PROJECT PROPOSAL

PREDICTING MOVIE SUCCESS USING LOGISTIC REGRESSION

PRESENTED BY

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PROBLEM STATEMENT

Can we predict whether a movie will be successful or not based on its metadata (e.g., budget, runtime, genre, and other pre-release attributes)?

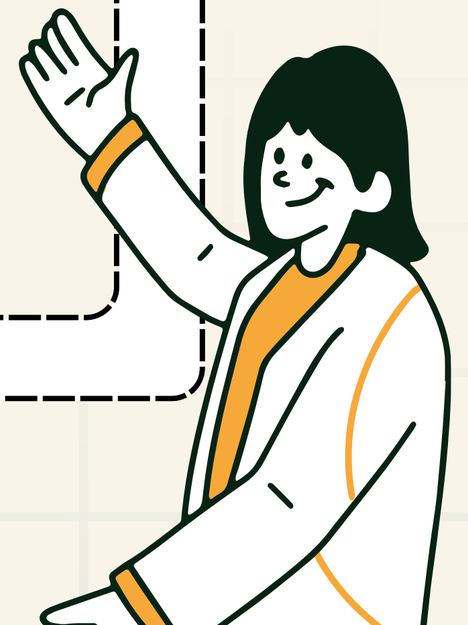
TYPE OF PROBLEM & STATISTICAL MODEL

Type of Problem:

- Binary Classification Problem
- Predictive Modeling Task

STATISTICAL TECHNIQUE CHOSEN

Logistic Regression



LOGISTIC REGRESSION

- A statistical model used for binary classification.
- Estimates the probability that a given input belongs to a particular category.
- Uses the sigmoid function to output a value between 0 and 1.
- Predicts outcomes like “Success (1)” or “Not Success (0)”.

KEY FEATURES

- It is ideal for binary outcomes (success vs. not success).
- It provides clear coefficients to understand how each feature (e.g., budget) impacts the probability of success.
- Suitable for a student project, as it's straightforward to implement and interpret.

LITERATURE REVIEW & DATASET SELECTION

DA, O., OM, S., AK, F., O, A., A, O., A, O., A, W., & M, Y. (2021). Movie success prediction using data mining. British Journal of Computer Networking and Information Technology, 4(2), 22–30. https://doi.org/10.52589/bjcnit-cqocirec

Zheng, Y. (2024). Predicting movie box office based on machine learning, deep learning, and statistical methods. Applied and Computational Engineering, 94(1), 20–32. https://doi.org/10.54254/2755-2721/94/2024melb0069

Subramaniyaswamy, V., Vaibhav, M. V., Prasad, R. V., & Logesh, R. (2017). Predicting movie box office success using multiple regression and SVM. Journal of Science & Statistics, 182–186. https://doi.org/10.1109/iss1.2017.8389394

Velingkar, G., Varadarajan, R., Lanka, S., & M, A. K. (2022). Movie Box-Office success Prediction using Machine Learning. 2022 Second International Conference on Power, Control and Computing Technologies (ICPC2T), 9, 1–6. https://doi.org/10.1109/icpc2t53885.2022.9776798

Mr, N. V., Mr, P. M., & Pb, S. B. (2014). Predicting movie success based on IMDB data. International Journal of Business Intelligents, 3(2). https://doi.org/10.20894/ijbi.105.003.002.004

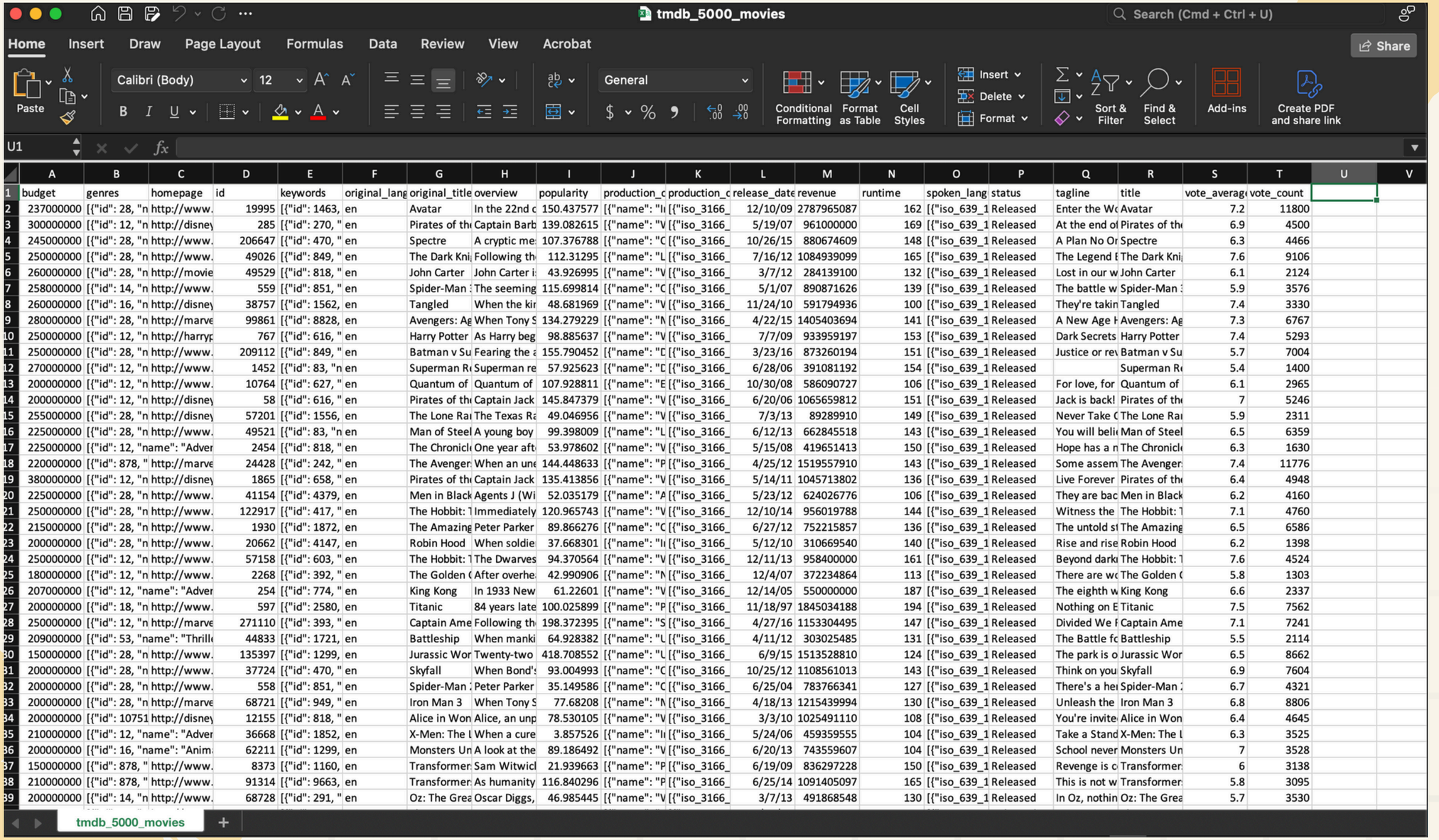
BRIEF OVERVIEW OF LITERATURE REVIEW

Proceedings Article • 10.1109/ISS1.2017.8389394 **3. Predicting movie box office success using multiple regression and SVM** V. Subramaniyaswamy, M. Viginesh Vaibhav, R. Vishnu Prasad +1 more 1 Dec 2017 66 26 Request PDF Podcast Chat 66	The paper you referenced is not the same as the one discussed here. This research focuses on predicting movie box office success using multiple regression and SVM, analyzing factors like trailer views, Wikipedia page views, and critic ratings.
Proceedings Article • 10.1109/ICPC2T53885.2022.9776798 **4. Movie Box-Office Success Prediction Using Machine Learning** Gaurang Velingkar, Rakshita Varadarajan, Sidharth Lanka +1 more 1 Mar 2022 66 4 Request PDF Podcast Chat 66	The paper focuses on predicting movie box office success using machine learning, specifically employing a Random Forest Regression model to analyze factors like genre, budget, and star power, aiding investors in making informed decisions before a movie's release.
• Proceedings Article • 10.1109/icpc2t53885.2022.9776798 **5. Movie Box-Office Success Prediction Using Machine Learning** 1 Mar 2022 66 8 PDF Podcast Chat	The paper focuses on predicting movie box office success using machine learning, specifically employing a Random Forest Regression model to analyze factors like genre, budget, and star power, aiding investors in making informed decisions before a movie's release.

DATASET SELECTION

- Source: TMDB / Kaggle (5,000+ movies)
- Features: Budget, Genre, Runtime, Country, Vote Count, Revenue

EXPLORATORY DATA ANALYSIS (EDA)



	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V
1	budget	genres	homepage	id	keywords	original_lang	original_title	overview	popularity	production_c	production_c	release_date	revenue	runtime	spoken_lang	status	tagline	title	vote_averag	vote_count		
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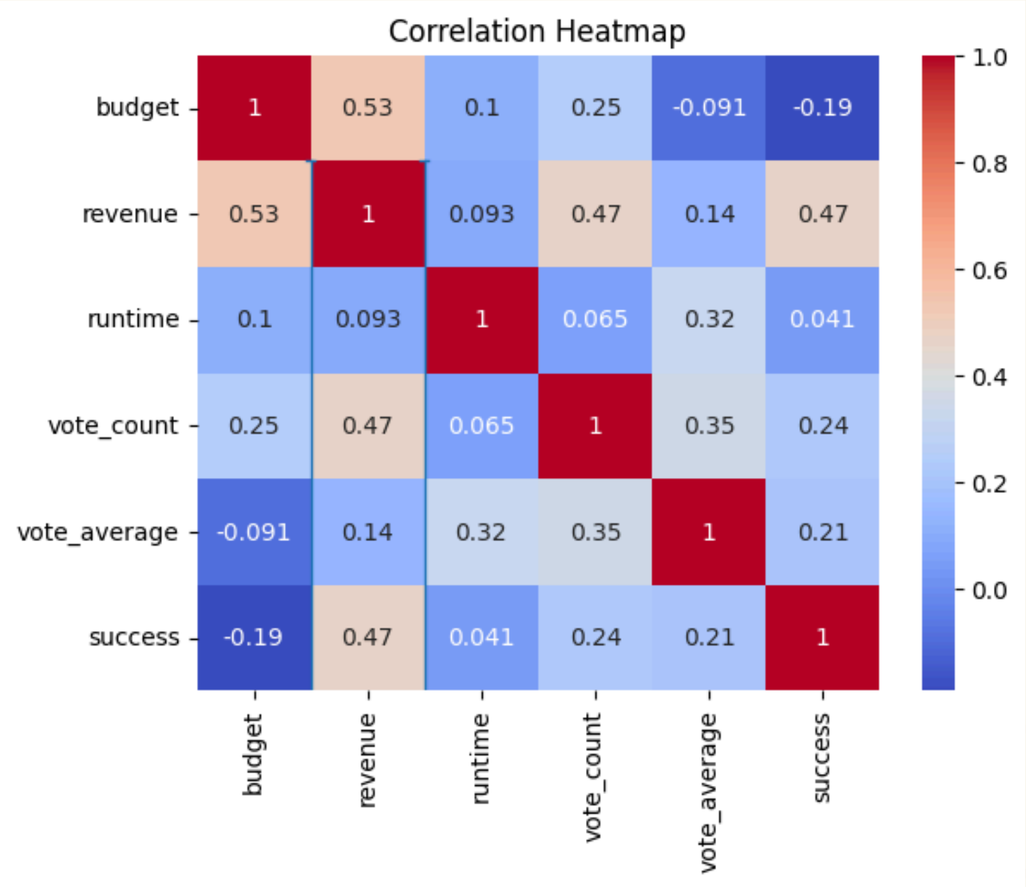
tmdb_5000_movies

EXPLORATORY DATA ANALYSIS (EDA)

Features Used for Analysis

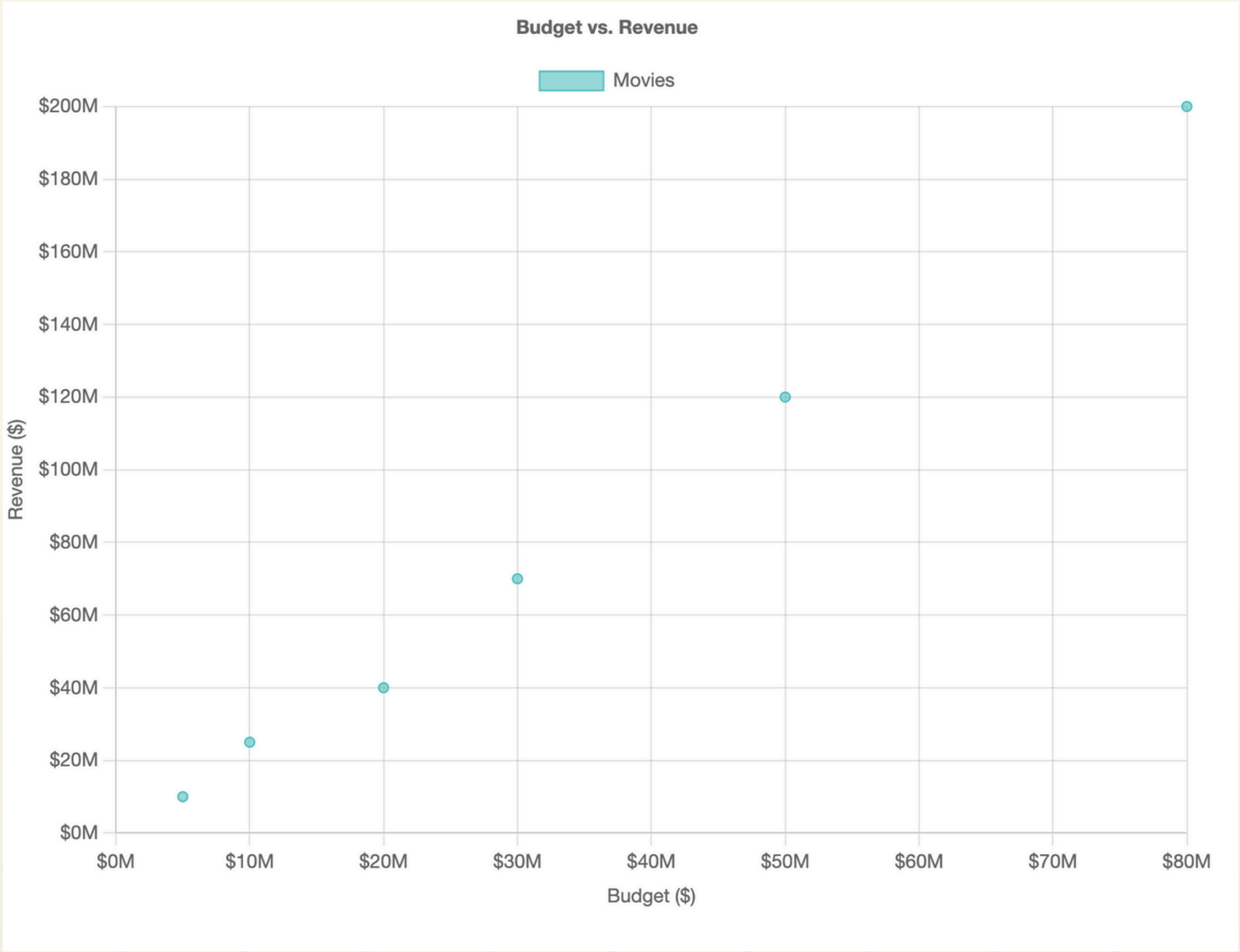
- **Numerical**: budget, revenue, runtime, year, vote_count (and possibly vote_average if not dropped).
- **Categorical**: certification_US, genre, country.
- **Target**: success (True/False, where True means revenue ≥ 2x budget).

WHY THOSE FEATURES?



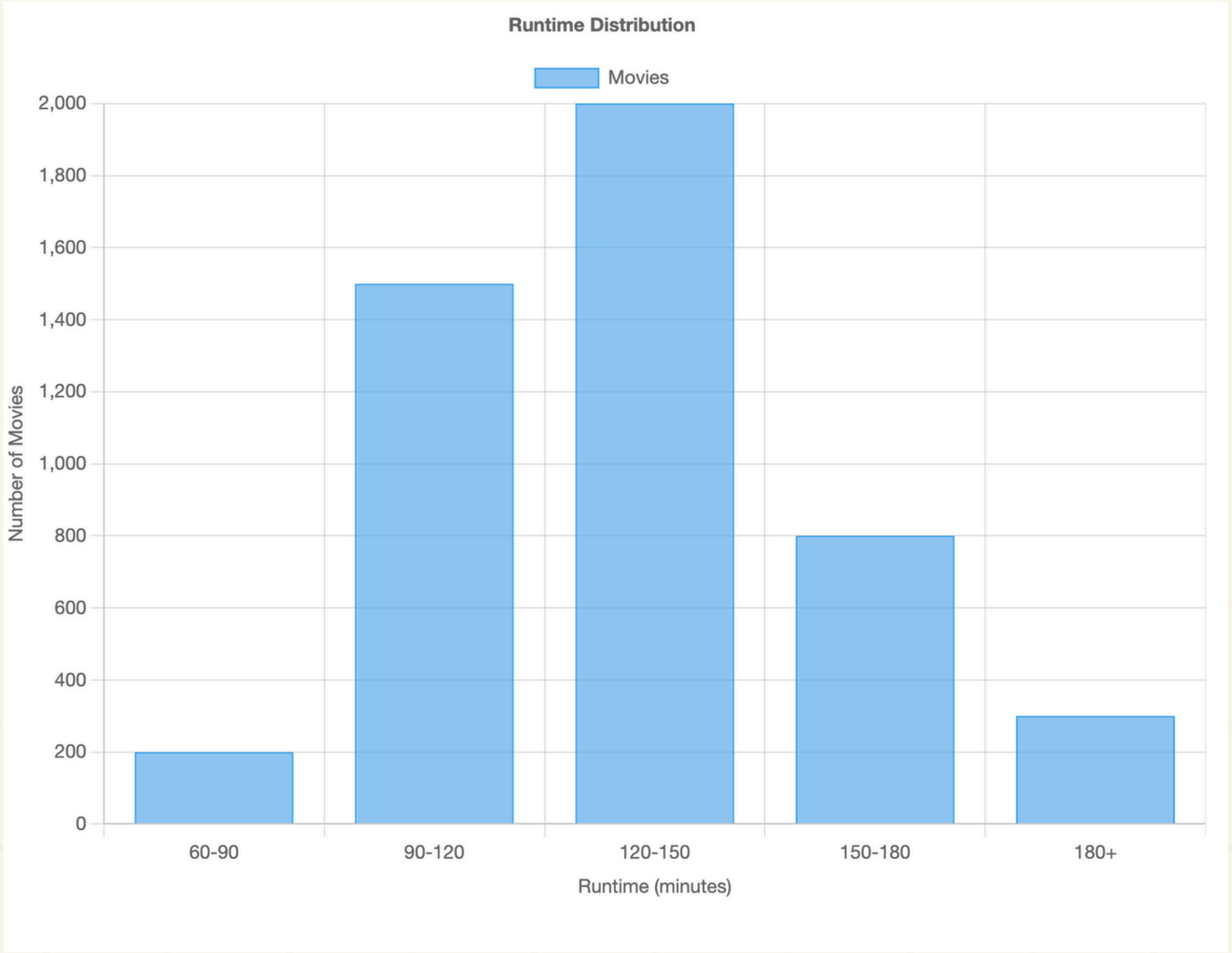
1. SUCCESS IS MOST TIED TO REVENUE (0.47) AND VOTE_COUNT (0.24), SO THESE FEATURES MIGHT PREDICT SUCCESS WELL.
2. BUDGET AND REVENUE ARE RELATED (0.53), MEANING BIGGER BUDGETS OFTEN LEAD TO HIGHER REVENUE.
3. RUNTIME HAS LITTLE CONNECTION TO OTHER FEATURES (ALL NEAR 0), SO IT MIGHT NOT BE A STRONG PREDICTOR OF SUCCESS.

WHY THOSE FEATURES?



PS: SHOWS IF HIGHER BUDGETS LEAD TO HIGHER REVENUE.

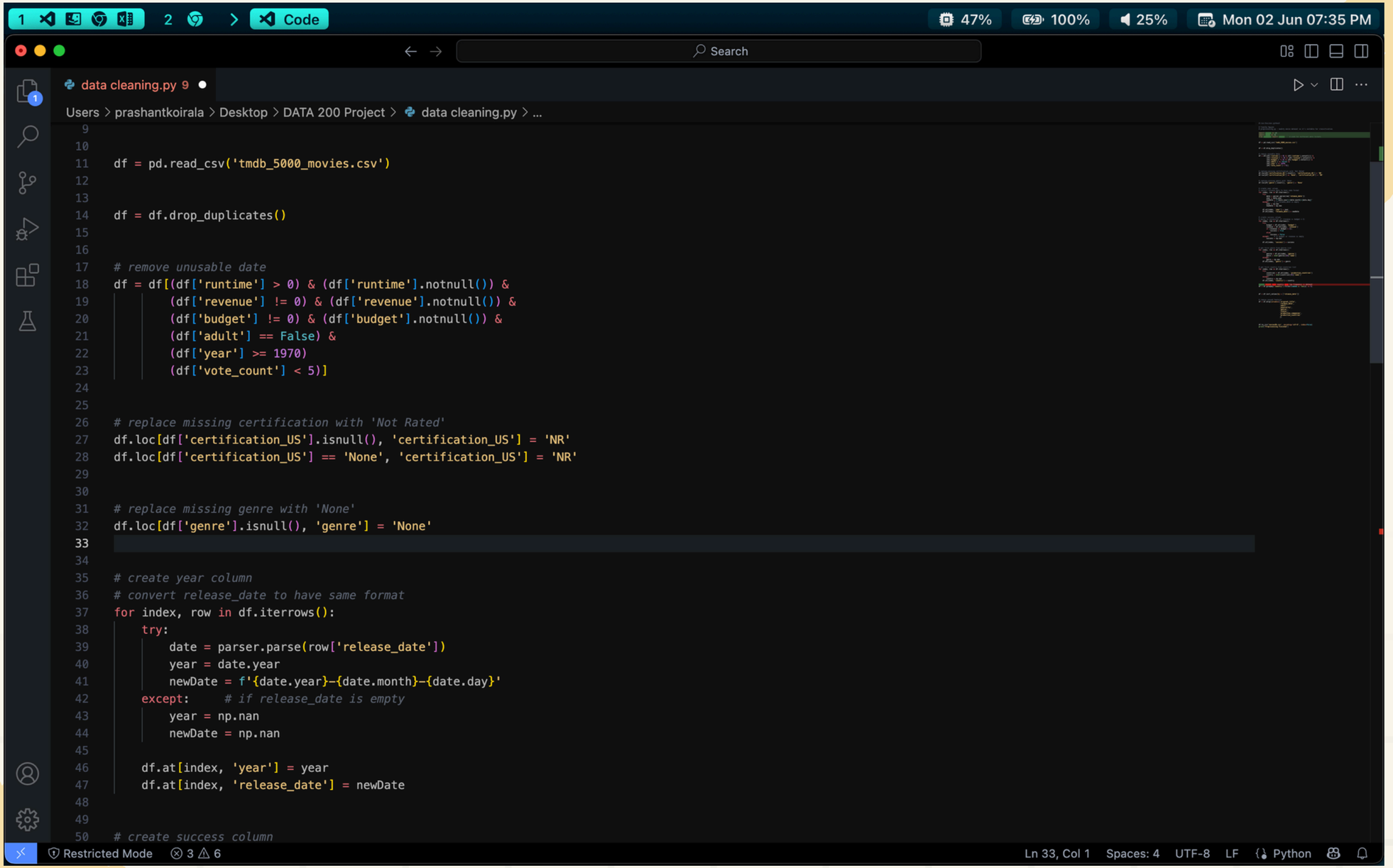
WHY THOSE FEATURES?



PS: SHOWS HOW RUNTIMES ARE DISTRIBUTED.

DATA CLEANING

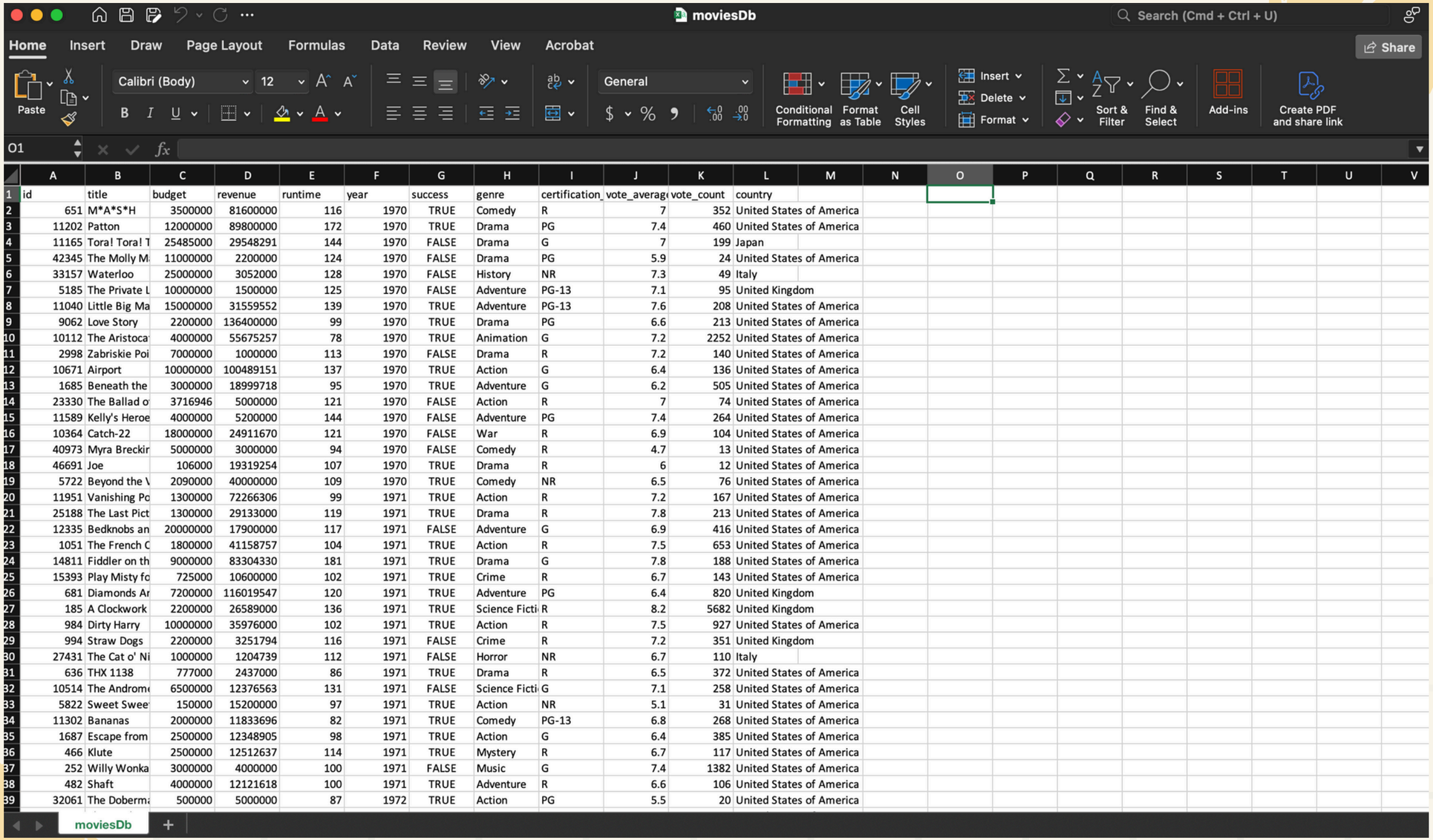
DATA CLEANING PROGRAM



DATA CLEANING

1. **Removed duplicates and movies with missing/zero budget, revenue, or runtime.**
2. **Replaced missing certification_US with “NR”; extracted first genre and country.**
3. **Filtered movies before 1970 and countries with < 5 occurrences.**
4. **Created success (True if revenue ≥ 2x budget) and year columns.**

AFTER DATA CLEANING



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1	id	title	budget	revenue	runtime	year	success	genre	certification_	vote_averag	vote_count	country										
2	651	M*A*S*H	3500000	81600000	116	1970	TRUE	Comedy	R	7	352	United States of America										
3	11202	Patton	12000000	89800000	172	1970	TRUE	Drama	PG	7.4	460	United States of America										
4	11165	Tora! Tora! T	25485000	29548291	144	1970	FALSE	Drama	G	7	199	Japan										
5	42345	The Molly M	11000000	2200000	124	1970	FALSE	Drama	PG	5.9	24	United States of America										
6	33157	Waterloo	25000000	3052000	128	1970	FALSE	History	NR	7.3	49	Italy										
7	5185	The Private L	10000000	1500000	125	1970	FALSE	Adventure	PG-13	7.1	95	United Kingdom										
8	11040	Little Big Ma	15000000	31559552	139	1970	TRUE	Adventure	PG-13	7.6	208	United States of America										
9	9062	Love Story	2200000	136400000	99	1970	TRUE	Drama	PG	6.6	213	United States of America										
10	10112	The Aristoca	4000000	55675257	78	1970	TRUE	Animation	G	7.2	2252	United States of America										
11	2998	Zabriskie Poi	7000000	1000000	113	1970	FALSE	Drama	R	7.2	140	United States of America										
12	10671	Airport	10000000	100489151	137	1970	TRUE	Action	G	6.4	136	United States of America										
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19	5722	Beyond the V	2090000	40000000	109	1970	TRUE	Comedy	NR	6.5	76	United States of America										
20	11951	Vanishing Po	1300000	72266306	99	1971	TRUE	Action	R	7.2	167	United States of America										
21	25188	The Last Pict	1300000	29133000	119	1971	TRUE	Drama	R	7.8	213	United States of America										
22	12335	Bedknobs an	20000000	17900000	117	1971	FALSE	Adventure	G	6.9	416	United States of America										
23	1051	The French C	1800000	41158757	104	1971	TRUE	Action	R	7.5	653	United States of America										
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26	681	Diamonds Ar	7200000	116019547	120	1971	TRUE	Adventure	PG	6.4	820	United Kingdom										
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28	984	Dirty Harry	10000000	35976000	102	1971	TRUE	Action	R	7.5	927	United States of America										
29	994	Straw Dogs	2200000	3251794	116	1971	FALSE	Crime	R	7.2	351	United Kingdom										
30	27431	The Cat o' Ni	1000000	1204739	112	1971	FALSE	Horror	NR	6.7	110	Italy										
31	636	THX 1138	777000	2437000	86	1971	TRUE	Drama	R	6.5	372	United States of America										
32	10514	The Androm	6500000	12376563	131	1971	FALSE	Science Ficti	G	7.1	258	United States of America										
33	5822	Sweet Swee	150000	15200000	97	1971	TRUE	Action	NR	5.1	31	United States of America										
34	11302	Bananas	2000000	11833696	82	1971	TRUE	Comedy	PG-13	6.8	268	United States of America										
35	1687	Escape from	2500000	12348905	98	1971	TRUE	Action	G	6.4	385	United States of America										
36	466	Klute	2500000	12512637	114	1971	TRUE	Mystery	R	6.7	117	United States of America										
37	252	Willy Wonka	3000000	4000000	100	1971	FALSE	Music	G	7.4	1382	United States of America										
38	482	Shaft	4000000	12121618	100	1971	TRUE	Adventure	R	6.6	106	United States of America										
39	32061	The Doberma	500000	5000000	87	1972	TRUE	Action	PG	5.5	20	United States of America										

CONCLUSION

We successfully cleaned the TMDB dataset, creating a success variable (revenue ≥ 2x budget) and identifying key features like budget, revenue, and vote count. The correlation analysis showed revenue (0.47) and vote count (0.24) as strong predictors of success, with budget (0.19) having a weaker link. This supports our logistic regression approach, and further analysis will refine these findings.

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THANK YOU