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Tracking Sentiment in Mail: How Genders Differ on Emotional Axes

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Abstract

With the widespread usage of email, we now have access to unprecedented amounts of text that we ourselves have written. In this paper, we show how sentiment analysis can be used in tandem with effective visualizations to quantify and track emotions in many types of mail. We create a large word–emotion association lexicon by crowdsourcing, and use it to compare emotions in love letters, hate mail, and suicide notes. We show that there are marked differences across genders in how they use emotion words in work-place email. For example, women use many words from the joy–sadness axis, whereas men prefer terms from the fear–trust axis. Finally, we show visualizations that can help people track emotions in their emails.

1 Introduction

Emotions are central to our well-being, yet it is hard to be objective of one's own emotional state. Letters have long been a channel to convey emotions, explicitly and implicitly, and now with the widespread usage of email, people have access to unprecedented amounts of text that they themselves have written and received. In this paper, we show how sentiment analysis can be used in tandem with effective visualizations to track emotions in letters and emails.

Automatic analysis and tracking of emotions in emails has a number of benefits including:

1. Determining the risk of a repeat attempt by suicide note analysis (Osgood and Walker, 1959; Matykiewicz et al., 2009; Pestian et al., 2008).[1]
2. Understanding how genders communicate through work-place and personal email (Boneva et al., 2001).
3. Tracking emotions towards people and entities, over time. For example, has a certain managerial course brought about a measurable change in one's inter-personal communication?
4. Determining if there is a correlation between the emotional content of letters and changes in a person's social, economic, or physiological state. Sudden and persistent changes in the amount of emotion words in mail may be a sign of psychological disorder.
5. Enabling affect-based search. For example, efforts to improve customer satisfaction can benefit by searching the received mail for snippets expressing anger (Díaz and Ruz, 2002; Dubé and Maute, 1996).
6. Assisting in writing emails that convey only the desired emotion, and avoiding misinterpretation (Liu et al., 2003).
7. Analyzing emotion words and their role in persuasion in communications by fervent letter writers such as Francois-Marie Arouet Voltaire and Karl Marx (Voltaire, 1973; Marx, 1982).[2]

In this paper, we describe how we created a large word–emotion association lexicon by crowdsourcing with effective quality control measures (Section

[1]The 2011 Informatics for Integrating Biology and the Bedside (i2b2) challenge by the National Center for Biomedical Computing is on detecting emotions in suicide notes.

[2]Voltaire: http://www.whitman.edu/VSA/letters
Marx: http://www.marxists.org/archive/marx/works/date

3). In Section 4, we show comparative analyses of emotion words in love letters, hate mail, and suicide notes. This is done: (a) To determine the distribution of emotion words in these types of mail, as a first step towards more sophisticated emotion analysis (for example, in developing a depression–happiness scale for Application 1), and (b) To use these corpora as a testbed to establish that the emotion lexicon and the visualizations we propose help interpret the emotions in text. In Section 5, we analyze how men and women differ in the kinds of emotion words they use in work-place email (Application 2). Finally, in Section 6, we show how emotion analysis can be integrated with email services such as Gmail to help people track emotions in the emails they send and receive (Application 3).

The emotion analyzer recognizes words with positive polarity (expressing a favorable sentiment towards an entity), negative polarity (expressing an unfavorable sentiment towards an entity), and no polarity (neutral). It also associates words with joy, sadness, anger, fear, trust, disgust, surprise, anticipation, which are argued to be the eight basic and prototypical emotions (Plutchik, 1980).

2 Related work

Over the last decade, there has been considerable work in sentiment analysis, especially in determining whether a term has a positive or negative polarity (Lehrer, 1974; Turney and Littman, 2003; Mohammad et al., 2009). There is also work in more sophisticated aspects of sentiment, for example, in detecting emotions such as anger, joy, sadness, fear, surprise, and disgust (Bellegarda, 2010; Mohammad and Turney, 2010; Alm et al., 2005; Alm et al., 2005). The technology is still developing and it can be unpredictable when dealing with short sentences, but it has been shown to be reliable when drawing conclusions from large amounts of text (Dodds and Danforth, 2010; Pang and Lee, 2008).

Automatically analyzing affect in emails has primarily been done for automatic gender identification (Cheng et al., 2009; Corney et al., 2002), but it has relied on mostly on surface features such as exclamations and very small emotion lexicons. The WordNet Affect Lexicon (WAL) (Strapparava and Valitutti, 2004) has a few hundred words annotated with associations to a number of affect categories including the six Ekman emotions (joy, sadness, anger, fear, disgust, and surprise).[3] General Inquirer (GI) (Stone et al., 1966) has 11,788 words labeled with 182 categories of word tags, including positive and negative polarity.[4] Affective Norms for English Words (ANEW) has pleasure (happy–unhappy), arousal (excited–calm), and dominance (controlled–in control) ratings for 1034 words.[5] Mohammad and Turney (2010) compiled emotion annotations for about 4000 words with eight emotions (six of Ekman, trust, and anticipation).

3 Emotion Analysis

3.1 Emotion Lexicon

We created a large word–emotion association lexicon by crowdsourcing to Amazon's mechanical Turk.[6] We follow the method outlined in Mohammad and Turney (2010; 2011). Unlike Mohammad and Turney, who used the *Macquarie Thesaurus* (Bernard, 1986), we use the *Roget Thesaurus* as the source for target terms.[7] Since the 1911 US edition of *Roget's* is available freely in the public domain, it allows us to distribute our emotion lexicon without the burden of restrictive licenses. We annotated only those words that occurred more than 120,000 times in the Google n-gram corpus.[8]

The *Roget's Thesaurus* groups related words into about a thousand categories, which can be thought of as coarse senses or concepts (Yarowsky, 1992). If a word is ambiguous, then it is listed in more than one category. Since a word may have different emotion associations when used in different senses, we obtained annotations at word-sense level by first asking an automatically generated word-choice question pertaining to the target:

Q1. Which word is closest in meaning to *shark* (target)?
- *car*
- *tree*
- *fish*
- *olive*

This is followed by ten questions asking if the target is associated with positive sentiment, negative

[3]WAL: http://wndomains.fbk.eu/wnaffect.html
[4]GI: http://www.wjh.harvard.edu/∼inquirer
[5]ANEW: http://csea.phhp.ufl.edu/media/anewmessage.html
[6]Mechanical Turk: www.mturk.com/mturk/welcome
[7]Macquarie Thesaurus: www.macquarieonline.com.au
Roget's Thesaurus: www.gutenberg.org/ebooks/10681
[8]The Google n-gram corpus is available through the LDC.

sentiment, anger, fear, joy, sadness, disgust, surprise, trust, and anticipation. The questions are phrased exactly as described in Mohammad and Turney (2010; 2011).

The near-synonym is taken from the thesaurus and the distractors are randomly chosen words. This question guides the annotator to the desired sense of the target word, after which we ask whether it is associated with different emotions and polarities or not. If an annotator answers Q1 incorrectly, then we discard information obtained from the remaining questions. Thus, even though we do not have correct answers to the emotion association questions, likely incorrect annotations are filtered out. About 10% of the annotations were discarded because of an incorrect response to Q1.

Each term is annotated by 5 different people. For 74.4% of the instances, all five annotators agreed on whether a term is associated with a particular emotion or not. For 16.9% of the instances four out of five people agreed with each other. The information from multiple annotators for a particular term is combined by taking the majority vote. The lexicon has entries for about 24,200 word–sense pairs. The information from different senses of a word is combined by taking the union of all emotions associated with the different senses of the word. This resulted in a word-level emotion association lexicon for about 14,200 word types. These files are together referred to as the *NRC Emotion Lexicon version 0.92*.

3.2 Text Analysis

Given a target text, the system determines which of the words exist in our emotion lexicon and calculates ratios such as the number of words associated with an emotion to the total number of emotion words in the text. This simple approach may not be reliable in determining if a particular sentence is expressing a certain emotion, but it is reliable in determining if a large piece of text has more emotional expressions compared to others in a corpus. Example applications include detecting spikes in anger words in close proximity to mentions of a target product in a twitter stream (Díaz and Ruz, 2002; Dubé and Maute, 1996), and literary analyses of text, for example, how novels and fairy tales differ in the use of emotion words (Mohammad, 2011b).

4 Love letters, hate mail, and suicide notes

In this section, we quantitatively compare the emotion words in love letters, hate mail, and suicide notes. We compiled a *love letters corpus (LLC) v 0.1* by extracting 348 postings from lovingyou.com.[9] We created a *hate mail corpus (HMC) v 0.1* by collecting 279 pieces of hate mail sent to the *Millenium Project*.[10] The *suicide notes corpus (SNC) v 0.1* has 21 notes taken from Art Kleiner's website.[11] We will continue to add more data to these corpora as we find them, and all three corpora are freely available.

Figures 1, 2, and 3 show the percentages of positive and negative words in the love letters corpus, hate mail corpus, and the suicide notes corpus. Figures 5, 6, and 7 show the percentages of different emotion words in the three corpora. Emotions are represented by colours as per a study on word–colour associations (Mohammad, 2011a). Figure 4 is a bar graph showing the difference of emotion percentages in love letters and hate mail. Observe that as expected, love letters have many more joy and trust words, whereas hate mail has many more fear, sadness, disgust, and anger.

The bar graph is effective at conveying the extent to which one emotion is more prominent in one text than another, but it does not convey the source of these emotions. Therefore, we calculate the *relative salience* of an emotion word w across two target texts T_1 and T_2:

$$\text{RelativeSalience}(w|T_1, T_2) = \frac{f_1}{N_1} - \frac{f_2}{N_2} \qquad (1)$$

Where, f_1 and f_2 are the frequencies of w in T_1 and T_2, respectively. N_1 and N_2 are the total number of word tokens in T_1 and T_2. Figure 8 depicts a relative-salience word cloud of joy words in the love letters corpus with respect to the hate mail corpus. As expected, love letters, much more than hate mail, have terms such as *loving, baby, beautiful, feeling,* and *smile*. This is a nice sanity check of the manually created emotion lexicon. We used Google's freely available software to create the word clouds shown in this paper.[12]

[9]LLC: http://www.lovingyou.com/content/inspiration/loveletters-topic.php?ID=loveyou

[10]HMC: http://www.ratbags.com

[11]SNC: http://www.well.com/ art/suicidenotes.html?w

[12]Google WordCloud: http://visapi-gadgets.googlecode.com/svn/trunk/wordcloud/doc.html

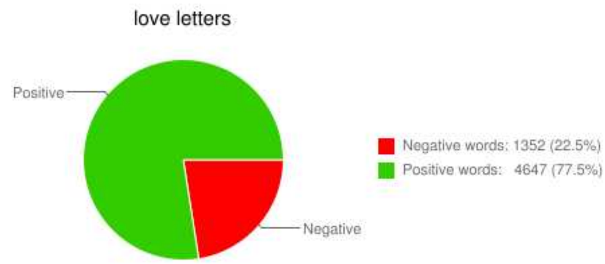


Figure 1: Percentage of positive and negative words in the love letters corpus.

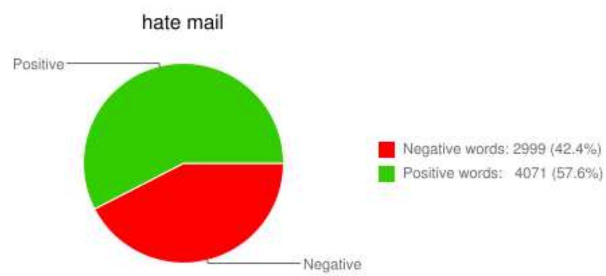


Figure 2: Percentage of positive and negative words in the hate mail corpus.

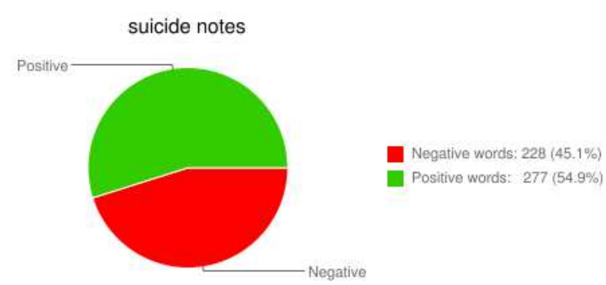


Figure 3: Percentage of positive and negative words in the suicide notes corpus.

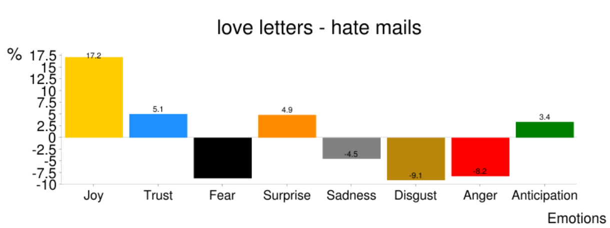


Figure 4: Difference in percentages of emotion words in the love letters corpus and the hate mail corpus. The relative-salience word cloud for the joy bar is shown in the figure to the right (Figure 8).

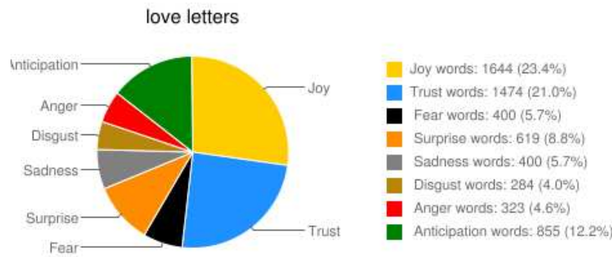


Figure 5: Percentage of emotion words in the love letters corpus.

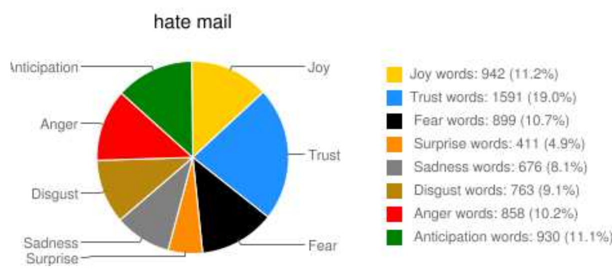


Figure 6: Percentage of emotion words in the hate mail corpus.

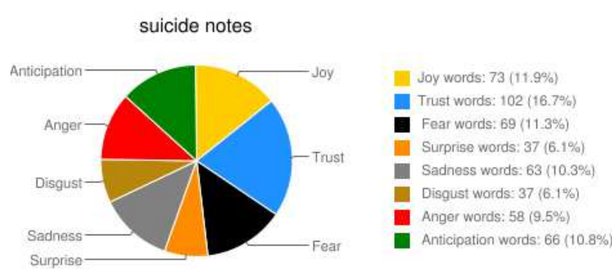


Figure 7: Percentage of emotion words in the suicide notes corpus.

Figure 8: Love letters corpus - hate mail corpus: relative-salience word cloud for **joy**.

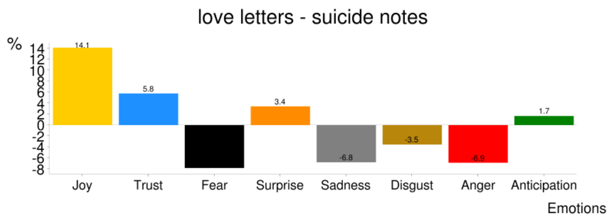


Figure 9: Difference in percentages of emotion words in the love letters corpus and the suicide notes corpus.

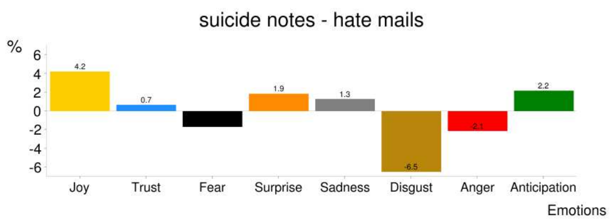


Figure 10: Difference in percentages of emotion words in the suicide notes corpus and the hate mail corpus.

Figure 9 is a bar graph showing the difference in percentages of emotion words in love letters and suicide notes. The most salient fear words in the suicide notes with respect to love letters, in decreasing order, were: *hell, kill, broke, worship, sorrow, afraid, loneliness, endless, shaking,* and *devil*.

Figure 10 is a similar bar graph, but for suicide notes and hate mail. Figure 11 depicts a relative-salience word cloud of disgust words in the hate mail corpus with respect to the suicide notes corpus. The cloud shows many words that seem expected, for example *ignorant, quack, fraudulent, illegal, lying,* and *damage*. Words such as *cancer* and *disease* are prominent in this hate mail corpus because the *Millenium Project* denigrates various alternative treatment websites for cancer and other diseases, and consequently receives angry emails from some cancer patients and physicians.

5 Emotions in email: men vs. women

There is a large amount of work at the intersection of gender and language (see bibliographies compiled by Schiffman (2002) and Sunderland et al. (2002)). It is widely believed that men and women use language differently, and this is true even in computer mediated communications such as email (Boneva et al., 2001). It is claimed that women tend to foster

Figure 11: Suicide notes - hate mail: relative-salience word cloud for **disgust**.

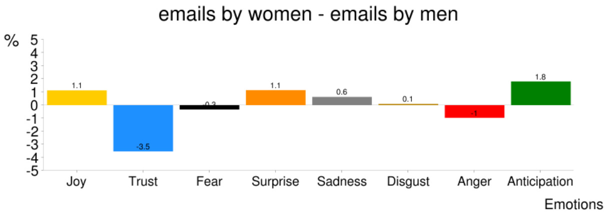
personal relations (Deaux and Major, 1987; Eagly and Steffen, 1984) whereas men communicate for social position (Tannen, 1991). Women tend to share concerns and support others (Boneva et al., 2001) whereas men prefer to talk about activities (Caldwell and Peplau, 1982; Davidson and Duberman, 1982). There are also claims that men tend to be more confrontational and challenging than women.[13]

Otterbacher (2010) investigated stylistic differences in how men and women write product reviews. Thelwall et al. (2010) examine how men and women communicate over social networks such as MySpace. Here, for the first time using an emotion lexicon of more than 15000 words, we investigate if there are gender differences in the use of emotion words in work-place communications, and if so, whether they support some of the claims mentioned in the above paragraph. The analysis shown here, does not prove the propositions; however, it provides empirical support to the claim that men and women use emotion words to different degrees.

We chose the Enron email corpus (Klimt and Yang, 2004)[14] as the source of work-place communications because it remains the only large publicly available collection of emails. It consists of more than 200,000 emails sent between October 1998 and June 2002 by 150 people in senior managerial posi-

[13]http://www.telegraph.co.uk/news/newstopics/howaboutthat/6272105/Why-men-write-short-email-and-women-write-emotional-messages.html

[14]The Enron email corpus is available at http://www-2.cs.cmu.edu/ enron



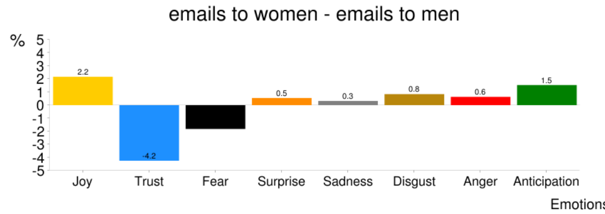


Figure 12: Difference in percentages of emotion words in emails sent by women and emails sent by men.

Figure 14: Difference in percentages of emotion words in emails sent to women and emails sent to men.

Figure 13: Emails by women - emails by men: relative-salience word cloud of **trust**.

Figure 15: Emails to women - emails to men: relative-salience word cloud of **joy**.

tions at the Enron Corporation, a former American energy, commodities, and services company. The emails largely pertain to official business but also contain personal communication.

In addition to the body of the email, the corpus provides meta-information such as the time stamp and the email addresses of the sender and receiver. Just as in Cheng et al. (2009), (1) we removed emails whose body had fewer than 50 words or more than 200 words, (2) the authors manually identified the gender of each of the 150 people solely from their names. If the name was not a clear indicator of gender, then the person was marked as "gender-untagged". This process resulted in tagging 41 employees as female and 89 as male; 20 were left gender-untagged. Emails sent from and to gender-untagged employees were removed from all further analysis, leaving 32,045 mails (19,920 mails sent by men and 12,125 mails sent by women). We then determined the number of emotion words in emails written by men, in emails written by women, in emails written by men to women, men to men, women to men, and women to women.

5.1 Analysis

Figure 12 shows the difference in percentages of emotion words in emails sent by men from the percentage of emotion words in emails sent by women. Observe the marked difference is in the percentage of trust words. The men used many more trust words than women. Figure 13 shows the relative-salience word cloud of these trust words.

Figure 14 shows the difference in percentages of emotion words in emails sent *to* women and the percentage of emotion words in emails sent *to* men. Observe the marked difference once again in the percentage of trust words and joy words. The men receive emails with more trust words, whereas women receive emails with more joy words. Figure 15 shows the relative-salience word cloud of joy.

Figure 16 shows the difference in emotion words in emails sent by men to women and the emotions in mails sent by men to men. Apart from trust words, there is a marked difference in the percentage of anticipation words. The men used many more anticipation words when writing to women, than when writing to other men. Figure 17 shows the relative-

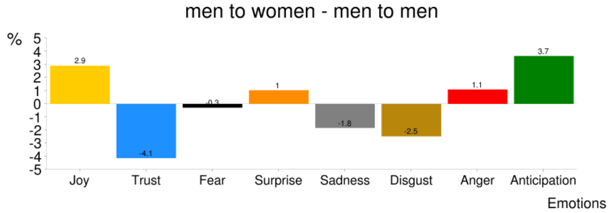


Figure 16: Difference in percentages of emotion words in emails sent by men to women and by men to men.

Figure 17: Emails by men to women - email by men to men: relative-salience word cloud of **anticipation**.

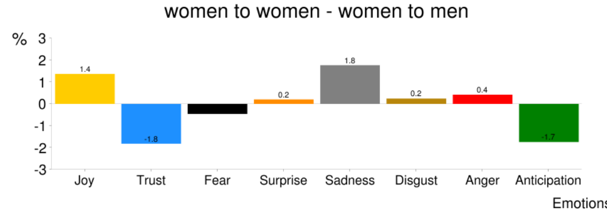


Figure 18: Difference in percentages of emotion words in emails sent by women to women and by women to men.

Figure 19: Emails by women to women - emails by women to men: relative-salience word cloud of **sadness**.

salience word cloud of these anticipation words.

Figures 18, 19, 20, and 21 show difference bar graphs and relative-salience word clouds analyzing some other possible pairs of correspondences.

5.2 Discussion

Figures 14, 16, 18, and 20 support the claim that when writing to women, both men and women use more joyous and cheerful words than when writing to men. Figures 14, 16 and 18 show that both men and women use lots of trust words when writing to men. Figures 12, 18, and 20 are consistent with the notion that women use more cheerful words in emails than men. The sadness values in these figures are consistent with the claim that women tend to share their worries with other women more often than men with other men, men with women, and women with men. The fear values in the Figures 16 and 20 suggest that men prefer to use a lot of fear words, especially when communicating with other men. Thus, women communicate relatively more on the joy–sadness axis, whereas men have a preference for the trust–fear axis. It is interesting how there is a markedly higher percentage of anticipation words in cross-gender communication than in same-sex communication (Figures 16, 18, and 20).

6 Tracking Sentiment in Personal Email

In the previous section, we showed analyses of sets of emails that were sent across a network of individuals. In this section, we show visualizations catered toward individuals—who in most cases have access to only the emails they send and receive. We are using Google Apps API to develop an application that integrates with Gmail (Google's email service), to provide users with the ability to track their emotions towards people they correspond with.[15] Below we show some of these visualizations by selecting John Arnold, a former employee at Enron, as a stand-in for the actual user.

Figure 22 shows the percentage of positive and negative words in emails sent by John Arnold to his colleagues. John can select any of the bars in the figure to reveal the difference in percentages of emotion words in emails sent to that particular person and all the emails sent out. Figure 23 shows the graph pertaining to Andy Zipper. Figure 24 shows the percentage of positive and negative words in each of the emails sent by John to Andy.

In the future, we will make a public call for vol-

[15] Google Apps API: http://code.google.com/googleapps/docs

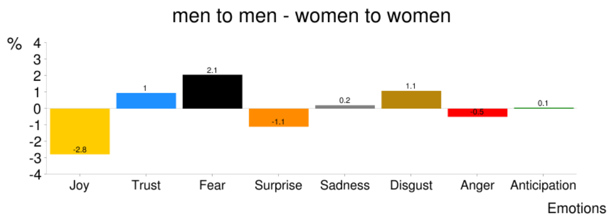


Figure 20: Difference in percentages of emotion words in emails sent by men to men and by women to women.

unteers interested in our Gmail emotion application, and we will request access to numbers of emotion words in their emails for a large-scale analysis of emotion words in personal email. The application will protect the privacy of the users by passing emotion word frequencies, gender, and age, but no text, names, or email ids.

7 Conclusions

We have created a large word–emotion association lexicon by crowdsourcing, and used it to analyze and track the distribution of emotion words in mail.[16] We compared emotion words in love letters, hate mail, and suicide notes. We analyzed the difference in emotion words used by men and women in work-place email. We showed that women use and receive relatively more number of joy and sadness words, whereas men use and receive relatively more trust and fear words. We also found that there is a markedly higher percentage of anticipation words in cross-gender communication (men to women and women to men) than in same-sex communication. We showed how different visualizations and word clouds can be used to effectively interpret the results of the emotion analysis. Finally, we showed additional visualizations and a Gmail application that can help people track emotion words in the emails they send and receive.

Acknowledgments

This research was funded by the National Research Council Canada (NRC). Grateful thanks to Peter Turney and Tara Small for many wonderful ideas. Thanks to the more than thousands of people who answered the emotion survey with diligence and care.

[16] Please send an e-mail to saif.mohammad@nrc-cnrc.gc.ca to obtain the latest version of the NRC emotion lexicon, suicide notes corpus, hate mail corpus, love letters corpus, or the Enron gender-specific emails.

Figure 21: Emails by men to men - emails by women to women: relative-salience word cloud of **fear**.

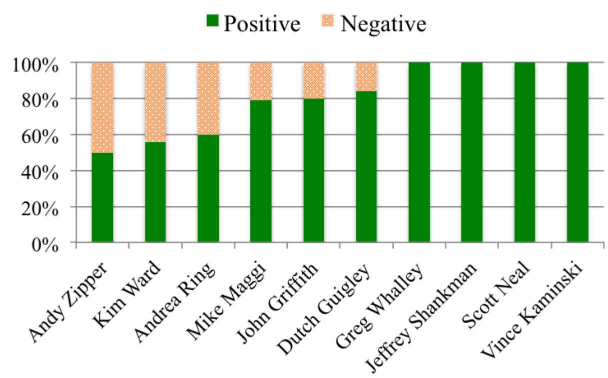


Figure 22: Emails sent by John Arnold.

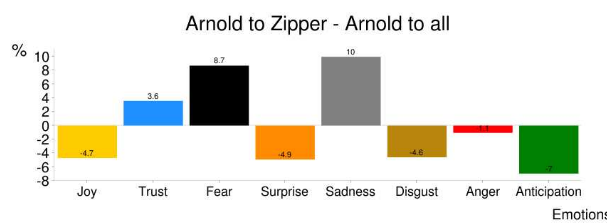


Figure 23: Difference in percentages of emotion words in emails sent by John Arnold to Andy Zipper and emails sent by John to all.

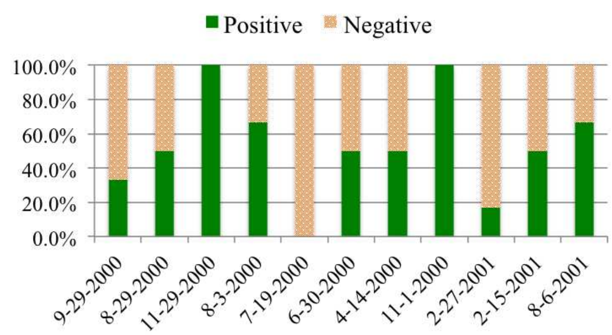


Figure 24: Emails sent by John Arnold to Andy Zipper.

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