Final Project Submission

Please fill out:

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- Student pace: part time
- Scheduled project review date/time: April 7th, 2020 at 4pm CST
- Instructor name: Lindsey Berlin

Introduction

With Android OS holding 87% of market share in 2019, a VC firm is looking to understand what characteristics are predictive of a positively rated app (4.5+ rating on a 1-5 scale). They want to be able to utilize this information to target possible companies to apply for investment. It can also be applied to weed out those that are not a fit. Given that there are strong signals, these learnings could also be operationally applied to targeting companies to invest in, application questions, and company screenings for more efficient filtering and assessment.

The modeling iterations below have been created using 2019 Google Play Store data with records consisting of apps, their rating, number of installs, reviews, content rating, and more. Throughout the model construction, a focus was placed on scoring high on recall and balanced with the goal of an accuracy score better than a random guess.

Recall was particularly chosen due to the risk of the model producing False Negatives, which would mean the VC firm would miss the opportunity to bring an app into the world. With recall emphasizing the importance of True Positives, we can focus on identifying apps that would most likely be positively rated.

Conversely, a precision score was *not* the focus because it focuses on lessening False Positives, which to the VC firm is investing in something that has less chance being successful, or in this case, an app less likelye to be positively rated. Within the business context, a VC firm is always going to be facing this risk; thus for this purpose recall was confirmed as the priority metric.

Notebook Summary

Models

Note: Models used for analysis italicized

Phase 1: Data Version 1 and Baseline Testing

Phase 2: Data Version 2 + 3 and Model Tuning

Phase 3: Feature Importance and Analysis (Baseline, eli5, rfpimp, Drop One Features)

Results

The final two models, Model 11 and Model 12, produced either:

1. **An accuracy score 1-2% above a random guess and a 50% recall score (Decision Tree) OR**
2. **A 56-58% recall score (and similar cross validation scores for recall, and an accuracy score 2% below a random guess (Random Forest)**

Although the model is not in a final versioning to be utilized in day-to-day decisions, the consistency from this version can be generally applied to say that marketing, promotion, and adoption of the app is foundationally important.

Along with the technical aptitude for efficient app development, the VC would want CEOs with strong marketing background, a network with these skills, and/or teams that have this expertise.

Intro Work

In [1]:

```
# Imports Data Discovery and Plotting
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns

# Imports Modeling
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split, cross_val_score, GridSearchCV
from sklearn.metrics import accuracy_score, recall_score, f1_score, roc_auc_score, plot_c
onfusion_matrix, r2_score

# Imports Feature Importance Assists
import operator
from sklearn.base import clone
import eli5
from eli5.sklearn import PermutationImportance
from rfpimp import permutation_importances
```

```
/opt/anaconda3/envs/learn-env/lib/python3.6/site-packages/sklearn/utils/deprecation.py:14
4: FutureWarning: The sklearn.feature_selection.base module is  deprecated in version 0.2
2 and will be removed in version 0.24. The corresponding classes / functions should inste
ad be imported from sklearn.feature_selection. Anything that cannot be imported from skle
arn.feature_selection is now part of the private API.
  warnings.warn(message, FutureWarning)
/opt/anaconda3/envs/learn-env/lib/python3.6/site-packages/sklearn/utils/deprecation.py:14
4: FutureWarning: The sklearn.ensemble.forest module is  deprecated in version 0.22 and w
ill be removed in version 0.24. The corresponding classes / functions should instead be i
mported from sklearn.ensemble. Anything that cannot be imported from sklearn.ensemble is
now part of the private API.
  warnings.warn(message, FutureWarning)
```

Functions

In [2]:

```
def eval_model(estimator, X_train, X_test, y_train, y_test):
    '''
    Evaluation function to show accuracy, recall, mean 3-fold cross-validation
    for both the train and test set, then shows confusion matrix for the test set
    '''
    # grab predictions
    train_preds = estimator.predict(X_train)
    test_preds = estimator.predict(X_test)

    # print scores
    print("Train Scores")
    print("------------")
    print(f"Accuracy: {accuracy_score(y_train, train_preds)}")
    print(f"Recall: {recall_score(y_train, train_preds)}")
    print(f"F1 Score: {f1_score(y_train, train_preds)}")
    print("----" * 5)
    print("Test Scores")
    print("-----------")
    print(f"Accuracy: {accuracy_score(y_test, test_preds)}")
    print(f"Recall: {recall_score(y_test, test_preds)}")
    print(f"Recall Mean Cross Val 3-Fold: {np.mean(cross_val_score(estimator,  X_train, y
_train, cv=3, scoring='recall'))}")
    print(f"F1 Score: {f1_score(y_test, test_preds)}")

    # plot test confusion matrix
    plot_confusion_matrix(estimator, X_test, y_test, values_format='')
    plt.show()
```

In [3]:

```
# source: https://towardsdatascience.com/explaining-feature-importance-by-example-of-a-ra
ndom-forest-d9166011959e
from sklearn.base import clone

def drop_col_feat_imp(model, X_train, y_train, random_state = 42):

    # clone the model to have the exact same specification as the one initially trained
    model_clone = clone(model)
    # set random_state for comparability
    model_clone.random_state = random_state
    # training and scoring the benchmark model
    model_clone.fit(X_train, y_train)
    benchmark_score = model_clone.score(X_train, y_train)
    # list for storing feature importances
    importances = []

    # iterating over all columns and storing feature importance (difference between bench
mark and new model)
    for col in X_train.columns:
        model_clone = clone(model)
        model_clone.random_state = random_state
        model_clone.fit(X_train.drop(col, axis = 1), y_train)
        drop_col_score = model_clone.score(X_train.drop(col, axis = 1), y_train)
        importances.append(benchmark_score - drop_col_score)

    importances_df = pd.DataFrame(X_train.columns, importances)
    return importances_df
```

In [4]:

```
# source: https://towardsdatascience.com/explaining-feature-importance-by-example-of-a-ra
ndom-forest-d9166011959e
def r2(rf, X_train, y_train):
    return r2_score(y_train, rf.predict(X_train))
```

Data Import

In [5]:

```
# Import data
data = pd.read_csv('data/googleplaystore.csv')
data.head()
```

Out[5]:

	App	Category	Rating	Reviews	Size	Installs	Type	Price	Content Rating	Genres	Last Updated	Cu
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	Coloring book moana	ART_AND_DESIGN	3.9	967	14M	500,000+	Free	0	Everyone	Art & Design;Pretend Play	January 15, 2018	
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	
3	Sketch - Draw & Paint	ART_AND_DESIGN	4.5	215644	25M	50,000,000+	Free	0	Teen	Art & Design	June 8, 2018	V d
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	

In [6]:

```
# create data copy for manipulation
df = data.copy()
```

In [7]:

```
# Overview
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10841 entries, 0 to 10840
Data columns (total 13 columns):
App               10841 non-null object
Category          10841 non-null object
Rating            9367 non-null float64
Reviews           10841 non-null object
Size              10841 non-null object
Installs          10841 non-null object
Type              10840 non-null object
Price             10841 non-null object
Content Rating    10840 non-null object
Genres            10841 non-null object
Last Updated      10841 non-null object
Current Ver       10833 non-null object
Android Ver       10838 non-null object
dtypes: float64(1), object(12)
memory usage: 1.1+ MB
```

Intial Data Cleansing and Review

Initial Data Cleansing and Review

In [8]:

```
# Rating is target so drop nulls
df = df.dropna()
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9360 entries, 0 to 10840
Data columns (total 13 columns):
App                  9360 non-null object
Category             9360 non-null object
Rating               9360 non-null float64
Reviews              9360 non-null object
Size                 9360 non-null object
Installs             9360 non-null object
Type                 9360 non-null object
Price                9360 non-null object
Content Rating       9360 non-null object
Genres               9360 non-null object
Last Updated         9360 non-null object
Current Ver          9360 non-null object
Android Ver          9360 non-null object
dtypes: float64(1), object(12)
memory usage: 1023.8+ KB
```

In [9]:

```
# Preview Rating values
df['Rating']
```

Out[9]:

```
0        4.1
1        3.9
2        4.7
3        4.5
4        4.3
        ...
10834    4.0
10836    4.5
10837    5.0
10839    4.5
10840    4.5
Name: Rating, Length: 9360, dtype: float64
```

In [10]:

```
# What % of Ratings are >= 4.5
# 4.5 out of 5 is high rating on Google Play Store
len(df[df['Rating'] >= 4.5])/len(df)
```

Out[10]:

```
0.3155982905982906
```

In [11]:

```
# Create target Positive Rating
df['Pos Rating'] = 0

for row in df['Rating'].index:
    if df['Rating'][row] >= 4.5:
        df['Pos Rating'][row] = 1
```

```
/opt/anaconda3/envs/learn-env/lib/python3.6/site-packages/ipykernel_launcher.py:6: Settin
gWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/user_gu
ide/indexing.html#returning-a-view-versus-a-copy
```

In [12]:

```
# Check work, target created
df['Pos Rating'].value_counts(normalize=True)
```

Out[12]:

```
0    0.684402
1    0.315598
Name: Pos Rating, dtype: float64
```

In [13]:

```
# Type versus Price - view Type distribution
df['Type'].value_counts(normalize=True)
```

Out[13]:

```
Free    0.93109
Paid    0.06891
Name: Type, dtype: float64
```

In [14]:

```
# Initial df cleans and conversions

# Convert to Reviews to numeric, integer
df['Reviews'] = df['Reviews'].astype(int)

# Drop Price column, use Type - 93% are Free or 0 in Price.
df = df.drop(columns='Price', axis=1)

# Drop Rating, duplicative of Pos Rating and is target
df = df.drop(columns='Rating', axis=1)
```

In [15]:

```
# Preview new df
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9360 entries, 0 to 10840
Data columns (total 12 columns):
App               9360 non-null object
Category          9360 non-null object
Reviews           9360 non-null int64
Size              9360 non-null object
Installs          9360 non-null object
Type              9360 non-null object
Content Rating    9360 non-null object
Genres            9360 non-null object
Last Updated      9360 non-null object
Current Ver       9360 non-null object
Android Ver       9360 non-null object
Pos Rating        9360 non-null int64
dtypes: int64(2), object(10)
memory usage: 1.2+ MB
```

In [16]:

```
# Many are objects - describe
df[[c for c in df.columns if df[c].dtype == 'object']].describe()

# App - drop, equivalent of ID
# Categorry - 33 uniques, OHE
# Size - 413 unique values, most common is Varies with device/in M and k
# will need to convert to same unites
# Installs - can keep as categories and OHE or try numeric
# Content Rating - categorical, but could be ordinal
# Genres - categorical, can OHE; see if there is an opportunity to bucket smaller genres
into
```

```
# larger ones
# Last Updated - leave out as do not have specific stats for age feature
# Current Version and Android Version are not controllable features
```

Out[16]:

	App	Category	Size	Installs	Type	Content Rating	Genres	Last Updated	Current Ver	Android Ver
count	9360	9360	9360	9360	9360	9360	9360	9360	9360	9360
unique	8190	33	413	19	2	6	115	1299	2638	31
top	ROBLOX	FAMILY	Varies with device	1,000,000+	Free	Everyone	Tools	August 3, 2018	Varies with device	4.1 and up
freq	9	1746	1637	1576	8715	7414	732	319	1415	2059

In [17]:

```
# Define X and y
X = df.drop(columns=['Pos Rating', 'App', 'Last Updated', 'Current Ver', 'Android Ver'])
y = df['Pos Rating']
```

In [18]:

```
# Review X columns for treatment assignment
X.columns
```

Out[18]:

```
Index(['Category', 'Reviews', 'Size', 'Installs', 'Type', 'Content Rating',
       'Genres'],
      dtype='object')
```

In [19]:

```
# Separate for different treatments (scaling and OHE)

num_cols = ['Reviews']

ohe_cols = ['Category', 'Size', 'Installs', 'Type', 'Content Rating', 'Genres']
```

Numeric Treatment - Scale

In [20]:

```
# Copy df for manipulation
scaled_features = df.copy()
```

In [21]:

```
# Scale num_col features
features = scaled_features[num_cols]
scaler = StandardScaler().fit(features.values)
features = scaler.transform(features.values)

# Put into DF for concatenation
scaled_features[num_cols] = features
scaled = scaled_features[['Reviews']]

# Check work
scaled.head()
```

Out[21]:

	Reviews
0	-0.163511
1	-0.163254

	Reviews
2	-0.135735
3	-0.094991
4	-0.163254

Categorical Treatment (OHE)

In [22]:

```
# Copy df for manipulation
ohe_features = df.copy()
```

In [23]:

```
# Filter down to just ohe_cols
ohe_features = ohe_features[ohe_cols]

# OHE/Get Dummies
ohe_features = pd.get_dummies(ohe_features)

# Preview, check work
ohe_features.head()
```

Out[23]:

	Category_ART_AND_DESIGN	Category_AUTO_AND_VEHICLES	Category_BEAUTY	Category_BOOKS_AND_REFERENCE	Cate
0	1	0	0	0	
1	1	0	0	0	
2	1	0	0	0	
3	1	0	0	0	
4	1	0	0	0	

5 rows × 588 columns

In [24]:

```
ohe_features = pd.get_dummies(ohe_features)
```

Combine - Data Version 1 - Many OHE, First Shitty Model

In [25]:

```
# Combine scaled numerical, OHE categoricals, and target into one df
preprocessed = pd.concat([scaled, ohe_features, y], axis=1)
```

In [26]:

```
# Review available columns, check work
preprocessed.columns
```

Out[26]:

```
Index(['Reviews', 'Category_ART_AND_DESIGN', 'Category_AUTO_AND_VEHICLES',
       'Category_BEAUTY', 'Category_BOOKS_AND_REFERENCE', 'Category_BUSINESS',
       'Category_COMICS', 'Category_COMMUNICATION', 'Category_DATING',
       'Category_EDUCATION',
       ...
       'Genres_Tools;Education', 'Genres_Travel & Local',
       'Genres_Travel & Local;Action & Adventure', 'Genres_Trivia',
       'Genres_Video Players & Editors',
       'Genres_Video Players & Editors;Creativity',
       'Genres_Video Players & Editors;Music & Video', 'Genres_Weather',
       'Genres_Video Players & Editors,Music & Video', 'Genres_Weather',
       'Genres_Word', 'Pos Rating'],
      dtype='object', length=590)
```

First Shitty Model and Estimator Exploration

In [27]:

```
# X and y split of preprocessed
X = preprocessed.drop(columns=['Pos Rating'], axis=1)
y = preprocessed['Pos Rating']
```

In [28]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=4
2)
```

Model 1 - LogReg with Balanced Class Weight

Class weight = 'balanced' to account for 68/32 split of Target

In [29]:

```
# X and y split of preprocessed
X = preprocessed.drop(columns=['Pos Rating'], axis=1)
y = preprocessed['Pos Rating']
```

In [30]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=4
2)
```

In [31]:

```
def eval_model(estimator, X_train, X_test, y_train, y_test):
    '''
    Evaluation function to show accuracy, recall, mean 3-fold cross-validation
    for both the train and test set, then shows confusion matrix for the test set
    '''
    # grab predictions
    train_preds = estimator.predict(X_train)
    test_preds = estimator.predict(X_test)

    # print scores
    print("Train Scores")
    print("------------")
    print(f"Accuracy: {accuracy_score(y_train, train_preds)}")
    print(f"Recall: {recall_score(y_train, train_preds)}")
    print(f"F1 Score: {f1_score(y_train, train_preds)}")
    print("----" * 5)
    print("Test Scores")
    print("-----------")
    print(f"Accuracy: {accuracy_score(y_test, test_preds)}")
    print(f"Recall: {recall_score(y_test, test_preds)}")
    print(f"Recall Mean Cross Val 3-Fold: {np.mean(cross_val_score(estimator,  X_train, y
_train, cv=3, scoring='recall'))}")
    print(f"F1 Score: {f1_score(y_test, test_preds)}")

    # plot test confusion matrix
    plot_confusion_matrix(estimator, X_test, y_test, values_format='')
    plt.show()
```

In [32]:

```
# Instantiate; adding class weight balanced since 70/30 split of target
logreg = LogisticRegression(class_weight='balanced')

# Fit
```

```
logreg.fit(X_train, y_train)
```

```
/opt/anaconda3/envs/learn-env/lib/python3.6/site-packages/sklearn/linear_model/_logistic.
py:940: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
```

Out[32]:

```
LogisticRegression(C=1.0, class_weight='balanced', dual=False,
                   fit_intercept=True, intercept_scaling=1, l1_ratio=None,
                   max_iter=100, multi_class='auto', n_jobs=None, penalty='l2',
                   random_state=None, solver='lbfgs', tol=0.0001, verbose=0,
                   warm_start=False)
```

In [33]:

```
# X and y split of preprocessed
X = preprocessed.drop(columns=['Pos Rating'], axis=1)
y = preprocessed['Pos Rating']
```

In [34]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=4
2)
```

In [35]:

```
eval_model(logreg, X_train, X_test, y_train, y_test)

# Overfit
# Accuracy worse than random guess (-.05)
# Lower F1 score than recall means precision < recall
```

```
Train Scores
------------
Accuracy: 0.6777777777777778
Recall: 0.644
F1 Score: 0.5616279069767441
--------------------
Test Scores
-----------
Accuracy: 0.6376068376068376
Recall: 0.5880681818181818
```

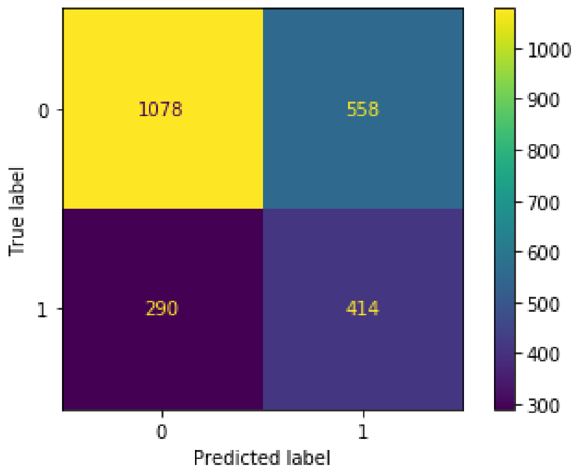
```
/opt/anaconda3/envs/learn-env/lib/python3.6/site-packages/sklearn/linear_model/_logistic.
py:940: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
```

```
Recall Mean Cross Val 3-Fold: 0.5755555555555556
F1 Score: 0.4940334128878281
```

```
/opt/anaconda3/envs/learn-env/lib/python3.6/site-packages/sklearn/linear_model/_logistic.
py:940: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
```



Model 2 - Decision Tree

Class weight = 'balanced' to account for 68/32 split of Target

In [36]:

```
# Instantiate
dt = DecisionTreeClassifier(class_weight='balanced')

# Fit
dt.fit(X_train, y_train)
```

Out[36]:

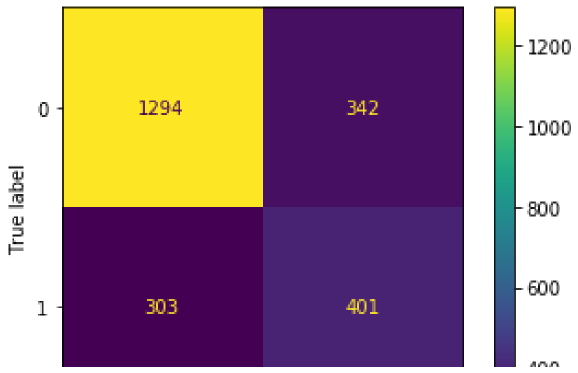
```
DecisionTreeClassifier(ccp_alpha=0.0, class_weight='balanced', criterion='gini',
                       max_depth=None, max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort='deprecated',
                       random_state=None, splitter='best')
```

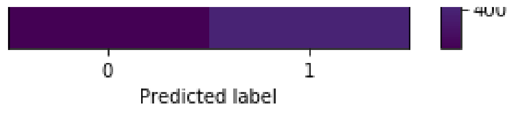
In [37]:

```
eval_model(dt, X_train, X_test, y_train, y_test)

# Overfit
# Better accuracy than balance logreg
# Similar recall to balanced logreg
# Higher f1 which also means higher precision
```

```
Train Scores
------------
Accuracy: 0.9998575498575498
Recall: 1.0
F1 Score: 0.9997778271495222
--------------------
Test Scores
-----------
Accuracy: 0.7243589743589743
Recall: 0.5696022727272727
Recall Mean Cross Val 3-Fold: 0.5631111111111111
F1 Score: 0.5542501727712509
```





Model 3 - KNN

In [38]:

```
# Instantiate
knn = KNeighborsClassifier()

# Fit
knn.fit(X_train, y_train)
```

Out[38]:

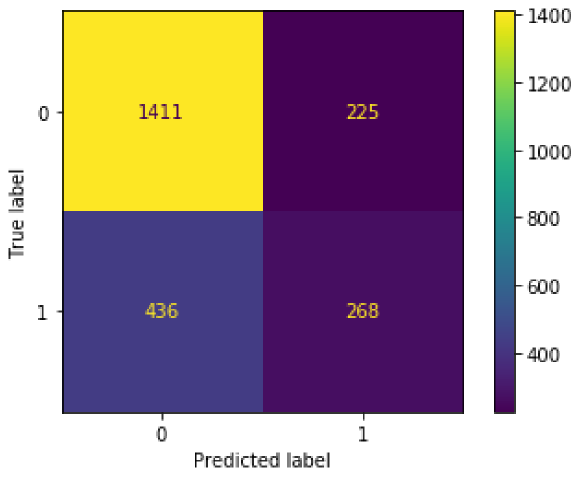
```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
                     metric_params=None, n_jobs=None, n_neighbors=5, p=2,
                     weights='uniform')
```

In [39]:

```
eval_model(knn, X_train, X_test, y_train, y_test)

# Overfit
# Similar accuracy to logreg and decision tree
# Recall and F1 suffers. Stick with decision tree since going for recall
```

```
Train Scores
------------
Accuracy: 0.8032763532763533
Recall: 0.5631111111111111
F1 Score: 0.6472541507024266
--------------------
Test Scores
-----------
Accuracy: 0.7175213675213675
Recall: 0.38068181818181818182
Recall Mean Cross Val 3-Fold: 0.3831111111111111
F1 Score: 0.4477861319966583
```



Model 4 - Random Forest

In [40]:

```
# Instantiate
rf = RandomForestClassifier(class_weight='balanced')

# Fit
rf.fit(X_train, y_train)
```

Out[40]:

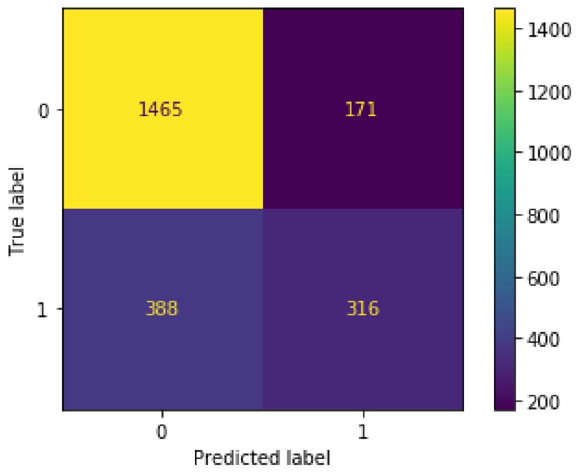
```
RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_weight='balanced',
RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_weight='balanced',
                       criterion='gini', max_depth=None, max_features='auto',
                       max_leaf_nodes=None, max_samples=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=100,
                       n_jobs=None, oob_score=False, random_state=None,
                       verbose=0, warm_start=False)
```

In [41]:

```
eval_model(rf, X_train, X_test, y_train, y_test)

# Overfit, but can tune
# Better accuracy similar to decision tree
# Recall is also similar
# Slightly lower f1 score
```

```
Train Scores
------------
Accuracy: 0.9998575498575498
Recall: 0.9995555555555555
F1 Score: 0.9997777283840853
--------------------
Test Scores
-----------
Accuracy: 0.7611111111111111
Recall: 0.44886363636363635
Recall Mean Cross Val 3-Fold: 0.42266666666666667
F1 Score: 0.5306465155331653
```



Decision: Continue with Decision Tree and Random Forest

Data Version 2 - Additional Data Cleansing

Too Many OHE Columns in baseline dataset to appropriately measure Genre has inconsistent values - some apps are assigned 2 genres and there are some genres with <100 apps. Cleanse all Genre values to 1 genre and consolidate the <100 app genres via re-bucketing.

Get to

- **Numeric = ['Reviews', 'Size Trans']**
- **Ordinal = ['Installs']**
- **OHE = ['Category', 'Type', 'Content Rating', 'Genres']**

Numeric - Translate Size to Numeric 'Size Trans'

In [42]:

```
# Preview values
```

```
df['Size']
```

Out[42]:

```
0                    19M
1                    14M
2                   8.7M
3                    25M
4                   2.8M
                ...
10834               2.6M
10836                53M
10837               3.6M
10839    Varies with device
10840                19M
Name: Size, Length: 9360, dtype: object
```

In [43]:

```
# Create new column for Size Type - this will be M (for MB) or k (for kb) for those that
do not have
# value 'Varies with device'
df['Size Type'] = 0

# For each value in Size, take the last character and put it in Size Type
for row in df['Size'].index:
    df['Size Type'][row] = df['Size'][row][-1]
```

```
/opt/anaconda3/envs/learn-env/lib/python3.6/site-packages/ipykernel_launcher.py:7: Settin
gWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/user_gu
ide/indexing.html#returning-a-view-versus-a-copy
  import sys
/opt/anaconda3/envs/learn-env/lib/python3.6/site-packages/pandas/core/indexing.py:205: Se
ttingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/user_gu
ide/indexing.html#returning-a-view-versus-a-copy
  self._setitem_with_indexer(indexer, value)
```

In [44]:

```
# Check work; Varies with device 1637
df['Size Type'].value_counts()
```

Out[44]:

```
M    7466
e    1637
k     257
Name: Size Type, dtype: int64
```

In [45]:

```
# Remove last character from Size, convert to numeric for math in Size Trans
for row in df['Size'].index:
    df['Size'][row] = df['Size'][row][:-1]
```

```
/opt/anaconda3/envs/learn-env/lib/python3.6/site-packages/ipykernel_launcher.py:3: Settin
gWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/user_gu
ide/indexing.html#returning-a-view-versus-a-copy
  This is separate from the ipykernel package so we can avoid doing imports until
```

In [46]:

```
# Create Size Translation column and convert Size in MBs to kbs
```

```
df['Size Trans'] = 0

# For each row in Size, check Size Type. If M (for MB) multiply by 1000 to convert to kb,

# otherwise k values stay the same and e for varies by devices stay at zero (will fill nu
lls)
for row in df['Size'].index:
    if df['Size Type'][row] == 'e':
        continue
    if df['Size Type'][row] == 'M':
        df['Size Trans'][row] = float(df['Size'][row]) * 1000
    if df['Size Type'][row] == 'k':
        df['Size Trans'][row] = df['Size'][row]

# Convert column to float
df['Size Trans'] = df['Size Trans'].astype(float)
```

```
/opt/anaconda3/envs/learn-env/lib/python3.6/site-packages/ipykernel_launcher.py:10: Setti
ngWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/user_gu
ide/indexing.html#returning-a-view-versus-a-copy
  # Remove the CWD from sys.path while we load stuff.
/opt/anaconda3/envs/learn-env/lib/python3.6/site-packages/ipykernel_launcher.py:12: Setti
ngWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/user_gu
ide/indexing.html#returning-a-view-versus-a-copy
  if sys.path[0] == '':
/opt/anaconda3/envs/learn-env/lib/python3.6/site-packages/pandas/core/indexing.py:205: Se
ttingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/user_gu
ide/indexing.html#returning-a-view-versus-a-copy
  self._setitem_with_indexer(indexer, value)
```

In [47]:

```
# Look at the Size Translations for those that did not have "Varies by device" value aka
Size Trans != 0
df[df['Size Trans'] != 0]['Size Trans'].describe()
# mean is nearly 1.5x median, so there are outliers
```

Out[47]:

```
count      7723.000000
mean      22970.456105
std       23449.628935
min           8.500000
25%        5300.000000
50%       14000.000000
75%       33000.000000
max      100000.000000
Name: Size Trans, dtype: float64
```

Delete the row under this. 0 will mean varies and be a place to recommend further analysis

In [48]:

```
# Name variable for Size median for filling nulls
size_median = df[df['Size Trans'] != 0]['Size Trans'].median()
```

In [49]:

```
# Fill Size Trans nulls with median
```

```
df['Size Trans'].fillna(size_median)
```

Out[49]:

```
0        19000.0
1        14000.0
2         8700.0
3        25000.0
4         2800.0
           ...
10834     2600.0
10836    53000.0
10837     3600.0
10839        0.0
10840    19000.0
Name: Size Trans, Length: 9360, dtype: float64
```

In [50]:

```
# Review table with changes
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9360 entries, 0 to 10840
Data columns (total 14 columns):
App               9360 non-null object
Category          9360 non-null object
Reviews           9360 non-null int64
Size              9360 non-null object
Installs          9360 non-null object
Type              9360 non-null object
Content Rating    9360 non-null object
Genres            9360 non-null object
Last Updated      9360 non-null object
Current Ver       9360 non-null object
Android Ver       9360 non-null object
Pos Rating        9360 non-null int64
Size Type         9360 non-null object
Size Trans        9360 non-null float64
dtypes: float64(1), int64(2), object(11)
memory usage: 1.4+ MB
```

In [51]:

```
# Drop helper columns for final value to be used in model Size Trans
df = df.drop(columns=['Size Type', 'Size'], axis=1)
```

In [52]:

```
# Review new table
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9360 entries, 0 to 10840
Data columns (total 12 columns):
App               9360 non-null object
Category          9360 non-null object
Reviews           9360 non-null int64
Installs          9360 non-null object
Type              9360 non-null object
Content Rating    9360 non-null object
Genres            9360 non-null object
Last Updated      9360 non-null object
Current Ver       9360 non-null object
Android Ver       9360 non-null object
Pos Rating        9360 non-null int64
Size Trans        9360 non-null float64
dtypes: float64(1), int64(2), object(9)
memory usage: 1.2+ MB
```

Ordinal - Translate Installs to ordinal values

In [53]:

```
# Make Installs ordinal instead of categorical
df['Installs'].value_counts()
```

Out[53]:

```
1,000,000+        1576
10,000,000+       1252
100,000+          1150
10,000+           1009
5,000,000+         752
1,000+             712
500,000+           537
50,000+            466
5,000+             431
100,000,000+       409
100+               309
50,000,000+        289
500+               201
500,000,000+        72
10+                 69
1,000,000,000+      58
50+                 56
5+                   9
1+                   3
Name: Installs, dtype: int64
```

In [54]:

```
# Combine those less than 500 and relabel
df['Installs'] = df['Installs'].replace(['1+', '5+', '10+', '50+', '100+', ], 'Less than
500')
```

In [55]:

```
# Check work
df['Installs'].value_counts()
```

Out[55]:

```
1,000,000+        1576
10,000,000+       1252
100,000+          1150
10,000+           1009
5,000,000+         752
1,000+             712
500,000+           537
50,000+            466
Less than 500      446
5,000+             431
100,000,000+       409
50,000,000+        289
500+               201
500,000,000+        72
1,000,000,000+      58
Name: Installs, dtype: int64
```

In [56]:

```
# Ordinal mapping
df['Installs'] = df['Installs'].replace(['1+', '5+', '10+', '50+', '100+'], 'Less than 5
00')
```

In [57]:

```
# Check work
df['Installs'].value_counts()
```

Out[57]:

```
1,000,000+        1576
```

```
10,000,000+       1252
100,000+          1150
10,000+           1009
5,000,000+         752
1,000+             712
500,000+           537
50,000+            466
Less than 500      446
5,000+             431
100,000,000+       409
50,000,000+        289
500+               201
500,000,000+        72
1,000,000,000+      58
Name: Installs, dtype: int64
```

In [58]:

```
# Map ordinal values
df['Installs'] = df['Installs'].map({'Less than 500': 0,
                                     '500+': 1,
                                     '1,000+': 2,
                                     '5,000+': 3,
                                     '10,000+': 4,
                                     '50,000+': 5,
                                     '100,000+': 6,
                                     '500,000+': 7,
                                     '1,000,000+': 8,
                                     '5,000,000+': 9,
                                     '10,000,000+': 10,
                                     '50,000,000+': 11,
                                     '100,000,000+': 12,
                                     '500,000,000+': 13,
                                     '1,000,000,000+': 14})
```

In [59]:

```
# Check results; matches counts table above
df['Installs'].value_counts()
```

Out[59]:

```
8     1576
10    1252
6     1150
4     1009
9      752
2      712
7      537
5      466
0      446
3      431
12     409
11     289
1      201
13      72
14      58
Name: Installs, dtype: int64
```

Genre cleanse and bucketing

In [60]:

```
# Preview Genres values
df['Genres']
```

Out[60]:

```
0                     Art & Design
1        Art & Design;Pretend Play
2                     Art & Design
```

```
3                      Art & Design
4           Art & Design;Creativity
                        ...
10834                     Education
10836                     Education
10837                     Education
10839              Books & Reference
10840                     Lifestyle
Name: Genres, Length: 9360, dtype: object
```

In [61]:

```
# Some have multiple values, create lists
df['Genres'] = df['Genres'].str.split(';')
```

In [62]:

```
# View multi-genre value
df['Genres'][1]
```

Out[62]:

```
['Art & Design', 'Pretend Play']
```

In [63]:

```
# Test references for for loop
len(df['Genres'][1])
```

Out[63]:

```
2
```

In [64]:

```
# Test references for for loop
df['Genres'][1][0]
```

Out[64]:

```
'Art & Design'
```

In [65]:

```
# Some apps have multiple Genres - take first listed genre as priority
for row in df['Genres'].index:
    df['Genres'][row] = df['Genres'][row][0]
```

```
/opt/anaconda3/envs/learn-env/lib/python3.6/site-packages/ipykernel_launcher.py:3: Settin
gWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/user_gu
ide/indexing.html#returning-a-view-versus-a-copy
  This is separate from the ipykernel package so we can avoid doing imports until
```

In [66]:

```
# Check work - can see all strings and all first Genres
df['Genres']
```

Out[66]:

```
0              Art & Design
1              Art & Design
2              Art & Design
3              Art & Design
4              Art & Design
                   ...
10834             Education
10836             Education
10837             Education
10839     Books & Reference
```

```
10840              Lifestyle
Name: Genres, Length: 9360, dtype: object
```

In [67]:

```
df['Genres'].value_counts()
# There are many Genres under 100, to help prevent overfitting - rebucket those under 100
```

Out[67]:

```
Tools                        733
Entertainment                577
Education                    563
Action                       375
Productivity                 351
Medical                      350
Sports                       337
Communication                329
Finance                      323
Photography                  317
Lifestyle                    315
Personalization              312
Business                     303
Health & Fitness             299
Casual                       262
Social                       259
Shopping                     238
News & Magazines             233
Travel & Local               226
Arcade                       223
Simulation                   212
Dating                       195
Books & Reference            180
Video Players & Editors      163
Puzzle                       147
Maps & Navigation            124
Role Playing                 119
Racing                       114
Food & Drink                 109
Strategy                     107
Educational                  103
Adventure                     89
House & Home                  76
Weather                       75
Auto & Vehicles               73
Libraries & Demo              64
Art & Design                  64
Board                         60
Comics                        58
Parenting                     50
Card                          48
Events                        45
Beauty                        42
Casino                        37
Word                          28
Trivia                        28
Music                         24
Music & Audio                  1
Name: Genres, dtype: int64
```

In [68]:

```
df[df['Category'] =='EVENTS']['Genres'].value_counts()
```

Out[68]:

```
Events    45
Name: Genres, dtype: int64
```

In [69]:

```
df[df['Genres'] == 'Lifestyle']
```

Out[69]:

	App	Category	Reviews	Installs	Type	Content Rating	Genres	Last Updated	Current Ver	Android Ver	Pos Rating	Size Trans
1562	Dollhouse Decorating Games	LIFESTYLE	18968	9	Free	Teen	Lifestyle	April 26, 2018	5.1	4.1 and up	0	32000.0
1563	metroZONE	LIFESTYLE	47497	10	Free	Everyone	Lifestyle	June 8, 2018	5.3.0.54.7	5.0 and up	0	34000.0
1564	Easy Hair Style Design	LIFESTYLE	601	6	Free	Everyone	Lifestyle	December 20, 2017	1.0	2.3 and up	0	5100.0
1565	Talking Babsy Baby: Baby Games	LIFESTYLE	140995	10	Free	Everyone	Lifestyle	July 16, 2018	9.0	4.0 and up	0	100000.0
1566	Black Wallpaper, AMOLED, Dark Background: Darkify	LIFESTYLE	51357	9	Free	Everyone	Lifestyle	July 31, 2018	8.0	4.0 and up	1	80000.0
...	...	...	...	...	...	...	...	...	...	...	...	...
10719	Sona - Nær við allastaðni	LIFESTYLE	31	2	Free	Everyone	Lifestyle	August 2, 2018	1.6.3	4.4 and up	0	25000.0
10742	GKPB FP Online Church	LIFESTYLE	32	2	Free	Everyone	Lifestyle	December 31, 2017	0.7.1	4.4 and up	1	7900.0
10797	Fuel Rewards® program	LIFESTYLE	32433	8	Free	Everyone	Lifestyle	June 26, 2018	2.9.1	5.0 and up	1	46000.0
10805	Scoreboard FR	LIFESTYLE	3	0	Free	Everyone	Lifestyle	August 7, 2018	2.1	4.2 and up	0	15000.0
10840	iHoroscope - 2018 Daily Horoscope & Astrology	LIFESTYLE	398307	10	Free	Everyone	Lifestyle	July 25, 2018	Varies with device	Varies with device	1	19000.0

315 rows × 12 columns

Genre Bucketing

In [70]:

```
# Genre buckets to reassign
# Adventure                     Action
# House & Home                  Lifestyle
# Weather                       Travel & Local
# Auto & Vehicles               Lifestyle
# Art & Design                  Lifestyle
# Libraries & Demo              Entertainment
# Board                         Casual - games
# Comics                        Entertainment
# Parenting                     Lifestyle
# Card                          Casual - games
# Events                        Lifestyle
# Beauty                        Lifestyle
# Casino                        Casual - games
# Word                          Casual - games
# Trivia                        Casual - games
# Music                         Entertainment
# Music & Audio                 Entertainment
```

In [71]:

```
# Code for mappings above

# Replace with Action
df['Genres'] = df['Genres'].replace(['Adventure'], 'Action')

# Replace with Travel & Local
df['Genres'] = df['Genres'].replace(['Weather'], 'Travel & Local')

# Replace with Lifestyle
df['Genres'] = df['Genres'].replace(['House & Home', 'Auto & Vehicles', 'Art & Design',
'Events', 'Beauty', 'Parenting'],
                                    'Lifestyle')
# Replace with Entertainment
df['Genres'] = df['Genres'].replace(['Libraries & Demo', 'Comics', 'Music', 'Music & Aud
io'], 'Entertainment')

# Replace with Casual
df['Genres'] = df['Genres'].replace(['Board', 'Card', 'Casino', 'Word', 'Trivia'], 'Casu
al')
```

Create new df for modeling

In [72]:

```
# New breakdown of column types for varying treatments before modeling
# Numerical columns
num_cols2 = ['Reviews', 'Size Trans']

# Ordinal columns
ord_cols = ['Installs']

# Categorical columns for OHE
ohe_cols2 = ['Category', 'Type', 'Content Rating', 'Genres']
```

Numeric Treatment - Scale

In [73]:

```
# Copy df for manipulation
scaled_features2 = df.copy()
```

In [74]:

```
# Scale num_col features
features2 = scaled_features2[num_cols2]
scaler2 = StandardScaler().fit(features2.values)
features2 = scaler2.transform(features2.values)

# Put into DF for concatenation
scaled_features2[num_cols2] = features2
scaled2 = scaled_features2[num_cols2]

# Check work
scaled2.head()
```

Out[74]:

	Reviews	Size Trans
0	-0.163511	0.002038
1	-0.163254	-0.215189
2	-0.135735	-0.445451
3	-0.094991	0.262712
4	-0.163254	-0.701779

Ordinal Features

In [75]:

```
# Assign remapped Installs values to ordinal variable
ordinal = df['Installs']
```

Categorical Treatment (OHE)

In [76]:

```
# Copy df for manipulation
ohe_features2 = df.copy()
```

In [77]:

```
# Filter down to just ohe_cols
ohe_features2 = ohe_features2[ohe_cols2]

# OHE/Get Dummies
ohe_features2 = pd.get_dummies(ohe_features2)

# Preview, check work, 72 columns versus 500+ in Data Version 1
ohe_features2.head()
```

Out[77]:

	Category_ART_AND_DESIGN	Category_AUTO_AND_VEHICLES	Category_BEAUTY	Category_BOOKS_AND_REFERENCE	Cate
0	1	0	0	0	
1	1	0	0	0	
2	1	0	0	0	
3	1	0	0	0	
4	1	0	0	0	

5 rows × 72 columns

Combine - Data Version 2

- **Numeric = ['Reviews', 'Size Trans']**
- **Ordinal = ['Installs']**
- **OHE = ['Category', 'Type', 'Content Rating', 'Genres']**

In [78]:

```
# Combine scaled numerical, OHE categoricals, and target into one df
preprocessed2 = pd.concat([scaled2, ordinal, ohe_features2, y], axis=1)
```

In [79]:

```
preprocessed2.columns
```

Out[79]:

```
Index(['Reviews', 'Size Trans', 'Installs', 'Category_ART_AND_DESIGN',
       'Category_AUTO_AND_VEHICLES', 'Category_BEAUTY',
       'Category_BOOKS_AND_REFERENCE', 'Category_BUSINESS', 'Category_COMICS',
       'Category_COMMUNICATION', 'Category_DATING', 'Category_EDUCATION',
       'Category_ENTERTAINMENT', 'Category_EVENTS', 'Category_FAMILY',
       'Category_FINANCE', 'Category_FOOD_AND_DRINK', 'Category_GAME',
       'Category_HEALTH_AND_FITNESS', 'Category_HOUSE_AND_HOME',
       'Category_LIBRARIES_AND_DEMO', 'Category_LIFESTYLE',
       'Category_MAPS_AND_NAVIGATION', 'Category_MEDICAL',
       'Category_NEWS_AND_MAGAZINES', 'Category_PARENTING',
       'Category_PERSONALIZATION', 'Category_PHOTOGRAPHY',
       'Category_PRODUCTIVITY', 'Category_SHOPPING', 'Category_SOCIAL',
       'Category_SPORTS', 'Category_TOOLS', 'Category_TRAVEL_AND_LOCAL',
       'Category_VIDEO_PLAYERS', 'Category_WEATHER', 'Type_Free', 'Type_Paid',
       'Content Rating_Adults only 18+', 'Content Rating_Everyone',
       'Content Rating_Everyone 10+', 'Content Rating_Mature 17+',
       'Content Rating_Teen', 'Content Rating_Unrated', 'Genres_Action',
       'Genres_Arcade', 'Genres_Books & Reference', 'Genres_Business',
       'Genres_Casual', 'Genres_Communication', 'Genres_Dating',
       'Genres_Education', 'Genres_Educational', 'Genres_Entertainment',
       'Genres_Finance', 'Genres_Food & Drink', 'Genres_Health & Fitness',
       'Genres_Lifestyle', 'Genres_Maps & Navigation', 'Genres_Medical',
       'Genres_News & Magazines', 'Genres_Personalization',
       'Genres_Photography', 'Genres_Productivity', 'Genres_Puzzle',
       'Genres_Racing', 'Genres_Role Playing', 'Genres_Shopping',
       'Genres_Simulation', 'Genres_Social', 'Genres_Sports',
       'Genres_Strategy', 'Genres_Tools', 'Genres_Travel & Local',
       'Genres_Video Players & Editors', 'Pos Rating'],
      dtype='object')
```

Model 5 - Decision Tree2 (Data Version 2)

Class weight = 'balanced' to account for 68/32 split of Target

In [80]:

```
# X and y split of preprocessed
X = preprocessed2.drop(columns=['Pos Rating'], axis=1)
y = preprocessed2['Pos Rating']
```

In [81]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=4
2)
```

In [82]:

```
# Instantiate
dt2 = DecisionTreeClassifier(class_weight='balanced', random_state=42)

# Fit
dt2.fit(X_train, y_train)
```

Out[82]:

```
DecisionTreeClassifier(ccp_alpha=0.0, class_weight='balanced', criterion='gini',
                       max_depth=None, max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort='deprecated',
                       random_state=42, splitter='best')
```

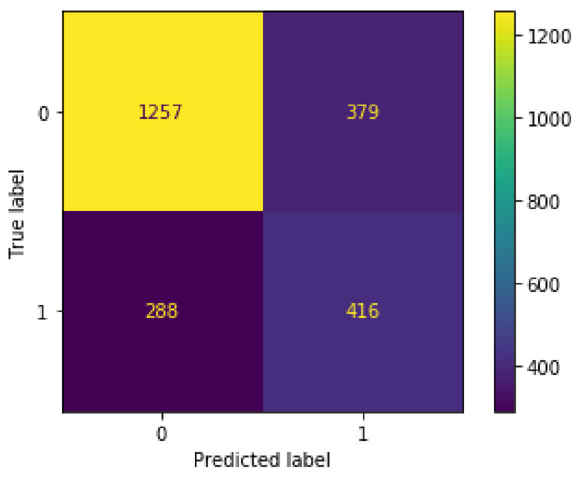
In [83]:

```
eval_model(dt2, X_train, X_test, y_train, y_test)

# Overfit, but can tune
# Accuracy similar to original decision tree
# Recall at highest at 0.59, validation lower at 0.53
# Similar f1 to original decision tree
```

```
Train Scores
------------
Accuracy: 0.9997150997150998
Recall: 1.0
F1 Score: 0.9995557529986673
--------------------
Test Scores
-----------
```

```
Accuracy: 0.7149572649572651
Recall: 0.5909090909090909
Recall Mean Cross Val 3-Fold: 0.5373333333333333
F1 Score: 0.5550366911274183
```



Tune Decision Tree

In [84]:

```
# What is current depth of overfit tree
dt2.tree_.max_depth
```

Out[84]:

```
53
```

Model 6 - Decision Tree3 (Data Version 2) with half depth

Doing this to understand best range of max_depth parameters for GridSearch

In [85]:

```
# Instantiate
dt3 = DecisionTreeClassifier(class_weight='balanced', random_state=42,
                              max_depth = 31)

# Fit
dt3.fit(X_train, y_train)
```

Out[85]:

```
DecisionTreeClassifier(ccp_alpha=0.0, class_weight='balanced', criterion='gini',
                       max_depth=31, max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort='deprecated',
                       random_state=42, splitter='best')
```

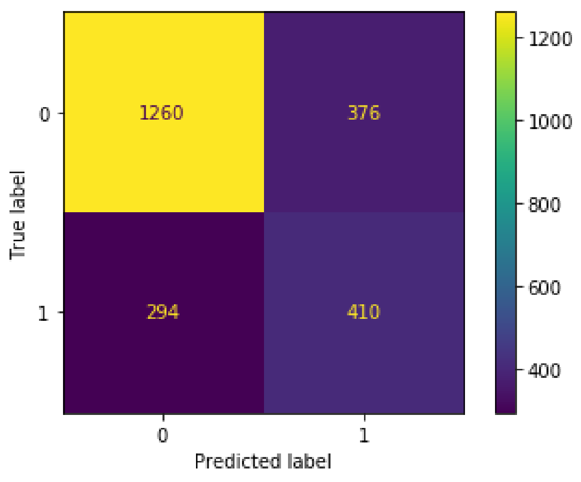
In [86]:

```
eval_model(dt3, X_train, X_test, y_train, y_test)

# Less overfit but still needs help
# in GridSearch, do range around this, aim for lower number as this is still very overfit
# Similar recall and validation
# Same F1 as with full depth
```

```
Train Scores
------------
Accuracy: 0.9816239316239316
Recall: 0.9671111111111111
F1 Score: 0.9712117830841329
--------------------
Test Scores
```

```
-----------
Accuracy: 0.7136752136752137
Recall: 0.5823863636363636
Recall Mean Cross Val 3-Fold: 0.5377777777777778
F1 Score: 0.5503355704697988
```



GridSearch

In [87]:

```
param_dict = {
    'criterion': ['gini', 'entropy'],
    'max_depth': [5, 10, 15, 20, 25, 30, 35],
    'min_samples_split': [2, 4, 6, 8, 10, 12, 14, 16, 18, 20],
    'min_samples_leaf': [2, 4, 6, 8, 10, 12, 14, 16, 18, 20]
}
```

In [88]:

```
grid = GridSearchCV(dt3,
                   param_grid = param_dict,
                   cv=5,
                   verbose=1)

grid.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 1400 candidates, totalling 7000 fits
```

```
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done 7000 out of 7000 | elapsed:  3.9min finished
```

Out[88]:

```
GridSearchCV(cv=5, error_score=nan,
             estimator=DecisionTreeClassifier(ccp_alpha=0.0,
                                              class_weight='balanced',
                                              criterion='gini', max_depth=31,
                                              max_features=None,
                                              max_leaf_nodes=None,
                                              min_impurity_decrease=0.0,
                                              min_impurity_split=None,
                                              min_samples_leaf=1,
                                              min_samples_split=2,
                                              min_weight_fraction_leaf=0.0,
                                              presort='deprecated',
                                              random_state=42,
                                              splitter='best'),
             iid='deprecated', n_jobs=None,
             param_grid={'criterion': ['gini', 'entropy'],
                         'max_depth': [5, 10, 15, 20, 25, 30, 35],
                         'min_samples_leaf': [2, 4, 6, 8, 10, 12, 14, 16, 18,
                                              20],
                         'min_samples_split': [2, 4, 6, 8, 10, 12, 14, 16, 18,
                                               20]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring=None, verbose=1)
```

In [89]:

```
grid.best_params_
```

Out[89]:

```
{'criterion': 'entropy',
 'max_depth': 10,
 'min_samples_leaf': 20,
 'min_samples_split': 2}
```

In [90]:

```
grid.best_score_
```

Out[90]:

```
0.6958689458689459
```

Model 7 - GridSearch Decision Tree

In [91]:

```
# Instantiate
dt_grid = DecisionTreeClassifier(class_weight='balanced',
                                 criterion = 'entropy',
                                 max_depth = 10,
                                 min_samples_leaf  = 20,
                                 min_samples_split = 2)

# Fit
dt_grid.fit(X_train, y_train)
```

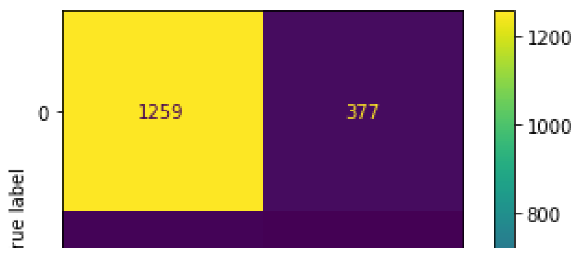
Out[91]:

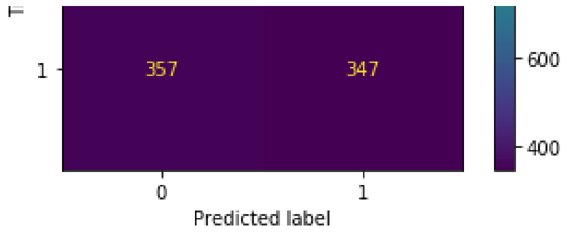
```
DecisionTreeClassifier(ccp_alpha=0.0, class_weight='balanced',
                       criterion='entropy', max_depth=10, max_features=None,
                       max_leaf_nodes=None, min_impurity_decrease=0.0,
                       min_impurity_split=None, min_samples_leaf=20,
                       min_samples_split=2, min_weight_fraction_leaf=0.0,
                       presort='deprecated', random_state=None,
                       splitter='best')
```

In [92]:

```
eval_model(dt_grid, X_train, X_test, y_train, y_test)
# Much less overfit - but accuracy down .2 - Same as random guess
# Recall much lower from 0.58 to 0.49 - but validation at 0.53
```

```
Train Scores
------------
Accuracy: 0.7215099715099715
Recall: 0.5542222222222222
F1 Score: 0.5605754102045403
--------------------
Test Scores
-----------
Accuracy: 0.6863247863247863
Recall: 0.49289772727272727
Recall Mean Cross Val 3-Fold: 0.5306666666666667
F1 Score: 0.48599439775910364
```





Model 8 - GridSearch Random Forest

In [93]:

```
# X and y split of preprocessed
X = preprocessed2.drop(columns=['Pos Rating'], axis=1)
y = preprocessed2['Pos Rating']
```

In [94]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=4
2)
```

In [95]:

```
# Instantiate
rf_grid = RandomForestClassifier(class_weight='balanced',
                             criterion = 'entropy',
                             max_depth = 10,
                             min_samples_leaf  = 20,
                             min_samples_split = 2)


# Fit
rf_grid.fit(X_train, y_train)
```

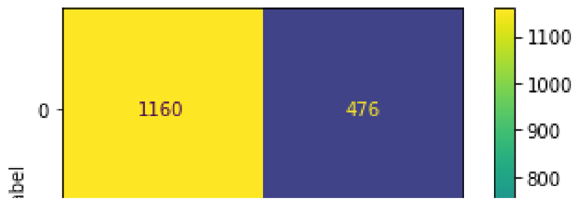
Out[95]:

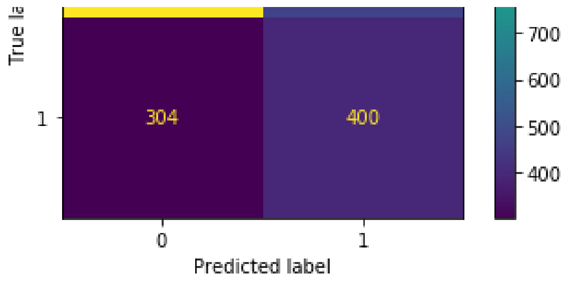
```
RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_weight='balanced',
                       criterion='entropy', max_depth=10, max_features='auto',
                       max_leaf_nodes=None, max_samples=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=20, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=100,
                       n_jobs=None, oob_score=False, random_state=None,
                       verbose=0, warm_start=False)
```

In [96]:

```
eval_model(rf_grid, X_train, X_test, y_train, y_test)
# Slightly overfit
# Accuracy is less than random guess although recall is at highest
# F1 also at similar highest
```

```
Train Scores
------------
Accuracy: 0.672934472934473
Recall: 0.5786666666666667
F1 Score: 0.5314285714285715
--------------------
Test Scores
-----------
Accuracy: 0.6666666666666666
Recall: 0.5681818181818182
Recall Mean Cross Val 3-Fold: 0.5573333333333333
F1 Score: 0.5063291139240507
```





Data Version 3 - Additional Ordinal Mapping

There is opportunity for Content Rating to be mapped to ordinal values. Edit this in dataset and retry top models.

Get to

- **Numeric = ['Reviews', 'Size Trans']**
- **Ordinal = ['Installs', 'Content Rating']**
- **OHE = ['Category', 'Type', 'Genres']**

In [97]:

```
df['Content Rating'].value_counts()
```

Out[97]:

```
Everyone            7414
Teen                1084
Mature 17+           461
Everyone 10+         397
Adults only 18+        3
Unrated                1
Name: Content Rating, dtype: int64
```

In [98]:

```
# Ordinal mapping
df['Content Rating'] = df['Content Rating'].map({'Everyone': 0, 'Everyone 10+': 1, 'Teen
': 2,
                                                 'Mature 17+': 3, 'Adults only 18+': 4,
'Unrated': 5})
```

In [99]:

```
df['Content Rating'].value_counts()
```

Out[99]:

```
0    7414
2    1084
3     461
1     397
4       3
5       1
Name: Content Rating, dtype: int64
```

Create new df for modeling

In [100]:

```
# New breakdown of column types for varying treatments before modeling
# Numerical columns, same as Data Version 2, use scaled2

# Ordinal columns
ord_cols2 = ['Installs', 'Content Rating']

# Categorical columns for OHE
ohe_cols3 = ['Category', 'Type', 'Genres']
```

Ordinal Features

In [101]:

```
# Assign remapped Content rating values to ordinal variable
ordinal2 = df[['Installs', 'Content Rating']]
```

Categorical Treatment (OHE)

In [102]:

```
# Copy df for manipulation
ohe_features3 = df.copy()
```

In [103]:

```
# Filter down to just ohe_cols
ohe_features3 = ohe_features3[ohe_cols3]

# OHE/Get Dummies
ohe_features3 = pd.get_dummies(ohe_features3)

# Preview, check work, 66 columns versus 72 in Data Version 1
ohe_features3.head()
```

Out[103]:

	Category_ART_AND_DESIGN	Category_AUTO_AND_VEHICLES	Category_BEAUTY	Category_BOOKS_AND_REFERENCE	Cate
0	1	0	0	0	
1	1	0	0	0	
2	1	0	0	0	
3	1	0	0	0	
4	1	0	0	0	

5 rows × 66 columns

Combine - Data Version 3

- Numeric = ['Reviews', 'Size Trans']
- Ordinal = ['Installs', 'Content Rating']
- OHE = ['Category', 'Type', 'Genres']

In [104]:

```
# Combine scaled numerical, OHE categoricals, and target into one df
preprocessed3 = pd.concat([scaled2, ordinal2, ohe_features3, y], axis=1)
```

In [105]:

```
preprocessed3.columns
```

Out[105]:

```
Index(['Reviews', 'Size Trans', 'Installs', 'Content Rating',
       'Category_ART_AND_DESIGN', 'Category_AUTO_AND_VEHICLES',
       'Category_BEAUTY', 'Category_BOOKS_AND_REFERENCE', 'Category_BUSINESS',
       'Category_COMICS', 'Category_COMMUNICATION', 'Category_DATING',
       'Category_EDUCATION', 'Category_ENTERTAINMENT', 'Category_EVENTS',
       'Category_FAMILY', 'Category_FINANCE', 'Category_FOOD_AND_DRINK',
       'Category_GAME', 'Category_HEALTH_AND_FITNESS',
       'Category_HOUSE_AND_HOME', 'Category_LIBRARIES_AND_DEMO',
       'Category_LIFESTYLE', 'Category_MAPS_AND_NAVIGATION',
       'Category_MEDICAL', 'Category_NEWS_AND_MAGAZINES', 'Category_PARENTING',
       'Category_PERSONALIZATION', 'Category_PHOTOGRAPHY',
       'Category_PRODUCTIVITY', 'Category_SHOPPING', 'Category_SOCIAL',
       'Category_SPORTS', 'Category_TOOLS', 'Category_TRAVEL_AND_LOCAL',
       'Category_VIDEO_PLAYERS', 'Category_WEATHER', 'Type_Free', 'Type_Paid',
       'Genres_Action', 'Genres_Arcade', 'Genres_Books & Reference',
       'Genres_Business', 'Genres_Casual', 'Genres_Communication',
       'Genres_Dating', 'Genres_Education', 'Genres_Educational',
       'Genres_Entertainment', 'Genres_Finance', 'Genres_Food & Drink',
       'Genres_Health & Fitness', 'Genres_Lifestyle',
       'Genres_Maps & Navigation', 'Genres_Medical', 'Genres_News & Magazines',
       'Genres_Personalization', 'Genres_Photography', 'Genres_Productivity',
       'Genres_Puzzle', 'Genres_Racing', 'Genres_Role Playing',
       'Genres_Shopping', 'Genres_Simulation', 'Genres_Social',
       'Genres_Sports', 'Genres_Strategy', 'Genres_Tools',
       'Genres_Travel & Local', 'Genres_Video Players & Editors',
       'Pos Rating'],
      dtype='object')
```

Model 9 - Decision Tree with Data Version 3

In [106]:

```
# X and y split of preprocessed
X = preprocessed3.drop(columns=['Pos Rating'], axis=1)
y = preprocessed3['Pos Rating']
```

In [107]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=4
2)
```

In [108]:

```
# Instantiate
dt4 = DecisionTreeClassifier(class_weight='balanced')

# Fit
dt4.fit(X_train, y_train)
```

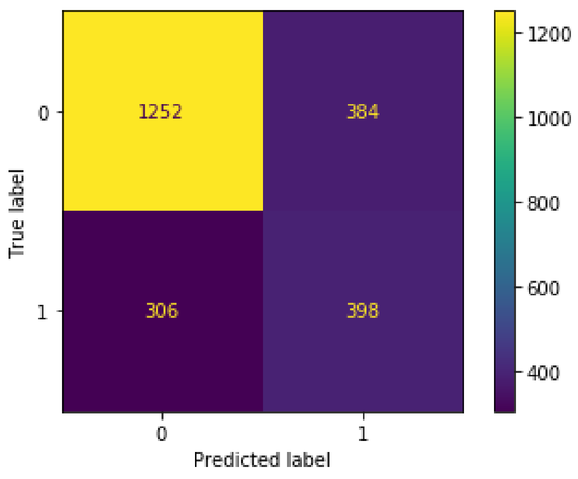
Out[108]:

```
DecisionTreeClassifier(ccp_alpha=0.0, class_weight='balanced', criterion='gini',
                       max_depth=None, max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort='deprecated',
                       random_state=None, splitter='best')
```

In [109]:

```
eval_model(dt4, X_train, X_test, y_train, y_test)
# Overfit, but can tune
# Similar accuracy to previous untuned decision trees
# Recall at 0.56
# F1 up at 0.53
```

```
Train Scores
------------
Accuracy: 0.9997150997150998
Recall: 1.0
F1 Score: 0.9995557529986673
--------------------
Test Scores
-----------
Accuracy: 0.7051282051282052
Recall: 0.5653409090909091
Recall Mean Cross Val 3-Fold: 0.5342222222222223
F1 Score: 0.5356662180349933
```



```
In [110]:
```

```
# What is current depth of overfit tree
dt4.tree_.max_depth
```

```
Out[110]:
```

```
58
```

Model 10 - Decision Tree3 (Data Version 3) with half depth

Doing this to understand best range of max_depth parameters for GridSearch

```
In [111]:
```

```
# Instantiate
dt5 = DecisionTreeClassifier(class_weight='balanced', random_state=42,
                            max_depth = 29)

# Fit
dt5.fit(X_train, y_train)
```

```
Out[111]:
```

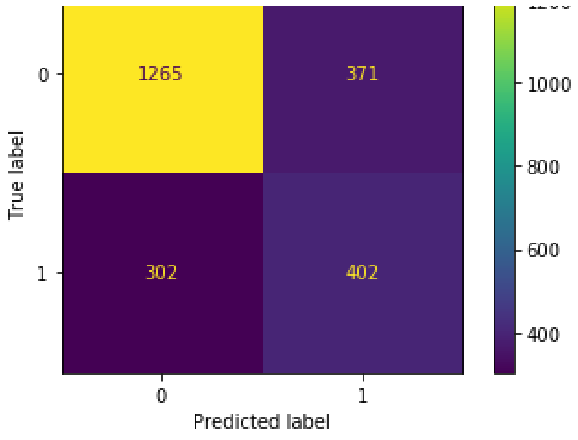
```
DecisionTreeClassifier(ccp_alpha=0.0, class_weight='balanced', criterion='gini',
                       max_depth=29, max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort='deprecated',
                       random_state=42, splitter='best')
```

```
In [112]:
```

```
eval_model(dt5, X_train, X_test, y_train, y_test)

# Not mcuh less overfit but still needs help
# in GridSearch, do range around this, aim for lower number as this is still very overfit
# Similar recall and validation
# Same F1 as with full depth
```

```
Train Scores
------------
Accuracy: 0.975925925925926
Recall: 0.9635555555555556
F1 Score: 0.9624861265260821
--------------------
Test Scores
-----------
Accuracy: 0.7123931623931624
Recall: 0.5710227272727273
Recall Mean Cross Val 3-Fold: 0.5399999999999999
F1 Score: 0.5443466486120515
```



Grid Search 3 - Expanding min_samples_split for higher range (previously 20) with Data Version 3

In [113]:

```
param_dict3 = {
    'criterion': ['gini', 'entropy'],
    'max_depth': [5, 10, 15, 20, 25, 30, 35],
    'min_samples_split': [15, 20, 25, 30, 35, 40],
    'min_samples_leaf': [2, 4, 6, 8, 10, 12, 14, 16, 18, 20]
}
```

In [114]:

```
grid = GridSearchCV(dt4,
                   param_grid = param_dict,
                   cv=5,
                   verbose=1)

grid.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 1400 candidates, totalling 7000 fits
```

```
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done 7000 out of 7000 | elapsed:  3.9min finished
```

Out[114]:

```
GridSearchCV(cv=5, error_score=nan,
             estimator=DecisionTreeClassifier(ccp_alpha=0.0,
                                              class_weight='balanced',
                                              criterion='gini', max_depth=None,
                                              max_features=None,
                                              max_leaf_nodes=None,
                                              min_impurity_decrease=0.0,
                                              min_impurity_split=None,
                                              min_samples_leaf=1,
                                              min_samples_split=2,
                                              min_weight_fraction_leaf=0.0,
                                              presort='deprecated',
                                              random_state=None,
                                              splitter='best'),
             iid='deprecated', n_jobs=None,
             param_grid={'criterion': ['gini', 'entropy'],
                         'max_depth': [5, 10, 15, 20, 25, 30, 35],
                         'min_samples_leaf': [2, 4, 6, 8, 10, 12, 14, 16, 18,
                                              20],
                         'min_samples_split': [2, 4, 6, 8, 10, 12, 14, 16, 18,
                                               20]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring=None, verbose=1)
```

In [115]:

```
grid.best_params_
```

Out[115]:

```
{'criterion': 'entropy',
 'max_depth': 10,
 'min_samples_leaf': 20,
 'min_samples_split': 2}
```

In [116]:

```
grid.best_score_
# 1% better than random guess
```

Out[116]:

```
0.6937321937321937
```

Decision: GridSearch output is consistent. In addition to class_weight = 'balanced', below parameters should be set:

- **'criterion': 'entropy'**
- **'max_depth': 10**
- **'min_samples_leaf': 20**
- **'min_samples_split': 2**

Model 11 - GridSearch2 Decision Tree

In [117]:

```
# Instantiate
dt_grid2 = DecisionTreeClassifier(class_weight='balanced',
                                  criterion = 'entropy',
                                  max_depth = 10,
                                  min_samples_leaf  = 20, #The minimum number of samples requ
ired to be at a leaf node.
                                  min_samples_split = 2)

# Fit
dt_grid2.fit(X_train, y_train)
```

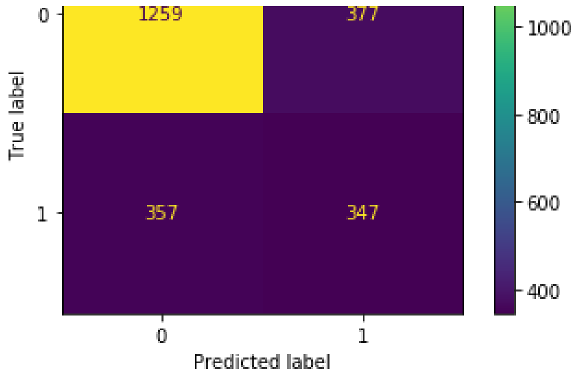
Out[117]:

```
DecisionTreeClassifier(ccp_alpha=0.0, class_weight='balanced',
                       criterion='entropy', max_depth=10, max_features=None,
                       max_leaf_nodes=None, min_impurity_decrease=0.0,
                       min_impurity_split=None, min_samples_leaf=20,
                       min_samples_split=2, min_weight_fraction_leaf=0.0,
                       presort='deprecated', random_state=None,
                       splitter='best')
```

In [118]:

```
eval_model(dt_grid2, X_train, X_test, y_train, y_test)
# Much less overfit - but accuracy down .2 - Same as random guess
# Recall much lower from 0.58 to 0.49 - but validation at 0.53
```

```
Train Scores
------------
Accuracy: 0.7215099715099715
Recall: 0.5542222222222222
F1 Score: 0.5605754102045403
--------------------
Test Scores
-----------
Accuracy: 0.6863247863247863
Recall: 0.4928977272727273
Recall Mean Cross Val 3-Fold: 0.5315555555555557
F1 Score: 0.48599439775910364
```



Model 12 - GridSearch2 Random Forest

In [119]:

```
# Instantiate
rf_grid2 = RandomForestClassifier(class_weight='balanced',
                                   criterion = 'entropy',
                                   max_depth = 10,
                                   min_samples_leaf  = 20,
                                   min_samples_split = 2)

# Fit
rf_grid2.fit(X_train, y_train)
```

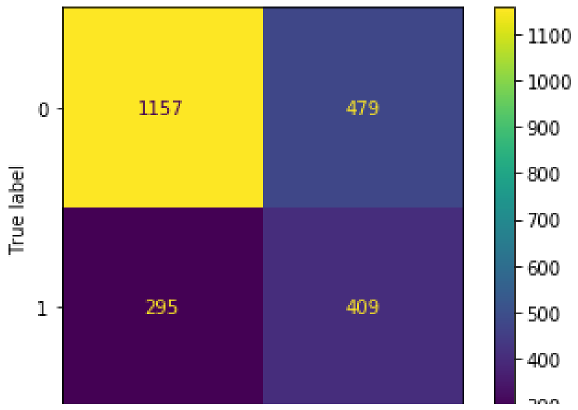
Out[119]:

```
RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_weight='balanced',
                       criterion='entropy', max_depth=10, max_features='auto',
                       max_leaf_nodes=None, max_samples=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=20, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=100,
                       n_jobs=None, oob_score=False, random_state=None,
                       verbose=0, warm_start=False)
```

In [120]:

```
eval_model(rf_grid2, X_train, X_test, y_train, y_test)
# Not overfit for once, but accuracy is less than random guess
# although recall is at highest
# F1 also at similar highest
```

```
Train Scores
------------
Accuracy: 0.6713675213675213
Recall: 0.5946666666666667
F1 Score: 0.5370258880192655
--------------------
Test Scores
-----------
Accuracy: 0.6692307692307692
Recall: 0.5809659090909091
Recall Mean Cross Val 3-Fold: 0.5573333333333333
F1 Score: 0.513819095477387
```



Feature Importance on Top Models

The best performing models either have:

1. **An accuracy score 1-2% above a random guess and a 50% recall score OR**
2. **A 56-58% recall score (and similar cross validation scores for recall, and an accuracy score 2% below a random guess.**

Models explored below include:

- **Model 11, dt_grid2, which falls into bucket #1 above**
- **Model 12, rf_grid2, which falls into bucket #2 above**

Looking to feature importance across both to look into any consistency.

Model 11 (dt_grid2) Feature Importance

Baseline

In [121]:

```
# Top 10 Feature Importance
coef = dt_grid2.feature_importances_
d = dict(zip(X.columns, coef))
sorted_dict = dict( sorted(d.items(), key=operator.itemgetter(1),reverse=True)[:10])
sorted_dict
# Reviews and Installs are main drivers
# Size next largest
```

Out[121]:

```
{'Reviews': 0.3514917474926996,
 'Installs': 0.2874481218337568,
 'Size Trans': 0.11458367450040421,
 'Type_Free': 0.05933202994323856,
 'Genres_Health & Fitness': 0.03420882182816005,
 'Category_TRAVEL_AND_LOCAL': 0.02509496675294812,
 'Category_TOOLS': 0.02102407444211158,
 'Content Rating': 0.01739450044668302,
 'Genres_Education': 0.0108069190939718,
 'Category_SOCIAL': 0.010230815349171177}
```

eli5

In [122]:

```
perm = PermutationImportance(dt_grid2, cv = None, refit = False, n_iter = 50).fit(X_trai
n, y_train)
perm_imp_eli5 = pd.DataFrame(X_train.columns, perm.feature_importances_)
perm_imp_eli5.sort_index(ascending=False)
# Reviews and Installs are main drivers
```

Out[122]:

	0
0.129920	Reviews
0.116821	Installs
0.021744	Type_Free
0.016923	Size Trans
0.009678	Content Rating

0.009078	Content Rating
	0
...	...
0.000000	Category_PRODUCTIVITY
0.000000	Category_SHOPPING
0.000000	Category_SPORTS
0.000000	Category_TOOLS
0.000000	Genres_Video Players & Editors

70 rows × 1 columns

rfpimp

In [123]:

```
perm_imp_rfpimp = permutation_importances(dt_grid2, X_train, y_train, r2)
perm_imp_rfpimp
# Reviews and Installs are main drivers
```

Out[123]:

	Importance
Feature	
Installs	0.791099
Reviews	0.751590
Size Trans	0.130472
Content Rating	0.051454
Type_Paid	0.040428
...	...
Category_SOCIAL	0.000000
Category_SPORTS	0.000000
Category_TOOLS	0.000000
Category_TRAVEL_AND_LOCAL	0.000000
Genres_Video Players & Editors	0.000000

70 rows × 1 columns

Drop column feature importance

In [124]:

```
importances_df = drop_col_feat_imp(dt_grid2, X_train, y_train, random_state = 42)
importances_df.sort_index(ascending=False)
# Reviews, Installs and Size are big drivers
# much higher here than other checks
```

Out[124]:

	0
0.060399	Reviews
0.052849	Installs
0.044017	Size Trans
0.002564	Genres_Action
0.001852	Genres_Education
...	...

	0
0.000000	Category_SPORTS
0.000000	Category_TOOLS
0.000000	Genres_Video Players & Editors
-0.002137	Category_GAME
-0.004558	Category_TRAVEL_AND_LOCAL

70 rows × 1 columns

Model 12 (rf_grid2) Feature Importance

Baseline

In [125]:

```
# Top 10 Feature Importance
coef = rf_grid2.feature_importances_
d = dict(zip(X.columns, coef))
sorted_dict = dict( sorted(d.items(), key=operator.itemgetter(1),reverse=True)[:10])
sorted_dict
# Reviews and Installs are main drivers
# Size next largest
# All have lower influence than in Decision Tree dt_grid2 above
```

Out[125]:

```
{'Reviews': 0.2806939751351103,
 'Installs': 0.23607909460983045,
 'Size Trans': 0.08130752016258495,
 'Genres_Health & Fitness': 0.040194403427215114,
 'Category_HEALTH_AND_FITNESS': 0.03174114489034901,
 'Type_Free': 0.02953003825624812,
 'Type_Paid': 0.0271303832002088,
 'Content Rating': 0.025052694889983664,
 'Category_TOOLS': 0.022898409037890397,
 'Genres_Tools': 0.022496419454335566}
```

eli5

In [126]:

```
perm = PermutationImportance(rf_grid2, cv = None, refit = False, n_iter = 50).fit(X_trai
n, y_train)
perm_imp_eli5 = pd.DataFrame(X_train.columns, perm.feature_importances_)
perm_imp_eli5.sort_index(ascending=False)
# Reviews and Installs are main drivers
```

Out[126]:

	0
0.055285	Reviews
0.032880	Installs
0.007171	Type_Free
0.006430	Type_Paid
0.004382	Genres_Health & Fitness
...	...
-0.000350	Category_GAME
-0.000533	Category_EDUCATION
-0.001191	Genres_Communication
-0.001627	Category_FAMILY

	0
-0.001658	Category_COMMUNICATION

70 rows × 1 columns

rfpimp

```
In [127]:
```

```
perm_imp_rfpimp = permutation_importances(rf_grid2, X_train, y_train, r2)
perm_imp_rfpimp
# Reviews and Installs are main drivers
```

```
Out[127]:
```

	Importance
Feature	
Reviews	0.293542
Installs	0.161766
Type_Free	0.030899
Type_Paid	0.025446
Genres_Health & Fitness	0.019994
...	...
Genres_Photography	-0.001818
Genres_Travel & Local	-0.002726
Category_COMMUNICATION	-0.005453
Genres_Entertainment	-0.008179
Category_FAMILY	-0.010906

70 rows × 1 columns

Drop column feature importance

```
In [128]:
```

```
importances_df = drop_col_feat_imp(rf_grid2, X_train, y_train, random_state = 42)
importances_df.sort_index(ascending=False)
# Installs is top driver, but very small time in comparison to
# other feature importance checks
```

```
Out[128]:
```

	0
0.012393	Installs
0.002707	Genres_Shopping
0.002279	Genres_Role Playing
0.002279	Genres_Personalization
0.001709	Genres_Lifestyle
...	...
-0.004558	Category_AUTO_AND_VEHICLES
-0.004701	Category_BUSINESS
-0.005271	Type_Paid
-0.005840	Genres_Communication
-0.007123	Type_Free

70 rows × 1 columns

Learning:

Across dt_grid and rf_grid2, 5 out 6 feature importance checks highlight Review and Installs followed by Size of the app as model drivers.

Although the model is not in a final versioning to be utilized in day-to-day decisions, the consistency from this version can be generally applied to say that marketing, promotion, and adoption of the app is foundationally important.

VC would want CEOs with strong marketing background, a network with these skills, and/or teams that have this expertise.

Analysis

Look into details of Installs, Reviews, and Size of apps that are Positively Rated in the data set (target = 1).

Installs - most consistent driver

In [129]:

```
# Map ordinal values back to original categorical values
df['Installs'] = df['Installs'].map({0:'Less than 500',
                                      1: '500+',
                                      2: '1,000+',
                                      3: '5,000+',
                                      4: '10,000+',
                                      5: '50,000+',
                                      6: '100,000+',
                                      7: '500,000+',
                                      8: '1,000,000+',
                                      9: '5,000,000+',
                                      10: '10,000,000+',
                                      11: '50,000,000+',
                                      12: '100,000,000+',
                                      13: '500,000,000+',
                                      14: '1,000,000,000+'})
```

In [130]:

```
# Filter down to only those with Positive Ratings (target = 1)
installs_df = pd.DataFrame(df[df['Pos Rating'] == 1]['Installs'].value_counts()).reset_i
ndex()
```

In [131]:

```
# Preview new df
installs_df
```

Out[131]:

	index	Installs
0	10,000,000+	431
1	1,000,000+	418
2	100,000+	297
3	Less than 500	294
4	1,000+	276
5	10,000+	270
6	5,000,000+	190
7	100,000,000+	166

	index	Installs
8	500,000+	153
9	5,000+	115
10	50,000+	111
11	50,000,000+	106
12	500+	90
13	500,000,000+	18
14	1,000,000,000+	14

In [132]:

```
# Create helper column that will put Install categories in order
installs_df['Install Num'] = 0

# For loop to place numerical versions of categories into Install Num column
for row in installs_df.index:
    if installs_df['index'][row] == 'Less than 500':
        installs_df['Install Num'][row] = 500
    else:
        installs_df['Install Num'][row] = int(installs_df['index'][row][:-1].replace(','
,''))
```

```
/opt/anaconda3/envs/learn-env/lib/python3.6/site-packages/ipykernel_launcher.py:9: Settin
gWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/user_gu
ide/indexing.html#returning-a-view-versus-a-copy
  if __name__ == '__main__':
/opt/anaconda3/envs/learn-env/lib/python3.6/site-packages/ipykernel_launcher.py:7: Settin
gWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/user_gu
ide/indexing.html#returning-a-view-versus-a-copy
  import sys
```

In [133]:

```
# Sort by new Install Num helper column and reset the index
installs_df = installs_df.sort_values(by='Install Num', ascending=True).reset_index(drop
=True)
```

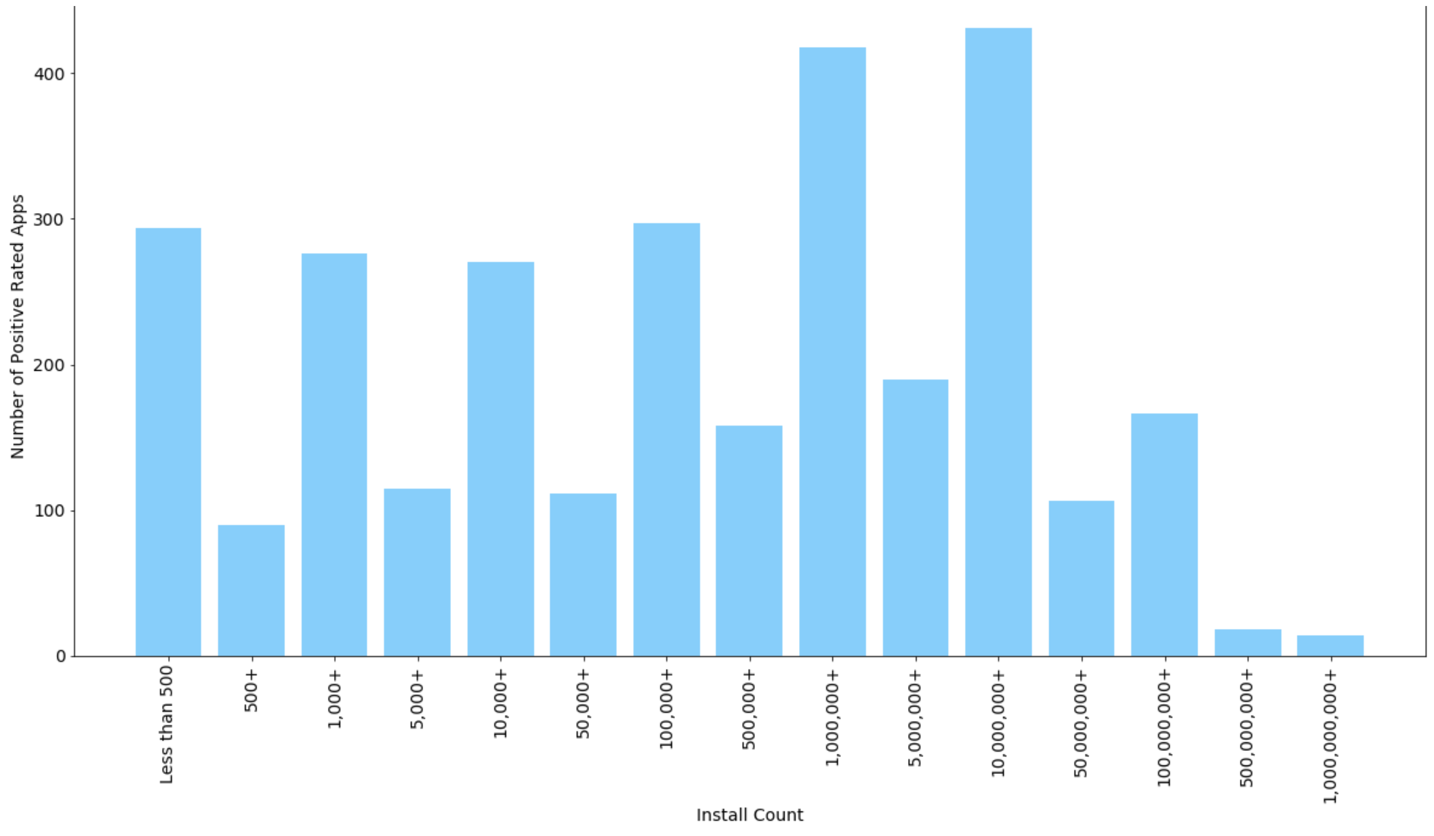
In [134]:

```
# Drop helper column
installs_df = installs_df.drop(columns='Install Num', axis=1)
```

In [135]:

```
# Plot bar chart with counts per category
x = installs_df['index']
y = installs_df['Installs']
plt.figure (figsize=(20,10))
plt.bar(x, y, color='lightskyblue')
plt.title('Positive Rated Apps by Install Count', fontsize=20, fontweight="bold")
plt.xlabel('Install Count', fontsize=14)
plt.xticks(rotation=90, fontsize=14)
plt.ylabel('Number of Positive Rated Apps', fontsize=14)
plt.yticks(fontsize=14)
plt.savefig("images/1_install_count_for_pos_apps")
plt.show()
# Not necessarily more installs = more positively reviewed app
# 1mm-1.5mm installs is sweet spot
# 10mm-50mm installs has second most (much larger range)
# More installs leaves more room for negative reviews
```

Positive Rated Apps by Install Count



Reviews - strongest and second most consistent driver (5 out of 6)

In [136]:

```
# Filter down to only those with Positive Ratings (target = 1)
pos_rated = df[df['Pos Rating'] == 1]
```

In [137]:

```
# Explore Reviews distribution
pos_rated['Reviews'].describe().apply(lambda x: format(x, 'f'))
```

Out[137]:

```
count         2954.000000
mean        784696.629316
std        3827048.578984
min              1.000000
25%            100.000000
50%           8358.500000
75%         172508.000000
max       66577446.000000
Name: Reviews, dtype: object
```

In [138]:

```
less_than_two_mm = pos_rated[pos_rated['Reviews'] <= 2000000]['Reviews']
```

In [139]:

```
len(less_than_two_mm)/2954
```

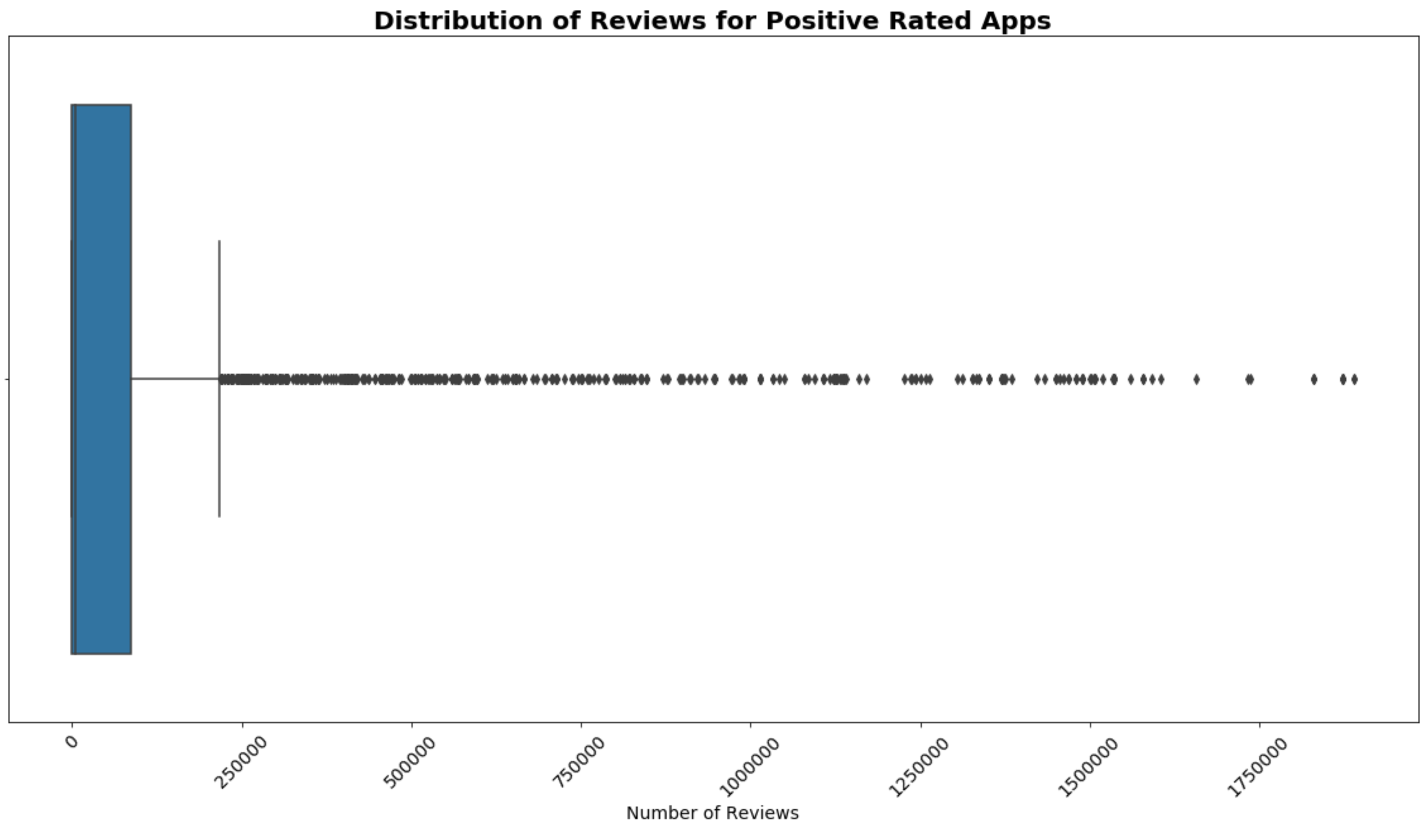
Out[139]:

```
0.9285714285714286
```

In [140]:

```
# Plot 92% of Positively Rated Reviews population
plt.figure(figsize=(20,10))
sns.boxplot(less_than_two_mm)
plt.title('Distribution of Reviews for Positive Rated Apps', fontsize=20, fontweight="bol
d")
```

```
plt.xlabel('Number of Reviews', fontsize=14)
plt.xticks(rotation=45, fontsize=14)
plt.savefig("images/2_review_dist_for_pos_apps")
plt.show()
```



In [141]:

```
# What % is accounted for less than or equal to 100k reviews
len(pos_rated[pos_rated['Reviews'] <=100000])/2954
```

Out[141]:

```
0.7071670954637778
```

In [142]:

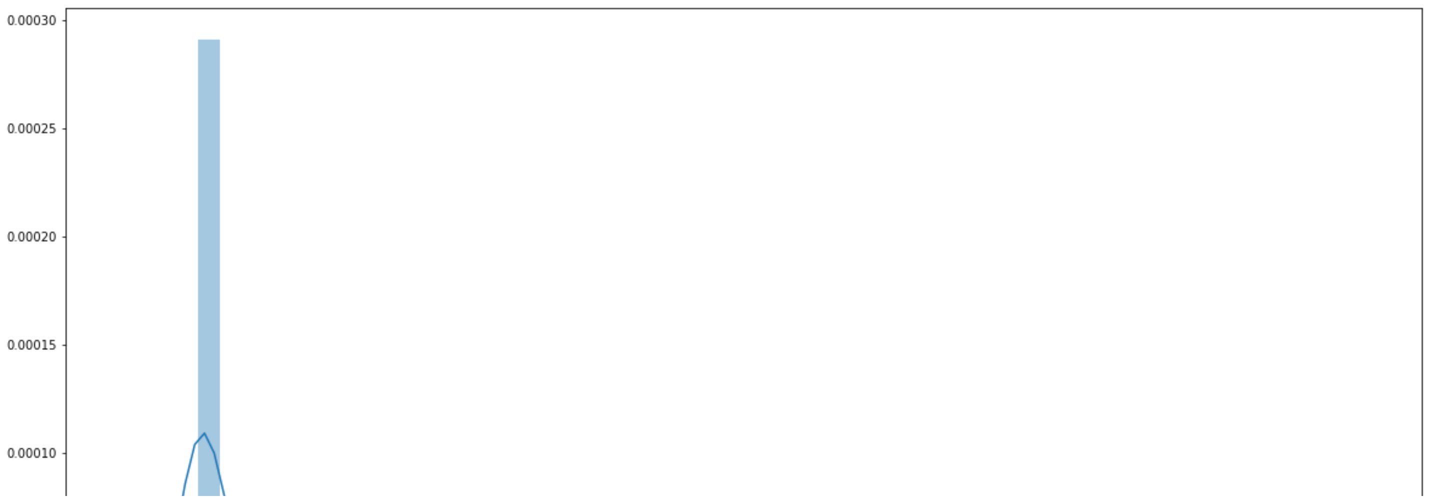
```
# Create filtered df
reviews_zoom = pos_rated[pos_rated['Reviews'] <=100000]
```

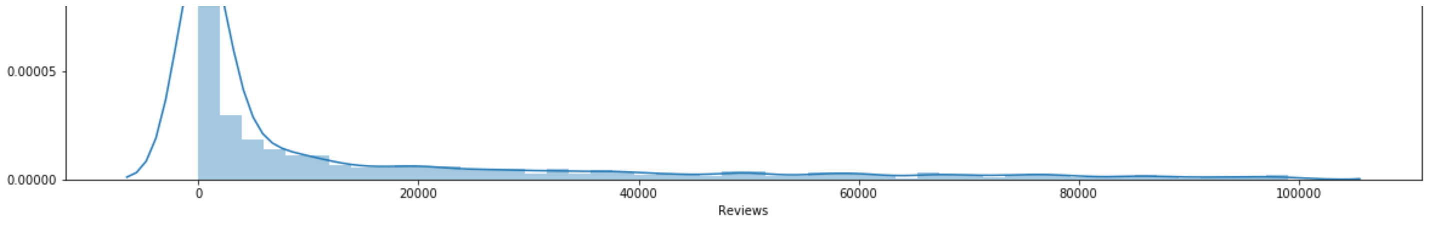
In [143]:

```
# Plot this 70%
plt.figure(figsize=(20, 10))
sns.distplot(reviews_zoom['Reviews'])
```

Out[143]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7ff755c12748>
```





In [144]:

```
# Spike is on lowest end, create further filtered df
reviews_zoom2 = pos_rated[pos_rated['Reviews'] <=500]
```

In [145]:

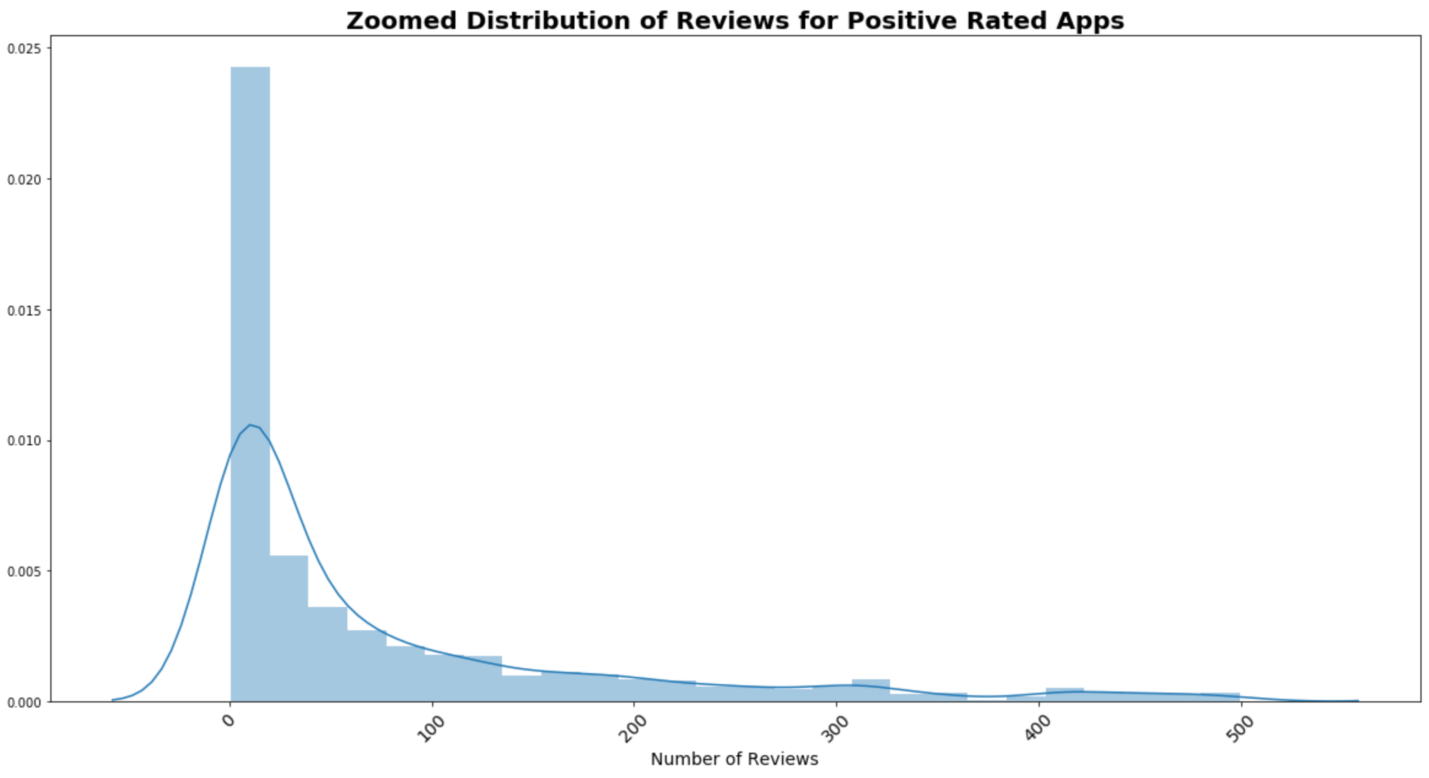
```
len(reviews_zoom2)/2954
```

Out[145]:

```
0.33818551117129314
```

In [146]:

```
# Plot the 34%
plt.figure(figsize=(20, 10))
sns.distplot(reviews_zoom2['Reviews'], hist=True)
plt.title('Zoomed Distribution of Reviews for Positive Rated Apps', fontsize=20, fontweig
ht="bold")
plt.xlabel('Number of Reviews', fontsize=14)
plt.xticks(rotation=45, fontsize=14)
plt.savefig("images/3_review_dist_zoom_for_pos_apps")
plt.show()
```



Learning:

Plots above are showing that the apps with positive ratings are the ones with 0-20 reviews. This could be a space for further iteration as the logic does not check out that higher installs, but very low number of reviews predict a successful app.

Size - third most consistent driver

In [147]:

```
# Review distribution of Size Trans which is Size in kb
pos_rated['Size Trans'].describe()
# 0 means varies by device and this would drag down mean
# Opportunity to edit this in further model development
# Mean is 2x that of median so have extreme outliers (high end)
```

Out[147]:

```
count      2954.000000
mean      19818.388795
std       24058.485396
min           0.000000
25%        3000.000000
50%       10000.000000
75%       26750.000000
max      100000.000000
Name: Size Trans, dtype: float64
```

In [148]:

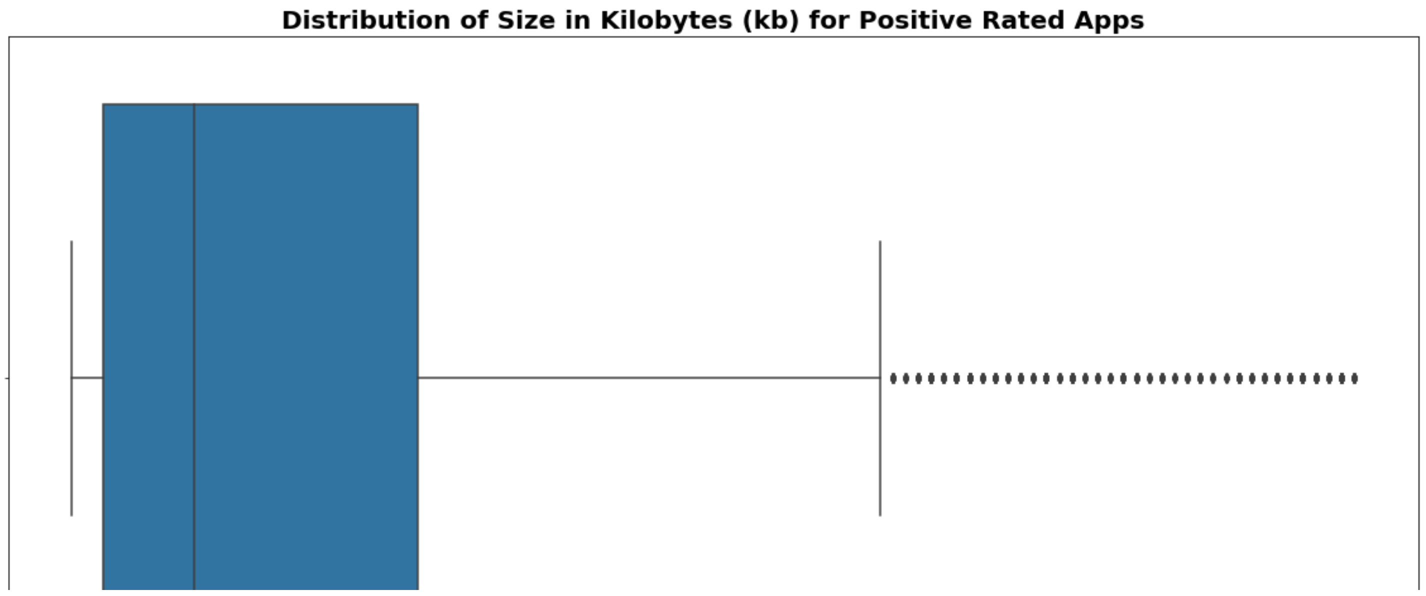
```
# Review distribution of Size Trans which is Size in kb of those that
pos_rated[pos_rated['Size Trans'] !=0]['Size Trans'].describe()
# Mean is 1.5x that of median so have outliers (high end)
```

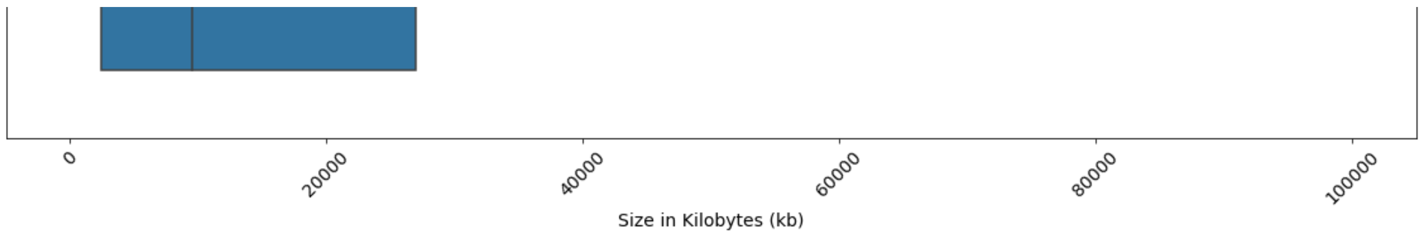
Out[148]:

```
count      2459.000000
mean      23807.857056
std       24502.125727
min           8.500000
25%        5700.000000
50%       14000.000000
75%       32000.000000
max      100000.000000
Name: Size Trans, dtype: float64
```

In [149]:

```
# Visualize distribution
plt.figure(figsize=(20,10))
sns.boxplot(df['Size Trans'])
plt.title('Distribution of Size in Kilobytes (kb) for Positive Rated Apps', fontsize=20,
fontweight="bold")
plt.xlabel('Size in Kilobytes (kb)', fontsize=14)
plt.xticks(rotation=45, fontsize=14)
plt.savefig("images/4_size_dist_for_pos_apps")
plt.show()
# 3,000-26,750 kbs is general range
# 10,000 kbs median
# average Android app is 14,600 kbs - more advanced phones with more baseline storage
# probably enabled this growth/support of larger apps
# source: https://shafi.com.au/mobile%20apps%20facts/iphone/android/big%204%20bank/2020/0
1/06/mobile-apps-fact-file-size.html
```





In [150]:

```
# Cite some apps  in presentation
# Sephora, SlickDeals, Fuel Rewards, Udemy - Online Courses
# LinkedIn Learning: Online Courses to Learn Skills, Fitbit Coach
# Redfin Real Estate, JOANN - Crafts & Coupons
pos_rated[(pos_rated['Installs'] == '1,000,000+') &
          (pos_rated['Size Trans'] !=0)]['App'].values
# Can see from values that there are app records duplicated
# Another opportunity to better model
# Also can visit correlations - some Genres and Categories are named the same
# Opportunity to bucket or just use one for more focused impact on model
```

Out[150]:

```
array(['Tickets + PDA 2018 Exam', 'auto fines',
       'Used car is the first car - used car purchase, used car quotation, dealer informa
tion to',
       'ipsy: Makeup, Beauty, and Tips',
       'Sephora: Skin Care, Beauty Makeup & Fragrance Shop',
       'Free Books - Spirit Fanfiction and Stories',
       'ReadEra – free ebook reader', 'eBoox: book reader fb2 epub zip',
       'Job Search by ZipRecruiter', 'Google Analytics',
       'Google Analytics',
       'GANMA! - All original stories free of charge for all original comics',
       'Tapas – Comics, Novels, and Stories', 'Should I Answer?',
       'Email TypeApp - Mail App', 'Learn Spanish - Español',
       'English for beginners', 'Flame - درب عقلك يوميا',
       'Learn Japanese, Korean, Chinese Offline & Free',
       'PINKFONG Baby Shark', 'Udemy - Online Courses',
       'edX - Online Courses by Harvard, MIT & more',
       'Udemy - Online Courses', 'Learn C++', 'Learn JavaScript',
       'Learn Java', 'Learn HTML', 'Learn SQL',
       'Socratic - Math Answers & Homework Help',
       'Udemy - Online Courses',
       'edX - Online Courses by Harvard, MIT & more',
       'LinkedIn Learning: Online Courses to Learn Skills',
       'Learn English with Aco',
       'Socratic - Math Answers & Homework Help',
       'SoloLearn: Learn to Code for Free',
       '□ Football Wallpapers 4K | Full HD Backgrounds 😍',
       'Low Poly – Puzzle art game', 'Investigation Discovery GO',
       'Vivid Seats – Event Tickets',
       'Gametime - Tickets to Sports, Concerts, Theater', 'IKO',
       'BZWBK24 mobile', 'Post Bank', 'Monefy - Money Manager',
       'Experian - Free Credit Report', 'Branch',
       'CreditWise from Capital One', 'Fresh EBT - Food Stamp Balance',
       'Mobills: Budget Planner',
       'MileIQ - Free Mileage Tracker for Business',
       'MSN Money- Stock Quotes & News',
       'DELISH KITCHEN - FREE recipe movies make food fun and easy!',
       'Eat Fast Prepare "Without Internet"',
       'Yummly Recipes & Shopping List', 'Seamless Food Delivery/Takeout',
       'Pedometer - Step Counter Free & Calorie Burner',
       'Sportractive GPS Running Cycling Distance Tracker',
       'Home Workout for Men - Bodybuilding', 'Sleep Sounds',
       'Calorie Counter - EasyFit free', 'Weight Loss Running by Verv',
       'StrongLifts 5x5 Workout Gym Log & Personal Trainer',
       'Fitbit Coach', 'Map My Ride GPS Cycling Riding',
       'Weight Loss Running by Verv', 'Meditate OM',
       'Meditation Music - Relax, Yoga', 'I'm Expecting - Pregnancy App',
       'The Bump Pregnancy Tracker',
       'Best Ovulation Tracker Fertility Calendar App Glow',
       'Eve Period Tracker - Love, Sex & Relationships App',
       'Fertility Friend Ovulation App',
       'Runtastic Mountain Bike GPS Tracker',
       'Weight Loss Running by Verv', 'Couch to 5K by RunDouble',
       'Fitbit Coach', 'Calorie Counter - MyNetDiary',
       'MyPlate Calorie Tracker', 'Calorie Counter - MyNetDiary',
       'MyPlate Calorie Tracker', 'Meditation Music - Relax, Yoga',
       'Prana Breath: Calm & Meditate',
       'Apartment List: Housing, Apt, and Property Rentals',
       'Redfin Real Estate', 'Redfin Real Estate',
       'Apartment List: Housing, Apt, and Property Rentals',
       'Cool Popular Ringtones 2018 □', 'ZenUI Safeguard',
       'Tattoodo - Find your next tattoo',
       'Super Slime Simulator - Satisfying Slime App',
       'JOANN - Crafts & Coupons', 'justWink Greeting Cards',
       'JOANN - Crafts & Coupons', 'Nature Sounds', 'White Noise Baby',
       'Super Jim Jump - pixel 3d', 'Super Jim Jump - pixel 3d',
       'Woody Puzzle', 'Looper!', 'Mad Skills BMX 2',
       'MLB TAP SPORTS BASEBALL 2018',
       'Ice Crush 2018 - A new Puzzle Matching Adventure',
       'SHADOWGUN LEGENDS', 'Chapters: Interactive Stories',
       'Honkai Impact 3rd', 'Honkai Impact 3rd',
       'Super Jim Jump - pixel 3d', 'Jewels Star: OZ adventure',
       'Once Upon a Tower', 'Jewels Star: OZ adventure',
       'Super ABC! Learning games for kids! Preschool apps',
       'Toy Pop Cubes', 'Candy Pop Story', 'Candy Smash',
       'Puzzle Kids - Animals Shapes and Jigsaw Puzzles', 'Candy Day',
       'Learn To Draw Glow Princess', 'Educational Games for Kids',
       'Super ABC! Learning games for kids! Preschool apps',
       'Drawing for Kids Learning Games for Toddlers age 3',
       'LEGO® Friends: Heartlake Rush',
       'Baby ABC in box! Kids alphabet games for toddlers!',
       'Henry Danger Crime Warp', 'Toddler Kids Puzzles PUZZINGO',
       'Leo and Tig', 'My Oasis - Calming and Relaxing Idle Clicker Game',
       'Monster High™ Minis Mania', 'GoodRx Drug Prices and Coupons',
       'FollowMyHealth®',
       'Ovia Pregnancy Tracker & Baby Countdown Calendar',
       'Pregnancy Week By Week',
       'Ovia Fertility Tracker & Ovulation Calculator',
       '1800 Contacts - Lens Store', 'Ada - Your Health Guide',
       'mySugr: the blood sugar tracker made just for you',
       'Pregnancy Calculator and Tracker app', 'Period Tracker',
       'Anatomy Learning - 3D Atlas',
       'mySugr: the blood sugar tracker made just for you',
       'Ada - Your Health Guide',
       'Ovia Fertility Tracker & Ovulation Calculator',
       '1800 Contacts - Lens Store', 'Jodel - The Hyperlocal App',
       'Love Sticker', '□ WhatsLov: Smileys of love, stickers and GIF',
       'Moment', 'Horn, free country requirements', 'Life market', 'Nike',
       'Ebates: Cash Back, Coupons, Rewards & Savings',
       'Slickdeals: Coupons & Shopping', 'Wanelo Shopping',
       'Wanelo Shopping', 'Receipt Hog - Receipts to Cash',
       'Newegg Mobile', 'Slickdeals: Coupons & Shopping',
       'FreePrints – Free Photos Delivered',
       'LALALAB prints your photos, photobooks and magnets',
       'HD Camera - Quick Snap Photo & Video', 'Waterfall Photo Frames',
       'Makeup Editor -Beauty Photo Editor & Selfie Camera',
       'Selfie Camera: Beauty Camera, Photo Editor,Collage',
       'Night Photo Frame', 'Selfie Photo Editor', 'Kids Photo Frames',
       'FilterGrid - Cam&Photo Editor', 'Telemundo Deportes - Live',
       'FanDuel: Daily Fantasy Sports',
       'DraftKings - Daily Fantasy Sports',
       'Yahoo Sports - scores, stats, news, & highlights',
       'Yahoo Sports - scores, stats, news, & highlights',
       'Yahoo Sports - scores, stats, news, & highlights',
       'Yoriza Pension - travel, lodging, pension, camping, caravan, pool villas accommod
ation discount',
       'Moto Suggestions ™', "I Can't Wake Up! Alarm Clock",
       'Calculator with Percent (Free)', 'Unit Converter',
       'Calculator ++', 'Speedcheck', 'Launcher',
       'Birds Sounds Ringtones & Wallpapers',
       'Funny Alarm Clock Ringtones',
       'Color Call - Caller Screen, LED Flash', 'Goku Wallpaper Art',
       'Cute wallpapers & kawaii backgrounds images', 'Wallpaper',
       'Power Booster - Junk Cleaner & CPU Cooler & Boost',
       'Loop - Habit Tracker', 'Pushbullet - SMS on PC',
       'Solid Explorer Classic', 'JotterPad - Writer, Screenplay, Novel',
       'New Calendar', 'Baby Sleep: White noise lullabies for newborns',
       'Feed Baby - Baby Tracker', 'Weather forecast',
       'weather - weather forecast',
       'Live Weather & Daily Local Weather Forecast',
       'HD Movie Video Player',
       'Video Editor,Crop Video,Movie Video,Music,Effects',
       'Video.Guru - Video Maker', 'daily News',
       'Free TV Shows App:News, TV Series, Episode, Movies',
       'BaBe Lite - Read Quota Saving News', 'РИА Новости',
       'Podcast App: Free & Offline Podcasts by Player FM',
       'RT News (Russia Today)', 'AP Mobile - Breaking News',
       'Mapy.cz - Cycling & Hiking offline maps',
       'Karta GPS - Offline Navigation', 'Snapp',
       'GPS Speedometer and Odometer',
       'Trucker Path – Truck Stops & Weigh Stations',
       'GPS Speedometer, Distance Meter',
       'Color by Number - Draw Sandbox Pixel Art', 'STARDOM: THE A-LIST',
       'Learn C++', 'CPlus for Craigslist - Officially Licensed',
       'Cut the Rope GOLD', 'EXO-L',
       "French to English Speaking - Apprendre l' Anglais",
       'Mobizen Screen Recorder for LG - Record, Capture',
       'I’m Expecting - Pregnancy App', "Drag'n'Boom",
       'S Player - Lightest and Most Powerful Video Player',
       'U LIVE – Video Chat & Stream', 'Flashlight X', 'iSwipe Phone X',
       'Anime X Wallpaper', 'Robocar X Ray',
       'Space X: Sky Wars of Air Force', 'Flashlight Ultimate',
       'Z Champions', 'Ultimate Ab & Core Workouts',
       'Abs workout - 21 Day Fitness Challenge', 'Replika',
       'Orbita AI — Exciting mobile puzzles & riddles',
       'Lyra Virtual Assistant', 'Weapon stripping 3D',
       'Al Quran Al karim', 'Al Quran Audio (Full 30 Juz)',
       'Koran Read &MP3 30 Juz Offline', 'Al Quran MP3 - Quran Reading®',
       'Hafizi Quran 15 lines per page', "Vikings: an Archer's Journey",
       'The PCH App', 'Virtual lover',
       'Princess Closet : Otome games free dating sim',
       'AP Mobile - Breaking News', 'QuickShortcutMaker',
       'Questland: Turn Based RPG',
       'Grow Stone Online : 2d pixel RPG, MMORPG game',
       'Sleep as Android Unlock', 'Seen', "Five Nights at Freddy's",
       'Bitdefender Antivirus Free', 'OK K.O.! Lakewood Plaza Turbo',
       'mySugr: the blood sugar tracker made just for you',
       'ALL-IN-ONE PACKAGE TRACKING', 'B&H Photo Video Pro Audio',
       'Newegg Mobile', 'Lesbian Chat & Dating - SPICY',
       'Bingo Party - Free Bingo Games', 'WebComics',
       'Go-Go-Goat! Free Game',
       'Brilliant Quotes: Life, Love, Family & Motivation',
       'Simple Gallery', 'Battery Notifier BT Free',
       'Pu - Cute giant panda bear, baby pet care game', 'Hypocam',
       'Sandbox Art-Sandbox Color by Number Coloring Pages',
       'Color By Number - Sandbox Pixel Coloring Book',
       'PixelDot - Color by Number Sandbox Pixel Art',
       'PixPanda - Color by Number Pixel Art Coloring Book',
       'PixBox Coloring - Color by number Sandbox',
       'Draw Color by Number - Sandbox Pixel Art',
       'Color by Number: Pixel Art',
       'Voxel - 3D Color by Number & Pixel Coloring Book',
       'No.Diamond – Colors by Number', 'BZ Reminder', 'BZWBK24 mobile',
       'Sonic CD Classic', 'CKZ ORIGINS',
       'CM Security Open VPN - Free, fast unlimited proxy',
       'Speed Booster - Ram, Battery & Game Speed Booster', 'Ruler',
       'Cartoon Network Match Land', 'Surely You Quest - Magiswords',
       'We Bare Bears Match3 Repairs',
       'Champions and Challengers - Adventure Time',
       'Dots & Co: A Puzzle Adventure', 'Poke Genie - Safe IV Calculator',
       'IV Go（get IV for Pokemon）',
       'ClanPlay: Community and Tools for Gamers', 'Calcy IV',
       'Ultimate Clash Royale Tracker', 'Stats Royale for Clash Royale',
       'Ultimate Chest Tracker', 'Resume Free',
       'Cymath - Math Problem Solver', 'Army of Heroes',
       'Mapy.cz - Cycling & Hiking offline maps', "The Zueira's Voice",
       'Krazy Coupon Lady', 'Pocket Heroes', 'Fancy Pants Adventures',
       '+Download 4 Instagram Twitter', 'TorrDroid - Torrent Downloader',
       'Guardian Hunter: SuperBrawlRPG', 'NoteToDo. Notes. To do list',
       'Notes : Colorful Notepad Note,To Do,Reminder,Memo',
       'The Walking Zombie: Dead City', 'Dr. Parker : Parking Simulator',
       'Dr. Parker : Real car parking simulation',
       'Dr. Battery - Fast Charger - Super Cleaner 2018',
       'DraStic DS Emulator', 'Bloons TD 5',
       'DU Launcher - Boost Your Phone', 'Lost Journey (Dreamsky)',
       'English Conversation Courses', 'EGW Writings',
       'Disaster Will Strike', 'Exiled Kingdoms RPG', 'El Falı',
       'The translator', 'The Holy Rosary', "Connect'Em",
       'Telemundo Deportes - En Vivo', 'Learn Top 300 English Words',
       'Masha and the Bear. Games for kids',
       'Masha and The Bear Jam Day Match 3 games for kids',
       "Where's My Water?", 'Masha and the Bear: Good Night!',
       'Masha and the Bear: Climb Racing and Car Games',
       'FilterGrid - Cam&Photo Editor', 'Friendly for Facebook',
       'FC Bayern Munich', 'Chelsea FC Official Keyboard',
       'Financial Calculator India', 'Burn Your Fat With Me! FG',
       'Lotto Results - Mega Millions Powerball Lottery US',
       'Podcast App: Free & Offline Podcasts by Player FM',
       'Magnum 3.0 Gun Custom SImulator',
       'Slickdeals: Coupons & Shopping',
       'Inf VPN - Global Proxy & Unlimited Free WIFI VPN',
       'Fuel Rewards® program', 'Castle Clash: RPG War and Strategy FR'],
      dtype=object)
```

Data Analysis Learnings

When looking across the two most successful models an app's number of installs and number of reviews were the biggest drivers along with the size of the app.

When looking at installs, the story is not necessarily the more installs an app has, the likely the app is positively reviewed. According to the Google Play Store data used, an app that has 1 million to 5 million installs is the sweet spot. In second, but with a much larger range is the 10 million to 50 million installs bucket. This is interesting as these were not the greatest number of installs. There were an additional four buckets 50 million all the way up to 1 billion. Conceptually, the more installs an app gets, there could be higher likelihood of negative reviews that can pull the app rating down. Recommend getting more app store data for higher installed apps for model to learn further.

Further analysis on the number of reviews for positively rated apps led us to an opportunity for further model improvement. Plotting showed that the apps with positive ratings are the ones with 0-20 reviews. This could be a space for further iteration as the logic does not check out that higher installs, but very low number of reviews predict a successful app.

Size was a feature that was tested with consistently in this process and in the final model iterations ended up as a translation of the size into kilobytes. On the other hand, there were many apps that had a size that varied based on the device. These values were left at 0 and this showed up in plotting the app sizes that are most tied to positively rated apps. For those that *had* a defined size, 3,000-26,750 kbs was the range with a median of 10,000kbs. In researching further, the average android app is 11,500kbs, so our data is similarly aligned (source). This sizing includes apps like: Sephora, SlickDeals, Fuel Rewards, LinkedIn Learning, Fitbit Coach, and Redfin Real Estate. In looking for relevant apps in that size range to understand functionality capabilities, it was found that there are duplicates in the dataset. The recommendation for further development would be to spend time deduplicating. The closest thing to an ID is the app name, but would also need to do comparisons on other columns to see if there are variations in the other feature values. Additionally going back to the apps that had a size that varied with devices, the recommendation would be to find additional data to support a true size translation for the particular app or to utilize the median size from this dataset.

Conclusion

Recommendations On Model Utilization:

Recommendations On Model Utilization:

Although the model is not in a final versioning to be utilized in day-to-day decisions, the consistency from this version can be generally applied to say that marketing, promotion, and adoption of the app is foundationally important.

Along with the technical aptitude for efficient app development, the VC would want CEOs with strong marketing background, a network with these skills, and/or teams that have this expertise.

Future Work

Internal VC Operations

VC should take the themes from the model and emphasize, in addition to the technical teams building and supporting the app, a" strong marketing capabilities. This can be translated into applications for funding, questions for in-person pitching, and more advanced personal interviews further down the line. It can also be applied as an approach in targeting organizations with these characteristics for VC investment.

Additional Data Analysis and Modeling

Further model iteration is needed from the data perspective. This includes opportunities to fold in more Google Play Store data (is it scrapeable? get more data for high install apps 50 million+, app age), continue to cleanse the current data (duplicates and additional size research and assignment), and revisit the number of reviews feature in the model to understand what is causing 0-20 reviews to pop as a consistent driving factor for a positively rated app. Finessing the model in these ways can aid not only in increasing priority scoring like recall, but with additional data features like age, can create post-funding goals for the app companies to achieve like install and review count milestones.