Home Actor Movie Top 20 About

Is Lacey Chabert really the "Center of the (Hallmark) Universe?!"

This project seeks to find out, using a subset of IMDB listed movies and actors from Hallmark original movies, romantic comedies, mysteries, and dramas.

Import modules to handle dataframes, plotting, graphing centrality, and shortest path

In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import networkx as nx
import matplotlib.colors as mcolors
```

Load movie data into dataframes, and drop unwanted rows

In [2]:
```
local_file = 'watchlist.txt'
header_field = ['tconst']
watchlist_info = pd.read_csv(local_file, names=header_field)
watchlist = []
watchlist = watchlist_info['tconst'].tolist() # refactor this to load direc
```

In [3]:
```
local_file = 'movie_info.csv'
movie_info = pd.read_csv(local_file, sep='\t')
```

In [4]:
```
movie_info = movie_info[movie_info['tconst'].isin(watchlist) == True]  # dr
```

In [5]:
```
local_file = 'cast_crew_info.csv'
cast_crew_info = pd.read_csv(local_file, sep='\t')
```

In [6]:
```
actorlist = cast_crew_info['nconst'].tolist()  # all the Hallmark actors
actorlist = list(set(actorlist))
```

In [7]:
```
cast_crew_info = cast_crew_info[cast_crew_info['nconst'].isin(actorlist) ==
```

In [8]:
```
local_file = 'movie_cast_crew.csv'
movie_cast_crew = pd.read_csv(local_file, sep='\t')
```

In [9]:
```
movie_cast_crew = movie_cast_crew[movie_cast_crew['tconst'].isin(watchlist)
```

In [10]:
```
unwantedValues = ['director', 'writer', 'producer', 'composer', 'cinematogr
                  'production_designer', 'self']  # leaves actor, actress,
```

In [11]:
```
movie_cast_crew = movie_cast_crew[movie_cast_crew['category'].isin(unwanted
# keep actor, actress rows
```

In [12]:
```
movielist = movie_cast_crew['tconst'].tolist()  # all the Hallmark movies
movielist = list(set(movielist))
```

Create lookup dictionaries for all four tables

In [13]:
```
df = movie_cast_crew.groupby('nconst')['tconst'].apply(list).reset_index(na
```

In [14]:
```
nm_tt = dict(zip(df.nconst, df.movieList))  # list of movies each actor sta
```

In [15]:
```
df = movie_cast_crew.groupby('tconst')['nconst'].apply(list).reset_index(na
```

In [16]:
```
tt_nm = dict(zip(df.tconst, df.actorList))  # list for dictionary lookup of
```

In [17]:
```
df = cast_crew_info  # source of ID no, full name, birth year, death year,
```

In [18]:
```
nm_name = dict(zip(df.nconst, df.primaryName))  # create a lookup dictionar
```

In [19]:
```
df = movie_info  # includes title, release year, runtime, ratings, num vote
```

In [20]:
```
tt_title = dict(zip(df.tconst, df.primaryTitle)) # create lookup table
```

In [21]:
```
title_tt = dict(zip(df.primaryTitle, df.tconst))  # create a dictionary map
```

In [22]:
```
tt_rating = dict(zip(df.tconst, df.averageRating)) # create lookup table
```

In [23]:
```
title_rating = dict(zip(df.primaryTitle, df.averageRating)) # create lookup
```

Analyze movie data using basic visualizations

In [24]:
```
%matplotlib inline
```

In [25]:
```
cast_crew_info.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2514 entries, 0 to 2513
Data columns (total 4 columns):
 #   Column       Non-Null Count  Dtype 
---  ------       --------------  ----- 
 0   nconst       2514 non-null   object
 1   primaryName  2514 non-null   object
 2   birthYear    2514 non-null   object
 3   deathYear    2514 non-null   object
dtypes: object(4)
memory usage: 98.2+ KB
```

In [26]:
```
cast_crew_info.head()  # mean age of actors/actresses could be a feature fo
```

Out[26]:

	nconst	primaryName	birthYear	deathYear
0	nm0000137	Bo Derek	1956	\N
1	nm0000145	Sherilyn Fenn	1965	\N
2	nm0000157	Linda Hamilton	1956	\N
3	nm0000162	Anne Heche	1969	\N
4	nm0000176	Nastassja Kinski	1961	\N

In [27]:
```
movie_cast_crew.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 4858 entries, 0 to 4857
Data columns (total 3 columns):
 #   Column    Non-Null Count  Dtype 
---  ------    --------------  ----- 
 0   tconst    4858 non-null   object
 1   nconst    4858 non-null   object
 2   category  4858 non-null   object
dtypes: object(3)
memory usage: 151.8+ KB
```

In [28]:
```
movie_cast_crew.head()  # could refactor and keep director, cinematographer
```

Out[28]:

	tconst	nconst	category
0	tt0102842	nm0000335	actress
1	tt0102842	nm0000686	actor
2	tt0102842	nm0709634	actress
3	tt0102842	nm0825555	actress
4	tt0108159	nm0000335	actress

In [29]:
```
movie_info.head()  # genres could be feature for research, maybe seasonal f
```

Out[29]:

	tconst	titleType	primaryTitle	startYear	runtimeMinutes	genres	averageRating
0	tt0102842	tvMovie	Sarah, Plain and Tall	1991	98	Drama,Family,Romance	7.3
1	tt0108159	tvMovie	Skylark	1993	95	Drama	7.2
2	tt0140340	tvMovie	The Love Letter	1998	99	Fantasy,Romance	7.2
3	tt0184799	tvMovie	Ordinary Miracles	2005	85	Drama	6.4
4	tt0192573	tvMovie	Sarah, Plain & Tall: Winter's End	1999	95	Drama	6.8

In [30]:
```
df = movie_info  #let's start with the movie database
```

In [31]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1180 entries, 0 to 1179
Data columns (total 8 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   tconst          1180 non-null   object 
 1   titleType       1180 non-null   object 
 2   primaryTitle    1180 non-null   object 
 3   startYear       1180 non-null   object 
 4   runtimeMinutes  1180 non-null   int64  
 5   genres          1180 non-null   object 
 6   averageRating   1180 non-null   float64
 7   numVotes        1180 non-null   int64  
dtypes: float64(1), int64(2), object(5)
memory usage: 83.0+ KB
```

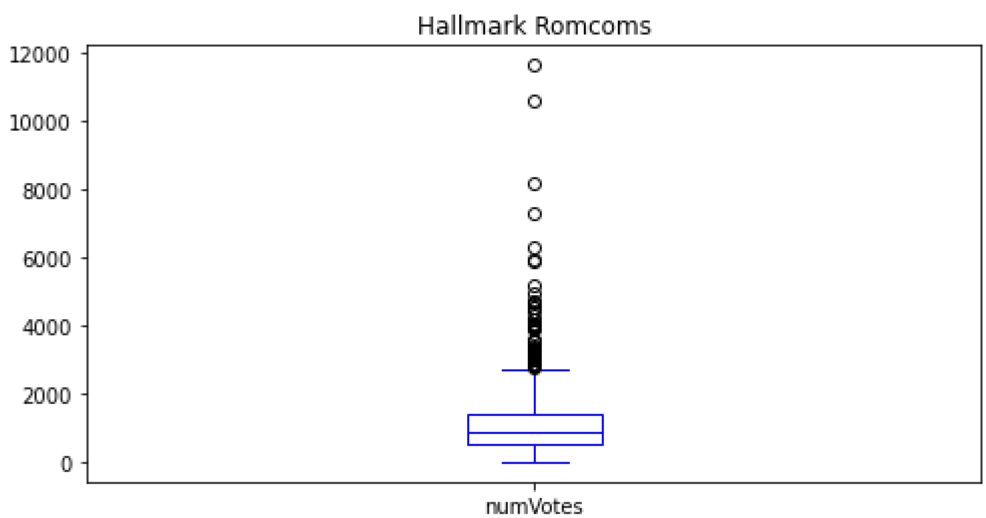
In [32]:
```
df['startYear'] = pd.to_numeric(df['startYear'], errors='coerce') #convert
df['startYear'] = df['startYear'].astype("Int64") #then back to integer (re
```

In [33]:
```
df.info()  #that's better!
```

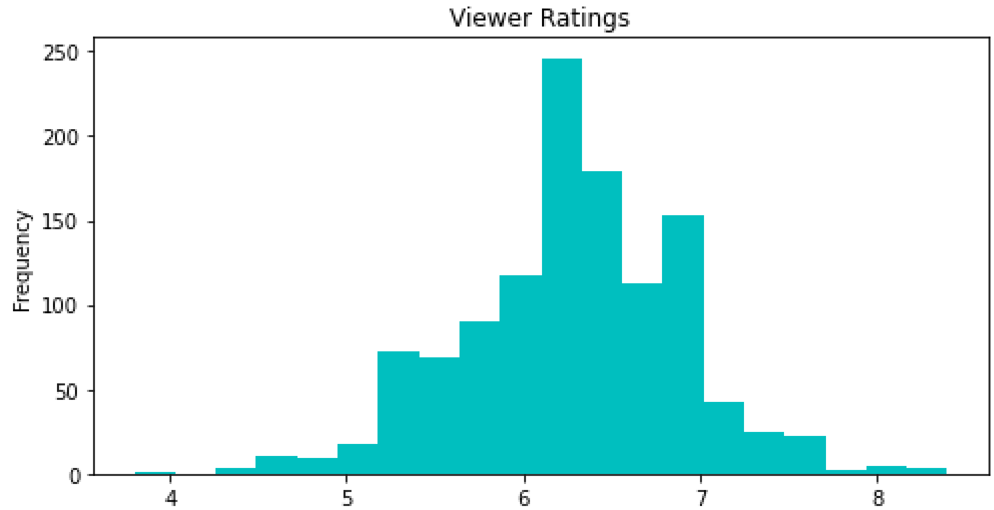
```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1180 entries, 0 to 1179
Data columns (total 8 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   tconst          1180 non-null   object
 1   titleType       1180 non-null   object
 2   primaryTitle    1180 non-null   object
 3   startYear       1175 non-null   Int64
 4   runtimeMinutes  1180 non-null   int64
 5   genres          1180 non-null   object
 6   averageRating   1180 non-null   float64
 7   numVotes        1180 non-null   int64
dtypes: Int64(1), float64(1), int64(2), object(4)
memory usage: 84.1+ KB
```

In [34]:
```
plt.rcParams["figure.figsize"] = (8,4)
```

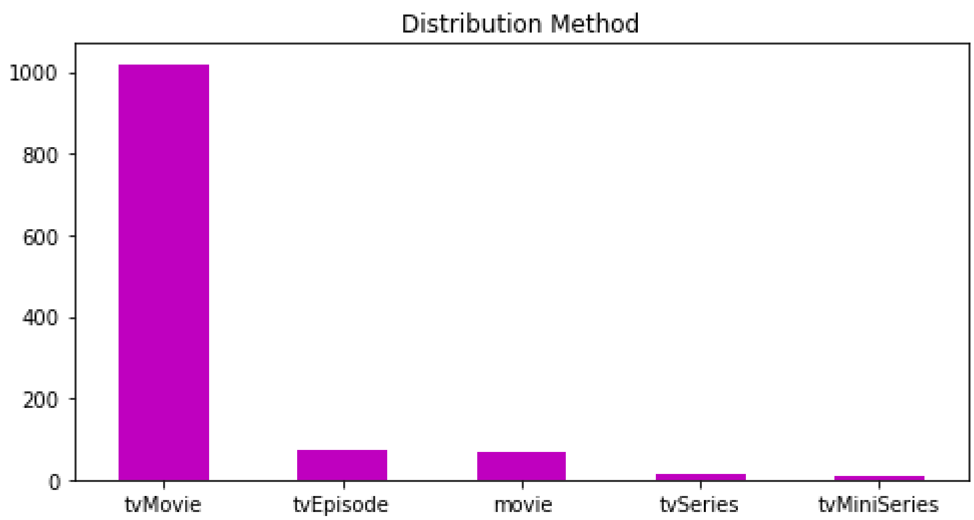
In [35]:
```
df.numVotes.plot(kind='box', title='Hallmark Romcoms', color='b');  #older,
```



In [36]:
```
df.averageRating.plot(kind='hist',
                      title='Viewer Ratings',
                      color='c',
                      bins=20);  # most people rate movies between 5 and 7,
```



In [37]:
```
df.titleType.value_counts().plot(kind='bar',
                                 rot=0,
                                 title='Distribution Method',
                                 color='m');  # could probably drop lowest
```

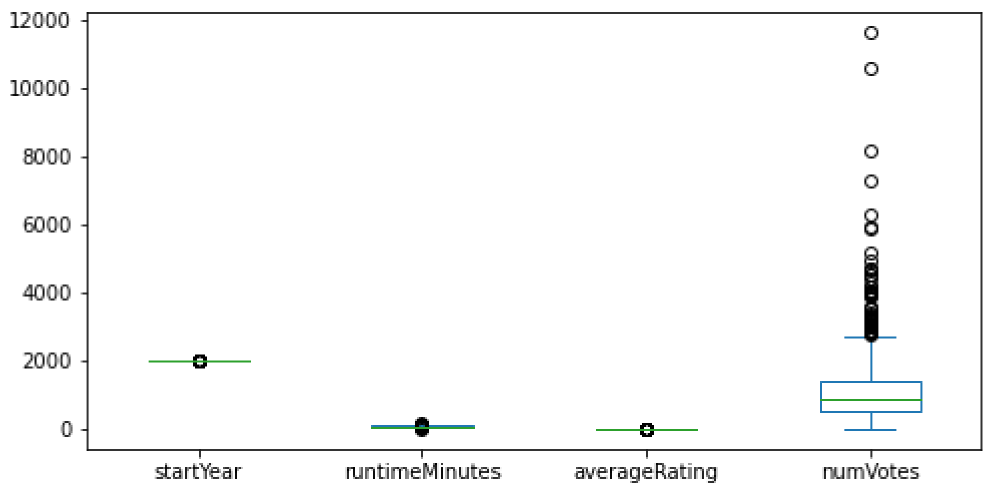


In [38]:
```python
df.groupby(['titleType']).agg({ 'numVotes': 'mean', 'averageRating': 'mean'
```

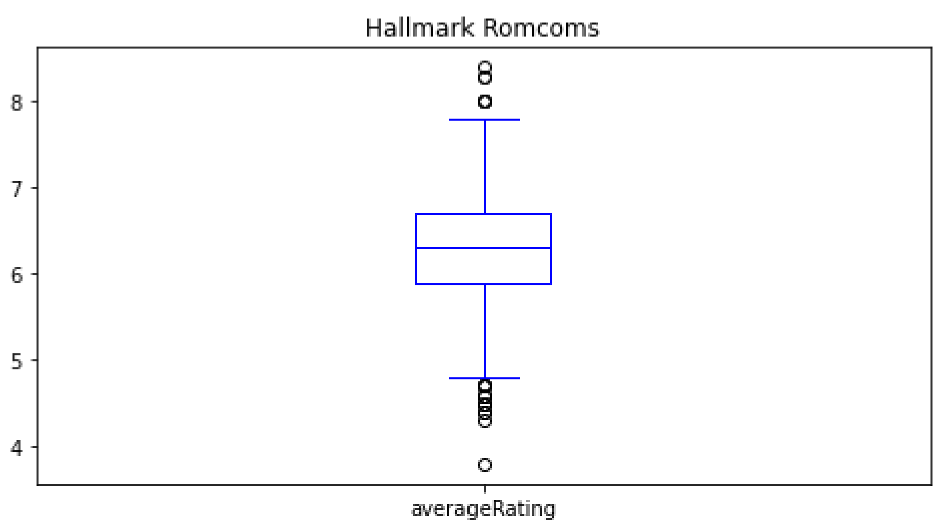
Out[38]:

titleType	numVotes	averageRating	runtimeMinutes
movie	747.362319	5.763768	89.0
tvEpisode	772.597222	6.761111	84.0
tvMiniSeries	296.000000	7.125000	80.0
tvMovie	1157.913641	6.250049	85.0
tvSeries	867.750000	7.400000	80.0

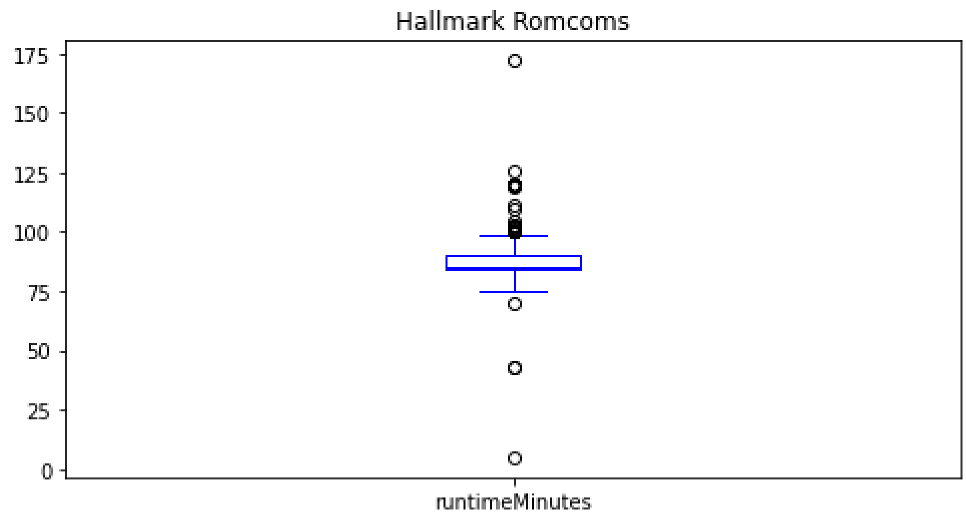
In [39]:
```python
df.plot(kind='box');
```



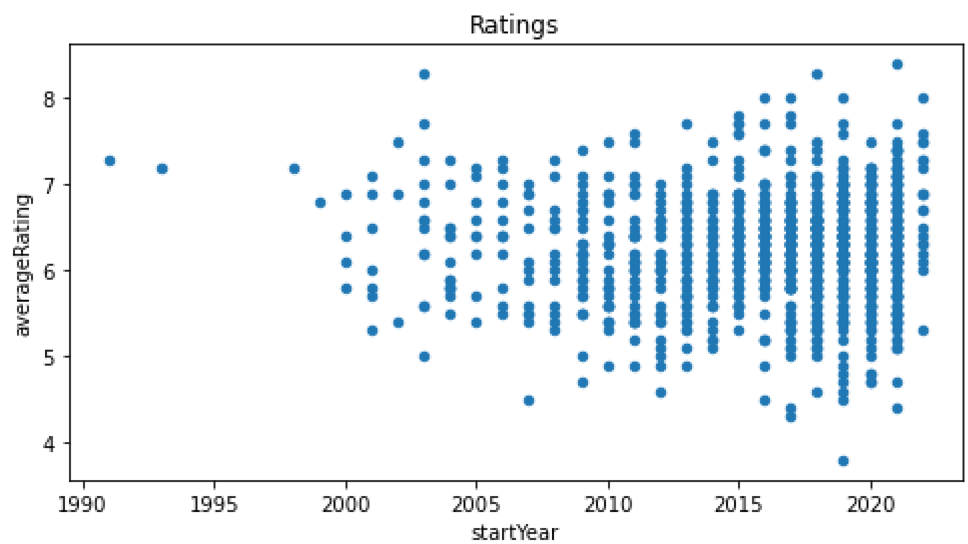
In [40]:
```python
df.averageRating.plot(kind='box', title='Hallmark Romcoms', color='b');   #
```



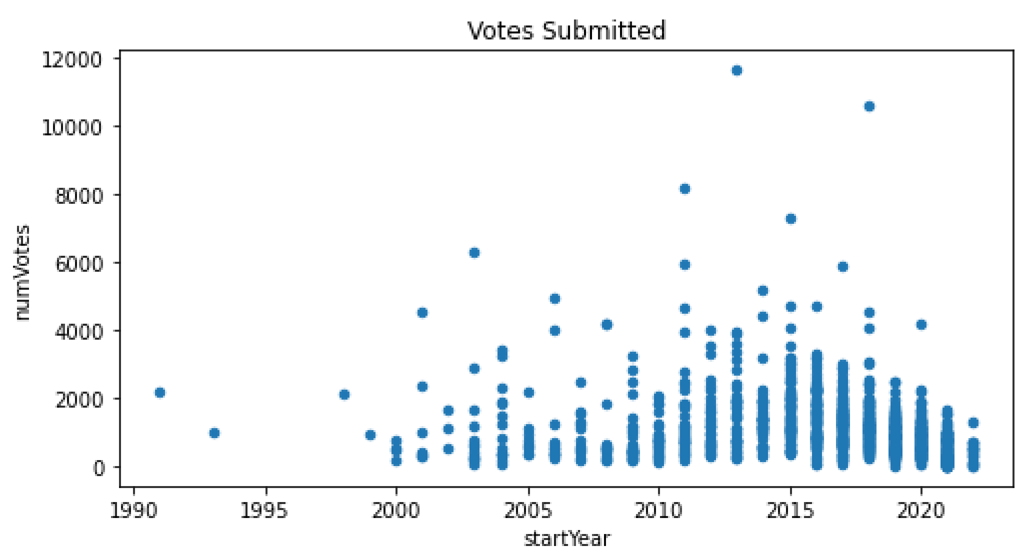
In [41]:
```
df.runtimeMinutes.plot(kind='box', title='Hallmark Romcoms', color='b');
```



In [42]:
```
df.plot.scatter(x='startYear', y='averageRating', title="Ratings");  # soci
```



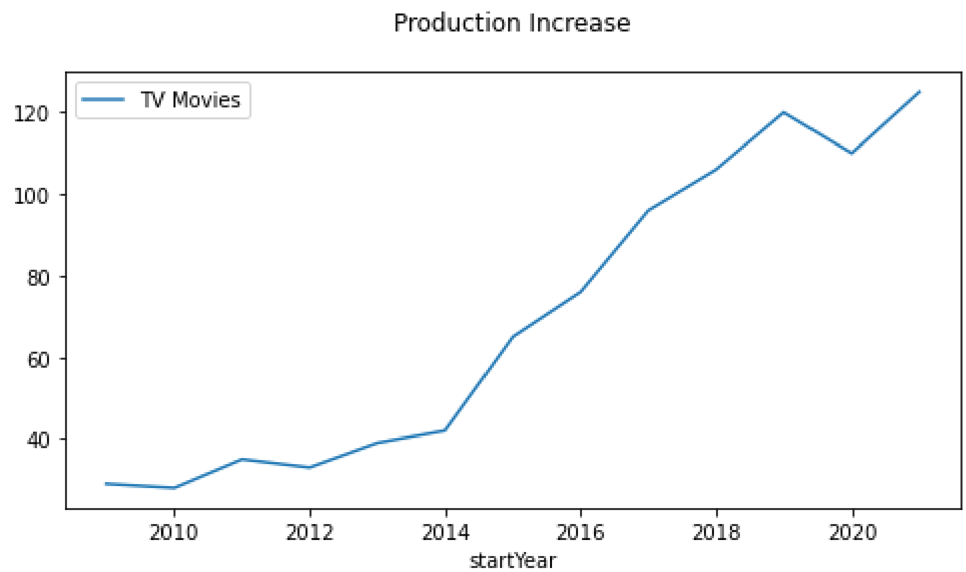
In [43]:
```
df.plot.scatter(x='startYear', y='numVotes', title="Votes Submitted"); # le
```



In [44]:
```
annual_volume = pd.crosstab(df.startYear, df.titleType)[-14:-1]  # movies p
```

In [45]:
```
annual_volume.tvMovie.plot(kind='line')
annual_volume.index.names = ['Year']  # change the index for graph
plt.legend(['TV Movies'])
plt.title('Production Increase\n')
```

Out[45]:
```
Text(0.5, 1.0, 'Production Increase\n')
```



In [46]:
```
pd.crosstab(df.startYear, df.titleType)[-14:-1]
```

Out[46]:

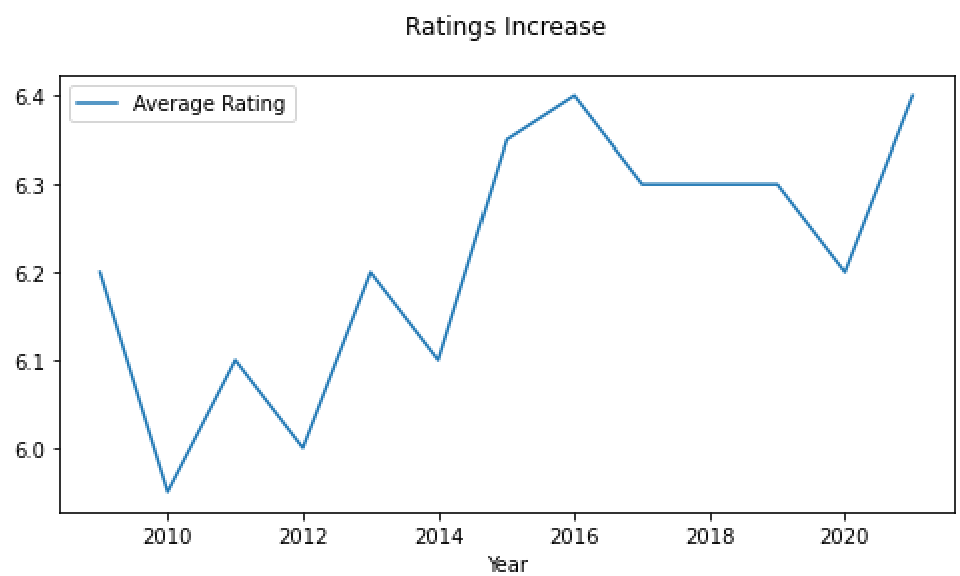
titleType	movie	tvEpisode	tvMiniSeries	tvMovie	tvSeries
startYear					
2009	0	0	0	29	0
2010	0	0	0	28	0
2011	1	0	0	35	0
2012	0	0	0	33	0
2013	0	1	0	39	1
2014	0	1	0	42	0
2015	2	6	2	65	1
2016	7	7	1	76	1
2017	9	8	3	96	0
2018	7	8	0	106	1
2019	15	23	2	120	3
2020	16	10	0	110	2
2021	12	7	0	125	1

In [47]:
```
annual_ratings = df.groupby(['startYear']).agg({ 'averageRating': 'median'})
annual_ratings.columns = ["Avg Rating"]  # change the name for graph
annual_ratings.index.names = ['Year']  # change the index for graph
annual_ratings
```

Out[47]:

	Avg Rating
Year	
2009	6.20
2010	5.95
2011	6.10
2012	6.00
2013	6.20
2014	6.10
2015	6.35
2016	6.40
2017	6.30
2018	6.30
2019	6.30
2020	6.20
2021	6.40

In [48]:
```
annual_ratings.plot(kind='line')
plt.legend(['Average Rating'])
plt.title('Ratings Increase\n');
```



Graph network plot and determine centrality

In [49]:
```
titles = watchlist
```

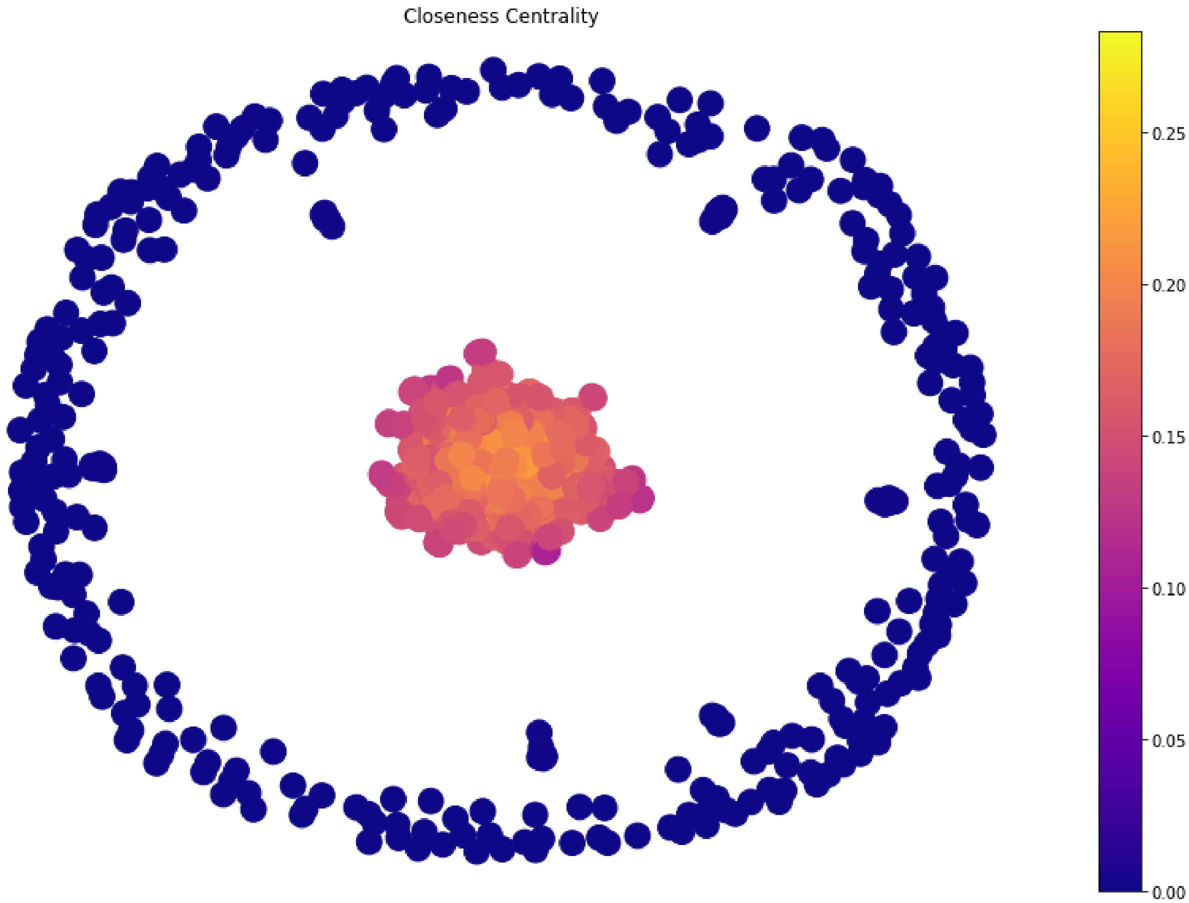
In [50]:
```
G = nx.Graph()  # prototype for logic in main project module
edge_attribute_dict = {}
for name_ID, titles in nm_tt.items():
    G.add_node(name_ID)  # save people as nodes
    for title in titles:
        for name_ID2, titles2 in nm_tt.items():
            if (title in titles2) and (titles2 != titles):
                G.add_edge(name_ID, name_ID2)  # save movies as edges
                name_ID_tuple = tuple(sorted((name_ID, name_ID2)))
                if name_ID_tuple not in edge_attribute_dict:
                    edge_attribute_dict[name_ID_tuple] = 1
                else:
                    edge_attribute_dict[name_ID_tuple] += 1 # keep count of
```

In [51]:
```
for k,v in edge_attribute_dict.items():  # calculate centrality with weight
    edge_attribute_dict[k] = {'weight':v}
```

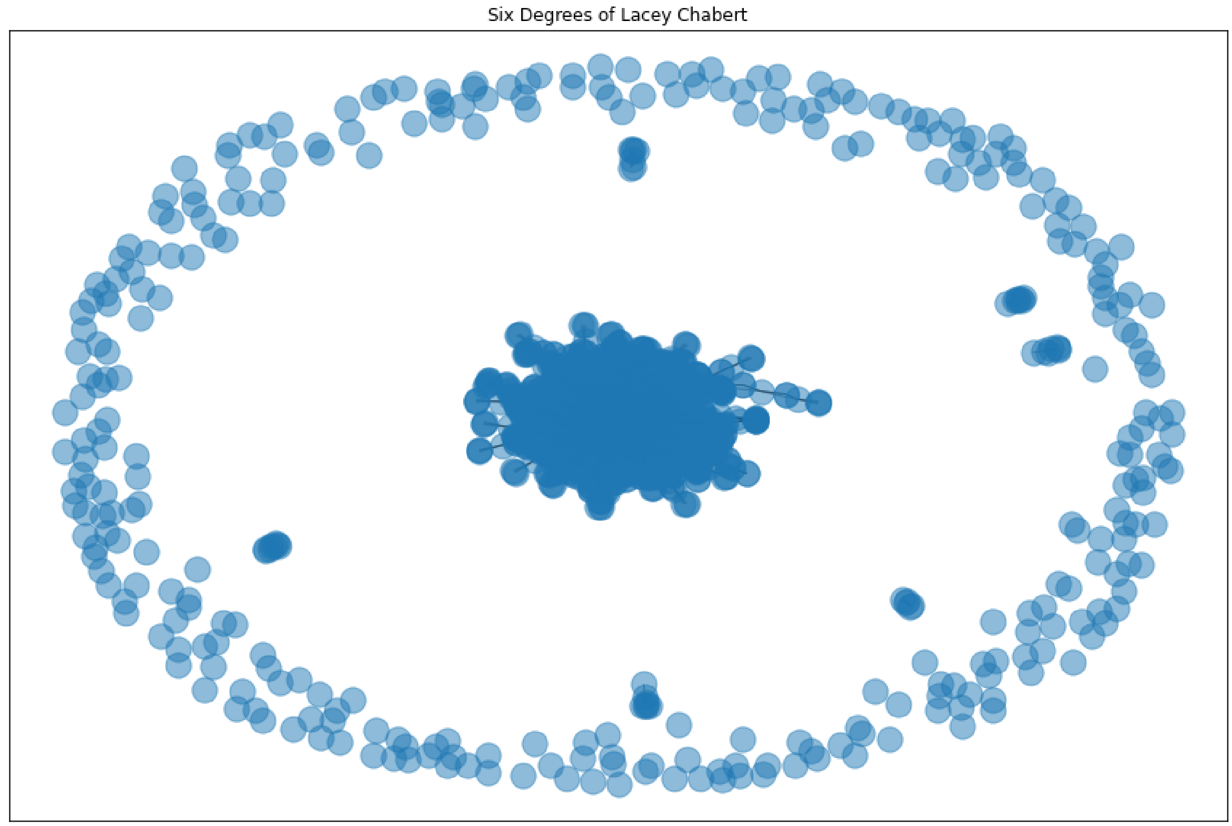
In [52]:
```
import matplotlib.colors as mcolors   # courtesy of aksakalli.github.io
pos = nx.spring_layout(G, seed=675)
def draw(G, pos, measures, measure_name):  # use this function for nicer lo
    nodes = nx.draw_networkx_nodes(G, pos, node_size=250, cmap=plt.cm.plasm
                                   node_color=list(measures.values()),
                                   nodelist=measures.keys())  # removed col
    # labels = nx.draw_networkx_labels(G, pos)
    edges = nx.draw_networkx_edges(G, pos)
    plt.title(measure_name)
    plt.colorbar(nodes)
    plt.axis('off')
    plt.show()
```

In [53]:
```
plt.rcParams["figure.figsize"] = (15, 10)  # make these three graphs a litt
```

```
In [54]: draw(G, pos, nx.closeness_centrality(G), 'Closeness Centrality')  # uses dr
```



In [55]:
```
labels = {n:n for n in G.nodes()}
plt.title('Six Degrees of Lacey Chabert')
nx.draw_networkx(G, alpha=0.5, labels=labels, with_labels=False)
```



In [56]:
```
between_ity = nx.betweenness_centrality(G)  # comfirms general results of m
[(nm_name[x], between_ity[x]) for x in sorted(between_ity, key=between_ity.
```

Out[56]:
```
[('Lacey Chabert', 0.05362316706681671),
 ('Andrew W. Walker', 0.04520482611973078 4),
 ('Danica McKellar', 0.03206073251987482),
 ('Cindy Busby', 0.031045406503442 45),
 ('Trevor Donovan', 0.030026740510035826),
 ('Candace Cameron Bure', 0.029839655717275 6),
 ('Jen Lilley', 0.027290130418788253),
 ('Alison Sweeney', 0.02674565099467195),
 ('Stephen Huszar', 0.022791611742354 45),
 ('Corey Sevier', 0.022630921628412456)]
```

In [57]:
```
close_ity = nx.closeness_centrality(G)  # not as useful without removing ti
[(nm_name[x], close_ity[x]) for x in sorted(close_ity, key=close_ity.get, r
```

Out[57]:
```
[('Lacey Chabert', 0.2830413024643861),
 ('Andrew W. Walker', 0.27794714842627943),
 ('Danica McKellar', 0.27015160891569706),
 ('Autumn Reeser', 0.26948928163684405),
 ('Barbara Niven', 0.2677516376085223),
 ('Alison Sweeney', 0.2671773918887442),
 ('Candace Cameron Bure', 0.2650927335607713),
 ('Victor Webster', 0.26479221749608567),
 ('Christopher Russell', 0.26333690513949787),
 ('Tyler Hynes', 0.26318854631970096)]
```

Actor analysis -- who starred in the most movies?

In [58]:
```
df = movie_info
```

In [59]:
```
name_count = {}  # create a dictionary to store the sorted movie count by a
for actor in actorlist:
    name_count[nm_name[actor]] = len(nm_tt[actor])  # count movies for each
sorted_dict = sorted([(value, key)
 for (key, value) in name_count.items()])  # sort the dictionary
df = pd.DataFrame(sorted_dict, columns =["Movies", "Actor"])  # rename the
df = df.sort_values(by='Movies', ascending=False) # reverse sort the movie
df[:10]  # Sure enough, data confirms Lacey Chabert is the Queen of RomComs
```

Out[59]:

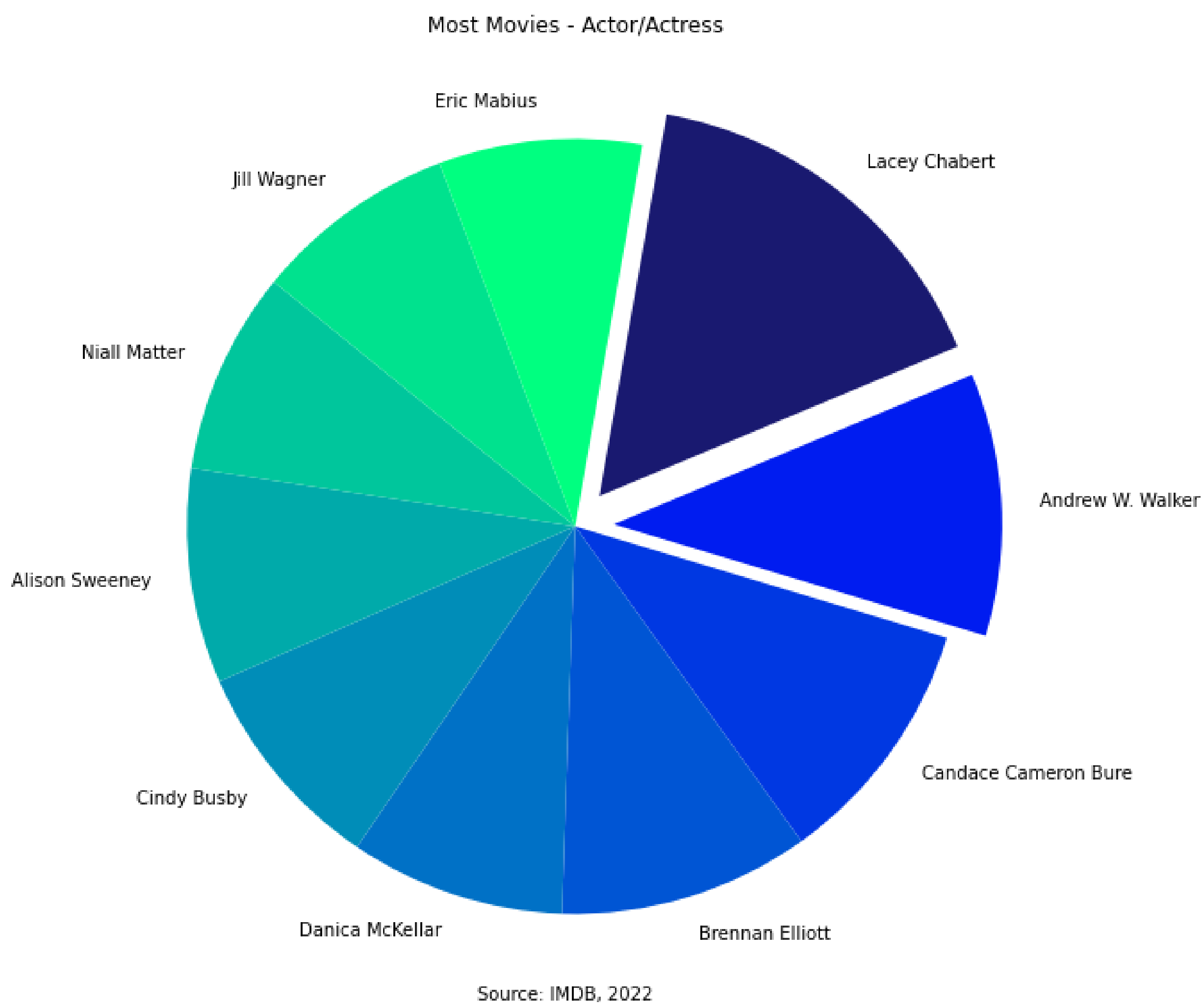
	Movies	Actor
2512	32	Lacey Chabert
2511	22	Andrew W. Walker
2510	21	Candace Cameron Bure
2509	21	Brennan Elliott
2508	18	Danica McKellar
2507	18	Cindy Busby
2506	18	Alison Sweeney
2505	17	Niall Matter
2504	17	Jill Wagner
2503	17	Eric Mabius

High percentile actors, very few have this many movies

In [60]:
```
print(df['Movies'].quantile(q=0.990), df['Movies'].quantile(q=0.993), df['M
```

```
13.0 14.416000000000167 16.0
```

In [61]:
```
top_10 = df[:10]
values = list(top_10['Movies'])  # let's chart the Top 10 on a pie chart, b
labels = list(top_10['Actor'])
plt.title('Most Movies - Actor/Actress')
plt.annotate(r'Source: IMDB, 2022', xy=(.4, .01), xycoords='axes fraction')
colors = ['#191970','#001CF0','#0038E2','#0055D4','#0071C6','#008DB8',\
          '#00AAAA','#00C69C','#00E28E','#00FF80']  # use a blue-green spec
explode = (.1, .1, 0, 0, 0, 0, 0, 0, 0, 0)  # callout the top two, female a
plt.pie(values, labels=labels, explode=explode, colors=colors, counterclock
plt.show()
```



Rating Analysis, for actor/actress with at least 20 movies

In [62]:
```
name_rating = {}  # create a dictionary to store the sorted movie count by
for actor in actorlist:
    sum = 0.0
    count = 0
    movies = nm_tt[actor]
    count = len(movies)
    for each in range(len(movies)):
        try:
            sum += tt_rating[movies[each]]
        except:
            count -= 1
        if count > 20:
            name_rating[nm_name[actor]] = sum/count  # count movies for eac
sorted_dict = sorted([(value, key)
 for (key, value) in name_rating.items()])  # sort the dictionary
df = pd.DataFrame(sorted_dict, columns =["Rating", "Actor"])  # rename the
df = df.sort_values(by='Rating', ascending=False) # reverse sort the movie
df[:10]  # Sure enough, data confirms Lacey Chabert is the Queen of RomComs
```

Out[62]:

	Rating	Actor
3	6.728125	Lacey Chabert
2	6.680952	Candace Cameron Bure
1	6.633333	Brennan Elliott
0	6.531818	Andrew W. Walker

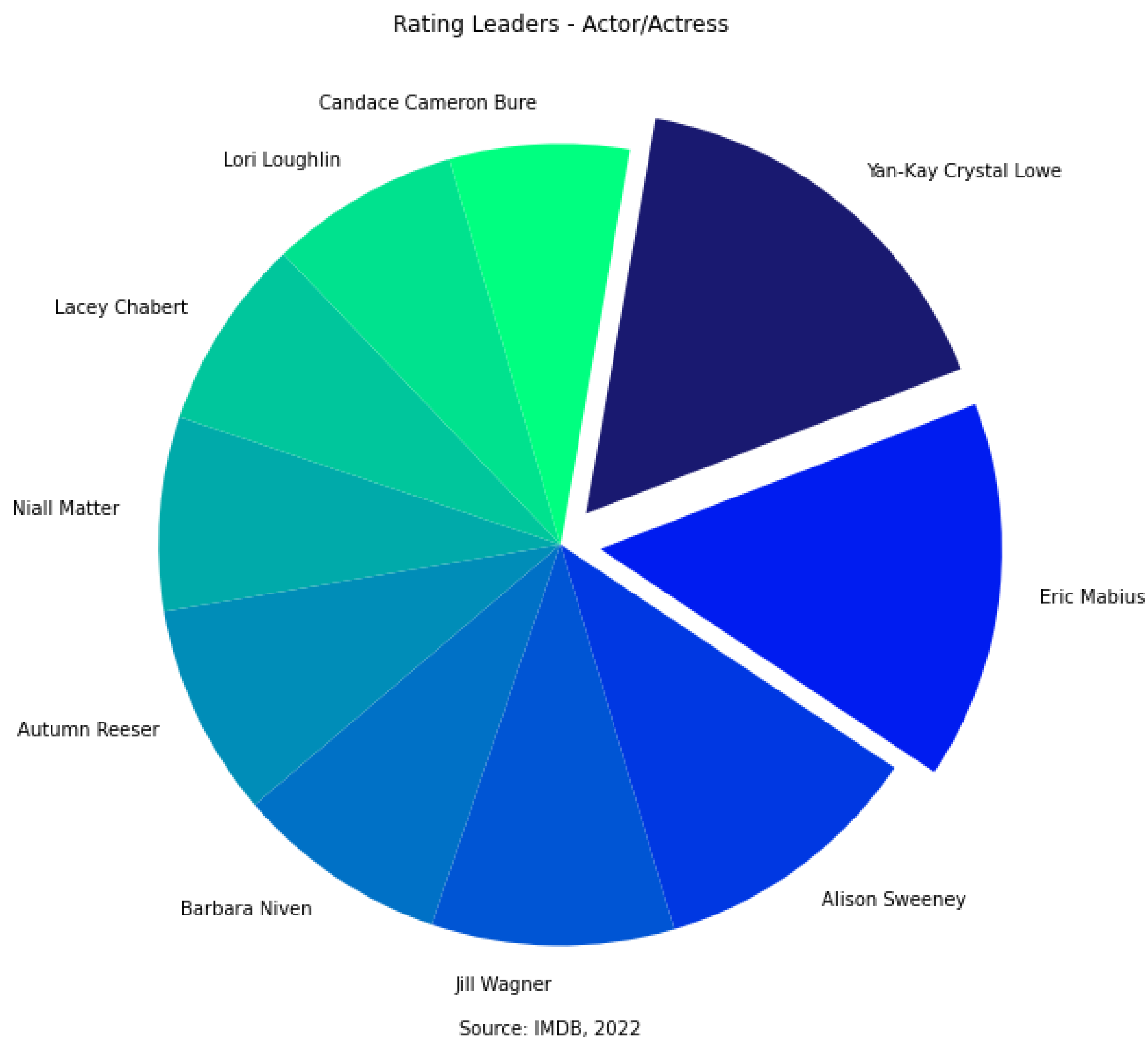
and for actor/actress with at least 15 movies

In [63]:
```
name_rating = {}  # create a dictionary to store the sorted movie count by
for actor in actorlist:
    sum = 0.0
    count = 0
    movies = nm_tt[actor]
    count = len(movies)
    for each in range(len(movies)):
        try:
            sum += tt_rating[movies[each]]
        except:
            count -= 1
        if count > 15:
            name_rating[nm_name[actor]] = sum/count  # count movies for eac
sorted_dict = sorted([(value, key)
 for (key, value) in name_rating.items()])  # sort the dictionary
df = pd.DataFrame(sorted_dict, columns =["Rating", "Actor"])  # rename the
df = df.sort_values(by='Rating', ascending=False) # reverse sort the movie
df[:10]  # There are some higher rated actors/actresses with less movies
```

Out[63]:

	Rating	Actor
14	7.537500	Yan-Kay Crystal Lowe
13	7.435294	Eric Mabius
12	7.038889	Alison Sweeney
11	6.917647	Jill Wagner
10	6.806250	Barbara Niven
9	6.806250	Autumn Reeser
8	6.735294	Niall Matter
7	6.728125	Lacey Chabert
6	6.718750	Lori Loughlin
5	6.680952	Candace Cameron Bure

```
In [64]: top_10 = df[:10]
values = list(top_10['Rating']-6)  # let's chart Top 10 on a pie chart, bas
labels = list(top_10['Actor'])
plt.title('Rating Leaders - Actor/Actress')
plt.annotate(r'Source: IMDB, 2022', xy=(.4, .01), xycoords='axes fraction')
colors = ['#191970','#001CF0','#0038E2','#0055D4','#0071C6','#008DB8',\
          '#00AAAA','#00C69C','#00E28E','#00FF80']  # use a blue-green spec
explode = (.1, .1, 0, 0, 0, 0, 0, 0, 0, 0)  # callout the top two, female a
plt.pie(values, labels=labels, explode=explode, colors=colors, counterclock
plt.show()
```



and for actor/actress with at least 10 movies

In [65]:

```
name_rating = {}  # create a dictionary to store the sorted movie count by
for actor in actorlist:
    sum = 0.0
    count = 0
    movies = nm_tt[actor]
    count = len(movies)
    for each in range(len(movies)):
        try:
            sum += tt_rating[movies[each]]
        except:
            count -= 1
        if count > 10:
            name_rating[nm_name[actor]] = sum/count  # count movies for eac
sorted_dict = sorted([(value, key)
 for (key, value) in name_rating.items()])  # sort the dictionary
df = pd.DataFrame(sorted_dict, columns =["Rating", "Actor"])  # rename the
df = df.sort_values(by='Rating', ascending=False) # reverse sort the movie
df[:10]  # Some high scoring actors, but not very well known
```

Out[65]:

	Rating	Actor
41	7.784615	Kristin Booth
40	7.784615	Geoff Gustafson
39	7.537500	Yan-Kay Crystal Lowe
38	7.435294	Eric Mabius
37	7.038889	Alison Sweeney
36	6.980000	Kristoffer Polaha
35	6.917647	Jill Wagner
34	6.833333	Catherine Bell
33	6.807143	Steve Bacic
32	6.806250	Barbara Niven

and for actor/actress with at least 5 movies

In [66]:
```
name_rating = {}  # create a dictionary to store the sorted movie count by
for actor in actorlist:
    sum = 0.0
    count = 0
    movies = nm_tt[actor]
    count = len(movies)
    for each in range(len(movies)):
        try:
            sum += tt_rating[movies[each]]
        except:
            count -= 1
        if count > 5:
            name_rating[nm_name[actor]] = sum/count  # count movies for eac
sorted_dict = sorted([(value, key)
 for (key, value) in name_rating.items()])  # sort the dictionary
df = pd.DataFrame(sorted_dict, columns =["Rating", "Actor"])  # rename the
df = df.sort_values(by='Rating', ascending=False) # reverse sort the movie
df[:10]  # range is flattening as we include more actors in selection
```

Out[66]:

	Rating	Actor
136	7.784615	Kristin Booth
135	7.784615	Geoff Gustafson
134	7.537500	Yan-Kay Crystal Lowe
133	7.435294	Eric Mabius
132	7.300000	Robin Thomas
131	7.137500	Preston Vanderslice
130	7.128571	Lexa Doig
129	7.050000	Catherine Disher
128	7.038889	Alison Sweeney
127	7.014286	Chris Potter

Let's Refactor, with Directors and Writers Included

In [67]:
```
local_file = 'cast_crew_info2.csv'  # have to use different file, because t
cast_crew_info = pd.read_csv(local_file, sep='\t')
```

In [68]:
```
crewlist = cast_crew_info['nconst'].tolist()  # all the Hallmark actors
crewlist = list(set(crewlist))
```

In [69]:
```
cast_crew_info = cast_crew_info[cast_crew_info['nconst'].isin(crewlist) ==
```

In [70]:
```
local_file = 'movie_cast_crew2.csv'  # have to use different file, because
movie_cast_crew = pd.read_csv(local_file, sep='\t')
```

In [71]:
```
movie_cast_crew = movie_cast_crew[movie_cast_crew['tconst'].isin(watchlist)
```

In [72]:
```
unwantedValues = ['producer', 'composer', 'cinematographer', 'editor', 'pro
                  'self']  # leaves actor, actress, writer, director catego
```

In [73]:
```
movie_cast_crew = movie_cast_crew[movie_cast_crew['category'].isin(unwanted
# keep actor, actress, director, writer rows
```

In [74]:
```
movielist = movie_cast_crew['tconst'].tolist()  # all the Hallmark movies
movielist = list(set(movielist))
```

Create lookup dictionaries for all four tables

In [75]:
```
df = movie_cast_crew.groupby('nconst')['tconst'].apply(list).reset_index(na
```

In [76]:
```
nm_tt = dict(zip(df.nconst, df.movieList))  # list of movies each person pa
```

In [77]:
```
df = movie_cast_crew.groupby('tconst')['nconst'].apply(list).reset_index(na
```

In [78]:
```
tt_nm = dict(zip(df.tconst, df.crewList))  # list for dictionary lookup of
```

In [79]:
```
df = cast_crew_info  # source of ID no, full name, birth year, death year,
```

In [80]:
```
nm_name = dict(zip(df.nconst, df.primaryName))  # create a lookup dictionar
```

In [81]:
```
df = movie_info  # includes title, release year, runtime, ratings, num vote
```

In [82]:
```
tt_title = dict(zip(df.tconst, df.primaryTitle)) # create lookup table
```

In [83]:
```
title_tt = dict(zip(df.primaryTitle, df.tconst))  # create a dictionary map
```

In [84]:
```
tt_rating = dict(zip(df.tconst, df.averageRating)) # create lookup table
```

In [85]:
```
title_rating = dict(zip(df.primaryTitle, df.averageRating)) # create lookup
```

Let's do some similar analysis and visualization with all crew

In [86]:
```
df = movie_info  #let's start with the movie database
```

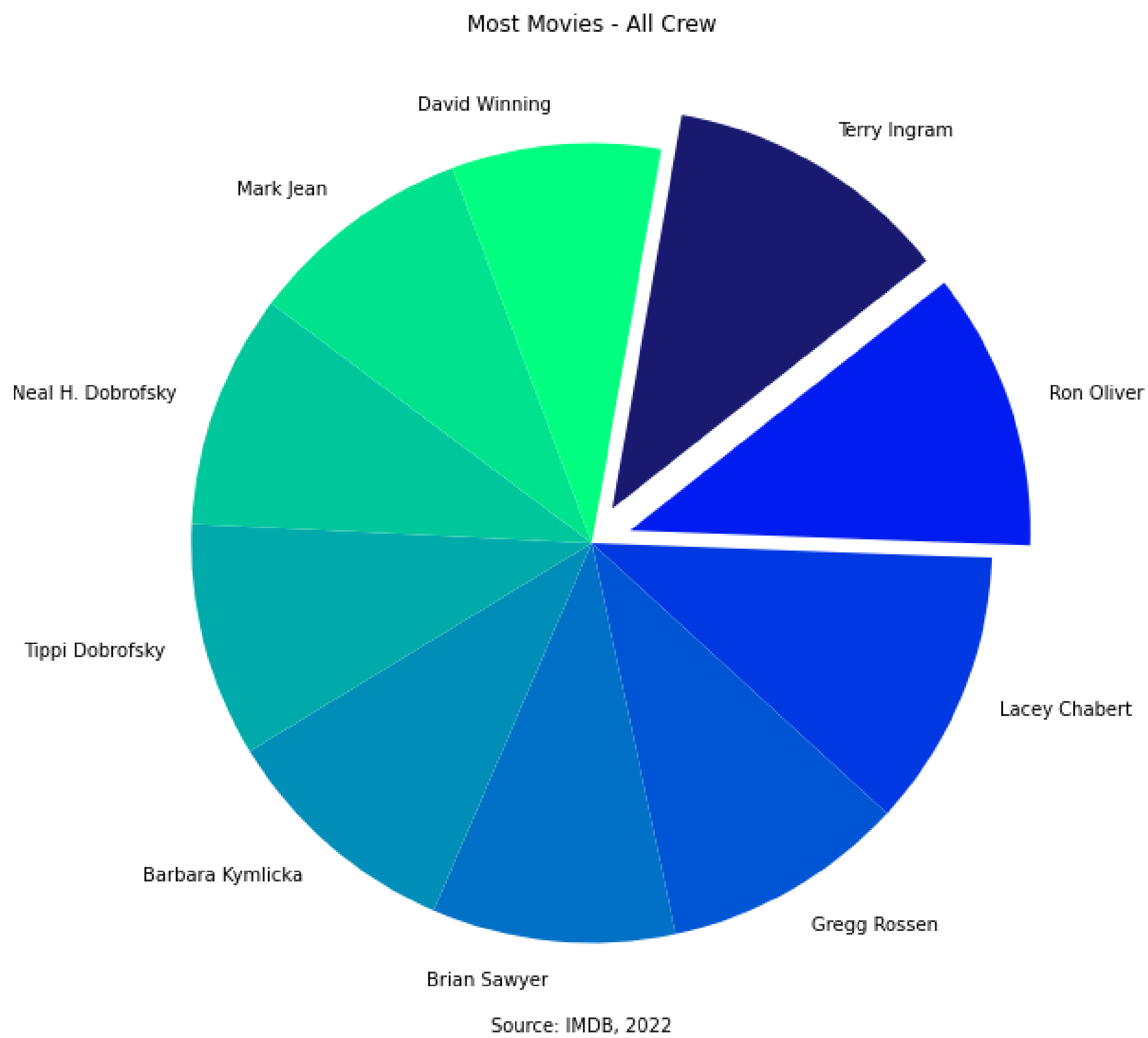
In [87]:

```
name_count = {}  # create a dictionary to store the sorted movie count by a
for crew in crewlist:
    name_count[nm_name[crew]] = len(nm_tt[crew])  # count movies for each a
sorted_dict = sorted([(value, key)
 for (key, value) in name_count.items()])  # sort the dictionary
df = pd.DataFrame(sorted_dict, columns =["Movies", "Crew Member"])  # renam
df = df.sort_values(by='Movies', ascending=False) # reverse sort the movie
df[:10]  # Sure enough, Lacey Chabert is still at the top for actors, Olive
```

Out[87]:

	Movies	Crew Member
3642	33	Terry Ingram
3641	32	Ron Oliver
3640	32	Lacey Chabert
3639	28	Gregg Rossen
3638	28	Brian Sawyer
3637	28	Barbara Kymlicka
3636	27	Tippi Dobrofsky
3635	27	Neal H. Dobrofsky
3634	26	Mark Jean
3632	24	David Winning

```
In [88]: top_10 = df[:10]
values = list(top_10['Movies'])  # let's chart the Top 10 on a pie chart, b
labels = list(top_10['Crew Member'])
plt.title('Most Movies - All Crew')
plt.annotate(r'Source: IMDB, 2022', xy=(.4, .01), xycoords='axes fraction')
colors = ['#191970','#001CF0','#0038E2','#0055D4','#0071C6','#008DB8',\
          '#00AAAA','#00C69C','#00E28E','#00FF80']  # use a blue-green spec
explode = (.1, .1, 0, 0, 0, 0, 0, 0, 0, 0)  # callout the top two, female a
plt.pie(values, labels=labels, explode=explode, colors=colors, counterclock
plt.show()
```



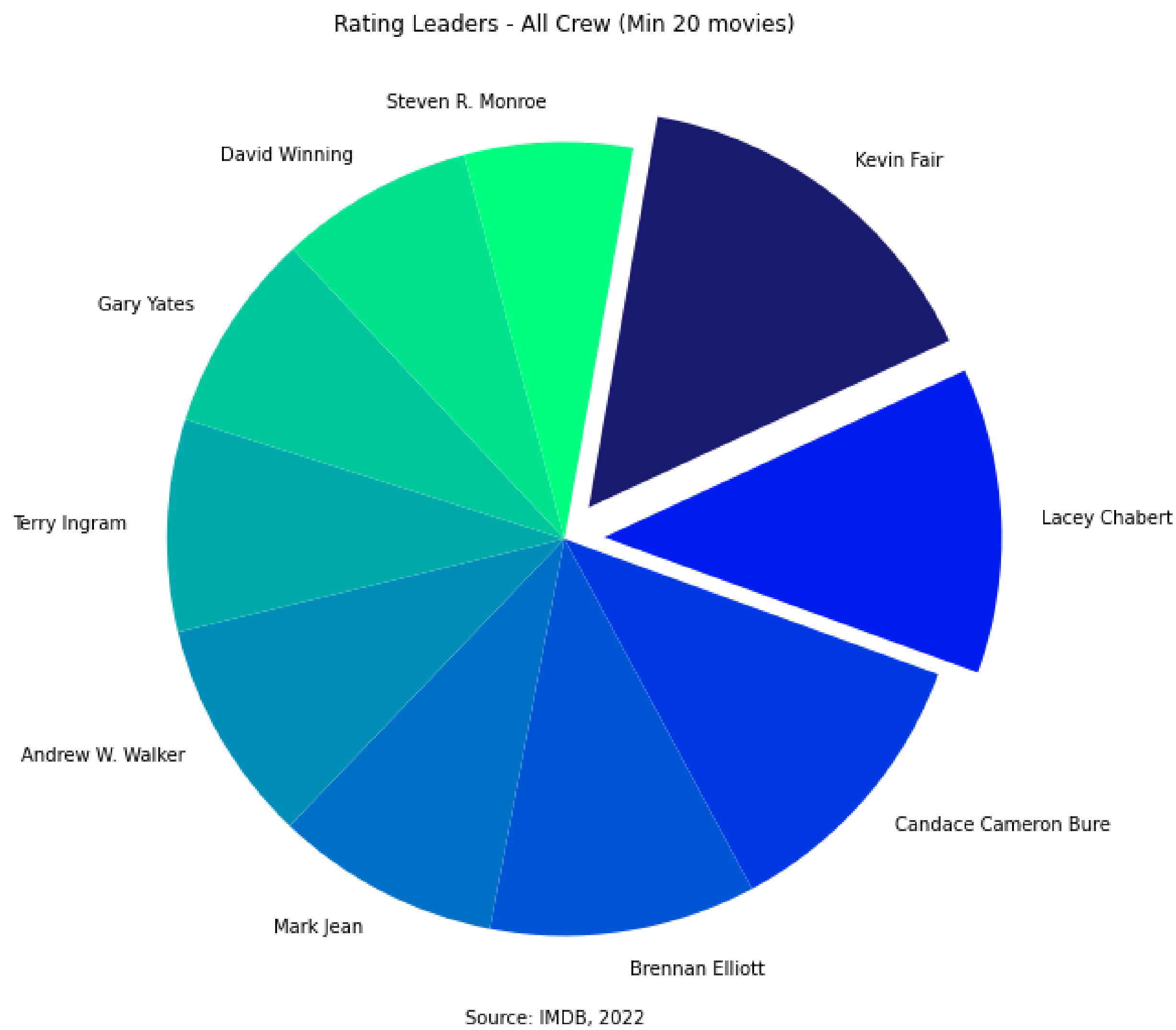
Lacey still prominent, but most other actors knocked off the list now

```
In [89]: name_rating = {}  # create a dictionary to store the sorted movie count by
for crew in crewlist:
    sum = 0.0
    count = 0
    movies = nm_tt[crew]
    count = len(movies)
    for each in range(len(movies)):
        try:
            sum += tt_rating[movies[each]]
        except:
            count -= 1
        if count > 20:
            name_rating[nm_name[crew]] = sum/count  # count movies for each
sorted_dict = sorted([(value, key)
 for (key, value) in name_rating.items()])  # sort the dictionary
df = pd.DataFrame(sorted_dict, columns =["Rating", "Crew Member"])  # renam
df = df.sort_values(by='Rating', ascending=False) # reverse sort the movie
df[:10]  # Lacey Chabert also the Queen of RomComs (as actress) at Hallmark
```

Out[89]:

	Rating	Crew Member
19	6.896154	Kevin Fair
18	6.728125	Lacey Chabert
17	6.680952	Candace Cameron Bure
16	6.633333	Brennan Elliott
15	6.534615	Mark Jean
14	6.531818	Andrew W. Walker
13	6.506061	Terry Ingram
12	6.477273	Gary Yates
11	6.462500	David Winning
10	6.400000	Steven R. Monroe

```
In [90]: top_10 = df[:10]
values = list(top_10['Rating']-6)  # let's chart Top 10 on a pie chart, bas
labels = list(top_10['Crew Member'])
plt.title('Rating Leaders - All Crew (Min 20 movies)')
plt.annotate(r'Source: IMDB, 2022', xy=(.4, .01), xycoords='axes fraction')
colors = ['#191970','#001CF0','#0038E2','#0055D4','#0071C6','#008DB8',\
          '#00AAAA','#00C69C','#00E28E','#00FF80']  # use a blue-green spec
explode = (.1, .1, 0, 0, 0, 0, 0, 0, 0, 0)  # callout the top two, female a
plt.pie(values, labels=labels, explode=explode, colors=colors, counterclock
plt.show()
```



Looking only at those with 15-20 movies, our main actors reappear, with some directors, writers

In [91]:

```
name_rating = {}  # create a dictionary to store the sorted movie count by
for crew in crewlist:
    sum = 0.0
    count = 0
    movies = nm_tt[crew]
    count = len(movies)
    for each in range(len(movies)):
        try:
            sum += tt_rating[movies[each]]
        except:
            count -= 1
        if count > 15:
            name_rating[nm_name[crew]] = sum/count  # count movies for each
sorted_dict = sorted([(value, key)
 for (key, value) in name_rating.items()])  # sort the dictionary
df = pd.DataFrame(sorted_dict, columns =["Rating", "Crew Member"])  # renam
df = df.sort_values(by='Rating', ascending=False) # reverse sort the movie
df[:10]  # Alison Sweeney is more popular for actresses only starring in 10
```

Out[91]:

	Rating	Crew Member
45	7.537500	Yan-Kay Crystal Lowe
44	7.435294	Eric Mabius
43	7.038889	Alison Sweeney
42	6.917647	Jill Wagner
41	6.896154	Kevin Fair
40	6.806250	Barbara Niven
39	6.806250	Autumn Reeser
38	6.750000	Peter Benson
37	6.735294	Niall Matter
36	6.728125	Lacey Chabert

```
In [92]: name_rating = {}  # create a dictionary to store the sorted movie count by
for crew in crewlist:
    sum = 0.0
    count = 0
    movies = nm_tt[crew]
    count = len(movies)
    for each in range(len(movies)):
        try:
            sum += tt_rating[movies[each]]
        except:
            count -= 1
        if count > 10:
            name_rating[nm_name[crew]] = sum/count  # count movies for each
sorted_dict = sorted([(value, key)
 for (key, value) in name_rating.items()])  # sort the dictionary
df = pd.DataFrame(sorted_dict, columns =["Rating", "Crew Member"])  # renam
df = df.sort_values(by='Rating', ascending=False) # reverse sort the movie
df[:10]  # Alison higher ratings in the 10-15 movie range. Conclusion: cast
```

Out[92]:

	Rating	Crew Member
100	7.784615	Martha Williamson
99	7.784615	Geoff Gustafson
98	7.671429	Kristin Booth
97	7.537500	Yan-Kay Crystal Lowe
96	7.435294	Eric Mabius
95	7.038889	Alison Sweeney
94	6.980000	Kristoffer Polaha
93	6.917647	Jill Wagner
92	6.896154	Kevin Fair
91	6.836364	Craig Pryce

In [93]:

```
name_rating = {}  # create a dictionary to store the sorted movie count by
for crew in crewlist:
    sum = 0.0
    count = 0
    movies = nm_tt[crew]
    count = len(movies)
    for each in range(len(movies)):
        try:
            sum += tt_rating[movies[each]]
        except:
            count -= 1
        if count > 5:
            name_rating[nm_name[crew]] = sum/count  # count movies for each
sorted_dict = sorted([(value, key)
 for (key, value) in name_rating.items()])  # sort the dictionary
df = pd.DataFrame(sorted_dict, columns =["Rating", "Crew Member"])  # renam
df = df.sort_values(by='Rating', ascending=False) # reverse sort the movie
df[:10]  # Don't know most of these people, dedicated following from series
```

Out[93]:

	Rating	Crew Member
263	7.784615	Martha Williamson
262	7.784615	Geoff Gustafson
261	7.677778	Brandi Harkonen
260	7.671429	Kristin Booth
259	7.537500	Yan-Kay Crystal Lowe
258	7.435294	Eric Mabius
257	7.300000	Robin Thomas
256	7.200000	Lee Goldberg
255	7.150000	John Christian Plummer
254	7.137500	Preston Vanderslice