Objective

In this assignment you will build and evaluate your own collaborative filtering recommender.

Instructions

1. Dataset selection
    - Choose a dataset that contains user-item feedback data.
    - You cannot use datasets explored in class during Sessions 13.
    - You may reuse a dataset from previous assignments or select a new one.
    - It is recommended to use the same dataset employed for building your non-personalized recommender in Assignment 4. This facilitates a direct comparison and deeper interpretation of the results.
    - You can use either explicit or implicit feedback.

2. Model training and evaluation
    - Build a collaborative filtering recommender using the Surprise library.
    - To pass this assignment, you must implement at least one type of collaborative filtering recommender from the families covered in class (user-based, item-based or model-based). Implementing two or three types will be positively rewarded.
    - All 3 families of collaborative filtering can be found here: https://surprise.readthedocs.io/en/latest/prediction_algorithms_package.html
    - Evaluate your collaborative filtering recommender and compare it with non-personalized recommenders. Correct application of evaluation methods and tools will be key to your grading.
    - Optional: Experiment with different values for the most relevant hyperparameters of the chosen recommenders. Evaluate the impact of these changes on the performance of your recommender and provide a clear interpretation of the results. Note that a complete hyperparameter tuning is not expected at this stage; the goal is to test a few distinct values (for example, neutral and extreme cases) and analyse their effects.

3. Submission
    - Use Google Colab for your analysis.
    - When finished, download the notebook (File -> Download -> Download ipynb) and upload it to the assignment portal.
    - Name the notebook file using the following format: **A5_Lastname_Firstname.iypnb**. For example: A5_Smith_John.ipynb

Grading criteria

Core implementation: Weight 50%, mandatory for passing

- Fundamental machine learning practices: Weight 25%
    - Minimum level of evaluation to demonstrate their functionality. Basic but sufficient evidence that the recommenders work as intended.
    - Correct application of tools and methods and proper use of best practices to build and evaluate recommenders.
- Interpretation and justification: Weight 20%
    - Clear, well-supported conclusions based on evaluation results.
    - Discussion of key insights, trade-offs, and practical implications.
- Code quality and organization: Weight 5%
    - Well-structured, readable, and efficient code.
    - Logical flow and clarity in the presentation of findings.

Advanced evaluation and comparison: Weight 45%

- Advanced machine learning evaluation: Weight 25%
    - Deeper analysis beyond minimal validation, consideration of all relevant evaluation perspectives covered in class.
    - Correct application of tools and methods and proper use of best practices to build and evaluate recommenders.
- Diversity of recommender models: Weight 10%
    - Compares the performance across different collaborative filtering approaches (e.g. model-based, user-based, and item-based methods).
- Hyperparameter analysis: Weight 10%
    - Experiments with relevant hyperparameter values, including both neutral and extreme cases.
    - Clearly evaluates the impact of these hyperparameter settings on performance, with detailed interpretation of the results

Optional advanced exploration (Bonus): Weight 5%

Each completed advanced exploration adds Weight 5%, meaning by completing one of these, you can reach the full Weight 100%.

- In-depth interpretation of latent factors if building a model-based recommender.
- Using additional libraries beyond Surprise to build a collaborative filtering recommender.
- Other advanced topic (requires prior approval).