GNNIE: GNN-Recommender-as-a-Service

MIMS '23 Capstone Project Proposal

Pratik Aher, Benjamin Fell, Heidi Lin, Aayushi Sanghi, Arogya Koirala, Faezeh Taghva, Michael Yang

Motivation

Until recently, many recommendation systems were based on two major approaches: Collaborative Filtering and Content-based Filtering. The former suffers from popularity bias, where the most popular products or content are recommended, instead of niche products.[1] The latter suffers from a lack of novelty and diversity, as it can only recommend based on existing interests of the user.

In recent years, Graph Neural Networks (GNN) have been shown to be effective in a variety of applications, including recommendation systems.[2] We believe that this third approach, GNN-based recommendation models, has the potential to make recommendations more diverse (i.e., not merely popular at large, or related to a specific search) and better personalized (i.e., more aware of interests and behaviors of the user). It is also highly scalable and more expressive than other neural network models. Further, it can leverage rich contextual information (e.g., date, location, weather) to provide more personalized recommendations. In short, GNN recommendation models has the potential to make recommendations better, faster, and explainable. It can help people discover what they want and need, but didn't know they did, in the sea of products and content online today.

Problem Statement

GNN recommendation models today are not yet accessible to most companies. Barring the biggest companies, most cannot develop customized GNN models for their own businesses. Making GNN recommendation models more widely accessible can not only help these companies compete, but more importantly, help people find the right product, person, or content at the right moment.

We believe one of the sectors that could benefit the most immediately is retail e-commerce. It has a vast number of smaller companies, and it has long been using recommendation engines. In the US, there are more than 4 million e-commerce companies, and by some measures, the top 10% accounts for the 90% of gross merchandise value.[3] GNNIE seeks to help the bottom 90% by leveraging GNN and rich contextual information to provide better product recommendations.

Related Works

In the past few years, research has demonstrated the efficacy of graph learning methods for recommendation tasks.[4] For example, Uber Eats has achieved a 12% increase in AUC compared to the baseline model by leveraging GNN.[5]

Separately, there has been research in the field of quantum chemistry that used edge contextual information in GNN.[6] Uber Eats recommendation model did not incorporate any contextual edge information in user-item bipartite graphs, only using ratings as the edge information. DiDi, the ridehailing company, has applied contextual information on physical environments to GNN and saw significant improvement in traffic predictions.[7]

We believe that rich contextual information could be applied to GNN-based recommendation engine for retail products in order to reduce the popularity bias and increase the representation of long tail recommendations, resulting in more personalized and diverse recommendations.

Proposed Methods

Our goal is to enable small e-commerce businesses to easily use a GNN-based recommendation engine and have more control over how recommendations are generated for their customers. We will do this by developing a recommendation-as-a-service platform, where business owners can import their data and design their own recommendation engine.

We envision this design to happen in two stages, from the user's perspective.

In the first stage, depending on the nature and variety of the data end-users upload, the platform will automatically make suggestions of different derived variables and embeddings they can take advantage of from the input data (such as time of purchase, or how close a customer's purchase was to a holiday season, geographical variables like state, country, etc.) when building a recommendation engine.

The second stage will provide business owners with high-level controls for the recommendation engine. For example, a slider can help business owners determine whether the recommendation engine should focus on giving more personalized recommendations based on each buyer's profile, or instead focus on providing more popular recommendations based on market demand. This is just one example we can think of at this stage, but part of the goal of the user research phase, and model development phase is to understand what other controls would help support business owners' needs better.

Once the user has specified parameters of their recommendation engine, the platform will provide API endpoints that the user can then use to integrate recommendations into their respective systems on various platforms (Shopify, WordPress, etc). Additionally, to promote transparency and explainability, we also want to enrich the API payload with contextual attributes that explain why certain items are being recommended (e.g., 50,000 users bought this item in the last week).

Finally, if time permits, we want to focus on providing business owners with transparency in understanding model outcomes. For this, we envision a model performance dashboard that provides business owners with information such as coverage (percentage of items recommended out of all the items), and diversity (how many shoppers receive similar sets of recommendations), and so on.

Milestones

Week	1	2	3	4	5	6	7	8	9	10	Break	11	12	13	14	15	16
Date	Jan 16	Jan 23	Jan 30	Feb 06	Feb 13	Feb 20	Feb 27	Mar 06	Mar 13	Mar 20	Mar 27	Apr 03	Apr 10	Apr 17	Apr 24	May 01	May 08

	Phase 1	Phase 2	Phase 3	Stretch Goals
GNN Model	**Initial Development** Develop an initial model with a toy dataset (Amazon Product Reviews) testing for elements such as: Initial Embeddings, Loss Functions, Contextual Variables, Structural Positions **People**: Pratik, Ben, Heidi, Arogya (50%), Aayushi (50%) **Milestones**: GNN recommendation model that generates desired recommendation on toy dataset and performs well against benchmarks	**Evaluation** Analyze the initial model for expressiveness **People**: Pratik, Heidi, Ben **Milestones**: Identify potential embeddings, list down derived features that can be extracted from the data and can be suggested to the user	**Generalizability** Test the MVP model with other items (with toy or client datasets) **People**: Pratik, Heidi, Ben Milestones: Identify other items that the model could be generalized to	**Research Paper** Compose research paper
Platform Backend	**Access Control** Implement login screens and unique API token generation modules **People:** Arogya (50%), Aayushi (50%) **Milestones:** Prototype hosted in cloud where users can login and create access tokens for using the API	**Data Upload & Feature Suggestions** Implement data upload and feature suggestion components **People:** Arogya, Aayushi, Pratik **Milestones:** Protype where end users can create an account, upload their data, and get feature suggestions (variables) based on their data	**Tuning / Training / API Endpoints** Develop backend that trains the model and exposes API endpoints for the user to integrate in their existing systems **People:** Arogya, Aayushi, Pratik, Heidi **Milestones:** API specification; working prototype of model tuning component; API in action	**Analytics Dashboard** **Activities:** Develop performance evaluation dashboards **People:** Arogya, Aayushi, Heidi **Milestones:** Implemented API for the partner site
UX / Frontend	**UX Research** Interview B2C e-commerce companies to: (1) understand their use of recommendation models, (2) identify pain points, (3) identify potential partners **People:** Faezeh, Michael **Milestones:** (1) Validation of best target segment, (2) Identification of clients willing to provide dataset	**UI/UX Design** Design wireframe for the product, including: landing, import, feature specification/suggestion, tuning, training, output (Stretch goal: visualization); Conduct usability assessments and iterate **People:** Faezeh, Michael **Milestones**: UI Wireframe for the product tested for usability	**Frontend Development** Develop frontend based on the UX design and backend components **People:** Faezeh, Michael, Arogya **Milestones**: Fully functional MVP website that can import datasets, generate visualizations and API	**Evaluation** Gather customer feedback

([Link to chart](#))

Contributors

Our capstone team has experience necessary to develop a GNN recommendation model, research and design user experience, and deploy an API service for a customer. This project will involve in-depth research around GNNs, recommendation systems, user experience, but also the design, evaluation, implementation and launch of an AI product that is able to create valuable and explanatory recommendations for a variety of real-world applications.

	Skills	**Primary Roles**
Pratik Aher	ML, Software Engineering	Model Development, Evaluation
Benjamin Fell	ML, Software Engineering	Model Development, Evaluation
Heidi Lin	ML, Software Engineering	Model Development, GNN Research
Aayushi Sanghi	ML, Software Engineering	Model Development, Viz, Backend
Arogya Koirala	ML, Software Engineering	Feature Engineering, Viz, Frontend
Faezeh Taghva	HCI Design, Human-Centered AI	UX Research & Design
Michael Yang	Product Management	Product Management, UX Research, Viz

References

1. Alejandro Bellogín, Pablo Castells ,Iván Cantador (2017). Statistical biases in Information Retrieval metrics for recommender systems. *Information Retrieval Journal* 20, 6 (2017), https://doi.org/10.1007/s10791-017-9312-z
2. Shiwen Wu, Fei Sun, Wentao Zhang, Xu Xie, Bin Cui (2020). Graph Neural Networks in Recommender Systems: A Survey. *ACM Computing Surveys*. https://dl.acm.org/doi/10.1145/3535101
3. Vittal, B. (2022, March 16). Dissecting the $4.9 Trillion industry with 2022 data. PipeCandy Blog. https://blog.pipecandy.com/post/e-commerce-companies-market-size
4. Rex Ying, Ruining He, Kaifeng Chen, Pong Eksombatchai, William L. Hamilton and Jure Leskovec. "Graph Convolutional Neural Networks for Web-Scale Recommender Systems." *KDD* (2018)
5. (2019, December 4). "Food Discovery with Uber Eats: Using Graph Learning to Power Recommendations." *Uber Blog*. https://www.uber.com/blog/uber-eats-graph-learning/
6. Gilmer, J., Schoenholz, S.S., Riley, P.F., Vinyals, O. and Dahl, G.E. "Neural message passing for quantum chemistry." *International conference on machine learning*, 1263-1272 (July 2017).
7. Wenjuan Luo, Han Zhang, Xiaodi Yang, Lin Bo, Xiaoqing Yang, Zang Li, Xiaohu Qie, and Jieping Ye. 2020. "Dynamic Heterogeneous Graph Neural Network for Real-time Event Prediction." KDD '20. 3213–3223.