Statistical Analysis for Evaluation and Improvement of Computer Science Education

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***Abstract*—Developing well-prepared and competent graduates is one of the main goals of all university programs globally. Recently, Computer Science (CS) has achieved tremendous success among all career fields driven by the strong competence in the market and the rapid changes in technology. Our goal is to develop an automated framework that provides efficient management, evaluation and improvement of the CS students education, as well as a profound establishment of a successful study tree for CS university programs. Such a challenging goal comprises major factors that should be inclusively considered. High school (HS) students are expected to join CS university programs with different educational backgrounds and learning capabilities. The strength of association among several performance-related factors including the academic performance of students in HS is evaluated to gain insights and infer indicators in CS programs. The automatic correlational analysis of the prerequisites for each course is also investigated to assess the program structure and dependencies among several CS courses. In this comprehensive study, all these factors are efficiently analyzed in order to investigate the valid causes of low and high performance of both CS university students and programs. Experimental results have concluded several major findings with validated associations that assure and prioritize the importance of evaluation and improvement of CS education.**

***Index Terms*—Statistical Program Evaluation, Computer Science Education, Program Structure Assessment, Courses Association**

I. Introduction

CS is one of the most competitive and fastest-growing career fields globally. Computer Engineers are expected to work in different areas, developing several applications in all life disciplines that have made our life easier and more accessible. They need strong backgrounds in both computer and life sciences. Local and regional markets have huge opportunities that are set to revolutionize the world's economy and society over the next few years. Consequently, there is an urgent need for well-prepared and competent graduates with the technical skills and industry awareness to create an innovation pipeline from academic research to global markets. There are different university programs offered for High School (HS) students who have a wide variety of educational backgrounds which make the transition from HS to university level programs much more difficult. How these students will succeed in CS programs, needs to be studied, articulating the minimum requirements to admit students into such programs is required. Another important consideration is the evaluation of courses to program offerings, how valid the courses' path is relevant as of prerequisites to higher level courses throughout different semesters until graduation. Considering general requirements in relation to CS core courses needs to be investigated as well. Basic science courses and how they will affect the students' skills as Software Engineers. The structures of several programming courses in relation to each other and the educational CS programs as a whole. Consequently, these courses should provide the Intended Learning Outcomes (ILOs) and required skills that will lead to such professional standards needed towards graduation.

In addition, the evaluation of the programs is another important aspect that educators have researched for a while [1]. The assessment of ILOs is required for the programs' accreditation and the university administration themselves as well to assess the learning environment and the offered educational services. Different stakeholders will also be interested in having quantitative and qualitative reviews of each offered program like learners, faculty, parents, administration and the surrounding society. Praslova [1] reviewed the definition of assessment of HS educational programs and explained that assessment can refer to students' performance assessment in courses to measure their learning achievements on one hand. On the other hand, assessment also refers to program evaluation by collecting data to measure the degree of students achieving the learning goals and skills required at graduation [2]. That will allow the program designers to create learning plans based on specific indicators of the ILOs.

As higher education shifts from teaching-based to learning-

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based, several studies have been investigated to monitor the learning goals of the learners and their successful achievements as well [3]. In our school, learning pedagogy is mainly based on project-based learning. Accordingly, our goal is to develop tools to infer insights of the learning process and generate mechanisms to assess the programs' ILOs considering the following factors: 1) students' background, 2) programs' structure 3) students' satisfaction and evaluation of the course; and 4) instructors' learning and teaching methodologies. In this study, we present an analytical framework for assessing and improving the performance of all students who enrolled in two CS undergraduate programs in our Egyptian school over the past few years. Students' performance is investigated in all offered courses in spring, summer and fall semesters throughout the last four academic years for the first CS program (CS). Considering students' grades in high school subjects, as well as their academic performances in different university level courses. Hence, this research investigates performance-related factors including: scores of different high school subjects and HS Average Grade (HS-AG), grades in university level courses and University cumulative GPA (U-GPA).

Consequently, the qualitative assessment in this study is based on statistical analysis of these several factors. One of which is students' grades in HS and university that have been used for the correlational analysis among several courses in each program structure. Another factor is the students' evaluation of each course, that may indicate their acceptance of the learning process in the course and/or the course's grades in relation to their acceptance of the course. Afterwards, we associated the whole correlational analysis of the program structure (four years plan), inferring rules for course offering relation in the study tree of the program.

II. Research Methodologies

In this paper, we introduce an automated framework for the statistical correlational analysis of several performance-related factors for evaluating the CS education. Such that management, evaluation and improvement of students performance in university courses can be quantitatively studied and program structure can be validated. The presented approach has been implemented and statistically validated in a complete automated scripting setup that comprises two main correlational analysis: one for measuring the strength of linear association and statistical dependence; as well as the linear/non-linear monotonic ordinal association among these several factors.

A. Study Objectives and Research Questions

Driven by our research questions, we set one main overarching goal that is the automatic analysis of the performance of CS university students using data from the undergraduate program. The performance in all courses over different semesters is collected in a progress plan document for the whole program offerings. Each document includes a matrix that maps students' grades in each course as in the study tree of the program as well as their academic records in different HS subjects before joining the program.

To study the development of the ILOs of the program, we incorporate several major focuses by examining different findings and outcomes that will lead to achieving such primary objectives. The research questions include:

- What are the related courses?
- How correlated are the perquisites with each other?
- Which basic science courses and general requirements correlate to the ILOs?
- What is the correlation among courses in the same year and subsequent years?
- Is high school education affecting particular university level courses or not?

Consequently, the main focuses of this study include:

- Automatic analysis of students' performance using their grades in different courses including their U-GPA across different semesters until graduation from each program.
- Automatic establishment of the progress plan of both programs across different semesters.
- Automatic validation of the structure of each program by measuring the association and correlation among university level courses using students' grades and U-GPA in both programs.
- Establishing clear measures to enhance the study tree of each program (requirements and prerequisites among courses) by inferring insights that have been developed from the association and correlation of students' grades and U-GPA in the program, and HS subjects including HS-AG as well.

B. Hypothesis of Research

In this study, the alternative hypothesis (H_1) of all the underlying correlational analysis is set as there are a specific association and statistical pair-wise dependence among our variables of interest, as specified in the succeeding section. Conversely, the null hypothesis (H_0) , is set as there are no specific associations nor statistical pair-wise dependence which means that these variables are statistically independent. Accordingly, the fundamental task of the hypothesis test and validation analysis is to provide a statistically validated evidence for our automated framework, under a certain level of confidence, whether to reject or fail to reject H_0, in order to figure out the statistical validation and level of significance of the obtained correlation results.

C. Dataset

This study was conducted in an Egyptian National University in school of Information Technology and Computer Science (ITCS). The school started the CS program four years ago. For the purpose of this study, an official approval was obtained from the University Registrar's office to conduct the underlying analysis using the provided dataset by the quality accreditation and association (QAA) unit. Our individual records of interest are represented by 252 students who enrolled in the CS program. Data has been collected for CS students who successfully completed the university level courses over the last four academic years 2016/17, 2017/18,

TABLE I
DESCRIPTIVE SUMMARY OF THE DEMOGRAPHICS OF THE DATASET

Academic Year	Number of CS Students	CS Students %
2019/2020	142	56.35%
2018/2019	73	28.97%
2017/2018	20	7.94%
2016/2017	16	6.35%
2014/2015	1	0.40%
Total	252	100%

2018/19 and 2019/20. high school grades have also been collected for all corresponding students in both programs. Any student who dropped out of the programs was not included. All students in the program are required to complete specific number of credit hours as well as the full programs requirements for graduation.

In Egypt, there exists different school educational systems for students from elementary to high school, the Egyptian National Certificate (ENC) and corresponding international ones as American IB, British IGCE, Canadian and others. Only high school data of the students with ENC was included in this study, since they are the majority and to unify the background under consideration. To be noticed, the National Beclobrate divides the students to three majors, Math, Science, and Arts; in our school we only accept the Math and Science high school graduates. Those two backgrounds were differentiated in this study. For all these reasons, assessing the correlation coefficients in the presence of some missing data was a challenging procedure.

There are different statistical methods such as multiple imputation [4], [5] that provides statistical estimation and inference for handling missing data by obtaining an overall estimate using some imputed data. However, in this study complete case analysis would relatively be a safe alternative to prevent any external bias or any more statistical variations. Consequently, all input data in which either one or both grades of the pair-wise courses being correlated were missing, were automatically excluded. Detailed descriptions of the demographics of dataset are reported in Table I.

D. Automatic Statistical Correlational Analysis

After generating the proper structure of the progress plan document of CS program, we developed scripts to automatically access them. The scripts generate an automatic descriptive statistics summary of all the underlying dataset. Listing different statistical quantitative measures and normality checks including mean, median, variance, standard deviation, skewness and Kurtosis [6]. In addition, Exploratory Data Analysis (EDA) were investigated to describe how the features of the grades of each course depart from the normal distribution. In order to direct our further correlational analysis as specified in the succeeding subsections.

1) Descriptive Statistics and Normality Checks: Several descriptive statistics were all calculated. Those measures are a starting investigation of the data, mapping the state of the programs ILOs achieved through the program, and evaluation of the programs in general. We used course grades mean, μ, the grades variance σ^2, the skewness Sk, that defines if the course grades are skewed to the lower grades (F, D or C) or the higher values (A or B). The kurtosis Ku, specifies the sharpness of the peak of the grade's distribution relative to the rest of the grades of each course. Skewness defines to which direction the grades mostly fall, towards failing grade or exceptional achievement grade. While the kurtosis defines how many students fall under such shifted grade.

Normally distributed grades have a kurtosis value of 3 and an excess kurtosis value of 0. A relatively peaked distributions, with higher and sharper peak, and wide tails, have positive values. A relatively flat distribution, with lower peak and narrow tails, have negative values.

After studying the course assessment outcomes, the correlations among all courses and the association of the program tree can then be calculated. In order to reject or fail to reject the null hypothesis, H_0, in relation to the study hypothesis, H_1, the underlying two tailed statistical tests were investigated under a probability of 0.05 [7] for rejecting H_0.

Consequently, the critical values of the test statistic for all the two tailed tests of the normal distribution with μ, σ and α of 0, 1 and 0.05 respectively were calculated by getting the inverse of the standard normal cumulative distribution. Based on a probability of $(1-(\alpha/2))$ [9], giving 1.96, which is approximately equal to two standard deviations (errors) from the mean. For all these reasons, it was concluded that obtaining absolute values of Sk and Ku more than twice the standard errors of each one of them [8], provided a strong statistical evidence for failing to reject H_0. Validating that the population was very likely skewed with non-zero excess kurtosis. Concluding that the grades of these courses were not normally distributed. The standard errors of Sk and Ku are calculated as in [9].

After being automatically generated by our scripts, all descriptive statistics summary and box plots of all courses of the CS program were analyzed. More than half of all the courses in the progress plan documents of CS (47 university level courses + 12 high school courses) including U-GPA and HS-AG, were found to have a normal grade distribution.

Driven by the results of the descriptive statistics, it was statistically validated that some of the dataset could have either parametric or non-parametric distribution patterns. According to the previous normality checks including the skewness and kurtosis analysis. Courses with normal grades distribution, were statistically considered to have parametric distribution patterns. Conversely, courses that did not follow a normal grades distribution, provided statistical evidence to have non-parametric distribution.

Correlation is one of the most common analysis that quantifies the strength of association and statistical dependence among the different courses under study [10], [11].

2) Automatic measurement of the strength of linear associations among different courses' grades: In order to calculate the linear correlation of courses to each other, Pearson productmoment correlation coefficient or Pearson's (r), [11], [12] was applied. Pearson is calculated according to equ.1 between each pair of courses. For the pair of courses with statistically invalidated r's (have p-value > 0.05) in the Pearson test, are analyzed by a non-parametric analysis test between the same pair of courses. We developed scripts to measure the linear association and statistical dependence among all courses. Although, some courses have non-parametric grade's distribution, we decided to include them in both Pearson parametric test and the non-parametric one. The outcomes are then statistically validated for all the obtained results, such that the invalidated outcomes are re-validated under the second non-parametric analysis as specified in the next subsection.

$$r = \frac{\sum_i^n (x_i - \bar{X})(y_i - \bar{Y})}{\sqrt{\sum_i^n (x_i - \bar{X})^2 \sum_i^n (y_i - \bar{Y})^2}} \quad (1)$$

Where r is the sample test statistic represented by correlation coefficient, n is the sample size between each pair-wise grades of courses x and y, i = 1, 2, ..., n and the sample mean of both course grades respectively.

$$r = \frac{cov(X,Y)}{\sigma_X \times \sigma_Y} \quad (2)$$

3) Automatic measurement of the strength of monotonic linear/non-linear ordinal associations among different courses' grades: The associations among the underlying courses' grades, that could not be correctly quantified nor statistically validated by Pearson parametric linear correlational analysis, are analyzed through another non-parametric analytical test. Spearman's rank correlation coefficient [15] is used to quantify any liner or non-liner monotonic increasing/decreasing ordinal associations among our data. It provides a measure of such correlation after assigning different ranks to the grades obtained from each pair of courses being investigated such that the conventional parametric analysis can then be applied using these ranks. Instead, the non-parametric Kendall's rank correlation coefficient [16] was considered to obtain the new results, applying the same ranking paradigm in assessing the same type of monotonicity relationships. Kendall's coefficient has shown more statistical robustness [17] including the considerations of having small samples as well as the existence of some outliers or many input values with the same grade [18] (i.e. tied data).

Kendall's correlation coefficient or Kendall's tau (τ) was early defined as tau-a version in 1938 [16] without considering the presence of ties in either one or both of paired data. This was considered as tau-b version in 1945 [19] which is automatically calculated in equ. 3 by our scripts, the obtained results are similarly interpreted such that getting -1 and +1 indicates a perfect monotonic decreasing and increasing ordinal association respectively. Correlation coefficient value of 0 (no monotonic correlation) and towards 0 (weak monotonic correlation).

$$\tau = \frac{n_c - n_d}{\sqrt{(C(n,2) - n_1))(C(n,2) - n_2))}} \quad (3)$$

TABLE II
CORRELATION RANGE CATEGORIES.

Strength of Association	Correlation Range
No Association	0
Negligible	0 to $\pm$ 0.25
Weak	$\pm$0.25 to $\pm$ 0.5
Moderate	$\pm$0.5 to $\pm$ 0.75
Very strong	$\pm$0.75 to $\pm$ 1
Perfect	$\pm$1

Where n_c is the number of concordant pairs, and n_d is the number of discordant pairs $C(n,2) = \frac{n(n-1)}{2}$ is the binomial coefficient for the number of possible ways of picking distinct pairs of values from the samples size (n). $n_1 = \sum_i t_i(t_i - 1)/2$, t_i is the number of tied values in the i^th group of ties for the first course. $n_2 = \sum_j t_j(t_j - 1)/2$, t_j is the number of tied values in the j^th group of ties for the other course. Similarly, the obtained correlation results should be hypothetically tested for the statistical validation and specification of the level of significance. In order to statistically test H_0 and the statistical dependence between the grades of each pair of courses, τ, that has statistical difficulties to characterize its distribution pattern in terms of known distributions. In [17] could approximately have a standard normal distribution of the test statistic (z) in equ. 4.

$$z = \frac{\tau}{s_\tau} \quad (4)$$

Where s_τ is the standard error for τ as calculated in equ. 5

$$s_\tau = \frac{1}{3}\sqrt{\frac{(2n+5)}{C(n,2)}} \quad (5)$$

Consequently, following the same calculation steps that are performed, under the significance level of 0.05 and standard normal distribution. Both p-value and confidence intervals are obtained. To statistically validate or invalidate all the obtained monotonic linear/non-linear associations. All the outputs of the non-parametric correlational analysis among all courses, including their statistical validations are automatically computed by our scripts and presented in the results section. Some invalidated relationships obtained from the first parametric analysis are validated under the second analysis that generates some invalidated results as well. All the invalidated results of both analyses were excluded.

III. DISCUSSION OF RESULTS

A. General Analytical Results

For the purpose of this study, all of the correlations results that are statistically validated in both parametric and non-parametric analysis are included and analyzed. In order to summarize all useful insights of the outcomes, the correlation ranges in Table II are considered.

The results, in Fig. 1, show that there are some courses in CS program and high school that have an average cumulative association (ACA) over all 59 courses. Representing their *major impact* on the CS program on all other courses of the study tree. The histogram represents the average correlation of each factor (course) on all other courses with a dark bar for linear correlation and light bar for non-parametric correlation. Highest, U-GPA has the major effect with ACA of 28.69 % and 24.11 % in both analysis respectively. Second, PHYS101 with 24.43 % and 20.6 %. HS-AG has the highest impact, with 18 % and 14.18 %, relative to the several high school subjects as well as the important effect of both common and specialized high school subjects. The results also assure the importance of different level Math courses as well as fundamental programming courses for freshmen, juniors, sophomores and graduating seniors. Those correlated courses were considered as justifications for the course prerequisites in the tree structure. From which program directors were able to review the most effective prerequisites in the CS program, recommendations were given accordingly.

In this section, different results are reported from a purely statistical perspective, which have been given to education experts including the program directors to be reviewed, such that:

- Any course that has one of the two ACA values, as shown in Figure 1, exceeds 10 % then it should be considered and investigated as a major factor for further association analysis.
- Any significantly validated correlation results, among any major factor and all other courses, are reported if it has moderate, very strong, or perfect association (i.e. greater than or equal to $\pm$ 0.50) in either one or both analysis, to assure, prioritize or investigate the importance of prerequisites.
- All of the significantly validated correlations among all of the prerequisite courses in the current study tree of the programs are reported disregarding the previous two restricted conditions, to investigate any possible modifications or required updates.

U-GPA has the highest ACA, naturally, as it is a cumulative sum of the grades of all courses. Second, first physics course (PHYS101) has a strong correlation with its prerequisite MATH111, as well as this course as a prerequisite for CSCI221. There is a weak monotonic decreasing ordinal association of -0.42 with Electrical Circuits course (ECEN101) with 14 students commonly enrolled; that should be carefully considered as PHYS101 as a prerequisite for ECEN101 in the current study tree. Third, MATH301 has significant positive correlations among all its prerequisites, such as MATH111, MATH112, and MATH203. However, there are no students enrolled yet in CSCI467 to investigate such prerequisite dependence. Moreover, some course dependence of prerequisites is not validated nor assured from the weak correlation, such as CSCI201, CSCI304 and MATH203. Which are all given to the program design and evaluation committee to assess and make such substantial changes wherever possible.

Another important finding is that the HS-AG has a significant positive correlation among some of the courses for freshmen as MATH100, MATH210 and CSCI217, which proves the importance of accepting students into the program based on their HS-AG. Although, we tried to study which specialized courses map directly to the success of students in CS, but only *high school Analytical Math* with CSCI322 and MATH210 courses have a significant positive correlation among each other. Similarly, twenty courses were analyzed and prerequisites were assessed based on this quantitative analysis.

On the other hand, Computer Systems course (CSCI205) has an inverse linear and monotonic decreasing ordinal association with Machine Intelligence (CSCI417) of -0.67 and -0.57 respectively, assuring the fact that these two courses are inversely dependent to each other. Concluding that students with AI skills do not have or need computer systems skills, both have different characteristics that allow them to succeed in their own track. Indicators as such can help us decide on the type of students to be allowed in each study direction. Similarly, between Physics and first Humanities course (HUMA101) with a significant monotonic decreasing association of -0.4 assuring that they are inversely dependent to each other.

Another important fact that has been induced from the analysis is that two basic programming courses (intermediate and advanced based on C++) have no validated correlation, although one of them is the base to the other. Thus, this should be carefully considered during program assessment and enhancement. The same advanced programming course has a direct positive correlations with Database systems. However, it has a significant inverse linear association with Computer Graphics (CSCI452) of - 0.97 with 4 students commonly enrolled. This needs further investigation of the course contents and causes of such inverse relationship.

B. *Programs related insights*

In this section, the results of the analysis for the program are presented and discussed. The results are also presented to and approved by the program director. To logically review the applicability of the results.

From the resulting correlation values, we needed to filter the outputs in order to concentrate on the significant relations among the courses. Based on courses with enough enrolled students, correlations with acceptable significance and so forth. We used three restricting criteria to decide on the correlation relations and assess each program study structure. Those restrictions shall reduce the possibility of having coincident relations. Thus, the real relations are inferred based on the following thresholds:

- Number of students enrolled in both courses are more than 10 students.
- Pearson correlation coefficient is more than 0.75.
- Correlation is significant in either linear analysis (Pearson) or monotonic linear/non-Linear (Kendall) with p-value less than 0.01.

After taking correlations among all offered courses alongside the courses taken in high school, correlations based on the same restricted criteria were filtered and summarized Figure 2 with the following insights:

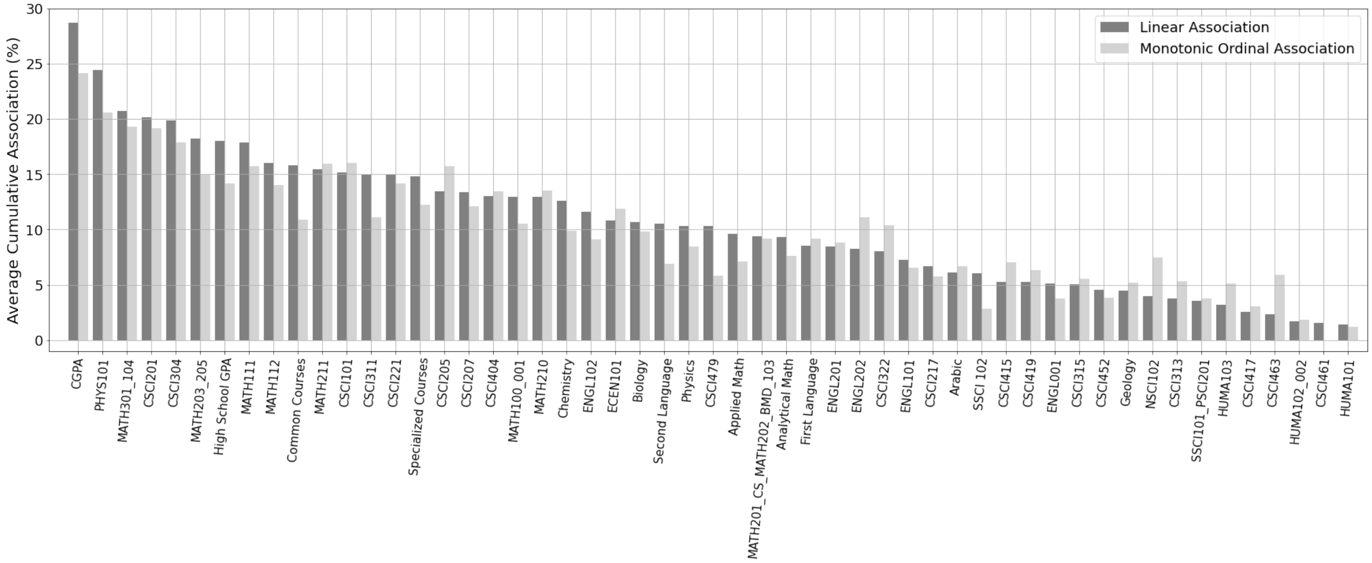

Fig. 1. Average cumulative association among CS students' grades in university level courses and high school subjects

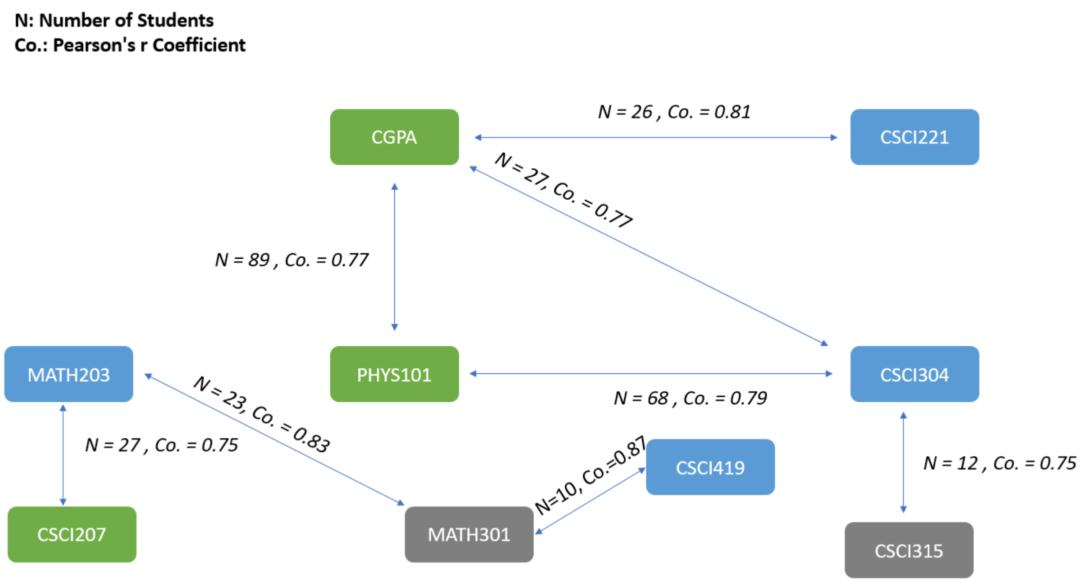

Fig. 2. Important CS Pearson correlations following the mentioned criteria

1) There were some high correlations among courses and their prerequisites, such as, between Linear Algebra (MATH301) and Differential Equations (MATH203). Also, between Analysis and Design of Algorithms (CSCI304) and Operating Systems (CSCI315).
2) The core courses like Math and Physics and some elementary courses like Logic Design and Analysis of Algorithms had high correlation with the U-GPA.
3) There were some insignificant correlations among some general elective courses and some core courses in the CS program.
4) For high school, HS-AG had high correlation with specialized courses and Biology was a very specialized course that was highly correlated with HS-AG.

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IV. Conclusion and Future Work

In this work, we introduced an automatic quantitative study for the investigation of several performance-related factors of a well-structured CS program. The analysis was used to assess the structure of the program. To efficiently analyze the valid causes of low and high performance of both CS university students and programs. These results are required by different stakeholders, from responsible administrative and faculty to interested parents and students. Experimental results have shown important considerations and significant results that were presented to each program director in order to investigate the academic requirements for updating the study tree and pedagogy in both underlying programs. For the future work, an extensive study is needed to investigate all the invalidated results of both analysis that were excluded. To be examined using multiple regression analysis that would give more insights regarding the causality alongside the obtained correlation results. In addition, this study will be applied to investigate our research considerations for a new undergraduate CS program as well as different postgraduate programs in our university.

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