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# Prototypical Emotion Developments in Literary Genres

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## Introduction

Storytelling is a central form of human artistic expression. An ingredient of the appeal of stories is their emotional content. Readers of literature form explicit mental representations of fictional characters' emotional states (Gernsbacher, Goldsmith, and Robertson, 1992; Vega, 1996). Even more, a gripping “[...] literary work produces a complex emotional experience in the reader. This experience is inseparable from the depictive content of the narrative” (Hogan, 2011). This raises the question of the relationship between the narrative and emotional levels in literature. We explore how computational emotion analysis can contribute to the characterization of story genres, which are difficult to define and for which various criteria have been proposed, including stylistic ones (Biber and Conrad, 2009) and narratological ones (Chatman, 1978).

Our hypothesis is that genres can be linked to the development of predominant emotions over the course of the text. To test this, we present a computational model of multi-label emotion analysis of literary genres and apply it to a set of English literary works from the [Project Gutenberg](#) for five genres, namely adventure, romance, mystery, science fiction, and humorous fiction. We identify prototypical shapes for each genre and show that this analysis produces results, which can find a place in the computational analysis of literary genres and extend existing stylometric approaches.

Cuddon (2012) defines adventure as “a form of fiction [...] in which the hero conventionally undergoes a series of testing and episodic adventures” and mystery as a narrative involving the “detection of crime, with the motives, actions, arraignment, judgement and punishment of a criminal”. Baldick (2015) defined Romance as narratives with “improbable adventures of idealized characters”. Today, however, the term covers many forms of fiction, including love stories. We use the term romance as a literary genre in this broader sense. Regarding science fiction stories, it is generally agreed that they are “[...] about an amazing variety of things, topics, ideas. They include trips to other worlds, quests, the exploration of space...” (Cuddon, 2012). Humorous fiction is comical literature “written chiefly to amuse its audience” (Cuddon, 2012).

## Methods

We calculate emotion scores for eight basic emotions, namely joy, sadness, trust, disgust, fear, anger, surprise, and anticipation (Plutchik, 2001). We use the NRC Emotion Lexicon (Mohammad and Turney, 2013). Since the data in Project Gutenberg is diachronic, this method of emotion recognition might not be appropriate for older texts and, in general, may suffer from low recall. However, it can be considered a high-precision approach suitable for our purpose.

To obtain an emotion analysis for a story, we start by computing emotion scores for spans of text (Klinger, Suliya, and Reiter, 2016). Formally, we compute the score  $es(e, S)$  for an emotion  $e$  and a span of tokens  $S = \langle t_n, \dots, t_m \rangle$  as

$$es(e, S) = \frac{1}{|D_e|} \sum_{t_i \in S} 1_{t_i \in D_e}$$

where  $D_e$  is a dictionary containing words associated with emotion  $e$  and  $1_{t \in D}$  is 1 if  $t \in D$  and 0 otherwise. We do this for each of our eight emotions, obtaining an eight dimensional “emotion vector” for each span. We analyzed the stability of our results across different settings and found that different dictionaries affect the actual values but not the relation between different time steps. These scores are not probabilities, but could be transformed if needed.

To observe development over time, we could use sliding windows; however, continuous time series are notoriously difficult to interpret. Therefore, we adopt a simpler scheme inspired by the five-act theory of dramatic acts (Freytag, 1863), according to which dramas are divided into five acts: exposition, rising action, climax, falling action, and denouement. We

consequently divide each text into five successive, equal-sized spans (since different texts have different length, the size of acts varies between texts) that we assume to correspond roughly to dramatic acts in Freytag’s theory, with exposition at position 1 and denouement at position 5, and compute an eight-element emotion vector for each Act.

## Experimental Evaluation

We now demonstrate how this emotion aggregation into five acts can contribute to the understanding of different literary genres.

### Data

We collect 2113 books from Project Gutenberg that belong to five genres found in the Brown corpus (Francis and Kucera, 1979), namely adventure (585 books), romance (383 books), mystery (380 books), science fiction (562 books), and humorous fiction (203 books). The corpus is available from the authors upon request.

The selection is based on the Library of Congress Subject Headings in the metadata. We select all books that contain the word “Fiction” in combination with one of the following labels: “Adventure stories”, “Love stories”, “Romantic fiction”, “Detective and mystery stories”, “Science fiction” or “Humor”. Furthermore, we reject books with the following labels: “Short stories”, “Complete works”, “Volume”, “Chapter”, “Collection”, “Part”. This constraint is aimed at excluding files which contain partial or multiple works.

### Qualitative analysis

Each plot in Figure 1 depicts the act-by-act development for one emotion with their emotion score  $es(e,S)$ . Since we interpret shapes rather than values, we omit the legend. The average over all books is shown in a dark-colored line. The area around that line corresponds to confidence intervals at a 95% confidence level.

For sadness, anger, fear, and disgust, all five genres show a close correspondence, namely a consistent increase of the emotion from Act 1 through Act 5 – corresponding to gripping narratives. Mystery and science fiction lack the drop in anger and tend to end with higher levels of this emotion. Joy is inverse to these emotions, showing a decreasing tendency from Act 1 to Act 5 for all genres with exception of humorous fiction that shows a plateau between Acts 1 and 4.

In adventures, all emotions increase in the first half of the books, but drop sharply between Act 4 and Act 5. This is consistent with Whetter (2008), according to whom adventures are marked by a late drop in emotional tension when the hero’s misfortunes come to an end. The only exception is trust that shows increase towards the end for all genres, which is especially noticeable in adventures. A potential reason is that prototypical adventure novels are ‘upbeat’ in that they cultivate virtues such as courage and loyalty (Baldick, 2015, p. 5) and depict heroes that do not lose trust even amid unexpected dangers.

The results for anticipation and surprise show less coherent tendencies which we find difficult to interpret. These two emotions appear less constitutive to the narrative structure of genres, at least those that we currently consider: anticipation and surprise can occur under (almost) any circumstances. Mystery fiction has a slightly different pattern, where anticipation exhibits steady increase from Acts 1 to 4 and its peak coincides with the peak for surprise at Act 4.

### Quantitative analysis

We analyze the genre-specific time course of emotions quantitatively by computing associations between genres and the Act in which an emotion “peaks” in a story. We define a random variable  $v_{ie}$  for an emotion peak as  $v_{ie}=1$  iff the highest value of emotion  $e$  is in Act  $i$ . The association between each genre and emotion peaks  $v_{ie}$  follows point-wise mutual information (Church and Hanks, 1990),

$$PMI(g, v_e^j) = \log \frac{p(v_e^j, g)}{p(g)p(v_e^j)},$$

where probabilities are computed as relative frequencies over the dataset.

Figure 2 gives insight into the genre-specific emotion patterns. For instance, disgust is characteristic of Act 4 for all genres. The only exception is science fiction that does not list disgust or surprise among the top 10 features. Trust is important at the beginning and in the end of adventures and science fiction, but is missing in mystery. Similarly, romance fiction is not characterized by anticipation among top-ranked features, corresponding to its “anticipation” curve that decreases monotone from beginning to end. Interestingly, humor is the only genre that does not contain joy among the top 10 features.

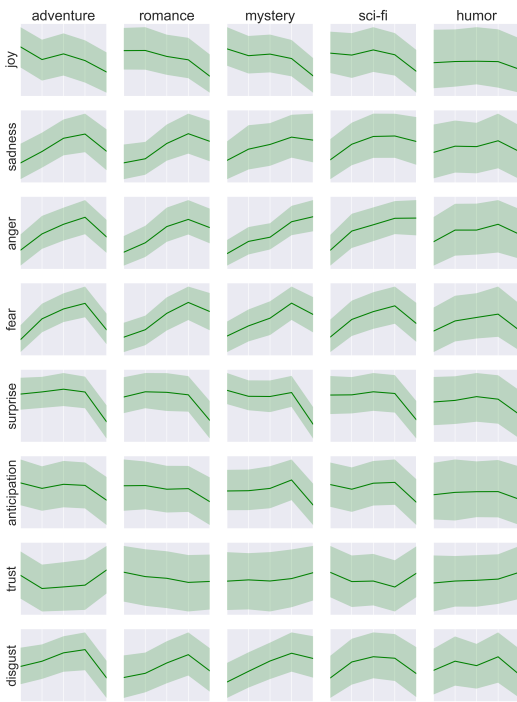


Figure 1: Genre-specific emotion curves

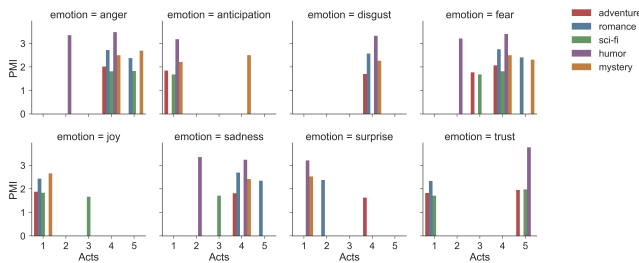


Figure 2: Top 10 PMI features for each genre

## Related work

Sentiment and emotion in fiction have been previously addressed computationally by Mohammad (2012), Nalisnick and Baird (2013), Heuser, Moretti, and Steiner (2016), among others. Samothrakakis and Fasli (2015) is the only work we are aware of which discusses emotions in context of genres.

The study most related to ours is Reagan et al. (2016). They propose a pipeline that tracks emotions in text. Their main claim is that stories typically follow one out of six “emotional arcs” regarding happiness.

## Conclusion, discussion and future work

We investigated the relationship between emotional development in literature and genre and observe differences among emotions. The genre of adventure stands out, especially concerning the end of

the story arc. Our results can provide a novel starting point for characterizing similarities and differences within and between literary genres.

Our observations require further investigation regarding the underlying factors. For instance, it might be argued that the pattern for mystery stories is dominated by the subgenre of crime fiction. Future work will combine our distant reading approach with close and scalable reading. Furthermore, to improve emotion recognition, we plan to use distributional methods for expanding the existing lexical resources and adapting them to texts from different historical periods (cf. Buechel, Hellrich, and Hahn, 2016).

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