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FUSING USER REVIEWS INTO HETEROGENEOUS INFORMATION NETWORK RECOMMENDED

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Abstract - A recommendation system's job is to make educated guesses about user mental processes and to make educated predictions about user interests. This system may tailor its responses to each individual user, taking into account their individual goals and preferences. More efficient data analysis is required for improved suggestion making. Different recommendation systems were developed using diverse methods. As the number of over-the-top (OTT) platforms, as well as retail, travel, and other types of websites, all of which seek to provide better suggestions to their customers, grows, so does the interest in studying such systems. The primary objective of this research is to survey the landscape of recommendation systems and conduct a comparative analysis of them according to a number of criteria. After looking at a number of articles, we saw that numerous recommendation systems were developed, most of which relied heavily on more conventional approaches. However, recently academics and businesses have been interested in knowledge graph-based recommendation systems due to its ability to solve a wide range of performance and information sparsity-related issues and provide superior suggestions.The system's efficiency is enhanced by combining machine learning with a knowledge graph. We'll also look at the many algorithms presented in the literature that make use of a knowledge graph to improve upon the recommendation process.We have also provided a high-level overview of the system we propose.Finally, we'll offer you some ideas on where the field of recommendation systems may go from here.

***Key Words*: Reviews, Heterogeneous, Network.**

INTRODUCTION

The purpose of a recommendation system is to provide the user with suggestions for additional services relevant to their interests and activities. In order to improve the user experience, recommendation systems are increasingly being used across a variety of industries, including e-commerce[4], entertainment, e-learning, search engines, and more.

Content-based filtering, collaborative filtering[22], hybrid filtering, and context-based filtering are just a few of the strategies utilised to construct a recommendation system. Therefore, the purpose of this work is to provide a comprehensive discussion of such approaches. Additionally, owing to the rapid growth of the internet, the amount of data included inside each application has ballooned. Therefore, it becomes challenging for the user to choose things or services relating to their interests from the vast quantity of data available.

The heart of every recommendation system is its algorithm. While content-based recommendation makes use of the item's content attributes, collaboration filtering recommendation makes suggestions based on the preferences of other users who are similar to the current one. When compared to content-based filtering, collaborative filtering's efficiency in collecting users' preferences and versatility make it a popular choice. On the other hand, feature extraction is a time-consuming process in content-based filtering. We also utilise the user's location, time, and other contextual data to tailor our service recommendations to him or her. Based on the user's prior actions inside the system, this model will gather patterns from the website or application and then provide suggestions. Data sparsity and cold start difficulties are two examples of challenges faced by collaborative filtering. Hybrid recommendation, which combines content-level similarity with interaction-level similarity, is presented as a solution to these problems. Product reviews, product qualities, and other supplementary data are all investigated in this model. Researchers and businesses alike have taken notice of the rising use of knowledge graphin recommendation systems in recent years. Knowledge graphs are a special kind of heterogeneous network in which the nodes represent things and the edges represent the connections between those entities.

We may map objects and their characteristics in the knowledge graph to better understand the interdependencies between the items. We may also capture user preferences more precisely by mapping user data into the knowledge graph, so forming a connection between consumers and products. We will also conduct a survey of knowledge-graph based recommendation systems in this study. C.Liu's suggested paper[16] described how to incorporate a knowledge graph into a recommendation system. In addition, Z. Sun's suggested paper[17] describes how a knowledge graph might serve as supplementary data for a recommendation system; nevertheless, the paper's classification of recommendation methods is rather broad.

Problem statement:

The problem now is to deliver better advice to the user when we have a vast quantity of data, since recommendation systems are employed in many fields. Because of its numerous benefits over more conventional methods, we have decided to construct our recommendation system on a knowledge graph. The performance of a system of recommendations based on a graph of knowledge will also be enhanced by the use of machine learning.. While most real-world systems are made up of many distinct kinds of interacting components, modern studies tend to describe these systems as single, homogenous networks. More and more scholars are starting to see these linked, multi-type datasets as heterogeneous information networks, and are developing structural analysis methodologies by capitalising on the rich semantic meaning of structural kinds of objects and linkages in the networks. The heterogeneous information network presents both new possibilities and new obstacles for data mining due to its richer structure and semantic content compared to the well researched homogeneous network.

SYSTEM ANALYSIS:

Existing System:

Similarity measure on heterogeneous information networks has recently attracted the attention of numerous scholars. The similarity measure on HIN differs from the similarity measure on homogeneous networks in that it takes into consideration both the structural similarity of two items and the meta route linking these objects. Meta-paths are the connections between items and may have semantic significance, which can influence the kind of similarities that emerge between them. That's why HIN uses a meta path constraint as its similarity measure.

Proposed System

Dilated RNN (Recurrent Neural Networks) is a cutting-edge embedding approach that may be used to the knowledge graph to boost system efficiency. We will evaluate the effectiveness of three algorithms: a Dilated RNN, a Dilated CNN, and an LSTM (Long Short Term Memory).Dilated RNN has the highest accuracy among these algorithms. Therefore, machine learning algorithms are crucial to the success of the system. We have built recommendation algorithms using the Movie, Travel, Health, Shopping, and Restaurant categories of the Yelp dataset. We'll begin by cleaning up the raw data. The model is then trained and tested using three different algorithms. After then, each of the three algorithms classifies the dataset. Next, we'll build a knowledge graph for each of those fields after implementing the recommendation prediction section and evaluating the efficacy of three methods to see which is better.

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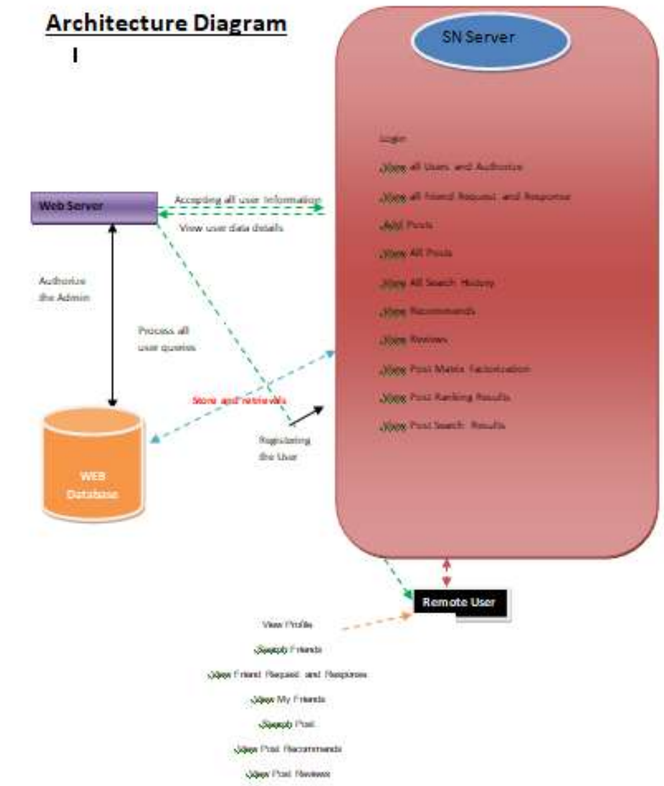
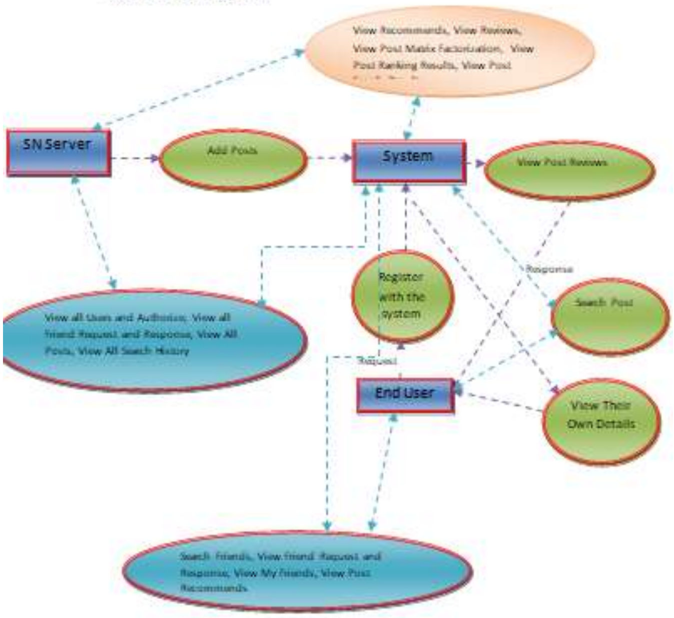
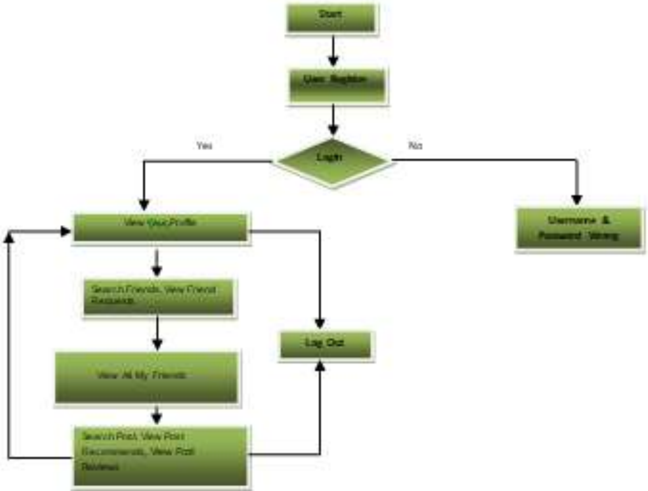
ARCHITECTURE



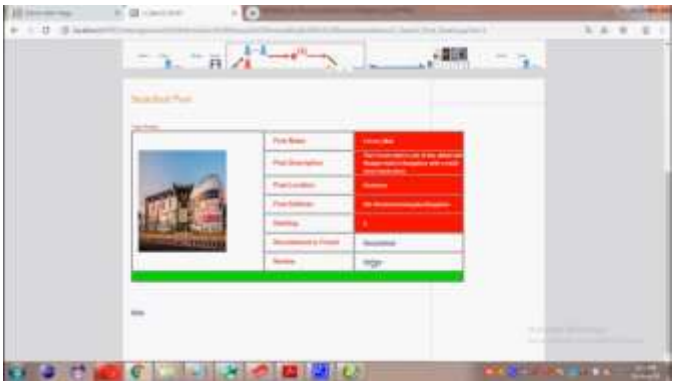
➢ Data Flow Diagram :



➢ **Flow Chart : User**



Results and Analysis:



Working:

Tokenization, stop word removal, and P-OS tagging 1. Collecting Information
In order to construct effective recommendation systems, we want to mine the Yelp dataset for information pertaining to the movie, travel, health, shopping, and dining industries. Parameters specific to each domain dataset will be necessary.
Model Training We will first do preprocessing of the dataset before beginning model training. The dataset will be divided into a training set and a testing set in order to train the model. We'll be using a mix of LS-TM, D-NN, and R-NN with a dilated layer. The processing complexity of the knowledge graph is decreased by using dilated R-NN to transform it into a low-dimensional vector space.
Third, we'll put our model through its paces on test data and analyse its results using a variety of measures, including accuracy, MRR(Mean Reciprocal Rank), recall, precision, the F1 measure, and more.

Conclusion:

We've looked at how different recommendation systems filter their suggestions and how different systems employ knowledge graphs to make recommendations. We've also seen methods where a knowledge graph is employed to provide context for the suggestions being made to the user.
We found that recommendations based on a knowledge graph were both superior and explicable.
In this research, we've also presented a knowledge-and-machine-learning-based approach that we want to test out on preexisting knowledge-graph-based recommendation systems. The resulting model will be more accurate on average than the previous one, allowing it to provide superior recommendations to the user. We want to develop a more effective and precise model for recommendation systems using the suggested method. With this overview article, we want to shed light on the many contributions made to the study of recommendations.

REFERENCES

[1] In the year 2021, the IEEE Transactions on Knowledge and Data Engineering published an article by Haithem Mezni, Djamal Benslimane, and Ladjel Bellatreche titled "Context-aware Service Recommendation based on Knowledge Graph Embedding." The article's DOI is 10.1109/TKDE.2021.3059506.

[2] 2019 IEEE International Conference on Services Computing (SCC), DOI: 10.1109/SCC.2019.00041, Sihang Hu, Zhiying Tu, Zhongjie Wang, "A POISensitive Knowledge Graph based Service Recommendation Method."

[3] "Contextual Correlation Preserving Multiview Featured Graph Clustering," 2019 IEEE Transaction on Cybernetics, DOI: 10.1109/ TCYB.2019.2926431, by Tiantian He,Yang Liu,Tobey H. Ko,Keith C. C. Chan, and YewSoon Ong.

[4] IEEE Access, DOI: 10.1109/ACCESS.2019.2928848 Cairong Yan and Yizhou Chen, "Differentiated Fashion Recommendation Using Knowledge Graph and Data Augmentation," 2017.

[5] "CASR-TSE: Context-aware Web Services Recommendation for Modelling Weighted Temporal-Spatial Effectiveness," 2017 IEEE Transactions on Services Computing, DOI: 10.1109/TSC.2017.2782793 Xiaoliang Fan, Yakun Hu, Zibin Zheng,Yujie Wang, Wenbo Chen, and Patrick Brezillon

[6] 2018 IEEE Transactions on Knowledge and Data Engineering, "GMC: Graph-based Multi-view Clustering," DOI: 10.1109/TKDE.2019.2903810; Hao Wang, Yan Yang, and Bing Liu.