Deep generative models for engineering design

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Summary

In this thesis, we have systematically studied deep generative models to better generate engineering designs in terms of plausibility, efficiency, reliability and dimensionality for industrial purposes. We discuss the background of this paper, the development and evolution of DGMs, and the latest advances in the application of DGMs in engineering design in Chapter 1. In Chapter 2, our research on noise scheduling of diffusion models highlights the importance of the focusing range of noise levels during both training and sampling in improving the plausibility of generated designs. We propose a data analysis method that is able to help with determining the focusing range for a given dataset. In developing diffusion models for better plausibility, most widely-implemented metrics (e.g., FID, KID, LPIPS) do not align well with human judgments in evaluating the plausibility, which makes it challenging to rank and select target DGMs. To address this issue, in Chapter 3, we subsequently build a new evaluation method driven by denoised autoencoder for better assessing the generated structural information. After successfully studying the performance of DGMs on 2D structural designs, our work moves on to the 3D design domain. In Chapter 4, we first delve into the field of mesh generation and we design a SVD-based encoding pipeline, with which we are able to reduce the source high-dimension shape into low-dimension spectral features in a learning-free manner. These spectral features are proven to be trainable with DGMs, hereby enabling DGMs on high-dimension data without training an autoencoder. In Chapter 5, we move to the field of CAD generation tasks and tackle the challenge of direct generation of B-Rep solids with surfaces represented in NURBS. Finally in Chapter 6, we bring insights of the application of our developed methods in real-world industrial design cases.

This thesis presents our pioneering attempts at bridging the gap between modern DGM research and industrial applications. While our work addresses the performance of DGMs in terms of efficiency and reliability in generating engineering designs, our proposed methods have also brought great contribution to the general DGM field. More precisely, our methods are evaluated on open-source datasets widely implemented in the general DGM field and compared to current state-of-the-art with sufficient assessments. However, a gap persists for industrial applications, with design data in industrial cases presenting exponentially more complicated structural information than general datasets and a much better representation and generation framework are required. In the following, we identify current limitations, suggest potential ideas to address the limitations, and consider future research directions of DGMs, particularly in industrial generative design field.