INFERRING AND DISENTANGLING IDENTITY FACTORS FOR GROUPED EXAMPLES

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ABSTRACT

We propose a method for modelling groups of face images from the same identity. The model is trained to infer a distribution over the latent space for identity given a small set of "training data". One can then sample images using that latent representation to produce images of the same identity. We demonstrate that the model extracts disentangled factors for identity factors and image-specific vectors. We also investigate the model's ability to perform few-shot face recognition.

1 INTRODUCTION AND BACKGROUND

An important task in machine learning is learning a new concept given a small number of examples. Lake et al. (2015) and Rezende et al. (2016) both aim to generate an example for a new concept inferred from one seen example. In this article, we propose a method to learn an inference model for a latent representation for an identity, given several examples of images for that identity. We should be able to leverage what can be learnt from a large dataset of images of faces about the commonalities between the people, and quickly infer the salient features for each identity.

Specifically, we explore the possibility of using a deep generative model for the same task. We use Variational Autoencoders (VAEs) (Kingma & Welling, 2013) that are trained to model the image through separate *identity* and *style* latent variables. During training, the model is presented with groups of faces that belong to the same identity, but is never discriminatively trained to perform recognition. As the method also allows us to perform face recognition, we perform experiments to verify its feasibility. The benefit of performing recognition this way is the ability to visualise what the model has learnt.

2 METHOD AND RELATED WORK

Consider a global dataset $\mathcal{G} = \{\mathcal{D}_1, \ldots, \mathcal{D}_G\}$, where each sub-dataset consists of individual datapoints, images of faces in this case, $\mathcal{D}_i = \{\mathbf{x}_{i,1}, \ldots, \mathbf{x}_{i,N}\}$. We propose learning a model that infers a latent variable shared by all datapoints in $\mathcal{D}_i$, and another for that particular datapoint. For each image $\mathbf{x}_i$, there are two associated random variables: $\mathbf{w}$, which contains information related to identity and $\mathbf{z}_i$ which contains image specific factors like pose, lighting, occlusions, etc. The related generative process is as follows,

$$\mathbf{w} \sim p(\mathbf{w}) = \mathcal{N}(\mathbf{0}, \mathbf{I}), \tag{1}$$

$$\mathbf{z}_i \sim p_\theta(\mathbf{z}_i|\mathbf{w}), \qquad \text{for } i = 1, \ldots, N \tag{2}$$

$$\mathbf{x}_i \sim p_\theta(\mathbf{x}_i|\mathbf{z}_i, \mathbf{w}), \qquad \text{for } i = 1, \ldots, N \tag{3}$$

To infer the identity, we design the approximate posterior to be conditioned all of the images. The per-image latent variable model $\mathbf{z}_i$ is conditioned on the identity as we believe that knowing the identity can help to disentangle certain underlying factors, for example, knowing a person's skin-tone can affect the inference of lighting factors in the image.

$$\mathbf{w} \sim q_\phi(\mathbf{w}|\mathbf{x}_{1:N}), \tag{4}$$

$$\mathbf{z}_i \sim q_\phi(\mathbf{z}_i|\mathbf{x}_i, \mathbf{w}), \qquad \text{for } i = 1, \ldots, N, \tag{5}$$

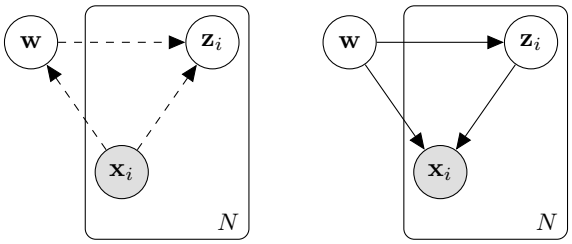


Figure 1: Left: The inference model q_ϕ Right: The generative model p_θ. N represents the number of images that are present for each identity.

Figure 1 illustrates the relationship between the three variables. The resulting loss for this structure is as follows,

$$\begin{aligned}\log p\left(\mathbf{x}_{1:N}\right) &\geq -\mathbb{E}\left[\log q_\phi\left(\mathbf{w}, \mathbf{z}_{1:N}|\mathbf{x}_{1:N}\right) - \log p\left(\mathbf{w}, \mathbf{z}_{1:N}, \mathbf{x}_{1:N}\right)\right] \\ &\approx D_{\mathrm{KL}}\left(q_\phi\left(\mathbf{w}|\mathbf{x}_{1:N}\right) \| p\left(\mathbf{w}\right) \mathbf{x}_{1:N}\right) \\ &\quad + \sum_i^N \mathbb{E}_{q_\phi(\mathbf{w}|\mathbf{x}_{1:N})}\left[D_{\mathrm{KL}}\left(q_\phi\left(\mathbf{z}_i|\mathbf{x}_i, \mathbf{w}\right) \| p_\theta\left(\mathbf{z}_i|\mathbf{w}\right)\right)\right] \\ &\quad - \mathbb{E}_{q_\phi(\mathbf{z}_{1:N}, \mathbf{w}|\mathbf{x}_{1:N})}\left[\sum_i^N \log p_\theta\left(\mathbf{x}_i|\mathbf{w}, \mathbf{z}_i\right)\right]\end{aligned}$$

If we view the KL-divergence term as a penalty on the information transmitted from the inference model to the generative model, the loss encourages the model to encode as much information as possible in $\mathbf{w}$ as opposed to in $\mathbf{z}_i$, which is penalised as many times as there are images.

Such a structure for conditioning on an entire set of data to approximate posterior distribution over a common latent variable has been proposed in Edwards & Storkey (2016), with some an experiment on face image data extracted from Youtube videos, but here, we make the simplifying assumption that the style latent variables are independent, given the identity. In speech, Tan & Sim (2016) uses the same technique to extract a latent representation for an utterance, which works well for robust speech recognition. Hsu et al. (2017) also proposed a similar structure, using an RNN for their encoder and decoder.

2.1 Generative Face Recognition

Given a set of images for a new identity, we can generate a new image with the same identity. We use the inference model $q_\phi\left(\mathbf{w}|\mathbf{x}_{1:N}\right)$ to obtain an estimate of $\mathbf{w}$ by sampling. We can then use ancestral sampling to obtain an image under the new identity.

We can use the same process to estimate the probability a given image given an identity vector $\mathbf{w}$, using importance sampling:

$$p\left(\mathbf{x}|\mathbf{w}\right) = \mathbb{E}_{q_\phi(\mathbf{z}|\mathbf{w},\mathbf{x})}\left[\frac{p_\theta\left(\mathbf{x}|\mathbf{z}, \mathbf{w}\right) p_\theta\left(\mathbf{z}|\mathbf{w}\right)}{q_\phi\left(\mathbf{z}|\mathbf{w}, \mathbf{x}\right)}\right] \tag{6}$$

$$\approx \frac{1}{K}\sum_{k=1}^{K} \frac{p_\theta\left(\mathbf{x}\middle|\mathbf{z}_{(k)}, \mathbf{w}\right) p_\theta\left(\mathbf{z}_{(k)}\middle|\mathbf{w}\right)}{q_\phi\left(\mathbf{z}_{(k)}\middle|\mathbf{w}, \mathbf{x}\right)} \qquad \mathbf{z}_{(1)}, \ldots, \mathbf{z}_{(K)} \sim q_\phi\left(\mathbf{z}|\mathbf{w}, \mathbf{x}\right) \tag{7}$$

We then define the probability of $\mathbf{w}$ given $\mathbf{x}$ as,

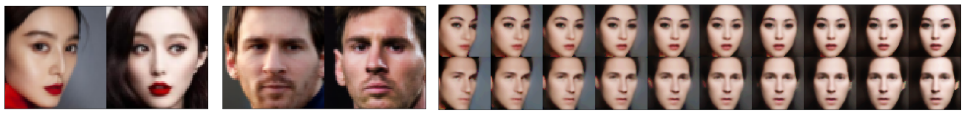
$$\tilde{p}\left(\mathbf{w}|\mathbf{x}\right) \triangleq \frac{p\left(\mathbf{x}|\mathbf{w}\right)}{\sum_{\mathbf{w}'} p\left(\mathbf{x}|\mathbf{w}'\right)} \tag{8}$$

3 Experiments

For our experiments, ϕ and θ are parameterised based on the architecture used in Tan & Sim (2016). $q_\phi\left(\mathbf{w}|\mathbf{x}_{1:N}\right)$ and $q_\phi\left(\mathbf{z}|\mathbf{w}, \mathbf{x}\right)$ have a shared convolution and max pooling transforms that we will

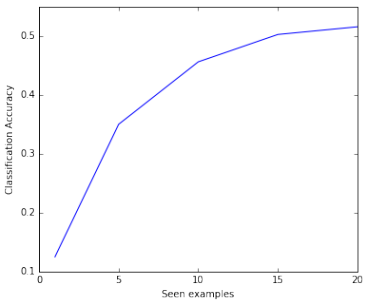
call $f(\mathbf{x}_i)$. For $q_\phi(\mathbf{w}|\mathbf{x}_{1:N})$, we perform a mean-pooling operation over the images in the dataset before passing it through an MLP to output the mean and standard deviation for $\mathbf{w}$. $q_\phi(\mathbf{z}|\mathbf{w},\mathbf{x})$ is also an MLP that takes in $\mathbf{w}$ and the output of $f(\mathbf{x}_i)$. For θ, $p_\theta(\mathbf{z}_i|\mathbf{w})$ is also an MLP. $p_\theta(\mathbf{x}_i|\mathbf{z}_i,\mathbf{w})$ is parameterised by a stack of upsampling and convolutional transforms, and we perform conditonal instance normalisation on $\mathbf{z}_i$ at each layer, in an architecture similar to the one presented in Dumoulin et al. (2016). The architecture was implemented in Theano (Team et al., 2016).

Learnt representation space To demonstrate that $\mathbf{z}_i$ and $\mathbf{w}$ encode different factors of variability in an image, we extract $\mathbf{w}_1$ and $\mathbf{w}_2$ from two different identities. Extracting from both images $\mathbf{z}_{1,1}$ and $\mathbf{z}_{1,2}$ respectively, we perform linear interpolation between these points. We then generate 10 images each using the sequence of $\mathbf{z}$ and $\mathbf{w}_1$ and $\mathbf{w}_2$. Figure 2c shows that traversing the $\mathbf{z}$ linearly for both identities results in the same pose and background change, with a different face.



(a) Identity 1 (b) Identity 2 (c) Interpolating in $\mathbf{z}$ space.

Face recognition We trained the model on the MSCeleb dataset perform face recognition on a held-out set of 2000 identities from the training set. We vary the number of examples (N) used to infer $\mathbf{w}$, and using the method in Section 2.1 to predict across 2000 identities on a separate image. The instances to accuracy trade-off can be seen in Figure 3a. Unfortunately, even with 20 seen examples, the model only performs just over 50% on a held-out testing image, but it is interesting to note that, while only training with 10 images per group, the model still shows an improvement even as we increase the group size beyond that. We can also visualise when $\mathbf{z}_i = \boldsymbol{\mu}_{\mathbf{z}_i}$ looks like, as seen in Figure 3b.



(a) As the number of seen instances (N) increases, the accuracy of recognition improves.

(b) Left: Seen examples from the MSCeleb dataset. Each row represents a group of images from one identity. Middle-Right: The mean of the seen examples. Right: Visualising $\mathbf{x}_i$ when $\mathbf{z}_i = \boldsymbol{\mu}_{\mathbf{z}_i}$.

4 Conclusion & Future Work

We believe that few-shot generalisation of a new concept is an important capability for machine learning systems to have and that being able to recognise a face after seeing just a few instances is one realisation of this capability, and also important enough to be able to have such systems be interpretable and diagnosable. Current state-of-the-art models for face recognition make use of discriminative learning over representations of the images (Guo & Zhang, 2017; Cheng et al., 2017). Being able to visualise what the model has learnt will prove useful in debugging problems with facial recognition system, especially as they become more prevalent with their introduction into everyday devices.

Therefore, we think this is a worthwhile direction with many possibilities for future work.

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REFERENCES

Yu Cheng, Jian Zhao, Zhecan Wang, Yan Xu, Karlekar Jayashree, Shengmei Shen, and Jiashi Feng. Know you at one glance: A compact vector representation for low-shot learning. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 1924–1932, 2017.

Vincent Dumoulin, Jonathon Shlens, and Manjunath Kudlur. A learned representation for artistic style. 2016.

Harrison Edwards and Amos Storkey. Towards a neural statistician. *arXiv preprint arXiv:1606.02185*, 2016.

Yandong Guo and Lei Zhang. One-shot face recognition by promoting underrepresented classes. *arXiv preprint arXiv:1707.05574*, 2017.

Wei-Ning Hsu, Yu Zhang, and James Glass. Unsupervised learning of disentangled and interpretable representations from sequential data. In *Advances in neural information processing systems*, pp. 1876–1887, 2017.

Diederik P Kingma and Max Welling. Auto-encoding variational bayes. *arXiv preprint arXiv:1312.6114*, 2013.

Brenden M Lake, Ruslan Salakhutdinov, and Joshua B Tenenbaum. Human-level concept learning through probabilistic program induction. *Science*, 350(6266):1332–1338, 2015.

Danilo Rezende, Ivo Danihelka, Karol Gregor, Daan Wierstra, et al. One-shot generalization in deep generative models. In *International Conference on Machine Learning*, pp. 1521–1529, 2016.

Shawn Tan and Khe Chai Sim. Learning utterance-level normalisation using variational autoencoders for robust automatic speech recognition. In *Spoken Language Technology Workshop (SLT), 2016 IEEE*, pp. 43–49. IEEE, 2016.

The Theano Development Team, Rami Al-Rfou, Guillaume Alain, Amjad Almahairi, Christof Angermueller, Dzmitry Bahdanau, Nicolas Ballas, Frédéric Bastien, Justin Bayer, Anatoly Belikov, et al. Theano: A python framework for fast computation of mathematical expressions. *arXiv preprint arXiv:1605.02688*, 2016.