ICPR 2020 – TRACK 1

Temporal Collaborative Filtering with Graph Convolutional Neural Networks

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*Acknowledgements
This research was supported by funding from the Flemish Government under the "Onderzoeksprogramma Artificiële Intelligentie (AI) Vlaanderen" programme.

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Motivation & Problem Formulation

- Recommender Systems are EVERYWHERE!
- Common approach: **Collaborative Filtering (CF)**
  - Matrix-Factorization-based approaches
  - Temporal CF (TCF):
    - Recurrent Neural Nets (RNNs)
- Recently…**GNNs!**

https://medium.com/towards-artificial-intelligence/diversity-recommender-systems-in-machine-learning-and-ai-a56849c5a256

TG-MC Architecture

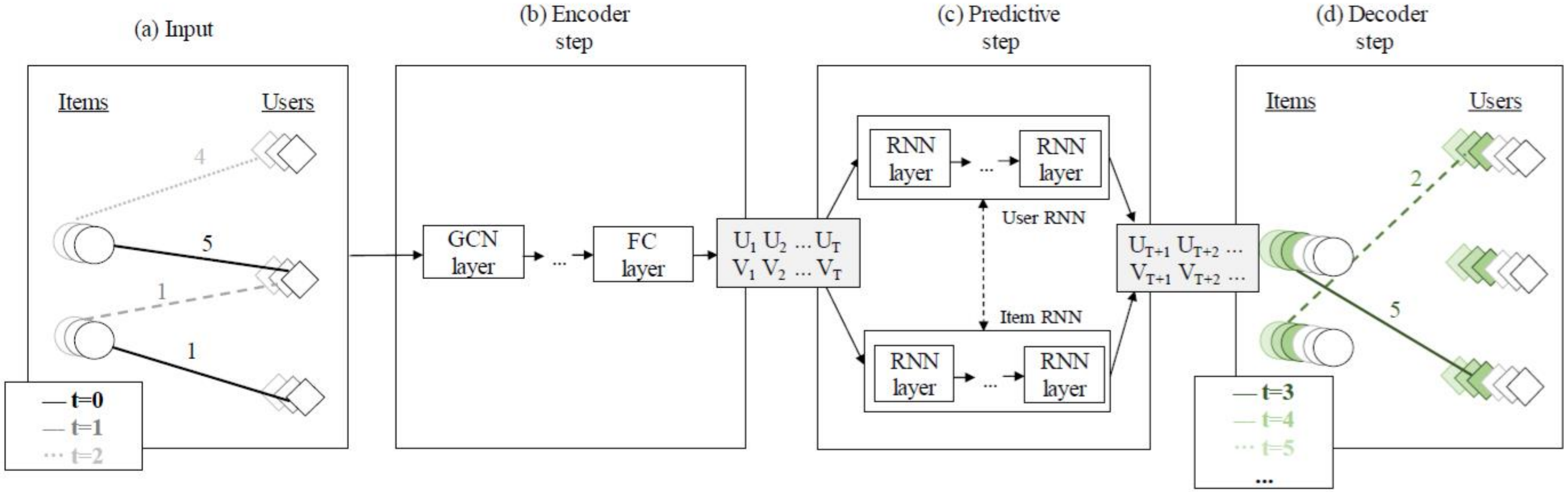

Fig. 1: The proposed time-aware graph-based matrix completion architecture for Recommender Systems (TG-MC). **(a)** The model receives as input a sparse tensor of ratings R$\in \mathbb{R}^{N_U \times N_V \times T}$ in three dimensions (users, items and time). The empty elements of R represent unknown rating scores from a user to a specific item. **(b)** The encoder is formed by combining GNNs and fully-connected layers. Running the encoder step for each time window results in two length-T sequences of latent representations for users and items. **(c)** The predictive step encompasses an RNN-, LSTM- or GRU-based architecture. Given the two sequences of users and items embeddings, two RNN models, which we refer to as user- and item-RNNs, predict the subsequent embeddings. The two RNNs can share weights or can be completely independent. **(d)** By matrix multiplication, the decoder step obtains, at the subsequent time instance, the output matrix $\hat{R}_{T+1}$ which contains the predicted ratings scores.

Experimental Results

TABLE I: Average test RMSE and MAE scores for all variations of our method on the Netflix and MovieLens 1M datasets.

Dataset	Method	Non-Accumulative Representation RMSE	Non-Accumulative Representation MAE	Accumulative Representation RMSE	Accumulative Representation MAE
Netflix	TG-MC RNN	1.008± 0.085	0.921±0.040	1.001 ± 0.033	0.822 ± 0.022
	TG-MC GRU	0.969 ± 0.034	0.876 ± 0.037	0.952 ± 0.023	**0.767±0.029**
	TG-MC LSTM	0.974 ± 0.028	0.918 ± 0.017	**0.931±0.009**	0.790±0.020
MovieLens 1M	TG-MC RNN	1.032± 0.030	0.830±0.027	0.876 ± 0.023	0.783 ± 0.027
	TG-MC GRU	1.019±0.028	0.818± 0.028	0.867 ± 0.013	0.697 ± 0.023
	TG-MC LSTM	1.015 ± 0.022	0.768± 0.026	**0.834 ± 0.011**	**0.664 ± 0.028**

Table II: RMSE scores obtained by our method and reference **static CF methods** on the Netflix and MovieLens 1M datasts.

Method	Netflix	MovieLens 1M
PMF [20]	0.957	0.883
I-AutoRec [21]	0.979	**0.833**
U-AutoRec [21]	0.985	0.877
GCMC [11]	1.264	1.001
TG-MC (ours)	**0.931**	0.834

Table III: Comparison of our method and reference **TCF methods** on the Netflix and MovieLens 1M datasets.

Method	RMSE
Temporal MF [26]	1.112
RRN [2]	0.944
TimeSVD++ [4]	0.962
NCF [27]	0.947
LFM [28]	0.936
TG-MC (ours)	**0.931**

Method	MAE
Temporal MF [26]	0.843
RRN [2]	0.793
$AM^{N=1}$ [25]	0.777
NTF [10]	0.689
TG-MC (ours)	**0.664**

CONCLUSION

- Method for Temporal Collaborative Filtering (TCF)
- Combines
  1. **GNNs** → learns/captures the latent user and item representations
  2. **RNNs** → models the temporal dynamics (trajectories of these representations across time) in the TCF setting
  3. increased **data sparsity** in the TCF setting → use an accumulative data representation technique
- Comprehensive experiments on the **Netflix and MovieLens 1M datasets** justified the benefits of **each** of the proposed components (1, 2 and 3)
- The experimental results also showed that our method yielded favorable performance compared to several state-of the-art TCF models.

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Thanks for listening!

Questions are very welcome