Description of the project

Often integral to captivating stories are the immersive emotional experiences that readers journey through while reading a book. *Plots* which revolve around key characters, and *structure* which encodes their delivery are fundamental building blocks of a book. Kurt Vonnegut believed that *"stories have shapes which can be drawn on graph paper, and that the shape of a given society's stories is at least as interesting as the shape of its pots or spearheads".* However, this idea that plots (key events) of various stories have simple shapes could be an over-simplification of a rather complex problem. Often ambiguous and contradicting emotions may be invoked simultaneously. Even more frequently, the emotional experience might vary with how the reader relates to the narrative. For example, an excerpt from a battle scene might invoke pleasure or anger differently depending on the side the reader is on. In this project we explore emotion trajectories; graphs capturing variations in intensities of emotions invoked through the words used in different parts of the book. These trajectories may not directly convey the author's true intended meaning, but to a large extent, they give an idea about how these plots have been structured. The increase/decrease of emotion words intensities signal occurrences of key events (i.e. something interesting is happening). These signals can be interpreted as a proxy for understanding a reader's emotional state.

Motivation

S. Maharajan[5] and A. Reagan[1] in their respective work show some correlations between the underlying shapes and predicting success of books (downloads). Identifying key emotion flows that form the book can be useful in many other ways: Understanding the emotion rhythm of the customers can help improve personalization efforts. Conversely, identifying recipes to immersive books can aid content creators and authors come up with more engaging content [citation?]. Macroscopically, emotional flows can help content creators understand the ever-changing demands across region and time.

Overview

Capturing emotional states

1. Plutchik's wheel of emotions
   Texts in books across the entire book catalogue was tagged with the 8 primary emotions (Joy, Anger, Trust, Fear, Anticipation, Sadness, Surprise, and Disgust) using Emolex[2,6].

2. PAD emotional state model
   PAD model uses three numerical dimensional (**P**leasure **A**rousal & **D**ominace) to represent all emotions. The second lexicon[2,6] capturing word level values along each of these dimensions was used to capture these latent dimensions which assign emotional meanings to every word.
3. Sentiment
   Positive/ Negative words were similarly tagged using Emolex.

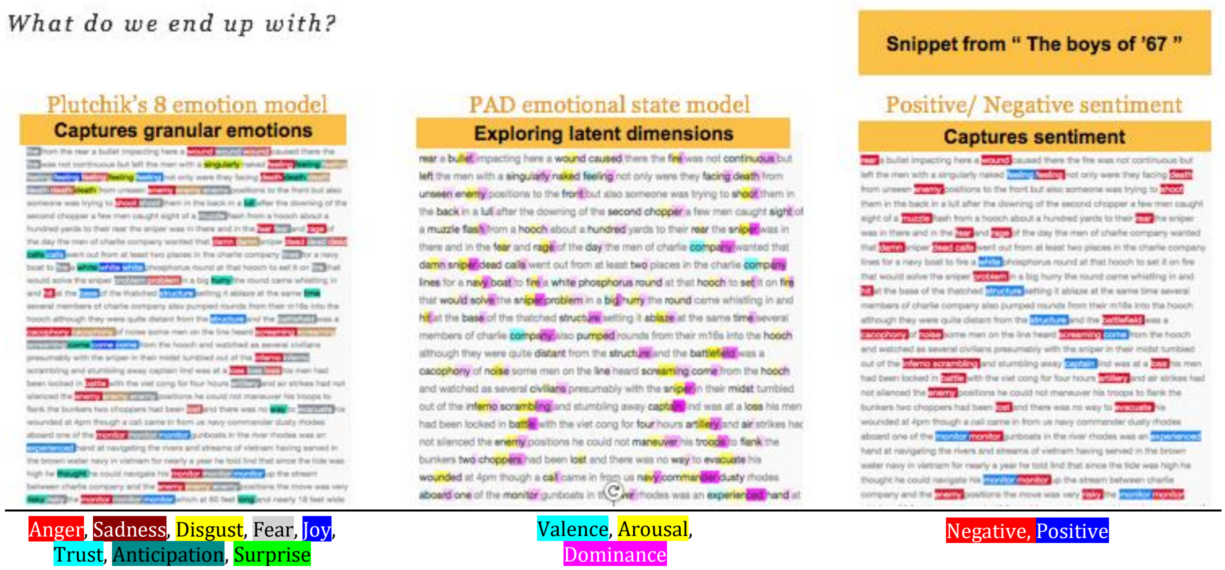


Fig 1: A snippet from a book displaying how tagged words would look like.

Figure 1 shows how complementary details get captured from the three approaches mentioned above. Sentiment (snippet on the extreme right) gives a high-level explanation that something negative is happening due to high concentration of negative words. Emotion wheel captures details of these binary tags; thus, providing more explainability on which negative emotion is more prominent [Anger (light red) frequently appears throughout the snippet; a battle scene is under execution]. The snippet in the middle shows how PAD reduces interpretability but at the same time increases the ease with which the features can be fed to the model [The entire emotional space is spanned by these three dimensions]. This led to 13 potential tags for each word [8 primary emotions, 2 positive and negative sentiments and 3: [Valence, Arousal, Dominance].

<u>Extracting meaningful features</u>

For each of the 13 emotions tags two sets of features were extracted from the tagging exercise discussed above.

1. Emotion progressions:
   For a given smoothing window N_w (5%, 10%, 20% etc.); calculate mean intensities (emotion words/total words) across n different points in the book (n = 50, 100, 200 etc.) where each of the n points are obtained by sliding the smoothing windows over a distance $L = (N - (N_w+1))/n$

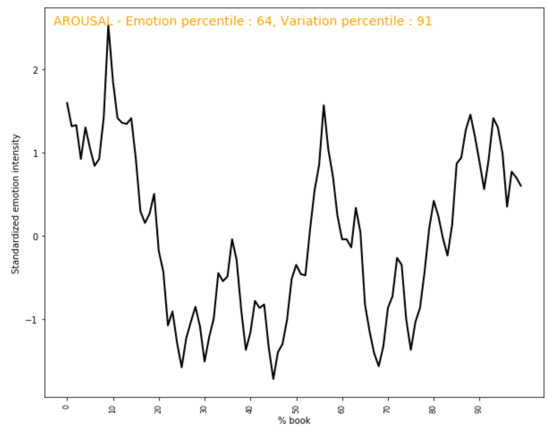


Fig 2: Emotion progression for a given book

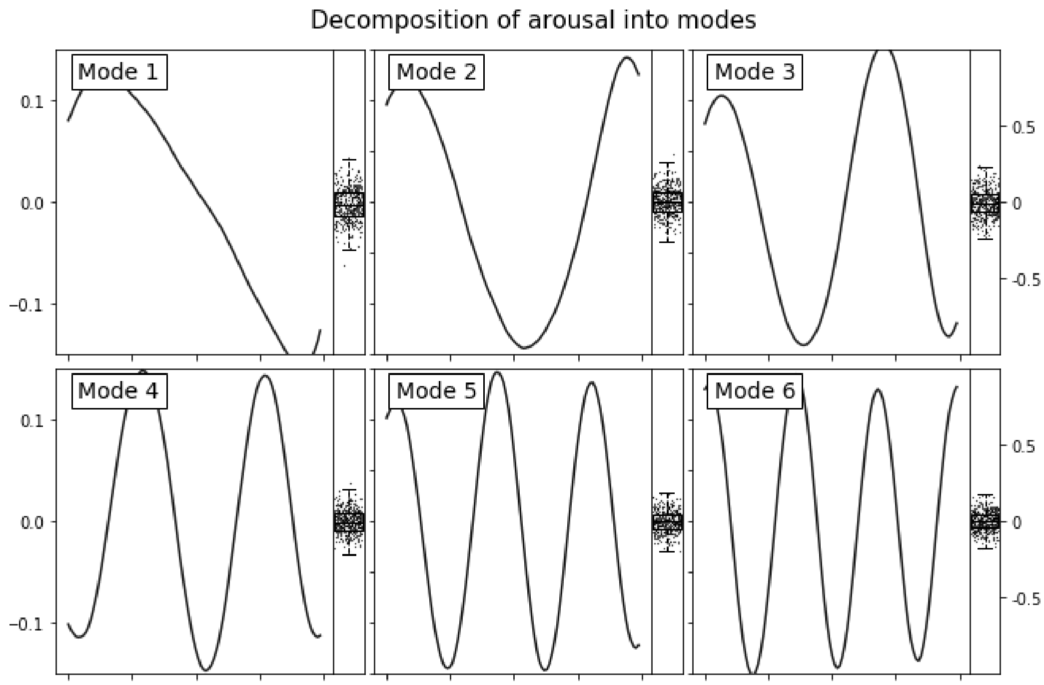
These emotion progressions capture continuous signals of how intensities corresponding to a given emotion vary across a book.

2. Emotion Vectors: These book level vectors capture statistics such as total words, total emotion words, emotion densities, emotion frequencies and mean & standard deviations of distances between each emotion words in discrete chunks of the books.

<u>Extracting shapes from the emotion progressions</u>

Matrix decomposition using SVD led to successful extraction of shapes underlying various emotion progressions that compose a book. The concept generally applied to signal extraction using Empirical Orthogonal Functions helped decompose a book into a linear combination of simple shapes.

Procedure:
Let’s assume we have a matrix A, where each row corresponds to a book in the catalogue and columns contain the respective intensities of each emotion. Then SVD on matrix A leads to its decomposition into U $\sum$ V, where **U** are the left-singular vectors of A; **V**, the right-singular vectors A and **Σ**, the non-negative singular values of A. Given, that rows of V* form the orthonormal basis of A, we can write each of the individual rows of A as linear combinations of rows of V*. Consequently, if rows of A are emotion progressions the rows of V* can be interpreted as independent shapes (called modes) that span the space of all possible emotion progressions arising from all possible books in the matrix A.



Left - The chart depicts right singular vectors (modes) which could be interpreted as underlying shapes that make up an emotion series in a given book. **Right –** Each box plot presents the distribution of weights for the respective shape in the book catalogue

Fig 3: Depicts the various shapes that arise out of SVD on A

Now, A = U ∑ V can be re-written as A = CV and the interpretation of C simplifies to the list of coefficients that can be used to linearly combine rows of V to get A given row in A. Thus, cells in C act as weights for combining the respective shapes in V. The figure below shows an example of how basic shapes discussed above were used to reconstruct the original series.

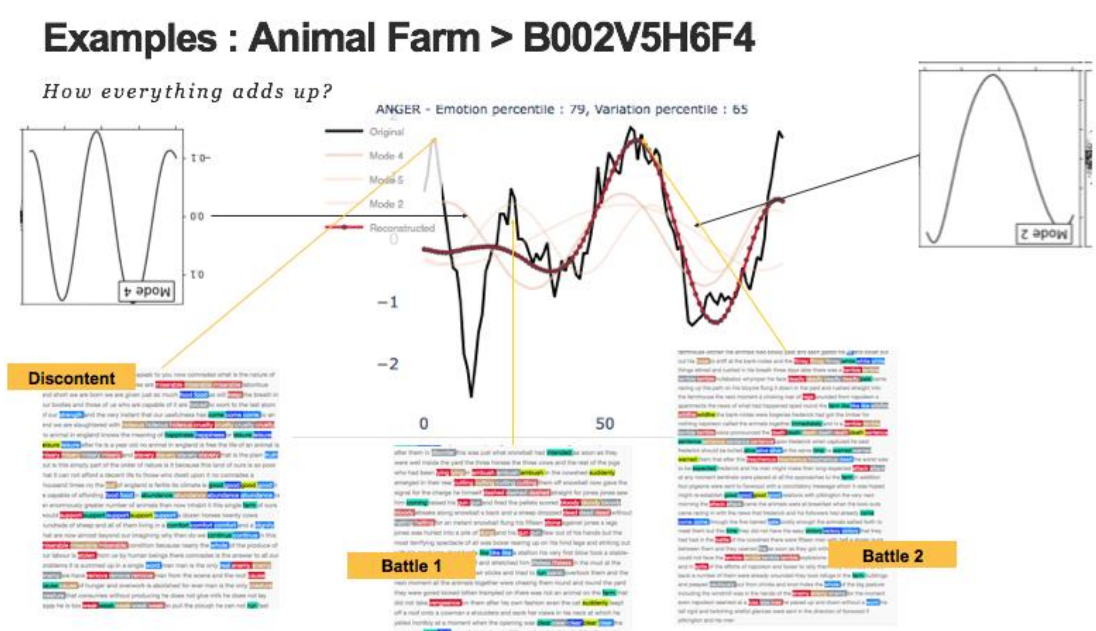


Fig 4: Shows how shape on the right (mode 2) and left (mode 4) add up to give the original progression

Finding books with similar emotion flows

We can now use these shapes to find books that present similar emotion journeys. Different runs of KNN were explored using Hamming and Euclidean distances.

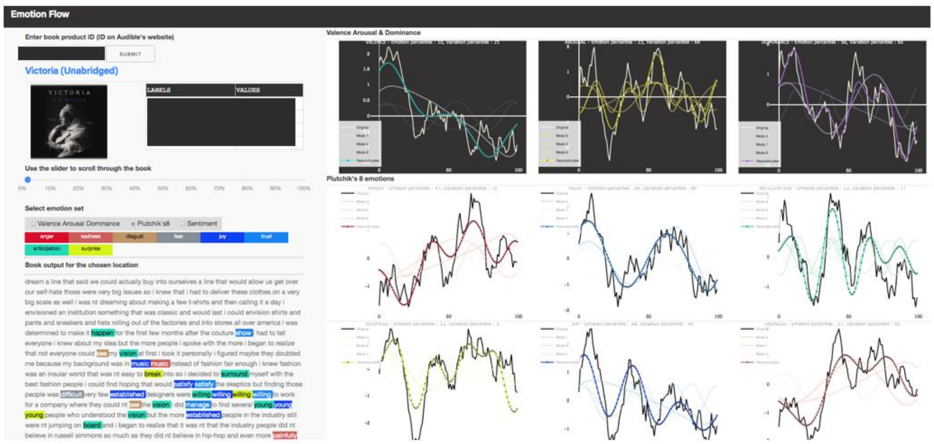


Fig 5a : Depicts the emotion progression Victoria

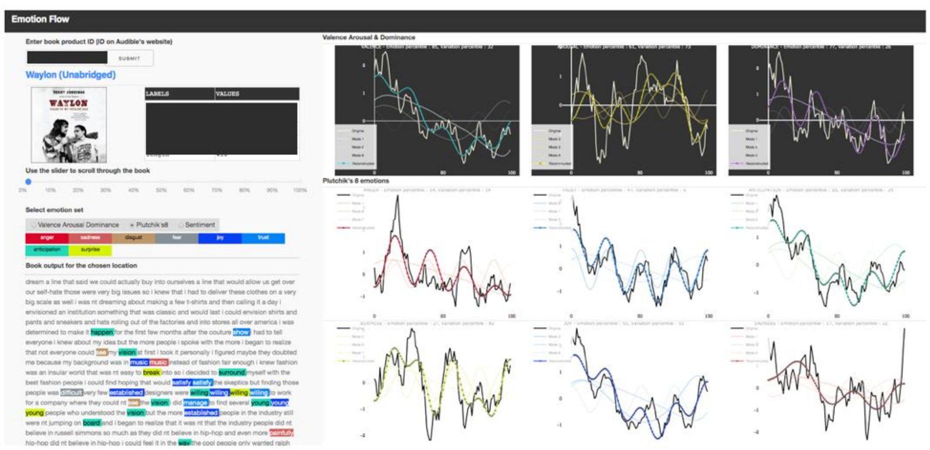


Fig 5b : Depicts the emotion progression Waylon (Book closest to Victoria)

Fig 5: Dashboard that captures the emotion progressions arising from different emotions in a book, books with similar shapes can be clustered together by using KNN*, figure 5a & 5b illustrate that.

*Note: Only Valence, Arousal and Dominance were used for finding similarity.

Main technical difficulties & limitations

How do we find books with similar emotional journeys? The PAD emotional state model uses the least number of dimensions to capture the various emotion signals. Even this 3 – dimensional model leads to (assuming top 10 modes are used to reconstruct the original progression) 10 x 10 x 10 number of possible combinations of potential modes to be matched. i.e. we end up with 1000 potential patterns by just considering the shape corresponding to highest weight. Emotional trajectories are very complex with multiple plotlines (key events) we easily end up distributing weights to multiple shapes which leads to even higher number of combinations making nearest neighbor search extremely difficult.

Future work

Shapes

Potential resolutions to the difficulties discussed above could emerge from further analyses such as finding key emotions for genres and picking similar books only for that key emotion thereby reducing the number of potential combinations. Quick improvements can be achieved by further smoothing the emotion progressions leading to a redistribution of weights from the high frequency modes to the low frequency ones. This could be achieved by increasing the smoothing window.

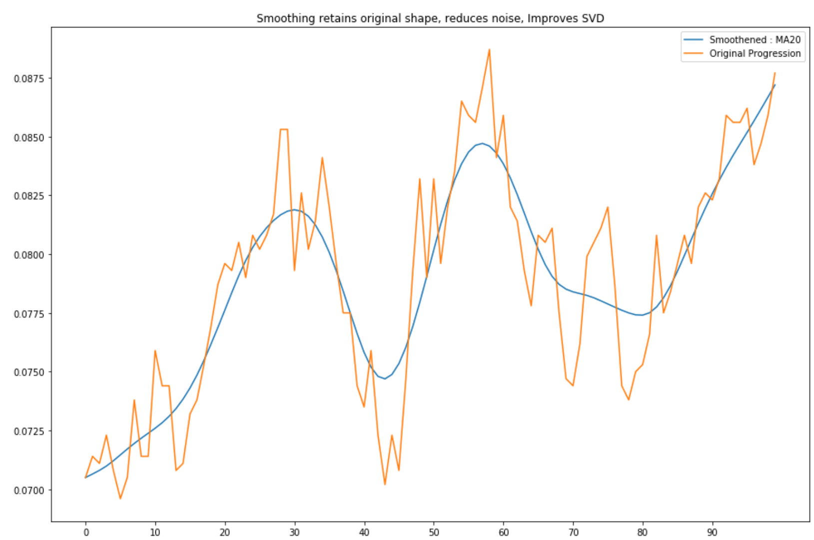


Fig 6: Smoothing emotion progressions helps redistribute weight to low frequency modes

Lexicons & Tagging

Words can have ambiguous emotion associations for ex: The word *monitor* would convey a negative emotion if it appears in a context where a reference to a battle ship is made, similarly in another situation could simply mean: an electronic device or observing the progress of something over a period of time; which doesn't have a negative meaning. Clearly context determines the right emotion to be tagged (currently, we are tagging all the emotions when we encounter such ambiguities). Similarly, POS tags could be used to disambiguate Verbs, Nouns etc. For instance, Harry could be used as a Proper Noun or could also mean - to persistently carry out attacks on (an enemy or an enemy's territory); having rather a negative connotation to it.

Further improvements can be achieved by following characters and plots throughout the book (Ex: who dies? The protagonist or the antagonist) which will give us a better understanding of the true emotional state of the reader.

Questions remain to be answered

We have discussed above that shapes and emotion progressions can be used in the predicting success of a book. Similar attempts can be tested to find correlations between shapes and book's success for all genres. Do readers prefer certain emotion journeys over others? Are certain emotions more dominant for certain genres over others? Can LSTMs capture the progressions better?

References

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