

Justification of Customer Complaints Using Emotional States and Mental Actions

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Abstract

We apply reasoning about mental attributes to process the scenarios of multiagent conflicts. Our approach is illustrated by the domain of complaint analysis: rather advanced methods are required to determine whether complaint is valid or not. We demonstrate that information on mental actions and emotional states of conflicting agents is frequently sufficient to justify a complaint.

Introduction

In the last two decades, the interest to formal modeling of various forms of human reasoning and mental behavior has strongly risen. A series of phenomena in human reasoning have been reflected in such approaches as game theory, reasoning about action and knowledge, nonmonotonic reasoning; these approaches have found applications in autonomous control, economy, finance and legal domains. The algorithms of information extraction that are expected to form an initial knowledge base for further reasoning have undergone dramatic improvement too (Yangarber 2000). However, to create a usable system that is capable of processing (understanding) the scenarios of multiagent interaction, the next level of reasoning about mental attitudes including emotions has to be achieved.

To understand the scenarios of multiagent conflicts, an extensive set of mental entities needs to be formally treated such as *satisfaction, trust, ignorance, deception, promise*. Therefore, the set of basic mental entities of *knowledge and belief, desire and intention* should be extended to adequately represent conflict scenarios (Wooldridge 2000, Oatley and Jenkins 1996). We need to proceed beyond the boundaries of BDI formalism to reason about a wider set of mental entities including emotions.

In this paper we aim to obtain an accurate description of agents' problems, intentions, emotional states and opinions to judge on complaints' validity. To adequately reason about agents' actions in our domains, it is necessary to differentiate mental and physical actions and resultant mental and physical states. It is quite important for the

models of multiagent conflicts that there is a mutual dependence between emotional states and mental actions of agents. In our previous studies we have witnessed a dramatic difference in knowledge representation for the domains of mental and non-mental nature (Galitsky 2003).

In our earlier studies (Galitsky and Pampapathi 2003, Galitsky and Mirkin 2003) we have explored a series of logical means to process customer complaints assuming the ideal natural language information extraction. In these studies we have planned textual complaints to be read and processed by the customer support personnel; the features have been extracted manually and submitted for automatic processing (advice generation). An alternative method of the partial feature extraction from text for submission to the reasoning units has been considered as well.

Designing the user interface to input mental entities

Analyzing the experience of previously designed system for understanding multiagent interaction one can easily come to conclusion the natural language processing unit limits the performance, because the vocabulary the plaintiffs express their problems is rather extensive and their emotional writing is rather hard to understand (even for humans). To develop a feasible complaint processing system, we decided to eliminate the natural language component, even though the mental attitudes and emotional states are tightly linked with natural language and are usually explored within its framework. Instead of natural language processing, we suggest interactive forms that are specially designed to accept mental entities. Such forms are intended as a means to input the multiagent conflict (a typical complaint is a description of interaction between a customer and a company).

Using software forms to plot scenarios which involve multiple agents is a challenging task, at which the users are encouraged to perform the initial information structuring step manually, and to fill in various fields with the parameters which require special representation.

In this study we suggest that world knowledge (which is the background for customers' complaints) is divided

into the domain- or problem-dependent component and the mental component, which is common for an arbitrary domain of multiagent conflict. The latter is worth investing formalization and commonsense reasoning efforts because it is compact and can be reused from domain to domain. We have explored applications of mental reasoning to such domains as constraint satisfaction problem in the environment of conflicting human and automatic agents, training of negotiation and other decision-making skills, rehabilitation of reasoning about mental states (autistic and schizophrenic patients), extraction of the mental behavior patterns from the wireless-based location services data and others. Division of the domain knowledge into domain-specific and mental components has led to successful implementation of reasoning (Galitsky 2003). Our model of mental component includes the basic mental entities of knowledge and intention and the machinery to define arbitrary mental state and action up to emotion in such a basis.

The working hypothesis for the current study is that mental reasoning deployed in multiple domains is adequate to handle the mental component specified in the interactive forms. In the case of complaint forms the mental entities are intended to be indicated explicitly. In this paper we will not present our approach to simulation of mental reasoning (the system NL_MAMS, (Galitsky 2002)); instead, we focus on reasoning about mental actions and the machine learning system Jasmine (Galitsky & Vinogradov 2002) and its version for analysis of the scenarios of multiagent interaction.

Building interactive forms to file complaints

Usually, complaints are filed via the free plain text. Writing a letter, a customer may become very emotional and passionate and base his letter on feelings rather than on logic. It brings in disadvantages both on the customer and company side, because it is harder for a company to evaluate the complaint validity, whereas the customer may lack the solid arguments to bring her point across (compare with Gilbert 1997). Therefore, in spite of being opponents, both customer and company would frequently benefit from more logical and structured complaint that uses conventional argumentation means. Often a complaint contains a description of interactions between the customer and customer service presented in an extremely emotional manner which is hard to evaluate. How to help a customer to build a more valid complaint?

In this paper we suggest the form-guided means to input a complaint. This is the interactive environment that assists a customer in filing a sound complaint, providing the immediate feedback concerning the status of this complaint (justified or unjustified). At the same time, a complaint submitted via form is ready for (usually)

unambiguous processing and quick response from the company.

Note that a non-mental component significantly varies from domain to domain (it is different for banking complaints (Galitsky and Mirkin 2002) and student complaints). The mental component describes mental attitudes and actions of multiagent scenario participants and can be reused from one domain complaint to another. To help a customer to express the mental component of his complaint more precisely, we use the form with the list of pre-selected mental states and actions to select from.

We introduce a complaint from our dataset of students' complaints, together with the detailed analysis of each statement (Table 1). Having read the left column only, the reader may feel that this student was treated badly. As we have observed, the usual impression by such a complaint is feeling sorry for the student. However, we encourage the reader to postpone the final judgment and read columns 2 and 3 carefully. Column 4 comments on the emotions associated with each statement.

The same complaint filed via interactive form is shown on Fig. 1.

Implementation of reasoning

To reason about the mental attitudes of agents which are involved in a multiagent conflict, we intend to use a hybrid system that includes the following units:

- 1) Logic programming implementation of reasoning about mental actions, predicting the opponent actions given the explicitly coded pre-conditions and effect axioms (similar to GOLOG, Levesque et al 1997));
- 2) Multiagent mental simulator NL_MAMS, which yields the consecutive mental states given the initial one, simulating the decision-making process of agents, http://www.dcs.bbk.ac.uk/~galitsky/NL_mams/
- 3) Machine learning system Jasmine capable of matching a current formalized complaint with the dataset of complaints with assigned status.

From now on we use the PROLOG notations; also, note that the software components mentioned above are implemented as logic programs.

As to the approach to reasoning about actions (unit 1), our environment for emotional states as pre-conditions and results of mental actions fits well the framework of reasoning about actions. The majority of opponent's mental actions, specified in Table 2, may effect the emotional *fluent* (using the terminology of situation calculus (McCarthy and Hayes 1969)).

The expression, $do(a,s)$, denotes the successor situation to s after action a is applied. For example, $do(complain(Customer, do(harm(Company), S_0)))$, is a situation expressing the world history that is based on the sequence of actions

$\{complain(Customer), harm(Company)\}$, where *Customer* and *Company* are variables (with explicit meanings).

The situations involve the *fluents*, whose values vary from situation to situation and denote them by predicates with the latter arguments ranging over the situations, for example,

$upset(Customer, do(harm(Company), S_0))$.

Actions have *preconditions* – the constraints on actions:

$poss(complain(Customer), s) \equiv upset(Customer, s)$.

Effect axioms (post-conditions) describe the effect of a given action on the fluents:

$poss(complain(Customer), s) \ \& \ responsive(Company) \supset settle_down(Customer, do(complain(Customer), s))$.

The search space for possible scenarios is dramatically decreased by using pre-conditions and effect axioms. If a particular complaint violates these axioms, we conclude that its status is *unjustified*. The *frame problem* (see e.g. Shanahan 1997) comes into play to reduce the number of effect axioms that do not change (the common sense law of inertia). The successor state axiom resolves the frame problem:

$poss(a,s) \supset [f(\hat{y}, do(a,s)) \equiv \gamma_f^+(\hat{y}, a,s) \vee (f(\hat{y},s) \ \& \ \neg\gamma_f^-(\hat{y}, a,s))]$, where $\gamma_f^+(\hat{y}, a,s)$ ($\gamma_f^-(\hat{y}, a,s)$) is a formula describing under what conditions doing action *a* in situation *s* makes fluent *f* become true (false, respectively) in the successor situation $do(a,s)$.

As an example, let us consider the effect axiom for the important emotional fluent *lost_trust*. A simple case which is implemented via the form (Fig.1) is:

$lost_trust:-remindS, deny_responsibilityT, explainsS, disagreeeT,$

where the first and third actions are student's, and second and forth – tutor's. As to the more complex effect axiom, we analyze the following mental actions and fluents:

$lost_trust(Customer, Fluent, Problem):-$

$ask(Customer, CS,$

$sequenceOfPhysActionsThatFix(Problem, SeqActions),$

$\% \ \% \ SeqActions \text{ is uninstantiated at this point}$

$suggest(CS, SeqActions), believe(Customer,$

$sequenceOfPhysActionsThatFix(Problem,SeqActions),$

$do(Customer, SeqActions),$

$not \ sequenceOfPhysActionsThatFix(Problem,$

$SeqActions), \ \% \ \% \ Problem \text{ has not been resolved}$

$ask(Customer, CS,$

$sequenceOfPhysActionsThatFix(Problem, SeqActions),$

$blame(CS, Customer, do(Customer, SeqActions)).$

The semantics of this clause (in our domain) are as follows: after a student *asks* how to fix a problem and gets *explanation*, he/she follows it and does not fix the problem, because the explanation was irrelevant. Nevertheless, the student is *blamed* by the tutor and finds himself in a situation when fluent *lost_trust* holds.

Student's statement	Relevant information	Analysis and evaluation	Emotional component
We were instructed to map our work onto the network drive	The student misunderstands the concept. It is not the file that is mapped to a drive, a network folder is mapped to a logical disk to save a file.	During the course, it was explained multiple times that submission of results is part of the required skills in computing and will be assessed.	None (at this point)
However, due to technical difficulties everyone on my row was unable to do this	This is a lie (citing "technical" difficulties): almost all other students have successfully submitted their work via the network and none seem now to be in his position.	Argumentation pattern (abduction): <i>others could not do it therefore I am not to be blamed for inability to do this</i> does not increase the complaint validity.	Being frightened to use network
I did not find our results... I waited three months...	This is true, the student did not receive his results. Waited for a reasonable time for a resolution.	Typical argumentation for interaction with a customer support agent. The student claims to have sought a resolution and to have waited some time. Supports claim.	Emotional expression that the expectations (to get the results sooner) did not match the reality
I was horrified to see... I was appalled to be told ...	This is a pure emotion	Emotional note that is intended to support the complaint validity but is ultimately irrelevant.	Pure emotional expression as a response to an emergent unpleasant information
I did the last question which depended on the previous ones...	This is a false statement. The last two questions were independent of the previous ones.	Decreases the complaint validity because of a false statement that is independent of others.	Emotional link between the facts, which are not causally linked.
I have worked extremely hard... Finally by failing this module I would jeopardise my degree...	May be true	Irrelevant	The fact with emotional underline.

Table 1: The student complaint, presented step-by-step, including the relevant background information, analysis and associated emotional states

Interactive form to file student complaint

Your problem in one sentence (or choose from the list)

Your initial request

way of submission

date of submission

essence of request

you that

also, you that

and you that

Your second request/iteration

way of submission

date of submission

essence of request

you that

also, you that

and you that

Initial response you received No response

way of response

date of response

essence of response

your tutor that

also, she/he that

and she/he that

Second response you received No response

way of response

date of response

essence of response

your tutor that

also, she/he that

and she/he that

No response

date of response

essence of response

your tutor that

also, she/he that

and she/he that

No response

date of response

essence of response

your tutor that

also, she/he that

and she/he that

Complaint status Tutor attitude

and I felt 3 I believe that he/she felt

and I felt 6 I thought that he/she felt

and I felt 4 I thought that he/she was

Fig.1: The interactive form for filing the students' complaints. The interactive form is suggested instead of plain text to present a conflict between a student and a tutor. On the left, the student plots her attempts to resolve the conflict, and on the right side the tutor's responses are specified. The soundness (status) of complaint is determined, using analysis of agents' mental states and experience with previous complaints: the system obtains the status of student (below on the left) and tutor (below on the right), given the student's perspective. The highlighted fragment on the bottom-right allows specification of the emotional states of both a student and a tutor (as being perceived by this student). This fragment is specified for each iteration above.

Matching the complaints with the training dataset

In this section we present the third reasoning unit that performs matching of a given complaint with ones with the known justification status. The JSM approach was inspired by the plausible similarity-based reasoning of the philosopher J.S. Mill who has suggested a set of five canons by means of which to analyze and interpret our observations for the purpose of drawing conclusions about the causal relationships they exhibit. Over the last few decades JSM approach has been developed as a practical reasoning system by Finn and his associates (Finn 1999). In this study we use the JSM system as a logic program, called Jasmine

<http://www.dcs.bbk.ac.uk/~galitsky/JaSMine/>, following the formal frameworks of (Anshakov et al 1989 and Vinogradov 1999).

The Jasmine environment consists of objects (scenarios), their features (particular mental actions and emotional states), and targets (resultant features we intend to predict, i.e. complaint justification status). In our language, scenarios are terms that include expressions for mental states and actions. We use metapredicates *mental(Agent, DoWhat)* that range over agents as well as over domain-specific and mental expressions *DoWhat*.

For a target (complaint status) there are four groups of scenarios with respect to the evidence that they lead to this target:

Positive – Negative – Inconsistent - Unknown.

An inference to obtain a target feature (satisfied or not) can be represented as one in a respective four-valued logic (Anshakov et al 1989, Finn 1999). The predictive machinery is based on building the set of hypotheses,

$status(S) :- mental1_s(agent1, P1),$
 $mental2_s(agent2, P2), mental3_s(agent1, P3), \dots$

which separate the scenarios with positive (justified) and negative (unjustified) target (complaint status).

Desired separation of the set of scenarios with unjustified status from unjustified status is based on the *similarity* of scenarios in terms of mental states and actions they consist from. Usually, such similarity is domain-dependent. However, building the general framework of inductive-based prediction, we use the anti-unification of formulas that express the totality of features of the given and other objects (our futures do not have to be unary predicates and are expressed by arbitrary first-order terms). Use of anti-unification (Pfenning 1991) seems to be well-suited for handling formal scenarios where there is a lack of quantitative estimate of similarity between them (the clauses are at http://www.dcs.bbk.ac.uk/~galitsky/JaSMine/anti_unification.ari)

Starting with the positive and negative scenarios, $jPos(S)$ and $jNeg(S)$ we form the totality of intersections for these scenarios. Recursive definitions of intersections are shown below (for positive case):

$iPos(S) :- jPos(X1), jPos(X2), X1 \setminus = X2, similar(X1, X2, S), S \setminus = []$.

$iPos(S) :- iPos(S1), jPos(X1), similar(X1, S1, S), S \setminus = []$.

As the logic program clauses that actually form the totality of intersection of examples, we derive the following (the negative case is analogous, $X1, X2$ range over scenarios):

$iPos(S) :- iPos(S, _)$.

$iPos(S, Accums) :- jPos(X1), jPos(X2), X1 \setminus = X2,$
 $similar(X1, X2, S), Accums = [X1, X2], S \setminus = []$.

$iPos(S, AccumsX1) :- iPos(S1, Accums), !, jPos(X1),$
 $not\ member(X1, Accums), similar(X1, S1, S),$
 $S \setminus = [], append(Accums, [X1], AccumsX1)$.

To obtain the actual positive and negative hypotheses from the respective intersections, we filter out the hypotheses that are satisfied by both positive and negative examples $j0Hyp(S)$:

$j0Hyp(S) :- iPos(S), iNeg(S)$.

$jPosHyp(S) :- iPos(S), not\ j0Hyp(S)$.

$jNegHyp(S) :- iNeg(S), not\ j0Hyp(S)$.

The following clauses deliver the background for (enumeration of scenarios that deliver) positive, negative and inconsistent hypotheses:

$ePos(X) :- jPos(X), jPosHyp(S), similar(X, S, S)$.

$eNeg(X) :- jNeg(X), jNegHyp(S), similar(X, S, S)$.

$j01(X) :- jT0(X), jPosHyp(S1), jNegHyp(S2), similar(X, S1, S1), similar(X, S2, S2)$.

Finally, we approach the clauses for prediction. For the scenarios with unknown status the system predicts that they either similar to the derived set of positive

examples (and therefore is assigned a justified status) or vice versa.

$jPos1(X) :- jT0(X), jPosHyp(S), similar(X, S, S), not\ j01(X)$.

$jNeg1(X) :- jT0(X), jNegHyp(S), similar(X, S, S), not\ j01(X)$.

$jT1(X) :- jT0(X), not\ jPos1(X), not\ jNeg1(X), not\ j01(X)$.

Also, if the scenario with the status to be predicted is similar to both sets of positive and negative examples, or similar to neither sets, then no status assignment can be made (the third case above). In such a case Jasmine tries to achieve a situation when the current scenario is similar to either set by eliminating the existing scenario in its training set that is suspected to deliver contradiction. In case of success the resultant prediction is conditional on the fact that the current scenario is *unlike* (non-similar) to the one that has been eliminated from the training set.

System Evaluation

Immediate determination of the complaint status is the essential interactivity feature of the complaint form. If, having the form completed, a student obtains the complaint status *unjustified*, then he/she would be inclined to modify the complaint to make it more convincing (and to save the time and passion of a tutor who would otherwise deny an unjustified complaint). To back up their argumentation and to turn a complaint into more sound one, a student would prefer the interactive form to check whether the status is *justified*.

The presented system is currently used in the undergraduate course "Introduction to Computing", www.dcs.bbk.ac.uk/~galitsky/outline.htm, allowing the students to provide a feedback (to complain) concerning the course. Frequently, student complaints describe interaction with the tutor concerning course operation or inadequate marking. Before the deployment, we introduced the initial dataset of 75 "artificial" complaints and assigned "justified" status to 47 of them. It has been verified that the initial dataset did not contain inconsistencies: if for a representative complaint its status is set as "unknown", prediction either delivers the correct or keeps the "unknown" status, but not a wrong one. Then, after the course have been taught, 14 students used the form explicitly instead of filing textual complaints, and for other 18 complaints we manually represented their written complaint scenarios via form and used it as an additional ("experimental") part of the training dataset. Most of these complaints raised the issues of inadequate marking and contain the description of dispute resolution scenarios which involve the students and the tutor (the first author of this paper).

11 out of 14 complaint were assigned the correct status (the same that was assigned by another course tutor who served as an expert). In 12 complaints (including 10 properly recognized) out of 14, emotional

states were specified. Deploying the complaint interactive forms in other courses, we expect to significantly increase the volume of our evaluation dataset.

As to related works, we mentioned that we have not found computational studies of complaint processing, so we do not present the comparative analysis of recognition accuracy of competitive approaches. We believe that processing of complaints is a novel yet quite appealing domain for AI because it requires the original approaches to reasoning about mental attitudes and actions, machine learning and information retrieval.

Conclusions

There has been a strong interest to computational issues of emotions over the last decade. A series of studies have addressed reasoning about emotional and mental states, building emotion-enabled automated agents, emotion recognition from text, facial image and speech. Emotions are considered as an important component of intelligence and its models which involve the mental world.

The universal formal model of emotion is one of the most difficult problems on the way to build an automated agent that demonstrates the behavior, perceived by humans as emotional one (El-Nasr and Skubic 1998, Sloman 1999). In this paper we do not target the construction of a computational model for emotional behavior that is adequate. Instead, we chose the class of practical problems where the emotions play a specific role. In this study we pose the problem of using the sequence of emotional states to improve the accuracy of extraction of information on multiagent conflict.

Analyzing the performance of our reasoning units, we came to the following conclusions:

- 1) NL_MAMS 's contribution to filtering out the implausible scenarios was least significant.
- 2) Reasoning about action unit filtered out the implausible scenarios; less than 20 percent of *unjustified* complaints were assigned by this unit taking into account axioms and not matching with the cases of our training dataset.
- 3) Machine learning unit's contribution was the highest.

When we started our project on processing customers' complaints a few years ago, we were initially impressed that emotions made it hard to judge on the complaint validity. We have also observed that the emotional component is frequently used by the complaint author to substitute for a lack of proper argumentation or a limited familiarity with the domain. However, after we have performed the machine learning presented above, we came to conclusions that emotions are strongly correlated with the complaint justification status as we

define it. Therefore, emotional states are in use together with the mental actions in the procedure of complaint understanding.

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