Final Project: Rating Analysis And Prediction For Books

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In [1]:
```
# Load libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn import linear_model
import matplotlib
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from math import sqrt
from sklearn.metrics import mean_squared_error
from sklearn import tree
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.ensemble import RandomForestRegressor

from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import BaggingClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import AdaBoostClassifier

import csv
from scipy.cluster.hierarchy import linkage, fcluster
from sklearn.preprocessing import StandardScaler
from sklearn.metrics.cluster import contingency_matrix, adjusted_rand_sc
ore, silhouette_score, homogeneity_score ,completeness_score
from sklearn.cluster import KMeans, DBSCAN
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn import metrics
```

Data Collection

In [2]:
```python
# read the dataset
data_publishers = pd.read_csv("publishers.csv")
data_publishers.head(10)
```

Out[2]:

	genre	sold by	daily average.amazon revenue	daily average.author revenue	daily average.gross sales	daily average.publisher revenue	ave
0	genre fiction	HarperCollins Publishers	6832.000	6832.000	34160.00	20496.000	
1	genre fiction	HarperCollins Publishers	2487.500	2487.500	12437.50	7462.500	
2	genre fiction	Amazon Digital Services, Inc.	9559.000	9559.000	47795.00	28677.000	
3	fiction	Hachette Book Group	8250.000	8250.000	41250.00	24750.000	
4	genre fiction	Penguin Group (USA) LLC	7590.500	7590.500	37952.50	22771.500	
5	genre fiction	Amazon Digital Services, Inc.	12974.000	6986.000	19960.00	0.000	
6	genre fiction	HarperCollins Publishers	5498.334	5498.334	27491.67	16495.002	
7	nonfiction	Hachette Book Group	5236.400	5236.400	26182.00	15709.200	
8	genre fiction	HarperCollins Publishers	5218.734	5218.734	26093.67	15656.202	
9	genre fiction	Random House LLC	4758.468	4758.468	23792.34	14275.404	

In [3]:
```python
# structure of the dataframe(rows, columns)
data_publishers.shape
```

Out[3]: (27027, 13)

In [4]:
```python
# information about each column of the dataframe
data_publishers.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 27027 entries, 0 to 27026
Data columns (total 13 columns):
genre                              27027 non-null object
sold by                            27027 non-null object
daily average.amazon revenue       27027 non-null float64
daily average.author revenue       27027 non-null float64
daily average.gross sales          27027 non-null float64
daily average.publisher revenue    27027 non-null float64
daily average.units sold           27027 non-null int64
publisher.name                     27027 non-null object
publisher.type                     27027 non-null object
statistics.average rating          27027 non-null float64
statistics.sale price              27027 non-null float64
statistics.sales rank              27027 non-null int64
statistics.total reviews           27027 non-null int64
dtypes: float64(6), int64(3), object(4)
memory usage: 2.7+ MB
```

Data Preparation

In [5]:
```python
# check if there are any missing values (NAN)
data_publishers[data_publishers.isnull().any(axis=1)]
```

Out[5]:

genre	sold by	daily average.amazon revenue	daily average.author revenue	daily average.gross sales	daily average.publisher revenue	daily average.units sold

In [6]:
```python
# check if there are any zero values
data_publishers.isin([0]).any().any()
```

Out[6]: True

In [7]:
```python
# check the number of zero values in 'daily average.publisher revenue' c
olumn
data_publishers.loc[data_publishers['daily average.publisher revenue']==
0]['daily average.publisher revenue'].count()
```

Out[7]: 6369

In [8]:
```python
# check the number of zero values in 'statistics.average rating' column
data_publishers.loc[data_publishers['statistics.average rating']==0]['st
atistics.average rating'].count()
```

Out[8]: 1182

In [9]:
```
# check the number of zero values in 'statistics.total reviews' column
data_publishers.loc[data_publishers['statistics.total reviews']==0]['statistics.total reviews'].count()
```

Out[9]:
```
1182
```

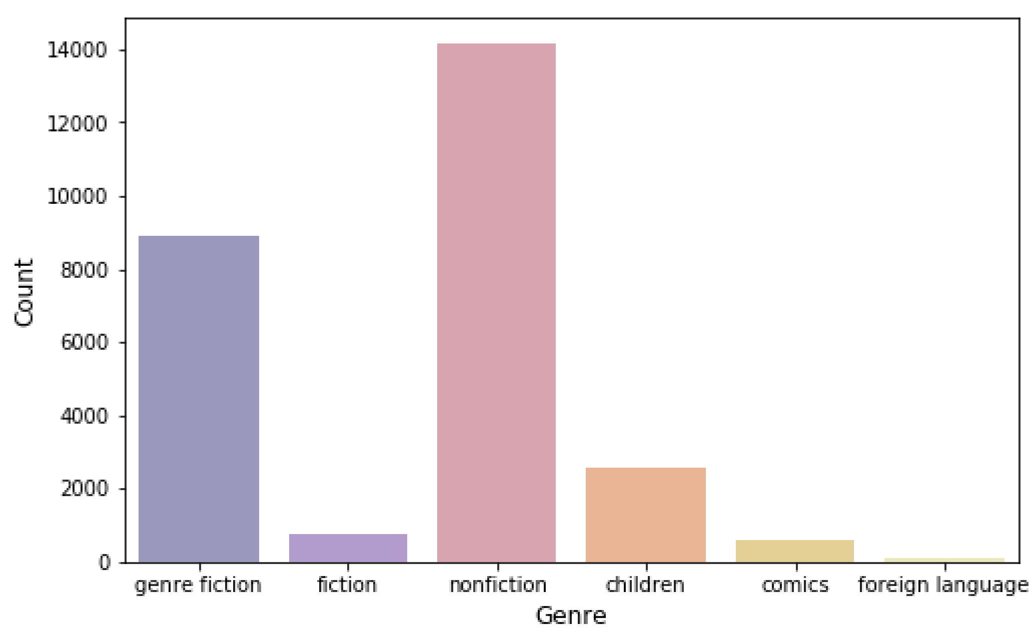
In [10]:
```
# get the unique values of genre
data_publishers.genre.unique()
```

Out[10]:
```
array(['genre fiction', 'fiction', 'nonfiction', 'children', 'comics',
       'foreign language'], dtype=object)
```

In [11]:
```
# get the proportion of each genre in the dataframe
data_publishers.groupby(['genre'])['statistics.average rating'].count()
print((data_publishers.groupby(['genre'])['statistics.average rating'].count() / data_publishers.shape[0])*100)
```

```
genre
children             9.401709
comics               2.101602
fiction              2.712103
foreign language     0.447700
genre fiction       32.941133
nonfiction          52.395752
Name: statistics.average rating, dtype: float64
```

In [12]:
```
# plot for proportion of each genre in the dataframe
plt.rcParams['figure.figsize'] = (8, 5)
ax = sns.countplot(data = data_publishers, x ='genre', palette = 'CMRmap', alpha = 0.5)
ax.set_ylabel('Count', fontsize = 12)
ax.set_xlabel('Genre', fontsize = 12)
plt.show()
```



In [13]:
```
# replace 'genre fiction' with 'fiction' to consider both as same genre
data_publishers_tidy = data_publishers.replace(to_replace = "genre fiction",  value = "fiction")
data_publishers_tidy.head()
```

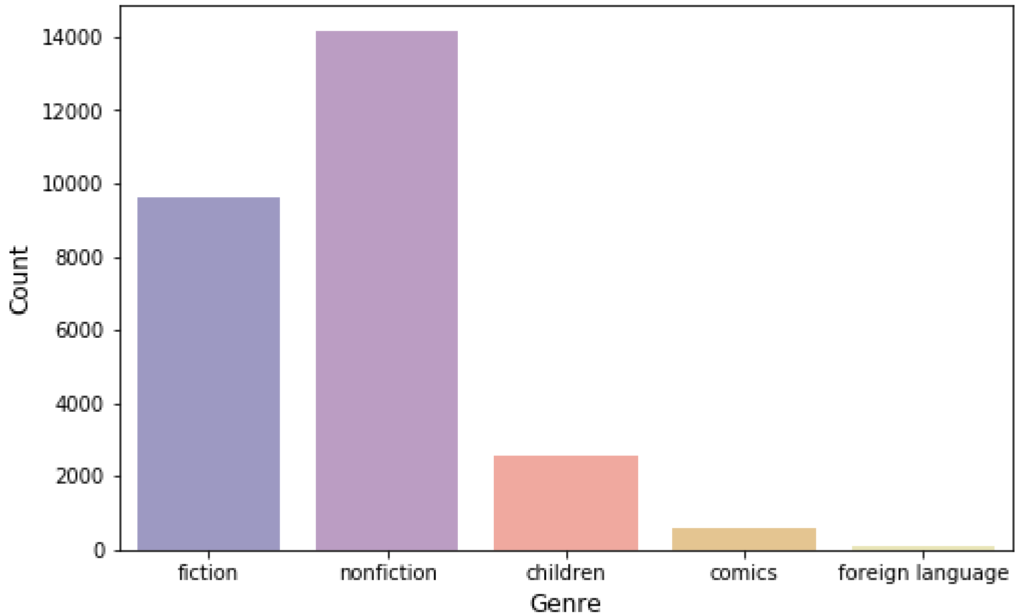
Out[13]:

	genre	sold by	daily average.amazon revenue	daily average.author revenue	daily average.gross sales	daily average.publisher revenue	averag
0	fiction	HarperCollins Publishers	6832.0	6832.0	34160.0	20496.0	
1	fiction	HarperCollins Publishers	2487.5	2487.5	12437.5	7462.5	
2	fiction	Amazon Digital Services, Inc.	9559.0	9559.0	47795.0	28677.0	
3	fiction	Hachette Book Group	8250.0	8250.0	41250.0	24750.0	
4	fiction	Penguin Group (USA) LLC	7590.5	7590.5	37952.5	22771.5	

In [14]:
```
# get the proportion of each genre in the dataframe again
print((data_publishers_tidy.groupby(['genre'])['statistics.average rating'].count()/data_publishers_tidy.shape[0])*100)
```

```
genre
children             9.401709
comics               2.101602
fiction             35.653236
foreign language     0.447700
nonfiction          52.395752
Name: statistics.average rating, dtype: float64
```

In [15]:
```
# plot for proportion of each genre in the dataframe
plt.rcParams['figure.figsize'] = (8, 5)
ax = sns.countplot(data = data_publishers_tidy, x ='genre', palette = 'C
MRmap', alpha = 0.5)
ax.set_ylabel('Count', fontsize = 12)
ax.set_xlabel('Genre', fontsize = 12)
plt.show()
```



In [16]:

```
# remove the genres that has very less proportion in the dataframe to av
oid class imbalance issues
data_publishers_tidy = data_publishers_tidy.drop(data_publishers_tidy[(d
ata_publishers_tidy['genre'] == 'children') |
                                                                      (da
ta_publishers_tidy['genre'] == 'comics') |
                                                                      (da
ta_publishers_tidy['genre'] == 'foreign language')]
                                                                      .in
dex)
data_publishers_tidy.head()
```

Out[16]:

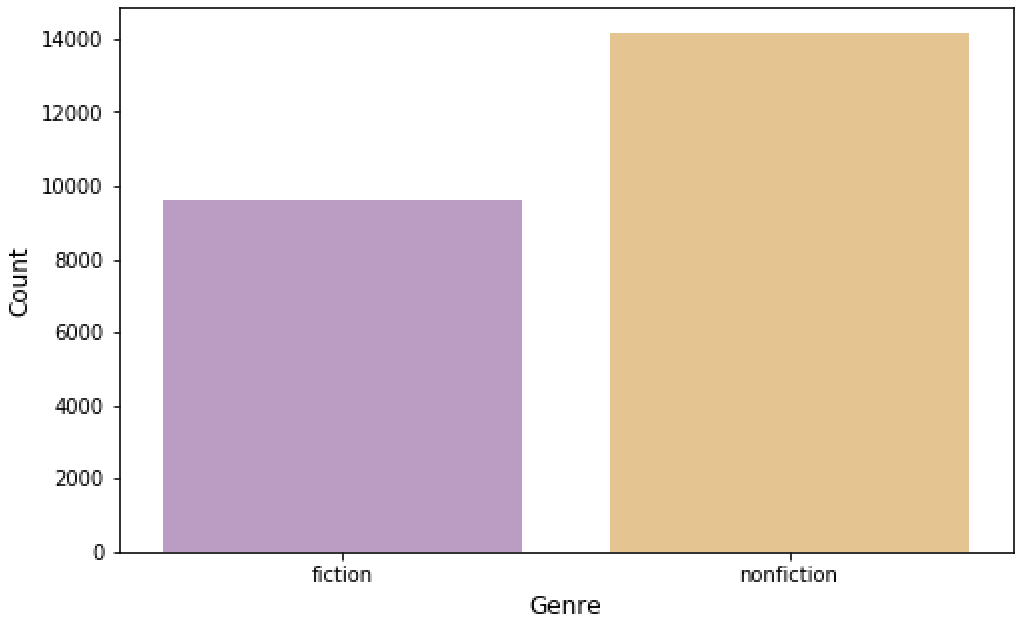
	genre	sold by	daily average.amazon revenue	daily average.author revenue	daily average.gross sales	daily average.publisher revenue	averag
0	fiction	HarperCollins Publishers	6832.0	6832.0	34160.0	20496.0	
1	fiction	HarperCollins Publishers	2487.5	2487.5	12437.5	7462.5	
2	fiction	Amazon Digital Services, Inc.	9559.0	9559.0	47795.0	28677.0	
3	fiction	Hachette Book Group	8250.0	8250.0	41250.0	24750.0	
4	fiction	Penguin Group (USA) LLC	7590.5	7590.5	37952.5	22771.5	

In [17]:

```
# get the proportion of each genre in the dataframe after removing a few
genres
print(data_publishers_tidy.shape)
print((data_publishers_tidy.groupby(['genre'])['statistics.average ratin
g'].count()/data_publishers_tidy.shape[0])*100)
```

```
(23797, 13)
genre
fiction       40.492499
nonfiction    59.507501
Name: statistics.average rating, dtype: float64
```

In [18]:
```python
# plot for proportion of each genre in the dataframe
plt.rcParams['figure.figsize'] = (8, 5)
ax = sns.countplot(data = data_publishers_tidy, x ='genre', palette = 'C
MRmap', alpha = 0.5)
ax.set_ylabel('Count', fontsize = 12)
ax.set_xlabel('Genre', fontsize = 12)
plt.show()
```



In [19]:
```python
# dropping sold by and publisher.name since they do not impact the ratin
g
# get the dummy values for genre and publisher.type
data_publishers_tidy = pd.get_dummies(data_publishers_tidy.iloc[:,[0,2,3
,4,5,6,8,9,10,11,12]], drop_first = True)
data_publishers_tidy.head()
```

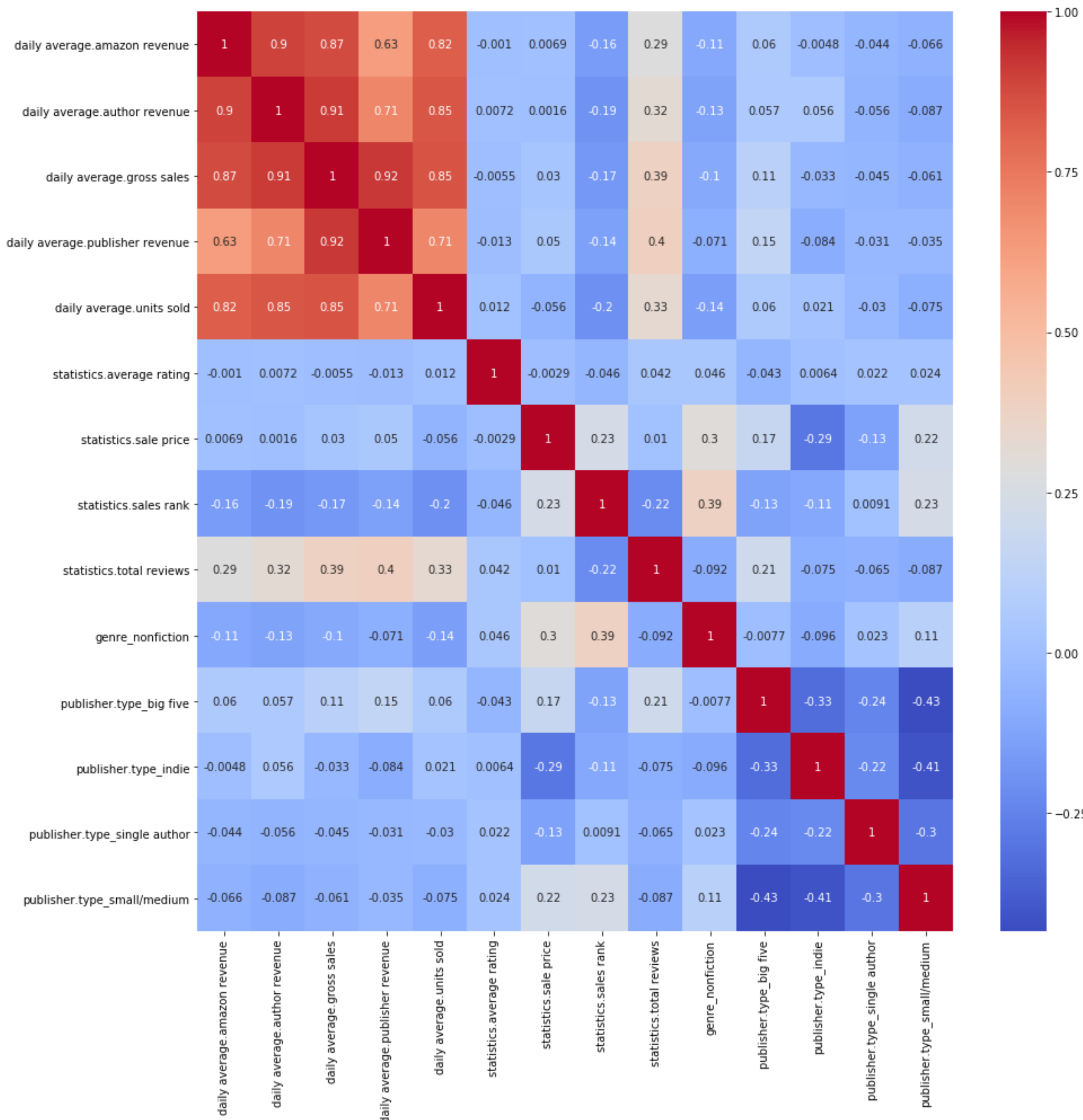
Out[19]:

	daily average.amazon revenue	daily average.author revenue	daily average.gross sales	daily average.publisher revenue	daily average.units sold	statistics.ave ra
0	6832.0	6832.0	34160.0	20496.0	7000	
1	2487.5	2487.5	12437.5	7462.5	6250	
2	9559.0	9559.0	47795.0	28677.0	5500	
3	8250.0	8250.0	41250.0	24750.0	5500	
4	7590.5	7590.5	37952.5	22771.5	4750	

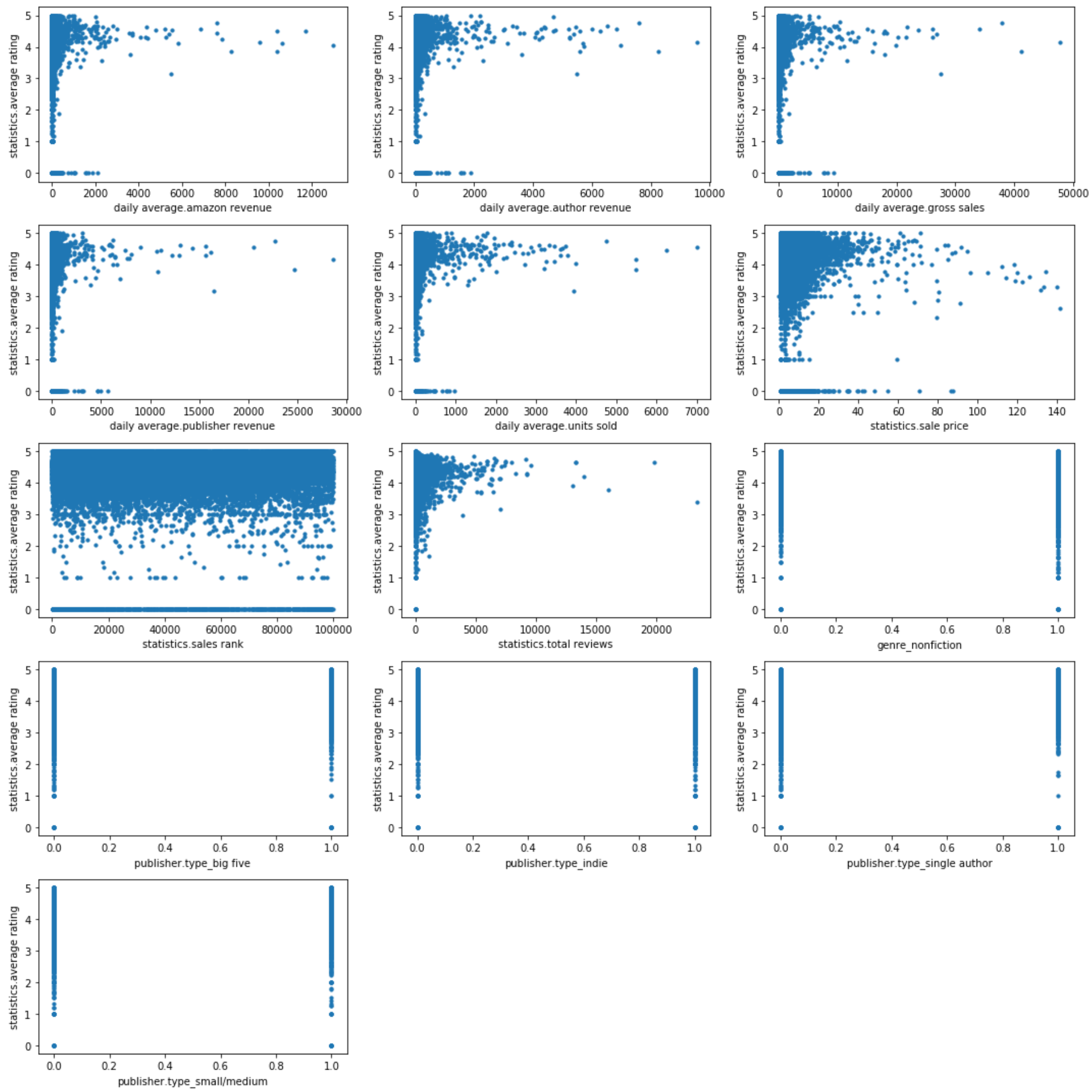
Data Exploration

In [20]:
```
# get the correlation matrix and plot heatmap to check the correlation o
f statistics.average rating with other variables
correlation_matrix = data_publishers_tidy.corr()
correlation_features = correlation_matrix.index
plt.figure(figsize=(15,15))
graph = sns.heatmap(data_publishers_tidy[correlation_features].corr(),an
not=True,cmap="coolwarm")

# get the variables with correlation > 0.01 as important variables
correlation_y = abs(correlation_matrix["statistics.average rating"])
important_features = correlation_y[correlation_y > 0.01]
print("The important variables to predict average rating of the book ar
e:")
print(important_features)
```

```
The important variables to predict average rating of the book are:
daily average.publisher revenue     0.012713
daily average.units sold            0.011972
statistics.average rating           1.000000
statistics.sales rank               0.045586
statistics.total reviews            0.041710
genre_nonfiction                    0.045907
publisher.type_big five             0.042833
publisher.type_single author        0.022082
publisher.type_small/medium         0.024398
Name: statistics.average rating, dtype: float64
```



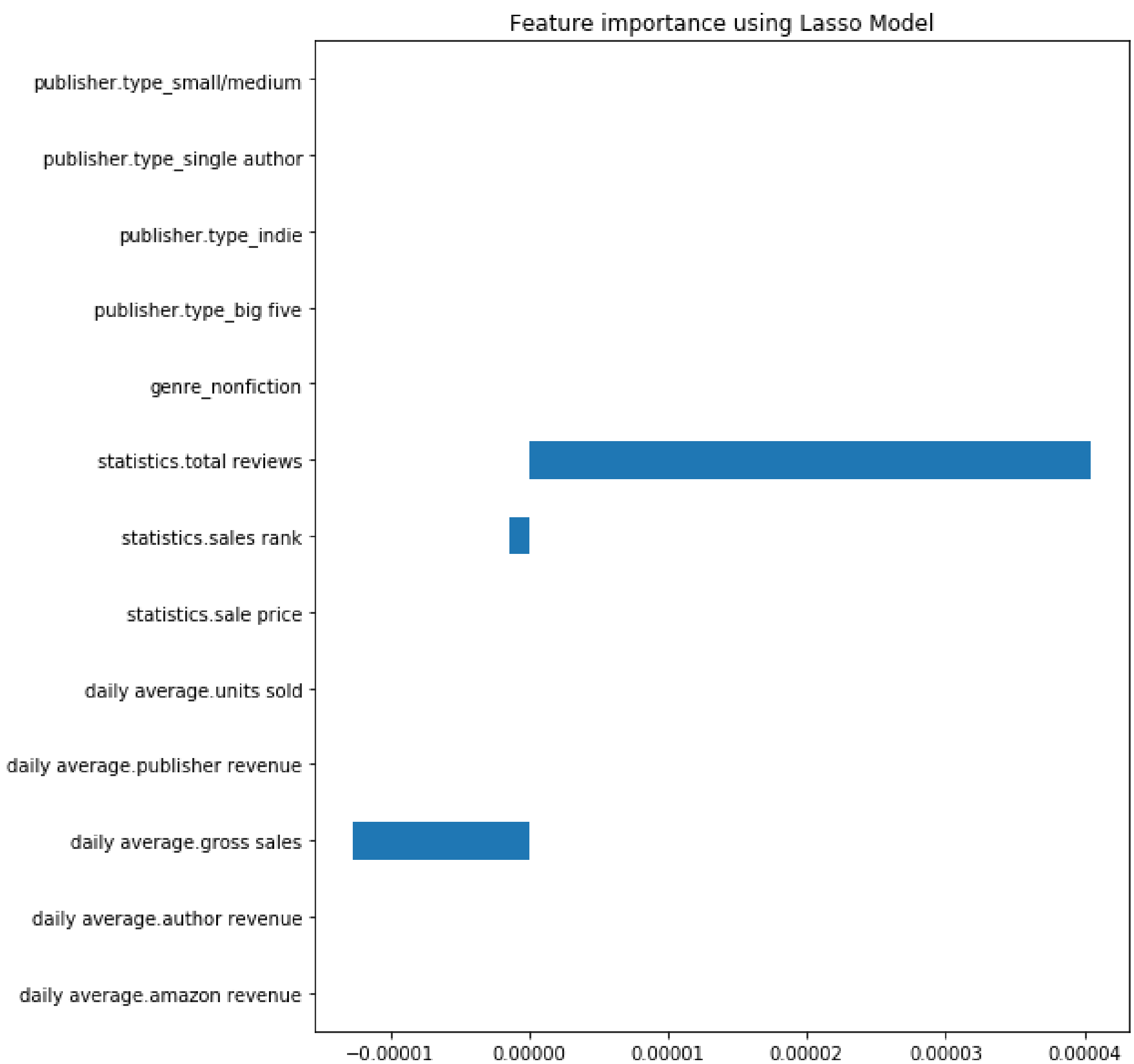
In [21]:
```
# Pair-wise Scatter Plots with 'statistics.average rating' and all other 
attributes to determine the relationship
# between 'statistics.average rating' and other variables

fig1, ((ax1, ax2, ax3), (ax4, ax5, ax6), (ax7, ax8, ax9), (ax10, ax11, a
x12),
      (ax13, ax14, ax15)) = plt.subplots(5,3, figsize = (15,15))

data_publishers_tidy.plot.scatter(x='daily average.amazon revenue', y='s
tatistics.average rating', s = 10, ax = ax1)

data_publishers_tidy.plot.scatter(x='daily average.author revenue', y='s
tatistics.average rating', s = 10, ax = ax2)

data_publishers_tidy.plot.scatter(x='daily average.gross sales', y='stat
istics.average rating', s = 10, ax = ax3)

data_publishers_tidy.plot.scatter(x='daily average.publisher revenue', y
='statistics.average rating', s = 10, ax = ax4)

data_publishers_tidy.plot.scatter(x='daily average.units sold', y='stati
stics.average rating', s = 10, ax = ax5)

data_publishers_tidy.plot.scatter(x='statistics.sale price', y='statisti
cs.average rating', s = 10, ax = ax6)

data_publishers_tidy.plot.scatter(x='statistics.sales rank', y='statisti
cs.average rating', s = 10, ax = ax7)

data_publishers_tidy.plot.scatter(x='statistics.total reviews', y='stati
stics.average rating', s = 10, ax = ax8)

data_publishers_tidy.plot.scatter(x='genre_nonfiction', y='statistics.av
erage rating', s = 10, ax = ax9)

data_publishers_tidy.plot.scatter(x='publisher.type_big five', y='statis
tics.average rating', s = 10, ax = ax10)

data_publishers_tidy.plot.scatter(x='publisher.type_indie', y='statistic
s.average rating', s = 10, ax = ax11)

data_publishers_tidy.plot.scatter(x='publisher.type_single author', y='s
tatistics.average rating', s = 10, ax = ax12)

data_publishers_tidy.plot.scatter(x='publisher.type_small/medium', y='st
atistics.average rating', s = 10, ax = ax13)

fig1.delaxes(ax= ax14)
fig1.delaxes(ax= ax15)

plt.tight_layout()
```


statistics.average rating
daily average.amazon revenue
daily average.author revenue
daily average.gross sales
daily average.publisher revenue
daily average.units sold
statistics.sale price
statistics.sales rank
statistics.total reviews
genre_nonfiction
publisher.type_big five
publisher.type_indie
publisher.type_single author
publisher.type_small/medium

In [22]:
```
# perform feature selection using LASSO model(LassoCV) to predict 'stati
stics.average rating'

X = data_publishers_tidy.iloc[:,[0,1,2,3,4,6,7,8,9,10,11,12,13]]
y = data_publishers_tidy.iloc[:,[5]]
lasso_model = linear_model.LassoCV(cv=5)
y = y.values.ravel()
lasso_model.fit(X, y)
print(lasso_model.coef_)
coef = pd.Series(lasso_model.coef_, index = X.columns)
print()
print("The coefficient values of the variables using Lasso model:")
print(coef)
important_features = coef
matplotlib.rcParams['figure.figsize'] = (8.0, 10.0)
important_features.plot(kind = "barh")
plt.title("Feature importance using Lasso Model")
```

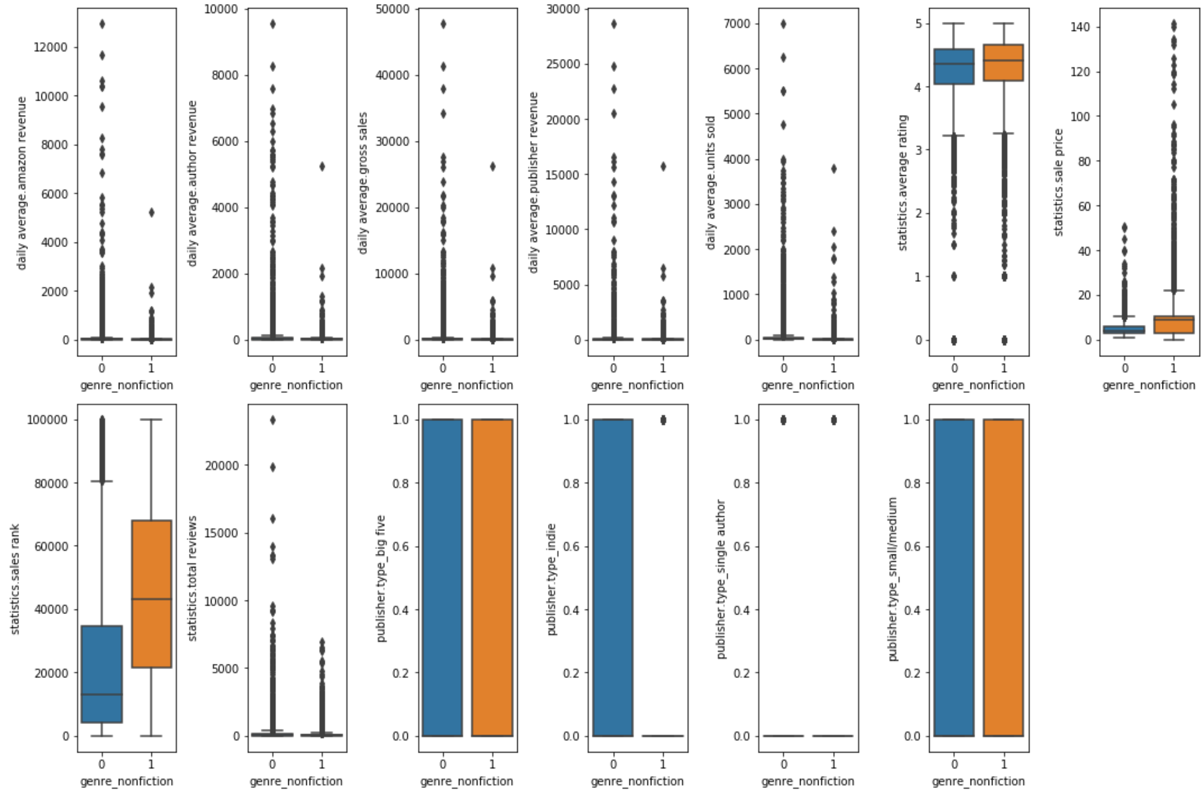
```
[-0.00000000e+00  0.00000000e+00 -1.27569833e-05 -0.00000000e+00
  0.00000000e+00  0.00000000e+00 -1.43437806e-06  4.05001288e-05
  0.00000000e+00 -0.00000000e+00  0.00000000e+00  0.00000000e+00
  0.00000000e+00]

The coefficient values of the variables using Lasso model:
daily average.amazon revenue      -0.000000
daily average.author revenue       0.000000
daily average.gross sales         -0.000013
daily average.publisher revenue   -0.000000
daily average.units sold           0.000000
statistics.sale price              0.000000
statistics.sales rank             -0.000001
statistics.total reviews           0.000041
genre_nonfiction                   0.000000
publisher.type_big five           -0.000000
publisher.type_indie               0.000000
publisher.type_single author       0.000000
publisher.type_small/medium        0.000000
dtype: float64
```

Out[22]:
```
Text(0.5, 1.0, 'Feature importance using Lasso Model')
```



In [23]:

```
# Descriptive Statistics with repect to 'genre' to determine the importa
nt variables for classifying the dataset into
# fiction and nonfiction

pd.set_option('display.max_column',None)
data_publishers_tidy.groupby(data_publishers_tidy['genre_nonfiction']).d
escribe()

fig2, axes = plt.subplots(2,7,figsize = (15,10))

sns.boxplot(y = 'daily average.amazon revenue', x = 'genre_nonfiction' ,
data = data_publishers_tidy, ax = axes[0,0])

sns.boxplot(y = 'daily average.author revenue', x = 'genre_nonfiction' ,
data = data_publishers_tidy, ax = axes[0,1])

sns.boxplot(y = 'daily average.gross sales', x = 'genre_nonfiction' ,dat
a = data_publishers_tidy, ax = axes[0,2])

sns.boxplot(y = 'daily average.publisher revenue', x = 'genre_nonfictio
n' ,data = data_publishers_tidy, ax = axes[0,3])

sns.boxplot(y = 'daily average.units sold', x = 'genre_nonfiction' ,data
= data_publishers_tidy, ax = axes[0,4])

sns.boxplot(y = 'statistics.average rating', x = 'genre_nonfiction' ,dat
a = data_publishers_tidy, ax = axes[0,5])

sns.boxplot(y = 'statistics.sale price', x = 'genre_nonfiction' ,data =
data_publishers_tidy, ax = axes[0,6])

sns.boxplot(y = 'statistics.sales rank', x = 'genre_nonfiction' ,data =
data_publishers_tidy, ax = axes[1,0])

sns.boxplot(y = 'statistics.total reviews', x = 'genre_nonfiction' ,data
= data_publishers_tidy, ax = axes[1,1])

sns.boxplot(y = 'publisher.type_big five', x = 'genre_nonfiction' ,data
= data_publishers_tidy, ax = axes[1,2])

sns.boxplot(y = 'publisher.type_indie', x = 'genre_nonfiction' ,data = d
ata_publishers_tidy, ax = axes[1,3])

sns.boxplot(y = 'publisher.type_single author', x = 'genre_nonfiction' ,
data = data_publishers_tidy, ax = axes[1,4])

sns.boxplot(y = 'publisher.type_small/medium', x = 'genre_nonfiction' ,d
ata = data_publishers_tidy, ax = axes[1,5])

fig2.delaxes(ax = axes[1,6])

plt.tight_layout()
```



Regression

In [24]:
```
data_publishers_tidy.head(10)
```

Out[24]:

	daily average.amazon revenue	daily average.author revenue	daily average.gross sales	daily average.publisher revenue	daily average.units sold	statistics.ave ra
0	6832.000	6832.000	34160.00	20496.000	7000	
1	2487.500	2487.500	12437.50	7462.500	6250	
2	9559.000	9559.000	47795.00	28677.000	5500	
3	8250.000	8250.000	41250.00	24750.000	5500	
4	7590.500	7590.500	37952.50	22771.500	4750	
5	12974.000	6986.000	19960.00	0.000	4000	
6	5498.334	5498.334	27491.67	16495.002	3933	
7	5236.400	5236.400	26182.00	15709.200	3800	
8	5218.734	5218.734	26093.67	15656.202	3733	
9	4758.468	4758.468	23792.34	14275.404	3666	

In [25]:
```
#splits into training and testing
x_train, x_test, y_train, y_test = train_test_split(data_publishers_tidy
[[ 'daily average.amazon revenue','daily average.author revenue',
                                                                      'da
ily average.gross sales','daily average.publisher revenue',
                                                                      'da
ily average.units sold',
                                                                      'st
atistics.sale price','statistics.sales rank','statistics.total reviews',

'genre_nonfiction','publisher.type_big five','publisher.type_indie',

'publisher.type_single author','publisher.type_small/medium'
                                                            ]], data_publis
hers_tidy['statistics.average rating'],test_size = 0.2, random_state = 0
)
#split into validation set
x_train,x_val,y_train,y_val = train_test_split(x_train, y_train, test_si
ze = 0.2, random_state = 1)
```

In [26]:
```
#Standardize the training set and the validation set
scaler = StandardScaler()
scaler.fit(x_train)
x_train_scaled = scaler.transform(x_train)
x_test_scaled = scaler.transform(x_test)
x_val_scaled = scaler.transform(x_val)
```

In [27]:
```
#linear regression

LR_model = linear_model.LinearRegression().fit(X=x_train_scaled[:,[6,7,8
,9,11]], y=y_train)

print()
print("Coefficients:")
print(LR_model.coef_)


print()
print("Intercept:")
print(LR_model.intercept_)
```

```
Coefficients:
[-0.06866589  0.04197282  0.07818464 -0.05498295  0.01133909]

Intercept:
4.154230087333377
```

In [28]:
```
#Linear regression - validation set

#predicting based on amazon revenue, author revenue, gross sales
LR_predicted = LR_model.predict(x_val_scaled[:,[6,7,8,9,11]])

R_squared = LR_model.score(X=x_val_scaled[:,[6,7,8,9,11]],y=y_val)
print('R sqaured')
print(R_squared)
print()

Adjusted_R_squared = 1-(((1-R_squared)*(len(x_val_scaled)-1))/(len(x_val
_scaled)-3))
print('Adjusted R squared')
print( Adjusted_R_squared)
print()

RootMeanSquare = sqrt(mean_squared_error(y_val, LR_predicted))
print('Root Mean Square')
print(RootMeanSquare)
```

```
R sqaured
0.010244985567628206

Adjusted R squared
0.009724746401040818

Root Mean Square
0.9342690384808173
```

In [29]:

```
#linear regression with different set of variables

LR_model = linear_model.LinearRegression().fit(X=x_train_scaled[:,[6,7,8
,9,11,12]], y=y_train)

print()
print("Coefficients:")
print(LR_model.coef_)

print()
print("Intercept:")
print(LR_model.intercept_)
print()

LR_predicted = LR_model.predict(x_val_scaled[:,[6,7,8,9,11,12]])

LR_R_squared = LR_model.score(X=x_val_scaled[:,[6,7,8,9,11,12]],y=y_val)
print('R sqaured')
print(LR_R_squared)
print()

LR_Adjusted_R_squared = 1-(((1-LR_R_squared)*(len(x_val_scaled)-1))/(len
(x_val_scaled)-5))
print('Adjusted R squared')
print( LR_Adjusted_R_squared)
print()

LR_RootMeanSquareError = sqrt(mean_squared_error(y_val, LR_predicted))
print('Root Mean Square Error')
print(LR_RootMeanSquareError)
```

```
Coefficients:
[-0.0708915   0.04145797  0.077324   -0.04737677  0.01754278  0.0145756
8]

Intercept:
4.154230087333377

R sqaured
0.010985032536789173

Adjusted R squared
0.00994478539772714

Root Mean Square Error
0.9339196933144313
```

In [30]:
```
#Ridge regression with selected features

Ridge_model = linear_model.Ridge(alpha = 1).fit(X=x_train_scaled[:,[6,7,
8,9,11,12]], y=y_train)

print()
print("Coefficients:")
print(Ridge_model.coef_)

print()
print("Intercept:")
print(Ridge_model.intercept_)
print()

Ridge_predicted = Ridge_model.predict(x_val_scaled[:,[6,7,8,9,11,12]])

Ridge_R_squared = Ridge_model.score(X=x_val_scaled[:,[6,7,8,9,11,12]],y=
y_val)
print('R sqaured')
print(Ridge_R_squared)
print()

Ridge_Adjusted_R_squared = 1-(((1-Ridge_R_squared)*(len(x_val_scaled)-1
))/(len(x_val_scaled)-5))
print('Adjusted R squared')
print( Ridge_Adjusted_R_squared)
print()

Ridge_RootMeanSquareError = sqrt(mean_squared_error(y_val, Ridge_predict
ed))
print('Root Mean Square Error')
print(Ridge_RootMeanSquareError)
```

```
Coefficients:
[-0.07088359  0.04145525  0.07731571 -0.04737235  0.01754259  0.0145754
5]

Intercept:
4.154230087333377

R sqaured
0.010985048833731414

Adjusted R squared
0.009944801711810558

Root Mean Square Error
0.9339196856198888
```

In [31]:
```
# Decision Tree regression with selected features

DT_model = tree.DecisionTreeRegressor().fit(X = x_train_scaled[:,[6,7,8,
9,11,12]], y = y_train)

DT_predicted = DT_model.predict(x_val_scaled[:,[6,7,8,9,11,12]])

DT_R_square = DT_model.score(X = x_val_scaled[:,[6,7,8,9,11,12]],y = y_v
al)
print('R squared')
print(DT_R_square)
print()

DT_Adjusted_R_squared = 1-(((1-DT_R_square)*(len(x_val_scaled)-1))/(len(
x_val_scaled)-5))
print('Adjusted R squared')
print( DT_Adjusted_R_squared)
print()

DT_RootMeanSquareError = np.sqrt(mean_squared_error(y_val, DT_predicted
))
print('Root Mean Square Error')
print(DT_RootMeanSquareError)
```

```
R squared
0.5427544763643035

Adjusted R squared
0.5422735449694724

Root Mean Square Error
0.6350133162105389
```

In [32]:

```
# Gradient Boost Regreesion with selected features

y_train =y_train.ravel()
GB_model = GradientBoostingRegressor(n_estimators=10, learning_rate=0.1,
          max_depth=1, random_state=0).fit(X = x_train_scaled[:,[6,7,8,9
,11,12]], y = y_train)

GB_predicted = GB_model.predict(x_val_scaled[:,[6,7,8,9,11,12]])

GB_R_square = GB_model.score(X = x_val_scaled[:,[6,7,8,9,11,12]],y = y_v
al)
print('R square')
print(GB_R_square)
print()

GB_Adjusted_R_squared = 1-(((1-GB_R_square)*(len(x_val_scaled)-1))/(len(
x_val_scaled)-5))
print('Adjusted R squared')
print( GB_Adjusted_R_squared)
print()

GB_RootMeanSquareError = np.sqrt(mean_squared_error(y_val, GB_predicted
))
print('Root Mean Square Error')
print(GB_RootMeanSquareError)

print(GB_model.feature_importances_ )
```

```
R square
0.6721424769608965

Adjusted R squared
0.6717976360215969

Root Mean Square Error
0.5377131754512429
[0. 1. 0. 0. 0. 0.]
```

In [33]:
```
# Random Forest Regression using selected variables

RF_model = RandomForestRegressor(n_estimators=10, random_state=42).fit(X
= x_train_scaled[:,[6,7,8,9,11,12]], y = y_train)

RF_predicted = RF_model.predict(x_val_scaled[:,[6,7,8,9,11,12]])

RF_R_square = RF_model.score(X = x_val_scaled[:,[6,7,8,9,11,12]],y = y_v
al)
print('R square')
print(RF_R_square)
print()

RF_Adjusted_R_squared = 1-(((1-RF_R_square)*(len(x_val)-1))/(len(x_val)-
5))
print('Adjusted R square')
print( RF_Adjusted_R_squared)
print()

RF_RootMeanSquareError = np.sqrt(mean_squared_error(y_val, RF_predicted
))
print('Root Mean Square Error')
print(RF_RootMeanSquareError)
print()

print(RF_model.feature_importances_ )
```

```
R square
0.7117231663837745

Adjusted R square
0.7114199564614856

Root Mean Square Error
0.5042117624864959

[0.13536336 0.85164254 0.00519983 0.00108384 0.00282789 0.00388253]
```

In [34]:
```
# Prediction on test set using the best model

#Standardize the training set and the validation set

output = pd.DataFrame(x_test)

RF_predicted_test = RF_model.predict(x_test_scaled[:,[6,7,8,9,11,12]])

Test_RF_R_square = RF_model.score(X = x_test_scaled[:,[6,7,8,9,11,12]],y
= y_test)
print('R square')
print(Test_RF_R_square)
print()

Test_RF_Adjusted_R_squared = 1-(((1-Test_RF_R_square)*(len(x_test)-1))/(
len(x_test)-5))
print('Adjusted R square')
print( Test_RF_Adjusted_R_squared)
print()

Test_RF_RootMeanSquareError = np.sqrt(mean_squared_error(y_test, RF_pred
icted_test))
print('Root Mean Square Error')
print(Test_RF_RootMeanSquareError)
print()

output['Average Rating'] = y_test
output['Predicted Rating'] = RF_predicted_test

output.head(10)
```

```
R square
0.7213627736193311

Adjusted R square
0.7211283784762138

Root Mean Square Error
0.495206410576065
```

Out[34]:

	daily average.amazon revenue	daily average.author revenue	daily average.gross sales	daily average.publisher revenue	daily average.units sold	statistics
18476	2.392	2.392	11.96	7.176	4	
2976	29.900	29.900	149.50	89.700	50	
20381	9.592	9.592	47.96	28.776	4	
17496	10.790	10.790	53.95	32.370	5	
7677	38.974	38.974	194.87	116.922	13	
18079	9.592	9.592	47.96	28.776	4	
11605	5.980	5.980	29.90	17.940	10	
16684	10.782	25.158	35.94	0.000	6	
25568	3.600	3.600	18.00	10.800	1	
3225	51.471	120.099	171.57	0.000	43	

In [35]:

```
# get the max and min of predicted rating
print("Max: ",output['Predicted Rating'].max())
print("Min: ",output['Predicted Rating'].min())
```

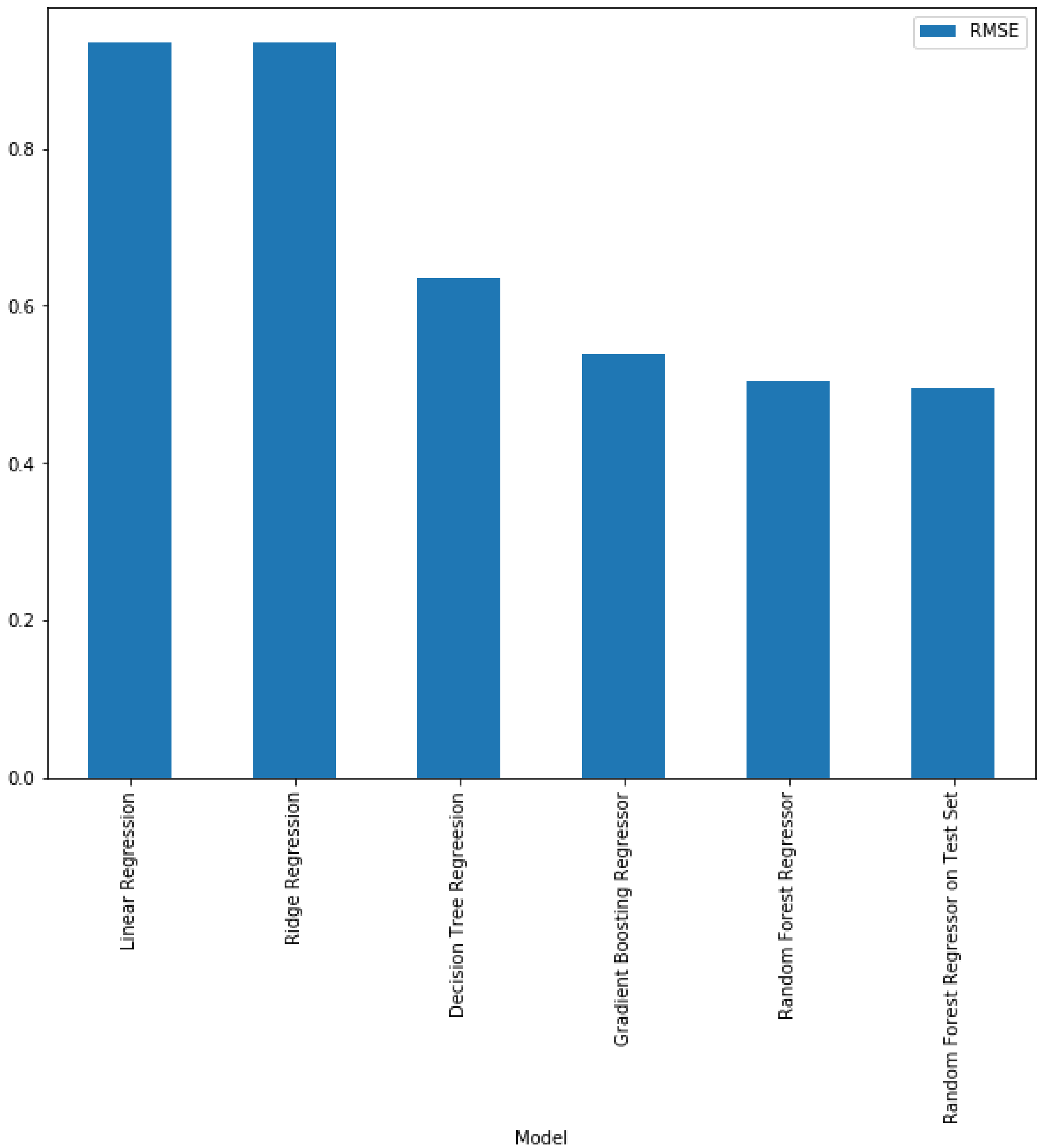
```
Max:  5.0
Min:  0.0
```

In [36]:

```
# create a data frame with RMSE and Adjusted R Square
AdjR2_RMSE = [['Linear Regression', LR_RootMeanSquareError, LR_Adjusted_
R_squared],
              ['Ridge Regression', Ridge_RootMeanSquareError, Ridge_Adju
sted_R_squared],
              ['Decision Tree Regreesion', DT_RootMeanSquareError, DT_Ad
justed_R_squared],
              ['Gradient Boosting Regressor', GB_RootMeanSquareError, GB
_Adjusted_R_squared],
              ['Random Forest Regressor', RF_RootMeanSquareError, RF_Adj
usted_R_squared],
              ['Random Forest Regressor on Test Set', Test_RF_RootMeanSq
uareError, Test_RF_Adjusted_R_squared]]
ModelEvaluation = pd.DataFrame(AdjR2_RMSE, columns = ['Model', 'RMSE',
'AdjR2'])
```

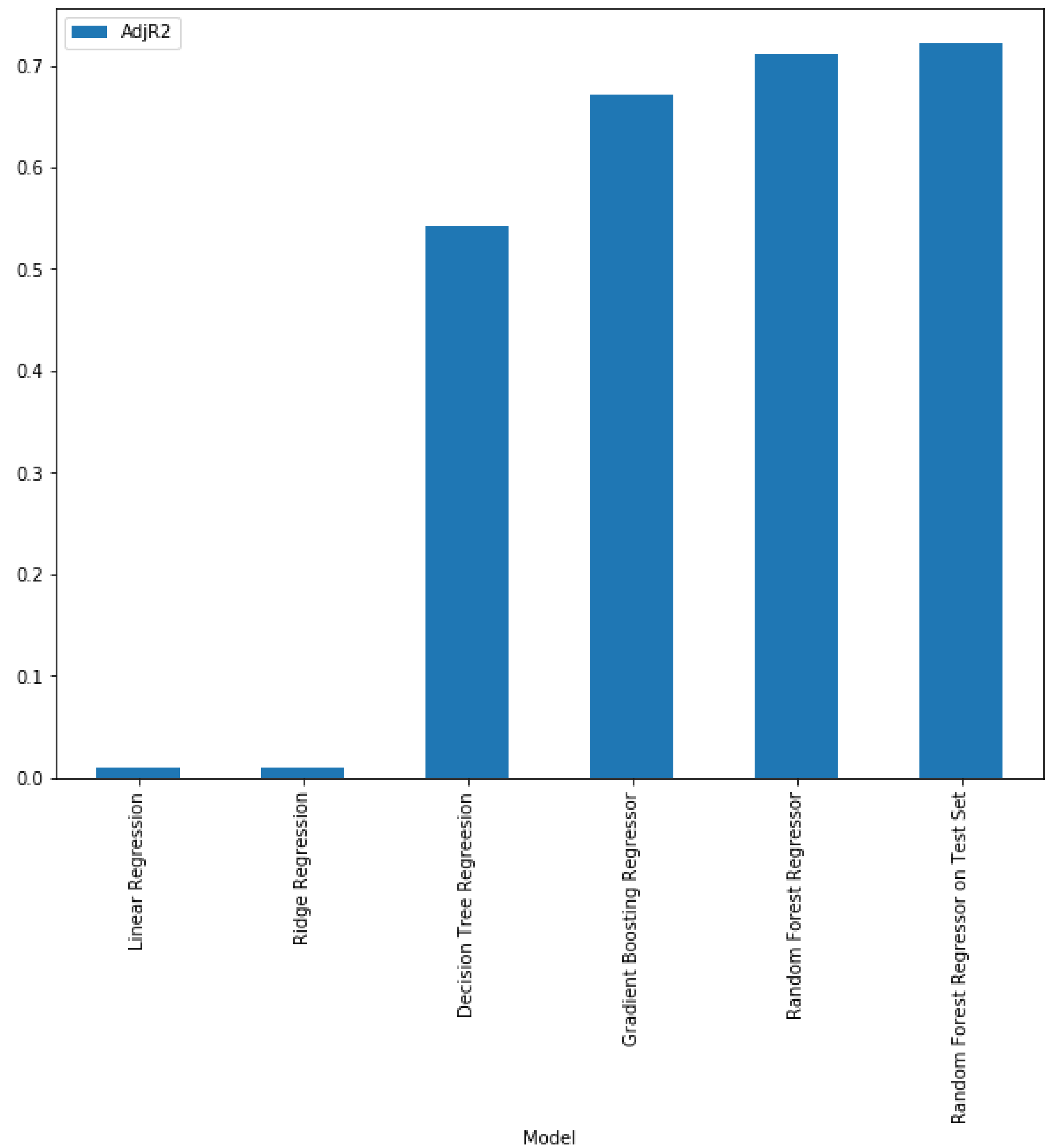
In [37]:
```
# plot showing the performance of the models with respect to RMSE
plt.rcParams['figure.figsize'] = (10, 8)
ModelEvaluation.plot(kind='bar',x='Model',y='RMSE')
```

Out[37]: <matplotlib.axes._subplots.AxesSubplot at 0x12cd23518>



In [38]:
```
# plot showing the performance of the models with respect to Adjuested R Square
plt.rcParams['figure.figsize'] = (10, 8)
ModelEvaluation.plot(kind='bar',x='Model',y='AdjR2')
```

Out[38]: <matplotlib.axes._subplots.AxesSubplot at 0x12fcbd048>



Classification

In [39]:

```
#splits into training and testing
x_clf_train, x_clf_test, y_clf_train, y_clf_test = train_test_split(data
_publishers_tidy[[ 'daily average.amazon revenue','daily average.author
 revenue',
                                                                       'da
ily average.gross sales','daily average.publisher revenue',
                                                                       'da
ily average.units sold', 'statistics.average rating',
                                                                       'st
atistics.sale price','statistics.sales rank','statistics.total reviews',

'publisher.type_big five','publisher.type_indie',

'publisher.type_single author','publisher.type_small/medium'
                                                             ]], data_publis
hers_tidy['genre_nonfiction'],test_size = 0.2, random_state = 0)
#split into validation set
x_clf_train, x_clf_val, y_clf_train, y_clf_val = train_test_split(x_clf_
train, y_clf_train, test_size = 0.2, random_state = 1)
```

In [40]:

```
#Standardize the training set and the validation set
scaler = StandardScaler()
scaler.fit(x_clf_train)
x_clf_train_scaled = scaler.transform(x_clf_train)
x_clf_test_scaled = scaler.transform(x_clf_test)
x_clf_val_scaled = scaler.transform(x_clf_val)
```

In [41]:

```
model = DecisionTreeClassifier(criterion = "entropy", random_state = 0)
model.fit(x_clf_train_scaled, y_clf_train)
y_pred = model.predict(x_clf_val_scaled)
conf_matrix = metrics.confusion_matrix(y_clf_val, y_pred)
print(conf_matrix)

# Compute evaluation metrics
print("Accuracy: ", metrics.accuracy_score(y_clf_val, y_pred)) # accurac
y
print("Error: ", 1 - metrics.accuracy_score(y_clf_val, y_pred)) # error
print("Precision: ", metrics.precision_score(y_clf_val, y_pred, average
= None)) # precision
print("Recall: ", metrics.recall_score(y_clf_val, y_pred, average = None
)) # recall
print("F1 score: ", metrics.f1_score(y_clf_val, y_pred, average = None))
# F1 score
```

```
[[1067  449]
 [ 546 1746]]
Accuracy:  0.7387079831932774
Error:  0.26129201680672265
Precision:  [0.66150031 0.79544419]
Recall:  [0.70382586 0.7617801 ]
F1 score:  [0.68200703 0.77824827]
```

In [42]:
```
model = DecisionTreeClassifier(criterion = "entropy", random_state = 0)
model.fit(x_clf_train_scaled[:,[5,6,7,9,10,12]], y_clf_train)
y_pred = model.predict(x_clf_val_scaled[:,[5,6,7,9,10,12]])
conf_matrix = metrics.confusion_matrix(y_clf_val, y_pred)
print(conf_matrix)

# Compute evaluation metrics
print("Accuracy: ", metrics.accuracy_score(y_clf_val, y_pred)) # accurac
y
print("Error: ", 1 - metrics.accuracy_score(y_clf_val, y_pred)) # error
print("Precision: ", metrics.precision_score(y_clf_val, y_pred, average
= None)) # precision
print("Recall: ", metrics.recall_score(y_clf_val, y_pred, average = None
)) # recall
print("F1 score: ", metrics.f1_score(y_clf_val, y_pred, average = None))
# F1 score
```

```
[[1055  461]
 [ 551 1741]]
Accuracy:  0.7342436974789915
Error:  0.26575630252100846
Precision:  [0.65691158 0.79064487]
Recall:  [0.69591029 0.7595986 ]
F1 score:  [0.67584881 0.77481086]
```

In [43]:
```
bag_clf = BaggingClassifier(base_estimator = DecisionTreeClassifier(crit
erion = "entropy", random_state = 0), n_estimators = 10, random_state =
0)
bag_clf.fit(x_clf_train_scaled, y_clf_train)
y_pred = bag_clf.predict(x_clf_val_scaled)
conf_matrix = metrics.confusion_matrix(y_clf_val, y_pred)
print(conf_matrix)

# Compute evaluation metrics
print("Accuracy: ", metrics.accuracy_score(y_clf_val, y_pred)) # accurac
y
print("Error: ", 1 - metrics.accuracy_score(y_clf_val, y_pred)) # error
print("Precision: ", metrics.precision_score(y_clf_val, y_pred, average
= None)) # precision
print("Recall: ", metrics.recall_score(y_clf_val, y_pred, average = None
)) # recall
print("F1 score: ", metrics.f1_score(y_clf_val, y_pred, average = None))
# F1 score
```

```
[[1170  346]
 [ 481 1811]]
Accuracy:  0.7828256302521008
Error:  0.21717436974789917
Precision:  [0.70866142 0.83959203]
Recall:  [0.77176781 0.79013962]
F1 score:  [0.73886959 0.81411553]
```

In [44]:
```
ada_clf = AdaBoostClassifier(base_estimator = DecisionTreeClassifier(cri
terion = "entropy", random_state = 0), n_estimators = 10, random_state =
0)
ada_clf.fit(x_clf_train_scaled, y_clf_train)
y_pred = ada_clf.predict(x_clf_val_scaled)
conf_matrix = metrics.confusion_matrix(y_clf_val, y_pred)
print(conf_matrix)

# Compute evaluation metrics
print("Accuracy: ", metrics.accuracy_score(y_clf_val, y_pred)) # accurac
y
print("Error: ", 1 - metrics.accuracy_score(y_clf_val, y_pred)) # error
print("Precision: ", metrics.precision_score(y_clf_val, y_pred, average
= None)) # precision
print("Recall: ", metrics.recall_score(y_clf_val, y_pred, average = None
)) # recall
print("F1 score: ", metrics.f1_score(y_clf_val, y_pred, average = None))
# F1 score
```

```
[[1066  450]
 [ 548 1744]]
Accuracy:  0.7379201680672269
Error:  0.26207983193277307
Precision:  [0.66047088 0.79489517]
Recall:  [0.70316623 0.7609075 ]
F1 score:  [0.68115016 0.77753009]
```

In [45]:
```
RF_clf = RandomForestClassifier(n_estimators = 10, criterion = "entropy"
, random_state = 0)
RF_clf.fit(x_clf_train_scaled, y_clf_train)
y_pred = RF_clf.predict(x_clf_val_scaled)
conf_matrix = metrics.confusion_matrix(y_clf_val, y_pred)
print(conf_matrix)

# Compute evaluation metrics
print("Accuracy: ", metrics.accuracy_score(y_clf_val, y_pred)) # accurac
y
print("Error: ", 1 - metrics.accuracy_score(y_clf_val, y_pred)) # error
print("Precision: ", metrics.precision_score(y_clf_val, y_pred, average
= None)) # precision
print("Recall: ", metrics.recall_score(y_clf_val, y_pred, average = None
)) # recall
print("F1 score: ", metrics.f1_score(y_clf_val, y_pred, average = None))
# F1 score
```

```
[[1170  346]
 [ 509 1783]]
Accuracy:  0.7754726890756303
Error:  0.22452731092436973
Precision:  [0.69684336 0.83748239]
Recall:  [0.77176781 0.77792321]
F1 score:  [0.73239437 0.80660484]
```

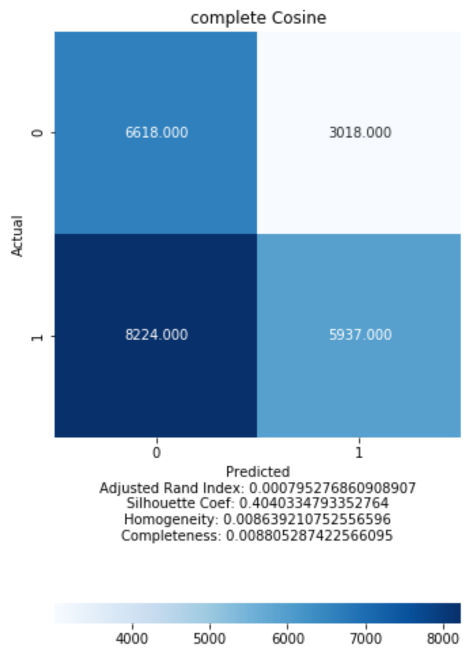
Clustering Analysis

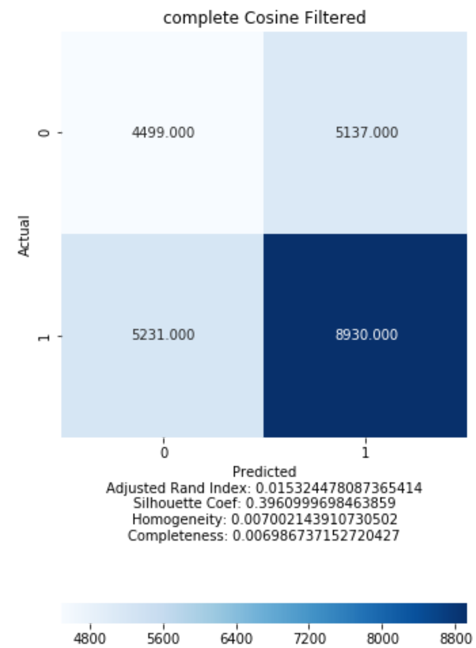
In [46]:
```
clusterFeatures = data_publishers_tidy.iloc[:,[0,1,2,3,4,5,6,7,8,10,11,1
2,13]]
clusterClass = data_publishers_tidy['genre_nonfiction']#.reshape(-1,1)
```

In [47]:
```
scalerClusters = StandardScaler()
scalerClusters.fit(clusterFeatures)
clusterFeatures_scaled = scalerClusters.transform(clusterFeatures)

##Function to plot contingency matrixes
def plotClusters(title_arr,cont_matrix, rand_i,  sil_h, hom, compl):
    fig, ax = plt.subplots(1,len(cont_matrix) ,figsize=(15,15))
    plt.subplots_adjust(
                    wspace = 0.8,  # the amount of width reserved for sp
ace between subplots,
                                  # expressed as a fraction of the avera
ge axis width
                    hspace = 0.2)  # the amount of height reserved for s
pace between subplots,
                                  # expressed as a fraction of the avera
ge axis height)
    index = 0
    for tmp in ax :
        tmp.title.set_text(title_arr[index])
        sns.heatmap(cont_matrix[index], annot = True, fmt = ".3f", squar
e = True, cmap = plt.cm.Blues, ax=tmp, cbar_kws = dict(orientation ='hor
izontal',use_gridspec=False))
        tmp.set_xlabel( 'Predicted\n' + 'Adjusted Rand Index: ' + str(ra
nd_i[index]) + '\nSilhouette Coef: ' + str(sil_h[index])
                       + '\nHomogeneity: ' + str(hom[index]) + '\nComple
teness: ' + str(compl[index]) )
        tmp.set_ylabel('Actual')
        index = index + 1
```

Hierarchical Complete

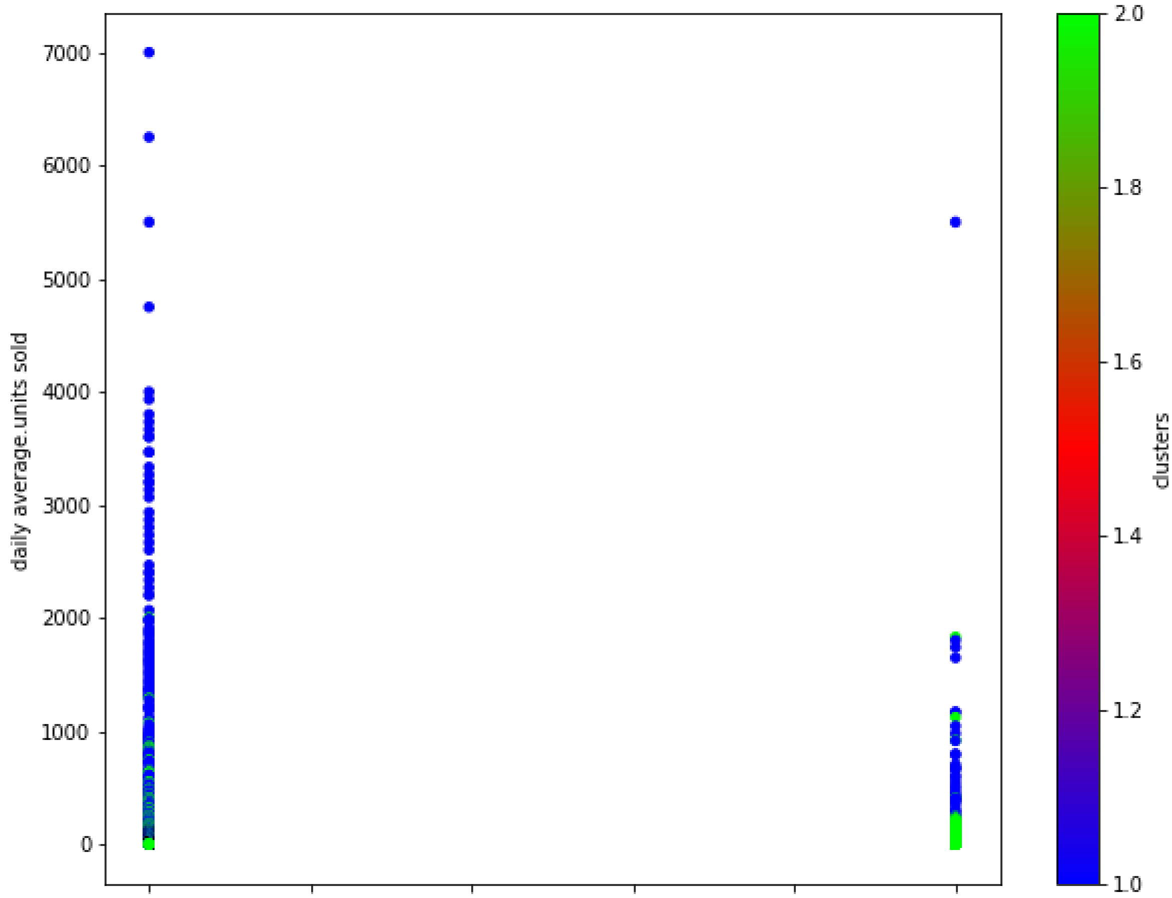
In [48]:
```
titles = []
cont_matrix_arr = []
sil_h_arr = []
adj_rand_i_arr = []
homog_arr = []
completeness_arr = []

#Hierarchical Complete - Cosine (All Variables)
clustering = linkage(clusterFeatures_scaled, method='complete', metric =
'cosine')
clusters = fcluster(clustering, 2, criterion = 'maxclust')
cont_matrix =  contingency_matrix(clusterClass, clusters)
adjusted_rand_index =   adjusted_rand_score(clusterClass, clusters)
silhouette_coefficient =  silhouette_score(clusterFeatures_scaled, clust
ers, metric='cosine')
#print([adjusted_rand_index, silhouette_coefficient])
titles.append("complete Cosine")
cont_matrix_arr.append(cont_matrix)
sil_h_arr.append(silhouette_coefficient)
adj_rand_i_arr.append(adjusted_rand_index)
homog_arr.append( homogeneity_score(clusterClass, clusters) )
completeness_arr.append( completeness_score(clusterClass, clusters))

vars = [
       'daily average.gross sales', 'daily average.publisher revenue',
       'daily average.units sold', 'statistics.average rating',
       'statistics.sale price', 'statistics.total reviews','publisher.ty
pe_single author',
       'publisher.type_small/medium']

scalerClustersFiltered = StandardScaler()
scalerClustersFiltered.fit(clusterFeatures[vars])
clusterFeatures_scaled_filtered = scalerClustersFiltered.transform(clust
erFeatures[vars])

#Hierarchical Complete - Cosine (Filtered Variables)
clustering = linkage(clusterFeatures_scaled_filtered, method='complete',
metric = 'cosine')
clusters = fcluster(clustering, 2, criterion = 'maxclust')
cont_matrix =  contingency_matrix(clusterClass, clusters)
adjusted_rand_index =   adjusted_rand_score(clusterClass, clusters)
silhouette_coefficient =  silhouette_score(clusterFeatures_scaled_filter
ed, clusters, metric='cosine')
#print([adjusted_rand_index, silhouette_coefficient])
titles.append("complete Cosine Filtered")
cont_matrix_arr.append(cont_matrix)
sil_h_arr.append(silhouette_coefficient)
adj_rand_i_arr.append(adjusted_rand_index)
homog_arr.append( homogeneity_score(clusterClass, clusters) )
completeness_arr.append( completeness_score(clusterClass, clusters))

plotClusters(titles,cont_matrix_arr,adj_rand_i_arr, sil_h_arr,homog_arr,
completeness_arr)
```


complete Cosine
6618.000
3018.000
8224.000
5937.000
Actual
Predicted
Adjusted Rand Index: 0.000795276860908907
Silhouette Coef: 0.4040334793352764
Homogeneity: 0.008639210752556596
Completeness: 0.008805287422566095
4000
5000
6000
7000
8000

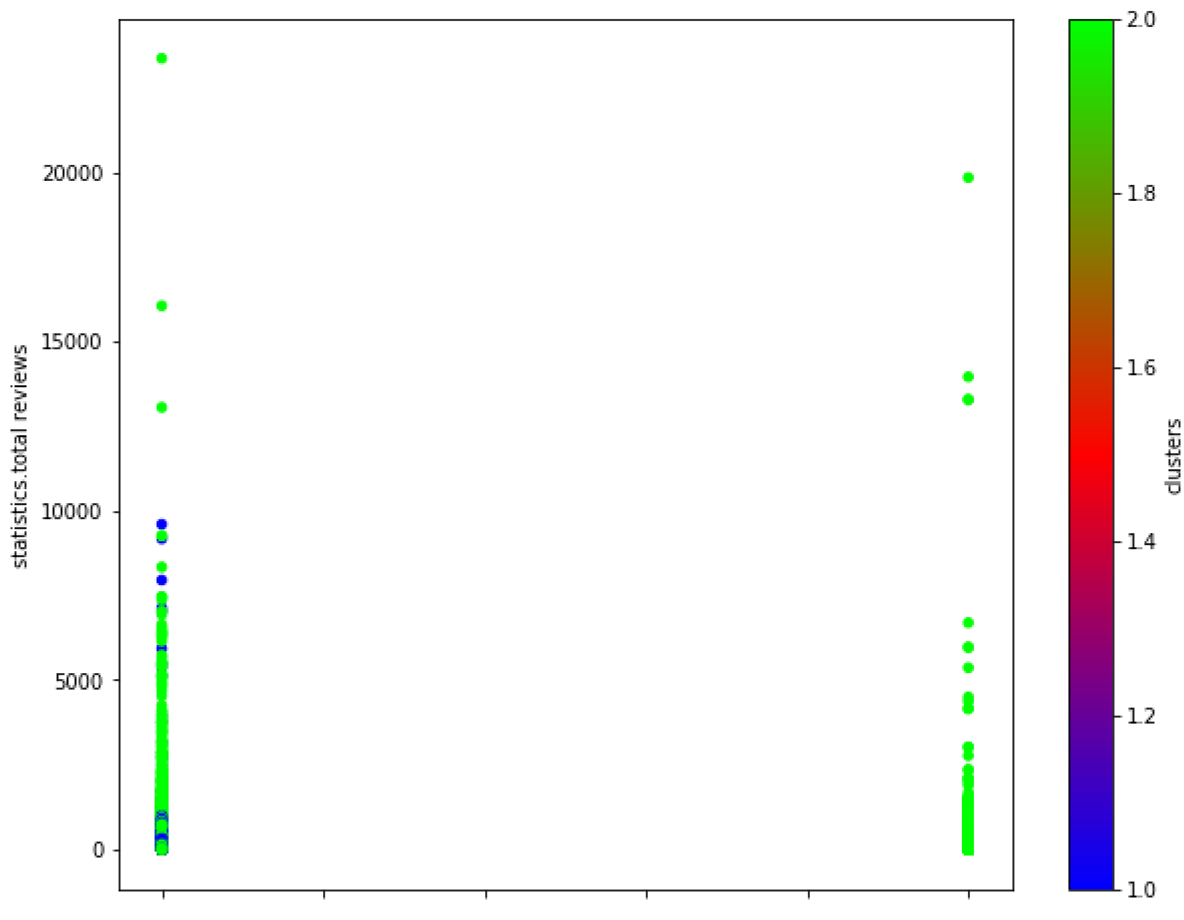

complete Cosine Filtered
4499.000
5137.000
5231.000
8930.000
Actual
Predicted
Adjusted Rand Index: 0.015324478087365414
Silhouette Coef: 0.3960999698463859
Homogeneity: 0.007002143910730502
Completeness: 0.006986737152720427
4800
5600
6400
7200
8000
8800

In [49]:

```
clusterFeatures['clusters'] = clusters
ax = clusterFeatures.plot(kind = 'scatter', x = 'publisher.type_small/me
dium', y = 'daily average.units sold', c = 'clusters', colormap = plt.cm
.brg)
ax = clusterFeatures.plot(kind = 'scatter', x = 'publisher.type_small/me
dium', y = 'statistics.total reviews', c = 'clusters', colormap = plt.cm
.brg)
```



7000
6000
5000
4000
3000
2000
1000
0
daily average.units sold
2.0
1.8
1.6
1.4
1.2
1.0
clusters

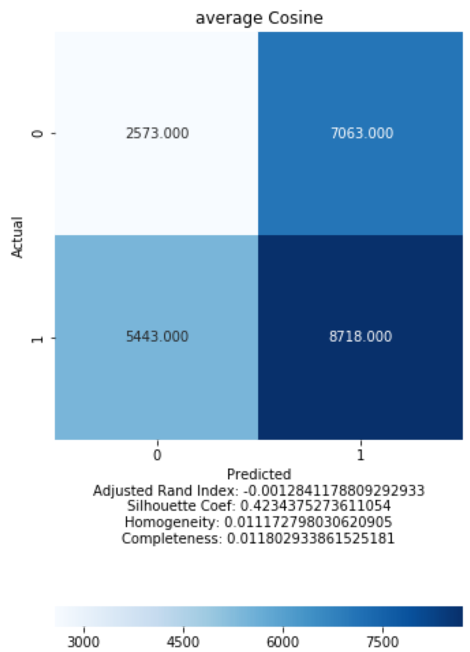


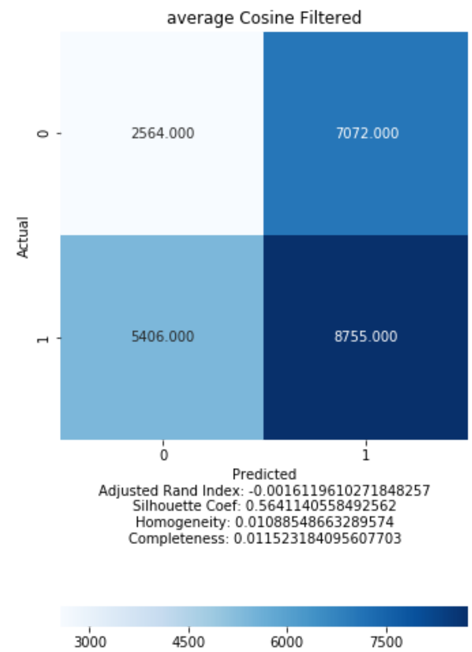
20000
15000
10000
5000
0
statistics.total reviews
2.0
1.8
1.6
1.4
1.2
1.0
clusters

Hierarchical Average - All Features

In [50]:

```
titles = []
cont_matrix_arr = []
sil_h_arr = []
adj_rand_i_arr = []
homog_arr = []
completeness_arr = []

#Hierarchical Average - Cosine (All Variables)
clustering = linkage(clusterFeatures_scaled, method='average', metric =
'cosine')
clusters = fcluster(clustering, 2, criterion = 'maxclust')
cont_matrix =  contingency_matrix(clusterClass, clusters)
adjusted_rand_index =   adjusted_rand_score(clusterClass, clusters)
silhouette_coefficient =  silhouette_score(clusterFeatures_scaled, clust
ers, metric='cosine')
#print([adjusted_rand_index, silhouette_coefficient])
titles.append("average Cosine")
cont_matrix_arr.append(cont_matrix)
sil_h_arr.append(silhouette_coefficient)
adj_rand_i_arr.append(adjusted_rand_index)
homog_arr.append( homogeneity_score(clusterClass, clusters) )
completeness_arr.append( completeness_score(clusterClass, clusters))

#Hierarchical Average - Minkowski (Filtered Variables)
clustering = linkage(clusterFeatures_scaled_filtered, method='average',
metric = 'cosine')
clusters = fcluster(clustering, 2, criterion = 'maxclust')
cont_matrix =  contingency_matrix(clusterClass, clusters)
adjusted_rand_index =   adjusted_rand_score(clusterClass, clusters)
silhouette_coefficient =  silhouette_score(clusterFeatures_scaled_filter
ed, clusters, metric='cosine')
#print([adjusted_rand_index, silhouette_coefficient])
titles.append("average Cosine Filtered")
cont_matrix_arr.append(cont_matrix)
sil_h_arr.append(silhouette_coefficient)
adj_rand_i_arr.append(adjusted_rand_index)
homog_arr.append( homogeneity_score(clusterClass, clusters) )
completeness_arr.append( completeness_score(clusterClass, clusters))


plotClusters(titles,cont_matrix_arr,adj_rand_i_arr, sil_h_arr,homog_arr,
completeness_arr)
```

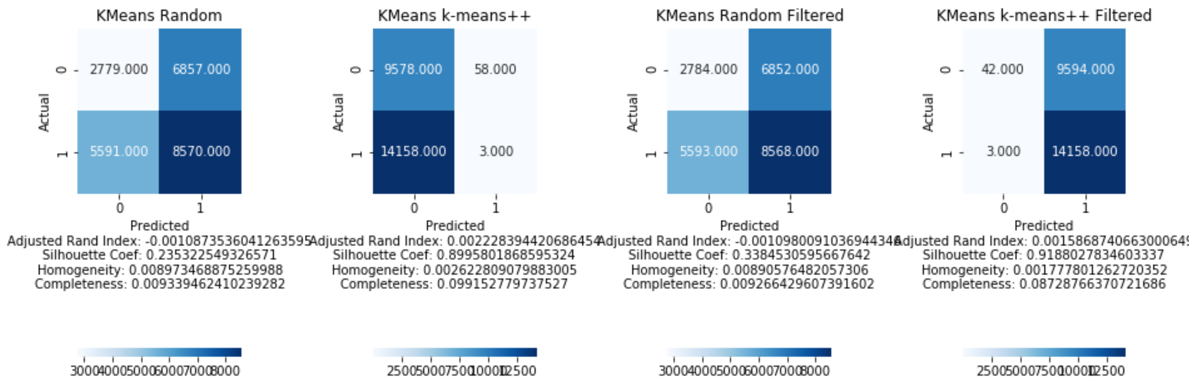




K-Means - All Features

In [51]:
```
titles = []
cont_matrix_arr = []
sil_h_arr = []
adj_rand_i_arr = []
homog_arr = []
completeness_arr = []

#KMeans
clustering = KMeans(n_clusters = 2, init ='random', n_init = 10, random_
state = 0).fit(clusterFeatures_scaled)
clusters = clustering.labels_
cont_matrix =  contingency_matrix(clusterClass, clusters)
adjusted_rand_index =   adjusted_rand_score(clusterClass, clusters)
silhouette_coefficient =  silhouette_score(clusterFeatures_scaled, clust
ers, metric='euclidean')
#print([adjusted_rand_index, silhouette_coefficient])
titles.append("KMeans Random")
cont_matrix_arr.append(cont_matrix)
sil_h_arr.append(silhouette_coefficient)
adj_rand_i_arr.append(adjusted_rand_index)
homog_arr.append( homogeneity_score(clusterClass, clusters) )
completeness_arr.append( completeness_score(clusterClass, clusters))

clustering = KMeans(n_clusters = 2, init ='k-means++', n_init = 10, rand
om_state = 0).fit(clusterFeatures_scaled)
clusters = clustering.labels_
cont_matrix =  contingency_matrix(clusterClass, clusters)
adjusted_rand_index =   adjusted_rand_score(clusterClass, clusters)
silhouette_coefficient =  silhouette_score(clusterFeatures_scaled, clust
ers, metric='euclidean')
#print([adjusted_rand_index, silhouette_coefficient])
titles.append("KMeans k-means++")
cont_matrix_arr.append(cont_matrix)
sil_h_arr.append(silhouette_coefficient)
adj_rand_i_arr.append(adjusted_rand_index)
homog_arr.append( homogeneity_score(clusterClass, clusters) )
completeness_arr.append( completeness_score(clusterClass, clusters))

#KMeans Filtered
clustering = KMeans(n_clusters = 2, init ='random', n_init = 10, random_
state = 0).fit(clusterFeatures_scaled_filtered)
clusters = clustering.labels_
cont_matrix =  contingency_matrix(clusterClass, clusters)
adjusted_rand_index =   adjusted_rand_score(clusterClass, clusters)
silhouette_coefficient =  silhouette_score(clusterFeatures_scaled_filter
ed, clusters, metric='euclidean')
#print([adjusted_rand_index, silhouette_coefficient])
titles.append("KMeans Random Filtered")
cont_matrix_arr.append(cont_matrix)
sil_h_arr.append(silhouette_coefficient)
adj_rand_i_arr.append(adjusted_rand_index)
homog_arr.append( homogeneity_score(clusterClass, clusters) )
completeness_arr.append( completeness_score(clusterClass, clusters))

#KMEANS Filtered
clustering = KMeans(n_clusters = 2, init ='k-means++', n_init = 10, rand
```

```
om_state = 0).fit(clusterFeatures_scaled_filtered)
clusters = clustering.labels_
cont_matrix =  contingency_matrix(clusterClass, clusters)
adjusted_rand_index =   adjusted_rand_score(clusterClass, clusters)
silhouette_coefficient =  silhouette_score(clusterFeatures_scaled_filter
ed, clusters, metric='euclidean')
#print([adjusted_rand_index, silhouette_coefficient])
titles.append("KMeans k-means++ Filtered")
cont_matrix_arr.append(cont_matrix)
sil_h_arr.append(silhouette_coefficient)
adj_rand_i_arr.append(adjusted_rand_index)
homog_arr.append( homogeneity_score(clusterClass, clusters) )
completeness_arr.append( completeness_score(clusterClass, clusters))


plotClusters(titles,cont_matrix_arr,adj_rand_i_arr, sil_h_arr,homog_arr,
completeness_arr)
```



True Clusters

In [52]:
```
silhouette_coefficient =  silhouette_score(clusterFeatures, clusterClass
, metric='euclidean')
print(silhouette_coefficient)
```

```
0.12241818173348551
```

In [53]:

```python
# Prediction of rating on test set using the best regresssion model

#Standardize the training set and the validation set

output = pd.DataFrame(x_test)

RF_predicted_test = RF_model.predict(x_test_scaled[:,[6,7,8,9,11,12]])

R_square = RF_model.score(X = x_test_scaled[:,[6,7,8,9,11,12]],y = y_tes
t)
print('R square')
print(R_square)
print()

Adjusted_R_square = 1-(((1-R_square)*(len(x_test)-1))/(len(x_test)-5))
print('Adjusted R square')
print( Adjusted_R_square)
print()

RootMeanSquareError = np.sqrt(mean_squared_error(y_test, RF_predicted_te
st))
print('Root Mean Square Error')
print(RootMeanSquareError)
print()

output['Average Rating'] = y_test
output['Predicted Rating'] = RF_predicted_test

output.head(10)
```

```
R square
0.7213627736193311

Adjusted R square
0.7211283784762138

Root Mean Square Error
0.495206410576065
```

Out[53]:

	daily average.amazon revenue	daily average.author revenue	daily average.gross sales	daily average.publisher revenue	daily average.units sold	statistics
18476	2.392	2.392	11.96	7.176	4	
2976	29.900	29.900	149.50	89.700	50	
20381	9.592	9.592	47.96	28.776	4	
17496	10.790	10.790	53.95	32.370	5	
7677	38.974	38.974	194.87	116.922	13	
18079	9.592	9.592	47.96	28.776	4	
11605	5.980	5.980	29.90	17.940	10	
16684	10.782	25.158	35.94	0.000	6	
25568	3.600	3.600	18.00	10.800	1	
3225	51.471	120.099	171.57	0.000	43	

In [54]:

```
print("Max: ",output['Predicted Rating'].max())
print("Min: ",output['Predicted Rating'].min())
```

```
Max:  5.0
Min:  0.0
```

In [55]:
```
# Prediction of Genre on test set using the best classification model

bag_clf = BaggingClassifier(base_estimator = DecisionTreeClassifier(crit
erion = "entropy", random_state = 0), n_estimators = 10, random_state =
0)
bag_clf.fit(x_clf_train_scaled, y_clf_train)
y_pred = bag_clf.predict(x_clf_test_scaled)
conf_matrix = metrics.confusion_matrix(y_clf_test, y_pred)

print(conf_matrix)

# Compute evaluation metrics
print("Accuracy: ", metrics.accuracy_score(y_clf_test, y_pred)) # accura
cy
print("Error: ", 1 - metrics.accuracy_score(y_clf_test, y_pred)) # error
print("Precision: ", metrics.precision_score(y_clf_test, y_pred, average
= None)) # precision
print("Recall: ", metrics.recall_score(y_clf_test, y_pred, average = Non
e)) # recall
print("F1 score: ", metrics.f1_score(y_clf_test, y_pred, average = None
)) # F1 score

output['True Genre'] = np.where(y_clf_test == 0, 'Fiction', 'Non-Fictio
n')
output['Predicted Genre'] = np.where(y_pred == 0, 'Fiction', 'Non-Fictio
n')

output.head(10)
```

```
[[1476  422]
 [ 633 2229]]
Accuracy:  0.7783613445378151
Error:  0.22163865546218486
Precision:  [0.69985775 0.84081479]
Recall:  [0.7776607 0.778826 ]
F1 score:  [0.73671076 0.80863414]
```

Out[55]:

	daily average.amazon revenue	daily average.author revenue	daily average.gross sales	daily average.publisher revenue	daily average.units sold	statistics
18476	2.392	2.392	11.96	7.176	4	
2976	29.900	29.900	149.50	89.700	50	
20381	9.592	9.592	47.96	28.776	4	
17496	10.790	10.790	53.95	32.370	5	
7677	38.974	38.974	194.87	116.922	13	
18079	9.592	9.592	47.96	28.776	4	
11605	5.980	5.980	29.90	17.940	10	
16684	10.782	25.158	35.94	0.000	6	
25568	3.600	3.600	18.00	10.800	1	
3225	51.471	120.099	171.57	0.000	43	

Output to CSV

In [56]:

```
results  = pd.DataFrame({'True Rating':output['Average Rating'] ,'Predic
ted Rating': output['Predicted Rating'] , 'True Genre': output['True Gen
re'] , 'Predicted Genre':output['Predicted Genre'] })
results = results.sort_index()
#numeric_results= results._get_numeric_data()
#numeric_results[numeric_results < 0] = 0

import os, errno
try:
    os.remove('classifier_results.csv')
except OSError:
    pass

with open('classifier_results.csv', mode = 'w',  newline = "" ) as file:
    results.to_csv('classifier_results.csv')
```

```
In [ ]:
```