FINAL PROJECT
PRESENTATION

PREDICTING MOVIE SUCCESS USING LOGISTIC REGRESSION

PRESENTED BY

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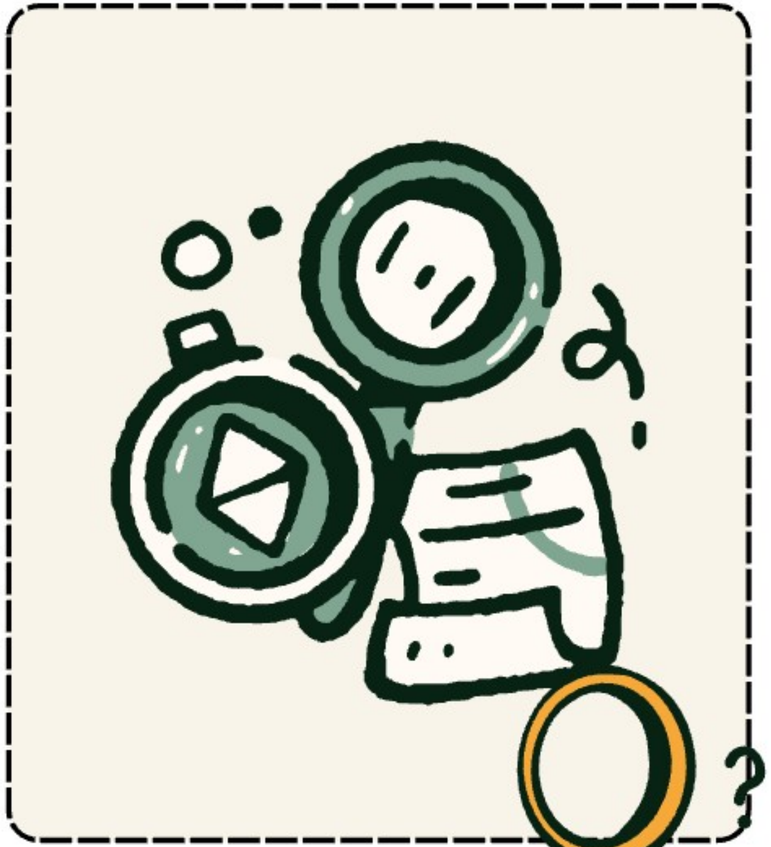
AISHMITA YONZAN

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:

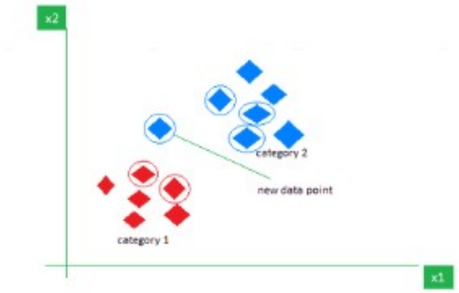
- Binary Classification Problem
- Predictive Modeling Task

MODEL SELECTION & JUSTIFICATION

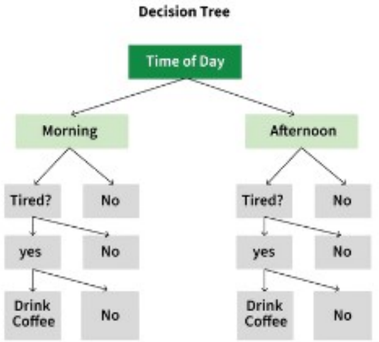
Models Evaluated

Logistic Regression

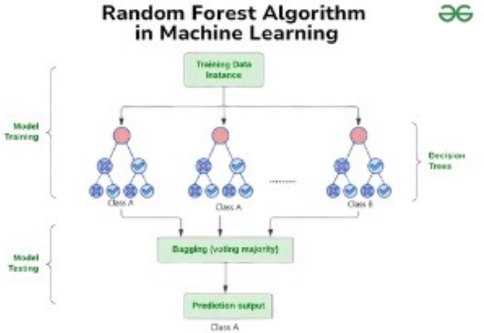
K-Nearest Neighbors



Decision Tree



Random Forest



Chosen Model

Logistic Regression ✅

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

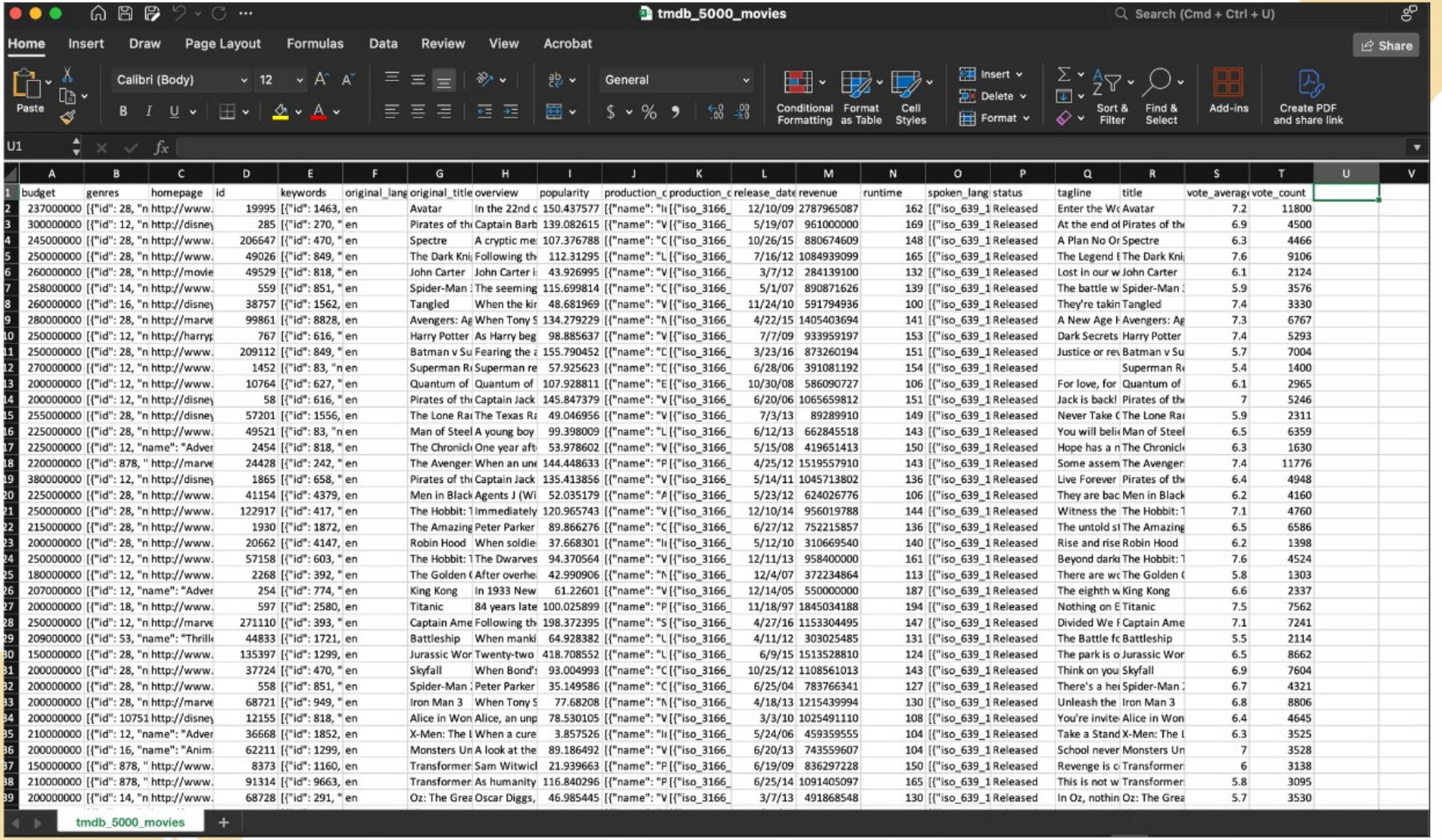
BRIEF OVERVIEW OF LITERATURE REVIEW

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)



tmdb_5000_movies

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	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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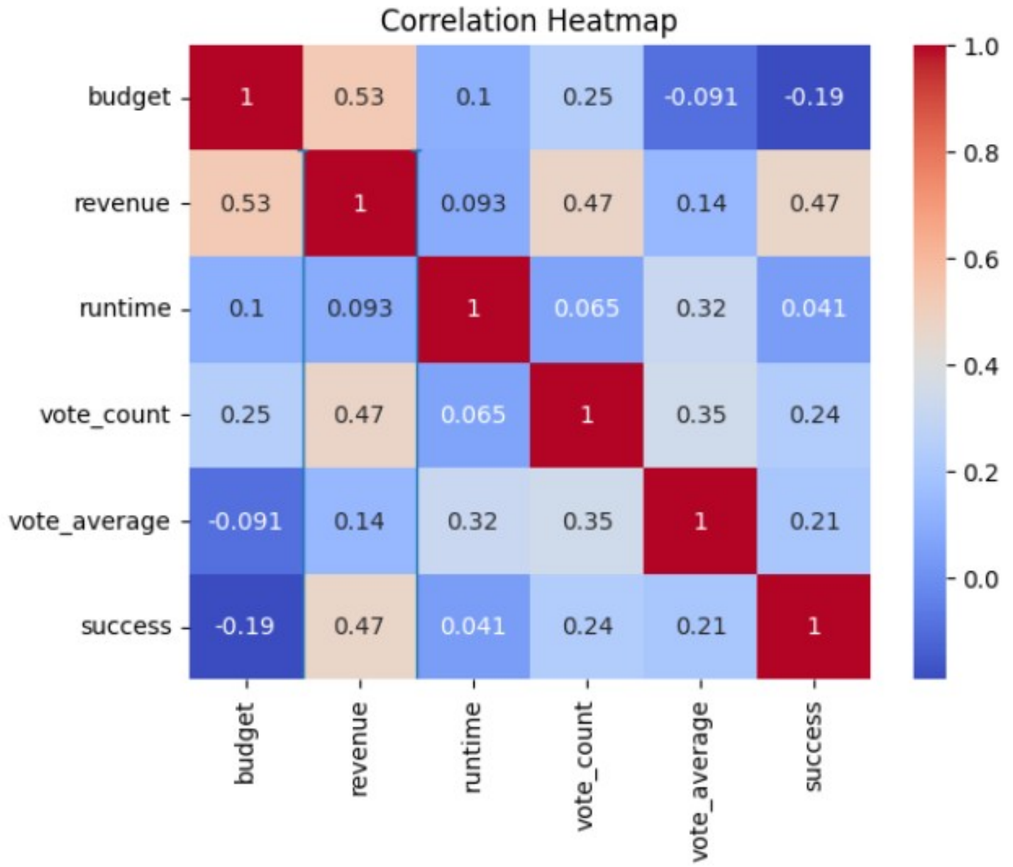
tmdb_5000_movies

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).

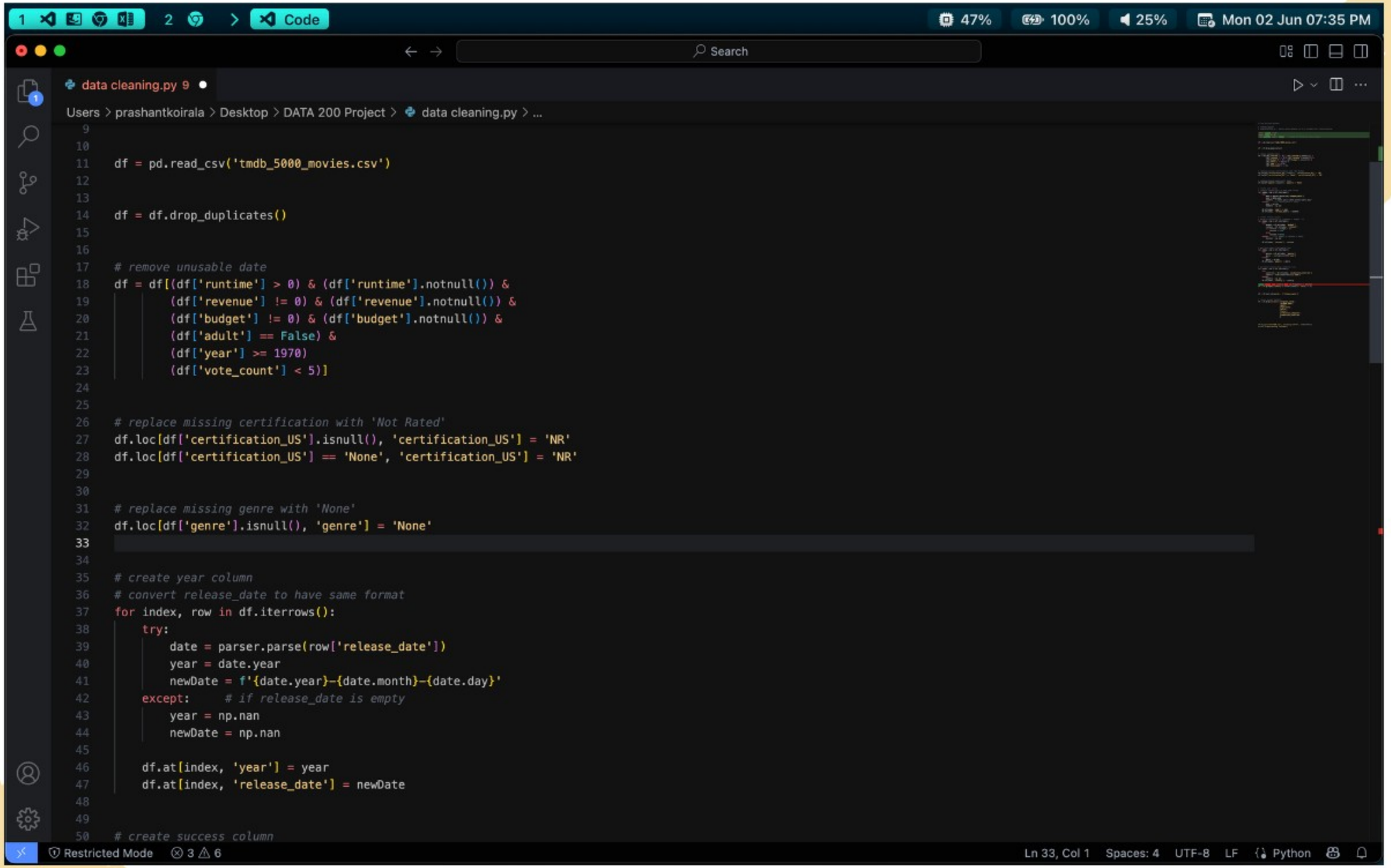
WHY THOSE FEATURES?



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.

DATA CLEANING

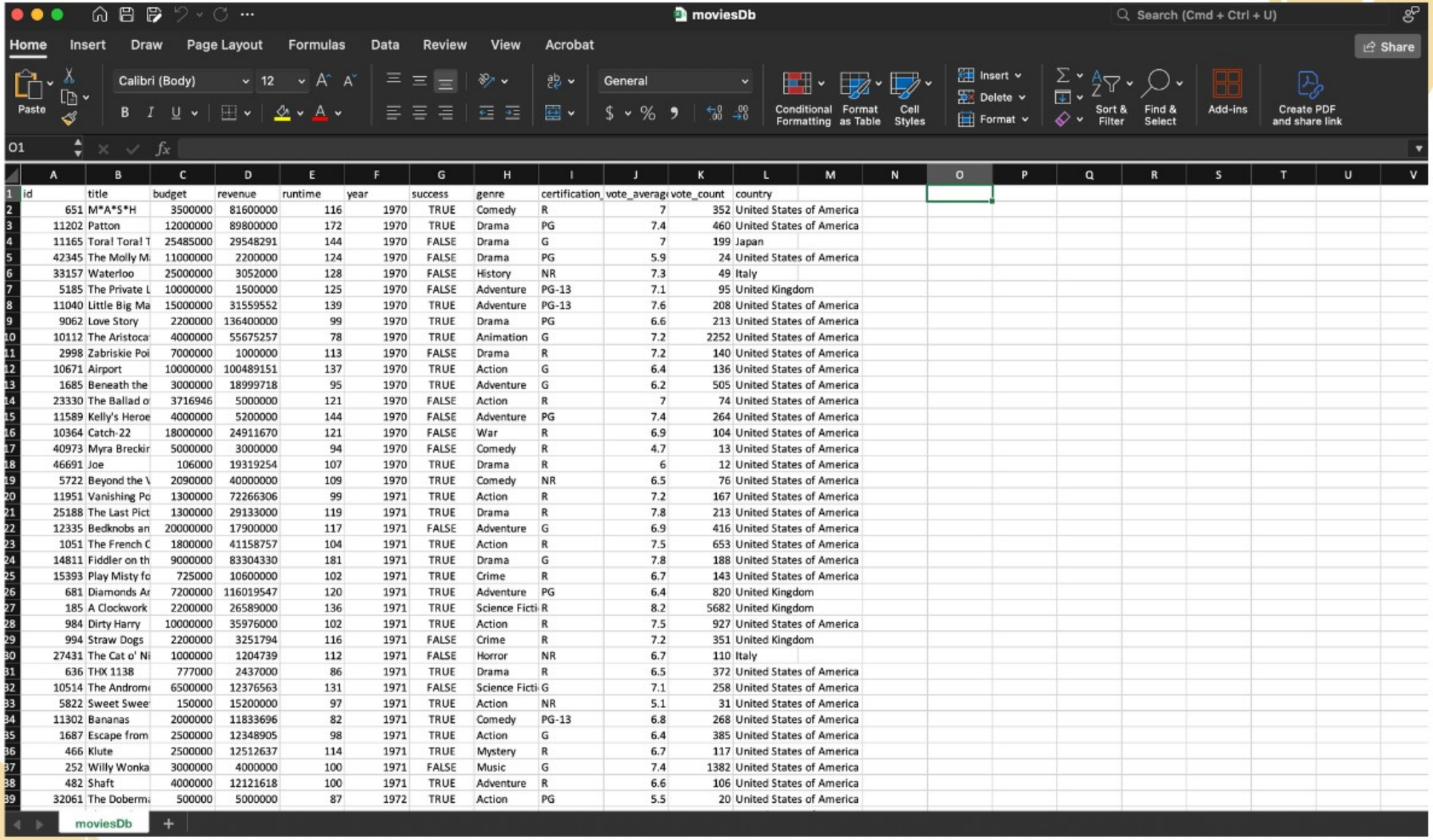
DATA CLEANING PROGRAM



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



	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V
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										
13	1685	Beneath the	3000000	18999718	95	1970	TRUE	Adventure	G	6.2	505	United States of America										
14	23330	The Ballad o	3716946	5000000	121	1970	FALSE	Action	R	7	74	United States of America										
15	11589	Kelly's Heroe	4000000	5200000	144	1970	FALSE	Adventure	PG	7.4	264	United States of America										
16	10364	Catch-22	18000000	24911670	121	1970	FALSE	War	R	6.9	104	United States of America										
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18	46691	Joe	106000	19319254	107	1970	TRUE	Drama	R	6	12	United States of America										
19	5722	Beyond the \	2090000	40000000	109	1970	TRUE	Comedy	NR	6.5	76	United States of America										
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23	1051	The French C	1800000	41158757	104	1971	TRUE	Action	R	7.5	653	United States of America										
24	14811	Fiddler on th	9000000	83304330	181	1971	TRUE	Drama	G	7.8	188	United States of America										
25	15393	Play Misty fo	725000	10600000	102	1971	TRUE	Crime	R	6.7	143	United States of America										
26	681	Diamonds Ar	7200000	116019547	120	1971	TRUE	Adventure	PG	6.4	820	United Kingdom										
27	185	A Clockwork	2200000	26589000	136	1971	TRUE	Science Ficti	R	8.2	5682	United Kingdom										
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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 Doberm	500000	5000000	87	1972	TRUE	Action	PG	5.5	20	United States of America										

MODEL TRAINING PROCESS

Trained on 5000+ movies

One-hot encoding for categorical features

If `Genre = Action`, it becomes:

```nginx
Action  Comedy  Drama
   1       0       0
```

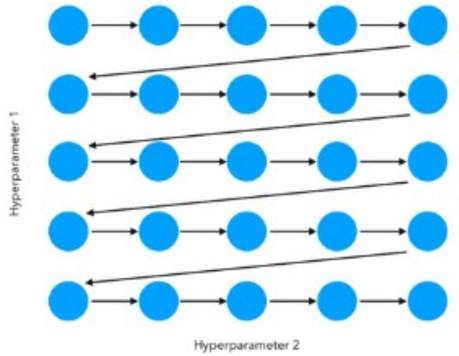
Model serialized using joblib

WORKFLOW

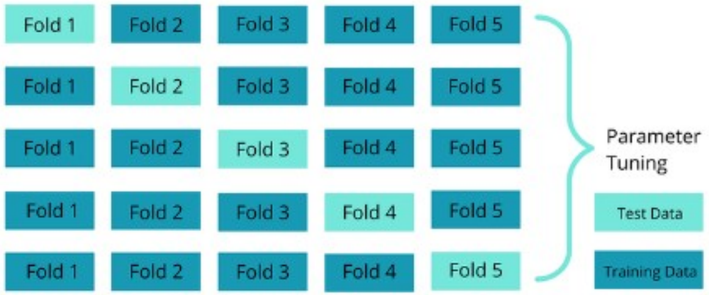
1. Data
2. Preprocessing
3. Train
4. Model
5. Saved Model File

HYPERPARAMETER TUNING

Hyperparameter Tuning (GridSearchCV)



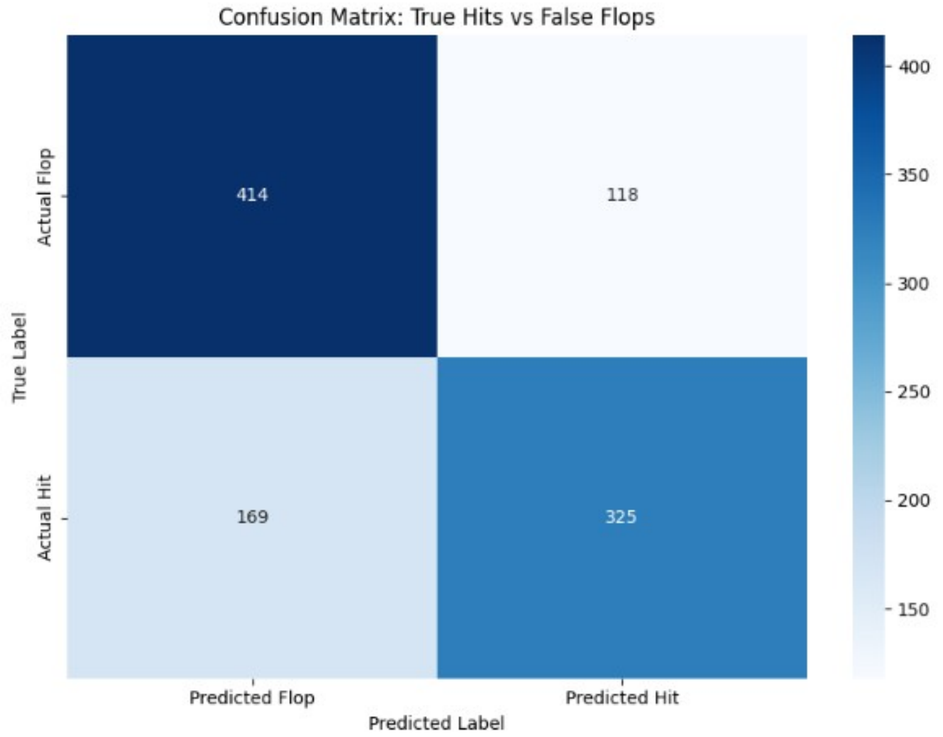
Used GridSearchCV with 10-fold cross-validation



Explored parameters: C, solver

Best Params:
C=1000
solver='newton-cg'

MODEL EVALUATION



MODEL EVALUATION

1. **Accuracy: 72.03%**
2. **Precision: 73.36%**
3. **Recall: 65.79%**
4. **F1 Score: 69.37%**

```
--- Model Evaluation Results ---
Accuracy: 0.7203
Precision: 0.7336
Recall: 0.6579
F1 Score: 0.6937

Classification Report:
              precision    recall  f1-score

        Flop       0.71      0.78      0.74
         Hit       0.73      0.66      0.69

    accuracy                           0.72
   macro avg       0.72      0.72      0.72
weighted avg       0.72      0.72      0.72
```

ARCHITECTURE

React

FRONTEND

BACKEND

BACKEND ARCHITECTURE

BACKEND

Built using Flask (Python web framework)

Responsible for:

Serving the REST API

Preprocessing data

Calling the logistic regression model

Returning prediction results

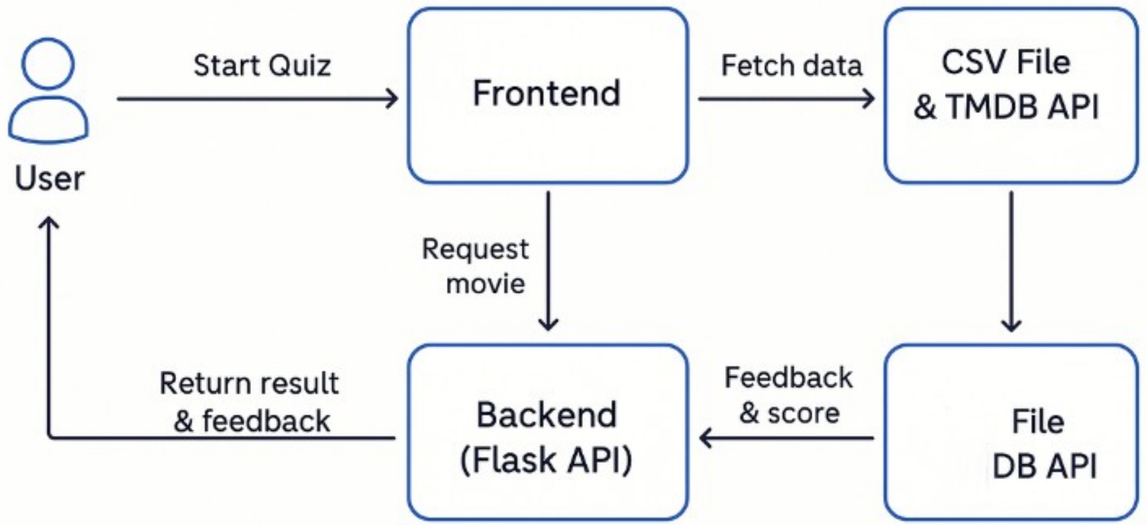
FRONTEND ARCHITECTURE

FRONTEND

Key features:

- **Responsive layout**
- **Interactive quiz game**
- **Filters by genre, country, and certification**
- **Animated feedback and score tracking**

SYSTEM INTEGRATION & DATA FLOW



DEMO

CHALLENGES FACED

- Handling missing/inconsistent movie data
- Encoding categorical variables with low frequency
- TMDB Movie Poster Loading
- Ensuring consistent one-hot encoding during training and inference
- Responsive UI across devices

FUTURE ENHANCEMENTS

- Improve prediction with ensemble models (Random Forest, XGBoost)
- Add user authentication and leaderboard
- Support movie trailers using YouTube API
- Enable feedback loop to refine model with real user guesses

CONCLUSION & KEY TAKEAWAYS

1. **Built an end-to-end movie success predictor**
2. **Applied logistic regression for real-world classification**
3. **Designed interactive UI for user engagement**
4. **Demonstrated machine learning integration with web development**
5. **Balanced accuracy, explainability, and usability**

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THANK YOU