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Editorial

Pathway of Mathematical Optimization Research: From Specialized Problems and Opaque Algorithms to Standardized Problems and Transparent Algorithms

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Mathematical optimization (MO) formulates a decision problem with a maximization or minimization objective and a set of constraints on the decision variables, and designs an algorithm to find the best solution. MO dates back centuries [1], but modern MO—initially and frequently still called mathematical programming—was motivated by the need for efficient planning and scheduling of military resources in World War II. A landmark early achievement and the foundation of a huge number of subsequent developments is the simplex algorithm invented by George Dantzig in the mid-20th century to solve linear optimization problems. To date, a large variety of problems have been solved by myriad MO algorithms; see the papers published in the MO application journal *INFORMS Journal on Applied Analytics* and algorithm journals *Mathematical Programming* and *Operations Research*.

Nevertheless, the MO field is far less prominent than other related fields, such as computer vision. For instance, virtually no MO researchers have more than 100,000 citations in Google Scholar, whereas as of 28 July 2022, the three 2018 Turing Awardees, Yoshua Bengio, Geoffrey Hinton, and Yann LeCun, all in the field of computer vision, had 0.54, 0.59, and 0.25 million citations, respectively, in Google Scholar, and a single computer vision paper proposing a deep residual neural network published in 2016 [2] has been cited over 120,000 times in Google Scholar. The contrast between the two fields has led us to consider two questions: why is the MO field less prominent than other fields, and how can the MO community make a change to increase its impact?

We argue that there are two main reasons for the limited impact of the MO field. The first reason relates to specialized problems—most MO researchers attempt to solve problems that differ from those solved by other people. A notable example is the vehicle routing problem [3], which has resulted in an astronomical number of variants. Typing "vehicle routing problem" in Google Scholar retrieves more than half a million entries. As a result, it is difficult for journal editors and reviewers to assess the contribution of a new submission because they find it difficult to compare its contribution with that of the literature. Even worse, practitioners confronting a vehicle routing problem cannot identify the most useful study for their purposes, as they face an overwhelming choice of studies. The other reason for the limited impact of the MO field is opaque algorithms. The codes of most algorithms in published papers are not publicly accessible; as a result, although readers can learn the main concept of the algorithms from the papers, they cannot reproduce all the details. An example from maritime transportation is the shipping service network design problem [4,5], which witnessed the frustrations from industry and its tremendous difficulty in theoretical advancement of solution algorithms due to the lack of code sharing and incremental iterations of algorithms. These two reasons for the limited impact of MO form a vicious circle. Because researchers cannot access the codes of other algorithms, they cannot justify that they have improved other algorithms and hence they tend to solve new specialized problems rather than trying to improve existing algorithms. In addition, because researchers solve specialized problems, sharing codes is of limited value to the community and hence few publishers and journal editors have the incentive to do so.

We believe that MO research should adopt a pathway toward standardized problems and transparent algorithms, following a similar paradigm in the computer vision field. For instance, in the computer vision field, a standard problem is the development of more accurate algorithms for classifying images in the ImageNet dataset [6] and COCO dataset [7]. A large number of computer vision researchers work on this standard problem and, as a result, it is easy for the community to compare different algorithms, to work on and improve those that are most accurate, and to apply or adapt the algorithm that represents the most state-of-the-art solution to practical problems. All of the papers that propose new algorithms must share their codes for testing, for other researchers to further work on, and for practical use. Enlighted by the practices of the computer vision field, we argue that the MO field should establish a few sets of standard problems, e.g., typical vehicle routing problems, inventory management problems, supply chain management problems, and location routing problems, among others, and that many researchers, especially prominent researchers, should work on these problems, make their algorithmic codes public, and continuously improve their own and other researchers' cutting-edge algorithms. If a data-driven MO problem is studied, it is also encouraged to share the code for data science and the trained data science models. For instance, in maritime transportation, MO researchers are starting to share their computer code and trained machine learning models for ship fuel efficiency analysis in GitHub [8–10]. In this way, the most efficient algorithms can be easily identified, researchers can identify the boundaries of knowledge, and practitioners can quickly adopt a state-of-the-art algorithm and adapt it to their own problems.

With standardized problems and transparent algorithms, the MO community can work together to expand the boundaries of knowledge, make MO knowledge freely accessible, increase the community's visibility in other research fields, both within the industry, and with the public, and, as a result, have a significant impact on society.

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