**STATS 402 - Interdisciplinary Data Analysis**

**Break the echo chamber:**

**Improvement of Video Recommendation System based on GNN**

Milestone Report: Stage 1

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##### Abstract

In this study, we aim to break information cocoons for users by leveraging graph neural networks (GNNs) built upon video content under a specific hashtag. The constructed GNNs represent ego networks, consisting of several interconnected subsets. Key nodes within these networks serve as crucial connectors between the subsets. By recommending videos featuring these key nodes to a specific user, we can efficiently expose the user to different subsets of content, thus breaking their information cocoon.

To validate our approach, we perform random walk simulations within one of the subsets to determine node importance. Afterward, we assign a probability for the random walk to transition to the key node set. By analyzing the change in node importance within the starting subset, we estimate the number of steps required to achieve the desired outcome. Through this methodology, we aim to demonstrate the effectiveness of key node-based recommendations in breaking information cocoons and promoting diverse content exposure.

# 1. The project rationale

Motivation:

“TikTok algorithms may know you better than you do”, “TikTok only takes 15 mins to figure out that I’m gay while my parent spent 20 years to know that”……. These are the words that people use to describe video platforms nowadays. Take us for an example, when we watched a YouTube video to learn the NLP course, then our YouTube homepage will be filled with other courses without your further search. For the users the implementation of this kind of recommendation algorithms provide efficiency as the algorithms simplify the progress of typing the information of video and then selecting into just clicking the videos in the homepage and in the recommendation list. For the video platform, these algorithms help them to keep users and increase their daily or monthly views. However, the video recommendation algorithms will harm users by building an information cocoon room and echo chamber. According to Sunstein (2008), who put forward the theory of information cocoon, in the dimension of information spreading, people’s own needs for information are not comprehensive. As people tend to select the information that they want or can bring them pleasure, the information and idea they come into contact with will become more and more limited over time (Sunstein 2008).

Though someone will think that the information cocoon will only lead to the knowledge of one narrow field, there is a more harmful effect that it will bring, which is the echo chamber. Imagine that you are in a room to speak, where everyone agrees with your idea and brings up more and more information to support you, this kind of environment will repeat and enhance your idea as an amplifier. Just like Sunstein (2008) argued, people will prefer the information that will bring them pleasure but not pressure, it is easy to imagine that people will take the information that supports their idea and keep ignoring the information that they dislike or disagree with. With enough time, people in the echo chamber will become clinging to one's own ideas and be ignorant of other knowledge and opinions. Therefore, the information cocoon itself is not harmful, however, if people in the cocoon only receive single messages, they might become more and more lopsided and misguided. Thus, to avoid this harmful effect that the video recommendation algorithms might have, we need to break the wall of the echo chamber.

In our assumptions, breaking the wall of the echo chamber does not require us to tear the whole information cocoon down, but to enlarge the information cocoon so that there is room for other resources from different areas to provide a variety of information and ideas. With the various information and ideas, the echo chamber will lose its power to enhance one opinion and block other ideas and opinions automatically. To enlarge the information cocoon, we need to create a new video recommendation algorithm that can involve more perspectives and more areas of videos with the ability to provide people with videos from one topic or subject to another. To implement this idea, our assumption is to use graphic neural networks to organize the videos and analyze the relationship between different videos to generate an algorithm to shift the video subjects in certain steps. Because users will prefer videos that related to their current interests rather than randomly recommended videos, the advantages of recommending videos on the edge of two topics is obvious to see. Therefore, we need to compare our methods with the commonly used method and see what improvements we can make and create a practical model that can apply our theories based on the data we select.

Related work

As the largest online video platform, YouTube describes its recommendation algorithm as “developing dynamically as your viewing habit changes” (Goodrow, 2021). In the official blog, Goodrow (2021) listed the features that the YouTube algorithm will take clicks, watch time, survey responses, sharing, likes, and dislikes. However, YouTube does not publicize the codes and models. In that case, we can only search for the papers and studies of YouTube’s algorithm. According to Covington et al. (2016), the methods of YouTube algorithm is divided into two sections. One section filters millions of videos into hundreds by using the vectorize the features of “IDs of video watches, search query tokens, and demographics” and then input into multiple layer of fully connected ReLU before the final feedforward neural network. In the second section, the model uses the desired objective function to rank the videos and select highest videos to recommend. Davidson et al. (2010) gave another algorithm based on the association rule mining method, where they also calculated a related score to rank videos to recommend to users. However, the goal of these algorithms is “to have views of borderline content from recommendations below 0.5% of overall views on YouTube” (Goodrow, 2021). In another word, the algorithm is to make the popular video more popular and reduce the importance of the borderline content. Thus, the algorithm that YouTube use is not suitable for our goal, which is to enlarge the information cocoon and includes more borderline content with fresh idea and information. However, the studies can help us to improve our method by including more features and using layers of filters.

Though TikTok’s algorithms are also interesting, we do not have enough time to do a deep dive into how it works. However, according to Klug et al. (2021), the TikTok algorithm does not only depends on the tags of the video but has the relation of times of repost, likes, and sharing, which also reflect the studies of YouTube algorithms.

Data

Though there is a lot of research about YouTube and TikTok, we choose Bilibili as the video platform to implement our model since we are more familiar with Bilibili as one of the largest video platforms in China. As with TikTok, Bilibili also covers various subjects of videos, as you can imagine. Moreover, Bilibili has its own API for us to scrape data according to the GitHub repo from SocialSisterYi (<https://github.com/SocialSisterYi/bilibili-API-collect>). With the API, we can access videos with their tags, and all the information as a JSON file. However, we have not look deep into the data scraping so we will discuss this part more in the next milestone.

# 2. The research content/objectives of this project and critical scientific problems to be solved

The primary goal of this project is to create a graph neural network-based recommendation system that can pinpoint and recommend pivotal videos to users, effectively disrupting information cocoons by connecting disparate subsets within a video-sharing platform's hashtag-based network. This project aspires to foster a more diverse and balanced consumption of information by motivating users to explore content beyond their usual interests. To achieve this, we will tackle several critical scientific problems, including accurately modeling and representing the video-sharing platform's hashtag-based network using graph neural networks, efficiently identifying key nodes in the graph that bridge different subsets and disrupt information cocoons, and designing an effective recommendation algorithm that balances user preferences with the objective of breaking information cocoons. The effectiveness of this recommendation system will be validated through simulated random walks and analyzing node importance and the number of steps required to achieve the desired outcome. By addressing these critical scientific challenges, this project aims to advance the development of more efficient and balanced recommendation systems, leading to a healthier information ecosystem on social video-sharing platforms.

# 3. The proposed research plan and feasibility analysis

Research Plan:

Our research plan aims to use graph neural networks (GNNs) to recommend videos featuring key nodes within interconnected subsets. We will use video content under a specific hashtag as the basis for constructing GNNs, which will represent ego networks consisting of interconnected subsets. We will then use a random walk simulation to determine the importance of nodes within one of the subsets and assign a probability for the random walk to transition to the key node set. By analyzing the change in node importance within the starting subset, we will estimate the number of steps required to achieve our desired outcome. The specific schedule is as follows.

Weeks 3:

* Data collection and cleaning
* Preliminary data analysis
* Designing the proposed method based on the data analysis
* Developing the proposed method

Week 4-6:

* Developing the proposed method
* Conducting random walk simulations to determine node importance
* Estimating the number of steps required to achieve the desired outcome
* Testing and evaluating the effectiveness of the proposed method

Week 7:

* Comparing the diversity of video content consumed by users before and after receiving key node-based recommendations
* Conducting a user survey to gather feedback on the usefulness of the method

Research Methods:

We will use a combination of machine learning techniques and network analysis to construct and analyze GNNs. We will use a random walk simulation to determine the node importance and analyze the results to estimate the number of steps required to achieve our desired outcome.

Evaluation Methods:

We will evaluate our approach by comparing the diversity of video content consumed by users before and after receiving key node-based recommendations. We will also conduct a user survey to gather feedback on the usefulness of our approach.

Key Technologies:

Our research will leverage key technologies in graph neural networks and machine learning. We will use GNNs to model the interconnected nature of video content and recommend key nodes to promote diverse content exposure. Graph Neural Networks (GNN) provide a unified framework to model rich data structures, especially in recommendation systems, where graph-based data is prevalent (Shiwen, 2021). GNN can effectively learn user-item interactions by capturing high-order dependencies through iterative message propagation. Additionally, GNN can integrate auxiliary information, such as social relationships or knowledge graphs, into the network structure. In academia, numerous studies have shown that GNN-based models outperform previous methods like , and many variants have been proposed and applied to various recommendation tasks, including session-based recommendation, Points-of-Interest (POI) recommendation, group recommendation, and bundle recommendation. In industry, GNN has been deployed in large-scale recommendation systems, such as Pinterest's PinSage model, which has achieved a significant increase in user engagement in online A/B testing on a graph with 3 billion nodes and 18 billion edges (Shiwen, 2021).

We will also use machine learning techniques to analyze the data and evaluate the effectiveness of our approach.

Feasibility Analysis:

Our research plan is feasible given the availability of data, computational resources, and existing tools and techniques in graph neural networks and machine learning. Although traditional deep learning methods have achieved great success in extracting features from Euclidean space data, many real-world applications generate data from non-Euclidean spaces, and the performance of traditional deep learning methods in processing non-Euclidean space data remains unsatisfactory. For example, in e-commerce, a graph-based learning system can use the interactions between users and products to make very accurate recommendations, but the complexity of the graph makes existing deep learning algorithms face huge challenges in processing it. This is because the graph is irregular, each graph has a variable number of unordered nodes, and each node in the graph has a different number of adjacent nodes, making some important operations (such as convolution) easy to compute on images, but no longer suitable for graphs. In addition, a core assumption of existing deep learning algorithms is that data samples are independent of each other. However, this is not the case for graphs, as each data sample (node) in the graph will be related to other real data samples (nodes) in the graph through edges, and this information can be used to capture the interdependence between instances (Zonghan, 2019).

However, there may be limitations to the accuracy of our results due to the stochastic nature of the random walk simulation and potential biases in the data. Additionally, user privacy concerns may limit the availability of data for analysis. We will address these limitations by conducting sensitivity analysis, using appropriate data preprocessing techniques, and ensuring that user data is anonymized and aggregated before analysis.

# 4. Features and innovations of this project and the expected results

This project features several innovations, including the use of Graph Neural Networks (GNNs) for accurate modeling and representation of video-sharing platforms' hashtag-based networks, a novel approach to identifying key nodes connecting different subsets, a balanced recommendation algorithm that considers both user preferences and the goal of breaking information cocoons, and a unique random walk validation method to assess the system's effectiveness. The anticipated results include a robust GNN model representing relationships between videos under a specific hashtag, efficient key node identification to bridge network subsets and disrupt information cocoons, a recommendation algorithm that successfully balances user preferences and diverse content exploration, and quantitative validation of the system's performance through random walk simulations. These achievements will contribute to the development of more effective and balanced recommendation systems for social video-sharing platforms, fostering a healthier information ecosystem.

This project proposes several features and innovations to improve the recommendation system of a video-sharing platform. Firstly, it suggests leveraging Graph Neural Network (GNN) modeling to capture the relationships between videos under specific hashtags. Secondly, it proposes an innovative approach to identifying key nodes that can bridge different subsets of the network, promoting diverse content exploration and breaking information cocoons. Additionally, the project proposes a recommendation algorithm that balances user preferences with the goal of encouraging users to explore a wider range of content, fostering a healthier information ecosystem. Finally, the use of random walks to validate the recommendation system's performance provides a novel approach to assessing the system's effectiveness in breaking information cocoons. The expected results of this project include an accurate GNN model, efficient identification of key nodes, a balanced recommendation algorithm, and a quantitatively validated recommendation system that promotes diverse content exploration, ultimately contributing to the development of more effective and balanced recommendation systems for social video-sharing platforms.

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