

Measures of Generated Image Quality

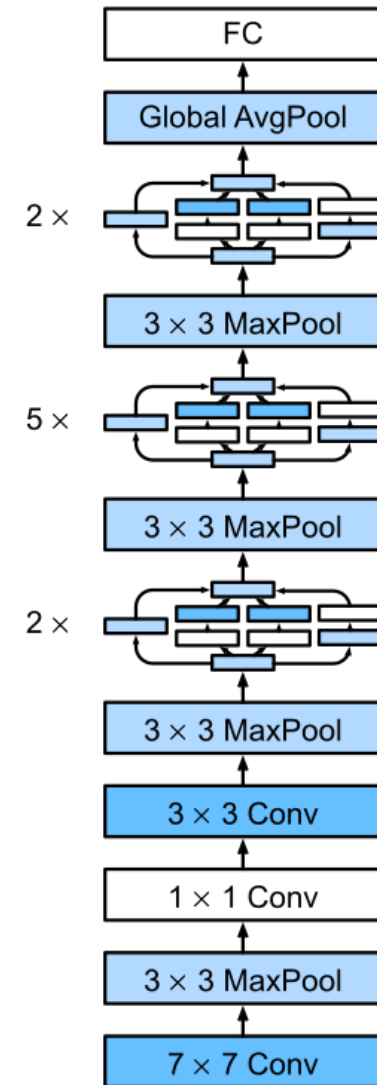
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What is Inception Score?

Inception V3

“We need to go deeper”

- Based on GoogLeNet
- Was the 3rd version of this net
- A famous image classifier released in 2016
- Trained on ImageNet (1000 class image data)
- Now mostly known for being used in calculating IS and FID



Inception Score

- Generate a bunch of images, conditioned on an ImageNet class (e.g. “dog”)
- Run each image through InceptionV3
- Gather their class probability distributions.
- Compare the distributions of things with similar labels to the distribution of things with different labels
- **HIGHER IS BETTER!**

Our ideal

Image classes are distinct

Similar labels sum to give focussed distribution

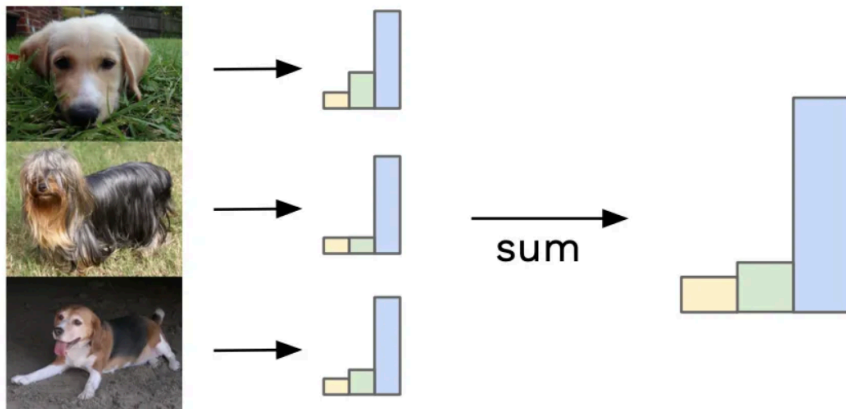
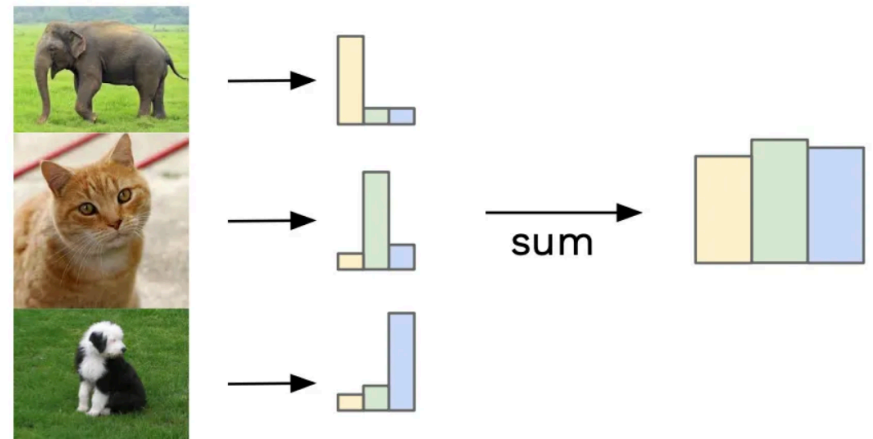


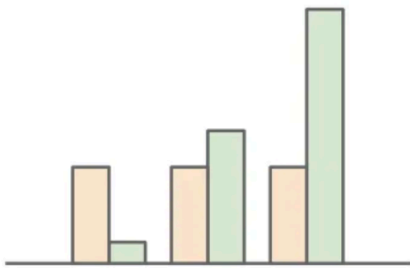
Image classes are diverse

Different labels sum to give uniform distribution



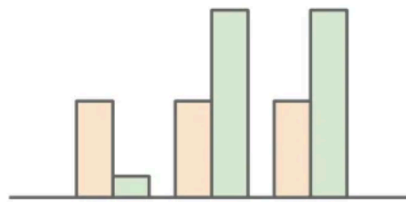
KL divergence between distributions

High KL divergence



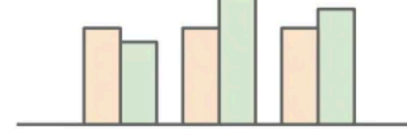
Ideal situation

Medium KL divergence



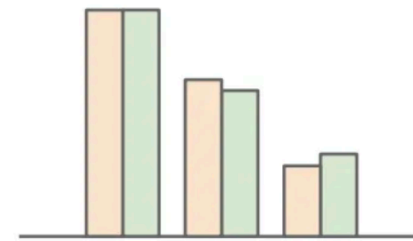
Generated images are not distinctly one label

Low KL divergence



Generated images are not distinctly one label

Low KL divergence



Generator lacks diversity

Label distribution
Marginal distribution

In the author's words

As an alternative to human annotators, we propose an automatic method to evaluate samples, which we find to correlate well with human evaluation: We apply the Inception model¹ [19] to every generated image to get the conditional label distribution $p(y|\mathbf{x})$. Images that contain meaningful objects should have a conditional label distribution $p(y|\mathbf{x})$ with low entropy. Moreover, we expect the model to generate varied images, so the marginal $\int p(y|\mathbf{x} = G(z))dz$ should have high entropy. Combining these two requirements, the metric that we propose is: $\exp(\mathbb{E}_{\mathbf{x}}\text{KL}(p(y|\mathbf{x})||p(y)))$, where we exponentiate results so the values are easier to compare.

$$\text{Inception Score} = \exp(\mathbb{E}_{\mathbf{x}}\text{KL}(p(y|\mathbf{x})||p(y)))$$

How to interpret IS

Higher = better

What is Frechet Inception Distance?

Make 2 sets of image embeddings

- Create a set of generated images: G
- Collect a set of real images: R
- Run every image through InceptionV3 to get its embedding
- Fit a single Gaussian to the distribution of the embeddings for G
- Fit a single Gaussian to the distribution of the embeddings for R
- Measure the KL divergence between the 2 Gaussians.

Frechet Distance

A measure of difference between distributions

the FID compares the mean and standard deviation of two image sets, as represented by the deepest layer in [Inception v3](#) (the 2048-dimensional activation vector of its last [pooling layer](#).)

$$d_F(\mathcal{N}(\mu, \Sigma), \mathcal{N}(\mu', \Sigma'))^2 = \|\mu - \mu'\|_2^2 + \text{tr}\left(\Sigma + \Sigma' - 2(\Sigma\Sigma')^{\frac{1}{2}}\right)$$

How to interpret FID

Lower = better

What is Precision/Recall?

<https://arxiv.org/pdf/1904.06991>

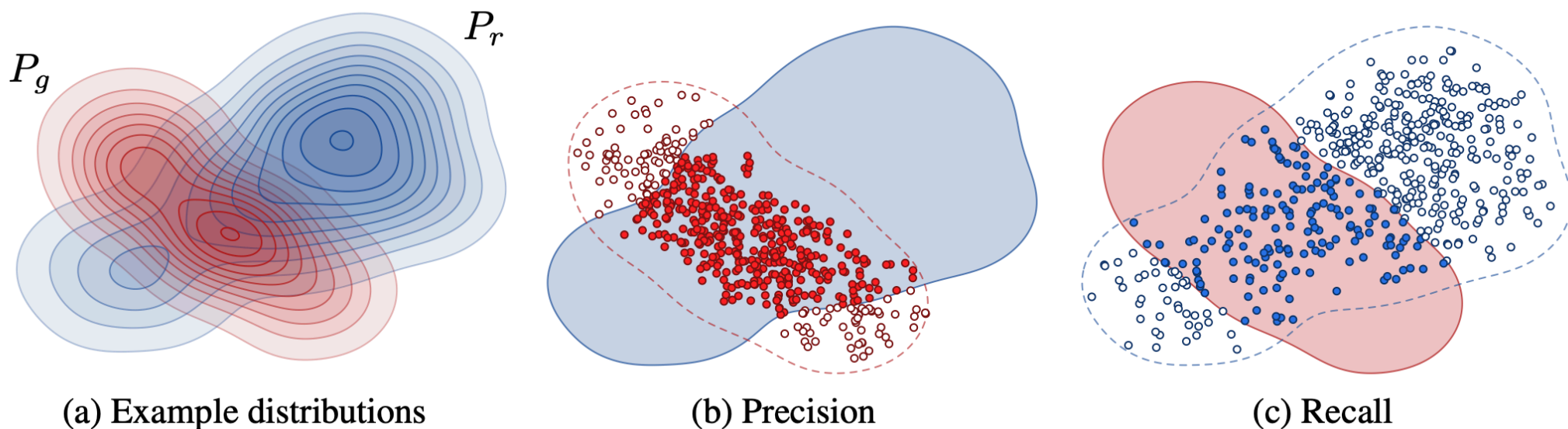


Figure 1: Definition of precision and recall for distributions [25]. (a) Denote the distribution of real images with P_r (blue) and the distribution of generated images with P_g (red). (b) Precision is the probability that a random image from P_g falls within the support of P_r . (c) Recall is the probability that a random image from P_r falls within the support of P_g .

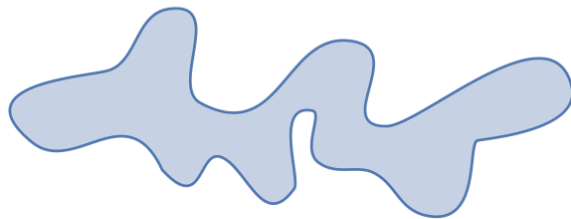
An image

$$f(\phi, \Phi) = \begin{cases} 1, & \text{if } \|\phi - \phi'\|_2 \leq \|\phi' - \text{NN}_k(\phi', \Phi)\|_2 \text{ for at least one } \phi' \in \Phi \\ 0, & \text{otherwise,} \end{cases}$$

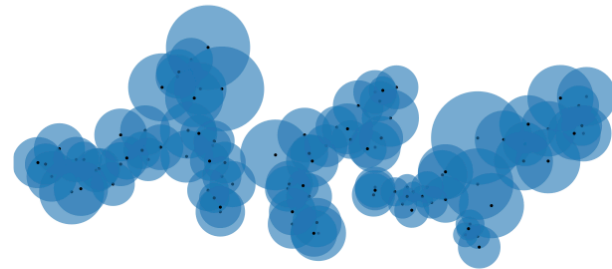
The set of images we compare to ϕ

The nearest neighbor to ϕ'

image from the comparison set



(a) True manifold



(b) Approx. manifold

Figure 2: (a) An example manifold in a feature space. (b) Estimate of the manifold obtained by sampling a set of points and surrounding each with a hypersphere that reaches its k th nearest neighbor.

How to interpret Precision & Recall

Higher = better