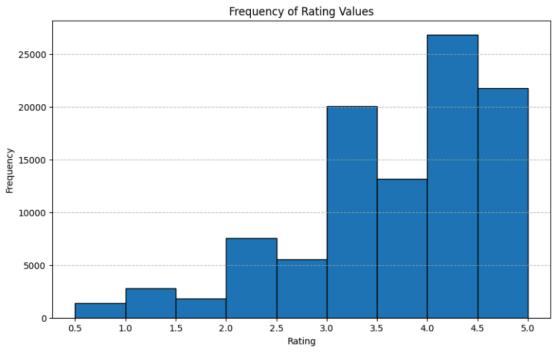
Project3

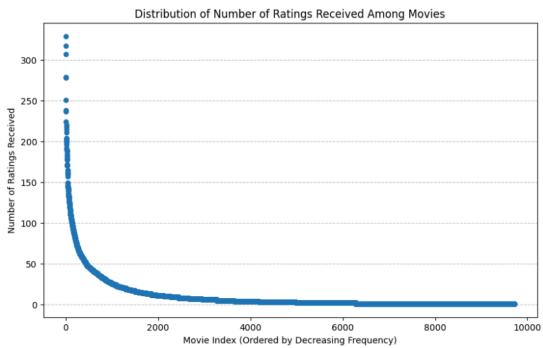
Hexi Meng (406200552), Zhanhong Liu (206152835)

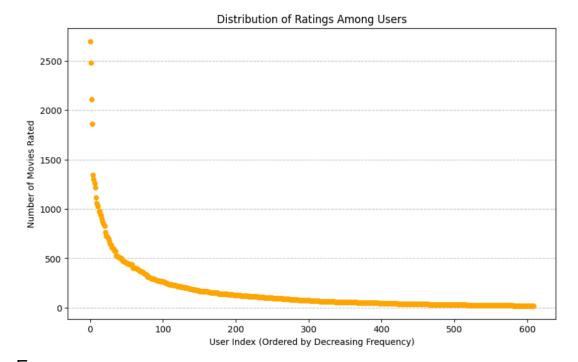
QUESTION 1:

Sparsity = 0.016999683055613623



С

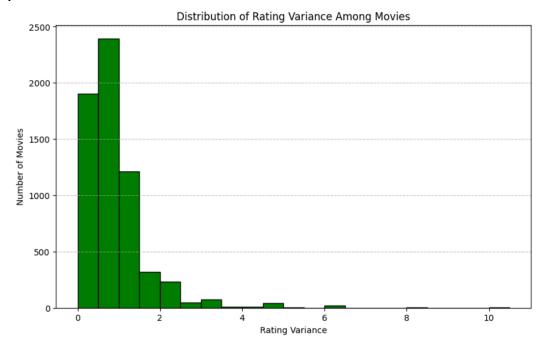




E
The key features from the distributions indicate:

- 1. **Long-tail distribution:** There are a few highly popular movies, suggesting the need for recommendations to balance between popular and niche movies for diversity.
- 2. **User engagement variability:** With users varying widely in the number of movies rated, recommendation systems must adapt to both active and less active users.
- 3. **Data sparsity:** The sparse nature of the dataset highlights the need for advanced techniques to accurately predict user preferences.





Α

$$\mu_u = \frac{1}{|I_u|} \sum_{k \in I_u} r_{uk}$$

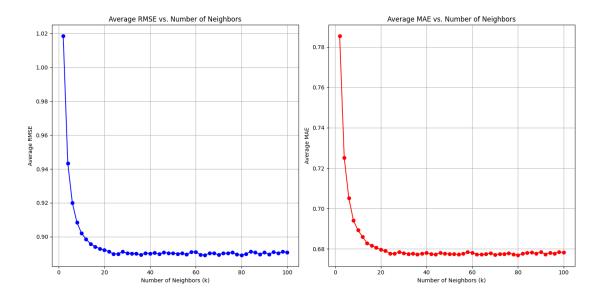
В

The term $I_u \cap I_v$ represents the intersection of the sets of item indices for which users u and v have both provided ratings. Given that the rating matrix R is sparse, it is entirely possible that $I_u \cap I_v = \emptyset$.

Question 3

Mean-centering the raw ratings $(r_{vj} - \mu_v)$ The prediction function helps to adjust for individual user biases in their rating scales, ensuring that the prediction reflects genuine preferences rather than skewed high or low ratings. This approach allows the model to accurately capture and compare the relative likes and dislikes of users, improving the quality of recommendations.

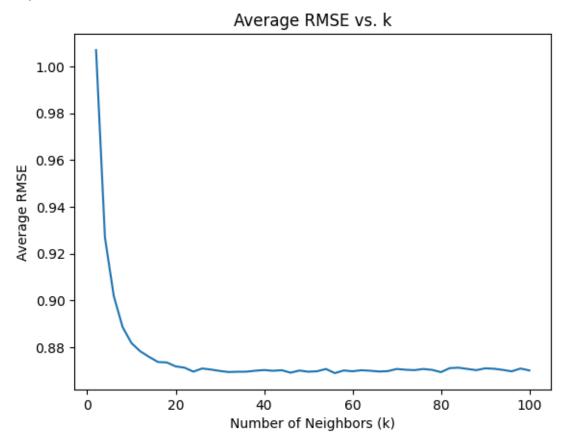
Question 4



minimum K = 22 average RMSE = 0.8912371255664379average MAE = 0.6790317342207222

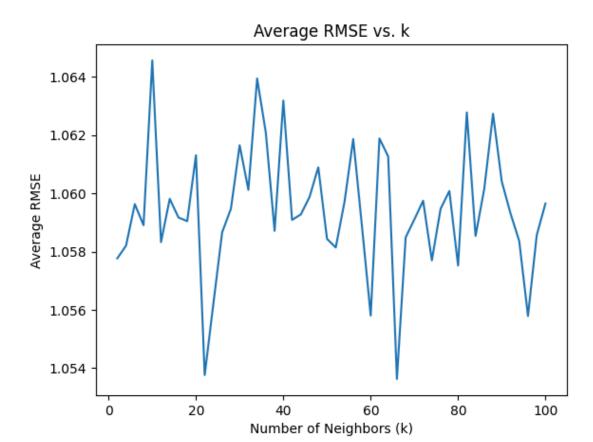
Question 6

Popular



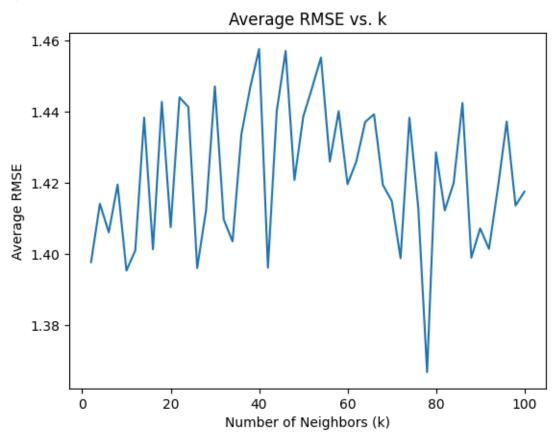
 $minimum\ average\ RMSE\ =\ 0.\,8689124913188335$

Unpopular



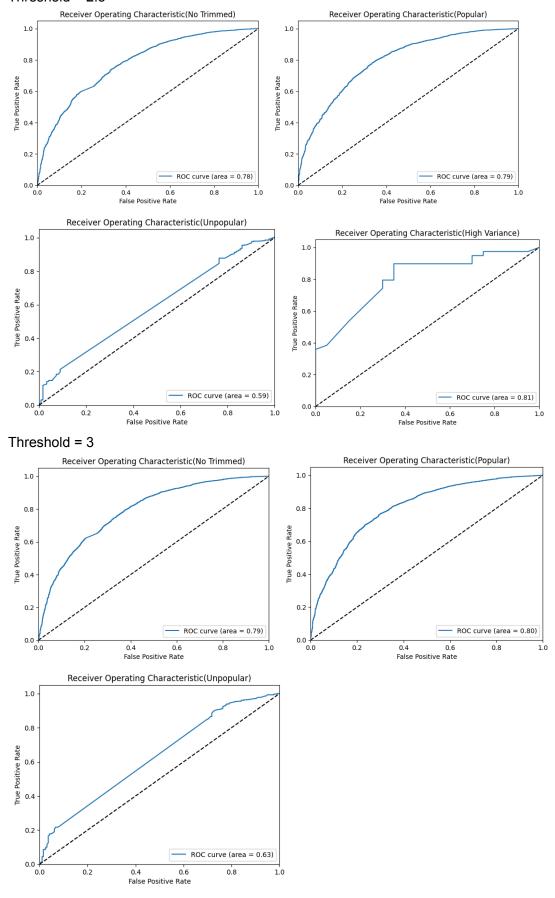
 $minimum\ average\ RMSE\ =\ 1.\,053621608103858$

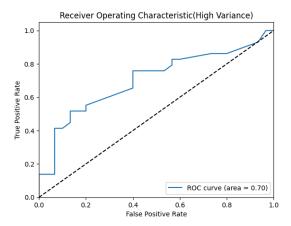
High-Variance



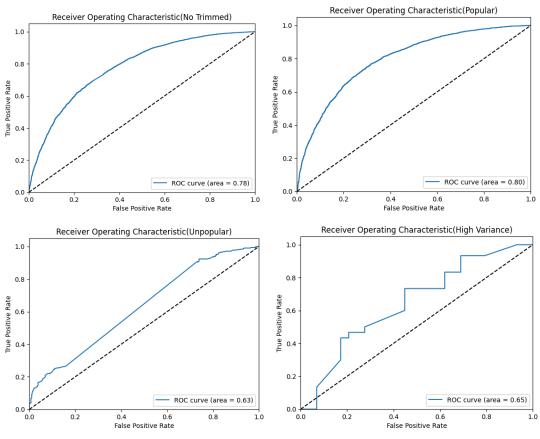
 $minimum\ average\ RMSE\ =\ 1.\,3668581671348572$

Threshold = 2.5

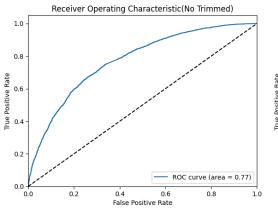


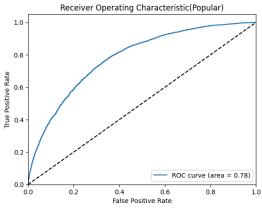


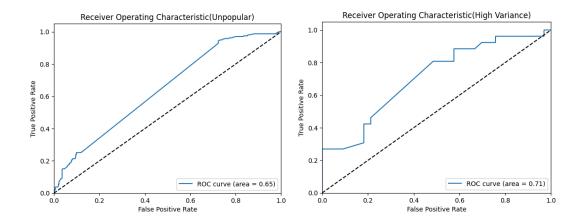
Threshold = 3.5



Threshold = 4







The NMF optimization problem is not jointly convex in U and V. When either U or V is held fixed, the problem becomes convex in the other variable.

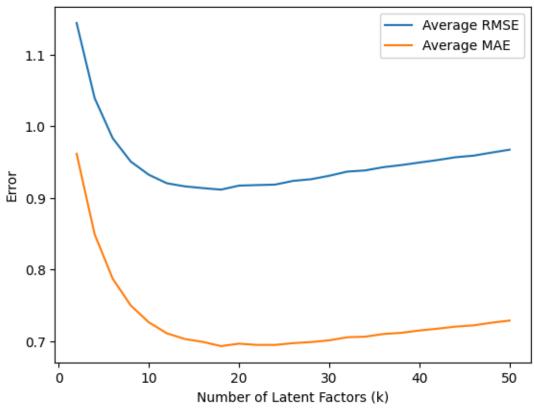
When *U* is fixed, the objective function becomes:

$$\sum_{i=1}^{m} \sum_{j=1}^{n} W_{ij} \left(r_{ij} - \left(UV^{T} \right)_{ij} \right)^{2} + \lambda \|V\|_{F}^{2}$$
Subject to $V \ge 0$

This can be viewed as a least-squares problem where you are trying to find V that minimizes the squared Frobenius norm of the difference between the observed ratings R and the product UV^T , with an added regularization term $\lambda \|V\|_F^2$ to prevent overfitting.

Α

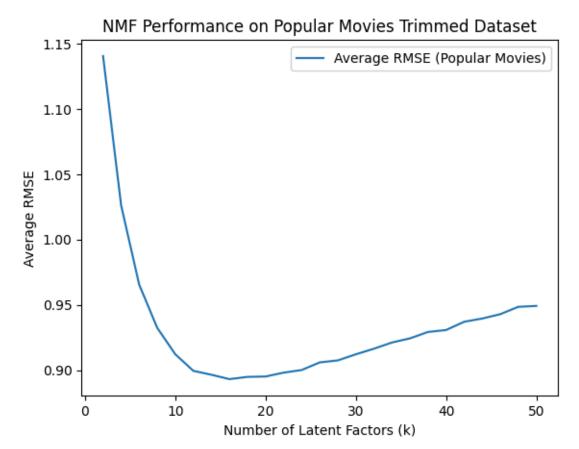




В

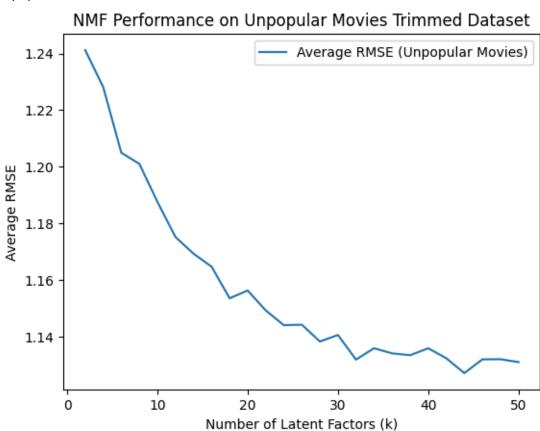
 $Optimal \ number \ of \ latent \ factors = 18$ $minimum \ average \ RMSE = 0.9116506399103693$ $minimum \ average \ MAE = 0.6932552267288592$ $the \ number \ of \ movie \ genres = 19$

C Popular



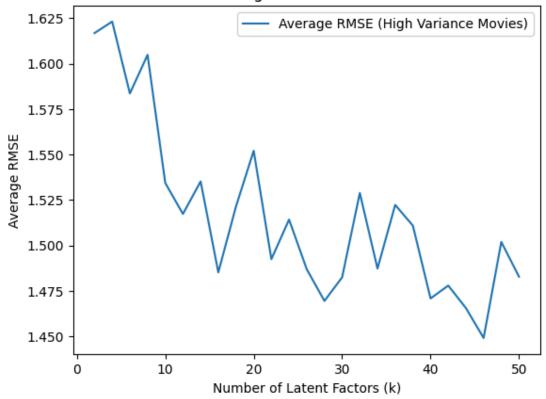
 $minimum\ average\ RMSE\ =\ 0.8931547399384527$

Unpopular



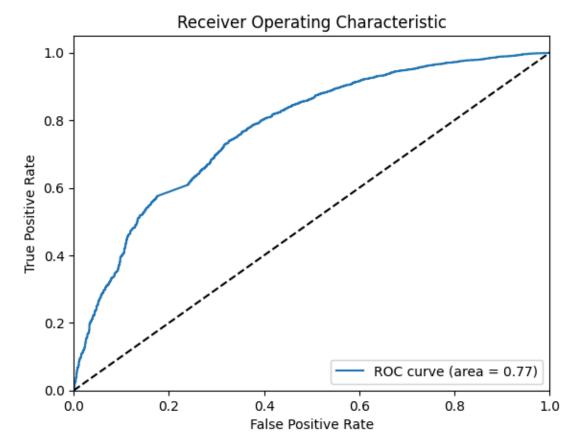
High-Variance



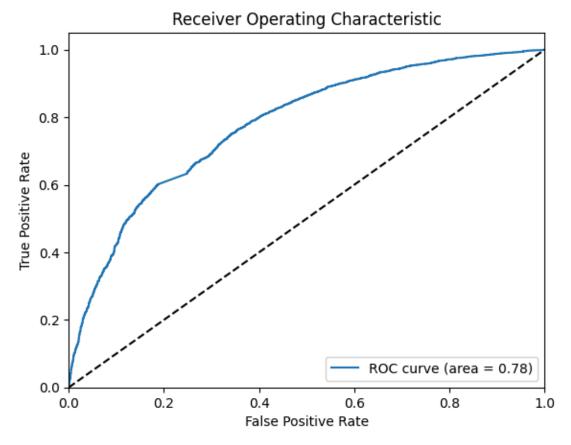


 $minimum\ average\ RMSE\ =\ 1.4491719193285797$

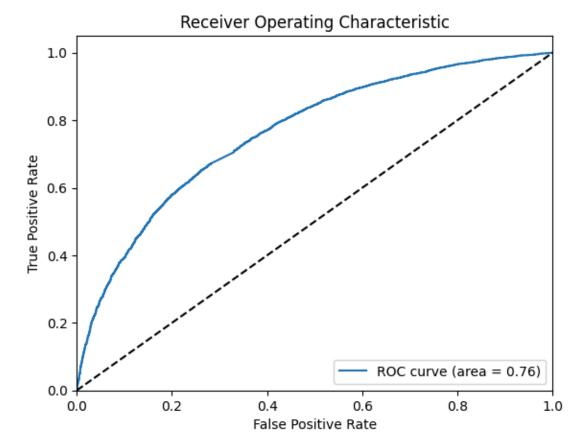
Threshold = 2.5



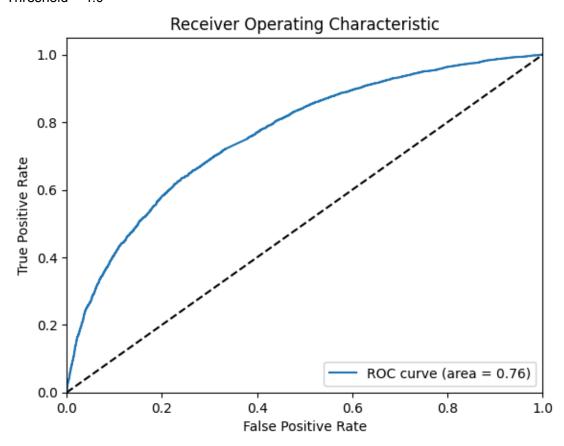
Threshold = 3.0



Threshold = 3.5



Threshold = 4.0



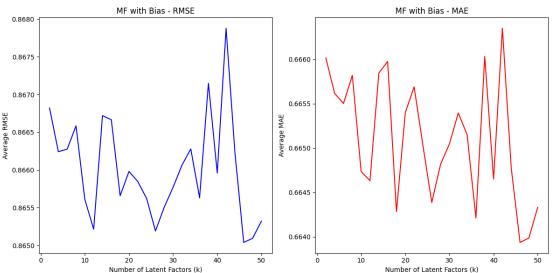
QUESTION 9

```
Top 10 Values for Latent Factor 0:
It's Such a Beautiful Day (2012): Animation|Comedy|Drama|Fantasy|Sci-Fi
Polar Express, The (2004): Adventure|Animation|Children|Fantasy|IMAX
Barbarella (1968): Adventure|Comedy|Sci-Fi
Dragon Ball 2: The History of Trunks (Doragon böru Z: Zetsubô e no hankô!! Nokosareta chô senshi - Gohan to Torankusu) (1993): Action|Adventure|Animation
Peter Pan (2003): Action|Adventure|Children|Fantasy
Neon Genesis Evangelion: Death & Rebirth (Shin seiki Evangelion Gekijô-ban: Shito shinsei) (1997): Action|Animation|Mystery|Sci-Fi
Dead Ringers (1988): Drama Horror|Thriller
Never Let Me Go (2010): Drama Riomance|Sci-Fi
Muse, The (1999): Comedy
Gothika (2003): Horror|Thriller
Top 10 Values for Latent Factor 1:
Troll 2 (1990): Fantasy|Horror
Master of the Flying Guillotine (Du bi quan wang da po xue di zi) (1975): Action
Piranha (1978): Horror|Sci-Fi
Crash (1996): Drama|Thriller
Dragon Ball Z the Movie: The Iree of Might (Doragon böru Z 3: Chikyû marugoto chô kessen) (1990): Action|Adventure|Animation|Sci-Fi
Inland Empire (2006): Drama|Mystery|Thriller
Horight (1960): Drama|Mystery|Thriller
Horight (1960): Drama|Mystery|Thriller
Waidan (Kaidan) (1964): Horror
Hangar 18 (1980): Action|Sci-Fi|Thriller
Clonus Horror, The (1979): Horror|Sci-Fi
Top 10 Values for Latent Factor 2:
Joy Ride (2001): Adventure|Animation|Children
UHF (1989): Drama
Rules of Attraction, The (2002): Comedy|Drama|Romance|Thriller
My Boss' Baughter (2003): Comedy|Romance
Rugrats in Paris: The Movie (2000): Animation|Children|Comedy
Armour of God II: Operation Condor (Operation Condor) (Fei ying gai wak) (1991): Action|Adventure|Comedy
Peggy Sue Got Married (1986): Comedy|Drama
```

The top 10 movies associated with a particular latent factor in an NMF model often belong to specific or a small collection of genres. This indicates a connection between the latent factors and movie genres, where each latent factor may represent underlying themes or genre characteristics common among certain movies.

Question 10

Α

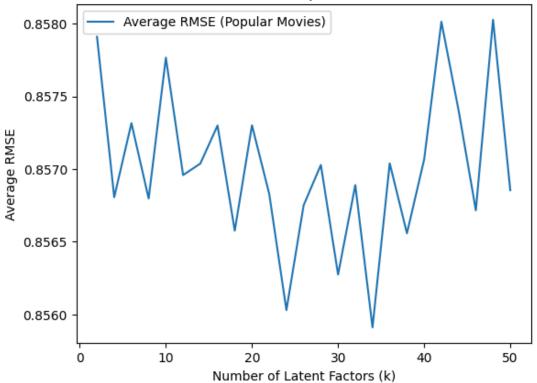


Optimal number of latent factors = 46minimum average RMSE = 0.8650394896157966minimum average MAE = 0.6639358146586974the number of movie genres = 19

C Popular

В

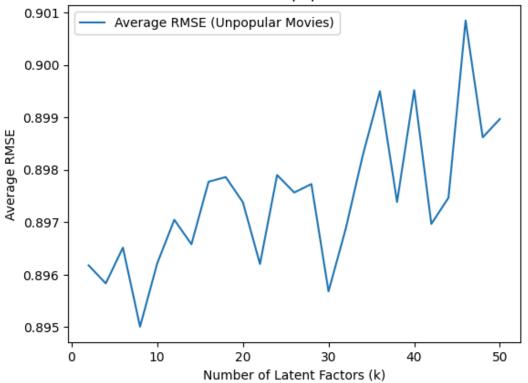
MF with bias Performance on Popular Movies Trimmed Dataset



 $minimum\ average\ RMSE\ =\ 0.8559110478080288$

Unpopular

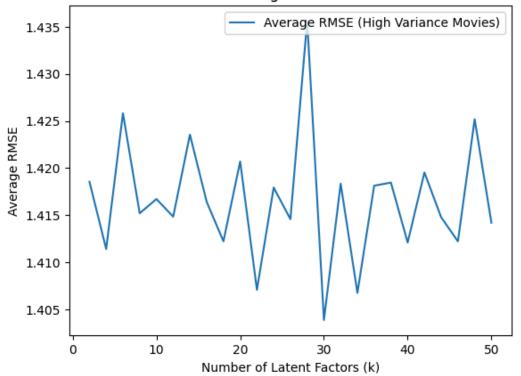
MF with bias Performance on Unpopular Movies Trimmed Dataset



 $minimum\ average\ RMSE\ =\ 0.8950073913298912$

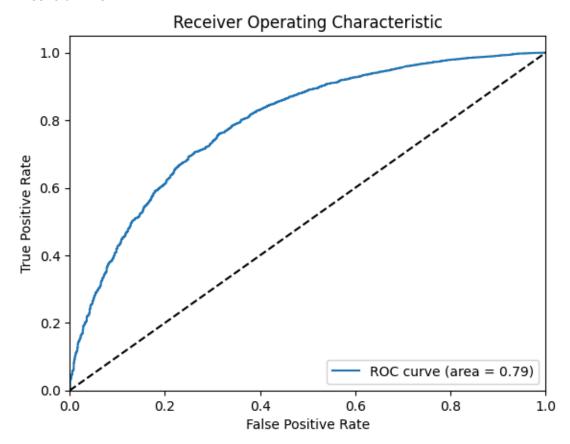
High-Variance

MF with bias Performance on High Variance Movies Trimmed Dataset

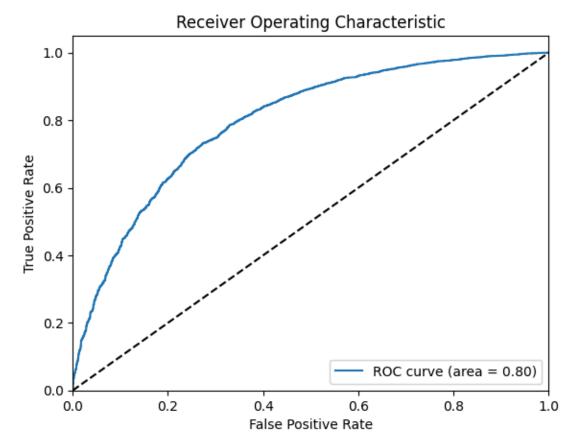


 $minimum \ average \ RMSE = 1.40386240191433$

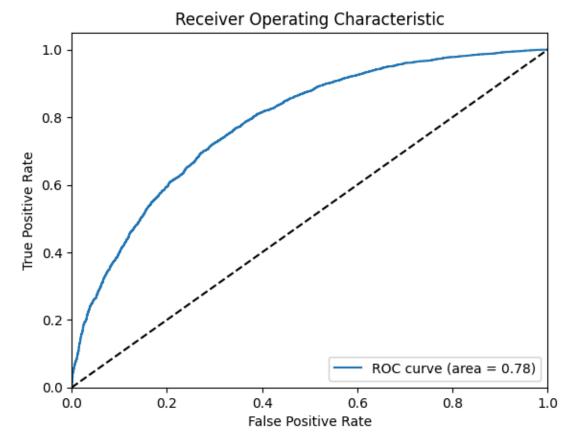
Threshold = 2.5



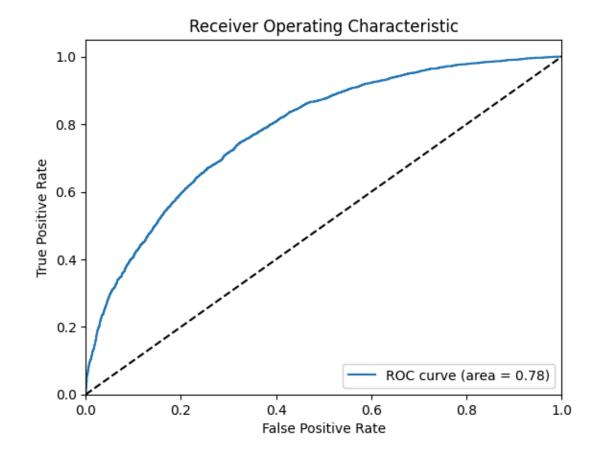
Threshold = 3.0



Threshold = 3.5



Threshold = 4.0



 $average\ RMSE\ =\ 1.0424923612421497$

Popular

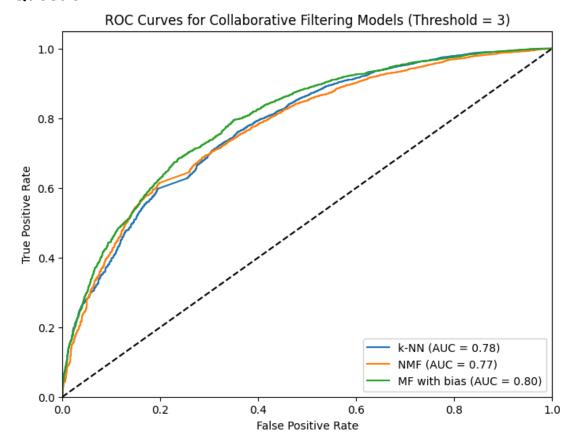
 $average\ RMSE\ =\ 1.\ 0355497670416107$

Unpopular

 $average\ RMSE\ =\ 1.\,1082375281838452$

High Variance

 $average\ RMSE\ =\ 1.510530220855013$



The performance of the MF with bias is the best.

Question 13

```
Total number of unique queries: 50000
Distribution of relevance labels:
0     0.520136
1     0.321849
2     0.132855
3     0.017761
4     0.007400
```

Question 14

```
Fold 1:
nDCG@3: 0.5307212739772434, nDCG@5: 0.6608397947263838, nDCG@10:
0.7480978396024439
Fold 2:
                       nDCG@5:
nDCG@3:
             1.0,
                                     nDCG@10:
0.933745776545611
nDCG@3: 0.9413401592471554, nDCG@5: 0.8845707994194446, nDCG@10:
0.8725071889285467
nDCG@3: 0.9413401592471554, nDCG@5: 0.9576049743407978, nDCG@10:
0.9551307237285457
Fold 5:
{\tt nDCG@3:} \quad {\tt 0.7653606369886218}, \quad {\tt nDCG@5:} \quad {\tt 0.8304198973631918}, \quad {\tt nDCG@10:} \\
0.8899541168509599
```

```
Fold 1:
Top 5 most important features:
        Feature Importance
133 feature_134 23829.122202
     feature 8 4256.551221
54
    feature 55 4055.480095
107 feature 108 4049.734442
129 feature 130 3655.614255
Fold 2:
Top 5 most important features:
        Feature Importance
133 feature_134 23587.659372
7
     feature_8 5133.581032
     feature 55 4366.728317
107 feature 108 4143.336742
129 feature 130 4079.324119
Fold 3:
Top 5 most important features:
       Feature Importance
133 feature_134 23211.959232
    feature 55 4998.220501
54
107 feature 108 4193.361015
129 feature 130 4028.027842
      feature 8 3690.110570
Fold 4:
Top 5 most important features:
        Feature Importance
133 feature 134 23760.985505
      feature_8 4632.884738
54
     feature 55 3899.246536
129 feature 130 3349.486992
128 feature 129 3220.559216
Fold 5:
Top 5 most important features:
       Feature Importance
133 feature_134 23480.303283
     feature_8 4791.326552
54
     feature_55 4058.867884
107 feature 108 3495.305341
129 feature 130 3188.522764
Question 16
Reduced: nDCG@3: 0.5307212739772434, nDCG@5: 0.6608397947263838,
nDCG@10: 0.7799082337019198
        60:
                    nDCG@3:
                            0.6173196815056892,
                                                       nDCG@5:
0.5557046000229097, nDCG@10: 0.5914468270998005
Fold 2:
                   1.0, nDCG@5: 0.9634829125393233, nDCG@10:
Reduced:
         nDCG@3:
0.9126821207086606
                   nDCG@3:
                                0.5586598407528446,
                                                      nDCG@5:
0.542395025659202, nDCG@10: 0.5471110380319288
Fold 3:
Reduced: nDCG@3: 0.8826803184943108, nDCG@5: 0.8824086793035104,
nDCG@10: 0.9236912790150748
```

Reduced 60: nDCG@3: 0.6173196815056892, nDCG@5:

0.6175913206964894, nDCG@10: 0.580138981986594

Fold 4:

Reduced: nDCG@3: 0.9413401592471554, nDCG@5: 0.9576049743407978,

nDCG@10: 0.97248852921274

Reduced 60: nDCG@3: 0.6173196815056892, nDCG@5:

0.654108408157166, nDCG@10: 0.6818128270805792

Fold 5:

Reduced: nDCG@3: 1.0, nDCG@5: 0.99999999999999, nDCG@10:

0.943718471705651

Reduced 60: nDCG@3: 0.75, nDCG@5: 0.7007980959328717, nDCG@10:

0.6703309994925489