Research on the Optimization of Combinatorial Strategies in Continuous Learning

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***Abstract*—This paper discusses the existing continuous learning framework, and briefly introduces the existing commonly used data sample selection algorithms. At the same time, it designs the continuous learning framework by selecting some sample selection algorithms, and uses the open source data set SCMD for experiments. Through designing the network architecture, it adjusts the proportion of different sample selection algorithms for experiments. Finally, the experiment proves that by effectively adjusting the proportion of results of different sample selection algorithms, It can effectively optimize the accuracy of the model.**

***Keywords*—Active learning, continuous learning, data annotation algorithm, artificial intelligence model**

I. Introduction

With the rapid development of information technology, more and more information storage, use and interaction processes occur in the computer processing process [1]. Massive information interaction and use have produced a variety of information data, and these data have a variety of internal relationships. These associations have great benefits for social production and practical activities. In order to excavate the hidden relationship between data, researchers have developed a variety of efficient and practical AI algorithms. These algorithms can learn their internal experience from wave data and produce AI models. Through iterative updating, these mature AI models can apply the knowledge they learned to new data, And achieved good recognition, prediction and correlation results [2].

Benefiting from the improvement of existing data sets, there are a large number of complete data sets, such as MNIST, ImageNet, etc. These data are labeled and verified by researchers with a lot of manpower and material resources, but there are still problems such as less labeled data and incomplete fields of trainable data [3]. Of course, for example, MNIST handwritten input recognition images have lower difficulty in data annotation, less professional knowledge requirements for personnel, and lower cost in the annotation process, but at the same time, there are also unmarked data that require higher professional knowledge, such as multiple similar flowers of pictures, or the number data of weapons and equipment, and the type of network attack [4]. Such data requires higher professional knowledge of the annotation personnel, It can better distinguish the categories of different professional data, and at the same time, it needs to carry out data label cross-validation [5]. The economic cost of this data label experiment is very surprising, especially in the field where there are few professional knowledge reserves [6].

For all AI tasks, a complete and correct standard data set is the premise of an effective model for training travel. However, in the process of data annotation, random sampling selection does not make use of the correlation between data, nor does it take into account the adaptability of AI models and data, which is obviously not feasible. In order to save the economic cost in the process of data annotation, the active learning method was proposed. The active learning method is mainly to improve the way of randomly selecting the data samples to be annotated in the past. By focusing on the performance parameters of the data itself and the interaction parameters between the data model, data analysis is carried out on the unmarked data sets, and the most valuable or representative sample data for the data model is selected, Through this screening method, the labeling pressure can be reduced as much as possible, and the labeling funds can be saved. At the same time, the AI model can also obtain a concise and effective data training set, which effectively alleviates the model training time [7].

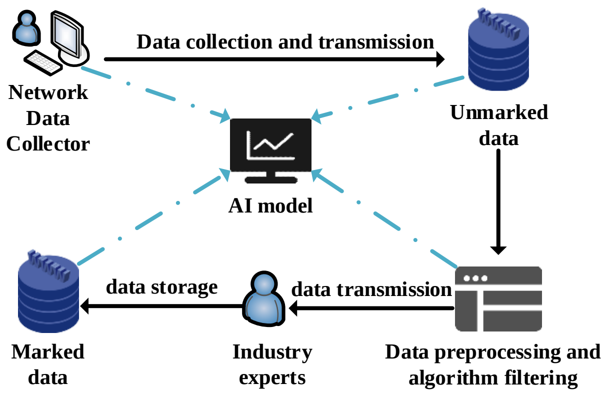

Fig. 1. Schematic flow chart of active learning

At the same time, most of the machine learning tasks that can be actually deployed are not isolated and one-time, and most of the information data has the characteristics of time dimension. Therefore, the database often sets the life cycle of the data, and continuously collects the latest data for multiple incremental updates of the data [8]. At the same time, the trained AI model also needs to be continuously updated. Therefore, The model is required to have the ability of continuous learning. In short, continuous learning is the ability to obtain continuous learning from one or more data streams and effectively apply knowledge. The continuous learning model is required to remember the knowledge learned in the past and adapt to the changing data environment efficiently [9].

II. Research Status

A. Research background

At present, the continuous learning method has been widely used in various AI business projects of well-known companies, such as Google and IBM [10]. At the same time, the way of continuous learning can be divided into data-pool-based learning method and data-flow based learning method. The difference between the flow-based learning method and the pool-based learning method is that the pool-based learning method has no life cycle of data. It can be considered that the data is effective and can reflect the reality in a sustainable period of time. The data based on flow has a life cycle, and the data is supplied to the model according to a certain time sequence. If the selection algorithm does not extract the data in time at the current time for data standard, the data sample will be discarded [11].

B. *Pool-based learning algorithm*

Pool-based learning algorithm: Pool-based learning algorithm is the most common and popular [12]. The main reason is that the pool-based learning method is applicable to most computing scenarios and can effectively store the previous annotation data without causing data loss. Pool-based learning data sample selection algorithm mainly includes uncertainty reduction method, version space reduction method, and generalization error reduction method [13].

The method of uncertainty reduction is mainly to determine which samples cannot be accurately recognized by the model [14]. Most methods based on uncertainty reduction are combined with classifiers, such as support vector machines, hidden Markov models, etc [15]. The method of version space reduction is to determine which data samples can split the version space to the maximum extent. Common calculation methods include voting entropy, Jensen-Shannon bifurcation degree, Kullback-Leibler bifurcation degree, etc [16]. The method of generalization error reduction is mainly to minimize the generalization error of data [17]. Common methods include naive Bayes, Bayesian network, nearest neighbor algorithm, etc [18].

C. *Stream-based learning algorithm*

Stream-based learning algorithm: A major feature of the stream-based learning method is that it cannot actively contact all the expected data sets, and can only evaluate the algorithm for one batch or individual samples at a time. Therefore, the stream-based learning method needs to identify data samples in different time sequences, and learn data samples, usually by means of threshold adjustment. For example, QBV is a pool-based learning method, which can also be used for the flow learning method [19]. For each incoming data sample collection, the sample divergence is calculated. If the current sample divergence is higher than the predetermined threshold, the data will be submitted to experts for sample standard [20]. Similarly, the threshold will be updated continuously with the continuous calculation of the flow data.

D. *Summary*

It can be simply said that there are many existing continuous learning frameworks and sample selection algorithms, but how to use these sub-algorithms to combine an effective continuous algorithm has always been based on artificial experience. At the same time, the adaptability of different algorithms depends on the characteristics of data sets. When the data model is incrementally learning, the previous learning algorithms may not achieve good model training effect, Therefore, this paper will build models for different data sets through different sub-algorithms, and analyze the effectiveness of their algorithms [21]. At the same time, it will build a set of laws to explore the adaptive algorithms of different data sets, so as to guide AI algorithms to use experts to design continuous learning algorithms efficiently [22].

III. Explore Multi-Strategy Combination Algorithm Scheme

A. *Design criteria for continuous learning sample selection algorithm*

The main influencing factor of sample selection is how to design and use the appropriate sample evaluation function. The function of the evaluation function is that it can select an unlabeled data set from the data sample to carry out expert manual annotation. When the labeled data is used for incremental training of the AI model, it can minimize the prediction error rate of the model. As mentioned in the background introduction, the different data characteristics of the data set make the algorithm of sample selection have no relative criteria in the continuous learning process. Generally, the most original idea of the sample selection algorithm is to select the extreme value of a certain attribute of the data, or to select the most representative and singular sample data for the corresponding sample of a certain attribute or feature. Such sample data labeling has certain significance, but for the actual data sample, it is difficult to observe who goes to the most representative sample and who is the most characteristic sample. The most commonly used sample selection algorithm is based on the "most uncertain criterion" and "most representative criterion" methods. The most uncertain criterion is to use the information entropy in the signal to calculate the amount of information in the data, and then determine the most uncertain sample. The most representative criteria are used to select the most representative samples for each category of data.

B. *Most uncertain criteria*

The most uncertain criterion is most commonly used in feature sample selection algorithm [23]. This criterion requires an artificial model that has been pre-trained according to the labeled data set. The artificial intelligence model is used to evaluate the classification index of the data set, but the most effective one is the category probability value before the model activation function. Its main process is to traverse every data in the data set, input the data into the model, get the probability distribution of each data type, and calculate the probability distribution using the formula of information entropy. If the value of information entropy is large, then the artificial intelligence model can not judge the type of the data sample well at present, on the contrary, if the value of information entropy is small, It is believed that the AI model can better judge the type of the data sample at present. Therefore, based on the most uncertain criteria, assuming that the current unlabeled data sample is $D_u = \{x_1, x_2, x_3, ..., x_n\}$, the following strategy will be adopted to complete the selection of unlabeled samples.

$$X_H = \arg\max_{x \in D_u} - \sum_i p(y_i / x) \log_2 p(y_i / x) \quad (1)$$

Where $p(y_i / x)$ is the probability that the current x is classified as y_i type, and X_H is the set of data templates to be labeled selected by the strategy method. The uncertainty criteria based on the information entropy theory can better reflect the characteristics of the data itself, which is very common in the continuous learning process.

C. Maximum expected gradient criterion

The maximum expected gradient criterion is similar to the most uncertain criterion [24]. This criterion also requires a pre-trained artificial intelligence model. The main strategy of this criterion is to select the data sample that can make the model gradient change the largest. In the process of using the maximum expected gradient criterion, each data sample is input into the pre-training model, but its actual gradient is not changed, By collecting the gradient change value of each data sample, it is arranged in order from large to small, and some data samples are taken for labeling training.

$$EGL(x) = \sum_{\tilde{y} \in N} p(y_i / x; \theta) \left\| \nabla L \left\langle x, \tilde{y} \right\rangle ; \theta \right\| \quad (2)$$

$p(y_i / x; \theta)$ is the posterior probability of the model after classification, $\left\| \nabla L \left\langle x, \tilde{y} \right\rangle ; \theta \right\|$ is the change value of the actual gradient of the model.

D. The most representative criterion

The demand of the model for data samples is not always only various templates with the best characteristics, but mainly from representative samples [25]. The most representative samples can enrich the sample data set of each training, so that the model will not forget the more standard data set learned in the past. Similarly, with the continuous training of the model, it is easy to send the over-fitting phenomenon, This leads to the failure of learning the sparse model. Because the data are filtered from unmarked data sets, the common methods based on the most representative criteria are carried out through clustering algorithms.

The steps to use this criterion are: first, for the unlabeled data D_u, the data will be imported into the peak clustering algorithm, and the cluster center will be continuously optimized, and then the samples of all the cluster centers will be selected for data training.

$$D_{AL} = Clustering(D_u, C) \quad (3)$$

Among them, D_u is the selected data sample set, C is the classification center, Clustering is the clustering algorithm, and Dal is the selected algorithm for the next batch of labeling.

E. Rules of the Adjudication Board

The adjudication committee criterion refers to dividing a feature selection algorithm into multiple sub-feature selection algorithms, using the idea of integrated learning, and taking the divergence procedure of the output results of multiple sub-feature selection algorithms as the main basis for sample selection [26].

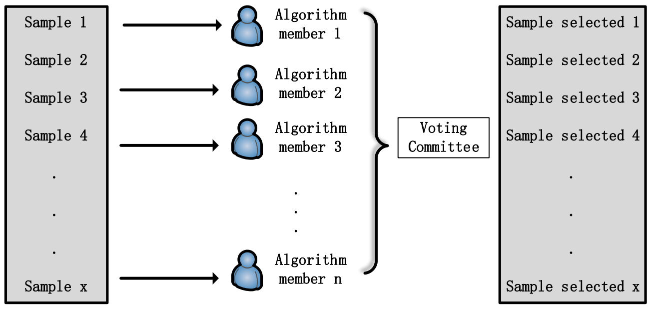

Fig. 2. Schematic diagram of voting committee

$$D(\mathrm{x}) = -\frac{1}{\log \min(K, |C|)} \sum_{C} \frac{V(c,x)}{K} \log \frac{V(c,x)}{K} \quad (4)$$

Voting entropy is used to select samples, where P is the number of selected samples and m is the total number of samples. The divergence of the committee output structure can be measured by voting entropy. Is the number of votes of the committee for category c of member sample x, K is the number of committees, and C is the number of categories. In order to make the comparison of voting entropy better, the normalization factor is used. It can be seen here that the more divergent the results of different selection algorithms are, the more valuable the sample will be.

IV. Multi-strategy Continuous Learning Algorithm Framework Design

In order to consider the actual application scenario, the continuous learning framework needs to train the incrementally updated data set in a large span of time, and its design needs to meet the following main criteria: (1) be able to learn new knowledge, even if the label does not appear in the pre-training process, and can correctly identify new classification categories after learning new knowledge. (2) To maintain the old knowledge, the model needs to be able to correctly respond to the previous learning knowledge in the continuous incremental updating process, that is, it can have certain anti-forgetting ability and can better avoid the transmission of catastrophic forgetting phenomenon. (3) A few categories can be found well, and the model needs to be able to identify all categories.

In order to fully consider the above multiple requirements, the paper proposes a continuous learning framework of unfixed proportion combination algorithm, which uses the above multiple sample selection algorithms, and constantly adjusts the proportion of the algorithm to explore its research results.

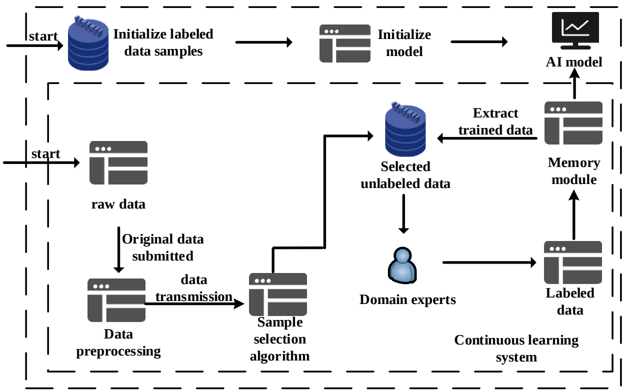

Fig. 3. The overall framework of continuous learning. The framework first trains and initializes the classification model (cNN) based on a small number of labeled samples, and then continuously sends the newly arrived unlabeled samples to the model for feature extraction and prediction; Using the prediction results and the depth characteristics of samples, the fusion strategy is used to select samples; Then use the new labeled active learning sample and the labeled previous sample subset to fine-tune and update the model to complete a model learning process

In the initialization phase, we need an initial model M0, which is trained according to a certain labeled dataset Ds. At the initialization stage, the artificial intelligence model will initialize the neural network. During the incremental learning process, after each sample selection, a certain amount of labeled data will be added, and then trained on the previously trained artificial intelligence model. The sample data to be labeled is carried out by the sample selection algorithm, but it mainly comes from different aspects. The first is the unlabeled data selected by the current sample data selection algorithm, and the second is the most representative subset of the trained data. This will strengthen the deepening of the model to previous knowledge, and summarize the sample data sets of both sides to obtain the labeled data set for training at the current time, The Mt model is obtained by training the model at Mt-1. According to the above process, the performance of the pre-training model can be continuously improved.

According to the process of the framework, the AI model needs some labeled data and initializes the data model. For the data learning process, the original data will be added to the unlabeled data set after data preprocessing, and the algorithm will be filtered through the AI model prediction results.

algorithm：Dynamic Proportional Multi-strategy Continuous Learning Framework

1: Set up dimensioned data sets D_L ;
2: Set up unlabeled data sets D_{UL};
3: Set sample data for one round S , Set AI model as M;
4: For $x^i \in D_{UL}$ DO ;
5: Data classification using artificial intelligence model M;
6: Calculate information entropy according to the least accurate principle;
7: Model gradient change of calculated data x^i ;
8: The sample set with the largest gradient change in the statistical model;
9: Calculate voting entropy according to voting committee algorithm;
10: end for
11: For $x^i \in D_L$ DO ;
12: Peak classification for data sets D_L ;
13: end for
14: Combine all the calculation results to get the next round of calculation data set;
15: finished;

Fig. 4. Schematic diagram of active learning algorithm code

V. Multi-strategy Continuous Learning Algorithm Framework Design

A. Data Set

The experiment uses the audio data set of Speech Commands (SCMD) to evaluate the effect of proportional grouping of different algorithms. The SCMD data set is the latest data set used to support the research of language command recognition. The data set contains 30 short words and a total of 65000 items of data. These audio data are provided by the Internet.

B. Experimental Setup

The experiment uses CNN's network architecture and fine-tuned some of its parameters.

TABLE I. Neural Network Parameter Setting

Layer type	Kernel size/stride	outputsize
BatchNormalization		60*41*2
Convolution	3*3/1	60*41*64
Max pool	2*2/2	30*20*128
Convolution	3*3/1	15*10*128
Max pool	2*2/2	15*10*128
BatchNormalization		1*1*128
FC(Dropout 50%)		1*1*32
Softmax		1*1*10

The BatchNormalization level and Max pool level are set to accelerate the convergence process of calculation

C. Experimental results

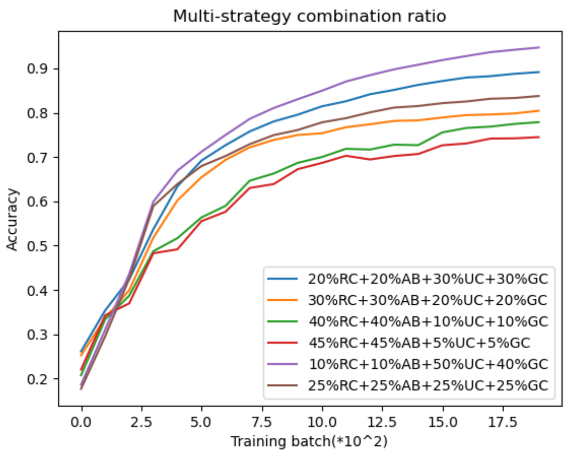

Fig. 5. experimental result

According to the experimental results, the continuous learning task of multi-strategy fusion is better than the random strategy task. At the same time, the active learning effect can be better by effectively adjusting the proportion of different algorithms. Therefore, in the process of active learning, if the proportion of different combination algorithms can be adjusted according to the characteristics of the data set, better results can be achieved.

Acknowledgment

In general, this paper adopts a multi-strategy continuous learning method and designs an appropriate continuous learning framework for experiments. The experimental results show that the effect of the model will also change with the adjustment of the multi-strategy data proportion. If a better strategy proportion can be selected, the prediction effect of the model will be better optimized.

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