УДК 616-073.757.1

A.S. Hrytsai, T.A. Levitskaya., N.A.Bouhlal

SYSTEMATIZATION OF ANOMALY SEARCH IN X-RAY PICTURES

The algorithms of pathological and structural structures using neural networks allow accelerating the process of diagnosing anomalies, reducing the number of errors and repeated polls of users. The article discusses methods of machine systematization and recognition of X-ray images (CXR), as well as the problems of improving artificial neural networks, which are used to enhance the properties of the systematization of X-ray syndromes. Since it is quite enough to implement a certain algorithm to detect a disease, neural networks are ideal for recognizing diseases using scanning. After analyzing research and publications on this topic, the main tasks for modeling the system were formed. The architectures of neural networks were also classified, indicating their disadvantages and advantages. It was revealed that modern methods of detecting anomalies in CXR have some difficulties, such as the missing number of training information, image typing, and preliminary segmentation of the training set. Deterministic specific methods for solving the problems of neural networks in data analysis. For implementation, it is proposed to apply deep machine learning methods, based on convolutional neural networks, using preliminary segmentation of a training sample with back propagation of error and gradient descent c and using transfer learning to systematize diseases on medical images. To solve the tasks, innovative IT technologies were selected. As a result, a certain architecture of the intelligent system was implemented, which allows us to detect anomalies in radiographs, which allow us to create effective structures of neural networks and increase the accuracy of recognition of pathological structures in radiographs.

Keywords: *deep machine learning; convolutional neural network; pattern recognition methods; image visualization; roentgenogram; learning algorithm.*

Formulation of the problem.

Today, only about 10% of the world population has access to quality health care, and most people do not even have access to basic health care. In developed countries, the healthcare system is under pressure, with increasing cost and long waiting times. Healthcare facilities can generate hundreds, if not thousands, of CXRs per day. In general, reading CXR is quite a challenge for both radiologists and doctors. This process requires a high degree of skill and concentration. The average time it takes a well-trained radiologist to read CXR is about 1-2 minutes.

Research using neural networks faces the following problems:

– quantification of uncertainty. In-depth machine learning solutions for biomedical applications can substantially benefit from guarantees of predictability and quantification of uncertainty. Due to the biological variability and accuracy of the equipment, the biomedical data do not consist of accurate measurements but of noise estimates. Therefore, it is crucial to obtain uncertainties that capture how noise in the input values propagates through deep neural networks;

– data limitations. The lack of large-scale, high-quality, properly labeled data affects deep machine learning in almost every direction;

– hardware limitations and scaling. Effective scaling of deep learning is challenging. Learning and using neural networks for forecasting involve large computational costs (such as time, memory, and energy);

– sharing data, code and models. A robust culture for sharing data, code and models will accelerate progress in this area. Cultural barriers to data exchange are best captured using the definition of "research parasite" to describe scientists using data from other researchers. In an area that considers discovery only, not hard work to gather useful data, it is difficult to encourage scientists to share their hard-won data;

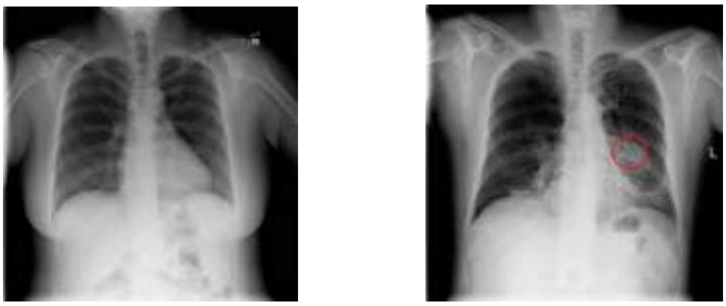
– limited amount of training data. Biomedical datasets often contain a limited number of instances or labels, which can lead to poor performance of deep learning algorithms. Transfer learning methods, also known as domain adaptation, allow you to transfer extracted templates between different datasets and even domains.

Analysis of recent research and publications.

A number of studies have been conducted to diagnose chest disease using artificial intelligence methodology. According to the article «Opportunities and Obstacles to the Deep Study of Biology and Medicine» deep machine learning can be applied to answer fundamental biological questions. This is particularly suitable for the use of large volumes of high-throughput studies [1].

One of the levels is the systematization of X-rays in two classes: healthy lungs and lungs that should be of any pathology.

Figure 1 really applies a healthy picture and a picture with pathology.



(a) without pathology (b) with pathology

Figure.1 – Sample Photos from the NIH Chest X-rays Dataset

For comparative analysis and systematization of chest X-ray diseases, three methods are considered: back propagation neural networks, competitive neural networks and convolutional neural networks [2].

Modeling of Chest Diseases Using NMR (BPNN).

Neural networks backscattering is based on the BPNN algorithm, they are very important and useful for image recognition problems. Training for backhaul networks involves updating the parameters to get good classification results. This uses a different number of hidden neurons, training speed and impulse to obtain a better classification result. Errors accumulated at the source layer are propagated back to the network for weight adjustment.

The architecture of the designed neural networks stellar scene for the 32 × 32 image is described in Figure 2.

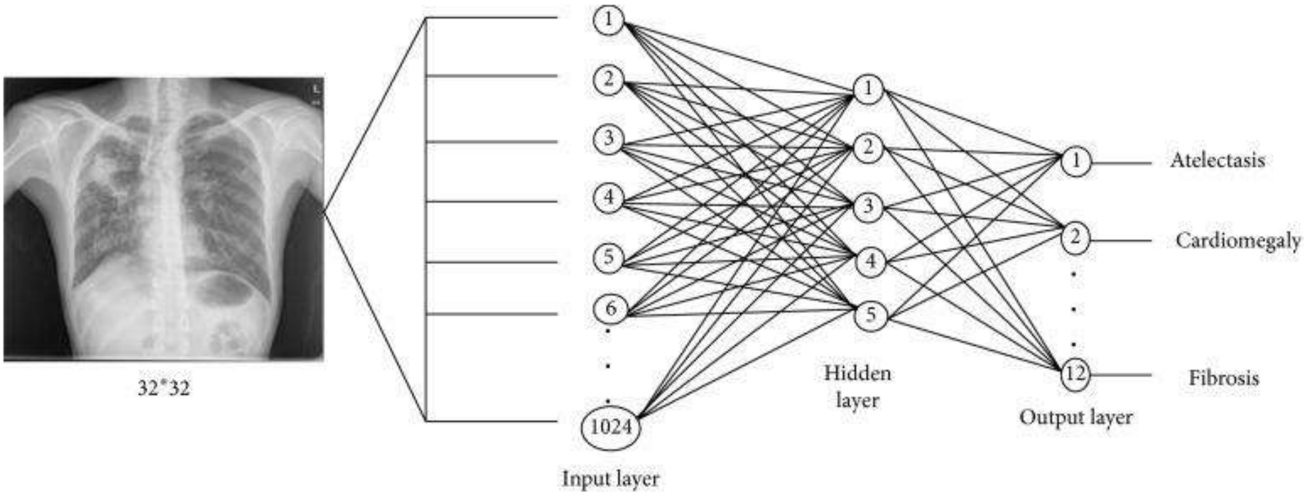


Figure.2 – Back propagation of NM

Because the backhaul network uses a managed learning algorithm, it is necessary that the training data is marked.

Modeling of Chest Diseases Using Competitive neural networks (CpNN).

CpNN is used to classify chest diseases using an unsupported training algorithm. By taking advantage of the fact that such networks do not require manual marking of data for training, they save time for the marking process. Competitive learning works by enhancing the specialization of each node in the network. The competitive learning rule is based on three elements:

– a set of identical neurons with randomly distributed synoptic weights, leading to a different response of neurons to a given set of input templates;
– restriction is imposed on the value of the "force" of each neuron;
– a mechanism that allows neurons to compete for the right to respond to a subset of input data, arranged so that only one output neuron (or only one neuron in a group) is active at a time.

Figure 3 shows the architecture of a competing neural network.

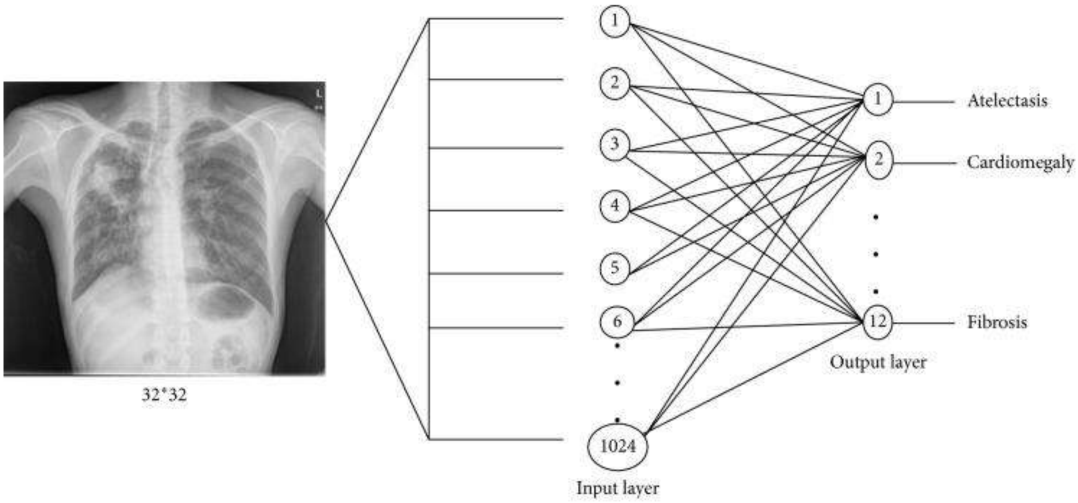


Figure 3 – Architecture of competitive neural networks

These networks use a winner-take-all strategy when only the scales associated with the winner-neuron are updated in a specific era, while the other scales are not updated. This learning process enhances the correlation between the input and the corresponding winning neurons in the learning process. Modeling of chest disease using convolutional neural networks (CNN).

Convolutional neural networks a deep learning algorithm that can take an input image, assign importance (training scales and biases) to different aspects / objects in the image, and be able to distinguish one from the other. The pre-processing required to operate the network is much lower than other classification algorithms. Although in primitive ways filters are made manually, with sufficient training, the network has the ability to study the characteristics. Stochastic gradient descent optimization is used for effective learning [3].

The corresponding values of network learning parameters are determined by experiments.

Figure 4 shows the architecture of a convolutional neural network.

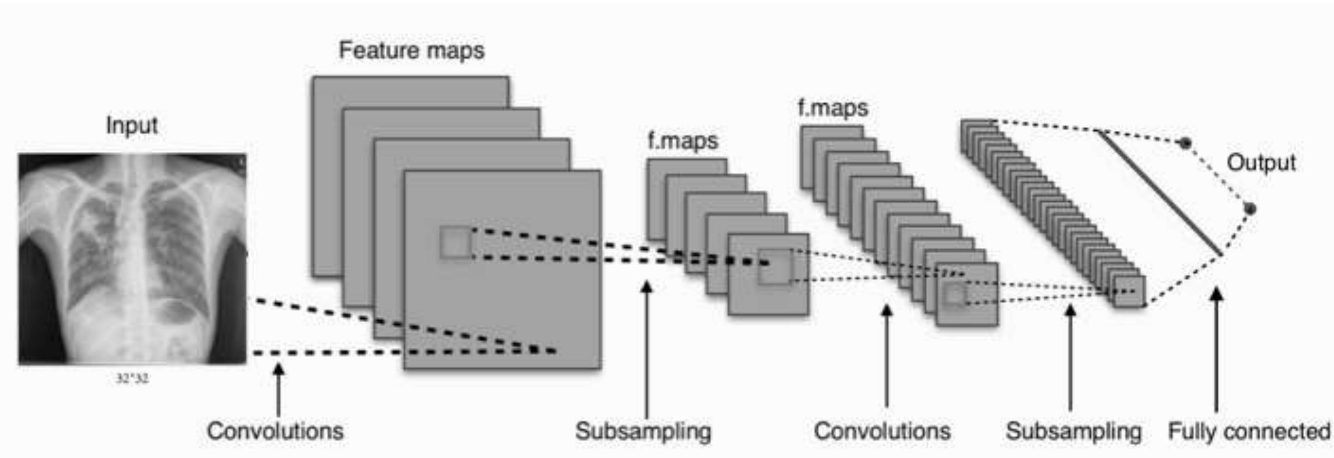


Figure 4 – Convolutional neural network architecture

The results of the comparison of neural networks work are presented in Table 1. The training sample for all CPNN and BPNN consisted of 1000 images, CNN - 100 000 images.

Table 1 - Comparison of neural networks

Model	Training time, s	Percentage of recognition,%	RMS error	Maximum number of iterations
BPNN	630	80,04	0,0025	5000
CPNN	300	89,57	0,0036	1000
CNN	2500	92,4	0,0013	40000

Analyzing Table 1, we can suggest that CNN has achieved a wide variety of levels of recognition for training and data testing, compared to the measurements used. But this transitional CNN is more so when there is more three-year time and more training iterations, lower in BPNN and CpNN. It can also be seen that three hours reached a low mean square error (MSE), and then CNN received the lowest (0.0013). The time it takes to use CNN is greater, less time is BPNN and CpNN. This is open with a depth that runs over much of the NM, which takes a long time, once, the number of fluctuations is large. Protest, this deep structure is a major factor in achieving greater high-frequency altitude, revealing in comparison to various measures such as BPNN and CpNN.

The aim of the study.

For more detailed information on setting up diagnosis of x-ray knowledge, you can use real-time methods and algorithms in the most common automated systems.

Basically, the task is to take effective architecture of the neural networks for the appearance of anomalies in the x-ray knowledge, to expand the algorithm to start the neural networks, to signify the overruns and the shortcomings of the neural networks.

On the basis of these methods of solving problems, it is possible to formulate an agreement on delivery, on the other hand, to register in the neural networks with the help of a violated inventory of anomalies on X-ray knowledge.

The main research material.

Analyzing existing articles and research, problems in the field of anomaly recognition by CXR have been identified and the methods and approaches described below are proposed to solve them.

Error back propagation method. It is a practice of fine-tuning the neural networks scales based on the error rate obtained in the previous era. Proper weight adjustment provides a lower error rate, which makes the model reliable by increasing its generalization. The neural networks propagates the input signal in the forward direction through its parameters until the decision is made, and then propagates the error information in the reverse direction over the network so that it can change the parameters. This happens step by step:

– the network assumes the data using their parameters;
– the network is measured by the loss function;
– the error is propagated back to adjust the wrong parameters.

Segmentation of the training sample. Pulmonary particle detection is a critical stage in the automatic CXR analysis for pulmonary disorders. Accurate localization of the lung area and image processing have a positive effect on the overall performance of the diagnostic / detection systems, increasing its accuracy and efficiency [4].

Improved lung image. The original image has low contrast, and further image processing techniques can produce unwanted results, so an initial step to improve the contrast is needed. The result of this step is an enhanced image that clearly distinguishes the lung area from the background.

Methods for solving insufficient training data. Large medical records are not easy to find for various reasons. Manual annotation of the CXR is quite time consuming. Clinical experts typically provide only small datasets. In recent years, sharing clinical data has become increasingly difficult due to strict patient privacy laws.

To solve the problem of insufficient data in the work we use a combination of the following methods of addition:

– translation. Translation is a shift about the center of the training image;
– rotation. Strategy of rotation of training images by an arbitrary number of degrees;
– stretching. Anatomical structures may appear differently in different x-ray images. Accidental zooming in or out can add variations to such changes;
– shift. The strategy of stretching an image in two opposite directions at the same time;
– contrast increases. Medical images obtained using equipment from different manufacturers may represent differences in image intensity.

In order to get the best neural networks training results, it is necessary to use a random generator of the type and size of supplement for each sample. Examples of application of image supplements are presented in Figure 5.

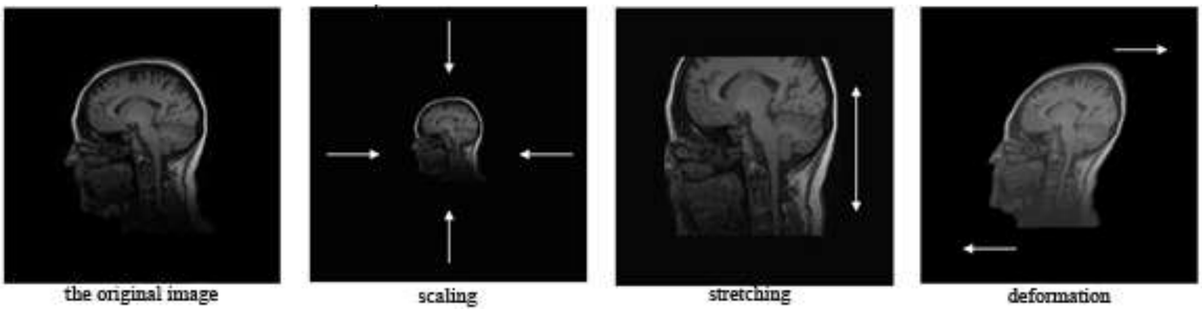


Figure 5 - Examples of CXR add-ons

Neural networks architecture. A convolutional neural networks was chosen to construct the neural networks model.

CNN is a type of deep learning model for processing data that has a network structure. CNN is a mathematical construction that typically consists of three types of layers: convolutions, merges, and fully connected layers. The first two, the convolution and merging layers, perform the object extraction, while the third, fully linked layer, displays the extracted objects in the final result, such as classification.Переваги використання CNN:

– does not require manual removal of features;

– CNN architecture does not necessarily require the segmentation of tumors or organs by human experts.

– Disadvantages:

– CNN requires a lot more data because of the abundance of parameters available for estimation and is therefore more expensive in computing, leading to the need for GPUs to train the model.

Generally, learning neural networks from scratch requires a lot of data, but access to this data is not always available. With transfer training, you can build a reliable machine learning model with relatively little data, since the model has already been pre-trained. In addition, training time is shortened because it can sometimes take days or even weeks to learn complex neural networks from scratch. Transfer training is a reuse of a previously learned model to solve a new problem. Transfer training has several advantages, but the main benefits are saving time on training, improving NNproductivity and the need for lots of data.

CONCLUSIONS

As a result, methods and approaches have been developed to address the problem of detecting anomalies on the CXR, which allow us to develop an effective neural networks architecture and to improve the accuracy of the recognition of pathological structures on radiographs.

Deep machine learning will greatly affect the practical reality of X-ray analysis. Deep neural networks are not currently used in clinical practice for medical imaging, although some are in clinical trials. Companies are starting to roll out the first products based on deep machine learning. This process will take some time as there are still problems ahead. There is a need to increase the number of medical images to train neural networks models, more experience with 3D images is needed, and the medical community needs to standardize the acquisition of images.

If neural networks can outperform people in image recognition, it does not mean that doctors will be out of work. The future of deep neural networks will make them work with doctors, not change them.

Despite the promising results, serious problems remain, especially with regard to a theoretical framework that would clearly explain how to determine the optimal model, type and structure for a particular task or for a thorough understanding of the reasons why a particular architecture or algorithm is effective in the task or not.

List of sources used

1. Travers Ch. Opportunities and obstacles to a deep study of biology and medicine / Ch. Travers. - Royal Society Interface Bulletin - 2018. - 141p.

2. Rabich G. Deep convolutional neural networks for the detection of chest diseases / G. Rabich. - Royal Society Interface Bulletin - 2018. - 141p.

3. Weinhoven R.G. Rapid object detection training using stochastic gradient output: International Conference on Image Presence (ICPR) / R.G. Weinhoven - Tsukuba, Japan, 2010 - 424 pp.

4. Pattrapisetwong P. Automatic lung segmentation in chest X-ray using a shadow filter: proceedings of the IEEE / P. Pattrapisetwong Conference. - Manchester, United Kingdom, 2016.

5. Goodfellow I., Bengio Y., Courville A. Deep Learning. — MIT Press, 2016. — Access mode: http://www.deeplearningbook.org.

6. Deep Learning with Lung Segmentation and Bone Shadow Exclusion Techniques for Chest X-Ray Analysis of Lung Cancer / Yu. Gordienko, P. Gang, J. Hui et al. // ArXiv. — 2017 — Access mode: https: // arxiv.org/abs/1712.07632.

Грицай А.С., Левицька Т.О., Бухлал Н.А.

СИСТЕМАТИЗАЦІЇ ПОШУКУ АНОМАЛІЙ В РЕНТГЕНІВСЬКИХ ЗНІМКАХ

Прискорити процес діагностики аномалій, знизити кількість помилок і повторних опитувань користувачів дозволяють алгоритми патолого-структурних структур, що використовують нейронні мережі. У статті розглядаються способи машинної систематизації та розпізнавання рентгенівських знімків (CXR), а також проблеми вдосконалення штучних нейронних мереж, які застосовуються з метою посилення властивостей систематизації рентгенологічних синдромів. З причини того, що для виявлення захворювання цілком достатньо реалізувати певний алгоритм, нейронні мережі є ідеальними для розпізнавання хвороб із застосуванням сканування. Проаналізувавши досліджень і публікацій з цієї теми були сформовані основні завдання для моделювання системи. Також були класифіковані архітектури нейронних мереж, із зазначенням їх недоліків і переваг. Виявлено, що сучасні методи виявлення аномалій в CXR мають деякі складності, такі як відсутні число тренувальних відомостей, типизацией зображень і попередньої сегментацією тренувального набору. Детерміновані конкретні способи вирішення проблем нейронних мереж при аналізі даних. Для реалізації запропоновано застосувати методи глибокого машинного навчання, на основі згортальних нейронних мереж застосовуючи попередню сегментацію тренувальної вибірки зі зворотним поширенням помилки і градієнтного спуску з і застосування трансферного навчання для систематизації захворювань на медичних зображеннях. Для вирішення поставлених завдань обрані інноваційні IT-технології. В результаті була реалізована певна архітектура інтелектуальної системи, що дозволяє виявляти аномалії на рентгенограмах, які дозволяють нам створювати ефективні структури нейронних мереж і підвищувати точність розпізнавання патологічних структур на рентгенограмах.

Ключові слова: *глибоке машинне навчання; сверточное нейронна мережа; методи розпізнавання образів; візуалізація зображень; рентгенограма; алгоритм навчання.*

Грицай А.С., Левицкая Т.А., Бухлал Н.А.

СИСТЕМАТИЗАЦИЯ ПОИСКА АНОМАЛИЙ В РЕНТГЕНОВСКИХ СНИМКАХ

Ускорить процесс диагностики аномалий, снизить количество ошибок и повторных опросов пользователей позволяют алгоритмы патолого-структурных структур, использующих нейронные сети. В статье рассматриваются способы машинной систематизации и распознавания рентгеновских снимков (CXR), а также проблемы совершенствования искусственных нейронных сетей, которые применяются с целью усиления свойств систематизации рентгенологических синдромов. В виду того, что для выявления заболевания вполне достаточно реализовать определенный алгоритм, нейронные сети являются идеальными для распознавания болезней с применением сканирования. Проанализировав исследований и публикаций по этой теме были сформированные основные задачи для моделирования системы. Также были классифицированы архитектуры нейронных сетей, с указанием их недостатков и преимуществ. Выявлено, что современные методы обнаружения аномалий в CXR имеют некоторые сложности, такие как недостающие число тренировочных сведений, типизацией изображений и предварительной сегментацией тренировочного набора. Детерминированные конкретные способы решения проблем нейронных сетей при анализе данных. Для реализации предложено применить методы глубокого машинного обучения, на основе сверточных нейронных сетей применяя предварительную сегментацию тренировочной выборки с обратным распространением ошибки и градиентного спуска с и применения трансферного обучения для систематизации заболеваний на медицинских изображениях. Для решения поставленных задач выбраны инновационные IT-технологии. В результате была реализована определенная архитектура интеллектуальной системы, позволяющая обнаруживать аномалии на рентгенограммах, которые позволяют нам создавать эффективные структуры нейронных сетей и повышать точность распознавания патологических структур на рентгенограммах.

Ключевые слова: *глубокое машинное обучение; сверточная нейронная сеть; методы распознавания образов; визуализация изображений; рентгенограмма; алгоритм обучения.*

Рецензент доц., к.т.н. Сорочан О.М.
Статья поступила 26.11.2019

УДК 004.032.24

Половинка О.Л., Нікулін Д.В., Дмитрієва О.А.

ДОСЛІДЖЕННЯ ШВИДКОДІЇ РОБОТИ АПРІОРНИХ АЛГОРИТМІВ НА ДАНИХ ВЕЛИКИХ ОБСЯГІВ

В статті обґрунтовано використання алгоритмів пошуку асоціативних правил для роботи з неструктурованими даними великих обсягів. Зазначено, що найбільш популярним алгоритмом пошуку асоціацій є алгоритм Apriori. Наведено результати аналізу роботи лінійних алгоритмів пошуку асоціацій з неструктурованими даними великих обсягів. Розглянуто найбільш відомі модифікації апріорних алгоритмів пошуку асоціативних правил,