Literature survey:

S.	PAPER NAME	JOURNAL NAME	DESCRIPTI	Arthur	year
NO			ON	-	
1.	Journal of King Saud University - Computer and	www.sciencedirect.com	Now a day's	Ravita Mishra,	2021-2022
1.	Information Sciences		recommendation	sheetal Rathi	
			system take care of		
			the issue of the		
			massive amount of		
			information overload		
			problem and it		
			provides the services		
			to the candidates to concentrate on		
			relevant information		
			on job domain only.		
			The		
			job <u>recommender</u>		
			system plays an		
			important role in		
			the recruitment		
			process of fresher as		
			well as experienced		
			today. Existing job		
			recommender system		
			mainly focuses on		
			content-based		
			filtering to extricate profile content and or		
			collaborative filtering		
			to capture the		
			behaviour of the user		
			in the form of rating.		
			Dynamic nature of		
			job market leads cold		
			start and scalability		
			issues. This problem		
			can be addressed by		
			item-based		
			collaborative filtering		
			with a <u>machine</u>		
			<u>learning technique</u> , it learns job embedding		
			vector and finds	,	
			similar jobs content-		
			wise. Existing model		
			in job recommender		
			domain uses the		
			confining model to		
			address the cold start		
			and scalability issue		
			and provide better		
			recommendation, but		
			they fail to accept the complex relationship		
			between job	3	
			description and		
			candidate profile.		
			In this paper, we are		
			proposing a		
			Deep Semantic		
			Structure Algorithm		
			that overcome the		
			issue of the existing		
			system. Deep		
			semantic structure		
L			modelling (DSSM)		

			system uses		
			the <u>semantic</u>		
			representation of		
			sparse data and it		
			represent the job		
			description and skill		
			entities in character		
			trigram format which		
			increases the efficacy		
			of the system. We are		
			comparing the results		
			to three variation of		
			DSSM model with		
			two different dataset		
			(Naukari.com and		
			CareerBuilder. com)		
			and it gives		
			satisfactory results.		
			Experimental results		
			shows that the DSSM		
			Embedding model		
			and its other variants		
			are provides		
			promising results in		
			solving cold start		
			problem in		
			comparison with		
			several variants of		
			embedding model.		
			We used Xavier		
			initializer to initialise		
			the model parameter		
			and Adam optimizer		
			to optimize the		
			system performance		
			system performance.		
2	Embedding-hased Recommender System for Joh			ling Thao lingya	
2.	Embedding-based Recommender System for Job J	https://arxiv.org/pdf/2107.00221	, we have	Jing Zhao, Jingya Wang Madhay	2020-2021
2.	Embedding-based Recommender System for Job to Candidate Matching on Scale	https://arxiv.org/pdf/2107.00221	, we have constructed a	Wang, <u>Madhav</u>	2020-2021
2.		https://arxiv.org/pdf/2107.00221	, we have constructed a fused-embedding	Wang, <u>Madhav</u> Sigdel, <u>Bopeng</u>	2020-2021
2.		https://arxiv.org/pdf/2107.00221	, we have constructed a fused-embedding via different	Wang, <u>Madhav</u> <u>Sigdel, Bopeng</u> <u>Zhang, Phuong</u>	2020-2021
2.		https://arxiv.org/pdf/2107.00221	, we have constructed a fused-embedding via different levels of	Wang, <u>Madhav</u> Sigdel, <u>Bopeng</u> Zhang, <u>Phuong</u> Hoang, <u>Mengshu</u>	2020-2021
2.		https://arxiv.org/pdf/2107.00221	, we have constructed a fused-embedding via different levels of representation	Wang, <u>Madhav</u> <u>Sigdel, Bopeng</u> <u>Zhang, Phuong</u>	2020-2021
2.		https://arxiv.org/pdf/2107.00221	, we have constructed a fused-embedding via different levels of	Wang, Madhav Sigdel, Bopeng Zhang, Phuong Hoang, Mengshu Liu, Mohammed	2020-2021
2.		https://arxiv.org/pdf/2107.00221	, we have constructed a fused-embedding via different levels of representation	Wang, Madhav Sigdel, Bopeng Zhang, Phuong Hoang, Mengshu Liu, Mohammed	2020-2021
2.		https://arxiv.org/pdf/2107.00221	, we have constructed a fused-embedding via different levels of representation learning from raw	Wang, Madhav Sigdel, Bopeng Zhang, Phuong Hoang, Mengshu Liu, Mohammed	2020-2021
2.		https://arxiv.org/pdf/2107.00221	, we have constructed a fused-embedding via different levels of representation learning from raw text, semantic	Wang, Madhav Sigdel, Bopeng Zhang, Phuong Hoang, Mengshu Liu, Mohammed	2020-2021
2.		https://arxiv.org/pdf/2107.00221	, we have constructed a fused-embedding via different levels of representation learning from raw text, semantic entities and location	Wang, Madhav Sigdel, Bopeng Zhang, Phuong Hoang, Mengshu Liu, Mohammed	2020-2021
2.		https://arxiv.org/pdf/2107.00221	, we have constructed a fused-embedding via different levels of representation learning from raw text, semantic entities and location information. The	Wang, Madhav Sigdel, Bopeng Zhang, Phuong Hoang, Mengshu Liu, Mohammed	2020-2021
2.		https://arxiv.org/pdf/2107.00221	, we have constructed a fused-embedding via different levels of representation learning from raw text, semantic entities and location information. The clusters of fused-	Wang, Madhav Sigdel, Bopeng Zhang, Phuong Hoang, Mengshu Liu, Mohammed	2020-2021
2.		https://arxiv.org/pdf/2107.00221	, we have constructed a fused-embedding via different levels of representation learning from raw text, semantic entities and location information. The clusters of fused-embedding of job	Wang, Madhav Sigdel, Bopeng Zhang, Phuong Hoang, Mengshu Liu, Mohammed	2020-2021
2.		https://arxiv.org/pdf/2107.00221	, we have constructed a fused-embedding via different levels of representation learning from raw text, semantic entities and location information. The clusters of fused- embedding of job and candidates	Wang, Madhav Sigdel, Bopeng Zhang, Phuong Hoang, Mengshu Liu, Mohammed	2020-2021
2.		https://arxiv.org/pdf/2107.00221	, we have constructed a fused-embedding via different levels of representation learning from raw text, semantic entities and location information. The clusters of fused-embedding of job and candidates are then used to	Wang, Madhav Sigdel, Bopeng Zhang, Phuong Hoang, Mengshu Liu, Mohammed	2020-2021
2.		https://arxiv.org/pdf/2107.00221	, we have constructed a fused-embedding via different levels of representation learning from raw text, semantic entities and location information. The clusters of fused-embedding of job and candidates are then used to build and train the	Wang, Madhav Sigdel, Bopeng Zhang, Phuong Hoang, Mengshu Liu, Mohammed	2020-2021
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2.		https://arxiv.org/pdf/2107.00221	, we have constructed a fused-embedding via different levels of representation learning from raw text, semantic entities and location information. The clusters of fused-embedding of job and candidates are then used to build and train the	Wang, Madhav Sigdel, Bopeng Zhang, Phuong Hoang, Mengshu Liu, Mohammed	2020-2021
2.		https://arxiv.org/pdf/2107.00221	, we have constructed a fused-embedding via different levels of representation learning from raw text, semantic entities and location information. The clusters of fused-embedding of job and candidates are then used to build and train the Faiss index that	Wang, Madhav Sigdel, Bopeng Zhang, Phuong Hoang, Mengshu Liu, Mohammed	2020-2021
2.		https://arxiv.org/pdf/2107.00221	, we have constructed a fused-embedding via different levels of representation learning from raw text, semantic entities and location information. The clusters of fused-embedding of job and candidates are then used to build and train the Faiss index that supports runtime approximate	Wang, Madhav Sigdel, Bopeng Zhang, Phuong Hoang, Mengshu Liu, Mohammed	2020-2021
2.		https://arxiv.org/pdf/2107.00221	, we have constructed a fused-embedding via different levels of representation learning from raw text, semantic entities and location information. The clusters of fused-embedding of job and candidates are then used to build and train the Faiss index that supports runtime approximate nearest neighbor	Wang, Madhav Sigdel, Bopeng Zhang, Phuong Hoang, Mengshu Liu, Mohammed	2020-2021
2.		https://arxiv.org/pdf/2107.00221	, we have constructed a fused-embedding via different levels of representation learning from raw text, semantic entities and location information. The clusters of fused-embedding of job and candidates are then used to build and train the Faiss index that supports runtime approximate nearest neighbor search for	Wang, Madhav Sigdel, Bopeng Zhang, Phuong Hoang, Mengshu Liu, Mohammed	2020-2021
2.		https://arxiv.org/pdf/2107.00221	, we have constructed a fused-embedding via different levels of representation learning from raw text, semantic entities and location information. The clusters of fused-embedding of job and candidates are then used to build and train the Faiss index that supports runtime approximate nearest neighbor search for candidate	Wang, Madhav Sigdel, Bopeng Zhang, Phuong Hoang, Mengshu Liu, Mohammed	2020-2021
2.		https://arxiv.org/pdf/2107.00221	, we have constructed a fused-embedding via different levels of representation learning from raw text, semantic entities and location information. The clusters of fused-embedding of job and candidates are then used to build and train the Faiss index that supports runtime approximate nearest neighbor search for candidate retrieval. After	Wang, Madhav Sigdel, Bopeng Zhang, Phuong Hoang, Mengshu Liu, Mohammed	2020-2021
2.		https://arxiv.org/pdf/2107.00221	, we have constructed a fused-embedding via different levels of representation learning from raw text, semantic entities and location information. The clusters of fused-embedding of job and candidates are then used to build and train the Faiss index that supports runtime approximate nearest neighbor search for candidate retrieval. After the first stage of	Wang, Madhav Sigdel, Bopeng Zhang, Phuong Hoang, Mengshu Liu, Mohammed	2020-2021
2.		https://arxiv.org/pdf/2107.00221	, we have constructed a fused-embedding via different levels of representation learning from raw text, semantic entities and location information. The clusters of fused-embedding of job and candidates are then used to build and train the Faiss index that supports runtime approximate nearest neighbor search for candidate retrieval. After the first stage of candidate	Wang, Madhav Sigdel, Bopeng Zhang, Phuong Hoang, Mengshu Liu, Mohammed	2020-2021
2.		https://arxiv.org/pdf/2107.00221	, we have constructed a fused-embedding via different levels of representation learning from raw text, semantic entities and location information. The clusters of fused-embedding of job and candidates are then used to build and train the Faiss index that supports runtime approximate nearest neighbor search for candidate retrieval. After the first stage of candidate retrieval, a second	Wang, Madhav Sigdel, Bopeng Zhang, Phuong Hoang, Mengshu Liu, Mohammed	2020-2021
2.		https://arxiv.org/pdf/2107.00221	, we have constructed a fused-embedding via different levels of representation learning from raw text, semantic entities and location information. The clusters of fused-embedding of job and candidates are then used to build and train the Faiss index that supports runtime approximate nearest neighbor search for candidate retrieval. After the first stage of candidate retrieval, a second stage reranking	Wang, Madhav Sigdel, Bopeng Zhang, Phuong Hoang, Mengshu Liu, Mohammed	2020-2021
2.		https://arxiv.org/pdf/2107.00221	, we have constructed a fused-embedding via different levels of representation learning from raw text, semantic entities and location information. The clusters of fused-embedding of job and candidates are then used to build and train the Faiss index that supports runtime approximate nearest neighbor search for candidate retrieval. After the first stage of candidate retrieval, a second	Wang, Madhav Sigdel, Bopeng Zhang, Phuong Hoang, Mengshu Liu, Mohammed	2020-2021
2.		https://arxiv.org/pdf/2107.00221	, we have constructed a fused-embedding via different levels of representation learning from raw text, semantic entities and location information. The clusters of fused-embedding of job and candidates are then used to build and train the Faiss index that supports runtime approximate nearest neighbor search for candidate retrieval. After the first stage of candidate retrieval, a second stage reranking	Wang, Madhav Sigdel, Bopeng Zhang, Phuong Hoang, Mengshu Liu, Mohammed	2020-2021
2.		https://arxiv.org/pdf/2107.00221	, we have constructed a fused-embedding via different levels of representation learning from raw text, semantic entities and location information. The clusters of fused-embedding of job and candidates are then used to build and train the Faiss index that supports runtime approximate nearest neighbor search for candidate retrieval. After the first stage of candidate retrieval, a second stage reranking model that	Wang, Madhav Sigdel, Bopeng Zhang, Phuong Hoang, Mengshu Liu, Mohammed	2020-2021
2.		https://arxiv.org/pdf/2107.00221	, we have constructed a fused-embedding via different levels of representation learning from raw text, semantic entities and location information. The clusters of fused-embedding of job and candidates are then used to build and train the Faiss index that supports runtime approximate nearest neighbor search for candidate retrieval. After the first stage of candidate retrieval, a second stage reranking model that utilizes other	Wang, Madhav Sigdel, Bopeng Zhang, Phuong Hoang, Mengshu Liu, Mohammed	2020-2021
2.		https://arxiv.org/pdf/2107.00221	, we have constructed a fused-embedding via different levels of representation learning from raw text, semantic entities and location information. The clusters of fused-embedding of job and candidates are then used to build and train the Faiss index that supports runtime approximate nearest neighbor search for candidate retrieval. After the first stage of candidate retrieval, a second stage reranking model that utilizes other contextual information was	Wang, Madhav Sigdel, Bopeng Zhang, Phuong Hoang, Mengshu Liu, Mohammed	2020-2021
2.		https://arxiv.org/pdf/2107.00221	, we have constructed a fused-embedding via different levels of representation learning from raw text, semantic entities and location information. The clusters of fused-embedding of job and candidates are then used to build and train the Faiss index that supports runtime approximate nearest neighbor search for candidate retrieval. After the first stage of candidate retrieval, a second stage reranking model that utilizes other contextual	Wang, Madhav Sigdel, Bopeng Zhang, Phuong Hoang, Mengshu Liu, Mohammed	2020-2021

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	result. Both	
	offline and online	
	evaluation results	
	indicate a	
	significant	
	improvement of	
	our proposed two-	
	staged	
	embeddingbased	
	system in terms	
	of click-through	
	rate (CTR),	
	quality and	
	normalized	
	discounted	
	accumulated gain	
	(nDCG),	
	compared to those	
	obtained from our	
	baseline system.	
	We further	
	described the	
	deployment of the	
	system that	
	supports the	
	million-scale job	
	and candidate	
	matching process	
	at CareerBuilder.	
	The overall	
	improvement of	
	our job to	
	candidate	
	matching system	
	has demonstrated	
	its feasibility and	
	scalability at a	
	major online	
	recruitment site.	
I		<u> </u>

	just by using their voice with a virtualpersonal assistantsuch as Amazon Alexa.	

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2	IEEE EXPLORE: University Based Job https://ieeexplore.ieee.org/	With the	Akeem	2018-2020
3	Recommender & Alumni System	advancement in	Olowolayemo,	
		technology, job	Kamaleiah Harun,	
		seekers who	Kamaician Harun,	
		among them are	Teddy Mantoro.	
		fresh graduates		
		will tend to use e-		
		recruiting to find		
		opportunity and		
		apply for jobs.		
		One of the desires		
		of any university		
		is to be able to		
		track the		
		employability of		
		their graduates.		
		After graduating,		
		they often require		
		their graduates to		
		fill an online		
		system prepared		
		by the university		
		which functions to		
		know whether		
		they are getting		
		jobs and to		
		records their jobs		
		details in order to		
		analyze the		
		university's		
		graduates		
		employability.		
		Unfortunately,		
		universities are		
		unable to track		
		down the progress		
		of their graduate		
		students in terms		
		of their job		
		application status.		
		This work aims to		
		propose a system		
		that enables		
		university to track		
		their graduate		
		students' job		
		information via a		
		mobile		
		application. It also		
		had a feature for		
		students who have		
		not secure a job		
		position or wish to		
		change their job to		
		apply for available		
		job opportunities		
		after graduating.		
		The profile of		
		each student in the		
		application is		
		auto-created from		
		information		
		extracted from		
		graduating		
		students' file from		
		university		
		database which		
		the student can		
		then customize to		
		then customize to		

status. applic potent the un gather inform regard gradus emplo	eation has the tial to help niversities in ring nation ding their ates byability and
gradua	ates
helps	graduates in g jobs.