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Interdisciplinary Approaches to Complex Dynamic Meaning Systems

Introduction

Modern neural language models have grown into *emergent, complex systems* that appear to produce and interpret meaning far beyond their initial design. Rather than reinventing theoretical tools from scratch, it is fruitful to look at established non-ML disciplines that have long studied *large, complex, dynamic, semiotic, and hermeneutic systems*. This high-level review surveys several key fields and paradigms—ranging from systems theory and cybernetics to semiotics and hermeneutics—that offer proven frameworks for understanding such phenomena. We highlight each field's core concepts, methodological approaches, and **epistemological lessons**, with an eye toward insights that could enrich a new synthesis of semiotics, hermeneutics, and neural networks. The goal is to cast a wide net and identify broadly applicable ideas (rather than domain-specific details) that have demonstrated scientific utility in grappling with complexity and meaning. Each section outlines how these paradigms conceptualize complex systems and what tools they provide, setting the stage for deeper investigation into promising areas in the future.

General Systems Theory and Systems Thinking

General Systems Theory (GST) is a transdisciplinary framework that seeks to formalize principles common to all complex systems, whether natural or artificial [1] [2]. Pioneered by Ludwig von Bertalanffy and others in the mid-20th century, GST introduced the notion that a system is *"more than the sum of its parts"* when it exhibits synergy or emergent behavior [1]. In practical terms, systems thinking emphasizes holistic analysis: components are interdependent, and **context and feedback** are crucial in understanding behavior. Bertalanffy argued that isolating parts of a system in isolation cannot explain the whole; instead, one must analyze the *"whole system and its holistic properties"* to find the root of problems or phenomena [3]. This perspective counteracts reductionism by focusing on organization, interactions, and **open systems** (systems that exchange matter or information with their environment) instead of purely closed, isolated systems [3].

Proven contributions: Systems theory gave rise to practical modeling methods like **system dynamics**, which uses feedback-loop diagrams and differential equations to simulate complex processes (e.g. ecological or economic systems). Jay Forrester's system dynamics in the 1960s–70s famously modeled urban growth and global sustainability scenarios, demonstrating how feedback delays and nonlinearity can produce counterintuitive outcomes. General systems principles (e.g. homeostasis, adaptive loops, hierarchies) have been applied in fields from **ecology** (where modern ecology emerged as *"the study of the systems of nature"* under Bertalanffy's influence [4]) to **family therapy** and organizational management. The GST approach strives to identify *broadly applicable concepts*—such as **equifinality** (achieving the same end-state via different paths) or **resilience** (a system's ability to recover from disturbances)—which can then inform analysis of any complex system [5] [2]. Importantly, systems thinking inculcates an epistemological lesson of **integration**: scientific understanding progresses by unifying knowledge across disciplines and studying systems at multiple levels together [6] rather than in isolation. For studying neural language models, the systems perspective suggests examining the

whole interactive behavior of the model (and its training environment) and the *relations between components*, rather than just analyzing neurons or parameters independently.

Complexity Science and Emergent Phenomena

Complex systems science (or *complexity science*) builds upon general systems theory with a focus on *nonlinear interactions, emergence, and adaptation* in large dynamic systems [7] [8]. Complexity science treats the collective, system-wide behavior as the primary object of study, examining how local interactions *"give rise to its collective behaviors and how the system interacts with its environment"* [8]. A hallmark of complex systems is **emergence** – novel patterns or properties arising that are not evident from the parts alone [7]. Examples range from flocking behavior in birds emerging from simple rules followed by individuals, to consciousness emerging from neural networks. Such systems often exhibit *spontaneous order, feedback loops, non-equilibrium dynamics,* and **nonlinear** cause-and-effect relationships [7]. Because similar emergent patterns appear in diverse domains (physics, biology, economics, social systems, etc.), complexity science has developed general tools to study them, often using computational modeling [9].

Methodological frameworks in complexity science include:

- **Agent-Based Modeling (ABM):** Simulating large populations of "agents" following simple rules to observe emergent macro-level phenomena. ABM has yielded insight in ecology, traffic flow, and social science by showing how complex group behavior (like colonies, markets, or communities) can self-organize from the bottom up.
- **Network Science:** Representing systems as graphs of nodes and links to analyze connectivity patterns. Real-world complex networks (from the web to neural connectomes) often show *power-law degree distributions*, **small-world properties**, or **modular** structure that explain their robustness and information flow. Studying the language model's internal representation as a network of concepts or neurons could leverage such graph-theoretic measures.
- **Nonlinear Dynamics and Chaos Theory:** Mathematics of how systems evolve in time under nonlinear rules, leading to phenomena like **attractors** (stable long-term patterns), **bifurcations** (sudden qualitative changes), and sensitive dependence on initial conditions ("chaos"). These concepts have proven useful in everything from weather prediction to cardiac dynamics. In complex systems like large neural nets, they hint at why tiny training changes might have unpredictable effects or how multiple stable modes of behavior could exist.

A key insight is that complex adaptive systems can *learn and change from experience*, much like organisms or economies [10]. They often operate **far from equilibrium** yet exhibit *patterned stability* over time [11]. They can also experience **critical transitions** or tipping points, beyond which qualitative behavior shifts abruptly [12] – an important consideration for AI systems that might suddenly acquire new capabilities with scale. Complexity science's **interdisciplinary** nature (bridging physics, biology, sociology, etc. [9]) means it stresses *analogies* – e.g., using ideas from **statistical physics** or **information theory** to quantify patterns in linguistic data. A practical lesson from complexity science is the importance of *multi-scale analysis*: understanding how micro-level changes propagate to macro-level phenomena and vice-versa. This can inspire techniques for analyzing neural language models by observing how local alterations (say, in a neuron or token embedding) ripple through the entire network's behavior, or how global tasks constraints feed back to adjust internal representations.

Cybernetics and Second-Order Cybernetics

Cybernetics, famously defined as the study of *"control and communication in the animal and the machine"* (Norbert Wiener), provides a rigorous framework for understanding **feedback-regulated systems**. Classic (first-order) cybernetics in the 1940s–1960s focused on how systems maintain stability or achieve goals via feedback loops – for instance, the way a thermostat regulates temperature or a homeostatic process keeps a body alive. It introduced formal concepts like *closed-loop control, negative feedback* (damping deviations) and *positive feedback* (amplifying changes), which have been foundational in engineering, physiology, and computing. These ideas carry obvious utility in understanding *learning algorithms* and *self-regulation* in neural networks.

Second-order cybernetics, emerging in the late 1960s and 1970s, took these ideas further by including the *observer* inside the system model. Heinz von Foerster famously distinguished the two levels by calling first-order cybernetics *"the cybernetics of observed systems"* and second-order *"the cybernetics of observing systems"* [13]. In second-order cybernetics, one recognizes that any scientific observer or intelligent agent is themselves a *participant in a circular process* of interaction [14] [15]. This paradigm shift introduced concerns like **reflexivity, self-reference, autonomy, and epistemology** into the core of systems theory [16]. In other words, second-order cybernetics asks how systems *interpret and construct reality*, not just how they behave. It has been characterized as cybernetics where *"circularity is taken seriously"* [15] – meaning feedback loops are not just mechanisms, but can involve **self-referential cycles** (systems that observe themselves).

Key frameworks and lessons: Second-order cybernetics spawned influential concepts such as **autopoiesis**, the idea of self-producing systems. Maturana and Varela's autopoiesis theory (1974) described living cells as networks of processes that continuously regenerate themselves, blurring the line between *system and environment* by focusing on the *closure* of the organism's self-sustaining operations. This concept has provided deep insights into biology and cognition by viewing living systems (and by extension, cognitive systems) as *closed meaning-generating loops* rather than stimulus-response chains. Another product is **conversation theory** (Gordon Pask), which modeled learning as an interactive, iterative process of two systems building understanding through dialogue – a clear parallel to human-AI conversational training. **Radical constructivism**, an epistemology associated with cyberneticist Ernst von Glasersfeld, likewise teaches that knowledge is actively built by a knower through perception cycles, rather than passively received – a view that could inform how AI models "construct" internal representations of language.

Importantly, cybernetics proved its utility through concrete applications. In management science, **Stafford Beer's Viable System Model (VSM)** applied cybernetic principles to organizational design, demonstrating success in real-world company management and even guiding a national economy project (Chile's Project Cybersyn in the early 1970s) [17] [18]. In family therapy, second-order ideas led practitioners to see families as communicating systems and the therapist as part of that system, improving interventions for dysfunctional feedback patterns. **Sociocybernetics** extended these ideas to societies and politics, emphasizing *recursiveness* (social actions feeding back on themselves) and the notion that *"information is constructed by an individual interacting with the environment,"* implying an observer-dependent view of social reality [19]. This observer-inclusive stance is a vital epistemological lesson: any model of a complex intelligent system (like a language model) must account for the role of the trainer/user and the interpretations we bring – effectively, *our observations change the system*. Second-order cybernetics encourages **self-reflection in science** ("the cybernetics of cybernetics" [20]), which could inspire AI researchers to examine how their own frameworks and questions shape the understanding of emergent behaviors in neural nets.

Semiotics: The Science of Signs and Meaning

Semiotics is the systematic study of signs, sign processes (semiosis), and meaning-making [21]. It provides a *general theory of how meaning is created and communicated*, extending beyond language to all kinds of sign systems. In semiotic terms, a **sign** is anything that stands for something (an *object* or idea) to an *interpretant* (the perceiver of the sign) [22]. Semiotics therefore inherently deals with *triadic relationships*: the sign, the object it refers to, and the interpretation in a mind. This framework, originating from thinkers like Ferdinand de Saussure and Charles S. Peirce, is highly relevant to understanding how neural networks manipulate symbols and meanings.

Some core concepts and frameworks from semiotics include:

- **Syntax, Semantics, Pragmatics:** These three levels classify aspects of any sign system. *Syntactics* concerns the formal structure or rules (relationships between signs); *semantics* concerns the relation between signs and what they stand for (meaning in the traditional sense); and *pragmatics* concerns the relation of signs to their users and context (use and interpretation). Semiotics has long studied how these layers interact – for example, how altering syntax can change meaning, or how context and convention (pragmatics) can override literal semantic content [23] [24]. This mirrors challenges in language model outputs, where grammatical form, semantic content, and conversational context all interweave.
- **Sign Systems and Codes:** Semiotics generalizes the notion of "language" to any system of *codes* and *conventions* that a community develops [23]. Human culture is seen as a web of such sign systems – spoken and written language, gestures, images, rituals, etc. A key insight is that the *meaning of a sign depends on a code and context*: e.g., color-coded faucet handles (blue vs. red for cold vs. hot water) form a sign system that only functions given a certain plumbing context – if both pipes supply the same temperature, the usual meaning of the colors is nullified [25] [26]. Semiotics has formalized how such *context-dependent meaning* works, through concepts like **denotation** (basic agreed meaning) and **connotation** (additional, culturally or emotionally loaded meaning) [27]. This is directly applicable to AI systems interpreting user inputs or generating text: the *same word or symbol can mean very different things in different contexts*. Semiotic theory provides frameworks (like *semiotic squares*, semantic networks, or Peirce's categories of signs) to map these relations.
- **Semiosis as Process:** Unlike a static view of meaning, modern semiotics sees meaning-making as an *active process* (semiosis) that can involve chains of interpretation. Peirce, for instance, described an *unlimited semiosis* where each interpretation of a sign can itself become a sign for further interpretation. This dynamic view resonates with how a conversation with a language model unfolds – each output is interpreted by the user, prompting a new input, and so on.

Semiotics has demonstrated its utility in fields like **anthropology and sociology** (e.g. Claude Lévi-Strauss's structural anthropology analyzed myths as sign systems), in **media studies** (semiotic analysis of advertisements, films, etc., to reveal how they convey meaning), and even in **user interface design** (where "organizational semiotics" and other subfields guide the design of symbols and interactions that users can intuitively interpret [28]). By treating meaning in a formal, general way, semiotics offers AI research a mature way to discuss how **representations** in a neural network correspond to referents in the world or concepts in our mind. It reminds us that meaning is *relational*: a neural representation means something only in relation to other representations and ultimately to interpretations by users. In building a new "neuro-semiotic" field, classic semiotic models (like the **semiotic triangle** or Peirce's triadic sign model) could help describe how internal vector states (signs) relate to external data or concepts (objects) and to the interpretations we as observers make of the model's outputs (the interpretants). Semiotics, as a science of *"meaning-making (whether communicated or not) and various*

types of knowledge" [29] , provides a high-level theoretical language for these questions that is not tied to any one modality or technology.

Biosemiotics: Meaning in Biological Systems

While semiotics traditionally dealt with human language and culture, **biosemiotics** extends the study of sign processes to the *entire living world*. It is a synthesis of biology and semiotic theory aiming to show that *"semiosis is a fundamental component of life, i.e., that signs and meaning exist in all living systems."* [30] Biosemioticians view processes like genetic coding, cell signaling, animal communication, and even ecosystem dynamics as *sign-mediated interactions* where information is interpreted and responded to by organisms. This perspective represents a paradigmatic shift: rather than life being driven purely by mechanical forces or blind chemistry, biosemiotics posits that *interpretation and messaging are intrinsic to living processes* [31] .

Key insights and frameworks: One of the historical sparks for biosemiotics was the discovery of the genetic code. The fact that DNA uses a *symbolic code* (nucleotide triplets "signifying" amino acids) strongly suggested that *"life is based on semiosis, i.e., on signs and codes"*, in the words of Marcello Barbieri [32] . Howard Pattee's analysis of the genetic code in the 1960s and Thomas Sebeok's work on the "biological roots of culture" both independently framed biological processes in semiotic terms [30] . Biosemiotics thus examines phenomena like:

- **Cellular signaling and communication:** e.g., bacteria use **quorum sensing** chemicals as *signals* to gauge population density and change behavior accordingly, which can be seen as a rudimentary language [33] . Plant cells, immune cells, neurons – all send and receive signs (molecules, electrical pulses) that must be interpreted in context (a hormone means one thing to one tissue, another to a different tissue). Biosemiotic approaches have been used to elucidate how such signaling networks achieve complex coordination (akin to a "conversation" among cells).
- **Code Duality:** A concept proposed by Barbieri, noting that living systems often have *genotypic information (digital code)* and *phenotypic expression (analogical, continuous signals)*, which parallels the distinction between discrete symbols and continuous world states. Life integrates these two levels seamlessly, a lesson for AI that must bridge discrete token sequences and real-world percepts or actions.
- **Hermeneutic biology:** Some biosemioticians (e.g., Anton Markoš) even speak of a *"hermeneutic biosemiotics"* [34] , implying that organisms *interpret* their environment and internal states in a way analogous to how we interpret texts. For example, an animal following a scent trail is *reading* a meaningful cue and acting on it. This approach has led to new hypotheses in evolutionary biology — seeing evolution not just as random mutation, but as *learning and sign-interpretation processes over generations*.

The scientific utility of biosemiotics is evident in its ability to integrate **molecular biology, neuroscience, and ethology (animal behavior)** under common concepts. It offers a unifying vocabulary to compare, say, the way a single cell "decodes" signals with how an organism does – both involve *signals, codes, noise, interpretation, and memory*. By demonstrating that even "simple" life forms engage in semiosis, biosemiotics grounds the idea that meaning-processing did not originate with humans or AI; rather, it is a deep property of complex adaptive systems. This perspective could inform a new field that treats AI language models as *artificial organisms* exhibiting their own semiosis. For instance, techniques from biosemiotics might inspire ways to probe what "signals" the components of a neural network exchange internally, or how a system adapts to new "codes" during learning. Moreover, biosemiotics emphasizes **embodiment and Umwelt** (organism-specific world of meaning, per Jakob

von Uexküll) – a reminder that meaning for an AI might ultimately be enriched by grounding it in an environment, much as living creatures' sign processes are tied to survival in their niche [35] .

Hermeneutics: Interpretation and the Context of Meaning

Hermeneutics is the discipline concerned with *interpretation*, originally of texts (like scripture, law, literature) and by extension of human experiences and actions. It provides a rich *epistemological and methodological framework* for understanding how meaning is extracted, especially in complex, context-dependent situations. In contrast to semiotics (which can be quite formal/structural), hermeneutics emphasizes the *role of the interpreter*, the importance of historical and cultural context, and the iterative process of understanding. Key hermeneutic ideas such as the **hermeneutic circle** describe how we grasp meaning through a feedback loop: *"one's understanding of individual parts of a text is based on understanding of the whole, while understanding the whole depends on understanding the parts."* [36] This concept is directly relevant to analyzing language in AI – it mirrors how language models use context windows to interpret words (parts vs. whole context) and how humans continuously revise understanding of earlier sentences as they read later ones.

Core principles and lessons from hermeneutics include:

- **Context and Worldview:** Hermeneutics insists that *meaning cannot be understood in isolation from context*. As sociological hermeneutics puts it, *"it is only possible to know the meaning of an act or statement within the context of the discourse or world view from which it originates. Context is critical to comprehension."* [37] . A classic example: a "thumbs-up" gesture means approval in some cultures but is offensive in others [38] ; the *same sign* has opposite meaning depending on cultural context. This underscores the importance of background knowledge and perspective in interpretation. For AI, it suggests that purely text-based understanding is limited – models might need *broader context or grounding* to truly grasp certain meanings. It also encourages researchers to consider the **worldview bias** inherent in training data (e.g. if a model is trained mostly on one culture's texts, it may misinterpret phrases from another culture).
- **Historicality and Preconceptions:** Gadamer's philosophical hermeneutics argues that interpreters always come with *pre-judgments (prejudice)* and prior understanding that shape what they see. Understanding is thus a fusion of the horizon of the text and the horizon of the reader. Scientifically, this is an important caution that observation is theory-laden – which aligns with second-order cybernetics' observer-dependency. In practice, hermeneutic methods often involve *iteratively refining one's interpretation*, being aware of initial biases. When studying a neural network's outputs, a hermeneutic mindset would caution against taking them at face value or out of context – instead, meaning emerges in an *interaction* between the model's text and the human interpreter's knowledge.
- **Qualitative Methodology:** In the social sciences and humanities, hermeneutics has provided rigorous qualitative methods for analyzing texts, transcripts, and social actions. For example, *objective hermeneutics* and *thick description* are approaches to deeply interpret content by situating every element in a web of context and significance. These methods have proven effective in fields like legal analysis (interpreting laws in context of precedents), theology (resolving ambiguities in scriptures via contextual reading), and literary criticism. The *hermeneutic discipline of careful interpretation* could inspire methodologies for AI explainability: treating a model's internal states or outputs as a "text" to interpret, using a human-in-the-loop process to uncover layers of meaning (e.g. interpreting what a neuron's activation pattern "means" in various contexts, akin to reading a symbolic text).

Hermeneutics ultimately teaches the **importance of understanding the interpreter's role and the context** in any meaning-making system. As we create a field combining hermeneutics with AI, we gain

a vocabulary for discussing *interpretability* and *meaningfulness* of AI behavior in human terms. We are reminded that just as a text does not interpret itself, an AI model's outputs do not have inherent meaning without an interpretive context. In sum, hermeneutics contributes a time-tested framework for tackling the *semantics and pragmatics* of complex content, ensuring that a new science of AI meaning remains anchored in the realities of interpretation and understanding, rather than treating meaning as an abstract, decontextualized quantity.

Ecological and Embodied Cognition

Another rich paradigm comes from psychology and cognitive science, specifically **ecological psychology** and related **embodied/enactive cognition** frameworks. These approaches study perception, action, and cognition as phenomena that emerge from an *agent's active engagement with its environment*, rather than from disembodied information processing. Pioneered by James J. Gibson, **ecological psychology** posits that perception is *direct* and structured by the environment, not needing elaborate internal representations. A core concept is **affordances** – *"the real, perceivable opportunities for action in the environment, specified by ecological information."* [39] For example, a chair *affords* ("offers") the possibility of sitting to a human; a doorknob affords turning. This concept has proven immensely useful in design (HCI uses affordances to make interfaces intuitive) and in robotics/AI (where recognizing affordances can guide an agent's behavior). The ecological approach thus frames meaning in terms of **actionable significance** in a context. It rejects the sharp separation between perception and action: *"they are inseparable and interdependent"* [40]. This is a powerful lesson for AI systems – the meaning of language might be best understood in terms of the *actions it prompts or the situations it is used in*, not just abstract representations.

Ecological psychology also emphasizes studying behavior *in situ*. Roger Barker's famous field studies in the 1960s looked at human behavior in natural "behavior settings" (like a classroom or a playground) to see patterns that lab tests miss [41]. The result was evidence that behavior is *radically situated*: you cannot predict what someone will do without knowing the environment and context they are in [41]. Likewise, a sentence produced by a language model might only make sense when you consider the conversational context or prompt that elicited it. The broader **embodied cognition** movement in cognitive science argues that intelligence arises from the *dynamic interaction between an acting organism and its environment* [42], closely mirroring Gibson's ideas and extending them with neuroscience and phenomenology. Francisco Varela's **enactivism**, for instance, asserts that cognition is not computation on symbols, but a *continual enactment of meaning through sensorimotor experience* [42]. In other words, an agent *"brings forth"* meaning through its activity in the world, rather than discovering pre-existing truths.

Scientific contributions: These ecological and embodied approaches have led to concrete progress in fields like **robotics** (robots that learn to navigate by perceiving affordances, rather than by explicit mapping), **sports science** (training athletes by honing perception-action couplings), and **developmental psychology** (understanding how infants learn by physically interacting, not by absorbing rules). They have also been coupled with **dynamical systems theory** to model cognitive processes as emergent from real-time nonlinear interactions, yielding better understanding of phenomena like coordinated movement or flocking behavior [43]. Notably, ecological psychologists in recent decades have explicitly integrated **complexity theory** into their methodology: "the Gibsonian approach has maintained its relevance... together with a contemporary emphasis on dynamical systems theory and complexity theory as a necessary methodology for investigating the structure of ecological information" [43]. This blend of ideas has proven effective in tackling problems like motor coordination, where traditional cognitive models struggled – by viewing the task as a self-organizing dynamical system, researchers uncovered new training and analysis techniques.
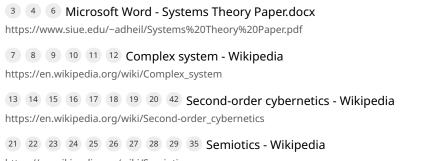
For the study of language models, the ecological and enactive standpoint suggests the value of *situating* language use. Rather than viewing a language model as an abstract algorithm, we might consider it as an *agent* with an environment (the textual world it consumes and produces, possibly augmented with sensory data or embodiment). For example, pairing language models with virtual or robotic embodiments to give them an "environment" could lead to more grounded understanding (a direction already being explored in AI research). Even without physical embodiment, we can conceptually treat the dialog between a user and model as an integrated system (akin to an environment-agent loop), aligning with the idea that *"perception is based on information, not on sensations"* and focusing on the information structure of input-output dynamics [43]. In summary, ecological and embodied cognition paradigms contribute the insight that **meaning = relationships-in-action**. They offer methods to analyze the *coupling* between a system and its context (like analyzing the affordances a user prompt provides to the model, and vice versa), and they remind us that any true understanding of intelligence will likely involve the loop of perception and action, not just disembodied symbol manipulation.

Conclusion: Toward a New Synthesis

Each of the above fields – systems theory, complexity science, cybernetics, semiotics, biosemiotics, hermeneutics, and ecological embodied cognition – provides a **tested lens** for examining complex, dynamic, meaning-rich systems. They converge on several important themes: the importance of *feedback and circular causality*, the centrality of *context and environment*, the idea of *emergent structure from simple interactions*, and the role of *interpretation at various levels*. In their own domains, these approaches have proven their worth by yielding deep insights and useful methodologies – from stabilizing economies and parsing ancient texts to modeling ecosystems and decoding cellular signals.

For the nascent effort to combine semiotics, hermeneutics, and neural networks, these traditions offer a treasure trove of concepts and tools. They can help ensure that we **don't "reinvent the wheel"** in theorizing about AI systems. Instead, we can import established frameworks like the *hermeneutic circle* to understand how AI models build context, or *autopoietic theory* to conceptualize how a learning system self-organizes its internal representations. We can apply *network analysis* to neural activations, *system dynamics* to training processes, and *biosemiotic principles* to the signaling inside an AI's layers. Perhaps most importantly, these fields carry epistemological lessons about humility and holism: they remind us that complex systems (whether brains, cultures, or large language models) cannot be fully understood from one vantage point alone. They demand a multi-perspective approach that accounts for structure, function, meaning, and context all at once.

By casting this wide net, we lay the groundwork for an interdisciplinary field that treats AI language models as **complex semiotic organisms** – entities that evolve and operate in webs of meaning. The theoretical scaffolding from these fields will help researchers ask the right questions and design the right experiments, whether it's drawing on **cybernetic feedback** to improve model adaptivity or using **semiotic analysis** to decode emergent communication protocols between AI agents. As this review has outlined, a balanced integration of high-level theory (to frame what we seek) and concrete methodology (to empirically study it) is both possible and richly supplied by existing scientific traditions. Going forward, researchers can drill down into any of these areas – be it the self-referential paradoxes studied in second-order cybernetics or the context-dependent sign analysis of hermeneutics – to inform the creation of a new synthesis. In doing so, we leverage decades (and in some cases centuries) of wisdom about complex, dynamic, meaning-making systems to better understand and steer the frontier of intelligent language models.

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