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THE TRANSFER LEARNING TASK AS THE MEANS OF METALEANING TASKS SOLUTION

The methods for solving the problems of transfer learning are reviewed from the point of view of solving the metalearning tasks. The concepts of metalearning, transfer learning, multi-task learning, inductive transfer and lifelong learning are given. A scheme for solving the metalearning problem using the inductive approach is proposed. Metalearning is a generalization of all previously solved problems. It gives a possibility to save resources and to use the existing experience in solving learning problems in an optimal way.

Keywords: *machine learning, transfer learning, modelling, inductive approach, generalization.*

Introduction

Data mining and machine learning technologies have made great strides in many fields of knowledge development. However, the traditional methods of machine learning learn every task from scratch, while the methods of transfer learning try to transfer the knowledge of some previously solved problems to a new problem in the process of learning.

The concept of transfer learning was introduced in 1993 [1], and it was considered more particularly in 1997 in [2]. The knowledge transfer providing methods aim to make the machine learning process as effective as when a person is taught.

The head of artificial intelligence at Google Jeff Dean recommended his colleagues to pay attention to such algorithms as multi-task and transfer learning, as he considers them to be promising and effective algorithms that give a possibility to achieve the same goal, but with the significantly lower learning costs [3].

Transfer training as one of the tools of machine learning serves to train and improve the productivity of the resulting model by transferring the knowledge from the solved problem to a new one that will need to be solved.

The study of transfer learning is motivated by the fact that people can optimally apply the earlier obtained knowledge in order to quickly solve new problems or to get the better solutions. The need for transfer training arises when the data are outdated and the distribution in them at the current moment of time does not correspond to the distribution in the previous period of time.

Thus, the transfer learning is the optimization and a quick way to save time or to improve productivity. It is not known whether the use of transfer learning in this area will be beneficial until the model is developed and evaluated on new data.

In practice, machine learning models are mainly designed to perform only one task. However, when configuring computers, they use past experiences not only to repeat the same task in the future, but also to learn completely new tasks, like humans do. That is, if a new problem that we are trying to solve is similar to some of our past experiences, it will be easier for us to learn. Thus, when using the same approach in machine learning, transfer learning includes the methods of past experience transfer on one or more original problems and uses it to accelerate learning in the current problem.

The aim of this work is to study the principles of transfer learning in order to learn how to optimally use the source data, as well as to compare such concepts as transfer learning, inductive transfer, metalearning. And as a result, to develop an approach to generalizing the results of solving previous problems based on the principles of metalearning.

Machine learning concepts for generalization of learning results

A number of machine learning methods have been developed by now. They give a possibility to generalize the previously obtained results of similar problems' solving. One of the methods for the generalizing of the previous outcomes of learning is called metalearning. The main principle of metalearning is learning to learn.

Metalearning is a department of machine learning [4], where the automatic learning algorithms based on meta-data about all earlier performed computer experiments are used. Today, this term has not found an unambiguous definition yet, but the main purpose of its application is to understand how automatic learning can help to solve learning problems. It will improve the efficiency of existing learning algorithms or to train the computer to invoke the learning algorithm itself automatically.

Metalearning (or learning-to-learn) is notable for the fact that previously solved learning problems are the precedents [5]. It is required to determine which of the heuristics used there work more efficiently. The ultimate goal is to provide continuous automatic improvement of the learning algorithm over time.

Metalearning includes the following learning methods:

- *Multi-task learning* [6–8]. A set of interrelated or similar learning problems is solved simultaneously using different learning algorithms that have a similar internal representation. Information on the similarity of tasks between each other gives a possibility to improve the learning algorithm and the quality of the main problem's solving more effectively.

One of the particular cases of multi-task learning when two tasks are considered is transfer learning [1].

- *Inductive transfer* [9, 10]. The experience of solving of individual particular learning problems by precedents is transferred to the solution of subsequent particular learning problems. Relational or hierarchical structures of knowledge representation are used in order to formalize and preserve this experience.

In [11], it is argued that the main idea of metalearning is to reduce the problem of choosing an algorithm to a problem of learning with a teacher, when the problem is described by the target-attributes. A meta-attribute is a property of a task, for example, the number of variables in the data, the number of possible labels, the dataset size, and many other parameters. This approach gives a possibility to choose from a variety of algorithms the most suitable algorithm for a particular task (sometimes immediately choosing its parameters as well).

Research in the field of transfer learning is attracting more and more attention under different names: learning for learning, lifelong learning, knowledge transfer, inductive transfer, multi-tasking learning, knowledge consolidation, context-sensitive learning, knowledge-based inductive bias, metalearning [12 –14]. A closely related technique of transfer learning is a multi-task learning structure that attempts to teach several tasks at the same time, even if they are different [15].

In [11], such concepts as metalearning, multitask learning, inductive transfer are compared.

Multi-task learning [4, 6] is one of the machine learning approaches based on the principles of metalearning, where a simultaneous learning of a group of interrelated tasks takes place, each of which is given its own pair "situation – solution" [8]. Multi-task learning solves multiple problems at the same time, exploiting common properties and differences between them, which can improve learning efficiency and forecast accuracy. Parallelization of operations can be attributed to multitask learning methods, but only if the tasks do not intersect with each other [11].

Multi-task learning is a form of inductive transfer. It expresses an approach to the simultaneous study of several interrelated tasks. In this way, the core task can be better learned through experience gained from other tasks. This approach is effective when the tasks have some similarity. This approach can be useful when there is a data scarcity problem.

The difference between multi-task and transfer learning is that in multi-task learning, different models can exchange information in any direction when solving a problem, and in transfer learning, it is possible to transfer information strictly in the direction from the original task to the current one [16].

Inductive transfer is one of the methods of transfer learning, the difference of which lies in the purpose of this transfer. The purpose of inductive transfer is to increase the performance of the model for solving a target task, and the purpose of transfer learning is to teach input and target tasks simultaneously by using information about a previously solved similar learning task [11].

Inductive transfer is usually used in the same sense as learning transfer.

Learning to learn can be used interchangeably with the term *inductive transfer*. It is mainly aimed at improving the learning process over time. Metadata, including past learning experiences, is used for future learning, even for learning in different fields. Thus, learning to learn or inductive transfer can be considered as an approach to metalearning.

Let's consider the principles of transfer learning in more detail.

The Transfer Learning Task

Transfer learning is the ability to combine a pretrained model with the customer's learning data. It means that you can use the functionality of the model and add your own data without having to create everything from scratch [17].

For example, if an algorithm has been trained by the thousands of images to create a classification model, then instead of the building of another model, transfer learning gives you a possibility to combine customer's image data with a pretrained model to create a new image classifier. This feature makes it quick and easy to have a custom classifier.

In transfer learning, the algorithm is split into two stages. The first stage consists of retraining, when the algorithm is trained on a reference dataset representing a variety of data. Then fine tuning follows, where the algorithm learns to perform a specific target task. The preliminary preparation stage helps to tune the model for general characteristics that can be used again in the target problem, increasing its accuracy [18].

In [19], the problem of using transfer learning for solving the problems of Neuro-linguistic programming was investigated.

Here the transfer learning tasks are roughly classified into three areas:

- based on whether the initial and target settings refer to the same task or not;
- on the nature of the initial and target tasks;
- based on the sequence in which the tasks are studied.

This classification of transfer learning tasks in various directions is shown in Fig. 1.

Figure 1 shows that transfer learning methods are divided into two classes: transductive and inductive transfer learning. They differ in that if they study the same or different learning tasks.

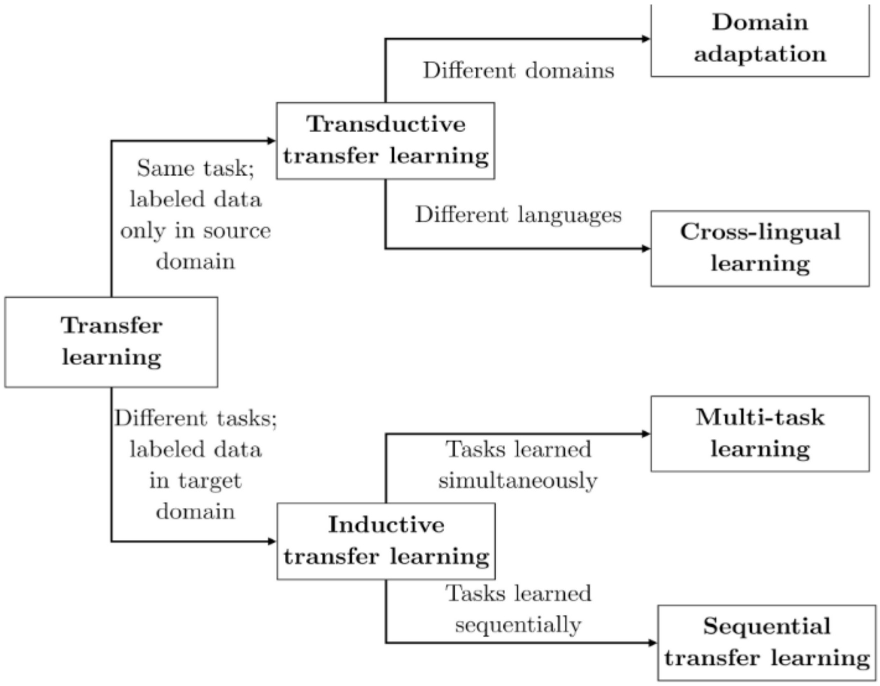

Fig. 1. Classification of methods of transfer learning in various directions [19]

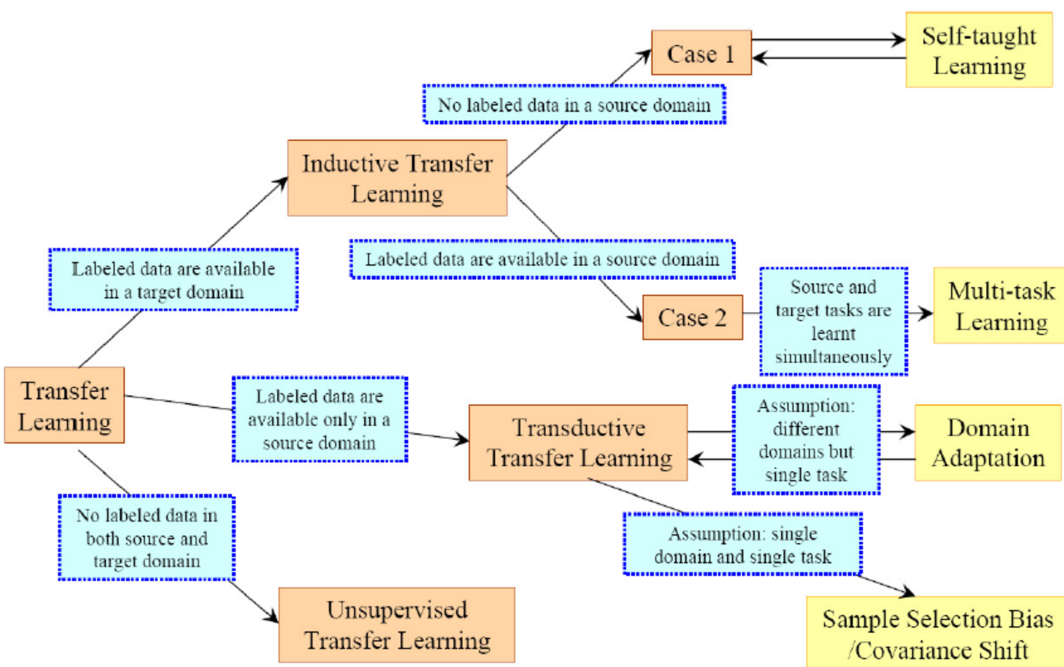

Fig. 2. An overview of different settings of transfer learning [20]

In [20], the tasks of transfer learning are divided into three classes: transductive, inductive, and unsupervised learning (Fig. 2).

Based on the Fig. 2 in [20], transfer learning methods are classified based on the type of traditional ML algorithms used, such as:

- *Inductive Learning Transfer*. In this scenario, the source and target domains are the same, but the source and target tasks are different from each other. The algorithms try to use inductive bias of the source domain in order to help improve the target task. Depending on whether the source domain contains labelled data or not, they can be further divided into two subcategories, similar to multitasking learning and self-learning, respectively.
- *Unsupervised transfer learning*. This parameter is similar to the inductive transfer itself, with an emphasis on unsupervised tasks in the target area. The source and target domains resemble, but the tasks are different. In this case, the labelled data is not available in any of the domains.
- *Transductive learning*. In this scenario, there is a similarity between the source and target tasks, but the corresponding domains are different. In this parameter, the source domain contains a lot of labelled data, but the target domain does not.

When to use transfer learning?

Transfer learning is an optimization, a fast way to save time or to increase productivity.

Authors of [17] and [21] describe three potential advantages to look for when using transfer learning:

These advantages can be described as follows:

- *Higher start*. The best starting model: in other types of learning you need to build a model without any knowledge. Transfer learning offers a better starting point and can perform the tasks at some level even without learning. Transfer learning offers a higher learning rate during learning as the problem is already prepared for a similar task.
- *Higher slope*. Higher accuracy after learning: with a better starting point and higher learning speed, transfer learning provides a machine learning model for convergence with a higher level of productivity, providing a more accurate result.

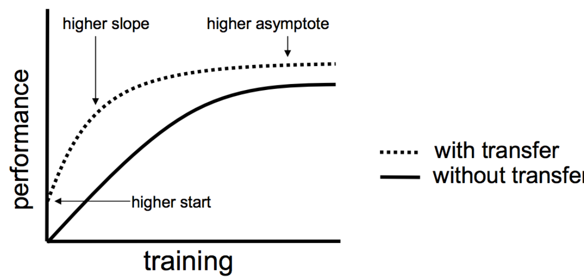

Fig. 3. Three benefits of successful transfer learning

- *Higher asymptote*. Faster learning: Learning can achieve desired performance faster than traditional learning methods because it uses a pre-trained model.

However, the effectiveness of transfer learning may be not much higher than that of traditional learning models. The impact of transfer learning cannot be determined until a target model is developed.

Ideally, one would reap all three benefits from the successful application of transfer learning. This is a way to try if you can identify a related task with abundant data, and you have the resources to develop a model for this task and reuse it for your own problem, or there is a pre-prepared model that you can use as a starting point for your own model.

The choice of input data or source model is an open issue and may require expert knowledge and/or intuition developed from experience.

Problem statement of transfer learning

Traditional machine learning methods try to learn every task from scratch, while transfer learning methods try to transfer knowledge from some previous tasks to the target task when the latter has less high-quality learning data [8].

In [1], the following statement of the transfer learning problem is considered.

The definition of transfer learning is given in terms of domain and task [23]. The domain D consists of: a feature space X and a marginal probability distribution $P(X)$, where $X = \{x_1, x_2, \dots x_n\} \in X$. Given a specific domain, $D = \{X, P(X)\}$, a task consists of two components: a label space y and an objective predictive function $f(\cdot)$, which is learned from the learning data consisting of pairs, which consist of pairs $\{x_i, y_i\}$, where $x_i \in X$ and $y_i \in Y$. The function $f(\cdot)$ can be used to predict the corresponding label, $f(x)$, of a new instance x.

Given a source domain D_s and learning task T_s, a target domain D_T and learning task T_T transfer learning aims to help improve the learning of the target predictive function $f_T(\cdot)$ in D_T using the knowledge in D_S and T_S, where $D_S \neq D_T$, or $T_S \neq T_T$.

In the process of distance learning, it is necessary to answer the following three important questions [23].

What to carry?

It involves the allocation of the part of the task that must be transferred. For this purpose, general knowledge is allocated for different tasks, which are true for many problems at the same time [17]. This is the first and the most important step in the whole process. Here you need to find answers about what part of knowledge can be transferred from the source to the target in order to improve the performance of the target task, i.e. how much of knowledge depends on the source, and what is common between the source and the target.

How to transfer?

If there is information about *what to transfer*, the question is *how to transfer*? is solved in a natural way. Here it is necessary to begin to determine how to actually transfer knowledge between the tasks. This includes changes in existing algorithms and various methods.

When to transfer?

The answer gives a possibility to assess the situations where the application of learning transfer is justified. If the tasks are not related to each other, then the learning transfer may be ineffective (the concept of "negative transfer" is known). We should strive to use transfer learning so as to improve the results of the target task, rather than to worsen them. We must be careful with the situation when it is useful to do so and when not to.

Applications of transfer learning method

Transfer learning is successfully applied in various real-life tasks.

One example of the application of the learning transfer methods is its use for *neuro-linguistic programming* [19]. Textual data present all kinds of problems when it comes to deep learning. They are usually transformed or vectorized using various techniques and are used in various tasks such as sentiment analysis and document classification by transferring knowledge from the original tasks.

In [24], the properties of transfer learning for the *visualization of medical images* are studied. Transferring learning from natural image data sets using standard large models and corresponding pre-trained weights has become a method for applying deep learning to medical visualization.

Transfer learning for audio/speech. Similar to areas such as NLP and Computer Vision, deep learning has been successfully used for tasks based on audio data [25]. For example, automatic speech recognition models developed for English have been successfully used to improve speech recognition performance for other languages, such as German. In addition, automatic speaker identification is another example where learning is very helpful.

Learning Transfer for Computer Vision. Deep learning has been used quite successfully for various computer vision tasks such as object recognition and identification using various neural network architectures. In [25], the authors present the findings on how the lower layers of the neural network act as conventional extractors of computer vision functions such as edge detectors, while the latter layers work towards task-specific functions [26].

In [16], it is proposed to use transfer learning to build artificial intelligence systems for the diagnosis of diabetic retinopathy and five other diseases based on chest X-ray. For this purpose, artificial neural networks are being built that use the transfer of learning using the approach of behavioral genetics proposed in [27] and demonstrate its effectiveness on financial data.

Inductive transfer and inductive bias

Inductive transfer is one of the names for transfer because it uses the principle of induction, i.e. the experience of solving individual particular problems of learning by precedents is transferred to the solution of subsequent particular problems of learning.

Two inductive approaches to knowledge transfer are Multi-task and Feature Net. In [28], they were used to build predictive neural networks. Unlike traditional modeling, learning with one task, focused only on one target property without any relation to other properties, and in the framework of inductive transfer, individual models are considered as nodes in a network of interconnected models built in parallel (Multi-task Learning) or sequentially (Feature Net). Both of these met-hods prooved to be extremely useful when mode-ling structure properties on small and structurally diverse datasets where traditional modeling cannot generate any predictive model.

Inductive transfer of learning is divided into two classes [23]:

- If there are marked learning data in the original problem, the inductive transfer of learning corresponds to the task of multitask learning. The difference lies in the transfer goal: for transfer learning the goal is to increase the productivity of the model when solving the target problem and the goal of multi-task learning is to train the source and target tasks at the same time.
- If the labeled learning data are absent in the original problem, inductive transfer of learning corresponds to self-taught learning. Label spaces in the domains of the source and target tasks can be different, which implies the inability to directly use side information of the source task.

IInductive bias is some a priori knowledge that modifies the learning mechanism in the process of solving of the learning problem [29]. In other words, while learning, the solution of the problem shifts toward the opening of certain hypotheses or patterns, and other temporal correlations between events are ignored.

The author [29] argues that the inclusion of a priori knowledge that displaces the learning process is a prerequisite for the success of learning algorithms. Developing tools to express domain knowledge, translating it into a learning algorithm bias, and quantifing the impact of this bias on learning success is a central theme in machine learning theory. The stronger the a priori knowledge or hypotheses with which we begin the learning process, the easier the learning is on further examples, however the less flexible the learning will be because it is limited by the need to comply with these assumptions.

The main problem of inductive bias is how to choose the learning hypothesis space in such a way that it will be large enough to find a solution to the problem under study, but at the same time it will be small enough to provide a reliable generalization from learning sets of reasonable size. As a rule, it is done manually using expert knowledge [30].

Inductive transfer methods use inductive bias of the original problem in order to help the target problem [25]. This can be done in various ways, for example, by adjusting the inductive bias of the target task by limiting the model space, narrowing the space of hypotheses, or making adjustments to the search process itself using knowledge from the original problem. This process is visually depicted in the following Figure 4.

Thus, having conducted a study of machine learning methods, we can conclude that the algorithms of the inductive approach or self-organization can be attributed to the learning methods without a teacher, when no hypotheses about the data on which the learning is performed are known.

The Solving of the Problem of Metalearning by Inductive Methods

The goal of metalearning is to study the *common* properties that are easily adaptable to new challenges. It studies them based on learning a lot of different tasks. In a certain sense, metalearning can be regarded as almost a *historical* multi-task learning, since it uses many different tasks to find the ideal set of properties [31]. Recently, metalearning

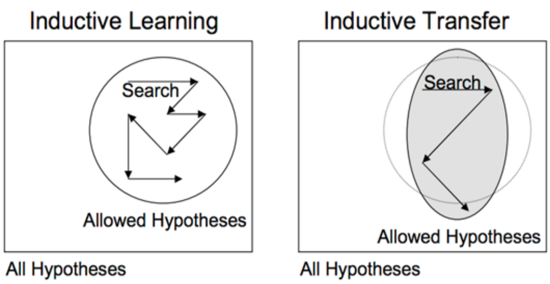

Fig. 4. Inductive transfer illustration [25]

has focused on a search for model-independent solutions where multi-task learning remains closely related to model architecture.

Metalearning gives a possibility to use the experience of previously solved problems in a specific area of knowledge in order to solve the current problem. Meta-data describing the solved tasks are used for this purpose. Some machine learning algorithms are applied to these meta-data.

Meta-data include the properties of the algorithm used, the learning task itself, and so on. Using meta-data, you can better make a decision

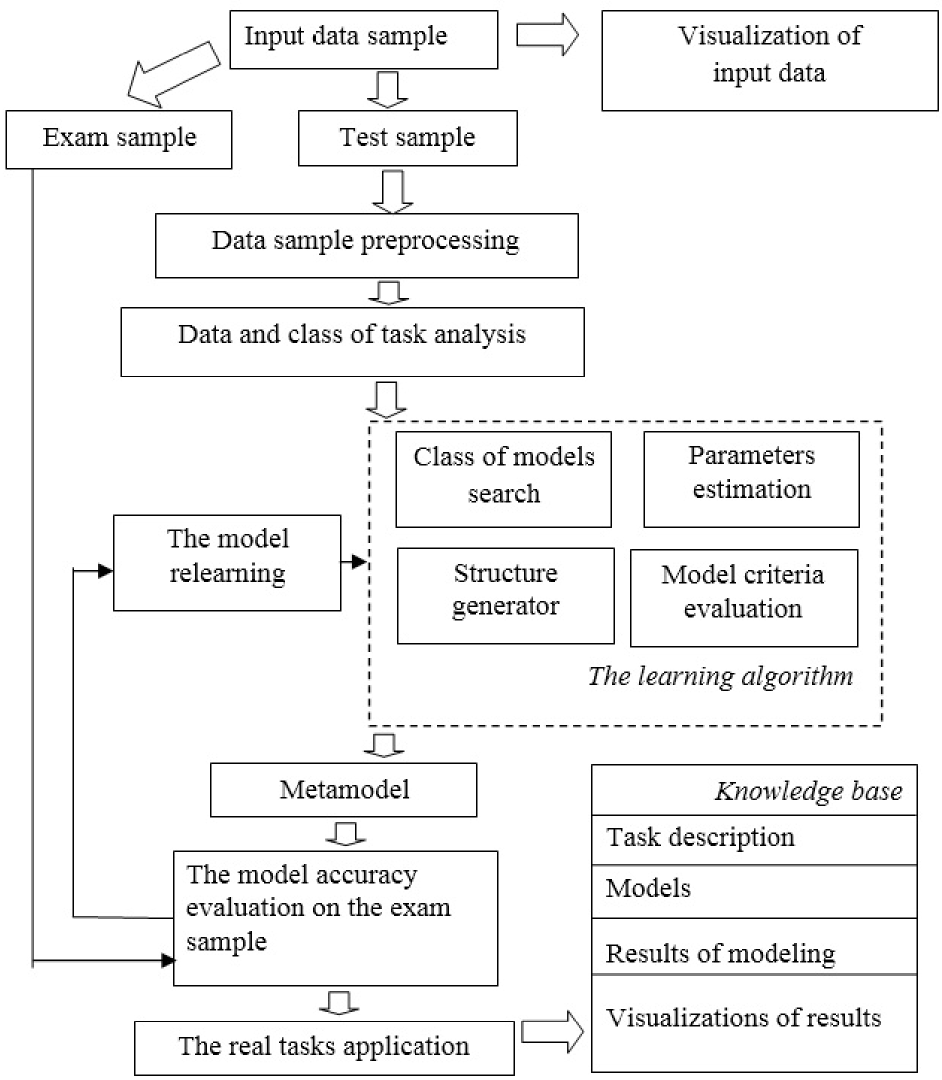

Fig. 5. Scheme of application of inductive methods for solving metalearning problems

about the chosen learning algorithm to solve the current problem more effectively.

After reviewing the tasks of transfer learning, we can come to conclusion that these algorithms can be considered as one of the metalearning units.

Inductive methods or methods of self-organization [32, 33] can be considered as one of the units of machine learning, i.e. case studies. The experience gained in the field of inductive modeling can be used to develop new approaches and methods in the field of metalearning and metamodeling.

Many approaches to improving the accuracy and speed of algorithms' performance in the field of inductive modeling have been developed by now. Databases, tasks, as well as a database of inductive modeling algorithms are accumulated.

Fig. 5 shows a diagram of the application of inductive methods for solving meta-learning problems.

In the future, it is planned to develop methods and tools based on the inductive approach using meta-data in order to generalize all the accumulated knowledge in this area in new approaches and to use them in order to solve the problem of metalearning and metamodeling.

Conclusions

Methods and tools of machine learning give a possibility to teach a computer to solve problems, like a human. The methods for solving the problems of transfer learning are reviewed from the point of view of solving of the metalearning task. The principles of metalearning allow summarizing a human experience in the knowledge and database to formulate rules for decision-making in the modeling process. Using the experience of solving of many problems gives a possibility to build a system based on the principles of metalearning and metamodelling.

Metalearning is a generalization of all previously solved problems. It allows you to save resources and use the available experience in solving learning tasks optimally. In a certain sense, meta-learning can be regarded as almost a "historical" multi-task learning, since it uses many different tasks to find the ideal set of properties. Recently, metalearning has focused on a search for "model-independent" solutions while multitask learning remains closely related to model architecture.

A scheme for solving the metalearning problem using the experience of transfer learning is proposed. Some problems may not contain a lot of initial data. That is why transfer learning can give a possibility to develop such a models, what simply could not be developed without using transfer learning.

In the future, it is planned to develop a computer system using the inductive approach and experience in solving of many applied problems in the field of inductive modeling.

REFERENCES

1. *Transfer learning*. [online] Available at: <https://en.wikipedia.org/wiki/Transfer_learning> [Accessed 20 Oct. 2019].
2. *Pratt, L. Y., Thrun, S.*, 1997. "Machine Learning - Special Issue on Inductive Transfer", 28 (1), 130 p.
3. *The head of Google AI* named the main trends in machine learning. [online] Available at: <https://ai-news.ru/2019/12/glava_google_ai_nazval_glavnye_trendy.html> [Accessed 24 Dec. 2019]. (In Russian).
4. *Machine Learning*. [online] Available at: <https://ru.wikipedia.org/wiki/ Mashinnoye_obucheniye> [Accessed 20 Feb. 2020] (in Russian).
5. *Machine Learning*. [online] Available at: <http://www.machinelearning.ru/wiki/index.php?title=Mashinnoye_obucheniye> [Accessed 14 Feb. 2020] (in Russian).
6. *Savchenko, Ye.A.*, 2019. "The multi-task learning as one of the most important problems in machine learning". Inductive modeling of complex systems. Zbirnik of sciences. prats. K.: IRTC ITS, 2019, pp. 103–111. (In Ukrainian).

7. *Multi-task learning*. [online] Available at: <https://en.wikipedia.org/wiki/Multi-task_learning> [Accessed 24 Feb. 2020].
8. *Caruana, R.*, 1997. “Multitask learning,” Machine Learning, 28 (1), pp. 41–75.
9. *Vilalta, R., Giraud-Carrier, C., Brazdil, P., Soares, C.* “Inductive Transfer”. In book: Encyclopedia of Machine Learning. DOI: 10.1007/978-0-387-30164-8_401.
10. *Inductive Transfer*. [online] Available at: <https://link.springer.com/referenceworkentry/10.1007%2F978-0-387-30164-8_401> [Accessed 14 Feb. 2020].
11. *In machine learning*, what is the difference between the terms transfer learning, multitask learning, inductive transfer, meta-learning, and learning to learn? [online] Available at: <https://www.quora.com/In-machine-learning-what-is-the-difference-between-the-terms-transfer-learning-multitask-learning-inductive-transfer-meta-learning-and-learning-to-learn> [Accessed 16 Feb. 2020].
12. *Pan, S., Yang, Q.*, 2010. “A Survey on Transfer Learning”. IEEE Transactions on Knowledge and Data Engineering, 22 (10), pp. 1345–1359.
13. *Silver, D.L., Yang, Q., Li, L.* Lifelong Machine Learning Systems: Beyond Learning Algorithms. IEEE transactions on knowledge and data engineering. [online] Available at: <https://www.aaai.org/ocs/index.php/SSS/SSS13/paper/view/5802> [Accessed 20 Feb. 2020].
14. *Thrun, S., Pratt, L.,* (Eds.), 1998. Learning to learn. Norwell, MA, USA: Kluwer Academic Publishers.
15. *Caruana, R.A.*, 1993. “Multitask Learning: A Knowledge-Based Source of Inductive Bias”. Proceedings of the Tenth International Conference ”Machine Learning”, University of Massachusetts, Amherst, June 27–29, pp. 41–48.
16. I*nvestigation of the transfer learning ability* of convolutional neural networks trained on Imagenet. [online] Available at: <http://www.applied-research.ru/ru/article/view?id=12808> [Accessed 16 Feb. 2020]. (In Russian).
17. *Nezhnoye vvedeniye v transfernoye obucheniye dlya glubokogo obucheniya*. [online] Available at: <www.machine-learningmastery.ru> [Accessed 20 Feb. 2020]. (In Russian).
18. *Google uses transfer training for medical image* decryption systems. [online] Available at: <https://www.everest.ua/ru/google-yspolzuet-transfernoe-obuchenye-dlya-system-rasshyfrovky-medyczynskyh-yzobrazhenyj/> [Accessed 16 Jan. 2020]. (In Russian).
19. *The state of transfer learning in NLP*. [online] Available at: <https://ai-news.ru/2019/08/sostoyanie_transferno-go_obucheniya_v_nlp.html> [Accessed 28 Feb. 2020]. (In Russian).
20. *Comprehensive Practical Guide to Learning Translation* Using Real-Time Deep Learning Applications. [online] Available at: <https://www.machinelearningmastery.ru/a-comprehensive-hands-on-guide-to-transfer-learning-with-real-world-applications-in-deep-learning-212bf3b2f27a/> [Accessed 1 March 2020]. (In Russian).
21. *Handbook of Research on Machine Learning Applications* and Trends: Algorithms, Methods and Techniques, 2009. (2 Vol.), 1st Edition. Information Science Reference. 834 p.
22. *A Gentle Introduction to Transfer Learning for Deep Learning*. [online] Available at: <https://machinelearningmastery.com/transfer-learning-for-deep-learning/> [Accessed 6 March 2020].
23. *Kustikova, V.N.* Transfer learning deep neural networks. [online] Available at: <http://hpc-education.unn.ru/files/courses/intel-neon-course/Rus/Lectures/Presentations/5_Transfer.pdf> [Accessed 16 Dec. 2019]. (In Russian).
24. *Raghu, M., Zhang, Ch., Kleinberg, J., Bengio, S.*, 2019. “Transfusion: Understanding Transfer Learning for Medical Imaging”. 33rd Conference on Neural Information Processing Systems (NeurIPS 2019), Vancouver, Canada. https://arxiv.org/abs/1902.07208.
25. *Sarkar, D.*, 2018. A Comprehensive Hands-on Guide to Transfer Learning with Real-World Applications in Deep Learning. [online] Available at: <https://towardsdatascience.com/a-comprehensive-hands-on-guide-to-transfer-learning-with-real-world-applications-in-deep-learning-212bf3b2f27a> [Accessed 6 Jan. 2020].
26. *How transferable are features in deep neural networks*? [online] Available at: <https://arxiv.org/abs/1411.1792> [Accessed 16 Dec. 2019].
27. *Stamate, C., Magoulas, G.D., Thomas, M.S.C.*, 2015. “Transfer learning approach for financial applications”. Neural and Evolutionary Computing, https://arxiv.org/abs/1509.02807.

28. *Inductive Transfer of Knowledge*: Application of Multi-Task Learning and Feature Net Approaches to Model Tissue-Air Partition Coefficients. [online] Available at: <https://pubs.acs.org/doi/10.1021/ci8002914> [Accessed 20 Feb. 2020].
29. *Shalev-Shwart, Sh., Ben-David, Sh.*, 2014. Understanding Machine Learning. Cambridge University Press, 2018.450 p.
30. *Baxter, J.*, 2000, "A Model of Inductive Bias Learning". Journal of Artificial Intelligence Research, 12, pp. 149–198.
31. *Godfried, I.*, 2018. ICML 2018: Advances in transfer, multitask, and semi-supervised learning. [online] Available at: <https://towardsdatascience.com/icml-2018-advances-in-transfer-multitask-and-semi-supervised-learning-2a15ef7208ec> [Accessed 16 Dec. 2019].
32. *Savchenko, Ye., Stepashko, V.* Metamodeling and Metalearning Approaches in Inductive Modelling Tools. Preprint. [online] Available at: <https://easychair.org/publications/preprint/6L1W> [Accessed 16 Dec. 2019].
33. *Savchenko, Ye., Stepashko, V.*, 2018. "Metamodeling as a Way to Universalization of Inductive Modeling Tools". Proceedings of the 13th IEEE International Conference CSIT-2018 & International Workshop on Inductive Modeling, September 11–14, Lviv, Ukraine. Lviv: Publisher "Vezha&Co", pp. 444–447.

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ЛІТЕРАТУРА

1. *Transfer learning*. URL: https://en.wikipedia.org/wiki/Transfer_learning. (дата звернення: 20.10.2019).
2. *Pratt L. Y., Thrun S.* Machine Learning - Special Issue on Inductive Transfer. 1997. 28 (1), 130 p.
3. *Глава Google AI назвал главные тренды машинного обучения*. URL: https://ai-news.ru/2019/12/glava_google_ai_nazval_glavnye_trendy.html (дата звернення: 24.12.2019).
4. *Машинное обучение*. URL: https://ru.wikipedia.org/wiki/Машинное_обучение (дата звернення: 20.02.2020).
5. *Машинное_обучение*. URL: http://www.machinelearning.ru/wiki/index.php?title=Машинное_обучение (дата звернення: 14.02.2020).
6. *Савченко Є.А.* Задача багатозадачного навчання як одна з важливих задач машинного навчання. Індуктивне моделювання складних систем. Збірник наук. праць. К.:МННЦтаІТС, 2019, С. 103–111.
7. *Multi-task learning*. URL: https://en.wikipedia.org/wiki/Multi-task_learning (дата звернення: 24.02.2020).
8. *Caruana R.* Multitask learning. Machine Learning. 1997. 28 (1). pp. 41–75.
9. *Vilalta R., Giraud-Carrier, C., Brazdil, P., Soares, C.* Inductive Transfer. In book: Encyclopedia of Machine Learning. DOI: 10.1007/978-0-387-30164-8_401.
10. I*nductive Transfer*. URL: https://link.springer.com/referenceworkentry/10.1007%2F978-0-387-30164-8_401 (дата звернення: 14.02.2020).
11. *In machine learning*, what is the difference between the terms transfer learning, multitask learning, inductive transfer, meta-learning, and learning to learn? URL: https://www.quora.com/In-machine-learning-what-is-the-difference-between-the-terms-transfer-learning-multitask-learning-inductive-transfer-meta-learning-and-learning-to-learn (дата звернення: 16.02.2020).
12. *Pan S., Yang Q.* A Survey on Transfer Learning. IEEE Transactions on Knowledge and Data Engineering. 2010. 22 (10). pp. 1345–1359.
13. *Silver D.L., Yang Q., Li, L.* Lifelong Machine Learning Systems: Beyond Learning Algorithms. IEEE transactions on knowledge and data engineering. URL: https://www.aaai.org/ocs/index.php/SSS/SSS13/paper/view/5802 (дата звернення: 20.02.2020).
14. *Thrun S., Pratt L.*, (Eds.). Learning to learn. Norwell, MA, USA: Kluwer Academic Publishers, 1998.
15. *Caruana R.A.* Multitask Learning: A Knowledge-Based Source of Inductive Bias. Proceedings of the Tenth International Conference "Machine Learning", University of Massachusetts, Amherst, June 27–29, 1993. pp. 41–48.

16. *Исследование способности к transfer learning* сверточных нейронных сетей, обученных на Imagenet. URL: http://www.applied-research.ru/ru/article/view?id=12808> [Accessed 16 Feb. 2020].
17. *Нежное введение в трансферное обучение* для глубокого обучения. [online] Available at: <www.machinelearningmastery.ru (дата звернення: 20.02.2020).
18. *Google использует трансферное обучение* для систем расшифровки медицинских изображений. URL: https://www.everest.ua/ru/google-yspolzuet-transfernoe-obuchenye-dlya-system-rasshyfrovky-medyczynskyh-yzobrazhenyj/ (дата звернення: 16.01.2020).
19. *Состояние трансферного обучения в НЛП*. URL: https://ai-news.ru/2019/08/sostoyanie_transfernogo_obucheniya_v_nlp.html (дата звернення: 28.02.2020).
20. *Комплексное практическое руководство* по переводу обучения с использованием реальных приложений для глубокого обучения. URL: https://www.machinelearningmastery.ru/a-comprehensive-hands-on-guide-to-transfer-learning-with-real-world-applications-in-deep-learning-212bf3b2f27a/ (дата звернення: 01.03.2020).
21. *Handbook of Research on Machine Learning* Applications and Trends: Algorithms, Methods and Techniques, 2009. (2 Vol.), 1st Ed. Information Science Reference. 834 p.
22. *A Gentle Introduction to Transfer Learning for Deep Learning*. URL: https://machinelearningmastery.com/transfer-learning-for-deep-learning/ (дата звернення: 06.03.2020).
23. *Кустикова В.Н.* Перенос обучения глубоких нейронных сетей. URL: http://hpc-education.unn.ru/files/courses/intel-neon-course/Rus/Lectures/Presentations/5_Transfer.pdf (дата звернення: 16.12.2019).
24. *Raghu M., Zhang Ch., Kleinberg J., Bengio S.* Transfusion: Understanding Transfer Learning for Medical Imaging. 33rd Conference on Neural Information Processing Systems (NeurIPS 2019), Vancouver, Canada. https://arxiv.org/abs/1902.07208.
25. *Sarkar D.* A Comprehensive Hands-on Guide to Transfer Learning with Real-World Applications in Deep Learning. URL: https://towardsdatascience.com/a-comprehensive-hands-on-guide-to-transfer-learning-with-real-world-applications-in-deep-learning-212bf3b2f27a (дата звернення: 06.01.2020).
26. *How transferable are features in deep neural networks*? URL: https://arxiv.org/abs/1411.1792 (дата звернення: 16.12.2019).
27. S*tamate C., Magoulas G.D., Thomas M.S.C.* Transfer learning approach for financial applications. Neural and Evolutionary Computing, https://arxiv.org/abs/1509.02807 (дата звернення: 16.12.2019).
28. *Inductive Transfer of Knowledge*: Application of Multi-Task Learning and Feature Net Approaches to Model Tissue-Air Partition Coefficients. URL: https://pubs.acs.org/doi/10.1021/ci8002914 (дата звернення: 20.02.2020).
29. *Шалев-Шварц Ш., Бен-Давид Ш.* Идеи машинного обучения. Москва: ДМК Пресс, 2018. 432 с.
30. *Baxter J.* A Model of Inductive Bias Learning. Journal of Artificial Intelligence Research. 2000. 12. pp. 149–198.
31. *Godfried I.* ICML 2018: Advances in transfer, multitask, and semi-supervised learning. URL: https://towardsdatascience.com/icml-2018-advances-in-transfer-multitask-and-semi-supervised-learning-2a15ef7208ec (дата звернення: 16.12.2019).
32. *Savchenko Ye., Stepashko V.* Metamodeling and Metalearning Approaches in Inductive Modelling Tools. Preprint. URL: https://easychair.org/publications/preprint/6L1W (дата звернення: 16.12.2019).
33. *Savchenko Ye., Stepashko V.* Metamodeling as a Way to Universalization of Inductive Modeling Tools. Proceedings of the 13th IEEE International Conference CSIT-2018 & International Workshop on Inductive Modeling, September 11–14, 2018, Lviv, Ukraine. Lviv: Publisher “Vezha&Co”, pp. 444–447.

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ЗАДАЧА ТРАНСФЕРНОГО НАВЧАННЯ ЯК ЗАСІБ РОЗВ'ЯЗАННЯ ЗАДАЧІ МЕТАНАВЧАННЯ

Вступ. Метанавчання – це узагальнення всіх раніше розв'язаних задач, яке дозволяє економити ресурси та оптимально використовувати наявний досвід такого розв'язання для нових завдень. Завдання метанавчання – автоматизувати процес навчання, використовуючи методи машинного навчання та індуктивного підходу.

Методи метанавчання засновані на багаторазовому використанні алгоритмів навчання з різними можливими компонентами та безпосередньому порівнянні результатів навчання. У разі розв'язання реальних завдань це вимагає високих обчислювальних потужностей та великих затрат часу. Можлива альтернатива — навчити модель, яка передбачає оптимальні компоненти на основі мета-властивостей вхідних даних.

Мета. У статті поставлено завдання вивчити принципи трансферного навчання, щоб навчитися оптимально використовувати вхідні дані, а також порівняти такі поняття як трансферне навчання, трансферне перенесення, багатозадачне навчання, індуктивного переносу, індуктивне зміщення та метанавчання. В результаті планується розробити підхід до узагальнення результатів розв'язання попередніх завдань на основі принципів метанавчання та метамоделювання.

Методи. Вивчаються методи машинного моделювання: метанавчання, трансферного навчання, індуктивного перенесення та індуктивного підходу.

Результати. Проведено огляд методів розв'язання задачі трансферного навчання з точки зору розв'язання задачі метанавчання. Запропоновано схему розв'язання задачі метанавчання з використанням досвіду трансферного навчання. Метанавчання це узагальнення всіх розв'язаних раніше задач, яке дозволяє економити ресурси та оптимально використовувати наявний досвід ров'язання цих задач.

Висновки. Таким чином, досліджено задачу трансферного навчання як одну з задач метанавчання. Наведено постановку задачі трансферного навчання, а також класифікацію завдань трансферного навчання з точки зору різних напрямків. Порівнюються поняття метанавчання, навчання протягом усього життя, передачі знань, індуктивної передачі, багатозадачного навчання, індуктивного перенесення та індуктивного зміщення. Запропоновано схему застосування індуктивного підходу для розвязання задач метанавчання та метамоделювання.

Ключові слова: *машинне навчання, трансферне навчання, моделювання, індуктивний підхід, узагальнення.*

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ЗАДАЧА ТРАНСФЕРНОГО ОБУЧЕНИЯ КАК СРЕДСТВО РЕШЕНИЯ ЗАДАЧИ МЕТАОБУЧЕНИЯ

Введение. Метаобучение – это обобщение всех ранее решенных задач, позволяющее экономить ресурсы и оптимально использовать имеющийся опыт решения всех предыдущих задач обучения.

Задача метаобучения – автоматизировать процесс обучения, используя методы машинного обучения и индуктивного моделирования.

Методы метаобучения основаны на многократном использовании алгоритмов обучения с разными возможными компонентами и непосредственном сравнении результатов обучения. В случае решения реальных задач это требует высоких вычислительных мощностей и больших временных затрат. Возможная альтернатива этого — обучить модель, которая предсказывает оптимальные компоненты на основе мета-свойств всех входящих данных.

Цель. В статье поставлена задача изучить принципы трансферного обучения, чтобы научиться оптимально использовать исходные данные, а также сравнить такие понятия как трансферное обучение, трансферный перенос, индуктивный перенос, индуктивное смещение и метаобучение. В результате планируется разработать подход к обобщению результатов решения предыдущих задач на основе принципов метаобучения и метамоделирования.

Методы. Изучаются методы машинного моделирования: метаобучение, трансферное обучение, индуктивный перенос и индуктивное моделирование.

Результаты. Проведен обзор методов решения задач трансферного обучения с точки зрения решения задачи метаобучения. Метаобучение — это обобщение всех решенных ранее задач, которое позволяет экономить ресурсы и оптимально использовать имеющийся опыт решения задач обучения. Предложена схема решения задачи метаобучения с использованием индуктивного подхода.

Выводы. Исследована задача трансферного обучения как одной из задач метаобучения. Приведена постановка задачи трансферного обучения, а также классификация задач трансферного обучения с точки зрения различных направлений. Сравниваются понятия метаобучения, многозадачного обучения, обучения в течение всей жизни, передачи знаний, индуктивной передачи, многозадачного обучения, индуктивного переноса и индуктивного смещения. Предложена схема применения индуктивного подхода для решения задач метаобучения.

Ключовые слова: *машинное обучение, трансферное обучение, моделирование, индуктивный подход, обобщение.*