# ROLE OF PLACEMENT OFFICES IN STUDENT'S CAREER DEVELOPMENT USING PREDICTION DATA MINING METHODS

P.ANITHA VAIRAMANY , DR. K.SUBRAMNIYAN,
(PhD Research scholar Bharathiyar University Coimbatore.)
(Professor, Department of computer science Govt Arts and science College Pudukottai.)

## ABSTRACT:

***The major problem faced by candidates after the completion of their graduation is to find out the right job. while industry is also facing the problem of finding skilled graduates. Through recognizing the importance of a qualified workforce has become one of the focal points various disciplines. The great effort must be dedicated to analyzing labour demand and supply, and actions are taken at many levels to match one with the other. In this work it must concentrate skill need in the work space with dynamic variables. The purpose of this paper is to propose a suitable classification model that can be used in making prediction and assessment of the attributes of the student's dataset to meet the selection criteria of work demanded by the industry. In this paper will introduce a relatively simple yet effective method of monitoring skills needs straight from the source—as expressed by potential employers in their job advertisements. The open source tools such as Rapid Miner and R as well as easily accessible online vacancy data. We demonstrate selected techniques Naïve Bayes,to determine effective ways of discovering knowledge from a given collection of vacancies.***

**Keywords:** ***Text mining: RapidMiner; R; skills; labour market***

## I.INTRODUCTION

The labour market is most niche market. Every day by day the need is increasing both job seekers and providers. There is an essential need for huge database and mining process. every job seekers or student from final year of school and colleges has to separate accounts like social media. It is not monatomic or single goal oriented like government website. It can be easily accessible .each and every account holder page must be updated of every announcement of their own discipline or requirements. It must be ranked and giving notice of training programs and exams. It must be open like single window systems. Mining process needs naivie bays classifiers and decision trees and decision rule techniques.

There is mass gap between job seekers and job providers .in one extreme a person need a job with highly qualified but less training in the labour market. In another extent provided need the manpower with training. So training is most important every individual. So employee site or centre must have training programs. The main objective of experimentation with R was to make the vacancy and skills analysis reliable,cost free, and reproducible. I followed the steps taken in Rapid Miner. I focused on improving the pre-processing and visualization techniques, namely automating the occupational labeling and extracting information from job descriptions. At this time, I used the data published through the IrishJobs.ie domain between January and December 2014, a sample of 7090 IT vacancies.

## II.DATA PREPARATION AND DATA CLEANING

After the data is collected, the process provides data that has been achieved. In this phase, the data that will be used will be first cleaned and formatting. Data cleaning is data pre-processing to reduce noise and handle missing values. This type of data has been modified and study. Prediction performance are checked by Rapid Miner. Rapid Miner is a data mining tool will then remove excess properties and public and or normalize the data. The raw data is still in the process of collection and after complete cleansing process data will be implemented. Data may only be processed if the data required has been obtained
R is the workspace. Before retrieving vacancies into a new dataset, It have to be examined the attributes to gain a better understanding of the vacancies registered .The primary interest lay with two textual attributes, Job Title and Job Description, containing information about the occupation and the skills demand for each vacancy. The review of a sample revealed enormous diversity among job descriptions. Vacancy data varied in length, structure, and type of information included. It also required extensive cleaning, primarily of HTML tags and a wide range of punctuation marks It could removed HTML tags and punctuation using pattern matching and replacement techniques on the JobTitle and Job Description attributes. I then created two corpuses, one for each variable, and completed the cleaning process by applying a number of functions such as transforming cases.

It is important to stress that the above case study is just a single perspective on the given vacancy data. However, R offers tools that implement a myriad of data processing and mining techniques to further enhance its effectiveness. For example, single terms can be analyzed, texts can be parsed applying different frequency measures, or vacancies can be split into distinctive occupational groups using various classification and clustering algorithms. A detailed discussion around data mining is beyond the scope of this paper, which is directed towards labour market practitioners. From this perspective, however, other approaches can be suggested. For example, instead of occupational classification, skill demands can be evaluated for vacancies belonging to various geographical locations, salary ranges, contract types, or employer categories. Digital vacancy data typically include a number of attributes that can be examined conjointly or in sequence to gain more insight into skills requirements

## III.Naive bayes classification in Mining techniques

The Naïve bayes classifier approach of mining improves the tasks of web mining. It must be important in the following areas E-mail Spamming, filtering document keeping, linear file categorization, Managing content with with automatic classification and other area of web mining.

Absolutely the probability model for conditional model. It works on Bayes theorem of probability to predict the class of unknown data set. Here, the large data set of Job seekers. NaïveBayes model is easy to build and particularly useful for very large data set using the calculating posterior Probability P(C/X)

Look at here

$R = P(C/X) = P(X_1/C) \times P(X_2/C) \times \ldots\ldots. P(X_n/C) \times P(C)$

Here R Job Requirements, P(C/X) is a target given predictor

X Attributes Like Qualification, discipline, interest, talent, training, rank etc.

It converts the given data set into frequency table. For example, condider the department of Mechanical Engineering. How many of them need from the Analyst Machine Programmer and quality tester.

| Job | Seeker |
|---|---|
| Analyst | yes |
| Pnp | yes |
| q.t | No |
| Ano | No |
| M.P | yes |
| q.T | No |
| A | yes |
| M.P | yes |
| Qt | No |

Frequency Table

Among the total group, find the seeking people and the requirements.

P(yes/Analyst) = P(A/Y) × P(yes) / P(A)

P(Yes/M.P) = P(M.P/Yes) × P(yes) / P(M.P)

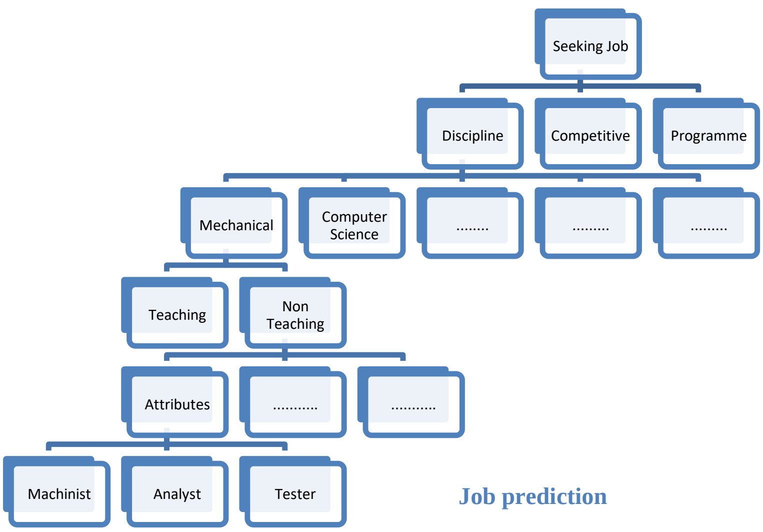
P(yes / q.T) = P(q.T / yes) × P(yes) / P(q.T)

Nanie Bayes uses similar method to predict the probability of different groups of discipline or group of Job Seekers based on various attributes which have multiple groups.

The decision tree is a structure that include root node branches and leaf nodes. Each internal node denotes a test on an attribute. Each branch outcome of a test. Here in this paper, the job seekers that indicates which job he or she may be want to go or fix their future internal nodes represents the job.

- Create the node N
- If tubes in D are all of the same class return N is the leaf labeled with Class C

Splitting the class according to input. If Mechanical discipline have been selected, create the sub nodes, teaching or non-Teaching. If Non-teaching is chosen, then create the sub tree with Node Machinist, Analyst, Quality checker etc. else the teaching is the end node, mark as a Leaf node, End if return T.




Job prediction

## IV.RAPID MINING IN STUDENT LABOUR MARKET

The student's data source would be built with the fundamental elements of the graphical user interface of Rapid Miner to execute an initial simple analysis process. Here the students must be easily access with placement offices. Rapid mining helped them to analyse their carrier and they can easily choose them. Text mining would help them to easy access. However the results got into the Result Perspective, each result is displayed within its own _le card. And in addition, there are other different ways of displaying a large number of results, which are also referred to as views within Rapid Miner. If they belong to computer science department they could easily see the number of vacancies in each sector. The views would be displayed from exist for a data set.For data sets for example there are three views, i.e. the display of the data itself (\Data View"), meta data and statistics (\Statistics View"), the display of different visualisations .

## V.CONCLUSION AND FUTURE WORK

Unemployment among graduates is a major issue in this country. This issue should be addressed first, particularly at the university level. In order to meet the needs of industry and the goals of higher education, various methods have been designed and implemented to identify the attributes that affecting the graduates either employed, further study, upgrading skills, waiting for work placement or unemployed. This study has analysed the problem by two different mining techniques .As a future work, there is a need of more attributes likes grade subjects taken during the study period, the results of the oral test and work status. The completed dataset can be used to test six of the proposed model.

## VI.REFERENCES


1. The UK Commission for Employment and Skills. *The Labour Market Story: Skills For the Future*, 1st ed.; The UK Commission for Employment and Skills (UKCES): London, UK, 2014.*Informatics* **2015**, *2* **49**

2. Handel, M. Trends in Job Skill Demands in OECD Countries. OECD Social, Employment andMigration Working Papers, No. 143, 2012. Available online: http://dx.doi.org/10.1787/5k8zk8pcq6td-en (accessed on 18 October 2015).

3. Cedefop. *User Guide to Developing an Employer Survey on Skill Needs*; Publications Office ofthe European Union: Luxembourg, 2013.

4. Manacorda, M.; Manning, A. *Just Can't Get Enough: More on Skill-Biassed Change and LabourMarket Performance*; London School of Economics and Political Science: London, UK, 1999.

5. EGFSN. *Tomorrow's Skills. Towards a National Skills Strategy*; Expert Group on Future Skills Needs: Dublin, Ireland, 2007.

6. UNESCO. *International Standard Classification of Education ISCED 2011*; UNESCO Institute for Statistics: Montreal, QC, Canada, 2012.

7. Litecky, C.; Aken, A.; Ahmad, A.; Nelson, H.J. Mining for Computing Jobs. *IEEE Softw*. **2010**, *27*, 78–85.

8. Ahmed, F.; Capretz, L.F.; Campbell, P. Evaluating the Demand for Soft Skills in Software Development. *IEEE IT Prof*. **2012**, *14*, 44–49.

9. Kurekova, L.; Haita, C.; Beblavy, M. *Qualifications or Soft Skills? Studying Demand for Low-Skilled from Job Advertisements*; NEUJOBS Working Paper No. 4.3.3; NEUJOBS: Brussels, Belgium, 2012.

10. Zhang, S.; Li, H.; Zhang, S. Job Opportunity Finding by Text Classification. *Procedia Eng.* **2012**, *29*, 1528–1532.

11. Jiang, W.; Huang, L.; Liu, O.; Lu, Y. A Cascaded Linear Model for Joint Chinese Word Segmentation and Part-of-Speech Tagging. In Proceedings of the 46th Annual Meeting of the Association for Computational Linguistics, Columbus, OH, USA, 15–20 June 2008; pp. 897–904.

12. Weiss, S.M.; Indurkhya, N.; Zhang, T. *Texts in Computer Science. Fundamentals of Predictive Text Mining*; Springer: London, UK, 2010.

13. Debortoli, S.; Müller, O.; vom Brocke, J. Comparing Business Intelligence and Big Data Skills—A Text Mining Study Using Job Advertisements. *Bus. Inf. Syst. Eng*. **2014**, *6*, 289–300.

14. Landauer, T.K.; Foltz, P.W.; Laham, D. Introduction to Latent Semantic Analysis. *Discourse Process.* **1998**, *25*, 259–284. 15. Albright, R. Taming Text with the SVD. Available online: ftp://ftp.dataflux.com/techsup/ download/EMiner/TamingTextwiththeSVD.pdf (accessed on 4 September 2015).

16. Cedefop Skills Supply and Demand in Europe. *Methodological Framework*; Research Paper No. 25;
Publications Office of the European Union: Luxembourg, 2012.

17. McNaboe, J; Cordon, N.; Milicevic, I.; Hogan, A.; Wowczko, I. Vacancy Overview 2014. Available online: http://www.solas.ie/docs/VacancyOverviewReport2015.pdf (accessed on 18 October 2015). © 2015 by the authors; licensee MDPI, Basel, Switzerland. This article is an open access article
distributed under the terms and conditions of the Creative Commons Attribution license

19.Skills and Vacancy Analysis with Data Mining Techniques Izabela A. Wowczko *Informatics* **2015**, *2*, 31-49; doi:10.3390/informatic204003