
SnapIt - Always get the best price!

- Team - Brute Force
 - Rachit Agrawal (IMT2020018)
 - Vyom Sharma (IMT2020026)
-

Basic Preprocessing

- NaN values -
 - 50% of the data had NaN values for PRODUCT_BRAND - Replaced with “missing”
 - 4% of the data had NaN values for CATEGORY - Removed the rows
 - 3 rows had NaN values for PRODUCT_DESCRIPTION - Removed the rows
- No duplicate rows
- Removed 731 rows with PRODUCT_PRICE < 0

```
(main_df.isna()).sum()
```

PRODUCT_ID	0
PRODUCT_NAME	0
PRODUCT_CONDITION	0
CATEGORY	5416
PRODUCT_BRAND	537885
SHIPPING_AVAILABILITY	0
PRODUCT_DESCRIPTION	3
PRODUCT_PRICE	0
dtype:	int64

```
print('Removed {} rows'.format(len(main_df[main_df.PRODUCT_PRICE <= 0])))  
main_df = main_df[main_df.PRODUCT_PRICE > 0].reset_index(drop=True)
```

Removed 731 rows

Analysing Category Feature

- We initially split the string in category and created a list of strings separated by '/' symbol.
- We observed that only 3692 (i.e 0.3 percent) rows have more than 3 sub categories. So, we can ignore them and can consider only 3 categories for all the rows.
- We created 3 new column of subcategories as 'CAT1', 'CAT2', 'CAT3' and removed the column 'CATEGORY'.

● Code Snippet

We first split the categories as general categories and further sub categories.

```
[11] main_df['CATEGORY'] = main_df['CATEGORY'].str.split("/", n = 5, expand=False)
test_df['CATEGORY'] = test_df['CATEGORY'].str.split("/", n = 5, expand=False)
```

```
[14] main_df['CAT1'] = main_df['CATEGORY'].str.get(0).replace('', 'missing').astype('category')
main_df['CAT2'] = main_df['CATEGORY'].str.get(1).fillna('missing').astype('category')
main_df['CAT3'] = main_df['CATEGORY'].str.get(2).fillna('missing').astype('category')
main_df.drop('CATEGORY', axis=1, inplace=True)
test_df['CAT1'] = test_df['CATEGORY'].str.get(0).replace('', 'missing').astype('category')
test_df['CAT2'] = test_df['CATEGORY'].str.get(1).fillna('missing').astype('category')
test_df['CAT3'] = test_df['CATEGORY'].str.get(2).fillna('missing').astype('category')
test_df.drop('CATEGORY', axis=1, inplace=True)
```

● Output

CATEGORY
Beauty/Makeup/Lips
Electronics/Media/Blu-Ray
Kids/Toys/Arts & Crafts
Women/Women's Accessories/Wallets
Sports & Outdoors/Outdoors/Other



CAT1	CAT2	CAT3
Beauty	Makeup	Lips
Electronics	Media	Blu-Ray
Kids	Toys	Arts & Crafts
Women	Women's Accessories	Wallets
Sports & Outdoors	Outdoors	Other



Correlation



What

Checked correlation between
PRODUCT_PRICE and features one at a
time.



Why

Helps to select which features to keep

PRODUCT_ID

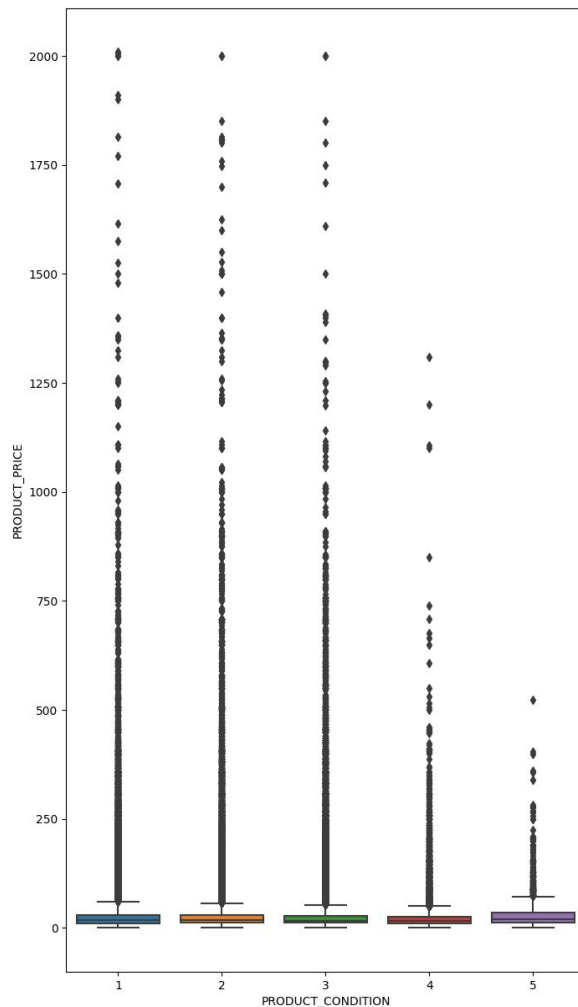
```
print(np.corrcoef(np.asarray(main_df["PRODUCT_ID"]), np.asarray(main_df["PRODUCT_PRICE"])))  
  
[[1.00000000e+00 9.46153025e-04]  
 [9.46153025e-04 1.00000000e+00]]
```

The correlation between PRODUCT_ID and PRODUCT_PRICE is 0.000946 which is very less. Thus dropped PRODUCT_ID.

PRODUCT_CONDITION

```
plt.figure(figsize=(8,15))  
sns.boxplot(x = main_df["PRODUCT_CONDITION"], y = main_df["PRODUCT_PRICE"])
```

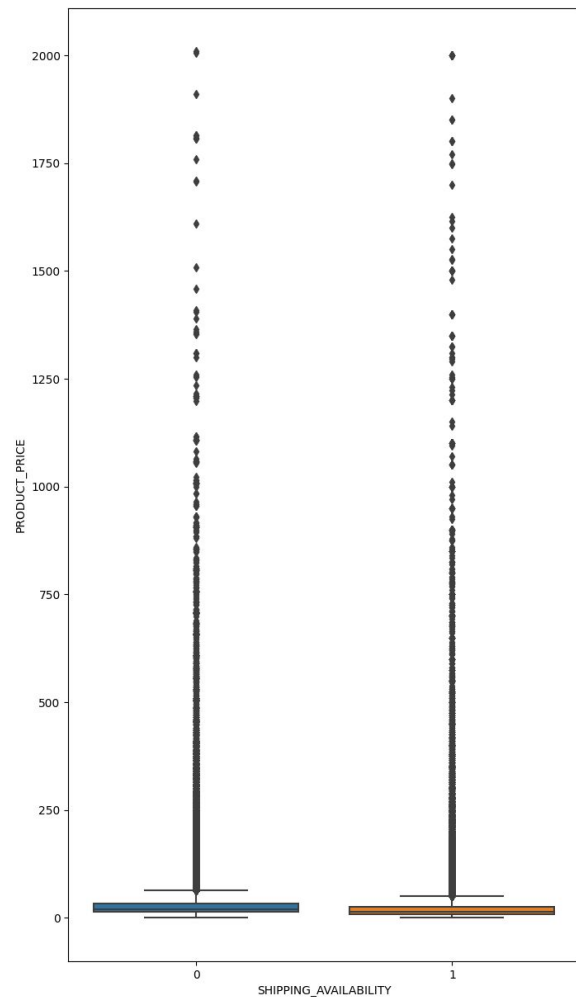
The median price decreases for product conditions 1 to 4 and slightly increases for product condition 5



SHIPPING_AVAILABILITY

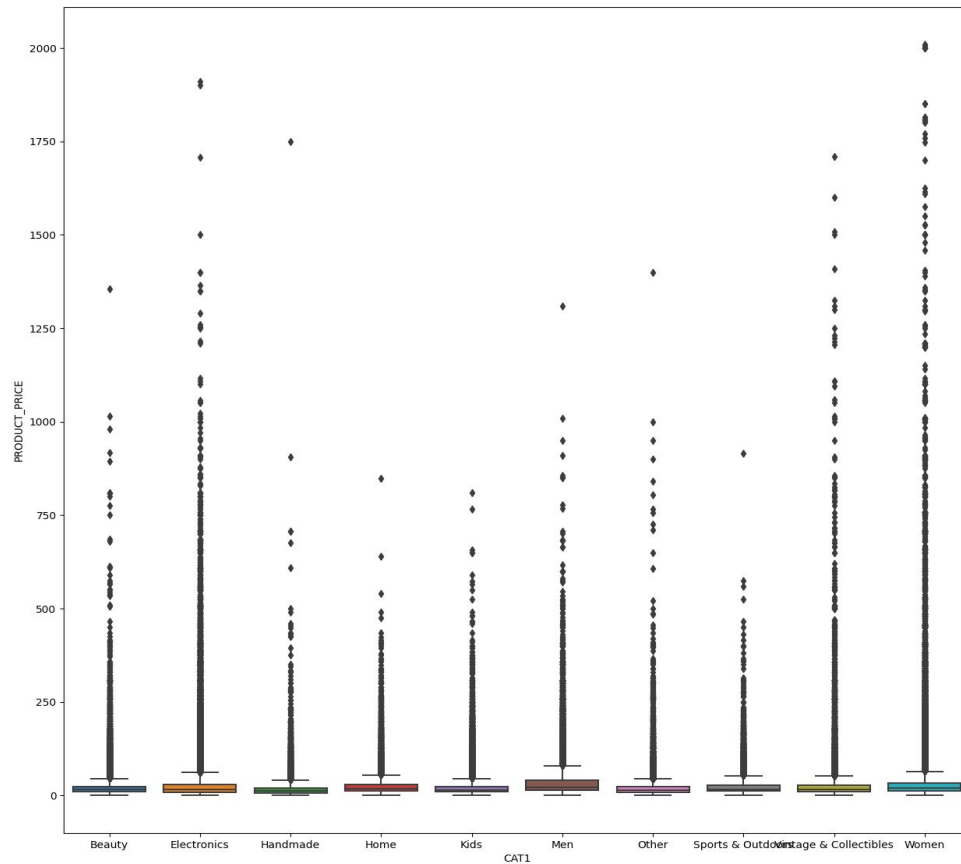
```
plt.figure(figsize=(8,15))  
sns.boxplot(x = main_df["SHIPPING_AVAILABILITY"], y = main_df["PRODUCT_PRICE"])
```

The median price slightly decreases when shipping availability is available.

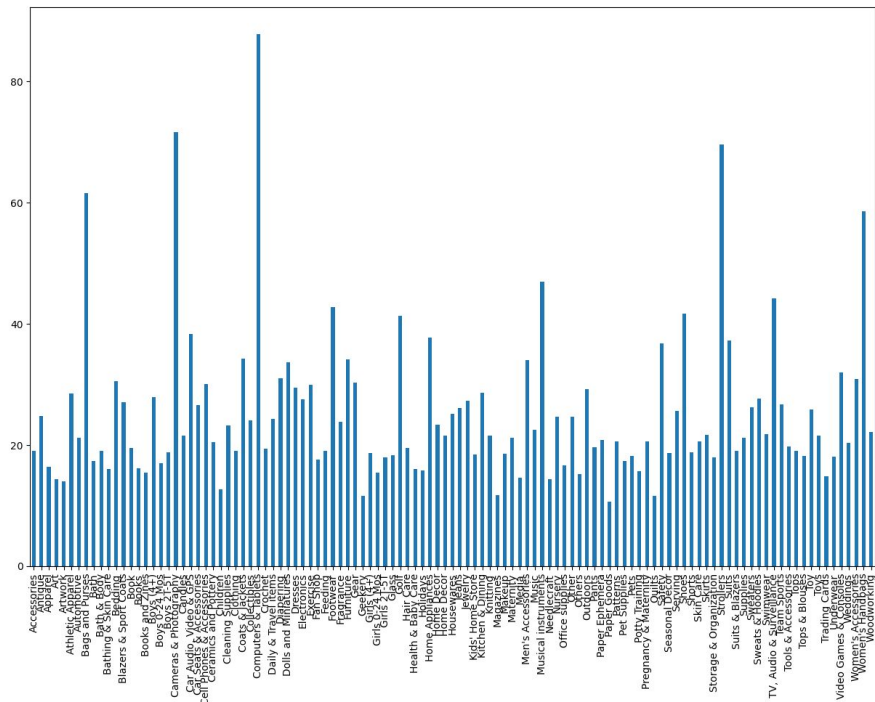


CAT1

```
plt.figure(figsize=(15,15))  
sns.boxplot(x = main_df["CAT1"], y = main_df["PRODUCT_PRICE"])
```

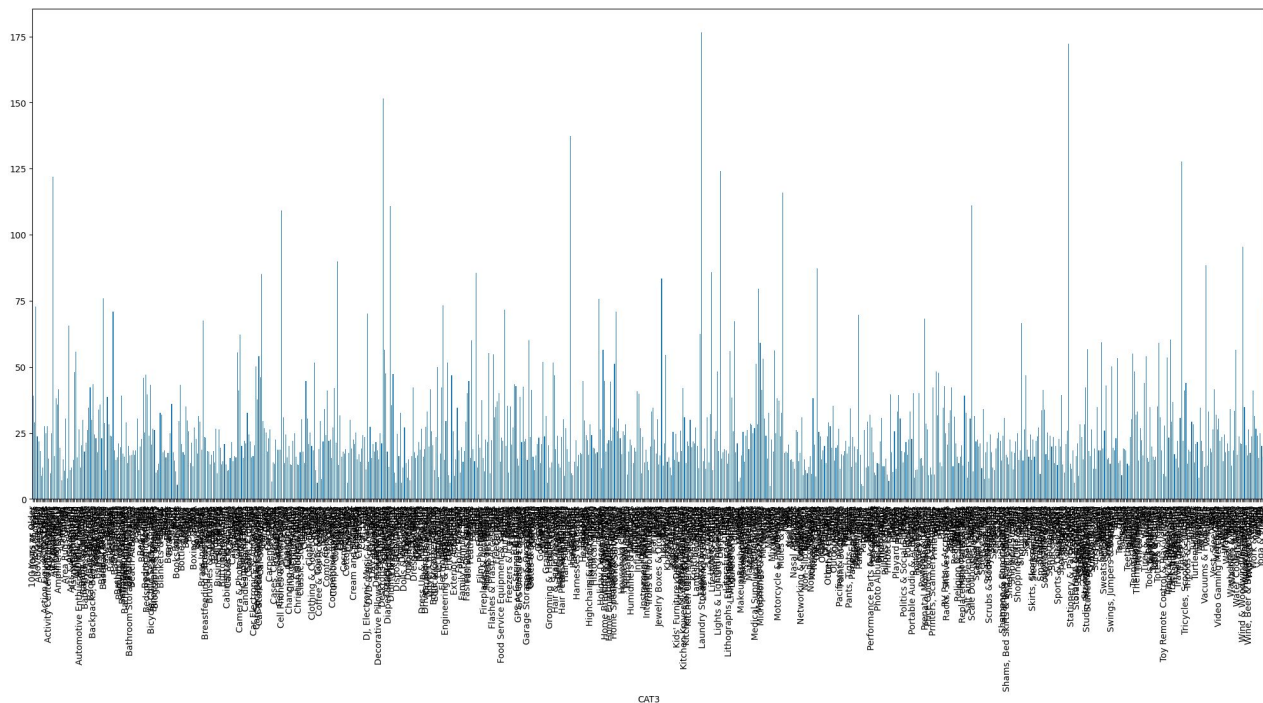


CAT2

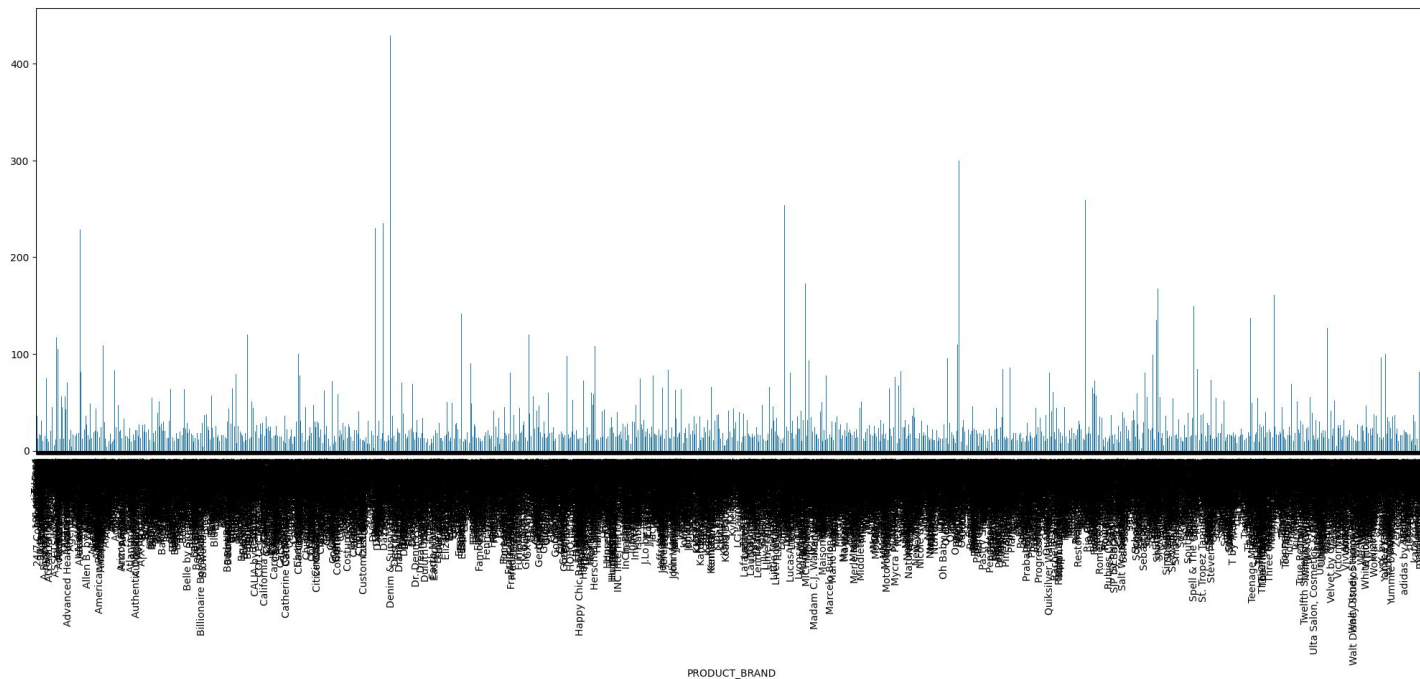


CAT3

```
plt.figure(figsize=(25,10))
cat3groupeddf = main_df.groupby("CAT3")["PRODUCT_PRICE"].mean().plot.bar()
plt.show()
```



PRODUCT_BRAND



Preprocessing Text

- We preprocessed the text of 'PRODUCT_NAME' and 'PRODUCT_DESCRIPTION'. We removed non-alphanumeric characters, regular expressions, stopwords, tab space, newline from the text.

```
def PreprocessName(name_col):
    preprocessed_names = []
    for sentence in tqdm(name_col.values):
        s = sentence.replace('\r', ' ')
        s = s.replace('\\"', ' ')
        s = s.replace('\n', ' ')
        s = re.sub('[^A-Za-z0-9]+', ' ', s)
        preprocessed_names.append(s.lower().strip())
    return preprocessed_names
```

[26]

Python

```
import nltk
nltk.download('stopwords')
from nltk.corpus import stopwords

stopwords = stopwords.words('english')
def PreprocessDescription(desc_col):
    preprocessed_descs = []
    for sentence in tqdm(desc_col.values):
        s = sentence.replace('\r', ' ')
        s = s.replace('\\"', ' ')
        s = s.replace('\n', ' ')
        s = re.sub('[^A-Za-z0-9]+', ' ', s)
        s = ' '.join(e for e in s.split() if e not in stopwords)
        preprocessed_descs.append(s.lower().strip())
    return preprocessed_descs
```

[27]

Python

- We preprocessed the text of CATEGORY. We removed blank spaces from the text.

```
def PreprocessCategory(cat_col):  
    categories = list(cat_col)  
  
    cat_list = []  
    for i in tqdm(categories):  
        i = re.sub('[^A-Za-z0-9]+', ' ', i)  
        i = i.replace(' ', '')  
        cat_list.append(i.strip())  
  
    return cat_list
```

[28]

Python

- Result : We observed that after text preprocessing the distinct values in 'PRODUCT_NAME', 'PRODUCT_DESCRIPTION' and 'CAT3' decreased.

```
✓ [25] for col in main_df:  
      print(col, len(main_df[col].unique()))
```

```
PRODUCT_NAME 1048068  
PRODUCT_CONDITION 5  
PRODUCT_BRAND 4616  
SHIPPING_AVAILABILITY 2  
PRODUCT_DESCRIPTION 1089018  
PRODUCT_PRICE 798  
CAT1 10  
CAT2 113  
CAT3 863
```



```
[33] for col in main_df:  
      print(col, len(main_df[col].unique()))
```

```
PRODUCT_NAME 956790  
PRODUCT_CONDITION 5  
PRODUCT_BRAND 4613  
SHIPPING_AVAILABILITY 2  
PRODUCT_DESCRIPTION 1063367  
PRODUCT_PRICE 797  
CAT1 10  
CAT2 113  
CAT3 861
```

One Hot Encoding

- Finally, we one hot encoded the columns 'PRODUCT_BRAND', 'CAT1', 'CAT2' and 'CAT3'.

```
from sklearn.feature_extraction.text import CountVectorizer

vectorizer = CountVectorizer(lowercase=False, binary=True)
train_brand_ohe = vectorizer.fit_transform(main_df['PRODUCT_BRAND'].values)
test_brand_ohe = vectorizer.transform(test_df['PRODUCT_BRAND'].values)

train_cat1_ohe = vectorizer.fit_transform(main_df['CAT1'].values)
test_cat1_ohe = vectorizer.transform(test_df['CAT1'].values)

train_cat2_ohe = vectorizer.fit_transform(main_df['CAT2'].values)
test_cat2_ohe = vectorizer.transform(test_df['CAT2'].values)

train_cat3_ohe = vectorizer.fit_transform(main_df['CAT3'].values)
test_cat3_ohe = vectorizer.transform(test_df['CAT3'].values)
```

PRODUCT_NAME and PRODUCT_DESCRIPTION

```
from sklearn.feature_extraction.text import TfidfVectorizer

# Creating a TF-IDF vectorizer with 1,2, and 3 ngrams together for PRODUCT_NAME
vectorizer = TfidfVectorizer(ngram_range=(1, 3), min_df=3, max_features=250000)

tfidf_name = vectorizer.fit_transform(main_df['PRODUCT_NAME'].values)
test_tfidf_name = vectorizer.transform(test_df['PRODUCT_NAME'].values)

# Creating a TF-IDF vectorizer with 1,2, and 3 ngrams together for PRODUCT_DESCRIPTION
vectorizer = TfidfVectorizer(ngram_range=(1, 3), min_df=5, max_features=500000)

tfidf_description = vectorizer.fit_transform(main_df['PRODUCT_DESCRIPTION'].values)
test_tfidf_description = vectorizer.transform(test_df['PRODUCT_DESCRIPTION'].values)
```

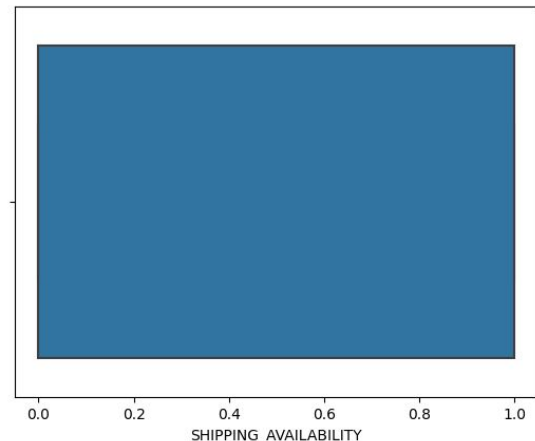
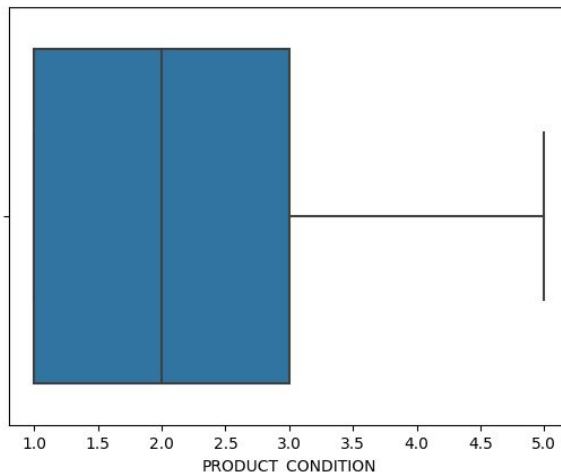
- Created sparse matrix containing TF-IDF scores for 1,2 and 3 grams for each document

$$\text{idf}(t) = \log \frac{n}{\text{df}(t)} + 1 \qquad w_{i,j} = \text{tf}_{i,j} \times \text{idf}_i$$

Outliers, Normalisation and Standardisation

- Only **PRODUCT_CONDITION** and **SHIPPING_AVAILABILITY** needs to be checked since other features are one hot encoded and **PRODUCT_NAME** and **PRODUCT_DESCRIPTION** have been converted to TF-IDF vectors.
- No Normalisation or Standardisation required

```
cols = ['PRODUCT_NAME', 'PRODUCT_DESCRIPTION', 'PRODUCT_PRICE', 'PRODUCT_BRAND', 'CAT1', 'CAT2', 'CAT3']  
for col in main_df:  
    if col in cols:  
        continue  
    sns.boxplot(x=main_df[col])  
plt.show()
```



References

- <https://towardsdatascience.com/nlp-preprocessing-with-nltk-3c04ee00edc0>
- <https://www.analyticsvidhya.com/blog/2021/05/feature-engineering-how-to-detect-and-remove-outliers-with-python-code/>
- https://scikit-learn.org/stable/modules/feature_extraction.html#text-feature-extraction
- https://scikit-learn.org/stable/modules/generated/sklearn.feature_extraction.text.CountVectorizer.html