A multi-agent game for sentiment analysis

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Abstract
The scientific literature provides substantial evidence that a considerable part of face-to-face communication depends on non-verbal cues. The emergence of Online Social Networks has altered the way individuals interact, promoting Computer-Mediated Communication (CMC). However, it is important to note that CMC does not completely capture the richness of in-person conversations. This is a major issue, especially when users engage in communication through instant messaging platforms. In this work, we conceptualize this kind of communication as a multi-agent game in which the winning conditions are expressed by means of ATL formulas. These winning conditions may express different conversational objectives, such as the group wanting a particular agent to reach a certain emotional state.

Keywords
Sentiment Analysis, Strategic Reasoning, Multi-agent systems, ATL

1. Introduction

The advent of Online Social Networks [2] (OSNs) has brought about a profound transformation in the way we communicate, fundamentally reshaping the social landscape. These digital platforms, such as Facebook, Twitter, Instagram, LinkedIn, and many others have redefined interpersonal interactions and the dissemination of information. One of the most notable changes is the shift from primarily face-to-face and phone-based communication to a predominant text and image-based format. People nowadays share their thoughts, emotions, and experiences through status updates, photos, videos, and short messages, favoring a culture of instant gratification and constant connection. Moreover, OSNs have transcended geographical barriers, enabling global conversations and connections that were previously unimaginable. Friendships can be maintained across continents, and individuals can participate in global discussions, breaking down cultural and linguistic boundaries.

On the other hand, this digital revolution has also introduced challenges, such as privacy concerns, the spread of misinformation, and the potential for addiction. Additionally, the brevity and informality of online communication took the place of deep and meaningful exchanges. Indeed, we are in the Computer-mediated communication [3] (CMC) era, that has revolutionized

the way we connect and share information. However, it is important to recognize that CMC has limitations when it comes to conveying emotions effectively.

Unlike face-to-face interactions, where non-verbal cues like facial expressions, tone of voice, and body language play a significant role in expressing and interpreting emotions, helping us discern between sarcasm and sincerity, empathy and indifference, excitement and apathy, CMC relies predominantly on text-based messages, emojis, and gifs. While these tools can help share some emotional aspects, they often fall short in capturing the full spectrum of human feelings. Written words alone may lack the context and the precision needed to accurately bring emotions. As a result, messages can be misread or misjudged, leading to misunderstandings and conflict. In instant messaging platforms, that enable us to connect with friends, family, and colleagues from anywhere in the world at the touch of a button, emojis, and emoticons attempt to bridge this emotional gap by providing users with a set of visual symbols to express their feelings. However, people have different interpretations of them, and this lack of standardized emotional expression can lead to miscommunication and even conflict in online interactions.

There are several existent techniques to obtain information about user's emotions, from machine learning approaches to lexicon-based ones, but still not enough has been done on employing these emotions to improve the quality of the services offered by instant messaging platforms. This work constitutes an important step forward in this direction, since it allows reasoning on strategic aspects of instant messaging framework formally. Indeed, we do not just observe the user's feelings, but we modify them to reach some goal, relying on the expressive power of the Alternate-Time Temporal Logic [4] (ATL). ATL is one of the most used logics introduced for formal strategic reasoning, that allows establishing if a coalition of agents has a winning strategy with respect to a goal. ATL has been largely studied in several directions and applications [5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15]. In this work, we model the message exchanging as a multi-agent game, where emotions are discretized through the Plutchik's wheel, and we express winning conditions by ATL formulas, with the goal of establishing if there exists a strategy for a coalition of agents to change how another agent feels.

Related Work   Social networks and strategic reasoning have been already used in literature, among the others [16, 17, 18]. We here present the state of the art on sentiment analysis, in particular on solutions using logic approaches, as we do. The authors of [19] propose an abstract model of the communication scenario in OSN containing a Virtual Counselor to help the interpretation of the messages and of the emotional state, by providing an implementation of it in [20].

In [21], the authors used a fuzzy-rough sets based sentiment analysis classifier for analyzing political Twitter data, while in [22] the authors provide a fuzzy natural logic for sentiment analysis to evaluate linguistic expressions.

theauthors of [23], instead, propose a new semantic and fuzzy aware content recommendation system for retrieving the suitable content for the users, while in [24] the authors present two models of opinion diffusion on a network, where the agents try to achieve their individual goals by deciding to enforce or not their opinions over the agents they can influence.

2. Sentiment Analysis

Sentiment analysis [25] is a natural language processing technique used to determine the emotional tone or sentiment expressed in a piece of text, such as a tweet, review, comment, or article. Its primary goal is to understand and classify the sentiment of the text as positive, negative, or neutral emotions like joy, anger, sadness. It has three main approaches:[25]:

- Lexicon Based Approach [26, 27]: it typically does not require training data and it relies on predefined dictionaries associated with specific sentiments (positive, negative, neutral). Each word or phrase in the text is assigned to a sentiment score. This approach can be computationally efficient but may struggle with handling sarcasm, context, or new words not present in the lexicon.
- Machine Learning Approach [28, 29]: it involves training a model on labeled data to learn patterns and relationships between words and sentiment labels. Common machine learning algorithms used for sentiment analysis include Support Vector Machines (SVM), Naive Bayes, Random Forests, and more recently, deep learning models like Recurrent Neural Networks (RNNs). These models can capture complex linguistic and contextual information and adapt to different domains and languages with sufficient training data.
- Hybrid Approach: it combines both lexicon-based and machine learning-based techniques to leverage their respective strengths. It can be more robust and flexible in handling diverse text sources but may require more computational resources.

There are also biometrics approaches based on wearable devices, such as EmotiBit, that do not rely on words analysis, but rather it can wirelessly stream and locally record data from a multi-modal constellation of sensors, including electrodermal activity, a medical-grade temperature sensor, and a growing list of derivative metrics [30].

Without lack of generality, in this work we get rid of the way emotions are discovered, and we assume that, by applying one of the existent approaches, it is possible to know how users feel.

3. A game-based setting

In this section, we demonstrate how a (very simple) example of communicative interaction among multiple agents, in which they traverse different emotional states, can be modeled using *Concurrent Game Structures*[4]. Intuitively, a Concurrent Game Structure is a labeled directed graph that represents the possible evolution of a given Multi-Agent System with respect to simultaneous choices of actions of a group of (autonomous) agents. Both states and edges are labeled by members of two disjoints alphabets. States are labeled by atomic propositions. These atomic propositions represent the properties that are true at a given state. Each edge is labeled by a tuple, and each member of a given tuple represents an action that is available for a given agent at the source state of the edge. The formal definition follows.

4. The Game Structure

Definition 1 (Concurrent Game Structure [4]). *Given a countable set of atomic proposition (or atoms)* Ap *and a finite non-empty set* Ag *of agents, a Concurrent Game Structure (CGS for short) over* Ap *and* Ag *is a tuple* $\mathcal{G} = \langle Q, q_I, Act, P, T, \mathcal{L} \rangle$ *where:*

- *Q is a non-empty finite set of states and q_I is a distinguished state dubbed initial state;*
- *Act is a finite non-empty set of actions. We let J denote the set of functions from Ag to Act, we call elements of this set* joint actions, *and we use bold small case letters $\mathbf{a}, \mathbf{b}, \mathbf{c}, \ldots$ to range over them;*
- *$P : Q \times \mathsf{Ag} \to (2^{Act} \smallsetminus \varnothing)$ is the protocol function, assigning to each pair $\langle q, i \rangle$ composed of one state and one agent a non-empty set of actions. These represent the action available to the agent i at the state q.*
- *$T : Q \times J \to Q$ is the (partial) transition function. Such a function associates to any state q and joint action $\mathbf{a}$ such that $\mathbf{a}(i) \in P(q, i)$ for all $i \in \mathsf{Ag}$, a state $q' = T(q, \mathbf{a})$.*
- *Finally, $\mathcal{L} : Q \to 2^{\mathsf{Ap}}$ is the labeling function, which assign to any state q a (possibly empty) subset of Ap.*

Given a CGS $\mathcal{G}$ a **path** is an infinite sequence of states of the CGS, $\pi = \pi_1, \pi_2, \ldots$ for which the following holds: for any $i \in \mathbb{N}^+$ there is a joint action $\mathbf{a} \in J$ such that $\pi_{i+1} = T(\pi_i, \mathbf{a})$. We will denote paths by the letters π, ρ, τ, and λ. If π is a path, then $\pi_{\leq i}$ denotes the finite prefix of π, $\pi_{\leq i} = \pi_1, \ldots, \pi_{\leq i}$. A finite sequence of states h is a **history** iff there is a path π such that $h = \pi_{\leq i}$ for some positive natural number i. We will denote by H the set of all histories over a given model $\mathcal{G}$, and if h is a history, then $last(h)$ denotes its last element. Given a state q of the model $\mathcal{G}$, we denote by $J(q)$ the set of joint actions that defines a transition from q, that is $J(q) = \{ \mathbf{a} \in J \mid T(q, \mathbf{a}) = q'$ for some $q' \in Q \}$. If A is a coalition, (a subset of agents) a A-action available at q is a function $f : A \to Act$ such that $f(i) \in P(q, i)$ for each $i \in A$. If f and g are actions available at q for the coalitions A and B we say that g **extends** f, if $A \subseteq B$ and $f(i) = g(i)$ for each $i \in A$. We write $f \leq g$ if g extends f. $F(A, q)$ denotes the set of A-actions available at q and $F(A, \mathcal{G})$ is $\bigcup_{q \in Q} F(A, q)$.

Definition 2 (Strategy). *Given a CGS $\mathcal{G}$ and a coalition A, a strategy for A (or simply A-strategy) is a function $\Sigma : H \to Act$ that maps each history h to an A-action f such that $f \in F(A, last(h))$. An A-strategy Σ is memoryless if $h = h'$ implies $\Sigma(h) = \Sigma(h')$ for every pair of histories h and h'.*

As usual, we can see a memoryless strategy for an agent as a function whose domain is the set of states of the CGS and whose co-domain is the set of agents actions. A path π is compatible with A-strategy Σ for the coalition A (Σ compatible for short) iff for every $i \geq 1$, we have that $\pi_{i+1} = T(\pi_i, \mathbf{a})$ implies $\Sigma(\pi_{\leq i}) \leq \mathbf{a}$. We denote with $\mathsf{Out}(\Sigma, q)$ the set of all Σ-compatible paths whose first state is q.

4.1. The Game Model

To define our multi-agent game, we need to represent emotions as discrete values. To this aim, we mention the Plutchik's Model [31], that consists of eight primary emotions, arranged in a

circular pattern, and various combinations and intensities of these primary emotions result in a wide range of complex emotion. For this work, it is enough to consider the set of the eight primary emotions, namely: *Joy Sadness, Anger, Fear, Trust, Disgust, Surprise, Anticipation*. To simplify our model we assume that for each of the participant i of our game, there is an atomic proposition p_i for each primitive emotion considered. The intended meaning of p_i is "the agent i feels the emotion p". More formally, if E is the set of emotions and Ag is the set of agents, then

$$\mathsf{Ap}^E = \bigcup_{i \in \mathsf{Ag}} \{p_i \mid p \in E\}$$

We here define our Game Model as a CGS over Ap^E and Ag having the following characteristics.

States : A state of our model will be a description of the emotions that each of the agents feels at a given moment of a conversational exchange. More precisely, a state will be identified with a set of atomic propositions containing exactly one atomic proposition p_i for each agent i. Thus, if $|E|$ is the cardinality of the set of emotions and $|\mathsf{Ag}|$ is those of Ag, then $|Q| = |E|^{|\mathsf{Ag}|}$

Actions : An action will be identified with a message that one of the player can send to another player.

Labeling : the labeling function will be simply the identity function on each state. This definition makes sense since each state of the model is a subset of Ap^E.

4.2. A 2agents-2emotions example

To enhance the understanding of our approach, we provide a minimal toy example. Let's assume that our set of agents consists solely of Bob and Alice. Furthermore, let's assume that the set of emotions E is $\{fear, joy\}$, and that our set of actions is $\{m_1, m_2\}$. Let's assume that the content of m_1 brings joy to its recipient, and conversely, let's assume that the content of m_2 makes its recipient feel fearful. A concurrent game structure specifying a possible communication pattern between Alice and Bob and the evolution of their emotional state is showed in Figure 1. In the figure, in a tuple $\langle x, y \rangle$ labeling an edge from one state to another, the first component represents the output of the joint action for Alice, while the second represent the output of the joint action for Bob. The protocol function can be easily retrieved. The intended meaning of a joint action $\langle m_i, m_j \rangle$ starting from a certain state s is "Alice sends the message m_i to Bob, and Bob sends the message m_j to Alice". According to our assumption that m_1 brings joy to his (or her) receiver and that m_2 makes its recipient fear fearful, if e.g., from a state s in which Alice is fearful and Bob is joyful, both Alice and Bob send m_1 to each other, they will arrive at a dialogue state in which Alice became joyful and Bob stays joyful[1].

5. ATL

The advantage of modeling a communicative exchange between agents through a CGS is that we can use Alternate-timeTemporal Logic [4] to reason about the conversation goals of the

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[1]In our model, we have omitted some possible transitions, for example, $T(\{f_A, j_B\}, \langle m_2, m_1 \rangle) = \{j_A, f_B\}$, to make it more understandable
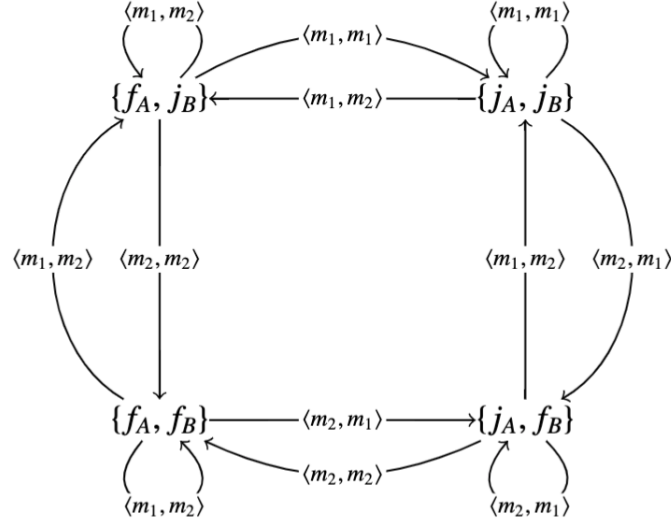
Figure 1: Example of the game structure

agents themselves. We briefly introduce the syntax and semantics of this logic.

The set of ATL formulae is specified inductively by the following grammar:

$$\varphi ::= p \mid \top \mid \neg\varphi \mid \varphi \wedge \varphi \mid \langle\!\langle A \rangle\!\rangle \mathsf{X}\,\varphi \mid \langle\!\langle A \rangle\!\rangle(\varphi\,\mathsf{U}\,\varphi) \mid \langle\!\langle A \rangle\!\rangle(\varphi\,\mathsf{R}\,\varphi)$$

where p is any atomic proposition and A is any subset of Ag. We define $\langle\!\langle A \rangle\!\rangle \mathsf{F}\,\varphi$ as $\langle\!\langle A \rangle\!\rangle(\top\,\mathsf{U}\,\varphi)$ and $\langle\!\langle A \rangle\!\rangle \mathsf{G}\,\varphi$ as $\langle\!\langle A \rangle\!\rangle(\neg\top\,\mathsf{R}\,\varphi)$.

The satisfaction relation $\mathcal{G}, q \vDash \varphi$ is inductively defined on the structure of φ by the following clauses:

- $\mathcal{G}, q \vDash p$ iff $p \in \mathcal{L}(q)$
- $\mathcal{G}, q \vDash \langle\!\langle A \rangle\!\rangle \mathsf{X}\,\varphi_1$ iff there is an A-strategy Σ such that $\mathcal{G}, \pi_2 \vDash \varphi_1$ for each $\pi \in \mathsf{Out}(\Sigma, q)$;
- $\mathcal{G}, q \vDash \langle\!\langle A \rangle\!\rangle(\varphi_1\,\mathsf{U}\,\varphi_2)$ iff there is an A-strategy Σ such that for every $\pi \in \mathsf{Out}(\Sigma, q)$ there is a $j \geq 1$ such that $\mathcal{G}, \pi_j \vDash \varphi_2$ and $\mathcal{G}, \pi_i \vDash \varphi_1$ for each $1 \leq i < j$;
- $\mathcal{G}, q \vDash \langle\!\langle A \rangle\!\rangle(\varphi_1\,\mathsf{R}\,\varphi_2)$ iff there is an A-strategy Σ such that for every $\pi \in \mathsf{Out}(\Sigma, q)$ either there is a $j \geq 1$ such that $\mathcal{G}, \pi_j \vDash \varphi_1$ and $\mathcal{G}, \pi_i \vDash \varphi_2$ for each $1 \leq i \leq j$ or $\mathcal{G}, \pi_i \vDash \varphi_2$ for every $i \geq 1$.

The clauses for the boolean connectives are immediate and thus omitted.

Using ATL formulas, we can reason about the objectives of the agents in our communication games. For instance, In the example of Figure 1, we can express the fact that, by cooperating, Alice and Bob can reach a state in which Alice is joyful i.e., $\langle\!\langle \{Alice, Bob\} \rangle\!\rangle \mathsf{F}\,j_A$ or that Bob can always keep Alice in a state of fear $\langle\!\langle \{Bob\} \rangle\!\rangle \mathsf{G}\,f_A$.

6. Conclusion

In this paper, we have defined a conversational game between multiple agents in which their emotional state evolves according to message exchange among them.

Our modeling is basic and relies on strong assumptions. For instance, we assume precise knowledge of an agent's emotional state and treat emotions as binary. These assumptions can be relaxed for a more realistic approach. We could consider emotions as fuzzy and message exchanges as probabilistic, leading to a variant of ATL logic. This variant could address questions like, "Can coalition A, with a probability exceeding X, reach a state where player Y is at happiness level Z?". This work provides an overview of a long-term project, whose main characters are sentiment analysis and strategic reasoning. Indeed, we plan to keep following this research line, by relaxing the assumption made in this work, and by letting the model more realistic with the introduction of fuzziness aspects.

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