Exploring the student experience of industry placements using sentiment analysis.

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STRUCTURED ABSTRACT

3. Beyond the classroom – tailoring engineering and STEM education to meet the needs of all stakeholders. (External Industry requirement)

CONTEXT
The Bachelor of Engineering (Honours)/ Master of Engineering (BE/ME) program features a compulsory 6-month placement in industry or research. To date our main source of information about these placements has been via student surveys. Although these have provided important information regarding the quality of the placement, they have not provided as much insight into the students' personal experiences of learning. This study seeks to redress this by adopting a novel approach to the analysis of post-placement interview data that incorporates sentiment analysis.

PURPOSE
The purpose of this study was to explore students' experiences of their BE/ME industry placement through the application of sentiment analysis techniques to themes developed in the interviews.

APPROACH
Adopting an approach based on sentiment analysis, and borrowed from computational linguistics, we explored key topics discussed during post-placement interviews with students. These topics were rated for the quality and type of emotional expression that accompanied them.

RESULTS
Students experienced mostly positive sentiment with regards to the topics of communication, confidence and development and in relation to the BE/ME program on a whole. Positive expressions of joy were predominantly associated with either teamwork or with the relationships formed between students, their colleagues and their supervisors. In contrast, sentiments of sadness, disgust, anger and uncertainty were predominantly expressed negatively. Negative sentiment was most commonly expressed by students in the form of uncertainty when discussing the scope of their project.

CONCLUSIONS
The approach adopted shows promise for further understanding the impact of industry placement on the student learning experience. More importantly, it highlighted key areas for improvement. Across the board, students struggled most with the level of uncertainty experienced during their industry placement. Thus, an important lesson learnt was to provide students with greater guidance in pre-placement workshops with regards to scoping a project and in dealing with unknowns so as to better prepare them as professional engineers who must adapt and function within an uncertain environment. Further research has explored the automation of sentiment analysis across the student transcripts to make the task more efficient, objective and consistent.

KEYWORDS
Industry placement, sentiment analysis, learning, emotion.

Introduction

This research focuses on the novel adaption and use of sentiment analysis to explore students' experiences of their industry placement. As part of the Bachelor of Engineering / Master of Engineering, students have the opportunity to complete a 6 month industry placement. To date there has been little in-depth analysis of students' expectations, learning and outcomes of their placement experience.

Theoretical framework

The theoretical framework for this study draws on the work carried out in computational linguistics on sentiment analysis. Sentiment analysis consists of analysis of ”opinion, sentiment, and subjectivity in text” (Pang & Lee, 2008, p. i). Wilson, Wiebe & Hoffman, (2005) further define sentiment analysis as “the task of identifying positive and negative opinions, emotions, and evaluations”. The analysis is usually done computationally and often classifies sentiment as positive, negative or neutral (Pak & Paroubek, 2010). Other analyses of sentiment make use of Plutchik’s (1980) theory of emotion where words have been linked to eight key emotional categories: anticipation, joy, trust, fear, surprise, sadness, disgust and anger. It should be noted that it is possible for surprise and anticipation to be either positive or negative in polarity. Human sentiment (emotion) is complex and although sadness is probably more readily thought of as negative, it could also have positive associations (such as being so happy that you cry to use clichéd example). The sentiment or emotion wheel also has different levels of intensity associated with each key emotion (Figure 1). The analyses typically make use of unstructured data or free text (Jonyer, Cook and Holder, 2001) found on the web and makes use of user generated content (Kumar & Sebastien, 2012). However, there is potential application of the techniques used in sentiment analysis to a wide range of fields including education.

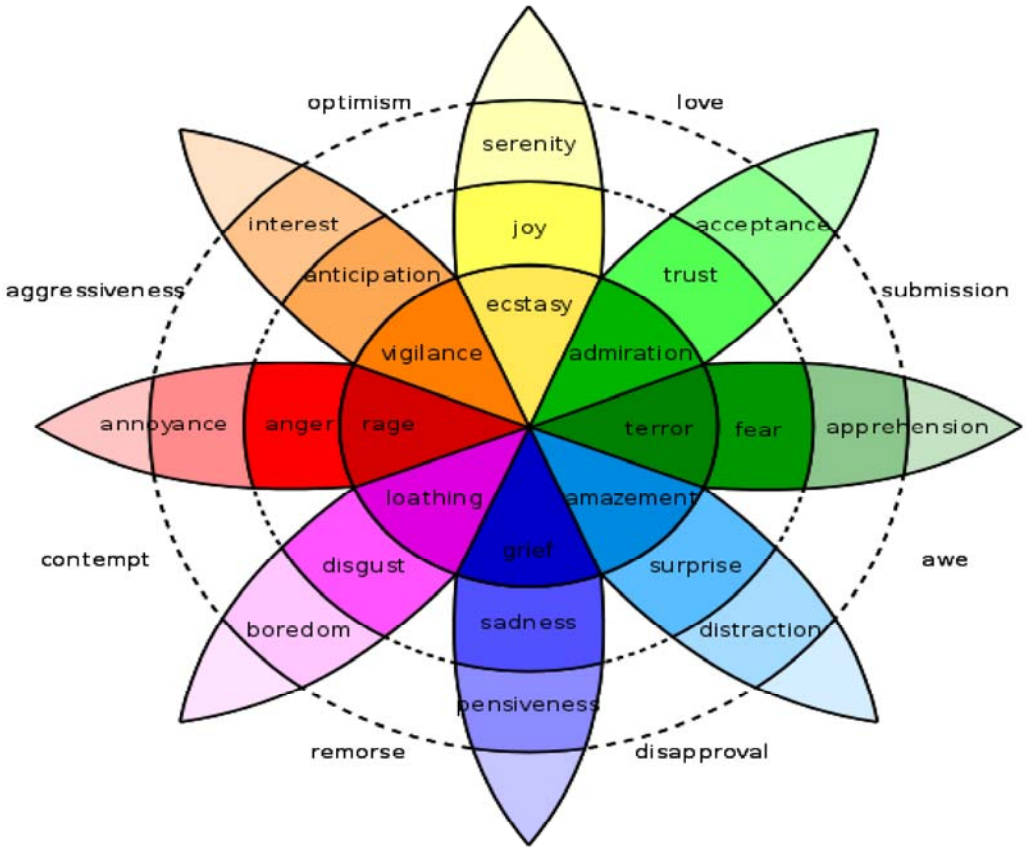

Figure 1. Plutchik’s wheel of emotions (Plutchik, 1980).

Sentiment analysis has primarily been used to analyse peoples’ views in a marketing context (such as their opinions on goods and services) or in politics (Pang & Lee, 2008). Despite its historical applications, sentiment analysis also proves useful in intelligence, diffusion of innovation, and potentially education (Pang & Lee). Previous research on sentiment analysis has tended to focus on the large scale analysis of data available online via twitter (Agarwal & et al, 2012; Martínez-Cámara et al., 2014), in blogs (Godbole, Srinivasaiah, & 2007) or online product or movie reviews (Pang & Lee, 2004).

This project was also developed in part to address the issue of performance when it comes to sentiment analysis between humans and computers. It is anticipated that a later phase of this project will enable a

comparison between transcripts analysed as part of this project and subsequently by a sentiment analysis classifier. Current opinion is that sentiment analysis, at least based on current technology, can rarely outperform humans trained to analyse the same data (Rosenthal et al. 2015), although see Gilbert, (2014) for development of a sentiment classifier that outperforms humans. However, the problem with using humans to analyse the information is that it is extremely resource-intensive. The process requires such humans to be well-trained and, is itself, a very time-hungry endeavour (Liu, 2010). Therefore, only a finite number of texts can be analysed. Additionally, subjectivity can creep into the analyses with flow on effects to inter-rater reliability issues (Wilson, Wiebe & Huffman, 2005). There is also debate over the most useful approach to take in order to best exploit available sentiment analysis techniques. Advances in artificial intelligence have enabled researchers to incorporate improved algorithms (Annett, & Kondrak, 2008).

There are also different approaches to the unit of analysis in sentiment analysis. Some researchers use the entire document as the unit of analysis and seek to state whether it is positive, negative or neutral in sentiment overall (Pang & Lee, 2004); others use the sentence (Yu and Hatzivassiloglou 2003), or phrase or expression as units of analysis (Wilson, Wiebe & Huffman, 2005). Document level analysis might work well for a movie or product review where the goal of the analysis is to determine whether a consumer rates the film or product favourably on the whole. However, in taking such a big picture view of the text, it overlooks the key features of the product or movie that the reviewers liked or disliked. For our application and context, a document analysis approach would reveal little about which specific aspects of their industry placement students responded positively or negatively to. We also needed to identify suitable topics by which a context-relevant sentiment analysis could occur. Basch and Fisher (1998) had developed a work event and emotions matrix that we used to form part of our approach and succeeding analysis.

Although there is a history of exploring human emotion as part of affective engineering in the context of developing more realistic robots (Balters & Steinert 2017), there is not as much in-depth research exploring engineers' emotional responses to their own work. There are however several studies that examine the role of emotion in learning (Kellam et al, 2011; Kellam et al. 2017). These studies link negative students' emotions such as anger and frustration as critical to learning. Winkler (2012) describes the transition from engineer to management as an unhappy one; it might be expected that transitioning from an undergraduate to an industry placement might be similarly confronting, although there is little data on this.

The primary aim of this study therefore, is to explore the students' experiences of their industry placement. A secondary aim is to explore the utility of applying sentiment analysis manually as a precursor to using an automated (computer-based) application of the technique more widely. The research is novel and innovative in its combination of sentiment analysis in an educational setting. It also provides an in-depth analysis of BE / ME students' placement experiences; something that had not been done to date. We were fortunate to have the luxury of a relatively small set of data that could be analysed by the researchers. To the best of our knowledge, this is the first time such an approach has been used in higher education to understand engineering students' experiences of their industry placement. The research was designed to answer the following questions.

1. What do engineering students think about their placement experience?
2. How positive (or negative) are students about this experience?
3. What sentiments do they typically express with regards to specific topics that are relevant to their industry placement?

Method

Procedure

Interviews were conducted with 11 BE / ME students at the end of their industry placement. We received ethics approval from the University of Queensland Human Research Ethics Committee to interview students about their placement experience. A semi-structured interview technique was used. The full interview protocol is available on request. However, a sample of questions are provided below:

1. Can tell me a little bit about yourself, and why did you choose the programme that you are in?
2. Could you describe a typical day while you were on placement?

3. What type of activities did you consider were non-typical but helped you with your development?
4. Let's talk now about the people you worked with. You kind of mentioned it, but I need to ask again: who did you work with on a daily basis?
5. Did you have any challenges while working on your project?
6. So how was your relationship with the engineers and the operators?

Students were interviewed by researchers independently of the teaching staff. This should have removed the potential for positively biased assessments of their placement experiences.

Data analysis

The interviews were then transcribed and prepared for analysis. Interview transcripts were annotated comprehensively for sentiment in an iterative process. Initially this involved completing polarity analysis for positive and negative sentiment expressions. Next we analysed the data using the eight sentiments on the Plutchik sentiment wheel and linked these to positive and negative polarity. Finally we analysed how these different sentiments were expressed in relation to key topics identified in Basch and Fisher's (1998) analysis of topics and emotions experienced at work. The key sentiments and topics analysed are presented in Table 1.

Polarity	**Sentiment (Plutchik, 1980)**	**Topics (based on Basch & Fisher, 1998)**
Positive, negative, neutral	joy, trust, fear, surprise, sadness, disgust, anger, anticipation or uncertainty	1. Relationships/ Team Work: colleagues, supervisors, group projects 2. Involvement: challenging tasks, planning, problem solving, influence and control 3. Communication: channels of communication, different approaches for different stakeholders 4. Confidence and Development: self-confidence in skills and readiness, perceived self-growth 5. Workload: time pressures, deadlines, challenges 6. BE/ME Degree: course structure, assessment, matching of students to industry placements etc. 7. Other/miscellaneous

Table 1: Data Analysis Approach – Stages of Refinement

Results and Analysis

Once all sentiment-carrying statements and terms within the interviews were classified, the researchers went back through these to determine the tilt – being either positive, negative or neutral – of the expression. For example, in the case of the following three statements which reflected anticipation, all three statements were also classified as discussing anticipation in a positive way.

"I wanted to try…I thought that was really interesting…I've always been interested" P#01 08052017

In comparison, the following statement displayed disinterest and disappointment thereby being negative expressions of both anticipation and sadness.

"Because at university you're just given a class sheet and you work according to that." #P01 08052017

The findings of this analysis were summarized in Table 2 (overleaf).

Based on the tables below, the results indicate that:

- Joy, trust, surprise, and anticipation most commonly carried a positive meaning;
- Fear, sadness, disgust, anger, and uncertainty most commonly carried a negative meaning;
- Trust, anticipation, and joy were the top three most common expressions of sentiment; and,
- Disgust, anger, and surprise were three least common expressions of sentiment.

Progressing beyond the sentiment classifications, each expression of sentiment was then categorized based on the topics listed in Table 1 and based on the work of Basch and Fisher (1998). Results from the categorisation of each sentiment carrying statement into topic groups is summarised in Table 3.

Sentiment	Positive	Negative	Neutral	Dominant Tilt	Sentiment Usage as % of Total
Joy	100%	0%	0%	Positive	13.35%
Trust	75.32%	24.68%	0.00%	Positive	29.15%
Fear	8.15%	89.63%	2.22%	Negative	10.01%
Surprise	68.92%	31.08%	0.00%	Positive	5.49%
Sadness	1.68%	98.32%	0.00%	Negative	8.83%
Disgust	0.00%	100.00%	0.00%	Negative	0.67%
Anger	2.78%	97.22%	0.00%	Negative	2.67%
Anticipation	88.78%	11.22%	0.00%	Positive	23.15%
Uncertainty	7.78%	80.00%	12.22%	Negative	6.68%

Table 2: Dominant Expressions of Sentiments and Overall Sentiment Usage

Note: Usage as % of Total implies the amount of times the sentiment was used across all interview transcripts as a % of the total number of sentiment-carrying statements and terms noted.

Student interview	Topics						
	1	**2**	**3**	**4**	**5**	**6**	**7**
P#01	66	22	28	46	8	34	10
P#02	56	35	28	45	16	33	22
P#03	19	8	8	20	4	14	6
P#04	16	8	4	16	5	13	8
P#06	21	14	19	22	11	9	4
P#07	16	11	18	21	8	9	9
P#08	98	39	23	104	24	29	9
P#09	17	15	11	17	6	17	7
P#10	50	28	12	48	22	31	20
P#12	6	2	1	17	8	10	8
Total	365	182	152	356	112	199	103
Grand Total	1469						
% of Grand Total	24.85%	12.39%	10.35%	24.23%	7.62%	13.55%	7.01%

Table 3*: Number of times each topic was mentioned across by i*nterviewees

Based on the above, the BE/ME students of 2016 tended to express opinion most readily in relation to:

- Relationships and team work (Topic 1);
- Confidence and development (Topic 4); and,
- The BE/ME degree (Topic 6).

The exact sentiment breakdown associated with each topic was identified to further expand on these findings. In doing so, researchers could comment on the nature in which students reflected on relationships and team work (Topic 1) for example to pinpoint student experience (Table 4).

		Sentiments		
		Dominant Sentiment	**Dominant Tilt**	**Dominant Tilt (%)**
Topics	**1**	Trust	Positive	77.92%
	2	Anticipation	Positive	89.06%
	3	Trust	Positive	66.15%
	4	Anticipation	Positive	93.38%
	5	Uncertainty	Negative	86.67%
	6	Anticipation	Positive	91.84%
	7	Anticipation	Positive	83.33%

Table 4: % Usage of Sentiments within each Topic

Note: Dominant tilt here refers to the dominant nature (positive, negative, neutral) as used when relating to the dominant sentiment. See Appendix F for Summary table of manipulated data from which this was derived.

Conclusions and discussion

On a sentiment-usage basis, student experience in the BE/ME industry placement was deemed positive due to the expression of mostly positive sentiments (trust, anticipation and joy).

On a topic-usage basis, students reflected most commonly on:

- Relationships and team work (Topic 1) – reflections were dominated by positive expressions of trust (admiration of supervisors and colleagues, the feeling of acceptance and self-acceptance based on their acknowledgement of their own skills);
- Confidence and development (Topic 4) – reflections were dominated by positive expressions of anticipation (interest in the engineering field, in the type of work offered at their placement, in the task at hand, and general interest taken during the placement); And,
- The BE/ME degree (Topic 6) reflections were dominated by positive expressions of anticipation (interest in the company with which they were placed, interest in the BE/ME coursework etc.).

Finally, the research uncovered the potential key to maximizing student experience in the BE/ME industry placement: relieving the uncertainty felt by students with regards to aspects of the workload they are faced with (time pressures, deadlines, challenges etc.). The School of Chemical Engineering could undertake any or all of the following steps to improve the way in which students' experience and respond to time pressures, deadlines, and challenges in their placement and beyond graduation:

- Reassure students that some degree of uncertainty regarding the placement experience is normal, whilst providing students with advice on how to deal with the stress of this situation;
- Organise pre-placement and during-placement student workshops on dealing with time pressures, deadlines, and various associated workload challenges;
- Ensure placement companies and their staff are prepared with a scope and project expectations for students upon arrival; and,
- Ensure that placement supervisors (in the company and at the Faculty) make themselves available to students to discuss workload concerns (i.e. scoping).

This paper has provided an in depth analysis of students experience of their industry placement. It has shown the utility of adopting a sentiment analysis approach to exploring spontaneous student

descriptions of their experiences. Through this process we have gained a better understanding of the issues that students face during placement and have identified potential ways to alleviate this transition and support them to be successful beyond the classroom.

It is possible that the sentiments expressed by this relatively small group of students are not representative of the entire cohort. It is acknowledged that some students are more spontaneously expressive of emotion, while others rarely express any. This limits the use of sentiment analysis as a means of understanding the student experience of their industry placement. However, as the study was conducted initially in order to test the feasibility of using sentiment analysis to explore students' experiences of industry placement, rather than with the intention to generalise across the entire cohort, our aim of exploring the utility of sentiment analysis has been supported. We also now have the means to compare this in depth human analysis of the interviews with an automated approach conducted by computer. Further work should focus on exploring the link between negative emotions (for instance uncertainty about the scope, workplace etc) with student learning.

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