Project: Investigate "The Movie Database"

(This project can also be found on [github (https://github.com/QuantificAid/tmdb_movie_data)](https://github.com/QuantificAid/tmdb_movie_data))

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Summary

- In course of Udacity's "Data Analyst Nanodegree", I investigated a movie dataset from "The Movie Database".
- The dataset included approx. 10,000 movies with information about e.g. artists involved, votings/ratings, revenue, release date etc.
- I was especially interested in how ratings relate
  1. to financials
  2. to parties involved and content (as expressed by genre, keywords)
- I found that
  1. there is a correlation of movie ratings to financials, but it is only weak. You can have a lot of budget and create a miserable movie, and you can make an excellent film, but lose money.
  2. there is a stronger correlation of movie ratings to the quality of its "ingredients". This seems intuitive, however, the results must be handled with care, as the "quality of the ingredient" was calculated using the `vote_average` and so - although thoughtfully executed - the is a feedback loop causing some part of the correlation.

Background

Whilst doing Udacity's "Data Analyst Nanodegree", I had to absolve an investigation of a dataset of my choice from a list of recommendations. I choosed a dataset from ["The Movie Database" (https://www.themoviedb.org/)](https://www.themoviedb.org/), which - in slight adaptation - is also published on [kaggle (http://www.kaggle.com)](http://www.kaggle.com).

The dataset contains information about 10,000 movies collected from The Movie Database (TMDb), including user ratings and revenue.

- Certain columns, like ‘cast’ and ‘genres’, contain multiple values separated by pipe (|) characters.
- There are some odd characters in the ‘cast’ column. Don’t worry about cleaning them. You can leave them as is.
- The final two columns ending with “_adj” show the budget and revenue of the associated movie in terms of 2010 dollars, accounting for inflation over time.

So let's get started:

In [1]:
```
# Import libraries

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

%matplotlib inline
```

I also load the dataset here, as this allows better for discussion of choices for further analysis:

In [2]:
```
# Import dataset

tmdb = pd.read_csv('./data/tmdb-movies.csv', encoding='raw_unicode_
escape')
```

In order to obtain an comprehensive overview, I created a function mixing the "best of" pandas's build-in functions:

In [3]:
```
def create_overview(df):
    # Function to create an aggregates overview from existing panda
s methods for reuse
    # Use 'describe' and flip it for better readability
    overview = df.describe(include='all').T
    # Integrate dtypes
    overview['dtype'] = df.dtypes
    # Integrate an example (1st row)
    overview['example'] = df.head(1).T
    # % of items compared to dataset
    overview['complete_%'] = 100 * overview['count'] / df.shape[0]
    # Rename median
    overview.rename(index=str, columns={'50%': 'median'}, inplace=T
rue)
    # Create new features (that, in 'describe', are normally only i
ncluded with object columns)
    overview['top_alt'] = ''
    overview['freq_alt'] = 0
    overview['unique_alt'] = 0
    # Calculate new features
    for col in df.columns:
        value_counts = df[col].value_counts()
        overview.loc[col, 'top_alt'] = str(value_counts.index[0])
        overview.loc[col, 'freq_alt'] = value_counts.iloc[0]
        overview.loc[col, 'unique_alt'] = df[col].drop_duplicates()
.count()
    # Reorganize the overview (whilst neglecting some columns from
'describe')
    overview = overview[[
        # Example and dtype
        'example', 'dtype',
        # Number of items
        'count', 'complete_%', 'unique_alt',
        # Info about most frequent item
        'top_alt', 'freq_alt',
        # Some statistics
        'mean', 'std', 'min', 'median', 'max'
        ]]
    return overview

create_overview(tmdb)
```

Out[3]:

	example	dtype	count	complete_%	unique_alt
id	135397	int64	10866	100	10865
imdb_id	tt0369610	object	10856	99.908	10855
popularity	32.9858	float64	10866	100	10814
budget	150000000	int64	10866	100	557
revenue	1513528810	int64	10866	100	4702
original_title	Jurassic World	object	10866	100	10571
cast	Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...	object	10790	99.3006	10719
homepage	http://www.jurassicworld.com/	object	2936	27.0201	2896
director	Colin Trevorrow	object	10822	99.5951	5067
tagline	The park is open.	object	8042	74.0107	7997
keywords	monster|dna|tyrannosaurus rex|velociraptor|island	object	9373	86.2599	8804
overview	Twenty-two years after the events of Jurassic ...	object	10862	99.9632	10847
runtime	124	int64	10866	100	247
genres	Action|Adventure|Science Fiction|Thriller	object	10843	99.7883	2039
production_companies	Universal Studios|Amblin Entertainment|Legenda...	object	9836	90.5209	7445
release_date	6/9/15	object	10866	100	5909
vote_count	5562	int64	10866	100	1289
vote_average	6.5	float64	10866	100	72
release_year	2015	int64	10866	100	56
budget_adj	1.38e+08	float64	10866	100	2614
revenue_adj	1.39245e+09	float64	10866	100	4840

Probably, this database has one duplicate row (max `count` = max `unique_alt` + 1 = 10.865).

However, before we dig a little deeper into the various features, it's useful to define the main purpose of the following analysis. This allows to focus on the features (hopefully) more relevant to this purpose.

There are two aspects, we analyze this dataset here, whilst **focussing on "goodness" in terms of `'vote_average'`**

- How do "good movies" perform "economically"?
- What are the artistic "ingredients" of a "good movie"? E.g., are genres and artists important to

"goodness"?

There may be many more questions, even more interesting ones and there may be more sophisticated methods to analyse the dataset. However, I focussed on practicing tools from the course. Furthermore, it must be stated, that all analysis included is preliminary.

Now, let's describe the fields, decide if they are being kept for the purposes of this special analysis, and describe, which issues are to be handled with in the data cleaning:

Field	Understanding & Assumptions	Keeper?	Issues
`'id'`	Serves as an identifier	Yes	Convert to `str`, otherwise probably none
`'imdb_id'`	Serves as an identifier	**No**	We take `'id'` instead
`'popularity'`	Popularity rating for TMDB's website purposes (s. [here (https://developers.themoviedb.org/3/getting-started/popularity)](https://developers.themoviedb.org/3/getting-started/popularity))	**No**	Neglecting this feature
`'budget'`	Film's budget in USD	*Maybe*	No, if `budget_adj` is calculated reasonably; Be aware of `0` values
`'revenue'`	Film's revenue in USD	*Maybe*	No, if `revenue_adj` is calculated reasonably; Be aware of `0` values
`'original_title'`	Film title	Yes	Be aware of duplicates
`'cast'`	Name of actors	Yes	Multiple items in a field and missing values
`'homepage'`	Url	**No**	Neglecting this feature
`'director'`	Name of director	Yes	Missing values
`'tagline'`	Short description of film	**No**	Neglecting this feature, using `keywords` instead
`'keywords'`	Tags for film description	Yes	Multiple items in a field and missing values
`'overview'`	Longer description of film	**No**	Neglecting this feature, using `keywords` instead
`'runtime'`	Runtime in minutes	Yes	Beware of `0` values
`'genres'`	Tags for genre of film	Yes	Multiple items in a field and missing values
`'production_companies'`	Name of production companies	Yes	Multiple items in a field and missing values
`'release_date'`	Date of film release	Yes	to be transformed into `datetime`
`'vote_count'`	Number of votes	Yes	Probably none

`'vote_average'`	Average of votes	Yes	Probably none
`'release_year'`	Year of film release	**No**	We take `'release_date'` instead
`'budget_adj'`	Film's budget in USD (in 2018 prices)	Yes	Be aware of `0` values
`'revenue_adj'`	Film's revenue in USD (in 2018 prices)	Yes	Be aware of `0` values

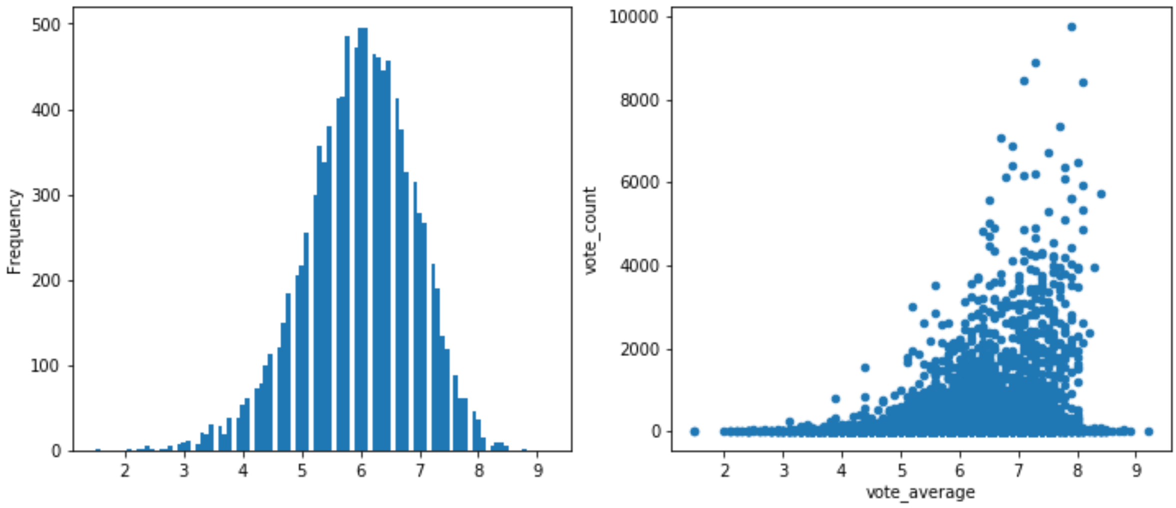
An indeed, there are some encoding issues in the strings, I wasn't able to fix.

Data Wrangling And Exploratory Analysis

As I already loaded the data and created an overview of the features, now I jump right into cleaning (and some analysis useful for doing so...)

Let's have a first look at the `vote_average` :

In [4]:
```
# First glance on 'vote_average' (and 'vote_count')

fig, [ax1, ax2] = plt.subplots(ncols=2, figsize=(12, 5))
tmdb.vote_average.plot.hist(bins=100, ax=ax1)
tmdb.plot.scatter(x='vote_average', y='vote_count', ax=ax2)
plt.show()
```



The `vote_Average` has some strange artefacts, however its bell-shaped distribution look reasonable.

Now, we follow the thing to repair ('Issues' in table above):

In [5]:
```
# Turning 'release_date' into 'datetime'

date = tmdb.release_date.str.split('/', expand=True)
day = date[1].astype(int)
month = date[0].astype(int)
year = tmdb.release_year
tmdb.release_date = pd.to_datetime((year*10000+month*100+day).apply
(str), infer_datetime_format=True)

del date, day, month, year
```

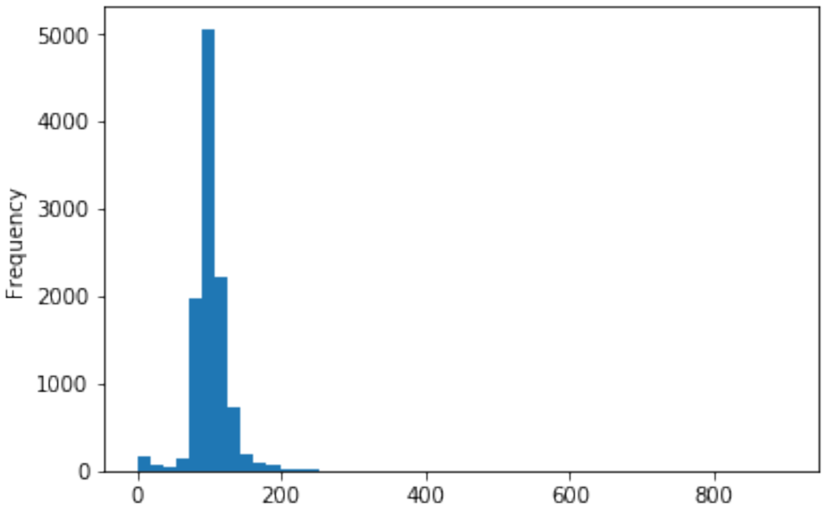
In [6]:
```
# Turning id into (immutable) 'string'

tmdb.id = tmdb.id.astype(str)
```

In [7]:
```
# Dropping duplicates and neglected features (in a new table)

stmdb = tmdb.drop_duplicates().copy()
stmdb.drop(axis=1, columns=['imdb_id', 'popularity', 'homepage', 't
agline', 'overview', 'release_year'], inplace=True)
```

In [8]:
```
# Analysing runtime

stmdb.runtime.plot.hist(bins=50)
stmdb.loc[stmdb['runtime'] == 0, 'runtime'] = np.nan
stmdb.sort_values(by='runtime', ascending=False).head(5)
```

Out[8]:

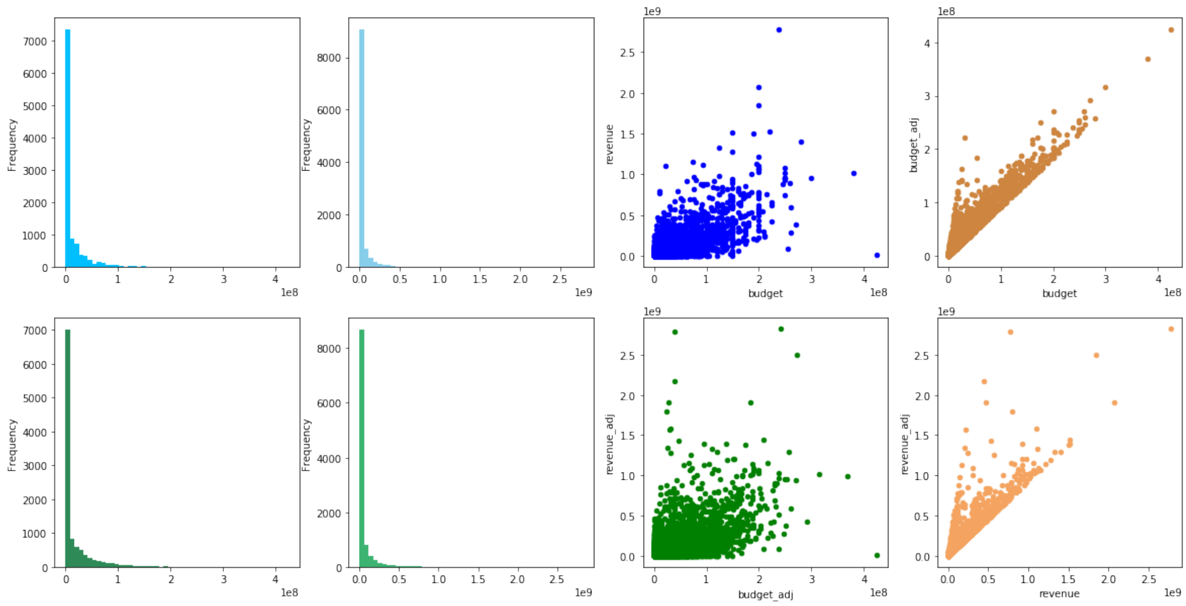
	id	budget	revenue	original_title	cast	director	
3894	125336	0	0	The Story of Film: An Odyssey	Mark Cousins|Jean-Michel Frodon|Cari Beauchamp...	Mark Cousins	cinema c
4041	150004	0	0	Taken	Dakota Fanning|Matt Frewer|Eric Close|Emily Be...	Breck Eisner|FÃÂ©lix EnrÃÂquez AlcalÃÂ¡|Jo...	
2722	331214	0	125000000	Band of Brothers	Damian Lewis|Ron Livingston|Frank John Hughes|...	Phil Alden Robinson|Richard Loncraine|Mikael S...	army|w
6176	42044	0	0	Shoah	Simon Srebnik|Michael Podchlebnik|Motke Zaidl	Claude Lanzmann	
6181	18729	0	0	North and South, Book I	Patrick Swayze|Philip Casnoff|Kirstie Alley|Ge...	NaN	



In [9]:

```
# Analysing `budget`, `revenue`, `budget_adj`, `revenue_adj`

fig, [[ax1, ax2, ax3, ax4], [ax5, ax6, ax7, ax8]] = plt.subplots(
    nrows=2, ncols=4, figsize=(20, 10))
fig.suptitle('Analysis of `budget`, `revenue`, `budget_adj` and `re
venue_adj`', size='x-large')
# Histograms of `budget`, `revenue`, `budget_adj` and `revenue_adj`
stmdb['budget'].plot.hist(bins=50, ax=ax1, color='deepskyblue')
stmdb['revenue'].plot.hist(bins=50, ax=ax2, color='skyblue')
stmdb['budget_adj'].plot.hist(bins=50, ax=ax5, color='seagreen')
stmdb['revenue_adj'].plot.hist(bins=50, ax=ax6, color='mediumseagre
en')
# Scatterplots of 'budget' vs. 'budget_adj' and 'revenue' vs. 'reve
nue_adj'
stmdb.plot.scatter(x='budget', y='revenue', ax=ax3, color='b')
stmdb.plot.scatter(x='budget_adj', y='revenue_adj', ax=ax7, color='
g')
# Scatterplots of 'budget' vs. 'revenue' and 'budget_adj' vs. 'reve
nue_adj'
stmdb.plot.scatter(x='budget', y='budget_adj', ax=ax4, color='peru'
)
stmdb.plot.scatter(x='revenue', y='revenue_adj', ax=ax8, color='san
dybrown')
plt.show()
```

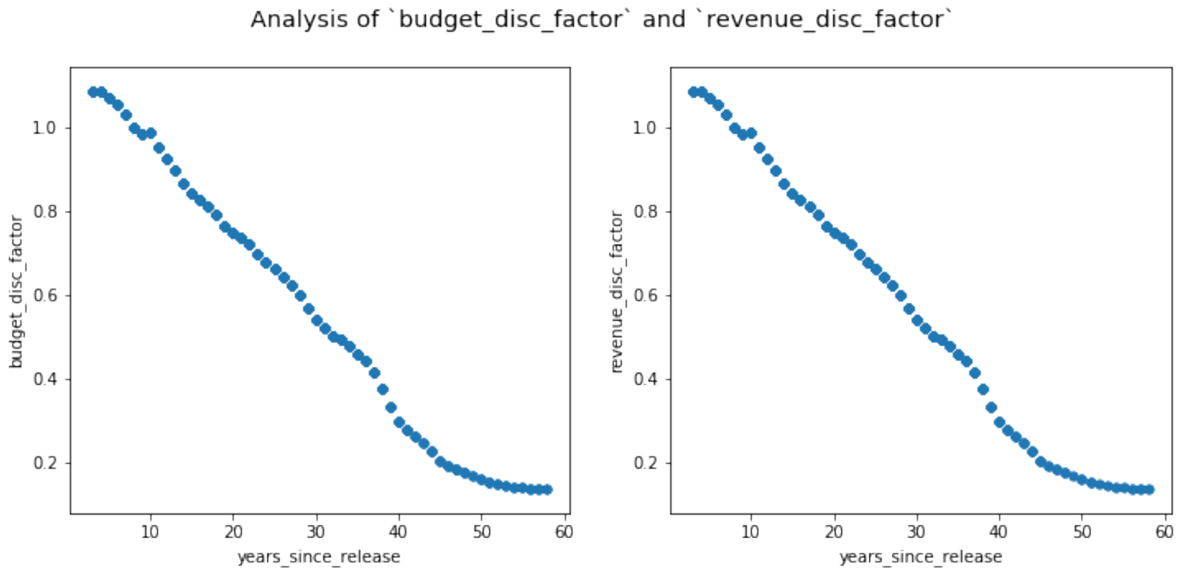
Analysis of `budget`, `revenue`, `budget_adj` and `revenue_adj`



In [10]:
```
# Turning `0` into NaN in `budget`, `revenue`, `budget_adj`and `rev
enue_adj` as 0 is implausible

stmdb.loc[stmdb['budget'] == 0, 'budget'] = np.nan
stmdb.loc[stmdb['revenue'] == 0, 'revenue'] = np.nan
stmdb.loc[stmdb['budget_adj'] == 0, 'budget_adj'] = np.nan
stmdb.loc[stmdb['revenue_adj'] == 0, 'revenue_adj'] = np.nan
print('\n',
      'Number of mismatches in `Nan` in `budget` and `budget_adj`:\
t\t', (stmdb['budget'].isna() != stmdb['budget_adj'].isna()).sum(),
'\n',
      'Number of mismatches in `Nan` in `revenue` and `revenue_adj`
:\t\t', (stmdb['revenue'].isna() != stmdb['revenue_adj'].isna()).su
m(), '\n',
      'Number of mismatches in `Nan` in `budget` and `revenue`:\t\t
', (stmdb['budget'].isna() != stmdb['revenue'].isna()).sum(), '\n',
      'Number of mismatches in `Nan` in `budget_adj` and `revenue_a
dj`:\t', (stmdb['budget_adj'].isna() != stmdb['revenue_adj'].isna()
).sum())
```

```
 Number of mismatches in `Nan` in `budget` and `budget_adj`:
0
 Number of mismatches in `Nan` in `revenue` and `revenue_adj`:
0
 Number of mismatches in `Nan` in `budget` and `revenue`:
2310
 Number of mismatches in `Nan` in `budget_adj` and `revenue_adj`:
2310
```

In [11]:
```
# Analysing discount factors in 'budget_adj' and 'revenue_adj'

discount_factor_df = stmdb[['budget', 'budget_adj', 'revenue', 'revenue_adj']].copy()
discount_factor_df['budget_disc_factor'] = discount_factor_df['budget'] / discount_factor_df['budget_adj']
discount_factor_df['revenue_disc_factor'] = discount_factor_df['revenue'] / discount_factor_df['revenue_adj']
discount_factor_df['years_since_release'] = 2018 - stmdb.release_date.dt.year.copy()

fig, [ax1, ax2] = plt.subplots(ncols=2, figsize=(12, 5))
fig.suptitle('Analysis of `budget_disc_factor` and `revenue_disc_factor`', size='x-large')
discount_factor_df.plot.scatter(x='years_since_release', y='budget_disc_factor', ax=ax1)
discount_factor_df.plot.scatter(x='years_since_release', y='revenue_disc_factor', ax=ax2)

del discount_factor_df
```



In [12]:
```
# Calculating 'profit' and 'profit_adj' as new derived feature

stmdb['profit'] = stmdb['revenue'] - stmdb['budget']
stmdb.loc[stmdb['budget'].isna() | stmdb['revenue'].isna(), 'profit'] = np.nan
stmdb['profit_adj'] = stmdb['revenue_adj'] - tmdb['budget_adj']
stmdb.loc[stmdb['budget_adj'].isna() | stmdb['revenue_adj'].isna(), 'profit_adj'] = np.nan
```

In [13]:
```
# Shortening and reorganizing columns for further analysis

stmdb = stmdb[
    [
        # Id and title
        'id', 'original_title',
        # Rating data
        'vote_average',
        # Adjusted economical data
        'budget_adj', 'revenue_adj', 'profit_adj',
        # Release- and run-time
        'release_date', 'runtime',
        # Genre and content/keywords tags
        'genres', 'keywords',
        #Companies and people involved
        'production_companies', 'director', 'cast'

    ]
]
```

I want to make use of the information contained in the features that include list-like information (`genres` , `keywords` , `production_companies` , `director` and `cast`).
In order to do so, I want to separate them in own lists. Then I calculate their quality, based on the `vote_average` of the films where they are connected to. This information shall be used later to combine the films `vote_average` with this quality. But we have to be careful: by calculating it this way, of course we have a correlation. To minimize this factor, we only include such items, that occur minimum e.g. 10 times in different films and thereby smear out the influence (and the correlation) to single films.
First, we have to write some helper functions:

In [14]:
```
# Caring for columns with list like entries

# Creating a function to create an expanded dataframe from columns
with list-like entries for later analysis
def expand_listlike_column_with_ids_long(df, id_col='', list_col=''
, pattern=''):
    # Function to create an expanded dataframe from list like entri
es for later reuse
    expanded = df[[id_col, list_col]].copy()
    expanded[list_col] = df[list_col].str.split(pat=pattern)
    # Borrowed from 'https://mikulskibartosz.name/how-to-split-a-li
st-inside-a-dataframe-cell-into-rows-in-pandas-9849d8ff2401'
    expanded = expanded[list_col].apply(pd.Series) \
        .merge(expanded, right_index = True, left_index = True) \
        .drop([list_col], axis = 1) \
        .melt(id_vars = [id_col], value_name = list_col) \
        .drop("variable", axis = 1) \
        .dropna() \
        .drop_duplicates()
    return expanded
```

In [15]:
```
def build_sets_from_list(list_col, min_count=10):
    # Customized function to make several trafos and lists for furt
her analysis
        # 'id_with_list_stats' will return a long dictionary of all
film ids and list items
        # 'list_stats' will return statistics (averages) of all lis
t items with relation to average votes etc.
        # 'id_with_list_stats' will return statistics (averages) of
all id with relation to list stats
        # 'min_count' provides the minimal number of occurances in
the list column to provide proper statistics

    # Create basic expanded list
    ids_with_list_long = expand_listlike_column_with_ids_long(stmdb
, 'id', list_col, '|')

    ids_with_list_long_count = pd.DataFrame(
        {
            list_col: ids_with_list_long[list_col].value_counts().i
ndex.values,
            list_col + '_count': ids_with_list_long[list_col].value
_counts().values
        }
    )
    ids_with_list_long = pd.merge(ids_with_list_long, ids_with_list
_long_count, on=list_col)
    ids_with_list_long = ids_with_list_long.loc[ids_with_list_long[
list_col + '_count'] >= min_count]

    ids_with_list_long.drop([list_col + '_count'], axis=1, inplace=
True)

    # Defined for further focus (main quantitative columns in tmdb)
    _additional_stmdb_info = [
        # focusses on 'vote_average', but could be expanded
        'id',
        'vote_average', #'vote_count',
        #'budget', 'revenue', 'profit',
        #'budget_adj', 'revenue_adj', 'profit_adj',
        #'release_date', 'runtime'
    ]

    # Intermediate list with info from tmdb
    _list = pd.merge(ids_with_list_long, stmdb[_additional_stmdb_in
fo], on='id', how='left')

    # Statistics on list (with info from tmdb)
    list_stats = _list.groupby(list_col).mean()

    # All crammed into one big (intermediate) list
    _list_with_ids_and_stats = pd.merge(_list, list_stats, on=list_
col, how='left', suffixes=('', '_' + list_col))
```

```
    # Stats from genres for ids
    id_with_list_stats = _list_with_ids_and_stats.groupby('id').mea
n().iloc[:, 1:]
    # if more stats are of interest, iloc needs to be changed

    return ids_with_list_long, list_stats, id_with_list_stats

ids_with_genres_long, genres_stats, ids_with_genres_stats = build_s
ets_from_list('genres')
ids_with_keywords_long, keywords_stats, ids_with_keywords_stats = b
uild_sets_from_list('keywords')
ids_with_prodcos_long, prodcos_stats, ids_with_prodcos_stats = buil
d_sets_from_list('production_companies')
ids_with_directors_long, directors_stats, ids_with_directors_stats
= build_sets_from_list('director')
ids_with_actors_long, actors_stats, ids_with_actors_stats = build_s
ets_from_list('cast')

# Just to see... (1/2)
genres_stats.head(5)
```

Out[15]:

genres	vote_average
Action	5.787752
Adventure	5.940585
Animation	6.403147
Comedy	5.905167
Crime	6.124889

In [16]:

```
# Just to see... (2/2)
ids_with_genres_stats.head(5)
```

Out[16]:

id	vote_average_genres
100	6.015028
10001	5.785375
10002	6.111103
10003	5.837493
10004	5.812798

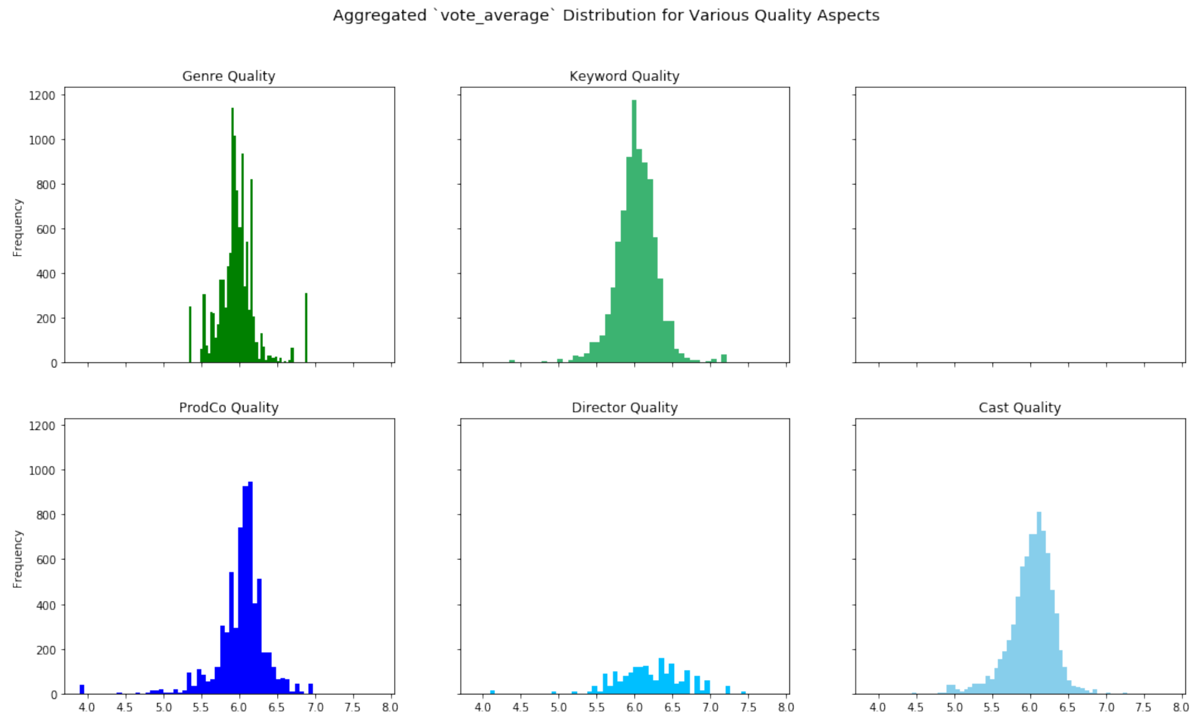
In [17]:
```
def make_final_stmdb():
    stmdb1 = pd.merge(stmdb, ids_with_genres_stats, on='id', how='left')
    stmdb2 = pd.merge(stmdb1, ids_with_keywords_stats, on='id', how='left')
    stmdb3 = pd.merge(stmdb2, ids_with_prodcos_stats, on='id', how='left')
    stmdb4 = pd.merge(stmdb3, ids_with_directors_stats, on='id', how='left')
    stmdb_final = pd.merge(stmdb4, ids_with_actors_stats, on='id', how='left')
    return stmdb_final

atmdb = make_final_stmdb()
```

In [18]:
```
create_overview(atmdb)
```

Out[18]:

	example	dtype	count	comple
id	135397	object	10865	
original_title	Jurassic World	object	10865	
vote_average	6.5	float64	10865	
budget_adj	1.38e+08	float64	5169	47
revenue_adj	1.39245e+09	float64	4849	44
profit_adj	1.25445e+09	float64	3854	35
release_date	2015-06-09 00:00:00	datetime64[ns]	10865	
runtime	124	float64	10834	99
genres	Action|Adventure|Science Fiction|Thriller	object	10842	99
keywords	monster|dna|tyrannosaurus rex|velociraptor|island	object	9372	86
production_companies	Universal Studios|Amblin Entertainment|Legenda...	object	9835	
director	Colin Trevorrow	object	10821	9
cast	Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...	object	10789	99
vote_average_genres	5.78615	float64	10842	99
vote_average_keywords	5.94246	float64	8496	7
vote_average_production_companies	6.33082	float64	6439	59
vote_average_director	NaN	float64	1819	16
vote_average_cast	6.18583	float64	7967	73

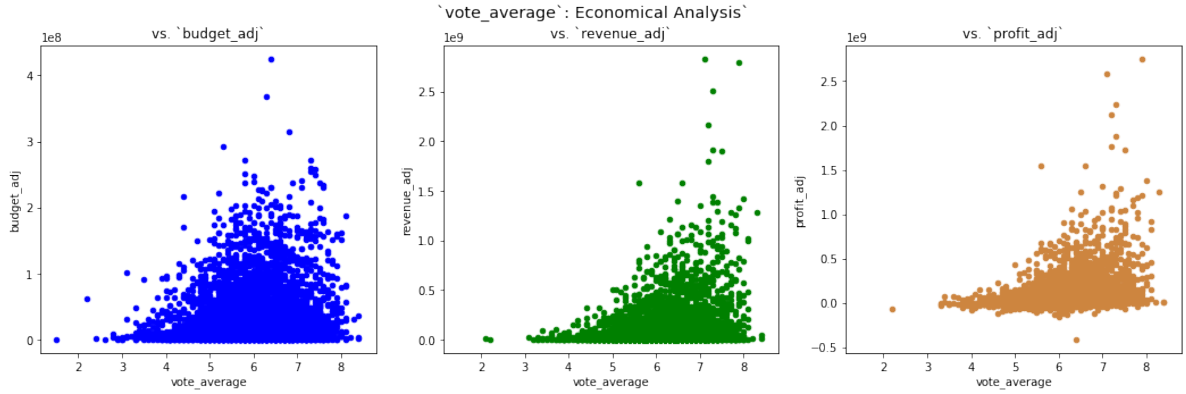
In [19]:
```
# Inspect the new features

fig, [[ax1, ax2, ax3], [ax4, ax5, ax6]] = plt.subplots(nrows=2, ncols=3, sharex=True, sharey=True, figsize=(18,10))
fig.suptitle('Aggregated `vote_average` Distribution for Various Quality Aspects' , size='x-large')
atmdb['vote_average_genres'].plot.hist(bins=50, ax=ax1, title='Genre Quality', color='g')
atmdb['vote_average_keywords'].plot.hist(bins=50, ax=ax2, title='Keyword Quality', color='mediumseagreen')
atmdb['vote_average_production_companies'].plot.hist(bins=50, ax=ax4, title='ProdCo Quality', color='b')
atmdb['vote_average_director'].plot.hist(bins=50, ax=ax5, title='Director Quality', color='deepskyblue')
atmdb['vote_average_cast'].plot.hist(bins=50, ax=ax6, title='Cast Quality', color='skyblue')
plt.show()
```



Analysis of Initial Questions

How Are Economics Factors Related to `vote_average`?

In [20]:
```
fig, [ax1, ax2, ax3] = plt.subplots(ncols=3, figsize=(18, 5), share
x=True)
fig.suptitle('`vote_average`: Economical Analysis`', size='x-large'
)
atmdb.plot.scatter(x='vote_average', y='budget_adj', ax=ax1, title=
'vs. `budget_adj`', color='b')
atmdb.plot.scatter(x='vote_average', y='revenue_adj', ax=ax2, title
='vs. `revenue_adj`', color='g')
atmdb.plot.scatter(x='vote_average', y='profit_adj', ax=ax3, title=
'vs. `profit_adj`', color='peru')
plt.show()
```



In [21]:
```
atmdb[['budget_adj', 'revenue_adj', 'profit_adj']].corrwith(atmdb.v
ote_average)
```

Out[21]:
```
budget_adj     0.112226
revenue_adj    0.242319
profit_adj     0.288651
dtype: float64
```

As one can see, economical factors are only weakly correlated to film quality in terms of `vote_average` .
Especially budget is only very weakly correlated: it's possible to make a "bad" film with lots of money, and pretty good films with a comparably small budget. On the other hand, it happens that "good" films make fantastic profits (*yay!*), but you can also make a nice film, and lose a lot on it.

In [22]:
```
atmdb[atmdb.profit_adj == atmdb.profit_adj.min()].T
```

Out[22]:

	2243
id	46528
original_title	The Warrior's Way
vote_average	6.4
budget_adj	4.25e+08
revenue_adj	1.10876e+07
profit_adj	-4.13912e+08
release_date	2010-12-02 00:00:00
runtime	100
genres	Adventure|Fantasy|Action|Western|Thriller
keywords	assassin|small town|revenge|deception|super speed
production_companies	Boram Entertainment Inc.
director	Sngmoo Lee
cast	Kate Bosworth|Jang Dong-gun|Geoffrey Rush|Dann...
vote_average_genres	5.88511
vote_average_keywords	5.93652
vote_average_production_companies	NaN
vote_average_director	NaN
vote_average_cast	6.11578

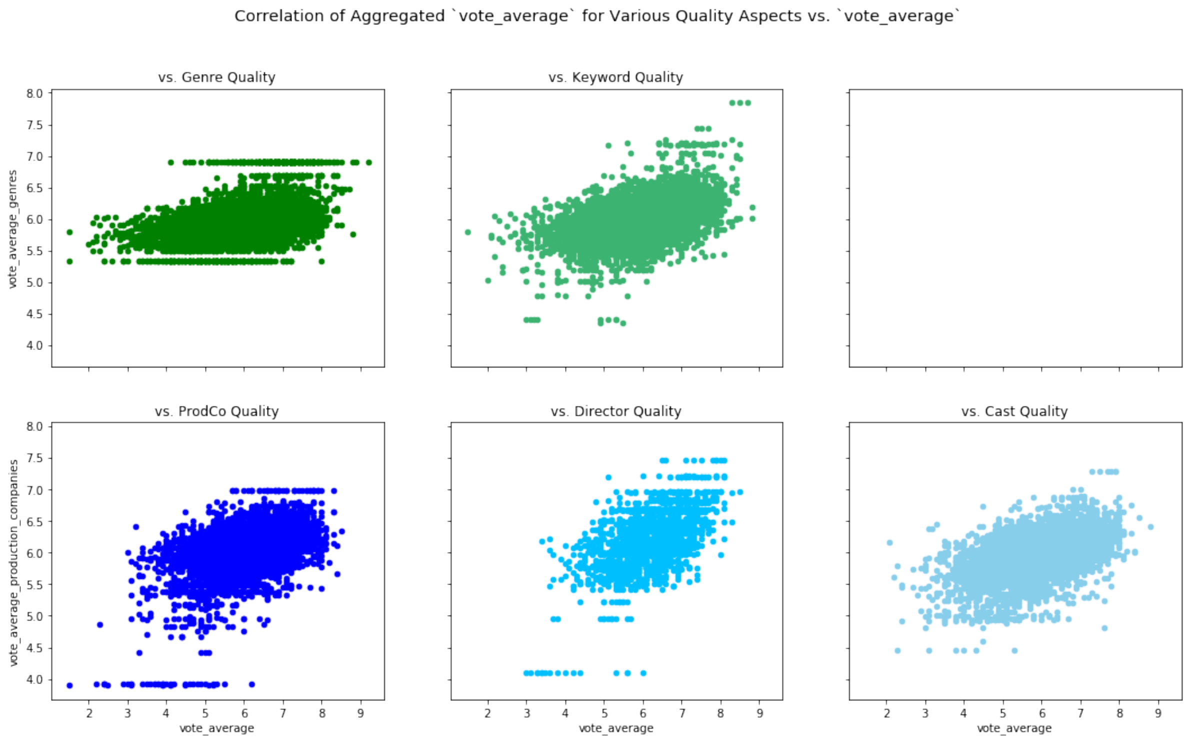
In [23]:
```
atmdb[atmdb.profit_adj == atmdb.profit_adj.max()].T
```

Out[23]:

	1329
id	11
original_title	Star Wars
vote_average	7.9
budget_adj	3.95756e+07
revenue_adj	2.78971e+09
profit_adj	2.75014e+09
release_date	1977-03-20 00:00:00
runtime	121
genres	Adventure|Action|Science Fiction
keywords	android|galaxy|hermit|death star|lightsaber
production_companies	Lucasfilm|Twentieth Century Fox Film Corporation
director	George Lucas
cast	Mark Hamill|Harrison Ford|Carrie Fisher|Peter ...
vote_average_genres	5.79797
vote_average_keywords	6.244
vote_average_production_companies	6.36971
vote_average_director	NaN
vote_average_cast	6.31459

How is "Ingredient" Quality Related to Film Quality?

In [24]:
```python
fig, [[ax1, ax2, ax3], [ax4, ax5, ax6]] = plt.subplots(nrows=2, ncols=3, sharex=True, sharey=True, figsize=(18,10))
fig.suptitle('Correlation of Aggregated `vote_average` for Various Quality Aspects vs. `vote_average`' , size='x-large')
atmdb.plot.scatter(x='vote_average', y='vote_average_genres', ax=ax1, title='vs. Genre Quality', color='g')
atmdb.plot.scatter(x='vote_average', y='vote_average_keywords', ax=ax2, title='vs. Keyword Quality', color='mediumseagreen')
atmdb.plot.scatter(x='vote_average', y='vote_average_production_companies', ax=ax4, title='vs. ProdCo Quality', color='b')
atmdb.plot.scatter(x='vote_average', y='vote_average_director', ax=ax5, title='vs. Director Quality', color='deepskyblue')
atmdb.plot.scatter(x='vote_average', y='vote_average_cast', ax=ax6, title='vs. Cast Quality', color='skyblue')
plt.show()
```



In [25]:
```python
atmdb[['vote_average_genres', 'vote_average_keywords', 'vote_average_production_companies', 'vote_average_director', 'vote_average_cast']].corrwith(atmdb.vote_average)
```

Out[25]:
```
vote_average_genres                  0.417699
vote_average_keywords                0.445270
vote_average_production_companies    0.452206
vote_average_director                0.570411
vote_average_cast                    0.500771
dtype: float64
```

There is a medium correlation of quality of the various "ingredients" to the `vote_average` of the films. As the definition of the quality of the ingredients is based on the `vote_average` , it's hard to tell, how strong the influence of the feedback is. This should be further investigated.
However, it seems - and this corresponds with my intuition - that the quality of a film is based on the quality of its components.

In [26]:
```
genres_stats.sort_values(by='vote_average', ascending=False).head(5
)
```

Out[26]:

genres	vote_average
Documentary	6.908462
Music	6.480392
History	6.410479
Animation	6.403147
War	6.297778

In [27]:
```
genres_stats.sort_values(by='vote_average', ascending=False).tail(5
)
```

Out[27]:

genres	vote_average
TV Movie	5.788024
Action	5.787752
Thriller	5.750671
Science Fiction	5.665582
Horror	5.337447

In [28]:
```
keywords_stats.sort_values(by='vote_average', ascending=False).head
()
```

Out[28]:

keywords	vote_average
live concert	7.850000
stand-up	7.207895
stand up comedy	7.163889
pixar animated short	7.039130
concert	7.015789

In [29]:
```
keywords_stats.sort_values(by='vote_average', ascending=False).tail
()
```

Out[29]:

keywords	vote_average
alien invasion	4.980000
bikini	4.890000
possession	4.783333
based on video game	4.409524
shark	4.353846

In [30]:
```
prodcos_stats.sort_values(by='vote_average', ascending=False).head(
5)
```

Out[30]:

production_companies	vote_average
Heyday Films	7.066667
Pixar Animation Studios	6.980769
WingNut Films	6.980000
BBC	6.976923
Bad Robot	6.830000

In [31]:
```
prodcos_stats.sort_values(by='vote_average', ascending=False).tail(
5)
```

Out[31]:

	vote_average
production_companies	
Steamroller Productions	4.763636
Castel Film Romania	4.661538
Hollywood Media Bridge	4.416667
The Asylum	3.925806
Asylum, The	3.900000

In [32]:
```
directors_stats.sort_values(by='vote_average', ascending=False).hea
d(5)
```

Out[32]:

	vote_average
director	
Christopher Nolan	7.470000
David Fincher	7.210000
Quentin Tarantino	7.207143
Wes Anderson	7.200000
Martin Scorsese	6.970968

In [33]:
```
directors_stats.sort_values(by='vote_average', ascending=False).tai
l(5)
```

Out[33]:

	vote_average
director	
Tobe Hooper	5.471429
Paul Hoen	5.410000
Brian Levant	5.230000
Stuart Gillard	4.954545
Uwe Boll	4.093750

In [34]:
```
actors_stats.sort_values(by='vote_average', ascending=False).head(5
)
```

Out[34]:

	vote_average
cast	
Louis C.K.	7.290000
Kevin Conroy	7.007692
Benedict Cumberbatch	6.892308
Paul McCartney	6.880000
Daniel Radcliffe	6.875000

In [35]:
```
actors_stats.sort_values(by='vote_average', ascending=False).tail(5
)
```

Out[35]:

	vote_average
cast	
Danny Trejo	4.910345
Bruce Payne	4.880000
Dominic Purcell	4.811765
Tara Reid	4.600000
Casper Van Dien	4.450000