Mercari Price Suggestion

1. Business Problem

1.1 Description

It can be hard to know how much something's really worth. Small details can mean big differences in pricing.

Product pricing gets even harder at scale, considering just how many products are sold online. Clothing has strong seasonal pricing trends and is heavily influenced by brand names, while electronics have fluctuating prices based on product specs.

Mercari, Japan's biggest community-powered shopping app, knows this problem deeply. They'd like to offer pricing suggestions to sellers, but this is tough because their sellers are enabled to put just about anything, or any bundle of things, on Mercari's marketplace.

In this case study, we try to build an algorithm that automatically suggests the right product prices. The input consists of user-inputted text descriptions of their products, including details like product category name, brand name, and item condition.

> Credits: Kaggle

Problem Statement:-

- Suggest the price to the product based on the input given by the user.

1.2 Sources/Useful Links

- Source : https://www.kaggle.com/c/mercari-price-suggestion-challenge (https://www.kaggle.com/c/mercari-price-suggestion-challenge)

2. Machine Learning Probelm

2.1 Data

2.1.1 Data Overview

All of the data is in 2 files: Train and Test.

```
Train.tsv contains 8 columns: train_id, name, item_condition_id, categor
y_name, brand_name, shipping, item_description, price.

Test.tsv contains the same columns but without the price, which is to be
predicted.

Size of Train.tsv - 322 MB

Size of Test.tsv - 147 MB

Number of rows in Train.tsv = 1482535
```

Data Field Explaination

Train Dataset contains 1,482,535 rows.
Test Dataset contains 693,359 rows.
The columns in the table are:

```
train_id or test_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 -

price - the price that the item was sold for. This is the target variabl
e that you will predict. The unit is USD. This column doesn't exist in t
est.tsv

shipping - boolean value, 1 if shipping fee is paid by seller and 0 by b
uyer

item_description - the full description of the item
```

2.1.2 Example Data point

```
train_id    name    item_condition_id    category_name    brand_name
price    shipping    item_description
0    MLB Cincinnati Reds T Shirt Size XL    3    Men/Tops/T-shirts
```

```
10.0    1    No description yet
1    Razer BlackWidow Chroma Keyboard    3    Electronics/Computers & Ta
blets/Components & Parts    Razer    52.0    0    This keyboard is in gr
eat condition and works like it came out of the box. All of the ports ar
e tested and work perfectly. The lights are customizable via the Razer S
ynapse app on your PC.
2    AVA-VIV Blouse    1    Women/Tops & Blouses/Blouse    Target    10.
0    1    Adorable top with a hint of lace and a key hole in the back! T
he pale pink is a 1X, and I also have a 3X available in white!
3    Leather Horse Statues    1    Home/Home Décor/Home Décor Accents
35.0    1    New with tags. Leather horses. Retail for [rm] each. Stand
about a foot high. They are being sold as a pair. Any questions please a
sk. Free shipping. Just got out of storage
4    24K GOLD plated rose    1    Women/Jewelry/Necklaces        44.0
0    Complete with certificate of authenticity
```

2.2 Mapping the real world problem to an ML problem

2.2.1 Type of Machine Leaning Problem

It is a Regression problem, for a given input information about the item we need ti predict the price.

2.2.2 Performance Metric

Source: [https://www.kaggle.com/c/mercari-price-suggestion-challenge/overview/evaluation (https://www.kaggle.com/c/mercari-price-suggestion-challenge/overview/evaluation)](https://www.kaggle.com/c/mercari-price-suggestion-challenge/overview/evaluation)

The evaluation metric for this competition is Root Mean Squared Logarithmic Error.

The RMSLE is calculated as

RMSLE.PNG

Where:

ϵ is the RMSLE value (score)
n is the total number of observations in the data set,
p_i is your prediction of price,
a_i is the actual sale price for i.
log(x) is the natural logarithm of x

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3. Exploratory Data Analysis

In [1]:
```
import warnings
warnings.filterwarnings("ignore")
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from wordcloud import WordCloud
import re
import os
import datetime as dt
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from nltk.stem.snowball import SnowballStemmer
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.preprocessing import OneHotEncoder
from datetime import datetime
```

Loading the data

In [2]:

```
#Loading train data
data_train=pd.read_csv('train.tsv',sep='\t')
print('Shape of the train data is : ',data_train.shape)
data_train.head()
```

```
Shape of the train data is :  (1482535, 8)
```

Out[2]:

	train_id	name	item_condition_id	category_name	brand_name	price	shippi
0	0	MLB Cincinnati Reds T Shirt Size XL	3	Men/Tops/T-shirts	NaN	10.0	
1	1	Razer BlackWidow Chroma Keyboard	3	Electronics/Computers & Tablets/Components & P...	Razer	52.0	
2	2	AVA-VIV Blouse	1	Women/Tops & Blouses/Blouse	Target	10.0	
3	3	Leather Horse Statues	1	Home/Home Décor/Home Décor Accents	NaN	35.0	
4	4	24K GOLD plated rose	1	Women/Jewelry/Necklaces	NaN	44.0	

In [3]:
```
test=pd.read_csv('test_stg2.tsv',sep='\t')
print('Shape of the test data is : ',test.shape)
test.head()
```

```
Shape of the test data is :  (3460725, 7)
```

Out[3]:

	test_id	name	item_condition_id	category_name	brand_name	shipping	item_d
0	0	Breast cancer "I fight like a girl" ring	1	Women/Jewelry/Rings	NaN	1	
1	1	25 pcs NEW 7.5"x12" Kraft Bubble Mailers	1	Other/Office supplies/Shipping Supplies	NaN	1	2 7.5 Bub
2	2	Coach bag	1	Vintage & Collectibles/Bags and Purses/Handbag	Coach	1	Brand bag. [rm] a
3	3	Floral Kimono	2	Women/Sweaters/Cardigan	NaN	0	-flor n light
4	4	Life after Death	3	Other/Books/Religion & Spirituality	NaN	1	Redisc after tl

In [5]:
```
#creating copies of train data
train=data_train.copy()
```

In [5]:
```
train.info()
```

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

Data Cleaning

In [6]:
```
#checking for rows which have price = 0
df = train[train['price'] == 0].reset_index(drop=True)
print('Number of rows with price = 0 are :',df.shape[0])
```

```
Number of rows with price = 0 are : 874
```

In [6]:
```
#dropping rows from train data where price=0
train = train[train['price'] > 0].reset_index(drop=True)
train.shape
```

Out[6]:
```
(1481661, 8)
```

In [8]:
```
#checking for null values in columns
train.isnull().any()
```

Out[8]:
```
train_id             False
name                 False
item_condition_id    False
category_name         True
brand_name            True
price                False
shipping             False
item_description      True
dtype: bool
```

- The columns category_name , brand_name , item_description have null values

In [7]:
```
#filling null values
train.category_name.fillna(value="Unknown/Unknown/Unknown", inplace = True)
train.brand_name.fillna(value="Unknown", inplace = True)
train.item_description.fillna(value="No description yet", inplace = True)
test.category_name.fillna(value="Unknown/Unknown/Unknown", inplace = True)
test.brand_name.fillna(value="Unknown", inplace = True)
test.item_description.fillna(value="No description yet", inplace = True)
```

In [9]:
```
train.head(2)
```

Out[9]:

	train_id	name	item_condition_id	category_name	brand_name	price	shipping
0	0	MLB Cincinnati Reds T Shirt Size XL	3	Men/Tops/T-shirts	Unknown	10.0	1
1	1	Razer BlackWidow Chroma Keyboard	3	Electronics/Computers & Tablets/Components & P...	Razer	52.0	0

Splitting category_name

In [8]:

```
#splitting the category_name column into 3 columns-main_category,sub_cat1,sub
category=list(train['category_name'].values)

main_cat=[]
sub_cat1=[]
sub_cat2=[]
for i in range(len(category)):
    cat=category[i].split("/")
    main_cat.append(cat[0])
    sub_cat1.append(cat[1])
    sub_cat2.append(cat[2])

train['main_category']=main_cat
train['sub_cat1']=sub_cat1
train['sub_cat2']=sub_cat2

#dropping the column category_name
train.drop('category_name', axis=1, inplace=True)
```

In [9]:

```
train.head(2)
```

Out[9]:

	train_id	name	item_condition_id	brand_name	price	shipping	item_description	mai
0	0	MLB Cincinnati Reds T Shirt Size XL	3	Unknown	10.0	1	No description yet	
1	1	Razer BlackWidow Chroma Keyboard	3	Razer	52.0	0	This keyboard is in great condition and works ...	

In [10]:
```
#splitting the category_name column into 3 columns-main_category,sub_cat1,sub
category=list(test['category_name'].values)

main_cat=[]
sub_cat1=[]
sub_cat2=[]
for i in range(len(category)):
    cat=category[i].split("/")
    main_cat.append(cat[0])
    sub_cat1.append(cat[1])
    sub_cat2.append(cat[2])

test['main_category']=main_cat
test['sub_cat1']=sub_cat1
test['sub_cat2']=sub_cat2

#dropping the column category_name
test.drop('category_name', axis=1, inplace=True)
```

In [11]:
```
test.head(2)
```

Out[11]:

	test_id	name	item_condition_id	brand_name	shipping	item_description	main_category
0	0	Breast cancer "I fight like a girl" ring	1	Unknown	1	Size 7	Women
1	1	25 pcs NEW 7.5"x12" Kraft Bubble Mailers	1	Unknown	1	25 pcs NEW 7.5"x12" Kraft Bubble Mailers Lined...	Other

1. Price

In [12]:
```
train['price'].describe()
```

Out[12]:
```
count    1.481661e+06
mean     2.675329e+01
std      3.859198e+01
min      3.000000e+00
25%      1.000000e+01
50%      1.700000e+01
75%      2.900000e+01
max      2.009000e+03
Name: price, dtype: float64
```

In [13]:
```
#@title Default title text
price=train['price'].values
log_price = np.log1p(price)
```

In [0]:
```
p=np.array(price)
r=np.arange(10,110,10)
q1=np.percentile(p,r)
for i in range(len(r)):
    print(str(r[i])+'th percentile value of price =',q1[i])
```

```
10th percentile value of price = 7.0
20th percentile value of price = 10.0
30th percentile value of price = 12.0
40th percentile value of price = 14.0
50th percentile value of price = 17.0
60th percentile value of price = 20.0
70th percentile value of price = 26.0
80th percentile value of price = 34.0
90th percentile value of price = 51.0
100th percentile value of price = 2009.0
```

In [0]:
```
p=np.array(price)
r=np.arange(90,101,1)
q1=np.percentile(p,r)
for i in range(len(r)):
    print(str(r[i])+'th percentile value of price =',q1[i])
```

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

PDF of price :-

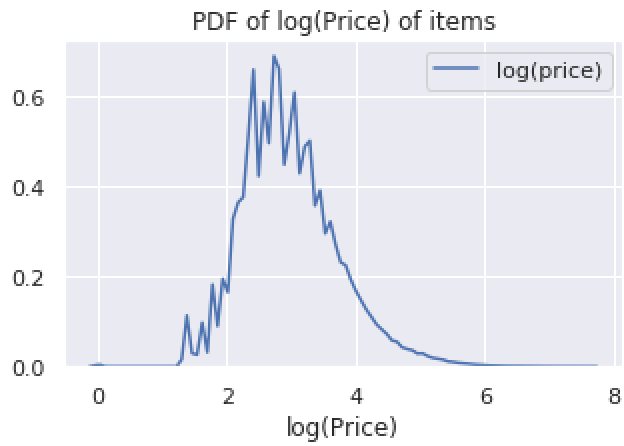
In [0]:
```
plt.figure(figsize=(5,3))
sns.distplot(price, hist=False, label="price")
plt.title('PDF of Price of items')
plt.xlabel('Price')
plt.legend()
```

Out[63]: `<matplotlib.legend.Legend at 0x7f78d79dafd0>`

PDF of log(price) :-

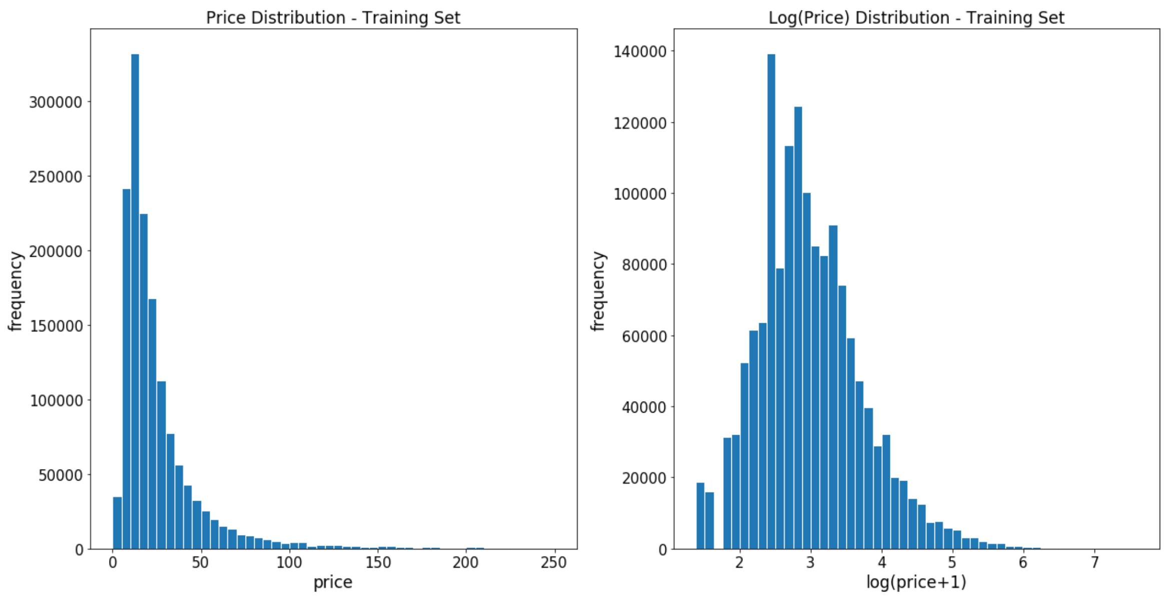
In [0]:

```
plt.figure(figsize=(5,3))
sns.distplot(log_price, hist=False, label="log(price)")
plt.title('PDF of log(Price) of items')
plt.xlabel('log(Price)')
plt.legend()
plt.show()
```



Histograms

In [15]:
```
plt.subplot(1, 2, 1)
(train['price']).plot.hist(bins=50, figsize=(20,10), edgecolor='white',range=
plt.xlabel('price', fontsize=17)
plt.ylabel('frequency', fontsize=17)
plt.tick_params(labelsize=15)
plt.title('Price Distribution - Training Set', fontsize=17)

plt.subplot(1, 2, 2)
np.log(train['price']+1).plot.hist(bins=50, figsize=(20,10), edgecolor='white
plt.xlabel('log(price+1)', fontsize=17)
plt.ylabel('frequency', fontsize=17)
plt.tick_params(labelsize=15)
plt.title('Log(Price) Distribution - Training Set', fontsize=17)
plt.show()
```



Observations :-

- 90 % of data points have price less than 51$
- 97 % of data points have price less than 99
- Log(price) distribution is more symmetric when compared to price distribution
- That is why we use RMLSE as error metric and not RMSE

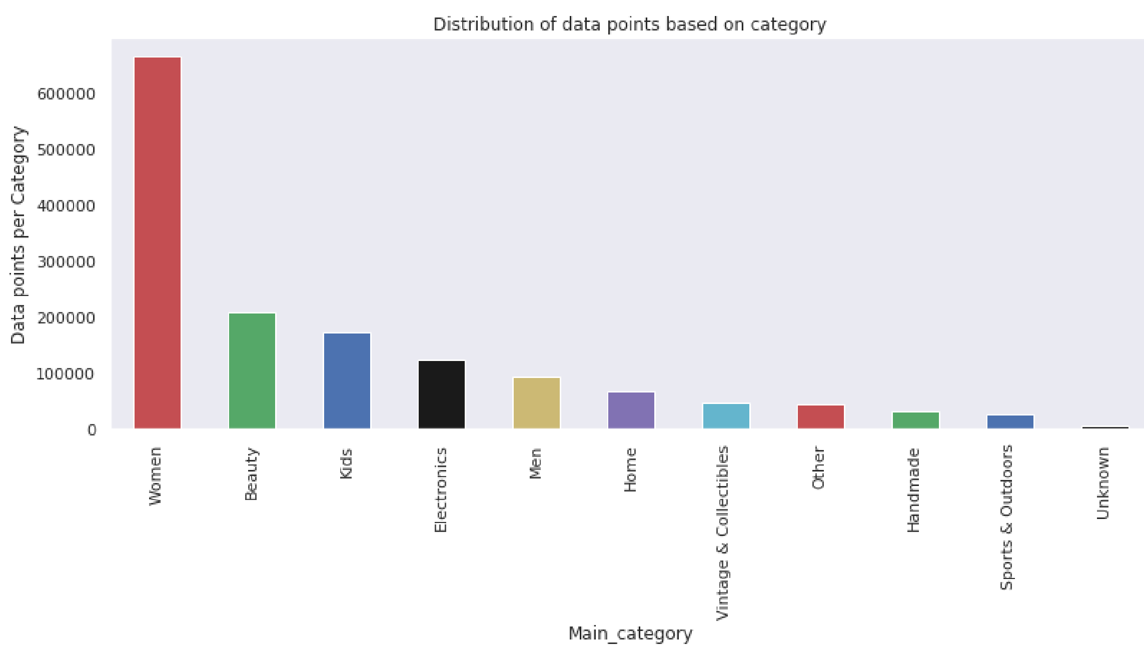
2. Main_category

In [17]:
```
sns.set(rc={'figure.figsize':(13,5)})
```

In [0]:

```
main_cat=train['main_category'].value_counts()
print('Number of unique main categories : ',main_cat.size)

my_colors = ['r','g','b','k','y','m','c']
main_cat.plot(kind='bar',color=my_colors)
plt.xlabel('Main_category')
plt.ylabel('Data points per Category')
plt.title('Distribution of data points based on category')
plt.grid()
plt.show()


keys=list(main_cat.keys())
values=list(main_cat.values)
percentage=[]
for i in range(len(main_cat)):
    percent=np.round(float(values[i]/len(train))*100,2)
    percentage.append(percent)
df=pd.DataFrame()
df['Main_Category']=keys
df['data points count']=values
df['%']=percentage
df
```

```
Number of unique main categories :  11
```



Out[23]:

Main_Category	data points count	%

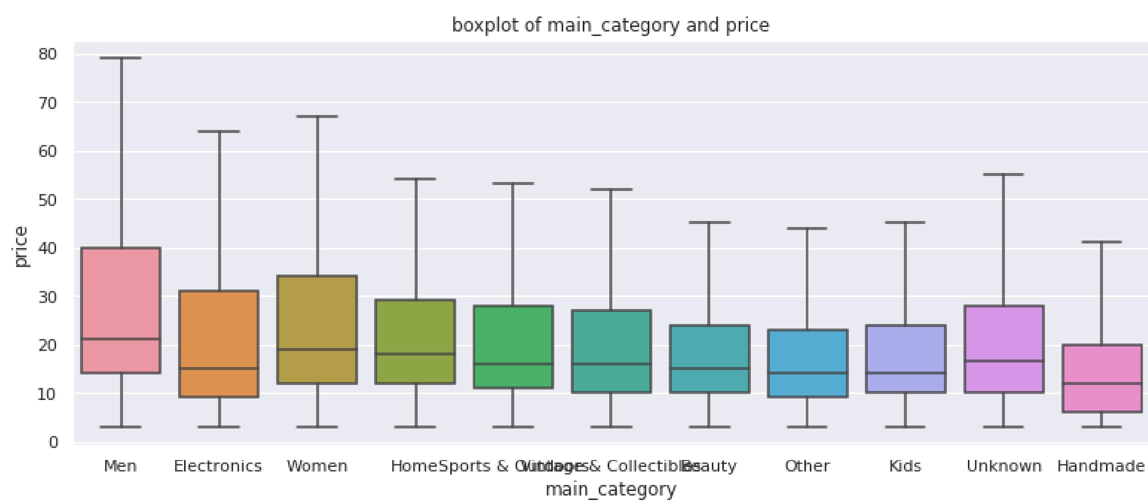
	Main_Category	data points count	%
0	Women	663990	44.81
1	Beauty	207725	14.02
2	Kids	171555	11.58
3	Electronics	122632	8.28
4	Men	93609	6.32
5	Home	67831	4.58
6	Vintage & Collectibles	46519	3.14
7	Other	45329	3.06
8	Handmade	30835	2.08
9	Sports & Outdoors	25322	1.71
10	Unknown	6314	0.43

Observations :-

- There are a total 11 unique main categories
- Women category itself contains almost 45% of the data points
- The top 3 categories Women,Beauty,Kids contain 60% of data points
- 0.43% of the data do not contain the category information

In [0]:

```
#boxplot of byte files
ax = sns.boxplot(x=train['main_category'], y=train['price'],showfliers = Fals
plt.title("boxplot of main_category and price")
plt.plot(figsize=(30,30))
plt.show()
```



Observations :-

- The data points belonging to Men category have a highest price range when compared to other categories

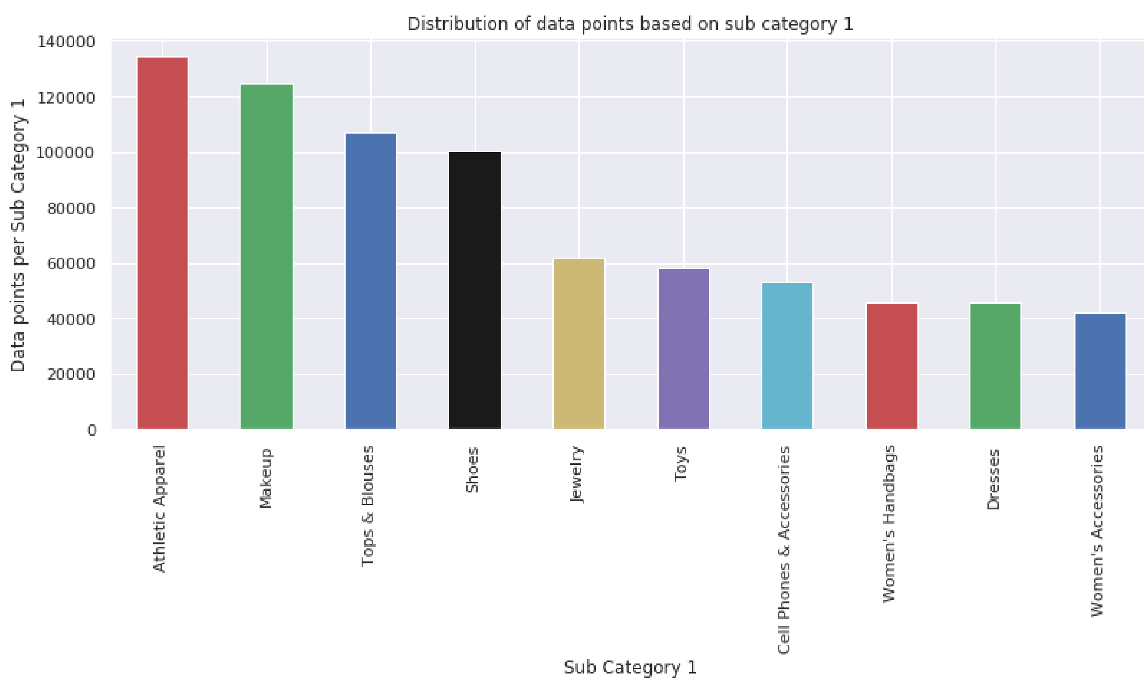
- The data points belonging to Handmade category have a lowest price range when compared to other categories

3. sub_cat1

In [0]:

```
sub_cat1=train['sub_cat1'].value_counts()
print('Number of unique sub categories 1 : ',sub_cat1.size)

my_colors = ['r','g','b','k','y','m','c']
sub_cat1[0:10].plot(kind='bar',color=my_colors)
plt.xlabel('Sub Category 1')
plt.ylabel('Data points per Sub Category 1')
plt.title('Distribution of data points based on sub category 1')
plt.show()


keys=list(sub_cat1[0:10].keys())
values=list(sub_cat1[0:10].values)
percentage=[]
for i in range(len(sub_cat1[0:10])):
    percent=np.round(float(values[i]/len(train))*100,2)
    percentage.append(percent)
df=pd.DataFrame()
df['sub_cat1']=keys
df['data points count']=values
df['%']=percentage
df
```

```
Number of unique sub categories 1 :  114
```



Out[34]:

	sub_cat1	data points count	%
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
5	Toys	58158	3.92

	sub_cat1	data points count	%
6	Cell Phones & Accessories	53290	3.59
7	Women's Handbags	45862	3.09
8	Dresses	45758	3.09
9	Women's Accessories	42350	2.86

Observations :-

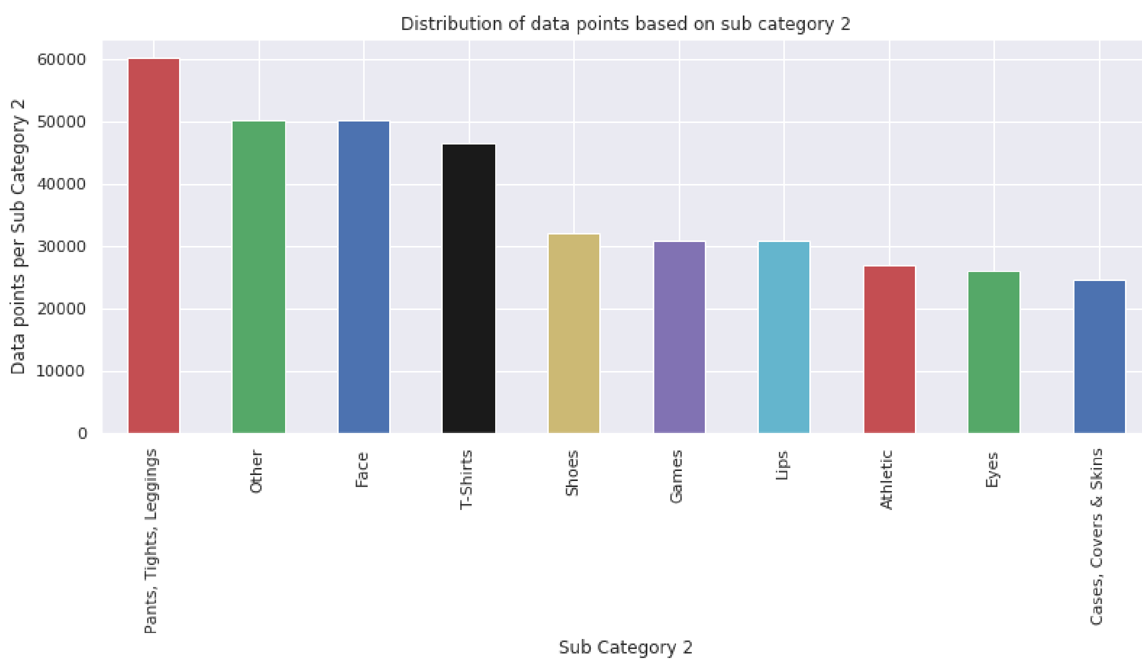
- There are a total 114 unique sub categories 1
- Athletic Apparel sub category1 contains more number of data points

sub_cat2

In [19]:

```
sub_cat2=train['sub_cat2'].value_counts()
print('Number of unique sub categories 2 : ',sub_cat2.size)

my_colors = ['r','g','b','k','y','m','c']
sub_cat2[0:10].plot(kind='bar',color=my_colors)
plt.xlabel('Sub Category 2')
plt.ylabel('Data points per Sub Category 2')
plt.title('Distribution of data points based on sub category 2')
plt.show()


keys=list(sub_cat2[0:10].keys())
values=list(sub_cat2[0:10].values)
percentage=[]
for i in range(len(sub_cat2[0:10])):
    percent=np.round(float(values[i]/len(train))*100,2)
    percentage.append(percent)
df=pd.DataFrame()
df['sub_cat2']=keys
df['data points count']=values
df['%']=percentage
df
```

```
Number of unique sub categories 2 :  871
```



Out[19]:

	sub_cat2	data points count	%
0	Pants, Tights, Leggings	60152	4.06
1	Other	50198	3.39
2	Face	50145	3.38
3	T-Shirts	46349	3.13
4	Shoes	32138	2.17
5	Games	30894	2.09

	sub_cat2	data points count	%
6	Lips	30861	2.08
7	Athletic	27037	1.82
8	Eyes	26021	1.76
9	Cases, Covers & Skins	24668	1.66

Observations :-

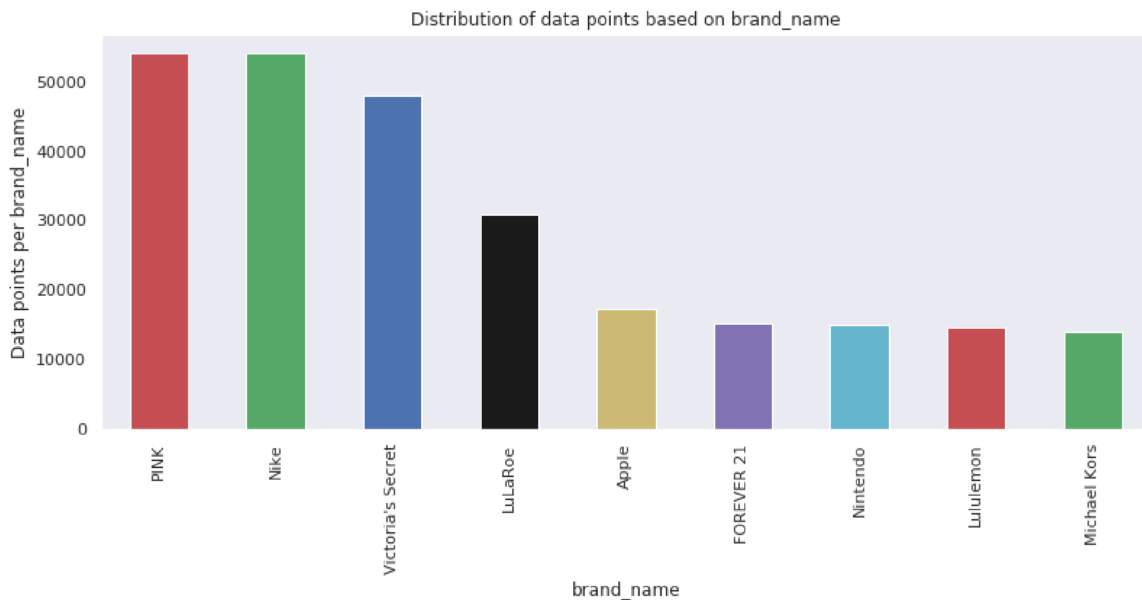
- There are a total 871 unique sub categories2
- Pants, Tights, Leggings sub category2 contains more number of data points

brand_name

In [20]:

```
brand=train['brand_name'].value_counts()
print('Number of unique brands : ',brand.size)

my_colors = ['r','g','b','k','y','m','c']
brand[1:10].plot(kind='bar',color=my_colors)
plt.xlabel('brand_name')
plt.ylabel('Data points per brand_name')
plt.title('Distribution of data points based on brand_name')
plt.grid()
plt.show()

keys=list(brand[1:10].keys())
values=list(brand[1:10].values)
percentage=[]
for i in range(len(brand[1:10])):
    percent=np.round(float(values[i]/len(train))*100,2)
    percentage.append(percent)
df=pd.DataFrame()
df['Brand']=keys
df['data points count']=values
df['%']=percentage
df
```

```
Number of unique brands :  4808
```



Out[20]:

	Brand	data points count	%
0	PINK	54072	3.65
1	Nike	54006	3.64
2	Victoria's Secret	48011	3.24
3	LuLaRoe	30995	2.09
4	Apple	17314	1.17
5	FOREVER 21	15178	1.02
6	Nintendo	14998	1.01

	Brand	data points count	%
7	Lululemon	14550	0.98
8	Michael Kors	13916	0.94

Observations :-
- There are a total 4808 unique brands
- PINK and Nike have almost same number of data points

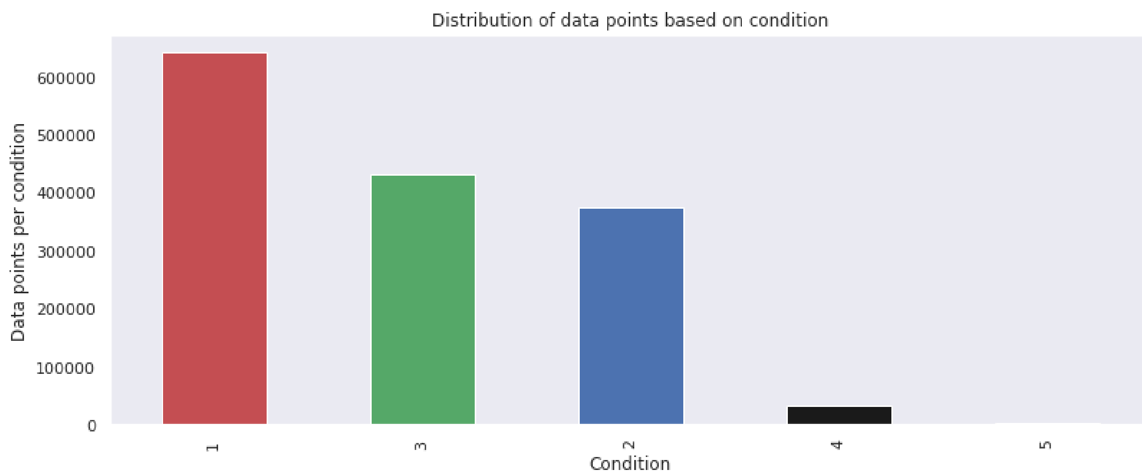
Item_condition_id

In [0]:
```
condition=train['item_condition_id'].value_counts()
condition
```

Out[44]:
```
1    640549
3    432161
2    375479
4     31962
5      2384
Name: item_condition_id, dtype: int64
```

In [0]:

```
my_colors = ['r','g','b','k','y']
condition.plot(kind='bar',color=my_colors)
plt.xlabel('Condition')
plt.ylabel('Data points per condition')
plt.title('Distribution of data points based on condition')
plt.grid()
plt.show()

keys=list(condition.keys())
values=list(condition.values)
percentage=[]
for i in range(len(condition)):
    percent=np.round(float(values[i]/len(train))*100,2)
    percentage.append(percent)
df=pd.DataFrame()
df['Item_Condition_Id']=keys
df['data points count']=values
df['%']=percentage
df
```



Out[45]:

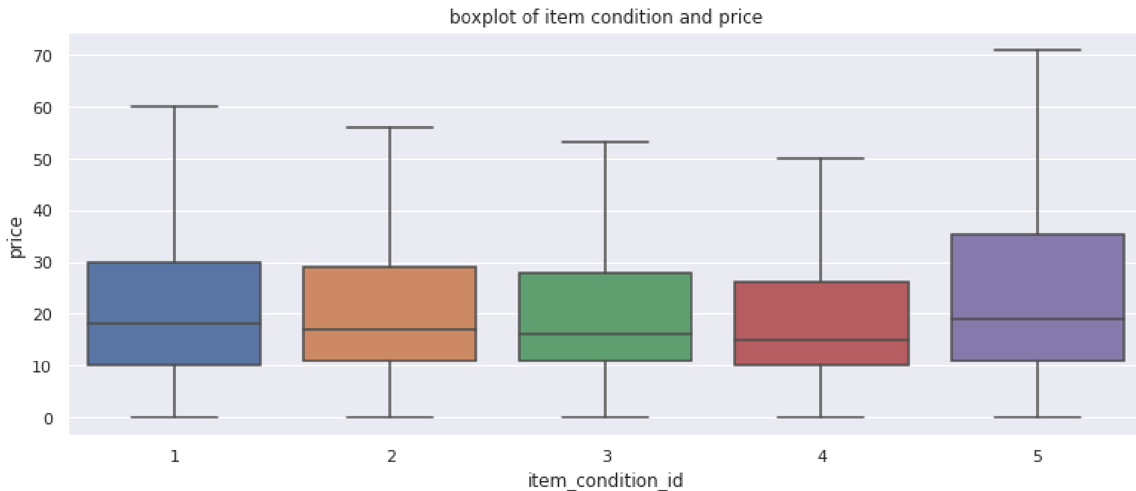
	Item_Condition_Id	data points count	%
0	1	640549	43.21
1	3	432161	29.15
2	2	375479	25.33
3	4	31962	2.16
4	5	2384	0.16

Observations :-

- There are a total 5 Item_Condition_Id's
- Item_Condition_Id '1' has 43.21% of the data points
- The Item_Condition_Id's '4' and '5' have less than 3% of data points

In [0]:

```
#boxplot of byte files
ax = sns.boxplot(x=train['item_condition_id'], y=train['price'],showfliers =
plt.title("boxplot of item condition and price")
plt.show()
```



Observations :-

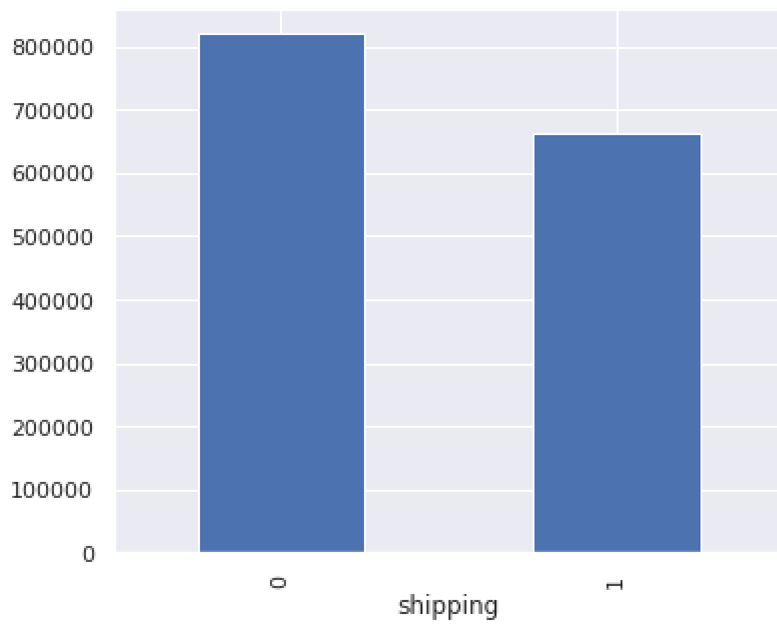
- The items having Item_Condition_Id '5' have a highest price range when compared to other Item_Condition_Id's

shipping

In [0]:
```
shipping=train['shipping'].value_counts()
train.groupby("shipping")['train_id'].count().plot.bar()

keys=list(shipping.keys())
values=list(shipping.values)
percentage=[]
for i in range(len(shipping)):
    percent=np.round(float(values[i]/len(train))*100,2)
    percentage.append(percent)
df=pd.DataFrame()
df['shipping']=keys
df['data points count']=values
df['%']=percentage
df
```

Out[51]:

	shipping	data points count	%
0	0	819435	55.27
1	1	663100	44.73



Observations :-

- Shipping = 0 ,shipping is paid by buyer
- Shipping = 1 ,shipping is paid by seller
- Items with shipping value = 0 are more in number than items with items with shipping value = 1

In [0]:
```
#boxplot of byte files
sns.set(rc={'figure.figsize':(6,5)})
ax = sns.boxplot(x=train['shipping'], y=train['price'],showfliers = False, or
plt.title("boxplot of shipping fee and price")
plt.show()
```

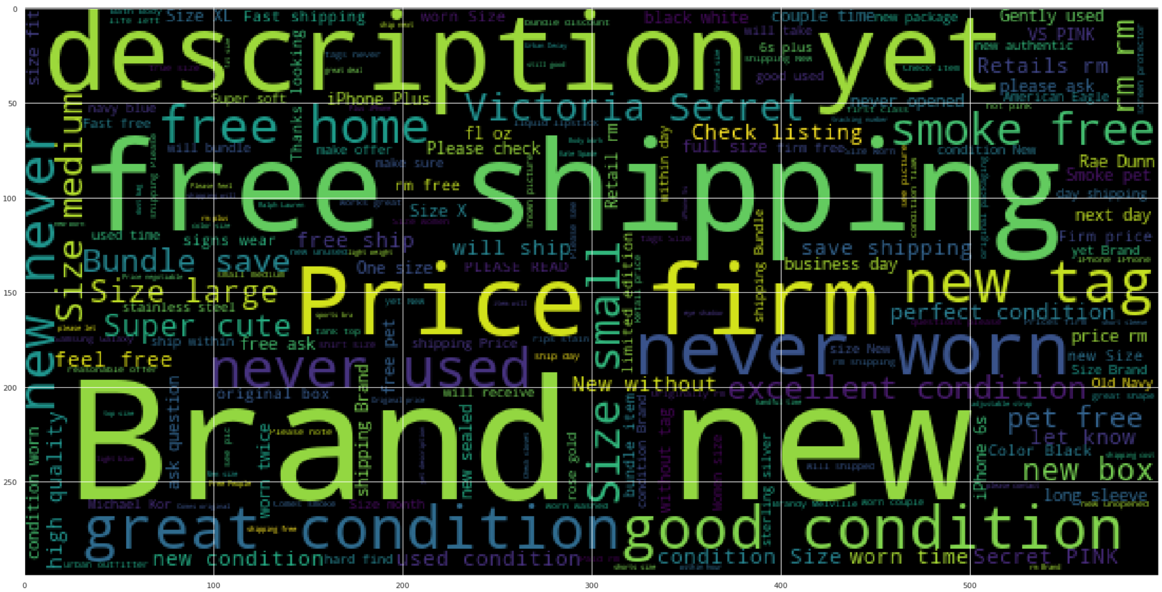
Observations :-

- The price range of items with shipping value = 0 is more when compared to items with items with shipping value = 1

item_description

In [0]:
```
desc=" ".join(train['item_description'].astype(str))
```

In [0]:
```
wordcloud = WordCloud(background_color='black',
                          width=600,
                          height=300,
                    ).generate(desc)

fig = plt.figure(figsize=(30,20))
plt.imshow(wordcloud)
plt.show()
```



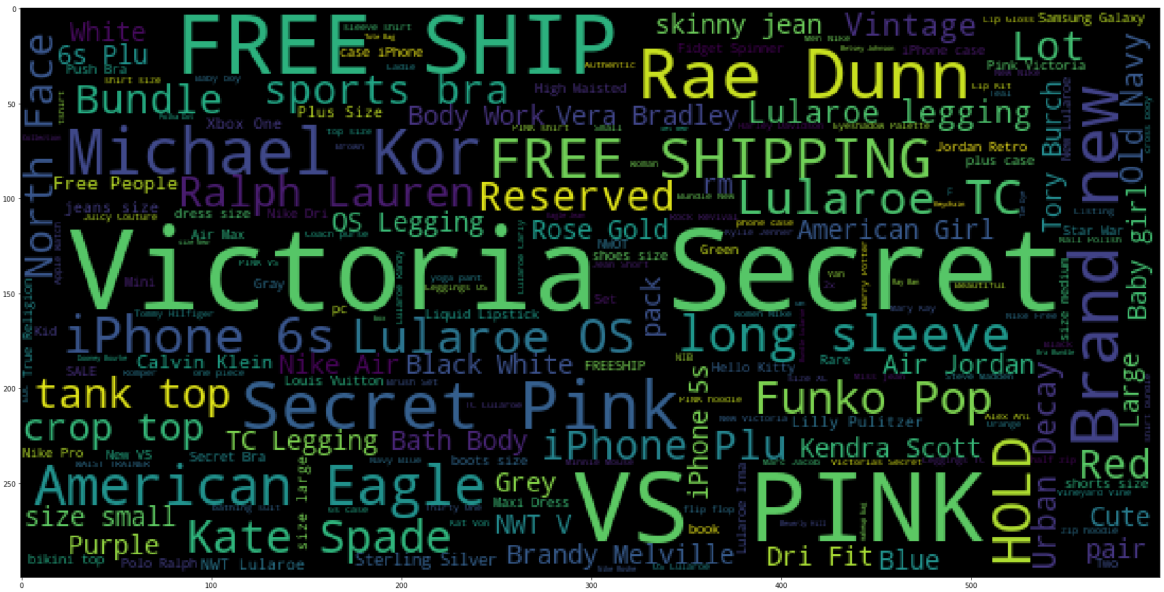
Observations :-

- The most frequent words in the item description are price,free shipping,firm,brand new,good condition,great condition,new tag,never worn,never used....

name

In [0]:
```
name_join=" ".join(train['name'].astype(str))
```

In [0]:
```
wordcloud = WordCloud(background_color='black',
                          width=600,
                          height=300,
                    ).generate(name_join)

fig = plt.figure(figsize=(30,20))
plt.imshow(wordcloud)
plt.show()
```



Observations :-

- The most frequent words in the name are mostly the brand names

4. Preparing data for models

In [11]:
```
from sklearn.model_selection import train_test_split
import pickle
from scipy.sparse import hstack
from sklearn.linear_model import Ridge
from sklearn.svm import SVR
from tqdm import tqdm
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import RandomizedSearchCV
from xgboost import XGBRegressor
```

In [12]:
```
train_price=train['price'].values
train.drop('price', axis=1, inplace=True)
```

4.1 Splitting data into Train, cross validation and test

In [13]:
```
x_train, x_cv, y_train, y_cv = train_test_split(train, train_price, test_size
```

In [14]:
```
print(x_train.shape)
print(x_cv.shape)
print(x_test.shape)
print(y_train.shape)
print(y_cv.shape)
```

```
(1037162, 9)
(444499, 9)
(3460725, 9)
(1037162,)
(444499,)
```

4.2 Encoding categorical and text features

Encoding categorical features : main_category

In [15]:
```
vectorizer = CountVectorizer()
vectorizer.fit(x_train['main_category'].values) # fit has to happen only on t

# we use the fitted CountVectorizer to convert the text to vector
X_train_main_cat = vectorizer.transform(x_train['main_category'].values)
X_cv_main_cat = vectorizer.transform(x_cv['main_category'].values)
X_test_main_cat = vectorizer.transform(x_test['main_category'].values)

print(X_train_main_cat.shape)
print(X_cv_main_cat.shape)
print(X_test_main_cat.shape)
```

```
(1037162, 13)
(444499, 13)
(3460725, 13)
```

Encoding categorical features : sub_cat1

In [16]:

```
vectorizer = CountVectorizer()
vectorizer.fit(x_train['sub_cat1'].values) # fit has to happen only on train

# we use the fitted CountVectorizer to convert the text to vector
X_train_sub_cat1 = vectorizer.transform(x_train['sub_cat1'].values)
X_cv_sub_cat1 = vectorizer.transform(x_cv['sub_cat1'].values)
X_test_sub_cat1 = vectorizer.transform(x_test['sub_cat1'].values)

print(X_train_sub_cat1.shape)
print(X_cv_sub_cat1.shape)
print(X_test_sub_cat1.shape)
```

```
(1037162, 142)
(444499, 142)
(3460725, 142)
```

Encoding categorical features : sub_cat2

In [17]:

```
vectorizer = CountVectorizer()
vectorizer.fit(x_train['sub_cat2'].values) # fit has to happen only on train

# we use the fitted CountVectorizer to convert the text to vector
X_train_sub_cat2 = vectorizer.transform(x_train['sub_cat2'].values)
X_cv_sub_cat2 = vectorizer.transform(x_cv['sub_cat2'].values)
X_test_sub_cat2 = vectorizer.transform(x_test['sub_cat2'].values)

print(X_train_sub_cat2.shape)
print(X_cv_sub_cat2.shape)
print(X_test_sub_cat2.shape)
```

```
(1037162, 955)
(444499, 955)
(3460725, 955)
```

Encoding categorical features : brand_name

In [18]:

```
vectorizer = CountVectorizer()
vectorizer.fit(x_train['brand_name'].values) # fit has to happen only on trai

# we use the fitted CountVectorizer to convert the text to vector
X_train_brand = vectorizer.transform(x_train['brand_name'].values)
X_cv_brand = vectorizer.transform(x_cv['brand_name'].values)
X_test_brand = vectorizer.transform(x_test['brand_name'].values)

print(X_train_brand.shape)
print(X_cv_brand.shape)
print(X_test_brand.shape)
```

```
(1037162, 4607)
(444499, 4607)
(3460725, 4607)
```

Encoding text features : item_description(BOW)

In [19]:

```
vectorizer = CountVectorizer(ngram_range=(1,2), max_features=100000)
vectorizer.fit(x_train['item_description'].values)

# we use the fitted CountVectorizer to convert the text to vector
X_train_desc_bow = vectorizer.transform(x_train['item_description'].values)
X_cv_desc_bow = vectorizer.transform(x_cv['item_description'].values)
X_test_desc_bow = vectorizer.transform(x_test['item_description'].values)

print("After vectorizations")
print(X_train_desc_bow.shape)
print(X_cv_desc_bow.shape)
print(X_test_desc_bow.shape)
print("="*100)
```

```
After vectorizations
(1037162, 100000)
(444499, 100000)
(3460725, 100000)
===========================================================================
=========================
```

Encoding text features : item_description(TF-IDF)

In [20]:

```
vectorizer = TfidfVectorizer(ngram_range=(1,2),max_features=100000)
vectorizer.fit(x_train['item_description'].values)

# we use the fitted CountVectorizer to convert the text to vector
X_train_desc_tfidf = vectorizer.transform(x_train['item_description'].values)
X_cv_desc_tfidf = vectorizer.transform(x_cv['item_description'].values)
X_test_desc_tfidf = vectorizer.transform(x_test['item_description'].values)

print("After vectorizations")
print(X_train_desc_tfidf.shape)
print(X_cv_desc_tfidf.shape)
print(X_test_desc_tfidf.shape)
print("="*100)
```

```
After vectorizations
(1037162, 100000)
(444499, 100000)
(3460725, 100000)
===========================================================================
=========================
```

Encoding text features : item_description(AVG W2V)

In [19]:

```
f = open('glove.6B.50d.txt','r')
model = {}
for line in f:
    splitLine = line.split()
    word = splitLine[0]
    embedding = np.array([float(val) for val in splitLine[1:]])
    model[word] = embedding
glove_words =  set(model.keys())
```

In [20]:

```
X_train_desc_avg_w2v = [];
X_cv_desc_avg_w2v = [];
X_test_desc_avg_w2v = [];

#X_train

for sentence in tqdm(x_train['item_description'].values): # for each review/s
    vector = np.zeros(50) # as word vectors are of zero length
    cnt_words =0; # num of words with a valid vector in the sentence/review
    for word in sentence.split(): # for each word in a review/sentence
        if word in glove_words:
            vector += model[word]
            cnt_words += 1
    if cnt_words != 0:
        vector /= cnt_words
    X_train_desc_avg_w2v.append(vector)

#X_cv
for sentence in tqdm(x_cv['item_description'].values): # for each review/sent
    vector = np.zeros(50) # as word vectors are of zero length
    cnt_words =0; # num of words with a valid vector in the sentence/review
    for word in sentence.split(): # for each word in a review/sentence
        if word in glove_words:
            vector += model[word]
            cnt_words += 1
    if cnt_words != 0:
        vector /= cnt_words
    X_cv_desc_avg_w2v.append(vector)

#X_test
for sentence in tqdm(x_test['item_description'].values): # for each review/se
    vector = np.zeros(50) # as word vectors are of zero length
    cnt_words =0; # num of words with a valid vector in the sentence/review
    for word in sentence.split(): # for each word in a review/sentence
        if word in glove_words:
            vector += model[word]
            cnt_words += 1
    if cnt_words != 0:
        vector /= cnt_words
    X_test_desc_avg_w2v.append(vector)

print("X_train:")
print(len(X_train_desc_avg_w2v))
print(len(X_train_desc_avg_w2v[0]))
print("="*50)

print("X_cv:")
print(len(X_cv_desc_avg_w2v))
print(len(X_cv_desc_avg_w2v[0]))
print("="*50)

print("X_test:")
print(len(X_test_desc_avg_w2v))
print(len(X_test_desc_avg_w2v[0]))
print("="*50)
```

```
100%|██████████| 1037162/1037162 [00:48<00:00, 21440.38it/s]
100%|██████████| 444499/444499 [00:18<00:00, 23795.79it/s]
100%|██████████| 3460725/3460725 [02:25<00:00, 23767.07it/s]

X_train:
1037162
50
==================================================
X_cv:
444499
50
==================================================
X_test:
3460725
50
==================================================
```

Encoding text features : name(BOW)

In [21]:

```
vectorizer = CountVectorizer(ngram_range=(1,2), max_features=100000)
vectorizer.fit(x_train['name'].values)

# we use the fitted CountVectorizer to convert the text to vector
X_train_name_bow = vectorizer.transform(x_train['name'].values)
X_cv_name_bow = vectorizer.transform(x_cv['name'].values)
X_test_name_bow = vectorizer.transform(x_test['name'].values)

print("After vectorizations")
print(X_train_name_bow.shape)
print(X_cv_name_bow.shape)
print(X_test_name_bow.shape)

print("="*100)
```

```
After vectorizations
(1037162, 100000)
(444499, 100000)
(3460725, 100000)
===========================================================================
=========================
```

Encoding text features : name(TF-IDF)

In [22]:

```
vectorizer = TfidfVectorizer(ngram_range=(1,2),max_features=100000)
vectorizer.fit(x_train['name'].values)

# we use the fitted CountVectorizer to convert the text to vector
X_train_name_tfidf = vectorizer.transform(x_train['name'].values)
X_cv_name_tfidf = vectorizer.transform(x_cv['name'].values)
X_test_name_tfidf = vectorizer.transform(x_test['name'].values)

print("After vectorizations")
print(X_train_name_tfidf.shape)
print(X_cv_name_tfidf.shape)
print(X_test_name_tfidf.shape)

print("="*100)
```

```
After vectorizations
(1037162, 100000)
(444499, 100000)
(3460725, 100000)
===========================================================================
=========================
```

Encoding text features : name(AVG W2V)

In [21]:

```
X_train_name_avg_w2v = [];
X_cv_name_avg_w2v = [];
X_test_name_avg_w2v = [];

#X_train

for sentence in tqdm(x_train['name'].values): # for each review/sentence
    vector = np.zeros(50) # as word vectors are of zero length
    cnt_words =0; # num of words with a valid vector in the sentence/review
    for word in sentence.split(): # for each word in a review/sentence
        if word in glove_words:
            vector += model[word]
            cnt_words += 1
    if cnt_words != 0:
        vector /= cnt_words
    X_train_name_avg_w2v.append(vector)

#X_cv
for sentence in tqdm(x_cv['name'].values): # for each review/sentence
    vector = np.zeros(50) # as word vectors are of zero length
    cnt_words =0; # num of words with a valid vector in the sentence/review
    for word in sentence.split(): # for each word in a review/sentence
        if word in glove_words:
            vector += model[word]
            cnt_words += 1
    if cnt_words != 0:
        vector /= cnt_words
    X_cv_name_avg_w2v.append(vector)

#X_test
for sentence in tqdm(x_test['name'].values): # for each review/sentence
    vector = np.zeros(50) # as word vectors are of zero length
    cnt_words =0; # num of words with a valid vector in the sentence/review
    for word in sentence.split(): # for each word in a review/sentence
        if word in glove_words:
            vector += model[word]
            cnt_words += 1
    if cnt_words != 0:
        vector /= cnt_words
    X_test_name_avg_w2v.append(vector)

print("X_train:")
print(len(X_train_name_avg_w2v))
print(len(X_train_name_avg_w2v[0]))
print("="*50)

print("X_cv:")
print(len(X_cv_name_avg_w2v))
print(len(X_cv_name_avg_w2v[0]))
print("="*50)

print("X_test:")
print(len(X_test_name_avg_w2v))
print(len(X_test_name_avg_w2v[0]))
print("="*50)
```

```
100%|██████████| 1037162/1037162 [00:12<00:00, 81822.36it/s]
100%|██████████| 444499/444499 [00:04<00:00, 90494.55it/s]
100%|██████████| 3460725/3460725 [00:37<00:00, 91569.57it/s]

X_train:
1037162
50
==================================================
X_cv:
444499
50
==================================================
X_test:
3460725
50
==================================================
```

One hot encoding categorical feature : item_condition_id

In [22]:

```
encoder=OneHotEncoder()

X_train_condition=encoder.fit_transform(x_train['item_condition_id'].values.r
X_cv_condition=encoder.transform(x_cv['item_condition_id'].values.reshape(-1,
X_test_condition=encoder.transform(x_test['item_condition_id'].values.reshape

print(X_train_condition.shape)
print(X_cv_condition.shape)
print(X_test_condition.shape)
```

```
(1037162, 5)
(444499, 5)
(3460725, 5)
```

One hot encoding categorical feature : shipping

In [23]:

```
encoder=OneHotEncoder()

X_train_shipping=encoder.fit_transform(x_train['shipping'].values.reshape(-1,
X_cv_shipping=encoder.transform(x_cv['shipping'].values.reshape(-1,1))
X_test_shipping=encoder.transform(x_test['shipping'].values.reshape(-1,1))

print(X_train_shipping.shape)
print(X_cv_shipping.shape)
print(X_test_shipping.shape)
```

```
(1037162, 2)
(444499, 2)
(3460725, 2)
```

Converting numerical feature price to log(price)

In [24]:
```
y_train_log = np.log1p(y_train)
y_cv_log = np.log1p(y_cv)
```

4.3 Concatinating all the features

SET 1 :- categorical + item_description(BOW) + name (BOW)

In [26]:
```
X1_tr=hstack((X_train_name_bow,X_train_desc_bow,X_train_condition,X_train_bra
              ,X_train_main_cat,X_train_sub_cat1,X_train_sub_cat2)).tocsr()

X1_cr=hstack((X_cv_name_bow,X_cv_desc_bow,X_cv_condition,X_cv_brand,X_cv_ship
              X_cv_main_cat,X_cv_sub_cat1,X_cv_sub_cat2)).tocsr()

X1_te=hstack((X_test_name_bow,X_test_desc_bow,X_test_condition,X_test_brand,X
              X_test_main_cat,X_test_sub_cat1,X_test_sub_cat2)).tocsr()
```

In [27]:
```
print(X1_tr.shape, y_train_log.shape)
print(X1_cr.shape, y_cv_log.shape)
print(X1_te.shape)
```

```
(1037162, 205724) (1037162,)
(444499, 205724) (444499,)
(3460725, 205724)
```

SET 2 :- categorical + item_description(TF-IDF) + name (TF-IDF)

In [28]:
```
X2_tr=hstack((X_train_name_tfidf,X_train_desc_tfidf,X_train_condition,X_trair
              ,X_train_main_cat,X_train_sub_cat1,X_train_sub_cat2)).tocsr()

X2_cr=hstack((X_cv_name_tfidf,X_cv_desc_tfidf,X_cv_condition,X_cv_brand,X_cv_
              X_cv_main_cat,X_cv_sub_cat1,X_cv_sub_cat2)).tocsr()

X2_te=hstack((X_test_name_tfidf,X_test_desc_tfidf,X_test_condition,X_test_bra
              X_test_main_cat,X_test_sub_cat1,X_test_sub_cat2)).tocsr()
```

In [29]:
```
print(X2_tr.shape, y_train_log.shape)
print(X2_cr.shape, y_cv_log.shape)
print(X2_te.shape)
```

```
(1037162, 205724) (1037162,)
(444499, 205724) (444499,)
(3460725, 205724)
```

SET 3 :- categorical + item_description(AVG W2V) + name (AVG W2V)

In [25]:

```
X3_tr=hstack((X_train_name_avg_w2v,X_train_desc_avg_w2v,X_train_condition,X_t
              ,X_train_main_cat,X_train_sub_cat1,X_train_sub_cat2)).tocsr()

X3_cr=hstack((X_cv_name_avg_w2v,X_cv_desc_avg_w2v,X_cv_condition,X_cv_brand,X
              X_cv_main_cat,X_cv_sub_cat1,X_cv_sub_cat2)).tocsr()

X3_te=hstack((X_test_name_avg_w2v,X_test_desc_avg_w2v,X_test_condition,X_test
              X_test_main_cat,X_test_sub_cat1,X_test_sub_cat2)).tocsr()
```

In [27]:

```
print(X3_tr.shape, y_train_log.shape)
print(X3_cr.shape, y_cv_log.shape)
print(X3_te.shape)
```

```
(1037162, 5824) (1037162,)
(444499, 5824) (444499,)
(3460725, 5824)
```

4.4 ML Models

Performance metric : Root Mean Square Logarithmic Error

In [28]:

```
def rmsle(y_test, y_pred):
    result = (np.sqrt(((y_test-y_pred)**2).mean())).round(4)
    return result
```

In [ ]:

4.4.1 Baseline model

In [32]:

```
#calculating mean of price of train data
y_train_mean = y_train_log.mean()

train_rmsle = rmsle(y_train_log,y_train_mean)
cv_rmsle = rmsle(y_cv_log,y_train_mean)

print("Train RMSLE for baseline model =",train_rmsle)
print("CV RMSLE for baseline model =",cv_rmsle)
```

```
Train RMSLE for baseline model = 0.745
CV RMSLE for baseline model = 0.7481
```

- Therefore the RMSLE for the ML models should be better than 0.7481

4.4.2 RIDGE (Linear Rigression with L2

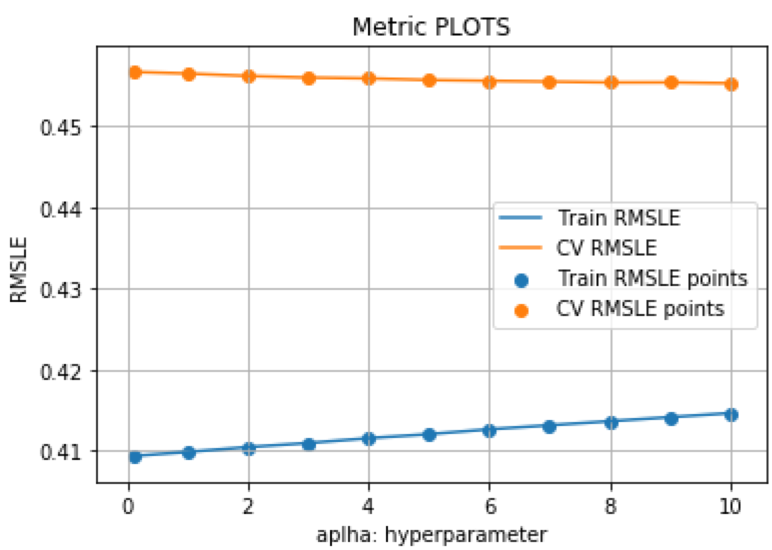
regularization)

SET 1 :- categorical + item_description(BOW) + name (BOW)

Training the model - Hyperparameter tuning

In [33]:
```
alpha= [0.1,1,2,3,4,5,6,7,8,9,10]
for i in alpha:
    clf = Ridge(alpha=i)
    clf.fit(X1_tr,y_train_log)

    y_train_pred = clf.predict(X1_tr)
    y_cv_pred = clf.predict(X1_cr)

    train_error = rmsle(y_train_log, y_train_pred)
    cv_error = rmsle(y_cv_log, y_cv_pred)

    print('alpha = '+str(i)+' : Train RMSLE = '+str(train_error)+', CV RMSLE
```

```
alpha = 0.1 : Train RMSLE = 0.4093, CV RMSLE = 0.4567
alpha = 1 : Train RMSLE = 0.4098, CV RMSLE = 0.4565
alpha = 2 : Train RMSLE = 0.4104, CV RMSLE = 0.4562
alpha = 3 : Train RMSLE = 0.4109, CV RMSLE = 0.456
alpha = 4 : Train RMSLE = 0.4115, CV RMSLE = 0.4559
alpha = 5 : Train RMSLE = 0.412, CV RMSLE = 0.4557
alpha = 6 : Train RMSLE = 0.4126, CV RMSLE = 0.4556
alpha = 7 : Train RMSLE = 0.4131, CV RMSLE = 0.4555
alpha = 8 : Train RMSLE = 0.4136, CV RMSLE = 0.4554
alpha = 9 : Train RMSLE = 0.4141, CV RMSLE = 0.4554
alpha = 10 : Train RMSLE = 0.4146, CV RMSLE = 0.4553
```



- Chosose best hyper parameter in such a way that the CV RMSLE is low and the difference between Train RMSLE and CV RMSLE is less

Best hyperparameter : alpha = 10

Predicting the price with best hyperparameter

In [35]:

```
clf = Ridge(alpha=10)
clf.fit(X1_tr,y_train_log)

y_train_pred11 = clf.predict(X1_tr)
y_cv_pred11 = clf.predict(X1_cr)
y_test_pred11 = clf.predict(X1_te)
y11 = np.expm1(y_test_pred11)

train_error = rmsle(y_train_log, y_train_pred11)
cv_error = rmsle(y_cv_log, y_cv_pred11)
print('alpha = 10 : Train RMSLE = '+str(train_error)+', CV RMSLE =',cv_error)

output = pd.DataFrame()
output['test_id']=test['test_id'].values
output['price']=y11
output.head()
```

```
alpha = 10 : Train RMSLE = 0.4146, CV RMSLE = 0.4553
```

Out[35]:

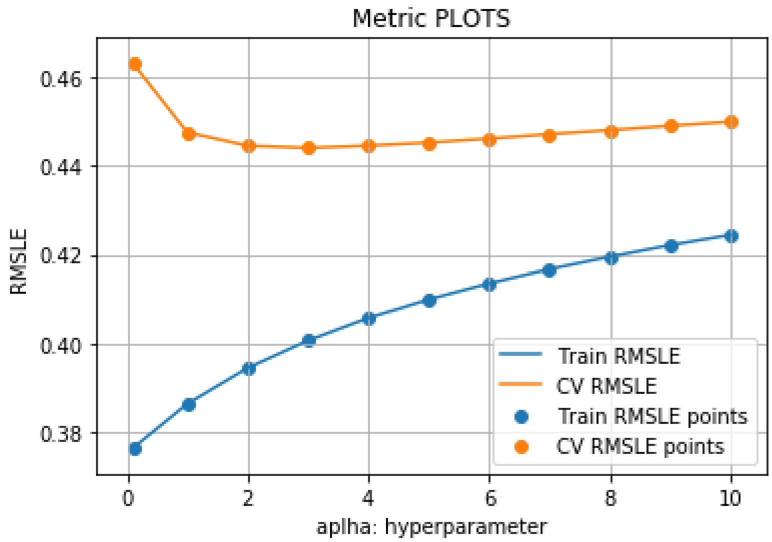
	test_id	price
0	0	10.117536
1	1	9.112697
2	2	44.461328
3	3	13.740187
4	4	7.102013

SET 2 :- categorical + item_description(TF-IDF) + name (TF-IDF)

In [29]:

```
from sklearn.linear_model import Ridge

train_rmsle=[]
cv_rmsle=[]
alpha= [0.1,1,2,3,4,5,6,7,8,9,10]
for i in alpha:
    clf = Ridge(alpha=i)
    clf.fit(X2_tr,y_train_log)

    y_train_pred = clf.predict(X2_tr)
    y_cv_pred = clf.predict(X2_cr)

    train_error = rmsle(y_train_log, y_train_pred)
    cv_error = rmsle(y_cv_log, y_cv_pred)
    train_rmsle.append(train_error)
    cv_rmsle.append(cv_error)

    print('alpha = '+str(i)+' : Train RMSLE = '+str(train_error)+', CV RMSLE

plt.plot(alpha, train_rmsle, label='Train RMSLE')
plt.plot(alpha, cv_rmsle, label='CV RMSLE')

plt.scatter(alpha, train_rmsle, label='Train RMSLE points')
plt.scatter(alpha, cv_rmsle, label='CV RMSLE points')

plt.legend()
plt.xlabel("aplha: hyperparameter")
plt.ylabel("RMSLE")
plt.title("Metric PLOTS")
plt.grid()
plt.show()
```

```
alpha = 0.1 : Train RMSLE = 0.3763, CV RMSLE = 0.4632
alpha = 1 : Train RMSLE = 0.3863, CV RMSLE = 0.4476
alpha = 2 : Train RMSLE = 0.3944, CV RMSLE = 0.4446
alpha = 3 : Train RMSLE = 0.4006, CV RMSLE = 0.4441
alpha = 4 : Train RMSLE = 0.4057, CV RMSLE = 0.4446
alpha = 5 : Train RMSLE = 0.4099, CV RMSLE = 0.4453
alpha = 6 : Train RMSLE = 0.4135, CV RMSLE = 0.4462
alpha = 7 : Train RMSLE = 0.4167, CV RMSLE = 0.4472
alpha = 8 : Train RMSLE = 0.4195, CV RMSLE = 0.4481
alpha = 9 : Train RMSLE = 0.4221, CV RMSLE = 0.4491
alpha = 10 : Train RMSLE = 0.4244, CV RMSLE = 0.45
```



- Chosose best hyper parameter in such a way that the CV RMSLE is low and the difference between Train RMSLE and CV RMSLE is less

Best hyperparameter : alpha = 3

Predicting the price with best hyperparameter

In [31]:
```
clf = Ridge(alpha=3)
clf.fit(X2_tr,y_train_log)

y_train_pred12 = clf.predict(X2_tr)
y_cv_pred12 = clf.predict(X2_cr)
y_test_pred12 = clf.predict(X2_te)
y12 = np.expm1(y_test_pred12)

train_error = rmsle(y_train_log, y_train_pred12)
cv_error = rmsle(y_cv_log, y_cv_pred12)
print('alpha = 3 : Train RMSLE = '+str(train_error)+', CV RMSLE =',cv_error)

output = pd.DataFrame()
output['test_id']=test['test_id'].values
output['price']=y12
output.head()
```

```
alpha = 3 : Train RMSLE = 0.4006, CV RMSLE = 0.4441
```

Out[31]:

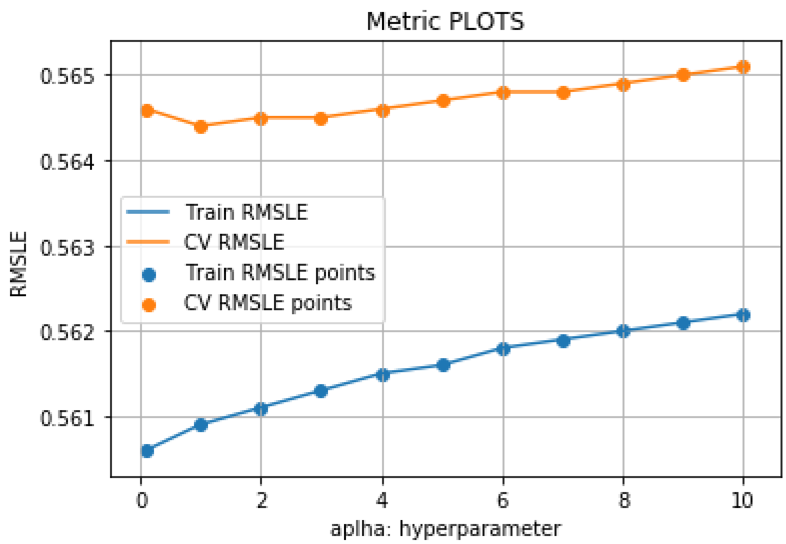
	test_id	price
0	0	10.034874
1	1	9.724997
2	2	47.595818
3	3	13.096653
4	4	7.438661

SET 3 :- categorical + item_description(AVG W2V) + name (AVG W2V)

In [31]:

```
from sklearn.linear_model import Ridge

train_rmsle=[]
cv_rmsle=[]
alpha= [0.1,1,2,3,4,5,6,7,8,9,10]
for i in alpha:
    clf = Ridge(alpha=i)
    clf.fit(X3_tr,y_train_log)

    y_train_pred = clf.predict(X3_tr)
    y_cv_pred = clf.predict(X3_cr)

    train_error = rmsle(y_train_log, y_train_pred)
    cv_error = rmsle(y_cv_log, y_cv_pred)
    train_rmsle.append(train_error)
    cv_rmsle.append(cv_error)

    print('alpha = '+str(i)+' : Train RMSLE = '+str(train_error)+', CV RMSLE

plt.plot(alpha, train_rmsle, label='Train RMSLE')
plt.plot(alpha, cv_rmsle, label='CV RMSLE')

plt.scatter(alpha, train_rmsle, label='Train RMSLE points')
plt.scatter(alpha, cv_rmsle, label='CV RMSLE points')

plt.legend()
plt.xlabel("aplha: hyperparameter")
plt.ylabel("RMSLE")
plt.title("Metric PLOTS")
plt.grid()
plt.show()
```

```
alpha = 0.1 : Train RMSLE = 0.5606, CV RMSLE = 0.5646
alpha = 1 : Train RMSLE = 0.5609, CV RMSLE = 0.5644
alpha = 2 : Train RMSLE = 0.5611, CV RMSLE = 0.5645
alpha = 3 : Train RMSLE = 0.5613, CV RMSLE = 0.5645
alpha = 4 : Train RMSLE = 0.5615, CV RMSLE = 0.5646
alpha = 5 : Train RMSLE = 0.5616, CV RMSLE = 0.5647
alpha = 6 : Train RMSLE = 0.5618, CV RMSLE = 0.5648
alpha = 7 : Train RMSLE = 0.5619, CV RMSLE = 0.5648
alpha = 8 : Train RMSLE = 0.562, CV RMSLE = 0.5649
alpha = 9 : Train RMSLE = 0.5621, CV RMSLE = 0.565
alpha = 10 : Train RMSLE = 0.5622, CV RMSLE = 0.5651
```



- Chosose best hyper parameter in such a way that the CV RMSLE is low and the difference between Train RMSLE and CV RMSLE is less

Best hyperparameter : alpha = 1

Predicting the price with best hyperparameter

In [86]:

```
clf = Ridge(alpha=1)
clf.fit(X3_tr,y_train_log)

y_train_pred13 = clf.predict(X3_tr)
y_cv_pred13 = clf.predict(X3_cr)
y_test_pred13 = clf.predict(X3_te)
y13 = np.expm1(y_test_pred13)

train_error = rmsle(y_train_log, y_train_pred13)
cv_error = rmsle(y_cv_log, y_cv_pred13)
print('alpha = 1: Train RMSLE = '+str(train_error)+', CV RMSLE =',cv_error)

output = pd.DataFrame()
output['test_id']=test['test_id'].values
output['price']=y13
output.head()
```

```
alpha = 1 : Train RMSLE = 0.5256, CV RMSLE = 0.5339
```

Out[86]:

	test_id	price
0	0	15.322902
1	1	9.898234
2	2	35.901699
3	3	22.456300
4	4	8.797033

4.4.3 Random Forest Regressor

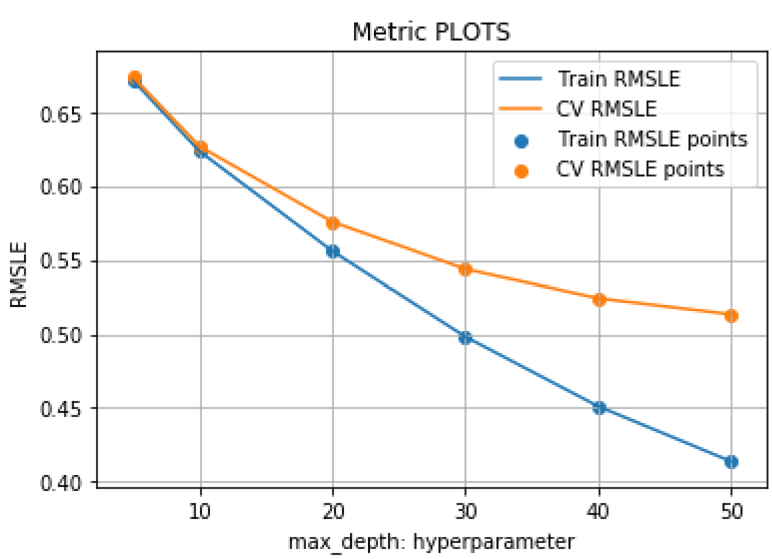
SET 1 :- categorical + item_description(BOW) + name (BOW)

Training the model - Hyperparameter tuning

In [36]:

```
train_rmsle=[]
cv_rmsle=[]
max_depth= [5,10,20,30,40,50]
for i in max_depth:
    RF1 = RandomForestRegressor(max_depth=i, n_jobs=-1)
    RF1.fit(X1_tr,y_train_log)

    y_train_pred = RF1.predict(X1_tr)
    y_cv_pred = RF1.predict(X1_cr)

    train_error = rmsle(y_train_log, y_train_pred)
    cv_error = rmsle(y_cv_log, y_cv_pred)
    train_rmsle.append(train_error)
    cv_rmsle.append(cv_error)

    print('max_depth = '+str(i)+' : Train RMSLE = '+str(train_error)+', CV RM

plt.plot(max_depth, train_rmsle, label='Train RMSLE')
plt.plot(max_depth, cv_rmsle, label='CV RMSLE')

plt.scatter(max_depth, train_rmsle, label='Train RMSLE points')
plt.scatter(max_depth, cv_rmsle, label='CV RMSLE points')

plt.legend()
plt.xlabel("max_depth: hyperparameter")
plt.ylabel("RMSLE")
plt.title("Metric PLOTS")
plt.grid()
plt.show()
```

```
max_depth = 5 : Train RMSLE = 0.6714, CV RMSLE = 0.6738
max_depth = 10 : Train RMSLE = 0.6235, CV RMSLE = 0.6268
max_depth = 20 : Train RMSLE = 0.556, CV RMSLE = 0.5758
max_depth = 30 : Train RMSLE = 0.4982, CV RMSLE = 0.5438
max_depth = 40 : Train RMSLE = 0.4511, CV RMSLE = 0.5242
max_depth = 50 : Train RMSLE = 0.4138, CV RMSLE = 0.5134
```



- Chosose best hyper parameter in such a way that the CV RMSLE is low and the difference between Train RMSLE and CV RMSLE is less

Best hyperparameter : max_depth = 50

Predicting the price with best hyperparameter

In [37]:

```
RF1 = RandomForestRegressor(max_depth=50, n_jobs=-1)
RF1.fit(X1_tr,y_traina_log)

y_train_pred21 = RF1.predict(X1_tr)
y_cv_pred21 = RF1.predict(X1_cr)
y_test_pred21 = RF1.predict(X1_te)
y21 = np.expm1(y_test_pred21)

train_error = rmsle(y_train_log, y_train_pred21)
cv_error = rmsle(y_cv_log, y_cv_pred21)
print('max_depth = 50: Train RMSLE = '+str(train_error)+', CV RMSLE =',cv_err

output = pd.DataFrame()
output['test_id']=test['test_id'].values
output['price']=y21
output.head()
```

```
max_depth = 50: Train RMSLE = 0.4138, CV RMSLE = 0.5134
```

Out[37]:

	test_id	price
0	0	8.413815
1	1	13.791215
2	2	21.588041
3	3	15.561349
4	4	11.093366

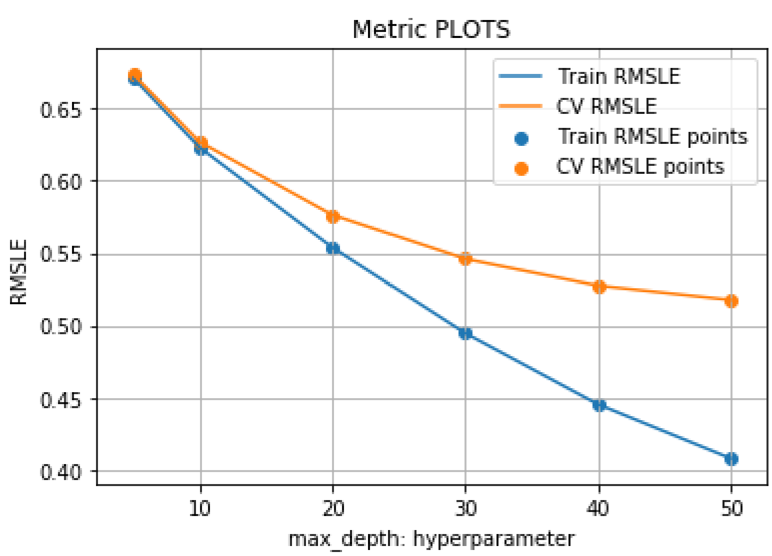
SET 2 :- categorical + item_description(TF-IDF) + name (TF-IDF)

Training the model - Hyperparameter tuning

In [30]:

```
train_rmsle=[]
cv_rmsle=[]
max_depth= [5,10,20,30,40,50]
for i in max_depth:
    RF2 = RandomForestRegressor(max_depth=i, n_jobs=-1)
    RF2.fit(X2_tr,y_train_log)

    y_train_pred = RF2.predict(X2_tr)
    y_cv_pred = RF2.predict(X2_cr)

    train_error = rmsle(y_train_log, y_train_pred)
    cv_error = rmsle(y_cv_log, y_cv_pred)
    train_rmsle.append(train_error)
    cv_rmsle.append(cv_error)

    print('max_depth = '+str(i)+' : Train RMSLE = '+str(train_error)+', CV RM

plt.plot(max_depth, train_rmsle, label='Train RMSLE')
plt.plot(max_depth, cv_rmsle, label='CV RMSLE')

plt.scatter(max_depth, train_rmsle, label='Train RMSLE points')
plt.scatter(max_depth, cv_rmsle, label='CV RMSLE points')

plt.legend()
plt.xlabel("max_depth: hyperparameter")
plt.ylabel("RMSLE")
plt.title("Metric PLOTS")
plt.grid()
plt.show()
```

```
max_depth = 5 : Train RMSLE = 0.671, CV RMSLE = 0.6734
max_depth = 10 : Train RMSLE = 0.6229, CV RMSLE = 0.6268
max_depth = 20 : Train RMSLE = 0.5538, CV RMSLE = 0.5763
max_depth = 30 : Train RMSLE = 0.4947, CV RMSLE = 0.5459
max_depth = 40 : Train RMSLE = 0.4455, CV RMSLE = 0.5275
max_depth = 50 : Train RMSLE = 0.4081, CV RMSLE = 0.5177
```



- Chosose best hyper parameter in such a way that the CV RMSLE is low and the difference between Train RMSLE and CV RMSLE is less

Best hyperparameter : max_depth = 50

Predicting the price with best hyperparameter

In [31]:

```
RF2 = RandomForestRegressor(max_depth=50, n_jobs=-1)
RF2.fit(X2_tr,y_train_log)

y_train_pred22 = RF2.predict(X2_tr)
y_cv_pred22 = RF2.predict(X2_cr)
y_test_pred22 = RF2.predict(X2_te)
y22 = np.expm1(y_test_pred22)

train_error = rmsle(y_train_log, y_train_pred22)
cv_error = rmsle(y_cv_log, y_cv_pred22)
print('max_depth = 50: Train RMSLE = '+str(train_error)+', CV RMSLE =',cv_err

output = pd.DataFrame()
output['test_id']=test['test_id'].values
output['price']=y22
output.head()
```

```
max_depth = 50: Train RMSLE = 0.4081, CV RMSLE = 0.5177
```

Out[31]:

	test_id	price
0	0	9.068544
1	1	13.329897
2	2	18.843231
3	3	15.651978
4	4	10.809444

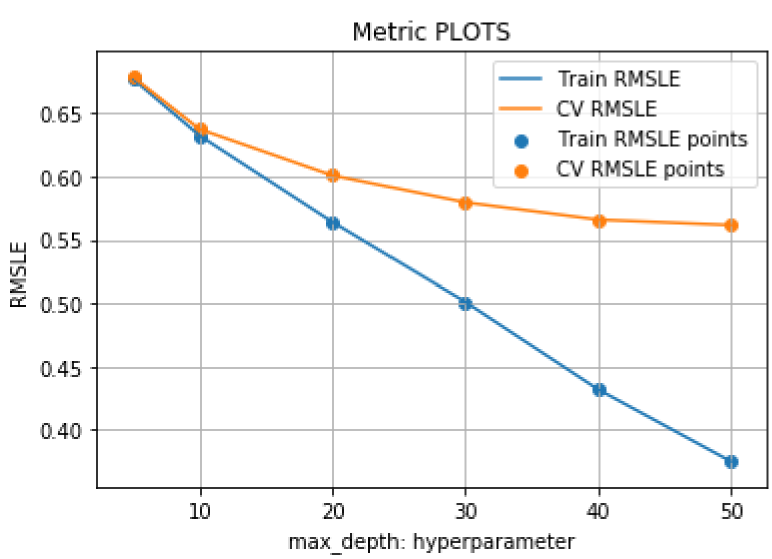
SET 3 :- categorical + item_description(AVG W2V) + name (AVG W2V)

Training the model - Hyperparameter tuning

In [30]:

```
train_rmsle=[]
cv_rmsle=[]
max_depth= [5,10,20,30,40,50]
for i in max_depth:
    RF3 = RandomForestRegressor(max_depth=i, n_jobs=-1)
    RF3.fit(X3_tr,y_train_log)

    y_train_pred = RF3.predict(X3_tr)
    y_cv_pred = RF3.predict(X3_cr)

    train_error = rmsle(y_train_log, y_train_pred)
    cv_error = rmsle(y_cv_log, y_cv_pred)
    train_rmsle.append(train_error)
    cv_rmsle.append(cv_error)

    print('max_depth = '+str(i)+' : Train RMSLE = '+str(train_error)+', CV RM

plt.plot(max_depth, train_rmsle, label='Train RMSLE')
plt.plot(max_depth, cv_rmsle, label='CV RMSLE')

plt.scatter(max_depth, train_rmsle, label='Train RMSLE points')
plt.scatter(max_depth, cv_rmsle, label='CV RMSLE points')

plt.legend()
plt.xlabel("max_depth: hyperparameter")
plt.ylabel("RMSLE")
plt.title("Metric PLOTS")
plt.grid()
plt.show()
```

```
max_depth = 5 : Train RMSLE = 0.6771, CV RMSLE = 0.6787
max_depth = 10 : Train RMSLE = 0.6324, CV RMSLE = 0.6375
max_depth = 20 : Train RMSLE = 0.5641, CV RMSLE = 0.6009
max_depth = 30 : Train RMSLE = 0.5011, CV RMSLE = 0.5796
max_depth = 40 : Train RMSLE = 0.432, CV RMSLE = 0.5659
max_depth = 50 : Train RMSLE = 0.3751, CV RMSLE = 0.5616
```



- Chosose best hyper parameter in such a way that the CV RMSLE is low and the difference between Train RMSLE and CV RMSLE is less

- If max_depth is increased more than 50,the difference between train and cv RMSLE increases further

Best hyperparameter : max_depth = 50

Predicting the price with best hyperparameter

In [31]:

```
RF3 = RandomForestRegressor(max_depth=50, n_jobs=-1)
RF3.fit(X3_tr,y_train_log)

y_train_pred23 = RF3.predict(X3_tr)
y_cv_pred23 = RF3.predict(X3_cr)
y_test_pred23 = RF3.predict(X3_te)
y23 = np.expm1(y_test_pred23)

train_error = rmsle(y_train_log, y_train_pred23)
cv_error = rmsle(y_cv_log, y_cv_pred23)
print('max_depth = 50: Train RMSLE = '+str(train_error)+', CV RMSLE =',cv_err

output = pd.DataFrame()
output['test_id']=test['test_id'].values
output['price']=y23
output.head()
```

```
max_depth = 50: Train RMSLE = 0.3751, CV RMSLE = 0.5616
```

Out[31]:

	test_id	price
0	0	7.682067
1	1	7.873678
2	2	18.109358
3	3	16.947522
4	4	12.140816

4.4.4 XGBOOST Regressor

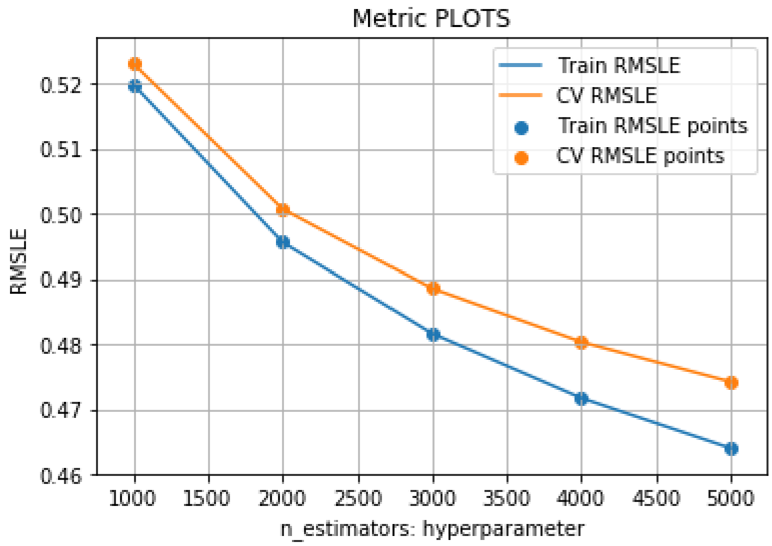
SET 1 :- categorical + item_description(BOW) + name (BOW)

Training the model - Hyperparameter tuning

In [42]:

```
n_estimators=[1000,2000,3000,4000,5000]
train_rmsle=[]
cv_rmsle=[]
for i in n_estimators:
    xgb1 = XGBRegressor(n_estimators=i, n_jobs=-1)
    xgb1.fit(X1_tr,y_train_log)

    y_train_pred = xgb1.predict(X1_tr)
    y_cv_pred = xgb1.predict(X1_cr)

    train_error = rmsle(y_train_log, y_train_pred)
    cv_error = rmsle(y_cv_log, y_cv_pred)

    train_rmsle.append(train_error)
    cv_rmsle.append(cv_error)

for i in range(len(n_estimators)):
    print('n_estimators = '+str(n_estimators[i])+' : Train RMSLE = '+str(trai

plt.plot(n_estimators, train_rmsle, label='Train RMSLE')
plt.plot(n_estimators, cv_rmsle, label='CV RMSLE')

plt.scatter(n_estimators, train_rmsle, label='Train RMSLE points')
plt.scatter(n_estimators, cv_rmsle, label='CV RMSLE points')

plt.legend()
plt.xlabel("n_estimators: hyperparameter")
plt.ylabel("RMSLE")
plt.title("Metric PLOTS")
plt.grid()
plt.show()
```

```
[16:46:41] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:lin
ear is now deprecated in favor of reg:squarederror.
[16:52:48] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:lin
ear is now deprecated in favor of reg:squarederror.
[17:03:24] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:lin
ear is now deprecated in favor of reg:squarederror.
[17:20:32] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:lin
ear is now deprecated in favor of reg:squarederror.
[17:40:51] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:lin
ear is now deprecated in favor of reg:squarederror.
n_estimators = 1000 : Train RMSLE = 0.5198, CV RMSLE = 0.523
n_estimators = 2000 : Train RMSLE = 0.4956, CV RMSLE = 0.5007
n_estimators = 3000 : Train RMSLE = 0.4816, CV RMSLE = 0.4885
n_estimators = 4000 : Train RMSLE = 0.4717, CV RMSLE = 0.4803
n_estimators = 5000 : Train RMSLE = 0.464, CV RMSLE = 0.4742
```



- Chosose best hyper parameter in such a way that the CV RMSLE is low and the difference between Train RMSLE and CV RMSLE is less

Best hyperparameter : n_estimators = 5000

Predicting the price with best hyperparameter

In [43]:

```
xgb1 = XGBRegressor(n_estimators=5000, n_jobs=-1)
xgb1.fit(X1_tr,y_train_log)

y_train_pred31 = xgb1.predict(X1_tr)
y_cv_pred31 = xgb1.predict(X1_cr)
y_test_pred31 = xgb1.predict(X1_te)
y31 = np.expm1(y_test_pred31)

train_error = rmsle(y_train_log, y_train_pred31)
cv_error = rmsle(y_cv_log, y_cv_pred31)
print('n_estimators = 5000: Train RMSLE = '+str(train_error)+', CV RMSLE =',c

output = pd.DataFrame()
output['test_id']=test['test_id'].values
output['price']=y31
output.head()
```

```
n_estimators = 5000: Train RMSLE = 0.464, CV RMSLE = 0.4742
```

Out[43]:

	test_id	price
0	0	10.101706
1	1	10.125776
2	2	41.787136
3	3	16.078148
4	4	8.644748

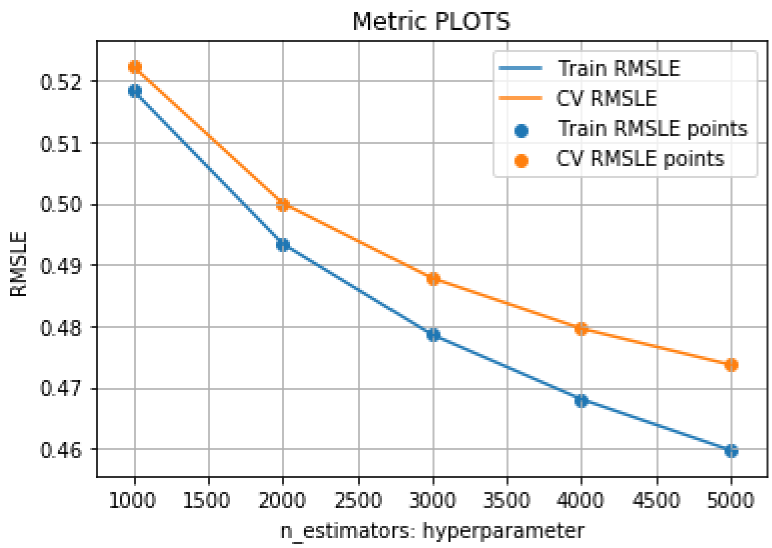
SET 2 :- categorical + item_description(TF-IDF) + name (TF-IDF)

Training the model - Hyperparameter tuning

In [32]:

```
n_estimators=[1000,2000,3000,4000,5000]
train_rmsle=[]
cv_rmsle=[]
for i in n_estimators:
    xgb2 = XGBRegressor(n_estimators=i, n_jobs=-1)
    xgb2.fit(X2_tr,y_train_log)

    y_train_pred = xgb2.predict(X2_tr)
    y_cv_pred = xgb2.predict(X2_cr)

    train_error = rmsle(y_train_log, y_train_pred)
    cv_error = rmsle(y_cv_log, y_cv_pred)

    train_rmsle.append(train_error)
    cv_rmsle.append(cv_error)

for i in range(len(n_estimators)):
    print('n_estimators = '+str(n_estimators[i])+' : Train RMSLE = '+str(trai

plt.plot(n_estimators, train_rmsle, label='Train RMSLE')
plt.plot(n_estimators, cv_rmsle, label='CV RMSLE')

plt.scatter(n_estimators, train_rmsle, label='Train RMSLE points')
plt.scatter(n_estimators, cv_rmsle, label='CV RMSLE points')

plt.legend()
plt.xlabel("n_estimators: hyperparameter")
plt.ylabel("RMSLE")
plt.title("Metric PLOTS")
plt.grid()
plt.show()
```

```
[12:15:53] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:lin
ear is now deprecated in favor of reg:squarederror.
[12:27:31] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:lin
ear is now deprecated in favor of reg:squarederror.
[12:49:34] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:lin
ear is now deprecated in favor of reg:squarederror.
[13:33:23] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:lin
ear is now deprecated in favor of reg:squarederror.
[14:16:36] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:lin
ear is now deprecated in favor of reg:squarederror.
n_estimators = 1000 : Train RMSLE = 0.5183, CV RMSLE = 0.5222
n_estimators = 2000 : Train RMSLE = 0.4934, CV RMSLE = 0.5
n_estimators = 3000 : Train RMSLE = 0.4786, CV RMSLE = 0.4878
n_estimators = 4000 : Train RMSLE = 0.4681, CV RMSLE = 0.4796
n_estimators = 5000 : Train RMSLE = 0.4598, CV RMSLE = 0.4737
```



- Chosose best hyper parameter in such a way that the CV RMSLE is low and the difference between Train RMSLE and CV RMSLE is less

Best hyperparameter : n_estimators = 5000

Predicting the price with best hyperparameter

In [40]:

```
xgb2 = XGBRegressor(n_estimators=5000, n_jobs=-1)
xgb2.fit(X2_tr,y_train_log)

y_train_pred32 = xgb2.predict(X2_tr)
y_cv_pred32 = xgb2.predict(X2_cr)
y_test_pred32 = xgb2.predict(X2_te)
y32 = np.expm1(y_test_pred32)

train_error = rmsle(y_train_log, y_train_pred32)
cv_error = rmsle(y_cv_log, y_cv_pred32)
print('n_estimators = 5000: Train RMSLE = '+str(train_error)+', CV RMSLE =',c

output = pd.DataFrame()
output['test_id']=test['test_id'].values
output['price']=y32
output.head()
```

```
n_estimators = 5000: Train RMSLE = 0.4598, CV RMSLE = 0.4737
```

Out[40]:

	test_id	price
0	0	10.054468
1	1	9.273506
2	2	36.111198
3	3	16.014009
4	4	8.687569

4.4.5 FM_FTRL : Factorization Machine Follow The Regularization Leader

- FTRL : Linear model Proximal-FTRL that has become the most popular algorithm for online learning of linear models in Kaggle competions.
- FM_FTRL : Factorization Machines. Linear effects estimated with FTRL and factor effects estimated with adaptive SGD. Prediction and estimation multithreaded across factors.
- The adaptive SGD optimizer works like Adagrad, but pools the adaptive learning rates across hidden nodes
- https://medium.com/@dhirajreddy13/factorization-machines-and-follow-the-regression-leader-for-dummies-7657652dce69
- https://github.com/anttttti/Wordbatch

In [35]:

```
import wordbatch

from wordbatch.extractors import WordBag, WordHash
from wordbatch.models import FTRL, FM_FTRL
```

SET 2 :- categorical + item_description(TF-IDF) + name (TF-IDF)

Training the model

In [35]:
```
model2 = FM_FTRL(D=X2_tr.shape[1], iters=30,threads=12)
model2.fit(X2_tr, y_train_log)
```

```
Total e: 377643.1475837479
Total e: 341803.12466171145
Total e: 330506.3605100804
Total e: 323437.69987354666
Total e: 318344.51223147573
Total e: 314403.7157800503
Total e: 311214.55642854807
Total e: 308545.0574811478
Total e: 306256.0323824083
Total e: 304256.45794740133
Total e: 302480.1005421136
Total e: 300881.9795513508
Total e: 299425.39580756065
Total e: 298086.5378725825
Total e: 296845.02048604883
Total e: 295684.9323144622
Total e: 294593.522086264
Total e: 293560.29587708524
Total e: 292575.8203008837
Total e: 291634.07565514586
Total e: 290729.6716189085
Total e: 289856.8120925457
Total e: 289011.63114346453
Total e: 288190.7873436062
Total e: 287391.4172179394
Total e: 286610.48094992316
Total e: 285845.8356756173
Total e: 285095.28089128213
Total e: 284357.3784256046
Total e: 283630.76408343716
```

Out[35]:
```
<wordbatch.models.fm_ftrl.FM_FTRL at 0x55edb181e4a0>
```

Predicting the price

In [36]:

```
y_train_pred42 = model2.predict(X2_tr)
y_cv_pred42 = model2.predict(X2_cr)
y_test_pred42 = model2.predict(X2_te)
y42 = np.expm1(y_test_pred42)

train_error = rmsle(y_train_log, y_train_pred42)
cv_error = rmsle(y_cv_log, y_cv_pred42)
print('For FM_FTRL model : Train RMSLE = '+str(train_error)+', CV RMSLE =',cv

output = pd.DataFrame()
output['test_id']=test['test_id'].values
output['price']=y42
output.head()
```

```
For FM_FTRL model : Train RMSLE = 0.3649, CV RMSLE = 0.4336
```

Out[36]:

	test_id	price
0	0	7.698370
1	1	9.614035
2	2	59.650479
3	3	11.601917
4	4	7.976456

SET 3 :- categorical + item_description(AVG W2V) + name (AVG W2V)

Training the model

In [36]:
```
model3 = FM_FTRL(D=X3_tr.shape[1], iters=30,threads=12)
model3.fit(X3_tr, y_train_log)
```

```
Total e: 442950.9680900332
Total e: 427700.8791989619
Total e: 424035.81006830034
Total e: 421871.7678670636
Total e: 420337.04699014913
Total e: 419150.49092827016
Total e: 418184.8218341588
Total e: 417369.65393494605
Total e: 416664.78371579916
Total e: 416045.0856029353
Total e: 415492.3370035744
Total e: 414993.1310035172
Total e: 414540.8973219683
Total e: 414129.0165711676
Total e: 413752.02360381064
Total e: 413406.4138166123
Total e: 413089.2309892627
Total e: 412799.00746255
Total e: 412533.4660628584
Total e: 412291.3258472642
Total e: 412071.51962643326
Total e: 411873.4947077818
Total e: 411696.52973678085
Total e: 411540.5063132007
Total e: 411405.85074343026
Total e: 411294.24748696666
Total e: 411206.0764196147
Total e: 411141.99366735347
Total e: 411102.6643412086
Total e: 411088.9743958102
```

Out[36]: <wordbatch.models.fm_ftrl.FM_FTRL at 0x56215e861a30>

In [38]:
```
y_train_pred43 = model3.predict(X3_tr)
y_cv_pred43 = model3.predict(X3_cr)
y_test_pred43 = model3.predict(X3_te)
y43 = np.expm1(y_test_pred43)

train_error = rmsle(y_train_log, y_train_pred43)
cv_error = rmsle(y_cv_log, y_cv_pred43)
print('For FM_FTRL model : Train RMSLE = '+str(train_error)+', CV RMSLE =',cv

output = pd.DataFrame()
output['test_id']=test['test_id'].values
output['price']=y43
output.head()
```

```
For FM_FTRL model : Train RMSLE = 0.5256, CV RMSLE = 0.5339
```

Out[38]:

	test_id	price
0	0	8.392869
1	1	8.601333
2	2	44.067662
3	3	18.482287
4	4	7.012417

DL models

4.4.7 MLP

In [39]:
```
import tensorflow as tf

import keras
from keras.models import Sequential,Model
from keras.layers import Dense, Dropout, Flatten,concatenate,Input,LSTM
from keras.layers import Conv2D, MaxPooling2D
from keras import backend as K
from keras.layers.normalization import BatchNormalization
from keras.layers.convolutional import Convolution2D, MaxPooling2D, ZeroPaddi
from numpy import asarray
from numpy import zeros
from keras.preprocessing.text import Tokenizer
from keras.preprocessing.sequence import pad_sequences
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import Flatten
from keras.layers import Embedding
from keras.initializers import he_normal
from keras.initializers import RandomNormal
```

```
Using TensorFlow backend.
```

In [40]:
```
def batch_generator(X, y, batch_size, shuffle):
    number_of_batches = X.shape[0]/batch_size
    counter = 0
    sample_index = np.arange(X.shape[0])
    if shuffle:
        np.random.shuffle(sample_index)
    while True:
        batch_index = sample_index[batch_size*counter:batch_size*(counter+1)]
        X_batch = X[batch_index,:].todense()
        y_batch = y[batch_index]
        counter += 1
        yield X_batch, y_batch
        if (counter == number_of_batches):
            if shuffle:
                np.random.shuffle(sample_index)
            counter = 0
```

In [41]:
```
def root_mean_squared_error(y_true, y_pred):
    return K.sqrt(K.mean(K.square(y_pred - y_true)))
```

In [47]:
```
def mlp_validate(model,X,Y):
    s=5000
    s1=int(Y%s)
    size=Y-s1
    test=[]
    for i in range(0,size,5000):
        ind=np.arange(i,i+5000)
        sample=X[ind,:].todense()
        y_pred=model.predict(sample)
        y_pred=list(map(float,y_pred))
        y_pred=list(np.array(y_pred))
        test=test+y_pred
    ind=np.arange(len(test),Y)
    sample=X[ind,:].todense()
    y_pred=model.predict(sample)
    y_pred=list(map(float,y_pred))
    y_pred=list(np.array(y_pred))
    test=test+y_pred
    return test
```

SET 1 :- categorical + item_description(BOW) + name (BOW)

In [34]:
```
model_batch1 = Sequential()

model_batch1.add(Dense(256, activation='relu', input_shape=(X1_tr.shape[1],),

model_batch1.add(Dense(128, activation='relu', kernel_initializer='normal'))

model_batch1.add(Dense(64, activation='relu', kernel_initializer='normal'))

model_batch1.add(Dense(output_dim=1))

model_batch1.summary()
```

```
WARNING:tensorflow:From /usr/local/lib/python3.5/dist-packages/tensorflow_c
ore/python/ops/resource_variable_ops.py:1630: calling BaseResourceVariable.
__init__ (from tensorflow.python.ops.resource_variable_ops) with constraint
is deprecated and will be removed in a future version.
Instructions for updating:
If using Keras pass *_constraint arguments to layers.
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_1 (Dense)              (None, 256)               52665600
_________________________________________________________________
dense_2 (Dense)              (None, 128)               32896
_________________________________________________________________
dense_3 (Dense)              (None, 64)                8256
_________________________________________________________________
dense_4 (Dense)              (None, 1)                 65
=================================================================
Total params: 52,706,817
Trainable params: 52,706,817
Non-trainable params: 0
_________________________________________________________________
```

In [35]:
```
model_batch1.compile(optimizer='adam', loss=root_mean_squared_error)
```

In [36]:
```
x1=X1_tr.shape[0]/128
```

In [37]:
```
model_batch1.fit_generator(generator=batch_generator(X1_tr, y_train_log, 128,
                           nb_epoch=1,steps_per_epoch=x1,
                           shuffle=True)
```

```
WARNING:tensorflow:From /usr/local/lib/python3.5/dist-packages/tensorflow_c
ore/python/ops/math_grad.py:1424: where (from tensorflow.python.ops.array_o
ps) is deprecated and will be removed in a future version.
Instructions for updating:
Use tf.where in 2.0, which has the same broadcast rule as np.where
WARNING:tensorflow:From /usr/local/lib/python3.5/dist-packages/keras/backen
d/tensorflow_backend.py:422: The name tf.global_variables is deprecated. Pl
ease use tf.compat.v1.global_variables instead.

Epoch 1/1
8103/8102 [==============================] - 4745s 586ms/step - loss: 0.470
3
```

Out[37]:
```
<keras.callbacks.callbacks.History at 0x7f2fe7d562e8>
```

In [45]:
```
y_train_pred51=mlp_validate(model_batch1,X1_tr,X1_tr.shape[0])
y_cv_pred51=mlp_validate(model_batch1,X1_cr,X1_cr.shape[0])
print('Train RMLSE =',rmsle(y_train_log,y_train_pred51))
print('CV RMLSE =',rmsle(y_cv_log,y_cv_pred51))
```

```
Train RMLSE = 0.3696
CV RMLSE = 0.4336
```

In [47]:
```
y_test_pred51=mlp_validate(model_batch1,X1_te,X1_te.shape[0])
y51 = np.expm1(y_test_pred51)
output = pd.DataFrame()
output['test_id']=test['test_id'].values
output['price']=y51
output.head()
```

Out[47]:

	test_id	price
0	0	5.725799
1	1	12.961642
2	2	66.329922
3	3	12.149285
4	4	7.716349

SET 2 :- categorical + item_description(TF-IDF) + name (TF-IDF)

In [89]:

```
model_batch = Sequential()

model_batch.add(Dense(256, activation='relu', input_shape=(X2_tr.shape[1],),

model_batch.add(Dense(128, activation='relu', kernel_initializer='normal'))

model_batch.add(Dense(64, activation='relu', kernel_initializer='normal'))

model_batch.add(Dense(output_dim=1))

model_batch.summary()
```

```
Model: "sequential_3"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_6 (Dense)              (None, 256)               52665600  
_________________________________________________________________
dense_7 (Dense)              (None, 128)               32896     
_________________________________________________________________
dense_8 (Dense)              (None, 64)                8256      
_________________________________________________________________
dense_9 (Dense)              (None, 1)                 65        
=================================================================
Total params: 52,706,817
Trainable params: 52,706,817
Non-trainable params: 0
_________________________________________________________________
```

In [41]:

```
model_batch.compile(optimizer='adam', loss=root_mean_squared_error)
```

In [42]:

```
x=X2_tr.shape[0]/128
```

In [43]:
```
model_batch.fit_generator(generator=batch_generator(X2_tr, y_train_log, 128,
                          nb_epoch=1,steps_per_epoch=x,
                          shuffle=True)
```

```
WARNING:tensorflow:From /usr/local/lib/python3.5/dist-packages/tensorflow_c
ore/python/ops/math_grad.py:1424: where (from tensorflow.python.ops.array_o
ps) is deprecated and will be removed in a future version.
Instructions for updating:
Use tf.where in 2.0, which has the same broadcast rule as np.where
WARNING:tensorflow:From /usr/local/lib/python3.5/dist-packages/keras/backen
d/tensorflow_backend.py:422: The name tf.global_variables is deprecated. Pl
ease use tf.compat.v1.global_variables instead.

Epoch 1/1
8103/8102 [==============================] - 3157s 390ms/step - loss: 0.462
6
```

Out[43]:
```
<keras.callbacks.callbacks.History at 0x7f0d98318d68>
```

In [78]:
```
y_train_pred52=mlp_validate(model_batch,X2_tr,X2_tr.shape[0])
y_cv_pred52=mlp_validate(model_batch,X2_cr,X2_cr.shape[0])
print('Train RMLSE =',rmsle(y_train_log,y_train_pred52))
print('CV RMLSE =',rmsle(y_cv_log,y_cv_pred52))
```

```
Train RMLSE = 3741
CV RMLSE = 4327
```

Predicting the price

In [81]:
```
y_test_pred52=mlp_validate(model_batch,X2_te,X2_te.shape[0])
y52 = np.expm1(y_test_pred52)
output = pd.DataFrame()
output['test_id']=test['test_id'].values
output['price']=y52
output.head()
```

Out[81]:

	test_id	price
0	0	8.264034
1	1	9.970138
2	2	81.184289
3	3	12.924566
4	4	8.285819

SET 3 :- categorical + item_description(AVG W2V) + name (AVG W2V)

In [43]:
```
model_batch3 = Sequential()

model_batch3.add(Dense(256, activation='relu', input_shape=(X3_tr.shape[1],),

model_batch3.add(Dense(128, activation='relu', kernel_initializer='normal'))

model_batch3.add(Dense(64, activation='relu', kernel_initializer='normal'))

model_batch3.add(Dense(output_dim=1))

model_batch3.summary()
```

```
WARNING:tensorflow:From /usr/local/lib/python3.5/dist-packages/tensorflow_c
ore/python/ops/resource_variable_ops.py:1630: calling BaseResourceVariable.
__init__ (from tensorflow.python.ops.resource_variable_ops) with constraint
is deprecated and will be removed in a future version.
Instructions for updating:
If using Keras pass *_constraint arguments to layers.
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_1 (Dense)              (None, 256)               1491200
_________________________________________________________________
dense_2 (Dense)              (None, 128)               32896
_________________________________________________________________
dense_3 (Dense)              (None, 64)                8256
_________________________________________________________________
dense_4 (Dense)              (None, 1)                 65
=================================================================
Total params: 1,532,417
Trainable params: 1,532,417
Non-trainable params: 0
_________________________________________________________________
```

In [44]:
```
model_batch3.compile(optimizer='adam', loss=root_mean_squared_error)
```

In [45]:
```
x3=X3_tr.shape[0]/128
```

In [46]:
```
model_batch3.fit_generator(generator=batch_generator(X3_tr, y_train_log, 128,
                    nb_epoch=1,steps_per_epoch=x3,
                    shuffle=True)
```

```
WARNING:tensorflow:From /usr/local/lib/python3.5/dist-packages/tensorflow_c
ore/python/ops/math_grad.py:1424: where (from tensorflow.python.ops.array_o
ps) is deprecated and will be removed in a future version.
Instructions for updating:
Use tf.where in 2.0, which has the same broadcast rule as np.where
WARNING:tensorflow:From /usr/local/lib/python3.5/dist-packages/keras/backen
d/tensorflow_backend.py:422: The name tf.global_variables is deprecated. Pl
ease use tf.compat.v1.global_variables instead.

Epoch 1/1
8103/8102 [==============================] - 244s 30ms/step - loss: 0.5527
```

Out[46]: <keras.callbacks.callbacks.History at 0x7f9d44fb64a8>

In [61]:
```
def mlp_validate(model,X,Y):
    s=20000
    s1=int(Y%s)
    size=Y-s1
    pred=[]
    for i in range(0,size,20000):
        ind=np.arange(i,i+20000)
        sample=X[ind,:].todense()
        y_pred=model.predict(sample)
        y_pred=list(map(float,y_pred))
        y_pred=list(np.array(y_pred))
        pred=pred+y_pred
    ind=np.arange(len(pred),Y)
    sample=X[ind,:].todense()
    y_pred=model.predict(sample)
    y_pred=list(map(float,y_pred))
    y_pred=list(np.array(y_pred))
    pred=pred+y_pred
    return pred
```

In [69]:
```
y_train_pred53=mlp_validate(model_batch3,X3_tr,X3_tr.shape[0])
y_cv_pred53=mlp_validate(model_batch3,X3_cr,X3_cr.shape[0])
print('Train RMLSE =',rmsle(y_train_log,y_train_pred53))
print('CV RMLSE =',rmsle(y_cv_log,y_v_pred53))
```

```
Train RMLSE = 0.5328
CV RMLSE = 0.5406
```

Predicting the price

In [72]:
```
y_test_pred53=mlp_validate(model_batch3,X3_te,X3_te.shape[0])
y53 = np.expm1(y_test_pred53)
output = pd.DataFrame()
output['test_id']=test['test_id'].values
output['price']=y53
output.head()
```

Out[72]:

	test_id	price
0	0	9.139111
1	1	8.705856
2	2	29.029055
3	3	19.025232
4	4	6.893620

Comparision of all models

In [79]:
```
# Please compare all your models using Prettytable library
from prettytable import PrettyTable
x = PrettyTable()

x.field_names = [ "Model",'Vectorizer',"Train RMSLE","CV RMSLE"]

x.add_row(["Ridge",'BOW',0.4146, 0.4553])
x.add_row(["Ridge",'TF-IDF',0.4006, 0.4441])
x.add_row(["Ridge",'Word2Vec',0.5609, 0.5644])

x.add_row(["Random Forest Regressor",'BOW',0.4138, 0.5134])
x.add_row(["Random Forest Regressor",'TF-IDF',0.4081, 0.5177])
x.add_row(["Random Forest Regressor",'Word2Vec',0.3751, 0.5616])

x.add_row(["XGBOOST Regressor",'BOW',0.4640, 0.4742])
x.add_row(["XGBOOST Regressor",'TF-IDF',0.4598, 0.4737])

x.add_row(["FM_FTRL",'TF-IDF', 0.3649,0.4336])
x.add_row(["FM_FTRL",'Word2Vec', 0.5256,0.5339])

x.add_row(["MLP",'BOW',0.3696, 0.4336])
x.add_row(["MLP",'TF-IDF',0.3741, 0.4327])
x.add_row(["MLP",'Word2Vec',0.5328, 0.5406])

print(x)
```

```
+-------------------------+------------+-------------+----------+
|          Model          | Vectorizer | Train RMSLE | CV RMSLE |
+-------------------------+------------+-------------+----------+
|          Ridge          |    BOW     |    0.4146   |  0.4553  |
|          Ridge          |   TF-IDF   |    0.4006   |  0.4441  |
|          Ridge          |  Word2Vec  |    0.5609   |  0.5644  |
| Random Forest Regressor |    BOW     |    0.4138   |  0.5134  |
| Random Forest Regressor |   TF-IDF   |    0.4081   |  0.5177  |
| Random Forest Regressor |  Word2Vec  |    0.3751   |  0.5616  |
|    XGBOOST Regressor    |    BOW     |    0.464    |  0.4742  |
|    XGBOOST Regressor    |   TF-IDF   |    0.4598   |  0.4737  |
|         FM_FTRL         |   TF-IDF   |    0.3649   |  0.4336  |
|         FM_FTRL         |  Word2Vec  |    0.5256   |  0.5339  |
|           MLP           |    BOW     |    0.3696   |  0.4336  |
|           MLP           |   TF-IDF   |    0.3741   |  0.4327  |
|           MLP           |  Word2Vec  |    0.5328   |  0.5406  |
+-------------------------+------------+-------------+----------+
```

```
<h4><font color='navy'>Out of 3 vectorizations, the TF-IDF vectorizations has given the least RMSLE value for all the models
```

Combining the best models : RIDGE + FM_FTRL + MLP

In [76]:
```
print(rmsle(y_cv_log,y_cv_pred12))   #Ridge
print(rmsle(y_cv_log,y_cv_pred42))   #FM_FTRL
print(rmsle(y_cv_log,y_cv_pred52))   #MLP
```

```
0.4441
0.4336
0.4327
```

In [77]:
```
p1=np.array(y_cv_pred12)
p2=np.array(y_cv_pred42)
p3=np.array(y_cv_pred52)
```

In [78]:

```
x1=[0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8]
x2=[0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8]
x3=[0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8]
for i in x1:
    for j in x2:
        for k in x3:
            if(i+j+k==1):
                y=(i*p1)+(j*p2)+(k*p3)
                error=rmsle(y_cv_log,y)
                print('i = '+str(i)+', j = '+str(j)+', k = '+str(k)+': RMSLE
```

```
i = 0.1, j = 0.1, k = 0.8: RMSLE = 0.4289
i = 0.1, j = 0.2, k = 0.7: RMSLE = 0.4274
i = 0.1, j = 0.3, k = 0.6: RMSLE = 0.4265
i = 0.1, j = 0.4, k = 0.5: RMSLE = 0.4261
i = 0.1, j = 0.5, k = 0.4: RMSLE = 0.4264
i = 0.1, j = 0.6, k = 0.3: RMSLE = 0.4272
i = 0.1, j = 0.7, k = 0.2: RMSLE = 0.4287
i = 0.1, j = 0.8, k = 0.1: RMSLE = 0.4307
i = 0.2, j = 0.1, k = 0.7: RMSLE = 0.4282
i = 0.2, j = 0.2, k = 0.6: RMSLE = 0.4271
i = 0.2, j = 0.3, k = 0.5: RMSLE = 0.4267
i = 0.2, j = 0.4, k = 0.4: RMSLE = 0.4268
i = 0.2, j = 0.5, k = 0.3: RMSLE = 0.4275
i = 0.2, j = 0.6, k = 0.2: RMSLE = 0.4288
i = 0.3, j = 0.1, k = 0.6: RMSLE = 0.4281
i = 0.3, j = 0.2, k = 0.5: RMSLE = 0.4276
i = 0.3, j = 0.3, k = 0.4: RMSLE = 0.4276
i = 0.3, j = 0.4, k = 0.3: RMSLE = 0.4282
i = 0.3, j = 0.5, k = 0.2: RMSLE = 0.4293
i = 0.4, j = 0.1, k = 0.5: RMSLE = 0.4288
i = 0.4, j = 0.2, k = 0.4: RMSLE = 0.4287
i = 0.4, j = 0.3, k = 0.3: RMSLE = 0.4291
i = 0.4, j = 0.4, k = 0.2: RMSLE = 0.4302
i = 0.4, j = 0.5, k = 0.1: RMSLE = 0.4318
i = 0.5, j = 0.1, k = 0.4: RMSLE = 0.4301
i = 0.5, j = 0.2, k = 0.3: RMSLE = 0.4304
i = 0.5, j = 0.3, k = 0.2: RMSLE = 0.4313
i = 0.5, j = 0.4, k = 0.1: RMSLE = 0.4328
i = 0.6, j = 0.1, k = 0.3: RMSLE = 0.432
i = 0.6, j = 0.2, k = 0.2: RMSLE = 0.4328
i = 0.7, j = 0.1, k = 0.2: RMSLE = 0.4346
i = 0.8, j = 0.1, k = 0.1: RMSLE = 0.4378
```

The best model : 0.1*(RIDGE) + 0.4*(FM_FTRL) + 0.5(MLP)

- **CV RMSLE = 0.4261**

In [85]:

```
test1=np.array(y_test_pred12)
test2=np.array(y_test_pred42)
test3=np.array(y_test_pred52)
```

In [88]:
```
test_price=(0.1*test1)+(0.4*test2)+(0.5*test3)
test_price = np.expm1(test_price)
output = pd.DataFrame()
output['test_id']=test['test_id'].values
output['price']=test_price
output.head()
```

Out[88]:

	test_id	price
0	0	8.215897
1	1	9.804983
2	2	69.209163
3	3	12.412479
4	4	8.078251

Steps followed in the case study:-

- Step 1:- Loading the data
- Step 2:- Data cleaning
- Step 3:- Exploratory Data Analysis on all columns
- Step 4:- Splitting the data into train and CV
- Step 5:- Encoding all catogorical features
- Step 6:- Applying various vectorizations on text features, BOW ,TF-IDF ,Word2Vec
- Step 7:- Concatenating all features and preparing 3 sets of data
- Step 8:- Applying various models and evaluating the model using RMSLE as metric
- Step 9:- Comparision of all Models
- Step 10:- Choosing the best models and vectorization
- Step 11:- Ridge , FM_FTRL , MLP with TF-IDF vectorization gave the least RMSLE
- Step 12:- The best model : 0.1*(RIDGE) + 0.4*(FM_FTRL) + 0.5(MLP) is submitted in kaggle and got a score of 0.42429

Conclusion :-

In [1]:

```
from prettytable import PrettyTable
x = PrettyTable()

x.field_names = [ "Model",'Vectorizer',"Train RMSLE","CV RMSLE"]

x.add_row(["Ridge",'BOW',0.4146, 0.4553])
x.add_row(["Ridge",'TF-IDF',0.4006, 0.4441])
x.add_row(["Ridge",'Word2Vec',0.5609, 0.5644])

x.add_row(["Random Forest Regressor",'BOW',0.4138, 0.5134])
x.add_row(["Random Forest Regressor",'TF-IDF',0.4081, 0.5177])
x.add_row(["Random Forest Regressor",'Word2Vec',0.3751, 0.5616])

x.add_row(["XGBOOST Regressor",'BOW',0.4640, 0.4742])
x.add_row(["XGBOOST Regressor",'TF-IDF',0.4598, 0.4737])

x.add_row(["FM_FTRL",'TF-IDF', 0.3649,0.4336])
x.add_row(["FM_FTRL",'Word2Vec', 0.5256,0.5339])

x.add_row(["MLP",'BOW',0.3696, 0.4336])
x.add_row(["MLP",'TF-IDF',0.3741, 0.4327])
x.add_row(["MLP",'Word2Vec',0.5328, 0.5406])

print(x)
```

```
+-------------------------+------------+-------------+----------+
|          Model          | Vectorizer | Train RMSLE | CV RMSLE |
+-------------------------+------------+-------------+----------+
|          Ridge          |    BOW     |    0.4146   |  0.4553  |
|          Ridge          |   TF-IDF   |    0.4006   |  0.4441  |
|          Ridge          |  Word2Vec  |    0.5609   |  0.5644  |
| Random Forest Regressor |    BOW     |    0.4138   |  0.5134  |
| Random Forest Regressor |   TF-IDF   |    0.4081   |  0.5177  |
| Random Forest Regressor |  Word2Vec  |    0.3751   |  0.5616  |
|    XGBOOST Regressor    |    BOW     |    0.464    |  0.4742  |
|    XGBOOST Regressor    |   TF-IDF   |    0.4598   |  0.4737  |
|         FM_FTRL         |   TF-IDF   |    0.3649   |  0.4336  |
|         FM_FTRL         |  Word2Vec  |    0.5256   |  0.5339  |
|           MLP           |    BOW     |    0.3696   |  0.4336  |
|           MLP           |   TF-IDF   |    0.3741   |  0.4327  |
|           MLP           |  Word2Vec  |    0.5328   |  0.5406  |
+-------------------------+------------+-------------+----------+
```

The best model : 0.1*(RIDGE) + 0.4*(FM_FTRL) + 0.5(MLP)

- **CV RMSLE = 0.4261**

In [ ]: