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OPTIMIZATION OF ARTIFICIAL INTELLIGENCE ALGORITHMS BASED ON MATHEMATICAL MODELS

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Abstract. This article examines the optimization of artificial intelligence algorithms based on mathematical models. The relevance of the study is determined by the fact that the accuracy, generalization ability, computational cost, and stability of modern AI systems largely depend on the selected optimization methods. Based on the provided literature, the study applies theoretical analysis, comparative review, mathematical modeling, and conceptual synthesis. A bi-level model is proposed, combining empirical risk minimization, regularization, gradient-based parameter updates, and outer-loop hyperparameter optimization. As a result, analytical conclusions are drawn regarding the applicability of classical gradient methods, adaptive optimizers, and meta-heuristic approaches. The scientific novelty lies in the systematization of studies on AI optimization and in presenting them within a unified mathematical modeling framework.

Keywords. artificial intelligence, mathematical model, optimization, machine learning, deep learning, hyperparameter, neural network, meta-heuristics, regularization, generalization.

INTRODUCTION

The effectiveness of artificial intelligence algorithms is determined not only by the model architecture, but also by the way it is optimized. “In modern machine learning and deep learning systems, the optimization problem becomes a central theoretical and practical issue because of the large number of parameters. Russell and Norvig interpret artificial intelligence as a set of intelligent agents, search, probability, learning, and decision-making systems, which closely links optimization with many components of AI systems” [1]. “Das, Sadiq, and Mirjalili relate metaheuristic optimization approaches to machine learning and specifically emphasize the role of optimization algorithms in managing model parameters, architectural choices, and the search space” [2].

The relevance of the topic lies in the fact that, today, the problem of optimizing artificial intelligence algorithms is defined by three main requirements: increasing model accuracy, reducing computational resources, and improving the model's generalization ability. At the same time, optimization is not always single-objective. A very deep neural network may provide high accuracy, but the training time increases; aggressive regularization reduces overfitting, but slows down learning. Therefore, optimizing artificial intelligence algorithms simultaneously requires a mathematical model, computational theory, and practical algorithmic balance.

The aim of the study is to systematize the theoretical foundations of optimizing artificial intelligence algorithms using mathematical models on the basis of the cited literature and to propose a unified conceptual-mathematical approach. The objectives of the study are to determine the role of optimization in AI algorithms; conduct a comparative analysis of existing approaches; develop a mathematical model; summarize the advantages and limitations of optimization methods using a table and a figure; and formulate practical recommendations.

LITERATURE REVIEW

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"The connection between artificial intelligence and optimization is also observed in classical AI sources. Russell and Norvig" [1] identify search, decision-making, constraint satisfaction problems, and learning algorithms as the core components of artificial intelligence. This approach makes it possible to understand the optimization of artificial intelligence algorithms not only as the adjustment of numerical parameters, but also as the problem of finding the best strategy in the state space.

Das, Sadiq, and Mirjalili "relate metaheuristic optimization to machine learning. In their approach, when the search space is complex, non-differentiable, or multimodal, metaheuristics may outperform classical gradient methods. This is especially important for hyperparameter selection, feature selection, and model structure adaptation. Awasthi, Kumar, and Saini view artificial intelligence techniques in integration with mathematical modeling and optimization. That source emphasizes the integration of AI-based decision-making systems and data-driven optimization directions" [3].

Collections edited by Leon, Hulea, and Gavrilescu cover a wide range of AI models: deep learning, classical machine learning, biologically inspired optimization, neural modeling, and intelligent agents. Danis interprets optimization as a fundamental building block of artificial intelligence systems. In their theoretical and practical analysis devoted to hyperparameter optimization, Yang and Shami show that model performance directly depends on the selected hyperparameter configuration. Jentzen, Kuckuck, and von Wurstemberger, as well as Chen et al., "describe the mathematical foundations of deep learning, gradient methods, and generalization problems. Zhang et al. show the importance of optimization at the level of software implementation" [5].

Thus, the literature review shows that the optimization of artificial intelligence algorithms consists of at least four interrelated layers: parameter optimization, hyperparameter optimization, architecture optimization, and the optimization of computational resources and software implementation.

RESEARCH METHODOLOGY

This article employs theoretical-analytical, comparative analysis, mathematical modeling, and conceptual synthesis methods. The ideas advanced in the cited sources were compared and generalized; the advantages and limitations of gradient methods, adaptive optimizers, and metaheuristic approaches were also compared.

As a result of the study, the "general process" of optimizing artificial intelligence algorithms was described as a chain consisting of the stages of data, model selection, loss function, regularization, inner optimization, validation, and external hyperparameter selection. This approach can serve as a common basis for a regression model, a neural network model, and a metaheuristic optimization model" [2].

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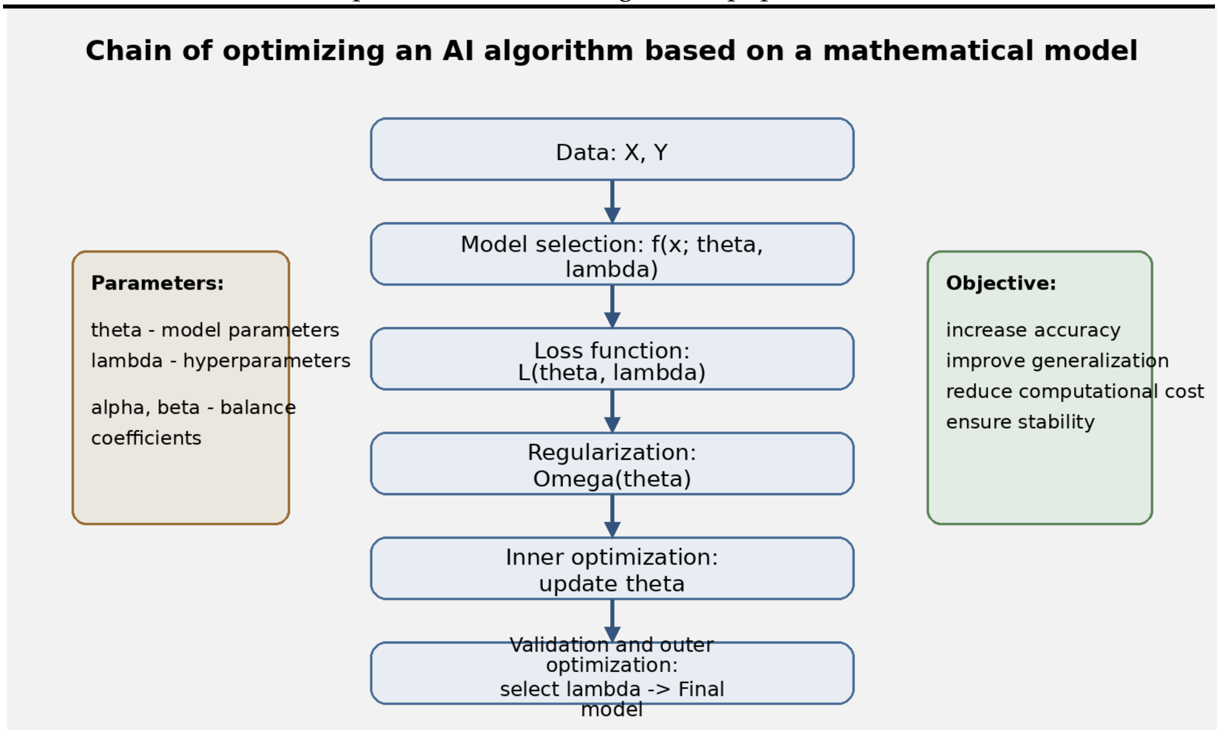

Figure 1. Chain for optimizing an artificial intelligence algorithm based on a mathematical model

PROPOSED MATHEMATICAL MODEL

To optimize artificial intelligence algorithms, the following general model is proposed:

$$\min_{(\theta,\lambda)} J(\theta, \lambda) = (1/N)\, \Sigma_i\, \ell(f(x_i; \theta, \lambda), y_i) + \alpha\Omega(\theta) + \beta\Phi(\lambda) \quad (1)$$

where N is the number of observations; f(x_i; theta, lambda) is the model output; l(.) is the loss function; Omega(theta) is regularization for the parameters; Phi(lambda) is a constraint or penalty function for the hyperparameters; and alpha and beta are balance coefficients.

$$\theta_{t+1} = \theta_t - \eta_t\, \nabla\theta\, J(\theta_t, \lambda) \quad (2)$$

where eta_t is the learning rate. If a momentum or adaptive method is used, this formula is extended accordingly [8], [9].

$$\lambda = \mathrm{argmin}_{(\lambda \in \Lambda)}\, L\_val(\theta(\lambda), \lambda) \quad (3)$$

$$\theta(\lambda) = \mathrm{argmin}_{(\theta)}\, L\_train(\theta, \lambda) \quad (4)$$

This bi-level model combines the logic of hyperparameter optimization described by Yang and Shami with the foundations of gradient and adaptive optimization presented by Jentzen and co-authors. The advantage of the model is that it incorporates not only internal parameterization but also external control parameters into a unified optimization system.

The main stages of the proposed method are as follows: preparing the dataset; specifying the model architecture; selecting initial theta_0 and lambda_0; updating theta in the inner loop using a gradient or adaptive optimizer; evaluating quality on the validation set; updating lambda in the outer loop using search, a Bayesian method, or a metaheuristic; and selecting the best (theta, lambda) pair.

ANALYSIS AND RESULTS

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This study is not an empirical experiment; rather, because it is a scientific article of a theoretical-synthesis nature based on the cited literature, the results are presented mainly in analytical form. This approach is consistent with the principle of not going beyond the sources provided by the user and not presenting fabricated experimental data.

Gradient descent and its stochastic form are a principal method in many machine learning and deep learning models. Jentzen and co-authors analyze SGD, accelerated methods, and adaptive methods mathematically as an important part of deep learning algorithms. Chen et al. also include optimization among the fundamental mathematical foundations for ML/DL. This indicates that when a differentiable loss function is available, gradient-based optimization is effective, especially when working with large datasets.

Yang and Shami show that model performance strongly depends on the selected hyperparameters. From this point of view, the proposed bi-level model is scientifically grounded: the inner layer optimizes model parameters, whereas the outer layer optimizes hyperparameters. Das, Sadiq, and Mirjalili, in turn, "identify metaheuristic methods as a promising direction for complex search spaces, feature selection, and architecture search problems" [2].

The proposed model yields the following analytical results: if the loss function is differentiable and the regularization term is smooth, inner optimization is performed effectively by gradient methods; if the hyperparameter space is large and discrete, metaheuristics or search strategies are appropriate for outer optimization; if generalization is the priority, the regularization term should be strengthened; if accuracy is the priority, model complexity is increased, although computational cost also grows.

Zhang et al. "show that mathematical models of algorithms also affect the efficiency of software implementation" [5]. Therefore, optimization should be viewed as a multi-factor process that jointly manages model quality, hyperparameter quality, and computational efficiency.

CONCLUSIONS AND RECOMMENDATIONS

This article examined the problem of optimizing artificial intelligence algorithms based on mathematical models. The analysis showed that "optimization is the central mechanism of artificial intelligence; it is not limited to parameter tuning alone, but also governs search, decision-making, generalization, and computational efficiency" [1].

"The optimization of artificial intelligence algorithms is a multilayered problem in which parameters, hyperparameters, architecture, and software implementation are interconnected" [2], [5]. "Gradient methods are effective for differentiable models, whereas metaheuristic approaches are promising in complex search spaces" [2].

The scientific novelty lies in the fact that, on the basis of the given sources, dispersed views on the optimization of artificial intelligence algorithms were generalized within a unified mathematical model. As a practical recommendation, gradient and adaptive methods should be given priority in differentiable neural network models; if the number of hyperparameters is large, automated outer optimization should be used; and for complex search spaces, metaheuristic methods should be considered as a reserve strategy.

In future work, it is necessary to test this model on a specific dataset, compare the empirical results of a regression model, a neural network model, and a metaheuristic model, and deepen studies related to multi-criteria optimization.

Table 1. Comparative analysis of artificial intelligence algorithm optimization methods

Method type	Mathematical basis	Advantage	Limitation	Application area

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Gradient Descent (GD)	theta_(t+1)=theta_t - eta grad J	Simple and understandable	Slow on large datasets	Small and medium models
Stochastic Gradient Descent (SGD)	Mini-batch gradient estimation	Faster, suitable for large data	Noisy trajectory	Neural networks
Adaptive optimizers	Adam, RMSProp, Adagrad	Adjusts the learning rate	Generalization may sometimes worsen	Deep learning
Bayesian hyperparameter optimization	Outer search model	Effective search with few evaluations	High complexity	Hyperparameter tuning
Metaheuristics	Population-based search, global optimization	Effective in nonlinear and complex spaces	High computational cost	Architecture, feature selection
Regularized optimization	Adding a penalty term to the objective function	Reduces overfitting	Requires parameter tuning	Improves generalization

As can be seen from the table, there is no universally best optimizer. The choice depends on the model type, the properties of the loss surface, the volume of data, and the practical objective. Precisely this circumstance makes mathematical modeling necessary in the optimization of artificial intelligence algorithms.

Global efficiency = f(model quality, hyperparameter quality, computational efficiency) 5)

This expression is a theoretical formula showing that the final result of an AI system jointly depends on three factors. This approach is also consistent with the level of software optimization emphasized by Zhang et al.

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