Journal of Theoretical and Applied Information Technology
15th August 2021. Vol.99. No 15

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

DEEP GRAPH EMBEDDINGS IN RECOMMENDER SYSTEMS: A SURVEY

[1]AMINA SAMIH, [2]ABDERRAHIM GHADI, [3]ABDELHADI FENNAN
[1,2,3] Computing, Systems and Telecommunications Laboratory, Faculty of Science and Technology,
Tangier, Morocco
E-mail: [1] amina.samih@etu.uae.ac.ma, [2]ghadi05@gmail.com,[3]afennan@gmail.com

ABSTRACT

In recent decades, the increasing quantity of products and services offered the possibility of collecting significant amounts of data, which require new techniques to sort it. Rather than manually filter these large quantities of information, it provides changes over time. Recommender systems help suggest articles to read on smartphones, posts to watch on Facebook, books to buy on Amazon. Their goal is to personalize data to increase the use of a service or to enable more sales. Their influence is not just a technical and commercial necessity. They have also become a part of the evolution of the human mass and his\her ideas. Because a book or a newspaper is not just a commercial object, many current recommendation techniques are challenged by information overload, which poses many issues like high cost, slow processing of data, and low time complexity. For this reason, many researchers in this field use graph embeddings algorithms in the recommendation area, as the last few years have also seen the success of these algorithms, especially the ones based on deep learning. Current recommender systems based on these algorithms have shown that they can obtain exciting results and improve the quality of recommendations offered to users. In this survey, we present an overview of recommender systems and graph embeddings based on deep learning. Then we provide a literature review of recent recommendations works based on deep graph embeddings to make a pragmatic analysis and showings common limitations.

Keywords: *Recommender Systems, Graph Embeddings, Deep Learning, Deep Graph Embeddings, Hybrid Recommendation.*

1. INTRODUCTION

Recommender Systems are powerful tools that help online users to solve the information overload problem [1]. Today; Those personalization systems present the most relevant content to users, using specific information about their past preferences [2]. Recommender Systems use profiles representing relatively stable user preferences to calculate recommendations [3]. They do this calculation by predicting the scores a user is likely to assign to the content.

Today many fields use these systems. As proof, they are present in online stores like Amazon, streaming services like Netflix or Spotify, or even specific recommendation systems for content-based advertising. These recommendation systems share the same principle. They filter among many objects likely to be of interest to the buyer (customer au lieu de buyer) (whether they are products, books, films, etc.).

The main Recommendation strategies are collaborative filtering (CF)[4], content-based filtering (CBF)[5], or a combination of these two approaches or more[6].

Recently graphs have been mainly applied to recommender systems to manage many challenges like the cold start problem [7]. Some researchers have put forward the application of diagrams to learn the correlation between users or items. With the vectors of users or elements mapped on the network, we can discover some latent relationships. For example, Shameem Ahamed Puthiya Parambath and al. have put forward a method applied to recommendation systems based on a similarity graph [8]. Li Xin et al. have proposed an approach based on the kernel graph to learn the relationship between users and items [9]. Yuan Zhang and al. have proposed a method based on charts and etiquette for recommender systems [10].

Generally, graph analysis in the recommendation area allows the use of implicit information, whose objective is to recommend, predict, classify nodes [11] in addition to predicting links [12], etc. Take the example of a graph-based on users' information from an e-commerce site specializing in household appliances. If we analyze it, we can recommend articles to users, define new communities, predict similar users, indicate links between users and recent items [13].

Despite the importance of graph analysis techniques, the general use of recommendation systems led to an increasingly extensive and sparse network of information networks representing the user and item content and their interactions.[62]

what makes the networking process a complex task for many existing techniques computationally expensive. Therefore, Graph embeddings algorithms are proposed to overcome these challenges by incorporating vertices into low-dimensional space vectors while retaining the topology and vertex structure of the network [63].

Graphs embedding [14] appears as a solution that aims to present the properties of graphs in a vector or a set of vectors in a low-dimensional space while preserving the graph's topology much as possible that offers more accurate recommendations.

Graph embeddings can be classified into three main categories [15]: factorization graph embedding, random-walk graph embedding, deep graph embedding.

Our interest is in the third category ;To our best knowledge, our survey is the first review of state-of-the-art deep graph embedding-based recommender systems on improving recommendation.

Contributions of this work: Our paper summarizes significant contributions:

1. A comprehensive study on the emergence, classification criteria of recommendation systems and deep graph embeddings algorithms.
2. Comprehensive literature: we give a comprehensive overview of current recommender systems based on deep graphs embeddings. We provide detailed descriptions of representative models, compare them, and discuss solutions to practical issues such as cold start, scalability.
3. Works analysis: we analyze existing studies in this field and define standard keys. We highlight the limitations and determine future directions.

In this regard, The rest of this paper is classified as follows:

1) In section 2, we propose a background of essential preliminaries in our study.
2) In section 3, we analyze deep graph embeddings in recommendation approache.
3) In section 4, we discuss the analyzed studies and suggests future research directions.
4) We conclude our work.

2. BACKGROUND

This section aims to present the background of our survey's two main components, Recommender systems, and deep graph embeddings.

2.1 Recommender systems

2.1.1 History

The recommendation is an ancient term used during ancient civilizations to address many issues such as which religion to follow, culture, crafts, and organized marriages. Nevertheless, the idea of recommender systems started to gain prominence after the industrial revolution due to the increase in the number of available products. Currently, aspects of modern life are becoming numerous, and we are lost in front of this information overload. These systems compare available data by recommending a single or a list of objects to active users while respecting their interests. These recommendations may relate to an article to read, a book to order, a film to watch or a restaurant to choose from, etc.

Among the first proposed approaches, we cite [17]-[19] and their respective approaches Tapestry, GroupLens, Ringo. We present the principle of each method in table 1.

Table 1. The First Proposed Approaches Of Recommendation

Auteur	Approche	Principle
[Rich, 1979][16]	Grundy	This approach categorizes users into "stereotypes" based on a short interview and uses those stereotypes to produce book recommendations. This work is the first step in the field of RS. However, its use has remained very limited.
[Goldberg and al., 1992][17]	Tapestry	Tapestry recommends to groups of users documents from newsgroups that may be of interest to them. The approach used is of the "nearest neighbors" type based on user history. This method is called manual collaborative filtering.
[Resnick and al., 1994][18]	GroupLens	GroupLens is a research lab that works explicitly on automatic recommendations in the Usenet news forums.
[Shardanand and Maes, 1995][19]	Ringo.	Ringo is interested in musical albums using collaborative filtering, but it also uses a manual item annotation system.
[Hill and al., 1995][20]	Bellcore	A video recommendation system.
[Herlocker, 1999][21] [Breese and al., 1998][22]	Movielens Eachmovie	The two approaches recommend movies to users based on their preferences, using collaborative filtering of their members' movie ratings and reviews.

2.1.2 Recommendation approaches

Several factors categorize recommendation systems [23].

a) Knowledge of users (their profile according to their tastes).

b) The positioning of a user with others (the notion of user classes or networks).

c) Knowledge of the items to recommend.

d) Knowledge of the different categories of articles to recommend.

These factors produce various types of recommendations. The most used in the literature are content-based filtering, collaborative filtering, and hybrid recommendation [24].

Content-Based Filtering:

As the name suggests, it uses the item's attributes to make recommendations, such as genres and types of songs, styles, categories of movies. It is based on the content information to make recommendations and does not need to use the user's evaluation opinions on the product [25].

This algorithm analyzes a set of content without taking users into account (at least not at first) and detects similarities for recommendation [26]. The content analysis consists, for example, of identifying the subject of a piece of content by listing all words of a press article (except stop words) then by comparing all the terms of the analyzed report to other items. The more an article has several similar words, the more we consider these articles "close," making it possible to detect similar subjects and deduce recommendations for the reader from them [27].

Collaborative Filtering:

It is a personalized prediction method based on the history of ratings given by users. The underlying assumption is that if several people have common interests in certain things, then those interests are likely to extend to other products [6].

As its name suggests, it works by using the power of collective intelligence and filters elements that interest users. Collaborative filtering work with the premise that the right way to find content that a particular user is interested in is to find other users who have similar interests with that user and then recommend the content that interested them to this user. We can categorize collaborative filtering recommendations into memory-based collaborative filtering (memory-based CF) recommendations and model-based collaborative filtering (model-based CF) recommendations depending on which machine learning algorithm we use [26][27].

Hybrid Recommendation:

As the name suggests, the hybrid-based recommendation is a fusion of the above algorithms or more [28]. It uses components of different types of recommendation approaches or relies on their logic to solve problems like cold start and sparsity [29].

It merges two or more recommendation approaches differently to benefit from the collaboration of their strengths. The most popular hybrid recommendation is that it utilizes both features and user ratings, that is, the combination of content-based filtering and collaborative filtering [26].

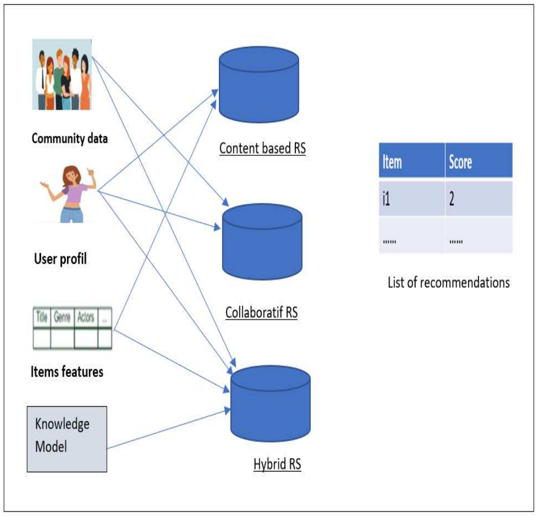

Figure 1: Principles Recommendations Approaches.

In addition to the three main approaches, we can cite more additional sub approaches.

Demographic Recommendation:

It is a simple recommendation that offers items concerning the user's demographic profile [30]. It involves dividing users into several classes or groups based on demographic information such as gender, age, profession, location, language, country.

This approach's principle is that two users who have evolved in a similar environment share familiar tastes more than two users who have grown in different environments [31].

Knowledge-based Recommendation:

It offers recommendations that already exist in databases or knowledge bases and are therefore not dynamically influenced by recent ratings or preferences [32]. They are divided into two sub-categories [33]:

- Case-based systems use case-based reasoning, which relies on the similarity between a current case and existing solutions in a database.
- Constraint-based systems use a given set of preferences; constraint-based systems provide a set of possible solutions, including explanations of why they selected those solutions.

Psychological knowledge-based recommendation

When a user accesses a website and makes decisions, they come from the subconscious, so people do not know and cannot say why they took their decisions. Therefore, developers of recommender systems need to study psychological aspects to understand these interactions better to create a system as effective as possible [34].

Context-aware recommender systems:

Integrating context into recommendation systems adds a dimension of complexity to the recommendation data model, as ratings may be valid in only one particular context. A vector of context attributes can describe the context, for example, time, place, or currently available network bandwidth in a mobile scenario. The actual context attributes used depend mainly on the application domain [35].

2.2 Deep learning-based Graph embedding

Graphs are widely used in various fields of modern life to model information [13][36] such as social networks, which are in reality only large graphs of people connected (person1 follow pesrson2), knowledge graphs [6].

Graph embeddings appeared at the beginning of the year 2000 as a part of dimensionality reduction [37] whose objective is to transform a graph of n nodes with a space of dimension D, into a reduced vector space of dimension d, where d < D, while preserving the neighborhood between the nodes in the vector space [38]. Except that the scalability was the challenge of this logic, researchers in this field started proposed methods that take into account the networks' scalability.

Most of the graphs of real applications are dynamic. Let us assume the example of an Instagram page of a famous artist; the number of followers increases every second, so the graph representing these followers must be dynamic since new links added over time. Similar to [15], we can classify graph embeddings methods into three categories:

1. Factorization based graph embeddings algorithms, we can cite LLE [39], Laplacian Eigenmaps [40], Graph Factorization [41].
2. Deep learning-based graph embeddings algorithms (the focus of this survey) like Graph Convolutional Networks [42].
3. Random walk-based graph embeddings algorithms as node2vec [43], Walklets [44].

The growing success of deep learning (DL) in the research field has led to applying deep neural network methods on graphs "DL based graph embedding methods" [15]. We can classify these methods into two categories [14]:

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

- DL-based Graph Embedding with Random Walk: we present the graph in this category as a set of samples of random walk paths from it, then a Dl technique is applied on the sampled tracks to embed the graph and preserve paths properties of the input graph. DeepWalk[45] is a famous example of this category, which uses a neural language model (SkipGram) to incorporate the graph.
- DL-based Graph Embedding without Random Walk: we apply deep models directly to the whole graph. The most used deep models in this category are:
  i) Deep Autoencoders [46]: have mainly been used for graph embedding due to their ability to represent the data's non-linear structure. Recently, many techniques in this field extended this ability to produce embeddings with preserving non_linearity in graphs.
  ii) Deep Neural Network[24][45]: the drawback of autoencoders-based embedding is sparse graphs' expansivity. Researchers used Graph Convolutional Networks and its variants to tackle this challenge that can aggregates embedded neighbors for a given node based on an iterative manner. The algorithm uses both embedding and embedding at the previous iteration to have the new embedding.

3. LITERATURE REVIEW

This section analyzes recent studies in the literature for recommender systems based on deep graph embedding. The reviewed works selection relies on two criteria, their recentness (date of the work) and their impact (number of citations).

Okura and al. [47] proposed an embedding-based method consisting of three steps, they initially used a denoising autoencoder to find news representations from news texts and adopt the recurrent neural network (RNN) to learn users' characteristics from their historical data. They calculated the similarity between the news and users' features to obtain the information preferred by them. The experiments carried out by the authors have proved the effectiveness of their method even with large-scale traceability systems.

To solve the problem of parsimony and cold start in the video recommendation field. Anna and al [48] proposed a deep auto-encoder method with convolutional text networks. This approach uses auxiliary information of users and elements processed and deeply extracted. They use four data preprocessing layers to make the extraction, incorporating layers, convolutional network layer, sharing layer, and automatic encoder layer of the proposed model. Then they conducted, the final predictive evaluation in multilayer perception to make the combination. The experiments carried out have shown the effectiveness of the proposed method.

[49] proposed a convolutional random walk graph (GCN) network named PinSage.That can learn vector representations of elements in large graphs containing billions of nodes. The proposed algorithm simulates random walks from the target nodes; it chooses the higher K nodes with the highest normalized number of visits. This method paves the way for recommendation systems based on a convolutional network of graphs to the ladder web.

In [50], the authors proposed a recommendation approach based on HIN (heterogeneous information network). This method uses the embeddings of heterogeneous networks called HERec; this method adopts meta paths to generate users and items' embeddings in a heterogeneous network with Deepwalk [45], then uses them in the recommendation process. Authors proposed three variants of this algorithm with different merge functions:

- The first variant with the simple linear merge function.
- The second variant with the custom linear merge function like HERecplare.
- The third variant with the custom nonlinear merge function like HERecpnlused.

The three variants used as reference models, numerous experiments on three real data sets have demonstrated the effectiveness of HERec.

In [51], the authors proposed a multi-criteria recommendation system to integrate user review embeddings going through three stages. They first used autoencoders to represent user reviews in a latent vector space, compress the embeddings into low-dimensional discrete vectors, and finally use the resulting compressed vectors to constitute a multi-latent-criteria in the recommendation process.

Li and al. [52] proposed a hashtag recommendation system for micro-videos by presenting a new model of embeddings (Graph Convolutional Network is used to generate the nodes' embeddings) that ensures the interactivity between the multi-view representations with the propagation of information. The authors' principal goal is to improve the quality of hashtag recommendation by considering three components: the sequential learning of the functionalities, the video-user-hashtag interaction, and the hashtag correlations. Experiment results prove that the proposed model surpasses the performance of traditional models of hashtag recommendation.

In [53], the authors proposed a recommendation model that uses a heterogeneous information network method based on the prediction of user behavior called HINE.

The HINE model uses a network connection, user network structure, and user behavior tag information to predict user behaviors, using low dimensional vectors generated by user network embedding.

Experiments have verified the superior effectiveness of the proposed approach on complex real-world data sets.

Yi and al [54] proposed deep learning (DL) recommendation model based on collaborative filtering, namely deep matrix factorization (DMF), which can integrate any information.

DMF uses two characteristic transformation functions to generate user latent factors and input information, including implicit feedback built into using a new method called IFE Implicit Feedback Embedding to integrate high dimensional implicit feedback information into a low dimensional real value vector space. The results of the conducted experiments show the effectiveness of the proposed technique.

In [55], the authors proposed a Named Knowledge Graph Convolutional Network (KGCN) model. Wich uses additional element information (attributes, ...) to find high-order structural information and semantic information of the constructed knowledge graph(kg); they used each neighbor entity in the KG to do the combination bias when calculating the integration of a given entity. The model's power is that it can both model order proximity information and preserve users' interest in the long term.

In [56], the authors proposed a recommendation method based on heterogeneous network integration called HetNERec.

The model uses a heterogeneous co-occurrence network to learn the embeddings of users and Items. It makes one representation to each node by combining its resulting vectorial representations from the beginning, then integrates these unique embedding of each node with the factorization matrix to produce recommendations.

This model's challenge is that it is oriented towards static data and does not take into account evolutive data.

In [57], the authors proposed social e-commerce recommendation model called "RecoGCN". RecoGCN uses a Relation-aware CO-attentive GCN model to model information in Heterogeneous Information Networks (HIN). It then applies a sampler based on meta-path to increase the efficacity of the model. Finally, the authors used a co_attentive embeddings combination concept, which considers the scalability of user transactions' complex motivations.The power of RecoGCN is that it can learn powerful node vector representations in a social-commerce network.

Wu and al [58] proposed a model named SocialGCN that integrates both the advantages of the graph convolutional network (GCN) to embed information from social networks and models of latent factors to preserve users' preferences. Embeddings of users and Items (with/without features) are a merge of free latent vectors. SocialGCN can manage the cold start problem, that is to say, a flexible model that preform the effectiveness of the recommendation process.

To tackle the challenge of the cold start problem in the recommendation field.

Zhang and al [59] proposed a new STAcked and Reconstructed Graph Convolutional Networks (STAR-GCN) to learn node embeddings by utilizing an aggregation of GCN encoder-decoders combined with a process of supervising to augment the quality of prediction. The model takes as input the learned embeddings of users and Items to restrain the complexity measure. Experiments have shown the quality of the proposed model in the rating prediction task.

4. LITERATURE REVIEW

Thanks to the reviewing work of existing studies in section 3, we find that recommendation based on deep graph embeddings chosen in this survey depends on six keys (see figure 2, table 2).

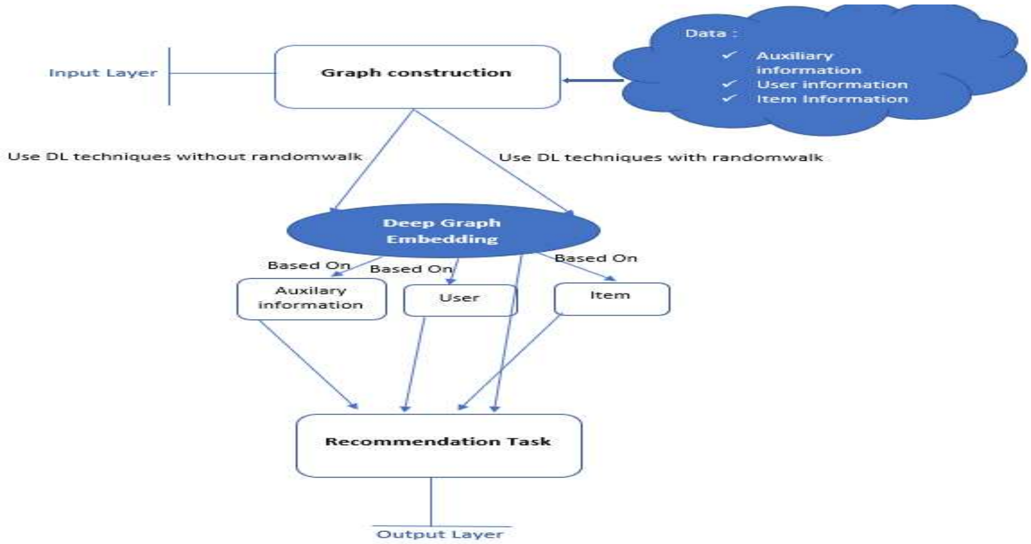

Figure 2. Standard Keys Elements Of The Reviewed Recommendation Approaches.

i. Graph construction: makes it possible to visually illustrate relationships between the data (Auxiliary information, User information, Item Information). The purpose of a graph in a recommendation system is to present data that is too large or too complicated to be described correctly [60].

ii. Graph embedding-based deep learning: deep learning (DL)is ubiquitous, and it has recently demonstrated its effectiveness in both recommendation and graph embeddings fields[61].

iii. Deep graph embedding in recommender systems is booming and achieves significant results in improving.

iv. recommended Items' quality. Similar to [14] deep graph embeddings can be classified into DL-based Graph Embedding with Random Walk and DL-based Graph Embedding without Random Walk.

v. Reviewed recommendation works in this survey based on deep graph embedding often use formal recommendation approaches like collaborative filtering and content-based filtering (see section 2.1.2).

vi. Deep graph embedding can use user data or item data or auxiliary information, or all of them, as on their descriptions encapsulate all graph data.

Table 2: Static Comparative Analysis Of Reviewed Studies

Approach	Recommendation approach	Embedding technique used	Based on (user-Item-auxiliary information)
Okura and al. 2017 [47]	Content based filtering	denoising autoencoder RNN	User_Item
Yan and al. [48] 2019	Collaborative filtering	Deep autoencoder	User-Item
Ying and al. 2018[49]	Hybrid Recommendation	Graph Convolutional Network	User-Item-auxiliary information
Shi and al.,2019 [50]	Hybrid Recommendation	DeepWalk	User-Item
Li and al 2019 [51]	multi-criteria model	Autoencoder	User
Li and al. ,2019[52]	Hashtag model	Graph Convolutional Network	User_Item
Yuan and al.,2019[53]	Collaborative filtering	Autoencoder	User-item

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Yi and al.,2019 [54]	Collaborative filtering	Deep matrix factorization Implicit Feedback Embedding	User
Wang and al.,2019 [55]	Hybrid Recommendation	Knowledge Graph Convolutional Network	User-item auxiliary information
Zhao and al.,2020 [56]	Collaborative filtering	Heterogeneous cooccurrence network	User-Item
Xu and al. ,2019 [57]	Social ecommerce recommendation	Graph Convolutional Network	User_Item
Wu and al.,2019 [58]	Collaborative filtering	STAcked and Reconstructed Graph Convolutional Networks	User_Item
Zhang and al. ,2020 [59]	Social Hybrid recommendation	Graph Convolutional Network Latent factors model	User_Item_auxiliary information

All reviewed works in this study use deep graph embeddings to map users and items (with/without auxiliary information) into a low dimensional vectorial space to make a recommendation (see figure 3). Some of them use only standard recommendation approaches, respectively, collaborative filtering or content-based filtering, which can pose a problem without mixing techniques. The first one suffers from many issues, including a new user starts without recommendation since their scores are all zero (same for new Items). In the case of a large number of Items, the matrix becomes hollow. It is difficult to "match" the correlated users (who have the same preferences). Otherwise, the second approach's prevention is how to answer the next question, "How to create a profile for new users?" an addition that finding the right "features" is not always easy.

These methods have different advantages and disadvantages, so that no single solution can answer all the problems. In reality, we have to use several approaches and combine them to have a better recommendation. So, to tackle these limitations, we plan in our next work to propose a hybrid recommender system that uses both a deep learning model and a random-walk model [26].

Even if existing work has laid a solid foundation for deep graph embeddings-based recommender systems, it is still a promising young field of research. Therefore, we propose several forward-looking directions for future research:

- ✓ *Improvement of item-item relations:* based on complementarity logic; as an example; If a user buys a Tablet, it is logical to recommend specific chargers or cases for the Tablets to this user because they are complementary elements of the tablet.
- ✓ *Integration of contextual information:* We can add another link between users based on the context; if two users share a defined context, they can be linked. Contextual information can include several types of information (see section 2.1.2), take the example of : (i) **location:** If two users live in the same city, they can have the same area of interest, so we can create another link based on this same_City information (U1, U2) where U1 and U2 live in Marrakech city, for example.(ii) **Time:** if two users access the site in a precise moment "morning" daily, they can have the same taste, same_Time (U1, U2) U1 and U2 see "lady gaga" daily every morning .
- ✓ *Integration of psychological knowledge:* Psychological knowledge can be described by psychological states like emotions, persuasion, attention, presence. These effects are then used to predict the person's psychological state using a system at a specific time. For example, the system will add an emotional link between the users; the user will tell the system why he chose such an Item according to his vision , on comments.The goal will be to extract the user's emotions in a specific moment from the textual reviews; after that, it will filter the emotions of all users that it put together and those who have the same feelings and likes at the exact times they can have the same taste.

5. CONCLUSION

Helping users discover and choose resources in large information space is a significant challenge that remains relevant today. Recommender systems are a solution, the primary purpose of these systems is to provide the user with recommendations that reflect their personal preferences. However, data overload is a challenge for many existing recommender systems. That opens a new research

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

field to reduce the large quantity of information by using graph embeddings algorithms into recommender systems.

In this survey, we conduct a comprehensive overview of Deep Graph Embeddings based Recommender systems. We provide a comprehensive overview for their components then we provide a thorough review to analyze studies to prove these algorithms' impact in the recommendation field. They can manage many issues like cold start problems, scalability, and augmentation of the quality of recommended results. Likewise, this paper presents an overview of a recommender system's existing studies based on deep graph embeddings and highlight future work in this young field.

We proposed a background of essential elements in our survey. We present a literature review of recent recommendation approaches based on deep graph embeddings. We presented our discussion that shows all basics keys concepts and the pragmatic analysis of reviewed studies plus all limitations that challenged these approaches. Nevertheless, deep graph embeddings led to a big success in the recommendation domain and deserved more exploration. Recommendation systems play an essential role in improving the user experience with online services. They vastly reduce human effort in finding objects of interest. So, performant recommended results are urgently needed. Many promising avenues of research in this field can be explored; we consider this work the second step of our research ([26] step 1).

We will use the analysis obtained from both the article [26] and this paper by drawing the strengths and improving all studied works' weaknesses. To propose our next approach to use a mix of deep, random-walk, translational graph embeddings to make a robust recommender system.

REFERENCES:

[1] P. Resnick and H. R. Varian, " Recommender systems ", Commun. ACM, vol. 40, no 3, p. 56-58, mars 1997, doi: 10.1145/245108.245121.

[2] P. Melville and V. Sindhwani ,"Recommender Systems". In: Sammut, Webb G.I. (eds) Encyclopedia of Machine Learning and Data Mining. Springer, Boston,2017,MA. https://doi.org/10.1007/978-1-4899-7687-1_964

[3] M. Jalili, S. Ahmadian, M. Izadi, P. Moradi and M. Salehi, "Evaluating Collaborative Filtering Recommender Algorithms: A Survey," in IEEE Access, vol. 6, pp. 74003-74024, 2018, doi: 10.1109/ACCESS.2018.2883742.

[4] P. Lops, M. de Gemmis and G.Semeraro ,"content-based Recommender Systems: State of the Art and Trends". In: Ricci F., Rokach L., Shapira B., Kantor P. (eds) Recommender Systems Handbook. Springer, Boston, 2011,MA. https://doi.org/10.1007/978-0-387-85820-3_

[5] R. Burke ,"Hybrid Recommender Systems: Survey and Experiments". User Model User-Adap Inter 12, 331–370 ,2002. https://doi.org/10.1023/A:1021240730564

[6] A. Samih, A. Adadi, and M. Berrada, " Towards a knowledge based Explainable Recommender Systems ", in Proceedings of the 4th International Conference on Big Data and Internet of Things, Rabat Morocco, oct. 2019, p. 1-5, doi: 10.1145/3372938.3372959.

[7] Z. Huang, W. Chung, and H. Chen," A graph model for E-commerce recommender systems ", p. 16.

[8] G. Ji, S .He, L. Xu, K. Liu and J. Zhao ," Knowledge Graph Embedding via Dynamic Mapping Matrix",Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing, pages 687–696,2015.

[9] A.Bordes, N.Usunier, A.Garcia-Duran. J.Weston and O.Yakhnenko,"Translating embeddings for modeling multirelational data, in Adv. Neural Inf. Process. Syst.,pp 2787–2795 ,2013.

[10] Z. Wang , J.Zhang , J.Feng and Z.Chen," Knowledge graph embedding by translating on hyperplanes", in Proc. 28th AAAI Conf. Artif. Intell, 1112–1119 (2014).

[11] B.J.Mirza , B.J.Keller, and N.Ramakrishnan, "Studying Recommendation Algorithms by Graph Analysis". Journal of Intelligent Information Systems 20, 131–160 ,2003. https://doi.org/10.1023/A:1021819901281

[12] G. Chen, C. Xu, J. Wang, J. Feng and J. Feng," Nonnegative matrix factorization for link prediction in directed complex networks using PageRank and asymmetric link clustering information",Expert Systems with Applications,Volume 148,2020, https://doi.org/10.1016/j.eswa.2020.113290.

[13] Q.Wang, Z.Mao, B.Wang and L.Guo, "Knowledge Graph Embedding: A Survey of

Approaches and Applications," in IEEE Transactions on Knowledge and Data Engineering, vol. 29, no. 12, pp. 2724-2743, 1 Dec. 2017, doi: 10.1109/TKDE.2017.2754499.

[14] H.Cai, V. W.Zheng and K.C.Chang, "A Comprehensive Survey of Graph Embedding: Problems, Techniques, and Applications," in IEEE Transactions on Knowledge and Data Engineering, vol. 30, no. 9, pp. 1616-1637, 1 Sept. 2018, doi: 10.1109/TKDE.2018.2807452.

[15] P.Goyal and E.Ferrara, " Graph embedding techniques, applications, and performance: A survey ", Knowledge-Based Systems, vol. 151, p. 78-94, juill. 2018, doi: 10.1016/j.knosys.2018.03.022.

[16] Y. Cao, X. Wang, X. He, Z. hu and T.-S. Chua, " Unifying Knowledge Graph Learning and Recommendation: Towards a Better Understanding of User Preferences ", The World Wide Web Conference on - WWW '19, p. 151-161, 2019, doi: 10.1145/3308558.3313705.

[17] E. Palumbo, G. Rizzo, R. Troncy, E. Baralis, M. Osella and E. Ferro, " Translational Models for Item Recommendation ", in The Semantic Web: ESWC 2018 Satellite Events, vol. 11155, A. Gangemi, A. L. Gentile, A. G. Nuzzolese, S. Rudolph, M. Maleshkova, H. Paulheim, J. Z. Pan, et M. Alam, Éd. Cham: Springer International Publishing, 2018, p. 478-490.

[18] Z.Xu, Y.Yuan, H.Wei and L.Wan, " A serendipity-biased Deepwalk for collaborators recommendation ", PeerJ Computer Science, vol. 5, p. e178, mars 2019, doi: 10.7717/peerj-cs.178.

[19] E.Palumbo, G. Rizzo and R. Troncy, "entity2rec: Learning User-Item Relatedness from Knowledge Graphs for Top-N Item Recommendation ", in Proceedings of the Eleventh ACM Conference on Recommender Systems, Como Italy, août 2017, p. 32-36, doi: 10.1145/3109859.3109889.

[20] Y. Lin, Z. Liu, M. Sun, Y. Liu and X. Zhu, "Learning Entity and Relation Embeddings for Knowledge Graph Completion", AAAI, vol. 29, no. 1, Feb. 2015.

[21] L. Cai, J. Wang, T. He, T. Meng and Q. Li, "A Novel Link Prediction Algorithm Based on Deepwalk and Clustering Method ", J. Phys.: Conf. Ser., vol. 1069, p. 012131, août 2018, doi: 10.1088/1742-6596/1069/1/012131.

[22] K.Yang and J. Zhu, " Next POI Recommendation via Graph Embedding Representation From H-Deepwalk on Hybrid Network ", IEEE Access, vol. 7, p. 171105-171113, 2019, doi: 10.1109/ACCESS.2019.2956138.

[23] M. Moustafa Reda, M. Nassef and A. Salah, "Categorization of Factors Affecting Classification Algorithms Selection ", IJDKP, vol. 9, no 4, p. 1-19, juill. 2019, doi: 10.5121/ijdkp.2019.9401.

[24] S. Zhang, L. Yao, A. Sun and Y. Tay, "Deep Learning based Recommender System: A Survey and New Perspectives ", ACM Comput. Surv., vol. 52, no 1, p. 1-38, févr. 2019, doi: 10.1145/3285029.

[25] R. Morsomme and S. V. Alferez, " Content-based Course Recommender System for Liberal Arts Education ", p. 6, 2019.

[26] A. Samih, A. Ghadi, and A. Fennan, "Translational-Randomwalk embeddings based RS: a pragmatic survey ", p. 9.

[27] D. Sánchez-Moreno, A. B. Gil González, M. D. Muñoz Vicente, V. F. López Batista, and M. N. Moreno García, " A collaborative filtering method for music recommendation using playing coefficients for artists and users ", Expert Systems with Applications, vol. 66, p. 234-244, déc. 2016, doi: 10.1016/j.eswa.2016.09.019.

[28] P. B.Thorat, R. M. Goudar, and S. Barve, " Survey on Collaborative Filtering, Content-based Filtering and Hybrid Recommendation System ", IJCA, vol. 110, no 4, p. 31-36, janv. 2015, doi: 10.5120/19308-0760.

[29] R. Chen, Q. Hua, Y.-S. Chang, B. Wang, L. Zhang, and X. Kong, "A Survey of Collaborative Filtering-Based Recommender Systems: From Traditional Methods to Hybrid Methods Based on Social Networks", IEEE Access, vol. 6, p. 64301-64320, 2018, doi: 10.1109/ACCESS.2018.2877208.

[30] W. X. Zhao, S. Li, Y. He, L. Wang, J.-R. Wen, and X. Li," Exploring demographic information in social media for product recommendation", Knowl Inf Syst, vol. 49, no 1, p. 61-89, oct. 2016, doi: 10.1007/s10115-015-0897-5.

[31] N. Korfiatis and M. Poulos," Using online consumer reviews as a source for demographic recommendations: A case study using online travel reviews ", Expert Systems with Applications, vol. 40, no 14, p. 5507-5515, oct. 2013, doi: 10.1016/j.eswa.2013.03.046.

[32] M. Karimi, D. Jannach, and M. Jugovac, News recommender systems – Survey and roads ahead , Information Processing & Management,

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

vol. 54, no 6, p. 1203-1227, nov. 2018, doi: 10.1016/j.ipm.2018.04.008.

[33] G. A. Sielis, A. Tzanavari, and G. A. Papadopoulos, " Recommender Systems Review: Types, Techniques and Applications ", p. 12,.

[34] N. Bechet, "E´etat de l'art sur les Syst`emes de Recommandation ", p. 23.

[35] Z. D. Champiri, S. R. Shahamiri, and S. S. B. Salim," A systematic review of scholar context-aware recommender systems ", Expert Systems with Applications, vol. 42, no 3, p. 1743-1758, févr. 2015, doi: 10.1016/j.eswa.2014.09.017.

[36] D.Wang, J.Xu,Principal Component Analysis in the local differential privacy model,Theoretical Computer Science,Volume 809,2020,Pages 296-312,ISSN 0304-3975, éahttps://doi.org/10.1016/j.tcs.2019.12.019.

[37] S. Surendran, " Graph Embedding and Dimensionality Reduction - A Survey ", Engineering Technology, vol. 4, no 01, p. 6, 2013.

[38] V. Sathish, T. Mehrotra, S. Dhinwa, and B. Das, " Graph Embedding Based Hybrid Social Recommendation System ", arXiv:1908.09454 [cs], 2019, Consulted in: oct. 20, 2020. [On ligne]. Disponible sur: http://arxiv.org/abs/1908.09454.

[39] S. T. Roweis and L. K. Saul, " Nonlinear Dimensionality Reduction by Locally Linear Embedding ", Science, New Series, vol. 290, no 5500, p. 2323-2326, 2000.

[40] M. Belkin and P. Niyogi," Laplacian Eigenmaps for Dimensionality Reduction and Data Representation ", Neural Computation, vol. 15, no 6, p. 1373-1396, juin 2003, doi: 10.1162/089976603321780317.

[41] A.Ahmed, N.Shervashidze, S. Narayanamurthy, V. Josifovski, and A. J. Smola," Distributed large-scale natural graph factorization ", in Proceedings of the 22nd international conference on World Wide Web - WWW '13, Rio de Janeiro, Brazil, 2013, p. 37-48, doi: 10.1145/2488388.2488393.

[42] T. N. Kipf and M. Welling, "Semi-Supervised Classification with Graph Convolutional Networks ", arXiv:1609.02907 [cs, stat], févr. 2017, Consulted le: oct. 20, 2020. [En ligne]. Disponible sur: http://arxiv.org/abs/1609.02907.

[43] A. Grover and J. Leskovec," node2vec: Scalable Feature Learning for Networks ", in Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, San Francisco California USA, août 2016, p. 855-864, doi: 10.1145/2939672.2939754.

[44] B. Perozzi, V. Kulkarni, H. Chen, and S. Skiena," Don't Walk, Skip! Online Learning of Multi-scale Network Embeddings ", arXiv:1605.02115 [physics], juin 2017, Consulté le: oct. 20, 2020. [En ligne]. Disponible sur: http://arxiv.org/abs/1605.02115.

[45] B. Perozzi, R. Al-Rfou, and S. Skiena, " DeepWalk: Online Learning of Social Representations ", Proceedings of the 20th ACM SIGKDD international conference on Knowledge discovery and data mining - KDD '14, p. 701-710, 2014, doi: 10.1145/2623330.2623732.

[46] W. Liu, Z. Wang, X. Liu, N. Zeng, Y. Liu, and F. E. Alsaadi, " A survey of deep neural network architectures and their applications ", Neurocomputing, vol. 234, p. 11-26, avr. 2017, doi: 10.1016/j.neucom.2016.12.038.

[47] S. Okura, Y. Tagami, S. Ono, et A. Tajima, " Embedding-based News Recommendation for Millions of Users ", in Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, Halifax NS Canada, août 2017, p. 1933-1942, doi: 10.1145/3097983.3098108.

[48] W. Yan, D. Wang, M. Cao, et J. Liu, " Deep Auto Encoder Model With Convolutional Text Networks for Video Recommendation", IEEE Access, vol. 7, p. 40333-40346, 2019, doi: 10.1109/ACCESS.2019.2905534.

[49] R. Ying, R. He, K. Chen, P. Eksombatchai, W. L. Hamilton, et J. Leskovec, "Graph Convolutional Neural Networks for Web-Scale Recommender Systems ", in Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, London United Kingdom, juill. 2018, p. 974-983, doi: 10.1145/3219819.3219890.

[50] C. Shi, B. Hu, W. X. Zhao, and P. S. Yu," Heterogeneous Information Network Embedding for Recommendation ", IEEE Trans. Knowl. Data Eng., vol. 31, no 2, p. 357-370, févr. 2019, doi: 10.1109/TKDE.2018.2833443.

[51] P. Li et A. Tuzhilin, "Latent multi-criteria ratings for recommendations ", in Proceedings of the 13th ACM Conference on Recommender Systems, Copenhagen Denmark, sept. 2019, p. 428-431, doi: 10.1145/3298689.3347068.

[52] M. Li, T. Gan, M. Liu, Z. Cheng, J. Yin,and L. Nie, " Long-tail Hashtag Recommendation for Micro-videos with Graph Convolutional Network", in Proceedings of the 28th ACM International Conference on Information and Knowledge Management, Beijing China, nov. 2019, p. 509-518, doi: 10.1145/3357384.3357912.

[53] W. Yuan, K. He, G. Han, D. Guan, et A. M. Khattak, "User behavior prediction via heterogeneous information preserving network embedding ", Future Generation Computer Systems, vol. 92, p. 52-58, mars 2019, doi: 10.1016/j.future.2018.09.036.

[54] B. Yi et al., " Deep Matrix Factorization With Implicit Feedback Embedding for Recommendation System ", IEEE Trans. Ind. Inf., vol. 15, no 8, p. 4591-4601, août 2019, doi: 10.1109/TII.2019.2893714.

[55] H. Wang, M. Zhao, X. Xie, W. Li, and M. Guo, " Knowledge Graph Convolutional Networks for Recommender Systems ", in The World Wide Web Conference on - WWW ’19, San Francisco, CA, USA, 2019, p. 3307-3313, doi: 10.1145/3308558.3313417.

[56] Z. Zhao, X. Zhang, H. Zhou, C. Li, M. Gong and Y. Wang,
"HetNERec: Heterogeneous network embedding based recommendation",
Knowledge-Based Systems,Volume 204,2020,106218,ISSN 0950-7051, https://doi.org/10.1016/j.knosys.2020.106218.

[57] F. Xu, J. Lian, Z. Han, Y. Li, Y. Xu, and X. Xie, "Relation-Aware Graph Convolutional Networks for Agent-Initiated Social E-Commerce Recommendation ", in Proceedings of the 28th ACM International Conference on Information and Knowledge Management, Beijing China, nov. 2019, p. 529-538, doi: 10.1145/3357384.3357924.

[58] L. Wu, P. Sun, R. Hong, Y. Fu, X. Wang, and M. Wang, " SocialGCN: An Efficient Graph Convolutional Network based Model for Social Recommendation ", arXiv:1811.02815 [cs], juill. 2019, Consulted le: oct. 21, 2020. [En ligne]. Disponible sur: http://arxiv.org/abs/1811.02815.

[59] J. Zhang, X. Shi, S. Zhao, and I. King, " STAR-GCN: Stacked and Reconstructed Graph Convolutional Networks for Recommender Systems ", arXiv:1905.13129 [cs, stat], mai 2019, Consulted in : oct. 21, 2020. [on ligne],http://arxiv.org/abs/1905.13129.

[60] D. Slutsky , The Effective Use of Graphs. Journal of wrist surgery. 3. 67-8. 10.1055/s-0034-1375704,2014.

[61] Y. Zhang, Q. Ai, X. Chen, and P. Wang," Learning over Knowledge-Base Embeddings for Recommendation ", Algorithms, vol. 11, no 9, p. 137, sept. 2018, doi: 10.3390/a11090137.

[62] C. Charu Aggarwal. Recommender systems: the textbook. Springer Science+Business Media, NewYork, NY, 1st edition edition, 2016.

[63] Z.Daokun, J.Yin, X.Zhu, and C.Zhang. Network Representation Learning: A Survey. arXiv:1801.05852 [cs, stat], July 2018. arXiv: 1801.05852.