Contextual Reasoning in Human Cognition and its Implications for Artificial Intelligence Systems

Raisonnement contextuel dans la cognition humaine et son implication pour les systèmes basés sur l'intelligence artificielle

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RÉSUMÉ. Les recherches de ces 50 dernières années ont montré que le raisonnement avec et à propos du contexte est un aspect essentiel de la cognition humaine, imprégnant le langage, la mémoire et les capacités de raisonnement. L'ensemble de ce processus est développé au cours du temps par un apprentissage basé sur l'expérience. En supposant que le but de l'intelligence artificielle est de doté une machine d'une intelligence proche de celle des humains, il est essentiel de considérer et incorporer le concept de contexte dans la conception et l'implémentation des systèmes intelligents. Ce papier discute du raisonnement contextuel chez l'humain et comment celui-ci aide les humains à faire face avec succès à des tâches cognitives complexes. Nous relions de plus cette recherche sur le contexte en psychologie cognitive aux recherches actuelles sur le raisonnement contextuel ans les systèmes d'intelligence artificielle.

ABSTRACT. Research over the last 50 years has shown that reasoning with and about context is an essential aspect of human cognition, permeating language, memory, and reasoning capabilities. This integral process is developed over a lifetime through experiential learning. Given the goal of artificial intelligence to create human-like intelligence in a machine, it is essential to consider and incorporate the concept of context in intelligent system design and implementation. This paper discusses contextual reasoning in humans and how it helps humans successfully deal with complex cognitive tasks. We further link this research on context in cognitive psychology with the current research in contextual reasoning in Artificial Intelligence systems.

MOTS-CLÉS. Contexte dans la cognition humaine, raisonnement contextuel, Contexte dans la cognition humaine, raisonnement contextuel.

KEYWORDS. Context in human cognition, contextual reasoning, role of context in learning.

1. Context in Human Cognition

The scientific study of the human brain and how it affects our behavior has long been the definition of psychology. Yet, this appears to be a simplistic definition of a subject that has roots not only in expressed behavior but also in the related mental and physiological processes involved in living on an everyday basis. Each human's body is composed of cells that transmit sensory information to other cells in the brain, which process that incoming information to help us react to and deal with the world around us. These brain cells also participate in the development of a plan of action. Thus, the use of previously inputted and processed information allows one to manage the situation at hand. As we shall discuss in this paper, cognitive psychology research has suggested that the cognitive process used to manage everyday situations is inextricably linked to the context of the situation or problem being faced. Several aspects of our cognitive system are said to be context-sensitive: learning, memory retention and retrieval, and decision making. Furthermore, most humans could not function in anything other than the short term without communication with other humans. Context plays an important role here too.

Contextual intelligence is often considered one of the most important pieces of the puzzle to resolve difficulties in our everyday interactions with the physical world. The concept of contextual intelligence in human cognition was first mentioned in 1960 by Treisman [80], and has subsequently been explored by several other researchers. Sternberg legitimatized this concept when he included contextual intelligence as the third component in his landmark Triarchic Theory of Intelligence [78] [79]. (Contextual intelligence is also known as *practical intelligence* because it allows humans to perform many practical, everyday reasoning tasks.) Since that time, it has been largely accepted by the research community that the ability to analyze and recognize the context of a situation and rank the different stimuli is essential to the ability of the human brain to act and react while engaged in the physical world. Contextual processing plays a vital role in human cognition, whether we are speaking, listening, encoding, recalling a memory, or in general using our reasoning capabilities [16]. Without the use of context, it becomes more problematic to recall specific information regarding an encounter [72].

In this paper we discuss how context is essential in our everyday cognitive process, and cite literature supporting this position. We then discuss how context has been used in Artificial Intelligence-based systems to perform intelligent tasks. However, first a brief discussion of what is context in the context of this paper.

1.1. *What is context in human cognition?*

There does not seem to be a single widely-accepted definition of context in the literature. It is practically redefined every time an author writes about context. See Bazire and Brézillon [9] for an extensive discussion of several definitions. In fact, Brezillon and Gonzalez [13] state that "*Definitions that originate from researchers and practitioners in specific domains have singular and often narrow viewpoints, and focus on some aspects of context that can be identified from data, information or knowledge obtained through sensors that are specific to their domain or discipline*". To avoid further confusion, we use here the definition provided by Kokinov, which states that "*Context is the set of all entities that influence human (or system's) cognitive behavior on a particular occasion*" [47]. Context amounts to learned associations and inferences in everyday routines that help accomplish a desired result. Context, therefore, is not a tangible thing, but rather, *a state of the human mind* [47].

Contextual (or practical) intelligence has been an acknowledged element in the ability of humans to think both logically and critically in problem solving, as well as being able to comprehend a component of a complex problem where many different components of such problems must be solved in order to find an overall solution. This reasoning element can come from the reasoning mechanism itself as it analyses the goals and sub-goals [47]. These elements form what we call *reasoning context* and are derived from the environment. Because they are recognized in the environment, we can call them the *perceived context*. In accordance with the statement above that context is a state of mind, what matters is how we perceive objects as being part of the context, and not the real objects in the environment [47]. This also leads us to understand that some of these superficial ideas or perceptions may be residuals of images previously seen [47].

This perceived context is assisted by expectancy. If one were to be told that there is a dog in a picture, it would be easier to find the dog because our perception of the shape that we have come to understand is a dog makes it easier to find if we know it's there. This expectancy of *schema* (defined later) is built on the perceived context of what we are processing intellectually [22] [64].

We assert that to create computational systems that are to have the full range of human-like intelligence requires imbuing them with the ability to process context. This would give the computer system an indication of where and (possibly) when the relevant situation that comprises the context was previously encountered, and what was the end result of that encounter. Thus, managing the current situation may have a solution that could contain products or stimuli that are related and relevant to the original context. In light of this necessity, we discuss in this paper the many aspects of contextual processing in human cognition, how this cognitive ability (or set of cognitive abilities) is developed (i.e., learned) in humans. We furthermore offer insights into how a context-based intelligent computing system (i.e., an Artificial Intelligence (AI) system) would operate if it were to be modelled on how human cognition seems to use context to its advantage. By using context in decision making, one is able to change a behavior or outcome based on past experiences, combine information and activities to produce new outcomes and compare previous modes of operation and thinking that may result in innovative ideas, products, and inventions.

As we mentioned earlier, these ways in which the human intellect uses context to assist in performing its various complex functions can be associated with different tasks. In these next few sections we discuss and cite literature from cognitive psychology that sheds light on the human aspect of context. We then link this discussion with how some existing computational systems use context in the same general manner (rarely identically). We begin in Section 2 by discussing how we use context to learn and remember things (Context and Memory – Learning and Remembering). In Section 3 we proceed to discuss how we learn, reason and problem solve with the help of contextualization. Then in Section 4 we discuss how we use context in language communication. Section 5 covers how context plays a role in a child's cognitive development. Section 6 puts together the previous discussions about context and human cognition and puts it in the context of AI systems. It describes some of the most popular reasoning paradigms that are context-centric. Finally, we conclude the paper with a summary in section 7.

2. Context and Memory - Learning and Remembering

The human memory system is a complex and fascinating mechanism that works to retain information and/or knowledge from raw data that it has received, interpreted and converted into information or knowledge. The human memory system is said to employ contextual processing to facilitate the encoding, storage and retrieval of such memories. *Schemas* are cognitive frameworks that help us retain knowledge about a specific aspect of our worlds [88] [60]. Schemas can be retained for short or long periods of time. These processes greatly influence our cognitive behaviors, including perception, attention, learning, and cognition. A general definition of learning is the acquisition of such schemas and commitment to memory (short- or long-term as appropriate) that is a result of practice and/or experience. The associations one forms using context help guide how one remembers information and what circumstances might trigger its retrieval.

There is evidence that when we encode new information, we also encode the context in which it was presented [31] [26]. This can assist in more accurate recall of the event and its relevant information and knowledge. This phenomenon is called *state dependent memories*. The idea is that, because we encode and store not only the information but also the context in which we learned it, replicating that context when it is time for recall will greatly increase accuracy. This ability to retrieve information is affected not only by the place where we happen to be but also how we were feeling about the situation at the time. According to Drace, Ric, and Desrichard [25], this *mood congruence* also amplifies the state in which we were at the time, and explains why we recall more pleasant thoughts when we are in a good mood and more negative thoughts when our mood is more negative.

This state or mood congruence was shown by Godden and Baddeley [31] in their SCUBA diver experiments, where they used a set of SCUBA divers as test subjects. They initially took half of the diver test subjects out into the water and had the other half stay on dry land to learn a set of words. Then, one week later, they took them out again, only this time half of the original dry land group went in the water and the other half remained on dry land. Likewise, half of the original water group stayed on dry land while the other half went back into the water. When asked to recall the words on the list from one week earlier, the subjects who were in consistent environments were able to accurately recall significantly more words than those subjects who switched environments [31].

The SCUBA diver experiment by Godden and Baddeley illustrates our need to organize information using context. In these, execution speed-up would be invaluable for use of schemata, as they would provide faster routes for recalling the most relevant information for a given request. Furthermore, this ability could also allow one to extrapolate experiences and assist individuals in filling in any experiential blanks when a situation is unclear, based upon previously ordered knowledge. It can be said that human experts possess this ability to transcend contexts and apply knowledge learned in similar (but not identical) contexts to the current situation.

The concept that contextual Intelligence allows one to reasonably recall knowledge and information more easily given the environment where that knowledge and/or information was first encountered became one of the basic premises for *implicit memory*. In this phenomenon, one is not consciously aware of a particular memory but is influenced in decision making based on the perception of that memory [36] [87].

It is widely recognized that for learning to be effective, it is necessary for what is learned to be placed into long-term memory, where it can be part of the schemata to be assimilated and built upon. The question then becomes how and when these schemata are updated for new contextual information to be added. Given that the general definition of learning is a change in behavior brought about by practice and/or experience, it is obvious that memories can be reactivated and made malleable through adaptation and assimilation, then modified with new information and re-established continually over time [43]. This happens because of the context that is available in the memory can be changed as a result of revised behavior and the occurrences of new experiences. In a study involving young children, Hubach, Gomez and Nadel [43] found that these long-term memories were very rarely activated when the children were in a familiar setting, such as their home. This indicates that when a situation is familiar, human cognition need not trouble itself with assimilating new information, and thereby avoids using extra resources on a context which is already learned and familiar. However, there was an observed difference when the children were placed in less familiar contextual situations, when the context did trigger the reactivation of the older memories. This indicates that the children were adding new information to their schemata and learning the contextual information for a new situation [43]. Hubach, Gomez, and Nadel's experiment reinforces the idea that the use of contextual processing in memory can significantly decrease the cognitive load placed on human beings in terms of active processing.

The formation of associations and schemata must take into account memory storage and transference from one type of memory system to another, most often using rehearsal to move information from short-term into long term memory [4]. Short term memory is often thought to have been given more importance because the immediate control of short term memory allows for the flow of information into memory. Long term memories can be more discretionary, but with more consequences for performance if one is unable to recall the event [4].

3. Reasoning with and about Context

As we discussed above, in most problem solving scenarios, individuals tend to draw on prior knowledge to help with problem solving. Humans normally reason largely in a top-down manner. This means that we draw from prior knowledge and situational understanding in order to make sense of a current situation. This is why the elders in a culture have been traditionally considered to be the wisest individuals; they have the most complex schemata as a result of their greater experience, for use in problem solving tasks. They have likely experienced many situations and in many different contexts, have appropriately structured and re-structured their schemata, and have learned to accommodate and assimilate information to more easily arrive at an appropriate solution. We should note, however, that the rapid pace of modern technology has to an increasing degree invalidated this model, as in modern times, it is the young who more readily adopt emerging technological trends. The elders have less time (and often less willingness) to experience the contexts involved in the use of these new technologies. Their wisdom can often and quickly become obsolete as a result.

The use of contextual facilitation in human learning is highlighted in mathematics education where there is a view that mathematics is much easier to understand if, instead of being presented in an abstract manner, it is presented in a contextualized form [84]. For example, a student who is having difficulty with understanding how to find the area in a two-dimensional figure may be able to understand the formula more easily if it is presented as a question of how to estimate how much paint would be needed to paint a bedroom, as one would not want to buy more paint than was necessary. Because the student would have a familiar situation in which to process the information, he/she could focus on the reorganization of the mathematics schemata as facilitated by a previously constructed situational schema. This view coordinates well with the previous assertion that the assimilation of knowledge into long-term memory is affected by context.

Another example could also look again at the progression of mathematics education. Students are first taught to count without relating the words they are learning to an actual number. That is normally the next step in the teaching of mathematics to young children. Once they understand that relationship, they are then introduced to addition, subtraction, multiplication and then finally division. If a student were introduced to division prior to understanding multiplication, they would likely be confused and may not be able to gain the understanding necessary to perform that skill because they do not have the needed context to comprehend what the numbers mean and how they were divided.

A study by Pratt et al. [61] carries this idea even further by evaluating statistical problems, which according to the authors are different from mathematical problems. The authors argue that they are not simply referenced using contextual information, but are actually about real world issues and are thus affected by context. More specifically, the authors' target for the study is risk assessment, which they assert is a highly complex example of statistical assessment and modeling. In this study, test subjects were given a hypothetical situation involving a medical risk and asked to determine how a decision could be reached as to whether or not they would authorize a risky procedure. In making their decision, all the subjects drew heavily on their knowledge of the context of the situation and on personal experience involving such a situation [61]. At the end of this hypothetical situation in a medically risky procedure, the researchers determined that there were three major contextual components that influenced the subjects' decisions. These included the likelihood of the procedure being performed successfully, the potential impact of the procedure on ensuing life events, and also a social dimension that revolved around who was making the decision [61].

Another study involving formal decision making was done by Pennycook and Thompson [58]. In this study, subjects were asked to place fictional individuals into one of two categories. They were given base rates for the probability of an individual belonging to a group and a personality profile that was either consistent with or at odds with the base rate. The profiles might indicate that the individual was a doctor or a nurse, and the test subjects were asked as to specify whether the person was a male or female and his/her living quarters (apartments or houses). The results found that subjects were much more likely to draw upon the personality profile to make their decision, even when it called for the subject to disregard very strong base rate probabilities [58]. The subjects made their decisions on these fictional people based on their prior knowledge (prior context) of actual people in these positions.

Penny cook & Thompson's study provides support for context-based reasoning over other types of information processing among humans. It shows that humans are much more likely **to draw upon previous experiences** (i.e. context) than rely on raw statistical analysis to make a decision. This can be invaluable when dealing with confounding variables.

The studies discussed above provide evidence for the use of contextual processing in formal human reasoning; however, it is also valuable to highlight its importance in informal (or inductive) reasoning. A study by Lee and Grace [51] explores the use of informal contextual reasoning in socio-scientific issues. The study used students in two different cultural contexts involving disparities in access to information, adherence to tradition, and materialistic concerns. The assertion was that the disparities in cultural context would lead to disparities in the respective decision making of the students of the two different regions [51]. This assertion was found to be justified, as the students in the two regions studied did have dissimilar conclusions in the reasoning situation based on expected differences in cultural (contextual) value systems [51].

4. Context and Language

The English language has many homophones (as do most other languages, albeit to a possibly lesser degree) – words that have multiple meanings for the same word sound. For example, a car brakes at a stop sign to stop the car from moving, but one breaks an egg to make an omelet for breakfast. There is even a type of dancing called break dancing and taking a coffee break. Most individuals are able to understand the meaning of a sentence because of the context of the conversation, as indicated by the surrounding words as well as by the commonly agreed upon general topic of the conversation. Therefore, it is widely accepted that humans utilize contextual processing in linguistic comprehension, whether written or spoken [30] [65] [49].

The question we entertain and discuss in this section then, is how this cognitive processing is achieved. There have been several theories proposed over the years as to how a person learns language as a communication skill, and some are more complicated than others. However, in this discussion we are not concerned about how language is learned but how it is used once it is learned.

We take the view that language, to some extent or another, activates representations within the mind that pertain to definitions and connotations of the words read and/or the sounds heard, and processing continues from there. The deeper and more meaningful the understanding is and has been, the greater the ability will be to retrieve that information at a later date. Simply put, the more time one spends recalling and reminiscing about an event, the more likely one is to recall not only the large details but also the smaller details of that event [3] [5]. We examine how the human mental processes are able to decide which representation and which definition are appropriate for properly interpreting an utterance in natural language, and how the irrelevant representations are kept from being activated depending on the context.

A relevant cognitive theory of linguistic contextual processing is the Attenuation Model outlined by Treisman [80]. This model states that there are different attention channels going into a selective filter in the brain. This filter determines how much attention should be paid to each channel based on the context. According to other researchers, being able to distinguish these learned sounds may play a part in the recognition of language [11]. This attenuation model was originally proposed by Broadbent in 1958 (see Broadbent and Gregory [14]) when he was experimenting with utilizing signal detection theory. He was curious about whether the intensity of the signal made a difference in attention to the signal.

Treisman’s Attenuation Model describes a vital process in human contextual reasoning; the idea that we use context in language to highlight relevant information to make the most sense out of the myriad of phrases we hear throughout a conversation [80]. Attending to everything we hear with equal weight would result in an impossibly large amount of information to sort through, thus highlighting the need for a contextual parsing system in the brain.

One answer as to how this might be accomplished was proposed by Gernsbacher [29] in a paper analyzing experiments with language comprehension. The Treisman Attenuation model suggests how related contextual information is activated and retrieved in the brain and how phonologically irrelevant information is filtered out. However, it does not seem to explain how contextually irrelevant information is filtered out in a situation such as a homophone, where there would be no phonological cue. Hearing such a word would seemingly highlight two representations, simultaneously, resulting in a bit of confusion as to which meaning is most appropriate.

In the break versus brake versus break (dancing) versus (coffee) break example, all meanings of the words would be activated until the relevant contextual information became clearly understood; then, the most appropriate meaning for the sentence being spoken or read would be (subconsciously) selected. However, this would mean that we would then have to sift through the extraneous information, thereby slowing down situational comprehension until we arrived at the correct scenario. This would take time; yet people seem to immediately recognize the correct meaning of a homophone. For truly successful comprehension to occur in real time, it is necessary to keep this extraneous information from affecting the other processes at work. To accomplish this goal, we develop a suppression mechanism. This happens as we learn to successfully order schemata and become more and more competent at intuitively understanding contextual cues. To borrow terminology from Treisman [80], this mechanism would increase the activation threshold for the inappropriate homophones, thus decreasing the likelihood of the activation of their mental representation [29]. This suppression mechanism plays a pivotal role in real time contextual understanding in human linguistics.

Another aspect of context in inter-human communication is that can serve to facilitate communication is the presence of a shared context between interlocutors. Context has the effect if simplifying and reducing the amount of information either one needs to include in an exchange of communication. For example, in the context of driving an automobile, the statement turn left is known to imply a rotation of the steering wheel to the left while possibly also pushing on the brake pedal to slow down the automobile. Furthermore, it also implies knowledge of the rules of the road, such as for example, one cannot turn or merge into on-coming traffic until there is a gap in traffic sufficiently large to avoid a collision. The automobile driving context, shared among the multiple interlocutors or listeners, would automatically include that information. This is one of the concerns of autonomous vehicles that use sensors to relay information to the “driver”. Without previous understanding of a collision situation, how is a decision made to limit injuries to the occupants of the vehicle. Cameras, sensors, and programmed components all contribute to this decision making process; however, the failure rate still plays a part in the logical decision making process [52].

5. Development of the Human Contextual Reasoning Capability

There is not simply one single aspect to human cognition, but rather a complex matrix of systems of which contextual processing is a major element. Our cognitive development is constantly undergoing changes that allow us to perceive changes in the context of a situation and in the environment, which we can manipulate and against which we can then react.

Contextual learning begins as early as the infant stages of human development [1] [60] [86]. Infants learn to navigate ambiguous situations by referring to the experience of social agents such as close caregivers in order to better understand the situation at hand. This socio-cultural context in learning was illustrated in a visual cliff study, which presents an infant with a threateningly deep chasm to cross, but that is safely covered by thick clear plastic. The participating infant cannot tell that it is safe to cross based on visual cues, and in fact views the situation as perilous. The majority of the infants crossed the deep side when their mother showed expressions of joy and encouragement, thereby indicating that their decision was based in a large part on the affectual displays of his/her mother [71].

The power of context learning is evident from the above experiments. They also indicate that contextual development begins in a child as he/she starts to explore his/her world. This contextual learning helps to gather information about the world and how we interact with it through other people and situations. There is also evidence that indicates that recalling a memory for an event reactivates the same brain areas that became excited during the event itself [20].

It is ideal that an individual begins to learn to develop autonomy to be able to reason through contextual environmental cues, and develop preferences and weighting systems on their own. Piaget [59] [60] began conceptualizing this goal as a means of developing children to be able to think for themselves and not have to be told what it was they were to do. According to Piaget [59] and Vygotsky

[86], this is accomplished, through the exchange of points of view and scaffolding of information and schemas [37] [10].

All information can be shaped by the socio-cultural context of culture, economics and gender. Culture affects the behavior of individual members through the context of knowledge that is reinforced by the other members of the group [66]. For example, one’s ability to pursue and acquire an education/career may be limited by the resources needed for one to succeed [19]. This may also be evident in the aspect of gender and how gender is contextually viewed in socio-cultural terms [44]. Instead of the explicit mimicry of more experienced social agents, children would begin to be able to understand and apply the guidance they receive to decide for themselves what would be appropriate in a given circumstance [60] [86].

For example, once the child has learned a particular way of thinking and interacting with the world as a social agent, then she would develop mental schemata, or blueprints, for future decisions. Then, as the child began to experience the world for herself, she could be confronted by discrepancies between these schemata and the events she perceives, and decides on a course of action. New contextual reasoning strategies would develop as a result of such discrepancies encountered in the world. The child learns to model and understand contextual cues from the social environment. This behavioral filter provides for more regularity of behavior, and maintains the performance of preferred behaviors [63].

The evidence for the contextual nature of situational propriety is found in the general definition of learning - a relatively permanent change in behavior brought about by practice or experience. A context does include the family, community, state, country and culture. Each of these settings is influenced by economic, social and historical factors [70] [15]. This experiential learning view of context does contribute to knowledge about how humans obtain their contextual processing abilities, as many researchers have found.

According to Baltes and Kunzmann [6], contexts either are normative age-graded influences; normative history-graded influences; or highly individualized life events. Each of these influences may have an environmental or biological developmental impact for each person. For example, normative age-graded influences are experienced by many people within a similar age range, such as graduation or retirement. The normative history-graded influences are generally similar to people in a particular age bracket because they remember historical events that may have influenced behavior for a period of time, such as the Great Depression of 1929, WWII or the Great Recession of 2008-2010. The highly individualized events influence how one person may be affected by their personal circumstances. This development may also be influenced by unusual life situations, such as winning the lottery or the effects of the Zika virus on developing babies [17] – events that can change one’s lifestyle significantly.

A cycle appears to develop between context and the environment that shapes internal preferences and the agentic action of the child. An agentic action in this case is defined as behavior that is performed with intentionality, forethought, self-reactiveness, and self-reflection [7]. Essentially, contextual and environmental cues and experiences shape the preferences and memories of individuals. Within these memories there exist vast amounts of contextual information assisting our decisions based on how issue and situations have proceeded in the past. This allows us to move forward and make more informed decisions as we discern the most appropriate course of action in any given situation.

Treisman’s [81] dichotic listening experiment confirmed that when a listener would hear her/his name spoken – she/he became much more attentive to the conversation. This demonstrates that the material analysis was dismissed quickly and no active cognitive resources were wasted on the phonologically unimportant material.

This experiment has implications for the application of contextual processing in computer systems. For example, a computer analysis of linguistic scans could greatly benefit from a system that processed the phonological properties of words such as tone, pitch, and timbre. If these properties were deemed to be inappropriate for the type of information it was receiving (i.e., out of context), then the computer could more quickly reject or ignore the extraneous information based on a preliminary filtering scan in lieu of having to actually analyze every piece of information, which would be computationally expensive.

The cognitive psychology literature surveyed in the sections above points to the conclusion that contextual processing is a necessary and inextricable part of human cognition in our lives – how we communicate, how we learn, how we solve problems, and not least importantly, how we grow and mature. This contextual processing is essential and permeates the cognitive aspects of life, including linguistic processing, memory encoding, storage and retrieval, thinking, and reasoning capabilities. Next we discuss how these concepts have been incorporated in some contextual reasoning paradigms reported in the Artificial Intelligence literature.

6. Contextual Reasoning in AI Systems

Artificial Intelligence research seeks to build computational systems that will ultimately equal, and possibly surpass the intellectual and cognitive capabilities of humans. We assert that to accomplish this, it will be imperative that contextual weighting and real-life experience be incorporated into these systems. Integrating context in computing has already been on-going for several years in a (relatively small) community of dedicated researchers. The AI literature contains several reports of the implementation of context in AI systems. Nevertheless, the concept of context in computing has been generally under-valued and under-utilized in the overall computing research community. In this section we discuss some of the major systems reported in the literature that are context-centric in their approach to creating intelligent computer systems. A full discussion of this cannot be done in the scope of this paper, but we focus on a few works which employ a context-centric approach and thus reflect, to a greater or lesser degree, the cognitive context-based processes discussed above.

We begin with *Context-based Reasoning*, or CxBR [33] [34] [38]. CxBR has been successfully used to represent tactical knowledge in simulated as well as physical agents. It filters the information by tying the environmental cues to a single context where all associated knowledge and expectations is grouped together for use by the performing agent. CxBR decomposes an agent’s capabilities to behave into *Major* and M*inor contexts*. Each of these contexts contains associated behavioral information that is relevant to the current situation. Thus, CxBR applies the principles of relevancy and exclusion that were discussed above. These contexts in CxBR provide access to the appropriate knowledge of how to behave in that situation for an agent being controlled. This includes the functionality that enables actions that support the desired behavior when in that context. CxBR is designed to recognize the context currently being experienced by the agent, and limits all computations to the rules and functions associated with the corresponding *active* context, thereby making for efficient computations. Additionally, each context contains environmental variables that have to be true for that context to be active – that is, to be “in control” of the agent (i.e., whose knowledge/functionality is made accessible to the agent when in that situation). As the situation evolves during a tactical event, another context may suddenly become more relevant to the (new) current situation than is the currently active one. This would be based on environmental cues and the objectives of the mission. The CxBR system then *transitions* the active context to the one that now best addresses the needs of the new situation. Within the CxBR model, all of the transitions between contexts are predefined within the model by the programmer of the system. CxBR has also been used for learning behaviors from observation of a human actor performing the behavior to be learned (an action). This is discussed further below.

CxBR can be related back to Treisman’s [80] Attenuation Model, as the human/agent observe the current situation and respond based upon what they know to be proper in the face of the situation encountered. In CxBR, as in the Treisman model [80], each situation is being monitored for key factors that help determine when to transition into a new context. It is imperative that the most relevant information to solve the problem be retained while the extraneous information becomes suppressed so that one becomes more competent at intuitively understanding contextual cues in the current situation.

Turner's *Context-Mediated Behaviors* or CMB [83] shares some similarities with CxBR, but has some critical differences. CMB and CxBR both associate behaviors with contexts. That is, for a recognized context, behaviors and expectations are defined that are considered appropriate for an agent (human or otherwise) to employ/recognize when in that context. Therefore, a context-driven agent only needs to recognize the current context that it is experiencing to open its access to all appropriate actions to be performed. Major differences between CMB and CxBR are that while the latter employs a distributed form of control where a context has the information on how to activate and de-activate itself when it is no longer valid, CMB depends on a centralized process for a similar procedure. More specifically, in CxBR, the criteria that trigger a transition between contexts are explicitly defined in each context. The environment is monitored every simulation cycle (or monitoring cycle if in the physical world) for presence of these criteria by functions that are part of the active context, making the process distributed and efficient. Furthermore, transitions are prohibited between some pairs of contexts as dictated by the contexts themselves. For example, an automobile driving agent cannot transition from a parking lot at a mall directly onto an interstate highway – there must be some intermediate context between them, such as a suburban road that leads to the interstate on-ramp. On the other hand, in CMB, every context is reviewed and analyzed for its suitability to the situation. That is, all contexts are checked to find the appropriate context to transition. More significantly, CMB allows the merging of contexts when a context by itself cannot successfully be used to address the situation. CMB may use multiple concurrent contexts, all of which could have some element of validity with respect to the complex situation faced by the agent. CxBR does not have this capability, and assumes that only the best suited context is to be active.

Lastly, we should note that CMB uses a bottom-up approach where two contexts (*context schemas* or *c-schemas* in its parlance) can be merged to form a new context to fit the current situation. This is a form of learning that is inherent in the CMB formalism. CxBR, on the other hand, uses a top-down hierarchy where more details are defined in the lower-level contexts. These contexts and their hierarchical organization in CxBR have to be defined a-priori before the system can be employed in practice. Both formalisms have been used successfully in applications such as self-driving automobiles [57], Helicopter training simulation [41], tactical agents [8], project management [35], smart building [27], dialog management [42] and controlling an autonomous undersea vehicle [83] among many others.

Bandura [7] also recognized the similarity of contexts such as is considered in Turner's model. In looking at Bandura's theory, he recognized that the variety of contexts must be considered when solving a newly encountered problem. A cycle appears to develop between context and the environment that shapes internal preferences and the agentic action of a child. (An agentic action is defined as behavior that is performed with intentionality, forethought, self-reactiveness and self-reflection, and is based on one's preferences as well as future behaviors, expectations and predictions of future events [7]).

Another contextual paradigm that addresses decision-making is that of *Contextual Graphs*, or CxG [12]. By representing context at a progressively more developed level, the situation can be identified clearly enough so that a decision may be made more efficiently and with greater confidence. In Contextual graphs, this decision making process is streamlined into simple questions/answers and actions. This allows the system to figure out a situation and respond accordingly.

Contextual Graphs also employ a top-down approach. It allows the user to progressively define the context at a finer and finer granularity by answering questions, either explicitly by a user or by acquiring the information directly from a database or data acquisition system. By defining the context at a sufficiently fine grain, appropriate actions and/or information can be identified unambiguously and subsequently used by the agent or the user.

According to Vygotsky [86] and Piaget [60], children learn the schema of decision making through modeling of different behaviors and patterns that would be considered acceptable in a particular culture or context. Instead of the explicit mimicry of more experienced social agents, children would begin to be able to understand and apply the guidance they receive to decide for themselves what would be appropriate under a given set of circumstances [60] [86]. For example, once the child learned a particular way of thinking and interacting with the world from a social agent then she would develop mental schemata, or blueprints, for future decisions. This is much like the contextual graph model.

Hollister and Gonzalez [40] developed a variation of CxBR called the Cooperating Context Method (CCM) that incorporates simultaneous active contexts that cooperate to solve a problem. It involves a complex and sophisticated mechanism to select and concurrently apply multiple contexts that are relevant to a situation. The application on which this approach was used was in digital storytelling systems that can generate a story automatically [39].

6.1. *Context in machine learning*

Little work seems to be on-going in explicitly using context in machine learning. This work would capitalize on the previously-stated concept that a context could be used to associate something to be learned. Nevertheless, there are some reports in the literature of machine learning based on context and we discuss these below.

Fernlund et al. [28] appear to be the first to base his machine learning approach on contextual reasoning when they manually parsed a trace of sensor information about a human subject driving a simulated automobile through various contexts that repeated over the length of the drive. Most salient of these was the traffic light context, to which the human decisions and actions exhibited by the test subjects in that context were “taught” to an agent as a way to manage its behavior in the presence of an oncoming traffic light of various possible states (i.e., colors – red, yellow and green). The agent would subsequently employ the same functionality when facing the same or other traffic lights. The results proved to be quite promising. The learning system (called GenCL) turned the actions exhibited by the human subjects into functions, and associated these with the traffic light context, which included information about the state of the light, its distance from the simulated automobile, the latter’s speed and surrounding traffic to better describe the context at hand. One interesting result was the learning agents’ ability to generalize what it had learned to similar, but far from identical situations (all dealing with traffic lights however).

Stensrud and Gonzalez [77] and Johnson and Gonzalez [45] also used context to assist in machine learning, the former to learn decision-making in poker while the latter to learn team behaviors and reproduce them in teams of task-oriented intelligent agents. Another very interesting work that used the concept of context to divide and conquer while learning was reported by Stein and Gonzalez [76]. Their original work [75] involved teaching an agent how to transfer large boxes (i.e., containers) from one area (e.g., aboard a docked ship) to a different area (e.g., the shipping dock). A moving crane was simulated and human test subjects were asked to manipulate the simulated crane to appropriately relocate several boxes within the simulated environment. The system used neuro-evolution as its base approach, but in a context-free manner. Initial results were very poor. A decision was then made to contextualize the traces of actions of the crane and apply neuro-evolution again to the context segments. The contextualized agents performed significantly better, clearly indicating the value of contextualization, at least in this case.

Lastly, Trinh and Gonzalez [82] employed several techniques to automatically contextualize a trace of human performance. While this work was not in machine learning per se, it would provide an automated way of parsing and clustering the trace segments of the trace that belonged to the same contexts, something that up to this time had to be done manually at great effort. Their work succeeded in identifying contexts in a trace without any a-priori knowledge of what a context should be. It focused on the similarities of the time-varying values of various variables as being part of the same context. Upon noticing significant deviations from these patterns, it assumed that the context had changed for the human test subject driving a simulated automobile, and segmented the trace accordingly. This suggests that contexts as seen by humans could follow the same general concept – the context remains the same until a meaningful change is perceived.

Other works that have an indirect relation to context should be mentioned here, even if their relationships to context are not explicitly expressed by their authors or practitioners. It has been said that humans often learn best when problem-solving. In other words, if our knowledge/memories cannot account for how to solve a previously-unseen problem, we tend to experiment with potential solutions until we find a successful one. Often this involves procedures that we already know, but not in the context of the current problem. In a somewhat similar fashion, the State Operator and Results technique (SOAR) implements a kind of machine learning to find new paths through a problem space when a specific goal (or sub-goal) cannot be directly reached (i.e., problem solved) with the current knowledge. SOAR does not discover new knowledge – instead, it seeks new paths that use its existing knowledge to reach a goal. It can be said that it creates a new context to which new solutions become associated, thus making future decisions more rapidly. See [55].

6.2. *Context in Artificial Memory*

The concept of retention of memories in context has been most prominently reproduced in AI as *Case-based Reasoning* (CBR) (see [68] and [48]) and as a very similar technique called *Memory-based Reasoning* (see [74]). These AI techniques center about solving present problems using solutions remembered to have been successfully used in similar past problems. It implicitly learns new knowledge when the current problem and its solution can be added to the *case base* for use in future problems. CBR in particular has become a very popular technique in AI over the years. Although these authors do not refer to such past experiences as contexts, it is easy to see the similarities between the prior problem definition and our definition of a context. Thus, we believe that CBR/MBR is an example of a practical application of contextual memory, even though it is not so labelled by their creators.

The machine learning works described in the preceding section "remembered" the learned knowledge as either neural networks (Stein's work) or as C functions (in Ferlund's work). Stensrud's work also used neural networks, albeit of a different kind (ARTMAP networks), and Johnson's COLT system used Case-based Reasoning. This was largely driven by their need to mostly learn actions and not facts. Nevertheless, there are several constructs reported in the literature that incorporate means to capture and store information and/or knowledge in a way that is easily retrievable. Some of these are semantic networks, associative networks, frames, conceptual maps, and contextual maps. These constructs reflect a network of linked concepts.

An *associative* or *semantic* network is a labelled, directed graph whose nodes are used to represent various objects or concepts. The arcs that connect the nodes represent the various relationships or associations that link the concepts according to some criteria [32]. These arcs are an important feature of associative networks because they provide a reason for the association of any two nodes so linked within the network. This feature makes associative graphs different from simple directed graphs. Semantic networks were originally conceived by Quillian [62] as a way to model how humans can recall words and their associated concepts.

Conceptual graphs were conceived by Sowa [73] as a knowledge representation paradigm. Unlike Quillian's semantic networks where the arcs provided the associations, conceptual graphs contain two types of nodes – "… *concept nodes representing entities and* relation nodes representing relationships between these entities." [73; p. 8]. Sowa himself explains the differences between his conceptual graphs and Quillian's semantic networks in this manner: "*Firstly, there is a clear distinction between ontological knowledge (e.g., concept or relation types) and other kinds of knowledge (such as factual or implicit type); secondly, relations can be of any arity, whereas the edges of a semantic network represent binary relations only; thirdly, conceptual graphs have logical semantics in first order logic*". Nevertheless, conceptual graphs at their most basic level still consist of a network of related concepts.

Minsky recognized that associative networks did not provide the ability to group facts into associated clusters. For example, when one thinks of an automobile, related facts immediately come to mind (e.g., four wheels, accelerator, brake, gear shift, steering wheel, etc.). Semantic networks also fail to associate relevant procedural knowledge with some fact or group of facts (e.g., how to shift gears in an automobile) [32]. To address this issue, he developed a representation scheme called *frames* [54] that seek to account for our ability to deal with new situations (either objects or actions), which are encountered each day, by using our existing knowledge of previous events, concepts, and situations.

Contextual maps have had several definitions and uses. The term was initially coined by Kennedy in the mid-1950s [46] as a way to easily visualize a large complex project with many different attributes and features. In his concept of a contextual map, time (in years) would be placed in the x-axis and the problem variables in the y-axis of a large Cartesian coordinate plane map. Several contexts from different domains (e.g., psychology, anthropology, and economics) would make use of some of these variables but in different ways. The contextual map was a way to see how these contexts linked the various domains (the forest), rather than the individual domains (the trees). In a more modern setting, Context-based Reasoning defines contextual maps as the allowable transitions from any one context to another context that would succeed it in a time-related scenario. That is, it specifically specified transitions from one context to another – some transitions between two contexts are allowed while others are not. In a way, such contextual maps in and of themselves contain knowledge by identifying what "next contexts" are permissible from the "current context" in a time-based scenario. One could argue that under this last definition, the employment of a contextual map in an intelligent system would also ideally have a similar effect to that of visual processing, while interpreting the input and then retrieving the information.

While context is not mentioned by the conceivers and other authors working with the above knowledge structures, it is clear that many of the concepts therein are what we define as context.

6.3. *Linguistics, Context and AI*

As discussed in a previous paper [56], context familiarity has an important role in how artificial intelligence handles natural language processing (NLP) and generation (NLG) [53] [5]. One of the most widely accepted models of linguistic processing and representation activation is the spreading activation model, proposed by Collins and Loftus in 1975 [18]. This was based on some ideas put forth by Meyer and Schvaneveldt [53]. The spreading activation model searches neural and associative (semantic) networks attempting to retrieve associated ideas within specific parameters delineated by the search algorithm. Anderson [2] proposed a model of the spreading activation concept for his theory of memory. Thus, Associative/semantic networks have been and continue to be a common and popular means of knowledge representation in artificial intelligence.

A difficulty that has long faced AI systems is that of inefficient contextual information suppression, resulting in a myriad of issues [21]. In the case of linguistic applications, it could include the correct interpretation of homophonic words, or even the use of the same word that has different meaning (e.g., break an egg, or take a break). However, suppression of such contextual information may be an inefficient way to accomplish this goal, given that suppression seeks to exclude several rather than to select one. An approach used in Context-based Reasoning called the *competing context concept* (CCC) (see [67]) compares the needs of the situation with what each major context can contribute to address these needs. The major context that can best address these needs is the one to become activated next. This is an alternative to the conventional way in Context-based Reasoning, which is to hardcode context transition criteria in each major context, with the transition rules executing the transitions from one context to another. The same concept could be used to identify the meaning of an ambiguous word in a dialog. The process of merging context schemas into one context schema used in CMB would not suffice here, as the process needs discrimination and not combination.

6.4. *Context Aware Computing*

A discussion of context in computing would not be complete without mentioning the significant and extensive work being done in context aware computing. This important area of research was introduced by Schilit, Adams and Want in their 1994 paper [69]. This body of research seeks to build digital assistants that are assisted in their function by knowing the context of the person whom they seek to assist. Their basis is that knowing the context in which one finds him/herself can be very helpful in what decisions are made. This is of course, is the crux of what this article is about – using context to make decisions – by the human and by a computer agent. See [24] for a description of this important area of research.

7. Summary and Conclusion

We have seen how recognizing the context and understanding its implications allows humans to perform a multitude of behaviors, and assists in our ability to learn. Context also helps us react and interact intelligently in new situations that have some similarities to previously encountered stimuli. In particular, one of the most important elements in human growth and development is learning. As a child develops physically, emotionally and cognitively, context is an essential component of that learning. As the child gains more experience in the environment, she is often able to depend on the context of the situation to help make appropriate decisions. Without the ability of one to understand and make inferences about the circumstances and situations being encountered in life, one would be in constant need of a monitoring agent that could make decisions regarding the appropriate behavior sequence. This would be inconvenient, especially because humans want to be able to make independent decisions. In fact, it is the goal of most parents that their children become independent and mature, both mentally and physically, so as to be able to live and work independently while continuing the family legacy. This is precisely the same desire that many individuals who work in the field of AI systems also desire of their creations. They want their systems to be able to learn what to do in the next problematic scenario without having to restructure and reprogram formats.

Finally, while we have not come close to covering all the material relevant to this subject that has been reported in the literature, it is our hope that researchers and application developers will at some point generally become convinced about that which we (and others) have preached in this paper - that context is an essential component in computing, especially for intelligent systems. (See [13].) Therefore, we agree with Dey [23] when he stated that utilizing context in computing has generally been a neglected approach in the past, and we further believe that this remains true today. We hope that the above discussion has shed some light into how humans use context in the hope that it can be more extensively used in future relevant applications.

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