Convolutional Neural Network Based Career Recommender System for Pakistani Engineering Students

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***Abstract*— In recent years, Recommender systems are utilized in a variety of areas. One reason behind why we want a recommender system in current society is that an individual has many alternatives to use because of the pervasiveness of the Internet. A recommender system seeks to estimate and predict user content preference. Old recommender systems used State-of-the-art recommender algorithms like content based filtering to predict ratings. Career Recommender system provides Engineering candidates the best possible available jobs relevant to their skills, qualification, etc. Four to six major engineering disciplines are covered in this recommender system. The proposed approach is tested using a career recommendation dataset which is collected from many students of different disciplines of various universities. A deep NLP based CNN model is used to predict the best jobs with maximum precision. 512 hidden layers are used to increase the performance of this system. Career recommendation takes care of the users and saves their cost and time spending on traditional job searching methods. Comparative study demonstrates that the proposed methodology of prediction of the best jobs achieves better results with an accuracy of 84% when matched with content based filtering technique where 81% accuracy is gained for content based career recommender system.**

Keywords-Content based Filtering, Deep NLP (Natural Language Processing), Convolutional neural network (CNN Model)

I. INTRODUCTION

Due to the invention of the internet, everyone now has access to online data. This huge amount of data poses the question: "From all this data how one can find useful information about his interest". To overcome this issue recommender systems are used, so that they can help users to find data of their own interests. Nowadays recommender systems are used in many applications like recommending movies, music, and books, etc. [8].

To facilitate engineering graduates about their career according to their area of interest is the need of this modern time. The career recommender system can suggest different career options to engineering graduates regarding their skills. This system have saved their time by recommending them relevant jobs of their fields.

Recommender systems mainly focus on predictions i.e. to predict that item or information which seems to be interesting or useful for the user. A recommender system usually consists of three elements.

- Recommendation Content
- User's preferences
- Recommendation Technique

Prediction of a recommender system depends upon user's profile. The aim of profile making is to get an idea about user's interests or skills. For this purpose, information from the user is extracted [10].

A. User Profile

The user profile is usually constructed by two things:

- Knowledge of the user
- Behavior of the user

Knowledge of the user can be gathered by arranging an interview or by doing a survey of a questionnaire.
In the second approach, the user's behavior acts as a model. Different machine learning techniques are used to find out useful patterns in the behavior.

1) Explicit Profile: Ask the candidate to fill out the questionnaire by a specific form. Advantage of this explicit profiling is that recommender system can determine user's needs directly through this technique.

2) Implicit Profile: In this technique, users' behavior is kept under observation. This method is usually obvious to the users. To track the user's browsing activity a log file is used. This file keeps some specific user's identification and behavior information. For example, amazon.com has a log file which has each customer's buying history and based on that history amazon.com recommends specific products to the customers.

B. *Types of Recommender System*

Important types of recommender systems are explained below:

1) Knowledge based recommender systems: recommend items to the user by knowing the knowledge of the item or the user.

2) Content Based Filtering: completely depends on information retrieval and filtering.

3) Collaborative Filtering: The basic idea in collaborative filtering is that if two users have exactly same likeliness for a number of items then they must have same likeliness for other items as well [12].

4) Hybrid Filtering: By combining content based and collaborative filtering, hybrid recommender systems are developed. These systems have qualities of both content and collaborative filtering recommender systems.

C. *Recommendation System Generations*

Recommender systems are growing day by day. Recommender systems can be categorized as first generation, second generation and third generation shown in Fig. 1.

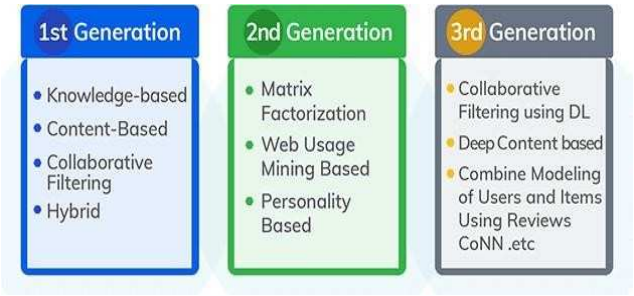

Fig. 1: Recommendation System Generation

In the rest of the paper, we will discuss the related work in Section 2. We will introduce problem statements and approaches in Section 3.Section 4 will tell about Dataset and implementation. Then, we present the results including comparison with other baseline models in section 5. Finally, we conclude the findings, limitations, and future work of this paper in section 6.

II. LITERATURE REVIEW

Karbhari, Deshmukh, Shinde (2018) proposed a job recommender system for college students on the behalf of their marks in the exams from 1st year to final year. The technique used to build job recommender system was content based filtering by finding out correlation between the content of jobs specifically words in a document and user's marks in each subject, add-ons like certificates, short courses etc. [1].

Almalis, Tsihrintzis, Karagiannis, Strati (2016) emphasized on updated minkowski distance to build a content based job recommender system. The dataset used in the recommendation were taken from an online data repository www.kaggle.com [2]. This paper proposes a Four Dimension Recommendation Algorithm (FoDRA) by using Content based filtering technique. Results of the content analysis for the job seeker is shown in table 1.

Table 1: CONTENT ANALYSIS RESULTS FOR THE JOB SEEKER

Attribute names (required skill)	Attribute values(required skill level)
S_1	25
S_2	20
S_3	11
S_4	20
S_5	29
S_6	19
S_7	21
S_8	21

By doing a comparison between Job seeker's profile and Job's profile, FoDRA suggested different top 5 jobs to the job seekers for different values of 'p' like Manhattan distance and Euclidean distances. The top 5 jobs are shown in the table 2.

Table 2: THE TOP 5 JOBS AFTER THE FODRA EXECUTION FOR DIFFERENT VALUES

Sorted List of jobs for different values of p			
$p = 1^e$		$p = 2^f$	
Job	Suitability Value	Job	Suitability Value
Job_5	10	Job_5	10.585786
Job_{25}	7	Job_{25}	7.763932
Job_{11}	6	Job_{11}	6.763932
Job_{14}	5	Job_{14}	6.171573
Job_{22}	3	Job_{22}	4.171573

$e_{\text{p=1 is Manhattan distance}}$

$f_{p=2 \textit{ is the Euclidian distance}}$

Paparrizos, Cambazoglu, Gionis (2011) provided supervised machine learning based job recommender system. This system predicts the next best job company/ institute for the employee, as job seeker wanted to switch his job from one company to the next [3]. Dataset statistics are shown in the table 3 below.

Table 3: DATASET STATISTICS

Description	Value
No. of profiles	5,298,912
No. of unique company affiliations	1,278,240
No. of unique university affiliations	195,849
Average no. of company affiliations	3.04
Average no. of university affiliations	1.27

Prediction model trained through a lot of job transition extracted from the web. Supervised machine learning naïve bayes hybrid classifier gave the highest prediction accuracy. Prediction accuracy is shown in table 4.

Table 4: PREDICTION ACCURACY

Setup	Accuracy (%)		Difference
	Baseline	DTNB	
I	15.21	66.78	51.57
II	15.40	78.26	62.86
III	15.97	86.09	70.12

Liu, Ouyang, Rong, Song, Tang, Xiong (2016) suggested a job recommender system to college students to help them in finding out best job according to their potential. Basic challenge in this study was zero working experience, as students had no history. This paper provides jobs to the students in a very short span of time. The dataset used in this research was real dataset obtained from Beihang University in 2016, which consists of 658 Master Graduates and 3830 ratings given by them to 856 employers. Experimental data included 80% ratings as the training data and 20% as the test data. Cold start ratings experimental data partition dataset is shown in table 5 [4].

Table 5: COLD START RATINGS EXPERIMENTAL DATA PARTITION DATASET

	#Student	#Employers	#Rating	#Acceptance
Training dataset	526	748	2858	1091
Test dataset	132	400	972	292

Similarity calculated on the basis of major subjects, Home town and GPA. Similarity then used to rate prediction. This paper proposes a rating based prediction algorithm to recommend jobs to the college students by obtaining the feedback from the graduates. For better performance, student's interest is also considered as an important attribute. Rating based job recommendation framework is shown in fig. 2.

Zhang, Yang, Niu (2014) proposed a job recommender system based on collaborative filtering. Model proposed was verified by using the real dataset in implementation of the algorithm.

Student's resume and details of recruitment information were extracted to suggest jobs to the users. Collaborative filtering technique is of two basic types, User-based and item based. This paper evaluates both of these types and choose item- based collaborative filtering algorithm for its better performance. Procedure of student job hunting recommendation model are shown in fig. 3 [5].

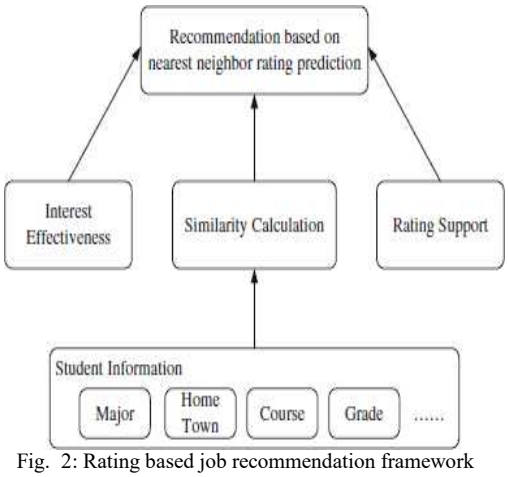

Fig. 2: Rating based job recommendation framework

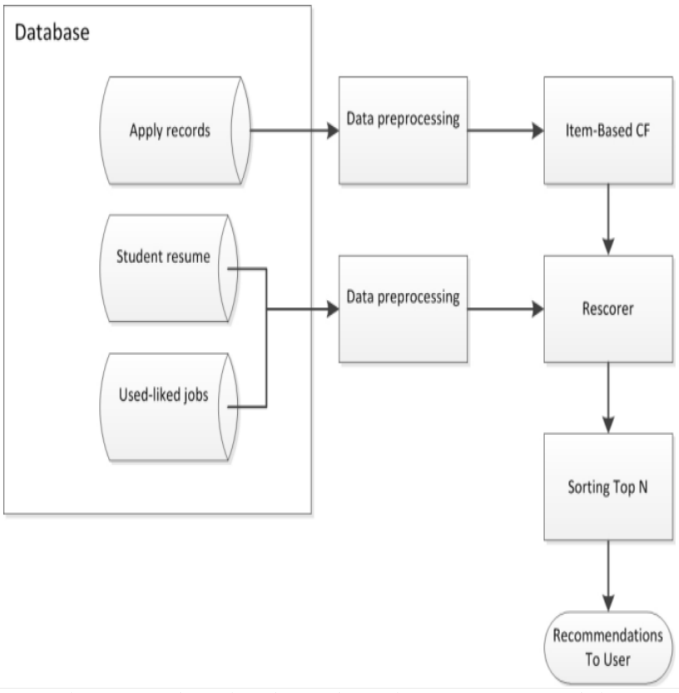

Fig. 3: Procedure of Students Job Hunting (SJH) recommendation

Hong, Zheng and Wang (2013) focused on those users who do not updated their user information in a specified time. For this purpose, a dynamic user profile-based recommender system presented. In this system based on the historical behavior of jobs and applied jobs they extend and update the user profile dynamically. Basic features which show users preferences were updated after regular intervals. Extracted features were used to extend the feature numbers. The basic features of a job applicant and post are shown in table 6 [6].

Table 6: THE BASIC FEATURES OF A JOB APPLICANT AND A JOB POST

Job Applicant	Job Post
Sex: Male Age: 26	Job_name: Programmer
Degree: Master	Salary: 7000
Education: Xiamen University	Location: Xiamen
Work_length: 1 year	Job_type: Full time
Need_Job_type: Full time	Need_sex: Unlimited
Need_salary: 8000	Need_age: 20-35
Need_location: Xiamen	Need_degree: Master

Dynamic user profile contain behavior and all the information on the recruiting website that belong to the job applicant. Dynamic user profile generated by extending the extracted feature and updating the basic features. The workflow of dynamic extracted feature is shown in fig. 4.

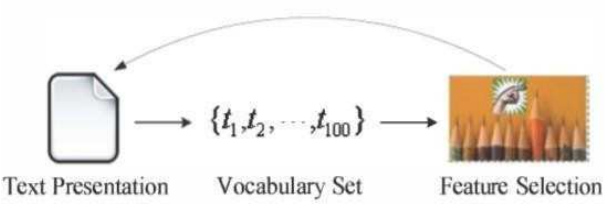

Fig. 4: The workflow of dynamic extracted feature

Based on the dynamic user profile, dynamic recommendation is achieved to improve the recommendation results. Initial recommendation was generated by using the user-based collaborative filtering. Workflow of initial recommendation is shown in fig. 5.

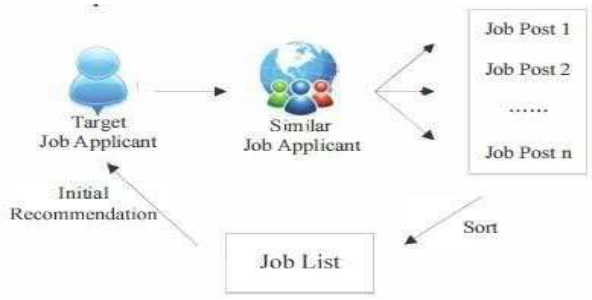

Fig. 5: The workflow of user-based collaborative initial recommendation

Diaby, Viennet and Launay (2013) discussed a recommender system which used a content-based technique and hit the LinkedIn and Facebook users to recommend a job. The technique match the job description with the user profile and recommend a job. The profile of a user divided into two types of data: users' personal information and users' friend's information. Furthermore, user profile divided into multiple parts called fields. Experiment predict the jobs similar with the user interest [7].

In general, by combining two feature which were extracted and basic features, dynamic user profile was created, and then dynamic recommendation achieved by using the hybrid recommendation algorithm. Recommender systems are becoming popular in academia as well as in enterprise domain. Due to rapid advancement of technology, huge amount of data slows down the utilization of relevant information for the recommendation in the academic domain. To overcome this challenge, researchers find a way of asking the users to upload their resume initially and on the basis of user's data and behavior, jobs are recommended to the users. Uploading the resume to recommend a job arises a problem of unstructured data, it contains unnecessary information too, which is not anymore useful for recommendation. To solve this issue FoDRA algorithm was proposed, which converted the unstructured form of data to the structured form. Candidate profile and job data recommends jobs to the users.

In traditional techniques, unstructured data used to recommend jobs and then later on it is converted into structured form through different algorithms. Now data is in the structured form but background of the user is unavailable. For recommendation to these users a rating based algorithms is presented. This algorithm worked by extracting rating from users and then calculating the similarity. Jobs recommended to those users whose ratings similarity is high. In case of dynamic users, social network based recommender systems used to recommend jobs. It targets fb and LinkedIn users. Personal data of user and their friend's data used to suggest jobs. Similarity measures improved through Linear SVM model. Limitation of this study shows most of the fields were empty. To solve this issue, Dynamic user profile based recommender system discussed. It targeted those users who didn't updated their profiles within time. Features extracted from applied jobs and used for empty fields. Jobs recommended on the basis of applied jobs.

III. PROBLEM STATEMENT AND APPROACH

A. Problem Statement

With the advent of the internet era, everyone has access to the overwhelming information available on the World Wide Web (www). Internet users have seldom idea of relevant information about their needs. To overcome this problem of information overload, recommender systems are becoming more popular nowadays for almost all fields. Netflix and amazon give us the best examples of recommender systems.

The most challenging task is to suggest a recommender system for engineering students in the education domain to give them ease for career selection by using machine learning techniques. This recommender system can help optimizing the efforts, which they have to do for searching and applying for a suitable job according to their skills.

B. Approach

1) Machine learning: Machine learning is the subset of AI (artificial intelligence). It provides us statistical tools to explore and understand the data and focuses on prediction models through the use of computers. Machine learning has three different approaches:

- Supervised learning
- Unsupervised learning
- Reinforcement or semi supervised learning

Supervised machine learning technique deals with labeled data and based on learning from this labeled data, they would be able to do some prediction for the future. In unsupervised learning, model works with unlabeled data and unaware of the output of this data initially. Usually unsupervised learning solves clustering type of problems like k-means clustering, hierarchical clustering. Clustering means, based on the similarity through mathematical concepts like Euclidean distance etc. it will grouped the data together. Reinforcement or semi supervised learning is the combination of supervised and unsupervised learning. Reinforcement learning trains models on reward and punishment basis.

2) Deep Learning: Deep learning is the subset of machine learning, which uses algorithms that are inspired by the working of brain. Usually we have a lot of neurons in our brain that is responsible for passing the signals from one part of the brain to the other and finally getting the output which is basically understanding the information. Basic idea behind deep learning is to mimic human brain as shown below in fig. 6.

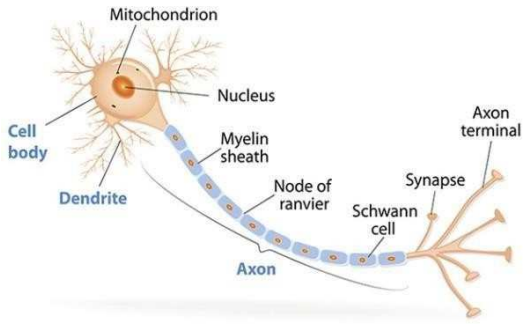

Fig. 6: Structure of the neuron

There are various deep learning architectures. We have basically deployed the following two:

- Artificial neural network (ANN)
- Convolutional neural network (CNN)

a) Artificial neural network (ANN)

Artificial neural network consists of an input layer, a hidden layer and an output layer. Input layer is basically the layer where we provide the input features for example images of a cat and dog. And model can classify the input data whether it is a cat or dog image at the output.

Similarly there is a hidden layer which is splitted into various neurons. Information from the input layer is passed to the hidden layer and from the hidden layer it is transferred to the output layer as shown in fig. 7.

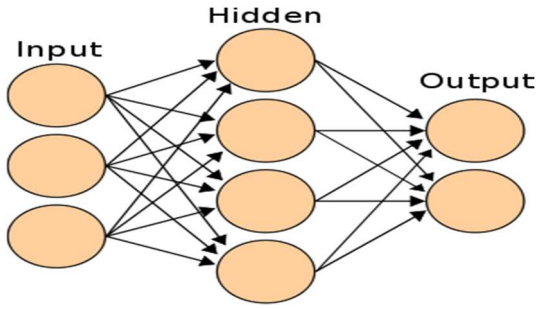

Fig. 7: An artificial neural network

b) Convolutional neural network (CNN)

Convolutional neural network usually works with image inputs to make them more simplified so it can be better processed and understood. A convolutional neural network is made up of multiple layers like convolutional layer and pooling layer etc. CNN learns by the back propagation algorithm as shown in fig. 8.

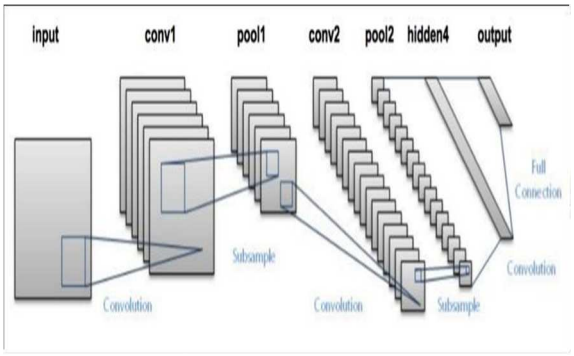

Fig. 8: A convolutional neural network

3) Python

Python is currently the most vastly used programming language for research and development in machine learning. Recently the google trend from the past five years has shown that the interest in python programming language has gone to a whole new level when compared to other programming language like Java, Julia, R etc. and also google trends shows python is the most popular machine learning language. It was created by Guido van Rossum during 1985-1990.

Python has following features:

- Python is easy to use
- It supports many libraries and frameworks
- Community and corporate support

a) Natural language processing in Python

Natural language processing deals with processing and inferring from text data. NLP falls under the broader domain of artificial intelligence. Artificial intelligence (AI) is about a computer performing tasks that a human can do so that includes how humans interpret language. NLP deals with how can, we make the machine interpret language. To start NLP in python the most popular library natural language toolkit (NLTK) is used. NLTK is written in python. It's an efficient Library for machine learning.

C. System Requirements

1) Hardware Requirements

- 8 GB RAM

2) Software Requirements

- Dataset in CSV format
- Windows OS
- Python 3.7

IV. DATASET AND IMPLEMENTATION

In this chapter we describe the dataset, the specific implementation details of the proposed model.

A. Dataset Description

The data collection phase consists of two main steps, one is collection of job data having details of the jobs from different engineers already working in different sectors of the country like industries, companies, universities, research areas etc. and second step is user data collection containing user information and description of those students who are almost graduating from different engineering universities.

B. Data Set regarding Job Profiles

Data regarding job is collected by conducting a survey from different job holders, doing jobs in different companies, industries and academia like universities etc. Job data extracts mainly from these Engineering categories:

- Electrical / Electronics
- Mechanical
- Computer / Software
- Mechatronics

The raw data which was obtained from the survey is converted into a CSV format to perform modifications on it. The list of

Job query: Job titles

Job-description: Explanation for each job in text form.

C. User Dataset

User dataset show the personal and academic details of the users. It is collected by doing a survey from different engineering candidates of various universities. The four major engineering disciplines are mainly involved in this survey. The raw data extracted from the survey is later on converted into a CVS format for processing in Python. It contains almost 10,000 entries. Some of the important features of the user dataset are as follows:

1. Qualification: formal education of the candidate either it is Bachelor's degree, Master's Degree or PhD.
2. Discipline: Engineering field either it is Electrical/ Electronics, Mechanical/ Computer/Software, Mechatronics
3. Major Subjects: subjects of undergraduate degree
4. GPA: Grade point average of the candidate
5. Languages: List of languages in which the candidate has worked
6. Frameworks: Frameworks in which the candidate has worked
7. Platforms: Platforms in which the candidate has worked.

D. Data preprocessing

Whenever the data is collected from different sources it has some abnormalities, contains inconsistency and has missing values. To make it feasible before feeding into an algorithm preprocessing is done. Preprocessing the data is an important task for the accuracy, its steps are shown in fig. 9 below.

Fig. 9: Data preprocessing steps

1) User data cleaning: Data cleaning was performed for user data. In User data some columns having attributes like name, gender, Contact details, hobbies, age etc. were removed as they are not useful in the further process.

2) Job data cleaning: In order to clean job data, NLTK packages were used in the python. The job attributes like job description and skills are mostly in the form of text therefore, numeric characters and stop words Form the entire text is removed by using NLTK packages. Text of the job description are tokenize into words, it means sentences are broken down into smaller meaningful chunks of the information. Lemmatizations of words is performed, words are reduced to their base form.

E. Implementation

1) Basic architecture of the Deep NLP based network: Convolutional Neural networks used for text processing generally takes a sentence as an input.

Models like word2vec or Glove used to get low dimensional representation of input. Sentence is then divided into words by using word2vec model. Features extracted from these words and then passed to a convolutional layer. The results obtained from convolutional layer fed into pooling layer, by using max pooling to get a maximum representative number. This maximum number is then passed to a fully connected neural network. This network assign weights to each feature of the text. Finally Neural network makes prediction/ classification decision based on these weights. Basic architecture of the Deep NLP based network is shown is fig. 10.

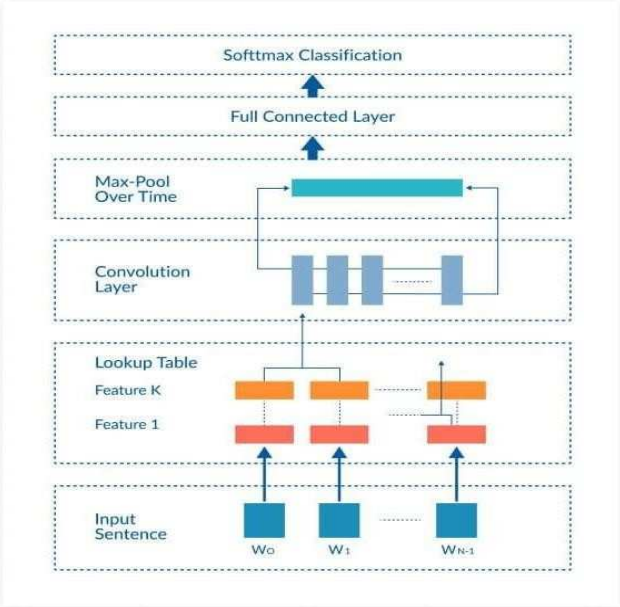

Fig. 10: Basic architecture of the Deep NLP based network

1) Deep NLP based Career Recommender System: Due to the advances in the machine learning and the artificial neural networks many applications in the natural language processing folds have also advanced. A natural language processing, computer vision all these fields have been the ones that were traditionally attributed to human perception and were quite hard to solve using the more traditional machine learning techniques . So due to this advancement in the field during the past couple of years so many tasks have been actually solved or we have the breakthroughs in them so that's the basic reason behind making of career recommender system using deep NLP technique CNN through which different career options are recommended to engineering candidates.

Deep NLP based Career Recommender System have following these steps:

- Load the Dataset. Split the dataset into training and testing data.
  X_train = train ['user_profile'], Y_train = train ['Jobs'], X_test = test ['user_profile'], Y_test = test ['Jobs']
- Tokenization, lemmatization over Job Description
- Features Extraction through Embedding Layer
- Features fed into Convolutional Layer
- Convolutional results pooled to a maximum number
- Number is fed to fully connected neural structure
- Job recommended based on the weights assigned to each feature

Define model parameters. Parameters involve Vocab_size = 1000 can create a dictionary consisting of 1000 words. Sequences length = 1200, this indicates actually user profile in which there are 1200 words. Embedding Dimensionality = 64, it represents feature matrix dimensionality. Max_features = 2000, maximum number of features are 2000. Num_lables = outcome, Lables represents jobs. Batch size = 32, Batch size means in one iteration 32 training samples are passing through the network at a time. Num_Epoch = 2000 to update the weights of the training samples, 2000 times training is carried out in this model. Num_filters = 200, 200 filters is used in the convolution layer. Kernel_size = 16, Convolutional filter is of dimensionality 16. Hidden_dims = 512, 512 hidden Layers are involved in the network.

Apply tokenization on user profile. Tokenization is a method of converting each and every word in the user profile to their respective indexes present in the vocabulary. Apply Pre/Post pad sequencing. This can equalize the length of each sentence in the user profile by appending zeros. Initialize sequential model, sequential means all the layers of CNN model are connected sequentially in the network. Add Embedding layer and its parameters (Vocab_size, Dimension, Sequences length) in the network. Word embedding mapped vocabulary based words or phrases into real number vectors. Embedding layer group similar words and it embed higher dimensional data into lower dimensional vector space. Generate word vectors for each word and Pass these word vectors to the future layers.

Add convolution layer of 1D and its parameters (Num_filters, Kernel_size and Activation Function). 'Relu' activation function is used in the model as it can reduce the linearity from the user profile. Add pooling layer, this layer uses GlobalMaxPooling function to extract the maximum value from the vector and reduces the vector size and as a result pooled feature map is retrieved. Add 512 hidden layers in the network, dropout of 0.3 and activation function 'relu'.

Add output layer i-e labels. Apply 'softmax' function to the labels to distribute their probabilities uniformly. Compile the model. Generate the model's summary. Top jobs/ career options are recommended. CNN based Career Recommender System is shown fig. 11 below.

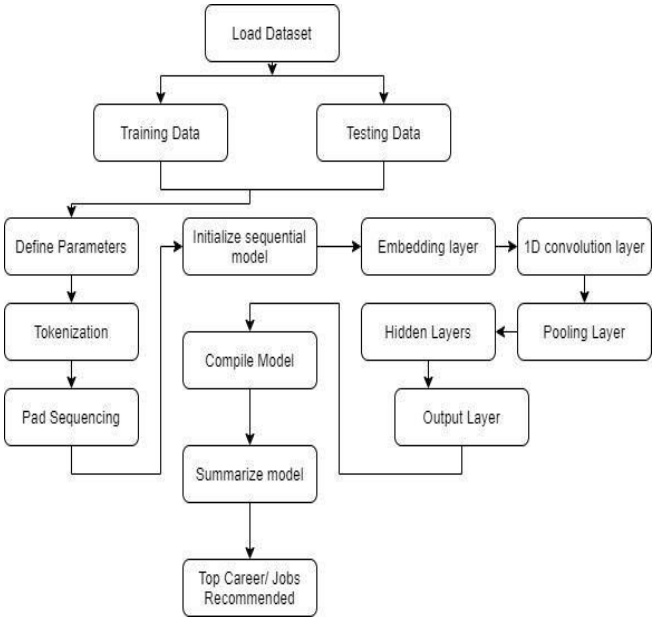

Fig. 11: CNN based Career Recommender System

V. RESULTS AND COMPARISON

A. Results

Our Proposed model CNN based career recommender system suggests different career/job options to engineering graduates based on their skills by using deep learning technique as compared to traditional content-based filtering recommender systems.

The fig. 12 demonstrates the web-based application which gives the user an interface through which he/she can enter the text data. There are four engineering disciplines are given. User has to select one of them. After selecting the engineering field, major subjects of that engineering discipline are listed down. Relevant subjects are then selected according to the discipline as shown in fig. 12.

The fig. 13 demonstrates the academic qualification of the user is asked if he/she has done B.Sc/MS or Ph.D. GPA of his/her last degree program is provided by the user. The interests are also being given like sports, book reading, etc. as shown in fig. 13. Click the submit button.

Fig. 12: web-based application for user interface

Fig. 13: Education details and Interests

Fig. 14: Education details and Interests

The best job recommendation as shown in fig. 14 is now at your hands. This framework produces the job role recommendation according to the skills required for a particular job. For better performance evaluation, same dataset is implemented on traditional content based filtering algorithm. Content based filtering technique recommends jobs to the candidates based on the cosine similarity calculations between user and job profiles.

```
Respondent 3 was recommended jobs from content based filtering in
['ICONMA' 'Cypress Group' 'SolTech, Inc' 'Saicon Consultants Inc.'
 'Samsung SDS America Inc' 'Strivector' 'Aria Systems' 'Aria Systems'
 'Strivector' 'Universal Software Corporation']
Respondent 3 was recommended job titles from content based filtering
['Python Developer' 'Full-Stack Python Developer'
 'Full Stack Javascript Engineer' 'Full Stack Developer'
 'System Administrator' 'System Administrator' 'Application Administrator'
 'Application Administrator' 'System Administrator' 'Full Stack Engineer']
```

Fig. 15: demonstrates content based job recommendations to user ID 3

The fig. 15 demonstrates content based job recommendations to user ID 3. First three rows indicates top 10 companies for recommended job titles. Last three rows shows top 10 job titles recommendations to user ID 3.

A. Comparison

The quality of a recommendation algorithm can be evaluated using different types of measurement which can be accuracy or coverage. The type of metrics used depends on the type of filtering technique. Accuracy is the fraction of correct recommendations out of total possible recommendations. The suitability of each metric depends on the features of the dataset and the type of tasks that the recommender system will do.

The fig. 16 demonstrates accuracy of CNN based career recommender system. X- Axis shows no. of epochs and accuracy is shown on y-Axis. The fig. 17 shows the similarity accuracy of content based career recommender system for top 10 recommendations. X-axis shows the job titles and y-axis has similarity score.

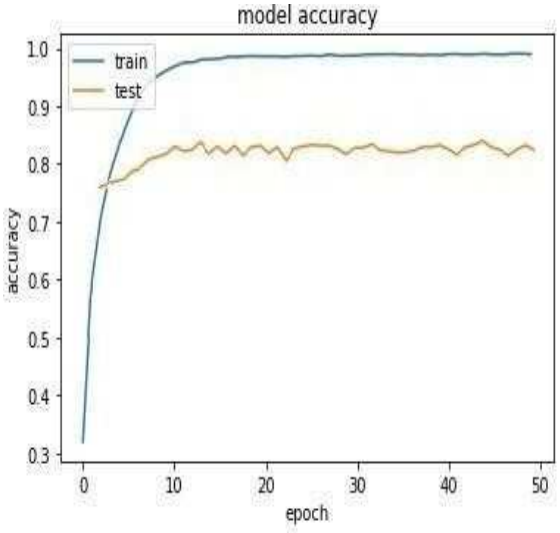

Fig. 17: Accuracy of CNN based career recommender system

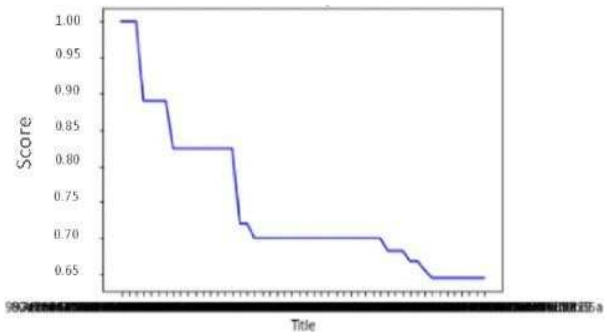

Fig. 16: Content based filtering model Accuracy

A comparison of different techniques discussed in table 7 below.

TABLE 7. COMPARISON OF DIFFERENT TECHNIQUES

Models	Predictor	Accuracy
Proposed Model	CNN based Career recommender system	84 %
Comparative Model	Content based career recommender system	81 %

VI. CONCLUSION AND FUTURE WORK

A. Conclusion

In the past couple of years, we have seen a big change in the recommendation domain which shifted from traditional matrix factorization algorithms to state-of-the-art deep learning-based methods. Recommender systems provide easiness to each individual because it predicts suggestions based on personal users interest. Our proposed approach comes up with suggestions about jobs for engineering candidates.

Engineering graduates find a lot of difficulty in terms of the best possible career according to their qualifications and interest. They don't know much about their relevant available jobs. They have to drop CV's at different places to get hired and this process requires a lot of time and cost. To overcome these problems we develop a recommender system named as career recommender system (CRS). We use different parameters such as Engineering Discipline, Gender, Qualification, GPA, interest and skills which will provide the best suitable job according to the individual

B. *Future Work*

Our proposed technique covers only four to six engineering disciplines. In the future, we will enhance the scope for our CRS which will include other engineering disciplines as well as other educational areas like medical, art, etc. Currently, this technique was only applied to a single dataset. To show generalizability, it is desirable to replicate this research on further datasets with different properties. Due to the ease of prediction and potential upside in this task, it is a valuable extension.

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