MOVIE RATINGS ANALYSIS USING SEABORN

In [1]:
```
import pandas as pd
import os
import numpy as np
import seaborn as sns
import plotly.express as px
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
```

In [2]:
```
movies = pd.read_csv(r'C:\Users\91939\Desktop\AI&DS\19thAug\Movie-Rating.csv')
```

In [3]:
```
movies
```

Out[3]:

	Film	Genre	Rotten Tomatoes Ratings %	Audience Ratings %	Budget (million $)	Year of release
0	(500) Days of Summer	Comedy	87	81	8	2009
1	10,000 B.C.	Adventure	9	44	105	2008
2	12 Rounds	Action	30	52	20	2009
3	127 Hours	Adventure	93	84	18	2010
4	17 Again	Comedy	55	70	20	2009
...	...	...	...	...	...	...
554	Your Highness	Comedy	26	36	50	2011
555	Youth in Revolt	Comedy	68	52	18	2009
556	Zodiac	Thriller	89	73	65	2007
557	Zombieland	Action	90	87	24	2009
558	Zookeeper	Comedy	14	42	80	2011

559 rows × 6 columns

In [4]:
```
len(movies)
```

Out[4]: 559

In [5]:
```
movies.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 559 entries, 0 to 558
Data columns (total 6 columns):
 #   Column                     Non-Null Count  Dtype 
---  ------                     --------------  ----- 
 0   Film                       559 non-null    object
 1   Genre                      559 non-null    object
 2   Rotten Tomatoes Ratings %  559 non-null    int64 
 3   Audience Ratings %         559 non-null    int64 
 4   Budget (million $)         559 non-null    int64 
 5   Year of release            559 non-null    int64 
dtypes: int64(4), object(2)
memory usage: 26.3+ KB
```

In [6]:
```
movies.describe()
```

Out[6]:

	Rotten Tomatoes Ratings %	Audience Ratings %	Budget (million $)	Year of release
count	559.000000	559.000000	559.000000	559.000000
mean	47.309481	58.744186	50.236136	2009.152057
std	26.413091	16.826887	48.731817	1.362632
min	0.000000	0.000000	0.000000	2007.000000
25%	25.000000	47.000000	20.000000	2008.000000
50%	46.000000	58.000000	35.000000	2009.000000
75%	70.000000	72.000000	65.000000	2010.000000
max	97.000000	96.000000	300.000000	2011.000000

In [7]:
```
movies.shape
```

Out[7]: (559, 6)

In [8]:
```
movies.head()
```

Out[8]:

	Film	Genre	Rotten Tomatoes Ratings %	Audience Ratings %	Budget (million $)	Year of release
0	(500) Days of Summer	Comedy	87	81	8	2009
1	10,000 B.C.	Adventure	9	44	105	2008
2	12 Rounds	Action	30	52	20	2009
3	127 Hours	Adventure	93	84	18	2010
4	17 Again	Comedy	55	70	20	2009

In [9]:
```
movies.tail()
```

Out[9]:

	Film	Genre	Rotten Tomatoes Ratings %	Audience Ratings %	Budget (million $)	Year of release
554	Your Highness	Comedy	26	36	50	2011
555	Youth in Revolt	Comedy	68	52	18	2009
556	Zodiac	Thriller	89	73	65	2007
557	Zombieland	Action	90	87	24	2009
558	Zookeeper	Comedy	14	42	80	2011

In [10]:
```
movies.columns
```

Out[10]:
```
Index(['Film', 'Genre', 'Rotten Tomatoes Ratings %', 'Audience Ratings %',
       'Budget (million $)', 'Year of release'],
      dtype='object')
```

In [11]:
```
movies.columns = ['Film', 'Genre', 'CriticRating', 'AudienceRating','BudgetMilli
```

In [12]:
```
movies.columns
```

Out[12]:
```
Index(['Film', 'Genre', 'CriticRating', 'AudienceRating', 'BudgetMillions',
       'Year'],
      dtype='object')
```

In [13]:
```
movies.isnull()
```

Out[13]:

	Film	Genre	CriticRating	AudienceRating	BudgetMillions	Year
0	False	False	False	False	False	False
1	False	False	False	False	False	False
2	False	False	False	False	False	False
3	False	False	False	False	False	False
4	False	False	False	False	False	False
...	...	...	...	...	...	...
554	False	False	False	False	False	False
555	False	False	False	False	False	False
556	False	False	False	False	False	False
557	False	False	False	False	False	False
558	False	False	False	False	False	False

559 rows × 6 columns

In [14]:
```
movies.isnull().all()
```

Out[14]:
```
Film              False
Genre             False
CriticRating      False
AudienceRating    False
BudgetMillions    False
Year              False
dtype: bool
```

In [15]:
```
movies.isnull().all().all()
```

Out[15]:
```
False
```

In [16]:
```
movies.Film = movies.Film.astype('category')
```

In [17]:
```
movies.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 559 entries, 0 to 558
Data columns (total 6 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   Film            559 non-null    category
 1   Genre           559 non-null    object
 2   CriticRating    559 non-null    int64
 3   AudienceRating  559 non-null    int64
 4   BudgetMillions  559 non-null    int64
 5   Year            559 non-null    int64
dtypes: category(1), int64(4), object(1)
memory usage: 43.6+ KB
```

In [18]:
```
movies.Genre = movies.Genre.astype('category')
movies.Year = movies.Year.astype('category')
```

In [19]:
```
movies.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 559 entries, 0 to 558
Data columns (total 6 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   Film            559 non-null    category
 1   Genre           559 non-null    category
 2   CriticRating    559 non-null    int64
 3   AudienceRating  559 non-null    int64
 4   BudgetMillions  559 non-null    int64
 5   Year            559 non-null    category
dtypes: category(3), int64(3)
memory usage: 36.5 KB
```

In [20]:
```
movies.describe()
```

Out[20]:

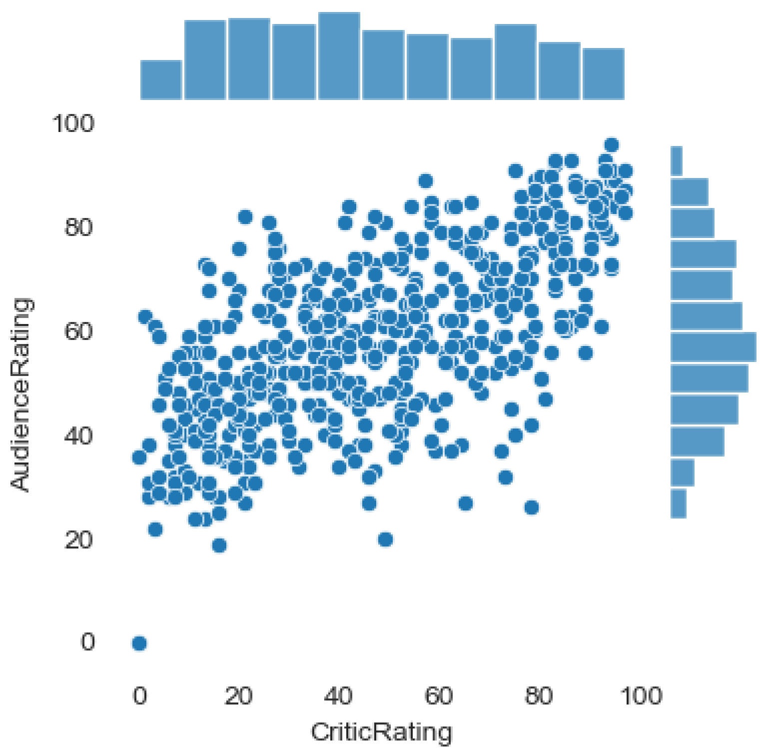
	CriticRating	AudienceRating	BudgetMillions
count	559.000000	559.000000	559.000000
mean	47.309481	58.744186	50.236136
std	26.413091	16.826887	48.731817
min	0.000000	0.000000	0.000000
25%	25.000000	47.000000	20.000000
50%	46.000000	58.000000	35.000000
75%	70.000000	72.000000	65.000000
max	97.000000	96.000000	300.000000

In [21]:
```
import warnings
warnings.filterwarnings('ignore')
```

JOINTPLOT

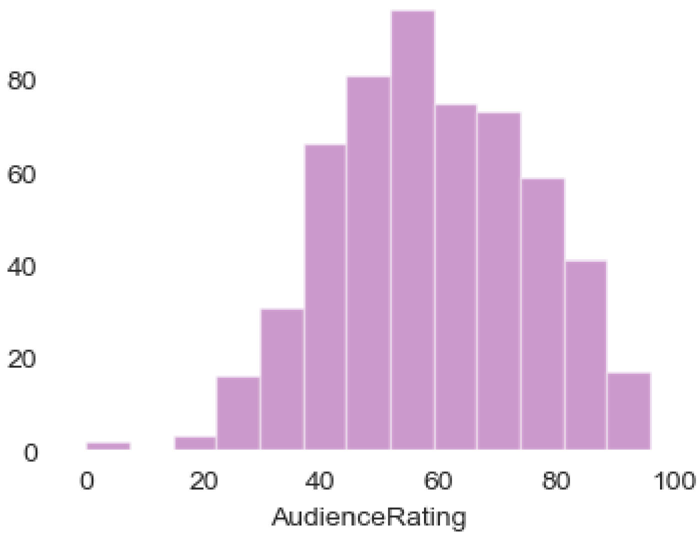
Draw a plot of two variables with bivariate and univariate graphs.

In [22]:
```
sns.set_style('dark', {'axes.facecolor': 'white'})
j=sns.jointplot(data = movies, x = 'CriticRating', y = 'AudienceRating', height=
```



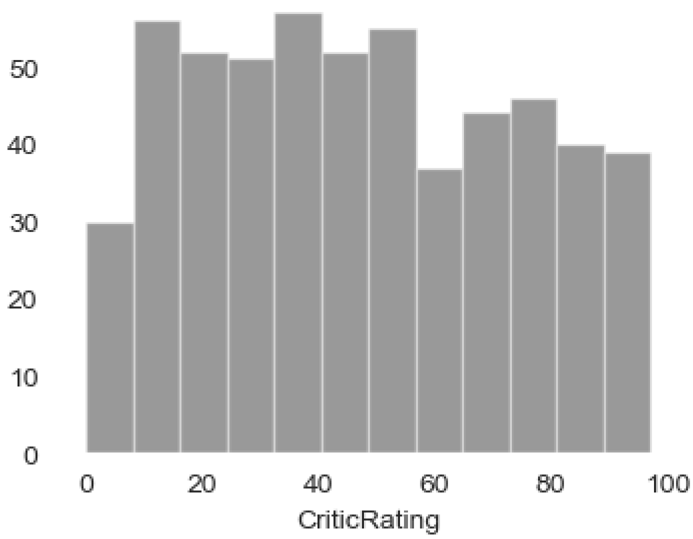
In [23]:
```
y=movies['AudienceRating']
plt.figure(figsize=(4,3))
sns.distplot(y,kde=False,bins=13,color='purple')
```

Out[23]: <Axes: xlabel='AudienceRating'>

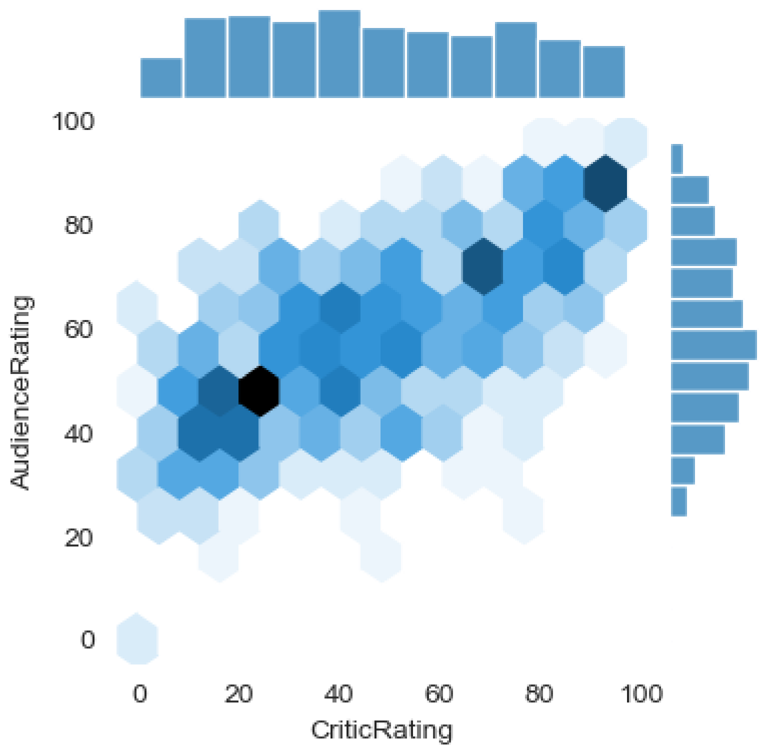


In [24]:
```
y=movies['CriticRating']
plt.figure(figsize=(4,3))
sns.distplot(y,kde=False,color='k',bins=12)
```

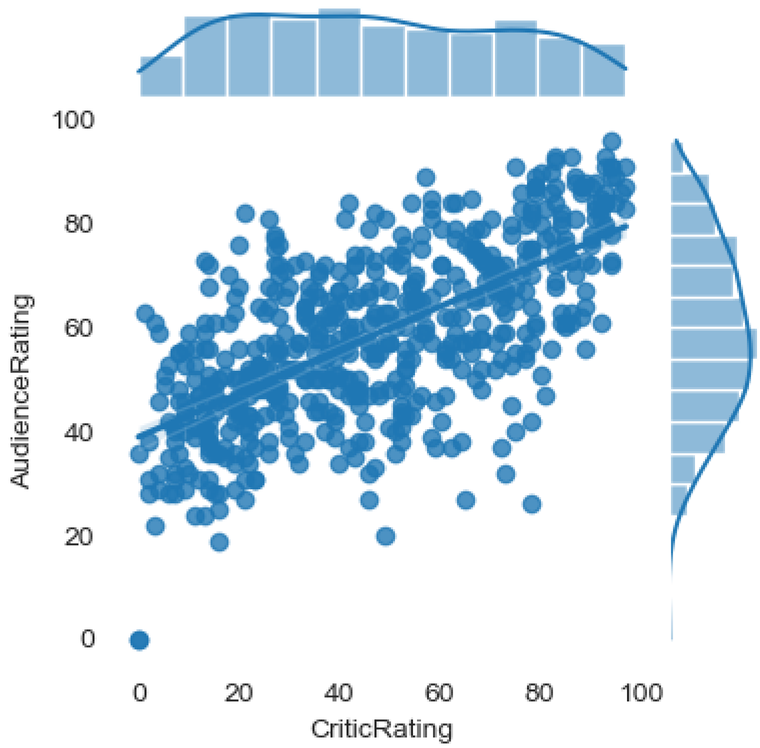
Out[24]: <Axes: xlabel='CriticRating'>



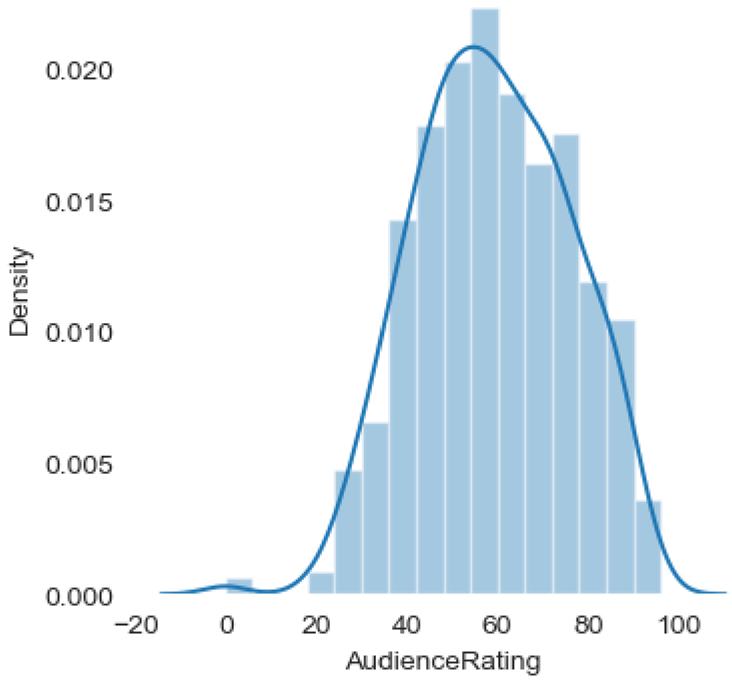
In [25]:
```
j = sns.jointplot(data = movies, x = 'CriticRating', y = 'AudienceRating',kind='
```



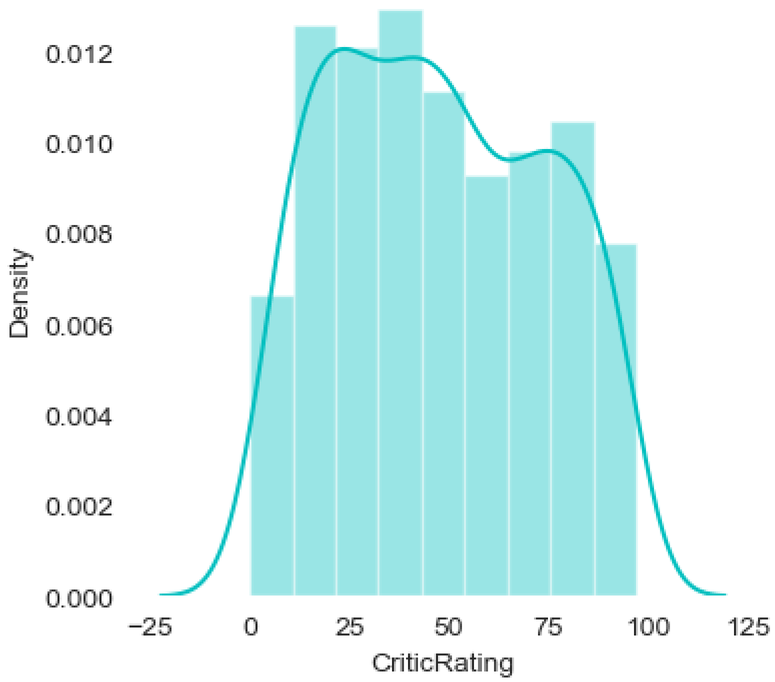
In [26]:
```
j = sns.jointplot(data = movies, x = 'CriticRating', y = 'AudienceRating',kind =
```



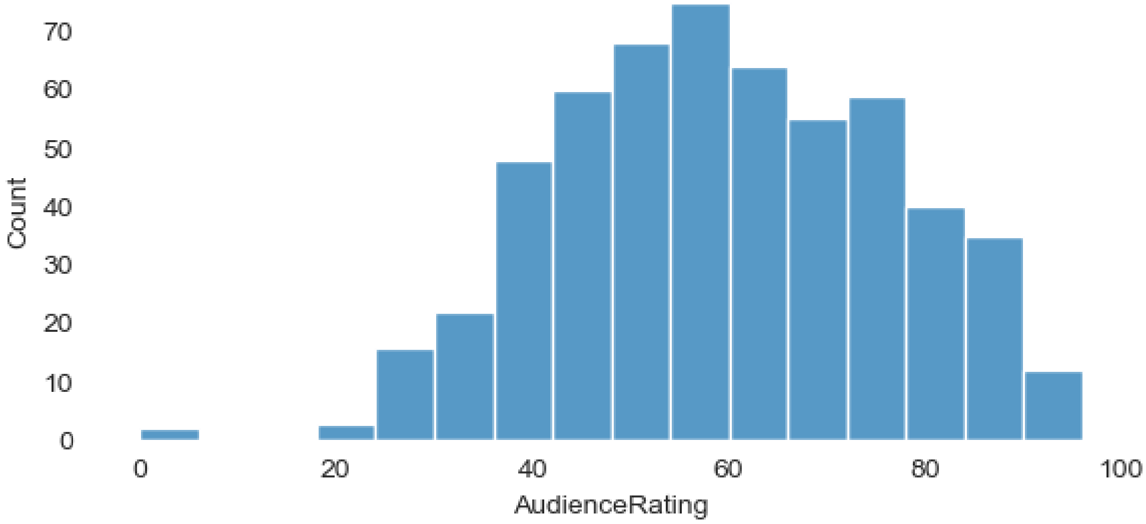
In [27]:
```
plt.figure(figsize=(4,4))
m1 = sns.distplot(movies['AudienceRating'])
```



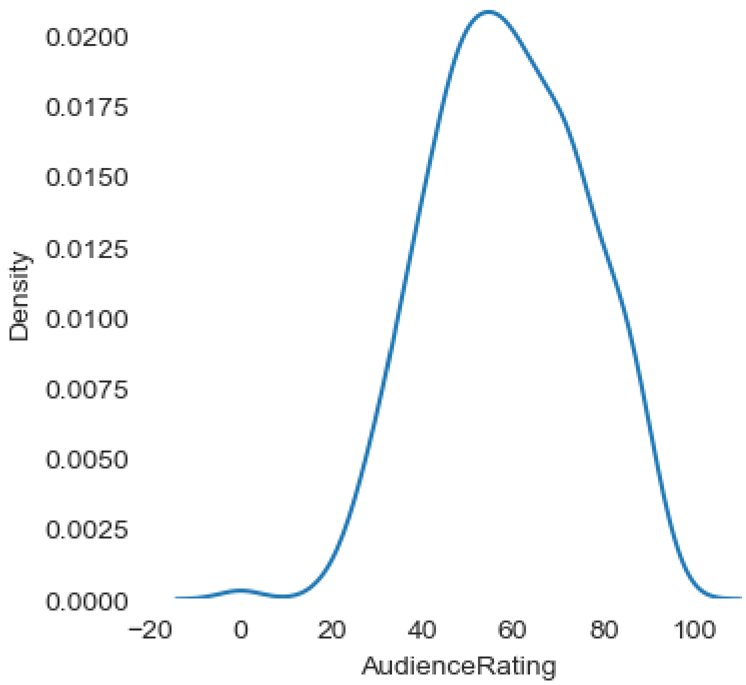
In [28]:
```
plt.figure(figsize=(4,4))
m1 = sns.distplot(movies['CriticRating'],color='c')
```



In [29]:
```
m1 = sns.displot(movies['AudienceRating'],height=3,aspect=2)
```

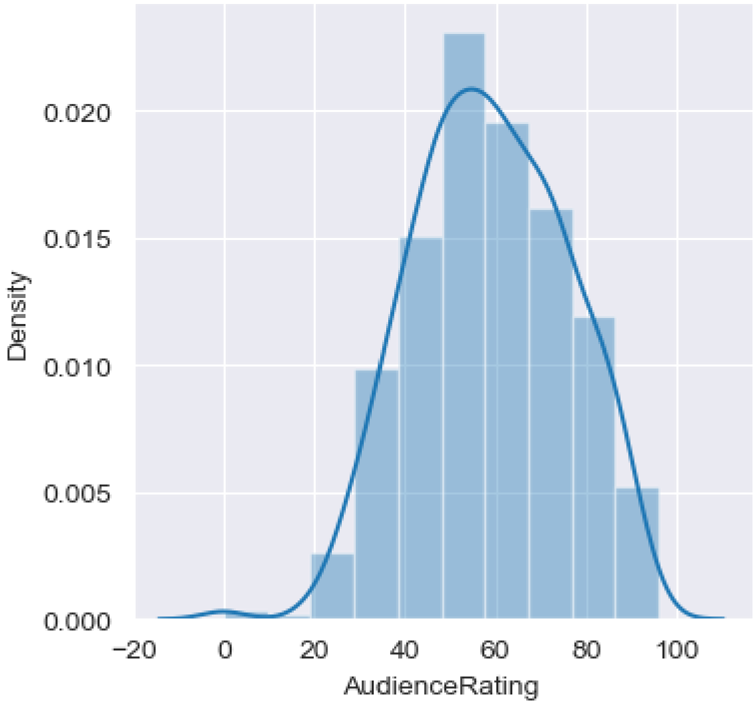


In [30]:
```
plt.figure(figsize=(4,4))
m1 = sns.kdeplot(movies['AudienceRating'])
```



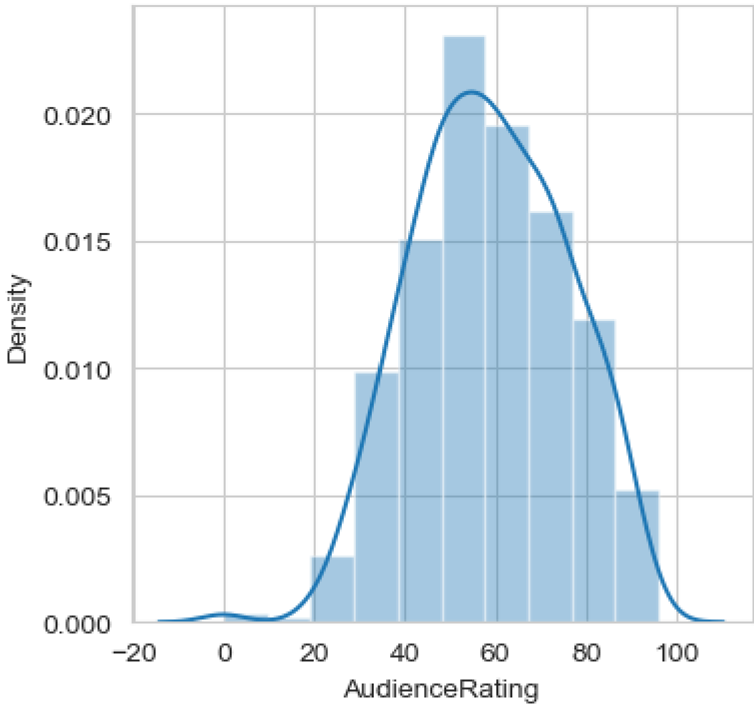
In [31]:
```
sns.set_style('darkgrid')
```

In [32]:
```
plt.figure(figsize=(4,4))
m1 = sns.distplot(movies['AudienceRating'],bins=10)
```

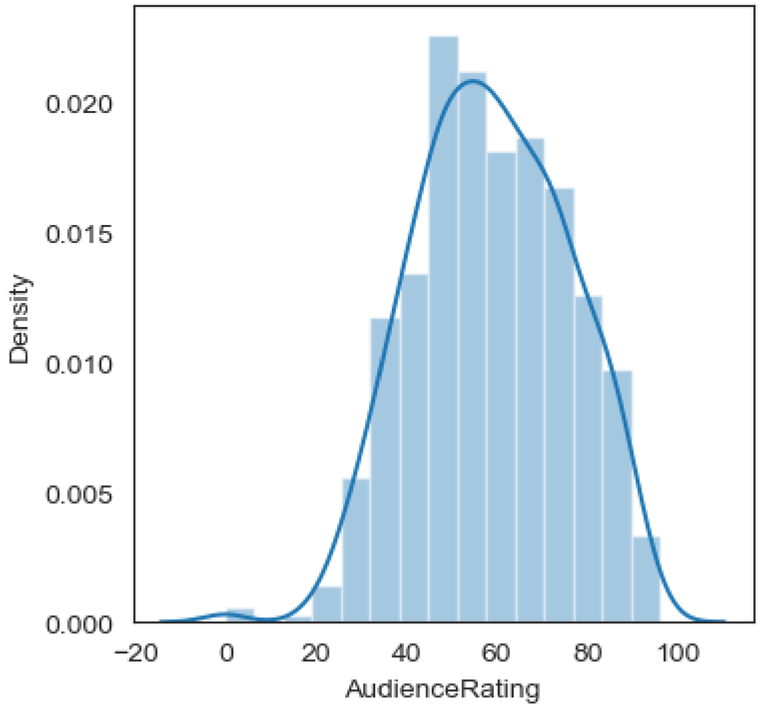


In [33]:
```
sns.set_style('whitegrid')
```

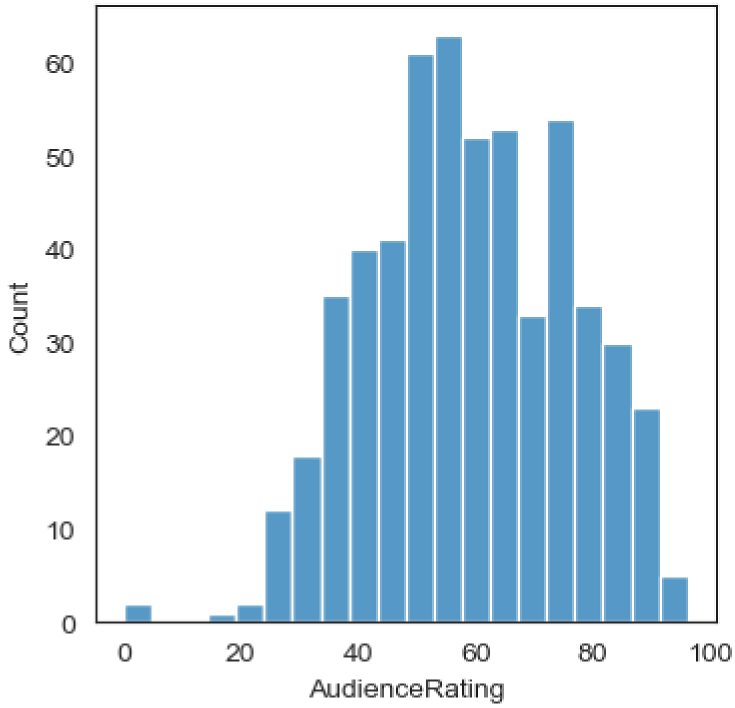
In [34]:
```
plt.figure(figsize=(4,4))
m1 = sns.distplot(movies['AudienceRating'],bins=10)
```



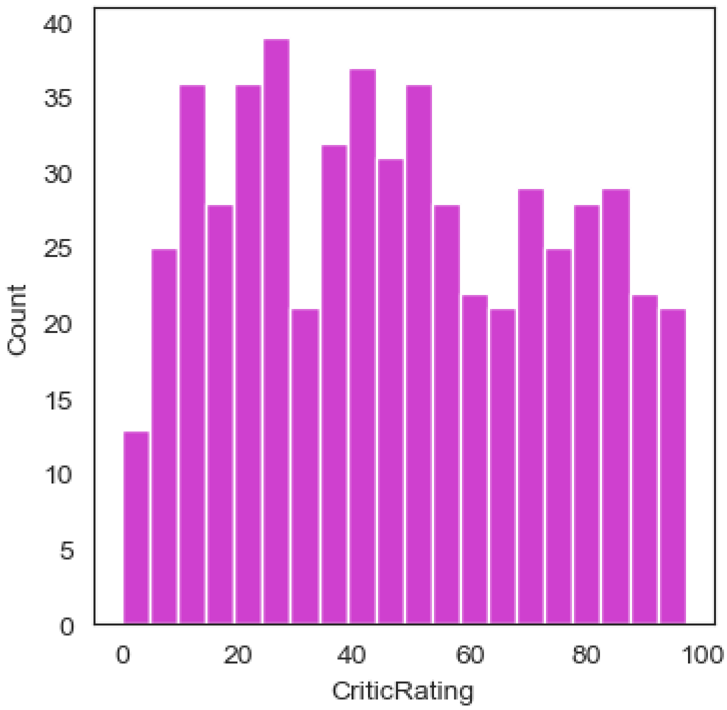
In [35]:
```
sns.set_style('white')
plt.figure(figsize=(4,4))
m1 = sns.distplot(movies['AudienceRating'],bins=15)
```



In [36]:
```
plt.figure(figsize=(4,4))
n1 = sns.histplot(movies['AudienceRating'],bins=20) #normal distribution & calle
```

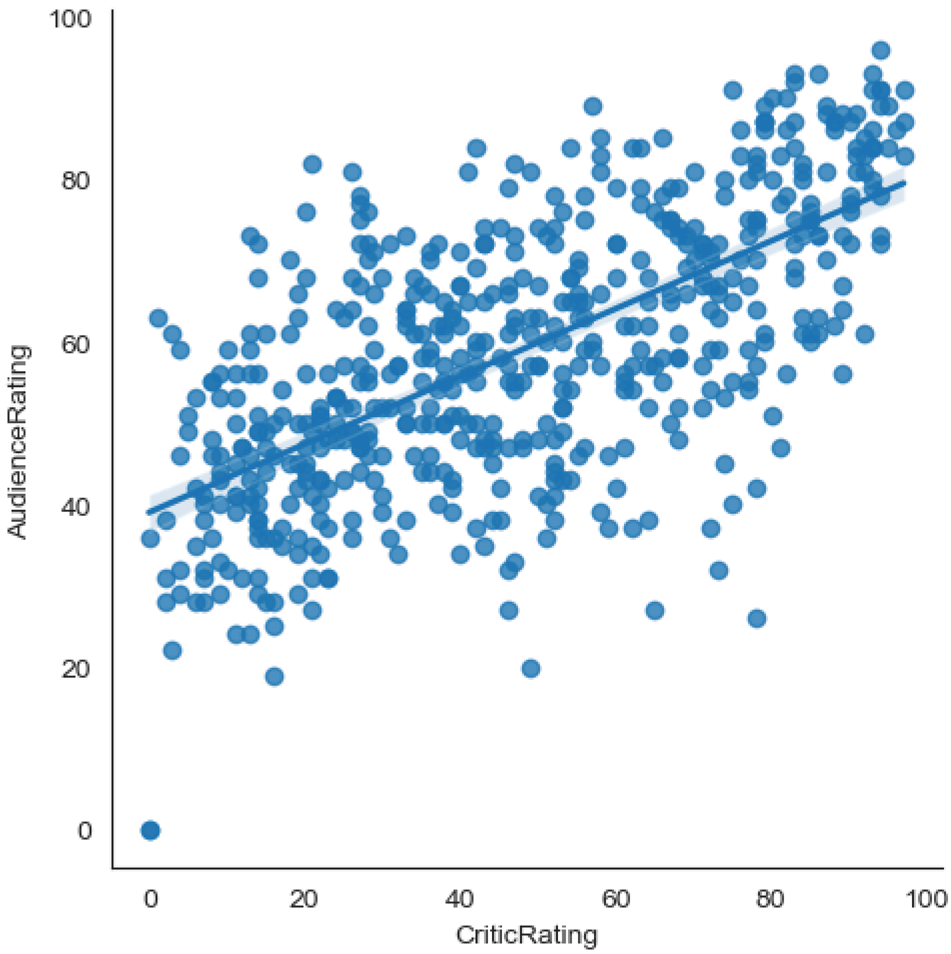


In [37]:
```
plt.figure(figsize=(4,4))
n1 = sns.histplot(movies['CriticRating'],bins=20,color='m')#uniform distribution
```



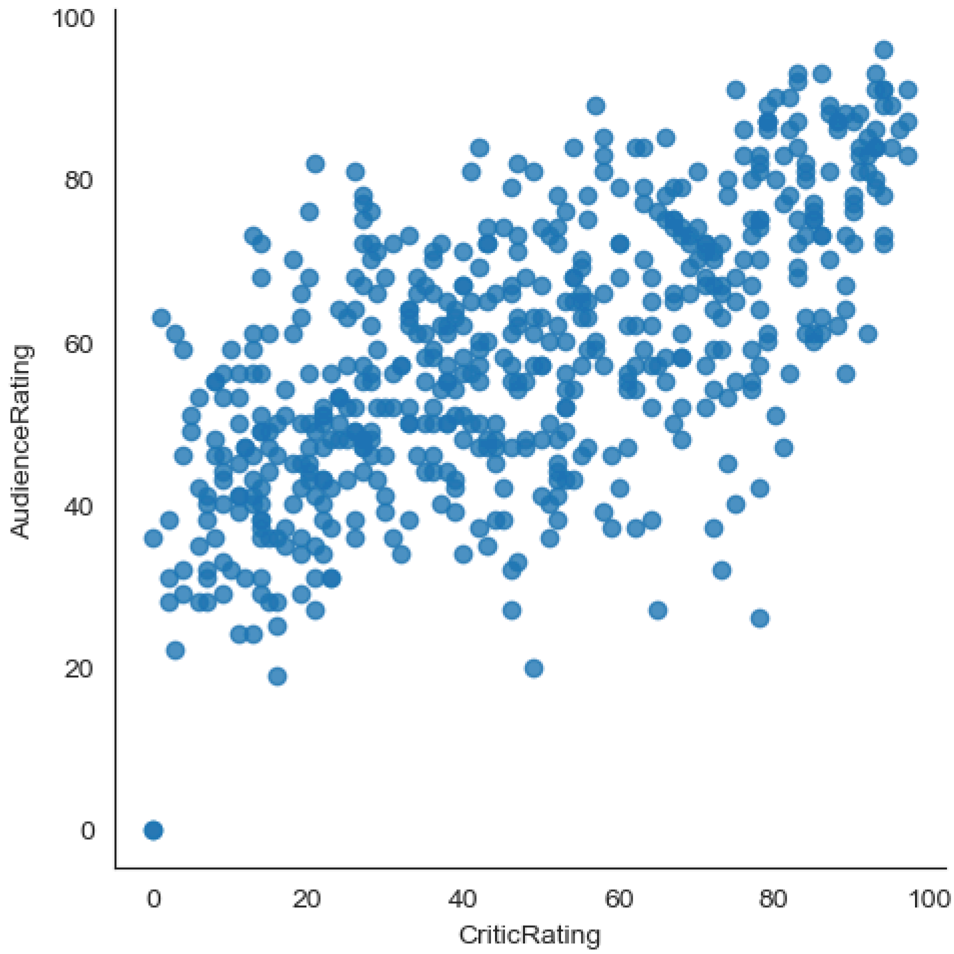
In [38]:
```
sns.lmplot(data = movies, x = 'CriticRating',y = 'AudienceRating')
```

Out[38]: <seaborn.axisgrid.FacetGrid at 0x1ec8efb2cf0>



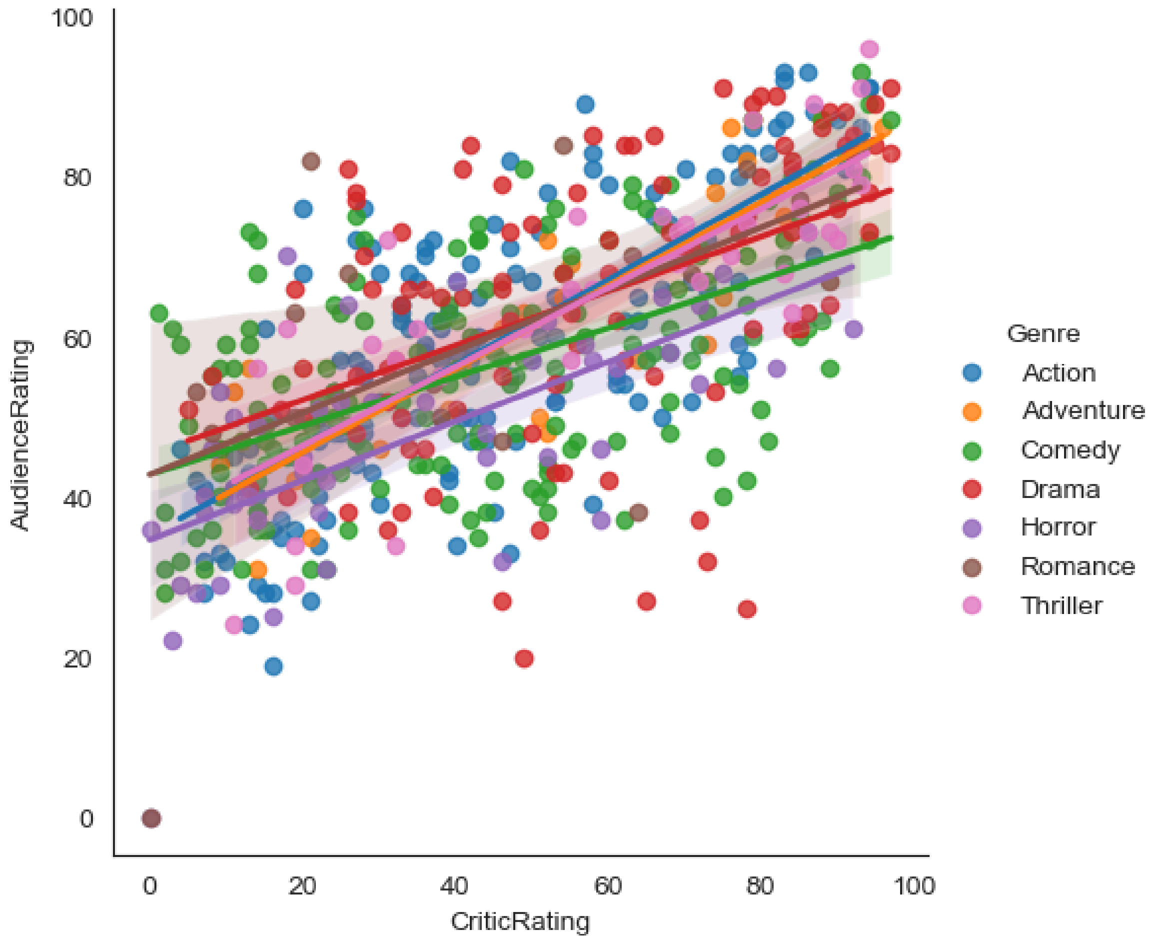
In [39]:
```
sns.lmplot(data = movies, x = 'CriticRating',y = 'AudienceRating',fit_reg = Fals
```

Out[39]: <seaborn.axisgrid.FacetGrid at 0x1ec8ee80350>




```
In [40]: sns.lmplot(data = movies, x = 'CriticRating',y = 'AudienceRating',fit_reg = True
```

```
Out[40]: <seaborn.axisgrid.FacetGrid at 0x1ec8ee5aed0>
```



In [41]:
```
movies.columns
```

Out[41]:
```
Index(['Film', 'Genre', 'CriticRating', 'AudienceRating', 'BudgetMillions',
       'Year'],
      dtype='object')
```

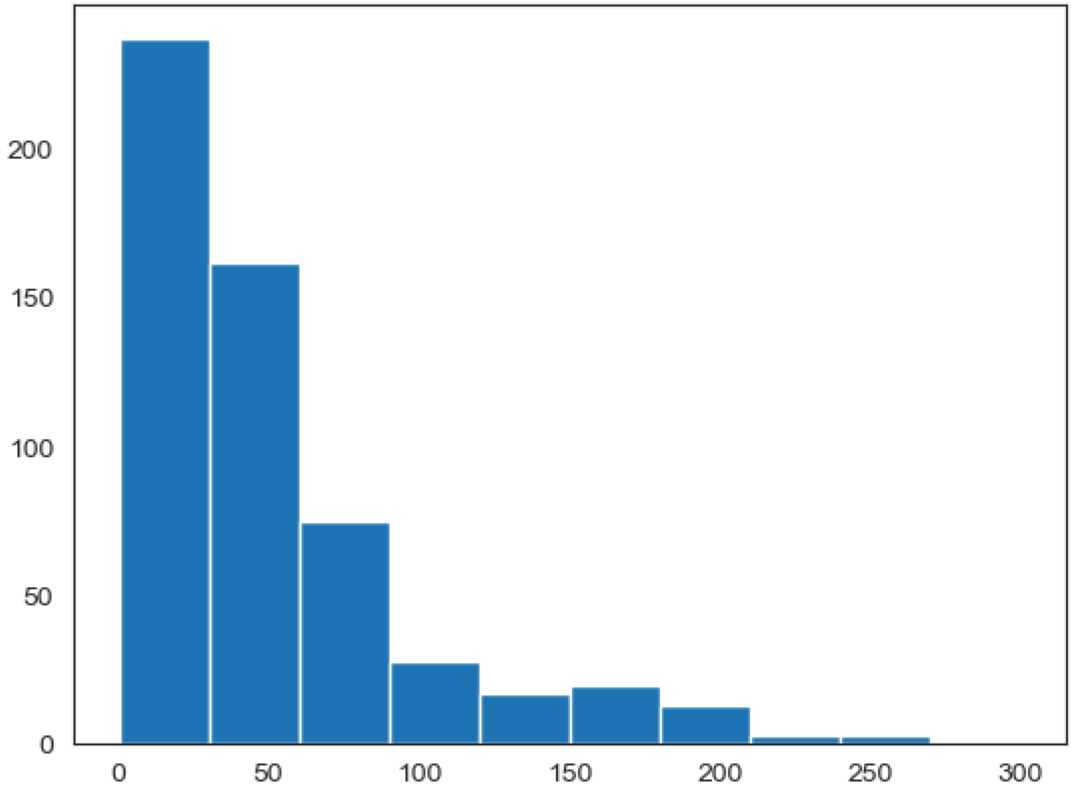
In [42]:
```
movies['BudgetMillions'].unique()
```

Out[42]:
```
array([  8, 105,  20,  18, 200,  30,  32,  28,  35,   7,  19,  45,  10,
        40,  15, 100,   5,  78, 237,  21,  70,  17,  80,   4, 150,  13,
        61,  68,  33,  26,  42,   2,  55,  37, 140,  85,   6,  38, 125,
        25,  90,  60, 163,  50,  58,  69,  75, 175,  31, 130,  24,   1,
        73,  52, 110,   0,  53, 112,  16,  36,  12, 250,  83,  11, 160,
       185, 186,  79,  47, 117,  27,  22,  66, 145,  56,   3,  95, 300,
       230,  48,  93,  39, 120, 258,  65,  82,  29,  51,  41, 155,  14,
       180, 138,  62,  59,   9, 195, 210, 170], dtype=int64)
```

In [43]:
```
movies['BudgetMillions'].nunique()
```

Out[43]:
```
99
```

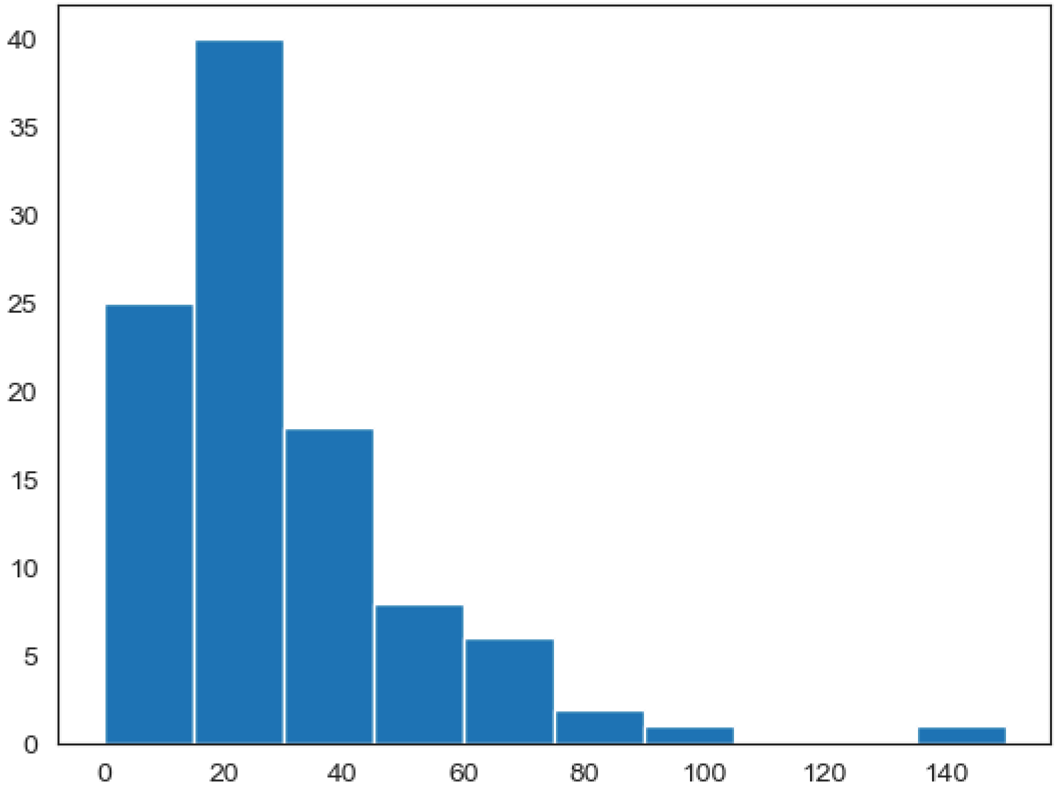
In [44]:
```
plt.hist(movies.BudgetMillions)
plt.show()
```



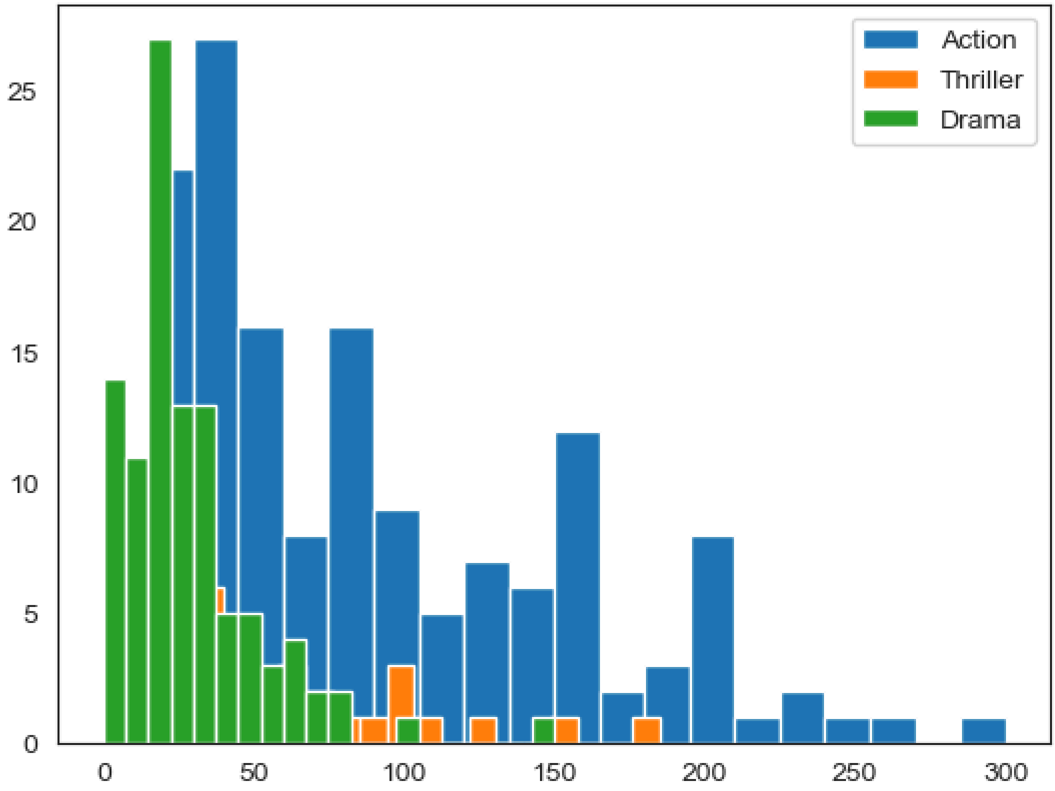
In [45]:
```
movies['Genre'].unique()
```

Out[45]:
```
['Comedy', 'Adventure', 'Action', 'Horror', 'Drama', 'Romance', 'Thriller']
Categories (7, object): ['Action', 'Adventure', 'Comedy', 'Drama', 'Horror', 'R
omance', 'Thriller']
```

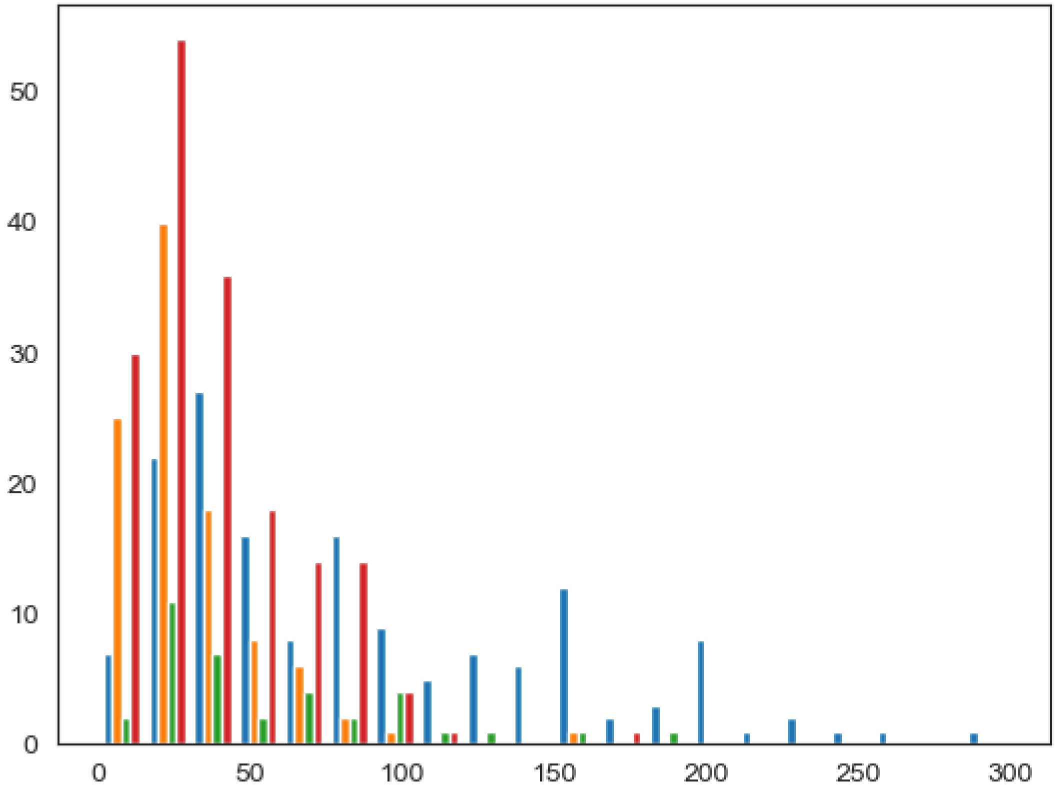
In [46]:
```
plt.hist(movies[movies.Genre == 'Drama'].BudgetMillions) # (histogram) showing h
plt.show()
```



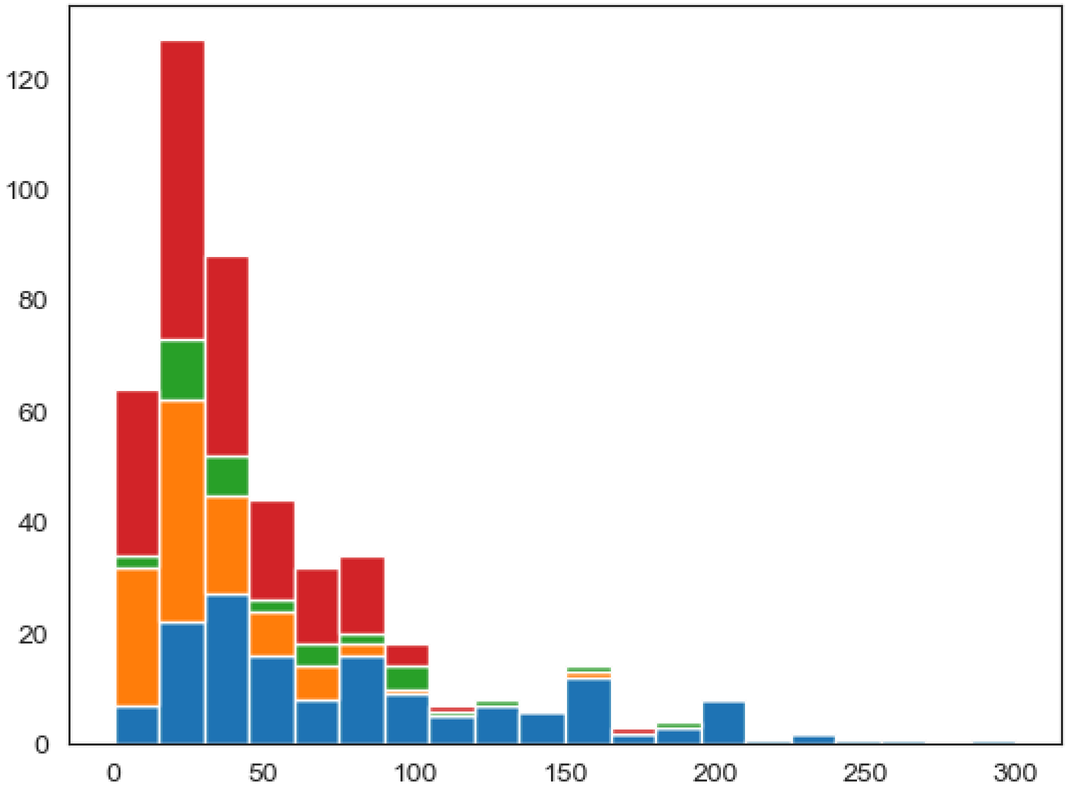
In [47]:
```
plt.hist(movies[movies.Genre == 'Action'].BudgetMillions, bins = 20,label='Actic
plt.hist(movies[movies.Genre == 'Thriller'].BudgetMillions, bins = 20,label='Thr
plt.hist(movies[movies.Genre == 'Drama'].BudgetMillions, bins = 20,label='Drama'
plt.legend()
plt.show()
```



In [48]:
```
plt.hist([movies[movies.Genre == 'Action'].BudgetMillions,\
          movies[movies.Genre == 'Drama'].BudgetMillions, \
          movies[movies.Genre == 'Thriller'].BudgetMillions, \
          movies[movies.Genre == 'Comedy'].BudgetMillions],
         bins = 20, stacked = False)
plt.show()
```



In [49]:
```
# Below plots are stacked histogram becuase overlaped
plt.hist([movies[movies.Genre == 'Action'].BudgetMillions,\
          movies[movies.Genre == 'Drama'].BudgetMillions, \
          movies[movies.Genre == 'Thriller'].BudgetMillions, \
          movies[movies.Genre == 'Comedy'].BudgetMillions],
         bins = 20, stacked = True)
plt.show()
```



In [50]:
```
# if you have 100 categories you cannot copy & paste all the things
```

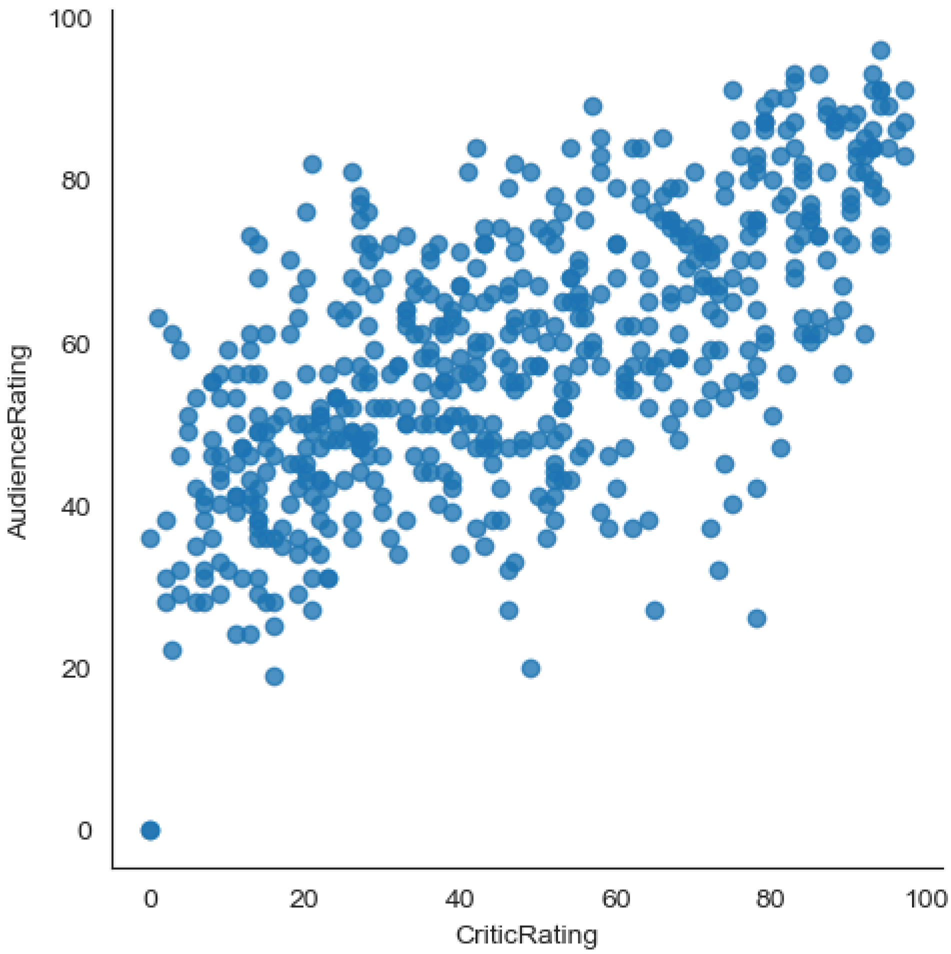
```
for gen in movies.Genre.unique():
    print(gen)
```

```
Comedy
Adventure
Action
Horror
Drama
Romance
Thriller
```

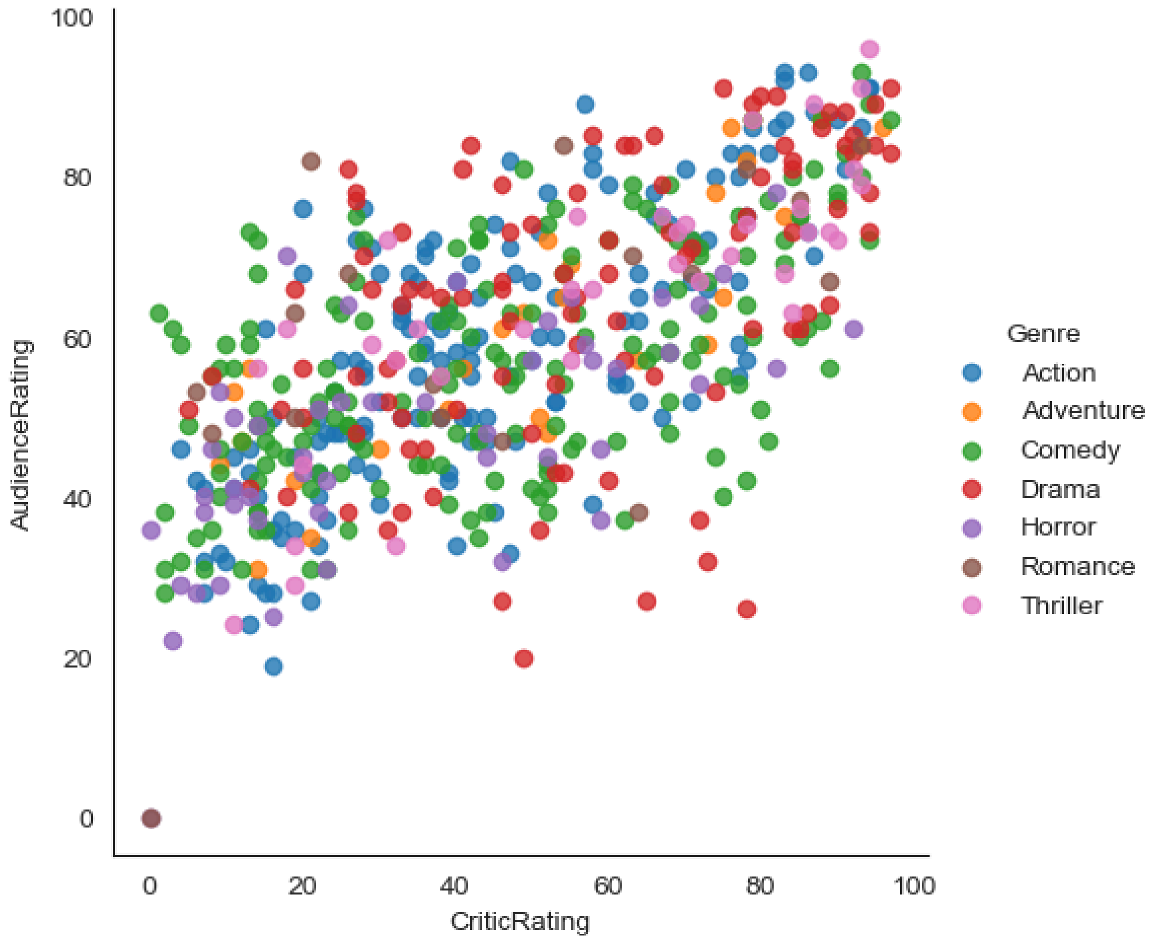
In [51]:
```
for gen in movies.Genre.cat.categories:
    print(gen)
```

```
Action
Adventure
Comedy
Drama
Horror
Romance
Thriller
```

In [52]:
```
vis1 = sns.lmplot(data=movies, x='CriticRating', y='AudienceRating',\
                  fit_reg=False)
```



In [53]:
```
vis1 = sns.lmplot(data=movies, x='CriticRating', y='AudienceRating',\
                  fit_reg=False, hue = 'Genre')
```

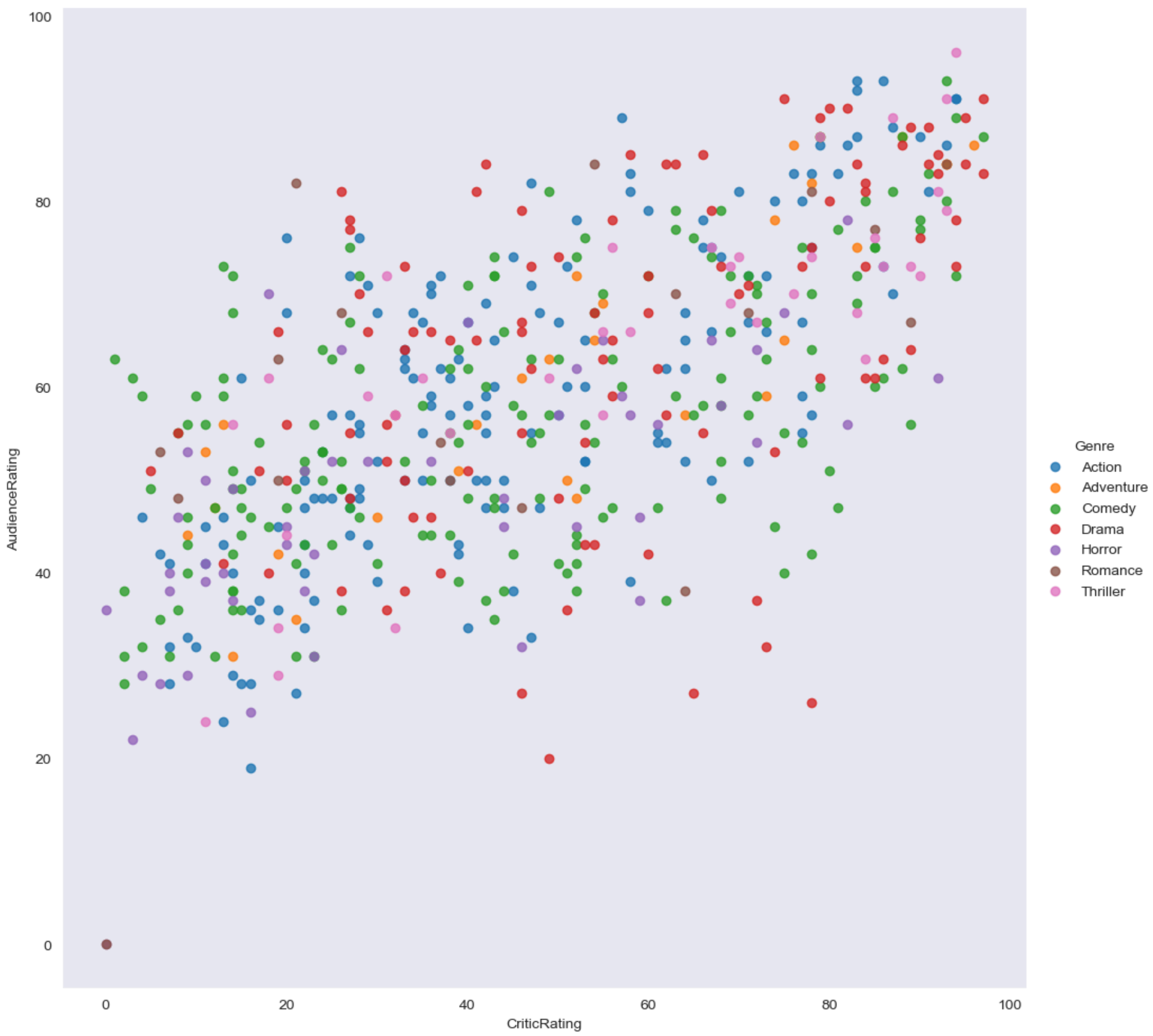


In [54]:
```
sns.set_style('dark')
```

height : scalar Height (in inches) of each facet. See also: `aspect`.

aspect : scalar Aspect ratio of each facet, so that `aspect * height` gives the width of each facet in inches.

In [55]:
```
vis1 = sns.lmplot(data=movies, x='CriticRating', y='AudienceRating',\
                  fit_reg=False, hue = 'Genre', height = 10,aspect=1)
```

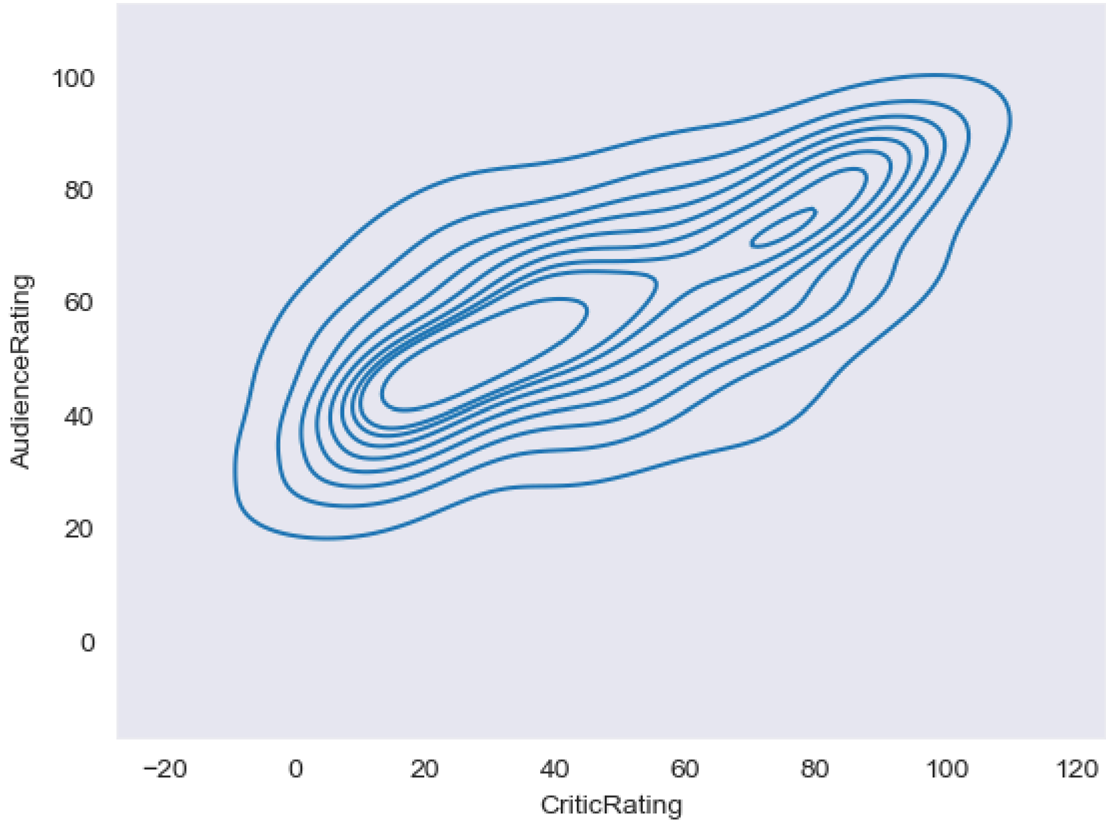


KDE Plot

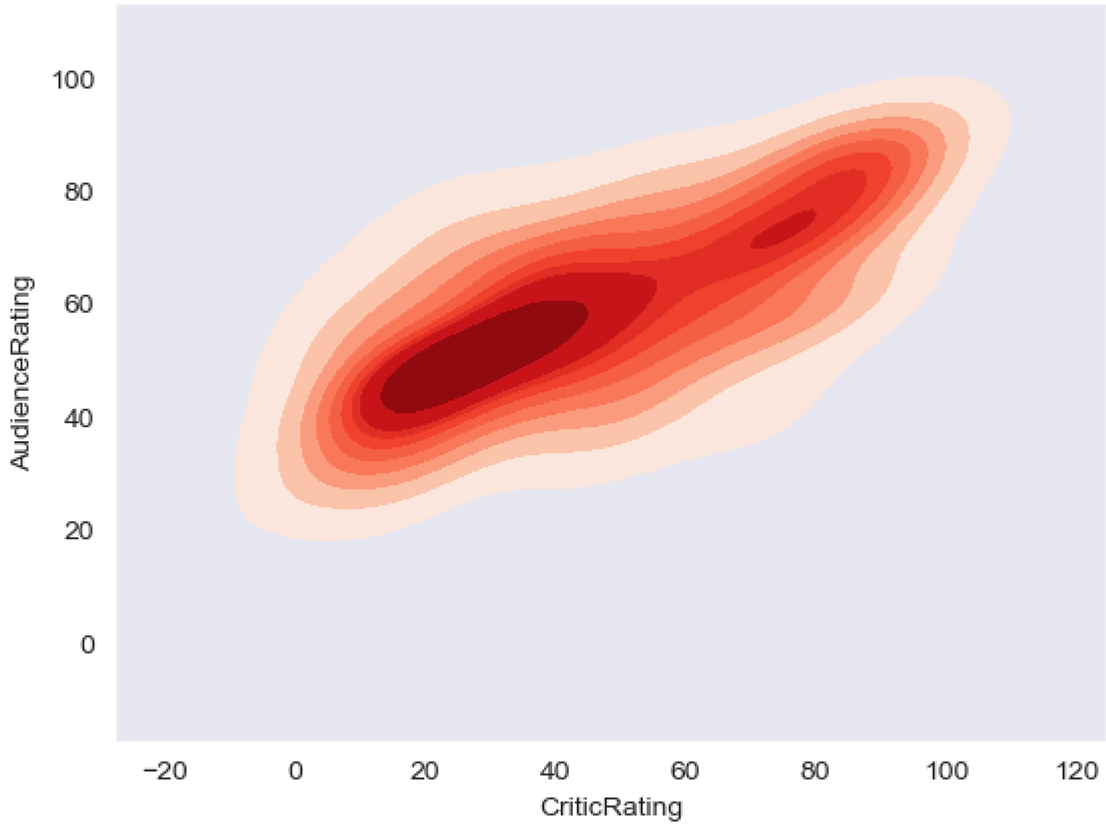
Plot univariate or bivariate distributions using kernel density estimation.

A kernel density estimate (KDE) plot is a method for visualizing the distribution of observations in a dataset, analogous to a histogram. KDE represents the data using a continuous probability density curve in one or more dimensions.

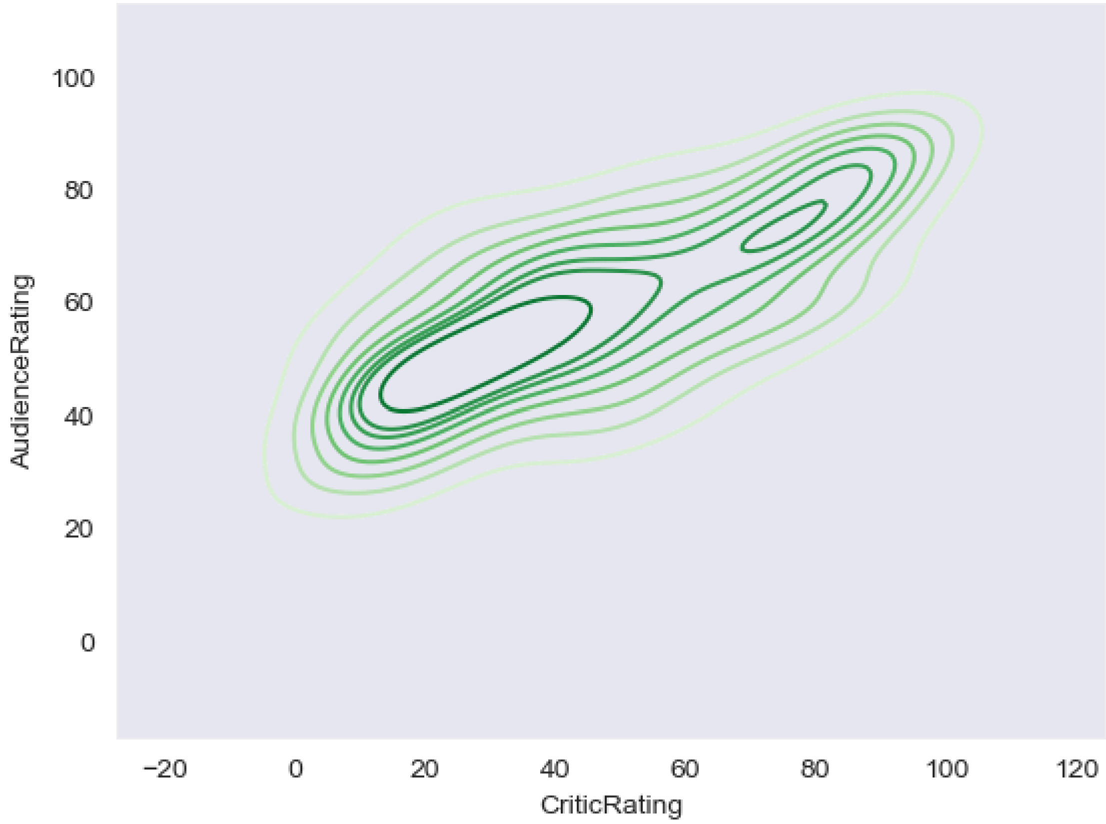
In [56]:
```
k1 = sns.kdeplot(x='CriticRating',y='AudienceRating',data = movies)
# where do u find more density and how density is distibuted across from the the
# center point is kernal this is calld KDE & insteade of dots it visualize like
# we can able to clearly see the spread at the audience ratings
```



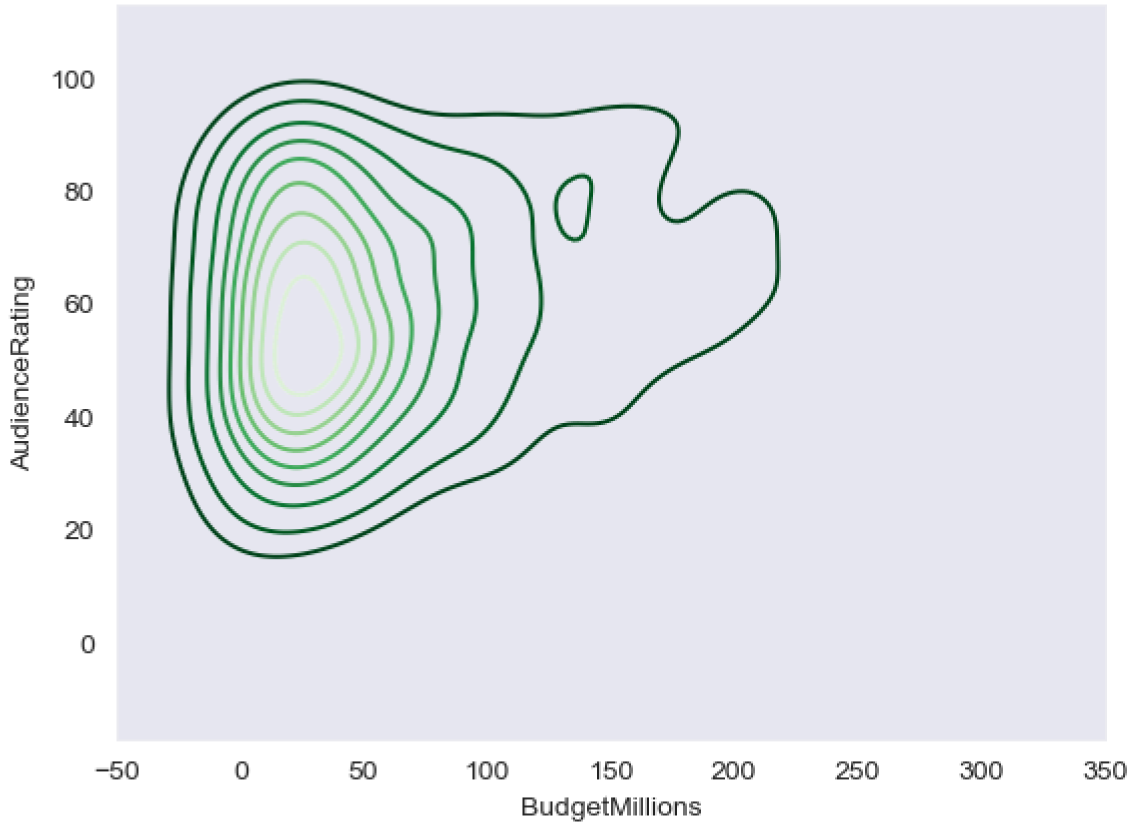
In [57]:
```
k1 = sns.kdeplot(x='CriticRating',y='AudienceRating',data = movies,shade = True,
```



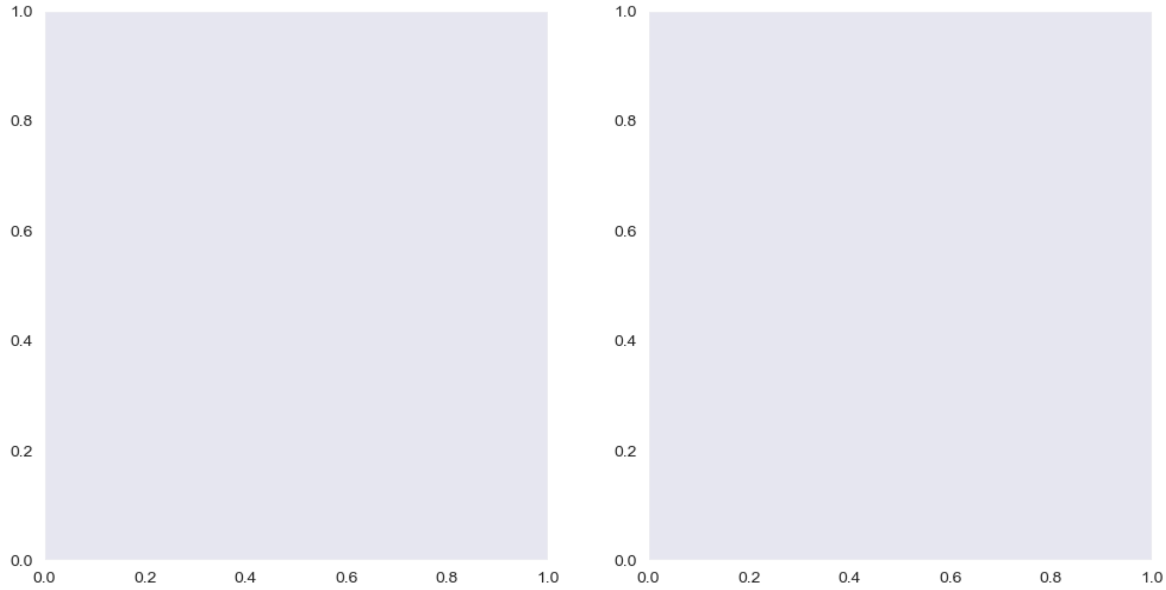
In [58]:
```
k1 = sns.kdeplot(x='CriticRating',y='AudienceRating',data = movies,shade = False
```



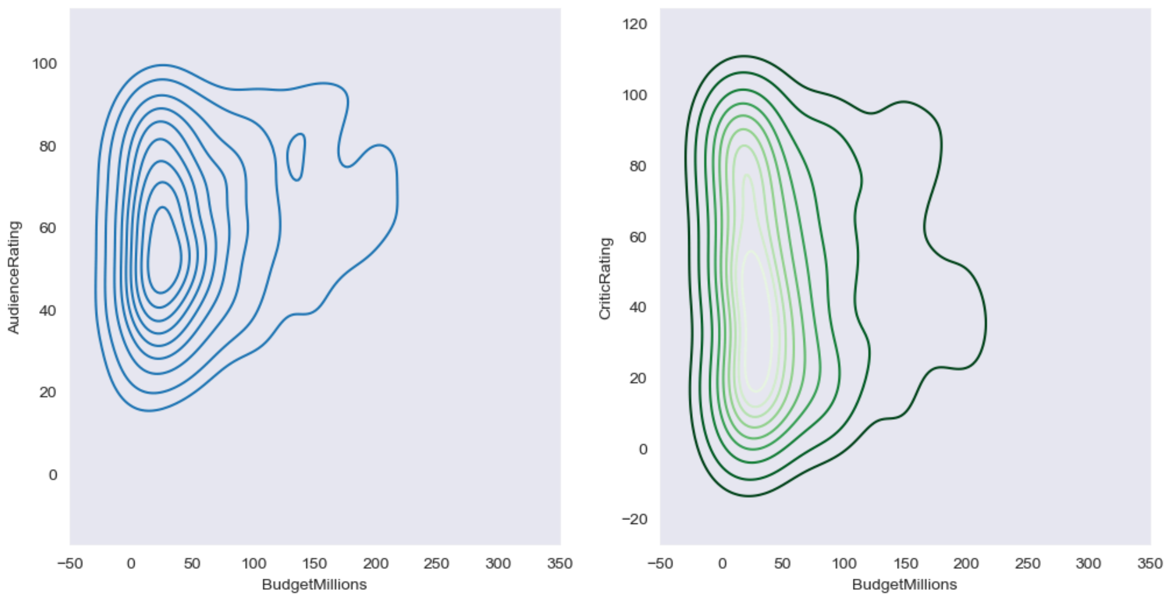
In [59]:
```
k2 = sns.kdeplot(x='BudgetMillions',y='AudienceRating',data = movies,shade_lowes
```



In [60]:
```
f, ax = plt.subplots(1,2, figsize =(12,6))
#f, ax = plt.subplots(3,3, figsize =(12,6))
```

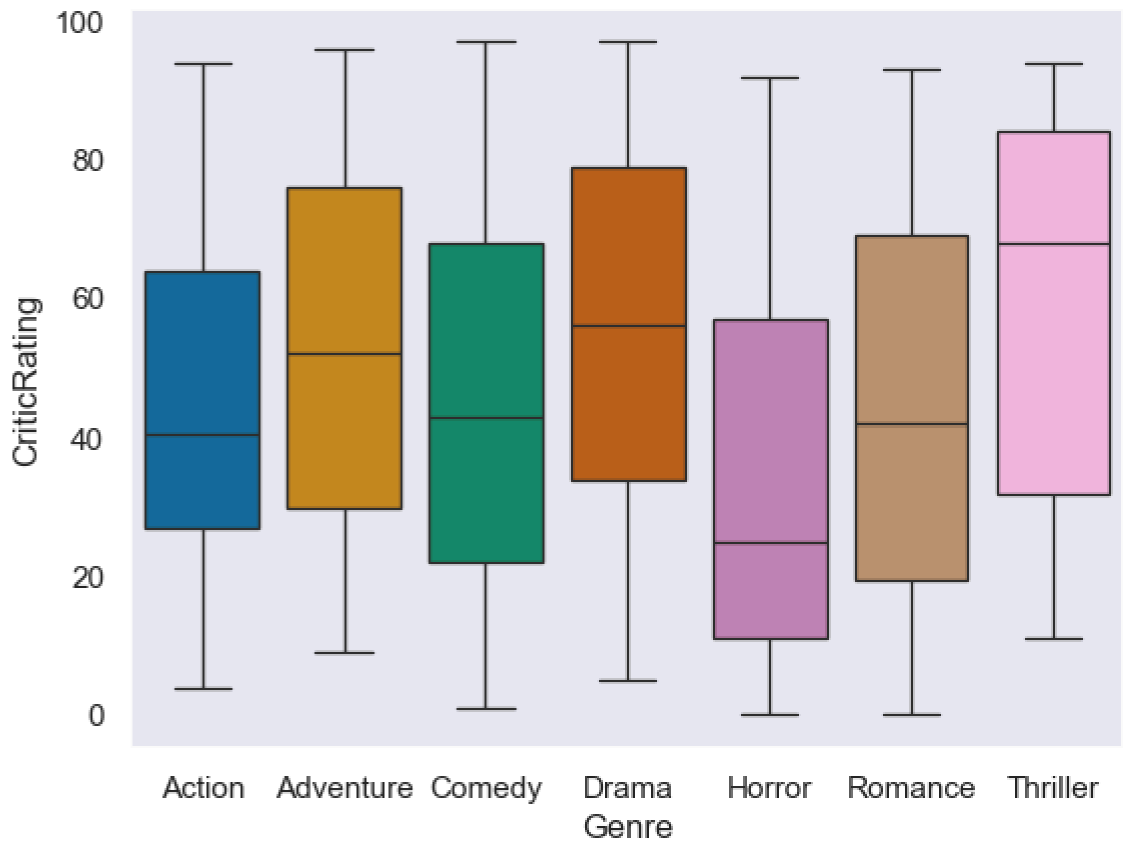


In [61]:
```
f, axes = plt.subplots(1,2, figsize =(12,6))
k1 = sns.kdeplot(x='BudgetMillions',y='AudienceRating',data = movies,ax=axes[0])
k2 = sns.kdeplot(x='BudgetMillions',y='CriticRating',data = movies,shade_lowest=
```



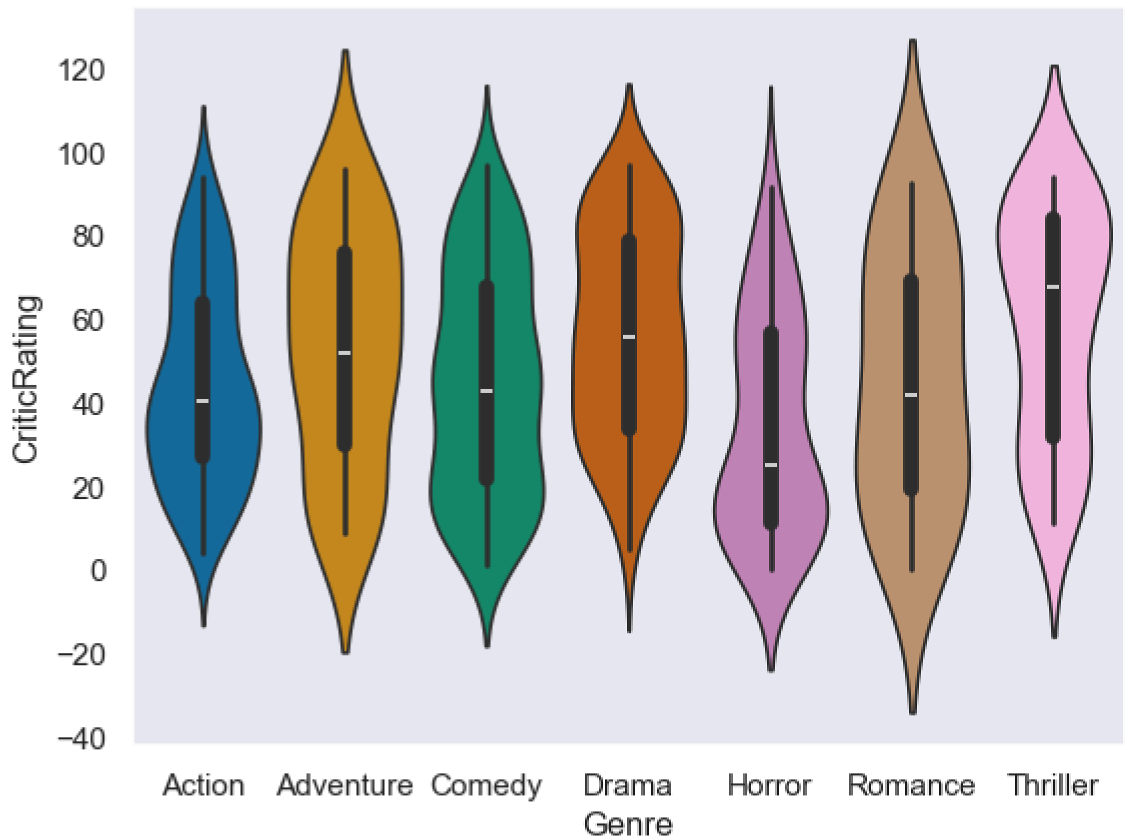
Boxplot

In [62]:
```
sns.set(style="dark")
w = sns.boxplot(data=movies, x='Genre', y = 'CriticRating',palette='colorblind')
```

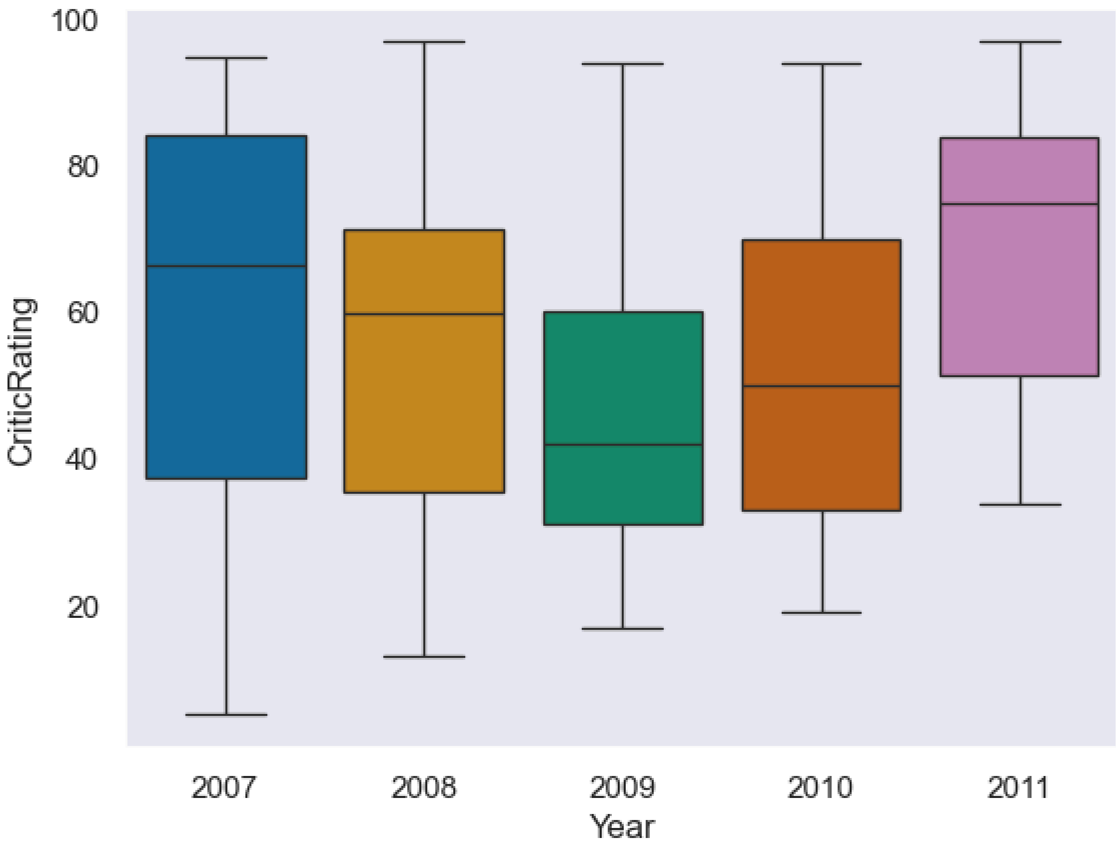


Violin plot

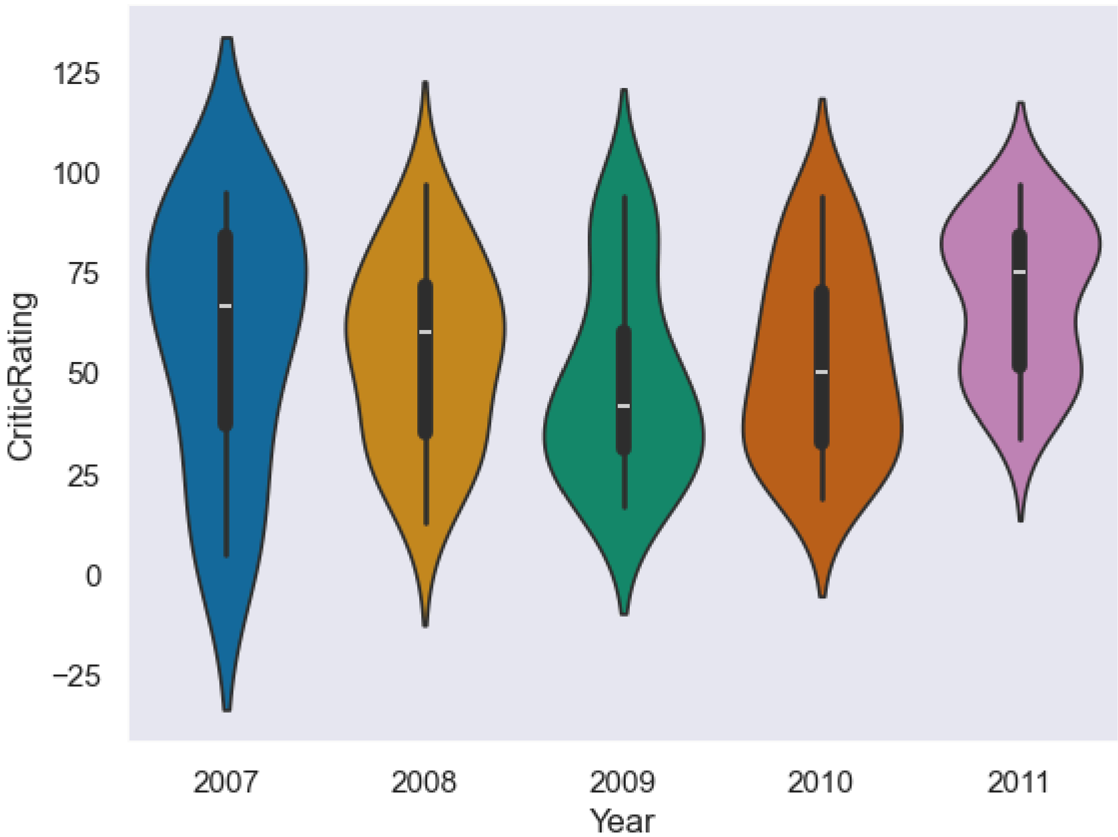
In [63]:
```
z = sns.violinplot(data=movies, x='Genre', y = 'CriticRating',palette='colorblin
```



In [64]:
```
w1 = sns.boxplot(data=movies[movies.Genre == 'Drama'], x='Year', y = 'CriticRati
```



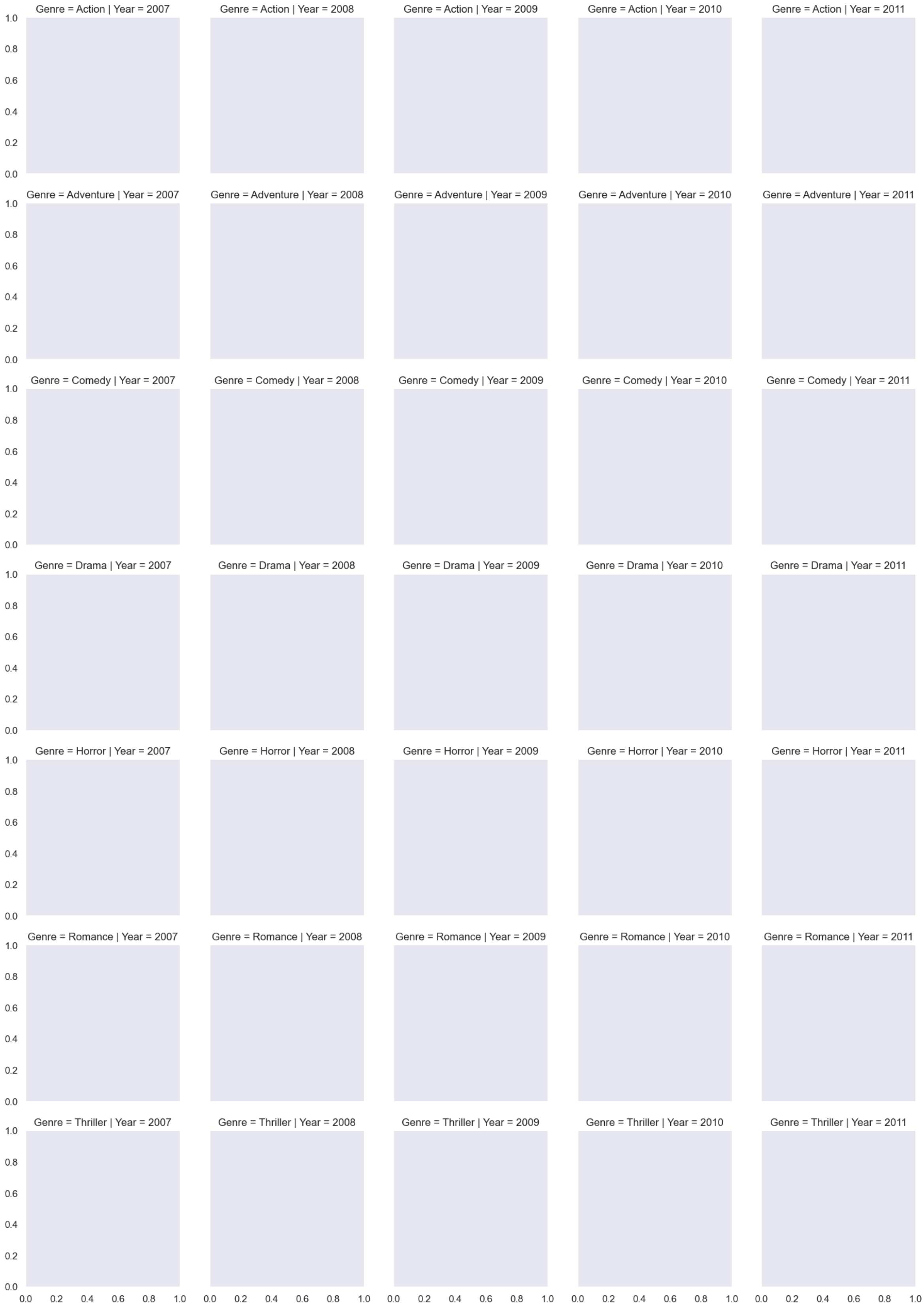
In [65]:
```
z = sns.violinplot(data=movies[movies.Genre == 'Drama'], x='Year', y = 'CriticRa
```



Facetgrid

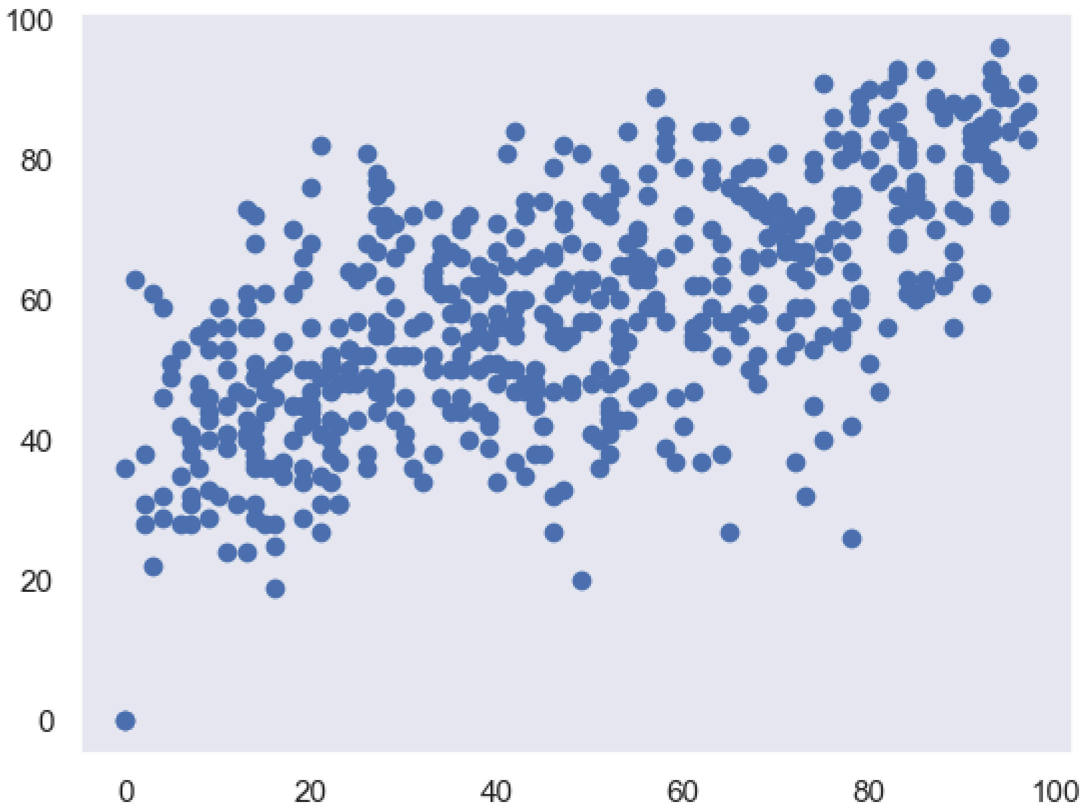
Multi-plot grid for plotting conditional relationships.

In [66]:
```
g =sns.FacetGrid (movies, row = 'Genre', col = 'Year', hue = 'Genre') #kind of s
```

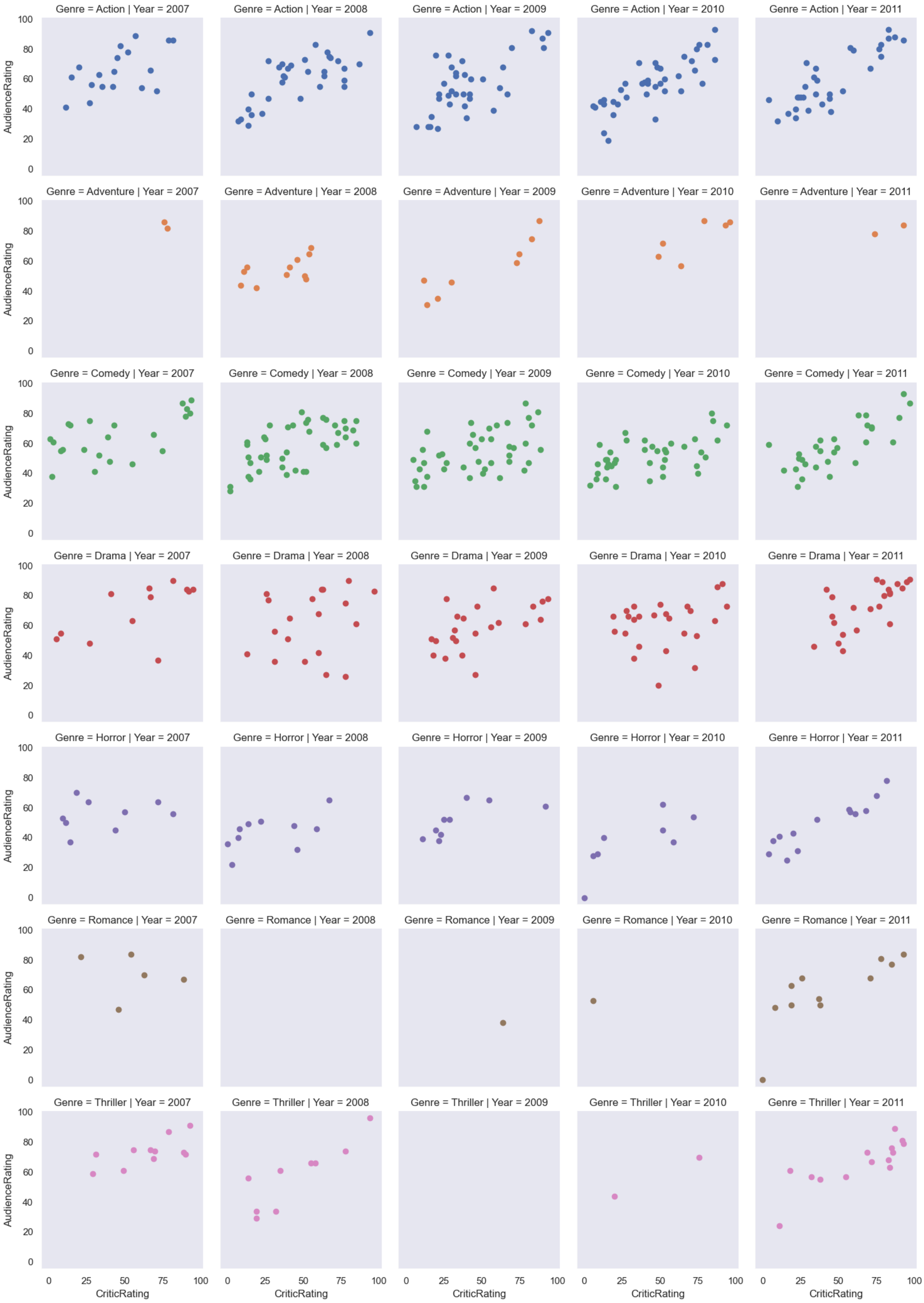


In [67]:
```
plt.scatter(movies.CriticRating,movies.AudienceRating)
```

Out[67]:
```
<matplotlib.collections.PathCollection at 0x1ec944cdb50>
```



In [68]:
```
g =sns.FacetGrid (movies, row = 'Genre', col = 'Year', hue = 'Genre')
g = g.map(plt.scatter, 'CriticRating', 'AudienceRating' )
```



row='Genre': This specifies that the rows of the facet grid will be divided by the 'Genre' column. Each row will display data for a specific genre.

col='Year': This specifies that the columns of the facet grid will be divided by the 'Year' column. Each column will display data for a specific year.

'CriticRating': This indicates the x-axis variable (horizontal axis) for the scatter plot, which is the Critic Rating.

'AudienceRating': This indicates the y-axis variable (vertical axis) for the scatter plot, which is the Audience Rating.

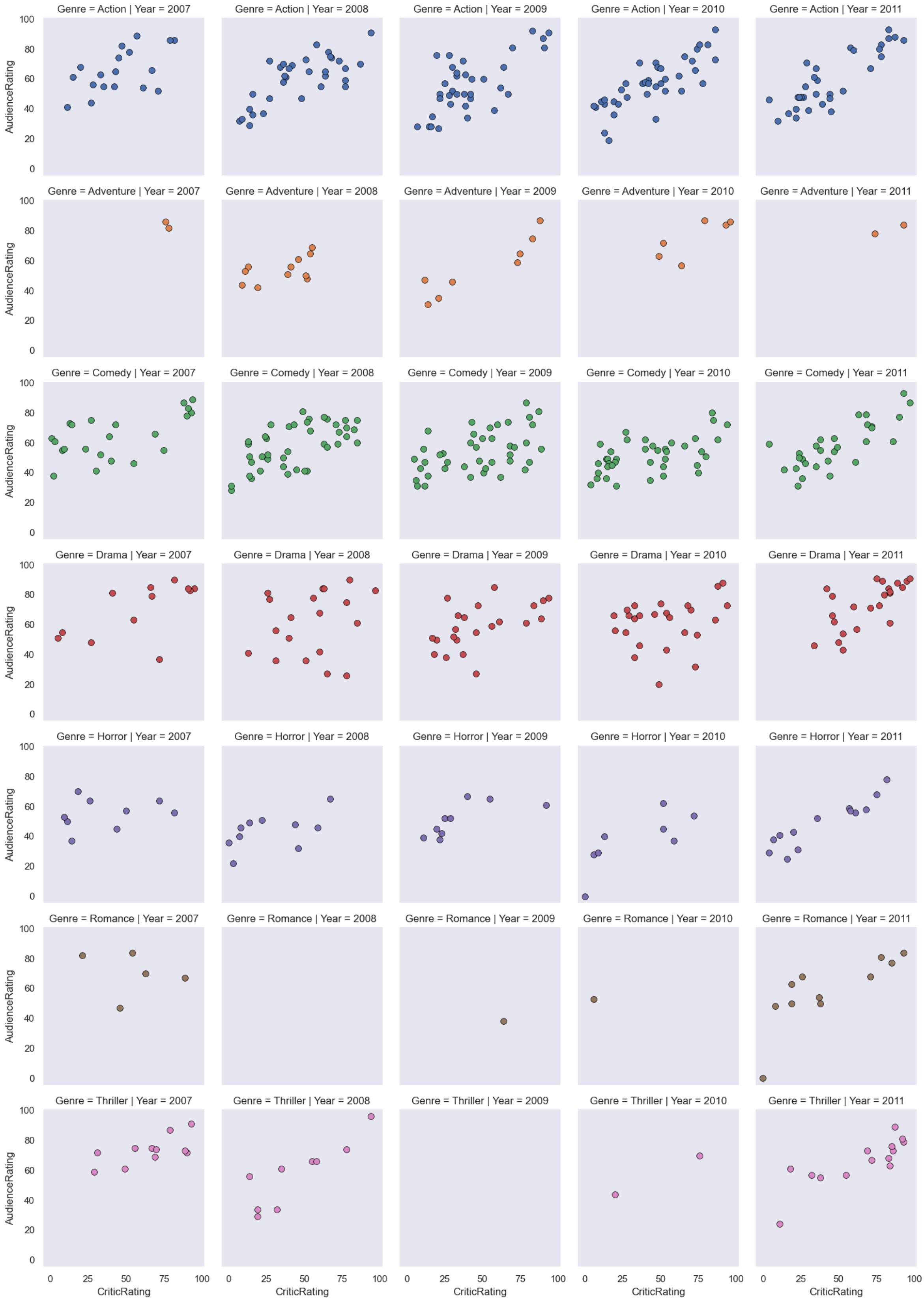
this code creates a grid of scatter plots where each plot represents a combination of Genre and Year. Each data point in a plot shows the Critic Rating and Audience Rating for a particular movie.

The coloring based on Genre helps visualize how the relationship between these ratings may differ across genres.

In [69]:
```
g =sns.FacetGrid (movies, row = 'Genre', col = 'Year', hue = 'Genre')
g = g.map(plt.hist, 'BudgetMillions') #scatterplots are mapped in facetgrid
```

In [70]:

```
# FacetGrid with scatter plots
g = sns.FacetGrid(movies, row='Genre', col='Year', hue='Genre')
kws = dict(s=50, linewidth=0.5, edgecolor='black')
g = g.map(plt.scatter, 'CriticRating', 'AudienceRating', **kws)

plt.show()
```

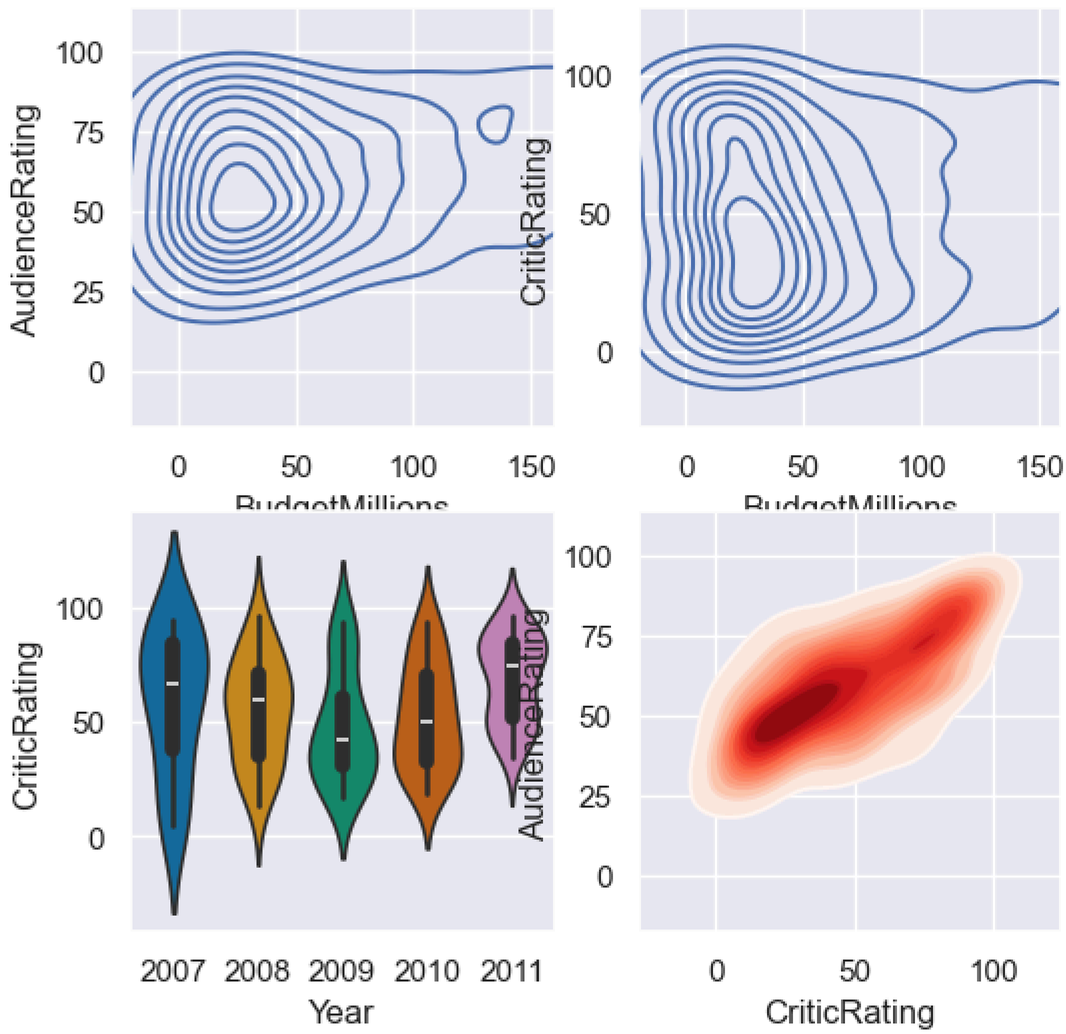


This line defines a dictionary named kws. Dictionaries are used to store key-value pairs. s=50: This key-value pair sets the marker size for the scatter plots to 50. The s parameter in plt.scatter controls the size of the markers.

linewidth=0.5: This sets the line width of the markers' edges to 0.5. The linewidth parameter controls the thickness of the lines around the markers.

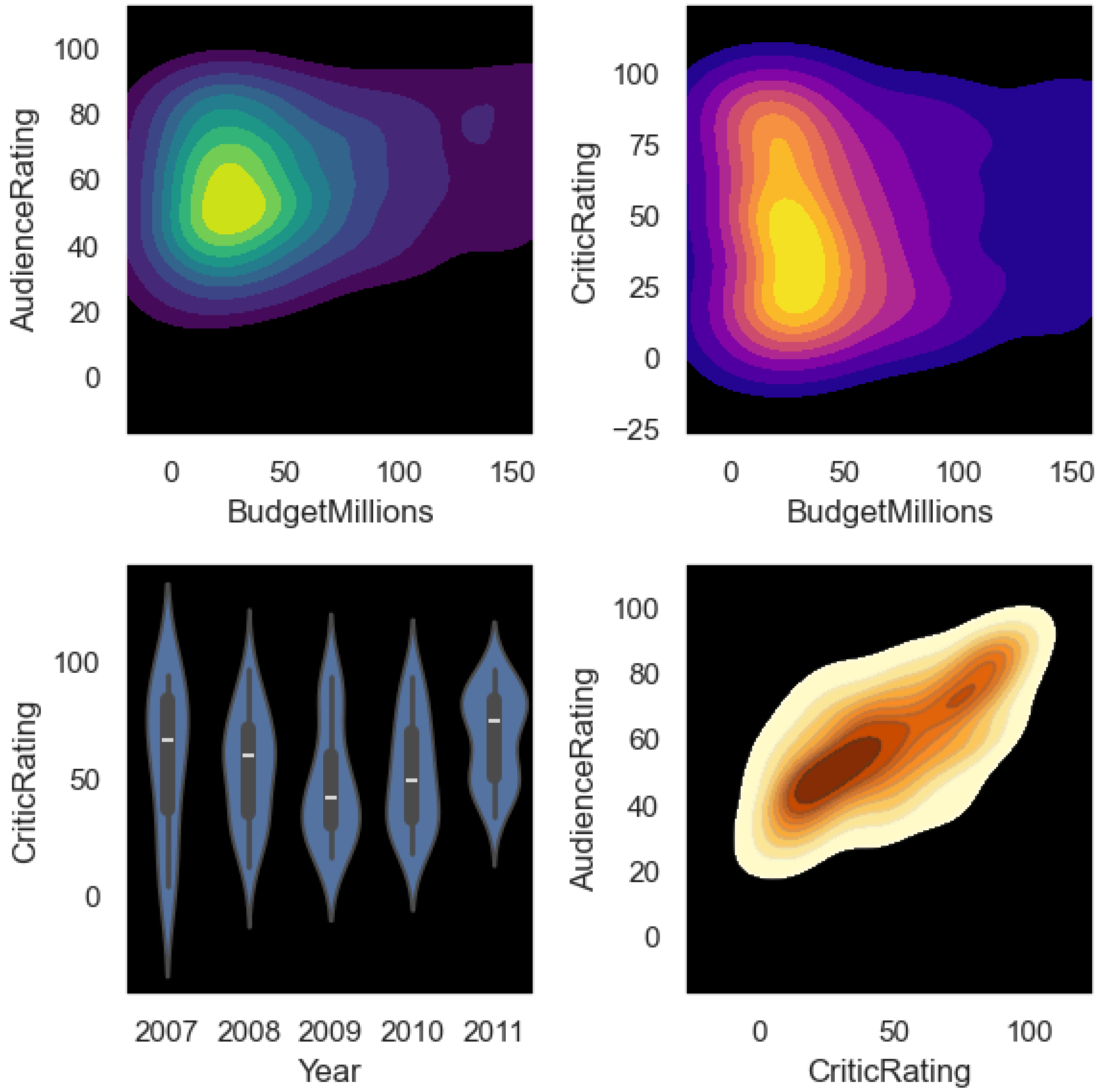
edgecolor='black': This sets the color of the markers' edges to black. The edgecolor parameter specifies the color for the border around the markers.

In [71]:
```
# python is not vectorize programming language
# Building dashboards (dashboard - combination of chats)

sns.set_style('darkgrid')
f, axes = plt.subplots (2,2, figsize = (6,6))

k1 = sns.kdeplot(x='BudgetMillions',y='AudienceRating',data=movies,ax=axes[0,0])
k2 = sns.kdeplot(x='BudgetMillions',y='CriticRating',data=movies,ax = axes[0,1])

k1.set(xlim=(-20,160))
k2.set(xlim=(-20,160))

z = sns.violinplot(data=movies[movies.Genre=='Drama'], x='Year', y = 'CriticRati

k4 = sns.kdeplot(x='CriticRating',y='AudienceRating',data=movies,shade = True,sh
k4b = sns.kdeplot(x='CriticRating',y='AudienceRating',data=movies,cmap='Reds',ax

plt.show()
```



In [72]:
```
sns.set_style('dark', {'axes.facecolor': 'black'})

# Create a figure and subplots
f, axes = plt.subplots(2, 2, figsize=(6, 6))

# Budget Millions vs. Audience Rating (top-left)
k1 = sns.kdeplot(
    x='BudgetMillions', y='AudienceRating', data=movies, shade=True, cmap='virid
```

```
)
k1.set(xlim=(-20, 160))  # Set x-axis limits for both plots

# Budget Millions vs. Critic Rating (top-right)
k2 = sns.kdeplot(
    x='BudgetMillions', y='CriticRating', data=movies, shade=True, cmap='plasma'
)
k2.set(xlim=(-20, 160))

# Violin Plot for Drama Movies (bottom-left)
z = sns.violinplot(data=movies[movies.Genre == 'Drama'], x='Year', y='CriticRati

# Critic Rating vs. Audience Rating (bottom-right) with highlight for high ratin
k4 = sns.kdeplot(
    x='CriticRating', y='AudienceRating', data=movies, shade=True, shade_lowest=
)
k4b = sns.kdeplot(x='CriticRating', y='AudienceRating', data=movies, cmap='Greys

plt.tight_layout()  # Adjust spacing between subplots
plt.show()
```



In [73]:
```
movies.head()
```

Out[73]:

	Film	Genre	CriticRating	AudienceRating	BudgetMillions	Year
0	(500) Days of Summer	Comedy	87	81	8	2009
1	10,000 B.C.	Adventure	9	44	105	2008
2	12 Rounds	Action	30	52	20	2009
3	127 Hours	Adventure	93	84	18	2010
4	17 Again	Comedy	55	70	20	2009

In [89]:
```
movies.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 559 entries, 0 to 558
Data columns (total 6 columns):
 #   Column          Non-Null Count  Dtype   
---  ------          --------------  -----   
 0   Film            559 non-null    category
 1   Genre           559 non-null    category
 2   CriticRating    559 non-null    int64   
 3   AudienceRating  559 non-null    int64   
 4   BudgetMillions  559 non-null    int64   
 5   Year            559 non-null    category
dtypes: category(3), int64(3)
memory usage: 36.5 KB
```

In [92]:
```
movies['Year'].astype('int64')
```

Out[92]:
```
0      2009
1      2008
2      2009
3      2010
4      2009
       ... 
554    2011
555    2009
556    2007
557    2009
558    2011
Name: Year, Length: 559, dtype: int64
```

In [100…
```
X = movies.drop(['Film', 'Genre', 'AudienceRating','Year'], axis=1)
y = movies['AudienceRating']
```

In [101…
```
X.head()
```

Out[101…

	CriticRating	BudgetMillions
0	87	8
1	9	105
2	30	20
3	93	18
4	55	20

In [102…

```
y.head()
```

Out[102…

```
0    81
1    44
2    52
3    84
4    70
Name: AudienceRating, dtype: int64
```

In [103…

```
x_train, x_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, randc
```

In [104…

```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score as score
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
from sklearn.tree import DecisionTreeRegressor
from xgboost import XGBRegressor
from lightgbm import LGBMRegressor
from sklearn.neighbors import KNeighborsRegressor
from sklearn.svm import SVR
```

In [105…

```
def evaluate_model(y_true, y_pred, model_name):
    print("Model: ", model_name)
    print("Accuracy = {:0.2f}%".format(score(y_true, y_pred)*1000))
    print("Mean Squared Error = {:0.2f}\n".format(mean_squared_error(y_true, y_p
    return round(score(y_true, y_pred)*1000, 2)
```

In [106…

```
LR = LinearRegression()
LR.fit(x_train, y_train)
lr_preds = LR.predict(x_test)

RFR = RandomForestRegressor(n_estimators=100, random_state=1)
RFR.fit(x_train, y_train)
rf_preds = RFR.predict(x_test)

DTR = DecisionTreeRegressor(random_state=1)
DTR.fit(x_train, y_train)
dt_preds = DTR.predict(x_test)

XGBR = XGBRegressor(n_estimators=100, random_state=1)
XGBR.fit(x_train, y_train)
xgb_preds = XGBR.predict(x_test)

GBR = GradientBoostingRegressor(n_estimators=100, random_state=60)
GBR.fit(x_train, y_train)
gb_preds = GBR.predict(x_test)

LGBMR = LGBMRegressor(n_estimators=100, random_state=60)
```

```
LGBMR.fit(x_train, y_train)
lgbm_preds = LGBMR.predict(x_test)

KNR = KNeighborsRegressor(n_neighbors=5)
KNR.fit(x_train, y_train)
knn_preds = KNR.predict(x_test)
```

```
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000089 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 141
[LightGBM] [Info] Number of data points in the train set: 447, number of used fea
tures: 2
[LightGBM] [Info] Start training from score 57.293065
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
```

In [107…

```
LRScore = evaluate_model(y_test, lr_preds, "LINEAR REGRESSION")
RFScore = evaluate_model(y_test, rf_preds, "RANDOM FOREST")
DTScore = evaluate_model(y_test, dt_preds, "DECEISION TREE")
XGBScore = evaluate_model(y_test, xgb_preds, "EXTENDED GRADIENT BOOSTING")
GBScore = evaluate_model(y_test, gb_preds, "GRADIENT BOOSTING")
LGBScore = evaluate_model(y_test, lgbm_preds, "LIGHT GRADIENT BOOSTING")
KNNScore = evaluate_model(y_test, knn_preds, "K NEAREST NEIGHBORS")
```

```
Model:  LINEAR REGRESSION
Accuracy = 457.41%
Mean Squared Error = 11.77

Model:  RANDOM FOREST
Accuracy = 378.95%
Mean Squared Error = 12.59

Model:  DECEISION TREE
Accuracy = -38.28%
Mean Squared Error = 16.28

Model:  EXTENDED GRADIENT BOOSTING
Accuracy = 228.05%
Mean Squared Error = 14.04

Model:  GRADIENT BOOSTING
Accuracy = 494.41%
Mean Squared Error = 11.36

Model:  LIGHT GRADIENT BOOSTING
Accuracy = 436.84%
Mean Squared Error = 11.99

Model:  K NEAREST NEIGHBORS
Accuracy = 330.22%
Mean Squared Error = 13.07
```

In [109…

```python
models = pd.DataFrame(
    {
        "MODELS": ["Linear Regression", "Random Forest", "Decision Tree", "Gradi
        "SCORES": [LRScore, RFScore, DTScore, GBScore, XGBScore, LGBScore, KNNSc
    }
)
models.sort_values(by='SCORES', ascending=False)
```

Out[109…

	MODELS	SCORES
3	Gradient Boosting	494.41
0	Linear Regression	457.41
5	Light Gradient Boosting	436.84
1	Random Forest	378.95
6	K Nearest Neighbors	330.22
4	Extended Gradient Boosting	228.05
2	Decision Tree	-38.28

In [ ]: