Executive Summary

The ability to use services and products on the go has been a major leap in this century. Applications on the Google play store aim to do exactly that. Owing to worldwide accessibility and the ease of use, it has not only become the most popular application download destination but also a hotbed for competing services to attract and gain customers. This project aims to employ machine learning & visual analytics concepts to gain insights into how applications become successful and achieve high user ratings.

The dataset chosen for this project was from the popular data website Kaggle. It contains over 10k application data, capturing various details like category, reviews, installs, size, etc. The aim of the capstone project was to first generally visualize the distribution of the dataset across categories, identify correlations among the parameters and to then find an accurate machine learning model which could fairly accurately predict user ratings on any app when similar data is available. Seaborn & Matplotlib libraries of python were used to perform visualizations on python. Subsequently, four different machine learning models were used and trained on this data.

Visualizations indicated that the apps were broadly distributed across 33 distinct categories and that the family category was the most popular within this dataset. It also showed that the user ratings in the dataset were either 0 or mostly between 3.0 to 5.0. In the latter ratings interval the distribution roughly followed a normal distribution with the peak at approximate ratings of 4.5. Correlations among some major parameters were also visualized for the data. After initial visualizing and data processing, the goal was to create a machine learning model to predict user ratings. Four different models namely Multiple Linear Regression, Neural Networks, Decision Tree Regression, and Light Gradient Boosted Tree Model were created and they were trained on the available data. The LightGBM model predicted user ratings with the least error rates and much better when compared to the other machine learning models. Finally the important parameters responsible for predicting were identified. It was highly enlightening to see that the size of an application had the highest say in user ratings followed by the more obvious presence of many user reviews.

The capstone project helped to answer various questions about the data with regards to the distribution of the data, which model to use for rating predictions and finally which parameters affected the ratings. The approach adopted in the project can easily be scaled for huge similar datasets and when implemented correctly can provide an insightful advantage over the competition in the market.

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1. INTRODUCTION

Dataset Link : https://www.kaggle.com/lava18/google-play-store-apps

Publish Date: April 22 , 2018

Data Type: Web scraped data of 10k Play Store apps for analyzing the Android market.

Prediction Models: App 'Rating' prediction utilizing Neural Network, Decision Tree, Gradient Boosted Decision trees, and Linear regression models

Parameters: The models are compared based on mean absolute error (MAE), Mean square Error(MSE), Root mean square error (RMSE), on test data set.

With over 3.5 Million applications on it, the Google Play Store boasts of being the most widely utilized location for application downloads. The App making business is highly competitive and any actionable insights into the factors promoting an Apps's success is vital.

The sample dataset on Kaggle is a subset of the google playstore . It contains information about 10,000 applications across 33 broad categories like gaming, productivity, family, etc. The data provides information about the respective sizes, downloads, reviews, category etc. of the app. Upon initial analysis it becomes clear that some of these factors definitely have a role to play in an app's rating and performance.

User Rating was narrowed down to be the focus target of this project. The main reason underlying this selection was that the average user rating can be perceived as a reflection of the general sentiment towards the app. This almost eventually materializes into Installs and increased usage. Additionally, App store ratings are crucial to discovery, downloads, and in-app purchases. They're an integral part of the search ranking algorithm in both Apple's App Store and Android's Play Store. (https://testlio.com/blog/app-ratings-matter-increase/) Lower ranked Applications are usually penalized and removed from the store.

This project done on this dataset utilizes 4 different prediction models to predict user rating. These are Neural Networks, Decision Trees, Gradient Boosted Decision trees, and Linear regression models. Prior to running the prediction models the important task of data cleaning & detecting outliers was performed. This was followed by a few data visualization insights to better understand the data.

1.2 QUESTIONS AND FINDINGS

How many categories of applications are covered in this Dataset?

What is a good model to predict User Rating?

Which parameters affect the ratings the most?

1.3 DATA DESCRIPTION

Google Play Store uses sophisticated modern-day techniques (like dynamic page load) using JQuery making scraping more challenging. Each app (row) has values for category, rating, size, and more. This information is scraped from the Google Play Store.

The different data fields in the dataset are as follows:

App: The name of the application

Category: The category to which the app belongs

Rating: User rating of the app when scraping was done

Reviews: Number of user reviews for the app

Size: Size of the app

Installs: Number of user downloads/installs for the app

Type: A binary variable which dentoes whether a

Price: The cost of the app in US Dollars

Content Rating: Age group the app is targeted at - Children / Mature 21+ / Adult

Genres: An app can belong to multiple genres (apart from its main category). For eg, a musical family game will belong to Music, Game, Family genres.

Last Updated: Date when the app was last updated on Play Store

Current Version: Current version of the app available on Play Store

Android Version: Min required Android version

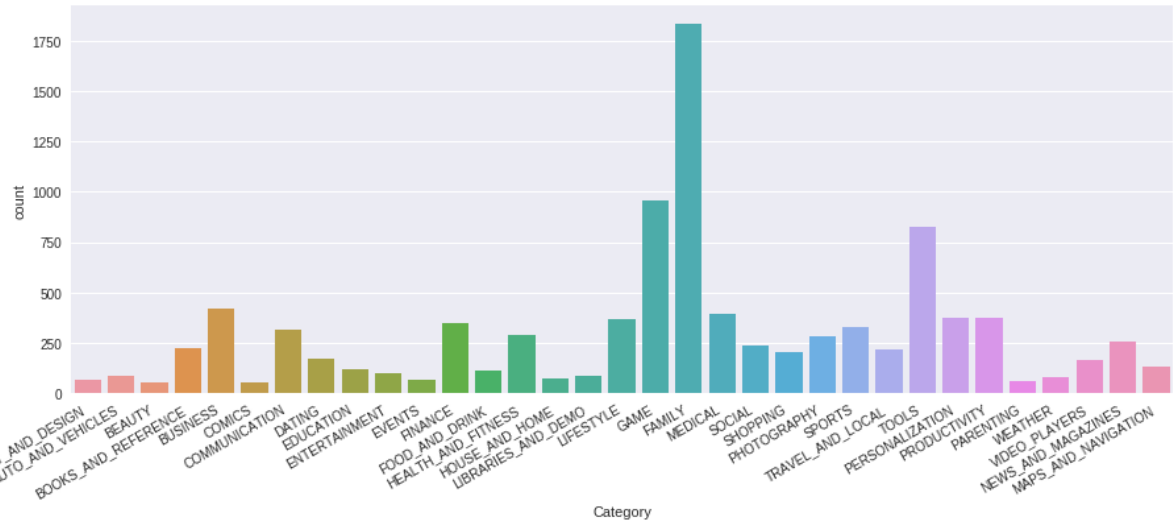
In total there are 13 attributes and 10841 Records in the original raw dataset. Each row corresponds to a single application and its performance across the 13 parameters. The 12 other attributes were used to predict “Rating” which is the user rating, where 5.0 is the maximum and 0 corresponds to the minimum user rating for the app.

2. Data Preparation & Exploratory Analysis

The first step in this process was to detect duplicate rows and extreme records with missing values. These create problems during prediction and hence were removed.

Upon removing duplicates and outliers using the ‘ drop_duplicates’ function and removing a single incomplete record the total number of clean records in the data set was 9659. This indicated that approximatel 10% of the raw data set was duplicated and had to be removed.

To get an overall picture of the dataset and how the different apps are present across different categories a categorical count plot was created using the python seaborn package. The image is as below:

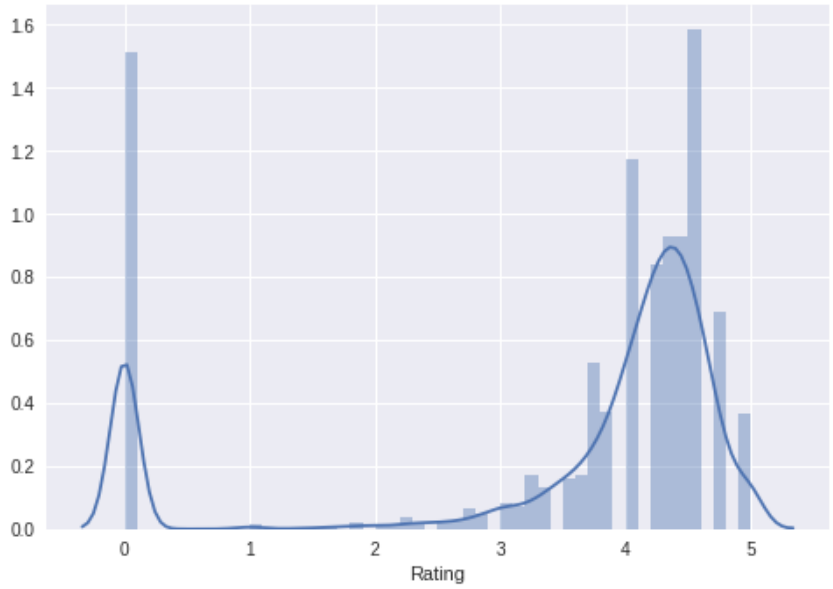


From the above analysis it was seen that the top 10 categories that the apps belonged to were as follows:

	Category	Count
11	FAMILY	1832
14	GAME	959
29	TOOLS	827
4	BUSINESS	420
20	MEDICAL	395
23	PERSONALIZATION	376
25	PRODUCTIVITY	374
18	LIFESTYLE	369
12	FINANCE	345
28	SPORTS	325

The top three categories Family, Game, and Tools nearly accounted for more than 30% of the data.

The next visualization was to get an idea of how the prediction variable 'Rating' was distributed across the data. This was found by creating a distribution plot using the seaborn package.



The above analysis yielded the insight that apart from the 0 rated app's the distribution was a type of a normal distribution from 3.0 to 5.0 with the average peak being somewhere close to 4.5.

A correlation matrix was then created to find the relationship between the numerical variables namely Rating, Reviews, Size, Installs, and Price. This correlation plot can be seen below:

An interesting point that could be inferred from the above analysis was that the variables Installs and Reviews are fairly correlated which makes sense as because the usage of the app increases the number of reviews also increases.

Preparation involves the proper selection and conversion of the predictor variables into numerical values which facilitates much more accurate predictions. The head of the dataset will give a better indication of this.

	App	Category	Rating	Reviews	Size	Installs	Type	Price	Content Rating	Genres	Last Updated	Current Ver	Android Ver
0	Photo Editor & Candy Camera & Grid & ScrapBook	ART_AND_DESIGN	4.1	159	19M	10,000+	Free	0	Everyone	Art & Design	January 7, 2018	1.0.0	4.0.3 and up
1	Coloring book moana	ART_AND_DESIGN	3.9	967	14M	500,000+	Free	0	Everyone	Art & Design;Pretend Play	January 15, 2018	2.0.0	4.0.3 and up
2	U Launcher Lite – FREE Live Cool Themes, Hide ...	ART_AND_DESIGN	4.7	87510	8.7M	5,000,000+	Free	0	Everyone	Art & Design	August 1, 2018	1.2.4	4.0.3 and up
3	Sketch - Draw & Paint	ART_AND_DESIGN	4.5	215644	25M	50,000,000+	Free	0	Teen	Art & Design	June 8, 2018	Varies with device	4.2 and up
4	Pixel Draw - Number Art Coloring Book	ART_AND_DESIGN	4.3	967	2.8M	100,000+	Free	0	Everyone	Art & Design;Creativity	June 20, 2018	1.1	4.4 and up

The initial categories were first looked at from a logical standpoint to judge whether they are useful predictors. This procedure yielded the removal of the categories app's name, genres, last updated and, current version.

So the main predictors were of two types:

- **Categorical Predictors:** Category, Type, Content Rating, Android Ver
- **Numerical Predictors:** Reviews, Size, Installs, Price

Creating dummy variables was the next step to create binary categories from the 4 categorical predictors. This increased the total predictor variables to 76. Minor changes were made to convert the numerical predictors to purely numerical columns. These involved removing the 'M' from the size column, The '+' sign from the Installs category and a complete conversion of these categories to the float data type. Similarly the prediction variable 'Rating' was also converted to the float format.

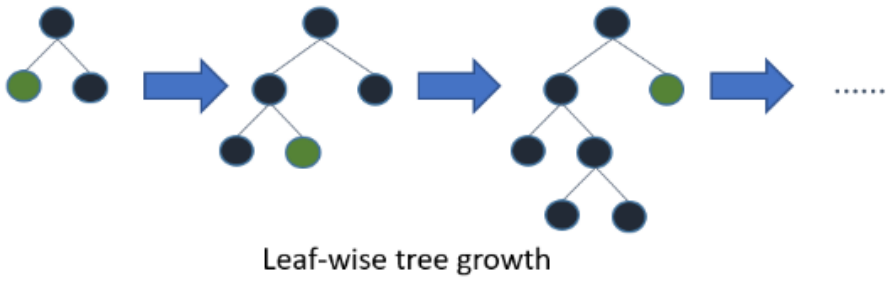
3. Prediction Models

Four powerful and widely used machine learning models were implemented to make 'Rating' predictions for the various apps. They are as follows:

- **Multiple Linear Regression:**Multiple linear regression tries to model the relationship between the predictor variables and the response variable 'Rating' by fitting a linear equation to the observed data. (http://www.stat.yale.edu/Courses/1997-98/101/linmult.htm)
- **Decision Tree Regression:** It decomposes a dataset into a series of smaller subsets while simultaneously developing an associated decision tree incrementally. The final result is a tree with decision nodes and leaf nodes which grows level wise. (https://www.saedsayad.com/decision_tree_reg.htm)

(source: analyticsvidhya.com, 2017)

- **Deep Learning Neural Network:** A computing system made up of a number of simple, highly interconnected processing elements, which process information by their dynamic state response to external inputs. (http://pages.cs.wisc.edu/~bolo/shipyard/neural/local.html)
- **Light Gradient Boosted Model (LightGBM):** Light GBM is a high-performance gradient boosting framework based on classical decision trees. The model splits the tree leaf wise instead of splitting trees depth wise or level wise as implemented in other boosting algorithms.



(source: analyticsvidhya.com, 2017)

3.1 Model Creation and Implementation of regression models

In creating the model the most basic step to split the data into 4 different and random sets is vital. The data was split into the following :

- **X_train** - Predictor Variables for training
- **y_train** - Target variable for training
- **X_test** - Known predictor Variables for testing
- **y_test** - Target variable for testing

To summarize the original dataset was split into a training dataset and testing dataset using a 70% - 30% split. The train_test_split functionality from the sklearn library was used to perform this action. The small code snippet to perform this split can be seen below

```
from sklearn.model_selection import train_test_split as ts
X_train, X_test, y_train, y_test = ts(preproc_data, target, test_size=0.3, random_state=101)
```

From the sklearn library the two regressors LinearRegression, and Decision Tree Regressor were imported and the data was fit into these regressors. Two code snippets showing this process can be seen below:

- Multiple Linear Regression:

```
[48]  from sklearn.linear_model import LinearRegression
      lr = LinearRegression()
      lr.fit(X_train,y_train)
```

- Decision Tree:

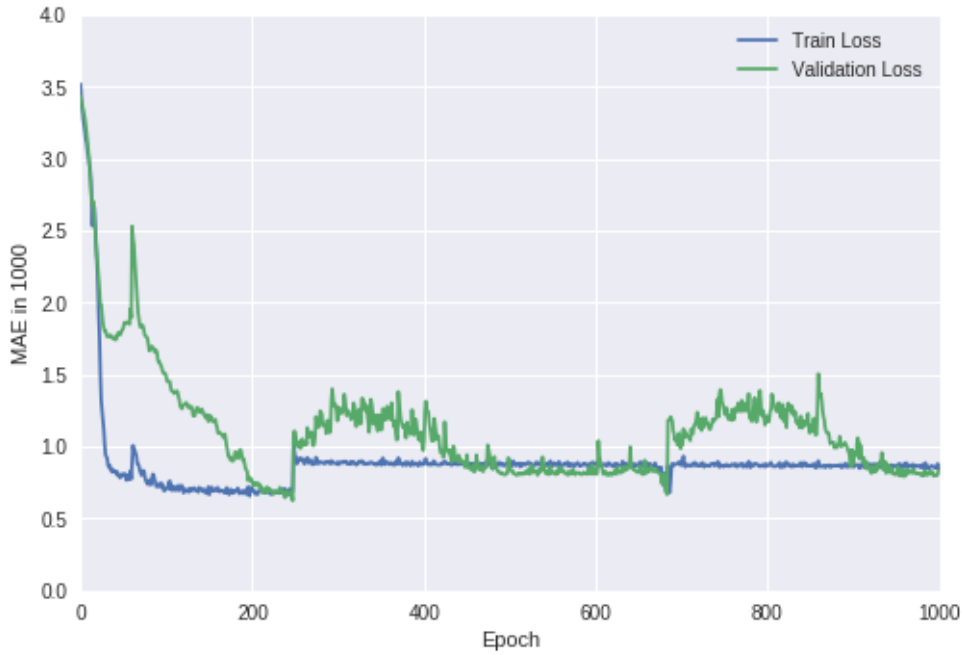
```
[50]  #Decision Tree Model
      from sklearn.tree import DecisionTreeRegressor
      dt = DecisionTreeRegressor()
      #Fitting
      dt.fit(X_train,y_train)
```

3.2 Deep Learning Neural Network Model

The Keras API was used to create a neural network model with 3 Dense input layers and 1 output layer with 64, 32,16, and 1 nodes respectively. Two Batch normalisation layers were inserted to increase the chances of smoothening of the error curve. The Adam optimizer was used in compiling the model .The model creation and its layers can be seen below:

Layer (type)	Output Shape	Param #
dense_16 (Dense)	(None, 64)	4928
dense_17 (Dense)	(None, 32)	2080
batch_normalization_v1_8 (Ba	(None, 32)	128
dense_18 (Dense)	(None, 16)	528
batch_normalization_v1_9 (Ba	(None, 16)	64
dense_19 (Dense)	(None, 1)	17

The model was run for 1000 iterations(epochs) which shows how the neural network gradually learns to predict the 'Rating' eventually predicting with a low mean absolute error of 0.8. The following graph shows this :



3.3 Light Gradient Boosted Model (LightGBM)

The model which predicted the best was the Light Gradient Boosted Model (LightGBM) model. Considering the model's efficiency and speed the Light GBM was implemented on the dataset. It requires and mostly relies on the correct parameter tuning of the learning rate and the number of leaves.

The model is structured as below:

```
import lightgbm as lgb

param = {'learning_rate': 0.1, 'boosting_type': 'gbdt', 'num_leaves':25,
         'nthread':4, 'num_trees':100, 'objective': 'regression',
         'metric':'mse'}
```

Gridsearchcv method was used to find the optimal parameters for learning rate and number of leaves. LGBM provided the least error parameters with a learning rate of 0.1 and number of leaves at 25.

3.4 Model Comparison

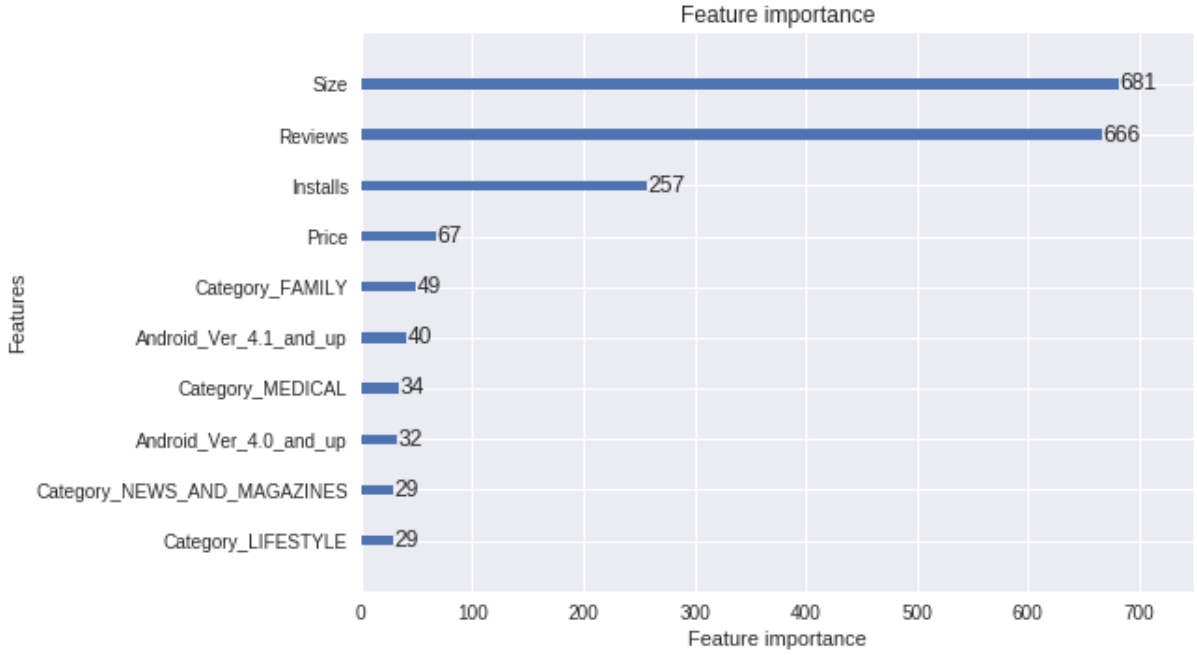
All the four above models were compared based on three parameters MAE(Mean Absolute Error), MSE(Mean Squared Error), RMSE(Root mean Squared Error). The comparison table can be found below:

	MAE	MSE	RMSE
Multiple Linear Regression	1.147578	2.425740	1.557479
Neural Networks	0.833658	2.224392	1.491440
Decision Tree Regression	0.767805	2.184993	1.478172
Light Gradient Boosted Model	0.623170	1.065379	1.032172

The Light Gradient Boosted Model provided the best results with MAE, MSE, and RMSE values as 0.62, 1.06, and 1.03 respectively.

4. Conclusion

The LightGBM model can be an excellent starting point to predict ratings for additional apps given the categories used in the model. To further analyze the insights provided the model the feature importance function of the model was implemented. This gave an interesting insight on which parameters helped the model to predict rating with low errors. This can be better understood by the following figure



The above analysis shows that from the current dataset it can be inferred that the variables Size, and Reviews are affecting the predictions the most. This capstone project thus gives a broad overview of how the data set was distributed across 33 categories of apps. It also shows how the LightGBM model predicted the 'Rating' variable with very low errors. The predictions for ratings can be further improved by gathering more data and arriving at more variables than currently available. Furthermore normalizing the entire predictor variable dataset can also help in arriving at more accurate predictions.

The approach adopted for this project is extremely flexible and can be scaled to accommodate huge datasets and many more predictor variables. Utilizing the methods in the project can thus predict user ratings beforehand, and vitally help in achieving a good competitive advantage in the tough Google Play Store market space.