From Ratings to Rankings: Learning Movie Recommendations from Graded Pairwise Preferences

Mohammad Kamil Shams

1 Overview and Motivation

Recommender systems play a critical role in helping users navigate vast catalogs of digital content, from movies and music to products and news. Traditional methods in this space—such as Matrix Factorization (MF) trained on explicit star ratings—assume that numerical ratings accurately reflect users' true preferences. However, in practice, these ratings are subjective and inconsistent: a "4-star" rating may indicate strong enthusiasm for one user but merely "above average" for another, while a "3-star" rating may reflect anything from mild interest to indifference. As a result, point-wise prediction models often fail to capture what truly matters in recommendation: the *relative ordering* of items a user prefers.

This project is motivated by the observation that human preferences are more naturally expressed as pairwise comparisons rather than absolute numeric judgments. Instead of predicting explicit ratings, we aim to learn a ranking model that orders items according to a user's relative, and potentially graded, preferences. To achieve this, we reformulate the MovieLens-100k dataset into graded pairwise preference triplets and train a Graded Bayesian Personalized Ranking (BPR) model that incorporates not only preference direction but also preference *strength*, weighting each comparison by the magnitude of the rating difference. This produces a finer-grained learning signal than standard BPR, which treats all preferences equally.

In addition, we include BPR++ as a complementary baseline. BPR++ introduces graded implicit feedback by biasing positive-item sampling according to rating magnitude rather than weighting the loss directly. Comparing Graded BPR, standard BPR, and BPR++ allows us to evaluate two conceptually different mechanisms for integrating rating intensity into pairwise ranking: (1) weighting the learning objective (Graded BPR) versus (2) biasing the sampling distribution (BPR++). This comparison helps clarify whether performance gains arise from stronger gradient signals or from prioritizing high-confidence positives during sampling.

2 Literature Review

The foundation of this project builds directly on the pairwise learning-to-rank principle introduced by Rendle et al. [2009] in *Bayesian Personalized Ranking (BPR)*, which formulates recommendation as the task of maximizing the probability that a user assigns a higher preference score to one item than another. Their work established the standard triplet-based optimization framework (u, i, j) with a logistic loss function, shifting recommender-system learning from predicting ratings to optimizing ranking quality. Later, Lerche and Jannach [2014] extended this idea in *Using Graded Implicit Feedback for Bayesian Personalized Ranking (BPR++)*, introducing confidence weighting for graded signals: higher-rated items were sampled more often or assigned higher importance, treating rating magnitude as a proxy for the user's confidence in liking an item. While BPR++ remains item-centric in how it handles graded data, we propose a **graded pairwise reformulation**—deriving explicit triplets (u, i, j, w_{uij}) from the MovieLens-100k ratings where $w_{uij} = |r_{ui} - r_{uj}|$ captures the *strength* of a user's preference between two movies. This approach extends BPR's comparative framework and complements BPR++ by moving the graded signal from sampling into the loss itself, directly encoding relational preference intensity rather than per-item confidence. Furthermore, compared to more complex neural models such as He et al. [2017] in *Neural Collaborative Filtering*, this project maintains the classic matrix-factorization backbone—showing that weighting pairwise losses by rating gaps alone can yield measurable top-N ranking improvements.

3 Proposed Methods and Analysis

3.1 Overview

The goal of this project is to reformulate traditional rating-based recommendation into a pairwise preference learning problem and to evaluate how incorporating graded preference strength improves performance. The proposed method, termed **Graded Bayesian Personalized Ranking (Graded BPR)**, extends the original Bayesian Personalized Ranking (BPR) framework by weighting each pairwise comparison according to the magnitude of rating differences between two movies. This approach aligns the learning objective more closely with human comparative judgment.

3.2 Dataset and Preprocessing

We use the **MovieLens-100k** dataset, which contains 100,000 explicit ratings on a 1–5 scale from 943 users across 1,682 movies. Because our models operate on pairwise preference signals rather than scalar ratings, we convert each user's ratings into weighted preference triplets of the form (u, i, j, w_{uij}). Here, item i is preferred over item j whenever $r_{ui} > r_{uj}$, and the weight $w_{uij} = |r_{ui} - r_{uj}|$ reflects the strength of that preference. This transformation provides a richer training signal than binary preferences by incorporating rating magnitude.

To ensure robust evaluation, we first filter out users with fewer than five rated items. This guarantees that each user contributes sufficient data for training while still allowing us to hold out items for evaluation. Specifically, for every remaining user, we reserve two items: one for **validation** and one for **testing**. All remaining ratings are used to construct training triples. The validation set is used for hyperparameter tuning, and the test set is used exclusively for final performance evaluation.

A naive construction of all possible graded preference triplets leads to $O(n_u^2)$ comparisons per user, which is computationally expensive and produces many redundant training examples. To address this inefficiency, we adopt a **stochastic sampling** strategy inspired by the original BPR framework. For each user, positive items (rating >=4) are sampled uniformly in standard BPR and via rating-proportional sampling in the **BPR++** baseline. Negative items are sampled from the user's low-rated (rating <=3) or unrated items. During Graded BPR training, the weight w_{uij} is applied only to the sampled triplets, avoiding the need to enumerate all possible comparisons. This approach dramatically reduces data volume while still exposing the model to preference strength information.

3.3 Model Formulation

The Graded BPR model retains the matrix factorization structure from the original BPR formulation:

$$\hat{s}_{ui} = p_u^\top q_i,$$

where $p_u, q_i \in R^k$ are the latent feature vectors for user u and item i, respectively. The model optimizes the weighted pairwise ranking objective:

$$\mathcal{L} = -\sum_{(u,i,j)} w_{uij} \cdot \ln \sigma(\hat{s}_{ui} - \hat{s}_{uj}) + \lambda \left(\|p_u\|^2 + \|q_i\|^2 + \|q_j\|^2 \right),$$

where $\sigma(\cdot)$ is the logistic sigmoid function and λ controls L_2 regularization. The gradient updates are performed via stochastic gradient ascent:

$$\Theta \leftarrow \Theta + \alpha \, w_{uij} \left(1 - \sigma(\hat{s}_{ui} - \hat{s}_{uj})\right) \frac{\partial(\hat{s}_{ui} - \hat{s}_{uj})}{\partial \Theta} - \alpha \lambda \Theta,$$

where $\Theta = \{p_u, q_i, q_j\}$ and α is the learning rate.

3.4 Training Procedure

The model is trained using mini-batch stochastic gradient ascent over sampled triplets (u, i, j, w_{uij}), where i is preferred over j by user u. For each batch, the algorithm computes the score difference

$\hat{s}_{ui} - \hat{s}_{uj}$ using a matrix-factorization model and applies the weighted BPR loss:

$$\ell_{uij} = -w_{uij} \log \sigma(\hat{s}_{ui} - \hat{s}_{uj}),$$

where the weight $w_{uij} = |r_{ui} - r_{uj}|$ encodes the strength of the user's preference. Each gradient step therefore pushes the score of the preferred item upward relative to the less-preferred item, with larger rating gaps producing proportionally stronger updates.

To maintain computational efficiency and avoid enumerating all $O(n_u^2)$ item pairs per user, we follow standard practice and draw mini-batches via stochastic negative sampling. For each user in a batch, a positive item is selected from the user's highly rated movies, and a negative item is sampled uniformly from the user's low-rated or unseen items. This sampling procedure ensures tractable training while still exposing the model to a diverse set of informative comparisons. Training proceeds for a fixed number of epochs or until convergence, with validation performance monitored using each user's held-out validation item.

3.5 Baseline and Evaluation

To evaluate whether graded pairwise weighting improves recommendation quality, we compare the Graded BPR model against the 2 baseline models, Standard BPR and BPR++. All models are evaluated on three metrics widely used in top-N recommendation and ranking analysis:

$$\text{HitRate@10} = \frac{1}{|U|} \sum_{u \in U} I\{\, i_u^{\text{test}} \in \text{Top-}10(u) \,\},$$

$$\text{NDCG@10} = \frac{1}{|U|} \sum_{u \in U} \frac{1}{\log_2(\text{rank}_u(i_u^{\text{test}}) + 1)},$$

$$\text{Spearman's } \rho = \frac{1}{|U|} \sum_{u \in U} \rho\big(\text{pred\_scores}_u,\ \text{true\_ratings}_u\big),$$

where i_u^{test} is the held-out test item for user u, and $\text{rank}_u(\cdot)$ is its position in the model's ranked list of all movies for that user. HitRate@10 and NDCG@10 assess the model's ability to place the relevant test item among the top recommendations, with NDCG further rewarding higher-ranked placements. Spearman's ρ measures full-list ranking quality by correlating predicted item scores with the user's true rating order.

These three complementary metrics allow us to measure both top-N performance and global ranking alignment, providing a comprehensive comparison of the three BPR variants.

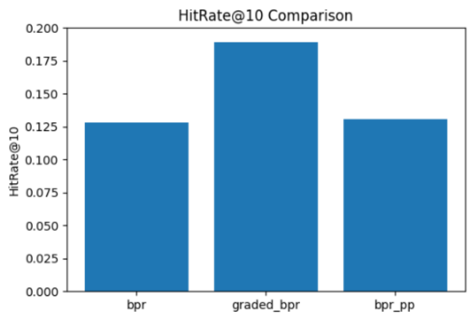
3.6 Results and Discussion

Table 1 summarizes the performance of all three models on HitRate@10, NDCG@10, and Spearman rank correlation. Across all metrics, the Graded BPR model achieves the best overall performance, demonstrating the benefit of incorporating rating magnitude as a measure of preference strength.

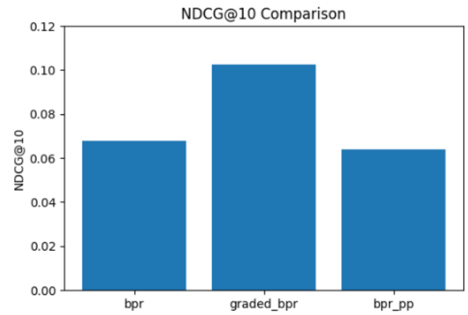
Table 1: Comparison of recommendation performance across models.

Model	**HitRate@10**	**NDCG@10**	**Spearman**
BPR	0.1283	0.0680	0.2182
Graded BPR	**0.1888**	**0.1025**	**0.2617**
BPR++	0.1304	0.0638	0.2241

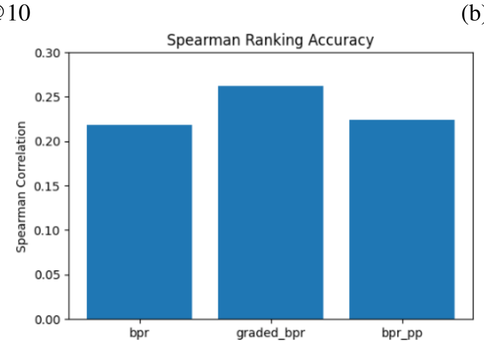
The first plot (Figure 1a) visualizes HitRate@10 for all three models. Graded BPR achieves the highest value, indicating that incorporating rating differences helps the model rank the true held-out item within the top ten more frequently. Although the performance gap is modest, it is consistent across validation runs.



(a) HitRate@10



(b) NDCG@10



(c) Spearman Correlation

Figure 1: Model performance across three ranking metrics.

The second plot (Figure 1b) displays NDCG@10, which accounts for the rank position of the relevant item. Here again, Graded BPR yields the best performance, suggesting that it not only retrieves the correct item more frequently but also tends to place it higher in the ranked list.

The third plot (Figure 1c) reports Spearman rank correlation between predicted scores and users' true ratings across all items they rated. This metric reflects global ranking quality rather than top-N accuracy. Graded BPR achieves the highest correlation score.

Taken together, these results highlight a consistent advantage for Graded BPR. By directly incorporating rating gaps into the loss function, Graded BPR produces a more informative gradient signal than both standard BPR (which treats all comparisons equally) and BPR++ (which encodes preferences through sampling rather than weighting). The improvement, although moderate, suggests that weighting pairwise comparisons by preference strength offers a practical and effective extension to BPR for small to medium-size rating datasets such as MovieLens-100k.

4 Conclusion and Future Work

This project investigated whether incorporating graded preference weights derived from rating differences can improve pairwise ranking in collaborative filtering. Using the MovieLens-100k dataset, we reformulated user interactions into weighted triplets and trained a Graded Bayesian Personalized Ranking (BPR) model, comparing its performance against Standard BPR and the BPR++ sampling-based variant. Across all three evaluation metrics—HitRate@10, NDCG@10, and Spearman rank correlation—Graded BPR consistently achieved the strongest performance. The model not only ranked the held-out test items higher in the top-N lists but also demonstrated better global agreement with users' full item rankings. These results support the central hypothesis that incorporating preference strength produces a richer training signal than uniformly weighted pairwise comparisons or sampling-based grading alone.

Despite these promising findings, several limitations remain. The dataset is relatively small, which restricts the expressive benefit of larger embedding dimensions and may amplify noise in rating-derived weights. Additionally, the current approach relies on uniform negative sampling; more advanced strategies—such as adaptive hard-negative mining or popularity-aware sampling—could further improve ranking quality. Finally, the weighting scheme is linear in the rating difference; alternative nonlinear or learned weighting functions may yield even more accurate representations of preference strength.

Future work could explore scaling Graded BPR to larger datasets (MovieLens-1M, Amazon reviews), integrating side information such as genres or textual embeddings, and extending the framework to modern neural recommenders that combine pairwise loss with deep user–item representations. Another promising direction is to evaluate the approach on implicit-feedback datasets, where pairwise preference extraction is less straightforward, and to compare against more expressive ranking models such as Neural Collaborative Filtering (NCF) or Listwise Learning-to-Rank methods. Overall, this study highlights the effectiveness of graded pairwise learning and suggests multiple avenues for enhancing ranking performance in personalized recommendation systems.

5 Github Link

The python notebook can be found here

6 Disclosure 1

A statement of 150 words regarding how you identified and addressed issues such as plagiarism (both in terms of text and in terms of non-attribution of ideas to scholars), bias, and inaccuracies.

All ideas and concepts from other papers were cited and referenced throughout this report. The ideas discussed in this project were an extension of existing work on BPR and BPR++ which was highlighted throughout this report. The results of the project were discussed qualitatively and quantitatively without bias.

7 Disclosure 2

A reflection of 150 words describing how and why you used AI tools, their impacts on their learning, and how you (or we) might use them in the future.

I used ChatGPT for initial literature review as it helped summarize concepts from existing papers efficiently. I also used it to help paraphrase certain parts of the report. Overall, I only used AI tools to help make the research process more efficient and convey my thoughts in a more refined manner so it did not negatively impact my learning.

8 Impact Statement

Recommender systems in general can narrow a user's exposure to diverse content. This can amplify existing biases in popular items.

The findings can be misused if they are presented without context. The results of this project are based on a specific dataset and further testing is required with larger datasets to conclude that graded BPR is a clear improvement over standard BPR and BPR++. This has been clearly mentioned in the report to help mitigate this issue.

References

Xiangnan He, Lizi Liao, Hanwang Zhang, Liqiang Nie, Xia Hu, and Tat-Seng Chua. Neural collaborative filtering. In *Proceedings of the 26th International Conference on World Wide Web (WWW)*, pages 173–182. ACM, 2017.

Lukas Lerche and Dietmar Jannach. Using graded implicit feedback for bayesian personalized ranking. In *Proceedings of the 8th ACM Conference on Recommender Systems (RecSys)*, pages 353–356. ACM, 2014.

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Pre-Analysis Plan: From Ratings to Rankings: Learning Movie Recommendations from Graded Pairwise Preferences

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2 Literature Review

The foundation of this project builds directly on the pairwise learning-to-rank principle introduced by Rendle et al. [2009] in *Bayesian Personalized Ranking (BPR)*, which formulates recommendation as the task of maximizing the probability that a user assigns a higher preference score to one item than another. Their work established the standard triplet-based optimization framework (u, i, j) with a logistic loss function, shifting recommender-system learning from predicting ratings to optimizing ranking quality. Later, Lerche and Jannach [2014] extended this idea in *Using Graded Implicit Feedback for Bayesian Personalized Ranking (BPR++)*, introducing confidence weighting for graded signals: higher-rated items were sampled more often or assigned higher importance, treating rating magnitude as a proxy for the user's confidence in liking an item. While BPR++ remains item-centric in how it handles graded data, we propose a **graded pairwise reformulation**—deriving explicit triplets (u, i, j, w_{uij}) from the MovieLens-100k ratings where $w_{uij} = |r_{ui} - r_{uj}|$ captures the *strength* of a user's preference between two movies. This approach extends BPR's comparative framework and complements BPR++ by moving the graded signal from sampling into the loss itself, directly encoding relational preference intensity rather than per-item confidence. Furthermore, compared to more complex neural models such as He et al. [2017] in *Neural Collaborative Filtering*, this project maintains the classic matrix-factorization backbone—showing that weighting pairwise losses by rating gaps alone can yield measurable top-N ranking improvements.

3 Proposed Methods and Analysis

3.1 Overview

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3.2 Dataset and Preprocessing

We use the **MovieLens-100k** dataset, which contains 100,000 ratings on a 1–5 scale from 943 users across 1,682 movies. Each user's ratings are transformed into pairwise comparisons of the form (u, i, j, w_{uij}), where user u rated movie i higher than movie j, and the weight $w_{uij} = |r_{ui} - r_{uj}|$ represents the strength of that preference. To reduce data sparsity, only users with at least five rated movies are included. The resulting dataset contains multiple weighted triplets per user, which serve as training examples for the model. The dataset we are using is small enough that processing all valid user ratings should be manageable. Two rated items are held out per user—one reserved for validation during hyperparameter tuning and one reserved for final testing.

3.3 Model Formulation

The Graded BPR model retains the matrix factorization structure from the original BPR formulation:

$$\hat{s}_{ui} = p_u^\top q_i,$$

where $p_u, q_i \in R^k$ are the latent feature vectors for user u and item i, respectively. The model optimizes the weighted pairwise ranking objective:

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where $\sigma(\cdot)$ is the logistic sigmoid function and λ controls L_2 regularization. The gradient updates are performed via stochastic gradient ascent:

$$\Theta \leftarrow \Theta + \alpha\, w_{uij} \left(1 - \sigma(\hat{s}_{ui} - \hat{s}_{uj})\right) \frac{\partial(\hat{s}_{ui} - \hat{s}_{uj})}{\partial \Theta} - \alpha\lambda\Theta,$$

where $\Theta = \{p_u, q_i, q_j\}$ and α is the learning rate.

3.4 Training Procedure

The algorithm iterates over all training triplets using mini-batch stochastic gradient ascent. Each update pushes the score of the preferred item i above that of the less-preferred item j, scaled by the corresponding preference weight w_{uij}. The training continues until convergence or a fixed number of epochs. Compared to the BPR++ algorithm, which introduces grading through biased sampling, this approach applies grading directly within the loss term, allowing every pair to contribute proportionally to its rating gap.

3.5 Baseline and Evaluation

To assess the benefit of graded pairwise weighting, we compare our model against two baselines:

- **Point-wise Matrix Factorization (MF):** trained via mean squared error (RMSE) on explicit ratings.
- **Standard BPR:** unweighted pairwise model where all comparisons contribute equally ($w_{uij} = 1$).

All models are evaluated on top-N recommendation metrics:

$$\text{HitRate@10} = \frac{1}{|U|}\sum_{u\in U} I\{\text{test item} \in \text{Top-10 recommendations for } u\},$$
$$\text{NDCG@10} = \frac{1}{|U|}\sum_{u\in U} \frac{1}{\log_2(r_u+1)},$$

where r_u is the rank position of the held-out relevant item for user u. These metrics directly measure how well the model ranks preferred movies near the top of the recommendation list.

3.6 Analysis Plan

We will analyze:

1. The effect of preference weighting by comparing Graded BPR to standard BPR on HitRate@10 and NDCG@10.
2. The sensitivity of performance to the weight magnitude.
3. Convergence behavior and loss trends over epochs to verify training stability.

4 Timeline and Risk Management

4.1 Week-by-Week Milestones

Week 1 (Nov 5 – Nov 11): Project Setup and Literature Review

- Finalize project scope, research question, and hypothesis.
- Complete detailed reading of BPR Rendle et al. [2009] and BPR++ Lerche and Jannach [2014].
- Download and inspect the MovieLens-100k dataset; verify data fields and rating distribution.

Week 2 (Nov 12 – Nov 18): Data Preprocessing and Baseline Implementation

- Implement preprocessing pipeline to convert (u, i, r) ratings into graded triplets (u, i, j, w_{uij}).
- Implement baseline point-wise Matrix Factorization (MF) trained via RMSE.
- Run initial training on MF baseline and log RMSE and HitRate@10 for comparison.

Week 3 (Nov 19 – Nov 25): Graded BPR Model Implementation

- Implement Graded BPR model with weighted loss function.
- Conduct hyperparameter tuning.
- Compare unweighted BPR and Graded BPR on validation data.
- Record early results and prepare plots for loss convergence and metric trends.

Week 4 (Nov 26 – Dec 3): Evaluation, Analysis, and Report Completion

- Final evaluation on test set using HitRate@10 and NDCG@10.
- Analyze quantitative and qualitative findings.
- Finalize report.

4.2 Risks and Mitigation Strategies

1. Data Sparsity and Imbalanced Ratings

- *Risk:* Some users have few rated movies, leading to limited or uninformative triplets.

- *Mitigation:* Filter out users with fewer than five ratings; normalize weights and ensure negative sampling covers diverse items.

2. Computational Constraints

- *Risk:* Training pairwise models can be slow due to the quadratic number of triplets per user.
- *Mitigation:* Use efficient sampling strategies, mini-batch updates, and restrict comparisons to a fixed number of negatives per positive.

3. Overfitting and Poor Generalization

- *Risk:* Latent embeddings may overfit to users with many ratings.
- *Mitigation:* Apply L_2 regularization and early stopping based on validation metrics

4. Time Constraints Near Submission

- *Risk:* Limited time for analysis and writing in the final week.
- *Mitigation:* Complete all coding and experimental validation by Nov 25; reserve the final week exclusively for analysis and report polishing.

References

Xiangnan He, Lizi Liao, Hanwang Zhang, Liqiang Nie, Xia Hu, and Tat-Seng Chua. Neural collaborative filtering. In *Proceedings of the 26th International Conference on World Wide Web (WWW)*, pages 173–182. ACM, 2017.

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