EMOFIEL: Mapping Emotions of Relationships in a Story

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ABSTRACT

We present EMOFIEL, a system that identifies characters and scenes in a story from a fictional narrative summary, generates appropriate scene descriptions, identifies the emotion flow between a given directed pair of story characters in each interaction, and organizes them along the story timeline. These emotions are identified using two emotion modelling approaches: categorical and dimensional emotion models. The generated plots show that in a particular scene, two characters can share multiple emotions together with different intensity. Furthermore, the directionality of the emotion can be captured as well, depending on which character is more dominant in each interaction. EMOFIEL provides a web-based GUI that allows users to query the annotated stories to explore the emotion mapping of a given character pair throughout a given story, and to explore scenes for which a certain emotion peaks.

CCS CONCEPTS

• **Information systems** → *Entity relationship models*; *Web mining*; *Data extraction and integration*;

KEYWORDS

Text mining, fictional narratives, emotion analysis

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1 INTRODUCTION

Motivation. We, as readers usually identify stories through their characters and character relationships. A good story includes well written scenes that portrays characters' emotions in order to evoke emotions on the readers. To create compelling scenes, characters' emotional development is described via dramatic interactions and situations, which lead to the characters' ultimate transformation at the overall story level. At the same time, there are characters' emotional reactions to events happening at the scene level. It is at these scene levels that characters' emotional relationships may change as the story progresses, depending on their interactions in each scene.

During a particular interaction, the emotion mapping from one character to another might be different than the mapping between the same characters in the reverse direction. Thus, it is important to consider the directionality of emotion flow between the characters while mapping their emotions.

Furthermore, in an interaction between story characters, emotions are not discrete but different emotions have a shared place-value in the emotion distribution for a given interaction. Thus, the emotion mapping is not only limited to binary existence of categorical emotions, e.g. Paul Ekman's basic emotions [4], but also their intensity. It is also interesting to include the emotional dimensions following the dimensional model approach to compare the two different approaches to model emotions.

Our proposed approach can be used to analyze the evolving emotions of character pairs for different fictional narratives, hence, the generated emotion trajectories are beneficial for mining emotional patterns of typical story relationships such as *lovers* or *enemies*. This can be useful to understand what would be the key ingredients, e.g., important actions and objects involved in character interactions, for writing compelling stories that reach out to readers emotionally.

Problem Statement. EMOFIEL (EMotion mapping of FIctional rELationships) addresses the problem of understanding the emotional relationship between fictional characters, given a summary of interactions and events happening between them. The task requires extensive text analysis to (i) identify story characters and coreference resolution to resolve character mentions in the text, (ii) extract interactions in terms of events and participating agents/patients and cluster such interactions, and (iii) mapping the emotion of such interactions to be used for analyzing emotional relationships between the interacting characters.

Related Work. There are several work focusing on analyzing the character relationships in fictional narratives, which consider either the trajectory on how the relationships evolve [3, 5], or the sentiment (positive or negative) of the relationships in general [14]. However, there is no work yet on analyzing the trajectory of emotional relationships between story characters following the established emotion modelling, such us categorical [4, 13] and dimensional [7] models. Furthermore, previous work did not take into account that character relationships can take a different form if viewed from different characters, e.g., a one-sided love relationship.

Contribution. We propose a fully unsupervised approach to annotate stories with emotion mappings of different character pairs as the story evolves, taking into account the different emotional situations in which a character pair interacts with each other. The mapped emotion are both categorical and dimensional. The direction of emotion flow from one character to another is also taken into consideration as in a particular situation, they can be different depending on the events and interactions. We have also developed a prototype that allows users to explore the annotated stories with

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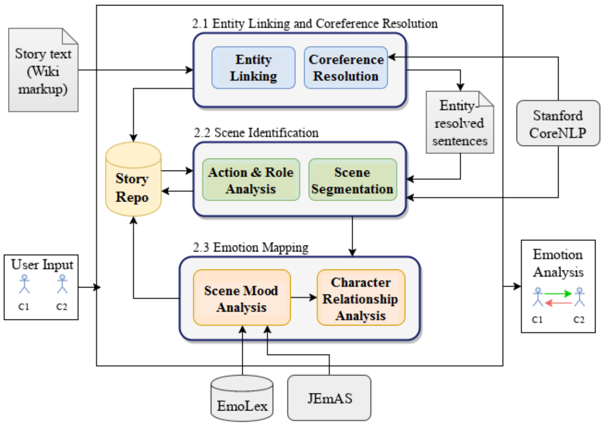


Figure 1: EMOFIEL's system architecture.

respect to evolving emotion plots between characters identified in the story.

2 EMOFIEL: SYSTEM DESCRIPTION

Given a story text as input, we identify *scenes* in the story by segmenting the text according to interactions between story characters. We assume a dense graph of character interaction in each scene. We then map each scene into the emotion space based on emotional words found in the text describing the scene. Using this information we then infer the emotion mapping of character interaction in each scene, and later the evolving emotions throughout the story. EMOFIEL's workflow is detailed in the following section and Figure 1.

2.1 Entity Linking and Coreference Resolution

We use story text available in Wiki markup from collaborative encyclopedias such as Wikipedia or Wikia, since it would simplify entity linking by skipping the entity disambiguation step, particularly for characters and important objects in the story. For example, in our use case scenarios, we took book summaries from the Harry Potter series, each book summary contains approximately 300-500 sentences.

Identifying story characters. For each link found in the summary text, we looked for its infobox in the corresponding page (if any) and inferred the entity type from the infobox name, e.g., *Individual* for *Harry Potter*, *Object* for *Remembrall*. From the infobox we then extracted information about entities, in particular *gender*, *aliases* and *family relations* with other entities, e.g., *'Lily Potter (mother)'* in Harry Potter's infobox. Since the entity mentions in the infobox usually link to entity pages, we recursively extracted entities and information about family members.

Note that alias information is also available from the links in the summary text, as sometimes links have different mentions than the entity page title, e.g., the mention of *You-Know-Who* that links to the page of *Tom Riddle*.

For each entity, we also extracted from the first sentence of the entity page, the entity description in the pattern of "[Entity name] is a ...", in order to obtain additional information such as "Harry Potter is a half-blood wizard" and "A Remembrall is a large marble sized glass ball". This would be useful to resolve the mention of *the ball* in the following text where *Remembrall* was previously mentioned.

Coreference resolution. We used Stanford CoreNLP [6] to resolve the coreference mentions in the text. Furthermore, we refine the results by (i) checking for gender accordance, (ii) taking into account alias information (e.g., *You-Know-Who* → *Tom Riddle*), and (iii) utilizing family relations (e.g., *his [Harry Potter's] aunt* → *Petunia*). Finally, whenever an entity of type Object is mentioned in the text, we resolved the mentions of common nouns with definite articles in the consecutive sentences, which conform to the entity description (*the ball* → *Remembrall*).

2.2 Scene Identification

Given a story text, we define a *scene* as a sequence of sentences describing a particular event in which a subset of story characters interact intensively. It is also possible for a scene to only contain one main story character.

Text Analysis. We first split the input text into sentences. For each sentence, we identified a set of: (i) *actions*, which are usually characterized by verbs, and (ii) *agents* and *patients* of the actions, based on the dependency relations between the action mention and nouns. Information about part-of-speech tags and dependency relations was acquired from the Stanford CoreNLP [6]. For instance, from the sentence *"Harry goes after Malfoy, who throws Remembrall in the air,"* we obtained two actions: (i) *goes after* [AGENT: *Harry*, PATIENT: *Malfoy*] and (ii) *throws* [AGENT: *Malfoy*, PATIENT: *Remembrall*].

Scene Segmentation. By exploiting the previously extracted information about agents and patients from the sentences, given a list of sentences we perform the scene segmentation step following Algorithm 1.

An illustrative example is given in Table 1, where sentences belonging to one paragraph in the text are split into three scenes.

2.3 Emotion Mapping

By assuming that all story characters occurring in a scene as either agents or patients are interacting with each other, we infer the emotion mapping of their relationships via the *mood* of the scene in which they co-occur. We followed these two lines of psychological research on modelling emotions, i.e., *categorical* and *dimensional models*, to model the mood of a scene based on existing emotional words. Following categorical models, emotional states can be categorized into a small set of emotion categories, e.g., *joy*, *sadness*. On the other hand, according to dimensional models, an emotional state is described relative to a small number of emotional dimensions, such as *valence*, *arousal* and *dominance*.

Categorical Model. We used the *NRC Word-Emotion Association Lexicon (EmoLex)* [10, 11], which contains a list of words and their associations with eight basic emotions. This lexicon serves our purpose of analyzing text in terms of categorical emotions instead of sentiment polarity (e.g., AFINN [12], SentiWordNet [1]) and with

input : list of sentences S of size n
output : list of scenes, each scene contains a list of sentence ID

Initialize the first scene containing the first sentence;
$H \leftarrow getAgents(S[1]) \cup getPatients(S[1])$;
for $i \leftarrow 2$ **to** n **do**
  if $(getAgents(S[i]) \cap H) = \emptyset$ **and** $(getPatients(S[i]) \cap H) = \emptyset$ **then**
    Initialize the new scene containing $S[i]$;
    $H \leftarrow getAgents(S[i]) \cup getPatients(S[i])$;
  else
    if $(getPatients(S[i]) \cap H) = \emptyset$ **and** $getPatients(S[i])$ *is not empty and does not contain only pronouns* **then**
      Initialize the new scene containing $S[i]$;
      $H \leftarrow getAgents(S[i]) \cup getPatients(S[i])$;
    else
      $S[i]$ *is added to the current scene*;
      $H \leftarrow H \cup getAgents(S[i]) \cup getPatients(S[i])$;
    end
  end
end

Algorithm 1: Interaction-based scene segmentation.

Scene		Sentence
s_{166}	l_{254}	Later, in his Potions class, *Harry* discovers that *Snape* hates him[Harry], mocking Harry as "our new celebrity" and then humiliating Harry for his ignorance of potion-making materials.
s_{167}	l_{255}	*Harry* brings Ron with him to HagridâĂŹs shack for tea.
	l_{256}	Harry and Ron are disconcerted by HagridâĂŹs huge and fierce-looking *dog*, Fang, but discover that he is gentle.
	l_{257}	*Hagrid* tells Harry that *he[Harry]* is overreacting to SnapeâĂŹs treatment, asserting that *Snape* would have no reason to hate him[Harry].
s_{168}	l_{258}	*Harry* happens to notice an article from the wizard newspaper, the Daily Prophet, detailing a *break-in* that occurred at Gringotts bank in a vault that had been emptied earlier in the day.
	l_{259}	*He[Harry]* realises that it happened on his birthday, the day *he[Harry]* and *Hagrid* went to Gringotts.

Table 1: Scene segmentation example, with annotated *agents* and patients.

richer emotion categories compared with the dataset released for the WASSA-2017 Shared Task on Emotion Intensity [8, 9]. Given emotion labels E ={*anger*, *fear*, *anticipation*, *trust*, *surprise*, *sadness*, *joy* and *disgust*} and a scene s containing n number of sentences, we compute the percentage of emotion e in the scene, $e \in E$, as:

$$\text{perc}_e(s) = \frac{\sum_n^{i=1} f_{ei}}{\sum_n^{i=1} \sum_{j \in E} f_{ji}} \quad (1)$$

where f_{ei} is the frequency of emotional words of label e in the i^{th} sentence of s.

Dimensional Model. Russell and Mehrabian's Valence-Arousal-Dominance (VAD) model [7] is among the most commonly used dimensional approach, in which the emotional states can be described relative to three fundamental emotional dimensions: *valence* (the degree of pleasure or displeasure of an emotion), *arousal* (level of mental activity, ranging from low engagement to ecstasy) and *dominance* (extent of control felt in a given situation). We utilized

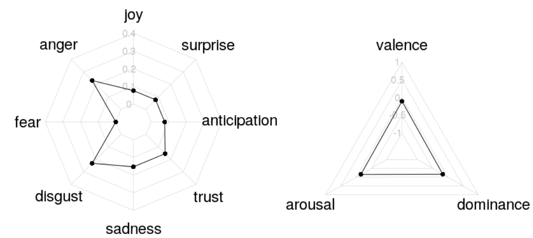


Figure 2: Emotion mapping for scene $s_{images/166}$.

Figure 3: Screenshot of EMOFIEL.

Jena Emotion Analysis System (JEmAS) [2] for analyzing the VAD score of each scene, giving as input all sentences in the scene.

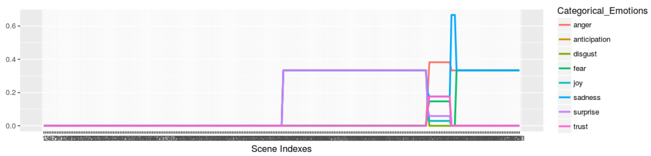
An illustrative example of emotion mapping with both categorical and dimensional models for scene s_{166} from Table 1 is given in Figure 2.

Emotion Mapping of Character Relationships. Given a pair of character pair $<c_1, c_2>$, we then inferred their directed evolving relationship $\text{rel}_{c_1 \rightarrow c_2}$ (and similarly for $\text{rel}_{c_2 \rightarrow c_1}$) throughout the story by retrieving a set of scenes $\{s_1, ..., s_n\}$ in which c_1 and c_2 co-occurs, and c_1 mostly acts as agents. This is based on an assumption that if a character mostly acts as agents in an emotional scene, then it is most likely that he/she is the causing agent of the invoked emotion felt by other characters. Given our previous examples, we can infer that scene s_{166} contributes in describing the emotionally negative relationship of *Snape* $\rightarrow$ *Harry* at that particular point in the story.

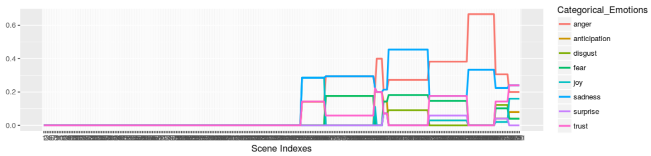
3 DEMONSTRATION OF THE SYSTEM

3.1 Implementation

EMOFIEL is implemented in Java and R, and makes use of external tools such as Stanford CoreNLP and JEmAS. Given a story text, EMOFIEL will build annotated story repository to be used for analyzing the emotion mapping of character relationships following the previously explained workflow. Finally, EMOFIEL provides querying and explorative navigation by its web-based application. Figure 3 shows the screenshot of EMOFIEL's prototype, which

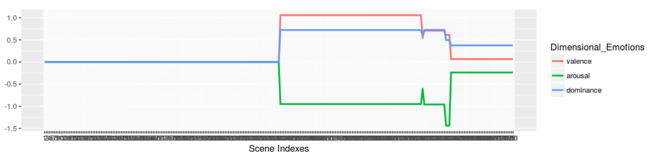


(a) Harry → Neville

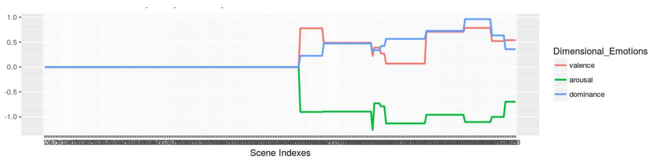


(b) Harry → Snape

Figure 4: Categorical Emotion Mapping: friends vs enemies

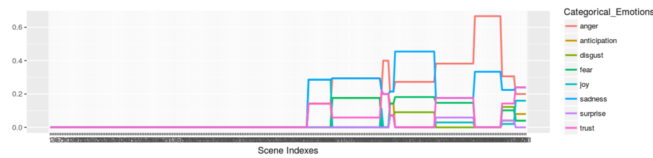


(a) Harry → Neville

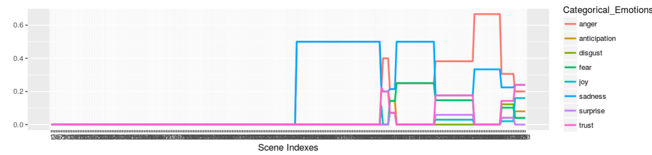


(b) Harry → Snape

Figure 5: Dimensional Emotion Mapping: friends vs enemies



(a) Harry → Snape



(b) Snape → Harry

Figure 6: Categorical Emotion Mapping: directional relationship

contains: (i) user input area, (ii) emotion mapping of character relationships throughout the story and (iii) scene's description and emotion mapping (given a particular scene). The system can be examined online at https://gate.d5.mpi-inf.mpg.de/emofiel/.

The system gives an insight into emotional character relationships in a story. We took the first book summary in the Harry Potter series, and analyze the character relationships in different scenarios.

Scenario 1: Friends vs enemies. We show in Figure 4 and Figure 5 the relationships between Harry-Neville and Harry-Snape, with categorical and dimensional emotion mapping, respectively. The relation of Harry and Snape is dominated by negative emotions such as *sadness* and *anger*, while Harry and Neville by more positive emotions such as *surprise* and *joy*. The same can be said regarding the valence from the dimensional emotion plots.

Scenario 2: Capturing directed relationships. Looking at Figure 6, it is evident that there is a difference between the directed relationship of Harry and Snape, that Harry caused a more complex emotion towards Snape than the other way around, even though both are dominated by negative emotions.

4 CONCLUSION

We have presented our system EMOFIEL, which maps and analyzes the dynamic flow of character relationships throughout a story, following the categorical and dimensional emotion models. They can be used to better understand a story in terms of character relationships, and for mining patterns of character relationships across stories in general, e.g., general plots for friends, enemies, lovers, etc.

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