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# Generative Design of Authentic 3D Shapes from 2D Sketches Using Target-Embedding Variational Autoencoder

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We introduce an approach for 3D shape generation from 2D sketches in support of creative engineering design. Specifically, we build a novel target-embedding variational autoencoder (TEVAE) neural network to enable the sketch-to-3D transformation. As shown in Figure 1, the TEVAE network consists of two modules: 1) A training module with an $E^2D$ network that has two encoders and one decoder. 2) An application module performing generative design, such as shape reconstruction, interpolation, and random generation of new 3D shapes, and 3D shape prediction from 2D contour sketches. We introduce a two-stage training strategy to train the TEVAE. In Stage 1, we aim to acquire good latent representations of the original authentic 3D shapes. So, for any arbitrary input, the neural network can reconstruct a 3D shape that is as close as that input target. In Stage 2, the neural network is trained to minimize the distance between representations encoded from the source shapes extruded from 2D sketches and those latent representations obtained from Stage 1. So, for any extrusion input, the neural network can predict an authentic 3D shape from the latent space built in Stage 1.

Sketching plays an essential role in triggering creative ideas and exploring emergent concepts central to most design activities, especially during the conceptual design phase [1]. But, in the later design stages, such as embodiment design and engineering analysis, a 3D shape (e.g., a CAD model) is often required to more accurately evaluate the design's engineering performance. On the one hand, from conceptual design in 2D to engineering analysis in 3D, a long design process is needed. If one particular design turns out to have an unsatisfactory engineering performance, this design option would not be adopted for further development, even if it could be visually aesthetic. Then, the designer has to go back to the early design stage for design iteration and refinement. Obviously, the cost of doing such iterations is very expensive.

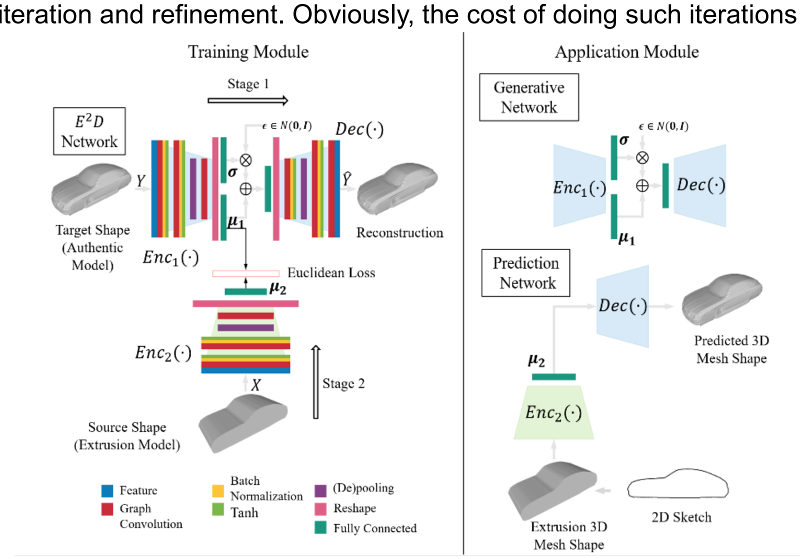


**Figure 1:** The target-embedding variational autoencoder (TEVAE) neural network

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On the other hand, designers typically need to draw many sketches to capture design inspirations in the conceptual design stage. When generative design tools are handy, thousands of visual concepts and alternatives can be obtained more efficiently. But, it would be unrealistic to manually construct the 3D model of every concept from the 2D sketches. So, the question is, can we predict and automatically generate the 3D shapes just based on the 2D sketches so as to advance the performance-driven design decision-making to the early design stage? The answer to this question will obviously have two benefits. First, all 2D sketches generated during the conceptual design phase can be automatically evaluated against the desired engineering performance. So, the designs that would have a better performance will not be ruled out too early when performance-driven decisions are not yet obtained. Second, such sketch-to-3D design automation will greatly promote designers' creativity and help reduce the risk of long and tedious inter-stage design iterations, thereby improving their willingness to invest additional efforts for better ideation.

However, automatically constructing 3D models directly from 2D sketches is challenging because it is essentially an ill-defined problem due to insufficient and imperfect information from simple strokes [2]. Geometric-based methods have been widely explored to solve this problem. These methods are usually developed based on assumptions of geometric constraints in sketches and 3D geometry, such as convexity, cross-section lines, and orthogonality, which requires users to have a clear mind on the desired 3D model in advance, so the accurate sketch can be created as input. This inevitably increases designers' cognitive load. Recently, data-driven approaches, such as deep learning techniques, have been explored to tackle this sketch-to-3D problem. Our approach falls into this category and is established based on a deep generative mesh variational autoencoder [3] with a structure inspired by the target-embedding autoencoder (TEA) [4]. Our approach features both generative and predictive functions. In a case study on 3D car shape design, we demonstrate the utility and effectiveness of the proposed approach. Figure 2(a) shows the generative design results of various car body shapes, and Figure 2(b) shows how authentic 3D car models can be predicted purely based on the 2D sketches. The resulting 3D car shapes are in the format of watertight polygon mesh with high-quality surface details ready for downstream engineering evaluation (e.g., drag coefficient) and prototyping (e.g., 3D printing).

With this technique, designers can more efficiently explore the design space, and their creative design ideas are expected to be further stimulated. In the next step, we plan to build a user interface to allow human-computer interactions, including hand drawing of 2D sketches on touchscreen and modification to the generated 3D shapes based on users' own preferences.

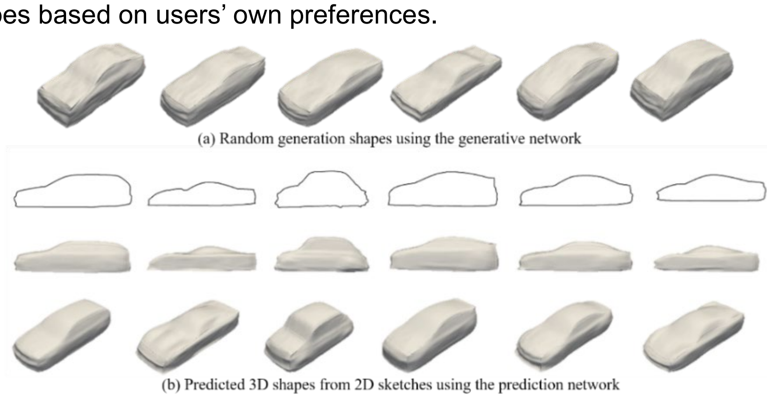


**Figure 1:** The results of the 3D shape generation and sketch-to-3D prediction

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