The International Journal Of Engineering And Science (IJES)
|| Volume || 5 || Issue || 4 || Pages || PP -15-24 || 2016 ||
ISSN (e): 2319 – 1813 ISSN (p): 2319 – 1805

Proposed Model for Predictive Mapping of Graduate's Skills to Industry Roles Using Machine Learnining Techniques

[1]Fullgence Mwachoo Mwakondo, [2]Dr. Lawrence Muchemi, [3]Prof. Elijah Isanda Omwenga

[1]Institute of Computing & Informatics Technical University of Mombasa, Kenya
[2]School of Computing & Informatics University of Nairobi, Kenya
[3]School of Computing & Informatics University of Nairobi, Kenya

Abstract

The main focus in training evaluation is not only to determine whether training objectives were achieved but also how to improve evaluation so as to enhance both employability of graduates and performance in the job. This is in response to challenges facing not only graduates in choosing industry jobs that befit their skills, but also employers in selecting graduates whose skills match to their needs. Problem solving is one of the skills acquired during training by graduates and strongly sought for by employers during evaluation to promote performance in the job. This paper presents a model for evaluating graduates' by mapping their problem solving skills to industry jobs' competence requirements and the potential of using machine learning techniques to train the model in predicting suitable industry jobs for new graduates from college. The paper outlines challenges facing both graduates and industry in selecting industry jobs and skilled graduates respectively, highlights trends, methods, and gaps in skill evaluation and prediction. A brief discussion is made of key strategies in skill evaluation and prediction that need to be undertaken and evaluation theories behind the key variables of the proposed model.

Keywords: *Gap, Mapping, Problem solving skills, Training evaluation, Trends*

Date of Submission: 16 March 2016 Date of Accepted: 05 April 2016

I. Introduction

The purpose of evaluation is to determine whether training objectives were achieved and whether they can result into enhanced performance on the job [1]. Evaluation improves employability of graduates and is not only crucial in the academia but also to recruitment processes in the industry [2]. Currently, graduates' skill variations and other factors contribute to industry academia gap [3] [4]. While industry academia partnership is key to bridging the gap [5], graduate evaluation against industry jobs is vital. Although employers describe staffing requirements in terms of competences while academia expresses skills and knowledge characteristics in terms of certifications and qualifications [6], evaluation method that is both industry and academia centered can reduce confusion among graduates in understanding employers' preferences [4] [7] [8].

Many degree programs have similar titles but lead to graduates with different competences [4] [9]. This is due to differences either in learning environments among institutions [10] or between students' abilities [1] [9] [4]. Besides, industry has a picture of competences that graduates should possess for each job such as problem solving skills [8] [11]. But, traditional classroom evaluation is limited to learning objectives and still uses grades to signal problem solving skills. Yet, apart from grades suffering variation from grader to grader [2], problem solving skill is multidimensional [12] and signals employers use to assess it such as interviews and grades, are not sufficient [8].

Graduates seek insight into which job prospects look favorable and understand requirements in terms of skills characteristics [13]. Although requirements thresholds for problem solving skills vary differently for different jobs [10] [14], precise levels and kind needed by each are poorly understood [13]. A standard evaluation method that helps employers see through the skill qualification mix of graduates but also evaluates all dimensions of problem solving skills is needed to bridge this gap [9] [4] [10].

This paper discusses the potential of applying machine learning techniques in the process of evaluating graduate skills for both the training processes of academia and recruitment processes of industry. The paper intends to reveal that industry academia gap is partly because of poor evaluation of graduates' skills by both industry and academia and can be reduced by mapping academic knowledge and skills of employed graduates to competence requirements of industry jobs. This paper is part of my on-going doctoral thesis work where different research methods have been used to evaluate the training knowledge and skills of employed graduates (e.g. past exam analysis, questionnaires). The rest of this work is organized as follows: section two highlights skills evaluation and prediction: trends, methods, and gaps, section three outlines key strategies in skill evaluation and job prediction, section four reviews related studies, section five statement of the research problem, section six outlines the theoretical background of the model, while section seven presents the proposed model and finally section eight closes with a conclusion.

II. Skills Evaluation and Prediction: Trends, Methods, and Gaps

Growing dissatisfaction by industry over graduates' productivity is as a result of industry academia gap emanating from poor evaluation of graduates' skills vis-à-vis competence requirements of industry jobs.

2.1 Trends in Skills Demanded By Industry

Trends indicate significant evolution of technologies that demand strong problem solving skills and evolution of skill requirements for professionals [15] [16] [17] [18] [19]. Long term trends have been towards jobs requiring more education and cognitive skills, but the precise levels and kinds of skills are poorly understood by graduates [13].

2.2 Underlying Cause of Industry Academia Gap

Studies reveal there is a gap between industry and academia, but none has been able to show one of the underlying causes is poor evaluation of problem solving skills of graduates by both industry and academia [14] [20] [22] [23] [24] [25]. Studies on evaluation of graduates' competences indicate problem solving skill is poorly evaluated [11] [8] hence causing industry academia gap.

2.3 Evaluation and Prediction of Graduate's Knowledge, Skills, and Competences

Competence is a useful concept in bridging the gap between industry and academia [26]. Traditional competence evaluation methods such as interviews, grades etc. are not sufficient for problem solving skills ([8]); are subjective [10] [26], and have no underlying framework of reference that is cognitively based [1]. Issues in evaluation and prediction of graduates' skills are: content knowledge evaluation is not adequate, we need to also evaluate competences [11]; qualifications and certifications alone do not adequately portray graduates' skill possession [4]; manual grading is subjective [26]; and no reliable formula to combine competences to predict overall graduate's capability [6].

III. Key Strategies in Skill Evaluation and Job Prediction

For solution, what is needed are strategies and key facts such as, to perform job tasks properly in the industry core content knowledge and experience are key requirements [24], content knowledge alone is difficult to apply in unfamiliar context [11]. Strategies to explore include: understanding the relationship between content knowledge and competences, competence evaluation frameworks, and automatic skill evaluation using computational intelligence techniques such as machine learning.

3.1 Relationship Between Content Knowledge and Competences

Studies reveal high correlation between conceptual understanding of content knowledge and transfer of problem solving skills as the main predictors of performance in transfer problems and successful performance [21]. However, indexes used for performance prediction in the studies are not transparent to interpret. To provide transparency while reducing assessment variation from grader to grader there is need to use frameworks as reference for skill evaluation [2].

3.2 Skill Evaluation Frameworks

Content knowledge is correlated to domain-specific knowledge and object of study in academic disciplines. Each academic discipline has a body of knowledge all graduates ought to acquire during training [28] [28] and this can be used as a framework of reference for content knowledge evaluation [20]. Professions have a competence framework that define a set of skill-based competences needed by all graduates entering the profession which can also be used as a framework of reference for problem solving skill evaluation [10]. However, frameworks provide skill transparency but not entire solution to variation problem from grader to grader, cost of hiring, or evaluation time wasted, and therefore, automatic skill evaluation can greatly provide solution to this for both training and recruitment processes of industry and academia [2].

3.3 Automatic Skill Evaluation and Prediction

Automatic skill evaluation is an attempt to lower cost of hiring, reduce evaluation time wasted and provide a standard way of graduate assessment [2]. Computationally, skill evaluation problem can be viewed as a pattern recognition problem and posed as a classification task where machine learning techniques can be used to solve it [29]. Therefore, machine learning classification methods and algorithms can possibly provide a reliable formula for combining competences to predict overall capability of a graduate.

IV. Machine Learning Classification Methods and Algorithms

Machine Learning (ML) is a branch of Artificial Intelligence (AI) concerned with designing programs (ML algorithms) that attempt to make computers behave intelligently by being able to sense, remember, learn, and recognize patterns [30]. ML is used to solve problems through a number of methods that are broadly classified into supervised and unsupervised learning methods. Classification is one of the ML methods used to predict group membership for data instances. There are two types of classification methods: supervised and unsupervised classification.

4.1 Supervised Classification Method

This is the construction of a classification procedure from a set of data for which the true classes are known, also known as supervised learning, pattern recognition or discrimination [32]. Objective of supervised classification method is to establish a classification rule from a given correctly classified data, or to construct a learning model from labeled training data set so as to be able to classify new objects with unknown labels [31].

4.2 Unsupervised Classification Method

This is the construction of a classification procedure from a set of data for which the true classes are unknown but are inferred from the data set, also known as clustering [32]. It can be viewed as aiming to identify natural groups or classes or clusters in the data.

4.3 ML Algorithms

ML algorithms are designed around a particular paradigm for the learning process which must be clear about the learner, domain, goal, representation, algorithmic technology, data source, training scenario, prior knowledge, success criteria, and performance [30]. However, ML algorithms suffer challenges of algorithmic approach, data representation, computational efficiency etc., and this has triggered research into various ways of improving them resulting into a number of techniques including: decision trees, rule-learners, Neural Networks, K-Nearest Neighbor, Support Vector Machine, Naïve Bayes.

Despite many ML algorithms available, classification methodology applied on a particular problem depends on data, model, and expected results of analysis. However, most basic ML algorithms were developed to solve the binary classification problem (i.e. two class case), while the multiclass classification problem is poorly approached [31] [33].

4.4 Multiclass Classification

Multiclass classification is a case of classification problem where there are many distinct classes while binary classification is a case of classification problem where there are only two distinct classes. A survey on multiclass classification methods [31] [33], reveals approaches proposed to solve the problem including extensible, decomposition and hierarchical methods. However, hierarchical methods perform better than others.

Hierarchical methods involve arranging classes hierarchically into a tree and using a simple classifier at each node. The goal is to use as fewer classifiers as possible. So far K-1 binary classifiers to classify K-classes problem have been proposed [34] [35]. Although experiments reveal none of the methods is perfect across all the data sets [31], conclusion that any one of the method can be used depending on the need was based on accuracy. However, multiclass classification is still a major problem [31] [33], and the following are some of the major issues: unclassified labels, large memory requirement, unbalanced training sample sizes, large number of classifiers i.e. for hierarchical (K-1 classifiers).

V. Related Studies

[3] proposed a model to find the gap between academia and industry. The model consists of three independent variables and one dependent variable. The dependent variable consists of well qualified graduates, while independent variables include solid courses and resources availability, academic staff capabilities and properties, and well equipped laboratories and adequate tools.

More recently, [36] developed a supervised learning model based on annotated data to automatically detect the student's personality based on their chat interaction in an educational game [36]. In their model they used machine learning algorithms, Support Vector Machine (SVM) , decision tree and Naïve Bayes.

VI. Statement of the Research Problem

Industry is facing a problem of finding skilled graduates who fit to their needs, while academia is facing a problem of matching graduates' skills with industry roles, partly because of poor evaluation of problem solving skills vis-à-vis industry jobs [10] [13] [14]; or lack of effective methods for assessing graduate's problem solving skills [8] [10] [37].

The purpose of this paper is to propose a model to help in evaluation and prediction of job competences demanded by industry from graduates' in the academia, in Kenya. The model can be used in collecting, analyzing data and profiling academic skills and knowledge of employed graduates in the industry and job competence requirements so as to create a mapping model in phase 1. The mapping model can then be used to conceptualize a prediction tool to evaluate and predict suitable industry jobs for new skilled graduates using machine learning techniques in phase 2. The prediction results of this tool can be compared with results of existing evaluation tools or methods to find validity of the prediction tool in phase 3.

VII. Theoretical Background and Models for Training Evaluation.

7.1 Models For Training Evaluation

Three theoretical models will be employed i.e. Kirkpatrick's model [38], CRESST model by [12], and theory of cognitive learning [1].

7.2 Kirkpatrick's Model of Training Evaluation

Kirkpatrick evaluation model consists of four hierarchical stages [38]. Stage 1 is *reaction* that assesses learners' satisfaction and reaction to learning program. Stage 2 is *learning* that assesses extent to which learners' improved knowledge, increased skills, and changed attitudes. Stage 3 is *transfers* which assesses extent to which learners' change in behavior and apply what they learn in the job. Stage 4 is *result* and assesses extent to which the company benefits as a result of training the learner. Therefore, trainee must *learn* relevant content knowledge before *transferring* it to the job. Further, evaluation should focus on relevance of content knowledge acquired. However, Kirkpatrick's model does not show measures/variables for assessing learning outcomes.

[39] suggest attributes can be used to predict transfer of learning: 1) motivation 2) self-efficacy 3) personality 4) expectations 5) control 6) ability 7) quality of training 8) relevancy of content to the job. Therefore, CRESST model elaborates more on types of learning outcomes that enhance performance in the job.

7.3 CRESST Model for Learning

[12] CRESST's model (Centre for Research on Evaluation, Standards and Students' Tests) identifies five families of cognitive demands that can be used as a framework for designing teaching, learning, and testing i.e. 1) *content understanding* 2) *problem solving* 3) *self-regulation* 4) *collaboration/teamwork* 5) *communication skills*. They observe, problem solving is a family that is a superset of other families, and consists of: 1) content understanding, problem solving strategies, and self-regulation. Self-regulation comprises of motivation and meta-cognition, while problem solving strategies comprise of domain dependent and domain independent aspects. Fig.1 summarizes the CRESST model.

[40] observes, problem solving competence is a cognitive process that transfers content knowledge learned to the job (new or unfamiliar situation) [41] and is fundamental in enhancing performance on the job. Besides, it is multi-dimensional consisting of:- content understanding, intelligence (domain independent), and technical (domain dependent), and self-regulation dimensions [12].

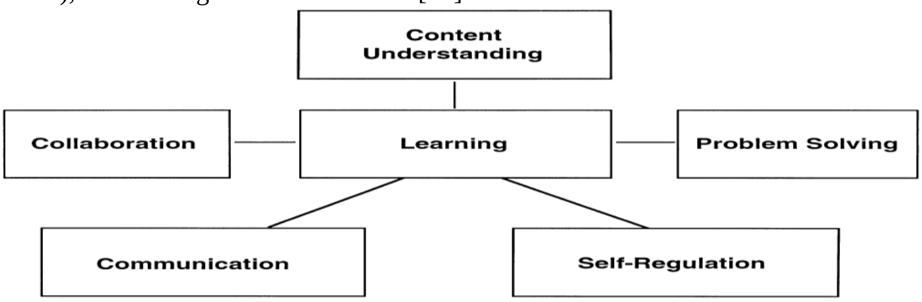

Figure 1: CRESST model for learning by [12]

Hence, evaluation of learning should not only focus on relevant content knowledge but also problem solving competence along the three dimensions. However, CRESST model does not provide cognitive tasks needed for each learning outcome and how to assess each. Hence, cognitive theory of training evaluation will provide various cognitive tasks and their measures of evaluation.

7.4 Cognitive Theory For Training Evaluation

Classification of learning outcomes was originally proposed by [42] who came up with six levels of cognitive skills needed during and after learning: Knowledge, Comprehension, Application, Analysis, Synthesis, and Evaluation. [45] proposed 19 types of cognitive processes that can be classified into the six levels.

[1] proposed multidimensional learning outcomes evident from cognitive, skill or affective changes. Cognitive outcomes consists of verbal knowledge whose measure is amount and accuracy of acquired knowledge, knowledge organization whose measure is mental models for deep understanding, and cognitive strategies whose measure is meta-cognition skills on self regulation. Skill-based outcomes consist of compilation whose measures are proceduralization, generalization and discrimination of verbal knowledge, and automacity whose measure is automatic operation after a long practice. Both compilation and automaticity require measures that test hands-on performance. Affective-based outcomes consist of attitude and motivation and both, although require measures that test internal states, are highly dynamic. Fig.2 shows the learning outcomes as proposed by [1].

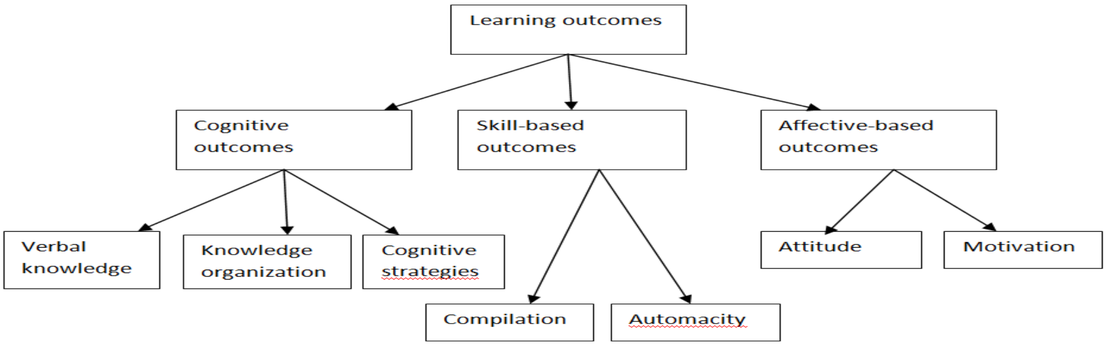

Figure 2: Learning outcomes as per [1].

From the three models, verbal knowledge is correlated to *content knowledge* acquired during training and can be measured directly from achievement tests by assessing content coverage and grades scored. Knowledge organization and cognitive strategies are correlated to *content understanding* dimension of problem solving skills, can be measured indirectly through performance expectation based on Bloom's cognitive skills as covered in the achievement tests [42].

Skill-based outcomes are correlated to *domain dependent dimension* of problem solving skills and require measures that test hands-on performance in *technical skill* areas. But can also be measured indirectly through performance expectation based on performance grades in practical related subjects. Affective-based outcomes are correlated to *self regulation* dimension of problem solving and can be measured directly or indirectly although are highly dynamic.

Although *domain independent dimension* of problem solving skill is not a direct learning outcome, it provides a strong foundation for other learning outcomes and is a general predictor of performance on the job [39]. Also, it is correlated to individual's academic capability relevant to both training and employment opportunities, and performance Grade Point Average (GPA) in both high school and university undergraduate are frequently used as predictor for this dimension [43]. TABLE 1 summarizes the relation between the three models.

Table 1: Learning outcomes and their measures

Leaning outcomes	**Theoretical Models for Learning Evaluation**			**Proposed factors**	**Measure of testing/ assessment**
	Kirkpatrick's model [38]	**CRESST model [12] (learning outcome)**	**Kraiger's model** [1] **(measures)**		
1) Content knowledge	Relevance to job	Prior knowledge	Verbal knowledge	1) Content knowledge	Domain exam questions
2) Problem solving competence		Content understanding	Knowledge organization & Cognitive strategies	2) Cognitive skills	Domain exam questions
		Domain independent (Intelligence)	N/A	3) Academic capacity	Student GPA
		Domain dependent (Technical)	Compilation & Automacity	4) Technical skills	Domain subjects performance

Therefore theoretically, performance in the job is directly determined by content knowledge, cognitive skills, technical skills, academic capacity, and indirectly by affective factors.

8.0 Proposed Model for Mapping Graduate Skills to Industry Jobs

Fig.3 shows the proposed model based on three theoretical models: Kirkpatrick's model, CRESST's model, and Kraiger's theory. Relevancy, Durability, Accuracy, and Capacity are independent variables that represent content knowledge, cognitive skills, technical skills, and academic capacity respectively. Attitude-Motivational factors are confounded variables while industry role is the dependent variable that is an indicator of employee's performance level in the job.

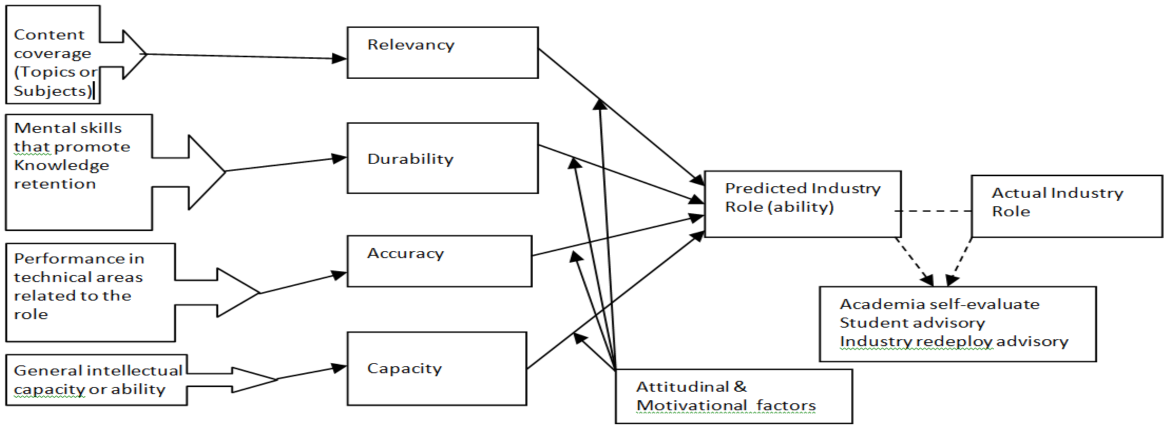

Figure 3: Proposed model (Kirpatrick, 1956; [12]; [1]**)**

The model derived will hypothesize the key competence requirements of industry jobs and can be used as a basis for data collection, analysis and to conceptualize the design model of the prediction tool for industry jobs. This model can be applied in any job occupation where two populations will be the target i.e. employed graduates in the industry and exams in the academia. To help use the proposed model the researcher proposes preprocessing procedure for collected data.

8.1 Predictive Mapping through Pattern Recognition and Classification using Proposed Model

Pattern recognition is the study of how machines can observe the environment, learn to distinguish patterns of interest in their background, and make reasonable decision about the categories of patterns [29]. According to [29], the pattern recognition problem is posed as a classification task where the classes are either predefined (supervised classification) or are learned based on similarities of patterns (unsupervised classification). Such kinds of pattern recognition problems are usually very complex and the best known approaches for solving them are machine learning techniques. A Pattern Recognition System (PRS) is a decision system which when given a pattern problem is able to recognize the pattern through supervised or unsupervised classification. Since, the classes in this particular problem shall be well defined consisting of industry roles whose features shall consist of role requirements to be revealed through data collection, the researcher proposes to use supervised classification approach.

The supervised classification approach (also known as machine learning) consists of the following main elements [44]:

1) Identification of required data
    - Involves identifying the most informative features
    - Methods which can be used include: experts, brute-force
2) Data pre-processing
    - Involves removing noisy features to enhance learning from very large data set
    - Methods used include: instance selection, features subset selection
3) Algorithm selection
    - Involves comparing two or more supervised learning algorithms
    - Methods used include: statistical comparisons, paired t-test
4) Training
    - Involves learning the model with a sample of existing correctly classified features/cases
    - Methods used include: Artificial Intelligence (AI), Neural Networks, Statistical techniques, Support Vector Machines (SVM)
5) Evaluation
    - Involves running the trained model with a set of classified cases it has never seen before to see whether it will classify correctly or not

Figure 5 below shows the conceptual model of a supervised machine learning process highlighting it‘s main elements.

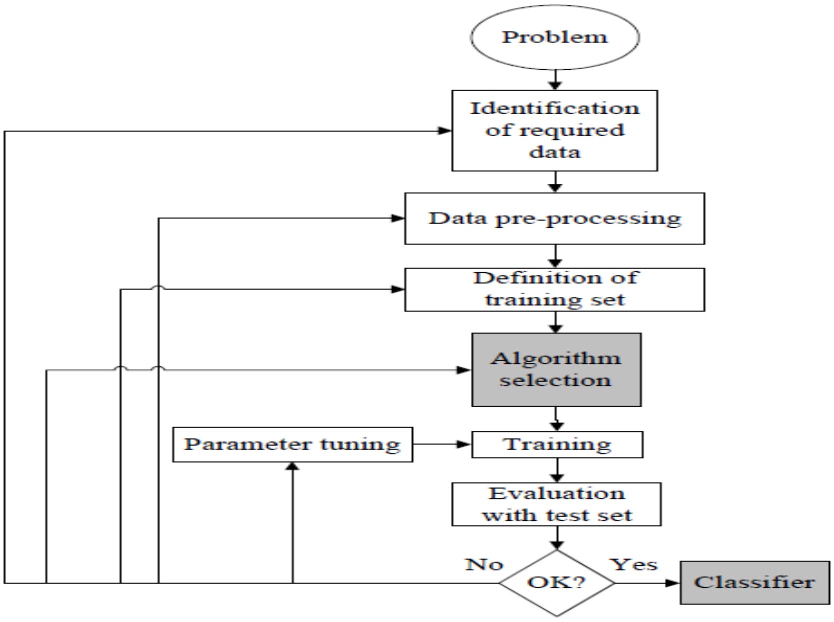

Figure 1: Supervised machine learning process by [44]

8.2 Data Preprocessing for the Proposed Model

In order to use the proposed model, data must be modeled according to the four variables: Relevancy, Accuracy, Durability, and Capacity. The requirements for each element of the content shall be captured and calculated using the tables below. Data collected from industry will be used to calculate baseline indexes for role classes and data collected from employed graduates and past exam will be used as values for individual cases.

1) **Relevancy:** Under each content type (subject or topic) a value on the scale of 1 to 12 is used to indicate the level of importance for each requirement, where 1 = not important, 12 = highly important. The totals are then calculated and a ratio R is calculated and rounded off to a whole number ranging from 1 to 12. R for each content type is then converted to a 4 digit binary number then the binary numbers are concatenated to get a 4xn (where n is the number of content type) digit binary number. The 4n digit binary number is finally converted to a decimal value which is divided by T (T=highest possible total) then multiplied by k (number of roles) and the answer rounded off to whole number to get a unique index value R for the role. TABLE 2 below shows the layout for calculating the relevancy index.

Table 2: Calculating Relevancy Index

Role/Career:	Relevant Content Required: (either Topics or Subjects denoted by C)				
Requirements	C 1	C 2	C 3	----------------	C n
a					
b					
c					
-					
-					
Possible Total(T)					
Calculated total(t)					
R=t*12/T					
4 digit binary					

2) **Durability:** Under each core area (subject or topic or competence) a value on the scale of 1 to 12 is used to indicate the level of importance for each requirement, where 1 = not important, 12 = highly important. The totals are then calculated and a ratio D is calculated and rounded off to a whole number ranging from 1 to 12. D for each content type is then converted to a 4 digit binary number then the binary numbers are concatenated to get a 4xn (where n is the number of content type) digit binary number. The 4n digit binary number is finally converted to a decimal value which is divided by T (T=highest possible total) then multiplied by k (number of roles) and the answer rounded off to whole number to get a unique index value D for the role. TABLE 3 below shows the layout for calculating the durability index.

Table 3: Calculating Durability Index

Role/Career:	Core Areas Clusters Required: (either Topics or Subjects or Competences denoted by C)				
Requirements	C 1	C 2	C 3	----------------	C n
a					
b					
c					
-					
Possible Total(T)					
Calculated total(t)					
D=t*12/T					
4 digit binary					

3) **Accuracy:** Under each core area (subject or topic or competence) a cluster point value on the scale of 1 to 12 is used to indicate the level of importance for each requirement, where 1 = not important, 12 = highly important. The totals are then calculated and a ratio A is calculated and rounded off to a whole number ranging from 1 to 12. D for each content type is then converted to a 4 digit binary number then the binary numbers are concatenated to get a 4xn (where n is the number of content type) digit binary number. The 4n digit binary number is finally converted to a decimal value which is divided by T (T=highest possible total) then multiplied by k (number of roles) and the answer rounded off to whole number to get a unique index value A for the role. TABLE 4 below shows the layout for calculating the accuracy index.

Table 4: Calculating Accuracy Index

Role/Career:	Core Areas Cluster Points: (either Topics or Subjects or Other denoted by C)				
Requirements	C 1	C 2	C 3	----------------	C n
a					
b					
c					
-					
Possible Total(T)					
Calculated total(t)					
A=t*12/T					
4 digit binary					

4) **Capacity:** Individual's capacity for each role/career is derived from either or both high school and undergraduate Grade Point Average (GPA) which each is converted to 4 digit binary number where 0001 = E, 0010 = D-, 0011 = D, 0100 = D+, 0101 = C-, 0110 = C, 0111 = C+, 1000 = B-, 1001 = B, 1010 = B+, 1011 = A-, 1100 = A. Then (if both, the two binary numbers are combined in sequence to give) the binary value for student capacity is then converted to decimal value (and divided by two for both) to indicate student capacity index value. TABLE 5 below shows the layout for calculating the capacity index.

Table 5: Calculating Capacity Index

	High school GPA	Undergraduate GPA
Grades Points		
4 digit Binary		

IX. Conclusion

In this paper the researcher has presented an overview of the challenges facing graduates in the academia and employers in the industry. Diversity of both graduate skills and industry roles was mentioned as one of the key features that characterized the industry academia gap to a skill mismatch problem. Also, the researcher outlined briefly skills evaluation and prediction trends methods, and gaps and the way forward to bridge the gap where industry academia collaboration was mentioned as key, while thorough evaluation of graduate skills and knowledge acquired during training was highly recommended.

In conclusion, the researcher strongly believes that the use of predictive mapping of graduates' skills to industry roles can greatly add relief to evaluation processes of both recruitment processes of industry and training processes of academia. The advantages emanating from this approach include: a) Reduction of confusion among graduates in understanding employers' preferences through online access of up-to-date employer preferences; b) increases transparency during recruitment through a standard evaluation tool; c) Essential dimensions of problem solving skills are evaluated by basing the model on practical experiences of employees; d) Helps graduates to instantly evaluate their skills so as to get insight into prospective industry jobs aligned with their skills. However, there are still a few limitations in this approach, especially as far as the time taken by academia to respond to changes in content standards in the industry.

There is a general belief that it is important to align content and skills taught in academia with content standards and industry job competences in a practical way, especially when evaluation is used for predictive purposes and performance enhancement in both industry and academia. This model can be used to reduce the growing dissatisfaction by industry over graduates' productivity as a result of poor evaluation of graduates' skills vis-à-vis industry job competence requirements.

REFERENCES

[1] Kraiger, K., Ford, K. & Salas, E. (1993).Application of Cognitive, Skill-Based, and Affective Theories of Learning Outcomes to New Methods of Training Evaluation. *Journal of Applied Psychology Monograph, 1993, Vol. 78,Pg 311-328.*

[2] Srikant, S. & Aggarwal, V.(2014).A System to Grade Computer Programming Skills using Machine Learning

[3] Shkoukani, M. (2013).Proposed Model to Find the Gap between Academic Supply and Industry Demand in Software Engineering Field in Jordan. *International Journal of Advanced Computational Engineering and Networking, ISSN (p): 2320-2106, Volume-1, Issue-2, 2013*

[4] Quintin, G. (2011). Right for the job: Overqualified or Underqualified.

[5] Thompson, j., Noro, M. & Edwards, H.(2007).Introduction to the Workshop: Bridging the University/Industry Gap. *Proceedings Workshop on Software Engineering Education. A workshop collocated with 14th Asia-Pacific Software Engineering Conference (APSEC'07) Nagoya, Japan, December 4, 2007*

[6] CWA16458 (2012). European ICT Professional Profiles. *CEN Workshop Agreement, May 2012*

[7] Hansen, R. S. & Hansen, K.(2007). Quintessential Careers: What Do Employers *Really* Want? Top Skills and Values Employers Seek from Job-Seekers. *Quintessential Careers*. Available at http://www.quintcareers.com/printable/job_skills_values.html. Accessed December 17, 2014.

[8] Norwood, B. & Briggemen, B. (2010). Assessing the College Graduate: How Employers Measure Graduates' Possession of General Skills

[9] Tockey, S.(1999).Recommended Skills for Software Engineers. *IEEE Proceedings 12th Conference on Software Engineering Education and Training, New Orleans, USA, 1999.*

[10] Korte, W.B, Husing, T., Hendriks, L., Dirkx, J.(2013). Towards a European Quality Label for ICT Industry Training and Certification. *Final Report.*

[11] Sutherland, L.M, Shin, N. & Krajcik, J.S.(2009). Exploring the Relationship between 21st Century Competencies and Core Science Content

[12] Baker, E.L & Mayer, R.E.(1999). Computer-Based Assessment of Problem Solving

[13] Handel, M.(2012). Trends in Job Skills Demands in OECD Countries.

[14] Shkoukani, M. & Lail, R.(2012).The Importance of Restructuring Software Engineering Education Strategies In Order To Minimize The Gap Between Academic Supply And Industry Demand In Software Engineering Field, *International Journal of Reviews in Computing, Vol. 11, pp. 26-31.*

[15] Shaw, M. (2000).Software Engineering Education Roadmap. The Future of Software Engineering. Anthony Finkelstein (Ed.), ACM Press 2000ACM: http://store.acm.org/acmstore

[16] Kanellos, M. (2003).Intel Scientists Find Wall for Moore's Law.ZDNet. Retrieved February 15, 2013 from http://www.zdnet.com/news/intel-scientists-find-wall-for-moores-law/133066

[17] Boehm, B. (2005). Some Future Trends and Implications for Systems and Software Engineering Processes. Retrieved February 20, 2013 from http://csse.usc.edu/csse/TECHRPTS/2005/usccse2005-507/usccse2005-507.pdf

[18] Surakka, S. (2005).Trend Analysis of Job Advertisements: What Technical Skills Do Software Developers Need?

[19] Houghton, R.S. (2012).Thinking & Teaching Tools for Digital Thought, August 2012. Retrieved September 20, 2013 from http://www.wcu.edu/ceap/houghton/readings/technology trends.html

[20] Ludi, S. & Collofello, J. (2001).An Analysis of The Gap Between The Knowledge And Skills Learned In Academic Software Engineering Course Projects And Those Required In Real Projects

[21] Robertson, W.C.(1990). Detection of Cognitive Structure with Protocol Data: Predicting Performance in Physics Transfer Problems.

[22] Saidian, H.(2002).Bridging Academic Software Engineering Education and Industrial Needs. *Computer Science Education 2002, Vol. 12, No. 1-2, pp. 5-9*

[23] Kolding, M. & Ahorlou, M. (2009).Post Crisis: e-Skills Are Needed to Drive Europe's Innovation Society. Retrieved September 20, 2013 from http://ec.europa.eu/enterprise/sectors/ict/files/idc_wp_november_2009_en.pdf

[24] Moreno, A.,Sanchez-Segurab, M., Medina-Dominguezb, F. & Carvajal, L.(2012).Balancing software engineering education and industrial needs

[25] OECD. (2012). ICT Skills and Employment:New Competences and Jobs for Greener and Smarter Economy. OECD Digital Economy Papers, No.198. http://dxdoi.org/10.1787/5k994f3prlr5_en

[26] Winterton ,J., Le Deist, F.D, & Strinfellow, E.(2005).Typology of Knowledge, Skills, and Competences: Clarification of the Concept and Prototype. Centre for European Research on Employment and Human Resources.

[27] Colvin, R. & Maeroff, G.(2007). Beyond the Ranking's: Measuring Learning in Higher Education.

[28] Krishnan, A.(2009). What are Academic Disciplines?

[29] Basu, J., Bhattacharyya, D. & Kim, T. (2010). Use of Artificial Neural Network in Pattern Recognition. *International Journal of Software Engineering and Its Applications Vol. 4, 2010*

[30] Lueewen, J.N. Chapter 1:Approaches in Machine Learning. Machine Learning

[31] Mehra, N. & Gupta, S.(2013). Survey on Multi-Class Classification Methods. Internation Journal of Computer Science and Information Technologies, Vol 4, 2013, Pg572-576

[32] Mitchie, D., Spiegelhalter, D.J, & Taylor C.C.(1994). Machine Learning, Neural and Statistical Classification.

[33] Aly, M.(2005). Survey on Multiclass Methods.

[34] Kumar, S, Ghosh,J. & Crawford, M. (2002). Hierarchical fusion of multiple classifiers for hyperspectral data analysis, Pattern Analysis& Applications, 5:210-220, 2002.

[35] Vural, V. & Dy, J.G.(2004). A hierarchical method for multi-class support vector machines. In Proceedings of the Twenty-First International Conference on Machine Learning, 2004.

[36] Keshtkar, F., Burkett, C., Li, H. & Graesser, A.(2014). Using Data Mining Techniques to Detect the Personality of Players in an Educational Game. *Studies in Computational Intelligence, Vol. 524,2014.*

[37] Cope, C., Staehr, L. & Horan, P.(2000).Towards Establishing the Best Ways to Teach and Learn about IT. The Challenge of IT Education in the 21st Century

[38] Winfrey, E.C. (1999). Kirkpatrick's Four Levels of Evaluation. In B. Hoffman (Ed.),*Encyclopedia of Educational Technology*. Retrieved March 24, 2015, from http://coe.sdsu.edu/eet/Articles/k4levels/start.htm

[39] Leake, R. & Parry, C. (2003).Training Evaluation: Methods to Measure Change in Comprehension and Retention of Information. Slides.

[40] O'Neil, H., Wainess, R., & Baker, E.(2005). Classification of Learning outcomes Evidence from the Computer Games Literature.

[41] Orhun, N. (2003).Effects of Some Properties 5. Grade Students on the Performance of Mathematical Problem Solving.

[42] Bloom, B.S. (Ed.), Engelhart, M.D., Furst, E.J., Hill, W.H., & Krathwohl, D.R. (1956). *Taxonomy of educational objectives: The classification of educational goals. Handbook 1: Cognitive domain*. New York: David McKay.

[43] Richardson, M. & Abraham, C.(2012). Psychological Correlates of University Students' Academic Performance: A Systematic Review and Meta-Analysis.*Psychological Bulletin 2012, Vol. 138, No. 2, Pg 353–387*

[44] Kotsiantis, S.B.(2007). Supervised Machine Learning: Review of Classification Technques. *Informatica, 2007, Vol 31, Pg249-268*

[45] Mayer, R.E.(2002). A Taxonomy for Computer-Based Assessment of Problem Solving