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SEMI-SUPERVIZED LEARNING IN INFORMATION PROCESSING PROBLEMS

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***Abstract*—*The article substantiates the need for further research of known methods and the development of new methods of machine learning – semi-supervized learning. It is shown that knowledge of the probability distribution density of the initial data obtained using unlabeled data should carry information useful for deriving the conditional probability distribution density of labels and input data. If this is not the case, semi-supervised learning will not provide any improvement over supervised learning. It may even happen that the use of unlabeled data reduces the accuracy of the prediction. For semi-supervised learning to work, certain assumptions must hold, namely: the semi-supervised smoothness assumption, the clustering assumption (low-density partitioning), and the manifold assumption. A new hybrid semi-supervised learning algorithm using the label propagation method has been developed. An example of using the proposed algorithm is given.*

Index Terms—Label propagation; semi-supervised learning; data processing; artificial intelligence; smoothness, manifold, clustering assumptions.

I. INTRODUCTION

Artificial intelligence (AI) is a branch of computational linguistics and informatics that deals with the formalization of problems and tasks similar to actions performed by a person. This concept was introduced in 1956 by Dartmouth College professor John McCarthy, who was interested in whether it was possible to teach a machine, like a child, abstract concepts, use language, and improve independently by trial and error. We encounter SHI every day. These are voice search – Siri and Alexa, which are available on iOs, Android and Windows, video games – characters that can be unpredictably driven for the player, autonomous cars that can analyze the situation on the road and act, online customer support on sites, product recommendations, which may be of interest to you, which is generated as a result of the analysis of the Internet pages you visit. On news portals, jobs create financial reports, sports reports, and notes.

Economic effect of AI technologies. Analysts at the international consulting agency PwC believe that in the next decade, AI will become the main market trend and the best business tool. According to the latest report, the contribution of smart technologies to the global world GDP is estimated at 15.7 trillion. USD According to experts, it is thanks to AI that this indicator will grow by another 14% by 2030. It will take up to 7 trillion rubles to increase productivity. dollars, and for the growth of consumption – more than 9 trillion. What is the economic impact of AI technologies? First of all, the following key processes will affect the growth of profits from the introduction and consumption of innovations: increasing productivity through the widespread automation of basic business processes (including the use of robots and autonomous transport systems); strengthening the labor resources already existing in the market with the help of AI (the so-called "universal artificial intelligence" aimed at helping and empowering a person); increasing demand for personalization and an individual approach to each client through the use of SHI assistants and analytical programs. According to PwC, in the next 5–10 years, China will be the leader in the successful exploitation and adaptation of AI technologies. By 2030, its GDP is expected to be another 26% above the world average. North America also has significant potential, which is likely to show about 14% in addition to GDP.

II. MACHINE LEARNING METHODS

Machine learning (ML) is a class of artificial intelligence methods, the characteristic feature of which is not the direct solution of a problem, but learning by applying solutions to many similar problems. To build such methods, mathematical statistics tools, numerical methods, mathematical analysis, optimization methods, probability theory, graph theory, various techniques for working with data in digital form are used. The idea is not to program the algorithm for solving the problem by hand, but to "learn" it from the data. Machine learning (ML) includes three components: representation (representation), evaluation (evaluation), optimization (optimization).

Performance. It is a model of what classes of problems it is capable (and not capable of) solving. **Examples:** split hyperplane, decision trees, neural networks. A separate question is how exactly the data is provided (including the stage of extracting the necessary features, feature extraction / engineering).

Grade. How to evaluate the quality of a model in the context of solving a problem, how to choose the best model from several. Examples: RMSE, Accuracy/Precision/Recall, Logistic Loss, …

Optimization. How to train a model, how to enumerate the space of possible models in order to find the best one. Examples: gradient stochastic descent, genetic algorithms, grid search, …

The process of solving a problem using machine learning is as follows:

1) Decide on a way to solve your problem using ML tools.
2) Select a quality metric.
3) Get data and highlight features.
4) Decide on the classes of models.
5) Prepare data for training and evaluation.
6) Train the models, evaluate the result, repeat the steps if necessary.

III. THE PROCESS OF MACHINE LEARNING

Before implementing the machine learning process, it is necessary to determine how a specific task can be reduced to one of the typical tasks of machine learning, which primarily involves the analysis of the training sample. There are many different types of learning from whole areas of learning to specific methods: areas of learning, such as learning with a "teacher", learning without a "teacher" and learning with reinforcement; hybrid types of learning, such as partially controlled and self-controlled learning; broad methods such as active, online and transfer learning. Some types of learning describe whole areas of research, consisting of many different types of algorithms, such as "teaching with a teacher." Others describe effective methods that can be used in their projects, such as transfer learning. There are 14 types of training, the classification of which can be represented as follows.

Learning objectives.
1) Supervised learning.
2) Unsupervised learning.
3) Reinforced training.

Tasks of hybrid learning
4) Semi-supervised learning.
5) Self-learning.
6) Multi-copy training.

Statistical conclusions
7) Inductive learning.
8) Deductive conclusion.
9) Transductive learning.

Teaching methods
10) Multitasking.
11) Active learning.
12) Online learning.
13) Transfer learning.
14) Ensemble training.

This paper considers a method of semi-supervised learning where a dataset consisting of both labeled and unlabeled data points, the task is to assign labels to an unlabeled subset.

Semi-supervised learning (SSL) is halfway between supervised learning and unsupervised learning. In addition to unlabeled data, some labeled information is provided to the algorithm, but not necessarily for all examples.

In this case, the dataset $X = (x_i)\ \ i \in [n]$ can be divided into two parts: points $X_l := (x_1,...,x_l)$ for which marks $Y_l := (y_1,..., .) . , y_l)$ there are known points $X_u := (x_{l+1}, ..., x_{l+u})$ whose labels are unknown. This is "standard" training with semi-supervised.

It is possible to obtain a more accurate forecast taking into account unlabeled points only if the distribution of unlabeled data examples corresponds to the classification task. In a more mathematical formulation, one could say that knowing $p(x)$ that one can get from unlabeled data should carry information useful for deriving $p(y|x)$. If this is not the case, semi-supervised learning will not provide any improvement over supervised learning. It may even happen that the use of unlabeled data reduces the accuracy of the prediction, misleading the conclusion. For semi-supervised learning to work, certain assumptions must be met.

IV. ASSUMPTIONS OF SEMI-SUPERVISED LEARNING

To associate knowledge from unlabeled data with the true class distribution, semi-supervised learning algorithms use one or more of the following three assumptions: semi-supervised smoothness assumption, cluster assumption, manifold assumption.

Assumption of semi-supervised smoothness: if two points x_1, x_2 in a high-density region are close, then the corresponding outputs y_1, y_2 must be the same.

Cluster assumption: If the points are in the same cluster, they are likely to belong to the same class. The cluster assumption can be formulated in an equivalent way:

Low density separation: The decision boundary must lie in a low density region.

The manifold assumption assumes that the true structure of the data lies in a low-dimensional manifold, if the data lies on a low-dimensional manifold, then the learning algorithm can essentially operate in the space of the appropriate dimension, thus avoiding the curse of dimension.

V. REVIEW

Semi-supervised learning is a field of machine learning that aims to combine approaches to learning with the teacher and without teacher processing [1], [2]. Typically, semi-supervised learning algorithms attempt to improve performance in one of these two tasks using information typically related to the other. For example, if a classification problem is resolved, additional data points for which the label is unknown can be used to facilitate the classification process. On the other hand, for clustering methods, the learning procedure can benefit from knowing that certain data points belong to the same class. As with machine learning in general, the vast majority of research on semi-controlled learning focuses on classifications. Semi-supervised classification methods are especially suitable for scenarios where there is little data. In such cases, it can be difficult to build a reliable classifier with a teacher. This situation arises in areas of applications where road data are marked or difficult to obtain, such as computer diagnostics, drug detection, and labeling of parts of speech. If there is enough unlabeled data and under certain assumptions about data distribution, unlabeled data can help build a better classifier. In practice, semi-supervised learning methods have also been applied to scenarios in which there is no significant lack of observed data: if labeled data points provide additional information regarding forecasting, they can potentially be used to improve classification efficiency. There are many supervised methods, each of which has its own characteristics, advantages and disadvantages.

The most recent comprehensive study on the subject was published by [3] and was last updated in [2]. The books by [1] also provide a good basis for studying earlier work on semi-guided learning. More recently, [4] presented a review of several graphical methods, and [5] considered and analyzed the methods of pseudo-labeling, a class of semi-supervised learning methods. Since the publication [2], some important changes have taken place in the field of semi- supervised learning. New approaches to learning have been proposed around the world, and existing approaches have been expanded, improved and analyzed in depth. In addition, the growing popularity of (deep) neural networks [6] for supervised learning has led to new approaches to semi-supervised learning involvement, based on the simplicity of including conditions of loss without a teacher in the cost of learning neural networks. Finally, special attention is paid to the development of reliable methods with semi-supervised learning, which reduce productivity, as well as the evaluation of semi-supervised methods for practical purposes. Domestic specialists and scientific organizations, except for the applicants, do not carry out similar research.

VI. PROBLEM STATEMENT

This article discusses a modification of one of the well-known semi-supervised learning approaches - the label propagation method (LP), which is a popular graph-based semi-supervised learning framework.

The key assumption of label propagation is that data points occupying the same manifold are likely to have the same semantic label. To this end, label propagation aims to "propagate" the labels of labeled data points to untagged data points according to the internal structures of the data set collectively detected by a large number of data points. This means that the label propagation algorithm can more successfully evaluate labels as the number of (labeled or untagged) data points increases. Obviously, this leads to an increase in computation time. However, there are two key limitations of the RM that hinder its efficiency:

- *performance degradation*: at the initial iterations, the performance of the LP improves. However, later it starts to decrease for graphs that do not respect the principles of local continuity, that is, neighboring nodes that have similar labels. Thus, the "stopping criterion" can have a significant impact on the performance of the LP;
- *inefficient use of node functions*: in most real scenarios, graph nodes have additional information. Unfortunately, LP does not use the node function direction to determine labels, but uses a kernel function to compute pairwise similarity.

Let $X = \{x_1, x_2, \dots, x_m, x_{m+1}, \dots, x_n\}$ represents a set of data points, and $L = \{l_1, l_2, \dots, l_c\}$ – set of labels. The first m data points, $\{x_1, x_2, \ldots, x_m\}$ are labeled $\{y(x_1), y(x_2), \ldots, y(x_m)|y(x_i) \in L\}$, and the other data points are unlabeled. The goal of label propagation is to forecast the labels of unlabeled data points, which can be achieved as follows.

When implementing the label propagation method, firstly the graph $G = \{V, E\}$ is constructed, where the node set V is the set of data points X, i.e. $V = X$. E is the set of edges whose weights reflect the similarity between the data points. The *k-NN* graph scheme is a more popular approach to building a graph. In a *k-NN* graph, a pair of nodes has an undirected edge if the two nodes are *k*-nearest neighbors [8]. This means that the number of edges is $O(n)$ and the graph is symmetric. Conventionally, the weight of the edge between points x_i and x_j, W_{ij}, is determined by the Gaussian kernel [9]; $W_{ij} = \exp\{-\| x_i - x_j \|^2/2\sigma^2\}$ if an edge connects data point x_i to x_j, otherwise $W_{ij} = 0$. In this equation, σ is a hyperparameter. Many researchers have proposed efficient approaches to constructing a *k-NN* graph [10] – [12].

Next, node estimates are computed for each label to determine labels for unlabeled data points. In label propagation, label estimates are defined as the optimal solution that minimizes the cost function.

VII. Problem Solution

For the analysis of unlabeled data, decision making criteria have been developed to include unlabeled data in the training sample, for which the optimal ratio between the amount of labeled and unlabeled data will be determined. A hybrid method for selecting a small amount of useful unlabeled data has been developed to improve the classification accuracy of semi-supervised learning algorithms.

Despite the large number of semi-supervised learning methods developed, choosing the optimal approach to solve the problem is a non-trivial task, the solution of which primarily depends on the quality of the analysis of labeled and unlabeled data of the original sample.

Improving the quality of solving the problem of structural-parametric synthesis of neural networks based on the use of semi-supervised learning methods can be achieved by constructing hybrid methods. When constructing a hybrid semi-supervised learning method, one of the known algorithms is selected, followed by combining its individual stages with elements of other approaches (methods, algorithms) for the task and training sample. It is possible to use optimization algorithms to automatically select the optimal hyperparameters of a neural network for which semi-supervised learning is used.

As an example of the implementation of the proposed approach, the label propagation algorithm was used.

We consider a noise-robust variant of LP [13] as our starting point. It estimates a label distribution matrix $\mathbf{f}$ whose columns $f_i \in R_c$ represent the label distribution for each node i. The matrix $\mathbf{f}$ is picked to minimize

$$Tr\left\{\mathbf{f}^T\left(I_n - S\right)\mathbf{f}\right\} + \mu\sum_{i=1}^{l}\left\|\mathbf{f}_i - \mathbf{y}_i\right\|_2^2 + \mu\sum_{i=l+1}^{n}\left\|\mathbf{f}_i\right\|_2^2, \quad (1)$$

where I_n is $n\times n$ identity matrix, $S = D^{-1/2}WD^{-1/2}$ is the normalized graph Laplacian with $D_{ii} = \sum_j W_{ij}$ being a diagonal matrix of node degrees. The first term fits a smooth $\mathbf{f}$ over all nodes, the second term encourages consistency with known labels and the last term is a regularizer.

In order to improve the accuracy of data labeling, it is proposed to additionally introduce an element in the criterion that is minimized, which determines the noise reduction at each iteration of data labeling.

This noise reducer could be a post-processing classifier that is trained to correct LP's output using the labeled set as training data

$$\Im_{LP} + \lambda_L\sum_{i=1}^{l}KL\left(\mathbf{y}_i \| g_i\right), \quad (2)$$

where the first term is LP loss (1) and the next term connects the noise reducer. For searching hyperparameters it is proposed to use Particle Swarm Optimization (PSO) algorithm. the prior knowledge of regularizer is more important than the input weights and hidden bias selection. The number of the labeled training data usually leads to different optimal hyper parameters. Without any systematic guidance, the optimized hyper parameters can be only determined by experienced worker through trial and error. The detailed consideration of PSO algorithm is represented in [14].

VIII. Examples

As an example it is considered a marketing campaign dataset Kaggle to test the proposed hybrid label propagation algorithm (Fig. 1).

	ID	Year_Birth	Marital_Status	Income	Kidhome	Teenhome	MntWines	MntMeatProducts	Dependents_Flag
0	5524	1957	Single	58138.0	0	0	635	546	0
1	2174	1954	Single	46344.0	1	1	11	6	1
2	4141	1965	Together	71613.0	0	0	426	127	0
3	6182	1984	Together	26646.0	1	0	11	20	1
4	5324	1981	Married	58293.0	1	0	173	118	1
...	...	...	...	...	...	...	...	...	...
2235	10870	1967	Married	61223.0	0	1	709	182	1
2236	4001	1946	Together	64014.0	2	1	406	30	1
2237	7270	1981	Divorced	56981.0	0	0	908	217	0
2238	8235	1956	Together	69245.0	0	1	428	214	1

Fig. 1. Snippet of marketing campaign data from Kaggle

VII. CONCLUSIONS

Semi-supervised learning can be used in cases where data is easy to obtain but difficult to label. It uses both labeled and unlabeled data to create a model that is usually more powerful than a model trained with a standard supervised method. These algorithms are often based on pseudo-labeling and/or consistency regularization. But one caveat: even though semi-supervised learning often improves over standard / supervised learning, there is no guarantee that this is true for your own task. Semi-supervised learning has a huge potential that will be implemented more every day.

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В. М. Синєглазов, О. І. Чумаченко, Е. В. Хейлик. Напівкероване навчання в задачах обробки інформації
У статті обгрунтовано необхідність подальшого дослідження відомих методів та розробки нових методів машинного навчання – напівкерованого навчання. Показано, що знання щільності розподілу ймовірностей вихідних даних, отриманих з використанням немаркованих даних, повинно нести інформацію, корисну для отримання умовної щільності розподілу ймовірностей міток і вхідних даних. Якщо це не так, напівкероване навчання не забезпечить жодних покращень у порівнянні з контрольованим навчанням. Може навіть статися так, що використання немаркованих даних зменшить точність передбачення. Щоб напівкероване навчання працювало, мають виконуватися певні припущення, а саме: напівкероване припущення гладкості, припущення кластеризації (поділ із низькою щільністю) і припущення різноманіття. Розроблено новий гібридний алгоритм напівкерованого навчання з використанням методу поширення мітки. Наведено приклад використання запропонованого алгоритму.
Ключові слова: розповсюдження міток; напівкероване навчання; обробка даних; штучний інтелект; припущення гладкості, різноманіття, кластеризації.

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В. М. Синеглазов, Е. И. Чумаченко, Е. В. Хейлик. Полууправляемое обучение в задачах обработки информации
В статье обосновывается необходимость дальнейшего исследования известных методов и разработки новых методов машинного обучения – обучения с полууправляемым обучением. Показано, что знание плотности распределения вероятностей исходных данных, полученных с использованием неразмеченных данных, должно нести информацию, полезную для вывода условной плотности распределения вероятностей меток и входных данных. Если это не так, обучение с полууправляемым обучением не даст никаких улучшений по сравнению с обучением с учителем. Может даже случиться так, что использование неразмеченных данных снижает точность прогноза. Чтобы обучение с полууправляемым обучением работало, должны выполняться определенные допущения, а именно: допущение о гладкости с полууправлением, допущение о кластеризации (разбиение с низкой плотностью) и допущение о многообразии. Разработан новый гибридный алгоритм полууправляемого

обучения с использованием метода распространения метки. Приведен пример использования предложенного алгоритма.
Ключевые слова: распространение меток; полууправляемое обучение; обработка данных; искусственный интеллект; предположения гладкости, разнообразия, кластеризации.

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