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IMPROVING QUALITY OF SERVICE AT SEEU THROUGH ADVANCED DATA ANALYSIS AND VISUALIZATION

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Abstract

Surveys represent popular, traditional tools for collecting data from users. They have been especially popular with the growth of convenient electronic delivery methods, through email, electronic forms and especially because of the ability to distribute them quickly through social networks. In the past years, South East European University has been relying a lot on surveys for the purpose of evaluating the quality of service offered by the university to its students. Through these surveys, the university has obtained a large amount of data which is used as an invaluable feedback tool from students and contributes to the improvement of the quality of service of the university. This paper aims to investigate the possibility of applying advanced statistical methods against these datasets with the purpose of uncovering hidden information and providing the office of Quality Assurance with a variety of methods that will aid the process of evaluating staff members.

Keywords: descriptive statistics, data mining, similarity measures, trend discovery

Disclaimer

All the datasets were obtained with permission from the Office of Quality Assurance. Where appropriate, we have analyzed the data using Stata or Microsoft Excel. Charts were also generated using the same tools. We have worked with the entire population as provided. Missing values have been replaced with the average of the variable in order to keep the consistency of the records. Additionally, we have identified and removed any incorrect values by either replacing them with the group average or removing them entirely from the dataset. For more information regarding the surveys and the questions asked, please refer to Appendix A.

Introduction

Each year the Office of Quality Assurance and Management at South East European University (SEEU) publish surveys aimed at gathering feedback from students with regard to their experience in the university. These surveys are distributed in a way that would cover each particular lecturer, and almost every student in SEEU has filled in a survey during their studies. In principle, the surveys are distributed to students and are designed to evaluate two major experiences: the academic aspect of student life and the experience of students with the administration in the university. The results of these surveys are used to compile suggestions and tips for further improving the quality of service towards students.

Surveys issued by the Office of Quality Assurance and Management at SEEU are designed to contain a set of closed type, Likert scale questions. In this way, the results of each question can be easily digitized and analyzed. The period that has been used for this study is from 2009 till 2012. During this time, a total of 19509 students have been surveyed from which 16388 have been from the main campus in Tetovo and 3121 students have studied in SEEU Skopje. The following chart depicts the distribution of the targeted population for each year.

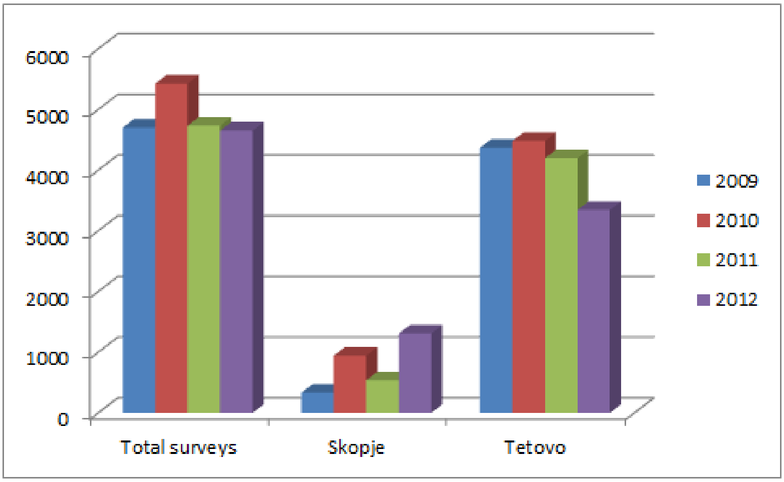

Figure 1. Distribution of surveys

Additionally, in order to cover a representative sample, the surveys are distributed to every faculty respectively (based on the total number of students per faculty). Figure 2 shows the number of surveys collected from each faculty (BE - Business and Economics, PAPS - Public Administration and Political Sciences, LAW - Law faculty, CST - Contemporary Sciences and Technologies, LCC – Languages, Cultures and Communications).

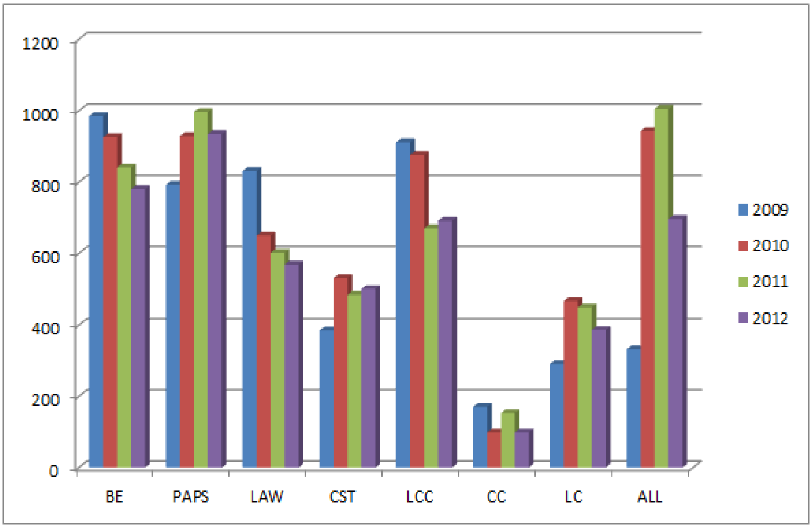

Figure 2. Distribution of surveys among faculties

The results of the surveys are published internally (including in summary form) on an annual basis to staff members of SEEU[1]. An example of how the collated findings are represented is given at the following charts (Figure 3 and Figure 4):

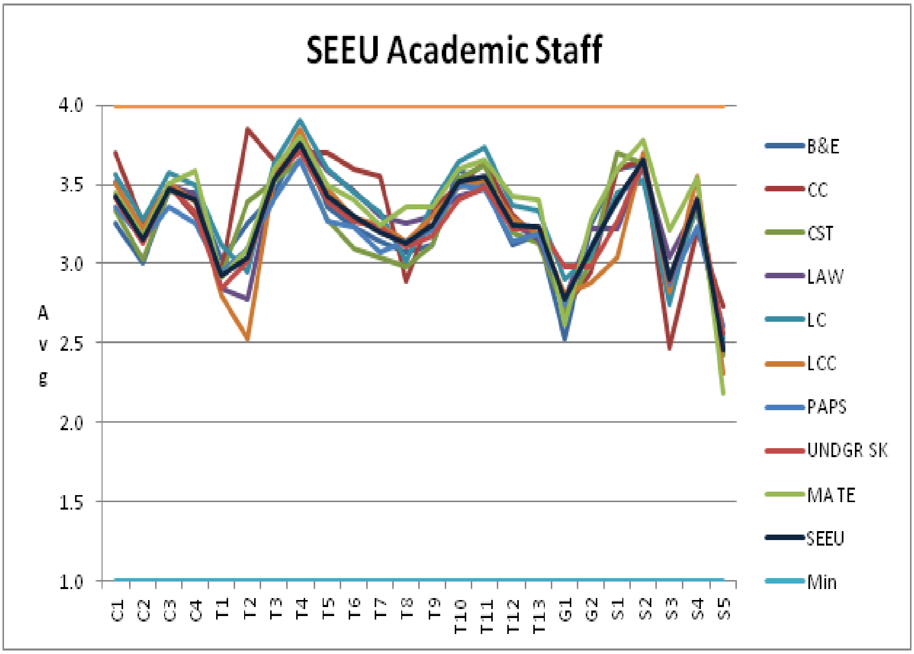

Figure 3. Summary report for student evaluation for 2010 - 2011

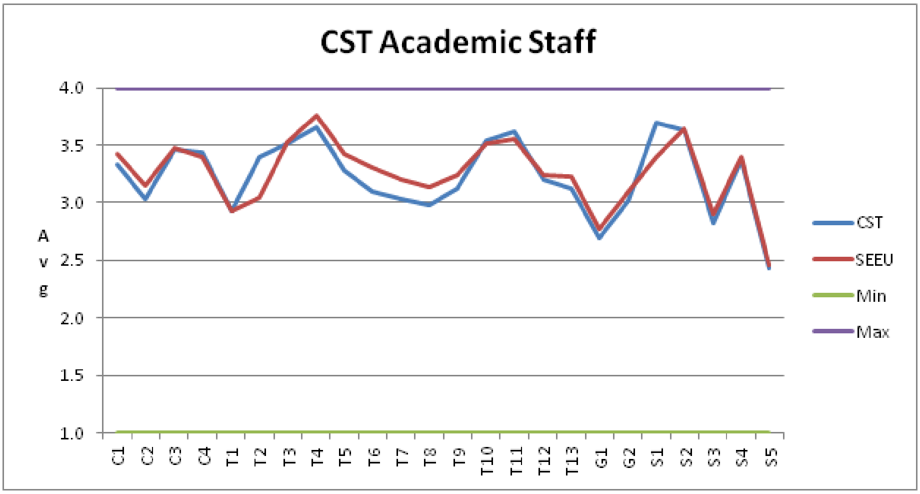

Figure 4. Summary report of evaluation of CST staff

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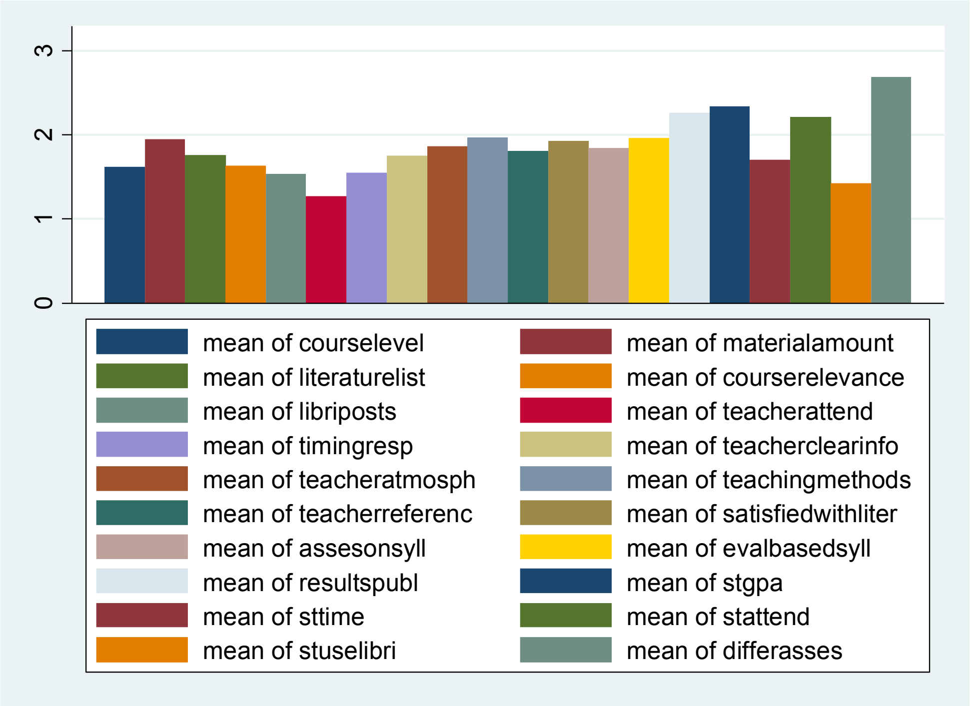
[1] South East European University. Self Evaluation Report. *South East Europen University.* [Online] 2011. [Cited: 8 30, 2013.] http://www.seeu.edu.mk/files/SEEU-Self-Evaluation-2010-2011-en.pdf.

One can see that these charts are lacking proper interpretation and analysis of the responses; however, they give a pretty good overview of the general sentiment of student opinions. One important observation is that the authors use line charts to represent some sort of trends / connection between questions which clearly is not an appropriate form for displaying the results. This method gives the false impression of progress and regress between data points, which are not appropriate in this case. To illustrate the point, consider the line between observations C1 and C2 in Figure 4. Normally, the reader would perceive this as some kind of increasing trend. However, these two points represent two different questions, not correlated between them.

A better approach would be to use dot or bar charts for representing the average of each question (Figure 1 – a, figure 1 – b). However, that approach poses another issue: the need to see the distribution of the results for each question. Namely, in the above charts we only see the average of the responses without information regarding the minimum, maximum, deviation of answers etc. Furthermore, information such as the sample size and any outliers in the responses are also hidden in that approach.



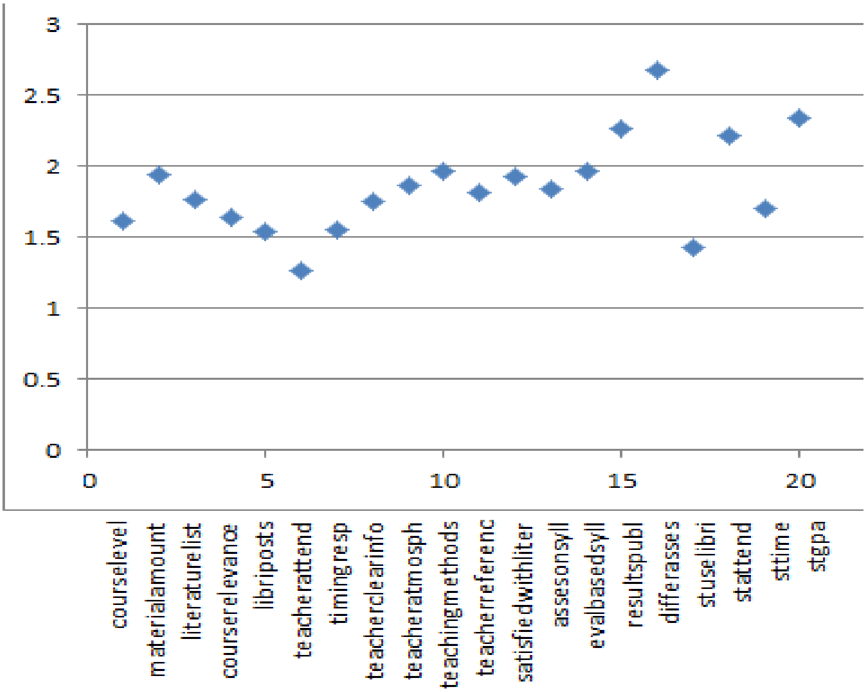


Figure 1 - Using barcharts or dotcharts to represent average results from 2009

In table 1, we have shown a summary of statistics for each variable as it would be generated by any statistical software tool. The table shows much more information than the average, basically describing the central tendency of the data through the average (mean), the distribution of data by using standard deviation and min / max and the exact sample size for each variable (observations). The table is much more informative than the charts shown above, however, it is much harder to be read and understood by the average reader.

Variable	Observations	Mean	Standard deviation	Min	Max
courselevel	4700	1.616809	0.851232	1	5
materialamt	4700	1.944255	0.910719	1	5
literaturet	4700	1.760213	1.132315	1	5
courserelee	4700	1.632979	0.839528	1	5
libriposts	4700	1.531702	0.737567	1	5
teacherattd	4700	1.264681	0.714478	1	5
timingresp	4700	1.549574	0.842509	1	5
teachercleo	4700	1.751277	0.971201	1	5
teacheratmh	4700	1.863404	0.963508	1	5
teachingmes	4700	1.96617	1.024245	1	5

teacherrefc	4700	1.80766	0.892155	1	5
satisfiedwr	4700	1.926596	1.354073	1	5
assesonsyll	4700	1.837447	1.313395	1	5
evalbasedsl	4700	1.960426	1.17745	1	5
resultspubl	4700	2.259681	1.384506	1	5
stgpa	4700	2.335319	1.11649	1	5
sttime	4700	1.698511	0.886852	1	5
stattend	4700	2.208936	0.986267	1	5
stuselibri	4700	1.422128	0.70966	1	5
differasses	4700	2.682128	1.321093	1	5

Table 1 - Summary statistics for each variable

Another feature that would be useful is if one could see the results in different granularity levels. While the current charts only display information for faculties in general, we believe that there is a need to display the results for smaller organizational units (faculties, individual staff members, courses etc). By being able to display results in different granularity levels (smallest possible unit of observation), one might be able to disregard cases where small sample sizes are observed.

An important observation to be made is that Likert scale questions are ordinal[2] discrete variables. Such variables have a limited scope and range. In the case of using students' questionnaires in SEEU, they can only answer a question with values from 1 to 5. Values outside that range are invalid as well as continuous answers in the form of 1.4 or 4.1 etc. They are ordinal since the order matters: it can be argued that a value of 1 is better than a value 5. One must be careful when analyzing this kind of data, since they cannot be treated as continues variables (Agresti, 2010).

Finally, we feel that the surveys would be much more beneficial if one could analyze correlation between different questions (variables). In this way, one would be able to decide if a question is connected to another or whether there are instances of redundant questions. Also, the datasets contain information that represents similarities between various observations. Namely, one could show how similar different faculties are, or if we delve into a more granular level, we could see groups of similar lecturers (lecturers that have similar performances).

Of course, different methods of presenting the results will be beneficial to

[2] Though there is a debate whether Likert scale data is ordinal or interval data. See: Borsboom, D., Cramer, A.O.J., Kievit, R.A., Zand Scholten, A., & Franic, S. (2009). The end of construct validity. In: Lissitz, R.W. (Ed.). The concept of validity: Revisions, new directions, and applications. Information Age Publishers

different groups of stakeholders.

Following, we continue with the discussion of the methods proposed to analyze this data, by arguing the benefits of the proposed methods and discussing further improvement in generating better surveys.

Data mining and visualization

Data mining and data visualization (or Information Visualization) are subfields of computer science. The first one, data mining, aims to find means to extract hidden information from big sets of data. The goal of the second discipline, data visualization, is to find means that will convert data from their native raw form to a visual, colorful representation. In this way, people can better understand the data.

Our approach in analyzing the survey data aims to combine the above mentioned fields with the purpose of better understanding what is hidden behind these vast datasets collected in the past years at SEEU.

Visualizing distribution

The first step in any analytical approach in data processing is to determine the descriptive properties of the dataset. Among the important measures that we want to determine are the average, standard deviation and quartiles.

As we have seen previously, the average is the only measure that has been calculated and presented to end users. The approach however is flawed, since the average only gives a very superficial view of the tendency of responses. The average is also very sensitive to outliers: if a teacher has been evaluated by all students with the highest mark, only one student evaluating him with the lowest mark will alter his average greatly.

To solve this issue, one can analyze the distribution of data. An effective measure for this purpose is the standard deviance. This measure allows us to determine how far away from the average the responses are. The greater the standard deviance, the higher the diversity of responses is, and if the standard deviance is small, then responses are more alike. E.g. if standard deviation is 0 then all the answers are the same.

A much better approach in presenting the information would be the one shown in Figure 5. The chart utilizes boxplots (Cox, 2009), a popular technique used to visualize a spread of data. The main part of the boxplot is a box which shows the region where approximately 63% of the data resides. Statistically the box represents the Interquartile Range (IQR), the difference between the third quartile (Q3 or the 75th percentile) and the first quartile (Q1 or the 25th percentile). Lines or whiskers in the boxplot are used to display information residing between the 1.5 IQR of the lower and upper quartile. Any observation above these points can be treated as an outlier.

If we analyze the chart in figure 5, we can see that most boxplots reside between 0 and 3. Some boxplots though differ from the general population. For the variable *teacher attend.* we can see that only one line has been drawn. This means that there is no diversity in the data, and probably most students have answered the question in a similar fashion. To confirm this, histograms are used in figure 6 that show the spread of the answers. It can be clearly seen that upon asked the question whether teachers have been attending classes regularly, the majority of students have answered with 1 (strongly agree).

The opposite of this problem can be seen for variable *differasses*. Here one can see a diversity of opinions. The histogram shown in figure 6 for this question confirms the assumption made.

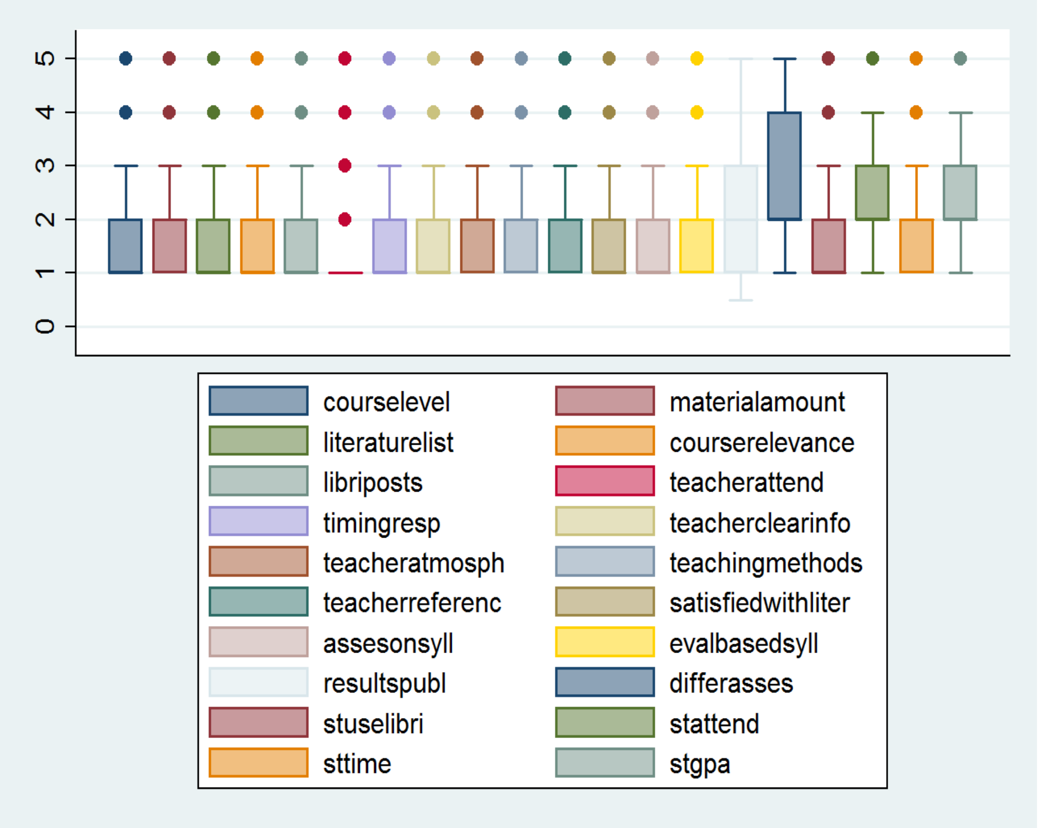
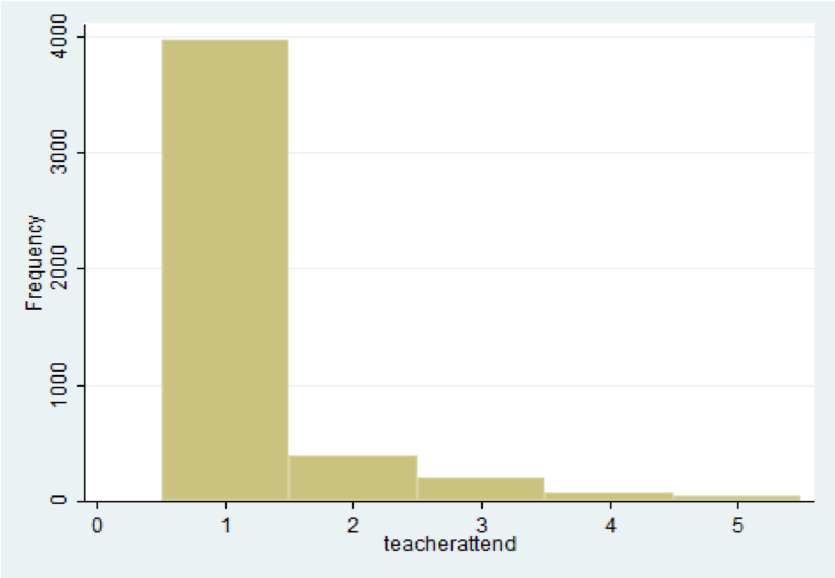


Figure 5 -Using boxplots to represent visually the results of surveys from 2012



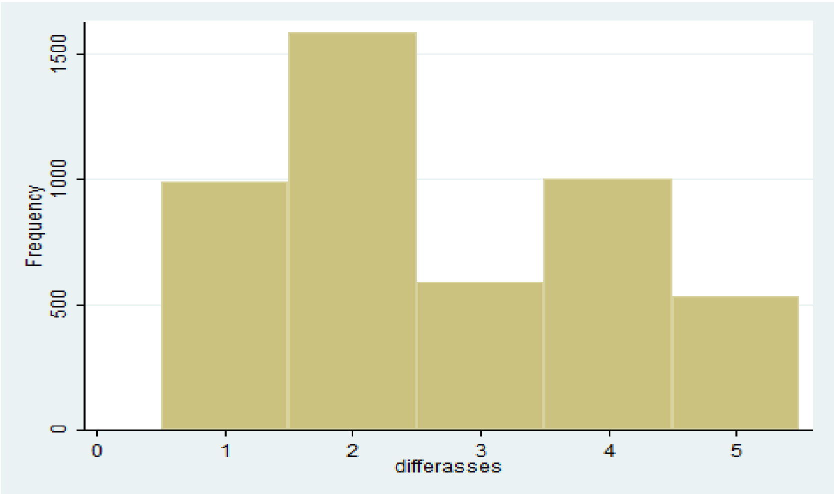


Figure 6 - Distribution of answers for variable *teacherattend* and *differasses*

Since we have applied boxplot analysis to the entire population, we see that most values converge towards the average. However, if we were to analyze the data in a less granular level (surveys for a particular professor or faculty) we would see that the boxplots show a more diverse picture. In figure 7, we have compared visually two different lecturers (randomly chosen with a similar sample of questions). One can clearly see that the opinion of students for the first lecturer in most questions is more consensual. A conclusion can be made that the first lecturer has been evaluated better by his students.

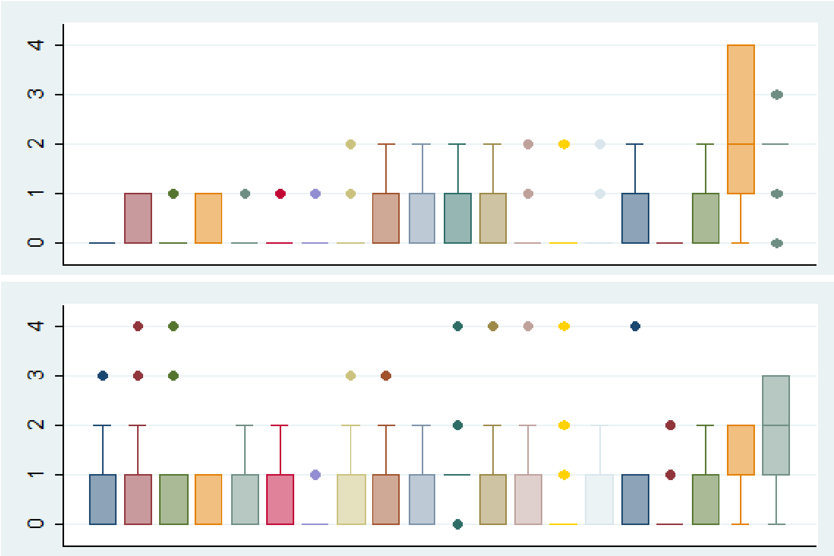


Figure 7 – Visual comparison of the performance of two lecturers based on surveys from 2012

In conclusion, we can see that by using boxplots we can present much more information than by just using line charts or dot charts. Additionally we can combine boxplots with histograms in order to give a better picture of our findings.

Cluster analysis

The data collected by the surveys can be used to create separate groups of observations. Using a naive approach, one could identify groups in the form of individuals, faculties, study programs or the whole university as one. It is called a naive approach since these groups are fixed and preset.

In data analysis however, one could apply clustering (grouping) algorithms with the purpose of generating groups based on some similarity measures. Such groups are created automatically and dynamically based on certain properties of each observation. In our case, we could apply clustering algorithms to identify lecturers with common problems across faculties. If identified, the university would be able to devise specialized training sessions that target specific groups of users across faculties.

For a clustering algorithm to function, one must be able to measure the similarity or distance between observations. These are statistical measures that tell how much two observations differ from each other. Based on the data that has been collected by surveys, we have used distance measures (cosine similarity), in which when two observations are compared, it will result with a numerical value depicting the similarity of two teachers.

To better understand the benefit of clustering, we have re-organized the data by summarizing the results for each teacher. This way, in our dataset we have a single record for every teacher representing the profile of that teacher. Doing this we can compare each teacher against his peers and determine who is more similar with him.

Clustering methods can also be used to identify and deal with outliers. Outliers can be individual lecturers who can either over-perform or under-perform. Both situations can be beneficial for the university, either to award good lecturers or to offer better training to the others. Finally, clusters give a better understanding of group sizes. Small groups of students surveying lecturers can be statistically insignificant and should be ignored during presentation of results.

Conclusive remarks and suggestions

In this research, we have shown that there are many statistical methods that can be applied to analyze survey data. Used correctly, they shed much more light and present information that is hidden in the dataset and therefore benefit the university in promoting good practices as well as supporting the lecturers in improving themselves. We believe that by actively using such data, the quality of learning and teaching will improve each year.

We are confident that the university will greatly benefit if there would be a central repository where all this data would reside, and each individual staff member is able to compare his progress over years. We strongly suggest this research to be extended by building a system accessible at any time by all staff members. Depending on who will be the end user of the reports generated by such a system, there should be different approaches in the methods used to analyze this data. In this regard, the following potential target groups can be separated:

- The University
- Faculty managers
- Lecturers being evaluated

For **the university** (Rector, Quality of Service manager etc) of interest are global reports that depict the overall achievement at university level, comparative studies that compare different faculties side by side, identification of trends, or general issues upon which the university can act.

Often when data is analyzed at a global level, analysts tend to use only descriptive statistics to give a general feel regarding the tendency of the data. We also suggest that these statistics ought to be used, but they also need to be extended to provide exploratory data analysis. These methods will show the dispersion of data (how much the data deviate from a central tendency), the shape of data (to show whether there are more positive or negative evaluations for a specific question) and also eliminate common data discrepancies in the form of missing values, incorrect/inconsistent data, outliers etc.

For the purpose of comparing different faculties, we propose the usage of distance measures, as statistical methods that accurately show how similarly two faculties perform. Using these methods we would be able to identify and emphasize problems in specific faculties but also detect common problems that seem to be replicated in every faculty.

By using regression analysis (yet another statistical tool), we will be able to identify trends regarding the performance at the university/faculty level for longer periods of time. The reports generated by applying regression analysis will help to anticipate the performance of specific faculties in the future. It will also help managers to set their future expectations regarding the quality of learning and teaching accurately and realistically.

Faculty managers (Directors, Deans) will benefit from such analysis in the form of detecting and identifying issues in their specific faculties. They will be able to see what the recurring issues in the faculties are, common problems shared by staff members and will be able to propose means to alleviate such problems.

Managers will also be able to identify extremes in the form of staff members performing better or worse than others and who affect the overall score of the faculties. This will provide a secondary benefit, in the form of being able to see the real scores of the faculty and not only general summarized reports that are affected by certain outliers.

The reports will also be useful to staff members. They will see key indicators regarding their performance, and how they stand compared to other staff members from their faculty and the university in general. Staff members will see areas where they excel but also problematic areas in which they need to improve. Additionally, they will be able to compare against their past performance by using the similarity measures described above.

Despite building a centralized information system that would aid the process of collecting and analyzing data, it can also help integrate and correlate data between different existing information systems at the university (e.g., Libri, the Learner Management System). In this way, one can apply business intelligence methods to predict enrollment trends, retention rates etc. For example, using data correlation, we can determine what are the factors that affect the retention rates for courses (is it the amount of the material, course level etc). The tool can also prove to be a tremendous aid in devising the marketing strategies of the university by analyzing decisive factors in student satisfaction.

As we are entering the era of big data, we believe that the practice of data collection by the university can be a great asset. If this data is organized and analyzed correctly we believe that it will open new perspectives in the everlasting process of improving the quality of learning and teaching. This advantage has been successfully utilized by many enterprises, and we are confident that our university can pioneer in applying the same approach in higher education.

Appendix A - Questions in surveys

The following table depicts all the questions asked on surveys that are used for analysis:

Variable name	Short Description	Values range
courselevel	The level of the course was...	1-5 (low-excellent)*
materialamount	The amount of material used in this course was…	1-5 (low-excellent)*
literaturelist	The list of literature given on the syllabus was...	1-5 (not appropriate - appropriate)*
courserelevance	The relevance of this course to this study program was...	1-5 (not important - important)*
libriposts	Does the teacher post information on 'Libri' or use it for helping with learning?	1-5 (never - all the time)*
teacherattend	The attendance of the teacher in classes was...	1-5 (never - all the time)*
timingresp	How much was the time of the lectures respected...	1-5 (never - all the time)*
teacherclearinfo	The teacher's ability to provide clear information was...	1-5 (low-excellent)*
teacheratmosph	The teacher's ability to create an open atmosphere in the classroom which encourages the students to express their opinion and to ask questions...	1-5 (low-excellent)*
teachingmethods	The usage of teaching methods and techniques by the teacher was...	1-5 (low-excellent)*
teacherreferenc	The teacher used references from a range of sources during the teaching...	1-5 (never - all the time)*
satisfiedwithliter	How satisfied is the student with the basic literature and the additional resources that the teacher offered...	1-5 (not satisfied - very much satisfied)*
assesonsyll	Were assessment criteria and guidelines included in the syllabus?	1-5 (no - yes in details)*

evalbasedsyll	Were you evaluated according to the criteria and guidelines provided in the syllabus?	1-5 (never - all the time)*
resultspubl	The way of communicating the results of assessments was...	1-5 (not good - very good)*
diffassesm	You were assessed with a range of different methods during the course...	1-5 (no - yes in different methods)*
stuselibri	Students used Libri to access the course materials, information and homework...	1-5 (never - all the time)*
stattend	Students attendance in this course was...	1-5 (not good-very good)*
sttime	The amount of time the student studied outside the class was...	1-5 (not at all - more than 8 hours a week)*
stgpa	Students GPA is…	1-5 (below 6 - 9 to 10)*

** The responses valued 1 refer to "no comment", rather than low response*

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