Exploratory Data Analysis on Movie Data

Business Problem

Microsoft is looking to create a new movie studio that can distribute films to movie theaters. They are looking for tangible advice towards creating movies that can compete at the box office. Specefically, they would like to know 'what types of films are currently doing the best at the box office'. They have given me data on the film industry and tasked me with finding three actionable insights.

General Overview of the Industy

Before approcahing this problem, I wanted to familiarize myself as much as possible with the film industry. Three questions, I needed to understand in order to provide actionable recommendations were.

- 1) <u>How do film studios make money (https://www.investopedia.com/articles/investing/093015/how-exactly-do-movies-make-money.asp)</u>. (investopedia.com)
- 2) What costs and revenue streams do film studios have (https://www.fticonsulting.com/emea/-/media/files/emea--files/insights/articles/2020/sep/economics-film-changing-dynamics-covid-19-world.pdf? rev=71d8d0ae3a2b413bb77950dd772bee74&hash=7B4F3893D68857623A232DCE9F062B1E). (fticonsulting.com)
- 3) What are some trends in the movie industry that a new company can capitalize on. (motionpictures.org)

One of the key takeaways from my preliminary research was that movie studios budgets are purposely misleading. The reported budget for movies is not reliable because it does not take into account marketing costs. Marketing and advertising costs for movies are oftentimes just as high as production budgets and that cost is not reported publicly.

This practice is so widespread that there is an entire wikipedia article on something called "Hollywood Accounting (https://en.wikipedia.org/wiki/Hollywood_accounting)". One of the most egregious examples of this is Star Wars Episode VI - Return of the Jedi, despite making 450 million dollars in 1983 (https://www.theatlantic.com/business/archive/2011/09/how-hollywood-accounting-can-make-a-450-million-movie-unprofitable/245134/) has yet to turn a profit according to LucasFilms.

Another key insight from my research was the average movie released from 2016-2019 did not recover its costs after its theatrical release. Most films only begin making a profit after the "home release" period of it's development. This insight whilst not valuable to answering the business problem could be a source for further data analysis moving forward.

The final conclusion I gleaned from my research was a general trend towards foreign markets. Whilst the U.S. and Canada are still the largest markets for theatrical releases, other countries made up 71% of the global box office. There is also a growing trend where some American made films to make more internationally than domestically. This is a new trend and one that I think Microsoft should exploit.

General Understanding Key Takeaways

- 1) Because the production cost is not reliable data uses gross revenue to identify which movies are doing best at the box office.
- 2) Test to see if foreign box office is connected to the total gross of the movie.
- 3) Use categorical data to identify some actionable insights Microsoft Film Studio can use.

Data Understanding

In [3]: ► # Open The Movie Database File to see what information is available in it tmdb_df

Out[3]:		Unnamed: 0	genre_ids	id	original_language	original_title	popularity	release_
	0	0	[12, 14, 10751]	12444	en	Harry Potter and the Deathly Hallows: Part 1	33.533	2010-1
	1	1	[14, 12, 16, 10751]	10191	en	How to Train Your Dragon	28.734	2010-0
	2	2	[12, 28, 878]	10138	en	Iron Man 2	28.515	2010-0
	3	3	[16, 35, 10751]	862	en	Toy Story	28.005	1995-1
	4	4	[28, 878, 12]	27205	en	Inception	27.920	2010-0
	26512	26512	[27, 18]	488143	en	Laboratory Conditions	0.600	2018-1
	26513	26513	[18, 53]	485975	en	_EXHIBIT_84xxx_	0.600	2018-0
	26514	26514	[14, 28, 12]	381231	en	The Last One	0.600	2018-1
	26515	26515	[10751, 12, 28]	366854	en	Trailer Made	0.600	2018-0
	26516	26516	[53, 27]	309885	en	The Church	0.600	2018-1

26517 rows × 10 columns



The Movie Database File appears to have information on the user reviews and some information on genres but would require information on the genre id codes

In [4]: ▶ 1 movie_gross_df

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	title	studio	domestic_gross	foreign_gross	year
0	Toy Story 3	BV	415000000.0	652000000	2010
1	Alice in Wonderland (2010)	BV	334200000.0	691300000	2010
2	Harry Potter and the Deathly Hallows Part 1	WB	296000000.0	664300000	2010
3	Inception	WB	292600000.0	535700000	2010
4	Shrek Forever After	P/DW	238700000.0	513900000	2010
3382	The Quake	Magn.	6200.0	NaN	2018
3383	Edward II (2018 re-release)	FM	4800.0	NaN	2018
3384	El Pacto	Sony	2500.0	NaN	2018
3385	The Swan	Synergetic	2400.0	NaN	2018
3386	An Actor Prepares	Grav.	1700.0	NaN	2018

3387 rows × 5 columns

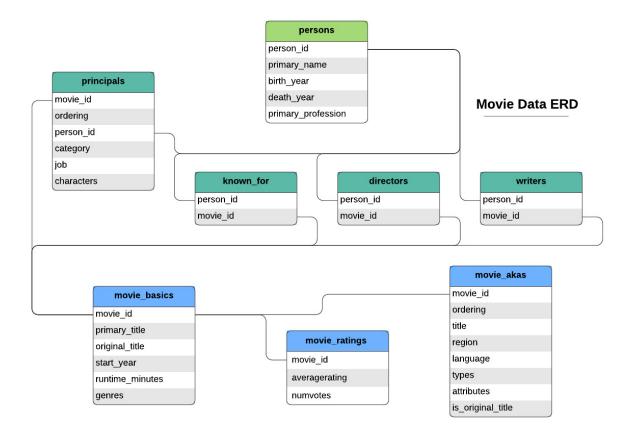
The Box Office Mojo has information on the domestic and foreign gross as long as the title. This will make it possible to combine the dataframes on title into one comprehensive data frame

Out[5]:

Table Names

- 0 movie basics
- 1 directors
- 2 known_for
- 3 movie_akas
- 4 movie_ratings
- 5 persons
- 6 principals
- 7 writers

Here is the ERD for the database



The IMDb data is a .df file so I will have to run some SQL queries to get the data I need. I'm most interested in grabbing categorical data so I'm going to grab the director data. I'm also going to grab the run time length, genres, and average rating. Although I already have information on genres and average rating, it may be useful to compare it if I have time.

```
query_1 = '''
In [6]:
              1
              2
                 SELECT
              3
                         primary_name as Director,
              4
                         primary title as Movie Name,
              5
                          runtime_minutes as Length,
              6
                          genres,
              7
                          averagerating as AVG_Rating
              8
              9
             10
                 FROM directors as d
             11
                     JOIN persons as p
             12
                         on p.person_id = d.person_id
                              JOIN movie_basics as mb
             13
                                  on d.movie id = mb.movie id
             14
             15
                                      JOIN movie ratings as mr
             16
                                          on mr.movie_id = mb.movie_id
             17
                 . . .
             18
             19
             20
                 director movie genre df = pd.read sql(query 1, con)
             21
             22
                 director_movie_genre_df
```

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()	нт	I h	ь.

	Director	Movie_Name	Length	genres	AVG_Rating
0	Tony Vitale	Life's a Beach	100.0	Comedy	3.9
1	Bill Haley	Steve Phoenix: The Untold Story	110.0	Drama	5.5
2	Jay Chandrasekhar	The Babymakers	95.0	Comedy	5.0
3	Jay Chandrasekhar	The Babymakers	95.0	Comedy	5.0
4	Albert Pyun	Bulletface	82.0	Thriller	5.8
181382	Anne Sundberg	Reversing Roe	99.0	Documentary	7.4
181383	Mike Rohl	The Princess Switch	101.0	Romance	6.0
181384	Mike Rohl	The Princess Switch	101.0	Romance	6.0
181385	Richard Squires	Doozy	70.0	Animation,Comedy	6.7
181386	Fredrik Horn Akselsen	Syndebukken: Prosessen mot Harry Lindstrøm	NaN	Documentary	8.4

181387 rows × 5 columns

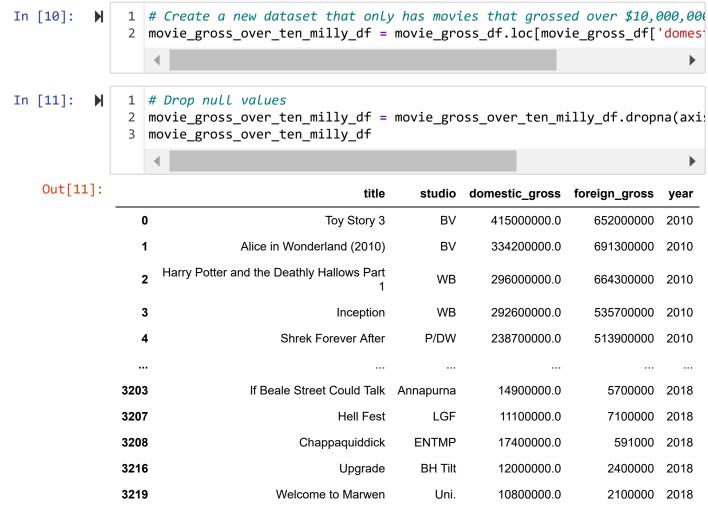
Now that I've taken a quick look at my data, I want to key in on the movie gross data. Total box office will be the key metric I judge success on so I want to look at that first

```
In [7]:
                movie gross df.info()
            <class 'pandas.core.frame.DataFrame'>
            RangeIndex: 3387 entries, 0 to 3386
            Data columns (total 5 columns):
             #
                 Column
                                 Non-Null Count
                                                 Dtype
                 _____
                                 -----
             0
                 title
                                 3387 non-null
                                                 object
                                                 object
             1
                 studio
                                 3382 non-null
             2
                 domestic gross 3359 non-null
                                                 float64
             3
                 foreign_gross
                                 2037 non-null
                                                 object
                                 3387 non-null
                                                 int64
                 vear
            dtypes: float64(1), int64(1), object(3)
            memory usage: 132.4+ KB
```

There are a lot of null values in the foreign gross column. But I wanted to see if that was a result of some movies not being released internationally. There is significantly less null values for the domestic gross so I can use a cutoff point to see if those null values are because the movie was unlikely and could not be sold to an international distributor.

```
In [8]:
         M
                 # Use a loc statement to subset the dataframe to where domestic gross is
                 movie gross df.loc[movie gross df['domestic gross'] > 10000000].info()
            <class 'pandas.core.frame.DataFrame'>
            Int64Index: 1169 entries, 0 to 3226
            Data columns (total 5 columns):
             #
                 Column
                                  Non-Null Count Dtype
             0
                 title
                                  1169 non-null
                                                  object
             1
                 studio
                                  1169 non-null
                                                  object
             2
                 domestic gross 1169 non-null
                                                  float64
                 foreign_gross
             3
                                  1116 non-null
                                                  object
                                                  int64
                 vear
                                  1169 non-null
            dtypes: float64(1), int64(1), object(3)
            memory usage: 54.8+ KB
In [9]:
         H
                # Use a loc statement to subset the dataframe to where domestic gross is
                 movie gross df.loc[movie gross df['domestic gross'] > 100000000].info()
              2
            <class 'pandas.core.frame.DataFrame'>
            Int64Index: 284 entries, 0 to 3129
            Data columns (total 5 columns):
             #
                 Column
                                  Non-Null Count
                                                  Dtype
                 -----
                                                  ----
             0
                 title
                                  284 non-null
                                                  object
             1
                 studio
                                  284 non-null
                                                  object
             2
                 domestic gross 284 non-null
                                                  float64
                 foreign_gross
                                  284 non-null
                                                  object
                                  284 non-null
                                                  int64
                 vear
            dtypes: float64(1), int64(1), object(3)
            memory usage: 13.3+ KB
```

When I look only at the movies that cross a threshold of domestic gross, most of the null values go away. This reinforces my idea that most of the movies missing a foreign gross value were probably not released internationally. Because I want to keep as much data as possible, I'm going to use 10,000,000 dollars as my cut-off threshold for my analysis and drop any columns that have a null value for foreign_gross.



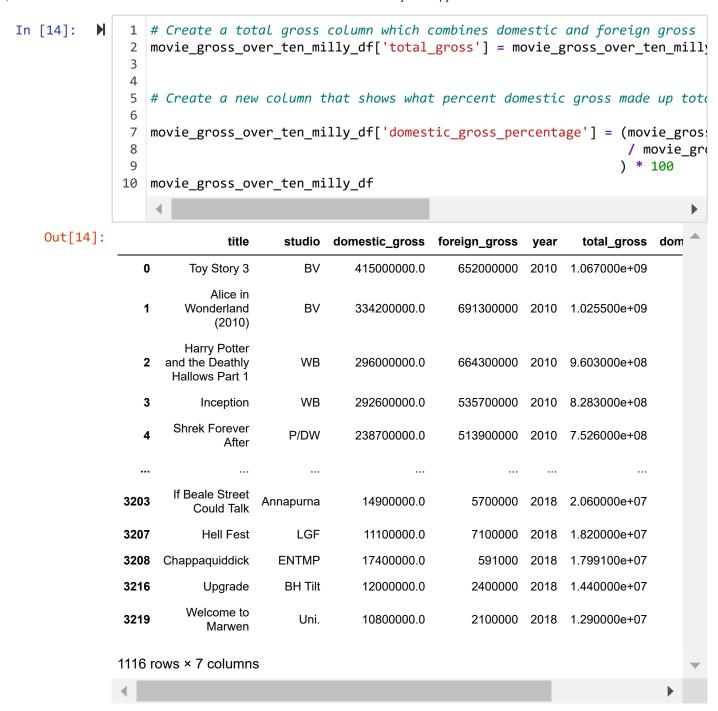
1116 rows × 5 columns

Unfortunately some of the data for foreign gross is not an intenger or float so I need to clean it up by eliminating some of the problematic characters.

```
In [12]: # Remove the commas from the dataset and then set it as float and then and movie_gross_over_ten_milly_df["foreign_gross"] = movie_gross_over_ten_milly_df['foreign_gross'] = movie_gross_over_ten_milly_df['foreign_gross_over_ten_milly_df['foreign_gross_over_ten_milly_df['foreign_gross_over_ten_milly_df['foreign_gross_over_ten_milly_df['foreign_gross_over_ten_milly_df['foreign_gross_over_ten_milly_df['foreign_gross_over_ten_milly_df['foreign_gross_over_ten_milly_df['foreign_gross_over_ten_milly_df['foreign_gross_over_ten_milly_df['foreign_gross_over_ten_milly_df['foreign_gross_over_ten_milly_df['foreign_gross_ov
```

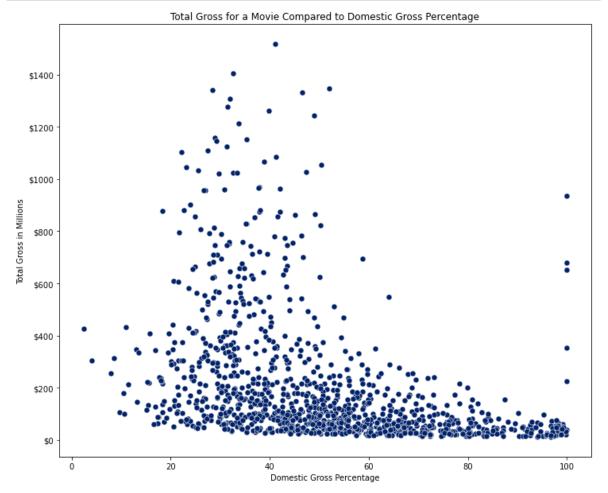
```
In [13]:
                 movie_gross_over_ten_milly_df.info()
             <class 'pandas.core.frame.DataFrame'>
             Int64Index: 1116 entries, 0 to 3219
             Data columns (total 5 columns):
              #
                  Column
                                  Non-Null Count Dtype
                  -----
                                  -----
                                                  ____
              0
                  title
                                  1116 non-null
                                                  object
              1
                  studio
                                  1116 non-null
                                                  object
              2
                  domestic_gross 1116 non-null
                                                  float64
              3
                  foreign_gross
                                  1116 non-null
                                                  int32
                                  1116 non-null
                                                  int64
              4
                  year
             dtypes: float64(1), int32(1), int64(1), object(2)
             memory usage: 48.0+ KB
```

Now that foreign gross is an intenger type, I can create new columns by doing some math between domestic gross and foreign gross



Now that I have some numerical data on domestic gross percentage and total gross I what to put that on a graph to see if I can glean anything from it

```
In [15]:
                  # Create a new column that is gross in millions so graphs are a bit easi
                  movie_gross_over_ten_milly_df['gross_in_millions'] = movie_gross_over_ter
               3
                  plt.figure(figsize=(12, 10))
               4
               5
                  dg_percentage_scatter = sns.scatterplot(x ='domestic_gross_percentage', )
               6
                                                           s = 50, color = '#012169', data
               7
               8
                  dg_percentage_scatter.set(xlabel ="Domestic Gross Percentage",
               9
                                         ylabel = "Total Gross in Millions",
              10
                                         title = 'Total Gross for a Movie Compared to Dome:
              11
              12
                  dg_percentage_scatter.yaxis.set_major_formatter('${x:1.0f}')
```

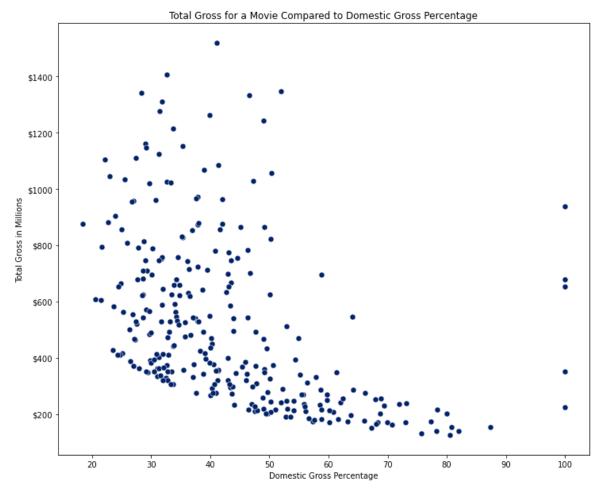


new subset to limit the data points. Because Microsoft is primarily interested in standing out in the box office. I'm going to create a "blockbuster" dataset that consists only of movies that made more than 100 Million Dollars domestically.

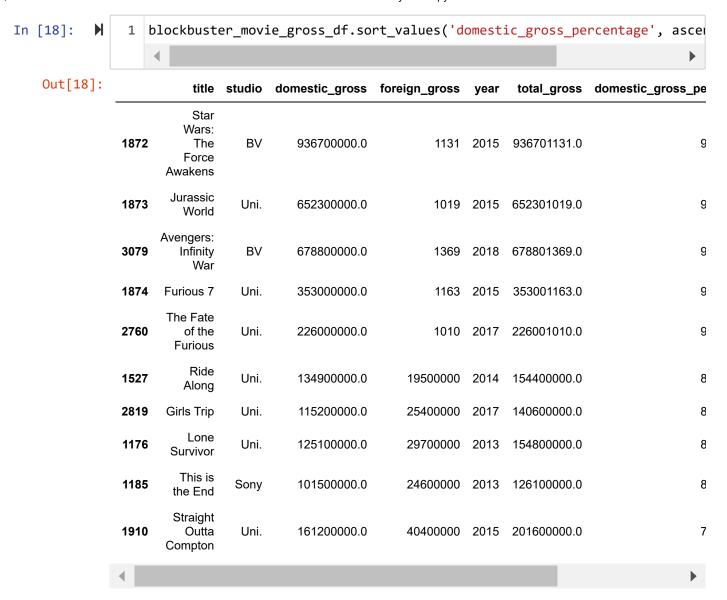


Let's plot this data the same way and see if a trend emerges

```
In [17]:
                  plt.figure(figsize=(12, 10))
                  dg_percentage_scatter = sns.scatterplot(x ='domestic_gross_percentage', )
               2
               3
                                                           color = '#012169', data = blockbu
               4
               5
                  dg_percentage_scatter.set(xlabel ="Domestic Gross Percentage",
               6
                                          ylabel = "Total Gross in Millions",
               7
                                          title = 'Total Gross for a Movie Compared to Dome:
               8
               9
                  dg_percentage_scatter.yaxis.set_major_formatter('${x:1.0f}')
```



This graph shows a much clearer trend, but it looks like there are some outliers where domestic gross percentage is higher. I'm going to clean those up and add a trend line to the graph



It looks like when the data was converted, movies that grossed over a billion dollars in international markets were incorrectly accounted for. I can quickly fix those numbers using a lambda function

```
In [19]: •
```

```
#Fix our first modified dataframe
             movie_gross_over_ten_milly_df['foreign_gross'] = movie_gross_over_ten_mil
   3
            movie_gross_over_ten_milly_df.sort_values('domestic_gross_percentage', a
   4
   5
            #Fix our second modified dataframe
   6
            blockbuster_movie_gross_df['foreign_gross'] = blockbuster_movie_gross_df
   7
             blockbuster movie gross df.sort values('domestic gross percentage', ascel
   8
   9
            # Reset the Total Gross fro both dataframes
10
11
            movie gross over ten milly df['total gross'] = movie gross over ten milly
12
13
            blockbuster_movie_gross_df['total_gross'] = blockbuster_movie_gross_df['d
14
15
            # Reset the domestic gross percentage column for both dataframes
16
             movie_gross_over_ten_milly_df['domestic_gross_percentage'] = (movie_gross_
17
                                                                                                                                                                                                                              / movie gro
18
                                                                                                                                                                                                                           * 100
19
             blockbuster_movie_gross_df['domestic_gross_percentage'] = (blockbuster_movie_gross_df['domestic_gross_percentage'] = (blockbuster_movie_gross_df['domestic_gross_df['domestic_gross_df['domestic_gross_df['domestic_gross_df['domestic_gross_df['domestic_gross_df['domestic_gross_df['domestic_gross_df['domestic_gross_df['domestic_gross_df['domestic_gross_df['domestic_gf['domestic_gf]'] = (blockbuster_df['domestic_gf]') = (blockbuster_df
20
                                                                                                                                                                                                                               / blockbust
21
                                                                                                                                                                                                                           * 100
```

<ipython-input-19-306458a7a27a>:6: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)

blockbuster_movie_gross_df['foreign_gross'] = blockbuster_movie_gross_df
['foreign_gross'].apply(lambda x: x * 1000000 if x < 2000 else x)
<ipython-input-19-306458a7a27a>:13: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)

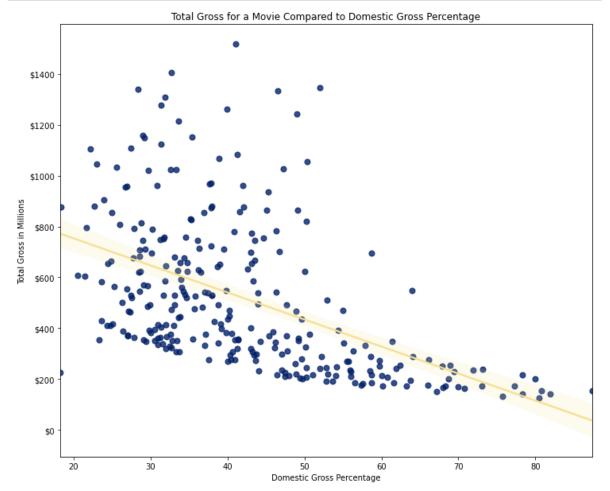
blockbuster_movie_gross_df['total_gross'] = blockbuster_movie_gross_df['d
omestic_gross'] + blockbuster_movie_gross_df['foreign_gross']
<ipython-input-19-306458a7a27a>:19: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)

blockbuster_movie_gross_df['domestic_gross_percentage'] = (blockbuster_mo
vie_gross_df['domestic_gross']

t[20]:		title	studio	domestic_gross	foreign_gross	year	total_gross	domestic_gross_p
	1527	Ride Along	Uni.	134900000.0	19500000	2014	154400000.0	
	2819	Girls Trip	Uni.	115200000.0	25400000	2017	140600000.0	
	1176	Lone Survivor	Uni.	125100000.0	29700000	2013	154800000.0	
	1185	This is the End	Sony	101500000.0	24600000	2013	126100000.0	
	1910	Straight Outta Compton	Uni.	161200000.0	40400000	2015	201600000.0	
	355	The Help	BV	169700000.0	46900000	2011	216600000.0	
	1921	Trainwreck	Uni.	110200000.0	30600000	2015	140800000.0	
	1172	Identity Thief	Uni.	134500000.0	39500000	2013	174000000.0	
	3129	A Wrinkle in Time	BV	100500000.0	32200000	2018	132700000.0	
	3116	Crazy Rich Asians	WB	174500000.0	64000000	2018	238500000.0	
	4							•

```
In [21]:
                  plt.figure(figsize=(12, 10))
               2
                  dg_percentage_plot = sns.regplot(x ='domestic_gross_percentage', y = 'group')
               3
                                                    fit reg=True,
               4
                                                    data = blockbuster movie gross df,
               5
                                                    scatter_kws={'s':50, "color": "#012169"]
               6
                                                      scatter_kws={"color": "#012169"},
               7
                                                    line_kws={"color": "#F8E08E"}
               8
               9
              10
                  dg_percentage_plot.set(xlabel ="Domestic Gross Percentage",
              11
                                          ylabel = "Total Gross in Millions",
                                          title = 'Total Gross for a Movie Compared to Dome:
              12
              13
                  dg percentage plot.yaxis.set major formatter('${x:1.0f}')
              14
```



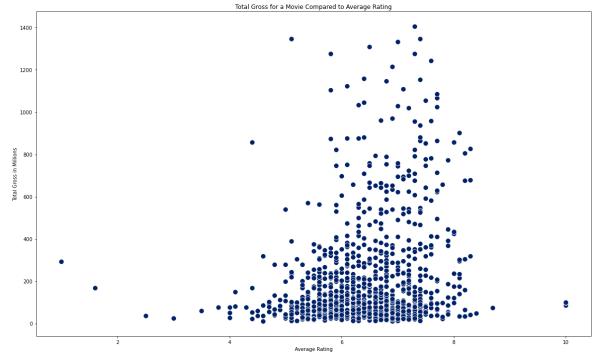
This graph suggests there is a a negative correlation between total gross and the domestic gross percentage. Movies that make more money are less reliant on the domestic box office.

I also want to explore the review data from The Movie DataBase to see if I can glean any insights from that. In order to do that I will have to merge the two dataframes.

```
In [22]:
             H
                  1
                      movie gross and rating df = tmdb df[['title', 'vote average', 'popularit'
                  2
                                                                        left_on='title',
                  3
                                                                        right on='title',
                  4
                                                                            how='inner')
                  5
                      movie_gross_and_rating_df
                                                                                                              Out[22]:
                                       vote_average
                                                      popularity
                                                                  release date
                                                                                 studio
                                                                                        domestic_gross
                                                                                                         foreign
                           How to Train
                    0
                                                 7.7
                                                          28.734
                                                                    2010-03-26
                                                                                 P/DW
                                                                                            217600000.0
                                                                                                             277:
                           Your Dragon
                     1
                            Iron Man 2
                                                 6.8
                                                          28.515
                                                                    2010-05-07
                                                                                   Par.
                                                                                            312400000.0
                                                                                                             311!
                    2
                              Inception
                                                 8.3
                                                          27.920
                                                                    2010-07-16
                                                                                   WB
                                                                                            292600000.0
                                                                                                             535
                    3
                            Toy Story 3
                                                 7.7
                                                          24.445
                                                                    2010-06-17
                                                                                    BV
                                                                                            415000000.0
                                                                                                             6520
                    4
                         Despicable Me
                                                 7.2
                                                          23.673
                                                                    2010-07-09
                                                                                   Uni.
                                                                                            251500000.0
                                                                                                             2910
                    ...
                                                   ...
                           The 15:17 to
                 1064
                                                 5.3
                                                          11.576
                                                                    2018-02-09
                                                                                   WB
                                                                                             36300000.0
                                                                                                              208
                                 Paris
                 1065
                                                                                             42500000.0
                            Uncle Drew
                                                 6.5
                                                          10.836
                                                                    2018-06-29
                                                                                  LG/S
                                                                                                               4:
                 1066
                        Chappaquiddick
                                                 6.0
                                                          10.737
                                                                    2018-04-06
                                                                               ENTMP
                                                                                             17400000.0
                 1067
                            Proud Mary
                                                 5.5
                                                           9.371
                                                                    2018-01-12
                                                                                 SGem
                                                                                             20900000.0
                                                                                                                1
                                                                                 Global
                 1068
                            Show Dogs
                                                 5.9
                                                           7.904
                                                                    2018-05-18
                                                                                             17900000.0
                                                                                                              21:
                                                                                  Road
                1069 rows × 11 columns
```

The merge appears to be sucessful as we only lost ~4% of the columns. It would be possible to further optimize this merge at a later date but I am confident it 'mostly worked'™

Let's plot a graph to see if we can glean anything



That plot looks like the first day of my statistics course!

It looks like a continuous uniform distribution. If I were to plot data with no correlation I would expect a graph like this. Though I can't necessarilyhelp build an actionable insight for Microsoft, but I can tell

them that fan ratings do not appear to be correlated with box office gross.

I do want to look at genres to see which genres perform best at the box office and see how those genres perform in international markets. In order to do that I'm going to add Directors and Genres to the dataframe with movies that exceeded 10 Million Dollars.

```
In [75]:
                    movie gross and director = director movie genre df.merge(movie gross over
                 2
                                                                 left on='Movie Name',
                 3
                                                                 right on='title',
                 4
                                                                     how='inner')
                 5
                    movie gross and director.head(5)
    Out[75]:
                    Director
                             Movie_Name
                                         Length
                                                                           AVG_Rating
                                                                                          title
                                                                                               studio
                                                                   genres
                      Roger
                                 Morning
                                                                                       Morning
                0
                                           107.0
                                                     Comedy, Drama, Romance
                                                                                   6.5
                                                                                                 Par.
                      Michell
                                   Glory
                                                                                         Glory
                      Adam
                                                                                       Rock of
                                                                                                 WB
                1
                             Rock of Ages
                                           123.0
                                                      Comedy, Drama, Musical
                                                                                   5.9
                  Shankman
                                                                                         Ages
                                                                                                 (NL)
                                                                                                 WB
                      Adam
                                                                                       Rock of
                2
                                                      Comedy, Drama, Musical
                                                                                   5.9
                             Rock of Ages
                                           123.0
                  Shankman
                                                                                                 (NL)
                                                                                         Ages
                                                                                                 WB
                      Adam
                                                                                       Rock of
                                                      Comedy, Drama, Musical
                                                                                   5.9
                3
                             Rock of Ages
                                           123.0
                  Shankman
                                                                                         Ages
                                                                                                 (NL)
                     Tim Hill
                                            95.0 Adventure, Animation, Comedy
                                                                                   5.4
                                                                                                 Uni.
                                     Hop
                                                                                          Hop
In [76]:
                    movie gross and director.info()
               <class 'pandas.core.frame.DataFrame'>
               Int64Index: 3403 entries, 0 to 3402
               Data columns (total 13 columns):
                #
                    Column
                                                   Non-Null Count
                                                                     Dtype
                     _ _ _ _ _ _
                0
                                                                     object
                    Director
                                                   3403 non-null
                1
                    Movie Name
                                                   3403 non-null
                                                                     object
                2
                    Length
                                                   3381 non-null
                                                                     float64
                3
                    genres
                                                   3397 non-null
                                                                     object
                4
                    AVG Rating
                                                   3403 non-null
                                                                     float64
                5
                                                                     object
                    title
                                                   3403 non-null
                6
                    studio
                                                   3403 non-null
                                                                     object
                7
                                                                     float64
                    domestic_gross
                                                   3403 non-null
                8
                    foreign gross
                                                   3403 non-null
                                                                     int64
                9
                    vear
                                                   3403 non-null
                                                                     int64
                10
                    total gross
                                                   3403 non-null
                                                                     float64
                    domestic_gross_percentage
                11
                                                   3403 non-null
                                                                     float64
                    gross in millions
                                                   3403 non-null
                                                                     float64
               dtypes: float64(6), int64(2), object(5)
               memory usage: 372.2+ KB
```

This dataframe returned more rows than movies we were looking at but we can tell from the preview there are some duplicates in there. So dropping the duplicates will most likely return something we can work with.

Out[77]: 	Director	Movie_Name	Length	genres	AVG_Rating	title	stu
0	Roger Michell	Morning Glory	107.0	Comedy,Drama,Romance	6.5	Morning Glory	F
1	Adam Shankman	Rock of Ages	123.0	Comedy,Drama,Musical	5.9	Rock of Ages	/ 1)
4	Tim Hill	Нор	95.0	Adventure, Animation, Comedy	5.4	Нор	ι
7	Darren Lynn Bousman	Mother's Day	112.0	Drama,Horror,Thriller	6.3	Mother's Day	0
15	Greg Strause	Skyline	92.0	Action,Sci-Fi,Thriller	4.4	Skyline	ι
3391	Frank Coraci	Here Comes the Boom	105.0	Action,Comedy,Sport	6.4	Here Comes the Boom	Sc
3394	Anne Fletcher	The Guilt Trip	95.0	Comedy,Drama	5.8	The Guilt Trip	F
3395	Scott Derrickson	Sinister	110.0	Horror, Mystery, Thriller	6.8	Sinister	L(
3397	3397 Steve Pink		93.0	Comedy,Mystery,Sci-Fi	5.1	Hot Tub Time Machine 2	F
3399	James Wan	The Conjuring 2	134.0	Drama,Horror,Mystery	7.4	The Conjuring 2	/ 1)

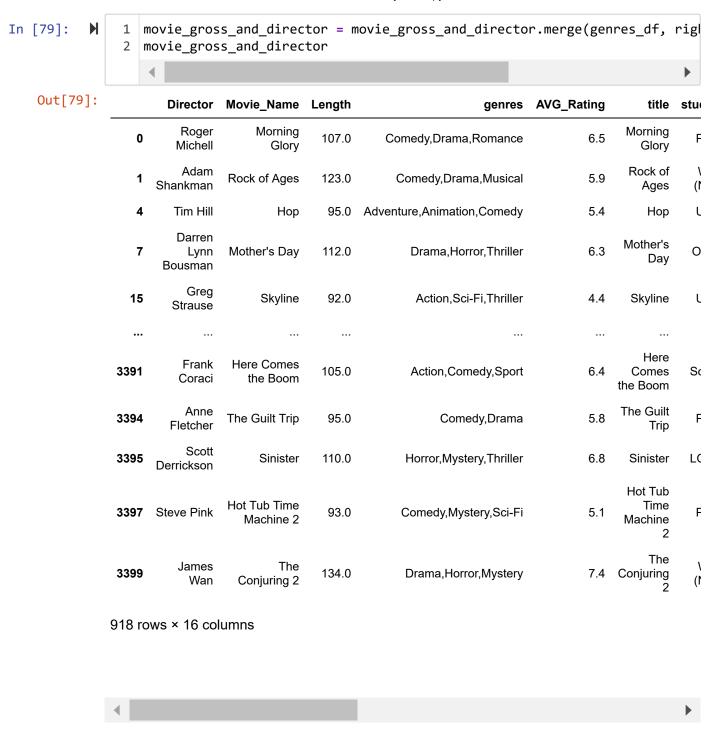
This looks much better and even though we lost some of our results, we can still glean some information from this new dataframe. If I had more time I could further refine the join but it 'mostly worked' $^{\text{TM}}$.

I do want to seperate the genre category so the dataframe has a seperate column for each unique genre.

```
In [78]:
                                                                                                   #Create a new dataframe that keeps the same index but splits the genre re
                                                                                                  genres_df = movie_gross_and_director['genres'].str.split(',', expand = Touristics of the structure of t
                                                                                    3
                                                                                                   genres_df.columns =['Genre1', 'Genre2', 'Genre3']
                                                                                                   genres df
                     Out[78]:
                                                                                                                      Genre1
                                                                                                                                                                       Genre2
                                                                                                                                                                                                                      Genre3
                                                                                              0
                                                                                                                   Comedy
                                                                                                                                                                          Drama
                                                                                                                                                                                                             Romance
                                                                                              1
                                                                                                                   Comedy
                                                                                                                                                                          Drama
                                                                                                                                                                                                                      Musical
                                                                                                            Adventure
                                                                                                                                                            Animation
                                                                                                                                                                                                                   Comedy
                                                                                              7
                                                                                                                          Drama
                                                                                                                                                                            Horror
                                                                                                                                                                                                                         Thriller
                                                                                         15
                                                                                                                           Action
                                                                                                                                                                              Sci-Fi
                                                                                                                                                                                                                         Thriller
                                                                                3391
                                                                                                                           Action
                                                                                                                                                                    Comedy
                                                                                                                                                                                                                               Sport
                                                                                3394
                                                                                                                   Comedy
                                                                                                                                                                                                                              None
                                                                                                                                                                          Drama
                                                                               3395
                                                                                                                           Horror
                                                                                                                                                                      Mystery
                                                                                                                                                                                                                         Thriller
                                                                                3397
                                                                                                                   Comedy
                                                                                                                                                                                                                             Sci-Fi
                                                                                                                                                                     Mystery
                                                                               3399
                                                                                                                                                                                                                     Mystery
                                                                                                                          Drama
                                                                                                                                                                            Horror
```

I can now merge the two dataframes together

918 rows × 3 columns



I want to find a way to get the average movie gross for each genre. The first step is to get a list of genres.

```
In [80]: # Create A New Dataframe where the genres are the columns
list_of_genres_df = genres_df[['Genre1', 'Genre2', 'Genre3']].apply(pd.Sc)
list_of_genres_df = list_of_genres_df.transpose()
list_of_genres_df
```

Out[80]:

	Action	Adventure	Animation	Biography	Comedy	Crime	Documentary	Drama	Fan
Genre1	308.0	129.0	7.0	67.0	178.0	33.0	14.0	126.0	١
Genre2	NaN	156.0	69.0	8.0	83.0	65.0	3.0	185.0	2
Genre3	NaN	NaN	12.0	2.0	85.0	30.0	NaN	79.0	3

3 rows × 21 columns

```
In [81]:
                  #Convert the Column Labels into a list
           H
                2
                  list_of_genres = list(list_of_genres_df.columns)
                  list_of_genres
   Out[81]: ['Action',
               'Adventure',
               'Animation',
               'Biography',
               'Comedy',
               'Crime',
               'Documentary',
               'Drama',
               'Family',
               'Fantasy',
               'History',
               'Horror',
               'Music',
               'Musical',
               'Mystery',
               'Romance',
               'Sci-Fi',
               'Sport',
               'Thriller',
               'War',
               'Western']
```

First I am going to go through the dataframe and assert whether that movie contains the genres. I used the boolean True or False for the assertion.

Now that I have a list of all the genres and have identified which movies contain which genres, I can create a loop that goest through the dataframe and gets the average gross and domestic box office percentage for those genres.

```
In [83]:
          M
                  #Create a new empty list to put the average gross values for each genre
               2
                  total gross genre = []
               3
                  for genre in list of genres:
               4
                          #Add the mean value for all the columsn
               5
                          total_gross_genre.append(movie_gross_and_director.loc[movie_gross
               6
               7
                  #Create a new empty list to put the average gross values for each genre
                  total gross genre
                                                                                           Out[83]: [318129301.9318182,
               394275140.32631576,
               387769318.14772725,
               129916064.92207792,
               184280297.37861273,
               138546617.1796875,
               107740294.05882353,
               127946916.13846155,
               197303761.9047619,
               277673285.70238096,
               137078249.9642857,
               131115088.8888889,
               132049440.0,
               208200000.0,
               125481520.0,
               105797566.64864865,
              434950744.43333334,
               157189993.33333334,
               188674780.63870966,
               123066666.66666667,
               256325000.0]
```

```
In [84]:
               1
                  #Create a new empty list to put the domestic gross percentage values for
               2
               3
                  domestic gross percentage genre = []
               4
                  for genre in list of genres:
               5
                          domestic_gross_percentage_genre.append(movie_gross_and_director.)
               6
               7
                  domestic gross percentage genre
                                                                                           Out[84]: [42.38097838612483,
              39.255730100079205,
               39.41045870997703,
               56.20198961639074,
               53.92797872090043,
               54.698373441845774,
              64.95473576658722,
              54.521062353888446,
               51.53358760392938,
              41.14422676675871,
               53.04935267573994,
               51.006193590898256,
              53.14174141717532,
              48.222498093369765,
              48.49637392226229,
               54.111280628072954,
              42.619232348624884,
              72.93264852727965,
              47.275360425770096,
              47.54061374917885,
              47.46483307992577]
```

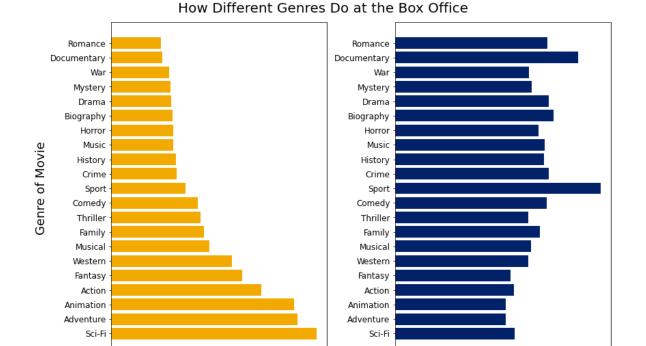
Now that I have three seperate lists, I can create a new dataframe object with those three values.

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			ᆫ	Τ.	

	Genre	Total_Gross_Genre	Domestic Gross Percentage	Total_Gross_In_Milions
16	Sci-Fi	4.349507e+08	42.619232	434.950744
1	Adventure	3.942751e+08	39.255730	394.275140
2	Animation	3.877693e+08	39.410459	387.769318
0	Action	3.181293e+08	42.380978	318.129302
9	Fantasy	2.776733e+08	41.144227	277.673286
20	Western	2.563250e+08	47.464833	256.325000
13	Musical	2.082000e+08	48.222498	208.200000
8	Family	1.973038e+08	51.533588	197.303762
18	Thriller	1.886748e+08	47.275360	188.674781
4	Comedy	1.842803e+08	53.927979	184.280297
17	Sport	1.571900e+08	72.932649	157.189993
5	Crime	1.385466e+08	54.698373	138.546617
10	History	1.370782e+08	53.049353	137.078250
12	Music	1.320494e+08	53.141741	132.049440
11	Horror	1.311151e+08	51.006194	131.115089
3	Biography	1.299161e+08	56.201990	129.916065
7	Drama	1.279469e+08	54.521062	127.946916
14	Mystery	1.254815e+08	48.496374	125.481520
19	War	1.230667e+08	47.540614	123.066667
6	Documentary	1.077403e+08	64.954736	107.740294
15	Romance	1.057976e+08	54.111281	105.797567

Now I want to visualize this data. I'm going to create two horizontal bar charts with the same y axis (genre).

```
In [86]:
                  fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(12, 8))
                  fig.suptitle('How Different Genres Do at the Box Office', fontsize = 20)
               3
                  ax1.barh(genre_data_df['Genre'], genre_data_df['Total_Gross_In_Mllions']
                  ax2.barh(genre data df['Genre'], genre data df['Domestic Gross Percentage
               4
               5
               6
                  # Below code does very specefic formatting
               7
                  ax1.set_xlabel('Average Total Gross in Millions', fontsize = 15)
               8
                  ax2.set xlabel('Domestic Gross Percent of Total Gross', fontsize = 15)
                  ax1.set_ylabel('Genre of Movie', fontsize = 18)
               9
                  ax1.xaxis.set_major_formatter('${x:1.0f}')
              10
                  ax2.xaxis.set major formatter('{x:1.0f}%')
              11
                  ax1.tick_params(axis='x', labelsize=12)
              12
              13
                  ax1.tick_params(axis='y', labelsize=12)
                  ax2.tick_params(axis='x', labelsize=12)
              14
                  ax2.tick params(axis='y', labelsize=12)
              15
              16
              17
                  plt.tight_layout()
              18
```



It appears that the genres with the most total gross are also less reliant on domestic revenue. This further supports my belief that making movies that can are just as appealing to an international audience is a

\$100 \$200 \$300 \$4 Average Total Gross in Millions 20% 30% 40%

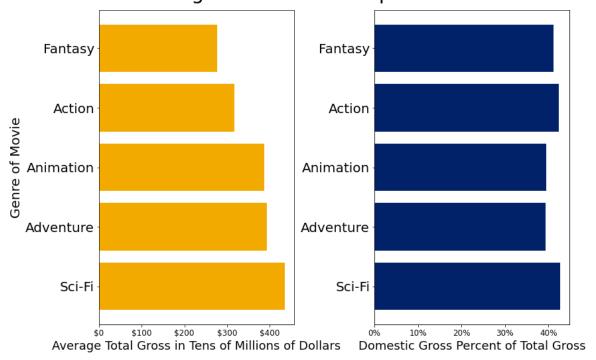
Domestic Gross Percent of Total Gross

50%

better strategy. It also allows me to give some actionable insights to Microsoft Film Studio about what type of movies they should make

```
H
                  fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(12, 8))
In [87]:
                 fig.suptitle('The Average Gross for the Top 5 Genres', fontsize = 30)
                  ax1.barh(genre_data_df['Genre'].head(5), genre_data_df['Total_Gross_In_M]
                  ax2.barh(genre data df['Genre'].head(5), genre data df['Domestic Gross Pe
               5
               6
               7
                 # Below code does very specefic formatting
                 ax1.set xlabel('Average Total Gross in Tens of Millions of Dollars', for
               8
               9
                 ax2.set_xlabel('Domestic Gross Percent of Total Gross', fontsize = 18)
                 ax1.set_ylabel('Genre of Movie', fontsize = 20)
              10
                 ax1.xaxis.set_major_formatter('${x:1.0f}')
              11
                 ax2.xaxis.set major formatter('{x:1.0f}%')
                 ax1.tick_params(axis='x', labelsize=12)
              13
                 ax1.tick params(axis='y', labelsize=20)
              15 | ax2.tick_params(axis='x', labelsize=12)
                 ax2.tick_params(axis='y', labelsize=20)
              17
                 plt.tight layout()
              18
```

The Average Gross for the Top 5 Genres



Sci-Fi, Adventure, Animation, Action, and Fantasy movies make more money than other movies and also have international appeal. This is an actionable insight I can give to Microsoft Film Studios.

I also want to recommend some directors to recommend hiring. I believe that hiring high-profile directors with a

history of making 'Blockbuster" movies will benefit Microsoft. In order to find the best directors for Microsoft to hire I'm going to segment my data again to only include films that grossed over 100 Million Dollars and find the directors who most appeal to international markets.

In [37]: | # Create a new dataframe using our combined

2 # Movie Gross, Director, and Genre DF where domestic gross is greater the

3 BB_gross_director_df = movie_gross_and_director.loc[movie_gross_and_director]

In [38]: | # Sort the new dataframe using a groupby method so every movie a director

2 director_percentage_sorted_df = BB_gross_director_df.groupby('Director')

3 # Grab only the top 10 directors by International Gross Percentage

4 ten_lowest_dom_percentage_directors = director_percentage_sorted_df.head

5 #Sort the dataframe by total gross so the graph is prettier

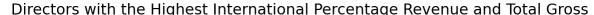
6 ten_lowest_dom_percentage_directors = ten_lowest_dom_percentage_director:

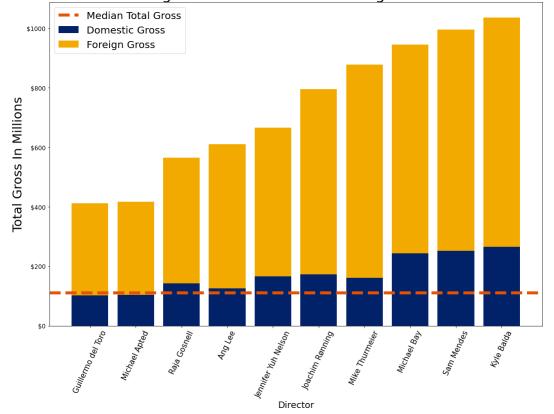
7 ten_lowest_dom_percentage_directors

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	Director	Length	AVG_Rating	domestic_gross	foreign_gross	year	total_gross
65	Guillermo del Toro	131.000000	6.9	1.018000e+08	3.092000e+08	2013.0	4.110000e+08
107	Michael Apted	113.000000	6.3	1.044000e+08	3.113000e+08	2010.0	4.157000e+08
132	Raja Gosnell	103.000000	5.5	1.426000e+08	4.211000e+08	2011.0	5.637000e+08
9	Ang Lee	127.000000	7.9	1.250000e+08	4.840000e+08	2012.0	6.090000e+08
78	Jennifer Yuh Nelson	90.000000	7.2	1.652000e+08	5.004000e+08	2011.0	6.656000e+08
79	Joachim Rønning	129.000000	6.6	1.726000e+08	6.223000e+08	2017.0	7.949000e+08
113	Mike Thurmeier	88.000000	6.6	1.613000e+08	7.159000e+08	2012.0	8.772000e+08
108	Michael Bay	157.666667	5.7	2.426667e+08	7.017667e+08	2014.0	9.444333e+08
146	Sam Mendes	145.500000	7.3	2.522500e+08	7.424000e+08	2013.5	9.946500e+08
94	Kyle Balda	89.000000	6.3	2.646000e+08	7.702000e+08	2017.0	1.034800e+09
4							•

```
In [49]:
                  #Find the median gross for all movies to see how much these directors exc
                  median_movie_gross = movie_gross_and_director['total_gross'].median()
               3
                  #Create new columns to make the graph prettier
                  ten lowest dom percentage directors['Domestic Gross In Millions'] = ten l
               4
                  ten lowest dom percentage directors['Foreign Gross In Millions'] = ten lo
               5
               7
                  fig, ax = plt.subplots(figsize=(15, 12))
               8
               9
                  # Plot both the doemstic gross and international gross on the same bar
                  ax.bar(ten_lowest_dom_percentage_directors['Director'], ten_lowest_dom_percentage_directors['Director'],
              10
                         color = '#012169', label = 'Domestic Gross')
              11
                  ax.bar(ten_lowest_dom_percentage_directors['Director'], ten_lowest_dom_pe
              12
              13
                         bottom = ten_lowest_dom_percentage_directors['Domestic_Gross_In_M;
              14
              15
                  # Below code does very specefic formatting
              16
                  plt.axhline(y = median_movie_gross/1000000, color = '#E35205', linestyle
              17
                  plt.xticks(rotation=65)
              18
                  plt.legend(loc="upper left", fontsize = 20)
              19
                  ax.set_title('Directors with the Highest International Percentage Revenue
              20
                  ax.set xlabel('Director', fontsize = 18)
              21
                  ax.set ylabel('Total Gross In Millions', fontsize = 25)
              22
                  ax.yaxis.set_major_formatter('${x:1.0f}')
              23
                  ax.tick params(axis='x', labelsize=15)
              24
                  ax.tick_params(axis='y', labelsize=12)
              25
              26
                  plt.tight layout()
              27
              28
```





This graph shows 'Blockbuster" directors with the highest foreign gross percentage and what portion of their movie gross comes from the Domestic Box Office and the Foreign Box Office. These directors make movies that gross much more than average and would be a good hire for Microsoft Film Studios.

70 percent of them are non-american and three of the top four make animated movies. Animated movies translate very well for international audiences because film studios can hire different voice actors and not rely on dubs. Another key insight is that foreign directors are much better at making money over seas.

Recommendations

Goal: Prioritize revenue over other factors such as ROI or reviews.

Higher total revenue is correlated with a higher international gross percentage.

Certain genres are more appealing to foreign markets.

- 1. Sci-Fi, Adventure, Action, Animation, and Fantasy are the highest grossing genres.
- 2. They also are genres that international audiences are keen to see.
- This is most likely because they are plot-driven vs character-driven films. (<u>NYBookEditors</u>
 <u>Article on the Difference (https://nybookeditors.com/2017/02/character-driven-vs-plot-driven-best/#:~:text=Character-driven-vs-plot-driven-driven-vs-plot-driven-vs-plot-driven-vs-plot-driven-best/#:~:text=Character-driven-vs-plot-driven</u>

Hire directors with a proven track record of releasing successfully outside the U.S./Canada.

- 1. International directors have a global perspective that helps to sell movies abroad.
- 2. In order to maximize the chances the movie will be high grossing, hire international directors who have a proven history of making "blockbuster" movies
- 3. Animation directors also have a lot of experience translating their movies internationally and can hire different voice actors for different regions.

Future Improvement Ideas

- Grab data from movies that were not released in the U.S.
 - Better understanding foreign markets will allow your studio to release more successfully abroad
- Adjust for Inflation.
- · Refine my join statements so that I can keep more data.

- Create Director/Genre pairings so Microsoft can commission directors to make certain types of movies
- Look into the importance of sequels and movie franchises as it pertains to this data.

Other Resources and Places to Contact Me

Presentation Deck:

Work Notebook I used:

Acknowledgements

I want to thank my professors at Flatiron School who helped me to create this report. Specifically, **Lindsey Berlin** and **Mark Barbour**.

I also could not have done this without all the public information available on the websites I linked in this notebook and the datasets I used.

I also want to give a shoutout to my dog *Haley* who oversaw all of my work on this project. She kept me on task throughout and was willing to listen when my code did not work.

Most importantly, I want to thank you the reader.

If you have any questions or want to get in touch with me please feel free to reach out via these platforms.

Thanks, John Bruemmer

Email: Johnnybruemmer@gmail.com (mailto:Johnnybruemmer@gmail.com)

LinkedIn: John Bruemmer (https://www.linkedin.com/in/john-bruemmer-407a58a4/)

GitHub: Jbruemmer (https://github.com/Jbruemmer)

