Computer Science Skills: Analyzing the Gap Between Academia and Industry

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ABSTRACT

This research paper examines the discrepancy between the skills taught in computer science programs at universities in Maharashtra and the abilities required by the technology industry. This analysis shows a noteworthy disparity, highlighting the necessity for curriculum revisions and improved coordination with the industry [10]. It proposes a holistic framework for synchronizing educational programs with the demands of the industry, encompassing the identification of relevant skills, hands-on training, and ongoing feedback systems. The analytical findings and visual data insights clearly identify the most significant gaps in abilities and underscore the value of continuously updating the curriculum. The report finishes by providing suggestions for future research and sustainable practices to ensure that they remain in line with current industry trends.

KEYWORDS: *Computer Science Education, Employability Skills, Curriculum Development, Industry Collaboration, Skill Gap, Maharashtra*

INTRODUCTION

The swift progress of technology has fundamentally changed the demands of the employment market, necessitating academic curricula to adapt accordingly. There is a notable discrepancy in Maharashtra between the abilities taught in computer science degrees and the skills required by the technology industry [4]. This disparity results in elevated levels of unemployment among individuals who have completed their education and a dearth of proficient experts in the field. The objective of this study is to examine the difference and suggest a complete framework to synchronize computer science curricula with the requirements of the industry.

As a result of rapid technological change in some fields of computer science and its effect on the way the computer science industry hires employees, most employers now value your ability to adapt and learn new skills more than your level of formal training. Examples include Cloud Native Software Development (Cloud SDCC), Artificial Intelligence Engineering (AIE) Data-Driven Decision Support Systems (DSS), Cyber Security Automation (CSAM), Automated Information System (AIS) and IT Technology (IT), which will have an impact on how companies judge the qualifications or education of graduates when they start their careers as professionals in Computer Science. This has caused tremendous pressure for colleges and universities to reevaluate their curriculum in

Computer Science with respect to what they teach, how they evaluate the outcomes of students, and what they expect of their students' ability to learn and work collaboratively within their networks [10]; [9].

Another key aspect of the difference between academe and industry is the increasing importance of applying problem solving and systems thinking to work within industries. As an example, many industry positions require skills such as developing products by integrating various types of technologies, conducting tradeoff analyses, and designing scalable solutions that work within real-world constraints, which are difficult to develop through an examination-driven approach. Although developing a strong foundation of theoretical knowledge is very important, that knowledge is enhanced greatly when combined with experiential learning opportunities such as project-based instruction, simulated experience, and assessments that closely match those required by industry [2]; [6]. Lack of integration of experiential learning and academic learning has been cited as one of the primary reasons for an overall decline in graduate readiness and an increase in time to onboard within the technology industry [4]; [1].

In Maharashtra (India) itself, institutional diversity and uneven access to industry ecosystems exacerbate this challenge. While metropolitan institutions enjoy the advantages of being located near technology hubs and having access to corporate support, many academic institutions do not have sufficient exposure to rapidly changing industry practices. This discrepancy creates varying levels of outcome for graduates from institutions that offer similar degree programs. It is thus important to conduct empirical investigations in specific geographic regions to determine local skill shortfalls and develop specific strategies for aligning curriculum with the needs of industry in that area [7]; [6]. Therefore, addressing the issue of employability of computer science graduates requires national-level policy frameworks, as well as regional data-based academic reform.

LITERATURE REVIEW

Recently, researchers have increasingly characterized the skill gap issue in the education of computer science as a structural problem, not simply a temporary issue. Researchers are finding that there is still a misalignment between academia and industry even at well-established and academically reputable institutions, which suggests that the misalignment extends beyond curriculum content. Misalignment also includes assessment strategies, faculty preparedness, and institutional flexibility [1]; [2]. Therefore, static curricula will be inadequate to meet the demands of rapidly changing technical fields, such that graduates will have only a conceptual understanding of their area of study; however, they will be lacking operational competency. As a result, employability is viewed as a product of the alignment of all systems in support of the student's education, and will not be solved simply by updating the curriculum [10].

The empirical analysis of education reform via policy shows an extremely varied level of implementation effectiveness among the educational institutions under study. Policy frameworks like the NEP [5] provide an opportunity for a flexible curriculum and encourage interdisciplinary education, industry partnerships, and other collaborations [3]; [8]. However, research conducted recently indicates that institutional readiness has a strong impact on the extent to which a given policy will achieve its intended results. Many of the factors affecting the successful implementation of curriculum change initiatives include industry experience of faculty members, administrative authority, and technology infrastructure. Therefore, scholars who study the effectiveness of educational policy reforms highlight the importance of institution-level capacity-building to realize sustained employability gains through these reforms [7].

Recent advances in labor market analytics have resulted in a far more precise ability to identify mismatches in skills between job seekers and employers via the analysis of a large number of job postings, networks of professionals, and other recruitment data on a national scale [6]; [1]. As a result of our ability to utilize a data-driven approach to analyse these sources of information, we now have the ability to determine with greater objectivity the extent of the mismatch between the skills provided through academic programs and those required by industries on the job market. Unfortunately, most of the studies that have been completed regarding skill mismatch only provide a descriptive analysis and lack an actionable framework for the alignment of curriculum offerings to industry needs [10]. This limitation necessitates the development of integrated models that not only identify skill shortages, but also convert the findings into clearly defined academic interventions.

Many experts agree that there is a disconnect between what computer science students learn and what employers need from them, but these experts do not yet agree on an agreed-upon method for validating the curriculum through industry demand. Some universities utilize temporary industry councils and short-term credential integration as ways to connect their programs with employers, but they do not provide a sufficient amount of time or data for either scalable solutions or sustainability assessments. Therefore, researchers are now calling for the development of repeatable and systematic processes for establishing alignment between empirical studies of labour market trends, developing ongoing feedback loops and producing quantifiable measures of student learning outcomes [10]; [8]. This is essential in areas of rapidly increasing technological advancement where educational systems are diverse, or where interventions that are not formally established or have been historically fragmented will only serve to exacerbate current inequalities.

PROPOSED MODEL

The objective of the suggested model is to include industry-specific skills into the computer science curricula, thereby improving job prospects and maintaining consistent alignment with industry requirements. The methodology comprises three primary components: Curriculum Development, Industry Collaboration, and Continuous Improvement.

1. Skill Mapping and Curriculum Update: Consistently assess the essential skills required by the industry and modify the curriculum accordingly.

2. Industry Collaboration: Encourage collaborations on curriculum development and internships between academic institutions and business stakeholders.

3. Practical Training and Experiential Learning: Offer opportunities for direct application of knowledge and skills through hands-on training and experiential learning.

4. Ongoing Feedback and Enhancement: Establish a feedback mechanism to consistently enhance the curriculum in accordance with industry requirements and student achievements.

5. Faculty Development and Training: Ensure that faculty members have the most up-to-date industry knowledge and instructional methods.

ALGORITHM EXPLANATION

1. Define the necessary skill sets: academic_skills and industry_skills.

2. Data collection: Extract skills from industry sources and curricula.
3. Normalize and analyze data: Classify related skills and eliminate duplicates.
4. Compare skills: Determine the corresponding skills between academic_skills and industry skills.
5. Calculate disparity: Determine the proportion of skills that match and compare it to a predetermined threshold.
6. Report results: Calculate the matching percentage and determine whether a significant disparity exists.

An analysis of the dataset discloses the subsequent significant discoveries:

Table 1: An analysis of the dataset

Total Academic Skills	Total Industry Skills	Total Matching Skills	Matching Percentage
500	500	8	1.6

COMPARISON OF ACADEMIC AND INDUSTRY SKILLS

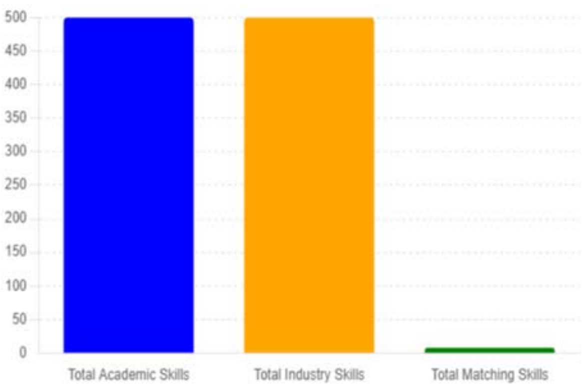

Figure 1: Comparison of Academic and Industrial Skills

The contrast of total industrial skills, total academic skills, and total matching skills is shown in this bar plot. The limited number of overlapping talents, indicated by a percentage, clearly demonstrates the discrepancy between the skills taught in academic programs and those demanded by the industry.

DATA VISUALIZATION OF TOP MISSING SKILLS

The analysis uncovered a substantial disparity between the skills that are taught in academia and those that are necessary in the industry. The following skills are highlighted as the most important ones that are lacking: Angular, Microservices, SQL, NLP, CI/CD, Data Science, IoT, Docker, Kubernetes, and React. The graphic presented below depicts the prevalence of these deficient competencies in job advertisements throughout the industry.

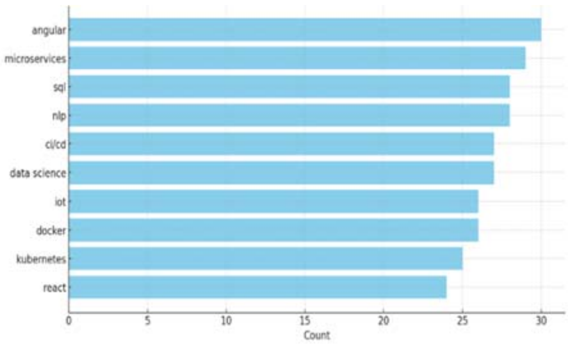

Figure 2: Top 10 Missing Skills in Computer Science Curricula

This is a bar chart that presents the top 10 skills that are lacking in computer science courses, as determined by the analysis. The chart displays the frequency of each ability that is lacking in the industry but is not typically included in academic programs. This visualization emphasizes crucial areas for curricular improvement in order to more effectively correspond with industry requirements.

REGRESSION ANALYSIS

The selected model has an R-squared value of -1.889, which suggests that the model does not well represent the data. A negative R-squared indicates that the model is underperforming compared to a horizontal line, indicating that it is not properly capturing the variability of the data. This could be attributed to several issues, including multi-collinearity, inadequate data, an unsuitable model selection, or, in the instance of actual positive results, the selected faculties' skills being very incompatible with industrial vocations.

INTERPRETATION OF COEFFICIENTS

Positive Coefficients: The positive coefficients of NLP, Micro-services, Data Science, Angular, and React indicate a positive correlation between these talents and the hiring rate.

Negative Coefficients: The skills of IoT, CI/CD, and Docker show negative coefficients, indicating a negative correlation with the hire rate in this dataset.

VISUALIZATION BASED ON REGRESSION ANALYSIS

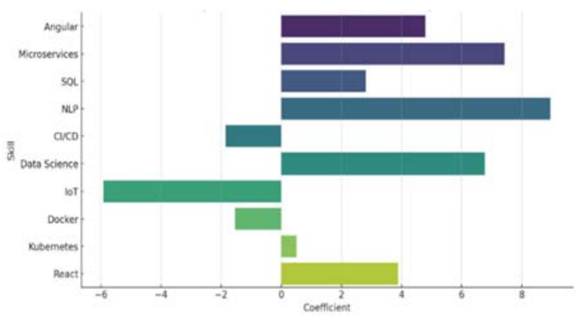

Figure 3: Regression Coefficients for Top 10 Missing Skills

1. **Bar Chart of Regression Coefficients:**

The coefficients for the top ten missing skills are shown in this chart. Positive coefficients signify talents that are positively correlated with the hire rate, whilst negative coefficients imply a negative correlation.

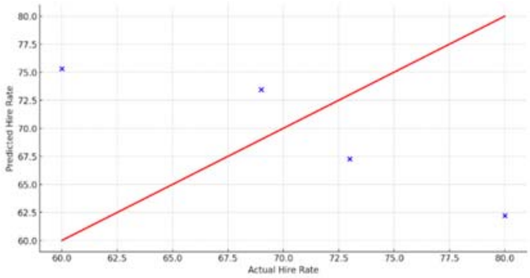

Figure 4: Actual vs. Predicted Hire Rates

2. **Scatter Plot of Actual vs. Predicted Hire Rates:**

The regression model's predicted hiring rates are juxtaposed with the actual hire rates in this plot. The red line depicts the optimal situation where the anticipated values precisely correspond to the actual values. The scatter plot facilitates the visualization of the degree of alignment between the model's predictions and the actual data.

These visualizations enhance comprehension of the connections between the top 10 deficient abilities and employment rates, emphasizing areas that may require additional improvement in the model.

CONCLUSION

An analysis of the top 10 deficient skills in the computer science curriculum in Maharashtra exposes a notable disparity between the skills taught in academic programs and those required by the technology industry. The discrepancy between these factors directly affects the capacity of graduates to find employment, as demonstrated by the regression analysis and graphic representations. The presence of key talents such as Angular, Micro-services, SQL, NLP, Data Science, and React was found to have a positive correlation with hire rates, highlighting their crucial significance in the employment market.

The regression model, while indicating the connection between these talents and employability, had a low level of accuracy, implying that the existing data and model may not completely encompass the intricacies of the matter. Possible factors that may have influenced this finding include multi-collinearity, inadequate data, and the intrinsic constraints of linear regression.

FUTURE SCOPE

In order to tackle this deficiency in skills, a thorough alignment model was suggested, with a specific emphasis on matching skills with appropriate training and updating the curriculum, fostering collaboration with industries, providing hands-on training, ensuring ongoing feedback, and enhancing the development of faculty members. By implementing this strategy, the divide between academics and industry can be narrowed, leading to improved job prospects for computer science graduates.

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List of Figures