The Impact of ChatGPT on Scientific Research and Literature Intelligence Work

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Abstract

ChatGPT is a dialogue system developed by OpenAI. Externally manifested as a chatbot, its essential nature is artificial intelligence generative technology, with the key foundation being the generative pre-trained transformer and the core technology being InstructGPT. Its main characteristic is that, compared with earlier similar products, hallucination is significantly reduced and the generation of toxic content is substantially decreased. This paper conducts a systematic investigation of ChatGPT from the perspectives of its technical architecture, related research and practice, and application status. It analyzes the implications brought by the rapid development of artificial intelligence technology and the impact of ChatGPT on scientific research and literature and information work. It proposes eight recommendations for the literature and information field. Overall, the literature and information field must identify its distinct value orientation in the AI era, both upholding and inheriting traditional scientific research paradigms and expanding the application of new technologies such as ChatGPT to assist scientific research.

Full Text

Preamble

The Influence of ChatGPT on Scientific Research and Library & Information Service

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ChatGPT is a dialogue system developed by OpenAI. While it appears as a chatbot, its essence is Artificial Intelligence Generated Content (AIGC) technology, with its key foundation being the Generative Pre-trained Transformer and its core technology being InstructGPT. Its main characteristic, compared to similar early-stage products, is a significant reduction in fabricated facts and toxic content generation. This paper presents a systematic investigation of ChatGPT' s technical architecture, relevant research and practice, and application scenarios. Based on this investigation, we analyze the insights from the rapid development of AI technology and the influence of ChatGPT on scientific research and library & information service. We propose eight suggestions for the library & information service field. Overall, the field should find its distinctive value orientation in the AI era, not only by maintaining conventional scientific research paradigms but also by exploring how new technologies like ChatGPT can boost scientific research.

Keywords: ChatGPT; Large Language Model; Artificial Intelligence; Library and Information Service; Scientific Research

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1 The Essence and R&D History of ChatGPT

1.1 What is ChatGPT?

ChatGPT[1] (Chat Generative Pre-training Transformer) was released on November 30, 2022, by OpenAI. Due to its ability to provide clear and detailed answers across numerous knowledge domains and even write articles approaching human quality, it quickly gained attention, surpassing 1 million registered users within five days.

ChatGPT can be understood from five perspectives. First, its external manifestation is a chatbot that can engage in dialogue by learning and understanding human language, with the ability to answer questions based on conversational context, enabling human-like chat interactions. Second, its actual essence is artificial intelligence generation technology—specifically, an application of Ar-

tificial Intelligence Generated Content (AIGC) technology that, after learning human language and domain knowledge, possesses intelligent content creation capabilities to automatically generate specific content. Third, its key foundation is the generative large-scale language model based on the Generative Pre-trained Transformer (GPT), which employs generative self-supervised learning to learn implicit linguistic patterns from terabyte-scale training data, resulting in a large language model with hundreds of billions of parameters. Fourth, its core technology is InstructGPT[2], which has attracted significant attention for introducing RLHF[3] (Reinforcement Learning with Human Feedback). RLHF addresses a core problem of generative models: how to align AI model outputs with human common sense, cognition, needs, and values, enabling ChatGPT to facilitate AI-assisted content creation and improve content production efficiency and richness. Fifth, its main characteristic is a substantial reduction in fabricated facts and toxic content compared to earlier similar products. Unlike other dialogue models, ChatGPT' s key value lies in addressing traditional language model deficiencies in complex multi-domain knowledge utilization[4], deductive reasoning[5], and deceptive responses[6], offering rich corpora, rapid response, accurate text generation, and powerful conversational abilities. ChatGPT effectively mitigates the harm and bias[7] in neural language model-generated text, making responses more useful and truthful, with significantly reduced fact fabrication and fewer imitative falsehoods and toxic outputs.

1.2 ChatGPT' s Functions

ChatGPT is powerful and suitable for multiple application scenarios. Based on mature functional examples, we categorize its applications into three types: intelligent Q&A, language conversion, and natural language generation.

Intelligent Q&A represents ChatGPT' s fundamental form of conversational interaction. This approach enables ChatGPT to answer follow-up questions in the same context and correct response deviations during dialogue to better align with target tasks. It also serves as a more flexible new retrieval method. Even when users provide no contextual information, ChatGPT can answer questions based on its existing knowledge; if users provide scenario information—for example, by inputting "You are a sarcastic Q&A assistant" —ChatGPT will generate answers appropriate to that context.

Language conversion enables semantic transformation across different language media. Beyond traditional translation between natural languages, ChatGPT also converts between programming languages and between natural and programming languages, significantly expanding business scope to support code writing, code reading, and translation functions.

Natural language generation provides value beyond answering factual questions and language conversion by enabling content creation. This includes three task types: first, summarization from complex to simple, such as summarizing materials to help users quickly grasp key points; second, creation from scratch, such

as constructing paper outlines to assist users in generating draft frameworks appropriate to the context; and third, expansion from little to much, such as story writing to help users rapidly expand content from short prompts.

-1 ChatGPT' s Resolved Issues and Typical Examples

1.3 ChatGPT' s Corpus Scale and Computing Investment

At its founding, OpenAI had pledged funding of $1 billion^{8}. Microsoft invested $1 billion in OpenAI LP in 2019 and made a second multi-year investment in January 2023. This multi-billion-dollar investment background allowed OpenAI to focus on R&D without revenue pressure for several years, providing financial support for ChatGPT as a large language model. According to media reports, OpenAI invests approximately $2.5 billion annually in ChatGPT^{9}.

Regarding data and computing resources, OpenAI has not publicly disclosed the specific sources and details of ChatGPT' s training datasets. According to official OpenAI information^{10}, ChatGPT' s training data is similar to its peer model InstructGPT, both improved and optimized based on GPT-3 and other models' data.

ChatGPT further expanded on GPT-3' s data foundation^{11}. GPT-3' s dataset^{12} consists of five sub-datasets: Common Crawl, WebText2, Books1, Books2, and Wikipedia, with Common Crawl alone reaching 570GB. To improve data quality, ChatGPT significantly increased manually annotated Q&A data sourced from human annotations and early user submissions. This dataset encompasses over nine data types including generation, open-domain Q&A, chat, summarization, rewriting, and classification, corresponding to common human chat scenarios. It also covers 20 languages including English, Chinese, French, and Spanish. However, since English datasets account for over 96%, performance in non-English environments remains limited.

According to OpenAI' s papers, GPT-3' s training hardware alone included over 285,000 CPU cores, 10,000 GPUs, and 400GB-per-second network links per GPU server. It is estimated that GPT-3' s training cost approached $12 *million*^{13}$.

1.4 ChatGPT' s R&D History

ChatGPT was developed based on the GPT series models through four years of iteration. GPT-1 (Generative Pre-training Transformer)[14] was announced in June 2018, focusing on generative tasks[15] and demonstrating excellent performance in language reasoning, text generation, and Q&A upon release. GPT-1 had 117 million parameters, a characteristic shared by subsequent GPT models: training large language models through semi-supervised and unsupervised methods on massive datasets. GPT-2 emerged in 2019[16], with its core idea being that when model capacity is sufficiently large and data sufficiently abundant, language model training alone can accomplish other supervised learning

tasks[17]. GPT-2 also used Prompt (text prompts), though not originally proposed by GPT-2 but referencing an 2018 paper[18]. The GPT-3 model released by OpenAI in 2020 had more parameters, greater network capacity, and richer thematic text, capable of converting web descriptions to code, imitating human narratives, creating custom poetry, and generating game scripts. However, in practical applications, it could not distinguish text quality and produced incorrect, maliciously offensive, or even aggressive outputs.

To address GPT-3' s defects in practical Q&A applications, OpenAI released WebGPT[19] in late 2021. Researchers trained reward models to predict human preferences by having the model learn how humans answer questions, using reinforcement learning or rejection sampling for optimization to improve answer usability and accuracy. The fine-tuned WebGPT model could learn real-time human answering methods, such as submitting searches, following links, and scrolling through web pages. However, issues remained, including the model' s tendency to reinforce existing knowledge rather than generate new knowledge and its propensity for basic errors.

In early 2022, OpenAI released InstructGPT[20], ChatGPT' s peer model, which used humans as "teachers" during training to provide feedback and guidance, reducing the probability of fabrications or biased outputs. ChatGPT, released in December 2022[21], also employed RLHF but differed in having multiple outputs versus InstructGPT' s single output. By learning human ranking of output results, ChatGPT could better perform contextual learning and dialogue, generating more human-aligned feedback.

2 Technical System Analysis of ChatGPT

Understanding ChatGPT' s underlying principles is crucial for fully leveraging its technical potential across domains. This section details ChatGPT' s overall technical architecture, model foundation, and core technical principles.

2.1 ChatGPT' s Overall Technical Architecture

ChatGPT is a fine-tuned version of GPT-3.5[22], a text-generative dialogue robot trained using RLHF (Reinforcement Learning from Human Feedback). Based on self-supervised pre-trained generative large models and employing high-quality data feedback for reinforcement learning, it achieves more human-aligned dialogue effects with significantly reduced fact fabrication and toxic content.

The following discussion covers AIGC (AI Generate Content) technologies, ChatGPT' s data foundation, generative pre-training technology, how ChatGPT uses human feedback to guide model training, and how to make model performance more human-like.

[Figure 2: see original paper].1 ChatGPT' s Overall Technical Architecture

2.2 AIGC Technical Foundation

Content production models have evolved from Professionally Generated Content (PGC) and User Generated Content (UGC) to the inevitable trend of Artificial Intelligence Generated Content (AIGC). The narrow concept of AIGC refers to using AI for automatic content production. Traditional AI emphasized analytical capabilities—discovering patterns in data for various applications like personalized recommendation algorithms. Now, AI is generating new content rather than merely analyzing existing content, achieving a leap from perceiving and understanding the world to generating and creating it.

Broadly, AIGC can be viewed as generative AI technology with human-like creative capabilities, which can autonomously generate various forms of content and data based on training data and generative algorithm models. Examples include AI writing, AI music composition, AI video generation, AI voice synthesis, and AI painting, where users input a few keywords and models generate content within seconds.

2.2.1 AIGC Model Introduction

AIGC models reconstruct input content through deep neural networks, with different learning approaches. Variational Autoencoders (VAE) consist of an encoder and decoder, where the encoder converts high-dimensional input to low-dimensional codes and the decoder reconstructs high-dimensional input from these codes, maximizing input-output similarity.

Generative Adversarial Networks (GAN) contain a generator and discriminator trained simultaneously, with the discriminator judging generated content' s authenticity. Through continuous "gaming" between generator and discriminator, generation quality is optimized.

Diffusion Models work by adding noise to corrupt training data, then learning to recover data by reversing this noise-addition process, ultimately enabling generation from latent variables.

2.2.2 Large-scale Pre-trained Models as AIGC Development Trend

Large Language Models (LLM) are deep learning algorithms that can recognize, summarize, translate, predict, and generate text and other content based on knowledge from massive datasets. LLMs typically use self-supervised learning to discover implicit linguistic patterns from terabyte-scale training text, generating new text that conforms to grammatical and semantic rules. With hundreds of millions of parameters, they demand high-performance computing resources and are considered by most experts as an important path toward AIGC.

ELMo addressed polysemy by using word embeddings as new features. ELMo is a bidirectional LSTM language model trained on large-scale unsupervised corpora, consisting of two stages: first, pre-training a language model on massive corpora; second, extracting corresponding word embeddings from each network

layer during downstream tasks as new features. Thus, ELMo is a typical feature-fusion-based pre-trained model.

BERT improved text understanding through contextual pre-training. BERT (Bidirectional Encoder Representations from Transformer) uses Transformer architecture, considering both preceding and following tokens when processing each token to capture contextual meaning. BERT employs Masked Language Modeling (MLM), randomly masking some input tokens and training the model to predict them correctly, achieving contextual feature extraction. It also uses Next Sentence Prediction (NSP), where sentences A and B serve as training samples: B is A' s next sentence in 50% of cases and a random sentence in the other 50%, enabling the model to determine whether B follows A, thereby enhancing contextual understanding.

2.2.3 Reinforcement Learning Applied to NLP Tasks

Reinforcement learning guides model training through reward mechanisms, which can be viewed as more flexible and diverse loss functions. However, rewards are often non-differentiable, preventing direct backpropagation. Reinforcement learning addresses this by sampling rewards extensively to approximate loss functions, enabling model training. Applications include improving information extraction accuracy[24], enhancing machine translation[25], and boosting text generation capabilities[26].

2.3 ChatGPT Enhances Raw Corpus Authenticity with Human Knowledge

ChatGPT' s training data sources include two aspects: the foundational pre-training data from GPT-1 to GPT-3, and manually annotated fine-tuning data.

Foreign scholar Alan D. Thompson statistically compiled the foundational pre-training data from GPT-1 to GPT-3, as shown below.

-1. GPT-n Foundational Pre-training Data (Unit: GB)

Regarding manually annotated data, OpenAI employed 40 labelers (recent reports indicate this number has risen to approximately 1,000) who received training to manually write text for ChatGPT' s training corpus. ChatGPT' s manually annotated corpus scale is similar to its peer model InstructGPT, as shown below:

-2. InstructGPT Training Data Volume and Distribution (Unit: Token Count)

To create a safe system enabling ChatGPT to identify potentially dangerous statements and reduce response "toxicity," OpenAI sent tens of thousands of text fragments to a Kenyan outsourcing company for labeling. These texts appeared to come from the internet' s darkest corners, with some graphically detailing murder, suicide, torture, self-harm, and incest. Labelers read and annotated 150-250 text segments per nine-hour shift, earning only $1.32-$2 per

hour. This "dehumanizing" annotation method has drawn widespread societal criticism.

2.4.1 Generative Pre-trained Model Foundation–Transformer

Transformer is the core component of current large-scale language models, first applied to cross-lingual machine translation tasks by encoding source language text and decoding it according to target language characteristics. Transformer consists of Encoder and Decoder components, employing self-attention mechanisms to predict unobserved text portions from observed parts, thereby learning contextual features. Common Transformer-based pre-trained language models include BERT, GPT, and BART.

2.4.2 Generative Pre-trained Model–GPT

GPT is a Transformer-based pre-trained language model[30] that predicts the next word given preceding word sequences as input, training natural language understanding capabilities and making the model more suitable for generative NLP tasks.

The GPT-3 model is the latest pre-trained model, with WebGPT, GPT-3.5, InstructGPT, and ChatGPT all fine-tuned based on it. GPT-3 improved upon GPT-1 and GPT-2 with larger model scale, more training data, and enhanced representation and generalization capabilities, delivering better performance across diverse tasks. During its large-scale unsupervised pre-training phase, GPT-3 used over 10 trillion word-level text data from Wikipedia, web pages, books, news articles, etc. GPT-3 employs autoregressive training, predicting the probability distribution of the next word in a sequence given preceding text. By continuously predicting subsequent words, the model learns word relationships, contextual semantics, and grammatical rules. Training also employed random masking, unlabeled data techniques, and multi-task pre-training concepts to increase generalization ability.

2.5 ChatGPT as the Result of Multiple Model Iterations from GPT-3 to GPT-3.5

The ChatGPT model was obtained by fine-tuning the GPT-3.5 model using RLHF. The progression from GPT-3 to GPT-3.5 to ChatGPT represents numerous model iterations. From early 2020 to February 2023, OpenAI developed over 50 derivative models based on GPT-3, with continuous iteration and updates forming the foundation for ChatGPT' s current outstanding performance.

Scholars have compiled GPT-3 series models online, as shown in Figure 2.4.

[Figure 2: see original paper].4 GPT-3 Series Models

2.5.1 Four Versions of GPT-3 Model

GPT-3 has four versions based on model scale: Ada, Babbage, Curie, and Davinci.

Ada is the lowest-parameter version for small tasks like text parsing, simple classification, address correction, and keyword extraction, offering the fastest response speed and least computational load.

Babbage has more parameters than Ada, capable of moderate classification and semantic search classification tasks, with relatively fast response speed and low computational load.

Curie has more parameters than Babbage, with moderate response speed and larger computational load, capable of language translation, complex classification, sentiment classification, and text summarization.

Davinci is GPT-3's largest model, commonly known as the 175-billion-parameter version. Many OpenAI large models, including InstructGPT and Codex, are fine-tuned based on Davinci. As the most capable GPT-3 model, Davinci can complete any task other models can perform, such as complex intent understanding, causal reasoning, and audience-specific text summarization, typically with higher quality.

2.5.2 Embeddings Models for Text Relevance Computation

Embeddings models are OpenAI APIs[32] primarily used to measure text string relevance for search, clustering, recommendation, and classification tasks. Embeddings are essentially vectors of floating-point numbers, with relevance measured by distance between vectors—small distances indicate high relevance, large distances indicate low relevance.

OpenAI released three embedding model series focusing on three tasks: text similarity measurement, text search, and code search. These models take text or code as input and return a vector.

1) Text Similarity Models: Provide embeddings capturing semantic similarity between text fragments, useful for clustering, data visualization, and classification. Text similarity is compared using dot products on text embeddings, with results expressed as "similarity scores" (cosine similarity) between -1 and 1, where higher numbers indicate greater similarity.

2) Text Search Models: Provide embeddings for large-scale search tasks like finding relevant documents in a collection given a text query. Document and query embeddings are generated separately, then compared using cosine similarity. Embedding-based search better captures text semantics than classic keyword search' s word overlap techniques.

3) Code Search Models: Provide code and text embeddings for code search tasks. Given a collection of code blocks, the task is to find relevant code

blocks for natural language queries.

2.5.3 Codex Model for Code Generation

Codex is a GPT-3 series model with the function of converting natural language to computer code. Codex' s development underwent multiple iterations, starting from GPT-3 and learning from code training corpora to obtain the Code-davinci-001 model. Adding human-annotated data for supervised fine-tuning yielded Code-davinci-002, the first model deeply integrating code training and instruction fine-tuning—the Codex model.

Codex' s training corpus includes billions of lines of public source code, such as open-source code from GitHub. Code functionality correctness evaluation differs from text generation correctness evaluation, rendering traditional BLEU score evaluation unsuitable. Therefore, Codex improved GPT-3' s code creation capabilities by optimizing evaluation algorithms during training and using human-annotated training sets. First, it optimized the pass@k algorithm to evaluate code functional correctness: for each programming problem, the model outputs n code answers, with c correct answers, requiring that incorrect answers (n-c) be fewer than k. OpenAI also constructed the HumanEval dataset[33] to incorporate human intelligence for further model optimization. Codex is proficient in JavaScript, Go, Perl, PHP, Ruby, Swift, and TypeScript, with Python being its strongest language.

ChatGPT's code generation function is further fine-tuned from the Codex model through Instruct Tuning, RLHF, and other methods.

2.5.4 Insert+Edit Model for Text Content Modification

Previous GPT-3 models only appended content at the end of given text or code. The Insert+Edit model enables GPT-3 to modify existing text or code without breaking original logic and insert large content blocks into existing text or code.

Specifically, the insertion function allows models to insert contextually relevant text or code into existing content, maintaining logical consistency. This capability shapes GPT-3' s functions for writing long texts, achieving paragraph transitions, and code writing. The editing function uses input editing instructions as "prompts" and "instructions" to modify text expression and structure or perform targeted modifications (e.g., spelling, grammar). For code modification, GPT-3 can complete translation between different programming languages and demonstrates outstanding performance in modifying code structure and changing code style.

As shown in Figure 2.5, insertion functions are supported by Text-davinci-insert-001 and Text-davinci-insert-002 models, while editing functions are supported by Text-davinci-edit-001 and Code-davinci-edit-002 models.

[Figure 2: see original paper].5 Insert+Edit Series Models

2.5.5 GPT-3.5 Series Models

GPT-3.5 is a collective term for a series of models. ChatGPT was obtained through reinforcement learning fine-tuning based on the text-davinci-002 model in GPT-3.5. As shown below, Code-davinci-002 is the base model for pure code completion tasks. Text-davinci-002 is an InstructGPT model based on Code-davinci-002, while Text-davinci-003 is further optimized through human feedback. Turbo belongs to the same model series as ChatGPT, optimized for chat and suitable for conversational input and output while performing excellently on other tasks like the Davinci series.

-3 OpenAI' s GPT-3.5 Model APIs

2.6.1 RLHF Based on Human Feedback

ChatGPT uses the RLHF (Reinforcement Learning from Human Feedback) algorithm to guide model training. Reinforcement learning guides training through reward mechanisms, which are more flexible and diverse than loss functions. Since rewards are often non-differentiable, RL approximates loss functions through extensive reward sampling to enable training. RLHF can be traced back to Google' s 2017 paper "Deep Reinforcement Learning from Human Preferences" [35], which used human annotations as feedback to improve reinforcement learning performance.

Under the RLHF framework, ChatGPT' s training process has three stages[36]: Stage 1 fine-tunes the GPT-3.5 model using manually annotated data to obtain the SFT (Supervised Fine-Tuning) model; Stage 2 uses the SFT model to generate k answers, manually ranks their quality, and trains a Reward Model (RM); Stage 3 uses the Proximal Policy Optimization (PPO) model to generate answers, evaluates them using the trained RM, and updates PPO model parameters until convergence, as shown in Figure 2.2 (from OpenAI' s official website).

Below is a brief overview of each stage' s workflow.

[Figure 2: see original paper].2 ChatGPT' s Training Process[37]

(1) Fine-tuning GPT-3.5 to obtain SFT: To enable GPT-3.5 to initially understand instructions' intent, a batch of prompt data (instructions or questions) submitted by test users is randomly sampled. Professional annotators provide high-quality answers to create <prompt, answer> data pairs, which are used to fine-tune GPT-3.5, helping the model better understand input instructions. This transforms a basic GPT-3.5 language model into the SFT model shown in the figure.

(2) Training reward model through human ranking: This stage aims to train the reward model through manually annotated data. First, a batch of user-submitted prompt data (mostly the same as Stage 1) is randomly sampled. The Stage 1 SFT model generates k different answers for each

prompt, producing data series <prompt, answer1>, <prompt, answer2> ···<prompt, answer k>. Annotators then comprehensively rank the k results by relevance, informativeness, harmfulness, and other criteria to obtain training data for the reward model.

Next, the reward model is trained using pair-wise learning-to-rank mode. For each input <prompt, answer>, the reward model provides a reward score evaluating answer quality. Specifically, for training data pairs <prompt, answer1> and <prompt, answer2>, if annotators rank answer1 before answer2, the reward model' s loss function encourages higher scoring for <prompt, answer1> than <prompt, answer2>. The trained reward model outputs quality scores for input data pairs <prompt, answer>, where higher scores indicate higher-quality generated answers.

(3) Training answer generation based on reward model output: This stage requires no manual annotation. Instead, it uses the trained reward model to score result quality and update pre-trained model parameters. First, a new batch of data is randomly sampled from user-submitted prompts, and PPO model parameters are initialized using the Stage 1 SFT model. This new data differs from Stages 1 and 2 to improve LLM' s generalization ability in understanding instructions.

Then, for randomly sampled prompts, the PPO model generates corresponding answers, which are evaluated and scored by the trained reward model. The reward is passed backward from each word as a time step, generating policy gradients to update PPO model parameters. This standard reinforcement learning process aims to train LLMs to obtain high-reward answers—i.e., generate high-quality answers meeting reward model standards. The entire process iterates until model convergence.

2.6.2 RLHF Characteristics and Advantages

Overall, RLHF can learn human preferences for all types of answers to the same prompt through human feedback, enabling language models to imitate human values, ensuring output consistency and generating answers aligned with human values. This mechanism gives ChatGPT the ability to distinguish good from bad (non-toxic) text, satisfying user-friendly dialogue principles and significantly enhancing user experience during conversations with ChatGPT. In contrast, BERT is a relatively general pre-trained model that may "speak without thinking" in downstream Q&A applications, with answers not well-suited to user needs.

2.7.1 Reward Model (RM)

Model Input: Prompt ( ), ILM' s output text ( ) for the prompt, and annotator preference ranking (>)
Model Output: Reward ((,)) for the ILM with parameters that generates text based on the prompt

Model Function: Learn human preferences for text, evaluate each prompt-text pair at the sentence level, and provide human preference rewards
Training Batch: Annotator ranking annotations (Rank) for multiple texts generated for the same prompt

Structurally, ChatGPT' s original RM model is derived from the SFT-trained GPT-3.5 with the unembedding layer removed. Based on the original RM model, annotator preference rankings are first converted to rewards (,) using the ELO method[38]. The conversion formulas are:

1 + 10(−)/400
1 + 10(−)/400
= + (−)

Where represents (,) before adjustment, represents A' s expected score (((,)> (,))), represents A' s actual score (cases where A>B in the actual dataset), represents adjusted (,) for A, and is the adjustment coefficient.

After obtaining scalarized (,), the model minimizes the cross-entropy loss function. The loss function between two texts[39] is calculated as:

Where K is the number of texts generated for the same prompt (typically 4-9), D is the entire training dataset, ( ) represents the combination number 2, and yw is the text preferred by annotators. Text evaluation is conducted at the sentence-level token granularity, so both and can be viewed as aggregations of multiple tokens, i.e., = .

2.7.2 RM Characteristics and Advantages

RM solves the problem of fine-tuning ultra-large-scale pre-trained models like ChatGPT. Since ChatGPT uses reinforcement learning for parameter tuning, training requires building an environment to provide feedback (Reward) on LM-generated outputs. In previous RL processes, environments typically relied on complex rules to construct reward functions, which is unfeasible for ChatGPT. RM can evaluate input prompt-output pairs and provide scalar feedback, serving the environment' s function in the RL process and enabling RLHF.

Additionally, RM' s training data introduces human-annotated preference ranking, avoiding issues like personal preference annotation bias and enormous annotation costs from direct prompt-output pair evaluation, which would limit optimization effectiveness.

2.8.1 Proximal Policy Optimization Model (PPO)

As the third stage of ChatGPT model training, the PPO (Proximal Policy Optimization) algorithm uses the Stage 2 trained reward model to update pre-trained model parameters through reward scoring. Questions are randomly sampled from datasets, PPO model parameters are initialized using the supervised learning model to generate answers, the reward model provides quality

scores, rewards are passed sequentially, and policy gradients are generated to update PPO model parameters[40].

The PPO algorithm samples data alternately through environmental interaction and optimizes a "surrogate"objective function using stochastic gradient ascent[41]. Standard policy gradient methods perform one gradient update per data sample, which is challenging for achieving good results due to high sensitivity to step size: too small steps increase data processing time and reduce computational efficiency, while too large steps may overwhelm effective information and degrade performance. Sample efficiency is typically poor, often requiring millions (or billions) of time steps to learn simple tasks. Compared to policy gradient methods, PPO achieves balance between ease of implementation, sample complexity, and tuning, attempting to compute updates at each step to minimize cost functions while ensuring relatively small deviations from previous policies[42].

Besides overcoming policy gradient limitations, PPO incorporates experience replay—storing each step' s estimated advantages and value targets in an experience buffer before updating policy and value parameters, then sampling batches from the buffer multiple times for replay and learning to update parameters. Thus, experience-replay-based proximal policy optimization retains on-policy learning advantages[43].

The PPO algorithm flow in ChatGPT is shown below:

[Figure 2: see original paper].3 Proximal Policy Optimization Model PPO Schematic

New commands are randomly sampled from user-submitted instructions/questions and passed to the PPO algorithm. Supervised learning model parameters initialize the PPO algorithm to generate corresponding answers, which are sent to the reward model for quality scoring. Each obtained score is passed sequentially, generating policy gradients as the basis for PPO model parameter updates, continuously updating the strategy.

2.8.2 PPO Characteristics and Advantages

PPO is an on-policy optimization method. Compared to Markovian value-based methods or off-policy methods, PPO' s optimization process uses experience generated by the current policy, enabling real-time optimization of the strategy used to generate output text and ensuring consistency between the estimated loss function (RM model output) and current generation strategy. This allows the generation strategy to change instantly as dialogue progresses, giving ChatGPT the ability to recognize previous conversation context and adjust subsequent outputs accordingly—providing ChatGPT with memory capabilities during user conversations.

Additionally, PPO introduces experience replay mechanisms, using trajectories from old policies to train new policies through random sampling, improving data utilization efficiency. It also limits the change magnitude between old and new

policies before and after updates, enhancing algorithm stability. In ChatGPT' s PPO optimization process, KL divergence[44] is also introduced as a penalty function, further limiting differences between old and new policies during single-generation optimization, improving ChatGPT' s stability and preventing it from pleasing humans through non-positive answers or opportunistic tactics to obtain high RM scores.

3 ChatGPT-Related Research and Practice

ChatGPT' s emergence has sparked a research boom in generative large-scale language models. Major domestic and international research institutions and technology enterprises view ChatGPT and related AI technologies as important strategies for driving industry paradigm transformation, investing heavily in research. This section compiles relevant research to understand the latest industry developments and track cutting-edge results.

3.1 Google

On February 7, Google CEO Sundar Pichai released Bard, Google' s AI conversational robot. Bard is a new experimental conversational Google AI service powered by LaMDA[45], seeking to combine the breadth of world knowledge with Google' s large language model power, intelligence, and creativity. It uses web information to provide current, high-quality responses. Google launched the LaMDA model in 2021, with a 2022 paper noting the model used 137 billion parameter sets for training to achieve near-human conversational experiences[46].

As chatbots, Google' s Bard and Microsoft-backed ChatGPT share similarities, requiring users to type questions or requests and responding accordingly. Bard' s main difference from ChatGPT is that while ChatGPT' s latest data only extends to 2021, Bard can answer current questions, achieving real-time search effects[47]. Currently, Bard uses a lightweight LaMDA version with lower computing requirements, enabling broader access to obtain more user feedback for continuous AI learning and improvement[48].

3.2 Baidu

Baidu' s ERNIE Bot (Wenxin Yiyan) will complete internal testing in March and open to the public, with the initial version embedded in its search service. Baidu' s official WeChat article announcing this news listed editors as "Xijiajia, Du Xiaoxiao, Ye Youyou, Lin Kaikai" —four of Baidu' s existing digital humans, demonstrating its AI model strength.

ERNIE Bot is an AI based on a knowledge-enhanced continuous learning semantic understanding framework that combines large-scale data pre-training with multi-source rich knowledge. Through continuous learning technology, it absorbs knowledge about vocabulary, structure, and semantics from text data, continuously optimizing model effects. Baidu has deep roots in AI for over a

decade, possessing the industry-level knowledge-enhanced ERNIE large model with cross-modal and cross-lingual deep semantic understanding and generation capabilities[49]. Baidu has full-stack layout in AI' s four-layer architecture, including chips, deep learning frameworks, large models, and upper-layer applications like search. Reports indicate ERNIE Bot has gradually developed capabilities for language understanding, language generation, and text-to-image generation, with Baidu' s goal of using the service as a standalone application and gradually integrating it into its search engine by incorporating chatbot-generated results[50].

3.3 Alibaba

Alibaba DAMO Academy has successively released multiple versions of multimodal and language large models, achieving breakthroughs in ultra-large models, low-carbon training technology, platform services, and applied implementation, leading Chinese large model development.

According to Alibaba Research Institute, DAMO Academy launched the Chinese multimodal pre-training model M6 project in early 2020, releasing a 300-million-parameter base model in June 2020. By October 2020, M6 expanded to 10 trillion parameters, becoming the world' s largest AI pre-training model at the time. Alibaba Cloud stated that as China' s first commercially deployed multimodal large model, M6 has been applied in over 40 scenarios with daily usage exceeding 100 million calls. Within Alibaba Cloud, M6 applications include clothing design for Xunxi Zhizao (now on Taobao), script creation for Tmall virtual anchors, and enhancing search and content understanding accuracy on Taobao and Alipay platforms. It excels particularly in design, writing, and Q&A, with prospects for implementation in e-commerce, manufacturing, literature and arts, and scientific research.

On February 7, DingTalk announced that its App could integrate ChatGPT-like functions in DingTalk robots for conversational operations. Reports indicate Alibaba DAMO Academy is developing a ChatGPT-like conversational robot currently being tested internally[51]. Exposed screenshots suggest Alibaba may deeply integrate AI large model technology with DingTalk productivity tools, with the model possessing not only pure text task capabilities but also multimodal task capabilities.

3.4 Tencent

Tencent's intelligent AIGC product Effidit integrates knowledge extraction, text understanding, text generation, pre-trained models, classic language models, and search technologies, already deployed in Tencent' s internal products for advertising, search, and dialogue, using the HunYuan series AI large model as its underlying pre-trained model[52].

In November 2022, HunYuan launched the HunYuan-NLP 1T large model via Tencent' s 太极 machine learning platform, topping the CLUE natural language

understanding task leaderboard. The model optimized warm-starting, MoE routing algorithms, model structure, and training acceleration, reducing training costs to only 1/8 of previous levels, completing training on 256 cards within one day[53].

3.5 JD.com

Based on industrial needs, JD Cloud's Yanxi AI application platform will launch ChatJD, positioned as an industrial version of ChatGPT, aiming to create an industrial general-purpose ChatGPT with advantages, high frequency, and rigid demand[54]. JD Cloud' s AIGC & ChatGPT layout focuses on five aspects: text, voice, dialogue generation, digital human generation, and general Chat AI technology. Text generation (NLG) includes product titles (10 characters), product selling point copy (100 characters), and product live-streaming copy (500 characters), focusing on product copywriting generation. Currently, product copywriting capabilities cover over 2,000 JD.com categories, with the technology having generated over 3 billion characters. Voice generation (TTS) is mainly applied to intelligent customer service, SaaS outbound calls, finance, and AI live-streaming products.

3.6 iFLYTEK

On February 8, iFLYTEK stated, "ChatGPT mainly involves natural language processing technologies, representing one application in cognitive intelligence, where our company has deep accumulation in technology and applications" [55]. Building on existing AI technology, industrial scenarios, and industry data, the company further launched generative pre-trained large model task 攻关 in December 2022. iFLYTEK' s AI learning machine will be the first product to implement this technology, with a product-level release on May 6, 2023[56]. This technological breakthrough will bring significant improvements in Chinese and English essay tutoring and oral language learning.

iFLYTEK won first place in multiple cognitive intelligence authoritative evaluations in 2022, including CommonsenseQA2.0 and OpenBookQA[57], demonstrating clear advantages in text recognition, speech recognition, and semantic understanding[58]. The company has open-sourced over 40 general-domain Chinese pre-trained language models across six categories, becoming one of the industry' s most widely used Chinese pre-trained models.

3.7 Huawei

Huawei' s MindSpore team and Peng Cheng Laboratory jointly released Pengcheng · Pangu in 2021, the world' s first 100-billion-parameter Chinese pre-trained model with 200 billion parameters. Another is the Huawei · Pangu large model jointly trained by Huawei Cloud and Peng Cheng Laboratory, with 110 billion parameters, both specifically for Chinese. These models support cloud search, intelligent customer service, medical guidance, interactive

education, literary creation, and automatic summarization generation. These models will break language barriers, support national strategies, and enable continuous exploration and innovation with Peng Cheng Laboratory across multiple scenarios.

3.8 Qihoo 360

The company' s AI Research Institute has continuously invested in AIGC technologies including ChatGPT-like technology since 2020, though currently only as internal productivity tools. The company plans to launch a ChatGPT-like technology DEMO product soon. Beyond search engine applications, AIGC technology can also enhance digital security capabilities[59].

3.9 Beijing Academy of Artificial Intelligence

By building the multilingual text-image representation model AltCLIP, researchers at the Beijing Academy of Artificial Intelligence first launched the bilingual Chinese-English image generation model AltDiffusion, supporting sophisticated long Chinese prompts for advanced creation. Building on this, they launched the multilingual upgraded version AltDiffusion-m9, becoming the first text-to-image generation model supporting nine languages[60]. This research' s main contribution is building a cornerstone for multilingual text-to-image generation models, enabling more creators using different languages to create through the AltDiffusion model.

3.10 IDEA Research Institute

On November 22, 2021, IDEA Research Institute' s founding chairman Shen Xiangyang officially announced the launch of the "Fengshenbang" large model open-source plan[61]. The center possesses China's largest open-source model system—Fengshenbang—with 98 open-sourced models including: (1) Erlang Shen series: Encoder-based bidirectional language models focusing on various natural language understanding tasks; (2) Yuyuan series: Models primarily for the medical domain; (3) King Wen series: New-structure large models jointly developed by IDEA Research Institute and Zhuiyi Technology, the largest Chinese models capable of both LM and MLM tasks; (4) Wen Zhong series: Decoder-based unidirectional language models, a series of powerful generative models; (5) Randeng series: Encoder-decoder language models based on Transformer structure for general tasks; (6) Bigan series: Models primarily for various error correction tasks. These open-source models explore personalized and customizable models adapted to various domains, supporting all natural language processing tasks, launching ChatGPT-like models, and fully supporting China' s AIGC development.

3.11 Institute of Automation, Chinese Academy of Sciences

The Institute of Automation, Chinese Academy of Sciences, and Huawei jointly developed "Zidong Taichu,"the world's first tri-modal large model. The platform achieves "unified representation" and "mutual generation" among image, text, and voice data through cross-modal multi-task self-supervised learning. Developed on a domestically autonomous AI basic software and hardware platform (Ascend), it represents a step toward more general artificial intelligence. At the 2022 World Artificial Intelligence Conference in Shanghai, the research team won the conference' s highest award, the Superior AI Leader (SAIL) prize[62].

3.12 Peng Cheng Laboratory

Peng Cheng Laboratory (Shenzhen Cyberspace Science and Technology Provincial Laboratory) and Huawei jointly released the Pangu large model in 2021. It was the first time domestic full-stack AI infrastructure supported 200-billion-level ultra-large-scale language model training, exploring and verifying the feasibility of core key technologies such as software-hardware collaborative optimization and large-scale distributed parallel training on domestic E-level intelligent computing platforms[63],[64]. In 2022, Peng Cheng Laboratory released Pengcheng·Shennong, a biomedical research platform for accelerating new drug screening and creation[65].

3.13 Others

Beyond the above enterprises and institutions, many other large-scale language models have been released, such as Meta AI' s OPT-IML and Hugging Face' s Bloom. In dialogue technology, multiple companies have released their own chatbots in recent years, including Meta' s BlenderBot, Google' s LaMDA, and DeepMind' s Sparrow[66]. As a standout among them, ChatGPT has reignited the dialogue generation technology boom, and through integration with search engines, is beginning to demonstrate greater application value. More enterprises and institutions will inevitably follow up on related AI technology R&D, with content creation, intelligent customer service, and other fields benefiting from this wave.

4 ChatGPT Applications

As a concrete application of AIGC technology, ChatGPT' s emergence validates new possibilities for various industries. Global sectors are analyzing and researching how to integrate it into their systems to seize market opportunities. Multiple enterprises have actively laid out and developed ChatGPT-related products and services. We believe it can demonstrate diverse potential in the following fields.

4.1 ChatGPT Applications in Scientific Research

AlphaFold and AlphaFold2, based on Transformer model modifications, achieved tremendous success in biochemistry, representing notable AI progress in scientific research. Biochemistry research institutions and enterprises have rapidly followed ChatGPT developments since its release, attempting to leverage it to improve research efficiency. Additionally, ChatGPT shows initial promise in scientific paper writing.

4.1.1 ChatGPT for Biochemical Research

(1) Drug Discovery: In an AstraZeneca study applying ChatGPT to drug discovery, researchers stated ChatGPT could identify novel targets undiscovered by traditional methods, demonstrating generative AI' s potential to accelerate drug discovery[67]. Cambridge University researchers used ChatGPT to analyze scientific literature and identify a new target for Alzheimer' s disease treatment; University of California, San Francisco researchers used ChatGPT to analyze electronic health records and identify potential drug interactions in real-world settings. Insilico Medicine founder and co-CEO Alex Zhavoronkov stated that generative AI can synthesize data based on conditions and has been applied across healthcare, but considering ChatGPT' s training set and AI trainer levels, accuracy issues exist, so direct application in biomedical fields is not currently recommended[68].

(2) Molecular Structure Prediction: Before ChatGPT, some studies explored GPT-3' s feasibility in scientific research. Research[69] investigated GPT-3' s low-data discovery capabilities in chemistry, finding that while GPT-3 could generate plausible molecular structures, it performed poorly in predicting their properties and stability. The study also identified limitations including language incoherence and chemical symbol parsing issues. In summary, while generative models like ChatGPT show potential in biochemistry, they have yet to produce effective results comparable to specialized models like AlphaFold.

4.1.2 ChatGPT for Scientific Writing Since ChatGPT' s launch last December, many have used it as a paper writing tool[70]. According to Nature, at least four papers have listed ChatGPT as an author. Alex Zhavoronkov, CEO of AI drug discovery company Insilico Medicine, revealed his institution has published over 80 papers generated by AI tools[71]. Top journals like Nature and Science have begun implementing usage restrictions on ChatGPT. Springer Nature published policies on AI writing tools in scientific papers, stating software like ChatGPT cannot be credited as authors in papers published in its thousands of journals[72]. Springer stated it has no objection to scientists using AI to assist writing or generate research ideas but requires authors to properly disclose such contributions.

4.2 ChatGPT Applications in Education

ChatGPT AI language model application development opens new learning opportunities, providing personalized learning experiences accessible anytime, anywhere as a cost-effective educational solution.

4.2.1 ChatGPT for Teaching In the US, teachers have students debate ChatGPT to train critical thinking, use it to generate questions to improve lesson preparation efficiency, and use it to quickly search materials to enrich courses. Domestic ChatGPT-like technologies have also landed in education.

On February 8, Xiaodu launched its first education hardware product equipped with ChatGPT 同源 technology—the Xiaodu Optical Eye-Protection Learning Tablet—where users can already experience AI functions like essay correction and active polishing. NetEase Youdao revealed its AI technology team has invested in ChatGPT 同源 technology (AIGC) R&D for education scenarios, currently trying applications in AI oral English teachers and Chinese essay correction. The company expects to launch related demo products soon, marking AIGC technology' s first landing in domestic internet education scenarios. iFLYTEK further launched generative pre-trained large model task 攻关 in December 2022, with iFLYTEK AI learning machines becoming the first product to implement this technology, with a product-level release on May 6, 2023.

However, students have already used ChatGPT as a cheating tool. As of January 2023, 89% of US college students used ChatGPT for assignments. Multiple schools globally have banned ChatGPT, fearing students will use it to cheat, becoming "pets"fed by ChatGPT and losing learning ability and critical thinking. OpenAI, ChatGPT' s parent company, fears students will become addicted to "ready-made-ism"and is developing anti-cheating systems to detect AI-generated text. Stanford researchers launched DetectGPT[73] to facilitate AI-generated text detection.

4.2.2 ChatGPT for Examinations Multiple studies have explored ChatGPT' s feasibility in course examinations. Research[74] used physics course assessment content, showing ChatGPT could barely pass the course but made beginner-level mistakes. Study[75] applied ChatGPT to four real law exams at the University of Minnesota, where ChatGPT achieved low but passing grades. Research[76] applied ChatGPT to the US Medical Licensing Examination (USMLE), which ChatGPT passed, demonstrating ability to process complex medical and clinical information. However, study[77] tested ChatGPT on software testing courses, finding it could only correctly answer a small portion of questions and failed the exam. Research[78] found that while ChatGPT could efficiently explain many concepts in various ways and vividly describe abstract concepts, it could not truly connect concepts and might provide incorrect information with plausible reasoning.

4.3 ChatGPT Applications in Healthcare

ChatGPT and similar AI technologies are expected to improve existing medical care, making it more intelligent, efficient, and personalized. Some studies have begun exploring ChatGPT' s feasibility in medical report simplification, medical decision-making, and doctor-patient communication.

4.3.1 ChatGPT for Report Writing and Information Extraction Research[79] used ChatGPT for medical report simplification, inviting 15 radiologists to evaluate quality. Most reports were considered authentic, correct, and harmless, though a few had issues with omitting key medical findings. Study[80] designed a method to automatically generate medical dialogue summary training corpora through GPT-3 models by analyzing medical literature and dialogue data, proving generated summary corpora effectively assist summary model supervised training. Research[81] explored GPT-3' s few-shot learning capabilities in biomedicine, finding GPT-3 showed no advantage over traditional rule-based or statistical methods in predicting biomedical entities, drug-gene relationships, and answering biomedical questions with limited samples. Study[82] experimented with GPT-3 for biomedical information extraction, finding GPT-3 could generate plausible entities, relationships, and events but performed poorly.

4.3.2 ChatGPT for Diagnostic Decision-Making and Triage Research[83] explored ChatGPT' s potential use in radiology decision-making, showing ChatGPT achieved good results in determining imaging examination decisions for breast cancer and breast pain patients. Given radiology decision-making complexity, the authors consider ChatGPT a potential auxiliary tool. Before ChatGPT, some GPT-3-based studies[84] explored GPT-3' s accuracy in medical diagnosis and triage, finding GPT-3 performed accurately in diagnosing certain diseases like COVID-19 and heart disease but could not adapt to specific cases.

4.3.3 ChatGPT for Doctor-Patient Communication To evaluate AI chatbots for doctor-patient communication, study[85] assessed ChatGPT' s effectiveness in answering medical questions. ChatGPT and providers respectively answered patient questions, then patients categorized the responses, showing nearly identical results between ChatGPT and providers, with laypeople largely trusting chatbot answers for low-risk health questions. However, credibility decreased as medical complexity increased. Study[86] explored ChatGPT' s effectiveness in causal discovery Q&A for neurodegenerative disease diagnosis, with similar results: ChatGPT could only understand commonly used descriptive language, not complex medical terminology, such as failing to recognize lower abdominal discomfort caused by T12 radiculopathy.

4.4 ChatGPT Applications in Information Technology

Born in the information field, ChatGPT first impacted the information technology industry. Multiple IT enterprises have explored internal ChatGPT usage scenarios to assist programmers in efficient development, while some have implemented ChatGPT plugins in applications to provide more personalized user experiences.

4.4.1 ChatGPT for Search Engines Traditional search engines match results based on keywords, while ChatGPT enables conversational search based on natural language and semantic understanding, providing better search experiences. Microsoft launched a new AI-powered Bing search engine and Edge browser to provide better search, more complete answers, new chat experiences, and content generation capabilities[87].

Microsoft developed the Prometheus model to work with OpenAI models, providing users with more relevant, timely, and targeted results while improving safety. Applying AI models to the core Bing search ranking engine achieved the biggest relevance retrieval jump in two decades, making even basic search queries more accurate and relevant. Microsoft integrates search, browsing, and chat into a unified experience, enabling users to invoke it from anywhere on the web for better service content.

4.4.2 ChatGPT for Code Generation and Bug Fixing ChatGPT can directly generate code based on user programming needs and help retrieve errors in existing code. Beyond conventional languages like Python and Java, ChatGPT can also generate special codes like literature search formulas. Research[88] experimented with ChatGPT' s performance in generating literature search formulas, showing it could generate search formulas with high precision but low recall, serving as an auxiliary tool for researchers conducting rapid systematic reviews. Automatically fixing bugs in software source code is an important and complex engineering task that can improve development efficiency and reduce maintenance costs. ChatGPT has also shown significant potential in code bug fixing, with research[89] evaluating ChatGPT' s bug-fixing performance and finding it outperformed existing state-of-the-art models.

4.5 ChatGPT Applications in Other Fields

More industries have explored ChatGPT applications. Content and gaming industries, born alongside internet development, have inherent advantages for embedded ChatGPT applications.

4.5.1 ChatGPT for Content Creation As a text generation model, ChatGPT and similar models have opened a new era for content creation, assisting creators in conception, polishing, continuation, rewriting, and translation based on large-scale corpora, or directly interfacing with users to build valuable content through Q&A generation and human screening, such as poetry, song lyrics,

and advertising copy. US news aggregator BuzzFeed laid off 180 employees last December, switching to OpenAI' s ChatGPT to "enhance" and "personalize" its content[90]. In applying AI to news writing, CNET went further but suffered consequences earlier. Starting November 2022, CNET used an internally developed AI engine to generate 77 news reports, over half of which contained factual errors or improper citations, leading CNET to discontinue the AI engine[91].

4.5.2 ChatGPT for Game Characters Technology is the core driver of game industry development, and the game industry itself offers significant value as a perfect experimental field with high degrees of freedom for applying various new technologies[92]. On February 15, NetEase' s open-world martial arts mobile game "Justice Online" announced implementation of China' s first in-game ChatGPT-like application, enabling intelligent NPCs (Non-Player Characters) to generate dialogue freely with players and autonomously provide logical behavioral feedback based on dialogue content[93]. This is also China' s first ChatGPT-like application in gaming. Officials stated that with "Justice Online GPT," intelligent NPCs form a huge social network where every player action may create butterfly effects. All NPC dialogue text, expressions, voices, and camera angles are freely generated by AI, with voices currently mechanical versions to be iteratively improved based on NPC personalities upon official launch.

4.5.3 ChatGPT for E-commerce Marketing and Intelligent Customer Service Intelligent customer service robots have been widely applied in e-commerce, answering common business consultation questions before human agents take over, greatly improving reception efficiency and reducing human workload. ChatGPT's conversational capabilities can help brands establish more natural, content-rich, and personalized customer service dialogue systems with consumers. Additionally, ChatGPT can analyze customer purchase history and preferences for personalized product recommendations, improving conversion rates and sales. Leveraging its excellent content generation capabilities, it can also describe products, highlight selling points, and enable content marketing.

On February 10, JD Cloud announced its Yanxi AI application platform will integrate past industrial practice and technical accumulation to launch an industrial version of ChatGPT called ChatJD, with a roadmap mentioning five applications: content generation, human-computer dialogue, user intent understanding, information extraction, and sentiment classification[94]. Qunar launched a ChatGPT-like intelligent Q&A robot "Universal AI Little Camel" that can help users customize itineraries and answer travel questions, covering topics like travel route recommendations, restroom locations, and mushroom poisoning.

4.5.4 ChatGPT for Industrial Task Scheduling ChatGPT also shows potential applicability for industrial task scheduling. Research[95] used ChatGPT to generate construction plans for building projects, organizing participants to evaluate output results and interaction experiences through human feedback mechanisms. Experimental results showed ChatGPT could generate coherent

schedules following reasonable task sequences for specified scopes, demonstrating significant potential for improving industrial efficiency through automatic execution of construction industrial tasks.

5 Insights from Rapid AI Technology Development

Represented by ChatGPT, AI technology has achieved rapid breakthroughs in recent years, with widely applied results creating massive impact across social industries.

Summarizing AI' s main development history over the past decade, we believe AI' s fundamental reason for rapid breakthrough lies in changed patterns of computer knowledge learning and utilization. The ability to quickly and efficiently learn knowledge hidden in various data resources (corpora) is the essence of AI' s rapid breakthrough.

The rapid development of ChatGPT-like AI technology stems from significantly improved knowledge learning capabilities, bringing the following insights:

5.1 Computer Problem-Solving Patterns Have Changed; Machine Learning Has Become an Important Means to Acquire Problem-Solving Knowledge

Machine learning has changed computer problem-solving patterns. Previously, humans input knowledge for machines to solve problems; now, machines learn knowledge from relevant corpora and use learned knowledge to solve related problems. In this process, large-sample training corpora containing important human knowledge are crucial. These corpora representing human knowledge are the key to machine learning' s rapid breakthrough.

5.2 Deep Learning Performance Improvements Are More Attributable to Corpora Than Model Breakthroughs

Various deep learning models are the foundation, large-scale computable data resources (training corpora) are the prerequisite, and large-scale computing power is the catalyst. Possessing large-sample training corpora and large-scale computing power enables significant performance improvements in knowledge learning based on artificial neural network deep learning.

5.3 Natural Language Processing Technology Has Been Rewritten; Unsupervised Pre-training Has Important Value for Knowledge Learning

The two-stage learning method based on pre-training and fine-tuning has rewritten natural language processing (NLP), with unsupervised pre-training holding important value. Using large-scale unlabeled corpora for unsupervised pre-training enables models to learn language expression patterns, text logic, and

knowledge element relationships, improving model generalization and robustness. Only small amounts of annotated data are needed for fine-tuning to achieve good results on specific downstream tasks.

5.4 ChatGPT Did Not Emerge from Nowhere; It Represents a Major Breakthrough from Quantitative to Qualitative Change in Learning Ability

Historically, from the initial GPT-1 model with 117 million parameters, 5GB corpora, and 12 Transformer layers, to the current ChatGPT model with 175 billion parameters, 45TB corpora, 96 Transformer layers, and human feedback reinforcement learning, ChatGPT is the accumulation of corpora, models, and algorithms through iterative training. Every small improvement in AI knowledge learning ability is valuable. Persistent progress over time ultimately achieved the transformation from quantitative to qualitative change.

5.5 ChatGPT Is an Integrated Innovation Result; Learning Ability Improvements Benefit from Effective Integration of Software, Hardware, Technology, and Corpora

To accommodate surging model parameters, OpenAI collected and annotated more raw training corpora; to achieve more human-like dialogue effects, it developed RLHF based on human feedback; to accelerate model training, it deployed supercomputers with 280,000 CPU cores and 10,000 GPUs. Only through effective integration of software, hardware, technology, and corpora did ChatGPT' s knowledge learning ability achieve qualitative leaps, creating its current outstanding performance.

6 ChatGPT' s Impact on Scientific Research and Library & Information Service

The enormous application potential of ChatGPT-like AI technology indicates it may bring disruptive impacts to various aspects of all fields. This section primarily explores its paradigm transformation of scientific research and direct impact and profound influence on library & information service.

6.1 ChatGPT' s Impact on Scientific Research

Currently, ChatGPT-like AI technology demonstrates enormous application potential that may overturn traditional scientific research methods, with new paradigms based on AI as the research foundation forming. For the scientific research process, ChatGPT can provide further support for researchers in knowledge acquisition, experimental planning, and research result writing. Simultaneously, we must fully address AI-related research ethics, fairness, and other issues, establishing and improving relevant policies and regulations to ensure scientific research properly applies AI technology on the right track.

6.1.1 Changing Scientific Research Paradigms, Driving Evolution from the Fourth Paradigm to New Research Paradigms In the history of scientific development, scientific research has experienced four paradigm shifts: from the first paradigm (empirical) to the second (theoretical), to the third (simulation), to the fourth (big scientific data, data-intensive). Paradigm changes essentially represent progress in scientific research' s fundamental driving forces. ChatGPT-like AI technology will penetrate all aspects of scientific research, becoming a new driving force for scientific development and pushing research into the new AI paradigm era.

6.1.2 Changing Scientific Research Knowledge Acquisition Patterns, Promoting Upgrade from Retrieval to Q&A Modes Traditional knowledge acquisition methods primarily use search engines to retrieve literature resources through keyword searching, combination filtering, faceting, and sorting. Users typically need multiple filtering iterations, search condition adjustments, and manual browsing to select literature resources. This knowledge acquisition process is time-consuming and suffers from incomplete retrieval. If search terms differ from literature terminology, same-topic literature won' t be retrieved, affecting researchers' judgment of research trends. AI large model-based Q&A knowledge services will be more like a knowledgeable "person" than an information service system—able to understand user semantic expressions, "comprehend" questions, and "answer" with results. Users asking practical questions can obtain more accurate and comprehensive results than traditional knowledge retrieval systems.

6.1.3 Changing Scientific Research Experimental Planning Patterns, Promoting Intelligent Experimental Design Experimental design is a key scientific research link and critical means for verifying innovation. Planning scientific, reasonable experimental processes, designing detailed experimental models, and clarifying correct operations for experimental environments, instruments, and software requires defining variable indicators, dosage controls, etc., consuming significant time and effort to form comprehensive experimental plans. AI systems oriented toward fine-grained semantic knowledge elements can systematically train on scientific research literature to form high-quality scientific experimental large models, providing suggestions for overall experimental planning, model design, parameter settings, and environmental requirements, with interactive adjustments to form experimental plans. Intelligent systems can also provide evidence-based functions to assist in forming scientific experimental evidence chains, ensuring research integrity. In the near future, intelligent systems assisting researchers in designing experiments and directly interfacing with experimental robots to conduct experiments may become commonplace.

6.1.4 Changing Scientific Research Result Writing Patterns, Assisting Paper Writing Nature magazine quoted University of Pennsylvania researcher Pividori, noting that generative large language model technologies like

ChatGPT can help researchers more efficiently edit manuscripts, check code, and brainstorm[96]. ChatGPT-like AI as a content creation intelligent assistant can provide recommended content for research background, frontiers, key problems, core solutions, and experimental result demonstrations, assisting researchers in efficiently writing scientific literature.

6.1.5 Raising Research Ethics Issues, Requiring Sound Policies and Regulations AI tools already exist that can predict whether an article comes from machines or humans. Such detection methods are useful for identifying LLM-generated content but may be circumvented by evolving AI technology and clever prompts. Scientific research should use AI large language models with integrity and transparency, not engage in uncontrollable technological competition between AI robots and AI detectors. Author contribution statements and acknowledgments in research papers should clearly and specifically state whether and to what extent authors used AI technologies like ChatGPT in manuscript preparation and analysis. Research institutions, publishers, and funders should establish clear policies constraining conversational AI usage conditions and extent in scientific research processes, requiring transparency to ensure open and fair scientific research environments.

6.2 ChatGPT' s Impact on Library & Information Service

The library & information field is one of ChatGPT' s main battlegrounds for intelligent functionality. New intelligence analysis paradigms driven by data and intelligence have begun delving into multimodal, multi-type, fine-grained knowledge element-based intelligent intelligence. ChatGPT-like AI systems have enormous integration space with library & information work in intelligent Q&A, intelligence analysis, content creation, data analysis, and paper reading. We believe new-generation ChatGPT-like AI technology will bring multi-level, multi-scenario direct impacts and profound influences on library & information work. Prohibition and resistance have never been development paths; properly applying and managing AI technology is the proper choice for library & information career development.

6.2.1 Changing Library & Information Data Organization, from Surface Information to Semantic Content Organization Traditional scientific literature organization primarily uses surface information like titles, abstracts, keywords, institutions, and journals, rarely delving into content. With AI technology development, the ability to precisely mine fine-grained knowledge objects from scientific literature has improved, making semantic content organization based on research problems, methods, experimental steps, and data materials possible.

6.2.2 Changing Library & Information Knowledge Acquisition, from Information Retrieval to Knowledge Q&A Current library & information knowledge acquisition services primarily use literature metadata and search

engine technology to retrieve massive scientific literature data. However, metadata models limit users'full utilization of literature knowledge. ChatGPT can understand paper content at the semantic level, extract and structure fine-grained knowledge elements, build large-scale knowledge networks, and form intelligent knowledge services. Users can ask questions based on semantic-level knowledge elements like problems, viewpoints, and technologies, saving researchers time in literature screening, reading, and analysis. ChatGPT drives the shift from index-based information retrieval to Q&A-based knowledge response. In the future, a new knowledge Q&A service may emerge where intelligent knowledge service platforms directly generate answers to questions and provide relevant evidence chains.

6.2.3 Changing Library & Information Analysis Methods, from Manual Workshops to Large-scale Intelligent Analysis Literature intelligence analysis involves problem definition, data source inventory, data preparation, key information extraction, statistical analysis, viewpoint extraction, and report writing—all previously done manually. The complexity of intelligence analysis itself limits analysts' productivity, especially in the "data is king" era where data construction and intelligence capabilities represent intelligence analysis levels. ChatGPT-like AI technology already possesses core content summarization, scenario Q&A, language translation, semantic analysis, and recommendation capabilities. Through building literature intelligence analysis large models with viewpoint extraction and decision recommendation functions, it can support intelligence analysis work, providing analysts with more ideas, broader perspectives, and higher-value knowledge.

6.2.4 Raising Library & Information Service Security Issues, Requiring Risk Management Mechanisms AI applications raise two issues for library & information services: service ownership and misinformation misleading intelligence analysis. Service security has always been a widely concerned and contested strategic high ground. When knowledge acquisition runs in more intelligent Q&A mode, service owners can easily achieve precise user profiling through user behavior data, clearly grasping research problems, technologies, progress, team members, experimental equipment, and other key information, posing major hidden dangers for national science and technology strategic security. Therefore, building China' s fully controllable library & information intelligent service system is necessary to defend service security.

Some scholars question how big data models trained on science fiction novels would answer questions—clearly untrustworthy. We see that general-knowledge large models cannot guarantee answer quality, while library & information fields have higher data credibility requirements. Intelligence reports generated based on pseudo-data and fabricated facts are inevitably untrustworthy. If using foreign services like ChatGPT to obtain relevant data, distinguishing data and fact authenticity is difficult for intelligence analysts. Therefore, mastering intelligent service data control is paramount, while establishing a sound data

evidence-based system with data evidence chains and source details achieves effective risk management and traceability.

6.2.5 Impact on User Reading Habits, Guiding New Human-AI Collaborative Reading Models Reading extensive literature is necessary for researchers, requiring significant time and effort, especially in the information explosion era where extracting key information from complex literature resources and finding potential relationships among multiple papers to obtain important data and technical support for scientific research is even more time-consuming. ChatGPT-like technology may bring disruptive changes to how users read literature, automatically achieving knowledge extraction and relationship revelation from input literature resources, displaying them through visualization, supporting multi-dimensional statistical analysis, and responding to user questions and settings interactively, forming a new human-AI collaborative reading model.

6.2.6 Challenging Traditional Library & Information Work, Requiring Overall Planning of Workforce Capabilities and Position Systems AI' s impact on traditional library & information work is multi-faceted and significant, from basic cataloging, literature data governance, customer service, code writing to information editing, hot paper recommendations, book reviews, dynamic sensing, and intelligence analysis—all will be affected by AI technology to varying degrees, with some work being optimized or replaced by AI, objectively creating situations where some positions no longer need as many personnel. Simultaneously, AI brings new job opportunities, requiring new positions for more intelligent services, forming new business directions and expanding library & information work scope.

7 Recommendations for Library & Information Field

ChatGPT focuses on content generation, while library & information work focuses on evidence-based practice. ChatGPT mainly solves content generation problems in natural language processing, but library & information work's focus is not here—our opportunity lies in how to evidence, mine supporting evidence and evidence chains for trustworthy intelligence. Library & information work must find its distinct value orientation in the AI era. Recommendations are as follows:

7.1 Build Core Capability in Mining and Utilizing Knowledge from Scientific Literature Content

Scientific literature contains human knowledge, expresses scientific mechanisms, and reveals research achievements, representing core strategic resources for national scientific and technological innovation and the important foundation for national scientific literature intelligence institutions to conduct knowledge services and scientific intelligence research. Currently, using intelligent technology to deeply mine scientific literature content to support intelligent knowledge

services and intelligence analysis, thereby supporting scientific innovation and strategic decision-making, has become an important development trend. The library & information field should build core capability in mining and utilizing knowledge from scientific literature.

7.2 Fully Recognize Library & Information Institutions' Advantages and Value in the AI Era

ChatGPT tells us again that high-value corpus work is the foundation of all AI. Library & information institutions must fully recognize their important value and new positioning in the AI era: AI corpus providers. Scientific literature contains vast knowledge and is an important foundation for AI. The library & information industry is the industry that obtains knowledge from literature. In the AI era, we should fully learn from and utilize deep learning models like ChatGPT to transform scientific literature libraries into knowledge libraries, using knowledge organization systems, cataloging data, and manual indexing content to support scientific literature mining and improve knowledge acquisition capabilities. Library & information institutions should fully recognize their mission and positioning in the new era, doing well in "corpus" foundational work.

7.3 Strengthen Research and Application of New AI Technologies and Methods

Breakthroughs in AI new technologies and methods like BERT and ChatGPT indicate that generation after generation of AI technology continues to advance by leaps and bounds. The library & information field cannot be superficial. We can learn from ChatGPT's R&D approach combining self-supervised pre-trained large models with reinforcement learning based on small amounts of high-quality data feedback to form closed-loop model-data feedback for further technological breakthroughs, strengthening the ability to extract fine-grained knowledge from literature and data. By mastering new technologies and methods, we can enhance knowledge mining and computing capabilities and strengthen research and application of knowledge acquisition methods.

7.4 Library & Information Field Should Actively Participate in "Professional and Vertical" Knowledge System Construction

ChatGPT has opened a new model bringing powerful comprehensive Q&A systems. For scientific fields, there remains much room for exploration in developing more in-depth specialized knowledge content acquisition and analysis technical methods. Library & information institutions' main task is serving scientific research, so we must seize opportunities to 挖掘 ChatGPT' s value in professional and vertical domains. To achieve this, we need to leverage our advantages in professional domain scientific literature to actively participate in "professional and vertical" knowledge system construction, developing knowledge service systems that meet practical application needs for specific disciplines and research fields.

7.5 Library & Information Field Should Strive to Innovate Knowledge Service Models

In ChatGPT-related applications, retrieval can already be performed during Q&A, causing great impact on traditional information retrieval models and bringing new opportunities for retrieval paradigm transformation. Library & information institutions should recognize the development value behind this opportunity—fully utilizing new ideas, technologies, models, and methods to improve existing information retrieval service paradigms and actively explore new forms and applications of knowledge services. Examples include Q&A-based knowledge retrieval for knowledge acquisition scenarios and automatic summarization of scientific literature sets for reading assistance scenarios.

7.6 Apply ChatGPT to Inspire Creativity in Intelligence Research

Application examples have confirmed ChatGPT can provide inspiring viewpoints and creativity. For instance, in joint ChatGPT and DALL·E applications, ChatGPT can output inspiring text to guide DALL·E in intelligent painting. From this example, we can see ChatGPT' s inspirational role. Therefore, we can utilize ChatGPT' s generative, inspiring dialogue mechanism in intelligence research work to seek new directions, questions, and perspectives. However, extra attention must be paid to ChatGPT' s lack of control over authenticity and professionalism, requiring professionals with certain expertise to conduct screening and verification.

7.7 Intelligence Traceability and Reliability Detection Will Become More Important

After ChatGPT's emergence, more "fake intelligence"generated by ChatGPT will appear, making intelligence traceability and reliability detection more important. Misusing ChatGPT may cause misinformation dissemination, information leakage, plagiarism, and other issues. When conducting services or research based on ChatGPT, intelligence workers must detect the reliability of generated answers to ensure authentic and reliable data sources. How to conduct intelligence traceability and reliability detection for machine-generated content deserves further research.

7.8 Build Integrated Capability in Data Resources, Infrastructure, and Intelligent Technology

Truly applicable AI products like ChatGPT result from effective integration of software, hardware, and various technical methods. Library & information work capability improvement requires coordinated accumulation of data resources, infrastructure upgrades, and intelligent technology research to achieve quantitative accumulation to qualitative leaps in all aspects, finally conducting effective integrated development of truly useful, durable, and user-willing library & information products.

Library & information needs self-revolution to embrace new technologies and opportunities. As a tool, ChatGPT itself won' t defeat people, but it will certainly bring about a situation where people who can use this tool defeat those who cannot. Traditional library & information work still has value, but new technology-driven change is the general trend. Against this background, the library & information field needs to maintain integrity while innovating. Library and information research must seize opportunities, both maintaining conventional scientific research paradigms and expanding to assist scientific research with new technologies like ChatGPT.

Note: Figure translations are in progress. See original paper for figures.