IR program 2: Personalized Item Recommendation

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Q1 : Describe your MF with BCE (e.g. parameters, loss function, negative sample method and MAP score on Kaggle public scoreboard)

$$BCELoss := -[\sum_{(u,i)\in D^+} \log(\sigma(u^T i)) + \sum_{(u,j)\in D^-} \log(1-\sigma(u^T j))]$$

Dim = 16

Matrix: p(n_user, dim)

Matrix q(n_item, dim)

Positive sample : Negative sample = 1 : 1

Epoch = 50

Kaggle: 0.01924, 0.02008

Q2 : Describe your MF with BPR (e.g. parameters, loss function, negative sample method and MAP score on Kaggle public scoreboard)

$$BPRLoss := \sum_{(u,i,j)\in D} ln\sigma(u^T i - u^T j) + \lambda \|\Theta\|^2$$

Dim = 16

Matrix: p(n_user, dim)

Matrix q(n_item, dim)

Positive sample : Negative sample = 1 : 1

Epoch = 100

Lambda = 1E-3

Kaggle: 0.01988, 0.02029

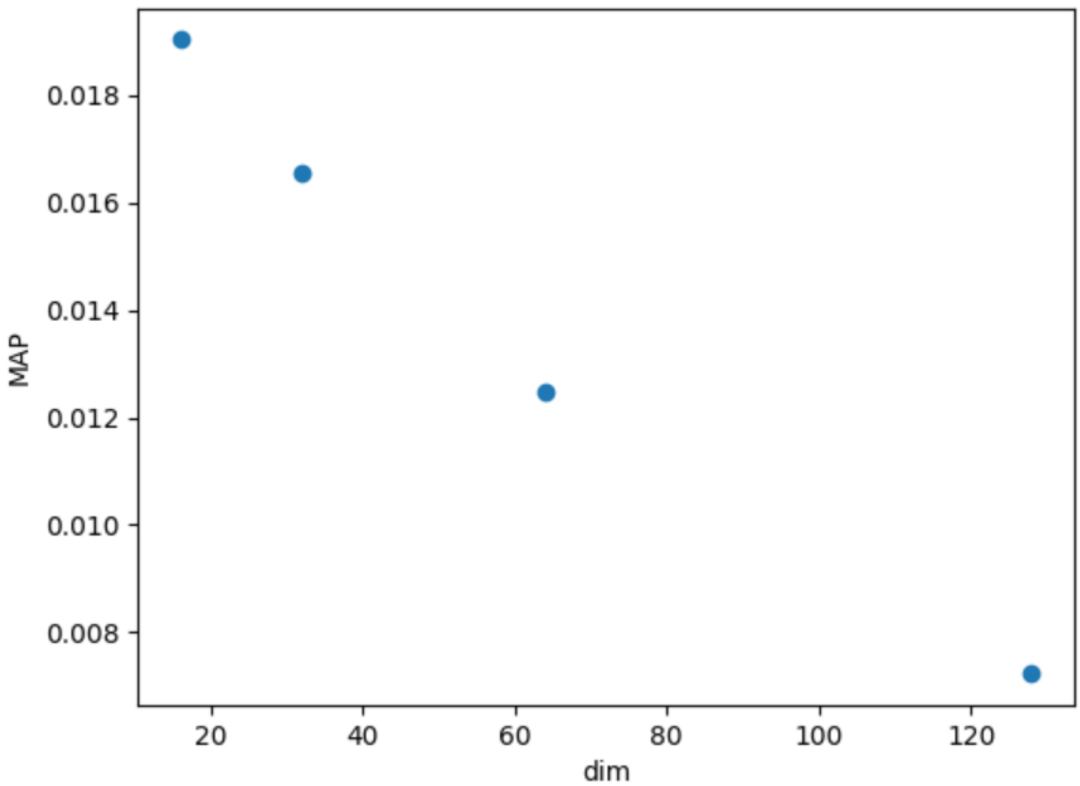
Q3 : Compare your results of Q1 and Q2. Do you think the BPR loss benefits the performance? If do, write some reasons of why BPR works well; If not, write some reasons of why BPR fails.

從實驗來看 BPR 稍微比 BCE 好一點，但沒差到很多。

排名的時候，比起預測分數準確度，更重要的是能判斷使用者更喜歡的哪個 item，所以希望給任意使用者和 item_i, item_j，判斷使用者是否喜歡 item_i 大於 item_j 的正確率越高越好。 預測出來喜歡的 item 分數>0 越大代表越喜歡，不喜歡的 item 則相反。

而 BCE 就單純是分類問題喜歡的 item 就會越接近 1，不喜歡的 item 就會越接近 0。

Q4 : Plot the MAP curve on testing data(Kaggle) for hidden factors d = 16, 32, 64, 128 and describe your finding.



Dim 越大分數有越低的趨勢。

Q5 : Change the ratio between positive and negative pairs, compare the results and discuss your finding.

dim 32 epoch 50 BPR ng=4:

0.01921

dim 32 epoch 50 BPR ng=1:

0.01906

差別沒到很大，但 negative pairs 的比例高一點能提升 MAP。