

Deep Neural Networks Techniques using for Learning Automata Based Incremental Learning Method

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Abstract -Surprisingly comprehensive learning methods are implemented in many large learning machine data, such as visual recognition and visual language processing. Much of the success of advanced training in recent years is due to leadership training, which requires a set of information for specific tasks, before such training. However, in reality, selected tasks related to personal study are gradually accumulated over time as it is difficult to collect and submit training data manually. It provides a way to continue learning some information columns and examples of steps that are specific to the new class and called additional learning. In this post, we recommend the best machine training method for further training for deep neural networks. The basic idea is to learn a deep system with strong connections that can be "activated" or "turned off" at different stages. The approach you suggest allows you to reduce the distribution of old services as you learn new for example new training, which increases the effectiveness of training in the additional training phase. Experiments with MNIST and CIFAR-100 show that our approach can be implemented in other long-term phases in deep neuron models and achieve better results from zero-base training.

Keywords:

1. INTRODUCTION

In recent years, the deep network has learned several machines, such as image sharing, speech recognition, native language processing, and much more. The performance of this great model benefits from the presence of partially translated data. For example, while ImageNet has 1.2 million images in 1,000 sounds, AudioSet is a collection of more than 2 million audio-video ontologies of 632 audio stories. Common with the millions of variables and hypothetical properties learned from raw data. In 2014, GoogLeNet developed a 22-unit network successfully integrating Tatar that created advanced technology to classify and recognize ImageNet data. In 2016, he and others successfully proposed a new architecture called archaeological network, which successfully created a network of 152 multi-sensory nerve layers, enabling temporary art on ImageNet. Leoro has developed modern algorithms that achieve remarkable results, for example in the use of large data-based data to identify the same types of humans and machines.

Much of the success in higher education depends on the learning that is being conducted, based on the many data that are collected today. Related to the concept of control learning, the complete neuron model is examined in the data prepared to solve the split or retrieval component, where the complete model can be considered as a measurement function with many data inputs and outputs. , Algorithms for the development of a comprehensive numerical network, such as stochastic schedules, are embedded in all training data to obtain the best measurement values and reduce employment waste. Big data plays an important role in teaching complete models such as millions and billions of layouts with no need to change. But in fact, we can have all the information at once. The information selected in the said class is collected step-by-step, as it is difficult to prepare and interpret training data manually. In some specialized areas, such as medical research, it takes a lot of time to create a lot of data because data registration is complicated and expensive. Therefore, it is very important to think about how to continue reading the news column and the training session series that is gradually added to the new subjects, this is called additional training.

Unlike the traditional way of learning a regular group of information, this is a general learning map based on step-by-step learning. For human beings, the training process is also a process of steps. We thought we would not immediately learn everything, but the concepts we have learned help us to identify new things quickly. Much research has been done to preserve new science and learn new information in a trained machine learning style. The authors suggest the idea of learning life by a machine based on the fact that learning n-task (n-1) should be simpler than learning to work. However, little research has been done on the deep kidney tissue in this area. Recent work in translation research suggests that an existing set of models can provide common properties that can be transformed into relevant fields of information. For example, the complete neural network trained on

ImageNet can be used to set up new models and add effects to image sharing problems. "Unforgettable Learning" focuses on the deep training conditions in the new database, at least without the use of new training data in use, and attempts to improve model performance on new data while maintaining your original capabilities. But they are all different from the state of higher education, we believe.

In this section, we look at situations where new types of classroom learning are slowly being incorporated into a set of teaching data. Each time we have to compare the model that has been trained with the most detailed data. The learning steps are shown in Figure 1. First, we learn the complete model of M0 neurons based on the original D0 datasets. When a new class is added, we need to add new items without affecting the existing services, so that we can change that model with an extended flow of data. Although not easily implemented in the full model. The two reasons discussed are discussed below. First, the pain of the "disaster-forgetting" problem, a pre-learning job is easily removed from the deep model as it learns again in new learning situations. Because the neuron model completely captures the hierarchical architecture, represents and divides the object class, and small changes in the parameter fields in the first column cause significant changes in later layers. Second, the complete model must be adapted to modern equipment and new classes added. However, it is not easy to determine the location and number of new devices. In this section, we've overcome these difficulties by creating deep and powerful neural networks, with each noun being taught as "enabled" or "disabled" in a different set of information in the plug-in learning process. Balham himself of the new repressive work, a more detailed example is further defined by the next link. Therefore, we recommend teaching a complete neuron model for each data set as the method and method recommended for cutting machine learning. Instead of immediately eliminating unwanted links, we use deleted links ("deleted") as part of the image and the remaining links ("enabled") as the basis for the model.

When new class cases are included in the data, we expand the boundary section, redesign the model, and reduce the main section by minor changes. This means that we cannot submit old works when we learn new works for a new learning period. We believe that as the best way to increase learning power and make decisions in a stochastic and non-stochastic environment, it can help to change the number and placement of connections in the deep nerve model for a set of information. , We believe that our donations are as follows.

To solve the teaching problem, we offer a negative torpedo architecture, which you can learn step by step, as new subjects gradually improve in the learning sequence. In the process of learning each set of data, we use machine learning to evaluate the value of each component and adjust its status. The path we thought could be damaged depends on the service being run while in the update. The results of the MNIST and CIFAR-100 experiments indicate that our approach to learning below zero and how to adapt to other learning tasks.

In this post, we recommend the best machine training method for further training for deep neural networks. The basic idea is to learn a deep system with strong connections that can be "activated" or "turned off" at different stages. The approach you suggest allows you to reduce the distribution of old services as you learn new for example new training, which increases the effectiveness of training in the additional training phase. Experiments with MNIST and CIFAR-100 show that our approach can be applied to step-by-step learning step by step in a complete neuron model and achieve the best results from learning with zero basic principles

2. LITERATURE SURVEY

A. INCREMENTAL LEARNING

In this regard, the lessons learned the flow of several roles in machine learning has long been studied. The author proposes the idea of learning life using old science to improve the preparation of new roles. The author recommends an ongoing online learning strategy for vector support engines. The authors discuss the problem of learning the nervous system through development and suggest ways to conduct learning through the development of neural networks based on distributor groups. When it comes to complete neuron models, this new study is based on the study that some classes of complete neuron models go beyond the science of one task to another with domain change. Other translation studies have shown that the early classes of the deep nervous system can isolate common functions that can be adapted to the information environment. For example, the sleek network trained in the ImageNet image sharing section can be used to introduce new models learned in other applications, such as semantic object and component recognition, and can improve efficiency. , Many professional learning methods use synonymous ideologies of long-term neuron models, namely. Freeze parts of the deep style (usually the previous layer) and prepare the final layer for the new job. Given the adequate criteria, disagreement can be extended through training and non-standard criteria (i.e. training from below). The harmonization method can be used in the concept to know more. But since architecture is architecture, production becomes worse over time. In this passage, our approach is the same as the way of reconciliation. Instead of freezing a few layers beforehand, however, we know the basics of the model, which affects the effect on the accuracy of the results in the old work, and then it will reduce the new tasks in the teaching steps again. If you need more options, it's easy to update our style. Additional education is done with the caution that the old learning system is not in the new learning stage. Silver and Mercer suggest using the results of previous models to find convincing examples. With new jobs, the use of these real models and including education, old knowledge can be preserved to some degree. Recently, the 'Regular Reading' approach, which aims to preserve

old knowledge and learn new settings, has been recommended by good management through such good strategies. However, the author has shown that the effect is only on the two stages of line learning. In this section, we explore further learning by adding new classes as we access older learning data and attempt to use old science to learn higher-level information quickly and accurately.

B. MODEL COMPRESSION

Our work has been partially motivated by recent research on the deep emphasis on nerve torpedo models. The concept of model suppression is proposed to reduce the cost of a comprehensive neurological model to facilitate the use of mobile devices and distribution. The most common networking process is to take the gym from a large network, redesign it, and set the parameters multiple times and reduce the weight. With the good measure, the suppression method in the complete neuron model does not significantly reduce the number of tests and does not reduce its accuracy. The author uses machine learning to select the appropriate weight. Machine learning is a learning process that allows you to choose the best performance through repetitive interactions with the stochastic environment. Increased machine learning has become widespread and reliable and has led to many applications and decision-making problems. In this section, we use machine learning to identify weak connections to specific tasks, rather than simply correcting unwanted connections; we see damaged limbs as a piece and the remaining limbs as the basis of the model. As data conversion is developed by the new class, we expand the peripheral parts with advanced tools, reducing major parts and minor changes and reusing models. This means that we cannot be fooled by old works when we learn the new functions of the new learning system are added.

Displaying unmarked data is a major problem in data. A variety of uncontrolled learning methods, such as aggregation and size reduction, indicate data representation. In such models, the effect of the combination of functions and their relation to the data is ignored. The representation model, supported by the concept of machine learning, can reveal more information about the types of core data. Here we introduce the Unparalleled Mental Solution Algorithm (UMAS), which selects tasks as class attributes, and APSG (New Level of Algorithm) which defines the creation of related task sets. Also consume electrical equipment. Using this algorithm, we provide a romantic representation called representational representation, which indicates the importance of interactions between related and unrelated assets in an unexplained set of data. We tested the two main data sectors of the energy sector and the financial sector and compared their relationship with the classification of other standards. In our approach, there are 92.187% and 87.32% for energy distribution and financial data and 74% and 82% controlled for line classification.

3. OVERVIEW OF THE SYSTEM

A. Existing System:

Much of the success in higher education depends on the learning that is being conducted, based on the many data that are collected today. Related to the concept of control learning, the complete neuron model is examined in the data prepared to solve the split or retrieval component, where the complete model can be considered as a measurement function with many data inputs and outputs. , Well-designed algorithms to enhance deep neurons work for all learning data, with continuous improvement, for example, to allow for better decomposition measures in the stochastic spectrum and to reduce waste function. Big data plays an important role in teaching complete models such as millions and billions of layouts with no need to change. Let's look at the situation in which the new model of classroom education is slowly slowing down in educational data. While the previously trained model should be adapted to the increase in the amount of data, we first read the complete model of the M0 neurons and the D0 specific data levels. When a new class is added, we need to add new items without affecting the existing services, so that we can change that model with an extended flow of data. The two reasons discussed are discussed below.

Disadvantages:

- Suffering from problems known as "poor memory", pre-developed behaviors are easily eliminated when learning in new learning situations. Because the neuron model completely captures the hierarchical architecture, represents and divides the object class, and small changes in the parameter fields in the first column cause significant changes in later layers.
- It is thought to expand the deep model with new neurological barriers to adding based on the class being introduced.
- However, it is not easy to determine the location and number of new units.

B. Proposed system:

In this section, we've overcome these difficulties by creating deep and powerful neural networks, with each noun being taught as "enabled" or "disabled" in a different set of information in the plug-in learning process. Bylhama himself of his new work and detailed examples of inclusive are often rebuilt by negative relationships. Therefore, we recommend teaching a complete neuronal model for each of the same data methods using machine learning cutting methods]. Instead of deleting unwanted contacts immediately, deleting the contact ("disabled") as the model boundary, and the remaining address ("function") is the basis for the model. When new class cases are included in the data, we expand the boundary and change the structure, which reduces the

number of items and minor changes. This means that we can not submit old works when we learn new works for a new learning period. As the best way to increase learning power and make decisions in stochastic and non-stochastic settings, we believe that machine learning tools can help define the number and state of relationships in deep nerve models with different numbers of data.

Advantages:

- We solve problems with further training and provide a comprehensive torpedo architecture, which you can learn slowly, as new lessons are slowly being added to the learning curve.
- We use machine learning to evaluate the importance and status of each communication in the learning process of each data set. The path we thought could be damaged depends on the service being run while in the update.

C. Modules Description

Pandas: Pandas is a BSD open-source library that provides powerful data structures, easy-to-use tools, and data analysis tools for Python software languages.

Numpy: NumPy is a common goal for the monitoring process. Provides advanced memory and tools to work with this line. This is a basic scientific computer package in Python.

MatPlotLib: matplotlib. Pyplot is a printing library used for 2D drawing in Python software. It can be used in Python documents, shells, web, and other GUI tools

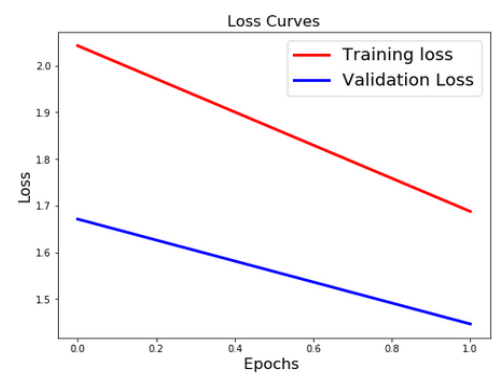
Scikit-learn: Scikit-learning is a free library learning machine for pythons. They include many digital and digital Python libraries such as vectors, forests, and k-neighbors, as well as NumPy and SciPy.

4. RESULTS

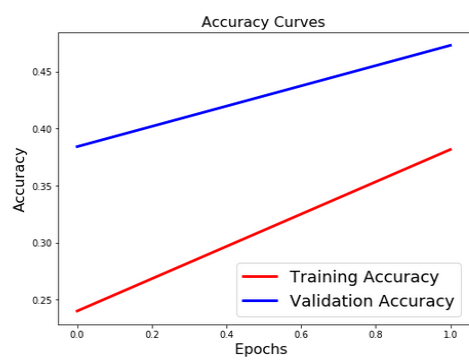
```

Layer (type)           Output Shape         Param #
-----
conv2d_10 (Conv2D)    [None, 32, 32, 32]   800
conv2d_11 (Conv2D)    [None, 32, 32, 32]   800
max_pooling2d_10 (MaxPooling2D) [None, 16, 16, 32]   0
conv2d_12 (Conv2D)    [None, 16, 16, 64]   1600
conv2d_13 (Conv2D)    [None, 16, 16, 64]   1600
max_pooling2d_11 (MaxPooling2D) [None, 8, 8, 64]     0
conv2d_14 (Conv2D)    [None, 8, 8, 64]     1600
conv2d_15 (Conv2D)    [None, 8, 8, 64]     1600
max_pooling2d_12 (MaxPooling2D) [None, 4, 4, 64]     0
conv2d_16 (Conv2D)    [None, 4, 4, 64]     1600
conv2d_17 (Conv2D)    [None, 4, 4, 64]     1600
max_pooling2d_13 (MaxPooling2D) [None, 2, 2, 64]     0
conv2d_18 (Conv2D)    [None, 2, 2, 64]     1600
conv2d_19 (Conv2D)    [None, 2, 2, 64]     1600
flatten_1 (Flatten)   [None, 256]           0
dense_1 (Dense)       [None, 256]           65536
dense_2 (Dense)       [None, 256]           65536
dense_3 (Dense)       [None, 256]           65536
Total params: 276,144
Trainable params: 276,144
Non-trainable params: 0
None
Epoch 1/10: 100% (1/1) [0.00000000] = 0.00 Loss: 0.1970 - acc: 0.2000 - val_loss: 1.7000 -
None
Epoch 2/10: 100% (1/1) [0.00000000] = 0.00 Loss: 0.1700 - acc: 0.2000 - val_loss: 1.6000 -
None
Epoch 3/10: 100% (1/1) [0.00000000] = 0.00 Loss: 0.1500 - acc: 0.2000 - val_loss: 1.5000 -
None
Epoch 4/10: 100% (1/1) [0.00000000] = 0.00 Loss: 0.1400 - acc: 0.2000 - val_loss: 1.4000 -
None
Epoch 5/10: 100% (1/1) [0.00000000] = 0.00 Loss: 0.1300 - acc: 0.2000 - val_loss: 1.3000 -
None
Epoch 6/10: 100% (1/1) [0.00000000] = 0.00 Loss: 0.1200 - acc: 0.2000 - val_loss: 1.2000 -
None
Epoch 7/10: 100% (1/1) [0.00000000] = 0.00 Loss: 0.1100 - acc: 0.2000 - val_loss: 1.1000 -
None
Epoch 8/10: 100% (1/1) [0.00000000] = 0.00 Loss: 0.1000 - acc: 0.2000 - val_loss: 1.0000 -
None
Epoch 9/10: 100% (1/1) [0.00000000] = 0.00 Loss: 0.0900 - acc: 0.2000 - val_loss: 0.9000 -
None
Epoch 10/10: 100% (1/1) [0.00000000] = 0.00 Loss: 0.0800 - acc: 0.2000 - val_loss: 0.8000 -
None
None
Out[17]: Text(0.5, 1.0, 'Loss Curves')

```



Out[18]: Text(0.5, 1.0, 'Accuracy Curves')



```

Epoch 1/2
196/196 [=====] - 278s 1s/step - loss: 2.0968 - acc: 0.2266 - val_loss: 1.8151 - val_
acc: 0.3213
Epoch 2/2
196/196 [=====] - 278s 1s/step - loss: 1.7848 - acc: 0.3481 - val_loss: 1.5289 - val_
acc: 0.4404
10000/10000 [=====] - 16s 2ms/step

|: [1.5292560497289396, 0.4404]

```

5. CONCLUSION AND FUTURE SCOPE

CONCLUSION

In this post, we will focus on step-by-step deep kidney tissue training, step-by-step exercise data. To overcome the problem of forgetfulness and modification accordingly, we recommend network architecture and power connectivity based on machine learning. Machine learning can help select the connections needed for a certain amount of data when extracting the stochastic axis of the negative model. The model learns after adding training data to a new course, as the key materials gradually change. This allows us to prevent the rapid deterioration of old jobs, as we learn to learn new jobs that have been adapted to new training conditions. Experiment with MNIST and CIFAR-100

The use of our method in a deep, complete multi-layer understanding, and in some learning steps in the field of vibrating nerve cells has allowed us to get the best results from better practice and traditional painting.

FUTURE ENHANCEMENTS

Further training in computer science is a machine learning method where the information used works to elaborate on the style applied, namely. teaching examples. Learning is a controlled, controlled, and uncontrolled learning technique that can be used when information is temporarily unavailable or when system memory is depleted. Learning algorithms that enable learning are called machine learning algorithms.

6. REFERENCES

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