Contents

0.0 Dataset

0.1 Source

[Google Play Store Apps | Kaggle]

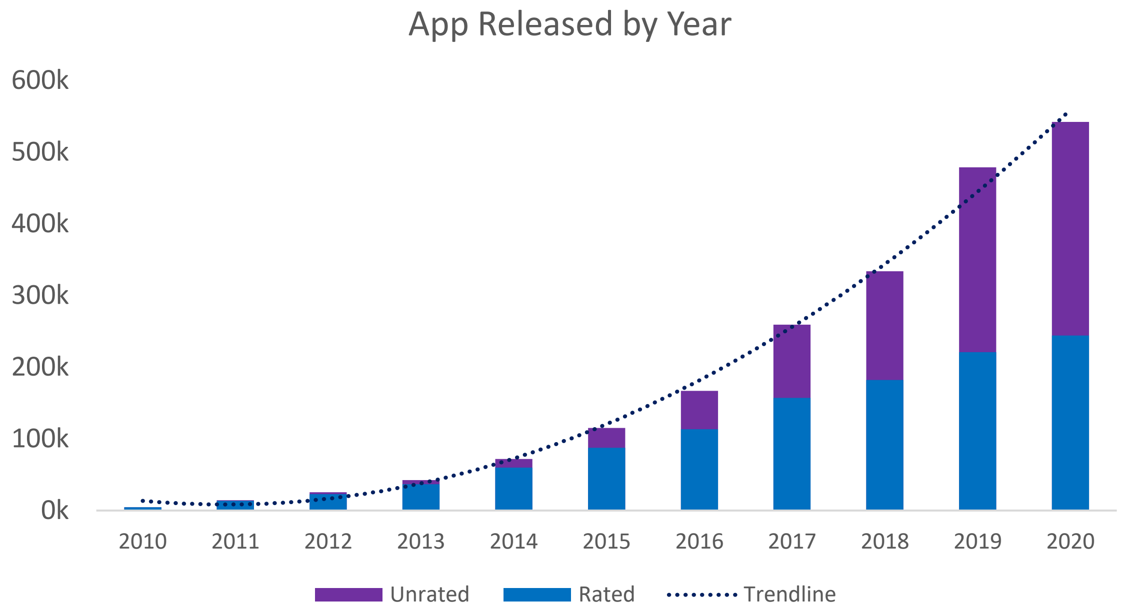
0.2 Variables

Contains data of 600k+ Google Play Store Android App. The data was updated on June 2021. It as 2.3 million+ rows and 24 columns/attributes. The following attributes are present. Not all of the attributes were used for data analysis.

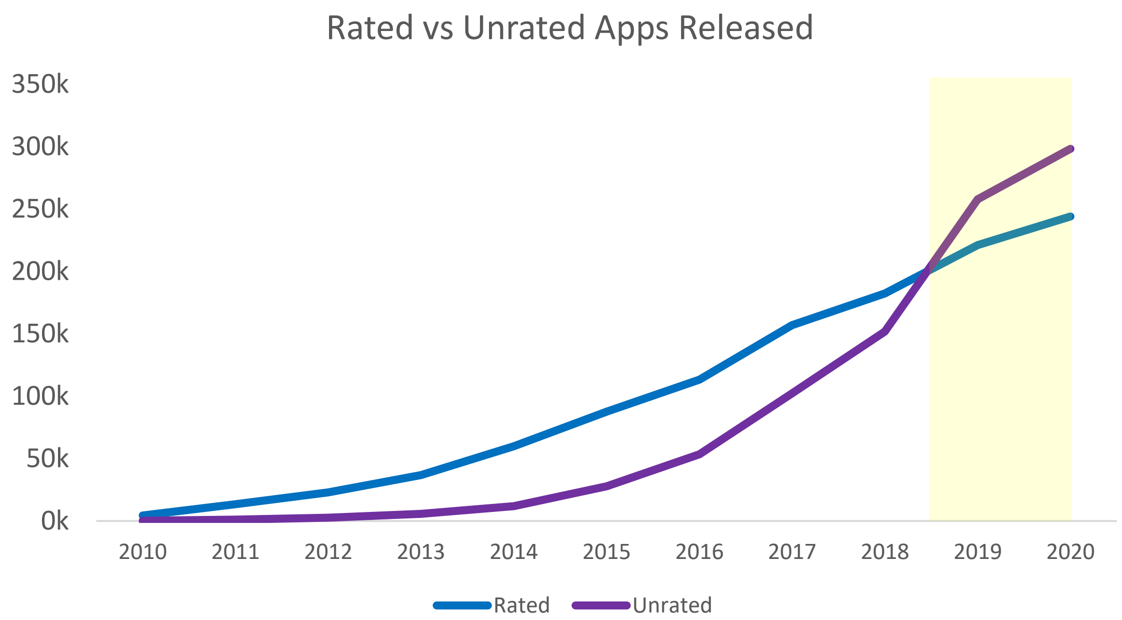
<table>
<tr><th>Time/Period</th><th>Nominal Variables</th><th>Categorical Variables</th><th>Numerical Variables</th></tr>
<tr><td>Released</td><td>App Id</td><td>Category</td><td>Installs</td></tr>
<tr><td rowspan="8">Last Updated</td><td>App Name</td><td>Minimum Installs</td><td>Maximum Installs</td></tr>
<tr><td>Developer Id</td><td>Currency</td><td>Price</td></tr>
<tr><td>Developer Website</td><td>Minimum Android</td><td>Rating Count</td></tr>
<tr><td>Privacy Policy</td><td>Content Rating</td><td rowspan="4">Size</td></tr>
<tr><td rowspan="4">Developer Email</td><td>Ad Supported</td></tr>
<tr><td>In app purchases</td></tr>
<tr><td>Editor Choice</td></tr>
<tr><td colspan="2">Rating</td></tr>
</table>

1.0 Exploratory Data Visualization

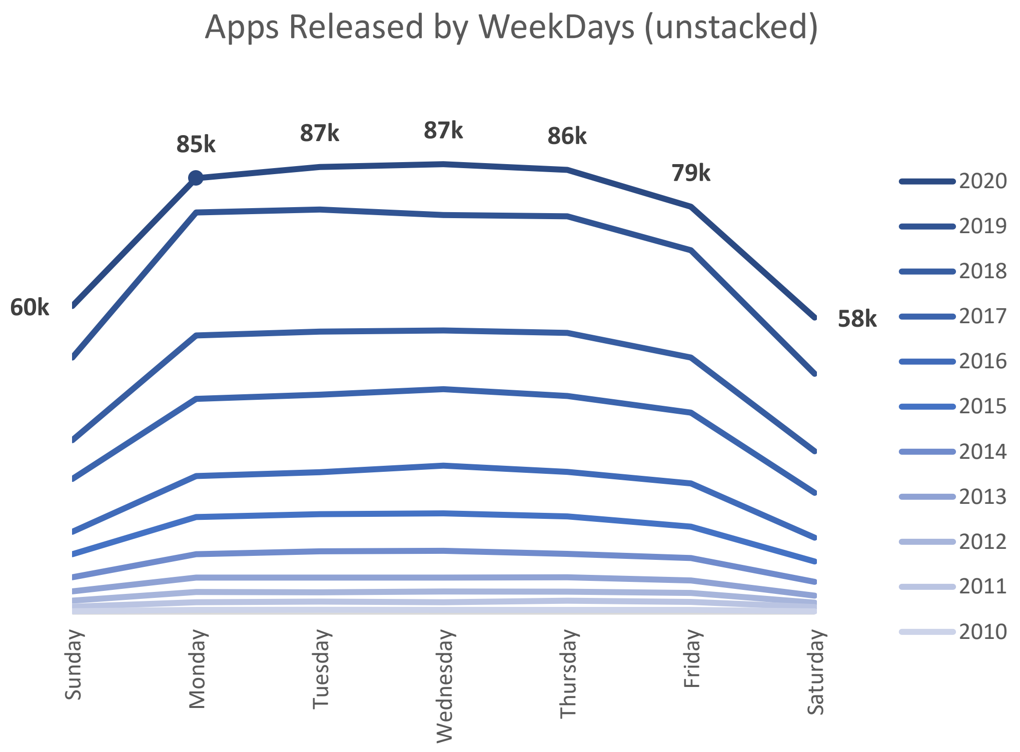
1.1 App Release Pattern



Insights: The total number of apps released have increased at an increasing rate. We can expect more apps to be released in the coming years based on the pattern.

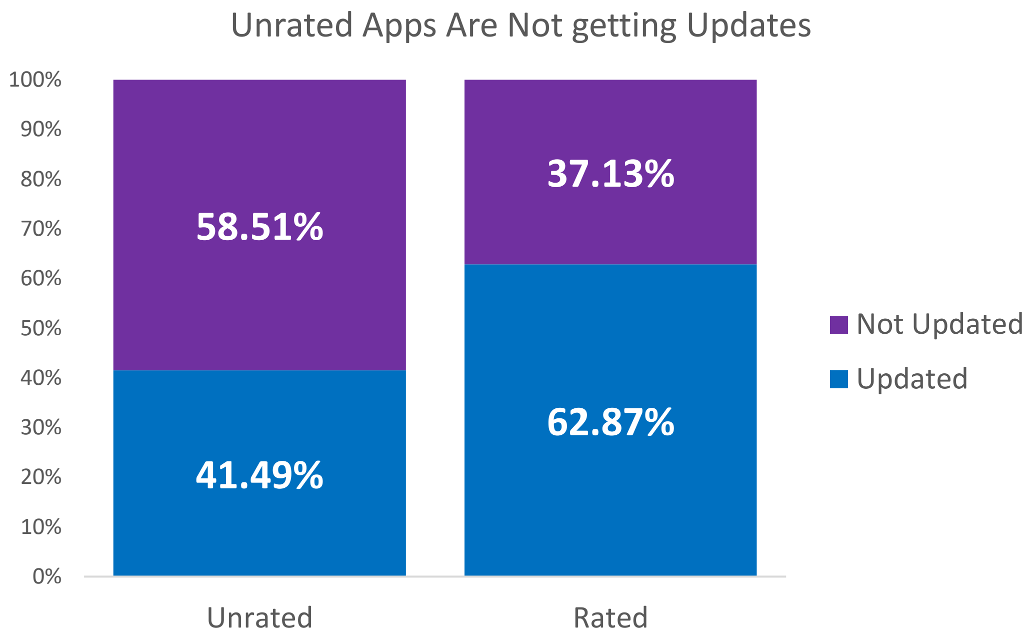


Insights: However, unrated apps have increased at a faster rate than rated apps. Although, the proportion of unrated apps was very low in the first few years of play store, the number of unrated apps was greater than rated ones by 2019.



Insights: Less apps are released on the weekends comparatively. This pattern has been seen on every year. Furthermore, the rate of releases seems to increase till Wednesday, before starting to drop again.

1.2 Updating Apps



Insights: When an app is not rated there is around 60% chance that it was not updated in the future. In the case of rated apps, 60% get updated eventually. (*in making the chart, apps released till 2019 were taken, as apps released later might not have gotten time to get updated*)

1.3 Ad placement in Apps

Top Categories Without Apps

Category	Ad not Supported	Ad Supported
Business	87%	13%
Shopping	82%	18%
Events	75%	25%
Medical	75%	25%
Finance	75%	25%

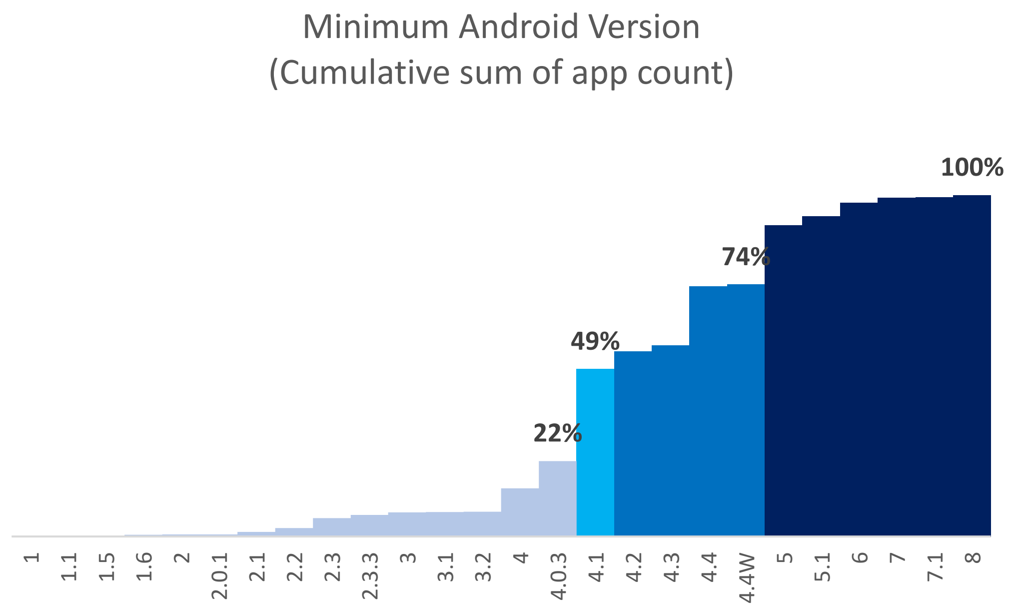
Insights: None of the categories having less ads were games. Furthermore, these categories are service oriented that might require financial transactions, and ads need not be placed for extra revenue.

Top Ad Supported Categories

Category	Ad not Supported	Ad Supported
Racing	9%	91%
Word	11%	89%
Simulation	11%	89%
Trivia	12%	88%
Music	13%	88%

Insights: Categories that include many apps with ads are "**games**". Furthermore, there might be less options for in-app purchase in such categories, hence ads are placed for revenue generation (*disambiguation: music category is a games category, "music and audio" is a non-game category*)

1.4 Apps & Android Version



Insights: Only 22% apps can be run on android version below 4.1. On the contrary, only 26% apps restrict android versions below 5. We can expect, that when new android versions will be released, there will be more apps that would not be usable in older phones. Android users can consider buying a phone with higher android version based on the insight.

1.5 App Rating

App Ratings

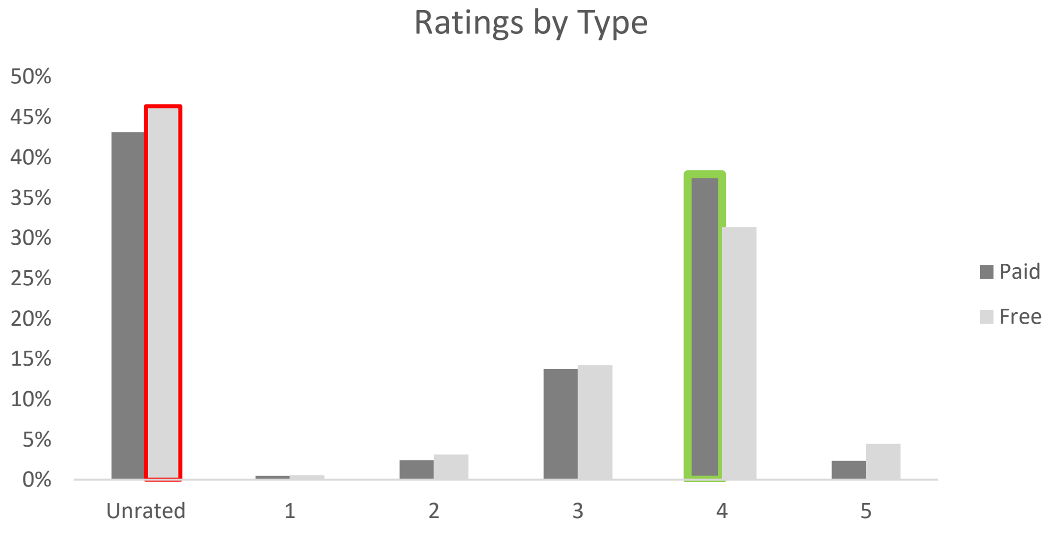
Category Type	Good (4 or above)	Bad (below 4)	Unrated
Games	42%	24%	34%
Others	35%	17%	48%
Grand Total	**36%**	**18%**	**46%**

Insights: About half of the apps that are not games remain unrated. Whereas, there is only a 1 in 3 probability that a game app will go unrated.

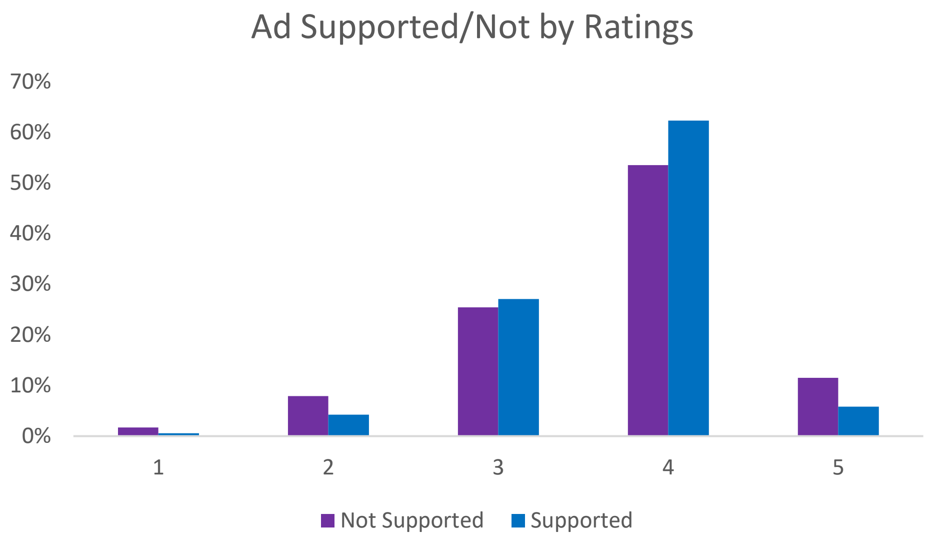
App Ratings (Rated Apps)

Category Type	Good (4 or above)	Bad (below 4)
Games	64%	36%
Others	67%	33%
Grand Total	**67%**	**33%**

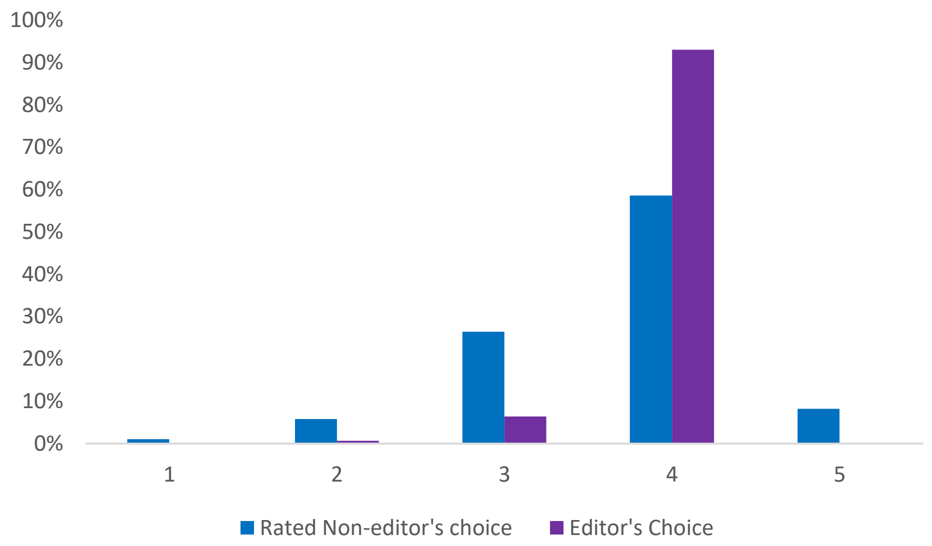
Insights: However, for rated apps, we see that similar proportion of apps got rated above 4. One explanation might be that, games categories do not have as many apps as the other ones. Hence, they do not go unnoticed often. When the apps are noticed by people, similar ratings are available for games and other categories.



Insights: Paid apps are rated better than the free ones (green highlight). At the same time, free apps are more unrated in comparison to the paid ones. (*Rating 5 is not being considered as rating 5 is easily possible through a small number of rating by the owners or their friends. The 'ratings vs installs" chart provided later confirms this assumption*)

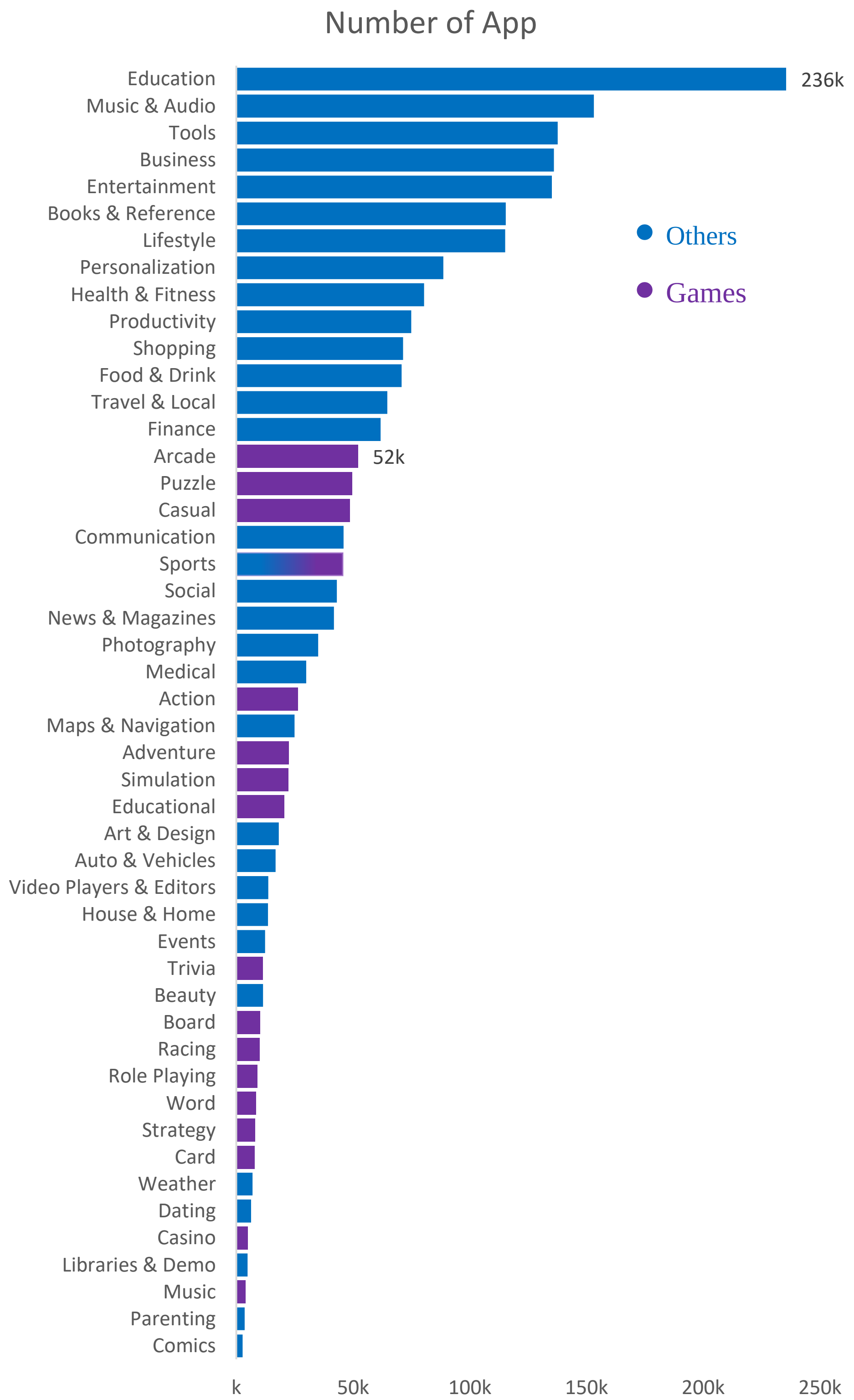


Insights: Ad supported apps have higher proportion of good ratings and a lower proportion of bad ratings.



Insights: A greater portion of Editor's Choice apps get a better rating when compared to apps not labeled editor's choice.

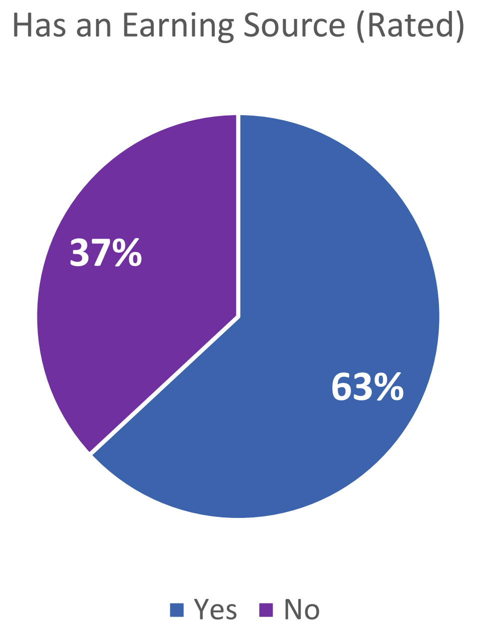
1.6 App Category



Insights: Education category has the highest number of apps. The first games category (15th overall) in the descending order of app counts is "Arcade" with less than 1/4th of education category apps.

Comics category has the least number of apps. Whereas, Music category is the games category with the lowest number of apps.

1.7 Revenue Generating Apps



Insights: There were 3 earning sources identified in this case: ads, in-app purchase and paid apps. 37% of the play store apps did not have any of those as an earning source. (*Unrated apps were not used in this analysis*).

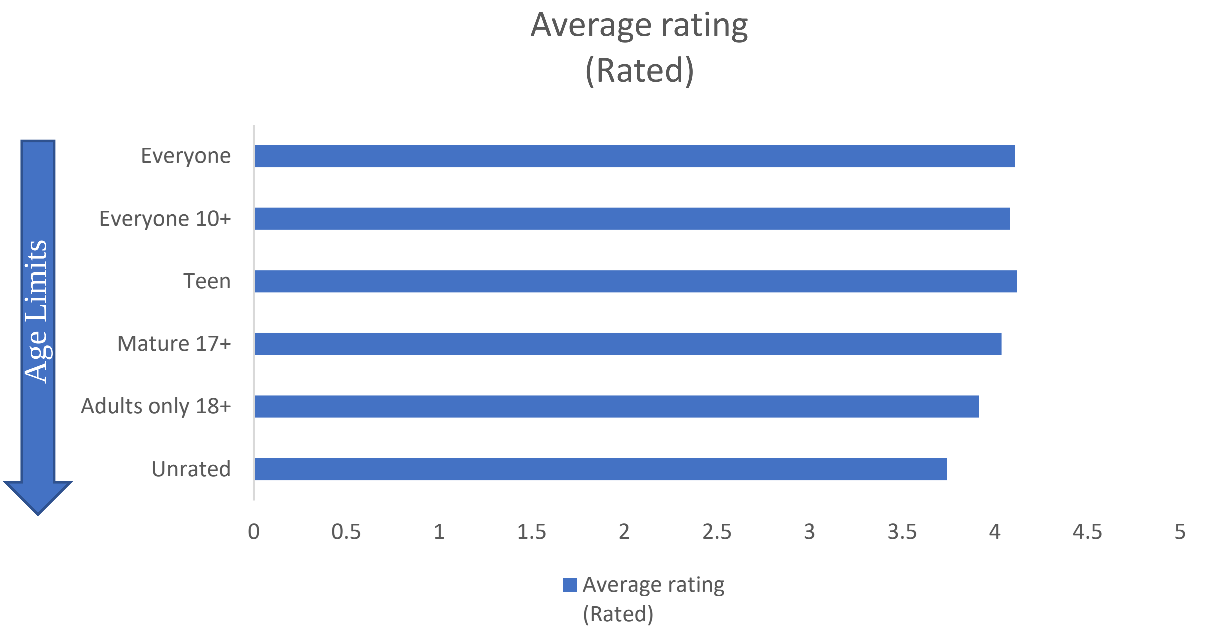
1.8 Characteristics of the Top App Developer Companies

Developers with 1000+ Apps	Avg. Rating (Rated Only)	Rated	Unrated
app smart GmbH	4.43	26%	74%
Apptegy	4.24	7%	93%
ArtStyle	4.33	8%	92%
BH App Development Ltd	4.07	1%	99%
Branded Apps by MINDBODY	4.20	15%	85%
Branded MINDBODY Apps	3.59	3%	97%
ChowNow	3.74	6%	94%
Currency Converter X Apps	4.51	14%	86%
CyJ Studio	4.30	5%	95%
Echurch	4.88	27%	73%
Flipdish	3.87	9%	91%
FoodSoul	4.04	33%	67%
J&M Studio	3.96	4%	96%
Lingua Apps	4.20	30%	70%
Magzter Inc.	3.86	41%	59%
MINDBODY Branded Apps	4.15	8%	92%
Multiple Radios Online AM FM Free - Apps	3.94	3%	97%
OrderYOYO	4.39	8%	92%
Phorest	4.51	2%	98%
Sharefaith	4.88	7%	93%

Skalpelis	3.18	4%	96%
Subsplash Inc	4.84	44%	56%
TRAINERIZE	4.06	2%	98%
TTMA Apps	4.26	27%	73%
Virtuagym Professional	4.70	57%	43%
+Home by A team	4.43	98%	2%

Insights: Among the app developers with 1000+ apps, +Home by A team seems to be the best in terms of getting noticed (98% rated apps). Contrarily BH App Development Ltd are the worst in terms of at least getting rated (1% rated apps). Echurch and Sharefaith are the best with high average of rated apps. Interestingly, both of them are related to religious practices. It is also noticeable that a most of these developers developing thousands of apps did not keep quality in mind.

1.9 Content Rating



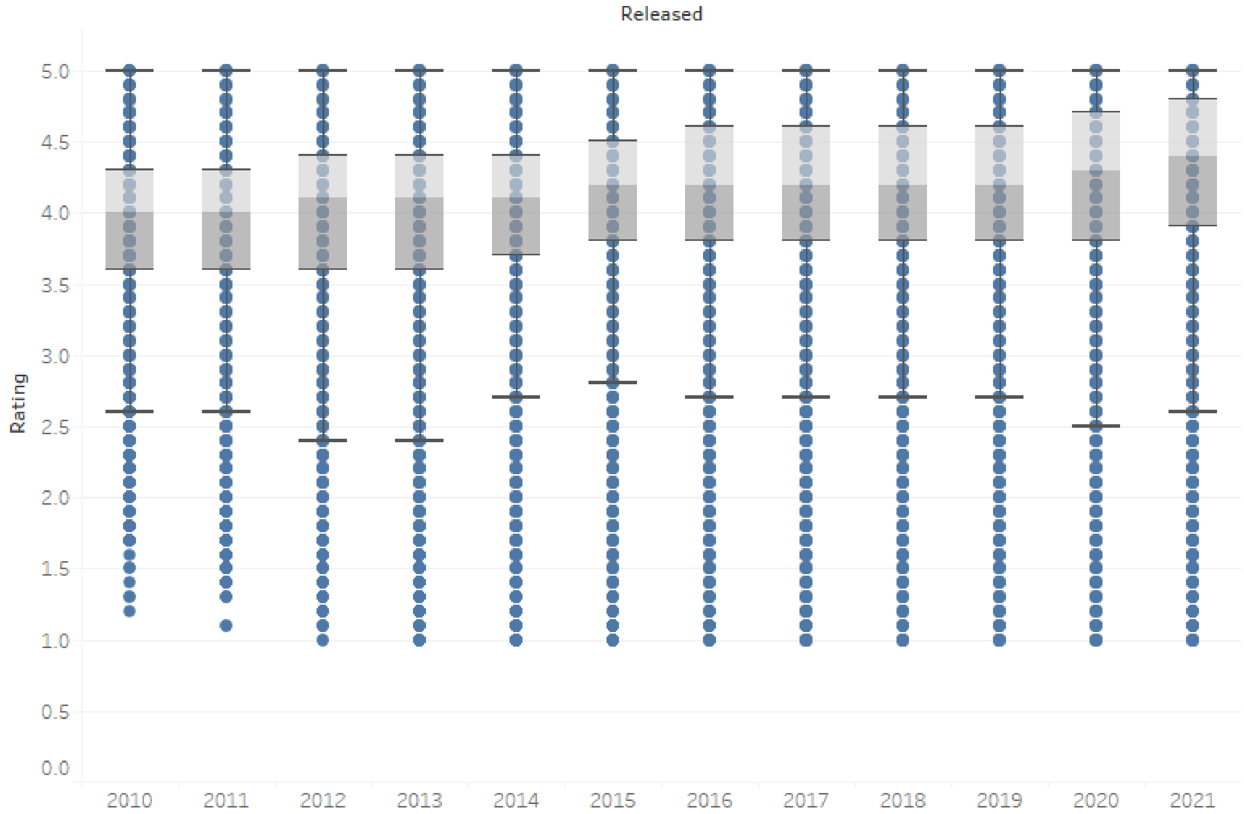
Insight: As the age limitation increases, the average rating decreased.

Number of Apps by Content Rating

Content rating	Count
Everyone	1,953,995
Teen	189,792
Mature 17+	58,526
Everyone 10+	32,706
Unrated	152
Adults only 18+	129

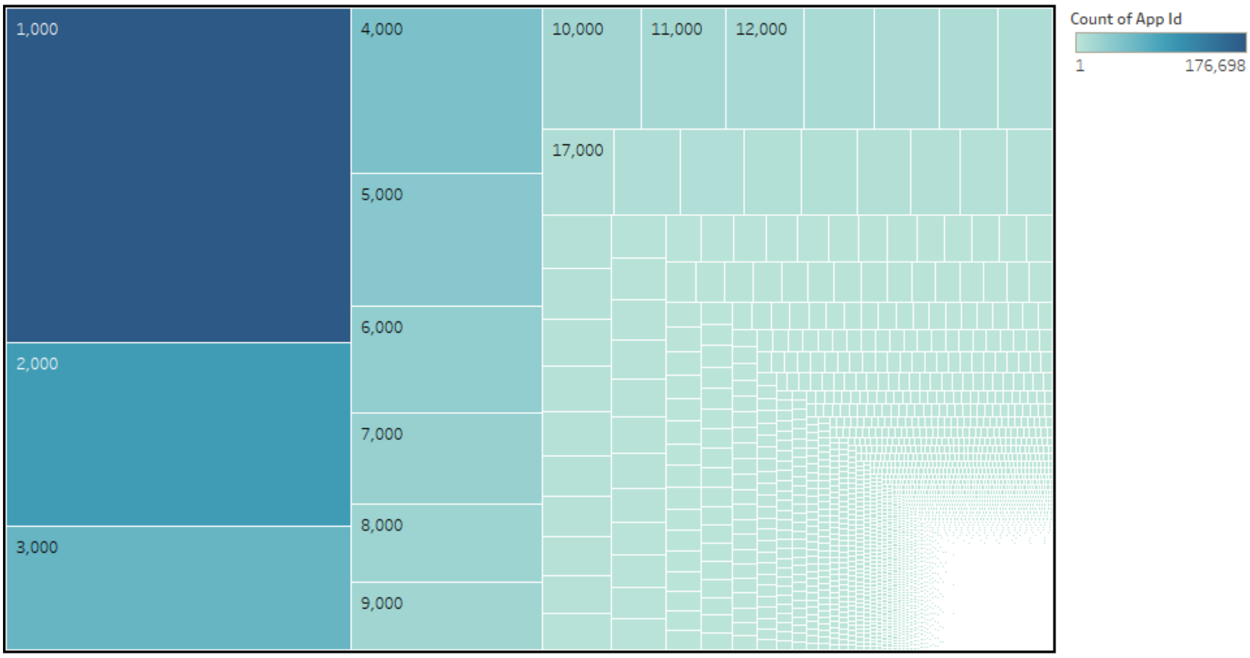
Insight: At the same time, the number of age restricted apps are less in comparison to apps with content rating “Everyone”

1.10 Rated Apps Rating Distribution



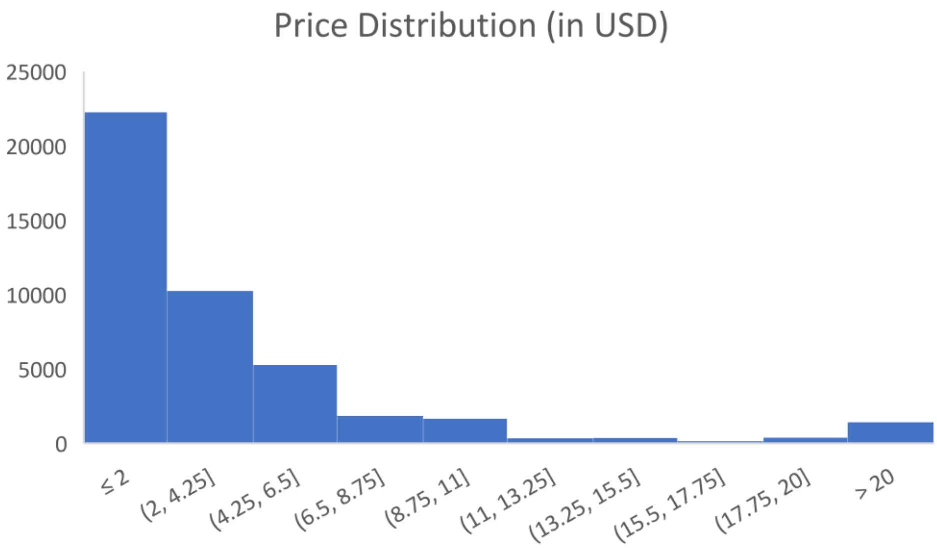
Insights: The overall rating distribution for apps are shown above. The median rating has increased over time consistently, which is a good sign of the increasing quality of apps. However, the lower quartile range fluctuated with no specific pattern.

1.11 Number of Installs

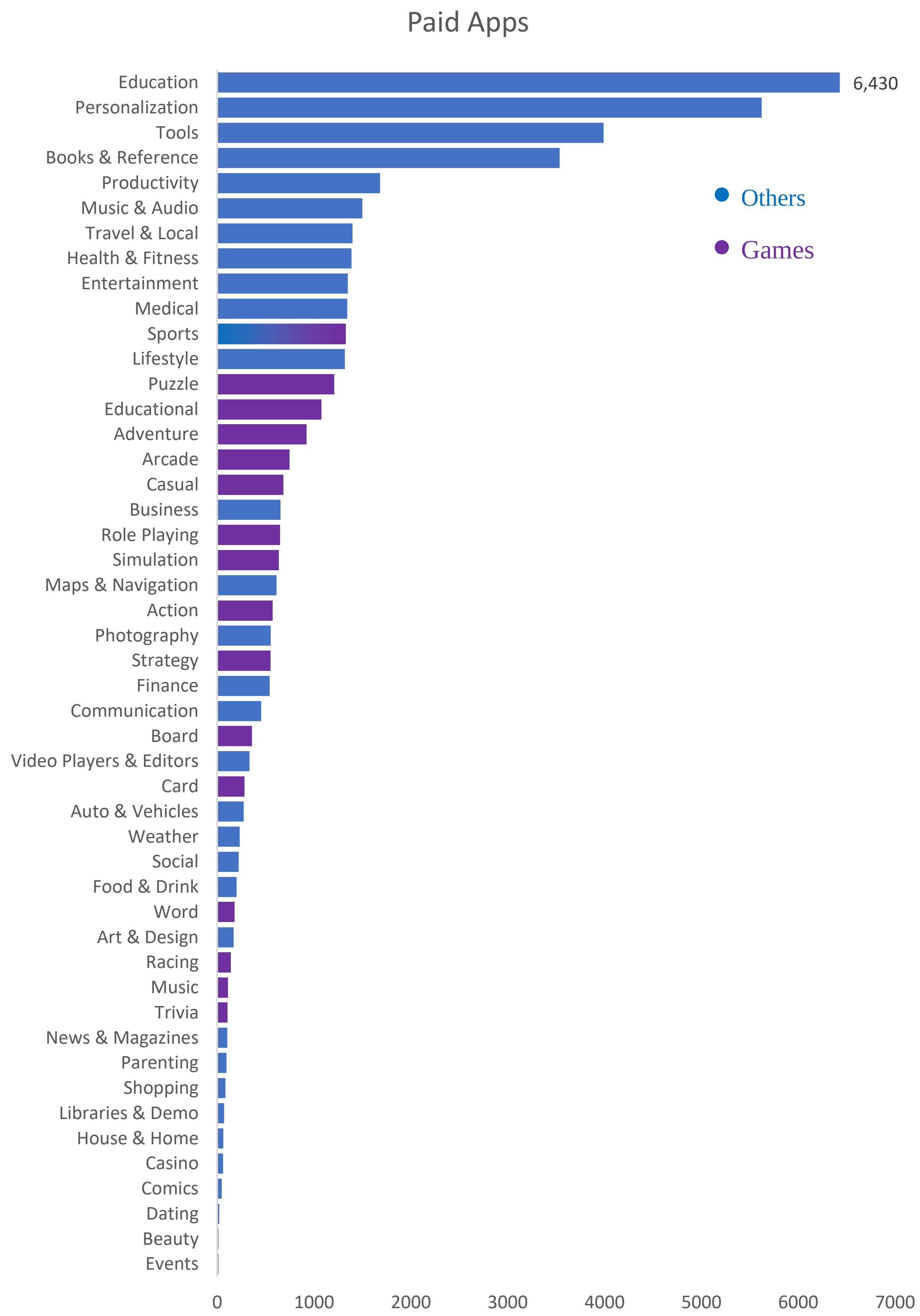


Insights: Lesser number of apps have high volume of downloads. Most apps have a small number of downloads.

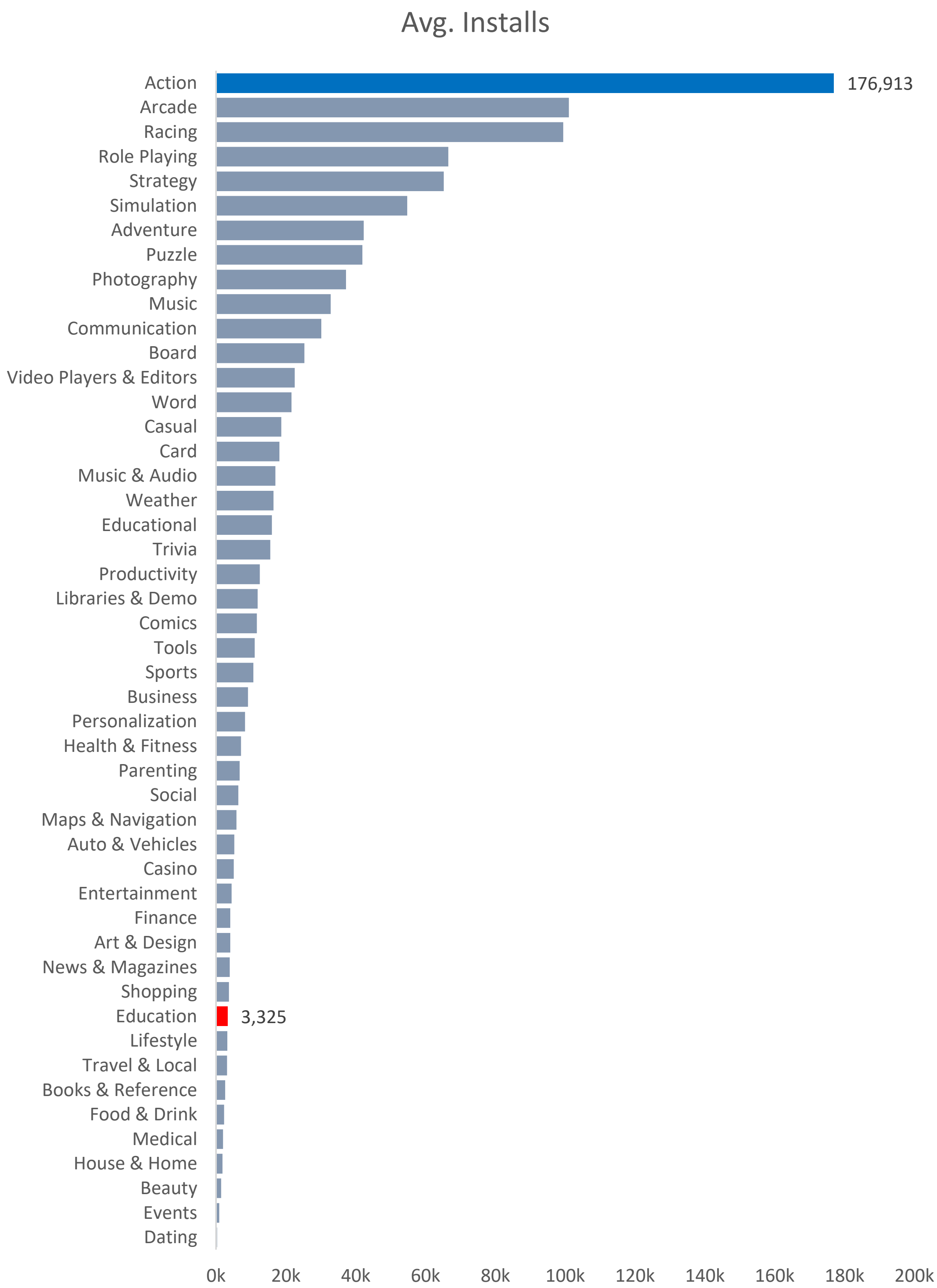
1.12 Paid Apps



Insights: The price distribution for paid apps have been shown above. Most of the apps are priced under $2. Prices can get as high as $400, but they have a lower frequency.

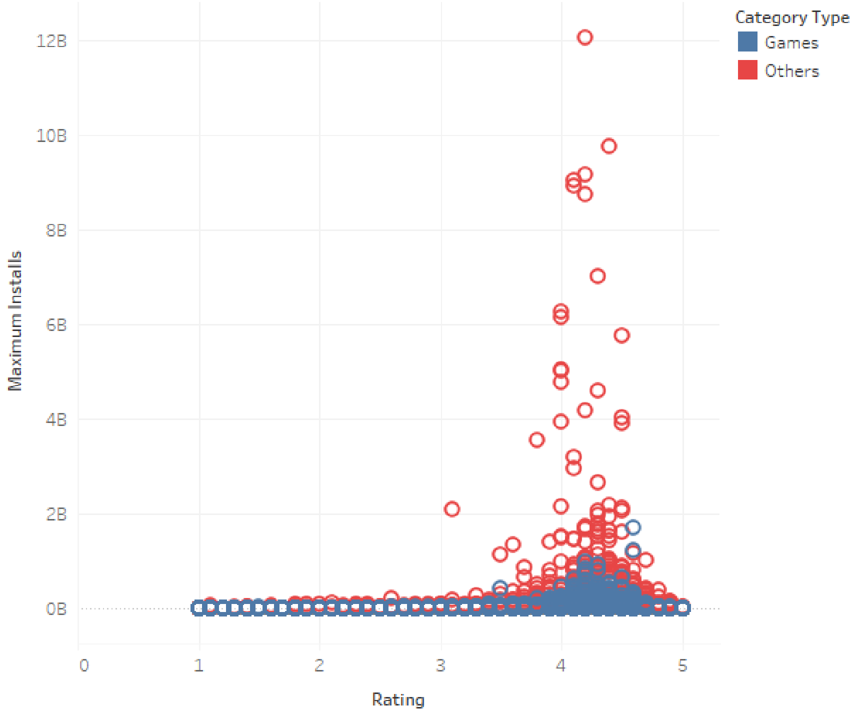


Insights: Education category has the highest number of apps that are paid. Puzzle category is the most common paid games category.



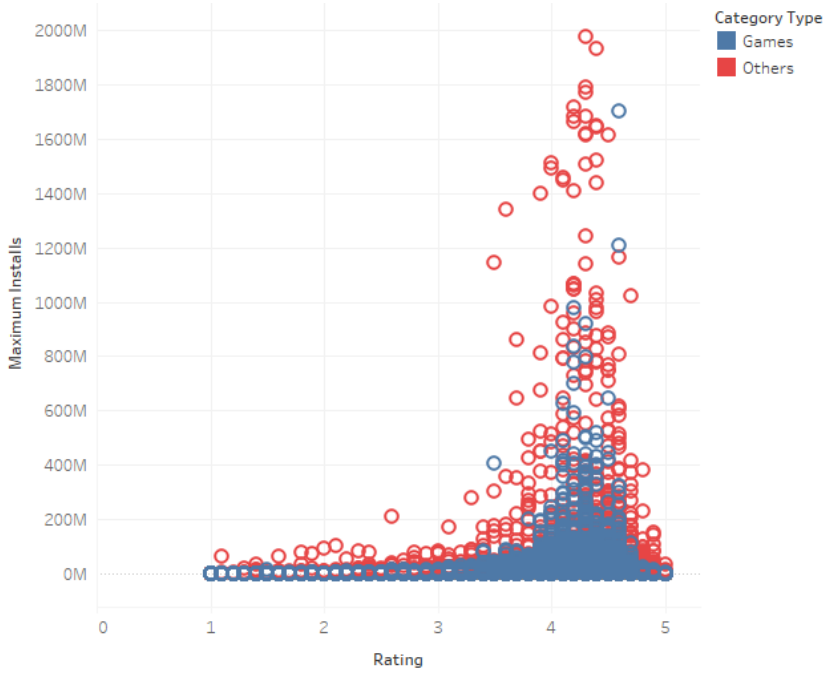
Insights: Although education category has the highest number of paid apps, they are not installed as much. Arcade categories have a higher average number of installs in comparison instead.

1.13 Ratings vs Installs



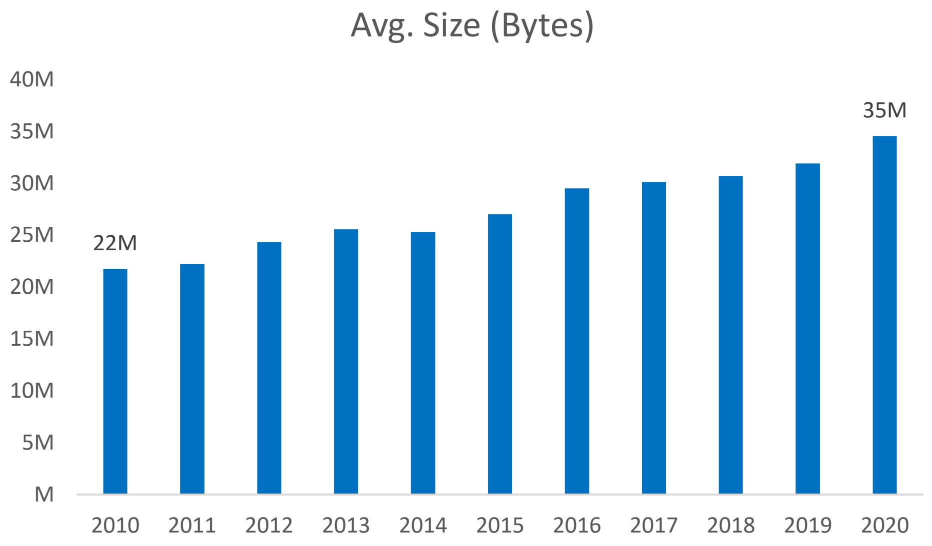
Insights: Higher number of installs are found for apps rated slightly above 4. However, not many of the apps with high downloads are rated as high.

Ratings vs Installs Zoomed In to 2 Billion Downloads

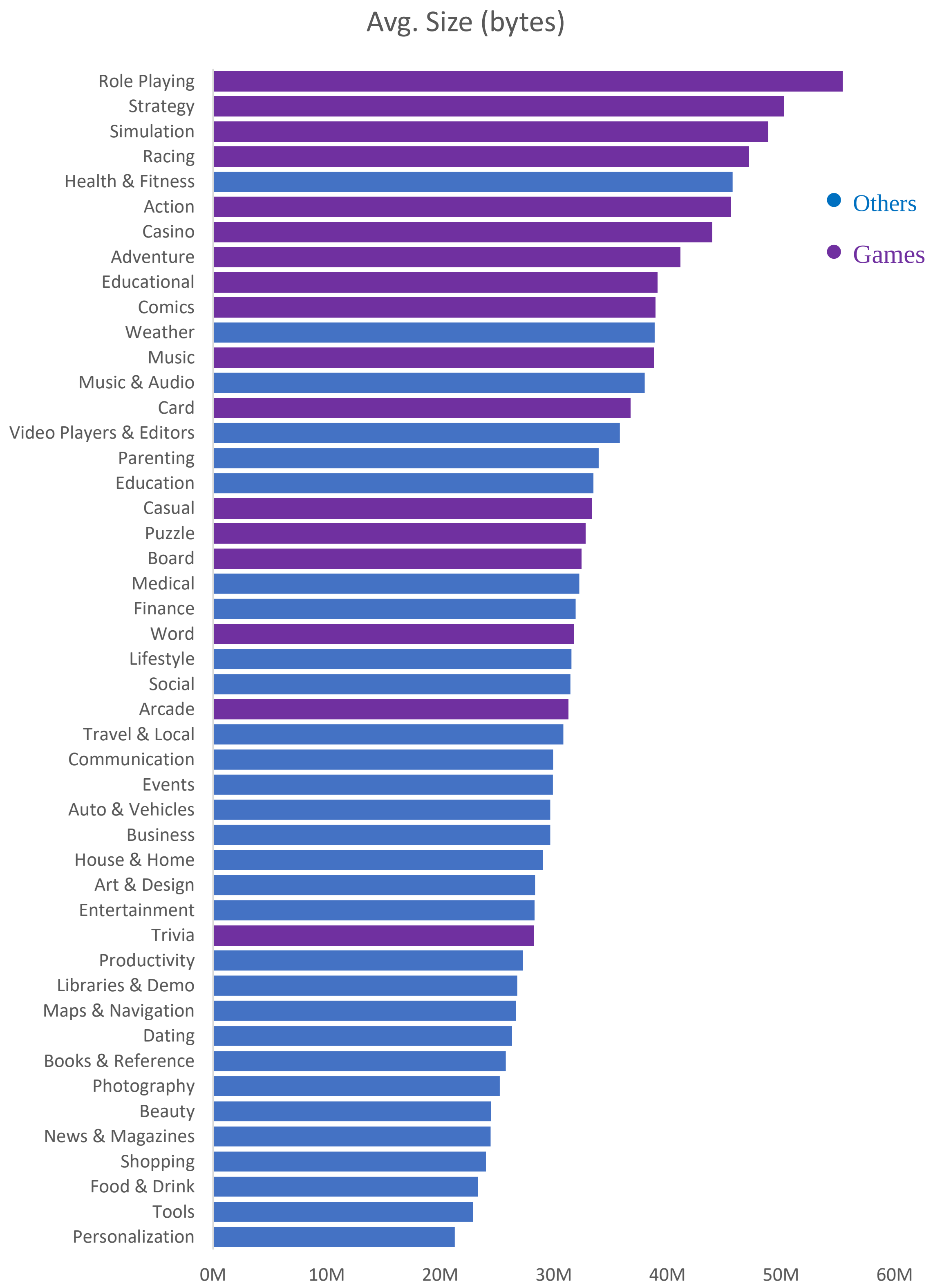


A closer look shows how most apps are rated between 4 and 5. Furthermore, rating 5 did not necessarily mean a high number of users for the app.

1.14 App Size



Insights: The average size of apps have increased over the time. The apps now have grown more than 50% in size on an average.



Insights: The games categories have greater size on average. 9 of the 10 categories from the top were games

2.0 Exploratory Data Analysis

2.1 Summary Statistics of the numeric variables

2.1.1 Feature Statistics

Feature	Mean	Median	Dispersion	Min.	Max.	Missing
Size (bytes)	31,867,838	24,000,000	0.85	10,000	1,020,000,000	1,095,684
Install Plus	113,540	100	76.88	0	10,000,000,000	0
Rating	2.20	3	0.96	0	5	0
Rating Count	2,760	6	72.02	0	138,557,570	0
Maximum Installs	308,117	706	71.69	0	12,057,627,016	0
Price	0	0	25.40	0	400	0
Released				1/28/2010	6/16/2021	0
Last Updated				2/9/2009	6/16/2021	0

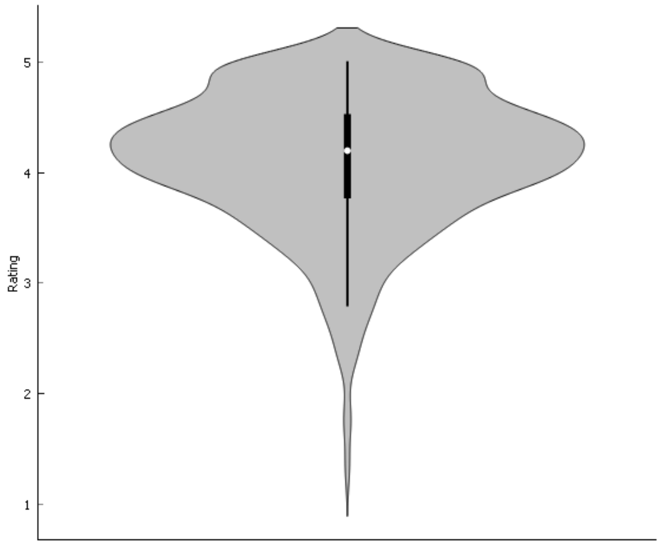
2.1.2 Feature statistics of the sample:

As the data was very large, they could not be analyzed directly through analysis. Hence, the focus was shifted to rated Games only, and a sample was created using *Data Sampler* from Orange with only 1000 data. The rest of the analyses were done based on this data.

Feature	Mean	Median	Dispersion	Min.	Max.	Missing
Size (bytes)	40,939,499	33,000,000	0.74	12,000	1,020,000,000	45,757
Install Plus	355,281	1,000	13.03	0	1,000,000,000	0
Rating	4.1	4.2	0.15	1	5	0
Rating Count	12,147	55	26.04	5	89,177,097	0
Maximum Installs	930,366	8,385	11.32	0	1,704,495,994	0
Price	0	0	17.33	0	400	0
Released				2/26/2010	6/27/2021	0
Last Updated				12/28/2010	6/15/2021	0

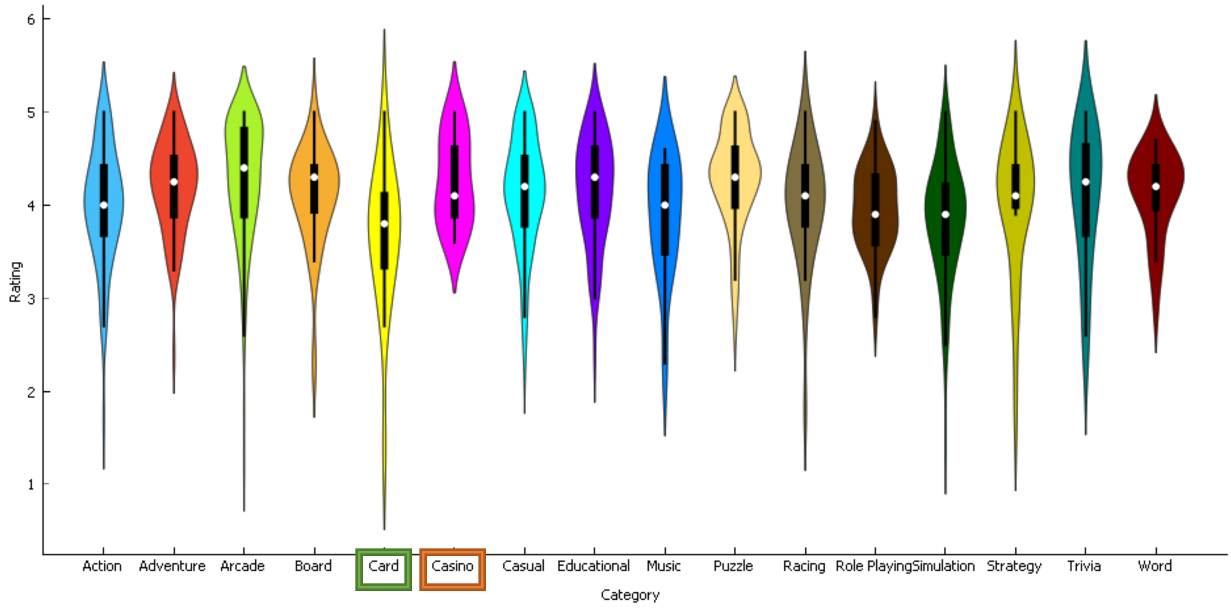
2.2 Distribution of the Ratings in sample data

2.2.1 Overall



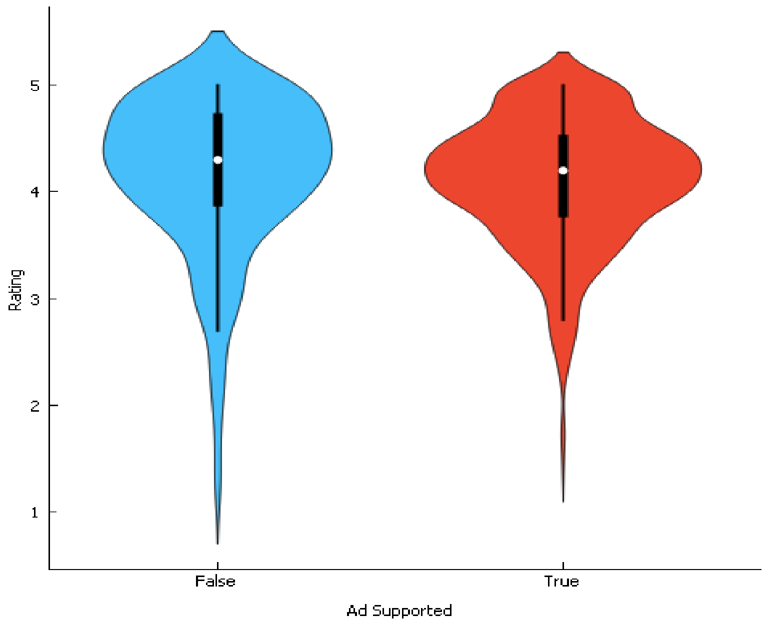
Most apps get rated slightly above 4.

2.2.2 By Category



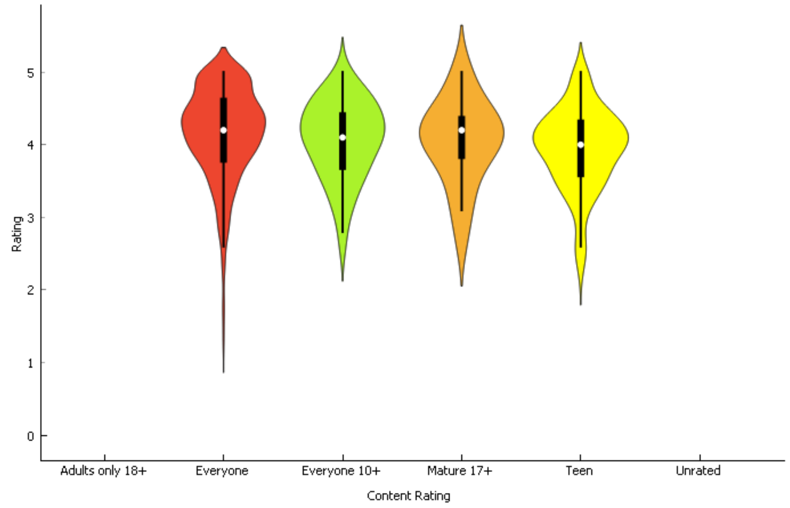
In the sample, some categories are more distributed than the others. **Casino** category was less distributed whereas **Card** category was more distributed than the rest. The average rating of each category looks different.

2.2.3 Whether the App supports Ads



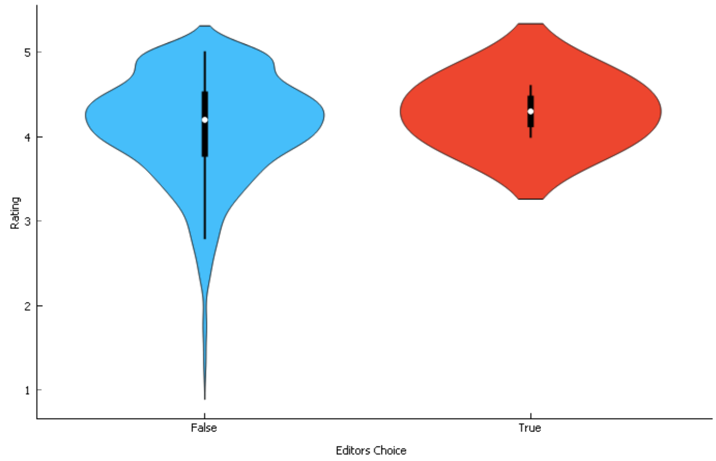
Apps not supporting apps have greater variations of rating than those which supports ad.

2.2.4 By Content rating



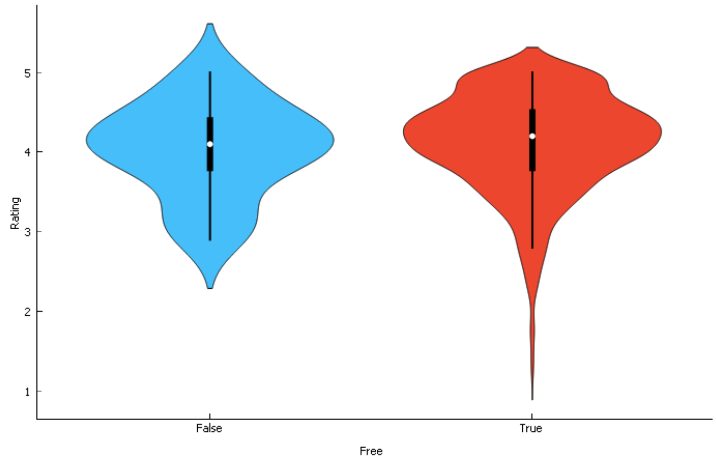
The distributions of age restricted apps look similar to each other but different from apps without restrictions. Age restricted apps were neither rated too high, nor too low in the sample.

2.2.5 Editor's Choice Apps



Editor's choice Apps do not seem to have very low ratings.

2.2.6 Free Apps



Paid apps do not seem to have very low ratings as seen in free apps.

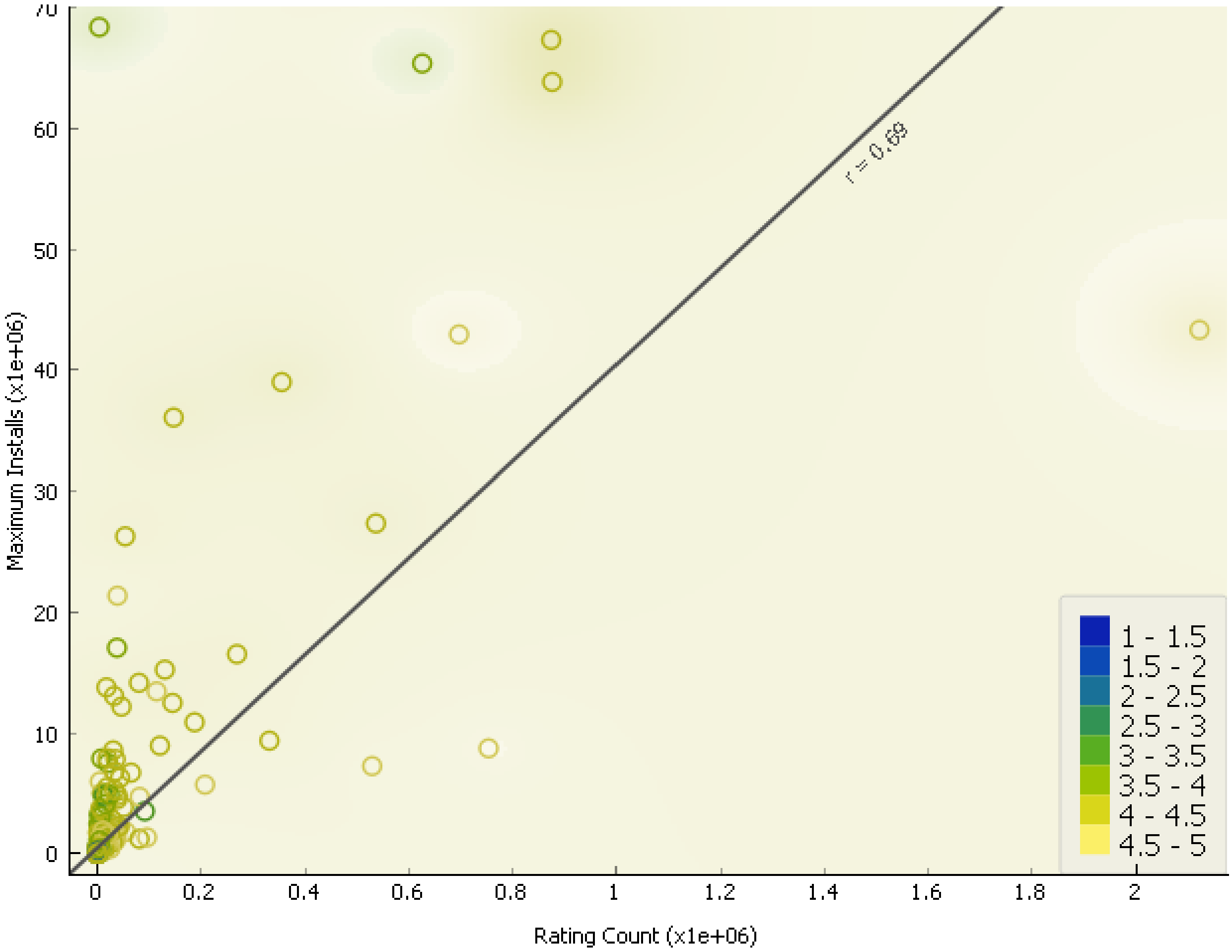
2.3 Correlations of the numeric variables

Feature 1	Feature 2	Correlation	False Discovery Rate
Maximum Installs	Rating Count	+0.69	5.83E-142
Last Updated	Released	+0.60	3.42E-97
Last Updated	Size (bytes)	+0.24	4.21E-14
Released	Size (bytes)	+0.18	2.15E-08
Rating Count	Released	-0.12	0.00028789
Maximum Installs	Released	-0.12	0.000295943
Last Updated	Maximum Installs	+0.12	0.000420386
Price	Released	-0.11	0.00185623
Last Updated	Rating Count	+0.09	0.0102406

Rating	Size (bytes)	-0.08	0.0162556
Rating	Released	+0.08	0.0206284
Maximum Installs	Size (bytes)	+0.07	0.0322879
Rating Count	Size (bytes)	+0.05	0.236459
Rating	Rating Count	+0.04	0.307187
Last Updated	Rating	+0.04	0.307187
Last Updated	Price	-0.02	0.619583
Maximum Installs	Price	-0.02	0.671249
Price	Rating	+0.01	0.817149
Maximum Installs	Rating	+0.01	0.817149
Price	Size (bytes)	+0.01	0.859692
Price	Rating Count	-0.01	0.859692

There is a weak correlation between most of the features. The only two good correlations are not relevant to app ratings. The strong correlation between the number of installs and the number of ratings is visualized in the following.

High Correlation Scatter Plot



Number of ratings are high when installs are more. There is a correlation of 0.69 between these two.

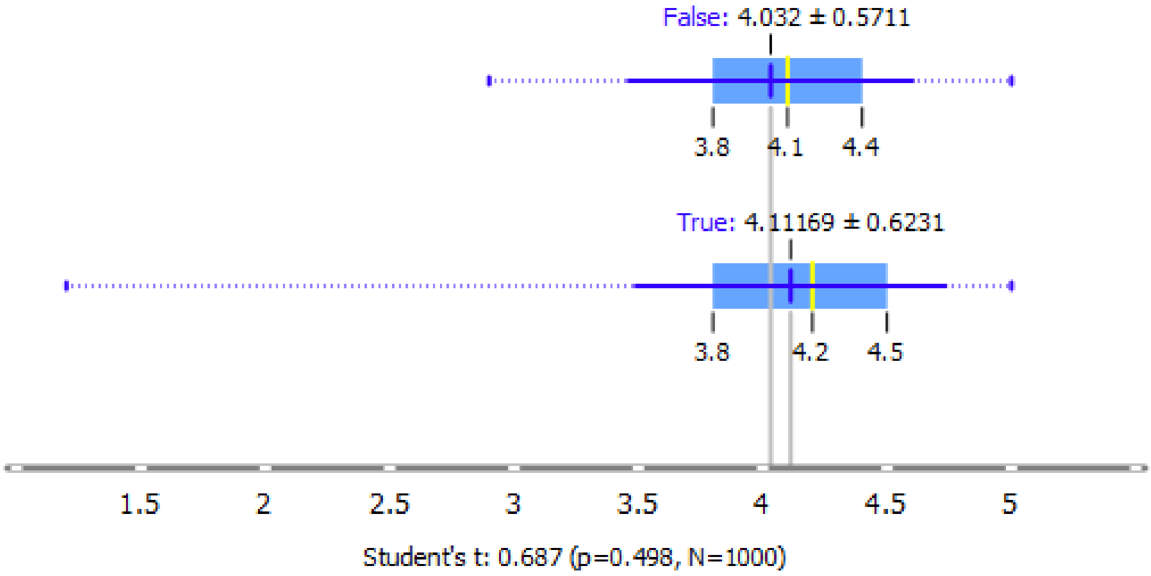
2.4 ANOVA and T-Test

2.4.1 T-Test

Ratings by Free Apps

H_0: There is no difference in rating between free and paid apps
H_1: Ratings are significantly different between the groups

In the following figure, True means Free Apps, whereas False means Paid.



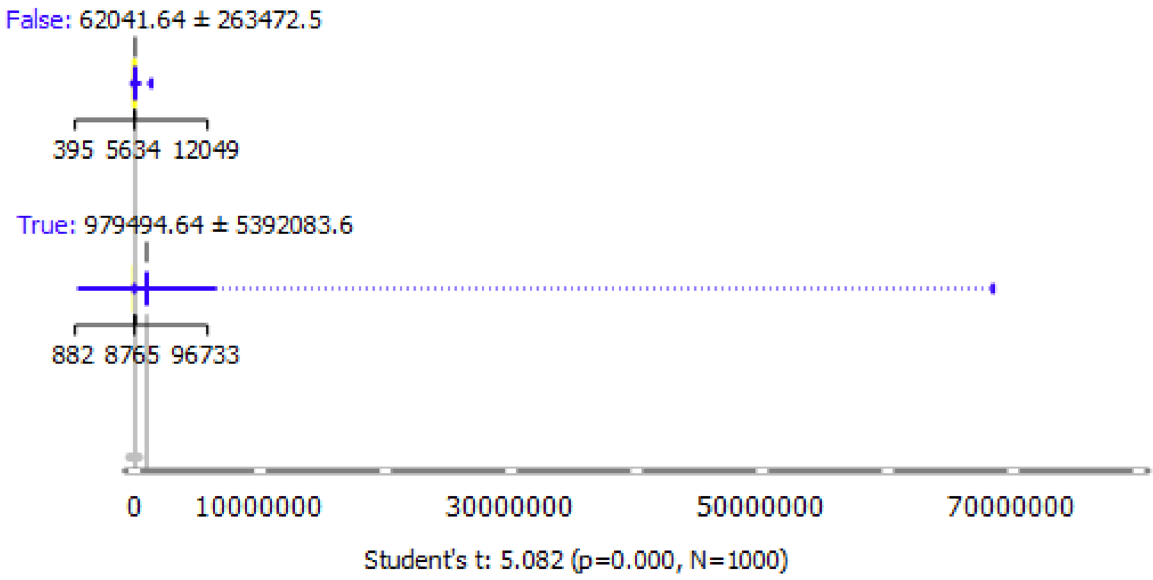
Result:
t= 0.687 (two-tailed, p=0.498, N=1000)
The null hypothesis is not rejected.
The result is not significant at $p < .05$

That is, app rating does not depend on whether it is free or not.

Installs by Free Apps

H_0: There is no difference in the number of installs between free and paid apps
H_1: Installs are significantly different between the groups

In the following figure, True means Free Apps, whereas False means Paid.



Result:

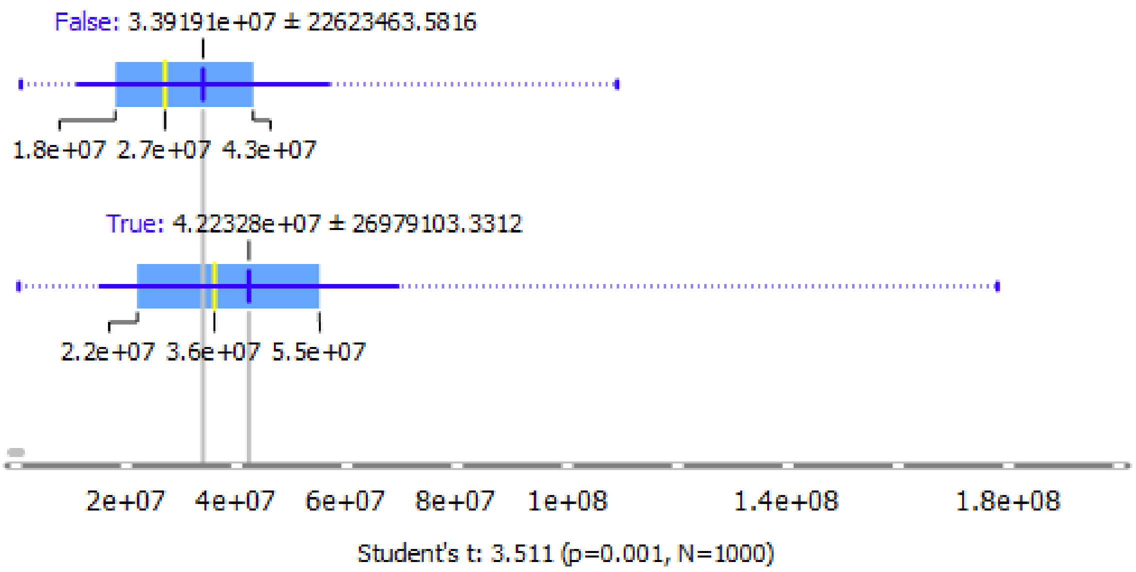
t=5.082 (two-tailed, p=0.000, N=1000)
The null hypothesis is rejected.
The result is significant at $p < .05$.

That is, a significant difference exists. From the box plot, free apps have a higher number of installs.

Size by Updated Apps

H_0: Size of apps are not dependent on whether apps have been updated or not
H_1: Size of the apps are significantly different between the groups

In the following figure, True means Updated, whereas False means Not Updated.



Result:

t = 3.511 (two-tailed, p=0.001, N=1000)
The null hypothesis is rejected.
The result is significant at $p < .05$.

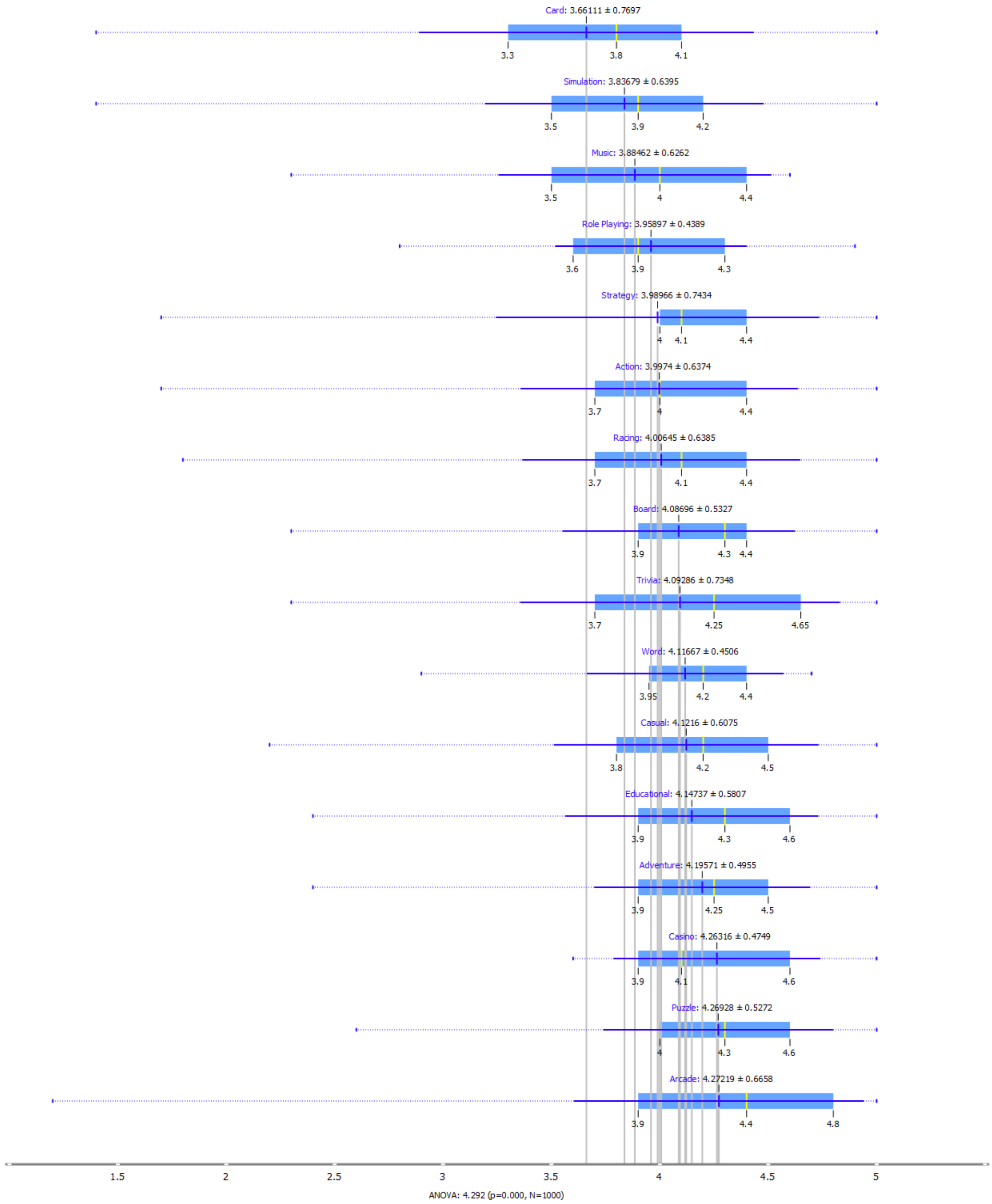
That is a significant difference exists. From the box plot, updated apps have a higher app size compared to those that are not.

2.4.2 ANOVA

Rating by Category

H_0: The mean ratings for all categories are equal.

H_1: The sample means are not all equal



Result: ANOVA= 4.292 (p=0, N=1000)

For p=0.0, we can reject the null hypothesis. **Therefore, the ratings are dependent on the categories for at least one of them.**

Install

H_0: The mean number of installs for all categories are equal.

H_1: The sample means are not all equal

Result: ANOVA= 2.211 (p=0.005, N=1000)

For p=0.005, we can reject the null hypothesis. **That is, the number of installs vary depending on the categories.**

2.5 Outlier Detection

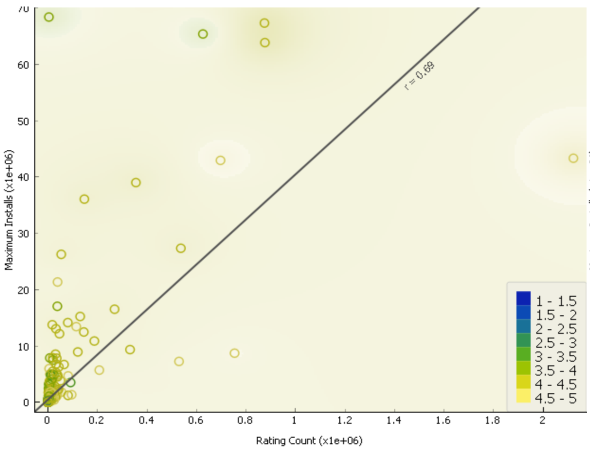
2.5.1 Feature Statistics of Outliers

The outlier’s that were common through 3 methods Covariance Estimator (100 outliers), Local Outlier Factor (100 outliers), and Isolation Forest (90 outliers) were chosen. A total of **15** rows were found common as outliers.

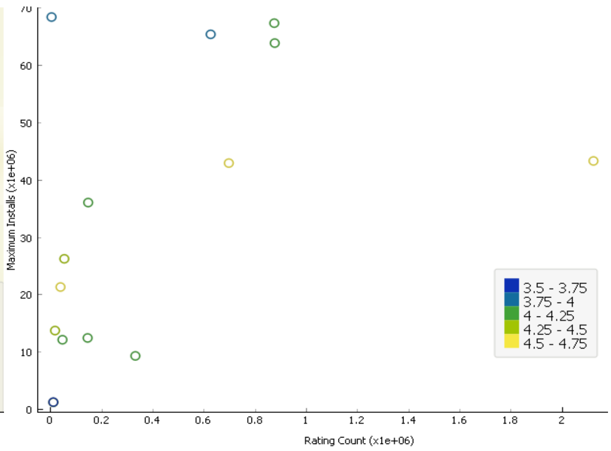
Feature	Mean	Median	Dispersion	Min.	Max.	Missing
Size (bytes)	78,090,909	77,000,000	0.45	36,000,000	151,000,000	4
Rating	4	4	0.08	4	5	0
Rating Count	399,610	144,367	1.40	3,269	2,122,374	0
Maximum Installs	32,354,101	26,272,965	0.74	1,268,404	68,398,433	0
Price	0	0		0	0	0
Released				44,373	43,848	0
Last Updated				43,437	44,362	0

2.6.2 Scatter Plot of the Highly Correlated Features

The highly correlated features are used below to show how the outliers are different.



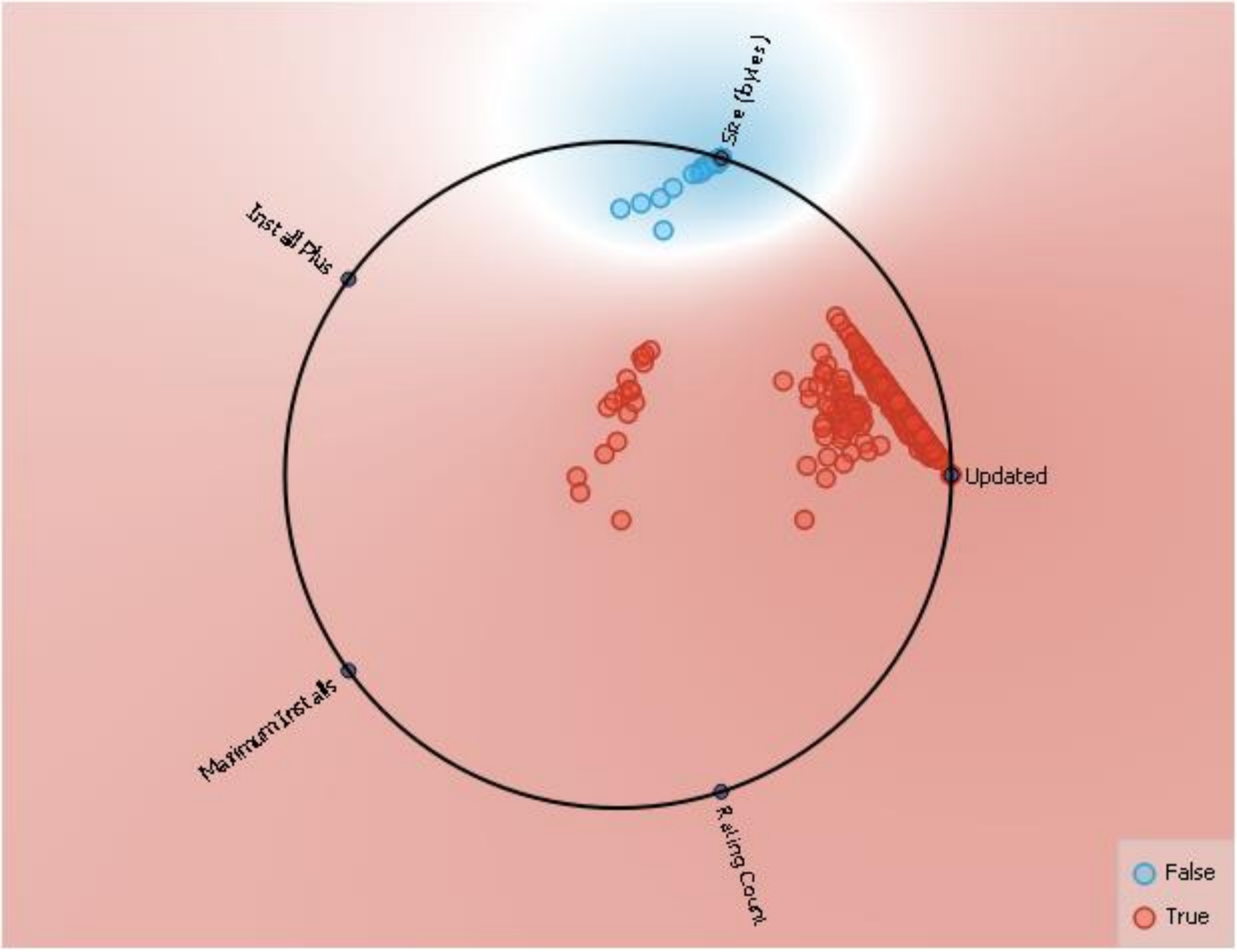
All



Outlier’s only

Most outliers remained above the regression line, which denotes high installs with a very low number of ratings given. Excluding such outliers may increase correlation.

2.6 RADVIZ



Of the features related to App Ratings, app size was relevant when, the app had not been updated.

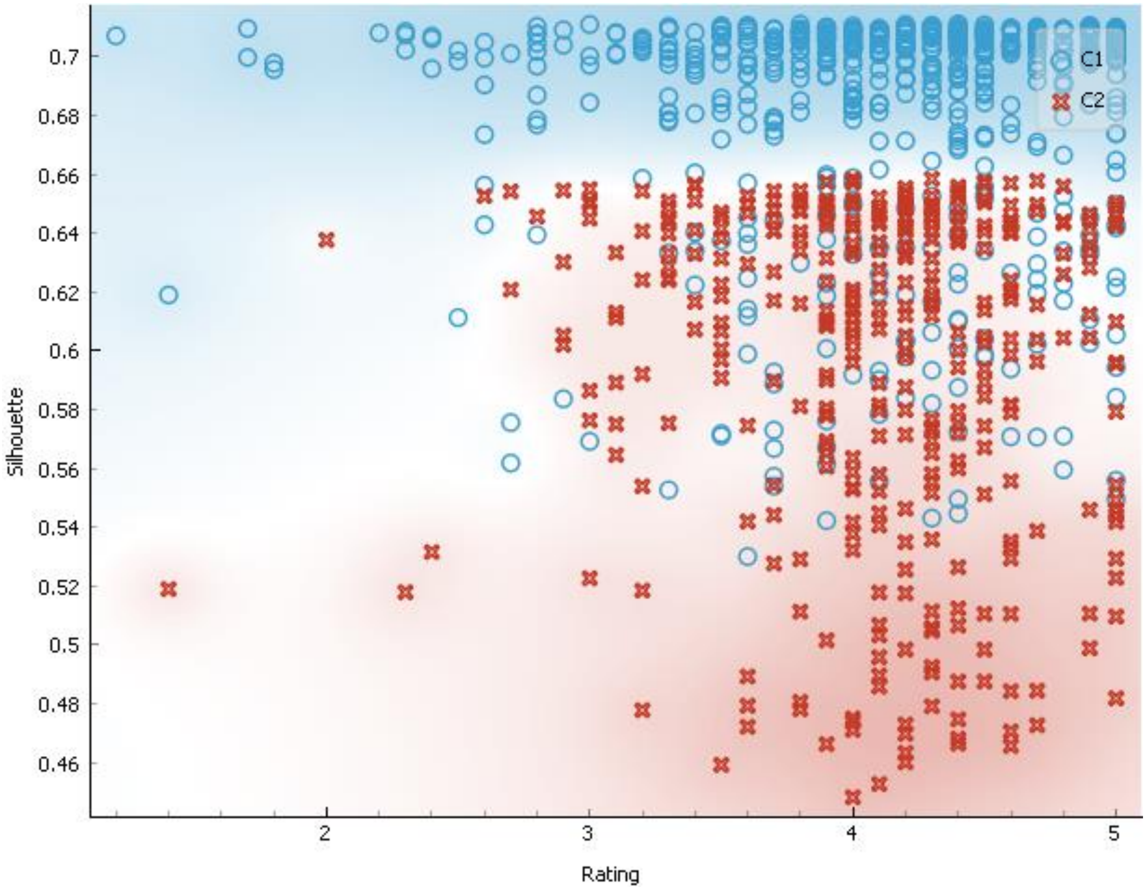
2.7 Unsupervised Machine Learning

2.7.1 K-means Clustering

Silhouette Scores

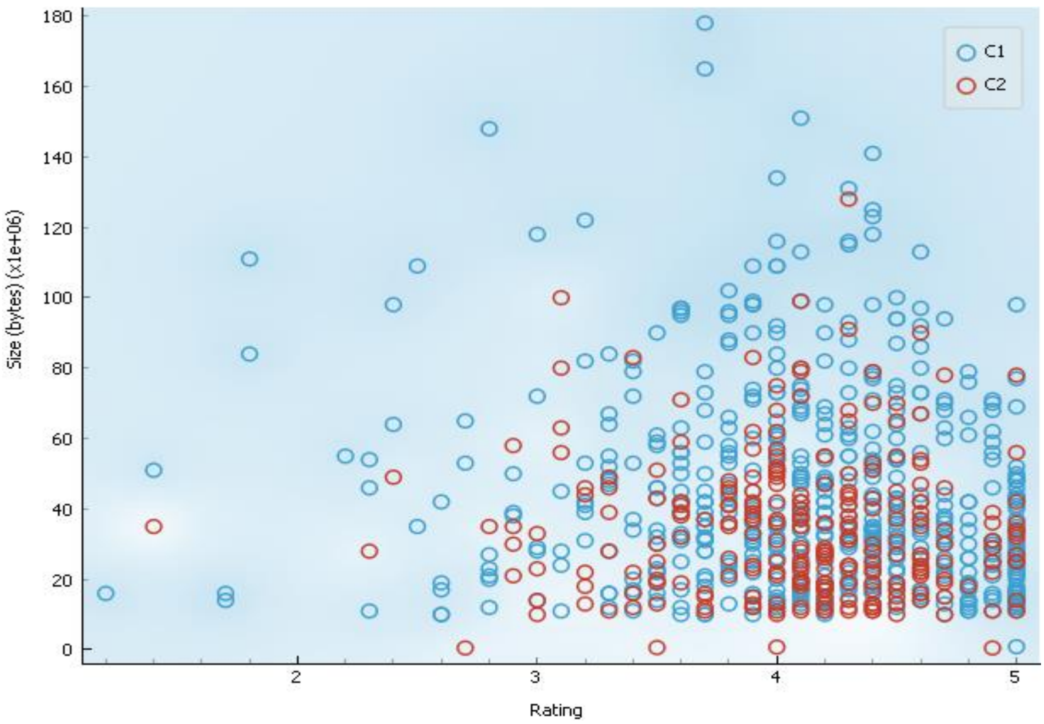
2	0.530
3	0.476
4	0.483
5	0.502
6	0.436
7	0.458
8	0.450

2 clusters were made as it showed the highest silhouette score. As shown in the chart below, clusters can be separated somewhat distinctively.

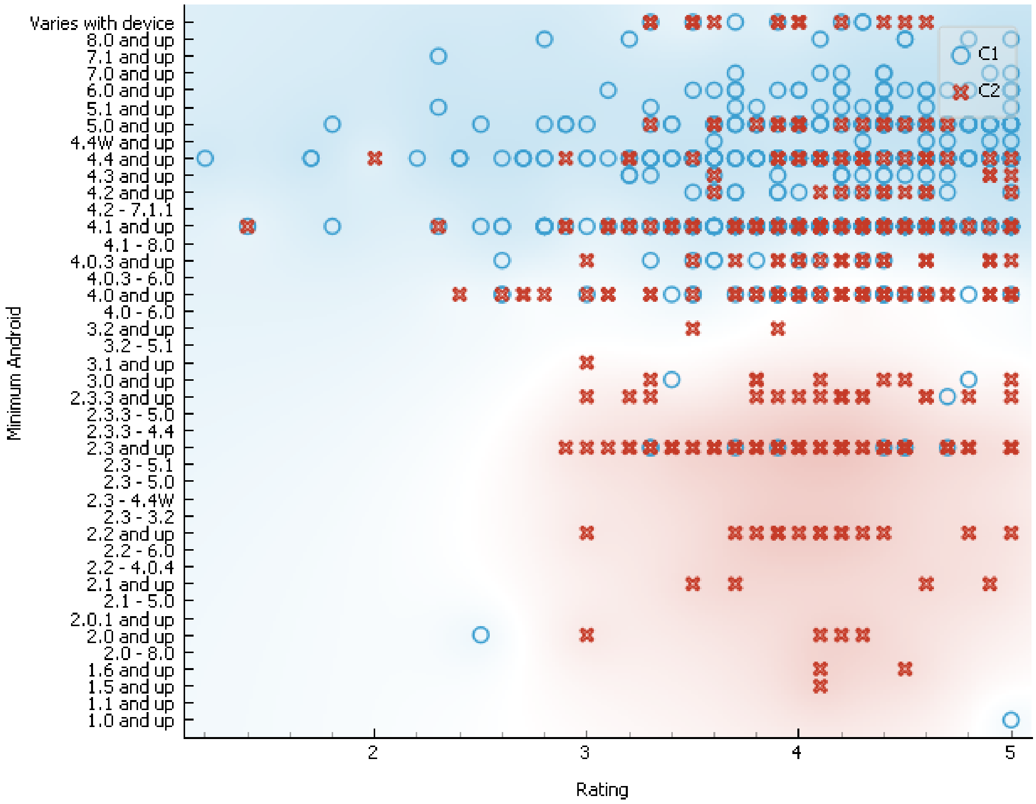


2.7.2 Cluster Characteristics

1. According to the chart below, cluster 1 can have very high app size, compared to cluster 2



2. According to the chart, cluster 2 consists of apps that support older app version. Whereas, cluster 1 consists of apps that are supported by only newer app versions.



3.0 Supervised Machine Learning

TYPE – 1

3.1 Target Variable (Rated/Unrated)

We will be checking whether an app gets rated or not and what models best predict such getting rated.

3.2 Removal of Collinearity

Ratings, and Rating Counts have been removed as they directly indicate whether an app is rated or not. For example, 0 rating means an app is unrated or, if the number of rating is 0, it means it was not rated. Last update date has been removed as it is highly related to the date of release. Categories have been brought under broader categories of Games vs Others.

3.3 Data Sampling

1000 data rows have been taken with random sampling. The proportion of rated and unrated apps were about 1:1 in the original set, hence no change was required to make the data sample more balanced.

3.4 Model Evaluation Results

Model	AUC	CA	F1	Precision	Recall
Constant	0.496	0.537	0.375	0.288	0.537
SGD	0.500	0.515	0.495	0.503	0.515
SVM	0.521	0.466	0.326	0.506	0.466
kNN	0.577	0.563	0.563	0.563	0.563
AdaBoost	0.731	0.733	0.733	0.733	0.733
Tree	0.808	0.809	0.809	0.810	0.809
Random Forest	0.879	0.812	0.812	0.812	0.812
Naive Bayes	0.895	0.832	0.832	0.832	0.832
Logistic Regression	0.896	0.783	0.779	0.828	0.783
Gradient Boosting	0.910	0.836	0.836	0.837	0.836
Stack	0.913	0.835	0.842	0.865	0.821

The blue highlights represent a better performance by a model, compared to red ones. There is no single model that predicts better than the others in terms of all the different scores.

3.5 Model Comparison by AUC (Area Under the Curve)

Model Comparison by AUC

	SVM	Constant	SGD	kNN	AdaBoost	Logistic Reg...	Tree	Random Fo...	Naive Bayes	Stack	Gradient Bo...
SVM		0.638	0.638	0.017	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Constant	0.362		0.500	0.003	0.000	0.000	0.000	0.000	0.000	0.000	0.000
SGD	0.362	0.500		0.003	0.000	0.000	0.000	0.000	0.000	0.000	0.000
kNN	0.983	0.997	0.997		0.000	0.000	0.000	0.000	0.000	0.000	0.000
AdaBoost	1.000	1.000	1.000	1.000		0.000	0.005	0.000	0.000	0.000	0.000
Logistic Regression	1.000	1.000	1.000	1.000	1.000		0.998	0.973	0.716	0.027	0.056
Tree	1.000	1.000	1.000	1.000	0.995	0.002		0.006	0.001	0.000	0.000
Random Forest	1.000	1.000	1.000	1.000	1.000	0.027	0.994		0.115	0.000	0.000
Naive Bayes	1.000	1.000	1.000	1.000	1.000	0.284	0.999	0.885		0.000	0.009
Stack	1.000	1.000	1.000	1.000	1.000	0.973	1.000	1.000	1.000		0.738
Gradient Boosting	1.000	1.000	1.000	1.000	1.000	0.944	1.000	1.000	0.991	0.262	

Table shows probabilities that the score for the model in the row is higher than that of the model in the column. Small numbers show the probability that the difference is negligible.

The above matrix shows the probability that a model in the row is better than the model in the corresponding column. From this matrix we can see that, the two models in the bottom rows show 100% probability to be better than most other models.

3.6 Confusion Matrix

3.6.1 Summary

From the confusion matrices mentioned in the next page, we can summarize the following about the models that have been used.

- kNN, SVM, and SGD perform similarly poor in comparison to the other models. Their predictions are nearly as good as the constant model, with around 50-60% chances to have predicted correctly.
- AdaBoost, Tree, and Random Forest performed moderately well. But as significantly better models were available, they are not focused as much.
- Logistic Regression was the best model to predict rated apps. 94.4% of the times, the app it predicts to be rated actually is rated.
- Naïve Bayes is the best in being accurate with its unrated prediction. 81.6% of the times, if this model predicts an app to be unrated, it actually is unrated.
- Gradient Boosting is the best model overall based on AUC, CA, F1, Precision, Recall scores. It has a good balance in predicting rated and unrated apps.

3.6.2 Bad Models

Constant

Proportion of actual

Actual \ Predicted	Rated	Unrated	Σ
Rated	100.0 %	0.0 %	537
Unrated	100.0 %	0.0 %	463
Σ	1000	0	1000

Proportion of Predicted

Actual \ Predicted	Rated	Unrated	Σ
Rated	53.7 %	NA	537
Unrated	46.3 %	NA	463
Σ	1000	0	1000

kNN

Proportion of actual

Actual \ Predicted	Rated	Unrated	Σ
Rated	59.2 %	40.8 %	537
Unrated	47.1 %	52.9 %	463
Σ	536	464	1000

Proportion of Predicted

Actual \ Predicted	Rated	Unrated	Σ
Rated	59.3 %	47.2 %	537
Unrated	40.7 %	52.8 %	463
Σ	536	464	1000

SVM

Proportion of actual

Actual \ Predicted	Rated	Unrated	Σ
Rated	3.5 %	96.5 %	537
Unrated	3.5 %	96.5 %	463
Σ	35	965	1000

Proportion of Predicted

Actual \ Predicted	Rated	Unrated	Σ
Rated	54.3 %	53.7 %	537
Unrated	45.7 %	46.3 %	463
Σ	35	965	1000

Stochastic Gradient Descent

Proportion of actual

Actual \ Predicted	Rated	Unrated	Σ
Rated	60.0 %	40.0 %	537
Unrated	60.0 %	40.0 %	463
Σ	600	400	1000

Proportion of Predicted

Actual \ Predicted	Rated	Unrated	Σ
Rated	53.7 %	53.8 %	537
Unrated	46.3 %	46.2 %	463
Σ	600	400	1000

3.6.3 Moderately Good Models

AdaBoost

Proportion of actual

Actual \ Predicted	Rated	Unrated	Σ
Rated	75.2 %	24.8 %	537
Unrated	28.9 %	71.1 %	463
Σ	538	462	1000

Proportion of Predicted

Actual \ Predicted	Rated	Unrated	Σ
Rated	75.1 %	28.8 %	537
Unrated	24.9 %	71.2 %	463
Σ	538	462	1000

Tree

Proportion of actual

Actual \ Predicted	Rated	Unrated	Σ
Rated	80.6 %	19.4 %	537
Unrated	18.8 %	81.2 %	463
Σ	520	480	1000

Proportion of Predicted

Actual \ Predicted	Rated	Unrated	Σ
Rated	83.3 %	21.7 %	537
Unrated	16.7 %	78.3 %	463
Σ	520	480	1000

Random Forest

Proportion of actual

Actual \ Predicted	Rated	Unrated	Σ
Rated	82.9 %	17.1 %	537
Unrated	18.4 %	81.6 %	463
Σ	530	470	1000

Proportion of Predicted

Actual \ Predicted	Rated	Unrated	Σ
Rated	84.0 %	19.6 %	537
Unrated	16.0 %	80.4 %	463
Σ	530	470	1000

3.6.3 Good Models

Logistic Regression

Proportion of actual

		Predicted		
		Rated	Unrated	Σ
Actual	Rated	63.3 %	36.7 %	537
	Unrated	4.3 %	95.7 %	463
	Σ	360	640	1000

Proportion of Predicted

		Predicted		
		Rated	Unrated	Σ
Actual	Rated	94.4 %	30.8 %	537
	Unrated	5.6 %	69.2 %	463
	Σ	360	640	1000

Comment: Apps are the most likely to be actually rated when it is predicted to be rated by Logistic Regression.

Gradient Boosting

Proportion of actual

		Predicted		
		Rated	Unrated	Σ
Actual	Rated	82.5 %	17.5 %	537
	Unrated	15.1 %	84.9 %	463
	Σ	513	487	1000

Proportion of Predicted

		Predicted		
		Rated	Unrated	Σ
Actual	Rated	86.4 %	19.3 %	537
	Unrated	13.6 %	80.7 %	463
	Σ	513	487	1000

Comment: Best model overall.

Naïve Bayes

Proportion of actual

		Predicted		
		Rated	Unrated	Σ
Actual	Rated	84.0 %	16.0 %	537
	Unrated	17.7 %	82.3 %	463
	Σ	533	467	1000

Proportion of Predicted

		Predicted		
		Rated	Unrated	Σ
Actual	Rated	84.6 %	18.4 %	537
	Unrated	15.4 %	81.6 %	463
	Σ	533	467	1000

Comment: Apps are the most likely to be actually unrated when it is predicted to be unrated by Naïve Bayes.

3.7 Combining Models

3.7.1 Stacking Models

Based on the confusion matrices, **Gradient boosting** was paired with **Logistic regression** and **Naïve Bayes**.

Proportion of actual

		Predicted		
		Rated	Unrated	Σ
Actual	Rated	82.1 %	17.9 %	537
	Unrated	14.9 %	85.1 %	463
	Σ	510	490	1000

Proportion of Predicted

		Predicted		
		Rated	Unrated	Σ
Actual	Rated	86.5 %	19.6 %	537
	Unrated	13.5 %	80.4 %	463
	Σ	510	490	1000

This model has slightly better AUC than the best lone model, Gradient Boosting. It has a comparatively lower precision and higher recall compared to Gradient Boosting.

3.7.2 Setting Priorities

Based on the confusion Matrices, we set priorities on which models will predict rated or unrated apps in the following order.

1. Logistic Regression will be used to predict Rated apps only
2. From the remaining apps, Naïve Bayes is used for predicting unrated apps
3. From the remaining apps, the predictions from Gradient Boosting are used.

Proportion of actual

		Predicted	
		Rated	Unrated
Actual	Rated	84.0%	16.0%
	Unrated	8.0%	92.0%

Proportion of Predicted

		Predicted	
		Rated	Unrated
Actual	Rated	92.4%	16.8%
	Unrated	7.6%	83.2%

Based on the table above, this combined model predicts both the rated and unrated apps better than all other models.

Hence, the model mentioned above, that uses three models on priority basis should be used.

TYPE – 2

3.8 Target Variable (App Rating)

We would attempt to predict the app ratings.

3.9 Model Comparison

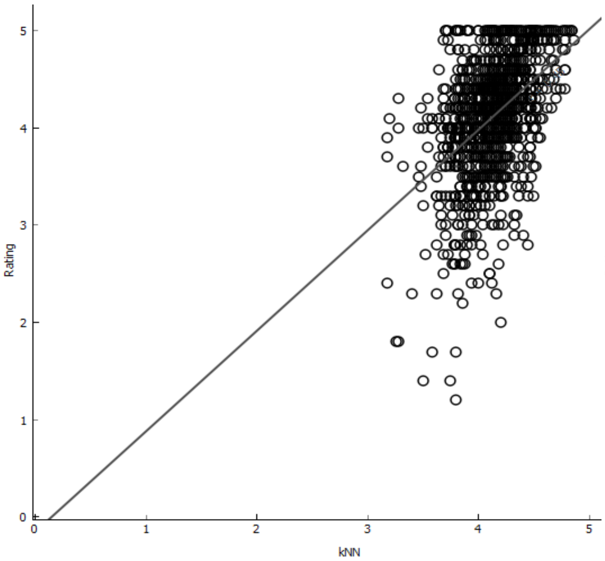
The errors from 5 models to predict ratings were compared below.

Model	MSE	RMSE	MAE	R^2
Linear Regression	0.336	0.580	0.438	0.130
kNN	0.307	0.554	0.425	0.206
SVM	0.162	0.403	0.314	0.580
Gradient Boosting	0.161	0.401	0.301	0.584
Random Forest	0.077	0.277	0.186	0.802

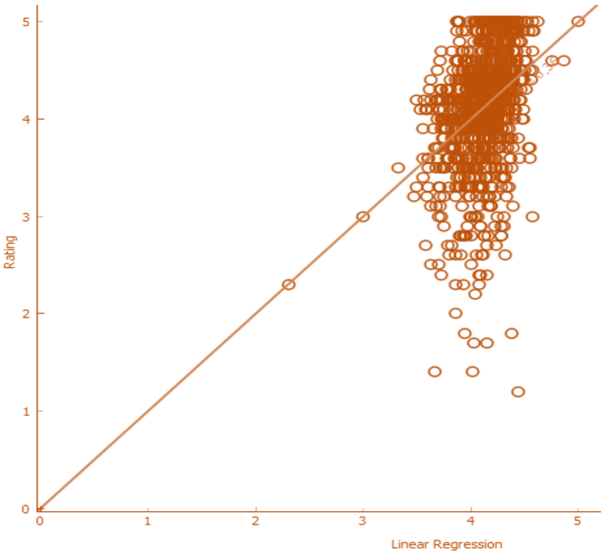
Based on the comparison table, **Random Forest** model gives the lowest error in all cases with R^2 value of 0.808. This is the best model to among the five tested. On the contrary, the **Linear Regression** method produced greater errors while having a lower R^2 value.

3.10 Visualizing Models

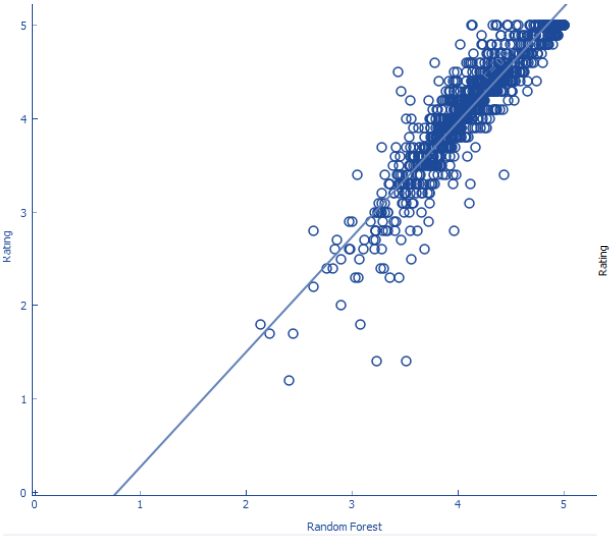
Below, the actual ratings are plotted against the predicted ratings to understand how the predictions are different from reality.



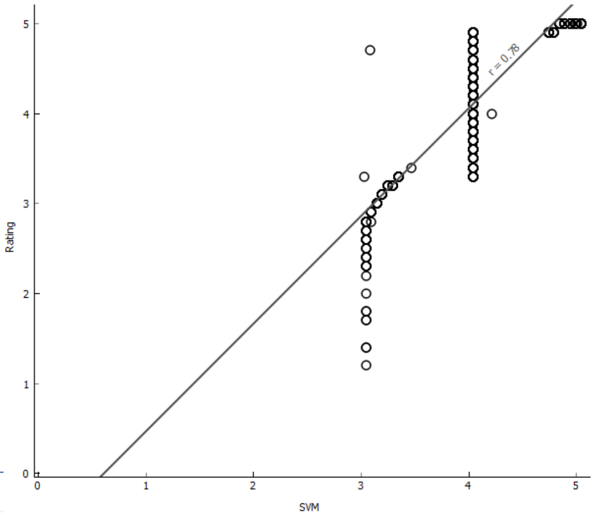
kNN



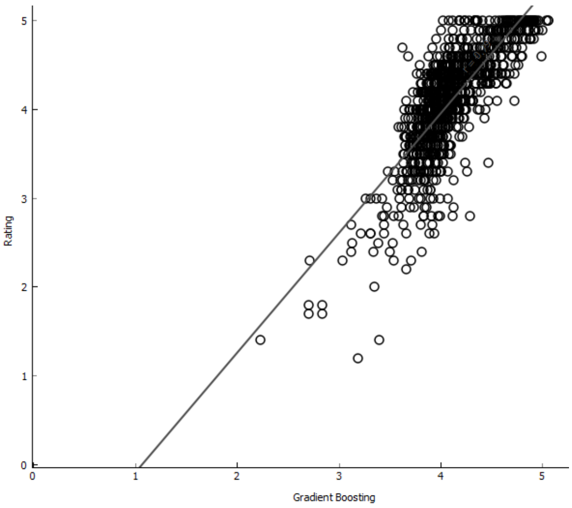
Linear Regression
(Bad fit)



Random Forest
(Best fit)



SVM



Gradient Boosting

As we can see, for Random forest, SVM and Gradient Boosting the predicted ratings are close to actual ratings. On the contrary, for linear regression and kNN the predicted values are scattered very distantly.

Hence, for predicting ratings, Random Forest is the better model.

END