Movie Database Analysis by Nicolle Ho

In [1]:
```
#Ask Questions
```

This report analyzes the tmbd-movies database. The purpose of the analysis is to gain insight into movie popularity. What are the attributes that are associated with movies that are popular?

In [2]:
```
#Wrangle Data
```

In [3]:
```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
from matplotlib.ticker import MaxNLocator
from collections import namedtuple
```

In [4]:
```
#Read Database
df = pd.read_csv("tmdb-movies.csv")
df.head()
df.shape
```

Out[4]:
```
(10866, 21)
```

In [5]:
```
#Check for missing values
df.isnull()
df.isnull().sum()
#below there are missing values for several fields
```

Out[5]:
```
id                         0
imdb_id                   10
popularity                 0
budget                     0
revenue                    0
original_title             0
cast                      76
homepage                7930
director                  44
tagline                 2824
keywords                1493
overview                   4
runtime                    0
genres                    23
production_companies    1030
release_date               0
vote_count                 0
vote_average               0
release_year               0
budget_adj                 0
revenue_adj                0
dtype: int64
```

In [6]:
```
#Dont need to drop null items because the fields we are analyzing do not ha
#df = df.dropna()
#df.isnull().sum()
```

In [7]:
```
#check for duplicate rows
df = df.drop_duplicates(keep = 'first')
#values return false so it is not a duplicate row
```

In [8]:
```
#check for unique responses to see if there are hidden trues
df.duplicated(keep='first').nunique()
#only one unique response, so all values are False (not duplicated)
```

Out[8]:
```
1
```

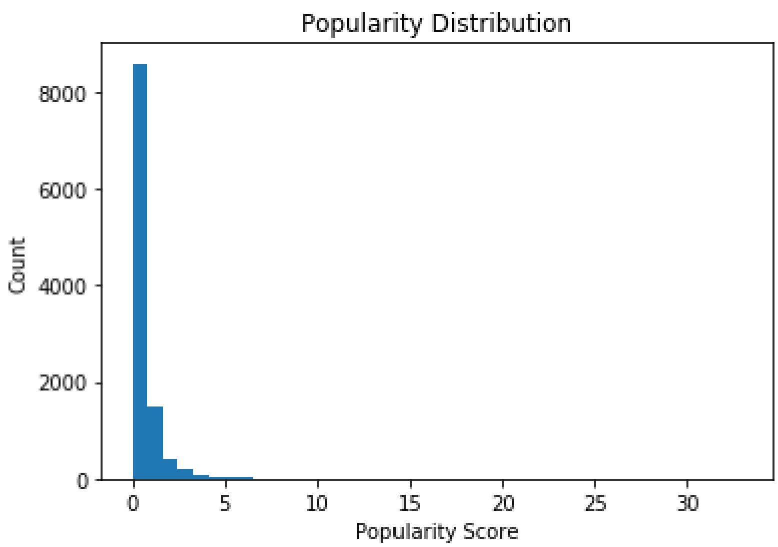
In [9]:
```
#check data types
df.dtypes
#the object data types have many values separated by | so this requires mor
```

Out[9]:
```
id                        int64
imdb_id                  object
popularity              float64
budget                    int64
revenue                   int64
original_title           object
cast                     object
homepage                 object
director                 object
tagline                  object
keywords                 object
overview                 object
runtime                   int64
genres                   object
production_companies     object
release_date             object
vote_count                int64
vote_average            float64
release_year              int64
budget_adj              float64
revenue_adj             float64
dtype: object
```

In [10]:
```
#Determine distribution of popularity and check for outliers
print(df['popularity'].describe())
pop = df['popularity']
n, bins, patches = plt.hist(x=pop, bins=40)
plt.title('Popularity Distribution')
plt.xlabel('Popularity Score')
plt.ylabel('Count')
```

```
count    10865.000000
mean         0.646446
std          1.000231
min          0.000065
25%          0.207575
50%          0.383831
75%          0.713857
max         32.985763
Name: popularity, dtype: float64
```

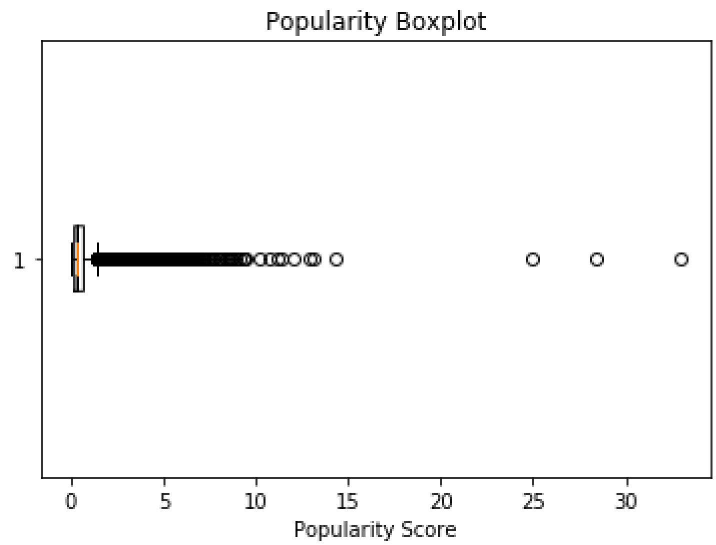
Out[10]: `Text(0, 0.5, 'Count')`



This graph shows how popularity scores are distributed across 10866 movies. The popularity scores are skewed right, so there are fewer movies that are popular. This is intuitive. We can also see that there are several outliers in the upperbound. There are several movies that are much more popular than the rest of the movies.

In [11]:
```
#Boxplot to view distribution and check for outliers
fig1, ax1 = plt.subplots()
ax1.set_title('Popularity Boxplot')
ax1.boxplot(pop, vert = False, notch = True)
ax1.set_xlabel('Popularity Score')
#Another view to show that popularity is skewed right
#Popularity scores are concentrated on the lower end
```

Out[11]:
```
Text(0.5, 0, 'Popularity Score')
```



This boxplot is another view of how popularity is distributed across all the movies. This view is interesting because we can see where are the quartiles. The first three quartiles are very concentrated in the lower popularity score region. The last quartile has the largest range. This confirms that the majority of movies are not popular. There is high variability in popularity for the popular movies. Because of these large outliers and variation, both the high and the low outliers will be excluded from the rest of the analysis.

In [13]:
```
#subset of the inner 50% to remove outliers
df2 = df.loc[(df.popularity > 0.384079) & (df.popularity < 1.538639)]
df2.head()
```

Out[13]:

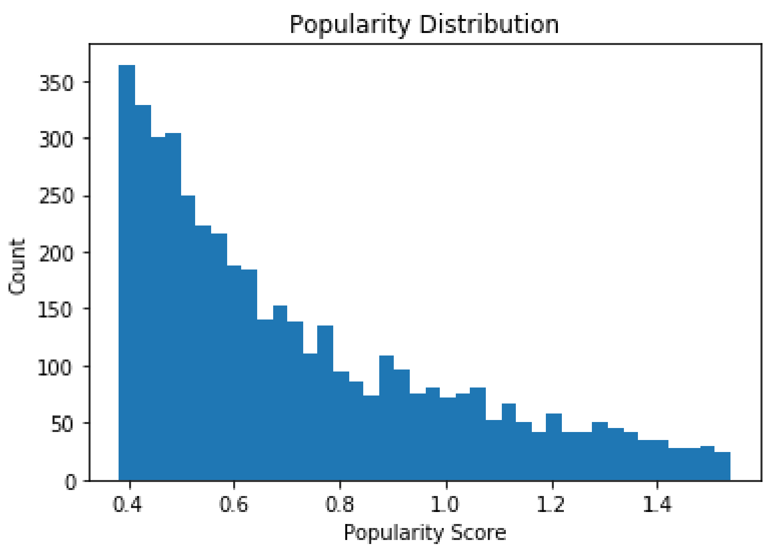
	id	imdb_id	popularity	budget	revenue	original_title	cast	
104	188222	tt1674771	1.532997	30000000	49263404	Entourage	Jeremy Piven|Adrian Grenier|Jerry Ferrara|Kevi...	
105	252838	tt0884732	1.510096	23000000	79799880	The Wedding Ringer	Kevin Hart|Josh Gad|Kaley Cuoco|Affion Crocket...	
106	273477	tt1727776	1.499614	15000000	14860766	Scouts Guide to the Zombie Apocalypse	Tye Sheridan|Logan Miller|Joey Morgan|Sarah Du...	http://www.
107	298312	tt3567288	1.495112	5000000	98450062	The Visit	Olivia DeJonge|Ed Oxenbould|Kathryn Hahn|Benja...	htt
108	261023	tt1355683	1.483246	53000000	99775678	Black Mass	Johnny Depp|Joel Edgerton|Benedict Cumberbatch...	

5 rows × 21 columns

In [14]:
```
#Determine popularity distribution of inner 50%
print(df2['popularity'].describe())
pop2 = df2['popularity']
n, bins, patches = plt.hist(x=pop2, bins=40)
plt.title('Popularity Distribution')
plt.xlabel('Popularity Score')
plt.ylabel('Count')
#There are fewer movies that are highly popular
#this is intuitive because most movies are not popular
```

```
count    4540.000000
mean        0.722664
std         0.292626
min         0.384097
25%         0.481688
50%         0.630672
75%         0.906316
max         1.538276
Name: popularity, dtype: float64
```

Out[14]:
```
Text(0, 0.5, 'Count')
```

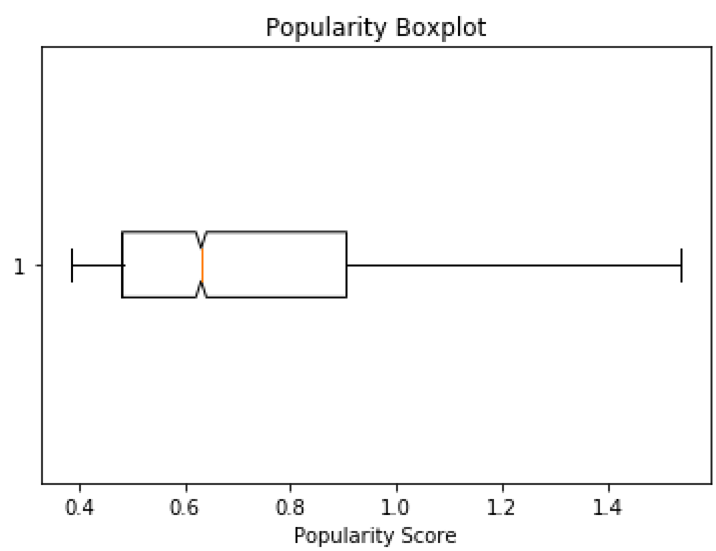


When examining the inner 50%, we can see that there is negative linear relationship between popularity score and count. The more popular a movie is, fewer movies exist with that level of popularity.

In [16]:
```
#Boxplot to view distribution and check for outliers
print(df2['popularity'].describe())
fig1, ax1 = plt.subplots()
ax1.set_title('Popularity Boxplot')
ax1.set_xlabel('Popularity Score')
ax1.boxplot(pop2, vert = False, notch = True)
#There are fewer movies that are highly popular
#this is intuitive because most movies are not popular
```

```
count    4540.000000
mean        0.722664
std         0.292626
min         0.384097
25%         0.481688
50%         0.630672
75%         0.906316
max         1.538276
Name: popularity, dtype: float64
```

Out[16]:
```
{'whiskers': [<matplotlib.lines.Line2D at 0x1140c5550>,
  <matplotlib.lines.Line2D at 0x1140c5898>],
 'caps': [<matplotlib.lines.Line2D at 0x1140c5be0>,
  <matplotlib.lines.Line2D at 0x1140c5f28>],
 'boxes': [<matplotlib.lines.Line2D at 0x1140c5160>],
 'medians': [<matplotlib.lines.Line2D at 0x1141822b0>],
 'fliers': [<matplotlib.lines.Line2D at 0x1141825f8>],
 'means': []}
```



This is a boxplot view of the inner 50%. The median popularity score is 0.63. Each quartile increases in size, which confirms that popularity is skewed right.

In [17]:
```
#Exploratory Data Analysis
```

In [19]:
```
#Remove erroneous zero budget / revenue values
df2 = df[(df.budget_adj != 0) & (df.revenue_adj != 0)]
```

In [21]:
```
#Split the data into quintiles by popularity to see how groups behave on av
df2['quantile'] = pd.qcut(df2['popularity'],5,labels=["Q1","Q2","Q3","Q4","
df2.head()
```

```
/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:2: SettingWi
thCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-doc
s/stable/indexing.html#indexing-view-versus-copy (http://pandas.pydata.or
g/pandas-docs/stable/indexing.html#indexing-view-versus-copy)
```

Out[21]:

genres	production_companies	release_date	vote_count	vote_average	release_year	budget_a
ıture|Science ·iction|Thriller	Universal Studios|Amblin Entertainment|Legenda...	6/9/15	5562	6.5	2015	1.379999e+
ıture|Science ·iction|Thriller	Village Roadshow Pictures|Kennedy Miller Produ...	5/13/15	6185	7.1	2015	1.379999e+
ıture|Science ·iction|Thriller	Summit Entertainment|Mandeville Films|Red Wago...	3/18/15	2480	6.3	2015	1.012000e+
ıture|Science ction|Fantasy	Lucasfilm|Truenorth Productions|Bad Robot	12/15/15	5292	7.5	2015	1.839999e+
Crime|Thriller	Universal Pictures|Original Film|Media Rights ...	4/1/15	2947	7.3	2015	1.747999e+

In [23]:
```
#confirm that errous zero budget / revenue movies were removed
df2 = df2.sort_values(by='budget_adj')
df2.head()
```

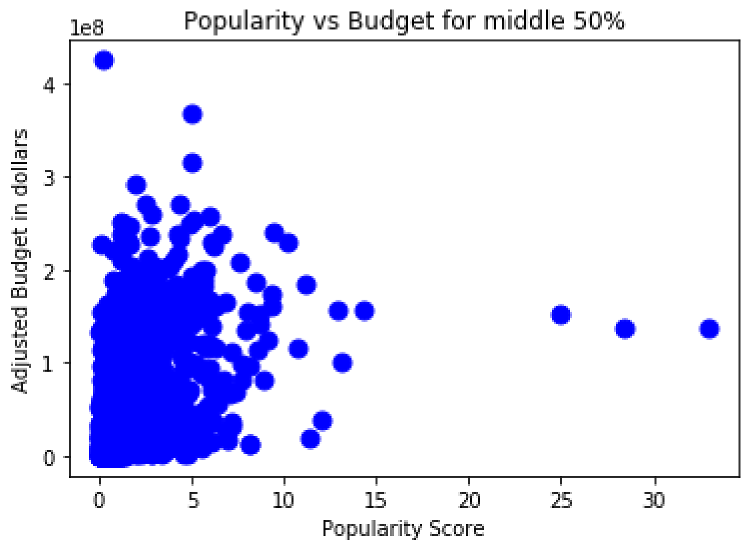
Out[23]:

	id	imdb_id	popularity	budget	revenue	original_title	cast	
3581	59296	tt1436559	0.520430	1	1378	Love, Wedding, Marriage	Mandy Moore|Kellan Lutz|Jessica Szohr|Autumn F...	http://www.ifcfiln
2618	39964	tt0120836	0.090186	1	100	Lost & Found	David Spade|Sophie Marceau|Ever Carradine|Step...	
2398	39356	tt1560139	0.028456	3	43	Boy	James Rolleston|Craig Hall|Taika Waititi|Te Ah...	http://www.b
8944	14373	tt0082250	0.464188	2	16	Death Wish 2	Charles Bronson|Jill Ireland|Vincent Gardenia|...	
10050	20701	tt0100740	0.317091	3	16	Tales from the Darkside: The Movie	Rae Dawn Chong|Christian Slater|Deborah Harry|...	

5 rows × 22 columns

In [24]:
```
#Plot popularity vs budget non outlier movies
plt.title("Popularity vs Budget for middle 50%")
plt.xlabel("Popularity Score")
plt.ylabel("Adjusted Budget in dollars")
plt.scatter(df2['popularity'], df2['budget_adj'], s=80, c='b', marker="o")
#Difficult to see a trend between popularity and budget
```

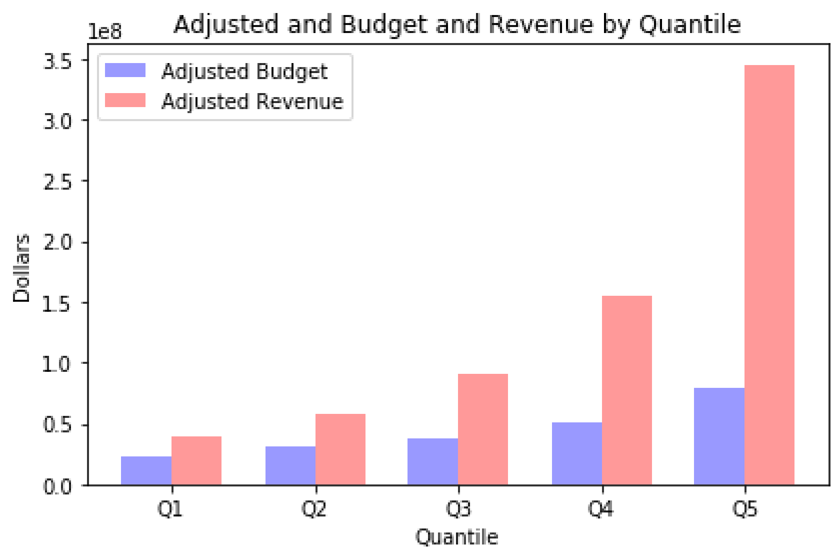
Out[24]: <matplotlib.collections.PathCollection at 0x1142fdb00>



We are plotting popularity vs budget to try to determine a relationship. However because of the numerous and cluttered data points it is difficult to see a clear trend.

In [25]:
```
#Calculate average budget and revenue for each quintile
budget = df2.groupby('quantile')['budget_adj'].mean()
revenue = df2.groupby('quantile')['revenue_adj'].mean()
```

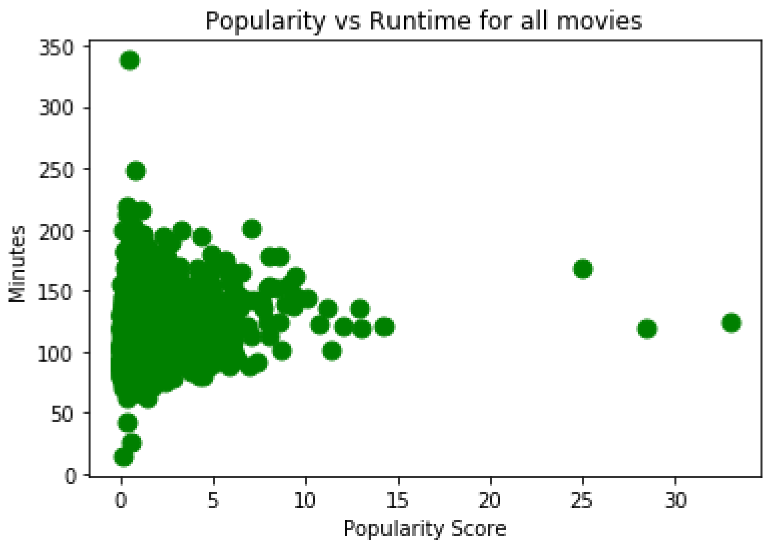
In [27]:
```
n_groups = 5

fig, ax = plt.subplots()

index = np.arange(n_groups)
bar_width = 0.35

opacity = 0.4
error_config = {'ecolor': '0.3'}

rects1 = ax.bar(index, budget, bar_width,
                alpha=opacity, color='b', error_kw=error_config,
                label='Adjusted Budget')

rects2 = ax.bar(index + bar_width, revenue, bar_width,
                alpha=opacity, color='r', error_kw=error_config,
                label='Adjusted Revenue')

ax.set_xlabel('Quantile')
ax.set_ylabel('Dollars')
ax.set_title('Adjusted and Budget and Revenue by Quantile')
ax.set_xticks(index + bar_width / 2)
ax.set_xticklabels(('Q1', 'Q2', 'Q3', 'Q4', 'Q5'))
ax.legend()

fig.tight_layout()
plt.show()
```



We can see trends more clearly when data is split into quantiles. More popular movies have larger budgets than less popular movies. More popular movies generate larger revenues than less popular movies.

In [28]:
```
#Popularity vs Runtime for all movies
plt.title("Popularity vs Runtime for all movies")
plt.xlabel("Popularity Score")
plt.ylabel("Minutes")
plt.scatter(df2['popularity'], df2['runtime'], s=80, c='g', marker="o")
#There are two outliers -- two movies that are really long
```

Out[28]: <matplotlib.collections.PathCollection at 0x114c3bba8>



Popularity is plotted against runtime to try and determine a relationship. The trend is unclear because of the concentration of data points on the left hand side of the graph.

In [29]:
```
#Sort the values by runtime to determine outliers which is the 338 min movi
df2 = df2.sort_values(by='runtime')
df2.tail()
```

Out[29]:

cast	homepage	director	tagline	...	runtime	genres	produc
›n Lang|Jeff iiels|Robert /all|Kevin ...	NaN	Ronald F. Maxwell	The nations heart was touched by...	...	214	Drama|History|War	Turner F
)'Toole|Alec :ss|Anthony uinn|Jack...	NaN	David Lean	A Mighty Motion Picture Of Action And Adventure!	...	216	Adventure|Drama|History|War	Hc
Kris Christopher |John Hur...	NaN	Michael Cimino	The only thing greater than their passion for ...	...	219	Action|Drama|History|Western	
/lor|Richard Harrison|R...	NaN	Joseph L. Mankiewicz|Rouben Mamoulian|Darryl F...	The motion picture the world has been waiting ...	...	248	Drama|History|Romance	Twent Film (
lgar RamÃ- z|Alexander \bi Samra...	NaN	Olivier Assayas	The man who hijacked the world	...	338	Crime|Drama|Thriller|History	I

In [30]:
```
#Drop runtime outliers
df2 = df2[(df2.runtime < 337)]
df2.tail()
#338 runtime values were dropped
```

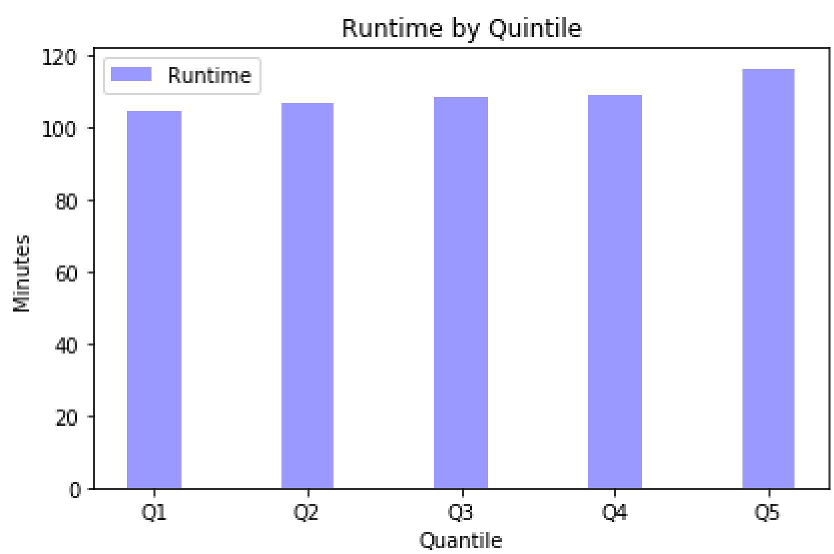
Out[30]:

	id	imdb_id	popularity	budget	revenue	original_title	cast	
3110	14073	tt0449994	0.389554	8376800	13000000	Jodhaa Akbar	Hrithik Roshan|Aishwarya Rai Bachchan|Sonu Soo...	http:/
5065	16072	tt0279111	0.469518	56000000	12923936	Gods and Generals	Stephen Lang|Jeff Daniels|Robert Duvall|Kevin ...	
9850	947	tt0056172	1.168767	15000000	70000000	Lawrence of Arabia	Peter O'Toole|Alec Guinness|Anthony Quinn|Jack...	
7332	10935	tt0080855	0.418950	44000000	3484331	Heaven's Gate	Kris Kristofferson|Christopher Walken|John Hur...	
10443	8095	tt0056937	0.804533	31115000	57750000	Cleopatra	Elizabeth Taylor|Richard Burton|Rex Harrison|R...	

5 rows × 22 columns

In [31]:

```
#Runtime by quintile
runtime = df2.groupby('quantile')['runtime'].mean()

n_groups = 5

fig, ax = plt.subplots()

index = np.arange(n_groups)
bar_width = 0.35

opacity = 0.4
error_config = {'ecolor': '0.3'}

rects1 = ax.bar(index+bar_width/2, runtime, bar_width,
                alpha=opacity, color='b', error_kw=error_config,
                label='Runtime')

ax.set_xlabel('Quantile')
ax.set_ylabel('Minutes')
ax.set_title('Runtime by Quintile')
ax.set_xticks(index + bar_width / 2)
ax.set_xticklabels(('Q1', 'Q2', 'Q3', 'Q4', 'Q5'))
ax.legend()
fig.tight_layout()
plt.show()
runtime
```



Out[31]:

```
quantile
Q1    104.795071
Q2    106.976623
Q3    108.609091
Q4    109.002594
Q5    116.417639
Name: runtime, dtype: float64
```

Breaking the data into quintiles allows us to view the data more clearly. All the bar heights are approximately the same size, so there does not appear to be a relationship between runtime and movie popularity.

In [32]:
```
df2['genres']
df2['genres'] = df2['genres'].str.split('|')
df2.groupby('quantile')['genres'].apply(list)
```

Out[32]:
```
quantile
Q1    [[Science Fiction, Animation], [Adventure, Act...
Q2    [[Family, Animation], [Music, Animation, Famil...
Q3    [[Adventure, Fantasy, Animation, Family], [Wes...
Q4    [[Animation, Family], [Drama, Music, Romance],...
Q5    [[Family, Animation, Adventure], [Fantasy, Ani...
Name: genres, dtype: object
```

In [33]:
```
df2['genres'].values.reshape(-1)
```

Out[33]:
```
array([list(['Science Fiction', 'Animation']),
       list(['Family', 'Animation']),
       list(['Adventure', 'Action', 'Comedy', 'Science Fiction', 'Musi
c']),
       ..., list(['Adventure', 'Drama', 'History', 'War']),
       list(['Action', 'Drama', 'History', 'Western']),
       list(['Drama', 'History', 'Romance'])], dtype=object)
```

In [34]:
```
df2.shape
```

Out[34]:
```
(3853, 22)
```

In [ ]:
```
#Draw Conclusions
```

This report analyzes attributes of popular movies.

The dataset is rich and sufficient for gaining greater insight into which factors are related to movie popularity. The original dataset had 10866 observations (movies) and 21 fields that include budget, revenue, runtime, genre, etc. After creating a subset of the inner 50% based on popularity and dropping movies with zero budget / revenue, the final analyzed dataset had 3853 observations and 22 fields (added quintile field). The dataset posed additional challenges because fields such as genre and production company had several attributes separated by |. This will require additional data cleaning and analytical reflection as some movies are listed as multiple genres.

More popular movies (higher quintiles) have higher average budgets and average revenues than less popular movies movies in (lower quintiles). There is no obvious relationship between runtime and movie popularity. Next steps of analysis include investigating how genres, production companies, acting casts, and directors contribute to movie popularity.

In [ ]:
```

```