The 2024 ACM SIGEVO Outstanding Contribution Awardees

The SIGEVO Outstanding Contribution Award recognizes remarkable contributions to Evolutionary Computation (EC) when evaluated over a sustained period of at least 15 years. These contributions can include technical innovations, publications, leadership, teaching, mentoring, and service to the EC community.

In 2024, two striking members of our community received this recognition: Dr. Anne Auger, and Prof. Dr. Franz Rothlauf. To celebrate these distinctions, Anne and Franz kindly answered our questions reflecting on their contributions and views on evolutionary computation as well as their advice to young researchers in the field.

Dr. Anne Auger

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Q1: Which are the service, editorial, leadership, mentoring or other contributions you are most proud of?
I am really proud of having served as General Chair for GECCO in 2019. I am also deeply honored to serve in the business committee of SIGEVO and to have been invited early in my career to join the SIGEVO board.

Equally fulfilling has been my role as a mentor to students. Guiding PhD students through their research endeavors is particularly rewarding. I also take great pride in mentoring Master's-level students, especially those learning about derivative-free optimization and evolutionary computation. Helping them grasp the foundational and advanced concepts of these areas while witnessing their enthusiasm and intellectual curiosity, is an experience that continually reinvigorates my own passion for these fields.

Q2: Which are your most significant technical contributions to Evolutionary Computation (EC)?

I am a mathematician by training. I started to study the theoretical convergence of Evolution Strategies before they became known outside the EC community.

Some of my most significant contributions relate to proving the linear convergence of adaptive evolution strategies. First, during my PhD, on functions with spherical level sets for a specific step-size adaptive algorithm [1]. It turned out that the technique I developed and used connecting the linear convergence of an ES to analyzing the stability of normalized Markov chains could be greatly generalized to larger classes of functions including in particular non quasi-convex functions and larger classes of algorithms [2]. This allowed us to obtain linear convergence proofs for state-of-the-art step-size adaptive algorithms [3]. This was done in collaboration with Nikolaus Hansen and our PhD student Cheikh Touré.

Together with Youhei Akimoto and Tobias Glasmarchers we also understood how to directly analyze the non-normalized Markov chains underlying adaptive ES and provide hitting time bounds pertaining to linear convergence [4,5].

These results specifically pertain to step-size adaptive Evolution Strategies, marking a significant step forward in theoretical analysis. Our ultimate objective, however, has always been to extend such analyses to algorithms with covariance matrix adaptation, a more complex and powerful class of ES. I am pleased to share that we have recently succeeded in proving linear convergence for CMA-ES, a milestone achieved in particular thanks to the exceptional Ph.D. work of Armand Gissler. While these findings are still in the process of being published, they represent a major advancement.

I also worked in multi-objective optimization formalizing and analyzing the optimization goal of hypervolume-based optimization algorithms [6,7].

Finally, an additional significant contribution lies in the area of benchmarking methodology. This work began as a collaborative effort with Nikolaus Hansen and some of our students back in 2009, well before benchmarking became a prominent focus in the

Evolutionary Computation (EC) community. Together, we developed and implemented this methodology within the COmparing Continuous Optimizers platform [8] which provides a seamless way to benchmark both deterministic and stochastic optimization algorithms, enabling direct performance comparisons with previously benchmarked methods. The results and data are openly accessible at COCO's data archive (see https://numbbo.it/data-archive/), fostering transparency and collaboration in the field.

As the project progressed, we were fortunate to have Dimo Brockhoff, Olaf Mersmann and Tea Tušar join the core COCO development team, bringing their expertise and further enhancing the platform's capabilities. Their contributions have been instrumental in advancing COCO into the robust benchmarking tool it is today.

Q3: What are the current open problems, or topics where you think there are opportunities for substantial contributions in our field?

I see opportunities for substantial contributions in areas that are very relevant in practice but to a great extent not yet deeply explored. I think for instance of mixed-integer/discrete optimization with/without constraints and the combination of this with multi-objective optimization. Those subdomains are much less mature than unconstrained continuous optimization where it is now accepted that CMA-ES is a powerful algorithm that is likely hard to improve further.

Q4: Do you think the current AI hype is an opportunity or a threat for EC?

I see it as a great opportunity. It attracts more students for topics connected closely or loosely to AI, it brings more funding opportunities.

It also helps that more and more people from the optimization community in particular accept that it is fine if practice and algorithm design are ahead of theory and even realize that it is actually an advantage. It has always been in the DNA of research in EC that we should have algorithms that provide solutions to (real/difficult) problems before having algorithms where we can prove (mathematically) that they work. I believe this approach has been a critical factor in the success of many EC methods, despite the challenges it has occasionally presented. However, I feel that this era of scepticism is to a great extent behind us and that the worldwide acceptance of how impactful AI methods are coined (practice before theory) has been helpful for the EC community.

Q5: How do you view the visibility of the EC community in the larger computer science community?

I am convinced that the visibility and recognition of methods originating from the field of Evolutionary Computation (EC) have significantly increased in recent years.

This is evident not only in evolutionary multi-objective optimization but also in single-objective continuous optimization, which is the area I am most familiar with. A prominent example is the CMA-ES algorithm, which has gained substantial recognition beyond the EC community. Its widespread adoption is reflected in its remarkable usage statistics, with over 70 million downloads of its source code, as tracked by platforms such as pepy.tech for CMA and pepy.tech for CMAES. This algorithm has found applications in artificial intelligence, where it is integrated into hyperparameter optimization frameworks and is extensively cited in papers presented at leading AI conferences.

Evolution Strategies (ES) are also achieving greater visibility within the mathematical optimization community. Papers on ES have been published in highly respected venues for mathematical optimization, such as the *SIAM Journal on Optimization* and the *Journal of Global Optimization* [2,3,5], further underscoring their growing relevance and acceptance in this domain.

Our work on benchmarking methodologies, particularly through the development of the COCO platform, is another example of EC research making an impact beyond its traditional boundaries. The support and momentum provided by the BBOB workshops at GECCO were instrumental in advancing these efforts, and the outcomes have been recognized and published outside the EC community as well.

These examples, which I am closely connected to through my own work, highlight the expanding influence of EC methods. However, I am confident that there are many more examples of such growth and visibility across the broader EC landscape!

Q6: What advice do you have for the younger generation of researchers in the field?

The Evolutionary Computation (EC) community is notably inclusive and open-minded, creating an excellent opportunity for innovation. This environment makes it more likely for original and unconventional ideas proposed by young researchers to gain acceptance and recognition compared to other, more rigid scientific communities, which is great! However, this open-mindedness can sometimes result in the acceptance of work of suboptimal quality.

Resist the temptation to publish vague or poorly executed ideas, or to present “novel algorithms” that merely make trivial adjustments—such as tweaking a minor parameter/adding an irrelevant component—without offering meaningful improvements. In the long term, publishing such works will not help you. Be critical during the entire process to obtain a scientific result: challenge your ideas, ask friends to challenge them, find out why and where they work/do not work and improve what does not work! Be welcoming if someone finds a problem in your algorithm: it will allow you to improve it and make it stronger!

References

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Prof. Dr. Franz Rothlauf

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Q1: Which are the service, editorial, leadership, mentoring or other contributions you are most proud of?

I am proud of serving for a long time as treasurer as well as chair of SIGEVO. During this time, the most challenging task was dealing with the Covid pandemic. During a few months continuous, rapid, and complete change was necessary to adapt the conferences to the changing environment. I am very happy that GECCO did very well through this time and even became a better and stronger conference after all these challenges. Especially I am happy that the hybrid character of GECCO also allows remote presentations which makes GECCO a much more inclusive and much more environment-friendly event. My hope is that not only SIGEVO but the whole scientific community continues this path towards environment-friendly events with much less physical traveling as continuously burning oil will have (and probably already has) a devastating effect on our way of life.

Q2: Which are your most significant technical contributions to Evolutionary Computation (EC)?

First, studying the combination of representation and operators and getting a better understanding on how locality and redundancy affects the performance of EC. This is not only relevant for problems of fixed size but (even more) genetic programming suffers a lot from representation-related problems. Besides my book on representations from 2010 [1], where I view the parts on redundancy as most relevant. There are many subsequent publications such as [3] that analyze the problems of EAs with
low locality.

Second, I view the use of machine learning models that replace the traditional search operators as a promising research field. Here, I see [2] as one of my most significant technical contributions.

Q3: What are the current open problems, or topics where you think there are opportunities for substantial contributions in our field?

We have a good understanding of the possibilities (but also limitations) of EC for problems of fixed size. For such problems, EC works well, and a successful application of EC “only” requires a problem-specific adaption of the used optimization method. However, the situation is completely different for GP, which still (after 30 years of research) does not work well and often acts as random search. All current approaches only work for small and toy problems, but not for larger problems of reasonable size. To me, this is mainly because the way we represent solutions in GP creates landscapes that are very rugged, and which cannot be efficiently searched by guided search methods like GP [3]. I see the development of approaches that lead to smoother search spaces as one of the largest open problems in our field.

Q4: Do you think the current AI hype is an opportunity or a threat for EC?

I see it as a great chance. Adaption is very relevant for machine learning approaches and there is more to find for ML researchers in EC than stochastic gradient descent 😉I am convinced that the machine learning models that came up in the last five years will have a large impact on optimization as they directly learn from training data what are good solutions for many real-world problems. This leads to solutions that are more attractive to use for humans in comparison to the traditional optimization approaches which require complicated problem modelling including the design of unrealistic fitness functions.

Unfortunately, currently ML people often re-invent many of the things that are established knowledge in EC, however, I am optimistic that on the long run there will be a fruitful cooperation between ML and EC researchers. And I clearly see the AI hype (as soon as it is not a hype any more) as an opportunity.

Q5: How do you view the visibility of the EC community in the larger computer science community?

We are not where we should be, but we are doing better in the last years. As side effect of the AI hype, the larger computer science community also accepts that neural networks (which are nature inspired) and also EC (which is also nature inspired) might do a good job for some tasks. The computer science community understands that EC is not just applying heuristics but there is a profound theoretical understanding and there are many problems that can be solved well using metaheuristics.

Q6: What advice do you have for the younger generation of researchers in the field?
Do not try to maximize your paper output or h-index, but enjoy what you are doing. Of course, especially young researchers have to fulfil expectations (at least to get tenured 😉 but it would be nice if matching the expectations from the outside could be fun. We currently live in a a world that becomes very digital and CS (and of course EC and ML) are one of the drivers for change. This is exciting!

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