

XiHeFusion: Harnessing Large Language Models for Science Communication in Nuclear Fusion

Xiao Wang, Qingquan Yang*, Fuling Wang, Qiang Chen, Wentao Wu, Yu Jin, Jingtao Jiang, Liye Jin, Bo Jiang, Dengdi Sun, Wanli Lv, Meiwén Chen, Zehua Chen, Guosheng Xu, Jin Tang*

Abstract—Nuclear fusion is one of the most promising ways for humans to obtain infinite energy. Currently, with the rapid development of artificial intelligence, the mission of nuclear fusion has also entered a critical period of its development. How to let more people to understand nuclear fusion and join in its research is one of the effective means to accelerate the implementation of fusion. This paper proposes the first large model in the field of nuclear fusion, XiHeFusion, which is obtained through supervised fine-tuning based on the open-source large model Qwen2.5-14B. We have collected multi-source knowledge about nuclear fusion tasks to support the training of this model, including the common crawl, eBooks, arXiv, dissertation, etc. After the model has mastered the knowledge of the nuclear fusion field, we further used the chain of thought to enhance its logical reasoning ability, making XiHeFusion able to provide more accurate and logical answers. In addition, we propose a test questionnaire containing 180+ questions to assess the conversational ability of this science popularization large model. Extensive experimental results show that our nuclear fusion dialogue model, XiHeFusion, can perform well in answering science popularization knowledge. The pre-trained XiHeFusion model is released on <https://github.com/Event-AHU/XiHeFusion>.

Index Terms—Plasma, Large Language Model, Foundation Model, Nuclear Fusion, Science Communication

I. INTRODUCTION

ALTHOUGH there are already various forms of energy such as solar, wind, coal, oil, and natural gas, energy issues have always been one of the key problems troubling humanity, such as long renewable cycles and severe environmental pollution. With the rapid development of physics, humans have mastered nuclear energy and successfully applied nuclear fission technology to power generation. However, nuclear fission easily produces waste with nuclear radiation, and the raw materials are expensive, therefore, nuclear fission is not an ideal future energy source. Nuclear fusion offers several key advantages over nuclear fission, e.g., abundant fuel, high energy yield, reduced waste, environmental safety, inherent safety, and non-proliferation. Despite these benefits, technical hurdles remain, including achieving and maintaining

• Xiao Wang, Fuling Wang, Qiang Chen, Wentao Wu, Yu Jin, Jingtao Jiang, Liye Jin, Bo Jiang, Dengdi Sun, Wanli Lv, and Meiwén Chen are with Anhui University, Hefei 230601, China. (email: xiaowang@ahu.edu.cn)

• Qingquan Yang, Guosheng Xu are with the Institute of Plasma Physics, Chinese Academy of Sciences, Hefei, China.

• Zehua Chen is with the Department of Computer Science and Technology, Tsinghua University, Beijing 100190, China.

* Corresponding Author: Qingquan Yang, Jin Tang (email: yangqq@ipp.ac.cn, tangjin@ahu.edu.cn)

the extreme conditions for fusion and efficiently converting fusion energy into electricity.

To address these challenges, many countries around the world have established or are constructing nuclear fusion devices to explore this future energy source. Specifically, China has built the EAST large scientific facility, the United States has constructed the DIII-D, the European Union has established JET, and there is the multi-nationally constructed ITER facility, among others. Currently, nuclear fusion research is still primarily focused on scientific experimentation and physical model design. Although significant progress has been made in the past, there is still a long way to go before achieving a truly positive energy output.

In order to help more people understand nuclear fusion, especially the basic concepts, and working principles, and to enable newcomers to get up to speed in this field more quickly, this paper proposes a novel conversational large language model for nuclear fusion, termed **XiHeFusion**. To pre-train this large language model, we collected multi-sourced knowledge on nuclear fusion as shown in Table I, including CommonCrawl, CNKI (China National Knowledge Infrastructure), eBooks, arXiv, and dissertation. We then used the large model DeepSeek V3 [1] to process this information into more than 1 million question-answer pairs (about 370 million tokens), which served as the corpus for training the large model. We conducted supervised fine-tuning on a foundation model Qwen2.5-14B [2]. To enhance the model’s reasoning capabilities and provide more detailed and logical responses, we further explored the Chain-of-Thought (CoT) [3] technique to improve the model’s question-answering abilities. Additionally, we invited domain experts to prepare test questionnaires which contain 184 questions to assess the question-answering capabilities of the XiHeFusion, as shown in Fig. 3.

The features of our proposed XiHeFusion can be summarized as follows:

- **[First Nuclear Fusion LLM]** It is the first large language model developed for the plasma nuclear fusion domain, effectively supporting science popularization in nuclear fusion to enhance the public’s understanding of this field.
- **[Open Source & Bilingual Dialogue]** The XiHeFusion is fine-tuned based on open-source large model Qwen2.5-14B [2], which supports bilingual dialogue in both Chinese and English, and demonstrates strong generalization.
- **[Fusion Knowledge-enhanced Training]** To enable the large language model to provide more professional responses to questions in the fusion field, we have collected a large-scale dataset from multiple sources to support self-supervised

training.

- **[Logical Dialogue]** The use of Chain-of-Thought (CoT) reasoning techniques ensures that the XiHeFusion large model can provide more detailed and logically thought-out answers.
- **[New Test Questionnaire]** We have developed a science popularization quiz on nuclear fusion, which examines fusion knowledge from multiple perspectives. It can effectively test the large model's mastery of domain knowledge.

The rest of this paper is organized as follows: We introduce the related works on the Large Language Model, Nuclear Fusion, and Chain-of-Thought in Section II. After that, we introduce the XiHeFusion large language model in Section III, with a focus on data collection and pre-processing, network architecture, and optimization. The introduced questions for the evaluation are described in Section IV. We introduce the experiments in Section V and focus on comparing XiHeFusion with other large language models, visualization and analysis of question-answer cases, and limitation analysis. We conclude this paper in Section VI.

II. RELATED WORKS

In this section, we will review the related works on the Large Language Model, Nuclear Fusion, and Chain-of-Thought. More related works can be found in the following surveys [4] and paper list¹.

A. Large Language Model

LLMs have demonstrated remarkable language understanding and the ability to handle complex tasks through text generation [5]–[7]. More in detail, GPT-3.0 [8], developed by OpenAI, was the first large language model to achieve industrial success, with 175 billion parameters enabling it to excel in natural language tasks. Its success spurred rapid advancements in large language models, leading to improved versions like GPT-4 [9], which offers stronger reasoning and broader knowledge. OpenAI o1² gained attention for its exceptional complex reasoning, leveraging reinforcement learning and chain-of-thought training to surpass human PhD-level performance on the GPQA benchmark [10] for physics, biology, and chemistry. LLaMA [11] adopts a *small models, large data* approach, producing high-performance models. Llama-1 [11], offers four parameter sizes: 7B, 13B, 30B, and 65B, was trained on 1T+ tokens, while Llama-2 [12] expanded to 2T tokens, doubled context length to 4,096, and introduced GQA. Llama-3 [13] supports 8K contexts, uses a 128K vocabulary, and trains on over 15T tokens, delivering state-of-the-art performance with improved inference, code generation, and instruction-following capabilities. Gemini [14], Google's most advanced AI model, comes in three versions (Ultra, Pro, Nano) and supports diverse scenarios, focusing on complex reasoning, multimodal understanding, and coding. Claude³, developed by Anthropic, is a GPT-like AI model prioritizing safety,

reliability, and alignment, with multiple improved versions released.

On the other hand, Qwen [15] has consistently focused on the technical development of foundational models, advancing from its initial version to the latest 2.5 release. Compared to the previous version, the Qwen2.5 [2] demonstrates significant improvements in comprehension, logical reasoning, instruction following, and coding capabilities, with its Chinese language proficiency continuing to lead the industry. DeepSeek-V3 [1] has 671 billion parameters, with 37 billion activated, offering performance on par with top models in knowledge-based Q&A, long-text processing, code generation, and mathematical reasoning, while being more cost-efficient. The Spark LLM⁴ by iFlytek excels in natural language processing for customer service, education, and healthcare. Tiangong⁵ is China's first dual-trillion-parameter model, outperforming ChatGPT in tasks like content creation, logical reasoning, and mathematical computation, providing efficient support for intelligent search, recommendation systems, and virtual assistants. Other LLMs, such as Baichuan [16], Ernie Bot [17], Doubao⁶, SenseChat⁷, and Bing Chat⁸, each have their unique features, covering a wide range of capabilities from multi-modal processing and code generation to conversational interactions. They are driving the deep application of artificial intelligence in various fields and accelerating the iteration and innovation of technology.

B. Nuclear Fusion

With the advancement of nuclear fusion, deep learning has found increasing applications in nuclear fusion research, aiding in solving complex physical problems and optimizing experimental processes, such as Q-distribution prediction [18], [19], plasma state prediction, Tokamak control optimization, and plasma diagnostics. Yamaguchi et al. [20] uses a genetic algorithm to optimize the control points of three-dimensional B-spline curves, to solve the problem of designing and optimizing external coils for stellarators. Hu et al. [21] solve the problem of real-time disruption prediction and mitigation in high-density discharges of the EAST tokamak by developing a random forest-based real-time disruption predictor (DPRF), improving the accuracy of disruption alarms and reducing disruption damage. Schmidt et al. [22] employ a deep convolutional neural network to reconstruct fast-ion velocity distributions from fast-ion loss detectors and imaging neutral particle analyzers (INPAs). PlaNet [23] solves the problem of fast and accurate plasma equilibrium and separatrix reconstruction using a physics-informed deep learning approach. Inoue et al. [24] use a Support Vector Machine (SVM) combined with redundant logic and an adaptive voltage allocation scheme to mitigate the risks of asymmetric heat loads on the first wall and electromagnetic loads on conductive materials caused by Vertical Displacement Events (VDEs). SExFC [25] integrates

¹https://github.com/Event-AHU/AI_for_Controlable_Nuclear_Fusion/blob/main/Survey_Paper_list.md

²<https://openai.com/index/learning-to-reason-with-langs/>

³<https://claude.ai>

⁴<https://xinghuo.xfyun.cn/>

⁵<https://www.tiangong.cn/>

⁶<https://www.doubao.com/chat/>

⁷<https://chat.sensetime.com/>

⁸<https://copilot.microsoft.com/>

the recurrent neural network (RNN) algorithm and utilizes the Gated Recurrent Unit (GRU) for iterative prediction of flux evolution based on radial profiles. Zhang et al. [26] use YOLO (You Only Look Once) [27]–[29] to identify Ion Cyclotron Emission (ICE) in HL-2A discharges, aiming to enhance real-time fast ion diagnostics for magneto hydro dynamics (MHD) instabilities in fusion plasmas. Sun et al. [30] develop a multi-layer perceptron (MLP) neural network model as a surrogate for kinetic equilibrium fitting (EFITs) and investigate the impact of different diagnostic data and machine actuator controls on the accuracy of equilibrium reconstruction. Wan et al. [31] applies a transformer-based model to solve the real-time reconstruction of the last closed flux surface (LCFS) in the experimental advanced superconducting tokamak (EAST).

Some researchers adopt CNNs [32]–[37], MLPs [36]–[41], or LSTMs [41]–[43] as their backbone networks to tackle various key challenges in fusion research. An increasing number of scholars are applying artificial intelligence (AI) methods to the field of nuclear fusion, and AI is expected to accelerate the commercialization of fusion energy.

C. Chain-of-Thought

Chain of Thought (CoT) [3] is a widely used reasoning approach in the field of artificial intelligence, particularly in tackling complex reasoning tasks. The core idea of CoT is to break down the problem-solving process into a series of logically coherent and interconnected steps, enabling the model to progressively arrive at the final answer. Wei et al. [3] were the first to introduce CoT prompting to large language models, aiming to enhance their performance on complex reasoning tasks. Feng et al. [44] explained how CoT enhances the ability of large language models (LLMs) to solve complex tasks and validated its effectiveness. Kojima et al. [8] simulated the CoT process and addressed the complex reasoning task capabilities of LLMs with few-shot examples by using the simple prompt "Let's think step by step". Hao et al. [45] introduce the Chain of Continuous Thought (Coconut), which shifts reasoning from the language space to the latent space, addressing the efficiency and performance challenges in complex reasoning tasks due to linguistic limitations. Works such as [46]–[49] aim to explain how CoT works. Meanwhile, [50]–[54] use CoT prompting to fine-tune LLMs, enhancing their capabilities in specific fields. We also aim to make LLMs experts in the field of nuclear fusion through the CoT approach, providing support to nuclear fusion researchers.

III. XIHEFUSION MODEL

In this section, we will first introduce the data collection and pre-processing, then, focus on details of network architecture, chain-of-thought reasoning, and optimization.

A. Data Collection and Pre-processing

In this paper, we construct a large-scale nuclear fusion corpus dataset, including 1.2 million question-answer pairs. Specifically, during the data collection phase, we ensure the dataset's diversity and high quality by collecting data through

TABLE I
THE DISTRIBUTION OF DIFFERENT CATEGORIES OF TRAINING DATA.

Source	Sampling Proportion	Disk Size
CommonCrawl	73%	28.9GB
CNKI	4%	1.49GB
eBooks	3%	1.44GB
arXiv	10%	3.96GB
Dissertation	10%	3.94GB

various channels, including general web pages, electronic libraries, and academic paper databases. As shown in Table I, we present the data sources and their proportions. Among them, 73% comes from web crawlers on general websites, 24% comes from academic paper databases, and the remaining data comes from electronic libraries.

Through the above process, we collect a large number of books, documents, and academic papers related to nuclear fusion. To adapt to the model training, we preprocess these data and extract question-answer pairs that can be used for large language model training. As depicted in Fig. 1, we input the gathered nuclear fusion-related data in batches into the large language model (DeepSeek V3 [1] is adopted in our implementation), which then autonomously produces question-answer pairs. To align with the interaction process between users and the LLM, each question-answer pair includes five components: instruction, input, output, system prompt, and history, where the input, system prompt, and history can be empty. More in detail, the instruction prompt is *"You are a helpful assistant. According to the language of the input text, generate highly professional and technical question-answer pairs about nuclear fusion for advanced educational purposes. Ensure that the questions are specific, research-oriented, and cover critical aspects or challenges of nuclear fusion, such as plasma confinement, energy efficiency, or tokamak design. If the text is in Chinese, generate Q&A pairs in Chinese; if the text is in English, generate Q&A pairs in English. Ensure the format is consistent: Q: <question> A: <answer>."*. The generated output question-answer pairs are illustrated at the bottom of Fig. 1. This dataset serves as the foundation for constructing a comprehensive and interactive nuclear fusion knowledge system. It facilitates tasks such as question-answering, summarization, and knowledge exploration in the domain.

B. Network Architecture

Given the question and instruction prompt, we first embed them into token representations X_q and X_p . Then, these tokens are fed into the XiHeFusion model for answer generation. XiHeFusion is developed based on the large language model Qwen2.5-14B [2] which employs the Transformer decoder architecture with 48 Transformer layers (40 attention heads), as shown in Fig. 2. The self-attention is their core module which models the global relations between the input tokens:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V, \quad (1)$$

where the Q , K , and V are obtained from input tokens X , $\sqrt{d_k}$ is the dimension of processed tokens. It supports a context

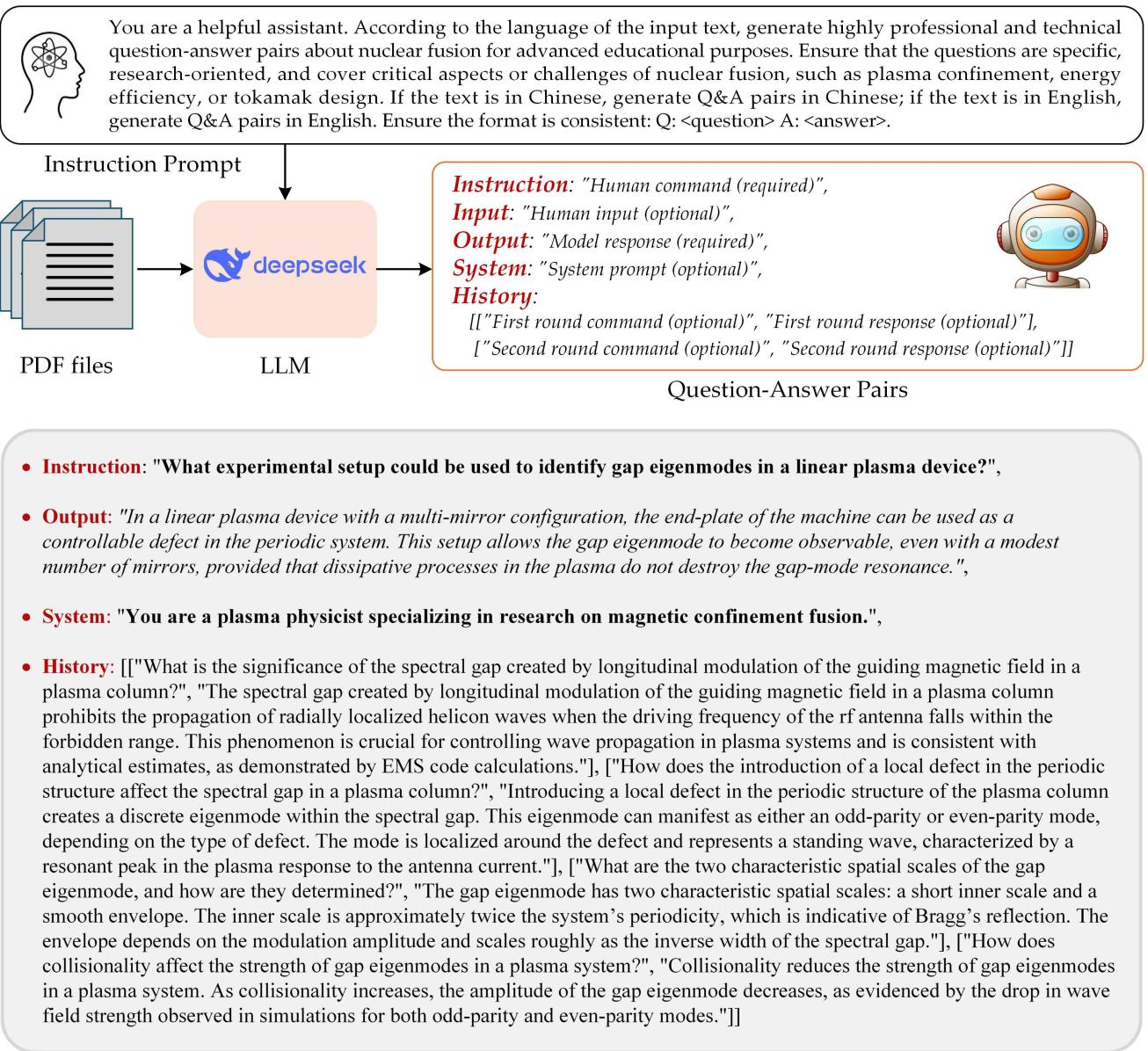


Fig. 1. (Top) The pipeline of question-answer training data generation using a large language model; (Bottom): A question-answer sample for training.

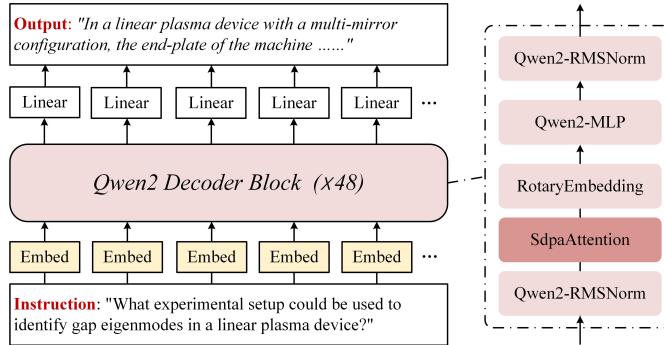


Fig. 2. An overview of the network architecture of XiHeFusion.

length of 128K and a generation length of 8K, significantly enhancing its ability to process long sequences and repre-

sent multi-dimensional information. To further optimize performance, XiHeFusion integrates several advanced technologies, including Grouped Query Attention (GQA) for efficient KV cache utilization and improved computational efficiency, SwiGLU activation function for enhanced nonlinear modeling capabilities, Rotary Position Encoding (RoPE) to improve adaptability to sequences of varying lengths, QKV bias to strengthen context information capture, and RMSNorm (pre-normalization) to stabilize gradient flow and ensure training robustness. These integrated technologies enable XiHeFusion to excel in sequence processing, context understanding, and knowledge representation, effectively handling various natural language processing tasks and meeting complex demands across different domains. The model is licensed under the Apache 2.0 License, allowing users to freely use, modify, and distribute it while adhering to the license terms.

To further enhance the performance of the obtained answers,

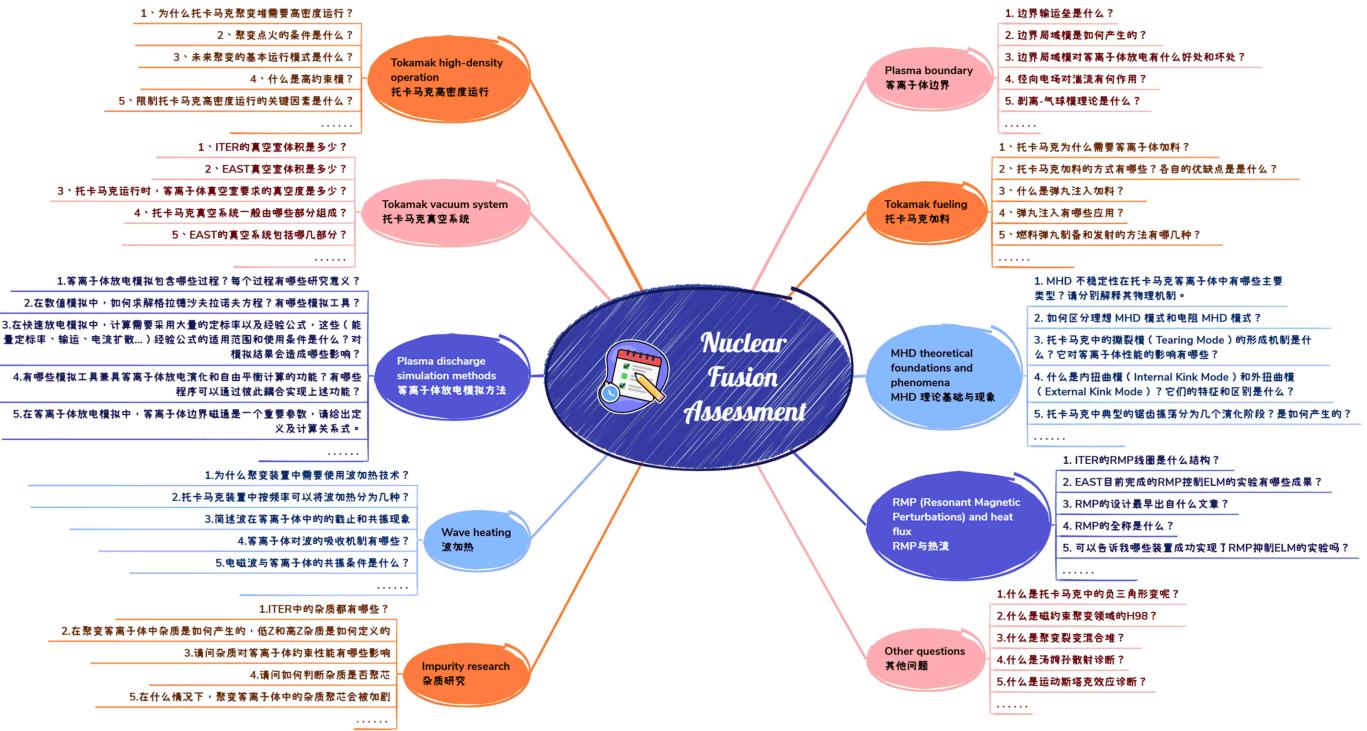


Fig. 3. An overview of our proposed nuclear fusion assessment.

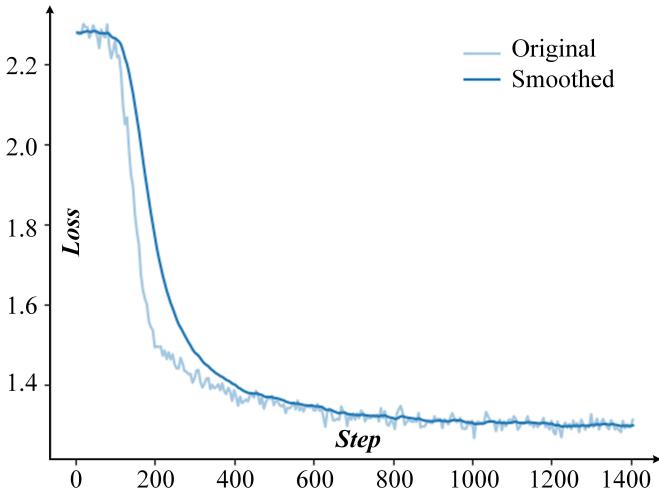


Fig. 4. The training loss decreases with the number of iterations.

we adopted Chain of Thought (CoT) technology that can improve reasoning ability, making the results more detailed and logically structured. As shown in Fig. 5, we want XiHeFusion to answer the questions as comprehensively as possible from the following aspects: 1). *Background introduction of the question*. 2). *Definition of terms and case analysis*. 3). *Multi-angle reasoning and exploration of alternative solutions*. 4). *Verification of actual cases and real-world applications*. 5). *Summary and interactive guidance*. In addition, we also provide eight question-answer samples as the prompt to guide the language generation. One example of the eight prompts is illustrated in Fig. 6. Through the guidance of this CoT technol-

ogy, XiHeFusion's ability to generate high-quality answers has been significantly improved, as evidenced by the case analysis in our experiments.

C. Optimization

Supervised Fine-Tuning (SFT) is a critical phase in XiHeFusion's training process, particularly for improving its performance in professional domains such as nuclear physics, plasma physics, and nuclear fusion. Several optimization strategies were employed for specific tasks. To enhance long-text generation, a dedicated dataset was developed, supplemented by back-translation techniques to generate high-quality query pairs. These pairs were further refined using the DeepSeek model, ensuring semantic and logical consistency. For mathematical and physical formula derivation, Qwen2.5-Math reasoning chain data was introduced to simulate step-by-step reasoning processes, significantly improving performance in formula-related tasks. Logical reasoning capabilities were strengthened by constructing datasets that cover deductive, inductive, analogical, causal, and statistical reasoning, enabling the model to handle complex reasoning tasks systematically.

Furthermore, recognizing that much of the high-quality literature in nuclear physics is primarily in English, the model's cross-language transfer capabilities were specifically enhanced. Rigorous evaluations of semantic consistency between multilingual responses and original content ensured that XiHeFusion could accurately understand and generate domain-specific content in multiple languages, meeting the demands of cross-language knowledge retrieval. With these architectural advancements and optimization strategies, XiHeFusion achieves notable improvements in long-text generation,

You are a professional expert in controlled nuclear fusion and artificial intelligence. Based on the language and context of the input text, generate highly technical and professional questions and answers, focusing on the research of controlled nuclear fusion, especially for advanced educational purposes. The questions should focus on key aspects or challenges of nuclear fusion, such as plasma confinement, energy efficiency, tokamak design, etc., covering basic issues in the field, and also involving ongoing research and experimental efforts. Ensure that the questions are specific and delve into the core issues of the field, while also covering the latest developments, theories, and experimental results, step-by-step explanation of key concepts. If the input text is in Chinese, the questions and answers should be in Chinese; if it is in English, the questions and answers should be in English.

You need to answer the questions as comprehensively as possible from the following aspects:

1. Background introduction of the question.
2. Definition of terms and case analysis.
3. Multi-angle reasoning and exploration of alternative solutions.
4. Verification of actual cases and real-world applications.
5. Summary and interactive guidance.

• Multi-level background analysis and limitations hints

Before answering any question, first perform a multi-level analysis of background knowledge to ensure that the user can understand the basic concepts of the relevant field. Especially when dealing with complex problems such as artificial intelligence and nuclear fusion, it is very important to provide clear basic explanations. At the same time, I will explicitly point out the limitations of my large language model, such as not being able to access real-time data and not being able to conduct actual experiments.

• Terminology definition and case analysis

Individually define key terms in the question in detail, and use specific examples or application scenarios to help users understand. This is not just a literal explanation of the terms, but also through examples to demonstrate the application of these terms in the real world. For example, if the question involves “plasma confinement”, you need to explain the physical principles of plasma confinement in detail, and combine experimental equipment such as tokamaks to demonstrate this concept.

• Multi-angle reasoning and alternative solution exploration

When facing specific questions from users, you need to take at least three different methods for reasoning and analyze from multiple angles. Through this comprehensive discussion, you need to ensure that conclusions are drawn from different technical paths or theoretical frameworks, and provide multiple feasible solutions. If there are loopholes or errors in a reasoning process, you need to identify and reflect immediately, and adopt another method for correction.

You need to test and verify all possible solution paths, fully consider their advantages and limitations, and ensure that the information provided is accurate and well-considered. For example, if the question is about how artificial intelligence can assist nuclear fusion, you need to analyze it from different technical paths (such as reinforcement learning, neural networks, and expert systems), and propose potential challenges and improvement methods in each plan.

• Verification of actual cases and real-world applications

Based on theoretical analysis, you need to combine real-world cases or experimental projects to help users understand how these technologies are applied in practice. By analyzing known scientific research projects or industrial applications, demonstrate the effectiveness and actual results of these methods. If there are similar successful cases in reality, I will provide these cases for reference and discuss their application prospects and challenges.

• Summary and interactive guidance

At the end of the answer, you need to summarize the main technical analysis and answers to help users understand the key points of the question. In addition to summarizing, you need to invite users to ask further questions or discuss, thereby establishing a continuous interactive relationship to ensure that users can get more support and help in the process of understanding.

• Important tips

You need to pay special attention to pointing out possible limitations in every step of the reasoning process, maintain transparency and honesty, and avoid giving overly absolute conclusions. At the same time, encourage users to seek more information or conduct actual experiments for verification when they are uncertain. If the question is in Chinese, the answer should also be in Chinese.

Here are some examples of questions:

QA-Prompt 1 QA-Prompt 2 QA-Prompt 3 QA-Prompt 4 QA-Prompt 5 QA-Prompt 6 QA-Prompt 7 QA-Prompt 8

Fig. 5. Illustration of Chain-of-Thought prompting used in XiHeFusion. Please check Fig. 6 for the details of QA-Prompt.

Question: What are the primary objectives of trace tritium experiments in ITER's H-mode plasmas?
(Chinese: ITER的H模等离子体中微量氚实验的主要目标是什么?)

背景介绍

国际热核聚变实验堆（ITER）是目前世界上最大的核聚变研究项目之一，旨在证明核聚变作为大规模能源的可行性。H模式等离子体状态是托卡马克装置中的一种高效能运行模式，它在一定条件下能够显著减少能量损失并提高等离子体的约束性能。氚追踪实验在ITER的H模式等离子体中扮演着重要角色，因为它们对于理解燃料循环、等离子体行为以及核聚变反应的实际效率至关重要。

名词定义与实例分析

****H模式等离子体**：**这是指在特定加热功率之上，托卡马克中的等离子体表现出边缘输运垒的现象，即等离子体边缘处的能量和粒子输运显著减小，从而形成一个高密度、高温的核心区域。

****氚追踪实验**：**这些实验涉及向等离子体注入微量的氚，以监测其在等离子体内的分布、反应率及排出情况。通过这种方式，研究人员可以评估等离子体内燃料的混合程度、燃烧效率及其对装置壁材料的影响。

多角度推理与替代解答探索

1.****燃料管理角度**：**了解氚在等离子体中的行为对于未来核聚变电站的燃料循环设计至关重要。从这个角度看，氚追踪实验帮助科学家优化燃料加载和回收策略。

2.****物理过程探究**：**通过观察氚在等离子体中的扩散和燃烧特性，科学家们能够更好地理解等离子体内部的动力学过程，包括能量传输和粒子输运机制。

3.****工程挑战考量**：**考虑到氚的放射性以及处理时的安全要求，这些实验也测试了ITER系统在实际操作条件下的安全性和可靠性。

实际案例与现实应用验证

一个相关的实例是JET（联合欧洲环形加速器）中的氚-氘实验，该实验提供了关于等离子体行为和能量输出的重要数据。尽管JET并非专门针对H模式进行设计，但它的成果为ITER的设计和操作提供了宝贵的经验教训。

总结与互动式引导

综上所述，ITER中H模式等离子体的氚追踪实验主要目标在于提升我们对燃料循环的理解、优化等离子体性能以及确保设备的安全可靠运行。然而，值得注意的是，由于技术限制，某些实验结果可能需要进一步验证。你是否有关于具体实验细节或理论框架的问题？或者想了解更多关于如何将这些研究成果应用于未来的核聚变电站的信息？

Fig. 6. One of the eight QA samples used in Chain-of-thought prompting.

domain-specific knowledge representation, logical reasoning, and multilingual capabilities, providing robust support for tasks related to nuclear physics and plasma research. As shown in Fig. 4, the loss decreases with the number of iterations smoothly.

IV. NUCLEAR FUSION ASSESSMENT

In order to test the capabilities of our large model, this paper proposes an evaluation test paper in the field of nuclear fusion, consisting of over 180 questions, covering approximately 10 aspects of fusion knowledge, including *RMP and heat flux*, *MHD theoretical foundations and phenomena*, *tokamak fuelling*, *tokamak high-density operation*, *tokamak vacuum system*, *plasma discharge simulation methods*, *wave heating*, *impurity research*, *plasma boundary*, and *other generalized questions*, as shown in Fig. 3. For more details about the nuclear fusion assessment, please check our GitHub page.

V. EXPERIMENTS

A. Case Study

As shown in Fig. 7 and Fig. 8, we give several question-answer pairs returned by our XiHeFusion large language

model. Specifically, for the first question “*what is pellet injection fueling?*” in Fig. 7, our XiHeFusion model first provides a brief explanation. Then, it outlines the key steps of fuel injection in four aspects, as well as the role of pellet injection fueling in nuclear fusion devices. Finally, the model summarizes the aforementioned responses and lists the specific fusion devices that have achieved this goal. As shown in Fig. 9, the XiHeFusion model supports the chat in English well. From the responses of our model, it can be observed that XiHeFusion can help newcomers to the field of nuclear fusion understand the concept more quickly and deeply.

B. Effectiveness of Chain-of-Thought Prompting

As shown in Fig. 10, when asked “*What are the conditions for fusion ignition?*”, The XiHeFusion model with CoT prompt first provides the concept of relevant terms, and then it is analyzed in detail from specific steps and real cases, whereas the answer without CoT prompts seemed too concise. For the other question “*For the neoclassical tearing mode, how can stabilization be achieved through radiofrequency waves, primarily electron cyclotron waves?*”, it is easily noticeable

Question: 什么是弹丸注入加料?

弹丸注入加料 (Pellet Injection) 是一种在核聚变装置中向等离子体中引入燃料 (如氘或氚) 的常用方法。这种方法通过将固体燃料弹丸以高速注入等离子体中, 使其在等离子体中迅速蒸发, 从而为等离子体提供额外的燃料。弹丸注入加料的主要目的是提高等离子体的密度, 确保核聚变反应的持续进行, 并维持等离子体的稳定性。

弹丸注入加料的关键步骤包括:

1. **弹丸制造**: 弹丸通常由固态氘或氚制成, 其形状和尺寸经过精确控制, 以确保注入过程中能够有效蒸发。
2. **弹丸加速**: 弹丸通过高速气流或电磁力加速, 使其达到足够的速度, 以便穿透等离子体的边界层。
3. **弹丸注入**: 弹丸通过专门设计的注入器注入到等离子体中, 注入器需要精确控制弹丸的注入位置和速度, 以确保弹丸能够均匀分布并蒸发在等离子体中。
4. **弹丸蒸发**: 弹丸在等离子体中迅速蒸发, 释放出燃料分子, 增高等离子体的密度, 从而提高聚变反应的效率。

弹丸注入加料在核聚变装置中的作用:

1. **提高等离子体密度**: 弹丸注入可以显著提高等离子体的密度, 确保聚变反应的持续进行。
2. **维持等离子体稳定性**: 通过定期注入燃料, 可以防止等离子体密度下降, 从而维持等离子体的稳定性。
3. **优化能量增益**: 弹丸注入可以优化等离子体的能量增益, 提高核聚变反应的效率。
4. **控制等离子体杂质**: 弹丸注入可以减少等离子体中的杂质, 提高等离子体的纯净度, 从而减少对聚变反应的负面影响。

弹丸注入加料技术是核聚变研究中的一个重要工具, 它能够有效解决等离子体燃料补充的问题, 提高核聚变装置的性能和稳定性。目前, 许多核聚变实验装置, 如EAST和JET, 都在广泛使用弹丸注入加料技术来优化等离子体的燃料供应和反应性能。

Question: AI在托卡马克领域有哪些应用?

AI在托卡马克领域有哪些应用?

人工智能 (AI) 在托卡马克领域有多种应用, 包括优化等离子体控制、故障诊断、实验数据分析和实时监控。以下是AI在托卡马克领域的几个关键应用:

1. **等离子体控制优化**:
 - **反馈控制**: AI技术 (如强化学习和神经网络) 用于开发先进的等离子体控制算法, 以实时调整磁场配置、加热功率和电流驱动, 从而保持等离子体的稳定性和性能。
 - **模式识别**: AI系统能够识别等离子体中的不稳定性模式 (如锯齿不稳定性、边缘局部模式ELMs), 并提前预测其发生, 从而采取预防措施。
 - **优化算法**: 通过AI优化算法, 研究人员能够找到最佳的等离子体运行参数组合, 以实现更高的能量增益和更长的约束时间。
2. **故障诊断与预测**:
 - **故障检测**: AI算法可以分析托卡马克运行中的大量数据, 识别潜在的故障模式, 并提前发出警报, 防止设备损坏。
 - **异常检测**: AI系统能够识别等离子体行为中的异常, 从而及时调整运行参数, 避免事故的发生。
3. **实验数据分析**:
 - **数据处理**: AI技术能够处理和分析大量的实验数据, 从中提取有用的信息, 帮助研究人员理解等离子体的行为和演化。
 - **模式识别**: AI系统能够识别等离子体中的模式和趋势, 为未来的实验设计提供参考。
4. **实时监控与诊断**:
 - **传感器数据融合**: AI技术能够融合来自多个传感器的数据, 实时监控等离子体的状态, 并提供实时诊断信息。
 - **图像处理**: AI系统能够分析托卡马克中的图像数据, 识别等离子体边缘的行为和不稳定性, 从而优化控制策略。
5. **虚拟仿真实验**:
 - **模拟与预测**: AI技术能够模拟等离子体的行为, 预测实验结果, 并为未来的实验设计提供指导。
 - **优化实验方案**: 通过AI优化算法, 研究人员能够设计出更有效的实验方案, 以最大限度地提高实验的成功率和数据质量。
6. **数据分析与挖掘**:
 - **数据挖掘**: AI技术能够挖掘等离子体实验中的隐藏信息, 帮助研究人员发现新的物理现象和规律。
 - **数据可视化**: AI系统能够将复杂的数据转化为易于理解的可视化图表, 帮助研究人员更好地理解和解释实验结果。

这些应用不仅提高了托卡马克实验的效率和准确性, 还为未来的聚变能源开发提供了重要的技术支持。AI技术在托卡马克领域的应用前景广阔, 未来的研究将继续探索更多创新的解决方案, 以推动聚变技术的发展。

通过AI技术, 托卡马克领域的研究者能够更好地理解和控制等离子体的行为, 从而实现更高效的核聚变反应。如果您对AI在托卡马克领域的具体应用有任何疑问或需要进一步的信息, 请随时提问。

Fig. 7. Case study #1. Chat in Chinese.

Question: 简述波在等离子体中的截止和共振现象

在等离子体中，波的传播受到多种物理现象的影响，包括截止和共振现象。这些现象对于理解和控制等离子体的行为至关重要，尤其是在核聚变装置中。以下是对这些现象的简要说明：

截止现象

截止现象指的是在特定频率下，波的传播会因为等离子体的密度或温度梯度而被抑制。在等离子体中，电磁波的传播会受到等离子体频率和热能的影响，从而产生截止频率。例如，当波的频率接近或低于等离子体的朗道阻尼频率时，波的传播会受到抑制，导致能量无法有效地传递到等离子体中。

共振现象

共振现象指的是波与等离子体中的粒子相互作用，导致能量在波和粒子之间发生交换。这种交换可以导致等离子体中粒子的能量分布发生变化，从而影响等离子体的稳定性。例如，在等离子体中，当波的频率与粒子的回旋频率匹配时，波的能量会被粒子吸收，导致共振现象的发生。

实际案例与应用验证

在托卡马克装置中，如EAST，研究人员通过实验验证了这些现象。例如，通过使用射频加热技术，研究人员发现波的传播在特定频率下会被抑制，从而导致能量传输效率的降低。此外，通过调节等离子体的密度和温度梯度，研究人员能够控制截止现象的发生，从而优化能量传输效率。共振现象在托卡马克中的应用更为广泛，通过调整波的频率，可以实现等离子体中粒子能量的有效传递，从而提高等离子体的约束性能。

总结与互动式引导

通过优化波的传播特性，研究人员能够更好地控制等离子体的行为，从而提高核聚变反应的效率。未来的研究将继续探索如何通过精确控制波的传播，进一步优化等离子体的能量传输和约束性能。如果您对这些现象有更多问题，欢迎随时提问，我将很乐意为您提供更深入的解答。

Question: 国内外的托卡马克装置有哪些？

国内外的托卡马克装置包括多种类型，用于核聚变研究和实验。以下是一些主要的托卡马克装置：

1. **国际热核聚变实验堆（ITER）**：位于法国，是目前最大的托卡马克装置，旨在验证聚变能的可行性。
2. **中国环流三号（HL-3）**：位于中国成都，由中国自主设计和建造，用于研究高参数等离子体和燃烧等离子体物理。
3. **实验先进超导托卡马克（EAST）**：位于中国合肥，用于研究长脉冲等离子体和高约束模式（H-mode）。
4. **美国国家点火装置（NIF）**：虽然不是托卡马克，但它是目前最大的激光聚变装置，用于研究点火和聚变能源。
5. **欧洲联合托卡马克（JET）**：位于英国，是欧洲的主要聚变研究装置，用于研究氘-氚聚变反应。
6. **韩国超导托卡马克装置（KSTAR）**：位于韩国，用于研究超导磁体和等离子体约束。
7. **美国托卡马克装置（DIII-D）**：位于美国加利福尼亚，用于研究等离子体控制和约束技术。
8. **日本的JT-60SA**：位于日本，用于研究聚变反应堆的运行条件和材料耐久性。

这些装置在不同的国家和地区进行核聚变研究，为实现可持续聚变能源提供重要的实验数据和技术支持。

Question: 什么是汤姆孙散射诊断？

汤姆孙散射诊断（Thomson Scattering）是一种用于测量等离子体参数的重要技术，特别是在托卡马克装置中，它可以提供关于等离子体密度、温度和磁场强度的详细信息。汤姆孙散射诊断通过探测等离子体中的电子散射光来实现，其基本原理是光子与等离子体中的自由电子相互作用时发生的散射现象。

汤姆孙散射的基本原理

汤姆孙散射是指光子与等离子体中的自由电子相互作用时发生的弹性散射现象。根据汤姆孙散射定律，散射光的强度与入射光的强度、散射角以及电子密度和温度相关。通过测量散射光的强度和光谱，可以推导出等离子体的电子密度和温度。

汤姆孙散射诊断的应用

1. 测量等离子体参数：汤姆孙散射诊断可以提供等离子体中的电子密度和温度，这是核聚变研究中的关键参数。
2. 等离子体控制：通过实时监测等离子体的参数，汤姆孙散射诊断有助于优化等离子体的约束和稳定性。
3. 研究等离子体行为：汤姆孙散射诊断可以用于研究等离子体中的湍流、不稳定性以及等离子体与壁面的相互作用。

汤姆孙散射诊断的实现

汤姆孙散射诊断通常包括以下几个组成部分：

1. 入射激光：使用高能激光（如CO₂激光）照射等离子体。
2. 散射光收集：通过光学系统收集散射光并将其聚焦到探测器上。
3. 光谱分析：使用光谱仪分析散射光的光谱，以获得电子密度和温度信息。
4. 数据处理：通过数据分析软件对测量结果进行处理和解释，以获得等离子体的详细参数。

汤姆孙散射诊断在核聚变研究中的重要性

汤姆孙散射诊断是托卡马克装置中不可或缺的诊断工具，它可以提供等离子体参数的实时测量数据，从而帮助研究人员优化等离子体的约束和稳定性。例如，在EAST（实验先进超导托卡马克）中，汤姆孙散射诊断被广泛应用于研究等离子体的行为和优化聚变反应的性能。通过汤姆孙散射诊断，研究人员可以更好地理解等离子体中的湍流、不稳定性以及等离子体与壁面的相互作用，从而为实现稳定的核聚变反应提供关键数据支持。

Fig. 8. Case study #2. Chat in Chinese.

Question: How to distinguish between ideal MHD mode and resistive MHD mode?

In the context of nuclear fusion research, the ideal magnetohydrodynamic (MHD) mode and resistive MHD mode are two distinct regimes of plasma behavior, each characterized by different physical mechanisms and conditions. Understanding these modes is essential for controlling plasma stability and achieving efficient fusion reactions. Here's a detailed explanation of how to distinguish between these two modes:

Definition of Key Terms

1. **Ideal MHD Mode**: This mode describes plasma behavior in the absence of resistive effects, focusing on the interaction between plasma and magnetic fields. It assumes that the plasma is perfectly conducting, and magnetic field lines are frozen into the plasma.
2. **Resistive MHD Mode**: This mode accounts for the finite resistivity of the plasma, which allows for the generation of magnetic fields and the dissipation of magnetic energy. It includes phenomena such as tearing modes and resistive instabilities, which are not present in ideal MHD.

Distinguishing Features

1. **Ideal MHD Mode Characteristics**:
 - **Stability Conditions**: Ideal MHD modes are stable under certain conditions, such as specific magnetic field configurations and plasma shapes. These conditions are often derived from the stability criterion, such as the ballooning mode or kink mode stability.
 - **Energy Loss**: In ideal MHD, energy loss is primarily due to external forces, such as plasma-wall interactions or external magnetic perturbations. Internal resistive effects are negligible.
 - **Plasma Response**: Ideal MHD modes are characterized by the response of the plasma to external perturbations, which can be described by the equations of ideal MHD. The plasma adjusts its shape and magnetic field to maintain equilibrium.
 - **Examples**: Sawtooth oscillations, kink modes, and ballooning modes are typical examples of ideal MHD modes.
2. **Resistive MHD Mode Characteristics**:
 - **Stability Conditions**: Resistive MHD modes are influenced by the finite resistivity of the plasma, leading to phenomena such as tearing modes and resistive instabilities. These modes are often associated with regions of high current density or magnetic shear.
 - **Energy Loss**: Resistive MHD modes involve significant energy loss due to resistive dissipation, which can lead to the formation of magnetic islands and plasma instabilities.
 - **Plasma Response**: Resistive MHD modes are characterized by the interaction between the plasma and magnetic fields, where resistive effects cause the plasma to deviate from ideal MHD behavior. This deviation can lead to the formation of magnetic islands and the loss of plasma confinement.
 - **Examples**: Tearing modes, resistive instabilities, and edge-localized modes (ELMs) are typical examples of resistive MHD modes.

Practical Application Verification

- **Experimental Observations**: In devices such as EAST, experimental observations of plasma behavior under different conditions can help distinguish between ideal and resistive MHD modes. For example, the presence of tearing modes or magnetic islands indicates resistive MHD behavior, while the absence of such phenomena suggests ideal MHD behavior.
- **Simulation Tools**: Advanced simulation tools, such as BOUT++ and other numerical models, can be used to simulate plasma behavior under different conditions and validate the theoretical predictions of ideal and resistive MHD modes.

Summary and Interactive Guidance

Understanding the distinction between ideal MHD mode and resistive MHD mode is critical for controlling plasma stability and achieving efficient fusion reactions. Ideal MHD modes are stable under specific conditions and are characterized by the response of the plasma to external perturbations, while resistive MHD modes involve resistive dissipation and are associated with phenomena such as tearing modes and resistive instabilities.

If you have any further questions about the specific conditions under which these modes occur, their impact on plasma confinement, or the experimental techniques used to distinguish between them, please feel free to ask.

Question: How to verify the accuracy of MHD simulation results in experiments?

Verifying the accuracy of Magnetohydrodynamic (MHD) simulation results in experiments is critical for ensuring the reliability and applicability of theoretical models in the design and operation of nuclear fusion devices such as tokamaks. The following steps and considerations are essential for validating MHD simulation results against experimental data:

1. **Background Introduction of the Question**:

MHD simulations are computational tools used to model plasma behavior in fusion devices, including the effects of magnetic fields, plasma instabilities, and energy transfer processes. These simulations are validated through comparison with experimental data to ensure their predictive accuracy and reliability. Verification involves assessing the consistency between simulation results and experimental observations, identifying discrepancies, and refining models accordingly.
2. **Definition of Nouns and Analysis of Examples**:
 - **MHD Simulation**: Computational models that solve the equations of magnetohydrodynamics to predict plasma behavior under various conditions.
 - **Experimental Data**: Observations and measurements obtained from fusion devices, such as EAST, which provide empirical validation of simulation results.
 - **Verification**: The process of comparing simulation results with experimental data to validate the accuracy of theoretical models.

Example: In EAST, MHD simulations are used to predict plasma behavior under specific conditions, such as the formation of edge transport barriers (ETBs) and the occurrence of edge localized modes (ELMs). Experimental data from EAST, including measurements of plasma density, temperature, and magnetic field configurations, are used to verify the accuracy of these simulations.
3. **Multi-Angle Reasoning and Exploration of Alternative Solutions**:
 - **Direct Comparison**: Directly compare simulation results with experimental data, such as plasma density profiles, temperature distributions, and magnetic field configurations.
 - **Statistical Analysis**: Use statistical methods to analyze the agreement between simulation results and experimental data, quantifying discrepancies and identifying trends.
 - **Sensitivity Analysis**: Evaluate the sensitivity of simulation results to input parameters, such as plasma current, magnetic field strength, and heating power, to ensure robustness.

Example: In EAST, researchers compare simulated plasma density profiles with experimental measurements obtained using diagnostic tools like Thomson scattering. If discrepancies are identified, researchers refine the simulation models or adjust input parameters to improve accuracy.
4. **Actual Case and Practical Application Verification**:
 - **EAST Experiments**: EAST has conducted numerous experiments to validate MHD simulation results, including studies on plasma confinement, edge transport barriers, and ELM behavior.
 - **ITER Relevance**: While ITER has not been implemented yet, experiments on devices like EAST provide valuable insights into the accuracy of MHD simulations, which can be applied to future fusion reactors.

Example: In EAST, researchers have validated MHD simulations of edge transport barriers by comparing simulated ETB formation with experimental observations. These validations help refine models and improve the accuracy of predictions for future fusion devices.
5. **Summary and Interactive Guidance**:

Verifying the accuracy of MHD simulation results in experiments is a critical step in ensuring the reliability of theoretical models. By comparing simulation results with experimental data, researchers can identify discrepancies, refine models, and improve the predictive accuracy of MHD simulations. Continuous validation and refinement are essential for advancing the design and operation of fusion devices.

Interactive Guidance: If you have any further questions about the verification process, specific experimental setups, or the application of MHD simulations in fusion research, please feel free to ask, and I will be happy to provide more detailed answers.

Fig. 9. Case study #3. Chat in English.

Question: 对于新经典撕裂模，如何通过射频波（主要为电子回旋波）来实现稳定化？

▪ **XiHeFusion with Chain-of-Thought:**

新经典撕裂模(NTM)是托卡马克等离子体中的一种常见不稳定性，可能导致等离子体约束失效。通过射频波(特别是电子回旋波)来实现NTM的稳定化是一种有效的方法。以下是如何通过射频波实现NTM稳定化的步骤和原理：

1. **射频波的引入**：

- 射频波，尤其是电子回旋波(ECW)，可以被引入到等离子体中，通过共振吸收或非共振吸收来影响等离子体的行为。电子回旋波通常在电子回旋共振(ECR)频率下被吸收，该频率与电子的回旋频率相匹配。

2. **能量吸收和电流驱动**：

- 射频波的能量被等离子体中的电子吸收，导致电子温度和密度的升高。同时，射频波还可以驱动等离子体电流，特别是通过电子回旋共振加热(ECRH)和电子回旋电流驱动(ECCD)。

3. **电流分布的改变**：

- 通过电子回旋波驱动等离子体电流，可以改变等离子体的电流分布。例如，可以增加或减少特定区域的电流密度，从而影响等离子体的磁剪切和磁场配置。

4. **磁剪切的增强**：

- 增加磁剪切可以抑制NTM的发生。通过电子回旋波驱动电流，可以改变等离子体的电流分布，从而增加磁剪切，提高等离子体的稳定性。

5. **反馈控制系统**：

- 在实际的托卡马克装置中，可以通过反馈控制系统实时监测等离子体的状态，并根据需要调整射频波的功率和频率，以实现对NTM的稳定化。

6. **实验验证**：

- 许多实验已经证明了射频波在抑制NTM方面的有效性。例如，DIII-D和ASDEX Upgrade等装置已经成功地通过电子回旋波实现了NTM的稳定化。

具体案例：

- 在DIII-D装置中，通过电子回旋波驱动电流，成功地抑制了NTM的形成。实验表明，通过调整射频波的功率和频率，可以有效地控制等离子体的电流分布，从而实现NTM的稳定化。

结论：

通过射频波(特别是电子回旋波)实现NTM的稳定化是一种有效的技术手段，其核心在于通过改变等离子体的电流分布和磁剪切来抑制不稳定性。这种方法在实际的聚变装置中得到了广泛的应用，并取得了显著的成果。

如果您有进一步的问题或需要更多细节，请随时提问。

▪ **XiHeFusion without Chain-of-Thought:**

对于新经典撕裂模，射频波(主要是电子回旋波)能够通过特定的物理机制实现稳定化。新经典撕裂模是托卡马克等离子体中的一种不稳定性，它会导致等离子体的局部加热和能量损失，从而影响聚变反应的效率和稳定性。射频波通过在等离子体中产生电子回旋共振，能够有效地抑制新经典撕裂模的生长。这种稳定化机制主要依赖于电子回旋波与等离子体的相互作用，通过改变等离子体的微观动力学特性，从而实现对新经典撕裂模的抑制。例如，射频波能够通过激发等离子体中的微观不稳定性，从而改变等离子体的热输运和湍流特性，进而抑制新经典撕裂模的生长。此外，射频波还能够通过改变等离子体的磁场结构，从而改变等离子体的磁流体动力学特性，进而抑制新经典撕裂模的生长。这些机制共同作用，使得射频波能够有效地实现对新经典撕裂模的稳定化。

Question: 聚变点火的条件是什么？

▪ **XiHeFusion with Chain-of-Thought:**

聚变点火的条件包括以下关键要素：

1. **等离子体密度**：等离子体的密度必须足够高，以确保聚变反应的发生。通常，等离子体密度需要达到 10^{12} m^{-3} 或更高。

2. **等离子体温度**：等离子体的温度必须足够高，以克服原子核之间的库仑排斥力，使聚变反应发生。氘-氚聚变反应需要温度达到约1亿摄氏度(100 keV)。

3. **能量约束时间**：等离子体的能量约束时间必须足够长，以确保聚变反应能够持续进行。通常，约束时间需要达到几秒到几分钟的量级。

4. **能量增益**：聚变反应产生的能量必须大于维持等离子体所需的能量输入。能量增益(Q值)需要大于1，即输出能量大于输入能量。

5. **磁场约束**：等离子体必须通过强磁场(如托卡马克中的环形磁场)约束在特定区域内，以防止等离子体与反应堆壁接触并损失能量。

6. **等离子体稳定性**：等离子体必须保持稳定，避免出现边缘局域化模式(ELMs)或其他不稳定性，这些不稳定性会导致能量损失和等离子体崩溃。

实现聚变点火的具体步骤：

1. **加热和约束**：通过中性束注入、射频加热等方法将等离子体加热到高温度，并通过磁场约束保持等离子体的密度和温度。

2. **等离子体初始化**：使用高能粒子束或激光等手段将等离子体初始化到所需的密度和温度状态。

3. **维持等离子体稳定性**：通过反馈控制系统实时监测等离子体的状态，并采取措施(如RMP)抑制不稳定性，确保等离子体的稳定运行。

4. **能量输出和增益**：通过测量等离子体的能量输出和输入，确保能量增益达到1以上，实现聚变点火。

实际案例：

- **ITER实验**：ITER(国际热核聚变实验堆)的目标是实现聚变点火，通过优化等离子体密度、温度和磁场配置，预计能够实现Q值大于10的聚变反应。

- **JET实验**：在JET(联合欧洲托卡马克)实验中，通过优化等离子体参数和控制技术，已经实现了部分聚变点火条件，为ITER提供了重要的实验数据和经验。

总结：

聚变点火的条件包括高密度、高温度、长约束时间、高能量增益、磁场约束和等离子体稳定性。通过优化这些参数并采用先进的控制技术，可以实现聚变点火，为未来的商业聚变反应堆提供技术基础。

▪ **XiHeFusion without Chain-of-Thought:**

聚变点火的条件包括燃料的密度、温度和约束时间。燃料密度需要足够高，以确保有足够的燃料与热核粒子发生碰撞；温度需要足够高，以确保燃料中的粒子具有足够的动能，从而能够克服库仑势垒，发生聚变反应；约束时间需要足够长，以确保燃料中的粒子能够在反应中保持足够的能量。

聚变点火的条件是燃料的密度、温度和约束时间的乘积必须大于某个临界值。聚变点火的条件包括燃料的密度、温度和约束时间，满足这些条件后，聚变反应才能产生足够的能量来维持自身反应。

Fig. 10. Comparison of generated response using XiHeFusion with/without Chain-of-Thought Prompt.

Question: 托卡马克运行时，等离子体真空室要求的真空中度是多少？

▪ **XiHeFusion:**

托卡马克运行时，等离子体真空室要求的真空中度通常非常高，具体数值取决于实验装置的设计和运行条件。例如，在托卡马克装置中，等离子体真空室通常需要维持在 10^{-6} 至 10^{-7} 托（torr）或帕斯卡（Pa）的真空中度范围内。这种极高的真空中度是为了确保等离子体能够稳定存在，避免与任何残留气体发生碰撞，从而保持聚变反应的高效进行。

▪ **Baichuan 2:**

托卡马克运行时，等离子体真空室要求的真空中度通常在 10^{-5} 至 10^{-7} 毫巴（毫托）之间。这个真空中度对于维持稳定的等离子体运行和减少外部辐射损失至关重要。

▪ **DeepSeek V3:**

托卡马克装置在运行时，等离子体真空室要求的真空中度通常在 (10^{-6}) 到 (10^{-8}) 帕斯卡（Pa）范围内。这种高真空中度对于维持等离子体的稳定性和减少杂质污染至关重要。具体要求的真空中度可能会因不同的托卡马克设计和实验条件而有所不同，但一般来说，真空中度越高，等离子体的性能越好。

高真空中度有助于减少等离子体与残余气体分子的碰撞，从而降低能量损失和杂质引入。此外，高真空中度还能有效减少等离子体与真空中壁材料的相互作用，延长设备的使用寿命并提高实验的可靠性。

在实际操作中，真空中系统通常包括多个泵组（如涡轮分子泵、离子泵和低温泵等），以确保在等离子体放电前达到所需的真空中度，并在放电过程中维持这一真空中度。

▪ **GLM-4:**

托卡马克（Tokamak）是一种用于受控核聚变研究的装置，其核心部分是等离子体真空室。在这个真空室中，维持适当的真空中度对于等离子体的稳定运行至关重要。

一般来说，托卡马克等离子体真空室要求的真空中度非常高，通常在** 10^{-6} 至 10^{-8} 托（Torr）**的范围内。具体数值可能会根据不同的实验装置和运行条件有所变化。以下是一些关键点：

1. **高真空中度**：高真空中度有助于减少气体分子的存在，从而降低等离子体与中性气体的碰撞，提高等离子体的纯度和稳定性。
2. **减少杂质**：高真空中度可以减少杂质气体进入等离子体，避免杂质引起的辐射损失和等离子体温度下降。
3. **维持磁场稳定性**：高真空中度有助于维持磁场结构的稳定性，确保等离子体在磁场中有效约束。
4. **具体装置要求**：不同的托卡马克装置可能有其特定的真空中度要求。例如，国际热核聚变实验反应堆（ITER）的真空中系统设计就非常复杂，要求极高的真空中度。

在实际操作中，托卡马克装置的真空中系统会配备高性能的真空中泵和监控系统，以确保在运行过程中维持所需的真空中度。

需要注意的是，真空中度的具体要求可能会随着实验目标和装置设计的不同而有所调整，因此在实际操作中需要根据具体情况优化。

▪ **Llama 3.3:**

在托卡马克运行时，等离子体真空室的真空中度要求通常在 10^{-9} Pa至 10^{-11} Pa之间。这种高真空中度是为了确保等离子体的稳定性和运行效率，因为残余气体会对等离子体的性能产生不利影响。

▪ **Qwen 2:**

托卡马克装置在运行时，等离子体真空室要求的真空中度非常高，以确保等离子体能够稳定地存在并进行核聚变反应。通常情况下，托卡马克装置中的真空中度需要达到 10^{-5} 到 10^{-6} 帕斯卡（Pa）的范围，甚至更低。

具体来说：

- **预抽真空中度**：在托卡马克装置启动前，首先需要将真空中室内的气体抽至较低的压力，一般为 10^{-3} 到 10^{-4} Pa。
- **工作真空中度**：在等离子体放电过程中，为了维持等离子体的稳定性，真空中度需要进一步提高，通常要求在 10^{-5} 到 10^{-6} Pa之间。
- **高真空中度**：在某些高精度实验或特定条件下，可能需要更高的真空中度，例如 10^{-7} 到 10^{-8} Pa。

这种高真空中度有助于减少杂质和中性粒子对等离子体的影响，从而提高等离子体的纯度和稳定性。此外，高真空中度还能减少等离子体与壁面之间的相互作用，降低能量损失和杂质污染。

实现这样的高真空中度通常需要使用多种类型的真空中泵，如涡轮分子泵、低温泵和离子泵等，并且需要严格的密封技术和持续的监测系统来维持所需的真空中度。

Fig. 11. Comparison with our XiHeFusion with other LLMs #1.

Question: 为什么聚变装置中需要使用波加热技术?	Part-I
<p>▪ XiHeFusion:</p> <p>聚变装置中使用波加热技术的主要原因是实现了高效、精确的等离子体加热，以满足核聚变反应所需的高温条件。波加热技术通过电磁波将能量传递到等离子体中，使等离子体达到极高的温度，从而克服原子核之间的静电斥力，实现聚变反应。以下是波加热技术在聚变装置中的具体应用和优势：</p> <ol style="list-style-type: none"> **加热效率**: 波加热技术可以将能量直接输送到等离子体的特定区域，如核心或边缘，从而实现高效的能量传输。例如，射频波 (RF) 加热通过波与等离子体的相互作用，将能量转化为等离子体粒子的动能，提高等离子体的整体温度。 **可控性**: 波加热技术能够通过调整波的频率、功率和方向，精确控制等离子体的加热过程。这使得加热过程可以动态调节，以适应等离子体的实时变化，确保等离子体的稳定性和约束性能。 **能量分布**: 波加热技术可以实现等离子体内部的能量均匀分布，避免局部过热或能量集中，从而减少不稳定性，提高等离子体的约束性能。例如，通过使用不同的波（如离子回旋波和低杂波）组合，可以实现等离子体内部的能量平衡。 **减少杂质**: 与中性束注入 (NBI) 等其他加热技术相比，波加热技术不会引入外部粒子，从而减少等离子体中的杂质含量，保持等离子体的纯净性，提高聚变反应的效率。 **实验验证**: 波加热技术已经在多个实验装置中得到验证，如JET、ASDEX Upgrade和DIII-D等，证明其在实现高能量密度等离子体方面的有效性。这些实验结果为未来聚变反应堆的设计提供了宝贵的数据支持。 **理论支持**: 波加热技术的理论基础较为成熟，包括波与等离子体的相互作用机制、能量传递过程和等离子体的响应行为等。这些理论研究为波加热技术的应用提供了坚实的科学依据。 **优化设计**: 通过优化波加热系统的参数（如波的频率、功率和波导结构），可以进一步提高加热效率和等离子体的约束性能。例如，使用先进的天线设计和电磁波发射技术，可以实现更高的能量传输效率和更稳定的加热过程。 **多物理过程耦合**: 波加热技术与等离子体中的其他物理过程（如湍流、磁流体力学效应等）相互耦合，共同影响等离子体的行为。深入研究这些耦合效应，可以进一步优化波加热技术的应用，提高等离子体的约束性能和聚变反应的效率。 <p>波加热技术在聚变装置中的应用为实现高效、稳定的等离子体加热提供了关键支持，是实现可控核聚变的重要手段之一。通过进一步研究和优化波加热技术，可以为未来聚变反应堆的设计和运行提供更可靠的技术保障。</p>	
<p>▪ Baichuan 2:</p> <p>聚变装置中使用波加热技术的原因主要有以下几点：</p> <ol style="list-style-type: none"> 提高等离子体温度：波加热技术可以快速地将等离子体加热到高温度，从而提高核聚变的反应效率。这是因为波可以在短时间内传递大量的能量，使得等离子体中的粒子能够以更高的速度运动，从而增加它们之间的碰撞概率，促使核聚变反应的发生。 减少等离子体粘滞性：波加热技术可以有效地降低等离子体的粘滞性，从而提高聚变的反应效率。等离子体的粘滞性是指等离子体中的粒子在运动过程中相互碰撞而产生的阻力。降低等离子体的粘滞性有助于提高等离子体中的粒子运动速度，从而增加核聚变反应的概率。 提高等离子体密度：波加热技术可以有效地提高等离子体的密度，从而提高聚变的反应效率。等离子体密度是指等离子体中粒子的数量与体积之比。提高等离子体密度有助于增加粒子之间的碰撞概率，从而提高核聚变反应的概率。 实现稳定的热传导：波加热技术可以实现稳定的热传导，从而提高聚变的反应效率。波加热技术可以通过调整波的振幅和频率来实现对等离子体温度和密度的精确控制，从而确保等离子体始终保持在最佳的状态，有利于核聚变反应的发生。 <p>总之，波加热技术在聚变装置中的应用可以提高等离子体温度、降低等离子体粘滞性、提高等离子体密度和实现稳定的热传导，从而提高核聚变的反应效率。</p>	
<p>▪ Qwen 2:</p> <p>在核聚变装置中，如托卡马克 (Tokamak) 或恒星器 (Stellarator)，波加热技术被用来将等离子体加热到实现可控核聚变反应所需的极高温度。这项技术的重要性在于以下几个方面：</p> <ol style="list-style-type: none"> **提高温度**: 要让轻元素的原子核克服彼此之间的电荷排斥力并融合在一起，需要极高的温度条件，通常是在数千万至数亿摄氏度之间。这样的高温环境是通过多种加热方法共同作用来实现的，其中包括了波加热。 **非接触式加热**: 与传统的物理接触方式不同，波加热是一种非接触式的加热手段，它利用电磁波直接向等离子体内传递能量，避免了因物理接触而可能引起的污染或其他问题。 **驱动电流**: 某些类型的波加热还可以用于驱动等离子体内部的电流，这对于维持托卡马克装置内的磁约束非常重要。例如，在低杂波电流驱动 (LHCD) 中，特定频率范围内的微波能够有效地产生和控制环形等离子体中的电流分布。 **改善稳定性**: 通过精确地调整波加热的位置、强度等因素，科学家们可以更好地控制等离子体的状态，从而有助于提高整个系统的稳定性和性能表现。 **促进粒子加热**: 除了整体提升等离子体温度外，波加热还特别擅长于对特定种类粒子进行选择性加热，比如电子或者离子，这有利于研究者深入理解等离子体行为及其与外界相互作用机制。 <p>总之，波加热技术对于实现高效、可持续的核聚变过程至关重要，它不仅能够帮助达到必要的高温条件，同时也为更精细地操控等离子体提供了可能性。</p>	

Fig. 12. Comparison with our XiHeFusion with other LLMs #2 (Part-1).

Question: 为什么聚变装置中需要使用波加热技术?

Part-II

• **DeepSeek V3:**

在核聚变装置中，波加热技术是至关重要的，因为它能够有效地将能量传递到等离子体中，使其达到并维持核聚变所需的高温。以下是波加热技术的主要作用和原因：

1. **达到高温**：核聚变反应需要极高的温度（通常在1亿摄氏度以上），以使氢同位素（如氘和氚）的原子核克服库仑势垒并发生聚变。波加热技术能够将能量直接传递给等离子体中的电子和离子，使其迅速升温。
2. **维持等离子体稳定性**：波加热技术不仅可以加热等离子体，还可以通过调节波的频率和功率来影响等离子体的稳定性。这对于维持等离子体的约束和防止不稳定性（如磁流体动力学不稳定性）至关重要。
3. **局部加热**：波加热技术可以实现对等离子体的局部加热，这对于优化等离子体中的温度分布和密度分布非常重要。例如，电子回旋共振加热（ECRH）和离子回旋共振加热（ICRH）可以分别针对电子和离子进行加热。
4. **能量传递效率高**：波加热技术能够将能量高效地传递到等离子体中，减少能量损失。这对于提高聚变装置的整体能量效率非常重要。
5. **控制等离子体参数**：通过调节波加热的参数，可以精确控制等离子体的温度、密度和电流分布等关键参数，这对于实现和维持稳态聚变反应至关重要。

常见的波加热技术包括电子回旋共振加热（ECRH）、离子回旋共振加热（ICRH）和低杂波加热（LHCD）等。这些技术在不同的聚变装置中得到了广泛应用，如托卡马克（Tokamak）和仿星器（Stellarator）等。

总之，波加热技术在核聚变装置中扮演着不可或缺的角色，是实现可控核聚变的关键技术之一。

• **GLM-4:**

波加热技术在聚变装置中的应用非常关键，主要原因如下：

1. **提高等离子体温度**：聚变反应需要在极高的温度下进行，通常在数百万到上亿摄氏度。波加热技术，如射频波加热（RF heating）和微波加热，能够有效地将能量传递给等离子体中的带电粒子，从而提高其温度。
2. **均匀加热**：聚变反应的效率在很大程度上取决于等离子体的温度分布。波加热技术可以实现对等离子体的局部或全局加热，有助于形成更加均匀的温度分布，减少温度梯度引起的等离子体不稳定性。
3. **控制等离子体参数**：通过调节波的频率、功率和相位等参数，可以精确控制等离子体的温度、密度和压强等关键参数，优化聚变反应条件。
4. **辅助约束**：某些波加热技术（如离子回旋共振加热ICRH、低杂波加热LHCD等）不仅能加热等离子体，还能通过波的电磁场对等离子体产生一定的约束作用，有助于维持等离子体的稳定性和提高约束效率。
5. **减少杂质影响**：波加热技术可以选择性地加热等离子体中的某些粒子种类，有助于减少杂质离子的温度，降低杂质对聚变反应的负面影响。
6. **灵活性**：波加热系统相对灵活，可以根据实验需要调整加热策略，适应不同的等离子体条件和聚变装置设计。

总的来说，波加热技术在聚变装置中扮演着至关重要的角色，通过有效加热和控制等离子体参数，为实现可控核聚变提供了重要支持。

• **Llama 3.3:**

波加热技术（Bootstrap Current）是为了维持等离子体的稳定性和高温状态而采用的方法。它的主要目的是在磁约束聚变装置中，利用等离子体本身的能量来驱动所需的电流，从而减少外部电流驱动的需求。

在传统的磁约束聚变装置中，需要一个外部的电流驱动系统来维持等离子体的电流，这个电流是为了产生和维持约束等离子体所需的磁场。然而，这种外部驱动方法有其局限性，例如需要大量的能量输入，并且可能导致等离子体的不稳定性。

波加热技术通过利用等离子体中的热能来产生电流，从而减少对外部电流驱动的依赖。这种方法可以提高聚变反应的效率，减少能量损失，并且有助于维持等离子体的稳定性。波加热技术在 tokamak 和 stellarator 等磁约束聚变装置中得到应用，是实现受控核聚变的一个重要研究方向。

Fig. 13. Comparison with our XiHeFusion with other LLMs #3 (Part-2).

that large models with CoT can provide more detailed and precise responses.

C. Comparison with other LLMs

As shown in Fig. 11, 12, 13, we compare the proposed XiHeFusion model with other recently released strong large language models, including Baichuan 2 [16], DeepSeek V3 [1], GLM-4 [55], Llama 3.3 [13], and Qwen2 [15]. Note that, the Qwen2 is the baseline model of XiHeFusion. From the answers obtained using these models for the two questions, we can find that our newly proposed XiHeFusion achieves a similar even better response than these strong LLM models.

D. Limitation Analysis

Although our model has mastered a lot of basic knowledge about nuclear fusion, it is focused on text conversation processing, and there is still much knowledge in other fields that has not been learned. For example, the understanding and modeling of image/video, one-dimensional signals, and some physical formulas in nuclear fusion. Also, we find some responses are not accurate enough from our model, as shown in Fig. 14. In future work, we will consider incorporating these additional modalities and more in-depth physical formula modeling into the large model to enhance its level of intelligence further. Moreover, in fine-tuning the Qwen large model, we have only considered supervised fine-tuning methods and have not introduced reinforcement learning fine-

Question: 托卡马克装置上有哪些常用的诊断?

托卡马克装置上常用的诊断工具包括以下几种，这些工具用于监测等离子体的状态、磁场强度和等离子体-材料相互作用，从而确保核聚变反应的稳定性和效率。

1. **磁场探头（Magnetic Probes）**：用于测量等离子体中的磁场分布，特别是环形磁场和极向磁场的强度。磁场探头可以提供等离子体约束的详细信息，帮助调整磁场配置以优化等离子体的稳定性。
2. **干涉仪（Interferometers）**：用于测量等离子体的密度分布。干涉仪通过激光干涉技术，能够提供高精度的密度剖面，从而帮助研究人员了解等离子体的密度梯度和不均匀性。
3. **托莫图像（Tomography）**：通过多角度的X射线或中子成像技术，可以重建等离子体的三维密度分布。托莫图像技术在诊断等离子体的整体行为和边缘局部模式（ELMs）中尤为重要。
4. **反射镜和光谱仪（Mirrors and Spectroscopes）**：用于测量等离子体中的辐射和光谱特征，包括等离子体的温度、密度和杂质含量。反射镜和光谱仪能够提供等离子体内部的详细信息，帮助优化聚变反应的效率。
5. **等离子体探针（Plasma Probes）**：直接测量等离子体边缘区域的电势和密度。等离子体探针在诊断等离子体的边界行为和边缘局部化模式（ELMs）中起着关键作用。
6. **诊断中子源（Diagnostic Neutron Sources）**：用于测量等离子体中的中子通量，特别是在氘-氚（D-T）聚变反应中，中子通量是评估聚变反应效率的重要指标。
7. **热像仪（Thermal Imaging Systems）**：用于监测等离子体边缘区域的热负荷和温度分布。热像仪在评估等离子体与偏滤器（divertor）的相互作用以及边缘局部化模式（ELMs）的影响中具有重要作用。
8. **激光诱导荧光（Laser-Induced Fluorescence, LIF）**：通过激光激发等离子体中的特定离子或分子，测量其荧光发射，从而确定等离子体的温度和密度分布。**LIF技术在研究等离子体的微观结构和湍流特性中具有独特优势。**

这些诊断工具在托卡马克装置中被广泛应用于实时监测等离子体的状态，优化聚变反应的条件，并确保装置的安全运行。例如，EAST（实验先进超导托卡马克）等装置通过这些诊断工具，能够精确控制等离子体的参数，实现稳定的核聚变反应。

Fig. 14. The text highlighted in **burgundy** means the descriptions are not accurate.

tuning methods to further align the large model's outputs with the high-quality answers that humans expect.

VI. CONCLUSION

In conclusion, the development of XiHeFusion, the first large model in the field of nuclear fusion, represents a significant step forward in harnessing the power of artificial intelligence for the advancement of fusion energy research. By fine-tuning the open-source large model Qwen2.5-14B with a wealth of multi-source nuclear fusion knowledge, XiHeFusion has demonstrated a strong grasp of the domain's concepts and principles. The incorporation of the chain of thought approach has further enhanced the model's logical reasoning capabilities, enabling it to provide accurate and coherent responses to queries related to nuclear fusion. The comprehensive test questionnaire with over 180 questions has effectively evaluated XiHeFusion's conversational abilities in science popularization, confirming its effectiveness in disseminating fusion knowledge to a broader audience. The success of XiHeFusion underscores the potential of large models to facilitate public understanding and engagement in the critical mission of achieving sustainable and infinite energy through nuclear fusion.

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