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Survey on Recommender Systems for Market Analysis using Deep Learning

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Abstract: Abstract— Deep learning and machine learning techniques in marketing analysis have gained tremendous popularity because of its" learning feature." These techniques are applied in various ways within business organizations specially in marketing to handle tasks such as prediction, feature extraction, natural language processing and recommendation etc. In the domain of recommender system relationship between items will create denser representations. For improved and successful recommendations, embeddings (continuous vector representations) are created to reduce categorical variables. Business intelligence in marketing 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 behavioral 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 create composite embedding from domain specific partial embeddings of customer data for market analysis which is shattered in silos. The study explains about graph convolution networks and knowledge graphs for learning disentangled embeddings to improve recommendation. The study reviews deep learning-based methods, algorithms, its applications and provide new perspective strategies in the area of recommender systems. The results and discussion section summarizes the trends of deep learning-based methods for recommender systems for market analysis and highlights open issues to improve recommendations.
Keywords: Data Mining and Big Data,Deep Learning,Graph convolutional 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 digitalization as well as Internet of things and sensors etc. To explore more about big data analysis research began and studies proposed on de sign, 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 com prehensive 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 dis tributed 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, it is 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 recommender systems are used for forecasting and decision making. Understanding customer preferences, customer retention and satisfaction are major tasks which can be handled by recommender systems. To improve the ac curacy of recommender systems and for consumer preference prediction tasks composite embeddings are used. Composite embeddings are integrated embeddings from data silos. One impact of improved

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recommendation by using composite embeddings can be seen in study proposed by Moshe Unger et. al [12]. These embeddings are constructed using deep learning framework and different methodologies as mentioned in [13], [14].

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. The study [15] proposed graph convolutional matrix completion (GC-MC): a graph-based auto-encoder framework for matrix completion. The framework generates user and item nodes latent features by forming a message passing on the bipartite interaction graph. The rating links are reconstructed through a bilinear decoder with the help of latent user and item representations. The study [16] focuses on knowledge graph convolutional 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 se mantic information of knowledge graph and to extract users personalized and potential interests. In [17] study authors provide brief understanding of knowledge graph where interactions of items with their attributes is represented via a link. The authors have discussed about importance of hybrid structure of KG and user-item graph, high-order relations shown by connecting two items with one or multiple linked at tributes for successful recommendation. To model the high order connectivity's of items and their attributes in knowledge graph with end-to-end manner. The importance of neighbors has been discriminated by an attention mechanism as well as method also refines the nodes embeddings by their neighbors. The studies have been proposed SR-GNN [18], GC-SAN [19] 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. The main contributions of this review paper study are: 1.We present overview of data silos, construction of composite embeddings. This will give guidance to researchers about more deep knowledge about data silos to embeddings related to user-item or user-user relationship. 2.We have presented deep learning-based recommender systems methodologies used based on types of data. This will be helpful to pick a recommender system for criteria and analyze the ongoing issues in that application area. 3.We have done survey on the past work to understand and analyze 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 embeddings and understand multi order relation between user and item for recommendations. This gives overview on new trends in the recommendations. Organization: This survey paper is organized as follows: section II 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 III highlights on partial embeddings and advantages of partial embeddings in prediction and recommendation tasks and deals with the previous work done in construction of embeddings and various difficulties in implementation. It also specifies various methodologies for construction of composite embeddings based on deep learning and machine learning techniques. It is useful to understand recent trends and research areas. Section IV reviews deep learning techniques for recommendations. In section V comparison results are shown based on survey regards to recommendations in E-Commerce and the methodologies used and review paper is concluded in section VI.

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.UNDERSTANDING WHAT IS DATA SILOS 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 [20]. This siloed data is used for different purposes. Integration of this siloed data is difficult because of heterogeneity of data.

A. 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 siloes also grow 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.

B. 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, dis likes, 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 online, browsing the Web, 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 trans forming 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* Customer data integration provides your company with a 360-degree customer data view. 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 miscommunication among customers, always refer to upto 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 EMBEDDINGS 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 embeddings" from study [12], [21] 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 embeddings under one composite embedding. In the study proposed by authors Moshe et.al [12]have defined a methodology to build composite embeddings by using domain specific partial view of customer data as shown in figure 1 [12].

These are the complex representations of customer data which shares complex relationships between their preferences, products, contextual information. This data is mapped into low dimensional latent Euclidean spaces and formed a single customer embedding. With these integrated constructs we will get comprehensive view of customer information in an encoded la tent form without missing data. This data can be used for prediction and recommendations

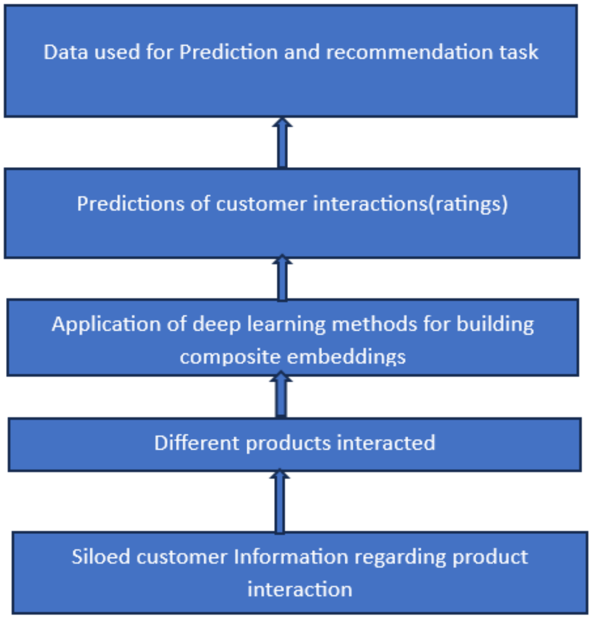

Figure 1. General description of need for data integration

[22]. This latent Euclidean space-based embeddings are advantage to build customer profiles and mathematical as well as statistical methods can be applied easily to them.

4. CONSTRUCTION OF EMBEDDINGS

This section describes various work done in past on construction of embeddings and discuss about proposed work, methodology, and its applications along with future scope. The study [23] 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 is evaluated in terms of accurate audience interest and demographic information. However, each study mentioned in the pa per 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 of CRM 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 CRM system.

In the proposed study by Tuzhilin et.al [24] 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 [25] 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 [26] 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. [26]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* [27] 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 [28]. we know that customer data plays a crucial role 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* [29], 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* [30] have presented cross domain recommender systems with basic ideas related to recommender systems. 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 recommender 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

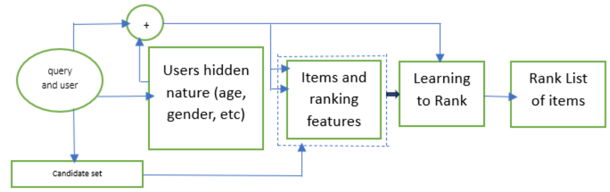

Figure 2. System Overview

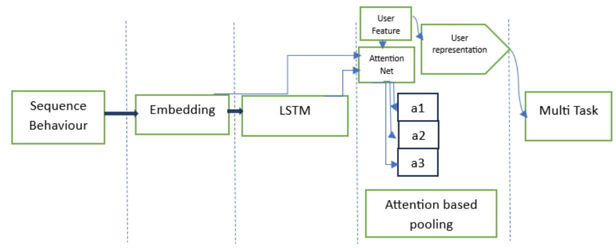

Figure 3. General Model Architecture

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

5. Deep learning methods for building composite embeddings

In this section we have reviewed deep learning methods to create single customer embedding. Authors Ni *et.al* [31] have discussed about multiple tasks in E-commerce such searching and recommendation [32] 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* [31] 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. These representations can be used for different tasks to improve performance. The design shown in figure 2 [31] 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 3 [31] denotes general network architecture of proposed method DUPN.

The model takes user behavior sequences as input and transfers each one into an embedded vector space then we apply LSTM and attention-based pooling to obtain a user representation vector. LSTM recurrent back propagation takes long time to learn to store information for long time interval because of inefficiency in back flow error as seen in work proposed by authors [31]. To address this issue new method is proposed called as LSTM-long short-term memory helps to model the user behavior sequence and attention net helps to draw information from the sequence by different weights. By sharing representations between related tasks, we can enable our model to generalize better both on our learning tasks and some new tasks. Experimental results show the competitive performance of DUPN and generality and transferability of the user representation. These embeddings 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 proposed by Hinton *et.al*[33] embeddings are defined as high dimensional data converted into low dimensional data with the help of neural network training 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, visualization, communication, and storage of high-dimensional data. They have proposed a nonlinear generalization of PCA (Principal component analysis) method which uses an adaptive, multi layer encoder network to transform the high-dimensional data into a low-dimensional code and a similar decoder network to recover the data from the code.

6. DEEP LEARNING TECHNIQUES FOR RECOMMENDER SYSTEMS

Deep learning techniques for recommender systems [34], [35] has become popular aspect now a days because compared to traditional feature-based methods it gives better feature extraction also used to show more complex abstractions as data representations in the higher layers, provide different views of the data, and can handle temporal structures and order in the data. Karatzoglou *et.al* [13] have provided deep learning techniques in the recommender system to improve the quality of recommendations for the users. The techniques reviewed are Recurrent Neural Networks, Convolutional Networks, and other deep learning methods in recent trends along with applications. In the recommender systems, 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 places data in order collaborative filtering techniques. Recurrent and convolutional neural network allow us to design temporal structure for this data with improved performance. Some deep learning methods have been briefed here

- Embedding methods
- Feedforward Networks and Autoencoders for Collaborative Filtering
- Deep Feature extraction methods
- Session-based Recommendation with Recurrent Neural Networks
- Adversarial Training, Siamese Networks, one-shot learning

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 embeddings are the representation of entities and their relations in very friendly language. Embeddings are used to capture accurate picture of training data. On different representation tools these embeddings are used to denote relationships between parameters or distributed representations as discussed in study [36], [37], [38], [39], [40], [41]. Deep learning methods are used to build embeddings of word representations [42], item and their attribute parameters [43]. These embeddings are used in recommendation tasks and considered as effective application in deep learning. Matrix factorization which is used in collaborative filtering [44] is also embed ding technique but little inflexible. Tomas Mikolov *et.al* [42] have shown that by using skip gram model, training of distributed representations of words and phrases ultimately get linear structure for precise analogical reasoning. Performance is based on type of architecture model used, algorithm, size of the vectors, sub sampling rate and on the size of the training window. With this perfect blend performance of the system can be improved. It is [43] the extension of previous work 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 metaProd2vec 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 I gives general information about previous work done on the similar concept with specific application. Feedforward Networks and Autoencoders for Collaborative Filtering: Wu *et.al*[45] have implemented a new approach called as CDAE- Collaborative Denoising Auto-Encoder where part of user item interaction is considered as corrupted version of user's full preference set to re construct full input. While training the model it will recover 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* [46] have proposed a new collaborative filtering model called AutoRec based on auto encoder methodology which came from the idea of neural network's application on vision and

TABLE I. 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*)	for top-N preference recommendations.	MovieLens 10M (*ML*)7, Netflix8 and Yelp (from Yelp Dataset Challenge in 2014)

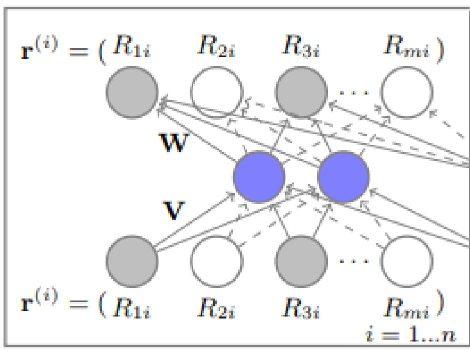

Figure 4. Item-based AutoRec Mode

speech tasks. Figure 4 [46] shows user item rating-based auto encoder which overcomes problem of over-fitting of observed ratings. As shown in the figure, 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* [47] have structured items in semantic space where items are arranged with respect to their substitute after that they have applied function for transformation of this data to get a ranked list of recommendations which matches user preferences. Evaluation of this method is done on MovieLens 1M dataset. Ruining He et.al proposed an approach [48] named VBPR: Visual Bayesian Personalized Ranking from implicit Feedback.in influencing people's opinion visual appearance plays a crucial role and to analyze these products visual dimensions tackle cold start issues. This study gives an improved accurate zed ranking method. It is a scalable factorization model to incorporate visual signals into predictors of people's opinions on huge real-world data. By using pre-trained deep networks products features are extracted over that one additional layer will discover visual dimensions to see people's feedback. Model is built on Bayesian Personalized Ranking (BPR) using stochastic gradient ascent. Authors have suggested future work directions towards extension of the prescribed model by adding temporal dynamics and to work on setting explicit feedback. Session-based Recommendation with Recurrent Neural Networks: Hidasi *et.al*[49] 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 [50] 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 embeddings in all layers in MLP To address this problem authors have proposed CIGCN method which is used to learn disentangled embeddings by using diagonal parameter matrices as filters in graph convolution to keep the enhanced embed ding size independent. To improve the expressivity of the model these parameters in diagonal matrices are used as trainable weights that makes each embedding in every layer important in each dimension. Alexandros *et.al*[51] have shown for session-based recommendations, RNNs with ranking loss function increase performance up to 35%. They have implemented new class of loss functions based with combination of deep learning. Recommendation accuracy in measured 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* [52] have introduced number of parallel RNN (p-RNN) architectures to design sessions based on features of clicked items. Results have compared with feature less session models and p-RNN models for checking improvements. Table II provides brief idea of deep learning techniques with basic idea of model along with its application areas based on previous research work.

7. RESULTS AND COMPARISON

We surveyed and categorized deep learning methods based on their application areas [59]. Here we have categorized the methods based on usage of data embeddings in the proposed method. For doing this comparison recent papers have been selected from the year 2016-2024 comparison results [60], [61], [62], [63], [64], [65], [66], [67], [45], [68], [69] are plotted are as shown in Figure 5. 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 systems depends. We tried to briefly highlight different strategies to explore this relationship specifically focusing on embeddings. Later, we have discussed about graph convolution to build user-item relation for successful recommendation. In the study [50] 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 embeddings in all layers in MLP. To address this problem authors have proposed CIGCN-Channel-Independent Graph Convolutional Network (CIGCN to learn disentangled embeddings. CIGCN uses diagonal parameter matrices as filters in graph convolution, keeping the updated embedding dimensions in dependent. In addition, with layer-aggregation strategies, the parameters in the diagonal matrices act as trainable weights that attach different importance to the embeddings in each layer and each dimension, enhancing the model expressivity. For successful recommendations learning relationship between user and items is very important which highly increases model's interpretability. To achieve this goal graph convolutions have been 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 which is summarized in fig 7 and fig 8. It's a short overview of used method and its application areas along with what type of issue can be handled for recommendation system.

In embeddings we will be keeping similar inputs closer in given embedding space. Reconstructed composite embeddings are used for prediction and recommendation tasks. As we have discussed to solve data silos issue, embeddings 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 embeddings modern techniques are defined based on sequential neural network. In this survey paper we have reviewed LSTM [70](Long Short-Term Memory), BERT [71] (Bidirectional Encoder Representations from Transformers), GRU [72] (Gated Recurrent Unit) and vanilla RNN [73] (Recurrent Neural Networks) techniques for generation of customer

TABLE II. Deep learning techniques with model description

Deep Learning Technique	Basic Model ideas	Application areas
Multilayer Perceptron (*MLP*)	This model 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 is a neural network that is trained to attempt to copy its input to its output. Algorithms used-recirculation and backpropagation. Variations in autoencoders: Undercomplete, Regularised/overcomplete, 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*) [53], [54]	CNNs are a specialized kind of neural network for processing data that has a known grid-like topology especially textual and visual data. Use of mathematical operation-Convolution-linear operation. It uses sparse interactions, parameter sharing 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*) [55], [56], [57], [53]	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*)	It is a two-layer architecture in which one is visible and other is hidden	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
Attentional Models (*AM*)	Basically, applies in Computer vision and natural language processing domain as it has n soft content addressing over an input sequence (or image)	deep recommender system research
Deep Reinforcement Learning (*DRL*) [58]	Trial and error paradigm. The framework consists of agents, environments, states, actions, and rewards	Games and self-driving cars

embeddings 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 [74], [75] recommendation performance is measured in terms of Recall@20 (the proportion of cases having the desired item amongst the top-20 items in all test cases) and MRR@20 ((Mean Reciprocal Rank-average of reciprocal ranks of the desired items) metric for getting rank of item and item recommendation. Also, figure 7 and 8 are providing summarised information from [76], [77], [78], [79], [80], [81], [82], about various recommendation methods with item relations and Graph convolution-based Recommendation methods referred methods from [83], [84], [85], [86] study.

8. 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

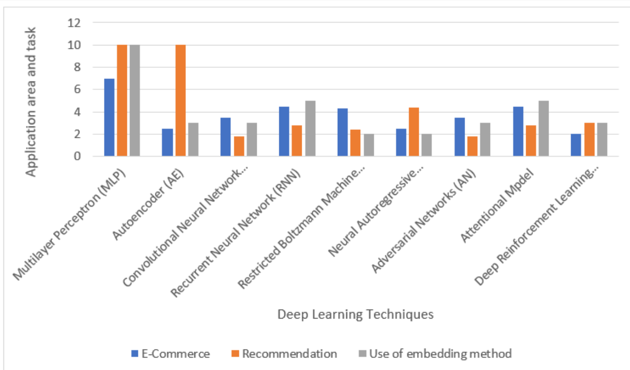

Figure 5. Distribution of embedding utilization for recommendation in E-commerce with deep learning technique

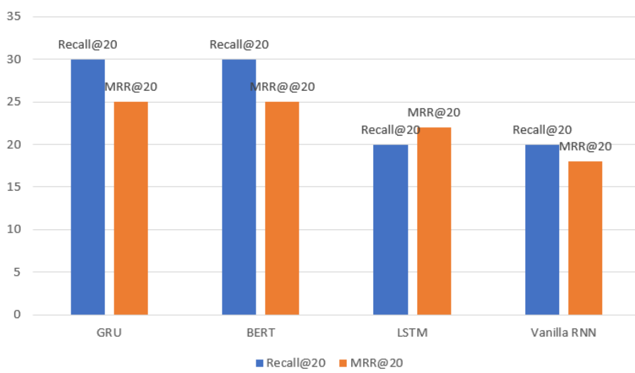

Figure 6. Deep Learning -based embedding techniques recommendation performance

recommendations. This study reviews about "data silos," its disadvantages, solution and as well as provides brief overview about composite embeddings, its construction methodologies in recent research work and how accuracy of the recommender systems is improved with composite embeddings. Also, the study provides future directions to make use of these composite embeddings 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 hot research areas. The study provides elaborative information on usage and application of Graph Convolution networks in recommender systems 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 aim of the study is to improve recommender systems performance by learning disentangled embeddings using GCNs. This provides further enhancement ideas and opportunities to enhance the proposed work. 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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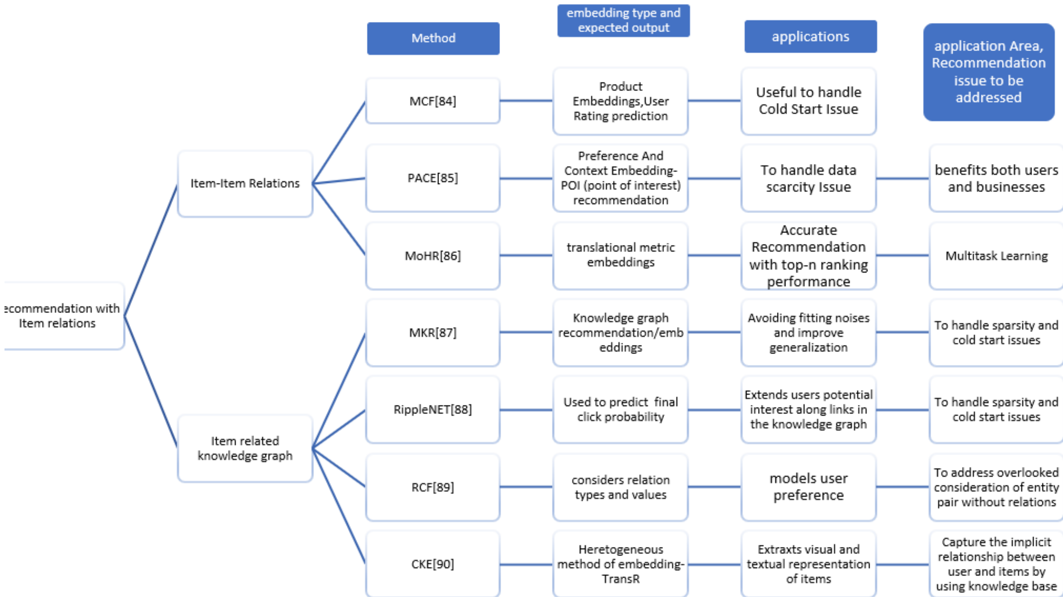

Figure 7. Recommendation methods with item relations

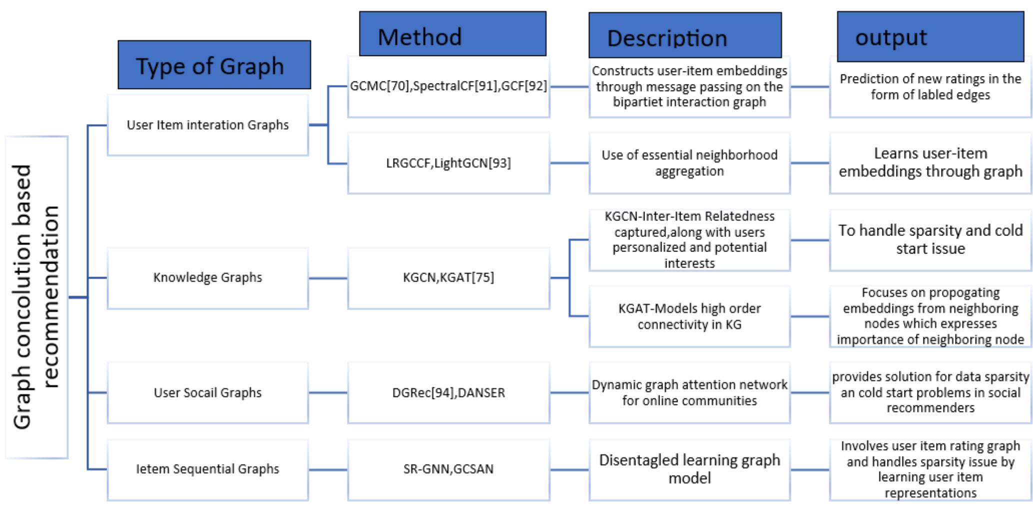

Figure 8. Graph convolution based Recommendation methods

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