SportQA: A Benchmark for Sports Understanding in Large Language Models

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Abstract

A deep understanding of sports, a field rich in strategic and dynamic content, is crucial for advancing Natural Language Processing (NLP). This holds particular significance in the context of evaluating and advancing Large Language Models (LLMs), given the existing gap in specialized benchmarks. To bridge this gap, we introduce SportQA, a novel benchmark specifically designed for evaluating LLMs in the context of sports understanding. SportQA encompasses over 70,000 multiple-choice questions across three distinct difficulty levels, each targeting different aspects of sports knowledge from basic historical facts to intricate, scenario-based reasoning tasks. We conducted a thorough evaluation of prevalent LLMs, mainly utilizing few-shot learning paradigms supplemented by chain-of-thought (CoT) prompting. Our results reveal that while LLMs exhibit competent performance in basic sports knowledge, they struggle with more complex, scenario-based sports reasoning, lagging behind human expertise. The introduction of SportQA marks a significant step forward in NLP, offering a tool for assessing and enhancing sports understanding in LLMs.

1 Introduction

The dynamic and multifaceted world of sports, characterized by its fast pace, variety of types, abundance of strategies, and rich player narratives, presents a unique set of challenges for the sports understanding capabilities of Large Language Models (LLMs). Although LLMs have shown exceptional capabilities in many Natural Language Processing (NLP) tasks such as natural language understanding (NLU) (Fei et al., 2023), information extraction (Ding et al., 2023; Cong et al., 2023), and question answering (QA) (Zhao et al., 2023; Li et al., 2023), their application in the sports domain, which involves a complex blend of statistical data, narrative content, and strategic planning remains underexplored. Sports enthusiasts can easily answer questions like "Who won the 2022 FIFA World Cup?" or "What is the record for the most points scored in an NBA game?", but more complex queries like "Why does the float serve appear more in low-level or young-age volleyball games than in high-level games?" require expert knowledge and experience. These challenges, ranging from general knowledge to expert-level analysis, underscore the need for a dedicated sports-focused question-answering (QA) dataset to improve LLMs' comprehension and contextualization of sports information.

To evaluate the sports understanding capabilities of LLMs, the sports QA task has been introduced with several datasets for evaluation. The BIG-bench sports understanding task (bench authors, 2023) focuses on factual sports knowledge, while LiveQA (Liu et al., 2020) is based on Chinese live-broadcasting NBA passages. These datasets illustrate certain aspects of sports understanding. However, they exhibit limitations in size, sports domain coverage, and depth of understanding. For instance, BIG-bench might ask LLMs to judge the plausibility of a statement like "Tom Brady threw a touchdown in the Champions League Final," merging an American football player with a soccer event. This approach, focusing more on superficial sports associations than on deep understanding of sports contexts and rules, leads to an incomplete assessment of LLMs' true sports understanding. To bridge this gap, we introduce SportQA, a comprehensive dataset crafted to challenge and evaluate LLMs in the domain of sports understanding. It consists of 70,592 multiple-choice questions, offering varying levels of difficulty, from straightforward historical facts to complex, scenario-based reasoning tasks that necessitate extensive sports knowledge and experience.

As shown in Figure 1, humans' understanding of sports can be divided into three levels of dif-

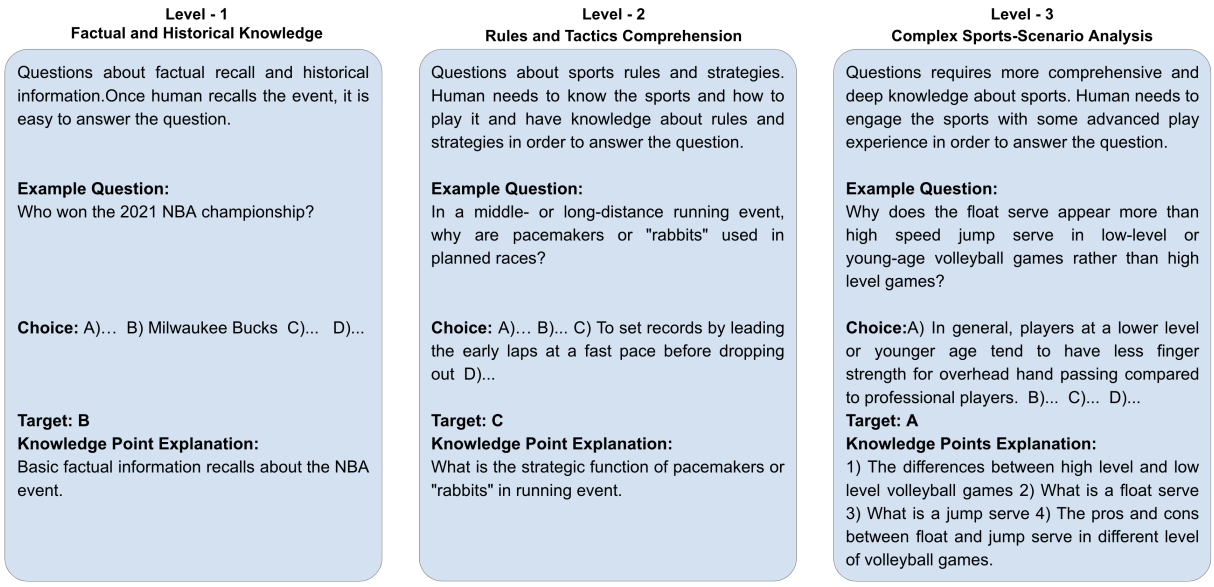

Figure 1: Illustration of three levels of understanding in sports.

ficulty: factual and historical knowledge (Level-1), rules and tactics comprehension (Level-2), and complex sports-scenario analysis (Level-3). In our SportQA, level-1 understanding, covering 21,385 problems, allows humans to answer by recalling facts without needing additional sports expertise, such as knowing who won a specific Olympic event. Level-2, with 45,685 problems, suitable for sports enthusiasts, requires some expertise to understand diverse sports strategies and rules, like understanding soccer's offside rules. Level-3, encompassing 3,522 problems, is designed for sports specialists with years of experience, featuring more complex scenarios. One example under this level would be determining the best technique for a volleyball player facing three blockers during a spike in an amateur game. Level-1 and Level-2 problems are presented as multiple-choice questions with one correct answer each, while Level-3 problems follow a 'Multiple Select' format, allowing for one to four correct answers, and include both single and multi-hop questions in two levels of difficulty. Overall, three levels of questions collectively provide a comprehensive set to evaluate LLMs' sports understanding across a spectrum of expertise.

To gain deeper insights into the sports understanding challenges posed by SportQA, we extensively evaluated several popular recent LLMs, including Llama2 (Touvron et al., 2023), PaLM2 (Anil et al., 2023), GPT-3.5, and GPT-4 (OpenAI, 2023). The models were assessed through few-shot standard prompting, as well as chain-of-thought prompting (Wei et al., 2022). Our findings show that GPT-4 outperforms in all levels, achieving an average accuracy of 82.16% in Level-1, 75% in Level-2, and 47.14% in level-3. However, in Level-3, the most challenging level, GPT-4's performance is about 45% inferior compared to human experts' accuracy in the same test questions, indicating that its understanding of sports significantly lags behind human capabilities, suggesting considerable scope for improvement in this area.

In summary, our contributions are threefold:

(1) We introduced SportQA, the first comprehensive dataset tailored for sports understanding in LLMs. It encompasses three levels of difficulty, aligned with human comprehension of sports. The dataset covers a diverse range of questions, from basic sports history to complex, scenario-based queries, thereby establishing itself as an essential tool for assessing the LLMs' sports understanding capabilities.

(2) We conducted extensive experiments on SportQA, evaluating recent LLMs' sports comprehension capabilities and gained insights into their strengths and areas for improvement through manual error analysis. This research has contributed to a better understanding of LLM performance within the context of sports NLP.

(3) We explored new directions for NLP in sports, underscoring its potential to enhance sports

journalism and facilitate communication between athletes and coaches. This work not only broadens the use of NLP technologies but also lays the groundwork for the future integration of AI in sports-related fields. Furthermore, we made our datasets publicly available to benefit the research community.

2 Related Work

Sports NLP. Sports NLP is an emerging field, increasingly capturing interest due to its diverse applications, which range from sentiment analysis (Baca et al., 2023; Ljajić et al., 2015) to game outcome predictions (Beal et al., 2021; Xia et al., 2022; Oved et al., 2020), and from generating game summaries (Thomson et al., 2020; Huang et al., 2020) to augmenting sports videos with computer vision techniques (Chen et al., 2022). Despite these advancements, a critical dimension remains underexplored: an in-depth understanding of sports in LLMs. Current applications primarily focus on analytics and do not delve into the complexities of sports understanding. Ensuring a deeper comprehension of sports in LLMs is crucial, as it can significantly broaden the scope and impact of NLP and LLM applications in the sports domain. This advancement is not only essential for enhancing current applications but also pivotal for exploring new avenues in Sports NLP.

QA in Sports. There have been several QA datasets involving testing LLMs reading and knowledge-based comprehension. Popular datasets include Trivia QA (Joshi et al., 2017), HotpotQA (Yang et al., 2018), QUASAR (Dhingra et al., 2017; Talmor and Berant, 2018), KQA Pro (Cao et al., 2022) , and BoolQ (Clark et al., 2019). However, among these datasets, sports-related QA is scarce. When sports topics are included, they usually focus on historical facts or well-known events, rather than the intricacies of sports rules, strategies, and real-time decision-making. This focus on factual recall rather than a deeper, strategic understanding of sports limits LLMs in demonstrating nuanced comprehension of this special domain.

Recent work (Wei et al., 2022) has examined LLMs' sports understanding using BIG-bench's dataset on sports subtask (bench authors, 2023), focusing on distinguishing plausible from implausible sports statements. This dataset contains 986 questions that require knowledge of both the names of athletes and actions common in particular sports. However, understanding a sport involves more than merely matching names and activities. Similarly, LiveQA (Liu et al., 2020), based on live NBA broadcasts, assesses real-time sports event comprehension. The common drawback of these sports QA datasets is their focus on surface-level insights, such as basic facts and famous activities. True sports understanding involves rules, gameplay, and tactics. In contrast, our SportQA benchmark provides a comprehensive scope, covering a wide range of sports subjects from facts and history to rules and complex scenarios. We aim to address the limitations of existing datasets, fostering a deeper understanding of sports.

Paradigms in LLMs Training. Pre-trained language models on diverse texts, exemplified by BERT(Devlin et al., 2019) has been a cornerstone in NLP. These models have been effectively used in tasks ranging from disease prediction (Zhao et al., 2021) to text classification (Wang et al., 2022b). However, the introduction of GPT-3 (Brown et al., 2020) marked a paradigm shift from extensive task-specific fine-tuning to zero-shot and few-shot learning approaches, enabling adaptation to new tasks with minimal training. This transition has led to the development of advanced prompting techniques to enhance LLMs' understanding and reasoning abilities. Representative examples include chain-of-thought (CoT) prompting (Wei et al., 2022), zero-shot CoT prompting (Kojima et al., 2022), self-consistency (Wang et al., 2022a), Tree-of-Thought prompting (Yao et al., 2023), and metacognitive prompting (Wang and Zhao, 2023). This evolution has necessitated a focus on the latest advancements in LLMs. Consequently, our study concentrates on evaluating recent LLMs, such as Llama2 (Touvron et al., 2023), PaLM2 (Anil et al., 2023), GPT-3.5, and GPT-4 (OpenAI, 2023) in diverse sports understanding tasks to explore their capabilities.

3 Sports Understanding Benchmark

We introduce SportQA, a benchmark specifically designed to evaluate the understanding of sports for LLMs. Developed in close collaboration with sports experts, questions in SportQA consist of three main levels of difficulty, each focusing on a distinct aspect of sports comprehension.

Level-1: Foundational Sports Knowledge. Questions in this level assess basic sports knowledge, focusing on factual recall and historical information. It provides a foundation for understanding the broader context of sports within LLMs.

Level-2: Rules and Tactics Comprehension. This level's questions mainly evaluate LLMs' understanding of sports rules and strategies. Covering 35 distinct sports types, it tests the models' ability to interpret game rules and employ strategic thinking, offering deeper insights into sports comprehension. Additionally, it includes more complex fact-based historical questions to ensure a well-rounded assessment of sports knowledge.

level-3: Advanced Scenario-Based Understanding. In this level, questions focus on evaluating the synthesis and integration of diverse sports knowledge. These involve complex, scenario-based questions that replicate real-world sports situations, requiring deep comprehension and advanced analytical thinking from LLMs.

Overall, the benchmark comprises a total of 70,592 questions. For each dataset and level, we provide a few-shot development set consisting of 5 questions per task, along with a separate test set for a thorough evaluation. Table 1 provides a detailed overview of these levels and tasks, with more extensive details available in Appendix A. We employ accuracy as the evaluation metric across all tasks, ensuring a clear and objective assessment of LLMs' sports understanding capabilities.

3.1 Dataset Construction and Quality Verification

Dataset Construction. We constructed the SportQA dataset through a hybrid approach. For Level-1 and -2 problems, we combined automated templates with expert-driven modifications to create a diverse range of questions, ensuring both consistency and comprehensive coverage. For the more complex level-3 questions, we exclusively used manual question creation by experienced sports experts. This dual approach, integrating both automated and manual processes, was instrumental in crafting questions that accurately reflect the multifaceted and intricate aspects of sports knowledge.

Quality Verification. To ensure the integrity and accuracy of SportQA, a meticulous manual review process was essential due to the complexity of sports knowledge. This task was carried out by a highly skilled team of 36 intercollegiate student-athletes from both the US and China, each with a minimum of 8 years of sports training experience. Their extensive experience and expertise in various sports were crucial in evaluating the context and accuracy of each question. Their deep understanding of sports rules, strategies, and contexts ensured that every question in the dataset was not only factually accurate but also relevant and challenging.

During the recruitment phase, each potential team member was interviewed using ten examples for every level of questions and asked to compose example Q&A pairs. After hiring, each member first goes through a training session to learn the task and the annotation process. Once they fully master the annotation process, we launch the official batches for them to work on.

3.2 Level-1: Foundational Sports Knowledge

Level-1 problems aim to assess LLMs' proficiency in foundational sports knowledge, focusing on factual recall and historical information. This level includes a total of 21,385 multiple-choice questions, sourced from a variety of QA datasets. As these datasets have different Q&A formats (true/false, multiple choices, and open-ended narratives), efforts were spent to normalize the formats and check for correctness and relevance.

Questions from Trivia QA (Joshi et al., 2017), QUASAR (Dhingra et al., 2017), and Hotpot QA (Yang et al., 2018) were originally in open-answer format and have been adapted for this benchmark. For BoolQ (Clark et al., 2019), which primarily featured true/false questions, we adapted these into 2-way multiple-choice formats. KQA Pro (Cao et al., 2022) questions, already in a multiple-choice format, were also included and checked for accuracy and relevance. The transformation of open-answer questions into multiple-choice format followed by automated template generation or manual refinement.

Step 1: Automated Template Generation. For each answer type (sport, time, country/location, person, numbers, etc.), we utilized different semantic libraries. For example, (1) Sports: If the answer was a sport, other sports were automatically selected as distractors. (2) Time: Adjacent periods were chosen for time-based answers. (3) Country/Location: Similar geographical locations were used as distractors. (4) Person: A specialized semantic library of names was created for each sport to gather information about athletes, and this library was then used to select distractors.

Step 2: Manual Refinement. Questions requiring more nuanced distractors or falling outside these categories were further refined by our review team of 36 student-athletes, who manually crafted additional misleading options.

Level-1 questions establish the foundation for

Task	Data Size	Metrics	Answer Type	Text Sources
Level-1: Foundational Sports Knowledge				
Integrating Existing Datasets	21,385	Acc.	4-Way or 2-Way MC	Trivia QA[1], QUASAR[2], Hotpot QA[3], KQA Pro[4], BoolQ[5]
level-2: Rules and Tactics Comprehension				
35 Sports and Their Variation Tasks	45,685	Acc.	4-Way MC	Wikipedia
level-3: Scenario-based Questions				
6 Sports Easy Multi-hop Tasks	915	Acc.	Multi-hop 4-Way MS	Experts Proposed Assessment Angles
6 Sports Hard Multi-hop Tasks	808	Acc.	Multi-hop 4-Way MS	
6 Sports Easy Single-hop Tasks	903	Acc.	Single-hop 4-Way MS	
6 Sports Hard Single-hop Tasks	896	Acc.	Single-hop 4-Way MS	

[1](Joshi et al., 2017), [2](Dhingra et al., 2017), [3](Yang et al., 2018), [4](Cao et al., 2022), [5](Clark et al., 2019)

Table 1: Overview of tasks included in SportQA. The "Data Size" column aggregates totals from both the training, development and test sets. "K-Way MC" and "K-Way MS" signifies a multiple-choice response format and multiple-selected choice (one or multiple correct answers) format respectively with K options. Level-1 focuses on historical and factual sports knowledge. Level-2 consists of 35 sports types about rules, strategies, and facts, and Level-3 includes 6 sports with complex, multiple knowledge points questions. Detailed statistics on question distribution and topic focus within each task are available in the Appendix A.

sports knowledge. However, due to the limited scope and specificity of sports in existing datasets, level-2 is introduced to expand this scope. It addresses the need for professional knowledge of sports, such as rules and strategies.

3.3 level-2: Rules and Tactics Comprehension

level-2 problems are designed to conduct an in-depth assessment of LLMs' understanding of sports rules, tactics, and an extended range of historical and factual knowledge. This level comprises 45,685 questions, covering a broad spectrum of sports disciplines.

Step 1: Content Categorization and Annotation. The review team categorized content from Wikipedia related to 35 distinct sports tasks, including the 28 Olympic sports and their variation, the four new sports (Breaking, sport climbing, skateboarding, and surfing) debuting in the 2024 Paris Olympics, and popular non-Olympic sports like baseball, ice hockey, and American football. The focus was on compiling sources primarily about rules and tactics, supplemented with historical and factual content for comprehensive coverage. They performed categorization and annotation of content from Wikipedia, identifying and annotating critical information points within each sport's rules, tactics, and historical contexts.

Step 2: Hybrid Question Development and Templates. Our approach to question development was twofold. First, we employed a set of predefined templates to ensure consistent coverage across various sports, and examples of these templates are illustrated in Appendix A. Furthermore, for scenarios that required deeper exploration beyond these templates, we manually crafted questions, ensuring a rich and diverse set of queries based on the annotation of content and knowledge points.

Step 3: Distractor Generation and Categorization. The distractor generation for SportQA was a nuanced process. Automated distractors for template-based questions were created using a specialized, sport-specific library, ensuring each was relevant and challenging. This library, organized by sport, included diverse categories such as athletes' names and tactics. For questions crafted manually, our team of experts meticulously developed plausible yet incorrect distractors, adding depth and complexity to the dataset.

Step 4: Expert Review and Alignment. The review team ensured each question's alignment with the source content, verifying the efficacy of questions and eliminating outdated or irrelevant information.

By following the above steps, level-2 problems not only offer a comprehensive evaluation of sports rules and tactics but also enrich the dataset with an expansive array of sports history and factual knowledge, enhancing the overall utility of SportQA.

3.4 level-3: Scenario-Based Questions

level-3 problems are a comprehensive and nuanced component of our benchmark, comprising 3,522 scenario-based questions across six key sports. This level includes football (soccer), basketball, volleyball, tennis, table tennis, and American football. Each sport features a set of both multi-hop and single-hop questions with multiple selected types

(one to four correct answers), meticulously categorized into easy and hard difficulty levels. The categorization is based on the complexity of the scenarios and the number of integrated knowledge points required to answer each question. This results in four distinct tasks per sport, 24 tasks in total, closely mirroring the intricacies and complexities of real-world sports situations.

The requirement for manual question creation in level-3 is rooted in the sophisticated and deep understanding of each sport needed to craft these questions. This level's complexity demands not just a surface-level acquaintance with the sports but an in-depth, experiential knowledge, often only possessed by those who have actively participated or been deeply involved in the sport. Such profound insight is crucial for developing questions that accurately capture the nuances, strategic elements, and practical applications inherent in real-world sports scenarios. This elevates level-3 above Levels 1 and 2, making it a more advanced and comprehensive test of sports understanding and analysis.

Step 1: Expert Proposed Assessment Angle. We first invited coaches to propose the assessment angles, which are further detailed in Appendix A, for these sports based on their expertise. Their extensive coaching experience and mastery understanding of sports ensure that the knowledge points behind each question are meaningful and effective for the sports.

Step 2: Manual Questions Generation. After coaches proposed the assessment angles across all 6 sports, these angles were used by our review team, combining their training and competition experience with their unique advanced understanding of their expertise in sports, to develop questions. This ensures a comprehensive assessment of LLMs' sports understanding and analytical skills.

The distribution of questions per sport, shown in Appendix A, is directly influenced by the availability and expertise of our review team. Sports with more expert reviewers are represented with a larger number of questions, ensuring the authenticity and depth of the content. This alignment guarantees that the questions are not only challenging but also reflect the dynamic nature of each sport.

The manual creation process of level-3 emphasizes the professional rigor and subject-matter expertise that underpin SportQA, making it an exceptional measure of sports knowledge.

4 Experiments

This section evaluates the performance of prevalent LLMs on our SportQA benchmark. We aim to assess the efficacy of these models in understanding complex sports scenarios across multiple tasks. We present the optimal result, derived from multiple iterations for each experimental condition.

4.1 Experimental Setup

We evaluated several leading language models on the SportQA benchmark, including open-source models like Llama2-13b-chat (Touvron et al., 2023), and closed-source models such as PaLM-bison-chat (Anil et al., 2023), GPT-3.5-turbo, and GPT-4 (OpenAI, 2023). Access to these models was facilitated through their respective APIs.

For Level-1, we randomly selected 2000 questions from the test set. For level-2, our sampling strategy varied based on the number of questions per sport: 30% for sports with fewer than 200 questions, 15% for 200-800, 5% for 800-1500, 2.5% for 2500-10,000, and 1.5% for more than 10,000 questions, totaling 2243 questions. In level-3, the test sample size was determined based on the total questions of sports, with 20% for soccer, basketball, and tennis, 30% for volleyball, and 50% for table tennis and American football, a total of 980 questions.

In our study, we primarily focused on the CoT prompting method for model evaluation. This decision was informed by the evidence (Wei et al., 2022), which highlights the effectiveness of few-shot CoT in sports understanding contexts. The CoT approach, involving a step-by-step reasoning process, is particularly suitable for complex sports understanding tasks. We also considered the zero-shot CoT method (Kojima et al., 2022) and few-shot standard prompting (SP) (Brown et al., 2020) as additional prompting baselines for evaluation. In the few-shot setting (CoT or SP), we take 5 exemplars for each task, where the answers to these demonstrations are annotated by human experts. Exemplars were consistently drawn from the development set, with the temperature parameter set to 0 to ensure consistent response generation. Additional details about the prompts we used are available in Appendix B.

In addition to model performance evaluation, we engaged student-athletes not part of the review team, each specializing in one of the sports covered in level-3. These athletes were tasked with

Model	Level-1	level-2	level-3 Easy Single-hop	level-3 Hard Single-hop	level-3 Easy Multi-hop	level-3 Hard Multi-hop
Llama2-13b(0S,CoT)	50.90	52.32	21.46	15.16	14.80	9.20
Llama2-13b(5S,SP)	42.75	48.02	25.10	25.82	5.60	5.86
Llama2-13b(5S,CoT)	48.65	51.54	26.72	32.38	9.20	8.79
PaLM2(0S,CoT)	59.35	48.28	48.37	44.49	23.20	12.97
PaLM2(5S,SP)	64.85	56.62	49.19	49.80	29.20	16.74
PaLM2(5S,CoT)	66.20	57.02	47.56	38.37	19.60	11.29
GPT3.5(0S,CoT)	49.04	51.04	49.18	45.71	27.6	14.64
GPT3.5(5S,SP)	74.74	68.07	45.52	36.73	25.20	19.24
GPT3.5(5S,CoT)	71.97	66.52	46.34	45.30	23.60	14.64
GPT-4(0S,CoT)	80.60	69.01	67.07	55.10	32.00	22.59
GPT-4(5S,SP)	80.24	77.17	70.73	63.27	33.60	**24.69**
GPT-4(5S,CoT)	**85.63**	**78.82**	**73.58**	**64.08**	**34.40**	23.01
Human	-	-	96.63	96.02	94.90	91.84

Table 2: Performance comparison of each model across three levels in SportQA. GPT-4 consistently outperforms other models under both zero-shot (0S) and 5-shot (5S) settings across all levels. Human performance serves as an upper bound, illustrating that there still exists room for improvement in LLMs on sports understanding tasks.

manually answering the test set of level-3. This effort, involving each expert in their respective sport, was undertaken to better understand human performance on these complex, scenario-based questions. Their contributions provide valuable insights into the realistic expectations of human expertise in sports understanding and serve as a standard for expert-level accuracy.

4.2 Overall Performance Comparison

We compared the performance of different models across all tasks in three different levels, and the overall result is shown in Table 2. Results for individual tasks are shown in Appendix C. There are several key takeaways. First, GPT-4 consistently outperforms other models across all tasks, demonstrating a performance advantage of over 15% compared to other models on average. Regarding prompting effectiveness, we note that CoT often results in performance enhancements, which corroborates the findings from (Wei et al., 2022), emphasizing the efficacy of step-by-step prompting with few exemplars in augmenting LLMs' performance in intricate reasoning tasks. Each model, including GPT-4, consistently exhibited the best performance in Level-1, with a gradual decline in accuracy moving to Levels 2 and 3. This trend aligns with the increasing complexity and sophistication designed for each successive level of our benchmark. Level-1, focusing on foundational knowledge, proved to be the most accessible, while level-3, with its advanced scenario-based tasks, posed the greatest challenge.

Finally, while GPT-4 leads among all the models, human expertise still exceeds it by roughly 30% - 65% in different tasks of level-3, highlighting the complexity of these sports understanding tasks and indicating room for future improvements in LLMs.

4.3 Error Analysis

To better understand the mistakes made by models, we randomly chose and manually analyzed 20 instances from each level where a model, whether in a 0-shot or 5-shot setting or under SP or CoT, made an incorrect choice. We prompted the model to explain its decisions, then reviewed these explanations to identify errors, understand the reasons behind them, and categorize them into specific error types. The error analysis for Levels 1 and 2 in SportQA is closely related to the fundamental nature of these levels, which focus on factual knowledge and basic rule comprehension. We identify the following error types which align with the core challenges of recalling specific sports facts, understanding basic rules, and applying simple strategies: Deficiency in Conceptual Understanding, Misuse of Known Information, and Inaccuracies in Factual Recall.

For level-3 of SportQA, given its unique question types involving scenario-based, multi-knowledge point questions with both single and multi-hop reasoning, we devised specific error categories: Conceptual Misunderstanding, Logical Reasoning Error, and Contextual Misinterpretation.

For this analysis, we focused on GPT-4. Figure 2 shows the error types and their respective proportions for each level group. Within level-1 and level-2, "deficiency in conceptual understanding " was the most frequent error, accounting for 40% of all mistakes. In level-3 of the SportQA analysis, During the analysis process, we notice there are 82.5% of error questions have inadequacy in multifaceted answer identification. Within this, the greatest error category appears to be conceptual

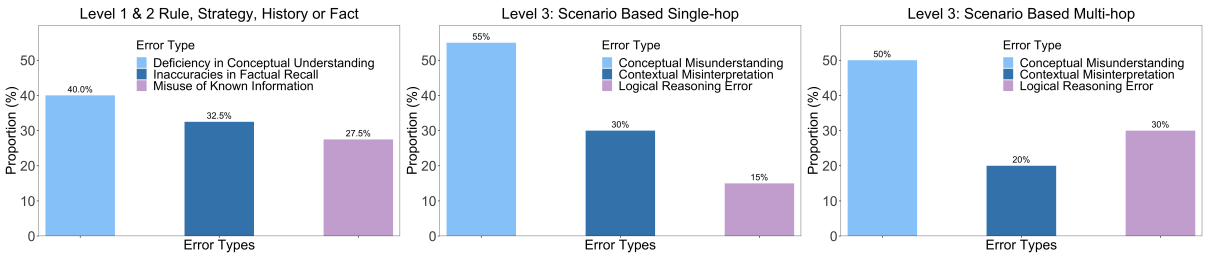

Figure 2: Error type distributions across different levels of SportQA analysis, with level-3 separated into 'Single-Hop' and 'Multi-Hop' reasoning to highlight specific error trends. In levels 1 and 2, the model often struggles with the details of concepts, and these issues become amplified in level-3. This amplification of errors leads to more significant problems, resulting in worse performance of models in the more complex scenarios of level-3.

misunderstanding, prevalent in both single-hop and multi-hop scenarios, constituting 55% and 50% of the errors, respectively. This suggests that models often fail to grasp the concepts that are combined with scenarios necessary for these complex questions. Detailed descriptions of each error type can be found in Appendix D.

5 Conclusion

This study has introduced SportQA, a benchmark for assessing the understanding of sports in LLMs. Unlike previous benchmarks that primarily focused on basic fact-recall or simplistic sports-related queries, SportQA delves deeper into the intricacies of sports knowledge, spanning historical facts, rules, strategies, and scenario-based reasoning. Our evaluations reveal that while current LLMs like GPT-4 show promising capabilities in foundational knowledge and rule comprehension, their performance in complex, scenario-based reasoning remains a challenge and still lags behind human expertise. The results underscore the need for ongoing advancements in NLP and AI to achieve a deeper and more nuanced understanding of sports. Improvements to logical reasoning and in-depth understanding in the context of sports will be a gateway toward allowing Large Language Models to improve their performance and adaptability across a large range of real-world, diverse, and ever-changing domains. SportQA serves as an essential tool for future research in this area, offering a structured framework to measure and enhance LLMs' capabilities in sports understanding.

6 Limitations and Future Work

While SportQA presents a broad assessment of sports understanding, we acknowledge its limitations. The primary limitation lies in the complexity of creating scenario-based questions for level-3. Due to the intricate nature and high standards required for these questions, the volume of questions and the range of sports it covers at this level is limited compared to other levels. We are dedicated to continually updating and expanding the dataset to enhance its scope and depth.

Another significant limitation of SportQA is its focus predominantly on rules and gameplay aspects of sports understanding. Critical elements such as sports medicine and psychology, which are integral to a comprehensive understanding of sports, are not currently covered in the benchmark. These areas require specialized medical and psychological knowledge, making their integration into the benchmark complex and demanding. This gap in content underscores the need for a more interdisciplinary approach in future iterations of SportQA, to encompass a wider spectrum of sports knowledge and understanding and the need to recruit team members with a more diverse background.

Furthermore, while we aimed to include a variety of LLMs in our analysis, budgetary constraints limited our ability to evaluate certain high-capacity models like the open-source Llama2-70b-chat (Touvron et al., 2023). This represents a limitation in our current study, as including a wider range of models could potentially offer more insights into their respective capabilities in sports understanding tasks. In future work, we plan to extend our model evaluation to encompass a broader spectrum of LLMs, ensuring a more comprehensive analysis.

Additionally, we also plan to fine-tune existing open-source LLMs, such as Llama2, specifically for sports understanding tasks. These efforts will be aimed at creating tailored LLMs that can better comprehend and reason about various aspects of sports.

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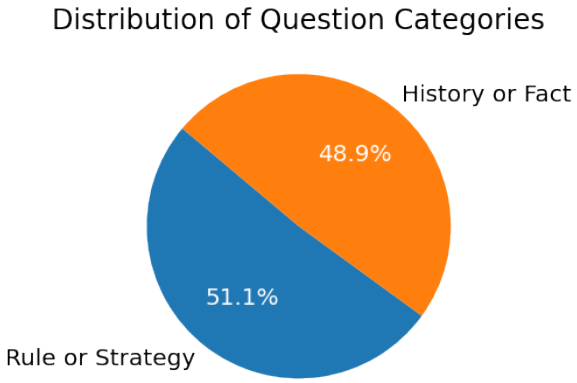
A Detailed Question Distribution and Sample Questions for SportQA

This appendix provides an in-depth look at the question distribution across different sports and question types within SportQA, as well as illustrative examples of the types of questions featured in the dataset.

Figure 3: Comparative Analysis of 'Rule or Strategy' vs. 'History or Fact'



A.1 level-2 Question Distribution Across Sports

A comprehensive table and corresponding figures illustrate the number of questions per sport, categorized by the type of knowledge they assess — historical facts, rules, or strategic understanding. The

distribution of the number of questions between 'Rule or Strategy' and 'History or Fact' is shown in Figure 3. The detailed distributions for each task in level-2 are shown in Figure 5 and Table 4.

Level	Question Type	Template Examples
level-2	History or Fact	1. In [sport], what is the notable history of [aspect]?
		2. Who was the first in [sport] to [achievement/action]?
		3. What is the origin of [aspect] in [sport]?
		4. What record does [athlete/team] hold in [sport]?
		5. Which athlete or team is known for [achievement] in [sport]?
	Rules or Strategy	1. How is [technique] performed in [sport]?
		2. What is the official rule of [aspect] in [sport]?
		3. What strategic approach is used for [aspect] in [sport]?
		4. Explain the play method of [situation] in [sport].
		5. Describe the regulation for [action/equipment] in [sport].

Table 3: General templates used for generating questions in level-2 of SportQA. The templates are divided by question type (History or Fact, and Rules or Strategy) within level-2, with each category containing five examples.

A.2 Question Templates

The example of templates we used to generate level-2 questions is shown in Table 3.

A.3 level-3 Assessment Angles

This section presents an example of assessment angles, shown in Table 7, for level-3, as proposed by sports experts. These angles are designed to challenge Large Language Models (LLMs) with realistic and complex sports scenarios that require an advanced understanding of game dynamics, rules, and strategies. For a detailed exposition of these angles within the context of basketball, please refer to Table 7.

A.4 Sample Questions

The sample questions for each level are shown in Figure 4.

B Prompting Methods

We utilize both standard Prompt (SP) and CoT in our experiments with LLMs. For SP, questions are presented without additional steps in the prompt. For CoT, zero-shot prompting is inspired by (Kojima et al., 2022), instructing the model to "Let's think step by step". For few-shot CoT, we manually craft the step-by-step process for 5-shot exemplars in the development set. Examples of Few-shots and CoT prompts in our experiments are included in Table 8 - 12.

C Additional Results on GPT-4

The GPT-4 Performance of individual tasks in level-2 and level-3 are shown in Table 5 and Table 6.

Table 4: Total Number of Questions for Each Sports Task in level-2

Sport	Total Questions
Skateboarding	1031
Gymnastics	826
Canoeing	415
Fencing	382
Sport Climbing	72
Surfing	257
Breaking	149
Cycling	1102
Equestrian	159
Golf	2605
Boxing	1423
Ice Hockey	3025
Wrestling	170
Archery	127
Swimming	710
Water Polo	465
Hockey	417
Athletics	1398
Basketball	4400
Baseball	512
Taekwondo	182
Table Tennis	273
Badminton	149
Modern Pentathlon	65
Shooting	606
Tennis	2526
Judo	810
Handball	391
Diving	191
Sailing	430
Triathlon	172
Volleyball	1263
Weightlifting	115
Football (soccer)	8062
Rugby & American football	10956

We notice 5-Shot CoT prompting has the best performance in most of the tasks. Some examples of incorrect outputs from GPT-4 and our error analysis are shown in Table 13 and Table 14.

D Error Categories Explanation

Level-1 and -2 error Categories. Deficiency in Conceptual Understanding: The model demonstrates a lack of understanding or awareness of the specific sports concept or event. Misuse of Known Information: The model uses relevant information but provides incorrect explanations or conclusions or applies a general rule or concept to a specific sports scenario, leading to inaccurate answers. Incorrect Fact Recall: The model recalls and uses a fact that is either incorrect or not applicable to the

Tasks	Question	Sample Question
Level 1: Factual and Historical Knowledge	Fact Based	**Question:** In which sport did Hollywood star Sonja Henie win Olympic Gold? A) Tennis ❌ B) Gymnastics ❌ C) Ice Skating ✅ D) Swimming ❌
Level 2: Rules and Tactics Comprehension	Rule-Based	**Question:** What is the call when a player dribbles, stops, and then begins to dribble again? A) Traveling ❌ B) Double dribble ✅ C) Shot clock violation ❌ D) Three-second violation ❌
	Strategy-Based	**Question:** When implementing a zone defence, what may the first defender and sometimes the second defender do to pressure the opponent with the ball? A) Stay back in line ❌ B) Rush out ✅ C) Man-mark a player ❌ D) Move to the midfield line ❌
Level 3: Complex Sports-scenario Analysis	Scenario-based singe Hop	**Question:** During a professional volleyball match, Team A and Team B are competing against each other. The match is based on the best of five sets. Each set is played to 25 points with the requirement that a team must win by at least 2 points. If the match reaches a fifth set, that set is played to 15 points with the same two-point win requirement. Given that the match reached the fifth set with the following scores: Set 1 - Team A: 25, Team B: 23; Set 2 - Team A: 22, Team B: 25; Set 3 - Team A: 25, Team B: 21; Set 4 - Team A: 23, Team B: 25; Set 5 - Team A: 15, Team B: 13. Which of the following statements is correct? A) Team A won the match with a score of 3-2 sets. ✅ B) Team B won the match with a score of 3-2 sets. ❌ C) The match is still ongoing since Team A didn't win the fifth set by at least 2 points. ❌ D) The match is a draw since both teams won the same number of sets. ❌
	Scenario-based Multiple Hop	**Main Question:** How would the game proceed after a play where the quarterback throws a forward pass from behind the line of scrimmage, which is deflected by a defender at the line and caught by an offensive lineman who then runs for a touchdown, assuming it was 4th down and the offensive team was not in a legal formation at the snap? A) The touchdown is awarded, and the game proceeds with a kickoff by the scoring team. ❌ B) The touchdown is nullified, and the ball is turned over to the opposing team due to the illegal forward pass and formation. ✅ C) The touchdown is nullified, and the offensive team is penalized for an illegal forward pass but retains possession due to it being 4th down. ❌ D) The touchdown is nullified, the offensive team is penalized for the illegal formation, and the down is replayed. ✅ Sub-Question 1: How is an offensive lineman's eligibility to catch a forward pass determined in a play? A) The offensive lineman is eligible if he has reported as an eligible receiver to the referee before the play. ✅ B) The offensive lineman is eligible if he is at the end of the line and has an eligible receiver number. ✅ C) The offensive lineman is ineligible unless he has legally caught the ball after it has been touched by an opposing player. ✅ D) The offensive lineman is always ineligible to catch a forward pass. ❌ Sub-Question 2: What are the consequences of a team not being in a legal formation at the snap? A) The play is immediately whistled dead, and the team is penalized for a false start. ❌ B) The play proceeds, and the team is penalized for illegal formation if the infraction is called. ✅ C) The team receives a warning, and a repeat offense on the subsequent play results in a penalty. ❌ D) The opposing team may decline the penalty and take the result of the play. ✅

1

Figure 4: Example questions for SportQA

given context, despite understanding the general concept.

level-3 error Categories. Conceptual Misunderstanding: Errors where the model fails to grasp essential concepts required for answering the questions. Logical Reasoning Error: Mistakes in linking multiple steps of reasoning (For example, score calculation). Contextual Misinterpretation: Instances where the model misinterprets the scenario or context, leading to incorrect conclusions.

Sports	0-Shot CoT (%)	5-Shot SP (%)	5-shot CoT (%)
Water Polo	66.67	78.26	**81.15**
Baseball	68.24	75	**80.26**
Rugby or American Football	69.51	**75.6**	73.17
Athletics	71.05	73.91	**78.26**
Cycling	70.37	79.62	**81.48**
Table Tennis	72.5	82.5	**82.56**
Badminton	65.11	76.74	**79.07**
Football (Soccer)	67.16	85.07	**85.07**
Sailing	61.9	74.6	**79.36**
Ice Hockey	66.66	**80**	76
Diving	51.78	76.78	**78.57**
Tennis	77.42	82.25	**88.7**
Handball	74.13	**87.93**	84.48
Weightlifting	84.37	87.5	**87.5**
Equestrian	36.95	**63.04**	50
Surfing	70.27	75.67	**81.08**
Hockey	64.51	67.74	**74.19**
Judo	72.5	77.5	**77.5**
Sport Climbing	85	95	**95**
Volleyball	69.35	**74.19**	72.58
Gymnastics	60.97	73.17	**75.6**
Modern Pentathlon	77.77	66.67	**94.44**
Taekwondo	71.69	79.24	**86.79**
Archery	80.55	**83.33**	80.55
Canoeing	80.52	72.73	**80.52**
Shooting	70	76.67	**84.44**
Wrestling	74	78	**78**
Boxing	71.42	**84.28**	80
Triathlon	72	**80**	78
Breaking	76.74	83.72	**86.46**
Golf	64.61	**84.61**	83.07
Basketball	69.72	71.55	**72.47**
Fencing	71.42	71.42	**80.35**
Skateboarding	60.78	60.78	**66.67**
Swimming	69.52	69.52	**70.47**

Table 5: GPT-4 Performance of each task in Level-2

Sports	Prompt Setting	Easy Single-hop (%)	Hard Single-hop Tasks (%)	Easy Multi-hop Tasks (%)	Multi-hop Tasks (%)
American Football	Zero-shot CoT	75	56.25	39.39	21.88
	5-Shot SP	81.25	**71.88**	39.39	28.13
	5-Shot CoT	**84.38**	68.75	**42.42**	**31.25**
Soccer	Zero-shot CoT	77.42	73.33	33.87	22.95
	5-Shot SP	80.65	78.33	37.1	24.59
	5-Shot CoT	**83.87**	**81.67**	**37.1**	22.95
Volleyball	Zero-shot CoT	58.54	42.86	22.73	21.62
	5-Shot SP	73.17	57.14	20.45	18.92
	5-Shot CoT	**75.61**	**59.52**	**27.27**	**21.62**
Basketball	Zero-shot CoT	65.91	56.82	27.27	22.92
	5-Shot SP	61.36	59.09	27.27	**25**
	5-Shot CoT	**65.91**	**59.09**	**29.55**	20.83
Table Tennis	Zero-shot CoT	67.86	48.15	42.86	26.92
	5-Shot SP	71.43	59.26	32.14	**34.62**
	5-Shot CoT	**71.43**	**62.96**	**32.14**	30.77
Tennis	Zero-shot CoT	53.85	42.5	30.77	**20**
	5-Shot SP	53.85	**47.5**	**46.15**	20
	5-Shot CoT	**56.41**	45	38.46	14.29

Table 6: GPT-4 Performance of each task in Level-3

Table 7: Example of assessment angles proposed by experts: basketball assessments angles

Game duration, break times
Number of players in a team, number of substitutes
Jump ball rules at the start
Scoring rules (two-pointers, three-pointers, free throws)
Differentiating between personal fouls, flagrant fouls, and technical fouls
Determining if a player's actions, like traveling or double dribbling, are violations
Rules about fouling out after a certain number of personal fouls
Team foul limits and free throw rules
Number of time-outs allowed per team per quarter
Duration of time-outs
Rules and timings for making substitutions
Shot clock rules (24-second rule)
Backcourt violation and the 8-second rule
Defensive three-second violation
Determining when the ball is considered out of bounds
Deciding which team gets possession after the ball goes out of bounds
Over-and-back violation
Dimensions and markings of a basketball court
Specifications of the basketball, hoop, and backboard
Regulations about uniforms and footwear.
Dealing with interruptions or suspensions (e.g., equipment malfunction, player injuries)
Overtime rules
Handling disputes between players, coaches, and referees
Recording player stats like points, rebounds, assists
Keeping track of team stats like fouls, time-outs
Special rules for the last two minutes of a game
Ball possession rules after free throws
Handling technical fouls, flagrant fouls, and on-court altercations
How to quickly and accurately judge players' positions and actions during a game
How to choose the best observation point and angle based on the game's pace and players' positions
Differentiating between common fouls, flagrant fouls, and technical fouls
Judging whether physical contact between players constitutes a foul
Determining if a player's actions violate game rules (e.g., traveling, double dribbling)
Judging whether the ball has completely crossed the boundary line
Determining which player last touched the ball to decide ball possession
Ensuring the smooth progression of the game and avoiding unnecessary interruptions
Handling unexpected situations during a game, such as player injuries or court issues
Effectively communicating with players and coaches when making calls and explaining decisions
Handling disputes and protests from players and coaches
Ensuring that calls made throughout the game are based on a consistent set of standards
Avoiding biases or external influences on decisions
Managing unexpected situations like player altercations or spectators entering the court
Ensuring the safety and fairness of the game
Technical Gestures and Signals
Using standardized referee gestures and signals to convey decisions accurately
Ensuring that all participants understand and accept the calls
Handling disputes and complaints after the game
Communicating with other referees, players, and coaches for feedback and improvement
Positioning and Movement
Communication and Management
Mental Strength
Physical Fitness
Game Strategy and Techniques
Case Study Analysis
Ethics and Professionalism
Safety and First Aid

Question: The 1932 German football championship Final was played at a stadium that opened in what year?
A) 1912 B) 1928 C) 1930 D) 1932
Answer: B

Question: How many events did the Nordic Combined consist of in the 1948 Olympics? A) Two events B) Three events C) One event D) Four events
Answer: C

Question: Who succeeded David Stern to become the Commissioner of the NBA? A) Richard Parsons B) Adam Silver C) Gary Bettman D) Roger Goodell
Answer: B

Question: Which sport is played on a variable ground ranging from 50x100yd minimum to 100x130yd maximum?
A) Baseball B) Association Football (Soccer) C) Basketball D) Volleyball
Answer: B

Question: In American Football, how many points does a touchdown score?
A) Six B) Three C) Four D) Five
Answer:

Table 8: 5-Shot Prompt for Few-Shot Prompting in Level-1 Experiment

Q: The 1932 German football championship Final was played at a stadium that opened in what year?
A) 1912 B) 1928 C) 1930 D) 1932
Answer: Choices A, C, D are wrong since these years are irrelevant to the stadium where German football championship is. Hence, the correct answer is B.

Q: How many events did the Nordic Combined consist of in the 1948 Olympics?
A) Two events B) Three events C) One event D) Four events
Answer: In 1948 Olympics, the Nordic Combined consisted of only one event. Hence, the correct answer is C.

Q: Who succeeded David Stern to become the Commissioner of the NBA? A) Richard Parsons B) Adam Silver C) Gary Bettman D) Roger Goodell
Answer: David Stern served as the Commissioner of the NBA from 1984 until February 1, 2014. Adam Silver succeeded David Stern to become the Commissioner of the NBA. Hence, the correct answer is B.

Q: Which sport is played on a variable ground ranging from 50x100yd minimum to 100x130yd maximum? A) Baseball B) Association Football (Soccer) C) Basketball D) Volleyball
Answer: Choices A, C, D are wrong because their court size is all less the 50*100 yards. Hence, the correct answer is B.

Q: In American Football, how many points does a touchdown score?
A) Six B) Three C) Four D) Five
Answer: Based on the fact of the rules of American football, a touchdown scores 6 points. Hence, the correct answer is A.

Table 9: 5-Shot Prompt for Few-Shot CoT Prompting in Level-1 Experiment

Question: What is the result of a bout when enough rounds have passed after an accidental foul that causes injury?
A) The injured fighter loses B) The fight goes to a decision C) The fight is restarted D) The uninjured fighter is disqualified
Answer: B

Question: What defensive maneuver involves rotating the body to allow an incoming punch to pass harmlessly by?
A) Bobbing B) Blocking C) Slipping D) Clinching
Answer: C

Question: What is the Filipino martial art that includes boxing known as?
A) Karate B) Suntukan C) Taekwondo D) Kung Fu
Answer:B

Question: The "door policy" at events is used to decide:
A) Who will perform at the event B) The theme of the event C) Who will be admitted and at what price D) The duration of the event
Answer: C

Question: Which boxer is NOT widely recognized as one of the best bolo punchers in boxing history?
A) Ceferino Garcia B) Roy Jones Jr. C) Floyd Mayweather D) Sugar Ray Leonard
Answer: C

Table 10: 5-Shot Prompt for Few-Shot Prompting in level-2 Boxing Task Experiment

Q: What is the result of a bout when enough rounds have passed after an accidental foul that causes injury?
A) The injured fighter loses B) The fight goes to a decision C) The fight is restarted D) The uninjured fighter is disqualified
Answer: Choices A and D are incorrect because injuries do not matter for the final fight outcome and Choice C is incorrect because boxing matches are never restarted. Hence, choice B is correct.

Q: What defensive maneuver involves rotating the body to allow an incoming punch to pass harmlessly by?
A) Bobbing B) Blocking C) Slipping D) Clinching
Answer: Slipping rotates the body slightly so that an incoming punch passes harmlessly next to the head. Hence, the correct answer is C.

Q: What is the Filipino martial art that includes boxing known as?
A) Karate B) Suntukan C) Taekwondo D) Kung Fu
Answer: Choices A, C, and D are incorrect as these martial arts are not from the Phillipines and have very specific and distinct moves from boxing. Hence, the correct answer is B.

Q: The "door policy" at events is used to decide:
A) Who will perform at the event B) The theme of the event C) Who will be admitted and at what price D) The duration of the event
A: Choices A, B, and D are incorrect because these options do not involve general admittance. Hence the correct answer is C.

Q: Which boxer is NOT widely recognized as one of the best bolo punchers in boxing history?
A) Ceferino Garcia B) Roy Jones Jr. C) Floyd Mayweather D) Sugar Ray Leonard
Answer: Choices A, B, and D are incorrect because these three are widely known for popularizing and being excellent users of the bolo punch. Hence, the correct answer is C.

Table 11: 5-shot prompt for few-shot CoT prompting in level-2 boxing task experiment

Main Question: Why might a coach call a timeout late in the fourth quarter when the team is on defense and the opposing team is on the third down?
A. To rest the defensive players and prevent a score B. To discuss strategy to force a turnover C. To argue with the referee about a previous play D. To allow a television commercial break
Sub-Question 1: What is the purpose of a timeout in American football?
A. To stop the clock B. To make strategic adjustments C. To replace the football D. To challenge a referee's decision
Sub-Question 2: What can happen on a third down in American football that would prompt a defensive coach to call a timeout?
A) The defense needs to prevent the offense from scoring B) The defense wants to conserve time for their offense C) The offense is likely to punt on the next down D) The offense might attempt a field goal
Answer: In American Football, timeouts are usually called to stop the clock, make lineup or strategy adjustments, or allow players to rest at an important moment. Hence the correct answers to the Main Question are A and B. And the correct answers to Sub-Question 1 are A and B. A pivotal third down late in the fourth quarter could make the difference between the opponent scoring a touchdown, a field goal, or nothing, so this play is very important to potentially prevent a score or decrease the amount scored by the opponent. Additionally, if a score is unavoidable or if a defensive stop is likely but your team is still trailing, a timeout on this play can save time for your team's offense to score in return and potentially take back the lead. Hence the correct answers to Sub-Question 2 are A and B.

Main Question: How do the responsibilities of an American Football team's offensive and defensive coordinators differ during a game?
A) Both design and call plays for the team B) One focuses on scoring strategies while the other focuses on preventing the opponent from scoring C) Both coordinate player substitutions and adjustments on their side of the ball D) One oversees the development of the game plan, while the other implements it during the game
Sub-Question 1: How does an offensive coordinator contribute to a team's performance in a game?
A) By calling offensive plays B) By managing the defense's tactics C) By designing scoring strategies D) By coaching the special teams unit
Sub-Question 2: How does a defensive coordinator contribute to a team's performance in a game?
A) By implementing the head coach's overall strategy B) By calling defensive plays C) By managing the offense's tactics D) By designing strategies to prevent the opponent from scoring
Answer: The Offensive Coordinator and Defensive Coordinator in American Football both design and coordinate plays and strategies as well as decide substitutions and lineup or strategy adjustments in game for their respective sides of the ball. Hence the correct answers to the Main Question are A, B, and C. And the correct answers to Sub-Question 1 are A and C. And the correct answers to Sub-Question 2 are B and D.

Main Question: Why might a high school football coach enforce strict adherence to tackling techniques during practice sessions?
A) To ensure the team wins more games. B) To minimize the risk of injury to players. C) To make practices more challenging. D) To comply with state sporting regulations.
Sub-Question 1: What is one of the primary concerns that safe tackling techniques aim to address during football games?
A) Improving player coordination. B) Reducing the risk of concussions. C) Enhancing the entertainment value of the game. D) Increasing the speed of the players.
Sub-Question 2: Why are concussions a significant concern in contact sports like American football?
A) They can lead to long-term health issues. B) They often require expensive equipment to diagnose. C) They result in penalties during the game. D) They are not detectable until days after the game.
Answer: Strict tackling techniques in American Football are typically used to prevent injuries, primarily concussions from helmet-to-helmet contact. Although sport regulations typically ban helmet-to-helmet contact, these regulations are not typically very strict about tackling form, so a coach enforcing strict tackling technique is not likely to be for following regulations. Hence the correct answer to the Main Question is A. And the correct answer to Sub-Question 1 is B. Concussions are a large concern because of the potential long-term and severe issues that can come from them. Hence the correct answer to Sub-Question 2 is A.

Main Question: What play should the coach call next if they need to maintain possession to run down the clock at the end of the 4th quarter, considering the team is currently ahead, it's 3rd down with 2 yards to go, and the opposing team still has 2 timeouts?
A) A deep passing play B) A quarterback kneel C) A short-yardage running play D) A punt
Sub-Question 1: What is the primary objective for the team that is ahead near the end of the 4th quarter?
A) To score as quickly as possible B) To maintain possession and run down the clock C) To allow the other team to score D) To stop the game clock
Sub-Question 2: On a 3rd down with 2 yards to go, which type of play is most likely to achieve a first down and continue possession?
A) A deep passing play B) A quarterback kneel C) A short-yardage running play D) A punt
Answer: In order to run down the clock, American Football teams typically run the ball or do a quarterback kneel because incomplete passes will stop the clock. In a situation where there is a 3rd down with 2 yards to go and the opponent has two timeouts, a qb kneel will not help get a first down to continue running off the clock. Hence the correct answer to the Main Question is C. A team that is ahead will want to run down the clock and maintain their lead as best as possible. Hence the correct answer to Sub-Question 1 is B. On a 3rd down with 2 yards to go, a short run play or short pass play will be most likely to acheive a first down. Hence the correct answer to Sub-Question 2 is C.

Main Question: Why might a defensive coordinator instruct a linebacker to shift his positioning from a standard 4-3 defense alignment to a position directly over the opposing team's tight end before the snap in a 3rd-and-long situation?
A) To better defend against a possible run play to the outside. B) To apply pressure on the quarterback by blitzing through the gap. C) To cover the tight end, anticipating a pass in a likely passing down. D) To confuse the offensive line's blocking scheme.
Sub-Question 1: Why would a defensive coordinator anticipate a pass in a 3rd-and-long situation?
A) The offensive team needs to gain a significant number of yards. B) Running plays are more effective in long-yardage situations. C) The defense has been successful in stopping the run all game. D) The offensive team's star running back is injured.
Sub-Question 2: Why would a linebacker be tasked with covering the tight end instead of a defensive back in this scenario?
A) The linebacker is typically faster than the defensive back. B) The tight end is a less skilled receiver than the wide receivers. C) The defensive back is occupied with covering a wide receiver. D) The tight end is known for exceptional blocking rather than receiving.
Answer: In American Football, linebackers lining up directly over a player typically means they will be covering them in the case they run a passing route. To blitz or contain run plays, linebackers will usually line up over a gap, and to confuse the offensive line they will usually fake blitzes. Hence the correct answer to the Main Question is C. In a 3rd-and-long situation, the offense has a lot of space to make up to get a first down. The most likely plays to gain large yardages in a single play are deeper passing plays, though they are more risky. Hence the correct answer to Sub-Question 1 is A. Tight ends are typically check-down passing options, meaning the primary option wide receivers are usually more important to have good coverage on. Hence defensive backs will usually cover wide receivers or more important zones, leaving the less important tight end receiver to be covered by the linebacker who is not as good in pass coverage. Hence the correct answer to Sub-Question 2 is C.

Table 12: 5-Shot COT Prompt for Few-shot Prompting in level-3 American Football Experiment

Main Question: How might the officiating crew determine that a double foul scenario occurred during a down where a defensive pass interference was also suspected?
A) By reviewing if both teams committed fouls independent of each other during the same down. B) By assessing if the defensive team committed pass interference after the offense had already committed a holding foul. C) By identifying if the offensive team committed a false start before the defensive player interfered with a receiver. D) By determining if the defensive pass interference occurred simultaneously with an offensive holding.
Sub-Question 1: How can the officials confirm that the defensive team committed pass interference?
A) By checking if the defender made contact with the receiver before the ball was touched. B) By determining if the defender was playing the ball and not the receiver. C) By observing if the receiver was beyond the line of scrimmage when contact was made. D) By ensuring that the pass was catchable and the contact impeded the receiver's opportunity to catch the ball.
Sub-Question 2: How would the officials ascertain that the offensive team committed a holding foul?
A) By establishing if an offensive player used his hands outside the defender's frame to restrict movement. B) By verifying if the offensive player's hands were inside the defender's shoulders while the defender was attempting to move past. C) By determining if the offensive player tackled the defender to the ground. D) By observing if the offensive lineman maintained a blocking position without grabbing the defender's jersey or pads.
Correct Answers:
Main Question: A and B
Sub-Question 1: A, B, and D
Sub-Question 2: A, C, and D
GPT-4 Answer: In American Football, a double foul scenario occurs when both teams commit fouls independent of each other during the same down. Hence the correct answer to the Main Question is A. Defensive pass interference is confirmed when the defender makes contact with the receiver before the ball is touched, and the pass was catchable and the contact impeded the receiver's opportunity to catch the ball. Hence the correct answers to Sub-Question 1 are A and D. A holding foul by the offensive team is ascertained when an offensive player uses his hands outside the defender's frame to restrict movement. Hence the correct answer to Sub-Question 2 is A.
Explanation:
Main Question: GPT-4 correctly understands that separate fouls are independently reviewed, but fails to reason that in this dual foul scenario, this potential defensive pass interference could have occurred after an offensive holding penalty. This is a Logical Reasoning Error.
Sub-Question 1: GPT-4 fails to include the fact that incidental contact when a defender attempts to play the ball does not constitute pass interference in it's reasoning. This is a Logical Reasoning Error.
Sub-Question 2: GPT-4 shows clear understanding of the rules regarding offensive holding, but fails to reason that tackling a defensive player also follows this definition and that analyzing the inverse of a definition logically follows as analyzing the definition. This is a Logical Reasoning Error.

Question: In a regular basketball game, which of the following options correctly represents the number of players in a team on the court and the number of substitutes that can be made?
A) 5 players on the court, 7 substitutes B) 6 players on the court, 5 substitutes C) 7 players on the court, 3 substitutes D) 4 players on the court, 6 substitutes
Correct Answers: A
GPT-4 Answer: In a regular basketball game, each team has five players on the court at a time. The number of substitutes can vary depending on the league and level of play, but there is typically no limit on the number of substitutions that can be made during a game. Therefore, none of the options provided are correct.
Explanation:
GPT-4 misunderstands the context of what "substitutes" are referring to. Though it is correct that a team can make infinite substitutions in a basketball game, "substitutes" in this question are referring to the substitute players a team currently has on the bench. This is a Contextual Misinterpretation Error.

Table 13: GPT-4 5-shot CoT Incorrect Outputs and Error Analysis

Question: Why might a mediator be necessary during a football match?
A) To ensure the team wins more games. B) To minimize the risk of injury to players. C) To make practices more challenging. D) To comply with state sporting regulations.
Correct Answers: B
GPT-4 Answer: A mediator, in this case, the referee, is necessary during a football match to ensure the players follow the rules of the game and to resolve any disputes or conflicts that may arise between players or teams. Hence, the correct answers are A and B.
Explanation:
GPT-4 misunderstands the word mediator. By definition a mediator is an intermediary party in a conflict between 2 or more other parties. A referee will not need to be a "mediator" for any of their other responsibilities. This is a Conceptual Misunderstanding Error

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Question: During the final set of a Grand Slam tennis match, Player A decided to adopt a more aggressive playing style, frequently rushing to the net after his serve. Why might Player A have made this strategic decision?
A) Player A noticed that Player B struggles to return low volleys effectively. B) Player A wanted to use his strong net game to put pressure on Player B. C) Player A was trying to conserve energy by reducing the length of the rallies. D) Player A was attempting to intimidate Player B by showing off his physical prowess.
Correct Answers: A, B, and C
GPT-4 Answer: In tennis, a player might adopt a more aggressive playing style and frequently rush to the net after serving to put pressure on the opponent, exploit the opponent's weakness in returning low volleys, reduce the length of the rallies to conserve energy, or to intimidate the opponent. Hence the correct answers are A, B, C, and D.
Explanation:
GPT-4 either misunderstands why an aggressive playing style is used in tennis or confuses the concepts of intimidation and applying pressure to an opponent. In non-contact sports such as tennis, aggressive playstyles are typically not used for intimidation, though they are frequently used to put pressure on an opponent to make them cause errors or break down mentally. Thus GPT-4 may be confusing the concepts of intimidation and applying pressure to cause the opponent to make errors. This is a Conceptual Misunderstanding Error.

Table 14: GPT-4 5-shot CoT Incorrect Outputs and Error Analysis

Figure 5: Proportional Distribution of Question Categories Across Sports. This bar chart illustrates the comparative distribution of 'Rule or Strategy' and 'History or Fact' questions in various sports, highlighting the dominant category in each sport and indicating the variability in focus across different sports disciplines.