

Predicting IMDb Ratings via Regression and Deep Learning

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Outline

- Business Problem
- Data and Methods
- Results
- Limitations and Conclusions
- Future Work

Business Problem



- Predict a film's IMDb rating given a select number of features
- Minimise the risk of producing a "razzie"
- Determine the features that have the biggest impact on the film's IMDb rating

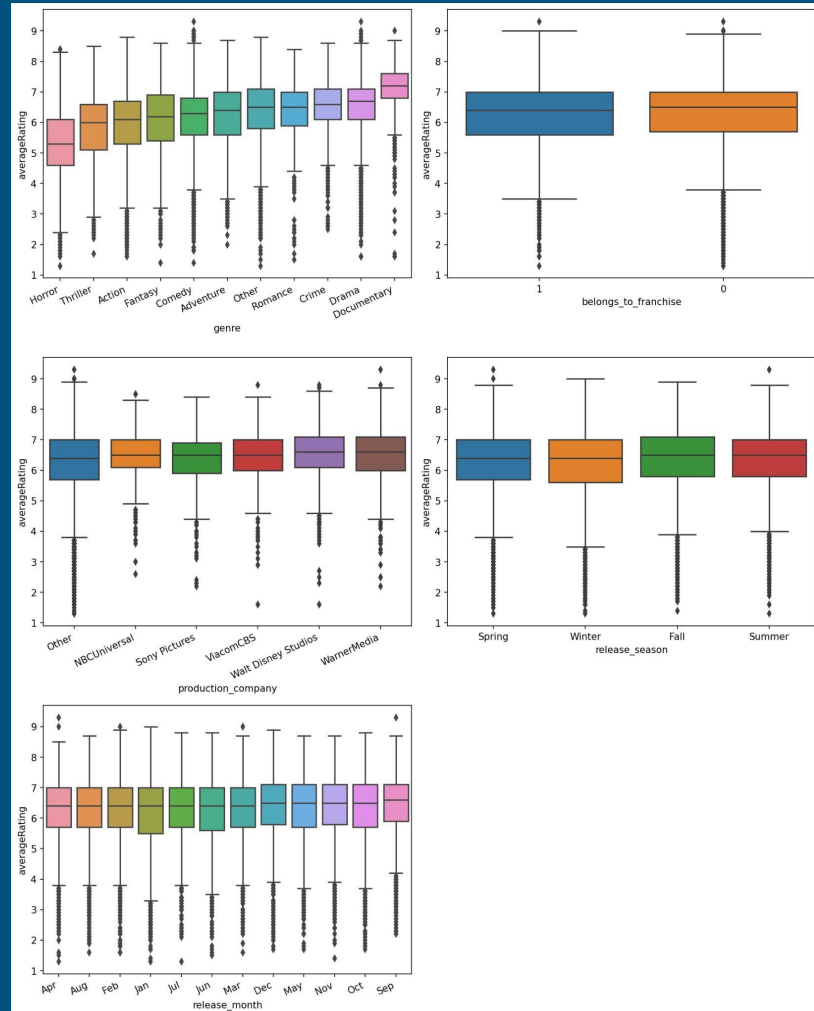
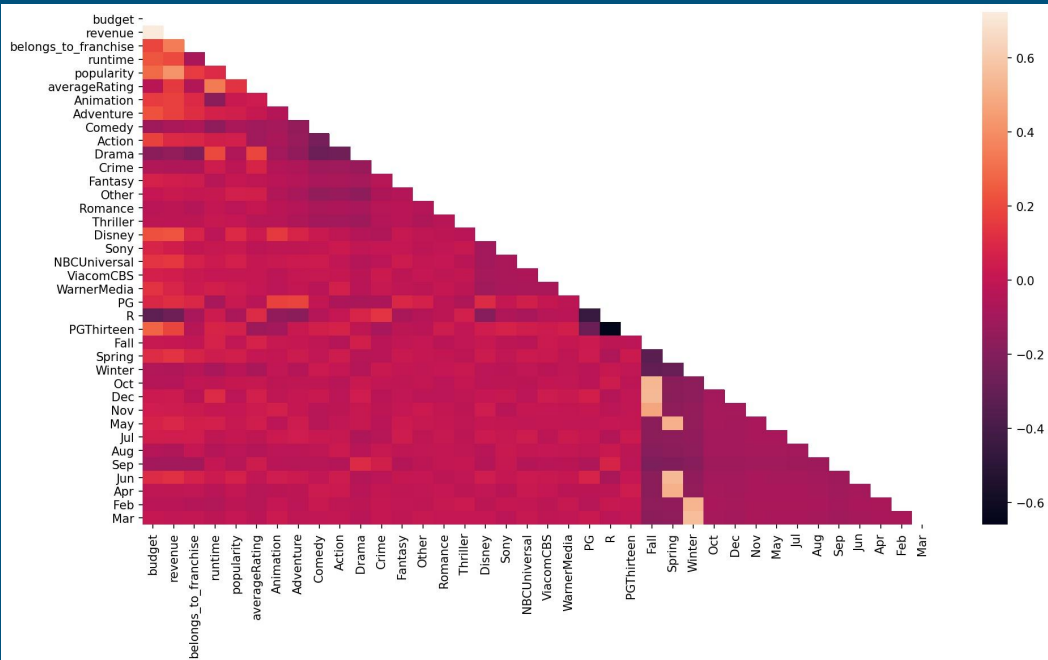
Data and Methods

- Dataset obtained from Kaggle's The Movies Dataset
- Contains information on over 40,000 movies such as genre, release date, IMDb rating, etc.
- Methods used: exploratory data analysis, regression modelling, neural networks

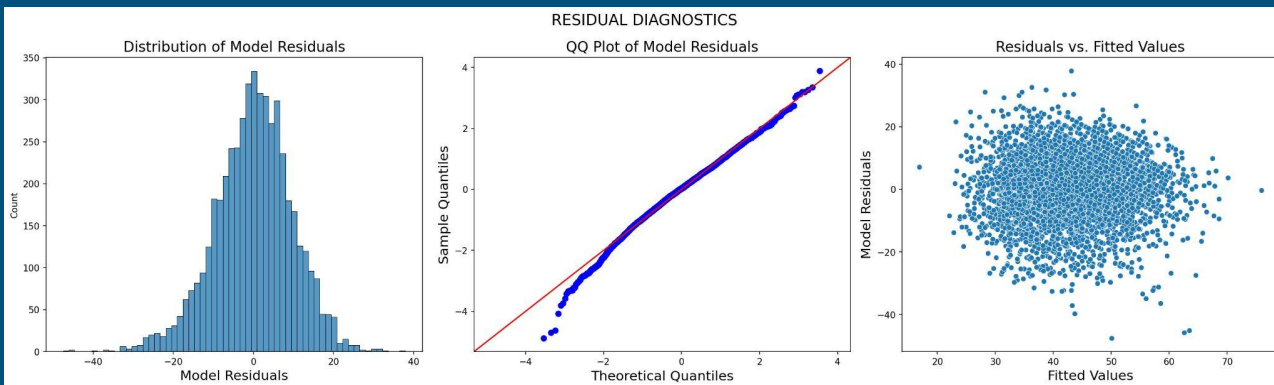
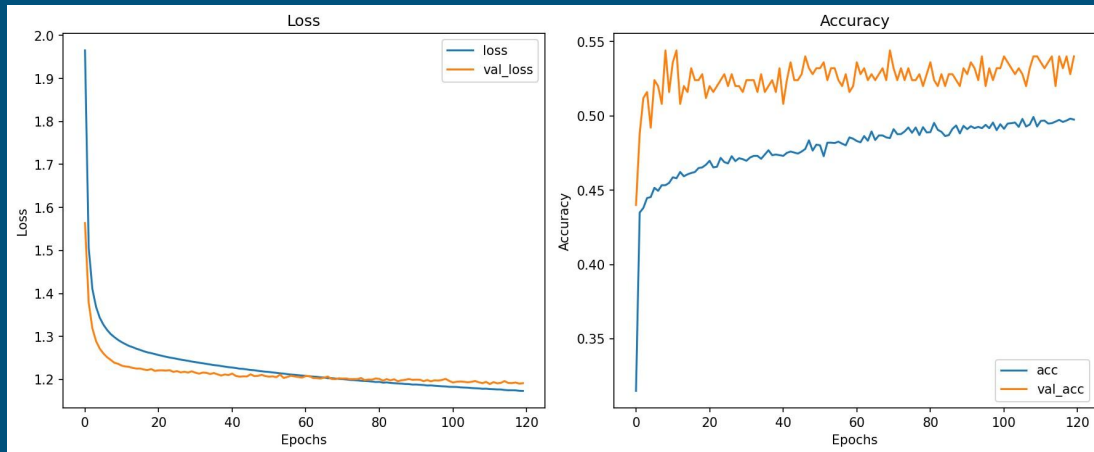


	title	genre	belongs_to_franchise	production_company	runtime	popularity	release_season	release_month	averageRating
0	Toy Story	Other	1	Walt Disney Studios	81.0	21.946943	Fall	Oct	8.3
1	Jumanji	Adventure	1	Sony Pictures	104.0	17.015539	Fall	Dec	7.0
2	Grumpier Old Men	Romance	1	Other	101.0	11.712900	Fall	Dec	6.7
3	Waiting to Exhale	Comedy	0	Walt Disney Studios	127.0	3.859495	Fall	Dec	6.0
4	Father of the Bride Part II	Comedy	1	Other	106.0	8.387519	Winter	Feb	6.1

Results



Results



Dep. Variable:	averageRating_squared	R-squared:	0.370			
Model:	OLS	Adj. R-squared:	0.367			
Method:	Least Squares	F-statistic:	139.2			
Date:	Thu, 29 Apr 2021	Prob (F-statistic):	0.00			
Time:	16:44:28	Log-Likelihood:	-18509.			
No. Observations:	5009	AIC:	3.706e+04			
Df Residuals:	4987	BIC:	3.721e+04			
Df Model:	21					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
Intercept	10.4847	1.372	7.640	0.000	7.794	13.175
belongs_to_franchise	-3.0963	0.359	-8.626	0.000	-3.800	-2.393
runtime	0.2537	0.010	25.875	0.000	0.234	0.273
budget_fourth	-0.2956	0.010	-31.037	0.000	-0.314	-0.277
revenue_fifth	0.3444	0.020	17.550	0.000	0.306	0.383
sqrt_popularity	3.7822	0.184	20.596	0.000	3.422	4.142
Animation	14.1255	1.085	13.023	0.000	11.999	16.252
Adventure	8.0535	0.793	10.154	0.000	6.499	9.608
Comedy	5.4510	0.647	8.422	0.000	4.182	6.720
Action	4.8501	0.663	7.313	0.000	3.550	6.150
Drama	9.0318	0.657	13.756	0.000	7.745	10.319
Crime	9.0464	0.844	10.719	0.000	7.392	10.701
Fantasy	7.6522	1.033	7.407	0.000	5.627	9.678
Other	8.5871	0.768	11.178	0.000	7.081	10.093
Romance	7.5661	1.095	6.912	0.000	5.420	9.712
Thriller	3.7258	0.902	4.130	0.000	1.957	5.494
PG	-4.3846	0.863	-5.081	0.000	-6.076	-2.693
R	-2.5119	0.858	-2.929	0.003	-4.193	-0.830
PGThirteen	-5.4071	0.873	-6.192	0.000	-7.119	-3.695
Fall	1.0212	0.374	2.729	0.006	0.288	1.755
Spring	0.2363	0.384	0.615	0.539	-0.517	0.989
Winter	-0.7173	0.396	-1.812	0.070	-1.493	0.059
Omnibus:	117.218	Durbin-Watson:	1.815			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	152.383			
Skew:	-0.290	Prob(JB):	8.14e-34			
Kurtosis:	3.628	Cond. No.	2.01e+03			

Limitations and Conclusions

- Dataset contained several missing values for features like budget and revenue
- Both models were heavily dependent on categorical data
- IMDb rating was not really affected by our categorical features
- Retrieving additional data was difficult and time-expensive

Future Work

- Natural Language Processing (NLP) could be used to identify key words and predict the IMDb rating
- Compare results between the same analysis done on TV shows
- Consider more continuous features! (opening weekend box office, marketing expenses)



Thank You!

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