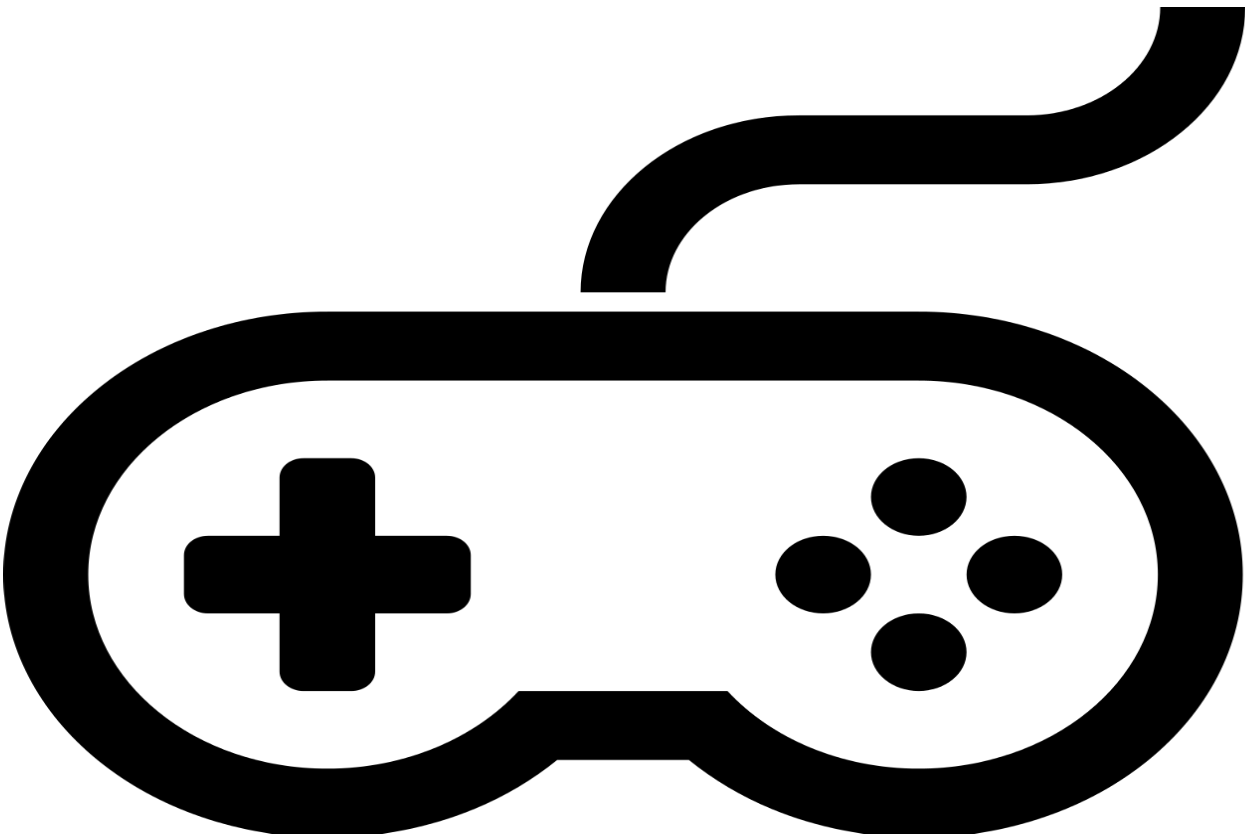
Live in Your World. Play In Ours



Video Game Sales

Final Report

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Introduction:

In this project, we propose to build a model that can predict video games sales based on features from dataset. Emphasis is placed on video game publishers like play station which will helpi them predict which games will be best sellers before they are released. The data we used identifies games based on genre, publisher, platform, etc. giving us multiple factors useful for predicting a game's success.

The main work that we have done includes: analyzing the features of data set via data-visualization, processing the data set, using four regression model to predict the model. Firstly, we read in data from the data set and explore the data, getting a brief recognition of features in this data set. After that, we modified the data set in following ways including renaming, processing the missing values and integrating significant features.

Then, we select 4 different machine learning models as candidates including linear regression, ridge regression, random forest regression and KNN. We use them to make predictions and evaluate their performance to decide which models are appropriate to be used for further modification.

Data Source

The original dataset has games ranging from 1980 to 2020 with 11,493 different game titles. There are 579 publishers with 31 platforms. Games are broken down into 12 unique categories as follows: Sports, Platform, Racing, Role-playing, Puzzle, Misc, Shooter, Simulation, Action, Fighting, Adventure,and Strategy. The dataset was taken off of Kaggle, but originates from VGChartz, a business intelligence and research firm. Additional data has been provided by Metacritic which has critics' scores, user scores, developer name, and rating for recommended maturity of player. The shape of dataset is **(16719, 16)**

Glimpse of the data:

Name	Platfor	Year_of	Genre	Publisher	NA_Sales	EU_Sales	JP_Sales	Other_Sal	Global_Sa	Critic_Sco	Critic_Cou	User_Scor	User_Cou	Develope	Rating
Wii Sports	Wii	2006	Sports	Nintendo	41.36	28.96	3.77	8.45	82.53	76	51	8	322	Nintendo	E
Super Mai	NES	1985	Platform	Nintendo	29.08	3.58	6.81	0.77	40.24						
Mario Kar	Wii	2008	Racing	Nintendo	15.68	12.76	3.79	3.29	35.52	82	73	8.3	709	Nintendo	E
Wii Sports	Wii	2009	Sports	Nintendo	15.61	10.93	3.28	2.95	32.77	80	73	8	192	Nintendo	E
Pokemon	GB	1996	Role-Playi	Nintendo	11.27	8.89	10.22	1	31.37						
Tetris	GB	1989	Puzzle	Nintendo	23.2	2.26	4.22	0.58	30.26						
New Supe	DS	2006	Platform	Nintendo	11.28	9.14	6.5	2.88	29.8	89	65	8.5	431	Nintendo	E
Wii Play	Wii	2006	Misc	Nintendo	13.96	9.18	2.93	2.84	28.92	58	41	6.6	129	Nintendo	E
New Supe	Wii	2009	Platform	Nintendo	14.44	6.94	4.7	2.24	28.32	87	80	8.4	594	Nintendo	E
Duck Hunt	NES	1984	Shooter	Nintendo	26.93	0.63	0.28	0.47	28.31						
Nintendo	DS	2005	Simulatio	Nintendo	9.05	10.95	1.93	2.74	24.67						
Mario Kar	DS	2005	Racing	Nintendo	9.71	7.47	4.13	1.9	23.21	91	64	8.6	464	Nintendo	E
Pokemon	GB	1999	Role-Playi	Nintendo	9	6.18	7.2	0.71	23.1						
Wii Fit	Wii	2007	Sports	Nintendo	8.92	8.03	3.6	2.15	22.7	80	63	7.7	146	Nintendo	E
Kinect Ad	X360	2010	Misc	Microsoft	15	4.89	0.24	1.69	21.81	61	45	6.3	106	Good Scie	E
Wii Fit Plu	Wii	2009	Sports	Nintendo	9.01	8.49	2.53	1.77	21.79	80	33	7.4	52	Nintendo	E
Grand The	PS3	2013	Action	Take-Two	7.02	9.09	0.98	3.96	21.04	97	50	8.2	3994	Rockstar N	M
Grand The	PS2	2004	Action	Take-Two	9.43	0.4	0.41	10.57	20.81	95	80	9	1588	Rockstar N	M
Super Mai	SNES	1990	Platform	Nintendo	12.78	3.75	3.54	0.55	20.61						
Brain Age	DS	2005	Misc	Nintendo	4.74	9.2	4.16	2.04	20.15	77	58	7.9	50	Nintendo	E
Pokemon	DS	2006	Role-Playi	Nintendo	6.38	4.46	6.04	1.36	18.25						

Variable Summaries:

Variable Name	**Var Type**	**Summary**
Name	String	Lists name of video game
Platform	String	31 distinct platform names in abbreviated form (i.e. Wii, GB)
YearofRelease	String	Lists year game was released from 1980 to 2020
Genre	String	12 distinct genres (i.e. Sports, Racing, Puzzle)
Publisher	String	580 distinct publishers (i.e. Nintendo, Microsoft, Sony)
NA_Sales	Numeric	North American sales for each game in millions of dollars Min: 0 Max: $41.36 million Mean: $.263 million
EU_Sales	Numeric	European sales for each game in millions of dollars

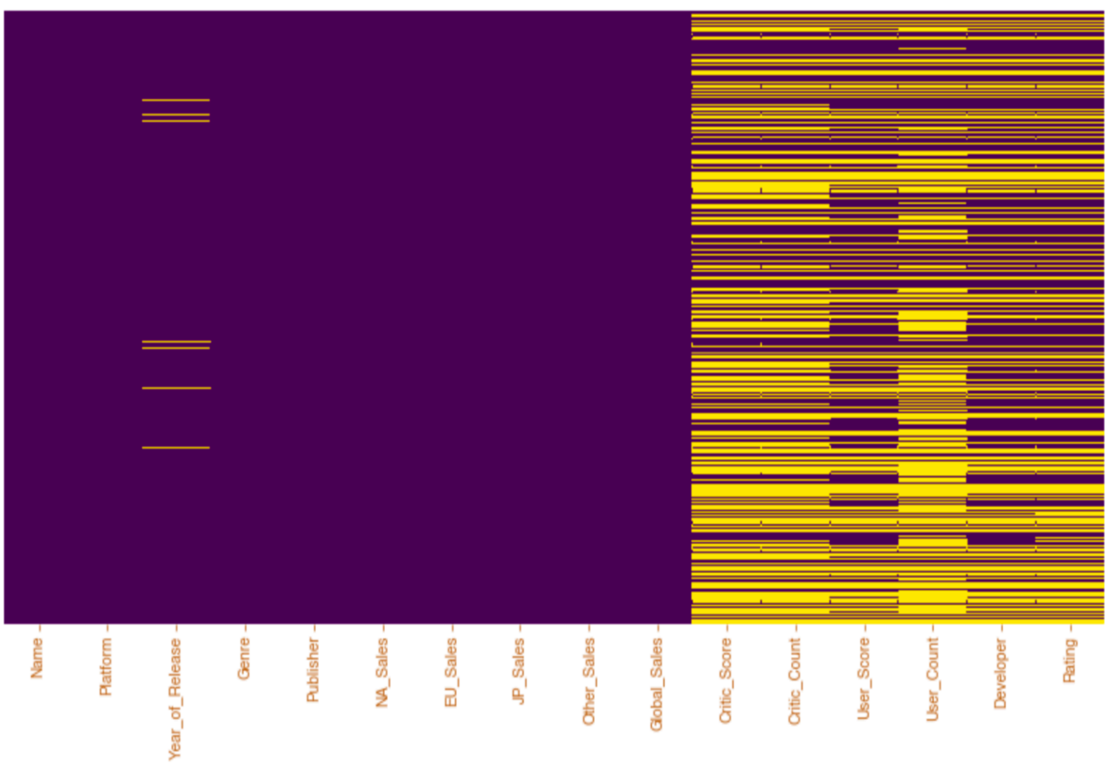
		Min: 0 Max: $28.96 million Mean: $.145 million
JP_Sales	Numeric	Japan sales for each game in millions of dollars Min: 0 Max: $10.22 million Mean: $.078 million
Other_Sales	Numeric	Sales for regions not included in North America, Europe, or Japan. In millions of dollars. Min: 0 Max: $10.57 million Mean: $.047 million
Global_Sales	Numeric	Total sales in millions of dollars Min: $.01 Max: $82.53 million Mean: $.534 million
Critic_Score	Numeric	Score from 0-100 based on critic reviews where higher scores indicate more favorable reviews *Missing 51% Min: 13 Max: 98 Mean: 68.963
Critic_Count	Numeric	Number of critic reviews used to form critic score *Missing 51% Min: 3 Max: 113 Mean: 26.361
User_Score	Numeric	Score from 0-10 based on user reviews *Missing 55% Min: 0 Max: 9.7 Mean: 7.125
User_Count	Numeric	Number of user reviews used to form User_Score *Missing 55% Min: 4 Max: 10665 Mean: 162.23
Developer	String	1696 distinct developer names *Missing 40% (i.e. Nintendo, Game Arts)
Rating	String	8 distinct ratings (E for everyone, M for mature) *Missing 40%

Data Cleaning

1. **CHANGING DATA TYPE.** From the overall review of our data set, we can see that the data are in different data type. Some of them are numerical data, like user score, user counts, critic score and critic counts. While some of them are text data, like Name of game, publisher and platform. We must change the data type for our further work.

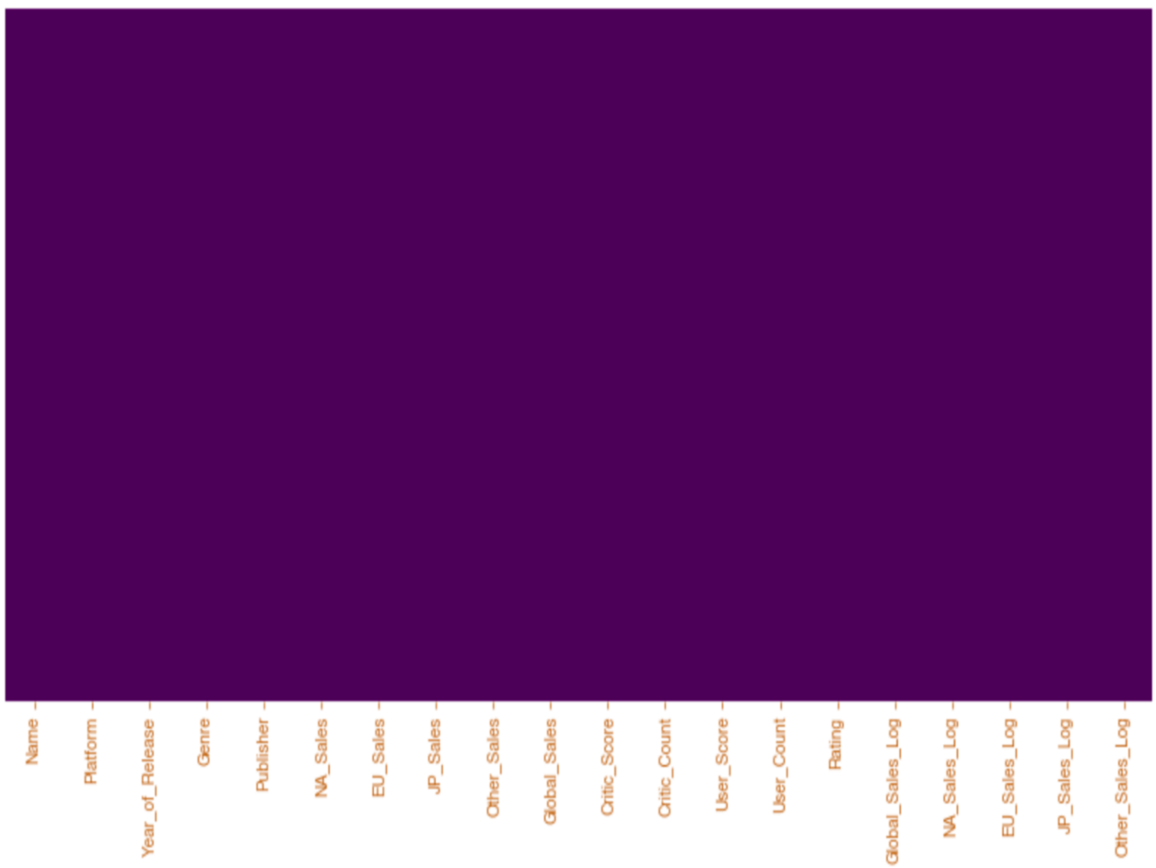
```
Name                          object
click to scroll output; double click to hide
Year_of_Release              float64
Genre                         object
Publisher                     object
NA_Sales                     float64
EU_Sales                     float64
JP_Sales                     float64
Other_Sales                  float64
Global_Sales                 float64
Critic_Score                 float64
Critic_Count                 float64
User_Score                    object
User_Count                   float64
Developer                     object
Rating                        object
dtype: object
```

2. **PROCESSING THE MISSING DATA**. We can see that lots of game do not have the feature critic score and user score, which will make a vital impact on our project. According to this poor data set, we must fill the missing values with some rational data. Below figure shows missing data in the corresponding data columns.



- *Textual data:* If the original data type is text, we need to fill the missing data with appropriate value or general text “TBD/ Unknown”.
- *Numerical data* If the original data type is numerical, we need to fill the missing data with this column’s mean value.
- *Outlier*: Outlier is an observation that lies an abnormal distance from other values in a random sample from a population. there are outliers in sales columns. They might be useful for training as they indicate bestseller games, but for now we are going to remove them and maybe add them later.

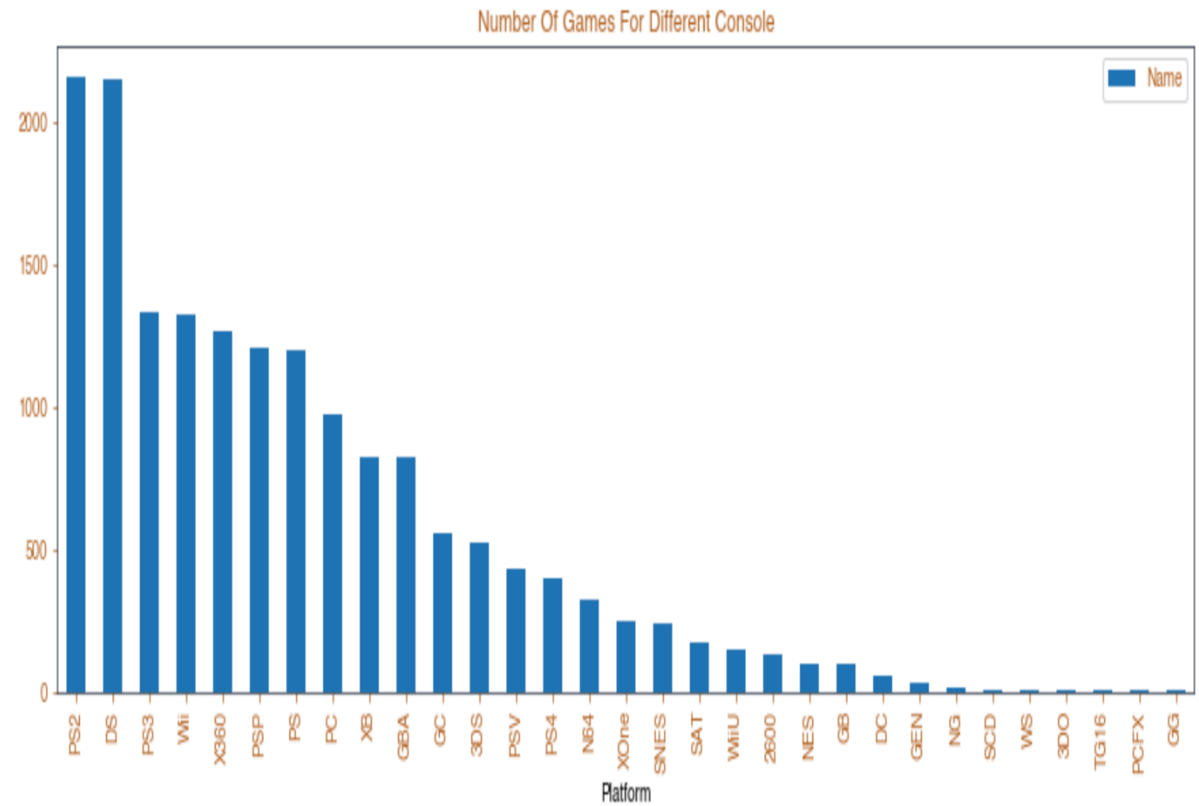
Below figure shows the data frames after data clean up.



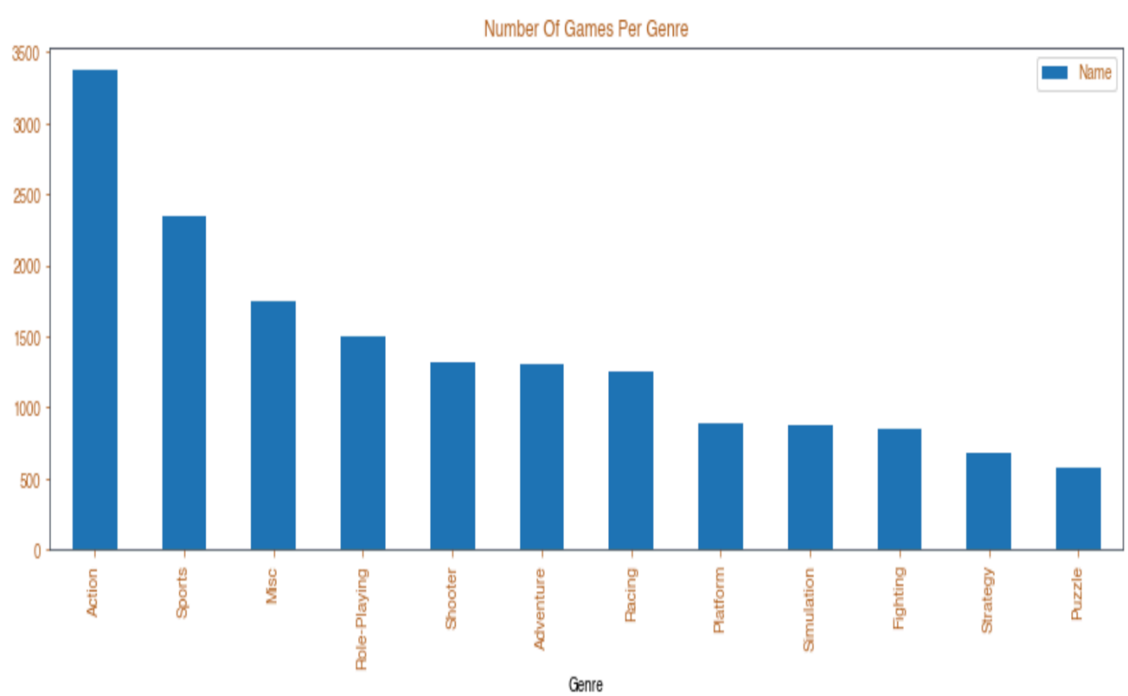
Data Analysis:

Below are few of the analytic questions which the dataset can answer

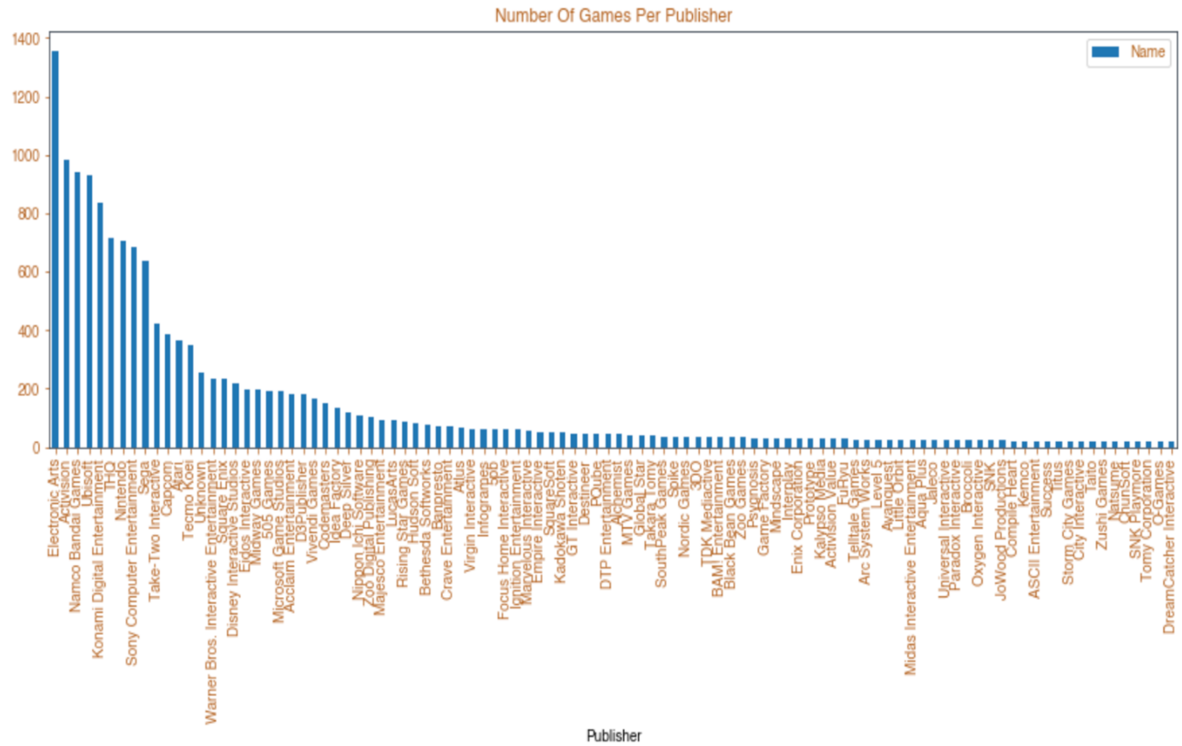
Number of Different Games Per Console:



Number Of Different Games Per Genre



Number Of Different Games Per Publisher



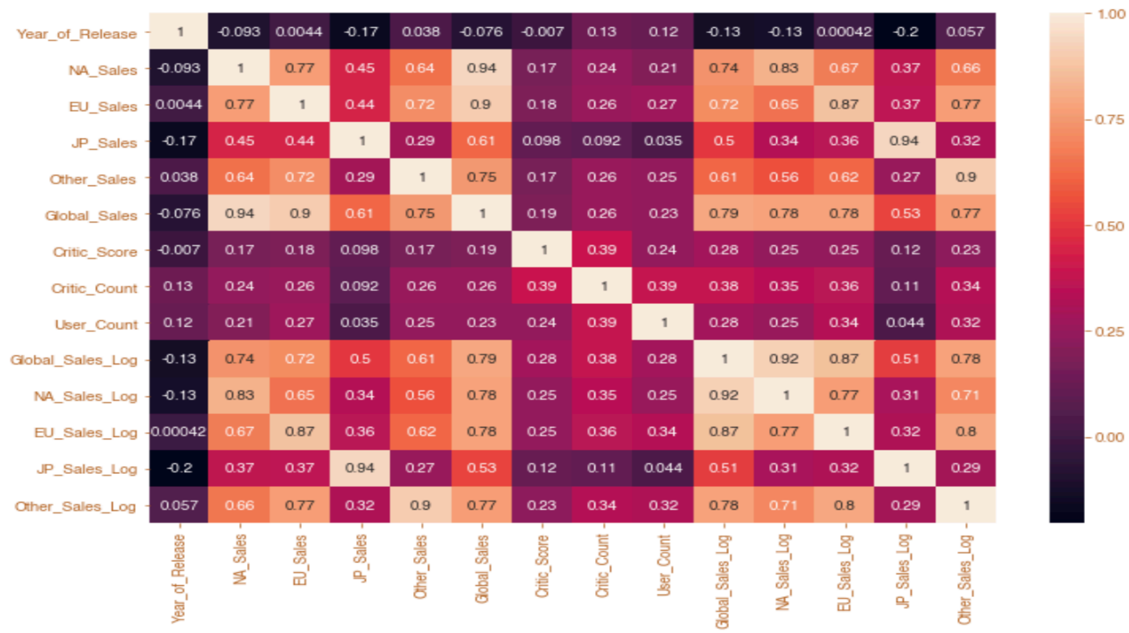
Data Correlation: Is a way to understand the relationship between multiple variables and attributes in your dataset. Using Correlation, you can get some insights such as

- One or multiple attributes depend on another attribute or a cause for another attribute.
- One or multiple attributes are associated with other attributes.

So, why is correlation useful?

- Correlation can help in predicting one attribute from another (Great way to impute missing values).
- Correlation can (sometimes) indicate the presence of a causal relationship.
- Correlation is used as a basic quantity for many modelling techniques

Below figure shows correlation for different columns, in the dataset.



Requirements:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from datetime import datetime
from pandas import Series
import seaborn as sns
import numpy as np
from sklearn.metrics import precision_recall_fscore_support
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.linear_model import Ridge
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, f1_score, accuracy_score, confusion_matrix
from sklearn import svm
from sklearn.metrics import roc_auc_score
from sklearn.metrics import roc_curve
from sklearn.metrics import auc
from sklearn.model_selection import learning_curve
from sklearn.neighbors import KNeighborsClassifier
```

First ML Problem Statement:

1. How Global Sales Gets affected with Critic_Score_x', 'Critic_Count_x', 'User_Score_x', 'User_Count_x', 'year_after_release_x'

   X: Critic_Score_x', 'Critic_Count_x', 'User_Score_x', 'User_Count_x','year_after_release_x'
   Y: Global_Sales_Log

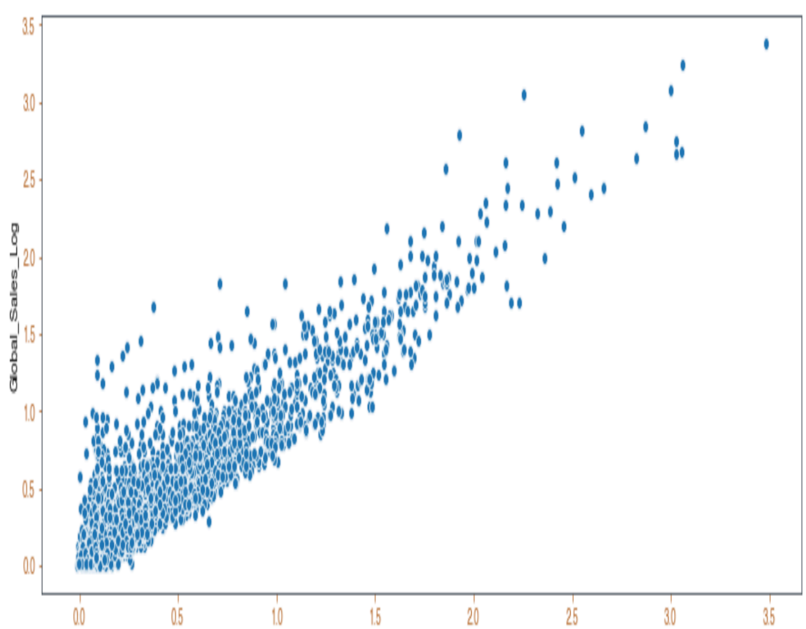
MODELING:

We use 1/2 of all data in the data set as training data and the left 1/2 data as testing data. we will evaluate the model performance by Mean Absolute Error(MAE). At the meanwhile, we will make plot graph of each models for visualized assessment of their performance.

LINEAR REGRESSION:

mean_absolute_error	0.09902835743695935
mean_squared_error	0.02286022063308966
accuracy	0.8523184660252421

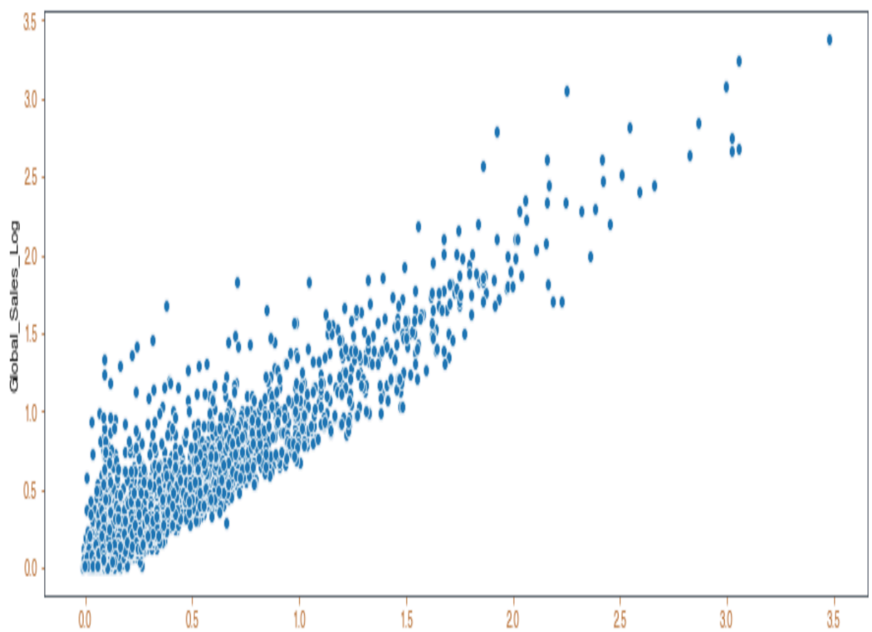
SCATTER PLOT:



RIDGE REGRESSION:

mean_absolute_error	0.09908128080265304
mean_squared_error	0.022863384030535606
Accuracy	0.8522980298538295

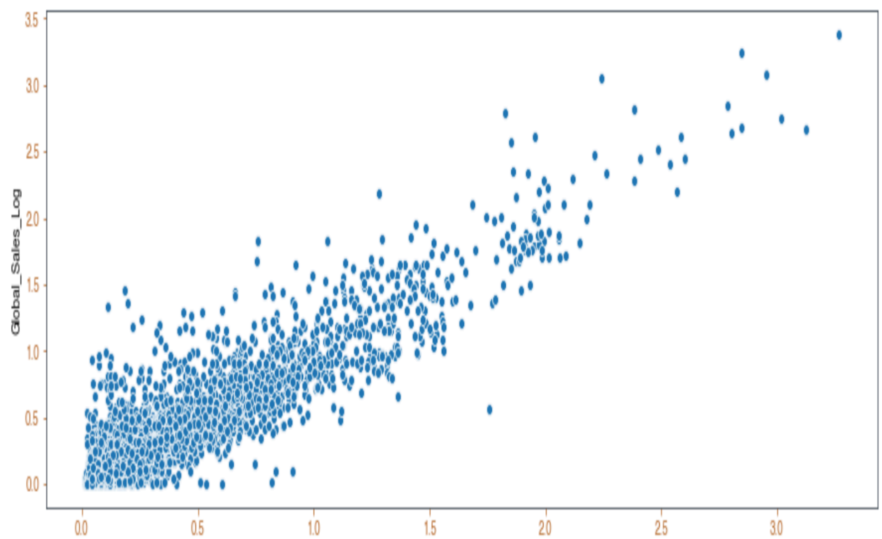
SCATTER PLOT:



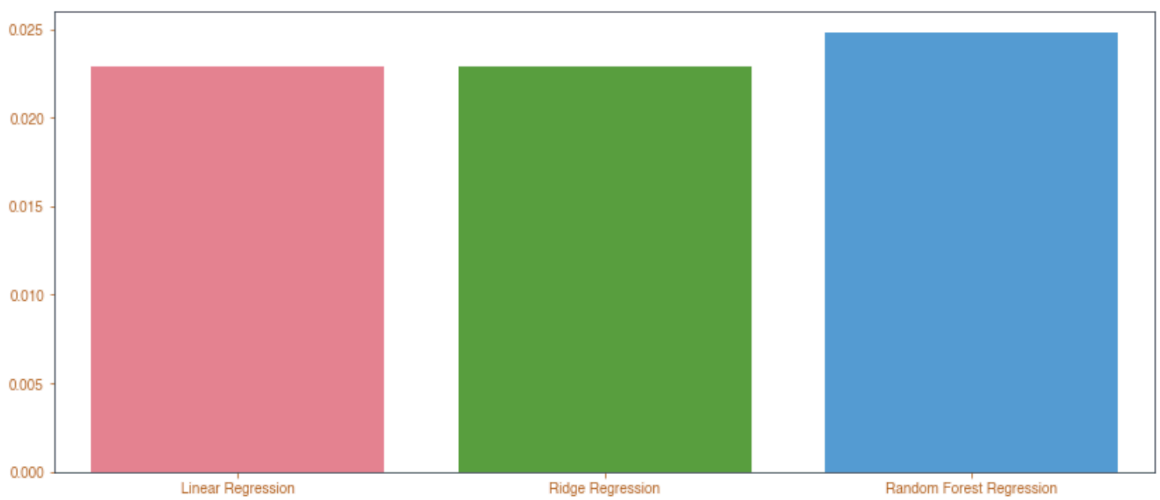
RANDOM FOREST REGRESSION:

mean_absolute_error	0.09884309984717227
mean_squared_error	0.02510867527810916
Accuracy	0.8379337860864112

SCATTER PLOT:



Evaluate different models based on MSE:



Second ML Problem Statement:

2. Does a game hit gets affected by *Year_of_Release Critic_Score*
   X: Year_of_Release ,Critic_Score
   Y: Hit

Modeling:

We use 1/2 of all data in the data set as training data and the left 1/2 data as testing data. we will evaluate the model performance by Mean Absolute Error(MAE).

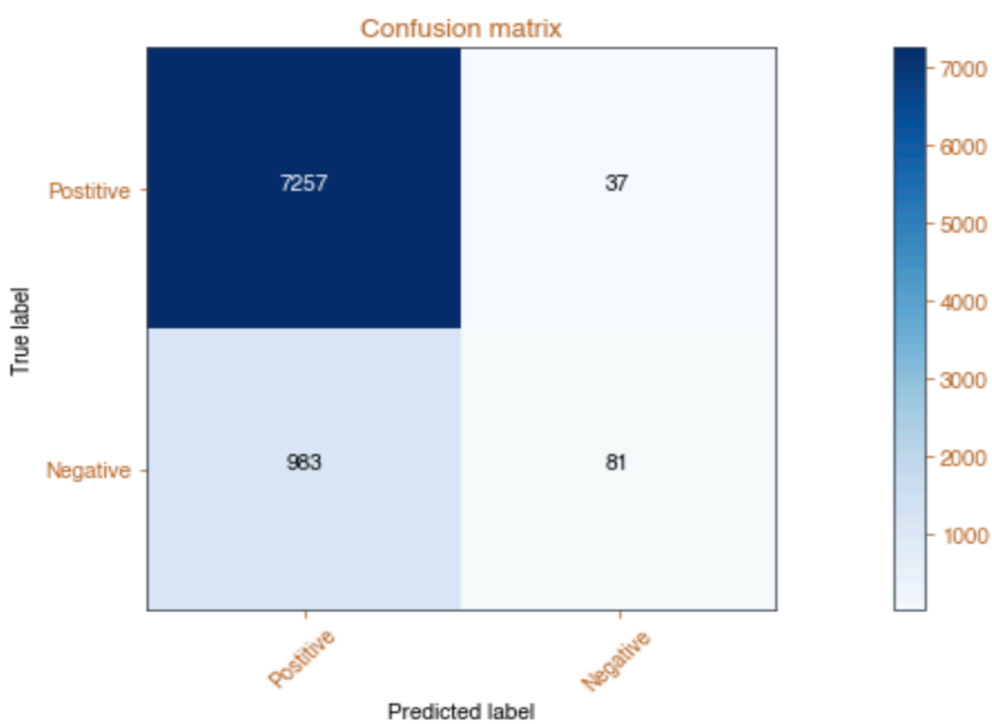
Random Forest Classifier:

mean_absolute_error	0.18015534953645704
mean_squared_error	0.18015534953645704
variance	0.20697724448893373
accuracy	0.8198446504635429

Logistic Regression:

mean_absolute_error	0.16612377850162866
mean_squared_error	0.16612377850162866
variance_score	0.014201230193749192
Accuracy	0.8338762214983714
Regression on training set	0.8466549736908043
Regression Score on test set	0.8338762214983714

Confusion Matrix:



CLASSIFICATION REPORT:

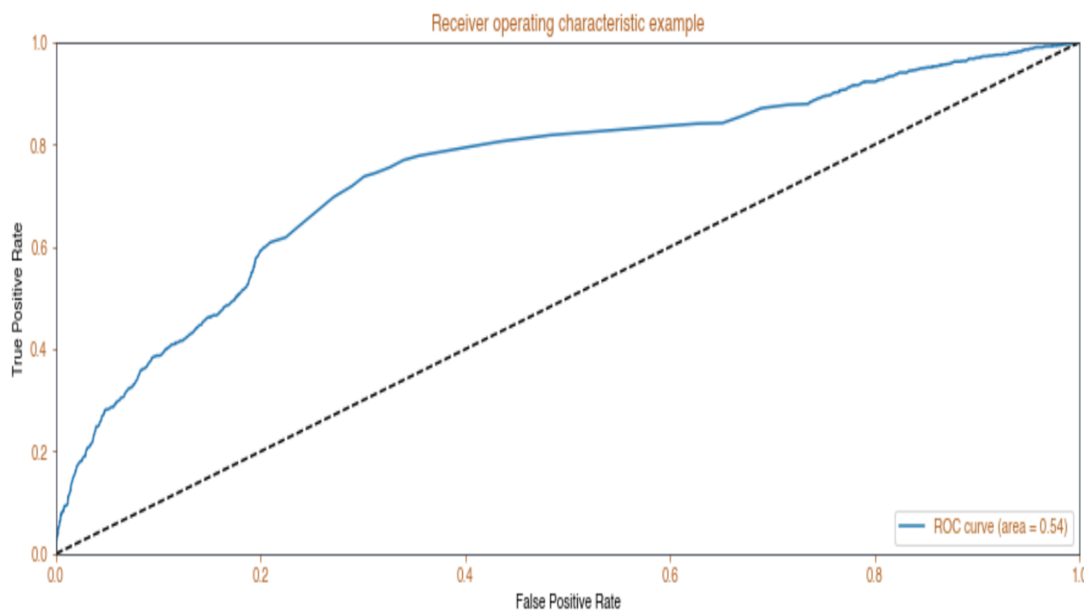
Receiver Operating Characteristic curve

This type of graph is called a *Receiver Operating Characteristic curve* (or ROC curve.) It is a plot of the true positive rate against the false positive rate for the different possible cutpoints of a diagnostic test.

An ROC curve demonstrates several things:

- It shows the tradeoff between sensitivity and specificity (any increase in sensitivity will be accompanied by a decrease in specificity).

- The closer the curve follows the left-hand border and then the top border of the ROC space, the more accurate the test.
- The closer the curve comes to the 45-degree diagonal of the ROC space, the less accurate the test.



Third ML Problem Statement:

1. How does the game rated as "RATING EVERYONE", changes with Year_of_Release Sales Platform

   X: 'Year_of_Release' ,'Sales','Platform'
   Y: 'Global_Sales_Log'

MODELING:

We use 1/2 of all data in the data set as training data and the left 1/2 data as testing data. we will evaluate the model performance by Mean Absolute Error(MAE). At the meanwhile, we will make plot graph of each models for visualized assessment of their performance.

Logistic Regression

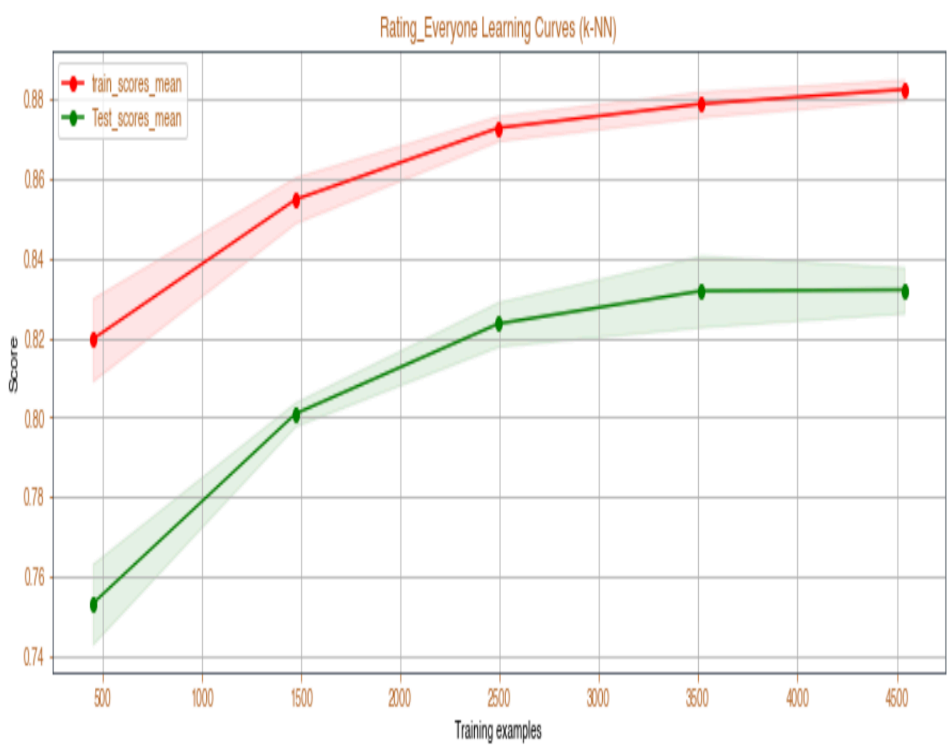
mean_absolute_error	0.16662490603858682

mean_squared_error	0.16662490603858682
variance	0.011810211222773925
accuracy	0.8333750939614132

K-NEIGHBOUR CLASSIFIER

mean_absolute_error	0.1623653219744425
mean_squared_error	0.1623653219744425
variance	0.03927400129078129
accuracy	0.8376346780255575

K-NEIGHBOR CLASSIFIER LEARNING CURVE TEST & TRAIN SCORE MEAN:

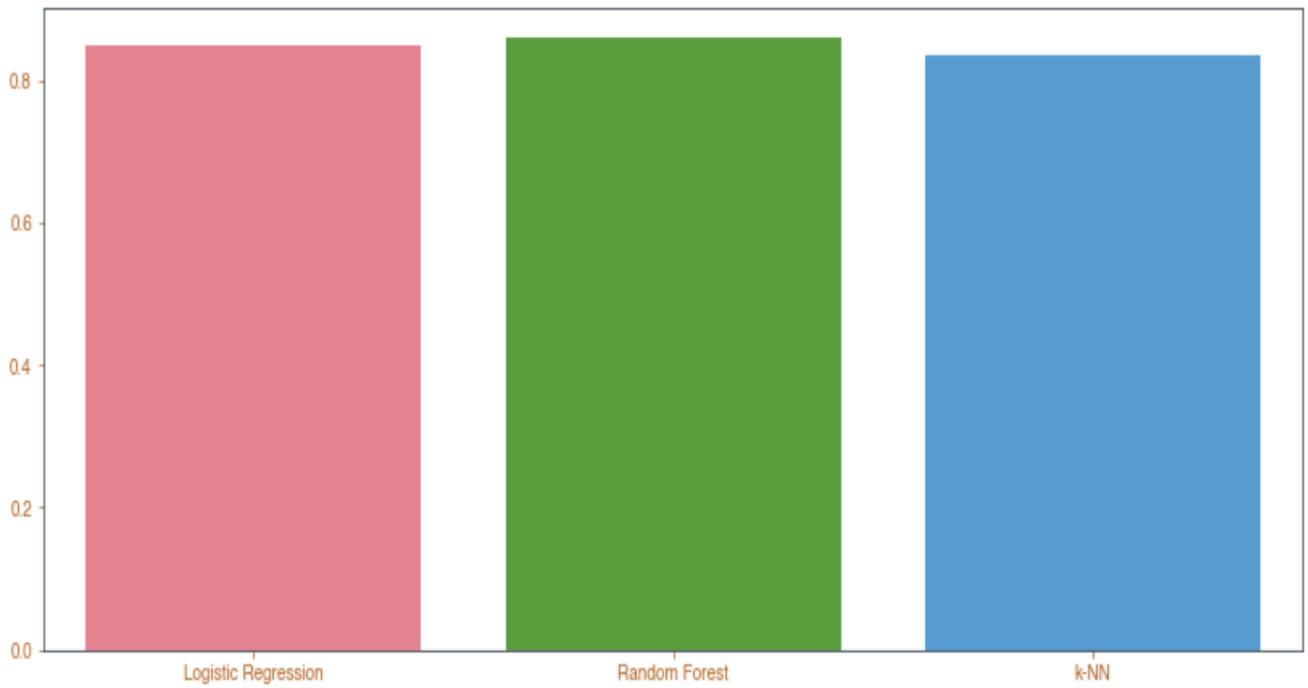


RANDOM Forest Classifier

mean_absolute_error	0.18466549736908044
mean_squared_error	0.18466549736908044

variance	-0.24269676733883894
accuracy	0.8153345026309196

Evaluate different models based on Accuracy:



CODE:

Attached PDF file, with all codes and output.

FinalProject

December 10, 2019

[218]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import calendar
from datetime import datetime
from pandas import Series
from math import ceil
import warnings
warnings.filterwarnings('ignore')
df = pd.read_csv('Video_Games_Sales.csv')
```

[218]:
```
Name                 object
Platform             object
Year_of_Release     float64
Genre                object
Publisher            object
NA_Sales            float64
EU_Sales            float64
JP_Sales            float64
Other_Sales         float64
Global_Sales        float64
Critic_Score        float64
Critic_Count        float64
User_Score           object
User_Count          float64
Developer            object
Rating               object
dtype: object
```

0.1 Data Analysis

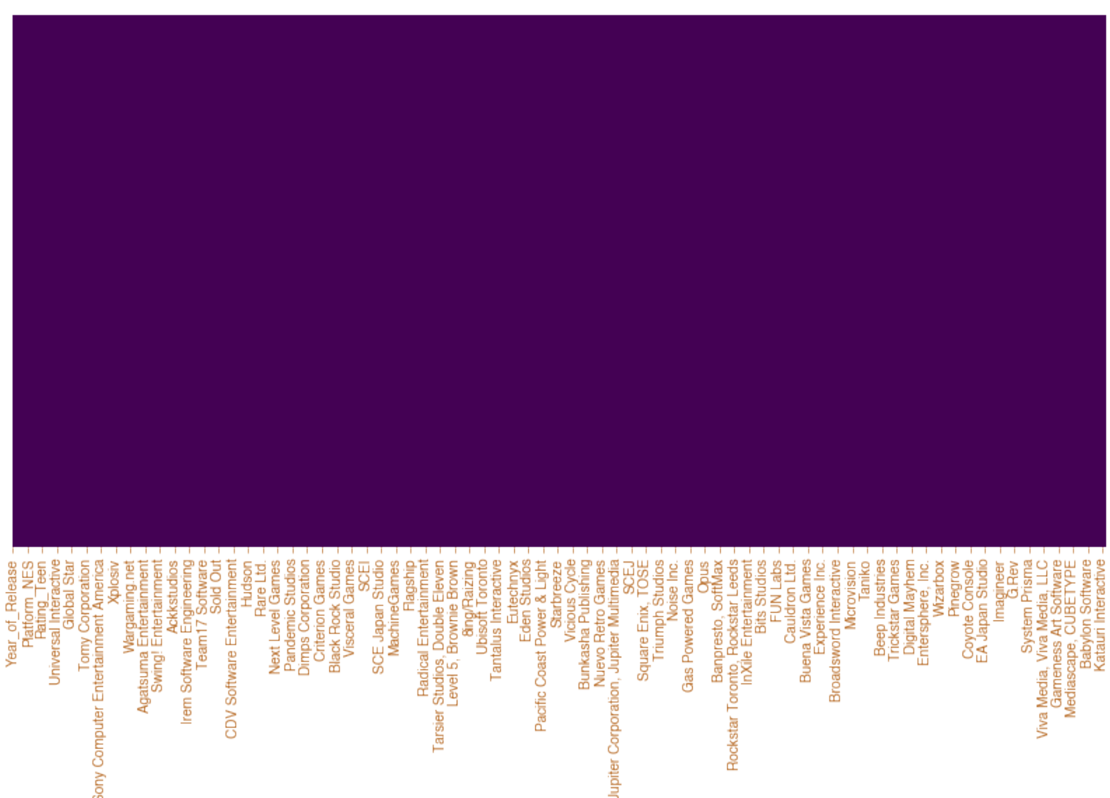
Missing Values Show the missing values distribution:

[217]:
```
plt.figure(figsize=(14,7))
sns.heatmap(df.isnull(),yticklabels=False,cbar=False,cmap='viridis')
df['Global_Sales_Log'] = np.log1p(df['Global_Sales'])
```

```python
df['NA_Sales_Log'] = np.log1p(df['NA_Sales'])
df['EU_Sales_Log'] = np.log1p(df['EU_Sales'])
df['JP_Sales_Log'] = np.log1p(df['JP_Sales'])
df['Other_Sales_Log'] = np.log1p(df['Other_Sales'])

null_columns=df.columns[df.isnull().any()]
df[null_columns].isnull().sum()
```

[217]:
```
Year_of_Release                       float64
NA_Sales                              float64
EU_Sales                              float64
JP_Sales                              float64
Other_Sales                           float64
Global_Sales                          float64
Platform_XB                           float64
Platform_X360                         float64
Platform_XOne                         float64
Platform_PC                           float64
Platform_PS                           float64
Platform_PS2                          float64
Platform_PS3                          float64
Platform_PS4                          float64
Platform_PSP                          float64
Platform_PSV                          float64
Platform_GB                           float64
Platform_GBA                          float64
Platform_DS                           float64
Platform_3DS                          float64
Platform_NES                          float64
Platform_SNES                         float64
Platform_N64                          float64
Platform_GC                           float64
Platform_Wii                          float64
Platform_WiiU                         float64
Genre_Action                          float64
Genre_Adventure                       float64
Genre_Fighting                        float64
Genre_Misc                            float64
                                       ...
Flying Lab Software                   float64
1C, Ino-Co, 1C Company                float64
Autumn Moon                           float64
Tate Interactive                      float64
Elixir Studios                        float64
Compulsion Games                      float64
Camouflaj, LLC                        float64
DMA Design, Rockstar North            float64
```

```
King of the Jungle                            float64
Spidersoft, Spiders                           float64
Tecmo, Graphic Research                       float64
Battlefront.com, 1C, 1C Company               float64
EA Phenomic                                   float64
Empty Clip Studios                            float64
Headgate                                      float64
Coffee Stain Studios                          float64
Boston Animation                              float64
React Games                                   float64
Inferno Games                                 float64
Katauri Interactive                           float64
High Moon Studios, Mercenary Technologies     float64
Infinite Dreams, Paragon 5                    float64
Big Red Software                              float64
Fluid Studios                                 float64
Atomic Games                                  float64
Global_Sales_Log                              float64
NA_Sales_Log                                  float64
EU_Sales_Log                                  float64
JP_Sales_Log                                  float64
Other_Sales_Log                               float64
Length: 1491, dtype: object
```



[186]:
```
# we can see there are lots of missing values in Critic_Score, Critic_Count,
#User_Score etc. While there are ONLY TWO missing in Name and Genre.
```

1 Data Cleaning

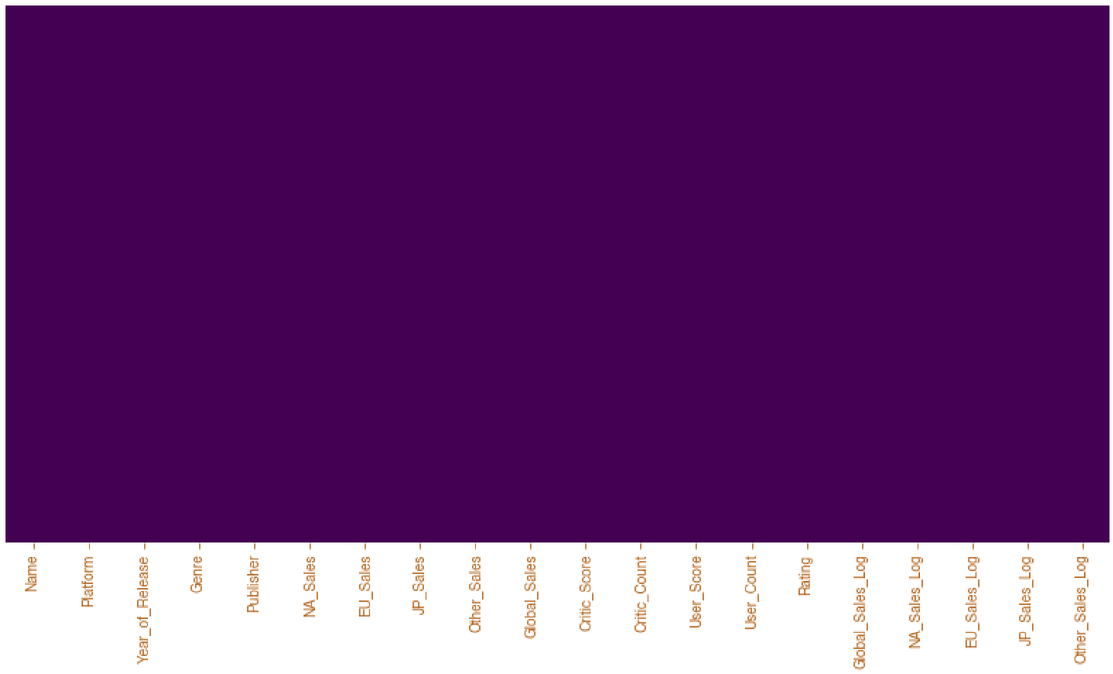
[187]:
```
df.drop(index=[659,14246],inplace=True)
df[df.Year_of_Release.isnull()]
df.Year_of_Release = df.Year_of_Release.fillna(0)
df[df['Year_of_Release']==0].Platform.unique()

PS2_median = df[df['Platform'] == 'PS2']['Year_of_Release'].median()
Wii_median = df[df['Platform'] == 'Wii']['Year_of_Release'].median()
x2600median = df[df['Platform'] == '2600']['Year_of_Release'].median()
X360_median = df[df['Platform'] == 'X360']['Year_of_Release'].median()
GBA_median = df[df['Platform'] == 'GBA']['Year_of_Release'].median()
PC_median = df[df['Platform'] == 'PC']['Year_of_Release'].median()
PS3_median = df[df['Platform'] == 'PS3']['Year_of_Release'].median()
PS_median = df[df['Platform'] == 'PS']['Year_of_Release'].median()
PSP_median = df[df['Platform'] == 'PSP']['Year_of_Release'].median()
XB_median = df[df['Platform'] == 'XB']['Year_of_Release'].median()
GB_median = df[df['Platform'] == 'GB']['Year_of_Release'].median()
DS_median = df[df['Platform'] == 'DS']['Year_of_Release'].median()
x3DS_median = df[df['Platform'] == '3DS']['Year_of_Release'].median()
N64_median = df[df['Platform'] == 'N64']['Year_of_Release'].median()
PSV_median = df[df['Platform'] == 'PSV']['Year_of_Release'].median()
GC_median = df[df['Platform'] == 'GC']['Year_of_Release'].median()


# Function that returns the median of the platform if year = 0. Else it returns
 ↪the year.
def year_filler(x):

    if x.Year_of_Release == 0:
        if x.Platform == 'PS2':
            return PS2_median
        elif x.Platform == 'Wii':
            return Wii_median
        elif x.Platform == '2600':
            return x2600median
        elif x.Platform == 'X360':
            return X360_median
        elif x.Platform == 'GBA':
            return GBA_median
        elif x.Platform == 'PC':
            return PC_median
```

```
        elif x.Platform == 'PS3':
            return PS3_median
        elif x.Platform == 'PS':
            return PS_median
        elif x.Platform == 'PSP':
            return PSP_median
        elif x.Platform == 'XB':
            return XB_median
        elif x.Platform == 'GB':
            return GB_median
        elif x.Platform == 'DS':
            return DS_median
        elif x.Platform == '3DS':
            return x3DS_median
        elif x.Platform == 'N64':
            return N64_median
        elif x.Platform == 'PSV':
            return PSV_median
        elif x.Platform == 'GC':
            return GC_median
        else:
            return 1900
    else:
        return x.Year_of_Release


# apply function to replace values
df.Year_of_Release = df.apply(year_filler, axis=1)

df['Publisher'].fillna(value='Unknown', inplace=True)
# We will start by filling the missing values of Critic_Score and Critic_Count.
df.Critic_Score = df.Critic_Score.fillna(df.Critic_Score.median())
df.Critic_Count = df.Critic_Count.fillna(df.Critic_Count.median())

# We will start by filling the missing values of Critic_Score and Critic_Count.
# Because Critic_Score has NaN values, we will first fill those NaN values with␣
 ↪0.

df.User_Score = df.User_Score.fillna(0)


# Some values of Critic_Score have the value'tbd'. These values need to be␣
 ↪replaces with 100.
df.User_Score.replace(to_replace='tbd',value=100,inplace=True)

# We will do the same for User_Count
df.User_Count = df.User_Count.fillna(df.User_Count.median())
```

```
# Replace the missing values of Rating with Unknown.
df.Rating.fillna('Unknown',inplace=True)

# Because Developer has too many unique values, we will drop this column.
df.drop('Developer',axis=1,inplace=True)

columns = df.columns
percent_missing = df.isnull().sum() * 100 / len(df)
missing_value_df = pd.DataFrame({'column_name': columns,
                                 'percent_missing': percent_missing})
print(missing_value_df)


### Missing Values Show the missing values distribution:
plt.figure(figsize=(14,7))
sns.heatmap(df.isnull(),yticklabels=False,cbar=False,cmap='viridis')
df['Global_Sales_Log'] = np.log1p(df['Global_Sales'])

df['NA_Sales_Log'] = np.log1p(df['NA_Sales'])
df['EU_Sales_Log'] = np.log1p(df['EU_Sales'])
df['JP_Sales_Log'] = np.log1p(df['JP_Sales'])
df['Other_Sales_Log'] = np.log1p(df['Other_Sales'])

null_columns=df.columns[df.isnull().any()]
df[null_columns].isnull().sum()

dforiginal=df;
```

```
                       column_name  percent_missing
Name                          Name              0.0
Platform                  Platform              0.0
Year_of_Release    Year_of_Release              0.0
Genre                        Genre              0.0
Publisher                Publisher              0.0
NA_Sales                  NA_Sales              0.0
EU_Sales                  EU_Sales              0.0
JP_Sales                  JP_Sales              0.0
Other_Sales            Other_Sales              0.0
Global_Sales          Global_Sales              0.0
Critic_Score          Critic_Score              0.0
Critic_Count          Critic_Count              0.0
User_Score              User_Score              0.0
User_Count              User_Count              0.0
Rating                      Rating              0.0
Global_Sales_Log  Global_Sales_Log              0.0
NA_Sales_Log          NA_Sales_Log              0.0
```

```
EU_Sales_Log          EU_Sales_Log            0.0
JP_Sales_Log          JP_Sales_Log            0.0
Other_Sales_Log    Other_Sales_Log            0.0
```

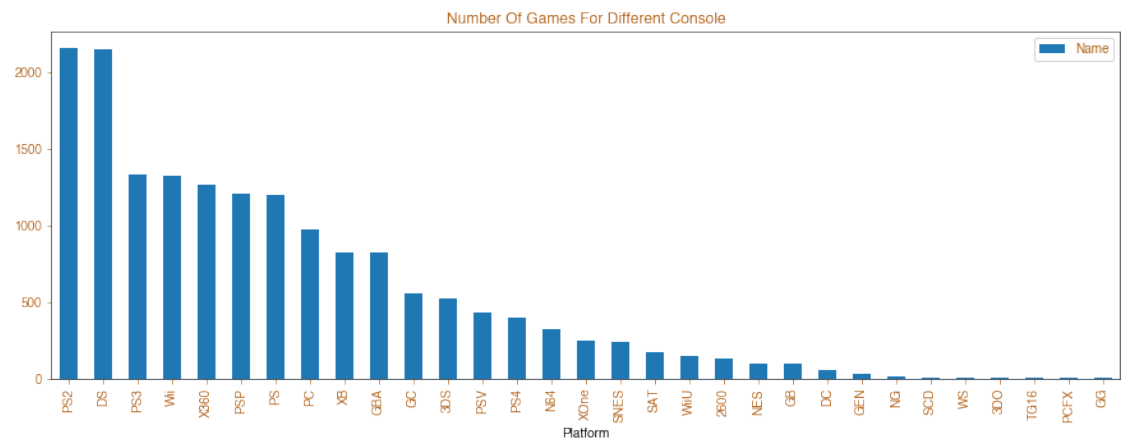


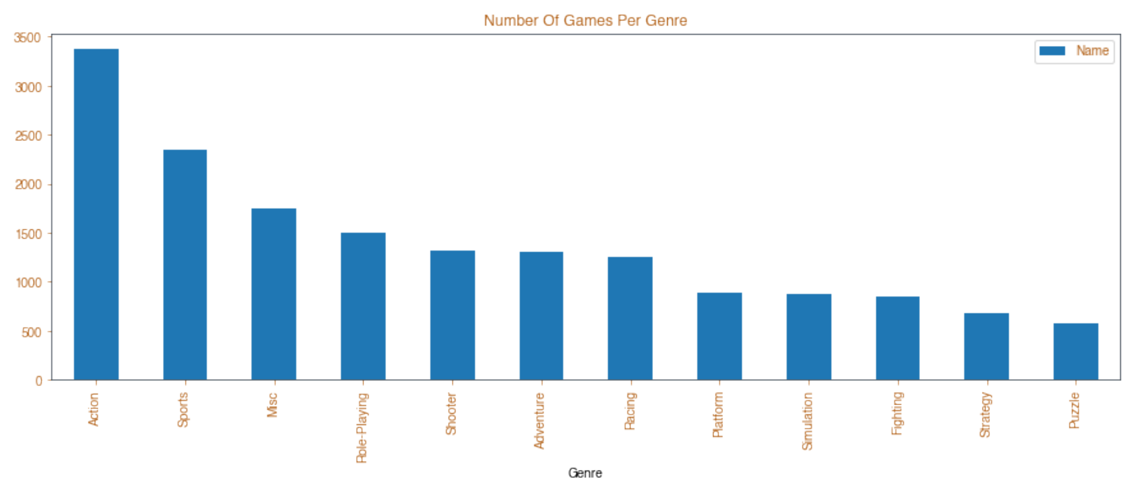
2 Data Analysis & Data visualization:

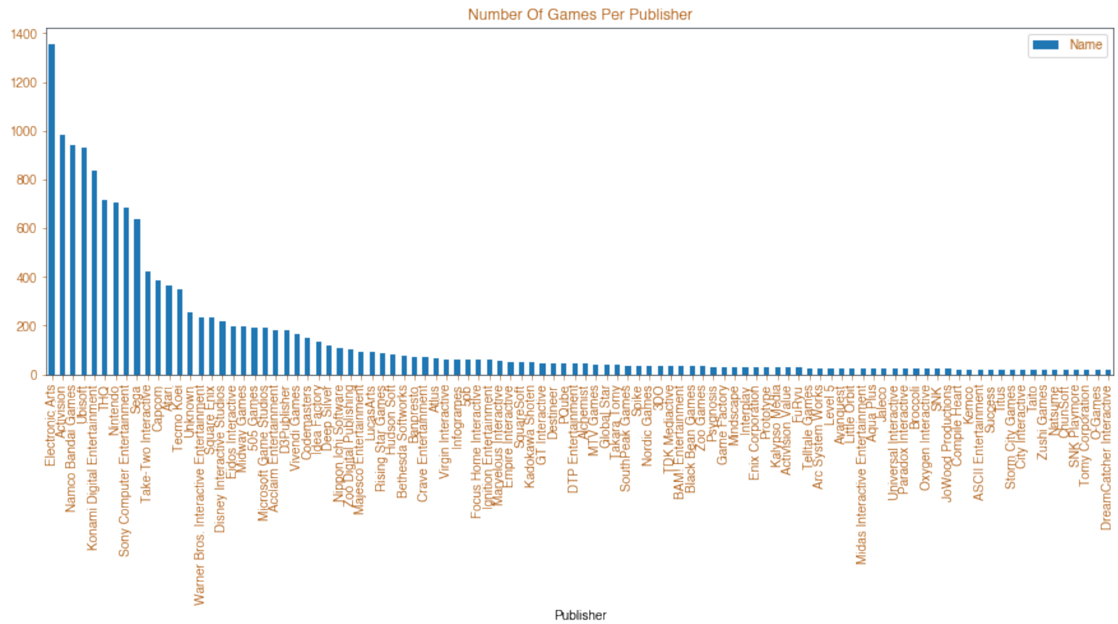
[188]:
```
#Plot Top values in the dataset By platform, developer and genre.
import matplotlib.pyplot as plt
%matplotlib inline

# set font
plt.rcParams['font.family'] = 'sans-serif'
plt.rcParams['font.sans-serif'] = 'Helvetica'

# set the style of the axes and the text color
plt.rcParams['axes.edgecolor']='#333F4B'
plt.rcParams['axes.linewidth']=0.8
plt.rcParams['xtick.color']='#b5651d'
plt.rcParams['ytick.color']='#b5651d'
plt.rcParams['text.color']='#b5651d'
plt.rcParams['figure.figsize'] = 15, 5
```

```
namePlatformDf = df[['Name', 'Platform']].groupby(['Platform']).count().
 ↪sort_values('Name', ascending=False).reset_index()
namePlatformDf.plot(kind='bar', x="Platform", y="Name",title="Number Of Games␣
 ↪For Different Console")

nameGenreDf = df[['Name', 'Genre']].groupby(['Genre']).count().
 ↪sort_values('Name', ascending=False).reset_index()
nameGenreDf.plot(kind='bar', x="Genre", y="Name",title="Number Of Games Per␣
 ↪Genre")

nameDeveloperDf = df[['Name', 'Publisher']].groupby(['Publisher']).count().
 ↪sort_values('Name', ascending=False).reset_index()
nameDeveloperDf[:100].plot(kind='bar', x="Publisher", y="Name",title="Number Of␣
 ↪Games Per Publisher")
```

[188]: <matplotlib.axes._subplots.AxesSubplot at 0x1a23eeacc0>

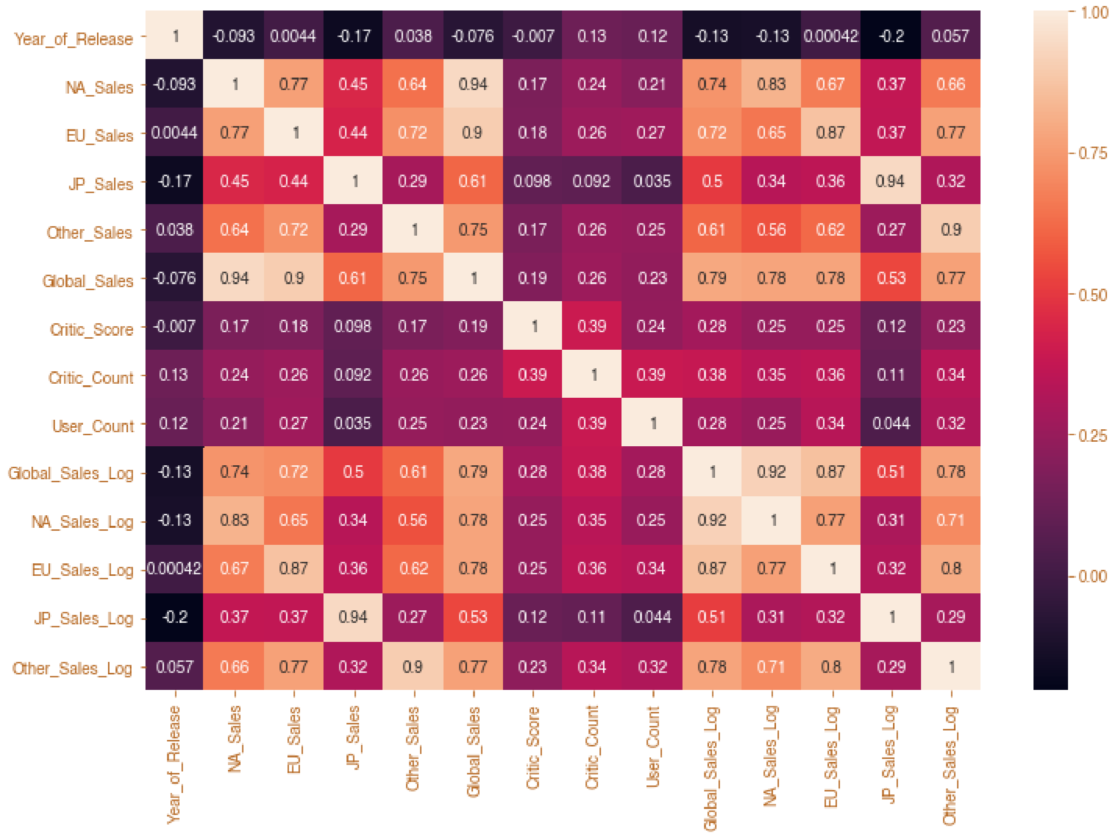






DATA CORRELATION

[189]:
```
plt.figure(figsize=(12, 8))

vg_corr = df.corr()
sns.heatmap(vg_corr,
            xticklabels = vg_corr.columns.values,
            yticklabels = vg_corr.columns.values,
            annot = True);
```



[190]:
```
## UTITLITY FUNCTION FOR PRINTING CLASSIFICATION REPORT
```

[191]:
```
import seaborn as sns
import numpy as np
from sklearn.metrics import precision_recall_fscore_support
import matplotlib.pyplot as plt

y = np.random.randint(low=0, high=10, size=100)
y_p = np.random.randint(low=0, high=10, size=100)

def plot_classification_report(y_tru, y_prd, figsize=(10, 10), ax=None):

    plt.figure(figsize=figsize)

    xticks = ['precision', 'recall', 'f1-score', 'support']
    yticks = list(np.unique(y_tru))
    yticks += ['avg']

    rep = np.array(precision_recall_fscore_support(y_tru, y_prd)).T
    avg = np.mean(rep, axis=0)
    avg[-1] = np.sum(rep[:, -1])
    rep = np.insert(rep, rep.shape[0], avg, axis=0)
```

```
    sns.heatmap(rep,
                annot=True,
                cbar=False,
                xticklabels=xticks,
                yticklabels=yticks,
                ax=ax)
```

[192]:
```
## UTITLITY FUNCTION FOR PRINTING CONFUSION MATRIX
```

[193]:
```
import itertools
import matplotlib.pyplot as plt
import numpy as np
from sklearn.metrics import confusion_matrix

# Source: http://scikit-learn.org/stable/auto_examples/model_selection/
#         plot_confusion_matrix.html#confusion-matrix

def plot_confusion_matrix(cm, classes,
                          normalize=False,
                          title='Confusion matrix',
                          cmap=plt.cm.Blues):
    """
    This function prints and plots the confusion matrix.
    Normalization can be applied by setting `normalize=True`.
    """
    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
        print("Normalized confusion matrix")
    else:
        print('Confusion matrix, without normalization')

    print(cm)

    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=45)
    plt.yticks(tick_marks, classes)

    fmt = '.2f' if normalize else 'd'
    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        plt.text(j, i, format(cm[i, j], fmt),
                 horizontalalignment="center",
                 color="white" if cm[i, j] > thresh else "black")
    plt.tight_layout()
```

```
    plt.ylabel('True label')
    plt.xlabel('Predicted label')
```

[194]:
```
# Data Transformation

df.drop(index=[0], inplace=True)

#Transform datatypeschange the datatypefrom real number -> integer
# Transform year from float to integer
df['Year_of_Release'] = df.Year_of_Release.astype(int)

# Transform Critic_Score from float to integer
df['Critic_Score'] = df.Critic_Score.astype(int)

# Transform Critic_Count from float to integer
df['Critic_Count'] = df.Critic_Count.astype(int)

# Transform User_Count from float to integer
df['User_Count'] = df.User_Count.astype(int)


# Transform User_Score to int
df.User_Score = pd.to_numeric(df.User_Score, errors='coerce')
```

[195]:
```
# Categorical encoding and standardization
# First we will create a new feature, based on the year of release.
# The new feature 'years_after_release' = year of release - release date of the␣
↪platform

# Create new, empty column
df['year_after_release'] = ''

# Create variables for all console relese years
PS2_release = 2000
Wii_release = 2006
x2600_release = 1977
X360_release = 2005
GBA_release = 2001
PS3_release = 2006
PS_release = 1994
PSP_release = 2004
XB_release = 2001
GB_release = 1989
DS_release = 2004
x3DS_release = 2011
N64_release = 1996
PSV_release = 2011
GC_release = 2001
```

```python
def year_after_release_filler(x):

        if x.Platform == 'PS2':
            return x.Year_of_Release - PS2_release
        elif x.Platform == 'Wii':
            return x.Year_of_Release - Wii_release
        elif x.Platform == '2600':
            return x.Year_of_Release - x2600_release
        elif x.Platform == 'X360':
            return x.Year_of_Release - X360_release
        elif x.Platform == 'GBA':
            return x.Year_of_Release - GBA_release
        elif x.Platform == 'PS3':
            return x.Year_of_Release - PS3_release
        elif x.Platform == 'PS':
            return x.Year_of_Release - PS_release
        elif x.Platform == 'PSP':
            return x.Year_of_Release - PSP_release
        elif x.Platform == 'XB':
            return x.Year_of_Release - XB_release
        elif x.Platform == 'GB':
            return x.Year_of_Release - GB_release
        elif x.Platform == 'DS':
            return x.Year_of_Release - DS_release
        elif x.Platform == '3DS':
            return x.Year_of_Release - x3DS_release
        elif x.Platform == 'N64':
            return x.Year_of_Release - N64_release
        elif x.Platform == 'PSV':
            return x.Year_of_Release - PSV_release
        elif x.Platform == 'GC':
            return x.Year_of_Release - GC_release
        else:
            return 1


df.year_after_release = df.apply(year_after_release_filler, axis=1)
df.drop(index=[15959],inplace=True)
df[df['year_after_release'] <0]
```

[195]:

```
                                    Name Platform  Year_of_Release  \
1340                   Disney's DuckTales       GB             1988
2076                       NFL Fever 2002       XB             2000
12301  ESPN Winter X-Games: Snowboarding 2002      GBA             2000
```

```
          Genre                      Publisher  NA_Sales  EU_Sales  JP_Sales  \
1340   Platform                        Capcom      0.82      0.23      0.35
2076     Sports         Microsoft Game Studios      0.74      0.21      0.00
12301    Sports  Konami Digital Entertainment      0.05      0.02      0.00

       Other_Sales  Global_Sales  ...  Critic_Count  User_Score  User_Count  \
1340          0.03          1.43  ...            21         0.0          24
2076          0.04          0.99  ...            24         8.5          10
12301         0.00          0.06  ...            21         0.0          24

        Rating Global_Sales_Log  NA_Sales_Log  EU_Sales_Log  JP_Sales_Log  \
1340   Unknown         0.887891      0.598837      0.207014      0.300105
2076         E         0.688135      0.553885      0.190620      0.000000
12301  Unknown         0.058269      0.048790      0.019803      0.000000

       Other_Sales_Log  year_after_release
1340          0.029559                  -1
2076          0.039221                  -1
12301         0.000000                  -1

[3 rows x 21 columns]
```

2.0.1 Learning(Training) and Evaluation(Testing)

2.0.2 Split Train Cases and Test Cases

[196]:
```
# Split training-test data
# For the first ML models, we will use 'Global_Sales_Log' as the target␣
↪variable.

# Standardizing numerical features
# User_Score features that need to be standardized are: Critic_Score,␣
↪Critic_Count, User_Count, year_after_release

df10=df

# Encoding categorical features
# We will now create dummy variables for Platform, Genre, Publisher and Rating.

df_dummies = pd.get_dummies(df10[['Platform','Genre','Publisher','Rating']],␣
↪drop_first = True)
# Merge the dummies dataframe with the original dataframe
df10 = pd.merge(df_dummies, df10, left_index=True, right_index=True)


from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
```

```
print(df10.columns)
scaled_features = scaler.fit_transform(df10[['Critic_Score',␣
↪'Critic_Count','User_Score','User_Count','year_after_release']])
scaled_df = pd.DataFrame(scaled_features, columns=['Critic_Score',␣
↪'Critic_Count','User_Score','User_Count','year_after_release'])

df10 = pd.merge(scaled_df, df, left_index=True, right_index=True)


# # Drop original non-standardized features
columns = ['Critic_Score_y',␣
↪'Critic_Count_y','User_Score_y','User_Count_y','NA_Sales',␣
↪'EU_Sales','JP_Sales','Other_Sales','Global_Sales','year_after_release_y']
df10.drop(columns, inplace=True, axis=1)

X = df10.
↪drop(['Global_Sales_Log','NA_Sales_Log','EU_Sales_Log','JP_Sales_Log','Other_Sales_Log'],␣
↪axis=1)
y = df10['Global_Sales_Log']
X=df10[['Critic_Score_x', 'Critic_Count_x', 'User_Score_x', 'User_Count_x',␣
↪'year_after_release_x', 'NA_Sales_Log']]
```

```
Index(['Platform_3DO', 'Platform_3DS', 'Platform_DC', 'Platform_DS',
       'Platform_GB', 'Platform_GBA', 'Platform_GC', 'Platform_GEN',
       'Platform_GG', 'Platform_N64',
       ...
       'Critic_Count', 'User_Score', 'User_Count', 'Rating',
       'Global_Sales_Log', 'NA_Sales_Log', 'EU_Sales_Log', 'JP_Sales_Log',
       'Other_Sales_Log', 'year_after_release'],
      dtype='object', length=649)
```

[197]:
```
##Learning and evaluation

from sklearn.model_selection import KFold
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33,␣
↪random_state=101)



from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import learning_curve
```

2.1 1.First ML Problem

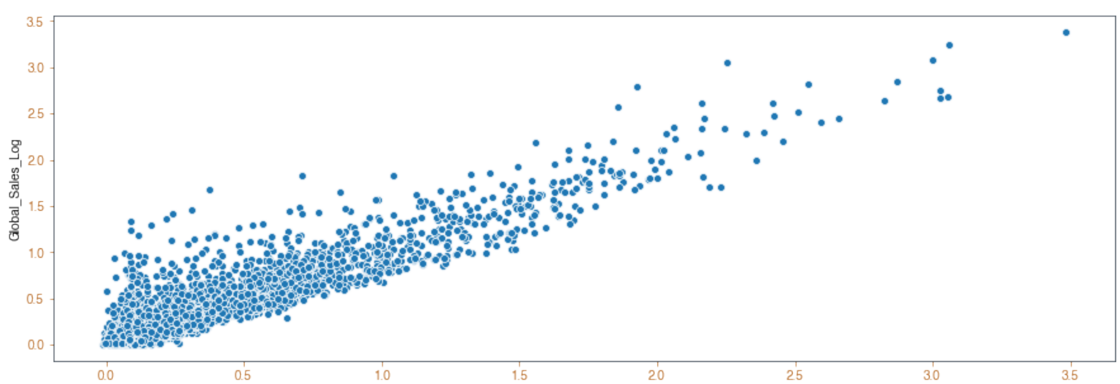
X=> Critic_Score_x', 'Critic_Count_x', 'User_Score_x', 'User_Count_x', 'year_after_release_x'

y=> Global_Sales_Log

1.Linear Regression

[222]:
```
# 1.Linear Regression

from sklearn.linear_model import LinearRegression

lr = LinearRegression()
lr.fit(X_train,y_train)
lr_predictions = lr.predict(X_test)
# Evaluate model
from sklearn.metrics import explained_variance_score, mean_squared_error,␣
 ↪mean_absolute_error

sns.scatterplot(lr_predictions,y_test)

MAE_lr = mean_absolute_error(y_test, lr_predictions)
MSE_lr = mean_squared_error(y_test, lr_predictions)
var_lr = explained_variance_score(y_test, lr_predictions)

print("accuracy :" + str(lr.score(X_test,y_test)))
print("mean_absolute_error :" + str(MAE_lr))
print("mean_squared_error :" + str(MSE_lr))
print("variance_score :" + str(var_lr))
```

```
accuracy :0.8523184660252421
mean_absolute_error :0.09902835743695935
mean_squared_error :0.02286022063308966
variance_score :0.8523184741545611
```

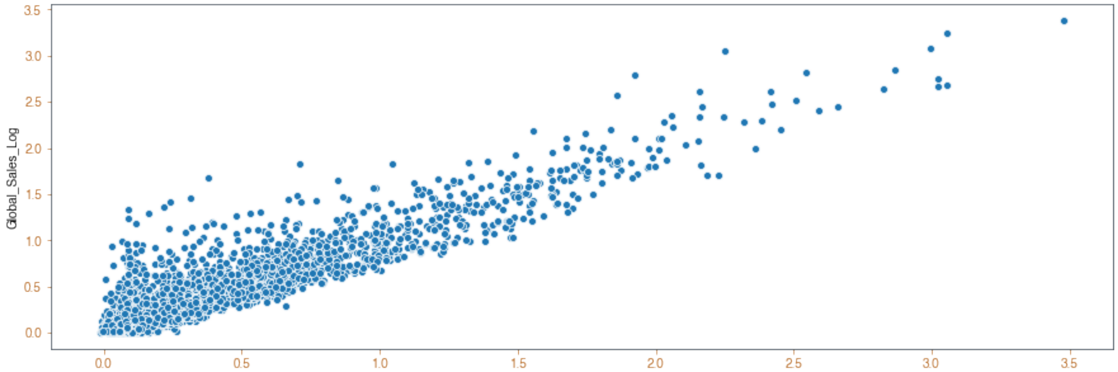


2. Ridge Regression

[223]:
```
# 2. Ridge Regression

from sklearn.linear_model import Ridge

ridge = Ridge()
parameters = {'alpha':[0.001,0.005,0.01,0.1,0.5,1], 'normalize':[True,False],␣
 ↪'tol':[1e-06,5e-06,1e-05,5e-05]}
grid_ridge = GridSearchCV(ridge, parameters, cv=10, verbose=1, scoring =␣
 ↪'explained_variance')
grid_ridge.fit(X_train, y_train)

print(grid_ridge.best_score_)
print(grid_ridge.best_params_)

ridge_optimized = Ridge(alpha= 1, normalize= False, tol=1e-06)

ridge_optimized.fit(X_train,y_train)

ridge_pred = ridge_optimized.predict(X_test)

MAE_ridge = mean_absolute_error(y_test, ridge_pred)
MSE_ridge = mean_squared_error(y_test, ridge_pred)
var_ridge = explained_variance_score(y_test, ridge_pred)
print("mean_absolute_error :" + str(MAE_ridge))
print("mean_squared_error :" + str(MSE_ridge))
print("variance :" + str(var_ridge))
print("accuracy :" + str(ridge_optimized.score(X_test,y_test)))
sns.scatterplot(ridge_pred,y_test)
```

```
Fitting 10 folds for each of 48 candidates, totalling 480 fits

[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.

0.8434304695922168
{'alpha': 0.1, 'normalize': False, 'tol': 1e-06}
mean_absolute_error :0.09908128080265304
mean_squared_error :0.022863384030535606
variance :0.8522980350467355
accuracy :0.8522980298538295

[Parallel(n_jobs=1)]: Done 480 out of 480 | elapsed:    1.3s finished
```

[223]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1a237acb38>
```



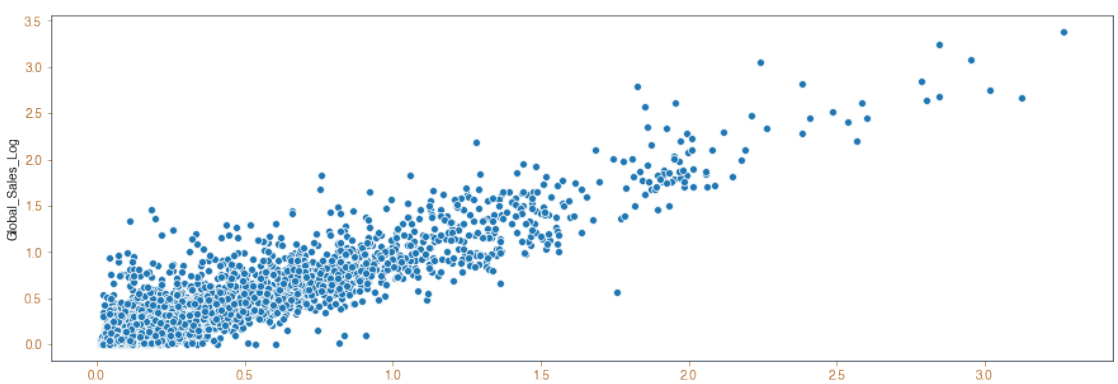
3. RandomForest Regression

[226]:
```
from sklearn.ensemble import RandomForestRegressor
rf = RandomForestRegressor()
rf.fit(X_train,y_train)
rf_predictions = rf.predict(X_test)
MAE_rf = mean_absolute_error(y_test, rf_predictions)
MSE_rf = mean_squared_error(y_test, rf_predictions)
print("mae: " + str(MAE_rf))
print("mse: " + str(MSE_rf))
print("accuracy :" + str(rf.score(X_test,y_test)))
print("variance :" + str(explained_variance_score(y_test, rf_predictions)))
```

```
mae: 0.09884309984717227
mse: 0.02510867527810916
accuracy :0.8377930055592785
variance :0.8379337860864112
```

[201]:
```
sns.scatterplot(rf_predictions,y_test)
```

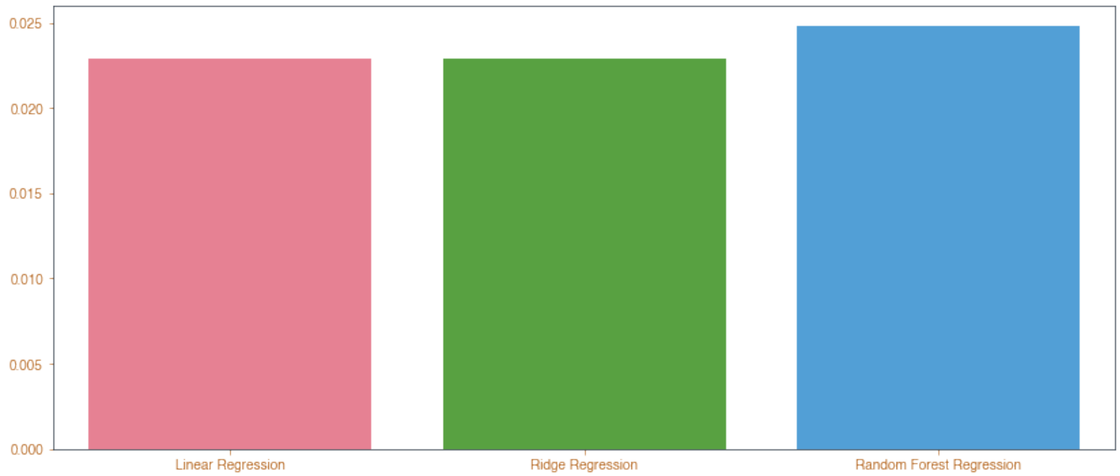
[201]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1a1be7a2b0>
```



2.1.1 Evaluate different models

[202]:
```
# # Comparison of MSE of the models
MSEs = [0.022860,0.022863,0.02479]

models = ['Linear Regression','Ridge Regression','Random Forest Regression']
plt.figure(figsize=(14,6))
sns.barplot(models,MSEs,palette='husl')
```

[202]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1a1cc63d68>
```



2.1.2 2. Second ML Problem

X=> Year_of_Release Critic_Score

y=> Hit

2.1.3 RandomForestClassifier,LogisticRegression

[231]:
```
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, f1_score, accuracy_score,␣
↪confusion_matrix
from sklearn import svm
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import roc_auc_score
from sklearn.metrics import classification_report
```

```
dfa= df.copy()
dfb =␣
↪dfa[['Name','Platform','Genre','Publisher','Year_of_Release','Critic_Score','Global_Sales']]
dfb = dfb.dropna().reset_index(drop=True)
df2 =␣
↪dfb[['Platform','Genre','Publisher','Year_of_Release','Critic_Score','Global_Sales']]
df2['Hit'] = df2['Global_Sales']
df2.drop('Global_Sales', axis=1, inplace=True)


def hit(sales):
    if sales >= 1:
        return 1
    else:
        return 0

df2['Hit'] = df2['Hit'].apply(lambda x: hit(x))

df3 = df2[['Year_of_Release','Critic_Score','Hit']]
y = df3['Hit'].values
df3 = df3.drop(['Hit'],axis=1)
X = df3.values

Xtrain, Xtest, ytrain, ytest = train_test_split(X, y, test_size=0.50,␣
↪random_state=2)

print('X Year_of_Release Critic_Score')
print('Y Hit')

radm = RandomForestClassifier(random_state=2).fit(Xtrain, ytrain)
y_val_1 = radm.predict_proba(Xtest)
ypred3 = radm.predict(Xtest)

print("Validation accuracy with RandomForestClassifier: %0.2f"␣
↪%(accuracy_score(ytest, ypred3)))

MAE_rf = mean_absolute_error(ytest, ypred3)
MSE_rf = mean_squared_error(ytest, ypred3)
print("mae for RandomForestClassifier: " + str(MAE_rf))
print("mse for RandomForestClassifier: " + str(MSE_rf))
print("accuracy for RandomForestClassifier:" + str(radm.score(Xtest,ytest)))
print("variance for RandomForestClassifier :" +␣
↪str(explained_variance_score(ytest, ypred3)))

log_reg = LogisticRegression().fit(Xtrain, ytrain)
y_val_2 = log_reg.predict_proba(Xtest)
ypred = log_reg.predict(Xtest)
```

```
print("Validation accuracy with LogisticRegression: %0.2f"␣
 ↪%(accuracy_score(ytest, ypred)))

print('Regression on training set:',log_reg.score(Xtrain, ytrain))
print('Regression Score on test set:',log_reg.score(Xtest, ytest))

print("mae for LogisticRegression: " + str(mean_absolute_error(ytest, ypred)))
print("mse for LogisticRegression: " + str(mean_squared_error(ytest, ypred)))
print("accuracy for LogisticRegression:" + str(log_reg.score(Xtest,ytest)))
print("variance for LogisticRegression :" + str(explained_variance_score(ytest,␣
 ↪ypred)))


from sklearn.linear_model import LinearRegression

LR = LinearRegression()
model = LR.fit(Xtrain, ytrain)
pd.DataFrame({'features': df3.columns, 'estimatedCoefficients': model.
 ↪coef_})[['features', 'estimatedCoefficients']].
 ↪sort_values(by='estimatedCoefficients', ascending=False)
```

```
X Year_of_Release Critic_Score
Y Hit
Validation accuracy with RandomForestClassifier: 0.82
mae for RandomForestClassifier: 0.18015534953645704
mse for RandomForestClassifier: 0.18015534953645704
accuracy for RandomForestClassifier:0.8198446504635429
variance for RandomForestClassifier :-0.20697724448893373
Validation accuracy with LogisticRegression: 0.83
Regression on training set: 0.8466549736908043
Regression Score on test set: 0.8338762214983714
mae for LogisticRegression: 0.16612377850162866
mse for LogisticRegression: 0.16612377850162866
accuracy for LogisticRegression:0.8338762214983714
variance for LogisticRegression :0.014201230193749192
```

[231]:

	features	estimatedCoefficients
1	Critic_Score	0.008154
0	Year_of_Release	0.002191

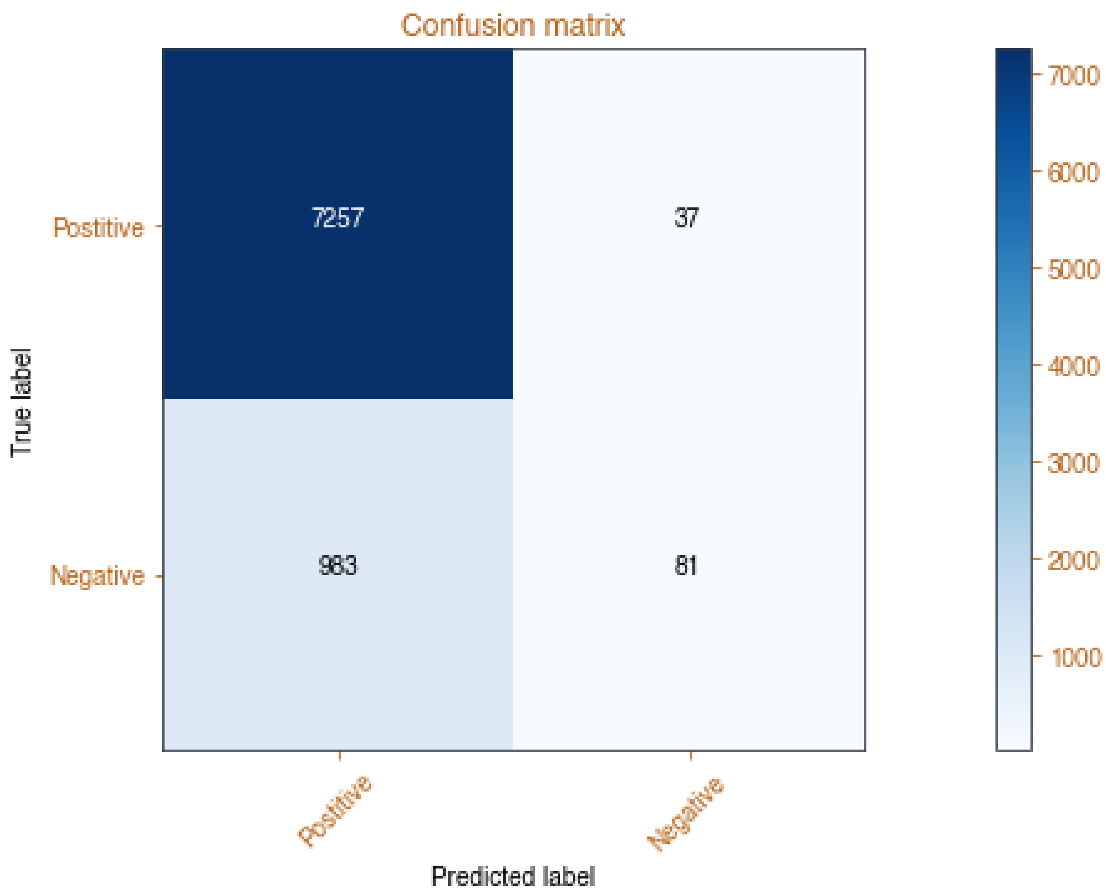
Confusion Matrix, Classification Report,ROC curve

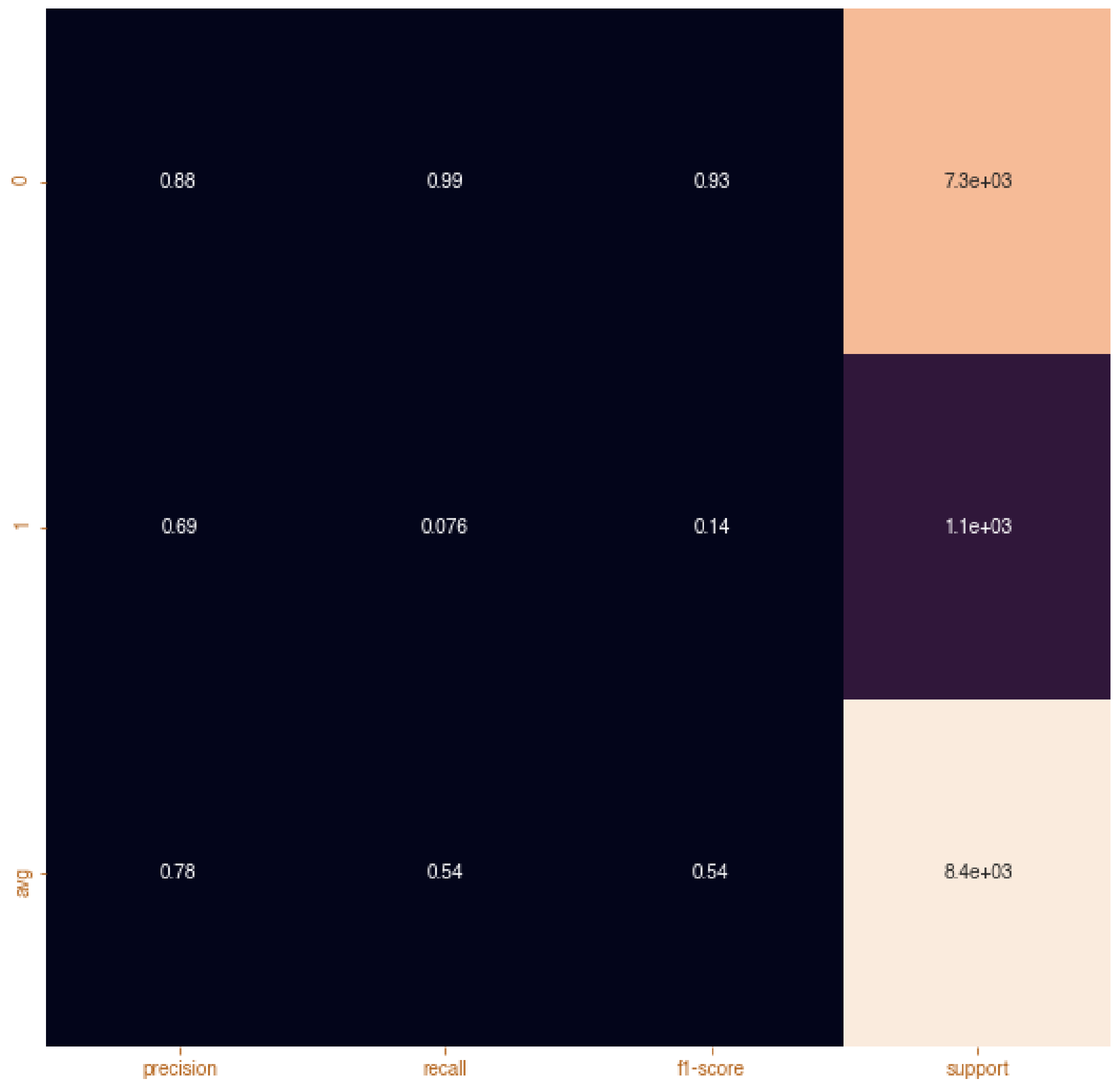
[204]:
```
from sklearn import metrics
from sklearn.metrics import roc_curve
from sklearn.metrics import auc
```

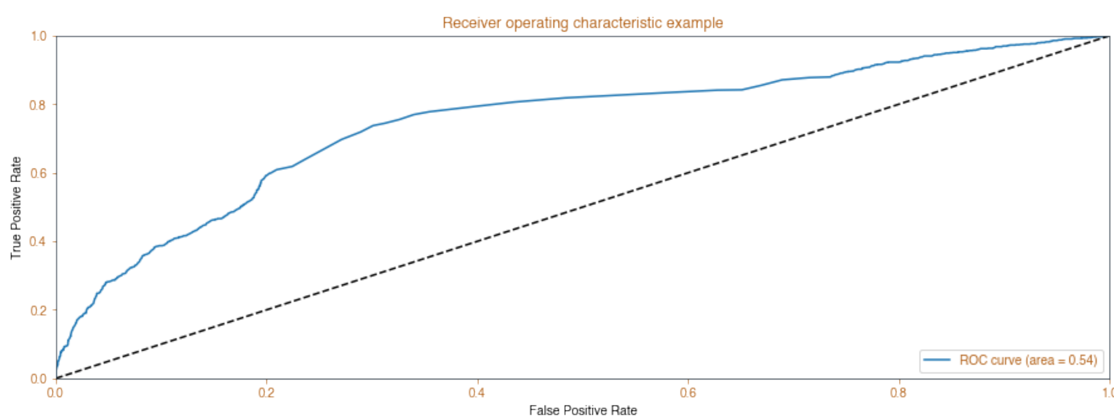
```python
ypred = log_reg.predict(Xtest)
print("Confusion Matrix")
print(confusion_matrix(ytest, ypred))
cm = confusion_matrix(ytest, ypred)
np.set_printoptions(precision=2)
plt.figure()
plot_confusion_matrix(cm, classes=["Postitive", "Negative"],
                      title='Confusion matrix')

print("Classification Report")
print(classification_report(ytest, ypred))
plot_classification_report(ytest, ypred)

logit_roc_auc = roc_auc_score(ytest, ypred)
print("Logistic AUC = %0.2f" %logit_roc_auc)

b = log_reg.predict_proba(Xtest)[:,1]
print(b[0:5])
fpr, tpr, threshold = roc_curve(ytest, b)

# plotting ROC curve
import matplotlib.pyplot as plt
plt.figure()
plt.plot(fpr, tpr, label='ROC curve (area = %0.2f)' %logit_roc_auc)
plt.plot([0,1], [0,1], 'k--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.0])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic example')
plt.legend(loc="lower right")
plt.show()
```

```
Confusion Matrix
[[7257   37]
 [ 983   81]]
Confusion matrix, without normalization
[[7257   37]
 [ 983   81]]
Classification Report
              precision    recall  f1-score   support

           0       0.88      0.99      0.93      7294
           1       0.69      0.08      0.14      1064

    accuracy                           0.88      8358
   macro avg       0.78      0.54      0.54      8358
```

```
weighted avg       0.86      0.88      0.83      8358

Logistic AUC = 0.54
[0.1  0.09 0.05 0.16 0.1 ]
```

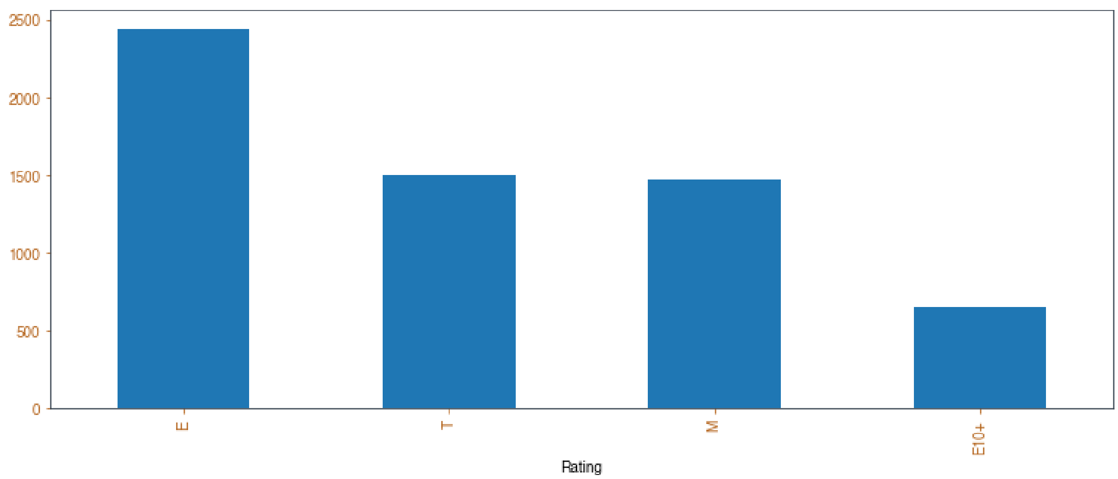



0
1
avg
0.88
0.99
0.93
7.3e+03
0.69
0.076
0.14
1.1e+03
0.78
0.54
0.54
8.4e+03
precision
recall
f1-score
support


Receiver operating characteristic example
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
ROC curve (area = 0.54)

Data Analysis for Ratings. Encoding Ratings and clean up.

[205]:
```
df = pd.read_csv('Video_Games_Sales.csv', encoding="utf-8")
df = df[df.Rating != "RP"]
df = df[df.Rating != "EC"]
df = df[df.Rating != "AO"]
df = df[df.Rating != "K-A"]

ax = df.groupby('Rating').sum().unstack().Global_Sales.
↪sort_values(ascending=False).head(10).plot(kind='bar',
                                                                          ␣
↪                            figsize=(
                                                                          ␣
↪                             13, 5));
```



[206]:
```
df = pd.read_csv('Video_Games_Sales.csv', encoding="utf-8")
df = df[df.Platform != "2600"]
df = df[df.Platform != "3DO"]
df = df[df.Platform != "DC"]
df = df[df.Platform != "GEN"]
df = df[df.Platform != "GG"]
df = df[df.Platform != "NG"]
df = df[df.Platform != "PCFX"]
df = df[df.Platform != "SAT"]
df = df[df.Platform != "SCD"]
df = df[df.Platform != "TG16"]
df = df[df.Platform != "WS"]


df = df[df.User_Score != "tbd"]
df = df.dropna().reset_index(drop=True)
```

```
    df["Platform_XB"] = 0
    df["Platform_X360"] = 0
    df["Platform_XOne"] = 0
    df["Platform_PC"] = 0
    df["Platform_PS"] = 0
    df["Platform_PS2"] = 0
    df["Platform_PS3"] = 0
    df["Platform_PS4"] = 0
    df["Platform_PSP"] = 0
    df["Platform_PSV"] = 0
    df["Platform_GB"] = 0
    df["Platform_GBA"] = 0
    df["Platform_DS"] = 0
    df["Platform_3DS"] = 0
    df["Platform_NES"] = 0
    df["Platform_SNES"] = 0
    df["Platform_N64"] = 0
    df["Platform_GC"] = 0
    df["Platform_Wii"] = 0
    df["Platform_WiiU"] = 0

    for elem in df.index.get_values():
        if df.get_value(elem, "Platform") == "XB": df.set_value(elem,␣
↪"Platform_XB", 1)
        if df.get_value(elem, "Platform") == "X360": df.set_value(elem,␣
↪"Platform_X360", 1)
        if df.get_value(elem, "Platform") == "XOne": df.set_value(elem,␣
↪"Platform_XOne", 1)
        if df.get_value(elem, "Platform") == "PS": df.set_value(elem,␣
↪"Platform_PS", 1)
        if df.get_value(elem, "Platform") == "PS2": df.set_value(elem,␣
↪"Platform_PS2", 1)
        if df.get_value(elem, "Platform") == "PS3": df.set_value(elem,␣
↪"Platform_PS3", 1)
        if df.get_value(elem, "Platform") == "PS4": df.set_value(elem,␣
↪"Platform_PS4", 1)
        if df.get_value(elem, "Platform") == "PSP": df.set_value(elem,␣
↪"Platform_PSP", 1)
        if df.get_value(elem, "Platform") == "PSV": df.set_value(elem,␣
↪"Platform_PSV", 1)
        if df.get_value(elem, "Platform") == "GB": df.set_value(elem,␣
↪"Platform_GB", 1)
        if df.get_value(elem, "Platform") == "GBA": df.set_value(elem,␣
↪"Platform_GBA", 1)
        if df.get_value(elem, "Platform") == "DS": df.set_value(elem,␣
↪"Platform_DS", 1)
```

```
        if df.get_value(elem, "Platform") == "3DS": df.set_value(elem,␣
↪"Platform_3DS", 1)
        if df.get_value(elem, "Platform") == "NES": df.set_value(elem,␣
↪"Platform_NES", 1)
        if df.get_value(elem, "Platform") == "SNES": df.set_value(elem,␣
↪"Platform_SNES", 1)
        if df.get_value(elem, "Platform") == "N64": df.set_value(elem,␣
↪"Platform_N64", 1)
        if df.get_value(elem, "Platform") == "GC": df.set_value(elem,␣
↪"Platform_GC", 1)
        if df.get_value(elem, "Platform") == "Wii": df.set_value(elem,␣
↪"Platform_Wii", 1)
        if df.get_value(elem, "Platform") == "WiiU": df.set_value(elem,␣
↪"Platform_WiiU", 1)

    # Discretizzazione feature Genre

    df["Genre_Action"] = 0
    df["Genre_Adventure"] = 0
    df["Genre_Fighting"] = 0
    df["Genre_Misc"] = 0
    df["Genre_Platform"] = 0
    df["Genre_Puzzle"] = 0
    df["Genre_Shooter"] = 0
    df["Genre_Sports"] = 0
    df["Genre_Simulation"] = 0
    df["Genre_Strategy"] = 0
    df["Genre_Racing"] = 0
    df["Genre_Role-Playing"] = 0

    for elem in df.index.get_values():
        if df.get_value(elem, "Genre") == "Action": df.set_value(elem,␣
↪"Genre_Action", 1)
        if df.get_value(elem, "Genre") == "Adventure": df.set_value(elem,␣
↪"Genre_Adventure", 1)
        if df.get_value(elem, "Genre") == "Fighting": df.set_value(elem,␣
↪"Genre_Fighting", 1)
        if df.get_value(elem, "Genre") == "Misc": df.set_value(elem,␣
↪"Genre_Misc", 1)
        if df.get_value(elem, "Genre") == "Platform": df.set_value(elem,␣
↪"Genre_Platform", 1)
        if df.get_value(elem, "Genre") == "Puzzle": df.set_value(elem,␣
↪"Genre_Puzzle", 1)
        if df.get_value(elem, "Genre") == "Shooter": df.set_value(elem,␣
↪"Genre_Shooter", 1)
```

```
        if df.get_value(elem, "Genre") == "Sports": df.set_value(elem,␣
↪"Genre_Sports", 1)
        if df.get_value(elem, "Genre") == "Simulation": df.set_value(elem,␣
↪"Genre_Simulation", 1)
        if df.get_value(elem, "Genre") == "Strategy": df.set_value(elem,␣
↪"Genre_Strategy", 1)
        if df.get_value(elem, "Genre") == "Racing": df.set_value(elem,␣
↪"Genre_Racing", 1)
        if df.get_value(elem, "Genre") == "Role-Playing": df.set_value(elem,␣
↪"Genre_Role-Playing", 1)


    df["Rating_Everyone"] = 0
    df["Rating_Everyone10"] = 0
    df["Rating_Teen"] = 0
    df["Rating_Mature"] = 0
    df["Rating_Adult"] = 0

    for elem in df.index.get_values():
        if df.get_value(elem, "Rating") == "E": df.set_value(elem,␣
↪"Rating_Everyone", 1)
        if df.get_value(elem, "Rating") == "E10+": df.set_value(elem,␣
↪"Rating_Everyone10", 1)
        if df.get_value(elem, "Rating") == "T": df.set_value(elem,␣
↪"Rating_Teen", 1)
        if df.get_value(elem, "Rating") == "M": df.set_value(elem,␣
↪"Rating_Mature", 1)
        if df.get_value(elem, "Rating") == "AO": df.set_value(elem,␣
↪"Rating_Adult", 1)

    # Discretizzazione feature Publisher

    publisher_list = []

    for elem in df.Publisher:
        if elem not in publisher_list:
            publisher_list.append(elem)

    for elem in publisher_list:
        df[elem] = 0

    for elem in df.index.get_values():
        df.set_value(elem, df.get_value(elem, "Publisher"), 1)

    # Discretizzazione feature Developer
```

```
developer_list = []

for elem in df.Developer:
    if elem not in developer_list:
        developer_list.append(elem)

for elem in developer_list:
    df[elem] = 0

for elem in df.index.get_values():
    df.set_value(elem, df.get_value(elem, "Developer"), 1)


df = df[df.Rating != 'AO']
df = df[df.Rating != 'K-A']
df = df[df.Rating != 'RP']
df = df[df.Rating != 'EC']


del df['User_Score']
del df['User_Count']
del df['Critic_Score']
del df['Critic_Count']

del df['Platform']
del df['Genre']
del df['Publisher']
del df['Developer']


del df['Rating_Adult']

df = df.reindex(np.random.permutation(df.index)).reset_index(drop=True)

y_true = np.array(df['Rating'])
vector_names = np.array(df['Name'])
del df['Name']

y_true_int = np.empty(len(y_true), dtype=int)
i = 0
for elem in y_true:
    if elem == "E":
        y_true_int[i] = 1
    elif elem == "E10+":
        y_true_int[i] = 2
    elif elem == "T":
        y_true_int[i] = 3
```

```
        else:
            y_true_int[i] = 4
        i += 1

    del df['Rating']

    df = df.astype('float64')

    print(" Dataset Analysis  ")

    print_e = df["Rating_Everyone"].value_counts()[1]
    print_e10 = df["Rating_Everyone10"].value_counts()[1]
    print_teen = df["Rating_Teen"].value_counts()[1]
    print_mature = df["Rating_Mature"].value_counts()[1]

    print("Number of elements: " + str(print_e + print_e10 + print_teen +␣
↪print_mature) + "\n")

    df_stampa = pd.DataFrame({"Rating": ['Everyone', 'Everyone 10+', 'Teen',␣
↪'Mature'],
                              "Counts": [print_e, print_e10, print_teen,␣
↪print_mature]})

    cols = df_stampa.columns.tolist()
    cols = cols[-1:] + cols[:-1]
    df_stampa = df_stampa[cols]

    print(df_stampa)
```

```
 Dataset Analysis
Number of elements: 6808

   Counts        Rating
0    2079      Everyone
1     930  Everyone 10+
2    2367          Teen
3    1432        Mature
```

Utility Function for plot_learning_curve.

[207]:
```
def plot_learning_curve(estimator, title, X, y, ylim=None, cv=None, n_jobs=1,␣
↪train_sizes=np.linspace(.1, 1.0, 5)):
    plt.figure()
    plt.title(title)
    if ylim is not None:
        plt.ylim(*ylim)
    plt.xlabel("Training examples")
```

```
    plt.ylabel("Score")
    train_sizes, train_scores, test_scores = learning_curve(estimator, X, y,␣
↪cv=cv, n_jobs=n_jobs,
                                                                        ␣
↪train_sizes=train_sizes)
    train_scores_mean = np.mean(train_scores, axis=1)
    train_scores_std = np.std(train_scores, axis=1)
    test_scores_mean = np.mean(test_scores, axis=1)
    test_scores_std = np.std(test_scores, axis=1)
    plt.grid()

    plt.fill_between(train_sizes, train_scores_mean - train_scores_std,
                     train_scores_mean + train_scores_std, alpha=0.1,
                     color="r")
    plt.fill_between(train_sizes, test_scores_mean - test_scores_std,
                     test_scores_mean + test_scores_std, alpha=0.1, color="g")
    plt.plot(train_sizes, train_scores_mean, 'o-', color="r",
             label="train_scores_mean")
    plt.plot(train_sizes, test_scores_mean, 'o-', color="g",
             label="Test_scores_mean")

    plt.legend(loc="best")
    return plt
```

[208]:
```
### 3. Third ML Problem
#### X=> Year_of_Release Sales Platform
#### y=> RATING EVERYONE
```

[209]:
```
#### Random Forest
```

[210]:
```
    from sklearn.model_selection import learning_curve
    import pandas as pd
    import numpy as np
    import seaborn as sns

    from sklearn.neighbors import KNeighborsClassifier
    from sklearn.model_selection import train_test_split
    from sklearn.metrics import accuracy_score
    from sklearn.model_selection import cross_val_score
    from sklearn.linear_model import LogisticRegression
    from sklearn.ensemble import RandomForestClassifier
    from sklearn.ensemble import VotingClassifier

    from sklearn.model_selection import learning_curve
    import matplotlib.pyplot as plt

    print("RATING EVERYONE")
```

```
    df2 = df
    y = df2['Rating_Everyone'].values
    df2 = df2.drop(['Rating_Everyone'], axis=1)
    df2 = df2.drop(['Rating_Everyone10'], axis=1)
    df2 = df2.drop(['Rating_Teen'], axis=1)
    df2 = df2.drop(['Rating_Mature'], axis=1)
    X = df2.values


    Xtrain, Xtest, ytrain, ytest = train_test_split(X, y, test_size=0.20)


    print("Random Forest: ")
    plot_learning_curve(RandomForestClassifier(), "Rating_Everyone Learning␣
↪Curves (Random Forest)", X, y,
                        n_jobs=-1)
```

```
RATING EVERYONE
Random Forest:
```

[210]:

```
<module 'matplotlib.pyplot' from
'/Users/nselvarajan/anaconda3/lib/python3.7/site-packages/matplotlib/pyplot.py'>
```

k-NN

[211]:

```
print("k-NN: ")
plot_learning_curve(KNeighborsClassifier(), "Rating_Everyone Learning Curves␣
 ↪(k-NN)", X, y, n_jobs=-1)
```

```
k-NN:
```

[211]: <module 'matplotlib.pyplot' from
'/Users/nselvarajan/anaconda3/lib/python3.7/site-packages/matplotlib/pyplot.py'>

LogisticRegression

[232]:
```
    log_reg1 = LogisticRegression(penalty='l1', dual=False, C=1.0,␣
↪fit_intercept=True, intercept_scaling=1,
                                  class_weight=None, random_state=None,␣
↪solver='liblinear', max_iter=100,
                                  multi_class='ovr', verbose=0,␣
↪warm_start=False, n_jobs=1)
    log_reg1.fit(Xtrain, ytrain)
    y_val_l = log_reg1.predict(Xtest)
    ris = accuracy_score(ytest, y_val_l)
    mis = accuracy_score(ytest, y_val_l, normalize=False)

    print("Logistic Regression Rating_Everyone accuracy: ", ris)
    print("Logistic Regression Rating_Everyone misclassification: ", ytest.size␣
↪- mis)
    MAE_rf = mean_absolute_error(ytest, y_val_l)
    MSE_rf = mean_squared_error(ytest, y_val_l)
    print("mae for Logistic Regression: " + str(MAE_rf))
    print("mse for Logistic Regression: " + str(MSE_rf))
    print("accuracy for Logistic Regression:" + str(log_reg1.
↪score(Xtest,y_val_l)))
    print("variance for Logistic Regression :" +␣
↪str(explained_variance_score(ytest, y_val_l)))
```

```
Logistic Regression Rating_Everyone accuracy:  0.8333750939614132
Logistic Regression Rating_Everyone misclassification:  665
mae for Logistic Regression: 0.16662490603858682
mse for Logistic Regression: 0.16662490603858682
```

```
accuracy for Logistic Regression:0.8333750939614132
variance for Logistic Regression :0.011810211222773925
```

RandomForestClassifier

[233]:
```
radm1 = RandomForestClassifier(n_estimators=240, criterion='gini',␣
↪max_depth=None, min_samples_split=2,
                               min_samples_leaf=1,
                               min_weight_fraction_leaf=0.0,␣
↪max_features='auto', max_leaf_nodes=None,
                               min_impurity_split=1e-07, bootstrap=True,
                               oob_score=True, n_jobs=1, random_state=None,␣
↪verbose=0, warm_start=False,
                               class_weight=None)
radm1.fit(Xtrain, ytrain)
y_val_l = radm1.predict(Xtest)
ris = accuracy_score(ytest, y_val_l)
mis = accuracy_score(ytest, y_val_l, normalize=False)
print("Random Forest Rating_Everyone accuracy: ", ris)
print("Random Forest Rating_Everyone misclassification: ", ytest.size - mis)
MAE_rf = mean_absolute_error(ytest, y_val_l)
MSE_rf = mean_squared_error(ytest, y_val_l)
print("mae for RandomForestClassifier: " + str(MAE_rf))
print("mse for RandomForestClassifier: " + str(MSE_rf))
print("accuracy for RandomForestClassifier:" + str(radm1.
↪score(Xtest,ytest)))
print("variance for RandomForestClassifier :" +␣
↪str(explained_variance_score(ytest, y_val_l)))
```

```
Random Forest Rating_Everyone accuracy:  0.8153345026309196
Random Forest Rating_Everyone misclassification:  737
mae for RandomForestClassifier: 0.18466549736908044
mse for RandomForestClassifier: 0.18466549736908044
accuracy for RandomForestClassifier:0.8153345026309196
variance for RandomForestClassifier :-0.24269676733883894
```

KNeighborsClassifier

[237]:
```
knn1 = KNeighborsClassifier(n_neighbors=10, weights='uniform',␣
↪algorithm='auto', leaf_size=30, p=1,
                            metric='minkowski', metric_params=None,␣
↪n_jobs=1)
knn1.fit(Xtrain, ytrain)
y_val_l = knn1.predict(Xtest)
ris = accuracy_score(ytest, y_val_l)
mis = accuracy_score(ytest, y_val_l, normalize=False)
print("K-Nearest Neighbors Rating_Everyone accuracy: ", ris)
```

```
    print("K-Nearest Neighbors Rating_Everyone misclassification: ", ytest.size␣
↪- mis)
    print("K-Nearest Neighbors Rating_Everyone accuracy: ", ris)
    print("K-Nearest Neighbors Rating_Everyone misclassification: ", ytest.size␣
↪- mis)
    MAE_rf = mean_absolute_error(ytest, y_val_l)
    MSE_rf = mean_squared_error(ytest, y_val_l)
    print("mae for K-Nearest Neighbors: " + str(MAE_rf))
    print("mse for K-Nearest Neighbors: " + str(MSE_rf))
    print("accuracy for K-Nearest Neighbors:" + str(ris))
    print("variance for K-Nearest Neighbors :" +␣
↪str(explained_variance_score(ytest, y_val_l)))

    print("\n")
```

```
K-Nearest Neighbors Rating_Everyone accuracy:  0.8376346780255575
K-Nearest Neighbors Rating_Everyone misclassification:  648
K-Nearest Neighbors Rating_Everyone accuracy:  0.8376346780255575
K-Nearest Neighbors Rating_Everyone misclassification:  648
mae for K-Nearest Neighbors: 0.1623653219744425
mse for K-Nearest Neighbors: 0.1623653219744425
accuracy for K-Nearest Neighbors:0.8376346780255575
variance for K-Nearest Neighbors :-0.03927400129078129
```

Evaluate Different Models

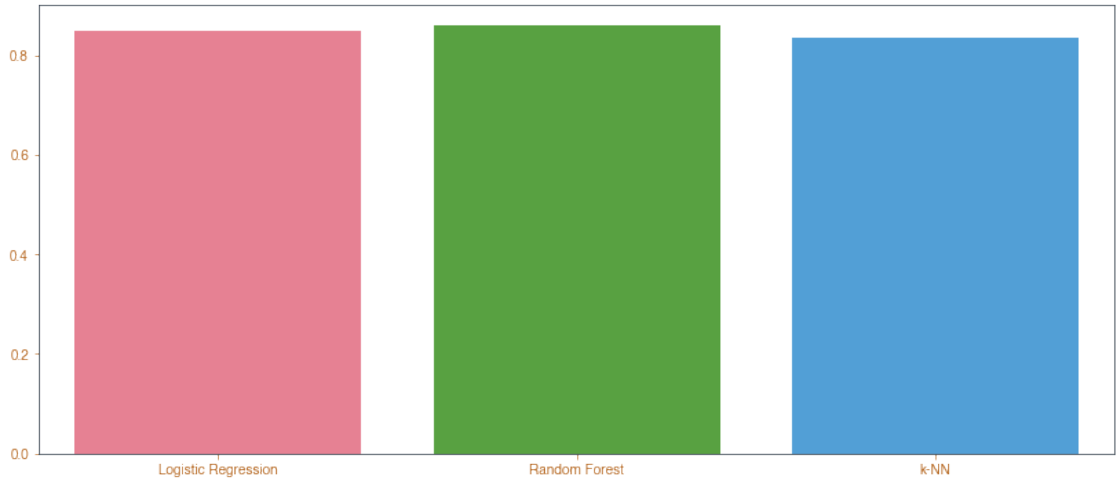
[215]:
```
    for clf, label in zip([log_reg1, radm1, knn1], ['Logistic Regression',␣
↪'Random Forest', 'k-NN']):
        scores = cross_val_score(clf, X, y, cv=5, scoring='accuracy')
        print("Accuracy Score: %0.5f [%s]" % (scores.mean(), label))
```

```
Accuracy Score: 0.85165 [Logistic Regression]
Accuracy Score: 0.85899 [Random Forest]
Accuracy Score: 0.83681 [k-NN]
```

2.2 Comparison of Accuracy of the models

[216]:
```
# # Comparison of Accuracy of the models
MSEs = [0.84768,0.85913,0.83519]

models = ['Logistic Regression','Random Forest','k-NN']
plt.figure(figsize=(14,6))
sns.barplot(models,MSEs,palette='husl')
```

[216]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1a208b35f8>
```


0.8
0.6
0.4
0.2
0.0
Logistic Regression
Random Forest
k-NN

[ ]:

[ ]:

[ ]: