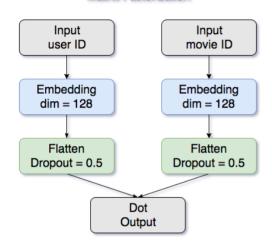
Machine Learning Project 6

Matrix Factorization

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Question 1. 3. 5. 使用的模型

Matrix Factorization



Questions

1. 請比較對評分(Rating)有無標準化(Normalize)的差別, 並說明如何標準化.

• Embedding Features: user ID, movie ID.

• latent dimensions: 128

• Validation Ratio: 0.05

RMSE	Not Normalized	Normalized
Epochs	327	74
Training	1.0348	0.7808
Validation	0.8562	0.8492
Kaggle Public	0.8588	0.8519
Kaggle Private	0.8634	0.8561

- 標準化之後成果會比較好,而且可以大幅減少訓練次數(Epochs).
- · Method of Normalization
 - 。 算出評分R的平均值 μ , 標準差 σ
 - 。 把每個評分做標準化:

$$R_n = \frac{(R - \mu)}{\sigma}$$

。 最後預測出來的結果 R_{n-p} 再反算回去原來的評分值 R_p

$$R_p = R_{n-p} \times \sigma + \mu$$

2. 比較不同的潛在維度(Latent Dimension)的結果.

• Embedding Features: user ID, movie ID.

• Without Dropouts.

• Validation Ratio: 0.05

Latent Dimension	Epochs	Validation RMSE
2	370	0.8803
4	211	0.8733
8	146	0.8636
16	96	0.8589
32	66	0.8535
64	34	0.8528
128	25	0.8470
256	16	0.8465
512	13	0.8438
1024	10	0.8470

• Latent Dimension = 512 的時候結果最佳.

3. 比較有無偏見(Bias)的結果.

• Embedding Features: user ID, movie ID.

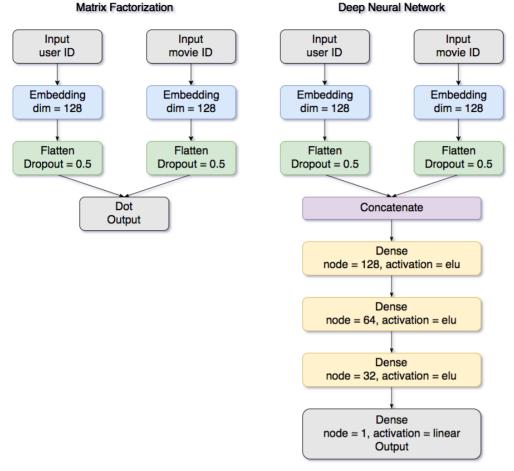
• latent dimensions: 128

• Validation Ratio: 0.05

RMSE	Without Bias	With Bias
Epochs	327	164
Training	1.0348	0.7687
Validation	0.8562	0.8434
Kaggle Public	0.8588	0.8460
Kaggle Private	0.8634	0.8503

• 加了偏見(Bias)之後成果會比較好, 而且可以大幅減少訓練次數(Epochs).

- 4. 請試著用DNN來解決這個問題,並且說明實作的方法. 比較MF和DNN的結果, 討論結果的差異.
 - MF, DNN模型架構



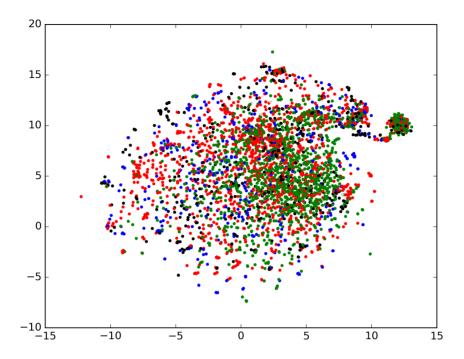
• 結果比較

RMSE	MF	DNN
Epochs	327	126
Training	1.0348	0.7816
Validation	0.8562	0.8547
Kaggle Public	0.8588	0.8574
Kaggle Private	0.8634	0.8608

• DNN的結果會比較差一點,而且DNN不能夠太多層,否則容易over fitting.

5. 請試著將電影的潛在維度(Embedding)用TSNE降維後[,]將電影類別當作標記(Label)來作圖

- Usage python3.5 plot_model.py <u>model file</u> --tsne
- 使用TSNE降維結果



• Legends

Color	Genre	
Red	Animation, Children's, Comedy, Adventure	
Green	Romance, Drama, Documentary, Musical	
Blue	Fantasy, Action, Sci-Fi, War, Western	
Black	Crime, Thriller, Horror, Film-Noir	
Gray	Other	

6. 試著使用除了評分以外的特徵(Feature), 並說明你的作法和結果, 結果好壞不會影響評分.

• 把user occupations和movie genres變成one-hot matrices.

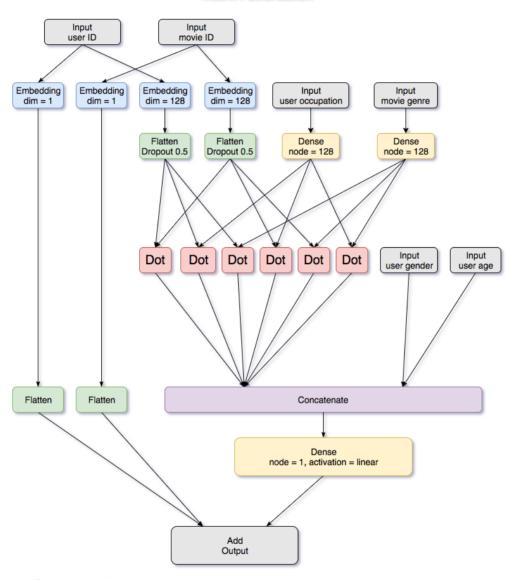
• User Occupations: dim = 21

• Movie Genres: dim = 18

• 把age除上標準差.

Latent Dimension: 128Validation Ratio: 0.05使用複雜版本的MF模型

Matrix Factorization

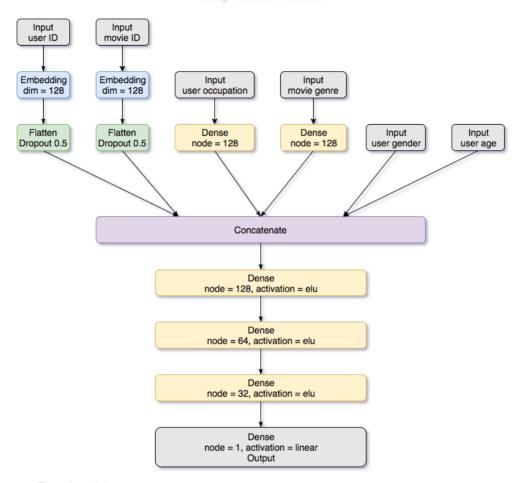


o Epochs: 114

Training RMSE: 0.7319
Validation RMSE: 0.8400
Kaggle Public RMSE: 0.8428
Kaggle Private RMSE: 0.8475

• 使用複雜版本的DNN模型

Deep Neural Network



o Epochs: 81

Training RMSE: 0.7879
Validation RMSE: 0.8472
Kaggle Public RMSE: 0.8493
Kaggle Private RMSE: 0.8551

Strong Baseline Model

- Usage
 - ./hw6.sh <u>data directory</u> <u>prediction file</u>
- Model
 - mf_simple_0.844605.h5 : MF, latent dimension=512, bias
- Result (RMSE)
 - o Kaggle Public Test: 0.8454
 - Kaggle Private Test: 0.8475

Best Model

- Usage
 - ./hw6_best.sh <u>data directory</u> <u>prediction file</u>
- Ensemble models
 - o mf_simple_0.842022.h5
 - o mf_simple_0.844605.h5
 - o mf_0.843316.h5
 - o mf_0.839976.h5
 - o mf_0.839977.h5
 - o mf_0.841615.h5
 - o mf_0.840972.h5
 - o mf_0.841453.h5
 - o mf_0.841394.h5
- Result (RMSE)
 - o Kaggle Public Test: 0.8320
 - Kaggle Private Test: 0.8365