In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import plotly.express as px
import plotly.graph_objects as go
import seaborn as sns
import os
from tqdm import tqdm
import nltk
from nltk.stem import WordNetLemmatizer
nltk.download('wordnet')
lemmatizer = WordNetLemmatizer()
from spacy.lang.en.stop_words import STOP_WORDS
# plt.xkcd()
```

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

In [2]:

```
# read the train and test tsv files (seperator is tab that's why tsv)
train = pd.read_csv("../input/mercari-dataset/train.tsv",sep = '\t')
print("Number of rows {} and columns {} ".format(train.shape[0],train.shape[1]))
train.sample(5)
```

```
Number of rows 1482535 and columns 8
```

Out[2]:

	train_id	name	item_condition_id	category_name	brand_name	price	shipping	item_description
582597	582597	Herbalife formula 1 protein drink bundle	1	Other/Daily & Travel items/Sports Nutrition	NaN	110.0	1	Pumpkin spice formula 1 healthy meal Protein d...
146818	146818	LULAROE OS SOLID BLACK NWT	1	Women/Jeans/Leggings	NaN	21.0	0	OS solid black nwt*
358843	358843	La vie est belle + Acqua di Gioia	1	Beauty/Fragrance/Women	Sephora	11.0	1	(4) Lancôme La Vie Est Belle (2) Acqua di Gioi...
17870	17870	10 jigsaw puzzles/ 1box	3	Kids/Toys/Puzzles	NaN	9.0	0	Assortment of 10 puzzles made in America great...
443286	443286	Miniature quartz brass mantle clock	3	Home/Home Décor/Clocks	NaN	5.0	1	Miniature quartz brass mantle clock . Needs a ...

In [3]:

```
test = pd.read_csv("../input/mercari-dataset/test.tsv",sep = "\t")
print("Number of rows {} and columns {} ".format(test.shape[0],test.shape[1]))
test.sample(5)
```

```
Number of rows 693359 and columns 7
```

Out[3]:

	test_id	name	item_condition_id	category_name	brand_name	shipping	item_description
167422	167422	Calvin Klein Wallet	4	Women/Women's Accessories/Wallets	Calvin Klein	0	In good condition. Does have signs of wear.
301639	301639	Napoleon Sheer Genius Look 3 Foundation	3	Beauty/Makeup/Face	NaN	1	I am selling a Napoleon Perdis foundation shee...
333932	333932	Boys Northface Jacket Sz L Reversible	4	Kids/Boys (4+)/Coats & Jackets	The North Face	0	**Part of 10% sale. Take advantage before it e...
472664	472664	Clean Cotton T Shirt Parfume	3	NaN	CLEAN	0	Used maybe 4-5 times

	test_id	name	item_condition_id	category_name	brand_name	shipping	item_description
215375	215375	Justice volleyball shirt with hood	2	Kids/Girls (4+)/Tops & T-Shirts	Justice	0	Size 12 Justice active volleyball shirt worn a...

In [4]:

```
train.info()
```

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

In [5]:

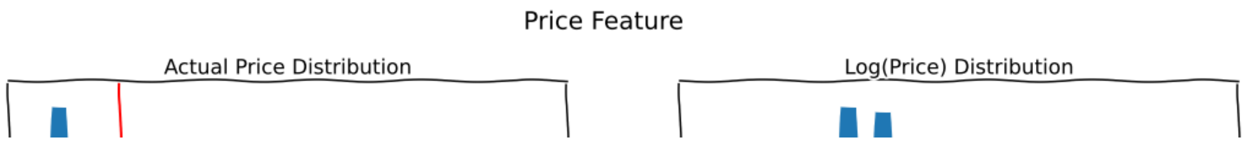
```
test.info()
```

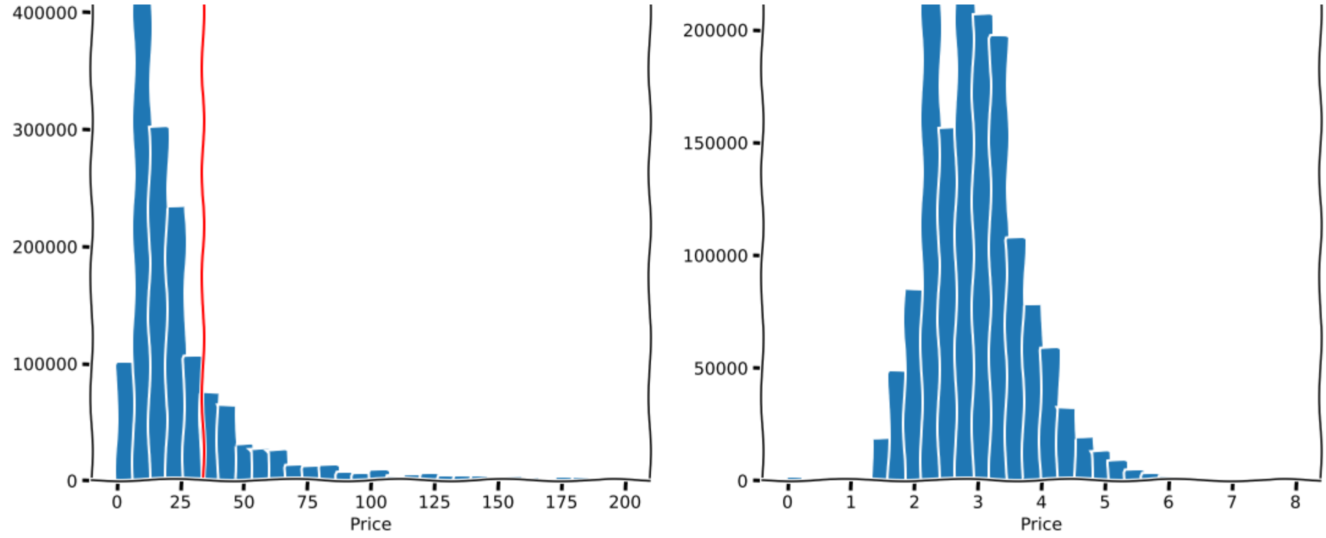
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 693359 entries, 0 to 693358
Data columns (total 7 columns):
 #   Column             Non-Null Count   Dtype 
---  ------             --------------   ----- 
 0   test_id            693359 non-null  int64 
 1   name               693359 non-null  object
 2   item_condition_id  693359 non-null  int64 
 3   category_name      690301 non-null  object
 4   brand_name         397834 non-null  object
 5   shipping           693359 non-null  int64 
 6   item_description   693359 non-null  object
dtypes: int64(3), object(4)
memory usage: 37.0+ MB
```

1. So from above train and test information we can conclude that there are null values in brand name and category name for both files.
2. We will counter this problem by filling in the missing or NaN values.But, first let's explore more features.

In [6]:

```
# let's first explore our target variable
# let's see target variable (price) distribution
plt.xkcd()
fig,(ax1,ax2) = plt.subplots(nrows = 1,ncols=2,figsize = (18,8))
ax1.hist(train.price,bins = 30,range = [0,200])
ax2.hist(np.log(train.price + 1),bins = 30,range = [0,8])
ax1.set_title("Actual Price Distribution")
ax1.axvline(x = np.percentile(train.price,q = 80),color = 'red',label = "80 percent of population l
ies on left")
ax1.set_xlabel("Price")
ax2.set_title("Log(Price) Distribution")
ax2.set_xlabel("Price")
#plt.legend()
plt.suptitle("Price Feature",fontsize = 20)
plt.show()
```





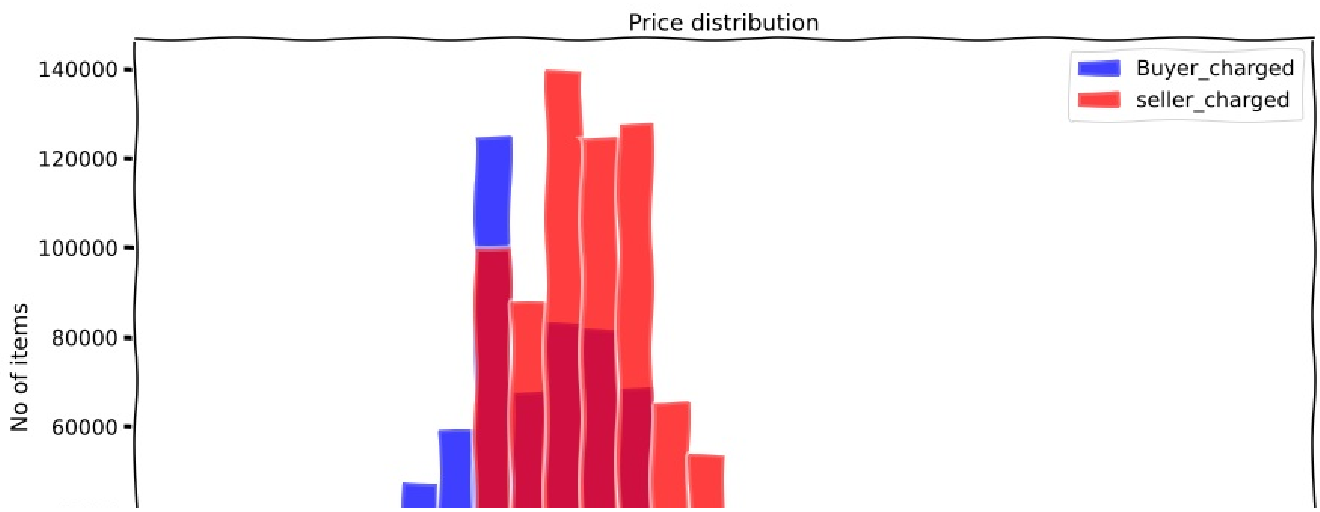
1. As you can see from above plot that price feature is having right skewed distribution or you might say it's having power law distribution.
2. It's just an intuition after seeing the plot that variable x (price) can be log-normal distribution i.e log of variable can be normally distributed.
3. After plotting **log(price)** we got normal distribution.
4. Red Line above is giving out the info that 80% of population lies on the left of that line.

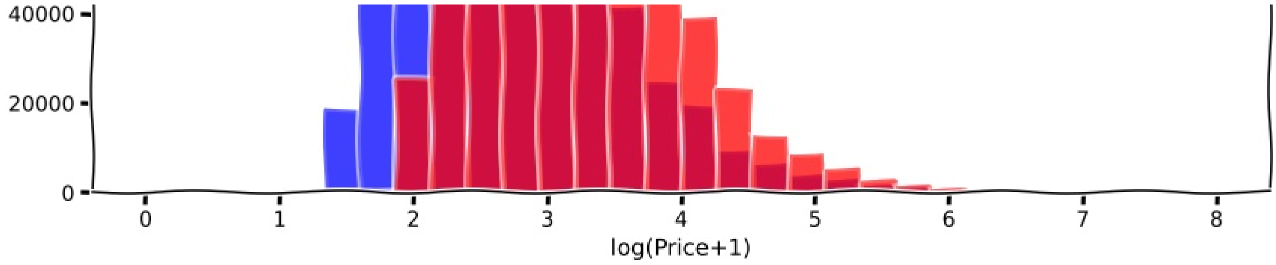
In [7]:

```
# from above analysis it will be better if we add log(Price) as different features, so that forthcoming analysis will be comfortable.
train['log(price)'] = np.log(train['price']+1)
# added new features
# this is called feature engineering where from the given features you come up with intuitive and useful features.
```

In [8]:

```
# shipping feature in data seems to be reasonable to explore.
# let's see distribution of shipping data with log(price)

fig, ax = plt.subplots(figsize=(14,8))
ax.hist(train[train.shipping==1]['log(price)'],bins=30,range=[0,8],label="Buyer_charged",color='b',alpha=0.5)
ax.hist(train[train.shipping==0]['log(price)'],bins=30,range=[0,8],label="seller_charged",color='r',alpha=0.5)
plt.title('Price distribution', fontsize=15)
ax.set_xlabel('log(Price+1)',fontsize=15)
ax.set_ylabel('No of items',fontsize=15)
plt.legend(loc='upper right')

plt.show()
```





1. From above we can't say seller pay the shipping charged if the amount is high because the distribution of both buyer and seller charged is highly overlapping. Hence, we can't come to the conclusion straightaway.
2. The shipping cost burden is decently splitted between sellers and buyers with more than half of the items' shipping fees are paid by the sellers (55%). In addition, the average price paid by users who have to pay for shipping fees is lower than those that don't require additional shipping cost. This matches with our perception that the sellers need a lower price to compensate for the additional shipping.

In [9]:

```
# let's fill in missing data for further analysis with brand name and category name
def fill_missing_data(data):
    data.category_name.fillna(value = "others", inplace = True)
    data.brand_name.fillna(value = "not known", inplace = True)
    data.item_description.fillna(value = "no description", inplace = True)
    return(data)
train = fill_missing_data(train)
#test  = fill_missing_data(test)
```

In [10]:

```
# let's also split category_name into 3 parts main_category, sub_category_1 and sub_category_2


# Let's split the categories into three different columns. We will see later that this information
is actually quite important from the seller's point of view and how we handle
# the missing information in the brand_name column will impact the model's prediction.

def split_cat(text):
    try:
        text1, text2, text3 = text.split('/')
        return text1, text2, text3
    except:
        return ("No Label", "No Label", "No Label")
train['main_cat'], train['subcat_1'], train['subcat_2'] = zip(*train['category_name'].apply(lambda
x: split_cat(x)))
#test['main_cat'], test['subcat_1'], test['subcat_2'] = zip(*test['category_name'].apply(lambda x:
split_cat(x)))
```

In [11]:

```
train['summary'] = train['name'] + train['item_description']
#test['summary'] = test['name'] + test['item_description']
train.head()
```

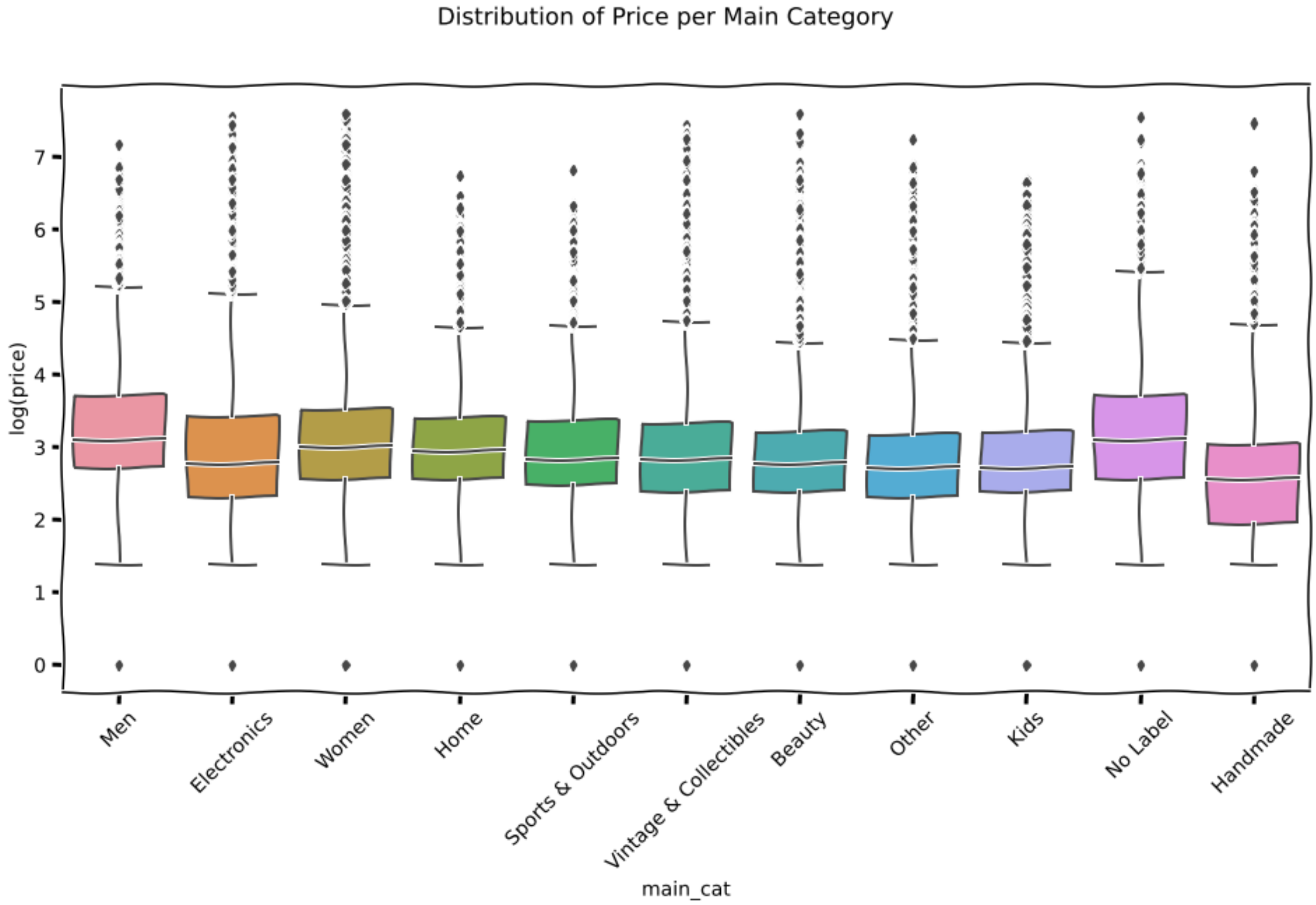
Out[11]:

	train_id	name	item_condition_id	category_name	brand_name	price	shipping	item_description	log(price)	main_(
0	0	MLB Cincinnati Reds T Shirt Size XL	3	Men/Tops/T-shirts	not known	10.0	1	No description yet	2.397895	M
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	Electron
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	Wom

	train_id	name	item_condition_id	category_name	brand_name	price	shipping	item_description	log(price)	main_
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	Ho
4	4	24K GOLD plated rose	1	Women/Jewelry/Necklaces	not known	44.0	0	Complete with certificate of authenticity	3.806662	Wom

In [12]:

```
plt.figure(figsize = (16,8))
plt.suptitle("Distribution of Price per Main Category")
sns.boxplot(y = 'log(price)', x = 'main_cat',data = train)
plt.xticks(rotation = 45)
plt.show()
```



1. Each main category has so much overlapping in prize distribution that no pair of categories price can be distinguished.
2. Price of each main category is almost completely overlapping.
3. Median of log(Pirce) of Men main category is higher then all present in main category (if we don't count No Label imputaion value.)

In [13]:

```
import plotly
x = train['subcat_1'].value_counts().index.values.astype('str')[:15]
y = train['subcat_1'].value_counts().values[:15]
pct = [("%.2f"%(v*100))+"%"for v in (y/len(train))][:15]

trace1 = go.Bar(x=x, y=y, text=pct)
layout = dict(title= 'Number of Items by Sub Category 1',
              yaxis = dict(title='Count'),
              xaxis = dict(title='Category'))
fig=go.Figure(data = trace1,layout=layout)
fig.show()
```

In [14]:

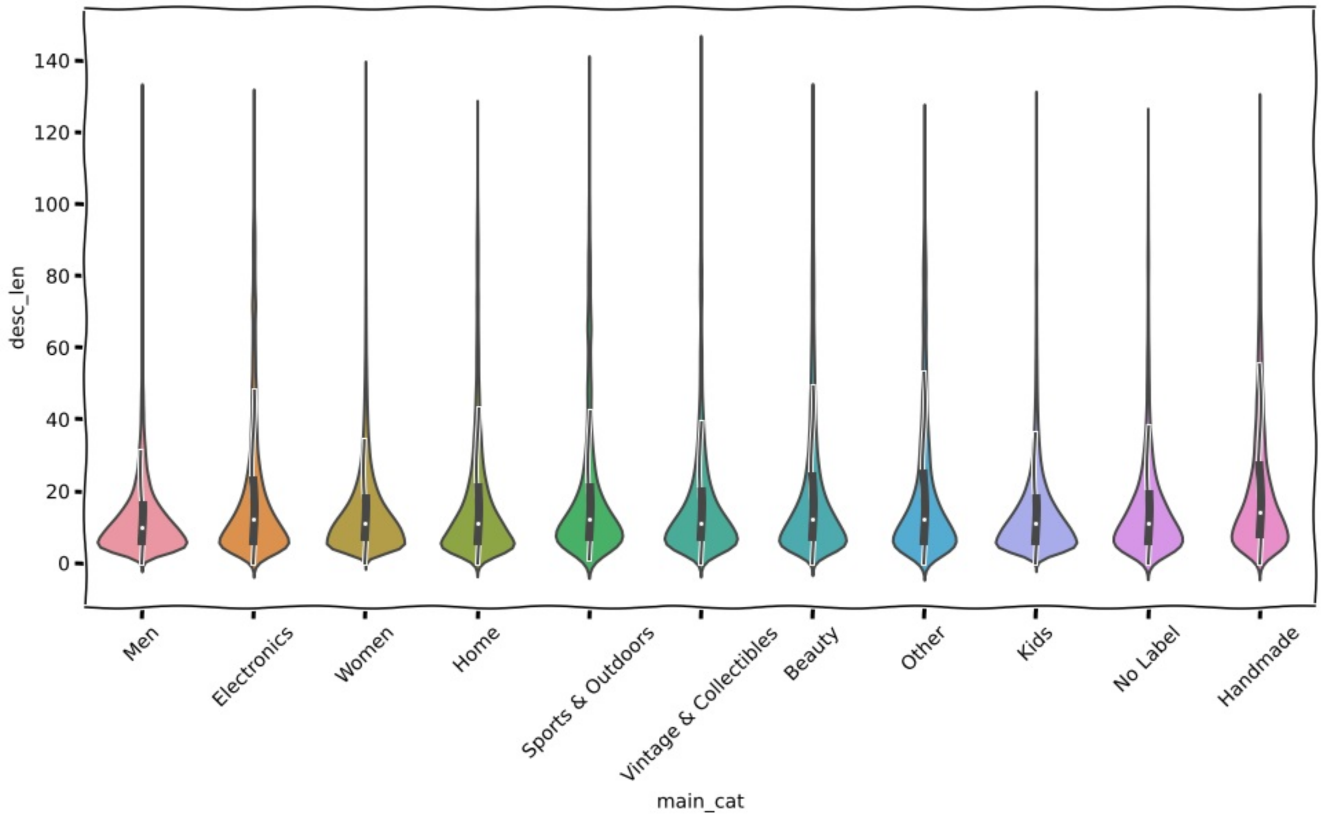
```
import plotly
x = train['subcat_2'].value_counts().index.values.astype('str')[:15]
y = train['subcat_2'].value_counts().values[:15]
pct = [("%.2f"%(v*100))+"%"for v in (y/len(train))][:15]

trace1 = go.Bar(x=x, y=y, text=pct)
layout = dict(title= 'Number of Items by Sub Category 2',
              yaxis = dict(title='Count'),
              xaxis = dict(title='Category'))
fig=go.Figure(data = trace1,layout=layout)
fig.show()
```

In [15]:

```
import re
# here STOP_WORDS is spacy stopwords list
def wordCount(text):
    # convert to lower case and strip regex
    try:
         # convert to lower case and strip regex
        text = text.lower()
        #regex = re.compile('[' +re.escape(string.punctuation) + '0-9\\r\\t\\n]')
        #txt = regex.sub(" ", text)
        txt = re.sub('[^a-zA-Z]+',' ',text)
        words = [lemmatizer.lemmatize(w) for w in txt.split(" ") \
                 if not w in STOP_WORDS and len(w)>3]
        return(len(words))
    except:
        return 0
```

In [16]:

```
# add a column of word counts to both the training and test set
train['desc_len'] = train['summary'].apply(lambda x: wordCount(x))
plt.figure(figsize = (16,8))
sns.violinplot(x = 'main_cat',y = 'desc_len',data = train)
plt.xticks(rotation = 45)
plt.show()
```



1. Description Length distribution for each main category is having almost same shape which is right skewed.
2. And even each category is perfectly aligned to each other, which means just taking desc_len as feature we can't not predict price precisely. They are so much overlapping.
3. You might be thinking why I am making such absurd conclusion even though we are comparing desc_len with main_category. Well, you are right and the reason is given below....
4. If A is correlated with B and B is correlated with C it does not always True that A and C are also correlated.
5. For more info go to https://stats.stackexchange.com/questions/5747/if-a-and-b-are-correlated-with-c-why-are-a-and-b-not-necessarily-correlated
6. But we will explore that is description has any effect on price. Does having long description means it'll have more price on tag?

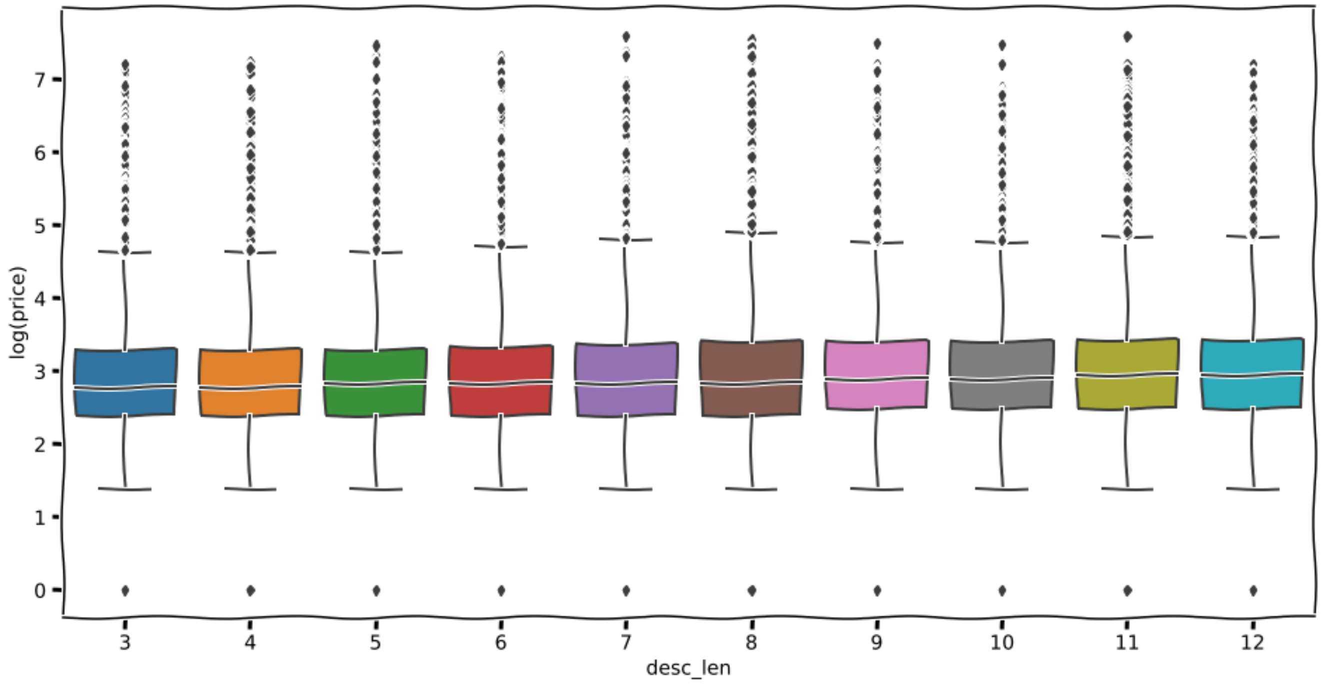
1. It will be more challenging to parse through this particular item since it's unstructured data. Does it mean a more detailed and

1. It will be more challenging to parse through this particular item since it's unstructured data. Does it mean a more detailed and lengthy description will result in a higher bidding price?

In [17]:

```
# let's see for top 10 description length the prize distribution.

temp = pd.DataFrame()
for i in tqdm(train['desc_len'].value_counts().index.values[:10]):
    temp = pd.concat([temp,train[train['desc_len']==i]],axis=0)

plt.figure(figsize = (16,8))
sns.boxplot(x = 'desc_len',y = 'log(price)',data = temp)
plt.show()
```

```
100%|██████████| 10/10 [00:07<00:00,  1.27it/s]
```



1. Boxplot of top 10 desc_len have almost the same mean,25th percentile and 75th percentile value.
2. Description Length feature alone can't distinguish the price.

Loading Twitter Glove Vectors

In [18]:

```
%%time
embeddings_index = {}
f = open('../input/glovetwitter27b100dtxt/glove.twitter.27B.100d.txt', encoding='utf-8')
for line in f:
    values = line.split()
    word = values[0]
    coefs = np.asarray(values[1:], dtype='float32')
    embeddings_index[word] = coefs
f.close()

print('Found %s word vectors.' % len(embeddings_index))
```

```
Found 1193514 word vectors.
CPU times: user 1min 4s, sys: 2.01 s, total: 1min 6s
Wall time: 1min 5s
```

Text Preprocessing, Stemming and Removing Stopwords

Most of the time, the first steps of an NLP project is to "tokenize" your documents, which main purpose is to normalize our texts. The three fundamental stages will usually include:

1. break the descriptions into sentences and then break the sentences into tokens
2. remove punctuation and stop words
3. lowercase the tokens

In [19]:

```
import re
stopwords= ['i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'ourselves', 'you', "you're", "you've",
\
            "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselves', 'he', 'him', 'his',
'himself', \
            'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'its', 'itself', 'they', 'them',
'their',\
            'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'this', 'that', "that'll",
'these', 'those', \
            'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have', 'has', 'had', 'having',
'do', 'does', \
            'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or', 'because', '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', 'both', 'e
ach', 'few', 'more',\
            'most', 'other', 'some', 'such', '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', "do
esn't", 'hadn',\
            "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "isn't", 'ma', 'mightn',
"mightn't", 'mustn',\
            "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn', "shouldn't", 'wasn',
"wasn't", 'weren', "weren't", \
            'won', "won't", 'wouldn', "wouldn't"]

def decontracted(phrase):
    # specific
    phrase = re.sub(r"won't", "will not", phrase)
    phrase = re.sub(r"can\'t", "can not", phrase)

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


def text_preprocess(df):
    pre_list = []
    for sentance in tqdm(df['summary'].values):
        sent = decontracted(sentance)
        sent = sent.replace('\\r', ' ')
        sent = sent.replace('\\"', ' ')
        sent = sent.replace('\\n', ' ')
        sent = re.sub('[^A-Za-z]+', ' ', sent)
        # https://gist.github.com/sebleier/554280
        sent = ' '.join(lemmatizer.lemmatize(e) for e in sent.split() if e.lower() not in stopwords
)
        pre_list.append(sent.lower().strip())
    return(pre_list)
```

In [20]:

```
train_preprocess = text_preprocess(train)
#test_preprocess = text_preprocess(test)
```

```
train['summary'] = train_preprocess
#test['summary'] = test_preprocess
```

```
100%|██████████| 1482535/1482535 [07:21<00:00, 3358.68it/s]
```

Average Word2Vec

In [23]:

```
vocab = embeddings_index.keys()
# this function will add the vectors of each word and returns the avg vector of given sentance
def build_avg_vec(sentence, num_features, doc_id, m_name):
    # sentace: its title of the apparel
    # num_features: the lenght of word2vec vector, its values = 300
    # m_name: model information it will take two values
        # if  m_name == 'avg', we will append the model[i], w2v representation of word i
        # if m_name == 'weighted', we will multiply each w2v[word] with the idf(word)

    featureVec = np.zeros((num_features,), dtype="float32")
    # we will intialize a vector of size 300 with all zeros
    # we add each word2vec(wordi) to this fetureVec
    nwords = 0

    for word in sentence.split():
        nwords += 1
        if word in vocab:
            if m_name == 'weighted' and word in  idf_title_vectorizer.vocabulary_:
                featureVec = np.add(featureVec, idf_title_features[doc_id, idf_title_vectorizer.voc
abulary_[word]] * embeddings_index[word])
            elif m_name == 'avg':
                featureVec = np.add(featureVec, embeddings_index[word])
    if(nwords>0):
        featureVec = np.divide(featureVec, nwords)
    # returns the avg vector of given sentance, its of shape (1, 300)
    return featureVec
```

In [21]:

```
def calc_avgw2v(train_preprocess,test_preprocess):
    doc_id = 0
    avg_w2v = []
    # for every description we build a avg vector representation
    for i in tqdm(train_preprocess):
        avg_w2v.append(build_avg_vec(i, 100, doc_id,'avg'))
        doc_id += 1
    # w2v_desc = np.array(# number of doc in courpus * 100), each row corresponds to a doc
    avg_w2v_train = np.array(avg_w2v)

    avg_w2v = []
    # for every title we build a avg vector representation
    for i in tqdm(test_preprocess):
        avg_w2v.append(build_avg_vec(i, 100, doc_id,'avg'))
        doc_id += 1
    # w2v_title = np.array(# number of doc in courpus * 100), each row corresponds to a doc
    avg_w2v_test = np.array(avg_w2v)
    return(avg_w2v_train,avg_w2v_test)
```

In [26]:

```
avg_w2v_train,_ = calc_avgw2v(train['summary'].values,[])

# splitting the data
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test = train_test_split(avg_w2v_train,train['log(price)'].values, test_siz
e = 0.2,random_state = 42)
```

```
100%|██████████| 1482535/1482535 [01:13<00:00, 20280.43it/s]
0it [00:00, ?it/s]
```

Let's Clear Doubt

1. If you know about data leakage problem you brain would have definitely striked that "what hell I am doing". How can I split the train data into X_train and X_test after doing featurization.
2. You are right, but you are wrong!!! **Confused Again...**
3. Well you are right in general case but, here for featurization I am using avg_w2v which doesn't need whole training data i.e I am not exposing my whole training data for featurization.
4. If I would have been using tfidf_w2v or idf_w2v then that could be the data leakage. Because tfidf,idf is calculated using all training data.
5. Hope I have clear your doubt...

First Model - DNN with FineTuning

In [28]:

```
import tensorflow as tf
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.models import Sequential,load_model
from tensorflow.keras.layers import Dense, Flatten, LSTM, Conv1D, MaxPooling1D, Dropout, Activation
,BatchNormalization,LeakyReLU
from tensorflow.keras.layers import Embedding
from sklearn.metrics import classification_report
from tensorflow.keras.callbacks import (
    ReduceLROnPlateau,
    EarlyStopping,
    ModelCheckpoint,
    TensorBoard
)
```

In [29]:

```
model = Sequential()
model.add(Dense(300,activation=LeakyReLU(),kernel_initializer='glorot_normal',input_shape = (100,))
)
model.add(Dropout(0.3))
model.add(BatchNormalization())
model.add(Dense(300,activation=LeakyReLU(),kernel_initializer='glorot_normal'))
model.add(Dropout(0.3))
model.add(BatchNormalization())
model.add(Dense(200,activation=LeakyReLU(),kernel_initializer='glorot_normal'))
model.add(Dropout(0.3))
model.add(BatchNormalization())
model.add(Dense(200,activation=LeakyReLU(),kernel_initializer='glorot_normal'))
model.add(Dropout(0.3))
model.add(BatchNormalization())
model.add(Dense(100,activation=LeakyReLU(),kernel_initializer='glorot_normal'))
model.add(Dropout(0.3))
model.add(BatchNormalization())
model.add(Dense(50,activation=LeakyReLU(),kernel_initializer='glorot_normal'))
model.add(Dropout(0.3))
model.add(BatchNormalization())
model.add(Dense(1,activation='linear'))
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense (Dense)                (None, 300)               30300
_________________________________________________________________
dropout (Dropout)            (None, 300)               0
_________________________________________________________________
batch_normalization (BatchNo (None, 300)               1200
_________________________________________________________________
dense_1 (Dense)              (None, 300)               90300
_________________________________________________________________
dropout_1 (Dropout)          (None, 300)               0
_________________________________________________________________
batch_normalization_1 (Batch (None, 300)               1200
_________________________________________________________________
dense_2 (Dense)              (None, 200)               60200
```

```
_________________________________________________________________
dropout_2 (Dropout)          (None, 200)              0         
_________________________________________________________________
batch_normalization_2 (Batch (None, 200)              800       
_________________________________________________________________
dense_3 (Dense)              (None, 200)              40200     
_________________________________________________________________
dropout_3 (Dropout)          (None, 200)              0         
_________________________________________________________________
batch_normalization_3 (Batch (None, 200)              800       
_________________________________________________________________
dense_4 (Dense)              (None, 100)              20100     
_________________________________________________________________
dropout_4 (Dropout)          (None, 100)              0         
_________________________________________________________________
batch_normalization_4 (Batch (None, 100)              400       
_________________________________________________________________
dense_5 (Dense)              (None, 50)               5050      
_________________________________________________________________
dropout_5 (Dropout)          (None, 50)               0         
_________________________________________________________________
batch_normalization_5 (Batch (None, 50)               200       
_________________________________________________________________
dense_6 (Dense)              (None, 1)                51        
=================================================================
Total params: 250,801
Trainable params: 248,501
Non-trainable params: 2,300
_________________________________________________________________
```

In [30]:

```
from tensorflow.keras.optimizers import Adam,Nadam

# tf.keras.losses.MeanSquaredLogarithmicError(
#     reduction="auto", name="mean_squared_logarithmic_error"
# )
# mae = tf.keras.losses.MeanAbsoluteError(name = "mean_absolute_error")

reduce_lr = ReduceLROnPlateau(monitor= "mse", factor=0.2,
                              patience=2, min_lr=0.00001)

tnsr_brd = TensorBoard(log_dir='logs')


ckpt = ModelCheckpoint('cnn_model.h5',
                            verbose=1, save_weights_only=True,save_best_only = True)

callbacks = [reduce_lr, tnsr_brd, ckpt ]

adam = Adam(learning_rate = 2e-3)
nadam = Nadam(learning_rate = 1e-4)
model.compile(loss=["mse"], optimizer=nadam)
```

In [31]:

```
history = model.fit(X_train,y_train,
                    batch_size=256,
                    epochs=20,
                    verbose=1,
                    validation_data = (X_test,y_test),callbacks = callbacks)
```

```
Epoch 1/20
4633/4633 [==============================] - ETA: 0s - loss: 3.0026
Epoch 00001: val_loss improved from inf to 0.48862, saving model to cnn_model.h5
4633/4633 [==============================] - 93s 20ms/step - loss: 3.0026 - val_loss: 0.4886 - lr: 1.0000e-04
Epoch 2/20
4632/4633 [============================>.] - ETA: 0s - loss: 0.6945
Epoch 00002: val_loss improved from 0.48862 to 0.46210, saving model to cnn_model.h5
4633/4633 [==============================] - 89s 19ms/step - loss: 0.6945 - val_loss: 0.4621 - lr: 1.0000e-04
Epoch 3/20
4632/4633 [============================>.] - ETA: 0s - loss: 0.5099
```

```
Epoch 00003: val_loss improved from 0.46210 to 0.43725, saving model to cnn_model.h5
4633/4633 [==============================] - 89s 19ms/step - loss: 0.5099 - val_loss: 0.4373 - lr:
1.0000e-04
Epoch 4/20
4633/4633 [==============================] - ETA: 0s - loss: 0.4593
Epoch 00004: val_loss improved from 0.43725 to 0.42065, saving model to cnn_model.h5
4633/4633 [==============================] - 89s 19ms/step - loss: 0.4593 - val_loss: 0.4206 - lr:
1.0000e-04
Epoch 5/20
4633/4633 [==============================] - ETA: 0s - loss: 0.4379
Epoch 00005: val_loss improved from 0.42065 to 0.40913, saving model to cnn_model.h5
4633/4633 [==============================] - 90s 19ms/step - loss: 0.4379 - val_loss: 0.4091 - lr:
1.0000e-04
Epoch 6/20
4632/4633 [============================>.] - ETA: 0s - loss: 0.4260
Epoch 00006: val_loss improved from 0.40913 to 0.40242, saving model to cnn_model.h5
4633/4633 [==============================] - 90s 19ms/step - loss: 0.4260 - val_loss: 0.4024 - lr:
1.0000e-04
Epoch 7/20
4632/4633 [============================>.] - ETA: 0s - loss: 0.4179
Epoch 00007: val_loss improved from 0.40242 to 0.39594, saving model to cnn_model.h5
4633/4633 [==============================] - 88s 19ms/step - loss: 0.4179 - val_loss: 0.3959 - lr:
1.0000e-04
Epoch 8/20
4631/4633 [============================>.] - ETA: 0s - loss: 0.4123
Epoch 00008: val_loss improved from 0.39594 to 0.39074, saving model to cnn_model.h5
4633/4633 [==============================] - 93s 20ms/step - loss: 0.4123 - val_loss: 0.3907 - lr:
1.0000e-04
Epoch 9/20
4631/4633 [============================>.] - ETA: 0s - loss: 0.4079
Epoch 00009: val_loss improved from 0.39074 to 0.38867, saving model to cnn_model.h5
4633/4633 [==============================] - 89s 19ms/step - loss: 0.4079 - val_loss: 0.3887 - lr:
1.0000e-04
Epoch 10/20
4631/4633 [============================>.] - ETA: 0s - loss: 0.4048
Epoch 00010: val_loss improved from 0.38867 to 0.38480, saving model to cnn_model.h5
4633/4633 [==============================] - 88s 19ms/step - loss: 0.4048 - val_loss: 0.3848 - lr:
1.0000e-04
Epoch 11/20
4631/4633 [============================>.] - ETA: 0s - loss: 0.4016
Epoch 00011: val_loss improved from 0.38480 to 0.38178, saving model to cnn_model.h5
4633/4633 [==============================] - 88s 19ms/step - loss: 0.4016 - val_loss: 0.3818 - lr:
1.0000e-04
Epoch 12/20
4633/4633 [==============================] - ETA: 0s - loss: 0.3996
Epoch 00012: val_loss improved from 0.38178 to 0.37891, saving model to cnn_model.h5
4633/4633 [==============================] - 90s 19ms/step - loss: 0.3996 - val_loss: 0.3789 - lr:
1.0000e-04
Epoch 13/20
4631/4633 [============================>.] - ETA: 0s - loss: 0.3974
Epoch 00013: val_loss improved from 0.37891 to 0.37675, saving model to cnn_model.h5
4633/4633 [==============================] - 88s 19ms/step - loss: 0.3974 - val_loss: 0.3767 - lr:
1.0000e-04
Epoch 14/20
4631/4633 [============================>.] - ETA: 0s - loss: 0.3956
Epoch 00014: val_loss improved from 0.37675 to 0.37560, saving model to cnn_model.h5
4633/4633 [==============================] - 88s 19ms/step - loss: 0.3956 - val_loss: 0.3756 - lr:
1.0000e-04
Epoch 15/20
4631/4633 [============================>.] - ETA: 0s - loss: 0.3942
Epoch 00015: val_loss improved from 0.37560 to 0.37267, saving model to cnn_model.h5
4633/4633 [==============================] - 88s 19ms/step - loss: 0.3942 - val_loss: 0.3727 - lr:
1.0000e-04
Epoch 16/20
4631/4633 [============================>.] - ETA: 0s - loss: 0.3927
Epoch 00016: val_loss did not improve from 0.37267
4633/4633 [==============================] - 92s 20ms/step - loss: 0.3927 - val_loss: 0.3734 - lr:
1.0000e-04
Epoch 17/20
4632/4633 [============================>.] - ETA: 0s - loss: 0.3914
Epoch 00017: val_loss improved from 0.37267 to 0.37036, saving model to cnn_model.h5
4633/4633 [==============================] - 87s 19ms/step - loss: 0.3914 - val_loss: 0.3704 - lr:
1.0000e-04
Epoch 18/20
4631/4633 [============================>.] - ETA: 0s - loss: 0.3905
Epoch 00018: val_loss improved from 0.37036 to 0.36980, saving model to cnn_model.h5
4633/4633 [==============================] - 88s 19ms/step - loss: 0.3905 - val_loss: 0.3698 - lr:
1.0000e-04
```

```
1.0000e-04
Epoch 19/20
4631/4633 [============================>.] - ETA: 0s - loss: 0.3890
Epoch 00019: val_loss improved from 0.36980 to 0.36910, saving model to cnn_model.h5
4633/4633 [==============================] - 89s 19ms/step - loss: 0.3890 - val_loss: 0.3691 - lr:
1.0000e-04
Epoch 20/20
4631/4633 [============================>.] - ETA: 0s - loss: 0.3883
Epoch 00020: val_loss did not improve from 0.36910
4633/4633 [==============================] - 88s 19ms/step - loss: 0.3883 - val_loss: 0.3695 - lr:
1.0000e-04
```

In [44]:

```
from sklearn.metrics import mean_squared_error

print("root mean squared error is : ",np.sqrt(mean_squared_error(y_test,model.predict(X_test))))
```

```
root mean squared error is :  0.6079019093689939
```

Model 2 - LightGBM

In [ ]:

```
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test = train_test_split(train.drop(['price','log(price)'],axis=1),train[[
'log(price)','price']],test_size = 0.05,random_state = 42)
```

Text Encoding --

Brand Name Feature

In [ ]:

```
from sklearn.feature_extraction.text import CountVectorizer
vectorizer_brnd = CountVectorizer()
vectorizer_brnd.fit(X_train['brand_name'].values) # fit has to happen only on train data

# we use the fitted CountVectorizer to convert the text to vector
train_brandname = vectorizer_brnd.transform(X_train['brand_name'].values)
test_brandname = vectorizer_brnd.transform(X_test['brand_name'].values)


print("After vectorizations")
print(train_brandname.shape)
print(test_brandname.shape)

print(len(vectorizer_brnd.get_feature_names()))
```

Name Feature

In [ ]:

```
from sklearn.feature_extraction.text import CountVectorizer
vectorizer_name = CountVectorizer()
vectorizer_name.fit(X_train['name'].values) # fit has to happen only on train data

# we use the fitted CountVectorizer to convert the text to vector
train_name = vectorizer_name.transform(X_train['name'].values)
test_name = vectorizer_name.transform(X_test['name'].values)


print("After vectorizations")
print(train_brandname.shape)
print(test_brandname.shape)

print(len(vectorizer_name.get_feature_names()))
```

```
print(len(vectorizer_name.get_feature_names()))
```

Main Category Feature

In [ ]:

```
from sklearn.feature_extraction.text import CountVectorizer
vectorizer_main = CountVectorizer()
vectorizer_main.fit(X_train['main_cat'].values) # fit has to happen only on train data

# we use the fitted CountVectorizer to convert the text to vector
train_cat = vectorizer_main.transform(X_train['main_cat'].values)
test_cat= vectorizer_main.transform(X_test['main_cat'].values)


print("After vectorizations")
print(train_cat.shape)
print(test_cat.shape)

print(len(vectorizer_main.get_feature_names()))
```

Subcategory 1 Feature

In [ ]:

```
from sklearn.feature_extraction.text import CountVectorizer
vectorizer_sub_1 = CountVectorizer()
vectorizer_sub_1.fit(X_train['subcat_1'].values) # fit has to happen only on train data

# we use the fitted CountVectorizer to convert the text to vector
train_subcat_1 = vectorizer_sub_1.transform(X_train['subcat_1'].values)
test_subcat_1 = vectorizer_sub_1.transform(X_test['subcat_1'].values)


print("After vectorizations")
print(train_subcat_1.shape)
print(test_subcat_1.shape)

print(len(vectorizer_sub_1.get_feature_names()))
```

Subcategory 2 Feature

In [ ]:

```
from sklearn.feature_extraction.text import CountVectorizer
vectorizer_sub_2 = CountVectorizer()
vectorizer_sub_2.fit(X_train['subcat_2'].values) # fit has to happen only on train data

# we use the fitted CountVectorizer to convert the text to vector
train_subcat_2 = vectorizer_sub_2.transform(X_train['subcat_2'].values)
test_subcat_2 = vectorizer_sub_2.transform(X_test['subcat_2'].values)


print("After vectorizations")
print(train_subcat_2.shape)
print(test_subcat_2.shape)

print(len(vectorizer_sub_2.get_feature_names()))
```

Description Length Feature

In [ ]:

```
## number of words in description

def tokens(text):
    text = re.sub("[^A-Za-z]+"," ",text)
    return(len(text.split(" ")))
```

```
X_train['description_len'] = X_train['item_description'].apply(tokens)
X_test['description_len'] = X_test['item_description'].apply(tokens)
```

Standard Scaling of Descripion Length

In [ ]:

```
from sklearn.preprocessing import Normalizer,StandardScaler,normalize
normalizer = StandardScaler()
normalizer.fit(X_train['description_len'].values.reshape(-1,1))

#X_train_price_norm = normalizer.transform(X_train['price'].values.reshape(-1,1))
train_des_norm = normalizer.transform(X_train['description_len'].values.reshape(-1,1))

test_des_norm = normalizer.transform(X_test['description_len'].values.reshape(-1,1))

print("After normalizations")
print(train_des_norm.shape, y_train.shape)

print(test_des_norm.shape, y_test.shape)
```

Sentiment Intensity of Each Item description

In [ ]:

```
import nltk
from nltk.sentiment.vader import SentimentIntensityAnalyzer

import nltk
nltk.download('vader_lexicon')

sid = SentimentIntensityAnalyzer()
def sentiment_analyzer(df,preprocess_text):
    temp = []
    for sentence in tqdm(preprocess_text):
        for_sentiment = sentence
        ss = sid.polarity_scores(for_sentiment)
        temp.append(ss)
    negative=[]
    neutral=[]
    positive=[]
    compounding=[]
    for i in temp:
        for polarity,score in i.items():
            if(polarity=='neg'):
                negative.append(score)
            if(polarity=='neu'):
                neutral.append(score)
            if(polarity=='pos'):
                positive.append(score)
            if(polarity=='compound'):
                compounding.append(score)
    df['negative']=negative
    df['neutral']=neutral
    df['positive']=positive
    df['compound']=compounding
    return(df)

X_train = sentiment_analyzer(X_train,X_train['item_description'].values)
X_test = sentiment_analyzer(X_test,X_test['item_description'].values)
```

Standard Scaling of Sentimental Features

In [28]:

```
def encoding(feature,tr,ts):
    vectorizer = CountVectorizer()
    vectorizer.fit(tr[feature].values) # fit has to happen only on train data
```

```
    # we use the fitted CountVectorizer to convert the text to vector
    train_temp = vectorizer.transform(tr[feature].values)
    test_temp= vectorizer.transform(ts[feature].values)


    print("After vectorizations")
    print(train_temp.shape)
    print(test_temp.shape)

    print(len(vectorizer.get_feature_names()))


def norm(feature,tr,ts):
    normalizer = StandardScaler()
    normalizer.fit(tr[feature].values.reshape(-1,1))

    #X_train_price_norm = normalizer.transform(X_train['price'].values.reshape(-1,1))
    train_temp = normalizer.transform(tr[feature].values.reshape(-1,1))

    test_temp = normalizer.transform(ts[feature].values.reshape(-1,1))

    print("After normalizations")
    print(train_temp.shape, y_train.shape)

    print(test_temp.shape, y_test.shape)
    return(train_temp,test_temp)
```

In [ ]:

```
train_neu,test_neu = norm('neutral',X_train,X_test)
train_pos,test_pos = norm('positive',X_train,X_test)
train_neg,test_neg = norm('negative',X_train,X_test)
train_comp,test_comp = norm('compound',X_train,X_test)
```

In [ ]:

```
avg_w2v_train,avg_w2v_test = calc_avgw2v(X_train['summary'].values,X_test['summary'].values)
```

In [ ]:

```
from scipy.sparse import csr_matrix
train_dummies = csr_matrix(pd.get_dummies(X_train[['item_condition_id', 'shipping']],
                                          sparse=True).values)

test_dummies = csr_matrix(pd.get_dummies(X_test[['item_condition_id', 'shipping']],
                                          sparse=True).values)
```

In [ ]:

```
%%time
from sklearn.feature_extraction.text import TfidfVectorizer
vectorizer = TfidfVectorizer(ngram_range=(1,2), min_df=10,max_features=5000)
vectorizer.fit(X_train['summary'].values)
X_train_itemdes = vectorizer.transform(X_train['summary'].values)
X_test_itemdes = vectorizer.transform(X_test['summary'].values)
```

Concatenating Each Feature

In [29]:

```
from scipy.sparse import hstack
train_data = hstack((X_train_itemdes,avg_w2v_train,train_brandname,
train_name,train_dummies,train_cat,train_subcat_1,train_subcat_2,train_des_norm,train_neu,train_neg
,train_pos,train_comp))
test_data = hstack((X_test_itemdes,avg_w2v_test,test_brandname,test_name,test_dummies
,test_cat,test_subcat_1,test_subcat_2,test_des_norm,test_neu,test_neg,test_pos,test_comp))
print("Final Data matrix")
print(train_data.shape, y_train['log(price)'].shape)

print(test_data.shape, y_test['log(price)'].shape)
print("="*100)
```

```
print('=' * 100)
```

```
Final Data matrix
(1408408, 114003) (1408408,)
(74127, 114003) (74127,)
====================================================================================================
```

In [30]:

```python
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
from lightgbm import LGBMRegressor
```

In [45]:

```python
lgbm_params ={'subsample': 0.8, 'colsample_bytree': 0.8, 'min_child_samples': 50, 'objective': 'reg
ression','boosting_type': 'gbdt','learning_rate': 0.5,
              'max_depth': 8,'n_estimators': 500,'num_leaves': 80,
      }
model = LGBMRegressor(**lgbm_params)
model.fit(train_data, y_train['log(price)'].values,
         verbose=True)

preds2 = model.predict(test_data)
```

In [32]:

```python
np.sqrt(mean_squared_error(y_test['log(price)'].values, preds2))
```

Out[32]:

```
0.47191275729394633
```

In [22]:

```python
sample_sub = pd.read_csv("../input/mercari-dataset-asd/sample_submission.csv")
```

In [40]:

```python
def predict(dataframe):

    dataframe  = fill_missing_data(dataframe)
    dataframe['main_cat'], dataframe['subcat_1'], dataframe['subcat_2'] = 
zip(*dataframe['category_name'].apply(lambda x: split_cat(x)))
    dataframe['summary'] = dataframe['name'] + dataframe['item_description']
    dataframe['summary'] = text_preprocess(dataframe)
    test_brand = vectorizer_brnd.transform(dataframe['brand_name'].values)
    test_name = vectorizer_name.transform(dataframe['name'].values)
    test_cat= vectorizer_main.transform(dataframe['main_cat'].values)
    test_subcat_1 = vectorizer_sub_1.transform(dataframe['subcat_1'].values)
    test_subcat_2 = vectorizer_sub_2.transform(dataframe['subcat_2'].values)
    dataframe['description_len'] = dataframe['item_description'].apply(tokens)
    test_dummies = csr_matrix(pd.get_dummies(dataframe[['item_condition_id', 'shipping']],
                                              sparse=True).values)
    test_des_norm = normalizer.transform(dataframe['description_len'].values.reshape(-1,1))
    dataframe = sentiment_analyzer(dataframe,dataframe['item_description'].values)
    train_neu,test_neu = norm('neutral',X_train,dataframe)
    train_pos,test_pos = norm('positive',X_train,dataframe)
    train_neg,test_neg = norm('negative',X_train,dataframe)
    train_comp,test_comp = norm('compound',X_train,dataframe)
    avg_w2v = []
    doc_id=0
    for i in tqdm(dataframe['summary'].values):
        avg_w2v.append(build_avg_vec(i, 100, doc_id,'avg'))
        doc_id += 1
    avg_w2v = np.array(avg_w2v)
    X_test_itemdes = vectorizer.transform(dataframe['summary'].values)
    test_data = 
hstack((X_test_itemdes,avg_w2v,test_brand,test_name,test_dummies,test_cat,test_subcat_1,test_subcat
_2,test_des_norm,test_neu,test_neg,test_pos,test_comp))
    return(test_data)
```

```
    return(test_data)
```

In [41]:

```
%%time
test_data = predict(test)
```

```
100%|██████████| 693359/693359 [03:27<00:00, 3340.10it/s]
100%|██████████| 693359/693359 [06:08<00:00, 1880.09it/s]
  0%|          | 355/693359 [00:00<03:15, 3548.22it/s]
```

```
After normalizations
(1408408, 1) (1408408, 2)
(693359, 1) (74127, 2)
After normalizations
(1408408, 1) (1408408, 2)
(693359, 1) (74127, 2)
After normalizations
(1408408, 1) (1408408, 2)
(693359, 1) (74127, 2)
After normalizations
(1408408, 1) (1408408, 2)
(693359, 1) (74127, 2)
```

```
100%|██████████| 693359/693359 [00:38<00:00, 18034.50it/s]
```

```
CPU times: user 11min 50s, sys: 8.47 s, total: 11min 59s
Wall time: 11min 53s
```

In [45]:

```
sample_sub['price'] = np.expm1(model.predict(test_data))
sample_sub.to_csv("submission_lgbm.csv")
```

Conclusion

1. I have done some feature engineering like description length, Sentiment Analyzer etc.
2. Price Feature seems to be having log-normal distributon. After taking log(Price) we can see it's forming nearly normal distribution.
3. First Model I have tried using only summary feature which is a combination of two prior faeture i.e item_description and name. I have trained Dense NN with little bit of fine tuning and got RMSLE as 0.60.
4. Second Model I have tried using Bag of Words for each feature and concatenate it with average word2vec feature. I have got RMSLE as 0.47.