Deep Autoencoders for eco recommendations

1) Introduce

In order to create an eco-friendly activity recommendation system using the data of users who will be launching the application, we developed a recommendation algorithm using movie dataset (Movielens 100k).

2) Observations

Rank	Model	RMSE↓ (u1 Splits)
1	Bayesian timeSVD++ flipped + Feat w/ Ordered Probit Regression	0.884
2	Bayesian timeSVD++ flipped + Feat	0.886
3	Bayesian timeSVD++ flipped	0.886
4	MG-GAT	0.890
5	GraphRec + Feat	0.897
6	GraphRec	0.904
7	IGMC	0.905
8	GC-MC + feat	0.905
9	GC-MC	0.910
10	Self-Supervised Exchangeable Model	0.91
11	GRAEM	0.9174
12	Factorized EAE	0.920
13	sRGCNN	0.929
14	GRALS	0.945
15	GMC	0.996

The above data shows the model, rank and RMSE loss values of the 'movielens 100k' from the 'paperswithcode' website. But Most of the above models for recommendations only consider the user and the ratings given by the user. Such recommendations do not take into account other attributes.

3) Data structure

First of all, the 'movielens 100k' dataset is composed as follows.

Users

UserID	Gender	Age	Job	Zip
1	F	1	10	48067
2	M	56	16	70072
3	M	25	15	55117
4	M	45	7	02460
5	M	25	20	55455

Ratings

UserID	MovieID	Rating	Timestemp
1	1193	1	978300760
1	661	56	978302109
1	914	25	978301968
1	3408	4	978300275
1	2355	5	978824291

Movies

MovieID	Title	Genres
1	Toy Story	Animation|Children's|Comedy
2	Jumanji	Adventure|Children's|Fantasy

It contains various attributes like gender and age of the user. The movies also contain the genre information.

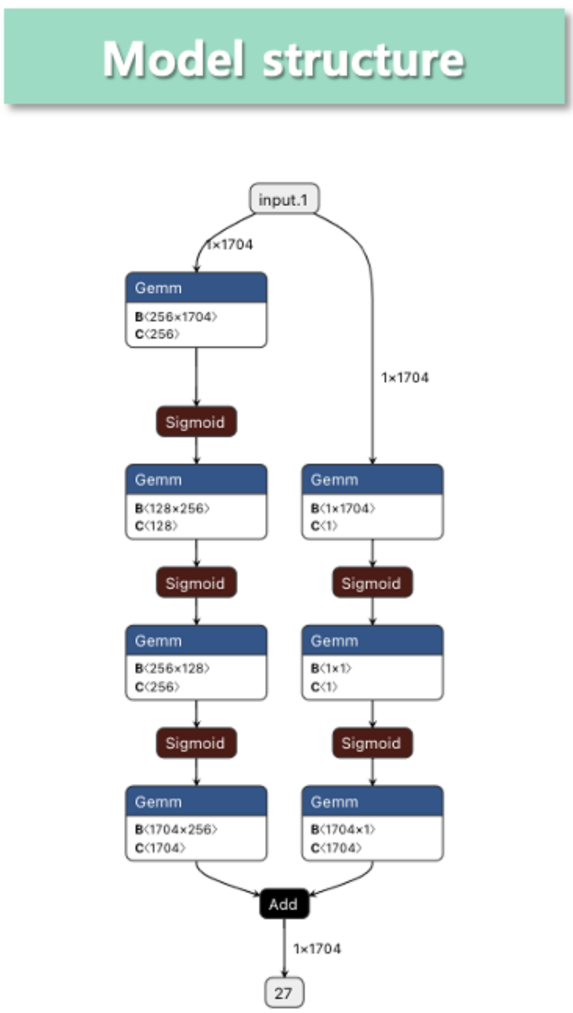
4) Data preprocessing

For AutoEncoder input, the data should represent a two-dimensional array where each row represents a user. The first N columns refer to N movies where the user has rated the movie. In case the user has not rated the movie, it will contain a value of 0. The next N columns will represent the number of genres. The last few rows indicate the user attributes like user gender, age and job.

Train_df

User	Movie 1	Movie 2	Movie 3	---	Movie n	Genre 1	Genre 2	---	Genre n	Male	Female	Age	Job
User 1	3	2	5	---	4	10	5	---	0	1	0	21	2
User 2	2	1	4	---	4	8	3	---	2	1	0	1	4
User 3	4	3	4	---	3	4	1	---	5	0	1	31	17
---	---	---	---	---	---	---	---	---	---	---	---	---	---
User n	3	2	3	---	5	14	23	---	1	0	1	51	6

5) AutoEncoder Model



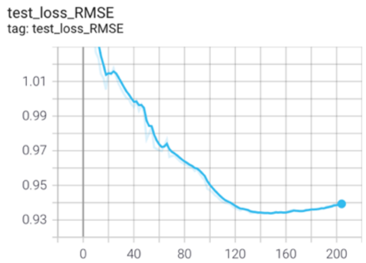
Our model basically shows the AutoEncoder structure. We have tried deep neural networks with 3, 5 and 7 layers. We have chosen 3 layers because computation exponentially increases with the increase in layers and hence neurons. In our case the results provided by 5 and 7 layered neural networks perform only marginally better than 3 layered network. We also propose a wide and deep model by adding a simple linear wide model.

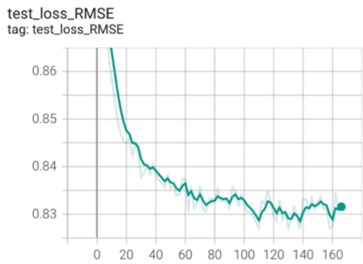
The input of the model is a tensor of the form (1, 1704) by connecting 1682 movies, 18 genres, and 4 user information. The deep model goes through [1704, 256, 128, 256, 1704] layers, and the wide model goes through [1704, 1, 1704] layers. All layers use the sigmoid activation function, and the out of the model is the sum of the deep model and the wide model.

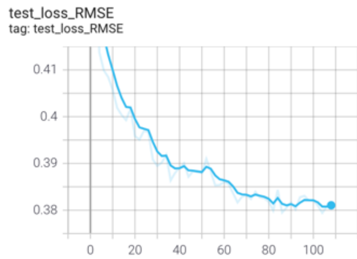
The optimizer used RMSprop and the loss function used RMSE. RMSE is a value rooted in the MSE value, and it enlarges a large error compared to a small error, so it is considered a small error as the difference between the score and the target data is small.

6) Train

Data Considered training	Number of Epochs	Testing RMSE Loss
Movie ratings only	300	0.932
Movie ratings + Genre	300	0.813
Movie ratings + Genre + User Attributes	300	0.379







The train was tested in three cases, and the epoch was fixed at 300 considering the learning time. As can be seen from the table above, unlike Movie ratings only and Movie Ratings + Genre, in the case of Movie Ratings + Genre + User Attributes, the Loss value is very low, so you can see how unique each individual is and how important personalized recommendations are.

7) conclusion

In the future, if eco-friendly data is accumulated after the application is released, we plan to improve the accuracy of the personalized recommendation algorithm and identify eco-friendly activities that users want through data analysis to induce people to engage in more eco-friendly activities.