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Strategic Pricing of Used Products for e-Commerce Sites

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Strategic Pricing of Used Products for e-Commerce Sites

by

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Dr. Anthony M. Townsend, Major Professor

The student author, whose presentation was approved by the program of the study committee, is solely responsible for the content of the report. The Graduate College will ensure this report is globally accessible and will not permit alteration after a degree is conferred.

Iowa State University

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NOMENCLATURE

EDA	Exploratory data analysis
LightGBM	Light Gradient Boosting Machine
Tf-Idf	Inverse Document Frequency Vectorizer
B2C	Business to Consumer
C2C	Consumer to Consumer
RSMLE	Root Mean Square Logarithmic Error

ACKNOWLEDGMENTS

I would like to start with thanking Professor, Dr. Antony M Townsend. He was a constant support and a good reference source during my project. Along with his immense knowledge in the field of Analytics, the standout attribute of Professor Townsend is his patience levels, he understands the student’s needs and guides them in the right direction. His creative component training course MIS 557x has helped me in structuring my project efficiently.

I would also like to thank all my professors at Iowa state College of business, during my program they have helped me a lot in nurturing my skills and the analytics courses provided in the MIS program have been the major motivation for this project.

Finally, I would like to thank my friends and family for their support during my journey at Iowa state university.

ABSTRACT

In the modern world, the e-commerce market is growing rapidly. The platform for shopping is shifting from retail stores to the online shopping applications. People are inclined towards sitting in their homes and purchasing products ranging from electronics, clothing to even groceries rather than going to malls or shopping centers. Along with the new products, the growth of online shopping has given users an opportunity to buy and sell used products easily like never before. One major issue in the used product sector compared to the new products sector is the pricing of used products. First time sellers in online marketplaces are finding it difficult to sell their products. The growth of online marketplaces has triggered the interest in building algorithms for price suggestions to the sellers. Also, the growth of machine learning and big data in predictive modeling has raised the importance of using them to improve the pricing in Used products business. By obtaining a solution for price prediction via product features for B2C and C2C online retailers, it will be easier for sellers to sell, and enlarge the selling-shopping community of such user-based marketplaces. It could also be a great competitive advantage for companies or individual sellers having highly accurate pricing decision-support. This is the motive for me to build the price prediction model. For this project. I have used a dataset provided by Mercari for price suggestion challenge. It contains 1.5 million records with product name, brand name, condition, shipping status and description. I have performed exploratory data analysis to understand the data and I have used modern analytics techniques like Label binarizer, feature extraction to cleanse and prepare the data for model. I have built a LightGBM regression model to predict the price of the product based on the categorical and textual features. I have tested my model against metrics like RSMLE and R square and I was able to achieve the best performance of 0.45 RSMLE for LightGBM model with learning rate 0.75

CHAPTER - 1

INTRODUCTION

Over the past decade, the online sales market has grown exponentially. E-Commerce is responsible for more than $2.3 Trillion in 2018 and it is expected to double by 2021. Statistics show an average human spends more than 3 hours on phone and 35 minutes out of those in surfing e-commerce Sites. With the availability of internet everywhere people are choosing to purchase their necessary products online. This trend is visible especially in case of youngsters, age group 20-30 who generate 75% of online sales. All the major players across different industries have established their presence online and are preferring to sell products online instead of maintaining stores. The advertising over the social media platforms is also contributing to the increase in online sales

Apart from having their own online portal’s. The company’s also sell their products on E-commerce sites. Over the past decade, Amazon, Ebay have emerged as the leaders in E-commerce market and presence of their products on these platforms have become a necessity for the companies. The major advantage of these sites is their ability to ship products across the country and globally. So, the regions which cannot be reached through retail stores are reached through these e- commerce sites.

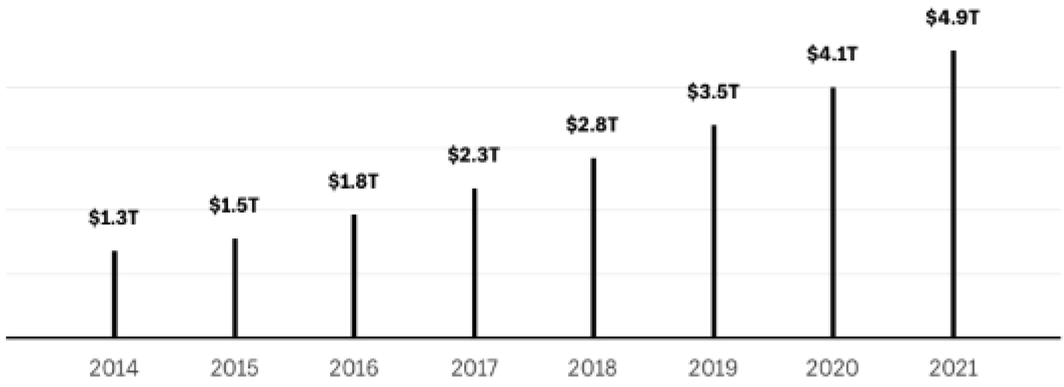
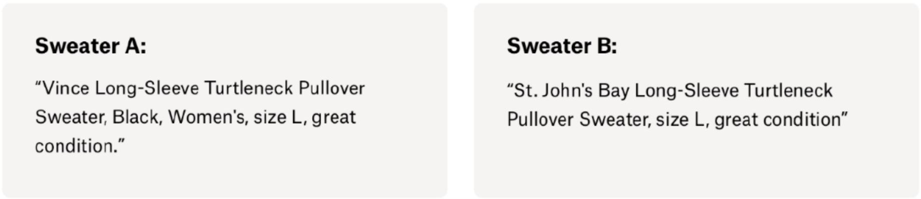


Figure 32: Source: Data vis eMarketer (Statista)

Along with the sale of new products, the silent giant in the online industry is the sale of used products. Resale market has generated a revenue of more than $8 billion last year. For example, A used old Yamaha guitar of a guitarist in Phoenix, Az could be the product which a minimum wage-earning music enthusiast in New York may be looking for. But earlier there was no platform to connect these two people and often the product will end up in trash or given away for free. The E-commerce giants like Ebay, Poshmark, Mercari have identified the potential of this segment and have launched their applications for used product sales. The revenue of resale market has grown by more than 50 percent over the decade at it is expected to double in the next 5 years.

In case of new products, the companies have their own strategies in deciding the price of the products but that’s not the case with used products. The websites give sellers the liberty in deciding the selling price of the product and they take a share of it for providing the platform. But this approach has resulted in many complications. Often, the seller’s listed selling price and the product specifications and brand values won’t be in sync and these products end up on websites for months without being sold. This approach won’t help the user as well as the website. So, almost all the used product websites have decided to have their own price prediction models.

There are 3 main factors that decide the sale of the product. First the product title, Users generally use keywords like brand name, product specification while searching the product. Second is the Category, the products need to be categorized properly as the user could also use the category to filter the products. Finally, the most important attribute is the Item description, the users go through the description keenly before choosing the product. So, the description needs to be specific. These factors will be the deciding elements in price prediction. The challenge of building a predictive model on these unstructured parameters is the inspiration behind this project.



Sweater A:

"Vince Long-Sleeve Turtleneck Pullover Sweater, Black, Women's, size L, great condition."

Sweater B:

"St. John's Bay Long-Sleeve Turtleneck Pullover Sweater, size L, great condition"

Figure 33: Source: Susan Li. (Jul 23,2018)." Machine Learning for Retail Price Recommendation with Python". https://towardsdatascience.com/machine-learning-for-retail-price-suggestion-with-python- 64531e64186d

The major factors Product Name, Product Category and Product Description are textual unstructured parameters. They cannot be directly fed into any unsupervised learning model. So, all the textual features need to be converted into fixed length vectors then they can be used as input for the machine learning models. Another issue is, while dealing with textual data it is important to have large amount of data to avoid overfitting

For this project, to tackle these issues, I have chosen the dataset from Mercari's price suggestion challenge where the training dataset has over 1 million records and has a test data of 700k records. On textual parameters I have performed feature extraction and built an unsupervised LightBGM regression algorithm to predict the price.

The target audience for this model would be the E-commerce sites whose focus area is used products. I have used description, condition and shipping features in building this model. This model can also be used on estimating the price of new products based on their brand name and category features.

The purpose of this quantitative study is to predict the price of the product based on the product features like Product Name, Category, Condition, Brand Name and shipping status for E-commerce sites and Used product markets. The data is taken from Online selling App Mercari's price suggestion challenge and a regression model is build using LightGBM algorithm for price prediction

CHAPTER - 2

LITERATURE REVIEW

I have performed extensive research on predictive analysis on unstructured data and observed that there are gaps in the existing literature. Many scholars have used either structured data or unstructured data for analysis but not many have tried to combine both of them in a model. From the limited literature available, I have researched on the price prediction issues, web market for sales and the metrics used to measure the performance of the model.

In a competing world where they're many players providing similar services, It is important from a company to have certain strategies and processes to leverage the advantages of modern technologies in order to survive in the market. "Case Study:Dan Hill.(20 Aug 2015) ."The Secret of Airbnb's Pricing Algorithm: The sharing economy needs machine intelligence to set prices" https://spectrum.ieee.org/computing/software/the- secret-of-airbnbs-pricing-algorithm takes about how machine learning algorithms and approaches help in setting prices. For this study, the author has taken Airbnb's source data and explained how

Airbnb provides price suggestions to the owners based on the features they have mentioned. Chapter 3 and 4 takes about the necessity of having a pricing algorithm and the features that needs to be considered.

Susan Li. (Jul 23,2018).” Machine Learning for Retail Price Recommendation with Python”.

https://towardsdatascience.com/machine-learning-for-retail-price-suggestion-with-python-64531e64186d This research paper takes about the rich machine learning libraries and approaches that can be built using Python. In this research, the retail stores are taken as the platform and the author talks about how the reviews, product description, sales and time of the year impacts the price of the product. The author based on these features also suggests the amount of discount that needs to be provided to the customers.

While building a machine learning model it is important to choose the right variables. Often the choice of variables, their collinearity and variation decides the performance of the model. During my research, I have gone through many articles and citations to study the factors that impact the price the most. “Duncan, A., & M. McPhail. (2013). “Price Optimization for the U.S. Market. Techniques and Implementation Strategies.” This article talks about the technique’s companies use to attract customers. Few of them would be, providing free shipping service to elite customers, providing combo saving options based on the customers prior purchases etc.

After performing researching on the necessity of price suggestion and the features that drive the price prediction. I have identified that, price is dependent on many unstructured data features like Product description, Product category, Brand description and reviews etc. These variables cannot be treated in a similar way as categorical or numerical variables. They should be grouped and converted into fixed length vectors for machine learning models to build over them. The research paper: “Tomas Mikolov, Kai Chen, Greg Corrado & Jeffrey Dean. (2013). “Efficient estimation of word representations in vector space. arXiv preprint arXiv:1301.3781” takes about how the textual features needs to be converted into numerical variables. The author presents how feature extraction can be used in building the vocabulary and later using the learnt vocabulary in the model.

After getting basic understanding on the price prediction, I felt it’s an evident case of regression problem. Where a dependent variable needs to be predicted based on the product features. Multi linear regression was by baseline approach but after understanding the multicollinearity challenges related to the multi linear regression model through the following article “Managing Piracy: Pricing and Sampling Strategies for Digital Experience Goods in Vertically Segmented Markets -Ramnath K. Chellappa, Shivendu Shivendu” I have decided to use the ridge regression model. The author here explains on how adding a calculated error can overcome multicollinearity and overfitting of data.

For building a machine learning model for price prediction, through my study I realized that, the model should be built on a large dataset containing various product features and many variations. The standard machine learning models can’t handle large size data. The research paper:”LightGBM: A Highly Efficient Gradient Boosting Decision Tree - Guolin Ke , Qi Meng , Thomas Finley , Taifeng Wang , Wei Chen , Weidong Ma , Qiwei Ye , Tie-Yan Liu” has introduced be the boosting machine learning algorithm LightGBM. This algorithm follows a decision tree classification where the growth is based on leaf rather than traditional level-based approach making it a fast and low memory consuming model.

As I’m using multiple machine learning approaches for the price prediction, I want to use a metric which can efficiently measure the performance of the model. The research paper:”

Root mean square error (RMSE) or mean absolute error (MAE)? - Chai, T.; Draxler, R. R. 10.5194/gmdd-7-1525-2014" explains why RMSE is considered as the standard metric for predictive analysis.

The existing literature has helped me in identifying the problems related to price prediction, the factors that needs to be considered during building a model, the approaches in handling the unstructured data and the machine learning models that are available for price prediction and the metrics to measure the performance of the model. But major drawback I have observed in the existing literature is on how to blend the structured and unstructured variables together in building the model. Through this project, I will be filling the gap by considering both kinds of variables and building a high-performance model over them.

CHAPTER - 3

SLEEPING GAINT OF ECOMMERCE: RESALE MARKET

The Ecommerce market is growing like never before. With the surge of internet, people are inclined towards purchasing products online. $2.3 trillion in revenue suggests the same and this number is expected to double every year. But my major focus in this project is on the subset of ecommerce, the resale market. It is one of the major markets which is expected to grow tremendously in the coming years.

Resale market also popularity called as the recommerce is outperforming most of the discount retail stores over the past few years. Although the retail market is huge, but the growth percentage is expected to be not more than 2%, from $361 billion to $400 billion according to eMarketer. On the other hand, the resale market is expected to double in the coming years from $21 billion to $41 billion.

There are more than 8000 used online marketplaces currently and they generate almost $8 billion of the $21 billion revenue generated through resale. Out of the all the categories, apparel resale holds 49% of whole revenue.

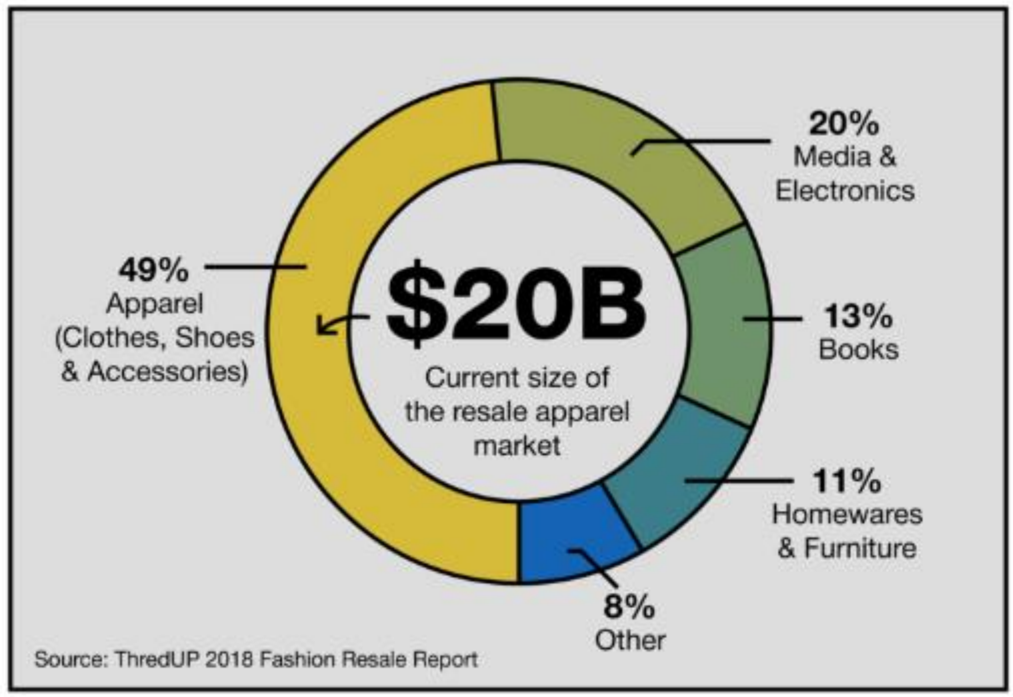


Figure 34: Source: TheredUP 2018 Fashion Resale Report

Earlier, there was negative stigma around the purchase of resale products. People preferred to purchase limited new products or discount products instead of the resale products considering the ambiguity surrounding the quality of the used products. But post-recession in 2008 the scenario has changed. The revenue of used products grown by 50% over the last decade contrast to that the sales in discount retail stores has gone down by 25 percent.

Other reason is, the used products help consumers to upgrade their wardrobe with quality products at the same price compared to the discount stores and with the availability of internet on hands people are inclined towards buying the resale products online.

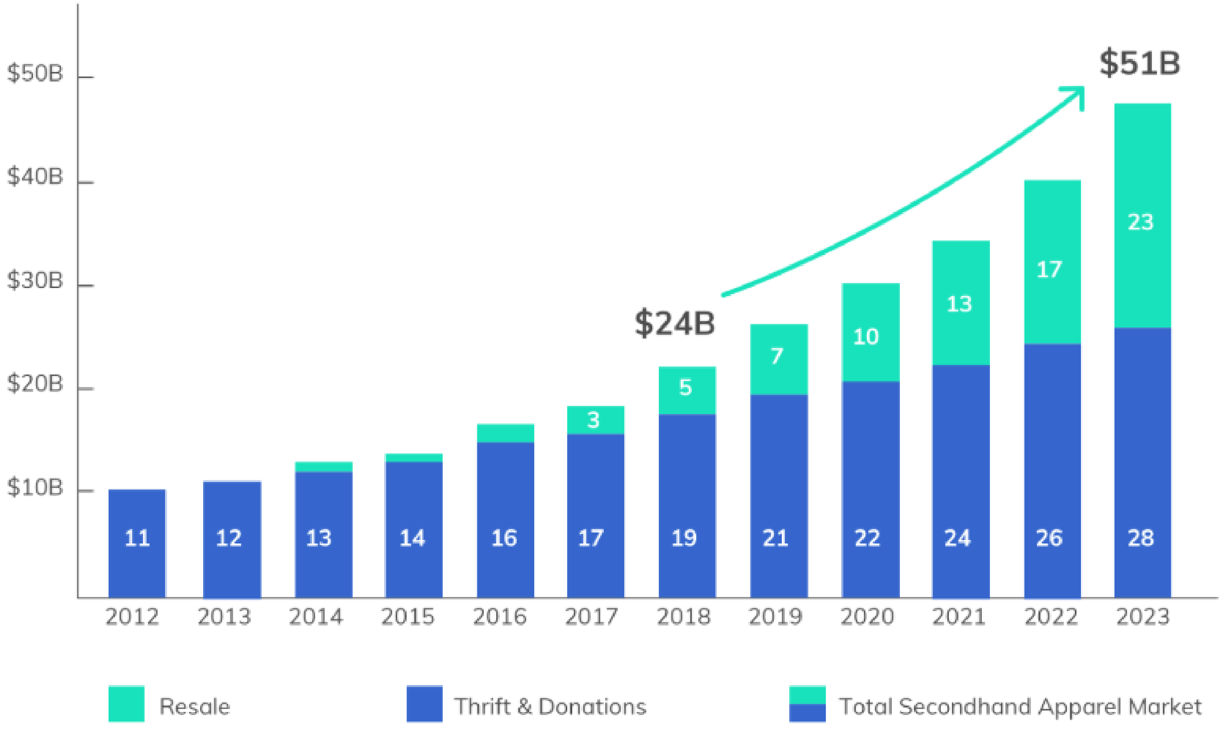


Figure 35: Source: ThredUP 2018 Fashion Resale Report

With the growth in the resale market it is important for the

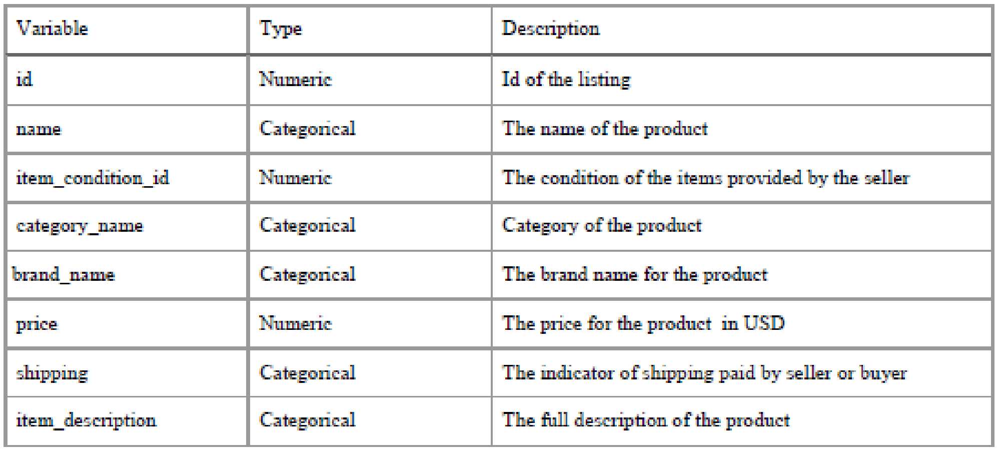
With the growth in the resale market, it is important for the online marketplaces to fix on some standards. The important feature that needs to be enhanced is the price suggestion for the products. Often, the product features are the ones which drive the price of the product. So, using the product features, in this project, I will be building an unsupervised learning machine learning algorithm which automatically predicts the price of the product

CHAPTER - 4

EXPLORATORY DATA ANALYSIS

I have taken the data set for a Kaggle competition “Mercari Price Suggestion Challenge. The data set is in tsv format and the training set has approximately 1 million records

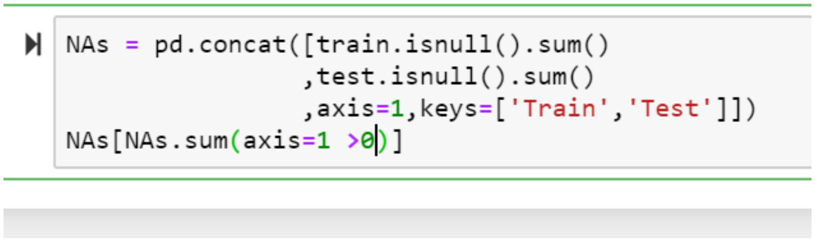
while the test set has 700k records. The data has 8 Numeric and Categorical types of variables. For this project, I have performed extensive exploratory data analysis to understand the data and thereby standardize it



Variable	Type	Description
id	Numeric	Id of the listing
name	Categorical	The name of the product
item_condition_id	Numeric	The condition of the items provided by the seller
category_name	Categorical	Category of the product
brand_name	Categorical	The brand name for the product
price	Numeric	The price for the product in USD
shipping	Categorical	The indicator of shipping paid by seller or buyer
item_description	Categorical	The full description of the product

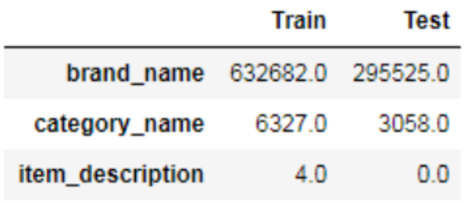
Figure 36: The various fields used in this project with their name, Data Type and description

To start with, I want to identify the missing values in the existing data. After running the code, I have identified Brand_name, Category_name and Item_description have the missing values out of which for more than half of training data and 40 % of testing data brand names are missing. I have addressed this issue by replacing the fielding with null values my “Missing”.



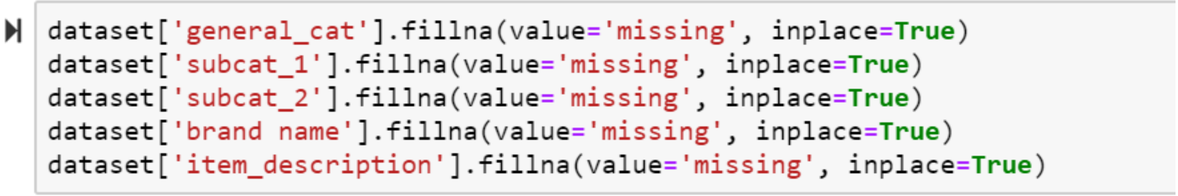
```
NAs = pd.concat([train.isnull().sum()
                 ,test.isnull().sum()
                 ,axis=1,keys=['Train','Test']])
NAs[NAs.sum(axis=1 >0)]
```

Figure 37: Python code to identify the missing values in the dataset



	Train	Test
brand_name	632682.0	295525.0
category_name	6327.0	3058.0
item_description	4.0	0.0

Figure 38: Result- Missing values in the training and testing dataset based on the variables

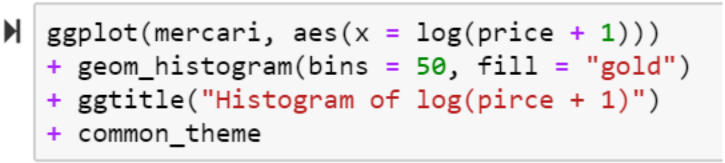


```
dataset['general_cat'].fillna(value='missing', inplace=True)
dataset['subcat_1'].fillna(value='missing', inplace=True)
dataset['subcat_2'].fillna(value='missing', inplace=True)
dataset['brand name'].fillna(value='missing', inplace=True)
dataset['item_description'].fillna(value='missing', inplace=True)
```

Figure 39: Python code to change the missing or blank records with keyword missing

Price

The average price of the data in the training set is $26.74 with values ranging from $- 0 $2009. The Mode is $10 and the Median is $17. These values indicate that even though the price range varies from 0 to 2009, most of the price values are not as high as $2009. Further analysis shows that 95% of the products are priced below 75%. The price variable is heavily right skewed, so it is transformed by applying logarithm to make it bell shaped distribution.



```
ggplot(mercari, aes(x = log(price + 1)))
+ geom_histogram(bins = 50, fill = "gold")
+ ggtitle("Histogram of log(pirce + 1)")
+ common_theme
```

Figure 40: R code to apply logarithmic error to the right skewed data

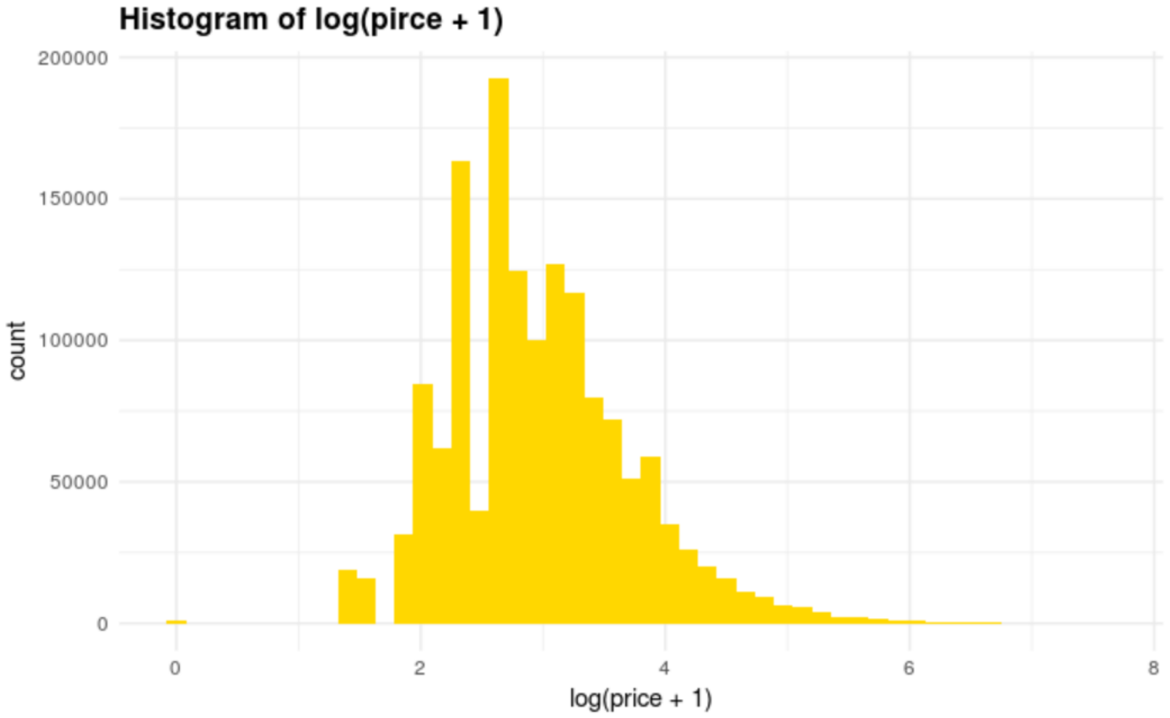
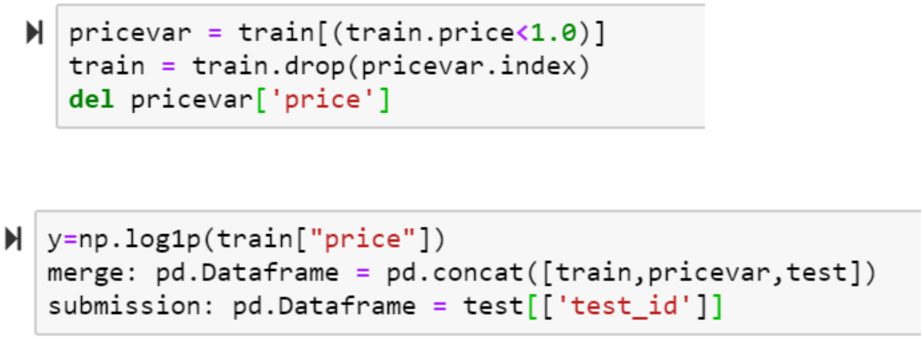


Figure 41: Histogram depicting the logarithmic range of price based on the count of products

In the training dataset it is observed that handful of products had products with o or no price. Even though the count is less, I have removed them from the dataset and later combined both the training and testing datasets and separated the target variables “Price” for modeling purposes.



```
pricevar = train[(train.price<1.0)]
train = train.drop(pricevar.index)
del pricevar['price']
```

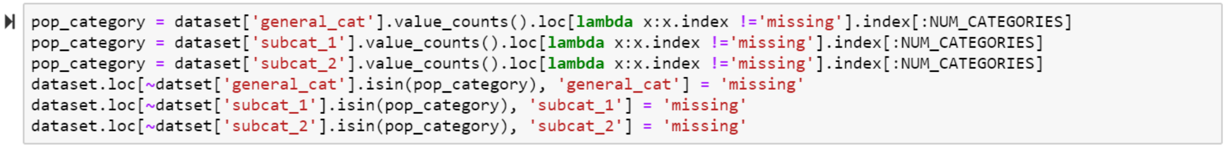
```
y=np.log1p(train["price"])
merge: pd.Dataframe = pd.concat([train,pricevar,test])
submission: pd.Dataframe = test[['test_id']]
```

Figure 42: Python code to combine the dataset and separate the target variable

Brand Category

There are 19 major categories and only few of them have commanding number of products. 10 of those categories are women, 8 are men and 1 is electronics. The Women's Category accounts for 54% of all records whereas the Men's Category accounts for only 8%. The variation among the categories can only be seen at level 3.

It is observed that Brand Category is a combination of three different categories, So for this project I have divided them into 3 individual categories "General Category", "Sub_Category1" and "Sub_Category2".



```
pop_category = dataset['general_cat'].value_counts().loc[lambda x:x.index !='missing'].index[:NUM_CATEGORIES]
pop_category = dataset['subcat_1'].value_counts().loc[lambda x:x.index !='missing'].index[:NUM_CATEGORIES]
pop_category = dataset['subcat_2'].value_counts().loc[lambda x:x.index !='missing'].index[:NUM_CATEGORIES]
dataset.loc[~datset['general_cat'].isin(pop_category), 'general_cat'] = 'missing'
dataset.loc[~datset['subcat_1'].isin(pop_category), 'subcat_1'] = 'missing'
dataset.loc[~datset['subcat_2'].isin(pop_category), 'subcat_2'] = 'missing'
```

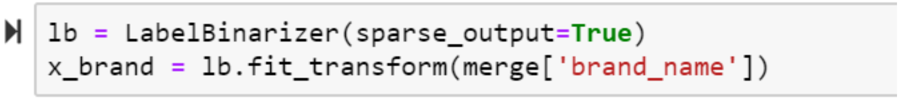
Figure 43: Python code to split the category into 3 different fields and assign "Missing" keyword to the missing and blank records

Brand Name

As mentioned before in total 42% of the products don't have a brand name associated with it. For the analysis purpose I have replaced them with 0. Going by category almost 75% of the men's category products have brand name but categories like Home goods, Sports & outdoors and handmade have less than 25% products with brand names.

Based one the category, I have listed the top brand names by category. It is observed that PINK, Nike, Victoria secret, LuLa Roe and Apple are the top products.

For modeling purpose, with majority of the brand names repeating in the dataset, including all of them could cause memory processing issues. So, I have applied LabelBinarizer to list out only distinct brand names.



```
lb = LabelBinarizer(sparse_output=True)
x_brand = lb.fit_transform(merge['brand_name'])
```

Figure 44: Python code to apply Label binarizer to identify the unique brand names

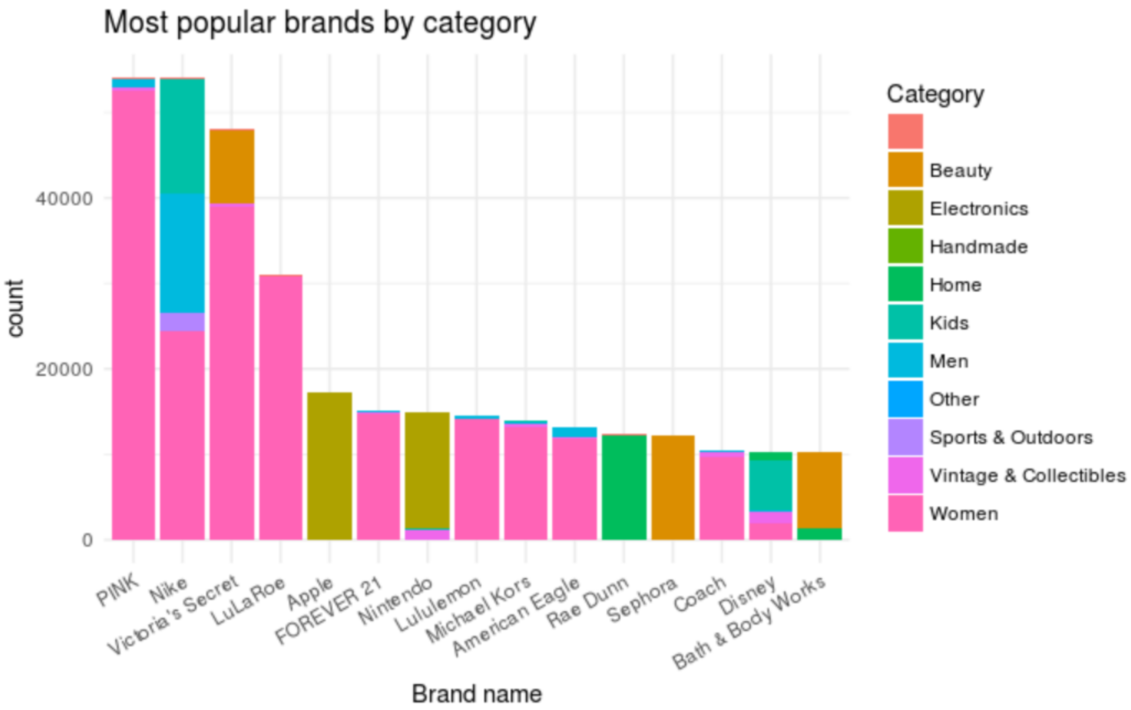
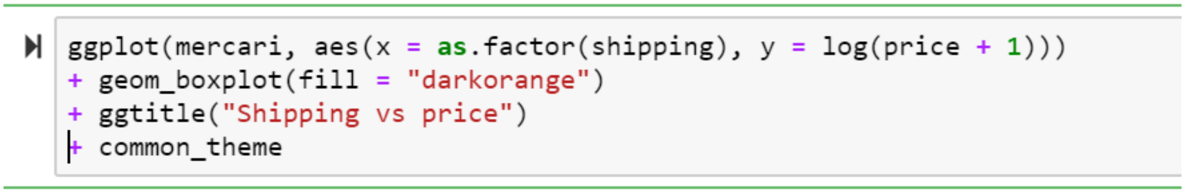


Figure 45: Histogram indicating the most popular brands based on brand category

Shipping

In this dataset and in case of used products as a whole, the shipping status plays a key role in deciding the price of the product. If the buyer pays for shipping, then the price of the product will be low compared to seller paying for shipping. To analyze the effect of Shipping on price, I have built a Box plot for shipping against the price and as assumed, if buyer pays (1) the price is less compared to when shipper pays(0)



```
ggplot(mercari, aes(x = as.factor(shipping), y = log(price + 1)))
+ geom_boxplot(fill = "darkorange")
+ ggtitle("Shipping vs price")
+ common_theme
```

Figure 46: R code to build the box plot between shipping ID and the log of price

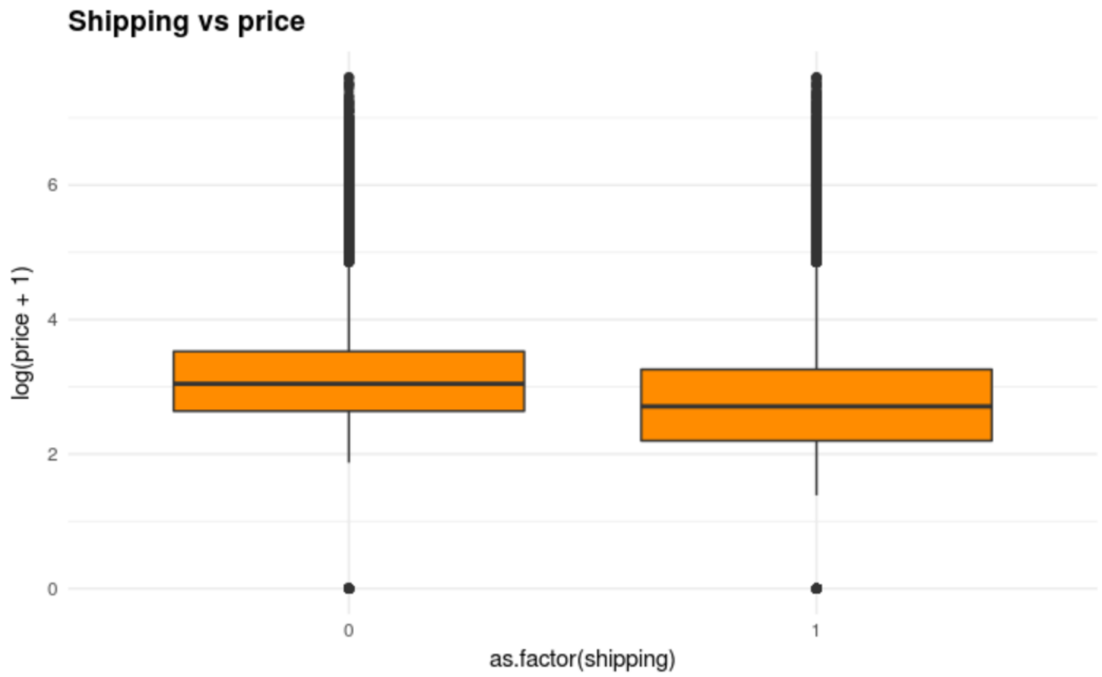
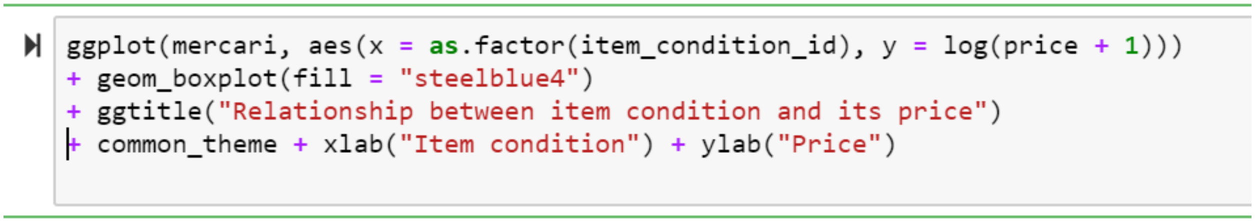


Figure 47: Box plot indicating the relationship between shipping ID and Price

Item Condition ID

This field is used to indicate the standard of the product. The values range from 1-5, 1 indicating like new products and 5 indicating worn out products. Majority of the products are under Item condition ID ranging from 1-3. I have built the box plot for condition ID against price to identify the variance in price based on the condition of the product but I have identified that there is no visible trend between them as almost all the ID’s have equal median of price



```
ggplot(mercari, aes(x = as.factor(item_condition_id), y = log(price + 1)))
+ geom_boxplot(fill = "steelblue4")
+ ggtitle("Relationship between item condition and its price")
+ common_theme + xlab("Item condition") + ylab("Price")
```

Figure 48: R code to build the Box plot between Item Condition ID and Price

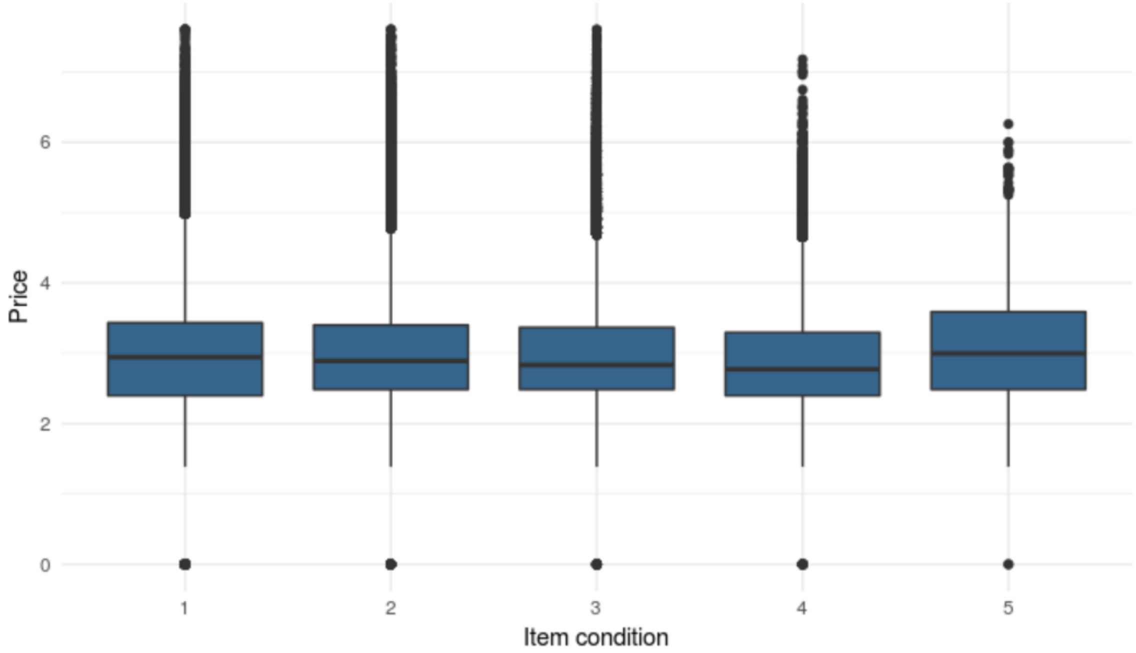
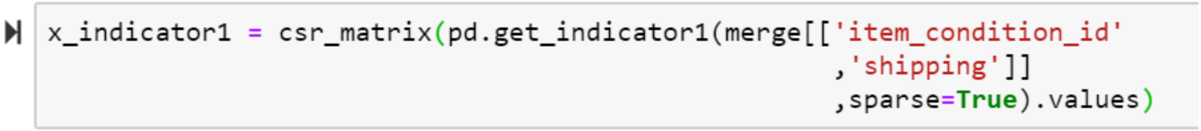


Figure 49: Box plot indicating the relationship between Item condition ID and Price

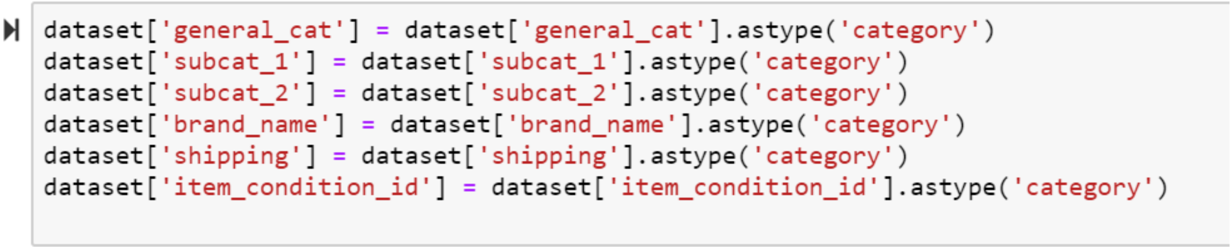


```
x_indicator1 = csr_matrix(pd.get_indicator1(merge[['item_condition_id'
                                                   ,'shipping']]
                                                   ,sparse=True).values)
```

Figure 50: Python code to combine Item condition ID and Shipping ID to a indicator variable

As both shipping status and Item condition ID are categorical and have less impact on the price prediction, I have combined them into a indicator variable thereby decreasing there memory usage.

All the categorical variables are now converted into panda categorical variables for effect modeling purpose.



```
dataset['general_cat'] = dataset['general_cat'].astype('category')
dataset['subcat_1'] = dataset['subcat_1'].astype('category')
dataset['subcat_2'] = dataset['subcat_2'].astype('category')
dataset['brand_name'] = dataset['brand_name'].astype('category')
dataset['shipping'] = dataset['shipping'].astype('category')
dataset['item_condition_id'] = dataset['item_condition_id'].astype('category')
```

Figure 51: Python code to convert all the categorical variables into panda categorical data type

CHAPTER – 5

METHODS

Feature extraction

The Categorical variables like Item Condition ID, Shipping have been converted into Panda categorical variables and combined to form a matrix. Another Categorical variable Brand_Name's features are extracted using the label Vectorizer. The other variables that can impact the price suggestion are Name of the product, Product Category and product description. All these are textual features and their value can be extracted using the feature extraction method.

The machine learning model won't take textual features as input. In predictive analysis, the textual information needs to be treated in a different way because the predictive model can take only numbers as input. So, all the textual features need to be converted into a fixed vector of number to extract their impact on price prediction.

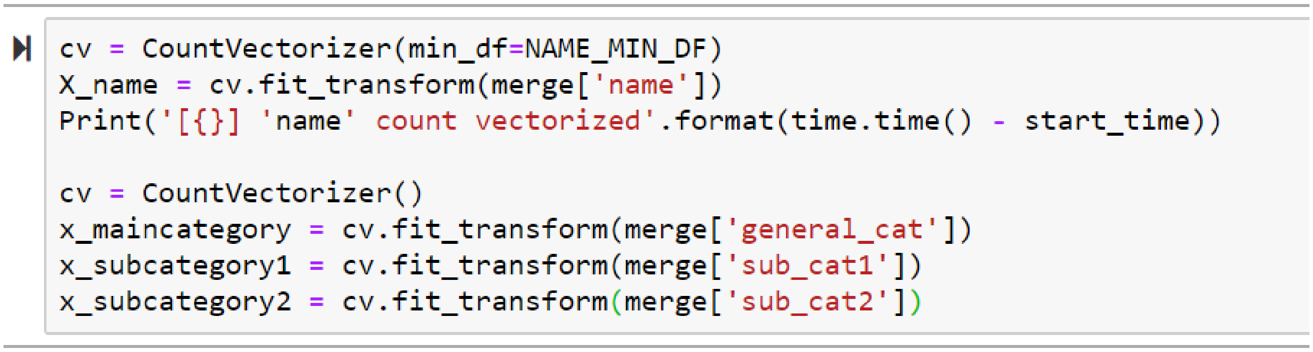
The key words present in the record are identified using tokenization and later they are converted into numerical values using feature extraction. The approach I used for building this model is the "**Bag of Words".** This is a simple model, where each record is taken as input and each word in the record is given a unique ID and the degree at which a particular word is repeated in the record is calculated. The order of the words is not considered. The output will be a fixed length vector of numbers and each number indicates the number of times a word is repeated.

There are multiple ways in which feature extraction can be performed. In this model, I'm using Count vectorization for Product name and Product category features and Tf-Idf vectorization for Item description

Count Vectorizer

The count vectorization is a process in which vocabulary is built out of known words by performing tokenization on all the records used in the model. This process involves two main steps, Fit () and Transform (). Fit () function is used to build the vocabulary and the transform () function called on the records to transform them into vectors. This approach will be used in transforming "Name" and "Category" textual data into numbers.

For example, the sentence "Jupiter is the biggest planet in the universe" is tokenized as { Jupiter: 1, is: 2, the: 3,biggest: 4, Planet: 5, in: 6, Universe :7}. This is a vector of 7 unique words, and it is encoded as [[1 1 2 1 1 1 1]] as the word "The" repeats twice. Now if we apply transform function on the sentence “Adidas Universe T-shirt” it will be encoded as [[0 0 0 0 0 0 1]] as it is picking only the word Jupiter from the vocabulary. Unimpactful words like The, of, is, on etc can be eliminated but as “Name” and “Category” won’t have these words that step can be skipped.



```
cv = CountVectorizer(min_df=NAME_MIN_DF)
X_name = cv.fit_transform(merge['name'])
Print('[{}] 'name' count vectorized'.format(time.time() - start_time))

cv = CountVectorizer()
x_maincategory = cv.fit_transform(merge['general_cat'])
x_subcategory1 = cv.fit_transform(merge['sub_cat1'])
x_subcategory2 = cv.fit_transform(merge['sub_cat2'])
```

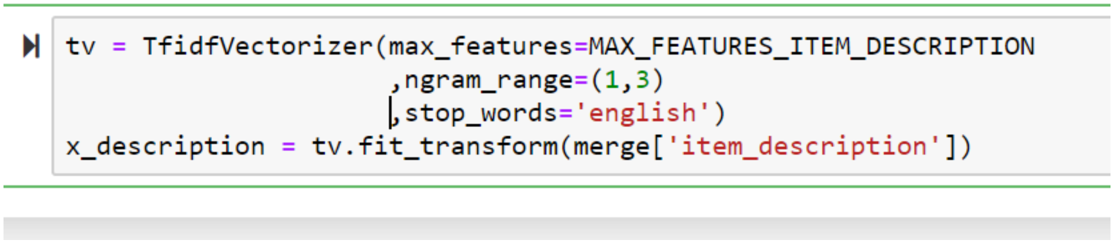
Figure 52: Count Vectorization

TF-IDF Vectorizer

The Count vectorizer is a basic approach as it just count the words in the vector and the in many scenarios the high count of less meaningful words won’t help in building an efficient algorithm. Words like “The, of, is, on” will have high weightage but it has very less impact. So, the count vectorizer becomes ineffective in case of records with large textual data. As the feature we are trying to extract “Item Description” has lot of less impactful words this approach cannot be used.

The other efficient alterative is Term frequency- Inverse document frequency vectorization. This process follows a similar approach of Fit() and Transform() but the inverse document frequency makes it more effective. The Term frequency gives the count of words and the Inverse document frequency reads the vectors and gives low score to the words which repeat across all the records.

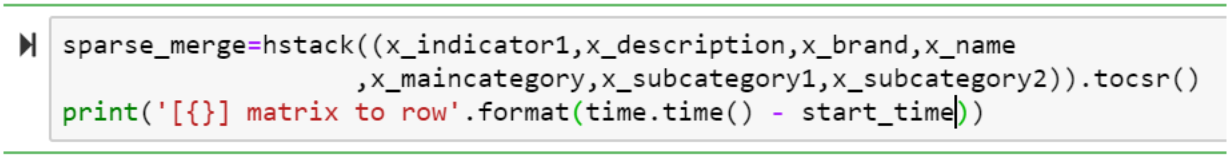
For example the model learn from these sentences “A lion is roaring”,. ” A dog is barking”. In this scenario the words “A and is” get low score. Basically, this approach gives importance to the words that are frequent with in a record over words frequent across all the records.



```
tv = TfidfVectorizer(max_features=MAX_FEATURES_ITEM_DESCRIPTION
                     ,ngram_range=(1,3)
                     ,stop_words='english')
x_description = tv.fit_transform(merge['item_description'])
```

Figure 53:Tf-Idf Vectorization

Now that all the features are extracted and cleaned, They are merged and converted from a matrix to a sparse record and fed into the model



```
sparse_merge=hstack((x_indicator1,x_description,x_brand,x_name
                   ,x_maincategory,x_subcategory1,x_subcategory2)).tocsr()
print('[{}] matrix to row'.format(time.time() - start_time))
```

Figure 54: Python code for converting all the matrices into a single sparse row

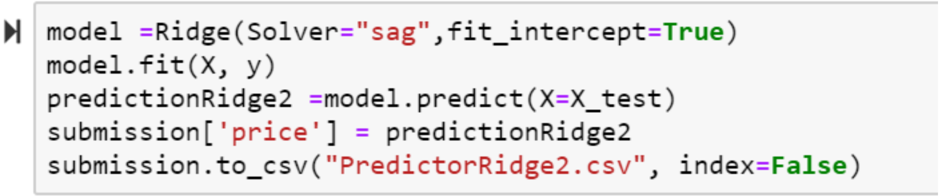
Ridge regression

This price prediction scenario is a multi-linear regression problem. A fitting linear equation need to be established between the two or more explanatory variables and the response variable. I have used the multi-linear regression model as the baseline model. The approach of using least square method is inefficient here because of the multicollinearity between the variables. The textual variable Item description has vocabulary containing “Brand Name”, “Brand category” and other information which causes multicollinearity between the textual variables. So, the accuracy of baseline model was very low.

Ridge Regression is a technique to analyze multiple regression data that has a problem of multicollinearity. When multicollinearity occurs, least squares estimates are unbiased, but their variances are large, so they may be far from the true value. By adding a degree of bias to the regression estimates, ridge regression help reducing the standard errors.

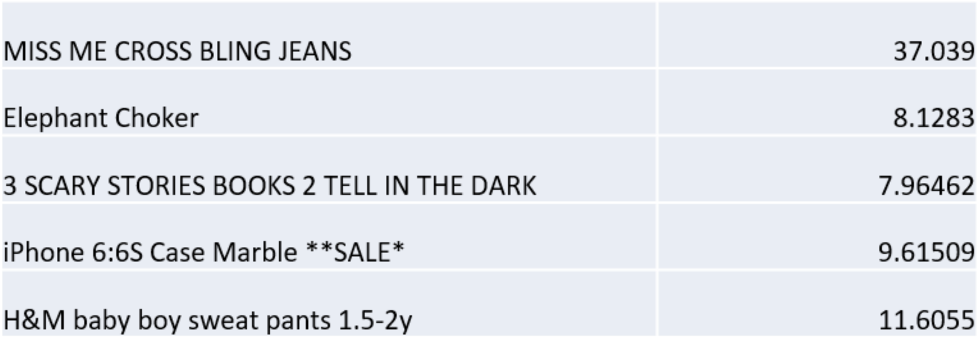
Two variants of Ridge Regression algorithm were used for the analysis with some tweaks in the number of features used and type of Ridge solver used. For this model, I have used two variants of ridge solver namely "Sag" and "LSQR" to analyze on how the dataset performs on different dimension.

Sag Solver



```
model =Ridge(Solver="sag",fit_intercept=True)
model.fit(X, y)
predictionRidge2 =model.predict(X=X_test)
submission['price'] = predictionRidge2
submission.to_csv("PredictorRidge2.csv", index=False)
```

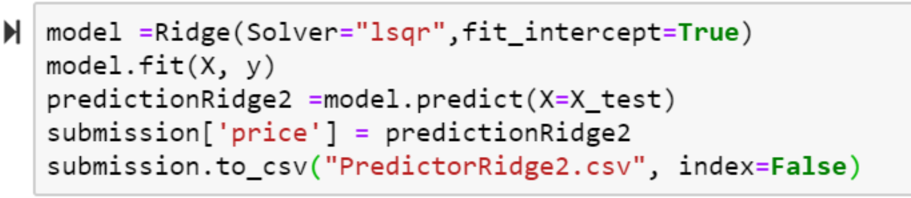
Figure 55: Ridge Regression Sag Solver



MISS ME CROSS BLING JEANS	37.039
Elephant Choker	8.1283
3 SCARY STORIES BOOKS 2 TELL IN THE DARK	7.96462
iPhone 6:6S Case Marble **SALE*	9.61509
H&M baby boy sweat pants 1.5-2y	11.6055

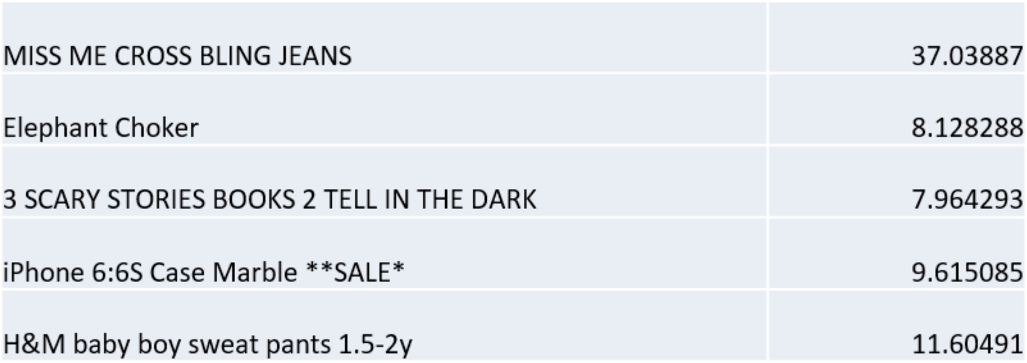
Figure 56: Result Sag solver

Lsqr Solver



```
model =Ridge(Solver="lsqr",fit_intercept=True)
model.fit(X, y)
predictionRidge2 =model.predict(X=X_test)
submission['price'] = predictionRidge2
submission.to_csv("PredictorRidge2.csv", index=False)
```

Figure 57:Ridge Regression Lsqr solver



MISS ME CROSS BLING JEANS	37.03887
Elephant Choker	8.128288
3 SCARY STORIES BOOKS 2 TELL IN THE DARK	7.964293
iPhone 6:6S Case Marble **SALE*	9.615085
H&M baby boy sweat pants 1.5-2y	11.60491

Figure 58:Result Lsqr solver

Light BGM

The Ridge regression model eliminates the Multicollinearity and overfitting issues and is considered the best amongst the regression models in predicting the price but the major issue in this scenario is the size of data. With close to million records in the training data set. Ridge regression has high memory usage and isn't capable of handling large-scale data. To tackle this issue, I have used a modern machine learning model LightGBM in this analysis.

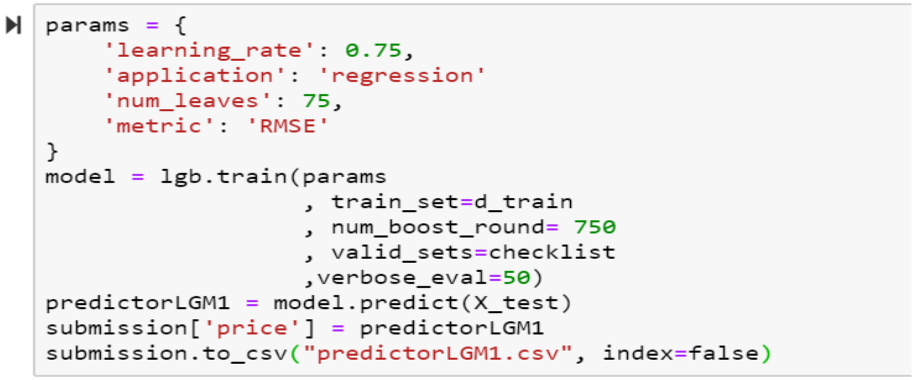
LightBGM is a gradient boosting technique where the learning process is tree based. This algorithm is widely considered while dealing with large data in the recent times because of its leaf based growth approach compared to the level based approach. The node with highest loss in delta will grow making it work at high speed consuming less memory space. One issue with the

LightGBM algorithm is, it can cause overfitting with small dataset. But considering the size of data in this prediction analysis it is considered as the most efficient approach.

This model has many parameters but for this scenario I have considered the only **learning rate**, rate at which a single tree effects the outcome. **Application,** which specifies the model. **No of Leaves,** the number of trees considered in the model. **Metric,** Used to specify the delta loss of the model.

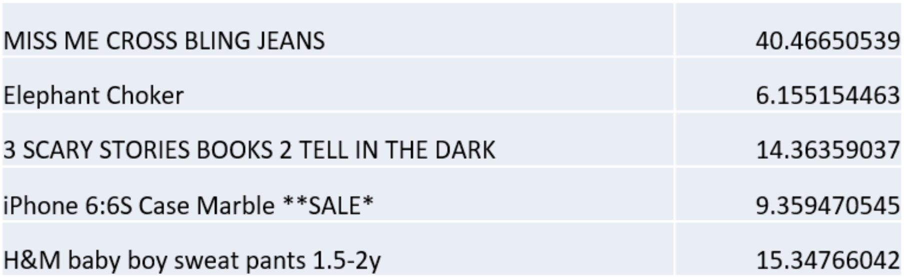
Gradient boosting decision tree (GBDT) is a widely used machine learning algorithm, due to its efficiency, accuracy, and interpretability. GBDT achieves state-of-the-art performances in many machine learning tasks, such as multi-class classification, click prediction, and learning to rank. LightGBM is one of the recent implementations of GBDT. Light GBM is a gradient boosting framework that uses tree-based learning algorithm. LightGBM speeds up the training process of conventional GBDT by up to over 20 times while achieving almost the same accuracy. Two variants of LightGBM algorithm were used for the analysis with some tweaks in parameters such as number of features used, learning rate, number of leaves, number of boost round etc which help to analyze on how the dataset performs on different dimension.

LightGBM1: Learning Rate:0.75



```
params = {
    'learning_rate': 0.75,
    'application': 'regression'
    'num_leaves': 75,
    'metric': 'RMSE'
}
model = lgb.train(params
                  , train_set=d_train
                  , num_boost_round= 750
                  , valid_sets=checklist
                  ,verbose_eval=50)
predictorLGM1 = model.predict(X_test)
submission['price'] = predictorLGM1
submission.to_csv("predictorLGM1.csv", index=false)
```

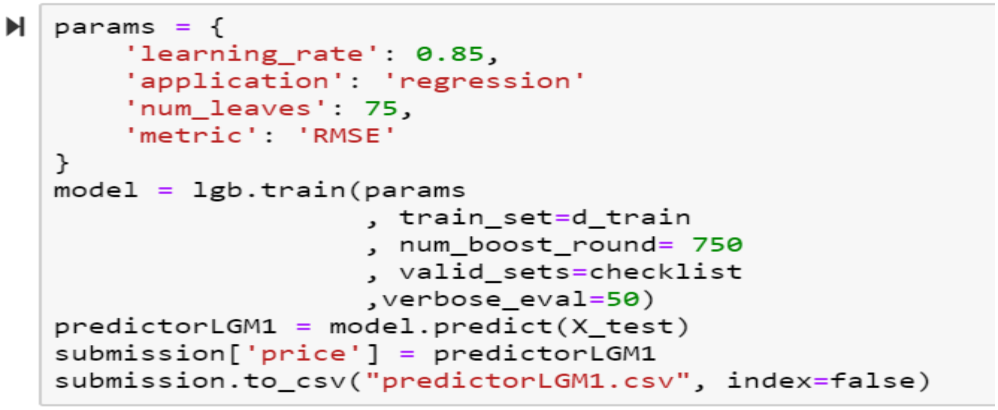
Figure 59:LightGBM Learning rate: 0.75



MISS ME CROSS BLING JEANS	40.46650539
Elephant Choker	6.155154463
3 SCARY STORIES BOOKS 2 TELL IN THE DARK	14.36359037
iPhone 6:6S Case Marble **SALE*	9.359470545
H&M baby boy sweat pants 1.5-2y	15.34766042

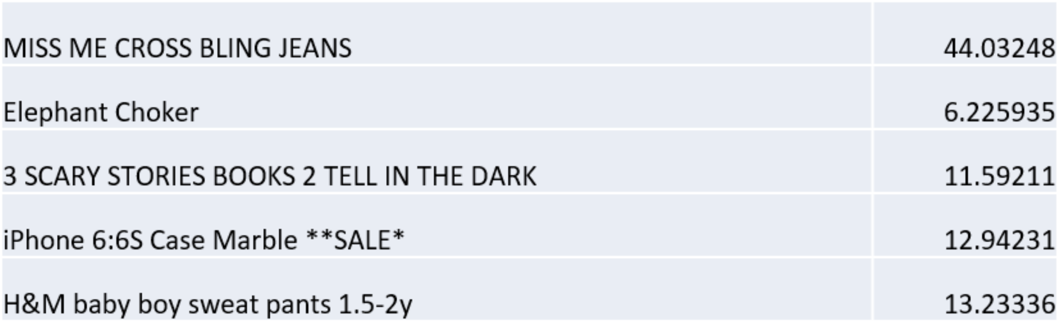
Figure 60:LightGBM1 Results

LightGBM2: Learning Rate: 0.85



```
params = {
    'learning_rate': 0.85,
    'application': 'regression'
    'num_leaves': 75,
    'metric': 'RMSE'
}
model = lgb.train(params
                  , train_set=d_train
                  , num_boost_round= 750
                  , valid_sets=checklist
                  ,verbose_eval=50)
predictorLGM1 = model.predict(X_test)
submission['price'] = predictorLGM1
submission.to_csv("predictorLGM1.csv", index=false)
```

Figure 61:LightGBM Learning rate:0.85



MISS ME CROSS BLING JEANS	44.03248
Elephant Choker	6.225935
3 SCARY STORIES BOOKS 2 TELL IN THE DARK	11.59211
iPhone 6:6S Case Marble **SALE*	12.94231
H&M baby boy sweat pants 1.5-2y	13.23336

Figure 62:LightGBM2 results

Measures and Metrics

To measure the accuracy and performance of both the models, I have used the metrics RSME and R square. These are the standard methods to check whether the prediction made by the algorithm on the test data aligns with the predictions made on the training data. For an Ideal model, these metrics will be same for both Training and Testing data. If one of those is more then the model must have badly overfit the data

RSME

RSME is used to measure the performance of regression analysis model. It basically points the Standard deviation between the results predicted by the model and the results observed. The standard deviation between observed results and predicted results is called residual. The residual is defined as distance of data points from the Regression line. Closer the data points to the regression line better the performance of the model. The RSME value can be measured in as follows,

$$\mathrm{RMSE}_{fo} = [\sum_{i=1}^{N} (z_{f_i} - z_{o_i})^2 / N]^{1/2}$$

Here the difference between the results is squared and divided by sample size N and the summation of all data points is square rooted

R Square

R Square is a measure that indicates the strength of your model's relationship to the independent variables. It points out to the amount of variance of dependent variable explained by the independent variable. The value of R square ranges from 0 -1 or 0-100%. R Square is also called as coefficient of determination. As it determines the spread of data points across the Regression line. Less the difference between predicted and observed values more the R square value.

$$\mathbf{r} = \frac{\mathbf{n}(\sum \mathbf{xy}) - (\sum \mathbf{x})(\sum \mathbf{y})}{\sqrt{[\mathbf{n}\sum \mathbf{x}^2 - (\sum \mathbf{x})^2][\mathbf{n}\sum \mathbf{y}^2 - (\sum \mathbf{y})^2]}}$$

CHAPTER - 6

RESULTSRMSE AND R Square results

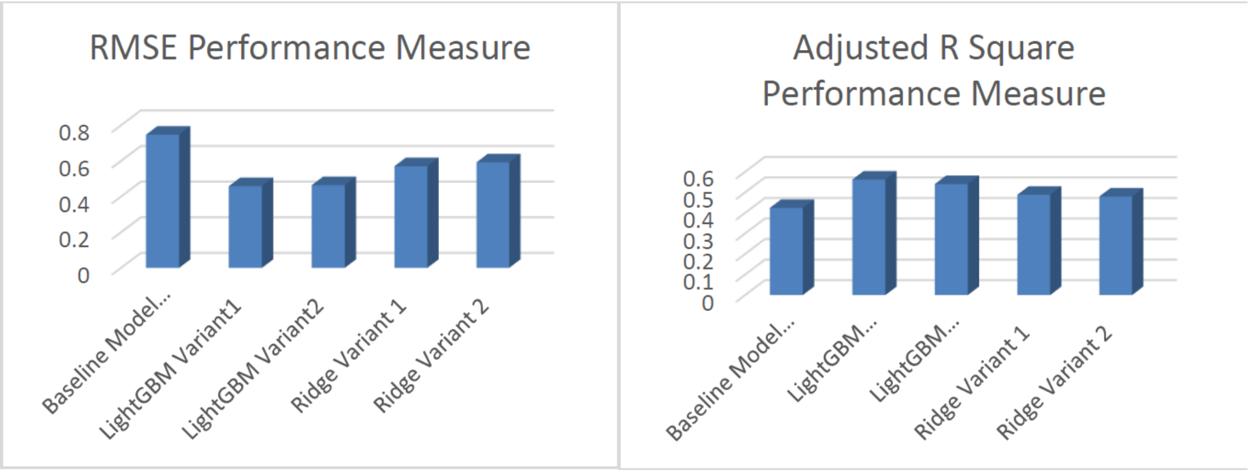


Figure 63:RSME and R Square results

The motive of this project is to predict the price of a product using its own features. So, the major objective is to find the data related to the products and design a model which efficiently predicts the price of the products.

I have chosen a very reliable dataset from one of the top 5 online shopping marketplaces Mercari and performed extensive exploratory data analysis and cleansing tasks like handling missing values, splitting categories, converting categorical variables to numerical variables and combining similar features. I have presented these steps in the exploratory data analysis chapter.

After preparing the standardized data, I have built Multi – linear regression model as the baseline model. Considering the inability in handling multi collinearity and high RSME measure of 0.71. I have discarded this model for my approach.

The other model that I have built are Ridge regression and LightGBM model. Both of them are efficient models and capable of handling multicollinearity and overfitting of data. I have tried couple of approaches for both the models, Lsqr and sag solvers for Ridge regression and Learning rate’s of 0.75 and 0.85 for LightGBM and I have observed that the LightGBM variant 1 with learning rate 0.75 stand out model amongst the variations I have tried with a low RSME score of 0.458476 and high R square value of 0.5310.

Considering the ability of handling large datasets and unstructured data along with high model performance. Through this project, I have observed that LightGBM is the most efficient model for Price prediction.

CHAPTER - 7

CONCLUSION AND FUTURE SCOPE

Price prediction has been a challenge for the online marketplaces. Sellers often are optimistic and label products with selling price way higher than what it's meant to be. The approach is to automatically generate a price for the product based on the product features which helps as a baseline for buyer and seller to negotiate on. With the exponential growth of big data and machine learning, everyone in the market wants to leverage the potential of it and built a model which predicts the price accurately.

Through this project, I successfully built a machine learning model using LightGBM regression-based algorithm. This model performs unsupervised learning on the testing data and automatically predicts the price on a given product. I have used the modern data preprocessing techniques using Python the cleanse and standardize the data. The feature extraction approach has helped me to indulge unstructured features into the model. The major takeaway from this project is the effective usage of the boosting algorithm LightGBM, it is fast and consumes very less memory making it an efficient machine learning model on big data platform.

For this project, I have used just the textual features and the structured data for the analysis. The future scope for price prediction would be inclined towards using visual features for the prediction. For every product, in majority of the marketplaces, the seller has to post at least 3 pictures of the product. These pictures can be analyzed, and the visual parameters can be used in building the model. Right now, it is difficult to perform this analysis at academic level considering the amount of size each image takes. Also, an effective machine learning model requires large amount of data for prediction. But considering the boon of Big data in coming future visual parameters along with the textual features can be used for price prediction.

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APPENDIX

Source Data: For this project, I have used the Mercari's: Price suggestion challenge dataset. This dataset is available in Kaggle. Kaggle is a google owned online platform providing Dataset for machine learning users. Mercari has provided both training and testing data separately for this challenge and for this challenge RMSE is used as performance metric

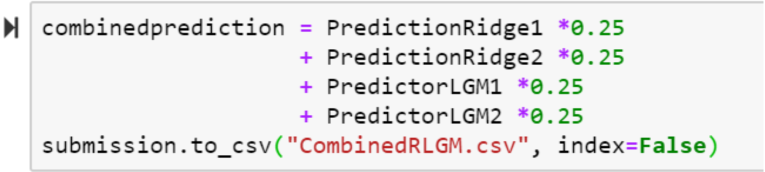
SOFTWARE: For this project, I have used Qliksense for data analysis and few visualizations and for building the price prediction model, I have used Python 3.5 on Jupyter notebook. I have also used R for statistical visualizations

PACKAGES: For this project I have used I have used multiple python and R libraries.

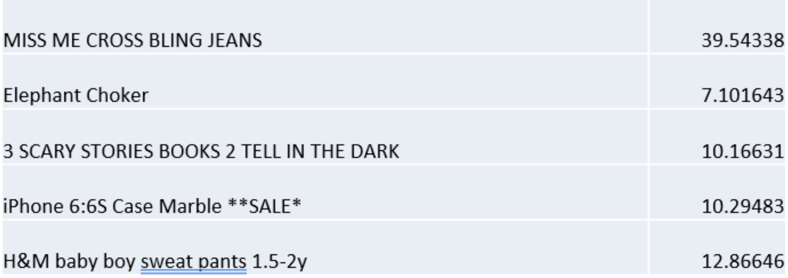
1) NumPy: Numercial Python, helps with quick computation of matrices
2) Pandas: Is used for the extensive data analysis and building structures
3) Ggplot2: This is an R package used for statistical visualizations
4) Scipy: Scientific python, used for integration of data and equation solving
5) Sklearn: This is a machine learning package used for building regression models

Combining Models:

After building the Ridge and LightGBM models. I have also tried to combine the prediction results from both the models expecting a more enhanced performance. But for the combination model the RMSE was 0.61 which is more than individual models.



```
combinedprediction = PredictionRidge1 *0.25
                   + PredictionRidge2 *0.25
                   + PredictorLGM1 *0.25
                   + PredictorLGM2 *0.25
submission.to_csv("CombinedRLGM.csv", index=False)
```



MISS ME CROSS BLING JEANS	39.54338
Elephant Choker	7.101643
3 SCARY STORIES BOOKS 2 TELL IN THE DARK	10.16631
iPhone 6:6S Case Marble **SALE*	10.29483
H&M baby boy sweat pants 1.5-2y	12.86646