SKILL AND JOB RECOMMENDER APPLICATION

A PROJECT REPORT

Submitted by

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Date
15/11/2022

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TITLE :

1. ABSTRACT

In the last years, job recommender systems have become popular since they successfully reduce information overload by generating personalized job suggestions. Although in the literature exists a variety of techniques and strategies . It is used as part of job recommender systems, most of them fail to recommending job vacancies that fit properly to the job seekers profiles. Thus, the contributions of this work are threefold, we :

i) made publicly available a new dataset formed by a set of job seekers profiles and a set of job vacancies collected from different job search engine sites

ii) put forward the proposal of a framework for job recommendation based on professional skills of job seekers.

iii) carried out an evaluation to quantify empirically the recommendation abilities of two state-of-the-art methods, considering different configurations, within the proposed framework. We thus present a general panorama of job recommendation task aiming to facilitate research and real-world application design regarding this important issue.

INTRODUCTION :

Nowadays , job search is a task commonly done on the Internet using job search engine sites like LinkedIn, Indeed?, and others. Commonly, a job seeker has two ways to search a job using these sites:

1) doing a query based on keywords related to the job vacancy that he/she is looking

2) creating and/or updating professional profile containing data related to his/her education, professional experience, professional skills and other, and receive personalized job recommendations based on this data. Sites providing support to the former

case are more popular and have a simpler structure: however, their recommendations are less accurate than those of the sites using profile data.

Personalized job recommendation sites implemented a variety of types of recommender systems, such as

content-based filtering, collaborative filtering, knowledge-based and hybrid approaches.

Moreover, most of these job recommender systems perform their suggestions based on the full profile of job seekers as well as by considering other data sources such as social networking activities, web search history, etc. Despite the fact that many data sources can be useful to improve the job recommendation, previous studies showed that the best person-job fit is possible when the personal skills of a job seeker match with the requirements of a job offer

Based on the person-job fit premise, we propose a framework for job recommendation based on professional skills of job seekers. We automatically extracted the skills from the job seeker profiles using a variety of text.

HISTORY OF RECOMMENDATIION SYSTEM :

The era of recommendation systems originally started in the 1990s based on the widespread research progress in Collective Intelligence. During this period, recommendations were generally provided to consumers based on their rating structure.

The first consumer-focused recommendation system was developed and commercialized by Goldberg, Nichols, Oki and Terry in 1992. Tapestry, an electronic messaging system was developed to allow users only to rate messages as either a good or bad product and service.

However, now there are plenty of methods to obtain information about the consumer’s liking for a product through the Internet.

These data can be retrieved in the forms of voting, tagging, reviewing and the number of likes or dislikes the user provides. It may also include reviews written in blogs, videos uploaded on YouTube or messages about a product.

RECOMMENDATION SYSTEM :

The selection of an effective and accurate filtering technique is crucial for developing a successful recommendation system. Therefore, an elaborate understanding of these techniques is required before implementing them in a commercial platform.

a. Content-Based Filtering Technique :

The content-based filtering (CBF) technique examines the features of a recommended item by classifying users and products profile data based on the products features.

The use of domain- dependent algorithms emphasizes the analysis of the products features, which are utilized to generate predictions. Although the applications of content-based filtering techniques have been more successful in recommending web pages, publications and news articles, researchers have implemented this technique to develop Skill and Job recommendation system as well. In this technique, user profiles are matched with the features extracted from the product content, which provides the recommendation where the user has evaluated a specific product in the past. The products that have the highest relation with the positively scored or rated items are generally recommended to users. The content-based technique uses different kinds of models to explore the similarity between items to generate a meaningful recommendation, which is the main distinctive feature between content-based and collaborative filtering techniques.

b. Collaborative Filtering (CF) Technique :

The collaborative filtering (CF) algorithm is one of the most successful techniques among all of the filtering techniques available for the recommendation system.

CF is a domain-independent prediction technique for analyzing hard-to describe content by observing metadata. This filtering technique is formed by using a dataset of the preferences of a group of users to make a recommendation to another group of users who show similar types of behavior.

The fundamental assumption of CF is based on the similarities of users, which build a neighborhood group. Therefore, this technique is called user-based collaborative filtering. In collaborative filtering, automatic predictions are made based on the reviews given by other people. Therefore, the major assumption is that if two people have similar interests in a common dataset then their interests would be similar for the rest as well. Although the CF technique is critical and has some issues, such as data sparseness and the cold-start problem, recommendation systems based on CF techniques have successfully worked for many renowned business stores and services. It proposed a collaborative clothing recommendation system that overcomes the problem of capturing the aesthetic preferences of users by using a novel tensor factorization model. They used the Amazon dataset and the Aesthetic Visual Analysis (AVA) dataset to train the recommendation models and the aesthetic network, respectively. The Amazon dataset contains records of 39,371 users and 23,022 items. The AVA dataset contains over 250,000 images with aesthetic ratings from 1 to 10 and 14 photographic styles representing complementary colors, duotones, light on white, long exposure, high dynamic range, motion blur, negative image, silhouettes, soft focus, vanishing point and image grain. They proposed a dynamic collaborative filtering model using both aesthetic features and CNN features (DCFA) and compared it with baseline models such as the matrix factorization (MF) method, state-of-the-art visual-based recommendation.

c. Hybrid Filtering Technique

The hybrid filtering (HF) technique combines multiple recommendation techniques to achieve better system optimization and avoid different limitations and challenges of a basic recommendation system. The concept behind implementing the hybrid technique is that the combination of algorithms would provide more appropriate and effective recommendations to users than a single algorithm. Hence, this is the disadvantage of using one algorithm-based recommendation system.

This construction is beneficial when the dataset lacks user preferences; information about such preferences builds the foundation of collaborative recommendations. Their recommendation system has two properties. Firstly, it is knowledge-based, which helps it learn a pairwise preference or occurrence matrix based on the knowledge learnt from examples such as images uploaded to fashion blogs. Secondly, it has features of contentbased filtering as it uses a deep learning network for learning the feature representation.

They used 10,000 street-style images for image segmentation, 45,645 street-style images for product localization and 14,000 online fashion images for texture classification. Their proposed Deep Lab-MSc-LargeFOV + CRF for image segmentation outperformed other baseline models such as fully convolutional networks (FCN), combination of convolutional networks (FCN) and the conditional random field (CRF) network model. The proposed model achieved 73.99% mean intersection over union (IoU), which was higher than the other baseline models.

d. Hyperpersonalization

Filtering Technique Personalization is a system that uses the profiling of customers to make certain assumptions about the users. These assumptions are based on certain specific features and traits gathered from the profiling.

For example, suggesting ads to buyers since they have ordered or searched for a similar product online is a very common strategy used these days. This technique of personalization can bring a huge boom in sales for companies according to their sales reports.

Hyperpersonalization uses the same strategy and works more on it. Hyperpersonalization is an advanced technique built over the concept of personalization, in which the model not only investigates the item or product that was bought, but also looks into other details such as location of purchase, mode of purchase, cost of purchase, keywords inserted during purchase, demographics of the person who purchased, etc

e. Strengths and Weakness of Filtering Techniques

The successful outcome of the recommendation system depends on the relevance of the filtering technique and its compatibility with the proposed model. Therefore, researchers should consider the strengths and weaknesses of the corresponding filtering techniques while conducting research on fashion recommendation systems. It presents the strengths and weakness of the each of the recommendation filtering techniques discussed above.

f. Prospects, Challenges and Recommendations for Future Research

There has been significant progress recently in skill and job recommendation system research, which will benefit both consumers and retailers soon. The use of product and user images, textual content, demographic history, and cultural information is crucial in developing recommendation frameworks. Product attributes and clothing style matching are common features of collaborative and content-based filtering techniques.

Researchers can develop more sophisticated hyper-personalized filtering techniques considering the correlation between consumers clothing styles and personalities. The use of virtual sales advisers in an online shopping portal would provide consumers with a real time offline shopping experience. Retailers can collect the data on users purchase history and product reviews from the recommendation system and subsequently use them in style prediction for the upcoming seasons.

The integration of different domain information strengthens the deep learning paradigm by enabling the detection of design component variation, which improves the performance of the recommendation system in the long run.

5. LITERATURE REVIEW

To put this survey in context, we identified and present related review and survey articles to explain in which ways our article differs from and extends earlier work. In a recent work, a survey of fashion recommend er application, i.e., visual, audio, and/or textual features. The domains studied in this survey include various ones such as media streaming for audio and video recommendation, e commerce for recommending different products including fashion items, news, and information recommendation, social media, and so forth. While fashion RS were also discussed, the authors only included a small portion of the topics and papers in this domain.

Here, we discuss and present a comprehensive survey of significant tasks, challenges, and types of content used in the fashion RS field. We have also identified surveys [29, 170] where the authors present a literature review of techniques at the intersection of fashion and computer vision (CV) and/or natural language processing (NLP).

While we find these works relevant to this article, they remain largely different from the review presented here as those systems are not focused on RS but on other aspects of the fashion domain, such as text generation from images or pose estimation. Moreover, as another point of difference, we also provide recent techniques dealing with item visual and textual content representation exploited by RS approaches. Perhaps the most relevant work to our current survey is a recent book chapter by Jaradat et al. on fashion RS. This chapter focuses on discussing the state of the art of fashion recommendation systems; in particular, the authors affirm that deep learning represented a turning point with respect to the canonical approaches and therefore the authors examined four different tasks that use this new approach. Additionally they provided examples and possible problems and their evaluation. In particular, the authors focused their review on tasks related to social media and the size recommendation problem (see Section 2.1.3, where we introduce this task in detail). In our survey, in addition to analyzing the state of the art of the most commonly used algorithms in a wide range of tasks, we went in depth to understand which are the main features used by the more modern fashion recommender systems. In fact, an extensive discussion is held on how both the user and the items, with their characteristics, can be a source for the definition of models with accurate recommendations.

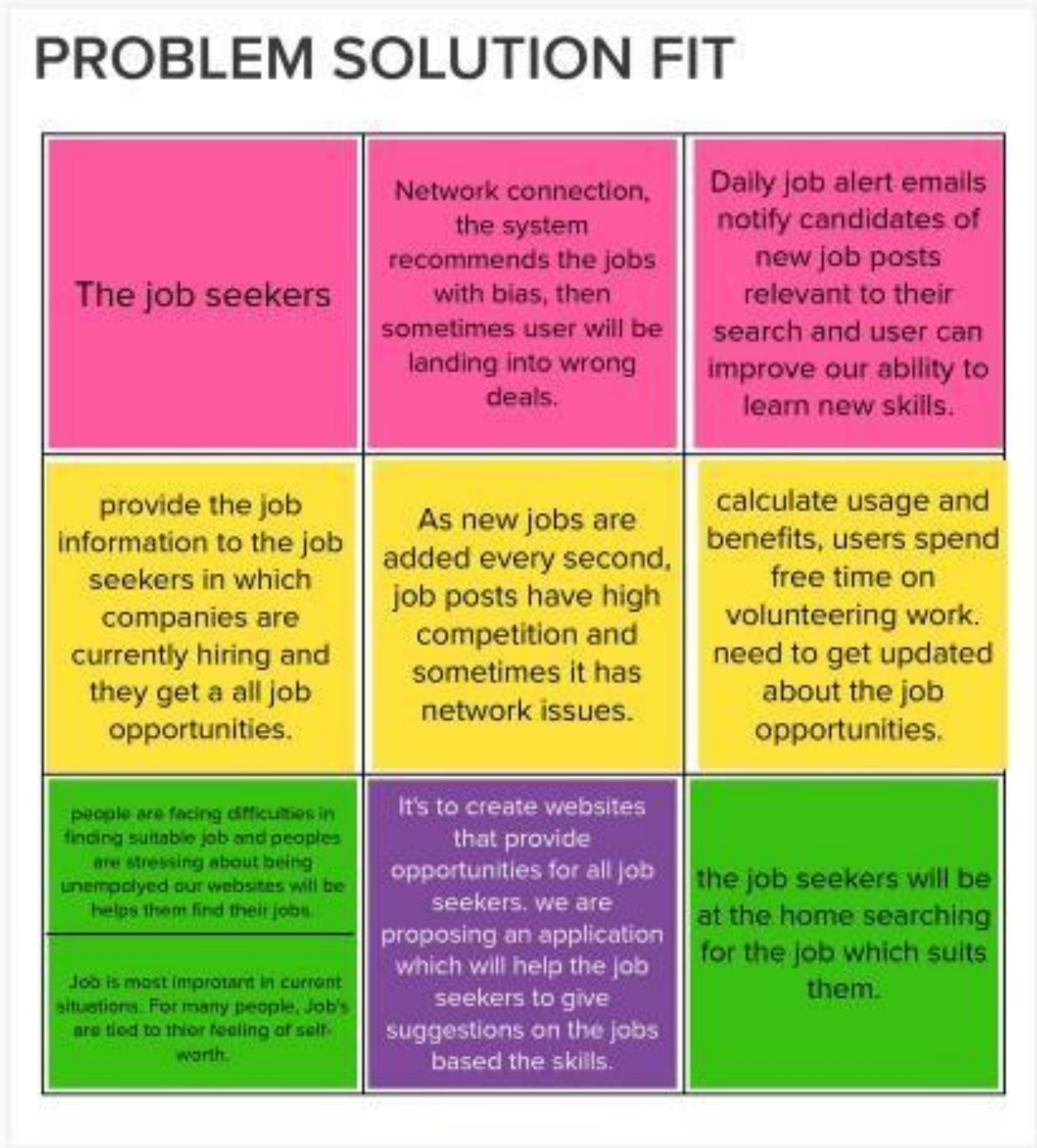
6. METHODLOGY

Learning Phase A learning algorithm is applied in this phase to filter and exploit the users' features based on the feedback collected in the information collection phase. The learning algorithms used in this phase are helpful for drawing out the appropriate patterns relevant for application during the recommendation stage.

Recommendation Phase The recommendation phase recommends the types of items that a user or consumer may prefer. Recommendations can be provided either directly based on the data set collected during the information collection phase (which might be memory- or model-based) or through the browsing history of users observed by the system .

Recommendations can also be provided by combining the learned information with the rating matrix to recommend learning resources. Researchers reported improved recommendation accuracy using hybrid models in comparison with product content-based or other user-preference-based collaborative models

7. PROJECT PHASE



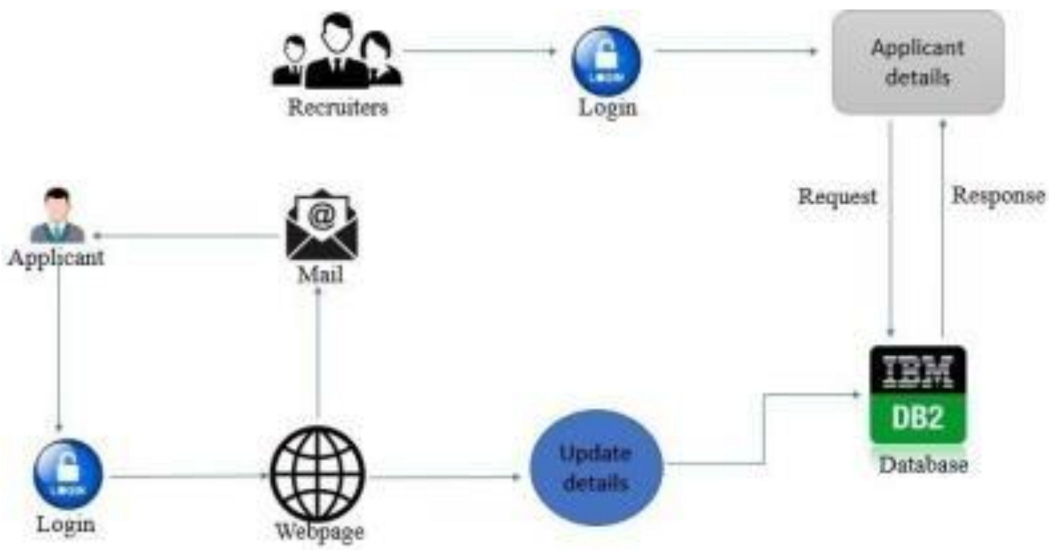
PROPOSED SOLUTION :

S.No	Parameter	Description
1.	Problem statement (Problem to be solved)	We are proposing an application which will help the job seekers to give suggestion on jobs based on the skills.The most effective recommendation show at a strong connection between the candidate skills and experience and those required for success in the position .they are applying For the job listing and the person's resume,and think the ways in which the person has demonstrated the skills necessary for the job.
2.	Idea / Solution description	We are providing Job opportunities for job seekers and providing additional information about jobs to seek their career brighter.Candidates have an opportunity to view the company's information. They get a list of all job opportunities and check photos.
3.	Novelty / Uniqueness	We are conducting webinar session for learning.Put your employees in the spotlight on social media and on our website,find ways to highlight our employees personalities,talents and stories.providing free learning links for programming languages.
4.	Social Impact / Customer Satisfaction	As customer data accumulates,the demand for job recommendation systems that provide customized services to customers is growing.we develop several job recommendation systems

4.	Social Impact / Customer Satisfaction	As customer data accumulates,the demand for job recommendation systems that provide customized services to customers is growing.we develop several job recommendation systems and measure their ability to deliver accurate and diverse job recommendations and their ability to generate customer satisfcation with diverse data sets. The results show that accuracy

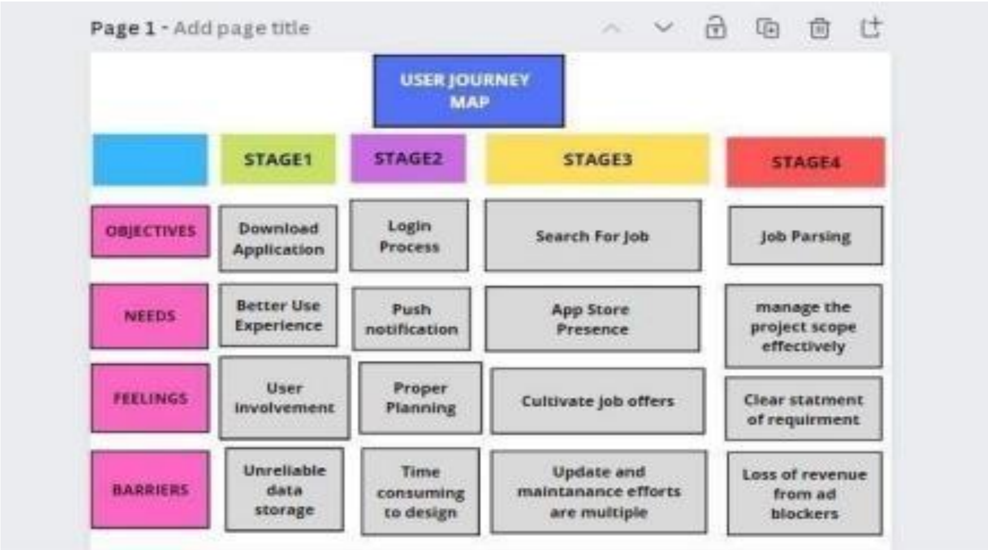
5.	Business Model (Revenue Model)	Sourcing candidates requires a lot of effort, which means it can cost a company both time and money. It was found in one study that referred candidates are 55% faster to hire, compared with employees sourced through career sites. An advantage of employee referrals is that your current team member makes the connection and saves the recruiter that initial time of sourcing the candidate. Further, the candidate could be a better match compared to other candidates who apply externally. This will also help expedite the process and cut back on the need to find alternative options.
6.	Scalability of the Solution	Being strong performers in developing the job recommendations system, decision making and delivering the best practices to the industry leaders, we are open to high-skilled guys from all over the world and offer the relocation pack and driving environment at the forefront of global fintech.

SOLUTION ARCHITECTURE :

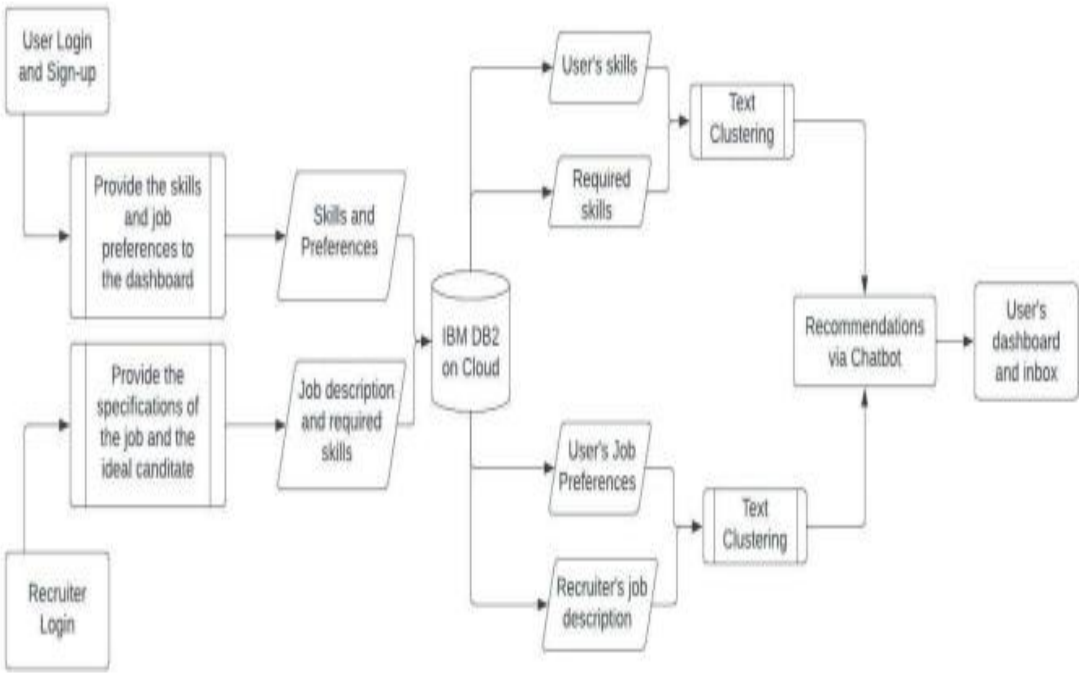


PHASE - 2 :

CUSTOMER JOURNEY :



Data Flow Diagram & User Stories :



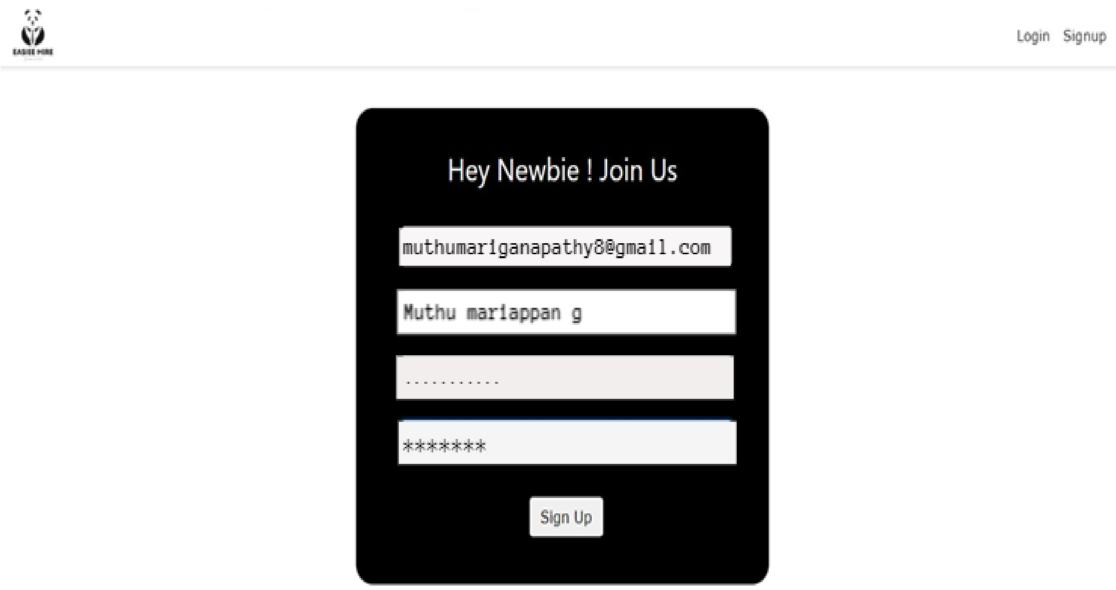
SOLUTION REQUIRMENT :

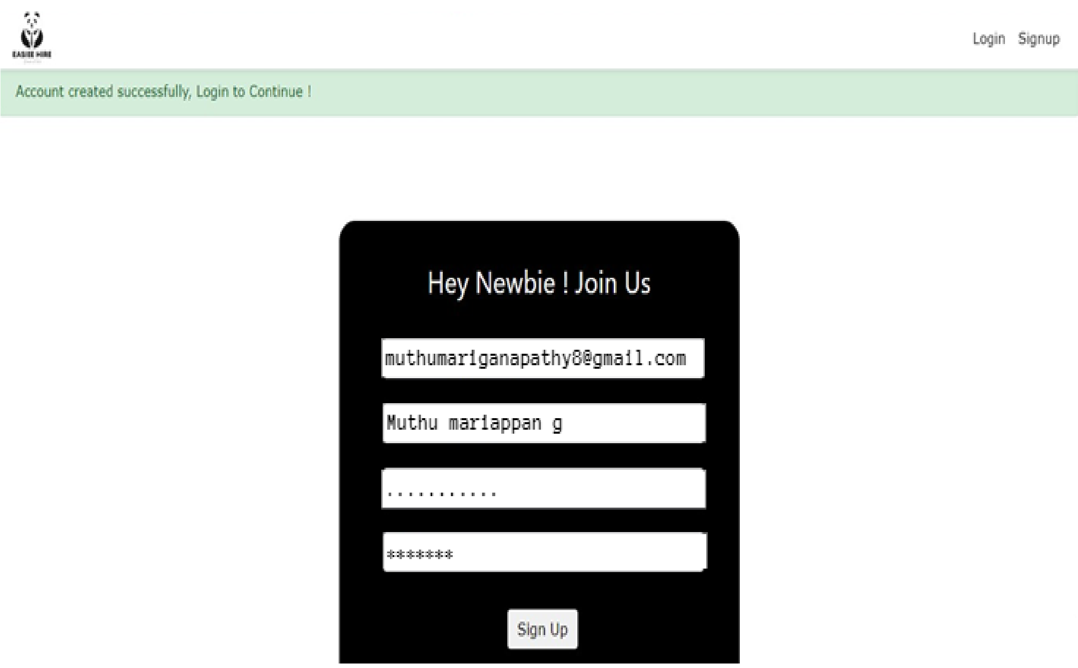
User Stories

User Type	Functional Requirement (Epic)	User Story Number	User Story / Task	Acceptance criteria	Priority	Release
Customer (Mobile user)	Registration	USN-1	As a user, I can register for the application by entering my email, password, and confirming my password.	I can access my account / dashboard	High	Sprint-1
		USN-2	As a user, I will receive confirmation email once I have registered for the application	I can receive confirmation email & click confirm	High	Sprint-1
		USN-3	As a user, I can register for the application through LinkedIn	I can register & access the dashboard with LinkedIn Login	Low	Sprint-2
		USN-4	As a user, I can register for the application through Gmail	I can register for the application through my own mail Id too.	Medium	Sprint-1
	Login	USN-5	As a user, I can log into the application by entering email & password	I can use my mail id and password to login.	High	Sprint-1
	Dashboard	USN-6	As a user, I can log into the application and search for suitable jobs and able to chat with chatbot.	After logging in to the application I can access all the services provided within the application.	High	Sprint-3
Customer (Web user)	Registration	USN-7	As a web user, I can log on and register for the application services which is being availed.	I can access services of the application.	High	Sprint-1
		USN-8	As a user, I will receive any confirmation mails, to ensure the completion of my registration.	By clicking, the confirm on my confirmation email, I'm now a registered user.	High	Sprint-1
	Login	USN-9	As a user, I can log into the application via email & password	I can log on to the application through email id and password.	High	Sprint-1
Customer care Executive	Recommendation monitoring and maintenance.	USN-10	As an executive, he/she must ensure that only the appropriate job recommendation are made based on their mentioned skillset.		High	Sprint-2
	Should monitor the chatbot regularly	USN-11	As an executive, providing the quality based service and high maintenance of chatbot becomes integral.		High	Sprint-2
Administrator	Monitor	USN-12	To monitor the overall functionalities of the application and ensure the quality of service.		High	Sprint-4

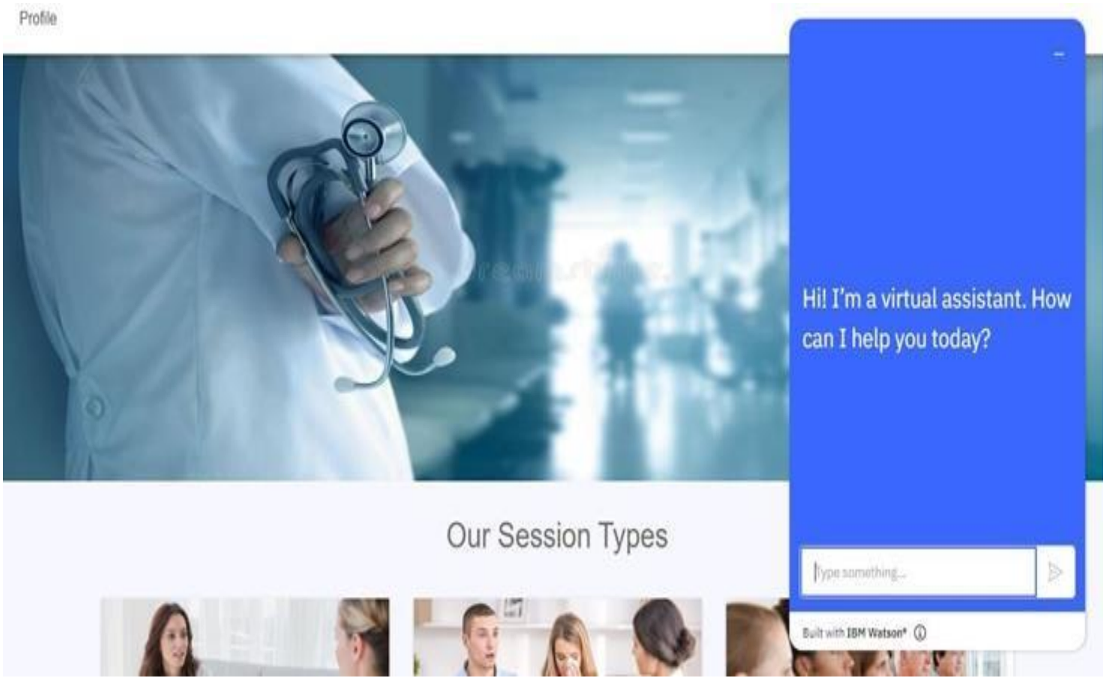
PROJECT DEVELOPMENT PHASE

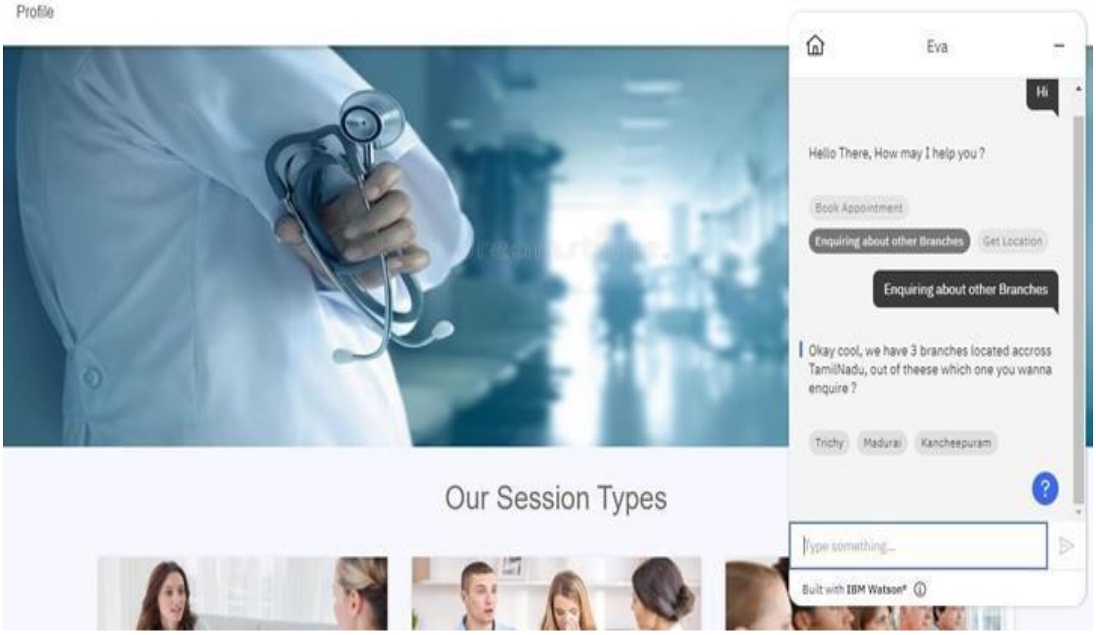
LOGIN PAGE

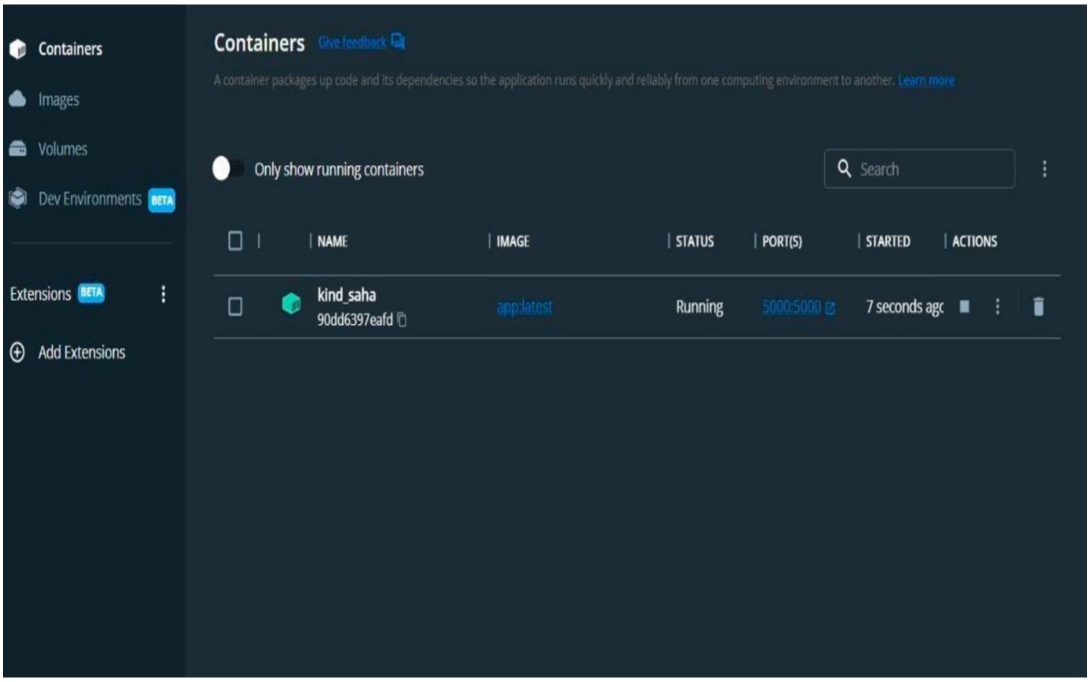




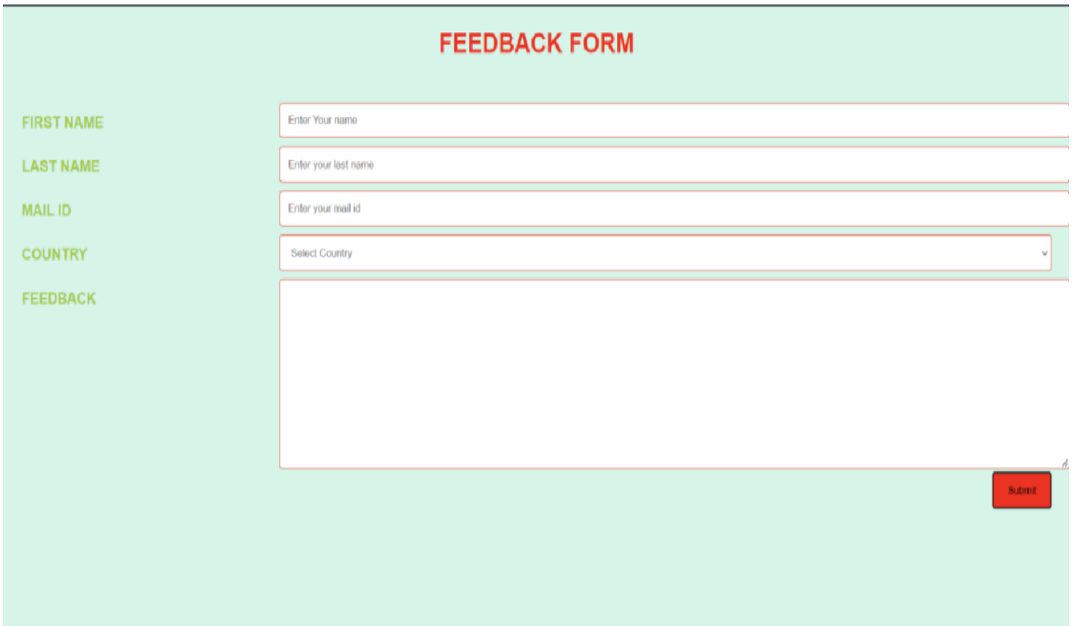
CHAT BOT


Profile
Hi! I'm a virtual assistant. How can I help you today?
Our Session Types
Type something...
Built with IBM Watson


Profile
Eva
Hi
Hello There, How may I help you ?
Book Appointment
Enquiring about other Branches
Get Location
Enquiring about other Branches
Okay cool, we have 3 branches located accross TamilNadu, out of theese which one you wanna enquire ?
Trichy
Madurai
Kancheepuram
Our Session Types
Type something...
Built with IBM Watson


Containers
Images
Volumes
Dev Environments BETA
Extensions BETA
Add Extensions
Containers Give feedback
A container packages up code and its dependencies so the application runs quickly and reliably from one computing environment to another. Learn more
Only show running containers
Search
NAME
IMAGE
STATUS
PORT(S)
STARTED
ACTIONS
kind_saha
90dd6397eafd
app:latest
Running
5000:5000
7 seconds ago

FEEDBACK


FEEDBACK FORM
FIRST NAME
LAST NAME
MAIL ID
COUNTRY
FEEDBACK
Enter Your name
Enter your last name
Enter your mail id
Select Country
Submit

8. DISCUSSION :

This scholarly article has provided a comprehensive review of the methods, algorithmic skills and filtering techniques used in the recent Job update recommendation-based research papers. However, this review paper has some limitations too.

Primarily, the focus of this comprehensive review paper was to explore skills recommendation-based articles published in last decade that explicitly described their frameworks, algorithms, and filtering techniques. To achieve this goal, the articles were searched using keywords relevant to the topic title instead of using the Skill technique. However, it did not affect the article extraction methodology, because the authors included and studied all the research papers relevant to the research focus. However, future researchers could conduct a systematic literature review on the same topic. The initial keyword searching did not include “skill” and “jobs”; however, this did not influence the search results because we also studied the job recommendation articles that contained these keywords. The future research can also conduct a review of the datasets that have been used in skill and job recommendation-based research articles.

Additionally, further reviews of skill/job recommendation systems can apply our proposed potential algorithms to any of the available job image datasets to evaluate the performance of the recommender systems.

10. CONCLUSION :

Recommendation systems have the potential to explore new opportunities for job searchers by enabling them to provide customized recommendations to searchers based on information retrieved from the Internet. They help searchers to instantly find the skills and jobs that closely match with their choices.

Moreover, different state-of-the-art algorithms have been developed to recommend products based on users’ interactions with their social groups. Therefore, research on embedding social media images within skill and job recommendation systems has gained huge popularity in recent times. This paper presented a review of the skill/job recommendation systems, algorithmic models and filtering techniques based on the academic articles related to this topic.

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12. FUTURE SCOPE :

The hybrid job recommendation approaches presented combined two or more techniques to overcome the problems that suffer from using each technique separately. For example, while the probability hybrid approaches in paragraph A realized a bidirectional recommendation and tried to cover different selection dimensions, they need to enhance by including more features for individuals and extending by various relational aspects other than trust. Additionally, they only adopted the binary representation with Yes and No when state user preferences, and it cannot measure the degree of users preferences for each index well, it is presented some approaches and systems based on CBF techniques. As mentioned in the CBF, it is limited by the features that explicitly associated with recommended objects. Therefore, since the applicants‟ resumes are usually represented by their most important features using some key words, CBF systems cannot distinguish between different keywords meaning. In addition, the problem usually associated with the pure CBF systems; it cannot recommend jobs that are different from anything the user has seen before. Jobs will be recommended if they are similar to other jobs that the applicant has already interested. Thus, the applicants have to rate a sufficient number of jobs before a CBF recommender .

system can really understand the applicant‟s preferences and present reliable recommendations. For example, the machine learned recommender system builds an automated system to recommend jobs for applicants based on their past job histories. This system is used a classifier that makes a recommendation by training them on content information. It suffered from scalability and data problems.