_frame,without_outliers_data=False):

  #import txt vector
  if without_outliers_data==False:
    with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/tfidf_vectorizer.pkl
      tfidf_vectorizer = pickle.load(fp)
  else:
    with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/vectorizer_without_ou
      tfidf_vectorizer = pickle.load(fp)
```

```
    tfidf_txt_data = tfidf_vectorizer.transform(data_frame['pre_processed_txt'].values)

    return tfidf_txt_data
```

In [ ]:

```
def categorical_clustering_1(data_frame):


    temp_data = data_frame[['main_category','sub_category_1','sub_category_2']]

    #import kmode model
    with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/kmode_1_category.pkl',
      kmode_1 = pickle.load(fp)

    clusters = kmode_1.predict(temp_data)
    data_frame['40_clusters_'] = clusters

    return data_frame
```

In [ ]:

```
def categorical_clustering_2(data_frame):

    temp_data = data_frame[['item_condition_id','shipping','main_category','sub_category_1']]

    #import kmode model
    with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/kmode_2_id_shp_category
      kmode_2 = pickle.load(fp)

    clusters = kmode_2.predict(temp_data)
    data_frame['70_clusters_'] = clusters

    return data_frame
```

In [ ]:

```
def one_hot_enc_categorical_feature(data_frame, without_outliers_data=False):

    categorical_features =['item_condition_id', 'main_category', 'sub_category_1', 'sub_category_2', 'brand_name
                         '40_clusters_','70_clusters_','imp_brand_name']

    one_hot_enc_dict=dict()

    for feature in categorical_features:

      if without_outliers_data==False:
        with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/one_hot_encode_'+st
          encoder = pickle.load(fp)
      else:
        with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/one_hot_encode_WoOu
          encoder = pickle.load(fp)

      one_hot_enc_dict[feature] = encoder.transform(data_frame[feature].values.reshape(-1,1))

    return one_hot_enc_dict
```

In [ ]:

```
def std_numeric_data(df,without_outliers_data=False):

    #import
    if without_outliers_data==False:
      with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/numeric_std.pkl', 'rb
        scaler = pickle.load(fp)
    else:
      with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/std_2_numeric_data.pl
        scaler = pickle.load(fp)

    std = scaler.transform(df[['no_of_words_in_txt','no_of_words_after_pre_process']].values)

    return std
```

Data pipline function

In [ ]:

```
def data_pipline(test_cv_df,brand_name_imputed = False,without_outliers_data=False):
    '''
```

```
This function takes dataframe as input and performs required pre processing on data
and gives us the final data which can be give to model to predicate output
'''
test_cv_df['imp_brand_name'] = test_cv_df['brand_name'].values

temp_category_name = test_cv_df['category_name'].apply(lambda x: len_fun(x))
test_cv_df['main_category'],test_cv_df['sub_category_1'],test_cv_df['sub_category_2']=zip(*temp_category_nar

test_cv_df['brand_name'].fillna(value='not known', inplace=True)

# filling the null values with no data
test_cv_df['item_description'].fillna(value='no data',inplace=True)
test_cv_df['name'].fillna(value='no data',inplace=True)


txt_data = test_cv_df['name']+' '+test_cv_df['item_description']
test_cv_df['no_of_words_in_txt'] = txt_data.str.split().apply(len)


pre_proc_txt_data = txt_data.apply(lambda x : rm_stp_wds(x))

# replacing '_' with space
pre_proc_txt_data = pre_proc_txt_data.str.replace('_',' ')

pre_proc_txt_data = pre_proc_txt_data.apply(lambda x : extract_words(x))

pre_proc_stm_txt_data  = pre_proc_txt_data.apply(lambda x: stemming(x))

final_txt_data = pre_proc_stm_txt_data.apply(lambda x:lemmatizer(x))

test_cv_df['pre_processed_txt'] = final_txt_data

test_cv_df['no_of_words_after_pre_process']=test_cv_df['pre_processed_txt'].str.split().apply(len)

#if brand_name_imputed == True:
test_cv_df = fill_missing_brand_name(test_cv_df,without_outliers_data)

tfidf_vect_txt = vect_txt_data(test_cv_df, without_outliers_data)

test_cv_df = categorical_clustering_1(test_cv_df)

test_cv_df = categorical_clustering_2(test_cv_df)

# one hot encoding

one_hot_enc_dict = one_hot_enc_categorical_feature(test_cv_df , without_outliers_data)

numeric_std_data = std_numeric_data(test_cv_df,without_outliers_data)
#print(test_cv_df.columns)
#print(one_hot_enc_dict.keys())
if (brand_name_imputed== False) and (without_outliers_data==False) :
  final_train_data = hstack((numeric_std_data,one_hot_enc_dict['40_clusters_'],one_hot_enc_dict['70_clusters
           one_hot_enc_dict['item_condition_id'],one_hot_enc_dict['main_category'],one_hot_enc_dict['sub_c
           one_hot_enc_dict['sub_category_2'],tfidf_vect_txt)).tocsr()

elif (brand_name_imputed== True) and (without_outliers_data==False) :
  final_train_data = hstack((numeric_std_data,one_hot_enc_dict['40_clusters_'],one_hot_enc_dict['70_clusters
                           one_hot_enc_dict['imp_brand_name'],one_hot_enc_dict['item_condition_id'],one_ho
                           one_hot_enc_dict['sub_category_1'],one_hot_enc_dict['sub_category_2'],tfidf_vec

elif (brand_name_imputed== False) and (without_outliers_data==True) :
  final_train_data = hstack((numeric_std_data,one_hot_enc_dict['40_clusters_'],one_hot_enc_dict['70_clusters
                         one_hot_enc_dict['brand_name'],one_hot_enc_dict['item_condition_id'],\
                         one_hot_enc_dict['main_category'],one_hot_enc_dict['sub_category_1'],\
                         one_hot_enc_dict['sub_category_2'],tfidf_vect_txt)).tocsr()



elif (brand_name_imputed== True) and (without_outliers_data==True) :
  final_train_data = hstack((numeric_std_data,one_hot_enc_dict['40_clusters_'],one_hot_enc_dict['70_clusters
                         one_hot_enc_dict['imp_brand_name'],one_hot_enc_dict['item_condition_id'],\
                         one_hot_enc_dict['main_category'],one_hot_enc_dict['sub_category_1'],\
                         one_hot_enc_dict['sub_category_2'],tfidf_vect_txt)).tocsr()
```

```
  return final_train_data
```

In [ ]:

```
'''
with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/final_cv_data_1.pkl', 'wb
    pickle.dump(final_cv_data_1, fp)
with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/final_cv_data_2.pkl', 'wb
    pickle.dump(final_cv_data_2, fp)
'''
```

In [ ]:

```
# save the vectorizer for data pipline
'''
with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/X_validation.pkl', 'wb')
    pickle.dump(X_validation, fp)

with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/y_validationt.pkl', 'wb')
    pickle.dump(y_validationt, fp)
'''
```

Out[ ]:

```
"\n# load it again\nwith open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/tfidf
_vectorizer.pkl', 'rb') as fp:\n    tfidf_vectorizer = Pickle.load(fp)\n"
```

Modeling :

Loading Data:

In [ ]:

```
with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/y_train.pkl', 'rb') as fp
    y_train = pickle.load(fp)

with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/final_cv_data_1.pkl', 'rb
    final_cv_data_1 = pickle.load(fp)

with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/y_validationt.pkl', 'rb')
    y_validation = pickle.load(fp)

with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/X_validation.pkl', 'rb')
    X_validation = pickle.load(fp)


final_train_data_1 = load_npz('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/train
```

In [ ]:

Linear Model: linear Regression with L2 reg

In [ ]:

```
import nltk
nltk.download('omw-1.4')
nltk.download()
```

In [ ]:

```
test_stg_2['train_id']=test_stg_2['test_id']
final_test = data_pipline(test_stg_2,brand_name_imputed=False)
```

In [ ]:

```
with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/final_test_stg2_pp.pkl',
    pickle.dump(final_test, fp)
```

In [ ]:

```
final_test.shape
```

Out[ ]:

```
(3460725, 66173)
```

Training on total data:

In [ ]:

```
final_cv_data_1 = data_pipline(X_validation,brand_name_imputed=False)
```

In [ ]:

```
final_cv_data_1.shape
```

Out[ ]:

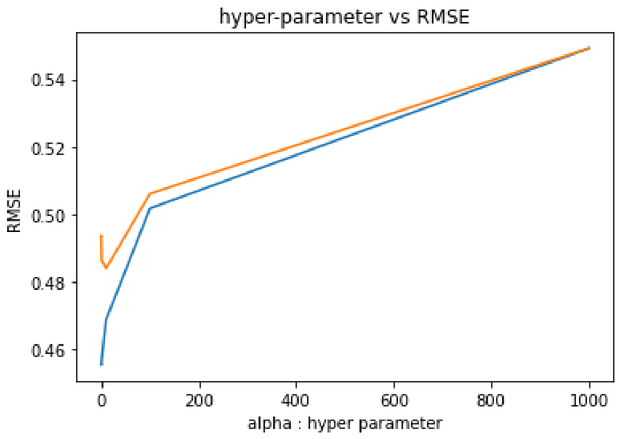
```
(148167, 66173)
```

In [ ]:

```
from sklearn.linear_model import Ridge
train_rmse = []
validation_rmse = []
alpha_s = [0.00001, 0.0001, 0.001, 0.01,0.1,1,10,100,1000]
for hy_para in alpha_s:
  reg_linear_model = Ridge(alpha = hy_para)
  reg_linear_model.fit(final_train_data_1,y_train.values)
  y_pred = reg_linear_model.predict(final_train_data_1)

  rmse = np.sqrt(sum((y_pred - y_train.values)**2)/len(y_pred))

  train_rmse.append(rmse)

  y_pred = reg_linear_model.predict(final_cv_data_1)

  rmse = np.sqrt(sum((y_pred - y_validationt.values)**2)/len(y_pred))

  validation_rmse.append(rmse)
```

In [ ]:

```
# importing the required module
import matplotlib.pyplot as plt


# plotting the points
plt.plot(alpha_s,train_rmse)
plt.plot(alpha_s,validation_rmse)

# naming the x axis
plt.xlabel('alpha : hyper parameter')
# naming the y axis
plt.ylabel('RMSE')

# giving a title to my graph
plt.title('hyper-parameter vs RMSE')

# function to show the plot
plt.show()
```



In [ ]:

```
tmp_dict = {'alpha_s' : alpha_s,
            'Train_rmse' : train_rmse ,
            'val_rmse' :validation_rmse}
pd.DataFrame(tmp_dict)
```

Out[ ]:

	alpha_s	Train_rmse	val_rmse
0	0.00001	0.455402	0.493693
1	0.00010	0.455384	0.493760
2	0.00100	0.455410	0.493668
3	0.01000	0.455442	0.493463
4	0.10000	0.455437	0.492387
5	1.00000	0.456935	0.486354
6	10.00000	0.468753	0.483938
7	100.00000	0.501716	0.506057
8	1000.00000	0.549092	0.549141

In [ ]:

```
best_alpha = 10
final_linear_model = Ridge(alpha = best_alpha)
final_linear_model.fit(final_train_data_1,y_train.values)
y_pred = final_linear_model.predict(final_train_data_1)
rmse = np.sqrt(sum((y_pred - y_train.values)**2)/len(y_pred))
print(' Train_RMSE : ',rmse)
y_pred = final_linear_model.predict(final_cv_data_1)
rmse = np.sqrt(sum((y_pred - y_validation.values)**2)/len(y_pred))
print('CV RMSE : ',rmse)
```

```
 Train_RMSE :  0.4693994981491512
CV RMSE :  0.4848529134295842
```

In [ ]:

```
#saving the model
'''with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/final_linear_model.pkl
  pickle.dump(final_linear_model, fp)
'''
```

Training on total data with brand name feature imputed:

In [ ]:

```
final_cv_data_2 = data_pipline(X_validation,brand_name_imputed=True)
```

In [ ]:

```
final_cv_data_2.shape
```

Out[ ]:

```
(148167, 66173)
```

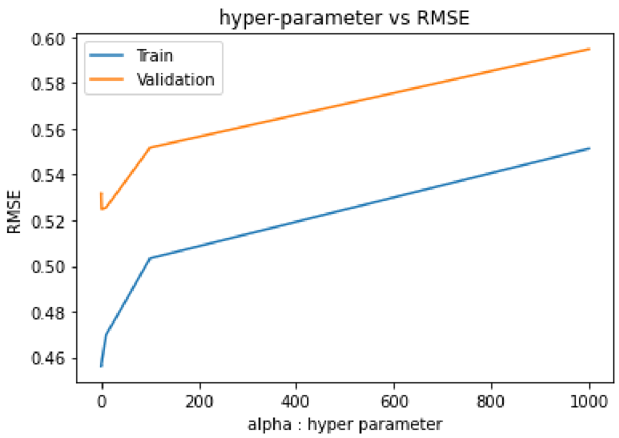
In [ ]:

```
from sklearn.linear_model import Ridge
train_rmse = []
validation_rmse = []
alpha_s = [0.00001, 0.0001, 0.001, 0.01,0.1,1,10,100,1000]
for hy_para in alpha_s:
  reg_linear_model = Ridge(alpha = hy_para)
  reg_linear_model.fit(final_train_data_2,y_train.values)
  y_pred = reg_linear_model.predict(final_train_data_2)

  rmse = np.sqrt(sum((y_pred - y_train.values)**2)/len(y_pred))

  train_rmse.append(rmse)

  y_pred = reg_linear_model.predict(final_cv_data_2)

  rmse = np.sqrt(sum((y_pred - y_validationt.values)**2)/len(y_pred))

  validation_rmse.append(rmse)
```

In [ ]:

```
# importing the required module
import matplotlib.pyplot as plt


# plotting the points
plt.plot(alpha_s,train_rmse,label='Train')
plt.plot(alpha_s,validation_rmse,label='Validation')
```

```
# naming the x axis
plt.xlabel('alpha : hyper parameter')
# naming the y axis
plt.ylabel('RMSE')
plt.legend()

# giving a title to my graph
plt.title('hyper-parameter vs RMSE')

# function to show the plot
plt.show()
```



In [ ]:

```
tmp_dict = {'alpha_s' : alpha_s,
            'Train_rmse' : train_rmse ,
            'val_rmse' :validation_rmse}
pd.DataFrame(tmp_dict)
```

Out[ ]:

	alpha_s	Train_rmse	val_rmse
0	0.00001	0.456297	0.531703
1	0.00010	0.456299	0.531682
2	0.00100	0.456341	0.531474
3	0.01000	0.456314	0.531479
4	0.10000	0.456378	0.530216
5	1.00000	0.457923	0.524828
6	10.00000	0.469835	0.525476
7	100.00000	0.503311	0.551684
8	1000.00000	0.551275	0.594775

In [ ]:

Training on data without oultiers (in price and number of words):

In [ ]:

```
final_cv_data_3 = data_pipline(X_validation,brand_name_imputed=False,without_outliers_data=True)
```

In [ ]:

```
final_cv_data_3.shape
```

Out[ ]:

```
(148167, 65757)
```

In [ ]:

```
'''
with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/final_cv_data_3.pkl', 'wb
    pickle.dump(final_cv_data_3, fp)
with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/y_train_without_outliers
    pickle.dump(y_train_without_outliers, fp)
'''
```

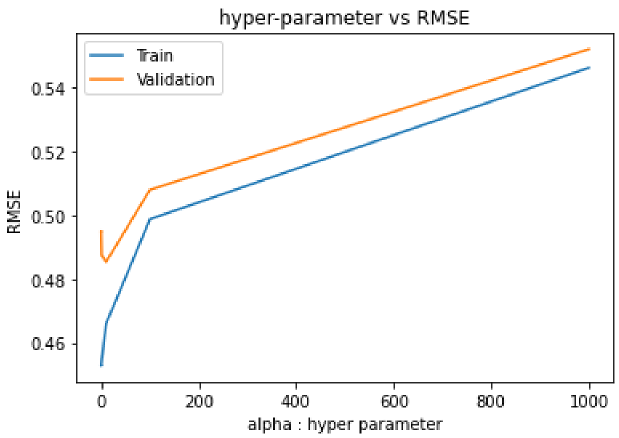
In [ ]:

In [ ]:

```
from sklearn.linear_model import Ridge
train_rmse = []
validation_rmse = []
alpha_s = [0.00001, 0.0001, 0.001, 0.01,0.1,1,10,100,1000]
for hy_para in alpha_s:
  reg_linear_model = Ridge(alpha = hy_para)
  reg_linear_model.fit(final_train_data_3,y_train_without_outliers)
  y_pred = reg_linear_model.predict(final_train_data_3)

  rmse = np.sqrt(sum((y_pred - y_train_without_outliers)**2)/len(y_pred))

  train_rmse.append(rmse)

  y_pred = reg_linear_model.predict(final_cv_data_3)

  rmse = np.sqrt(sum((y_pred - y_validationt.values)**2)/len(y_pred))

  validation_rmse.append(rmse)
```

In [ ]:

```
# importing the required module
import matplotlib.pyplot as plt


# plotting the points
plt.plot(alpha_s,train_rmse,label='Train')
plt.plot(alpha_s,validation_rmse,label='Validation')

# naming the x axis
plt.xlabel('alpha : hyper parameter')
# naming the y axis
plt.ylabel('RMSE')
plt.legend()

# giving a title to my graph
plt.title('hyper-parameter vs RMSE')

# function to show the plot
plt.show()
```



In [ ]:

```
tmp_dict = {'alpha_s' : alpha_s,
            'Train_rmse' : train_rmse ,
            'val_rmse' :validation_rmse}
pd.DataFrame(tmp_dict)
```

Out[ ]:

	alpha_s	Train_rmse	val_rmse
0	0.00001	0.452784	0.495122
1	0.00010	0.452776	0.495154
2	0.00100	0.452776	0.495142
3	0.01000	0.452775	0.495014
4	0.10000	0.452835	0.493723
5	1.00000	0.454337	0.487512
6	10.00000	0.465992	0.485360
7	100.00000	0.498787	0.508005
8	1000.00000	0.546261	0.552101

In [ ]:

Traing on data after removing outliers and brand name feature imputed:

In [ ]:

```
final_cv_data_4 = data_pipline(X_validation,brand_name_imputed=True,without_outliers_data=True)
```

In [ ]:

```
final_cv_data_4.shape
```

Out[ ]:

```
(148167, 65757)
```

In [ ]:

```
'''
with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/final_cv_data_4.pkl', 'wb
    pickle.dump(final_cv_data_4, fp)
'''
```

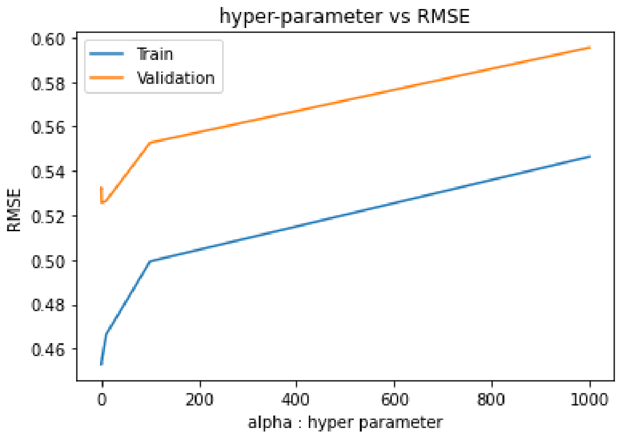
In [ ]:

```
from sklearn.linear_model import Ridge
train_rmse = []
validation_rmse = []
alpha_s = [0.00001, 0.0001, 0.001, 0.01,0.1,1,10,100,1000]
for hy_para in alpha_s:
  reg_linear_model = Ridge(alpha = hy_para)
  reg_linear_model.fit(final_train_data_4,y_train_without_outliers)
  y_pred = reg_linear_model.predict(final_train_data_4)

  rmse = np.sqrt(sum((y_pred - y_train_without_outliers)**2)/len(y_pred))

  train_rmse.append(rmse)

  y_pred = reg_linear_model.predict(final_cv_data_4)

  rmse = np.sqrt(sum((y_pred - y_validationt.values)**2)/len(y_pred))

  validation_rmse.append(rmse)
```

In [ ]:

```
# importing the required module
import matplotlib.pyplot as plt


# plotting the points
plt.plot(alpha_s,train_rmse,label='Train')
plt.plot(alpha_s,validation_rmse,label='Validation')

# naming the x axis
plt.xlabel('alpha : hyper parameter')
# naming the y axis
plt.ylabel('RMSE')
plt.legend()

# giving a title to my graph
plt.title('hyper-parameter vs RMSE')

# function to show the plot
```

```
plt.show()
```



In [ ]:

```
tmp_dict = {'alpha_s' : alpha_s,
            'Train_rmse' : train_rmse ,
            'val_rmse' :validation_rmse}
pd.DataFrame(tmp_dict)
```

Out[ ]:

	alpha_s	Train_rmse	val_rmse
0	0.00001	0.453159	0.532083
1	0.00010	0.453168	0.532032
2	0.00100	0.453140	0.532196
3	0.01000	0.453141	0.532076
4	0.10000	0.453212	0.530824
5	1.00000	0.454623	0.525604
6	10.00000	0.466403	0.526522
7	100.00000	0.499319	0.552655
8	1000.00000	0.546397	0.595440

In [ ]:

Summary:

In [ ]:

```
from prettytable import PrettyTable

# Specify the Column Names while initializing the Table
myTable = PrettyTable(["Model", "Dataset","hyper-parameter", "Train RMSE", "CV RMSE"])

# Add rows
myTable.add_row(["Linear Regression-L2", "Total data","10.0", "0.4687", "0.4839"])
myTable.add_row(["Linear Regression-L2", "total data +brand_name imputed",'1.0','0.4579', '0.5248'])
myTable.add_row(["Linear Regression-L2", "without outliers data","10.0", "0.4659", "0.4853"])
myTable.add_row(["Linear Regression-L2", "without outliers data + brand_name imputed",'1.0','0.4546','0.5256'

print(myTable)
```

```
+----------------------+--------------------------------------------+-----------------+------------+---------+
|        Model         |                  Dataset                   | hyper-parameter | Train RMSE | CV RMSE |
+----------------------+--------------------------------------------+-----------------+------------+---------+
| Linear Regression-L2 |                 Total data                 |       10.0      |   0.4687   |  0.4839 |
| Linear Regression-L2 |       total data +brand_name imputed       |       1.0       |   0.4579   |  0.5248 |
| Linear Regression-L2 |           without outliers data            |       10.0      |   0.4659   |  0.4853 |
| Linear Regression-L2 | without outliers data + brand_name imputed |       1.0       |   0.4546   |  0.5256 |
+----------------------+--------------------------------------------+-----------------+------------+---------+
```

Observation:

- Linear regression -L2 is not performing well on imputed data when compared with no imputation data.
- There is no significant difference in scores with total data and without outliers data.
- The above scores also tell us that "brand name" feature is an important feature to predicate the price value, predicating brand name wrong is very costly.
- So, working on only Total data for further modeling .

LGBM model:

In [ ]:

```
!pip install lightgbm
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Requirement already satisfied: lightgbm in /usr/local/lib/python3.7/dist-packages (2.2.3)
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.7/dist-packages (from lightgbm) (1.0.2)
Requirement already satisfied: numpy in /usr/local/lib/python3.7/dist-packages (from lightgbm) (1.21.6)
Requirement already satisfied: scipy in /usr/local/lib/python3.7/dist-packages (from lightgbm) (1.4.1)
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.7/dist-packages (from scikit-learn->ligh
tgbm) (1.1.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.7/dist-packages (from scikit-lea
rn->lightgbm) (3.1.0)
```

In [ ]:

```
param_distributions={'num_leaves'      : [50,80,110,150],
                     'max_depth'       : [8,12,16,20],
                    'learning_rate'    : [0.05,0.1,0.3],
                     'n_estimators'    : [100,150,200],
                    'colsample_bytree' : [1,0.8,0.6],
                     'reg_alpha' : [0,0.01,0.001],
                     'reg_lambda' : [0,0.01,0.001]}


model = LGBMRegressor(boosting_type='gbdt', objective='regression',  min_child_samples=50, reg_lambda=0.0,\
              random_state=30, n_jobs=- 1 )

random_search_cv = RandomizedSearchCV(model, param_distributions, scoring='neg_root_mean_squared_error',\
                    n_jobs=-1, refit=True, cv=3, verbose=1, random_state=30, return_train_score=True)

random_search_cv.fit(final_train_data_1,y_train.values)
```

```
Fitting 3 folds for each of 10 candidates, totalling 30 fits
```

Out[ ]:

```
RandomizedSearchCV(cv=3,
                   estimator=LGBMRegressor(min_child_samples=50,
                                           objective='regression',
                                           random_state=30),
                   n_jobs=-1,
                   param_distributions={'colsample_bytree': [1, 0.8, 0.6],
                                        'learning_rate': [0.05, 0.1, 0.3],
                                        'max_depth': [8, 12, 16, 20],
                                        'n_estimators': [100, 150, 200],
                                        'num_leaves': [50, 80, 110, 150],
                                        'reg_alpha': [0, 0.01, 0.001],
                                        'reg_lambda': [0, 0.01, 0.001]},
                   random_state=30, return_train_score=True,
                   scoring='neg_root_mean_squared_error', verbose=1)
```

In [ ]:

```
'''
  with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/random_search_lgbm.pkl
    pickle.dump(random_search_cv, fp)
'''
```

In [ ]:

```
random_search_cv.best_params_
```

Out[ ]:

```
{'colsample_bytree': 0.6,
 'learning_rate': 0.3,
 'max_depth': 20,
 'n_estimators': 200,
 'num_leaves': 150,
 'reg_alpha': 0.001,
 'reg_lambda': 0}
```

In [ ]:

```
tmp = pd.DataFrame(random_search_cv.cv_results_)
tmp
```

Out[ ]:

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_reg_lambda	param_reg_alpha	param_num_leaves	param_n_estimators	para
0	382.269156	6.038462	6.368858	0.230810	0.001	0	150	200	
1	981.197103	3.724313	13.901081	1.571830	0.01	0.001	110	200	
2	703.969930	6.110003	11.521920	0.217589	0.01	0	50	200	
3	750.410344	4.057715	13.209126	0.102244	0	0.001	150	200	
4	322.150085	4.525755	4.952972	0.082642	0.001	0.01	150	150	
5	660.784664	1.145472	9.997682	0.134815	0	0.01	80	200	
6	280.216433	0.518896	4.780698	0.075350	0.01	0	110	150	
7	208.082496	2.279016	3.397583	0.019419	0.01	0.001	150	100	
8	307.372089	2.723423	4.433932	0.085555	0	0	80	100	
9	379.522496	44.305266	5.013766	0.936519	0.01	0.001	50	100	

10 rows × 23 columns

In [ ]:

```
with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/random_search_lgbm.pkl',
    random_search_cv = pickle.load(fp)
```

In [ ]:

```
y_train_pred = random_search_cv.predict(final_train_data_1)
rmse = np.sqrt(sum((y_train_pred - y_train.values)**2)/len(y_train_pred))
rmse
```

Out[ ]:

```
0.45717518878545615
```

In [ ]:

```
y_cv_pred = random_search_cv.predict(final_cv_data_1)
rmse = np.sqrt(sum((y_cv_pred - y_validation.values)**2)/len(y_cv_pred))
rmse
```

Out[ ]:

```
0.47719296497835695
```

In [ ]:

```
# trying to use above param and fine tuning it

lgbm_regressor3=LGBMRegressor(learning_rate=0.3,max_depth=20,n_estimators=200,num_leaves=200,objective='regres
                             boosting_type='gbdt',colsample_bytree=0.8,min_child_samples=25,param_reg_alpha=1(
                             random_state=30, n_jobs=- 1 )
lgbm_regressor3.fit(final_train_data_1,y_train.values)
```

Out[ ]:

```
LGBMRegressor(colsample_bytree=0.8, learning_rate=0.3, max_depth=20,
              min_child_samples=25, n_estimators=200, num_leaves=200,
              objective='regression', param_reg_alpha=10, param_reg_lambda=10,
              random_state=30)
```

In [ ]:

```
# saving the model

'''
with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/lgbm_regressor3.pkl', 'wb
    pickle.dump(lgbm_regressor3, fp)
'''
```

In [ ]:

```
with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/lgbm_regressor3.pkl', 'rb
    lgbm_regressor = pickle.load(fp)
```

In [ ]:

```
y_train_pred = lgbm_regressor.predict(final_train_data_1)
rmse_tr = np.sqrt(sum((y_train_pred - y_train.values)**2)/len(y_train_pred))

y_cv_pred = lgbm_regressor.predict(final_cv_data_1)
rmse_cv = np.sqrt(sum((y_cv_pred - y_validation.values)**2)/len(y_cv_pred))

print('train RMSE : ',rmse_tr)
```

```
print('CV RMSE : ',rmse_cv)
```

```
train RMSE :  0.4436795447251455
CV RMSE :  0.4721704121682103
```

Score summary:

In [ ]:

```
from prettytable import PrettyTable

table = PrettyTable(["Model", "Dataset", "Train RMSE", "CV RMSE"])
table.add_row(["LGBM", "Total data","0.4436", "0.4721"])
print(table)
```

```
+-------+------------+------------+---------+
| Model |  Dataset   | Train RMSE | CV RMSE |
+-------+------------+------------+---------+
|  LGBM | Total data |   0.4436   |  0.4721 |
+-------+------------+------------+---------+
```

FM_FTRL Model:

In [ ]:

```
!pip install Wordbatch
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Collecting Wordbatch
  Downloading Wordbatch-1.4.9.tar.gz (1.2 MB)
     |████████████████████████████████| 1.2 MB 5.1 MB/s
Requirement already satisfied: Cython in /usr/local/lib/python3.7/dist-packages (from Wordbatch) (0.29.30)
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.7/dist-packages (from Wordbatch) (1.0.2)
Collecting python-Levenshtein
  Downloading python-Levenshtein-0.12.2.tar.gz (50 kB)
     |████████████████████████████████| 50 kB 7.8 MB/s
Collecting py-lz4framed
  Downloading py-lz4framed-0.14.0.tar.gz (128 kB)
     |████████████████████████████████| 128 kB 62.9 MB/s
Collecting randomgen>=1.16.6
  Downloading randomgen-1.21.2-cp37-cp37m-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (3.5 MB)
     |████████████████████████████████| 3.5 MB 59.2 MB/s
Requirement already satisfied: numpy in /usr/local/lib/python3.7/dist-packages (from Wordbatch) (1.21.6)
Requirement already satisfied: scipy in /usr/local/lib/python3.7/dist-packages (from Wordbatch) (1.4.1)
Requirement already satisfied: pandas in /usr/local/lib/python3.7/dist-packages (from Wordbatch) (1.3.5)
Requirement already satisfied: wheel>=0.33.4 in /usr/local/lib/python3.7/dist-packages (from Wordbatch) (0.37.
1)
Requirement already satisfied: python-dateutil>=2.7.3 in /usr/local/lib/python3.7/dist-packages (from pandas->
Wordbatch) (2.8.2)
Requirement already satisfied: pytz>=2017.3 in /usr/local/lib/python3.7/dist-packages (from pandas->Wordbatch)
(2022.1)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.7/dist-packages (from python-dateutil>=2.7.3
->pandas->Wordbatch) (1.15.0)
Requirement already satisfied: setuptools in /usr/local/lib/python3.7/dist-packages (from python-Levenshtein->
Wordbatch) (57.4.0)
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.7/dist-packages (from scikit-learn->Word
batch) (1.1.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.7/dist-packages (from scikit-lea
rn->Wordbatch) (3.1.0)
Building wheels for collected packages: Wordbatch, py-lz4framed, python-Levenshtein
  Building wheel for Wordbatch (setup.py) ... done
  Created wheel for Wordbatch: filename=Wordbatch-1.4.9-cp37-cp37m-linux_x86_64.whl size=2768564 sha256=ac8ca7
382b5190cf276fef70e2eee57025c85082d64da84e871606f7a29c5b92
  Stored in directory: /root/.cache/pip/wheels/7c/c6/17/9c8d8c8e37a08ea8a9a3d7e75aaa642ae0e1d2f4079ce11d93
  Building wheel for py-lz4framed (setup.py) ... done
  Created wheel for py-lz4framed: filename=py_lz4framed-0.14.0-cp37-cp37m-linux_x86_64.whl size=346637 sha256=
4ccb51281f5b1d1ddc527c3bf96bea7ffc5dafdaa27867054f56ca04dfc113ff
  Stored in directory: /root/.cache/pip/wheels/5c/9c/8e/5d008dfcbb83cfb99763f100d10b6b2d953274f48744b7be81
  Building wheel for python-Levenshtein (setup.py) ... done
  Created wheel for python-Levenshtein: filename=python_Levenshtein-0.12.2-cp37-cp37m-linux_x86_64.whl size=14
9867 sha256=51c29fc72babea1a3028bc4539a4886a1f879b245c4bd3addd27328ec6e5e666
  Stored in directory: /root/.cache/pip/wheels/05/5f/ca/7c4367734892581bb5ff896f15027a932c551080b2abd3e00d
Successfully built Wordbatch py-lz4framed python-Levenshtein
Installing collected packages: randomgen, python-Levenshtein, py-lz4framed, Wordbatch
Successfully installed Wordbatch-1.4.9 py-lz4framed-0.14.0 python-Levenshtein-0.12.2 randomgen-1.21.2
```

In [ ]:

```
from wordbatch.models import FTRL, FM_FTRL

fm_ftrl_model = FM_FTRL(alpha=0.001, L1=0.001, D=final_train_data_1.shape[1], alpha_fm=0.01, D_fm=2000, L2_fm=
```

```
fm_ftrl_model.fit(final_train_data_1,y_train.values)
```

```
Total e: 530985.4707256819
Total e: 482955.1786247989
Total e: 471828.01893927465
Total e: 465209.5456027133
Total e: 460534.7333585366
Total e: 456932.8335815594
Total e: 454007.95796603843
Total e: 451547.07231063436
Total e: 449420.22151273536
Total e: 447546.5972309013
Total e: 445869.5609797643
Total e: 444348.5993648588
Total e: 442955.0384733522
Total e: 441668.392030732
Total e: 440471.5075950971
Total e: 439351.16829551803
Total e: 438297.13300020737
Total e: 437301.39260982285
Total e: 436356.5443841036
Total e: 435456.52653268323
Total e: 434596.3112655434
Total e: 433772.32996040944
Total e: 432980.63310059346
Total e: 432218.1556351889
Total e: 431482.22806656116
Total e: 430770.5887849419
Total e: 430081.5804523434
Total e: 429413.1923760871
Total e: 428764.1070188214
Total e: 428133.07954354025
Total e: 427518.5230822315
Total e: 426919.23958667053
Total e: 426334.5020757995
Total e: 425763.2225248232
Total e: 425204.66208460776
Total e: 424657.8235878745
Total e: 424122.040292381
Total e: 423596.78304775455
Total e: 423081.4580899359
Total e: 422575.4801399355
Total e: 422078.49768000876
Total e: 421590.0921463353
Total e: 421109.82661227736
Total e: 420637.39069655904
Total e: 420172.3287982214
```

Out[ ]:

```
<wordbatch.models.fm_ftrl.FM_FTRL at 0xf234100>
```

In [ ]:

```
y_train_pred = fm_ftrl_model.predict(final_train_data_1)
rmse_tr = np.sqrt(sum((y_train_pred - y_train.values)**2)/len(y_train_pred))

y_cv_pred = fm_ftrl_model.predict(final_cv_data_1)
rmse_cv = np.sqrt(sum((y_cv_pred - y_validation.values)**2)/len(y_cv_pred))

print('train RMSE : ',rmse_tr)
print('CV RMSE : ',rmse_cv)
```

```
train RMSE :  0.42282345023353607
CV RMSE :  0.457447692639594
```

In [ ]:

```
#saving the model
'''
with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/fm_ftrl_model.pkl', 'wb')
    pickle.dump(fm_ftrl_model, fp)
'''
```

Score summary:

In [ ]:

```
from prettytable import PrettyTable

table = PrettyTable(["Model", "Dataset", "Train RMSE", "CV RMSE"])
table.add_row(["FM_FTRL", "Total data","0.4228", "0.4574"])
print(table)
```

```
+---------+------------+------------+---------+
|  Model  |  Dataset   | Train RMSE | CV RMSE |
+---------+------------+------------+---------+
| FM_FTRL | Total data |   0.4228   |  0.4574 |
+---------+------------+------------+---------+
```

In [ ]:

Stacking above models with linear regression as meta model:

In [ ]:

```
# getting the predication of above models

with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/final_linear_model.pkl',
    final_linear_model = pickle.load(fp)

y_linear_train_pred = final_linear_model.predict(final_train_data_1)
y_linear_cv_pred = final_linear_model.predict(final_cv_data_1)

with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/lgbm_regressor3.pkl', 'rk
    lgbm_regressor = pickle.load(fp)

y_lgbm_train_pred = lgbm_regressor.predict(final_train_data_1)
y_lgbm_cv_pred = lgbm_regressor.predict(final_cv_data_1)

with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/fm_ftrl_model.pkl', 'rb')
    fm_ftrl_model = pickle.load(fp)

y_fm_ftrl_train_pred = fm_ftrl_model.predict(final_train_data_1)
y_fm_ftrl_cv_pred = fm_ftrl_model.predict(final_cv_data_1)
```

In [ ]:

```
train_predicated_data = np.vstack((y_linear_train_pred,y_lgbm_train_pred,y_fm_ftrl_train_pred)).T
cv_predicated_data =  np.vstack((y_linear_cv_pred,y_lgbm_cv_pred,y_fm_ftrl_cv_pred)).T

train_predicated_data.shape
```

Out[ ]:

```
(1333494, 3)
```

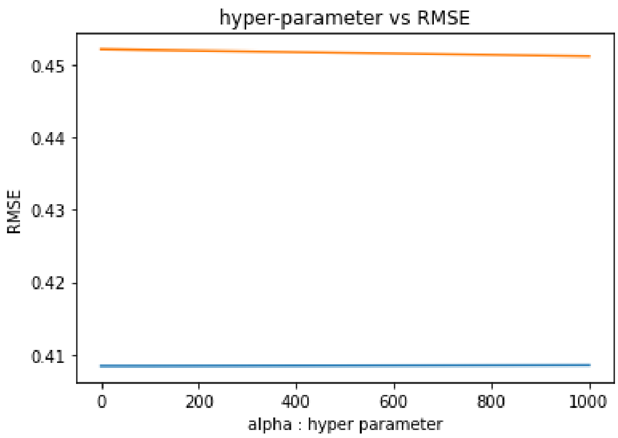
In [ ]:

```
from sklearn.linear_model import Ridge
train_rmse = []
validation_rmse = []
alpha_s = [0.00001, 0.0001, 0.001, 0.01,0.1,1,10,100,1000]
for hy_para in alpha_s:
  reg_linear_model = Ridge(alpha = hy_para)
  reg_linear_model.fit(train_predicated_data,y_train.values)
  y_pred = reg_linear_model.predict(train_predicated_data)

  rmse = np.sqrt(sum((y_pred - y_train.values)**2)/len(y_pred))

  train_rmse.append(rmse)

  y_pred = reg_linear_model.predict(cv_predicated_data)

  rmse = np.sqrt(sum((y_pred - y_validation.values)**2)/len(y_pred))

  validation_rmse.append(rmse)
```

In [ ]:

```
# importing the required module
import matplotlib.pyplot as plt


# plotting the points
plt.plot(alpha_s,train_rmse)
plt.plot(alpha_s,validation_rmse)

# naming the x axis
plt.xlabel('alpha : hyper parameter')
# naming the y axis
plt.ylabel('RMSE')

# giving a title to my graph
```

```
plt.title('hyper-parameter vs RMSE')

# function to show the plot
plt.show()
```



In [ ]:

```
tmp_dict = {'alpha_s' : alpha_s,
            'Train_rmse' : train_rmse ,
            'val_rmse' :validation_rmse}
pd.DataFrame(tmp_dict)
```

Out[ ]:

	alpha_s	Train_rmse	val_rmse
0	0.00001	0.408418	0.452136
1	0.00010	0.408418	0.452136
2	0.00100	0.408418	0.452136
3	0.01000	0.408418	0.452136
4	0.10000	0.408418	0.452136
5	1.00000	0.408418	0.452135
6	10.00000	0.408418	0.452124
7	100.00000	0.408419	0.452021
8	1000.00000	0.408522	0.451148

In [ ]:

```
stacking = Ridge(alpha = 1000)
stacking.fit(train_predicated_data,y_train.values)
# saving model
'''
with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/stacking_model.pkl', 'wb
    pickle.dump(stacking, fp)
'''
```

In [ ]:

```
with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/stacking_model.pkl', 'rb
    stacking = pickle.load(fp)


tr_pred = stacking.predict(train_predicated_data)
test_pred = stacking.predict(cv_predicated_data)
```

In [ ]:

```
rmse = np.sqrt(sum((test_pred - y_validation.values)**2)/len(test_pred))
rmse
```

Out[ ]:

```
0.4511477045979708
```

In [ ]:

```
train_predicated_data
```

Out[ ]:

```
array([[2.2548003 , 2.34697356, 2.25675449],
       [3.51312017, 3.59872077, 3.64312704],
       [3.16440236, 3.03286881, 3.13524992],
       ...,
       [2.49853652, 2.62955646, 2.45645277],
       [2.60437102, 2.72706885, 2.69715285],
       [3.06988967, 3.04044236, 3.19228886]])
```

In [ ]:

```
y_pred = stacking.predict(train_predicated_data)
rmse = np.sqrt(sum((y_pred - y_train.values)**2)/len(y_pred))
rmse
```

Out[ ]:

```
0.4085222213282852
```

In [ ]:

```
x = np.array([[2.2548003 , 2.34697356, 2.25675449]])
z= stacking.predict(x)
z[0]
```

Out[ ]:

```
2.280858181223407
```

In [ ]:

```
# getting the predication of above models

with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/final_linear_model.pkl',
    final_linear_model = pickle.load(fp)



with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/lgbm_regressor3.pkl', 'rk
    lgbm_regressor = pickle.load(fp)



with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/fm_ftrl_model.pkl', 'rb')
    fm_ftrl_model = pickle.load(fp)

y_linear_test_2_pred = final_linear_model.predict(final_test)
y_lgbm_test_2_pred = lgbm_regressor.predict(final_test)
y_fm_ftrl_test_2_pred = fm_ftrl_model.predict(final_test)
```

In [ ]:

```
test_2_predicated_data = np.vstack((y_linear_test_2_pred,y_lgbm_test_2_pred,y_fm_ftrl_test_2_pred)).T
```

In [ ]:

```
with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/stacking_model.pkl', 'rb
    stacking = pickle.load(fp)


test_2_pred = stacking.predict(test_2_predicated_data)
```

In [ ]:

```
my_submission = pd.DataFrame({'test_id': test_stg_2.test_id, 'price': np.exp(test_2_pred)})
# you could use any filename. We choose submission here
my_submission.to_csv('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/submission.csv', index=False)
```

In [ ]:

Summary of all Models:

In [ ]:

```
from prettytable import PrettyTable

table = PrettyTable(["Model", "Dataset", "Train RMSE", "CV RMSE"])
table.add_row(["Linear Regression-L2", "Total data", "0.4687", "0.4839"])
table.add_row(["LGBM", "Total data","0.4436", "0.4721"])
table.add_row(["FM_FTRL", "Total data","0.4228", "0.4574"])
table.add_row(["Stacking ", "Total data","0.4170", "0.4507"])

print(table)
```

```
+----------------------+------------+------------+---------+
|        Model         |  Dataset   | Train RMSE | CV RMSE |
+----------------------+------------+------------+---------+
| Linear Regression-L2 | Total data |   0.4687   |  0.4839 |
|         LGBM         | Total data |   0.4436   |  0.4721 |
|       FM_FTRL        | Total data |   0.4228   |  0.4574 |
|       Stacking       | Total data |   0.4170   |  0.4507 |
+----------------------+------------+------------+---------+
```

In [ ]:

Experiment with MLP:

In [ ]:

```
with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/y_train.pkl', 'rb') as fp
    y_train = pickle.load(fp)

with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/final_cv_data_1.pkl', 'rb
    final_cv_data_1 = pickle.load(fp)

with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/y_validationt.pkl', 'rb')
    y_validation = pickle.load(fp)

with open('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/X_validation.pkl', 'rb')
    X_validation = pickle.load(fp)


final_train_data_1 = load_npz('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/train
```

In [5]:

```
from sklearn.preprocessing import Normalizer
import tensorflow as tf
from numpy import array
from numpy import asarray
from numpy import zeros
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
from sklearn.preprocessing import LabelEncoder
import tensorflow.keras as ks
from tensorflow.keras.layers import Input, Embedding, Conv1D, MaxPool1D, Flatten, Dropout, Dense, BatchNormali
from tensorflow.keras.layers import ReLU
from tensorflow.keras.layers import LeakyReLU
from tensorflow.keras.models import Model
from tensorflow.keras import initializers, regularizers
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.layers import LSTM
```

In [7]:

```
def mlp_model(input_shape):    #input_shape=X_train.shape[1]
    model_in = Input(shape=(input_shape,), dtype='float32', sparse=True)
    out = Dense(256, activation='relu', kernel_regularizer=regularizers.l2(0.001))(model_in)
    out = Dropout(0.10)(out)
    out = Dense(128, activation='relu',  kernel_regularizer=regularizers.l1(0.0001))(out)

    out = Dense(64, activation='relu')(out)
    out = Dense(1)(out)
    model = Model(model_in, out)
    return model
```

In [8]:

```
model = mlp_model(final_train_data_1.shape[1])
model.summary()
```

```
Model: "model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_1 (InputLayer)        [(None, 66173)]           0

 dense (Dense)               (None, 256)               16940544

 dropout (Dropout)           (None, 256)               0

 dense_1 (Dense)             (None, 128)               32896

 dense_2 (Dense)             (None, 64)                8256

 dense_3 (Dense)             (None, 1)                 65

=================================================================
Total params: 16,981,761
Trainable params: 16,981,761
Non-trainable params: 0
_________________________________________________________________
```

In [9]:

```
from tensorflow.keras.callbacks import ModelCheckpoint
model_path = "/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/BEST_MODEL.hdfs"
checkpoint_best = ModelCheckpoint(filepath=model_path, monitor='val_loss',verbose=1, save_best_only=True, mode
```

In [10]:

```
from tensorflow.keras.callbacks import ReduceLROnPlateau
# https://stackoverflow.com/a/42963385/7697658
lrschedule = ReduceLROnPlateau(monitor='val_loss', patience=2, verbose=1, factor=0.70, mode='min')
```

In [11]:

```
model.compile(loss='mse', optimizer=ks.optimizers.Adam(lr=0.0003), metrics=[tf.keras.metrics.RootMeanSquaredE
model.fit(x=final_train_data_1, y=y_train.values, batch_size=192, epochs=20, verbose=True, validation_data=(f
                 callbacks=[lrschedule,checkpoint_best])
```

```
/usr/local/lib/python3.7/dist-packages/keras/optimizer_v2/adam.py:105: UserWarning: The `lr` argument is depre
cated, use `learning_rate` instead.
  super(Adam, self).__init__(name, **kwargs)
Epoch 1/20
/usr/local/lib/python3.7/dist-packages/tensorflow/python/framework/indexed_slices.py:446: UserWarning: Convert
ing sparse IndexedSlices(IndexedSlices(indices=Tensor("gradient_tape/model/dense/embedding_lookup_sparse/Resha
pe_1:0", shape=(None,), dtype=int32), values=Tensor("gradient_tape/model/dense/embedding_lookup_sparse/Reshape
:0", shape=(None, 256), dtype=float32), dense_shape=Tensor("gradient_tape/model/dense/embedding_lookup_sparse/
Cast:0", shape=(2,), dtype=int32))) to a dense Tensor of unknown shape. This may consume a large amount of mem
ory.
  "shape. This may consume a large amount of memory." % value)
6945/6946 [============================>.] - ETA: 0s - loss: 0.4021 - root_mean_squared_error: 0.5485
Epoch 1: val_loss improved from inf to 0.29826, saving model to /content/drive/MyDrive/Colab Notebooks/Self_Ca
se_Study_1/train_data_files/BEST_MODEL.hdfs
WARNING:absl:Function `_wrapped_model` contains input name(s) args_0 with unsupported characters which will be
renamed to args_0_2 in the SavedModel.
INFO:tensorflow:Assets written to: /content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/B
EST_MODEL.hdfs/assets
INFO:tensorflow:Assets written to: /content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/B
EST_MODEL.hdfs/assets
6946/6946 [==============================] - 92s 12ms/step - loss: 0.4021 - root_mean_squared_error: 0.5485 -
val_loss: 0.2983 - val_root_mean_squared_error: 0.4922 - lr: 3.0000e-04
Epoch 2/20
6944/6946 [============================>.] - ETA: 0s - loss: 0.2895 - root_mean_squared_error: 0.4906
Epoch 2: val_loss improved from 0.29826 to 0.27802, saving model to /content/drive/MyDrive/Colab Notebooks/Sel
f_Case_Study_1/train_data_files/BEST_MODEL.hdfs
WARNING:absl:Function `_wrapped_model` contains input name(s) args_0 with unsupported characters which will be
renamed to args_0_2 in the SavedModel.
INFO:tensorflow:Assets written to: /content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/B
EST_MODEL.hdfs/assets
INFO:tensorflow:Assets written to: /content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/B
EST_MODEL.hdfs/assets
6946/6946 [==============================] - 90s 12ms/step - loss: 0.2895 - root_mean_squared_error: 0.4906 -
val_loss: 0.2780 - val_root_mean_squared_error: 0.4822 - lr: 3.0000e-04
Epoch 3/20
6946/6946 [==============================] - ETA: 0s - loss: 0.2788 - root_mean_squared_error: 0.4839
Epoch 3: val_loss improved from 0.27802 to 0.27330, saving model to /content/drive/MyDrive/Colab Notebooks/Sel
f_Case_Study_1/train_data_files/BEST_MODEL.hdfs
WARNING:absl:Function `_wrapped_model` contains input name(s) args_0 with unsupported characters which will be
renamed to args_0_2 in the SavedModel.
INFO:tensorflow:Assets written to: /content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/B
```

```
EST_MODEL.hdfs/assets
INFO:tensorflow:Assets written to: /content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/B
EST_MODEL.hdfs/assets
6946/6946 [==============================] - 89s 12ms/step - loss: 0.2788 - root_mean_squared_error: 0.4839 -
val_loss: 0.2733 - val_root_mean_squared_error: 0.4789 - lr: 3.0000e-04
Epoch 4/20
6942/6946 [============================>.] - ETA: 0s - loss: 0.2754 - root_mean_squared_error: 0.4810
Epoch 4: val_loss improved from 0.27330 to 0.26947, saving model to /content/drive/MyDrive/Colab Notebooks/Sel
f_Case_Study_1/train_data_files/BEST_MODEL.hdfs
WARNING:absl:Function `_wrapped_model` contains input name(s) args_0 with unsupported characters which will be
renamed to args_0_2 in the SavedModel.
INFO:tensorflow:Assets written to: /content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/B
EST_MODEL.hdfs/assets
INFO:tensorflow:Assets written to: /content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/B
EST_MODEL.hdfs/assets
6946/6946 [==============================] - 89s 12ms/step - loss: 0.2754 - root_mean_squared_error: 0.4810 -
val_loss: 0.2695 - val_root_mean_squared_error: 0.4755 - lr: 3.0000e-04
Epoch 5/20
6942/6946 [============================>.] - ETA: 0s - loss: 0.2740 - root_mean_squared_error: 0.4796
Epoch 5: val_loss improved from 0.26947 to 0.26925, saving model to /content/drive/MyDrive/Colab Notebooks/Sel
f_Case_Study_1/train_data_files/BEST_MODEL.hdfs
WARNING:absl:Function `_wrapped_model` contains input name(s) args_0 with unsupported characters which will be
renamed to args_0_2 in the SavedModel.
INFO:tensorflow:Assets written to: /content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/B
EST_MODEL.hdfs/assets
INFO:tensorflow:Assets written to: /content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/B
EST_MODEL.hdfs/assets
6946/6946 [==============================] - 89s 12ms/step - loss: 0.2740 - root_mean_squared_error: 0.4796 -
val_loss: 0.2692 - val_root_mean_squared_error: 0.4750 - lr: 3.0000e-04
Epoch 6/20
6945/6946 [============================>.] - ETA: 0s - loss: 0.2732 - root_mean_squared_error: 0.4788
Epoch 6: val_loss did not improve from 0.26925
6946/6946 [==============================] - 87s 12ms/step - loss: 0.2732 - root_mean_squared_error: 0.4788 -
val_loss: 0.2701 - val_root_mean_squared_error: 0.4761 - lr: 3.0000e-04
Epoch 7/20
6946/6946 [==============================] - ETA: 0s - loss: 0.2728 - root_mean_squared_error: 0.4784
Epoch 7: ReduceLROnPlateau reducing learning rate to 0.00021000000997446476.

Epoch 7: val_loss did not improve from 0.26925
6946/6946 [==============================] - 88s 12ms/step - loss: 0.2728 - root_mean_squared_error: 0.4784 -
val_loss: 0.2699 - val_root_mean_squared_error: 0.4760 - lr: 3.0000e-04
Epoch 8/20
6943/6946 [============================>.] - ETA: 0s - loss: 0.2592 - root_mean_squared_error: 0.4710
Epoch 8: val_loss improved from 0.26925 to 0.25574, saving model to /content/drive/MyDrive/Colab Notebooks/Sel
f_Case_Study_1/train_data_files/BEST_MODEL.hdfs
WARNING:absl:Function `_wrapped_model` contains input name(s) args_0 with unsupported characters which will be
renamed to args_0_2 in the SavedModel.
INFO:tensorflow:Assets written to: /content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/B
EST_MODEL.hdfs/assets
INFO:tensorflow:Assets written to: /content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/B
EST_MODEL.hdfs/assets
6946/6946 [==============================] - 88s 12ms/step - loss: 0.2592 - root_mean_squared_error: 0.4711 -
val_loss: 0.2557 - val_root_mean_squared_error: 0.4685 - lr: 2.1000e-04
Epoch 9/20
6945/6946 [============================>.] - ETA: 0s - loss: 0.2569 - root_mean_squared_error: 0.4691
Epoch 9: val_loss did not improve from 0.25574
6946/6946 [==============================] - 87s 12ms/step - loss: 0.2569 - root_mean_squared_error: 0.4691 -
val_loss: 0.2574 - val_root_mean_squared_error: 0.4699 - lr: 2.1000e-04
Epoch 10/20
6942/6946 [============================>.] - ETA: 0s - loss: 0.2566 - root_mean_squared_error: 0.4684
Epoch 10: ReduceLROnPlateau reducing learning rate to 0.00014700000901939346.

Epoch 10: val_loss did not improve from 0.25574
6946/6946 [==============================] - 87s 12ms/step - loss: 0.2566 - root_mean_squared_error: 0.4684 -
val_loss: 0.2565 - val_root_mean_squared_error: 0.4685 - lr: 2.1000e-04
Epoch 11/20
6944/6946 [============================>.] - ETA: 0s - loss: 0.2453 - root_mean_squared_error: 0.4613
Epoch 11: val_loss improved from 0.25574 to 0.24513, saving model to /content/drive/MyDrive/Colab Notebooks/Se
lf_Case_Study_1/train_data_files/BEST_MODEL.hdfs
WARNING:absl:Function `_wrapped_model` contains input name(s) args_0 with unsupported characters which will be
renamed to args_0_2 in the SavedModel.
INFO:tensorflow:Assets written to: /content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/B
EST_MODEL.hdfs/assets
INFO:tensorflow:Assets written to: /content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/B
EST_MODEL.hdfs/assets
6946/6946 [==============================] - 89s 12ms/step - loss: 0.2453 - root_mean_squared_error: 0.4614 -
val_loss: 0.2451 - val_root_mean_squared_error: 0.4625 - lr: 1.4700e-04
```

```
Epoch 12/20
6946/6946 [==============================] - ETA: 0s - loss: 0.2429 - root_mean_squared_error: 0.4594
Epoch 12: val_loss improved from 0.24513 to 0.24480, saving model to /content/drive/MyDrive/Colab Notebooks/Se
lf_Case_Study_1/train_data_files/BEST_MODEL.hdfs
WARNING:absl:Function `_wrapped_model` contains input name(s) args_0 with unsupported characters which will be
renamed to args_0_2 in the SavedModel.
INFO:tensorflow:Assets written to: /content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/B
EST_MODEL.hdfs/assets
INFO:tensorflow:Assets written to: /content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/B
EST_MODEL.hdfs/assets
6946/6946 [==============================] - 89s 12ms/step - loss: 0.2429 - root_mean_squared_error: 0.4594 -
val_loss: 0.2448 - val_root_mean_squared_error: 0.4619 - lr: 1.4700e-04
Epoch 13/20
6945/6946 [============================>.] - ETA: 0s - loss: 0.2425 - root_mean_squared_error: 0.4588
Epoch 13: val_loss improved from 0.24480 to 0.24410, saving model to /content/drive/MyDrive/Colab Notebooks/Se
lf_Case_Study_1/train_data_files/BEST_MODEL.hdfs
WARNING:absl:Function `_wrapped_model` contains input name(s) args_0 with unsupported characters which will be
renamed to args_0_2 in the SavedModel.
INFO:tensorflow:Assets written to: /content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/B
EST_MODEL.hdfs/assets
INFO:tensorflow:Assets written to: /content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/B
EST_MODEL.hdfs/assets
6946/6946 [==============================] - 89s 12ms/step - loss: 0.2425 - root_mean_squared_error: 0.4588 -
val_loss: 0.2441 - val_root_mean_squared_error: 0.4610 - lr: 1.4700e-04
Epoch 14/20
6945/6946 [============================>.] - ETA: 0s - loss: 0.2422 - root_mean_squared_error: 0.4582
Epoch 14: val_loss did not improve from 0.24410
6946/6946 [==============================] - 87s 12ms/step - loss: 0.2422 - root_mean_squared_error: 0.4582 -
val_loss: 0.2444 - val_root_mean_squared_error: 0.4611 - lr: 1.4700e-04
Epoch 15/20
6946/6946 [==============================] - ETA: 0s - loss: 0.2419 - root_mean_squared_error: 0.4577
Epoch 15: ReduceLROnPlateau reducing learning rate to 0.00010290000936947763.

Epoch 15: val_loss did not improve from 0.24410
6946/6946 [==============================] - 87s 12ms/step - loss: 0.2419 - root_mean_squared_error: 0.4577 -
val_loss: 0.2457 - val_root_mean_squared_error: 0.4623 - lr: 1.4700e-04
Epoch 16/20
6945/6946 [============================>.] - ETA: 0s - loss: 0.2318 - root_mean_squared_error: 0.4505
Epoch 16: val_loss improved from 0.24410 to 0.23621, saving model to /content/drive/MyDrive/Colab Notebooks/Se
lf_Case_Study_1/train_data_files/BEST_MODEL.hdfs
WARNING:absl:Function `_wrapped_model` contains input name(s) args_0 with unsupported characters which will be
renamed to args_0_2 in the SavedModel.
INFO:tensorflow:Assets written to: /content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/B
EST_MODEL.hdfs/assets
INFO:tensorflow:Assets written to: /content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/B
EST_MODEL.hdfs/assets
6946/6946 [==============================] - 88s 12ms/step - loss: 0.2318 - root_mean_squared_error: 0.4505 -
val_loss: 0.2362 - val_root_mean_squared_error: 0.4567 - lr: 1.0290e-04
Epoch 17/20
6945/6946 [============================>.] - ETA: 0s - loss: 0.2293 - root_mean_squared_error: 0.4486
Epoch 17: val_loss improved from 0.23621 to 0.23502, saving model to /content/drive/MyDrive/Colab Notebooks/Se
lf_Case_Study_1/train_data_files/BEST_MODEL.hdfs
WARNING:absl:Function `_wrapped_model` contains input name(s) args_0 with unsupported characters which will be
renamed to args_0_2 in the SavedModel.
INFO:tensorflow:Assets written to: /content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/B
EST_MODEL.hdfs/assets
INFO:tensorflow:Assets written to: /content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/B
EST_MODEL.hdfs/assets
6946/6946 [==============================] - 89s 12ms/step - loss: 0.2293 - root_mean_squared_error: 0.4486 -
val_loss: 0.2350 - val_root_mean_squared_error: 0.4554 - lr: 1.0290e-04
Epoch 18/20
6943/6946 [============================>.] - ETA: 0s - loss: 0.2284 - root_mean_squared_error: 0.4474
Epoch 18: val_loss did not improve from 0.23502
6946/6946 [==============================] - 89s 12ms/step - loss: 0.2284 - root_mean_squared_error: 0.4474 -
val_loss: 0.2356 - val_root_mean_squared_error: 0.4558 - lr: 1.0290e-04
Epoch 19/20
6943/6946 [============================>.] - ETA: 0s - loss: 0.2279 - root_mean_squared_error: 0.4466
Epoch 19: ReduceLROnPlateau reducing learning rate to 7.203000859590247e-05.

Epoch 19: val_loss did not improve from 0.23502
6946/6946 [==============================] - 88s 12ms/step - loss: 0.2279 - root_mean_squared_error: 0.4466 -
val_loss: 0.2359 - val_root_mean_squared_error: 0.4560 - lr: 1.0290e-04
Epoch 20/20
6946/6946 [==============================] - ETA: 0s - loss: 0.2187 - root_mean_squared_error: 0.4388
Epoch 20: val_loss improved from 0.23502 to 0.22998, saving model to /content/drive/MyDrive/Colab Notebooks/Se
lf_Case_Study_1/train_data_files/BEST_MODEL.hdfs
WARNING:absl:Function `_wrapped_model` contains input name(s) args_0 with unsupported characters which will be
```

```
renamed to args_0_2 in the SavedModel.
INFO:tensorflow:Assets written to: /content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/B
EST_MODEL.hdfs/assets
INFO:tensorflow:Assets written to: /content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/B
EST_MODEL.hdfs/assets
6946/6946 [==============================] - 91s 13ms/step - loss: 0.2187 - root_mean_squared_error: 0.4388 -
val_loss: 0.2300 - val_root_mean_squared_error: 0.4529 - lr: 7.2030e-05
```

Out[11]:

```
<keras.callbacks.History at 0x7fc0c01ede90>
```

In [12]:

```
model.fit(x=final_train_data_1, y=y_train.values, batch_size=192, epochs=10, verbose=True, validation_data=(f
              callbacks=[lrschedule_1,checkpoint_best])
```

```
Epoch 1/10
6943/6946 [============================>.] - ETA: 0s - loss: 0.2160 - root_mean_squared_error: 0.4367
Epoch 1: val_loss improved from 0.22998 to 0.22957, saving model to /content/drive/MyDrive/Colab Notebooks/Sel
f_Case_Study_1/train_data_files/BEST_MODEL.hdfs
WARNING:absl:Function `_wrapped_model` contains input name(s) args_0 with unsupported characters which will be
renamed to args_0_2 in the SavedModel.
INFO:tensorflow:Assets written to: /content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/B
EST_MODEL.hdfs/assets
INFO:tensorflow:Assets written to: /content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/B
EST_MODEL.hdfs/assets
6946/6946 [==============================] - 90s 13ms/step - loss: 0.2160 - root_mean_squared_error: 0.4367 -
val_loss: 0.2296 - val_root_mean_squared_error: 0.4525 - lr: 7.2030e-05
Epoch 2/10
6946/6946 [==============================] - ETA: 0s - loss: 0.2149 - root_mean_squared_error: 0.4353
Epoch 2: val_loss did not improve from 0.22957
6946/6946 [==============================] - 88s 12ms/step - loss: 0.2149 - root_mean_squared_error: 0.4353 -
val_loss: 0.2303 - val_root_mean_squared_error: 0.4531 - lr: 7.2030e-05
Epoch 3/10
6944/6946 [============================>.] - ETA: 0s - loss: 0.2143 - root_mean_squared_error: 0.4345
Epoch 3: ReduceLROnPlateau reducing learning rate to 5.042100601713173e-05.

Epoch 3: val_loss did not improve from 0.22957
6946/6946 [==============================] - 87s 12ms/step - loss: 0.2143 - root_mean_squared_error: 0.4345 -
val_loss: 0.2296 - val_root_mean_squared_error: 0.4521 - lr: 7.2030e-05
Epoch 4/10
6944/6946 [============================>.] - ETA: 0s - loss: 0.2056 - root_mean_squared_error: 0.4260
Epoch 4: val_loss improved from 0.22957 to 0.22524, saving model to /content/drive/MyDrive/Colab Notebooks/Sel
f_Case_Study_1/train_data_files/BEST_MODEL.hdfs
WARNING:absl:Function `_wrapped_model` contains input name(s) args_0 with unsupported characters which will be
renamed to args_0_2 in the SavedModel.
INFO:tensorflow:Assets written to: /content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/B
EST_MODEL.hdfs/assets
INFO:tensorflow:Assets written to: /content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/B
EST_MODEL.hdfs/assets
6946/6946 [==============================] - 89s 12ms/step - loss: 0.2056 - root_mean_squared_error: 0.4260 -
val_loss: 0.2252 - val_root_mean_squared_error: 0.4495 - lr: 5.0421e-05
Epoch 5/10
6942/6946 [============================>.] - ETA: 0s - loss: 0.2029 - root_mean_squared_error: 0.4236
Epoch 5: val_loss did not improve from 0.22524
6946/6946 [==============================] - 87s 12ms/step - loss: 0.2029 - root_mean_squared_error: 0.4236 -
val_loss: 0.2268 - val_root_mean_squared_error: 0.4515 - lr: 5.0421e-05
Epoch 6/10
6942/6946 [============================>.] - ETA: 0s - loss: 0.2016 - root_mean_squared_error: 0.4222
Epoch 6: ReduceLROnPlateau reducing learning rate to 3.5294705230626275e-05.

Epoch 6: val_loss did not improve from 0.22524
6946/6946 [==============================] - 87s 12ms/step - loss: 0.2016 - root_mean_squared_error: 0.4222 -
val_loss: 0.2261 - val_root_mean_squared_error: 0.4507 - lr: 5.0421e-05
Epoch 7/10
6942/6946 [============================>.] - ETA: 0s - loss: 0.1938 - root_mean_squared_error: 0.4139
Epoch 7: val_loss improved from 0.22524 to 0.22306, saving model to /content/drive/MyDrive/Colab Notebooks/Sel
f_Case_Study_1/train_data_files/BEST_MODEL.hdfs
WARNING:absl:Function `_wrapped_model` contains input name(s) args_0 with unsupported characters which will be
renamed to args_0_2 in the SavedModel.
INFO:tensorflow:Assets written to: /content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/B
EST_MODEL.hdfs/assets
INFO:tensorflow:Assets written to: /content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/B
EST_MODEL.hdfs/assets
6946/6946 [==============================] - 89s 12ms/step - loss: 0.1938 - root_mean_squared_error: 0.4139 -
val_loss: 0.2231 - val_root_mean_squared_error: 0.4486 - lr: 3.5295e-05
Epoch 8/10
6944/6946 [============================>.] - ETA: 0s - loss: 0.1911 - root_mean_squared_error: 0.4112
Epoch 8: val_loss improved from 0.22306 to 0.22272, saving model to /content/drive/MyDrive/Colab Notebooks/Sel
f_Case_Study_1/train_data_files/BEST_MODEL.hdfs
```

```
WARNING:absl:Function `_wrapped_model` contains input name(s) args_0 with unsupported characters which will be renamed to args_0_2 in the SavedModel.
INFO:tensorflow:Assets written to: /content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/BEST_MODEL.hdfs/assets
INFO:tensorflow:Assets written to: /content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/BEST_MODEL.hdfs/assets
6946/6946 [==============================] - 89s 12ms/step - loss: 0.1911 - root_mean_squared_error: 0.4112 - val_loss: 0.2227 - val_root_mean_squared_error: 0.4484 - lr: 3.5295e-05
Epoch 9/10
6946/6946 [==============================] - ETA: 0s - loss: 0.1895 - root_mean_squared_error: 0.4094
Epoch 9: val_loss did not improve from 0.22272
6946/6946 [==============================] - 87s 12ms/step - loss: 0.1895 - root_mean_squared_error: 0.4094 - val_loss: 0.2237 - val_root_mean_squared_error: 0.4496 - lr: 3.5295e-05
Epoch 10/10
6945/6946 [============================>.] - ETA: 0s - loss: 0.1881 - root_mean_squared_error: 0.4077
Epoch 10: ReduceLROnPlateau reducing learning rate to 2.4706294425413944e-05.

Epoch 10: val_loss did not improve from 0.22272
6946/6946 [==============================] - 87s 12ms/step - loss: 0.1881 - root_mean_squared_error: 0.4077 - val_loss: 0.2245 - val_root_mean_squared_error: 0.4504 - lr: 3.5295e-05
```

Out[12]:

```
<keras.callbacks.History at 0x7fc0461051d0>
```

In [13]:

```python
model.fit(x=final_train_data_1, y=y_train.values, batch_size=192, epochs=10, verbose=True, validation_data=(f
                 callbacks=[lrschedule_1,checkpoint_best])
```

```
Epoch 1/10
6946/6946 [==============================] - ETA: 0s - loss: 0.1811 - root_mean_squared_error: 0.3996
Epoch 1: val_loss improved from 0.22272 to 0.22262, saving model to /content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/BEST_MODEL.hdfs
WARNING:absl:Function `_wrapped_model` contains input name(s) args_0 with unsupported characters which will be renamed to args_0_2 in the SavedModel.
INFO:tensorflow:Assets written to: /content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/BEST_MODEL.hdfs/assets
INFO:tensorflow:Assets written to: /content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/BEST_MODEL.hdfs/assets
6946/6946 [==============================] - 89s 12ms/step - loss: 0.1811 - root_mean_squared_error: 0.3996 - val_loss: 0.2226 - val_root_mean_squared_error: 0.4491 - lr: 2.4706e-05
Epoch 2/10
6942/6946 [============================>.] - ETA: 0s - loss: 0.1788 - root_mean_squared_error: 0.3973
Epoch 2: val_loss did not improve from 0.22262
6946/6946 [==============================] - 88s 12ms/step - loss: 0.1788 - root_mean_squared_error: 0.3973 - val_loss: 0.2229 - val_root_mean_squared_error: 0.4496 - lr: 2.4706e-05
Epoch 3/10
6943/6946 [============================>.] - ETA: 0s - loss: 0.1773 - root_mean_squared_error: 0.3955
Epoch 3: ReduceLROnPlateau reducing learning rate to 1.729440609778976e-05.

Epoch 3: val_loss did not improve from 0.22262
6946/6946 [==============================] - 87s 12ms/step - loss: 0.1773 - root_mean_squared_error: 0.3955 - val_loss: 0.2238 - val_root_mean_squared_error: 0.4507 - lr: 2.4706e-05
Epoch 4/10
6944/6946 [============================>.] - ETA: 0s - loss: 0.1712 - root_mean_squared_error: 0.3881
Epoch 4: val_loss did not improve from 0.22262
6946/6946 [==============================] - 87s 12ms/step - loss: 0.1712 - root_mean_squared_error: 0.3881 - val_loss: 0.2230 - val_root_mean_squared_error: 0.4503 - lr: 1.7294e-05
Epoch 5/10
6943/6946 [============================>.] - ETA: 0s - loss: 0.1693 - root_mean_squared_error: 0.3860
Epoch 5: val_loss improved from 0.22262 to 0.22249, saving model to /content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/BEST_MODEL.hdfs
WARNING:absl:Function `_wrapped_model` contains input name(s) args_0 with unsupported characters which will be renamed to args_0_2 in the SavedModel.
INFO:tensorflow:Assets written to: /content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/BEST_MODEL.hdfs/assets
INFO:tensorflow:Assets written to: /content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/train_data_files/BEST_MODEL.hdfs/assets
6946/6946 [==============================] - 88s 12ms/step - loss: 0.1693 - root_mean_squared_error: 0.3860 - val_loss: 0.2225 - val_root_mean_squared_error: 0.4498 - lr: 1.7294e-05
Epoch 6/10
6946/6946 [==============================] - ETA: 0s - loss: 0.1677 - root_mean_squared_error: 0.3841
Epoch 6: val_loss did not improve from 0.22249
6946/6946 [==============================] - 87s 12ms/step - loss: 0.1677 - root_mean_squared_error: 0.3841 - val_loss: 0.2230 - val_root_mean_squared_error: 0.4505 - lr: 1.7294e-05
Epoch 7/10
6942/6946 [============================>.] - ETA: 0s - loss: 0.1663 - root_mean_squared_error: 0.3824
Epoch 7: ReduceLROnPlateau reducing learning rate to 1.2106083886465058e-05.

Epoch 7: val_loss did not improve from 0.22249
6946/6946 [==============================] - 86s 12ms/step - loss: 0.1663 - root_mean_squared_error: 0.3824 - val_loss: 0.2238 - val_root_mean_squared_error: 0.4514 - lr: 1.7294e-05
Epoch 8/10
6943/6946 [============================>.] - ETA: 0s - loss: 0.1613 - root_mean_squared_error: 0.3760
Epoch 8: val_loss did not improve from 0.22249
6946/6946 [==============================] - 86s 12ms/step - loss: 0.1613 - root_mean_squared_error: 0.3760 - val_loss: 0.2233 - val_root_mean_squared_error: 0.4511 - lr: 1.2106e-05
Epoch 9/10
6945/6946 [============================>.] - ETA: 0s - loss: 0.1598 - root_mean_squared_error: 0.3743
Epoch 9: ReduceLROnPlateau reducing learning rate to 8.47425872052554e-06.

Epoch 9: val_loss did not improve from 0.22249
6946/6946 [==============================] - 87s 12ms/step - loss: 0.1598 - root_mean_squared_error: 0.3743 - val_loss: 0.2237 - val_root_mean_squared_error: 0.4517 - lr: 1.2106e-05
Epoch 10/10
6946/6946 [==============================] - ETA: 0s - loss: 0.1559 - root_mean_squared_error: 0.3692
Epoch 10: val_loss did not improve from 0.22249
6946/6946 [==============================] - 87s 12ms/step - loss: 0.1559 - root_mean_squared_error: 0.3692 - val_loss: 0.2234 - val_root_mean_squared_error: 0.4516 - lr: 8.4743e-06
```

Out[13]:

```
<keras.callbacks.History at 0x7fc05a3bbd10>
```

In [17]:

```python
with open('/content/final_test_stg2_pp.pkl', 'rb') as fp:
    test_pp_stg2 = pickle.load(fp)
```

In [19]:

```python
pred_test_stg2 = model.predict(test_pp_stg2, batch_size=64)
```

In [29]:

```python
my_submission = pd.DataFrame({'test_id': test_stg_2['test_id'].values, 'price': np.exp(pred_test_stg2[:,0])+1
# you could use any filename. We choose submission here
my_submission.to_csv('/content/drive/MyDrive/Colab Notebooks/Self_Case_Study_1/submission2.csv', index=False)
```

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