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Detecting eigenmoods in individual human emotions.

Keywords: social media, language, sentiment, SVD, eigenmoods

Extended Abstract

Social media platforms record a multitude of information pertaining to the behavior and language of billions of individuals. Emotions play a crucial role in these phenomena but are rarely explicitly expressed [2]. They must therefore be assessed from text content by sentiment analysis algorithms. However, the high frequencies of common terms in a language can obscure actual expressions of sentiment. For example, the positive sentiment values of holiday greetings (e.g. "happy holidays") will bias many sentiment analysis tools towards positive assessment regardless of actual sentiment fluctuations. This same effect may obscure the diverging emotional responses of sub-populations, e.g. in the case of significant sports events or elections (e.g. "win" vs "lose"). A similar issue may occur in the case where individual sentiment fluctuates simultaneously along different dimensions or instances of mood, such as Valence and Arousal, or Activation [3, 6, 1].

Following [8], we leverage the Singular Value Decomposition (SVD) [4] of a sentiment-time matrix to separate actual changes in user sentiment from sentiment observations resulting from default term frequencies in a language. In effect, we show that the SVD reveals so-called "eigenmoods" from sentiment analysis data by their decomposition into singular value approximations.

We demonstrate this approach using a sample of 3,624 *Twitter* users that mentioned a mental health issue such as depression in at least 1 tweet. We obtained their individual timelines, i.e. a longitudinal record of their most recent 3,200 messages, from the Twitter API. We estimate a tweet's Valence, Arousal, and Dominance sentiment from the average CRR ANEW lexicon [5] ratings of its terms. From these scores, we create a time-series of weekly averaged sentiment scores for each individual user.

Aggregating these time-series for all users in our data set, we obtain a probability distribution of mean sentiment values for each week in our data. This results in a matrix of weekly sentiment distributions which we use as the basis of our analysis. For all users we consider sentiment values for a time span of 80 weeks, i.e. January 2$^{\text{nd}}$ 2017 through July 15$^{\text{th}}$ 2018. The resulting matrices are visualized in Fig. 1A and **??** as heat maps in which the color intensity of each cell indicates the number of tweets whose sentiment value falls in a given sentiment bin.

The SVD factorizes a matrix M in three matrices $U \cdot \Sigma \cdot V$ where the matrix Σ contains the singular values of the matrix M. Our approach isolates distinct eigenmoods from these singular values, the distribution of which is shown in Fig. 1D. The largest singular value has a disproportionate magnitude earlier shown to correspond to the base sentiment distribution of the English language [8, 7].

We can construct different approximations of M or remove noise by retaining singular vectors of interest. For instance, if we only retain the first singular value in the top-left spot of a matrix $\tilde{\Sigma}$ (by setting every other entry in the diagonal matrix to 0) and compute $U \cdot \tilde{\Sigma} \cdot V$, we obtain an approximation $\tilde{M}^1$ of M shown in Fig. 1B and **??**. These reconstructed matrices capture the expected stable sentiment distribution of the English language. In contrast, if we remove the first singular vector, by calculating $M - \tilde{M}^1$, we obtain the matrices shown in Fig. 1C and **??**. In Fig. 1C we observe a bi-modal sentiment distribution in our sample group (two yellow bands in Fig. 1C), ending approximately at week 50, which was previously hidden in the overall sentiment distribution captured by $\tilde{M}^1$. We obtain similar but visually less pronounced effects when applying this technique to the longitudinal sentiment of single individuals (an example shown in Figs. 1E to 1G).

The detection of eigenmoods in aggregate or individual social media sentiment may enable the characterization of change points by projecting the sentiment distribution of individual weeks along different singular vectors of our decomposition as previously demonstrated by [8]. This approach may have applications to the detection of changes in individual sentiment related to the dynamics of mood disorders.

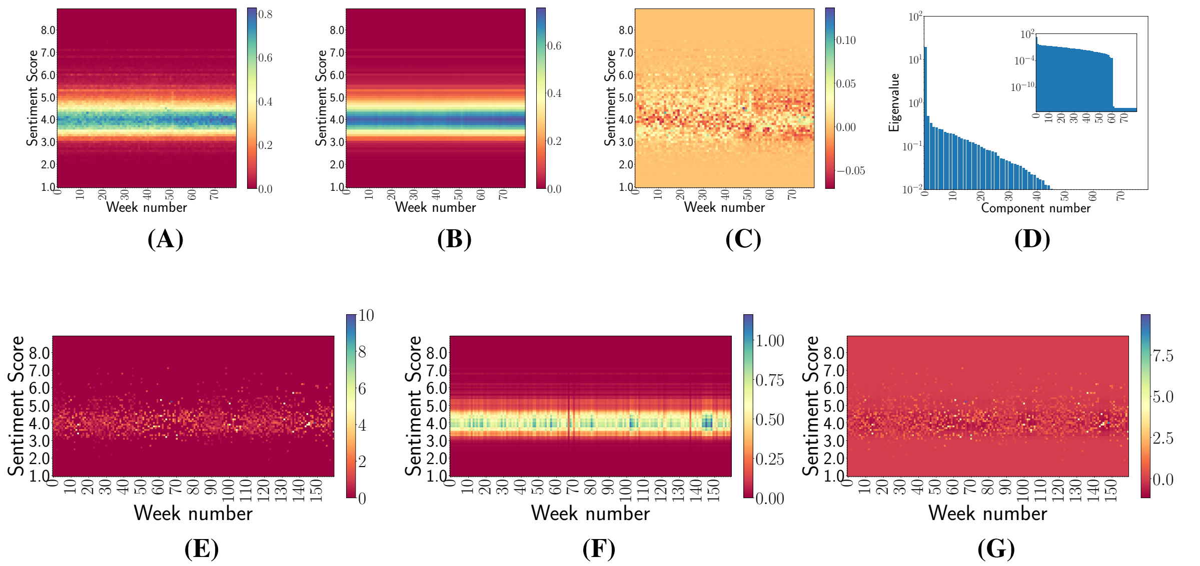

Figure 1: Eigenmood analysis of Twitter sentiment distributions. Panels A and E: mood matrix (M) for a group of users and randomly chosen individual respectively. Panels B and F: first singular value approximation ($\tilde{M}^1$). Panels C and G: remaining sentiment signal after removal of first singular value approximation from original $M - \tilde{M}^1$). Panel D: spectrum of singular values for group sentiment-time matrix.

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