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Classifying Self-Reflection Notes: Automation Approaches for GOAL System

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Abstract Self-directed learning (SDL) is considered a crucial skill for 21st-century learners, promoting personalized and responsive educational experiences. This study explores the untapped potential of self-reflection, particularly in e-learning environments. The research focuses on self-reflection notes, which contain strategies past students adopted when facing different situations or challenges. These notes can help current or future students facing similar situations. In this study, students take tests weekly and leave their self-reflection notes after tests. In these notes students recorded their feelings and issues, offering perspectives and insights that experts might overlook or misunderstand in some details, thus failing to provide appropriate assistance. Extracting and categorizing information from self-reflection notes is crucial to further utilize this data. Our research introduces a machine learning-based approach that effectively classifies these self-reflection notes such as cognitive, metacognitive, experiential, and irrelevant text. We compare the performance of BERT, based on the transformer architecture, with traditional machine learning classifiers such as Support Vector Machines (SVM) and Random Forests (RF). Additionally, we enhanced the BERT model by training it on synthetic data generated through GPT-4 and employing a hybrid loss combining Supervised Contrastive Learning (SCL) and Cross-Entropy (CE) to improve classification capabilities. Our results indicate that the BERT model, enhanced with advanced training techniques, outperforms traditional models in classifying learning strategies from self-reflection notes. This study not only advances the understanding of SDL in online learning environments but also demonstrates the potential of tailored machine-learning solutions to foster more effective and adaptive learning strategies.

Keywords: Self-directed Learning (SDL), Self-reflection, BERT, Supervised Contrastive Learning, GOAL system

1. Introduction

Self-directed learning (SDL) is a crucial skill for the 21st century, providing significant benefits to students' learning (Partnership for 21st Century Skills, 2016). Within SDL, learning strategies can generally be categorized into four groups: cognitive strategies, metacognitive strategies, emotional management strategies, and resource management strategies (Conley, 2014). These strategies aid students in managing their learning processes more effectively and improving learning outcomes.

Self-reflection, a key component of SDL, helps students gain a better understanding of themselves, enabling them to make more informed decisions in both academic and personal contexts. It requires students to recognize their activity patterns, identify problems, and adjust their learning methods or plans to meet changing needs and environments (Majumdar et al., 2018).

In electronic educational environments that support SDL, numerous self-reflection notes are typically collected. These notes usually contain information about students' current states within specific learning contexts, including experiences of success or failure, challenges faced, and strategies employed. Although these insights are valuable, they are often underutilized. For example, experiences of success or failure could be shared with other students to replicate successes and avoid similar mistakes. Additionally, when new students encounter problems similar to those experienced in the past, strategies used by previous students could be recommended to assist them.

In past research, Benedict et al. (2022) attempted to gather challenges faced by former students and their solutions through surveys to guide current students. However, this approach has several limitations. Simply comparing the cosine similarity of difficulties sometimes fails to meet the specific needs of students. Moreover, as data collection relies on questionnaires, it is challenging to automate and difficult to generalize across different courses and environments.

To overcome these limitations and not only rely on the data already collected but also continuously gather data from current and future students to build a richer dataset that can more comprehensively address complex situations and assist students, it is necessary to automate the classification of the content and features of these notes. Previous research has used BERT to classify self-reflection notes, but this classification is limited to determining whether they are valuable (Wang et al., 2024). To address this gap, we propose extracting valuable information from self-reflection notes and classifying them using machine learning techniques such as Support Vector Machine(SVM), Random Forest(RF), and Logistics Regression(LR). We pose the following research questions:

RQ1: How do large language models (LLMs) based on the transformer architecture, such as BERT, perform compared to traditional machine learning classification models?

RQ2: How can we fine-tune the model to better fit the current self-reflection note classification task?

2. Context

2.1 GOAL system

The Goal-Oriented Active Learner (GOAL) system is a student-oriented digital platform that focuses on enhancing students' Self-Directed Learning (SDL) capabilities (Majumdar et al., 2018). Figure 1 shows the architecture of the GOAL system. In collaboration with a combined junior and senior high school in Japan, students can use the GOAL system to track their activities and collect data on their learning or other activities. The GOAL system records and visualizes students' past activity data. This allows students to easily monitor their progress and understand their situation by comparing with students' past data and the data of other students, and to analyze, set goals, execute monitoring, and reflect on various activities related to learning and health. It encourages them to take control of their learning process and develop self-directed learning behaviors.

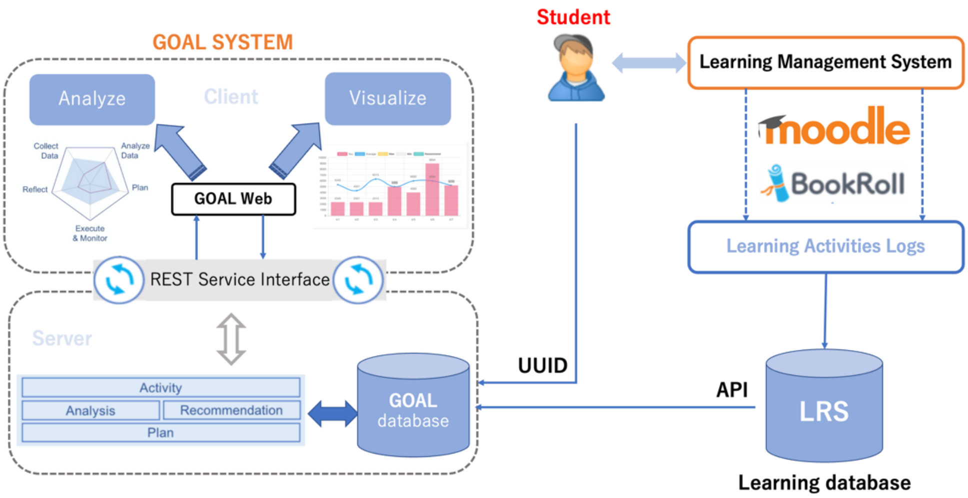

Figure 1. Architecture of the GOAL system.

2.2 Students' context

Japan's GIGA School program aims to promote e-learning through personal tablets. The school collaborating with us extensively utilizes digital materials for management, teaching, and examinations. Students are required each week to take short quizzes on their tablets in mathematics and English. After these quizzes, students enter data into the GOAL system about their weekly study times and quiz results. The GOAL system provides visual feedback that encourages students to engage in self-reflection, identify any potential problems, and contemplate solutions to these issues. Figure 2 shows the interface of self-reflection in the GOAL system. In this context, we have collected many self-reflection notes from students. These notes include the learning strategies they used during actual study sessions, their experiences with exams and learning, as well as information and insights that are unique to the students' environments.

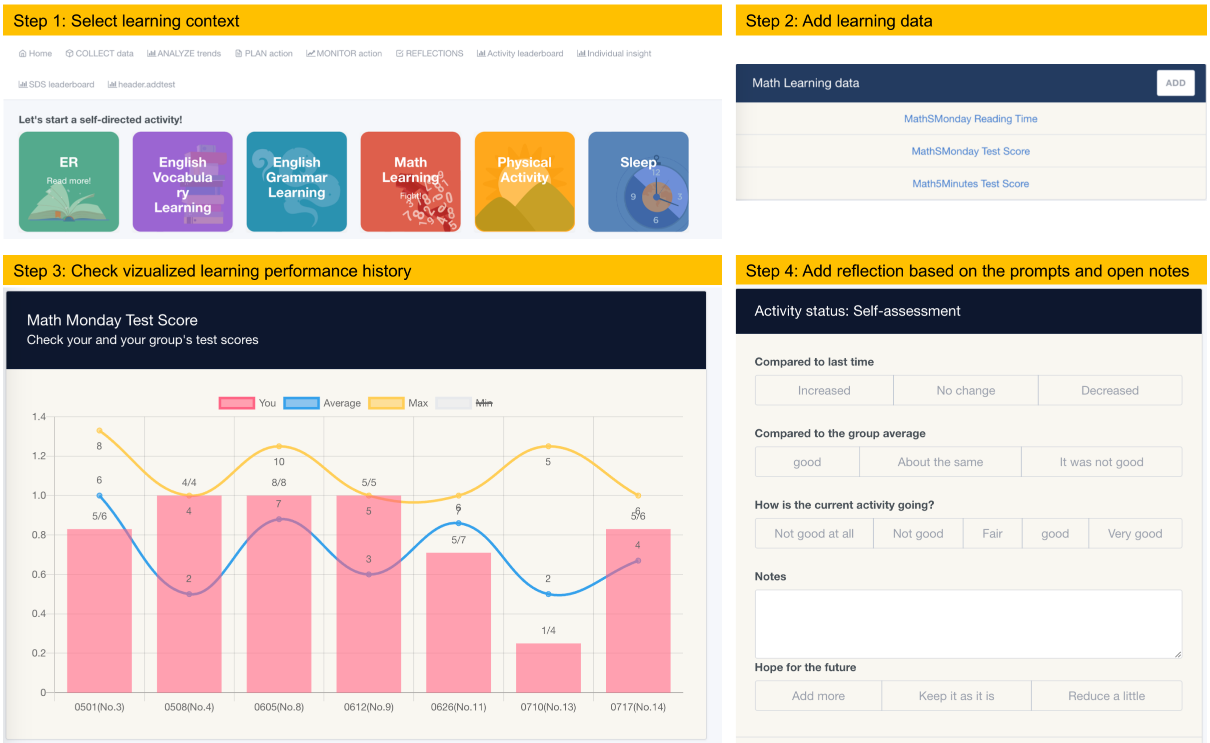

Figure 2. Self-reflection workflow in the GOAL system.

3. Research Study and Findings

3.1 Data Collection

We collected records from 706 junior high school students with an average age of 13, regarding their weekly tests, from April 2021 to March 2023. A total of 10,613 entries were collected, of which 2,304 entries contained their self-reflection on learning and weekly tests. Since this study focuses on mathematics learning, we extracted 1,498 self-reflection notes related to mathematics from it.

In self-directed learning theory, learning strategies are typically categorized into four levels: cognitive strategies, metacognitive strategies, resource management strategies, and emotional management strategies. Cognitive strategies involve the basic processing of learning materials. Metacognitive strategies focus on monitoring and adjusting the learning process. Resource management strategies include time management and optimizing the learning environment. Emotional management strategies help regulate emotions and motivation to sustain learning efficiency and effectiveness. Integrating these strategies can significantly enhance learning outcomes (Conley, 2014).

Therefore, we manually categorized the data into four categories: cognitive strategies which include basic learning methods (306 entries), metacognitive strategies which include learning plans or learning goals (279 entries), experience accumulated or noted during exams or studying (516 entries), and useless texts content unrelated to learning (357 entries). The lack of categories for resource and emotional management strategies is because our dataset is collected from students' self-reflection after tests or studying, which rarely contains content related to resource and emotional management strategies. It includes specific intelligence that can only be obtained from the student's environment. In terms of the categorization results, the first author and the co-author reached a Cohen's Kappa score of 0.792. Table 1 shows some examples of self-reflection notes.

Table 1. *Examples* of *Self-reflection Notes*

Categories*	Definition	Self-reflection Notes
cognitive strategies	Specific Learning & Doing Methods	Calculate calmly and carefully.
metacognitive strategies	Learning Plans & Objects	I want to approach my writing with more mindfulness.
experience	Valuable experiences that a student has gone through (positive or negative).	It's really hard to write or erase because there's a delay of about 5 seconds before the text appears on the PC.
irrelevant notes	Experiences that are meaningless or have no reference value.	Nothing particular

* Adopted from (Conley, 2014).

After completing the classification, to effectively label the text and convert it into IDs that the model can process, we adopted the BERT model specifically designed for Japanese text, cl-tohoku/bert-japanese[1].

In this study, we use cl-tohoku/bert-japanese as the vectorization converter because it differs from traditional bag-of-words models or TF-IDF by providing context-sensitive feature extraction capabilities. It learns deep language features through pre-training on a large corpus, allowing each word's representation to depend on its context, thereby capturing the diversity and subtleties of word meanings. This approach not only enhances the richness and accuracy of text representations but also handles complex semantic relationships and linguistic structures, ultimately improving the performance of various NLP tasks.

At the same time, it offers significant advantages in processing Japanese text, especially in understanding context and disambiguating word meanings. Due to the complex grammatical structure of Japanese, which heavily relies on context, BERT's bidirectional context understanding capability effectively handles subtle language differences. Additionally, BERT's pre-training and fine-tuning mechanisms allow it to adapt to specific tasks even with limited labeled data, significantly outperforming traditional bag-of-words models or TF-IDF methods, thus enhancing the accuracy and efficiency of Japanese text processing.

Then, we divided the data set into a training set and a test set (8:2), after that, we used several traditional classification machine learning models like SVM, RF, LR and fine-tuned the BERT model to verify the preliminary classification effects. Figure 3 shows the specific data pipeline and Table 2 shows the preliminary results.

[1] https://huggingface.co/cl-tohoku/bert-base-japanese

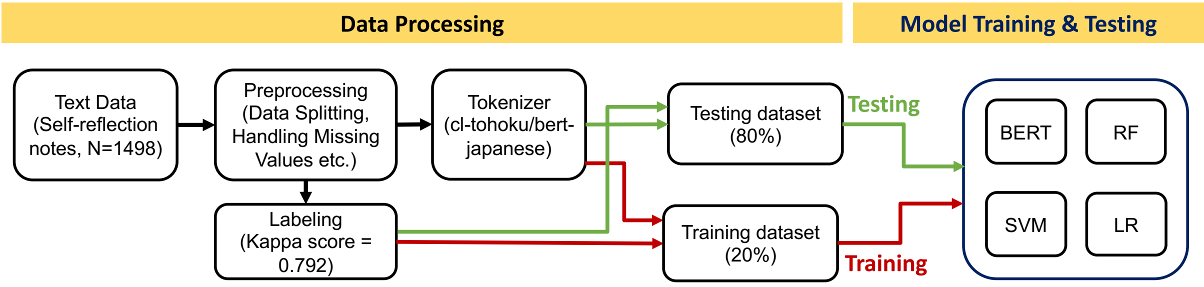

Figure 3. Data flow diagram for direct training and testing of various models for RQ1.

Table 2. *The Result of Preliminary Classification Using Several Traditional ML and Fine-Tuned the BERT Model*

	Accuracy	Precision	Recall	F1 score
BERT	**0.679**	**0.688**	**0.668**	**0.699**
RF	0.587	0.606	0.587	0.570
SVM	0.638	0.642	0.638	0.631
LR	0.611	0.627	0.611	0.617

From the preliminary results, we can see that BERT has demonstrated relatively good performance in the initial classification tasks. Next, we will adjust and refine it further to try and enhance BERT's performance.

3.2 Data Augmentation by GPT4

In the field of natural language processing, data augmentation is a common technique that can help us expand the training dataset and improve the generalization ability of the model. Recently, data augmentation methods based on generative models have become one of the hot topics in research, among which GPT is one of the most popular generative models.

In our research, we designed a conversational prompt that includes system and user roles, simulating a Japanese middle school student's situation to guide the model in generating suggestions for a study plan. The system role sets the user's background, while the user role specifies the generation task, providing several specific examples left by students for the model to reference and propose concrete learning objectives while excluding any titles, serial numbers, or brackets to focus on content generation.

3.3 Supervised Contrastive Learning

Contrastive learning is a method of machine learning whose core idea involves comparing different data points to learn representations of data, strengthening the relationships between similar data points while reducing the relationships between dissimilar ones. Within the framework of contrastive learning, positive and negative sample pairs are typically constructed. Positive pairs consist of samples from the same category or with similar attributes, whereas negative pairs consist of samples from different categories. Through this approach, the model learns to distinguish which features are key to differentiating between categories, thereby enhancing its ability to generalize to unseen data (Chen, 2020).

Contrastive learning began with image classification. However, Contrastive learning is not limited to image classification; it has also shown excellent results in text classification tasks. Particularly when fine-tuning downstream tasks with pre-trained language models like BERT, incorporating a contrastive learning loss can help the model better understand and differentiate text features (Gunel, 2021).

In this study, we propose the use of contrastive learning because our data, which originates from texts written by students, does not form a perfect dataset for classification tasks, necessitating robustness. In contrastive learning, by incorporating a large number of positive and negative sample pairs during training, the method enhances the model's robustness against noise and sample variation. This is because the model learns not just the characteristics of individual samples, but the relationships between samples, which helps maintain good performance even when faced with unknown or rare samples. Additionally, contrastive learning can effectively utilize data, thus reducing the need for a large amount of labeled data, which aligns well with our situation.

3.4 Specific methods and comparative results

In this study, we primarily used GPT to generate 718 cognitive strategies and 320 metacognitive strategies, which were only used as a training set. This time, generating these two categories of text data to enhance the dataset, it is because both types have clear definitions and directions. The other two categories (experiences and useless information), due to their lack of clear definitions, cannot effectively control the quality of the generated text, which might impair the performance of the model. Additionally, we utilized a contrastive loss function in the form of InfoNCE combined with the cross-entropy loss function. This approach aims to help the model enhance feature discrimination and generalization performance while learning classification tasks. The loss is in the following:

$$L = L_{CE} + \gamma L_{scl} \tag{1}$$

$$L_{CE} = -\sum_{i=1}^{C} y_i log\,(p_i) \tag{2}$$

$$L_{\mathrm{scl}} = -\frac{1}{N}\sum_{i=1}^{N}\log\left(\frac{\exp\left(\frac{f_i \cdot f_j}{\tau}\right)}{\sum_{k=1}^{N}\exp\left(\frac{f_i \cdot f_k}{\tau}\right) - \exp\left(\frac{f_i \cdot f_i}{\tau}\right) + \epsilon}\right) \tag{3}$$

In the above formula, (3) represents the InfoNCE contrastive learning loss, (2) represents the cross-entropy loss, and (1) represents the combination of contrastive learning loss and cross-entropy loss.

In the formula, γ is used to adjust the importance of the contrastive loss within the overall loss. If γ is too high, the model will focus more on clustering the data rather than learning according to the labels. C is the total number of categories. y_i is the true label for the i-th category. p represents the probability distribution predicted by the model. f_i and f_k are normalized feature vectors. τ is the temperature parameter, used to control the softness of the softmax function. ϵ is a very small constant, used to prevent division by zero. N is the number of samples in the batch. Figure 4 shows the data pipeline for the proposal.

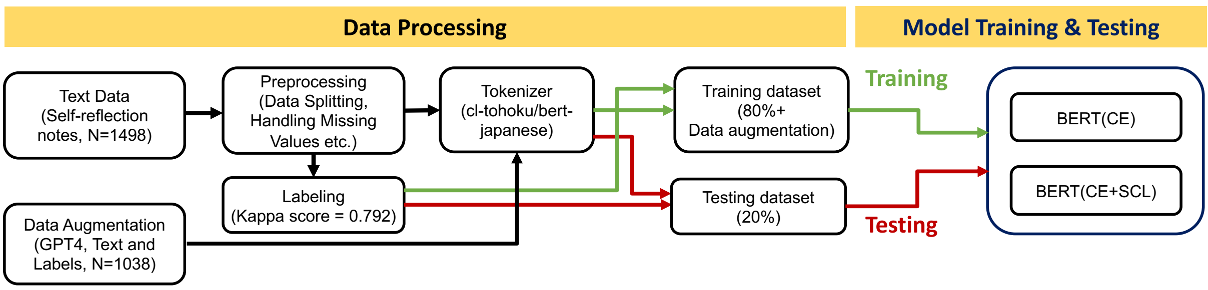

Figure 4. The data flow diagram for data augmentation and loss function (SE+SCL) adjustment for the BERT model for RQ2.

The model was trained for 10 epochs, with each epoch consisting of 32 batches. To preserve the original performance of the BERT model, the initial learning rate was set at 1e-5 and reduced by 20% each epoch. Additionally, early stopping was employed, terminating the training when the average test loss did not decrease for three consecutive epochs. The training loss, test loss, and performance on the test set were recorded for each epoch. Figure

5 shows the process of test loss changing as epoch increases of two models and Table 3 shows the performance of the three models when the training loss is minimized.

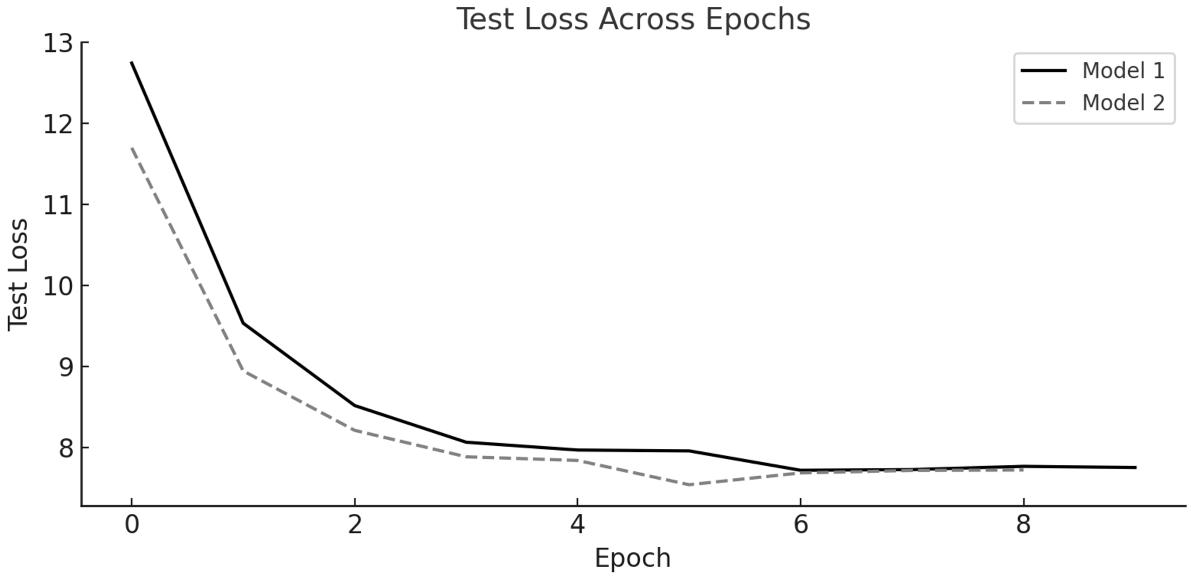

Figure 5. The test loss across epochs for two models.

Table 3. *Performance of each model at its best (lowest test_loss)*

	Training Loss	Test Loss	Accuracy	Precision	Recall	F1	LR
Data & SCL Loss	35.3188	7.5416	0.7661	0.7553	0.7474	0.7478	3e-6
Data augmentation	25.3763	7.7197	0.7525	0.7425	0.7336	0.7346	3e-6
Original	57.9906	10.1282	0.6790	0.6880	0.6880	0.6990	2e-6

4. Discussion

In RQ 1, BERT demonstrated superior performance, likely due to its deep feature understanding and extensive pre-training knowledge. Utilizing the self-attention mechanism, BERT captures intricate details and contextual relationships in text. Thus, it allows for a more effective understanding of the meaning of individual words within sentences as well as the overall context of the entire sentence and extracting high-quality features. Moreover, having been pre-trained on a large corpus, BERT has acquired a wealth of language knowledge, enabling it to rapidly adapt to specific tasks through fine-tuning. On the other hand, the second-best performer, SVM, excels in handling high-dimensional data, especially when the sample size is not particularly large. In contrast, the worst performer, Random Forest, a tree-based ensemble learning method, typically shows robustness and generalizability across various datasets. However, it may not be well-suited for handling very sparse or high-dimensional data, such as the vectors generated by BERT in this study.

In RQ 2, analysis of the data reveals that utilizing a training set generated by GPT-4 substantially enhances the model's classification capabilities. Furthermore, although the combination of cross-entropy loss (CE) with supervised contrastive loss (SCL) did not significantly improve overall performance metrics, it expedited the learning process and augmented the stability of model convergence. This improvement can likely be attributed to the expanded diversity and volume of (training data provided by GPT-4, which in turn enhances the model's ability to generalize across unseen samples. Additionally, supervised contrastive loss, which prioritizes the learning of similarities and differences among samples, facilitates the model's capacity to effectively differentiate between categories. While this approach does not drastically improve final performance outcomes, the implementation of contrastive loss can more efficiently organize the feature space, thereby accelerating convergence and bolstering the stability of the training phase.

5. Conclusion

In this study, we focused on self-reflection notes left by students during the self-reflection phase of self-directed learning. These notes usually contain information about students' current states within specific learning contexts, including experiences of success or failure, challenges faced, and strategies employed. The content of these notes holds value for being passed on to other students. To fully utilize the self-reflection notes and pass on the experiences of predecessors to successors, we initially proposed using machine learning (ML) technology to automatically classify students' self-reflection notes into four specific categories: cognitive strategies, metacognitive strategies, experiences, and irrelevant notes. After data preprocessing and labeling, we chose the cl-tohoku/bert-japanese model for tokenization and systematically evaluated the performance of several classification algorithms including BERT, SVM, RF, and LR for this task.

As a result, the BERT model, which was pre-trained on a large corpus and gained extensive language knowledge, performed the best, although the overall performance was still lacking. At the same time, RF performed the least ideally due to its insensitivity to high-dimensional data. To further improve the accuracy of classification, we used GPT-4 to generate notes related to cognitive and metacognitive strategies for dataset expansion and data augmentation. Additionally, we attempted to integrate contrastive learning loss into the training process of the BERT model.

Through multiple rounds of training and testing, we found that using text data generated by GPT-4 as the training set significantly enhanced the model's performance. This improvement is attributed to the fact that the GPT-4-generated dataset expanded the diversity and quantity of the training data, thereby enhancing the model's generalization ability for unseen samples. At the same time, we observed that although the introduction of contrastive learning loss did not significantly enhance the overall performance of the model, it accelerated the model's learning and convergence speed, ensuring high stability during the training process.

In our future research plans, we will continue to optimize the model's loss function to explore the potential impact of different loss functions on model performance. Moreover, in this study, we primarily used the cl-tohoku/bert-base-japanese model. Moving forward, we plan to experiment with different Japanese pre-trained BERT models and advanced models such as RoBERTa and ALBERT to see if they can further enhance classification performance. Additionally, in this study, we used GPT-4 to generate texts related to cognitive and metacognitive strategies. Next, we plan to extend the use of GPT-4 to generate more data related and unrelated to learning experiences to verify the specific impact of these data on the effectiveness of model classification.

Additionally, to further validate and improve the outcomes of this research, we plan to develop new recommendation features based on the existing GOAL system. By analyzing student activity data and investigating the challenges they encounter during the learning process, we aim to identify their needs and provide personalized learning suggestions based on the categories and content of self-reflective notes identified in this study. This will enable more effective utilization of the collected self-reflective notes.

However, in this process, what we need is not only the types of self-reflective notes in this study but also a deeper understanding of their content to better align with the themes of the challenges students face. In this study, the model we developed does not delve deeply into the content of the self-reflective notes, which is one of the key research directions we need to address moving forward.

At the same time, self-reflective notes are records left by students regarding their learning outcomes and processes, making them not entirely suitable for direct recommendation to other students. Therefore, how to effectively utilize the content of self-reflective notes for recommendations is another issue that needs to be addressed. On the other hand, the depth and quality of the content in self-reflective notes vary greatly. How to select appropriate self-reflective notes based on students' learning conditions and efficiency, rather than simply making recommendations, is also a challenge (Zhao, 2023).

Despite these numerous challenges, this approach not only allows us to replicate past successes and avoid similar mistakes but also helps broaden students' perspectives and improve their learning efficiency by continuously recommending the learning strategies of previous students to new ones. Furthermore, it enables us to accumulate the learning strategies adopted by current students. This method allows us to gather a large amount of data, thereby providing personalized assistance to each student.

Acknowledgements

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References

Gunel, B., Du, J. F., Conneau, A., & Stoyanov, V. (2021) Supervised Contrastive Learning for Pre-trained Language Model Fine-tuning. The Ninth International Conference on Learning Representations (ICLR021).

Benedict, A., Al-Hossami, E., Dorodchi, M., Benedict, A., & Wiktor, S. (2022). Pilot Recommender System Enabling Students to Indirectly Help Each Other and Foster Belonging Through Reflections. In LAK22: 12th International Learning Analytics and Knowledge Conference (pp. 521-527).

Conley, D. (2014). Learning strategies as metacognitive factors: A critical review. Eugene, OR: Educational Policy Improvement Center.

Partnership for 21st Century Skills. (2016). A state leader's action guide to 21st-century skills: A new vision for education. Tucson, AZ: Partnership for 21st Century Skills.

Majumdar, R., Yang, Y. Y., Li, H., Akçapınar, G., Flanagan, B., & Ogata, H. (2018). GOAL: Supporting learner's development of self-direction skills using health and learning data. In Proceedings of the 26th International Conference on Computers in Education (pp. 406–415).

Chen, T., Kornblith, S., Norouzi, M., & Hinton, G. (2020) A Simple Framework for Contrastive Learning of Visual Representations. Proceedings of the 37th International Conference on Machine Learning, PMLR 119:1597-1607, 2020.

Zhao, L. T., Wang, D. S., Liang, F. Y., & Chen, J. (2023) A recommendation system for effective learning strategies: An integrated approach using context-dependent DEA. Expert Systems with Applications 211 (2023) 118535.

Wang, Z., Hsu, C. Y., Atake, J., Horikoshi, I., Li, H., Majumdar, R., & Ogata, H. (2024). Automated Classification of Student's Self-reflection Using BERT: Consideration and Possibilities for Self-Directed Learning Support. Proceedings of the 14th International Conference on Learning Analytics and Knowledge (LAK24), 206-208.