

Joshua Banks Mailman

# Predicting film-director ratings

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# Questions investigated

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## Characterizing response to film directors

The investor, sponsor, or granting agency that funds film directors may be interested in...

- Besides profit margins they may be interested in alternative gauges of success of a movie
- Crowd-sourced critical response to the films of prolific acclaimed directors are a valuable resource to exploit to address this.

## Predicting the ratings of their films

Based on data freely available to the general public, it may be possible to build predictive models tailored to various film directors of the past.

- Such types of models can also be applied to directors that are still active.
- Most of the film directors examined are still active today.

# Who?

**Seven acclaimed directors who are prolific**



Alfred  
Hitchcock



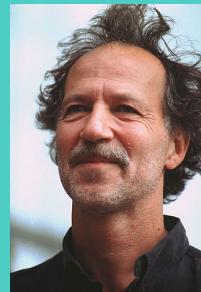
Ingmar  
Bergman



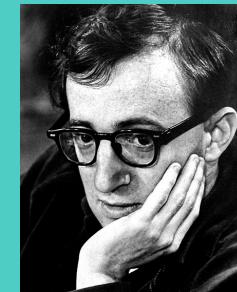
Jean-Luc  
Godard



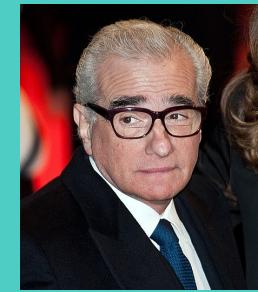
Rainer  
Fassbinder



Werner  
Herzog



Woody  
Allen

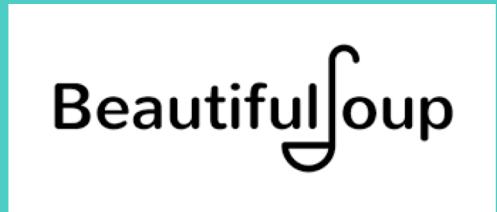


Martin  
Scorsese

# Source

## IMDB

(Internet Movie Database)



- A ***nested web-scraping algorithm*** was required, since IMDB lists all of a director's films on one page, but includes cast members and other info on a separate page dedicated to each film
- To improve on the ***worldwide gross*** box office returns data, [www.the-numbers.com](http://www.the-numbers.com), was also scraped and joined, but this data was ultimately ***discarded*** for being incomplete

# Target variable

Viewers' Ratings

(scale from 1 to 10)



Maria marries Hermann Braun in the last days of World War II, only for him to go missing in the war. Alone, Maria puts to use her beauty and ambition in order to find prosperity during Germany's "economic miracle" of the 1950s.

Director: Rainer Werner Fassbinder

# Target variable

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Viewers' Ratings

## Features examined

### continuous

- Year released
- Duration (in minutes)
- Rating count (total number of times the film was rated on IMDB)
- Budget

### categorical

- TV series vs. theatrical release
- Documentary or not
- Cinematographer
- Cast members

7 directors x ~50 films each  
x 15 actors & 10 other features

> 9,000  
data points

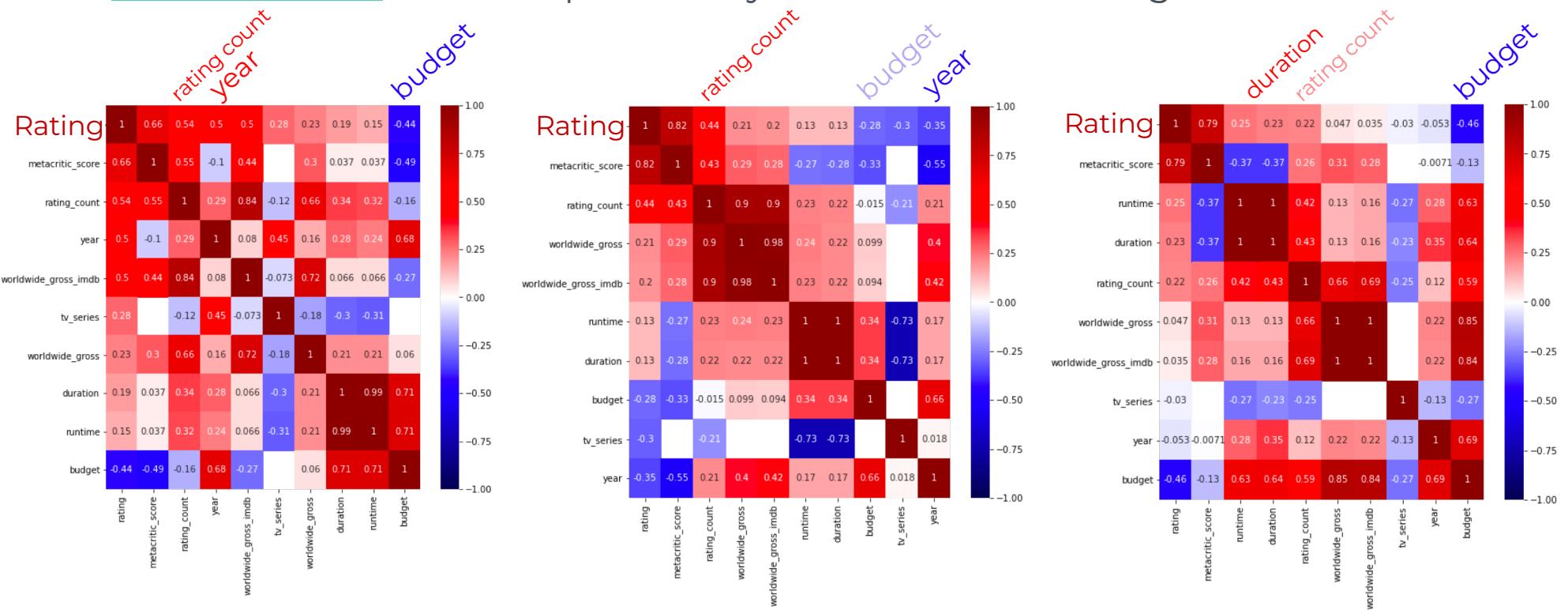
## Cleaned and Filtered

As follows:

- Exclude actors appearing in < 3 films & one-off cinematographers
- Exclude films < 60 minutes
- Exclude films with crucial missing data and obvious outliers
- Exclude collinear features and those too often missing

# Patterns in the data

Heatmap sorted by correlation to the target variable



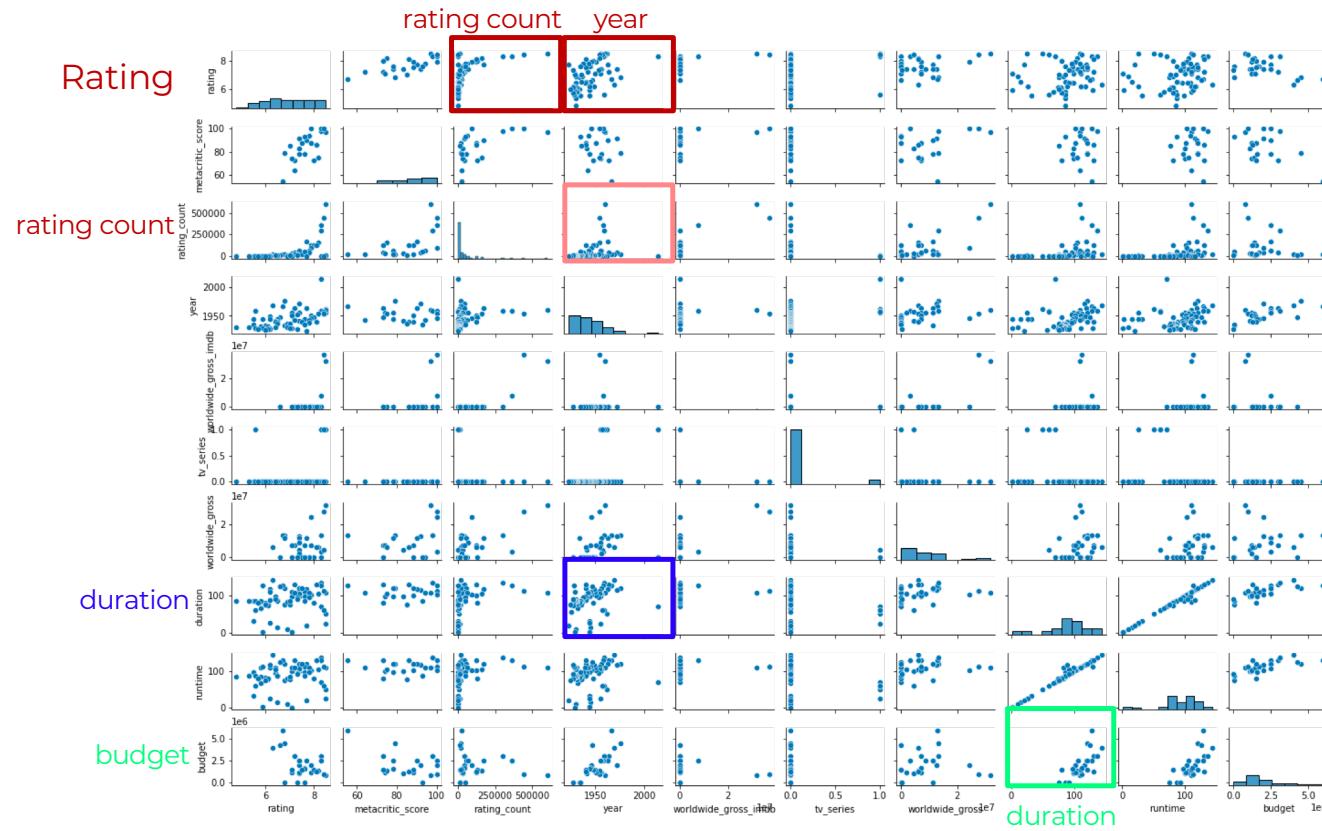
Hitchcock

Allen

Herzog

# Patterns in the data

## Shapes of correlation



Alfred Hitchcock

Multicollinearity as expected between features and proxies for them, such as *rating* and *metacritic score*, and *runtime* and *duration*

# To predict ratings:

# Linear Regression

with train-test split to enable cross-validation

## continuous features

- Year released
- Duration (in minutes)
- Rating count (total number of times the film was rated on IMDB)

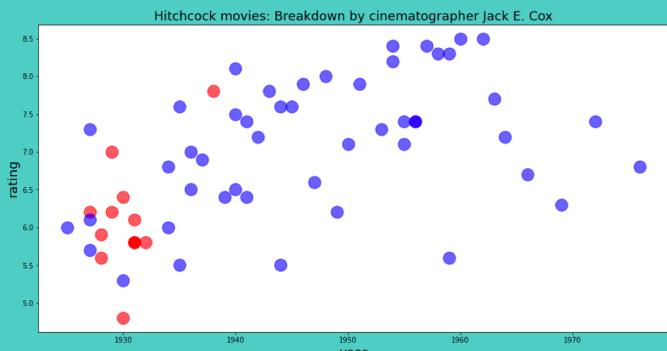
## categorical features

- TV series vs. theatrical release
- Documentary or not
- Cinematographer (excluding those who worked the least number of times with that director)
- Cast members (if appearing in > 3 films)

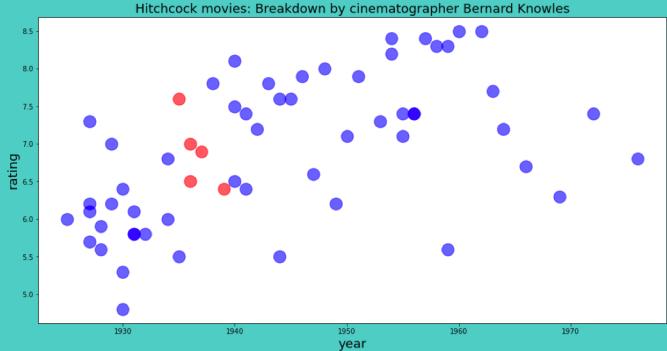


## Three of Hitchcock's cinematographers

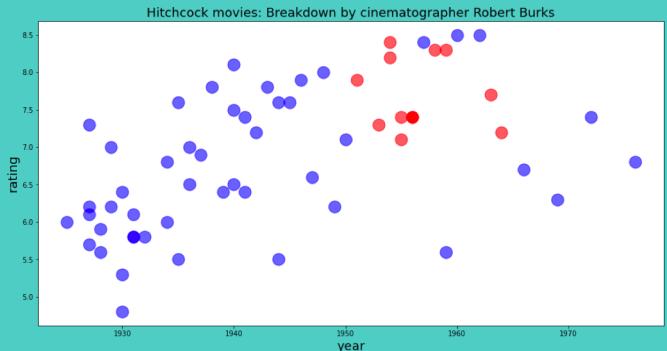
Jack E. Cox  
(1920-30s)



Bernard Knowles  
(late 1930s)



Robert Burks  
(1950s-60s)



Alfred Hitchcock and other directors, use a particular cinematographer during a particular phase of their career

Therefore  
cinematographer  
somewhat serves as  
a proxy for the time  
variable in years

# Linear regression models

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**R<sup>2</sup> values**

on test-set after  
training

\* Including two additional Allen films excluded for their genre and duration yielded slightly different results

# Linear regression models

## **R<sup>2</sup> values on test-set after training**

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# Linear regression models

R<sup>2</sup> values on test-set after training

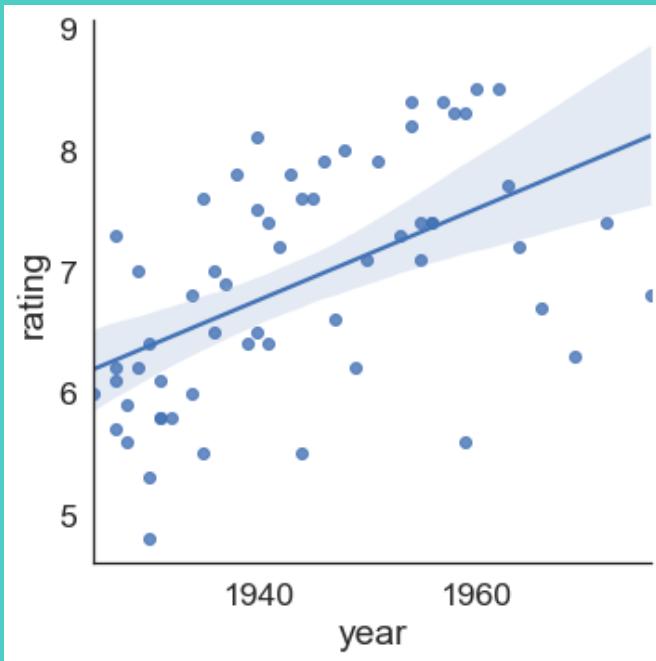


Feature sets	Hitchcock	Bergman	Godard	Allen	Allen*	Fassbinder	Herzog	Scorsese
All (continuous & categories)	-0.97	-1.41	-0.09	-14.3	0.21	-1.26	-0.07	-0.41
Continuous only	0.38	0.15	0.26	<b>0.51</b>	0.4	0.27	0.07	0.17
Year	0.28	-0.15	-0.11	0.24	0.04	-0.08	0.04	-0.18
Year & Rating count	0.37	-0.1	0.11	<b>0.51</b>	<b>0.46</b>	0.21	0.06	-0.19
Year & Duration only	0.27	0.16	0.25	0.23	-0.04	-0.02	0.03	0.19

\* Including two additional Allen films excluded for their genre and duration yielded slightly different results

# How Hitchcock's ratings rise

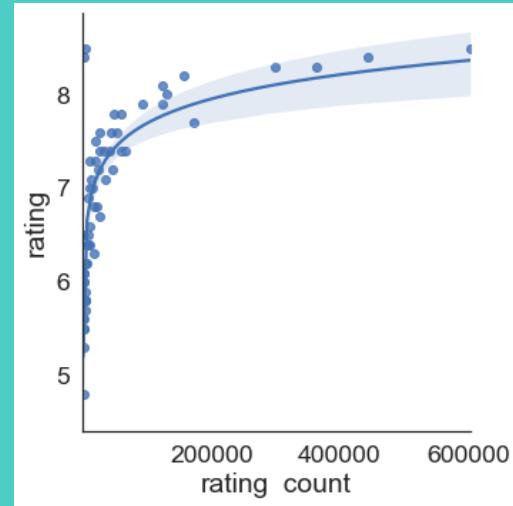
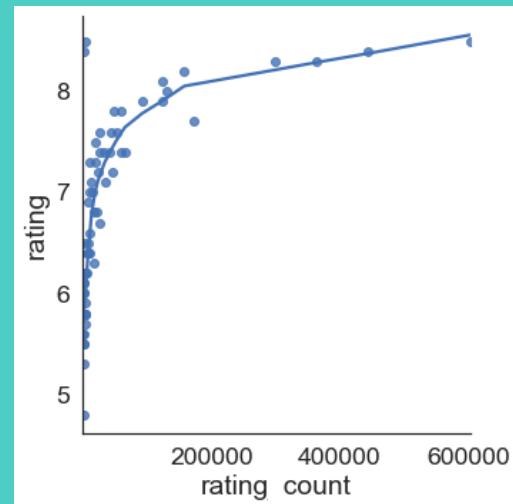
Hitchcock movies tend to be rated higher to the extent they are released later in his career and are rated by many



## Feature engineering

Regression on log of ratings count

Smoothed moving average (lowess)



# Linear regression models

R<sup>2</sup> values on test-set after training



Feature sets	Hitchcock	Bergman	Godard	Allen	Allen*	Fassbinder	Herzog	Scorsese
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Year & Rating count	0.37	-0.1	0.11	<b>0.51</b>	<b>0.46</b>	0.21	0.06	-0.19
Year & Duration only	0.27	0.16	0.25	0.23	-0.04	-0.02	0.03	0.19
Year & Rating count & their logs	<b>0.8</b>	<b>0.84</b>	0.35	<b>0.48</b>	0.37	<b>0.48</b>	<b>0.16</b>	-0.22
Year & log(rating count)	<b>0.78</b>	<b>0.8</b>	<b>0.34</b>	0.36	<b>0.45</b>	0.12	0.11	<b>0.25</b>
Lasso CV with polynomials on all features Include budget but w/ smaller dataset	<b>0.68</b>				<b>0.41</b>			<b>0.69</b>

\* Including two additional Allen films excluded for their genre and duration yielded slightly different results

# Linear regression models

R<sup>2</sup> values on test-set after training

Less stable  
(higher variance, overfitting)

Allen

Lasso regression on polynomial features, with cross validation

	validation	test
	-7.315	0.455
	-0.897	0.29
	-315.4	0.275

slightly more stable  
(less variance, less overfitting)

Hitchcock

Lasso regression on polynomial features, with cross validation

	validation	test
	-0.09	0.508
	0.747	0.4
	0.324	0.567

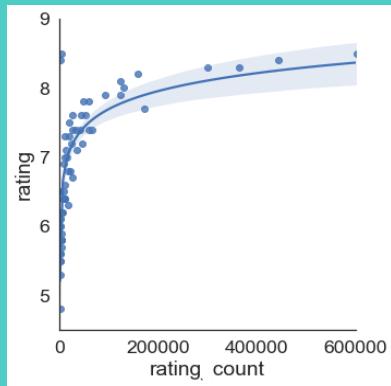
*year, duration, rating count, log(year), log(rating count)*

Hitchcock Important coefficients: -50.668,

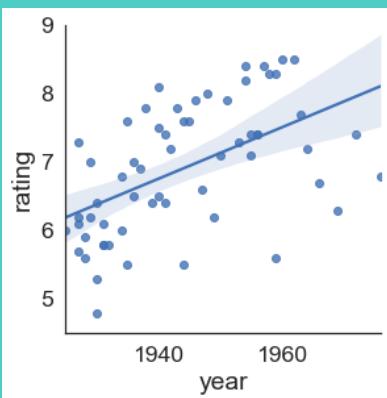
-0.198, 0.101, 50.892, 0.560

# Opposite trends

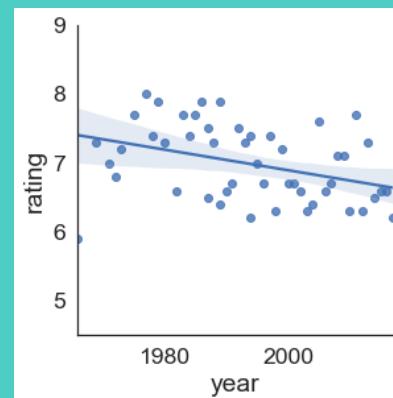
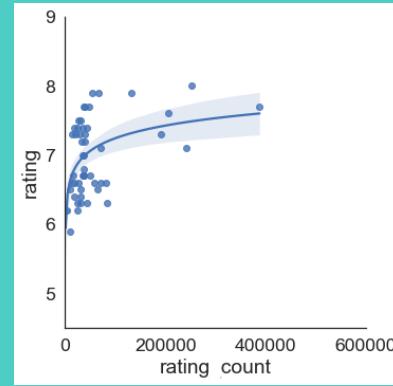
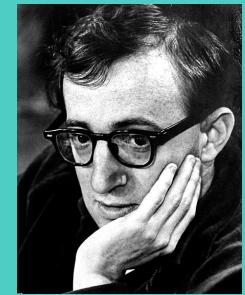
Hitchcock



	$R^2$ on test set
Year & Ratings count	0.44
Year & Duration only	0.28
Year & Ratings count & their logs	<b>0.8</b>
Year & log(rating count)	0.68
Lasso CV with polynomials on all features	<b>0.41</b>



Allen



	$R^2$ on test set
Year & Ratings count	<b>0.51</b>
Year & Duration only	0.23
Year & Ratings count & their logs	<b>0.48</b>
Year & log(rating count)	0.36

$R^2$  values shown in blue represent the best model for the given director, based on comparisons of *mean absolute error (mae)* between different sets of features and rows, and within the same set of features and rows, choosing Lasso vs. Ridge based on lower  $R^2$

# Linear regression models

## A more thorough investigation using Lasso CV on all features

w/ rating count		Hitchcock	Bergman	Godard	Fassbinder	Herzog	Allen	Scorsese
<b>Lasso CV</b>	$r^2$	<b>0.7979</b>	<b>0.4737</b>	<b>-0.0246</b>	<b>0.0060</b>	<b>0.0968</b>	<b>0.2947</b>	<b>0.3369</b>
	mae	0.3070	0.4795	0.4863	0.3856	0.5787	0.3606	0.3049
<b>Polynomial Features</b>								
w/ rating count		Hitchcock	Bergman	Godard	Fassbinder	Herzog	Allen	Scorsese
<b>Lasso CV</b>	$r^2$	<b>0.7695</b>	<b>0.2721</b>	<b>0.0893</b>	<b>-0.4796</b>	<b>0.2804</b>	<b>0.2571</b>	<b>-1.6643</b>
	mae	0.3297	0.5312	0.4864	0.5080	0.5526	0.3464	0.3483

Contributors  
(positive coefficients)

tv series  
**log(rating cnt)**



Edward Chapman

Ewa Froling  
duration  
**log(rating cnt)**



Georg Funkquist  
Stig Olin

Gottfried John  
El Hedi ben Salem  
Walter Sedlmayr  
Irm Hermann  
Duration  
rating count  
docu x Peter Zeitlinger (DOP)  
tv series x Werner Herzog (appears)  
log(rating cnt) x documentary



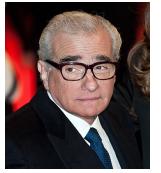
Ulli Lommel  
Margarethe von Trotta

Mia Farrow  
Carlo Di Palma (DOP)  
Diane Keaton  
Gordon Willis (DOP)  
**log(rating cnt)**



year  
Vilmos Zsigmond (DOP)  
Darius Khondji (DOP)

Joe Pesci  
Ringo Starr  
rating cnt  
log(rating cnt)  
Michael Chapman (DOP)



Greatest coefficients\*:

Detractors  
(negative coefficients)

\* Font sizes are roughly proportional to absolute value of coefficients

DOP stands for *director of photography*, which is the cinematographer

## Caveat:

Although average *rating* of a movie could vary up or down regardless of the *rating count*, the particular ratings can only exist in so far as there already exist ratings to count up. Therefore there is some question of:

### Reflexivity

Therefore, can the ratings be predicted or interpreted without using *rating count* as a feature?

# Linear regression models *without rating count as a feature*

## A more thorough investigation using Lasso CV on all features

<u>w/out rating count</u>		Hitchcock	Bergman	Godard	Fassbinder	Herzog	Allen	Scorsese
<b>Lasso CV</b>	r <sup>2</sup>	<b>0.1460</b>	<b>0.0493</b>	<b>0.0756</b>	<b>-0.3318</b>	<b>-0.0343</b>	<b>0.1838</b>	<b>-0.0687</b>
<b>Ridge CV</b>		<b>0.3806</b>	<b>0.2071</b>	<b>-0.1495</b>	<b>-0.2123</b>	<b>0.0726</b>	<b>0.1070</b>	<b>-0.0527</b>
Lasso CV	mae	0.5909	0.6981	0.4722	0.4211	0.6497	0.3904	0.3505
Ridge CV		0.5097	0.6138	0.5023	0.4375	0.6325	0.3489	0.3709

## Polynomial Features

<u>w/out rating count</u>		Hitchcock	Bergman	Godard	Fassbinder	Herzog	Allen	Scorsese
<b>Lasso CV</b>	r <sup>2</sup>	<b>0.0955</b>	<b>0.0522</b>	<b>-0.3081</b>	<b>-0.5940</b>	<b>0.2086</b>	<b>0.1925</b>	<b>-0.0687</b>
<b>Ridge CV</b>		<b>0.3285</b>	<b>0.4565</b>	<b>-0.0069</b>	<b>-0.2809</b>	<b>0.1282</b>	<b>-0.1373</b>	<b>-1.3768</b>
Lasso CV	mae	0.6239	0.6926	0.5072	0.5122	0.6415	0.3859	0.3585
Ridge CV		0.4904	0.5152	0.4767	0.4494	0.6180	0.3826	0.5560



Pairs of *mean absolute errors (mae)* are boxed if they are lower than the corresponding *mae* for a different sized set of features here (and slightly different sets of rows shown on the next slide).

# Linear regression models

using *budget* as a feature

## A more thorough investigation using Lasso CV on all features

w/ budget (w/out rating count)		Hitchcock	Bergman	Godard	Fassbinder	Herzog	Allen	Scorsese
Lasso CV	r <sup>2</sup>		<b>0.2442</b>	<b>-0.3382</b>	<b>0.1542</b>	<b>-0.1116</b>		<b>-1.2286</b>
Ridge CV			<b>0.2264</b>	<b>-0.7183</b>	<b>-0.0693</b>	<b>-0.0269</b>	insufficient	<b>-1.3884</b>
Lasso CV	mae	0.3993	0.7500	0.4608	0.3550	data	0.4518	0.5210
Ridge CV		0.4135	0.8255	0.3717	0.3279		0.4553	0.5690

## Polynomial Features

w/ budget (w/out rating count)

		Hitchcock	Bergman	Godard	Fassbinder	Herzog	Allen	Scorsese
Lasso CV	r <sup>2</sup>		<b>0.2905</b>	<b>-0.4779</b>	<b>0.3768</b>	<b>-0.1116</b>		<b>-1.3102</b>
Ridge CV			<b>0.1001</b>	<b>-0.1964</b>	<b>-0.1767</b>	<b>-0.6524</b>	insufficient	<b>-1.9036</b>
Lasso CV	mae	0.3862	0.8424	0.3952	0.3550	data	0.4518	0.9911
Ridge CV		0.4289	0.92812	0.4942	0.4118		0.4426	0.6627

## Contributors (positive coefficients)

Greatest coefficients\*:

Detractors  
(negative coefficients)



Pairs of *mean absolute errors (mae)* are boxed if they are lower than the corresponding *mae* for a different sized set of features here (and slightly different sets of rows shown on the previous slide).

# Further investigations

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## Probe regularization with polynomial features to improve prediction

- Examine quantile-quantile plots and individual interactions

## Develop explanation

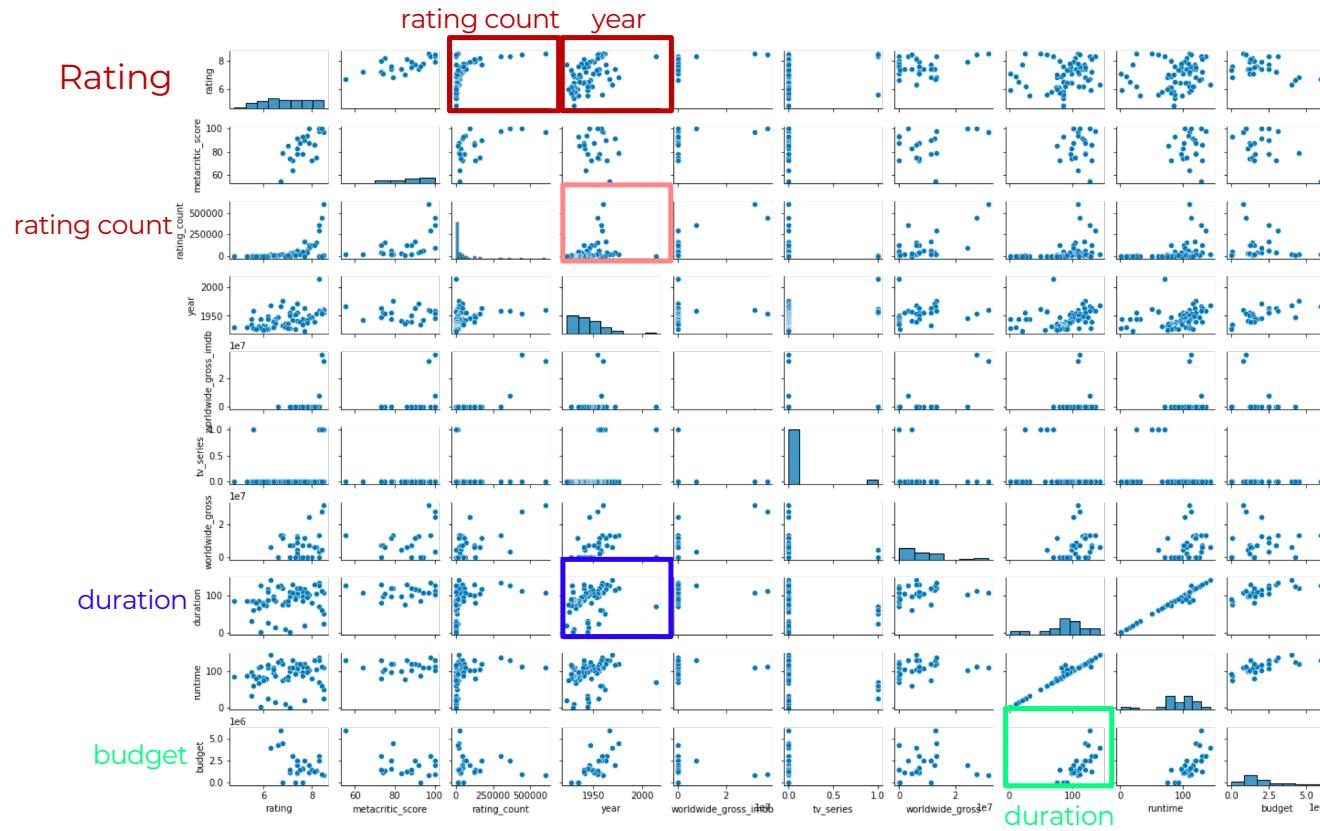
- Examine **residuals** in tandem with *domain knowledge* to discover and explain **interactions** between features, such as:

- budget & rating:  
inversely correlated?
- duration ~ budget ?
- more visualizations

# Alfred Hitchcock

# Further investigations

# Shapes of correlation

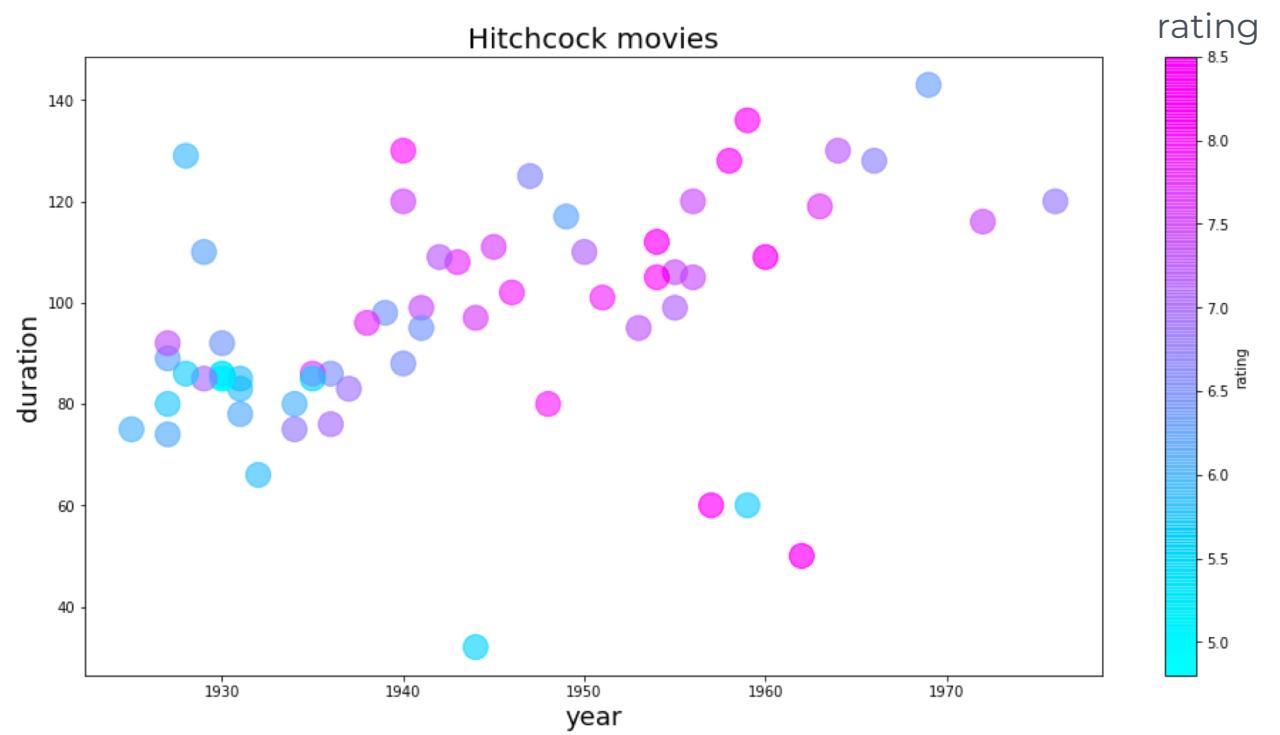


and...

# More visualizations for exploratory data analysis

## Hitchcock's movies increased in duration

Their ratings have a sweet spot just past the middle



# Further investigations

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- Examine quantile-quantile plots and individual interactions

## Develop explanation

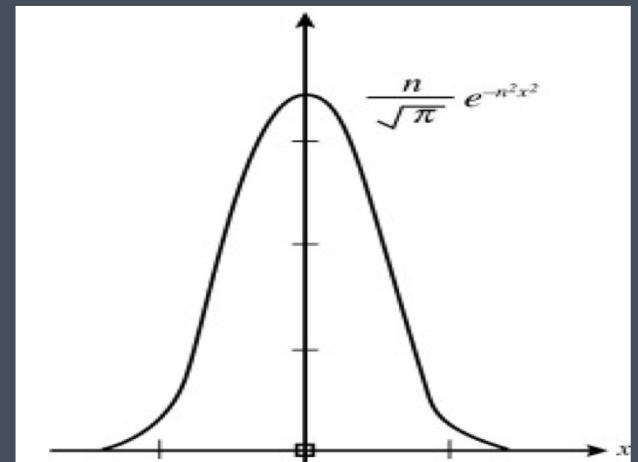
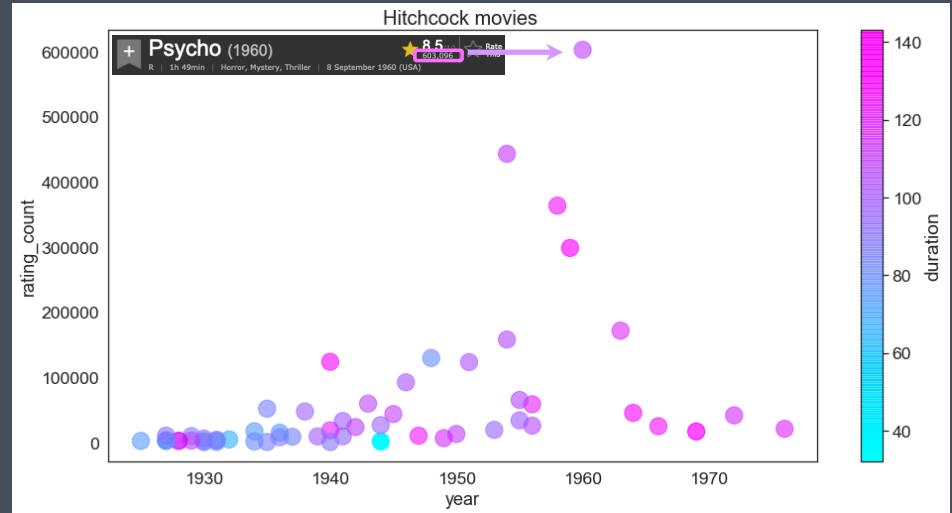
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and...

# Feature engineering

Model the spike in rating count, using the *Dirac Delta* function ("impulse" function)



Joshua Banks Mailman

joshuabanksmailman@gmail.com

# Thanks!

# Predicting film- director ratings

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