A Dissection of the Academy's Most Sought After Award: Best Picture

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Abstract

The Academy Awards are the oldest international worldwide entertainment ceremony which also bestows the most prestigious accolades in the film industry. Winning an Academy Award/Oscar can be considered the single-greatest critical accomplishment for film professionals. These Oscars have long drawn media attention, but the ending of the 89th Academy Awards created new scrutiny. The mix-up between announcing *La La Land* (which was the predicted top winner by many critics) as Best Picture when the award actually went to *Moonlight*, sparked numerous articles and think-pieces revolving issues of race, PR stunts, and how the Oscars really work. Following the event, the general public learned about the backstage procedures set in place that are theoretically supposed to prevent these types of mistakes. Not only did this put the spotlight on how the Oscars operates during the awards show, but it also sparked interest into what exactly makes a film Best Picture worthy in the first place. *What does it take to win this award?*

Our question: What are the key components of a Best Picture and how do they compare to those of the "average" movie? And if we were to make a film today, what characteristics should we implement in order to give our film a better chance of winning Best Picture (e.g. genre, runtime, rating, star, director, production company, etc).

We will be conducting our report using two datasets. One is from Kaggle and is a list of 6000 movies between the years 1986-2016. Its original variables include: name, budget, company, country, director, genre, gross, rating, released, runtime, score, star, votes, writer, and year. The original data in this csv file is from IMDB. The other dataset is from the University of Waterloo and is a list of all of the Oscar Best Pictures from 1927- 2014. Its original variables include: name, year, nominations, rating duration, genre1, genre 2, release, metacritic, and synopsis.

https://www.kaggle.com/danielgrijalvas/movies (https://www.kaggle.com/danielgrijalvas/movies)

https://cs.uwaterloo.ca/~s255khan/oscars.html (https://cs.uwaterloo.ca/~s255khan/oscars.html)

We will be comparing observations in the respective variables between Movies and Best Pictures to see how much the statistics for a Best Picture deviate from the average movie.

Our report will be broken down into 3 sections:

- Data Cleaning
- Data Analysis and Plotting
- Conclusion

Importing Packages

First, we will begin by importing the necessary packages before we import our datasets.

In [1]:

```
import sys                                  # system module
import pandas as pd                         # data package
import matplotlib.pyplot as plt             # graphics module
import matplotlib as mpl
%matplotlib inline
import datetime as dt                       # date and time module
import numpy as np                          # foundation for pandas
import seaborn as sns                       # seaborn for data visualization
```

We'll be starting with our *movies* dataset containing over 6000 movies released between 1986 to 2016. As we import this data, we will also be checking the dtypes of each variable using the **.dtypes** function.

In [2]:

```
movies = '/Users/heatherpena/Desktop/movies.csv'
movies = pd.read_csv(movies, encoding = 'latin-1')

print('Variable dtypes:\n\n', movies.dtypes, sep='')

movies.head()
```

```
Variable dtypes:

budget        int64
company      object
country      object
director     object
genre        object
gross         int64
name         object
rating       object
released     object
runtime       int64
score       float64
star         object
votes         int64
writer       object
year          int64
dtype: object
```

Out[2]:

	budget	company	country	director	genre	gross	name	rating	re
0	8000000	Columbia Pictures Corporation	USA	Rob Reiner	Adventure	52287414	Stand by Me	R	19 08
1	6000000	Paramount Pictures	USA	John Hughes	Comedy	70136369	Ferris Bueller's Day Off	PG-13	19 06
2	15000000	Paramount Pictures	USA	Tony Scott	Action	179800601	Top Gun	PG	19 05
3	18500000	Twentieth Century Fox Film Corporation	USA	James Cameron	Action	85160248	Aliens	R	19 07
4	9000000	Walt Disney Pictures	USA	Randal Kleiser	Adventure	18564613	Flight of the Navigator	PG	19 08

Comment: This is mostly text data, which means it's assigned the dtype object. The variables are already short and lowercased, making the data easier to work with while we analyze.

In [3]:

```
print('Dimensions:',movies.shape) #check number of rows and columns in dataframe
```

```
Dimensions: (6819, 15)
```

Data Cleaning

Next Steps: We are assuming there will be duplicates in this dataframe, which will skew the data. We'll begin by checking for duplicates, and if they are found we will drop them using the **drop_dupicates( )** function.

In [4]:

```
movies.name.duplicated().sum() #find total sum of duplicates
```

Out[4]:

```
88
```

In [5]:

```
movies = movies.drop_duplicates(subset= 'name', keep='first', inplace=False)

movies.head()
```

Out[5]:

	budget	company	country	director	genre	gross	name	rating	re
0	8000000	Columbia Pictures Corporation	USA	Rob Reiner	Adventure	52287414	Stand by Me	R	19 08
1	6000000	Paramount Pictures	USA	John Hughes	Comedy	70136369	Ferris Bueller's Day Off	PG-13	19 06
2	15000000	Paramount Pictures	USA	Tony Scott	Action	179800601	Top Gun	PG	19 05
3	18500000	Twentieth Century Fox Film Corporation	USA	James Cameron	Action	85160248	Aliens	R	19 07
4	9000000	Walt Disney Pictures	USA	Randal Kleiser	Adventure	18564613	Flight of the Navigator	PG	19 08

We are printing the dimensions once again to ensure the duplicates were dropped. We can see here that 88 rows have indeed been dropped.

In [6]:

```
print('Dimensions:', movies.shape) #find new dimensions
```

```
Dimensions: (6731, 15)
```

In [7]:

```
movies['profitability']=movies['gross']/movies['budget'] #create profitability c
olumn
movies['title']=movies['name'] #create title column
movies['release_year']=movies['year'] #create release year column
```

We are adding 3 new columns. Title and release year are being added in case we later decide to index the dataframe by those two variables. This way, we can still use the two new columns as variables for analysis. We added a profitabilty variable to by using gross/budget as a multiple to see how profitable each respective movie is compared to its budget.

In [8]:

```
movies #run to make sure new variables were added
```

Out[8]:

	budget	company	country	director	genre	gross	
0	8000000	Columbia Pictures Corporation	USA	Rob Reiner	Adventure	52287414	Stand by M
1	6000000	Paramount Pictures	USA	John Hughes	Comedy	70136369	Ferris Buell Day Off
2	15000000	Paramount Pictures	USA	Tony Scott	Action	179800601	Top Gun
3	18500000	Twentieth Century Fox Film Corporation	USA	James Cameron	Action	85160248	Aliens
4	9000000	Walt Disney Pictures	USA	Randal Kleiser	Adventure	18564613	Flight of the Navigator
5	6000000	Hemdale	UK	Oliver Stone	Drama	138530565	Platoon
6	25000000	Henson Associates (HA)	UK	Jim Henson	Adventure	12729917	Labyrinth
7	6000000	De Laurentiis Entertainment Group (DEG)	USA	David Lynch	Drama	8551228	Blue Velvet
8	9000000	Paramount Pictures	USA	Howard Deutch	Comedy	40471663	Pretty in Pir
9	15000000	SLM Production Group	USA	David Cronenberg	Drama	40456565	The Fly
				Peter			Crocodile

10	8800000	Rimfire Films	Australia	Faiman	Adventure	174635000	Dundee
11	16000000	Thorn EMI Screen Entertainment	UK	Russell Mulcahy	Action	5900000	Highlander
12	6000000	Twentieth Century Fox Film Corporation	USA	David Seltzer	Comedy	8200000	Lucas
13	25000000	Twentieth Century Fox Film Corporation	USA	John Carpenter	Action	11100000	Big Trouble Little China
14	15000000	De Laurentiis Entertainment Group (DEG)	USA	Michael Mann	Crime	8620929	Manhunter
15	17000000	Producers Sales Organization (PSO)	USA	Adrian Lyne	Drama	6734844	9Â½ Weeks
16	10000000	De Laurentiis Entertainment Group (DEG)	USA	Stephen King	Action	7433663	Maximum Overdrive
17	25000000	Geffen Company, The	USA	Frank Oz	Comedy	38747385	Little Shop Horrors
18	2700000	New Century Entertainment Corporation	USA	Mike Marvin	Action	3500000	The Wraith
19	35000000	Universal Pictures	USA	Willard Huyck	Action	16295774	Howard the Duck
20	2000000	New Line Cinema	USA	Stephen Herek	Action	13167232	Critters
21	11000000	Orion Pictures	USA	Alan Metter	Comedy	91258000	Back to Scl
22	4700000	Cannon Films	USA	Tobe Hooper	Comedy	8025872	The Texas Chainsaw Massacre 2
23	15000000	Jay Weston Productions	USA	Clint Eastwood	Action	42724017	Heartbreak Ridge

24	25000000	Paramount Pictures	USA	Leonard Nimoy	Adventure	109713132	Star Trek IV Voyage Hor
25	0	TriStar Pictures	USA	John Badham	Comedy	40697761	Short Circu
26	0	Neue Constantin Film	Italy	Jean-Jacques Annaud	Crime	7153487	The Name (Rose
27	0	TriStar Pictures	USA	Sidney J. Furie	Action	24159872	Iron Eagle
28	25000000	Paramount Pictures	USA	Michael Ritchie	Action	79817937	The Golder Child
29	1900000	Hemdale	USA	Tim Hunter	Crime	4600000	River's Edg
...	...	...	...	...	...	...	...
6789	26000000	Broad Green Pictures	USA	Mark Waters	Comedy	17664973	Bad Santa :
6790	0	AZ Films	Chile	Pablo LarraÃn	Biography	938875	Neruda
6791	130000	Changing Film Productions	USA	Bank Tangjaitrong	Adventure	13557	Till We Mee Again
6792	8000000	Cinelou Films	USA	Bruce Beresford	Comedy	685143	Mr. Church
6793	900000	Hidden Empire Film Group	USA	Deon Taylor	Comedy	9093856	Meet the Bl
6794	0	RabbitBandini Productions	USA	Justin Kelly	Crime	28505	King Cobra
6795	15000000	Demarest Films	USA	D.J. Caruso	Drama	2411580	The Disappointr Room
6796	10000000	BBC Films	UK	Mick Jackson	Biography	4072226	Denial
6797	20000000	StudioCanal	UK	James Watkins	Action	39000	The Take
6798	18000000	Gold Circle Films	USA	Kirk Jones	Comedy	59573085	My Big Fat Greek Wed

							2
6799	17000000	Perfect World Pictures (Beijing)	USA	David E. Talbert	Comedy	41715860	Almost Christmas
6800	0	42	UK	Johannes Roberts	Horror	2987063	The Other S of the Door
6801	0	Mandarin Films	France	FranÃ§ois Ozon	Drama	880474	Frantz
6802	5000000	IM Global	USA	Brad Peyton	Horror	4790573	Incarnate
6803	0	Digic Pictures	Japan	Takeshi Nozue	Animation	233569	Kingsglaive Final Fanta
6804	0	Parts and Labor	USA	Joshua Marston	Drama	166827	Complete Unknown
6805	0	Bing Feng Bao Entertainment	USA	James Schamus	Drama	3399841	Indignation
6806	4000000	Blumhouse Productions	USA	Greg McLean	Horror	10732841	The Darkne
6807	3000000	Westerly Films	Ireland	Whit Stillman	Comedy	14013564	Love & Friendship
6808	3800000	Sycamore Pictures	USA	John Krasinski	Comedy	1016872	The Hollars
6809	0	StudioCanal	UK	Susanna White	Crime	3152725	Our Kind of Traitor
6810	8500000	CBS Films	USA	Steve Carr	Animation	19985196	Middle Sch The Worst Y of My Life
6811	0	Killer Films	USA	Andrew Neel	Drama	23020	Goat
6812	0	Anna Biller Productions	USA	Anna Biller	Comedy	228894	The Love W
6813	20000000	LD Entertainment	USA	Kevin Reynolds	Action	36874745	Risen
		Fox		Mandie			Absolutely

6814	0	Searchlight Pictures	UK	Fletcher	Comedy	4750497	Fabulous: T Movie
6815	0	Siempre Viva Productions	USA	Paul Duddridge	Drama	28368	Mothers an Daughters
6816	3500000	Warner Bros. Animation	USA	Sam Liu	Animation	3775000	Batman: Th Killing Joke
6817	0	Borderline Presents	USA	Nicolas Pesce	Drama	25981	The Eyes o Mother
6818	0	Les Productions	France	Nicole Garcia	Drama	37757	From the La of the Moor

Although profitability has been added, there are many rows that have been calculated with a profitability of infinity. This is because many movies in the dataframe have budgets of 0, so gross/0 equals infinity. We will be addressing this next.

In [9]:

```
mean_profit = (movies.loc[movies['profitability'] != np.inf]['profitability'].me
an()) #calculate mean profit but disregard infinity
```

In [10]:

```
print(mean_profit) #print mean profit
```

```
4.221052580440213
```

In [11]:

```
for index,row in movies.iterrows():
    if(row['budget'] == 0):
        movies.at[index,'budget'] = (movies.at[index,'gross']/mean_profit)#calcu
late estimated budget for moves with no budget
```

Although the dataframe had numerous 0 values in the budget category, we decided not to drop those respective movies. However, we had to change them from 0 to something else. Taking the average budget later on with values of 0 would skew the data to be less than it should be. However, we noticed that the repective movies with 0 budget were low-profile movies, so changing all the 0 values to null values or even dropping them altogether would make the average movie budget biased toward higher-budget movies. Therefore, we decided to use the profitability variable to calculate the average profitabilty across the 6000 movies (we didn't have the budget for all movies, but we have the domestic gross for all movies). But since the profitabilty multiple = gross/budget, all the movies with 0 (or null when we converted it) resulted in a profitability multiple of infinity. To avoid this, we wrote a line which disregarded the infinity values when calculating profitability. Using the average profitability, we divided the gross of each movie with a 0 budget by this number (4.22) to calculate a more accurate budget that those respective movies should have been around, thus making the data less skewed.

In [12]:

```
movies['profitability']=movies['gross']/movies['budget']
movies #run to make sure profitability variable is fixed with no infinity values
```

Out[12]:

	budget	company	country	director	genre	gross	
0	8000000	Columbia Pictures Corporation	USA	Rob Reiner	Adventure	52287414	Stand by M
1	6000000	Paramount Pictures	USA	John Hughes	Comedy	70136369	Ferris Buell Day Off
2	15000000	Paramount Pictures	USA	Tony Scott	Action	179800601	Top Gun
3	18500000	Twentieth Century Fox Film Corporation	USA	James Cameron	Action	85160248	Aliens
4	9000000	Walt Disney Pictures	USA	Randal Kleiser	Adventure	18564613	Flight of the Navigator
5	6000000	Hemdale	UK	Oliver Stone	Drama	138530565	Platoon
6	25000000	Henson Associates (HA)	UK	Jim Henson	Adventure	12729917	Labyrinth
7	6000000	De Laurentiis Entertainment Group (DEG)	USA	David Lynch	Drama	8551228	Blue Velvet

8	9000000	Paramount Pictures	USA	Howard Deutch	Comedy	40471663	Pretty in Pi
9	15000000	SLM Production Group	USA	David Cronenberg	Drama	40456565	The Fly
10	8800000	Rimfire Films	Australia	Peter Faiman	Adventure	174635000	Crocodile Dundee
11	16000000	Thorn EMI Screen Entertainment	UK	Russell Mulcahy	Action	5900000	Highlander
12	6000000	Twentieth Century Fox Film Corporation	USA	David Seltzer	Comedy	8200000	Lucas
13	25000000	Twentieth Century Fox Film Corporation	USA	John Carpenter	Action	11100000	Big Trouble Little China
14	15000000	De Laurentiis Entertainment Group (DEG)	USA	Michael Mann	Crime	8620929	Manhunter
15	17000000	Producers Sales Organization (PSO)	USA	Adrian Lyne	Drama	6734844	9Â½ Weeks
16	10000000	De Laurentiis Entertainment Group (DEG)	USA	Stephen King	Action	7433663	Maximum Overdrive
17	25000000	Geffen Company, The	USA	Frank Oz	Comedy	38747385	Little Shop Horrors
18	2700000	New Century Entertainment Corporation	USA	Mike Marvin	Action	3500000	The Wraith
19	35000000	Universal Pictures	USA	Willard Huyck	Action	16295774	Howard the Duck
20	2000000	New Line Cinema	USA	Stephen Herek	Action	13167232	Critters
		Orion					

21	11000000	Pictures	USA	Alan Metter	Comedy	91258000	Back to Scl
22	4700000	Cannon Films	USA	Tobe Hooper	Comedy	8025872	The Texas Chainsaw Massacre 2
23	15000000	Jay Weston Productions	USA	Clint Eastwood	Action	42724017	Heartbreak Ridge
24	25000000	Paramount Pictures	USA	Leonard Nimoy	Adventure	109713132	Star Trek IV Voyage Hor
25	9641614	TriStar Pictures	USA	John Badham	Comedy	40697761	Short Circu
26	1694716	Neue Constantin Film	Italy	Jean-Jacques Annaud	Crime	7153487	The Name (Rose
27	5723660	TriStar Pictures	USA	Sidney J. Furie	Action	24159872	Iron Eagle
28	25000000	Paramount Pictures	USA	Michael Ritchie	Action	79817937	The Golden Child
29	1900000	Hemdale	USA	Tim Hunter	Crime	4600000	River's Edg
...	...	...	...	...	...	...	...
6789	26000000	Broad Green Pictures	USA	Mark Waters	Comedy	17664973	Bad Santa :
6790	222426	AZ Films	Chile	Pablo LarraÃn	Biography	938875	Neruda
6791	130000	Changing Film Productions	USA	Bank Tangjaitrong	Adventure	13557	Till We Mee Again
6792	8000000	Cinelou Films	USA	Bruce Beresford	Comedy	685143	Mr. Church
6793	900000	Hidden Empire Film Group	USA	Deon Taylor	Comedy	9093856	Meet the Bl
6794	6753	RabbitBandini Productions	USA	Justin Kelly	Crime	28505	King Cobra
6795	15000000	Demarest Films	USA	D.J. Caruso	Drama	2411580	The Disappointr Room

6796	10000000	BBC Films	UK	Mick Jackson	Biography	4072226	Denial
6797	20000000	StudioCanal	UK	James Watkins	Action	39000	The Take
6798	18000000	Gold Circle Films	USA	Kirk Jones	Comedy	59573085	My Big Fat Greek Wed 2
6799	17000000	Perfect World Pictures (Beijing)	USA	David E. Talbert	Comedy	41715860	Almost Christmas
6800	707658	42	UK	Johannes Roberts	Horror	2987063	The Other S of the Door
6801	208591	Mandarin Films	France	FranÃ§ois Ozon	Drama	880474	Frantz
6802	5000000	IM Global	USA	Brad Peyton	Horror	4790573	Incarnate
6803	55334	Digic Pictures	Japan	Takeshi Nozue	Animation	233569	Kingsglaive Final Fantas
6804	39522	Parts and Labor	USA	Joshua Marston	Drama	166827	Complete Unknown
6805	805448	Bing Feng Bao Entertainment	USA	James Schamus	Drama	3399841	Indignation
6806	4000000	Blumhouse Productions	USA	Greg McLean	Horror	10732841	The Darkne
6807	3000000	Westerly Films	Ireland	Whit Stillman	Comedy	14013564	Love & Friendship
6808	3800000	Sycamore Pictures	USA	John Krasinski	Comedy	1016872	The Hollars
6809	746904	StudioCanal	UK	Susanna White	Crime	3152725	Our Kind of Traitor
6810	8500000	CBS Films	USA	Steve Carr	Animation	19985196	Middle Sch The Worst Y of My Life
6811	5453	Killer Films	USA	Andrew Neel	Drama	23020	Goat

6812	54226	Anna Biller Productions	USA	Anna Biller	Comedy	228894	The Love W
6813	20000000	LD Entertainment	USA	Kevin Reynolds	Action	36874745	Risen
6814	1125429	Fox Searchlight Pictures	UK	Mandie Fletcher	Comedy	4750497	Absolutely Fabulous: T Movie
6815	6720	Siempre Viva Productions	USA	Paul Duddridge	Drama	28368	Mothers an Daughters
6816	3500000	Warner Bros. Animation	USA	Sam Liu	Animation	3775000	Batman: Th Killing Joke
6817	6155	Borderline Presents	USA	Nicolas Pesce	Drama	25981	The Eyes o Mother
6818	8944	Les Productions du TrÃ©sor	France	Nicole Garcia	Drama	37757	From the La of the Moor

In [13]:

```
movies.isnull().any() #checks if there are any null values in the dataframe
```

Out[13]:

```
budget           False
company          False
country          False
director         False
genre            False
gross            False
name             False
rating           False
released         False
runtime          False
score            False
star             False
votes            False
writer           False
year             False
profitability    False
title            False
release_year     False
dtype: bool
```

Now we can see the Movies dataframe has been cleaned and there are no null values.

Oscar Winners Dataframe

Next, we will import the dataset containing the full list of Oscar winners from 1927 to 2014.

Comment: It is important to note that this dataset is missing the years 2015 and 2016. We will later be appending the missing data manually to match the 2016 endate from the Movies dataframe. Additionally, the original Movies dataframe has movies from 1986 - 2016 and the oscar_winners dataframe contains movies from 1927-2014. In order to have a more accurate analysis of the key characteristics of Best Pictures compared to Movies, we are making sure the years parallel. Therefore, we will only be using oscar_winners rows from 1986-2014. But this leaves us with n<30, another reason why we will be appending the dataframe to include winners up until 2016.

In [14]:

```
oscar_winners = pd.read_csv('/Users/heatherpena/Desktop/pictures.csv')
oscar_winners.head()
```

Out[14]:

	name	year	nominations	rating	duration	genre1	genre2	release	metacrit
0	Birdman	2014	9	7.8	119	Comedy	Drama	November	88.0
1	12 Years a Slave	2013	9	8.1	134	Biography	Drama	November	97.0
2	Argo	2012	7	7.8	120	Biography	Drama	October	86.0
3	The Artist	2011	10	8.0	100	Comedy	Drama	October	89.0
4	The King's Speech	2010	12	8.0	118	Biography	Drama	December	88.0

In [15]:

```
oscar_winners.shape #find length of rows/columns
```

Out[15]:

```
(87, 10)
```

In [16]:

```
print('Variable dtypes:\n\n', oscar_winners.dtypes, sep='') #print dtypes
```

```
Variable dtypes:

name            object
year             int64
nominations     object
rating         float64
duration         int64
genre1          object
genre2          object
release         object
metacritic     float64
synopsis        object
dtype: object
```

Similar to the Movies dataframe, most of this is text data, meaning our dtype is object. The column names are already lowercase, so these will not need to be changed.

We will be removing the white space at the beginning of each name (It took a great deal of time to figure out that there were white spaces before the movie titles, which at first prevented us from being able to write a loop of extracting the oscar_winners into a new dataframe).

In [17]:

```
oscar_winners['name'].replace("\\s(.*)", value=r"\1", regex=True, inplace=True)
#get rid of white space before movie name
```

In [18]:

```
oscar_winners.head()
```

Out[18]:

	name	year	nominations	rating	duration	genre1	genre2	release	metacrit
0	Birdman	2014	9	7.8	119	Comedy	Drama	November	88.0
1	12 Years a Slave	2013	9	8.1	134	Biography	Drama	November	97.0
2	Argo	2012	7	7.8	120	Biography	Drama	October	86.0
3	The Artist	2011	10	8.0	100	Comedy	Drama	October	89.0
4	The King's Speech	2010	12	8.0	118	Biography	Drama	December	88.0

In [19]:

```
oscar_winners.isnull().any() #checks if there are any null values in the datafra
me
```

Out[19]:

```
name           False
year           False
nominations    False
rating         False
duration       False
genre1         False
genre2          True
release         True
metacritic      True
synopsis       False
dtype: bool
```

Although there are still null values in the dataframe, it is ok because we will only be using two variables from it (name and nominations) in order to make a new Winners dataframe. Neither of those respective variables have null values.

Marking Oscar Winners

Rather than merging the two dataframes together, we are instead marking all of the winning movies within the original Movies dataframe using the "is_winner" column we created. We realized that this way, both dataframes will have the same variables, making it easier and more accurate to do our analysis. For example, even though the oscar_winners dataframe has Metacritic scores, the fact that the Movies dataframe doesn't makes it impossible to compare Movies and Winners based on that variable. Nonetheless, the original Movies dataframe has many interesting variables we can use to compare to Winners.

In [20]:

```
movies['is_winner'] = 'false'#any that are not true are false


for index,row in movies.iterrows():
  if row["title"] in oscar_winners["name"].values: #if it's inside oscar_winners
then declare it winner in movies as well
    movies.at[index, 'is_winner'] = 'true'
```

Setting the Index

We will be setting the index by "name" in order to easily locate and manipulate the data by movie title.

In [21]:

```
movies = movies.set_index(['name'])
movies.head()
```

Out[21]:

	budget	company	country	director	genre	gross	rating	rele
name								
Stand by Me	8000000	Columbia Pictures Corporation	USA	Rob Reiner	Adventure	52287414	R	198 08-2
Ferris Bueller's Day Off	6000000	Paramount Pictures	USA	John Hughes	Comedy	70136369	PG-13	198 06-1
Top Gun	15000000	Paramount Pictures	USA	Tony Scott	Action	179800601	PG	198 05-1
Aliens	18500000	Twentieth Century Fox Film Corporation	USA	James Cameron	Action	85160248	R	198 07-1
Flight of the Navigator	9000000	Walt Disney Pictures	USA	Randal Kleiser	Adventure	18564613	PG	198 08-0

In [22]:

```
movies.loc['Forrest Gump'] #locate Forrest Gump film from movies dataframe
```

Out[22]:

```
budget                     55000000
company          Paramount Pictures
country                         USA
director            Robert Zemeckis
genre                        Comedy
gross                     330252182
rating                        PG-13
released                 1994-07-06
runtime                         142
score                           8.8
star                      Tom Hanks
votes                       1402876
writer                Winston Groom
year                           1994
profitability               6.00459
title                  Forrest Gump
release_year                   1994
is_winner                      true
Name: Forrest Gump, dtype: object
```

We are locating a specific Best Picture that we know won from the top of our heads to ensure that the respective "is_winners" loop works and has correctly marked the respective movies with "true."

Winners Dataframe

Next, we will comb through the movies marked true in the "is_winner" column and pull them out to analyze and double check that they were marked correctly.

In [23]:

```
winners = movies.loc[movies['is_winner'] == 'true']
```

In [24]:

```
winners
```

Out[24]:

	budget	company	country	director	genre	gross
name						
Platoon	6000000	Hemdale	UK	Oliver Stone	Drama	138530565

The Last Emperor	23000000	Recorded Picture Company (RPC)	UK	Bernardo Bertolucci	Biography	43984230
Rain Man	25000000	United Artists	USA	Barry Levinson	Drama	172825435
Driving Miss Daisy	7500000	Zanuck Company, The	USA	Bruce Beresford	Drama	106593296
Dances with Wolves	22000000	Tig Productions	USA	Kevin Costner	Adventure	184208848
Hamlet	4906466	Canal+	USA	Franco Zeffirelli	Drama	20710451
The Silence of the Lambs	19000000	Strong Heart/Demme Production	USA	Jonathan Demme	Crime	130742922
Unforgiven	14400000	Warner Bros.	USA	Clint Eastwood	Drama	101157447
Schindler's List	22000000	Universal Pictures	USA	Steven Spielberg	Biography	96067179
Forrest Gump	55000000	Paramount Pictures	USA	Robert Zemeckis	Comedy	330252182
Braveheart	72000000	Icon Entertainment International	USA	Mel Gibson	Biography	75600000
The English Patient	27000000	Miramax	USA	Anthony Minghella	Drama	78651430
Titanic	200000000	Twentieth Century Fox Film Corporation	USA	James Cameron	Drama	658672302
Shakespeare in Love	25000000	Universal Pictures	USA	John Madden	Comedy	100317794
American Beauty	15000000	DreamWorks	USA	Sam Mendes	Drama	130096601
Gladiator	103000000	DreamWorks	USA	Ridley Scott	Action	187705427
A Beautiful		Universal				

Mind	58000000	Pictures	USA	Ron Howard	Biography	170742341
Chicago	45000000	Miramax	USA	Rob Marshall	Comedy	170687518
The Lord of the Rings: The Return of the King	94000000	New Line Cinema	USA	Peter Jackson	Adventure	377845905
Crash	6500000	Bob Yari Productions	USA	Paul Haggis	Crime	54580300
Million Dollar Baby	30000000	Warner Bros.	USA	Clint Eastwood	Drama	100492203
Around the World in 80 Days	110000000	Walden Media	USA	Frank Coraci	Action	24008137
The Departed	90000000	Warner Bros.	USA	Martin Scorsese	Crime	132384315
All the King's Men	55000000	Columbia Pictures Corporation	Germany	Steven Zaillian	Drama	7221458
No Country for Old Men	25000000	Paramount Vantage	USA	Ethan Coen	Crime	74283625
Slumdog Millionaire	15000000	Warner Bros.	UK	Danny Boyle	Drama	141319928
The Hurt Locker	15000000	Voltage Pictures	USA	Kathryn Bigelow	Drama	17017811
The King's Speech	15000000	See-Saw Films	UK	Tom Hooper	Biography	138797449
The Artist	15000000	Studio 37	France	Michel Hazanavicius	Comedy	44671682
Argo	44500000	Warner Bros.	USA	Ben Affleck	Adventure	136025503
12 Years a Slave	20000000	Regency Enterprises	USA	Steve McQueen	Biography	56671993
Ben-Hur	100000000	LightWorkers Media	USA	Timur Bekmambetov	Action	26384681

There are four movies in this dataset incorrectly marked as winners. This must be because these movies had remakes, which interfered with our "is_winner" loop function. For example, a movie titled *Ben-Hur* was made twice, once in 1959 and another in 2016. However, when we dropped the duplicate in the original Movies dataframe, it must have dropped the 1959 version. Meanwhile, in the oscar_winners dataframe, *Ben-Hur* is still listed from 1959 as a winner. Using the oscar_winners list to loop through movies, the 2016 *Ben-Hur* must have been flagged. The same goes for the other 3 movies (which all are remakes of Oscar Best Picture Winners prior to 1986). The 4 titles are:

- Ben-Hur (2016)
- Hamlet (1990)
- Around the World in 80 Days (2004)
- All the King's Men (2006)

In [25]:

```
winners = winners.drop(['Ben-Hur', 'Hamlet', 'Around the World in 80 Days', "All the King's Men"])
```

Next, we are manually appending any missing Oscar winning films to make the dataframe as recent as 2016 and so n > 30.

These films include:

- Birdman (2014)
- Spotlight (2015)
- Moonlight (2016)

In [26]:

```
append_dict = {
    'name': {2014: 'Birdman', 2015: 'Spotlight', 2016: 'Moonlight'},
    'year': {2014: '2014', 2015: '2015', 2016: '2016'},
    'budget': {2014: '18000000.0', 2015: '20000000.0', 2016: '4000000.0'},
    'company': {2014: 'Regency Enterprises', 2015: 'Participant Media', 2016: 'A
24',},
    'country': {2014: 'USA', 2015: 'USA', 2016: 'USA',},
    'director': {2014: 'Alejandro Gonzalez Inarritu', 2015: 'Tom McCarthy', 2016
: 'Barry Jenkins'},
    'genre': {2014: 'Drama', 2015: 'Drama', 2016: 'Drama',},
    'gross': {2014: '42340598.0', 2015: '45055776.0', 2016: '27854932.0'},
    'rating': {2014: 'R', 2015: 'R', 2016: 'R'},
    'released': {2014: '2014-10-17', 2015: '2015-11-20', 2016: '2016-10-21'},
    'runtime': {2014: '119', 2015: '129', 2016: '115',},
    'score': {2014: '7.8', 2015: '8.1', 2016: '7.4'},
    'star': {2014: 'Michael Keaton', 2015: 'Mark Ruffalo', 2016: 'Trevante Rhode
s'},
    'votes': {2014: '498151', 2015: '344554', 2016: '209986'},
    'writer': {2014: 'Alejandro Gonzalez Inarritu', 2015: 'Tom McCarthy', 2016:
'Barry Jenkins'},
    'is_winner': {2014: 'true', 2015: 'true', 2016: 'true'},
}

append_df = pd.DataFrame(append_dict)
append_df = append_df.set_index(['name'])
append_df
```

Out[26]:

	year	budget	company	country	director	genre	gross	rating
name								
Birdman	2014	18000000.0	Regency Enterprises	USA	Alejandro Gonzalez Inarritu	Drama	42340598.0	R
Spotlight	2015	20000000.0	Participant Media	USA	Tom McCarthy	Drama	45055776.0	R
Moonlight	2016	4000000.0	A24	USA	Barry Jenkins	Drama	27854932.0	R

In [27]:

```
winners=winners.append(append_df)
```

```
/anaconda3/lib/python3.6/site-packages/pandas/core/frame.py:6201: Fu
tureWarning: Sorting because non-concatenation axis is not aligned.
A future version
of pandas will change to not sort by default.

To accept the future behavior, pass 'sort=True'.

To retain the current behavior and silence the warning, pass sort=Fa
lse

  sort=sort)
```

In [28]:

```
winners #run to make sure the respective winners were properly added
```

Out[28]:

	budget	company	country	director	genre	gross
name						
Platoon	6000000	Hemdale	UK	Oliver Stone	Drama	138530565
The Last Emperor	23000000	Recorded Picture Company (RPC)	UK	Bernardo Bertolucci	Biography	43984230
Rain Man	25000000	United Artists	USA	Barry Levinson	Drama	172825435
Driving Miss Daisy	7500000	Zanuck Company, The	USA	Bruce Beresford	Drama	106593296
Dances with Wolves	22000000	Tig Productions	USA	Kevin Costner	Adventure	184208848
The Silence of the Lambs	19000000	Strong Heart/Demme Production	USA	Jonathan Demme	Crime	130742922
Unforgiven	14400000	Warner Bros.	USA	Clint Eastwood	Drama	101157447
Schindler's		Universal		Steven		

List	22000000	Pictures	USA	Spielberg	Biography	96067179
Forrest Gump	55000000	Paramount Pictures	USA	Robert Zemeckis	Comedy	330252182
Braveheart	72000000	Icon Entertainment International	USA	Mel Gibson	Biography	75600000
The English Patient	27000000	Miramax	USA	Anthony Minghella	Drama	78651430
Titanic	200000000	Twentieth Century Fox Film Corporation	USA	James Cameron	Drama	658672302
Shakespeare in Love	25000000	Universal Pictures	USA	John Madden	Comedy	100317794
American Beauty	15000000	DreamWorks	USA	Sam Mendes	Drama	130096601
Gladiator	103000000	DreamWorks	USA	Ridley Scott	Action	187705427
A Beautiful Mind	58000000	Universal Pictures	USA	Ron Howard	Biography	170742341
Chicago	45000000	Miramax	USA	Rob Marshall	Comedy	170687518
The Lord of the Rings: The Return of the King	94000000	New Line Cinema	USA	Peter Jackson	Adventure	377845905
Crash	6500000	Bob Yari Productions	USA	Paul Haggis	Crime	54580300
Million Dollar Baby	30000000	Warner Bros.	USA	Clint Eastwood	Drama	100492203
The Departed	90000000	Warner Bros.	USA	Martin Scorsese	Crime	132384315
No Country for Old Men	25000000	Paramount Vantage	USA	Ethan Coen	Crime	74283625
Slumdog Millionaire	15000000	Warner Bros.	UK	Danny Boyle	Drama	141319928

The Hurt Locker	15000000	Voltage Pictures	USA	Kathryn Bigelow	Drama	17017811
The King's Speech	15000000	See-Saw Films	UK	Tom Hooper	Biography	138797449
The Artist	15000000	Studio 37	France	Michel Hazanavicius	Comedy	44671682
Argo	44500000	Warner Bros.	USA	Ben Affleck	Adventure	136025503
12 Years a Slave	20000000	Regency Enterprises	USA	Steve McQueen	Biography	56671993
Birdman	18000000.0	Regency Enterprises	USA	Alejandro Gonzalez Inarritu	Drama	42340598.0
Spotlight	20000000.0	Participant Media	USA	Tom McCarthy	Drama	45055776.0
Moonlight	4000000.0	A24	USA	Barry Jenkins	Drama	27854932.0

The additional data was appended at the end of the dataframe, causing the dataframe to no longer be in chronological order by year. In order to solve this, we need to sort the dataframe by year.

In [29]:

```
winners = winners.iloc[winners['year'].astype(int).argsort()]
```

In [30]:

```
winners
```

Out[30]:

	budget	company	country	director	genre	gross
name						
Platoon	6000000	Hemdale	UK	Oliver Stone	Drama	138530565
The Last Emperor	23000000	Recorded Picture Company (RPC)	UK	Bernardo Bertolucci	Biography	43984230
Rain Man	25000000	United Artists	USA	Barry Levinson	Drama	172825435

Driving Miss Daisy	7500000	Zanuck Company, The	USA	Bruce Beresford	Drama	106593296
Dances with Wolves	22000000	Tig Productions	USA	Kevin Costner	Adventure	184208848
The Silence of the Lambs	19000000	Strong Heart/Demme Production	USA	Jonathan Demme	Crime	130742922
Unforgiven	14400000	Warner Bros.	USA	Clint Eastwood	Drama	101157447
Schindler's List	22000000	Universal Pictures	USA	Steven Spielberg	Biography	96067179
Forrest Gump	55000000	Paramount Pictures	USA	Robert Zemeckis	Comedy	330252182
Braveheart	72000000	Icon Entertainment International	USA	Mel Gibson	Biography	75600000
The English Patient	27000000	Miramax	USA	Anthony Minghella	Drama	78651430
Titanic	200000000	Twentieth Century Fox Film Corporation	USA	James Cameron	Drama	658672302
Shakespeare in Love	25000000	Universal Pictures	USA	John Madden	Comedy	100317794
American Beauty	15000000	DreamWorks	USA	Sam Mendes	Drama	130096601
Gladiator	103000000	DreamWorks	USA	Ridley Scott	Action	187705427
A Beautiful Mind	58000000	Universal Pictures	USA	Ron Howard	Biography	170742341
Chicago	45000000	Miramax	USA	Rob Marshall	Comedy	170687518
The Lord of the Rings: The Return of the King	94000000	New Line Cinema	USA	Peter Jackson	Adventure	377845905
Million Dollar Baby	30000000	Warner Bros.	USA	Clint Eastwood	Drama	100492203

Crash	6500000	Bob Yari Productions	USA	Paul Haggis	Crime	54580300
The Departed	90000000	Warner Bros.	USA	Martin Scorsese	Crime	132384315
No Country for Old Men	25000000	Paramount Vantage	USA	Ethan Coen	Crime	74283625
Slumdog Millionaire	15000000	Warner Bros.	UK	Danny Boyle	Drama	141319928
The Hurt Locker	15000000	Voltage Pictures	USA	Kathryn Bigelow	Drama	17017811
The King's Speech	15000000	See-Saw Films	UK	Tom Hooper	Biography	138797449
The Artist	15000000	Studio 37	France	Michel Hazanavicius	Comedy	44671682
Argo	44500000	Warner Bros.	USA	Ben Affleck	Adventure	136025503
12 Years a Slave	20000000	Regency Enterprises	USA	Steve McQueen	Biography	56671993
Birdman	18000000.0	Regency Enterprises	USA	Alejandro Gonzalez Inarritu	Drama	42340598.0
Spotlight	20000000.0	Participant Media	USA	Tom McCarthy	Drama	45055776.0
Moonlight	4000000.0	A24	USA	Barry Jenkins	Drama	27854932.0

We realize the data will be much easier to work with (especially when it comes to graphing) if the index is already set to the year. Therefore, we will reset the index and change it from "name" to "year".

In [31]:

```
winners = winners.reset_index()
winners = winners.set_index('year')
winners.head()
```

Out[31]:

	name	budget	company	country	director	genre	gross	is_wir
year								
1986	Platoon	6000000	Hemdale	UK	Oliver Stone	Drama	138530565	true
1987	The Last Emperor	23000000	Recorded Picture Company (RPC)	UK	Bernardo Bertolucci	Biography	43984230	true
1988	Rain Man	25000000	United Artists	USA	Barry Levinson	Drama	172825435	true
1989	Driving Miss Daisy	7500000	Zanuck Company, The	USA	Bruce Beresford	Drama	106593296	true
1990	Dances with Wolves	22000000	Tig Productions	USA	Kevin Costner	Adventure	184208848	true

We decided to add a nominations column from oscar_winners for winners, but that's the only other variable from oscar_winners we will use.

In [32]:

```
winners["nominations"] = 0
```

In [33]:

```
#manually adding movies that are not in Oscar dataset
winners.loc[winners["name"] == "Birdman", "nominations"] = 9
winners.loc[winners["name"] == "Spotlight", "nominations"] = 6
winners.loc[winners["name"] == "Moonlight", "nominations"] = 8
```

In [34]:

```
#move nominations from oscar_winners to winners
for index,row in winners.iterrows():
    winner_name = row['name']
    if winner_name in oscar_winners["name"].values:
        winners.at[index, "nominations"] = oscar_winners.loc[oscar_winners['name
'] == winner_name]["nominations"]
```

In [35]:

```
#add release years to appended movies
winners.loc[winners["name"] == "Birdman", "release_year"] = 2014
winners.loc[winners["name"] == "Spotlight", "release_year"] = 2015
winners.loc[winners["name"] == "Moonlight", "release_year"] = 2016
```

In [36]:

```
#add title to appended movies
winners.loc[winners["name"] == "Birdman", "title"] = "Birdman"
winners.loc[winners["name"] == "Spotlight", "title"] = "Spotlight"
winners.loc[winners["name"] == "Moonlight", "title"] = "Moonlight"
```

In [37]:

```
#calculate profitability for last 3 movies since it wasn't in original dataframe
winners.loc[winners["name"] == "Birdman", "profitability"] = 42340598.0/18000000
.0
winners.loc[winners["name"] == "Spotlight", "profitability"] = 45055776.0/200000
00.0
winners.loc[winners["name"] == "Moonlight", "profitability"] = 27854932.0/400000
0.0
```

In [38]:

```
winners
```

Out[38]:

	name	budget	company	country	director	genre	g
year							
1986	Platoon	6000000	Hemdale	UK	Oliver Stone	Drama	138530
1987	The Last Emperor	23000000	Recorded Picture Company (RPC)	UK	Bernardo Bertolucci	Biography	439842

1988	Rain Man	25000000	United Artists	USA	Barry Levinson	Drama	172825
1989	Driving Miss Daisy	7500000	Zanuck Company, The	USA	Bruce Beresford	Drama	106593
1990	Dances with Wolves	22000000	Tig Productions	USA	Kevin Costner	Adventure	184208
1991	The Silence of the Lambs	19000000	Strong Heart/Demme Production	USA	Jonathan Demme	Crime	130742
1992	Unforgiven	14400000	Warner Bros.	USA	Clint Eastwood	Drama	101157
1993	Schindler's List	22000000	Universal Pictures	USA	Steven Spielberg	Biography	960671
1994	Forrest Gump	55000000	Paramount Pictures	USA	Robert Zemeckis	Comedy	330252
1995	Braveheart	72000000	Icon Entertainment International	USA	Mel Gibson	Biography	756000
1996	The English Patient	27000000	Miramax	USA	Anthony Minghella	Drama	786514
1997	Titanic	200000000	Twentieth Century Fox Film Corporation	USA	James Cameron	Drama	658672
1998	Shakespeare in Love	25000000	Universal Pictures	USA	John Madden	Comedy	100317
1999	American Beauty	15000000	DreamWorks	USA	Sam Mendes	Drama	130096
2000	Gladiator	103000000	DreamWorks	USA	Ridley Scott	Action	187705
2001	A Beautiful Mind	58000000	Universal Pictures	USA	Ron Howard	Biography	170742
2002	Chicago	45000000	Miramax	USA	Rob Marshall	Comedy	170687
2003	The Lord of the Rings: The Return of the King	94000000	New Line Cinema	USA	Peter Jackson	Adventure	377845

2004	Million Dollar Baby	30000000	Warner Bros.	USA	Clint Eastwood	Drama	100492
2005	Crash	6500000	Bob Yari Productions	USA	Paul Haggis	Crime	545803
2006	The Departed	90000000	Warner Bros.	USA	Martin Scorsese	Crime	132384
2007	No Country for Old Men	25000000	Paramount Vantage	USA	Ethan Coen	Crime	742836
2008	Slumdog Millionaire	15000000	Warner Bros.	UK	Danny Boyle	Drama	141319
2009	The Hurt Locker	15000000	Voltage Pictures	USA	Kathryn Bigelow	Drama	170178
2010	The King's Speech	15000000	See-Saw Films	UK	Tom Hooper	Biography	138797
2011	The Artist	15000000	Studio 37	France	Michel Hazanavicius	Comedy	446716
2012	Argo	44500000	Warner Bros.	USA	Ben Affleck	Adventure	136025
2013	12 Years a Slave	20000000	Regency Enterprises	USA	Steve McQueen	Biography	566719
2014	Birdman	18000000.0	Regency Enterprises	USA	Alejandro Gonzalez Inarritu	Drama	423405
2015	Spotlight	20000000.0	Participant Media	USA	Tom McCarthy	Drama	450557
2016	Moonlight	4000000.0	A24	USA	Barry Jenkins	Drama	278549

In [39]:

```
winners.isnull().any() #check null values for Winners
```

Out[39]:

```
name              False
budget            False
company           False
country           False
director          False
genre             False
gross             False
is_winner         False
profitability     False
rating            False
release_year      False
released          False
runtime           False
score             False
star              False
title             False
votes             False
writer            False
nominations       False
dtype: bool
```

There are now no null values in the Winners dataframe.

While checking the dtypes for the new dataframe, we found that when the data was extracted all of the variables were changed to object. This will cause problems when running an analysis on numerical data, as these variables will not be recognized by functions.

In order to fix this, we attempted to change dtypes using type casting, but this method did not work. Instead, we are using the **.to_numeric()** function to convert all of the numeric variables back into what they should be.

In [40]:

```
movies.dtypes #check dtypes of Movies
```

Out[40]:

```
budget              int64
company            object
country            object
director           object
genre              object
gross               int64
rating             object
released           object
runtime             int64
score             float64
star               object
votes               int64
writer             object
year                int64
profitability     float64
title              object
release_year        int64
is_winner          object
dtype: object
```

In [41]:

```
winners.dtypes #check dtypes of Winners
```

Out[41]:

```
name               object
budget             object
company            object
country            object
director           object
genre              object
gross              object
is_winner          object
profitability     float64
rating             object
release_year      float64
released           object
runtime            object
score              object
star               object
title              object
votes              object
writer             object
nominations         int64
dtype: object
```

In [42]:

```
#change respective Winners dtypes from objects to floats

winners['votes'] = pd.to_numeric(winners.votes)

winners['runtime'] = pd.to_numeric(winners.runtime)

winners['budget'] = pd.to_numeric(winners.budget)

winners['gross'] = pd.to_numeric(winners.gross)

winners['score'] = pd.to_numeric(winners.score)
```

In [43]:

```
winners.dtypes #make sure dtypes have been changed
```

Out[43]:

```
name                 object
budget              float64
company              object
country              object
director             object
genre                object
gross               float64
is_winner            object
profitability       float64
rating               object
release_year        float64
released             object
runtime               int64
score               float64
star                 object
title                object
votes                 int64
writer               object
nominations           int64
dtype: object
```

Analysis and Graphs

We will be calculating the means, modes, and standard deviations of respective variables between Movies and Winners to find similarities and differences and see how much the observations deviate from each other in certain categories. For example, how much longer is the runtime of a Winner than your average movie? How much higher is the IMDB score? Budget? Gross? Etc. We will also be plotting graphs, charts, and correlations to compliment our calculations and further our analysis.

In [44]:

```
year_budget_values = {}#average out data to graph

year_parameter_values = {"budget": {}, "score": {}, "gross": {}, "profitability"
: {}, "runtime": {}, "votes": {}} #organize data

for index,row in movies.iterrows():
    yearstring = str(row['year'])
    for parameter in year_parameter_values.keys():
        if not yearstring in year_parameter_values[parameter]:
            year_parameter_values[parameter][yearstring] = []
        year_parameter_values[parameter][yearstring].append(row[parameter])
#data is now formatted properly to calculate averages

year_parameter_averages = {}
for parameter in year_parameter_values.keys():
    year_parameter_averages[parameter] = {}
    for year in year_parameter_values[parameter].keys():
        year_parameter_averages[parameter][year] = np.mean(year_parameter_values
[parameter][year])
```

The code above will allow us to plot the historical averages of Movies across desired variables

IMDB Score

In [45]:

```
#print respective score statistics
print(movies[['score']].mean())
print(movies[['score']].mode())
print(movies[['score']].std())

print(winners[['score']].mean())
print(winners[['score']].mode())
print(winners[['score']].std())
```

```
score    6.374031
dtype: float64
   score
0    6.7
score    1.003406
dtype: float64
score    8.029032
dtype: float64
   score
0    8.1
score    0.459125
dtype: float64
```

In [46]:

```
(8.029032-6.374031)/6.374031 #(score of winners - score of movies)/score of winn
ers
```

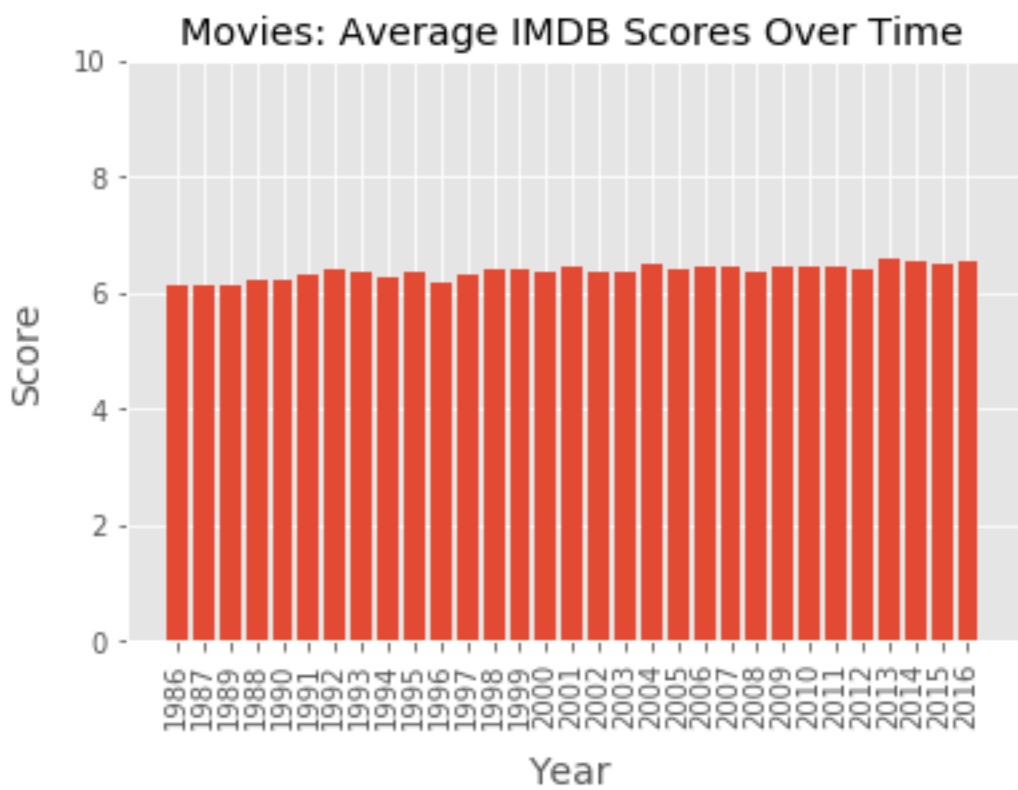
Out[46]:

```
0.2596474664148953
```

IMDB scores are roughly **26% higher for Winners** than Movies. Winners scores also have **a low standard deviation**, emphasizing the certainty of all Winners indeed having high scores.

In [47]:

```
#plot average score of Movies
plt.style.use('ggplot')

plt.bar(range(len(year_parameter_averages["score"])), year_parameter_averages["s
core"].values(), align="center")
plt.xticks(range(len(year_parameter_averages["score"])), list(year_parameter_ave
rages["score"].keys()))
plt.xticks(rotation=90)

plt.title("Movies: Average IMDB Scores Over Time")
plt.ylabel("Score", fontsize = 14, labelpad = 10)
plt.xlabel("Year", fontsize = 14, labelpad = 10)
plt.ylim([0,10])
plt.show()
```

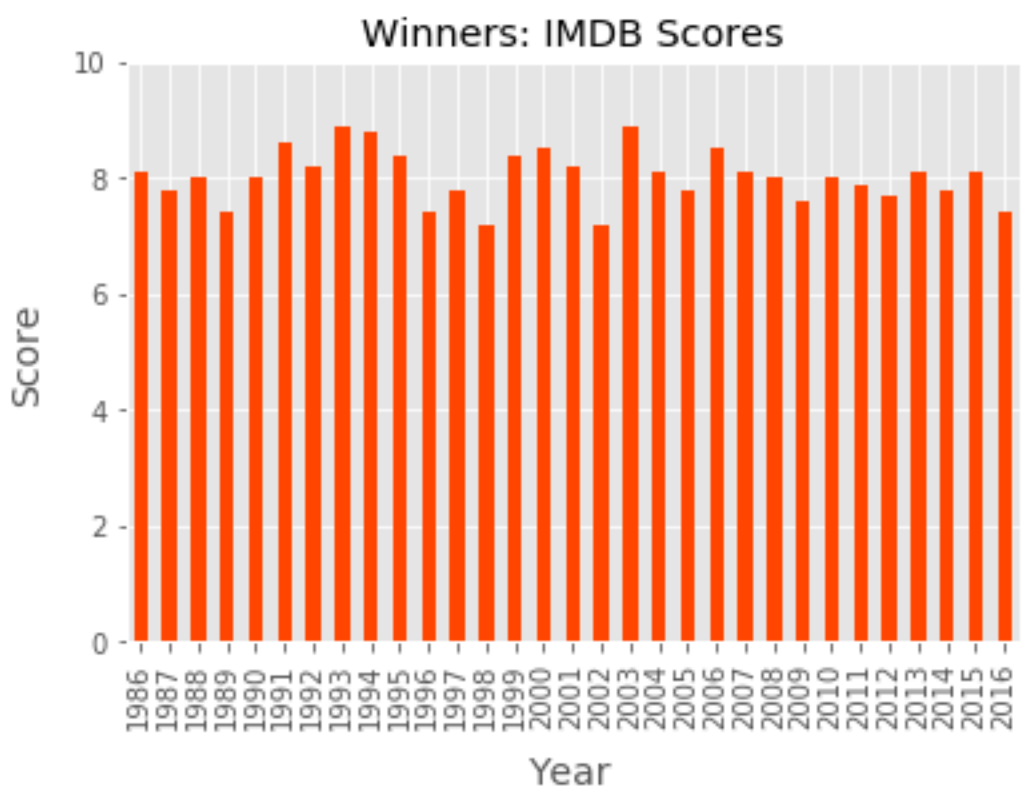


In [48]:

```
#plot Winners score
plt.style.use('ggplot')

winners['score'].plot(x='year',y='score',kind='bar', figsize = (6,4), color = 'o
rangered')

plt.title("Winners: IMDB Scores")
plt.ylabel("Score", fontsize = 14, labelpad = 10)
plt.xlabel("Year", fontsize = 14, labelpad = 10)
plt.ylim([0,10])
```

Out[48]:

```
(0, 10)
```



The average IMDB score in the movie industry has been **fairly constant** since 1986. We can see **more variance in the IMDB scores for Best Pictures.**

It gets even more interesting when you separate movies by low scores, medium scores, and high scores.

In [49]:

```
low_scored_movies= movies.query('(score > 0) & (score < 4.0)') #create set with movies scored between 0 - 4.0
low_scored_movies.head()
```

Out[49]:

	budget	company	country	director	genre	gross	rating
name							
King Kong Lives	10000000	De Laurentiis Entertainment Group (DEG)	USA	John Guillermin	Action	4711220	PG-13
Shanghai Surprise	17000000	HandMade Films	UK	Jim Goddard	Adventure	2315683	PG-13
Meatballs III: Summer Job	508694	TMS Pictures	Canada	George Mendeluk	Comedy	2147228	R
Hardbodies 2	18494	Chroma III Productions	USA	Mark Griffiths	Comedy	78068	R
Low Blow	15128	Action Communications	USA	Frank Harris	Action	63860	R

In [50]:

```
medium_scored_movies= movies.query('(score > 4.0) & (score < 7.0)') #create set
with movies scored between 4.0 - 7.0
medium_scored_movies.head()
```

Out[50]:

	budget	company	country	director	genre	gross	rating	relea
name								
Top Gun	15000000	Paramount Pictures	USA	Tony Scott	Action	179800601	PG	1986 05-1
Flight of the Navigator	9000000	Walt Disney Pictures	USA	Randal Kleiser	Adventure	18564613	PG	1986 08-0
Pretty in Pink	9000000	Paramount Pictures	USA	Howard Deutch	Comedy	40471663	PG-13	1986 02-2
Crocodile Dundee	8800000	Rimfire Films	Australia	Peter Faiman	Adventure	174635000	PG-13	1986 09-2
Lucas	6000000	Twentieth Century Fox Film Corporation	USA	David Seltzer	Comedy	8200000	PG-13	1986 03-2

In [51]:

```
high_scored_movies= movies.query('(score > 7.0) & (score < 10.0)') #create set w
ith movies scored between 7.0 - 10.0
high_scored_movies.head()
```

Out[51]:

	budget	company	country	director	genre	gross	rating	relea
name								
Stand by Me	8000000	Columbia Pictures Corporation	USA	Rob Reiner	Adventure	52287414	R	1986 08-2
Ferris Bueller's Day Off	6000000	Paramount Pictures	USA	John Hughes	Comedy	70136369	PG-13	1986 06-1
Aliens	18500000	Twentieth Century Fox Film Corporation	USA	James Cameron	Action	85160248	R	1986 07-1
Platoon	6000000	Hemdale	UK	Oliver Stone	Drama	138530565	R	1987 02-0
Labyrinth	25000000	Henson Associates (HA)	UK	Jim Henson	Adventure	12729917	PG	1986 06-2

In [52]:

```
print('Number of Low Scored Movies:')
print(len(low_scored_movies)) #show count
```

```
Number of Low Scored Movies:
127
```

In [53]:

```
print('Number of Medium Scored Movies:')
print(len(medium_scored_movies)) #show count
```

```
Number of Medium Scored Movies:
4562
```

In [54]:

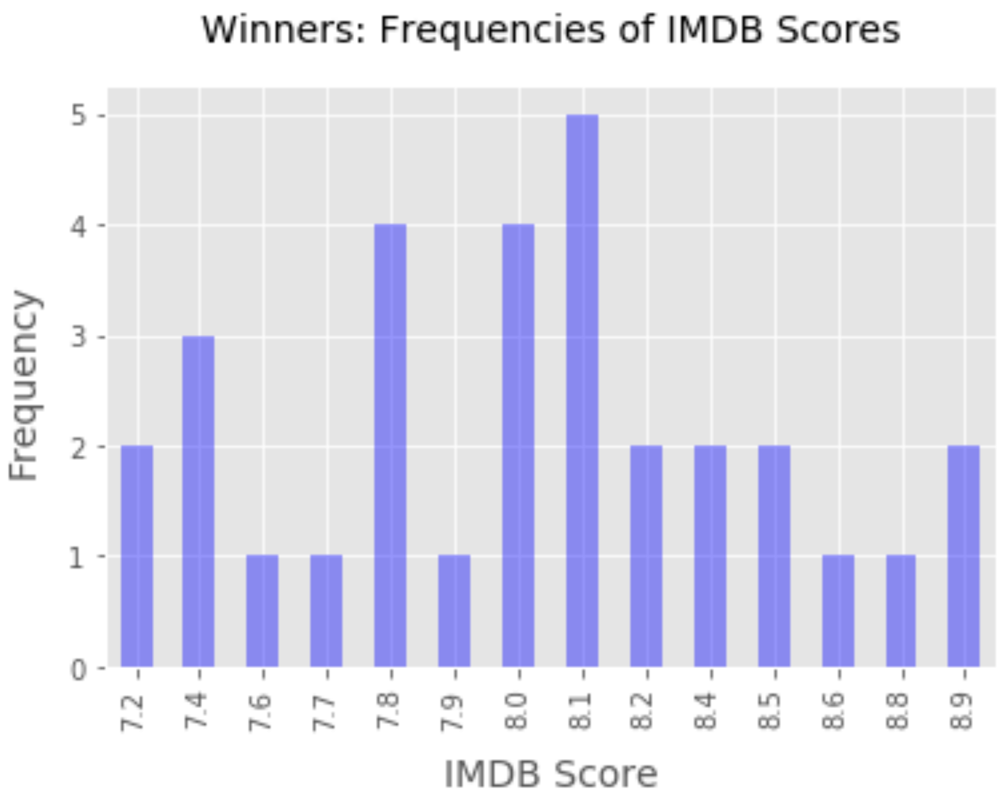
```
print('Number of High Scored Movies:')
print(len(high_scored_movies)) #show count
```

```
Number of High Scored Movies:
1788
```

In [55]:

```
#plot Winners score frequency
plt.style.use('ggplot')

winners['score'].value_counts().sort_index().plot.bar(cmap="winter", alpha=0.4 )

plt.title('Winners: Frequencies of IMDB Scores', fontsize = 14, y = 1.05)
plt.ylabel("Frequency", fontsize = 14, labelpad = 10)
plt.xlabel("IMDB Score", fontsize = 14, labelpad = 10)

winners['score'].value_counts()
```

```
Out[55]:

8.1    5
7.8    4
8.0    4
7.4    3
8.4    2
8.2    2
8.9    2
7.2    2
8.5    2
7.6    1
8.6    1
7.7    1
8.8    1
7.9    1
Name: score, dtype: int64
```



The frequencies chart shows that 8.1 is the most common score given to a Best Picture. Additionally, Best Pictures have a minimum score of 7.2 and maximum score of 8.9, indicating that all them are high-scoring movies compared to the movie industry where most movies are medium-scoring. This insight is a good indiction that if you want to make a Best Picture, it should be in the high-scoring category. But let's see how many of the top 30 highest scores in the Movies dataframe actually won Best Picture.

In [56]:

```
sorted_score_movies= movies.sort_values(['score'], ascending=False) #create new set sorting Movies by highest score

w_w = sorted_score_movies.head(30).loc[(sorted_score_movies["is_winner"] == "true")]#locate winners in sorted_score_movies
w_w
```

Out[56]:

	budget	company	country	director	genre	gross	rating
name							
The Lord of the Rings: The Return of the King	94000000	New Line Cinema	USA	Peter Jackson	Adventure	377845905	PG-13
Schindler's List	22000000	Universal Pictures	USA	Steven Spielberg	Biography	96067179	R
Forrest Gump	55000000	Paramount Pictures	USA	Robert Zemeckis	Comedy	330252182	PG-13
The Silence of the Lambs	19000000	Strong Heart/Demme Production	USA	Jonathan Demme	Crime	130742922	R
Gladiator	103000000	DreamWorks	USA	Ridley Scott	Action	187705427	R

Surprisingly, only five films out of the top 30 IMDB scores in the last 31 years have won Best Picture. This goes to show that although a high score is an extremely important characteristic, there are still other variables that are good indicators of Best Picture likelihood. However, it is still a good idea to have a minimum score threshold above 7.2 since that has been the lowest score in the last 31 years to win. What are other key characteristics for a Best Picture? Let's dive in.

Nominations

In [57]:

```
#calculate statistics of nominations
print(winners[['nominations']].mean())
print(winners[['nominations']].median())
print(winners[['nominations']].std())
print(winners[['nominations']].mode())
```

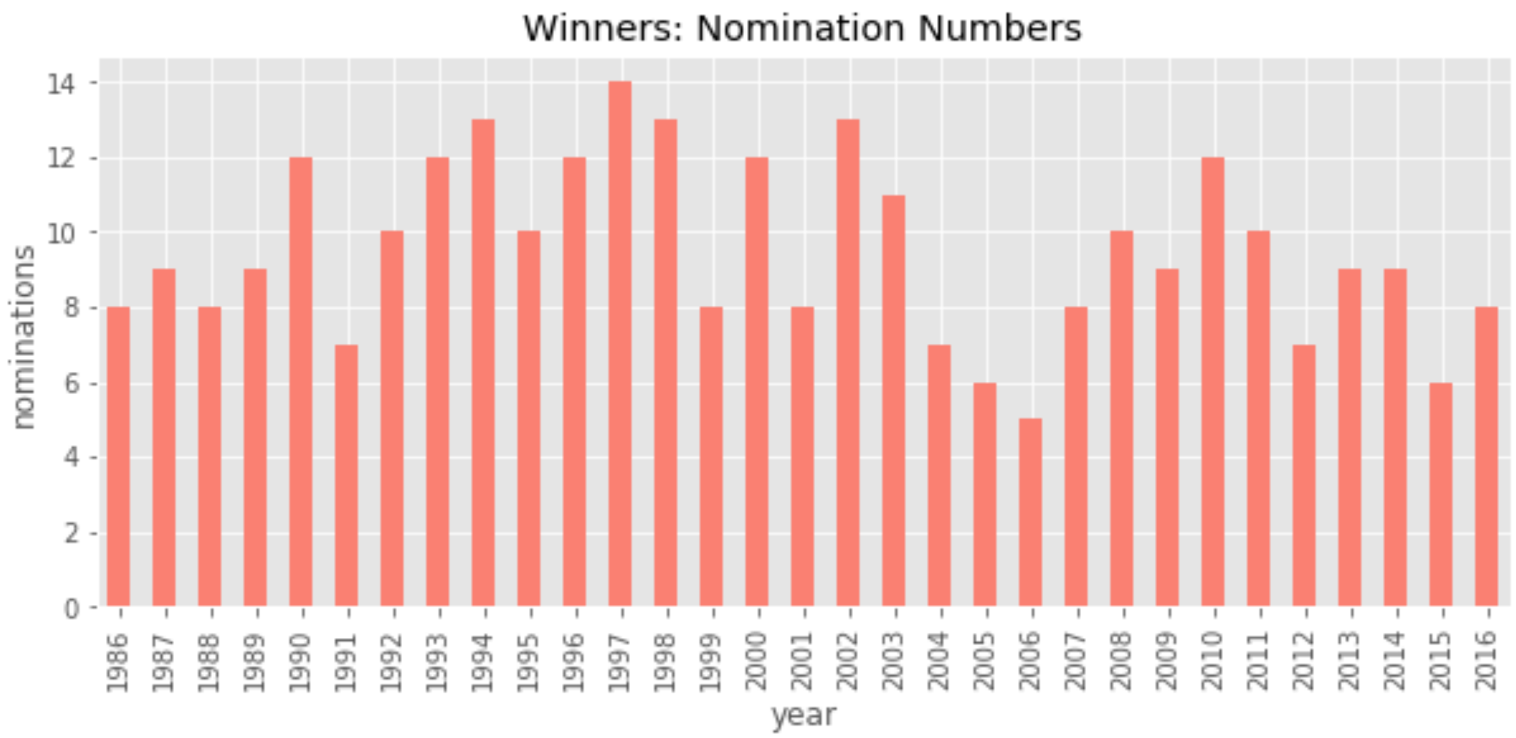
```
nominations    9.516129
dtype: float64
nominations    9.0
dtype: float64
nominations    2.378669
dtype: float64
   nominations
0            8
```

In [58]:

```
#plot Winners' nominations
plt.style.use('ggplot')

winners['nominations'].plot(x='year',kind='bar', figsize = (10,4), color = 'salm
on' )
winners['nominations'].value_counts()

plt.title("Winners: Nomination Numbers")
plt.ylabel('nominations', labelpad = 2)
```

Out[58]:

```
Text(0,0.5,'nominations')
```



Although Best Picture is only one Academy Award, we can see that most Winners actually have at least 8 Academy Award nominations. In fact, the lowest number of nominations for a Best Picture winner since 1986 has been 5, and that has only happened once. This goes to show that even if a film has been nominated for Best Picture, it is very unlikely to win unless it has several nominations. This pattern does make sense since a film worthy of Best Picture is likely comprised of excellent acting, directing, writing, sound/makeup, etc.

In [59]:

```
#print correlation between nominations and score
print(winners['nominations'].corr(winners['score']))
```

```
-0.08132653675846391
```

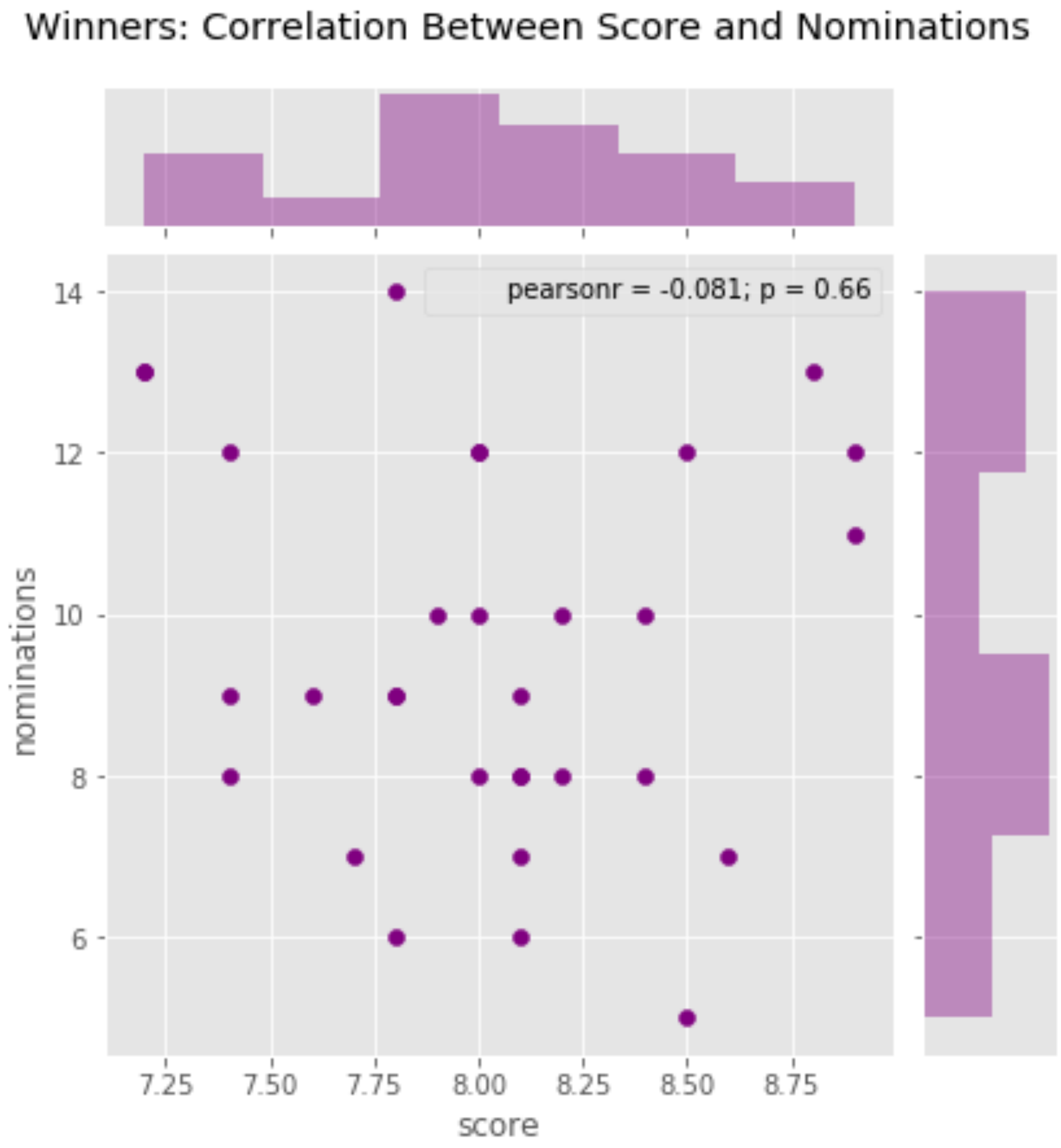
In [60]:

```
#plot correlation

plt.style.use('ggplot')

sns.jointplot(x="score", y="nominations", data=winners, color = 'purple');
plt.title('Winners: Correlation Between Score and Nominations', x = -2.9,y = 1.2
5)
```

```
/anaconda3/lib/python3.6/site-packages/matplotlib/axes/_axes.py:6462
: UserWarning: The 'normed' kwarg is deprecated, and has been replac
ed by the 'density' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
/anaconda3/lib/python3.6/site-packages/matplotlib/axes/_axes.py:6462
: UserWarning: The 'normed' kwarg is deprecated, and has been replac
ed by the 'density' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
```

Out[60]:

```
Text(-2.9,1.25,'Winners: Correlation Between Score and Nominations')
```



Surprisingly, there appears to be no correlation between the IMDB score of a Winner and its number of nominations. Because the p-value is greater than .05, this observation is statistically insignificant, which is also reflected in the visual.

Obviously you need a nomination to win Best Picture, so we will be looking at other variables to compare to nominations. Let's see what other characteristics are important for winning Best Picture.

Note: In 2010, the Academy expanded the number of nominations for Best Picture from five to ten. This increases a film's chances of getting nominated, but makes it harder to win the award since your film is now competing with more nominees.

Budget

In [61]:

```
#print respective budget statistics
print(movies[['budget']].mean())
print(movies[['budget']].std())

print(winners[['budget']].mean())
print(winners[['budget']].std())
```

```
budget    2.495835e+07
dtype: float64
budget    3.667269e+07
dtype: float64
budget    3.712581e+07
dtype: float64
budget    4.015139e+07
dtype: float64
```

In [62]:

```
(3.712581e+07-2.495835e+07)/2.495835e+07 #(mean budget of winners - mean budget
of movies)/ mean budget of movies
```

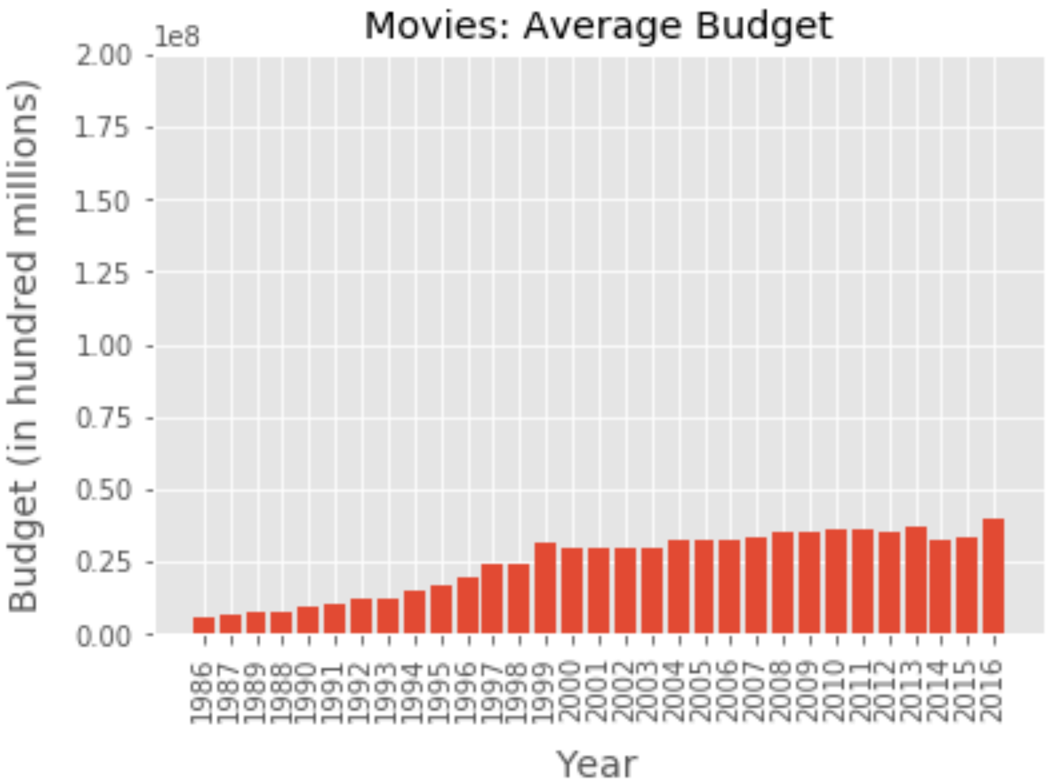
Out[62]:

```
0.48751059264735047
```

Here, we can see that the average budget of a Winner is **significantly higher (49%)** than that of your typical Movie. **The standard deviation is also higher for Winners.** A higher budget gives the film the ability to hire more talent and obtain more resources, which can lead to a better quality film.

In [63]:

```
#plot average budget for Movies

plt.style.use('ggplot')

plt.bar(range(len(year_parameter_averages["budget"])), year_parameter_averages["
budget"].values(), align="center")
plt.xticks(range(len(year_parameter_averages["budget"])), list(year_parameter_av
erages["budget"].keys()))
plt.xticks(rotation=90)

plt.title("Movies: Average Budget")
plt.ylabel("Budget (in hundred millions)", fontsize = 14, labelpad = 10)
plt.xlabel("Year", fontsize = 14, labelpad = 10)
plt.ylim([0,200000000])
plt.show()
```

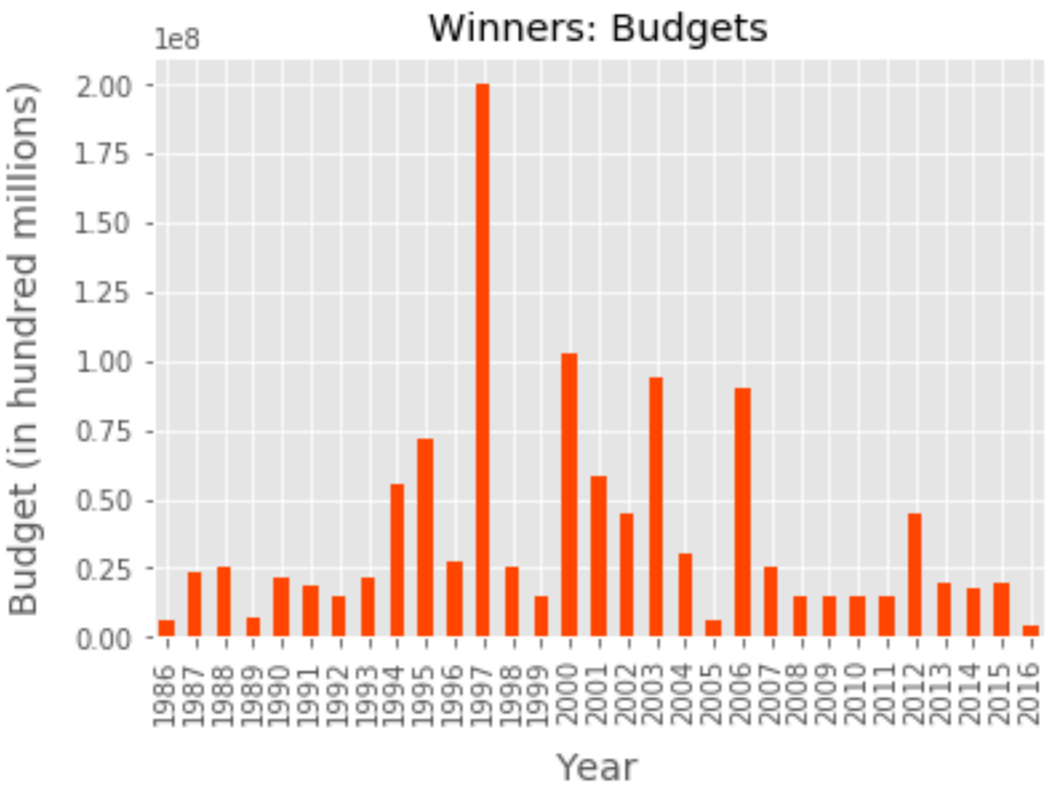


In [64]:

```
#plot Budget for Winners

plt.style.use('ggplot')

winners['budget'].plot(x='year',y='budget',kind='bar', figsize = (6,4), color =
'orangered')

plt.title("Winners: Budgets")
plt.ylabel("Budget (in hundred millions)", fontsize = 14, labelpad = 10)
plt.xlabel("Year", fontsize = 14, labelpad = 10)
```

Out[64]:

```
Text(0.5,0,'Year')
```



When comparing the two bar graphs, we can also see a significant difference between the historical trends of the average budget in the movie industry and the budgets of Best Pictures. The movie industry had a **steady increase in the average budget from 1986-1999 and a modest increase since then** (other than between 2013-2016). **Meanwhile, the budget of a Best Picture from a given year has fluctuated greatly.** For example, we can see that no other Best Picture budget has even come close to *Titanic* in 1997.

This bar graph illustrates that even though the average budget of a Best Picture is 49% higher than the average movie, it is still very possible to win the Oscar with a "low" budget. Best Pictures from 2013-2016 all had budgets below 25 million USD (which is the industry average), noticably Moonlight (2016) with a budget of only 4 million USD.

In [65]:

```
#print correlations between budget and score/nominations
print(winners['score'].corr(winners['budget']))
print(winners['nominations'].corr(winners['budget']))
```

```
0.24015975667972178
0.35525797909807383
```

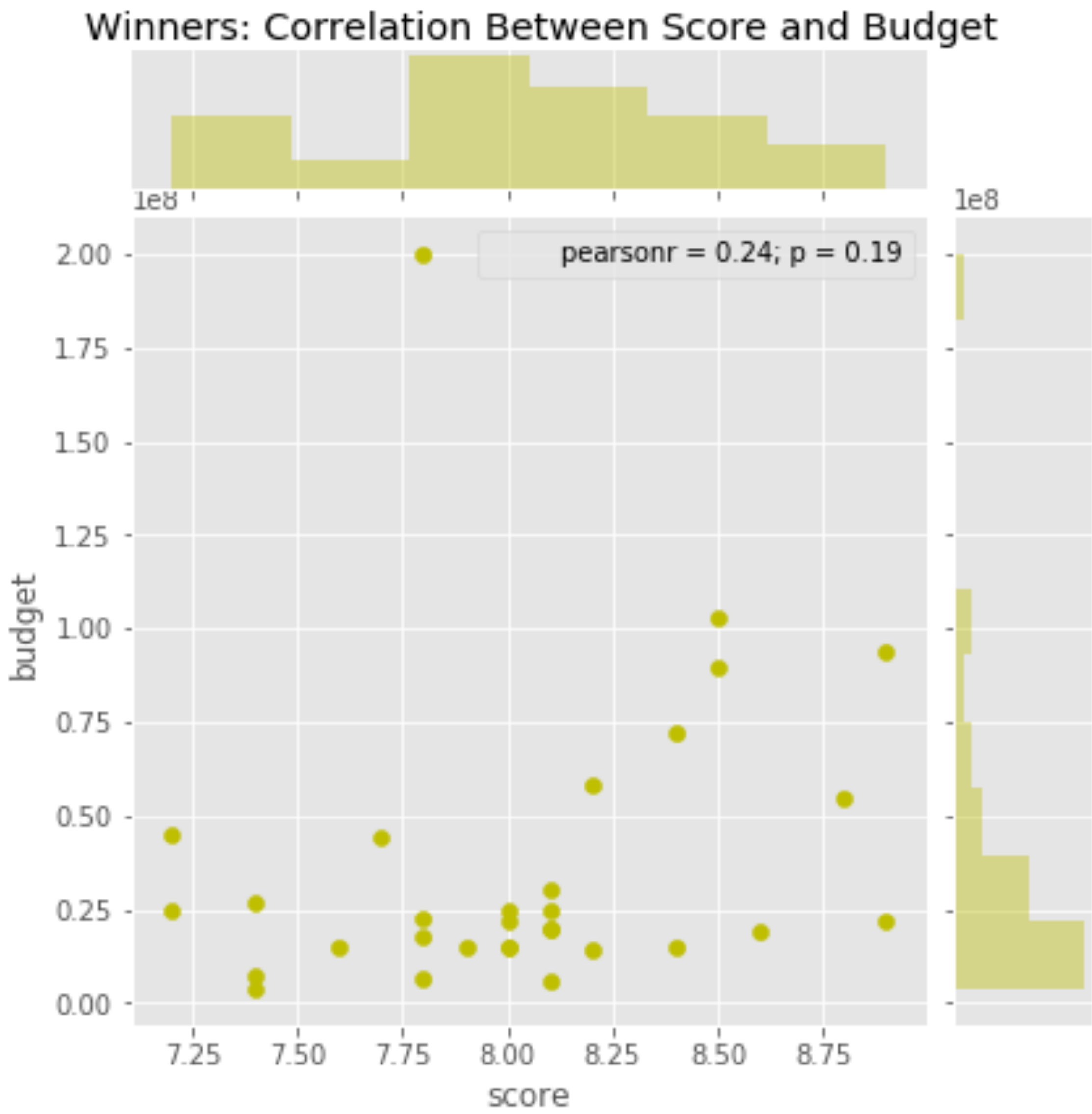
In [66]:

```
#plot correlation

plt.style.use('ggplot')

sns.jointplot(x="score", y="budget", data=winners, color = 'y');
plt.title('Winners: Correlation Between Score and Budget',x = -3, y = 1.2)
```

```
/anaconda3/lib/python3.6/site-packages/matplotlib/axes/_axes.py:6462
: UserWarning: The 'normed' kwarg is deprecated, and has been replac
ed by the 'density' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
/anaconda3/lib/python3.6/site-packages/matplotlib/axes/_axes.py:6462
: UserWarning: The 'normed' kwarg is deprecated, and has been replac
ed by the 'density' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
```

Out[66]:

```
Text(-3,1.2,'Winners: Correlation Between Score and Budget')
```



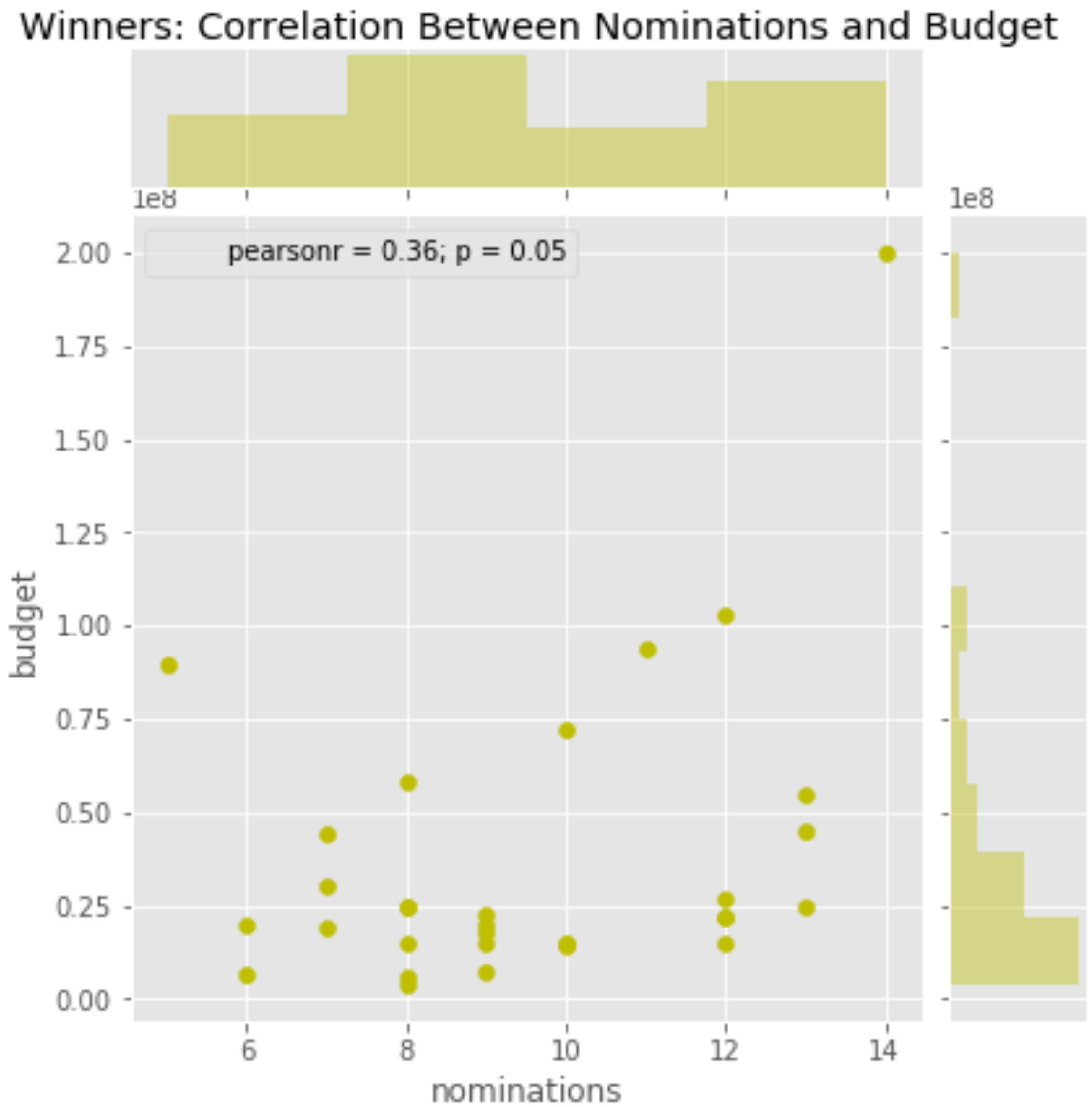
In [67]:

```
#plot correlation

plt.style.use('ggplot')

sns.jointplot(x="nominations", y="budget", data=winners, color = 'y');
plt.title('Winners: Correlation Between Nominations and Budget', x = -3, y = 1.2
)
```

```
/anaconda3/lib/python3.6/site-packages/matplotlib/axes/_axes.py:6462
: UserWarning: The 'normed' kwarg is deprecated, and has been replac
ed by the 'density' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
/anaconda3/lib/python3.6/site-packages/matplotlib/axes/_axes.py:6462
: UserWarning: The 'normed' kwarg is deprecated, and has been replac
ed by the 'density' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
```

```
Out[67]:
```

```
Text(-3,1.2,'Winners: Correlation Between Nominations and Budget')
```



The correlation does not seem to be that strong between score and budget, and there is a slightly moderate correlation between number of nominations and budget (the p-value for nominations and budget is .05, which makes the statistical signifigance a little open-ended). This makes sense, as a higher-budget will be able to afford you higher caliber movie stars, sound editors, costume designers, technology etc. It might not be as high as anticipated because it is not every movie's goal to win Best Picture. Many high-budget action films, for example, care more about putting money into sound editing, special effects, and stars/directors with the goal of achieving a high box office, not winning an Oscar award (although Oscar nominations/awards tend to give a movie more buzz, which leads to more people going out and seeing it). Nonetheless, we can see some significant outliers in the bar graph, especially with low-budget movies. While *Titanic* with a 200 million USD budget won Best Picture, a few relatively "low-budget" movies have also won such as *Moonlight* (2016) and *Crash* (2005).

Domestic Gross

In [68]:

```
#print respective gross statistics
print(movies[['gross']].mean())
print(movies[['gross']].std())

print(winners[['gross']].mean())
print(winners[['gross']].std())
```

```
gross    3.329592e+07
dtype: float64
gross    5.769639e+07
dtype: float64
gross    1.376186e+08
dtype: float64
gross    1.248718e+08
dtype: float64
```

In [69]:

```
1.376186e+08/3.329592e+07 #(mean gross of winners)/ mean gross of movies
```

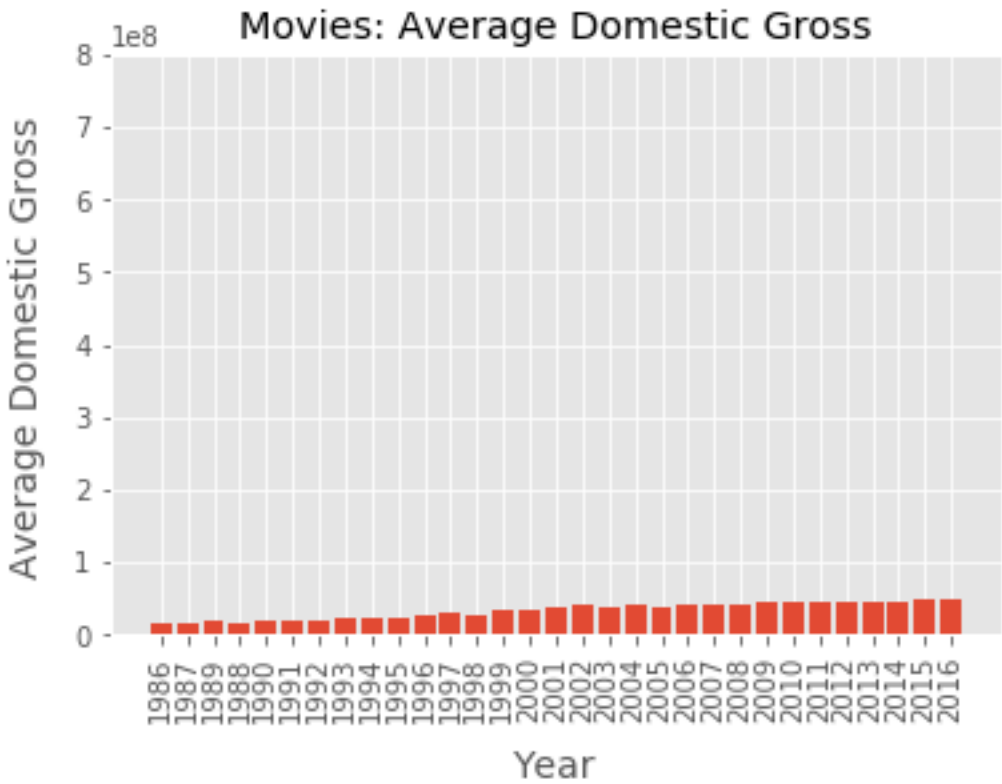
Out[69]:

```
4.133197100425518
```

Here, we can see that **the average gross of a Winner is not only much higher (over 4x) than the average gross of a Movie, but also has a lower standard deviation.** From these statistics, we can assume audiences would rather see a high-scoring, hyped-up film than an average, medium-scored movie.

In [70]:

```
#plot average domestic gross of Movies

plt.style.use('ggplot')

plt.bar(range(len(year_parameter_averages["gross"])), year_parameter_averages["g
ross"].values(), align="center")
plt.xticks(range(len(year_parameter_averages["gross"])), list(year_parameter_ave
rages["gross"].keys()))
plt.xticks(rotation=90)

plt.title("Movies: Average Domestic Gross")
plt.ylabel("Average Domestic Gross", fontsize = 14, labelpad = 10)
plt.xlabel("Year", fontsize = 14, labelpad = 10)
plt.ylim([0,800000000])

plt.show()
```



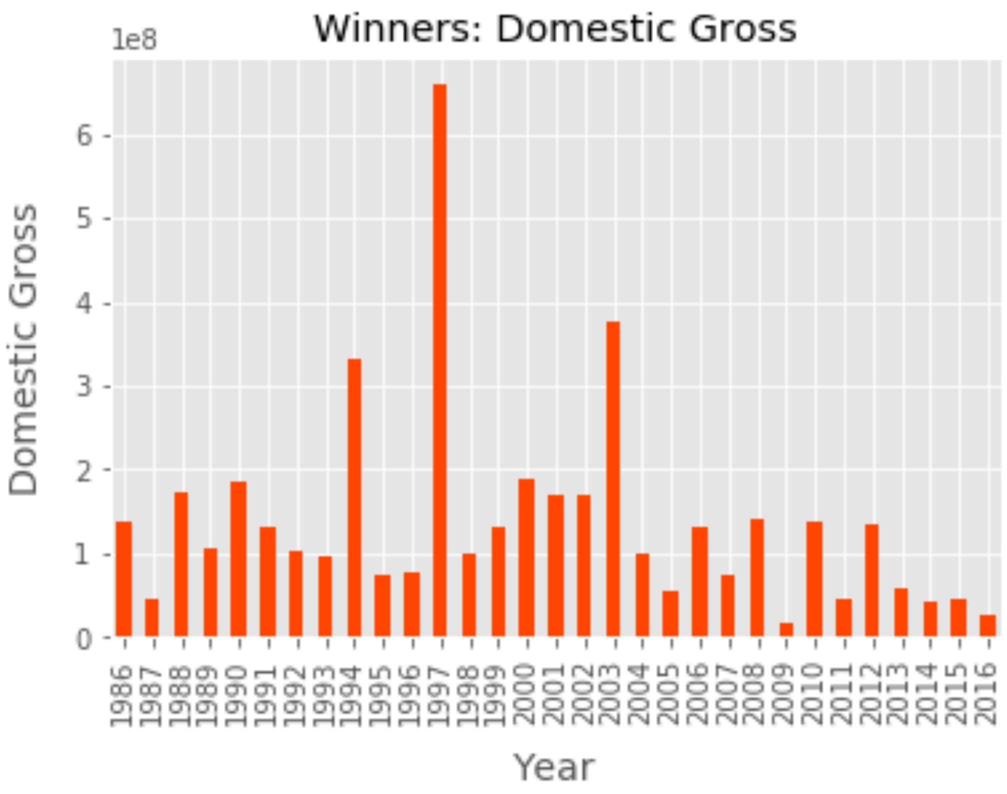
Note: We set the y-axis limit to as high as 800,000,000 because *Titanic* (from the Winners dataframe) had a gross close to that, and we wanted both graphs to have the same axis scale. Other graphs in our project also have large y-axis scales in order be consistent between Movies and Winners graphs and to properly display Winners outliers.

In [71]:

```
#plot domestic gross of Winners

plt.style.use('ggplot')

winners['gross'].plot(x='year',y='gross',kind='bar', figsize = (6,4), color = 'o
rangered')

plt.title("Winners: Domestic Gross")
plt.ylabel("Domestic Gross", fontsize = 14, labelpad = 10)
plt.xlabel("Year", fontsize = 14, labelpad = 10)
```

Out[71]:

```
Text(0.5,0,'Year')
```



The Domestic Gross graphs between Movies and Winners are very different. For the most part, since 1986, the movie industry has had a steady increase in domestic gross. However, this is mostly due to ticket prices going up (partially inflation) and an increase in the number of theaters. But Best Pictures have had a lot of variance. In fact, looking at the graph, Best Pictures from 2004 onwards have grossed significantly less than 1986-2003, especially when you take inflation into account.

In [72]:

```
#print respective correlations
print(winners['score'].corr(winners['gross']))
print(winners['nominations'].corr(winners['gross']))
```

```
0.24818010599041154
0.49309794277344726
```

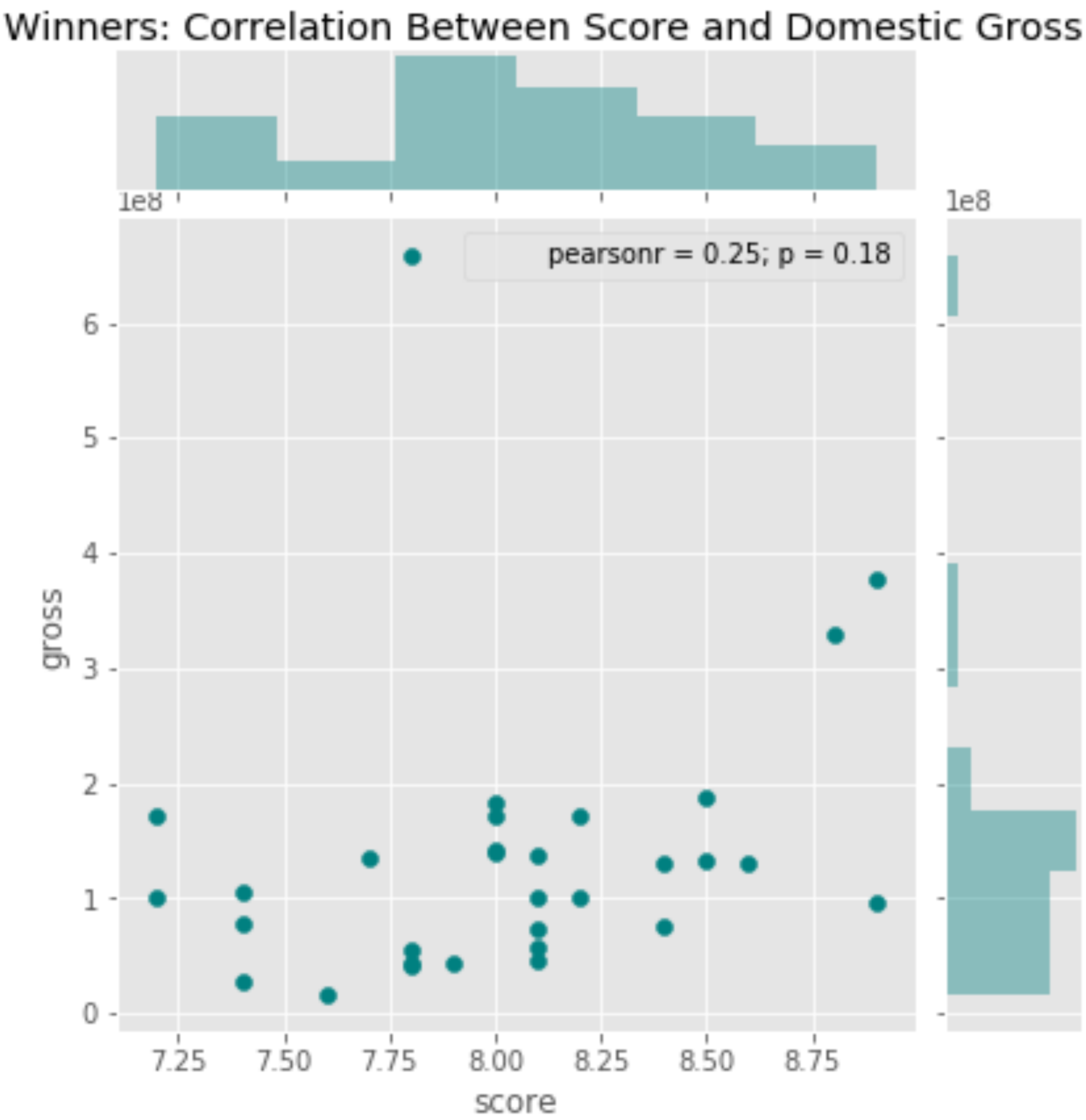
In [73]:

```
#plot correlation
plt.style.use('ggplot')

sns.jointplot(x="score", y="gross", data=winners, color = 'teal');
plt.title('Winners: Correlation Between Score and Domestic Gross', x = -2.9 , y
= 1.2)
```

```
/anaconda3/lib/python3.6/site-packages/matplotlib/axes/_axes.py:6462
: UserWarning: The 'normed' kwarg is deprecated, and has been replac
ed by the 'density' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
/anaconda3/lib/python3.6/site-packages/matplotlib/axes/_axes.py:6462
: UserWarning: The 'normed' kwarg is deprecated, and has been replac
ed by the 'density' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
```

Out[73]:

```
Text(-2.9,1.2,'Winners: Correlation Between Score and Domestic Gross
')
```



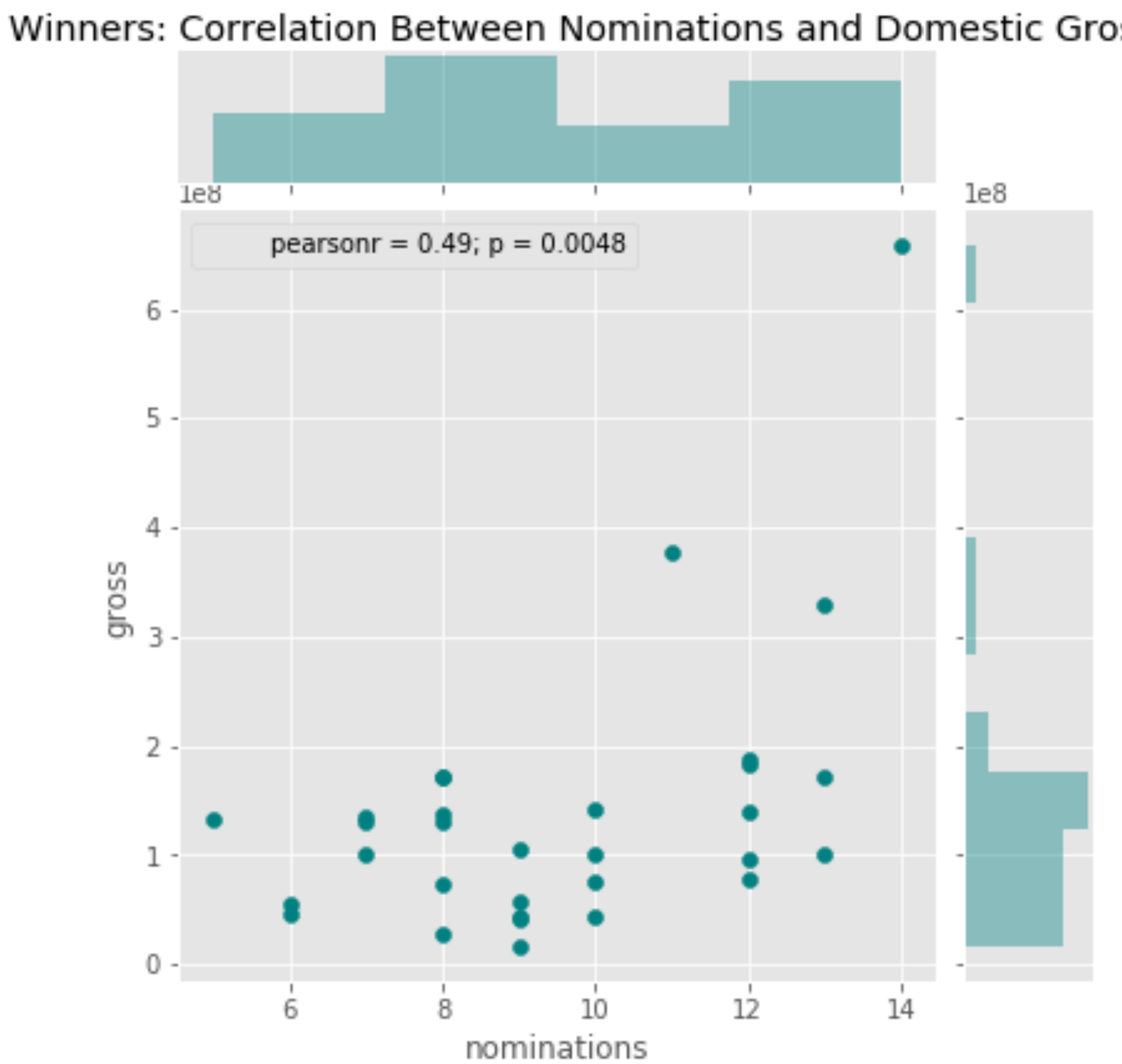
In [74]:

```
#plot correlation
plt.style.use('ggplot')

sns.jointplot(x="nominations", y="gross", data=winners, color = 'teal');
plt.title('Winners: Correlation Between Nominations and Domestic Gross', x = -2.
9, y = 1.2)
```

```
/anaconda3/lib/python3.6/site-packages/matplotlib/axes/_axes.py:6462
: UserWarning: The 'normed' kwarg is deprecated, and has been replac
ed by the 'density' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
/anaconda3/lib/python3.6/site-packages/matplotlib/axes/_axes.py:6462
: UserWarning: The 'normed' kwarg is deprecated, and has been replac
ed by the 'density' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
```

Out[74]:

```
Text(-2.9,1.2,'Winners: Correlation Between Nominations and Domestic
Gross')
```



While there is a very weak/ no correlation between score and gross, there is still a moderate positive correlation between nominations and gross (p-value is also less than .05).

Profitability

In [75]:

```
#print respective profitability statistics
print(movies[['profitability']].mean())
print(movies[['profitability']].std())

print(winners[['profitability']].mean())
print(winners[['profitability']].std())
```

```
profitability    4.221122
dtype: float64
profitability    92.53111
dtype: float64
profitability    5.410743
dtype: float64
profitability    4.505234
dtype: float64
```

In [76]:

```
(5.577295-4.221122)/4.221122 #(profitabilty of winners - profitabilty of movies)
/profitabilty of movies
```

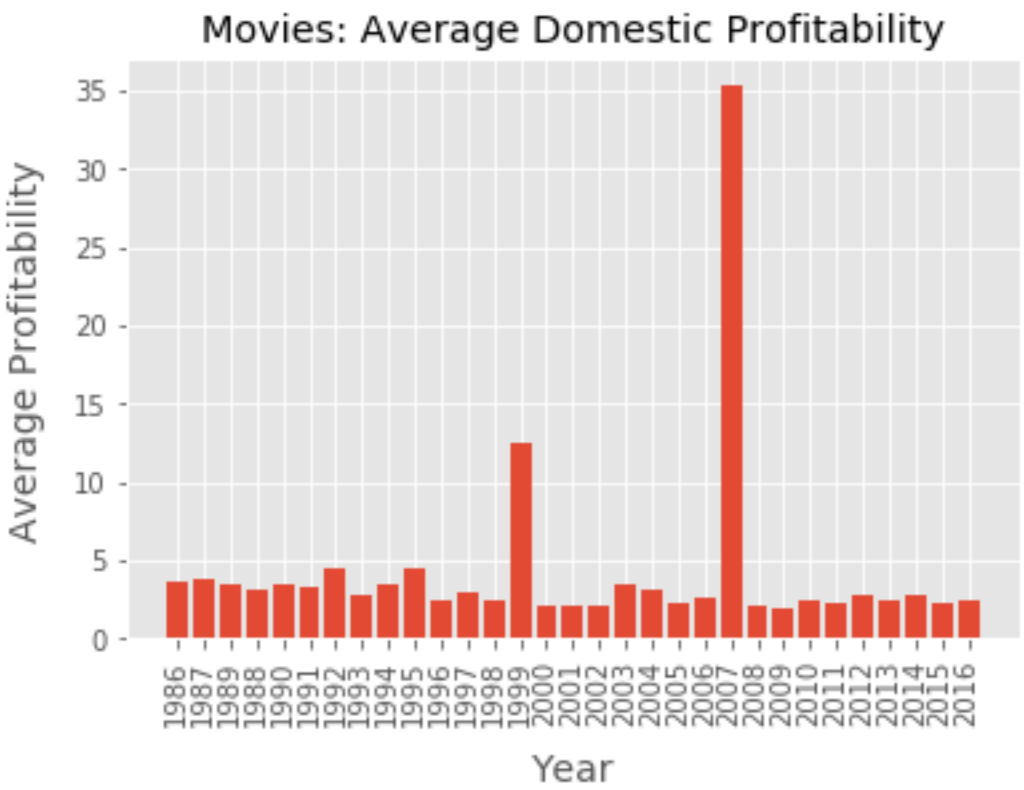
Out[76]:

```
0.32128258789961534
```

Winners on average are 32% more profitable (domestically) than Movies and also have a much lower standard deviation. This is likely because of the high number of flops and box office successes in Movies, making the standard deviation much higher for the set of 6000.

In [77]:

```
#plot average profitability of Movies
plt.style.use('ggplot')

plt.bar(range(len(year_parameter_averages["profitability"])), year_parameter_ave
rages["profitability"].values(), align="center")
plt.xticks(range(len(year_parameter_averages["profitability"])), list(year_param
eter_averages["profitability"].keys()))
plt.xticks(rotation=90)
plt.ylabel("Average Profitability", fontsize = 14, labelpad = 10)
plt.xlabel("Year", fontsize = 14, labelpad = 10)
plt.title('Movies: Average Domestic Profitability')
plt.show()
```



Other than the two outliers, profitability is relatively consistent, but there has still been a slight decrease in recent years compared to the 20th century.

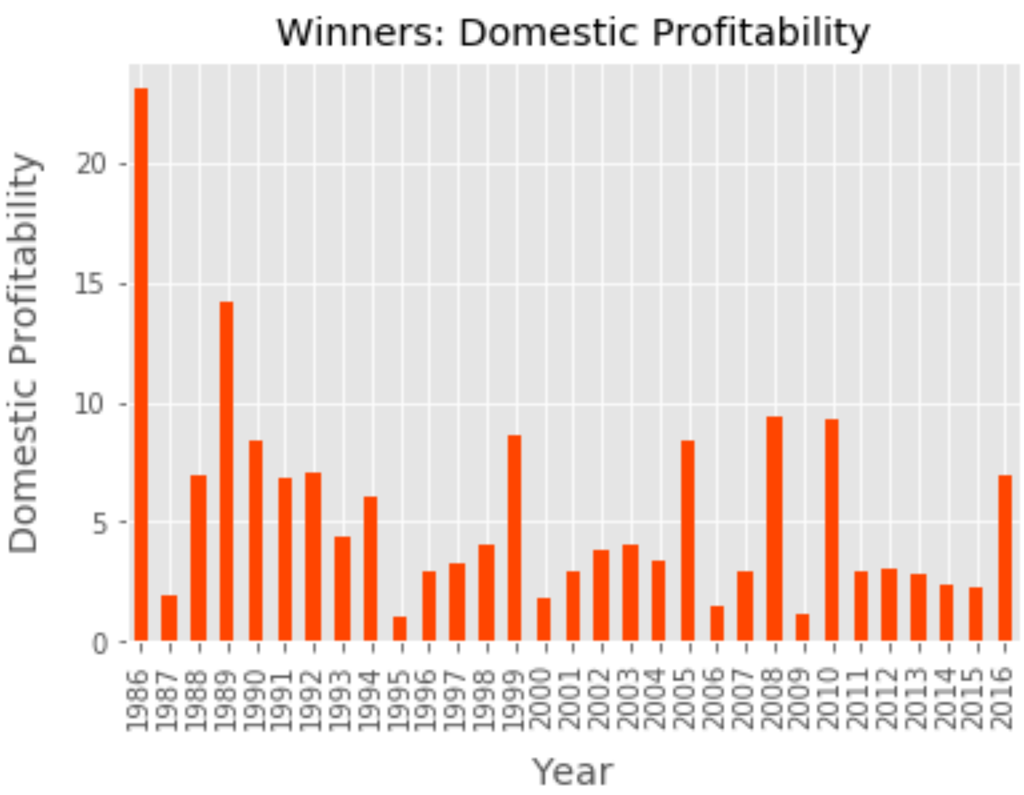
Note: Unfortunately, we were unable to figure out why 2007 and 1999 are such big outliers in the chart. We looked through our code extensively and could not find a cause/error for this strange outcome. O

In [78]:

```
#plot profitability of Winners
plt.style.use('ggplot')

winners['profitability'].plot(x='year',y='profitability',kind='bar', figsize = (
6,4), color = 'orangered')

plt.title("Winners: Domestic Profitability")
plt.ylabel("Domestic Profitability", fontsize = 14, labelpad = 10)
plt.xlabel("Year", fontsize = 14, labelpad = 10)
```

Out[78]:

```
Text(0.5,0,'Year')
```



As shown above, the profitability of Winners has fluctuated significantly since 1986.

In [79]:

```
#print respective correlations
print(winners['score'].corr(winners['profitability']))
print(winners['nominations'].corr(winners['profitability']))
```

```
-0.04783127174247695
-0.06882518479015814
```

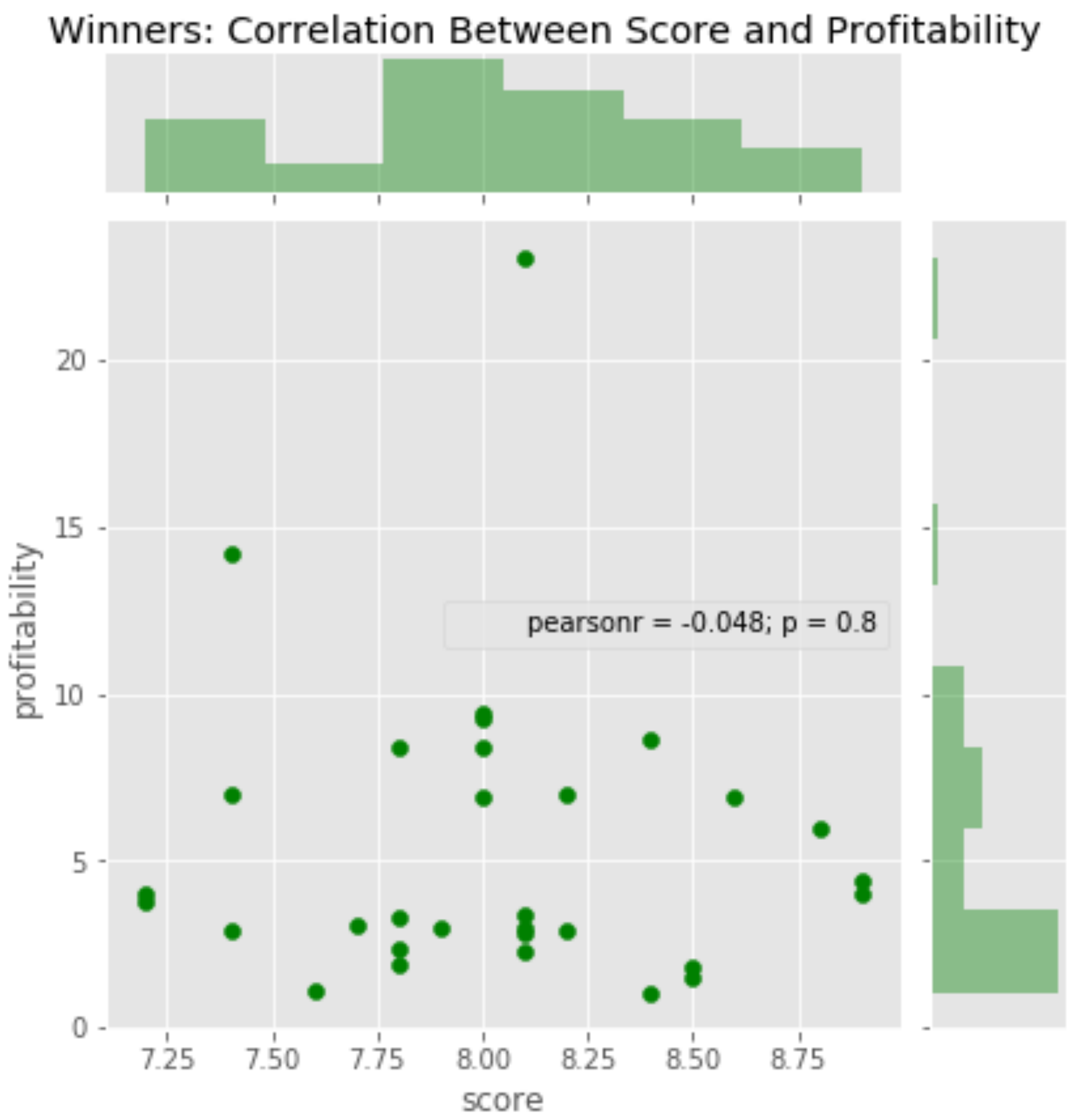
In [80]:

```
#plot correlation

sns.jointplot(x="score", y="profitability", data=winners, color = 'g');
plt.title('Winners: Correlation Between Score and Profitability', x = -2.8, y =
1.2)
```

```
/anaconda3/lib/python3.6/site-packages/matplotlib/axes/_axes.py:6462
: UserWarning: The 'normed' kwarg is deprecated, and has been replac
ed by the 'density' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
/anaconda3/lib/python3.6/site-packages/matplotlib/axes/_axes.py:6462
: UserWarning: The 'normed' kwarg is deprecated, and has been replac
ed by the 'density' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
```

Out[80]:

```
Text(-2.8,1.2,'Winners: Correlation Between Score and Profitability'
)
```



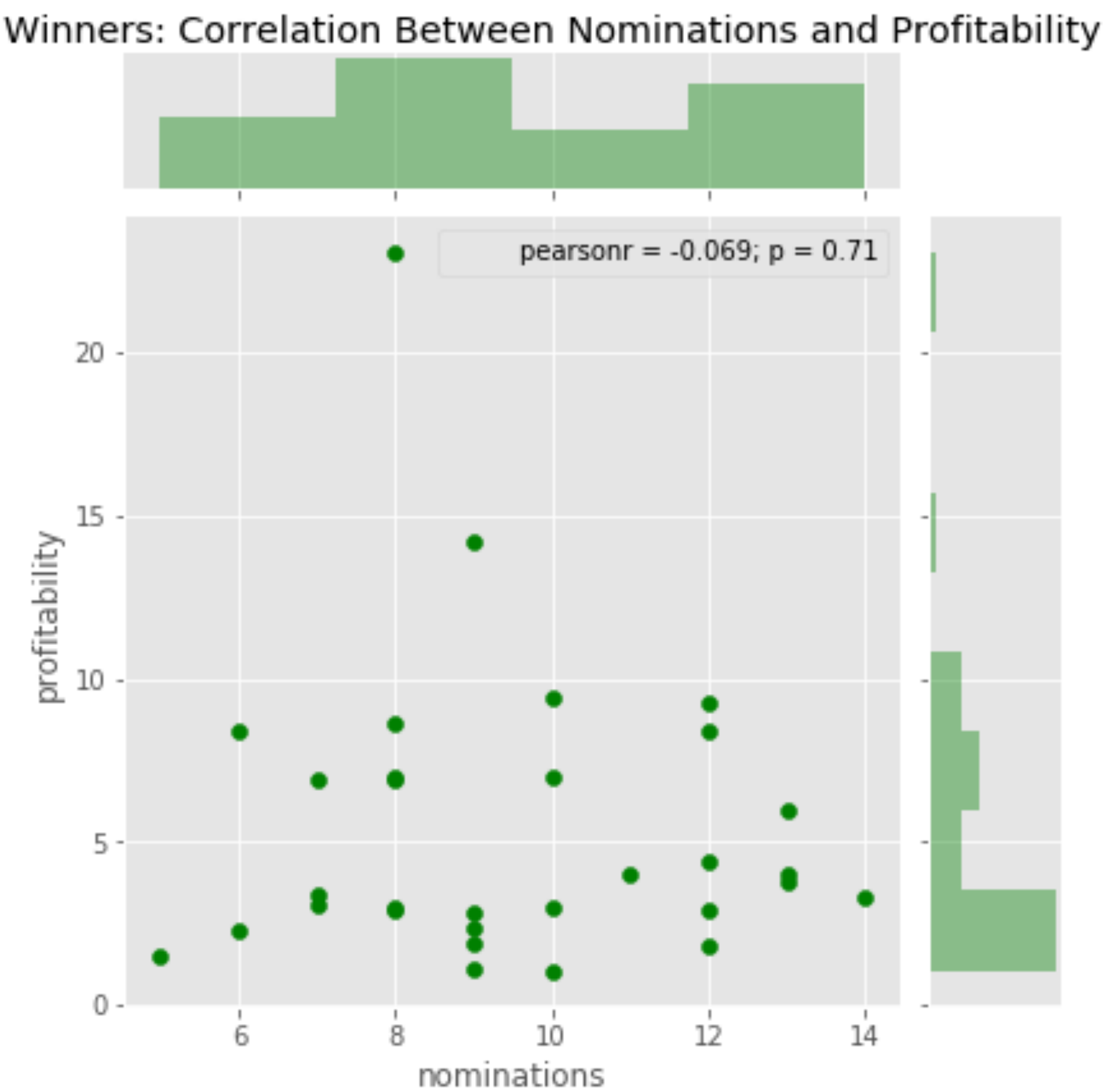
In [81]:

```
#plot correlation
plt.style.use('ggplot')

sns.jointplot(x="nominations", y="profitability", data=winners, color = 'g');
plt.title('Winners: Correlation Between Nominations and Profitability', x = -2.8
, y = 1.2)
```

```
/anaconda3/lib/python3.6/site-packages/matplotlib/axes/_axes.py:6462
: UserWarning: The 'normed' kwarg is deprecated, and has been replac
ed by the 'density' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
/anaconda3/lib/python3.6/site-packages/matplotlib/axes/_axes.py:6462
: UserWarning: The 'normed' kwarg is deprecated, and has been replac
ed by the 'density' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
```

Out[81]:

```
Text(-2.8,1.2,'Winners: Correlation Between Nominations and Profitab
ility')
```



There are no correlations between the domestic profitability of a winner and its score/ nominations. P-values are very high at p = 0.8 and 0.71.

Runtime

In [82]:

```
#print respective runtime statistics
print(movies[['runtime']].mean())
print(movies[['runtime']].std())

print(winners[['runtime']].mean())
print(winners[['runtime']].std())
```

```
runtime    106.485069
dtype: float64
runtime    17.95083
dtype: float64
runtime    137.677419
dtype: float64
runtime    27.931329
dtype: float64
```

In [83]:

```
(137.677419-106.485069)/106.485069 #(runtime of winners - runtime of movies)/run
time of movies
```

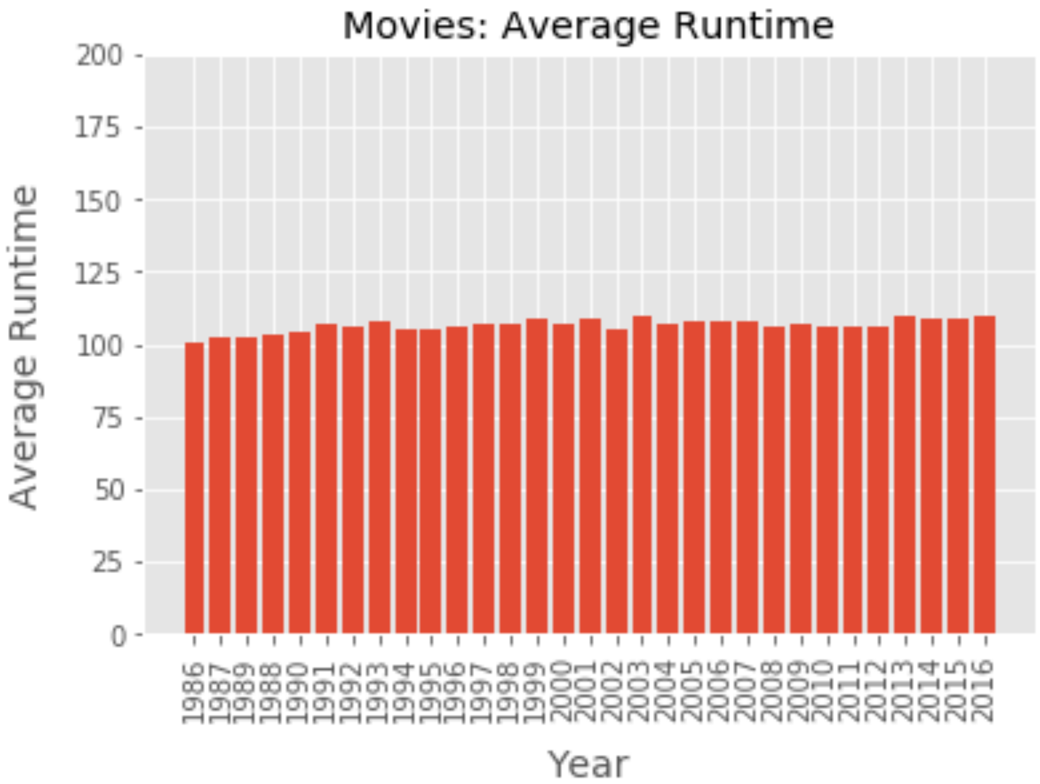
Out[83]:

```
0.29292698303083214
```

At 2 hours and 17 minutes on average, winners have 29% (31 minute) longer runtimes than a typical movie, but the standard deviation is also higher. This shows a trend that the Academy prefers longer movies.

In [84]:

```
#plot average runtime of Movies
plt.style.use('ggplot')

plt.bar(range(len(year_parameter_averages["runtime"])), year_parameter_averages[
"runtime"].values(), align="center")

plt.xticks(range(len(year_parameter_averages["runtime"])), list(year_parameter_a
verages["runtime"].keys()))
plt.xticks(rotation=90)

plt.title("Movies: Average Runtime")
plt.ylabel("Average Runtime", fontsize = 14, labelpad = 10)
plt.xlabel("Year", fontsize = 14, labelpad = 10)
plt.ylim([0,200])
plt.show()
```

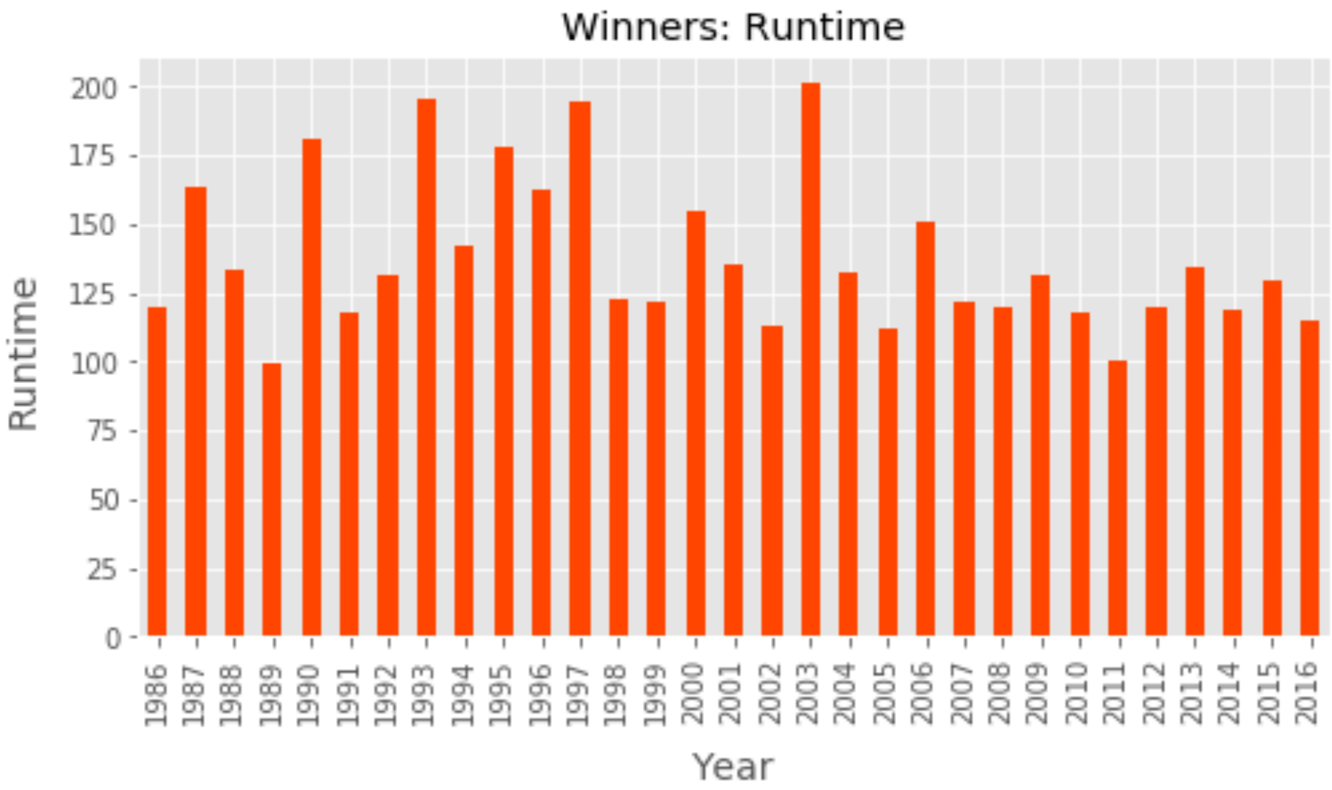


In [85]:

```
#plot runtime of winners
plt.style.use('ggplot')

winners['runtime'].plot(x='year',y='runtime',kind='bar', figsize = (8,4), color
= 'orangered')

plt.title("Winners: Runtime")
plt.ylabel("Runtime", fontsize = 14, labelpad = 10)
plt.xlabel("Year", fontsize = 14, labelpad = 10)
```

Out[85]:

```
Text(0.5,0,'Year')
```



Through these two graphs, one can see the signifcant difference in variance between Runtimes in *Movies* comparied to Runtimes in *Winners*. The movie industry as a whole has maintained pretty much the same average runtime since 1986 (106 minutes). But Best Picture runtimes have fluctuated quite a bit over the years. It also makes sense that Best Pictures are significantly longer films.

The sole purpose of the average movie in the industry is to make as much money as possible at the box office. A shorter runtime allows a theater to have more showings of your movie per day, which makes the film more profitable. The longer the runtime, the more it messes up that strategy, which is why there is a real pressure in the movie industry to keep films shorter. However, when a major goal/purpose of your film is to get nominated for an Academy Award or win Best Picture, the crew is more willing to have a longer runtime if that helps increase the quality of the movie.

In [86]:

```
#print respective correlations
print(winners['score'].corr(winners['runtime']))
print(winners['nominations'].corr(winners['runtime']))
```

```
0.45849122346369797
0.4159989323471434
```

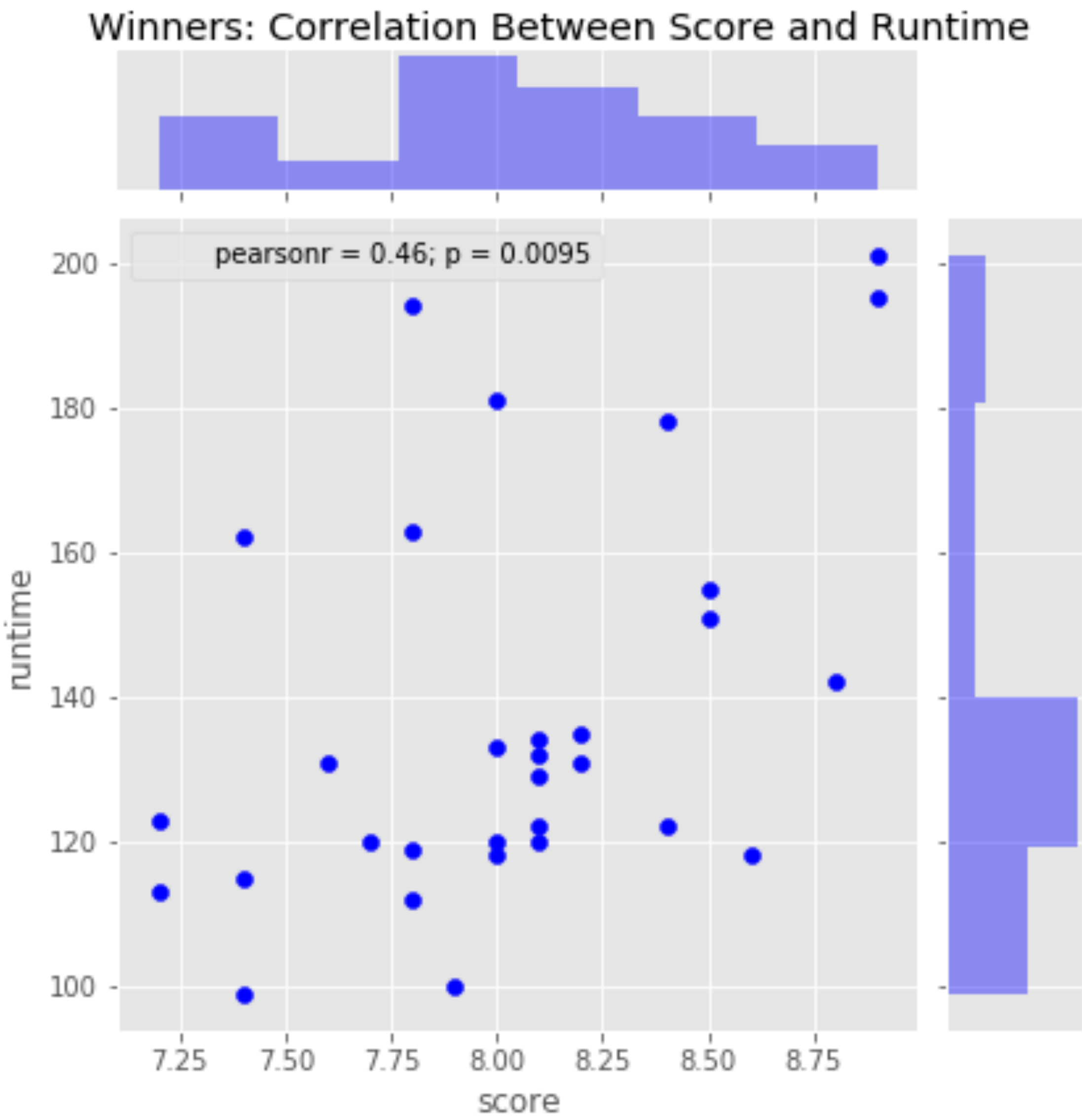
In [87]:

```
#plot correlation
plt.style.use('ggplot')

sns.jointplot(x="score", y="runtime", data=winners, color = 'b');
plt.title('Winners: Correlation Between Score and Runtime', x = -2.8, y = 1.2)
```

```
/anaconda3/lib/python3.6/site-packages/matplotlib/axes/_axes.py:6462
: UserWarning: The 'normed' kwarg is deprecated, and has been replac
ed by the 'density' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
/anaconda3/lib/python3.6/site-packages/matplotlib/axes/_axes.py:6462
: UserWarning: The 'normed' kwarg is deprecated, and has been replac
ed by the 'density' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
```

Out[87]:

```
Text(-2.8,1.2,'Winners: Correlation Between Score and Runtime')
```



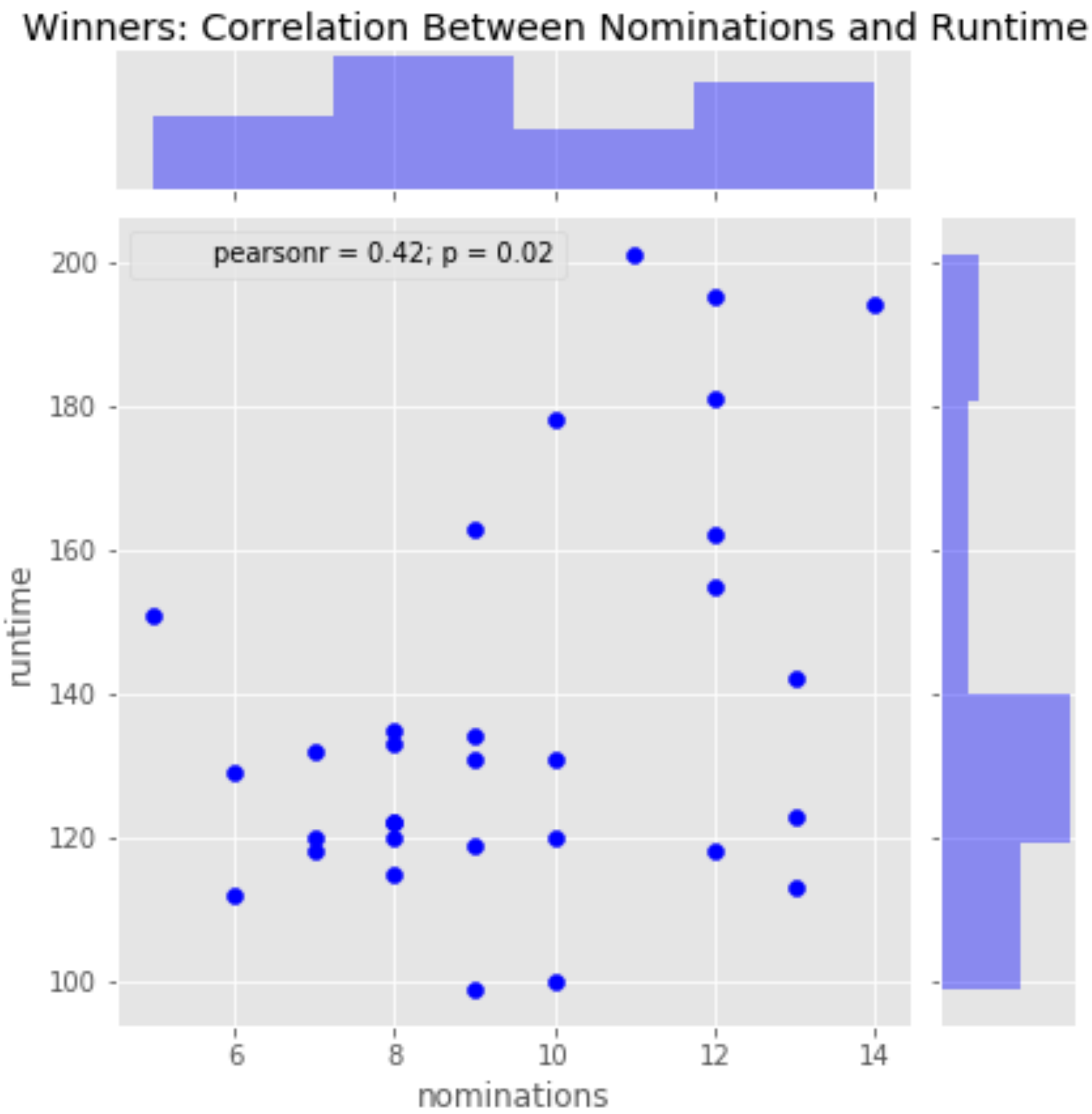
In [88]:

```
#plot correlation
plt.style.use('ggplot')

sns.jointplot(x="nominations", y="runtime", data=winners, color = "b");
plt.title('Winners: Correlation Between Nominations and Runtime', x = -2.8, y =
1.2)
```

```
/anaconda3/lib/python3.6/site-packages/matplotlib/axes/_axes.py:6462
: UserWarning: The 'normed' kwarg is deprecated, and has been replac
ed by the 'density' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
/anaconda3/lib/python3.6/site-packages/matplotlib/axes/_axes.py:6462
: UserWarning: The 'normed' kwarg is deprecated, and has been replac
ed by the 'density' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
```

```
Out[88]:
```

```
Text(-2.8,1.2,'Winners: Correlation Between Nominations and Runtime'
)
```



There are also moderate correlations between the runtime of a winner and its score/nominations **(p-values for both plots are less than .05 which indicates statistical significance).** It appears both users and the Academy prefer longer movies.

Note: When we say users, we mean IMDB users, but we are using them to represent the general movie-going/movie-watching public since users are the data we have and the fact that anybody can make an IMDB account.

Votes

In [89]:

```
#print respective votes statistics
print(movies[['votes']].mean())
print(movies[['votes']].std())

print(winners[['votes']].mean())
print(winners[['votes']].std())
```

```
votes    70851.33888
dtype: float64
votes    130262.213792
dtype: float64
votes    558711.548387
dtype: float64
votes    363520.905427
dtype: float64
```

In [90]:

```
558711.548387/70851.33888 #(votes of winners)/votes of movies
```

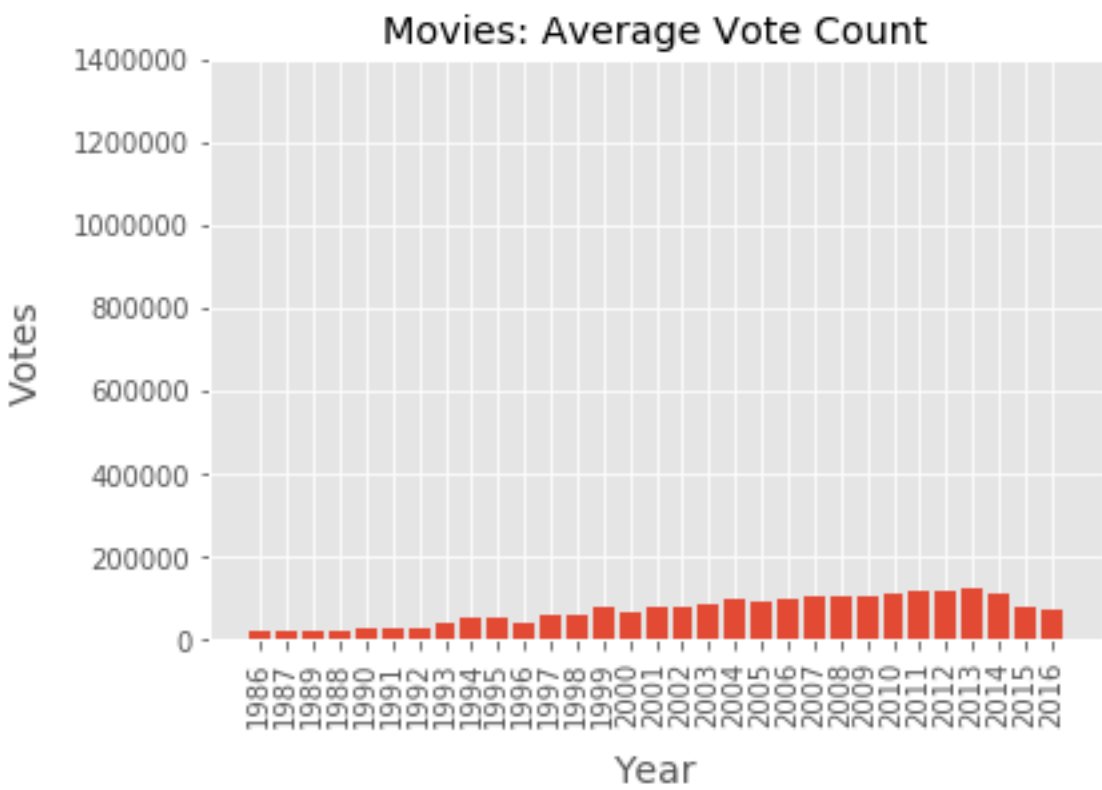
Out[90]:

```
7.885687937856511
```

Surprisingly, Winners have almost 8x more votes on IMDB than Movies!

In [91]:

```
#plot average vote count of Movies
plt.style.use('ggplot')

plt.bar(range(len(year_parameter_averages["votes"])), year_parameter_averages["v
otes"].values(), align="center")
plt.xticks(range(len(year_parameter_averages["votes"])), list(year_parameter_ave
rages["votes"].keys()))
plt.xticks(rotation=90)

plt.title("Movies: Average Vote Count")
plt.ylabel("Votes", fontsize = 14, labelpad = 10)
plt.xlabel("Year", fontsize = 14, labelpad = 10)
plt.ylim([0,1400000])
plt.show()
```

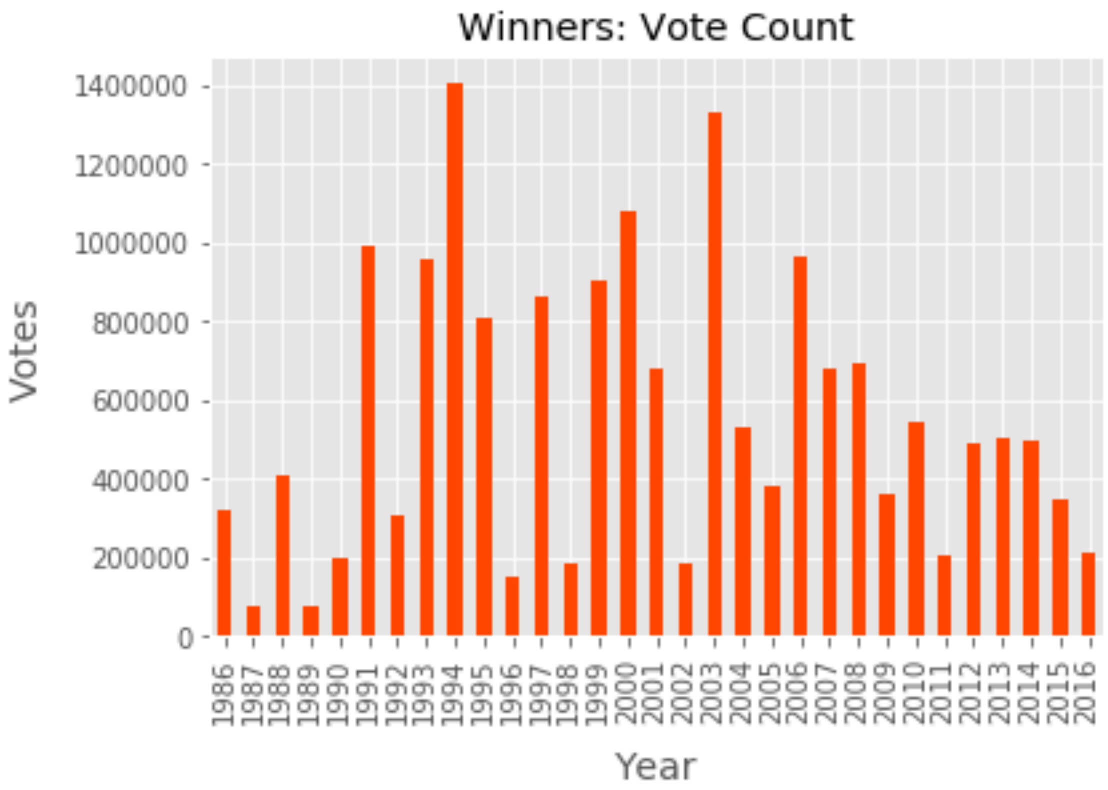


In [92]:

```
#plot vote count of Winners
plt.style.use('ggplot')

winners['votes'].plot(x='year',y='votes',kind='bar', figsize = (6,4), color = 'o
rangered')

plt.title("Winners: Vote Count")
plt.ylabel("Votes", fontsize = 14, labelpad = 10)
plt.xlabel("Year", fontsize = 14, labelpad = 10)
```

Out[92]:

```
Text(0.5,0,'Year')
```



Comparing both Votes graphs, the sheer volume of votes between Movies and Winners is astonishing. The movie industry has also seen an overall slightly upward trend in vote counts over the years while the Best Pictures have fluctuated greatly. However, both graphs show a dropping off in recent years. Our rationale behind the large number difference is that in order to win Best Picture, your movie should have received a lot of buzz/hype prior to the awards. In addition, more IMDB users may have a bias towards only taking the time to review a movie they enjoyed. As long the score reviews are positive, votes in the hundreds of thousands means the film has been exposed to more people and thus may have a higher chance than your average movie of winning Best Picture.

In [93]:

```
#print respective correlations
print(winners['score'].corr(winners['votes']))
print(winners['nominations'].corr(winners['votes']))
```

```
0.8337311276158713
0.1045567042788928
```

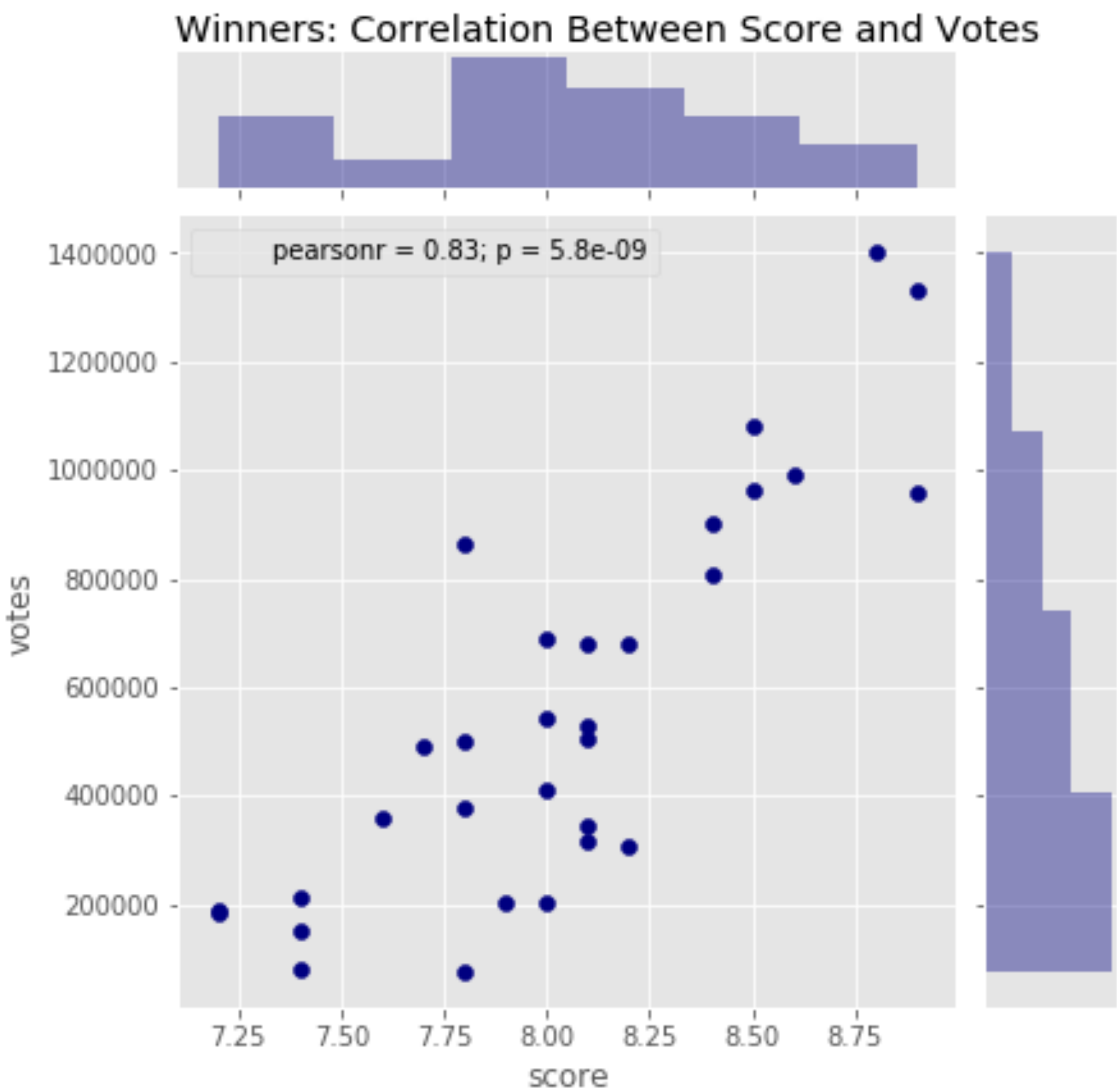
In [94]:

```
#plot correlation
plt.style.use('ggplot')

sns.jointplot(x="score", y="votes", data=winners, color = 'navy');
plt.title('Winners: Correlation Between Score and Votes', x = -2.8, y = 1.2)
```

```
/anaconda3/lib/python3.6/site-packages/matplotlib/axes/_axes.py:6462
: UserWarning: The 'normed' kwarg is deprecated, and has been replac
ed by the 'density' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
/anaconda3/lib/python3.6/site-packages/matplotlib/axes/_axes.py:6462
: UserWarning: The 'normed' kwarg is deprecated, and has been replac
ed by the 'density' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
```

Out[94]:

```
Text(-2.8,1.2,'Winners: Correlation Between Score and Votes')
```



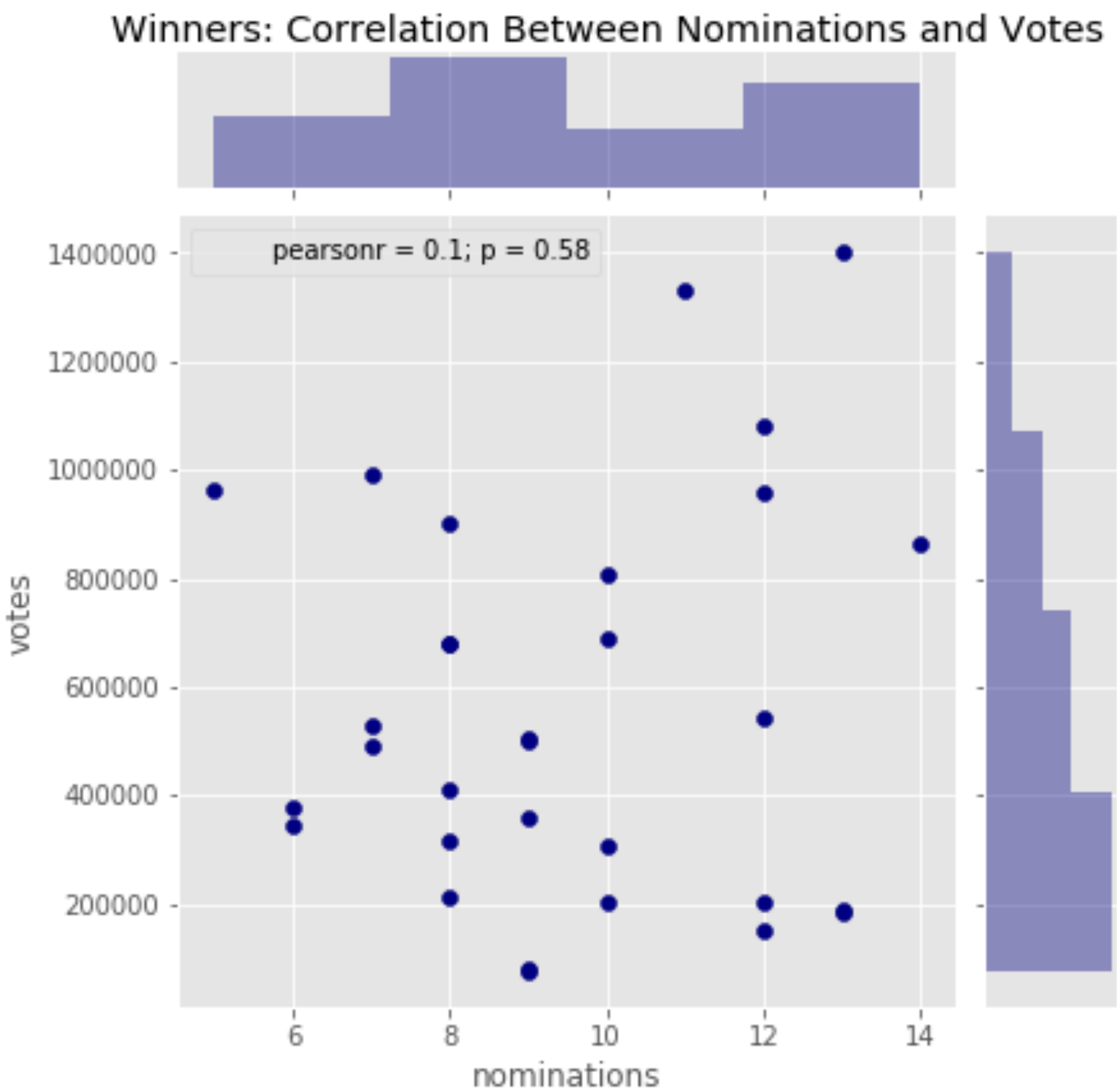
In [95]:

```
#plot correlation
sns.jointplot(x="nominations", y="votes", data=winners, color = 'navy');
plt.title('Winners: Correlation Between Nominations and Votes', x = -2.8, y = 1.
2)
```

```
/anaconda3/lib/python3.6/site-packages/matplotlib/axes/_axes.py:6462
: UserWarning: The 'normed' kwarg is deprecated, and has been replac
ed by the 'density' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
/anaconda3/lib/python3.6/site-packages/matplotlib/axes/_axes.py:6462
: UserWarning: The 'normed' kwarg is deprecated, and has been replac
ed by the 'density' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
```

Out[95]:

```
Text(-2.8,1.2,'Winners: Correlation Between Nominations and Votes')
```



While there is no correlation between nominations and votes, there is a surprisingly strong correlation between score and votes of .83 (p-value is much less than .05). Again, this might be because of what we explained earlier: user bias in reviewing movies one really likes compared to ones they found mediocre or disliked.

Production Companies

In [96]:

```
#print respective modes
print(movies[['company']].mode())
print(winners[['company']].mode())
```

```
             company
0  Universal Pictures
       company
0  Warner Bros.
```

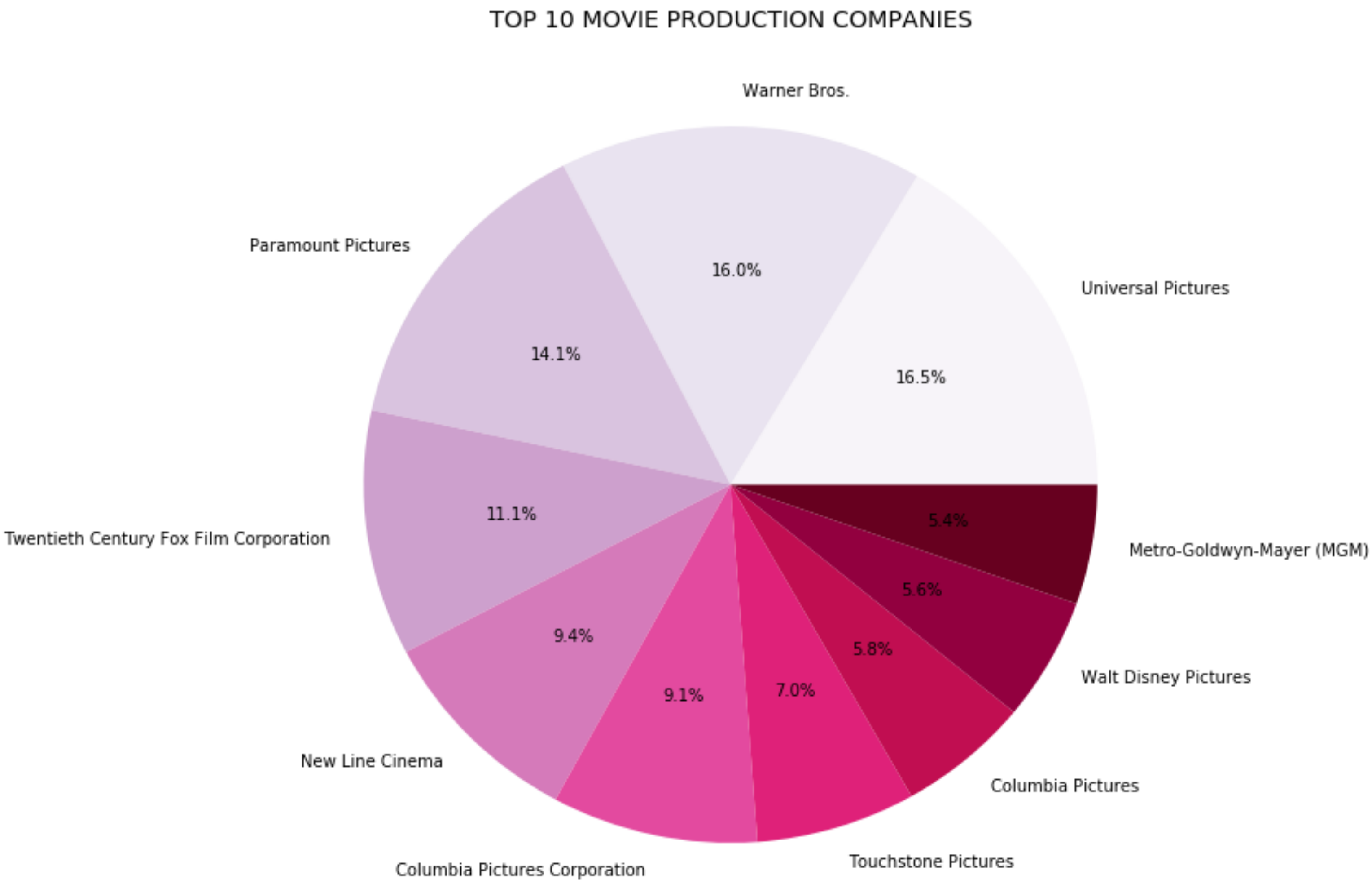
The most common production company in the movie industry is Universal Pictures, but Warner Bros. has been most successful in winning Best Picture.

In [97]:

```
#create Movies top production companies pie chart
plt.style.use('ggplot')

movies.company.value_counts()[:10].plot.pie(autopct='%1.1f%%',figsize=(10,10), c
map = 'PuRd')
plt.title('TOP 10 MOVIE PRODUCTION COMPANIES')
plt.ylabel("")
```

Out[97]:

```
Text(0,0.5,'')
```

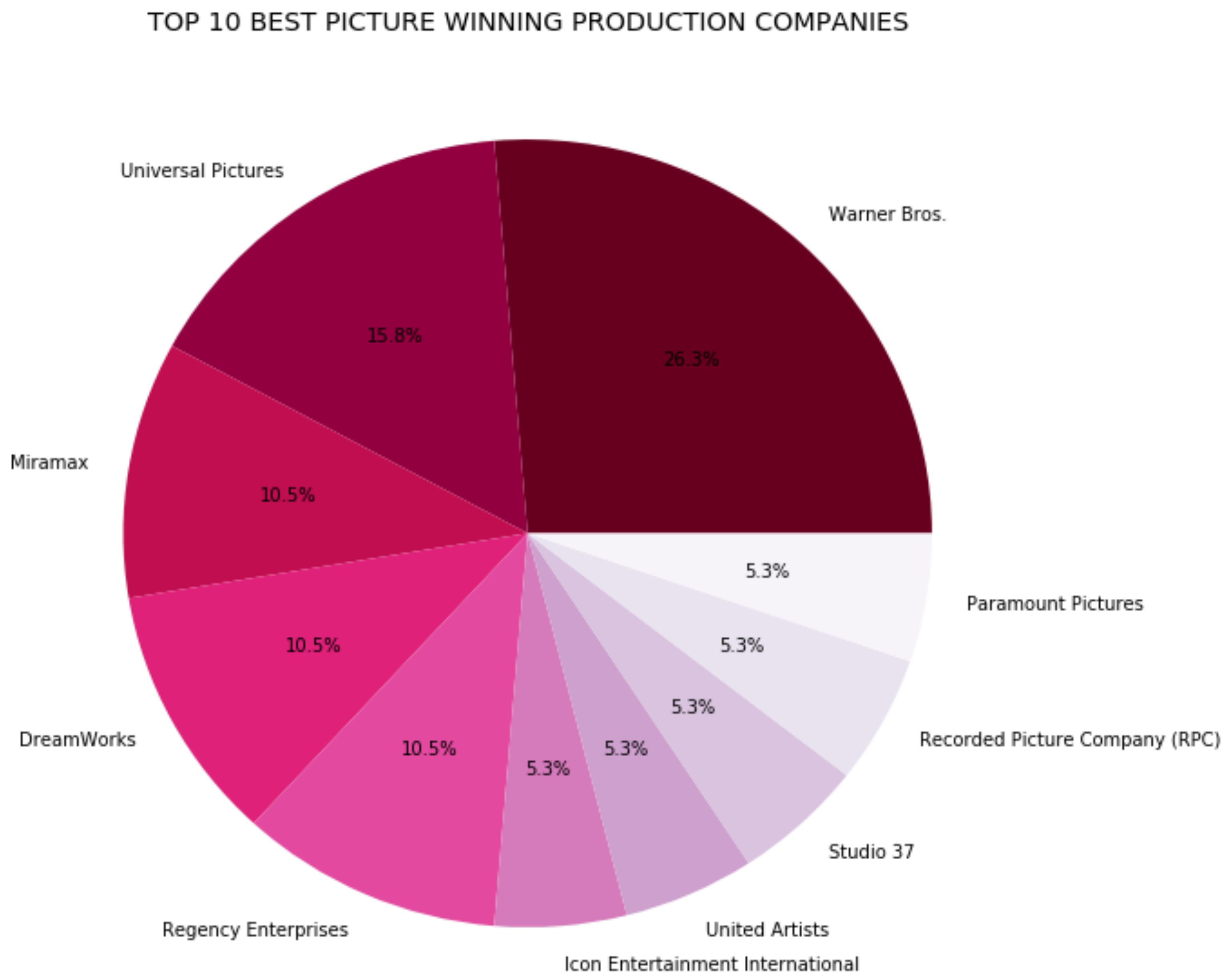


In [98]:

```
#create Winners top production companies pie chart
plt.style.use('ggplot')

winners.company.value_counts()[:10].plot.pie(autopct='%1.1f%%',figsize=(10,10),
cmap='PuRd_r')
plt.title('TOP 10 BEST PICTURE WINNING PRODUCTION COMPANIES')
plt.ylabel("")
```

Out[98]:

```
Text(0,0.5,'')
```



There seems to be some overlap between the top production companies in the movie industry and the top Best Picture production companies. The top 4 production companies are also included in the top 10 Best Picture companies: Warner Bros, Paramount, Twentieth Centry Fox Film Corporation, and Universal Pictures.

Directors

In [99]:

```
#print respective modes
print(movies[['director']].mode())
print(winners[['director']].mode())
```

```
      director
0  Woody Allen
         director
0  Clint Eastwood
```

The most popular director in the movie industry by count is Woody Allen, but Clint Eastwood has directed the most Best Pictures.

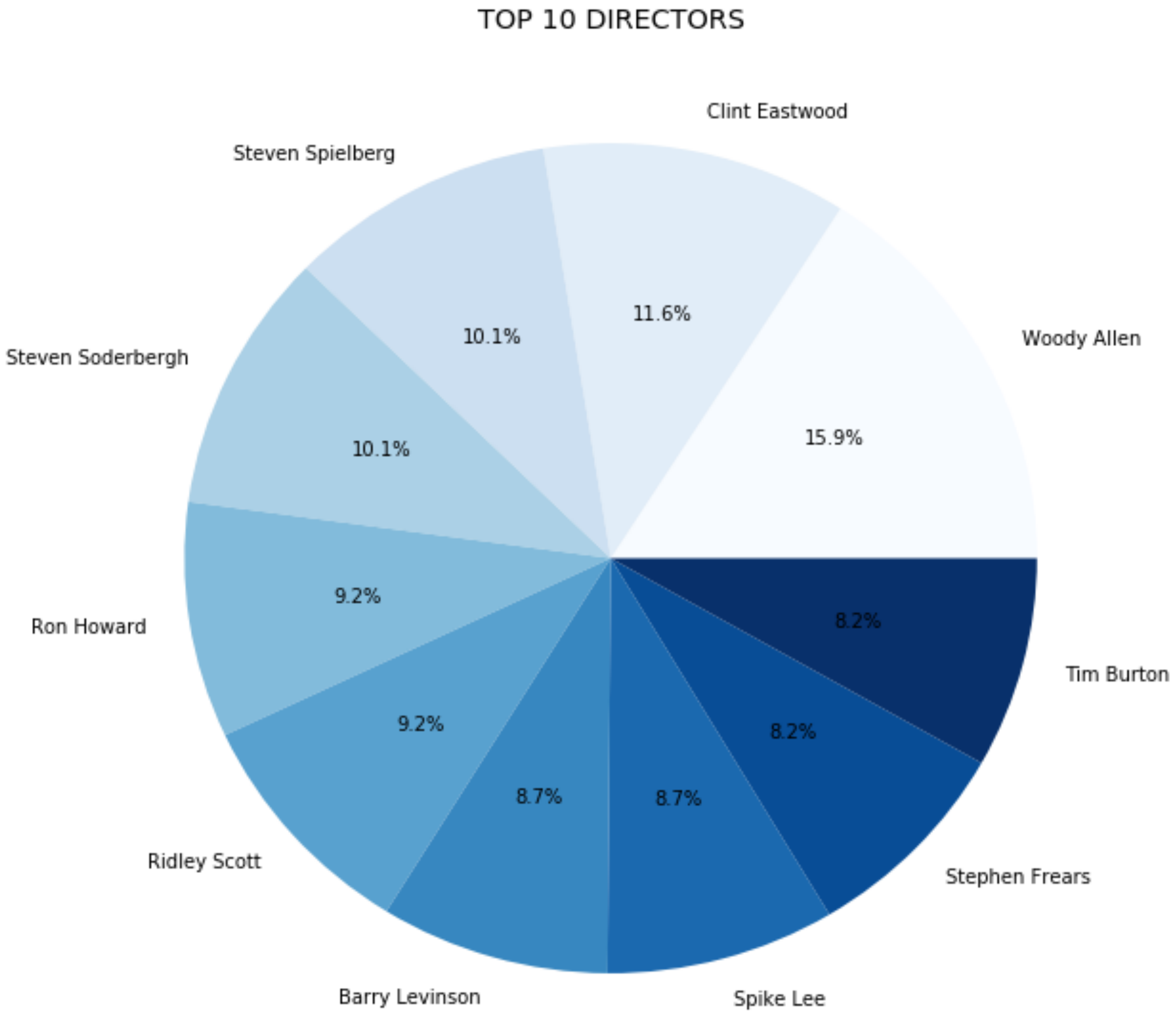
In [100]:

```
#create Movies top directors pie chart with value counts
plt.style.use('ggplot')

movies.director.value_counts()[:10].plot.pie(autopct='%1.1f%%',figsize=(10,10),
cmap = 'Blues')
plt.title('TOP 10 DIRECTORS')
plt.ylabel('')

movies['director'].value_counts()
```

Out[100]:

```
Woody Allen            33
Clint Eastwood         24
Steven Spielberg       21
Steven Soderbergh      21
Ron Howard             19
Ridley Scott           19
Barry Levinson         18
Spike Lee              18
Stephen Frears         17
Tim Burton             17
Richard Linklater      17
Oliver Stone           17
Bruce Beresford        16
Joel Schumacher        16
Garry Marshall         15
Martin Scorsese        15
Rob Reiner             15
Renny Harlin           15
Chris Columbus         15
Tony Scott             14
Wes Craven             14
Robert Zemeckis        14
Dennis Dugan           14
Pedro AlmodÃ³var       14
Robert Rodriguez       13
Neil Jordan            13
Roger Donaldson        13
Ang Lee                13
Michael Apted          13
David Cronenberg       12
                       ..
John Ottman             1
GÃ©rard KikoÃ¯ne        1
Olatunde Osunsanmi      1
Paul King               1
William Richert         1
```

```
Rob Hedden                1

Ben Bolt                  1
Susan Johnson             1
Justin Zackham            1
Takeshi Nozue             1
George C. Wolfe           1
Jim Henson                1
Topper Carew              1
Jack Bender               1
Chuck Parello             1
Jonathan Milott           1
Neil Armfield             1
Gary Sinyor               1
Lee David Zlotoff         1
Frank De Felitta          1
Robert B. Weide           1
David Hillenbrand         1
Michael Lindsay-Hogg      1
Boaz Davidson             1
Babak Najafi              1
Bob Logan                 1
Britt Allcroft            1
Jeb Stuart                1
Peter Ho-Sun Chan         1
Paul Lynch                1
Name: director, Length: 2747, dtype: int64
```



Interesting Observation: all 30 of the top directors in Hollywood are men; 0 women. Is this changing? We will revisit this after we analyze all of the respective variables.

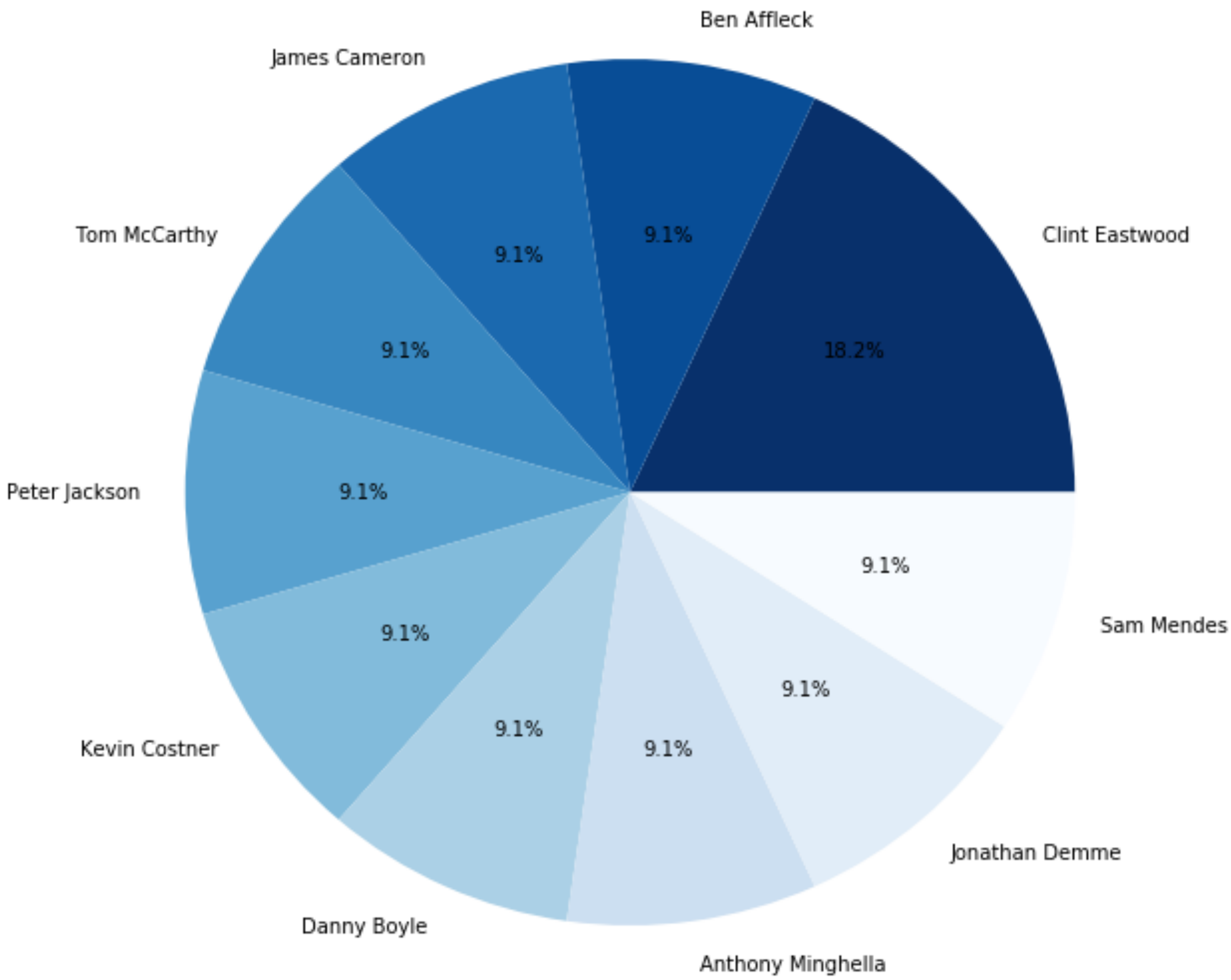
In [101]:

```
#create Winners top directors pie chart with value counts
plt.style.use('ggplot')

winners.director.value_counts()[:10].plot.pie(autopct='%1.1f%%',figsize=(10,10),
cmap = 'Blues_r')
plt.title('TOP 10 BEST PICTURE WINNING DIRECTORS')
plt.ylabel('')
winners['director'].value_counts()
```

Out[101]:

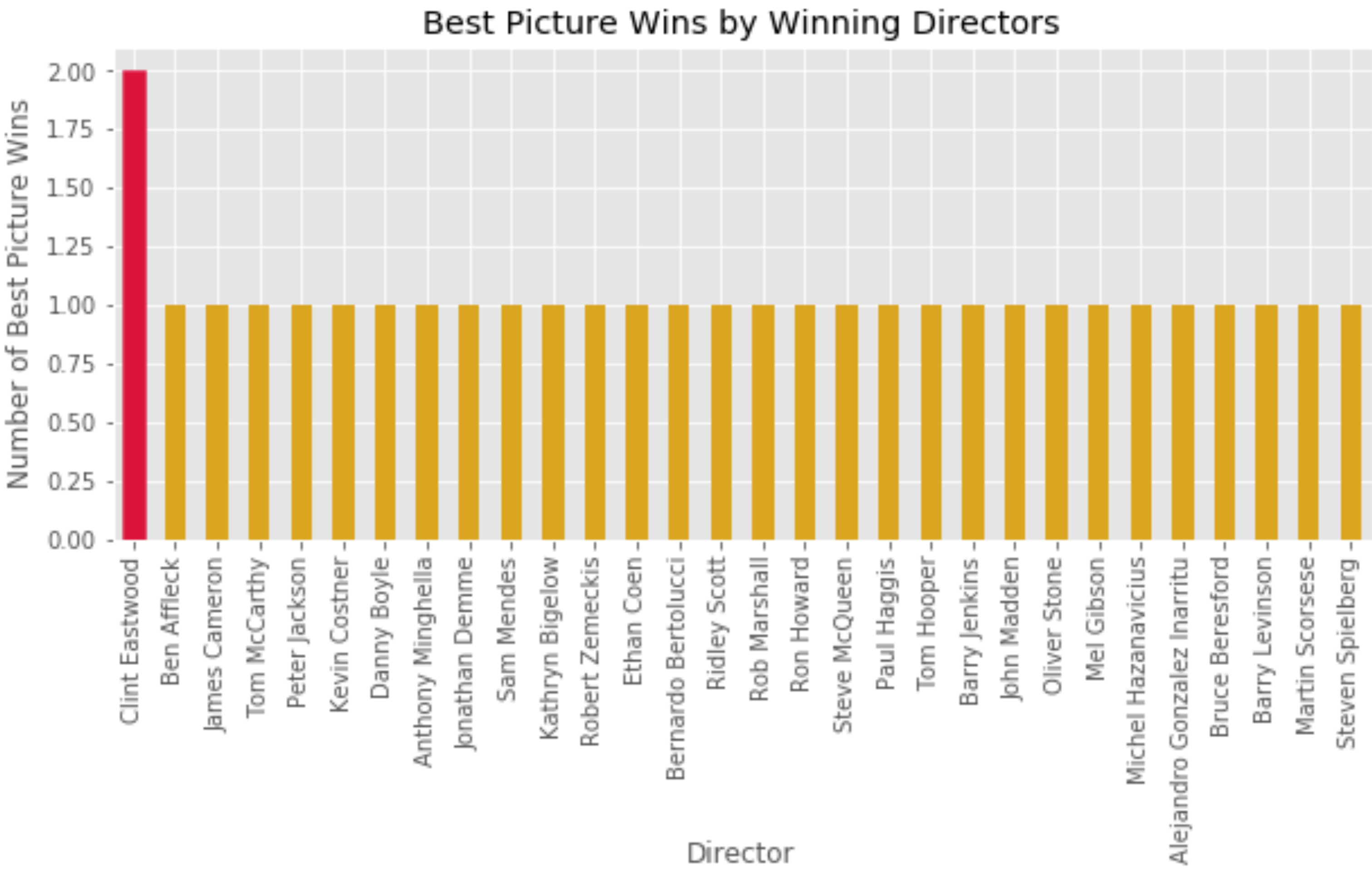
```
Clint Eastwood                 2
Ben Affleck                    1
James Cameron                  1
Tom McCarthy                   1
Peter Jackson                  1
Kevin Costner                  1
Danny Boyle                    1
Anthony Minghella              1
Jonathan Demme                 1
Sam Mendes                     1
Kathryn Bigelow                1
Robert Zemeckis                1
Ethan Coen                     1
Bernardo Bertolucci            1
Ridley Scott                   1
Rob Marshall                   1
Ron Howard                     1
Steve McQueen                  1
Paul Haggis                    1
Tom Hooper                     1
Barry Jenkins                  1
John Madden                    1
Oliver Stone                   1
Mel Gibson                     1
Michel Hazanavicius            1
Alejandro Gonzalez Inarritu    1
Bruce Beresford                1
Barry Levinson                 1
Martin Scorsese                1
Steven Spielberg               1
Name: director, dtype: int64
```

TOP 10 BEST PICTURE WINNING DIRECTORS



In [102]:

```
plt.style.use('ggplot')

ax = winners['director'].value_counts().plot(kind = 'bar', figsize=(10,4), color
= 'goldenrod')

plt.title('Best Picture Wins by Winning Directors')
plt.ylabel('Number of Best Picture Wins')
plt.xlabel('Director', labelpad = -10)
ax.get_children()[0].set_color('crimson')
```



While the Top 10 Directors Pie Chart illustrates that there are several directors who have dominated Hollywood, the Top 10 Best Picture Directors charts and value counts show that other than Clint Eastwood, not a single director in the last 30 years has directed more than one Best Picture.

Movie Stars

In [103]:

```
#print respective modes
print(movies[['star']].mode())
print(winners[['star']].mode())
```

```
           star
0  Nicolas Cage
                star
0  Leonardo DiCaprio
1      Russell Crowe
```

Nicolas Cage is the most popular star in the movie industry by star appearances, but Leonardo DiCaprio and Russell Crowe have been the stars in the most Best Pictures.

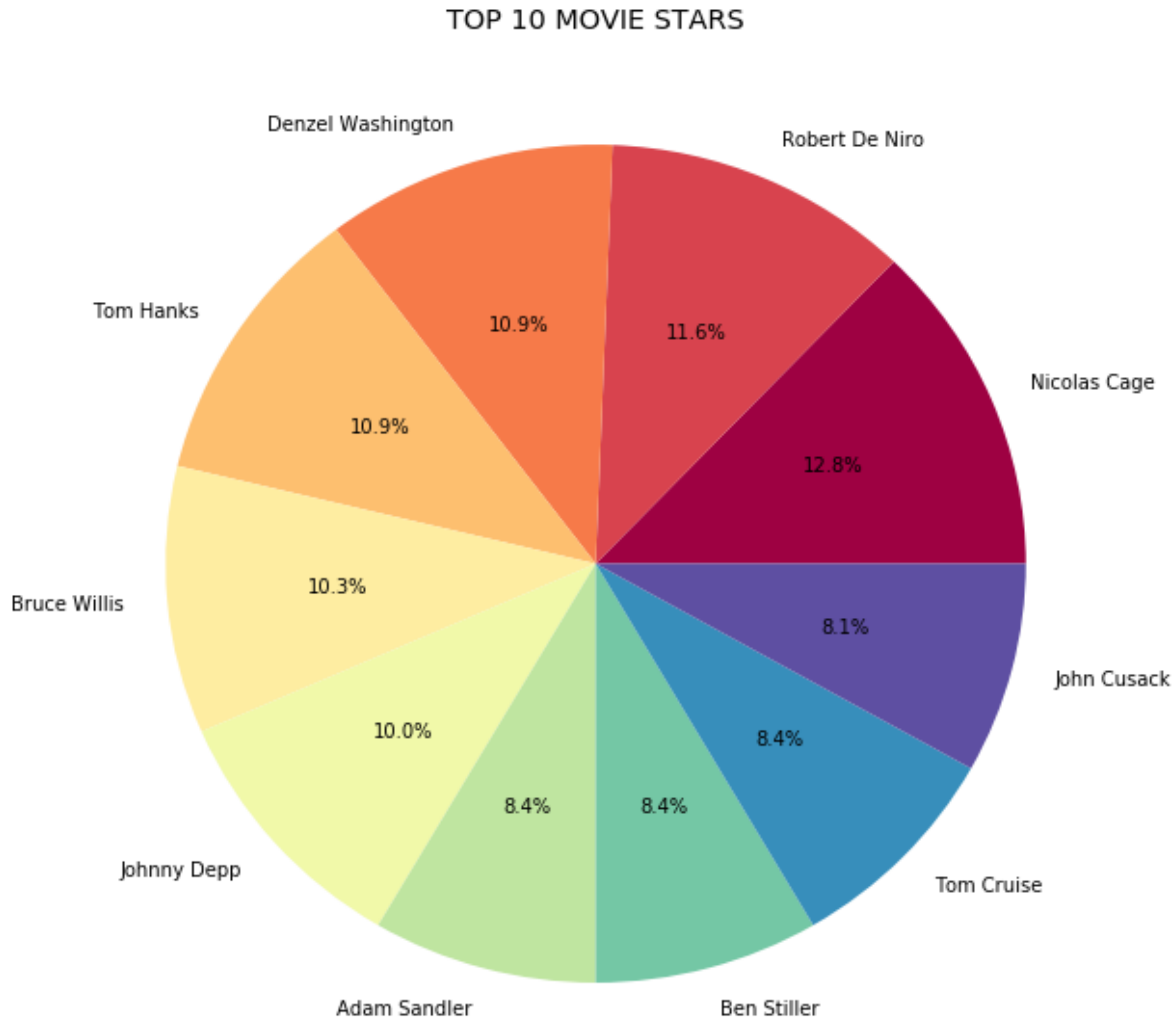
In [104]:

```
#create Movies top stars pie chart with value counts
plt.style.use('ggplot')

movies.star.value_counts()[:10].plot.pie(autopct='%1.1f%%',figsize=(10,10), cmap
= 'Spectral')
plt.title('TOP 10 MOVIE STARS')
plt.ylabel('')
movies["star"].value_counts()
```

Out[104]:

```
Nicolas Cage             41
Robert De Niro           37
Denzel Washington        35
Tom Hanks                35
Bruce Willis             33
Johnny Depp              32
Adam Sandler             27
Ben Stiller              27
Tom Cruise               27
John Cusack              26
Eddie Murphy             25
Sylvester Stallone       25
Robin Williams           25
Kevin Costner            25
John Travolta            24
Steve Martin             24
Keanu Reeves             24
Mel Gibson               23
Jim Carrey               22
Brad Pitt                22
Arnold Schwarzenegger    22
George Clooney           22
Mark Wahlberg            22
Ben Affleck              22
Sandra Bullock           21
```

```
Jeff Bridges              21
Matthew McConaughey       21
Matt Damon                21
Harrison Ford             20
Anthony Hopkins           20
                          ..
Kristy Young               1
StÃ©phane Audran           1
Jerry O'Connell            1
Shannen Doherty            1
William Ragsdale           1
Al Franken                 1
Paige Turco                1
Danny Dyer                 1
Miguel Ferrer              1
Martijn Lakemeier          1
Kathy Baker                1
Jon Favreau                1
Sharon Leal                1
Karen Black                1
Jeffrey Combs              1
Neil Patrick Harris        1
Craig T. Nelson            1
Thure Lindhardt            1
Emmanuel Garijo            1
Kristin Kreuk              1
Mary-Kate Olsen            1
Craig Roberts              1
Louise Smith               1
Linnea Quigley             1
Hiep Thi Le                1
Marcia Gay Harden          1
Steven Waddington          1
Homayoun Ershadi           1
Christina Hendricks        1
Olivia Cooke               1
Name: star, Length: 2485, dtype: int64
```

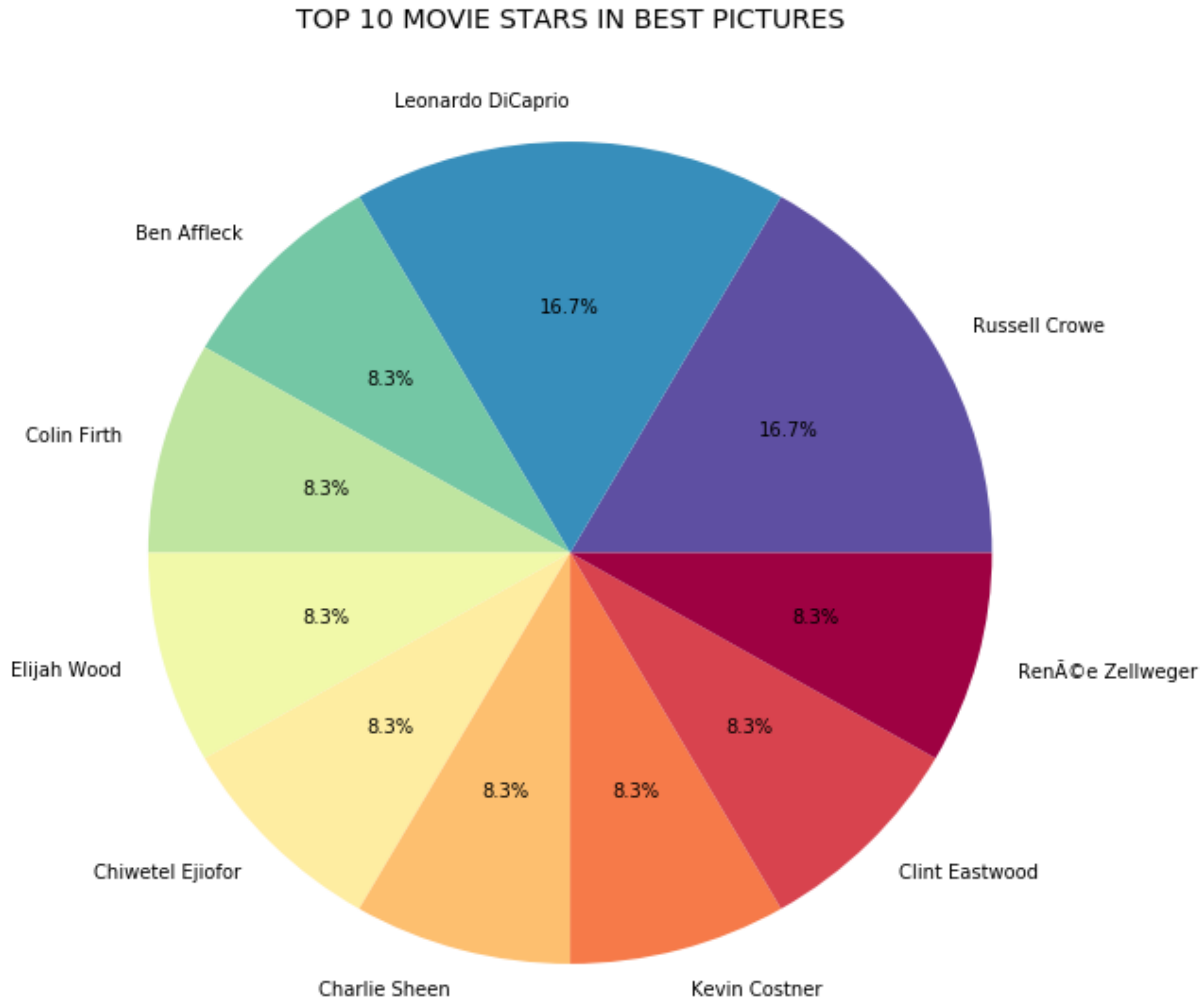


Many of the top actors that come to mind appear in this chart, as expected. But the most interesting insight about this pie chart and its value counts is that only one out of the top 30 stars in the last thirty years has been a woman (Sandra Bullock).

In [105]:

```
#create Winners top stars pie chart with value counts
plt.style.use('ggplot')

winners.star.value_counts()[:10].plot.pie(autopct='%1.1f%%',figsize=(10,10), cma
p = 'Spectral_r')
plt.title('TOP 10 MOVIE STARS IN BEST PICTURES')
plt.ylabel('')
winners["star"].value_counts()
```

```
Out[105]:

Russell Crowe         2
Leonardo DiCaprio     2
Ben Affleck           1
Colin Firth           1
Elijah Wood           1
Chiwetel Ejiofor      1
Charlie Sheen         1
Kevin Costner         1
Clint Eastwood        1
RenÃ©e Zellweger      1
Jodie Foster          1
Trevante Rhodes       1
Hilary Swank          1
Morgan Freeman        1
Kevin Spacey          1
Liam Neeson           1
Jeremy Renner         1
Gwyneth Paltrow       1
Jean Dujardin         1
Tommy Lee Jones       1
Dustin Hoffman        1
Ralph Fiennes         1
Mel Gibson            1
Don Cheadle           1
Michael Keaton        1
John Lone             1
Tom Hanks             1
Mark Ruffalo          1
Dev Patel             1
Name: star, dtype: int64
```



Similar to our observations on directors: while many actors (e.g. Cage, De Niro, Washington, Hanks, Willis, Depp) have dominated Hollywood, only two actors (Crowe and DiCaprio) have starred in more than one Best Picture, each with a count of two.

Writers

In [106]:

```
#print respective modes
print(movies[['writer']].mode())
print(winners[['writer']].mode())
```

```
       writer
0  Woody Allen
       writer
0  Paul Haggis
```

Woody Allen is the industry's top writer by volume, but Paul Haggis has written the most Best Pictures.

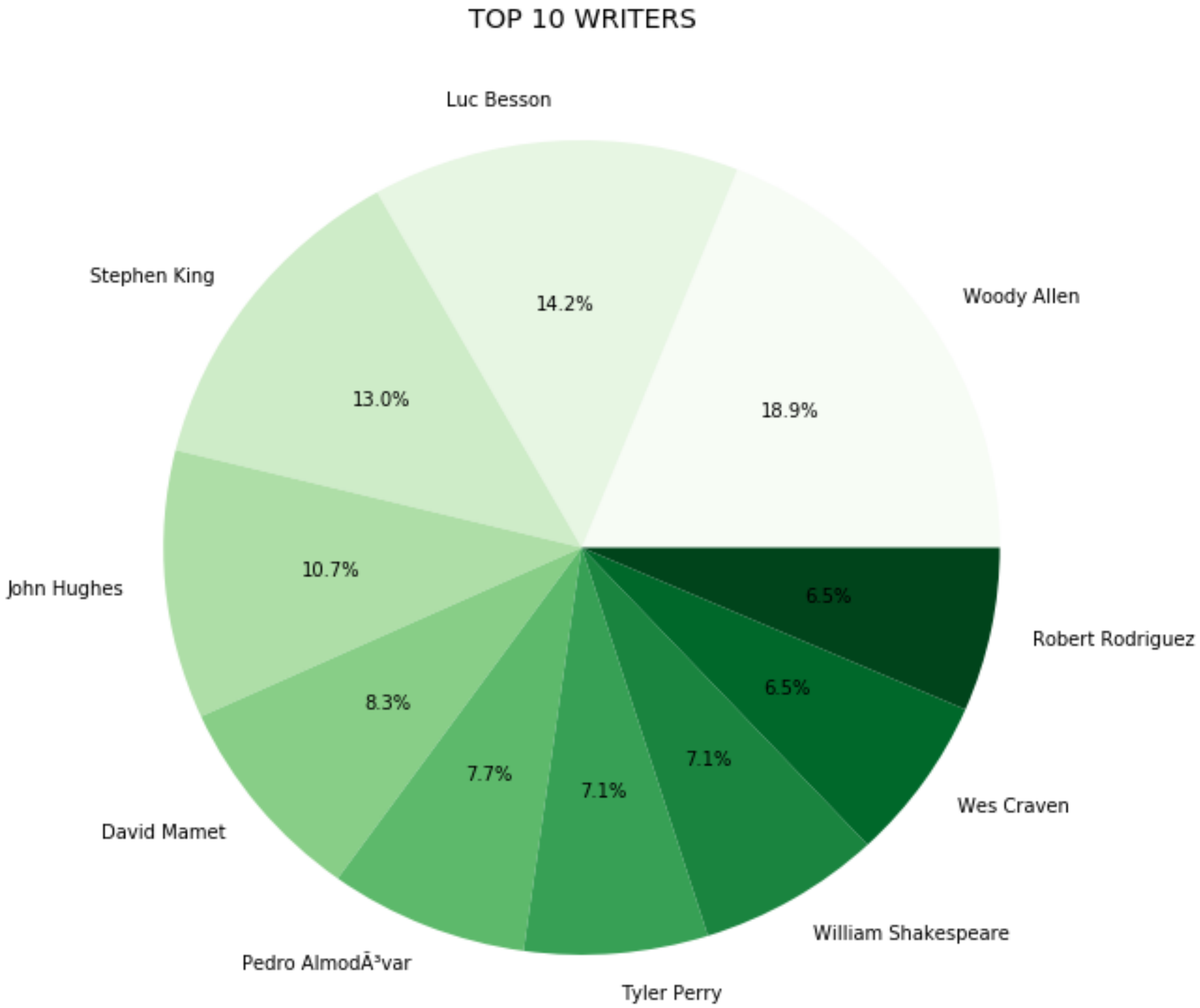
In [107]:

```
#create Movies top writers pie chart with value counts
plt.style.use('ggplot')

movies.writer.value_counts()[:10].plot.pie(autopct='%1.1f%%',figsize=(10,10), cm
ap = 'Greens')
plt.title('TOP 10 WRITERS')
plt.ylabel('')

movies["writer"].value_counts()
```

Out[107]:

```
Woody Allen            32
Luc Besson             24
Stephen King           22
John Hughes            18
David Mamet            14
Pedro AlmodÃ³var       13
Tyler Perry            12
William Shakespeare    12
Wes Craven             11
Robert Rodriguez       11
Joel Coen              11
Lars von Trier         10
John Logan             10
Quentin Tarantino      10
Kevin Smith            10
M. Night Shyamalan     10
Jim Jarmusch           10
Brian Helgeland        10
Ehren Kruger           10
Michael Crichton       10
Steven Knight           9
Mike Leigh              9
John Grisham            9
Joe Eszterhas           8
Jane Austen             8
Judd Apatow             8
Leigh Whannell          8
Richard Linklater       8
Lilly Wachowski         8
Larry Cohen             8
                       ..
Ken Sanzel              1
RyÃ» Murakami           1
Ed Rosenbaum            1
Tom Kalin               1
Michael Radford         1
Peter HÃ¸eg             1
Sean Macaulay           1
Stephen Neigher         1
Jason Freeland          1
```

```
Bill Cosby                1

Ari Schlossberg           1
Sherry Mills              1
Julia Leigh               1
Emi Mochizuki             1
Ruben Ãstlund            1
Roger Towne               1
Eric England              1
Trey Edward Shults        1
Su Tong                   1
Bob Dylan                 1
Scott Stewart             1
HergÃ©                    1
Roy Frumkes               1
Vince Vaughn              1
Vera Blasi                1
Justin Benson             1
Saket Chaudhary           1
Ralph Sall                1
Alex S. Kim               1
Omar Naim                 1
Name: writer, Length: 4170, dtype: int64
```

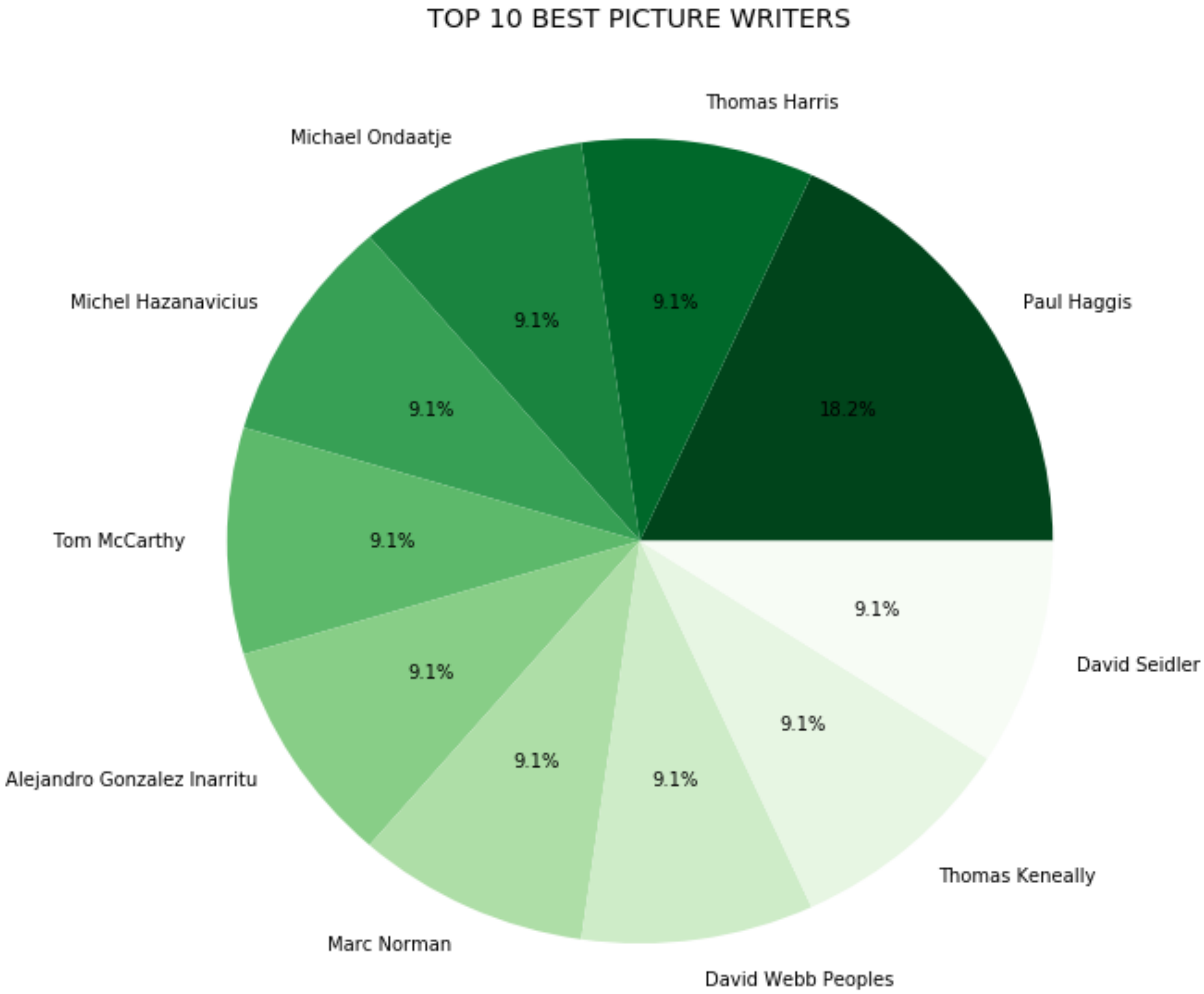


Only one writer out of the top 30 in Hollywood is a woman: Lilly Wachowski.

In [108]:

```
#create Winners top writers pie chart with value counts
plt.style.use('ggplot')

winners.writer.value_counts()[:10].plot.pie(autopct='%1.1f%%',figsize=(10,10), c
map= 'Greens_r')
plt.title('TOP 10 BEST PICTURE WRITERS')
plt.ylabel('')
winners["writer"].value_counts()
```

```
Out[108]:

Paul Haggis                    2
Thomas Harris                  1
Michael Ondaatje               1
Michel Hazanavicius            1
Tom McCarthy                   1
Alejandro Gonzalez Inarritu    1
Marc Norman                    1
David Webb Peoples             1
Thomas Keneally                1
David Seidler                  1
Winston Groom                  1
Mark Boal                      1
Bill Condon                    1
James Cameron                  1
Alfred Uhry                    1
Akiva Goldsman                 1
Michael Blake                  1
John Ridley                    1
Simon Beaufoy                  1
William Monahan                1
Chris Terrio                   1
J.R.R. Tolkien                 1
Mark Peploe                    1
Barry Jenkins                  1
Alan Ball                      1
Oliver Stone                   1
Joel Coen                      1
David Franzoni                 1
Barry Morrow                   1
Randall Wallace                1
Name: writer, dtype: int64
```



Again, this is a very similar pattern as both directors and stars. There are several prominent writers in the movie industry (e.g. Woody Allen, Luc Besson, Stephen King), but Paul Haggis is the only person who has written more than one Best Picture, with two under his belt.

Genres

In [109]:

```
#print respective modes
print(movies[['genre']].mode())
print(winners[['genre']].mode())
```

```
    genre
0  Comedy
   genre
0  Drama
```

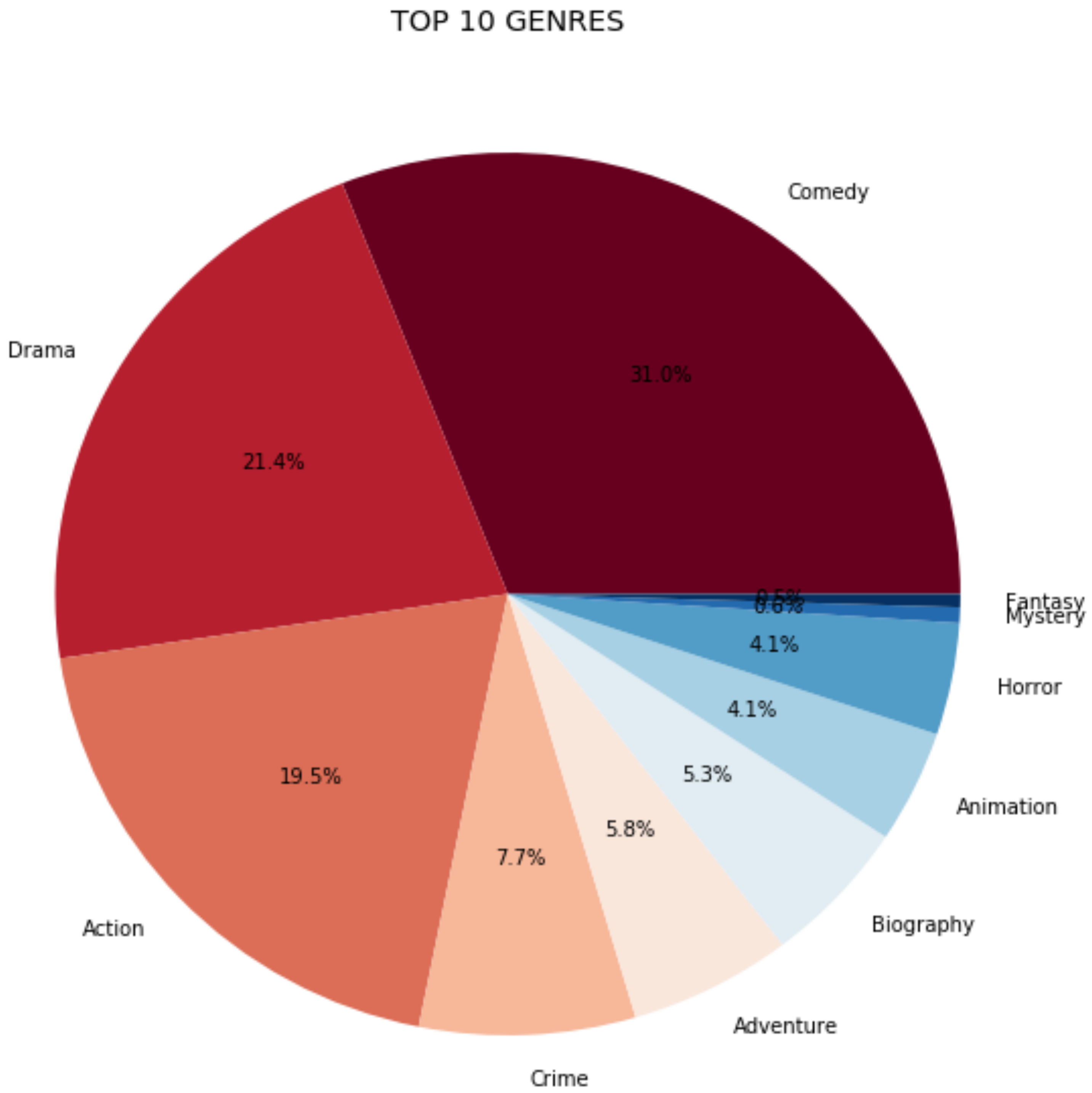
The most common genre in the movie industry is comedy, but dramas are the most common Best Picture genre.

In [110]:

```
#create Movies top genres pie chart with value counts
plt.style.use('ggplot')

movies.genre.value_counts()[:10].plot.pie(autopct='%1.1f%%',figsize=(10,10), cma
p = 'RdBu')
plt.title('TOP 10 GENRES')
plt.ylabel('')
movies["genre"].value_counts()
```

Out[110]:

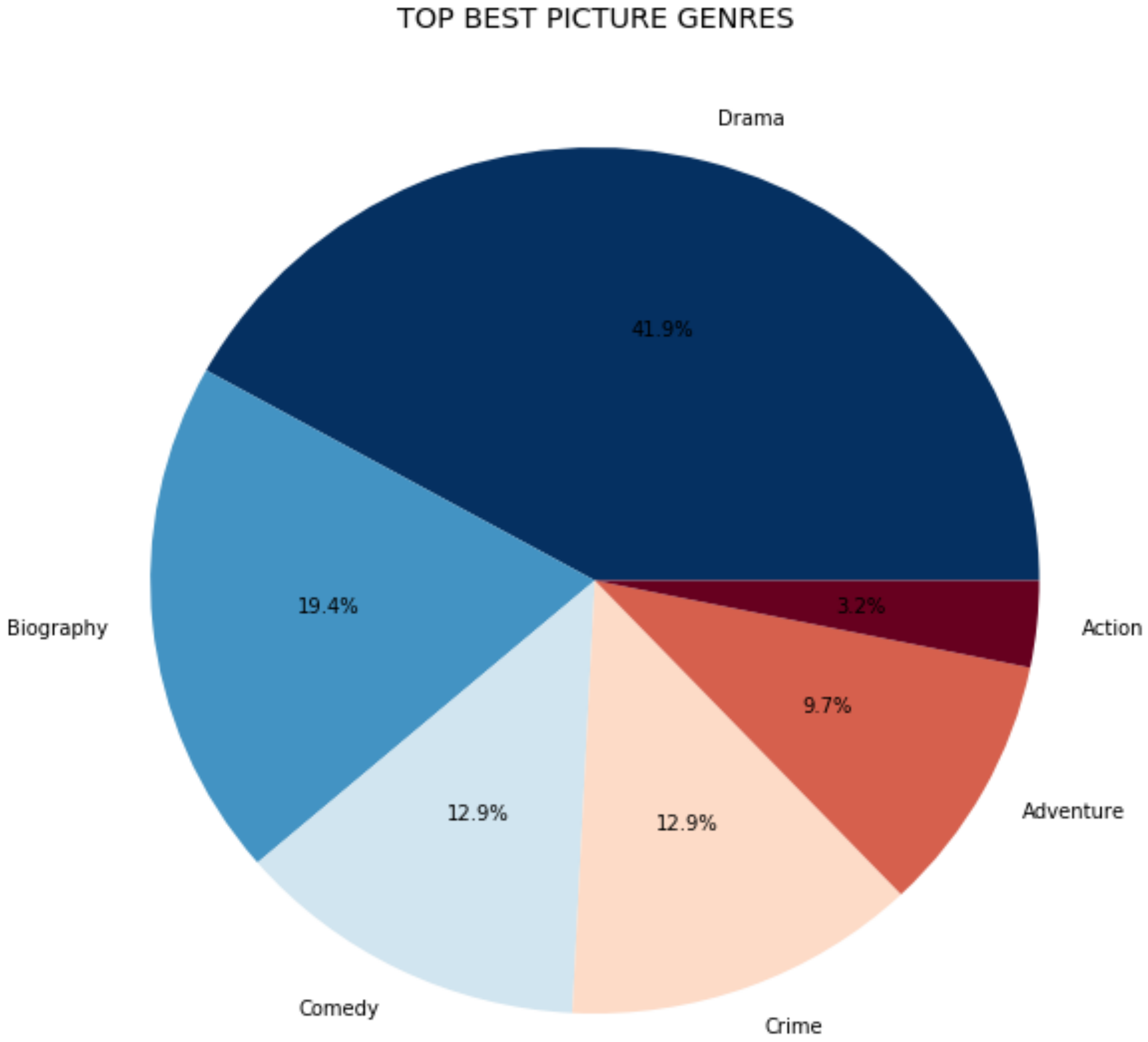
```
Comedy       2063
Drama        1424
Action       1300
Crime         514
Adventure     388
Biography     356
Animation     275
Horror        273
Mystery        38
Fantasy        32
Thriller       18
Romance        15
Family         14
Sci-Fi         13
Musical         4
War             2
Western         2
Name: genre, dtype: int64
```



In [111]:

```
#create Winners top genres pie chart with value counts
plt.style.use('ggplot')

winners.genre.value_counts()[:10].plot.pie(autopct='%1.1f%%',figsize=(10,10), cm
ap = 'RdBu_r')
plt.title('TOP BEST PICTURE GENRES')
plt.ylabel('')
winners["genre"].value_counts()
```

```
Out[111]:

Drama        13
Biography     6
Comedy        4
Crime         4
Adventure     3
Action        1
Name: genre, dtype: int64
```



There is quite a difference in the genre distribution between Movies and Winners. For example, while drama is the 2nd most popular genre in the movie industry, it is by far the most common type of Best Picture. Four of the top 10 genres in the movie industry have also never even won Best Picture. Let's dive deeper into the different genres of Movies and Winners to gain further insight.

We will be separating Movies and Winners into sets by their respective genres in order to figure out why comedy Movies and drama Winners are so popular to make compared to other genres.

We will be using the .describe function (which displays key numerical statistics) in order to compare the different genres.

Note: There is still a bias here because each movie is only categorized under one genre when many of them could fall under several genres.

In [112]:

```
#separate Movies into respective sets of genres
drama_movies=movies['genre'].str.contains('Drama')
comedy_movies=movies['genre'].str.contains('Comedy')
action_movies=movies['genre'].str.contains('Action')
```

In [113]:

```
#separate Winners into respective sets of genres
drama_winners=winners['genre'].str.contains('Drama')
biography_winners=winners['genre'].str.contains('Biography')
comedy_winners=winners['genre'].str.contains('Comedy')
crime_winners=winners['genre'].str.contains('Crime')
```

Note: We tried to do the movies.describe() function instead of include 'all' since we will only be looking at numerical data and the table looks cleaner, but for some reason nominations (which we needed) was not included even though it was already an integer. We are unsure as to why this happened, but our final display is describe () because it looks much cleaner.

In [114]:

```
winners.nominations.dtypes
```

Out[114]:

```
dtype('int64')
```

In [115]:

```
movies.describe()
```

Out[115]:

	budget	gross	runtime	score	votes	y
count	6.731000e+03	6.731000e+03	6731.000000	6731.000000	6.731000e+03	6731.00
mean	2.495835e+07	3.329592e+07	106.485069	6.374031	7.085134e+04	2000.91
std	3.667269e+07	5.769639e+07	17.950830	1.003406	1.302622e+05	8.94460
min	1.600000e+01	7.000000e+01	50.000000	1.500000	2.700000e+01	1986.00
25%	1.159671e+06	1.500892e+06	95.000000	5.800000	7.598500e+03	1993.00
50%	1.100000e+07	1.199040e+07	102.000000	6.400000	2.551100e+04	2001.00
75%	3.200000e+07	3.976220e+07	114.000000	7.100000	7.525450e+04	2009.00
max	3.000000e+08	9.366622e+08	366.000000	9.300000	1.861666e+06	2016.00

In [116]:

```
movies[drama_movies].describe()
```

Out[116]:

	budget	gross	runtime	score	votes	y
count	1.424000e+03	1.424000e+03	1424.000000	1424.000000	1.424000e+03	1424.00
mean	1.359989e+07	1.716308e+07	111.747191	6.716854	5.293862e+04	2000.85
std	2.154761e+07	3.632944e+07	21.161445	0.873743	1.112430e+05	8.89983
min	4.280000e+02	1.800000e+03	71.000000	2.200000	1.390000e+02	1986.00
25%	2.388800e+05	4.996152e+05	100.000000	6.200000	4.848500e+03	1993.00
50%	4.000000e+06	3.438953e+06	107.000000	6.800000	1.611700e+04	2001.00
75%	1.800000e+07	1.870289e+07	120.000000	7.400000	5.073475e+04	2009.00
max	2.000000e+08	6.586723e+08	366.000000	8.800000	1.492073e+06	2016.00

Drama movies have a lower budget than the average movie, but average gross and profitability is also lower. Gross also has a lower standard deviation. Dramas also have a slightly higher average score than typical movies.

In [132]:

```
movies[comedy_movies].describe()
```

Out[132]:

	budget	gross	runtime	score	votes	
count	2.063000e+03	2.063000e+03	2063.000000	2063.000000	2.063000e+03	2063.00
mean	1.569056e+07	2.572557e+07	101.200194	6.166505	4.481649e+04	1999.81
std	1.990194e+07	3.748671e+07	12.057097	0.982602	7.766335e+04	8.64599
min	1.280000e+02	3.090000e+02	73.000000	1.500000	1.250000e+02	1986.00
25%	9.826295e+05	1.665158e+06	93.000000	5.600000	6.585000e+03	1992.00
50%	8.000000e+06	1.081418e+07	100.000000	6.200000	1.851900e+04	1999.00
75%	2.200000e+07	3.446131e+07	107.000000	6.800000	5.100000e+04	2007.00
max	1.750000e+08	3.302522e+08	188.000000	8.800000	1.402876e+06	2016.00

Comedies have lower budgets, lower scores, lower profitability multiples, lower runtimes, lower gross, and lower gross standard deviations than the average movie. The lower gross standard deviation means it is a less risky film to make. Comedies are also more profitable than dramas. The combination of these characteristics provides a deeper understanding of why comedies are the most common genre in the movie industry.

In [133]:

```
movies[action_movies].describe()
```

Out[133]:

	budget	gross	runtime	score	votes	
count	1.300000e+03	1.300000e+03	1300.000000	1300.000000	1.300000e+03	1300.00
mean	4.905829e+07	5.601506e+07	108.940769	6.099769	1.113170e+05	2001.43
std	5.290977e+07	8.285557e+07	17.647355	1.018985	1.631606e+05	9.27216
min	1.290000e+02	5.470000e+02	75.000000	1.600000	1.030000e+02	1986.00
25%	8.493250e+06	6.738856e+06	97.000000	5.500000	1.544850e+04	1993.00
50%	3.200000e+07	2.648919e+07	105.500000	6.200000	5.436850e+04	2002.00
75%	7.000000e+07	6.929980e+07	118.000000	6.700000	1.438198e+05	2010.00
max	3.000000e+08	9.366622e+08	280.000000	9.000000	1.839571e+06	2016.00

Action movies are riskier movies to make, but the higher standard deviation could mean more potential than other genres. Action movies also have a higher average budget, but shorter runtime than other top genres.

In [119]:

```
winners.describe()
```

Out[119]:

	budget	gross	profitability	release_year	runtime	score
count	3.100000e+01	3.100000e+01	31.000000	31.000000	31.000000	31.000000
mean	3.712581e+07	1.376186e+08	5.410743	2001.000000	137.677419	8.029032
std	4.015139e+07	1.248718e+08	4.505234	9.092121	27.931329	0.459125
min	4.000000e+06	1.701781e+07	1.050000	1986.000000	99.000000	7.200000
25%	1.500000e+07	6.547781e+07	2.873308	1993.500000	119.500000	7.800000
50%	2.200000e+07	1.065933e+08	3.793056	2001.000000	131.000000	8.000000
75%	4.475000e+07	1.560037e+08	6.994278	2008.500000	153.000000	8.300000
max	2.000000e+08	6.586723e+08	23.088428	2016.000000	201.000000	8.900000

In [120]:

```
winners[drama_winners].describe()
```

Out[120]:

	budget	gross	profitability	release_year	runtime	score
count	1.300000e+01	1.300000e+01	13.000000	13.000000	13.000000	13.000000
mean	3.053077e+07	1.354314e+08	7.045581	2001.000000	131.307692	7.869231
std	5.151937e+07	1.643501e+08	6.067741	10.708252	23.602205	0.332627
min	4.000000e+06	1.701781e+07	1.134521	1986.000000	99.000000	7.400000
25%	1.440000e+07	4.505578e+07	2.913016	1992.000000	120.000000	7.600000
50%	1.500000e+07	1.011574e+08	6.913017	1999.000000	129.000000	8.000000
75%	2.500000e+07	1.385306e+08	8.673107	2009.000000	132.000000	8.100000
max	2.000000e+08	6.586723e+08	23.088428	2016.000000	194.000000	8.400000

Making a drama Winner is very profitable and has a lower average budget than the typical Best Picture. It also has a shorter runtime and a lower average score. It has fewer nominations than your average Winner. All of these make it an attractive genre to make for the Best Picture Academy Award.

In [121]:

```
winners[comedy_winners].describe()
```

Out[121]:

	budget	gross	profitability	release_year	runtime	score	
count	4.000000e+00	4.000000e+00	4.000000	4.000000	4.000000	4.000000	4
mean	3.500000e+07	1.614823e+08	4.197116	2001.250000	119.500000	7.775000	4
std	1.825742e+07	1.237657e+08	1.284547	7.274384	17.710637	0.758837	6
min	1.500000e+07	4.467168e+07	2.978112	1994.000000	100.000000	7.200000	1
25%	2.250000e+07	8.640627e+07	3.589320	1997.000000	109.750000	7.200000	1
50%	3.500000e+07	1.355027e+08	3.902884	2000.000000	118.000000	7.550000	1
75%	4.750000e+07	2.105787e+08	4.510680	2004.250000	127.750000	8.125000	5
max	5.500000e+07	3.302522e+08	6.004585	2011.000000	142.000000	8.800000	1

If you decide to make a comedy Best Winner, it better have a lot of nominations (average number of nominations is more than 12). Also, there have only been four comedy Best Pictures in the last 31 years.

In [122]:

```
winners[biography_winners].describe()
```

Out[122]:

	budget	gross	profitability	release_year	runtime	score	
count	6.000000e+00	6.000000e+00	6.000000	6.000000	6.000000	6.000000	6
mean	3.500000e+07	9.697720e+07	3.726607	1999.833333	153.833333	8.233333	5
std	2.381596e+07	4.915446e+07	2.926378	10.127520	29.647372	0.382971	3
min	1.500000e+07	4.398423e+07	1.050000	1987.000000	118.000000	7.800000	7
25%	2.050000e+07	6.140399e+07	2.142668	1993.500000	134.250000	8.025000	5
50%	2.250000e+07	8.583359e+07	2.888717	1998.000000	149.000000	8.150000	6
75%	4.925000e+07	1.281149e+08	4.010976	2007.750000	174.250000	8.350000	7
max	7.200000e+07	1.707423e+08	9.253163	2013.000000	195.000000	8.900000	9

Biography Winners are not as profitable as the average winner, have a higher average score, more nominations (10) and a longer runtime, making it a less attractive type of film to make compared to a drama Winner.

In [123]:

```
winners[crime_winners].describe()
```

Out[123]:

	budget	gross	profitability	release_year	runtime	score	
count	4.000000e+00	4.000000e+00	4.000000	4.000000	4.000000	4.000000	4
mean	3.512500e+07	9.799779e+07	4.930114	2002.250000	125.750000	8.250000	7
std	3.738622e+07	3.959005e+07	3.246974	7.544314	17.327723	0.369685	2
min	6.500000e+06	5.458030e+07	1.470937	1991.000000	112.000000	7.800000	3
25%	1.587500e+07	6.935779e+07	2.596243	2001.500000	116.500000	8.025000	6
50%	2.200000e+07	1.025133e+08	4.926276	2005.500000	120.000000	8.300000	8
75%	4.125000e+07	1.311533e+08	7.260147	2006.250000	129.250000	8.525000	9
max	9.000000e+07	1.323843e+08	8.396969	2007.000000	151.000000	8.600000	9

Crime Winners have a lower budget, lower gross, lower profitability, shorter runtime, higher score, and lower average nomination count (6.5) than the average Winner.

MPAA Rating

In [124]:

```
#print respective modes
print(movies[['rating']].mode())
print(winners[['rating']].mode())
```

```
  rating
0      R
  rating
0      R
```

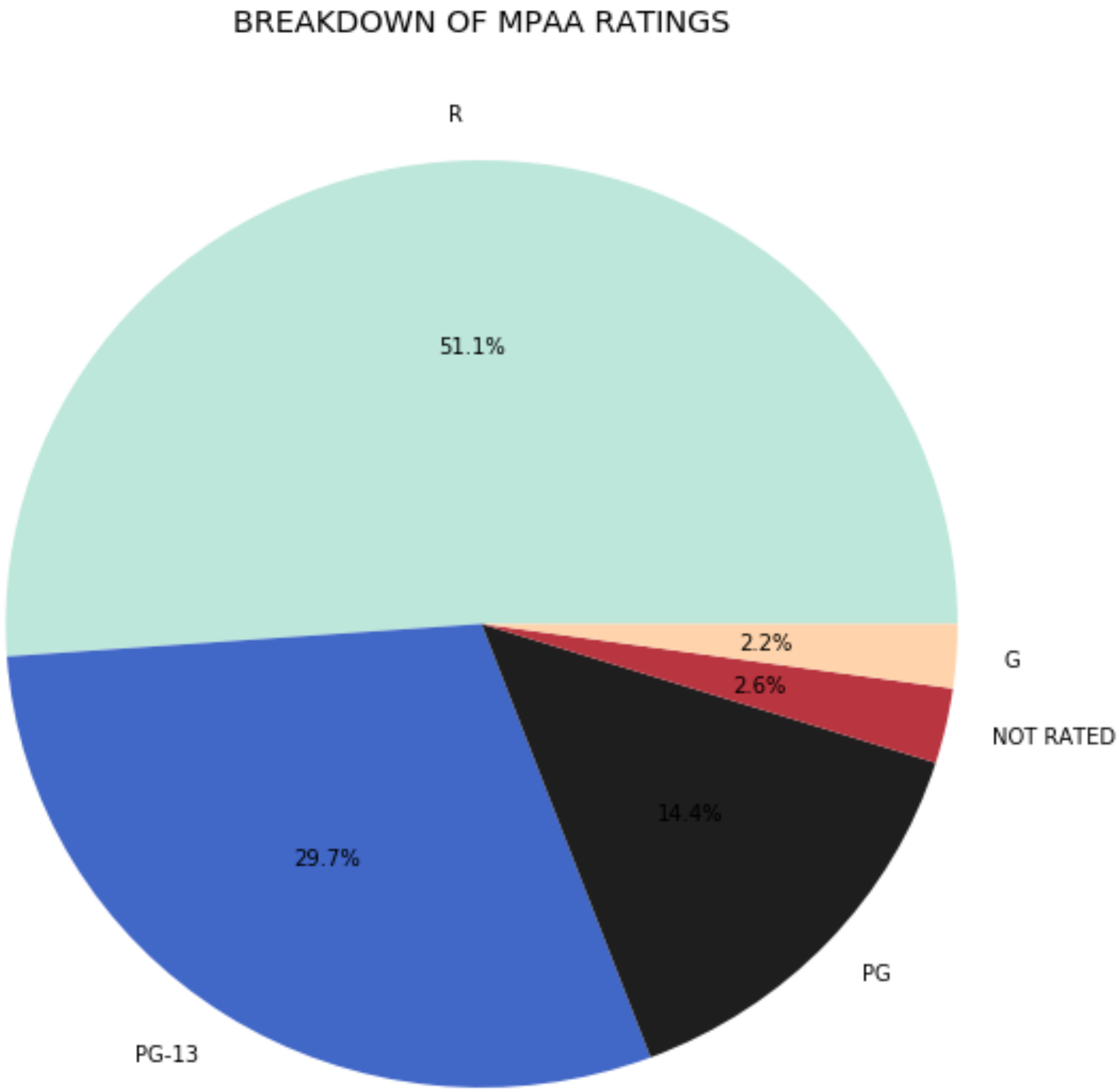
The most common MPAA rating for both the overall movie industry and Best Pictures is R. But let's see if we gather any more insights through analyzing their respective pie charts.

In [125]:

```
#create Movies MPAA rating pie chart with value counts
plt.style.use('ggplot')
movies.rating.value_counts()[:5].plot.pie(autopct='%1.1f%%',figsize=(10,10), cma
p = 'icefire')
plt.title('BREAKDOWN OF MPAA RATINGS')
plt.ylabel('')
movies["rating"].value_counts()
```

Out[125]:

```
R                3359
PG-13            1949
PG                945
NOT RATED         172
G                 146
UNRATED            71
Not specified      62
NC-17              22
TV-PG               1
B15                 1
B                   1
TV-14               1
TV-MA               1
Name: rating, dtype: int64
```

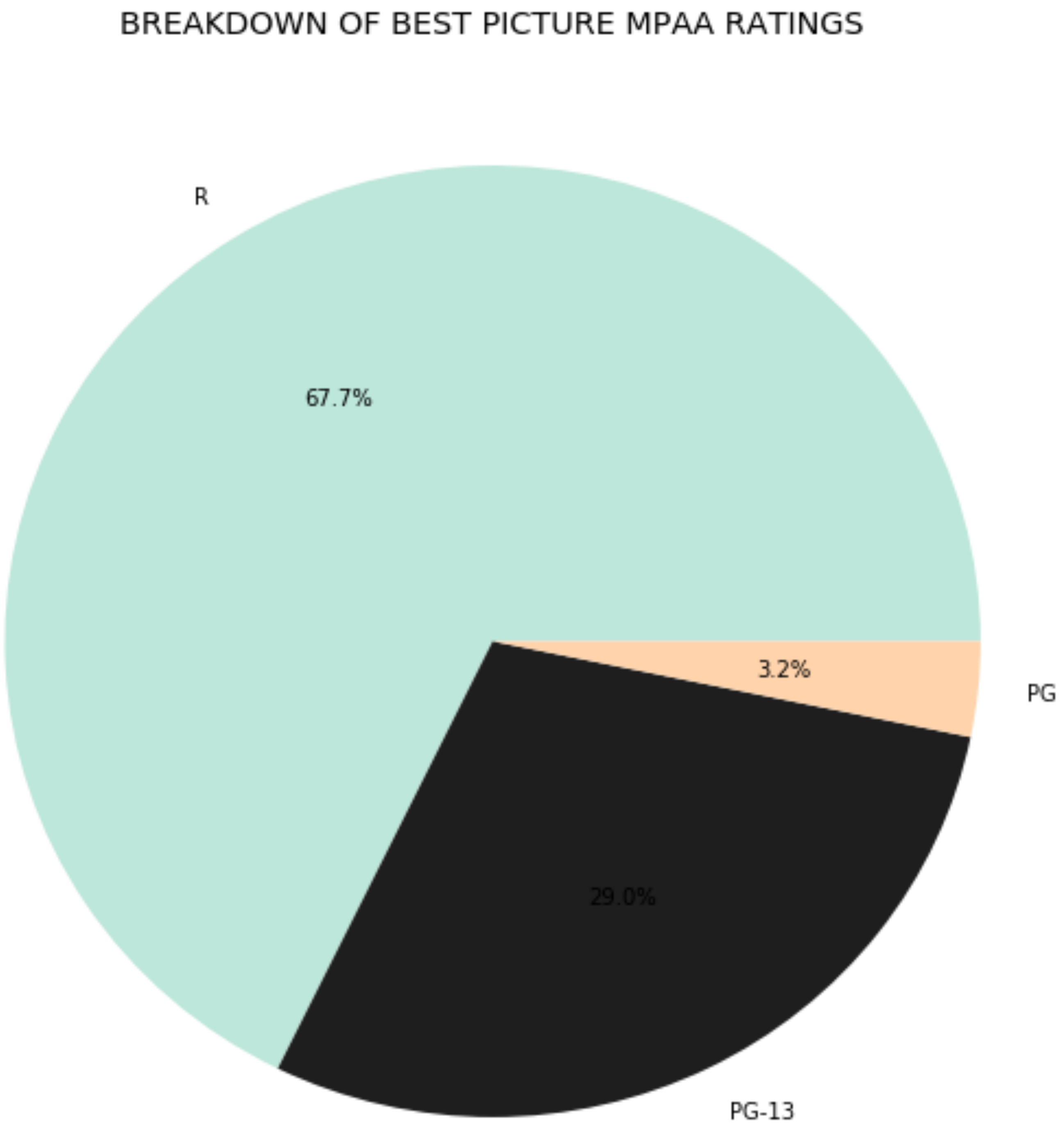


In [126]:

```
#create Winners MPAA rating pie chart with value counts
plt.style.use('ggplot')
winners.rating.value_counts()[:5].plot.pie(autopct='%1.1f%%',figsize=(10,10), cm
ap = 'icefire')
plt.title('BREAKDOWN OF BEST PICTURE MPAA RATINGS')
plt.ylabel("")
winners["rating"].value_counts()
```

Out[126]:

```
R        21
PG-13     9
PG        1
Name: rating, dtype: int64
```



The R rating is much more common in Best Pictures, as it makes up over 2/3 of Winners. Another interesting observation is that only 1 PG rated movie since 1986 has won Best Picture: *Driving Miss Daisy* (1990).

Other Interesting Characteristics

We have a couple other miscellaneous chacteristics that we thought were very interesting.

Character Length

We wanted to see whether there was a large difference between the length of the average Movie and the average Winner.

In [127]:

```
average_movie_charlength = np.average(movies['title'].astype(str).map(len).value
s)
average_winner_charlength = np.average(winners['name'].astype(str).map(len).valu
es)

print(average_movie_charlength)
print(average_winner_charlength)
```

```
15.047689793492795
14.193548387096774
```

It turns out the average character length of a Best Picture is a mere one character less than the average movie, so it looks like sticking to an average title length is a safe bet.

Country

Although the Academy Awards are based in the United States, we were curious to see how many non-American Oscar Best Pictures there have been since 1986.

In [128]:

```
winners['country'].value_counts()
```

Out[128]:

```
USA       26
UK         4
France     1
Name: country, dtype: int64
```

In [129]:

```
uk_winners=winners.loc[(winners["country"] == "UK")] #define new set that locate
s UK Winners
uk_winners
```

Out[129]:

	name	budget	company	country	director	genre	gross	is_
year								
1986	Platoon	6000000.0	Hemdale	UK	Oliver Stone	Drama	138530565.0	tru
1987	The Last Emperor	23000000.0	Recorded Picture Company (RPC)	UK	Bernardo Bertolucci	Biography	43984230.0	tru
2008	Slumdog Millionaire	15000000.0	Warner Bros.	UK	Danny Boyle	Drama	141319928.0	tru
2010	The King's Speech	15000000.0	See-Saw Films	UK	Tom Hooper	Biography	138797449.0	tru

In [130]:

```
french_winners=winners.loc[(winners["country"] == "France")] #define new set tha
t locates French Winners
french_winners
```

Out[130]:

	name	budget	company	country	director	genre	gross	is_winı
year								
2011	The Artist	15000000.0	Studio 37	France	Michel Hazanavicius	Comedy	44671682.0	true

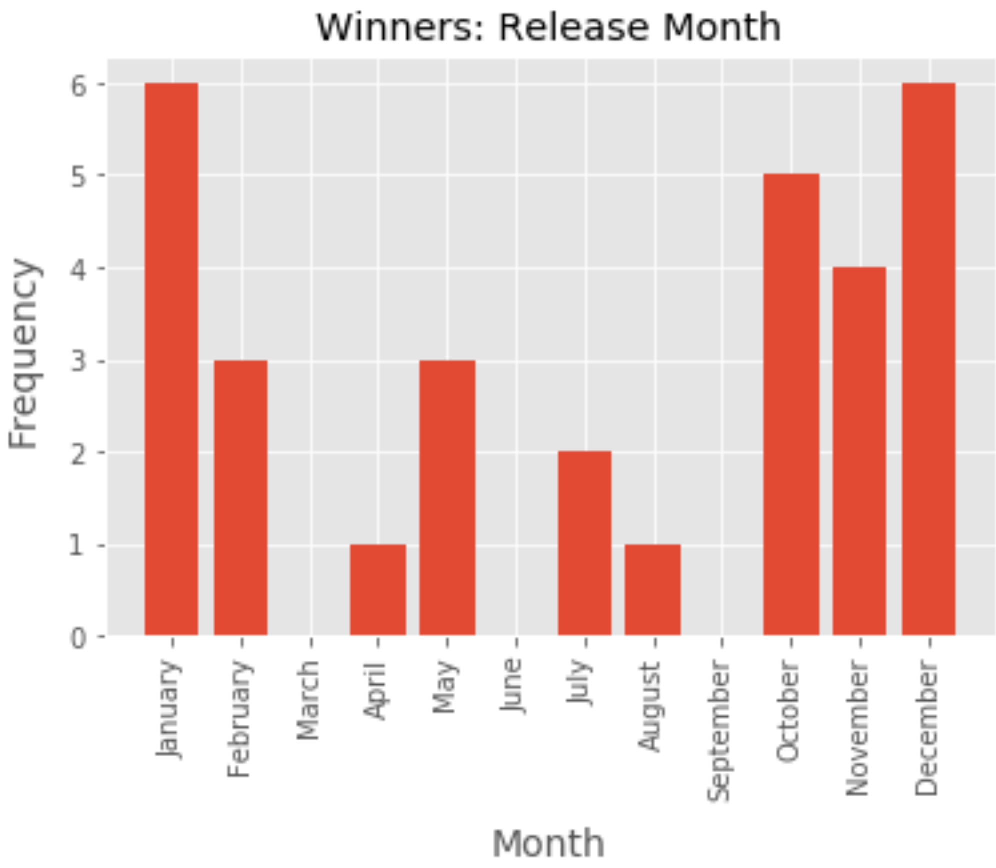
Only two other countries have made Oscar Best Pictures: the United Kingdom and France.
UK films include: *Platoon*, *The Last Emperor*, *Slumdog Millionaire*, and *The King's Speech*
French films include: *The Artist*

Best Picture Release Months

We decided to loop through the release dates of our Winners dataframe to plot the release month distribution of Best Pictures. We were curious whether there was a skew towards the end of the year for Best Picture releases.

In [131]:

```
plt.style.use('ggplot')

winners["released_month"] = winners["released"].str.slice(5,7).astype(int)#creat
e a new column released_month by splicing released
winner_release_dict = winners["released_month"].value_counts().sort_index().to_d
ict()#sort it and dictionary it

#array of months for readability
months = ["January", "February", "March", "April", "May", "June", "July", "Augus
t", "September", "October", "November", "December"]

#map numerical months to names
for i in range(len(months)):
  x = i+1
  if x in winner_release_dict.keys():
    winner_release_dict[months[i]] = winner_release_dict.pop(x)
  else:#add month for readability in graph even if it had no movies
    winner_release_dict[months[i]] = 0

#plot
plt.bar(range(len(winner_release_dict)), winner_release_dict.values(), align="ce
nter")
plt.xticks(range(len(winner_release_dict)), list(winner_release_dict.keys()))
plt.xticks(rotation=90)
plt.ylabel("Frequency", fontsize = 14, labelpad = 10)
plt.xlabel("Month", fontsize = 14, labelpad = 10)
plt.title('Winners: Release Month')
plt.show()
```



There is in fact a heavy skew towards the end of the year to release a Best Picture! 15 out of the last 31 Best Pictures were released in the last quarter of the year (Oct., Nov. , Dec.)! Surprisingly, 6 out of the last 31 Best Pictures were released in the very beginning of the year in January. Also, in the last 31 years, there has not been a single film released in March, June, or September that has won Best Picture.

Conclusion

As shown through our data analysis, there are *significant* differences between Movies and Winners. Now that we know exactly and to what extent these differences are, we can hypothesize a movie that will have a better chance of winning Best Picture. However, before we break it down, we would like to address the biases in our report.

Although the csv files were fairly extensive, the respective variables still limited us. And of course, we are limited to the data that we can find/ is released to the general public. There are still several other variables not present in the csv files (or perhaps not fully available at all) which would have helped further our analysis. These include: more Oscar nomination data, international/worldwide gross, marketing budgets, supporting actors/actresses, Metacritic scores, Rotten Tomatoes scores, Cinemascores, IMDB keywords, and themes.

Nonetheless, based on our analysis, we have decided on the specifics for our hypothetical movie to increase its chances of winning Best Picture:

Genre: We should make a Drama, as they are by far the most common genre for Best Picture (42%). Additionally, the fact that previous Drama Winners have had lower budgets, lower scores, fewer nominations, and higher profitability multiples and still won makes it the most logical genre for us to pursue.

Production Company: Warner Bros. should be the production company considering they have had the most success in producing Best Pictures (five out of the last 31, 16%).

Country: The film should be a U.S. film considering 87% of Best Pictures in the last 31 years have been U.S.-made.

Director: Since Clint Eastwood is the only director to have directed more than one Best Picture in the last 31 years, it could be argued that he should direct the film. However, given that he is 88 years old, it might be better to hire a trending director who has never directed a Best Picture.

Writer: We would consider hiring Paul Haggis to write the script. He is the writer of two Best Pictures: Crash and Million Dollar Baby. However, he also directed Crash. If not Paul Haggis, we would hire another Hollywood writer who has never written a Best Picture.

Star: We could hire either Russell Crowe or Leonardo DiCaprio because both are high-caliber actors and are the only people to star in more than one Best Picture.

MPAA Rating: We would want to make an R-rated film for two reasons. First, 21 out of the last 31 Best Pictures have been R-rated. Second, if our movie is rated R, then we wouldn't have to worry about toning down/filtering our content (e.g. violence, language, substance abuse, sexual content, etc.) compared to PG-13 and PG films.

Runtime: Our runtime should be relatively long. Although this would mean less showtimes in movie theaters per day, our primary goal is to win Best Picture, not to have the highest possible box office. Since our data shows that both audiences and the Academy prefer longer runtimes, any runtime around 2 hours and 17 minutes should do.

Score: If we want a chance of winning Best Picture, we need to have a high IMDB score. Our goal would be to have a score above 8.0. This is the average score of prior Best Pictures and is also slightly above the average score of prior Drama Best Pictures (7.9).

Vote Count: There is a strong correlation between Score and Number of Votes (0.83). Of course correlation does not mean causation, but nonetheless we feel we should try to get at least 500,000 votes to stick close to the Best Pictures votes average (558,000). Also, receiving hundreds of thousands of votes could lead to a lot of buzz, which could help convey a positive perception of our film.

Budget: Anything more than 25 million USD is good considering only one Best Picture (*Argo*) between 2008 and 2016 had a budget above 25 million USD. Dramas also do not require super high budgets compared to other genres such as action or adventure. Ultimately, a good budget will allow for more talent and resources, which will increase the overall likelihood of a better quality movie.

Domestic Gross: Winners typically gross significantly more than the average movie. However, recent Winners have not grossed nearly as much as the average Winner. Although box office is not the most important variable, we would still like to have a successful domestic gross around 150 million USD.

Profitability: The profitability (domestic gross/ budget) of the average Best Picture is 5.41. However, the average Drama Best Picture has a profitability of 7.05. As stated earlier, our desired budget is 25 million USD and our desired domestic gross is 150 million USD (which means profitability would = 6). We would like our profitability to be anywhere between 5.41 and 7.05.

Title Length: Since Best Pictures have similar title lengths as average Movies (14 chracters vs. 15 characters), we are not too concerned with this variable as long as our title is not extremely short or extremely long.

Release Month: We consider this a very important variable because of the large skew of Best Pictures being released towards the end of the year. Movies released around this time are closer to the actual Awards date (February of the following year) and therefore are fresher in viewers' minds. We would plan for a release during the peak holiday weekends of either October, November, or December.

While these analytics provide numerous insights into the movie industry, it's important to note that ultimately Best Picture in the eyes of viewers and the Academy is a considered a reflection of "quality." It is extremely difficult, if not impossible, to quantify the quality of a movie and the talent, skill, and overall subjectivity behind the perception of films.

It is also fascinating to see that the movie industry is changing radically right now, as it becomes more inclusive towards gender, race, and overall diversity. In fact, you could argue that given the political atmosphere of Hollywood, the Academy may even now have a bias towards these types of films (e.g., 2016 Winner: *Moonlight* and its themes of race and homosexuality; 2017 Winner: *The Shape of Water* and its themes of being an outsider or part of a minority). For example, we noted earlier in our analysis of directors, stars, and writers that women are almost non-existent in the value counts over the last 31 years. However, we expect that over the next few years, we will see more representation among women in Best Pictures. Perhaps, if we were to make a movie and try to increase its chances of winning Best Picture, we should also focus on diversity and strong social themes. But of course, this is a new trend and there is currently limited-to-no data to support this. Hopefully, in the coming years, if this trend continues, more data on these variables will be available, and one can create an even more accurate analysis of the key characteristics for winning Best Picture.

Note: While the two of us (as avid movie lovers) used general knoweledge of the movie industry, the information on the movie industry changing radically was validated in a personal interview we conducted with professional screenwriter, David Ransil.