Learning Common Outcomes of Communicative Actions Represented by Labeled Graphs

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Abstract. We build a generic methodology based on learning and reasoning to detect specific attitudes of human agents and patterns of their interactions. Human attitudes are determined in terms of communicative actions of agents; models of machine learning are used when it is rather hard to identify attitudes in a rule-based form directly. We employ scenario knowledge representation and learning techniques in such problems as predicting an outcome of international conflicts, assessment of an attitude of a security clearance candidate, mining emails for suspicious emotional profiles, mining wireless location data for suspicious behavior, and classification of textual customer complaints. A preliminary performance estimate evaluation is conducted in the above domains. Successful use of the proposed methodology in rather distinct domains shows its adequacy for mining human attitude-related data in a wide range of applications.

1 Introduction: Reasoning with Conflict Scenarios

Scenarios of interaction between agents are an important subject of study in AI. An extensive body of literature addresses the problem of logical simulation of behavior of autonomous agents and assistants, taking into account their beliefs, desires and intentions [5,15]. A substantial advancement has been achieved in building the scenarios of multiagent interaction, given properties of agent including their attitudes. Recent work in agent communications has been in argumentation [3], in dialog games [1,2], in formal models of dialog [9], in conversation policies [11], in social semantics [12] and in collaborative learning [4]. In terms of temporal conceptual semantic system [14] interaction between agents can be considered as a life track of a temporal system consisting of agents.

However, means of automated comparative analysis for interaction scenarios for *human* agents are still lacking. The comparative analysis of interaction scenarios between human agents for automated decision making, decision support and recommendations is needed in many applications. In this paper we build a representation machinery and continue our development of a machine learning technique [7,10] towards operating with a *wide range of scenarios* which include a sequence of

U. Priss, S. Polovina, and R. Hill (Eds.): ICCS 2007, LNAI 4604, pp. 387–400, 2007.

communicative actions. We also propose a framework for classifying scenarios of inter-human conflicts and prediction of their outcomes. Formalized inter-human conflict is a special case of formal scenario where the agents have inconsistent and dynamic goals; a negotiation procedure is required to achieve a compromise. In this paper we explore a series of domains of various natures with respect to how the structure of conflict resolution and negotiation can be visually represented and automatically learned within a unified framework. We follow along the line of our previous studies demonstrating that it is possible to judge about consistency of these scenarios based on the extracted communicative actions [7].

The paper is organized as follows. The introduction of the domain of conflict scenarios is followed by a formal treatment of communicative actions, defining a conflict scenario as a graph, and machine learning of such graphs. We then present our domains and give respective examples of a variety of graphs consisting from communicative actions. The paper is concluded with comparative analysis of graph learning results in these domains.

2 Formalizing Conflict Scenarios for Learning

In this section we present our model of multiagent scenarios oriented to the use in a machine learning setting. Here we develop a knowledge representation methodology based on approximation of a natural language description of a conflict (Galitsky 2003). Further details are available online in the full version of the paper [8].

To form a data structure for machine learning, we approximate an inter-human interaction scenario as a sequence of communicative actions, ordered in time, with a causal relation between certain communicative actions (more precisely, the *subjects* of these actions). Scenarios are simplified to allow for effective matching by means of graphs: only communicative actions remain as a most important component to reflect the dialogue structure and express similarities between scenarios. Each vertex corresponds to a communicative action, which is performed by either *proponent*, or *opponent*. An arc (oriented edge) denotes a sequence of two actions.

In our model mental actions have two parameters: *agent name* and *subject* (information transmitted, a cause addressed, a reason explained, an object described, etc.). Representing scenarios as graphs, we take into account both parameters. Arc types bear information whether the subject stays the same. Thick arcs link vertices that correspond to communicative actions with the same subject; thin arcs link vertices that correspond to communicative actions with different subject. The curve arcs denote a causal link between the arguments of mental actions, e.g., [*ask*]- *the service is not as advertised* $\Rightarrow$ [*disagree*]- *failures in the service contract* (and, therefore, *the service is not as advertised*). Let us consider an example of a scenario and its graph (Figure 1). Further examples are available in the extended version of this paper [8].

One of the most important tasks in assisting negotiations and resolving inter-human conflicts is the *validity* assessment. A scenario (in particular, a complaint) is *valid* if it is plausible, internally consistent, and also consistent with available domain-specific knowledge. In case of inter-human conflicts or negotiations, such domain-specific knowledge is frequently unavailable. In this study we demonstrate that a

- **I asked** why the service was not as advertised
- They **explained** that I did not understand the advertised features properly
- I **disagreed** and **confirmed** the particular failures in a service contract
- They **agreed** with my points and **suggested** compensation
- I **accepted** it and **requested** to send it to my home address together with explanations on how it happened.
- They **promised** to send it to me.
- In a month time I **reminded** them to mail it to me
- After two months I **asked** what happened with my compensation…

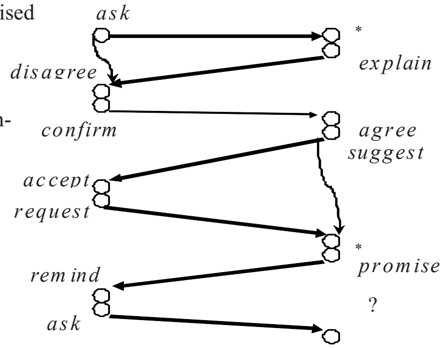


Fig. 1. A sample complaint scenario and its graph representation. * stands for an arbitrary action, ? – the action to be predicted.

scenario can be assigned to a class *valid* or *invalid* based on communicative actions *only* with the accuracy sufficient for deployment in decision-support systems. To provide a framework for learning communicative actions, we need to select their attributes (Figure 2).

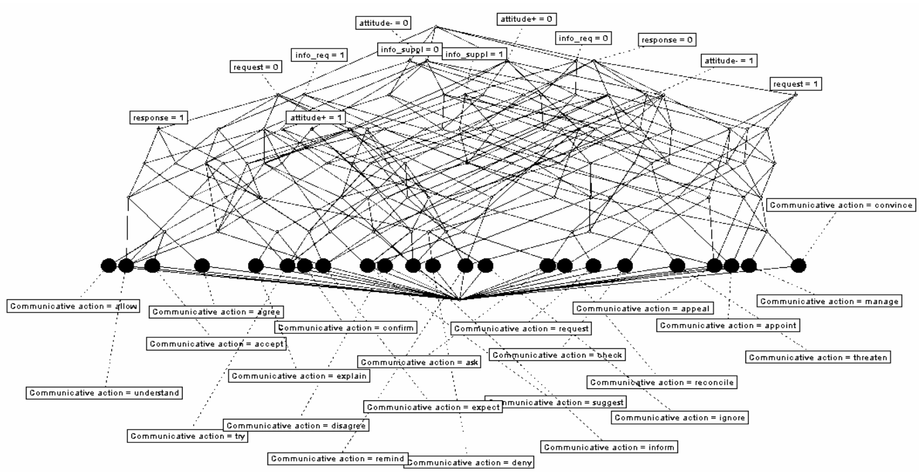


Fig. 2. The concept lattice for communicative actions

Based on the speech act theory, we selected the attributes of communicative actions to provide an adequate coverage of their meanings (further details are in [8]).

3 Defining Scenarios as Graphs

Each scenario includes multiple interaction *steps*, each consisting of mental actions with the alternating first attribute {*request – respond - additional request or other* *follow up*}. A step comprises one or more consequent actions with the same subject. Within a step, vertices for mental actions with common argument are linked with *thick* arcs.

For example, *suggest* from scenario V2 (Figure 3) is linked by a thin arc to mental action *ignore*, whose argument is not logically linked to the argument of *suggest* (the subject of suggestion). The first step of V2 includes *ignore-deny-ignore-threaten*; these mental actions have the same subject (it is not specified in the graph of conflict scenario). The vertices of these mental actions with the same argument are linked by the *thick* arcs. For example, it could be ***ignored** refund because of a wrong mailing address, **deny** the reason that the refund has been ignored* [*because of a wrong mailing address*], ***ignore** the denial* [*…concerning a wrong mailing address*]*, and **threatening** for that ignorant behavior* [*…concerning a wrong mailing address*]. We have *wrong mailing address* as the common subject *S* of mental actions *ignore-deny-ignore-threaten* which we approximate as

ignore(A1, S) & deny(A2,S) & ignore(A1,S) & threaten(A2, S), keeping in mind the scenario graph . In such approximation we write *deny(A2, S)* for the fact that *A2 denied the reason that the refund has been ignored because of S*. Indeed, *ignore(A1, S) & deny(A2,S) & ignore(A1,S) & threaten(A2, S).* Without a scenario graph, the best representation of the above in our language would be

ignore(A1, S) & deny(A2, ignore(A1, S)) & ignore(A1, deny(A2, ignore(A1, S))) & threaten(A2, ignore(A1, deny(A2, ignore(A1, S)))).

Let us enumerate the constraints for the scenario graph:

1) All vertices are fully ordered by the temporal sequence (earlier-later);
2) Each vertex has a special label relating it either to the proponent (drawn on the right side in Figure 3) or to the opponent (drawn on the left side);
3) Vertices denote actions either of the proponent or of the opponent;
4) The arcs of the graph are oriented from earlier vertices to later ones;
5) Thin and thick arcs point from a vertex to the subsequent one in the temporal sequence (from the proponent to the opponent or vice versa);
6) Curly arcs, staying for causal links, argumentative relation or other kind of non-temporal relation, can jump over several vertices.

Similarity between scenarios is defined by means of maximal common sub-scenarios. Since we describe scenarios by means of labeled graphs, first we consider formal definitions of labeled graphs and domination relation on them (see, e.g., [6,10]).

Given ordered set G of graphs (V,E) with vertex- and edge-labels from the sets $(\mathcal{L}_V, \preceq)$ and $(\mathcal{L}_\mathcal{E}, \preceq)$. A labeled graph Γ from G is a quadruple of the form $((V,l),(E,b))$, where V is a set of vertices, E is a set of edges, $l\colon V \to \mathcal{L}_V$ is a function assigning labels to vertices, and $b\colon E \to \mathcal{L}_\mathcal{E}$ is a function assigning labels to edges. We do not distinguish isomorphic graphs with identical labelings.

The order is defined as follows: For two graphs $\Gamma_1 := ((V_1,l_1),(E_1,b_1))$ and $\Gamma_2 := ((V_2,l_2),(E_2,b_2))$ from G we say that Γ_1 **dominates** Γ_2 or $\Gamma_2 \leq \Gamma_1$ (or Γ_2 is a **subgraph** of Γ_1) if there exists a one-to-one mapping $\varphi\colon V_2 \to V_1$ such that it

- respects edges: $(v,w) \in E_2 \Rightarrow (\varphi(v), \varphi(w)) \in E_1$,
- fits under labels: $l_2(v) \preceq l_1(\varphi(v)), (v,w) \in E_2 \Rightarrow b_2(v,w) \preceq b_1(\varphi(v), \varphi(w))$.

Note that this definition allows generalization ("weakening") of labels of matched vertices when passing from the "larger" graph G_1 to "smaller" graph G_2.

Now, generalization Z of a pair of scenario graphs X and Y (or their similarity), denoted by X ∏ Y = Z, is the set of all inclusion-maximal (in terms of relation $\preceq$) common subgraphs of X and Y, each of them satisfying the following additional conditions:

- To be matched, two vertices from graphs X and Y must denote mental actions of the same agent;
- Each common subgraph from Z contains at least one thick arc.

This definition is easily extended to finding generalizations of several graphs (e.g., see [6, 10]). We denote X $\sqsubseteq$ Y if X ∏ Y = {X}.

4 Nearest-Neighbor Classification

The following conditions hold when a scenario graph U is assigned to a class (we consider positive classification, i.e., to valid complaints, the classification to invalid complaints is made similarly):

1) U is similar to (has a nonempty common scenario subgraph of) a positive example R^+. It is possible that the same graph has also a nonempty common scenario subgraph with a negative example R^- . This means that the graph is similar to both positive and negative examples.

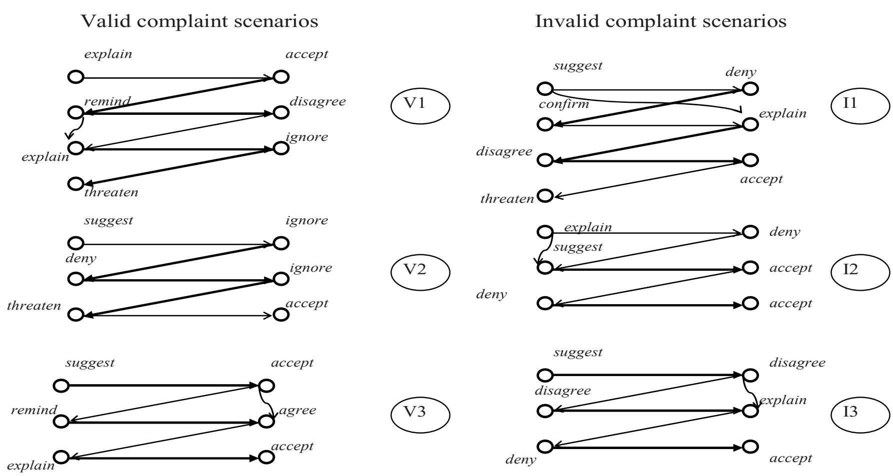


Fig. 3. A scenario with unassigned complaint status and the procedure of relating this scenario to a class

2) For any negative example R^-, if U is similar to R^- (i.e., $U \sqcap R^- \neq \emptyset$) then $U \sqcap R^- \sqsubseteq U \sqcap R^+$. This condition introduces the measure of similarity and says that to be assigned to a class, the similarity between the unknown graph U and the closest (in terms of $\sqsubseteq$) scenario from the positive class should be higher than the similarity between U and each negative example (i.e., representative of the class of invalid complaints).

5 Supporting Scenarios of Security Clearance Assessment

It is well known that assessment of mental attitude of a security clearance candidate is an important feature which is worth developing and automation. Obviously, there is some correlation between basic parameters of candidates such as bad habits, problematic career history, distrustful relationships, education failures etc. and skills/capabilities required to obtain a security clearance. However, there is no direct link between these parameters and a mental attitude of candidates; and the role of the latter is crucial to clearance-related decisions. Therefore, assessment of mental attitude, which is independent of the history of candidate career and personal life, is desirable for the purpose of the clearance-related decision.

In accordance to psychological studies, **inter-personal conflicts** may serve as an adequate means to assess such personal qualities of individuals as their mental attitudes. In the course of conflict, an individual with proper mental attitude is expected to demonstrate a stable and clear desire to resolve the conflict, cooperation with opponents and other involved parties when/if their actions are intended to assist conflict resolution, treating involved parties honestly and with respect. A candidate will show a stable emotional profile in the course of conflict resolution: absence of being depressed, absence of give up – type of mood, strong belief in a successful/fair conflict resolution result and an attempt to find her/his own active role in conflict resolution. Also, this candidate will provide consistent, concise, and valid argumentation for the candidate's own position. All statements concerning the untruthful/invalid behavior of opponents should be backed up. A successful candidate is expected to describe the history of conflict, display the objectivity, and fairness with respect to opponents.

Hence we propose *an artificial conflict resolution environment* which would assist in the assessment of mental attitudes of a candidate which is expected to participate in the conflict resolution procedure. For each candidate, we find some deviation from a norm, which may be minor or irrelevant to a security clearance decision, but serves as a good ground for additional questions. Such deviation may include a driving accident, bank transaction, peculiarities of spending patterns from those in a neighborhood, etc. We are therefore suggesting using likely irrelevant or minor red flags in the context of how a candidate may react to associated conflicts. It is believed to be a more reliable way of clearance assessment then just ignoring such red flags. In the case that exploration of these minor red flags reveals significant deviation from normal mental attitude, a new important component for security assessment will be available.

We outline a possible framework and scenario for the assessment.

A candidate *submits* (requests consideration of) an application for security clearance.

In response the candidate *receives* the following:

"Thank you for applying. We regret to *inform* you that in the course of consideration we have discovered certain circumstances which may negatively impact the decision with regard to the security clearance award. Our concern goes back to your years in college/military service/probation period in a company/performance in a company… which we believe may compromise your eligibility for the security clearance. If you believe we obtain this information in error or believe that it is irrelevant to the decision with regard to the clearance, please *contact* Mr #1 who is your caseworker."

Then the candidate *contacts* the mentioned caseworker with explanations. In *response*, the candidate gets the following letter:

"Thank you for your attempts to clarify the situation and your explanation that the evidence available has been obtained by us in error or irrelevant. However, in accordance to the other case worker, Mr #2 the facts provided by yourself do not fully exclude the possibility that what we have found is not plausible at all. I would encourage yourself to contact Mr #2 and clear this out. In case of positive decision with Mr #2 we will proceed with your case.

The candidate is then expected to contact Mr #2 with *request* for further details about his ambiguous circumstances. Having *received* no definitive response from Mr #2 (being *ignored*), the candidate sends a message to Mr #1 requesting a response from him or Mr #2. Mr #1 comes back to the candidate *claiming* that another piece of evidence has been found that compromises candidate's eligibility to the security clearance.

The candidate is expected to *respond* to Mr #1 with *explanation* and argumentation against the second piece of evidence. Meanwhile, Mr #2 *responds* to the candidate confirming that the candidate's explanation defeating the first piece of evidence has been *accepted* and the respective application unacceptability claim has been *dismissed*. Also, Mr #2 states that he believes that the second piece of evidence could be *dismissed* in his opinion as well, but there is a *disagreement* with Mr #1 who still believes that the second piece of evidence is valid. Mr #2 then *encourages* the candidate to address a number of points regarding the second piece of evidence. Then the candidate is nevertheless *expected* to communicate the raised issues with both agents which would lead to the successful *dismissal* of the second piece of evidence as well. Finally, the candidate is *requested* to describe the conflict and resolution strategy.

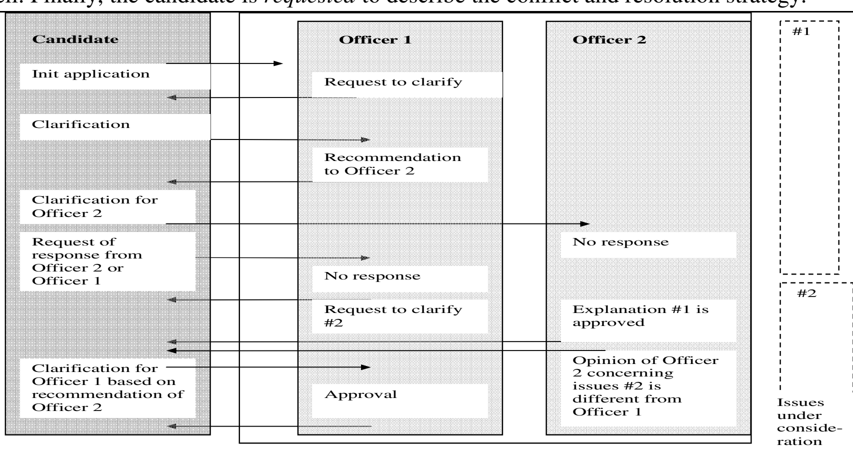


Fig. 4. Scenario representation for security clearance assessment

The interaction between the candidate and officers is shown at Figure 4.

6 Revealing Suspicious Emotional Profiles of Agents

In this section we introduce the idea of building emotional profile of an email message to characterize the emotional possible distress of the author. Emotional profile is a way to combine meanings of individual words in sentences and then to merge expressions for emotions in these sentences for deriving a high-level characteristic of emotional load of a textual message. It turns out that explicit expressions for emotions are amplified by the words which are not explicit indications of emotions but characterize interaction between involved agents (their communicative actions, Searle; 1969).

We call *Emotional profile* a formal representation of a sequence of emotional states through a textual discourse. *Intensity* of linguistic expressions for emotions has been the subject of extensive psychological studies (see references in [8]); we base our categorization of emotions and qualitative expression for emotion intensity in these studies. We apply computational treatment to our observations in the domain of customer complaints [7] that emotions are *amplified* by communicative actions. For example the expression *I was upset because of him* is considered to express a weaker intensity of emotion than the expression *He ignored my request and I got upset* with

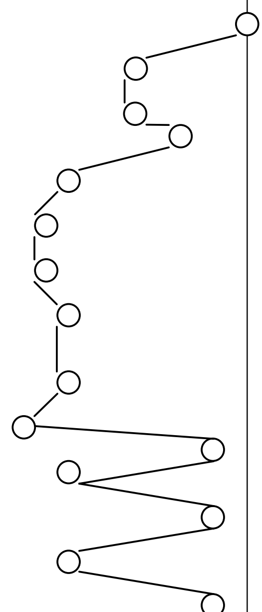
Selected text	neg → pos
…We are **happy** that you are focused in your studies. …We all have to be ***firm*** and ***focused*** with reality as time is slipping away, and there is really ***no time*** to be **weak** and **emotional**… …It does not ***matter*** **of consequences** to us in this life because we do ***not*** **fear** or ***allow*** to be **weak** ... …The trouble is when our minds are a little **idle** and wander to **negative** ***thoughts***, which is an old trick of Satan… Do not ***attach yourself*** to anything so much that your **suffering** is ongoing... We were ***told to rejoice*** not to be in a **depression** as we have the best of news for all our loved ones which will come to pass very quickly. You should not be **sad** but determined in your aims as we have a **tremendous** burden and duty on our heads in these times. .. Try to see life in this world as a job with variety of duties without emotions except to your Lord. In your spare time make … rather than **worrying**. I wonder what **punishment** … **ignorant** … this **scares** me. … is **happy** that you are in a **happy** ***frame of mind***…Do not **worry** about …kids. …You married a real good woman she is very **happy** with you… Our **worry** is for religion…Everything else is emotional struggle.…you will be specially **blessed** and **successful**……stay focused and determined…	

Fig. 5. Example of an email message where a detection of emotional distress could prevent a would-be terrorist attack. On the right: emotion intensity profile, negative to positive from left to right.

communicative actions *request-upset*. In our formal representation of the latter case the communicative action *ignore* is substituted into the emotion *upset* as the second parameter: *upset(i, ignore(he, request(i,_))).* Emotional profile of a textual scenario includes one or more expressions in predicates for emotions, communicative actions and mental states for each sentence from this scenario mentioning emotional state. Moreover, we compute the intensity of emotion for each such sentence.

To access the emotion level of the whole scenario, we track the evolution of the intensity of emotions. If it goes up and then goes down, one may conclude that a conflict occurred, and then has been resolved. A monotonous increase of emotion intensity would happen in case of an unresolved conflict (dispute). Conversely, a decrease in intensity means that involved parties are coming to an agreement. An oscillating intensity profile indicates more complex pattern of activity, and in most cases it reveals a strong emotional distress.

As an example, we present a fragment of correspondence between a would-be British suicide bomber and his relatives, who have been charged in connection to failing to notify authorities of a potential terrorist attack (Fig.5). We show expressions for emotions in bold, and associated expressions for communicative actions or mental states in bold italic. As the reader observes, emotional profile in this email is very peculiar. Primarily, there are very strong oscillations of the emotional intensity. These oscillations are medium at the beginning of message, stay negative at the middle portion of it and become very volatile towards the end of the message.

7 Revealing Suspicious Behavior of Cell Phone Users

In this section we introduce the idea of using telecommunication data for detection possible suspicious behavior of cell phone users. Providing telecommunication services is heavily dependent on the accurate determination of the handset locations to promptly switch from one service station to another. Telecommunication servers accumulate huge amount of data that includes the recording of locations of handsets at certain time intervals. Also, the phone numbers of both callers and call addressees are recorded. Crimes might be prevented and networks of criminals groups with peculiar inter-connections identified if it were possible to discover sets of unusual patterns of coordinated movement for groups of cell phones.

The raw data for our analysis includes the series of absolute locations (detected with certain accuracy at certain time intervals) for wireless subscribers (agents) and the selected locations where these agents are making a call or a receiving a call. We assume that conversation recordings are unavailable due to privacy of conversations, expensive recordings and unreliable speech recognition techniques. Having obtained the location data vs time, it is possible to extract the patterns of movement on a rule-based basis. The set of movement patterns we use is *turn right/lef, U-turn, keep going, stop*. Detecting movement patterns, we distinguish ones which were deliberately selected, and ones where a vehicle just follow a road. In our further considerations the default movement patterns for is *turn right/le* and *U-turn* will be deliberate. We use a labeled graph representation of a sequence of movements and phone calls as abstract communicative actions. If movements and phone calls are coordinated, the sequence of calls and movements is important to hypothesize on possible intentions of the agents in involved vehicles. Discovering correspondence between the movement patterns and communications, we attempt to determine what is the direction of information transmission between agents, and how is this information linked to what has been observed in connection.

The purpose of the analysis is to understand whether surveillance (as a partial case of a suspicious behavior) is taking place, and to discover the roles of involved agents. Obviously, the earlier it is possible to detect a suspicious behavior of parties, the sooner an interception is possible to assure security. Initially we do not know which agent is leading which is reporting, and we hypothesis about this assignment in the course of determining whether activity of these agents is normal or suspicious.

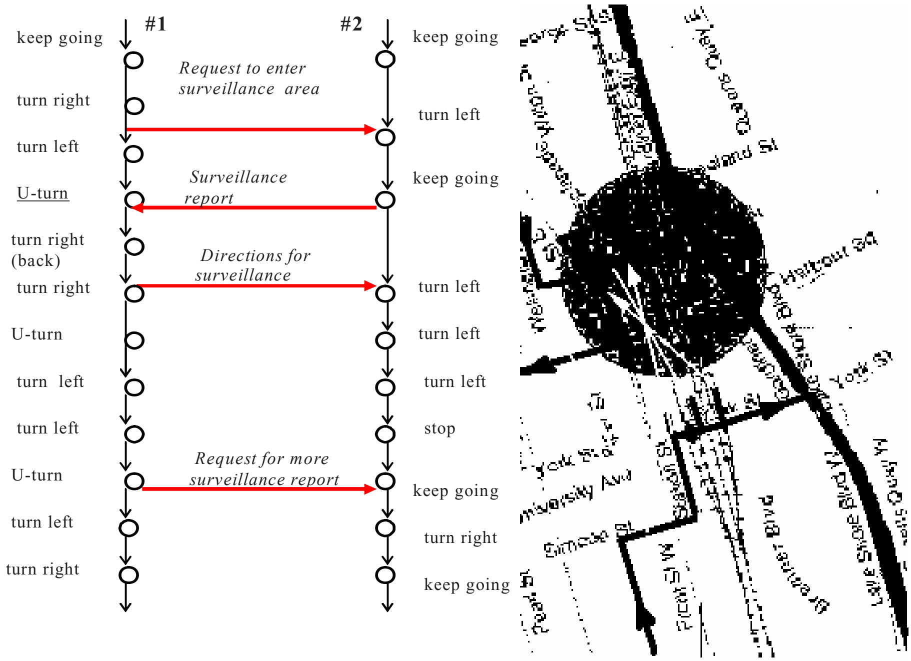


Fig. 6. Detected move and call patterns Interpreted movement and call patterns (on the right)

We show the trajectory of movements for two agents (Fig.6 on the right) and the constructed communication scenario graph (on the left). In this example, we suspect that there is an area surveillance by two agents. One can see that the leading agent is #1 and reporting is #2. The agent #1 investigates a number of approaches to the high security area (depicted by a circle) and leads the agent # 2 through this area (#1 is on the left at the map and in the graph, and #2 is on the right).

8 Evaluation of Representation Adequateness

To demonstrate that the proposed representation language of labeled graphs is adequate to represent scenarios of interactions between human agents in various domains, we performed the evaluation of coding to graph / decoding from graph and evaluate distortion of communicative action-related information. We conducted the evaluation with respect to the criteria on how the suggested model based on communicative actions can represent real-world scenarios including complaints, conflict between communities of agents, emotional interactions, induced conflict interactions while security clearance assessment, and wireless interaction under possible suspicious behavior.

We start the evaluation from textual complaints which were downloaded from the public website PlanetFeedback.com in 2005. For the purpose of this evaluation, each complaint was manually coded as a sequence of communicative actions, being assigned with a particular status. We formed the dataset for three banks, each of which consisted of 20 complaints. The usability and adequacy of our formalism was evaluated on the basis of a team of individuals divided into three classes: complainants, company representatives and judges.

Complainants had a task to read a textual complaint and draw a graph so that another team member (a company representative) could comprehend it (and briefly sketch the plot as a text). A third team member (judge) then compared the original complaint and the one written by the company representative as perceived from the form. The result of this comparison was the judgment on whether the scenario structure has been dramatically distorted in respect to the validity of a given complaint. It must be noted that less than 15% of complaints were hard to capture by means of communicative actions. We also observed that about a third of complaints lost important details and could not be adequately restored (although they might still be properly related to a class). Nevertheless, one can see that the proposed representation mechanism is adequate for representing so complex and ambiguous structures as textual complaints in most cases.

Note that in our approach the role of defeat relationships and causal links between the subjects of communicative actions is to represent common features of scenarios, and not to determine the validity of claims being communicated. Communicative actions of one scenario are matched against those of another scenario, and attack relationships between arguments are matched against those of another scenario, irrespectively of the validity of these arguments.

Conducting the evaluation of adequateness in other domains, we split the members of evaluation team into reporters, assessors and judges. Reporters represented scenarios as graphs, and assessors decoded the perceived structure of communicative actions back into text. Finally, the judges compared the original description (be it text or other media in the case of wireless interaction) with the respective originals.

For the banks, one can track deviation of one dataset versus another, which is 10-15% of the third set versus the first two sets. This is due to the lower variability of scenarios, which makes it easier to represent and reconstruct it (classification accuracy is comparable). Recognition for banking complaints is almost as accurate as coding via graph (representation), but not the reconstruction of the structure of interactions between complainants and their opponents.

Coding emotional profiles via graphs similar to Fig.5 was not as expressive as in the case of complaints, and classification accuracy is closer to the scenario reconstruction than to the scenario representation accuracy. Indeed, the proposed language via communicative actions captures peculiarity of emotional profiles in a lesser degree than the structure of complaint scenarios. We were unable to evaluate the security

Table 1. Evaluation of the adequacy of complaint representation language

Domain/dataset	Number of scenarios	% of scenarios which were successfully represented as graphs by experts	% of scenarios which were (at least partially) reconstructed from the	% of scenarios which were properly represented and reconstructed	% of properly related to a class (being adequately represented), 2 classes
Compalints-Bank 1 (Galitsky 2006)	20	85	75	65	72
Complaints-Bank 2	20	80	75	60	75
Complaints-Bank 3	20	95	85	75	78
Conflict between communities of agents (presented in [8])	2	50	50	50	No eval
Domain Sect. 5	12	75	67	58	60
Domain Sect. 6	4	No eval	No eval	No eval	No eval
Domain Sect. 7	38	84	74	55	61
Average	18.7	78.2	71	60.5	69.2

assessment scenarios in real world; however we obtained sufficient data to track the accuracy for wireless interactions. In terms of representation it is as good as complaint scenarios, but the reconstruction (which is the most important operation) accuracy is lower than for complaints, and the accuracy of classification lies in between representation and reconstruction. In such domain as Wireless interaction and Emotional interaction there is much higher loss of information then in the other domains, however proper classification (with providing background on *why* a given scenario is related to a class) gives a little bit better results. For complaints, where the representation and classification machinery was tuned, the accuracy is naturally higher than in the other domains we started to tackle recently, and the available dataset is rather limited.

Hence for an average number of almost 19 scenarios per dataset, almost 80% can be somehow represented via labeled graphs, about 70% reconstructed from graph without major loss of the conflict structure, and 60% both correct representation and reconstruction. The classification accuracy of relating to one out of two classes is close to the reconstruction accuracy. Note that the setting of the Nearest Neighbor classification is different from random classification which gives 50% for two classes.

9 Conclusions

We explored the role of communicative actions in representing various kinds of conflicts in multiagent systems and discovered that proper formalization of communicative actions are essential to judge on conflicts. A machine learning approach to relate a formalized conflict scenario to a class is proposed, which takes into account structures of communicative actions represented via labeled graphs. It has been developed and evaluated in the domain of customer complaints in our previous studies, and then used in other domains of inter-human conflicts of distinct natures. The representation language is that of labeled directed acyclic graphs with generalization operator on them. For machine learning, the scenarios are represented as a sequence of communicative actions attached to agents; these actions are grouped by subjects. Causal and argumentation defeat relationships between the subjects of communicative actions are coded in the graph and used by machine learning as well.

The structure of graphs, as well as the number and structure of classes depend on a domain, but the criteria of sequences of communicative actions have been shown useful to express commonalities between scenarios. Hence domain-independent communicative actions' representation via labeled graphs, once developed, can be reused from one conflict domain to another. At the same time, having the common representation language, scenarios from one domain are dissimilar to the ones from another domain, so only the knowledge about communicative actions structure is common between these domains. In each domain, graph structures are different, so we cannot export experience from domain to domain.

Based on speech act theory, we designed a set of attributes for communicative actions and showed how the procedure of relating a complaint to a class can be implemented as Nearest Neighbor learning machinery. The approach to learn scenarios of inter-human interactions (encoded as sequences of communicative actions) is believed to be original on one hand and universal on the other hand. We believe that rather few computational approach has been applied to such problem as understanding customer complaints, and the other domains where mining for communicative actions is useful, have not been tackled computationally either.

We believe that suggested approach is appropriate for deployment in decision support settings in the respective domains. One needs to integrate scenario encoding into graphs, classification and predication, and visualization [13] components to assist human experts in making decisions in the explored domains.

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