SKETCHEMBEDNET: LEARNING NOVEL CONCEPTS BY IMITATING DRAWINGS

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ABSTRACT

Sketch drawings are an intuitive visual domain that appeals to human instinct. Previous work has shown that recurrent neural networks are capable of producing sketch drawings of a single or few classes at a time. In this work we investigate representations developed by training a generative model to produce sketches from pixel images across many classes in a sketch domain. We find that the embeddings learned by this sketching model are extremely informative for visual tasks and infer a unique visual understanding. We then use them to exceed state-of-the-art performance in unsupervised few-shot classification on the Omniglot and mini-ImageNet benchmarks. We also leverage the generative capacity of our model to produce high quality sketches of novel classes based on just a single example.

1 INTRODUCTION

Upon encountering a novel concept, such as a six-legged turtle, humans can quickly generalize this concept by composing a mental picture. The ability to generate drawings greatly facilitates communicating new ideas. This dates back to the advent of writing, as many ancient written languages are based on logograms, such as Chinese hanzi and Egyptian hieroglyphs, where each character is essentially a sketch of the object it represents. We often see complex visual concepts summarized by a few simple strokes.

Inspired by the human ability to draw, recent research has explored the potential to generate sketches using a wide variety of machine learning models, ranging from hierarchical Bayesian models (Lake et al., 2015), to more recent deep autoregressive models (Gregor et al., 2015; Ha & Eck, 2018; Chen et al., 2017) and generative adversarial nets (GANs) (Li et al., 2019). It is a natural question to ask whether we can obtain useful intermediate representations from models that produce sketches in the output space, as has been shown by other generative models (Ranzato et al., 2006; Kingma & Welling, 2014; Goodfellow et al., 2014; Donahue et al., 2017; Doersch et al., 2015). Unfortunately, a hierarchical Bayesian model suffers from prolonged inference time, while other current sketch models mostly focus on producing drawings in a closed set setting with a few classes (Ha & Eck, 2018; Chen et al., 2017), or on improving log likelihood at the pixel level (Rezende et al., 2016). Leveraging the learned representation from these drawing models remains a rather unexplored topic.

In this paper, we pose the following question: *Can we learn a generalized embedding function that captures salient and compositional features by directly imitating human sketches?* The answer is affirmative. In our experiments we develop SketchEmbedNet, an RNN-based sketch model trained to map grayscale and natural image pixels to the sketch domain. It is trained on hundreds of classes without the use of class labels to learn a robust drawing model that can sketch diverse and unseen inputs. We evaluate the latent "SketchEmbedding" on unsupervised few-shot classification, and achieve state-of-the-art performance on the Omniglot (Lake et al., 2015) dataset. We then explore how the embeddings depend on image components and their spatial relations. As well, we investigate the generative variance and recognizability of samples in one-shot generation.

We also push the boundary further by applying our sketch model to natural images—to our knowledge, we are the first to extend stroke-based autoregressive models to produce drawings of open domain natural images. We train our model with adapted SVG images from the Sketchy dataset (Sangkloy et al., 2016) and then evaluate the embedding quality directly on unseen classes in the mini-ImageNet task for few-shot classification (Vinyals et al., 2016). Our approach out-performs existing unsupervised few-shot learning methods (Hsu et al., 2019; Khodadadeh et al., 2019; Antoniou & Storkey, 2019) on this natural image benchmark. In both the sketch and natural image domain, we show that by learning to draw, our methods generalize well even across different datasets and classes.

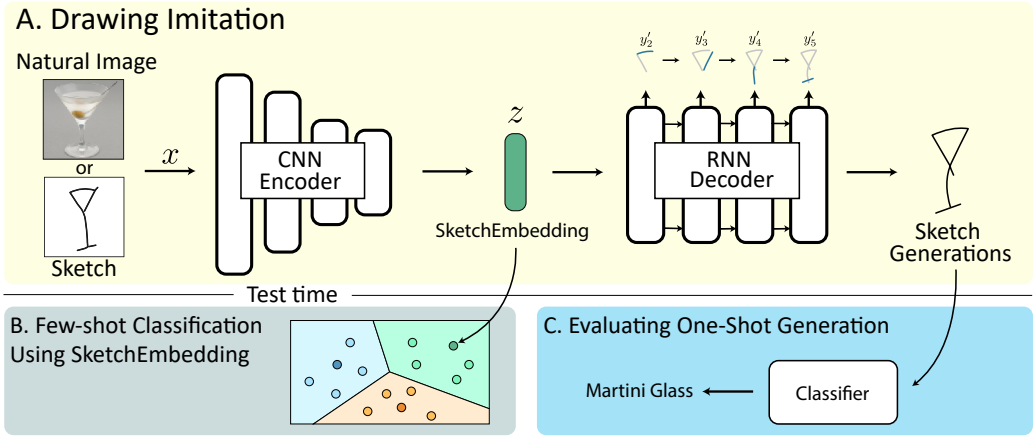

Figure 1: **A:** A natural or sketch pixel image is passed into the CNN encoder to obtain Gaussian SketchEmbedding z, which is concatenated with the previous stroke y_{t-1} as the decoder input at each timestep to generate y_t. **B+C:** Downstream tasks performed after training is complete.

2 Related Work

In this section we review relevant literature including generating sketch-like images, unsupervised representation learning, unsupervised few-shot classification and sketch-based image retrieval (SBIR).

Autoregressive drawing models: Graves (2013) use an LSTM to directly output the pen coordinates to imitate handwriting sequences. SketchRNN (Ha & Eck, 2018) builds on this by applying it to general sketches beyond characters. Song et al. (2018); Cao et al. (2019); Ribeiro et al. (2020) all extend SketchRNN through architectural improvements. Chen et al. (2017) change inputs to be pixel images. This and the previous 3 works consider multi-class sketching, but none handle more than 20 classes. Autoregressive models also generate images directly in the pixel domain. DRAW (Gregor et al., 2015) uses recurrent attention to plot pixels; Rezende et al. (2016) extends this to one-shot generation and PixelCNN (van den Oord et al., 2016) generates image pixels sequentially.

Image processing methods & GANs: Other works produce sketch-like images based on style transfer or low-level image processing techniques. Classic methods are based on edge detection and image segmentation (Arbelaez et al., 2011; Xie & Tu, 2017). Zhang et al. (2015) use a CNN to directly produce sketch-like pixels for face images. Photo-sketch and pix2pix (Li et al., 2019; Isola et al., 2017) propose a conditional GAN to generate images across different style domains. Image processing based methods do not acquire high-level image understanding, as all the operations are in terms of low-level filtering; none of the GAN sketching methods are designed to mimic human drawings on open domain natural images.

Unsupervised representation learning: In the sketch image domain, our method is similar to the large category of generative models which learn unsupervised representations by the principle of analysis-by-synthesis. Work by Hinton & Nair (2005) operates in a sketch domain and learns to draw by synthesizing an interpretable motor program. Bayesian Program Learning (Lake et al., 2015) draws through exact inference of common strokes but learning and inference are computationally challenging. As such, a variety of deep generative models aim to perform approximate Bayesian inference by using an encoder structure that directly predicts the embedding, e.g., deep autoencoders (Vincent et al., 2010), Helmholtz Machine (Dayan et al., 1995), variational autoencoder (VAE) (Kingma & Welling, 2014), BiGAN (Donahue et al., 2017), etc. Our method is also related to the literature of self-supervised representation learning (Doersch et al., 2015; Noroozi & Favaro, 2016; Gidaris et al., 2018; Zhang et al., 2016), as sketch strokes are part of the input data itself. In few-shot learning (Vinyals et al., 2016; Snell et al., 2017; Finn et al., 2017), recent work has explored unsupervised meta-training. CACTUs, AAL and UMTRA (Hsu et al., 2019; Antoniou & Storkey, 2019; Khodadadeh et al., 2019) all operate by generating pseudo-labels for training.

Sketch-based image retrieval (SBIR): In SBIR, a model is provided a sketch-drawing and retrieves a photo of the same class. The area is split into fine-grained (FG-SBIR) (Yu et al., 2016; Sangkloy et al., 2016; Bhunia et al., 2020) and a zero-shot setting (ZS-SBIR) (Dutta & Akata, 2019; Pandey et al., 2020; Dey et al., 2019). FG-SBIR considers minute details while ZS-SBIR learns high-level cross-domain semantics and a joint latent space to perform retrieval.

(a) Sketchy samples (b) Quickdraw samples

Figure 2: Examples from Sketchy (Sangkloy et al., 2016) and Quickdraw (Jongejan et al., 2016) datasets. Sketchy examples are reshaped and padded to increase image–sketch spatial agreement.

3 LEARNING TO IMITATE DRAWINGS

Here we describe learning to draw through sketch imitation. Our architecture is a generative encoder-decoder model with a CNN encoder for pixel images and an RNN decoder to output vector sketches as shown in Figure 1. Unlike other drawing models that only train on a single or few classes (Ha & Eck, 2018; Chen et al., 2017), SketchEmbedNet is not limited by class inputs and can sketch a wide variety of images. We also introduce a differentiable rasterization function for computing an additional pixel-based training loss.

Input & output representation Unlike SketchRNN which encodes drawing sequences, we learn an image embedding by mapping pixels to sketches, similar to Chen et al. (2017). Training data for this task (adopted from Ha & Eck (2018)) consists of a tuple $(\boldsymbol{x}, \boldsymbol{y})$, where $\boldsymbol{x} \in \mathbb{R}^{H \times W \times C}$ is the input image and $\boldsymbol{y} \in \mathbb{R}^{T \times 5}$ is the stroke target. T is the maximum sequence length of the stroke data $\boldsymbol{y}$, and each stroke $\boldsymbol{y}_t$ consists of 5 elements, $(\Delta_x, \Delta_y, s_1, s_2, s_3)$. The first 2 elements are horizontal and vertical displacements on the drawing canvas from the endpoint of the previous stroke. The latter 3 elements are mutually exclusive pen states: s_1 indicates the pen is on paper for the next stroke, s_2 indicates the pen is lifted, and s_3 indicates the sketch sequence has ended. $\boldsymbol{y}_0$ is initialized with (0, 0, 1, 0, 0) to start the generative process. Note that no class information is available while training.

SketchEmbedding as a compositional encoding of images We use a CNN to encode the input image $\boldsymbol{x}$ and obtain the latent space representation $\boldsymbol{z}$, as shown in Figure 1. To model intra-class variance, $\boldsymbol{z}$ is a Gaussian random variable parameterized by CNN outputs, similar to a VAE (Kingma & Welling, 2014). Throughout this paper, we refer to $\boldsymbol{z}$ as the *SketchEmbedding*. In typical image representations the embedding is trained to classify object classes, or to reconstruct the input pixels. Here, since the SketchEmbedding is fed into an RNN decoder to produce a sequence of drawing actions, $\boldsymbol{z}$ is additionally encouraged to have a compositional understanding of the object structure, instead of just an unstructured set of pixel features. For instance, if the input image is a turtle with six legs, a regular CNN embedding will have salient features of legs in multiple places of the feature map. After an average pooling layer, it will only retain information about a leg-like feature but not how many legs are present and where they are positioned with respect to the canvas. The loss of compositional information of regular CNN embeddings is also observed in the GAN literature (Goodfellow, 2017). By contrast, the SketchEmbedNet must preserve the information for drawing six distinct legs in order to succeed in the imitation task.

To accommodate the increased training data complexity by including hundreds of classes, we also upscale the size of our model in comparison to work by Chen et al. (2017); Ha & Eck (2018); Song et al. (2018). The backbone is either a 4-layer CNN (Conv4) (Vinyals et al., 2016) for consistent comparisons in the few-shot setting or a ResNet12 (Oreshkin et al., 2018) which produces better drawing results. In comparison, Chen et al. (2017) only use 2D convolution with a maximum of 8 filters.

RNN decoder The RNN decoder used in SketchEmbedNet is the same as in SketchRNN (Ha & Eck, 2018). The decoder outputs a mixture density which represents the stroke distribution at each timestep. Specifically, the stroke distribution is a mixture of some hyperparameter M bivariate Gaussians denoting spatial offsets as well as the probability of the three pen states s_{1-3}. The spatial offsets $\boldsymbol{\Delta} = (\Delta x, \Delta y)$ are sampled from the mixture of Gaussians, described by: (1) the normalized mixture weight π_j; (2) mixture means $\boldsymbol{\mu}_j = (\mu_x, \mu_y)_j$; and (3) covariance matrices Σ_j. We further reparameterize each Σ_j with its standard deviation $\boldsymbol{\sigma}_j = (\sigma_x, \sigma_y)_j$ and correlation coefficient $\rho_{xy,j}$. Thus, the stroke offset distribution is $p(\boldsymbol{\Delta}) = \sum_{j=1}^{M} \pi_j \mathcal{N}(\boldsymbol{\Delta} | \boldsymbol{\mu}_j, \Sigma_j)$.

The RNN is implemented using a HyperLSTM (Ha et al., 2017); LSTM weights are generated at each timestep by a smaller recurrent "hypernetwork" to improve training stability. Generation is autoregressive, using $\boldsymbol{z} \in \mathbb{R}^D$, concatenated with the stroke from the previous timestep $\boldsymbol{y}_{t-1}$, to form the input to the LSTM. Stroke $\boldsymbol{y}_{t-1}$ is the ground truth supervision at train time (teacher forcing), or a sample $\boldsymbol{y}'_{t-1}$, from the mixture distribution output by the model during from timestep $t-1$.

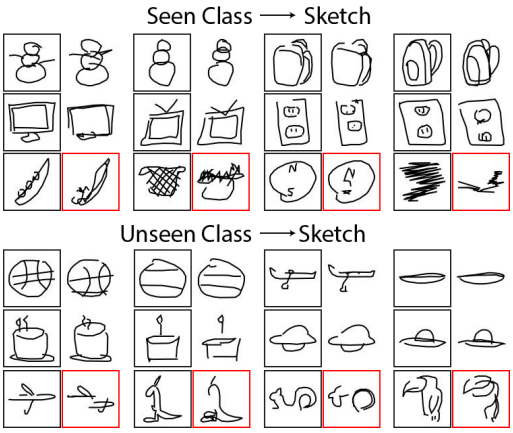

Figure 3: Sampled generated drawings of Quickdraw examples. Weaker drawings boxed in red.

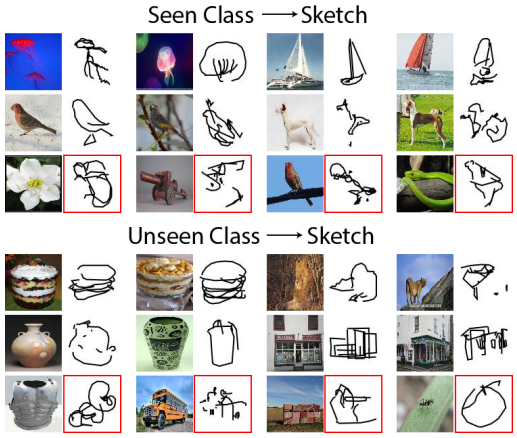

Figure 4: Sampled drawings of mini-ImageNet examples. Weaker drawings boxed in red.

3.1 LEARNING

We train the drawing model in an end-to-end fashion by jointly optimizing three losses: a pen loss $\mathcal{L}_{\text{pen}}$ for learning pen states, a stroke loss $\mathcal{L}_{\text{stroke}}$ for learning pen offsets, and our proposed pixel loss $\mathcal{L}_{\text{pixel}}$ for matching the visual similarity of the predicted and the target sketch:

$$\mathcal{L} = \mathcal{L}_{\text{pen}} + (1-\alpha)\mathcal{L}_{\text{stroke}} + \alpha\mathcal{L}_{\text{pixel}}, \tag{1}$$

where α is a loss weighting hyperparameter. Both $\mathcal{L}_{\text{pen}}$ and $\mathcal{L}_{\text{stroke}}$ were in SketchRNN, while the $\mathcal{L}_{\text{pixel}}$ is our novel contribution to stroke-based generative models. Unlike SketchRNN, we do not impose a prior using a KL term as it negatively impacted later experiments.

Pen loss The pen-states predictions $\{s'_1, s'_2, s'_3\}$ are optimized as a simple 3-way classification with the softmax cross-entropy loss, $\mathcal{L}_{\text{pen}} = -\frac{1}{T}\sum_{t=1}^{T}\sum_{m=1}^{3} s_{m,t}\log(s'_{m,t})$.

Stroke loss The stroke loss maximizes the log-likelihood of the spatial offsets of each ground truth stroke $\mathbf{\Delta}_t$ given the mixture density distribution p_t at each timestep: $\mathcal{L}_{\text{stroke}} = -\frac{1}{T}\sum_{t=1}^{T}\log p_t(\mathbf{\Delta}_t)$.

Pixel loss While pixel-level reconstruction objectives are common in generative models (Kingma & Welling, 2014; Vincent et al., 2010; Gregor et al., 2015), we introduce a pixel-based objective for vector sketch generation. After decoding, a *differentiable rasterization* function f_{raster} is used to map the sketch into a pixel image. f_{raster} transforms a stroke sequence $\boldsymbol{y}$ into a set of 2D line segments $(l_0, l_1), (l_1, l_2) \ldots (l_{T-1}, l_T)$ where $l_t = \sum_{\tau=0}^{t}\mathbf{\Delta}_\tau$. It renders by fixing canvas dimensions, scaling and centering strokes before determining pixel intensity based on the L_2 distance between each pixel to lines in the drawing. Further details on f_{raster} can be found in Appendix A. f_{raster} is applied to both the prediction $\boldsymbol{y}'$ and ground truth $\boldsymbol{y}$, to produce two pixel images. Gaussian blur $g_{\text{blur}}(\cdot)$ is used to reduce strictness before computing the binary cross-entropy loss, $\mathcal{L}_{\text{pixel}}$:

$$I = g_{\text{blur}}(f_{\text{raster}}(\boldsymbol{y})), \quad I' = g_{\text{blur}}(f_{\text{raster}}(\boldsymbol{y}')), \quad \mathcal{L}_{\text{pixel}} = -\frac{1}{HW}\sum_{i=1}^{H}\sum_{j=1}^{W} I_{ij}\log(I'_{ij}). \tag{2}$$

Curriculum training schedule We find that α (in Equation 1) is an important hyperparameter that impacts both the learned embedding space and the generation quality of SketchEmbedNet. A curriculum training schedule is used, increasing α to prioritize $\mathcal{L}_{\text{pixel}}$ relative to $\mathcal{L}_{\text{stroke}}$ as training progresses; this makes intuitive sense as a single drawing can be produced by many different stroke sequences but learning to draw in a fixed manner is easier. While $\mathcal{L}_{\text{pen}}$ promotes reproducing a specific drawing sequence, $\mathcal{L}_{\text{pixel}}$ only requires that the generated drawing visually matches the image. Like a human, the model should learn to follow one drawing style (a la paint-by-numbers) before learning to draw freely.

4 DRAWING IMITATION EXPERIMENTS

In this section, we introduce our experiments on training SketchEmbedNet using two sketching datasets. The first is based on pure stroke-based drawings, and the second consists of natural image and drawing pairs.

Table 1: Few-shot classification results on Omniglot

Omniglot			**(way, shot)**			
Algorithm	**Backbone**	**Train Data**	**(5,1)**	**(5,5)**	**(20,1)**	**(20,5)**
Training from Scratch (Hsu et al., 2019)	N/A	Omniglot	52.50 ± 0.84	74.78 ± 0.69	24.91 ± 0.33	47.62 ± 0.44
CACTUs-MAML (Hsu et al., 2019)	Conv4	Omniglot	68.84 ± 0.80	87.78 ± 0.50	48.09 ± 0.41	73.36 ± 0.34
CACTUs-ProtoNet (Hsu et al., 2019)	Conv4	Omniglot	68.12 ± 0.84	83.58 ± 0.61	47.75 ± 0.43	66.27 ± 0.37
AAL-ProtoNet (Antoniou & Storkey, 2019)	Conv4	Omniglot	84.66 ± 0.70	88.41 ± 0.27	68.79 ± 1.03	74.05 ± 0.46
AAL-MAML (Antoniou & Storkey, 2019)	Conv4	Omniglot	88.40 ± 0.75	98.00 ± 0.32	70.20 ± 0.86	88.30 ± 1.22
UMTRA (Khodadadeh et al., 2019)	Conv4	Omniglot	83.80	95.43	74.25	92.12
Random CNN	Conv4	N/A	67.96 ± 0.44	83.85 ± 0.31	44.39 ± 0.23	60.87 ± 0.22
Conv-VAE	Conv4	Omniglot	77.83 ± 0.41	92.91 ± 0.19	62.59 ± 0.24	84.01 ± 0.15
Conv-VAE	Conv4	Quickdraw	81.49 ± 0.39	94.09 ± 0.17	66.24 ± 0.23	86.02 ± 0.14
SketchEmbedding *(Ours)*	Conv4	Omniglot	94.88 ± 0.22	99.01 ± 0.08	86.18 ± 0.18	96.69 ± 0.07
SketchEmbedding-avg *(Ours)*	Conv4	Quickdraw	96.37	99.43	90.69	98.07
SketchEmbedding-best *(Ours)*	Conv4	Quickdraw	$\mathbf{96.96} \pm 0.17$	$\mathbf{99.50} \pm 0.06$	$\mathbf{91.67} \pm 0.14$	$\mathbf{98.30} \pm 0.05$
MAML *(Supervised)* (Finn et al., 2017)	Conv4	Omniglot	94.46 ± 0.35	98.83 ± 0.12	84.60 ± 0.32	96.29 ± 0.13
ProtoNet *(Supervised)* (Snell et al., 2017)	Conv4	Omniglot	98.35 ± 0.22	99.58 ± 0.09	95.31 ± 0.18	98.81 ± 0.07

Quickdraw: Stroke-based image sketching The Quickdraw (Jongejan et al., 2016) dataset consists of 345 classes of each with 70,000 examples, produced by human players participating in the game "Quick, Draw!". Examples from the Quickdraw dataset are shown in Figure 2b. The input image $\boldsymbol{x}$ is a direct rasterization of the drawing data $\boldsymbol{y}$. 300 of 345 classes are randomly selected for training; $\boldsymbol{x}$ is rasterized to a resolution of 28×28 and stroke labels $\boldsymbol{y}$ padded up to length $T = 64$. Any drawing samples exceeding this length were discarded. Note that this an unsupervised representation learning approach, as no class information is used by the system.

Sketchy: Open domain natural image sketching We further extend our stroke-based generation model on open domain natural images. Here, the input is an RGB photo, and the output is a human drawing which does not align with the photo precisely and also does not match with the low-level image details. This is a novel setting, as prior efforts by Ha & Eck (2018); Chen et al. (2017); Song et al. (2018) have only applied their sketch RNN models on the Quickdraw dataset or natural images with only two object classes (shoe/chair) and scrubbed backgrounds (Yu et al., 2016). Learning to sketch open domain natural images is very challenging as it requires the model to identify the subject and filter unnecessary details not present in the sketch. At test time, we further challenge our method by evaluating on unseen data distributions necessitating generalization over natural images.

For this task we use the Sketchy dataset (Sangkloy et al., 2016) which consists of ImageNet images paired with vector sketches for a total of 56k examples after processing. Sketches are stored as SVGs that we adapt to our format by sampling path elements. Images are also centered, padded and resized to resolution 84×84 (see Figure 2a). We fix the maximum sequence length to $T = 100$, and use all 125 categories but remove classes that have overlapping child synsets with the test classes of mini-ImageNet (Vinyals et al., 2016). This enables testing on mini-ImageNet without any alterations to the benchmark. Once again this is an unsupervised learning formulation.

Results and visualizations Figure 3 shows drawings conditioned on sketch image inputs. There is little noticeable drop in quality when we sample sketches from unseen classes compared to those it has seen before. Figure 4 shows examples of sketches generated from natural images. While they are not fine-grained copies, these sketches clearly demonstrate SketchEmbedNet's ability to capture key components of seen and unseen classes. Unlike pixel-based auto-encoder models, our sketches do not follow the exact pose of the original strokes, but rather capture a general notion of component groupings. As shown in the basketball example of Figure 3, the lines are not a good pixel-wise match to those in the original image yet they are placed in sensible relative positions. Weaker examples are presented in the last row of Figure 3 and 4; regardless, even poorer examples still capture some structural aspects of the original image. Implementation details can be found in Appendix B.

In later sections we explore the uses of SketchEmbeddings and fix models for all downstream tasks.

5 Few-shot Classification using SketchEmbedding

We would like to assess the benefits of learning to draw by performing few-shot classification with our learned embedding space. Examining performance on discriminative tasks reveals that learning to imitate sketches allows the embeddings to capture salient and compositional information of a novel object class. Below we describe our few-shot classification procedure and summarize results on the Omniglot (Lake et al., 2015) and mini-ImageNet benchmarks (Vinyals et al., 2016).

Table 2: Few-shot classification results on mini-ImageNet

mini-ImageNet			**(way, shot)**			
Algorithm	**Backbone**	**Train Data**	**(5,1)**	**(5,5)**	**(5,20)**	**(5,50)**
Training from Scratch (Hsu et al., 2019)	N/A	mini-ImageNet	27.59 ± 0.59	38.48 ± 0.66	51.53 ± 0.72	59.63 ± 0.74
CACTUs-MAML (Hsu et al., 2019)	Conv4	mini-ImageNet	39.90 ± 0.74	53.97 ± 0.70	63.84 ± 0.70	69.64 ± 0.63
CACTUs-ProtoNet (Hsu et al., 2019)	Conv4	mini-ImageNet	39.18 ± 0.71	53.36 ± 0.70	61.54 ± 0.68	63.55 ± 0.64
AAL-ProtoNet (Antoniou & Storkey, 2019)	Conv4	mini-ImageNet	37.67 ± 0.39	40.29 ± 0.68	-	-
AAL-MAML (Antoniou & Storkey, 2019)	Conv4	mini-ImageNet	34.57 ± 0.74	49.18 ± 0.47	-	-
UMTRA (Khodadadeh et al., 2019)	Conv4	mini-ImageNet	39.93	50.73	61.11	67.15
Random CNN	Conv4	N/A	26.85 ± 0.31	33.37 ± 0.32	38.51 ± 0.28	41.41 ± 0.28
Conv-VAE	Conv4	mini-ImageNet	28.68 ± 0.36	35.30 ± 0.35	39.45 ± 0.30	41.46 ± 0.29
Conv-VAE	Conv4	Sketchy	28.87 ± 0.37	34.91 ± 0.36	39.09 ± 0.31	41.28 ± 0.31
SketchEmbedding-avg *(ours)*	ResNet12	Sketchy	38.55	54.39	65.14	69.70
SketchEmbedding-best *(ours)*	ResNet12	Sketchy	**40.39** ± 0.44	**57.15** ± 0.38	**67.60** ± 0.33	**71.99** ± 0.3
MAML *(supervised)* (Finn et al., 2017)	Conv4	mini-ImageNet	46.81 ± 0.77	62.13 ± 0.72	71.03 ± 0.69	75.54 ± 0.62
ProtoNet *(supervised)* (Snell et al., 2017)	Conv4	mini-ImageNet	46.56 ± 0.76	62.29 ± 0.71	70.05 ± 0.65	72.04 ± 0.60

Comparison to unsupervised few-shot classification In unsupervised few-shot classification, a model is not provided with any class labels during meta-training, until it is given a few labeled examples ("shots") of the novel classes at meta-test time. While our model is provided a "target"—a sequence of strokes—during training, it is not given any class information. Therefore, we propose that the presented sketch imitation training is comparable to other class-label-free representation learning approaches (Berthelot et al., 2019; Donahue et al., 2017; Caron et al., 2018) and the learned SketchEmbeddings can be applied to unsupervised few-shot classification methods.

In our experiments, we compare to previous unsupervised few-shot learning approaches: CACTUs (Hsu et al., 2019), AAL (Antoniou & Storkey, 2019), and UMTRA (Khodadadeh et al., 2019). These methods create pseudo-labels during meta-training using either clustering or data augmentation. As additional baselines, a Conv-VAE (Kingma & Welling, 2014) and a random CNN are also included, both using the same Conv4 backbone.

Few-shot experimental setup The CNN encoder of SketchEmbedNet is used as an embedding function combined with a linear classification head to perform few-shot classification. The embedding is made deterministic by taking the mean of the random normal latent space $\boldsymbol{z}$ and discarding the variance parameter from the encoder. Otherwise, the conventional episodic setup for few-shot classification is used; each episode consists of a labeled "support" set of $N \times K$ (N-way K-shot) embeddings and an unlabeled "query" set. The linear classification head is trained on the labeled support set and evaluated on the query set.

Few-shot classification on Omniglot The Omniglot (Lake et al., 2015) dataset contains 50 alphabets, 1623 unique character types, each with 20 examples and is presented as both a greyscale image and a stroke drawing. We use the same train-test split as Vinyals et al. (2016) along with randomly sampled episodes. Experiments using the more challenging Lake split where episodes are sampled within alphabet, as proposed by Lake et al. (2015), are in Appendix E.

To ensure a fair comparison with other few-shot classification models, we use the same convolutional encoder (Conv4) as Vinyals et al. (2016). Results from training only on Omniglot (Lake et al., 2015) are also presented to demonstrate effectiveness without the larger Quickdraw(Jongejan et al., 2016) dataset. No significant improvements were observed using the deeper ResNet12(Oreshkin et al., 2018) architecture; additional results are in Appendix I.

All of our methods out-perform the previous state-of-the-art on the unsupervised Omniglot benchmark (Table 1). The Quickdraw trained model surpasses supervised MAML (Finn et al., 2017), and is on par with a supervised ProtoNet (Snell et al., 2017) model despite training on an entirely different distribution of sketches rather than handwritten characters. We report both the best seed and an average of 15 random seeds. The demonstrated approach excels in higher-shot settings and also manages to match the supervised ProtoNet model in the 5-shot regime. Both baselines, a Conv-VAE and a random CNN, perform well compared to other unsupervised methods.

Few-shot classification on mini-ImageNet We extend our investigation and assess SketchEmbeddings for the classification of natural images in the mini-ImageNet benchmark (Vinyals et al., 2016). The same CNN encoder model from the natural image sketching task is used to match the visual domain of the examples we hope to classify.

The mini-ImageNet (Vinyals et al., 2016) dataset consists of 100 classes each with 600 examples. The setup proposed by Ravi & Larochelle (2017) is used, where the classes are split 64-16-20 for training,

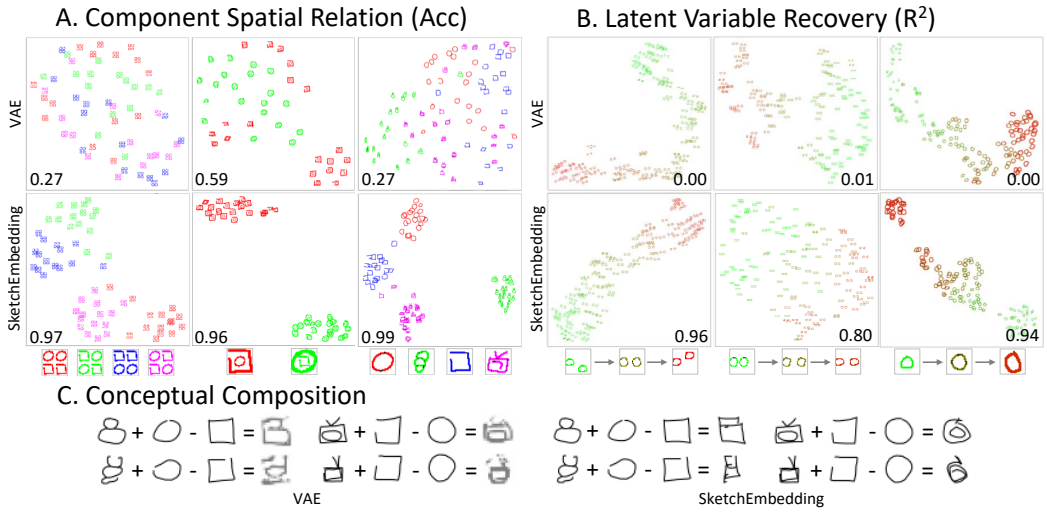

Figure 5: Experiments exploring properties of SketchEmbeddings. Numbers in **A, B** are linear model classification accuracy and regression R^2 respectively. Images colored for understandability.

validation and test. As noted earlier, any examples in the Sketchy dataset that are also present in the mini-ImageNet test were removed by filtering the synset (and children synset) IDs ensuring train and test classes are disjoint.

Classification results on mini-ImageNet are shown in Table 2. Our best model out-performs previous state-of-the-art unsupervised methods on few-shot settings and stays competitive on average. Seeding results are in Appendix F.

Varying weighting of pixel-loss We sweep the pixel loss coefficient α_{max} to quantify its impact on model performance on the Omniglot task (Table 3). There is a substantial improvement in few-shot classification when α_{max} is non-zero. α_{max}= 0.50 achieves the best results, and the trend goes downward when α_{max} approaches to 1.0, i.e. the weighting for $\mathcal{L}_{\text{stroke}}$ goes to 0.0. This is reasonable as the training of SketchEmbedNet is more stable under the guidance of ground truth strokes.

6 Properties of SketchEmbeddings

We hypothesize that reproducing a sketch drawing rather than a pixel-based approach requires the preservation of more structural information in the image. We examine this through several comparisons of embeddings generated by a Conv-VAE to those of SketchEmbedding.

Spatial component relation We construct images that contain the same set of objects but with different spatial relations to test sensitivity to object arrangements in image space. We embed these examples with both generative models then project into 2D space using UMAP (McInnes et al., 2018). We also apply a simple linear classifier trained on 100 examples and tested on 200 to predict the class of each embedding. In the first 2 panels of Figure 5**A**, we see that the SketchEmbeddings are more informative than those of the VAE as they are easily separated and are classified with higher accuracy shown in the bottom left. The rightmost panel of Figure 5**A** exhibits non-synthetic classes with duplicated shapes; snowmen with circles and televisions with squares. This shows that learning to draw facilitates an understanding of pen actions that vary for different, but visually similar shapes.

Latent variable recovery Drawing also builds awareness of canvas localization and subject scale. We examine how varying an underlying latent variable is captured in embeddings, by constructing images that vary in angle, distance or size. The embeddings are visualized by 2D projection in Figure 5**B** and used for a regression task with a simple linear model. R^2 values are in the bottom right; once again 100 training examples and 200 test examples are used. The 2D projection of SketchEmbeddings arranges the examples in each task along an axis corresponding to the latent variable and is far more successful in the regression task when compared to a Conv-VAE.

Conceptual composition Finally, we explore conceptual composition using SketchEmbeddings (Figure 5**C**) by embedding different Quickdraw examples then performing arithmetic with the latent vectors. By subtracting a circle embedding and adding a square embedding from a snowman composed of stacked circles, we produce stacked boxes. This property of vector arithmetic is

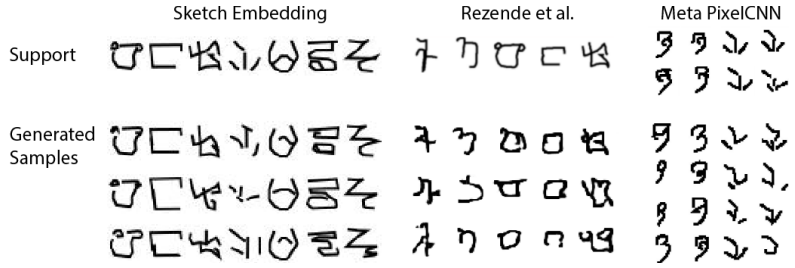

Figure 6: One-shot Omniglot generation compared to Rezende et al. (2016); Reed et al. (2017).

Table 3: Effect of pixel loss coefficient α on Omniglot few-shot classification

α_{max}	20-way 1-shot Acc.
0.00	87.17 $\pm$ 0.36
0.25	87.82 $\pm$ 0.36
0.50	**91.39** $\pm$ 0.31
0.75	90.59 $\pm$ 0.32
0.95	89.77 $\pm$ 0.32

Table 4: ResNet-101 45-way classification score on 1-shot generated sketches of seen and unseen classes.

Generation Method	**Seen**	**Unseen**
Original Data	97.66	96.09
Conv-VAE	76.28 $\pm$ 0.93	75.07 $\pm$ 0.84
SketchEmbedNet	**81.44** $\pm$ 0.95	**77.94** $\pm$ 1.07

reminiscent of language representations and is evidenced in analogies like King - Man + Woman = Queen (Ethayarajh et al., 2019). Surprisingly, this property is present in SketchEmbedding and is not shown in the pixel-based VAE embeddings.

7 One-Shot Generation

To evaluate the sketches generated by our model, we make qualitative comparisons to other one-shot generative models and quantitatively assess our model through visual classification via a ResNet101 model. In this section, all models use the ResNet12 (Oreshkin et al., 2018) backbone.

Qualitative comparisons We compare SketchEmbedNet one-shot generations of Omniglot characters with examples from other few-shot (Reed et al., 2017) and one-shot (Rezende et al., 2016) approaches (Figure 6). In the settings shown, none of the models have seen any examples from the character class, or the parent alphabet. Furthermore, the drawer has seen no written characters during training and is trained only on the Quickdraw dataset. Visually, our generated images better resemble the support examples and the variations by stretching and shifting strokes better preserves the semantics of each character. Generations in pixel space may disrupt strokes and alter the character to human perception. This is especially true for written characters as they are frequently defined by a specific set of strokes instead of blurry clusters of pixels.

Quantitative evaluation of generation quality Evaluating generative models is often challenging. Per-pixel metrics like in Reed et al. (2017); Rezende et al. (2016) may penalize generative variance that still preserves meaning. We propose an Inception Score (Salimans et al., 2016) inspired metric to quantify class-recognizability and generalization of generated examples. We train two separate ResNet classifiers (He et al., 2016), each on a different set of 45 Quickdraw classes. One set was part of the training set of SketchEmbedNet (referred to as "seen") and the other set was held out during training (referred to as "unseen"). We then have SketchEmbedNet generate one-shot sketches from each set and have the corresponding classifier predict a class. The accuracy of the classifier on generated examples is compared with its training accuracy in Table 4. For a ResNet classifier, SketchEmbedNet generations are more recognizable for both classes seen and unseen classes.

8 Conclusion

Learning to draw is not only an artistic pursuit but drives a distillation of real-world visual concepts. We present a generalized drawing model capable of producing accurate sketches and visual summaries of open-domain natural images. While sketch data may be challenging to source, we show that training to draw either sketch or natural images can generalize not only within each domain but also well beyond the training data. More generally research in this direction may lead to more lifelike image understanding inspired by how humans communicate visual concepts.

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