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A Comprehensive Survey on Deep Learning-based Recommender Systems for Market Analysis

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Abstract: Deep learning and machine learning techniques in market analysis have gained tremendous popularity because of its" learning feature." These techniques are applied in various ways within business organizations to handle tasks such as prediction, feature extraction, natural language processing and recommendation etc. In the domain of recommendation system relationship between items and users will create denser representations. For improved and successful recommendations, embedding (continuous vector representations) are created to reduce categorical variables and explore various representations of user-item. Market analysis is about understanding structure and growth of market for estimating beneficial policies for cost minimization and maximization profit based on the customer data. The consumer behavioural data is shattered in different silos, which makes data processing and analysis difficult. This study aims to provide comprehensive review of deep learning-based methodologies for recommendation task along with embedding techniques to learn user-item representations. Also, it briefs about data silos, its existence, advantages, and disadvantages and how to create composite embedding from domain specific partial embedding of customer data for market analysis. The study reviews deep learning-based methods, algorithms, its applications and provide new perspective strategies in the area. The study explains about graph convolution networks and knowledge graphs for learning disentangled embedding to improve recommendation. The results and discussion section summarize the use of embedding in deep learning-based methods for recommendation systems for market analysis and highlights open issues to improve recommendations.

Keywords: Data Mining and Big Data,Deep Learning,Graph convolution networks,Information systems,Recommender systems.

1. Introduction

In marketing business, big data is the crucial "tech" disruption from couple of decades. Big data, data warehouse and data analytics have become "Buzz" words. In this digital world [1] data growth rate is exponential because of digitization as well as Internet of things and sensors etc. To explore more about big data analysis research began and studies proposed on design, implementation, and challenges in big data analysis [2], [3], [4], [5]. While analyzing marketing data we could have come across terminologies such as *ETL* (extract, transform and load), *CRM* (customer relationship management), *CDI* (customer data Integration) etc. *CDI* is customer data integration software tool [6] to define, manage, and consolidate enormous customer data from different resources under one roof i.e., "360-degree view of customer data". The real time view of customers information including purchase history and other interactions with the business parties is nothing but 360-degree comprehensive view of customer data. This customer" data" is of enormous volume and it must be maintained in such a way that at enterprise level it should be beneficial for forecasting and decision making. *CRM* [7] is customer relationship management software to manage customer data and to track customer behavior. In marketing, many applications need customers data in comprehensive manner because of distributed data and it is a challenge [8] to create "360-degree comprehensive view" of data from multiple resources i.e. data silos. In simple words we call it as data integration. Integrating customer data from different sources is difficult task as data can be of different type and size. During data integration security as well as privacy are the major concern as it belongs to customers. Understanding data silos,usage and implementation techniques will make data integration process simplified. The customers are heart of any business, study proposed in [9], [10], [11] explains about major role of customer profile. When it comes to marketing analysis recommendation systems are used for forecasting and decision making. Understanding customer preferences, customer retention and satisfaction are major tasks which can be handled by these systems. For en-

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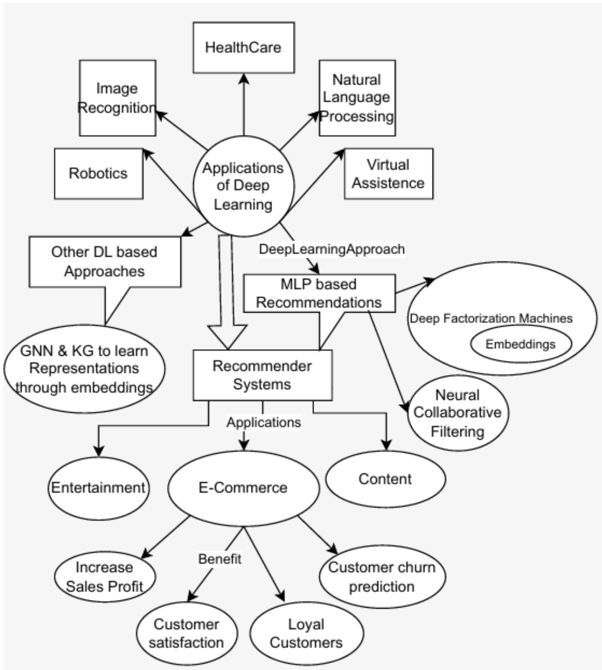

Figure 1. flow of survey paper

hancing recommendation systems accuracy and consumer preference prediction tasks composite embedding are used. Composite embedding are integrated embedding from data silos. One impact of improved recommendation by using composite embedding can be seen in study proposed by Moshe Unger *et al.* [12]. These embedding are constructed using deep learning framework and different methodologies as mentioned in [13], [14].Market analysis will provide direction to increase sales, reduce customer churn, increase customer satisfaction, and improve loyalty. To achieve these goals, we need customer data as well as product data which is present is silos. Hence this study briefs about data silos, how to integrate them, what tools are available and how recommendation system can be used to perform market analysis task by using deep learning-based embedding to learn user-item relations.This study flow can be summarised by flow diagram shown in figure 1. The review paper contributions are focused on:

1) We have presented overview of data silos, construction of composite embedding. This will give guidance to researchers about more deep knowledge about data silos,usage and to build embedding related to user-item or user-user relationship.
2) We have presented deep learning-based recommendation system methodologies used based on types of data. This will be helpful to pick a recommendation system for criteria and analyse the ongoing issues in that application area e.g E-Commerce.
3) We have done survey on the past work to understand and analyse deep learning-based embedding method and plotted its accuracy for recommendations.
4) We have described *GCN* (Graph Convolution Networks) and *KG* (Knowledge graphs) to learn disentangled embedding and understand multi order relation between user and item for recommendations. This gives overview on new trends in the recommendations.

A. Research Methodology

In this review paper, we have collected and studied over a hundred of associated articles on deep learning and recommender systems from major journals such as IEEE Transactions, ACM Transactions on Information Systems, and other databases from the year 2016-2024.To move further to understand the algorithm, technique, and dataset, literature search is done from ACM Conference on Recommender Systems (RecSys) and other databases such as arxiv.org, ResearchGate. The major keywords used to discover related paper were: deep learning-based recommender system, recommender system and embedding, recommender system for market analysis. The resulting articles were segregated based on method and the application area as it was covering mix of application market such as music, healthcare, E-Commerce etc.The major information we wanted to include in the study was embedding concept and its relevant data associated with recommendations. Hence, this review paper highlights basics about data silos and moves towards composite embedding. This review paper explores details about implementation of recommender systems using embedding and deep learning-based techniques. This study focuses on highlighting methods on embedding representations and its applications in prediction task. The goal of this review paper is to survey recent learning on deep learning-based recommender system using embedding. The table I shows summary of selection of articles with selected parameters for recommender systems. In the result section a summary graph is plotted based on the application area of recommender system as E-Commerce and the methodology used for accuracy of recommendation.

Organization: The section 2 of the review paper describes basic understanding of data silos, its pros and cons. Overview of technical solution for data silos followed by brief introduction about customer data integration. In section 3 and 4 highlights on partial embedding and advantages of partial embedding in prediction and recommendation tasks and deals with the previous work done in construction of embedding and various difficulties in implementation. It also specifies various methodologies for construction of composite embedding based on deep learning and machine learning techniques. It is useful to understand recent trends and research areas. Section 5 reviews deep learning techniques for recommendations and briefs about graph convolutions,knowledge graphs and reviews its related recent work in recommendations. In section 6 comparison results are shown based on survey regards on recommendations in E-Commerce and the methodologies used.The review paper is concluded in section 7.

TABLE I. selection criteria for articles

Criteria	Selected for review
Recommender system	Proposed article focuses on recommendations in E-commerce platform
Methodology	Study explores deep learning-based method for recommendation
Learning Representations	Study includes embedding technique for learning user-item representations
Year of Publication	Recent studies from 2020-2024

2. Data Silos

In simple words" silos" are nothing but compartments. Data silos are defined as collection of data stored at different locations with limitation of access. Due to access limitation and inconsistency of data at silos, make siloed data an issue.

A. Understanding What is Data Silo

In the Marketing business, data is all about customers and customer data is stored in different places. These places are nothing but" silos" like compartments. The data can be similar or different types. If we consider a customer profile as data, according to the requirement, department wise data will be collected. It includes browsing details, purchasing details, loans or other transactional data, investments and it would be demographic information about the customer [15]. This siloed data is used for different purposes. Integration of this siloed data is difficult because of heterogeneity of data.

B. How Data Collection Becomes a Silo

When it comes to the organization, different departments collect data in specific format as required. For example, HR department, finance department, administration, marketing team and other departments. Hence this department wise data becomes a silo and as the new information added along with data, this silo too grows.

Siloed data an issue: The siloed data creates security issues as data has to be moved from one department to another as per the requirement. Quality of data is another disadvantage of siloed data as stored data is inconsistent and may overlap across the silos. There is also a limitation on collaboration and sharing the data among departments. Exact view of data is not available because of siloed data. Overall, organizations data is not clear. Data integrity is a major drawback with this siloed data. As the data gets larger, the silo also grows and the aged data becomes less accurate in terms of updated information and becomes useless. For example, suppose a customer could have entered his current location sometime and now if he/she relocated to another place that previous data is also there in silo as well as the new location address is also there for the same person. Such type of information creates a lot of inconsistencies.

C. Technical Solution to Siloed Data

The siloed data must be centralized and given access to each department or individual person. While consolidating data, one can use cloud technology or go with a data lake. For efficient data analysis data lake will give an optimized central data repository. Data integration is another solution to solve siloed data issues.

Role of Customer data Integration in breaking down silos: Customers are the heart of any business especially economy and targeted marketing. Targeted marketing is the method where strategies are built to attract customers, advertise product to specific group and increase revenue to company as well as help organization to grow. In other words, we can say consumers and consumer behavior play an important role in a successful business strategy. The consumer behavior is nothing but understanding requirements of customers, their browsing history, their likes, dislikes, basically interest in products. Data can be anything which is shared by a person by himself. If We are online and our actions such as when we "like" someone or something, browsing the Web pages,and when we walk around in a store, or even on the street, data is generated via sensors, cameras, or Google glasses. This information is very important for prediction and recommendation so that maximizing the revenue of business. If we have this information together it will be great help to change the way business can be done including a lot of opportunities. The customer data integrity tool performs the task of collection of heterogeneous customer data from different resources and managing them in an organized way so that it can be efficiently shared between individuals or groups of the business such as customer service, management, executives, sales, and marketing. When we say data is heterogeneous it could be of any type, maybe it could have generated from emails, search behavior, website browsing, social media or data given in person to the concern person. We can say that in all terms, data is variant with respect to time, type, or its appearance. This heterogeneous data must be made valuable by transforming and analyzing. It must be cleaned and distributed based on type. Once we know how in organizations data silos are present and how difficult it is to manage compartmentalized data, these *CDI* (customer data integration) tools provide solutions for giving "360-degree comprehensive view of data" for improving customer service and managing customer relations. This will give a clear strategy for improving business processes. As *CDI* tools have categorized data, it will be used for the applications such as quality control, current trends in market, launch of new products or could be applied in betterment of customer services. By using this tool, we can expect less crisis as they permit sharing of valuable information on time among groups hence can design successful strategy. *Advantages of CDI* A 360-degree customer data view can be achieved with the help of Customer data integration. Major advantages can be:

- Discounted Products: To improve revenue by selling products in seasons or by checking customers timely interest with special discount based on availability of companies budget.
- Identify exact customer or group of customers for offering special benefits: To avoid duplicity or mis-communication among customers, always refer to up-to date data so that exact entity will be communicated and benefited for target marketing, predictive insight, improved customer service, and finally having loyal customers.

There are different customer data integration tools available in the market for businesses. Data integration methods define the application area of *CDI* such as data consolidation, data propagation, data warehousing and data federation. These are some names of available *CDI* tools, Informatica PowerCenter, SQL Server Integration Services (SSIS), Denodo Platform AWS Glue Alteryx, Designer Pentaho Data Integration (PDI), Oracle Golden Gate and many more based on type of data integration. Challenges of customer data integration: *CDI* also has its challenges while dealing with heterogeneous and multiplatform data.

1) Whenever any organization starts using a *CDI* tool it must fix its purpose so that it will be an easy process of selection of type of data, the source and periodic generation of reports.
2) Removal of aged data which is of no use and optimize data
3) Data integration is a continuous process as data grows day by day. *CDI* must become an evolving system
4) should able to manage all type of data formats with accuracy and quality
5) running the system efficiently with updates
6) providing security

3. Benefits of Composite Embedding in Multiple Recommendation and Prediction Tasks

After understanding what is siloed data and how customer data integration solves the problem related to them, let us see another terminology, partial-view-of-the-customer. As we have seen from the above discussion, creating a 360-degree comprehensive view of data is a challenging task. If we see these terminologies like “Domain specific data” or “partial embedding” from study [12], [16] it is nothing but data which is stored in different databases and there in no connection between them. Basically, we need to bring together these partial embedding under one composite embedding. In the study proposed by authors Moshe *et al.* [12]have defined a methodology to build composite embedding by using domain specific partial view of customer data.The method flow can be described in figure 2 [12]. These are the complicated representations of customer data which shares complex relationships between their preferences, products, contextual information. A single customer embedding is created by mapping low dimensional latent Euclidean spaces. With these integrated constructs we will get comprehensive view of customer information in an encoded latent form without missing data. This data can be used for prediction and recommendations [17]. This latent Euclidean space-based embedding are advantage to build customer profiles and mathematical as well as statistical methods can be applied easily to them.

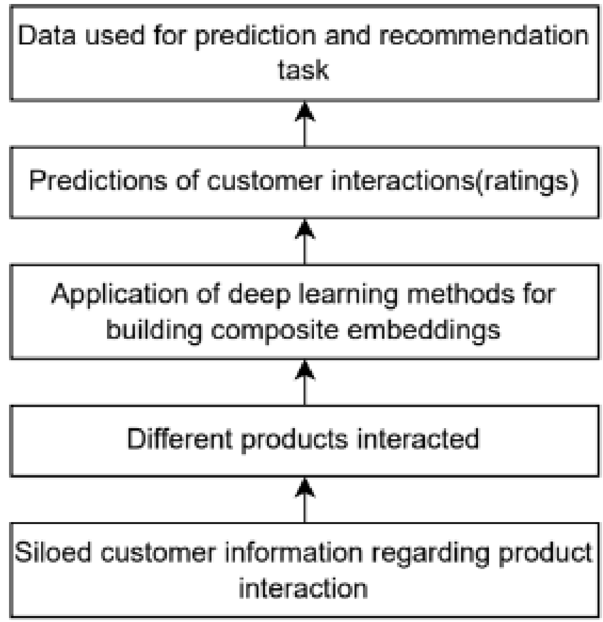

Figure 2. General description of need for data integration

4. Embedding Construction

This section describes various work done in past on construction of embedding and discuss about proposed work, methodology, and its applications along with future scope.

The study [18] proposed by authors Gu *et al.*, describes big data user modelling as the key issue. It is associated with behaviors of users hence based on that; quality of commercial service is improved. By using neural networks low dimensional representations are produced with user behavior data and this work is done by an encoder. Hence this solution is considered as factor for improving performance compared to other methods. They developed universal user representation model different from common user modelling.These representations are used for prediction and profiling task as they will contain lot of information together. Authors have proposed methodology called as *SUMN* (Self-supervised User Modeling Network) in which this encoder will work on a large amount of unlabeled user logs and then infer user representations which is categorized into self-supervised learning paradigm, more like a user behavior sequence which itself can provide supervisory signal. This is a pure neural network design. In the study major focus is on handling diversity problem with help of multi hop aggregation layer which clears user representations. As the future direction, authors have suggested that these types of universal user representations could be applied in commodity recommendations and check for accuracy after design. In the study, proposed method is applied only on user profiling and predicting preferences.

Neuman *et.al* [9] enlightens on ad targeting accuracy check, where creation of digital consumer profile building is done based on online browsing records. This browsing data is taken from data brokers hence investigation on reliability of data is must. Authors have investigated reliability based on 3 field tests and a questionnaire. The performance of ad targeting is evaluated based on accurate audience interest and demographic information. However, each study mentioned in the paper does comparison between data taken from data brokers and from ad buying platforms and validates data from data brokers itself and finally checks only audience interest attributes for accuracy. In the future direction authors have suggested to work towards providing validation accuracy when data must be taken from third party and estimation of cost benefit ratio approximation guidelines. Authors have suggested that, in case of lack of data, its will be a challenge to use cookies data for validation while it was restricted in proposed study.

Soltani *et al.* [10] have proposed a study about *CRM* that is customer relationship management. This study gives a whole idea about what is *CRM*, major application areas, existing techniques in *CRM*, challenges, and future direction. In Economy customers play an important role and hence understanding *CRM* and having knowledge about it is must for successful business. It will improve customer service which will be helpful for retaining customers as well as acquiring new customers. Future direction could be proposing more secure *CRM* techniques along with privacy and behavioral modelling of few techniques for same along with formal verification. The work must be proposed for finding the usage pattern of *CRM* system in organization and checking the effectiveness of it in its success. Identifying differences in cross-cultural domain in an organizational process which fill the gap to improve customer information in the system.

In the proposed study by Tuzhilin *et al.* [19] have reviewed important aspects and key terminologies of *CRM*, have described certain issues from industry and academia which can be solved by web mining and *CRM*. The study focuses on importance of *CRM* in organizations specially to tackle problems of customer lifetime value (LTV) and customer equity (CE) in marketing. While talking about future research trends, those would be applications of *CRM* from a computing perspective: how to get, keep and grow customers, building customer profiles and modelling also dealing with customer feedback problems and conversation recommender systems.

Nicolaus Henke *et al.* [20] have discussed various analytics capabilities and data silos. Initially the study is divided into topics related to variety of data and importance of data analytics with wise talent. Later authors have given a glimpse of machine learning algorithms and its application areas along without come. At last, he has discussed deep learning methodologies and how it will change the future trends. Wedel *et al.* [21] have discussed about recent market trends, big data, data analytics and security issues. The proposed study highlights on how an organization can implement data analytics in this data driven market. How to improve customer's data privacy and security which will lead to retention of customers which will also improve customer service. For achieving these goals, they have thoroughly studied the sources of data, where it gets generated, at which phase analytics is applied and based on that what decisions must be made according to the application areas. This study has reviewed almost 2 decades of trends in data and analytics. The wide range of analytics for firm's benefit also can be seen in different formats such as web analytics, social analytics, path to purchase etc. [21]to set the objectives.

The proposed study enhances knowledge on necessity of customer centric approach of any industry. It provides pathway for becoming customer centric and states challenges in the area. Personalization is defined as collection of customer data for prediction of product preferences and recommendations which accurately matches the customer's taste. To improve the customer service in terms of search criteria personalization plays important role. Murthi *et al.* [22] gives brief idea about personalization and with this criteria study reviews the industry perspective where it stands and how it can develop towards personalization. They have presented a personalization framework which is the clear process to build it and discussed key issues while implementation as well as data collection. While stating research direction authors have emphasizes on finding relationship between personalization and firms' operational field as well as connect them to solve problems in particular perspective. Also, study can be done on, designing different techniques and tools for the same [23]. we know that customer data is crucial in the marketplace and is a must for recommendations as well as prediction for growth of industry. If we take an example of a particular industry such as banking, customers are the heart of banking sector. In the study proposed by Tyagi *et al.* [24], is about targeting banking sector. Authors have focused on the importance of Information governance program i.e., dedicated program for collection of data, storage, and analysis. Study revolves around implementation of this governance program in organization, its key strategies, risk factors and performance of system after establishing this program. While we saw that data silos are present in every organization, combining this data is very critical due to security issues as well as regulatory issues according to countries laws and regulations but scientists may need this data, particularly customer transaction data for analysis. Cantor *et al.* [25] have presented cross domain

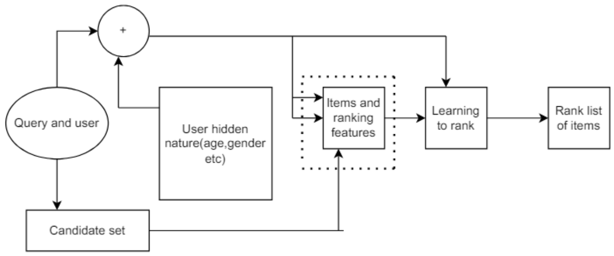

Figure 3. System Overview

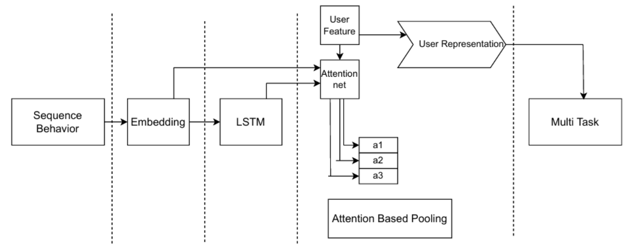

Figure 4. General Model Architecture

recommender systems with basic ideas related to it. They have defined domain, if it's a cross domain means respective data will be of multiple types, what are its goals and to achieve it what work it must do also what are different techniques are available for cross domain recommendation and how to evaluate performance of it and lastly discussed open issues. Goals of Cross-domain recommendation could be any one of them like:

- solving cold-start problem
- accuracy improvement
- Offering added value to recommendations, Enhancement of user models
- discovering new user preferences, security toward vulnerability in social networks

A. Deep learning methods for building composite embedding

This section presents deep learning methods to create single customer embedding. Authors Ni *et al.* [26] have discussed about multiple tasks in E-commerce such searching and recommendation [27] over information which is facing overload problem. If we talk about E-commerce, amazon or Taobao have applied these searching or recommendation mechanisms to get outcome such as personalization. Ni *et al.* [26] proposed study, where universal user representations have built for different tasks in marketing which are used to apply understanding of user behavior sequence based on *LSTM* (Long Short-Term Memory) and attention mechanisms by integrating data. Here this integration is nothing but creating single data embedding by collection of data such as temporal information, behavior or interest and other data. The entire work is named *DUPN* i.e., deep user perception network. To improve the performance of recommender system these embedding are used for different tasks. The design shown in figure 3 [26] is basically a RNN (Recurrent Neuron Network) based deep architecture to build users and items as behavioral sequence. Basically, diagram denotes system overview for ranking personalization in retrieval system and figure 4 [26] denotes *DUPN* general network architecture.

To obtain user representation vector the model is fed with sequences of user behaviour as input.Each input is converted into an embedded vector space and later applied *LSTM* and attention based pooling methods. *LSTM* recurrent back propagation takes long time to learn to hold data for long time interval because of inefficiency in back flow error as seen in work proposed by authors [26]. To address this issue new method is proposed called as LSTM-long short-term memory.The user behavior sequence is designed and attention net used to get information by using sequence with various weights.The model can be generalized for new tasks by using representations among related tasks. These user embedding will be a comprehensive view of customer data in encoded latent form which has all related information that can be used for prediction and recommendation tasks. In study Hinton *et al.*[28] proposed training of neural network model by adding hidden layer to get high-dimensional input vectors. In this type of auto encoder networks initial input weight play crucial role as by applying gradient descent these weights can be fine tuned but there should not be much difference in values. To tackle this issue authors have proposed method for initialization of weight in such way that these networks will be used to reduce dimension of data. This Dimension reduction is used for classification,storage of high-dimensional data,and communication etc. They have proposed a nonlinear generalization of PCA (Principal component analysis) method.Transformation of high-dimensional data into a minimum features code and vice versa is done by an adaptive, multi layer encoder-decoder network.

5. Deep Learning Techniques for Recommender Systems

Deep learning techniques for recommender systems [29], [30] have become popular aspect now a days because compared to traditional feature-based methods it gives better feature extraction and used to show more complex abstractions of data due to its multi view representation. Karatzoglou *et al.* [13] have provided deep learning techniques in the recommender system by using which accuracy of recommendations for the users is improved. The techniques reviewed are Recurrent Neural Networks, Convolution Networks, and other deep learning methods in recent trends along with applications. In the recommender system, usually we have seen Machine learning methods such as matrix factorization and tensor factorization are used which are like deep learning methods. We can see blend of domains it is because presence of stochastic gradient descent for optimization and other one is a neural network. Different views of data are possible as we see matrix factorization which is part of matrix structured data of user item interaction. By removing temporal structure and placing data in order for collaborative filtering techniques.Recurrent and convolution neural network allow us to design temporal structure for this data with improved performance.Some deep learning methods have been briefed here:

- Embedding methods
- Feed forward Networks and Auto encoders for Collaborative Filtering
- Deep Feature extraction methods
- Session-based Recommendation with Recurrent Neural Networks
- Adversarial Training

Here we will review work done in past to understand the basic method and its application area.
Embedding methods: In simple words, in learning system embedding are the representation of entities and their relations in very friendly language. Embedding are used to capture accurate picture of training data. On different representation tools these embedding are used to denote relationships between parameters or distributed representations as discussed in study [31], [32], [33], [34], [35], [36]. Deep learning methods are used to build embedding of item and their attribute parameters [37]. These embedding are used in recommendation tasks and considered as effective application in deep learning. Matrix factorization which is used in collaborative filtering [38] is also an embedding technique but little inflexible. Tomas Mikolov *et al.* [**?**] have shown that by using skip gram model,for precise analogical reasoning build a linear structure of words and phrases by training their distributed forms. Performance is based on type of architecture model used, algorithm, size of the attributes,training window size and sampling rate of each subset. With this perfect blend, system performance can be improved. This work [37] is the extension of previous study of Prod2Vec algorithm which takes local product co-occurrence data generated by product sequence and produce product representations in distributed format but does not leave its meta data. Basically, for recommendation task this Meta-Prod2Vec algorithm is used as a method for adding categorical side data to the model in effective way.
This Section highlights on some of the work done in embedding technique for recommendation task. Table II gives general information about previous work done on the similar concept with specific application.

Feedforward Networks and Autoencoders for Collaborative Filtering: Wu *et al.*[39] have implemented a new approach called as CDAE- Collaborative Denoising Auto-Encoder. The input is reconstructed fully due to users preferences(interaction with items) are not correct.It is considered corrupted. While training the model it will recover

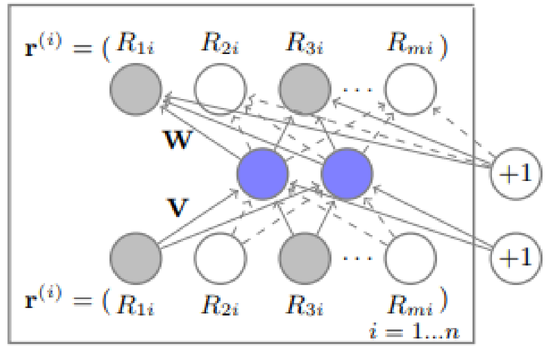

Figure 5. Item-based AutoRec Mode

the full item set with the feeding of subset of user's item set and while prediction it would recommend the user with new product based on existing preference set as in put. Sedhain *et al.* [40] have built collaborative filtering model called AutoRec based on auto encoder methodology which came from the idea of neural network's application on vision and speech tasks. Figure 5 [40] shows user item rating-based auto encoder which overcomes problem of over-fitting of observed ratings. As shown in the figure 5 , R is rating matrix form users and n items. Basically, this method is used to build matrix reconstruction from partially observed rating of user-items rating matrix and then predict missing ratings for recommendation. Recommendation results have checked on a subset of the 30Music listening and playlists datasets.
Deep Feature extraction methods: Vuurens *et al.* [41] have structured items in semantic space where items are arranged with respect to their substitute.The method applies a function for transformation of this data to get a user preferred ranked list as recommendations. Evaluation of this method is done on MovieLens 1M dataset.
Session-based Recommendation with Recurrent Neural Networks: Hidasi *et al.*[42] proposed an approach for accurate recommendations based on Gated Recurrent Unit (GRU) which is elaboration of *RNN* to handle disappearing gradient issue.Vanishing Gradient issue occurs in larger data sets specially in recommender systems hence to tackle that modelled session-based recommendations. The model defined has slight modifications in basic *RNN* by addition of ranking loss function. In the study [43] focuses on two issues:1)improvement of embedding expressivity which has been either doubled by *MLP* 2)Over simplified limited expressivity of model Simplified graph convolution removes parameter matrices by attaching same weight to embedding in all layers in *MLP*. To address these problems authors have proposed *CIGCN-Channel Independent Graph convolution network* method which is used to learn disentangled embedding. Graph convolutions are used to keep the enhanced embedding size independent. This is achieved by adding filters which are diagonal parameter matrices. To improve the expressivity of the model these diagonal parameters

TABLE II. summary of embedding technique with model description

Method of embedding	Model Used	Task Performed	Dataset Used
Word2vec text embedding method	Skip gram model	to apprehend many precise syntactic and semantic word relationships	(An internal Google dataset with one billion words)
Prod2vec- item embedding method	Prod2vec model	Find item similarities	30Music dataset
a normalized t-*SNE* projection model of item, paragraph vector architecture	Semantic space model	In recommendation task to arrange the items for user specific transformation and then rank that item based on preference	MovieLens 1M dataset
Collaborative Denoising Auto-Encoder (*CDAE*)	Neural network (*ML*)	recommends top-N preference.	MovieLens 10M (*ML*)7, Netflix8 and Yelp (from Yelp Dataset Challenge in 2014)

in matrices are used as trainable weights that makes each embedding in every layer important in each dimension. Alexandros *et al.*[44] have shown for session-based recommendations,increase performance up to 35% with RNNs and ranking loss function. They have implemented new class of loss functions based with combination of deep learning.Accuracy of recommendation calculated by MRR (Mean Reciprocal Rank) and Recall @20 showing potential of deep learning in recommendations with difference of 53% between *RNNs* and conventional memory-based collaborative filtering. Massimo *et al.* [45] have designed sessions depending on features of items clicked by user. The sessions are built by architecture parallel *RNN* (p-RNN). Results have compared with feature less session models and p-RNN models for checking improvements. Table III provides brief idea of deep learning techniques with basic idea of model along with its application areas based on previous research work.

A. Graph Convolutions

Convolutions are used in recommendations to handle graph structured data such as user-item interaction graphs, Knowledge graphs, User social graphs and item sequential graphs.Rianne van den Berg *et al.* [52] proposed graph convolution matrix completion (GC-MC): a graph-based auto-encoder framework for matrix completion. It is a bipartite interaction graph of user and items. The framework uses message passing to generate user and item nodes latent features.The rating links are reconstructed through a bi linear decoder with the help of latent user and item representations. The study by Wang *et al.* [53] focuses on knowledge graph convolution networks for recommender systems. In this method knowledge graphs are aggregated with the use of neighborhood information selectively and intolerantly. It will help to understand detailed structural as well as semantic information of knowledge graph and to extract users personalized and potential interests. In [54] study Xiang Wang *et al.* provided brief understanding of knowledge graph where interactions of items with their attributes is represented via a link. The authors have discussed about successful recommendation depends on high order relations denoted by joining two nodes with one or more connected attributes as well as hybrid KG structure. To model the high order connectivity's of items and their attributes in knowledge graph with end-to-end manner.Neighbors crucial role has been discriminated by an attention mechanism as well as method also refines the nodes embedding by their neighbors. The studies have been proposed *SR-GNN* [55], *GC-SAN* [56] to catch the complex interactions of items in session-based recommendation. The aim is to build graph structure data by keeping together all session sequences and the use of gated graph neural networks on it.

B. Knowledge Graphs

Yao Ma *et al.* have defined in [57] a labelled edge multi graph is a knowledge graph.Edges represents type of the relationship.A set of relation type is defined by $R = r1, r2, \ldots r[R]$. E ⊆ V *x* R *x* V shows each edge is a triple form of (source,relation,target).Knowledge graphs are heterogeneous information networks where different learning forms of entities are studied by applying embedding techniques. Structural and semantic relation is unchanged while constructing expressing data into a low dimensional vector space. Embedding approaches are *KGE* [58], [59] *DKFM*[60],*BEM*[61], [62],*TransE*[63],*KTUP*[64],*TransH*[36],*KPRN*[65], *McRec*[66],path based approaches[67].

C. Related Work

In this study [68] Ye *et al.* have provided overview about knowledge graph (KG) and graph neural network (GNN). The study highlights knowledge graph embedding and GNN methods to find solution for KG problems such as link prediction, knowledge graph reasoning, knowledge graph alignment, and node classification. The study emphasizes on role of KG embedding in recommendation system and exploits its relation to upgrade business domain. Wu *et al.* [69] have proposed a time-decay adaptive latent factor model (TDADLFM) model for item score prediction

TABLE III. Deep learning techniques with model description

Deep Learning Technique	Basic Model ideas	Application areas
Multi layer Perceptron (*MLP*)	This technique is based on backpropagation to adjust the weights and biases to minimize the error, used to model non-linear interaction of user and item	prediction, function approximation, or pattern classification
Autoencoder (*AE*)	An autoencoder network input is copied to output.Algorithms used-recirculation and backpropagation. Variations in autoencoders: Under-complete, Regularised/over complete, Sparse Autoencoders Denoising Autoencoders Stochastic Encoders and Decoders Contractive autoencoders Predictive sparse decomposition	dimensionality reduction or feature learning, generative modelling, information retrieval task, anomaly detection, noise removal, collaborative filtering
Convolution Neural Network (*CNN*) [46], [47]	*CNN* are used for processing textual and visual data. Use of mathematical operation-Convolution-linear operation. *CNN* components are parameter sharing,sparse interactions, and equivariant representations.Pooling function is used to modify output.	to output a high-dimensional structured object, works with all size data
Recurrent Neural Network (*RNN*) [48], [49], [50], [46]	Used for processing sequential data as loops and memories for further calculations are present. Used in recommender system to design temporal dynamics of data. Variants: Long Short-Term Memory network (*LSTM*) and *GRU* (Gradient recurrent unit) to deal with gradient issues	Prediction, machine translation, speech recognition generating text models, signal processing
Restricted Boltzmann Machine (*RBM*)	The architecture comprises one visible layer and one hidden layer	dimensionality reduction, classification, regression, collaborative filtering, feature learning and topic modelling
Adversarial Networks (*AN*)	Applied to a model with multilayer perceptron. There will be a discriminator and generator and model are trained on basis of minmax game framework	Video prediction, creation of image dataset, face aging, photo blending
Deep Reinforcement Learning (*DRL*) [51]	apply and crosscheck paradigm. The algorithm consists of environments, states,agents, actions, and awards	Games and self-driving cars

improving recommendation performance. This proposed method is combination of deep learning and latent factor model along with time decay factors to address individual diversity issue.In this[70] survey paper Wu *et al.* have given insight into neural recommendation model focusing on usage of data such as user-item interaction data, side information for the same and contextual information. Authors have provided future directions on ongoing evaluation perspective and reproducible problems in recommender systems. In the study [71] Xia *et al.* have explored users multi type behaviour towards item by proposing multi-behaviour graph neural network (MBRec). This method is used to reveal diverse interaction pattern by using behaviour aware message passing mechanism and graph neural architecture is used for high order mutual learning design. The study provides direction to extract rich information required for improving recommendation. Li *et al.* have presented [72] a new perspective to handle cold start problem in recommender system by using Neural processing in cross domain recommendations. The method uses meta-learning paradigm to save user specific mapping function. It generates preference correlations between users with NP. Chen *et al.* [73] have discussed about recommendations issues in E-commerce and online activities such as data scarcity and cold start. They have proposed a new model Cross-Domain Evolution Learning Recommendation (CD-ELR) developed to disseminate data from different domains. Matrix factorization is done with new approach called as ENF (evolving matrix factorization) and user preferences and item attributes are captured dynamically *RNN* based model called is developed. Overall, authors have shown *CD-ELR* outperforms state of art based on considered metrics. In study [74] Wang *et al.* have proposed a new GNN based idea to improve performance of recommender system called as *LASGRec*-learnable attribute sampling and heterogeneous graph neural network.Their model comprises 3 modules,first is a graph with attributes of users and items,in the second module they have removed unnecessary attributes for improved representations of users and item and in the third module comprises embedding aggregation of users and items.The model focuses to solve issue of unnecessary item parameter preference to user. The study suggest to work further on dynamic relations of users and items using dynamic graph construct. Ansong Li *et al.* [75] provided a novel approach called *Disen-GNN*-Disentangled Graph Neural Network to identify purpose of users session.Item embedding are converted into different factors of embedding having multiple factors.*GGNN*-gated graph neural network is applied to understand parameter of embedding which is selected by similarity matrix of adjacent items.Authors have built attention technique to find users intention towards multiple factor's of items in particular session.For the future direction,authors have suggested to consider global view of all the sessions by user to find out intentions of user towards factors of items. The [76] study focuses on handling data sparsity issue in reconmmender system.To identify the user-item-attribute relationship as well as user-item information a GCN beased model is proposed by authors Yue *et al.*.Attribute impact is addressed by attention module and then 4 node graph is constructed and finally to explore that graph Laplacian matrix is composed which have attribute data of nodes. Li*et al.* [77] proposed a method to tackle issue of data sparsity and cold start in recommendations named *CEPR*-intelligent recommendation model for consumer electronics products in *IoE*-Internet of Electronics.The graph embedding technique is utilised other side information of commodities.This study focuses on consumer electronics and can be further extended for other domain recommendations.

6. Results and Comparison

We surveyed and categorized deep learning methods based on their application areas [78]. Here we have categorized the methods based on usage of data embedding in the proposed method. For doing this comparison recent papers have been studied from the year 2016-2024, comparison results [79], [80], [81], [82], [83], [84], [85], [86], [39], [87], [88] are plotted are as shown in Figure 6. In the chart [6] X-axis represents no of papers referred based on application area i.e. E-commerce,task is recommendation and for accomplishing the task embedding method is used.

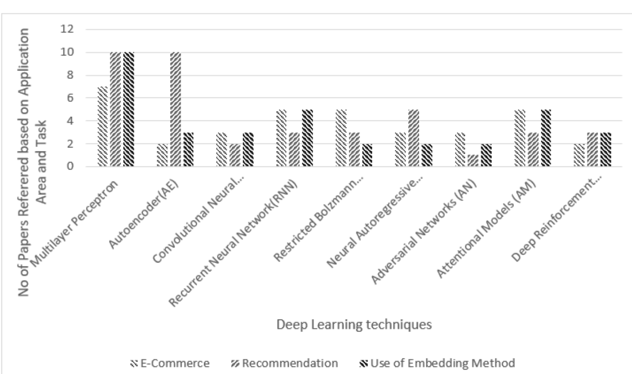

Figure 6. Distribution of embedding utilization for recommendation in E-commerce with deep learning technique

In this survey paper we have discussed about different deep learning based embedding techniques used for recommendations. In the recommender systems user-item relations are very crucial information based on which the performance of recommender system depends. We tried to briefly highlight different strategies to explore this relationship specifically by using data embedding.Later, we have discussed about graph convolution to build user-item relation for successful recommendation. In the study [43] focuses on two issues:1) Improvement of embedding expressivity which has been either doubled by *MLP* 2) Over simplified limited expressivity of model- Simplified graph convolution removes parameter matrices by keeping embedding weight all layers in *MLP*. To address this problem authors have proposed CIGCN-Channel-Independent Graph Convolution Network (CIGCN to learn disentangled embedding. As mentioned earlier graph convolutions with specific filters are used. These filters are diagonal parameter matrices. They used as trainable weights that makes each embedding in every layer important in each dimension improving model's expressivity.

For successful recommendations learning relationship between user and items is very important which highly increases model's interpret-ability. To achieve this goal graph convolutions are explored and widely used. It deals with graph structured data. This survey paper briefly describes 4 types of graphs (user-item interaction graphs, Knowledge graphs, User social graphs, Item sequential graphs) and embedding techniques used to represent each type. It is a short overview of used method and its application areas along with what type of issue can be handled for recommendation system. In embedding we will be keeping similar inputs closer in given embedding space.

Reconstructed composite embedding are used for prediction and recommendation tasks. As we have discussed to solve data silos issue, embedding will play a key role to get 360-degree comprehensive view of customer data so that every crucial information of customer will be visible. Hence it will be used for recommendation and accurate predictions. Nowadays, for market analysis, to generate customer embedding modern techniques are defined based on sequential neural network. In this survey paper we have reviewed LSTM [89](Long Short-Term Memory), BERT [90] (Bidirectional Encoder Representations from Transformers), GRU [91] (Gated Recurrent Unit) and vanilla RNN [92] (Recurrent Neural Networks) techniques for generation of customer embedding and studied the recommendation performance and customer behavioral information. The comparison of techniques is based on recommendation performance, data security, scalability, and ability to handle data sparsity issue. In the study [93], [94] recommendation performance is measured in terms of Recall@20 (the proportion of cases having the intended item amongst the top-20 items in all test cases) and MRR@20 ((Mean Reciprocal Rank-average of reciprocal ranks of the intended items) metric for getting rank of item and item recommendation same has been summarized in fig 9. Figure 7 and 8 are providing summarised information from related study[95],

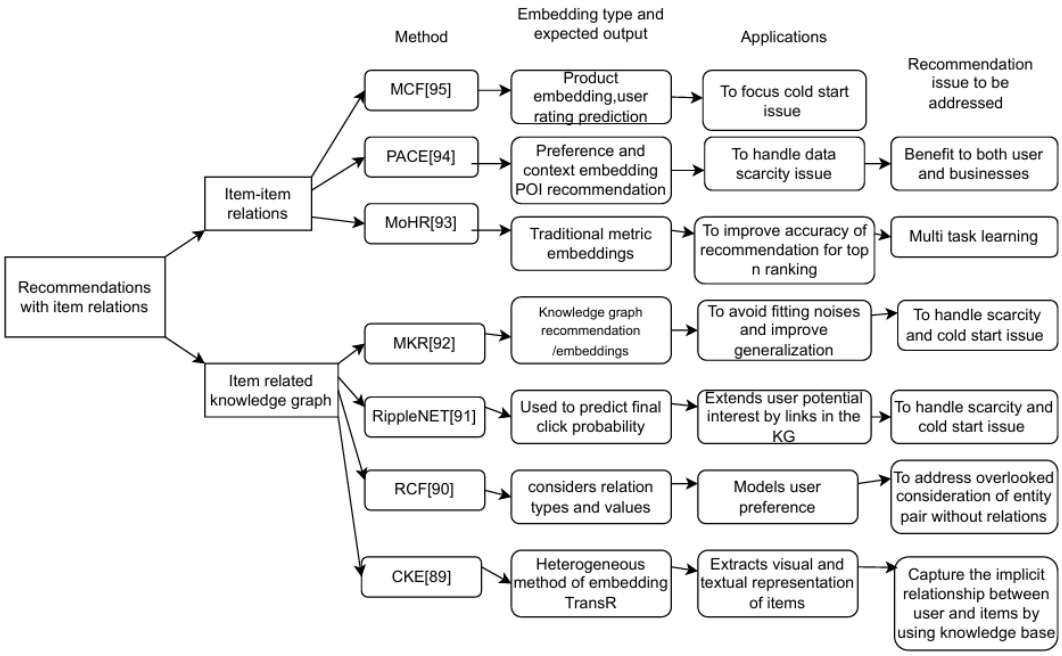

Figure 7. Recommendation methods with item relations

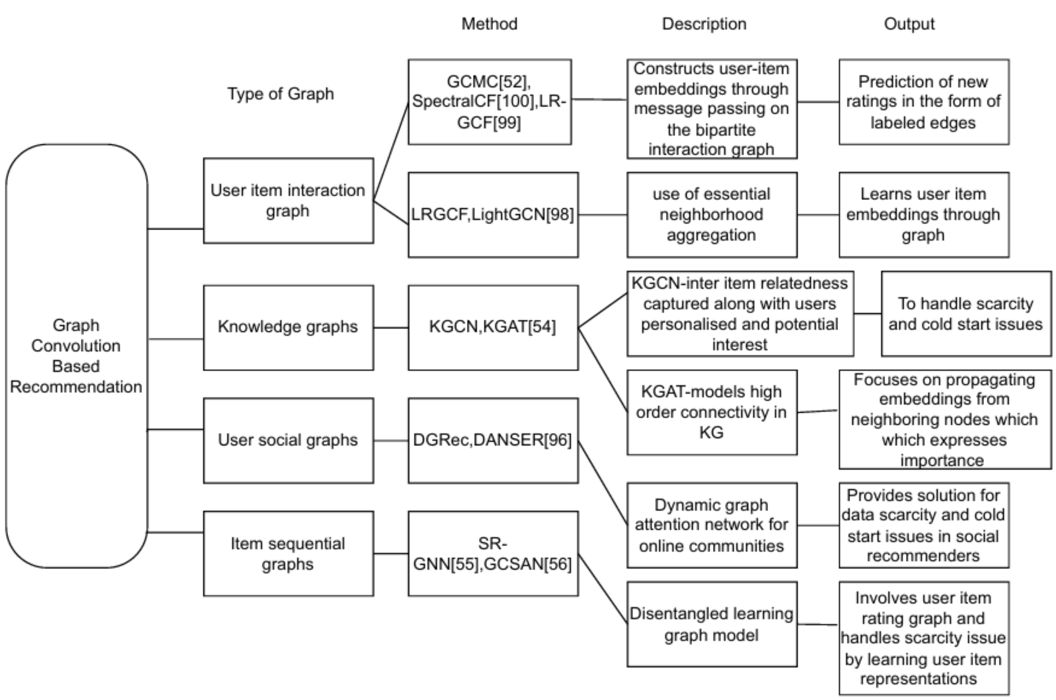

Figure 8. Graph convolution based Recommendation methods

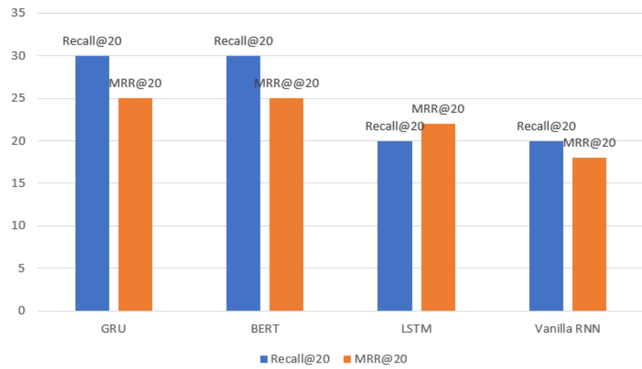

Figure 9. Deep Learning -based embedding techniques recommendation performance

[96], [97], [98], [99], [100], [101], [102],about methods for exploring relations of user-items to improve recommendations and GCN-based Recommendation methods [103], [104], [105], [106]. This review paper strongly discusses significance of learning embedding for understanding relationship between user and items using their attributes in simpler ways and use them for various prediction task in the field of online business platforms. In this review paper we have considered deep learning-based recommender system for E-Commerce business. We have focused on current research in learning embedding of user-item for improved accuracy of recommender system and other related task using GNN and KG. The same can be explored for other application areas of recommender systems.

7. Conclusions

we have been talking about different recommender systems based on choice of interests. Recommendation of items (all types of products), person in social platforms, places, restaurants, and research papers or sometimes you might have come across word" you may like" product list. We wonder that how this recommender system works! and sometimes very accurate preference we might get. Technically we say that it is an estimation based on users' preference on items or based on their historical data. This survey paper gives glimpse of understanding of customer behavioral information, data silos which are important for recommendations. This study reviews about "data silos," its disadvantages, solution and provides brief overview about composite embedding, its construction methodologies in recent research work and how accuracy of the recommender systems is improved with composite embedding. Also, the study provides future directions to make use of these composite embedding of customer data for recommendations and predictions. In this paper we have provided extensive review on impact of recommender systems in marketing analysis. We also discussed about prediction and recommendation task in marketing analysis for which deep learning methods are used efficiently. We have mentioned promising future extensions along with study reviewed as deep learning and recommender systems are latest trending research areas. The study provides elaborated information on usage and application of Graph Convolution networks in recommender system with existing work. The emphasize of adding this information is to learn multi order relations between user and items. Once we learn disentangled embedding about this relation, it can be applied for predictions and other tasks. The focus of this article is to provide recent trend in the field of recommendations to improve its performance by learning disentangled embedding using GCNs and KGs. This provides further enhancement ideas and opportunities to enhance the many proposed work mentioned in review article. We have discussed about deep learning based embedding construction methodologies which is used to empower business intelligence by improving prediction and recommendation task.

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