Computable cognitive model based on social evidence and restricted by resources

Applications for personalized search and social media in multi-agent environments

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***Abstract*—The paper presents computable cognitive model of generic social agent suitable for development of applications for personalized search, information filtering and intelligent content delivery.**

***Keywords*—cognitive; social; agent; belief; system; personalization; information; filtering; marketing; propaganda**

I. Introduction

The theory of human intelligence and cognitive abilities have been always key for fundamental sciences and amount of research made in this area is enormous [1]. Over the last 50 years, exponential burst has happened in information technologies, enabling light-of-speed social communications between any two humans on Earth and causing appearance of intelligent artificial agents operating on behalf on marketing, political and government agencies (such as Google and Facebook) to act in social networks against global human communities – collecting Earth-wide social information, building predictive models of mass behavior and manipulating consumer, social and political activity.

Respectively, the need to have representative working model of multi-agent interactions in social environment in order to predict social phenomena and be able to impact on it has been addressed. One of the major pioneer work is done by Lefebvre [2] who created working mathematical model of social agents with different kinds of beliefs (ethical models) – which has been proven to predict outcome of conflict in multi-agent interaction for two participants. There are more recent works modeling multi-agent dynamic in social environments [3] and discussing phenomena of mass behavior [4].

In the very last years, it has happened so that entire scope of knowledge accumulated by humanity could be uploaded into computer software system using computable graph representation [5]. Accompanied with available computational models of intelligence [6,7], it is now theoretically possible to create "in silico" models of cognitive behavior of a single human or social interactions for entire societies.

Such models could be invaluable for wide range of applications on consumer and corporate markets. For personal use, it could be built into intelligent software assistants providing intelligent filtering of incoming electronic media and automatic predictive search for desired information – accordingly to cognitive profile of a user [8,9,10]. For use by media supplier, it could be beneficial to have psychologically correct dynamic models of target audience to ensure precise account for consumer intent and desire, eliminating irrelevant noise in advertisement information and respective rejection on consumer side.

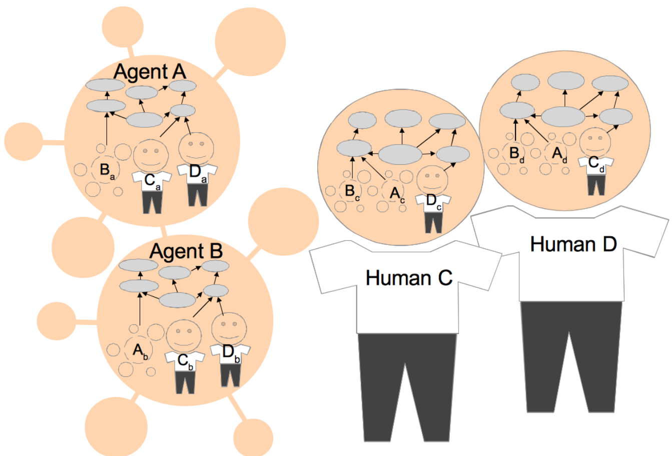

Fig. 1. Modern social communication environment, where participant of the communication may be either human being or software system (agent), latter implementing knowledge acquisition and content delivery functions, typically as an online advertisement and marketing platform implemented as "search engine" or "social network". Each peer member of the environment has capability to maintain internal "belief system", describing owner's view of the environment, including "images" of the corresponding peers.

In the further discussion, we will advance with development of computable model of human cognition for social engineering applications, mostly relying on knowledge representation in graphs [5], fuzzy logical inference [7] and resource-based definition of intelligence as "ability to reach complex goals in complex environments, giving limited resources" [6].

Moreover, the cognitive behavior model could be considered in respect to an abstract agent of social interactions – human being or artificial software creation (Fig. 1).

II. Approach

In accordance with earlier work [5,6,7], we will be representing entire set of an intelligent agent knowledge (be it human or software system) as a graph. That is, regardless of actual physiological implementation of cognitive functions in human brain, we assume that knowledge accumulated by human over the life time and used on everyday basis (starting from elementary stimulus-response chains and ending with high-level abstract reasoning) is represented in terms of nodes and links between them.

The nodes and links in the graph represent concepts and relationships between them, respectively. They can be organized in clusters with internal hierarchical structures (reflecting different levels of knowledge granularity and abstraction). The clusters could be included into larger hierarchy accordingly to their specialization and level of abstraction (Fig. 2).

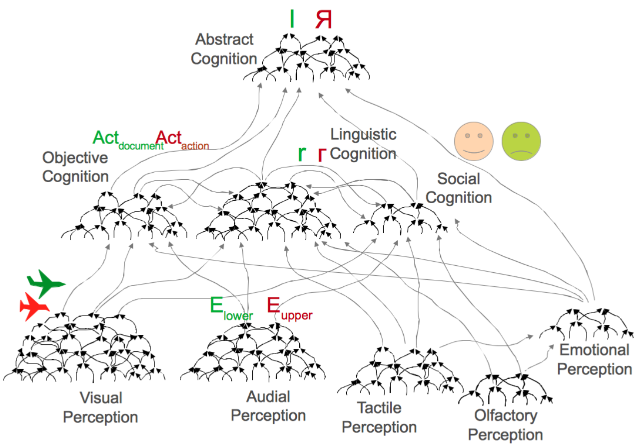

Fig. 2. Representing human cognition model by means of hierarchically clustered multi-level graph. Lower levels of the cognitive graph correspond to "older" and more cognitively primitive perceptual channels, starting with the most "ancient" olfactory perception and historically extended with tactile, audial and visual perceptual cores. Middle layers of cognition are represented with object-level cognition and co-evolved linguistic and social cognitive cores. Highest layer aggregates everything below keeping basic and ultimate concepts defining existence of an intelligent being and driving its goals. There is also emotional perception core laterally related to all layers above – grounded on lowest-level hormonal regulation but highly connected to higher cognitive layers in respect to basic self-awareness, self-development and self-protection functions of an intelligent live organism.

For the purpose of our work, we will be focusing on middle and upper layers of the entire cognitive graph, considering areas responsible for object-level reasoning about events and processes in surrounding world, in context of social environments framed by interactions with peer social agents in human communities by means of textual communications with human languages. We consider entities encompassed by these sub-graph could be relatively lower-level and higher-level. The higher-level are corresponding to evidential facts and events experienced in everyday life as matter of fact in physical world as well as communicated over social communication channels for the peer agents within society. The higher-level entities could be more abstract ones, partially "imprinted" in the course of very early stages of human brain and cognition development [1] and to greater extent inferred during life time by means of neurophysiologically implemented algorithms of "fuzzy logical inference" [7].

In order to construct working model of an intelligent being driven to reach its goals in complex environments being constrained by resources [6], we assume the most important part of a human environment is social one and basic goals of any human being are nearly the same – assuring safety of the being itself and closest neighbors of its social environment. Then, we can focus on building model that would enable us to consider resources needed to minimize energy spendings on reaching these goals while performing cognitive functions.

These functions could taken from the earlier work on Non-Axiomatic Logic (NAL) [7], where four basic functions are identified: 1) "revision" – accumulating evidence for certain concept or relationship between them, 2) "deduction" – performing optimization of simple stimulus-response paths and more abstract reasoning trails among the concepts and relationships with known evidence, 3) "induction" and "deduction" which are responsible for creating new hypothetical knowledge in the cognitive system, making guesses on basis of known concepts and relationships, so the evidence of that knowledge could be confirmed or negated in the course of further system interaction with the environment.

The key part of NAL is maintenance of complex truth value for a link in the graph. The truth value consists of independent strength and confidence components, with joint yet separate account for the two during inference process. The strength is treated as decisive characteristic of a link, while the confidence incorporates supporting evidence. Further, we will be extending this model, focusing on the way the strength and confidence can be evaluated in dynamic social environments, affecting the entire cognitive behavior.

III. Cognitive Model

What we suggest could be called "dynamic social evidence-based knowledge representation model" [8], as it accounts for dynamic scoping of evidence calculation base over time scale, modulated by social connections and constrained by physical resources. The key part of the model is evaluation of confidence as cumulative evidence, collected in specific time frame and modulated by relevant social context, normalized to standard interval between 0 (no supporting evidence) and 1 (maximum supporting evidence) inclusively. It is anticipated this model could provide psychologically plausible results for cognitive agent interacting in social multi-agent environment, perceiving information from it in order to make decisions and take actions, with possibility to change its own knowledge about the environment in the course of operations.

In order to communicate, agents are implied to have some jointly shared system of fundamental knowledge (called "belief system") regarding the surrounding environment and themselves. They should also have a mechanism for either accepting the knowledge coming to an agent from its outer world (if it is compatible with the agent's belief system), or rejecting it (in the opposite case). Further, for different sorts of accepted knowledge, an agent should be able to make judgments regarding reliability of different facts, which can be done based on the amount of evidence associated with these facts. Each evidence is considered in terms of trust towards its source such as social connection supporting the evidence.

It is known that, within massively distributed data processing system with many-to-many style replication, synchronization of concurrent changes (especially, such as updates and deletes) become a big problem. For one instance, if agent A communicates fact P to agent B while B communicates fact Q to A, it is just matter of mutual exchange of novel knowledge between agents. For another instance, if agent A tells there are relationships X and Y between P and Q, while agent B argues there is Y and Z but not X, who is to be trusted in such case? In this scenario, agents are arguing about validity of the same matter X, suggesting conflicting changes to the beliefs of each other. Obviously, both can agree on presence of Y, while X may remain as personal belief of A and B can stay believing in Z only. That is, assuming part of the message can be accepted and the reminder can be rejected, it can be possible to make each of the agents more knowledgeable in the course of communication, yet not having to destroy the belief system of each of them. At the same time, the incoming evidence for facts contradicting current agent's belief could get retained and eventually get more supporting evidence causing belief system of the agent finally changed – either agent A removes X from its belief or B starts believing in it, so they both get greater part of their beliefs shared.

Within the dynamic social evidence-based knowledge representation model, truth value of any piece of information for given period of time is calculated as sum of truth values of evidential facts supporting it in the given time frame and communicated by peer agents, multiplied by the trust levels given to each of these peer agents. Each fact or event of elementary evidence is specific to particular source in social environment and time. To deal with this model, segmentation of the entire agent's "knowledge graph" [5] can be described as semantic hyper-graph split in four major sub-graphs (Fig. 3).

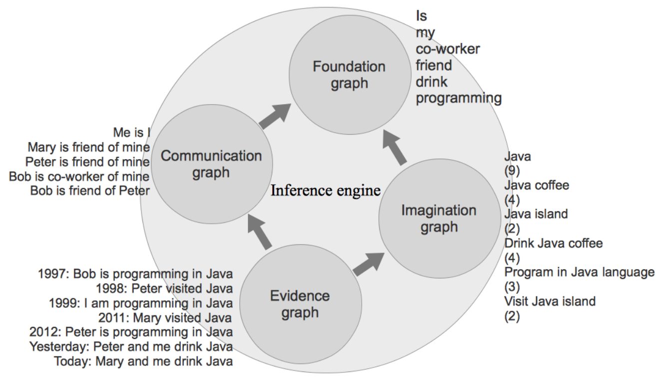

Fig. 3. Specialized subgraphs of the agent knowledge base and dynamic truth value calculation in the social evidence-based knowledge representation model.

The "foundation graph" part is cornerstone cognitive base, storing basic "belief system" of each of the agents. Without having that shared, the two agents speaking the same language syntactically, would not understand each other. It is assumed that, under normal circumstances, foundation graph does not need any fuzzy inference applied to it, so the cognitive functions and respective decision making operations relying on this sub-graph are executed rapidly, consuming few resources (using "binary logic" inference). The model assumes that portions of "imagination graph" (discussed further) exceeding given threshold of relative amount of evidence (i.e. confidence) can be "hardwired" to the foundation graph. Reasoning on this part of knowledge might be called orthodox, stereotypic or closed-minded thinking.

The "imagination graph" is dynamic pool of novel evidence-based knowledge coming to an agent via communication channels over time. Given the trust levels specific to particular communication peers providing the inputs, as well as sign of evidence (positive or negative) supplied for relationships in the "evidence graph" (discussed further) within actual time frame, the agent is capable to collect cumulative evidence and draw inferred trust values for respective relationships to communicate them back to the outer world later or upload to the foundation graph eventually. Obviously, maintenance of the dynamic "truth values" by means of "fuzzy logic" inference, might be more time consuming and allocate more resources than operations in "foundation graph". This part of the knowledge graph can be considered as dynamic, non-stereotypic or open-minded core.

The "communication graph" part describes social interaction channels possessed by an agent and provides the basis for account of subjectivity, so that each fact in the imagination graph is supplied by trust given to a particular communication agent at a time. This is effectively the social core, or personal social network of the agent, maintaining trust levels for each of peer agents in two dimensions. First – how much confidence can be given to incoming information communicated by the peer. Second – to which extent the private knowledge owned by the agent itself can be shared to given peer.

The "evidence graph" records temporal events or facts of evidence exposed by peer agents (residing in communication graph) to draw cumulative assertions in the imagination graph on that basis. This pool of socially relevant temporal facts serves as an evidence base for the inference engine calculating the truth values with account to subjective grounds and temporal context. Each piece of information here is timestamped and labeled by a peer communicating it. Data stored here can be subject of "evidence compression" with either clustering of fractional time slices into larger time intervals or aggregating evidences from individual peers into larger groups of peers. Further, in the course of "evidence consolidation", it can be removed from this pool with transition of knowledge (derived from the evidence) from the imagination graph to the foundation graph – if the cumulative evidence gets high enough. Also, the "evidence forgetting" can effect in complete removal of evidence from the graph if no extra supporting evidence is experienced for long time. The processes of "compressing", "consolidating" and "forgetting" evidence are driven by physical resource constrains, so the system assures the amounts of all data fit the existing memory and allocates less resources to store and process the knowledge. The basic goal of the agent is – maintain the most reliable knowledge fitting the system's internal belief to a greater extent, spending as much less resources on it as possible.

The knowledge representation model described above leads to possible technical implementation architecture, to a certain extent inspired by OpenCog [6]. The major specific feature of the architecture is ability to support resource-constrained maintenance of the evidence base, using evidence compression, consolidation and forgetting in order to fit physical restrictions. The physical restrictions could be identified as memory capacity (of a human brain or a computer system), energy consumption (spent on neurophysiological activity or digital calculations) and requirements for response times posed by environment so that decisions are made and actions are taken timely enough for agent survival.

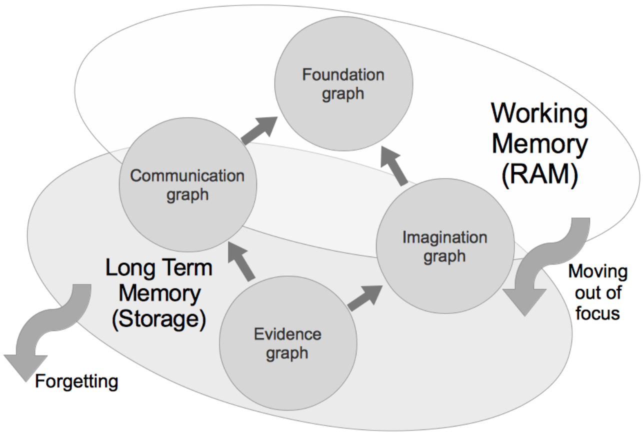

Fig. 4. Specifics of implementing the agent's subgraphs residing in different kinds of memory within the cognitive architecture.

For the described model and architecture to be practical, there is performance and capacity problem to be addressed (as known well for software system and holds true for human cognition if modeled "in silico", at least). That is, graph-based operations are very sensitive to memory access speed, so the optimal implementation would rely on fast memory operations on graphs (operating memory in a software system). However, the call for the evidence-based knowledge representation model implies the need for a tremendous amount of linked data which might require too much expensive fast memory.

The trade-off described above would get solved with mechanisms of moving knowledge items in-focus and out-of-focus and forgetting the irrelevant and outdated knowledge accordingly to the existing hardware or physiological constraints (Fig. 4). That is, we assume that the foundation graph as well as most of (if not all) communication graph and imagination graph reside in fast memory, corresponding to working memory of human brain [1,6] (RAM, in case of software agent), as long as parts of the entire graph are connected to any items that need current attention. Respectively, moving knowledge items out of the attention focus would correspond to moving them out of an fast memory still keeping them in long term memory of human brain (corresponding to slow persistent storage in software terms). Such process can be enforced by restrictions on consumable memory with new data requiring attention pushed into working memory. Further, the items not recalled for a long time (not linked at all, or having an insufficient supporting evidence, or not being moved to the attention focus for a substantial amount of time), can be forgotten and so removed even from the long term memory – saving the storage space.

There are important implications of such model and architecture. First, having different amounts of supporting evidence, different social context of the evidence acquisition and different temporal frames to consider the evidence can effect in quite different truth values obtained in respect to the same concepts and relationships. Next, having one or another size of memory (working or long-term or both) and possessing one or another amount of resources to spent on the reasoning process, the same amount of supporting evidence in respect to these concepts and relationships may lead to different truth values.

IV. Model Parameters and Analysis

Within the model described above, performance of an agent implementing the model would be bound to physical constraints. There are "hard" constraints that can not be changed, and there are "soft" constraints that can be relaxed, based on the importance of the constrained task for the agent's safety and other primary goals. The "soft" constraints are incurred by limits on available energy that can be re-allocated between particular reasoning subjects based on their importance – they could be either recurring, taking place on regular (e.g. daily) basis, or occasional – when really needed.

1) The hard constrains are physical capacity limits for different kinds of memory, defining certain cognitive and psychological capabilities of an agent to great extent.

a) Foundation graph size (S_f) – can be treated as "broad-mindedness" of an agent.

b) Communication graph size (S_c) – "social communicability" of an agent.

c) Imagination graph size (S_i) - "imagination power" (capability of "general intelligence").

d) Evidence graph size (S_e) - "generic capability to memorize".

2) The soft constraints on recurring energy spendings are defined on the need to spend limited amount of it to maintain storage of information in these graphs (specific to each or same for all), accordingly to daily energy income. It could be anticipated that impact on these could be either negligible or considered as constant component part of the previous group of constraints, however we consider this as part of the model.

3) The soft constraints on occasional energy spendings are incurred by limits on energy spendings, accordingly to its daily income, on occasional reasoning activities, which change current state of agent's mind – creating new paths in the graph and making other paths obsolete.

a) "Revision" (evidence accumulation).

b) "Deduction" (knowledge optimization).

c) "Induction" and "abduction" (knowledge discovery).

In the working cognition model, importance of the parameters discussed above can vary in context of agent's activity and operational context. That is, in passive mode with no incoming stimuli, most energy spendings are recurring plus possible background occasional spendings due to "self-reflections". In active mode however, occasional spendings start to dominate.

Based on the primary parameters above, few secondary (dependent) parameters can be inferred as thresholds for confidence (normalized evidence) value to: 1) move highly confident information from imagination to foundation graph (and get rid of the need to maintain respective evidence data); 2) move data from foundation to imagination graph, if it gets too much contradicting data in imagination graph (with substantial amount of supporting evidence); 3) move data from working memory to long-term memory (lose attention); 4) move data out of long-term memory (forget entirely).

There are few practical observations that could be obtained from this model, such as non-linear dynamics of moving information from foundation to imagination graph. That is, once data get in foundation graph (so it becomes energetically profitable to keep it there), it is hard to get it out of there.

The other observation is that if certain stimulus is introduced to an agent (so there is a need to evaluate the truth values of the graph chains leading from it to respective responses) more often, then it becomes more beneficial for the agent to keep it in foundation graph (with cheap decision making using straight "deduction") rather than in imagination graph (with expensive "revision" on massive evidence data).

V. Practical Applications

One of the practical applications is changing belief system of a target agent which is typical task of business advertising or political propaganda. The essence of the task is change the belief system of an agent so it takes certain action, not reasonable given the original belief system.

Let us assume someone has belief in relationship X(A,B) connecting concepts A and B and there is a need to change it to Y(A,B), while X and Y are mutually exclusive concepts. Let say it has to be changed – because of educational, medical, business or any other reasons. Let us further assume the belief is "hardwired" in agent's foundation graph so no reasoning generally applies to associate A with B – so agent does "believe" in truth of this relationship. Given the model described above, there could be few potential ways to change belief of the agent, as described below.

1) Repetitive temporal evidence. That means exposing redundant evidence of the same information for the target agent (typical technology used by most of high-end advertising channels).

2) Redundant social evidence. That means delivering same evidence to the target agent over different communication channels over existing communities or communities created intentionally for the purpose (that is principle grounding technologies of creating consumer communities and political parties).

3) Highly-valuable social evidence. That means delivering the evidence over the communication channel with high trust level for the target agent (the way how "network marketing works" and why celebrities are involved in brand marketing).

4) Injection of implicit evidence. Unlike the former three solutions based on brute-force "social evidence" boosting, this is the way to change piece of belief tolerable in respect to these if the information being communicated is incompatible with current belief. That means, the amount of evidence, implicit in respect to target one is given in amount sufficient to get it uploaded into foundation graph. Once this happens, it may turn out there is a way to save energetically compacting all the new information by means of "deduction" rule sacrificing with removal of single original contradicting piece information.

While the former can be considered as use case for corporate, political and governmental applications, the opposite scenario would be giving consumer end user a tool enabling to model its own belief system and either defend themselves from above-mentioned technologies or make it possible to fine-tune personal information filters – sorting out which kind of evidence from which sources and what kind of evidence should be trusted or rejected.

VI. Conclusion And Future Work

While the analysis of the suggested model appears psychologically and sociologically plausible, our future work is dedicated to creation of multi-agent simulations relying on this model – in order confirm suggested dynamics experimentally as well as create end-user applications based on the model to prove validity of its usefulness.

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