Augmenting High-dimensional Nonlinear Optimization with Conditional GANs

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ABSTRACT

Many mathematical optimization algorithms fail to sufficiently explore the solution space of high-dimensional nonlinear optimization problems due to the curse of dimensionality. This paper proposes generative models as a complement to optimization algorithms to improve performance in problems with high dimensionality. To demonstrate this method, a conditional generative adversarial network (C-GAN) is used to augment the solutions produced by a genetic algorithm (GA) for a 311-dimensional nonconvex multi-objective mixed-integer nonlinear optimization. The C-GAN, composed of two networks with three fully connected hidden layers, is trained on solutions generated by GA, and then given sets of desired labels (i.e., objective function values), generates complementary solutions corresponding to those labels. Six experiments are conducted to evaluate the capabilities of the proposed method. The generated complementary solutions are compared to the original solutions in terms of optimality and diversity. The generative model generates solutions with objective functions up to 79% better, and with hypervolumes up to 58% higher, than the original solutions. These findings show that a C-GAN with even a simple training approach and architecture can, with a much shorter runtime, highly improve the diversity and optimality of solutions found by an optimization algorithm for a high-dimensional nonlinear optimization problem.

[GitHub repository: https://github.com/PouyaREZ/GAN_GA]

CCS CONCEPTS

• Theory of computation → Mathematical optimization.

KEYWORDS

C-GAN, GA, multiobjective optimization, sustainable urban system

1 INTRODUCTION

Mathematical optimization faces challenges when solving highly non-linear and high-dimensional optimization problems [4, 6], since the solution space for these problems is too vast that the optimization algorithm fails to properly explore the optimal solutions of the entire space in a reasonable amount of time [4, 6]. To solve this issue, this paper proposes using conditional generative adversarial networks (C-GANs) to learn the underlying distribution of the solutions generated by the optimization algorithm, and then generating unseen, more optimized solutions to the original optimization problem using the generative model (c.f. [3]). C-GAN consists of two adversarial models, a generator and a discriminator [7]. The generator learns the data distribution of the input solutions to generate new solutions, and the discriminator learns to detect if a solution belongs to the input data distribution or not. The adversarial training as well as conditioning on the data labels enable C-GAN to generate unseen solutions for given desired labels [7].

Research to date on applying GANs to optimization has focused on random generation rather than targeted generation of data points with desired labels [5, 6, 9].

The proposed method is tested on a nonconvex multi-objective mixed-integer nonlinear program (MINLP), which is solved using a genetic algorithm (GA). This optimization problem concerns the sustainable design of the buildings, energy plant, and energy distribution network in an urban district [1, 2] by minimizing the life-cycle cost (LCC) and greenhouse gas emissions (GHG) and maximizing the walkability (WLK) [8] of the district. A C-GAN generates complementary solutions for the optimization problem based on the solutions found by the GA. This paper handles the problem of training the C-GAN on the solutions of the optimization problem as one of multi-variate multiple regression, where the features (independent variables) of the training set are the 10 main integer inputs of the optimization problem, and the labels (dependent variables) are the 3 real-valued objective functions (OFs). The contributions of this work include, (i) a new method for augmenting traditional optimization for highly complex optimization problems, (ii) the first application in the literature of C-GANs to multi-variate multiple regression, and (iii) the first direct application in the literature of C-GANs to mathematical optimization.

2 METHOD

This paper uses a C-GAN (Figure 1) to complement the performance of a genetic algorithm on a high-dimensional nonlinear optimization. The C-GAN trains on the results from the GA, then generates more diverse and more optimized solutions to the optimization problem than the GA has identified. Those generated solutions that satisfy the constraints of the original optimization problem
The generated solutions have produced 79% lower LCCs, 15.0 WLKs of 15.0 (highest possible value of WLK in the studied problem) and 21.0% lower GHGs, LCCs, and WLKs compared to training sets composed of solutions with all three OFs in the best half of the OF values and hypervolume. Nonetheless, in the third and fourth experiments, the generator has not generated solutions with better OF values than those of the entire original solutions in the FullData experiment. This probably indicates that the original optimization algorithm has discovered solutions with OF values close to their global optima.

The C-GAN has achieved these improvements in less than 3% of the time needed to run the original optimization method. These results speak to the promise of using generative models, specifically C-GANs, for improving the performance of optimization algorithms, like genetic algorithms, for high-dimensional optimization.

This paper also demonstrates that C-GANs, even with simple architectures and small training iterations on low-quality solutions, can significantly improve the results of complex optimization problems.

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REFERENCES

[1] Robert E Best, Robert E Best, Forest Flager, and Michael D Lepech. 2015. Modeling and optimization of building mix and energy supply technology for urban districts. Applied energy 159 (2015), 161–177.
[2] Robert E Best, P Rezaadze Khalidbacthi, and Michael D Lepech. 2020. A novel approach to district heating and cooling network design based on life cycle cost optimization. Energy 194 (2020), 116837.
[3] Paidamoyo Chapfuwa, Chenyang Tao, Chunyuan Li, Courtney Page, Benjamin Goldstein, Lawrence Carin Duke, and Ricardo Henao. 2018. Adversarial time-to-event modeling. In International Conference on Machine Learning. PMLR, 735–744.
[4] Stephen Chen, James Montgomery, and Antonio Bohfle-Rohler. 2015. Measuring the curse of dimensionality and its effects on particle swarm optimization and differential evolution. Applied Intelligence 42, 3 (2015), 514–526.
[5] Yi-nan Guo, Jianjiao Ji, Ying Tan, and Shi Cheng. 2020. Multi-objective Combinatorial Generative Adversarial Optimization and Its Application in Crowdsensing. In International Conference on Swarm Intelligence. Springer, 423–434.
[6] Cheng He, Shuhua Huang, Ran Cheng, Kay Chen Tan, and Yaqiu Xu. 2020. Evolutionary multiobjective optimization driven by generative adversarial networks (GANs). IEEE transactions on cybernetics (2020).
[7] Mehdiz Mirza and Simon Osindero. 2014. Conditional generative adversarial nets. arXiv preprint arXiv:1411.1784 (2014).
[8] Walk Score. 2011. Walk score methodology. Walk Score, Seattle, USA.
[9] Shipu Zhao and Fengqi You. 2020. Distributionally robust chance constrained programming with generative adversarial networks (GANs). AIChE Journal 66, 6 (2020), e16963.