Project 4
Guided Active Learning for Cold-Start Recommendation

Task 1: Implemented Method

Our implementation addresses the cold-start problem in movie recommendation using a matrix factorization (MF) based recommender system. The recommender (see `recommender.py`) loads the MovieLens dataset (ml-100kl), applies a singular value decomposition (SVD) to learn latent factors for users and items, and uses ridge regression to infer new user vectors based on their ratings. The key novelty is that during the interactive session, the system does not only ask the user to rate movies (on a 0.5–5.0 scale), but also provides **guidance** about how that rating could change their future recommendations. This is implemented in `MFRecommender.select_next_item`, which computes "what-if" previews: if the current movie were rated low (0.5) vs. high (5.0), the system predicts the top-10 recommendations under each scenario and compares them. The Jaccard distance between these two sets quantifies the **effect** of the answer. The most informative movie to rate next is chosen as the one with the highest effect. The frontend (`interface.html`) displays these previews to participants in the treatment group: two side-by-side lists of movies ("Rate it low" vs. "Rate it high") plus a percentage estimate of how many top suggestions would be altered by their rating. In the control group, users only see the plain request for ratings without previews. This setup implements guided active learning for the cold-start scenario.

Task 2: User Study Design

Hypothesis: Providing what-if previews of how ratings affect recommendations will improve user satisfaction and the quality of collected ratings compared to a standard rating interface.

Study Design: Participants are first shown a consent form. Once consent is given, they are randomly assigned (via `views.assign`) to either the control group (no previews) or treatment group (with previews). Each participant is asked to rate a sequence of movies until they choose to stop. After rating, their personalized top-10 recommendations are shown. Finally, they complete a short feedback survey. All responses (ratings, group assignment, survey feedback) are logged anonymously with a random participant ID.

Recruitment: Participants could be recruited from a university subject pool, online crowdsourcing platforms, or via course peers. No personal data is collected; only anonymous ratings and feedback are stored in a CSV file (`project4_survey.csv`).

Measurements: Primary outcomes include:
(a) number of ratings given before stopping,
(b) diversity and stability of recommendations, and
(c) subjective feedback from the post-study survey.

Comparisons between control and treatment groups will test the hypothesis that previews increase
engagement and satisfaction.

Ethical considerations: The study interface provides an explicit consent form. Data is anonymous, participation is voluntary, and users may exit at any time without penalty.