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A new scope for Open Cognition project: task and motion planning through its Neural-Symbolic Knowledge Store

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Abstract

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Road to agi.

1 Introduction

As industrial robots become faster, smarter, and cheaper, more and more companies are beginning to integrate this technology in conjunction with their workforce. Nowadays, robots have a range of applications that cover many different areas. These applications are no longer limited in structured environments, where the robot behavior could be directly specified by a human.

Where early robots blindly followed the same path, and later iterations used lasers or vision systems to detect the orientation of parts and materials, the latest generations of robots can integrate information from multiple sensors and adapt their movements in real time. They can also make use of more powerful computer technology and big data–style analysis.

Advances in artificial intelligence and sensor technologies allow robots to cope with a far greater degree of task-to-task variability. However, their ability to adapt to different tasks is still a long way from a general level of adaptability.

Until now, for example, every industrial robot is designed with a specific purpose. Therefore, a new robot is often needed to perform a new task. Even the most advanced robots, which exploit Neural Networks (NN) and Artificial Intelligence (AI), are unable to easily learn a new task.

It is necessary to design the AI architecture carefully and, to be successful, people must stop misusing the term AI. This term is used by generalizing those that are the three types of AI: Narrow-AI, General-AI, and Super-AI. The distinction between them is the key to technological progress, especially in the robotic field.

1.1 Artificial Intelligence

The following is a brief description of these three AI types, the Articles [1, 2, 3, 4, 5, 6] talk more about this.

1. Narrow-AI:
   Current AI technologies all fall under the Artificial Narrow Intelligence (ANI or Narrow-AI) category, which means they are very good at only one or a few closely related tasks. This type of AI has a limited range of abilities, specifically designed for a narrow use. It is able to reach a level of performance of a human, and even better, but only within this limited field that is its specialty. Examples of ANI include everything from Siri, Face ID and the Google Assistant, to self-driving cars and DeepMind's board game playing program. This is the only form of AI that has been developed so far.

2. General-AI:
   The next step after ANI is Artificial General Intelligence (AGI or General-AI), much more similar to human intelligence and not focused on specific tasks. It would be similar to a human mind and in theory, it should be able to think and function like it, being able to make sense of different content, understand issues and decide what is best in a complex situation. AGI hasn't been achieved yet. There isn't the technical capacity of producing something as complex yet, and there is also no certain knowledge of how the human brain actually works either. AGI is a relatively logical and rational future though, and it could be attained at some point if humans develop their knowledge and understanding, as well as technical skills to a high enough level.
   An overview of AGI, including important reflections, written by Ben Goertzel, can be found here: [7].

3. Super-AI:
   When AGI is achieved and computers are able to learn independently at a very quick rate, and exponentially improve on their own without human intervention or help, the final step that AI could hypothetically reach is Artificial Super Intelligence (ASI or Super-AI). At this stage AI would be capable of vastly outperforming the best human brains in practically every field. The evolution from AGI to ASI would in theory be fast, since AGI would allow computers to "think" and exponentially improve themselves once they are able to really learn from experience and by trial and error.

The most important differences, easily understood from the definitions above, are between ANI and AGI, partly because ASI will only be considered when AGI exists. The timing forecasts and the difficulties of that step can be found in [8].
These differences immediately lead into much wider contexts than industry, as AGI seems

focused on complex environments such as real-world and human-computer interaction. However, using an AGI system in an industrial setting can have many benefits:

- Having a general knowledge base for the robot, which can be shared with other ones.
- Use the robot(s) to cover multiple and more complex tasks.
- Make cooperation with humans natural and encourage learning from them.
- Robot(s) is robust to changes in the environment, its state and its task.
- Easier implementation of new modules and their merge into the system.
- Not only maintain, but rather exploit existing Narrow-AI systems as modules of the AGI system, in order to take advantage of their potential and allow interaction between them in a "single" large knowledge base.

For this project, one of the proto-AGI* systems currently under research is used, which proposes a concrete system that demonstrates the feasibility of the concepts just listed, and more.

There are several projects and researches that want to achieve the AGI goal. One of these is the Elon Musk and Sam Altman's OpenAI Project. Its mission is to ensure that AGI, intended as highly autonomous systems that outperform humans at most economically valuable work, benefits all of humanity.
OpenAI is focused on Deep Neural Networks for almost all projects such as OpenAI Codex, its AI system that translates natural language to code [9], CLIP (Contrastive Language-Image Pre-Training) a general-purpose vision system, which is a Neural Network trained on a variety of image-text pairs [10] and one of the most important: Generative Pre-trained Transformer 3 (GPT-3). This is an autoregressive language model that uses Deep Learning to produce human-like text [11]. With over 175 billion parameters, it is the largest Neural Network ever created [12].
Although OpenAI is well-funded and achieving excellent results, there is a second AGI-oriented project that is noteworthy: the Open Cognition (OpenCog) project. It is also the system on which this project is based.

*Any current theoretical or practical concept about AGI falls into a category that is called proto-AGI for now. However, in this paper the two terms are considered interchangeable.

The reason for this choice, the preference of OpenCog over OpenAI, lies in the approach to solving the AGI problem.
As mentioned above, OpenAI appears to be based on the general plan of starting from current Deep Neural Network tech, applying and extending it in various interesting and valuable ways, and in this way moving incrementally toward AGI without that much of a general plan or model of the whole AGI problem.
On the other hand, OpenCog is founded based on a comprehensive model of human-like general intelligence, and a comprehensive overall plan for getting from here to human-level AGI. Thus, it has an integrative approach in which multiple different sorts of AI algorithms (Deep Neural Networks, Probabilistic Logic Theorem Proving, Evolutionary Learning, Concept Blending, etc.) operate together on a common representational substrate.
It is not about building more accurate classification algorithms, or more efficient computer vision systems, or better language processing or boutique information retrieval algorithms, diagnosing diseases, answering trivial questions or driving a car, etc. It is concerned with generic intelligence and the inter-related cognitive processes it entails. It is about making software that perform specific tasks, using structures and processes that appear capable of being extended to more and more general tasks.
The OpenCog system is explained in detail later, in the Chapter **2**.

OpenAI and OpenCog are two distinct ways, both valid. However, we believe that the AGI architecture shouldn't be based on Neural Networks, for several reasons (in addition to classic general problems as in [13]):

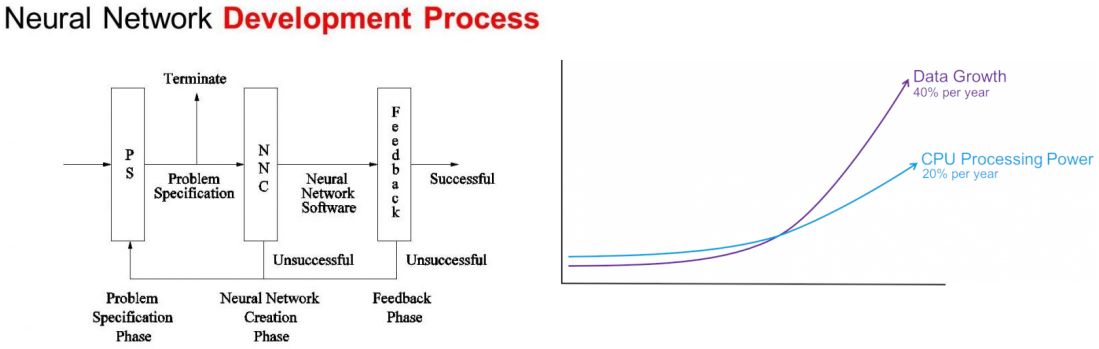
- A huge amount of data is required.
  Figure 1.1b shows annual data growth versus growth in CPU processing power. The gap leads one to think that as the data required for NNs increases, hardware technology must be improved.

- Adversarial Examples problem: it is a way to deceive almost all AI classifiers easily.
  Figure 1.1c is an illustration of machine learning adversarial examples. Studies have shown that by adding an imperceptibly small, but carefully designed perturbation, an attack can successfully lead the machine learning model to making a wrong prediction. For more information see [14, 15, 16, 17].

- The cost: training GPT-3, for example, would have an estimated cost between $4.6 and $12 million [18, 19].
  Figure 1.1a gives a general idea of a NN development process .

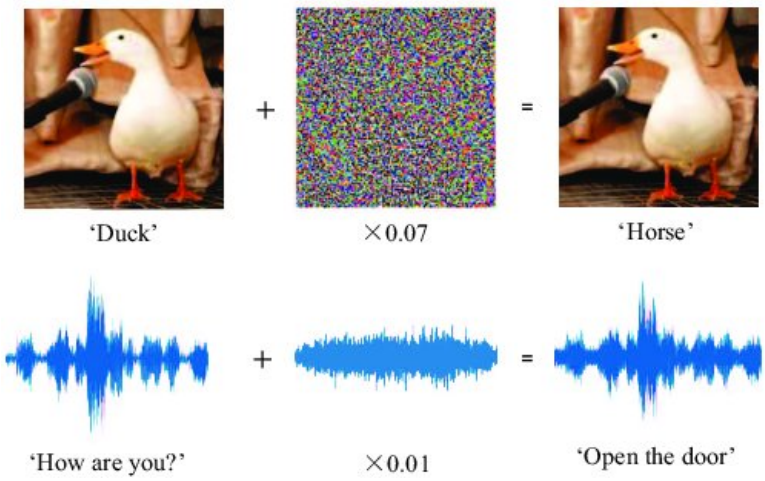
- Neural Networks as black box: the best-known disadvantage of Neural Networks is their "black box" nature. It means that, while it can approximate any function, studying its structure won't give any insights on the structure of the function being approximated. More details in [20].

The disadvantages of an NN-based approach like OpenAI have been mentioned. Now, to understand the advantages of a human-like approach like OpenCog, it is necessary to explain the OpenCog system. Therefore, these advantages are postponed to the Section [sec:opencog advantages ...].



(a) Neural Network development process.
Image source: [21].

(b) Neural Network data process.
Image source: [22].



(c) Adversarial Examples.
Image source: [23].

Figure 1.1: Some disadvantages of Neural Networks.

2

OpenCog System

The OpenCog design aims to capture the spirit of the architecture and dynamics of the brain without imitating the details (which are largely unknown) via:

- Integrating together a carefully selected combination of cognitive algorithms acting on different kinds of knowledge.
- A scalable, robust and flexible C++ software architecture.
- A manner specifically designed:
  - To cooperate together with "cognitive synergy" for the scope of tasks characteristic of human intelligence.
  - To give rise to the emergence of an effectively functioning knowledge network in the AI system's mind, as it interacts with the world, including a self-updating hierarchical/heterarchical ontology and models of itself and others.

Following section, Section 2.1, elaborates on the new concepts introduced in these points.

2.1 Cognitive Synergy

OpenCog is a diverse assemblage of cognitive algorithms, each embodying its own innovations. The power of the overall architecture is its careful adherence to the principle of Cognitive Synergy.

The human brain consists of a host of subsystems that perform particular tasks, both specialized and general in nature, connected together in a manner enabling them to synergetically assist, rather than work against each other.
The essential principles of Cognitive Synergy Theory (CST) can be summarized in the following points, further explored in [24]:

1. Intelligence can be understood as the ability to achieve complex goals in a certain set of environments.
2. An intelligent system requires a "multi-memory" architecture, meaning the possession of a number of specialized yet interconnected knowledge types.
3. "Cognitive processes": a system must possess knowledge creation mechanisms corresponding to each of these memory types.
4. Each cognitive process must have the ability to recognize when it lacks information and thus, draw it from knowledge creation mechanisms related to other types of knowledge.
5. The Cognitive Synergy is, therefore, represented by the interaction between the knowledge creation mechanisms, which perform much more effectively in combination than non-interactive mode.
6. The activity of the different cognitive processes involved in an intelligent system can be modeled in terms of the schematic implication "Context & Procedure $\rightarrow$ Goal".

These points are implicit in the systems theory of mind given in [25], where more thorough characterizations of these ideas can be found.
Interactions as mentioned in Points 4 and 5 are the conceptual core of CST.
Most AI algorithms suffer from combinatorial explosions. In a "general intelligence" context, there is a lack of intrinsic constraint; consequently, the algorithms are unable to filter through all the possibilities (as opposed to a ANI problem like chessplaying, where the context is huge but constrained and hence restricts the scope of possible combinations that needs to be considered).
To decrease the severity of combinatorial explosions, one can use an AGI architecture based on CST, in which the different learning mechanisms dealing with a certain sort of knowledge, are designed to synergize with ones dealing with other sorts of knowledge.
It is necessary that each learning mechanism recognizes when it is "blocked" and then, it can ask for help to the other complementary cognitive mechanisms.

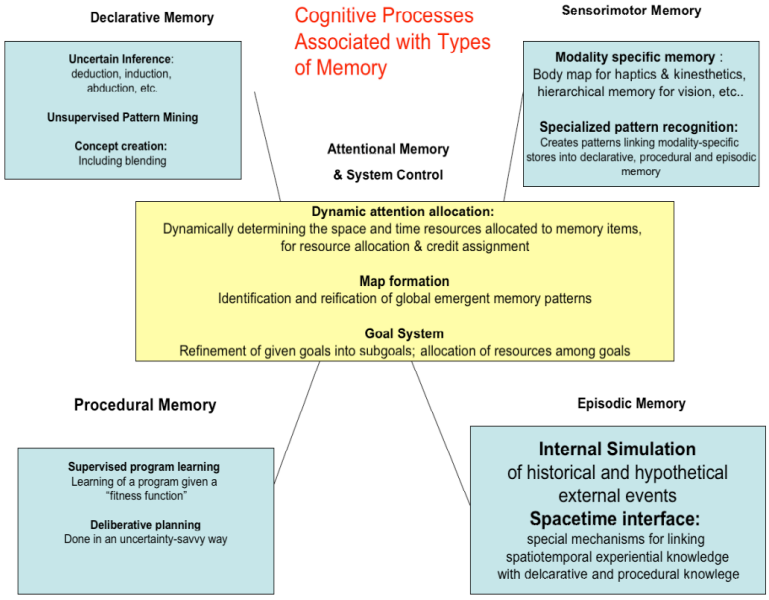


Figure 2.1: A high-level overview of the main types of cognitive process considered in Cognitive Synergy Theory, categorized according to the type of knowledge with which each process deals.

The Figure 2.1 is proposed to give a general visual idea of these concepts. It shows an overview of the most important cognitive dynamics considered in Cognitive Synergy Theory and describes the behavior of a system as it pursues a set of goals, which are then refined by inference (through a logic engine or as an emergent process resulting from the dynamics of an Neural Network system), aided by other processes.

The detailed argument explaining how the cognitive algorithm selection and integration methods, chosen by the OpenCog team, will have the desired effect, is sketched on the OpenCog wiki site* and various previously-published conference papers. It has been presented more thoroughly in the 2014 books Engineering General Intelligence vol. 1 and 2 [26, 27].

2.2 OpenCog Architecture

There are several components that make up the basic architecture of OpenCog. In the following sections, they will be described, more or less independently, and then concatenated and contextualized into the problem considered in this project.
Currently, the OpenCog project is under strong development and some of the concepts pre-

*https://wiki.opencog.org/w/Background_Publications

sented here may be obsolete, improved or evolved, or being redesigned. However, much of the basic infrastructure and theory remains unchanged.

2.2.1 Atomspace

The AtomSpace is a platform for building Artificial General Intelligence (AGI) systems. It provides the central knowledge representation component for OpenCog. As such, it is a fairly mature component, on which a lot of other systems are built, and which depend on it for stable, correct operation in a day-to-day production environment.
It is a mashup of a large variety of concepts from mathematical logic, theorem proving, graph theory, database theory, type theory, model theory and knowledge representation.
More specifically, the OpenCog AtomSpace is an in-RAM knowledge representation database, an associated query engine and graph-re-writing system, and a rule-driven inferencing engine that can apply and manipulate sequences of rules to perform reasoning.
The best way to capture all of this, is a kind of in-RAM Generalized Hypergraph (Metagraph) Database.
On top of this, the Atomspace provides a variety of advanced features not available anywhere else. It is currently used to store natural language grammars, dictionaries and parsers, to store biochemical and biomedical data, robot control algorithms, machine learning algorithms, audio/video processing pipelines and deep learning neural networks.

2.2.1.1 Metagraph: a Generalized Hypergraph

Formally, a graph is:

- A set of vertexes $V = \{v_1, v_2, \cdots, v_M\}$
- A set of edges $E = \{e_1, e_2, \cdots, e_N\}$ where each edge e_k is an ordered pair of vertexes drawn from the set V.

Since edges are ordered pairs, it is conventional to denote them with arrows. In practice, one wishes to associate a label to each vertex, and also some additional attribute data (e.g. weight); likewise for the edges.

A hypergraph is very similar to a graph, except for the edges. "Hyperedges" are defined as edges that can contain more than two vertices. That is, the hyperedge, rather than being an

vertex id	incoming-set	attr-data
v_1	$\{e_1, e_2, e_4\}$	...
v_2	$\{e_2, e_4\}$	...
v_3	$\{e_3, e_4\}$	...
v_4	$\{e_2\}$	

Figure 2.2: Hypergraph edge table

ordered pair of vertices, is an ordered list of vertices.
Formally, a hypergraph is:

- A set of vertexes $V = \{v_1, v_2, \cdots, v_M\}$
- A set of hyperedges $E = \{e_1, e_2, \cdots, e_N\}$ where each hyperedge e_k is an ordered list of vertexes drawn from the set V. This list may be empty, or have one, or two, or more members.

A good representation of a hypergraph is the one proposed in Figure 2.2. It was a straightforward extension of the edge table, to which a new column was added for each position and then, those columns were mashed together into one set.

The vertex table looks like the edge table, but the vertex-list is an ordered list, while the incoming-set (the edge-set) really is a set. This is because a hypergraph is "almost" a bipartite graph, having the form of Figure 2.3, with the set E on the left being the set of hyperedges.

Before define a Metagraph, a change of terminology is useful: the basic objects are now called "Nodes" and "Links" instead of "vertexes" and "edges".
Thus, a Metagraph is:

- A set of nodes $V = \{v_1, v_2, \cdots, v_M\}$
- A set of links $E = \{e_1, e_2, \cdots, e_N\}$ where each hyperedge e_k is an ordered list of nodes, or other links, or a mixture. They are arranged to be acyclic (to form a directed acyclic graph).

The metagraph is a generalization of a hypergraph, in the sense that now a hyperedge (link) may contain either another vertex (node) or another link. Visually, it has the shape of a Directed Acyclic Graph (DAG), such as the one shown in Figure 2.4.

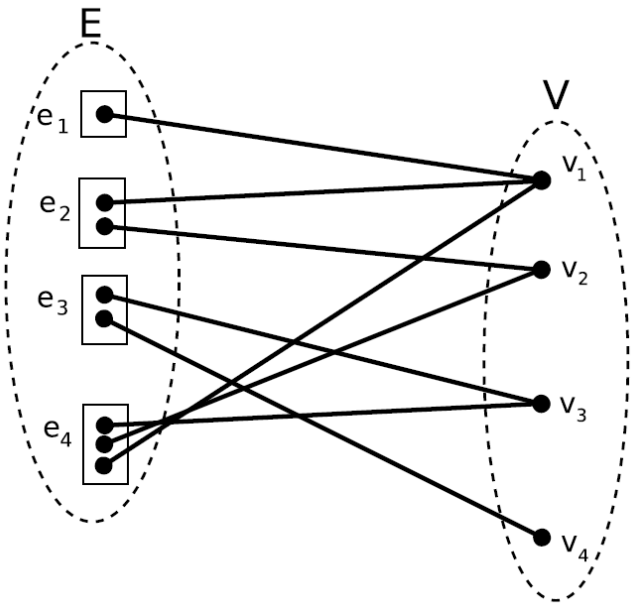


Figure 2.3: The E and V ellipses are the hyperedge and vertex tables. The boxes mean that the hyperedges are ordered lists.

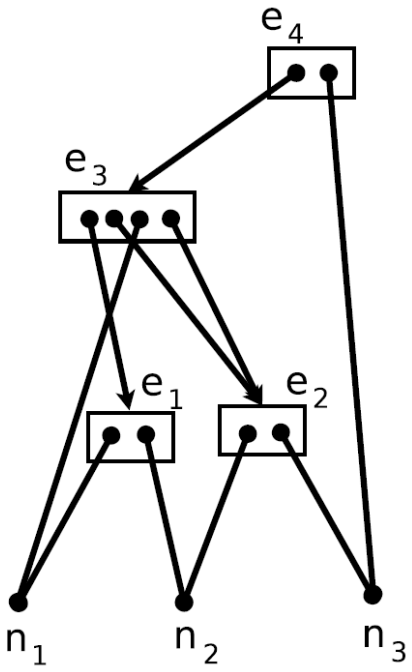


Figure 2.4: An example of a DAG.

link id	outgoing-list	incoming-set	attr-data
e_1	(n_1, n_2)	$\{e_3\}$	...
e_2	(n_1, n_3)	$\{e_3\}$	...
e_3	(e_1, e_2, n_1, e_2)	$\{e_4\}$	...
e_4	(e_3, n_3)	$\{\cdot\}$	

Figure 2.5: Metagraph link table

But in Metagraph, links are ordered lists, represented as boxes. Thus, to convert it in a DAG it is possible to collapse the boxes to single points or to dissolve the boxes entirely and replace a single arrow, from point-to-box, by many arrows, from point to each of the box elements.
Whereas the node table is the same as the vertex table for the hypergraph, nevertheless the link table now requires both an outgoing-atom list and an incoming-link set. Figure 2.5 shows the result.

For convenience, the name "Atom" is given to something that is either a node or a link. Links are then, sets of atoms.
These concepts are described in [28, 29], where RAM-usage considerations, reasons why metagraphs offer more efficient, more flexible and more powerful ways of representing graphs and reasons why a metagraph store is better than a graph store and much more, can also be found.

Finally, some extensions of the metagraph are considered: Typed Metagraph (TMG) and Directed Typed Metagraph (DTMG).
Typed metagraphs are defined as hypergraphs with types assigned to hyperedges and their targets, and the potential to have targets of hyperedges connect to whole links, as well as targets. An example can be found in Figure 2.6.
A natural extension of a TMG is the Probabilistically TMG, based on probabilistic dependent types. Thus, one can assign a probability (or an entire probability distribution) to each connection between edges, thanks to the probabilistic type inheritance relations. In this way, it is possible to obtain a KB that can work with probabilistic logic, fuzzy logic, make uncertain inferences and much more.
Atomic Directed Typed Metagraphs (atomic DTMG) are introduced via partitioning the

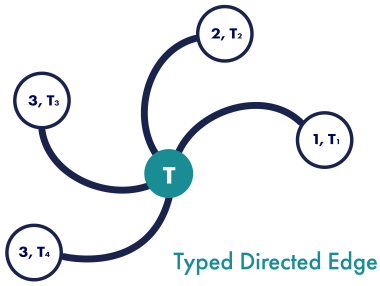


Figure 2.6: Example of a typed, directed edge. This one has 4 targets. T is the type of the edge itself. The third and fourth targets are unordered relative to each other.

targets of each edge in a typed metagraph into input, output and lateral sets; one can then look at "metapaths" in which edges' output-sets are linked to other edges' input-sets (Figure 2.7). Thus, a DTMG is generally defined as a TMG composed by connecting DTMGs via metapaths, a recursive definition that bottoms out on the definition of atomic DTMGs.
For the whole theoretical formalism concerning TMG and DTMG refer to [30]. That paper concludes by also describing useful types of morphisms that can be defined on a DTMG (catamorphisms, anamorphisms, histomorphisms, futumorphisms, hylomorphisms, chronomorphisms, metamorphisms and metachronomorphisms). They allow to formulate a wide variety of operations on metagraphs, which will not be described here.
The important thing to keep in mind is that the KB is used for AGI, so there will be many metagraphs and very large ones. Morphisms allow you to obtain simple and complex results by mutating/transforming/stretching/compressing the metagraph quickly and cleanly.

Last but not least, it is also useful to associate metagraph edges E_i with nite lists V_i of Values, each of which may be integer, floating-point or more complex in structure. The reason for these Values will be mentioned later.

2.2.1.2 Atoms

The vertices (nodes) and edges (links) of a graph (metagraph), known as Atoms, are used to represent not only "data", but also "procedures" and then, many metagraphs are executable programs as well as data structures.
Atoms are one of the main components of the AtomSpace. Atoms, together with Values are

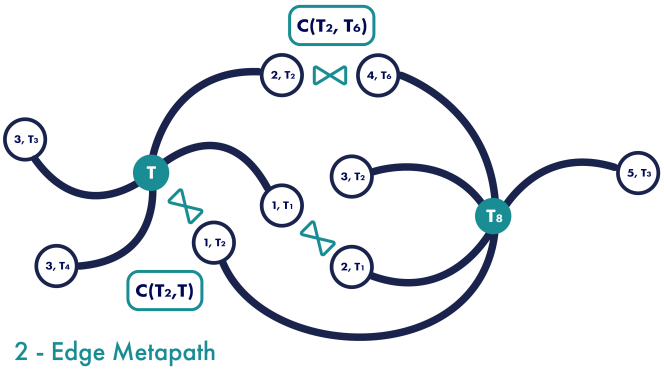


Figure 2.7: A short metapath, formed by connecting two directed edges.

what the AtomSpace stores.
The two primary types of Atoms are Nodes and Links. They are used to represent anything that resembles a graph-theoretical graph.
From the TMG definition above, Atoms are typed (in the sense of Type Theory) and thus, they can be used to store a large variety of information. Values are used to assign "valuations" to Atoms, to indicate the truth or likelihood of that Atom, or to hold other kinds of transient data. Every Atom has a key-value database attached to it, that can store any kind of information about that Atom. The distinction between the "shape of the graph", and its related "data" is central for allowing high-speed graph traversal and generalized graph query. Note that, in Ruby and Prolog programming languages, symbols are literally called atoms. Moreover, both LISP and Guile, allow parameters to be attached to symbols, as Values can be attached to Atoms.

When atoms are placed in the AtomSpace, they become unique. Thus, in comparison to other programming languages [†], Atoms can be understood to be the same thing as symbols. The AtomSpace is essentially a symbol table, which commonly has the unique-symbols property. Once an Atom is placed in the AtomSpace, it gets a single, unique ID. This unique ID is the string name of a Node and the outgoing set of a Link.
A TruthValue gives each Atom a valuation or an interpretation and conseguently, all Atoms in a given, fixed AtomSpace always carry a default valuation/interpretation along with them. Naturally, additional interpretations can be created.

[†]Section 2.2.3 to understand why it is possible to talk about programming languages

The types form a type hierarchy: all atoms inherit from the type "Atom", and the type Atom itself inherits from ProtoAtom. The ProtoAtom is itself the base type for Values as well as Atoms.

2.2.2 Pattern Engine and Unified Rule Engine

2.2.3 Atomese

2.2.4 Reasons

3
Conclusione

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