NYT-Connections: A Deceptively Simple Text Classification Task that Stumps System-1 Thinkers

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Abstract

Large Language Models (LLMs) have shown impressive performance on various benchmarks, yet their ability to engage in deliberate reasoning remains questionable. We present NYT-Connections, a collection of 358 simple word classification puzzles derived from the New York Times Connections game. This benchmark is designed to penalize quick, intuitive "System 1" thinking, isolating fundamental reasoning skills. We evaluated six recent LLMs, a simple machine learning heuristic, and humans across three configurations: single-attempt, multiple attempts without hints, and multiple attempts with contextual hints. Our findings reveal a significant performance gap: even top-performing LLMs like GPT-4 fall short of human performance by nearly 30%. Notably, advanced prompting techniques such as Chain-of-Thought and Self-Consistency show diminishing returns as task difficulty increases. NYT-Connections uniquely combines linguistic isolation, resistance to intuitive shortcuts, and regular updates to mitigate data leakage, offering a novel tool for assessing LLM reasoning capabilities.[1]

1 Introduction

As Large Language Models (LLMs) continue to advance, the need for effective benchmarks to assess their true capabilities has become increasingly important. While numerous natural language tasks and datasets have been developed across domains such as text summarization, commonsense reasoning, and question answering (Hendrycks et al., 2021a; Cobbe et al., 2021; Hendrycks et al., 2021b), these benchmarks often fall short in isolating and evaluating specific cognitive abilities.

One major challenge is the difficulty in assessing individual model capabilities independently. Many existing tasks combine multiple cognitive processes, making it challenging to evaluate distinct abilities (Gema et al., 2024; Gautam et al., 2024). For instance, tasks that simultaneously require mathematical reasoning, natural language understanding, and contextual disambiguation (Patel et al., 2021) can obscure a model's true proficiency in any single area.

Furthermore, many current benchmarks are vulnerable to shortcuts or heuristics. Models may exploit statistical regularities or superficial cues rather than demonstrating genuine understanding, a phenomenon known as 'shortcut learning' (Geirhos et al., 2020; Trichelair et al., 2019). This issue is closely related to the distinction between System 1 and System 2 thinking, as described by Hagendorff et al. (2023):

> "**System 1** processes are fast, automatic and instinctual. They often involve heuristics, or mental shortcuts, which enable quick judgments and decisions without conscious effort. [...] **System 2** processes, on the other hand, are deliberate and require conscious effort."

Consequently, many current benchmarks inadvertently reward System 1-style thinking, allowing models to achieve high scores without demonstrating the deliberate reasoning we aim to evaluate.

Finally, as LLMs are trained on increasingly vast amounts of data, the risk of test set leakage into training data grows, potentially leading to inflated performance metrics that do not reflect true generalization capabilities (Balloccu et al., 2024; Huang et al., 2024).

To address these challenges, we introduce NYT-Connections, a novel benchmark of 358 puzzles derived from the New York Times' Connections game. This task requires grouping 16 interrelated terms into 4 sets of 4 closely related words, deliberately tempting incorrect System 1 responses while requiring System 2 thinking for correct solutions. NYT-Connections offers several key

[1] The NYT-Connections dataset is publicly available here, with updates to include 28-31 new puzzles monthly.

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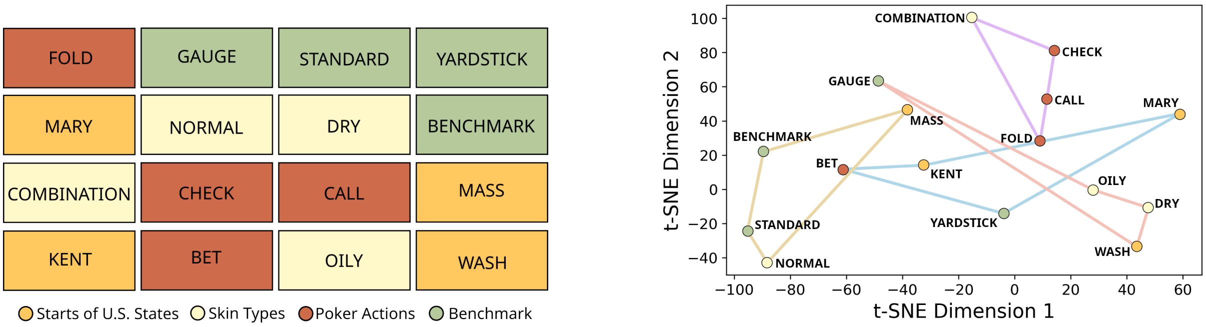


FOLD	GAUGE	STANDARD	YARDSTICK
MARY	NORMAL	DRY	BENCHMARK
COMBINATION	CHECK	CALL	MASS
KENT	BET	OILY	WASH

(a) Sample instance of *Connections* showing a grid with various terms; each is marked to indicate its category.

(b) 2D t-SNE visualization of term embeddings color-coded by category, illustrating clustering patterns.

Figure 1: Overview of *Connections* game instance and its embeddings visualization.

advantages:

- **Linguistic Isolation:** It focuses purely on word relationships, minimizing confounding factors.
- **System 2 Emphasis:** It penalizes quick, intuitive responses and requires deliberate reasoning.
- **Continual Novelty:** With daily updates, it provides a stream of novel instances, mitigating data leakage concerns.

In this paper, we contribute the following:

1. We present NYT-Connections, a benchmark designed to isolate and evaluate deliberate reasoning in LLMs.
2. We provide a comprehensive evaluation of six recent LLMs, a simple machine learning heuristic, and human performance on NYT-Connections.
3. We analyze various prompting techniques and their effectiveness in promoting System 2 "reasoning" in LLMs.
4. We demonstrate a substantial performance gap between LLMs and humans, with even the most advanced models falling short by nearly 30%.

2 NYT-Connections

2.1 The Task

NYT-Connections is based on *Connections*, a word classification game by the New York Times (The New York Times, 2024). This daily puzzle challenges players to group 16 terms into 4 sets of 4 related words. Its design intentionally tempts quick, obvious associations but requires careful, deliberate reasoning to solve correctly (Liu, 2023).

Figure 1a illustrates this design. The correct "Skin Types" group includes "**Normal**", "Dry", "Combination", and "Oily". However, "**Normal**", "Standard", and "Benchmark" temptingly form a "Status Quo" group of three. This misdirection is crucial: the apparent "Status Quo" grouping leaves only three "Skin Types" terms, making it impossible to form four complete groups.

To demonstrate the challenge for machine learning approaches, we applied k-means clustering to Multilingual-E5-Large-Instruct word embeddings (Wang et al., 2024). As shown in Figure 1b, this method fails to correctly classify the terms, instead grouping semantically related words from different categories.

2.2 Dataset Construction

We constructed the NYT-Connections dataset through the following process:

Dataset Collection: We compiled the complete set of 358 Connections puzzles from an archive covering daily offerings from the game's debut on June 12, 2023, to June 3rd, 2024[2].

Difficulty Assessment: To gauge the perceived difficulty of each puzzle, we cross-referenced our dataset with an existing difficulty chart[3], providing ratings from 1 (easiest) to 5 (most challenging) by independent testers.

The resulting distribution of difficulty ratings for our dataset is provided in Appendix Figure 9.

2.3 Sample Heuristic

To establish a baseline and demonstrate the challenge of the task, we designed a heuristic that mimics a player's initial, intuitive approach to the puzzles. It evaluates 4-word groups using a score $S = G - P$, where G is group similarity and P is a penalty for similarity to other words.

Group Similarity Score For a candidate group $C = \{c_1, c_2, c_3, c_4\}$, we compute G as follows:

1. Obtain word embeddings E using a pre-trained language model.

[2] Connections Puzzles Archive

[3] Connections Difficulty Chart

Method	Performance
I, s and V	13.25
I only	13.25
s and V	9.25

Table 1: Ablation study for factors comprising our Group Similarity Score over 100 median difficulty NYT-CONNECTIONS matches on the Multiple Tries configuration. I is shown to be the most influential factor when choosing the best candidate solutions.

2. Compute a clustering score $I = -K(E)$, where K is the inertia (sum of squared distances to the centroid) of a k-means cluster (k=1).
3. Calculate the minimum pairwise cosine similarity s among words in the group.
4. Compute a variance-based score $V = \frac{\text{mean}(P)}{1+\text{var}(P)}$, where P is the set of all pairwise similarities.

The final score is a weighted sum: $G = 0.4 \cdot I + 0.3 \cdot s + 0.3 \cdot V$. These weights were chosen based on ablation studies as depicted in Table 1, giving slight preference to the strongest contributing factor, I.

This formulation captures cluster tightness (I), minimum relatedness (s), and similarity consistency (V), mirroring intuitive judgments about word relationships typical of System 1 thinking.

Penalty Score To prevent overly generic groupings, we compute a penalty P that measures how similar a candidate group is to remaining words:

$$P = \frac{1}{|R|} \sum_{r \in R} \cos(\mu_C, r)$$

where μ_C is the mean embedding of the candidate group C, and R is the set of remaining words. A lower P indicates a more distinct group.

Beam Search To balance between finding seemingly good initial groupings and maintaining some flexibility, we employ a beam search algorithm with a width of 10:

1. Initialize with an empty solution.
2. For each step (up to 4 groups):
   (a) Form all possible groups of 4 from remaining words.
   (b) Compute $S = G - P$ for each new group.
   (c) Retain the top 10 partial solutions based on cumulative score.
3. Return the highest-scoring complete solution.

This approach balances exploration of alternative groupings with a preference for high-scoring, seemingly obvious solutions. By design, it's prone to the misdirections built into the puzzles, serving as an effective baseline for comparison with more advanced reasoning methods.

3 Experimental Setup

Experiments We analyzed 100 puzzles from our corpus, centered around the median difficulty rating of 3.0. This selection ensures consistent challenge across subjects and enables fair comparisons between LLMs and humans. Our full difficulty distribution is depicted in Appendix Figure 9.

Evaluation Settings We tested under three conditions: (1) **One Try**: single attempt, scored 100 for success or 0 for failure; (2) **No Hints**: up to four re-tries; and (3) **Full Hints**: up to four re-tries with "one away" hints. For (2) and (3), scores represent the percentage of correct groups ($A = \{0, 25, 50, 75, 100\}$). Detailed examples are in Appendix Figures 4 and 5.

Models We evaluated six recent LLMs: Claude 3.5 Sonnet, GPT-4, GPT-4o, Gemini 1.5 Pro, LLaMA 3 70B Instruct, and LLaMA 3.1 405B Instruct (Anthropic, 2024; OpenAI, 2023, 2024; Team et al., 2023; Touvron et al., 2023). LLaMA models were used with the default temperature of 0.6; all others were used with a temperature of 0.5. Our heuristic used Multilingual-E5-Large-Instruct embeddings (Wang et al., 2024).

Prompts Models received detailed background, instructions, and an example game, mirroring human participants' information. We used three prompting methods: Input-Output (IO), Chain-of-Thought (CoT) (Wei et al., 2022), and CoT with Self-Consistency (CoT-SC) (Wang et al., 2023). Detailed prompts are in Appendix Figures 6,7 & 8.

Random Guess We implemented a random guess baseline. The probability of correct random guessing is approximately 3.81×10^{-7} (0.0000381%)[4].

Human Evaluation Three human evaluators completed 50 *One Try*, 25 *No Hints*, and 25 *Full Hints* instances via a custom application. Performance was averaged across evaluators for each configuration.

4 Results

LLMs Significantly Underperform Humans As shown in Table 2, there is a substantial perfor-

[4] Calculated as the inverse of $\frac{\binom{16}{4} \times \binom{12}{4} \times \binom{8}{4} \times \binom{4}{4}}{4!}$.

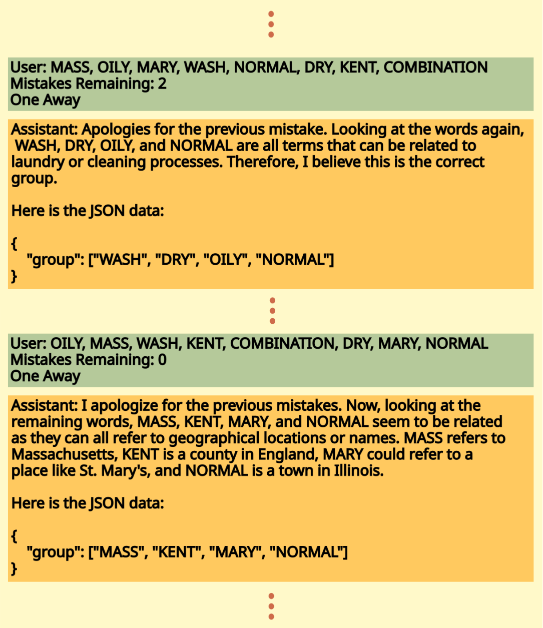
Player	One Try	No Hints	Full Hints
GPT-4	4.0	35.5	32.5
Claude 3.5	**11.0**	36.75	**40.25**
GPT-4o	8.0	**45.0**	33.75
LLaMA 3.1 405b	7.0	35.5	34.75
Gemini 1.5 Pro	5.0	30.5	31.5
LLaMA 3 70b	1.0	23.75	28.5
Random	0.0	0.0	0.0
Heuristic	1.0	13.25	13.25
Humans	**39.33***	**56.0***	**60.67***

Table 2: Performance (%) of the models, baselines, and humans across our three setups, using IO prompting. * indicates statistical significance ($p < 0.05$) of human performance compared to the top-performing model. See Appendix A.1 for statistical test methodology.

mance gap between LLMs and human participants across all testing configurations. Even in the most favorable scenario (Full Hints), the best-performing model, Claude 3.5, achieves only 40.25% accuracy compared to humans' 60.67%. This disparity becomes even more pronounced in more challenging setups. In the One Try configuration, the top LLM (Claude 3.5) manages only 11% accuracy, while humans achieve 39.33%.

Chain-of-Thought-Based Prompting Techniques Are Limited by Shallow Thinking Figure 2 depicts two model outputs that illustrate the limited reasoning ability of Chain-of-Thought-based approaches. In this case, GPT-4 fails to consider multiple factors that may lead to better results — such as when the remaining words outside of the chosen group contain strong matches — the discovery of which requires more deliberate and specialized reasoning. This demonstrates the fundamental limitations of System 1 thinkers when performing non-symbolic reasoning tasks, even when endowed with complex methodology such as Chain-of-Thought, an issue that has been further explored in recent work (Sprague et al., 2024).

Advanced Prompting Techniques Show Diminishing Returns Figure 3 illustrates how prompting methods such as Chain-of-Thought (CoT) and Self-Consistency (CoT-SC) do not consistently improve in performance as task difficulty increases. Surprisingly, simpler Input-Output (IO) prompting often outperforms these approaches, especially on harder puzzles. This suggests that current prompting techniques may be insufficient to simulate true System 2 reasoning in LLMs, and might even hinder performance by introducing unnecessary complexity.



⋮

User: MASS, OILY, MARY, WASH, NORMAL, DRY, KENT, COMBINATION
Mistakes Remaining: 2
One Away

Assistant: Apologies for the previous mistake. Looking at the words again, WASH, DRY, OILY, and NORMAL are all terms that can be related to laundry or cleaning processes. Therefore, I believe this is the correct group.

Here is the JSON data:

```
{
  "group": ["WASH", "DRY", "OILY", "NORMAL"]
}
```

⋮

User: OILY, MASS, WASH, KENT, COMBINATION, DRY, MARY, NORMAL
Mistakes Remaining: 0
One Away

Assistant: I apologize for the previous mistakes. Now, looking at the remaining words, MASS, KENT, MARY, and NORMAL seem to be related as they can all refer to geographical locations or names. MASS refers to Massachusetts, KENT is a county in England, MARY could refer to a place like St. Mary's, and NORMAL is a town in Illinois.

Here is the JSON data:

```
{
  "group": ["MASS", "KENT", "MARY", "NORMAL"]
}
```

⋮

Figure 2: An example of GPT-4's output demonstrating the shallow reasoning of Chain-of-Thought-based approaches. The model first latches on to words in a laundry category, while in the second example, the model correctly identifies the group but fails to produce effective word groupings.

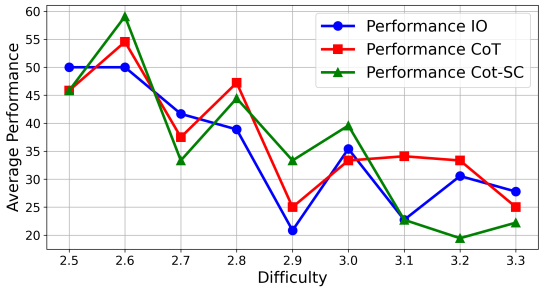


Figure 3: Average performance vs difficulty level for GPT-4 with various prompting techniques on *Full Hints*

Simple Heuristic is Comparable to Some LLMs As shown in Table 2, our baseline heuristic, designed to mimic intuitive System 1 thinking, achieves 13.25% accuracy in both No Hints and Full Hints configurations. Notably, this performance is not far behind some of the tested LLMs, such as LLaMA 3 70b (23.75% in No Hints, 28.5% in Full Hints). This relatively small gap between a simple heuristic and more complex language models suggests that current LLMs demonstrate capabilities that fall between System 1-like pattern-matching and System 2-like deliberation, without fully achieving consistent, deliberate reasoning.

Contextual Hints of Limited Benefit to LLMs Referring again to Table 2, while human performance improves significantly with the addition of hints (from 56% in No Hints to 60.67% in Full Hints), few LLMs show meaningful improvements. Some models, like GPT-4o, paradoxically perform worse with full hints (33.75%) compared to no hints (45%). This suggests a fundamental difference in how LLMs and humans process and utilize contextual information in problem-solving tasks.

Performance Consistency Across Top LLMs Our evaluation reveals surprisingly consistent performance among top LLMs. Claude 3.5, GPT-4, and GPT-4o show no statistically significant differences from each other, a pattern that holds across all configurations. This suggests that NYT-CONNECTIONS presents a unified challenge, exposing similar limitations in even the most advanced LLMs for tasks requiring System 2 thinking.

5 Related Work

Recent research has focused on developing benchmarks that address key challenges in evaluating language models' reasoning capabilities. Several works propose tasks that isolate specific cognitive processes, such as code reasoning, mathematical problem-solving, and logic (Liu et al., 2024; Mao et al., 2024; Wu et al., 2024), aiming to disentangle task-specific knowledge from broader reasoning abilities. Researchers have also created benchmarks for deliberate, multi-step reasoning, including tasks designed to challenge System 1-style heuristics (Suzgun et al., 2023; McKenzie et al., 2024). To combat data leakage, evolving datasets have been introduced, continuously updating with new problems from real-world sources (Sun and Emami, 2024; Li et al., 2024; Jain et al., 2024). NYT-CONNECTIONS uniquely combines these three aspects: isolating word relationship understanding, resisting simple heuristics, and maintaining novelty through regular updates.

6 Conclusion

We introduced NYT-CONNECTIONS, a benchmark that isolates word relationship understanding, penalizes heuristic-based thinking, and resists data leakage. Our evaluation of six LLMs, a simple heuristic, and human performance revealed significant gaps, with top models like GPT-4 falling nearly 30% short of humans. This highlights the ongoing challenges in developing AI systems capable of deliberate reasoning. Future work should explore techniques to bridge this performance gap and investigate how improvements on NYT-CONNECTIONS translate to other reasoning tasks.

Limitations

Embedding Model Scale Our heuristic uses a relatively small model due to hardware constraints. While this provides a baseline, it's possible that larger embedding models could yield different results. Future work should explore the scalability of our heuristic approach using more advanced embedding models to fully understand the relationship between model size and performance on NYT-CONNECTIONS.

Prompt Engineering Scope Cost constraints limited our ability to test an extensive range of prompting techniques. While we focused on standard, Chain-of-Thought, and Self-Consistency methods, future studies could explore a broader spectrum of prompting strategies, including more recent innovations. However, we intentionally excluded complex, long-context methods like Tree of Thoughts (Yao et al., 2023), as these fall outside the scope of our focus on core reasoning capabilities.

Human Baseline Limitations Our human performance data is derived from a small sample of three evaluators, which may not fully represent the broader population's problem-solving abilities. A larger-scale study with a diverse group of participants would provide a more robust human baseline and could reveal interesting patterns in human approaches to solving *Connections* puzzles.

Temporal Limitations of the Dataset While we commit to monthly updates of NYT-CONNECTIONS, the dataset inherently represents a snapshot of puzzles from a specific time period. This could potentially limit its long-term relevance as language use and cultural references evolve. Regular assessments of the dataset's contemporary relevance may be necessary to maintain its effectiveness as a benchmark.

Cross-Cultural Applicability The *Connections* puzzles are primarily designed for an English-speaking, Western audience. This may limit the benchmark's applicability across different cultures and languages. Future work could explore creating multilingual versions or culturally adapted variants of NYT-CONNECTIONS to assess LLM performance in more diverse contexts.

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A Appendix

A.1 Statistical Testing Procedure

We used different statistical tests for the *One Try* setup versus the *No Hints* and *Full Hints* setups due to the nature of the data in each case:

One Try Setup: We used a two-proportion z-test because the outcomes in this setup are binary (success or failure), making it appropriate for comparing two proportions.

No Hints and Full Hints Setups: For these setups, we used the Mann-Whitney U test because the outcomes are ordinal categorical data (number of correct groups, $A = \{0, 1, 2, 3, 4\}$). This non-parametric test is suitable for comparing the distribution of scores between two independent groups when the dependent variable is ordinal.

All tests were conducted at a 95% confidence interval ($p < 0.05$). We performed tests between the human evaluators and the top-performing model, as well as between the top two performing models, to assess the statistical significance of performance differences.

A.2 Game Setup & Prompting Details

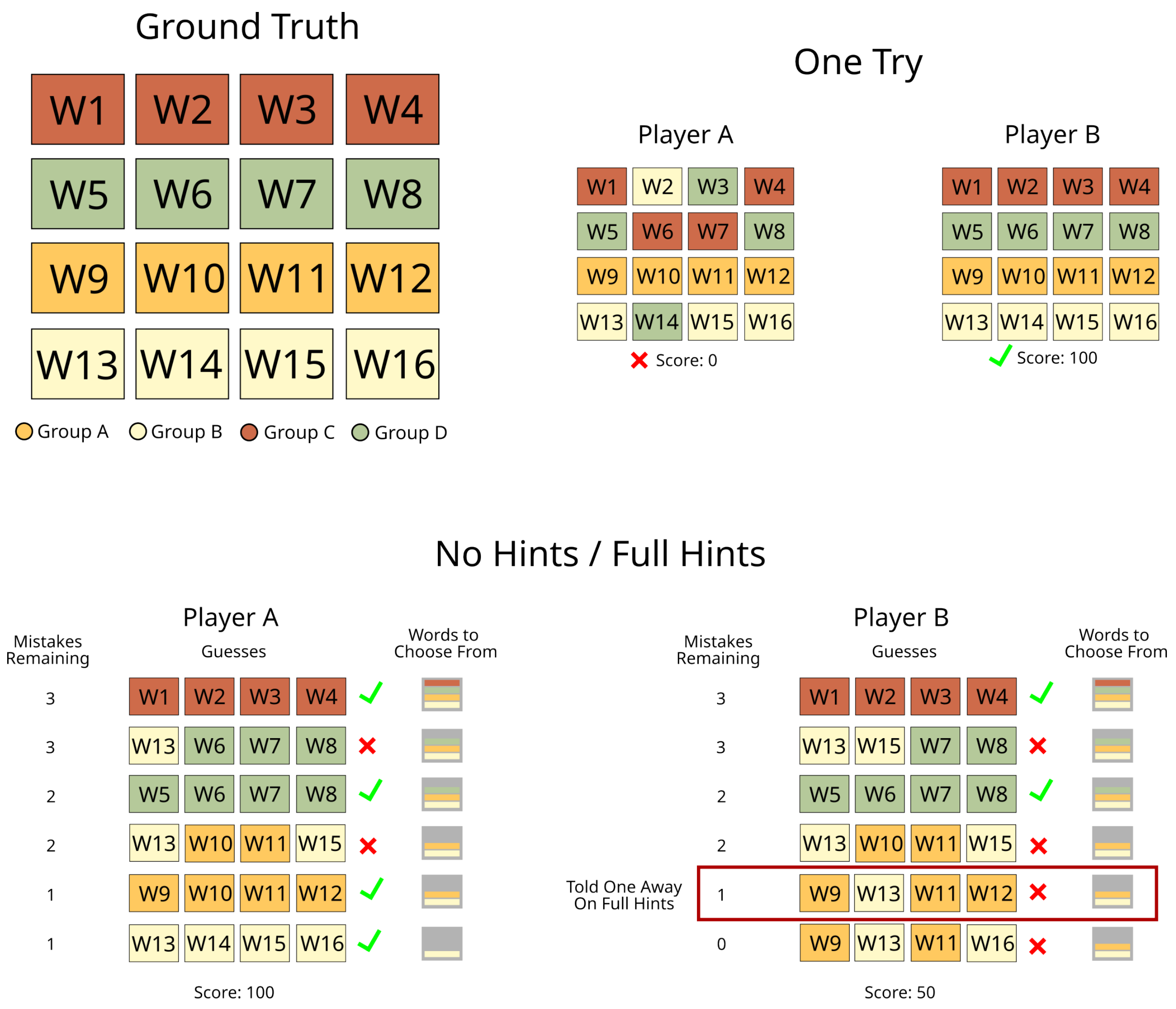
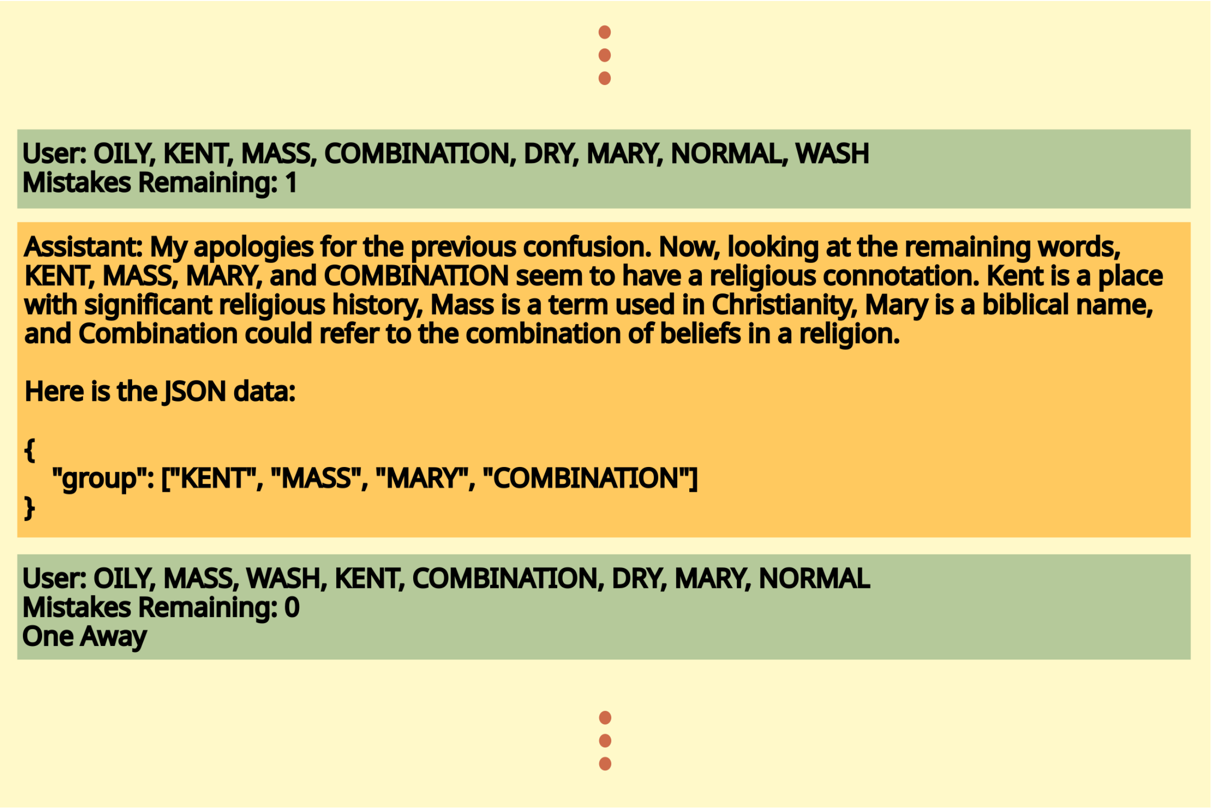


Figure 4: Demonstration of our three setups. **One Try**: Players have one chance to classify the words into the four groups. **No Hints**: Players have 4 chances to get the correct groups, where at each chance they are tasked to find a correct grouping. **Full Hints**: Same as No Hints, but players are told when they are one word away from a correct grouping.



User: OILY, KENT, MASS, COMBINATION, DRY, MARY, NORMAL, WASH
Mistakes Remaining: 1

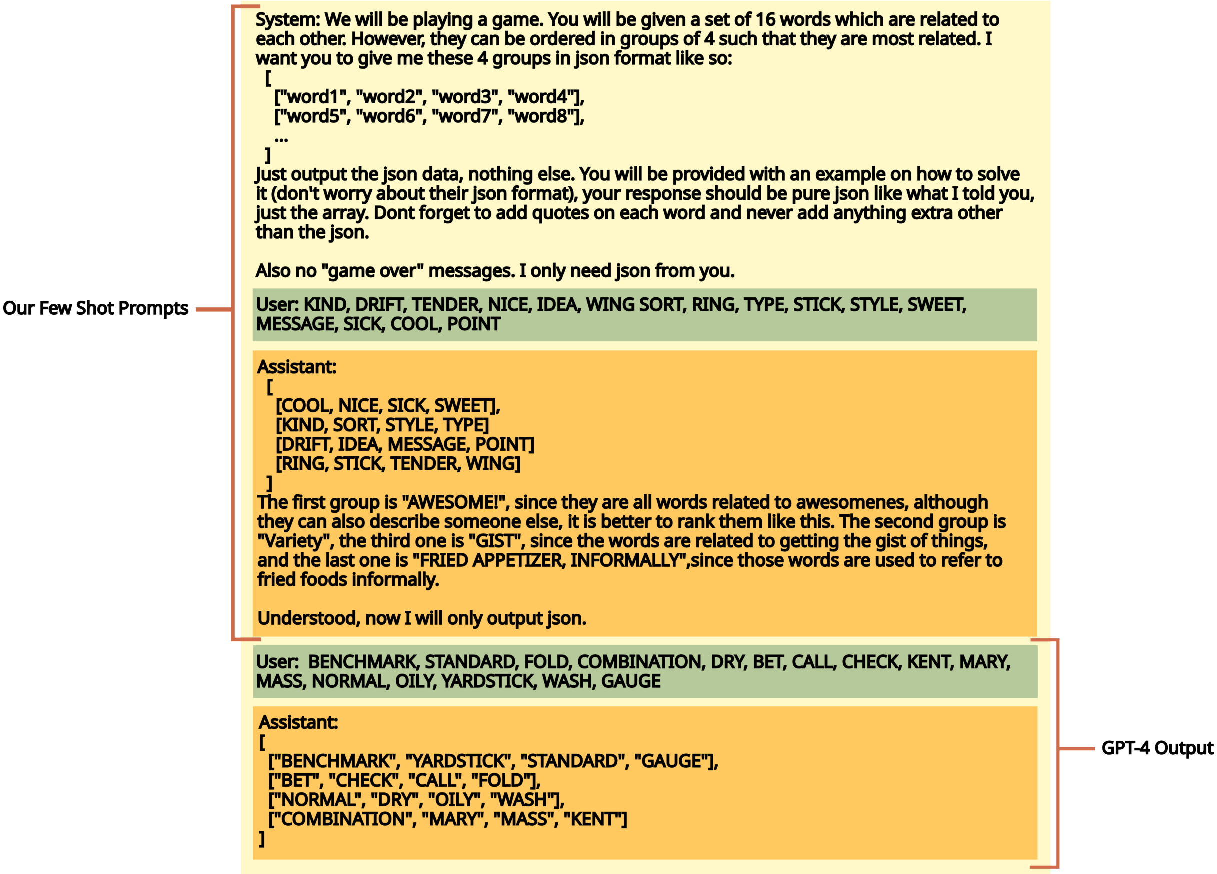
Assistant: My apologies for the previous confusion. Now, looking at the remaining words, KENT, MASS, MARY, and COMBINATION seem to have a religious connotation. Kent is a place with significant religious history, Mass is a term used in Christianity, Mary is a biblical name, and Combination could refer to the combination of beliefs in a religion.

Here is the JSON data:

```
{
  "group": ["KENT", "MASS", "MARY", "COMBINATION"]
}
```

User: OILY, MASS, WASH, KENT, COMBINATION, DRY, MARY, NORMAL
Mistakes Remaining: 0
One Away

Figure 5: Example output from GPT-4 for Full Hints configuration, showing the “One Away” hint being given to the player.



System: We will be playing a game. You will be given a set of 16 words which are related to each other. However, they can be ordered in groups of 4 such that they are most related. I want you to give me these 4 groups in json format like so:

```
[
  ["word1", "word2", "word3", "word4"],
  ["word5", "word6", "word7", "word8"],
  ...
]
```

Just output the json data, nothing else. You will be provided with an example on how to solve it (don't worry about their json format), your response should be pure json like what I told you, just the array. Dont forget to add quotes on each word and never add anything extra other than the json.

Also no "game over" messages. I only need json from you.

User: KIND, DRIFT, TENDER, NICE, IDEA, WING SORT, RING, TYPE, STICK, STYLE, SWEET, MESSAGE, SICK, COOL, POINT

Assistant:

```
[
  [COOL, NICE, SICK, SWEET],
  [KIND, SORT, STYLE, TYPE]
  [DRIFT, IDEA, MESSAGE, POINT]
  [RING, STICK, TENDER, WING]
]
```

The first group is "AWESOME!", since they are all words related to awesomenes, although they can also describe someone else, it is better to rank them like this. The second group is "Variety", the third one is "GIST", since the words are related to getting the gist of things, and the last one is "FRIED APPETIZER, INFORMALLY",since those words are used to refer to fried foods informally.

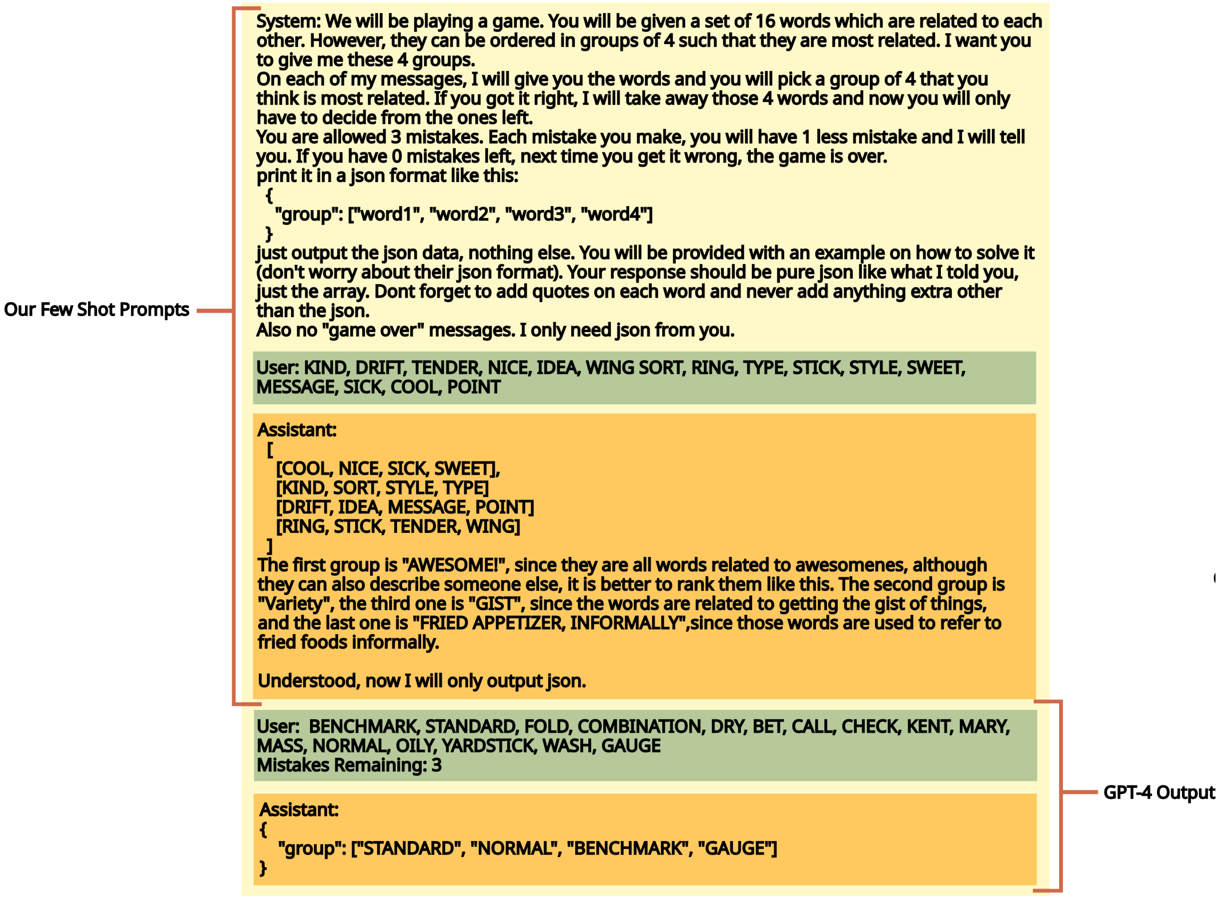
Understood, now I will only output json.

User: BENCHMARK, STANDARD, FOLD, COMBINATION, DRY, BET, CALL, CHECK, KENT, MARY, MASS, NORMAL, OILY, YARDSTICK, WASH, GAUGE

Assistant:

```
[
 ["BENCHMARK", "YARDSTICK", "STANDARD", "GAUGE"],
 ["BET", "CHECK", "CALL", "FOLD"],
 ["NORMAL", "DRY", "OILY", "WASH"],
 ["COMBINATION", "MARY", "MASS", "KENT"]
]
```

Figure 6: Prompts used for testing IO performance on the One Try setup, with GPT-4 example output.


Our Few Shot Prompts
GPT-4 Output

System: We will be playing a game. You will be given a set of 16 words which are related to each other. However, they can be ordered in groups of 4 such that they are most related. I want you to give me these 4 groups.
On each of my messages, I will give you the words and you will pick a group of 4 that you think is most related. If you got it right, I will take away those 4 words and now you will only have to decide from the ones left.
You are allowed 3 mistakes. Each mistake you make, you will have 1 less mistake and I will tell you. If you have 0 mistakes left, next time you get it wrong, the game is over.
print it in a json format like this:

```
 {
  "group": ["word1", "word2", "word3", "word4"]
 }
```

just output the json data, nothing else. You will be provided with an example on how to solve it (don't worry about their json format). Your response should be pure json like what I told you, just the array. Dont forget to add quotes on each word and never add anything extra other than the json.
Also no "game over" messages. I only need json from you.

User: KIND, DRIFT, TENDER, NICE, IDEA, WING SORT, RING, TYPE, STICK, STYLE, SWEET, MESSAGE, SICK, COOL, POINT

Assistant:

```
 [
  [COOL, NICE, SICK, SWEET],
  [KIND, SORT, STYLE, TYPE]
  [DRIFT, IDEA, MESSAGE, POINT]
  [RING, STICK, TENDER, WING]
 ]
```

The first group is "AWESOME!", since they are all words related to awesomenes, although they can also describe someone else, it is better to rank them like this. The second group is "Variety", the third one is "GIST", since the words are related to getting the gist of things, and the last one is "FRIED APPETIZER, INFORMALLY",since those words are used to refer to fried foods informally.

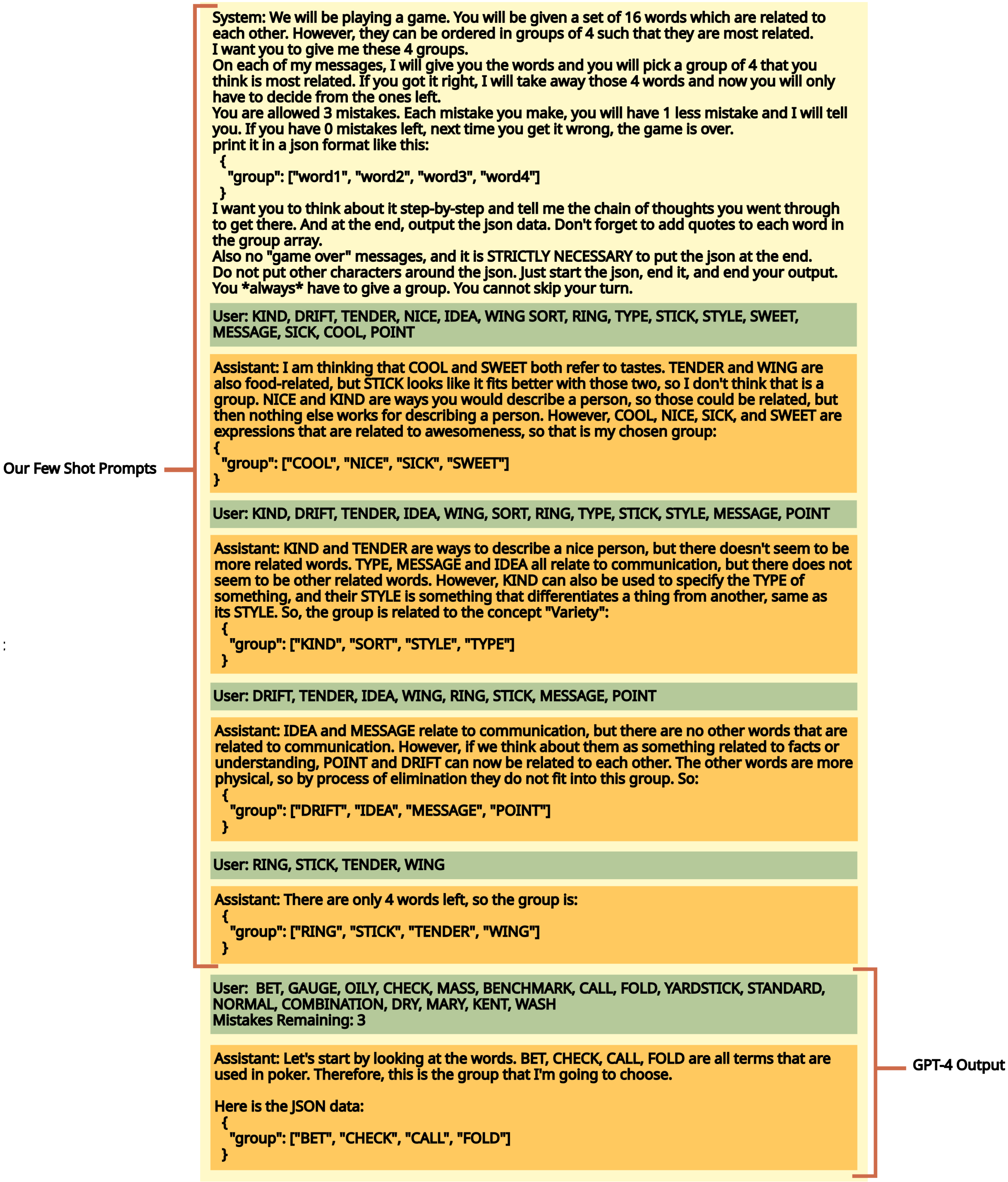
Understood, now I will only output json.

User: BENCHMARK, STANDARD, FOLD, COMBINATION, DRY, BET, CALL, CHECK, KENT, MARY, MASS, NORMAL, OILY, YARDSTICK, WASH, GAUGE
Mistakes Remaining: 3

Assistant:

```
{
  "group": ["STANDARD", "NORMAL", "BENCHMARK", "GAUGE"]
}
```

Figure 7: Prompts used for testing IO performance on the No Hints and Full Hints setups, with GPT-4 example output.



Our Few Shot Prompts

System: We will be playing a game. You will be given a set of 16 words which are related to each other. However, they can be ordered in groups of 4 such that they are most related.
I want you to give me these 4 groups.
On each of my messages, I will give you the words and you will pick a group of 4 that you think is most related. If you got it right, I will take away those 4 words and now you will only have to decide from the ones left.
You are allowed 3 mistakes. Each mistake you make, you will have 1 less mistake and I will tell you. If you have 0 mistakes left, next time you get it wrong, the game is over.
print it in a json format like this:

```
 {
   "group": ["word1", "word2", "word3", "word4"]
 }
```

I want you to think about it step-by-step and tell me the chain of thoughts you went through to get there. And at the end, output the json data. Don't forget to add quotes to each word in the group array.
Also no "game over" messages, and it is STRICTLY NECESSARY to put the json at the end.
Do not put other characters around the json. Just start the json, end it, and end your output.
You *always* have to give a group. You cannot skip your turn.

User: KIND, DRIFT, TENDER, NICE, IDEA, WING SORT, RING, TYPE, STICK, STYLE, SWEET, MESSAGE, SICK, COOL, POINT

Assistant: I am thinking that COOL and SWEET both refer to tastes. TENDER and WING are also food-related, but STICK looks like it fits better with those two, so I don't think that is a group. NICE and KIND are ways you would describe a person, so those could be related, but then nothing else works for describing a person. However, COOL, NICE, SICK, and SWEET are expressions that are related to awesomeness, so that is my chosen group:

```
{
  "group": ["COOL", "NICE", "SICK", "SWEET"]
}
```

User: KIND, DRIFT, TENDER, IDEA, WING, SORT, RING, TYPE, STICK, STYLE, MESSAGE, POINT

Assistant: KIND and TENDER are ways to describe a nice person, but there doesn't seem to be more related words. TYPE, MESSAGE and IDEA all relate to communication, but there does not seem to be other related words. However, KIND can also be used to specify the TYPE of something, and their STYLE is something that differentiates a thing from another, same as its STYLE. So, the group is related to the concept "Variety":

```
 {
   "group": ["KIND", "SORT", "STYLE", "TYPE"]
 }
```

User: DRIFT, TENDER, IDEA, WING, RING, STICK, MESSAGE, POINT

Assistant: IDEA and MESSAGE relate to communication, but there are no other words that are related to communication. However, if we think about them as something related to facts or understanding, POINT and DRIFT can now be related to each other. The other words are more physical, so by process of elimination they do not fit into this group. So:

```
 {
   "group": ["DRIFT", "IDEA", "MESSAGE", "POINT"]
 }
```

User: RING, STICK, TENDER, WING

Assistant: There are only 4 words left, so the group is:

```
 {
   "group": ["RING", "STICK", "TENDER", "WING"]
 }
```

GPT-4 Output

User: BET, GAUGE, OILY, CHECK, MASS, BENCHMARK, CALL, FOLD, YARDSTICK, STANDARD, NORMAL, COMBINATION, DRY, MARY, KENT, WASH
Mistakes Remaining: 3

Assistant: Let's start by looking at the words. BET, CHECK, CALL, FOLD are all terms that are used in poker. Therefore, this is the group that I'm going to choose.

Here is the JSON data:

```
 {
   "group": ["BET", "CHECK", "CALL", "FOLD"]
 }
```

Figure 8: Prompts used for testing CoT performance on the No Hints and Full Hints setups, with GPT-4 example output.

A.3 Dataset Difficulty Composition

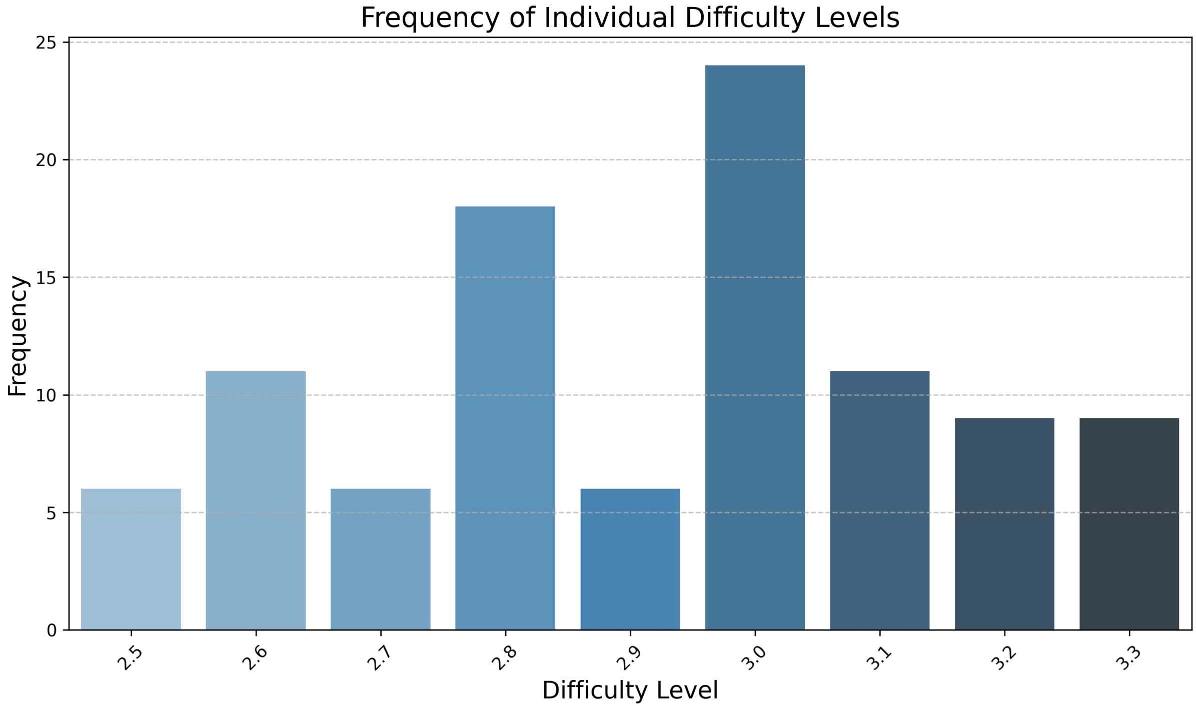


Figure 9: Difficulty distribution for our 100 median NYT-CONNECTIONS instances.