Graph Neural Networks for Recommender Systems

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***Index Terms*—Graph, Graph Embedding, Graph Convolutional Network, Recommender System.**

I. Introduction

Introduction should have background of the problem, problem description, motivation behind picking this problem, and methodology being employed, and short results summary. (approximately 1000 - 1100 words)

II. Related work

We have explored some articles about the topic of our projects. Currently we have read how our initially chosen data set of Amazon Product co-purchasing networks has been used already. First two papers below are covering this topic. We were also interested what algorithms have been used for Recommend Systems and we found lot of material about it. First three papers cover shallow algorithms. And, as our final goal is to implement Graph Convolutional Network, then half of the current papers cover different GCN topics. For the beginning, we have shortly described the papers and later we will find the connections with our project work.

A. Analysis of Product Purchase Patterns in a Co-purchase Network

Article [1] analyses the Amazon co-purchase network from the dynamic aspect. Analysis is done based on sub-category instead of item IDs for better pattern clarity. It is shown that patterns present in time t-1 are also present in time t with high probability. The authors suggest using Markov chain model on this type of data for implementing generalized recommendation system.

B. Rank the Top-N Products in Co-Purchasing Network through Discovering Overlapping Communities Using (LC-BDL) Algorithm

Paper [2] focuses on overlapping community detection algorithm based on cliques and finding top N nodes in those communities. Maximal cliques and then overlapping communities among them are identified. Top N nodes are either ranked by overlapping frequencies or by occurrence frequencies in the adjacent sub cliques that combine the discovered communities. Results obtained are evaluated using clustering coefficient and cluster density. Named techniques have also been applied on Amazon co-purchase network data.

C. entity2rec: Property-specific knowledge graph embeddings for item recommendation

entity2rec [3][4], based on node2vec [5], is tailored for Knowledge Graphs and measures user-item relatedness for top-N item recommendation. It works by creating property-specific subgraphs and finding their corresponding embeddings using node2vec. From there, similarity measures can be calculated. The advantage of entity2rec is that features can be clearly interpreted, and it works well on sparse datasets. It outperforms other commonly used collaborative filtering techniques and has slight advantage over node2vec.

D. Graph Convolutional Neural Networks for Web-Scale Recommender Systems

Paper [6] introduces GCN algorithm PinSage which combines random walks and graph convolutions to generate embeddings of nodes involving the graph structure and node feature information. PinSage is made for large scale graphs, and it is deployed at Pinterest. PinSage comes with new fundamental advancements in scalability (Big Data flavors) and introduces new training techniques and algorithmic innovations (random walks, importance pooling). PinSage results, the graph embeddings are further used in nearest neighbour lookup for recommendations or for use in a re-ranking system.

E. Knowledge Graph Convolutional Networks for Recommender Systems

KGCN [7] uses the Knowledge Graph which is usually a directed heterogeneous graph where nodes correspond to items or item attributes, while usual GCNs use mostly homogeneous graphs which nodes represent solely items. KGCNs are able to capture both the high-order structure and semantic information of the Knowledge Graph. This neural network can also learn user's current and potential interests with the help of receptive field which can be extended multiple hops away from node. KGCN uses techniques that help to train it on large scale data.

F. Structured Graph Convolutional Networks with Stochastic Masks for Recommender Systems

In the paper [8] it is pointed out that key function of GCNs is neighbourhood aggregation mechanism while real-world user-item graphs are often incomplete and noisy. It causes low performance for all graph embeddings as the aggregations are used recurrently. Authors' goal was to utilize the graph properties as the sparsity and low rank to alleviate this problem. SGCN uses NGCF and LightGCN as backbone algorithms and implements additionally the stochastic gradient mask to gain clean and sparsified graph and the nuclear norm regularization to maintain the low-rank property. Both methods appear in final loss function as regularization methods.

TABLE I
DESCRIPTION OF PROVIDED DATA

Field	Description
Id	Product ID (numbers from 0 to 548551)
ASIN	Amazon Standard Identification Number
Title	Name or title of the product
Group	Product group (Book, DVD, Video, Music, etc)
Salesrank	Amazon Salesrank
Similar	ASIN of co-purchased products
Categories	Location in product category hierarchy to which the product belongs
Reviews	Product review information: date, user id, rating, total number of votes on the review, total number of helpfulness votes

III. DATASET

As the purpose of the project is to create **recommender system**, we needed some customer and product data. We found the Amazon product co-puchasing network metadata a good initial dataset. This open data was fetched from the page of Stanford University https://snap.stanford.edu/data/amazon-meta.html. This dataset provides 548,552 products with 1,788,725 similar product-product connections, 7,781,990 customer reviews and ratings for products by date and much more. The products are divided into product groups from which we selected the biggest groups: Books, Music, Video and DVD. This dataset is from year 1995 till 2006. So, the data is quite old, but very big and good enough for a toy dataset. See the field descriptions in the table I.

The initial dataset is given as a text file which is read into pandas dataframe with specific function written by ourselves. It is then cleaned more and divided into different dataframes. Several analysis is done on the dataset and based on that we have applied some filters for selecting the most interesting part of the data. First, we selected only products from four product groups. Secondly we selected only those product-product connections where both products have additional data like title, product group, sales rank, etc. Named filters give us the undirected graph of product-product relationships which properties can be seen in the second column of the table II.

Customer reviews on the products give the relationships between customers and products. These links are used to create the bipartite graph with nodes of customers and nodes of products. As a result of filters we are left with fewer nodes and edges also in bipartite graph as seen in the last column of table II.

The code of fetching data from source file and data cleansing is provided in Notebook.ipynb with some additional python files with necessary methods. Strategic intermediate results are saved into csv files. So, it is not mandatory to execute all the code for the final steps. All needed files can be found in our Github repository. Readme file guides the user through the neccessary steps.

TABLE II
MEASURES OF PRODUCT-PRODUCT GRAPH AND CUSTOMER-PRODUCT BIPARTITE GRAPH

Measure	Product-Product	Customer-Product
No of nodes	296,458	639,793
No of edges	236,429	410480
Transitivity	0.0071	0.0
Average clustering	0.0072	0.0
Edge density	5.3803e-06	2.0056e-06
Average degree	1.5950	1.2832
Total triangles	3372	0
No of connected components	61,292	229,313

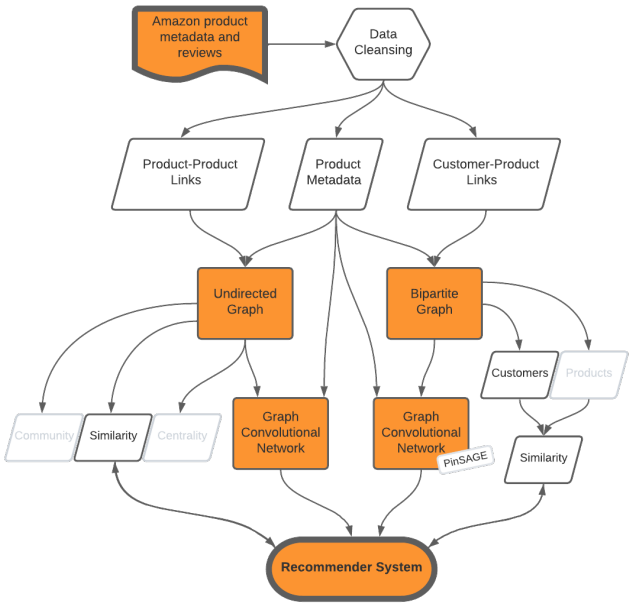

Fig. 1. Methodology flowchart

IV. METHODOLOGY

The main goal is to create a recommender system based on a graph neural network. Our methodology for achieving it is as in figure 1. We started with searching a relevant dataset which we found from Stanford University homepage. In dataset of **Amazon product co-purchasing network** is provided huge number of products and customers and connections between them.

We used the product-product relationships for constructing an undirected graph and the customer-product relationships for creating the bipartite graph. After the graph creation we made the standard graph analysis. It is needed to research the basic measures as number of nodes and edges, transivity, density, number of connected components, etc. Also, it is good to calculate the centrality and similary measures and find communities. We find especially the similarity measures as baselines for the recommendations.

We are not making any graph calculations for neural networks as inputs. Only the graphs can be used to build and train the network for recommendation system. Graph traditional statistics are used as baselines for comparison purposes.

V. Results

Here you should have some Qualitative (Visualizations), Quantitative (Tables, numbers, etc.)

VI. Conclusion

No more than 300 words.

VII. Github

You may find our GitHub Repository at the link https://github.com/h31d1/network_science. The **Readme File** guides how to find the necessary information from the notebook and code.

References

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