Creating and Optimizing Learning Maps by Negative and Positive Convolutional Neural Networks

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Abstract. In this paper, a model of creating and optimizing learning maps by negative and positive convolutional neural networks is established. Firstly, the ontology knowledge base, learning maps and convolutional neural network are introduced. Then after three steps of reverse link, reverse pooling, reverse convolution of negative convolutional neural networks (RCNN), three kinds of learning maps: linear learning map, tree learning map, and graphic learning map are created. Learners learn knowledge by the direction of learning maps, different learning matrices are obtained in the process of learning, and notes and ideas are recorded in electric note books. At last, positive convolutional neural networks (CNN) are used to optimize leaning maps. After three operations of convolution learning map matrix, pooling learning nodes, link knowledge domains, the results of weakening what learners are not interested in, weakening the task that learner think is difficult, reducing the repetition of public knowledge and randomly selecting according to the complexity of the learning map can reach. Improving learners' confidence and Enriching the content of the learning maps have been done also.

1. Introduction
"The study and ethical practice of facilitating learning and improving performance by creating, using and managing appropriate technological processes and resources" [1], Richey defined the educational technology. E-learning is one of the most important educational technologies [2] and is an efficient way to realize online educational. With the popularization of E-learning technology, the main research focuses on organizing and optimizing educational resources. NCM Horizon Report report 2017 [3] said several key technologies would be adopted in recent years. The key trend technologies including advancing cultures of innovation, deeper learning approaches, measuring learning, redesigning learning spaces, blended learning designs, collaborative learning, have been adopted by various e-learning system. For example, PERFORM is a project carried out jointly by Beijing Normal University and La Rioja University of international, which not only is committed to improving outcomes, but also allows researchers to observe the learning patterns of students from different cultures.

The next generation digital learning environments (NGDLE) [2] refer to the development of more flexible spaces, support personalization, meet generic design standards, and play a greater role in formative learning evaluation. And new technology that will be adopted on a large scale over the next 2-3 years, should be more flexible and convenient and closely follow changes in new technologies. Convolutional Neural Networks (CNN) is a kind of feed forward neural network, and has excellent performance for large image processing [7, 8], natural language understanding [9, 10], data set processing [11, 12] and the important properties are translation invariance and space invariance.

In this paper, with the aid of translation invariance and space invariance, the concept of convolutional neural networks is introduced into the online learning platform to organize and optimize learning maps. Learning map is an organizational form of learning content in online learning platform,
2. Related Works

2.1. Related Knowledge of Ontology Knowledge Base

In literature [13], the design of ontology knowledge base are explained in detail. And in [14], a personalized E-learning system was designed and relevant information was stored in ontology knowledge base. And in the educational reform project of 2017, the following improvements are made in the content storage of the ontology knowledge repository and figure 1 shows the structure of ontology knowledge base:

- Set up curriculum groups and store the sequence relation between curriculum.
- Fragment each curriculum and store the knowledge units and knowledge points of each curriculum.
- Develop or collect learning objects to support knowledge units and knowledge points.

![Figure 1. Organization Structure of Ontology Knowledge Base](image)

In the organization structure of ontology knowledge base, 5 main data tables are established which are Curriculum, Kind, Curriculum Creator, Curriculum Content, and Learning Object.

Each curriculum belongs to (Belong To) some curriculum kind, has a curriculum creator (Creator Of), contains prior (Prior To) curriculum and subsequent (Sub To) curriculum, and contains (Content Of) curriculum contents. The contents of each curriculum are supported by (Support By) learning objects and contains preamble knowledge (K Pre), subsequent knowledge (K Sub), and relevant knowledge (K Rel). With the support of ontology knowledge base, learning maps can be constructed.

2.2. Related Knowledge of Learning Maps

Learning maps are a kind of organization form of knowledge units and knowledge points. Knowledge information form different learning maps through different organization mode for learners. At the same time, adding motivational elements into the learning map improves learner participation. In this paper, use three organization forms of learning maps: linear learning map, tree learning map, and graphic learning map. Every learning map contains learning nodes and learning path. Learning nodes...
consist of knowledge points or knowledge units, and learning path shows the organization order of the learning nodes. Figure 2 shows the three forms of learning maps.

![Figure 2. Three Forms of Learning Maps](image)

2.3 Related Knowledge of Convolutional Neural Networks (CNN)

Convolutional Neural Networks is one of the artificial neural networks, and has become the focus of speech analysis and image recognition and has achieved considerable results. The high degree of invariance is the greatest advantage of convolutional neural networks. Convolutional neural networks are composed of three layers: convolution layer, pooling layer and full link layer.

Convolution layer: The main function of the convolution layer is to extract features. If required, multiple convolutions can be performed to refine the features by choosing different convolution kernels (which also called filter).

Pooling layer: Compressing input features. On the one hand, the features are reduced and the computational complexity of the network is simplified, on the one hand, the main features are extracted.

Full Link layer: Link all the features and send out the output values. The working process of CNN is showed in figure 3.

![Figure 3. Working Process of CNN](image)

3. Create Learning Maps by Reverse Convolution Neural Networks (RCNN)

In this section, through the cooperation of the ontology knowledge base and the reverse convolutional neural networks, the organization of learning maps would be completed. That is, the working process is: reverse link, reverse pooling, and reverse convolution. Figure 4 shows the creating of learning maps by reverse convolution neural networks (RCNN).

![Figure 4. Process of Creating Learning Maps by RCNN](image)
3.1. Organize the Key Path of Learning Maps by Reverse Link

When getting a problem that needs to be solved, the first task is to get the key path of the problem. The key path can be gained by reverse link. The result of the full link is to map multiple features into a feature, that is mapping $N \times N \to 1 \times 1$, while reverse link mapping is: $1 \times 1 \to N \times N$.

A problem is a matrix of $1 \times 1$. The problem is broken up into $M \times N$ ($M \neq N$, $M \geq 1$, $N \geq 1$) tasks by reverse link. Then $M$ path is obtained, and each path contains $N$ tasks (maybe have several empty tasks expressed by 0). That is $M \times N$ elements or tasks in matrix of $M \times N$. Then we obtain a learning map path matrix of $M \times N$ in linear, tree, or graphic structure.

3.2. Decompose Learning Maps Nodes by Reverse Pooling

After reverse link, $M$ key paths and $M \times N$ learning map nodes are obtained. Every learning map nodes are made up of knowledge units or knowledge points. And Knowledge units and knowledge points are collectively referred to as knowledge domains.

- If a learning map nodes can be finished by one knowledge points, then the reverse pooling matrix is $1 \times 1$.
- If a learning map nodes must be finished by more than one knowledge points, then the reverse pooling matrix is $J \times K$ (generally $J \geq 1$ and $K \geq 2$). And $J \times K$ knowledge points form knowledge units.
- If $J=1$, $K$ knowledge points are executed in sequencing order, if $j>1$, $K$ knowledge points maybe executed in parallel order.

3.3. Refine Knowledge Domains by Reverse Convolution

After section 3.2, learning maps have been finished. The learning maps can be improved by employing reverse convolution. How to do it?

- The introduction of knowledge domains by means of relevant knowledge domains.
- Refine the knowledge domains using the optimization policy of section 5.

4. Use Learning Maps

The purpose of creating learning maps is to learn knowledge by using the maps. The learning process is as follows in figure 5. The usage process of learning maps is similar to the three handshake.

![Figure 5. The Three Handshake of Learning Map Usage Process](image)

4.1. Select a Learning Map

Each learning map has a functional description. Before using the map, learners need to map their own needs. And according to the current knowledge learned, select the required learning map, such as linear learning map is simple, tree and graphic learning map is difficult.

4.2. Learn Knowledge Domains Sequentially

After gaining a required learning map, all needed knowledge domains have been arranged sequentially. Knowledge domains include knowledge units and knowledge points, and maybe have some fixed order. All knowledge in a learning maps are stored in the form of matrices.
If learners complete the learning of some knowledge point, the corresponding knowledge point is marked 1, otherwise marked -1. If learners complete the learning of some knowledge unit, the corresponding knowledge unit is marked 1, otherwise marked -1. The above operation marks the learning results of the knowledge domains. Then different learning result matrices are formed and stored in the learning result database.

4.3. Sort Out Ideas and Take Notes
Of course, in the process of learning, there would be some suggestions and notes that can be recorded by electronic note books system provided. The records can help to refine knowledge domain and can be used for later review.

5. Optimize Learning Maps by Convolutional Neural Networks (CNN)
In section 3, the creation of learning maps by reverse convolutional neural networks (RCNN) have been done. In this section, the optimization of learning maps can draw support from feedback information of electronic note books and learning result matrices and other results in section 4.3 by convolutional neural networks (CNN).

**Figure 6. Process of Optimizing Learning Map by CNN**

5.1. Convolution Learning Maps Matrix
From section 3, different forms of learning maps matrices are established. Then different learners will accumulate different learning result matrices in the course of learning. The learning result matrices can show the learners' learning state and the degree of interest in the learning process of each learners. The following results may be improved:
- If a learner learns a map from the beginning to the end, he is more likely to be interested in the content of the map, if a learner learns only part of the map, he may be less interested in the content of the map.
- If a learner learns only a few lines of a learning map, he may be interested in only a few paths, or the process of learning is rather difficult to give up.
- If a learner learns only parts of a path of a learning map, may be the learning content is complex, or the learner is less interested in some learning nodes.
In the learning process, different learning result matrices can be gained and adopt convolution layer to process data. In this part, different specifications filters are selected to optimize learning nodes. The selection of filters according to the follow rules:
- Weakening what learners are not interested in and weakening the task that learners think is difficult.
- Reducing the repetition of public knowledge.
- The number of filters is randomly selected according to the complexity of the learning map.

5.2. Pooling Learning Nodes
After convolution, the redundancy of learning nodes has been reduced, and it is more in line with the needs of learners. However, with the increase of the number of learning result matrices, convolution can only optimize parts of the learning content. In order to generate more finer knowledge domains, a down sampling compression is used. Each learning node will be compressed into a domain of knowledge, that is, knowledge units or knowledge points, requiring that the results of compression be no less than the number of knowledge points before. Adopting 2×2 matrix to connect neighborhood,
then gain the result by probability results. Of course, a bias is added into the result to fine tune the connection results to weaken errors.

5.3. Link Knowledge Domains

Here refined knowledge domains have been well done. The next step is to link all knowledge domains forming learning maps. The process of link can split learning maps forming part learning maps or forming a whole learning map. Then learners can select part maps to finish part tasks or select whole maps to finish the whole task. By doing this, the following advantages can be presented:

- Improve learners' confidence.
- Enrich the content of the learning map for learners to use.

6. Conclusions

The initial results have been completed and applied to teaching. Teachers and learners who are using learning maps propose following advantages:

- Learning resources have a fixed organizational model.
- Learning content has a definite purpose.
- Completion of part task brings confidence to finish a larger task.

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