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Quadruplet Alignment Loss Function for Representing the Stages of Behavior Change

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Abstract. This study proposes a method to estimate the stages of behavior change in research activities using text data from progress reports submitted by students periodically. Motivation is crucial in student research activities. It is essential for the supervisor to provide students with guidance tailored to their motivational states. However, since motivation levels vary with students, uniform instruction fails to yield sufficient results. To provide appropriate support, it is necessary to understand the motivation level of each student. Existing methods for measuring motivation tend to rely on subjective evaluations, placing a significant burden on respondents. The method focuses on behavioral changes reflected in progress reports periodically presented. The text data from progress reports is converted into vectors indicating the stage of behavior change through the Quadruplet Alignment Loss proposed in this study. The loss function models the sequential relationship among the contemplation stage, the preparation stage, and the action stage. The results of the experiment have confirmed that the proposed method improves the estimation accuracy of the stage of behavior change. In particular, the estimation accuracy during the preparation stage has significantly improved, which demonstrates successful estimation of the critical transitional stage leading to action. It suggests the potential to support supervisors in providing research guidance tailored to students' individual motivation.

Keywords. stages of behavior change, Quadruplet Alignment Loss, progress reports, Text Analysis

1. Introduction

Research activities involve trial and error. The activities experience many failures. It is said that maintaining and promoting motivation is important to overcome these challenges (Horodnic and Zaiţ, 2015). It is believed that motivation for actions toward research goals improves as people raise their intrinsic motivation, which is based on interest and satisfaction derived from the activities themselves. According to self-determination theory (Ryan and Deci, 2000), it is necessary to satisfy three psychological needs to raise the intrinsic motivation. The three psychological needs consist of autonomy, ability, and relatedness. Their fulfillment promotes intrinsic motivation. Supervisors in institutions to train engineers, such as universities, must provide an environment in which students can engage in research. Students get more proactive in their research by fulfilling these needs.

To satisfy the three psychological needs, a coach is indispensable. Guidance appropriate to the motivation level encourages sustained participation in activities (Charbonneau et al., 2001). However, a single standardized teaching method would not be effective because motivation levels vary among students. To provide tailored guidance to each student, we need to understand the student's motivation.

Various approaches have been used to estimate individual motivation. Pintrich et al. proposes the Motivated Strategies for Learning Questionnaire (MSLQ) to measure learners' motivation （Pintrich, 1999） . Furthermore, longitudinal self-report–based methods, such as learning diaries (Zimmerman & Kitsantas, 2005; Schmitz & Wiese, 2006) and experience sampling (Hektner et al., 2007), have been proposed to assess learners 'motivation. However, methods for measuring such motivation tend to rely on subjective evaluations, placing a significant burden on respondents.

Human behavior would take place through the state change of motivation. In other words, we can estimate an individual's motivation state from the perspective of how much their behavior has changed. The Transtheoretical Model has introduced the stages of behavior change to explain the estimation. The study esteems its ability to assess students' state based on the stages of behavior change rather than motivation itself. Among the five stages of behavior change in the model, the study focuses on the three stages: contemplation, preparation, and action, aiming to estimate which stage a specific student stays in.

The study proposes a method to estimate the stages of behavior change in students 'research activities using text data on progress reports periodically presented by students. Progress reports are considered to reflect the status of students' research activities because they include the organization of research content and the manifestations of their actions. Texts in progress reports are converted into vector representations, positioned on a space that depicts each student's stage of behavior change. The method estimates the stage of behavior change using the positional relationships within the space. However, it is difficult to estimate the stages of behavioral change using the texts in progress reports as they are. Writing styles vary greatly among individuals, simple metrics like word frequency or sentence length may not adequately capture differences in the stages of behavioral change.

The study introduces a distance learning method. It proposes to minimize Quadruplet Alignment Loss (QAL) to associate vectors in the space with the stage of behavior change. It biases the distribution of the vectors representing students 'stages in the space, allowing us to identify the corresponding stage of behavior change for each progress report they submit. The boundaries between clusters of vectors define stages. The boundary corresponds to the behavioral boundary in Fogg's Behavior Model (Fogg, 2009).

The method enables us to objectively estimate the stage of behavior change without imposing additional burdens on students. A vector corresponding to the periodic progress reports moves continuously through space. When a student crosses a boundary, behavioral change is considered to have occurred. A sequence of progress reports lets supervisors grasp that the student is approaching the behavior boundary. As a result, supervisors can consider the intensity and the timing of intervention. It enables them to provide more appropriate research guidance according to the student's condition, which leads to improving the quality of students' research activities.

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2. Vector Representing Stages of Behavior Change

2.1. Transtheoretical Model

Transtheoretical Model (Prochaska & DiClemente, 1982), hereinafter referred to as the stages of behavior change, depicts the process of human behavior change. This model integrates various theories of psychotherapy and behavioral change.

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Figure 2-1 shows an overview of the Transtheoretical Model. This model explains behavioral change, dividing it into five stages: the precontemplation stage, the contemplation stage, the preparation stage, the action stage, and the maintenance stage. The model assumes that individuals would make progress through the five stages gradually over time under external support.

Individuals in the precontemplation stage have not recognized the necessity for behavioral change. Since they are unaware of the problem, they have no intention of changing their behavior. In the contemplation stage, individuals begin to recognize the need for behavioral change. They consider changing their behavior but have not put it into practice. Individuals in the preparation stage possess the intention to act in the near future. Small actions or concrete plans may sometimes be observed. The action stage is the one where behavioral change begins. Desirable behaviors manifest in an observable form. In the maintenance stage, the desirable behavioral changes are sustained over a certain period. The challenge lies in preventing undesired behaviors from recurring as well as establishing desirable behaviors.

The model, developed to explain behavioral change in smoking cessation, has been applied in many fields, for example, health behaviors such as exercise habits and dietary actions (Nakabayashi et al., 2020; Prochaska & Velicer, 1997), as well as in the educational field targeting improvements in college students' learning skills (Grant and Franklin, 2007).

Figure 2.1 Transtheoretical Model

2.2. Word Vectorization Methods

A method for treating words as numerical values is necessary to quantitatively evaluate text. Word2Vec is a method that uses neural networks to obtain distributed representations of words (Mikolov et al., 2013; Géron, 2019). Word2Vec is based on the distribution hypothesis. The distributional hypothesis posits that a word's meaning is shaped by the words that appear around it, assuming that a word's meaning can be inferred from its surrounding context. Skip-gram is a neural network learning algorithm that learns a distributed representation of a target word using the probability distribution of multiple words appearing around it. Skip-gram can obtain highly accurate word embeddings through training with large amounts of data. On the other hand, it demands high learning costs (Lauc et al., 2020). The resulting distributed representations are expressed as vectors of the specified dimension in the intermediate layer of the neural network. It enables us to convert any word into a numerical vector.

Word2Vec represents words as multidimensional feature vectors. If each dimension is learned appropriately, the representation will reflect the relationships between words. For example, suppose words are represented as 4-dimensional vectors. If the 0th, 1st, 2nd, and 3rd elements of the vector correspond to "gender," "adultness," "royalty," and "others," respectively, the word can be represented as shown in Table 2.1.

Vectors enable us to treat the relationships between words with vector operations. For example, if we compute "princess - female + male," the answer is prince according to human intuition. From Table 2.1, we compute the vectors, which roughly correspond to the vectors representing the princes, as shown in Equation (2.1).

$$\begin{aligned}\text{Princess} - \text{Female} + \text{Male} &= (0.1, 0.1, 0.8, 0.0) - (1.0, 0.0, 0.0, 0.0) + (0.1, 0.0, 0.0, 0.0)\\ &= (1.0, 0.1, 0.8, 0.0)\\ &\approx (0.9, 0.1, 0.8, 0.0)\\ &= \text{Prince}\end{aligned} \tag{2.1}$$

Table 2.1 Examples of vector representations of words

Word	Vector representation	0th element (gender)	1st element (adultness)	2nd element (royalty)	3rd element (others)
Prince	(0.9, 0.1, 0.8, 0.0	0.9	0.1	0.8	0.0
Princess	(0.1, 0.1, 0.8, 0.0)	0.1	0.1	0.8	0.0
Female	(1.0, 0.0, 0.0, 0.0)	1.0	0.0	0.0	0.0
Male	(0.1, 0.0, 0.0, 0.0)	0.1	0.0	0.0	0.0

2.3. *Class Separation via Deep Metric Learning*

Metric learning trains data points represented with vectors so that they represent similarities and relationships between them as their distances in a feature space. Deep Metric Learning (DML) uses neural networks to map data points into an embedding space. Through learning, it constructs an embedded space where semantically similar data clusters gather while dissimilar ones separate. Spaces represented through the learning are utilized in various applications, such as search and classification of images and texts.

Various loss functions in DML have been proposed to control the structure of the embedded space (Hadsell et al., 2006; Song et al., 2016; Sohn, 2016; Movshovitz-Attias et al., 2017). Triplet Loss (Schroff et al., 2015) is one of the most widely used techniques in DML. Triplet Loss is a learning method that utilizes triplets consisting of an anchor sample, a positive sample, and a negative sample. In this method, anchors and positive examples belong to the same class, while anchors and negative examples belong to different classes. Triplet Loss is expressed with Equation 2.2.

$$L_{triplet} = \max\left(0, \left\|f(x_a) - f(x_p)\right\|^2 - \|f(x_a) - f(x_n)\|^2 + m\right) \tag{2.2}$$

$L_{triplet}$ is minimized in the learning. The learning aims that the distance between anchor x_a and positive example x_p is smaller than the distance between anchor x_a and negative example x_n by at least a certain margin m. The constraint that maximizes Equation 2.2 encourages samples of the same class to cluster together while promoting the separation of samples from different classes. Figure 2.2 shows the changes in the representation space before and after training using the Triplet Loss described in Equation (2.2). After Triplet Loss training, the representation space is optimized such that the distance between anchors and positive examples decreases, while that between anchors and negative examples increases. In other

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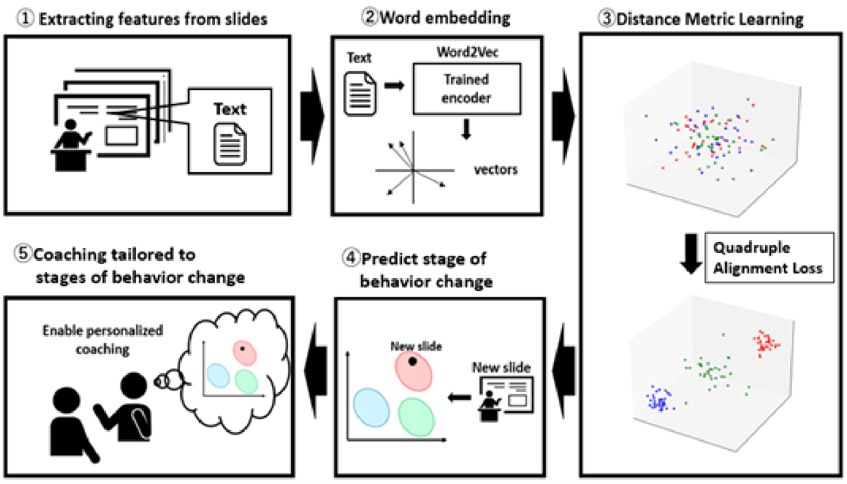
words, Triplet Loss is a loss function that learns a distance structure where examples in the same classes get closer, while ones in different classes are placed far apart.

The feature of Triplet Loss is to acquire the distance relationships, rather than the minimization of classification errors based on class labels. It can flexibly express learning independent of the number of classes. Despite its simplicity, it is widely used as a representative DML method due to its high versatility.

Figure 2.2 Representation Space Before and After Triplet Loss

3. Estimating Stages of Behavior Change Using Progress Reports

Figure 3.1 Method Overview



3.1. Stages Estimated from Text Features

This study focuses on research activities. It captures behavioral states based on the stage of the behavior change model. Specifically, the study estimates states corresponding to the contemplation stage, the preparation stage, and the action stage from the textual information. In particular, it emphasizes the preparation stage as a phase positioned between the contemplation stage and the action stage, aiming to view the stages of behavior change as a continuous process of change. This method supports research supervisors in providing guidance tailored to students' individual needs. Since progress reports are created regularly without fail, they can be collected without imposing additional burdens on students. Furthermore, they are considered to contain objective information to estimate the stage of behavioral change because it reflects research content and progress.

Previous methods estimated the stage of behavior change from questionnaires and diaries completed by participants. These previous studies have the limitation that they rely solely on the subject's subjective perspective and place a burden on the subject themselves.

Students must prepare progress reports regularly during the course of their research activities, to explain the progress to their supervisor in seminars. Progress reports are usually created in a slide format. This study proposes a method to estimate the students' stage of behavior change from their progress reports.

Figure 3.1 shows an overview of the proposed method. First, the method obtains progress reports regularly presented by the subjects. Next, textual features are extracted from the progress reports. Extracted text features are vectorized using the word2vec method. The method classifies vectorized text features into separate classes, each of which is pre-labeled with a stage of behavior change. To separate points within each class in the embedding space, the method utilizes Quadruplet Alignment Loss, which is proposed in the study. It places points for the preparation stage between those for the contemplation stage and the action stage. Finally, the method plots vectors of the newly acquired progress reports onto the embedded space. The result serves as an indicator showing which stage of behavior change the new progress report resembles. This method visualizes students' stages of behavior change, which enables supervisors to provide coaching tailored to the stages.

3.2. Vectorization of Progress Reports

Each word represented with appropriate feature dimensions enables its vector to adequately represent the relationships with other words.

The extracted text features are segmented into individual words through morphological analysis. Next, the extracted textual features are tokenized using morphological analysis. On the other hand, words that contribute little to analysis, such as symbols and frequently occurring function words, are excluded. This process represents each progress reports as a sequence of words. To convert the word sequence into a numerical vector, the study employs Word2Vec.

This study fine-tunes a pre-trained Word2Vec model using text from the labeled progress reports. This study embeds all words in progress reports into vectors with the fine-tuned Word2Vec model. Furthermore, by averaging the word vectors contained in each material, a document vector representing each progress report is constructed. This enables the acquisition of vector representations that reflect the overall semantic tendencies of the vocabulary contained within the materials.

Using the above methods, each progress report is represented as a document vector that preserves semantic information. This method uses this document vector for Metric Learning and estimating stage of behavior change.

3.3. Labeling Progress Reports

The progress reports present the process of idea development in a slide format. They contain text reflecting the student's research progress. Initial ones may contain research background and objectives, while intermediate ones often explain methodology. When research is about to be finalized, they may show experimental results. When students come to the action stages in their research, they would logically organize their ideas, while ones in the contemplation stage have not yet reached logical thinking. Even within a progress report for a single seminar, if students build their ideas logically, there will be strong relationships among the words used in the slides. On the other hand, if they lack logical thinking, little relationship would be found among the words. The parts include sentences or phrases. Some of them correspond to the student’s logical thinking, while others indicate that the student fails to organize ideas. They show text features of progress reports.

After listening to the students' progress reports, supervisors make evaluation sheets. To consider how to best lead the students, supervisors add comments for meaningful parts in each slide page created by the students. Evaluation sheets are records of comments. Some comments praise the students, while others criticise them. The comments are opened to them, so that the comments have the effect of encouraging and inspiring them. In the comments, the supervisors will indicate whether the research is progressing, stagnating, or neutral. Evaluation sheets enable us to classify sentences and phrases that provide text features.

Text features are extracted from each progress report. The study will analyze text features, assuming that they reflect students' stage of behavior change.

3.4. Quadruplet Alignment Loss

When texts contained in progress reports are converted into document vectors, they are uniformly distributed in space. They do not form a clear structure corresponding to the stages of behavior change. It is difficult to accurately estimate the stage of behavior change with the distance between document vectors in the pretrained space. To make the distance among document vectors express the relationships on the stages of behavior change, the study employs Metric Learning to reform the pretrained space.

Triplet Loss, a representative Deep Metric Learning method described in Section 2.3, separates classes by bringing positive examples closer to the anchor while pushing negative examples farther away. However, stage of behavior change addressed in the study are a concept possessing a sequential structure consisting of the contemplation stage, the preparation stage, and the action stage. Specifically, the preparation stage is an intermediate state placed between the contemplation stage and the action stage. The Triplet Loss, which considers no sequential relationship, fails to place vectors corresponding to the preparation stage at an appropriate position in the space. The study proposes Quadruplet Alignment Loss, which incorporates neutral examples corresponding to the preparation stage in addition to anchors, positive examples, and negative examples. It is a loss function that aims to learn a representation space where samples from the preparation stage are placed between those from the contemplation stage and the action stage, in addition to sufficiently separating samples from the contemplation and action stages.

The Quadruplet Alignment Loss is defined with Equation (3.1). The embedding function $f(\cdot)$ maps the input data to a d-dimensional vector. For anchor x_a, positive example x_p, negative example x_n, and neutral example x_z, the loss function addresses the following two constraints. First, Triplet Loss shown in Equation (3.1) should be minimized under the goal of separating positive and negative examples, where m denotes the margin.

$$L_{triplet} = \max\left(0, \left\|f(x_a) - f(x_p)\right\|^2 - \|f(x_a) - f(x_n)\|^2 + m\right) \quad (3.1)$$

In addition, the study introduces a constraint on distance so that neutral examples are positioned between positive and negative examples relative to the anchor. Specifically, it is expected that the distance between the anchor and the neutral example falls within the interval $[t_{min}, t_{max}]$. The constraint is shown in Equation (3.2). Note that t_{min} is the sample in the negative example set closest to the anchor, while t_{max} is the sample in the positive example set farthest from the anchor. t_{min} and t_{max} are dynamically updated as the learning progresses.

$$L_{neutral} = \max(0, \|f(x_a) - f(x_z)\|^2 - t_{max}) + \max(0, t_{min} - \|f(x_a) - f(x_z)\|^2)$$
(3.2)

Finally, Quadruplet Alignment Loss is defined as a weighted combination of these two losses, as shown in Equation (3.3). In this formulation, λ is a hyperparameter that controls the configuration of neutral examples.

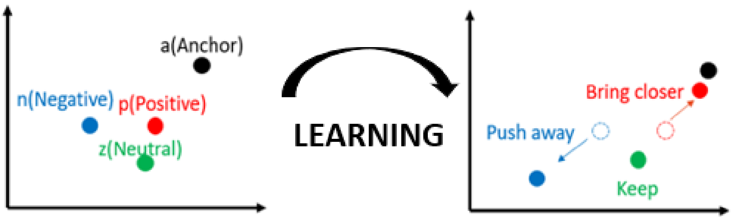
$$L_{QAL} = L_{triplet} + \lambda L_{neutral} \tag{3.3}$$

Figure 3.2 illustrates the effect of the Quadruplet Alignment Loss defined by Equations (3.1) – (3.3) on the space. The model learns to bring positive examples closer to the anchor as well as push negative examples farther away. The positions of neutral examples are kept relatively between positive and negative examples. As a result, the learning reforms the space so that positive and negative examples are separated toward the outer edges, with neutral examples positioned between them.

When students change their behavior, they move from the contemplation stage to the action stage via the preparation stage. It is thought that there is a behavioral boundary that distinguishes the action stage, where they engage in desired behavior, from the attention stage, which they do not.

Let us consider informing supervisors that students are approaching the behavioral boundary that should be crossed. It will provide the supervisors with suggestions to be presented. If students are informed that they have crossed a behavioral boundary, they will be aware of what is necessary for behavior change. The loss function enables us to represent the preparation stage as a behavioral boundary placed between the contemplation stage and the action stage in the space.

Figure 3.2 Effect of Quadruplet Alignment Loss on the Representation Space



3.5. Estimation Using Expression Space

Quadruplet Alignment Loss is expected to separate the contemplation stage and the action stage from each other, with the preparation stage placed between them. A new progress report is embedded in the space. We can visualize where the new progress report is placed relative to the stages of behavior change, along with progress reports whose stages are known. It enables supervisors to image the stages of behavioral change in students' research activities.

Additionally, the study trains a machine learning model to discriminate the stages of vectors representing each progress report. Hereinafter, the vectors that can be plotted in the space are referred to as representation vectors. The stage of a new progress report is predicted with the trained model. The model presents an automatic and objective estimation of the stage. The method enables supervisors to estimate students' stages of behavior change from both introspective and external perspectives, without imposing additional burden on the students.

The corresponding stage turns out for each progress report a student presents in a series of seminars. A sequence of stages lets supervisors grasp that the student is approaching the behavior boundary. As a result, supervisors can consider the intensity and the timing of intervention. It enables more appropriate research guidance to be provided according to the student's condition, which leads to improving the quality of students' research activities.

4. Experiment

Let us confirm we can estimate behavioral change stages using textual features extracted from progress reports with an experiment. The purpose of the experiment is to verify whether the space trained with Quadruplet Alignment Loss is effective for estimating behavioral change stages. First, the experiment collects the materials used in the regular research progress presentations held in a laboratory. Each obtained progress report is labeled into one of three classes: the contemplation stage, preparation stage, and action stage. The experiment extracts text features to evaluate the space trained with Quadruplet Alignment Loss.

4.1. Datasets and Labeling

This experiment adopts a dataset consisting of a series of research progress reports presented by 19 students in a university laboratory. Each progress report is created in Microsoft PowerPoint format. Each presentation slide is treated as one sample. Progress reports for one year reaches to 103 items in total.

First, text features are extracted from each progress report. The extraction focuses on the main text within the documents, excluding analyze g figures and tables. Morphological analysis is applied to the extracted text to obtain a sequence of words, mainly nouns, verbs, and adjectives. The analysis removes particles, general function words, and fixed expressions specific to presentation as stop words.

Next, the extracted text features are vectorized using Word2Vec. The experiment uses a pre-trained Japanese Word2Vec model provided by the Python library genism (Řehůřek & Sojka, 2010; Řehůřek, 2009). Furthermore, this model is finetuned using text data extracted from the progress reports labeled according to the criteria explained below. It enables the representation of word vectors that preserve the semantic structure of general vocabulary while reflecting the specialized terminology and context specific to research presentation. Averaging the 50dimensional word vectors from each progress report, the experiment obtains a document vector representing the progress report. This document vector is used as a feature for each progress report.

Each progress report is labeled with the stage of behavior change of the students into three categories: the contemplation stage, the preparation stage, and the action stage. The labeling uses evaluation sheets recording discussions on the content of presentations when each progress report is presented. These evaluation sheets record the researcher’s statements during the presentation, as well as the supervisors ’questions and advice in response. Furthermore, sections that may directly contribute to research outcomes, such as important results or discoveries, are recorded in colored or bold text.

The study assumes evaluation sheets corresponding to each stage of behavior change has the following features. In the contemplation stage, the supervisors ’remarks are recorded with colored text and bolded text in a high proportion. In the preparation stage, evaluation sheets contain few colored texts or bold texts. In the action stage, a high proportion of colored text and bold text appears in student comments.

During the contemplation stage, it is considered that students themselves have not yet fully organized their research content. It leads to a reduction in students’ contributions. The supervisors will need to present many comments to make the research viable, which leads to a higher proportion of emphatic expressions in their statements. During the preparation stage, the research direction is established. However, no substantial progress has yet been made toward advancing the research. Therefore, professors tend to adopt a stance of quiet observation toward students' independent trial and error, so as not to hinder the progress of their research. As a result, emphatic expressions become less likely to appear in columns of both students and professors. During the action stage, it is considered that students are capable of independently advancing their research and clearly identifying key points on their own. Discussions tend to proceed with students' utterances. It increases the proportion of emphatic expressions in students' statements.

The progress reports are labeled based on the above features. The labeling results yielded 35, 36, and 32 items in the contemplation stage, the preparation stage, and the action stage, respectively.

4.2. Training the Quadruplet Alignment Loss

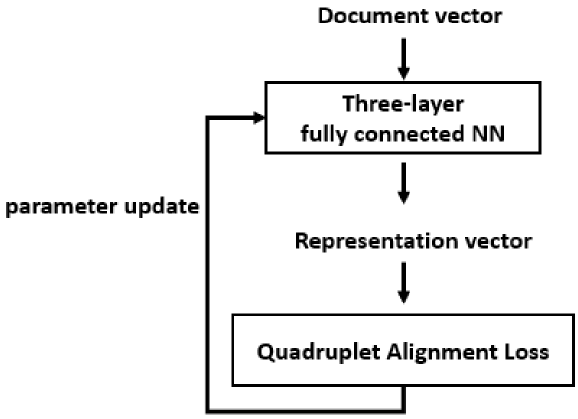
The Quadruplet Alignment Loss is reduced in the following procedures. First, the study splits the dataset described in Section 4.1 into 80% training data and 20% test data.

Next, based on the labels of the stage of behavior change, the procedure creates sample sets consisting of anchors, positive examples, negative examples, and neutral examples from the training data. Anchors are randomly selected from samples belonging to either the contemplation stage or the action stage. Positive examples are randomly selected from samples belonging to the same stage of the behavior change cycle as that of the anchor, while negative examples are random samples belonging to different stages of the behavior change cycle. Additionally, neutral examples are randomly picked from the samples of the preparation stage. These datasets were designed to enable sufficient training even with small datasets by including the same progress reports across multiple groups. As a result, a total of 1,000 datasets are created in the experiment.

Figure 4.1 shows the overall configuration of the neural network used in the learning of the space. The document vectors created in Section 4.1 are converted into representation vectors using a three-layer fully connected neural network. A simple neural network model is employed to minimize the influence of the model structure and focus on the effect of the loss function.

The Quadruplet Alignment Loss is computed for the representation vectors. Based on that loss, the parameters of the neural network are updated using the backpropagation algorithm. Repeating the procedure, an expression space reflecting the stages of behavior change is constructed step by step.

Figure 4.1 Architecture of Representation Space Learning via Quadruplet Alignment Loss



4.3. Evaluation of the Representation Space

The study evaluates the usefulness of the proposed method based on its predictive performance for the test data, according to the following procedure. First, using the embedding function obtained from the Quadruplet Alignment Loss trained in Section 4.2, the document vectors of the test data are converted into representation vectors. Next, the experiment trains XGBoost (Chen & Guestrin, 2016) using the representation vectors of the training data. XGBoost is a gradient boosting method that sequentially trains decision trees as weak learners. This learning model is characterized by its ability to flexibly represent nonlinear relationships between features. It works well even with small amounts of data.

The expression vectors from the test data are fed to the XGBoost model to classify the stage of behavior change. The study evaluates the classification performance with the F-1 score. The small amount of data in the study may present high accuracy values in the predictions. Therefore, the study adopted the F-1 score, which allows for a comprehensive evaluation of the impact of misclassification across all classes.

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5. Result and Discussion

5.1. Estimation Results and Model Evaluation

Progress reports in the experiment are converted into a 50-dimensional document vector. Figure 5.1 shows their compression into two dimensions using Principal Component Analysis (PCA). From Figure 5.1, no clear separation between classes is observed in the vector space before learning based on Quadruplet Alignment Loss.

After the learning based on the Quadruplet Alignment Loss, each progress report is converted into a representation vector in the 16-dimensional space. Figure 5.2 shows the result of compressing the space into two dimensions using PCA. Figure 5.2 shows that the vectors of the contemplation stage, the action stage, and the preparation stage are clustered on the right side, the left side, and the center, respectively. The figure shows that the preparation stage is positioned between the contemplation stage and the action stage. It suggests that the sequential relationship between the stages is reflected in the embedded space. However, some samples in different stages overlap. It is difficult to say that the separation between classes is complete.

Tables 5.1 and 5.2 show the results of estimating the stages of behavior change using representations before and after learning based on the Quadruplet Alignment Loss. In Table 5.1, the F1 score remains around 0.40 at every stage of behavior change. On the other hand, Table 5.2 shows that the learning improves the estimation performance; the F1-score is 0.68, 0.75,

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and 0.61 for the contemplation stage, the preparation stage, and the action stage, respectively. While the overall estimated performance cannot be said to be high, it is evident that classification performance has improved through learning.

It is noteworthy that the highest F1-score is achieved for the preparation stage. In the Transtheoretical Model, the preparation stage is characterized by the formation of an intention to change behavior. External supports such as advice and feedback are most likely to lead to strong intention at this stage (Prochaska & DiClemente, 1982; Vansteenkiste et al., 2009). The estimation of the stage with high precision indicates that the embedded space after the learning appropriately captures states particularly important in research supervision.

On the other hand, a tendency for accuracy to plateau is observed after long training. One factor causing it is the limiting of generalization performance due to information compression of the representation vectors. In the PCA applied to the 16-dimensional representation after the learning, it is confirmed that the contribution rate of the first principal component reaches approximately 60It indicates that the majority of the variance in the representation vectors after the learning is concentrated in a few directions. The learning strongly compresses the information represented by the vectors.

Roth et al., 2020 report that, in deep distance learning, over-compression of embedding representations deteriorates generalization performance for test data, while discriminative power for training data improves. The result of the experiment similarly suggests that the compression of the representation vectors may have resulted in insufficient retention of the diverse features necessary for estimating the stage of behavior change. As a result, the learning based on the Quadruplet Alignment Loss, which improves the structural consistency of the representation space, would encounter certain limitations in enhancing generalization performance.

As discussed above, the method developed in this study has certain utility in that it reflects the continuous relationship between stages of behavior change in the embedded space to improve estimation performance to a certain degree. On the other hand, it has also become clear that compression of representations leaves challenges for generalization performance.

Figure 5.1 Document vectors (PCA)

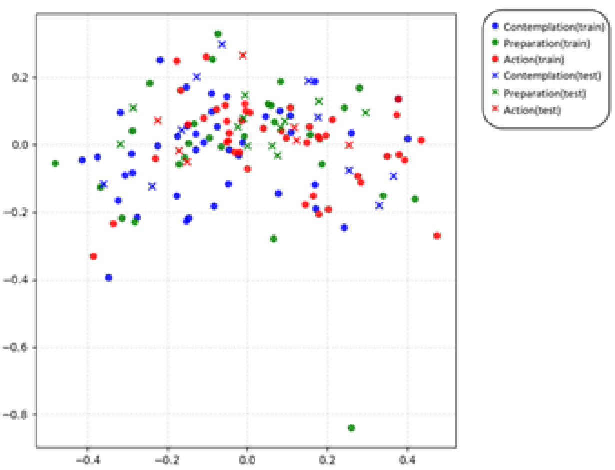

Figure 5.2 Representation vectors (PCA)

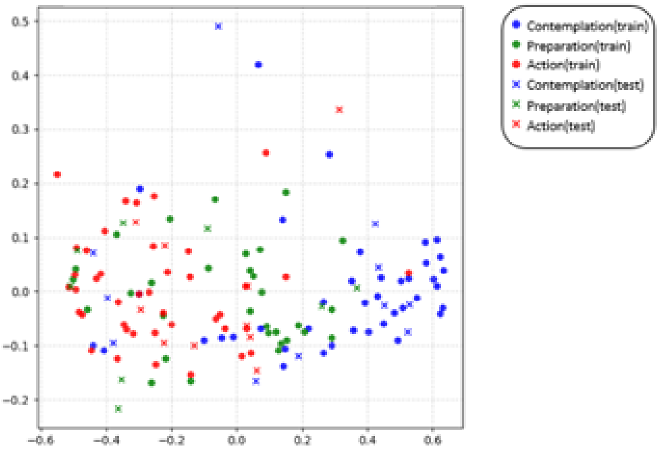

Table 5.1 Class Estimation Results Before Quadruplet Alignment Loss Training

Stage of behavior change	Precision	Recall	F1 score
contemplation	0.62	0.45	0.53
preparation	0.36	0.50	0.42
action	0.40	0.40	0.40

Table 5.2 Class Estimation Results After Quadruplet Alignment Loss Training

Stage of behavior change	Precision	Recall	F1 score
contemplation	0.70	0.67	0.68
preparation	0.75	0.75	0.75
action	0.59	0.63	0.61

5.2. Effectiveness of Alignment

The study introduced alignment constraints into the embedded space using Quadruplet Alignment Loss. It enables us to represent the continuity between stages of behavior change, which is difficult to express with triplet loss functions. Let us discuss the effects of introducing alignment constraints into the embedded space.

First, as shown in Figure 5.2, in the post-learning representation space, the contemplation stage, the preparation stage, and the action stage are distributed such that they form a continuous spatial relationship. The approach enables us to determine not only which class each sample belongs to, but also what position the current progress report has within the continuous progression of stages of behavior change. Especially, samples of the preparation stage are continuously distributed in the intermediate position of the contemplation stage and the action stage. The distribution structure suggests that the preparation stage expresses the degree of transition from the preceding state to the subsequent states, rather than working as an independent state.

To confirm it, let us examine the samples of the preparation stage that are misclassified by XGBoost. Many of them are located near the contemplation stage or the action stage in the representation space. Additionally, the words appearing in these misclassified samples contained numerous terms commonly used to indicate results, such as “results,” “accuracy,” “seconds,” and “%”. On the other hand, samples misclassified as the contemplation stage contain many words that explore research plans, such as “purpose,” “background,” and “challenge.”

Based on these results, misclassifications in the preparation stage can be attributed to the fact that the progress reports partially contained characteristics of both preceding and subsequent stages. It suggests that the embedded space trained with the proposed method can express the stages of behavior change as a continuous progression. From the progress reports of target students, supervisors can estimate whether their stage is closer to the contemplation stage or the action stage. The estimation greatly contributes to determining the strategies of supervision.

6. Limitations

This study has several limitations. The first limitation is that it requires progress reports from a large number of students over a long period of time. Distance learning methods require a certain amount of data to reliably learn the distance relationships between samples. progress reports used in the study is collected over approximately one year from . A sufficient amount of data must be accumulated to apply this method. However, there is no clear standard for sample size in estimating stages of behavior change. It is impossible to determine whether the amount of data used in this study is sufficient for the tuning of the embedded space through distance learning. The second limitation is that labeling progress reports with the stages requires evaluation sheets. The progress reports are labeled using the evaluation sheets recorded during the presentation. The evaluation sheets include the Q&A during the presentation and the supervisor ’s remarks. Such information provides important clues for understanding the presenter’s research status and behavioral state. However, it needs much effort from supervisors to get detailed evaluation sheets. Furthermore, labeling based on evaluation sheets involves aspects dependent on the supervisor’s interpretation. Labeling results may contain a certain degree of subjectivity. It is necessary to standardize evaluators’ criteria or have multiple evaluators conduct assessments. The third limitation is that it relies solely on textual features from progress reports to estimate the stage of behavior change. Progress reports contain many features beyond text, such as charts, diagrams, and animations. When presenting research findings, progress reports are likely to include charts and graphs illustrating those results. Currently, the method cannot reflect such characteristics. These limitations indicate that there may be room for further research development in the future.

7. Conclusion

The study proposed a method to estimate the stage of behavior change from students’ progress reports.

In the proposed method, students’ progress reports are converted into document vectors using Word2Vec. The vectors represent the behavioral characteristics reflected in each report, such as research progress, planning, and reflection. The study introduces a newly devised metric learning loss function, Quadruplet Alignment Loss, to capture the structure of the stage of behavior change. With progress reports labeled using the evaluation sheets by the supervisor, the proposed method constructs the relationship among the contemplation stage, the preparation stage, and the action stage in the space. The method estimates the stage of behavior change of students based on the vector position of each progress report in the space.

To verify the effectiveness of the proposed method, the study conducted an experiment to classify the stages of behavior change for students. The experimental results demonstrated that the proposed method improves estimation accuracy, particularly during the preparatory stage, which is a crucial transitional stage leading to actions. The experiment provides plausible spatial distribution of the vectors. It suggests that the method appropriately captures the relationships between different stages.

The Quadruplet Alignment Loss provides the representation of students' stages of behavior change in an interpretable form. The representations allow supervisors to identify whether students are approaching key behavioral boundaries, to adjust the timing and intensity of academic guidance accordingly. It enables the supervisor guide students reflecting their condition, which promotes the quality of students' research activities.

In the future, it is planned to examine results of the study changes under larger and more diverse datasets. The method will also be improved to use all information from progress reports, including charts and presentation structures. It is expected to further enhance the practicality of the proposed method.

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