Courses-Concepts-Graphs as a Tool to Measure the Importance of Concepts in University Programmes

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***Abstract*— This paper investigates methods for quantitatively assessing the importance and relative importance of concepts taught in a university program. This assessment has many uses, e.g., to aid program design and inventory, and for communicating what concepts a course may rely on at a given point in the program.**

We propose to perform this quantitative assessment in two steps: first, representing the university program as an opportune graph with courses and concepts as nodes and connections between courses and concepts as edges; second, by quantitatively defining each concept's importance as its centrality as a node within the network.

We thus perform two investigations, both leveraging a practical case – data collected from two engineering programs at two Swedish university: a) how to represent university programs in terms of graphs (here called Courses-Concepts Graph (CCG)), and b) how to reinterpret the most classical graph-theoretical node centrality indexes in the pedagogical term of concept centrality index.

***Index Terms*— Courses Concepts Matrix, Courses Concepts Graph, University Program Design, Centrality Indexes**

I. Introduction

Developing and maintaining a university program has historically been a subjective task. Indeed, to the best of our knowledge and experience as teachers at university level, no quantitative tool is typically used to steer development to check for design flaws and prevent disruptions, that may be involuntarily caused by teachers making small changes to the contents of their courses.

Instead, common practices for designing and modifying courses include program board meetings, written exchanges and face-to-face discussions among peers. See also the literature review for further discussion. These discussions are typically based on personal intuitions and usually not accompanied by numerical evidence. In a sense, established approaches to program development in higher education are often based on tradition or teachers' intuition rather than quantitative criteria or research findings.

This approach comes with some intrinsic risks. Decisions may be steered by a charismatic person with strong opinions, affected by board members' lack of time/interest, or by communication difficulties, especially when program design involves cooperation between academics from different disciplines or traditions.

A. Intended goals of the proposed methodology

Our intuition is that course and program development may benefit from following evidence-based approaches. Indeed, identifying and articulating a valid quantitative method that can integrate the classical discussions-based approaches should – at least intuitively – lead to a more sustainable and efficient management of university programs.

However, to the best of our knowledge, there is little research analyzing how different program designs affect students' engagement and knowledge development during the course of their university education [1], [2]. This lack of public knowledge suggests that we cannot rely on discoveries from previous research to steer our quantitative-methods-design efforts.

Given the need to start from scratch, we decided, after considering our roles as university teachers, that any quantitative methods we develop should ideally favor the following stakeholders:

students by helping them develop a quantitative and holistic view of the program, and see the connections between the various courses in the program;

teachers by favoring a program-centered approach to the execution of their individual courses (instead of course-centered approaches) in order to avoid compartmentalization;

boards by aiding integration of the different courses, minimizing the risks of compartmentalization, and limiting taking decisions based only on subjective feelings and opinions.

B. Literature review

There is a significant body of literature dealing with models of curriculum design, [3]. Two established models dominate, [4]: the Objectives Model - starting by specifying the objectives or learning outcomes defined as measurable performances; the Process Model - starting by

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defining course content and specifying criteria to assess students' knowledge of these contents. There are also several variations on these models, e.g., Tyler's Model, Wheeler's Model, Kerr's Model.

Very often, however, curriculum design at primary and secondary level follows a subject-centered approach, which involves dividing the curriculum into different subjects - e.g., history, math, science, etc. At tertiary level this becomes a discipline-centered approach. This strategy seems to be one of the most prominent ones, because it is easy to implement and practical, and promotes organizing the curriculum into basic concepts to then be combined based on what they have in common. An advantage of this approach is that there are numerous complementary books and support materials to aid course designers. Such approaches, however, risk compartmentalizing learning, since they may fail to integrate courses, and may also fail in enabling students to understand how courses within a program are connected (which in turn has been shown to negatively impact learning [5]). Moreover, dividing a program into different courses is largely arbitrary and not necessarily focused on promoting students' acquisition of skills or knowledge.

A third point to be considered is that higher education institutions are now investing more heavily in attempts to ensure that research-based practices are integrated at all levels from teaching to program design and development. As pointed out in [6, p. 6], this institution-level transformation is important, and should be reflected in opportune transformations of the university programs. However, the vagueness and lack of facility to objectively measure the goals of higher education may lead faculty members to realize and prioritize these goals based on their own interpretations [7], [8]. Understanding how knowledge within a course or across courses that make up a program is conceptualised can provide a clearer basis for creating a structure and progression that better supports student learning.

A renown strategy for accomplishing this goal is the so-called *black-box* approach to the sequencing of a curriculum [9]. This development tool has been proposed within the Conceiving, Designing, Implementing, and Operating (CDIO) standard to the management of university programs, and consists in representing every course within a program as a set of inputs (e.g., pre-required knowledge and skills) and outputs (e.g., contributions to the final learning outcomes). Coupling this information from all courses is expected to enable discussions, makes connections (or their lack) visible, provide an overview of the program, eventually serving as a basis for both planning and improving. However, this tool is still qualitative, and does not provide quantitative indications that are not subject to personal interpretations.

Research in the area of quantitative analysis and design of university program is, in our opinion as university teachers, necessary. Results also need to be disseminated in a format that best supports uptake and assimilation into everyday practice for all stakeholders - students, teachers and program development boards. Despite this need, we have not been able to find publically available documentation proposing quantitative (or engineer-friendly) approaches for dealing with the issues presented above.

C. *Statement of contributions*

The methodology described in this manuscript has been derived using the following approach (summarized here and presented in more detail in the following sections): We begin by considering the relationship between courses and concepts. At university level, individual concepts may be repeated and expanded on multiple times across multiple courses throughout a program (e.g. linearity, linear independence, Fourier transforms, etc.). We then describe the relations between courses and concepts using opportune graphs. This allows us to use concepts from graph theory to analyze the properties of these relations. Finally, we address the problem of analyzing university programs in terms of graph analysis. In this text, we seek, therefore, to do the following:

- propose a strategy to collect information on the structure of the program from the individual teachers that is amenable to quantitative analysis;
- propose algorithms to transform this raw information into opportune bipartite graphs;
- discuss how classical graph-theoretical connectivity indexes can be interpreted for the pedagogical purpose of inferring potential flaws in a given university program;
- apply this methodology to two real-world cases in Swedish universities, analyze the consequent numerical results, and briefly relate them to the feedback received from the program coordinators on the meaningfulness and usefulness of the obtained quantitative results.

D. *Structure of the manuscript*

Section II describes the tools for collecting and representing quantitative information about a generic university program. Section III discusses how classical node centrality indexes can be interpreted and applied in our university programs analysis context. Section IV reports and examines the results obtained from field applications of the proposed methodology. Finally, Section V presents some concluding remarks and suggests some future research and development efforts.

II. The Courses-Concepts Matrix and the Courses-Concepts Graph

To quantitatively evaluate and analyze the structure of university programs, we exploit how courses within a program are connected through the concepts taught throughout the various courses. We develop this connection following two separate steps: *data acquisition*, described in Section II-A, and *data visualization*, described in Section II-B.

A. Data acquisition through the Courses-Concepts Matrix tool

In its simplest form, a Courses-Concepts Matrix (CCM) is a table where the columns / rows headers are the courses / concepts within the program (see Table I for an example). A CCM thus allocates one column per course j and one row per concept k, so that the value of each (k, j)-th element may be used to quantify how relevant concept k is for course j on a predefined scale. As for which scale to use, as indicated in [10] a simple option consists in "0" = not relevant, "1" = somewhat relevant but not central, and "2' = very relevant / central for the course.

	1TE705 Intro to El. Eng.	1TE704 Components & Circuits	1MA008 Algebra & Vector Geom.	1TE667 El. Circ. Theory
complex num.			2	2
vectors			2	1
sys. of lin. eq.			2	2
Ohm's law		2		2
Kirchoff's laws		2		2
pot. voltage		2		2
linearity				
matrices	1	1	2	2
work, energy		2		2
int. calculus	1			

TABLE I: Example of part of a Courses-Concepts Matrix taken from the field case of Electrical Engineering, academic year 2017 / 2018, Uppsala University, Sweden.

Building a complete CCM for a specific program at a specific institution requires executing two steps: *a)* defining which concepts shall be included, and *b)* interviewing (also through Internet-based tools) experts that may give indications on the values of the various (k, j)-th elements in the matrix.

As for step *a)*, a natural strategy is to first build an initial list by inspecting each course description in the program, and then ask for feedback on this list to the board and the various teachers involved in the program. A more sophisticated version may be to consider which questions are asked in the various exams of the various courses, but this requires much more human efforts and is not easily automatable.

As for step *b)*, one may instead exploit several possibilities:

Inputs from the teachers: One option is to collect relevant data for each individual course from the teacher teaching that specific course, as she/he can be regarded as an expert on her/his particular subject (so that she/he can often produce such information with ease). However, in our experience we noticed that this strategy has several disadvantages. First, teachers might be unwilling to spend time on preparing such data, especially when the CCM comprises a long list of concepts, or if they do not see immediate benefits from doing so. Further, such information will inevitably reflect what each teacher thinks or desires to teach in her/his course. This information might be quite different from the perception of both students and other teachers or the effects actually achieved in terms of what students learn. Hence, there is the need for mitigating these subjective distortions. Strategies for doing so are proposed and analyzed in Section IV below.

Inputs from the students: To complement and validate the inputs from the teachers we propose also asking students to provide information on the various courses that they have been taking. This information may however be distorted too. For instance, students might not always understand how concepts are interrelated or which concepts they need to learn or understand as a prerequisite for a given course. To do so, a metacognitive understanding of the course is required, but in our experience this does not happen for all the students. Hence, a tradeoff between asking students relatively soon after the course (to avoid them forgetting details) and asking at a later stage (to allow for reflection on the course material) is important. We expect that some of these issues can be resolved or attenuated by averaging over the data from several students. However this claim should be considered as a guess, since – as discussed in Section IV – our field data comprises too few data points to enable us to make statistically rigorous claims.

Analysis of the exam questions: Another option (not explored in our field tests) is to inspect which questions are asked in the various exams of the various courses, and link those to the list of concepts created in step *a)*. This information would also complement the teacher input about her/his Intended Learning Outcomes (ILOs) with what is actually examined.

B. Data visualization through the Courses-Concepts Graph tool

The CCM described above can then be immediately converted into an undirected weighted bipartite graph, here denoted as Courses-Concepts Graph (CCG). The two sets of nodes in this graph correspond namely to the courses and the concepts within the program. Each (k, j)-th element in the CCM corresponds then to the weight of the edge between the concept node k and the course node j. The intuition is then the following: the properties of a university program (e.g., its structure, the relations and the relevance of the various courses and concepts in a program, the existence of potential flaws in its design) should translate into opportune topological properties of the CCG. If this intuition is true, then the problem of quantitatively analyzing a university program can be cast as the problem of analyzing an opportune graph. The problem of understanding what can actually be inferred about a university program through analyses of its CCG is discussed in Sections III and IV.

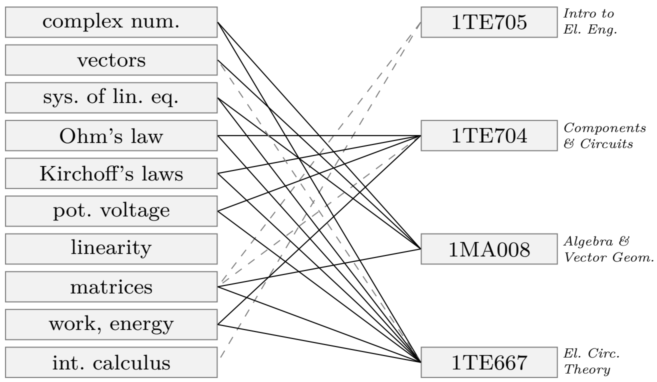

Fig. 1: Example of a CCG corresponding to the CCM in Table I.

C. Potential extensions of the CCM and CCG tools

The CCM and CCG tools described above may be structured in a more complex way so to include more information. For example, one may consider:

• **Directed CCMs and CCGs:** One major shortcoming of the CCM and CCG introduced above is the fact that they do not take into account why a given concept is relevant for a course. For instance, a concept could be relevant because it is a relevant prerequisite to follow a course, rather than because it is developed and taught in the course. To collect this type of information (so to allow more detailed analyses) one may let the CCM have two columns for each course: one allocated for weights to quantify the relevance of prerequisite concepts, and the other one allocated for weights of concepts taught or developed in that course. Correspondingly, the CCG could embed this information by becoming a directed, weighted, bipartite graph where quantities in the first column of each course in the CCM indicate the weights of edges from the corresponding concept to the given course, and quantities in the second column for a given course indicate the weights of the edges from the course to the taught / developed concept. This additional information can intuitively be used to, e.g., discover where early courses treat a given concept as prior knowledge despite it being only introduced in a later course.

In this paper we build up knowledge that may eventually lead to understanding how to face this complicated trade-off issue. More precisely, we focus on analyzing what can be done with the simplest form of information (i.e., an undirected CCM defined and compiled as described in II-A).

III. Data analysis methodologies

In this section we assume to have collected enough information so that, for a given university program, both the relative CCM described in Section II-A and the corresponding CCG in Section II-B have been compiled. Due to the special structure of these tools (i.e., a matrix and a graph), one can cast the problem of analyzing the properties of the program into the problem of analyzing the properties of the matrix or graph. This means that one may use well known and established tools from matrix and graph theory.

For instance, it can be revealing to understand how "important" or "central" certain courses and concepts are in a program, since this may give indications on which courses and concepts should receive special attention (e.g., in the form of additional students learning monitoring actions). Further, it can be important to understand how courses and concepts are connected: this may give quantitative indications on how well connected the program is, which courses / concepts complement each other, and plan further learning / teaching monitoring & assessment activities.

Due to the lack of space, in this paper we will focus our attention on the first problem, and thus investigate how and which centrality measures can be used to extract relevant information on the program structure from the relative CCG. To this aim, we notice that several well-established node centrality indexes exist in the literature (see, e.g., [11]). Our goal is now to overview them, reinterpreting each of them from a pedagogical point of view and evaluating how meaningful these indexes are for the purpose of assessing potential criticalities within a given university program.

Formally, we thus let the CCG be defined as the graph $\mathcal{G} = \{\mathcal{V}, \mathcal{E}\}$, where $\mathcal{V} = \{1, \ldots, S\}$ is the set of nodes composing the graph and $\mathcal{E} \subseteq \mathcal{V} \times \mathcal{V}$ is the set of the edges between the nodes. To every edge $(i, j) \in \mathcal{E}$ corresponds an associated edge weight $w_{ij} \geq 0$. Given that we are considering the situation as in Section II-B, $\mathcal{G}$ is static (i.e., not time-varying) and undirected (i.e., $(i, j) \in \mathcal{E} \Leftrightarrow (j, i) \in \mathcal{E}$, $w_{ij} = w_{ji}$). Given this, the set of neighbors of a generic node i is defined as $\mathcal{N}_i := \{j \mid (i, j) \in \mathcal{E}\}$. Finally note that $\mathcal{V}$ is bipartite, i.e., $\mathcal{V} = \mathcal{V}_{\text{courses}} \cup \mathcal{V}_{\text{concepts}}$, and $(i, j) \in \mathcal{E}$ must be so that either $i \in \mathcal{V}_{\text{courses}}$ and $j \in \mathcal{V}_{\text{concepts}}$ or viceversa.

A. Degree centrality

This centrality index is one of the simplest ones, being the sum of the weights of all edges connected to a particular node, i.e.,

$$d(i) = \sum_{j \in \mathcal{N}_i} w_{ij}. \tag{1}$$

In our pedagogical-oriented interpretation of $\mathcal{G}$, the degree-centrality indicates to how many courses a particular concept is relevant (connected to) or how many concepts are taught or are connected to a particular course. However, this metric is very sensitive to how the connections are weighted. For instance, consider that, to compile the CCM as we indicated in Section II-A, teachers have to add "1"s or "2"s to the concepts relevant to their courses. As we noticed in our field tests, different teachers have different compilation approaches (i.e., more conservative teachers might think that the compilation should focus just on core concepts, and hence assign less overall weights than other teachers that assume that the compilation should be "exhaustive") . What we noticed, thus, is that the degree centrality scores are very sensitive to the personality of the various teachers, and this is not a desirable property. In order to compensate for this effect, one may then think that weights can be adjusted or normalised; however, normalising weights so that the accumulated weights of each course add up to an assigned number (e.g., the credit points associated to that course or simply 1), then the degree will inevitably be this number, so that the metric loses its value. Hence, weights should be chosen with great care and establishing a common understanding among teachers on how to assign weights is essential to retrieve meaningful insights from this specific metric.

B. *Closeness centrality*

This metric is intuitively defined as the average length of the shortest path between a specific node and all other nodes in the graph. Formally, for a connected graph, it corresponds to

$$c(i) = \frac{1}{\sum_j \mathrm{dist}(i,j)} \tag{2}$$

where $\mathrm{dist}(i,j)$ is the distance between node i and j and edges with higher weights here correspond to shorter paths[1]. Closeness roughly expresses how close the particular node is to the remaining nodes of the network. When used in our context, a pedagogical interpretation may be how logically "far" a certain course or concept is from other courses or concepts. In other words, if i is a course node, and i has a very high closeness index, then it means that it is focusing on concepts that are used by several other courses. When i is a concept node, this index corresponds to how diverse the related concepts are, e.g., if they span over a large group of different subareas of the overall concept repertoire or not. When used for concepts, we expect this metric to be high for concepts that are taught or brought up in courses whose contents span over the entire program. Consequently, concepts that are only taken up by some courses or only during some time periods of the program are expected to be less close.

C. *Eigenvector centrality (a.k.a. eigencentrality)*

This index assigns relative scores to all nodes in the network based on the idea that connections to high-scoring nodes contribute more to the score of a particular node than connections to low-scoring nodes with the same weights. Formally, the measure is defined as

$$e(i) = \frac{1}{\lambda} \sum_{j \in N(i)} e(j) = \frac{1}{\lambda} \sum_{j \in \mathcal{N}(i)} w_{ij} e(j) \tag{3}$$

[1]For details on how to calculate distances between nodes, see [11].

where λ is a constant and turns out to be the largest eigenvalue of the adjacency matrix. A possible pedagogical interpretation for this measure is a quantification of how *influential* a course or concept is within the program. We expect this metric to give meaningful insights into the program structure for two main reasons: First, it is likely to be high for courses that cover many concepts that are also (very) relevant in (many) other courses. Second, this more complex measure goes well beyond what can be achieved by simply adding weights or manual analysis of the data, and is expected to be less sensitive to the teachers' personal interpretations of how to compile the CCM. Hence, we expect this measure to offer insights that can complement the ones that more intuitive and simpler metrics may give.

D. *PageRank centrality*

This is an adaptation of the eigenvector centrality discussed above, which assigns different scaling factors to the edges. More precisely, it is defined as

$$p(i) = \alpha \sum_{j \in N(i)} w_{ij} \frac{p(j)}{\sum_{k \in \mathcal{N}_j} w_{jk}} + \frac{1-\alpha}{N} \tag{4}$$

where the attenuation factor satisfies $\alpha \in (0,1)$. Due to the similarities with the eigencentrality, we expect the results from using this metric to be of similar usefulness. A discussion on the practical differences that we notice using the two metrics is given in Section IV.

E. *Betweenness centrality*

The graph-oriented interpretation of this centrality index is the one of a measure of how often the node acts as a "bridge" along the shortest paths between two any other nodes. Formally, the metric is defined as

$$b(i) = \sum_{j \neq i \neq k \in \mathcal{V}} \frac{\sigma_{jk}(i)}{\sigma_{jk}} \tag{5}$$

where σ_{jk} denotes the total number of shortest paths between nodes j and k and $\sigma_{jk}(i)$ is the number of those, that pass through node i. In our pedagogical setting this classical index,however, seems to be of limited importance. The CCG is indeed by design a bipartite graph, where concepts are exclusively connected to courses and vice versa. Hence, betweenness metrics are expected to be low for almost all nodes in the graph. This implies that the index might not discriminate among different nodes, and hence might not provide strong insights on the properties of a program.

IV. Results

We gathered data for the Electrical Engineering program at Uppsala University (UU), Sweden, and the Engineering physics program at Luleå University of Technology (LTU), Sweden, by asking teachers to allocate weights of the scale $\{0,1,2\}$ for the concepts in their course in the program according to the method described in Section II-A. The data were then analysed by computing the different centrality indices described in Section III.

The results for the centrality indices for the courses for both programs are visualised in Figure 2 (for LTU) and Figure 3 (for UU). As discussed above, we noticed large variations between how many accumulated weights teachers assigned to a course, which suggests different interpretations on the scale $\{0, 1, 2\}$. Hence, the degree centrality for the courses for the Engineering physics program at LTU, reflect the accumulated weights assigned for each course. This highly correlates with the teachers' interpretation of the scale and eagerness to contribute to the project. Further, the pagerank and eigencentrality mostly follow this trend and do not offer additional insights. Lastly, the closeness index is generally high for all courses (with some drops for courses with very low degree) whereas the betweenness is low for most courses with some exceptions for courses with high degrees. In fact, interviewing the head of the corresponding program board, showed that these data do not reflect the perceived importance of the courses in the program but rather the teachers' understanding of the scale.

In order to compensate for this effect, we normalized the weights in the CCM for the Electrical engineering program at UU such that all weights for a course accumulate to one. Hence, the degree centrality, shown in Figure 3 is equal to one for all courses and no information can be extracted for this index. Further, as expected, the betweenness index is low for almost all courses with the exception of some courses, that include a large number of concepts and hence connect many nodes in the graph. For the collected data, the eigenvalue index and closeness index offer insights into the program structure. Indeed, the courses with high eigenvalue and closeness indices were clearly indicated as central courses in the programs by the program board.

Figures 4 and 5 show the centrality indices for all concepts in the CCMs for LTU and UU, respectively. The concepts are ordered by their degree index and are calculated using the original data (i.e., not normalized) for LTU and the normalized data for UU. Note that normalising the degree for each course node to one, does not imply a normalisation of the concept nodes. The degree centrality and the pagerank centrality, which is very similar to the degree, do appear to provide an overall reflection of how often a concept is taken up during the program in both the normalized and the unnormalized case. As expected, the betweenness index is low for almost all concepts. However, for the normalized case (UU) the concepts with high betweenness seem to indicate concepts that are taken up by many different courses. Further, for the normalized CCM, in cases where the degree centrality is low for the same concept, it refers to a concept that is taken up often but also often weighted with a 1 (compared with important concepts receiving weight 2). The opposite seems to be true for closeness in the normalized CCM, which is high for almost all concepts in the program. However, some concepts have a low closeness despite a comparatively high degree. These are concepts that play a relatively strong role in the program but are only taken up in some courses in a rather intensive fashion. Note that such insights cannot be extracted for the unnormalized CCM for the program at LTU.

Hence, these results indicate not only that relevant information can be extracted for the CCM by considering centrality indices of concepts and courses, but also shows the importance of adequate normalisation of the weights.

V. Conclusions

In this paper, we proposed a method to analyse quantitative data about which concepts are relevant for which courses in a university program (provided by the corresponding teachers) and the connections between them. We showed how this information can be described by a CCM and the corresponding CCG. Further, by analysing the centrality indices of the involved courses and concepts for two programs at UU and LTU in Sweden, relevant information could be extracted. It appears that the results are better aligned with the program boards perceptions and insights if the weights in the CCM are normalized in an adequate way.

Additionally, input from students might be of use in the process of establishing concepts for courses in two major ways. Firstly, to determine whether the concepts identified by the teachers match the experiences of the students. Secondly, the concepts identified by the students function as feedback for teachers and program boards on how courses are experienced by students. This is valuable input for course and program development. Large discrepancies indicate that the course misses the target, which could be an issue in ensuring development and progression of an intended learning curve.

In our future work we will focus on exploring directed CCMs and CCGs, also including other aspects of knowledge such as facts and procedures (instead of only concepts) and as well as using more sophisticated scales of instance Blooms taxonomy to extract more relevant information. Another important aspect is to better understand how the list of concepts should be created since it is an essential building block of the later analysis. Further, methods should be derived on how to use the extracted information from a CCM or CCG to improve the program.

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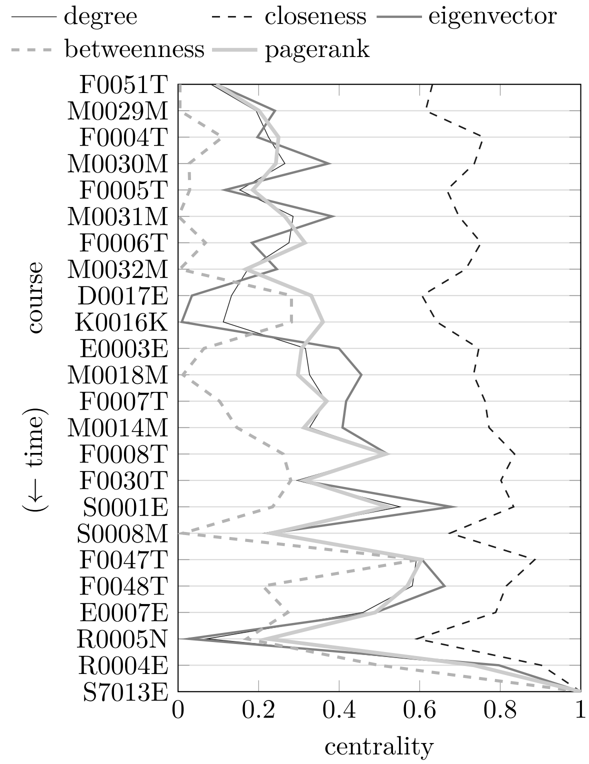

Fig. 2: Measured courses centrality indexes for the Engineering physics program at LTU, Luleå, Sweden.

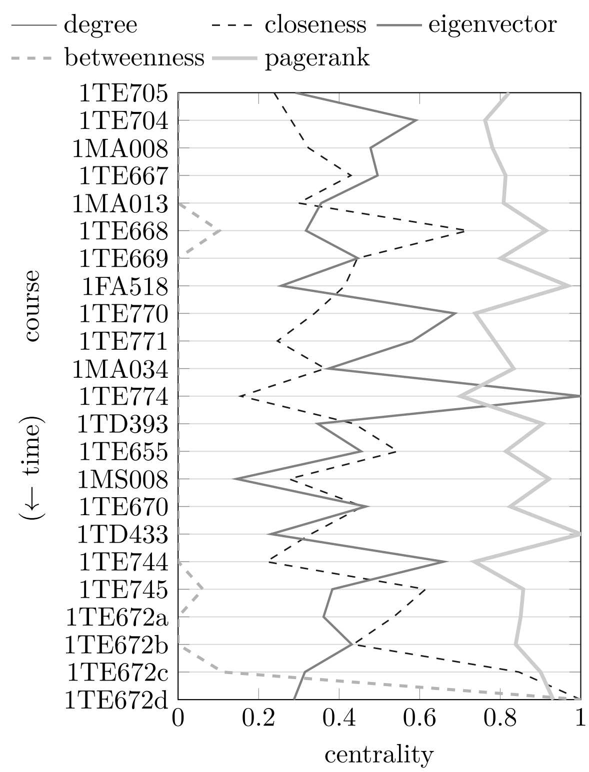

Fig. 3: Measured courses centrality indexes for the Electrical Engineering program at UU, Uppsala, Sweden.

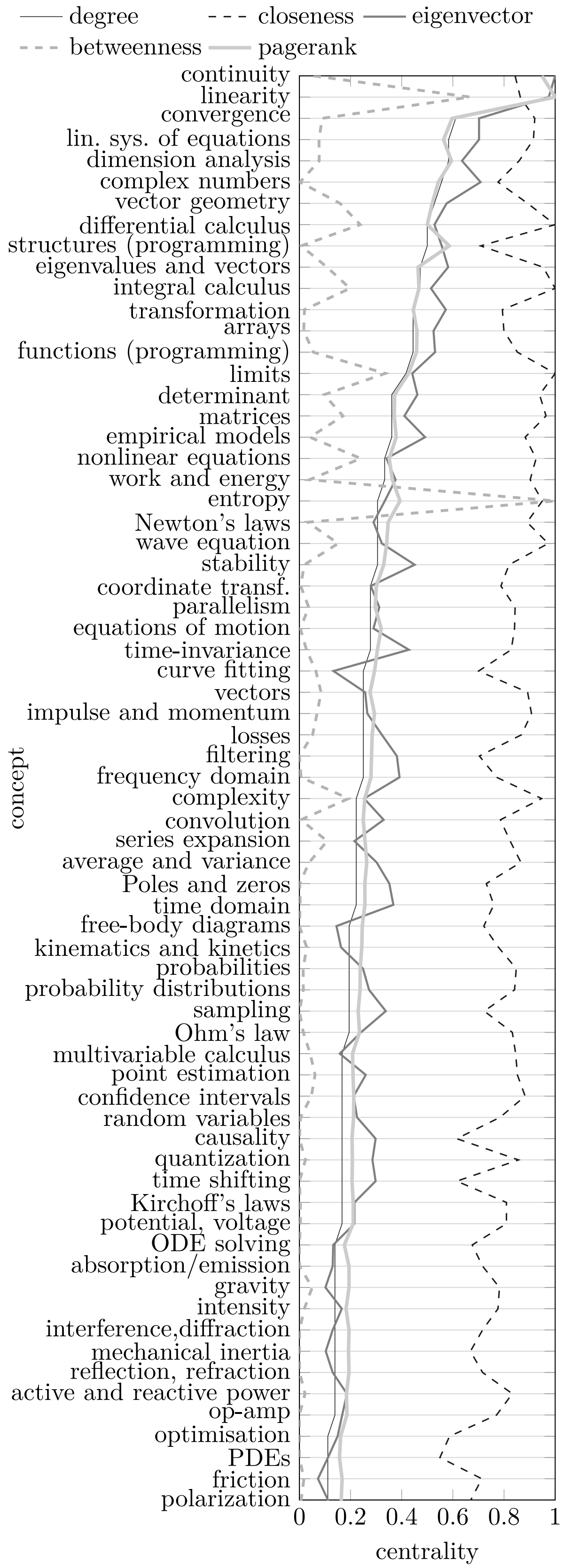

Fig. 4: Measured concepts centrality indexes for the Engineering physics program at LTU, Luleå, Sweden.

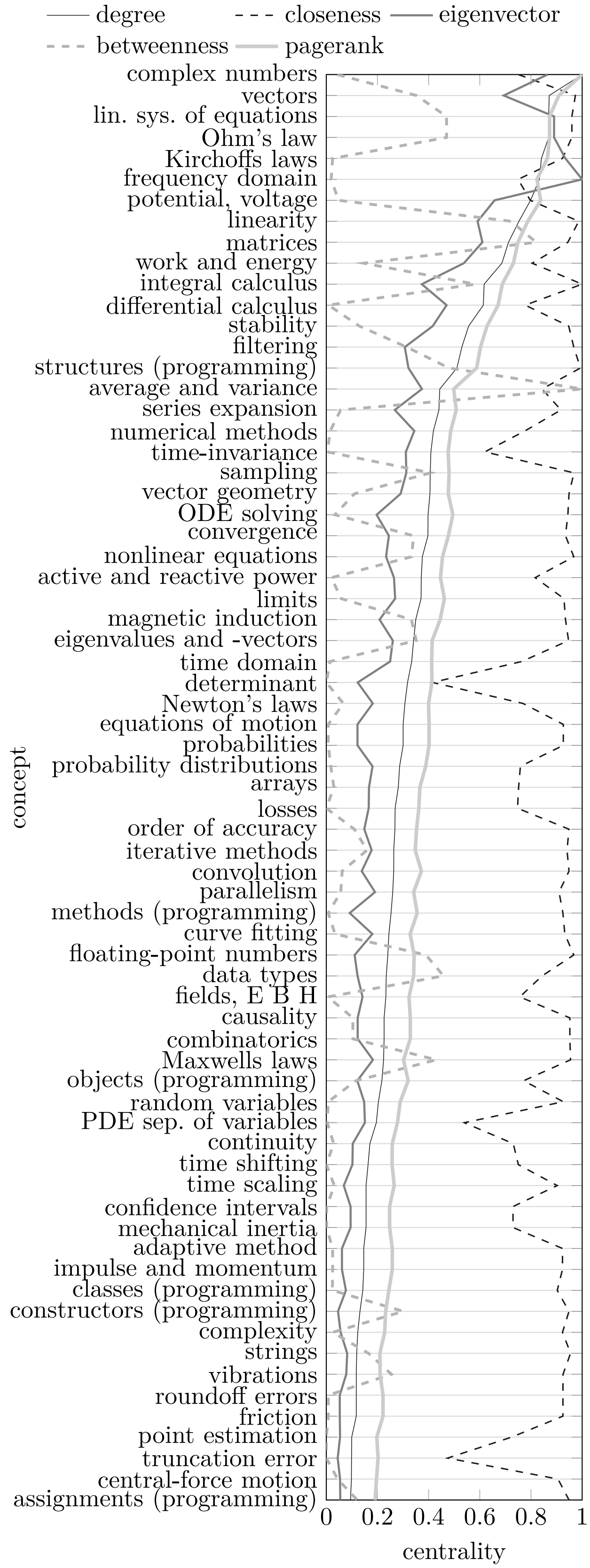

Fig. 5: Measured concepts centrality indexes for the Electrical Engineering program at UU, Uppsala, Sweden.