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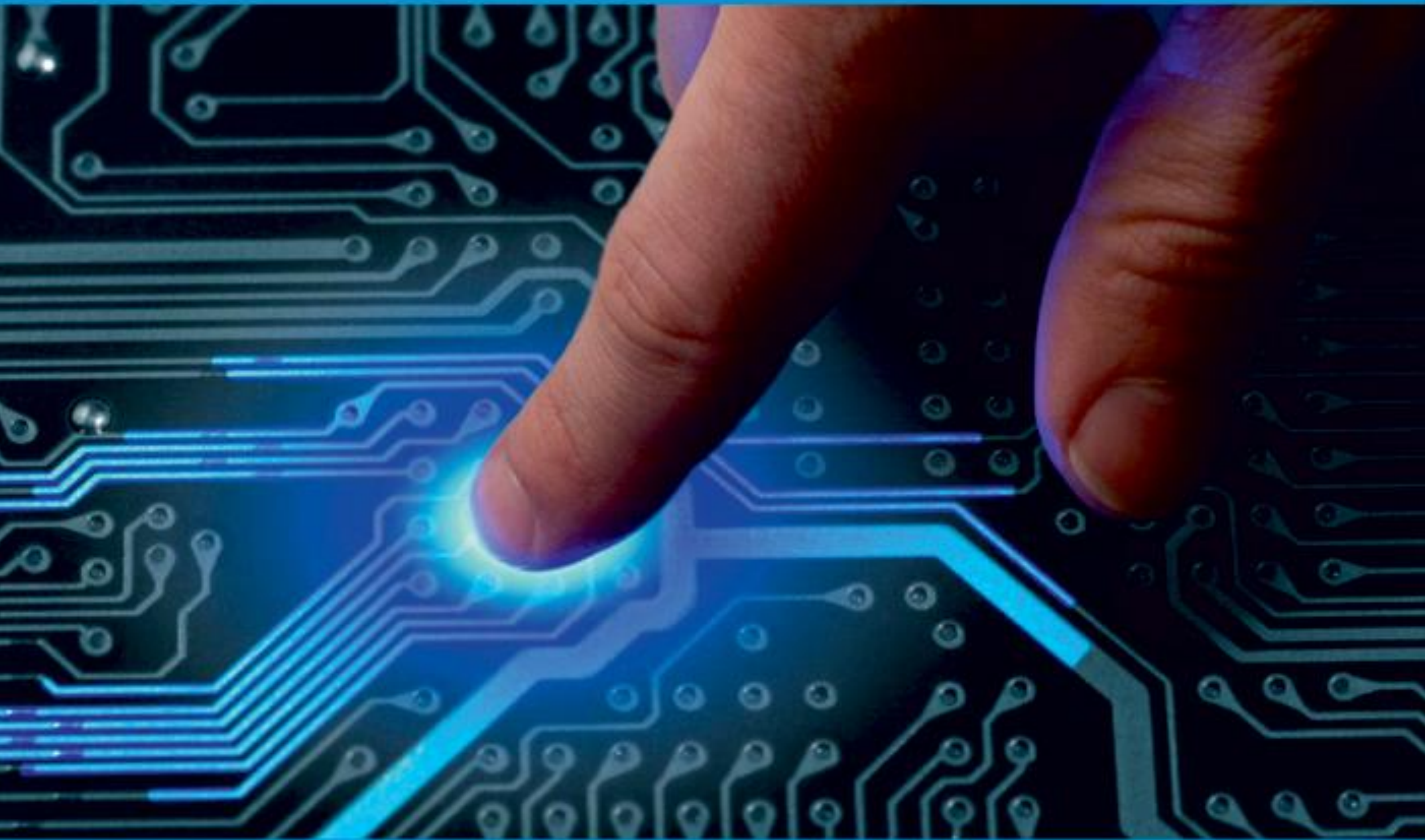

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E Commerce Product Recommender System Based on Hybrid Collaborative Light GCN

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ABSTRACT: When working with data that is naturally structured as graphs or networks, Graph Learning has a number of advantages over other machine learning techniques. This is evidenced by the recent rapid development of the field. It performs well in a variety of real-world applications, including biological networks, community identification, drug discovery, recommender systems, and social networks. in that a well-liked architecture called the Graph Convolution Network (GCN) offers a wide range of uses, including suggestions Personalised recommendation systems based on the preferences and interactions of users in a graph can be created using GCNs. GCNs can be used, for instance, to suggest films to users based on their prior viewing behaviour or to suggest products to users based on their prior purchasing behaviour. We develop a new method using collaborative filtering method that can be given to the light GCN architecture, which is the lighten and avoiding complicated layers of GCN for easy implementation and training, and our approach is given significant improvements in an Amazon product review dataset. In this work, our goal is to integrate the user-item interactions more can be mapped as bipartite graph structure into the embedding process.

KEYWORDS: Collaborative Filtering, Recommendation System, Graph Learning, Graph Convolution Networks.

I. INTRODUCTION

Personalised recommendations are widely used in internet services including social media, markets, e-commerce, and movie recommendations. Its fundamental function is to predict user adoption rates based on past interactions like clicks and transactions. One of the most common and significant uses of artificial intelligence (AI) is recommender systems, or RS. They have been widely used to make it simpler for users of numerous well-known content sharing and e-commerce websites to locate pertinent content, goods, or services. Meanwhile, Graph Learning (GL), a recently created AI method that applies machine learning to data with a graph structure, has recently shown off its enormous potential. A common method used in recommendation systems to forecast a user's preferences based on the preferences of similar users is collaborative filtering. It functions by looking at big datasets of user behaviour, such movie preferences or product evaluations, and finding patterns that show which products are most likely to be favoured by a specific user. Collaborative filtering can generate precise recommendations even for users with scant or insufficient data by drawing on the collective expertise of numerous individuals.

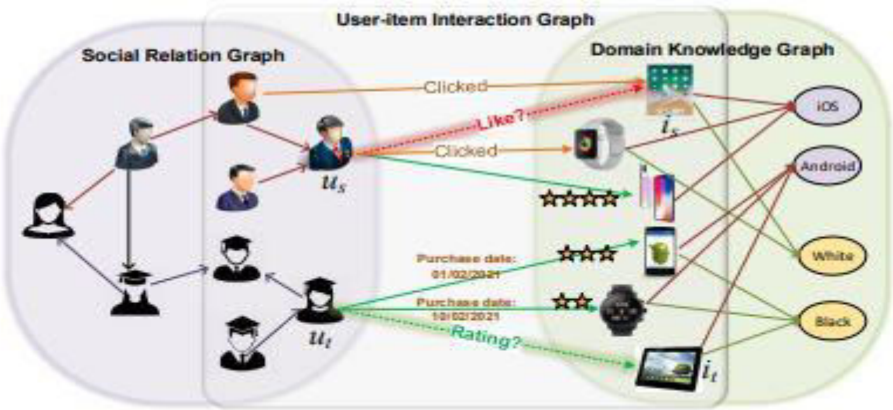

Figure 1 User Item Interaction Graph

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Graph learning has become a potent technique for deconstructing intricate data structures and formulating predictions from them. The purpose of recommendation systems, where graph-based algorithms have been effectively implemented, is to forecast a user's preferences for goods based on their interactions with a set of goods or services. Because individuals and things are represented as nodes in a graph and interactions between them are represented as edges, graph-based methods can capture rich relationship information that is sometimes overlooked by conventional techniques. This makes recommendations more customised and exact, even when there is few or no data. in order to ensure the reliability of recommendation systems.

II. RELATED WORKS

The most relevant research for this task is model-based graph neural network-based methods and collaborative filtering-based RS. Here, we draw attention to the differences between our shared light GCN. In order to review the relevant works in more detail.

Light GCN uses a straightforward graph propagation method that just requires multiplying the feature matrix by the graph Laplacian to simplify the graph convolution operation, which is computationally expensive and challenging to optimise [1] and the neural graph collaborative filtering (NGCF), a new recommendation method that takes advantage of the user item graph structure by propagating embedding on it. This results in the explicit injection of the collaborative signal into the embedding process and the expressive modelling of high-order connections in the user item graph [2] while in Deep learning models called convolutional graph neural networks (GCNs) can operate directly on graphs and other non-Euclidean data structures. They gather data from nearby nodes in the graph using convolutional filters, which enables them to identify regional structural patterns and features. GCNs include advantages such as handling variable-sized graphs, being good at capturing complicated dependencies and relationships between nodes, and having a wide range of applications. Their susceptibility to graph heterogeneity and sparsity, as well as their high computing cost for big graphs, are notable drawbacks [3] and The Graph Learning Recommendation Systems are based on graphs, in contrast to other RS systems like content-based filtering and collaborative filtering, where significant elements like people, items, and qualities are either explicitly or implicitly associated. Exploring and using homogeneous or heterogeneous connections in graphs is a potential technique for producing most effective RS given the rapid development of graph learning algorithms. [4] Gaussian Mixture Model (GMM) can be used to determine the predicted activation of neurons in the first hidden layer of GCN, preventing data from being missed in the GCN process when the graph data is not connected (missing features) [5].

III. PROPOSED WORK

Since light GCN removes nonlinear activation functions, the proposed solution is intended to improve the work that has already been done in order to further optimise for better training. Rather than adding any activation functions, however, we choose to use collaborative filtering. which is included, the user-item matrix may be further decomposed using the SVD approach, and it can be mapped to the user and the items as various nodes, and their interactions as edges, to provide input as a bipartite graph for training and testing in the light GCN.

SYSTEM ARCHITECTURE

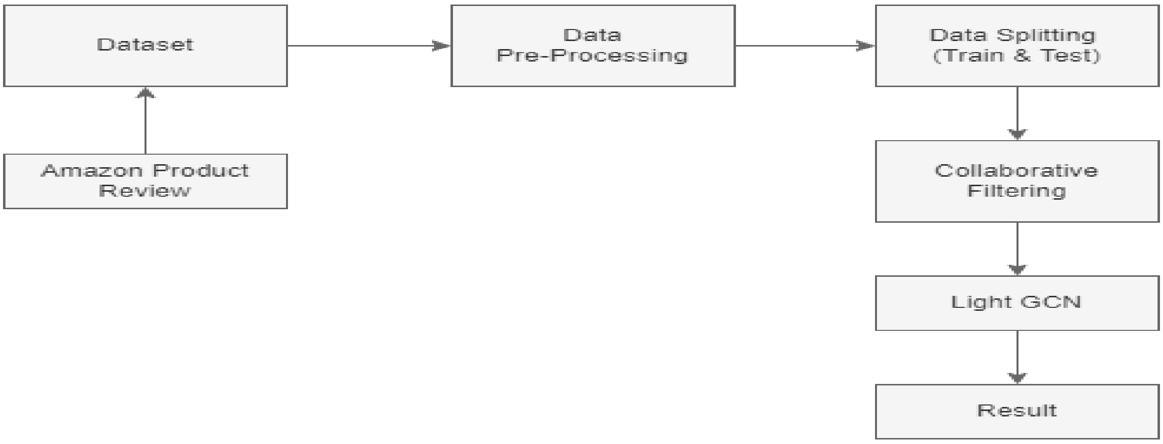

Figure Proposed Architecture Diagram

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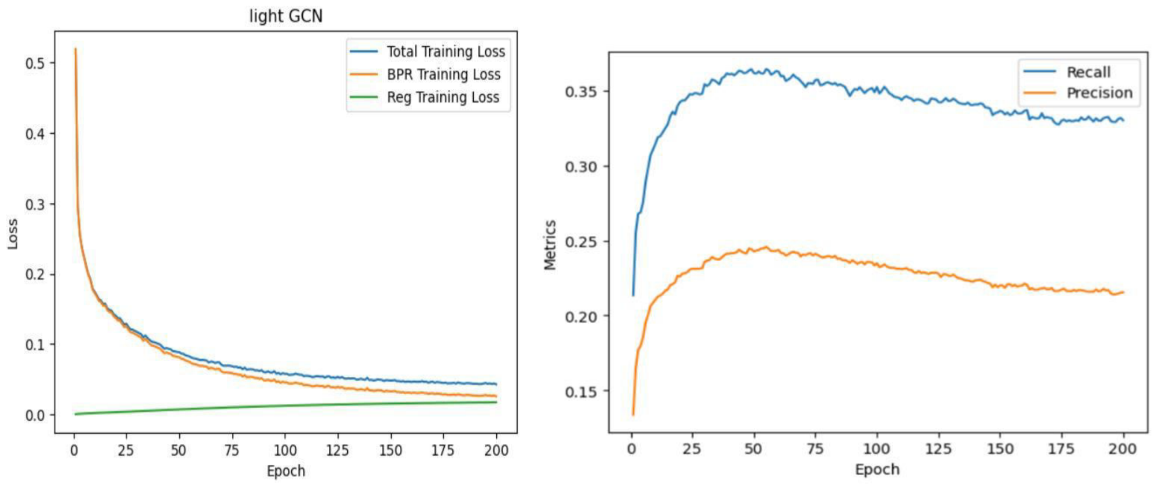
The dataset can be pre-processed to check for missing data and take the nodes we needed, and the data set can then be further divided as 80% for training and 20% for training.
Collaborative filtering method is used to get user-item interaction matrix, which can be decomposed by a number of different methods. In our system, we can take the Amazon product review dataset for building recommendation systems suggesting products to the users based on purchase history and their interactions with users which give better results even when the data is limited.

IV. COLLABORATIVE LIGHT GCN ALGORITHM

1. Initialize user and item embeddings
2. Normalize the adjacency matrix
3. Collaborative filtering with SVD
4. Train the model for number of epochs
5. Propagate item embeddings through each layer
6. Define the light graph convolutional layer
   $H0=XHl+1=A\hat{}HlZ=HL$
7. Compute the loss and gradients
8. Return the learned embeddings.

V. RESULTS & DISCUSSSION

The dataset can be trained for a recommendation system, but there will be loss during training. To measure and minimise this loss, BPR loss, which is based on the idea of ranking pairs of items in the context of a user, can be used. The objective is to learn a model that can rank the items so that the item the user interacted with is ranked higher than the item they did not interact with, given a user and two items.



The accuracy of the system's recommendations is then used to determine how effective the system is for this purpose. In this test, we use the precision and recall values of collobarative light GCN, which are common accuracy measurements.

VI. CONCULSION

In this work we develop the system where Products can be suggested to the user based on previous purchases and interactions, which can be processed in the convolution message passing process of the light GCN in order to find more similar interactions between nodes' edges. We put forth a system in which the user-item matrix from collaborative filtering may be used as nodes and edges, which can then be reduced using SVD, and these mappings are employed as graphs for the light GCN. Although we are aware of different types of sampling techniques, we only employ micro batch sampling for straightforward, equal batches of data. However, as connected graph data is increasingly common in practical applications, we predict that graph-based models will become more and more crucial in the future recommendation systems.

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