Temporal Graphs for Music Recommendation Systems

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Streaming services are popular

"Nearly 616.2 million people listen to their favorite artists or discover new ones via online streaming platforms" [1]

Creating a recommendation system

We aim to develop a data-driven recommendation model that predicts the genres a user is expected to like the next months, based on the music genre preferences of 1000 users over 4 years of records.

The tgbn-genre dataset

Temporal Graph Benchmark for Machine Learning on Temporal Graphs

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Abstract

We present the *Temporal Graph Benchmark (TGB)*, a collection of challenging and diverse benchmark datasets for realistic, reproducible, and robust evaluation of machine learning models on temporal graphs. TGB datasets are of large scale, spanning years in duration, incorporate both node and edge-level prediction tasks and cover a diverse set of domains including social, trade, transaction, and transportation networks. For both tasks, we design evaluation protocols based on realistic use-cases. We extensively benchmark each dataset and find that the performance of common models can vary drastically across datasets. In addition, on dynamic node property prediction tasks, we show that simple methods often achieve superior performance compared to existing temporal graph models. We believe that these findings open up opportunities for future research on temporal graphs. Finally, TGB provides an automated machine learning pipeline for reproducible and accessible temporal graph research, including data loading, experiment setup and performance evaluation. TGB will be maintained and updated on a regular basis and welcomes community feedback. TGB datasets, data loaders, example codes, evaluation setup, and leaderboards are publicly available at https://tgb.complexdatalab.com/.

`tgbn-genre`. This is a bipartite and weighted interaction network between users and the music genres of songs they listen to. Both users and music genres are represented as nodes while an interaction specifies a user listens to a music genre at a given time. The edge weights denote the percentage of which a song belongs to a certain genre. The dataset is constructed by cross referencing the songs in the *LastFM-song-listens* dataset [24, 15] with that of music genres in the *million-song* dataset [2]. The *LastFM-song-listens* dataset has one month of who-listens-to-which-song information for 1000 users and the *million-song* dataset provides genre weights for all songs in the *LastFM-song-listens* dataset. We only retain genres with at least 10% weights for each song that are repeated at least a thousand times in the dataset. Genre names are cleaned to remove typos. Here, the task is to predict how frequently each user will interact with music genres over the next week. This is applicable to many music recommendation systems where providing personalized recommendation is important and user preference shifts over time.

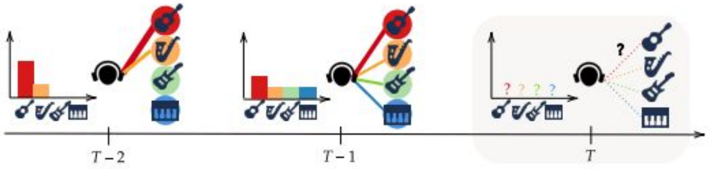
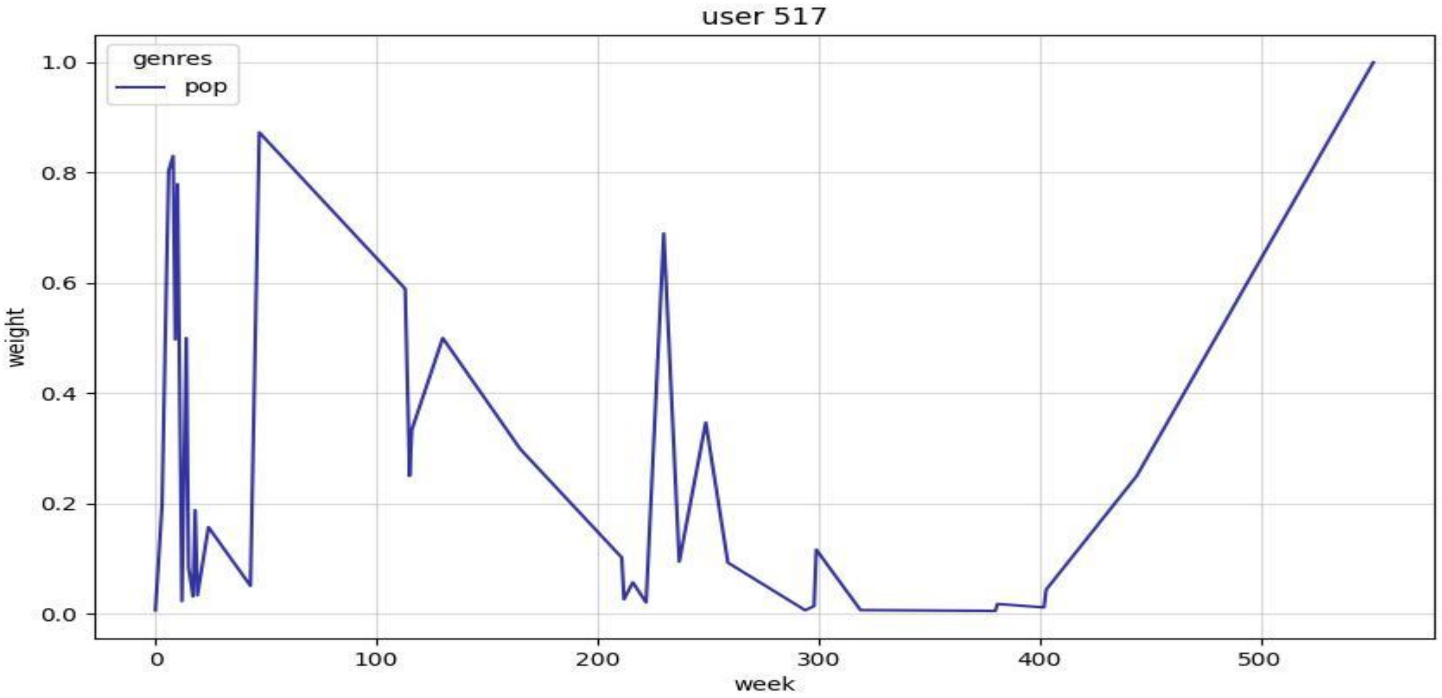


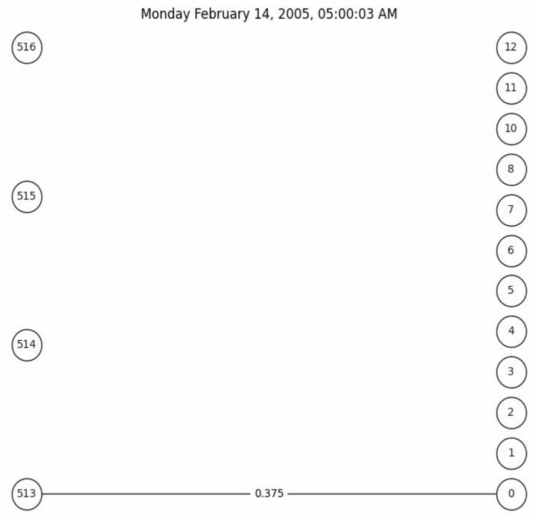
Figure 3: The *node affinity prediction* task aims to predict how the preference of a user towards items change over time. In the `tgbn-genre` example, the task is to predict the frequency at which the user would listen to each genre over the next week given their listening history until today.

$$\begin{bmatrix} 0.02 & 0.00 & \dots & 0.57 \\ 0.07 & 0.33 & \dots & 0.06 \\ \vdots & \vdots & \ddots & \vdots \\ 0.00 & 0.00 & \dots & 0.57 \end{bmatrix}$$

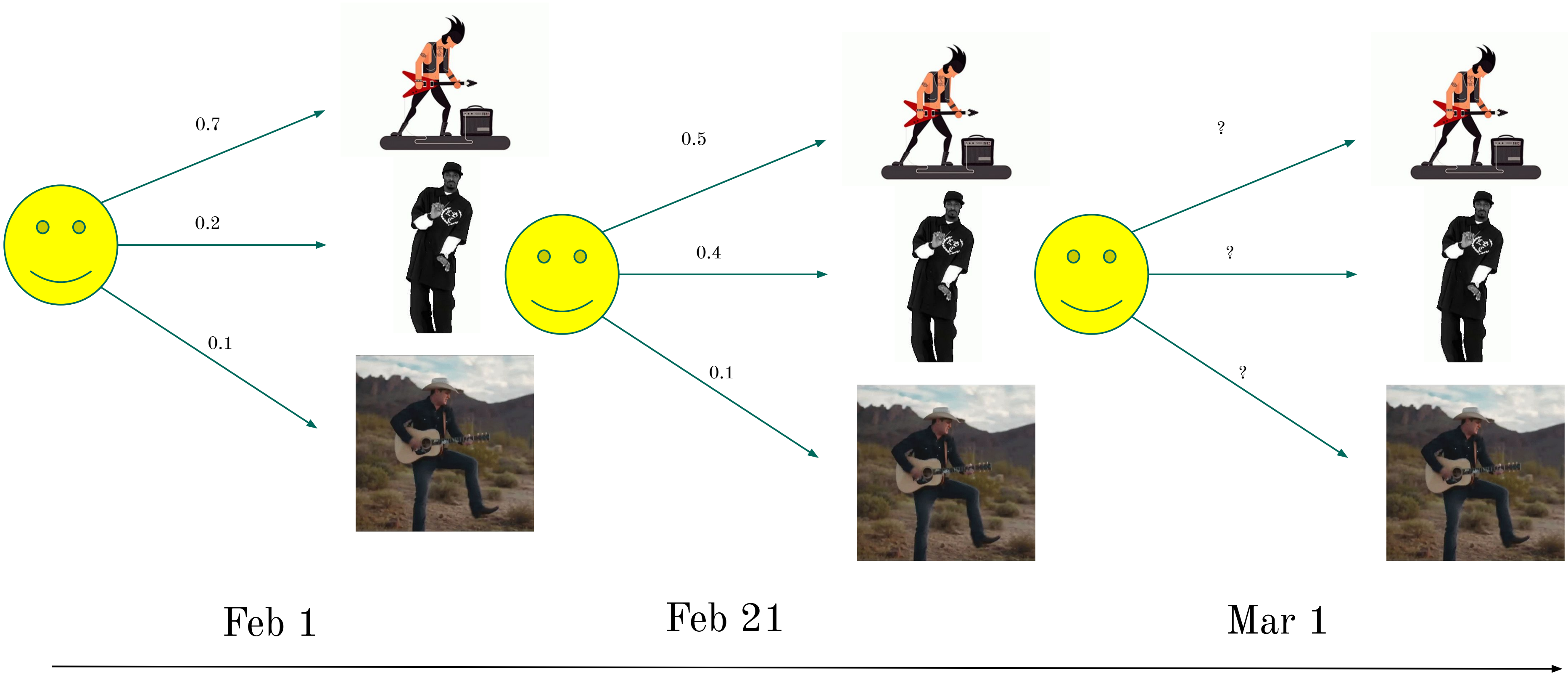
For 1500+ week-long sliding windows, a row in a 992x513 array represents a listener's musical taste in the form of a dist. of genre weights.



- Each column represents the popularity of a genre.
- We can conceptualize each user-genre interaction at a given moment as a weighted edge connecting a user node to a genre node in a bipartite graph.
- The graph evolves over time: we have a *temporal graph*.



Task



Normalized Discounted Cumulative Gain (NDCG)

$$DCG_p = \sum_{i=1}^{p} \frac{rel_i}{log_2(i+1)}$$

$$\mathrm{NDCG_p} = \frac{DCG_p}{\text{max.possible score}}$$

Results

Model	NDCG@10 (Validation)	NDCG@10 (Test)
Latest genre rating (Baseline)	0.18068	0.1575
Mean genre rating	0.2310	0.2034
Rolling Average (Window= 7 days)	0.2242	0.1951
Rolling Average (Window= 14 days)	**0.2333**	0.2008
Rolling Average (Window= 21 days)	0.2345	**0.2014**
Exponential Smoothing (α=0.8)	0.1941	0.1662
Exponential Smoothing (α=0.4)	0.1827	0.1619

Future directions

- Exploit the graph structure of our data to train graph neural networks and learn the interaction of users and music genres.
- Train classical and deep learning multivariate time series models to analyze the music genre preferences of one user.
- Ultimately, offer streaming services a recommendation system that can create a great and unique experience for each user.

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Sources

[1] Götting M. "Music streaming worldwide - statistics \& facts". 10 Jan 2024. https://www.statista.com/topics/6408/music-streaming/#topicOverview. Accessed May 28, 2024.
[2] Huang, S., et al."Temporal graph benchmark for machine learning on temporal graphs" *Advances in Neural Information Processing Systems* , 2023. Preprint: arXiv:2307.01026]

Images

[1] Spotify icons created by Freepik -Flaticon.com
[2] https://1000logos.net/apple-music-logo/
[3]https://www.prnewswire.com/news-releases/deezer-reveals-bold-new-brand-identity-and-logo--setting-the-stage-for-an-era-of-music-experiences-301980468.html