Title: Do reflective students learn more in the Emergency Department?

Abstract:

**Background:** Medical schools have begun to incorporate self-reflection exercises into their curricula. It is thought that these exercises help students master the material more deeply and perform better on exams. There are few data supporting this hypothesis.

**Objectives:** We evaluated the relationship between the degree of reflection after a student’s shift in an emergency room and that student’s final grade.

**Methods:** We conducted a retrospective case series by analyzing the performance and reflective statements of 116 students who participated in an emergency medicine clerkship at two clinical sites from 2013-14. After each shift, an attending emergency medicine physician evaluated the student and the student could complete an optional reflection freetext section. We extracted the text from those comments, removed stopwords, and lemmatized the remaining words. Stopwords are words that occur frequently and serve only a grammatical functions, such as “a, the, of”. We analyzed the correlation between a comprehensive exam grade and the fraction of reflections with at least one content word. We determined the most common words and pairs of adjacent words that students used to describe their reflections. We compared the median scores of those who wrote reflections more than half of the time with those who wrote reflections less than half of the time.

**Results:** Of the 145 possible records, 116 were included for analysis. The other 29 were excluded as they were visiting students. The correlation between exam grade and the number of completed self-reflections was 0.32. The correlation between exam grade and the average number of words in each self-reflection was 0.21. The first correlation is significantly greater than 0 (p=0.03, t-test), but the second correlation is not (p=0.16, t-test). The median score of those who wrote reflections on more than half of their shifts was significantly greater than those who wrote reflections half of the time, 83.675 versus 79.23 (p=0.05, 2-sample Kolmogorov-Smirnov test).

**Conclusions:** Students who reflected more frequently scored more highly on a final written exam in an emergency medicine clerkship designed for fourth year medical students. The number of words in each reflection was not significantly correlated with exam performance. A more formal reflection program, perhaps including data from the clinical notes students write during their rotation, could help identify students struggling to master the content before they take the final exam.

**Introduction**

Undergraduate medical education is becoming, increasingly, self-directed (CITATION). Reflection is an essential aspect of self-regulated learning, and may also be required to develop a therapeutic relationship and professional expertise**[[1]](#footnote-1)**.

- Importance of self-reflection in self-regulated learning

- Increasing prevalence of self-regulated learning in medical school

- Methodologic difficulty of assessing reflection, especially in retrospective surveys; we captured the thoughts immediately after each shift.

**Methods**

We conducted a retrospective analysis of all student performances from October 2014 to October 2015. Figure 1 summarizes our study design.

**Grading.** At the end of each shift, an attending physician in Emergency Medicine evaluated the student according to the scheme in Table 1. Medical students rotate in one of four hospitals, one city hospital, two community hospitals, and one academic hospital. We only included fourth-year students from our institution taking the Emergency Medicine clerkship for the first time. We did not include visiting students.

**Software.** All analysis was written by MC and performed in Python**[[2]](#footnote-2)**. Natural language processing was performed using the Natural Language Toolkit for Python, version 3.0**[[3]](#footnote-3)**. Bootstrapping and the calculation of Jaccard similarity were performed using NumPy/SciPy**[[4]](#footnote-4)**. Figures were made using the matplotlib**[[5]](#footnote-5)** plugin. Multinomial Naive Bayes Classification was performed using NLTK and sci-kitlearn**[[6]](#footnote-6)**. All code used to analyze and generate the figures as well as supporting documents are available at the following GitHub repository: [**https://github.com/mac389/leuthauser**](https://github.com/mac389/leuthauser).

**Data Acquisition.** After each rotation a student fills out an evaluation form, which is a page in a booklet. At the end of the rotation, every student returned his booklet to the directors of the Emergency Medicine Clerkship (AL, BH). Author MC transcribed the booklets into a database. In transcribing, all medical abbreviations and contractions were replaced with their long form and all illegible comments were ignored. A deidentified version of the database is available at our GitHub repository. The text of each student comment was processed as follows:

1. All text converted to lower case
2. Comments tokenized into words
3. Stopwords removed
4. Remaining words lemmatized

*Stopwords.* The term *stopwords* refers to words that occur frequently in a corpus but are unlikely to be informative. The removal of stopwords is a common preprocessing step in natural language processing. It can increase the sensitivity and specificity of analyses**[[7]](#footnote-7)**. The list of stopwords depends on the task. The list of stopwords we used is available at our repository. We used an amalgamation of the English stopwords list in the Natural Language Tooklit 3.0 package for Python and the 10,000 most frequently occurring words in the transcript of all episodes of *The Simpsons*. The list is available as the file *stopwords* in our GitHub repository.

*Lemmatization.* The term *lemmatization* refers to the mapping of all inflected forms of a word to a base form so that they can be analyzed as a single item. For example lemmatization maps “infect”, “infected”, “infection”, “infections”, and so on to “infect”. To lemmatize words in our study we used the *WordNetLemmatize* function in NLTK 3.0. This function is a thin wrapper to WordNet’s *morphy* function, which removes all suffixes that occur in the WordNet database. *WordNetLemmatize* is more accurate if it known the part of the speech of the word it is asked to lemmatize. For example, *patient* and *patients* should only be considered one item if *patient* is a noun. To identify the part of speech of each word, we used the *pos\_tag* function in NLTK 3.0. *Pos\_tag* is trained on the treebank corpus*[[8]](#footnote-8)*.

*Tokenization.* The term *tokenization* refers to breaking a string of words into those words. Tokenization can be difficult when abbreviations and nonstandard punctuation are used. We used the *word\_tokenize* function in NLTK 3.0. This tokenizer uses regular expressions and is appropriate for pieces of text that do not have emoticons nor use contractions extensively.

*Jaccard similarity.*The Jaccard similarity**[[9]](#footnote-9)** quantifies the similarity between two sets of objects. The Euclidean distance, in contrast, quantifies the distance between an ordered series of numbers. The Jaccard similarity is defined as the ratio of number of objects two sets have in common to the total number of unique objects across both sets.

*Bootstrapping.* In statistics *boostrapping* refers to a process of resampling without replacement to generate an empirical probability density function**[[10]](#footnote-10)**. It allows the estimation of the statistical significance of a parameter when the underlying distribution is not known. In this paper we use it to estimate the statistical significance of Jaccard similarities.

**Results**

*Demographics.* Figure 1 shows the distributions of faculty ratings (left) and exam performances (right). Hyphenated categories, such as *Reporter-Interpreter* refer to evaluations where the attending circled two adjacent categories evenly. Figure 2 shows the fifty most common words and nine most common bigrams, two-word phrases, in all student comments that remained after the processing described in the **Methods** section. As an example, after processing the phrase *loss of consciousness* becomes (*loss*, *consciousness*). That phrase has two unigrams *loss* and *consciousness* and one bigram *loss consciousness*.

*Correlation between reflection and exam performance.* Figure 3 shows the correlation between the fraction of comments each student completed (left) or the average lengths of each student’s comments and that student’s performance on the final exam. We considered a comment completed if the comment had at least one legible word. The correlation between the fraction of comments each student completed and exam performance was significant (two-tailed t-test; p=0.03). The correlation between the average length of comments and exam performance was not significant (two-tailed t-test; p=0.16). There are two clusters in the right panel of Figure 3. The cluster of hollow circles corresponds to students who commented on their experience more than half of the time. The cluster of solid circles corresponds to those who commented less than half of the time. The median test scores of the completes and non-completers, 83 +/-4 and 79 +/- 3 (median +/- interquartile range) are not significantly different. The 95% confidence intervals for the medians overlap (Figure 5). The clusters do come from different distributions (Kolmogorov-Smirnov test; D statistic 0.5; p=.005). With a larger sample the difference may become statistically significant.

*Analysis of text.* Figure 4 shows the most common words in the clusters Figure 3 identified. The Jaccard similarity between these two clusters was 0.06. Figure 6 shows the most common words in each category described in Table 1. We excluded student rated as inadequate because too few students were rated as “Inadequate”. We also excluded hybrid categories.

Table 2 shows the Jaccard similarity between all pairs of panels in Figure 4. It suggests that those rated “Manager” used more words in common with those rated “Superior” than did those rater “Reporter” or “Interpreter”.

**Conclusions**

The main result of this study is that the number of comments a medical student makes after his shift correlates with his performance on a final written exam in an Emergency Medicine clerkship. Students who wrote more reflective comments scored higher on the final exam, although this increase was not statistically significant. Counting comments with single legible words as “complete” may have diluted our statistical power. The association between completion of a reflection exercise and exam performance may reflect an underlying attribute, such as diligence.

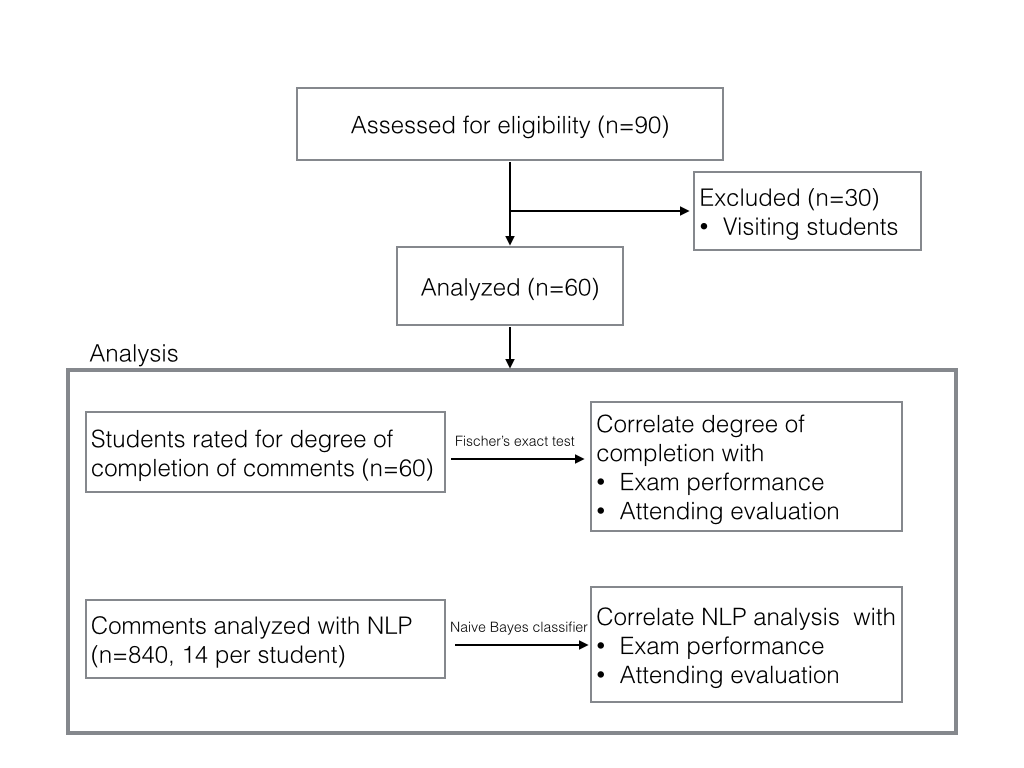
A secondary result is that “Reporters”, “Interpreters”, “Managers”, and “Educators” use different words to describe their reflections**[[11]](#footnote-11)**. The word frequencies were tabulated once the attending evaluations were known. We could not determine the statistical significance of this association. A chi-square test is inappropriate. The observations are not independent. Each student generated 14 comments and attending evaluations. It is not known, however, whether the students wrote their reflections after each shift or in bunches. Over 200 were evaluated as “superior”. Disproportionate representation of some categories at the expense of others makes it harder to find distinguishing features of each category. We excluded hybrid categories. In many cases it was unclear whether the attending meant to circle both categories, indicate performance between two categories, or meant to circle only one category. Excluding those comments may have decreased the power. There were insufficient data to train a naive Bayes classifier to predict attending evaluations from student comments.

We could not control for seasonality. We had only one year of data. We did not have data on the specialties students were interested in. Medical students looking to pursue residency in emergency medicine may perform better than students interested in other specialties. They may schedule the clerkship earlier than other students to obtain letters of recommendation, or because, at our institutions, students must rotate through our emergency department before they rotate at other institutions.

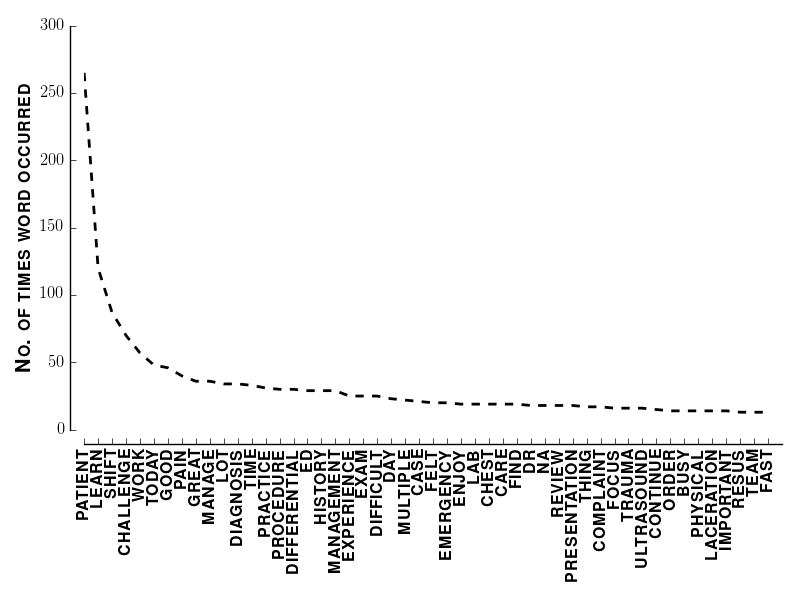
This study is the first to use natural language processing to quantify the relationships between how medical students perceive their performance, how attendings perceive their performance, and student performance on an objective measure, a final exam. Natural language processing has been used previously in more restrictive cases, such as to partially automate detecting when medical students have met procedural requirements**[[12]](#footnote-12)**. This study suggests a large role for natural language processing in medical education.

Quantifying the degree of reflection is challenging in medical school. What constitutes reflection changes as students progress through their education. Students may use similar words to describe different levels of reflection. Our study demonstrates a relationship between the pattern of exposition of medical students and their academic performance these limitations notwithstanding.

**Figure 1. Study design.**



**Figure 1. Left:** Most common words in all student comments. **Right:** Most common bigrams.



Bigram (frequency)

learn lot (23)

differential diagnosis (19)

chest pain (14)

manage patient (12)

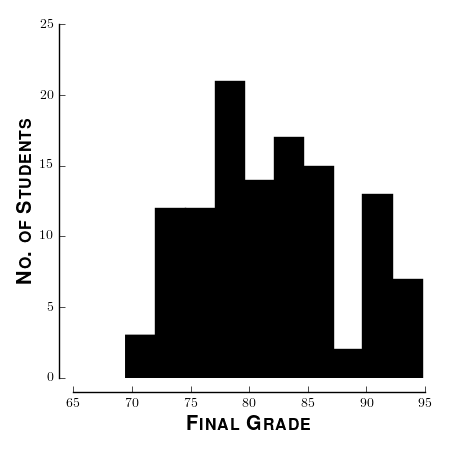
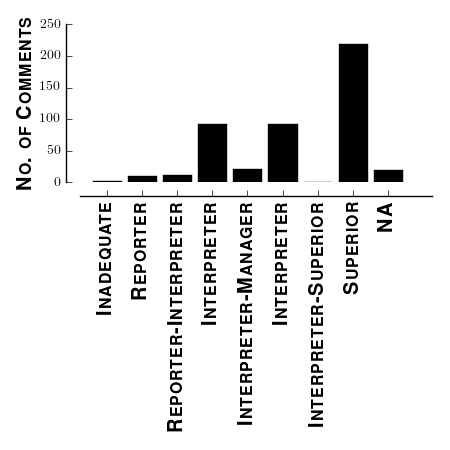
multiple patient (11)

patient learn (9)

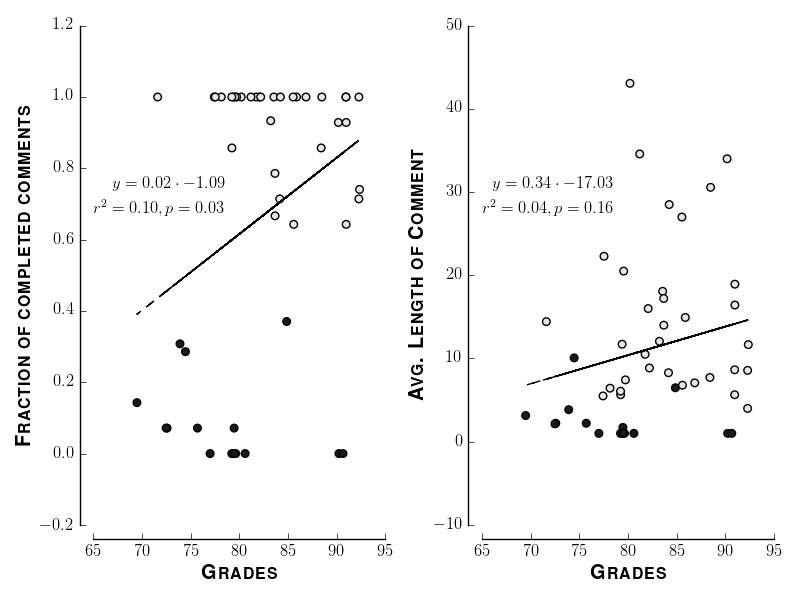
emergency department (8)

incision drainage (8)

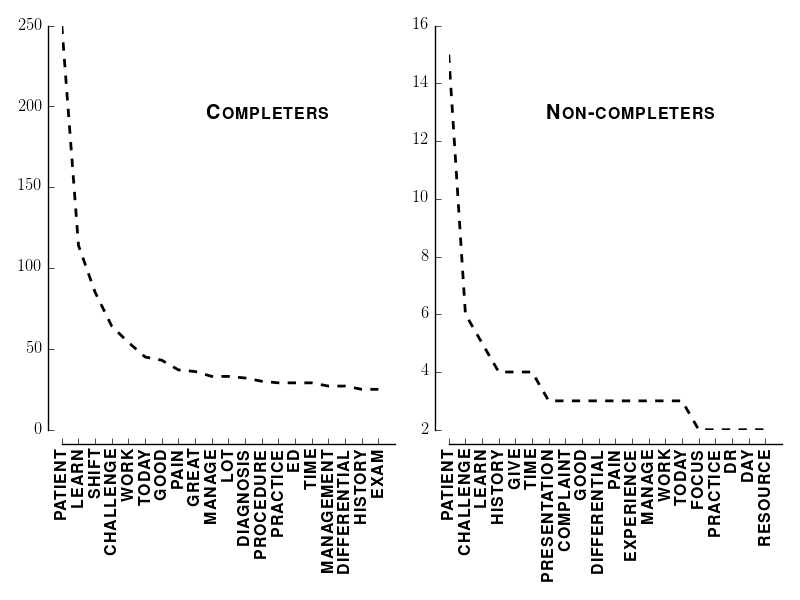
abdominal pain (8)

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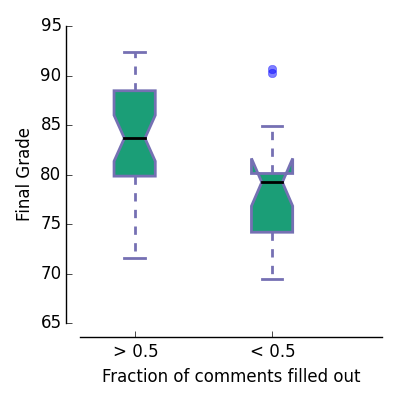
**Figure 2. Study demographics. Left:** Distribution of attending ratings. Hyphenated ratings indicate that an attending circled two categories. **Right:** Distribution of final grades.



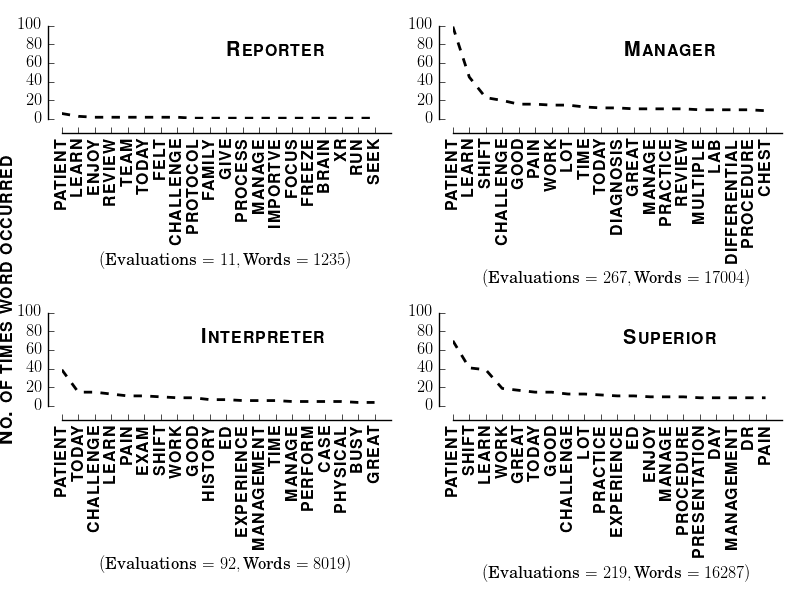
**Figure 3. Correlation between exam performance and reflection.** **Left:** Scatter plot of grades versus fraction of completed comments. Each point represents one student. Dashed line indicates regression of fraction of completed reflections against grades. **Inset:** Top line shows equation of regression line. Bottom line shows coefficient of determination and p-value that the slope of the regression line is significantly different from zero. **Right:** Scatter plot of grades versus average length of comments. Each point represents one student. Dashed line and inset indicate the same as in the left panel. In both panels solid circles represent those who completed less than half of the comments. Hollow circles represent those who completed more than half of the comments.



**Figure 4. Word frequencies. Left:** Twenty most common words used by those who completed more than half of their comments. **Right:** Twenty most common words used by those who completed less than half of their comments.



**Figure 5. Comparison of final grade in students who commented on more than half of their shifts with those who commented on less than half.** Tukey boxplot. Black horizontal line denotes median. Dimple denotes 95% confidence interval for median. Box denotes interquartile range. Whiskers denote 2nd and 97th percentiles. Dot indicates an outlier.

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**Figure 6. Most common words in each RIME category.** Text in upper right of each inset denotes category. Label on x-axis details how many evaluations and total number of words used before lemmatization and removing stopwords.

|  |  |
| --- | --- |
| Category | Description |
| Inadequate | Well below expected |
| Reporter | Obtains and reports information, beginning to interpret |
| Interpreter | Consistently access data. Actively participates in care |
| Manager | Suggests treatment options based on data. Deep knowledge of his/her patients |
| Superior | Fewer than 5% of students. Works at or above the level of EM intern. Cana manage patients independently |

**Table 1. RIME Rating scheme.**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Reporter | Interpreter | Manager | Educator |
| Reporter |  |  |  |  |
| Interpreter | 0.989 (p=0.436) |  |  |  |
| Manager | 0.1494 (p=0.2694) | **0.3699 (p<0.001)** |  |  |
| Educator | 0.1364 (p=0.3166) | **0.3158 (p<0.01)** | **0.4286 (p<0.01)** |  |

**Table 2.** Jaccard similarity.

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