Monitoring Mood in a Stream of Self-reflections

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Abstract: Burnout and job stress are tragic events that unfortunately occur in many professions. In the teaching profession, however, it affects not just the individual, but also several concomitant parties: students, school, and parents. This has lead to the widespread problem of teacher attrition, where the challenge has become not so much to attract teachers, but to retain them. The present research is based on the reflective writing of early career teachers (ECTs). These ECTs volunteered to write short weekly reflections during a period of about half a year. Spotting potential wellbeing problems in these series of reflections, however, calls for careful reading and studying of such large amounts of texts that manual processing became impracticable. Hence, we developed an algorithm which transforms such a stream of reflections into a 3-D visualization of mood changes, in which times of stress and potential for burnout can be detected more easily. This in turns makes it possible to notice points of concern when there is still time to intervene.

1 INTRODUCTION

This paper looks at the potential for tracking mood of early career teachers through the computational analysis of their reflective writing.

Previous work (Crosswell et al., 2018) has shown the value of using reflective writing to gain greater insights into the experiences of Early Career Teachers (ECTs). This work involved the collection of regular (usually every week or fortnight) personal reflections for a period of 6 months or more using a web application called "GoingOK" (Gibson, 2020).

It has been estimated that up to 25% of ECTs leave the profession within the first 5 years. Compounding the problems associated with attrition is the lack of understanding of why it is occurring and consequently the lack of action in addressing it. Personal well-being of ECTs has been identified as a significant indicator of how ECTs are personally coping with their transition to teaching. Significantly, the process of reflective writing has been shown to both be effective in capturing aspects of well-being, but also a way of helping the writer come to terms with problematic circumstances.

Previous studies have demonstrated the value of doing this but they have tended to be small. Hence, the reflective writing is now being collected and analyzed on a much greater scale. They are part of the growing data set we just mentioned and which we will refer to as the *GoingOK corpus*.

Manually analyzing this corpus, however, is not practicable for several reasons a priori. First, and most obvious, there is the sheer number of reflections to be read (for the current data set in the order of tens of thousands). Second, reading the reflections requires attention at a different levels of detail, from passages to phrases, as especially for this material, participants may be uncomfortable with detailed self-disclosure. And third, it requires close reading, to not overlook the subtle changes in mood that could be important to notice. In short, performing this type of analysis on large numbers of ECTs is impracticable. The solution we propose here is to use computational rather than human analysis. Such an approach may also allow factors of well-being to be discovered in data patterns that are too subtle or diffuse to be visible to the human analyst. Further, any links between data patterns and factors of well-being could be used predictively to provide early warning of impending issues associated with well-being and ultimately risk of departing the profession.

A feature of this type of writing is that characteristics with analytical value are rarely stated explicitly in the writing. For example, it is more likely that

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Table 1: Part of a stream of reflections from the 'Going OK' corpus.

08/02/2013	60.0	Am still feeling stressed about the workload, so am not 'soaring.' Overall a good week though.
13/02/2013	27.0	Need to revisit explicit teaching strategies. Beh man is difficult with 1 student. Tried all strats! Introduced 'Thinking Space.'
13/02/2013	33.0	Finding behaviour management difficult at the moment for 1 student. Am running very behind on my lessons... but will hopefully catch up soon!
20/02/2013	18.0	Lots of reflecting to do... lots of changing/adapting of my strategies... Behavior management is still a little challenging but getting better. So many of my really planned lessons havenÕt gone right... and the ones i havenÕt planned that much have gone really well! How does that happen?
07/03/2013	67.0	Am feeling exhausted... but am feeling like this week is going better. Behaviour management is getting easier... am trying some new strategies. Still need to work on extending and challenging students.

writing exhibit a depressive tone with use of words like 'struggling' and 'frustrated' than it include language like 'I am depressed'. Further, reflections can include negative recollections of problematic events together with optimistic characterizations of how a similar event might be handled in future.

This paper describes how a stream of reflections can be transformed into a graphical representation that quickly and easily locates important turning points in the stream of reflections. These are usually accompanied by a change in *mood*, in the APA (American Psychological Association) definition of "any short-lived emotional state, usually of low intensity" (VandenBos and American Psychological Association, 2015). Hence this work makes it possible to monitor mood without the need or necessity to read all reflections individually or in their entirety. This obviates the otherwise prohibitive task of manually processing thousands of reflections created continually in short periods of time.

2 AUTOMATIC PROCESSING OF REFLECTIONS

Reflections are snippets of text in which participants share how they feel they are going, and write about why they feel that way. Since participants write reflections on a regular basis, we refer to this as a stream of reflections. Let us start with the example of a stream of reflections from the GoingOK site (Gibson, 2020), as depicted in Table 1. It shows just a sample of a 'Going OK' corpus with scores that we will explain later in this article. Using the terms used in Information Retrieval (IR), the corpus in the current context consists of around two dozen reflections. They were anonymized, and the recurring example in this article was taken from (Gibson, 2017) where it was referred to as *rulguz*. Initial text processing follows the IR *bag-of-words* approach, paying no heed to word order or grammar.

2.1 Preprocessing the *'bag-of-words'*

The first step is as usual, to remove stopwords from the text. This already puts more emphasis on the words that are relevant to the domain. The next routine step is *tf-idf*[1] term weighting. This helps distinguishing reflections from one another, which in turn helps in studying reflections over time. After the preprocessing, the weighted frequencies are recorded as entries into a table with a column for each word and a row for each reflection, the *word-by-document matrix*. Figure 1 shows this matrix for *rulguz*.

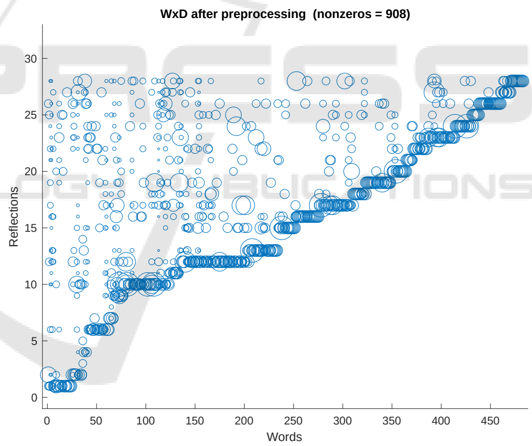


Figure 1: The word-by-document matrix for the *rulguz* reflections, after linguistic preprocessing. The size of the circles represent the weighted word frequencies (*tf-idf*).

Two decades ago the first author proposed to interpret the entries of the word-by-document matrix as grey-scale pixels in an image (Hoenkamp, 2003). Henceforth algorithms for dimension reduction in IR could be replaced by more efficient image processing algorithms. The current work extends that approach.

Two things can be noted (1) the matrix is sparse, i.e. the majority of the entries are zero. This is to be expected, as documents contain far fewer words than the total present in the corpus. And (2) although the

[1] Term frequency - inverse document frequency.

words have to be ordered to construct the table (or matrix), the order assigned to words is irrelevant[2].

Usually in IR, the corpus is an unordered set of documents. But the present case is more like a book and its pages, where the order of the pages makes all the difference. It is obvious that the time direction distinguishes whether mood improves or worsens in the stream. It is like a book, where the mood developing over time forms the storyline. In what follows we therefore pursue the approach proposed in (Hoenkamp, 2019) to reconstruct a storyline from the experiences of early career teachers (ECTs).

2.2 The Role of '*outliers*'

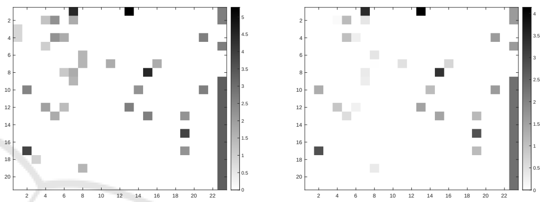
Many things happen in the lives of early career teachers (ECT) and the reflections are just a small sample of those events. What we would like to accomplish, is to separate the important events and experiences reported in the reflections from the more quotidian ones that are also mentioned. This has an analogy in data analysis where we want to separate outliers from the general trend. Outliers therefore usually receive special treatment in data analysis, sometimes by explaining them away, or by removing them from consideration. In the last decade an effective approach to the problem of locating outliers has been proposed in the form of *Robust PCA*, which has been developed in the area of *Compressive Sensing* (CS). In section 2.3 we will see how this technique is useful to detect a 'foreground' in reflections, representing the important events in ECT's life that stand out against a 'background' of mundane experiences.

One of the areas where Compressive Sensing has been remarkably effective, is the processing of video surveillance data: Unless something eventful happens, such as an intruder entering the premises, each video frame consists of thousands of pixels highly correlated with the next frame. Consequently, these data form a low dimensional subspace of the high dimensional space of all possible pixel combinations. The static background therefore is the low dimensional highly correlated space. In video surveillance one wants to isolate a moving foreground that stands out from a low dimensional background. Similarly, in the case of reflections we want to isolate the important events that stand out from the less interesting surrounding text, as we will see next.

[2]For example, one could choose to order the words alphabetically. Or, as we did here, choose to number them in the order of appearance in the stream of reflections. As a result, a word that appears for the first time in a later reflection will have a higher number. This explains the illusion of the 'diagonal' that appears in figure 1.

2.3 'Foreground Detection' as Metaphor

The way video data are processed can be used as a metaphor for understanding the way we processed the reflections for this article. This metaphor is so apt that we first wrote a program that can transform the (bag-of-words) representation of reflections into a video stream, without changing the data properties as far as Robust PCA is concerned. That way we could start experimenting with a plethora of open source programs written for video processing, but applied to reflections. That in turn allowed us to find out what underlying algorithms would be most appropriate to support automatic processing of the reflections. Recall that a series of reflections is represented



(a) (b)

Figure 2: The sequence of reflections is transformed into a video clip. For example, the last reflection which is the top row in figure 1) is rolled up into the frame in (a). Figure (b) shows the same reflection after RPCA.

as a word-by-document matrix, where the corpus is formed by the reflections. Let us denote the series of reflections by M, the lackluster, repetitive (hence highly correlated and dense) part of the reflections by L, and the important events that seem to spring off the page by S. So to find the important events — in other words the outliers — we used Robust PCA to solve the equation $M = L + S$ given the restrictions of which we just spoke. The equation is underdetermined obviously (since any L and S that add up to M would be a solution) but from the video processing domain we chose the optimization problem:

$$\begin{array}{ll} \text{minimize} & ||L||_* + \lambda ||S||_1 \\ \text{subject to} & L + S = M \end{array}$$

where $||.||_*$ and $||.||_1$ are the nuclear and Manhattan norm respectively. There are many approaches to solve the equation, each with its own benefits and drawbacks (Bouwmans et al., 2018). From the domain of video processing we focused on algorithms for motion detection (see e.g. (Goyette et al., 2012)), which we will, in the spirit of our metaphor, apply to detect change of mood.

Note that we already completed the first step in the

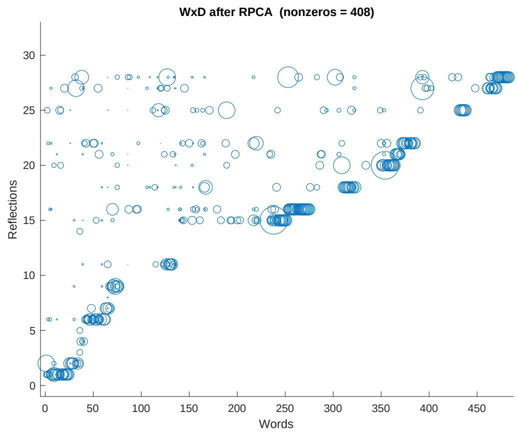


Figure 3: Step 2. Robust principle component analysis (RPCA) is used to subtract the 'background' from the reflection data in figure 1, resulting in a sparser word-by-document matrix.

processing of reflections which for the *rulguz* corpus resulted in figure 1. In the current section we present the tools for the second step, namely to compute the 'foreground' of the reflections.

To accomplish this, reflections are turned into picture frames, as per the example in figure 2: For each row in the matrix the *tf-idf* values are turned into gray-scale pixel and then the row is rolled into a (rectangular) video frame. The sequence of all frames can then be processed as if it were a video clip, processed with RPCA[3], and unrolled back into the new word-by-document matrix of figure 3. This way RPCA is used to separate foreground from background (which is discarded) for further processing. So figure 3 shows the word-by-document matrix of figure 1 after removing the background. Once the foreground of the reflections has been isolated, i.e. the points that stand out according to the algorithm, we can compute affective values for these points, as we will show in the next section.

3 AFFECT DETECTION AFTER BACKGROUND SUBTRACTION

Many publications[4], shed light on how to detect affect for different media, such as facial expressions, voice, and brain signals. We recommend (Calvo and D'Mello, 2010) for an early but comprehensive overview. Of course for the current paper the relevant medium is language (section 6.3 in (Calvo and D'Mello, 2010)). The earliest systematic work in detecting affect in language use is Osgood et al.'s (Osgood et al., 1976) 'atlas of affective meaning.' It is an elaborate study into the relationships between emotion and language universals, and one of the earlier successes in psycholinguistics. The present article studies the relationship between narrative text and the mood it expresses, applied to the 'going OK' collection mentioned earlier (Gibson, 2020). Researchers have studied this relationship for various reasons. For example (Pennebaker and Francis, 1996) studied if writing about emotions can have a positive influence on mental health. Another (Hasan et al., 2019) wanted to detect emotion bursts in live text streams (Twitter). These and other studies need some way to relate text to affect or mood. What they have in common is that they work with individual pieces of text, such as reports in (Pennebaker and Francis, 1996) (on becoming a student) or separate tweets in (Hasan et al., 2019). What sets our current presentation apart from these studies is that we study series of subsequent reflections. In other words we study *change in mood and affect over time*. So, next we will present how we did this in case of the Going OK corpus.

3.1 Detecting Positive and Negative Mood

Recall that table 1 is only a small sample of the data collected from one participant. All participants received the same instruction, which was played as a youtube clip (Gibson, 2019). *The instruction asked the participants to express their mood in two modalities.* The first was to position a slider between two extremes marked as 'distressed' on one end and 'soaring' on the other, with a midpoint marked 'going OK.' Obviously, the farther participants move the slider towards 'soaring' the more positive we expect their mood to be, and the farther towards 'distressed' the more negative. The second modality recorded right after having set the slider, was to write a free form description of their mood. Both modalities presumably express the same underlying affect, and we will show how the affect in the first modality can be computed given the second.

We assume that typically the mood of the participants is parallelled in the text they subsequently type in. But instead of working with the original text, as in the publications by other researchers, we start from text where the 'background' has been removed. Now for each reflection we have a value for the slider position modality, and a value for the text modality. The slider modality is shown in column **R** (recorded) in

[3]For our running example we computed RPCA using 'bilateral random projections' for which the Matlab code is available on-line (Zhou and Tao, 2011).

[4]IEEE Trans. on Affective Computing

Table 2: Positive and negative words remaining after background subtraction. Column **R** shows the slide position and column **C** is the *tf-idf* weighted sum of positive and negative words.

#	Negatives	Positives	R	C
1	stress	confident helping calm amazingly helpful love	48	52
2	difficulty	enjoying	30	37
3			50	12
4	frustrated		14	6
5			17	12
6	frustrating missed sorry exhausted overwhelming stressful	ready enjoying	15	38
7	exhausted desperate break		22	24
8			50	50
9	break worried	enjoying	50	45
10			67	50
11	scared	helped clear	50	51
12			38	50
13	frustrated poor nervous	friendly excited	50	44
14			50	50
15	poor stressed issues angry	top enjoying	33	43
16	tired freaking slow issue unsure excuse		36	40
17			50	50
18	worried worse annoying silly rude		50	34
19		positive easier	40	46
20	worried bad cold struggling suffering	wise	35	39
21	tiring stressed worry		50	43
22	missed hard bad impossible hate disheartening refusal draining	decent motivated	32	30
23	anxious hate draining depressing complained dislike	fun happy progress interesting pretty nice smile comforting	31	47
24	nervous negative worst crazy	improve fun	32	43
25	stress tiring difficult issues miss waste	happy helped	50	50
26			50	50
27	stressful hard bullying sick negative	pretty nice lucky supportive	37	42
28	worried loose negative	happy improve	42	43

Table 2. For the text modality, we used the *tf-idf* weighted sum of positive and negative words, which is shown in column **C** of Table 2. To more easily compare these columns, they are summarized as (5-degree) spline interpolations in Figure 4. The figure shows the relationship between both recording modalities is as we expected.

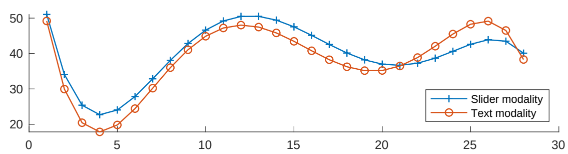


Figure 4: Comparing the slider modality and text modality by comparing the splines for the values in column **R** and **C** of table 2, showing strong correlation $r(26) = .94, p < .001$.

Given that we can compute the slider modality from the text modality, would it then not be redundant to ask participants to position the slider? This raises two issues: First, if all we wanted to know was a self-assessment of the participant's well-being on an ordinal scale, then it seems redundant. But second, this would beg the question, as you can only know that the assessment is redundant after you have done the assessment. But interestingly, and perhaps surprisingly, we can use the assessment to compute emotional dimensions that go beyond the slider setting, as we will see in a moment. We used crowdsourced data to feed the exact same algorithms that derived positive/negative values from the text modality to compute other emotional dimensions.

3.2 Computing Dimensions of Emotion

The most prominent dimensions for emotion words found by Osgood et al. have reappeared in the literature, but varying in name, number, and detail. Agreement remains, however, by and large over the positive/negative (or pleasure/displeasure) dimension, which we already used. We could introduce a second dimension, but "the world of emotions is not two-dimensional," as the title of (Fontaine et al., 2007) already contends. Instead we will use three dimensions that continue to be studied, namely *valence* which is closely related to the positive/negative scale, *arousal* comparable to a scale from active to inert, and *dominance* positioned on a scale from powerful to weak. The ratings for these dimensions, compiled for around 20.000 words, can be obtained from (Mohammad, 2018a). It includes an attractive interface to interact with the tables to find for each word the values on each of the three dimensions (Mohammad, 2018b).

The step from one dimension (positive/negative) to three dimensions is almost trivial. We will use the same example (*rulguz*) from the GoingOK corpus, do the same linguistic preprocessing and Robust PCA, and hence arrive at the same word-by-reflection matrix. For every word we have the values on each emotional dimension. The result of the computation using the tables from (Mohammad, 2018a) is depicted in figure 5.

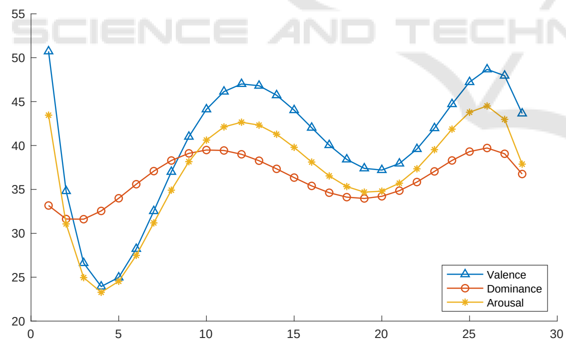


Figure 5: Three emotional dimensions computed from the reflections (on the horizontal axis). The correlations with the slider positions (cf table 2) are for valence $r(26) = .95, p < .001$, dominance $r(26) = .41, p < .03$, and arousal $r(26) = .89, p < .001$.

3.3 Enriching the Data through Dimension 'Expansion'

In 3.1 we already found a strong (.94) correlation between the values for the slider and text modalities, and wondered if that would not make the slider values disposable. But here is an interesting twist. The participants were forced to fit the emotions which they could freely express in their verbal accounts, into the procrustes bed of a one-dimensional slider. In other words, the value they chose on the one-dimensional (bi-polar) scale had to be some weighted sum of the values on the three dimension that would have been sufficient had they been given the choice. So what

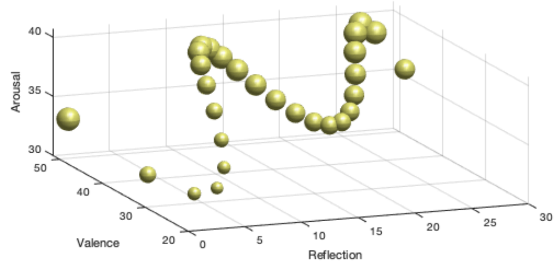


Figure 6: The emotional dimensions of figure 5 rendered in 3-D. Dominance is represented by the size of the spheres. The figure shows how reflections 13 and 27 stand out, scoring high on all three dimensions.

we have is (1) the values computed on each of the dimensions, and (2) the weighted sum. From these two we can compute the weights themselves as follows: Let A_{vad} be a matrix of emotional values by the number of refections. So each row contains the three emotional values computed per reflection. We also have the slider values, let's call them $\vec{r}$ after column **R** of Table 2, and denote the weight vector as $\vec{w}$. That participants had to compress their emotions from a higher dimensional representation (underlying their texts) onto a one-dimensional (bi-polar) scale can be expressed as:

$$A_{vad} \cdot \vec{w} = \vec{r}$$

The weights can thus be approximated by a least squares solution of the equation above[5]. So in essence we have 'expanded' the 1-dimensional history of slider values to a more informative 3-dimensional history of the participant's mood. Applied to our running example it means that the one dimensional spline for the slider modality in figure 4 will be expanded to the three dimensional representation of Figure 6.

3.4 Monitoring Mood in 3-D

The ECT reflections in the GoingOK corpus are being collected in the wider context of teacher attrition in Australia. As the literature review (Yarrow et al., 1999) shows, the main issue is not so much in attracting teachers, but to retain them. As teacher attrition

[5] In MATLAB® code: `w=A\r` which in the case of figure 6 solves for `w=[1.51,0.06,-0.62]`.

is a recurring problem in many other countries, studies have tried to find conditions under which teachers stay or leave. As an example (Howard and Johnson, 2004) studied the role of 'resilience' in stress and burnout. Such studies are important to improve the conditions under which teachers stay in their jobs, but it is perhaps even more important to react in time when they are prone to leave. In the overview of

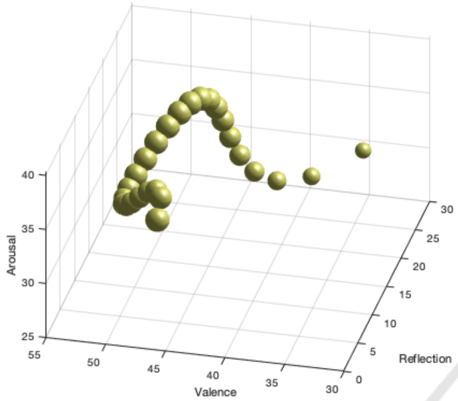


Figure 7: Monitoring the mood of an early career teacher. After arousal has been building up for a while, around reflection 20 the valence suddenly drops quickly. Around that point, the teacher's written reflections show that her mood starts to go south when she struggles with unwanted attention from a parent who she has to communicate with professionally.

(Yarrow et al., 1999) on page 406, the authors lay out six stressors that the system we present here may monitor for. From these six we select two examples for which the reflections have been published already, so we can avoid privacy issues with the participants' self disclosures in unpublished material. One such a stressor is "need to take leave to deal with work-related stress" and figure 7[6] explains an example of it So instead of carefully reading all reflections from beginning to end, the picture suggests to start around reflection 20 to discover the incident that causes the mood swing. This promises an ability to process the reflection data for which a manual approach is prohibitive in principle. But it opens an additional avenue, as we will see in a moment.

3.5 Intervention

Recall that our approach to monitoring mood was inspired by the approach to video surveillance, as elaborated in section 2.3. In that domain it is valuable to have recordings after an intruder entered the premises. But would it not be more valuable to be able to catch the intruder red-handed and prevent the theft? The available algorithms in principle allow for such intervention, witness the growing interest in warning systems based on 'visual object tracking' (see e.g. (Li et al., 2013) for an overview). Once the trajectory of an object can be predicted from a video stream, this may allow e.g. a self-driving car to prevent an imminent collision. In a similar way one might want to extrapolate a change of mood in order to detect growing dissatisfaction of a beginning teacher, or possibly prevent an imminent burn out. Such a change in mood can readily be observed from the visible representation, as in figures 7. Obviously, when mood goes in a negative direction, it is important to pay attention. The program could easily issue a notification when the derivative of the plot line goes negative.

In the case of video surveillance, some systems apply Newton's laws of motion to extrapolate a trajectory of moving objects to calculate where they will be next (see e.g. (Rudenko et al., 2020) for human motion detection) . So it would be wonderful if we could extend the metaphor from the visual domain in the domain of affection. In our case that would mean trying to find psychological laws that apply to mood changes. Such laws might look like Kübler-Ross's five stages of loss (Kübler-Ross and Kessler, 2005), but such laws are very rare in the psychological literature. And unfortunately, the few that we found, such as the five stages model just mentioned, turned out to lack sound empirical evidence (Maciejewski et al., 2007). Absent such theories we leave a further elaboration in that direction for future work.

4 CONCLUSION

The motivation for this article is found in the problem of teacher attrition. The latter forms a challenge in many parts of the world, a situation which over and again seems difficult to mitigate. In Australia especially, programs have been developed for pre-service preparation of teachers for rural and remote teaching positions. These are followed up with mentorship and internship programs. This is the context in which a growing data base is being built from teachers who volunteered to reflect and report on their well-being early in their career. The result is a treasure trove of information.

Unfortunately processing this data manually by reading and studying the teachers' reflections is not practicable. In contrast to manual processing, this article presented an algorithm that transforms a stream of reflections into a 3-D visualization, in which possible points of concern can easily be located. This trans-

[6]We have changed the point of view for the 3-D figures to optimize the visibility of data points.

formation can be performed in real-time (typically in the order of milliseconds), so that an up-to-date graphical summary is always available, in which potential points of concern stand out, allowing for timely intervention. More generally, we can see how the method could also be used in other contexts, as in corporations with a high incidence of burnout. Note however, that the application of Robust PCA described in this paper is novel in language processing.

For the time being we want to stay focused on early career teachers. These teachers usually start out as idealists with a sense of calling and a lifetime before them. Yet often in a matter of years, they leave the profession they love, disillusioned and disappointed. We consider it a success if even for a fraction of these teachers the approach outlined above can help to intervene when there is still time to prevent this from happening.

REFERENCES

Bouwmans, T., Javed, S., Zhang, H., Lin, Z., and Otazo, R. (2018). On the applications of Robust PCA in image and video processing. *Proc. of the IEEE*, 106(8):1427–1457.

Calvo, R. A. and D'Mello, S. (2010). Affect detection: An interdisciplinary review of models, methods, and their applications. *IEEE Trans. Affective Computing*, 1(1):18–37.

Crosswell, L., Willis, J., Morrison, C., Gibson, A., and Ryan, M. (2018). Early career teachers in rural schools: Plotlines of resilience. In *Resilience in education*, pages 131–146. Springer.

Fontaine, J. R., Scherer, K. R., Roesch, E. B., and Ellsworth, P. C. (2007). The world of emotions is not two-dimensional. *Psychological Science*, 18(12):1050–1057.

Gibson, A. (2017). *Reflective writing analytics and transepistemic abduction*. PhD thesis, Queensland University of Technology.

Gibson, A. (2019). *Going OK instructions*. [Online; accessed 13-July-2022].

Gibson, A. (2020). GoingkOK. http://www.goingok.org. [Online; accessed 13-July-2022].

Goyette, N., Jodoin, P.-M., Porikli, F., Konrad, J., and Ishwar, P. (2012). Changedetection.net: A new change detection benchmark dataset. In *2012 IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops*, pages 1–8.

Hasan, M., Rundensteiner, E., and Agu, E. (2019). Automatic emotion detection in text streams by analyzing twitter data. *International Journal of Data Science and Analytics*, 7(1):35–51.

Hoenkamp, E. (2003). Unitary operators on the document space. *Journal of the American Society for Information Science and Technology*, 54(4):314–320.

Hoenkamp, E. (2019). Discovering the geometry of narratives and their embedded storylines. In Fred, A. and Filipe, J., editors, *Proceedings of the 11th Int. J. Conf. IC3K*, volume 1, pages 483–490. SciTePress.

Howard, S. and Johnson, B. (2004). Resilient teachers: resisting stress and burnout. *Social Psychology of Education*, 7(4):399–420.

Kübler-Ross, E. and Kessler, D. (2005). *On Grief and Grieving: Finding the Meaning of Grief Through the Five Stages of Loss*. Scribner.

Li, X., Hu, W., Shen, C., Zhang, Z., Dick, A., and Hengel, A. V. D. (2013). A survey of appearance models in visual object tracking. *ACM Trans. Intell. Syst. Technol.*, 4(4).

Maciejewski, P. K., Zhang, B., Block, S. D., and Prigerson, H. G. (2007). An empirical examination of the stage theory of grief. *JAMA*, 297(7):716–723.

Mohammad, S. (2018a). The NRC Valence, Arousal, and Dominance (NRC-VAD) Lexicon. http://saifmohammad.com/WebPages/nrc-vad.html. [Online; accessed 6 december 2020].

Mohammad, S. M. (2018b). Obtaining reliable human ratings of valence, arousal, and dominance for 20,000 english words. In *Proceedings of The Annual Conference of the Association for Computational Linguistics (ACL)*, Melbourne, Australia.

Osgood, C., May, W. H., and Miron, M. (1976). *Cross-cultural Universals of Affective Meaning: An Introductory Atlas of Affective Meanings*. University of Illinois Press.

Pennebaker, J. W. and Francis, M. E. (1996). Cognitive, emotional, and language processes in disclosure. *Cognition and Emotion*, 10(6):601–626.

Rudenko, A., Palmieri, L., Herman, M., Kitani, K. M., Gavrila, D. M., and Arras, K. O. (2020). Human motion trajectory prediction: a survey. *The International Journal of Robotics Research*, 39(8):895–935.

VandenBos, G. R. and American Psychological Association (2015). APA dictionary of psychology.

Yarrow, A., Ballantyne, R., Hansford, B., Herschell, P., and Millwater, J. (1999). Teaching in rural and remote schools: a literature review. *Teaching and Teacher Education*, 15(1):1 – 13.

Zhou, T. and Tao, D. (2011). Godec: Randomized low-rank & sparse matrix decomposition in noisy case. In Getoor, L. and Scheffer, T., editors, *Proc. 28th Int. Conf. on Machine Learning (ICML-11)*, ICML '11, pages 33–40, New York, NY, USA. ACM.