Capstone Project - 1

Team: Reality

Team Members

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World of Android & Malwares!

"Obviously, you will always see more malware targeting Android because Android is used more than any smartphone platform by a pretty substantial difference." - Sundar Pichai

A new malicious app is released every 7.5 seconds, 10,000 new samples everyday!

Apple CEO Tim Cook says "*Android has 47 times*" more Malwares than iOS.

Malware attack trends

Information Extraction: The malware in this category also endangers the device then steal your personal information such as IMEI number, user details and many more.

Automatic Calls and SMS: This malware group increase the billing of the user. This took the user's phone access like contact books and make automatic calls and send SMS to other numbers.

Root Exploits: This malware seek to gain system root rights in order to control the system and modify the system configuration with another application details.

Dynamically Downloaded Code: This method enables the installed application to download malicious code and use it on mobile devices without the user's knowledge.

Our Problem

- To identify whether an application is **malware(1)** or **benign(0)**
- Based on data collected over 3 years during installation and runtime of an application.

Digging up Malware Android Dataset..

- The data was collected from different app markets such as google play store and has **30k records.**
- The dataset consists of four **textual** columns:

  App :- Name of the App

  Package :- OBB/Data package installed in root folder

  Category :- App Category (eg. Entertainment, Adventure, puzzle, Action, Antivirus, etc.)

  Description :- App Description

Digging up Malware Android Dataset..

- The dataset consists of some **numeric** columns:

  Rating :- Rating out of 5

  Number of ratings :- No. of Ratings given by users

  Price :- Price of the App

  Related apps :- Apps related to installed App

  Dangerous (D) permissions count :- No. of Dangerous Permissions allowed by user

  Safe (S) permissions count :- No. of Safe Permissions allowed by user

Digging up Malware Android Dataset..

- The rest of the columns are **binary columns** specifying certain kind

  of permissions:

  Default Permissions
  Development Tools Permissions
  Hardware Controls
  Network Communications
  Phone Calls

Digging up Malware Android Dataset..

- The rest of the columns are **binary columns** specifying certain kind

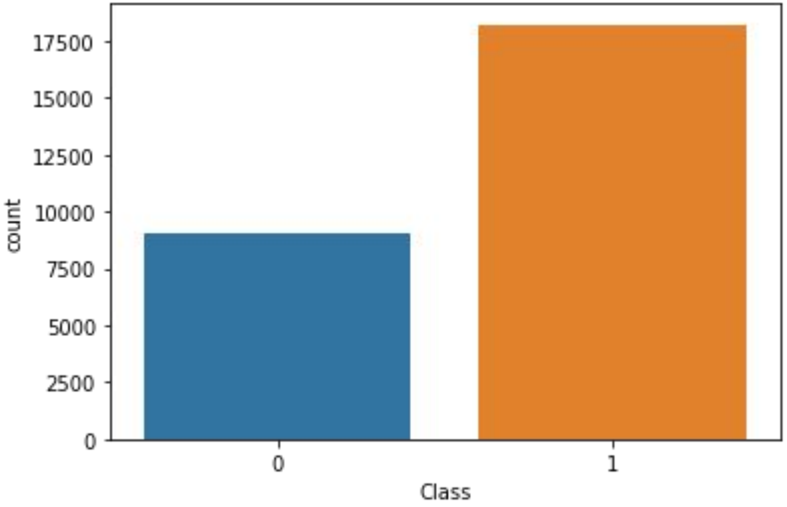
  of permissions:

  Service That cost you money
  Storage
  Systems tools
  Personal info: Your accounts, Your Location, Your messages, Other personal info

Digging up Malware Android Dataset..

- The dataset has 2.6k duplicate records across all columns
- It has over 720 null records in related apps and 202 null records in dangerous permissions counts.

Digging up Malware Android Dataset..



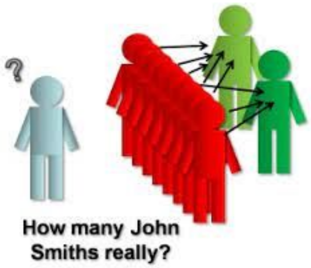
Class Distribution for Target Classes

*The dependent variable is a class count with **67%** count of malware apps and **33%** count of benign apps.*

Where is my broom..??

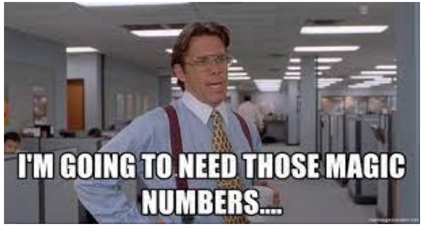
1 — 2 — 3 — 4

Handling Duplicates



Handling Null Values

Handling Numerical Columns



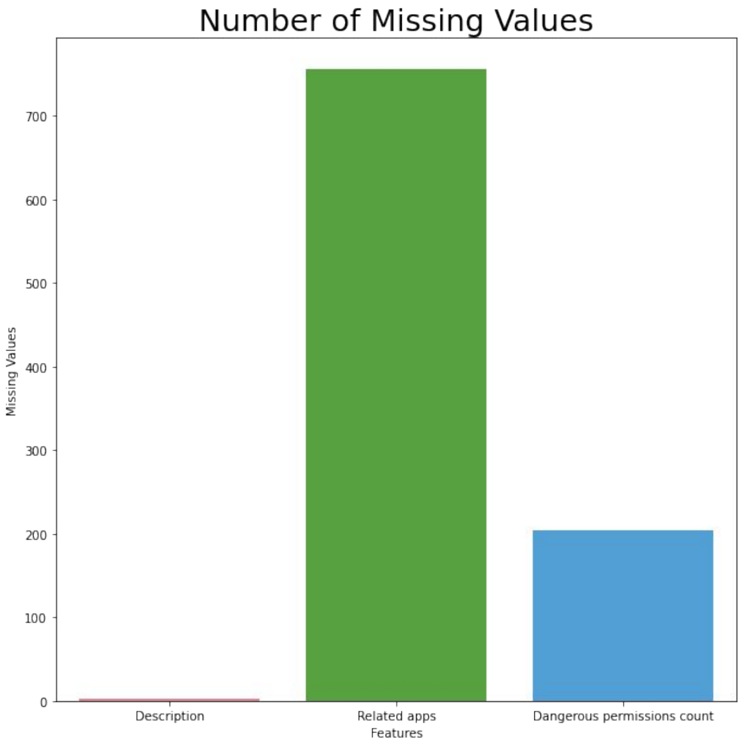
Handling Outliers

~~UN~~CLEAN DATA

- There are 2689 Duplicates (Class 0: 921, Class 1: 1768)

- Dropped Duplicates, Shape of data(after dropping): 27310,184

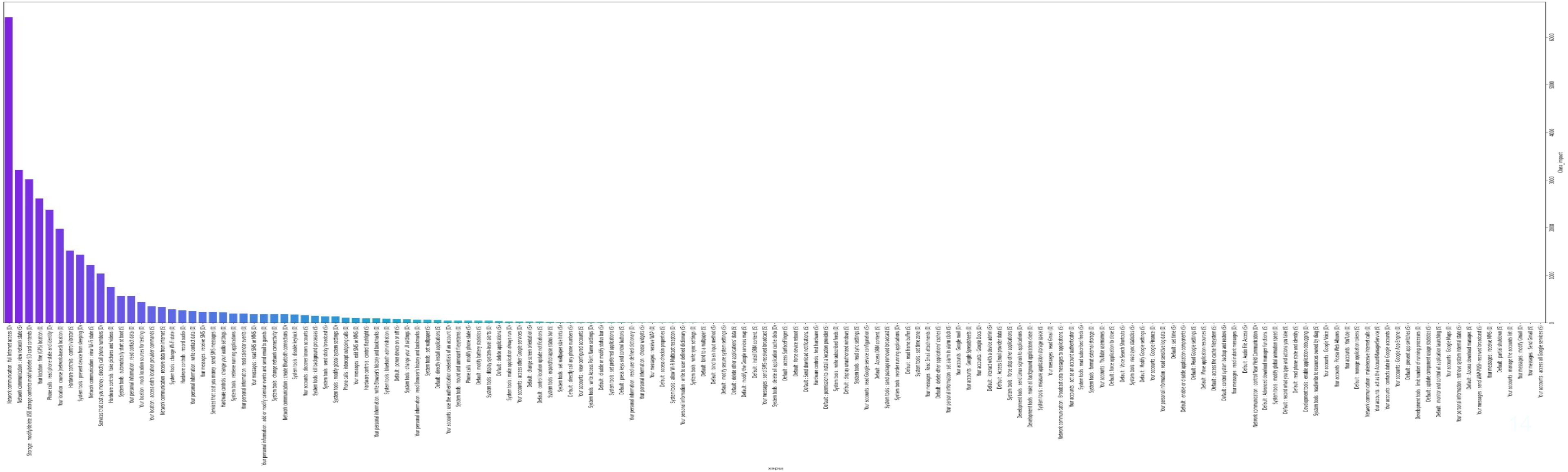
Handling Nulls!



- **Related Apps:** There are 720 null values in this column.
- We have used **Datawig imputer package** to impute values for Related apps.
- **Dangerous permission count :** There are 201 null values in this column. We had imputed them with the mean value of 3.

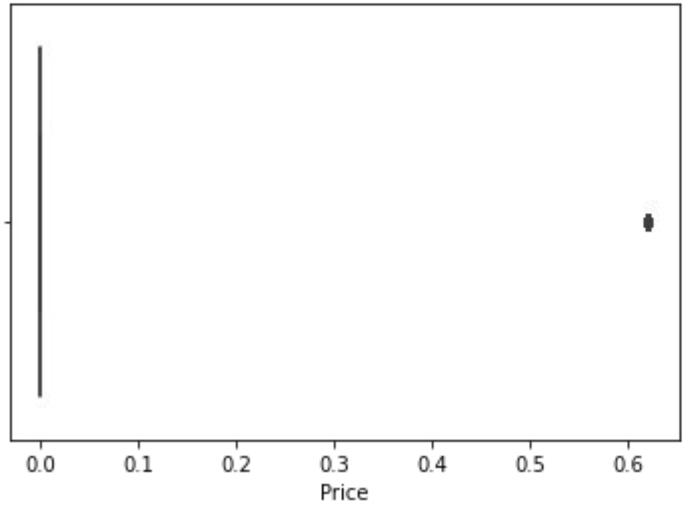
Handling Numerical Columns

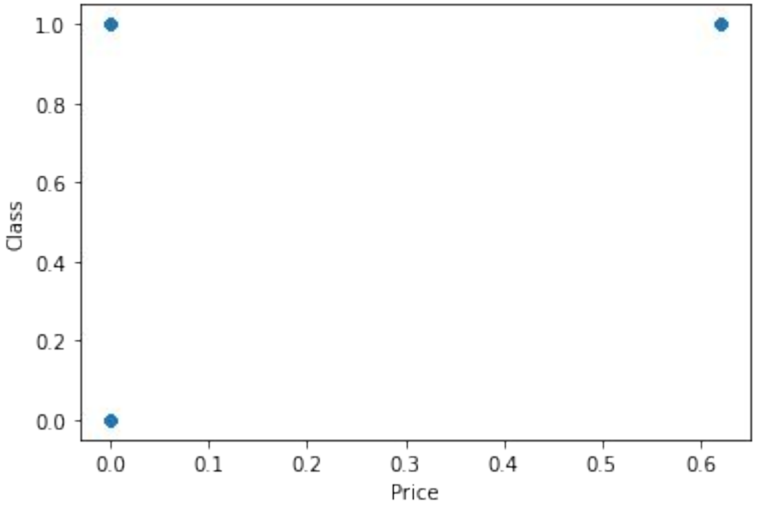
- There were 22 columns in which all the values are 0. So removed them as they are not impacting Target Class.



Handling Outliers

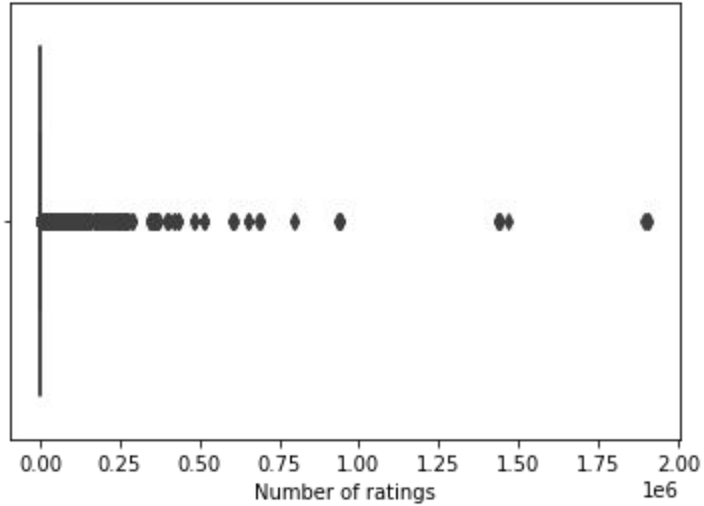
- We have outliers in **Price column** and **Number of Ratings** column.
- We handled outliers in Price by doing **Mean Encoding**.





Handling Outliers

- Number of ratings column

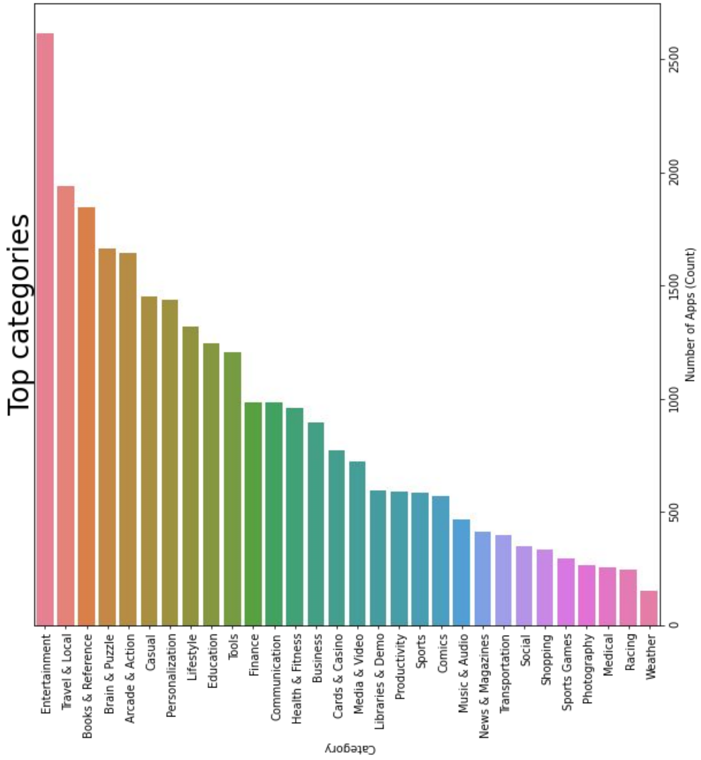


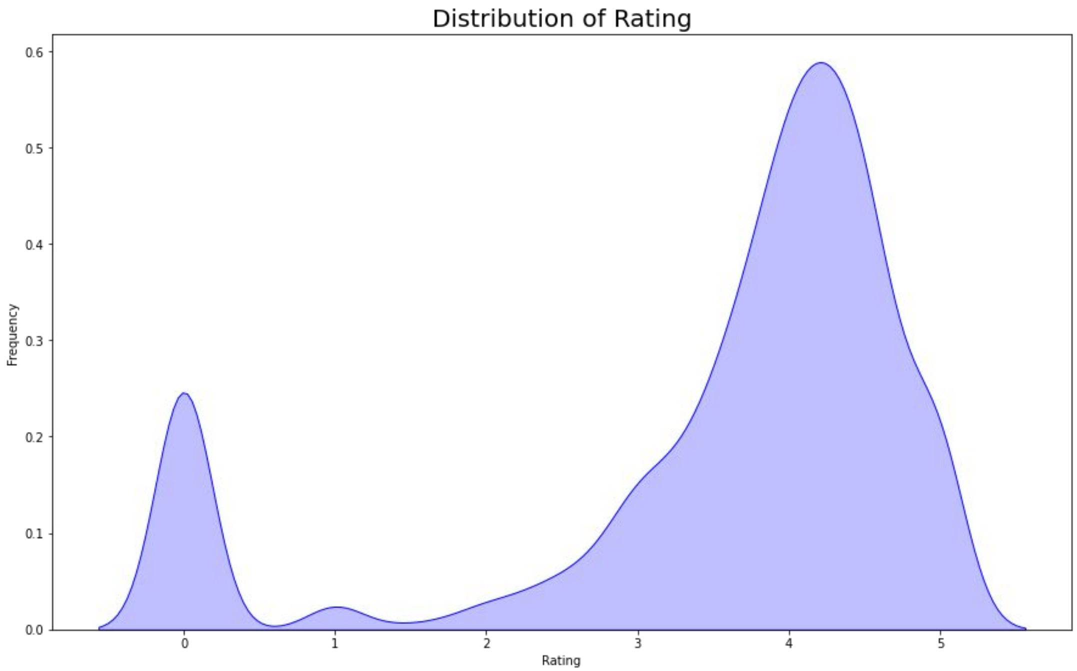
Mean Encoding

Category	
Arcade & Action	0.607453
Books & Reference	0.725370
Brain & Puzzle	0.635878
Business	0.448677
Cards & Casino	0.321226
Casual	0.487485
Comics	0.133333
Communication	0.477788
Education	0.609962
Entertainment	0.779625
Finance	0.493780
Health & Fitness	0.487476
Libraries & Demo	0.168576
Lifestyle	0.613937
Media & Video	0.475703
Medical	0.988889
Music & Audio	0.844485
News & Magazines	0.925000
Personalization	0.678454
Photography	0.885522
Productivity	0.834532
Racing	0.722222
Shopping	0.920200
Social	0.827068
Sports	0.963608

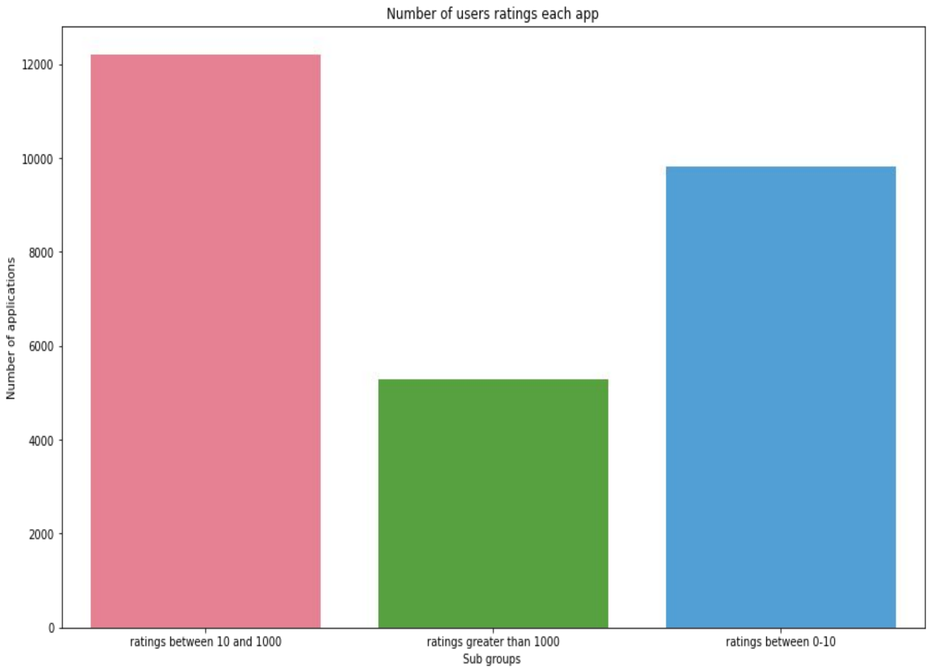
- We have "Category" column which is Categorical so we applied Mean encoding to convert each category into the respective mean.

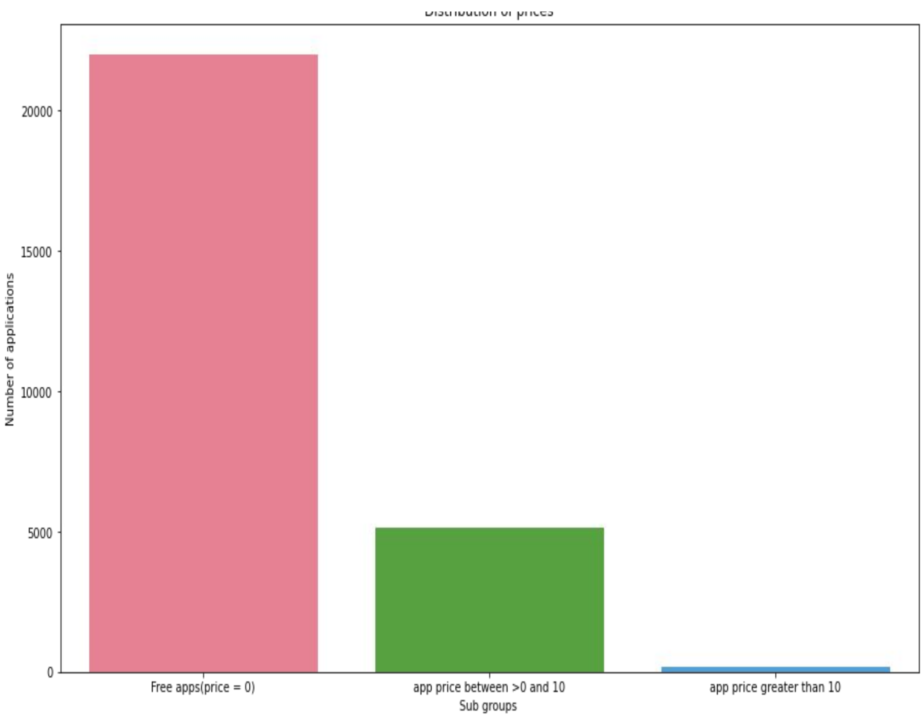
Exploratory Data Analysis



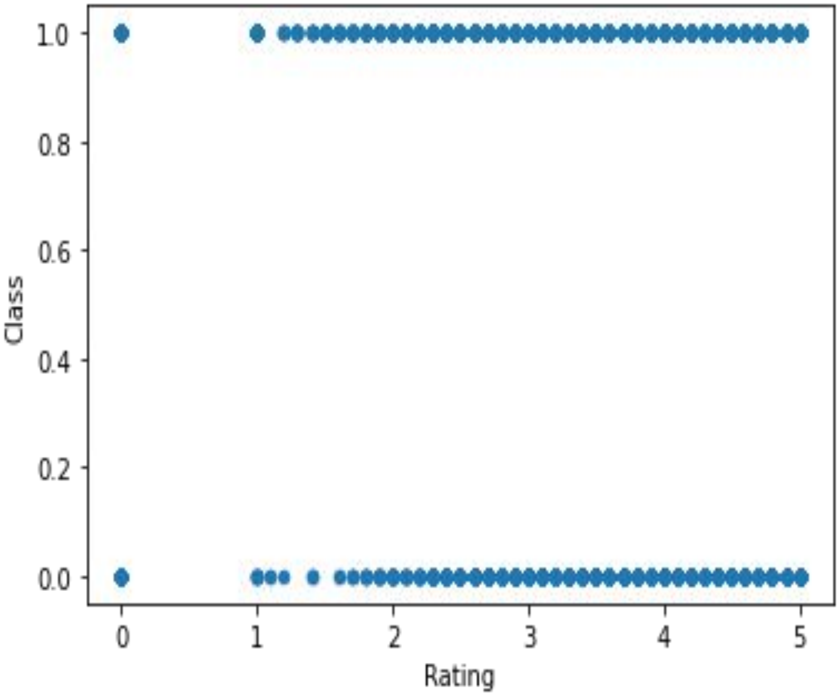


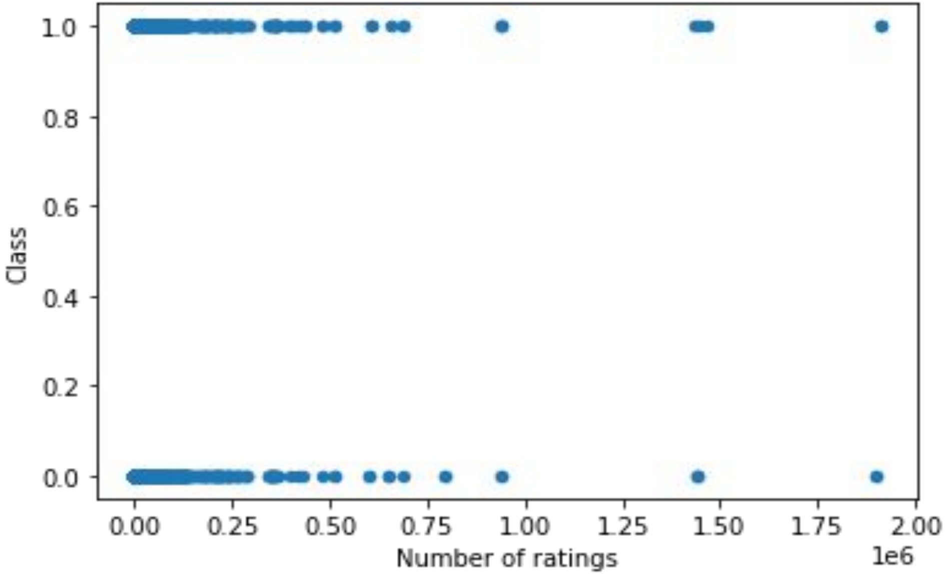
EDA (Continued..)



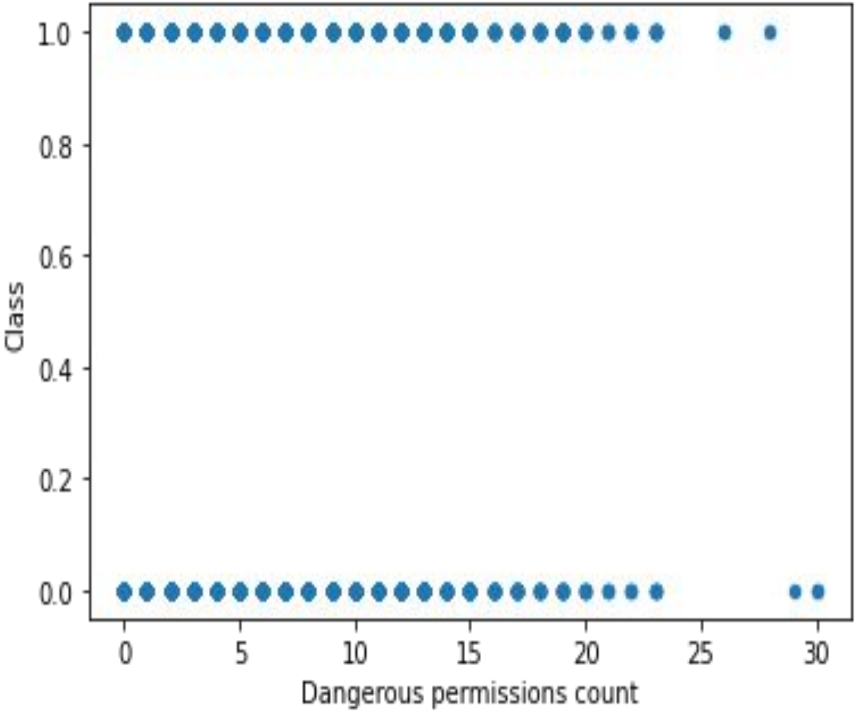


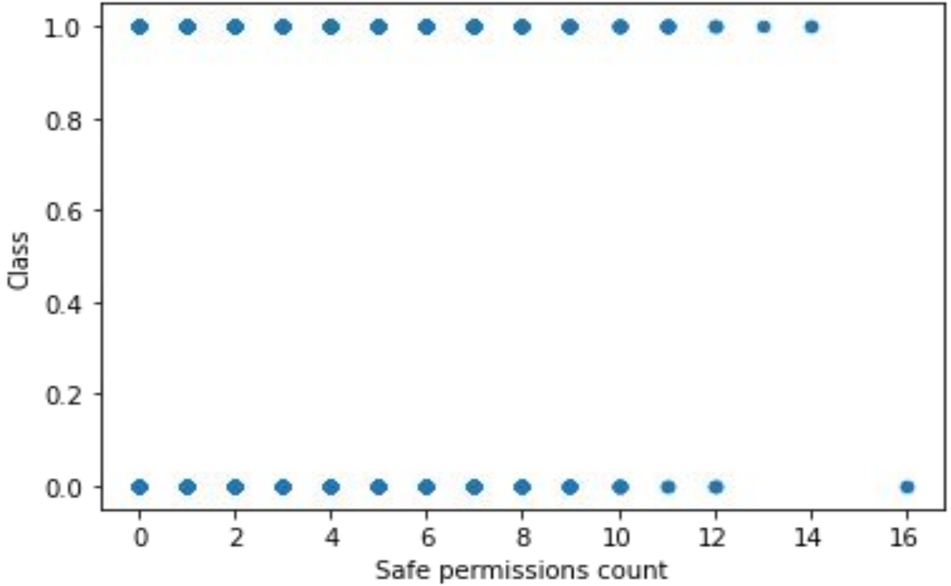
EDA (Continued..)



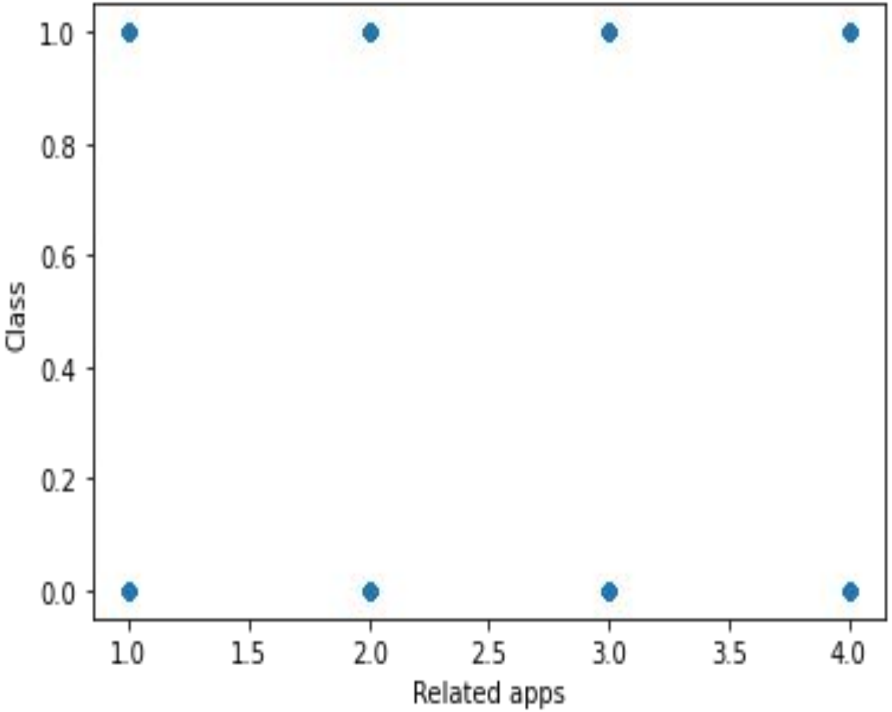


EDA (Continued..)



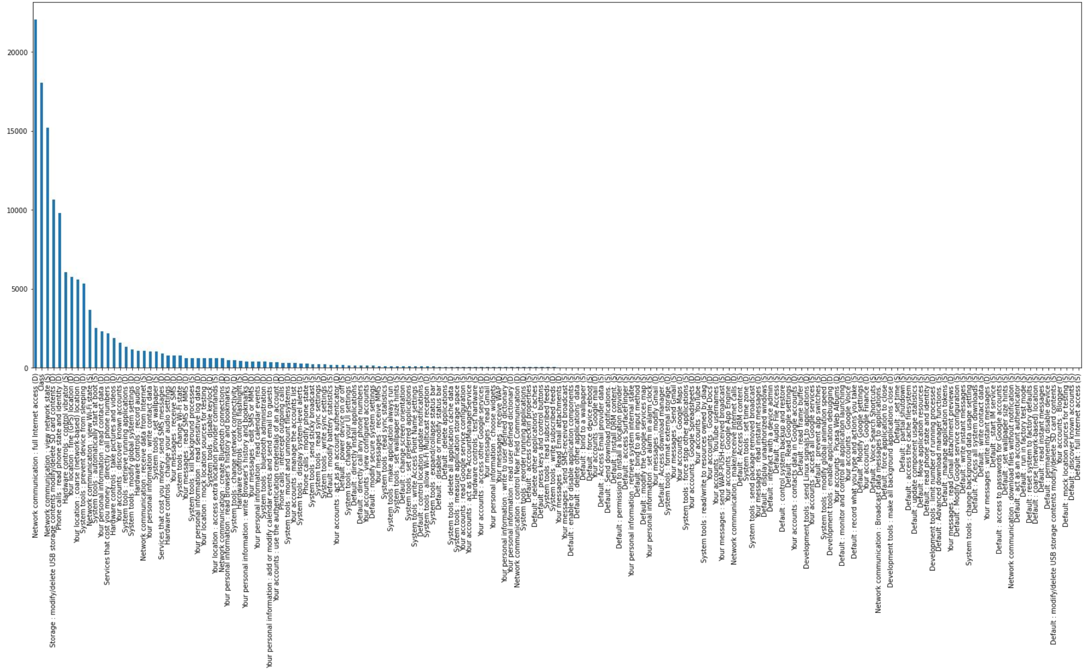


EDA (Continued..)



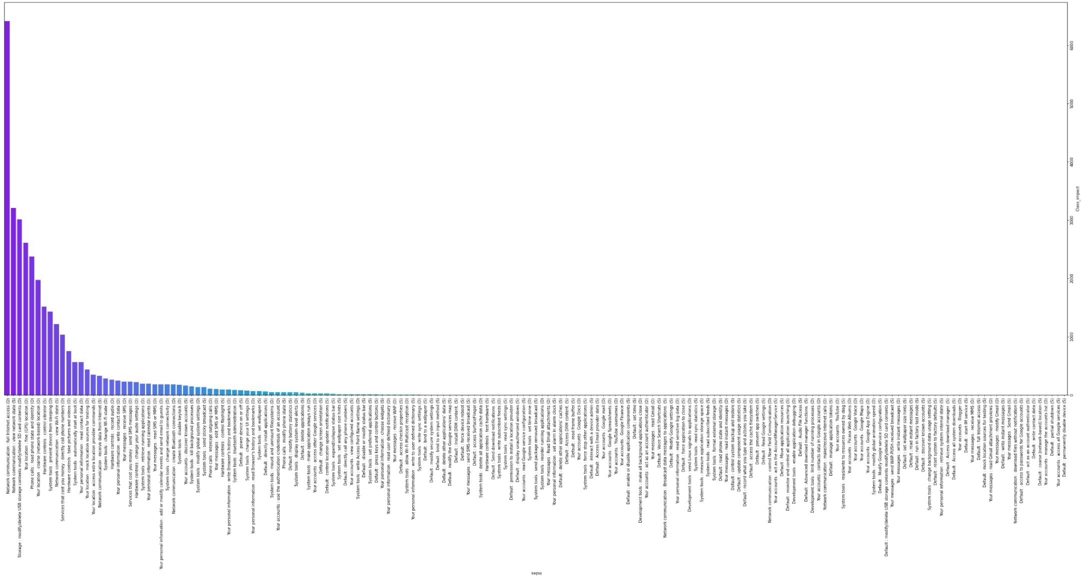
Correlation plot

Number of Apps per Permission



It can be seen from the graph that the permission count is huge overall but only **30%** of permissions are required by majority of apps.

Impact on Target Variable per Permission



It can be seen from graph there are few permissions out of total **173 permissions** which has impacted our target variable to a **malware** or **benign**.

permissions out of total 173 permissions which has impacted our target variable to a malware or benign.

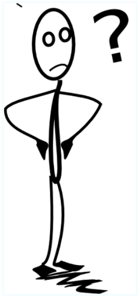
Playing around with Text Data!

Description

Minecraft Pocket Edition starts with a random stage. You'll find yourself on a chaotic land in the middle of the ocean, surrounded by mountains, valleys, trees, and animals. In survival mode, the target becomes more vital as the sun sets.

com.mojang.minecraftpe.demo

Can Text Columns be Significant?

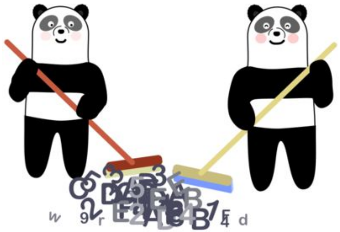


Let’s Clean them all!

```
df.isnull().sum().sort_values(ascending=False)
```

```
Related apps                                 720
Dangerous permissions count                  201
Description                                    3
App                                            1
Default : read phone state and identity (S)    0
                                             ...
```

__App__ Column: __1__ Missing Value
__Description__: __3__ missing values



	App	Package	Category	Description	Rating
18470	Comic Books	com.eddie.comic_reader	0.125000	NaN	3.6
21129	Stop Watch	dxp.nandalky.stopwatch	0.609977	NaN	3.5
26148	Pedometer ***NEW***	com.lexapps.pedometer	0.468815	NaN	3.0

```
df.at[18470,'Description'] = 'Comic Reader is a next-gen comic reader 
df.at[21129,'Description']= 'Stopwatch and Timer is a simple, easy and
df.at[26148,'Description'] = 'The best pedometer app and step counter 
```

__Description__ Column Text Cleaning!

Text Preprocessing!

1. CLEANING

- Description: Removed HTML tags
- Package: Separated words from APKs
- All Columns: Only characters selected by regex
- All words to lowercase
- Merged text columns

2. STOPWORDS

- Removed Stop words
- Normal english words & problem specific (app, android)

3. TOKENIZATION

- Splitted sentences to tokens
- Used word_tokenise from nltk

4. STEMMING

- Transformed words to roots
- Used Snowball Stemmer

Everybody stand back, I know regex expressions!

Time to Model..

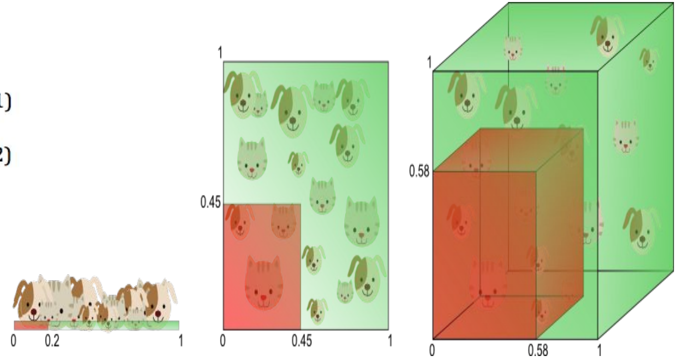
Vectorization | **Dimensionality Reduction** | **Classification Model** | **Evaluation & Insights**

TFIDF Vectorizer

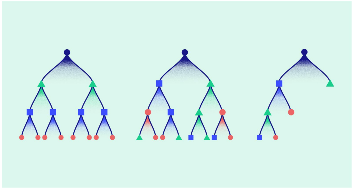
$$\text{tf-idf} = \text{tf} \times \text{idf} \quad (1)$$

$$\text{idf}(t) = \log\frac{n+1}{\text{df}(d,t)+1} + 1 \quad (2)$$

PCA

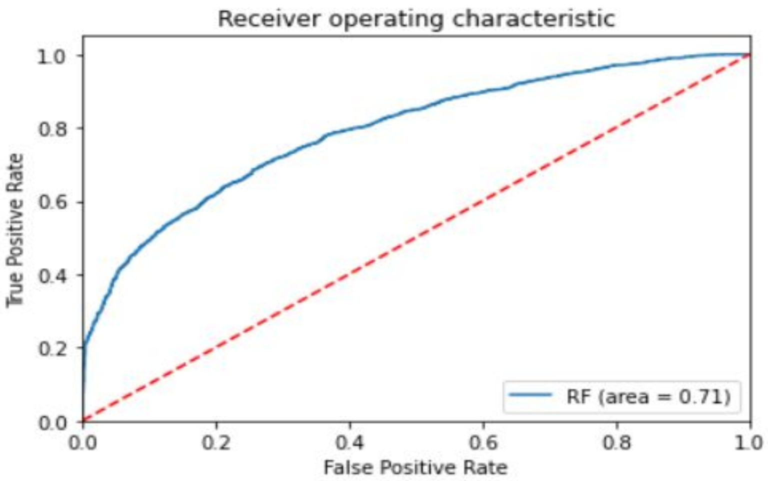


XGBoost via Bayes Search



What could we infer?

Evaluation & Insights: Surprised!



ROC Curve

	precision	recall	f1-score	support
0	0.56	0.72	0.63	1864
1	0.83	0.71	0.76	3598
accuracy			0.71	5462
macro avg	0.69	0.71	0.70	5462
weighted avg	0.74	0.71	0.72	5462

Classification Report

Definitely not bad for a text column based Prediction! Let's see…!

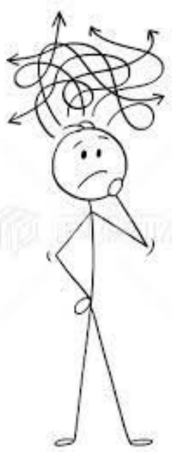
Should we or shouldn't we? -A Dilemma

Class	Derived_Prob_Text
0	0.651585
0	0.756145
0	0.365056
0	0.838322
0	0.921213
...	...
1	0.097495
0	0.810635
1	0.208205

Target Class and Derived text Column probability for the class

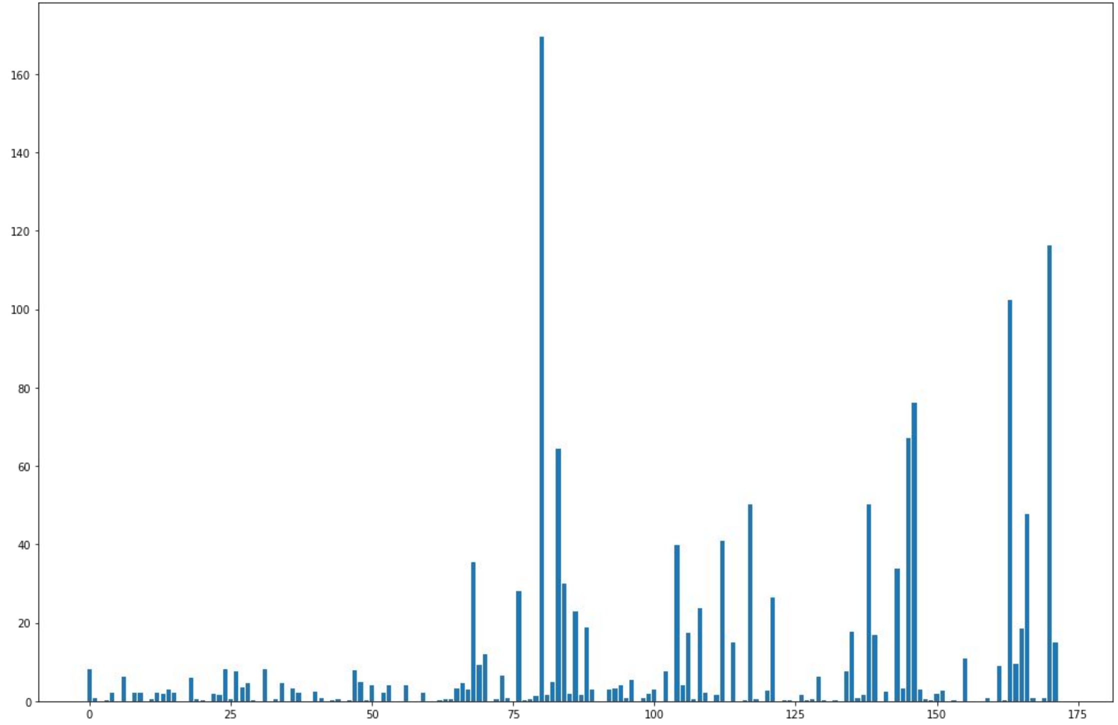
How about we have a derived column from NLP Model?

Let's use a probability score derived from the Best NLP Model for a class!



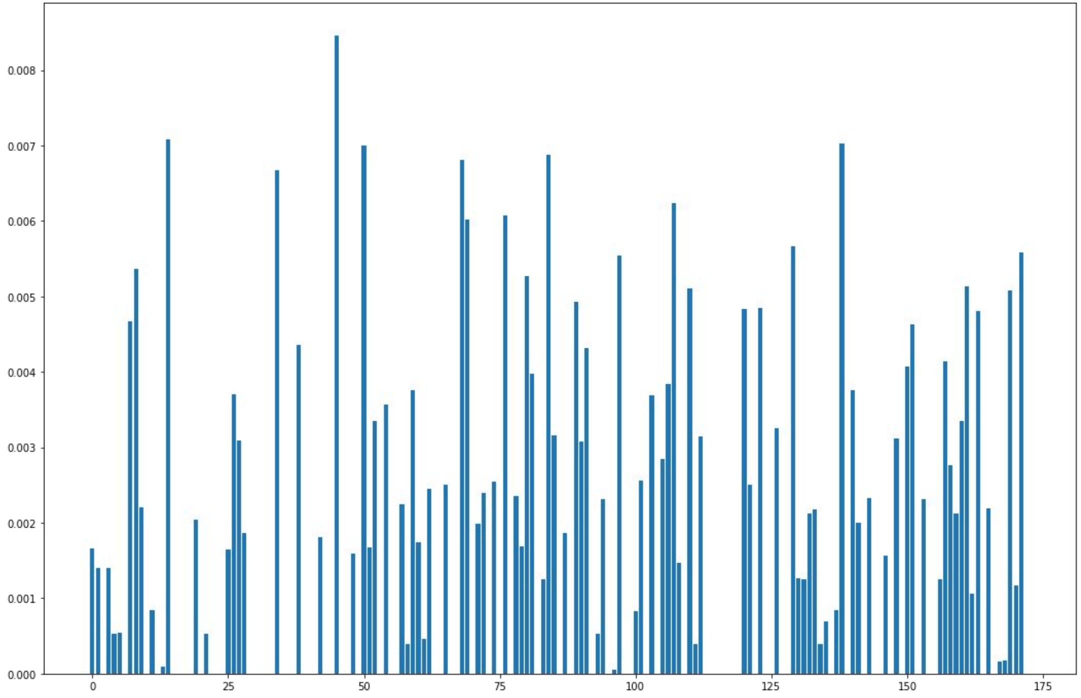
How about a Hybrid Model???

Mathematics to the rescue: 1. Chi-Square Feature Selection



Test for Using **Chi-Square test** for **binary categorical variable** we did **feature selection** for permission columns.

2. Mutual Information Feature Selection

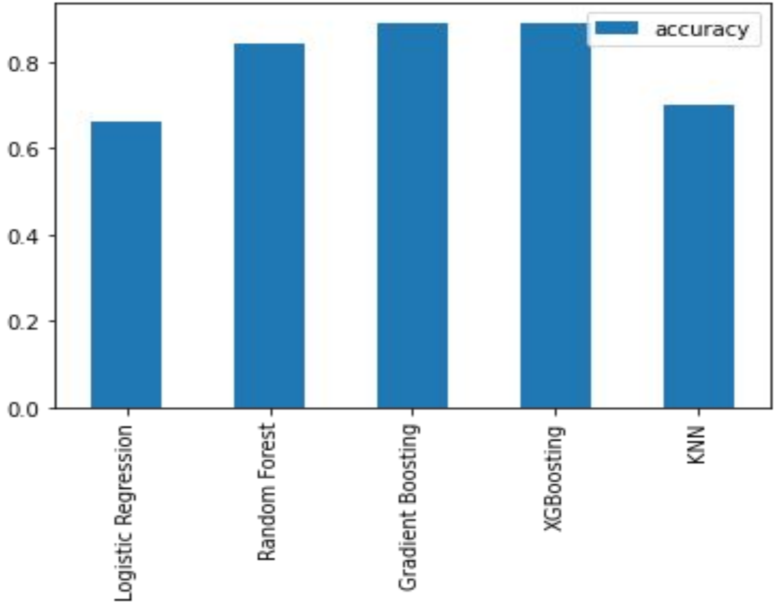


Feature selection for **permission columns** using **mutual information**.

Finally!

- **Text Columns ----> Probability Derived Column**
- **Permissions Columns**: Removed columns with **0 impact** on Target
- **Category ----> Mean Encoded**
- **Related App** -> **Count** of Related Apps
- **Price** -> Imputed for **mean price** (null values)
- **Number of Ratings**
- **Ratings**

Let's start Modelling!



Accuracy Comparison for Different Models

5 Models: XGBoost, Random Forest, GBM, Logistic Regression, KNN with and without Text Derived Columns

Best of all worlds!

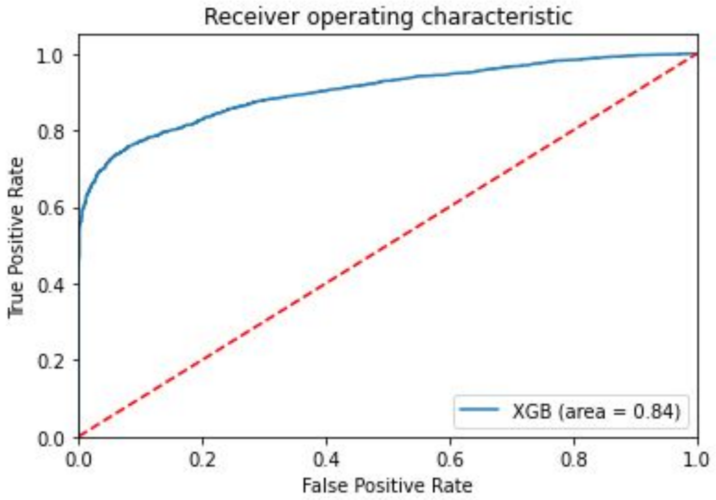
XGBoost: Hyper parameter tuning using Random Search CV

```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0,
              learning_rate=0.16777466758976015, max_delta_step=0, max_depth=2,
              min_child_weight=1, missing=None, n_estimators=160, n_jobs=1,
              nthread=None, objective='binary:logistic', random_state=0,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
              silent=None, subsample=1, verbosity=1)
```

Evaluation of Best Model Without Text Column

	precision	recall	f1-score	support
0	0.65	0.93	0.76	1832
1	0.95	0.75	0.84	3630
accuracy			0.81	5462
macro avg	0.80	0.84	0.80	5462
weighted avg	0.85	0.81	0.81	5462

Classification Report of XGB Without Text derived Column



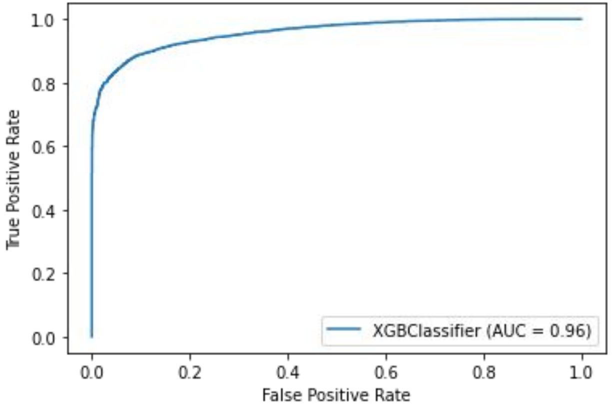
ROC Curve of XGB Without Text Derived Column

*So, does adding a new derived Column like **Text derived probability score** really make a difference?*

Surprise!Surprise!

	0	1
0	1936	340
1	404	4148

Confusion Matrix



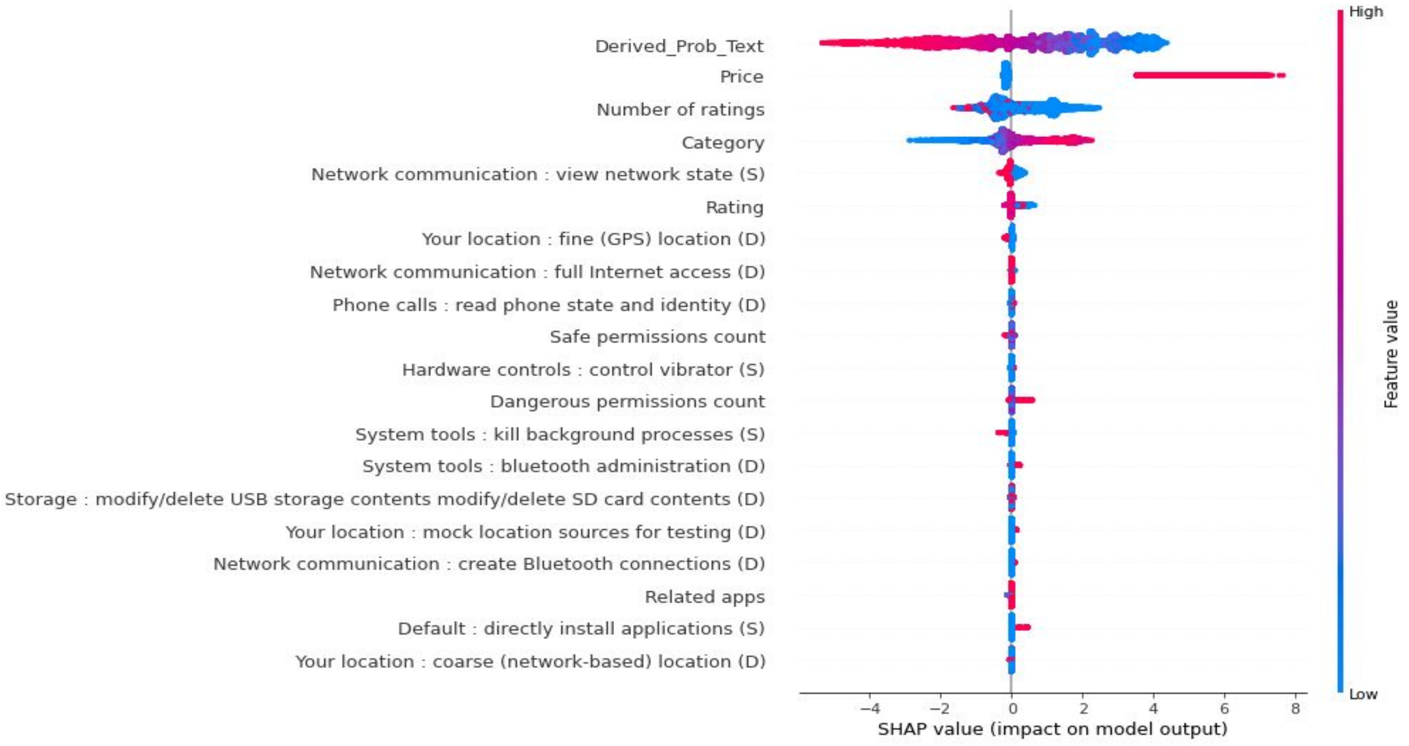
ROC Curve for XGBoost with Text Derived Column

	precision	recall	f1-score	support
0	0.83	0.85	0.84	2276
1	0.92	0.91	0.92	4552
accuracy			0.89	6828
macro avg	0.88	0.88	0.88	6828
weighted avg	0.89	0.89	0.89	6828

Classification Report

*Adding a **Text Derived Column** from NLP increased the overall F1 score from **81%** to **89%!***

What’s Important?



If only we had more time: Future Scope!

- **Individual probability** for each Text Column via NLP Modelling
- **Handling Outliers** well
- Deep Learning Using Transformers (BERT, RoBERTa etc.)
- Improve overall Accuracy of the model
- Deploy the Model on an App
- More Research on the Use Case and domain

Conclusion

- Performed **EDA** and **Cleaned Dataset**
- Univariate & multivariate **analysis**
- Visualised Data, inferred **insights**
- **NLP Model** for Text Column
- **Hybrid Model** : Power of NLP with XGBoost!
- Classified **92%** of Malware Apps & **82%** of Benign Apps!
- Identified Future Scopes

Suggestions

"Torture the data, and it will confess to anything."

-Ronald Coase, Nobel Prize winner

Together Everyone Achieves More!

Time for Q&A!!