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KNOWLEDGE TRANSFER IN ARTIFICIAL NEURAL NETWORKS: STATE-OF-THE-ART TECHNIQUES FOR EFFICIENT LEARNING AND PERFORMANCE IMPROVEMENT

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Abstract: *Artificial Neural Networks (ANNs) are powerful tools used in machine learning for various applications. One of the key factors that determine the performance of ANNs is the knowledge transfer between different networks or different layers of the same network. In this paper, we review the state-of-the-art techniques for knowledge transfer in ANNs. We start by discussing the different types of information data that can be transferred between networks, followed by a detailed analysis of the methods used for it. We also provide a brief discussion on the challenges and future directions in the field of knowledge transfer in ANNs.*

ТРАНСФЕР НА ЗНАНИЯ В ИЗКУСТВЕНИ НЕВРОННИ МРЕЖИ: НАЙ-СЪВРЕМЕННИТЕ ТЕХНИКИ ЗА ЕФЕКТИВНО ОБУЧЕНИЕ И ПОДОБРЯВАНЕ НА ПРОИЗВОДИТЕЛНОСТТА

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Ключови думи: *Изкуствените невронни мрежи, машинно обучение, трансфер на знания*

Резюме: *Изкуствените невронни мрежи са мощни инструменти, използвани в машинното обучение за различни приложения. Един от ключовите фактори, които определят ефективността на им, е трансферът на знания между различни мрежи или различни слоеве на една и съща мрежа. В тази статия правим преглед на най-съвременните техники за трансфер на знания в изкуствените невронни мрежи. Започваме с обсъждане на различните видове информационни данни, които могат да се прехвърлят между мрежите, последвано от подробен анализ на използваните за това методи. Представяме също така кратка дискусия относно предизвикателствата и бъдещите насоки в областта на трансфера на знания в изкуствените невронни мрежи.*

Introduction

Artificial Neural Networks (ANNs) are computational models inspired by the structure and function of biological neural networks. ANNs are widely used in various applications such as image recognition, speech recognition, natural language processing, and many more. ANNs consist of layers of interconnected nodes, known as neurons, that process information and perform computations. The performance of ANNs depends on various factors such as the number of layers, the number of neurons in each layer, and the activation functions used.

Knowledge transfer refers to the process of transferring knowledge from one network to another. This can be useful in situations where the target network has limited data or computational resources, or where the target task is related to a source task. In this paper, we discuss the different types of knowledge that can be transferred, and the methods used for knowledge transfer.

Types of Knowledge Transfer:

There are several types of knowledge that can be transferred between networks. The following are some of the most common types of knowledge transfer:

- Knowledge Transfer between Networks: This refers to the transfer of knowledge from a source network to a target network. The source network can be a pre-trained network, or it can be a network that has been trained on a similar task.
- Knowledge Transfer within Networks: This refers to the transfer of knowledge between different layers of the same network. This can be useful in situations where the target task is related to a previous task, and the lower layers of the network can be reused.
- Multi-Task Learning: This refers to the simultaneous training of a network on multiple tasks. This can be useful in situations where the tasks are related, and the network can learn to perform both tasks simultaneously [1, 2].

Methods of Knowledge Transfer:

There are different methods used for knowledge transfer. The following are some of the most common methods:

- Fine-tuning: This is a popular method for knowledge transfer between networks. In fine-tuning, a pre-trained network is used as a starting point, and the network is further trained on the target task [3].
- Transfer Learning: Transfer learning involves training a network on a source task and then using the pre-trained network as a starting point for the target task. The lower layers of the network are usually frozen, while the higher layers are trained on the target task.[2].
- Knowledge Distillation: Knowledge distillation involves transferring the knowledge from a large network to a smaller network. This can be useful in situations where the target network has limited computational resources [4].
- Cross-Stitch Networks: Cross-stitch networks are a type of multi-task learning where the different tasks share the same layers of the network. This allows the network to learn to perform multiple tasks simultaneously [5, 6]

Using of Fine-tuning

Fine-tuning is a popular method for knowledge transfer in which a pre-trained network is used as a starting point, and the network is further trained on a target task. The pre-trained network is typically a deep neural network that has been trained on a large dataset for a related task, such as image classification or natural language processing.

To use fine-tuning for a new task, the last layer(s) of the pre-trained network are replaced with new layers that are specific to the target task. These new layers are randomly initialized, and the entire network is then trained on the target task using a smaller dataset than the original pre-training dataset. The pre-trained weights are used as the initial weights for the rest of the network, which helps the network converge faster and improves performance.

Fine-tuning can be used for a variety of tasks, including image and speech recognition, natural language processing, and other machine learning applications. The effectiveness of fine-tuning depends on the similarity between the pre-trained task and the target task, as well as the size of the target dataset.

In summary, fine-tuning is a powerful technique for knowledge transfer that allows for the transfer of knowledge from a pre-trained network to a target task, by initializing the weights of the target network with the pre-trained weights and further training it on the target task.

Fine-tuning can be used for image classification tasks using different sizes of images and different categories. In fact, one of the advantages of fine-tuning is that it can be applied to a wide range of tasks and datasets.

To use fine-tuning for image classification with different sizes of images, the pre-trained network can be trained on a dataset with images of varying sizes. The pre-trained weights can then be used to initialize the target network, and the network can be fine-tuned on the target task with images of different sizes.

Similarly, fine-tuning can be used for image classification tasks with different categories. The pre-trained network can be trained on a large dataset with a wide range of categories, and the pre-trained weights can then be used to initialize the target network. The network can be fine-tuned on the target task with a new set of categories, and the performance of the network can be evaluated on a test dataset.

It is worth noting that the effectiveness of fine-tuning for a specific image classification task depends on the similarity between the pre-trained task and the target task. If the pre-trained network has been trained on a dataset with images and categories that are similar to the target dataset, then fine-tuning can be highly effective. However, if the pre-trained network has been trained on a very different task, then the transfer of knowledge may be less effective, and other methods may need to be considered.

In summary, fine-tuning can be used for image classification tasks with different sizes of images and different categories, as long as the pre-trained network is trained on a similar task and dataset. The effectiveness of fine-tuning depends on the similarity between the pre-trained task and the target task, and other methods may need to be considered if the transfer of knowledge is not effective.

Sources to use for knowledge transfer

As a source to transfer knowledge from we use Google ImageNet pre-trained models. Google has developed several pre-trained models that are based on the ImageNet dataset, which is a large-scale dataset of images that is commonly used for training and benchmarking image classification models.

The most well-known pre-trained model developed by Google is the Inception model, which was first introduced in 2014. The Inception model uses a deep neural network architecture that includes several "inception modules," which are designed to capture local features at different scales within an image. The Inception model has been shown to achieve state-of-the-art performance on several image classification benchmarks.

Since the introduction of the Inception model, Google has continued to develop and release pre-trained models based on the ImageNet dataset. These models include the Inception-v2, Inception-v3, Inception-v4, and Inception-ResNet models, as well as other models such as MobileNet and ResNet.

One of the advantages of using pre-trained models like those developed by Google is that they can be fine-tuned on a specific task using a smaller dataset, which can save time and resources compared to training a model from scratch. Additionally, pre-trained models can be used as a starting point for developing more complex models that are tailored to a specific task.

In summary, Google has developed several pre-trained models based on the ImageNet dataset, including the Inception models, which have achieved state-of-the-art performance on several image classification benchmarks. These pre-trained models can be fine-tuned on a specific task using a smaller dataset, which can save time and resources compared to training a model from scratch.

The ImageNet training dataset consists of approximately 1.2 million labeled images that are divided into 1,000 categories. These categories cover a wide range of objects and scenes, including animals, plants, vehicles, buildings, and many more.

The 1,000 categories in the ImageNet dataset [7] were selected based on the WordNet hierarchy, which is a large lexical database of English words and their relationships. The categories in the ImageNet dataset are organized into a hierarchy, with higher-level categories representing more general concepts and lower-level categories representing more specific concepts.

Some examples of higher-level categories in the ImageNet dataset include "animal", "plant", "vehicle", "building", "person", and "food". Lower-level categories within these higher-level categories include specific types of animals (such as "cat", "dog", and "bird"), specific types of plants (such as "tree" and "flower"), specific types of vehicles (such as "car" and "airplane"), specific types of buildings (such as "house" and "church"), specific types of people (such as "baby" and "doctor"), and specific types of food (such as "pizza" and "sushi").

The ImageNet dataset has been widely used for training and benchmarking deep learning models for image classification, object detection, and other computer vision tasks. The large number of categories in the dataset and the hierarchical organization of the categories make it a challenging and diverse dataset for developing and evaluating deep learning models.

The experiment

We have chosen patch-based classification because of the access to training data. Like publicly available EuroSAT data set [8]. The given data set contains high-resolution satellite images of 10 land cover classes, including urban areas, croplands, forests, and water bodies. The data set has been widely used for training machine learning models for land cover classification and vegetation estimation [9].

Data set consists of two major variants:

- EuroSAT Dataset (MS).

The data set contains 27,000 labeled and geo-referenced image patches size 64 by 64. Patches are produced from Sentinel-2 MSI: Multi Spectral Instrument, Level-1C and contain all 13 spectral bands Fig. 1 [10].

Name	**Scale**	**Pixel Size**	**Wavelength**	**Description**
B1	0.0001	60 meters	443.9nm (S2A) / 442.3nm (S2B)	Aerosols
B2	0.0001	10 meters	496.6nm (S2A) / 492.1nm (S2B)	Blue
B3	0.0001	10 meters	560nm (S2A) / 559nm (S2B)	Green
B4	0.0001	10 meters	664.5nm (S2A) / 665nm (S2B)	Red
B5	0.0001	20 meters	703.9nm (S2A) / 703.8nm (S2B)	Red Edge 1
B6	0.0001	20 meters	740.2nm (S2A) / 739.1nm (S2B)	Red Edge 2
B7	0.0001	20 meters	782.5nm (S2A) / 779.7nm (S2B)	Red Edge 3
B8	0.0001	10 meters	835.1nm (S2A) / 833nm (S2B)	NIR
B8A	0.0001	20 meters	864.8nm (S2A) / 864nm (S2B)	Red Edge 4
B9	0.0001	60 meters Sentinel 2 MSi group	945nm (S2A) / 943.2nm (S2B)	Water vapor
B10	0.0001	60 meters	1373.5nm (S2A) / 1376.9nm (S2B)	Cirrus
B11	0.0001	20 meters	1613.7nm (S2A) / 1610.4nm (S2B)	SWIR 1
B12	0.0001	20 meters	2202.4nm (S2A) / 2185.7nm (S2B)	SWIR 2

Fig. 1. Santinel 2 MSI Groups

EuroSAT Dataset (RGB)
Images are converted to JPEG format, the three visual bands are extracted and downscale to integer values between 0 and 256. Command used for downsizing is:

```
gdal_translate--configGDAL_PAM_ENABLEDNO-ofJPEG-coQUALITY=100-otByte
    -a_nodata0-scale0 2750 1 255-b4-b3-b2-ofJPEG<input><output>
```

Images are converted to JPEG format, the three visual bands are extracted and downscaled to integer values between 0 and 256.
We chose to work with EuroSAT Dataset (MS) and slice out needed bends instead of producing JPEG fails from real data, every downscaling 2751 values to 256 values will result in information loss.
We decided to use EfficientNetV2 model [11], because of model reported good performances in anther patch-based classification tasks.
Our first attempt to train the model we used EfficientNetV2L without pre-trained weights.

Total params: 117,762,538
Trainable params: 117,249,962
Non-trainable params: 512,576

We achieved:

Accuracy 0.6408
F1_score: 0.6300

in tree training epochs using 20% of dataset as validation and all 13 spectral bands from the data set images.

This efficiency was not enough for our goals, so we tried to train the same model using feature vectors of images with EfficientNet V2 with input size 480x480, trained on imagenet-ilsvrc-2012-cls (ILSVRC-2012-CLS) [12]. This time we had to use only the 3 visual bands red (B4), green (B3), blue (B2), from our data set as the pre-trained features vector allow input tensors of shape [None, None, None, 3]. After fine tuning the model for 4 epochs we achieved:

Accuracy 0.9700
F1_score: 0.9695

with using 20% of data set as validation. With these results we are ready to test the model over a real Satellite image from the selected polygon. We prepared an image captured on 07/28/2019. We split the image into 2041 patches with size 64x64. Then we applied categorization based on trained model predictions, with the foaling result Fig. 2.

Categorizes:	**Counts:**
Forest:	292
HerbaceousVegetation:	233
Highway:	200
Industrial:	185
Pasture:	300
PermanentCrop:	47
Residential:	367
River:	67
SeaLake:	350
Total	**2041**

Fig. 2

Given categorization was visually expected and corrected, and then we calculated again the accuracy and F1_score between predictions and corrected categorization. Result is:

Accuracy 0.9520
F1_score: 0.9500
[13]

Using partitions of the same dataset as both training and validation data and achieving an increase in accuracy from 0.6408 to 0.9700, we immediately suspected overfitting of the network. But we achieved similar accuracy with patches extracted from images acquired over the ground polygon of our research, non-present in the training dataset. Overfitting was rejected as a hypothesis. And the increase of accuracy was so significant that we changed our method to incorporate patch-based classification. Knowledge transfer in form of fine-tuning in our case was very successful even though source of the knowledge was the ImageNet dataset that primarily contains natural images associated with object recognition, covering a wide range of categories like animals, objects, scenes, and more, as organized by the WordNet hierarchy. It doesn't specifically contain geospatial images or satellite imagery.

Up to now the most important element when choosing AI model for an engineering task to consider, was existence and shape of the training dataset.

In the future when we prepare an AI model, we also have to consider a source and type of knowledge to transfer.

Challenges and Future Directions:

One of the main challenges in knowledge transfer is determining which knowledge to transfer and how to transfer it. There is also a need for more research on how to combine different types of knowledge transfer methods. Another challenge is determining the optimal architecture for the target network.

In the future, there is a need for more research on unsupervised and self-supervised learning methods for knowledge transfer. These methods can be useful in situations where the target task has limited data. There is also a need for more research on meta-learning methods for knowledge transfer, which can enable a network to learn how to transfer knowledge between tasks more efficiently.

Another important direction for future research is the development of more efficient and scalable methods for knowledge transfer. This is especially important in the era of big data, where large-scale datasets are becoming increasingly common. The development of more efficient methods for knowledge transfer can enable the development of more powerful and robust ANNs that can handle the demands of large-scale datasets and complex tasks.

Knowledge transfer is a crucial factor in the performance of ANNs. The ability to transfer knowledge between different networks or different layers of the same network can enable the development of more powerful and efficient ANNs. In this paper, we reviewed the different types of knowledge transfer and the methods used for knowledge transfer. We also discussed the challenges and future directions in the field of knowledge transfer in ANNs. The development of more efficient and scalable methods for knowledge transfer can enable the development of more powerful and robust ANNs that can handle the demands of large-scale datasets and complex tasks.

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