Flatiron School Phase 1 Project

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- Blog post URL: https://medium.com/@angelo.turri/data-science-the-state-of-the-field-1f955c0e906b (https://medium.com/@angelo.turri/data-science-the-state-of-the-field-1f955c0e906b)

This Jupyter Notebook contains analyses of various movie-related datasets. The point the of these analyses is to produce three recommendations for fictional stakeholders at Microsoft, who are looking to get into the movie business.

After conducting initial EDA on these datasets, I have produced my three recommendations. I will divide this notebook into three sections: one focusing on budget, another focusing on genre, and one focusing on the type of cast and crew.

Importing packages & data

In [1]:
```
import patoolib
import os.path
import pandas as pd
import numpy as np
import math
from pandasql import sqldf
pysqldf = lambda q: sqldf(q, globals()) # So I don't have to call 'glo
bals()' every time
import sqlite3
from matplotlib import pyplot as plt
import seaborn as sns
%matplotlib inline
sns.set(style="whitegrid") # For aesthetic purposes
```

In [2]:
```
datafiles = ['zippedData/im.db.zip',
             'zippedData/tn.movie_budgets.csv.gz']

uncompressed = ['data/im.db',
                'data/tn.movie_budgets.csv']

for i in range(2):
    if os.path.isfile(uncompressed[i]):
        print("File already extracted.")
    else:
        patoolib.extract_archive(datafiles[i], outdir="data")
```

```
File already extracted.
File already extracted.
```

In [3]:
```
# Importing plain text-formatted data files
thenumbers = pd.read_csv("data/tn.movie_budgets.csv")

 # Connecting to the imdb SQLite database
conn = sqlite3.connect("data/im.db")

# Retreiving relevant tables from the imdb database
movie_basics = pd.read_sql(""" SELECT * FROM movie_basics """, conn)
persons = pd.read_sql(""" SELECT * FROM persons """, conn)
principals = pd.read_sql(""" SELECT * FROM principals """, conn)
```

Areas of Focus

Throughout this notebook, I will be focusing on three different areas of the movie industry. Each area will have its own section, where I will explain my methods and interpret my results. At the end of each section I will outline my recommendation.

- **Cast & Crew**: *which professions to prioritize*
- **Advertising**: *which areas to prioritize*
- **Genre**: *which ones to avoid and which ones are safe bets*

Measures of Success

It is important to define how I am measuring a movie's success going forward. I am using two statistics for this. These are *my own* metrics and, outside of common knowledge, I have not taken these ideas from anywhere else.

- ROI (return on investment, continuous variable)
  - Calculated as **the overall gross of a movie divided by its budget.**
  - A movie breaks even if its ROI is 100% – this means it made just as much as it put in.
  - A movie is profitable if ROI > 100%, and unprofitable if ROI < 100%.
  - If a movie's ROI is 450%, it made 4.5x as much as it spent.

- Profitable (boolean variable)
  - Equals True or 1 if ROI > 100%
  - Equals False or 0 if ROI <= 100%

These metrics can also be used to help evaluate a person's success in the movie industry.

- Average ROI
  - The average ROI of all the movies a person has participated in
  - If a person's average ROI is 258%, the movies they're in have made, on average, 2.58x more than they're spent.
- Hitrate
  - The average value of the Profitable boolean across all movies a person has participated in.
  - If a person's hitrate is 67%, then 67% of the movies they're in have been profitable.

Advertising – Data Selection

Among our datasets, there is only one with good budget data: **thenumbers** and **boxofficemojo**, of which the first has far more data points. Ideally, we want as many data points as possible to analyze. So, for this section, we will be analyzing **thenumbers** dataset.

In [4]:
```
advertisingdf = thenumbers.copy()
advertisingdf.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5782 entries, 0 to 5781
Data columns (total 6 columns):
 #   Column             Non-Null Count  Dtype 
---  ------             --------------  ----- 
 0   id                 5782 non-null   int64 
 1   release_date       5782 non-null   object
 2   movie              5782 non-null   object
 3   production_budget  5782 non-null   object
 4   domestic_gross     5782 non-null   object
 5   worldwide_gross    5782 non-null   object
dtypes: int64(1), object(5)
memory usage: 271.2+ KB
```

In [5]:
```
# Giving some columns simpler names
advertisingdf.rename(columns={'production_budget': 'budget', 'release_date': 'date'}, inplace=True)
```

In [6]:
```
advertisingdf.head(1)
```

Out[6]:

	id	date	movie	budget	domestic_gross	worldwide_gross
0	1	Dec 18, 2009	Avatar	$425,000,000	$760,507,625	$2,776,345,279

Advertising – Data Prep & Cleaning

Looking at the data above, we see there are no null values, which is a good thing. For the data to be in a suitable format for analysis, several things still need to be done.

- The production budget, domestic gross, worldwide gross, and release date columns need to be re-formatted as integers.
- We need to create foreign gross, ROI, profitable, and ROI-tier columns.
- We need to remove outliers from out dataset to avoid making unwarranted conclusions.

Converting data columns to integer types

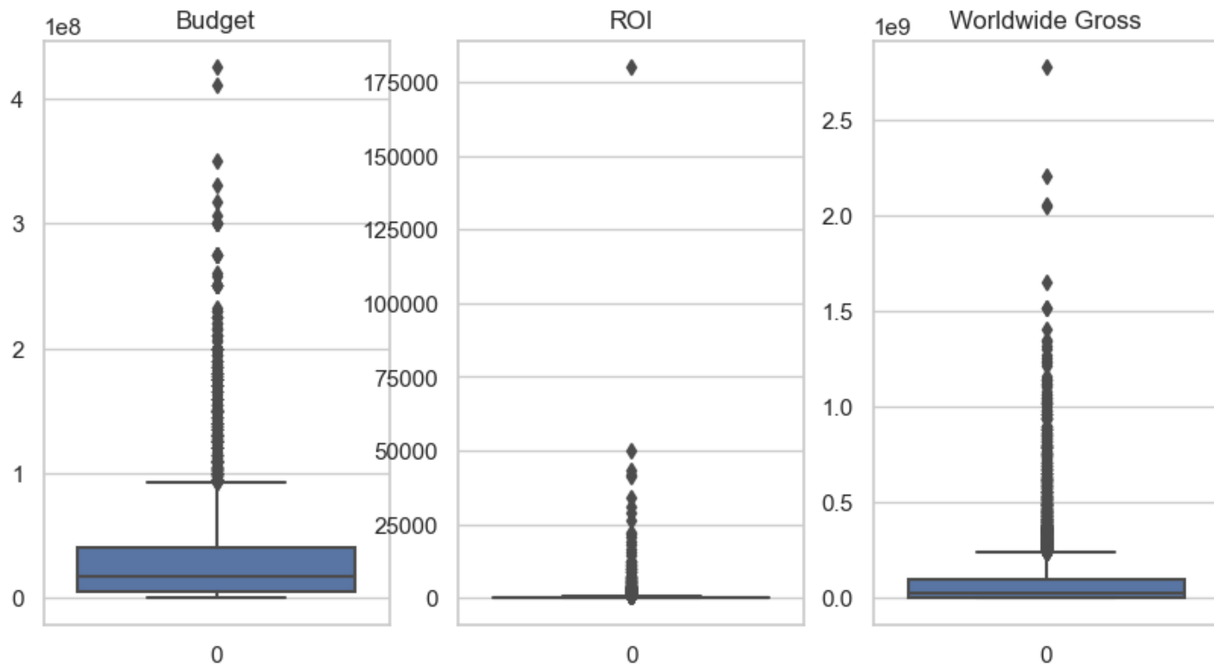
In [7]:
```
def money_to_int(x):
    """
    This function turns a money-formatted string with commas
    into an integer.
    """
    x = x[1:] #Eliminating the dollar sign

    #Removing the commas
    split = x.split(",")
    joined = "".join(split)

    #Turns the resulting string into an integer
    integer = int(joined)
    return integer

# Using our function to re-format three columns
to_convert = ['budget', 'domestic_gross', 'worldwide_gross']

for x in to_convert:
    advertisingdf[x] = advertisingdf[x].map(lambda x: money_to_int(x))

# Re-formatting the date column
advertisingdf['date'] = advertisingdf['date'].map(lambda x: int(x[-4:]
))
```

Creating foreign gross, profitable, and ROI columns

In [8]:
```
ROI = advertisingdf['worldwide_gross'] / advertisingdf['budget']
ROI = round(ROI*100, 2)
advertisingdf['ROI'] = ROI

advertisingdf['foreign_gross'] = advertisingdf['worldwide_gross'] - ad
vertisingdf['domestic_gross']
advertisingdf['profitable'] = advertisingdf['ROI'].map(lambda x: True
if x>100 else False)
```

Looking at the spread of our data

In [9]:
```
fig, ax = plt.subplots(1, 3, figsize=(10,5))

sns.boxplot(advertisingdf['budget'], ax=ax[0])
sns.boxplot(advertisingdf['ROI'], ax=ax[1])
sns.boxplot(advertisingdf['worldwide_gross'], ax=ax[2])

ax[0].set_title('Budget')
ax[1].set_title('ROI')
ax[2].set_title('Worldwide Gross');
```



Eliminating outliers in budget, ROI, and worldwide gross columns

As you can see in the above boxplots, there are many outliers in the budget, ROI, and gross columns. The presence of such outliers can skew our results and lead to unwarranted conclusions and/or recommendations. I am going to remove these outliers using the same method a boxplot uses to find them.

Any value more than the 75th percentile + the IQR is eliminated. Any value less than the 25th percentile - the IQR is also eliminated. The IQR is the distance between the 75th and 25th percentile.

In [10]:
```
def is_outlier(x, df):
    """
    This function takes a value and its associated
    group of values as its arguments. It determines whether
    or not the value is an outlier in its dataset; if it is,
    it returns a null value. If not, it returns the original value.
    """

    q1, q3 = df.quantile([.25, .75])
    iqr = q3-q1

    lower_limit = q1 - (iqr*1.5)
    upper_limit = q3 + (iqr*1.5)

    if any([(x<lower_limit), (x>upper_limit)]):
        return np.nan
    else:
        return x
```

In [11]:
```
# Number of rows pre-cleaning
print("The previous dataframe had {} rows.\n".format(advertisingdf.sha
pe[0]))

to_clean = [
    'budget',
    'ROI',
    'worldwide_gross']

for i in to_clean:
    advertisingdf[i] = advertisingdf[i].map(lambda x: is_outlier(x, ad
vertisingdf[i]))


# This shows us how many 'outliers' are in each column.
for i in to_clean:
    print(advertisingdf[i].isnull().value_counts())

advertisingdf.dropna(inplace=True)

# Resetting the index
advertisingdf = advertisingdf.reset_index(drop=True)


# Number of rows post-cleaning
print("\nThe current dataframe has {} rows.".format(advertisingdf.shap
e[0]))
```

```
The previous dataframe had 5782 rows.

False    5351
True      431
Name: budget, dtype: int64
False    5287
True      495
Name: ROI, dtype: int64
False    5178
True      604
Name: worldwide_gross, dtype: int64

The current dataframe has 4695 rows.
```

Creating the ROI-tier column

This categorizes a movie based on its ROI.

In [12]:
```
# The number of bins we split ROI into
num_bins = 15

# Creating the endpoints for our ranges
ROI_range = np.linspace(0,
                        1000,
                        num_bins, dtype=int)

# Creating neatly formatted strings for our ranges
ROIstrings = [str(round(i,1)) + ' percent' for i in ROI_range]
ROIranges = ["{} – {}".format(ROIstrings[i], ROIstrings[i+1]) for i in range(len(ROIstrings)-1)]

# Creating the budget category column for our dataframe
ROItier = pd.cut(advertisingdf['ROI'], bins=ROI_range, labels=ROIranges)
advertisingdf['ROItier'] = ROItier
```

Creating the budget-tier column

This categorizes a movie based on its budget.

In [13]:
```
# The number of bins we split budget into
num_bins = 10

# Creating the endpoints for our ranges
budget_range = np.linspace(0,
                           advertisingdf['budget'].max(),
                           num_bins, dtype=int)

# Creating neatly formatted strings for our ranges
tierstrings = [str(round(i/1000000, 1)) + ' million' for i in budget_range]
tierranges = ["{} – {}".format(tierstrings[i], tierstrings[i+1]) for i in range(len(tierstrings)-1)]

# Creating the budget category column for our dataframe
money_range = pd.cut(advertisingdf['budget'], bins=budget_range, labels=tierranges)
advertisingdf['budget_category'] = money_range.astype(object)
```

Re-ordering columns

In [14]:
```
advertisingdf = advertisingdf[['id', 'date', 'movie', 'budget', 'budge
t_category',
                               'domestic_gross', 'foreign_gross',
                               'worldwide_gross', 'ROI', 'ROItier',
                               'profitable']]
advertisingdf.head(1)
```

Out[14]:

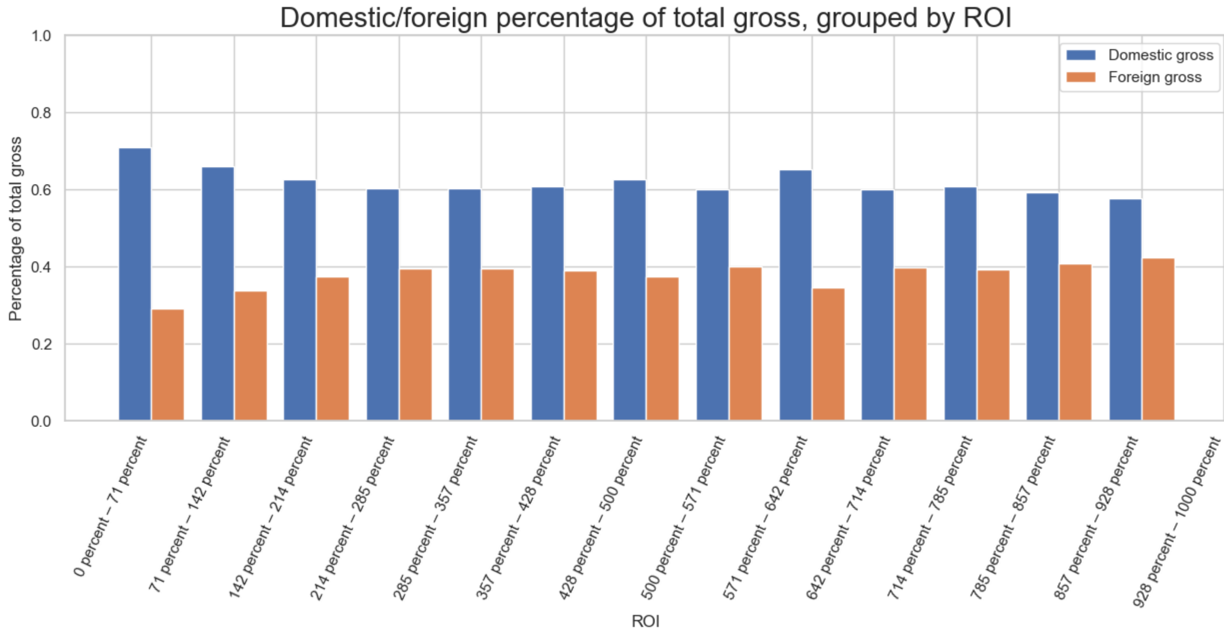
	id	date	movie	budget	budget_category	domestic_gross	foreign_gross	worldwi
0	32	2008	The Spiderwick Chronicles	92500000.0	82.2 million – 92.5 million	71195053	91644614	162

Advertising – Question and Analysis

Our question for this section is: which areas of advertising should be prioritized? There are two such areas to compare – domestic advertising and foreign advertising. I will create three visualizations in this section:

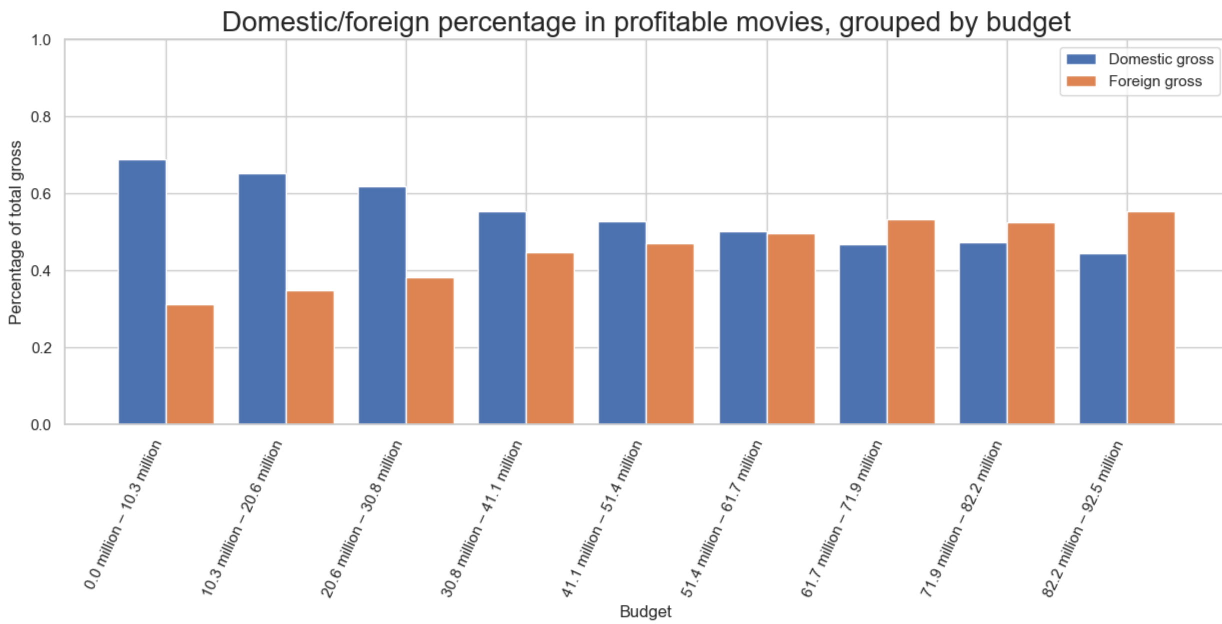
- Comparing the domestic and foreign percentage of total gross for movies of different levels of success
- Comparing the comestic and foreign percentage of total gross for movies with different budgets
  - Do this for both profitable and unprofitable movies

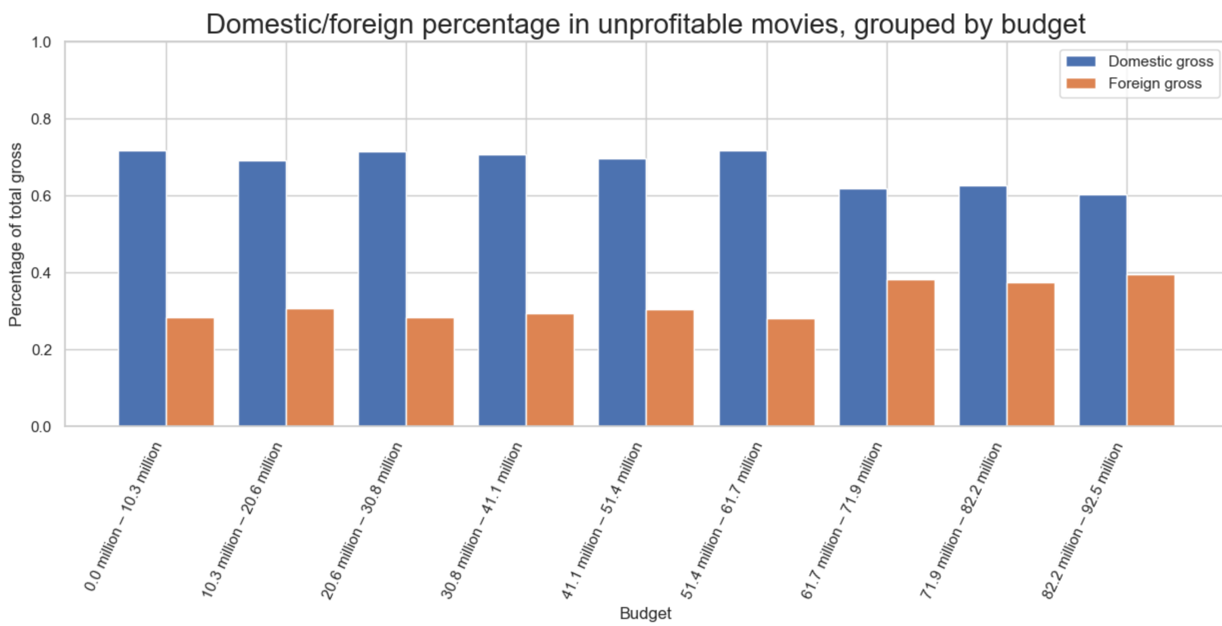
In [15]:
```
fig, ax = plt.subplots(figsize=(15,5))

x = ROIranges # the clearly formatted string for all ROI tiers
domestic_percentage_means = [] # domestic gross percentage of total gr
oss per ROI tier
foreign_percentage_means = [] # foreign gross percentage of total gros
s per ROI tier

for i in ROIranges:
    df = advertisingdf[advertisingdf.ROItier == i]

    try:
        domestic_percentage = df['domestic_gross'] / df['worldwide_gro
ss']
        foreign_percentage = df['foreign_gross'] / df['worldwide_gross
']

        domestic_percentage_means.append(domestic_percentage.mean())
        foreign_percentage_means.append(foreign_percentage.mean())
    except:
        continue

x_axis = np.arange(len(x))
barplot1 = ax.bar(x_axis-0.2, domestic_percentage_means,0.4, label='Do
mestic gross')
barplot2 = ax.bar(x_axis+0.2, foreign_percentage_means,0.4, label='For
eign gross')

ax.set_xticks(x_axis, x, rotation=65, horizontalalignment='right')
ax.set_xlabel("ROI")
ax.set_ylabel("Percentage of total gross")

ax.set_ylim(0,1)

ax.legend(loc='upper right')
ax.set_title("Domestic/foreign percentage of total gross, grouped by R
OI", fontsize=20);
```



In [16]:
```
# Two datasets for use in the visualizations below
unprofitable = advertisingdf[advertisingdf.profitable==False] # All un
profitable movies
profitable = advertisingdf[advertisingdf.profitable==True] # All profi
table movies

datasets = [(profitable, 'profitable'), (unprofitable, 'unprofitable')
]
```

In [17]:
```python
for dataset in datasets:

    fig, ax = plt.subplots(figsize=(15,5))

    x = tierranges # the clearly formatted string for all ROI tiers
    domestic_percentage_means = [] # domestic gross percentage of total gross per ROI tier
    foreign_percentage_means = [] # foreign gross percentage of total gross per ROI tier

    for i in x:
        df = dataset[0][dataset[0].budget_category == i]

        try:
            domestic_percentage = df['domestic_gross'] / df['worldwide_gross']
            foreign_percentage = df['foreign_gross'] / df['worldwide_gross']

            domestic_percentage_means.append(domestic_percentage.mean())
            foreign_percentage_means.append(foreign_percentage.mean())
        except:
            continue

    x_axis = np.arange(len(x))
    barplot1 = ax.bar(x_axis-0.2, domestic_percentage_means,0.4, label='Domestic gross')
    barplot2 = ax.bar(x_axis+0.2, foreign_percentage_means,0.4, label='Foreign gross')

    ax.set_xticks(x_axis, x, rotation=65, horizontalalignment='right')
    ax.set_xlabel("Budget")
    ax.set_ylabel("Percentage of total gross")

    ax.set_ylim(0,1)

    ax.legend(loc='upper right')
    ax.set_title(f"Domestic/foreign percentage in {dataset[1]} movies, grouped by budget", fontsize=20);
```





Advertising – Recommendation

- Place a heavier emphasis on domestic rather than foreign advertising; it's a common theme among films of all different levels of success
- At the same time do not neglect foreign advertising; more successful films place a slightly heavier emphasis on foreign advertising, as do films with higher budgets.

This recommendation helps Microsoft because it helps them allocate their resources wisely, which is a good practice for anyone.

Genre – Data Collecting & Cleaning

Our biggest and best set of genre data comes from the im.db dataset. However, this dataset does not contain budget or gross information; if we want to measure the effects of genre on ROI or profitability, we will have to join several tables.

In [18]:
```
q = """
SELECT movie_basics.movie_id,
       advertisingdf.date,
       movie_basics.genres,
       advertisingdf.movie,
       advertisingdf.budget,
       advertisingdf.ROI,
       advertisingdf.profitable

FROM advertisingdf
JOIN movie_basics
    ON movie = primary_title
"""

genredf = pysqldf(q)
genredf.head(1)
```

Out[18]:

	movie_id	date	genres	movie	budget	ROI	profitable
0	tt0359950	2013	Adventure,Comedy,Drama	The Secret Life of Walter Mitty	91000000.0	206.44	1

Eliminating Duplicates

In [19]:
```
genredf.movie_id.value_counts().value_counts() # There are many duplic
ate entries
```

Out[19]:
```
1    2902
2      84
Name: movie_id, dtype: int64
```

In [20]:
```
genredf.movie_id.value_counts().head(2)
```

Out[20]:
```
tt1321509    2
tt4463894    2
Name: movie_id, dtype: int64
```

In [21]:
```
genredf[genredf.movie_id == 'tt3555036']
```

Out[21]:

	movie_id	date	genres	movie	budget	ROI	profitable
1005	tt3555036	1986	Action,Drama	Legend	25000000.0	94.02	0
1042	tt3555036	2015	Action,Drama	Legend	25000000.0	169.70	1

In [22]:
```
genredf[genredf.movie_id == 'tt2467046']
```

Out[22]:

	movie_id	date	genres	movie	budget	ROI	profitable
1286	tt2467046	2001	Action,Drama,Fantasy	Left Behind	18500000.0	22.82	0
1405	tt2467046	2014	Action,Drama,Fantasy	Left Behind	16000000.0	129.81	1

It looks like the 'duplicate' entries contain conflicting data. It's clear we have to remove them.

In [23]:
```
q = """
SELECT * FROM genredf
WHERE movie_id NOT IN (SELECT movie_id
                       FROM genredf
                       GROUP BY movie_id
                       HAVING COUNT(*)>=2)
"""

genredf = pysqldf(q)
```

In [24]:
```
genredf.movie_id.value_counts().value_counts() # The duplicate entries are now gone
```

Out[24]:
```
1    2902
Name: movie_id, dtype: int64
```

Genre – Correlation with profitability

The most obvious question to ask is: which genres correlate most highly with success? To answer, we need to extract a list of all the genres available in our dataset. Once we do, we need to create a boolean column for each genre whose value is 1 if a movie is in that genre and 0 if not.

Those columns will be used to create a boolean table that is used to create a correlation matrix, which will be used to create a heatmap with the seaborn package. This heatmap will provide an easy visual method of identifying strong/weak correlations.

You might ask why we are selecting our boolean 'profitable' variable to correlate with genre choice. The other measure of success we have, ROI, is a continuous variable, and I am not sure of how to correlate a boolean variable (genre) with a continuous variable (ROI).

In [25]:
```
# Extracting list of unique genres

genres = (list(genredf['genres'].unique()))
genres.remove(None) # Removing Nonetypes from the list
genres = ",".join(genres)
genres = genres.split(",")
genres = sorted(list(set(genres)))

genres
```

Out[25]:
```
['Action',
 'Adventure',
 'Animation',
 'Biography',
 'Comedy',
 'Crime',
 'Documentary',
 'Drama',
 'Family',
 'Fantasy',
 'History',
 'Horror',
 'Music',
 'Musical',
 'Mystery',
 'News',
 'Reality-TV',
 'Romance',
 'Sci-Fi',
 'Sport',
 'Thriller',
 'War',
 'Western']
```

In [26]:
```
# Eliminating null values from genres column
genredf['genres'] = genredf['genres'].map(lambda x: 'None' if not x else x)
```

Creating boolean dataframe for genres

In [27]:
```
genrebooldf = pd.DataFrame()

# Populating boolean dataframe
for i in genres:
    genrebooldf["is_"+i] = genredf['genres'].map(lambda x: True if i in x else False)

# Adding profitable column to boolean dataframe
genrebooldf['profitable'] = genredf['profitable']

# Adding ROI column to boolean dataframe
genrebooldf['ROI'] = genredf['ROI']
```

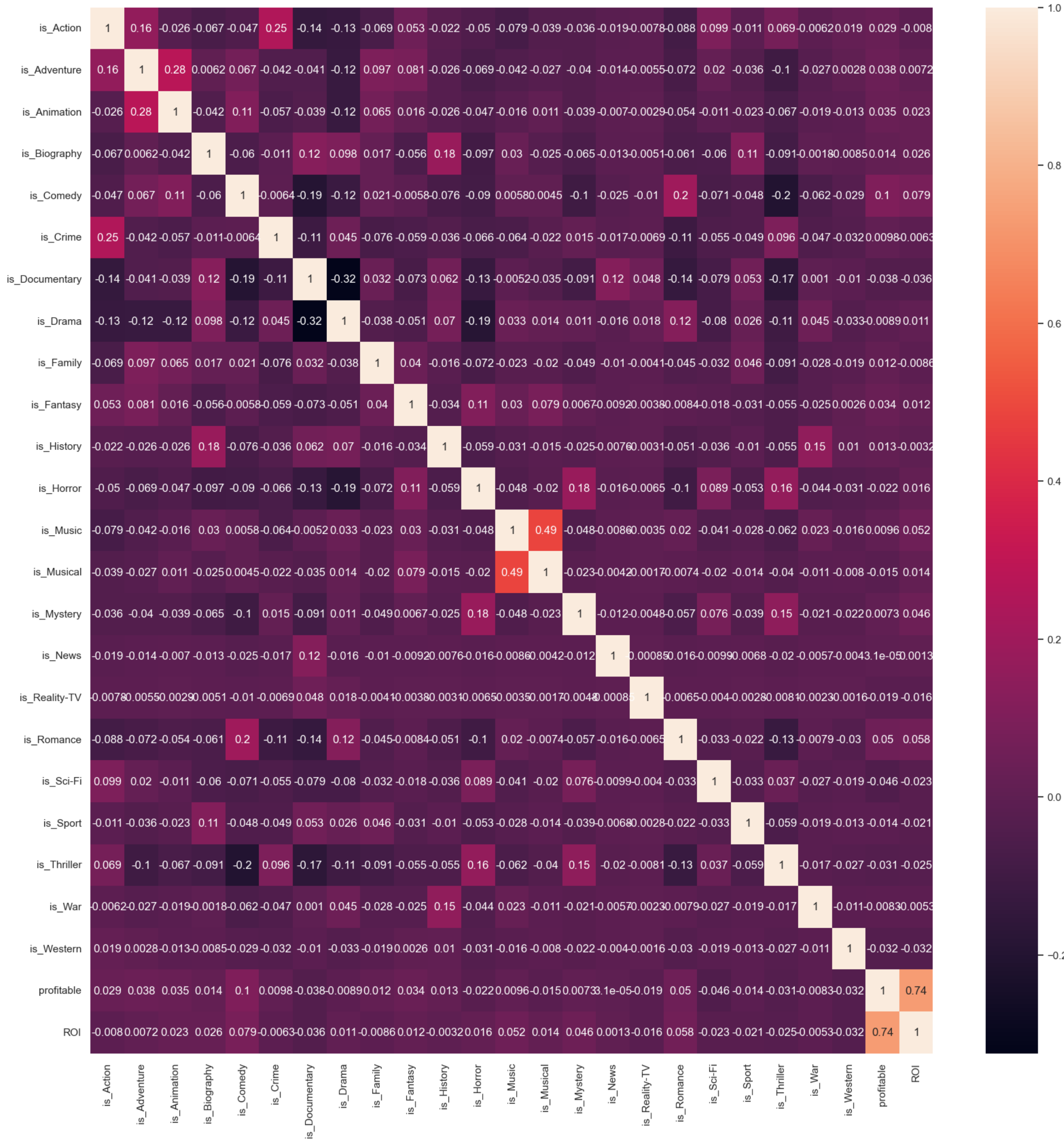
In [28]:
```
genrebooldf
```

Out[28]:

	is_Action	is_Adventure	is_Animation	is_Biography	is_Comedy	is_Crime	is_Documenta
0	False	True	False	False	True	False	Fal
1	False	False	False	False	False	False	Tr
2	False	False	False	False	False	False	Tr
3	True	True	False	False	False	False	Fal
4	False	False	False	False	True	False	Fal
...	...	...	...	...	...	...	
2897	False	False	False	False	False	False	Fal
2898	False	False	False	False	False	False	Fal
2899	False	False	False	False	True	False	Fal
2900	False	False	False	False	False	False	Fal
2901	False	False	False	False	False	False	Fal

2902 rows × 25 columns

In [29]:
```
fig, ax = plt.subplots(figsize=(20,20))
sns.heatmap(genrebooldf.corr(), ax=ax, annot=True);
```



Conclusion

The correlations we have from this analysis are so weak that they can't inform any recommendations.

Genre - Average ROI and rate of profitabilty by genre

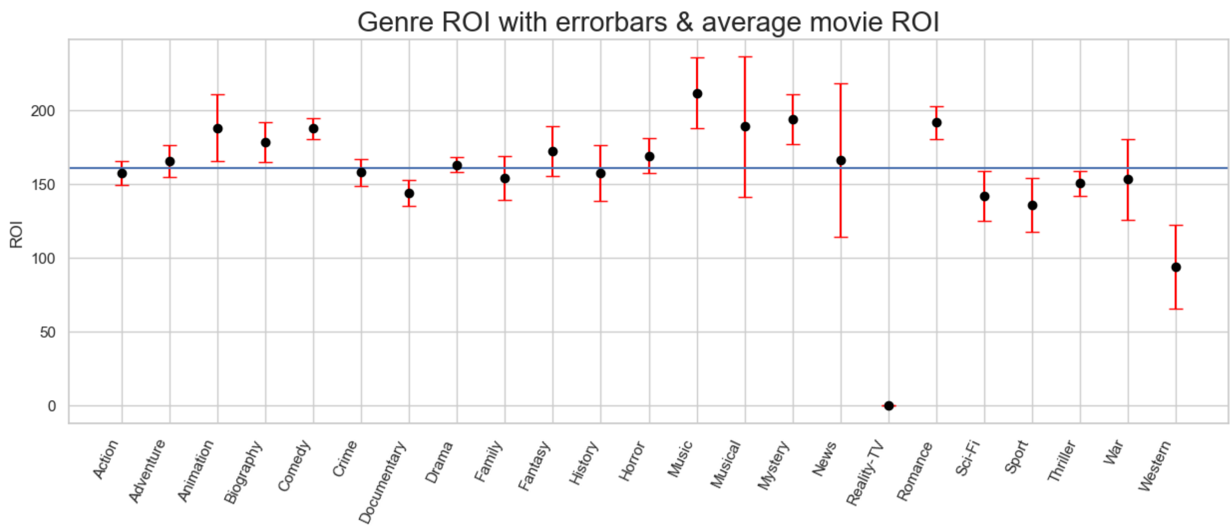
We should approach this differently. What if we measured the average hitrate (rate of profitability) and ROI for movies with a specific genre, and compared all the genres side by side? The two visualizations in this section will answer this question.

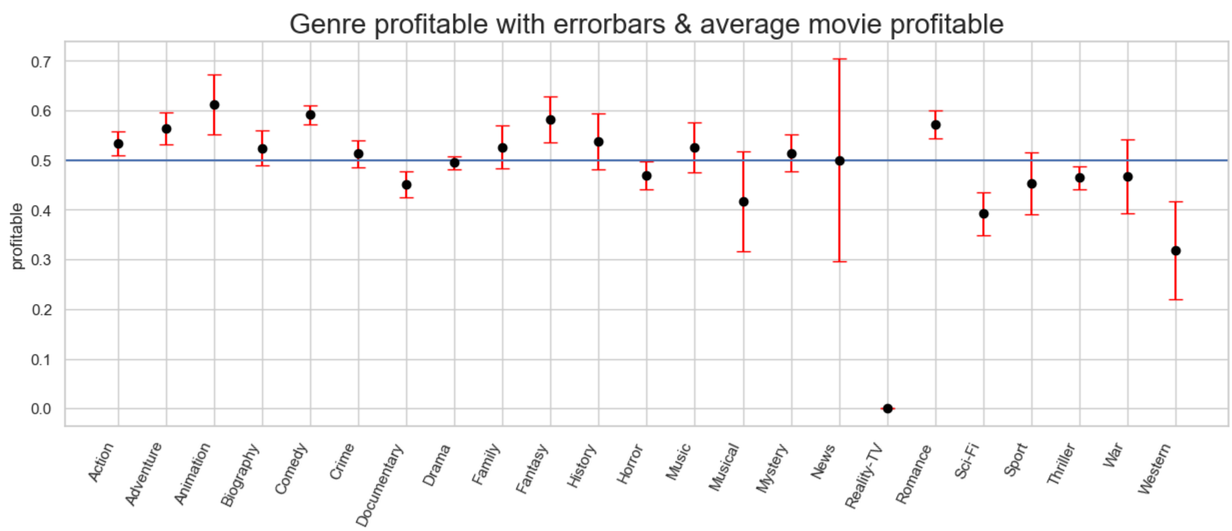
I am also going to calculate error bars with the standard error (standard deviation of sample divided by sample size).

In [30]:
```
attributes = ['ROI', 'profitable']
```

In [31]:
```
for attribute in attributes:

    # This list will contain:
    # average attribute with the genre and the std/sample sizes necess
ary
    # to calculate the standard errors for all three of those.
    genre_attributes=[]

    # Average attribute here
    average = genrebooldf[attribute].mean() # Average attribute across
whole dataset

    for i in range(len(genres)):

        genre = genres[i]
        colname = "is_" + genre

        on = genrebooldf[(genrebooldf[colname]==1)][attribute].mean()
# Attribute with genre

        std = (np.std(genrebooldf[(genrebooldf[colname]==1)])[attribut
e])

        sample_size = len(genrebooldf[(genrebooldf[colname]==1)])

        root = math.sqrt(sample_size)

        # Appending to main list
        genre_attributes.append([on, std, root])


    fig, ax = plt.subplots(figsize=(15,5))
```

```
    ax.set_title(f"Genre {attribute} with errorbars & average movie {a
ttribute}", fontsize=20)

    x = genres
    y = [i[0] for i in genre_attributes]

    errorbars = []

    for i in range(len(genre_attributes)):
        std = genre_attributes[i][1]
        root = genre_attributes[i][2]
        errorbar = std/root
        errorbars.append(errorbar)


    plt.errorbar(x,y, yerr=errorbars, fmt='o', color='black', ecolor='
red', capsize=5)

    plt.xticks(rotation=65, horizontalalignment='right')

    plt.ylabel(attribute)

    ax.axhline(average, xmin=0, xmax=250);
```


Genre ROI with errorbars & average movie ROI
ROI
200
150
100
50
0
Action
Adventure
Animation
Biography
Comedy
Crime
Documentary
Drama
Family
Fantasy
History
Horror
Music
Musical
Mystery
News
Reality-TV
Romance
Sci-Fi
Sport
Thriller
War
Western


Genre profitable with errorbars & average movie profitable
profitable
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
Action
Adventure
Animation
Biography
Comedy
Crime
Documentary
Drama
Family
Fantasy
History
Horror
Music
Musical
Mystery
News
Reality-TV
Romance
Sci-Fi
Sport
Thriller
War
Western

Genre – Recommendation

- Avoid (do not use if possible):
  - Documentary
  - Reality TV
  - Sci-Fi
  - Sport
  - Thriller
  - Western
  - News
- Safe bets (use these if possible):
  - Comedy
  - Fantasy
  - Romance
- Average (the recommendation does not say to avoid or use these):
  - Action
  - Adventure
  - Biography
  - Crime
  - Drama
  - Family
  - History
  - Horror
  - Music
  - Musical
  - Mystery
  - War

This recommendation helps Microsoft because it prevents them from making financially unwise decisions, which is a good practice for anybody.

Cast – Data Collection & Cleaning

Look at the principals dataset below. It lists the entire cast for each movie, with details on their job in the movie and characters they play (if applicable). The dataset for this section should have similar data, with some added/re-arranged columns:

- person_id (from principals)
- primary_name (from persons)
- profession (from principals)
- movie_id (from our dataset in the last section)
- year (from our dataset in the last section)
- ROI (from our dataset in the last section)
- profitable (from our dataset in the last section)

We can eliminate the following columns, as they are no longer needed for analysis:

- runtime
- budget
- budget category
- all gross columns

In [32]:

```
principals.head(1)
```

Out[32]:

	movie_id	ordering	person_id	category	job	characters
0	tt0111414	1	nm0246005	actor	None	["The Man"]

In [33]:
```
q = """
SELECT person_id,
       primary_name AS name,
       category AS profession,
       movie_id,
       date AS year,
       ROI,
       profitable AS hitrate

FROM genredf
JOIN principals
    USING(movie_id)
JOIN persons
    USING(person_id)
"""

castdf = pysqldf(q)
```

In [34]:
```
castdf.head(1)
```

Out[34]:

	person_id	name	profession	movie_id	year	ROI	hitrate
0	nm0001774	Ben Stiller	actor	tt0359950	2013	206.44	1

Cast – Choice of Profession

For the questions in this section, we will focus on the following professions:

- Actors
- Actresses
- Directors
- Producers
- Writers

As you can see from the list below, we are choosing to ignore the following professions:

- Composers
- Editors
- 'Self' (?)
- Cinematographers
- Production designers
- Archive_footage

In [35]:
```
professions = list(castdf['profession'].unique())
professions
```

Out[35]:
```
['actor',
 'writer',
 'producer',
 'composer',
 'actress',
 'director',
 'editor',
 'self',
 'cinematographer',
 'production_designer',
 'archive_footage']
```

In [36]:
```
# Updating professions list
professions = ['actor', 'actress', 'director', 'producer', 'writer']
```

Cast – Predictive Questions

In this section, we will find out the impact each profession has on a movie's success. We can approach this in four different ways:

- Impact of profession's ROI on movie's ROI
- Impact of profession's ROI on movie's hitrate
- Impact of profession's hitrate on movie's ROI
- Impact of profession's hitrate on movie's hitrate

Each of these questions is a predictive question, and cannot be done with a single dataset. In order to answer any of these, we will have to **split** our dataset into two parts, along a particular year. We will then find out how well a variable in the first dataset correlates with a variable in the second dataset. This can give us at least some idea of any underlying causal relationships.

The idea is: if you were to select people in a profession based on one of their attributes, and make a movie with these people, what are the chances of your movie succeeding? Splitting our dataset down a year and comparing values is as close as we can come to answering this question.

In [37]:
```
years = sorted(castdf.year.unique())
len(years)
```

Out[37]:
```
61
```

That's a lot of years!

When you split down a year, you want to make sure of two things:

- You maximized the number of people in common between the two datasets (even if you have 5000 people in one and 5000 in the second, what good does that do if none of the people from the first are in the second?)
- The characteristics of the people in common do not differ wildly between the two datasets.

In [38]:
```
attributes = ('ROI', 'hitrate')

for year in years:

    differences = []

    before = castdf[castdf.year <= year].copy() # All data before or d
uring that year
    after = castdf[castdf.year > year].copy() # All data after that ye
ar


    # Getting the list of people in common
    intersection = set(before.person_id.unique()).intersection(set(aft
er.person_id.unique()))
    len(intersection)


    # Reducing each dataset to only include people from the intersecti
on
    before = before[before.person_id.isin(intersection)]
    after = after[after.person_id.isin(intersection)]

    for a in attributes:
        for i in professions:
            mean1 = before[before.profession==i][a].mean()
            mean2 = after[after.profession==i][a].mean()
            difference = abs(mean1 - mean2)
            average = np.mean([mean1, mean2], dtype=float)
            percentage = (difference/average)*100

            differences.append(percentage)

    average_difference = np.mean(differences)

    print(
        str(year) + " - intersection: ",
        len(intersection), # Number of unique people in common between
datasets
        " ||  ",
        "average percentage difference: ",
        average_difference
    )
```

```
1927 - intersection:  1  ||   average percentage difference:  nan
1931 - intersection:  2  ||   average percentage difference:  nan
1940 - intersection:  2  ||   average percentage difference:  nan
1944 - intersection:  5  ||   average percentage difference:  nan
1945 - intersection:  7  ||   average percentage difference:  nan
```

```
1948 — intersection:  8  ||   average percentage difference:  nan
1950 — intersection:  12  ||   average percentage difference:  nan
1951 — intersection:  20  ||   average percentage difference:  nan
1956 — intersection:  25  ||   average percentage difference:  nan
1959 — intersection:  32  ||   average percentage difference:  83.96
787669408687
1960 — intersection:  35  ||   average percentage difference:  72.00
65787555531
1961 — intersection:  39  ||   average percentage difference:  51.06
04688209428
1964 — intersection:  39  ||   average percentage difference:  51.06
04688209428
1965 — intersection:  41  ||   average percentage difference:  51.25
6383053914405
1966 — intersection:  42  ||   average percentage difference:  49.19
5113942504406
1967 — intersection:  47  ||   average percentage difference:  42.22
877582336483
1972 — intersection:  48  ||   average percentage difference:  42.25
299095468392
1974 — intersection:  54  ||   average percentage difference:  37.58
894007641583
1976 — intersection:  56  ||   average percentage difference:  39.36
824799253536
1979 — intersection:  57  ||   average percentage difference:  40.39
623432626831
1980 — intersection:  62  ||   average percentage difference:  33.28
890340892404
1981 — intersection:  70  ||   average percentage difference:  28.40
0434834111206
1982 — intersection:  70  ||   average percentage difference:  28.40
0434834111206
1983 — intersection:  83  ||   average percentage difference:  25.66
1647620318927
1984 — intersection:  90  ||   average percentage difference:  23.00
6137278579736
1985 — intersection:  92  ||   average percentage difference:  23.63
163837661355
1986 — intersection:  100  ||   average percentage difference:  27.4
3391364153022
1987 — intersection:  107  ||   average percentage difference:  25.0
44347476011474
1988 — intersection:  114  ||   average percentage difference:  23.0
05773675635034
1989 — intersection:  117  ||   average percentage difference:  22.8
04655393948742
1990 — intersection:  118  ||   average percentage difference:  22.7
04548333375744
1991 — intersection:  130  ||   average percentage difference:  22.2
02325307304356
```

```
1992 — intersection:  137  ||   average percentage difference:  21.7
15768813737615
1993 — intersection:  147  ||   average percentage difference:  23.0
0084025287157
1994 — intersection:  176  ||   average percentage difference:  23.2
5934627345224
1995 — intersection:  198  ||   average percentage difference:  20.3
8861617412395
1996 — intersection:  215  ||   average percentage difference:  17.7
51484870330014
1997 — intersection:  223  ||   average percentage difference:  17.4
0531947234441
1998 — intersection:  250  ||   average percentage difference:  14.5
81207865484458
1999 — intersection:  285  ||   average percentage difference:  17.8
1907502674016
2000 — intersection:  321  ||   average percentage difference:  17.9
21413981323678
2001 — intersection:  352  ||   average percentage difference:  15.0
6025425892914
2002 — intersection:  363  ||   average percentage difference:  15.6
3468965603964
2003 — intersection:  382  ||   average percentage difference:  17.9
6096336062469
2004 — intersection:  390  ||   average percentage difference:  16.7
39077784646167
2005 — intersection:  408  ||   average percentage difference:  15.0
4229017747896
2006 — intersection:  424  ||   average percentage difference:  16.8
2202599624933
2007 — intersection:  436  ||   average percentage difference:  13.3
30410318506718
2008 — intersection:  438  ||   average percentage difference:  11.6
9467388315466
2009 — intersection:  455  ||   average percentage difference:  13.4
20143944544003
2010 — intersection:  933  ||   average percentage difference:  9.82
5268223057039
2011 — intersection:  1331  ||   average percentage difference:  6.3
06717210837637
2012 — intersection:  1539  ||   average percentage difference:  5.9
91084959833037
2013 — intersection:  1591  ||   average percentage difference:  7.1
79601324066037
2014 — intersection:  1517  ||   average percentage difference:  10.
114524683378686
2015 — intersection:  1233  ||   average percentage difference:  9.7
61211454070715
2016 — intersection:  881  ||   average percentage difference:  11.5
58380655732968
```

```
2017 — intersection:  547  ||   average percentage difference:  11.4
32036142472446
2018 — intersection:  152  ||   average percentage difference:  54.7
62549494019424
2019 — intersection:  5  ||   average percentage difference:  nan
2020 — intersection:  0  ||   average percentage difference:  nan
```

It looks like splitting down the year 2012 would be a good balance between maximizing people and minimizing percentage difference. However, any of the years between 2011 and 2015 would be good candidates, as they offer a lot of people and an average percentage difference under 10%.

In [39]:

```
year = 2013
before = castdf[castdf.year <= year].copy() # All data before or durin
g 2013
after = castdf[castdf.year > year].copy() # All data after 2013


# Getting the list of people in common
intersection = set(before.person_id.unique()).intersection(set(after.p
erson_id.unique()))
len(intersection)


# Reducing each dataset to only include people from the intersection
before = before[before.person_id.isin(intersection)]
after = after[after.person_id.isin(intersection)]
```

Cast – Impact of profession's ROI on movie's ROI

We started off this section with a lot of questions, but we should only tackle one to begin with. Our strategy is as follows:

- Divide ROI into bins (e.g., between 200-300%, 400-500%, etc.)
- Find the people from the first dataset in each profession that fall into these bins
- Locate the same people in the second dataset and measure the success of the movies they're in
- Plot each ROI bin against movie success from the second dataset
- Measure the correlation and predictive power for each profession

In [40]:

```
def query(profession, profession_attribute, movie_attribute):

    """
    This function takes three arguments: a profession, one attribute o
f the profession,
```

```
    and one attribute of the movies that involve people from that prof
ession.

    Example: query('actor', 'ROI', 'hitrate')

    The function will query a subset from the first dataset that conta
ins only actors, and categorize
    the ROI column in that subset into multiple bins. For each of thos
e bins, it will locate the people
    that fall into those bins. The function then locates all movies in
the second dataset with those people
    and evaluates the hitrate of those movies.

    The function will return:

    1) The profession it examined ('actor')
    2) The attributes it examined ('ROI' and 'hitrate')
    3) The bins that it divided ROI into
    4) The corresponding mean for each bin
    5) The correlation between actor ROI and movie hitrate
    6) The rsquared value of this correlation (just the correlation sq
uared)
    """

    means = [] # Average movie attribute per bin
    bins = [] # Bins denoted in string form

    # Creating local references to datasets for use within function
    beforelocal = before
    afterlocal = after

    # Creating bins based on whether selected attribute is ROI or prof
itable
    # ROI will have much higher values, profitable will only have valu
es between 0 and 1
    if profession_attribute == "ROI":
        linspace = np.linspace(0,1000,20, dtype=int)
    elif profession_attribute == "hitrate":
        linspace = np.linspace(0,1.01,20)
    else:
        return "Invalid profession attribute"

    for i in range(len(linspace)-1):

        # Gets all people from first dataset with ROI within a range
        q = """
        SELECT person_id
        FROM beforelocal
        GROUP BY person_id
        HAVING profession == '{}' AND AVG({})>{} AND AVG({})<{}
```

```
        """.format(profession, profession_attribute, linspace[i], prof
ession_attribute, linspace[i+1])

        df1 = sqldf(q, locals())

        # Only gathering bins of a certain size to prevent misleading
data
        if len(df1) < 5:
            continue

        # Retreiving data from the same people in the second dataset
        q2 = """
        SELECT *
        FROM afterlocal
        WHERE person_id IN (SELECT person_id FROM df1)
        """

        df2 = sqldf(q2, locals())

        # Appending the average ROI to our list
        means.append(df2[movie_attribute].mean())

        # Creating the strings for each bin
        start = linspace[i]
        end = linspace[i+1]
        bins.append('{} - {}, [{} values]'.format(round(start, 2), rou
nd(end, 2), len(df1)))


    # Correlation
    # This is calculated on the list of means we gathered from the mov
ies in the second dataset.
    # If there are fewer than five means in this list, the correlation
will not be meaningful.
    # The function will return a NaN value unless we have five or more
data points.
    if len(means)>= 5:
        correlation = np.corrcoef(range(0,len(means)),means)[0,1]
    else:
        correlation = np.nan

    # R Squared values (predictive power)
    rsquared = correlation**2

    return (profession,
           profession_attribute,
           movie_attribute,
           bins,
           means,
           correlation,
```

```
             rsquared)
```

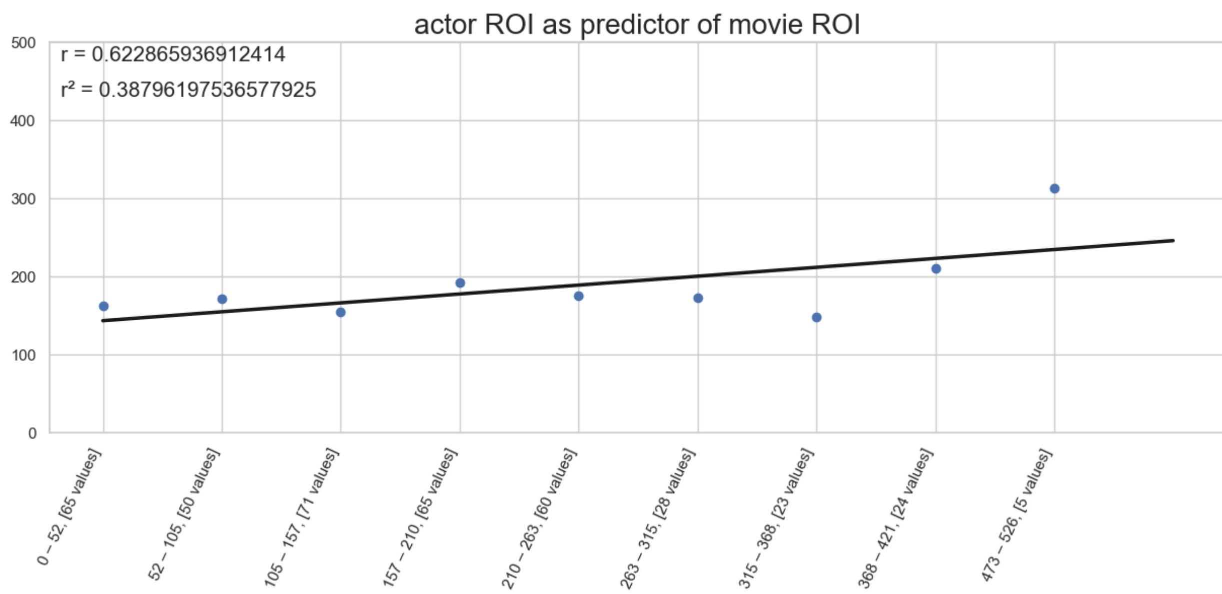
In [41]:
```python
def plot(data):

    """
    This function creates a plot based on the results of the query fun
ction we created
    in this project. The title, x- and y- data, and annotations are al
l based on what the
    query function returns.

    title: 0th, 1st, and 2nd items of query return
    x data: 3rd item
    y data: 4th item
    r annotation: 5th item
    r squared annotation: 6th item
    """

    fig, ax = plt.subplots(figsize=(15,5))

    title = "{} {} as predictor of movie {}".format(data[0], data[1],
data[2])
    ax.set_title(title, fontsize='20')

    x = data[3]
    y = data[4]

    # Sets limits of graph depending on the range of values available
    if max(y)>1:
        ax.set_ylim(0, 500)
    else:
        ax.set_ylim(0,1)


    plt.xticks(
        rotation=65,
        horizontalalignment = 'right'
    )

    # Code comes from https://www.python-graph-gallery.com/scatterplot
-with-regression-fit-in-matplotlib
    b, a = np.polyfit(range(0,len(y)), y, deg=1)
    xseq = np.linspace(0, len(y), num=100)
    ax.plot(xseq, a + b * xseq, color="k", lw=2.5);

    ax.text(.01,
            .99,
            "r = {}".format(str(data[5])),
            ha='left',
```

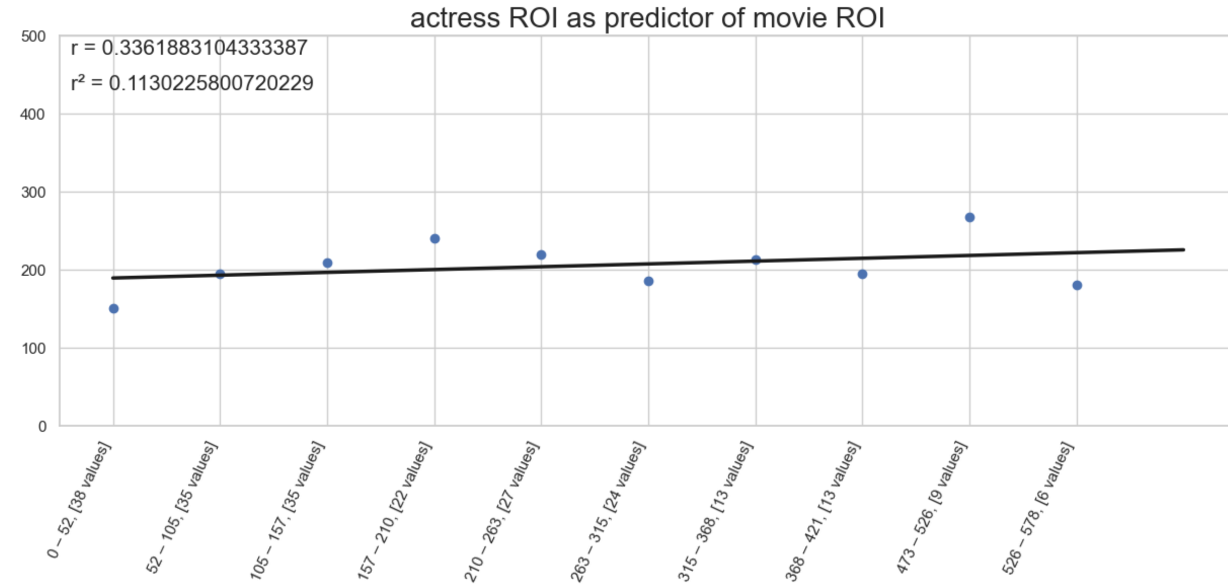
```
            va='top',
            transform=ax.transAxes,
            fontsize = 15)

    ax.text(.01,
            .9,
            "r² = {}".format(str(data[6])),
            ha='left',
            va='top',
            transform=ax.transAxes,
            fontsize = 15)

    ax.scatter(x, y);
```

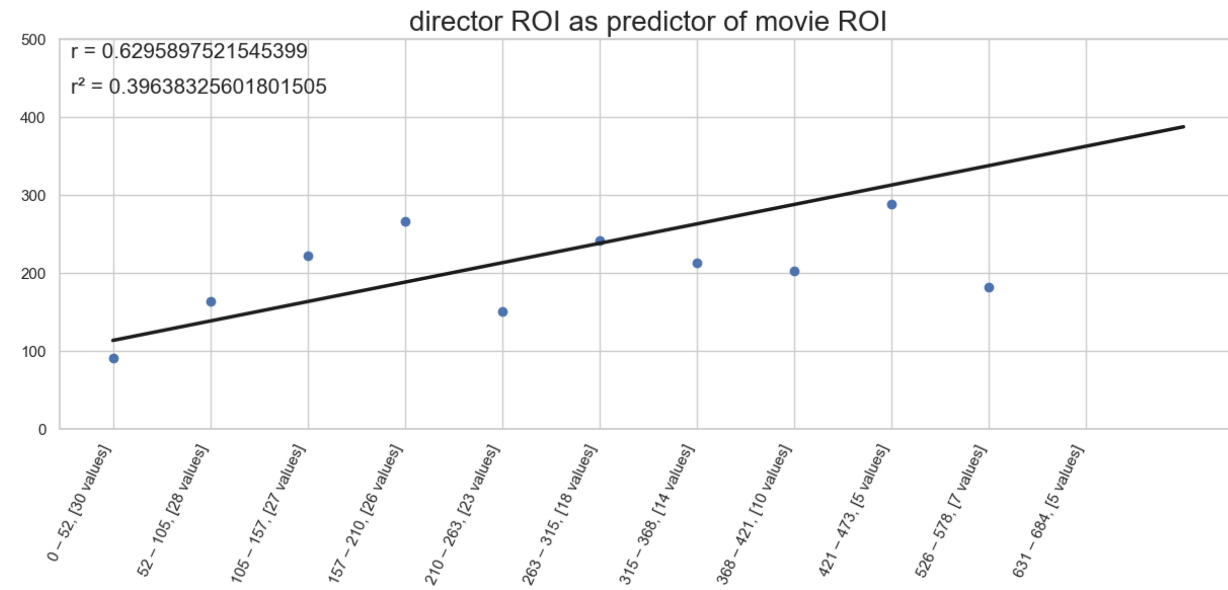
Cast – Example of Correlation

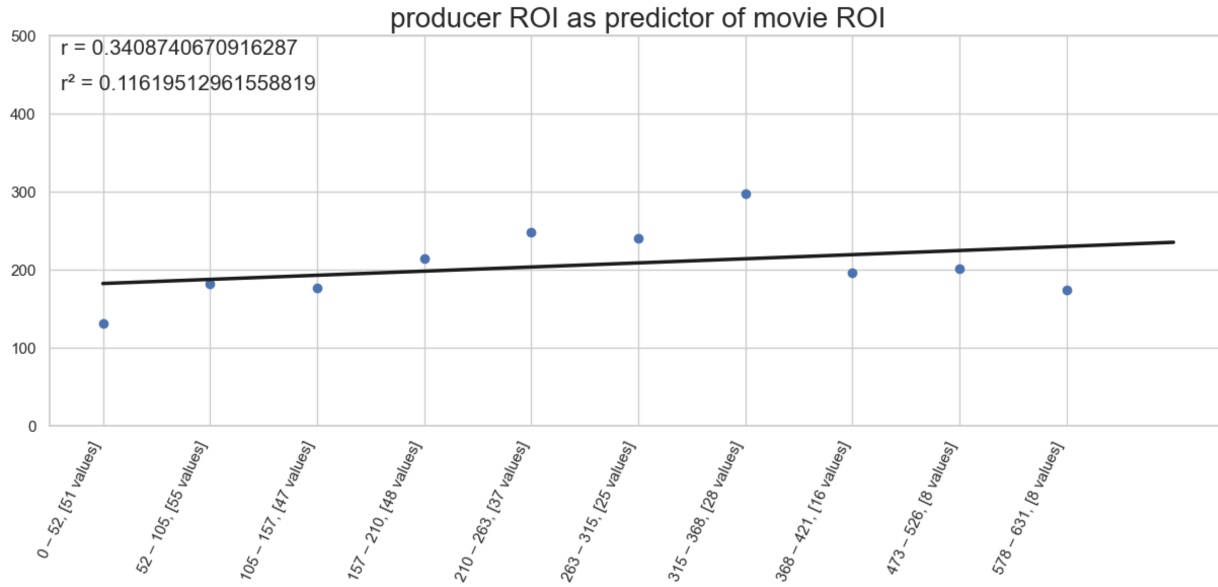
We have defined two functions, a data query function and a plot function. We will now iterate through the list of professions we chose and plot average ROI vs movie ROI, as an example of the kind of correlations we're collecting.

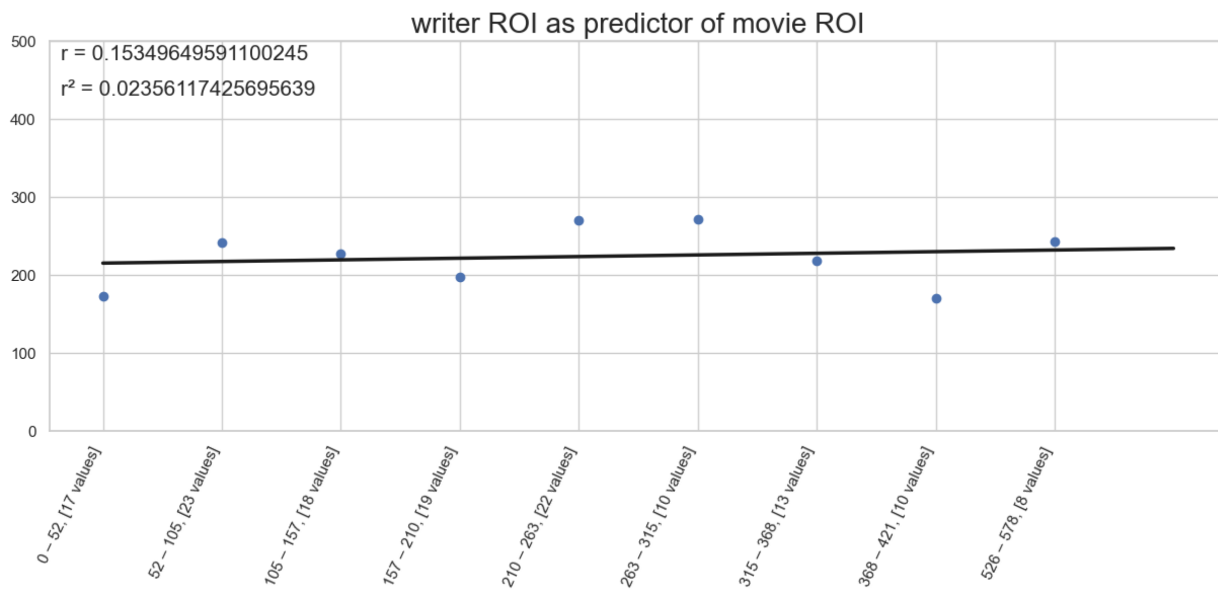
In [42]:
```
for profession in professions:
    plot(query(profession, 'ROI', 'ROI'))
```




actress ROI as predictor of movie ROI
r = 0.3361883104333387
r² = 0.1130225800720229
500
400
300
200
100
0
0 – 52, [38 values]
52 – 105, [35 values]
105 – 157, [35 values]
157 – 210, [22 values]
210 – 263, [27 values]
263 – 315, [24 values]
315 – 368, [13 values]
368 – 421, [13 values]
473 – 526, [9 values]
526 – 578, [6 values]


director ROI as predictor of movie ROI
r = 0.6295897521545399
r² = 0.39638325601801505
500
400
300
200
100
0
0 – 52, [30 values]
52 – 105, [28 values]
105 – 157, [27 values]
157 – 210, [26 values]
210 – 263, [23 values]
263 – 315, [18 values]
315 – 368, [14 values]
368 – 421, [10 values]
421 – 473, [5 values]
526 – 578, [7 values]
631 – 684, [5 values]


producer ROI as predictor of movie ROI
r = 0.3408740670916287
r² = 0.11619512961558819
500
400
300
200
100
0
0 – 52, [51 values]
52 – 105, [55 values]
105 – 157, [47 values]
157 – 210, [48 values]
210 – 263, [37 values]
263 – 315, [25 values]
315 – 368, [28 values]
368 – 421, [16 values]
473 – 526, [8 values]
578 – 631, [8 values]


writer ROI as predictor of movie ROI
r = 0.15349649591100245
r² = 0.02356117425695639
500
400
300
200
100
0
0 – 52, [17 values]
52 – 105, [23 values]
105 – 157, [18 values]
157 – 210, [19 values]
210 – 263, [22 values]
263 – 315, [10 values]
315 – 368, [13 values]
368 – 421, [10 values]
526 – 578, [8 values]

Cast – Level Up: Gathering more Data

This data is not informative enough. It's only from one year, and it only correlates profession ROI and movie ROI. Ideally, we would have information from multiple years, and we would also correlate:

- profession ROI and movie hitrate
- profession hitrate and movie hitrate
- profession hitrate and movie ROI

And then combine these correlations for an overall indicator on profession correlation with movie success.

Which years?

Selecting years 2011-2015 is appropriate, since they all have >1000 unique people – and after we split the dataset, the average stat difference between people across datasets is under 10%, which is good for the accuracy of our results.

In [43]:
```
acceptable_years = range(2011,2016)
```

Creating the shell of our dataframe

Our dataframe must have columns for each year and three indexes which indicate the values of the variables we're correlating:

- the type of profession
- the profession stat selected (ROI/profitable)
- the movie stat selected (ROI/profitable)

In [44]:
```
# Creating the first columns of our dataframe
attributes = ['ROI', 'hitrate']

profession = []
profession_attribute = []
movie_attribute = []


for p in professions:
    for a in attributes:
        for b in attributes:
            profession.append(p)
            profession_attribute.append(a)
            movie_attribute.append(b)


# The shell of our dataframe
data = {
    'profession': profession,
    'profession_attribute': profession_attribute,
    'movie_attribute': movie_attribute
}

pd.DataFrame(data)
```

Out[44]:

	profession	profession_attribute	movie_attribute
0	actor	ROI	ROI
1	actor	ROI	hitrate
2	actor	hitrate	ROI
3	actor	hitrate	hitrate
4	actress	ROI	ROI
5	actress	ROI	hitrate
6	actress	hitrate	ROI
7	actress	hitrate	hitrate
8	director	ROI	ROI
9	director	ROI	hitrate
10	director	hitrate	ROI
11	director	hitrate	hitrate
12	producer	ROI	ROI
13	producer	ROI	hitrate
14	producer	hitrate	ROI
15	producer	hitrate	hitrate
16	writer	ROI	ROI
17	writer	ROI	hitrate
18	writer	hitrate	ROI
19	writer	hitrate	hitrate

This looks good enough. Now we just need to populate more columns and append them to this dataframe.

In [45]:
```
# This loop gathers correlation data and appends it to new columns in
the dataframe.
for year in acceptable_years:

    # Splitting our dataset down the year
    before = castdf[castdf.year <= year].copy()
    after = castdf[castdf.year > year].copy()

    # Getting the list of people in common
    intersection = set(before.person_id.unique()).intersection(set(aft
er.person_id.unique()))
    len(intersection)

    # Reducing each dataset to only include people from the intersecti
on
    before = before[before.person_id.isin(intersection)]
    after = after[after.person_id.isin(intersection)]

    # A column of correlations in a specific year — reset and appended
to the dataframe every loop
    column = []

    # Creating the year column
    for p in professions:
        for a in attributes:
            for b in attributes:
                correlation = query(p, a, b)[5] # Retrieves correlatio
n from query
                column.append(correlation) # Appends correlation to ou
r column

    # Appends year column to the dataframe
    data[year] = column

    # A ticker to show you the progress of the loop (it takes a minute
to complete)
    print("{} done.".format(year), end=" ")
```

```
2011 done. 2012 done. 2013 done. 2014 done. 2015 done.
```

In [46]:
```
correlationsdf = pd.DataFrame(data)
correlationsdf
```

Out[46]:

	profession	profession_attribute	movie_attribute	2011	2012	2013	2014
0	actor	ROI	ROI	-0.156716	-0.412497	0.622866	0.724551
1	actor	ROI	hitrate	-0.107841	-0.281808	0.601287	0.828959
2	actor	hitrate	ROI	NaN	0.410339	-0.446581	0.257748
3	actor	hitrate	hitrate	NaN	0.351818	-0.609317	0.259359
4	actress	ROI	ROI	0.800327	0.159858	0.336188	0.209806
5	actress	ROI	hitrate	0.628224	0.153364	0.290413	0.395016
6	actress	hitrate	ROI	NaN	0.684529	0.190501	0.472533
7	actress	hitrate	hitrate	NaN	0.702102	0.314299	0.590750
8	director	ROI	ROI	0.363742	0.538020	0.629590	0.585066
9	director	ROI	hitrate	0.318104	0.595163	0.720457	0.811061
10	director	hitrate	ROI	NaN	NaN	NaN	NaN
11	director	hitrate	hitrate	NaN	NaN	NaN	NaN
12	producer	ROI	ROI	0.316967	0.519037	0.340874	0.038394
13	producer	ROI	hitrate	0.472896	0.632275	0.411751	0.251965
14	producer	hitrate	ROI	NaN	NaN	0.754979	0.240090
15	producer	hitrate	hitrate	NaN	NaN	-0.525200	-0.416759
16	writer	ROI	ROI	0.501664	-0.059368	0.153496	0.126194
17	writer	ROI	hitrate	0.013359	0.471148	0.660452	0.814549
18	writer	hitrate	ROI	NaN	NaN	NaN	NaN
19	writer	hitrate	hitrate	NaN	NaN	NaN	NaN

We have quite a few NaN values in this dataset, but it's better than including correlations that were otherwise meaningless or outright misleading, which could lead us to draw unwarranted conclusions.

Aggregating data

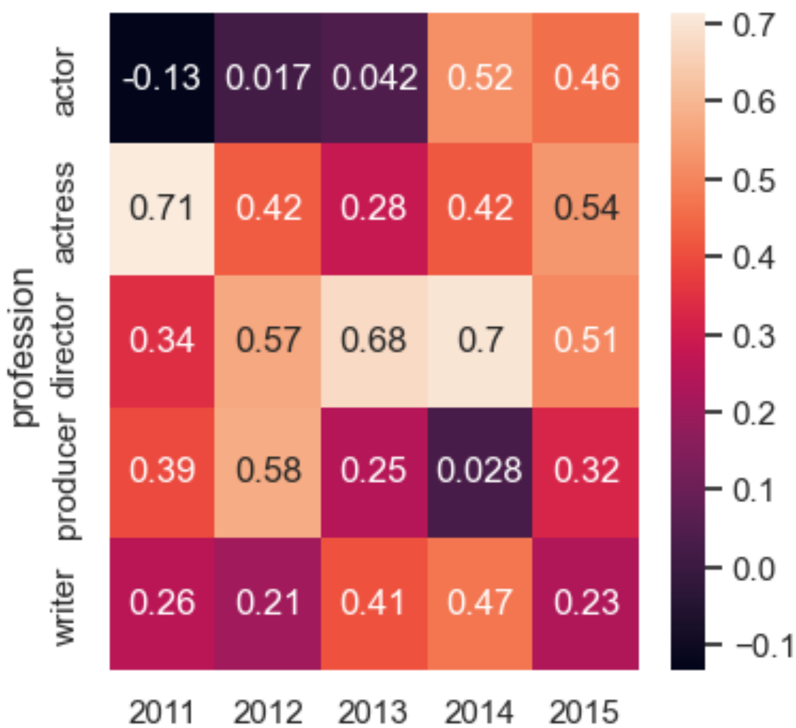
Now let's aggregate all correlations accross profession and see what we have.

In [47]:
```
correlationsdf.groupby('profession').mean(numeric_only=True)
```

Out[47]:

profession	2011	2012	2013	2014	2015
actor	-0.132279	0.016963	0.042064	0.517654	0.458377
actress	0.714275	0.424963	0.282850	0.417026	0.535101
director	0.340923	0.566591	0.675023	0.698064	0.505536
producer	0.394931	0.575656	0.245601	0.028422	0.320919
writer	0.257511	0.205890	0.406974	0.470371	0.233514

In [48]:
```
fig, ax = plt.subplots(figsize=(4,4))
sns.heatmap(correlationsdf.groupby('profession').mean(numeric_only=True), ax=ax, annot=True);
```



Averaging across year

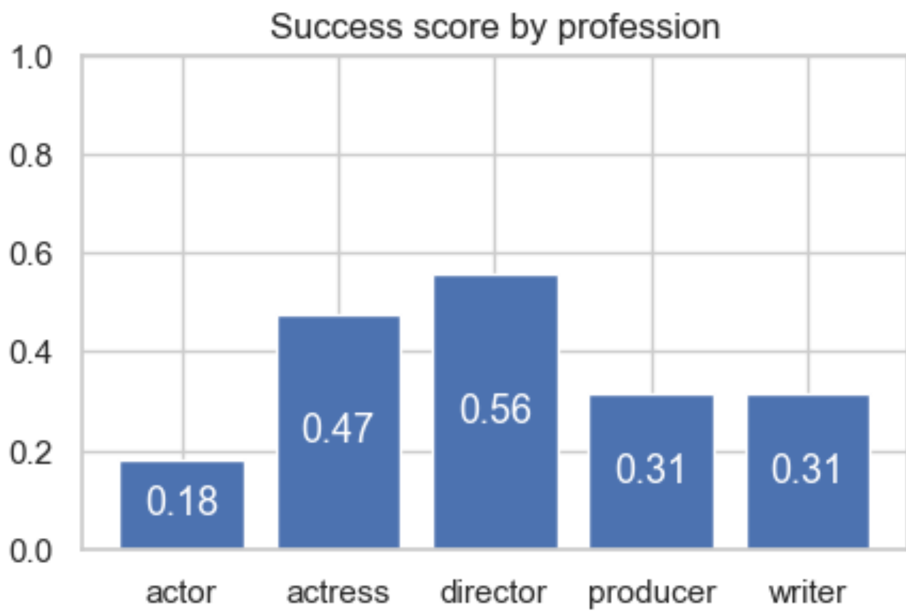
There is only one negative correlation (there should be none), so that's good to see. Every profession's success here should correlate positively with movie success – the only question is, which professions correlate *more strongly* with movie success.

To know that, we need to aggregate one more time, this time across years, to get an overall indicator of a profession's success with movie success.

In [49]:
```
profession_correlations = \
            correlationsdf.groupby('profession').mean(numeric_only=True).mean(numeric_only=True, axis=1)

profession_correlations
```

Out[49]:
```
profession
actor       0.180556
actress     0.474843
director    0.557227
producer    0.313106
writer      0.314852
dtype: float64
```

In [50]:
```
fig, ax = plt.subplots(figsize = (5,3))

x = profession_correlations.index
y = profession_correlations.values

barplot = ax.bar(x,y)
ax.set_ylim(0,1)

ax.bar_label(barplot, labels=[round(i,2) for i in y], label_type='cent
er', color='white', fontsize='13');
ax.set_title('Success score by profession');
```



This is the data we've been after this entire section. The types of professions here can be broken down into two basic categories: on-screen and off-screen. Although there is some variability within these categories, its clear that the off-screen crew are more important to a movie's success than the on-screen crew – which makes sense, since the off-screen crew make decisions on who the on-screen crew will be.

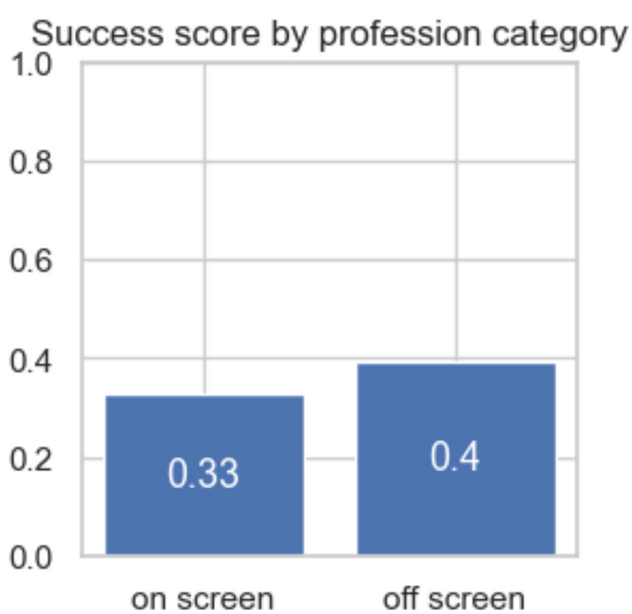
In fact, we could aggregate this data *one more time* (!) by averaging the score for on-screen and off-screen crew.

Averaging across profession

In [51]:
```
on_screen = (profession_correlations['actor'] +
             profession_correlations['actress'])/2

off_screen = (profession_correlations['director'] +
              profession_correlations['producer'] +
              profession_correlations['writer'])/3

print(f"The average correlation between on-screen crew success and movie success is {on_screen}.")
print(f"The average correlation between off-screen crew success and movie success is {off_screen}.")
```

```
The average correlation between on-screen crew success and movie success is 0.32769952582287626.
The average correlation between off-screen crew success and movie success is 0.3950617902418694.
```

In [52]:
```
fig, ax = plt.subplots(figsize = (3,3))

x = ['on screen', 'off screen']
y = [on_screen, off_screen]

barplot = ax.bar(x,y)
ax.set_ylim(0,1)

ax.bar_label(barplot, labels=[round(i,2) for i in y], label_type='center', color='white', fontsize='13');
ax.set_title('Success score by profession category');
```



Cast – Recommendation

The general recommendation for Microsoft when hiring cast & crew is to prioritize off-screen crew before the on-screen crew. More specifically, when allocating time and money to selecting and hiring off-screen crew, prioritize the directors before the producers and writers.

This recommendation helps Microsoft because it helps them prioritize the most important cast members, which improves their chances of creating a successful movie.