DeepSVG: A Hierarchical Generative Network for Vector Graphics Animation

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Abstract

Scalable Vector Graphics (SVG) are ubiquitous in modern 2D interfaces due to their ability to scale to different resolutions. However, despite the success of deep learning-based models applied to rasterized images, the problem of vector graphics representation learning and generation remains largely unexplored. In this work, we propose a novel hierarchical generative network, called DeepSVG, for complex SVG icons generation and interpolation. Our architecture effectively disentangles high-level shapes from the low-level commands that encode the shape itself. The network directly predicts a set of shapes in a non-autoregressive fashion. We introduce the task of complex SVG icons generation by releasing a new large-scale dataset along with an open-source library for SVG manipulation. We demonstrate that our network learns to accurately reconstruct diverse vector graphics, and can serve as a powerful animation tool by performing interpolations and other latent space operations. Our code is available at \url{https://github.com/alexandre01/deepsvg}.

Figure 1: DeepSVG generates vector graphics by predicting draw commands, such as lines and Bézier curves. Our latent space allows meaningful animations between complex vector graphics icons.

1 Introduction

Despite recent success of rasterized image generation and content creation, little effort has been directed towards generation of vector graphics. Yet, vector images, often in the form of Scalable Vector Graphics [23] (SVG), have become a standard in digital graphics, publication-ready image assets, and web-animations. The main advantage over their rasterized counterpart is their scaling ability, making the same image file suitable for both tiny web-icons or billboard-scale graphics. Generative models for vector graphics could serve as powerful tools, allowing artists to generate, manipulate, and animate vector graphics, potentially enhancing their creativity and productivity.

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We address the task of learning generative models of complex vector graphics. To this end, we propose a Hierarchical Transformer-based architecture that effectively disentangles high-level shapes from the low-level commands that encode the shape itself. Our encoder exploits the permutation invariance of its input by first encoding every shape separately, then producing the latent vector by reasoning about the relations between the encoded shapes. Our decoder mirrors this 2-stage approach by first predicting, in a single forward pass, a set of shape representations along with their associated attributes. These vectors are finally decoded into sequences of draw commands, which combined produce the output SVG image. A schematic overview of our architecture is given in Fig. 2.

Contributions Our contributions are three-fold: 1. We propose DeepSVG, a hierarchical transformer-based generative model for vector graphics. Our model is capable of both encoding and predicting the draw commands that constitute an SVG image. 2. We perform comprehensive experiments, demonstrating successful interpolation and manipulation of complex icons in vector-graphics format. Examples are presented in Fig. 1. 3. We introduce a large-scale dataset of SVG icons along with a framework for deep learning-based SVG manipulation, in order to facilitate further research in this area. To the best of our knowledge, this is the first work to explore generative models of complex vector graphics, and to show successful interpolation and manipulation results for this task.

2 Related Work

Previous works [20, 14] for icon and logo generation mainly address rasterized image, by building on Generative Adversarial Networks [3]. Unlike raster graphics, vector graphics generation has not received extensive attention yet, and has been mostly limited to the simplified task of sketch generation, using the 'Quick, Draw!' [23] dataset. SketchRNN [5] was the first Long Short Term Memory (LSTM) [6] based variational auto-encoder (VAE) [7] addressing the generation of sketches. More recently, Sketchformer [19] has shown that a Transformer-based architecture enables more stable interpolations between sketches, without tackling the generation task. One reason of this success is the ability of transformers [24] to more effectively represent long temporal dependencies.

SVG-VAE [11] was one of the first deep learning-based works that generate full vector graphics outputs, composed of straight lines and Bézier curves. However, it only tackles glyph icons, without global attributes, using an LSTM-based model. In contrast, we consider the hierarchical nature of SVG images, crucial for representing and generating complex vector graphics, such as icons. Fig. 2 compares previous one-stage autoregressive approaches [5, 11, 19] to our hierarchical architecture. Our work is also related to the very recent PolyGen [16] for generating 3D polygon meshes using sequential prediction vertices and faces using a Transformer-based architecture.
Figure 3: Samples from the SVG-Icons8 dataset in vector graphics format. Although icons have similar scale and style, they have drastically diverse semantic meanings, shapes and number of paths.

3 DeepSVG

Here, we introduce our DeepSVG method. First, we propose a dataset of complex vector graphics and describe the SVG data representation in Sec. 3.1. We describe our learned embedding in Sec. 3.2. Finally, we present our architecture in Sec. 3.3 and training strategy in Sec. 3.4.

3.1 SVG Dataset and Representation

SVG-Icons8 Dataset. Existing vector graphics datasets either only contain straight lines [22] or are constrained to font generation [11]. These datasets therefore do not pose the challenges associated with the generation of complex vector graphics, addressed in this work. Thus, we first introduce a new dataset, called SVG-Icons8. It is composed of SVG icons obtained from the https://icons8.com website. In the compilation of the dataset, we carefully considered the consistency and diversity of the collected icons. This was mainly performed by ensuring that the vector graphics have similar scale, colors and style, while capturing diverse real-world graphics allowing to learn meaningful and generalizable shape representations. In summary, our dataset consists of 100,000 high-quality icons in 56 different categories. Samples from the dataset are shown in Fig. 3. We believe that the SVG-Icons8 dataset, which is to be released upon acceptance, will serve as a challenging new benchmark for the growing task of vector graphics generation and representation learning.

Vector Graphics and SVG. In contrast to Raster graphics, where the content is represented by a rectangular grid of pixels, Vector graphics employs in essence mathematical formulas to encode different shapes. Importantly, this allows vector graphics to be scaled without any aliasing or loss in detail. Scalable Vector Graphics (SVG) is an XML-based format for vector graphics [23]. In its simplest form, an SVG image is built up hierarchically as a set of shapes, called paths. A path is itself defined as a sequence of specific draw-commands (see Tab. 1) that constitute a closed or open curve.

Data structure. In order to learn deep neural networks capable of encoding and predicting vector graphics, we first need a well defined and simple representation of the data. This is obtained by adopting the SVG format with the following simplifications. We employ the commands listed in Tab. 1. In fact, this does not significantly reduce the expressivity since other basic shapes can be converted into a sequence of Bézier curves and lines. We consider a Vector graphics image \( V = \{ P_1, \ldots, P_{N_P} \} \) to be a set of \( N_P \) paths \( P_i \). Each path is itself defined as a triplet \( P_i = (S_i, f_i, v_i) \), where \( v_i \in \{0, 1\} \) indicates the visibility of the path and \( f_i \in \{0, 1, 2\} \) determines...

Table 1: List of the SVG draw-commands, along with their arguments and a visualization, used in this work. The start-position \((x_1, y_1)\) is implicitly defined as the end-position of the preceding command.

| Command | Arguments | Description | Visualization |
|---------|-----------|-------------|---------------|
| <SOS>   | \(\emptyset\) | 'Start of SVG' token. | |
| M (MoveTo) | \(x_2, y_2\) | Move the cursor to the end-point \((x_2, y_2)\) without drawing anything. | \((x_2, y_2)\) |
| L (LineTo) | \(x_2, y_2\) | Draw a line to the point \((x_2, y_2)\). | \((x_2, y_2)\) |
| C (Cubic Bézier) | \(q_{x_1}, q_{y_1}\) \(q_{x_2}, q_{y_2}\) \(x_2, y_2\) | Draw a cubic Bézier curve with control points \((q_{x_1}, q_{y_1})\), \((q_{x_2}, q_{y_2})\) and end-point \((x_2, y_2)\). | \((x_2, y_2)\) |
| Z (ClosePath) | \(\emptyset\) | Close the path by moving the cursor back to the path’s starting position \((x_0, y_0)\). | \((x_0, y_0)\) |
| <EOS> | \(\emptyset\) | 'End of SVG' token. | |
the fill property. Each \( S_i = (C_i^1, \ldots, C_i^{N_C}) \) contains a sequence of \( N_C \) commands \( C_i^j \). The command \( C_i^j = (c_i^j, X_i^j) \) itself is defined by its type \( c_i^j \in \{\text{\textless~$\text{SOS}$~$\text{\textgreater}$}, m, 1, e, z, \text{\textless~$\text{EOS}$~$\text{\textgreater}$}\} \) and arguments, as listed in Tab. 1. To ensure efficient parallel processing, we use a fixed-length argument list \( X_i^j = (q_{x_1,i}^j, q_{y_1,i}^j, q_{x_2,i}^j, q_{y_2,i}^j, x_{2,i}^j, y_{2,i}^j) \in \mathbb{R}^6 \), where any unused argument is set to \(-1\). Therefore, we also use a fixed number of paths \( N_p \) and commands \( N_C \) by simply padding with invisible elements in each case. Further details are given in appendix.

3.2 SVG Embedding

By the discrete nature of the data and in order to let the encoder reason between the different commands, every \( C_i^j \) is projected to a common continuous embedding space of dimension \( d_E \), similarly to the \textit{de facto} approach used in Natural Language Processing [24]. This enables the encoder to perform operations across embedded vectors and learn complex dependencies between argument types, coordinate values and relative order of commands in the sequence. We formulate the embedding of the SVG command in a fashion similar to [1]. In particular, the command \( C_i^j \) is embedded to a vector \( e_i^j \in \mathbb{R}^{d_E} \) as the sum of three embeddings, \( e_i^j = e_{\text{cmd},i}^j + e_{\text{coord},i}^j + e_{\text{ind},i}^j \). We describe each individual embedding next.

**Command embedding.** The command type (see Tab. 1) is converted to a vector of dimension \( d_E \) using a learnable matrix \( W_{\text{cmd}} \in \mathbb{R}^{d_E \times 6} \) as \( e_{\text{cmd},i}^j = W_{\text{cmd}} \delta_{c_i^j}^j \in \mathbb{R}^{d_E} \), where \( \delta_{c_i^j} \) designates the 6-dimensional one-hot vector containing a 1 at the command index \( c_i^j \).

**Coordinate embedding.** Inspired by works such as PixelCNN [17] and PolyGen [16], which discretize continuous signals, we first quantize the input coordinates to 8-bits. We also include a coordinate embedding.

**Index embedding.** Similar to [1], we finally use a learned index embedding that indicates the index of the command in the given sequence using the weight \( W_{\text{pos}} \in \mathbb{R}^{d_E \times N_C} \) as \( e_{\text{ind},i}^j = W_{\text{ind}} \delta_j \in \mathbb{R}^{d_E} \), where \( \delta_j \) is the one-hot vector of dimension \( N_C \) filled with a 1 at index \( j \).

3.3 Hierarchical Generative Network

In this section, we describe our Hierarchical Generative Network architecture for complex vector graphics interpolation and generation, called DeepSVG. A schematic representation of the model is shown in Fig 1. Our network is a variational auto-encoder (VAE) [7], consisting of an encoder and a decoder network. Both networks are designed by considering the hierarchical representation of an SVG image, which consists of a set of paths, each path being a sequence of commands.

**Feed-forward prediction.** For every path, we propose to predict the \( N_C \) commands \((\hat{c}_i^j, \hat{X}_i^j)\) in a purely feed-forward manner. Our generative model is thus factorized as,

\[
p \left( \hat{V} \mid z, \theta \right) = \prod_{i=1}^{N_p} p(\hat{v}_i \mid z, \theta) p(\hat{f}_i \mid z, \theta) \prod_{j=1}^{N_C} p(\hat{c}_i^j \mid z, \theta) p(\hat{X}_i^j \mid z, \theta),
\]

where \( z \) is the latent vector and \( p(\hat{X}_i^j \mid z, \theta) \) further factorizes into the individual arguments. Note that our approach is conceptually different to the autoregressive strategy used in previous works [5, 11], which learns a model predicting the next command conditioned on the history. We found our approach to lead to significantly better reconstructions and smoother interpolations, as analyzed in Sec. 4.

Intuitively, the feed-forward strategy allows the network to primarily rely on the latent encoding to reconstruct the input, without taking advantage of the additional information of previous commands.

\[\text{ Known as } \text{positional embedding} \text{ in the Natural Language Processing literature [24].}\]
Figure 4: Our Hierarchical Generative Network, DeepSVG. Input paths \( \{ P_i \}_{1}^{N_P} \) are encoded separately using the path encoder \( E^{(1)} \). The encoded vectors are then aggregated using the second encoder \( E^{(2)} \), which produces the latent vector \( z \). The decoder \( D^{(2)} \) outputs the path representations along with their fill and visibility attributes \( \{(\hat{u}_i, \hat{f}_i, \hat{v}_i)\}_{1}^{N_P} \). Finally \( \{\hat{u}_i\}_{1}^{N_P} \) are decoded independently using the path decoder \( D^{(1)} \), which outputs the actual draw commands and arguments.

and arguments. Importantly, a feed-forward model brings major advantages during training, since inference can be directly modeled during training. On the other hand, autoregressive methods \[4, 24\] condition on ground-truth to ensure efficient training through masking, while the inference stage conditions on the previously generated commands.

**Encoder.** To keep the permutation invariance property of the paths set \( \{ P_i \}_{1}^{N_P} \), we first encode every path \( P_i \) independently using path encoder \( E^{(1)} \). More specifically, \( E^{(1)} \) takes the embeddings \( (e^j_i)_{j=1}^{C_j} \) as input and outputs vectors \( (e'_j_i)_{j=1}^{C_j} \) of same dimension. To retrieve the single \( d_E \)-dimensional path encoding \( u_i \), we average-pool the output vectors along the sequential dimension. The \( N_P \) path encodings \( \{u_i\}_{1}^{N_P} \) are then input in encoder \( E^{(2)} \) which, after pooling along the set-dimension, outputs the parameters of a Gaussian distribution \( \hat{\mu} \) and \( \hat{\sigma} \). Note how the index embedding in vector \( e^j_i \) enables \( E^{(1)} \) to reason about the sequential nature of its input while \( E^{(2)} \) maintains the permutation invariance of the input paths. The latent vector is finally obtained using the reparametrization trick \[7\] as \( z = \hat{\mu} + \hat{\sigma} \cdot \epsilon \), where \( \epsilon \sim \mathcal{N}(0, I) \).

**Decoder.** The decoder mirrors the two-stage construction of the encoder. \( D^{(2)} \) inputs the latent vector \( z \) repeatedly, at each transformer block, and predicts a representation of each shape in the image. Unlike the corresponding encoder stage, permutation invariance is not a desired property for \( D^{(2)} \), since its purpose is to generate the shapes in the image. We achieve this by using a learned index embedding as input to the decoder. The embeddings are thus distinct for each path, breaking the symmetry during generation. The decoder is followed by a Fully Connected Network (FCN) that outputs, for each index \( 1 \leq i \leq N_P \), the predicted path encoding \( \hat{u}_i \), filling \( \hat{f}_i \), and visibility \( \hat{v}_i \) attributes. Symmetrically to the encoder, the vectors \( \{\hat{u}_i\}_{1}^{N_P} \) are decoded by \( D^{(1)} \) into the final output path representations \( \{(\hat{C}^1_i, \ldots, \hat{C}^{N_{C_i}}_i)\}_{1}^{N_P} \). As for \( D^{(2)} \), we use learned constant embeddings as input and an FCN to predict the command and argument logits. Detailed descriptions about the architectures are given in the appendix.

**Transformer.** Inspired by the success of transformer-based architectures for a variety of tasks \[19, 10, 1, 25\], we also adopt it as the basic building block for our network. Both the Encoders and the Decoders are Transformer-based. Specifically, as in \[19\], we use \( L = 4 \) layers, with a feed-forward dimension of 512 and \( d_E = 256 \).
3.4 Training Objective

Next, we present the training loss used by our DeepSVG. We first define the loss between a predicted path \((\hat{S}_i, \hat{f}_i, \hat{v}_i)\) and a ground-truth path \((S_i, f_i, v_i)\) as,

\[
L_{i,i}(\theta) = w_{\text{vis}}\ell(v_i, \hat{v}_i) + v_i \cdot \left( w_{\text{ml}}\ell(f_i, \hat{f}_i) + \sum_{j=1}^{N_C} \left( w_{\text{cmd}}\ell(c_i^j, \hat{c}_i^j) + w_{\text{args}}\ell^j_{\text{args},i,i} \right) \right). \tag{3}
\]

Here, \(\ell\) denotes the Cross-Entropy loss. The impact of each term is controlled by its weight \(w\). The losses for filling, commands and arguments are masked when the groundtruth path is not visible. The loss \(\ell^j_{\text{args},i,i}\) over the argument prediction is defined as,

\[
\ell^j_{\text{args},i,i} = 1_{c_j \in \{1, c\}} \left( \ell(x_{2,i}^j, \hat{x}_{2,i}^j) + \ell(y_{2,i}^j, \hat{y}_{2,i}^j) \right) + 1_{c_j = c} \sum_{k \in \{1, 2\}} \ell(q_{2,k,i}^j, \hat{q}_{2,k,i}^j) + \ell(q_{y_k,i}^j, \hat{q}_{y_k,i}^j). \tag{4}
\]

Having formulated the loss for a single path, the next question regards how to this can be used to achieve a loss on the entire prediction. However, recall that the collection of paths in a vector image has no natural ordering, raising the question of how to assign ground-truth paths to each prediction. Formally, a ground-truth assignment \(\pi\) is a permutation \(\pi \in \mathcal{S}_{N_p}\), mapping the path index of the prediction \(i\) to the corresponding ground-truth path index \(\pi(i)\). We discuss two alternatives for solving the ground-truth assignment problem.

**Ordered assignment.** One strategy is to define the assignment \(\pi\) by sorting the ground-truth paths according to some specific criterion. This induces an ordering \(\pi_{\text{ord}}\), which the network learns to reproduce. We found defining the ground-truth assignment using the lexicographic order of the starting location of the paths to yield good results. Given any sorting criterion, the loss is defined as,

\[
L(\theta) = w_{\text{KL}}\text{KL} \left( p_\theta(z) || \mathcal{N}(0, I) \right) + \sum_{i=1}^{N_p} L_{i,\pi_{\text{ord}}(i)}(\theta), \tag{5}
\]

where the first term corresponds to the latent space prior induced by the VAE learning.

**Hungarian assignment.** We also investigate a strategy that does not require defining a sorting criterion. For each prediction, we instead find the best possible assignment \(\pi\) in terms of loss,

\[
L(\theta) = w_{\text{KL}}\text{KL} \left( p_\theta(z) || \mathcal{N}(0, I) \right) + \min_{\pi \in \mathcal{S}_{N_p}} \sum_{i=1}^{N_p} L_{i,\pi(i)}(\theta). \tag{6}
\]

The best permutation is found through the Hungarian algorithm [8][15].

**Training details.** We use the AdamW [12] optimizer with initial learning rate \(10^{-4}\), reduced by a factor of 0.9 every 5 epochs and a linear warmup period of 500 initial steps. We use a dropout rate of 0.1 in all transformer layers and gradient clipping of 1.0. We train our networks for 100 epochs with a total batch-size of 120 on two 1080Ti GPUs, which takes about one day.

![Figure 5: Comparison of interpolations between baseline (top row, in green), one-stage feed-forward (2nd row, in pink), ours – Hungarian (3rd row, in orange) and ours – ordered (bottom row, in blue). Ordered generally leads to the smoothest interpolations. The last two examples show interpolations where Hungarian yields visually more meaningful shape transitions. For a better visualisation of these transitions, paths are colored according to their index (or order for one-stage architectures).](image-url)
Table 2: Human study ablating our DeepSVG model.

| Model                  | Feed-forward | Hierarchical | Matching | 1st rank % | Average rank |
|------------------------|--------------|--------------|----------|------------|--------------|
| Baseline               |              |              |          | 9.7        | 3.26         |
| One-stage feed-forward | ✓            |              |          | 19.5       | 2.40         |
| Our – Hungarian        | ✓            | ✓            | Hungarian| 25.8       | 2.29         |
| Our – Ordered          | ✓            | ✓            | Ordered  | 44.8       | 1.99         |

4 Experiments

We validate the performance of our DeepSVG method on the introduced SVG-Icons8 dataset. We also demonstrate results for glyph generation on the SVG-Fonts dataset. Further experiments and interactive examples are presented in the supplementary material.

4.1 Ablation study

We ablate our model by conducting a human study. As baseline, we use an autoregressive one-stage architecture by concatenating the set of (unpadded) input sequences, sorted using the Ordered criterion. The number of paths therefore becomes \( N_P = 1 \) and only Encoder \( E(1) \) and Decoder \( D^{(1)} \) are used; filling is ignored in that case. We analyze the effect of feed-forward prediction, and then our hierarchical DeepSVG architecture, using either the Ordered or Hungarian assignment loss. The human study is conducted by randomly selecting 100 pairs of SVG icons, and showing the interpolations generated by the four models to 10 human participants, which rank them best (1) to worst (4). In Tab. 2 we present the results of this study by reporting the percentage of 1st rank votes, as well as the average rank for each model. We also show qualitative results in Fig. 5 here ignoring the filling attribute since it is not supported by one-stage architectures. Compared to the autoregressive baseline, the use of feed-forward prediction brings substantial improvement in reconstruction and interpolation quality, as also confirmed by the qualitative results. In our human study, our hierarchical architecture with ordered assignment yields superior results. Although providing notably better reconstruction quality, this version provides much more stable and meaningful interpolations compared to the other approaches.

The Hungarian assignment achieves notably worse results compared to ordered assignment in average. Note that the latter is more related to the loss employed for the one-stage baselines, although there acting on a command level. We hypothesize that the introduction of a sensible ordering during training helps the decoder learning by providing an explicit prior, which better breaks symmetries and reduces competition between the predicted paths. Fig. 6 further shows how the latent SVG representation translates to meaningful decodings by performing interpolation between 4 SVG icons.

4.2 Animation by interpolation

As visually demonstrated in the previous subsection, we observe significantly better reconstruction capability of our model than previous works. This property is crucial for real-world applications involving SVGs since users should be able to perform various operations on vector graphics while keeping their original drawings unchanged. With this requirement in mind, we examine if DeepSVG can be used to animate SVGs, by interpolating between two user-drawn ones. Fig. 7 shows the results

![Figure 6: Interpolation between multiple icons in the latent space of DeepSVG – Ordered.](image-url)
of challenging scenes, after finetuning the model on the both frames for about 1,000 steps. Notice how DeepSVG handles well both translations and deformations.

4.3 Latent space algebra

Given DeepSVG’s smooth latent space and accurate reconstruction ability, we next ask if latent directions may enable to manipulate SVGs globally in a semantically meaningful way. We present two experiments in Fig. 8. In both cases, we note $\Delta$ the difference between encodings of two similar SVGs differing by some visual semantics. We show how this latent direction can be added or subtracted to the latent vector $z$ of arbitrary SVG icons. More experiments are presented in the appendix. In particular, we examine whether DeepSVG’s hierarchical construction enables similar operations to be performed on single paths instead of globally.

4.4 Font generation

Our experiments have demonstrated so far reconstruction, interpolation and manipulation of vector graphics. In this section, we further show the generative capability of our method, by decoding random vectors sampled from the latent space. We train our model on the SVG-Fonts dataset, for the task of class-conditioned glyph generation. DeepSVG is extended by adding label embeddings at every layer of each Transformer block. Fig. 9 presents random samples of our model. More details on the architecture, results and comparisons are shown in the appendix.

Figure 7: Animating SVG scenes by interpolation. Leftmost and rightmost frames are drawn by a user, while images in between are interpolations. DeepSVG smoothly interpolates between challenging path deformations while accurately reconstructing the first and last frames. A failure case is shown in the last row where the deformation of the player’s right leg is not smoothly interpolated.

Figure 8: Global operations on SVG representations using latent directions. Subtracting/adding $\Delta_{\text{square}}$ makes an icon look more round/rectangular, while $\Delta_{\text{add}}$ adds or removes paths. $\Delta_{\text{add}}$ is obtained by removing the last path of an icon, and averaging the difference over 500 random icons.

Figure 9: Glyph generation samples of our method, by conditioning on each class label. We sample the latent vector $z$ from a Gaussian distribution with standard deviation $\sigma = 0.5$.

5 Conclusion

We have demonstrated how our hierarchical network can successfully perform SVG icons interpolations and manipulation. We hope that our architecture will serve as a strong baseline for future research in this, to date, little-explored field. Interesting applications of our architecture include raster-to-vector conversion or the more general task of XML generation by extending the two-level hierarchy used in this work. Furthermore, while DeepSVG was designed specifically for the natural representation of SVGs, our architecture can be used for any task involving data represented as a set.
of sequences. We therefore believe it can be used, with minimal modifications, in a wide variety of
tasks, including multi-instrument audio generation, multi-human motion trajectory generation, etc.

Broader Impact

DeepSVG can be used as animation tool by performing interpolations and other latent space operations
on user-drawn SVGs. Similarly to recent advances in rasterized content creation, we believe this
work will serve as a potential way for creators and digital artists to enhance their creativity and
productivity.

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Appendix

In this appendix, we first present a visualization of the data structure used for SVGs in Sec. A. We provide detailed instructions used to preprocess our data in Sec. B. Additional details on training and architectures are given in Sec. C and Sec. D. Sec. E goes through the procedure to predict filling along with SVG paths. Finally, additional results for font generation, icons generation, latent space algebra, animations and interpolations are presented in sections F, G, H, I, and J respectively.

A SVG Representation visualization

For a visual depiction of the data structure described in Sec. 3.1, we present in Fig. 10 an example of SVG image along with its tensor representation. The SVG image consists of 2 paths, P₁ and P₂. The former, P₁ starts with a move m command from the top left corner. The arc is constructed from two Cubic Bézier curve c commands. This is followed by a line l and close path z command. The <EOS> command indicates the end of path P₁. P₂ is constructed in a similar fashion using only a single Cubic Bézier curve.

![Figure 10: Example of SVG representation. Left: Input SVG image. Right: Corresponding tensor representations with 2 paths and 7 commands (Np = 2, Nc = 7). Commands in the image and the corresponding tensor are color-coded for a better visualization. The arguments are listed in the order q₁x₁, q₁y₁, q₂x₂, q₂y₂, x₂ and y₂. Best viewed in color.](image)

B SVG Preprocessing

In Sec. 3.1, we consider that SVG images are given as a set of paths, restricted to the 6 commands described in Tab. 1. As mentioned, this does not reduce the expressivity of vector graphics since other basic shapes and commands can be converted to that format. We describe next the details of these conversions.

Path commands conversion. Lower-case letters in SVG path commands are used to specify that their corresponding arguments are relative to the preceding command’s end-position, as opposed to absolute for upper-case letters. We start by converting all commands to absolute. Other available commands (H: HorizontalLineTo, V: VerticalLineTo, S: SmoothBezier, Q: QuadraticBezier, T: SmoothQuadraticBezier) can be trivially converted to the commands subset of Tab. 1. The only missing command that needs further consideration is the elliptical-arc command A, described below.

Elliptical arc conversion. As illustrated in Fig. 11, command A draws an elliptical arc with radii rₓ and rᵧ (semi-major and semi-minor axes), rotated by angle ϕ to the x-axis, and end-point (x₂, y₂). The bit-flags f₁ and f₂ are used to uniquely determine which one of the four possible arcs is chosen: large-arc-flag f₁ is set to 1 if the arc spanning more than 180° is chosen, 0 otherwise; and sweep-flag f₂ is set to 0 if the arc is oriented clockwise, 1 otherwise. We argue that this parametrization, while being intuitive from a user-perspective, adds unnecessary complexity to the commands argument space described in Sec. 3.1 and the bit-flags make shapes non-continuous w.r.t. their arguments, which would result in less smooth animations. We therefore convert A commands to multiple Cubic Bézier curves. We first start by converting the endpoint parametrization (x₁, y₁), (x₂, y₂) to a center parametrization (cx, cy). The center of the ellipse is
computed using:

\[
\begin{pmatrix}
    c_x \\
    c_y
\end{pmatrix}
= \begin{pmatrix}
    \cos \varphi & -\sin \varphi \\
    \sin \varphi & \cos \varphi
\end{pmatrix}
\begin{pmatrix}
    c'_x \\
    c'_y
\end{pmatrix}
+ \left( \frac{x_1+x_2}{y_1-y_2} \right)
\]

where,

\[
\begin{pmatrix}
    c'_x \\
    c'_y
\end{pmatrix}
= \pm \sqrt{r_x^2 r_y^2 - r_y^2 (x'_1)^2 - r_x^2 (y'_1)^2 + r_y^2 (x'_1)^2 + r_x^2 (y'_1)^2}
\]

\[
\begin{pmatrix}
    x'_1 \\
    y'_1
\end{pmatrix}
= \begin{pmatrix}
    \cos \varphi & \sin \varphi \\
    -\sin \varphi & \cos \varphi
\end{pmatrix}
\begin{pmatrix}
    \frac{x_1-x_2}{y_1-y_2} \\
    \frac{y_1-y_2}{2}
\end{pmatrix}
\]

We then determine the start angle \( \theta_1 \) and angle range \( \Delta \theta \) which are given by computing:

\[
\theta_1 = \angle \left( \begin{pmatrix} 1 \\ 0 \end{pmatrix}, \frac{x'_1-c'_x}{y'_1-c'_y} \right)
\]

\[
\Delta \theta = \angle \left( \begin{pmatrix} x'_1-c'_x \\ y'_1-c'_y \end{pmatrix}, \frac{-x'_1-c'_x}{y'_1-c'_y} \right)
\]

Using \((c_x, c_y), \theta_1\) and \(\Delta \theta\), we obtain the parametric elliptical arc equation as follows (for \(\theta\) ranging from \(\theta_1\) to \(\theta_1 + \Delta \theta\)):

\[
E(\theta) = \begin{pmatrix}
    c_x + r_x \cos \varphi \cos \theta - r_y \sin \varphi \sin \theta \\
    c_y + r_x \sin \varphi \cos \theta - r_y \cos \varphi \sin \theta
\end{pmatrix}
\]

and the derivative of the parametric curve is:

\[
E'(\theta) = \begin{pmatrix}
    -r_x \cos \varphi \sin \theta - r_y \sin \varphi \cos \theta \\
    -r_x \sin \varphi \sin \theta - r_y \cos \varphi \cos \theta
\end{pmatrix}
\]

Given both equations, \([13]\) shows that the section of elliptical arc between angles \(\theta_1\) and \(\theta_2\) can be approximated by a cubic Bézier curve whose control points are computed as follows:

\[
\begin{align*}
P_1 &= E(\theta_1) \\
P_2 &= E(\theta_2) \\
Q_1 &= P_1 + \alpha E'(\theta_1) \\
Q_2 &= P_2 - \alpha E'(\theta_2)
\end{align*}
\]

where \(\alpha = \sin \theta_2 - \theta_1 \sqrt{4+3\tan^2 \frac{\theta_2-\theta_1}{2}-1} \).

**Basic shape conversion.** In addition to paths, SVG images can be built using 6 basic shapes: rectangles, lines, polylines, polygons, circles and ellipses. The first four can be converted to paths.
Table 3: Examples of conversion from basic shapes (rectangle, circle, ellipse, line, polyline and polygon) to paths.

| Basic Shape | Path equivalent |
|-------------|-----------------|
| <rect x="0" y="0" width="1" height="1" /> | <path d="M0,0 L1,0 L1,1 L0,1 L0,0 z" /> |
| <circle cx="1" cy="1" r="1" /> | <path d="M1,0 A1,1 0 0 1 2,1 A1,1 0 0 1 1,2 A1,1 0 0 1 0,1 A1,1 0 0 1 1,0 z" /> |
| <ellipse cx="1" cy="1" rx="1" ry="1" /> | <path d="M0,0 L1,0 A1,1 0 0 1 0,1 A1,1 0 0 1 1,0 z" /> |
| <line x1="0" x2="1" y1="0" y2="1" /> | <path d="M0,0 L1,1" /> |
| <polyline points="0, 0 1, 0 1, 1" /> | <path d="M0,0 L1,0 L1,1" /> |
| <polygon points="0, 0 1, 0 1, 1" /> | <path d="M0,0 L1,0 L1,1 z" /> |

using Line commands, while the latter two are transformed to a path using four Elliptical Arc commands, which themselves are converted to Bézier curves using the previous section. Table 3 below shows examples of these conversions.

Path simplification. Similarly to Sketch-RNN [5], we preprocess our dataset in order to simplify the network’s task of representation learning. However, unlike the latter work, our input consists of both straight lines and parametric curves. Ideally, if shapes were completely smooth, one could reparametrize points on a curve so that they are placed equidistantly from one another. In practice though, SVG shapes contain sharp angles, at which location points should remain unchanged. We therefore first split paths at points that form a sharp angle (e.g. where the angle between the incoming and outgoing tangents is less than some threshold $\eta = 150^\circ$). We then apply either the Ramer-Douglas-Peucker [2] algorithm to simplify line segments or the Philip J. Schneider algorithm [21] for segments of cubic Bézier curves. Finally, we divide the resulting lines and Bézier curves in multiple subsegments when their lengths is larger than some distance $\Delta = 5$. Examples of SVG simplifications are shown in Fig. 12. Notice how our algorithm both adds points when curve segments are too long or reduces the amount of points when the curve resolution is too high.
**SVG normalization.** All SVGs are scaled to a normalized viewbox of size $256 \times 256$, and paths are canonicalized, meaning that a shape’s starting position is chosen to be the topmost leftmost point, and commands are oriented clockwise.

## C Additional Training details

We augment every SVG of the dataset using 20 random augmentations with the simple transformations described as follows.

**Scaling.** We scale the SVG by a random factor $s$ in the interval $[0.8, 1.2]$.

**Translation.** We translate the SVG by a random translation vector $t$ where $t_x$ and $t_y$ are sampled independently in the interval $[-2.5, 2.5]$.

We believe further robustness in shape representation learning and interpolation stability can be obtained by simply implementing more complex data augmentation strategies.

## D Architectural details

Fig. 4 presents an overview illustration of our Hierarchical autoencoder architecture. In Fig. 13, we here show a more detailed view of the four main components of DeepSVG, i.e. the two encoders $E^{(1)}$, $E^{(2)}$ and decoders $D^{(2)}$, $D^{(1)}$. Similarly to [16], we use the improved Transformer variant described in [1, 18] as building block in all our components. $E^{(1)}$ and $E^{(2)}$ employ a temporal pooling module to retrieve a single $d_E$-dimensional vector from the $N_C$ and $N_P$ outputs respectively. $D^{(2)}$ and $D^{(1)}$ use learned embeddings as input in order to generate all predictions in a single forward-pass (non-autoregressively) and break the symmetry. The decoders are conditioned on latent vector $z$ or path representation $u_i$ by applying a linear transformation and adding it to the intermediate transformer representation in every block.

![Figure 13: Detailed view of architectures of $E^{(1)}$, $E^{(2)}$, $D^{(2)}$ and $D^{(1)}$.](image-url)
E Filling procedure visualization

Thanks to its hierarchical construction, DeepSVG can predict any number of global path-level attributes, which could be e.g. color, dash size, stroke-width or opacity. As a first step towards a network modeling all path attributes supported by the SVG format, we demonstrate support for filling. When using the default non-zero fill-rule in the SVG specification, a point in an SVG path is considered inside or outside the path based on the draw orientations (clockwise or counter-clockwise) of the shapes surrounding it. In particular, the insideness of a point in the shape is determined by drawing a ray from that point to infinity in any direction, and then examining the places where a segment of the shape crosses the ray. Starting with a count of zero, add one each time a path segment crosses the ray from left to right and subtract one each time a path segment crosses the ray from right to left. We argue that this parametrization is not optimal for neural networks to encode filling/erasing. Therefore, we simply let the network output a fill-attribute that can take one of three values: outline, fill or erase. This attribute is trained in a supervised way along with the other losses and is then used to export the actual SVG file. In particular, overlapping fill and erase shapes are grouped together in a same path and oriented in a clockwise/counterclockwise fashion respectively, while outlined shapes remain unchanged.

Figure 14: Examples of icon interpolations when using the fill attribute, predicted by the global decoder $D^{(1)}$. Look at how shapes’ filling generally changes at the middle of interpolation, while being deformed in a smooth way.
F Font generation

In this section, we provide details and additional results for font generation, presented in Sec. 4.4.

Experimental setup. We train our models on the SVG-Fonts dataset \cite{11} for 5 epochs using the same training hyper-parameters as described in Sec. 3.4, reducing the learning rate by a factor 0.9 every quarter epoch. Furthermore, all encoder and decoder Transformer blocks are extended to be class-conditioned. Similarly to how latent vector $z$ is fed into $D^{(2)}$, we add the learned label embedding to the intermediate transformer representation, after linear transformation. This is done in $E^{(1)}$, $E^{(2)}$, $D^{(2)}$ and $D^{(1)}$ and applies for both our final model and the one-stage baselines.

Results. We compare the generative capability of our final model with the same baselines as in Sec. 4.1. In addition, we show random samples from SVG-VAE \cite{11}. Results are shown in Fig. [15]. Notice how the non-autoregressive settings generate consistently visually more precise font characters, without having to pick the best example from a larger set or use any post-processing. We also note that due to the simplicity of the SVG-Font dataset, no significant visual improvement from our hierarchical architecture can be observed here. To validate that our model generates diverse font samples, we also present in Fig. [16] different samples for every glyph. Note how the latent vector $z$ is decoded into a style-consistent set of font characters. Diversity here includes different levels of boldness and more or less italic glyphs.

Figure 15: Comparison of samples for font generation using the same latent vector $z$, without careful selection of generated samples nor post-processing. Top row: SVG-VAE \cite{11}. 2nd row: baseline. 3rd row: one-stage feed-forward. 4th row: ours – Hungarian. Bottom row: ours – Ordered.
Figure 16: Font samples from DeepSVG – Ordered, generated from 7 different latent vectors. As observed in SVG-VAE [11], we notice a style consistency across the generated glyphs for a same latent vector. For instance, note how columns 5 & 6 correspond to an italic font style, column 4 to an extra thin one, and column 2 to a bolder one.

G Random samples of icons

In this section, we show random samples of icons by our model. Fig.17 presents a set of icons generated by DeepSVG, obtained by sampling a random latent vector $\mathbf{z}$ for each. These results show diverse icons that look visually reasonable. Note that the problem of generic icon generation is much more challenging than font generation. These results are promising, but much scope for improvement remains.
**H  Additional results on latent space algebra**

As mentioned in Sec.4.3, operations on vectors in the latent space lead to semantically meaningful SVG manipulations. By the hierarchical nature of our architecture, we here demonstrate that such operations can also be performed at the *path*-level, using path encodings $(\hat{u}_i)_i^{NP}$. In Fig. [18] we consider the difference $\Delta$ between path encodings of similar shapes, that differ by a horizontal or vertical translation. Adding or removing $\Delta$ from a path encoding in arbitrary SVG images applies the same translation to it.

Figure 18: Vector operations at the path-level. $\hat{u}_1$ corresponds to the path encoding of the blue shape, while $\hat{u}_2$ corresponds to the shape in green.

**I  Additional animations by interpolation**

We here show three additional animations, generated by DeepSVG from two user-created drawings. DeepSVG handles well deformation, scaling and rotation of shapes, see Fig. [19].

Figure 19: Additional animation examples.

**J  Additional interpolations**

Finally, we present additional interpolation results in Fig. [20] using our DeepSVG – ordered model, showing successful interpolations between challenging pairs of icons, along with some failure cases.
Figure 20: Additional interpolations of DeepSVG – ordered. The last two rows show examples of challenging icons, where interpolations appear visually less smooth.