Peer Learning: Observation of the Cluster Effect in Multidisciplinary Team Settings

Jennifer L. Miskimins
Colorado School of Mines

Introduction

Teamwork education and multidisciplinary integration have become progressively more important over the last decade. The Accreditation Board for Engineering and Technology (ABET), which is responsible for the accreditation of engineering programs, specifically states that engineering programs "must demonstrate that their graduates have an ability to function on multi-disciplinary teams.[1]" In addition to educational standards, the industries that hire engineering graduates expect these graduates to be able to function fully in interdisciplinary settings.[2,3,4]

In multidisciplinary teamwork settings, one of the most difficult obstacles to overcome is the "languages" used by the different disciplines involved in the interdisciplinary teams. In most upper level undergraduate design classes, the students have just begun to understand the technical language of their own disciplines and have little patience for learning another. These technical language barriers can frustrate team members, impede team progress, and lead to severe dysfunction in team processes.

One way to overcome interdisciplinary technical language barriers is to foster peer learning between team members. Peer learning provides many benefits for students including the opportunity to teach others about their chosen field of study. There is significant documentation that suggests if a student is responsible for instructing others, they will have greater retention of the subject matter and gain a deeper insight into it themselves.[5] This interaction between team members also serves to reinforce terminology that is essential for communication between disciplines and leads to the discovery of expressions which have dual meanings.

The study presented in this paper discusses a method used to measure the value of peer learning in a multidisciplinary team setting using cluster analysis. Cluster analysis is a multivariate statistical technique used to group objects based on their similar characteristics. An outline of the study participants and class setting is provided followed by a discussion of cluster analysis techniques. The results of the study are then presented along with a discussion of the validity of the technique and the ongoing measurement efforts.

Study Participants

The Colorado School of Mines has a history of teamwork education and provides undergraduates the opportunity to take design classes at all levels of their undergraduate studies.[6,7,8] Seniors from the Multidisciplinary Petroleum Design (MPD) class at the Colorado School of Mines were selected for this study. This class is comprised of students from the disciplines of geology and geological engineering (GE), geophysical engineering (GP), and petroleum engineering (PE).

This class is a senior design capstone course and is required for graduation from the Petroleum Engineering Department. The class is an elective for undergraduates from the Geology and Geological Engineering and Geophysical Engineering Departments who are interested in pursuing a career in the petroleum industry. The class is taught by a faculty team comprised of one member from each of the three disciplines.

The main objectives of the MPD course are the development of team skills, the development of critical problem-solving skills for open-ended problems, and the practical application of techniques learned in other courses of the three departmental curriculums. The course is designed to mimic assignments that newly hired petroleum engineers, geologists, or geophysicists may encounter. Two major projects, each lasting 6-7 weeks, are assigned during this semester-long course. For each of the projects, the students are divided into self-directed work teams of 4-6 members. Ideally, each team is comprised of a least one GE member and one GP member, with the remaining members from the PE discipline. Historically, the class contains a majority of PE majors (60-80%) since it is a required course for this discipline and optional for the GE and GP students.

Data from three projects, spanning two semesters, is used in this analysis. Table 1 shows the class composition for the two semesters.

Table 1
Class Composition Organized By Discipline and Gender

Discipline	Gender	Number of Subjects in Semester A	Number of Subjects in Semester B
Geology and Geological Engineering (GE)	M	5	5
	F	1	2
Geophysical Engineering (GP)	M	4	2
	F	2	3
Petroleum Engineering (PE)	M	17	13
	F	9	4

Data Collection

Assessing student competence in design classes is difficult.[9] For the MPD course, the faculty uses a variety of techniques including peer reviews,[10] faculty observations, written team reports, oral team presentations, student interviews, and individual student quizzes. Data gathered from individual quizzes is used in this analysis. The quizzes were unannounced and consisted of questions from all three of the subject disciplines. The quizzes were given in multiple choice formats to eliminate concerns about subjective grading. Each of the quizzes contains 20 to 25 questions. In an attempt to measure the students' knowledge of the technical languages for their discipline as well as for the other two disciplines, the questions are composed to test this

knowledge in the context of the project data set.

Two quizzes were given during each of the three projects studied. The first quiz was given approximately three weeks into the project, and the second quiz was given at the conclusion of that project. Not only were the quizzes unannounced, but the content of the quizzes was not varied between the middle and end of the project. The students were not informed that the content would not change. The intent of this format is to establish if interdisciplinary discussion and peer learning occurs between the two quizzes for each project. Since no faculty lectures are given during the class, the assumption is that the most likely way students will gain this knowledge is through peer interaction and discussion. Obviously, the students are aware of the process during the second semester project, but results indicate this may actually lead to increased peer mentoring.

Cluster Effect Analysis

Standard statistical analysis was initially performed on the results of each quiz. This included averages, standard deviations, etc, for each discipline as well as for the class as a whole. Although this data provided information about the class knowledge in the three disciplines, it does not allow for measurement of interdisciplinary learning. Again, it is extremely important for these three disciplines to be able to work together and understand each other since they will be working in such settings during their careers.[2,3,4,11] In a recent survey of CSM petroleum engineering alumni, each person spends an average of 51% of their time working in team settings. Additionally, each person spends an average of 42% of their time working in multidisciplinary team settings. Therefore, the question for the faculty team is—are we preparing our students for their careers to the best of our ability? And, if so or if not, how do we measure this preparation? These questions and concerns lead to the idea of using cluster analysis on the individual quizzes.

Cluster analysis is a multivariate statistical technique that can be used to group objects based on the characteristics they possess.[12, 13] Ideally, "clusters" of homogeneous features will form that are separated from each other by distances. The further the distance between these homogeneous clusters, the larger the perceived heterogeneity is between clusters. Cluster analysis is unlike any other multivariate technique since it does not estimate a variate empirically, but instead uses a chosen variate to group the objects into clusters. Cluster analysis is used in areas such as biology to group organisms and marketing to evaluate consumer purchasing patterns. Although cluster analysis has numerous applications, it does have some significant limitations. Cluster analysis has been depicted as "descriptive, atheoretical, and noninferential."[12] The user must be aware that solutions are not unique and the choice of the variables used to develop the clusters can have a large effect on the results. Additionally, the cluster analysis techniques will always form clusters, no matter if there is structure in the data or not. The user needs to be aware of these drawbacks and take necessary precautions during data analysis.

For the research presented in this paper, cluster analysis is used to evaluate if significant clustering can be observed between the three subject disciplines. The answers to each of the quiz questions are used as observations to define the clusters. Three definitive clusters, consisting of students from each discipline, are expected based on the results of each of the first project quizzes since it

is anticipated that the students will correctly answer the questions developed for their specific discipline. For each of the second project quizzes, if peer learning is occurring between disciplines, the three clusters would be expected to dissolve. The blurring of the clusters would signify that interdisciplinary information exchange is occurring, either for the benefits of increased knowledge or improved grades.

Results

The first step in analyzing the quiz results was to verify the number of clusters that were present in each of the six quiz data sets (three mid-project quizzes and three end-of-project quizzes). Since there are three disciplines participating in the class, it was anticipated that three clusters would emerge from analysis. However, this assumption needed to be verified, and hierarchical procedures were used to define the numbers of clusters present. A hierarchical procedure in cluster analysis will join individual objects in steps until all clusters are combined. The final number of actual clusters present is determined based on the distances present between the growing clusters. This procedure is generally represented graphically as a dendrogram. Three hierarchical procedures were employed to examine the data including average linkage, complete linkage, and Ward's method.

The first technique, average linkage, provided little value. Figure 1 shows the dendrogram for this option for the mid-project quiz, Project 2, Semester B. The results show a stair-step pattern with little cluster structure. This is likely due to the choice of variables used in the analysis and the lack of significant variance measurements between them, which is the driving force for average linkage. Due to this lack of structure, which appeared in all six data sets, average linkage calculations were eliminated from further consideration.

The second technique, complete linkage, showed slightly better results than the average linkage technique. Figure 2 shows the dendrogram for this option for the same data set as in Figure 1. Figure 2 shows cluster definitions without the stair-step pattern in Figure 1. However, there is little variation in the lengths of the rescaled distances between the each tier of clusters. This similarity in distances prohibits a final cluster selection using the complete linkage technique.

The third technique, Ward's method, provides the best overall results and was used for the final cluster selection. Figure 3 shows the dendrogram using the same data set as in Figures 1 and 2. The rescaled distance for the last two tiers (right side of figure) is significantly larger than the average linkage and complete linkage clusters. This difference gives a strong indication of homogeneous clusters being developed prior to these longer dendrogram branches. Elimination of the last tier, which always combines the final remaining clusters, and considering the largest distances, shows three distinct clusters occurring. The same results and distinctions were seen on the remaining five data sets, with the Ward's method always indicating three distinct clusters. Based on this analysis, the hypothesis that three clusters should emerge holds true.

Once the number of clusters was verified, the second step in the analysis consisted of using nonhierarchical techniques, or K-means clustering, to determine the composition of the cluster sets based on the category of questions asked. Nonhierarchical methods require the number of

clusters be specified (determined from Ward's method in this example). The parallel threshold method was used is this study which allows objects to remain unclustered if they lie outside a pre-specified distance threshold.

Each quiz data set was broken into the questions specific for each of the disciplines (one set of GE questions, one set of GP questions, and one set of PE questions), and K-means clustering was performed to develop the clusters for each set of questions. Because of the cluster technique used and the variables selected for measurement, the clusters tended to group according to points deducted on the quiz. This information could easily be used in conventional statistical analyses such as means, variances, etc. However, the important outcomes were the make-up of the clusters by GP/GE/PE students. Tables 2, 3, and 4 show the outcomes for the three projects broken into the final clusters.

Table 2
Final Cluster Results, Project 2, Semester A

	Mid-Project Quiz			End-of-Project Quiz		
Question Type	Cluster Number	Total Number of Objects in Cluster	Cluster Composition Based on Discipline	Cluster Number	Total Number of Objects in Cluster	Cluster Composition Based on Discipline
GE	1	8	1 GE, 1 GP, 6 PE	1	3	0 GE, 1 GP, 2 PE
	2	12	3 GE, 2 GP, 7 PE	2	22	4 GE, 4 GP, 14 PE
	3	18	2 GE, 3 GP, 13 PE	3	13	2 GE, 1 GP, 10 PE
GP	1	11	1 GE, 0 GP, 10 PE	1	8	1 GE, 1 GP, 6 PE
	2	24	5 GE, 6 GP, 13 PE	2	28	5 GE, 5 GP, 18 PE
	3	3	0 GE, 0 GP, 3 PE	3	2	0 GE, 0 GP, 2 PE
PE	1	10	0 GE, 1 GP, 9 PE	1	16	4 GE, 1 GP, 11 PE
	2	21	3 GE, 3 GP, 15 PE	2	19	2 GE, 5 GP, 12 PE
	3	7	3 GE, 2 GP, 2 PE	3	3	0 GE, 0 GP, 3 PE

Table 3
Final Cluster Results, Project 1, Semester B
(Note: GE and GP questions were grouped for this quiz due to the nature of the project.)

	Mid-Project Quiz			End-of-Project Quiz		
Question Type	Cluster Number	Total Number of Objects in Cluster	Cluster Composition Based on Discipline	Cluster Number	Total Number of Objects in Cluster	Cluster Composition Based on Discipline
GE & GP	1	13	5 GE, 1 GP, 7 PE	1	17	6 GE, 2 GP, 9 PE
	2	6	2 GE, 1 GP, 3 PE	2	5	0 GE, 2 GP, 3 PE
	3	10	0 GE, 3 GP, 7 PE	3	7	1 GE, 1 GP, 5 PE
PE	1	11	1 GE, 1 GP, 9 PE	1	4	2 GE, 1 GP, 1 PE
	2	16	6 GE, 3 GP, 7 PE	2	13	1 GE, 0 GP, 12 PE
	3	2	0 GE, 1 GP, 1 PE	3	12	4 GE, 4 GP, 4 PE

Table 4
Final Cluster Results, Project 2, Semester B

	Mid-Project Quiz			End-of-Project Quiz		
Question Type	Cluster Number	Total Number of Objects in Cluster	Cluster Composition Based on Discipline	Cluster Number	Total Number of Objects in Cluster	Cluster Composition Based on Discipline
GE	1	8	3 GE, 0 GP, 5 PE	1	5	0 GE, 1 GP, 4 PE
	2	17	4 GE, 3 GP, 10 PE	2	6	1 GE, 2 GP, 3 PE
	3	4	0 GE, 2 GP, 2 PE	3	18	6 GE, 2 GP, 10 PE
GP	1	5	2 GE, 2 GP, 1 PE	1	17	5 GE, 3 GP, 9 PE
	2	2	0 GE, 1 GP, 1 PE	2	10	2 GE, 1 GP, 7 PE
	3	22	5 GE, 2 GP, 15 PE	3	2	0 GE, 1 GP, 1 PE
PE	1	6	3 GE, 2 GP, 1 PE	1	10	5 GE, 1 GP, 4 PE
	2	12	1 GE, 1 GP, 10 PE	2	7	2 GE, 3 GP, 2 PE
	3	11	3 GE, 2 GP, 6 PE	3	12	0 GE, 1 GP, 11 PE

Discussion

Examination of the K-means clustering results provides some interesting information and does suggest that interdisciplinary peer learning is occurring. The largest changes emerge with the questions in the area of geophysical engineering. All three projects indicate an increase in learning from the PE and GE students with regards to the GP questions. Project 2, Semester A, shows a gain in the Cluster 2, however, the distance between Clusters 1 and 2 decreases between quizzes and Cluster 3 moves away from Clusters 1 and 2. The small number present in Cluster 3 suggests these students are anomalies. The merging of Clusters 1 and 2 suggests interaction is occurring. Projects 1 and 2, Semester B, also show a gaining of GE and PE students into higher brackets of understanding for the GP questions. The quiz results from these two projects show an average gain of ten percentage points. The fact that the largest changes were seen in the GP area is not unexpected. Throughout their respected curriculums, the GE and PE students have little exposure to GP concepts. Most of the GE students have never seen seismic (the main GP component of the project data sets), and the PE students are only introduced to seismic during a two week field session.

The second largest improvement was in the area of petroleum engineering. The results from Project 2, Semester A, show a clear movement from three clusters into two stronger clusters. GE and GP students are completely eliminated from Cluster 3, which contains only three PE students. Again, the small number remaining in Cluster 3 suggests these students are anomalies. The two projects from Semester B show similar results. Project 1, Semester B, shows a distance decrease between the three clusters indicating less heterogeneity between the sets. The distances for Project 2, Semester B, show large decreases. As with the GP questions, the average grades for the GE and GP students increased for the PE questions in all three projects. Ironically, for Project 1, Semester B, the average for the GE and GP students was higher for the PE questions than was the average for the PE students. As with geophysical engineering, the GE and GP students have little exposure to petroleum engineering prior to this class, which may explain the large increases on the learning curve.

The questions for the third discipline, geology and geological engineering, showed little movement between clusters as far as the three disciplines are concerned. This is not unexpected since all three disciplines have significant exposure to geological classes prior to their participation in the MPD class. No conclusions are drawn from these data based on the poor structure of the cluster movements and the lack of changes in any distances between the clusters.

Overall, the cluster analysis performed on these data sets provided some interesting information. The results are not entirely conclusive, but do suggest that cluster analysis may be a valid tool for evaluating peer interaction. Other evaluation techniques, such as interviews, would likely aid the cluster analysis. Student interviews would be beneficial in determining the extent that students feel they were aided by their classmates. This information could be combined with the cluster analysis to determine how peer learning and mentoring could be promoted.

Ongoing Efforts

The benefits of cooperative learning are well documented,[14] and any efforts to foster this procedure in multidisciplinary teamwork settings would be extremely beneficial. Efforts are continuing to improve the use of cluster analysis in evaluating peer learning. Acquisition of additional data is continuing with the MPD class to improve the database. Future quizzes are being developed that are more focused on evaluating peer learning and the associated interdisciplinary languages. The use and practicality of student interviews to aid in cluster analysis evaluation is also being reviewed.

Conclusion

The results of this study show that the multivariate statistical technique of cluster analysis can be used to aid in assessing interdisciplinary peer learning. The limitations of cluster analysis require that the technique be used carefully in this type of study, but the results are promising. A database is continuing to be developed that should aid in further quantification of the cluster analysis results. Other types of data, such as student interviews, would assist in the examination of the results. The importance of functioning on multidisciplinary teams and the communication skills needed to do so can not be understated. Peer learning is an excellent vehicle to promote these skills and cultivating it will be extremely beneficial to the students involved.

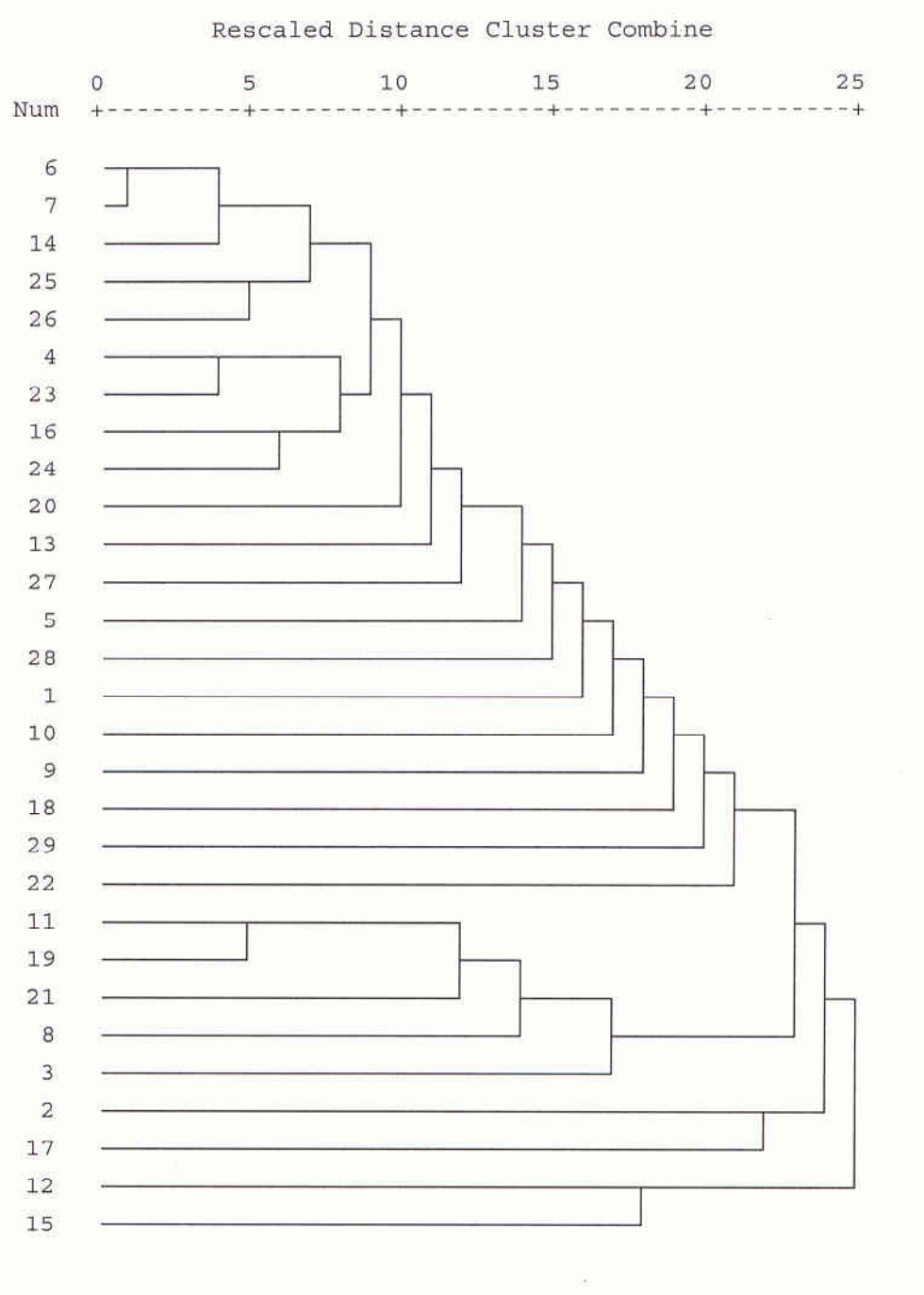

Figure 1: Average linkage dendrogram for the mid-project quiz, Project 2, Semester B.

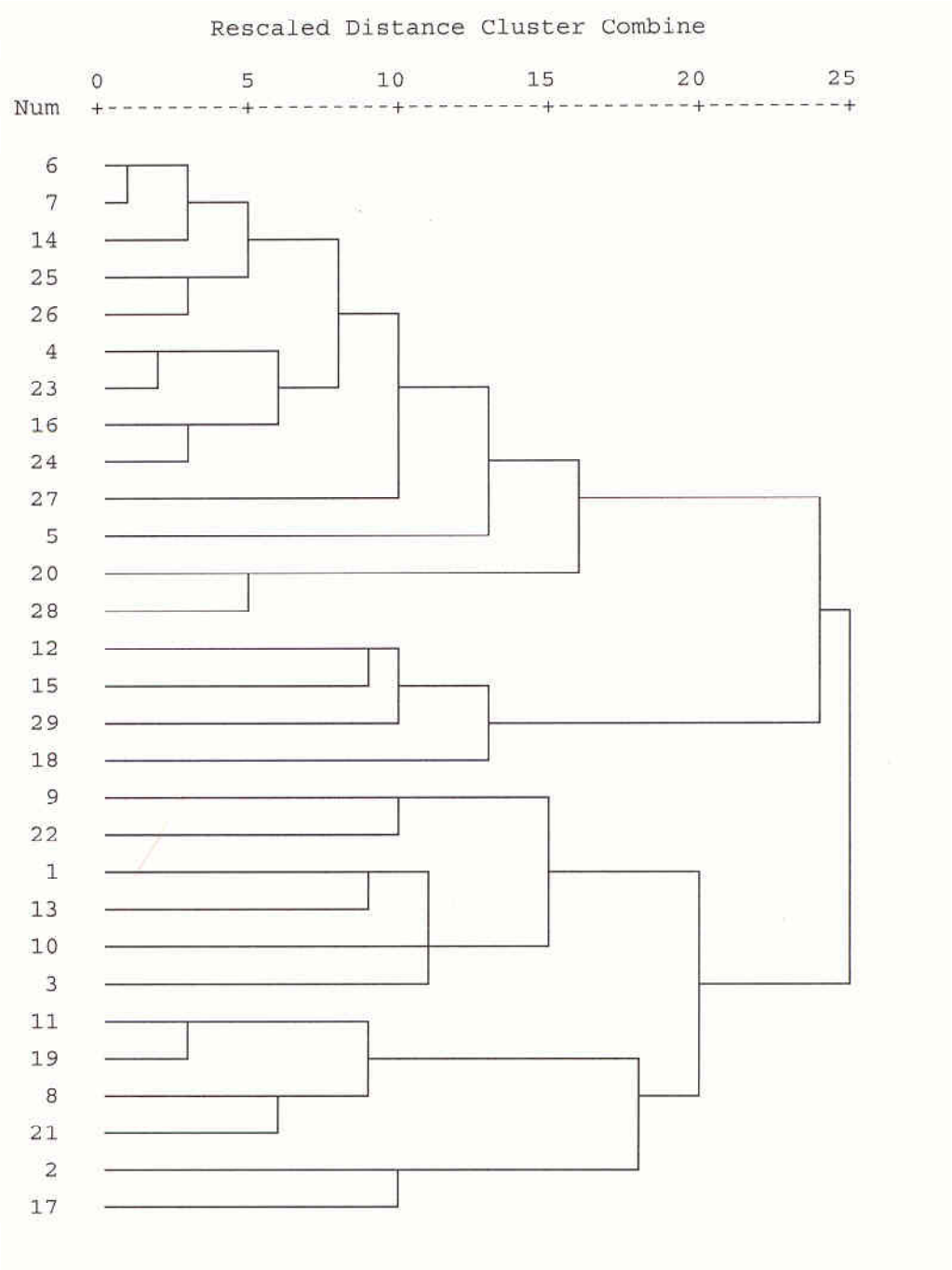

Figure 2: Complete linkage dendrogram for the mid-project quiz, Project 2, Semester B.

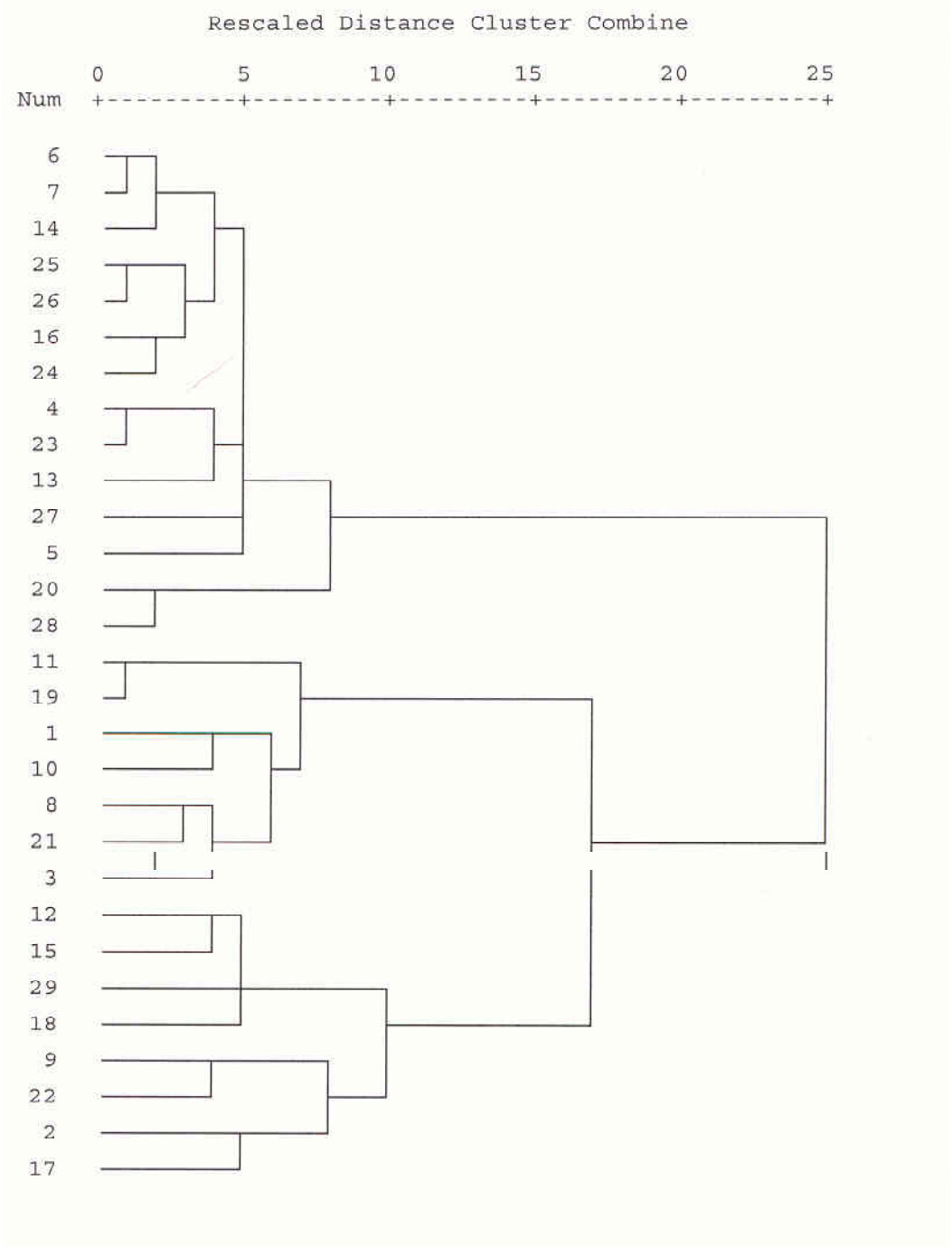

Figure 3: Ward's method dendrogram for the mid-project quiz, Project 2, Semester B.

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JENNIFER L. MISKIMINS

Jennifer L. Miskimins is an Assistant Research Professor in Petroleum Engineering at the Colorado School of Mines (CSM). Jennifer received her B.S. degree in petroleum engineering from the Montana College of Mineral Science and Technology and her M.S. and Ph.D. degrees in petroleum engineering from the Colorado School of Mines.