App Store Analysis

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Research Questions

Can you predict an app's popularity on the Google Play Store using A Machine Learning Decision Tree Classifier?

If a developer were to create a new app, what qualities should this app have in order to generate the most ad revenue?

Motivation

GAIN EDGE OVER THE INDUSTRY COMPETITION FOR APP SUCCESS.

PROVIDE INSIGHT FOR ADVERTISEMENT COMPANIES ON WHICH APPS WOULD GENERATE THE MOST REVENUE IF ADS WERE INCLUDED.

ASSIST ANDROID DEVELOPERS TO DEVELOP STATE-OF-THE-ART APPS THAT THE PUBLIC DESERVES.

Dataset Used for Analysis

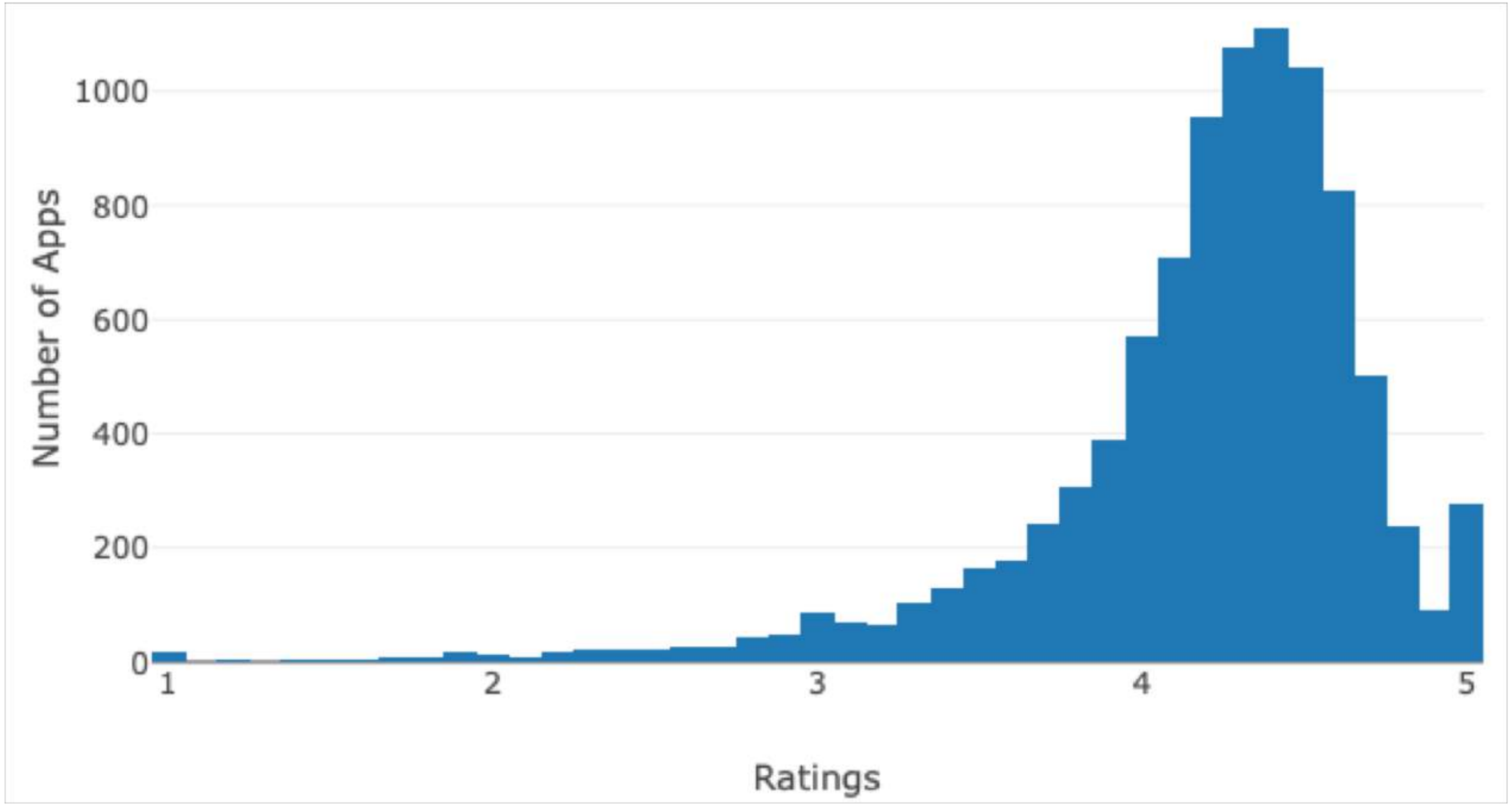
- Kaggle's Google Play Store Apps Dataset
- The columns used are App Name, Category, Genre, Rating, Reviews, Installs, Size, Type, Price, and Content Rating.
- https://www.kaggle.com/lava18/google-play-store-apps

Data Cleaning

Null values were removed, as well as a misclassified app under a category titled "1.9."

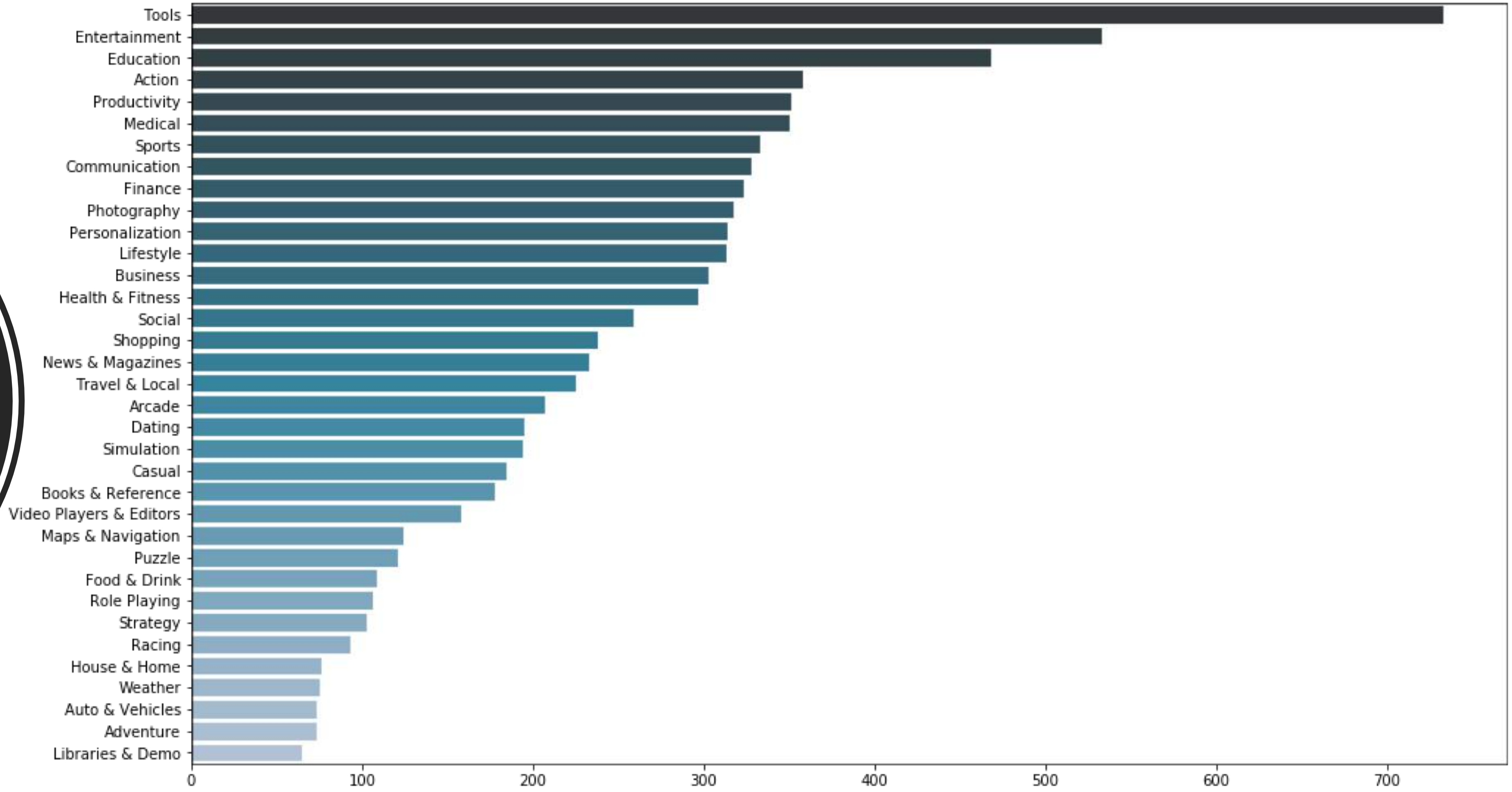
Data preprocessing and methods for the ML Decision Tree Classifier are described in the next slides.

Findings



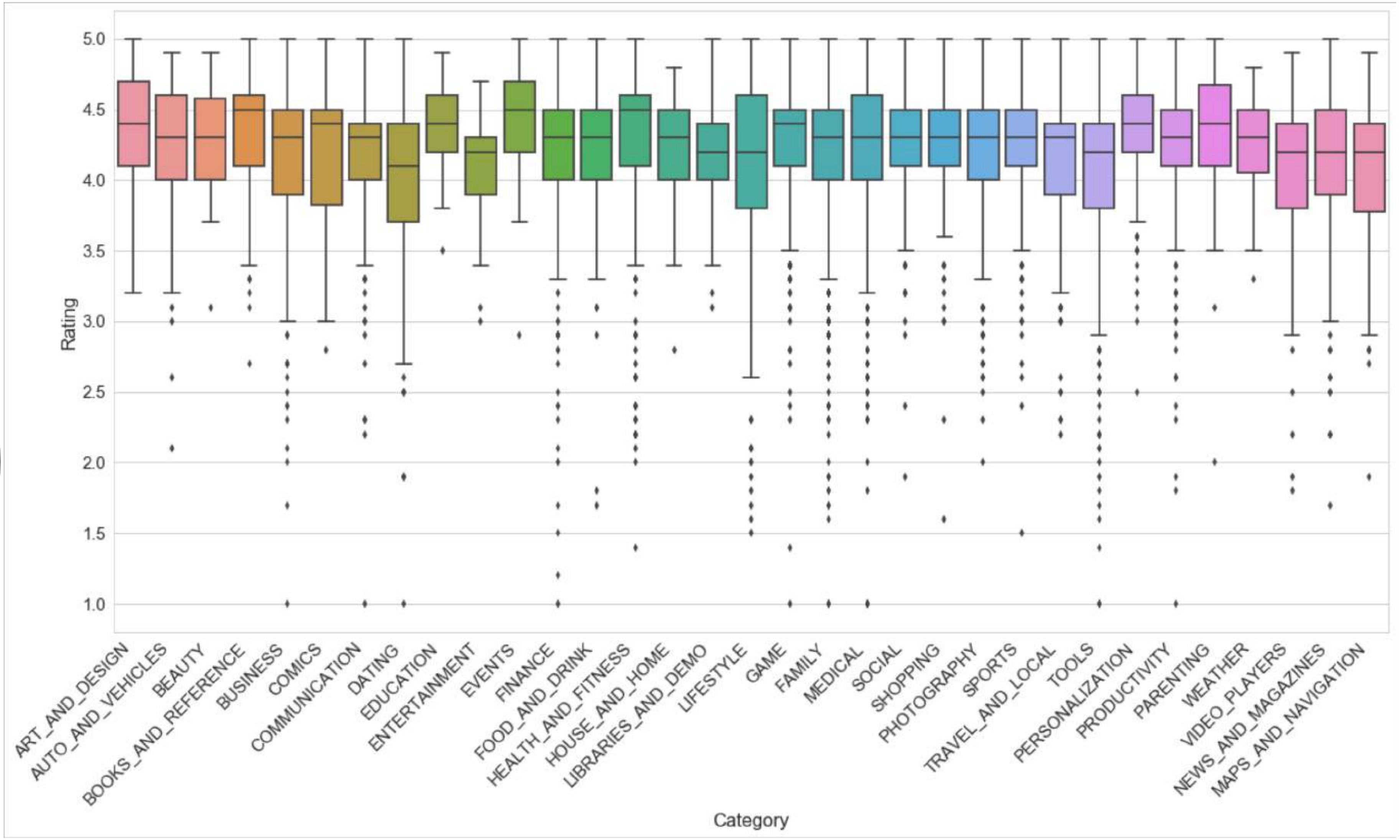
Most apps are rated around 4.5/5 on the app store.

Findings continued



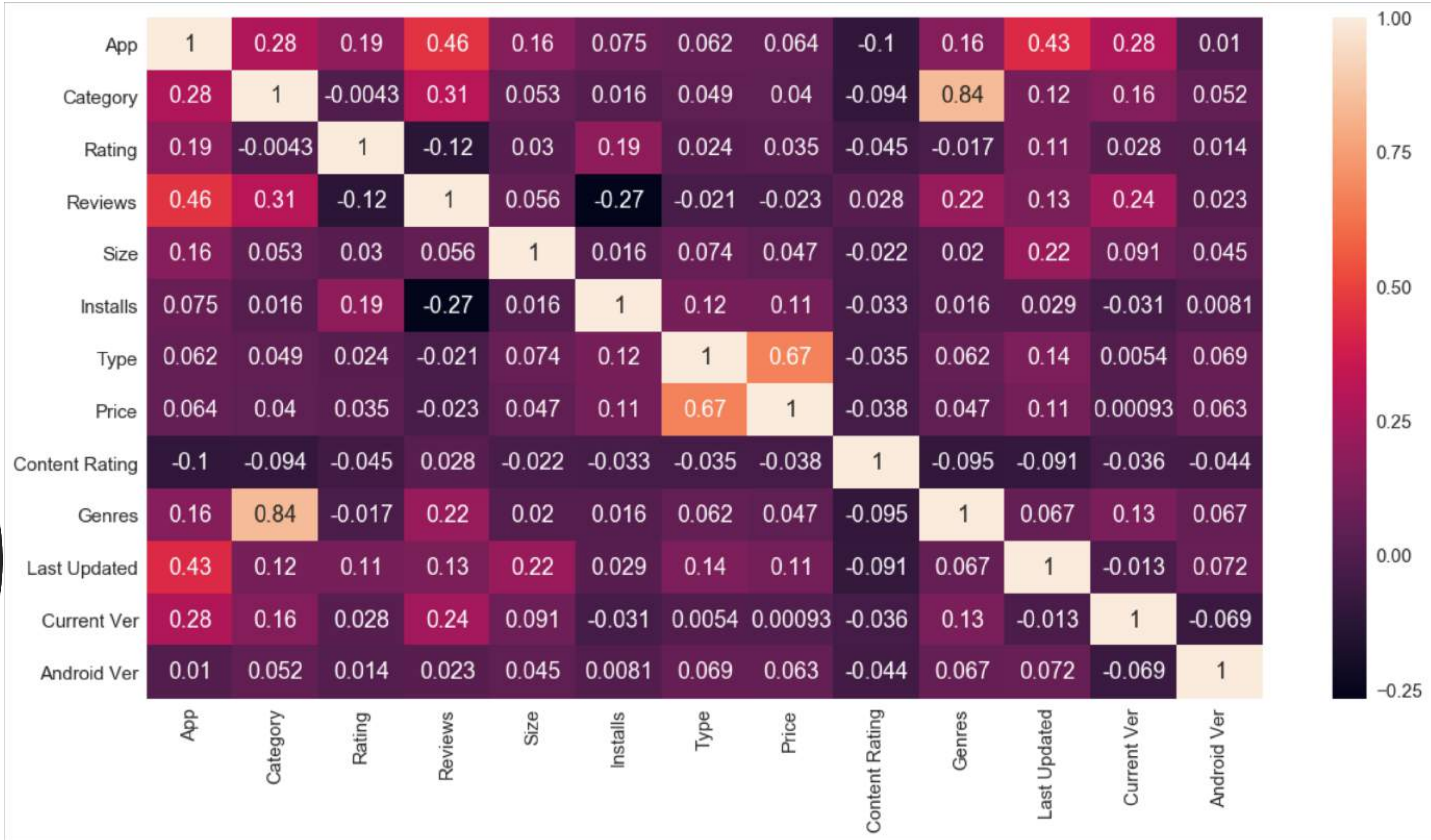
The top genre for apps to be classified under is “Tools.”

Findings continued



Difficult to tell from this plot, however, the least amount of apps that are rated high belong to the Auto & Vehicle and Entertainment category. This is more clearly shown in the Jupyter Notebook.

Finding continued



Above, we can see that Installs and Reviews has the strongest inverse correlation. This is reasonable because more reviews are conducted on apps that are the most popular. Since Installs was not correlated to Type, this disproves our intuition that free apps lead to more installs. Since the Installs parameter is independent and not correlated to any other parameters, we must only use Installs to show the popularity of an app. Apps with larger amounts of installs would generate the most revenue.

Machine Learning – Decision Tree Classifier

The Installs column was binarized as >100,000 installs = 1 (popular), and <100,000 installs = 0 (unpopular). All other columns are label encoded with sklearn library.

The optimal leaf node number was found to be 29. Popular and unpopular apps were made to be 50-50 in the training data. Data was shuffled and partitioned into an 80-20 training/test split to ensure unbiased prediction.

When testing model using Reviews and Ratings columns, the accuracy of prediction was around 95%. However, a more realistic approach was using all columns except Reviews and Ratings. By doing so, the model gave about 72% accuracy when determining app popularity.

Better accuracy could be achieved with other models such as Logistic Regression.

Limitations

THE DECISION TREE CLASSIFIER RESULTED IN AN ADEQUATE PREDICTION PERFORMANCE IF REVIEWS AND RATINGS WAS INCLUDED, HOWEVER, IF THESE FEATURES ARE NOT INCLUDED, THEN ACCURACY IS DOWN TO AN UNACCEPTABLE 72%.

THIS MODEL IS LIMITING, HOWEVER, I BELIEVE EVEN BETTER PERFORMANCE CAN BE ACHIEVED USING ANOTHER MODEL SUCH AS LOGISTIC REGRESSION. THIS WILL MORE THAN LIKELY INCREASE PREDICTION ACCURACY TO AROUND 80% OR ABOVE.

Conclusion

For Innovation - **Developers** should focus in on apps with a category of **Auto and Vehicles** and **Entertainment**, as there are not many highly rated apps in these categories.

For Revenue - **Marketers** should advertise on the top 40 most installed apps listed in the Jupyter notebook, in order to reach the maximum viewing of their advertisements.

For Popularity - **Everyone** building apps should consider that the Category and Genre of an app may strongly dictate if an app will be popular or not. However, the Size, Type, Price, Content Rating, and Genre features should all be used to most accurately determine if an app will gain maximum installs.

References

- Gupta, L. (2019, February 03). Google Play Store Apps. Retrieved from https://www.kaggle.com/lava18/google-play-store-apps
- jPlotly. (n.d.). Retrieved from https://plot.ly/python/
- API reference¶. (n.d.). Retrieved from https://seaborn.pydata.org/api.html

Google Play Store Applications Analysis

Contents

Research Questions:

- Can you predict an app's popularity on the Google Play Store?
- If a developer were to create a new app, what qualities should this app have in order to generate the most ad revenue?

Motivation:

- Gain edge over the industry competition for app success.
- Provide insight for advertisement companies on which apps would generate the most revenue if ads were added.
- Assist Android developers to develop state-of-the-art apps that the public deserve.

In [1]:

```
import pandas as pd
import numpy as np
import seaborn as sns #plotting
from plotly.offline import download_plotlyjs, init_notebook_mode, plot, iplot
import plotly.plotly as py
import plotly.graph_objs as go
import matplotlib.pyplot as plt
from sklearn import preprocessing
from sklearn.metrics import accuracy_score
from sklearn.tree import DecisionTreeClassifier
%matplotlib inline
init_notebook_mode(connected=True)
```

The Data

Load the datasets into pandas dataframes

```
df_reviews = pd.read_csv("./GooglePlayStoreApps/googleplaystore_user_reviews.csv")
df_reviews.head()
```

	App	Translated_Review	Sentiment	Sentiment_Polarity	Sentiment_Subjectivity
0	10 Best Foods for You	I like eat delicious food. That's I'm cooking ...	Positive	1.00	0.533333
1	10 Best Foods for You	This help eating healthy exercise regular basis	Positive	0.25	0.288462
2	10 Best Foods for You	NaN	NaN	NaN	NaN
3	10 Best Foods for You	Works great especially going grocery store	Positive	0.40	0.875000
4	10 Best Foods for You	Best idea us	Positive	1.00	0.300000

```
df_apps = pd.read_csv("./GooglePlayStoreApps/googleplaystore.csv")
df_apps.head()
```

ut[24]:

	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

We will only be using the df_apps dataframe.

Next, find the number of unique app categories.

In [4]:
```
categories = list(df_apps["Category"].unique())
print("There are {0:.0f} categories! (Excluding/Removing Category 1.9)".format(len(categories)-1))
print(categories)
#Remove Category 1.9
categories.remove('1.9')
```

```
There are 33 categories! (Excluding/Removing Category 1.9)
['ART_AND_DESIGN', 'AUTO_AND_VEHICLES', 'BEAUTY', 'BOOKS_AND_REFERENCE', 'BUSINESS', 'COMICS', 'COMMUNICATION', 'DATI
NG', 'EDUCATION', 'ENTERTAINMENT', 'EVENTS', 'FINANCE', 'FOOD_AND_DRINK', 'HEALTH_AND_FITNESS', 'HOUSE_AND_HOME', 'LI
BRARIES_AND_DEMO', 'LIFESTYLE', 'GAME', 'FAMILY', 'MEDICAL', 'SOCIAL', 'SHOPPING', 'PHOTOGRAPHY', 'SPORTS', 'TRAVEL_A
ND_LOCAL', 'TOOLS', 'PERSONALIZATION', 'PRODUCTIVITY', 'PARENTING', 'WEATHER', 'VIDEO_PLAYERS', 'NEWS_AND_MAGAZINES',
'MAPS_AND_NAVIGATION', '1.9']
```

Drop rows with Category "1.9" from dataframe. As seen below, this incorrectly labeled app category only affected one app. We can remove this row from the dataframe.

In [5]:
```
a = df_apps.loc[df_apps["Category"] == "1.9"]
print(a.head())
print("This mislabeled app category affects {} app at index {}.".format(len(a),int(a.index.values)))
df_apps = df_apps.drop(int(a.index.values),axis=0)
```

```
                                           App Category  Rating Reviews  \
10472  Life Made WI-Fi Touchscreen Photo Frame      1.9    19.0    3.0M

         Size Installs Type     Price Content Rating             Genres  \
10472  1,000+     Free    0  Everyone            NaN  February 11, 2018

      Last Updated Current Ver Android Ver
10472       1.0.19  4.0 and up         NaN
This mislabeled app category affects 1 app at index 10472.
```

In [6]:
```
df_apps['Rating'].isnull().sum()
```

Out[6]:
```
1474
```

Delete rows that don't have any ratings.

In [7]:
```
df_apps = df_apps.drop(df_apps[df_apps['Rating'].isnull()].index, axis=0)
```

The Exploration

In [8]:
```
df_apps.info()
```

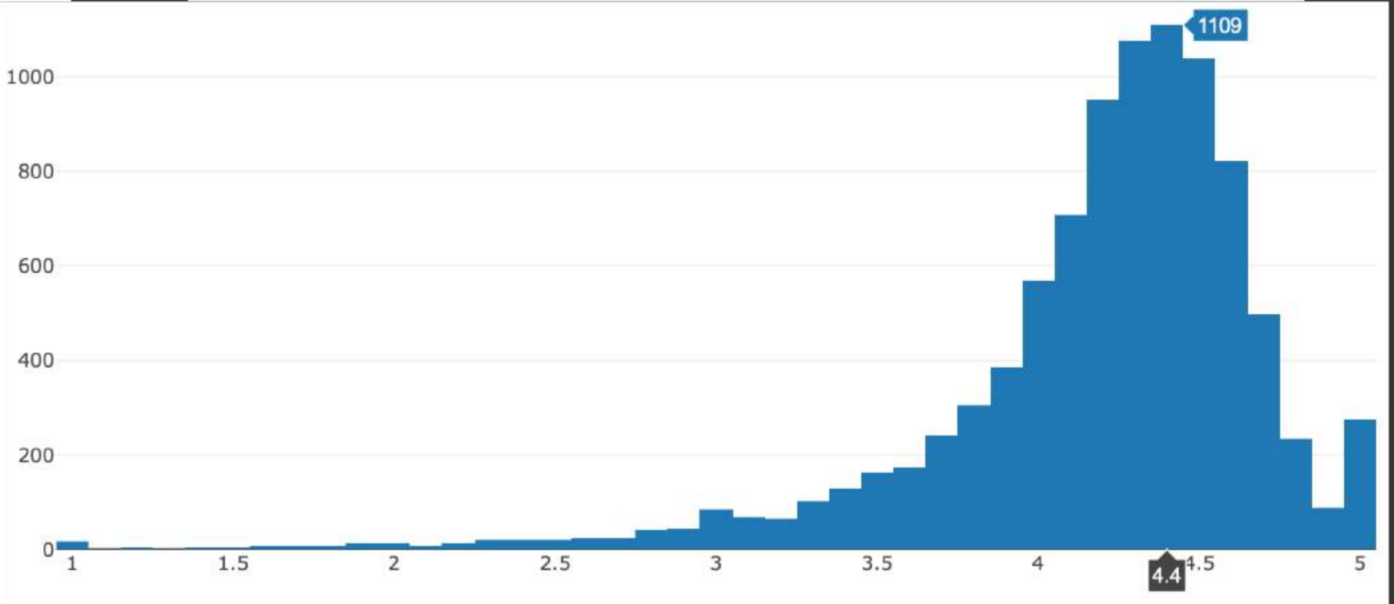
```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9366 entries, 0 to 10840
Data columns (total 13 columns):
App               9366 non-null object
Category          9366 non-null object
Rating            9366 non-null float64
Reviews           9366 non-null object
Size              9366 non-null object
Installs          9366 non-null object
Type              9366 non-null object
Price             9366 non-null object
Content Rating    9366 non-null object
Genres            9366 non-null object
Last Updated      9366 non-null object
Current Ver       9362 non-null object
Android Ver       9364 non-null object
dtypes: float64(1), object(12)
memory usage: 1.0+ MB
```

As seen above, there are not any null values.

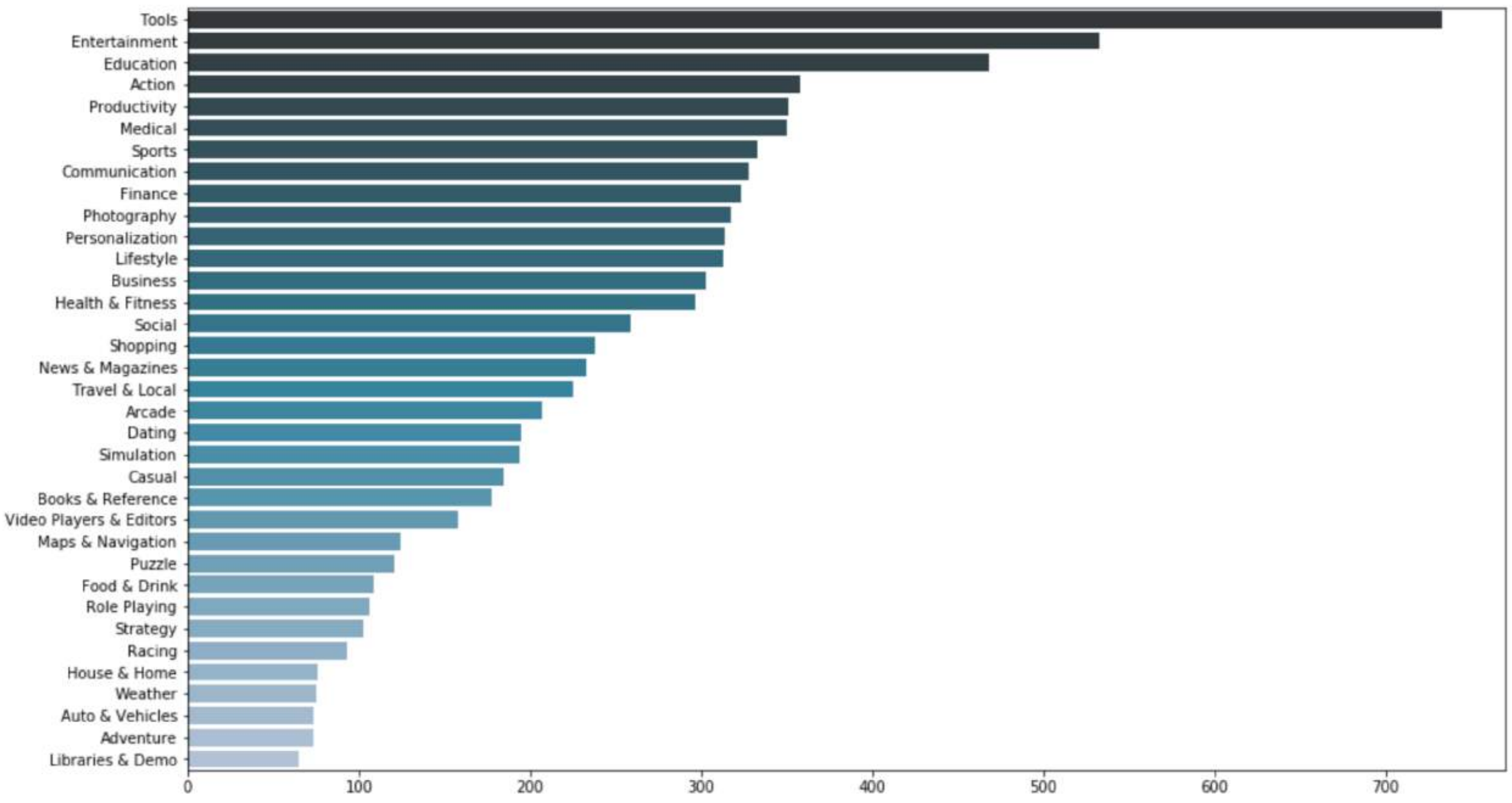
In [9]:
```
df_apps["Rating"].describe()
```

Out[9]:
```
count    9366.000000
mean        4.191757
std         0.515219
min         1.000000
25%         4.000000
50%         4.300000
75%         4.500000
max         5.000000
Name: Rating, dtype: float64
```

In [10]:
```
data = [go.Histogram(x=df_apps["Rating"])]
iplot(data, filename='basic histogram')
```

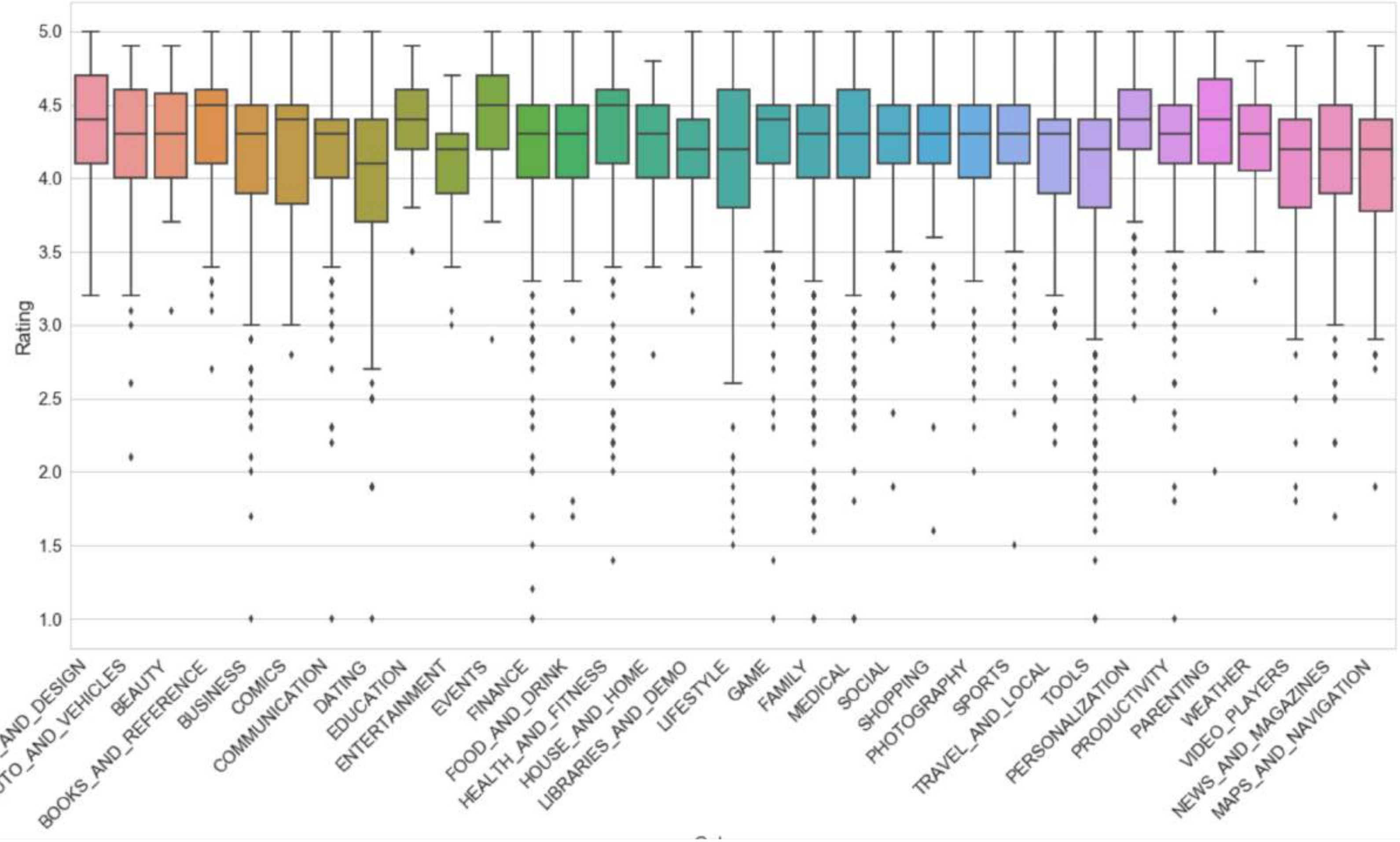


In [11]:
```
#Show top 35 app genres
plt.figure(figsize=(16, 9.5))
genres = df_apps["Genres"].value_counts()[:35]
ax = sns.barplot(x=genres.values, y=genres.index, palette="PuBuGn_d")
```



Which categories have the best overall rating? Also, which category had the most installs? Let's find out!

```
sns.set(rc={'figure.figsize':(20,10)}, font_scale=1.5, style='whitegrid')
ax = sns.boxplot(x="Category",y="Rating",data=df_apps)
labels = ax.set_xticklabels(ax.get_xticklabels(), rotation=45,ha='right')
```



```
In [13]: #Cut away rows which have < 4.0 ratings
highRating = df_apps.copy()
highRating = highRating.loc[highRating["Rating"] >= 4.0]
highRateNum = highRating.groupby('Category')['Rating'].nunique()
highRateNum
```

```
Out[13]: Category
ART_AND_DESIGN          10
AUTO_AND_VEHICLES        8
BEAUTY                  10
BOOKS_AND_REFERENCE     11
BUSINESS                11
COMICS                  10
COMMUNICATION           10
DATING                  11
EDUCATION               10
ENTERTAINMENT            8
EVENTS                  11
FAMILY                  11
FINANCE                 11
FOOD_AND_DRINK          10
GAME                    11
HEALTH_AND_FITNESS      11
HOUSE_AND_HOME           9
LIBRARIES_AND_DEMO       9
LIFESTYLE               11
MAPS_AND_NAVIGATION     10
MEDICAL                 11
NEWS_AND_MAGAZINES      11
PARENTING               11
PERSONALIZATION         11
PHOTOGRAPHY             11
PRODUCTIVITY            11
SHOPPING                10
SOCIAL                  11
SPORTS                  11
TOOLS                   11
TRAVEL_AND_LOCAL        10
VIDEO_PLAYERS           10
WEATHER                  9
Name: Rating, dtype: int64
```

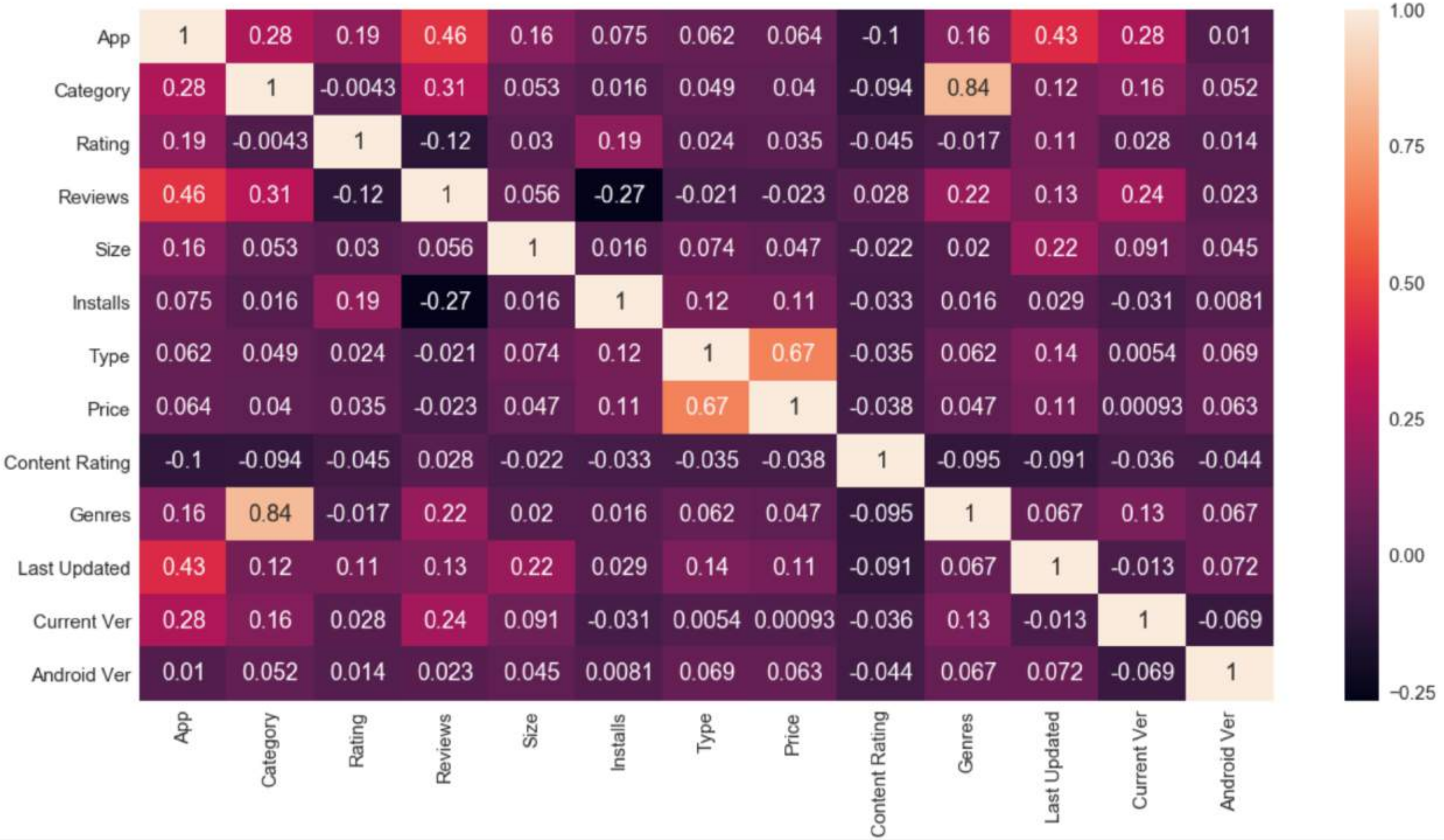
There are many categories of apps that are equal in terms of being the highest rated. This is great, however, the interest should lie within the app categories which have the lowest number of high ratings. These poorly rated apps deserve more attention because if a new sleek new app in that category were to be pu on the app store, then the developers could satisfy the demand for innovation in this area. In this case, **The Categories of Importance are "AUTO_AND_VEHICLES"and "ENTERTAINMENT."**

Now to analyze the apps which would produce the most ad revenue

One parameter that would affect ad revenue the most is the number of installs an app has. More installs means more people are opening the app and viewing the embedded ads, hence, there is more money being made. A free application may lead to more installs, however, other parameters may alter how many installs an app will have. **Let's see if there is a correlation between installs and other parameters!**

```
In [14]: df_apps.dtypes
         df_apps["Type"] = (df_apps["Type"] == "Paid").astype(int)
         corr = df_apps.apply(lambda x: x.factorize()[0]).corr()
         sns.heatmap(corr, xticklabels=corr.columns, yticklabels=corr.columns,annot=True)
```

```
Out[14]: <matplotlib.axes._subplots.AxesSubplot at 0x10d7214e0>
```



I apologize for the line being cut off.

Above, we can see that Installs and Reviews has the strongest inverse correlation. This is resonable because more reviews are conducted on apps that are the most popular. Since Installs was not correlated to Type, this disproves our intuition that free apps lead to more installs. Since the Installs parameter is independent and not correlated to any other parameters, we must only use Installs to show the popularity of an app. Apps with larger amounts of installs would generate the most revenue. Let's take a look at the **Top 40 Apps that businesses should consider signing advertising deals with!**

In [15]:

```
#Extract App, Installs, & Content Rating from df_apps
popApps = df_apps.copy()
popApps = popApps.drop_duplicates()
#Remove characters preventing values from being floats and integers
popApps["Installs"] = popApps["Installs"].str.replace("+","")
popApps["Installs"] = popApps["Installs"].str.replace(",","")
popApps["Installs"] = popApps["Installs"].astype("int64")
popApps["Price"] = popApps["Price"].str.replace("$","")
popApps["Price"] = popApps["Price"].astype("float64")
popApps["Size"] = popApps["Size"].str.replace("Varies with device","0")
popApps["Size"] = (popApps["Size"].replace(r'[kM]+$', '', regex=True).astype(float) *\
        popApps["Size"].str.extract(r'[\d\.]+([kM]+)', expand=False).fillna(1).replace(['k','M'], [10**3, 10**6]).astyp
popApps["Reviews"] = popApps["Reviews"].astype("int64")

popApps = popApps.sort_values(by="Installs",ascending=False)
popApps.reset_index(inplace=True)
popApps.drop(["index"],axis=1,inplace=True)
popApps.loc[:40,['App','Installs','Content Rating']]
```

	App	Installs	Content Rating
0	Messenger – Text and Video Chat for Free	1000000000	Everyone
1	Google Drive	1000000000	Everyone
2	Instagram	1000000000	Teen
3	Google	1000000000	Everyone
4	Instagram	1000000000	Teen
5	Google+	1000000000	Teen
6	Subway Surfers	1000000000	Everyone 10+
7	Maps - Navigate & Explore	1000000000	Everyone
8	Google	1000000000	Everyone
9	Hangouts	1000000000	Everyone
10	Google+	1000000000	Teen
11	Google Drive	1000000000	Everyone
12	Google Play Movies & TV	1000000000	Teen
13	Google Photos	1000000000	Everyone
14	Google Street View	1000000000	Everyone
15	Subway Surfers	1000000000	Everyone 10+
16	Maps - Navigate & Explore	1000000000	Everyone
17	Subway Surfers	1000000000	Everyone 10+
18	Google Drive	1000000000	Everyone
19	Instagram	1000000000	Teen
20	Google Chrome: Fast & Secure	1000000000	Everyone
21	Subway Surfers	1000000000	Everyone 10+
22	YouTube	1000000000	Teen
23	Google Play Books	1000000000	Teen
24	Google Photos	1000000000	Everyone
25	WhatsApp Messenger	1000000000	Everyone
26	Google Photos	1000000000	Everyone
27	Facebook	1000000000	Teen
28	Google Play Games	1000000000	Teen
29	YouTube	1000000000	Teen
30	Google Photos	1000000000	Everyone
31	Facebook	1000000000	Teen
32	Google Street View	1000000000	Everyone
33	Google News	1000000000	Teen
34	Subway Surfers	1000000000	Everyone 10+
35	Messenger – Text and Video Chat for Free	1000000000	Everyone
36	Gmail	1000000000	Everyone
37	Hangouts	1000000000	Everyone
38	Gmail	1000000000	Everyone
39	Hangouts	1000000000	Everyone
40	WhatsApp Messenger	1000000000	Everyone

```
In [16]: popAppsCopy = popApps.copy()
         label_encoder = preprocessing.LabelEncoder()

         # Encode labels in column 'Category'.
         popAppsCopy['Category']= label_encoder.fit_transform(popAppsCopy['Category'])
         popAppsCopy['Content Rating']= label_encoder.fit_transform(popAppsCopy['Content Rating'])
         popAppsCopy['Genres']= label_encoder.fit_transform(popAppsCopy['Genres'])
         popAppsCopy.dtypes
```

```
Out[16]: App                object
         Category            int64
         Rating            float64
         Reviews             int64
         Size              float64
         Installs            int64
         Type                int64
         Price             float64
         Content Rating      int64
         Genres              int64
         Last Updated       object
         Current Ver        object
         Android Ver        object
         dtype: object
```

Since the important data is already preprocessed into floats and integers, we can drop the object features and build an 80/20 training/test split.

```
popAppsCopy = popAppsCopy.drop(["App","Last Updated","Current Ver","Android Ver"],axis=1)
print("There are {} total rows.".format(popAppsCopy.shape[0]))
countPop = popAppsCopy[popAppsCopy["Installs"] > 100000].count()
print("{} Apps are Popular!".format(countPop[0]))
print("{} Apps are Unpopular!\n".format((popAppsCopy.shape[0]-countPop)[0]))
print("For an 80-20 training/test split, we need about {} apps for testing\n".format(popAppsCopy.shape[0]*.20))
popAppsCopy["Installs"] = (popAppsCopy["Installs"] > 100000)*1 #Installs Binarized
print("Cut {} apps off Popular df for a total of 3558 training apps.".format(int(4568*.22132)))
print("Cut {} apps off Unpopular df for a total of 3558 training apps.\n".format(int(4324*.17738)))

testPop1 = popAppsCopy[popAppsCopy["Installs"] == 1].sample(1010,random_state=0)
popAppsCopy = popAppsCopy.drop(testPop1.index)
print("Values were not dropped from training dataframe.",testPop1.index[0] in popAppsCopy.index)

testPop0 = popAppsCopy[popAppsCopy["Installs"] == 0].sample(766,random_state=0)
popAppsCopy = popAppsCopy.drop(testPop0.index)
print("Values were not dropped from training dataframe.",testPop0.index[0] in popAppsCopy.index)

testDf = testPop1.append(testPop0)
trainDf = popAppsCopy

#Shuffle rows in test & training data set
testDf = testDf.sample(frac=1,random_state=0).reset_index(drop=True)
trainDf = trainDf.sample(frac=1,random_state=0).reset_index(drop=True)

#Form training and test data split
y_train = trainDf.pop("Installs")
X_train = trainDf.copy()
y_test = testDf.pop("Installs")
X_test = testDf.copy()

X_train = X_train.drop(['Reviews', 'Rating'], axis=1) #REMOVE ROW TO INCLUDE REVIEWS & RATINGS IN ML MODEL ~93% accurat
X_test = X_test.drop(['Reviews', 'Rating'], axis=1)   #REMOVE ROW TO INCLUDE REVIEWS & RATINGS IN ML MODEL ~93% accurat
```

```
There are 8892 total rows.
4568 Apps are Popular!
4324 Apps are Unpopular!

For an 80-20 training/test split, we need about 1778.4 apps for testing

Cut 1010 apps off Popular df for a total of 3558 training apps.
Cut 766 apps off Unpopular df for a total of 3558 training apps.

Values were not dropped from training dataframe. False
Values were not dropped from training dataframe. False
```

In [18]:
```
print("{} Apps are used for Training.".format(y_train.count()))
print("{} Apps are used for Testing.".format(y_test.count()))
X_test.head(3)
```

```
7116 Apps are used for Training.
1776 Apps are used for Testing.
```

Out[18]:

	Category	Size	Type	Price	Content Rating	Genres
0	11	60000000.0	0	0.0	1	101
1	14	31000000.0	0	0.0	4	0
2	11	48000000.0	0	0.0	1	94

Fit on Train Set

In [19]:
```
popularity_classifier = DecisionTreeClassifier(max_leaf_nodes=29, random_state=0)
popularity_classifier.fit(X_train, y_train)
```

Out[19]:
```
DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=None,
            max_features=None, max_leaf_nodes=29,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, presort=False, random_state=0,
            splitter='best')
```

Predict on Test Set

In [20]:
```
predictions = popularity_classifier.predict(X_test)
print("Predicted: ",predictions[:30])
print("Actual:    ",np.array(y_test[:30]))
```

```
Predicted:  [1 1 1 0 0 0 0 1 1 1 1 0 0 0 1 0 1 1 0 1 1 0 0 1 1 0 0 1 1 0]
Actual:     [1 1 0 1 0 0 0 1 1 0 1 1 1 0 1 1 1 0 0 1 1 0 0 1 0 0 1 1 1 1]
```

Measure Accuracy of Classifier

In [21]:
```
accuracy_score(y_true = y_test, y_pred = predictions)
```

Out[21]:
```
0.722972972972973
```

Find out what caused higher popularity

If different apps with the same app sizes are compared, we can see that the Category and the Genres columns are the only parameters that differ when determining popularity. Shown below, the 1's in the "Popular?" column may be outliers, so as a whole, given all columns below, we can predict with ~70% accuracy the success of an app.

In [22]:
```
X_testCopy = X_test.copy()
X_testCopy["Popular?"] = y_test
X_testCopy[X_test["Size"] == 3600000].head(10)
```

Out[22]:

	Category	Size	Type	Price	Content Rating	Genres	Popular?
112	11	3600000.0	0	0.00	1	50	0
616	12	3600000.0	0	0.00	1	58	0
1297	19	3600000.0	0	0.00	1	68	1
1310	31	3600000.0	0	0.00	4	110	0
1352	23	3600000.0	1	0.99	1	78	0

When running the kernel, the Accuracy of this Decision Tree Classifier will be about 95% (IF INCLUDING REVIEWS & RATINGS). When not including the rating and reviews features, the Classifier has around 72% Accuracy. This shows that **given the Size, Type, Price, Content Rating, and Genre of an app, we can predict within 72% certainty if an app will have more than 100,000 installs and be a hit on the Google Play Store.**

Conclusion

- **For Innovation** - **Developers** should focus in on apps with a category of **Auto and Vehicles** and **Entertainment**, as there are not many highly rated apps in these categories.

- **For Revenue** - **Marketers** should advertise on the top 40 most installed apps list above, in order to reach the maximum viewing of their advertisements.

- **For Popularity** - **Everyone** building apps should consider that the Category and Genre of an app may strongly dictate if an app will be popular or not. However, the Size, Type, Price, Content Rating, and Genre features should all be used to most accurately determine if an app will gain maximum installs.