Novel Smart Algorithms used to Assist and Encourage STEM Group Participation among members with Autism Spectrum Disorders

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Abstract

The population of people with autism spectrum disorders (ASD) has been continuously increasing. Only16% of autistic adults are currently full-time employed, as compared to 47% of people with other disabilities. People with ASD have fewer career chances, in spite of 77% of them wanting to work. While autistic adults show high levels of interest in STEM activities, they continue to be marginalized in such careers. It has been argued that persons with ASD experience serious difficulties with social interactions, due to their arguably less developed emotional intelligence (EI). EI is the ability to recognize and express emotions in social environments. Since many STEM activities are team-oriented, and team members require emotion recognition and tracking skills, this research project devised novel computer algorithms to improve the participation of persons having an ASD and wishing to participate in team activities. The feedback through the algorithms compensates for difficulties people with ASD have in understanding social and emotional cues during teamwork. This proposed technology can also use machine learning to create aids, like questions about aspects of the idea discussed by a team or use emotionally-laden words and scripted phrases to reinforce language skills if the person with the ASD does not participate or if there is a dissonance between his/her emotions and those of the team. Using the algorithms in ASD therapy is expected to identify a more effective set of neurobioloogical patterns, thus hopefully leading to more potent and cost-effective therapies.

1 Introduction

The population of persons with Autism Syndrome Disorder (ASD) has been continuously increasing [1–3]. Only 16% of autistic adults are currently full-time employed, as compared to 47% of people with other disabilities [3, 4]. People with ASD have fewer career opportunities [2], in spite of 77% of them wanting to work [3, 4]. While autistic adults show high levels of interest in STEM activities [4], like computer programming, robotics and machineries, statistics, and so on, they continue to be marginalized in such careers. It has been argued that persons with ASD experience serious difficulties with social interactions, due to their arguably less developed emotional intelligence (EI). EI is the ability to recognize and express emotions in social environments, so that participants respond in cognitive, emotional, and social ways that are considered appropriate by the rest of a group [5]. Many STEM activities are team-oriented. A person's ability to be effective in a team is decided by tasks with a strong social and emotional component, like communication, sub-goal identification, compromising, and coordination with others. Often, such activities are the main weaknesses of individuals with ASD [5–7].

We will discuss next a short yet typical example provided to us by an ASD therapist. During a therapy session, a thirteen year old boy with mild ASD had to analyze a picture story about a girl that recently joined a new school. One of the pictures presents the girl focused on her class work, while a group of boys try to capture her attention by acting silly. The patient with mild ASD had difficulties understanding the reasons behind the group's acting. He picked up inaccurate interpretations of their facial expressions. After a longer pause, the boy with mild ASD suggested that they acted silly because they wanted the girl to join their group. However, an additional sequence of cues offered by the therapist helped him realize that another, more likely reason is that the silly boys wanted to get the girl's attention to signal her that they are friendly towards her.

This short example shows that the boy with ASD had difficulties in understanding emotional cues. It is likely that his difficulties produce poor social interactions too, as correctly understanding others' emotions is a main requirement to having effective social interactions [2, 3, 5, 6]. Emotional dissonance is likely to occur between the boy with ASD and other team members working on the same problem. Also, the example showed that the boy was more likely to stay fixated on details, rather than exploring more abstract (conceptual) alternatives. Cognitive dissonance occurs when team members move on to exploring other ideas, while the boy with ASD remains fixated on details. It has been well documented that persons with ASD are likely to stay fixated on specific solutions while the rest of the group shifts to other ideas, produce fewer abstract concepts, or misinterpret the emotional and social cues produced by others. It is also likely that they learn and focus on different aspects than neurotypical persons, or they might not use the knowledge learned and communicated by others. Different interaction patterns and behavior might emerge from the group, which might further complicate efficient balancing between the demands set to the group and what the group actually offers.

1.1 Project Goal

This research project focused on devising a novel computer game for therapy to improve the capacity of a person with ASD to adapt to others' ideas and to their emotional and social cues. The game challenges the players to create an integrated story. Story creation is an example of open-ended problem solving, similar to the experiment in psychology discussed in Section 3.

The game is summarized as follows. The person undergoing therapy plays a game in which his/her builds a story jointly with three or four virtual game characters. The person and every character take turns in suggesting one or two sentences in the story, so that the story can score high in terms of its quality (e.g., novelty, being captivating, etc.). Story quality is rated by a trained person, such as the healthcare specialist in charge of therapy. The cognitive, social, and emotional characteristics of every character mimic the characteristics of real persons. These characteristics are captured using an embedded device, such as a smart badge monitoring team interactions and emotions [8]. The virtual characters probabilistically select sentences from a database based on their cognitive, social, and emotional characteristics. The person with ASD will be encouraged to create integrated stories, which is expected to help them improve their skills in coordinating with the other team members with respect to suggested ideas. Improving the reading of social and emotional cues is achieved by showing specific visual cues (e.g., faces) and reading the sentence with a specific emotional intonation. During the game, the ASD person is shown scores that indicate how well his/her outputs connect with the other sentences.

The proposed game for computational therapy uses new Machine Learning (ML) algorithms to identify the sequence of cues that is likely to address dissonance situations at a minimum effort. The sequence is reinforced depending on its rate of success. The algorithm comprises of two main steps: (i) identification of dissonances, and (ii) finding the minimum effort cue sequence that solves the dissonance. Identified dissonances include lack of idea variation, significant differences in idea variations for different participants, differences in accessing more abstract ideas, differences in identifying causal relations between solutions and parameters, or different interpretations of the same outcomes. The latter cases are possible situations of cognitive dissonance. In addition, social and emotional dissonance are situations in which a patient does not understand the way in which others' interpret certain outcomes. Emotional and social cues are important in "synchronizing" the participants that jointly solve the same problem.

We define *computational psychology* as the collection of mathematical representations and algorithms that model and tackle the cognitive, social, and emotional aspects of individual humans or groups, as well as the relations among the aspects of the three kinds. It is well known that social interactions and emotions are critical in problem solving and decision making [9–11]. Computational psychology mines and learns invariant patterns that characterize relations among the cognitive, social, and emotional aspects. *Computational* therapy means using the mined patterns to teach patients how to adjust their behavior, so that the specific defficiences are improved, like the patient's ability to read emotions, or to understand the degree to which a certain unique capabilities (e.g., focusing on details for long time) can improve the results of the entire group.

In this project, the objective of computational therapy was to automatically find the sequence of cues that maximizes the likelihood of addressing the cognitive, social, and emotional dissonances that exist for a person with ASD. For example, computational therapy would find cues that can help the boy with mild ASD correctly understand a picture story. Such cues are currently produced by a therapist. The justification for this approach is the "manual shift therapy paradigm" that has been used in various therapies, including ASD [5], depression, or Obsessive Compulsory Disorder [12, 13]. The therapy assumes that the existence of "faulty" neural connections that prevent patients from naturally switching to thoughts to address the current situations. This would explain why persons with ASD stay fixated on specific details without switching to other ideas, including more abstract concepts. The paradigm considers that patients must learn how to intentionally change their thoughts, similar to using manual shift to change the speed gears. The sequence of cues represents the process of “manually shifting” to other thoughts, such as to solve any dissonance with the other team members. The main advantage of computational therapy is in that it offers more flexibility and superior therapy customization. Traditionally, patients meet weekly with their therapist for sessions of about 20 or 40 minutes. This offers less opportunity for exploiting all the opportunities to customize their therapies to the specific needs of the patient.

The paper has the following structure. Section 2 offers a detailed description of the studied problem. Section 3 proposes a theoretical model that tackles the two types of questions on group behavior for applications with social aspects. Section 4 discusses supporting experiments. Conclusions end the paper.

2 Problem Description: Computational Psychology for ASD Therapy

The proposed game for ASD therapy pertains to the broader paradigm of Cyber-Social Computing (CSC). CSC offers intriguing opportunities to compensate for difficulties people with ASD have in understanding social and emotional cues. For example, technology could automatically generate questions about which aspects are discussed if the ASD person does not participate, or use emotionally-laden words and scripted phrases if there is a dissonance between his/her emotions and those of the team [5]. Another opportunity is to explore ideas or procedures that draw the attention of people with ASD during ritualistic behavior. ASD persons are encouraged to identify themselves during team work, or to express their opinions about the ideas proposed by others [5]. Using CSC platforms in ASD therapy is expected to identify a broader and more effective set of patterns, thus hopefully lead to more potent and cost-effective therapies.

From a computation point-of-view, during therapy every participant (agent) accesses new information, learns new knowledge, makes predictions about possible outcomes, and produces outcomes that affect other participants. Agents execute multiple decision strategies using different alternatives, and targeting various objectives, some of which are implicit and/or partially defined [14–18]. Agents continuously adapt to new conditions and optimize, as new information is accessed and new knowledge is learned based on previous actions. Agents discover new ways of improving existing solutions, understand the causalities that relate parameters to outcomes, get insight about the trade-offs, benefits and limitations of a solution compared to its alternatives, combine two or more solutions in new outcomes, and create new building blocks, which are then used to create solutions that diverge from previous outcomes. Agent behavior adaptation has been traditionally explained up to a certain degree using game theoretic methods [19–23]. However, given the broader, faster, and more customized interaction through technology, agent behavior, adaptation and learning are significantly more dependent on cognitive, social, and emotional aspects. This dependency introduces new challenges that must be studied in order to devise more effective applications using social aspects.

There are three types of limitations that occur for applications with significant social aspects: (i) poor adaptation skills of the agents due to imperfect learning, such as insufficient information processing or used knowledge learned for different conditions, (ii) volatility of the acquired information, i.e. information loss, poor management and processing, and (iii) imperfections and uncertainties in the nature of the problems to be solved, in accessing the available knowledge, and in the distribution of rewards and social feedback. The consequence is a poor balance between the demands posed to the group (the available resources) and the outcomes offered by agents. It is very often that the poor synchronization between offers and demands creates situations of over-abundance of similar outcomes, even though there is already little demand for such outcomes, or incapability of a group to adapt to new problem requirements (even if resources are available), as its current knowledge and experience does not give a good transition to the new problem. When the imbalances becomes too acute, the group stops existing as it cannot further access resources [24–26]. This is obviously a significant limitation, as important expertise, knowledge, and insight are lost by dissolving the group.

There is a first main issue that occurs between agent adaptation and learning, and the evolution of the entire group behavior. Agents use mainly previous behavior to adapt and learn, however, a community’s transition (migration) to a new problem apparently invalidates the learned knowledge, as the new problem represents new conditions. (1) This issue raises questions about the nature of the evolutionary mechanism through which a community utilizes available resources to generate continuously more customized solutions (e.g., problem specific solutions), while being able to find and switch to a new problem when the current resources disappear. The second main issue refers to the way in which the cognitive, social, and emotional specifics of an agent relate to group characteristics, like agent interaction and distribution of new knowledge and resources, and group behavior (evolution), such as the dynamics of demands and offers in a group. (2) This issue raises questions about the relations that connect agent specifics, group characteristics, group behavior, and dynamics between knowledge and resources. Providing theoretical models for the two types of questions is an important element in devising strategies to improve group behavior in applications with social aspects.

The proposed model describes the evolutionary mechanism as a dual-mode behavior, in which the population continuously repeats a process during which (a) it stays in a current state as long as there are resources, and then (b) moves to another state when transition conditions are met, with the objective of accessing new resources. The dual-mode behavior tackles the supply - demand balance of a community, thus maintaining the balance between the resources that are available to the community (demand) and the produced outcomes (supply). The model defines the necessary conditions to maintain a group in the current state (mode (a)), and the sufficient conditions that maintain its transition (mode (b)). Both conditions capture the incentives of an agent, its existing knowledge (experience), problem flexibility, emotion, attention, social cues, and access to resources. For mode (a), as there are sufficient resources, agents use previous experience to estimate the effort required to solve a new problem and the expected reward. This situation encourages agents to maximize the expected benefit (difference between rewards and effort) by minimizing the effort, e.g., through maximizing the similarity with previous solutions and the reusing of core concepts (called templates in the model). This favors incremental solution modifications by the agents. Diminishing resources increase the pressure to access new resources by using current solutions for new problems (new requirements), or by restructuring the solution blocks to solve previous limitations. Available resources can be predicted based on the similarity with previous conditions. For mode (b), new resources are accessed either by combining existing yet orthogonal knowledge, or by starting a new evolutionary process based on dissimilar knowledge. Previous experience cannot be used to predict the expected rewards or social cues. Hence, sufficient conditions require that there is enough problem flexibility, and agents have enough variety of their knowledge because they previously maximized the creation of new knowledge.

The interplay of the necessary and sufficient conditions produceses a mixture of problem solving strategies pursued by the agents. A community's behavior is tightly connected to the agent's learning, which depends on the agent specifics, group characteristics, group behavior, and dynamics between access to knowledge and resources. An agent's likelihood to perform a certain type of decision depends on the type of interactions with others, which depends on the similarity of their previous experience and interpretation of the experience (e.g., the obtained rewards). The model expresses the mathematical relations of these dependencies. Algorithms connect these models to the expected behavior of the community and its likelihood of survival as expressed by the interplay between the necessary and sufficient conditions.

A number of conceptual activities can benefit from the proposed work, including identifying the opportunities missed by a community, perpetuating the evolution of a community's outputs (e.g., by suggesting specific cues), managing dissonances in the member's beliefs and emotions, and aiding the learning of new insight. These activities can be used in applications, like managing echo chamber effect in communities, addressing cultural dissonance, devise new therapies for neurodiverse members, improve team management, and improve human-machine interfaces.

2.1 Theoretical Description of the Problem

Figure 1(a) summarizes the main concepts of the theoretical model of a team. The model incorporates k agents that interact with each other through the distribution network and resource allocation scheme. The distribution network propagates to the other agents the results produced by each agent, e.g., the produced outputs and shared insight. Every agent performs a set of activities: first, it samples the information of the distribution network through various selection algorithms, like using weights that express reputation, visibility, credibility, previous experience, and so on. Every agent has its own local beliefs (e.g., previously learned information with various degrees of strength), local goals and objectives, as well as emotions that change during the agent's activity. Every agent makes decisions to produce new outputs. A byproduct of decision making is learning new insight, such as new information that is not explicit in the sampled information. A fragment of the new insight is shared with the other agents. Every agent also receives incentives depending on the resource allocation scheme of the model.

In addition to the explicit behavior of a team, its implicit behavior includes emergent conditions that result from the team's behavior, like the occurrence of resonance or dissonance between the produced outputs and shared insight by the agents,

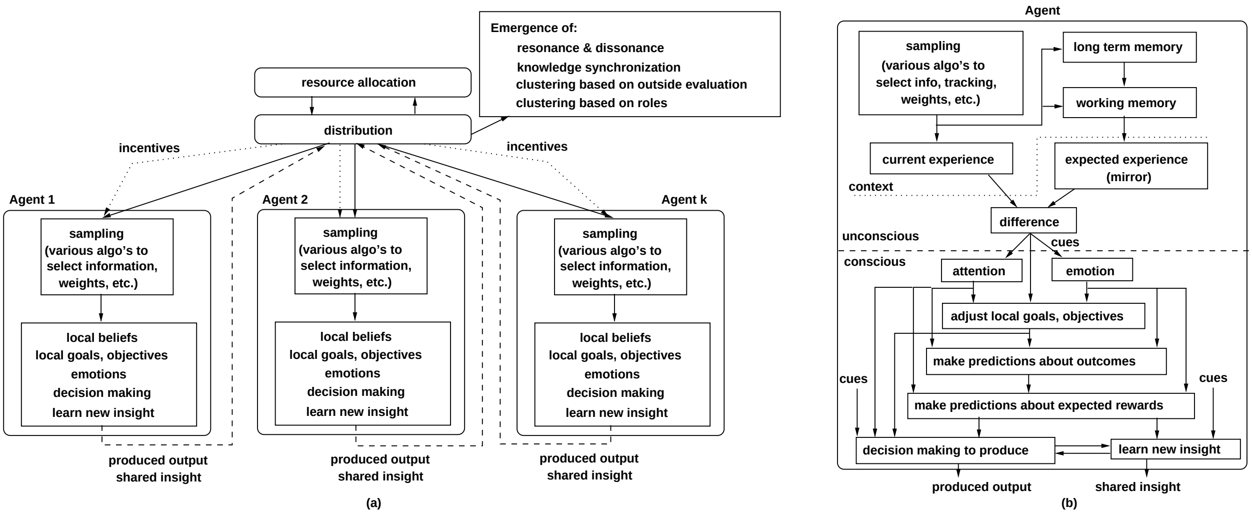

Figure 1: **Theoretical model for a team: (a) overall description and (b) agent model**

the identification of new commonly-accepted knowledge (knowledge synchronization), various agent clustering situations (i.e. agent clustering based on the similarity of their produced results, the degree to which their results are evaluated as being useful to the team, and the roles that agents play in their team), or the team's capability as whole to reach certain conditions that support its further evolution in time. The theoretical model in Figure 1(a) is further detailed along various facets following a bottom-up approach.

Figure 1(b) details the bottom level, which corresponds to the individual agents. Every agent samples the knowledge transferred through the distribution network. Sampling conceptually implements an information filtering using previously learned means, e.g., similarity with own beliefs, goals and objectives, and produced outputs, prestige of the information producer, credibility of the producer or the information, information visibility, biasing created by the current emotions, and so on. The sampled information creates a representation of the current experience. At the same time, cues observed in the sampled information are used to query the long-term and working memories [27–29] to create a second representation, called expected experience. The expected experience mirrors the previous situations [5, 6].

The main differences between the expected and the current experiences are cues that trigger the agent's attention and emotion. Cues, attention, and emotion are then used to adjust the current goals and objectives of the agent starting from its long-term goals and objectives. Also, the same information is utilized by the agent to make predictions about the expected outcomes of the decision making process, as well as the expected rewards (if the outcomes are successful). These inputs, together with the incentives from outside, decide the agent's motivation in a creating a new output through a certain decision making procedure. The agent learns new insight as a result of conducting through the decision making process.

Similar to findings in psychology [30–32], the agent model assumes a conscious and unconscious part. Moreover, the context of constructing the expected experience, observing differences between the two representations and then subsequently executing the conscious activities includes the sampled input, long term and working memories, and the representation of the current experience, as shown in the figure.

Figure 2(a) illustrates the connection between the main parameters of a pair of agents' interactions when creating new outputs and insight and the behavior of the team. There is an alignment between the goals, objectives, and beliefs of the agents. This information is stored in the long-term memory. External cues emerge as a result of the alignment. Similar to the cues in Figure 1(b), they can originate changes in attention and emotion, thus subsequently affect the local goals and objectives of their agents, their expected outputs and rewards, as well as their decision making activities. Hence, the outputs of the pair are influenced by the nature of their interaction.

Moreover, solutions cluster depending on their similarity, as shown in Figure 2(a). The behavior of the team is the trace of such cluster over time. Every cluster represents a variety of solutions around a certain common pattern (template), shown as a red bubble for each cluster in the figure. Every cluster covers a certain local region of the solution space. Other parameters describe the cluster, like solution similarity, credibility, importance (e.g., capability to satisfy a certain

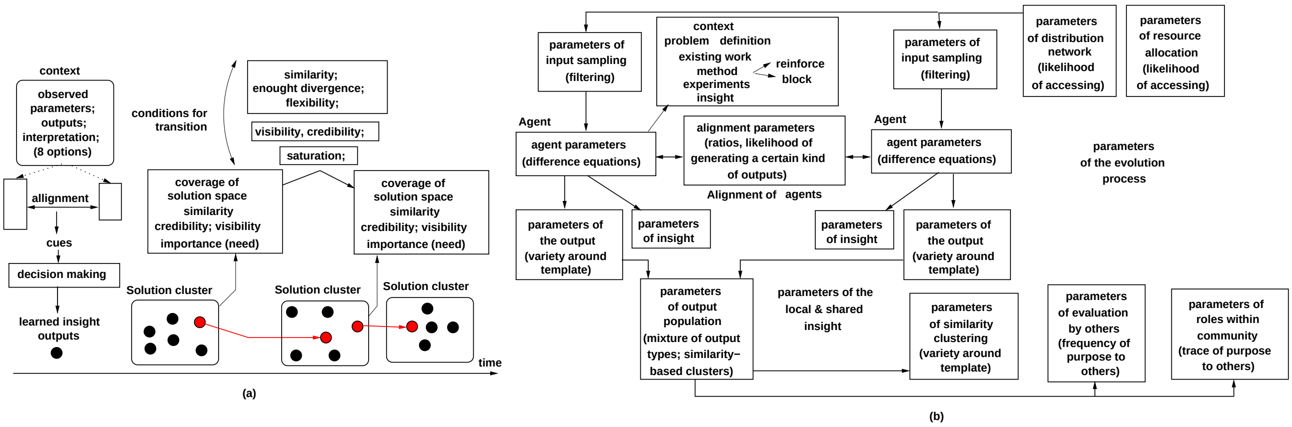

Figure 2: **(a) Summary of a team's behavior, and (b) structure of the proposed theoretical model**

need), and so on. There are transitions from a cluster to another whenever certain conditions for transitions are met. For example, an important condition for transitioning to another cluster is that the current solution space coverage is saturated in the local vicinity, meaning that new solutions are likely to be similar to the already existing solutions. Saturations are an important incentive for agents to move to another cluster. Another requirement is the availability of a new template around which the new cluster can form. The new template must be not only sufficiently visible and credible, but also have enough divergence from the current template to support a new local cluster, be sufficiently flexible in supporting the devising of sufficiently many new outputs, and still be related to the previous cluster, so that agents can embrace the new template at the expense of reasonable effort.

Figure 2(b) summarizes the structure of the theoretical model. Every agent is mathematically described as two parameterized models: a filtering activity characterized by the parameters of input knowledge sampling, and a decision making activity expressed using parameterized difference equation. The outputs created by an agents represent a template shared by all similar solutions, and a variety vector from the template. Moreover, every agent produces new insight (e.g., information not present in the input). The outputs of all agents in a team form the team output. It is characterized by a mixture of output types, such as a clusters that are collections of varieties around shared templates, generalizations, enumerations, analogies, and combinations. The new insight of all agents is a collection of insight, which in part remains local to the agent and in part is shared among all agents, thus, becoming part of the team's common knowledge (beliefs).

The output population is clustered according to three criteria, as shown in Figure 2(b). Similarity clustering represents clusters of outputs that share a common template, which they extend with a certain variety. The second cluster groups outputs based on their perceived usefulness to the team. Every output serves different purposes, which can change over time: context, problem definition, related work, proposed method, experimental results, and obtained insight. The method might reinforce existing work, or it might block it. The third clustering reflects the roles played by the outputs within the team, e.g., the traces of how the purposes to others evolve over time for the output population.

A parameterized model describes the evolution process of the entire team.

The model is completed by the parameterized equations describing the distribution network., e.g., the likelihood of accessing the output pool and insight created by the team. Another component is the parameterized sub-model for resource allocation to the agents, i.e. an agent's likelihood of receiving a certain amount of resources.

3 Materials and Methods: Model Description and Related Algorithms

A. Description of the solution space. The following examples illustrate typical examples that participants produced for an open-ended problem, like providing solutions to improve the health care system in the USA [33]. Produced solutions included the following descriptions: "Provide classes to people, so that they can take care of themselves"; "Educate the population about mental diseases"; "Better and more sufficient payment plans to pay off doctors and hospital bills"; "Being able to schedule doctor appointments online would cut down on time in the waiting room", and so on.

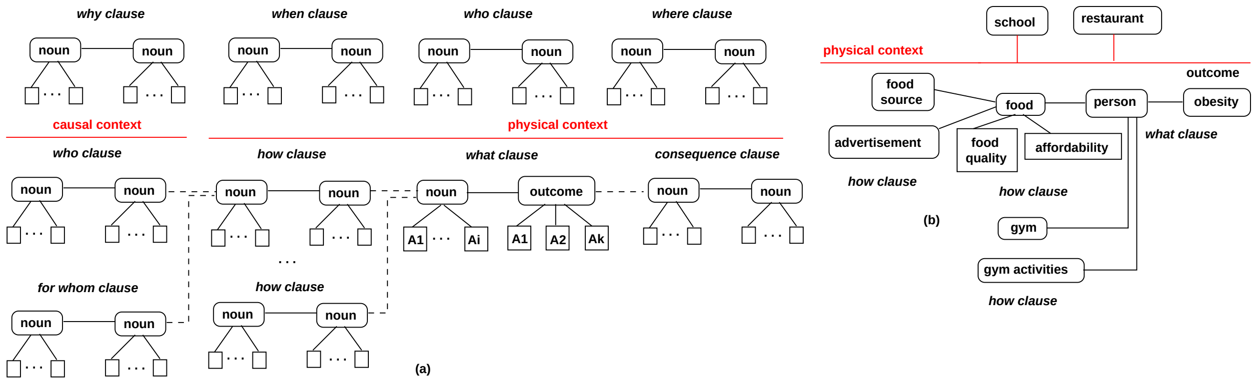

Figure 3: **(a) Description of the solution space and (b) illustrating example**

Outputs can be characterized by the following structure:

1. Outputs range from a single sentence to entire paragraphs of about four, five sentences. There have been a few instances of very long answers, like more than two hundred and fifty words, e.g., half a page. However, outputs are mostly focused on a certain, well defined aspect.

2. From the point of view of their abstraction level, outputs span a range from very specific topics, like "maybe make a general app for smart phones that can be used to schedule appointments", to more general, broader topics, like "The money spent on marketing healthcare options and prescription drugs should be redirected in the system", or "People who can afford it (the wealthy) should be iencouraged to self-insure" and "provide free healthcare to everyone".

3. Participants associate various degrees of strength to their answers: some describe opinions, which are mostly a suggestion to improve the system, hence are likely to undergo further changes. Other outputs express beliefs of participants, thus are unlikely to change during the community problem solving process.

4. Outputs are formed from sub-structures created around a verb expressing a property or an action. We call these sub-structures Building Blocks (BBs) of the solution space description. Every BB includes the corresponding verb, and all associated nouns, attributes, adverbs, and prepositions.

5. From semantic point of view, BBs express various facets, like (i) *what* is the solution (called what clause), (ii) *who* is performing the what clause (who clause), (iii) *for whom* is the what performed, the beneficiary of the clause (for whom clause), (iv) *how* is the what clause implemented (how clause), (v) *why* is the what clause suggested (motivation for the output) (why clause), and (vi) *expected consequences* of the what clause (consequences clause).

6. Outputs can also describe the context or assumptions for a proposed solution. The *physical context* describes clauses that refer to the time (when clause), or place (where clause). The *causal context* explains the reason that justifies the outcome (why clause).

Figure 3(a) summarizes the description representing the various clauses for the outputs. Each BB produces a fragment that includes the nouns of the corresponding output sub-structure, as well as the attributes (A_i) associated to the nouns. Arcs are labeled with the associated verbs. Note that the clauses might not occur in this order in the provided output, however, it is trivial to reorder them as such. There might exist a number of alternatives for each clause type, or certain clause types might miss from the representation. It has been observed in experiments that there is an amount of fixation of the participants to produce a certain kind of clauses, such as some participants repeatedly enumerated concerns and issues with an existing solution, or kept adding details to an output.

Example: Figure 3(b) depicts the description for a set of outputs created during the experiment discussed in [33]. The *what* clause includes two nouns, person and obesity, which is the outcome of the solution. There are three *how* clauses associated to the *what* clause, the first refers to food, the second to the school gym, and the third to gym activities. Noun food has two associated attributes, food quality and affordability. There is a second *how* clause, which further refines concept food, e.g., finding proper food sources and offering advertisements on food quality. Two *where* clauses were mentioned as physical context for the *what* clause, schools and restaurants. The example shows that clauses can be related to each other through sequences, so that more details are offered, like providing healthy food to persons. The

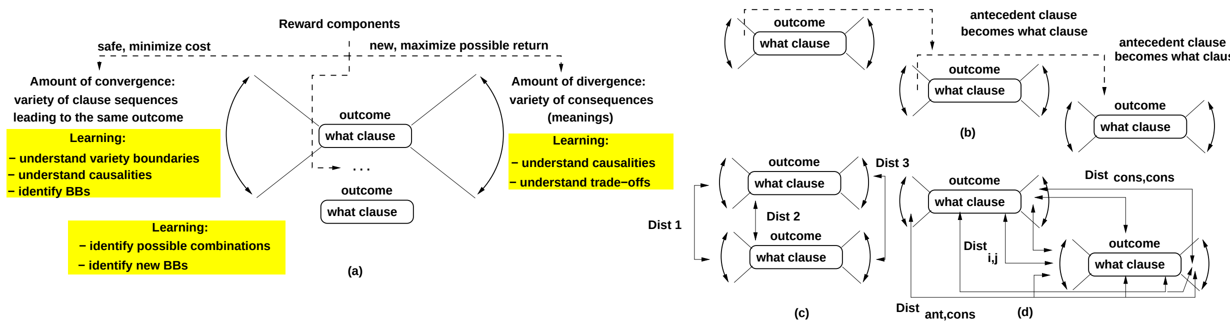

Figure 4: **(a) Solution space description, (b) sequence of clause transformations, (c) distance types among two solution space regions, and (d) distance types among two *what* clauses**

representation includes two more interesting steps during open-ended problem solving: context change, i.e. changing the *where* clause from schools to restaurants, and generalizing, e.g., from gym in schools to gym activities not only in schools.

The solution space represents the collection of all BBs connected through arcs showing how the BBs relate to each other is solutions, and labeled showing the nature of the clauses they represent. The description has the following properties:

1. The representation illustrates different facets of the outputs, like the mode of implementation of a solution (i.e. sequence of how clauses) or the properties of the solution (e.g., sequence of what clauses).

2. The common BBs for various sequences describe the common template of the solutions. The variable part represents the variations around the template.

3. Arcs between BBs describe the relatedness of BBs. Also, BBs representing the same clause kind for the same BB have the role of *synonyms* for the common clause (they have the same meaning). A BB is an *homonym* if it represents different clause kinds for different clauses. It indicates that the BB has different meaning in different situations.

4. Noun attributes indicate the nature of the impact on the corresponding BB.

5. The main operators for managing the representation include changing the physical context clauses, adding new causal clauses, reinforcing an existing context (physical or causal), adding a new attribute, dropping an attribute, adding a new BB, adding a new clause type for a BB, creating a new arc (connection) between BBs, generalizing existing BBs, adding labels showing the similarity of BBs, indicating that BBs represent options or alternatives, and attaching emotion label to outcomes and BBs.

6. The context of the outputs include information pertaining to the previous experience as well as cognitive, emotional and social factors, like attention, emotion, motivation, urgency of thoughts, constraints (e.g., time and energy), capacity to diversify (flexibility) by combining other's ideas and considering ideas that are less similar with own ideas, and capacity for understanding implicit information.

$$context \equiv attention \sqcup emotion \sqcup influence \sqcup experience \tag{1}$$

Figure 4(a) illustrates the solution-space description. The description is centered around *what* clauses that describe outcomes. Clause antecedents present the variety of clause sequences that create the outcome. This part describes the identified solution space convergence. The variety of consequences (meanings) of the outcomes describe the identified solution space divergence. Having a maximum number of paths through the outcome of a *what* clause indicates a maximum input variety and a maximum consequence variety. Solution space exploration can focus on three parts: variety of clause sequences in the antecedents, variety of *what* clauses, and variety of the consequences. Exploration is guided by the two components of rewards functions: (i) safely creating valid outcomes by minimizing the cost of their production, and (ii) emphasizing the novelty (dissimilarity) of the outcomes while maximizing the expected rewards (returns).

Figure 4(a) highlights (as yellow boxes) the learning steps during solution space exploration: the variety of clause sequences to outcomes enable understanding the variety boundaries (e.g., BB parameter ranges), understanding causalities among parameters and outcomes, and identifying BBs. The variety of outcomes supports identifying possible combinations. The variety of consequences (meanings) enables learning to understand causalities and to understand trade-offs.

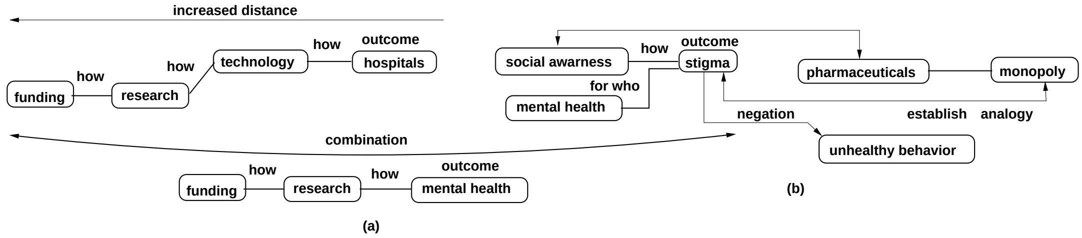

Figure 5: **Reaching new solution space regions by (a) increasing distance and through combination, or (b) by analogies and opposite alternatives**

Lemma: Most information is learned by the individual agents, if the following learning sequence is pursued during solution space exploration: (a) understand parameter variety boundaries, (b) understand trade-offs and limitations, (c) understand causalities and identify BBs, (d) create alternative templates for same outcome and consequence, (e) identify other consequences for the same outcome, (f) identify new combinations, and (g) create new BBs.

Example: Learning is affected if agents speculate about causalities and limitations of a template without first completing step (a). Without accurately understanding the boundaries and effects of parameters on outcomes, it is difficult to correctly express limitations and causalities, as the data required for this activity is unavailable.

There are various reasons for not following the suggested sequence. For example, persons with ADS are likely to be challenged in generalizing examples, moving to new ideas, and correctly reading the social and emotional cues of the other agents. As a result, their outcomes might not follow the nature of the solution space exploration of the other agents. External interventions, including therapy, are needed to increase the flexibility of their outcomes by emphasizing certain idea changes, social cues, and emotions.

The nature of the clauses is transformed during solution space exploration, as shown in Figure 4(b). A clause of the antecedent, e.g., *who* or *how* clause, becomes a *what* clause for a subsequent outcome. The transformation can continue when another clause of the second antecedent becomes a *what* clause for the third outcome. Similar transformations can happen also for consequences.

Figure 4(c) shows the three kind of distances between two solution space regions: $Dist_1$ is the distance between the varieties of the antecedents, $Dist_2$ is the distance between the outcomes, and $Dist_3$ is the distance between consequences.

Figure 4(d) illustrates the different kind of distances depending on the nature of transformations that exist in a sequence. For example, $Dist_{ant,cons}$ represents the distance between an initial clause that is part of the antecedent, and then becomes part of the consequence. $Dist_{cons,cons}$ is the distance between a clause that is part of the consequence and remains part of the consequence in the sequence. There can be nine types of distances depending on the nature of the transformation, $Dist_{i,j}$, where $i, j, \in \{ant, outcome, cons\}$, as shown in Figure 4(d).

Lemma: Clause extensions through *how*, *who*, *for who*, *what* increases the distance to the starting outcome, and increases the likelihood of creating a new cluster of similar outcomes.

Lemma: Combinations provide a bridging way between the clusters of ideas, so that the distance between the initial clusters requires less effort to address.

Example: Figure 5 describes an example to illustrate the previous lemmas. Figure 5(a) shows the increasing of the distances between clauses as new *how* clauses are added to the antecedents of outcome *hospitals*. As the distance to the initial outcome increases, a new outcome might emerge, if words or clauses are reached with a high emotional content for the agents, e.g., research. Hence, the sequence of *how* clauses enables a reliable extension of the outcome, as each *how* clause increases the feasibility of the entire sequence. Another opportunity to reach an unconnected region of the solution space is through combination, like combining funding research with mental health (Figure 5(a)). Figure 5(b) illustrates two other possibilities to reach more remote solution space regions. One is through opposite alternatives (negations), like unhealthy behavior becomes a stigma. The other opportunity is to use analogies, in which different concept pairs are connected through the same relations. For example, pair mental health - stigma and pair pharmaceuticals monopoly are connected by the same relation, i.e. verb break.

B. Difference equations for agent behavior. The following equation describes an agent's creation of a new output ($output_{new}$):

$$output_{new} = output_{current} \uplus concepts_{illuminated} \uplus local\ model_{verified}|context \tag{2}$$

The equation components have the following meaning:

- $output_{current}$ is the output currently used by the agent to devise the new output.
- $concepts_{illuminated}$ represents the concepts, ideas that are illuminated by the current output. Illumination involves both depth-first (e.g., detailing) and breadth-first search (e.g., associative memory).
- local model$_{verified}$ represents the sequential causal path that is formulated by the agent in support to the correctness of the new output. A possible (even though not necessarily correct) parameterized causal sequence is hypothesized during the step, involving the newly illuminated concepts, and the sequence parameters are identified. An outcome of the hypothesizing step is suggesting which parameters, by how much, and in what order they must change to satisfy the problem requirements. This step is greedy, local exploration, including trial-and-error using as priorities the elements of the hypothesis. The step represent the agent's attempt to understand the new output.
- Operator $\uplus$ denotes the mechanism to combine the three right-side components of the equation.
- The equation is performed in the context set-up by previous experience, social influence, and the agent's attention and emotion. The context set-up the directions along which search (illumination) is conducted. Attention highlights with priority the differences among outputs and previous experience, which then under the effect of emotion lead to the specific parameter identification in the causal sequence.

Equation (2) can be recasted as follows:

$$output_{new} = (F \uplus_p \Delta) \uplus_p (S \uplus_p \Delta')|context \tag{3}$$

Where $\uplus_p$ is the mechanism to combine under the context set-up by the agent's attention, emotion, social influence, and experience. F is the template of the solution of the agent, and Δ is its noted difference (variety) from the solutions of the same cluster. S is the template of another agent's solution (which illuminates new concepts in equation (2)), and Δ' is the observed difference (variety) by the agent. The BBs of equation (3) are as follows: F, S, Δ, Δ', $F \uplus_p \Delta$, $S \uplus_p \Delta'$, $F \uplus_p S$, $F \uplus_p \Delta'$, $S \uplus_p \Delta$, and $\Delta \uplus_p \Delta'$. Note that the first six BBs pertain to the two current outputs in equation (3), while the latter four BBs represent new BBs that can diversify the set of outputs. The process characterizes the impact (sensitivity) of Δ for its output using template F, as well as the impact of Δ' for its output using template S.

The components that represent new BBs have the following meanings:

- Strategy 1, $F \uplus_p \Delta'$: Represents a broader diversification of template F by illuminating and then combining concepts related to template S.
- Strategy 2, $S \uplus_p \Delta$: Describes a broader diversification of template S by illuminating and then combining concepts related to template F.
- Strategy 3, $F \uplus_p S$: Produces a new template by combining the initial templates F and S.
- Strategy 4 is the negation (blocking) of a previous solution.
- Strategy 5, $\Delta \uplus_p \Delta'$: Presents a strong diversification by combining the BBs Δ and Δ' (the two variations). The combination exists initially for templates F, S, or $F \uplus_p S$, but it can be further used with another template too.

Figure 1(b) details the model of an agent. The four components of equation (3) are selected based on a cost function applied in the current context (equation (1)). The context includes attention, emotion, social cues, and previous experience (existing knowledge). Figure 6(b) presents the models of the context.

An agent uses its own cost function to decide the next action, e.g., select one of the four kinds of combinations. The cost function embeds two strategies, two minimize the expected effort to create a new outcome and to maximize the expected reward in case of success:

$$Cost\ function = \omega_1\ \min E[effort] + \omega_2\ maxE[reward] \tag{4}$$

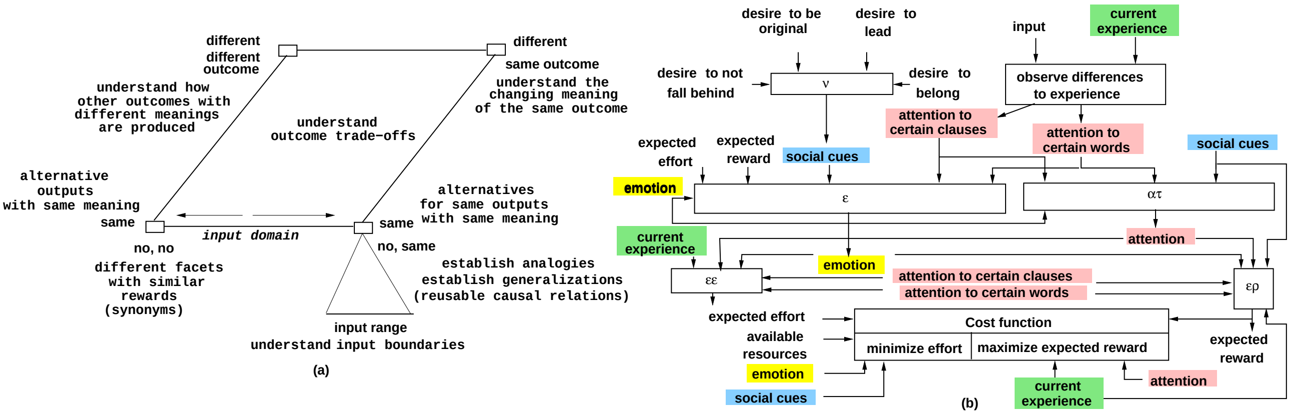

Figure 6: **(a) Learning during solution space exploration and (b) modeling of an agent's context**

The cost function changes depending on the emotion, attention, experience including beliefs, available resources, social cues, observed words, and observed clauses.

The agent's attention depends on four parameters: emotion, observation of certain words (OCW), observation of certain clauses (OCC), and social cues. The observed words and clauses depend on the recognized differences between inputs and current experience.

$$attention = \alpha\tau(emotion, OCW, OCC, social\ cues) \tag{5}$$

Emotion change depends on four parameters: emotion, observation of certain words (OCW), observation of certain clauses (OCC), and social cues.

$$\dot{emotion} = \epsilon(emotion, OCW, OCC, social\ cues, E[effort], E[reward]) \tag{6}$$

Social influence describes the influence of social cues on an agent's emotion, attention, and expected reward for an outcome it produced.

$$social\ cues = \nu(DTNF, DTBO, DTL, DTB) \tag{7}$$

The four parameters are as follows: $DTNF$ is the agent's desire to create outcomes that are not significantly worse than the outcomes of other agents. $DTBO$ is the agent's desire to create original outcomes, including being different or contradicting others. DTL is the agent's desire to produce outcomes that serve as basis for the outcomes of other agents. DTB is the agent's desire to generate outcomes similar to the outcomes of other agents. The four parameters change over time, their rate of change depending on the agent's personality. Personality traits are invariants in the model.

The expected effort to produce an outcome depends on the experience (including beliefs), attention, emotion, observed words (OCW), and observed clauses (OCC). The new outcome uses knowledge described by parameters experience, OCW, and OCC.

$$E[effort] = \epsilon\epsilon(experience, attention, emotion, OCW, OCC) \tag{8}$$

The expected effort changes as the agent learns new information either on its own or being presented by others. It has a subjective character, as different agents by predict different levels of effort to realize similar outcomes.

The expected reward for an expected output is as follows:

$$E[reward](E[outcome]) = \epsilon\rho(Sim(E[outcome], experience), attention, emotion, OCW, OCC, social\ cues) \tag{9}$$

The expected reward function is learned by an agent, hence it has a subjective character. Different agents can different expected rewards for the same expected outputs. Certain parts of it are explicit and certain parts are implicit, e.g., they are expressed as emotions. The expected reward is also a description of the expected needs of the community as they are perceived by the agent.

The combination operator $\uplus$ can describe property-based combinations [34–36] or relation-based combinations [37, 38]. Property-based combinations transfer attributes from a concept to another. Relation-based combinations migrate relationships among BBs from a concept to another. Previous work has shown that property-based combinations are more difficult to produce, but can generate higher output novelty [36]. Also, they span a broader area of the solution space, as multiple

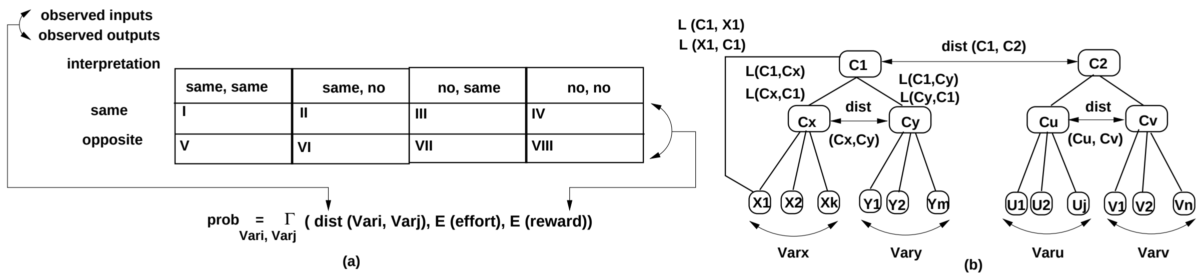

Figure 7: **(a) Modeling of agent interactions, and (b) learning structure created during interactions**

relation-based combinations can correspond to a single property-based combination (e.g., there are multiple implementations to achieve a property). However, property-based combinations offer less opportunities to verify the validity of the property transfer. In contrast, relation-based combinations span a smaller solution space, but offer superior verification of the combination validity through the causal sequences.

The effort to create property-based or relation-based combinations depends on the nature of the clauses that form the outputs. Changing the type of clauses during output creation can help generating new causal sequences among the BBs of the outputs. Creating property-based combinations requires less effort if *what* clauses are combined, while *how* and *why* clauses favor relation-based combinations. *where*, *when*, *who*, and *for who* clauses change the context of an output. They introduce an analogy [39], which is a concept isomorphism (matching) that transfers a causal sequence from a set of concepts to another set of concepts.

The variations corresponding to the difference equation (3) produce the following four variates around the templates:

$$Var_F =< F, (\Delta_j)_j > |context \tag{10}$$

Variety Var_F include template F that was combined with a sequence of incremental variations Δ_j.

$$Var_{F \uplus S} =< F \uplus S, (\Delta_k)_k > |context \tag{11}$$

Variety $Var_{F \uplus S}$ includes the combination of templates F and S, which are then combined with a sequence of incremental variations Δ_k.

$$Var_S =< S, (\Delta_j)_j > |context \tag{12}$$

$$Var_{\Delta,\Delta'} =< \Delta \uplus \Delta', (\Delta_t)_t > |context \tag{13}$$

$$prob_{Var_i,Var_j} = \Gamma(dist(Var_i, Var_j), E(effort), E(reward))|context \tag{14}$$

C. Mixture of output types for agent interactions. Figure 7(a) illustrates the situations that can emerge during agent interactions. They decide the behavior of equations (14). The eight situations, (i)-(viii), depend on the similarity of the inputs and outputs observed by the agents, and the similarity of the interpretation attached to the outputs, according to the agents' experience and beliefs. The distance in equation (14) increases with the dissimilarity of the observed inputs and outputs, and the dissimilarity of the expected rewards increases with the higher discrepancy between the interpretations of the outcomes by the agents.

Situation (i) describes agents previously that observed similar inputs and outputs and have similar interpretations of the outputs according to their previous experience and received rewards. In this case, the sequence of outputs realize incremental modifications of the common template. The modifications help understanding the boundaries of the parameters (e.g., parameter Var_x for concept C_x, parameter V_y for concept C_y, etc. in Figure 7(b)), how parameters affect the outputs (e.g., coefficients $L(X, C_1)$, $L(X, C_x)$, etc. in Figure 7(b)), and the trade-offs and limitations of a template.

Situation (ii) shows agents that observed the same inputs and different outputs, but have similar interpretation of the noticed outputs with respect to the expected rewards. In this situation, the same inputs acts as homonyms for the different agents, as they contribute to different outputs, hence have different meanings (e.g., different possible causalities). However, the outputs act as alternatives with similar interpretations, e.g., expected rewards.

Situation (iii) describes the case in which different inputs produce the same outputs, with the same interpretations. This situation describes analogies, when mappings (matchings) of different inputs can be identified to create the same outcome with the same expected reward. Also, the different inputs can be used in generalizations. Having causalities for different inputs to produce similar results helps understanding the causalities.

Situation (iv) show different cases (e.g., different inputs and outcomes) that create similar interpretations, i.e. rewards. These cases enumerate alternatives with the same consequences. They correspond to different learning experiences, based on different contexts and observed inputs and outputs, but which resulted in learning similar expected rewards.

Situation (v) presents agents that previously observed similar inputs and outputs, but have different interpretations of the outputs due to their previous experience and rewards. Learning exposes limitations of the outputs, i.e. due to different contexts that originated different rewards or output quality.

Situation (vi) show agents that observed the same inputs, different outputs, and assigned different interpretations to the outputs. Similar to situation (ii), the same inputs are homonyms as they create different outputs. Moreover, the assigned meaning to the inputs is not general enough, as there can be opposite expected rewards.

Situation (vii) illustrates cases in which different inputs produce the same outcomes, but with different interpretations. It indicates that the meaning of the outcomes, e.g., its expected rewards, depend on the inputs too. Hence, the outcome meaning is conditioned by the inputs.

Situation (viii) describes cases in which agents experience different inputs and outcomes with different interpretations. As they have dissimilar experiences, they cannot validate or invalidate the knowledge learned by the others. Hence, they can decide to adopt or reject the knowledge based on other criteria, e.g., social aspects like reputation and visibility.

Figure 7(b) illustrates the learning structure that is created as new outputs are being generated.

- *Sequence of how clauses*: Sequences of *how* clauses add details to a fixed template through relation-based combinations. Most inputs are expected to be such clauses, as they are likely to require the least effort to produce. Every clause sample represents a de facto training set, as repeating the sample produces the output. Sequences of related *how* clauses creates a depth-first (incremental, detailed) robust search along directions that are likely to offer valid solutions. Also, there is a strong link between each clause and the related (expected) output. As emotions are mainly linked to outputs, a higher degree of similarity is expected for the different sequences of the same output.

  Sequences of *how* clauses during repeated output generation can increase the distance to the original output. It is possible during the expansion process that a certain concept is reached, which by itself attracts attention or already has a high level of attached emotion, hence it can trigger the emergence of a new template around that concept. This step corresponds to a generalization activity, which drops most of the other concepts of the sequence of *how* clauses. Such a situation represents a strong divergence during solution space exploration. However, there is no guarantee that such a high attention / high emotion concept is reached during the depth-first traversal of the space.

- *Sequences of where and when clauses*: Such sequences are used to enumerate the contexts for the outcomes. Different contexts are likely to illuminate new facets and consequences for the outputs, including expected rewards. The sequence allows to frame the relations and concept attributes that make the template usable for different contexts. It also highlights the reasons (*why* clauses) that make the output effective (i.e. good quality) solution for a problem.

- *Sequences of what clauses*: The sequence is used to generate a sequence of details about a clause.

- *Sequences of why clauses*: The sequence produces a sequence of details that justify an outcome.

The execution of the algorithm in Figure 8 is guided by the elements that characterize the supply - demand balance of the community. The supply relates to the resources available to the agent as well as the effort required to create new output clauses, and the new knowledge that is learned during the process. The demand relates to knowledge needs of the other agents, and the community's capability to continuously generated outputs of sufficient reward to support the existence and evolution of the community.

Knowledge learning during repeated execution of the algorithm addresses the following aspects:

1. Identifying BBs and understanding their parameter boundaries.

2. Identifying the causalities of templates.

```
match the mindesets;
if (similar mindsets) {
  match outputs;
  if (matched outputs) {
    match the observed parameters and learned casalties;
    if (matched) {
      transfer and combine properties and relations depending on the degree of matching;
      create generalizations;
    }
    else {
      establish analogies;
      transfer and combine properties and relations depending on the analogies;
      create generalizations;
    }
  }
  else {
    match the observed parameters;
    identify the causalities associated to the observed parameters;
    if (matched inputs) {
      create different causalities starting from the matched parameters;
      these causalities produce similar expected rewards;
    }
    else {
      enumarte situations with similar expected rewards, and are part of the same context;
      negate the reward of the output;
      negate the causalities that create the output;
      suggest another causality, but which generates same expected reward;
    }
  }
  else {
    match outputs;
    if (matched outputs) {
      match the observed parameters and learned casalties;
      if (matched) {
        detect contradiction;
        explore limitations;
      }
      else {
        detect situations in which different parameters affect same outputs, but create different rewards;
      }
    }
    else {
      match the observed parameters;
      identify the causalities associated to the observed parameters;
      if (matched inputs) {
        insufficient understanding of parameters, as same parameters relate to different tputs and rewards
      }
      else {
        associate another meaning to the same concept;
      }
  }
```

Figure 8: **Model of agent interaction**

3. Characterizing trade-offs and understanding limitations.
4. Creating generalizations.
5. Combining BB properties and template relations.

The learned information is implicit, and becomes available during the learning process. It is important in guiding the exploration process of the agents, hence the evolution of the entire community. The learned information is also utilized in devising new outputs, hence for addressing the open-ended nature of the solving process.

3.1 Software Implementation of the Computational Model

Figure 9 presents the implementation of the agent model. Every agent stores its own experience in two separate tables.

Table `cogintion_table` saves the clauses that are known to the agent, such as the clauses it possessed at the beginning of problem solving and the outcomes that were generated and learned during the process. Every entry of the table stores an outcome, including its related clauses, like the *what*, *consequences*, *why*, *how*, *who*, *for who*, *where*, *when*, and *not* clauses. In addition, the entry stores the abstraction level of the outcome, as well as two indexes that point to the outcome for which the present row is an instance. Index `index_table` is a pointer to the table entry including the more abstract outcome,

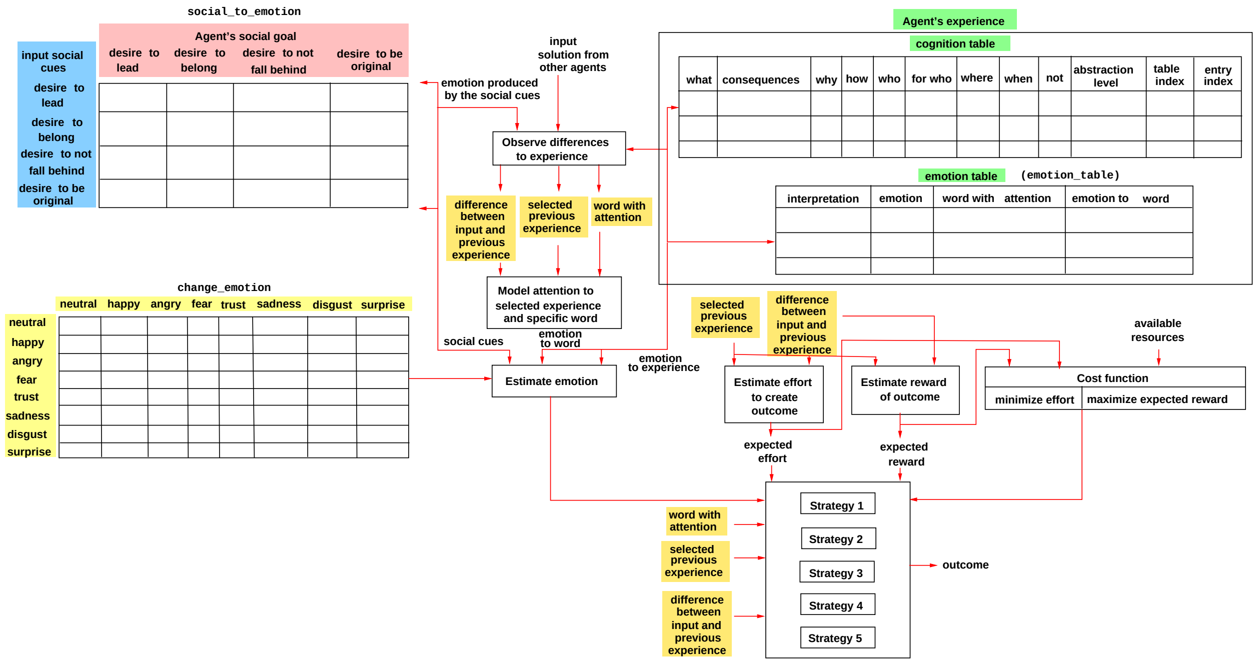

Figure 9: **Block structure of an agent's implementation**

and entry_index points to the clause of the abstract outcome that is detailed by the current row. The abstraction level is incremented every time a new outcome is added to detail one of the clauses. Every entry also stores the pair of pointers synonym_table and synonym_entry pointing to another table entry which includes a similar outcome, but having a different consequence. This shows situations in which the same outcome has different meanings in different contexts. Another pair of pointers, similar_table and similar_entry, point to the output and clause that instantiate the same abstract outcome and clause while being different than that at the current index. The table also stores for each clause the variety of its detailing outcomes.

The second table, emotion_table stores aspects related to the attention and emotion associated to each outcome. It includes the interpretation of the outcomes, such as its gain which is the expected rewards minus the effort needed to produce the outcome. Entries associated_attention and emotion store the degree of attention and the emotion associated to the entire outcome. Entry word_with_attention presents the clause that is perceived to be the most significant in setting the *what* clause and the consequence of the outcome. This clause represents the main parameter of the causal relation of the outcome. Entries attention_to_word and emotion_to_word describe the attention and emotion associated to the most significant clause of the outcome.

The agent model in Figure 9 first observes the differences of the solutions from other agents and the agent's experience in table cognition_table. The module identifies the previous outcomes that are most similar to the current input (selected previous experience), the clauses that differ in the previous experience and input, and the word in the difference that captures the highest attention of the agent. Note that the module finds the differences between input and most similar experience while receiving emotion information that corresponds to social cues from others. The emotion information is used to select outcomes that are emotionally consonant with the social cues, like outcomes for which the agent's interpretation and attention are high, and also their associated emotion does not conflict with the social cues.

The next component models the attention of the selected outcome experience and the most dominant word to decide if they exceed the attention threshold of the agent. A threshold constant (Thresh_Attention) is used to model different kind of personalities. The outcomes and dominant words that exceed the threshold barrier are further processed by the agent. Module Estimate_emotion predicts the emotion produced by aggregating the received social cues, the agent's current emotion, and the emotions associated to the selected outcomes and dominant word (stored in Table emotion_table). Then, module Estimate effort to create outcome uses the Bass model to predict the effort required to create an output, and module Estimate reward of outcome predicts the expected reward of the new outcome using the similarity with previous, similar outcomes.

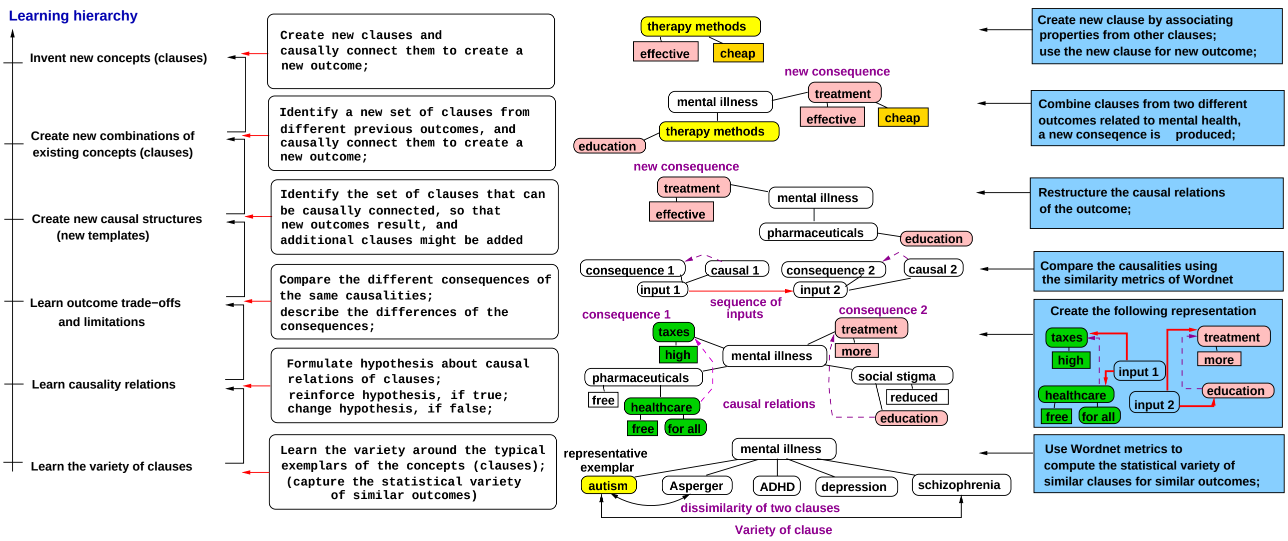

Figure 10: **Learning hierarchy**

Next, the agent creates and then learns a new outcome. The outcome uses the selected outcome stored in the experience table as well as the observed differences, the predicted rewards and efforts, the modeled emotions, and the agent's objectives as represented by the cost function. The created outcome implements five situations corresponding to the four kinds of variations and the contradiction (blocking) of a previous outcome, situation in which an outcome for the same *what* clause uses different other clauses in the solution.

Social interactions are modeled as Finite State Machines (FSMs), in which every state indicates the current dominant social attitude of the agent towards the other agents in the group. Every agent has a social profile that is defined with respect to its own social goals, like the desire to lead, the desire to belong to a group, the desire to not fall behind with respect to the produced outcomes, and the desire to be original as compared to the other agents. The social cues an agent receives from the others are also of the four kinds. Table *social_to_emotion* encodes the emotions that result from the social interactions, e.g., happiness, angry, trust, and so on.

Emotions are also modeled as an FSM with its current state corresponding to the present emotional state of the agent. The states of the FSM correspond to basic emotions, i.e. neutral, happy, angry, fear, trust, sadness, disgust, and surprised. The FSM includes two different states for each kind of emotion, one for the medium level and one for the acute level. Table `change_emotion` encodes the transitions between different states of emotions due to the emotional cues received by the agent.

Figure 10 illustrates the learning hierarchy implemented for each agent. The hierarchy has the following six levels:

1. The bottom level learns the variety of clauses, such as the statistical variety of the clauses used in outcomes. Each clause has a typical exemplar and the variety of the related alternatives. The implementation uses the similarity metrics provided by WordNet [40]. For example, the concept "mental illness" has "autism" as a typical exemplars, and "Asperger", "ADHD", "depression", and "schizophrenia" as related instances. The variety associated to "mental illness" includes the similarities of the four latter instances and the typical exemplar. This level mainly implements associative learning, which identifies the invariant attributes of the concepts [41, 42].

2. The next bottom level learns the main causal relations of the outcomes. The algorithm produces a relation (shown as a purple dashed line in the figure) between the most dominant clause of the outcome and the outcome consequence. Two causal relations are shown in the figure, one used green boxes and the other pink boxes. The first causal relation indicates that "free healthcare for all", one of the *how* clauses used in an outcome, acts as a causal relation to the consequence that "taxes will be high". The second causal relation describes that "education" produces "more treatment". Note that the same outcome, "mental illness care" has two causal relations defined by two distinct outcomes. The learning algorithm generates a representation as shown by the bottom second, light blue box.

3. The third level learns the trade-offs and limitations of certain outcomes. It pairwise compares all the causal relations

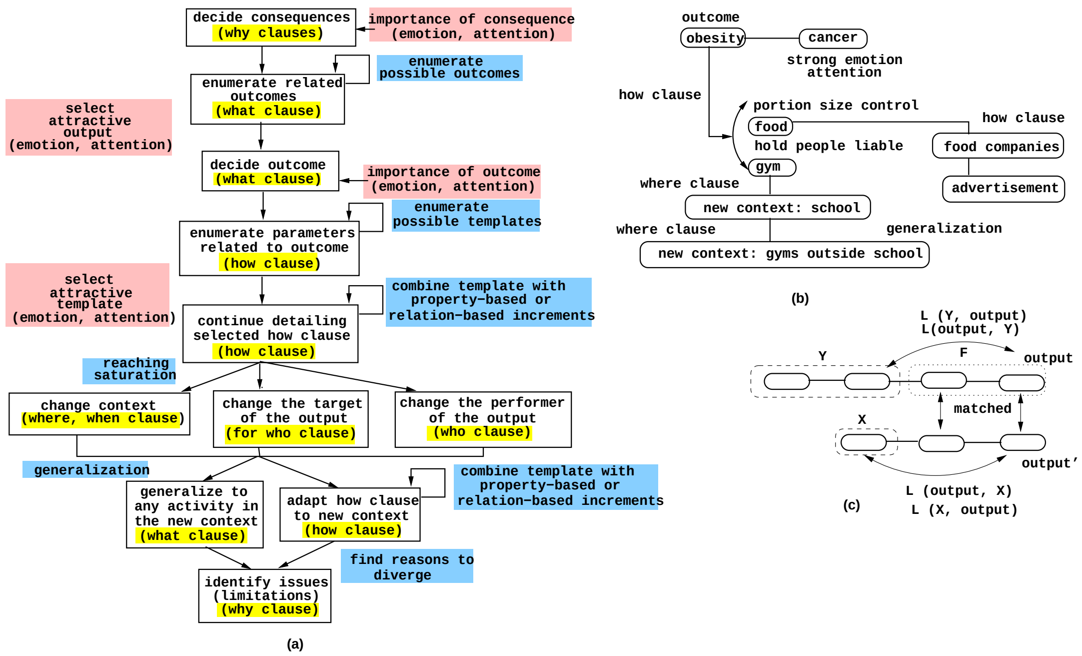

Figure 11: **(a) Sequence of repeated incremental modifications, (b) illustrating example, and (c) associated learning**

associated to the same outcome. The similarity of the consequences is again found using the metrics offered by WordNet.

4. The fourth level creates new causal structures (templates) through restructuring of the causal relations of the current templates. For example, "education about pharmaceuticals" is used to produce the new consequence that "effective treatment" is produced for "mental illness".

5. The fifth level creates new combinations using clauses from different outcomes for the same *what* clause, e.g., "mental illness". For example, "education" and "therapy methods" are combined together in a new solution. Both where previously *how clauses*, but after combination, one became the new *what* clause, e.g., "therapy methods".

6. The top most learning method involves creating a new clause, and then using it in producing a new outcome. This is achieved by adding new properties to an existing clause, i.e. "effective" and "cheap" are added to "therapy methods".

4 Results

The results section presents two case studies describing the idea evolution in a team of four persons. Next, the section discusses the characteristics of the solution spaces that were produced by the agents during story generation. This step is very important to understand the differences between the solution space traversed by teams of neurotypical persons Vs. teams which also include persons with ASD. Experiments also characterized the nature of interactions between team members, and how these interactions relate to the characteristics of the team's solutions. Finally, experiments studied team behavior depending on team characteristics.

4.1 Case Study 1

The first case study discusses story building by a group of four persons. The goal was to build a story about improving health care. Figure 11(a) presents the strategy for repeated incremental modifications of a template, and then Figure 11(b) shows how the strategy was used for a concrete situations. The strategy is minimizes resources, and improves the quality of the outputs, even though the outputs tackle the same requirements as the previous outputs.

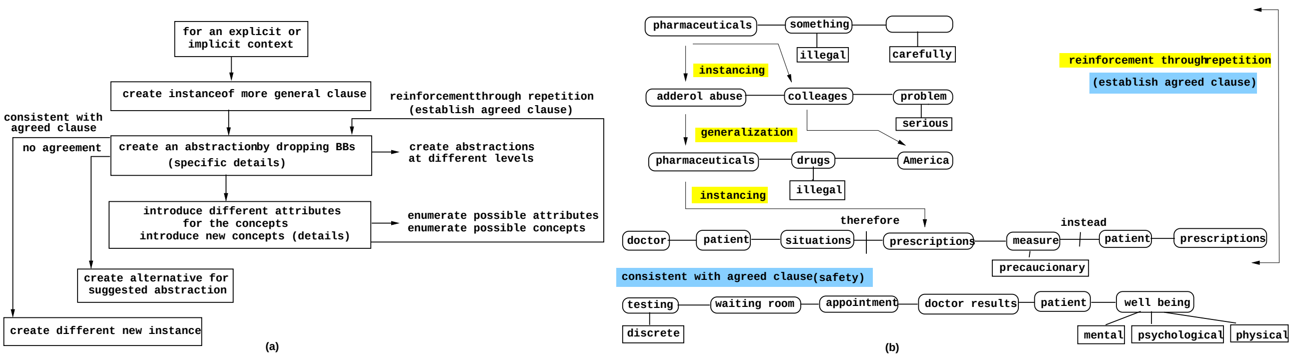

Figure 12: **Establishing agreed clauses**

The strategy starts with deciding an important outcome *what* clause, such that the emotion already attached to the outcome attracts the attention of other agents. Next, a number of *how* clauses enumerate different parameters that relate to the outcome. Each alternative represents a possible template for the outcome, and possibly a certain context for the template. The template describes a causal connection between the mentioned parameter and outcome, i.e. a certain action on the parameter produces the wanted outcome. The most attractive template was selected, e.g., the template that is estimated to offer the highest rewards, or which has the largest emotion attached to it. Then, a sequence of *how* clauses continued to detail the template by sequentially combining the template with property-based and relation-based incremental details (*elaboration of the template*).

After reaching *saturation* (no more similar outcomes were created) by generating details, the context of the output was changed by using *where* or *when* clauses. Alternatively, generalization could change the target of the outcome (i.e. using *for who* clause), or modify the performer of the outcome (e.g., using *who* clause).

Next, the new context originated two situations: (i) generalization of the template to a new activity in the context, and (ii) adaptation of the output for the new context through further combination of the template with more context-dependent property-based and relation-based increments. Also, the limitations of the previous outcomes were identified by using *why* clauses.

Figure 11(c) presents the associated learning process. It presents two related outcomes, $output$ and $output'$, which both use the same template F, but with incremental modifications represented by the unmatched parts in the figure. The unmatched parts are labeled X and Y in the figure. The learned strengths between the incremental modifications and outcomes are characterized by the following equations, which are valid in the context (e.g., constraints set by template F):

$$L(outcome, Y) \sim \frac{outcome - outcome'}{Y} | F \tag{15}$$

$$L(outcome', X) \sim \frac{outcome' - outcome}{X} | F \tag{16}$$

Lemma 1 indicates that most reliable information learning implies the following sequence of steps: (i) identify parameter boundaries for a given template, including relationships between outcomes and parameters, (ii) identify the causalities and BBs of a template, (iii) understand the trade-offs and bottlenecks (limitations) of a template, (iv) identify BBs and suggest other templates for the same outcome, (v) identify new combinations among existing BBs, and (vi) create new BBs.

4.2 Case Study 2

The second case study discusses story building by a group of four persons. Same goal was used as for the first case study. Figure 12(a) presents the strategy for reaching an agreement on a clause by agents who initial have different views. Figure 12(b) shows how the strategy was used for a concrete case.

In this case, the agents did not initially agree on the suggested outcomes. The details used by one of the participants were invalidated by another agent. Next, the agent created an abstraction of the outcome by dropping the clauses that caused

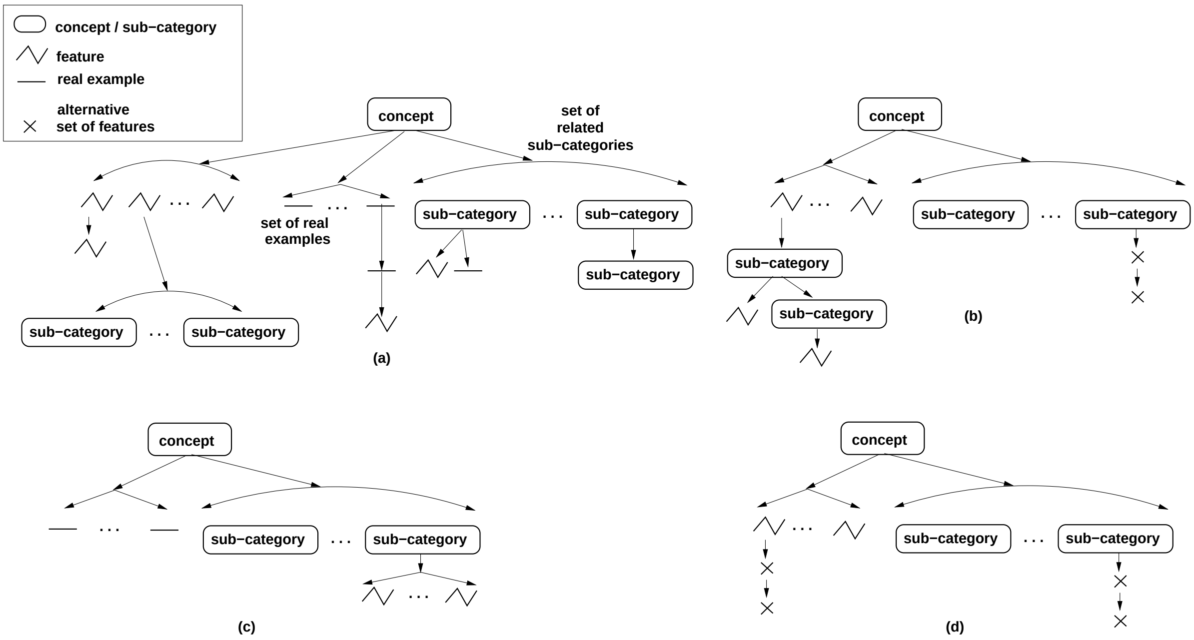

Figure 13: **Different solution space topologies for teams**

disagreement. After establishing agreement of the general clause, it was instantiated by adding clauses upon which every agent agreed. The agreed clause was reinforced a few times by different agents. Finally, a new clause was created that remains valid under the agreed clause.

4.3 Solution space representations

This subsection first offers a comprehensive description of all representations, followed by the depiction of a set of solution space representations characteristic for the teams with the highest, median, and lowest solution novelty. We argue that the shown representations are representative for all teams. These figures describe the topological features of the solution space representations for different kinds of novelties. A more detailed presentation of the nature of the categories that emerged in different groups was also discussed in this subsection.

Figure 13 and Tables 1 and 2 present the characteristics of the solutions space representations for the twenty teams that participated to the experiment. Figure 13(a) summarizes the solution space produced by the most creative team, Group 1. As also shown in Table 1, the proposed solutions pertain to a smaller number of different concepts as compared to the other teams. However, some concepts are well explored, as shown in the figure, including a set of proposed features, a set of real examples that are identified as being important for the concepts, and a number of related sub-categories. Concept features might be further developed by responses that indicate related sub-categories, like *what* or *how* frames presenting what the feature actually means or how it is achieved. Similarly, subsequent responses add extra features to the identified real examples or to the selected sub-categories. The solution space representation is reasonably deep in terms of its number of abstraction levels. Also, it includes only very few instances in which Strategy 4 and Strategy 5 were utilized, suggesting that team members did not attempt to create competing alternatives for the same concept, or to generalize concrete aspects as more abstract concepts. Also, there was a very small number of reinforcements showing that one member fully agrees with another solution. It suggests that team members, while accepting each other's solutions, were mainly preoccupied by proposing responses that had a certain amount of modifications (Δ).

Partially similar solution spaces exist for the other teams with more novel responses, such as teams 2, 3, 4, and 5 in Table 1. The space representations include a similar number of abstraction levels, even though not all components (features, real examples, and sub-categories) are always present for the most developed concepts. Also, there is a larger number of real examples that were provided in the responses. There is an increased number of times when group members proposed

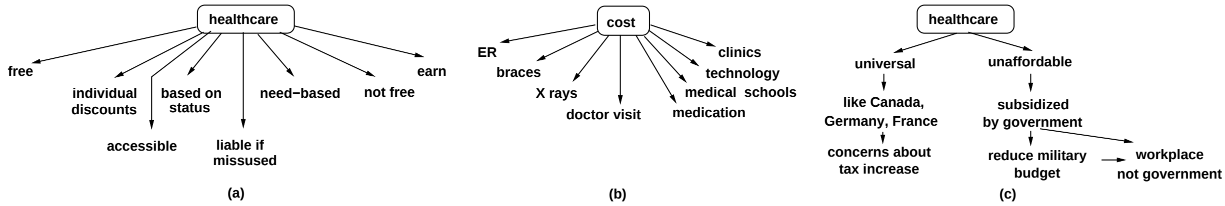

Figure 14: **Types of interactions between team members**

alternative solutions through Strategy 4, and a larger number of reinforced solutions, showing that certain members fully agreed with the solutions proposed by others. The results suggest an increased number of more detailed responses and more responses that are in disagreement with each other.

Figures 13(b) and (c) depict the solution space representations for groups 8 and 9, which created solutions of median novelty (according to human raters). The two corresponding rows in Table 1 summarize the topological features of the representations. The most discussed concepts are less elaborated as compared to the previous groups, like they include a set of sub-categories and a set of features or a set of real examples, but not both. The graph structure is in general less deep than the previous representations, while concepts with more levels of abstraction indicate situations, in which group members disagreed with each other, therefore repeatedly used Strategy 4 to argument their responses (*why* frames). The real examples described concrete situations, constraints, or specific cases that presented *for who* and *why* frames.

Figure 13(d) and the corresponding row in Table 2 show the characteristics of the solution space representation created by team Group 19. The team produced answers of very low novelty. Similar to team Group 1, responses referred to a small number of broad concepts. While similarly to teams with responses of median novelty, the representation includes a set of features and a set of sub-categories, there is an increased number of alternative responses, which are created through Strategy 4, hence meant to replace each other. Strategy 4 was applied to frames *what* and *who* suggesting that there were disagreements on problem framing, such as the significance of the needs to be addressed to improve healthcare.

4.4 Interactions during team work

Team interactions can be distinguished depending on the amount of overlapping of the team members' beliefs and how these beliefs were interpreted with respect to the problem goal. The following interaction types were observed after analyzing the experimental data:

1. Focused belief overlaps. A set of members had the same beliefs about a certain aspect. For example, three members had similar responses about offering health insurance at work. The broad idea was further detailed by one participant, who added the constraint on offering full coverage in case of accidents at the work place. The new response was produced using Strategy 3. Another member distinguished the accidents that were avoidable (Strategy 4), and changed the response by adding a detailed feature related to the identified limitation. Starting from a common, shared abstract belief, the three members pursued a set of steps that added more details to the abstract concept. The final response is likely to be acceptable to the participating members.

2. Mediated belief overlaps. A set of members shared beliefs that while not entirely identical, they defined a semantic region that was acceptable to them. For example, one team member suggested free health insurance, while another one proposed low cost insurance followed by free insurance for persons with low income (Strategy 2). While the three responses are not semantically equivalent, the second members mediated the two responses by adding the constraint referring to low income persons. The final response was acceptable to the first member. A similar situation occurred also in another team between the responses of having free insurance and free insurance discounts.

3. Abstract belief overlaps. A set of members agreed on an abstract belief, but had different interpretation of the belief. For example, Figure 14(a) shows the situation in which all team members agreed that healthcare must be affordable. Eight different interpretations were offered by the group on what affordable healthcare actually means. The responses span a broad range, including opposing responses that healthcare should be free or not free. This case represents a situation in which team (Group 1) produced a large variety of responses. Even though some responses conflicted with each other, the

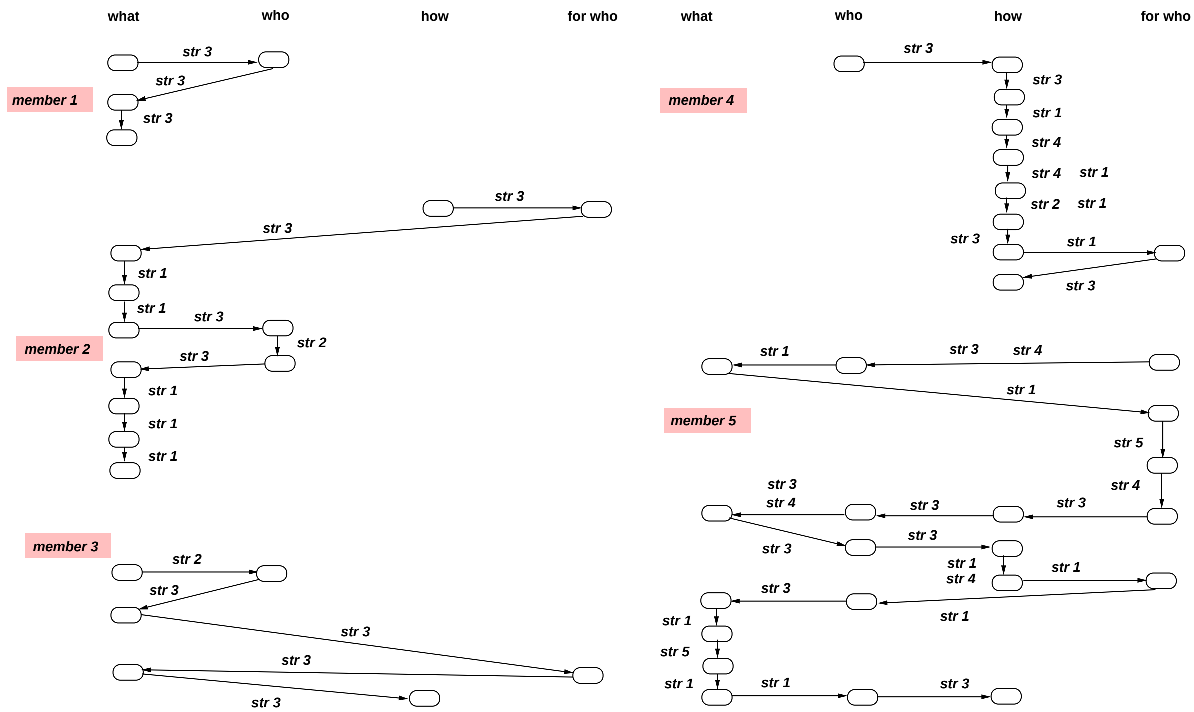

Figure 15: **Solution space evolution for the most creative team**

members did not engage in using Strategy 4 to build their opposing views. A more constrained version of this situation is if a new response was a special case of two more general responses produced by two other members. While one of the members did not adopt the new response, the other member elaborated on it by adding more details.

4. Repeated instantiations. A broad concept accepted by the group was further extended, as members produced real examples describing the concept. Arguably, the concrete examples acted as cues that illuminated other related examples by the same person or by another member of the team. For example, Figure 14(b) shows a case in which the cost aspect of health services was instantiated for concrete cases, like ER, braces, X rays, doctor visits, and so on. Another example considered the broad concept of offering cheap pharmaceuticals, which then was further instantiated as concrete examples, like using natural remedies, and offering cheap vaccination or cheap condoms.

5. Consolidated beliefs. The team members had conflicting beliefs about a response. Figure 14(c) illustrates this case. Responses mainly followed Strategy 4. New responses were mostly *why* frames and added few new features or sub-categories to the more abstract concept. Another case is the one in which the members fully agreed with each other, hence reinforced their beliefs, without adding any new details to the responses.

The following observations were made about the beliefs shared by team members. All members of the group with highest novelty (Group 1) were concerned about insurance, as all provided a response on this topic. However, there were less common beliefs. Three members agreed about having insurance at the job, out of which two agreed on having job-related insurance with the exception of avoidable accidents. Two members agreed on giving free insurance to low income persons. Two members agreed that every doctor must accept any insurance. Even though four members were concerned about pharmaceuticals, there was only a reduced belief overlapping, as one member indicated that pharmaceuticals should be affordable, a response that was cited by a second member when suggesting that their cost must be reduced. Similarly, for the team with the next highest novelty, four team members were concerned about the need to offer affordable insurance, however, there were only pairwise agreements between them on the more detailed issues, like different member pairs agreed that insurance should be offered at work and be provided in case of lay-offs too, taxing marijuana, free or affordable medicine, and low interest rates for medical expenses. As team response novelty decreases, there was higher incidence of cases in which members had opposite beliefs. For example, two members of team Group 5 had distinct responses on how to prevent abusing the healthcare system. There was disagreement between them on how the verification process should be implemented. Also, there was a higher incidents of more detailed agreements between team members. For example,

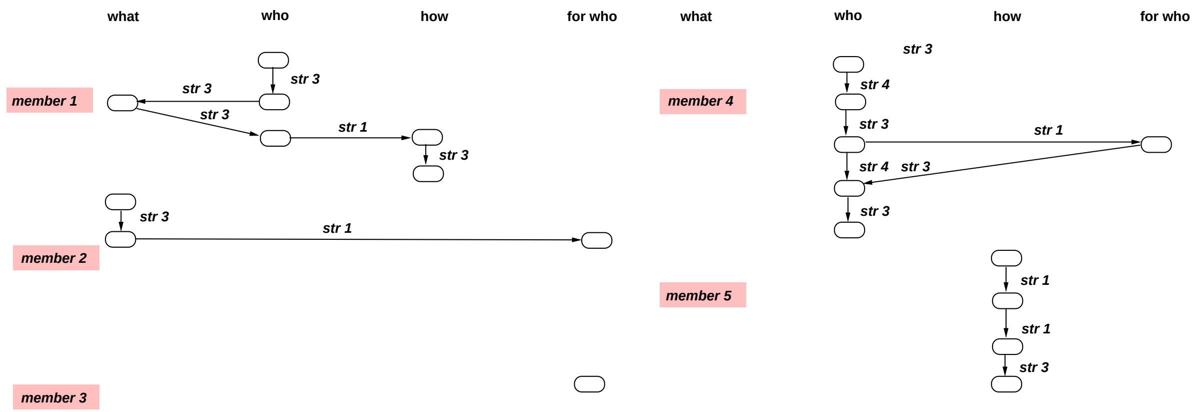

Figure 16: **Solution space evolution for the least creative team. Such responses are expected to be similar to teams including persons with ASD**

three members of team Group 6 agreed not only on healthcare having a lower price, but also on offering a bare minimum of services to everyone. Still, similar to teams with high novelty, there were instances when members agreed on the more abstract concepts, while they generated an increased variety of more detailed responses for abstract concepts. Members in teams with low novelty often disagreed about topics with high emotional content, like vaccination, replicating medical services in other western countries, globalization, universal insurance, or health insurance for illegal immigrants.

4.5 Response evolution depending on team characteristics

Figure 15 presents the evolution of the solution space that was rated by human raters as having the highest novelty. Responses were relatively equally distributed among the four frame categories, *what*, *who*, *for who*, and *how*. Responses transitioned among the four categories, usually by using Strategy 3 to create a new outcome. Strategy 2 was applied to create a sub-category by adding constraints and conditions to a more abstract concept, like concept "health insurance given by employer" was further refined into a new sub-category by adding the constraint "in case of work accidents". Strategy 2 was only rarely utilized. The longer sequences of responses pertaining to the same category were mostly produced by using Strategy 1, when multiple related real examples were enumerated by a member, like "long term care", "vaccination", "drugs", and "natural remedies". Strategy 1 was also used for creating responses that described a very concrete, but well-known situation (example), like offering health insurance to college students. Longer sequences of responses in the same frame category were created by repeatedly using Strategy 4. Strategy 5 was seldom used, however, when used, the general concept was not further developed by the group. Thus, Strategy 5 had little impact on the solution space.

Figure 16 illustrates the evolution of the solution space for the team with the least novel responses. We expect that teams with ASD members show similar behavior. In addition to responses that sampled the four categories, there was also a strong modularity of the outcomes indicating that responses had a higher similarity with each other, hence performing a localized sampling (search) of a certain aspect. There were much fewer responses describing *what* frames as compared to the previous group. Most of the responses were *how* frames with some indication of elements referring to *what* and *for who*, but with very few mentioning *who* elements. The proposed solutions were mostly a subset of the solutions found by the previous group, such as the idea that healthcare for students should be supported by parents' insurance until students graduate from college.

Each member produced a much smaller number of responses as compared to the previous group. The transition from one category of responses to another category was produced mostly through responses produced by using Strategy 3. Hence, responses described more abstract outcomes that could have served as categories or sub-categories of the solution space. However, these responses were usually not followed-up by further elaborations to increase the diversity of their category (sub-category). Strategy 1 was used to add details to a given situation, including responses that were suggested through Strategy 4 as alternatives to another response. Responses describing *how* frames referred to concepts with strong emotional content (and likely to trigger a certain kind of response from the others), e.g., taxation, involvement of government, and military budget. Such concepts might quickly trigger the using of Strategy 4, if other members did not agree with a certain response, as well as detailed arguments (i.e. specific cases or examples) in order to support the alternative.

5 Discussion and Conclusions

This research project focused on devising a novel computer game for ASD therapy. Its goal was to improve the capacity of persons with ASD to adapt to others' ideas and to their emotional and social cues. Players must create an integrated story jointly with three or four virtual game characters. The ASD individual and every character take turns in suggesting sentences of the story, so that the story scores high in terms of its quality. Hence, the person with ASD is encouraged to create more integrated stories, which is expected to help improve his/her skills to coordinate with the other team members.

The proposed game for therapy uses new Machine Learning (ML) algorithms to identify the sequence of cues that is likely to address dissonance situations at a minimum effort. The sequence is reinforced depending on its rate of success. The algorithm comprises of two main steps: (i) identification of dissonances, and (ii) finding the minimum effort cue sequence that solves the dissonance. Identified dissonances include lack of idea variation, significant differences in idea variations for different participants, differences in the accessing more abstract ideas, differences in identifying causal relations between solutions and parameters, or different interpretations of the same outcomes. The latter cases are possible situations of cognitive dissonance. In addition, social and emotional dissonance are situations in which a patient does not understand the way in which others' interpret certain outcomes.

Responses with low creativity are a good predictor of the responses produced by teams also including people with ASD.

Teams produced solution spaces with different degrees of fragmentation in terms of the nature and similarity of the concepts of their proposed solutions. Teams that originated responses with the highest and lowest novelty have lesser fragmentation (e.g., fewer number of abstract concepts to which responses belong), while the median teams created responses of higher fragmentation. During interaction, team members performed a matching (alignment) of their responses with responses by other members during which conditions, constraints, and concrete cases (situations) under which an acceptable matching was found were explicitly or implicitly identified. The analysis also pointed out the elements that members associated to certain belief and response, like attention and priority (which are indicators of the related emotional load and expected utility), inconsistencies in using beliefs for reasoning, and the flexibility in accepting different beliefs, e.g., beliefs with an amount of overlapping with the member's own beliefs. Some sets of responses showed the emergence of stable, invariant relations between specific concepts, e.g., health insurance provided by the employer. The meaning of a concept related with the meaning of other concepts in a fixed way, independent on the variations of the responses in the set. Hence, the set of responses can be theoretically characterized by a pair of components, in which the first component indicates the invariant part and the second component the variations (e.g., specific concepts) of the set.

Experiments show that team members were rarely aware of the trade-offs involved in a response. For example, the solution to have free health care conflicted with the economic costs of the solution, the quality of the solution, its scalability for a large population, need, and possibly other criteria. Participants were usually concerned only about one main goal while ignoring the other facets of the problem. Tackling a broad concept from the different perspectives of a trade-off was a way of creating a larger variety of similar responses by using strategies 2 and 3. However, in other cases, the existence of a trade-off had a negative impact, if the competing aspects had a high priority for two participants. Not being aware of the intrinsic trade-off of the solution was likely to trigger using Strategy 4 through which incompatible solutions were proposed. This suggests that the existence of trade-offs for a certain response frames it as an ill-defined problem, and hence encourages the using of solving strategies specific to such problems. Moreover, the same participant might have used inconsistent decision making, when they argued for a certain solution considering a certain facet of the trade-off, or argued against the same solution, if another facet is analyzed. For example, a participant suggested free healthcare as a global solution to improve healthcare, but then in a different context, proposed that users should be hold accountable if they misuse the insurance.

There can be different kind of inconsistencies between the beliefs of each participant and the beliefs of a participant and the team. Beliefs tend to stay unchanged during the experiment showing that received responses, including proposing frames *why* and using Strategy 4, did not change the beliefs of members. Inconsistencies occurred when more details were added to a general concept or if a new goal facet was considered by a member.

There is some similarity at a more abstract level between the responses proposed by different teams, but the similarity decreases as more details were added. The novelty of the responses was higher, if the team identified a larger variety that instantiated the same higher-level concept. The variety was more likely to emerge, if the members had beliefs that partially overlapped, hence bordered a solution space region in which the differences in responses could be addressed without triggering strong opposing responses, like those produced using Strategy 4. Such a resolve was more likely to occur, if the differences were due to different trade-off facets that were considered by the participants, while sufficient flexibility was maintained in the participants beliefs for the responses by others. The response novelty was lower when participants enumerated concrete features and real examples, even if the number of such instances was higher. Even if there might be a certain overlapping between the meaning (semantics) of the real examples, there was less triggering of new responses that bridge the meaning of the real examples. It can be argued that the real examples represented concrete, previous experiences. Participants with similar experiences were more likely to enumerate or to agree on the same concrete features or real examples. Solution spaces with average novelty had a higher fragmentation than those for team responses with high or low novelty. However, there is less elaboration of the variants (e.g., the branches of a concept in the graph representation), which suggests that the beliefs of the members had less overlapping with each other. Also, there is a higher semantic distance between the enumerated variants. Finally, team responses had low novelty when members had opposing beliefs on an issue, hence they pursued a sequence of contradicting steps (Strategy 4) or when they fully agreed with each other, hence creating a large number of belief reinforcements. Novelty was also reduced, if members used many synonyms to denote the same concept or feature.

Responses of teams with high novelty continuously shifted between different frame types (*what*, *who*, *for who* and *how* frames). Shifts from one category to another were mostly achieved by using Strategy 3 applied to more abstract concepts. It suggests that the cognitive effort was smaller, if the combined concepts are more abstract. In contrast, responses of teams with low novelty stayed mostly in a single category, such as *how* frame. This observation suggests that more creative teams sampled to a higher degree the meaning of a concept, features, or sub-category in terms of the goal facets, even though without considering the specifics of the trade-offs that exist. Team interactions included rare cases when a member used within his/her own solution context a certain change suggested by another member, or the case in which a change previously used by the member was applied again, but to the response of another member. The two cases describe situations in which knowledge was moved across the contexts of different responses. The connections between facets were not explored. The observation suggests that participants mainly considered direct connections between goals, concepts, and outcomes, and neglected any situations that can emerge due to the interactions between two or multiple changes that were made to a response.

From the point of view of mathematical logic, it can be argued that responses including multiple changes cannot produce superior results than those including a single change, as those with multiple changes are a special case of those with a single change. However, this observation is valid only if the two changes are not correlated with each other through the problem definition. For example, providing cheaper ER for everyone might be unsustainable due to the large costs involved. The high cost is a bottleneck of the solution. Reducing the ER cost involves reducing the cost of regular treatment that is likely to lower its quality. Reducing cost without reducing quality can be achieved only if the number of ER visits is reduced, such as by superior prevention, or if new technology is created that can lower cost, such as by increasing automation. The relation that exists between cost and technology or prevention can explain responses with higher novelty than responses with a single modification.

The main advantage of computational therapy is in that it offers more flexibility and superior therapy customization. Traditionally, patients meet weekly with their therapist for sessions of about 20 or 40 minutes. This offers less opportunity for exploiting all opportunities to customize their therapies to the specific needs of the patient.

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Table 1: Parameter ranges and correlation coefficients

Group	concept (category)	# abstr. levels	#concepts / # features	# real examples	# str. 4	# str. 5	# common abstr. / # common detail.	# reinforc.
Group 1	pharmaceuticals	4	5 / 1	1	0	0	7 / 0	1
	insurance	4	23 / 5	4	1	0	14 / 0	0
	employers	4	6 / 0	0	0	0	2 / 0	0
Group 2	insurance	4	8 / 2	1	0	0	12/ 2	0
	medicine	2	2 / 1	0	0	0	2 / 0	0
Group 3	pharmaceuticals	2	3 / 3	1	0	0	5 / 0	0
	insurance	3	17 / 2	6	1	0	15 / 2	0
	emergency	2	1 / 2	0	0	0	2 / 0	0
	SF	2	4 / 0	4	1	0	0 / 0	0
	treatment	3	8 / 1	4	0	1	4 / 0	0
	dentist	2	1 / 1	0	0	0	0 / 0	0
Group 4	pharmaceuticals	3	4 / 4	2	1	0	2 / 0	1
	insurance	3	4 / 3	1	2	0	17 / 11	2
	cost	3	3 / 1	0	0	0	0 / 0	1
	healthcare	4	19 / 10	3	0	1	14 / 21	4
	doctors	2	3 / 0	0	1	0	6 / 0	2
	people	2	3 / 3	0	0	0	0 / 0	1
	senior citizens	2	3 / 0	0	0	0	0 / 0	1
	payment plan	4	9 / 1	1	2	0	11 / 0	5
Group 5	insurance	4	23 / 4	3	6	0	15 / 0	0
	treatment	2	7 / 3	5	1	0	0 / 2	0
	health professionals	4	11 / 0	2	2	0	6 / 0	1
	people help	2	2 / 0	2	1	1	0 / 0	0
	people	2	7 / 0	3	3	0	8 / 0	0
	like Canada	2	3 / 0	1	1	0	0 / 2	0
	government	2	2 / 0	0	0	0	2 / 2	0
	health education	3	2 / 1	0	2	0	0 / 0	0
Group 7	medication	3	3 / 3	0	0	0	3 / 0	0
	treatment	4	13 / 4	3	1	0	4 / 2	2
	health coverage	6	20 / 13	0	3	0	24 / 0	1
	people	4	5 / 1	0	0	0	0 / 0	0
	not connected	3	4 / 1	1	0	0	0 / 0	0
	doctors	3	5 / 0	0	0	0	4 / 0	0
	medical school	3	3 / 2	0	0	0	4 / 0	0
Group 8	medicine	4	4 / 6	1	0	1	5 / 0	1
	surgeries	5	5 / 1	0	0	0	2 / 0	2
	mentally ill	3	3 / 1	0	0	0	0 / 0	0
	ER	3	4 / 1	3	1	1	3 / 0	1
	ambulance	3	2 / 1	1	0	0	0 / 0	0
	hospitals	3	2 / 1	3	0	0	0 / 0	0
	insurance	3	2 / 1	0	0	0	0 / 0	0
	insurance company	2	3 / 0	0	1	0	2 / 0	0
	people	3	6 / 0	0	0	0	4 / 0	2
	low income	3	4 / 0	1	0	0	2 / 0	1
	students	2	2 / 0	0	0	0	0 / 0	0
	company	2	2 / 0	0	0	0	0 / 0	0
	healthcare	4	11 / 11	3	3	1	13 / 0	4
	medical students	2	2 / 1	0	1	1	0 / 0	1
Group 9	insurance	2	9 / 1	1	3	0	2 / 0	0
	cost	7	34 / 10	9	11	0	23 / 8	6
	elderly, impaired	2	2 / 0	1	0	0	0 / 0	0
	schools	3	3 / 1	1	1	0	0 / 0	0
	government	3	7 / 1	1	0	0	2 / 0	0
	healthcare	5	9 / 1	4	8	0	6 / 0	2
Group 10	insurance	4	13 / 1	3	1	0	9 / 2	1
	cost	3	5 / 4	3	0	0	2 / 2	0
	people	4	4 / 1	1	0	0	4 / 0	0
	based on income	3	7 / 2	3	0	0	0 / 0	0
	students	3	4 / 1	1	0	0	2 / 2	1
	pharmaceutical companies	3	3 / 0	0	0	0	0 / 0	0
	health care	4	16 / 3	2	0	0	10 / 2	3

Table 2: Parameter ranges and correlation coefficients

Group	concept (category)	# abstr. levels	#concepts / # features	# real examples	# str. 4	# str. 5	# common abstr. / # common detail.	# reinforc.
Group 11	pharmaceuticals	3	3 / 2	0	0	0	2 / 0	0
	insurance	4	19 / 6	3	6	0	17 / 4	3
	people	4	9 / 2	1	1	1	6 / 0	2
	illegals	2	2 / 0	0	0	0	0 / 0	0
	cost	3	3 / 3	2	0	0	2 / 0	0
	government	2	2 / 0	0	1	0	0 / 0	0
	borders	2	1 / 1	0	0	0	0 / 0	0
Group 12	pharmaceuticals	3	3 / 1	0	0	0	2 / 0	0
	insurance	5	12 / 6	1	4	0	11 / 0	2
	finance	4	5 / 4	1	0	0	0 / 0	0
	everyone	2	2 / 0	1	0	0	0 / 0	0
	people	4	10 / 1	1	1	0	5 / 0	1
	most Americans	3	3 / 0	0	1	0	2 / 0	0
	preexisting conditions	3	2 / 1	1	1	0	0 / 0	0
	government help	3	2 / 1	0	1	0	0 / 0	0
	healthcare	4	19 / 1	4	2	1	6 / 2	3
Group 13	prescriptions	3	2 / 1	0	0	0	0 / 0	0
	cost	5	10 / 1	3	0	0	2 / 0	1
	those	4	10 / 0	4	4	0	10 / 0	1
	primary care	3	3 / 1	1	1	0	2 / 0	0
	government	3	4 / 0	0	0	1	0 / 0	3
	like Canada	2	2 / 0	1	0	0	0 / 0	0
	healthcare	5	21 / 5	3	1	1	13 / 2	3
Group 15	insurance	3	6 / 5	1	0	0	2 / 0	0
	insurance companies	3	4 / 0	1	0	0	0 / 0	0
	everyone	6	14 / 0	0	8	0	9 / 0	1
	cost	6	15 / 5	2	7	1	13 / 1	3
	doctors	4	5 / 0	0	1	0	4 / 0	0
	healthcare	5	31 / 5	2	9	1	18 / 0	3
Group 16	medicine	5	6 / 1	0	2	0	2 / 0	0
	insurance	4	4 / 1	1	1	0	2 / 2	0
	machines	2	1 / 1	1	0	0	0 / 0	0
	healthcare	3	2 / 1	3	0	0	0 / 0	0
	taxes	3	5 / 0	0	1	0	0 / 0	0
	doctors	4	3 / 2	1	1	0	2 / 0	0
	healthcare	9	43 / 9	6	9	1	20 / 3	8
Group 17	drugs	3	4 / 0	0	0	0	6 / 0	1
	insurance	2	4 / 0	0	0	0	3 / 0	0
	HIV/AIDS	4	5 / 1	1	0	0	0 / 0	0
	government	4	7 / 0	0	0	0	0 / 0	0
	healthcare	4	14 / 5	2	0	0	3 / 0	1
	healthcare	5	40 / 7	6	5	0	20 / 9	14
Group 18	insurance	4	5 / 2	1	1	0	5 / 0	1
	America	5	4 / 1	0	0	0	0 / 0	0
	finances	5	7 / 1	0	4	0	9 / 0	1
	healthcare	4	/ 10	2	5	0	14 / 0	3
Group 19	pharmaceuticals	4	7 / 2	0	2	0	5 / 0	0
	companies	2	2 / 0	0	0	0	0 / 0	1
	healthcare	5	27 / 6	2	11	0	15 / 2	1
Group 20	insurance companies	5	9 / 2	3	5	0	9 / 2	0
	like other countries	10	15 / 1	2	8	0	16 / 2	4
	healthcare	6	27 / 7	2	11	0	20 / 0	1