```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```

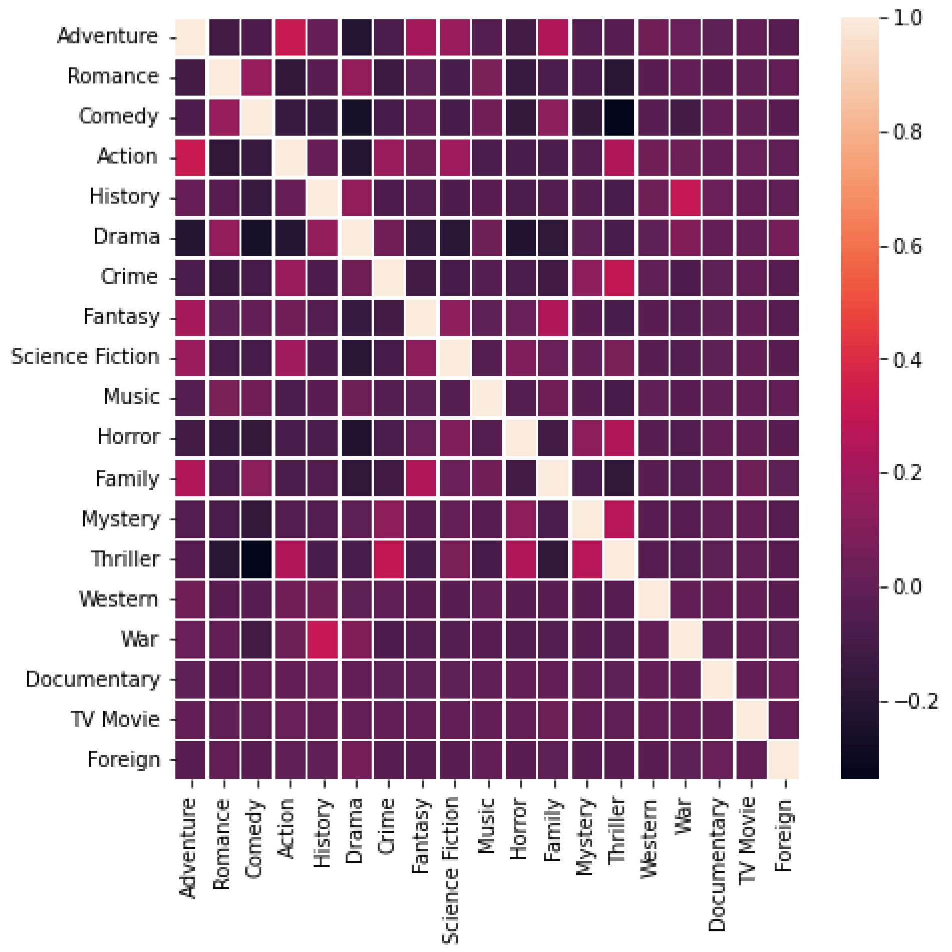
```
# Pandas is used to convert our csv to workable dataframe.
import pandas as pd

# Seabord is an advanced visualising tool, used here , for Heat maps.
import seaborn as sns

# Matplotlib is used to plot data into graphs.
import matplotlib.pyplot as plt

# Using Sklearn to model and retrieve evaluation metrics.
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix
from sklearn.metrics import precision_score, f1_score, roc_curve
from sklearn.metrics import auc, recall_score, roc_auc_score
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn import tree
from sklearn.ensemble import RandomForestClassifier
```

```
# Importing the cleaned Dataset into a pandas variable called df
df  = pd.read_csv("/content/drive/MyDrive/IDMP PROJECT/Final  Dataset/Final Dataset.csv")
```

```
# Accessing only the genres related columns from the dataframe
genres = df[df.columns[126:146]]
```

```
# Using the matplotlib library to retireve a subplot of size 7x7
fig, ax = plt.subplots(figsize=(7,7))
# Using the Seaborn library to plot the heatmap on our subplot
sns.heatmap(genres.corr(), linewidths=.5, ax=ax)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f7632591ad0>
```




```
# Converting the Bool column "adult" into 1s and 0s
df["adult"].replace(True,'1', inplace=True)
df['adult'].replace(False,'0', inplace=True)
```

```
# Retriving the correlation values of only the target variable
# corr() gives the correlation values of all variables against each other.
# Since df is a pandas dataframe, we use column name(hit/not)
# to retrieve the correlation vlaues relative to that column

cor = df.corr()
cor_tar = cor["hit/not"]

#Using a threshold value of 0.04 we choose the columns only that
# have correlation greater than threshold

```

```
threshold = 0.04
rel_cor = cor_tar[abs(cor_tar) > threshold ]
```

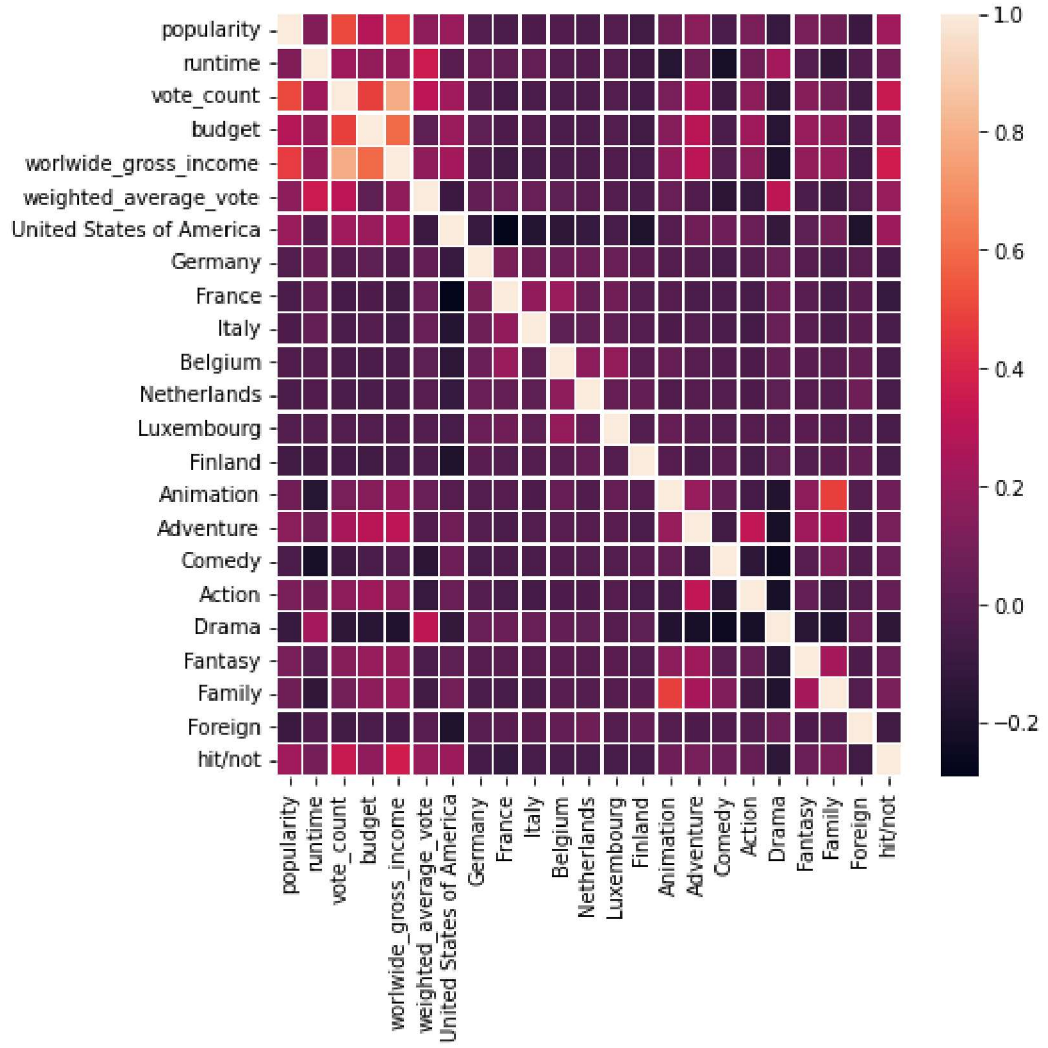
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8992 entries, 0 to 8991
Columns: 147 entries, adult to hit/not
dtypes: float64(4), int64(135), object(8)
memory usage: 10.1+ MB
```

```
# rel_cols only contain those columns that have greater correlation with our
# target variable.

rel_cols = ["popularity","runtime","vote_count","budget","worlwide_gross_income",
            "weighted_average_vote","United States of America","Germany","France",
            "Italy","Belgium","Netherlands","Luxembourg","Finland","Animation",
            "Adventure","Comedy","Action","Drama","Fantasy","Family","Foreign",
            "hit/not"]
# Filtering out the columns that are irrelevant to our model
non_rel = []
for col in df.columns:
    if col not in rel_cols:
        non_rel.append(col)

# using drop() to drop those columns from our dataframe
df = df.drop(non_rel, axis=1)
```

```
# creating a Heat map for relevant Columns
fig, ax = plt.subplots(figsize=(7,7))
sns.heatmap(df.corr(), linewidths=.5, ax=ax)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f763c010710>
```




```
## Splitting data into Test and Training set

X = df.iloc[:, :-1:]
y = df.iloc[:, -1]

x_train, x_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
                                                    random_state=0)
```

```
# Evaluation Metrics
# Using Sklearns to calculate metrics
# We are calculating accuracy, precision, F1-score, AUC and Specificity
def eval_metrics(y_test, y_pred):
  accuracy = accuracy_score(y_test, y_pred)
  cm = confusion_matrix(y_test, y_pred)
  precision = precision_score(y_test, y_pred)
  recall = recall_score(y_test, y_pred)
  f1 = f1_score(y_test, y_pred)
  fpr, tpr, thresholds = roc_curve(y_test, y_pred, pos_label=1)
```

```
    A = auc(fpr, tpr)
    roc = roc_auc_score(y_test, y_pred)
    tn, fp, fn, tp = cm.ravel()
    specificity = tn / (tn+fp)
    return accuracy*100, precision, recall, f1, A, specificity

```

Logistic Regression

```
# Using Logistic Regression model from Sklearn to model our data.
# Since it is a basic model, the we used mse to calculate error.

# loading the LogisticRegression module in to lr
lr = LogisticRegression()

# Fitting the model to our train set
lr.fit(x_train, y_train)

# Using the trained model to predict out X_Test
pred = lr.predict(x_test)

# Calculating our evaluation metrics using sklearn build-in package.
acc_lr,precision_lr, rec_lr, f1_lr, areaUnderCurve_lr, spec_lr= eval_metrics(y_test, pred)

# Printing out the Evaluation Metrics
print(f"The metrics for Logistic regression are: \n Accuracy: {acc_lr}% ",
      f"\nPrecision: {precision_lr} \nRecall: {rec_lr} \nF1 score: {f1_lr} ",
      f"\nArea Under Curve: {areaUnderCurve_lr}  \nSpecificity: {spec_lr}")

```

```
The metrics for Logistic regression are:
 Accuracy: 100.0%
Precision: 1.0
Recall: 1.0
F1 score: 1.0
Area Under Curve: 1.0
Specificity: 1.0
```

KNN:

```
# Using KneighborsClassifier model from Sklearn to model our data.
# Since it is a basic model, the we used mse to calculate error.

# loading the KNeighborsClassifier module in to knn
knn = KNeighborsClassifier()

# Fitting the model to our train set
knn.fit(x_train, y_train)

#  Using the trained model to predict out X_Test
y_pred_knn = knn.predict(x_test)

# Calculating our evaluation metrics using sklearn build-in package.
acc_knn, precision_knn, rec_knn, f1_knn, areaUnderCurve_knn, spec_knn = eval_metrics(y_test, y_pred_knn)

# Printing out the Evaluation Metrics
print(f"The metrics for KNN are: \n Accuracy: {acc_knn}%  \nPrecision: {precision_knn}"+
      f" \nRecall: {rec_knn} \nF1 score: {f1_knn} \nArea Under Curve: {areaUnderCurve_knn}"+
      f" \nSpecificity: {spec_knn}")

```

```
The metrics for KNN are:
 Accuracy: 99.27737632017788%
Precision: 0.9913606911447084
Recall: 0.9945828819068255
F1 score: 0.9929691725256895
Area Under Curve: 0.9927252309077507
Specificity: 0.9908675799086758
```

Decision Tree:

```
# Using KneighborsClassifier model from Sklearn to model our data.
# For Decision Tree we take Cross-Entropy Loss as loss function.
# We set that minimum split samples to be 5
# minimum number of leaf nodes is 6
# and we set the max_features to auto to facilitate the model to random skip a few features.
# Random State is set as 50.

# loading the KNeighborsClassifier module in to dt with hyperparameters
dt = tree.DecisionTreeClassifier(criterion='entropy', min_samples_split=5,
                                 min_samples_leaf=6, max_features='auto',
```

```
                                  random_state=50)

# Fitting the model to our train set
dt.fit(x_train, y_train)

#  Using the trained model to predict out X_Test
y_pred_dt = dt.predict(x_test)

# Calculating our evaluation metrics using sklearn build-in package.
acc_dt, precision_dt, rec_dt, f1_dt, areaUnderCurve_dt, spec_dt = eval_metrics(y_test, y_pred_dt)

# Printing out the Evaluation Metrics
print(f"The metrics for Decision Tree are: \n Accuracy: {acc_dt}%",
      f" \nPrecision: {precision_dt} \nRecall: {rec_dt} \nF1 score:",
      f" {f1_dt} \nArea Under Curve: {areaUnderCurve_dt}",
      f" \nSpecificity: {spec_dt}")

```

```
The metrics for Decision Tree are:
 Accuracy: 85.38076709282934%
Precision: 0.8395061728395061
Recall: 0.8840736728060672
F1 score:  0.8612137203166227
Area Under Curve: 0.8529957405126226
Specificity: 0.821917808219178
```

Random Forest

```
# Using RandomForestClassifier model from Sklearn to model our data.
# For Random Forest, we take Cross-Entropy Loss as loss function.
# We set that minimum split samples to be 5
# minimum number of leaf nodes is 6
# and we set the max_features to auto to facilitate the model to random skip a few features.
# Random State is set as 50.

# loading the KNeighborsClassifier module in to rf with hyperparameters
rf = RandomForestClassifier(n_estimators=50,
                            criterion='entropy', min_samples_split=5,
                            min_samples_leaf=6, max_features='auto',
                            random_state=50)

# Fitting the model to our train set
rf.fit(x_train, y_train)

#  Using the trained model to predict out X_Test
y_pred_rf = rf.predict(x_test)

# Calculating our evaluation metrics using sklearn build-in package.
acc_rf, precision_rf, rec_rf, f1_rf, areaUnderCurve_rf, spec_rf = eval_metrics(y_test, y_pred_rf)

# Printing out the Evaluation Metrics
print(f"The metrics for Random Forest are: \n Accuracy: {acc_rf}%"+
      f" \nPrecision: {precision_rf} \nRecall: {rec_rf} \nF1 score: {f1_rf} "+
      f"\nArea Under Curve: {areaUnderCurve_rf} \nSpecificity: {areaUnderCurve_rf}")


```

```
The metrics for Random Forest are:
 Accuracy: 95.27515286270149%
Precision: 0.9554347826086956
Recall: 0.952329360780065
F1 score: 0.9538795442213781
Area Under Curve: 0.9527628539060143
Specificity: 0.9527628539060143
```

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