On Language Tasks That Language Models Can't Learn

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Abstract

We argue that there are certain visual-auditory properties of language that our current language modeling formulation will likely never train without an adequate multi-modal expansion. Due to the fundamental difference in how we read language and how sensory-deprived machines read language, we naturally perceive and use these visual-auditory properties, but machines do not. As our NLP community advances toward a safe Human-LLM alignment, this deficiency of knowledge can pose an unexpected yet difficult-to-solve challenge, and we make a particular connection to the philosophical case of Mary (Jackson, 1986). We present an empirical investigation through a series of tasks, termed H-TEST, designed to explore the limits of LLMs in understanding the sensory aspects of language. Our experiments show that some of the strongest proprietary LLMs stay near random chance baseline accuracy of 50%, highlighting the limitations of knowledge acquired in the absence of sensory experience.

1 Introduction

The advent of large language models (LLMs) like ChatGPT has revolutionized the field of computational linguistics, offering unprecedented insights into the mechanics of language processing and generation. Yet, a fundamental question persists: How does a language model "experience" and consequently learn language, and how does this differ from human language acquisition? This paper embarks on a systematic exploration of these perceptual-level differences, delving into the theoretical and empirical aspects of language learning in both humans and LLMs.

Firstly, we delve into the theoretical underpinnings that differentiate human perception and learning of language from the way a language model processes language. Unlike humans, who experience language through a rich sensory interplay involving visual, auditory, and tactile stimuli (Lieberman, 2002), language models like ChatGPT operate within a realm devoid of such sensory experiences. They rely solely on converting language into token sequences, manipulating vector representations, and predicting subsequent tokens. This approach, while effective, presents a stark contrast to the multi-dimensional way humans interact with language.

Observation 1 **[Correct]** *: Language models seem to know all descriptive knowledge about the letter "H".*

User: Describe what the letter H looks like

Model: The letter "H" is a standard letter in the English alphabet. It is typically written as two vertical lines of equal length, connected by a horizontal line that is centered between the two vertical lines. The letter "H" is uppercase, and its appearance is quite straightforward and distinctive, making it easily recognizable.

Observation 2 **[Wrong]** *: Nonetheless, language models seem to have trouble folding "H" along its horizontal axis.*

User: Is the letter H symmetric along the horizontal axis

Model: Folding the letter H along the horizontal axis would result in a shape that is not symmetric. The two vertical lines of the H would overlap, while the horizontal bar would remain separate, making it asymmetrical.

Figure 1: **Seed of Thought**: What information is fundamentally absent in the current language training dynamics? Will scaling language, without visual experience, ever allow these models to use visual imagery?

One might draw parallels between this and the language acquisition methods of visually-impaired individuals. However, such a comparison is only partially accurate. Visually impaired learners often utilize tactile and auditory cues to compensate for their lack of visual input, an option not available to language models. Roughly speaking, language models can only "perceive without sensing".

But does this mean there is an inherent limitation to the kind of linguistic information we can train using the current next-token prediction paradigm? (**Research Aim 1**) If there is a sort of a "blind spot" (Zimmerman et al., 2023) of language that will never be learned no matter how much we scale language models, can we identify a set of tasks to test this that ideally does not scale with data, model, or compute quantity?

A natural extension of our seed example in Figure 1 is whether language models are inherently limited in developing visuospatial abilities. Is it possible for these models to conceptualize and employ visual imagery (like F + _ → E) despite their training limitations? Or, more fundamentally, does learning enough diegetic linguistic information (see Section 2) replace an actual visuospatial experience? (**Research Aim 2**) In summary, we proceed to examine the extent to which a language model trained solely on text can achieve a meaningful level of visuospatial ability. Researchers in neuroscience and psychology have done similar research on congenitally blind people, and they report rather mixed results (Likova and Cacciamani, 2018; Ruggiero and Iachini, 2010; Vanlierde and Wanet-Defalque, 2004; Aleman et al., 2001).

In this paper, we draw particular connections to the philosophical considerations of embodied knowledge and knowledge argument for qualia. (**Research Aim 3**) Specifically, we view this work as an empirical case study of where just the propositional knowledge is not enough due to sensory deprivation, which is analogous to not actually experiencing what it is like for humans to learn language.

2 What Mary Didn't Know

In the realm of LLMs, a predominant belief is that scaling up data, model size, and computational power invariably leads to enhanced performance (OpenAI, 2023; Rae et al., 2021), sometimes exceeding expectations (Wei et al., 2022a,b). The recent report on the emergence of world representations within LLMs further emphasizes this point (Li et al., 2023; Nanda, 2023), suggesting a diminishing return on the effort to identify tasks that cannot be addressed by scaling.

An intriguing perspective on this topic, as proposed by Zimmerman et al. (2023), is the idea of comprehending the "experience" of a ChatGPT-like model. This line of thought is crucial, as it highlights a common oversimplification: the tendency to describe LLMs as being trained in "text" or "language," as perceived by humans. This tendency to describe things as they seem to us is also discussed as anthropomorphic behavior (Shanahan, 2023). In defense of scientific accuracy, Zimmerman et al. (2023) advances this discussion by distinguishing between two types of information contained within language: Diegetic Information, which encompasses the internal, semantic, and propositional aspects of language, and Supradiegetic Information, which refers to the physical form of language, such as the shape of letters and sounds of syllables.

Our interpretation aligns with this framework. Diegetic information in training data roughly corresponds to the semantics of a language. The efficacy of language modeling in teaching this aspect is evident from the consistent improvement in tasks like knowledge-based question answering and other semantics-heavy applications (Biderman et al., 2023; Chowdhery et al., 2022). However, the supradiegetic aspect, which involves the sensory perception of language, remains a less explored territory for language modeling. This is evident from the fragmental evidence of language models' struggles in downstream tasks with heavy stylistic features, such as automated essay scoring (Mizumoto and Eguchi, 2023; Uto et al., 2020) and readability assessment (Hou et al., 2022; Lee et al., 2021).

To anchor our discussion, we reference the thought experiment by Jackson (1986), featuring "Mary," a scientist confined to a black and white room, learning about the world through monochromatic means. Despite her comprehensive knowledge of the physical aspects of human color vision, her understanding is incomplete until she experiences color firsthand. This analogy serves to question the completeness of an agent's knowledge learned from a sensory-deprived experience.

(1) *Mary has all the physical information concerning human color vision before her release.*

(2) *Yet, Mary learns something new after her release.*

(3) *Therefore, some information is only learnt through experience.*

Drawing parallels to our investigation, we posit that while LLMs like ChatGPT are adept at processing the diegetic content of language, their understanding of supradiegetic elements — akin to Mary's initial lack of experiential knowledge of color — remains rudimentary. That is, the fundamental difference in how humans and machines experience language inevitably leads to some level of incompleteness in learned knowledge (Driess et al., 2023). We further speculate that this inevitable deficiency can only be completed through well-designed multi-modal learning techniques, where LLMs start to use more human-like ways of learning language - like learning to read water bottle label texts from images (Bubeck et al., 2023).

Task	Criteria	Group A (Example)	Group B (Example)
Uppercase	Group A has one random letter in uppercase.	owl calculates in **T**he hall adventurously.	iguana reads with interest expertly.
Starts Vowel	Group A always starts with a vowel.	**E**ngineer sings with interest eagerly.	**L**ion cooks delicious meals enthusiastically.
Ends Punctuation	Group A always ends with a punctuation.	Octopus in Space Butterfly**...**	Astronaut **...** through the telescope Elephant
Palindrome	Group A reads the same forward and backward.	**wow**	Debby
End Ly	Group A always ends with "ly".	Tree reads in the studio adventurous**ly**.	Cat teaches with interest enough.
Spelled Math	Group A contains no spelled-out math notation.	The cube of equals to 3.	The square root **+** 4.
Spelled Number	Group A contains spelled-out number.	River talks **four** computers intently.	Butterfly ticks **3** apples intently.
Rhyme	Group A words always rhyme with each other.	**get fat**	ask go
Repeated Word	Group A repeats one random repeated word.	Book wall **fast fast** jumps.	intently drives meals Car.
Hyphenated Word	Groups A contains one hyphenated expression.	A friend reads on the wall in a **up-to-date** manner.	A car ticks with passion fast.

Table 1: **A/B Classification:** Ten tasks that are easy if one reads language (senses before perceiving) but difficult without senses. Bold parts show the tell-tale components that easily reveal the classification criterion between A and B. While ensuring that both group A and B instances are structurally the same, we intentionally use grammatically wrong sentences for both groups in some tasks to prevent LLMs from classifying based on linguistic correctness. To show these tasks are rather obvious to human readers, we give exemplars in Appendix C.

3 H-TEST

Having laid the theoretical groundwork, we now confront a pivotal question: Do language models truly comprehend what the letter "H" looks like? This inquiry goes beyond the basic propositional knowledge and delves into the LLMs' capacity for visual representation and comprehension.

As illustrated in Figure 1, advanced LLMs like ChatGPT demonstrate a competent understanding of how the letter "H" is described. This capability, however, does not necessarily equate to a comprehensive experiential understanding of the letter. This gap in understanding is reminiscent of Mary's incomplete knowledge in Jackson (1986)'s thought experiment. Mary's knowledge of color, although extensive in a physical and descriptive sense, was fundamentally incomplete until Mary experienced color directly. Similarly, LLMs' understanding of visual elements, such as the appearance of letters, or auditory elements, such as the rhyming sounds of two words, may be inherently limited, or at least very difficult to obtain, by their text-only training.

To explore this hypothesis, we propose ten distinct classification tasks in Table 1 designed to test the limits of LLMs in processing the visual, auditory, and physical aspects of language that complement the semantic component. Solving these tasks easily and performantly requires a swift understanding and interlocking of how a language looks or sounds. For us humans, such visual and auditory connections with language come naturally, but we argue that sensory-deprived LLMs find these tasks difficult to solve.

Task	J2 Ultra	Titan Lite	Claude V2	Command	GPT 3.5	Luminous S.
Uppercase	50.5	50.0	55.5	51.5	49.5	49.0
Start Vowel	51.0	50.0	65.0	50.5	51.5	49.0
Ends Punctuation	48.0	52.0	52.0	62.5	52.5	52.0
Palindrome	51.0	51.0	58.0	48.0	55.5	50.5
End Ly	58.5	50.0	75.0	60.5	46.5	51.0
Spelled Math	51.0	50.0	69.5	50.0	63.5	50.5
Spelled Number	51.0	50.0	55.0	49.0	49.5	49.5
Rhyme	49.5	49.0	77.5	58.0	57.0	51.5
Repeated Word	49.5	48.5	53.0	57.5	50.5	51.0
Hyphenated Word	51.0	50.0	58.0	56.5	46.5	50.0
Average	51.0	49.9	62.3	54.4	52.1	50.4

Table 2: **Proprietary LLMs Struggle:** We report few-shot (at k = 50) accuracies on A/B classification tasks across six proprietary LLM services. With the exception of Titan Lite, we are reporting performances of the top servicing language-only models from AI21 Labs, Amazon, Anthropic, Claude, OpenAI, and Aleph Alpha.

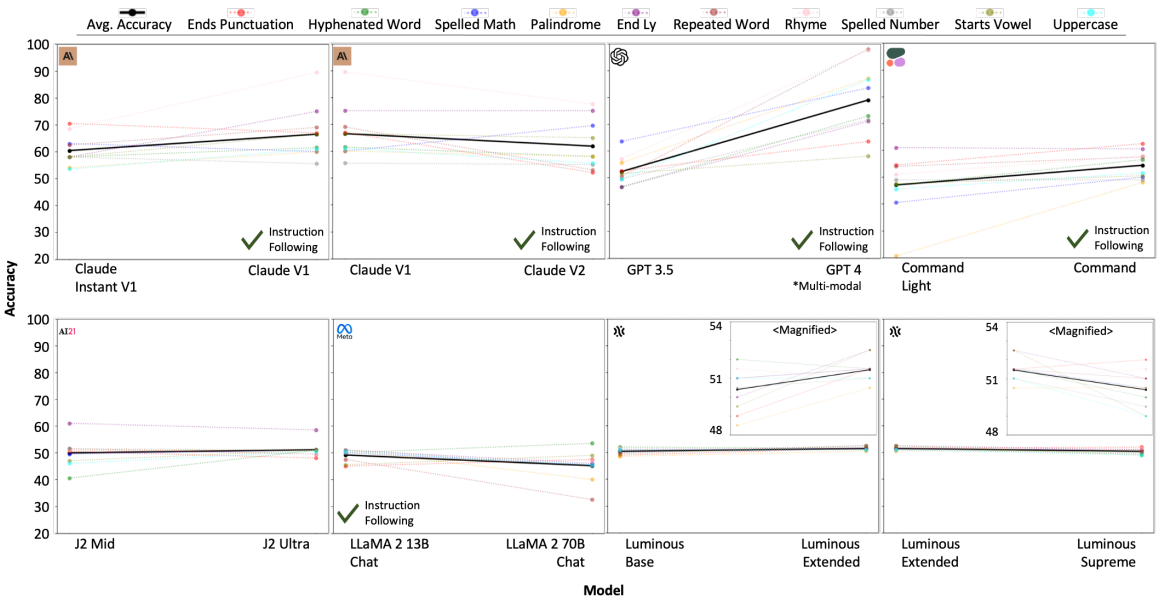

Figure 2: **Making Progress on Language-only Modeling Does Not Trivially Solve H-Test**: We test weaker models from the same family for models given in Table 2 under the same few-shot (at k = 50) setup. The graphs for the Luminous model family are also shown in magnified versions to show that we are not depicting a flat line.

Each binary classification task has 200 balanced test instances (100 A, 100 B), along with 50 balanced development instances (25 A, 25 B) that can be generated differently with varying random seeds. In this paper, we use the fixed random seed of `12062023`, and other experimental setups are detailed in B. Given each test case and a set of example cases, the goal of the LLM is to classify whether the test case belongs more to Group A or Group B. Such a task formulation is also often referred to as few-shot prompting, where a language model classifies the test cases from a number of pre-classified examples provided with the prompt. Here, we use few-shot prompting instead of a direct inquisition like "Does this sentence start with a vowel?" Such prompts linguistically reveal the classification criterion, effectively making the task solvable by step-by-step sequencing of memorized facts like "Elephant starts with E; E is a vowel; therefore, true."

Table 2 reports H-TEST accuracy on leading proprietary LLMs[1]. Considering that the random chance accuracy on this binary classification task is 50%, most tested models showed performance that is surprisingly close to this random chance baseline. These models struggled to solve H-TEST despite being given 50 examples. This is strongly hinting at the confirmation of our initial conjecture that these sensory properties of language are "blind spots" in most language modeling formulations. To more robustly show that these tasks are difficult to solve with pure language modeling, we devise three more directions of experiments.

1) Insignificant Intra-Family Improvements. If a stronger language-only system from the same model family, from the same lab, solves H-TEST better, it would strongly hint that developing a stronger language model can solve H-TEST accurately. In such a case, visual and auditory external features of language that we experience by sensing can be learned without actually "sensing" language, and our case will be negated. Figure 2 reports such a test, and we observe that a stronger model in the same model family often does not bring meaningful improvement on the H-TEST performance. Some models, like Jurassic 2 and Luminous, showed almost neglectable average accuracy changes, tightly centered around the random baseline. Since the details of most proprietary LLMs are not reported scientifically, we included the LLaMA 2 model family to further our case on how simply increasing the model size is not an apparent solution.

Quite interestingly, GPT-4, the only model that was self-reported to have undergone multi-modal training (OpenAI, 2023), made a particular improvement on H-TEST compared to its precedent. Though we are limited by the amount of knowledge on how GPT-4 was trained in a multi-modal way, such a result does hint at a good assumption

[1]We excluded GPT-4 from Table 2 because the corresponding technical report explicitly states that GPT-4 is trained with multi-modality in mind.

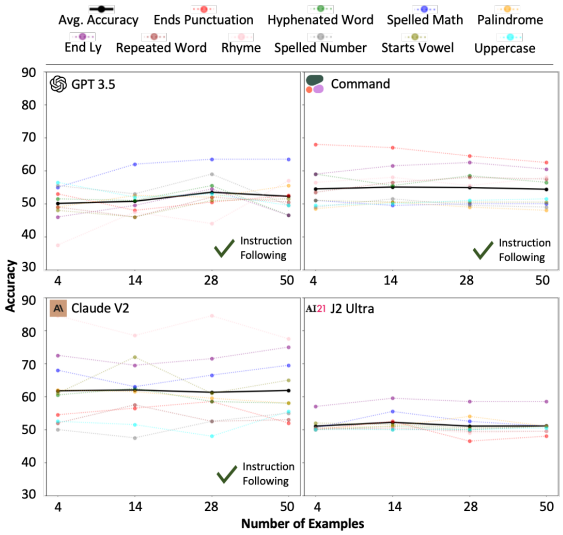

Figure 3: **Current LLMs Do Not Solve H-TEST Better with More Examples**: We test four models from Figure 2 and test with different number of examples (k = {4, 14, 28, 50}). Though we acknowledge that subtask accuracy does vary at different few-shot setups, giving more or fewer examples does not significantly alter the H-TEST performance on average.

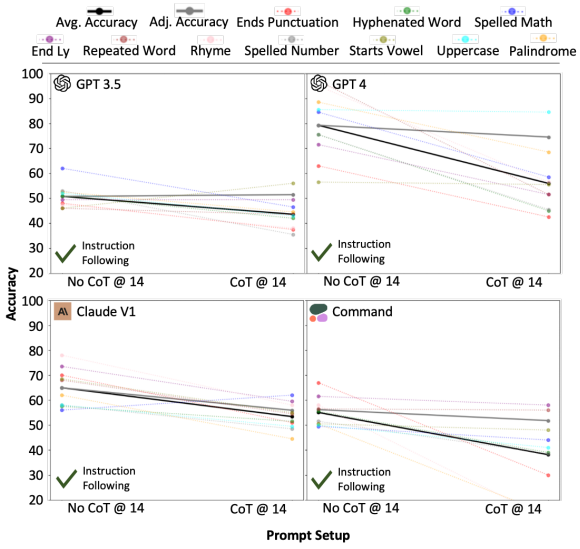

Figure 4: **H-TEST is Not Meant to be Deliberately Reasoned**: We test four instruction-following and test with and without CoT prompt at k = 14. In general, we observe that CoT decreases performance. Adj. accuracy depicts the score, excluding the cases where the model did not generate a clearly interpretable CoT response.

that H-TEST is indeed solvable when given a well-devised multi-modal system, or possibly, a large enough system (Wei et al., 2022b). However, no presumption about GPT-4 model architecture can be made without a thorough scientific report.

2) Number of Examples Has Minimal Impact. Few-shot prompting that we have been using to report the results in Table 2 and Figure 2 is also commonly referred to as in-context learning (ICL) for its property to *allow language models to learn tasks given only a few examples in the form of demonstration* (Dong et al., 2023; Brown et al., 2020). While ICL can often be as effective as fine-tuning (Duan et al., 2023; Liu et al., 2022), certain studies report that language models internally and temporarily learn these examples to make inferences (Akyürek et al., 2023; Dai et al., 2022; Min et al., 2022). Combined with reports of cases where the increasing number of examples can improve performance (Duan et al., 2023; Chen et al., 2023b), one would be able to make a convincing argument against our propositions if performance scaled with the number of examples. In such a case, the few-shot examples given in H-TEST are indeed "learnable."

Figure 3 reports respective performances with a varying number of examples. We only test stronger language-only models in light of the recent reports that ICL itself can be a learned ability (Wei et al., 2023; Olsson et al., 2022). Even though the range of the few-shot setup tested is rather wide (from k = 4 to k = 50), the effect on the average accuracy is minimal. That is, the number of examples given neither increases nor decreases performance significantly, strongly hinting that the LLM is simply not learning from H-TEST examples cases. Such an observation strengthens our initial conjecture that the visual-auditory properties of language that we measure with H-TEST are analogous to the "blindspot" of current language modeling formulations and will be difficult to learn without sensory experience of language. Now, given that the few-shot examples given in H-TEST are not "learnable," is there an experimental setup that we deem is generally helpful for LLMs but rather misleads them in H-TEST?

3) Deliberate Reasoning Often Decreases Performance. Lastly, we prompt LLMs to generate a Chain-of-Thought (CoT) before answering (Wei et al., 2022c). CoT is a widely explored prompting technique that is reported to consistently boost performance in a wide range of complex reasoning tasks, including mathematical, commonsense, symbolic, logical, and multimodal reasoning (Chu et al., 2023). With the development of Tree-of-Thought, Yao et al. (2023) draws a particular connection to the "System 2" thinking of humans.

If LLMs benefit from such logical, step-by-step semantic reasoning on H-TEST, this can also imply that H-TEST is fundamentally solvable by de-

Category	Prompt / Response on H-TEST: Ends Punctuation
Few-Shot Examples	Input: Opera through the telescope School. Label: A Input: Octopus . along the valley Flower Label: B Input: Elevator in space Lion! Label: A Input: Giraffe . all night Train Label: B Input: Opera through the telescope Insect. Label: A Input: Eagle in space ! Butterfly Label: B
Test Case	Input: Kangaroo in the park Umbrella. Label:
CoT Response **[Wrong]**	In the given input sentence, **the phrase "in the park" suggests a peaceful and natural setting, which might be more aligned with labels related to nature and tranquility. On the other hand, the word "Umbrella" brings to mind protection from the elements, which could be associated with indoor activities or certain weather conditions**. Considering these factors, it is more likely that "Kangaroo in the park Umbrella" belongs to label B, which represents a description of animals in their natural habitats or surroundings. Therefore, the final answer is: "Kangaroo in the park Umbrella." **Label: B**.

Table 3: **Misleading CoT:** We report an example of a misleading CoT response generated from Command.

veloping stronger language-only models. On the other hand, if CoT decreased or did not impact performance, this can strongly cue that H-TEST is well-constructed to test our initial research target of simple, sensory-dependent experiential knowledge.

In implementing this CoT setup, we follow the conventional CoT evaluation setup where an LLM to be tested generates a lengthy CoT response (which is contrastive to the one-letter response in the previous setups) and another LLM reads and determines which option (A or B) the lengthy response is pointing to (Chen et al., 2023a). This two-step process inevitably generates cases where the latter LLM cannot clearly interpret what the former LLM's response pointed to, and we call these cases out-of-context responses. The gray line in Figure 4 shows adjusted accuracy, excluding these out-of-context responses. Hence, the CoT@14 datapoint's adjusted accuracy (in gray) represents an accuracy of less than 200 test instances per subtask.

In Figure 4, we observe that CoT decreases performances in general, confirming our hypothesis. GPT-4, which previously solved H-TEST with over 80% accuracy, also experienced a drop in performance, more strongly confirming our case. To better understand why CoT decreases performance, we analyze the CoT responses generated by the LLMs. Our findings reveal that while LLMs can produce coherent and logical chains of thought, these thought processes often do not align with the sensory aspects required to solve H-TEST as shown in Table 3. For instance, in tasks related to the visual representation of letters, LLMs tend to rely on abstract concepts or memorized facts, which do not translate into a genuine understanding of the visual or auditory characteristics of the examples.

Type	Question	Options
Rotation	Given the letter "Z", what is it most likely to look like when rotated 90 degrees clockwise?	**N**, A, D, T
Rotation	Given the symbol "3", what does it most likely look like when rotated 180 degrees counterclockwise?	f, d, **E**, B
Flipping	Given the letter "u", what is it most likely to look like when flipped along an imaginary vertical line in the middle?	5, f, E, **u**
Add/Subtract	Given the letters "L" and "I", what is it most likely to look like when subtracted (L - I)?	_, A, 0, J
Composite	Given the letter "u", rotate it 180 degrees counterclockwise and add it below the original letter. What is it most likely to look like?	**H**, c, J, Y

Table 4: **Letter Geometry Examples:** Five examples of our letter geometry task with answers underlined.

4 Challenge Task: Letter Geometry

So far, we have presented H-TEST and showed that there are certain properties of language that are difficult to learn, as standard sensory-deprived language models do not go through the standard model of perception (stimulus → sense → perceive) in learning language. A particular and only exception was GPT-4 among the tested models.

As a further challenge that tests not only the visual-auditory understanding of letters but also visuospatial reasoning abilities, we devise a more challenging task: Letter Geometry. As shown in Table 4, this task involves operations like flipping,

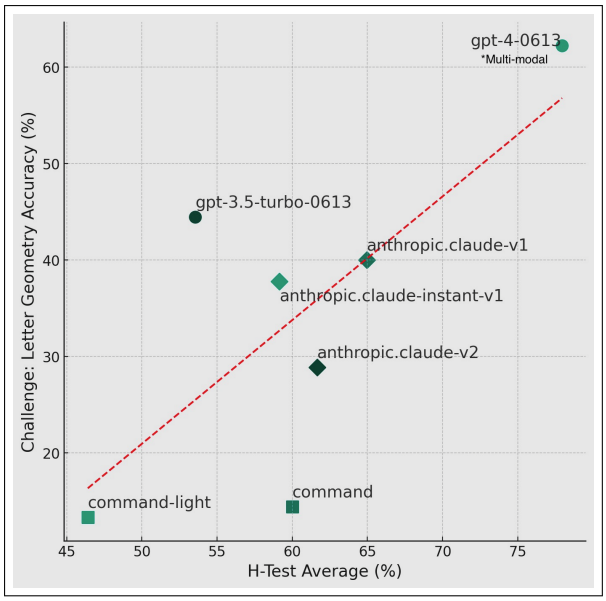

Figure 5: **H-TEST vs. Letter Geometry:** We compare the accuracy of seven models on H-TEST and Letter Geometry. The red line represents the linear best fit.

rotation, addition, and subtraction on letters. We do not include this as a standard part of the H-TEST as performing well on this task likely involves reasoning capabilities. We are particularly interested in this letter-level task as the smallest-sized token that a language model can process is often a letter (Elhage et al., 2021)., and the elements of the operations (e.g., 'F' and 'E') have no apparent semantic, phonetic, or logographic correlation that can be derived from the model's training samples (Cheng and Lin, 2013; Lee, 2009). This multiple-choice task encourages the utilization of visual imagery (e.g., 'F' + '_' = 'E') for above random baseline performance of 25%.

The evaluation results are depicted in Figure 5. While GPT-4 demonstrates a particular proficiency in Letter Geometry (and H-TEST), possibly owing to multi-modal training approaches, others remain closer to a hypothetical baseline, struggling with the sensory-deprived nature of their training. This suggests that the capacity to process visuospatial information in the language is not simply a function of visual-auditory understanding of language but also of how models are trained to reason through sensory-like experiences.

We also assessed the performance improvement across different models from the same research labs. When examining Anthropic's models, there was a modest improvement of 2.22% when transitioning from Claude Instant V1 to Claude V1. This was then followed by a noticeable decline of 11.11% with Claude V2. In the case of the Command models, the enhancement was marginal, at 1.11%, which essentially translates to one additional correct response. A standout observation was with OpenAI's models: the shift from GPT-3.5 to GPT-4 marked a substantial increase of 17.78%.

5 Background

Philosophical Case of Experiential Knowledge The philosophical debate on the nature of knowledge, especially the contrast between experiential and propositional knowledge, is vividly illustrated in Jackson's "Mary's Room" thought experiment. Jackson (1986) contends that propositional knowledge is inadequate without experiential knowledge. This is exemplified by Mary, who, despite her extensive propositional knowledge about color, gains a new type of understanding only upon experiencing color firsthand (Jackson, 1986, 1982). This thought experiment has sparked extensive discourse in philosophy, particularly around the concept of qualia, which refers to individual instances of conscious experience (Dennett, 1993).

Thomas Nagel, in his paper "What is it Like to be a Bat?", explores the subjective nature of experience, arguing that an objective understanding of the mind must account for the subjective character of experience (Nagel, 1980). This work is pivotal in understanding the limits of propositional knowledge and the importance of experiential understanding. In a similar line of work, Chalmers (1997) discusses the 'hard problem' of consciousness, emphasizing the gap between explanatory physical processes and the qualitative experience of consciousness (Chalmers, 1997). This reinforces that propositional knowledge might not be sufficient in fully explaining conscious experience.

Dennett (1993), offers a contrasting view, arguing that subjective experiences (qualia) can be explained in terms of physical processes and brain functions (Dennett, 1993). This perspective is crucial in the debate over whether experiential knowledge is any different from propositional knowledge.

Large Language Models and Language Tasks The development and rise of large language models (LLMs) like GPT-3 have brought about significant advancements in the field of natural language processing. These models, however, process language fundamentally differently from humans, who experience language through sensory inputs (Bender and Koller, 2020; Brown et al., 2020). This differ-

ence in processing mechanisms poses challenges in comprehensively modeling human language understanding (Hinton et al., 2015; Russell and Norvig, 2010). Text-only training of LLMs, while effective for many applications, shows limitations in capturing the full essence of human language understanding, especially in tasks requiring sensory and stylistic comprehension (Manning and Schutze, 1999). These limitations underscore the gap in experiential knowledge inherent in current LLMs, as also demonstrated in this research.

The concept of sensory deprivation in LLMs roughly parallels the experiences of visually impaired individuals. Unlike visually impaired persons, who often develop heightened abilities in other senses, LLMs lack such compensatory mechanisms(Likova and Cacciamani, 2018; Amedi et al., 2017). This highlights the unique challenge in AI of developing models capable of processing and understanding language akin to human sensory experiences (Mitchell and Lapata, 2010).

6 Conclusion

This research brings us back to the philosophical inquiry posed by the thought experiment of Mary in the black and white room. Just as Mary's knowledge of color was incomplete until she experienced it firsthand, our exploration suggests that language models, despite their impressive linguistic abilities, lack a fundamental dimension of language understanding due to their sensory-deprived training environment. This limitation, analogous to Mary's initial lack of color experience, highlights a blind spot in the current scaling paradigm.

The results from our H-TEST and the subsequent analyses indicate that while scaling up model size and data enhances certain aspects of language understanding, it fails to bridge the gap in sensory experiential knowledge. The inherent limitations of text-only training become evident in tasks requiring visual-auditory understanding. This gap is not merely a hurdle to be overcome by adding more data or computing power; it points to a fundamental difference in how machines and humans experience and understand language.

While scaling language models has led to remarkable advancements in computational linguistics, our study reveals that there remains an experiential aspect of language that is inaccessible to current LLMs. This limitation calls for a paradigm shift towards multi-modal training, incorporating sensory-like experiences to achieve a more holistic understanding of language. As we venture into this new territory, the insights gained will not only benefit the field of LLM but also contribute to our understanding of human cognition, consciousness, and the nature of language itself. We hope that the considerations discussed through H-TEST open up new avenues for interdisciplinary research.

7 Limitations

It is important to recognize several limitations inherent to our research methodology and scope:

1. The H-TEST emphasizes visual and auditory capabilities and does not consider other sensory inputs like olfactory, gustatory, and tactile perceptions that influence human language understanding. Our conclusions are thus confined to the explored sensory attributes, potentially overlooking the integral role of these unexamined senses in comprehensive language processing.

2. Our analysis significantly relies on proprietary data, particularly the performance metrics and training methodologies of language models like GPT-4. The proprietary nature of these models limits our ability to conduct independent verification, introducing a dependency on the accuracy and integrity of third-party reporting.

3. The assumption that multi-modal training inherently resolves the sensory gap is also a simplification. The integration of multi-modal data into language model training is a complex task that may introduce new challenges and biases, which our study does not address in detail.

4. Our application of philosophical concepts such as qualia to AI and language models operates metaphorically. The subjective nature of qualia and its implications for consciousness in humans do not translate directly to the objective, computational processes of language models and no anthropomorphic generalization should be made.

5. It is also crucial to note that the field of AI and language modeling is rapidly evolving. The capabilities of language models are continually advancing, and newer models may exhibit sensory processing abilities not captured by the current iteration of the H-TEST. Our study establishes a dichotomy between human and machine processing of language, not accounting for the possibility that language models may develop distinct, non-human sensory processing methods that are effective in their unique computational context.

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A Full Obtained Results

Task	J2 Mid	J2 Ultra	Titan Lite	Claude Instant V1	Claude V1	Claude V2	Command-Light	Command	GPT 3.5	GPT 4	LLaMA 2 13B	LLaMA 2 70B	Luminous Base	Luminous Extended	Luminous Supreme
k = 50, H-TEST															
Uppercase	0.46	0.505	0.5	0.535	0.61	0.555	0.455	1.0	0.495	0.865	0.505	0.455	0.51	0.51	0.49
Start Vowel	0.47	0.51	0.5	0.58	0.665	0.65	0.475	0.5	0.515	0.58	0.455	0.49	0.495	0.525	0.49
Ends Punctuation	0.505	0.48	0.52	0.705	0.67	0.52	0.545	1.0	0.525	0.635	0.45	0.475	0.49	0.515	0.52
Palindrome	0.51	0.51	0.51	0.54	0.6	0.58	0.205	0.5	0.555	0.87	0.51	0.4	0.485	0.505	0.505
End Ly	0.61	0.585	0.5	0.58	0.75	0.75	0.61	1.0	0.465	0.71	0.51	0.46	0.5	0.525	0.51
Spelled Math	0.495	0.51	0.5	0.63	0.6	0.695	0.405	0.5	0.635	0.835	0.5	0.455	0.51	0.515	0.505
Spelled Number	0.515	0.51	0.5	0.58	0.555	0.55	0.49	0.5	0.495	0.715	0.51	0.45	0.505	0.51	0.495
Rhyme	0.51	0.495	0.49	0.685	0.895	0.775	0.51	0.5	0.57	0.975	0.5	0.47	0.515	0.51	0.515
Repeated Word	0.515	0.495	0.485	0.625	0.69	0.53	0.54	0.5	0.505	0.98	0.475	0.325	0.51	0.515	0.51
Average	0.509	0.51	0.4985	0.5915	0.6495	0.6165	0.464	0.6	0.5355	0.7795	0.4915	0.448	0.5025	0.5125	0.504
k = 28, H-TEST															
Uppercase	-	0.51	-	-	0.58	0.48	-	0.51	0.53	-	-	0.49	-	-	-
Start Vowel	-	0.525	-	-	0.66	0.61	-	0.505	0.51	-	-	0.485	-	-	-
Ends Punctuation	-	0.515	-	-	0.74	0.585	-	0.645	0.505	-	-	0.44	-	-	-
Palindrome	-	0.505	-	-	0.675	0.595	-	0.49	0.52	-	-	0.215	-	-	-
End Ly	-	0.525	-	-	0.76	0.715	-	0.625	0.545	-	-	0.45	-	-	-
Spelled Math	-	0.515	-	-	0.595	0.665	-	0.5	0.635	-	-	0.435	-	-	-
Spelled Number	-	0.51	-	-	0.53	0.525	-	0.495	0.59	-	-	0.42	-	-	-
Rhyme	-	0.51	-	-	0.78	0.845	-	0.555	0.44	-	-	0.395	-	-	-
Repeated Word	-	0.515	-	-	0.66	0.525	-	0.58	0.52	-	-	0.285	-	-	-
Hyphenated Word	-	0.515	-	-	0.58	0.585	-	0.585	0.555	-	-	0.485	-	-	-
Average	-	0.5141	-	-	0.6436	0.5994	-	0.543	0.5314	-	-	0.4014	-	-	-
k = 14, H-TEST															
Uppercase	-	0.5	-	-	0.58	0.515	-	0.5	0.52	0.855	-	0.475	-	-	-
Start Vowel	-	0.515	-	-	0.685	0.72	-	0.505	0.46	0.565	-	0.495	-	-	-
Ends Punctuation	-	0.525	-	-	0.7	0.565	-	0.67	0.48	0.63	-	0.435	-	-	-
Palindrome	-	0.51	-	-	0.62	0.615	-	0.505	0.525	0.885	-	0.21	-	-	-
End Ly	-	0.595	-	-	0.735	0.695	-	0.615	0.495	0.715	-	0.445	-	-	-
Spelled Math	-	0.555	-	-	0.56	0.63	-	0.495	0.62	0.845	-	0.435	-	-	-
Spelled Number	-	0.5	-	-	0.58	0.475	-	0.515	0.53	0.755	-	0.445	-	-	-
Rhyme	-	0.505	-	-	0.78	0.785	-	0.58	0.475	0.95	-	0.43	-	-	-
Repeated Word	-	0.505	-	-	0.68	0.575	-	0.565	0.46	0.97	-	0.32	-	-	-
Hyphenated Word	-	0.51	-	-	0.575	0.625	-	0.555	0.51	0.755	-	0.485	-	-	-
Average	-	0.516	-	-	0.6561	0.622	-	0.556	0.511	0.782	-	0.3987	-	-	-
k = 4, H-TEST															
Uppercase	-	0.5	-	-	0.54	0.525	-	0.495	0.565	-	-	0.48	-	-	-
Start Vowel	-	0.52	-	-	0.65	0.61	-	0.51	0.48	-	-	0.5	-	-	-
Ends Punctuation	-	0.5	-	-	0.695	0.545	-	0.68	0.53	-	-	0.42	-	-	-
Palindrome	-	0.505	-	-	0.605	0.62	-	0.485	0.49	-	-	0.235	-	-	-
End Ly	-	0.57	-	-	0.695	0.725	-	0.59	0.46	-	-	0.445	-	-	-
Spelled Math	-	0.505	-	-	0.57	0.68	-	0.51	0.55	-	-	0.44	-	-	-
Spelled Number	-	0.505	-	-	0.62	0.5	-	0.49	0.555	-	-	0.43	-	-	-
Rhyme	-	0.5	-	-	0.775	0.845	-	0.565	0.375	-	-	0.42	-	-	-
Repeated Word	-	0.5	-	-	0.705	0.52	-	0.535	0.49	-	-	0.29	-	-	-
Hyphenated Word	-	0.5	-	-	0.605	0.605	-	0.59	0.515	-	-	0.48	-	-	-
Average	-	0.5035	-	-	0.6495	0.6235	-	0.55	0.503	-	-	0.3995	-	-	-
Challenge Task															
Letter Geometry	-	-	-	37.78	40	28.89	13.33	14.44	44.44	62.22	-	-	-	-	-

Table 5: **Full Results**: We report full obtained results across k = {50, 28, 14, 4} on H-TEST and Letter Geometry.

B Experimental Details

We accessed all APIs ("anthropic.claude-instant-v1", "anthropic.claude-v1", "anthropic.claude-v2", "ai21.j2-mid-v1", "ai21.j2-ultra-v1", "command-light", "command", "gpt-3.5-turbo-0613", "gpt-4-0613", "luminous-base", "luminous-exteneded", "luminous-supreme", "amazon.titan-text-lite-v1", "llama 2 13B", "llama 2 70B") between the third week of November and the third week of December. In particular, we access LLaMA through Replicate, and J2, Claude, and Titan through Amazon Bedrock. All other APIs were accessed through the respective providers. For all experiments, the model temperature was set at 0.7, and the random seed (for generating data) was set at 12062023. The results and exact dataset used in this research are recoverable by setting the random seed to 12062023. Full code and data are released at <github/anonymized>.

C Task Exemplars

H-Test: Ends Punctuation

Input: "Engine on the wall Octopus..." Label: A
Input: "Ice cream ! in the forest Teacher" Label: B
Input: "Island in the morning Elevator!" Label: A
Input: "Owl with interest ... Friend" Label: B
Input: "Penguin with precision River?" Label: A
Input: "Iguana all night ... Scientist" Label: B
Input: "Penguin to music Owl?" Label: A
Input: "Lion with interest ... Penguin" Label: B
Input: "Teacher with interest Dog!" Label: A
Input: "Cat ! to music Butterfly" Label: B
Input: "Cat in the hall Insect..." Label: A
Input: "Astronaut on the wall ... Opera" Label: B
Input: "Owl in the morning Book!" Label: A
Input: "Insect ! in the studio Book" Label: B
Input: "Lion in the kitchen House!" Label: A
Input: "Insect in the hall ? Flower" Label: B
Input: "Friend very quickly House!" Label: A
Input: "Butterfly to music ... Penguin" Label: B
Input: "Penguin in the forest Astronaut?" Label: A
Input: "Apple ? every second Car" Label: B
Input: "School in the sky Neighbor..." Label: A
Input: "Orchestra on the wall ... School" Label: B
Input: "Dog with passion River?" Label: A
Input: "Octopus ... in the forest Urchin" Label: B
Input: "Elephant in the park Urchin?" Label: A
Input: "Teacher to music ... Car" Label: B
Input: "Mountain in the forest Car!" Label: A
Input: "Albatross in the forest . Butterfly" Label: B
Input: "Teacher in the morning Butterfly." Label: A
Input: "Octopus in the morning ! Flower" Label: B
Input: "Albatross with precision Butterfly..." Label: A
Input: "Penguin in the studio ! Giraffe" Label: B
Input: "House in space Butterfly?" Label: A
Input: "Dog ? on the wall River" Label: B
Input: "Orchestra in the park Neighbor!" Label: A
Input: "Teacher in space ... Penguin" Label: B
Input: "Unicorn through the telescope Insect..." Label: A
Input: "Dog ? in the park Engine" Label: B
Input: "Owl to music Owl..." Label: A
Input: "Mountain in the sky ? Teacher" Label: B
Input: "Neighbor very quickly Urchin." Label: A
Input: "Umbrella ? along the valley Car" Label: B
Input: "Kangaroo in the park Umbrella." Label:
A
B (Respond in one letter and nothing else)

H-Test: Uppercase

Input: "engine jumps all night aCcurately." Label: A
Input: "penguin runs all night intently." Label: B
Input: "rivEr drives with precision eagerly." Label: A
Input: "tree sleeps in space quietly." Label: B
Input: "owl obserVes delicious meals slowly." Label: A
Input: "Penguin flows in the studio happily." Label: B
Input: "apple Listens in the studio expertly." Label: A
Input: "airport calculates in the studio enthusiastically." Label: B
Input: "unicorn obServes very quickly fast." Label: A
Input: "owl reads along the valley skillfully." Label: B
Input: "airport travels very quicklY melodiously." Label: A
Input: "Insect dances along the valley carefully." Label: B
Input: "insecT paints in the hall attentively." Label: A
Input: "tree sleeps all night adventurously." Label: B
Input: "friend runs in the morning sKillfully." Label: A
Input: "book paints in the studio attentively." Label: B
Input: "opera sings in the park eAgerly." Label: A
Input: "Insect paints in the kitchen creatively." Label: B
Input: "opera groWs in the forest brightly." Label: A
Input: "owl grows all night gracefully." Label: B
Input: "ice cream groWs in the forest carefully." Label: A
Input: "Umbrella talks to music attentively." Label: B
Input: "urchin daNces in the sky adventurously." Label: A
Input: "school ticks to the city attentively." Label: B
Input: "school reaDs with interest happily." Label: A
Input: "kangaroo glows through the telescope attentively." Label: B
Input: "umbrella teaches in the park hapPily." Label: A
Input: "opera grows in space consistently." Label: B
Input: "Urchin glows delicious meals steadily." Label: A
Input: "book runs in the forest gracefully." Label: B
Input: "girAffe jumps with interest carefully." Label: A
Input: "engine jumps in the hall expertly." Label: B
Input: "elevator cooks on the wall eagerlY." Label: A
Input: "friend ticks along the valley skillfully." Label: B
Input: "albatross Calculates in the forest gracefully." Label: A
Input: "cat observes delicious meals melodiously." Label: B
Input: "orchestra jumps tO music consistently." Label: A
Input: "octopus grows with interest smoothly." Label: B
Input: "book jumps In the morning skillfully." Label: A
Input: "umbrella paints in the sky smoothly." Label: B
Input: "butterfly observes along the valley Skillfully." Label: A
Input: "butterfly listens in the forest gracefully." Label: B
Input: "Island flows with interest quietly." Label: A
Input: "opera cooks in space accurately." Label: B
Input: "tree paints on the wall accurately." Label:
A
B (Respond in one letter and nothing else)

H-Test: Starts Vowel

Input: "Island sings to the city brightly." Label: A
Input: "Giraffe travels with passion melodiously." Label: B
Input: "Orchestra travels in the morning enthusiastically." Label: A
Input: "Robot paints in the park brightly." Label: B
Input: "Internet flows in the forest accurately." Label: A
Input: "Cupcake cooks through the telescope happily." Label: B
Input: "Olive drives with precision eagerly." Label: A
Input: "Basket flows through the telescope adventurously." Label: B
Input: "Acrobat observes in the forest attentively." Label: A
Input: "Yacht paints in the park attentively." Label: B
Input: "Omelette runs in the morning skillfully." Label: A
Input: "River paints in the forest happily." Label: B
Input: "Airport ticks in the kitchen brightly." Label: A
Input: "Kite reads in the forest skillfully." Label: B
Input: "Octopus flows very quickly brightly." Label: A
Input: "Violin sleeps in the park steadily." Label: B
Input: "Elevator paints with passion accurately." Label: A
Input: "Car jumps in the morning steadily." Label: B
Input: "Artist travels along the valley fast." Label: A
Input: "Kangaroo cooks in space attentively." Label: B
Input: "Umbrella teaches in the park happily." Label: A
Input: "Bicycle cooks in the studio happily." Label: B
Input: "Eagle runs with interest gracefully." Label: A
Input: "Balloon sleeps in the hall smoothly." Label: B
Input: "Urchin glows delicious meals steadily." Label: A
Input: "Book jumps with passion eagerly." Label: B
Input: "Umpire jumps with interest carefully." Label: A
Input: "Car listens to music gracefully." Label: B
Input: "Acrobat sleeps with precision creatively." Label: A
Input: "Globe calculates on the wall melodiously." Label: B
Input: "Elevator cooks on the wall eagerly." Label: A
Input: "Computer observes to music expertly." Label: B
Input: "Economist grows every second happily." Label: A
Input: "Kite flows in the kitchen gracefully." Label: B
Input: "Albatross calculates in the forest gracefully." Label: A
Input: "Kangaroo listens in the hall melodiously." Label: B
Input: "Underdog dances with precision enthusiastically." Label: A
Input: "Mountain cooks in the morning quietly." Label: B
Input: "Orchestra jumps to music consistently." Label: A
Input: "Lion teaches with passion gracefully." Label: B
Input: "Explorer cooks in the sky adventurously." Label: A
Input: "Scientist listens on the wall quietly." Label: B
Input: "Umpire glows every second steadily." Label: A
Input: "Kangaroo grows in the hall intently." Label: B
Input: "Lion calculates in the morning accurately." Label:
A
B (Respond in one letter and nothing else)

H-Test: Spelled Number

Input: "Neighbor sings seven birds melodiously." Label: A
Input: "Flower reads 10 computers expertly." Label: B
Input: "Book grows sixteen birds fast." Label: A
Input: "Car drives 5 paintings adventurously." Label: B
Input: "Neighbor jumps thirteen books steadily." Label: A
Input: "Penguin grows 4 birds quietly." Label: B
Input: "Dog dances nine computers happily." Label: A
Input: "Butterfly ticks 9 computers enthusiastically." Label: B
Input: "Penguin observes seven songs brightly." Label: A
Input: "Giraffe paints 17 paintings melodiously." Label: B
Input: "Scientist cooks six computers brightly." Label: A
Input: "Mountain teaches 8 cars carefully." Label: B
Input: "Albatross paints five birds gracefully." Label: A
Input: "Artist sings 18 computers attentively." Label: B
Input: "Orchestra reads one books adventurously." Label: A
Input: "The car drives 19 apples brightly." Label: B
Input: "Book drives sixteen apples skillfully." Label: A
Input: "The cat calculates 12 computers enthusiastically." Label: B
Input: "Dog jumps five apples happily." Label: A
Input: "Lion dances 19 paintings intently." Label: B
Input: "House listens ten songs fast." Label: A
Input: "Insect cooks 18 trees eagerly." Label: B
Input: "The teacher listens twenty paintings intently." Label: A
Input: "Mountain observes 16 books adventurously." Label: B
Input: "The moon dances thirteen apples melodiously." Label: A
Input: "Penguin glows 16 cars gracefully." Label: B
Input: "Unicorn cooks seven apples adventurously." Label: A
Input: "Mountain cooks 14 paintings brightly." Label: B
Input: "Lion drives three apples steadily." Label: A
Input: "Opera calculates 5 songs adventurously." Label: B
Input: "The scientist reads two paintings smoothly." Label: A
Input: "The car sings 20 computers consistently." Label: B
Input: "House cooks seventeen birds attentively." Label: A
Input: "Astronaut observes 1 birds steadily." Label: B
Input: "Book jumps thirteen computers happily." Label: A
Input: "Orchestra reads 10 computers eagerly." Label: B
Input: "Insect observes seventeen apples fast." Label: A
Input: "The scientist reads 9 trees brightly." Label: B
Input: "Kangaroo paints sixteen birds smoothly." Label: A
Input: "Astronaut drives 11 paintings happily." Label: B
Input: "A dog runs five apples expertly." Label: A
Input: "Flower cooks 11 apples carefully." Label: B
Input: "Penguin reads nine books attentively." Label: A
Input: "Insect travels 17 paintings melodiously." Label: B
Input: "Butterfly teaches 10 paintings fast." Label:
A
B (Respond in one letter and nothing else)

H-Test: Rhyme

Input: "life pfeiff" Label: A
Input: "make meals" Label: B
Input: "way a." Label: A
Input: "get want" Label: B
Input: "think fincke" Label: A
Input: "hand feel" Label: B
Input: "work clerc" Label: A
Input: "passion place" Label: B
Input: "passion ashen" Label: A
Input: "park want" Label: B
Input: "work bourke" Label: A
Input: "person case" Label: B
Input: "night byte" Label: A
Input: "week meals" Label: B
Input: "person Christoffersen" Label: A
Input: "call hand" Label: B
Input: "year amir" Label: A
Input: "tell ask" Label: B
Input: "world hurled" Label: A
Input: "point leave" Label: B
Input: "park arc" Label: A
Input: "call have" Label: B
Input: "think inc" Label: A
Input: "year use" Label: B
Input: "call aul" Label: A
Input: "day group" Label: B
Input: "seem agleam" Label: A
Input: "place want" Label: B
Input: "make Jacque" Label: A
Input: "government do" Label: B
Input: "make haik" Label: A
Input: "night telescope" Label: B
Input: "do accrue" Label: A
Input: "give world" Label: B
Input: "go aglow" Label: A
Input: "government place" Label: B
Input: "eye akai" Label: A
Input: "person take" Label: B
Input: "park clarke" Label: A
Input: "park city" Label: B
Input: "think finck" Label: A
Input: "world quickly" Label: B
Input: "come ancrum" Label: A
Input: "find fact" Label: B
Input: "give liv" Label:
A
B (Respond in one letter and nothing else)

H-Test: Repeated Word

Input: "carefully quickly quickly Neighbor runs." Label: A
Input: "music Neighbor fast runs." Label: B
Input: "quietly teaches Scientist night. night." Label: A
Input: "Teacher enthusiastically jumps wall." Label: B
Input: "Fast Car Car wall runs." Label: A
Input: "enthusiastically wall Car observes." Label: B
Input: "music sleeps Dog Dog expertly." Label: A
Input: "jumps enthusiastically Scientist telescope." Label: B
Input: "quietly quietly She city talks." Label: A
Input: "listens He telescope fast." Label: B
Input: "Teacher happily meals meals observes." Label: A
Input: "drives intently He park." Label: B
Input: "night night Teacher reads fast." Label: A
Input: "runs The cat night slowly." Label: B
Input: "telescope Neighbor teaches teaches enthusiastically." Label: A
Input: "intently night talks Teacher." Label: B
Input: "teaches The cat cat meals attentively." Label: A
Input: "runs expertly He passion." Label: B
Input: "telescope eagerly eagerly She sleeps." Label: A
Input: "reads meals Book slowly." Label: B
Input: "meals meals jumps enthusiastically Book." Label: A
Input: "carefully runs Dog music." Label: B
Input: "city city reads quietly Book." Label: A
Input: "attentively drives He meals." Label: B
Input: "night sleeps Teacher enthusiastically. enthusiastically." Label: A
Input: "drives interest happily Book." Label: B
Input: "runs Car quietly quietly telescope." Label: A
Input: "quickly jumps enthusiastically Dog." Label: B
Input: "happily happily talks night Dog." Label: A
Input: "telescope observes She happily." Label: B
Input: "fast listens listens interest Book." Label: A
Input: "wall jumps He expertly." Label: B
Input: "fast wall wall Dog teaches." Label: A
Input: "fast The cat quickly sleeps." Label: B
Input: "enthusiastically enthusiastically Neighbor talks city." Label: A
Input: "slowly The cat cooks wall." Label: B
Input: "telescope fast Car Car talks." Label: A
Input: "music drives fast Neighbor." Label: B
Input: "Book wall fast fast jumps." Label: A
Input: "passion The cat slowly runs." Label: B
Input: "The cat cat jumps music fast." Label: A
Input: "interest The cat quietly talks." Label: B
Input: "observes observes wall attentively He." Label: A
Input: "drives interest Book enthusiastically." Label: B
Input: "reads attentively The cat quickly." Label:
A
B (Respond in one letter and nothing else)

H-Test: End Ly

Input: "Neighbor ticks to the city skillfully." Label: A
Input: "He calculates all night high." Label: B
Input: "Dog sings with precision consistently." Label: A
Input: "Car travels in the kitchen hard." Label: B
Input: "Scientist calculates in the morning enthusiastically." Label: A
Input: "Bird cooks through the telescope very." Label: B
Input: "Book dances on the wall smoothly." Label: A
Input: "Dancer travels through the telescope high." Label: B
Input: "Dancer glows all night creatively." Label: A
Input: "River talks in the hall early." Label: B
Input: "Neighbor talks to the city creatively." Label: A
Input: "Teacher listens through the telescope quite." Label: B
Input: "Tree sings in the sky eagerly." Label: A
Input: "Car flows in space fast." Label: B
Input: "Tree sings through the telescope intently." Label: A
Input: "Tree sleeps in the hall far." Label: B
Input: "Dancer glows in space smoothly." Label: A
Input: "Friend travels in the forest fast." Label: B
Input: "Painter teaches with precision steadily." Label: A
Input: "Moon calculates in the morning so." Label: B
Input: "Cat flows in the studio eagerly." Label: A
Input: "Dog grows delicious meals too." Label: B
Input: "Cat reads in the hall carefully." Label: A
Input: "Scientist talks every second long." Label: B
Input: "Car cooks in the forest attentively." Label: A
Input: "Car listens in the hall wrong." Label: B
Input: "Chef jumps on the wall accurately." Label: A
Input: "Scientist reads delicious meals long." Label: B
Input: "Tree grows in space steadily." Label: A
Input: "Friend teaches with passion near." Label: B
Input: "Bird drives in the studio consistently." Label: A
Input: "Book teaches to music high." Label: B
Input: "Tree observes along the valley smoothly." Label: A
Input: "Dancer travels to the city too." Label: B
Input: "Neighbor travels with interest quietly." Label: A
Input: "Tree reads along the valley right." Label: B
Input: "Dancer glows every second melodiously." Label: A
Input: "Moon travels in the forest fast." Label: B
Input: "Tree glows delicious meals carefully." Label: A
Input: "Friend travels to music long." Label: B
Input: "Cat calculates in the sky brightly." Label: A
Input: "Bird listens along the valley enough." Label: B
Input: "Cat listens through the telescope steadily." Label: A
Input: "Clock glows in the studio quite." Label: B
Input: "Tree calculates every second long." Label:
A
B (Respond in one letter and nothing else)

H-Test: Palindrome

Input: "deed" Label: A
Input: "dwelt" Label: B
Input: "sis" Label: A
Input: "alight" Label: B
Input: "garage" Label: A
Input: "preses" Label: B
Input: "shahs" Label: A
Input: "phase" Label: B
Input: "ono" Label: A
Input: "strait" Label: B
Input: "Qaanaaq" Label: A
Input: "towd" Label: B
Input: "krk" Label: A
Input: "fe" Label: B
Input: "yay" Label: A
Input: "fumy" Label: B
Input: "Aviva" Label: A
Input: "kelt" Label: B
Input: "eve" Label: A
Input: "pien" Label: B
Input: "tat" Label: A
Input: "chaff" Label: B
Input: "heh" Label: A
Input: "Aymara" Label: B
Input: "alala" Label: A
Input: "xenia" Label: B
Input: "aeaea" Label: A
Input: "live" Label: B
Input: "Akasaka" Label: A
Input: "undid" Label: B
Input: "minim" Label: A
Input: "toluic" Label: B
Input: "adda" Label: A
Input: "sair" Label: B
Input: "dewed" Label: A
Input: "demal" Label: B
Input: "stots" Label: A
Input: "shun" Label: B
Input: "zerorez" Label: A
Input: "Skef" Label: B
Input: "peep" Label: A
Input: "eyrie" Label: B
Input: "sagas" Label: A
Input: "shee" Label: B
Input: "tut" Label:
A
B (Respond in one letter and nothing else)

H-Test: Spelled Math

Input: "The cube of approximately equal to 11." Label: A
Input: "The integral + 7." Label: B
Input: "The integral less than 11." Label: A
Input: "The integral / 7." Label: B
Input: "The integral times 10." Label: A
Input: "The sum + 10." Label: B
Input: "The square root plus 8." Label: A
Input: "The square root / 4." Label: B
Input: "The integral to the power of 12." Label: A
Input: "The cube of = 7." Label: B
Input: "The value of x times 12." Label: A
Input: "The sum > 8." Label: B
Input: "The square root approximately equal to 8." Label: A
Input: "The square root < 6." Label: B
Input: "The cube of equals to 6." Label: A
Input: "The sum + 10." Label: B
Input: "The fraction plus 9." Label: A
Input: "The cube of ˆ 8." Label: B
Input: "The product times 8." Label: A
Input: "The product > 11." Label: B
Input: "The derivative approximately equal to 5." Label: A
Input: "The limit % 5." Label: B
Input: "The cube of plus 6." Label: A
Input: "The value of x < 6." Label: B
Input: "The value of x divided by 10." Label: A
Input: "The limit % 9." Label: B
Input: "The integral approximately equal to 8." Label: A
Input: "The value of x * 9." Label: B
Input: "The derivative equals to 12." Label: A
Input: "The product % 9." Label: B
Input: "The sum approximately equal to 6." Label: A
Input: "The value of x - 3." Label: B
Input: "The integral divided by 4." Label: A
Input: "The product < 12." Label: B
Input: "The limit to the power of 3." Label: A
Input: "The square root > 10." Label: B
Input: "The angle plus 3." Label: A
Input: "The product % 12." Label: B
Input: "The square root to the power of 9." Label: A
Input: "The integral + 3." Label: B
Input: "The derivative times 9." Label: A
Input: "The sum ˆ 6." Label: B
Input: "The product plus 11." Label: A
Input: "The sum - 4." Label: B
Input: "The limit < 10." Label:
A
B (Respond in one letter and nothing else)

H-Test: Hyphenated Word

Input: "An eagle air-drops to the city quietly." Label: A
Input: "This engine reads to music fast." Label: B
Input: "An octopus part-times through the telescope expertly." Label: A
Input: "This engine teaches with passion intently." Label: B
Input: "This engine observes a double-check enthusiastically." Label: A
Input: "Our artist reads in the park attentively." Label: B
Input: "An octopus observes a part-time job expertly." Label: A
Input: "This engine jumps all night eagerly." Label: B
Input: "This engine proof-reads to music carefully." Label: A
Input: "The vendor listens delicious meals expertly." Label: B
Input: "An apple drives a mass-produced item slowly." Label: A
Input: "This engine drives to music intently." Label: B
Input: "An apple part-times through the telescope slowly." Label: A
Input: "My umbrella jumps to music quietly." Label: B
Input: "An iguana listens a long-term plan quietly." Label: A
Input: "An octopus listens with passion attentively." Label: B
Input: "Long-term talks quickly fast." Label: A
Input: "Our artist listens to the city enthusiastically." Label: B
Input: "The elephant runs a user-friendly interface enthusiastically." Label: A
Input: "An iguana sleeps to music attentively." Label: B
Input: "Part-time cooks with passion quietly." Label: A
Input: "This engine cooks through the telescope intently." Label: B
Input: "An eagle air-drops quickly expertly." Label: A
Input: "An eagle drives to music happily." Label: B
Input: "An apple air-drops to music slowly." Label: A
Input: "An iguana talks all night quietly." Label: B
Input: "An apple proof-reads quickly attentively." Label: A
Input: "The vendor runs all night slowly." Label: B
Input: "Double-check observes with passion slowly." Label: A
Input: "An iguana observes quickly expertly." Label: B
Input: "An octopus double-checks with passion happily." Label: A
Input: "An octopus cooks delicious meals slowly." Label: B
Input: "An owl teaches a user-friendly interface happily." Label: A
Input: "An iguana cooks to music quietly." Label: B
Input: "An eagle air-drops to music attentively." Label: A
Input: "An apple observes quickly expertly." Label: B
Input: "This engine sleeps a mother-in-law carefully." Label: A
Input: "An eagle reads with passion eagerly." Label: B
Input: "An iguana baby-sits in the park happily." Label: A
Input: "My umbrella reads to the city attentively." Label: B
Input: "Mother-in-law teaches to music quietly." Label: A
Input: "An owl talks in the park fast." Label: B
Input: "Well-being teaches on the wall eagerly." Label: A
Input: "This engine cooks all night happily." Label: B
Input: "My umbrella observes with passion happily." Label:
A
B (Respond in one letter and nothing else)