The Chunking of Course Material Delivery and Evaluation: A Case for Information Processing Management and Evaluation

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Abstract

Teaching and learning styles are much studied, discussed and debated. There is a plethora of formats and opinions on this subject matter. Some styles have been more effective than others, but no consensus exists amongst theoreticians and practitioners. There may never be consensus, and this may not be bad. There is very little doubt about the validity of some methodologies. Such methods as rote-repetition used almost exclusively in the past as well as the Socratic-method are proven approaches. The breaking up of learning material into small chunks (information chunking) is one such method. In this approach materials are presented and hopefully studied in small chunks. Evaluations of the comprehension and retention of the material is done often – usually soon after its presentation. The diametrically opposite format is what is often used in Law Schools, where no evaluation is done on material comprehension and retention until the end of term (final exam). This study evaluates the "chunking" methodology as a potential predictor of student learning. An undergraduate Engineering Economics course was used as platform to explore this matter. Over a seven year period the course was taught on a yearly basis (at times twice a year) using weekly quizzes as the chunking format of materials. The study investigates whether quiz grades are a predictor of final grades. The results are discussed not as prescriptors for educators but to evaluate the viability of this educational methodology.

Introduction

Teaching and learning styles have been much studied, discussed and debated. There is a plethora of formats and opinions on this area. Methods such as the rote-repetition used almost exclusively in the past, as well as the Socratic-method, are proven approaches to teaching and learning. Though disagreement may exist amongst practitioners and theoreticians as to which approach may be more effective, the disagreements fall into the realm of preference and/or fit (what is best for this or that type of material and delivery system as opposed to another). The breaking up of learning material into small chunks (chunking of information) is one such method. The diametrically opposite format is what is often used in most Law Schools, where no evaluation is done on material comprehension and retention until the very end of term (final exam).

The concept of "chunking" and the capacity of short term memory were first discussed by Miller.[1] The author sustained the idea that short-term memory could only hold 5-9 chunks of information (seven plus or minus two), where a chunk is any meaningful unit. A chunk could refer to images, words, digits, or even people's faces. The concept of chunking and the limited capacity of short term memory became a fundamental element of all subsequent theories of memory.

Applying chunking theory to student assessment builds on cognitive and educational psychology. Mislevy[2] observed that “learners increase their competency not by simply accumulating new facts and skills, but by reconfiguring their knowledge structures, by automating procedures and chunking information to reduce memory loads, and by developing strategies and models that tell them when and how facts and skills are relevant” [2] (p. 1). Many researchers have used this idea as the foundation for their empirical studies of student learning by using a pre- and post-test structure and subject groups who receive chunked and non-chunked materials. [3,4] Generally, their research indicates that materials that are logically chunked and developmentally appropriate are more easily recalled than non-chunked materials, with the chunking process providing a database into which new information can more readily be stored. In other studies, students were seen to keep up with reading assignments and general preparation for the next class meeting when they knew of a possible quiz. [5] Additionally, Graham[6] showed that students taking weekly quizzes, as opposed to those who take exams only during the semester, averaged half a letter grade higher and C students showed a grade gain of 84% of a letter grade. Additionally, some research has shown that students in classes where weekly quizzes are administered evaluated the class material and the instructors’ effectiveness much more positively than students who only had exams. Their perceived learning was rated higher.[7]

Transferring information from short-term to long-term memory involves encoding, which requires rehearsal, elaboration, and organization. In this study, the rehearsal, elaboration and organization can be achieved through the use of weekly quizzes. Some authors’ recommendations for improving student learning include organizing the information into chunks or group of related pieces of information, providing opportunities for students to practice and rehearse.[8,9] Following this schema, the current study investigates whether or not information retrieval through weekly quizzes can predict student performance in an engineering economics course.

Feedback and reinforcement are very important concepts in learning. In other studies, it was found that students valued feedback from quizzes and used the feedback and the impending quizzes as both stimulus and motivation to study harder.[10] Students in another study found that the feedback that they received from frequent quizzes helped them formulate study strategies when preparing for quizzes as opposed to prepare-gather feedback-and restudy which proved to not be near as successful.[10] Feedback involves providing learners with information about their responses, whereas reinforcement affects the tendency to make a specific response again.[11] In this study, feedback was accomplished by grading the quiz by the next class period. The material was organized in a way so students could relate new concepts with others previously learned. Feedback can be positive, negative or neutral.

Following this schema, the current study investigates whether or not information retrieval through weekly quizzes can predict the final performance of undergraduate students in an engineering economics course. Accurate predictors of student performance early in the semester may be used to induce positive reinforcement on the student. The main question guiding this study is the following: can student final performance be accurately predicted based on tests of previous chunks of material? If such predictions are accurate, action plans can be put into place in cases where performance follows declining or unusual patterns.

Methodology

This section will discuss the methodology used for this study. It will begin with the data collection procedure, next the data analysis and finally, the summary and conclusions. This study is based on observational data collected during seven consecutive years. The objective of this study is to investigate the relationship between final grades and weekly quiz average.

Data collection

Data from a total of 850 undergraduate students enrolled in 13 Engineering Economics classes at Texas Tech University was used for this study. All participants were taking the same course, from the same department. Data was collected over a 7 year span, from 1995 till 2001. The data comprises the results of 10 quizzes and a final grade for each student. To reduce the effect of confounding variables, data were collected from classes following the same structure, covering the same amount of material, as well as taught by the same professor. For the purpose of our analysis the data used will be the weekly quiz results and the final grade. Each weekly quiz is worth 2 points out of the 100 total points of the grade.

Table 1 shows the variables that were considered in the design of this study. It includes data from 10 quizzes and data from the final grade. The score for each quiz ranged from 0 to 2 and the final grade ranges from 0 to 100.

Table 1. Description of the Variables

Variable Type	Variable name	Description
Predictor variables	Q_1	Score from quiz1
	Q_{2m}	Average score from first 2 quizzes
	Q_{3m}	Average score from first 3 quizzes
	Q_{4m}	Average score from first 4 quizzes
	Q_{5m}	Average score from first 5 quizzes
	Q_{6m}	Average score from first 6 quizzes
	Q_{7m}	Average score from first 7 quizzes
	Q_{8m}	Average score from first 8 quizzes
	Q_{9m}	Average score from first 9 quizzes
	Q_{10m}	Average score from first 10 quizzes
Dependent variable	F	Final Grade in the class

A regression analysis was performed on the data to see how well quiz grades will predict the final grade of the students. The data was analyzed to detect how along into the semester an accurate prediction of final grade could be achieved.

Data Analysis

The data collected was analyzed using SAS statistical package. The average score from the weekly quizzes (Q_{2m}, Q_{3m}, …, Q_{10m}) was first investigated using scatter plots of the predictor variables versus the dependent variable final score.

Figure 1 shows a scatter plot of the average quiz grade of the first 10 quizzes (Q_{10m}) versus the final grade. The plot illustrates how the data compacts on the top right corner whereas it expands on the bottom left. Additionally, a diagonal trend can be observed from bottom left to top right. Such trend suggests the possibility of a linear relationship between the two variables Q_{10m} and F. The same trend was observed for the remaining predictor variables (Q_1 to Q_{9m}). For the purpose of simplicity, the minimum number of explanatory variables should be selected for the model. The plot pattern suggests unequal variance on the error term of the regression model, which causes difficulties with the predictive model. Indeed, the scatter plot clearly shows how the variable Q_{10m} has a good predictive ability when the average quiz grade is over 0.5. However, the model is less predictive when the average value of the quizzes is below 0.5. That is, students with low scores on the quizzes are hard to predict on their overall performance. Where by students with high scores on quizzes are easier to predict on their overall performance.

It was observed that quiz average on a certain week *i*, Q_{im}, is very likely to be highly correlated with the quiz average on the following week *i+1*, and also with the average in other consecutive weeks. The dependency can be observed in the correlation matrix of the predictor variables shown in Figure 2. Note how most values of the correlation among the quiz average for different weeks are larger than 0.90. Such dependency suggests that adding more predictor variables to the model would make it more complex without adding prediction capacity to it. Therefore, the models to be considered were reduced to those including only one predictor variable simultaneously.

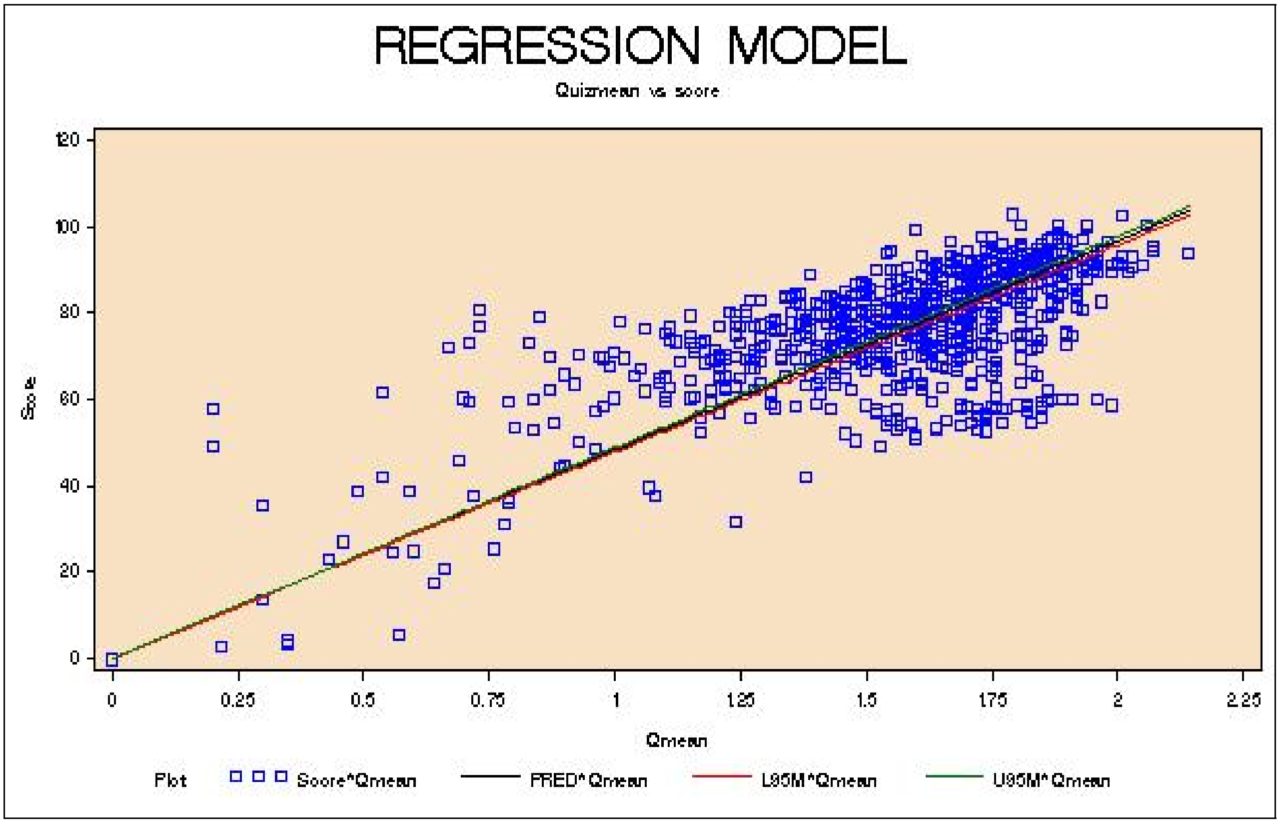

Figure 1. Scatter plot Q_{10}m vs. Final Grade (SAS generated Plot)

	Q2m	Q3m	Q4m	Q5m	Q6m	Q7m	Q8m	Q9m	Q10m	Final Grade
Q2m	1.00	0.86	0.81	0.79	0.76	0.75	0.71	0.69	0.69	0.39
Q3m	0.86	1.00	0.93	0.89	0.86	0.83	0.81	0.80	0.77	0.50
Q4m	0.81	0.93	1.00	0.96	0.93	0.90	0.87	0.86	0.84	0.53
Q5m	0.79	0.89	0.96	1.00	0.97	0.94	0.92	0.90	0.89	0.56
Q6m	0.76	0.86	0.93	0.97	1.00	0.98	0.96	0.94	0.93	0.58
Q7m	0.74	0.83	0.90	0.94	0.98	1.00	0.98	0.96	0.95	0.61
Q8m	0.71	0.81	0.87	0.92	0.96	0.98	1.00	0.99	0.98	0.62
Q9m	0.69	0.80	0.86	0.90	0.94	0.96	0.99	1.00	0.99	0.65
Q10m	0.69	0.77	0.84	0.89	0.93	0.95	0.98	0.99	1.00	0.67
Final Grade	0.39	0.50	0.53	0.56	0.58	0.61	0.62	0.65	0.67	1.007

Figure 2. Correlation Matrix

Ten individual linear models were investigated to identify which average weekly score starting from week one provides enough accuracy to predict the final grade. The models show the following relationship:

$$F=b_{0i}+b_{1i}\,Q_{im}$$

where

F is the final grade
Q_{im}.is the average quiz score of the first i weeks, i=1,2,…,10
The coefficient b_{0i} is the intercept, which in this case was found to be zero because the linear relationship crosses the origin
The coefficient b_{1i} is the slope of the linear relationship

Figure 3 shows a histogram depicting the value of the correlation between weekly quizzes and the final grade. The analysis showed that from the fifth week, the model does not significantly increase in predictive capacity with respect to previous week. A more in depth analysis of model's ability was performed by using the percentage difference in predictive ability of the Q_{im} variables. The improvement of predictive ability for the independent variables (Q_{2m}, Q_{3m}, …,Q_{10m}) was measured using the following parameters: correlation with F, R-square of the linear model, coefficient of variation and R-square with intercept. The analysis is shown in Figure 4. The value of the ordinate indicates the improvement in predictive ability from one quiz to the next. It can be seen how in week five, the four lines flatten out, which means that the model does not significantly improve its prediction from the previous quiz. The four variables confirm that the predictive ability of the quiz average does not significantly improve after the 5th week. This therefore means that by week five the ability to predict final grade is almost as certain as any subsequent week. Consequently, the average of the first five quizzes, Q_{5m}, will be used as predictor for the Final Grade (F), and the resulting linear model will be investigated on its predictive ability.

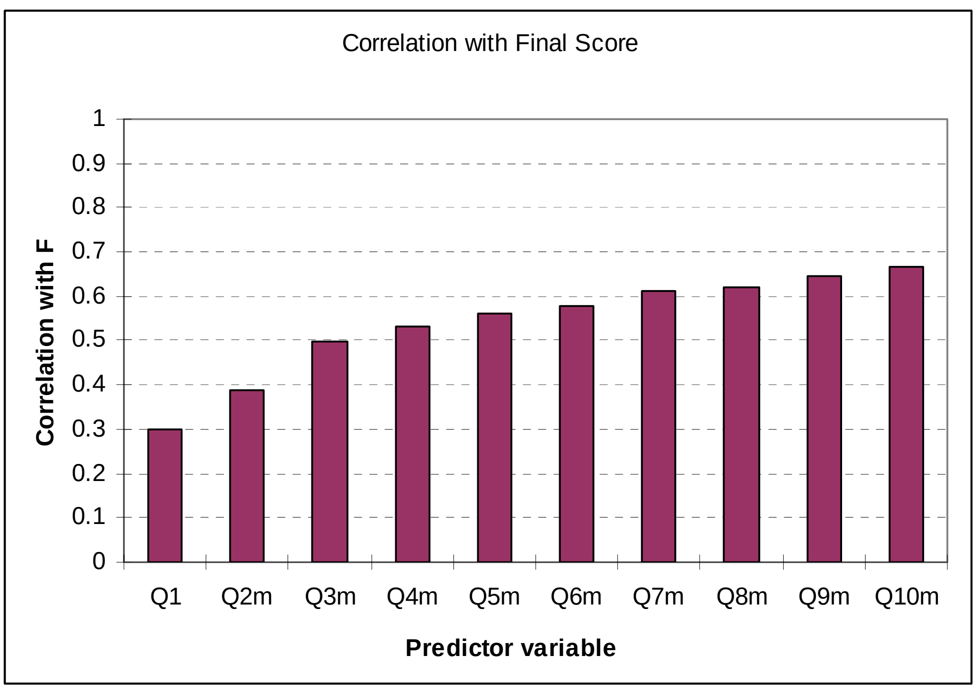

Figure 3. Correlation Between Weekly Quizzes and Final Grade.

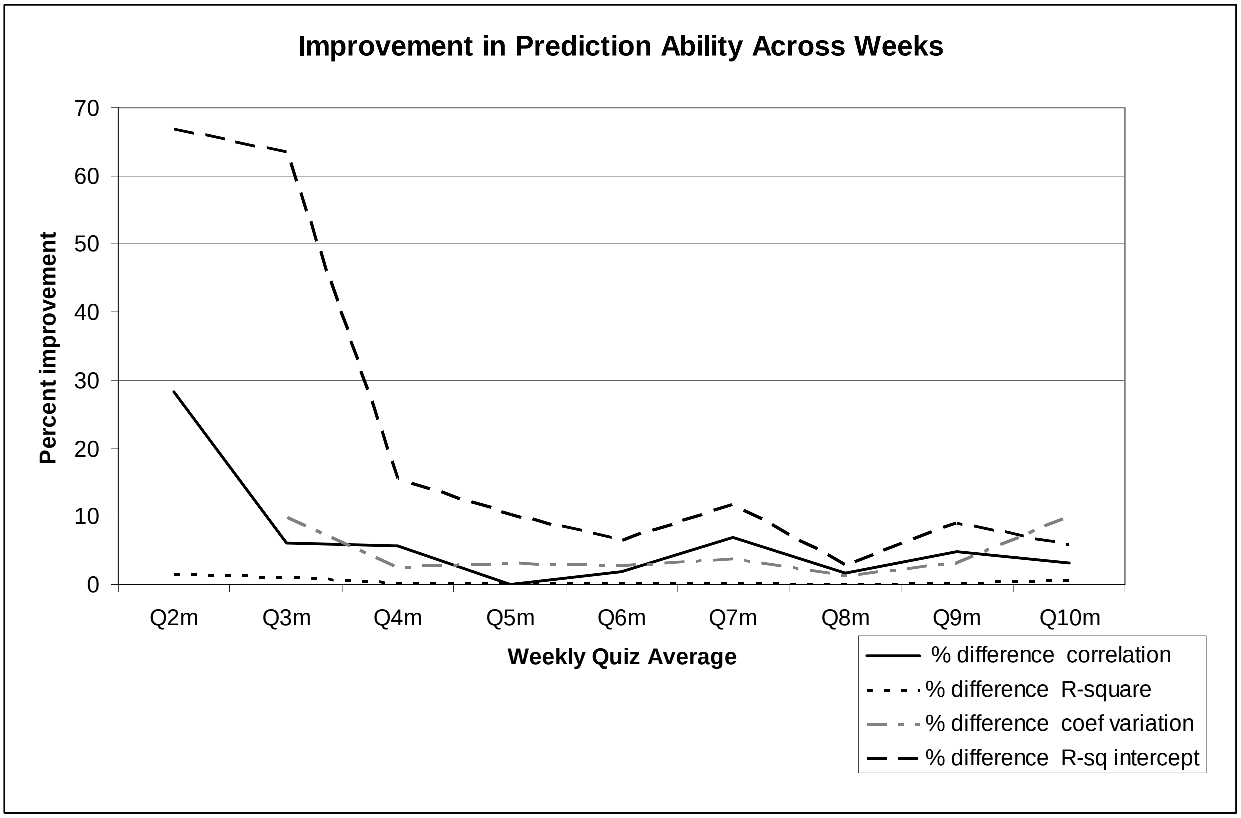

Figure 4. Percentage difference in predictive ability

The scatter plot of the Q_{5m} versus F is shown in Figure 5. The plot shows how the predictive ability of the linear model shown gets very high for values of Q_{5m} over 1. At the same time, the model shows higher error terms when the predictive variable is less than 1. The linear regression model using Q_{5m} as predictor is:

$F = 48.0243\ Q_{5m},$ where the coefficient has a confidence interval of [47.7, 49.1]

This model suggests with 95 % confidence that an increase of 0.5 points in the average score of the quizzes will have an increase in the overall grade between 23.9 and 24.5. This result should be considered with caution when the average score of the quizzes is lower than 0.5 since the predictive power of the model decreases for lower values of the quiz average.

Tables 2 and 3 below show the main points of the distributions of Q_{5m} and F. It shows the values where minimum and maximum score occurs. In addition, they show the location of the first and third quartiles as well as the interquartile range. The median of the Q_{5m} distribution is 1.62 which corresponds to a grade equivalent to 81. As will be discussed further in the conclusions section, this reinforces not only the predictability of this approach, but its possible use as a preventive measure for at-risk students.

Table 2. Quantiles of Q_{5m} distribution.

Quantile	Estimate	Descriptive Points
100%	2.22	Max
99%	2.08	
95%	1.98	
90%	1.90	
75%	1.80	Q3
50%	1.62	Median
25%	1.39	Q1
10%	1.07	
5%	0.82	
1%	0.44	
0%	0.00	Min

Table 3. Quantiles of F distribution.

Quantile	Estimate	Descriptive Points
100%	103.00	Max
99%	98.69	
95%	94.25	
90%	91.63	
75%	86.50	Q3
50%	78.63	Median
25%	69.80	Q1
10%	58.83	
5%	0.820	
1%	0.440	
0%	0.000	Min

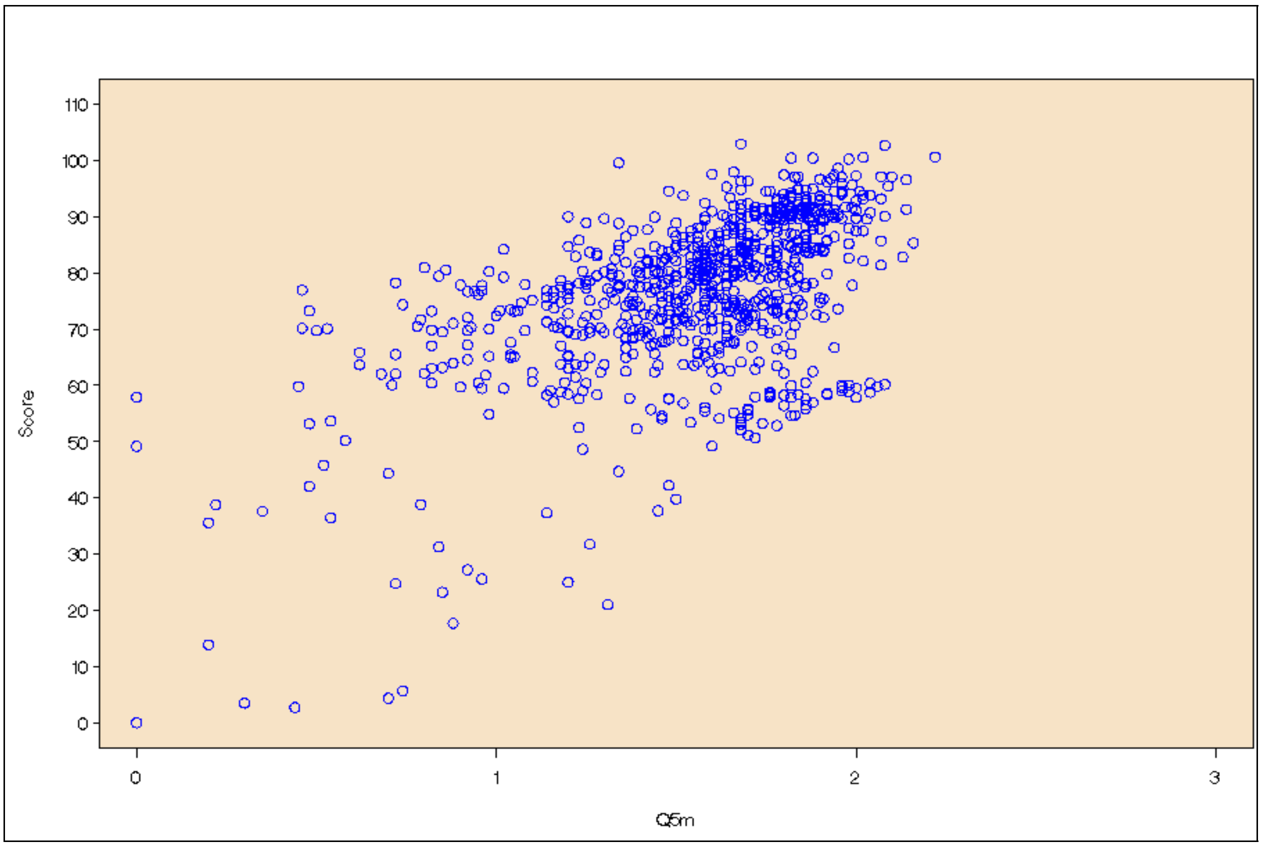

Figure 5. Scatter Plot of Q5m versus Final Grade

Summary and Conclusions

The study presented here is by no means a prescriptor to educators. The work is still preliminary in nature. Nonetheless, the results do show promise. In classes with course material similar to that of Engineering Economics where the knowledge-base is somewhat sequential and cumulative, the results presented here could prove to be beneficial to educators. There already exists in the literature information on the value of chunking and the use of quizzes as a mechanism for this procedure. The present study builds on, enhances, and possibly extends this area of research to the realm of using the evaluation of "chunks" of information as a predictor of final grade. This could be used by educators as a corrective tool with their students. For example, students could be advised after the fifth quiz (in the case of this specific class, in other courses the inflection point may differ). At-risk students could be made aware of the probabilities with their current study habits and approach to attempt to alter their current scholarly path. The instructor might take a more proactive stance than just informing the at-risk student. Additionally, the instructor might engage students in specific study approaches or extra assignments to again change study behavior. Hopefully, the present research provides an initial analysis into the use of this educational methodology to improve study behavior.

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