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Intelligent Numerical Design of Components and their Production Processes

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Numerical optimization methods are an important tool in the design of both individualized components and their respective production processes. Despite this vital role of numerical optimization, the creative aspects of the design process are still left to the human designer. In fact, for centuries, creativity has been perceived as a purely human attribute, if not even a defining element of a human being. With recent advances in Artificial Intelligence (AI), this perception has been shaken to its roots. Bit by bit, creative rational agents have clawed their way into our daily lives. Inspired by these advancements, we will explore different ways in which Machine Learning algorithms can help to improve numerical design in terms of (1) geometry parameterization and (2) optimization strategies.

To this end, we will demonstrate how Variational Autoencoders (VAE) can be employed to learn low-dimensional, yet feature-rich shape representations. A VAE can discover common properties among a variety of shapes without an explicit, human-made parametric representation of the original designs. A VAE is a neural network architecture that learns the underlying structure of a 3D shape in an unsupervised fashion. It will infer a latent, hierarchical representation of objects. This approach promises significant enhancements in both performance and variety of attainable shapes. The resulting geometric representation is then included into a shape-optimization framework.

Furthermore, we will explore the potential of Reinforcement Learning (RL) as an optimization strategy. RL is based on trial-and-error interaction of an agent with an environment. As such, RL can be characterized as experience-driven, autonomous learning. For each interaction, the agent is informed about a reward and the subsequent state of the environment, but there is no information about long-term interests as classical optimization algorithms would provide. Instead, the strategy needs to be acquired by the algorithm. While not necessarily superior to classic optimization algorithms (such as gradient-based approaches) for one single optimization problem, based on existing literature, we expect RL techniques to thrive when recurrent optimization tasks arise.