Artificial Intelligence and Semiotics: Using Semiotic Learning to Bolster AI

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***Abstract*— Artificial Intelligence (AI) continues to grow into areas such as Natural Language Processing (NLP) and other arenas where understanding the meaning behind speech, images, and symbols is of increasing importance, such as education. These realms of understanding are not merely semantic, but semiotic in scope, carrying with them the potential for AI to grow toward the understanding of the meaning behind what is being said, written, pictured, or symbolized. This growth necessitates the advancement of techniques in semiotic learning such as neural sketch learning, paradigmatic associations, and advanced heuristics. In this paper, semiotic learning will be defined and discussed. Additionally, some techniques and strategies for AI semiotic learning will be discussed and modeled including an AI accommodation/assimilation model. These strategies are ultimately useful for defensive cyber operations and offensive cyber operations through the use of semiotic context matching to improve defensive and offensive strategies.**

Keywords- cyber; artificial intelligence; semiotics; accommodation; assimilation; heuristics.

I. INTRODUCTION

As the world of Artificial Intelligence (AI) continues to expand exponentially, the need for these technologies to comprehend various types of discrete and esoteric information grows as well. AI is one of those terms that is often confusing, with many people inferring that it means only one thing. The reality, however, is that AI expresses itself in at least three major ways: semantic, semiotic, and singular. The semantic characterization deals primarily with data associations with some decision functions at a basic level, absent of the true "understanding" of how those data interrelate. Semiotic relationships include much of the data association methodologies in semantic AI but work toward helping neural networks to make idiomatic associations for a level of networked "meaning" regarding the data within a particular system or framework. The "singular" or "singularity" refers to machine consciousness with a full understanding of meaning, relationships, idioms, and feelings similar in scope to how human beings navigate stimuli, data, and personal emotions. This discussion will focus primarily on the semiotic realm of AI with some explanation of semantic AI for differentiation. These strategies are ultimately useful for defensive cyber operations and offensive cyber operations through the use of semiotic context matching to improve defensive and offensive strategies. The rest of the paper is structured as follows. In Section II, computational semiotics will be defined. Section III details neural sketch learning for semiosis. Paradigmatic associations will be discussed in Section IV to give a solid frame of reference for how to translate paradigms into code and algorithms. Section V deals with advanced heuristics or mental shortcuts and how these can be used to improve efficiency and understanding in algorithmic applications. The AI accommodation and assimilation model will be detailed in Section VI followed by the conclusion in Section VII.

II. DEFINING COMPUTATIONAL SEMIOTICS

Before one can embark upon sifting through the complex territory of semiotic support for AI, a full understanding of computational semiotics is necessary. Semiosis is the "study of meaning and communication processes…from the point of view of formal sciences, linguistics, and philosophy" including the situational control of logical systems to produce automatic control of systems [1]. This definition flows directly into the fundamental premise of AI to provide meaningful and intelligible information to humans for use in understanding and using information more rapidly while also making improved predictions concerning numerous systems and data. Semiotics is the study of signs and symbols, especially as a means of language or communication. It is a multidisciplinary perspective that incorporates the thinking and theory fragments of many different thinkers, including linguists, phenomenologists, and philosophers. The foundation of semiotic computational relationships was developed in the 1970s by Russian AI researcher D.A. Pospelov who connected AI theory to human reasoning through studying two models: a deductive "maze model" and an inductive "chess model" [2]. The "maze model" was an earlier concept developed in the 1950s drawing on the work of cognitive psychologists who based human thought on the premise of linear decision-making.

However, the maze hypothesis began to fall into dispute as it came under increased scrutiny, leading to the more inductive "chess model" which offered more probability across human thought and meaning construction. This divergence of human and computer thought is captured well by Deb Roy in her study concerning schema theory and

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semiotics. Human beings generally construct meaning through forming concepts around ideas in scaffolds called "schemas" which are used constantly to produce and express ideas between humans that are filled with meaning [3]. This leads to "a causal-predictive cycle of action and perception" where people create meaning and share complex relationships about events, places, and numerous other value associations [3]. While numerous methodologies for meaning-making have been explored in recent years, the use of automatic reasoning through pattern recognition has shown a great deal of promise [4]. This method of semiotic computing is based on systems that learn paradigms, which are then transformed into new symbols on which syntagmatic and paradigmatic analysis can be performed again [4]. This analysis and reanalysis of concepts, words, paradigms, and schemas leads to semiotic functions that can then be bolstered through iterative processing and syntactic connection scaffolding. This spiral model allows for the exponential reinforcement of syntax and paradigms similar to how humans learn and integrate knowledge and complex information through language using accommodation and assimilation. Accommodation can best be described as the changing of one's knowledge schema to accommodate new information. Whereas assimilation is the changing of the information being adopted into one's knowledge schema to more easily fit current information and understanding. This action of assimilation and accommodation is performed primarily through symbolic understanding.

Humans are very skilled at grouping information into semiotic symbolic databases within our schemata allowing us to rapidly understand and predict numerous, complex circumstances [5]. Generally, this process is seen as intuitive and related to human ability to make predictive decisions. This is commonly based on probabilistic decision-making similar to the processes found in quantum computers [6]. Taking this intuitive approach and combining it with symbolic reasoning, has the potential to transform semantic reasoning machines into semiotic reasoning machines capable of understanding symbolic meaning and constructing that meaning into higher order understanding and schemas [5]. If AI is to become the powerhouse it is meant to be, semantic constructions must be transformed into semiotic scaffolds. While Generative Pre-trained Transformers (GPTs) and Generative Adversarial Networks (GANs) will continue to be useful for general understanding and information construction, semiotic AI offers a bridge into a world where Artificial General Intelligence (AGI) is a reality. With this capability within the reach of human use and development, humanity is poised to see enormous leaps in rapidity of decision-making and predictive analysis. Through these predictive algorithms and with the use of more rapid decision-making as a result, cyber offense and defense will be transformed in rapidity, accuracy, and utility.

III. NEURAL SKETCH LEARNING FOR SEMIOSIS

If computational semiotics are the connection between human schematic symbolic understanding, neural sketch learning is the network of pathways mapped out in the most anthropomorphic sense. Human beings are naturally suited to making connections semiotically that allow us to reason and connect disparate data seamlessly. However, computer systems are not innately so capable of tying concepts together as humans. This is where the strategy of neural sketch learning can potentially undergird semiotic learning processes for AI systems. In the following discussion, learning compositional rules through neural program synthesis will be explored to gain insight into how neural sketch learning may be used to support symbolic information scaffolding. Also, neural models for Natural Language Processing (NLP) will be discussed in reference to how we might use neural sketches to bridge the gaps between semantic NLP and semiotic processing with symbolic sketch models. Next, learning to infer program sketches will be examined for information regarding inference-based programs and methods that can be used semiotically for higher-level computational understanding. Then, neural sketch learning for conditional program generation will be analyzed to reveal how conditional programs can be leveraged more robustly through neural sketch learning for symbolic understanding and reasoning in emerging semiotic processing. Finally, idiomatic synthesis and parsing will be defined and discussed to make connections between human idiomatic understanding and teaching semantic and semiotic processing platforms how to recognize and connect these difficult, esoteric linguistic obstacles.

When human beings reason and connect thoughts and patterns, we often tend to draw on connected meaning between numerous words and meaning constructs. For example, when two people talk about growing up in different places with different parents, and different siblings, they automatically form meaningful constructs around the people and places being represented by the other person in the conversation based on meaning constructs held within their own emotional, social, and cultural schemata. This act of meta-cognition or thinking about thinking, allows each person to accommodate and assimilate information about the other person's experiences and emotions. In semantic relationships using NLP, these relationships, as complex as they are, are not present. One way to potentially address this lack of connection is through what can be referred to as "meta-grammar" and "meta-learning [7]." These learning methodologies for semantic systems have the propensity to learn entire rule systems from examples. In other words, schemas can be generated and then taught to these learning systems to promote and sustain semiotic connections to form meaning for semiotic reasoning. Meta-learning or learning about learning is supported through scaffolding and explaining informational attributes and connected concepts within semantic programs with NLP. This is further supported through meta-grammar or grammar about grammar that takes conceptual, holistic frameworks and teaches them to semantic systems to build and bolster discrete connections between words, phrases, and concepts [7].

Part of the roadblock to semiotic expression in computing frameworks has been the inability of these systems to parse and understand formal language that is not machine-friendly [8]. To avoid this issue, natural language

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interfaces have been developed to assist in linguistic connections between humans and machines. What machines often do not grasp is the underlying meaning of human expression, however, though symbolically modeling these expressions and building appliances in code using algorithmic means, a functionally semiotic interpretation could be manifested [8]. This method, overlaid with program synthesis [7] reveals promise toward semiosis due to its NLP underpinnings; namely the ability to take multiple complex concepts and scaffold them together to promote language accommodation and assimilation.

Another area inherently connected to semiotic processing is the ability for machine systems to infer meaning from data provided by human input. As humans, we are able to take large sets of disparate and convoluted data and draw inferences from that data to synthesize and explain new data. This complex cognitive computation is part of the non-linear capability human beings have developed through communication with other humans and experiences in the natural world that present a particular survival advantage. However, these inferences are not intrinsic to machine systems due to several reasons including complexity and the lack of imprint of human survival instincts on these systems. Nye, et. al., propose "a system which mimics the human ability to dynamically incorporate pattern recognition and reasoning to solve programming problems from examples or natural language specification [9]. It is this ability to recognize and respond to patterns and symbolic meaning that lends itself to semiosis. Through understanding and connecting information at the meta level, machines can address the gaps found in semantic processing where machines cannot understand the multiple levels of connected meaning innately found through human cognition.

Semantic programming through syntactical interpretation has traditionally been a roadblock to conditional program generation, but great strides have been made in recent years toward semantic and potential semiotic solutions. Through leveraging combinatorial and neural techniques, conditional programs could make the leap toward human-like decisions and predictions by creating and synthesizing language and patterns such that rapid processing of large and complex data sets will be tenable [10]. This is accomplished through neural sketches that combine numerous data attributes and connections allowing for program synthesis of data for program generation [10]. This capability can be further supported using programs like SKETCHADAPT, which are useful for data and program synthesis [9]. Ultimately, the goal is to flow together methods and tools that can bolster complex data combinations for potential semiosis.

One of the most interesting expressions of human thought and experience is our linguistic propensity for creating idioms. An idiom is usually a word or phrase that is directly tied to a social or cultural concept. For instance, in the United States people often use idioms taken from American sports like football and baseball. If someone says that you "hit a home run" or "knocked that one out of the park" they are complimenting you on a great success since these phrases are ties to the concept of great success in the game of baseball in America that allows the team to score points and win the game. However, terms like this are not just a potential language barrier between different cultures, but also present numerous difficulties for semantic AI. The idiomatic problem is in fact even more pronounced in machine systems since idioms are a peculiarly human way of communication. A potential solution for this issue is to incorporate high-level and low-level reasoning at every step of the linguistic translation process in semantic programming and NLP [11]. While most idiomatic interpretations in code language are accomplished through the use of tokens that symbolically represent common patterns, human beings use high-level and low-level reasoning to ascertain idiomatic language, formulate definitions and predictions, and select appropriate linguistic responses. Shin, et. al., suggest alleviating this issue by "interleav[ing] high-level idioms with low-level tokens at all levels of program synthesis, generalizing beyond fixed top-level sketch generation [11]." This method of neural sketch learning offers the advantage of incorporating complex levels of language interpretation and generation to assist in translating language semantically within AI systems. This level of understanding and meaning making has great potential in further supporting semiotic AI translation and generation.

Neural sketch learning offers numerous opportunities to support and grow AI toward semiosis by allowing for the synthesis and translation of large, complex, and esoteric datasets. Compositional rules are a first step toward forming a linguistic foundation for semiotic learning and processing. These rules can then be expanded into learning models using neural interfaces and sketches for cognitive modeling like how humans accommodate and assimilate information. The next level of semiotic understanding can be supported by the ability of semiotic machines to infer data and meaning from large and complex datasets for the purpose of understanding seemingly disparate information and making inferred connections for complex language processing and generation. From these large datasets, cyber defense and offense can also be bolstered through the rapid association of threats and vulnerabilities to identify and assess cyber risks and offensive cyber opportunities. Conditional program generation adds another layer to the foundation of semiosis using neural sketch learning for making conditional connections. Finally, idiomatic understanding and processing through low-level and high-level reasoning bolsters semiosis through supporting AI synthesis of language based on a wide array of human social and cultural understandings. All of these neural processing and learning schemas can be mutually beneficial for semiotic AI language and task processing.

IV. PARADIGMATIC ASSOCIATIONS

Paradigms hold great power in human estimation as they often define the zeitgeist surrounding historical, societal, and cultural events and experiences. The same is true at the logical later of coding, processing, and parsing information as paradigms are powerful representations of symbolic realities meant to be understood by the AI systems in question. As we explore paradigmatic associations in semiotic AI, the areas of structural linguistics, implicitly learned paradigmatic relations, syntagmatic and paradigmatic associations, computation of word associations, and a syntagmatic paradigmatic model will be discussed. As discussed earlier, linguistic structures are foundational to building meaning in semiotic AI as they provide the basis for understanding paradigms. Also, taking these linguistic approaches and applying them directly to implicit structures where paradigms can be associated discretely with each other adds another layer of potential semiosis. The process of relating syntactical paradigms across numerous levels of computational understanding is the next level of meaning making. This is undertaken through the association of words, syntax, symbols, and groups of related data to form complex computational models and relationships for building meaning for accommodating and assimilating information. Finally, modeling these syntagmatic and paradigmatic relationships is necessary to make the final meaning generation imperative for paradigmatic semiosis.

Structural linguistics have been used for human communication for as long as language has existed. As we navigate social and cultural relationships, human beings build immense cognitive databases for understanding linguistic structures such as symbols, paradigms, syntax, and numerous other linguistic relationships. In AI systems, these connections are extremely advantageous since semantic processing is central to the ability of GPTs to translate information into actionable syntagmatic content. The central proposition of structural linguistics rests on the ability to interpret the meaning of a word based on its paradigmatic and syntagmatic associations [12]. In other words, when a person reads the word “wet”, they automatically associate that word with multiple other words and build meaning maps for those terms. One might associate “wet” with rain, water, clouds, ocean, river, etc. This is a syntagmatic association model. However, when building a paradigm, all of these terms and perhaps even antonyms might be grouped together to form a central concept of the word “wet.” This understanding of word associations has led to the advent of synonymous models such as the Tensor Encoding (TE) model which can perform numerous semantic tasks including synonym judgement [12]. In AI semiotic systems, the ability to form paradigmatic and syntagmatic associations for meaning creation is at the center of the process of semiosis. Without the basic association of words and scaffolding of paradigmatic content, meaning creation and association would not be possible. With these semiotic strategies, however, query expansion, intrinsic linguistic synthesis and expression, and internal paradigmatic evaluation are made possible, contributing to the realization of semiosis.

Paradigmatic relationships are another important area associated with semiosis since these connections happen “within the same event, either simultaneously, immediately following each other, or separated by one or more other elements [13].” These close connections between words, phrases, occurrences, and other events make the construction of paradigms possible. The question posed by Yim, et. al. in their 2019 article is: “Can paradigmatic relations be learned implicitly?” This question has been posed numerous times in research as it deals with the central tenet of meaning-making around syntagmatic and paradigmatic structures. Interestingly, this research was performed on human subjects to grasp how humans might associate words syntagmatically to build paradigms implicitly. The research supported the implicit learning of paradigmatic relations where participants had strong syntagmatic connections [13] suggesting that paradigmatic relationships were implicitly possible. This is a promising finding for potential semiosis in machine constructs as well, since similar syntagmatic relationships have been noted in semantic processing and relationship building.

Syntagmatic and paradigmatic associations share many connected articulations with semiotic AI. Attributional and relational similarities form the central base for understanding semantic similarity in human and machine systems, supporting learning schemas at numerous levels [14]. Humans depend on semantic similarity for numerous communication and socialization circumstances. For instance, when someone says, “you wear that well” they might be referring to shoes, clothes, a particular social or work position, a smile, or many other semantic possibilities. As humans, we learn to draw on these semantic similarities to interpret meaning. These same meaning-making and semantic relationships are central to semiosis in machines as these are relationships that are idiomatic and require potentially massive amounts of context to understand and interpret. The simplest way to begin these associations is through forming semantic relationships between pairs of words [14] and subsequently building expanded paradigms and syntax around them. This action of paradigmatic and syntagmatic scaffolding can enrich the semiotic relationships necessary for semiosis in AI.

Computing word associations carries a heavy burden of the necessary capability to form and process semiotic AI scaffolds. The construction of paradigmatic algorithms for semiotic AI is tied directly to their relationship as either relationally paradigmatic or syntagmatic. “There is a syntagmatic relation between two words if they co-occur in spoken or written language more frequently than expected from chance and if they have different grammatical roles in the sentences in which they occur. Typical examples are the word pairs coffee – drink, sun – hot, or teacher – school. The relation between two words is paradigmatic if the two words can substitute for one another in a sentence without affecting the grammaticality or acceptability of the sentence. Typical examples are synonyms or antonyms like quick – fast, or eat – drink [15].” Given this example, semiosis is possible in systems (human and machine) with paradigmatic and syntagmatic connections that can be made, sustained, synthesized, and perpetuated incorporating hyper-assimilation and -accommodation. With these capabilities brought to bear, meaning-making and understanding at a basic level have the potential to support and develop semiotic AI capabilities. This is accomplished using “algorithms that automatically retrieve words with either the syntagmatic or the paradigmatic type of relationship from corpora [15] suggesting meaningful connections between semantic-layer information and semiotic-layer schemata. Through building scaffolds and schemata through associations, cyber defense systems such as Intrusion Prevention Systems (IPS) can make informed and accurate predictions concerning malicious programs, thereby adding virtually precognitive protections to networks, databases, and critical information.

In their work on sentence processing, Dennis and Harrington developed a Syntagmatic Paradigmatic (SP) model that makes associations across large linguistic frameworks, suggesting that semiotic AI schemas are potentially rooted in complex meaning generation and association. This is accomplished through characterizing sentence processing as retrieval from memory using distributed representations [16]. This ability to “generalize beyond the specific instances in memory” lends credence to the potential semiotic capacity of AI systems in that it is based more on large, complex attributes instead of more discrete increments. Another area of promise with the SP model is its ability to provide systematicity, making arbitrary relationships using relational representations [16]. This function of the model allows the system to make connections between numerous disparate data sets suggesting potential semiotic utility for AI. From a structural linguistic perspective [12], the use of sentence processing is the next level in syntagmatic and paradigmatic processing adding potential to the development of semiotic AI.

Semiosis is dependent on numerous, complex methods to construct meaning across systems, language, and algorithms. This is nowhere more evident than in the areas of syntagmatic and paradigmatic associations. With a view into how syntax and paradigms are constructed and used in language, logic, and processing, semiotic AI has the potential to draw together numerous complex threads algorithmically to support greater communication, understanding, and meaning generation. With the use of automatic query expansion for structuring language exponentially, AI systems can generate more meaningful responses and process larger, deeper data stores for increased meaning and context. Through implicitly learned paradigmatic associations, semiosis can be supported intrinsically to offer more endemic capability and data synthesis. Syntagmatic and paradigmatic word associations through understanding word similarity also undergirds semiosis as the connections between words can created syntax and paradigms necessary for meaning-making and algorithmic growth and synthesis. Additionally, computation of word associations adds another layer of capability to AI semiosis as the syntagmatic and paradigmatic capabilities inherent in these processes underscores the process of connectedness of language for making meaning. All of these methods and capabilities together construct potential sentence analysis and synthesis withing semiotic AI to further grow and expand understanding and meaning across the AI enterprise.

V. ADVANCED HEURISTICS

Heuristics or mental shortcuts, have been an item of study related to semantic AI for some time as they are focused on efficiency and rapidity of processing. However, the power of heuristics also have deep application within the realm of semiotic AI, since these mental shortcuts are directly related to the abstract symbolic thought necessary for the synthesis of meaning in human cognition. There are numerous ways to explore heuristic models, from the basis of efficient, parallel processing to the application of heuristics to cybersecurity. However, the following analysis will delve primarily into how heuristic capabilities can support cognitive and affective frameworks for semiosis. First, an examination of heuristics using rules-based algorithms for aggregation of common data sets will be employed. Next, metaheuristics for metacognition and information depth will be examined. Then, an empirical study related to heuristics will be explored to get a sense of the discretely scientific and mathematical processes being used to produce more complex heuristic models. Finally, two game-related heuristics models will be explored and related to how humans use semiosis when playing games.

Rules are the currency humans and machines use to understand and navigate data in complex systems. Algorithms contain numerous rule sets in their detailed instructions to ensure an AI is operating efficiently and correctly. Within heuristic frameworks, rules are also of critical importance as they help direct the processing and confluence of data for synthesis [17]. Heuristic frameworks operate on the premise of providing efficient, direct correlation of data within specific scaffolds to build schemas capable of assimilating and accommodating various types of information. This is a critical aspect of meaning making in semiotic frameworks since symbolic intricacies related to metacognition rest in understanding the information behind the information. This means that grouping parallel information and using primary, secondary, and tertiary rule sets to check and relate disparate data can lead to building efficient and effective mental shortcuts within machine systems that allow them to recognize and communicate effectively at the semiotic level [17]. This is generally accomplished using multiple running processing threads, load balancing, and granularity control to ensure the data is being sorted, related, and processed efficiently and rapidly [17].

The act of using rules to bring together disparate data to establish schemata relates directly to the next level of heuristic semiosis: metaheuristics. “Metaheuristics exploit not only the problem characteristics but also ideas based on artificial intelligence methodologies, such as different types of memory structures and learning mechanisms, as well as analogies with optimization methods found in nature [18].” Built on this methodology, mechanisms for information synthesis toward semiosis have potentially solid purchase. This method of forming data connections and relationships is akin to what has been observed for centuries in human metacognitive capability. The act of “thinking about thinking” carries with it the most foundational characteristics of building and creating meaning [4]. In machine systems, the act of metacognition and

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metaheuristics rests primarily on the ability of the system to correlate not only data, but complex sets of data that can be semiotically woven together. IPS and other mechanisms used form cyber defense use heuristics to make predictions and decisions concerning protective tactics for information networks. Tarantilis, et. al. suggests that, “a metaheuristic algorithm can also use one or various neighbor structures during the search process…or metaheuristic algorithm or a sophisticated combination of different metaheuristic concepts, a hybrid metaheuristic algorithm [18].” Using these metaheuristic structures, semiosis can be promoted by the interleaving of data and concepts toward the building of semiotic AI.

Kask and Dechter espouse an empirical framework in their study concerning mini-bucket heuristics [19]. The concept rests on “using a branch and bound search for finding the Most Probable Explanation (MPE) in Bayesian networks [19].” The use of Bayesian networks in this case can be leveraged for predictive analysis, which is critical for semiotic approaches. Part of the human ability to tie information together for the construction and synthesis of meaning is based on what most people would consider Bayesian or historical data. This is a foundational precept from the affective domain of learning as it draws on past information and experiences to develop cognitive, psychomotor, and affective linkages for accessing and creating meaning [3]. Through the use of elimination of mini-buckets through Bayesian analysis, Kask and Dechter found that, “search can be competitive with the best known approximation algorithms for probabilistic decoding such as Iterative Belief Propagation (IBP) when the networks are relatively small, in which case search solved the problems optimally [19]” indicating heuristic capabilities offer a way toward connecting information and efficiently processing and interrelating said data.

Games have been used as mechanisms toward meaning synthesis in the human experience from time immemorial. Games are a way to not only model human and machine learning, but to guide meaningful interactions that can be used to scaffold connections for semiosis. Ancient historical and cutting-edge modern context surround the eastern game of Go; a mainstay in China and one studied most recently through a contest between a Chinese Go champion and Google’s Deep Mind. Bergmark and Stenberg study the heuristic relationships surrounding Go as they examine heuristics using a Monte Carlo Tree Search (MCTS) model [20]. The outcome of their research gave insight into how decisions can be made and related to one’s opponent in a game situation; a central aspect of AI algorithmic representations in GANs. Interestingly, AI can use metaheuristic analysis to predict all possible moves to probabilistically select the best move; [20] a metacognitive advantage over the semantic capabilities of most humans. While this capability is more closely related to semantics, there are numerous foundational components present which allow for the construction of meaning based on the machine capability to “outthink” an opponent. Another study using the game of Connect Four, delves into teaching computers to “think [21].” The researchers in this case decided to build a “genetic algorithm” to “evolve” proper weight values in the systemic thought processes of the program. “A genetic algorithm is an optimization technique that uses a fitness function to attempt to find the best value for a variable over many iterations, in a manner that mimics natural selection [21].” Again, this is a more semantic representation of data, but has direct application to potentially semiotic AI due to the decision processes that leverage integrated meaning behind the thought processes employed.

Heuristic models and techniques lend themselves well to semiotic AI through their ability to groups information into mental shortcuts that can be used for the construction of meaning in machine systems. Rules-based systems are a natural starting point for establishing algorithmic properties for building meaning since it is those rule sets that make processing and interleaving of data practicable. This naturally leads to the process of metaheuristics where heuristic methods are further refined and based on analogies; another particularly meaning-based area of human thought in the affective domain. Bayesian analysis adds another important later to this framework as it is based on prior information that can be leveraged for semiosis, much the same way we as humans use memory. Of course, human experience and processing of information through gamification is an area of human practice that has existed for as long as humanity. Through gaming, machine systems have the opportunity to game out information and begin to build potential meaning scaffolds that may be used in assimilation and accommodation of data into future schemata.

VI. AI ACCOMMODATION/ASSIMILATION MODEL

The following model is descriptive of the aforementioned data concerning neural sketch learning, paradigmatic associations, semiotics, and advanced heuristics for semiotic AI scaffolding. As mentioned earlier, accommodation and assimilation are integral parts of learning theory. Accommodation “is where the new element does not and cannot fit the new schema and thus a process of transformation of both takes place, involving the original stimulus or object of learning and the schema that is attempting some form of accommodation with it [21].” As relates to semiotic machine systems, accommodation is the level at which an AI would necessarily have to make allowances for information not specific to its particular learning or knowledge schema. As a contrast, assimilation “is where a new element has to be addressed and made sense of by the individual, but this process is still essentially passive. The new elements are easily absorbed, indeed assimilated, into the existing schema of the individual [21].” Again, assimilation requires a semiotic AI to take information that may be unfamiliar or new and make sense of that information; an integral aspect of semiosis.

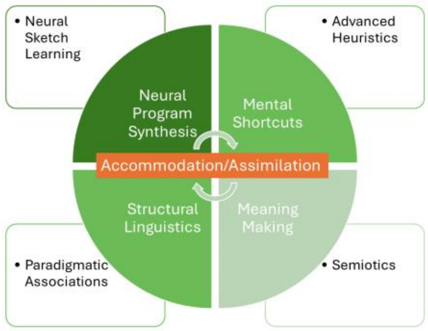

Figure 1. AI Accommodation/Assimilation Model

Figure 1 depicts the AI Accommodation/Assimilation Model, indicating the four areas discussed earlier and relating these areas to their functions and support to AI semiosis through inputs for accommodation and assimilation of information and meaning for semiotic AI. Neural Sketch Learning supports semiosis through neural program synthesis where structures mimicking human neural networks can provide the underlying layer of logical and semiotic pathways necessary for information construction and creation. Advanced Heuristics provide the mental shortcuts machines will need to take abstract concepts and disconnected data and provide inputs into the neural networks within a semiotic AI superstructure. Paradigmatic Associations are pivotal for creating the structural linguistics necessary to form words, phrases, sentences, etc. for the construction of meaning from a semantic standpoint. Paradigmatic Associations further carry the weight of bridging the linguistic infrastructure between neural networks and heuristic structures. Finally, Semiotics are the glue that binds all of the other structures together through the process of meaning making, allowing for the construction of meaning for accommodation and assimilation. All of these elements work together to form the necessary basis for AI to accommodate and assimilate new knowledge and meaning (understanding) for the synthesis necessary for basic semiosis.

VII. CONCLUSION

Semiotic AI, from a meaning-making perspective, is essentially the next level of artificial intelligence following the semantic AGI so many are striving for currently. If we are to reach this next echelon, several types of programming, learning theories, and linguistic structures must first be understood and modeled. Semiotics in general must first be understood as they are not merely about pure information, but also about the accommodation and assimilation of meaning. To get closer to this level of understanding and meaning synthesis, neural sketches must be considered as they provide components of information that can be leveraged across neural networks. Layered atop these network scaffolds are paradigmatic associations necessary for understanding the paradigmatic, syntagmatic, and idiomatic language and components necessary for semiosis. Also, advanced heuristics must be considered as they provide the mental shortcuts generally missing across current AI structures that could assist with the further construction and synthesis of semiotic meaning. Finally, a holistic model is presented above to suggest a way toward a confluence of these disparate methodologies into an apparatus for the accommodation and assimilation of information into and by semiotic AI. These strategies are foundational to cyber offensive and defensive operations through the use of predictive decision support to ensure advanced risk avoidance and mitigation. Altogether, the research and recommendations herein provide an overview of the potential tools and methods for machine semiosis.

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