Movie Recommendation System.

Leveraging Data to Enhance User Engagement on Streaming Platforms.

Smart Movie Recommendations

- **What it is:** A system designed to predict what movies individual users love.
- **Our Goal:** To provide highly personalized "Top 5" movie recommendations, making content discovery intuitive and enjoyable.
- **Why it Matters:** Drives user satisfaction, increases engagement, and helps users find films they truly love.
- **Approach:** Built upon extensive analysis of historical movie ratings using advanced machine learning techniques.

Business Understanding.

- Addressing the Challenge of Choice, whereby in a vast library of movies, users often struggle to find content relevant to their tastes, leading to fatique and missed opportunities.
- Our solution is to develop a predictive engine that anticipates user preferences by seamlessly connecting users with movies they'll enjoy.

Key Questions

- **User Preferences:** What are the most common movie ratings? Do users typically rate positively or negatively?
- **Movie Popularity:** Which movies are widely seen and discussed? Are highly-rated movies also popular?
- **Reliability of Ratings:** How can we ensure recommendations aren't based on unreliable reviews from very few users?
- **Hidden Patterns:** Can we uncover underlying trends in user tastes that aren't immediately obvious?

Modelling

- **Collaborative Filtering:** Which defines "Movies Like This" Approach by Recommending films that are similar to others a user has already liked.
- **Predictive Models (Linear Regression and K-Nearest Neighbors):** Used top directly forecast how a user might rate a movie, apply rigorous statistical methods and optimization
- **Smart Training and Tuning:** Using efficient pipelines and hyper-parameters to ensure they are robust and perform at their best.

Evaluation.

- **RMSE (Root Mean Squared Error):** This tells us, on average, how close our predicted movie ratings are to the actual ratings given by users. A lower number means more accurate predictions.
- Our **User-based Collaborative Filtering** achieved an RMSE of **0.9690**, meaning predictions were, on average, less than one full rating point off.
- Our **tuned K-Nearest Neighbors** model also showed strong performance with an RMSE of approximately **0.9809**.

Conclusion Towards a Smarter Content Experience

- **Continuous Learning:** The system can constantly improve as new user ratings come in.
- **Content Enrichment:** Explore integrating more movie details for even smarter recommendations.
- **Real-time Recommendations:** Develop capabilities for instant, dynamic suggestions as users interact with the platform.