Business, Management and Economics Engineering
ISSN: 2669-2481 / eISSN: 2669-249X
2024 Volume 22 Issue 02

THE ROLE OF GENERATIVE AI IN THE OPTIMIZATION OF HYPERPARAMETERS FOR STRATEGY MAKING: AN ANALYSIS OF ITS IMPACT ON DECISION-MAKING PROCESSES.

Atharva Raghorte[1], Paras Ghugal[2], Shiwali Charjan[3], Animesh Kumar[4], Chetan Selote[5]
Student[1], Student[2], Teaching Associate[3], Student[4], System Engineer[5]
SDA Bocconi Asia Centre[1], IIT Jodhpur[2], Cardiff University[3], SDA Bocconi Asia Center[4], Infosys Limited[5]

Abstract

The optimal hyperparameters issue is a critical issue in the field of machine learning (ML) and artificial intelligence (AI) techniques developing, with the traditional strategies are mostly a waste of time and not efficient. In this context, the emergence of generative AI presents a promising opportunity to automate and enhance the hyperparameter optimization process. This research paper delves into the role of generative AI in optimizing hyperparameters for strategy-making, focusing on its potential impact on decision-making processes.The applicability of generative AI techniques in the area of strategy search space definition is explored in this study. Moreover, it delves into whether the generative AI adds an additional advantage for strategies over those traditional methods. Finally, this study also examines the capability of generative AI to improve the interpretability of strategy models.Through a combination of theoretical analysis and empirical assessment across numerous datasets and complexities, these studies will benchmark generative AI techniques in opposition to established optimization techniques using key metrics which include method performance, computational performance, and robustness. Ultimately, this paper seeks to make contributions to the continued discourse on the transformative capacity of generative AI in optimizing hyperparameters for strategic decisions-making.

Keywords: Hyperparameter optimization, Machine learning (ML), Artificial intelligence (AI), Generative AI, Strategy-making, Decision-making processes,Strategy search space definition, Traditional optimization methods.

1. The Efficiency of Generative AI in Hyperparameter Optimization

1.1 How does generative AI compare to traditional optimization methods in terms of efficiency?

Generative AI and traditional optimization techniques each basically involve the critical manner of hyperparameter tuning to enhance model performance, however they approach this task from different views. In the world of generative AI, the emphasis is placed on fine-tuning a base model with a particular training dataset, in which the selection of hyperparameters is meticulously indexed and optimized to tailor the model closely to the dataset in question [1]. This contrasts with conventional methods where hyperparameter optimization is seen greater as an art, concerning running more than one trial to fine-tune models inside detailed limits, thereby requiring a complete understanding of the model's architecture and the results of each hyperparameter [2][3]. Furthermore, the application of a Hyperparameter Optimization (HOpt) framework in generative AI, which employs surrogate modeling to systematically improve the values of hyperparameters, showcases a targeted approach to enhancing the accuracy and robustness of models, distinguishing it from broader traditional approaches that might not leverage such superior strategies [4]. This strategic and focused optimization process underscores the performance of generative AI strategies in attaining the ultimate goal of ML learning: model generalization, that is the model's capacity to perform properly on unseen data [5].

1.2 In what ways does generative AI streamline the hyperparameter optimization process?

Considering a generative AI context, the contribution of the hyperparameter cannot be underestimated. These knobs and dials are, in fact, the leverage points on which these ML models can be efficiently adjusted and these, in turn, can significantly increase the overall performance of the model on unseen data which, scientifically, is known as model generalization [5]. The manner includes setting particular limits for hyperparameters and running more than one trial to locate the finest settings [3]. This isn't always a simple undertaking, as it requires a deep comprehension of how unique hyperparameters like batch size, epochs, and learning rates affect the gaining learning process [6]. However, while generative AI is implemented to this challenge, it streamlines the hyperparameter optimization via efficiently fine-tuning the model with a provided dataset. This approach not only bolsters the model’s potential to generalize but additionally optimizes its performance, efficiency, and reliability [1][7]. Through this meticulous procedure of hyperparameter tuning, generative AI models attain progressed convergence rates, making sure that every iteration brings them closer to the final goal of the most advantageous overall performance [8].

1.3 What metrics are most effective for measuring the success of generative AI in strategy optimization?

The reality is that AI models can only reach their potential if the algorithms are optimized through hyperparameter tuning which is, perhaps, even more important. The process involved in hyperparameter tuning is basically doing multiple trials where a certain set of parameters specified in advance are varied within some known constraints [3]. This way is usually regarded as crucial in the context of generative AI, where the architectural framework enhanced by the key hyperparameters like batch size, epochs, and learning rates is tweaked during the training phase for a better output [6]. In addition, this parameter tuning is useful for generative AI algorithms because it allows the models to be tailored to the particular training dataset, and the tuning of hyperparameters is carried out in a manner that ensures the model works as efficiently as possible and makes accurate predictions. [1] Hence towards the achievement of optimum performance in the models, generative AI needs a more detailed approach to training through hyperparameter tuning, making this process the cornerstone of strategic optimization in AI systems development.

2. The Role of Generative AI in Strategy Search Space Definition

2.1 How does generative AI assist in defining strategy search spaces?

The Generative AI not only changes the primary business strategy and search space layout by design but also enables the use of superior algorithms to make content optimizing and keyword selection processes providing the maximum organic traffic. Through analyzing the huge amount of data, generative AI can reveal keywords that have over search volumes as well as a lower level of competition, which will serve a dual purpose that the normal methods would possibly miss out on [9] This process, however, differs from simple keyword and phrase determination; it is also highly dependent on algorithmic specifications and on the strategic behavior of the users [9]. Such information is important because it allows corporations to improve tactics and strategies during the campaign itself and makes it possible to choose the right keywords and, therefore, concentrate efforts on the most efficient directions. As this fine-tuned approach leans on generative AI, it not only increases the visibility of a business online but also lowers the CPC (cost per click) empowering the marketers to spend on more marketing assets that are effectively equity-driven with a stronger marketing coverage [10]. Moreover, taking advantage of the generative AI for keyword optimization means that with search engine algorithms which are continually going to evolve with AI developments, businesses stay in tune with the AI momentum, placing them at the forefront of growth and improvement of the search strategy more effectively.

2.2 What advantages does generative AI offer over traditional methods in search space exploration?

Developing deep learning algorithms even further, generative AI is another significant advance that is more capable of overshooting conventional scope search techniques. Among the best features of intelligent AI, which is facilitated by deep learning and neural networks, is their capacity to get deeper and more diverse in searching for possible solutions [9]. Thus, the major issue here lies within the fact that the development of this advance allows the forming of intricate models with the highest level of realism and coherence which in turn, adds to the list of the positions, that can be taken when exploring search space [9].

Additionally, the creative, generative AI wouldn't only fulfill the SEO requirements but also be a powerful tool to emphasize the incorporation of this technology in the SEO strategy to have a competitive edge. The data utilized in this novel strategy may not be limited to text and images only but it may even include videos and audio, which facilitate training of models that are flexible and capable of recognizing complex structures and patterns evident in the content. This process results in creative new output generations; therefore, generative AI got the opportunity to kick out content creation and space around search as well [9].

2.2 How does the definition of search spaces impact the overall strategy-making process

Proceeding from the concept of improving AI algorithms and adjusting searching spaces becomes quite important in implementing a strategy aimed at boosting AI device's performance. Assessing a company's conduct towards the increasingly widespread age of search [13] is an imperative move in comprehending the fast-changing balance between consumer-technology interaction. In addition to this, this section of evaluation is reinforced by our strategic partnerships as an example is illustrated by the deep cooperation that we have with Microsoft [11] through which we point out the fact that in the AI field, it is especially important to collaborate to make improvements in the querying methods. Also, the company's complete consideration for all the alternatives can be seen from the fact that they open the board for [11] discussions in all the aspects of search space, this provides an extraordinary approach to how the dimension of search space is analyzed. Therefore, this combined strategy would play a crucial role in tackling various AI areas, such as consumer behavior, where they start with broad topics about AI before they narrow down to specialized brand searches. This transformation from non-brand to brand queries in search engines exemplifies the significant role that logo recognition and brand trust have in client decisions, [10]. As a result, processes to define the search space that is convergent and consider consumers' search behaviors achieve a much higher influence on the whole strategy-making process confirming that the AI systems are not the most optimal ones for their performance but for the search patterns and alternatives of consumers.

3. The Impact of Generative AI on Strategy Model Interpretability

3.1 How does generative AI improve the interpretability of strategy models?

Developing AI generators, especially in the integration of the causal principles into the depth generative models (DGMs) in the system is considered to be a big step forward on the way to improve the interpretability of strategy models. The architecture of these models enables the embedding of causal mechanisms, thus the prediction goes beyond the observation of data patterns and also gives a deeper understanding of the 'why' which lies behind the predictions, as such providing the knowledge about the underlying processes. The inductive art learning approach plays a significant role in differentiating the generative AI from data-driven models, the latter often act as 'black boxes' which display very limited insights into the problem of how decisions are made in an appropriate way. Hence causal representation learning using DGMs ensures a lot of interpretabilities are embedded in the strategy of choice and selection of the actors. They can not only forecast results but also comprehend the causal relationships that drive these outcomes. The realization of this understanding will enable us to develop campaign strategies that are purposed not only to be effective but also to be responsive to the shortfalls of changing circumstances thus creating an edge or competitive advantage in the dynamic environments [12].

3.2 What are the challenges in interpreting strategy models optimized by generative AI?

Following the exploration of hyperparameter optimization as an important process for boosting AI version overall performance, it turns vital to deal with the inherent challenges in deciphering strategy models optimized via generative AI. One of the primary difficulties lies in the complexity of simulating numerous eventualities, a task that appreciably complicates understanding the capability results of these models [13]. In addition to this, as companies try to exploit generative AI for the purpose of making decisions and improving the efficiency of their operations, understanding its role becomes an overwhelming task given the complex nature of the technology. This challenge is further propagated by the need to integrate the generative AI well into the existing business structures, which is inevitable for correct perception but involves lots of problems [13]. Integrative AI requires a skillful approach to handling and interpreting the richness of the insights it produces. This demonstrates the significance of understanding the predictive nature of its technology and strategic decision making [13].

3.3 How does improved interpretability affect decision-making processes in strategy development?

Building on the foundation of optimizing AI algorithms, the focus shifts in the direction of enhancing decision-making procedures in strategy development through advanced interpretability of generative AI. By developing explanation strategies that might be comprehensible to humans, improved interpretability not only demystifies the decision-making procedure but also guarantees that the strategies evolved are in alignment with the organization's ethical requirements and compliance necessities [12]. This is a technique that is very important to build an environment that will allow the leadership teams to develop ethical ideas concepts and principles so that AI usage can be properly guided and responsible and informed decision-making can be used [14]. Additionally, in machine learning technology, issues related to testing low-risk cases and human supervision can help appropriately and reliably make decisions during strategy development [14]. It implies that financial services companies must conduct their operations with a trend for the future. Companies in this industry must put in place controls and management guidelines for AI usage which is necessary over the current rapidly changing legal framework for AI [14]. As a consequence, the in-built interpretability of the generative AI is not only the source of higher competitiveness strategies but also of ethics and compliance with the regulations.

The research paper showcases the great importance of AI models in the process of strategy making, especially for finding the optimal values of the hyperparameters, but also in aiding the strategic decision-making process. The assessment of Generative AI results in the traditional optimization methods exhibits the closing goal of the generalization of models, which is major for the effectiveness of models when working on unseen data and the generalization it. One of the key strengths of Generative AI is the comprehensive method it employs the process of hyperparameter tuning with the help of techniques such as the Hyperparameter Optimization framework to optimize the accuracy and robustness of the models. The incorporation of built-in interpretability into generative AI systems not only amends the decision-making process but also safeguards ethics and regulation in strategic development implementation. Through enhancing models with queer datasets and fine-tuning several crucial hyper-parameters such as batch size, epochs, and learning rate, generative AIs achieve higher performance grades and their speed of convergence is increased.

Moreover, the discussion focuses on the nature of intelligent AI enhancements as they relate to strategic space definition, content optimization, and traffic maximization due to clever algorithms. The addition of human supervision leads to the usage of risks which can be reduced and incorporated towards the reliability and quality of decisions in the strategy development process. Further, the research presents predictive principles of strategic models integrated with the causal understanding of search space, for significantly enhanced interpretability of the models. In general, results confirm that hyperparameter tuning is an important factor in achieving reliable AI algorithm performance and generative AI is an architectural pillar for the optimization of strategic processes laying the foundation for future improvements of existing algorithm improvements.

References

1. *Fine-tuning Hyperparameters in Generative AI*. (n.d.) retrieved April 12, 2024, from docs.oracle.com
2. *Fine-tuning Models: Hyperparameter Optimization*. (n.d.) retrieved April 12, 2024, from encord.com
3. *Overview of hyperparameter tuning | Vertex AI*. (n.d.) retrieved April 12, 2024, from cloud.google.com
4. *Understanding the Effect of Hyperparameter Optimization ...*. (n.d.) retrieved April 12, 2024, from www.sciencedirect.com
5. *Hyperparameter Optimization in Machine Learning*. (n.d.) retrieved April 12, 2024, from www.linkedin.com
6. *Maximizing AI Performance: A Guide to Optimization*. (n.d.) retrieved April 12, 2024, from medium.com
7. *What are some tools for optimizing AI algorithms?*. (n.d.) retrieved April 12, 2024, from www.linkedin.com
8. *Hyperparameter Tuning*. (n.d.) retrieved April 12, 2024, from www.larksuite.com
9. *Generative AI for SEO: Unveiling the Future of Search Optimization*. (n.d.) retrieved April 12, 2024, from www.upgrow.io/blog/generative-ai-for-seo
10. *The rise of Generative AI: Insights from search trends*. (n.d.) retrieved April 12, 2024, from about.ads.microsoft.com
11. *Will Search Be Generative AI or Blue Links? Actually It's Both*. (n.d.) retrieved April 12, 2024, from www.cmswire.com
12. *On the Challenges and Opportunities in Generative AI*. (n.d.) retrieved April 12, 2024, from arxiv.org/html/2403.00025v1
13. *How to Harness the Potential of Generative AI in Your Business Strategy Frameworks*.

(n.d.) retrieved April 12, 2024, from www.untaylored.com

14. *What every CEO should know about generative AI. (n.d.) retrieved April 12, 2024, from www.mckinsey.com*
15. *R. Ramesh, M. Kannan and M. Seenivasan, "Achievement Estimations of Priority Queue System in Fuzzy Environment", Advances in Mathematical Modelling and Scientific Computing, Trends in Mathematics, Springer Link (Book Chapter),2024, pp. 637-658.*
16. *R. Ramesh and M. Seenivasan, "Analysis of Attainment Estimates of Loss System Queue", Advances in Mathematical Modelling and Scientific Computing, Trends in Mathematics, Springer Link (Book Chapter),2024, pp. 519 – 531.*
17. *K. Sakthivel, N. Paramaguru, R. Ramesh and P. Syamala., " Accomplishment Expedients of Batch Arrival Queuing Model by Fuzzy Ordering Approach ", Advances in Mathematical Modelling and Scientific Computing, Trends in Mathematics, Springer Link (Book Chapter),2024, pp. 487 – 496.*
18. *A. Hari Ganesh, N. Jaimurthi, R. Ramesh and M. Seenivasan, "On testing of Fuzzy Hypothesis for mean and variance using centroid-based new distance functions under symmetric fuzzy environment", Contemporary Mathematics, Vol. 5. Issue 1, December 26, 2023, pp. 60-92, https://doi.org/10.37256/cm.5120243317.*
19. *M. Seenivasan, S. Chandiraleka, H. Manikandan and R. Ramesh, "Single Server Queueing Model with Multiple Working Vacation, Feedback and Catastrophe", 4th International Conference on Material Science and Applications, AIP Conference Proceedings 2822, November 14, 2023,pp.020245-1 – 020245-9,ISBN NO: 978-0-7354-4724-0.*
20. *M. Seenivasan, F. Patricia and R. Ramesh, "Analysis of Single Server Queue with single working vacation subject to Catastrophe", 4th International Conference on Material Science and Applications, AIP Conference Proceedings 2822, November 14, 2023,Pp.020246-1to 020246-6,ISBN NO: 978-0-7354-4724-0.*
21. *R. Ramesh and M. Seenivasan, "Cost Appraises of a Phosphorescent Bulk Arrival Queueing system by Wingspans Fuzzy Ranking Approach", Stochastic Processes and Their Applications in Artificial UIntelligence chapter 5, Pp. 50-64 ACIR Book Series: ISSN NO: 2327-0411 (Scopus).*
22. *P. Syamala, R. Ramesh, M. Seenivasan and R. Singaravel, "3D Based CT Scan Retrial Queuing Models by Fuzzy*
23. *Ordering Approach", 2023 Second International Conference on Electrical, Electronics, Information and Communication Technologies (ICEEICT), Trichirappalli, India, 2023, Pp. 01-05,(Scopus).*
24. *P. Gnaanachandra, A.M. Kumar, M. Seenivasan and R. Ramesh, "On Generalization of Fuzzy Topological Groups and Modelling Robotic Crash*",IEEE Xplore, 2023 Second International Conference on Electrical, Electronics, Information and Communication Technologies (ICEEICT), Trichirappalli, India 2023, Pp.1-8, DOI: 10.1109/ICEEICT56924.2023.10157226 (Scopus).*
25. *R. Ramesh and M. Seenivasan, "Discouraged Arrivals Queuing System in Inter valued*

type-2 Fuzzy Environment, Recent trends on Type-2 Fuzzy Logic systems: Theory, methodology and Application", Studies in Fuzziness and Soft Computating, Pp. 235-247, 2023, Volume 425, (Springer): ISSN: 1434 – 9922.

26. *R. Ramesh and M. Seenivasan, Performance Analysis of Single Server Low Priority Queue Based on Electronic Transmitter, Lecture Notes in Electrical Engineering, Springer Book Series, (ICAECT 2021), Vol.881,Pp.347-359,June 26th, 2022, ISBN: 978-981-19-1110-1&ISBN 978-981-19-1111-8.*

27. *R. Ramesh and M. Seenivasan, "Achievement expedients of fuzzy queuing models with an unreliable electrical transformer", IEEE Xplore (ICEEICT 2022) Vol. 22, February 2022(Scopus), ISBN:978-1-6654-3647-2.*

28. *Bhaskaran, S. S. (2024). Discovery of contextual factors using clustering. Multimedia Tools and Applications, 1-30.*

29. *Bhaskaran, S. S. (2021). Investigation of student performance with contextual factors using association rules in higher educational institutions (HEIs). In Data Engineering and Intelligent Computing: Proceedings of ICICC 2020 (pp. 431-442). Springer Singapore.*

30. *Bhaskaran, S. S., Al Aali, M., & Lu, K. Contextual Data Mining for Higher Educational Institutions.*

31. *Bhaskaran, S. S. (2017). An Investigation into the Knowledge Discovery and Data Mining (KDDM) process to generate course taking pattern characterised by contextual factors of students in Higher Education Institution (HEI) (Doctoral dissertation, Brunel University London).*

32. *Bhaskaran, S. S. (2021). Investigation of factors affecting adoption of FinTech in financial institutions. In Innovative strategies for implementing FinTech in banking (pp. 222-241). IGI Global.*

33. *Sailesh, S. B. (2022). Adapting IT governance policies and technology to cope with COVID-19 at Ahlia University. In COVID-19 Challenges to University Information Technology Governance (pp. 359-372). Cham: Springer International Publishing.*

34. *Intelligent context driven data mining to analyse student performance in higher educational institutions (HEIs)*
Bhaskaran, S.S

35. *International Journal of Recent Technology and Engineering, 2019, 8(2), pp. 856–861*

36. *Khalaf, F., & Baskaran, S. S. (2023, March). Predicting Acute Respiratory Failure Using Fuzzy Classifier. In 2023 International Conference on IT Innovation and Knowledge Discovery (ITIKD) (pp. 1-4). IEEE.*

37. *Hasan, Z., & Baskaran, S. S. (2023, March). Propose a Recommender System to Dynamically Align Higher Education Curriculums With 4IR Market Needs. In 2023 International Conference on IT Innovation and Knowledge Discovery (ITIKD) (pp. 1-7). IEEE.*

38. *Bhaskaran, S. S., & Al Aali, M. (2021). Investigation on the Influence of English Expertise on Non-native English-Speaking Students' Scholastic Performance Using Data Mining. In Smart Computing Techniques and Applications: Proceedings of the Fourth*

International Conference on Smart Computing and Informatics, Volume 2 (pp. 9-14). Springer Singapore.

39. *Bhaskaran, S. S., & Aali, M. A. (2021). Data mining model for better admissions in higher educational institutions (heis)—a case study of bahrain. In Advanced Machine Learning Technologies and Applications: Proceedings of AMLTA 2020 (pp. 141-150). Springer Singapore.*

40. *Sailesh, S. B., Lu, K. J., & Al Aali, M. (2016, August). Profiling students on their course-taking patterns in higher educational institutions (HEIs). In 2016 international conference on information science (icis) (pp. 160-167). IEEE.*

41. *Sailesh, S. B., Lu, K. J., & Al Aali, M. (2016, August). Context driven data mining to classify students of higher educational institutions. In 2016 International Conference on Inventive Computation Technologies (ICICT) (Vol. 2, pp. 1-7). IEEE.*

42. *Bhaskaran, S. S., Lu, K., & Aali, M. A. (2017). Student performance and time-to-degree analysis by the study of course-taking patterns using J48 decision tree algorithm. International Journal of Modelling in Operations Management, 6(3), 194-213.*

43. *Bhaskaran, S. S. (2018). Facilitate decision making in higher educational institutions by linking course-taking pattern and student performance characterised by contextual knowledge. International Journal of Society Systems Science, 10(3), 182-200.*