Regression

Internet Movie Database

IMDb

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Introduction

Here in this project we will predict the gross of movies from IMDB website (Internet Movie Database)

and we will apply the ML models to reach to the best result and best accuracy.

we will start with:

- DataStructure
- DataCleaning
- DataAnalysis
- Experimental ML Models
- Final Predict
- Conclusion

01 - DataStructure

Here is the top 5 of the dataset before the cleaning .

5043 rows and 28 columns

```
df.head()
```

	color	director_name	num_critic_for_reviews	duration	director_facebook_likes	actor_3_facebook_like
0	Color	James Cameron	723.0	178.0	0.0	855.
1	Color	Gore Verbinski	302.0	169.0	563.0	1000.
2	Color	Sam Mendes	602.0	148.0	0.0	161.
3	Color	Christopher Nolan	813.0	164.0	22000.0	23000.
4	NaN	Doug Walker	NaN	NaN	131.0	Na

5 rows × 28 columns

```
#show number of rows and columns
print("DataSet dimension      :",df.shape)
```

```
DataSet dimension      : (5043, 28)
```

```
#show information
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5043 entries, 0 to 5042
Data columns (total 28 columns):
 #   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
 0   color                      5024 non-null   object
 1   director_name              4939 non-null   object
 2   num_critic_for_reviews     4993 non-null   float64
 3   duration                   5028 non-null   float64
 4   director_facebook_likes    4939 non-null   float64
 5   actor_3_facebook_likes     5020 non-null   float64
 6   actor_2_name               5030 non-null   object
 7   actor_1_facebook_likes     5036 non-null   float64
 8   gross                      4159 non-null   float64
 9   genres                     5043 non-null   object
 10  actor_1_name               5036 non-null   object
 11  movie_title                5043 non-null   object
 12  num_voted_users            5043 non-null   int64
 13  cast_total_facebook_likes  5043 non-null   int64
 14  actor_3_name               5020 non-null   object
 15  facenumber_in_poster       5030 non-null   float64
 16  plot_keywords              4890 non-null   object
 17  movie_imdb_link            5043 non-null   object
 18  num_user_for_reviews       5022 non-null   float64
 19  language                   5031 non-null   object
 20  country                    5038 non-null   object
 21  content_rating             4740 non-null   object
 22  budget                     4551 non-null   float64
 23  title_year                 4935 non-null   float64
 24  actor_2_facebook_likes     5030 non-null   float64
 25  imdb_score                 5043 non-null   float64
 26  aspect_ratio               4714 non-null   float64
 27  movie_facebook_likes       5043 non-null   int64
dtypes: float64(13), int64(3), object(12)
memory usage: 1.1+ MB
```

```
#know the type of data
df.dtypes
```

```
color                         object
director_name                 object
num_critic_for_reviews       float64
duration                     float64
director_facebook_likes      float64
actor_3_facebook_likes       float64
actor_2_name                  object
actor_1_facebook_likes       float64
gross                        float64
genres                        object
actor_1_name                  object
movie_title                   object
num_voted_users                int64
cast_total_facebook_likes      int64
actor_3_name                  object
facenumber_in_poster         float64
plot_keywords                 object
movie_imdb_link               object
num_user_for_reviews         float64
language                      object
country                       object
content_rating                object
budget                       float64
title_year                   float64
actor_2_facebook_likes       float64
imdb_score                   float64
aspect_ratio                 float64
movie_facebook_likes           int64
dtype: object
```

02- DataCleaning

- We found missing values

- delete unnecessary columns and rows

- delete outliers

- after cleaning 3653 rows and 21 columns

```
#show all null value in columns
df.isnull().sum()
```

```
color                        19
director_name               104
num_critic_for_reviews       50
duration                     15
director_facebook_likes     104
actor_3_facebook_likes       23
actor_2_name                 13
actor_1_facebook_likes        7
gross                       884
genres                        0
actor_1_name                  7
movie_title                   0
num_voted_users               0
cast_total_facebook_likes     0
actor_3_name                 23
facenumber_in_poster         13
plot_keywords               153
movie_imdb_link               0
num_user_for_reviews         21
language                     12
country                       5
content_rating              303
budget                      492
title_year                  108
actor_2_facebook_likes       13
imdb_score                    0
aspect_ratio                329
movie_facebook_likes          0
dtype: int64
```

```
df['gross'][df['gross']< 6.5] = None
df.dropna(subset = ["gross"], inplace=True)
```

```
df['num_voted_users'][df['num_voted_users']< 4.4] = None
df.dropna(subset = ["num_voted_users"], inplace=True)
```

```
#drop actor_1_facebook_likes column
df.drop(['actor_1_facebook_likes'], axis = 1, inplace = True)
```

```
#drop num_user_for_reviews column
df.drop(['num_user_for_reviews'], axis = 1, inplace = True)
```

```
#drop movie_facebook_likes column
df.drop(['movie_facebook_likes'], axis = 1, inplace = True)
```

```
#drop num_critic_for_reviews column
df.drop(['num_critic_for_reviews'], axis = 1, inplace = True)
```

```
#drop actor_2_facebook_likes column
df.drop(['actor_2_facebook_likes'], axis = 1, inplace = True)
```

```
#drop actor_3_facebook_likes column
df.drop(['actor_3_facebook_likes'], axis = 1, inplace = True)
```

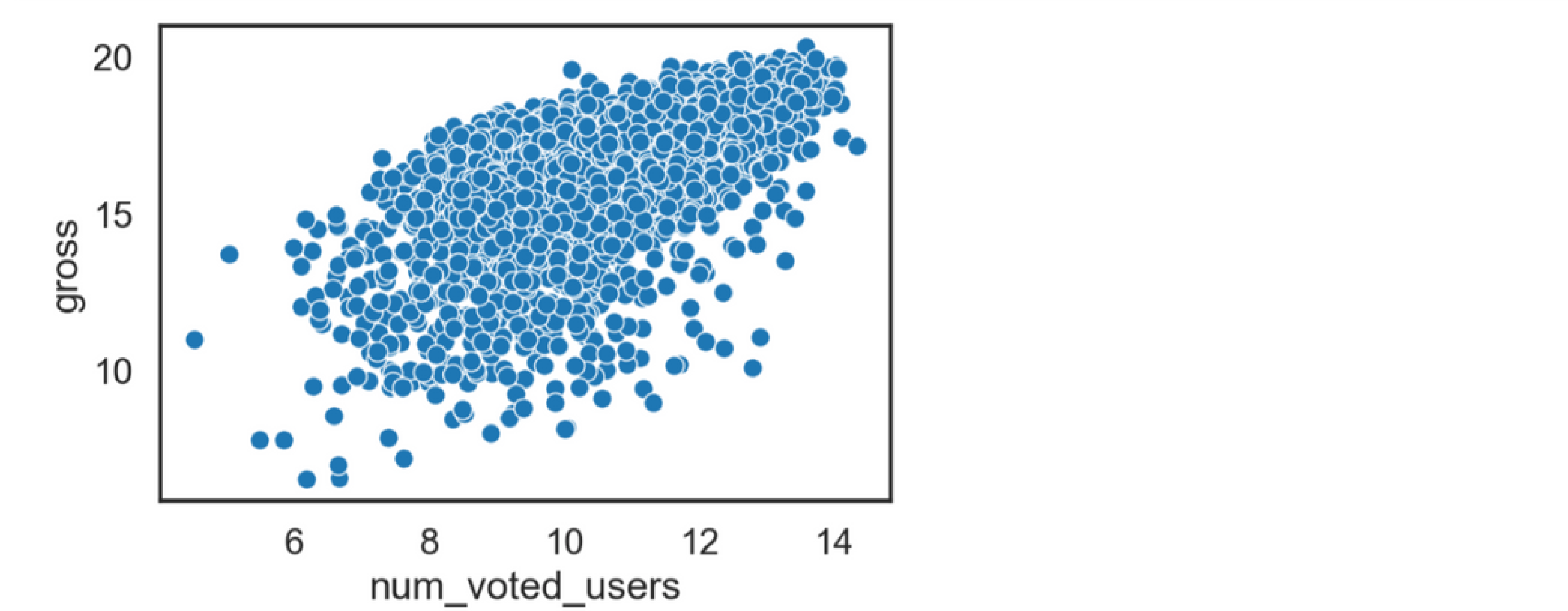
```
#drop imdb_score column
df.drop(['imdb_score'], axis = 1, inplace = True)
```

```
115]: df.shape
115]: (3653, 21)
```

03- DataAnalysis

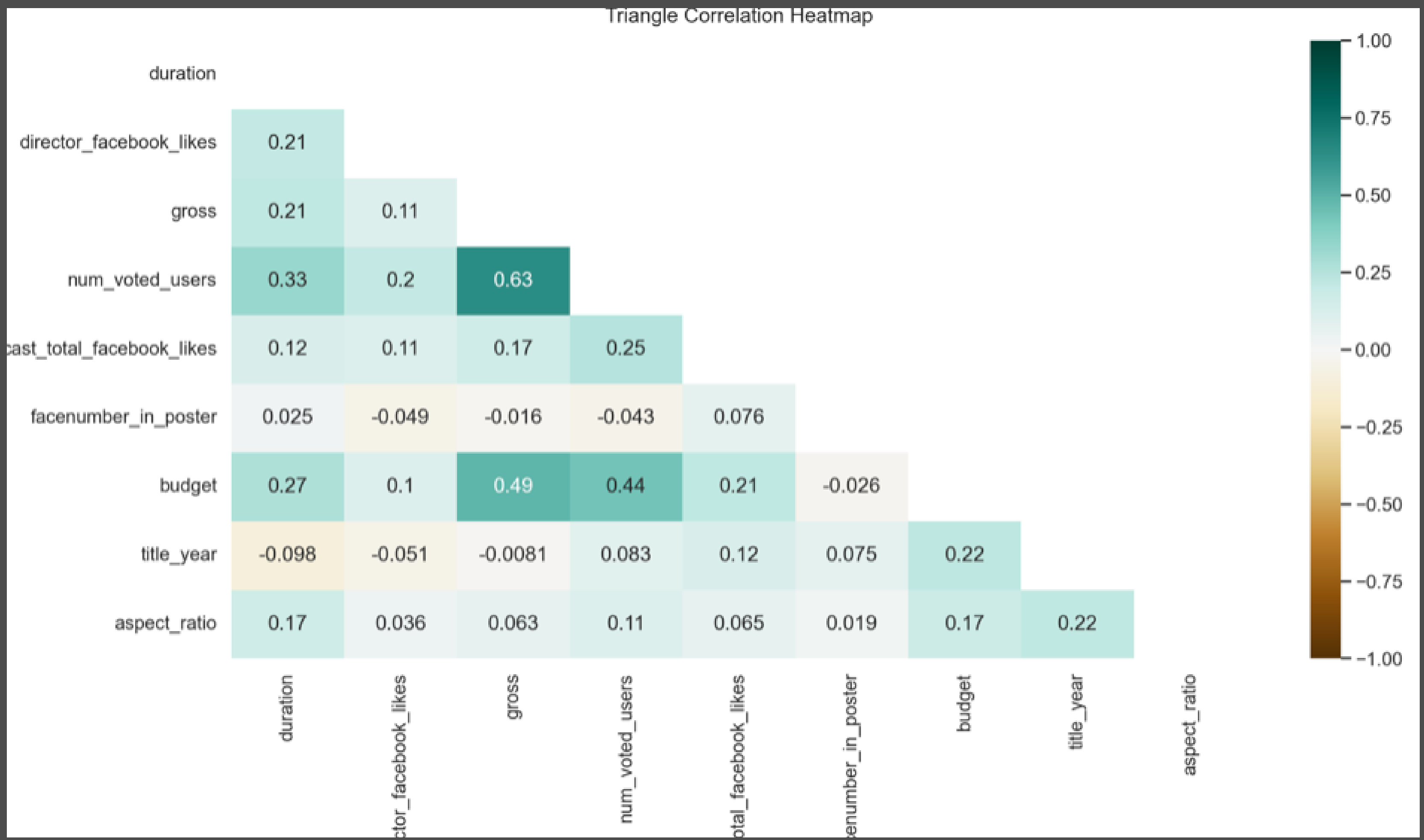
- We found there is positive relationship between number voted users and gross .

```
sns.scatterplot(x = 'num_voted_users', y = 'gross', data = df);
```



-

- Here is the corrections between features



04 Experimental ML Models

-Dummy's:

```
df_dummy=pd.get_dummies(df)
df_dummy.columns
```

```
Index(['duration', 'director_facebook_likes', 'gross', 'num_voted_users',
       'cast_total_facebook_likes', 'facenumber_in_poster', 'budget',
       'title_year', 'aspect_ratio', 'color_ Black and White',
       ...
       'content_rating_GP', 'content_rating_M', 'content_rating_NC-17',
       'content_rating_Not Rated', 'content_rating_PG', 'content_rating_PG-13',
       'content_rating_Passed', 'content_rating_R', 'content_rating_Unrated',
       'content_rating_X'],
      dtype='object', length=20070)
```

```
X = df_dummy[['duration', 'director_facebook_likes', 'num_voted_users',
              'cast_total_facebook_likes', 'facenumber_in_poster',
              'budget', 'title_year',
              'aspect_ratio']]
y = df_dummy['gross']
```

```
df_dummy
```

	duration	director_facebook_likes	gross	num_voted_users	cast_total_facebook_likes	facenumber
12	106.00	395.00	18.94	12.71	2023	
22	156.00	0.00	18.47	12.26	3244	
24	113.00	129.00	18.07	11.91	24106	
26	194.00	0.00	20.31	13.58	45223	
29	124.00	365.00	20.30	12.94	8458	
...	...	...	...	...	...	
5027	90.00	397.00	13.42	8.42	5	
5029	111.00	62.00	11.46	8.75	115	
5033	77.00	291.00	12.96	11.19	368	
5035	81.00	0.00	14.53	10.86	147	
5042	90.00	16.00	11.35	8.36	163	

3703 rows × 20070 columns

04 Experimental ML Models

-Split data :

```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=10)
```

```
from sklearn import metrics
from sklearn.model_selection import cross_val_score

def cross_val(model):
    pred = cross_val_score(model, X, y, cv=5)
    return pred.mean()

def print_evaluate(true, predicted):
    mae = metrics.mean_absolute_error(true, predicted)
    mse = metrics.mean_squared_error(true, predicted)
    rmse = np.sqrt(metrics.mean_squared_error(true, predicted))
    r2_square = metrics.r2_score(true, predicted)
    print('MAE:', mae)
    print('MSE:', mse)
    print('RMSE:', rmse)
    print('R2 Square', r2_square)
    print('__________________________________')

def evaluate(true, predicted):
    mae = metrics.mean_absolute_error(true, predicted)
    mse = metrics.mean_squared_error(true, predicted)
    rmse = np.sqrt(metrics.mean_squared_error(true, predicted))
    r2_square = metrics.r2_score(true, predicted)
    return mae, mse, rmse, r2_square
```

04- Experimental ML Models

Linear regression :

```python
from sklearn.linear_model import LinearRegression

lin_reg = LinearRegression(normalize=True)
lin_reg.fit(X_train,y_train)
```

R2 Square in Test = 0.47

R2 Square in Test = 0.49

```python
test_pred = lin_reg.predict(X_test)
train_pred = lin_reg.predict(X_train)

print('Test set evaluation:\n_____________')
print_evaluate(y_test, test_pred)
print('Train set evaluation:\n_____________')
print_evaluate(y_train, train_pred)
```

```
Test set evaluation:
_____________
MAE: 1.1237325546186263
MSE: 2.6085103096661646
RMSE: 1.615088328750525
R2 Square 0.47136891371734335
__________________________________
Train set evaluation:
_____________
MAE: 1.042646157916681
MSE: 2.2129910196619655
RMSE: 1.4876125233614987
R2 Square 0.4957116065139111
__________________________________
```

```python
results_df = pd.DataFrame(data=[["Linear Regression", *evaluate(y_test, test_pred) ,
                                 cross_val(LinearRegression())]],
                          columns=['Model', 'MAE', 'MSE', 'RMSE', 'R2 Square',
                                   "Cross Validation"])
results_df
```

	Model	MAE	MSE	RMSE	R2 Square	Cross Validation
0	Linear Regression	1.12	2.61	1.62	0.47	-0.15

04- Experimental ML Models

Polynomial regression :

R2 Square in Test = 0.53

R2 Square in Test = 0.54

```
from sklearn.preprocessing import PolynomialFeatures

poly_reg = PolynomialFeatures(degree=2)

X_train_2_d = poly_reg.fit_transform(X_train)
X_test_2_d = poly_reg.transform(X_test)

lin_reg = LinearRegression(normalize=True)
lin_reg.fit(X_train_2_d,y_train)

test_pred = lin_reg.predict(X_test_2_d)
train_pred = lin_reg.predict(X_train_2_d)

print('Test set evaluation:\n_____________________________________')
print_evaluate(y_test, test_pred)
print('====================================')
print('Train set evaluation:\n_____________________________________')
print_evaluate(y_train, train_pred)
```

```
Test set evaluation:
_____________________________________
MAE: 1.0409578575698533
MSE: 2.318483091584654
RMSE: 1.5226565901688582
R2 Square 0.5301447609040801
__________________________________
====================================
Train set evaluation:
_____________________________________
MAE: 0.9749047838239859
MSE: 1.9818434471296518
RMSE: 1.4077796159660971
R2 Square 0.5483846797324075
```

04- Experimental ML Models

- Ridge regression :

R2 Square in Test = 0.47

R2 Square in Test = 0.49

```
from sklearn.linear_model import Ridge

model = Ridge(alpha=100, solver='cholesky', tol=0.0001, random_state=42)
model.fit(X_train, y_train)
pred = model.predict(X_test)

test_pred = model.predict(X_test)
train_pred = model.predict(X_train)

print('Test set evaluation:\n_____________________________________')
print_evaluate(y_test, test_pred)
print('====================================')
print('Train set evaluation:\n_____________________________________')
print_evaluate(y_train, train_pred)
```

```
Test set evaluation:
_____________________________________
MAE: 1.1216994054790823
MSE: 2.612184769507832
RMSE: 1.6162254698858796
R2 Square 0.470624261227221
__________________________________
====================================
Train set evaluation:
_____________________________________
MAE: 1.0419562314393351
MSE: 2.2151833463127892
RMSE: 1.4883492017375457
R2 Square 0.4952120270420932
__________________________________
```

04- Experimental ML Models

- Lasso regression :

R2 Square in Test = 0.45

R2 Square in Test = 0.47

```
from sklearn.linear_model import Lasso

model = Lasso(alpha=0.1,
              precompute=True,
#               warm_start=True,
              positive=True,
              selection='random',
              random_state=42)
model.fit(X_train, y_train)

test_pred = model.predict(X_test)
train_pred = model.predict(X_train)

print('Test set evaluation:\n_____________________________________')
print_evaluate(y_test, test_pred)
print('====================================')
print('Train set evaluation:\n_____________________________________')
print_evaluate(y_train, train_pred)
```

```
Test set evaluation:
_____________________________________
MAE: 1.1389648759914734
MSE: 2.707774748267592
RMSE: 1.6455317524337207
R2 Square 0.45125234840699724
__________________________________
====================================
Train set evaluation:
_____________________________________
MAE: 1.0677804997566571
MSE: 2.2991322475263796
RMSE: 1.5162889723025685
R2 Square 0.47608205491306466
```

04- Experimental ML Models

- RandomForest regression :

```
from sklearn.ensemble import RandomForestRegressor

rf_reg = RandomForestRegressor(n_estimators=1000)
rf_reg.fit(X_train, y_train)

test_pred = rf_reg.predict(X_test)
train_pred = rf_reg.predict(X_train)

print('Test set evaluation:\n_____________________________________')
print_evaluate(y_test, test_pred)

print('Train set evaluation:\n_____________________________________')
print_evaluate(y_train, train_pred)
```

```
Test set evaluation:
_____________________________________
MAE: 0.9596129441669611
MSE: 2.06400680921934
RMSE: 1.436665169487776
R2 Square 0.5817159864734989
__________________________________
Train set evaluation:
_____________________________________
MAE: 0.32967788573087553
MSE: 0.23896883815356398
RMSE: 0.48884439053093776
R2 Square 0.945544645046004
__________________________________
```

R2 Square in Test = 0.58

R2 Square in Test = 0.95

04- Experimental ML Models

- Regression Models :

```
results_df_2 = pd.DataFrame(data=[["Random Forest", *evaluate(y_test, test_pred),
                                    cross_val(RandomForestRegressor())]],
                            columns=['Model', 'MAE', 'MSE', 'RMSE', 'R2 Square',
                                     'Cross Validation'])
results_df = results_df.append(results_df_2, ignore_index=True)
results_df
```

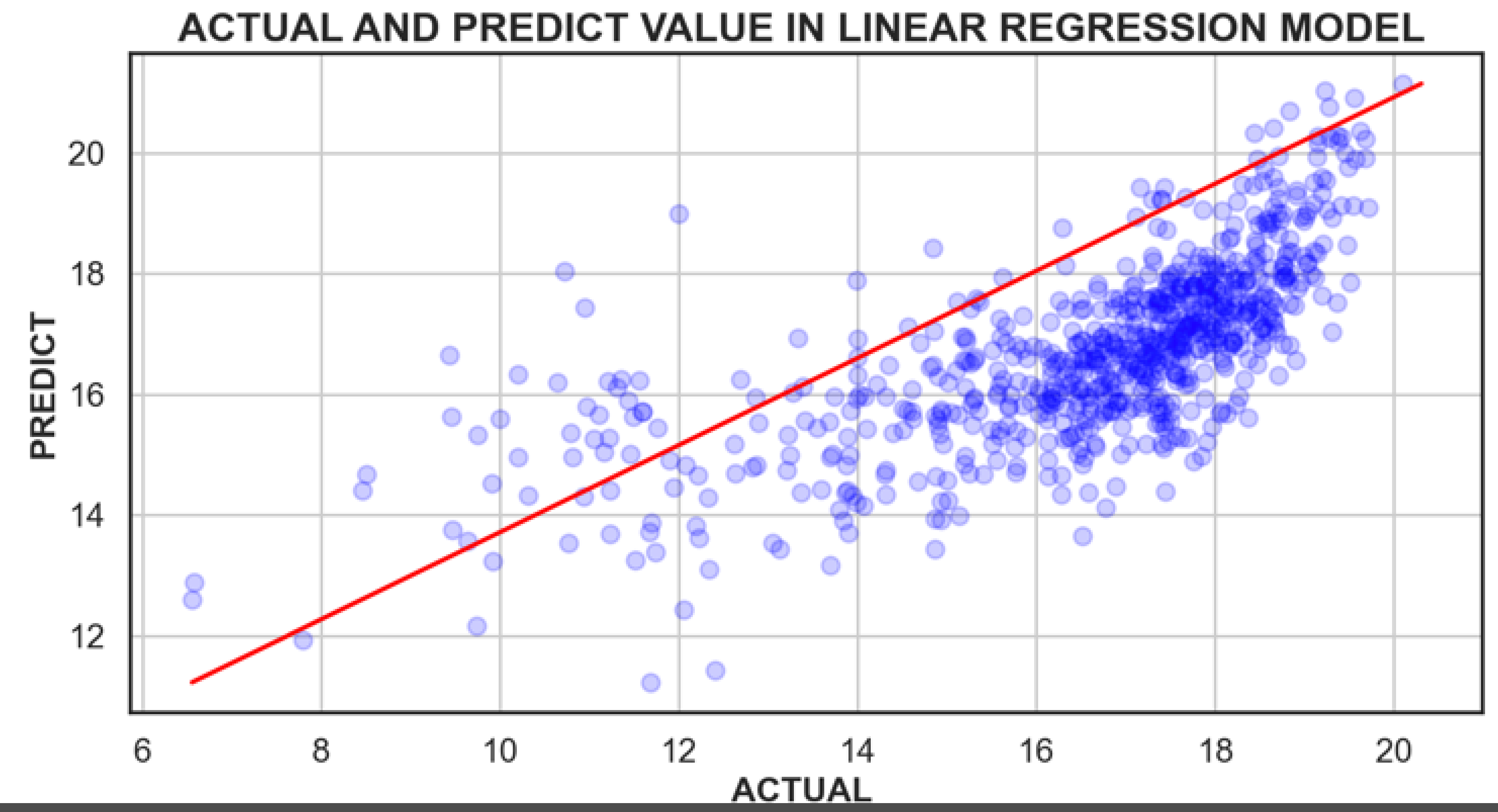
	Model	MAE	MSE	RMSE	R2 Square	Cross Validation
0	Linear Regression	1.12	2.61	1.62	0.47	-0.15
1	Polynomail Regression	1.04	2.32	1.52	0.53	0.00
2	Ridge Regression	1.12	2.61	1.62	0.47	-0.15
3	Lasso Regression	1.14	2.71	1.65	0.45	-0.52
4	Random Forest	0.96	2.06	1.44	0.58	0.29

We chose polynomial regression because it's the best model to fit our dataset

04- Experimental ML Models

-Prediction

```
plt.figure(figsize = [12,6])
sns.set_style("white")
x_plt_range = [y.min(),y.max()]
y_plt_range = [y_haat.min(),y_haat.max()]
plt.grid()
plt.scatter(y_test,y_haat,alpha=0.2,color='Blue',s=75)
plt.plot(x_plt_range,y_plt_range,c="r")
plt.title("ACTUAL AND PREDICT VALUE IN LINEAR REGRESSION MODEL "
          ,fontsize = 20, weight = 'bold')
plt.xlabel("ACTUAL ",fontsize = 17, weight = 'bold')
plt.ylabel('PREDICT',fontsize = 17, weight = 'bold');
plt.savefig('SDAIA.png')
```



Conclusion

We found the best model that will predict the response of our data
from a website such as predict the gross of a brunch of movies and see the correlation between each other.