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1. (1%)請比較有無normalize(rating)的差別。並說明如何normalize.

| Normalized? | Kaggle Score |
|---|---|
| Yes | 0.91386 |
| No | 0.91856 |

From the above results, we can see that normalization does improve the score. The rating is normalized using the following formula:

$$\frac{X-\mu}{\sigma}$$ (standard score)

2. (1%)比較不同的latent dimension的結果。

| Latent Dimension | Kaggle Score |
|---|---|
| 168 | 0.91856 |
| 666 | 0.91857 |

The two latent dimensions that I chose barely affected the results. Perhaps it is because the difference between these two numbers is not big.

3. (1%)比較有無bias的結果。

| Bias? | Kaggle Score |
|---|---|
| Yes | 0.91862 |
| No | 0.91856 |

Surprisingly, with bias, my kaggle ascore actually worsen by a little. For user bias and item bias, I picked keras default random normal initializer.

4. (1%)請試著用DNN來解決這個問題，並且說明實做的方法(方法不限)。並比較MF和NN的結果，討論結果的差異。

| Method | Kaggle Score |
|---|---|
| MF | 0.91856 |
| DNN | 0.87488 |

As we can see, DNN is significantly better than MF. The DNN model that I used is the one provided by TA, where the hidden layers are: Dense(150, activation = 'relu'), Dense(50, activation = 'relu'). In my opinion, the reason that MF did not do so well is because rating is based on people's opinions and is scale-free. For example, many people might love Toy Story, but there will always be some people who do not and give it a low rating. However, it is hard to predict that since everyone thinks differently. To get a better result, I think that more features are needed, such as user preferences and movie categories. Unfortunately, I did not have the time to implement it.

5. (1%)請試著將movie的embedding用tsne降維後，將movie category當作label來作圖。