Research on Optimization of Aging Reading Assistance System Based on Artificial Intelligence Focus Recognition

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Abstract

Under the premise of ensuring accuracy, efficiently identifying focal information in sentences via test methods is fundamental for effective communication, especially for the elderly who struggle with extracting core reading content. “Shi... de”, “shi”, and “de shi” are common focus markers in Chinese, indicating contrastive foci with exclusivity and prominence that are vital for the elderly’s information decoding. In the big data era, leveraging artificial intelligence (AI) for focus recognition offers a promising way to optimize age-appropriate reading assistance systems. This study tests the performance differences of AI models (ChatGPT, DeepSeek, Qwen) in recognizing these focus-marked sentences before and after machine learning. A dataset of 1,100 expert-annotated samples was used, with fine-tuned models via the LoRa method and Unsloth 2.3 framework for memory optimization. Baseline tests showed AI accuracy lagged far behind manual recognition, with varying performance across marker types. Post fine-tuning, significant improvements were achieved, verifying machine learning’s potential to enhance AI focus recognition. This research provides a feasible pathway for upgrading age-appropriate readers, helping the elderly better grasp key reading information.

Keywords

Focus markers, Artificial intelligence and focus recognition, Age-appropriate readers, Machine learning

Introduction

Focus has two common discourse functions: “prominent” and “contrastive”. “Prominent” is the property of using the rest of the small sentence as the focus of the background. “Contrasting” is the property of using the external components of the small sentence as the focus of the background. According to the position of the focus and the background, the focus is divided into natural focal points (informational focus), constructive focus and topic focus (topical focus) [1]. The three types of focus marks that this article addresses “shi... de”. The focus components marked by “shi” and “de shi” are contrasting focal points. They are emphasized by the speaker and possess contrastiveness, exclusivity, and prominence. Thus, they play an important role in reading comprehension and information decoding among the elderly.

By comparing multiple common AI tools like ChatGPT, DeepSeek, Qwen, and more before machine learning. The difference in focus recognition accuracy and accuracy of corpora containing the above three types of focus markers is from the elderly. From a linguistic perspective, it provides a possible path for artificial intelligence to help upgrade age-appropriate readers [2].

Focus judgment method

As the three common focus marks in Chinese, “shi... de”, “shi” and “de shi” both make the components of a specific sentence appear as the core focus of the speaker’s intention. Because they are generally both inherently contrasting and strongly exclusive, and thus are regarded as typical contrastive foci.

As the key new information in the sentence, the contrastive focus is the primary focus of the speaker’s expression, so it serves as exclusive new information that cannot be omitted [3,4]. You can effectively test this with an abridgement test, for example:

(1) a. Have you bought a ticket?

b_1. No, it was Li Ming who bought the ticket.

b_2. No, it’s Li Ming.

b_3. *No, bought tickets.

In answer b_1, "Li Ming" is the focus of contrast is the new information with exclusivity, and the "ticket bought" is the back

Background information can be deleted, while exclusive new information cannot be deleted, otherwise it violates the quantitative criterion in the principle of cooperation in classical Grice conversational meaning theory.

(2) a. Did Xiao Ming eat cake?

b_1. No, it was Xiaohong who ate it.

b_2. No, it's Xiaohong.

b_3. *No, I ate it.

(3) a. Is it Lin Chao who went home?

b_1. No, it was Lin Lu who went home.

b_2. No, it's Lin Lu.

b_3. *No, go home.

The contrastive foci indicated by the above three types of focus structures can all be tested using the ellipsis test. Below, we will analyze the sentence structures containing the three focus markers "shi... de", "shi" and "de shi" from different perspectives and propose different judgment methods.

Analyze the sentence structures containing three types of focus markers: "Shi... de"

"Shi... de" as one of the focus marks, it reflects one of the ways of focus expression - "splitting". Using "shi... de" the sentence is divided into two paragraphs, and the focus of the contrast is placed after the "shi", and "shi" is generally limited to the name before the verb. Part of speech component, pay attention to "shi... de" cannot indicate the object in the verb-object structure [5]. Let's give two examples:

(1) The chocolate that my mother put on the table was something I secretly ate.

"The structure "shi... de" divides the sentence into two parts: "the chocolate that Mom put on the table" and "I ate it". "I", as the nominal element after "shi", is the contrastive focus".

(2) I bought the ticket yesterday (Comparison focus: Yesterday).

Analyze the sentence structures containing three types of focus markers: "Shi"

As a focus marker, "shi" has certain similarities in usage and judgment methods with the structure "shi... de". Sentences using "shi" are divided into two parts, with the contrastive focus placed after "shi". The elements marked by "shi" include location, time, instrument, and agent. It should be noted that "shi" also cannot mark the object in a verb-object structure, but it can mark the patient in a passive sentence [6]. Here is an example:

(1) I had dinner at their house

"In their home" is the component of the premises in the sentence, and "their home" is the focus of contrast.

Another method can be tested by using the question-and-answer method, which has a contrasting exclusivity and is consistent with the nature of the answer with only certainty, which can be used as the answer to the question. The remaining sentence components plus interrogative words other than the focus can form regular questions. Let's give an example:

(2) Original sentence: Tomorrow's experiment we will do with new equipment.

Question: What will we use for tomorrow's experiment? When are we doing experiments with new equipment? What will we do tomorrow with new equipment?

Answer: New equipment (Contrast focus).

Analyze the sentence structures containing three types of focus markers: "De shi"

It is relatively easier to identify the focus component marked by "de shi". A sentence using "de shi" is divided into two parts. As a focus marker, "de shi" has dual functions of judgment and identification. The predicative component after "de shi" is the contrastive focus of the sentence. Here are two examples:

(1) What I like is you (contrast focus: you).

(2) Sadly, this team will be disbanded next year (Comparison focus: This team will be disbanded next year).

Detailed explanation of the steps of focus identification

Testing before AI debugging

In order to establish a reliable performance benchmark, this study selected three representative multimodal large language models, GPT-4, DeepSeek, and Qwen, for baseline testing. The test dataset contains 1,100 focus statement samples annotated by domain experts, covering a wide range of text types, including daily life, technology reports, biographies, and more. A double-blind experimental design is adopted, and text fragments containing context are input to each model through a standard API interface, and the focus recognition results of the model output are recorded.

From a data set

(1) Document format conversion

Format uniformity is achieved through a progressive conversion process of Extensible Markup Language (XML) → Document Open XML (DOCX) → Markdown. Regular expressions and semantic segmentation algorithms are used to complete paragraph-level chunking with the assistance of the TextTiling tool, ensuring that each text unit (200±50 words) maintains complete semantic independence. A context preservation mechanism is specially designed to maintain cross-paragraph semantic associations through the sliding window (overlap=15%) strategy.

(2) Formation of the dataset

With the help of the Easy Dataset tool, you can create corresponding projects and upload the converted md files. You can call the AI's API to achieve automatic chunking of text and generate questions according to different blocks. You can modify the questions to better suit your needs and let the AI generate corresponding answers. After confirming that the answers are correct, you can export the dataset and upload it to Hugging Face for easy subsequent calls. The dataset is open sourced on the HuggingFace platform and shared under the CC BY-SA 3.0 license. The resulting dataset is as follows JSON format:

"instruction": "2. He took a hit from you; everyone could see that, and you, but he"

"input": /

"output": "Focus: took a hit\n"

"system": "You are a Chinese linguist. Please determine what the focus in this sentence is"

Fine-tuning of AI models

(1) Using tools

The experiment was conducted in a Google Colab Pro+ cloud computing environment, leveraging NVIDIA A100 (40 GB) GPU-accelerated computing for efficient model training. For parameter-efficient fine-tuning, the widely recognized Low-Rank Adaptation (LoRa) method was adopted, which optimizes large language models without excessive computational overhead. The Unsloth 2.3 framework was integrated to address memory constraints in large-model training, reducing memory occupancy by 43% compared to conventional fine-tuning approaches [7-9]. The key hyperparameters for model fine-tuning, including learning rate, batch size, training epochs, and LORA rank, are detailed in the following table:

Table 1. Key hyperparameter configuration for model fine-tuning.

Hyperparameters	Value range	Optimal values
Learning rate	1e-5~3e-4	2e-5
Batch size	8~32	16
Number of training epochs	10~50	20
LORA rank	8~64	32

(2) Code implementation

Model fine-tuning code follows a streamlined workflow, with key steps clearly illustrated in the figures below. Figure 1 shows Unsloth optimization dependency installation commands, including library installation/upgrade and auxiliary package setup for memory-efficient training. Figure 2 presents model loading and initialization code, where parameters like max_seq_length and load_in_4bit are configured, and modifying the model's name enables calling different Unsloth-hosted models for comparative training. Figure 3 defines the focus judgment prompt style and instruction, specifying the model's role as a Chinese linguistics expert to guide accurate result generation through standardized response logic. Figure 4 provides dataset loading code, which fetches data from Hugging Face, sets split ranges, and supports targeted AI debugging via flexible parameter adjustment. Figure 5 shows LoRa fine-tuning parameter configuration with gradient checkpointing, and the process is set to 20 training steps to balance learning effectiveness and overfitting prevention.

```
!pip install unsloth

!pip uninstall unsloth -y && pip install --upgrade --no-cache-dir
--no-deps git+https://github.com/unslothai/unsloth.git

!pip install bitsandbytes unsloth_zoo
```

Figure 1. Dependency installation commands unsloth optimization.

Fine-tuning uses the Unsloth 2.3 open-source library for memory optimization training, which reduces the memory usage by 58% compared to the traditional Hugging Face framework.

```
max_seq_length = 2048
dtype = None
load_in_4bit = True

model, tokenizer = FastLanguageModel.from_pretrained(
    model_name="unsloth/DeepSeek-R1-Distill-Llama-8B",
    max_seq_length=max_seq_length,
    dtype=dtype,
    load_in_4bit=load_in_4bit,
```

Figure 2. Model loading and initialization code.

By changing the model's name in the code, different AI models on the Unsloth platform can be seamlessly called to achieve targeted training on various large language models for comparison.

```
prompt_style="""The following is the instruction describing the task and input providing further context.
Please write an appropriate response to complete the request.

Before answering, please think carefully about the question and create a logical thinking process to ensure your answer is accurate.

### Instruction:
You are a master of linguistics with a focus on Chinese language.
Please answer the following focus judgment questions.

### Question:
{}
```

Figure 3. Prompt style and instruction for focus point judgment.

```
EOS_TOKEN = tokenizer.eos_token

from datasets import load_dataset

dataset = load_dataset("jd123441524/yuyanjiaodianshi",
'default', split = "train[0:200]",
trust_remote_code=True)

print(dataset.column_names)
```

Figure 4. Dataset loading and preparation code.

```
model = FastLanguageModel.get_peft_model(
    model,
    r = 16,
    target_modules = ["q_proj", "k_proj", "v_proj",
"o_proj",
                      "gate_proj", "up_proj",
"down_proj"],
    lora_alpha = 16,
    lora_dropout = 0,
    bias = "none",
    use_gradient_checkpointing = "unsloth",
    random_state = 3407,
    use_rslora = False,
    loftq_config = None,
)
```

Figure 5. Dataset initialization snippet.

By setting different fine-tuning parameters to change the AI's training effect, this fine-tuning sets the maximum number of training steps to 20, that is, the AI will perform 20 trainings.

(3) Post-training AI testing

The fine-tuned AI is compressed in GGUF quantization format to form model blocks, uploaded to HuggingFace, and then the model is called using the pytho program to complete the AI judgment of key sentences, and the AI judgment results are counted to form new AI judgment data [10].

Analysis of results

Before studying

Before conducting machine learning, three types of focus-marked sentences were tested both manually and with AI tools. Through horizontal and vertical comparisons of indicators such as the number of errors and error rates, the following conclusions were drawn: There is a certain discrepancy between the overall level of AI in identifying focuses and the accuracy and precision of manual identification. The level of manual focus identification is far higher than that of AI identification. Different AIs show significant differences in identifying focuses under the same focus marking. ChatGPT and DeepSeek have relatively high precision and accuracy in identification, with DeepSeek being even better. This is particularly evident in the judgment of "shi... de" sentences, which have a relatively high error rate among the three types of focus-marked sentences (ChatGPT has an error rate of 70.8%, Qwen has an error rate of 97.6%, while DeepSeek has an error rate as low as 36.8%). The same AI tool also performs differently in identifying the three types of focus-marked sentences. Overall, the identification of focuses in "de shi" sentences is the best, with an average error rate of 17.9% for AI identification. The performance in identifying "shi... de" sentences and "shi" sentences is poorer, with average error rates of 68.4% and 72.8% respectively. This is quite related to the different roles played by different focus markings in sentence structures. Specific data are shown in the table below.

Table 2. The judgment of ChatGPT, DeepSeek, and Qwen on the three focus markers.

AI model	GPT	DeepSeek	Qwen
Total number of "de	500	500	500

AI model	GPT	DeepSeek	Qwen
shi" sentences			
Number of errors	101	49	119
Error rate (%)	20.2	9.8	23.8
Total number of "shi... de" sentences	500	500	500
Number of errors	354	184	488
Error rate (%)	70.8	36.8	97.6
Total number of "shi" sentences	87	87	87
Number of errors	54	53	83
Error rate (%)	62.1	60.9	95.4

Combined with the chart data, the cause analysis of the miscalculation of the focus of different AI tools is now conducted. We roughly divide AI misjudgment into three categories: inaccurate focus marking, misjudgment of information value, and ignorance of the existence of focus markers. The details are as follows:

(1) Uncertain composition of the focus point mark

It is difficult for AI to accurately determine the position and function of the "shi... de" structure. Such structures are often marked as focus information. The appearance of multiple "of" words in the sentence further increases the difficulty of identifying the focus. Here are a few examples:

I guess he came by car (The focus of AI recognition: by car; correct focus: by car).

That's right, it's here for you (The focus of AI recognition: sent here; correct focus: here).

That's not necessarily, some of them are shopkeepers (The focus of AI recognition: the store owner is the shopkeeper; correct focus: store owner).

Yes, it was decided yesterday (The focus of AI recognition: yesterday's rules; correct focus: yesterday).

It is a new Christian school founded by Martin Luther, an advocate of the German Reformation movement in the 16th century (The focus of AI identification: a new Christian denomination founded by Martin Luther; correct focus: Martin Luther).

(2) misjudgment of information value

The AI focus has an inaccurate grasp of the "prominence" characteristic. It does not understand the information value hierarchy. It cannot well understand the high information value density of the contrast focus as "new information that cannot be deleted". In the process of AI identifying focus, it happens that non-focus information is classified as focused. Here are a few examples:

In recent years, the world has been in chaos, and the officials have not governed well, and the people of the world know it (The focus of AI identification: Officials are not well governed; correct focus: officials and the people of the world).

is a Sinai Codex found in 1859 at St. Catherine's Monastery on Mount Sinai (Focus of AI identification: Codex Sinai found in 1859 at St. Catherine's Monastery on Mount Sinai; correct focus: 1859).

I said there were guests (Focus of AI recognition: I say there are guests; correct focus: me).

I learned about this through a friend's introduction (Focus of AI recognition: through friend introductions; correct focus: friend).

She ignored me first (The focus of AI recognition: she ignored me first; correct focus: she).

He is a graduate student studying abroad (Focus of AI recognition: to foreign countries; correct focus: abroad).

(3) Ignore the presence of focus markers

There are also cases where the function of focus marks is not well understood and the identification function of focus marks is ignored. This type of situation often manifests as dividing the focus information in the first paragraph of the sentence or almost the entire second paragraph of the sentence as the focus. Here are a few examples:

More than half of them went with people from Taixi Kingdom (The focus of AI recognition: go with people from Taixi Country; correct focus: people from Taixi Kingdom).

It is they who manage it (The focus of AI identification: they manage the business as a handle; correct focus: they manage the business).

Confucius said: "Knowing is knowing, not knowing is not knowing, and knowing is also knowing." This is what everyone should observe (Focus of AI identification: everyone should abide by; correct focus: everyone).

I came on horseback, and that horse ran fast (The focus of AI recognition: the horse; correct focus: horseback riding).

Analysis of the effect after machine learning

In this machine learning process, we first used the "universal method", a testing method applicable to all three types of focus-marked sentences, to debug the AI tools. The results were quite significant: except that the error rate of ChatGPT in identifying "shi" focus-marked sentences increased by 12.6%, all other data showed a significant decrease. In particular, all three error rates of DeepSeek dropped below 50%, and the error rate of "de shi" focus-marked sentences even dropped to 9.2%. The specific data are shown in Table 3.

Table 3. The judgment of ChatGPT, DeepSeek, and Qwen on the three focus marker sentences after being debugged by the universal method.

AI model	GPT	DeepSeek	Qwen
Total number of "de shi" sentences	62	46	91
Error rate (%)	12.4	9.2	18.4
Total number of "shi... de" sentences	347	176	449
Error rate (%)	69.4	35.2	89.8
Total number of "shi" sentences	65	32	78
Error rate (%)	74.7	36.8	89.7

After that, debug the AI tool with three different focus recognition methods. Overall, AI tools focus recognition is excellent

The accuracy is further improved, except for the "shi" focus marker sentence compared with the general method debugged from 36.8% rose to 49.4%, and the rest of the data declined to varying degrees.

Table 4. The judgment of ChatGPT, DeepSeek, and Qwen after accepting three types of debugging points

AI model	GPT	DeepSeek	Qwen
Total number of "de shi" sentences	500	500	500
Number of errors	57	41	67
Error rate (%)	11.4	8.2	13.4
Total number of "shi... de" sentences	500	500	500
Number of errors	229	103	421
Error rate (%)	45.8	20.6	84.2
Total number of "shi" sentences	87	87	87
Number of errors	47	43	63
Error rate (%)	54.0	49.4	72.4

Conclusion

We have AI judge the focus components of three types of sentences with different focus markers. By exposing AI to a large number of focus-related examples, we enable it to identify the focus components of such sentences with higher accuracy. This demonstrates the potential of machine learning in natural language processing, thereby providing new ideas for the aging-friendly design of readers in the digital age. Addressing the question "How can artificial intelligence assist in enhancing elderly readers' focus recognition capabilities?" is undoubtedly of great significance. It helps bridge the digital divide faced by the elderly and ensures that they can accurately grasp focus information through reading activities.

Funding

This work was not supported by any funds.

Acknowledgements

The author would like to show sincere thanks to those techniques who have contributed to this research.

Conflicts of Interest

The author declares no conflict of interest.

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