Deducing a Believable Model for Affective Behavior from Perceived Emotional Data

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Abstract. Recently, there has been considerable interest in building lifelike computer systems that manage a believable model for affective behavior. In this paper, we investigate an approach to deducing a probabilistic model for affective behavior from perceived emotional data that can be facilitated to build such systems. In addition, we discuss the obtained results and show potential opportunities for future work.

1 Introduction

Recently, there has been considerable interest in implementing believable computer agents that have ”personality” and ”emotions” and can handle the surrounding environment corresponding to emotions they ”feel”. Indeed, humanity develops a powerful desire to own technical artifacts that provide not only necessary functions, but also something beyond it, the ability to ”understand” human intelligence. Such artifacts behave adequately to human actions, as well as comprehend and experience emotions. Humans are more eager to communicate with such agents since the communication with them is very much similar to that with a human.

Different sciences investigate emotions [6]. Psychology studies emotions as its major research topic [1], [3], [8], [10] and develops computer systems based on proposed theories [4]. Sociology investigates how emotions are influenced by society [14].

Computer science provides a basis for implementing emotional software systems and develops corresponding computer models [11]. Castellano and Mancini [5] describe a system working with the video information that processes information related to the expressivity of human movement establishing corresponding affective responses. Expressivity is modelled as a set of parameters that affect the gesture, quality of execution, speed of arms / head etc. Mairesse and Walker [9] describe a computer system that analyzes texts according to the personality of the speaker using the Big Five model (Extraversion vs. Introversion, Emotional stability vs. Neuroticism, Agreeableness vs. Disagreeable, Conscientiousness vs. Unconscientious, Openness to experience).

In this paper, we concentrate on acquiring a model for affective behavior from perceived data. Thereby, we compose a probabilistic model and describe an approach to populate it with data. Finally, we explain why the yielded model can be considered to be comprehensible using the commonsense knowledge and discuss possibilities for future work.

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2 Corpus

In our study, we build a model for affective behavior for the characters in the SAL corpus [7]. SAL is a set of affective dialogues presenting four psychologically different characters: optimistic and outgoing (Poppy), confrontational and argumentative (Spike), pragmatic and practical (Prudence), depressing and gloomy (Obadiah) that try to draw the user into their own emotional state. The corpus consists of at most 27 dialogues annotated by four critics *dr*, *em*, *jd*, *cc* with FEELTRACE data [12]: 27 dialogues (672 turns annotated by critics *dr*, *em*, *jd*), 23 dialogues (569 turns annotated by critic *cc*). In this study, the FEELTRACE annotation supplied as numerical data is mapped onto affect segments (Figure 1).

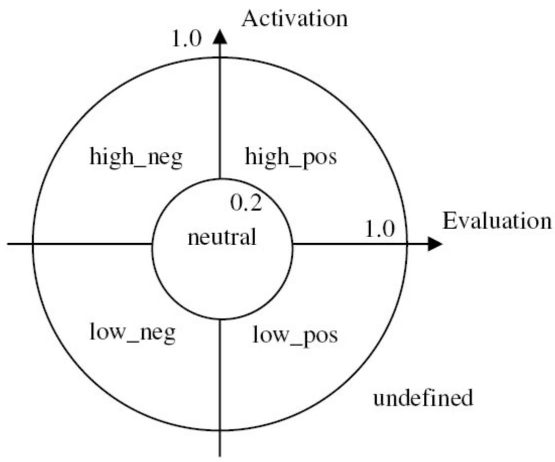

Figure 1. Affect segmentation in the E/A space

Figure 1 shows the chosen affect segmentation in Osgood’s Evaluation/Activation space. The final affect segment of a turn corresponds to the vote of the majority of the annotators at its end. Hence, 35 out of 672 turns are discarded due to the missing agreement between annotators. For remaining 637 turns, a majority vote could be obtained yielding the following counts: 182 turns are annotated as *high_neg*, 112 turns as *low_neg*, 139 turns as *neutral*, 24 turns as *low_pos*, 180 turns as *high_pos*. The inter-annotator agreement value yields the value, 94.79%.

Figure 2 shows an example dialogue from SAL. The affect segment as calculated using the segmentation in Figure 1 is shown in square brackets.

...
[1 - low_pos] Well, I can see that, but you're a very gloomy character.
[2 - neutral] Erm, that's possible. Why don't you lighten up?
[3 - low_neg Well that's true too, but if you dwell on that your not gonna get by life in a very (laugh) positive frame of mind.
[4 - neutral] Sometimes it does, that's true.
[5 - low_pos] Erm, I guess it changes over time, you have ... good days and you have bad days.
[6 - neutral] Erm, well, you just happen to have caught me on a good day.
...

Figure 2. A dialogue from SAL

We map turns in SAL dialogues onto affect segments using the affect segmentation in Figure 1. In order to get evidence that this segmentation can be used for further experiments we assess it using distributions of affect segments in dialogue turns (Table 1).

Table 1. Distribution of affect segments in dialogue turns for different characters

Character	*Turns #*	*Distribution*
Poppy	176	*high_neg*: 20, *low_neg*: 11, *neutral*: 30, *low_pos*: 7, *high_pos*: 108
Spike	169	*high_neg*: 103, *low_neg*: 14, *neutral*: 24, *low_pos*: 1, *high_pos*: 27
Prudence	169	*high_neg*: 41, *low_neg*: 36, *neutral*: 46, *low_pos*: 6, *high_pos*: 40
Obadiah	112	*high_neg*: 9, *low_neg*: 51, *neutral*: 29, *low_pos*: 12, *high_pos*: 11

Table 1 shows in column *Character* the name of a SAL character that took part in a dialogue with the user, the column *Turns #* contains the numbers of turns as annotated by the majority of annotators at the end of a turn, column *Distribution* shows the corresponding distribution of affect segments using the counts of dialogue turns.

Table 1 confirms the psychological characteristics of the SAL characters. Hence, in dialogues with "optimistic and outgoing" (Poppy) the highest number (108 turns) is annotated as *high_pos*, with "confrontational and argumentative" (Spike) the highest number 103 turns is labeled as *high_neg*, dialogues with "pragmatic and practical" (Prudence) have the almost uniform distribution of all affect segments, dialogues with depressing and gloomy (Obadiah) have a noticeably high number of negative turns (turns annotated as low or high negative *low_neg*, *high_neg*).

3 Proposed Approach

In our study, we use a probabilistic model for affective behavior in [11]. This model is a HMM, a complete graph containing three affect states that are connected using probability transitions. The HMM can be extended using the baseline or neutral state of "no emotion" (Figure 3).

Figure 3 shows a HMM containing three affect states (*Interest*, *Joy*, *Distress*). The *Pr* arrows describe the probability of transition between two affect states where the letters in transition labels stand for the beginning letter in the name of the corresponding affect state.

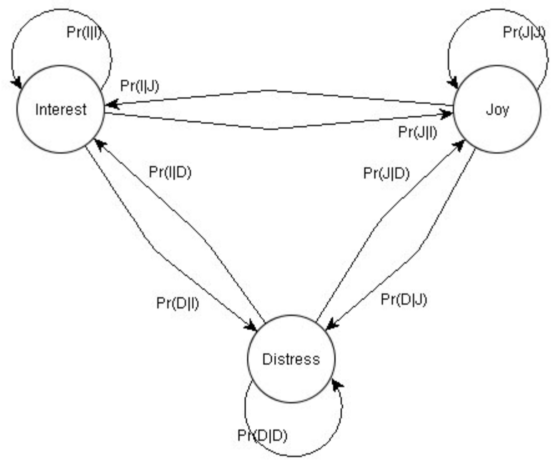

Figure 3. A HMM for affective behavior

For instance, *Pr(D|I)* specifies the conditional probability of the transition from the ***Interest*** affect state to the ***Distress*** affect state.

We apply the proposed HMM approach to the SAL corpus and compose the emotional HMMs for every SAL character consisting of five affect states that correspond to affect segments in Figure 1. Thereby, we generalize the humanly comprehensible states in Picard's HMMs to more generic states given in terms of the evaluation and the activation, for instance, the *Interest* state can be interpreted as a state with the low activation and the positive evaluation, the *Joy* state as a state with the high activation and the positive evaluation, and the *Distress* state as a state with the high activation and the negative evaluation. Thus, the resulting HMMs contain states *high_neg*, *high_pos*, *low_neg*, *low_pos*, *neutral*. The transition arcs are initialized with the transition value, 0.2, a value corresponding to the transition by chance.

We train the affect HMMs using the Baum-Welch algorithm by utilizing the training sequences composed from each of 27 SAL dialogues. For instance, we extract the training sequence corresponding to the dialogue with depressing and gloomy Obadiah in Figure 2 yielding a training sequence *low_pos neutral low_neg neutral low_pos neutral* that results from the first, second, ... sixth turn in the dialogue. The Baum-Welch algorithm is based on an iterative procedure that maximizes the probability of a given state sequence by adjusting the corresponding probability transitions. For a detailed description of HMMs see [13].

Figure 4 shows the HMMs trained using the dialogues with the SAL characters. The HMMs contain five emotional states (*high_pos*, *low_pos*, *high_neg*, *low_neg*, *neutral*) connected with arcs characterizing probabilities of emotional transitions. For better readability, the arcs weighted with the probability less than 0.01 are omitted.

Since the SAL characters are psychologically different characters, dialogues with them are expected to be reflected in the composed HMMs. Hence, in Figure 4(a) standing for dialogues with the optimistic and outgoing Poppy the *high_pos-high_pos* transition has the highest probability, 94.21% and the *low_neg-neutral* transition the value, 79.9%. Figure 4(b) shows a HMM for dialogues with the confrontational and argumentative Spike where the probability of the *high_neg-high_neg* transition is 97.04%, the *low_pos-high_pos* transition probability value, 100%. The HMM in Figure 4(d) with depress-

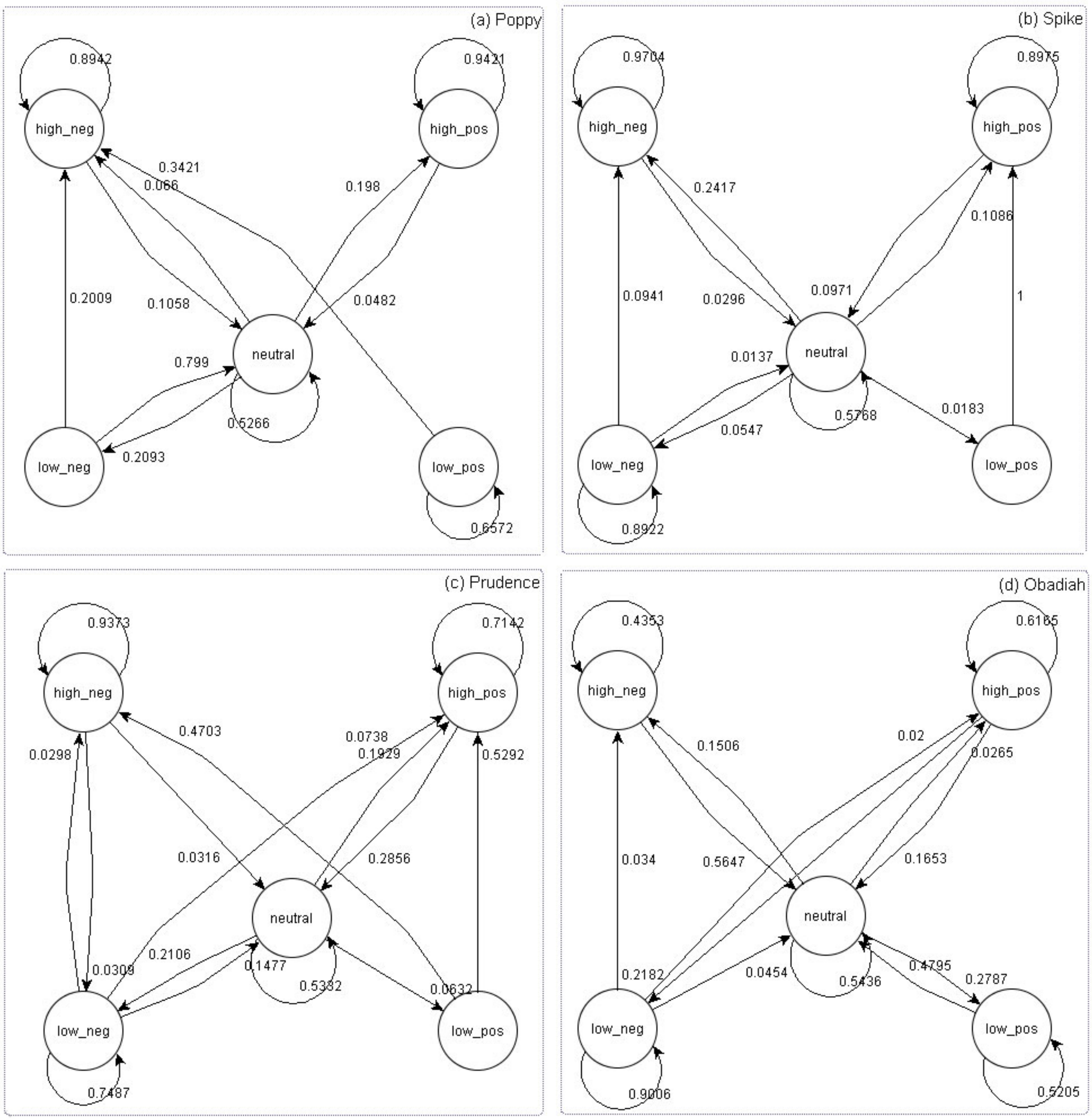

Figure 4. HMMs for dialogues with the SAL characters

ing and gloomy Obadiah indicates a passive behaviour with relative low transition probabilities: the *high_pos-high_pos* transition has the low 61.65% probability and the HMM in the *high_pos* state can transit either to the *low_neg* state with the 21.82% probability or to the neutral state with the 16.53% probability, the *high_neg-neutral* transition has the 56.47% probability, the highest *low_neg-low_neg* transition is 90.06%.

However, dialogues with pragmatic and practical Prudence yield a HMM in Figure 4(c) with at first unforeseeable probabilities: the *high_pos-high_pos* transition probability is 71.42%, the probability of the *high_neg-high_neg* transition is 93.73%, the *low_neg-low_neg* transition is 74.87%. Such transitions are unexplainable: the probabilities are unexpectedly high and are attributed to the small size of the SAL corpus.

Moreover, to facilitate comparison between the yielded HMMs, we represent them as the adjacency matrices (Table 2).

The numbers in Table 2 show the probabilities of transitions between affect states in the corresponding SAL character. For instance, the probability of transition between the *neutral* and the *neutral* state in Spike is 0.5768.

Table 2. Adjacency matrices for different characters

Poppy (Optimistic and outgoing)

	neutral	*high_pos*	*high_neg*	*low_pos*	*low_neg*
neutral	0.5266	0.198	0.0661	0	0.2093
high_pos	0.0482	0.9421	0	0.0097	0
high_neg	0.1058	0	0.8942	0	0
low_pos	0.0007	0	0.3421	0.6572	0
low_neg	0.799	0	0.2009	0	0

Spike (Confrontational and argumentive)

	neutral	*high_pos*	*high_neg*	*low_pos*	*low_neg*
neutral	0.5768	0.1086	0.2417	0.0183	0.0547
high_pos	0.0971	0.8975	0.0054	0	0
high_neg	0.0296	0	0.9704	0	0
low_pos	0	1	0	0	0
low_neg	0.0137	0	0.0941	0	0.8922

Prudence (Pragmatic and practical)

	neutral	*high_pos*	*high_neg*	*low_pos*	*low_neg*
neutral	0.5332	0.1929	0.0001	0.0632	0.2106
high_pos	0.2856	0.7142	0	0.0002	0
high_neg	0.0316	0.0001	0.9373	0	0.0309
low_pos	0.0005	0.5292	0.4703	0	0
low_neg	0.1477	0.0738	0.0298	0	0.7487

Obadiah (Depressing and gloomy))

	neutral	*high_pos*	*high_neg*	*low_pos*	*low_neg*
neutral	0.5436	0.0265	0.1506	0.2787	0.0006
high_pos	0.1653	0.6165	0	0	0.2182
high_neg	0.5647	0	0.4353	0	0
low_pos	0.4795	0	0	0.5205	0
low_neg	0.0454	0.02	0.034	0	0.9006

4 Discussion & Future Work

In this paper, we investigated an approach to deducing a believable probabilistic model for affective behavior from perceived emotional data and showed an approach for building models for psychologically different characters. Moreover, we argued their comprehensibility using the commonsense knowledge. In our opinion, the proposed models are easy to manage and, thus, can be facilitated for building lifelike computer systems.

The yielded results show that the SAL characters tend to retain their affect states: the probability of transition in the same state has in most cases the highest value. We attribute this state of affairs to a phenomenon of psychological inertia: the psychological state once changed is not easy to change in future.

We assume that the proposed model can be facilitated to analyse the Big Five personality traits. For instance, the *Extraversion* trait as a property of a labile personality can be estimated as the sum of probabilities of transitions in the high positive state and the high negative state – states supposed to characterize a person readily open to change; the *Emotional stability* trait can be calculated as the sum of probabilities of the transition in the low positive state, the neutral state, and the low negative state – states supposed to characterize a psychologically stable person.

HMMs for affective behavior can be used to build systems that generate emotional dialogues. For instance, the Viterbi algorithm can utilize the HMMs to create a most probable sequence of states that are in case of emotional HMMs affect states. Hence, the model can be facilitated for planning emotional dialogues.

We composed a comprehensible model for affective behavior based on the SAL corpus. However, this state of affairs can be also attributed to the accident since the corpus is very small and contains a limited number of dialogues, i.e. training sequences for the HMMs. In future, we will revise our approach, for instance, we will test it using the Switchboard corpus [2].

The SAL characters try to draw the user in their emotional state that is a reaction defined in the interaction adaption as ”behavioral matching”. Such reaction refers in the case of emotional dialogue analysis to a phenomenon of converging behaviors of dialogue participants. Since in our opinion, behavioral matching can be best studied using the proposed probabilistic model, it will be investigated thoroughly in future.

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