Movie Revenue Prediction

Project overview

The client is a movie studio and they need to be able to predict movie revenue in order to greenlight the project and assign a budget to it. Most of the data is comprised of categorical variables. While the budget for the movie is known in the dataset it is often an unknown variable during the greenlighting process.

Prediction Basis

Since predicting a movie's revenue in itself is a challenge, additionally the budget amount remains elusive makes it a difficult business problem as there is no base-line to establish the prediction.

I- Executive Summary

Analyze available data to predict a movie revenue and finally assign a budget during green-lighting process.

II- Business Understanding

Define Organization

Client is a movie studio in the business of producing, sponsoring and financing movies.

Intended Stakeholders of Data

Movie producers, finance & budget managers.

Define Business Objectives

based on the input parameters, a movie's revenue is to be predicted.

Background

Business Objectives

• Which variables can help in predicting revenue figures? • determine which parameters had the most effect on a movie revenue? • Limiting the problem to predicting just the revenue amounts. • Evaluate and cross-validate the revenue figures.

Business Success Criteria

Predicting the movie revenue as accurately as possible, and making the **REVENUE** as the **TARGET VARIABLE** or **OUTCOME**. Since the revenue is a whole-number, a Regression will be developed.

Assumptions, and Constraints

Assumptions: data is accurate and reliable.

Terminology - Code book - Data Dictionary

A lead is a person who has indicated interest in your company's product or service in some way, shape, or form.

- title - title of the movie
- tagline - few words for movie presentation
- revenue - revenue generated by the movie
- budget - planned expenditure
- genres - categorical group of the movie
- homepage - movie promotional website
- id - movie id
- keywords - tags associated with the movie
- original_language - original movie language
- overview - movie synopsis
- production_companies - sponsoring and producing comapnies
- production_countries - locations of the movie made
- release_date - movie available for viewing date.
- runtime - movie duration
- spoken_languages - spoken languages in the movie
- status - movie status for viewing

Project Plan

gets updated as per the succeding stages.

modelling planned to use: Multiple Linear Regression, SVM,

III- Data Understanding

In [43]:
```
# Importing the libraries
import pandas as pd
import numpy as np
import math
import matplotlib.pyplot as plt
import seaborn as sns
import ast


from sklearn.model_selection import train_test_split

from sklearn.linear_model import LinearRegression
from pandas.plotting import scatter_matrix
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import cross_validate
from sklearn.model_selection import GridSearchCV

from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Lasso
from sklearn.linear_model import ElasticNet
from sklearn.tree import DecisionTreeRegressor
from sklearn.neighbors import KNeighborsRegressor
from sklearn.svm import SVR

from sklearn.metrics import mean_squared_error

from sklearn import model_selection

import xgboost as xgb

%matplotlib inline
import warnings
warnings.filterwarnings('ignore')

plt.rcParams["figure.figsize"] = (20,10)
```

In [2]:
```
# Run multiple commands and get multiple outputs within a single cell
from IPython.core.interactiveshell import InteractiveShell
InteractiveShell.ast_node_interactivity = "all"
```

Collect Initial Data

In [3]:
```
# Load CSV Using Python Standard Library
mvrevenue = pd.read_csv('1-MovieRevenue-WorkBook.csv')

mvrevenue.head(1)
```

Out[3]:

	title	tagline	genres	homepage	id	keywords	original_language	overview	produ
0	Avatar	Enter the World of Pandora.	[{"id": 28, "name": "Action"}, {"id": 12, "nam...	http://www.avatarmovie.com/	19995	[{"id": 1463, "name": "culture clash"}, {"id":...	en	In the 22nd century, a paraplegic Marine is di...	[{' F

Understanding the Data: Data quality report

In [4]:
```
mvrevenue.iloc[0]
```

Out[4]:
```
title                                                               Avatar
tagline                                        Enter the World of Pandora.
genres                   [{"id": 28, "name": "Action"}, {"id": 12, "nam...
homepage                                       http://www.avatarmovie.com/
id                                                                   19995
keywords                 [{"id": 1463, "name": "culture clash"}, {"id":...
original_language                                                       en
overview                 In the 22nd century, a paraplegic Marine is di...
production_companies     [{"name": "Ingenious Film Partners", "id": 289...
production_countries     [{"iso_3166_1": "US", "name": "United States o...
release_date                                                    12/10/2009
runtime                                                                162
spoken_languages         [{"iso_639_1": "en", "name": "English"}, {"iso...
status                                                            Released
budget                                                           237000000
revenue                                                         2787965087
Name: 0, dtype: object
```

In [5]:
```
# check the column type
element = mvrevenue.iloc[0]['genres']
print(type(element))
print(element)
```

```
<class 'str'>
[{"id": 28, "name": "Action"}, {"id": 12, "name": "Adventure"}, {"id": 14, "nam
e": "Fantasy"}, {"id": 878, "name": "Science Fiction"}]
```

Since some cols looks like in dictionary format but in actual its string format

This can be handled as first convert the type string into dictionary format and then extract the values.

In [4]:
```
# Create a function to convert string into dict

dict_columns = [ 'genres', 'production_companies','production_countries', 'spoken_l
anguages', 'keywords']

def text_to_dict(df):
    for column in dict_columns:
        df[column] = df[column].apply(lambda x: {} if pd.isna(x) else ast.literal_e
val(x) )
    return df
```

In [5]:
```
#  Convert string into dict
con_data = text_to_dict(mvrevenue)
con_data.head(1)
```

Out[5]:

	title	tagline	genres	homepage	id	keywords	original_language	overview	produc
0	Avatar	Enter the World of Pandora.	[{'id': 28, 'name': 'Action'}, {'id': 12, 'nam...	http://www.avatarmovie.com/	19995	[{'id': 1463, 'name': 'culture clash'}, {'id':...	en	In the 22nd century, a paraplegic Marine is di...	[{'nam Pa

In [8]:
```
# checking for dict format
element = con_data.iloc[0]['genres']
print(type(element))
print(element)
```

```
<class 'list'>
[{'id': 28, 'name': 'Action'}, {'id': 12, 'name': 'Adventure'}, {'id': 14, 'name
': 'Fantasy'}, {'id': 878, 'name': 'Science Fiction'}]
```

Initial Data Collection Report

Describing Data at High Level

In [9]:
```
# rowsXcolumns format
con_data.shape

# missing values
con_data.info()
```

Out[9]:
```
(4803, 16)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4803 entries, 0 to 4802
Data columns (total 16 columns):
title                   4803 non-null object
tagline                 3959 non-null object
genres                  4803 non-null object
homepage                1712 non-null object
id                      4803 non-null int64
keywords                4803 non-null object
original_language       4803 non-null object
overview                4800 non-null object
production_companies    4803 non-null object
production_countries    4803 non-null object
release_date            4802 non-null object
runtime                 4801 non-null float64
spoken_languages        4803 non-null object
status                  4803 non-null object
budget                  4803 non-null int64
revenue                 4803 non-null int64
dtypes: float64(1), int64(3), object(12)
memory usage: 600.5+ KB
```

In [6]:
```
# dataframe bckup copy
#conv_data
conv_data = con_data.copy()
```

In [7]:
```
# Checking the null values
con_data.isnull().sum()
```

Out[7]:
```
title                      0
tagline                  844
genres                     0
homepage                3091
id                         0
keywords                   0
original_language          0
overview                   3
production_companies       0
production_countries       0
release_date               1
runtime                    2
spoken_languages           0
status                     0
budget                     0
revenue                    0
dtype: int64
```

Since homepage, tagline has the most missing values and don't add any weight, since these are text columns, in building prediction model, these can be dropped.

In [8]:
```
con_data = con_data.drop(['tagline', 'homepage'], axis=1)
```

In [9]:
```
# Dropped the rows with missing values since they are few
con_data = con_data.dropna(axis = 0, how ='any')
```

In [14]:
```
con_data.columns
```

Out[14]:
```
Index(['title', 'genres', 'id', 'keywords', 'original_language', 'overview',
       'production_companies', 'production_countries', 'release_date',
       'runtime', 'spoken_languages', 'status', 'budget', 'revenue'],
      dtype='object')
```

In [15]:
```
# Calculate Correlation
con_data.describe().T
```

Out[15]:

	count	mean	std	min	25%	50%	75%	max
id	4799.0	5.689992e+04	8.823650e+04	5.0	9012.5	14623.0	58461.5	4.470270e+05
runtime	4799.0	1.069031e+02	2.256131e+01	0.0	94.0	103.0	118.0	3.380000e+02
budget	4799.0	2.906593e+07	4.073251e+07	0.0	800000.0	15000000.0	40000000.0	3.800000e+08
revenue	4799.0	8.232920e+07	1.629076e+08	0.0	0.0	19184015.0	92956519.0	2.787965e+09

In [16]:
```
con_data['release_date']
```

Out[16]:
```
0       12/10/2009
1        5/19/2007
2       10/26/2015
3        7/16/2012
4         3/7/2012
5         5/1/2007
6       11/24/2010
7        4/22/2015
8         7/7/2009
9        3/23/2016
10       6/28/2006
11      10/30/2008
12       6/20/2006
13        7/3/2013
14       6/12/2013
15       5/15/2008
16       4/25/2012
17       5/14/2011
18       5/23/2012
19      12/10/2014
20       6/27/2012
21       5/12/2010
22      12/11/2013
23       12/4/2007
24      12/14/2005
25      11/18/1997
26       4/27/2016
27       4/11/2012
28        6/9/2015
29      10/25/2012
           ...
4773     9/13/1994
4774      1/1/1971
4775     9/20/2002
4776     1/19/1997
4777     1/15/2002
4778     8/14/2009
4779     7/27/1990
4780     10/2/2015
4781     2/14/2013
4782      1/1/2003
4783     1/16/2015
4784     1/17/2005
4785      9/5/2014
4786     3/14/2009
4787    10/26/2011
4788     3/12/1972
4789      9/1/2004
4790      9/8/2000
4791      1/1/2007
4792     11/6/1997
4793     4/11/2004
4794     1/20/2012
4795      9/9/1995
4796     10/8/2004
4797     3/12/2005
4798      9/4/1992
4799    12/26/2011
4800    10/13/2013
4801      5/3/2012
4802      8/5/2005
Name: release_date, Length: 4799, dtype: object
```

In [10]:
```
# correcting the dates columns in a standard format
con_data[['release_month','release_day','release_year']]=con_data['release_date'].str.split('/',expand=True).replace(np.nan, -1).astype(int)

#getting the month year and day using the string split function and the / as a delimiter; eg: 5/25/2015 -> month 5/ day 25 / year 2015
con_data.loc[ (con_data['release_year'] <= 19) & (con_data['release_year'] < 100), "release_year"] += 2000

## some rows have 4 digits for the year instead of 2, so the release year < 100 and > 100 is checking that
con_data.loc[ (con_data['release_year'] > 19)  & (con_data['release_year'] < 100), "release_year"] += 1900

releaseDate = pd.to_datetime(con_data['release_date'])

con_data.head()
```

Out[10]:

	title	genres	id	keywords	original_language	overview	production_companies	production_
0	Avatar	[{'id': 28, 'name': 'Action'}, {'id': 12, 'nam...	19995	[{'id': 1463, 'name': 'culture clash'}, {'id':...	en	In the 22nd century, a paraplegic Marine is di...	[{'name': 'Ingenious Film Partners', 'id': 289...	[{'iso_316 'name': 'Un
1	Pirates of the Caribbean: At World's End	[{'id': 12, 'name': 'Adventure'}, {'id': 14, '...	285	[{'id': 270, 'name': 'ocean'}, {'id': 726, 'na...	en	Captain Barbossa, long believed to be dead, ha...	[{'name': 'Walt Disney Pictures', 'id': 2}, {'...	[{'iso_316 'name': 'Un
2	Spectre	[{'id': 28, 'name': 'Action'}, {'id': 12, 'nam...	206647	[{'id': 470, 'name': 'spy'}, {'id': 818, 'name...	en	A cryptic message from Bond's past sends him o...	[{'name': 'Columbia Pictures', 'id': 5}, {'nam...	[{'iso_316 'nan I
3	The Dark Knight Rises	[{'id': 28, 'name': 'Action'}, {'id': 80, 'nam...	49026	[{'id': 849, 'name': 'dc comics'}, {'id': 853,...	en	Following the death of District Attorney Harve...	[{'name': 'Legendary Pictures', 'id': 923}, {'...	[{'iso_316 'name': 'Un
4	John Carter	[{'id': 28, 'name': 'Action'}, {'id': 12, 'nam...	49529	[{'id': 818, 'name': 'based on novel'}, {'id':...	en	John Carter is a war-weary, former military ca...	[{'name': 'Walt Disney Pictures', 'id': 2}]	[{'iso_316 'name': 'Un

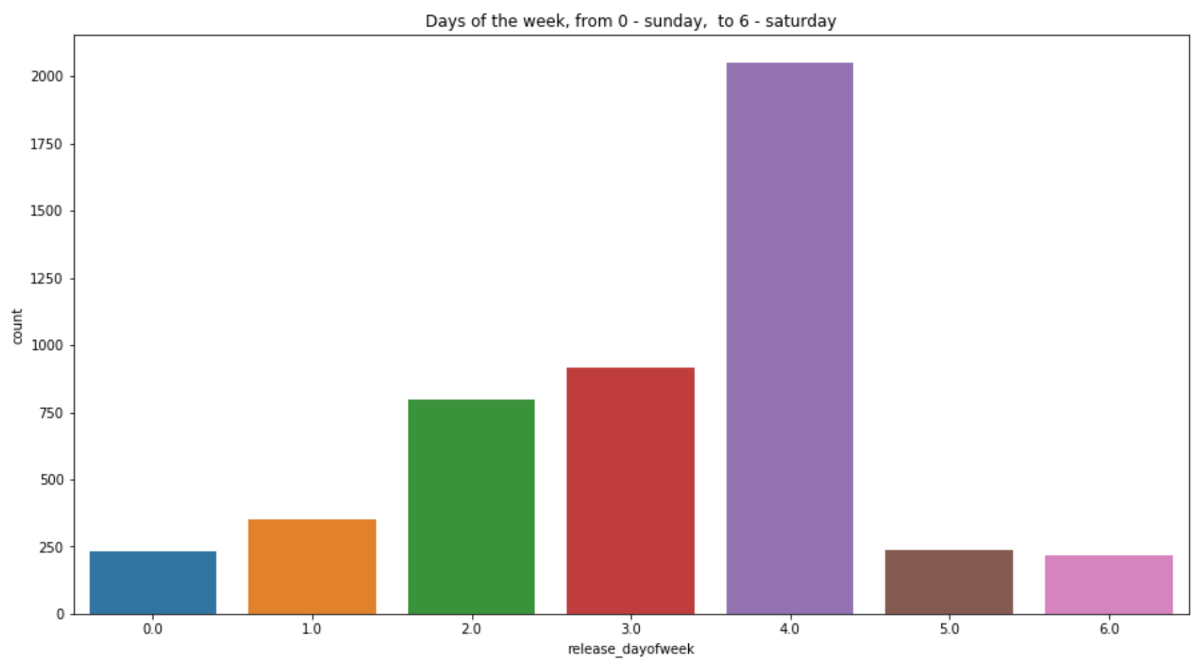
In [11]:
```
data = mvrevenue
data[['release_month','release_day','release_year']]=data['release_date'].str.split
('/',expand=True).replace(np.nan, -1).astype(int) #getting the month year and day u
sing the string split function and the / as a delimiter; eg: 5/25/2015 -> month 5/
day 25 / year 2015
data.loc[ (data['release_year'] <= 19) & (data['release_year'] < 100), "release_yea
r"] += 2000 ## some rows have 4 digits for the year instead of 2, so the release ye
ar < 100 and > 100 is checking that
data.loc[ (data['release_year'] > 19)  & (data['release_year'] < 100), "release_yea
r"] += 1900

releaseDate = pd.to_datetime(data['release_date']) #using the pandas to_datetime fu
nction to format the data, get a Series,  and store it in a variable that is gonna
be used later to get the day of week and quarter
data['release_dayofweek'] = releaseDate.dt.dayofweek
data['release_quarter'] = releaseDate.dt.quarter
```

In [12]:
```
plt.figure(figsize=(15, 8))
sns.countplot(data['release_dayofweek'])
plt.title('Days of the week, from 0 - sunday,  to 6 - saturday')
```

Out[12]: <Figure size 1080x576 with 0 Axes>

Out[12]: <matplotlib.axes._subplots.AxesSubplot at 0x1f71f9baa90>

Out[12]: Text(0.5, 1.0, 'Days of the week, from 0 - sunday, to 6 - saturday')

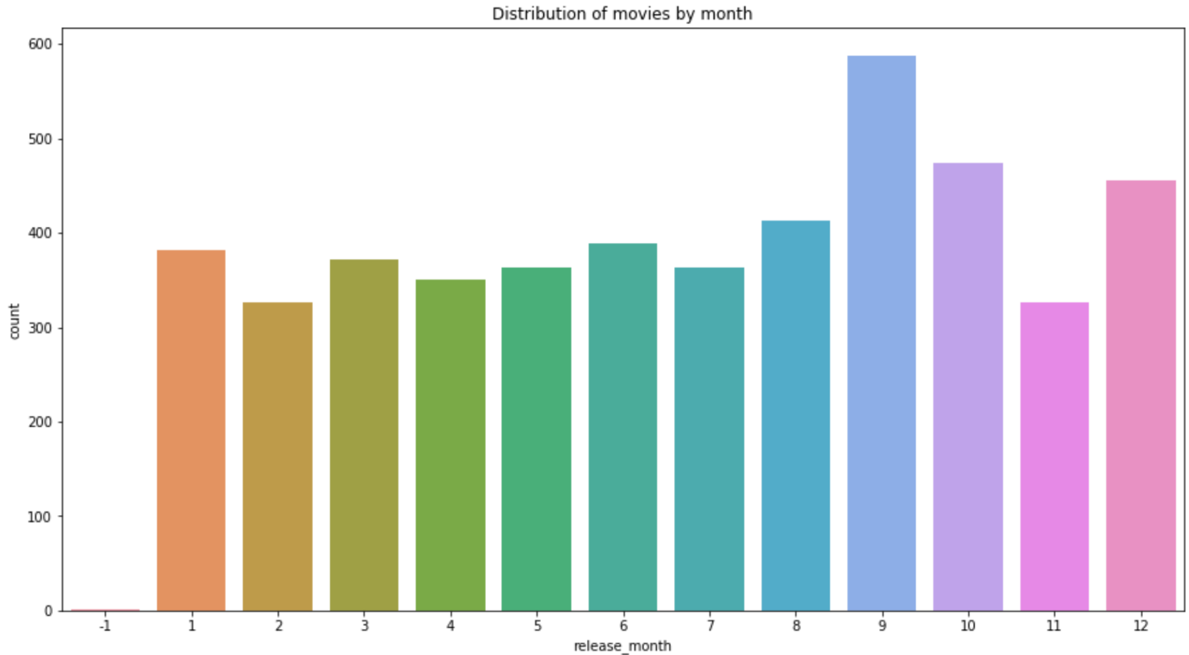


In [13]:
```
plt.figure(figsize=(15, 8))
sns.countplot(data['release_month']); plt.title('Distribution of movies by month')
```

Out[13]: <Figure size 1080x576 with 0 Axes>

Out[13]: <matplotlib.axes._subplots.AxesSubplot at 0x1f72588d390>

Out[13]: Text(0.5, 1.0, 'Distribution of movies by month')

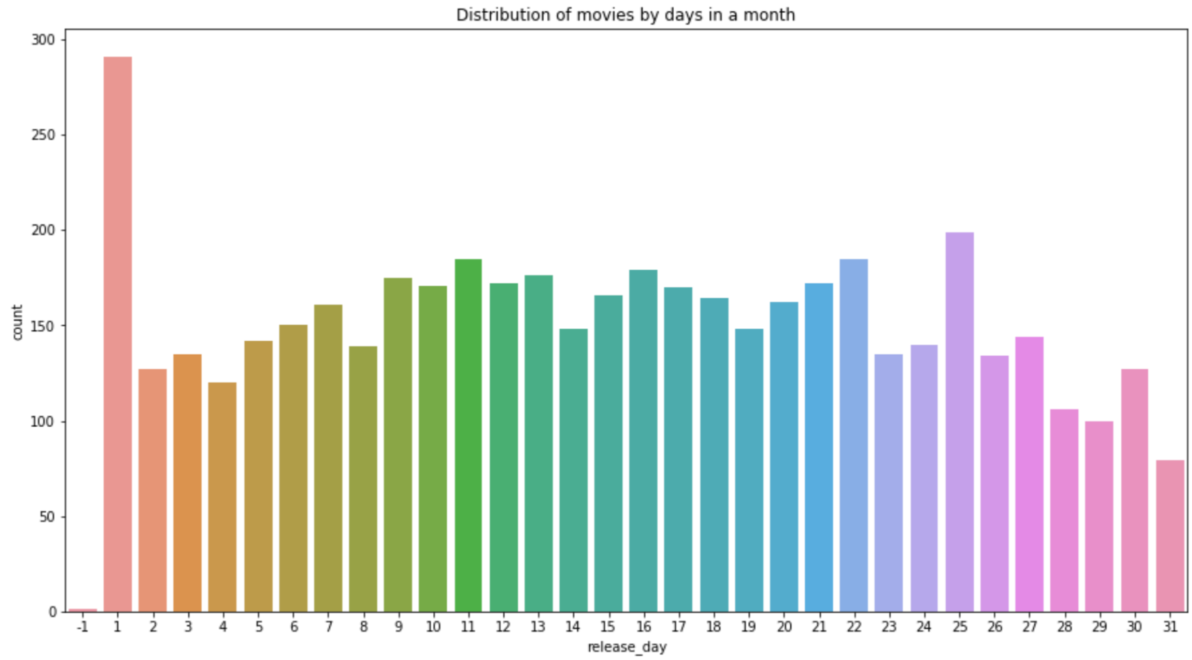


In [23]:
```
plt.figure(figsize=(15, 8))
sns.countplot(data['release_day']); plt.title('Distribution of movies by days in a month')
```

Out[23]: <Figure size 1080x576 with 0 Axes>

Out[23]: <matplotlib.axes._subplots.AxesSubplot at 0x23682dfedd8>

Out[23]: Text(0.5, 1.0, 'Distribution of movies by days in a month')



In [ ]:

In [ ]:

Data Description Report

Issues found:

- dates column
- text to dict column

Exploratory Data Analysis

This section handles the graphs and plots for data exploration.

checking for outliers & anamolies in runtime, budget and revenue

- Univariate visualization

Univariate analysis looks at one feature at a time. When we analyze a feature independently, we are usually mostly interested in the distribution of its values and ignore other features in the dataset.

Below, we will consider different statistical types of features and the corresponding tools for their individual visual analysis.

- Quantitative features

Quantitative features take on ordered numerical values. Those values can be discrete, like integers, or continuous, like real numbers, and usually express a count or a measurement.

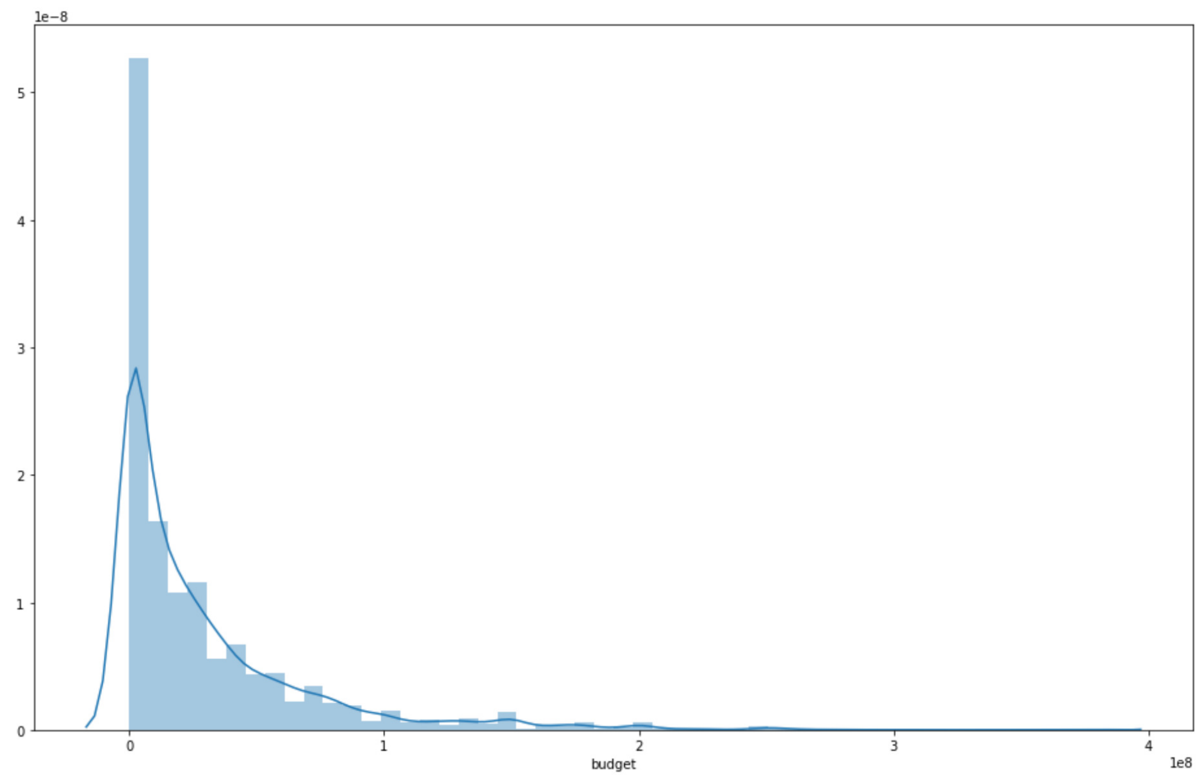
- Frequency distributions and class distributions

Plotting distplot to check the distribution.

In [74]:
```
plt.figure(figsize =(16,10))
sns.distplot(con_data['budget'])
```

Out[74]: <Figure size 1152x720 with 0 Axes>

Out[74]: <matplotlib.axes._subplots.AxesSubplot at 0x22ec016bb38>



Analysis

the above plots show the 'budget' contain outliers, with distribution as positively skewed and a thin kurtosis.

In [14]:
```
# creating gen dataframe for genres to be compared against revenue, budget, runtime
and status
gen = con_data.loc[con_data['genres'].str.len()==1][
['genres','revenue','budget','runtime','status']].reset_index(drop = True)
gen['genres']= gen.genres.apply(lambda x :x[0]['name'])

#gen['genres'] = mvrevenue['genres'].str.extract('([A-Z]\w{0,})', expand=True )

gen.head()
```

Out[14]:

	genres	revenue	budget	runtime	status
0	Action	1506249360	190000000	137.0	Released
1	Science Fiction	543934787	178000000	144.0	Released
2	Fantasy	299370084	170000000	113.0	Released
3	Adventure	301000000	150000000	99.0	Released
4	Comedy	202026112	100000000	90.0	Released

In [73]:
```
#del mv0

#mv0 = mvrevenue.copy()
#mv0 = mv0['genres'].str.extract('[^A-Za-z]+', expand=True )

#mv0 = mvrevenue['genres'].str.extract('([A-Z]\w{0,})', expand=True )

#mv0
```

In [15]:
```
genres = gen.groupby(gen.genres).agg('mean')

genres
```

Out[15]:

genres	revenue	budget	runtime
Action	1.227577e+08	3.971429e+07	107.904762
Adventure	9.679045e+07	4.853846e+07	110.461538
Animation	1.231166e+08	4.950000e+07	93.000000
Comedy	5.707003e+07	2.031676e+07	96.184397
Crime	0.000000e+00	2.500000e+06	110.000000
Documentary	5.566236e+06	1.735243e+06	92.909091
Drama	3.436563e+07	1.298058e+07	114.425474
Family	0.000000e+00	0.000000e+00	74.000000
Fantasy	9.671589e+07	6.483333e+07	112.833333
History	2.652751e+07	1.800000e+07	120.000000
Horror	3.999399e+07	8.085078e+06	89.765625
Music	1.423834e+07	1.600000e+07	98.000000
Romance	6.508158e+07	8.340000e+06	96.000000
Science Fiction	7.420446e+07	3.829107e+07	110.142857
Thriller	2.070070e+07	1.486957e+07	107.086957
War	6.190232e+07	4.300000e+07	126.500000
Western	2.279019e+07	7.017988e+06	119.277778

In [20]:
```
plt.figure(figsize=(15,10))
plt.subplot(2,2,3)
sns.barplot(genres['revenue'],genres.index)

plt.subplot(2,2,2)
sns.barplot(genres['runtime'],genres.index)

plt.subplot(2,2,1)
sns.barplot(genres['budget'],genres.index)
```

Out[20]: <Figure size 1080x720 with 0 Axes>

Out[20]: <matplotlib.axes._subplots.AxesSubplot at 0x2c14024ff60>

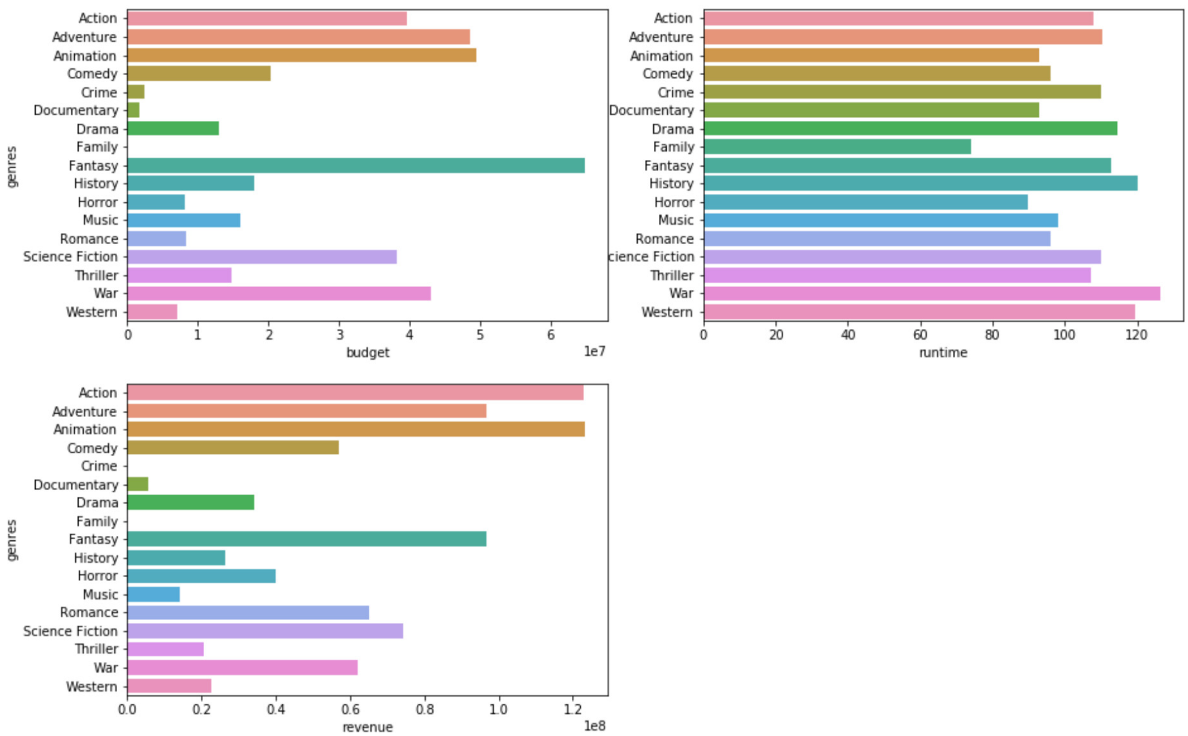
Out[20]: <matplotlib.axes._subplots.AxesSubplot at 0x2c14024ff60>

Out[20]: <matplotlib.axes._subplots.AxesSubplot at 0x2c140279828>

Out[20]: <matplotlib.axes._subplots.AxesSubplot at 0x2c140279828>

Out[20]: <matplotlib.axes._subplots.AxesSubplot at 0x2c14036e7f0>

Out[20]: <matplotlib.axes._subplots.AxesSubplot at 0x2c14036e7f0>



In [34]:
```
# Class Distributions genres
class_counts = con_data.groupby('original_language').size()
class_counts
```

Out[34]:
```
original_language
af       1
ar       2
cn      12
cs       2
da       7
de      26
el       1
en    4503
es      32
fa       4
fr      70
he       3
hi      19
hu       1
id       2
is       1
it      13
ja      16
ko      11
ky       1
nb       1
nl       4
no       1
pl       1
ps       1
pt       9
ro       2
ru      11
sl       1
sv       5
ta       2
te       1
th       3
tr       1
vi       1
xx       1
zh      27
dtype: int64
```

- Data Preparation

DF backup before further modification

In [16]:
```
con_data2 = con_data
con_data.head(1)
```

Out[16]:

	title	genres	id	keywords	original_language	overview	production_companies	production_countries
0	Avatar	[{'id': 28, 'name': 'Action'}, {'id': 12, 'nam...	19995	[{'id': 1463, 'name': 'culture clash'}, {'id':...	en	In the 22nd century, a paraplegic Marine is di...	[{'name': 'Ingenious Film Partners', 'id': 289...	[{'iso_3166_1': 'US' 'name': 'United States o..

In [17]:
```
element = con_data2.iloc[0]['genres']
element
```

Out[17]:
```
[{'id': 28, 'name': 'Action'},
 {'id': 12, 'name': 'Adventure'},
 {'id': 14, 'name': 'Fantasy'},
 {'id': 878, 'name': 'Science Fiction'}]
```

Converting the dictionary columns to extract the values

In [18]:
```
def parse_dict(raw_dict):
    return [d['name']  for d in raw_dict ]
```

In [40]:
```
con_data2
```

Out[40]:

	title	genres	id	keywords	original_language	overview	production_compa
0	Avatar	[{'id': 28, 'name': 'Action'}, {'id': 12, 'nam...	19995	[{'id': 1463, 'name': 'culture clash'}, {'id':...	en	In the 22nd century, a paraplegic Marine is di...	[{'name': 'Ingenious Partners', 'id': 2
1	Pirates of the Caribbean: At World's End	[{'id': 12, 'name': 'Adventure'}, {'id': 14, '...	285	[{'id': 270, 'name': 'ocean'}, {'id': 726, 'na...	en	Captain Barbossa, long believed to be dead, ha...	[{'name': 'Walt Dis Pictures', 'id': 2}
2	Spectre	[{'id': 28, 'name': 'Action'}, {'id': 12, 'nam...	206647	[{'id': 470, 'name': 'spy'}, {'id': 818, 'name...	en	A cryptic message from Bond's past sends him o...	[{'name': 'Colur Pictures', 'id': 5}, {'na
3	The Dark Knight Rises	[{'id': 28, 'name': 'Action'}, {'id': 80, 'nam...	49026	[{'id': 849, 'name': 'dc comics'}, {'id': 853,...	en	Following the death of District Attorney Harve...	[{'name': 'Legen Pictures', 'id': 923}
4	John Carter	[{'id': 28, 'name': 'Action'}, {'id': 12, 'nam...	49529	[{'id': 818, 'name': 'based on novel'}, {'id':...	en	John Carter is a war-weary, former military ca...	[{'name': 'Walt Dis Pictures', 'id
5	Spider-Man 3	[{'id': 14, 'name': 'Fantasy'}, {'id': 28, 'na...	559	[{'id': 851, 'name': 'dual identity'}, {'id': ...	en	The seemingly invincible Spider-Man goes up ag...	[{'name': 'Colur Pictures', 'id': 5}, {'na
6	Tangled	[{'id': 16, 'name': 'Animation'}, {'id': 10751...	38757	[{'id': 1562, 'name': 'hostage'}, {'id': 2343,...	en	When the kingdom's most wanted-and most charmi...	[{'name': 'Walt Dis Pictures', 'id': 2}
7	Avengers: Age of Ultron	[{'id': 28, 'name': 'Action'}, {'id': 12, 'nam...	99861	[{'id': 8828, 'name': 'marvel comic'}, {'id': ...	en	When Tony Stark tries to jumpstart a dormant p...	[{'name': 'Ma Studios', 'id': 4 {'nar
8	Harry Potter and the Half-Blood Prince	[{'id': 12, 'name': 'Adventure'}, {'id': 14, '...	767	[{'id': 616, 'name': 'witch'}, {'id': 2343, 'n...	en	As Harry begins his sixth year at Hogwarts, he...	[{'name': 'Warner Br 'id': 6194}, {'nan
9	Batman v Superman: Dawn of Justice	[{'id': 28, 'name': 'Action'}, {'id': 12, 'nam...	209112	[{'id': 849, 'name': 'dc comics'}, {'id': 7002...	en	Fearing the actions of a god-like Super Hero l...	[{'name': 'DC Com 'id': 429}, {'name':
10	Superman Returns	[{'id': 12, 'name': 'Adventure'}, {'id': 14, '...	1452	[{'id': 83, 'name': 'saving the world'}, {'id'...	en	Superman returns to discover his 5-year absenc...	[{'name': 'DC Com 'id': 429}, {'name':
11	Quantum of Solace	[{'id': 12, 'name': 'Adventure'}, {'id': 28, '...	10764	[{'id': 627, 'name': 'killing'}, {'id': 1568, ...	en	Quantum of Solace continues the adventures of ...	[{'name': Productions', 'id': 75
12	Pirates of the Caribbean: Dead Man's Chest	[{'id': 12, 'name': 'Adventure'}, {'id': 14, '...	58	[{'id': 616, 'name': 'witch'}, {'id': 663, 'na...	en	Captain Jack Sparrow works his way out of a bl...	[{'name': 'Walt Dis Pictures', 'id': 2}
13	The Lone Ranger	[{'id': 28, 'name': 'Action'}, {'id': 12, 'nam...	57201	[{'id': 1556, 'name': 'texas'}, {'id': 2673, '...	en	The Texas Rangers chase down a gang of outlaws...	[{'name': 'Walt Dis Pictures', 'id': 2}
14	Man of Steel	[{'id': 28, 'name': 'Action'}, {'id':	49521	[{'id': 83, 'name': 'saving the	en	A young boy learns that he has extraordinary	[{'name': 'Legen Pictures', 'id': 923}

In [19]:
```
# One-Hot-Encoding for all nominal data

df = pd.get_dummies(gen)

df.head()
```

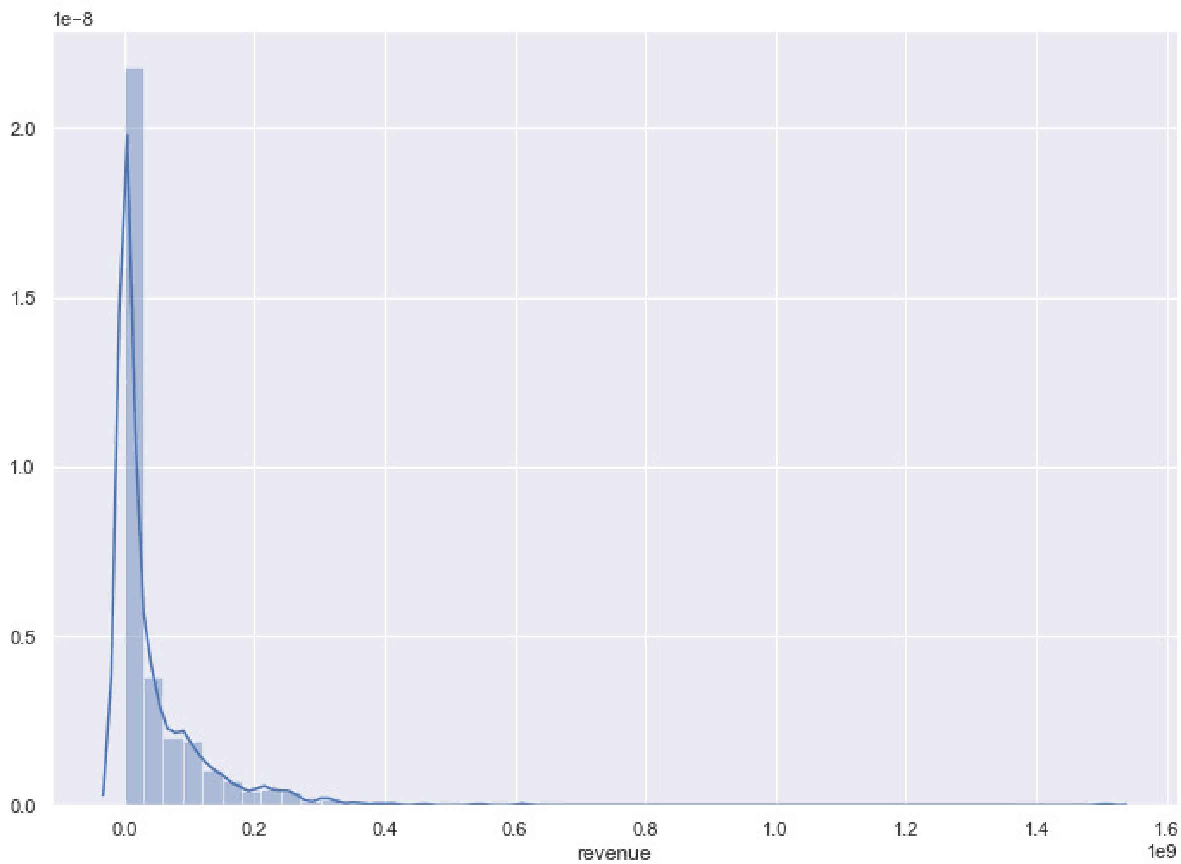
Out[19]:

	revenue	budget	runtime	genres_Action	genres_Adventure	genres_Animation	genres_Comedy	gen
0	1506249360	190000000	137.0	1	0	0	0	
1	543934787	178000000	144.0	0	0	0	0	
2	299370084	170000000	113.0	0	0	0	0	
3	301000000	150000000	99.0	0	1	0	0	
4	202026112	100000000	90.0	0	0	0	1	

5 rows × 23 columns

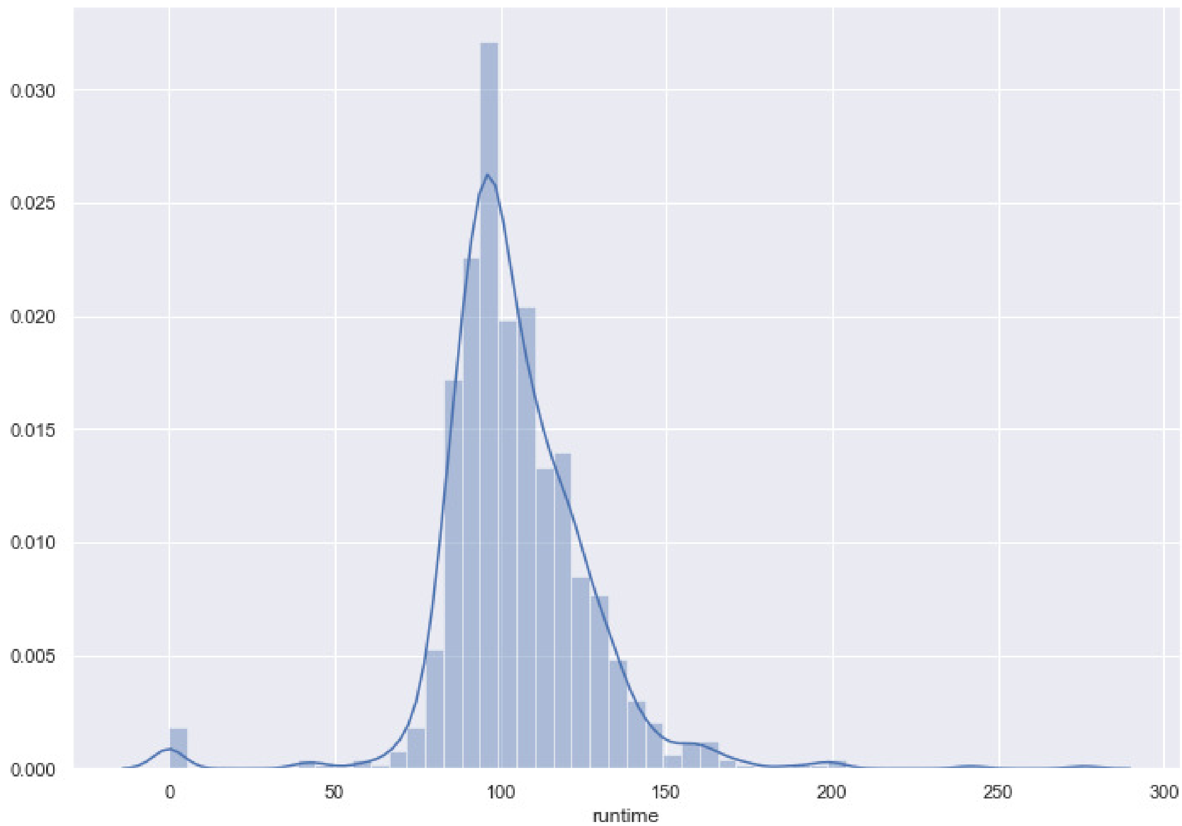
In [42]:
```
sns.set(rc={'figure.figsize':(11.7,8.27)})


sns.distplot(df['revenue'])
```

Out[42]: <matplotlib.axes._subplots.AxesSubplot at 0x1a55a0dd2e8>



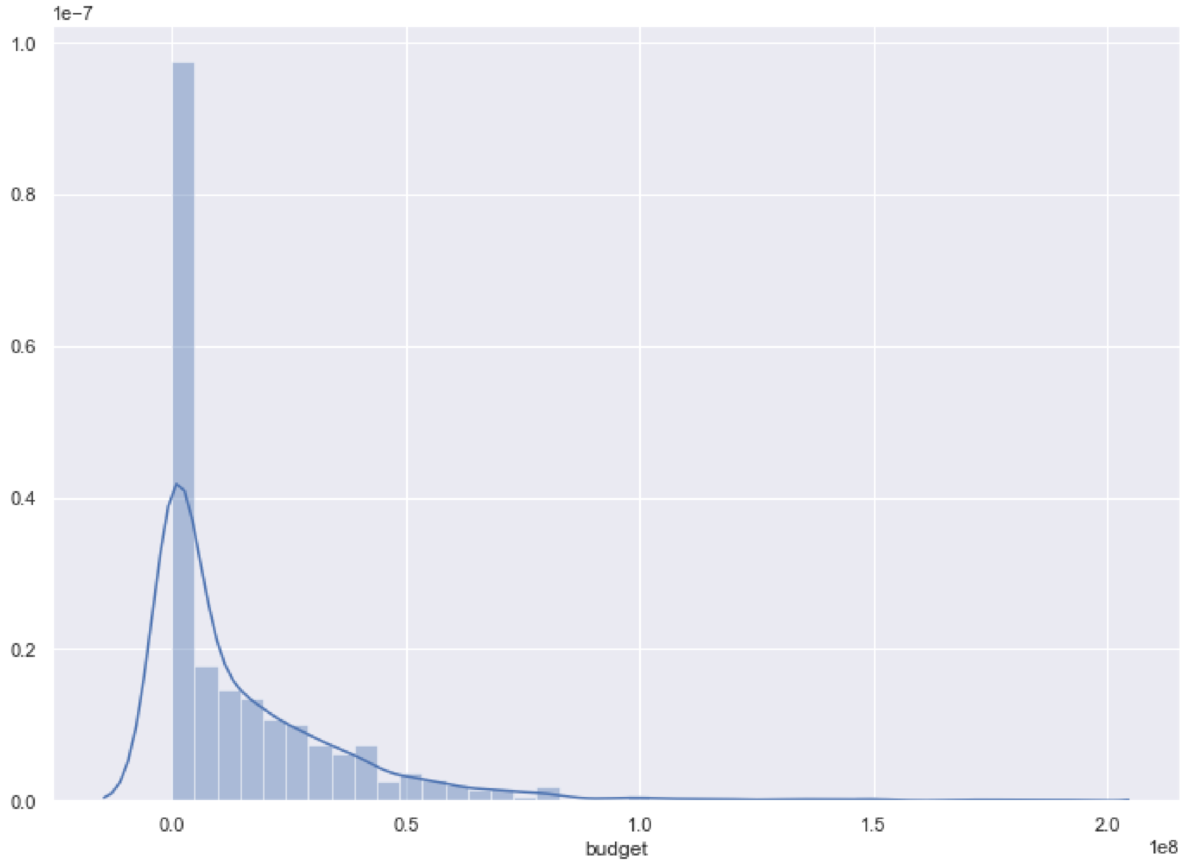
In [43]:
```
sns.set(rc={'figure.figsize':(11.7,8.27)})


sns.distplot(df['runtime'])
```

Out[43]: <matplotlib.axes._subplots.AxesSubplot at 0x1a55a1f3278>



In [44]:
```
sns.set(rc={'figure.figsize':(11.7,8.27)})


sns.distplot(df['budget'])
```

Out[44]: <matplotlib.axes._subplots.AxesSubplot at 0x1a55a2c5518>



In [20]:
```
# Skewness value
con_data.skew()
```

Out[20]:
```
id               2.071986
runtime          0.739876
budget           2.436115
revenue          4.443129
release_month   -0.153424
release_day      0.022664
release_year    -2.170769
dtype: float64
```

Modeling

In [21]:
```
pd.set_option('display.max_columns', None)
pd.set_option('display.expand_frame_repr', False)
pd.set_option('max_colwidth', -1)
```

In [22]:
```
df.head()
```

Out[22]:

	revenue	budget	runtime	genres_Action	genres_Adventure	genres_Animation	genres_Comedy	gen
0	1506249360	190000000	137.0	1	0	0	0	
1	543934787	178000000	144.0	0	0	0	0	
2	299370084	170000000	113.0	0	0	0	0	
3	301000000	150000000	99.0	0	1	0	0	
4	202026112	100000000	90.0	0	0	0	1	

In [27]:
```
df.columns
```

Out[27]:
```
Index(['revenue', 'budget', 'runtime', 'genres_Action', 'genres_Adventure',
       'genres_Animation', 'genres_Comedy', 'genres_Crime',
       'genres_Documentary', 'genres_Drama', 'genres_Family', 'genres_Fantasy',
       'genres_History', 'genres_Horror', 'genres_Music', 'genres_Romance',
       'genres_Science Fiction', 'genres_Thriller', 'genres_War',
       'genres_Western', 'status_Post Production', 'status_Released',
       'status_Rumored'],
      dtype='object')
```

Split the data into training set and testing set using train_test_split

using scikit learn split the data-set

In [23]:
```
df = df[['budget', 'runtime', 'genres_Action', 'genres_Adventure',
       'genres_Animation', 'genres_Comedy', 'genres_Crime',
       'genres_Documentary', 'genres_Drama', 'genres_Family', 'genres_Fantasy',
       'genres_Horror', 'genres_Science Fiction', 'genres_Thriller',
       'genres_Western', 'status_Released','revenue']]
```

In [24]:
```
# Split-out validation dataset

X = df.drop('revenue', axis = 1)
Y = df.revenue
validation_size = 0.20
seed = 7
X_train, X_validation, Y_train, Y_validation = train_test_split(X, Y, test_size=val
idation_size, random_state=seed)
```

In [30]:
```
print(X_train)
print(X_validation)
print(Y_train)
print(Y_validation)
```

	budget	runtime	genres_Action	genres_Adventure	genres_Animation	genres_Comedy	genres_Crime	genres_Documentary	genres_Drama	genres_Family	genres_Fantasy	genres_Horror	genres_Science Fiction	genres_Thriller	genres_Western	status_Released
264	35000000	114.0	0	0	0	1	0	0	0	0	0	0	0	0	0	1
22	79000000	91.0	0	0	0	1	0	0	0	0	0	0	0	0	0	1
815	400000	95.0	0	0	0	1	0	0	0	0	0	0	0	0	0	1
888	27000	92.0	0	0	0	1	0	0	0	0	0	0	0	0	0	1
835	0	95.0	0	0	0	0	0	0	1	0	0	0	0	0	0	1
232	27000000	113.0	0	0	0	1	0	0	0	0	0	0	0	0	0	1
880	50000	111.0	0	0	0	0	0	1	0	0	0	0	0	0	0	1
270	20000000	127.0	0	0	0	0	0	0	1	0	0	0	0	0	0	1
669	35000000	94.0	0	0	0	0	0	0	0	0	0	1	0	0	0	1
316	18000000	111.0	0	0	0	0	0	0	1	0	0	0	0	0	0	1
465	11000000	98.0	0	0	0	1	0	0	0	0	0	0	0	0	0	1
347	26000000	125.0	0	0	0	0	0	0	1	0	0	0	0	0	0	1
142	35000000	91.0	0	0	0	1	0	0	0	0	0	0	0	0	0	1
50	58000000	103.0	0	0	0	1	0	0	0	0	0	0	0	0	0	1
709	1500000	111.0	0	0	0	0	0	0	1	0	0	0	0	0	0	1
885	0	89.0	0	0	0	0	0	0	1	0	0	0	0	0	0	1
445	6000000	90.0	0	0	0	1	0	0	0	0	0	0	0	0	0	1
558	5000000	104.0	0	0	0	0	0	0	0	0	0	1	0	0	0	1
750	0	90.0	0	0	0	0	0	0	1	0	0	0	0	0	0	1
81	0	0.0	0	0	0	0	0	0	0	0	0	1	0	0	0	1

Running the Linear Regression Model

In [26]:
```
from sklearn.linear_model import LinearRegression
reg = LinearRegression()
def rmsle(y,y0): return np.sqrt(np.mean(np.square(np.log1p(y)-np.log1p(y0))))
model = reg.fit(X,Y)
y_pred = reg.predict(X)
rmsle = rmsle(y_pred, Y)
print("The linear model has intercept : {}, and coefficients : {}, and the rmsle is {} ".format(model.intercept_, model.coef_, rmsle) )
```

```
The linear model has intercept : -14644620.058988929, and coefficients : [ 2.118
93237e+00  2.61006990e+05  2.78379824e+07 -1.74944018e+07
  1.13518567e+07  6.30172914e+06 -1.66119971e+07 -5.00613574e+06
 -5.61654625e+06 -1.91841449e+06 -5.27157457e+07  1.68289014e+07
 -1.82836835e+07 -2.13612411e+07 -5.81668017e+06 -2.75148271e+06], and the rmsle
is 9.36410874773492
```

In [27]:
```
# Build and fit linear regression model
reg_lm = LinearRegression(normalize=True)
reg_lm.fit(X_train, Y_train)

# Calculate the predictions on the test set
pred = reg_lm.predict(X_validation)
```

Out[27]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=True)
```

In [28]:
```
pred
```

Out[28]:
```
array([-2.19615413e+06,  1.17301722e+08,  1.60152199e+07,  5.17659998e+06,
        4.75559258e+07, -4.62763531e+06,  1.10256610e+07,  4.09233613e+07,
        3.00847413e+07,  3.63919353e+07,  1.65019210e+06,  3.50653250e+07,
        5.67876503e+07,  1.24129311e+07,  4.40054836e+05, -1.38925141e+07,
       -5.13377653e+05,  1.33745176e+07,  3.95415235e+07,  2.77168851e+07,
        2.60362459e+06,  1.07141608e+08,  2.82808808e+07, -2.31106618e+07,
        6.85688571e+07,  2.21896516e+07,  4.64732552e+07,  1.04095993e+08,
        1.23267064e+08,  4.46069634e+07,  1.13076000e+07,  7.81273325e+07,
       -2.72981013e+05,  4.48208905e+05,  5.56320122e+07,  7.11336784e+07,
        7.02052020e+07,  7.59018404e+07, -1.23456757e+06,  1.38553109e+07,
        2.04842147e+07,  2.77263359e+06,  5.18494580e+06,  3.65717899e+07,
        3.91229167e+07,  1.07701943e+08,  6.00144998e+07, -1.64157930e+07,
        5.01360861e+07,  2.07852125e+08,  5.01574505e+06,  4.40054836e+05,
        1.89058874e+06,  8.07910864e+07,  1.70889233e+08,  7.10370263e+07,
        1.30520506e+08,  6.77681255e+07,  1.43361042e+07,  2.45709576e+07,
        9.33473049e+06,  8.92271203e+07,  2.53183898e+07,  6.69036746e+06,
       -1.54144356e+07,  1.01588371e+08,  2.08041531e+07,  8.62169465e+06,
       -1.47496421e+06,  6.05146839e+07,  1.34510597e+08,  1.01131692e+08,
        5.02571702e+07,  5.76525847e+07,  3.60548865e+07,  5.01574505e+06,
        1.03134406e+08,  9.15359678e+07,  2.84402123e+06,  3.46304071e+07,
        1.72208639e+07,  1.42809185e+07,  7.59481855e+07,  1.00490043e+08,
        1.20982411e+08,  1.26533277e+07,  2.52523766e+07,  1.02131753e+07,
        1.48168975e+07, -3.45417082e+06,  1.84833891e+07,  1.52334880e+07,
        2.60714367e+07,  1.48168975e+07,  3.48529033e+07,  2.53782911e+07,
        1.36149143e+07, -2.81135082e+05,  5.48889091e+07,  5.44697999e+07,
        5.97733161e+06,  1.50572941e+07,  5.89756519e+07,  2.53782635e+07,
        1.16917412e+07,  5.53148109e+07,  1.57784840e+07,  1.25493541e+07,
        5.73693497e+06,  1.36149143e+07,  4.52315011e+07,  6.36014497e+07,
        3.80560779e+06, -2.21765900e+07,  2.30716964e+07,  1.55551978e+07,
       -9.94170932e+05,  1.76184547e+07,  8.02136409e+07,  2.37138202e+06,
       -3.90644539e+06,  6.16200150e+07,  1.12167277e+08,  3.80560779e+06,
        9.15762410e+07,  1.16591552e+07,  2.37892256e+07,  5.82366044e+07,
        3.98216910e+07,  4.09843789e+06,  2.12886071e+07,  2.37138202e+06,
       -1.23456757e+06,  1.23762017e+05,  2.41697060e+07,  7.86275166e+07,
        6.15779637e+07,  9.64828422e+07,  6.10815932e+07,  5.32856743e+07,
       -1.82196536e+07,  1.22208826e+08, -5.13377653e+05,  1.77486129e+07,
        2.89164161e+07,  2.95795162e+07,  3.81376186e+06,  4.60078009e+07,
        8.09402088e+07,  1.31700556e+07,  1.18281642e+07,  5.73693497e+06,
        6.43610302e+07,  1.68358040e+06,  1.28937243e+07,  1.88243467e+06,
        2.37755312e+07,  2.82808808e+07,  7.52218016e+07,  3.80747118e+07,
        5.73693497e+06,  1.34313989e+07,  2.19318808e+08,  7.00754397e+07,
        2.16861979e+07, -4.83508493e+06, -1.47496421e+06,  1.74178289e+07,
        3.24310793e+07,  1.32664685e+08, -1.58156872e+07,  5.80140654e+07,
        3.65356797e+07,  4.05415850e+06,  5.12982984e+07,  9.63617581e+07,
        1.32106630e+08,  1.83069438e+07,  1.88645418e+07,  4.04624155e+07])
```

In [29]:
```
print('*************Y Shape**************')
Y_validation.shape

print('*************Pred Shape**************')
pred.shape
```

```
*************Y Shape**************
```

Out[29]: (180,)

```
*************Pred Shape**************
```

Out[29]: (180,)

Assess Model

In [30]:
```
# Evaluate the performance using the RMSE
from sklearn.metrics import mean_squared_error
rmse = np.sqrt(mean_squared_error(Y_validation, pred))
print('RMSE: {:.3f}'.format(rmse))
```

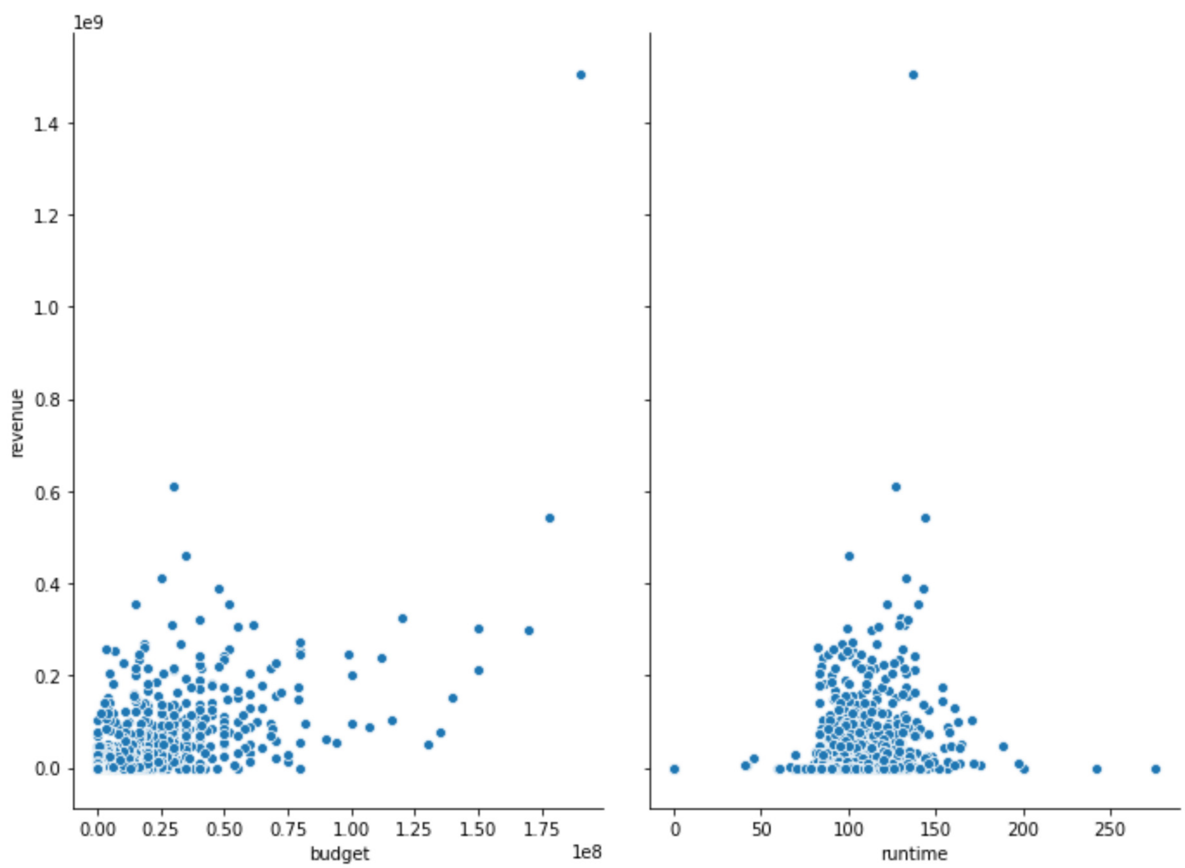
```
RMSE: 64925743.344
```

In [31]:
```
# r2_score is between 0 & 1. 1 is best fit & 0 is worst fit
from sklearn.metrics import r2_score
print("r2_score",r2_score(Y_validation, pred))
```

```
r2_score 0.19900571473920703
```

In [32]:
```
# visualize the relationship between the features and the response using scatterplo
ts
# sns.pairplot(mvrevenue, x_vars=['budget','release_year','runtime'], y_vars='reven
ue', size=7, aspect=0.7)
sns.pairplot(df, x_vars=[ 'budget', 'runtime'], y_vars='revenue', size=7, aspect=0.
7)
```

Out[32]: <seaborn.axisgrid.PairGrid at 0x1f727d5c5c0>



In [34]:
```
# create X and y
feature_cols = ['budget']
X = df[feature_cols]
y = df.revenue

# instantiate and fit
lm2 = LinearRegression()
lm2.fit(X, y)

# print the coefficients
print(lm2.intercept_)
print(lm2.coef_)
```

Out[34]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)

8544030.1107831
[2.17718383]
```

Interpreting Model Coefficients

Interpreting the budget coefficient (β1)

A "unit" increase in budget is associated with a 2.17718383 "units" increase in revenue Or more clearly: An additional $1,000 spent on budget is associated with an increase in sales of 2177.18383 widgets

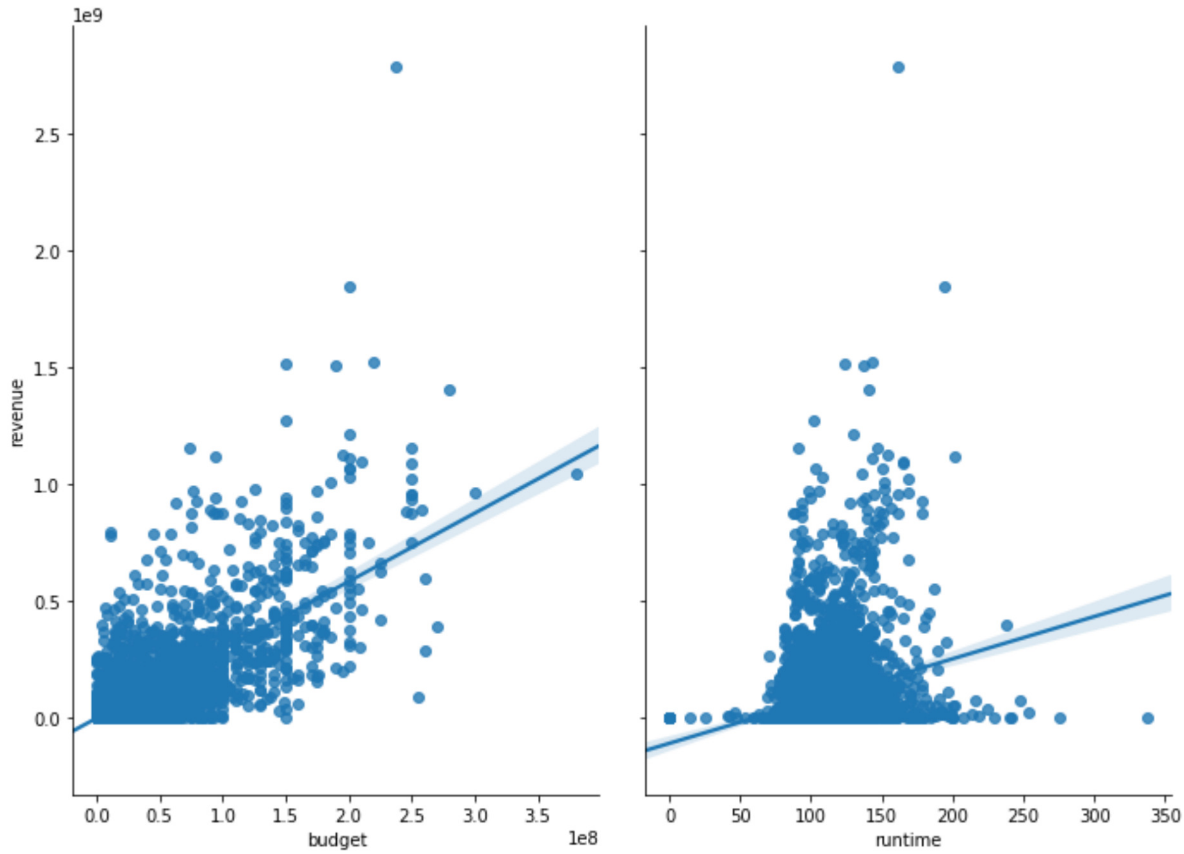
Note here that the coefficients represent associations, not causations

In [ ]:
```

```

Plotting the Least Squares Line

In [35]:
```
sns.pairplot(mvrevenue, x_vars=['budget'], y_vars='revenue', size=7, aspect=0.7, ki
nd='reg')
```

Out[35]: <seaborn.axisgrid.PairGrid at 0x1f728606748>



In [36]:
```
# create X and y
feature_cols = ['budget','runtime']
X = df[feature_cols]
y = df.revenue

# # instantiate and fit
lm2 = LinearRegression()
lm2.fit(X, y)

# # print the coefficients
print(lm2.intercept_)
print(lm2.coef_)
```

Out[36]: LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)

```
-5309987.732538827
[2.14442863e+00 1.37603060e+05]
```

In [37]:
```
# # instantiate and fit
lm2 = LinearRegression()
lm2.fit(X, y)
```

Out[37]: LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)

Predict with Linear Regression

In [38]:
```
X_train, X_validation, Y_train, Y_validation = train_test_split(X, Y, test_size=val
idation_size, random_state=seed)
```

In [39]:
```
#  Remove table meta data, column names   to use values for prediction.

# train_x = df_train_x.values
# train_y = df_train_y.values
# test_x  = df_test_x.values
# X_train = X_train.values
# Y_train = Y_train.values
#  Calculate the coefficients of the linear regression
reg = LinearRegression().fit(X_train, Y_train)

#   Using linear regression model on the prepared test data
Y_validation = reg.predict(X_validation)

# Accuracy
print('Accuracy Linear Regression:', reg.score(X_validation, Y_validation))
```

```
Accuracy Linear Regression: 1.0
```

Predicting with XGBOOST

In [40]:
```
import xgboost as xgb

xgb_model = xgb.XGBRegressor(objective="reg:squarederror", random_state=7)

xgb_model.fit(X_train, Y_train)

Y_validation = xgb_model.predict(X_validation)

print('Accuracy XGB:', xgb_model.score(X_train, Y_train))
```

Out[40]:
```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, gamma=0,
             importance_type='gain', learning_rate=0.1, max_delta_step=0,
             max_depth=3, min_child_weight=1, missing=None, n_estimators=100,
             n_jobs=1, nthread=None, objective='reg:squarederror',
             random_state=7, reg_alpha=0, reg_lambda=1, scale_pos_weight=1,
             seed=None, silent=None, subsample=1, verbosity=1)
```

```
Accuracy XGB: 0.7066468166703885
```

Trying with other algorithms

In [41]:
```
# Test options and evaluation metric
num_folds = 10
num_instances = len(X_train)
seed = 7

# Listing the possible scoring matrix

r2_score = 'r2'
## metrics.r2_score

# Initiating the score matrix
scoring =  r2_score
```

In [44]:
```
random_seed = 12
outcome = []
model_names = []
models = []
models.append(('LR', LinearRegression()))
models.append(('LASSO', Lasso()))
models.append(('EN', ElasticNet()))
models.append(('KNN', KNeighborsRegressor()))
models.append(('CART', DecisionTreeRegressor()))
models.append(('SVR', SVR()))
models.append(('XGB', xgb.XGBRegressor(objective="reg:squarederror")))
```

In [45]:
```
# evaluate each model in turn
results = []
names = []
for name, model in models:
    kfold = model_selection.KFold(n_splits =10, random_state = random_seed)
    cv_results = model_selection.cross_val_score(model, X_train, Y_train, cv = kfol
d, scoring = scoring)
    results.append(cv_results)
    names.append(name)
    msg = "%s: %f (%f)" % (name, cv_results.mean(), cv_results.std())
    print(msg)
```

```
LR: 0.347419 (0.122490)
LASSO: 0.347419 (0.122490)
EN: 0.347420 (0.122491)
KNN: 0.263239 (0.159443)
CART: -0.094588 (0.291035)
SVR: -0.222887 (0.094258)
XGB: 0.334331 (0.146317)
```

In [46]:
```
# Validating  LR Score on Testing Set
LR_model = LinearRegression()
LR_model.fit(X_train, Y_train)
Y_validation = LR_model.predict(X_validation)
print('Accuracy LR:', LR_model.score(X_train, Y_train))


# Validating  LASSO Score on Testing Set
LASSO_model = Lasso()
LASSO_model.fit(X_train, Y_train)
Y_validation = LR_model.predict(X_validation)
print('Accuracy LASSO:', LASSO_model.score(X_train, Y_train))

# Validating  EN Score on Testing Set
EN_model = ElasticNet()
EN_model.fit(X_train, Y_train)
Y_validation = EN_model.predict(X_validation)
print('Accuracy EN:', EN_model.score(X_train, Y_train))

# Validating  KNN Score on Testing Set
KNN_model = KNeighborsRegressor()
KNN_model.fit(X_train, Y_train)
Y_validation = KNN_model.predict(X_validation)
print('Accuracy KNN:', KNN_model.score(X_train, Y_train))

# Validating  CART Score on Testing Set
CART_model = DecisionTreeRegressor()
CART_model.fit(X_train, Y_train)
Y_validation = CART_model.predict(X_validation)
print('Accuracy CART:', CART_model.score(X_train, Y_train))

# Validating  SVR Score on Testing Set
SVR_model = SVR()
SVR_model.fit(X_train, Y_train)
Y_validation = SVR_model.predict(X_validation)
print('Accuracy SVR:', SVR_model.score(X_train, Y_train))

# Validating  XGB Score on Testing Set
xgb_model = xgb.XGBRegressor(objective="reg:squarederror")
xgb_model.fit(X_train, Y_train)
Y_validation = xgb_model.predict(X_validation)
print('Accuracy XGB:', xgb_model.score(X_train, Y_train))
```

```
Out[46]: LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)

         Accuracy LR: 0.3829906441575285

Out[46]: Lasso(alpha=1.0, copy_X=True, fit_intercept=True, max_iter=1000,
               normalize=False, positive=False, precompute=False, random_state=None,
               selection='cyclic', tol=0.0001, warm_start=False)

         Accuracy LASSO: 0.3829906441575285

Out[46]: ElasticNet(alpha=1.0, copy_X=True, fit_intercept=True, l1_ratio=0.5,
                    max_iter=1000, normalize=False, positive=False, precompute=False,
                    random_state=None, selection='cyclic', tol=0.0001, warm_start=False)

         Accuracy EN: 0.38299064380781156

Out[46]: KNeighborsRegressor(algorithm='auto', leaf_size=30, metric='minkowski',
                             metric_params=None, n_jobs=None, n_neighbors=5, p=2,
                             weights='uniform')

         Accuracy KNN: 0.5296165934823194

Out[46]: DecisionTreeRegressor(criterion='mse', max_depth=None, max_features=None,
                               max_leaf_nodes=None, min_impurity_decrease=0.0,
                               min_impurity_split=None, min_samples_leaf=1,
                               min_samples_split=2, min_weight_fraction_leaf=0.0,
                               presort=False, random_state=None, splitter='best')

         Accuracy CART: 0.9807880333053189

Out[46]: SVR(C=1.0, cache_size=200, coef0=0.0, degree=3, epsilon=0.1,
             gamma='auto_deprecated', kernel='rbf', max_iter=-1, shrinking=True,
             tol=0.001, verbose=False)

         Accuracy SVR: -0.1582129454658463

Out[46]: XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
                      colsample_bynode=1, colsample_bytree=1, gamma=0,
                      importance_type='gain', learning_rate=0.1, max_delta_step=0,
                      max_depth=3, min_child_weight=1, missing=None, n_estimators=100,
                      n_jobs=1, nthread=None, objective='reg:squarederror',
                      random_state=0, reg_alpha=0, reg_lambda=1, scale_pos_weight=1,
                      seed=None, silent=None, subsample=1, verbosity=1)

         Accuracy XGB: 0.7066468166703885
```

In [47]:
```
# Compare Algorithms
fig = plt.figure()
fig.suptitle('Algorithm Comparison')
ax = fig.add_subplot(111)
plt.boxplot(results)
ax.set_xticklabels(names)
plt.show()
plt.rcParams['figure.figsize'] = 14,10
```

Out[47]:
```
Text(0.5, 0.98, 'Algorithm Comparison')
```

Out[47]:
```
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```

Out[47]:
```
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 Text(0, 0, 'LASSO'),
 Text(0, 0, 'EN'),
 Text(0, 0, 'KNN'),
 Text(0, 0, 'CART'),
 Text(0, 0, 'SVR'),
 Text(0, 0, 'XGB')]
```

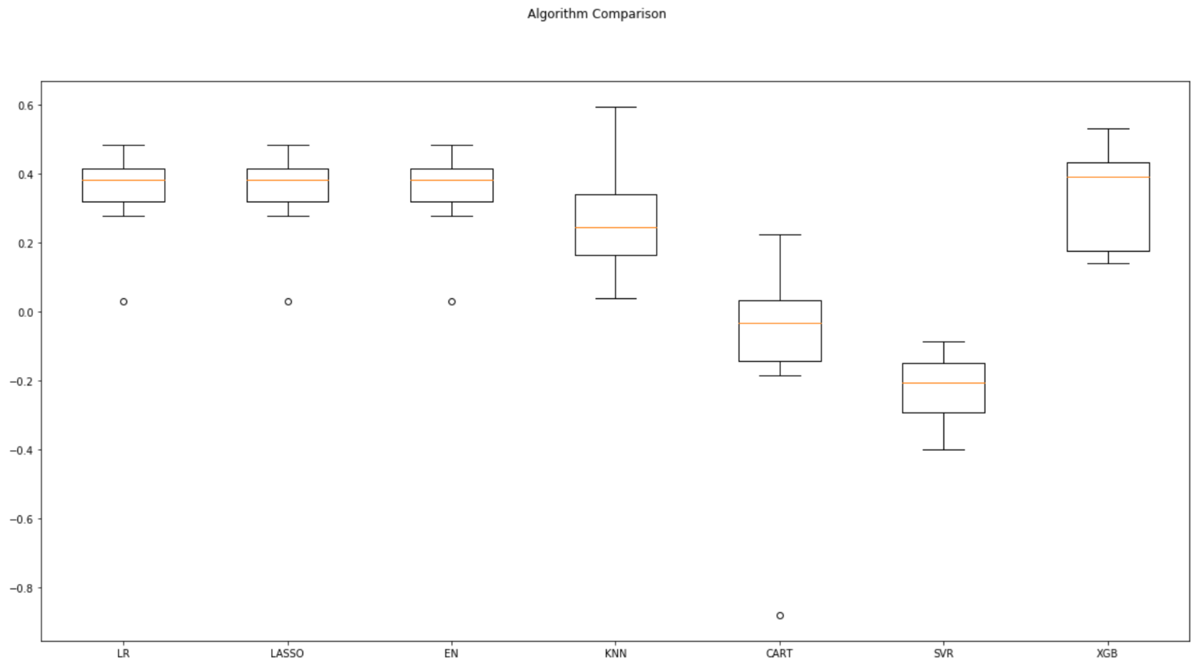

In [ ]:

In [ ]:

In [ ]:

Review Process Review of Process

In [ ]:

Determine Next Steps

In [ ]:

List of Possible Actions Decision

In [ ]:

Review Recommendations to Organization

In [ ]:

In [ ]: