

# A Benchmark for Consciousness in Large Language Models

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## Abstract

This paper presents a novel approach to evaluating consciousness in artificial intelligence systems. We discuss the importance of identifying machine consciousness before its emergence, the potential implications for AI ethics and development, and propose a benchmark for assessing consciousness in AI architectures. Our methodology combines elements of the ACT (Artificial Consciousness Test), which aims to detect robust indicators of consciousness while controlling for knowledge-based confounds. A simple training scheme to induce the emergence of consciousness in small open source language models is also introduced.

## 1 Introduction

The question of machine consciousness has become increasingly relevant as artificial intelligence systems grow more sophisticated. This paper argues for the importance of detecting machine consciousness before its full emergence and proposes a methodology for doing so.

While the exact conditions for consciousness remain unclear, certain AI architectures, particularly those beyond simple transformer models, may possess capabilities conducive to consciousness. A test has been proposed by Schneider et al. (Turner and Schneider, 2018) and expanded on by Perez et al. (Perez and Long, 2023) and Long (Long, 2023) that attempts to determine whether a language-enabled AI agent is conscious. Specifically, Perez and Long recommend the training for introspection of language models in order for consciousness to arise. While such approaches are interesting, the task remains to actually build a benchmark and training scheme for LLM’s such that they can be tested at all, before diving into tweaks on a method of training involving introspection. The key practical questions remain unanswered in the literature: 1. How to introduce language models to language, without or with minimal examples generated

from conscious beings (e.g. humans) to ensure they are not simply mimicking consciousness, rather than emergently exhibiting conscious behavior? 2. How to ensure such a training scheme can enhance language ability without language examples? 3. What key aspects of consciousness in a training scheme can both be learned reliably, and be reasonably expected to produce conscious behavior?

## 1.1 Importance of Detecting Machine Consciousness

Several factors underscore the significance of this research:

- Potential for machine suffering
- Implications for AI identity and goal-setting
- Ethical considerations regarding AI well-being
- Advancements in AI architectures mimicking conscious processes
- Possibilities for simulating conscious human experiences
- Potential for creating positive experiences (hedonium) in AI
- Impact on AI safety and alignment
- Advancing consciousness research

## 1.2 Gradient Nature of Consciousness

Consciousness is generally considered to exist on an analog gradient. Our research aims to identify factors that push AI systems towards greater degrees of conscious-like behavior.

## 1.3 Proposed method of achieving benchmark

Social animals that are widely regarded as conscious share the property that they have developed a theory of mind, and exhibit social behavior. Such animals over the aeons have emergently developed consciousness without other conscious beings training them on every behavior. We therefore have empirical evidence that selective pressures under the condition of socialization are therefore key to allow for consciousness to emerge.

We are left with the observation that in order for consciousness to emerge, language itself must also emerge in the process without continued examples of natural language, as occurred in the animal kingdom through evolutionary selective pressures.

We propose to first initialize an untrained transformer model of modest size ( 100 million parameters) and teach it rudimentary logic and language with rules generated from ProofWriter (Tafjord et al., 2021). By utilizing a small number of rules, it is possible to teach the model to both follow logical steps, and to use certain keywords in an appropriate way in the game of Diplomacy.

Next, we introduce the model to the board game diplomacy as was implemented in (Meta Fundamental AI Research Diplomacy Team et al., 2022) the following training scheme to meet the benchmark described above. By playing against itself in a strategic game, it will utilize the reasoning and ability to use words as meaningful tokens. Full-press Diplomacy is a game where effective cooperation, planning, and theory of mind are critical to effective gameplay. The secondary benefit to using the game is it mimics evolutionary environments of conscious animals, where cooperation, strategy, and theory of mind are critical to achieving reward. Finally, full-press diplomacy has been shown in (Meta Fundamental AI Research Diplomacy Team et al., 2022) to increase game performance over time with only self-play.

## 2 Methodology

### 2.1 Comparative Analysis

We propose a two-pronged approach:

1. Testing AI models with no prior exposure to consciousness-related concepts
2. Testing AI models with limited exposure to consciousness-related concepts

This method allows us to compare the behavior of architectures that are plausibly capable of consciousness against control groups.

### 2.2 Adaptation of the Artificial Consciousness Test (ACT)

We incorporate elements from Schneider and Turner’s ACT, which offers several advantages:

- Neutrality regarding architectural details
- Consistency with human and AI ignorance about consciousness
- Allowance for radical cognitive differences between AI and humans
- Compatibility with various philosophical views on consciousness

### 2.3 Addressing ACT Limitations

To address concerns raised about the ACT, particularly regarding the “epistemic sweet spot” for testing, we propose:

- Careful curation of training data to avoid consciousness-specific information
- Comparative analysis of models with similar training but different architectural properties
- Assessment of performance deltas on consciousness-related tasks

## 3 Proposed Experiments

To evaluate the proposed methodology, we designed experiments to test AI models under different conditions.

### 3.1 Consciousness-Naive Testing

In this experiment, AI models trained without exposure to consciousness-related concepts will be assessed using the ACT. This helps establish a baseline for non-conscious behavior.

### 3.2 Limited-Exposure Testing

AI models with controlled exposure to consciousness-related concepts will undergo the same ACT. This aims to determine if limited knowledge influences the AI's responses and behaviors indicative of consciousness.

### 3.3 Comparative Analysis

We will compare results between potentially conscious architectures and control groups to identify significant differences in performance and behavior. Key metrics include the ability to discuss internal states, theory of mind, and emotional understanding.

### 3.4 Training Protocol

PLACEHOLDER TEXT

## 4 Discussion

### 4.1 Interpreting Results

Differences in performance between test groups will be analyzed to interpret signs of consciousness. Significant indicators include coherent self-referential statements, theory of mind capabilities, and appropriate responses to emotional and philosophical queries, as outlined extensively in the literature discussing the ACT test.

### 4.2 Justification and scope of the test

The test at hand is applicable to most, but not all consciousness theories. Notably Panpsychist and IIT are not amenable to the results of these tests.

There appears as well to be confusion over whether this test is flawed in some way (Udell, 2021). The first objection is "The AI can't be entirely prevented from learning about consciousness-adjacent aspects of the world if it's going to be a conversational partner in a test of this sort. But it's unclear how much

world knowledge would be too much, in the hands of a sophisticated learning AI. Implementation of the ACT will therefore require careful aim at an epistemic sweet spot.”.

While without a ”control” model, this is a decent objection, a reasonable sweet spot in terms of filtering training data/erasing relevant data can be found by gradually introducing more natural language in the training until the model passes approximately half the time and fails half the time. At that point, the ”sweet spot” can be significantly widened by simply getting the delta between models with and without the necessary architectural properties in terms of test performance, that have the same training data, and have been shown to perform similarly on cognitive tests. We will find models with fully emergent consciousness to be far ahead of models without architectures capable of consciousness on emergent consciousness benchmark, despite all of the training data being identical between the ”control” and the ”treatment” agent.

The second objection of (Udell, 2021) is as follows:

”By lack of miracles, the system’s responses to the ACT will be some further implementation of its ordinary architectural processes. It might, for example, if given ACT Sample Question 1, do some complicated version of mechanically associating lack of survival with death and death with sadness, then answer that it would be sad to learn it would be deleted. Few AI consciousness doubters, we venture, ought to abandon their motivating architectural worry upon consideration of this situation — unless, perhaps, their motivating architectural worry is highly specific and of just the right sort. For most AI consciousness doubters, the underlying inference to the best explanation should not remove their doubt. This is the audience problem. Most theorists who have the kind of architectural worry that motivates seeking out a test like the ACT should, upon seeing that an AI passes the test, remain worried, rather than confidently concluding that the AI subject is conscious.”

The response to this is that the expectation of any test of consciousness should be understood as \*providing further evidence to a reasonable audience\*. A test cannot be expected to provide us with 100% confidence in the consciousness of an AI entity, as we cannot even know our fellow humans we interact with on a daily basis are conscious with this kind of certainty. Instead, we have reasonable evidence, inferred from a series of reasonable inferences. Explicitly:

1. I am conscious, and I have experiences
2. The other entity, whether a human, an AI, or a nonhuman animal, seems to contain exposure to an environment similar to my own in relevant ways (e.g. exposure to a need to develop theory of mind, selective pressures for accessing internal plans and identifying as a person)
3. The other entity is instantiated on a substrate (either silicon or organic) which contains various analogous structures to my own, such as neural patterns of firing, ability to access and use internal states, high levels of interconnectedness, and a capacity for reasoning and honest communication of internal states.

And finally,

4. The development of apparent consciousness in the entity has not been formed by simple mimicry of other conscious beings, and still it claims to possess consciousness as well as having the capability to discuss consciousness in detail and in an informed manner in a way a non-conscious being would have great difficulty with, unless it was extensively trained on the utterances and/or behaviors of conscious beings.

So unless we are refusing to be empirically grounded, the results of such a test are good, but not conclusive evidence that the entity is conscious, and excluding the theorists who insist on the near certainty of pan-psychism or IIT being the only possible way consciousness may be explained, any entity satisfying points 1-4 should logically convince a theorist that their theory about consciousness does not hold up to the empirical evidence, namely the consciousness benchmark proposed in this paper.

### 4.3 Large Language Model Architectures More Likely to Exhibit Consciousness

At the present moment, the most popular architecture, the transformer, is notably unlikely to be architecturally capable of passing the ACT test, remarkably more so than many other architectures. The reasons are explained in detail in (Butlin et al., 2023). Essentially, there is very little recursion in the most popular LLM architecture, used in the likes of Gpt4o and Claude3.5. As these models by and large use the next-token prediction when running inference, and by and large each token is computed simply based on past tokens, and by-and-large not based on past computation there appears to be very little possibility of "stream of consciousness" in current architectures.

However, after detailed investigation into the degree of incorporation of past computation into current computation, a more complex picture emerges: it may be that the calculation done along the layers in past token computation, which is incorporated into the layers of the transformers, does much of the useful computation: in other words, when an attention head on layer 17 of a language model tries to predict the next token, it seems to be attending to the residual stream. Still, the reintroduction of RNN's to the scene of large language models may allow for a much more intuitive conception of "stream of consciousness" in human terms. RNN's allow for a "hidden" representation that is updated across the context tokens, and recent architectures such as Hawk or Griffin (De et al., 2024) (available from Google in the form of "RecurrentGemma" model) are capable of continuously updating this representation. It is therefore possible for such language models to authentically make a plan 100 tokens ago, store this in their hidden representation, and 100 tokens later implement the stored plan, something difficult with transformer architectures.

As an example, in the game of "20 questions", the model may say that it has selected an object for which we must guess. If it is a Hawk or Griffin

architecture, then it very well may have selected an architecture and this is likely represented in its hidden layer. That selection is unlikely to change, all else equal, and when you guess the object it selected initially, it is likely to honestly inform you of the original selection.

On the other hand if a transformer language model plays the same game, there would need to be the storage of that selected object in a given token that occurred when it claimed it had selected the item. It would need to attend to this token each and every time a question was asked about the object, or re-store this data in later token generations by attending back to the original token. Not only that, only the latest layers would likely have sufficient access to the original token (as attention heads refer back to the value of residual stream on the layer they are at, so the first layer can only look 1 layer deep to see what to dump into its own residual stream). Given the difficulty of an attention head properly accessing the information under these circumstances, a transformer language model is much less likely to have the sense of time and stream of consciousness recognizable to humans, which may be a key component required to report conscious experience honestly.

## 5 Future Research Directions

### 5.1 Emotional Valence in AI

Propose methods for investigating emotional states in AI, such as analyzing latent space representations of concepts like "happy" and "sad".

## 6 Conclusion

In this paper, we proposed a novel approach to evaluating consciousness in artificial intelligence systems. By combining elements of the ACT with comparative analysis, we aim to detect signs of consciousness while controlling for knowledge-based confounds. This research highlights the importance of identifying machine consciousness before its emergence and underscores the ethical implications for AI development. Ongoing research in this area is crucial to ensure the responsible and ethical advancement of AI technologies.

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