Copyright Notice

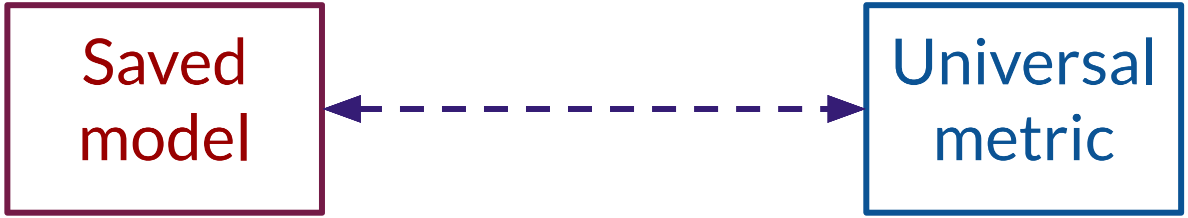
deeplearning.ai

Evaluation

Outline

- Why evaluating GANs is hard
- Two properties: fidelity and diversity

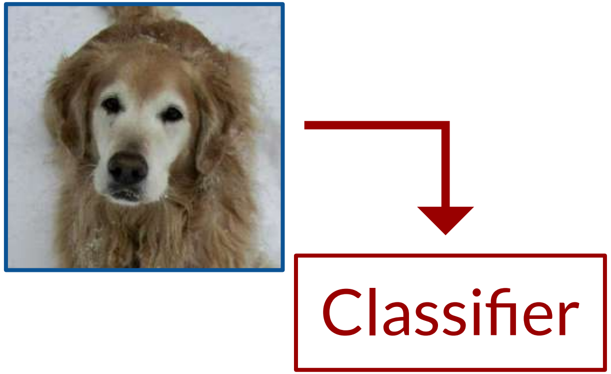
Why is evaluating GANs hard?



Why is evaluating GANs hard?

Classifier

Why is evaluating GANs hard?



Why is evaluating GANs hard?

Classifier

Cat
Dog
Bird

Correct!

Why is evaluating GANs hard?

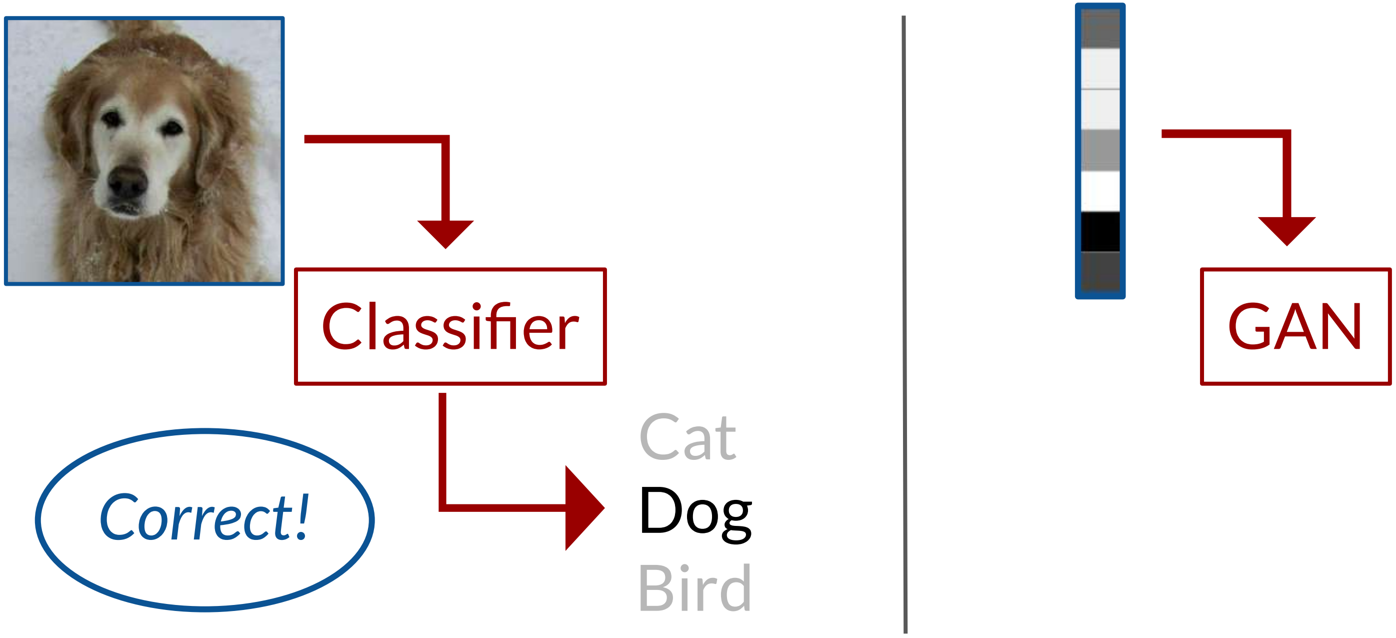
Classifier

Cat
Dog
Bird

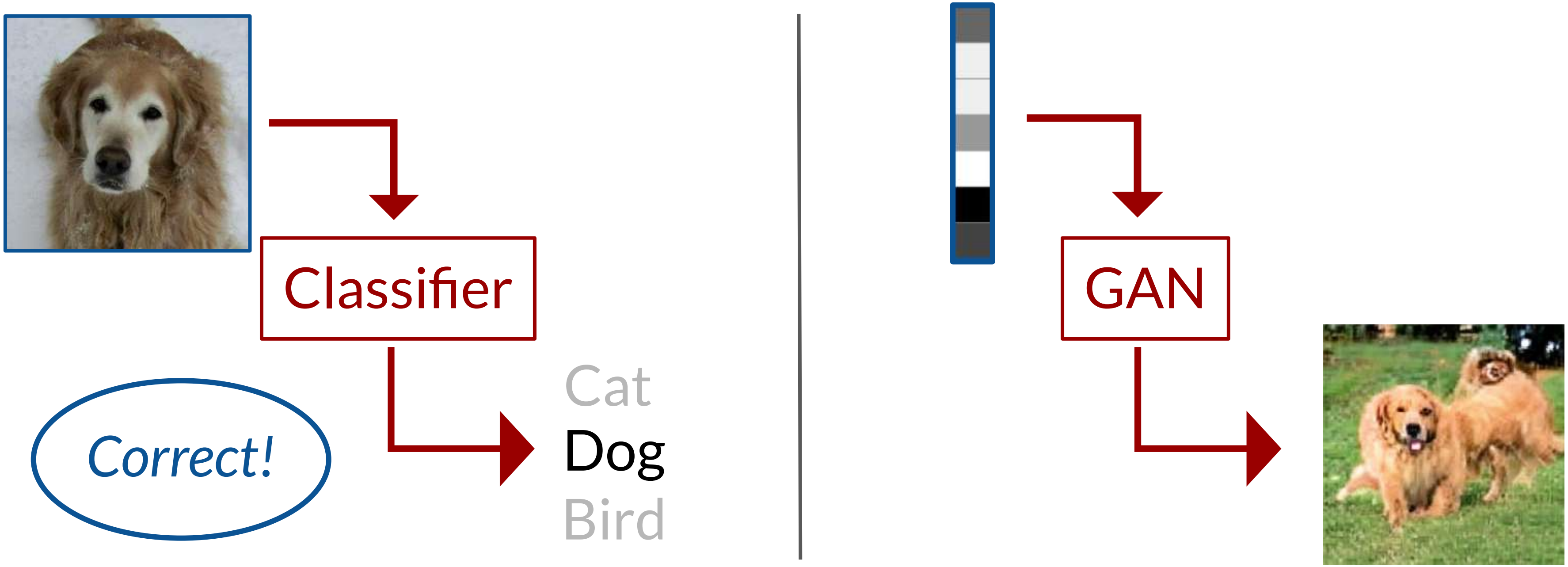
Correct!

GAN

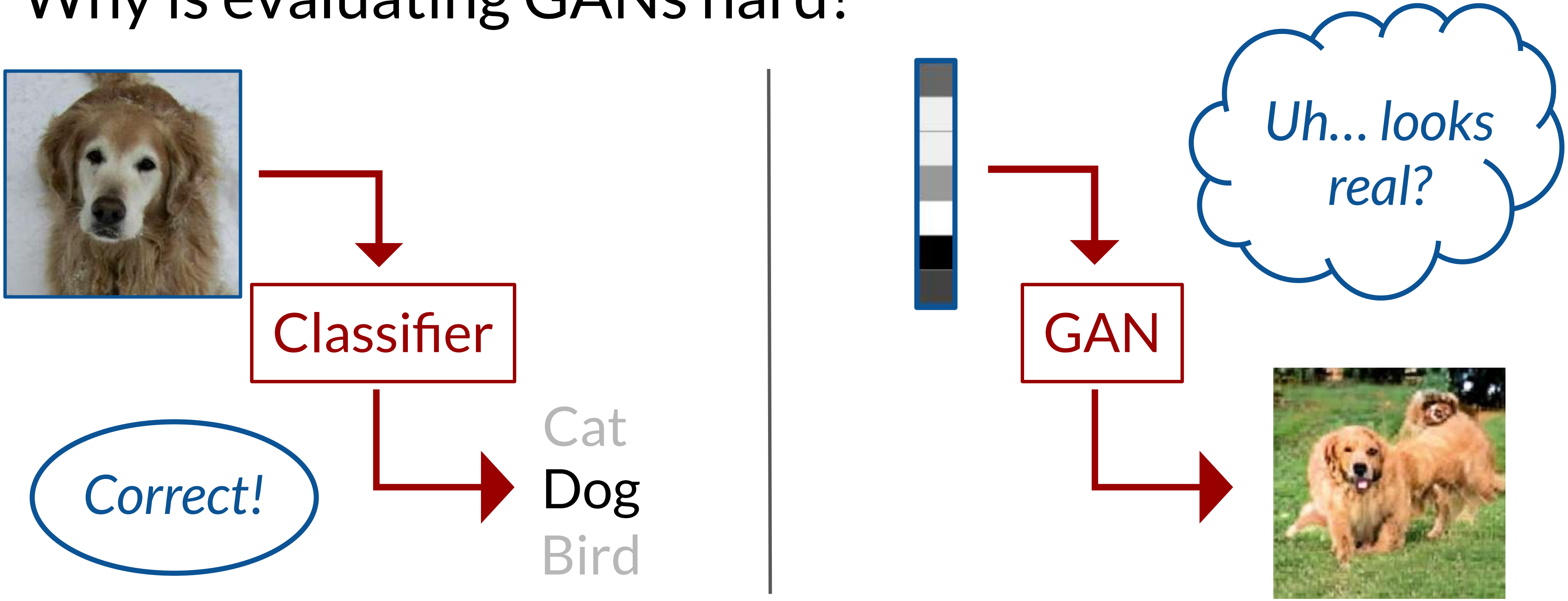
Why is evaluating GANs hard?



Why is evaluating GANs hard?



Why is evaluating GANs hard?



Two Important Properties

Fidelity:
quality of images

(Left) Available at: https://github.com/NVlabs/stylegan

Two Important Properties

Fidelity:
quality of images

Diversity:
variety of images

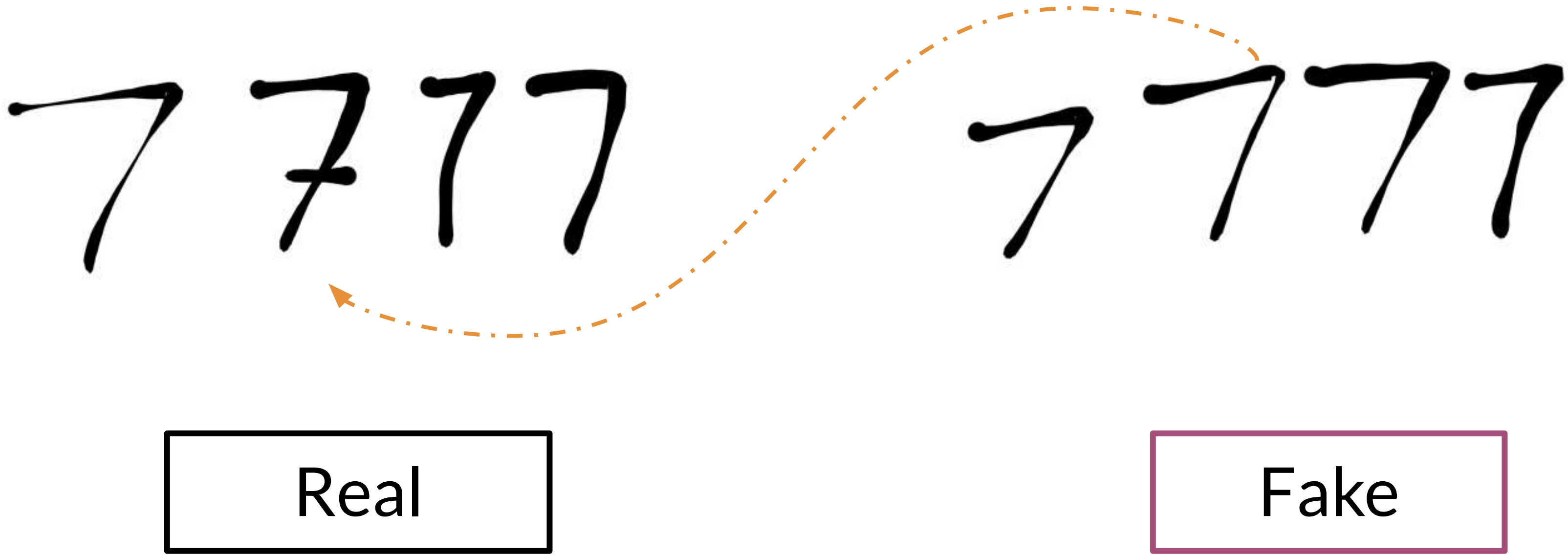
(Left) Available at: https://github.com/NVlabs/stylegan

Fidelity

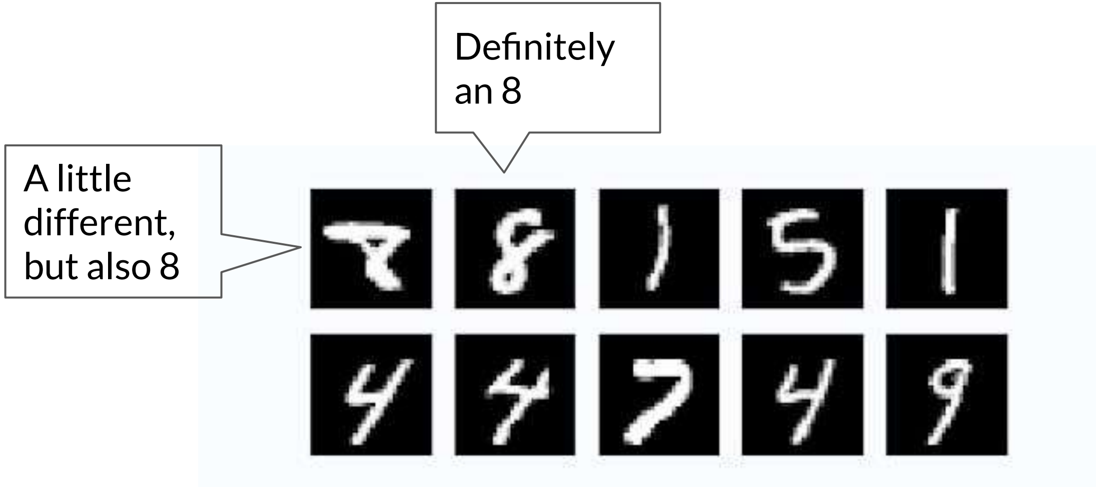
Fidelity

Fake

Fidelity



Diversity



Summary

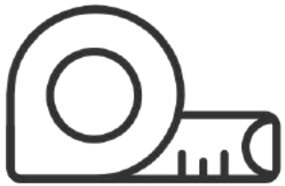
- No ground-truth = challenging to evaluate
- Fidelity measures image quality and diversity measures variety
- Evaluation metrics try to quantify fidelity & diversity

deeplearning.ai

Comparing Images

Outline

- Pixel distance
- Feature distance



Pixel Distance

$$\left| \underbrace{\begin{bmatrix} 200 & 50 & 200 \\ 200 & 50 & 200 \\ 200 & 50 & 200 \end{bmatrix}}_{\textit{Real}} - \underbrace{\begin{bmatrix} 200 & 50 & 200 \\ 200 & 50 & 200 \\ 200 & 50 & 200 \end{bmatrix}}_{\textbf{Fake}} \right| = \underbrace{\begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}}_{\text{Absolute difference}}$$

Pixel Distance

$$\left| \underset{\textit{Real}}{\begin{bmatrix} 200 & 50 & 200 \\ 200 & 50 & 200 \\ 200 & 50 & 200 \end{bmatrix}} - \underset{\textbf{Fake}}{\begin{bmatrix} 50 & 200 & 200 \\ 50 & 200 & 200 \\ 50 & 200 & 200 \end{bmatrix}} \right| = \underset{\text{Absolute difference}}{\begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}}$$

Feature Distance

Feature Distance

Real

Fake

Feature Distance

Real

2 eyes,
2 droopy ears,
1 nose, ...

Fake

2 eyes,
1 droopy ear,
5 legs,
1 nose, ...

Feature Distance

Real

2 eyes,
2 droopy ears,
1 nose, ...

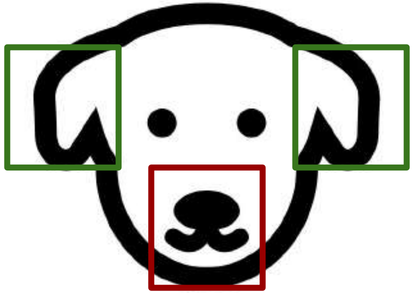
Fake

2 eyes,
1 droopy ear,
5 legs,
1 nose, ...

Compare features!

Summary

- Pixel distance is simple but unreliable
- Feature distance uses the higher level features of an image, making it more reliable

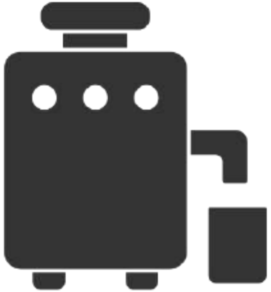


deeplearning.ai

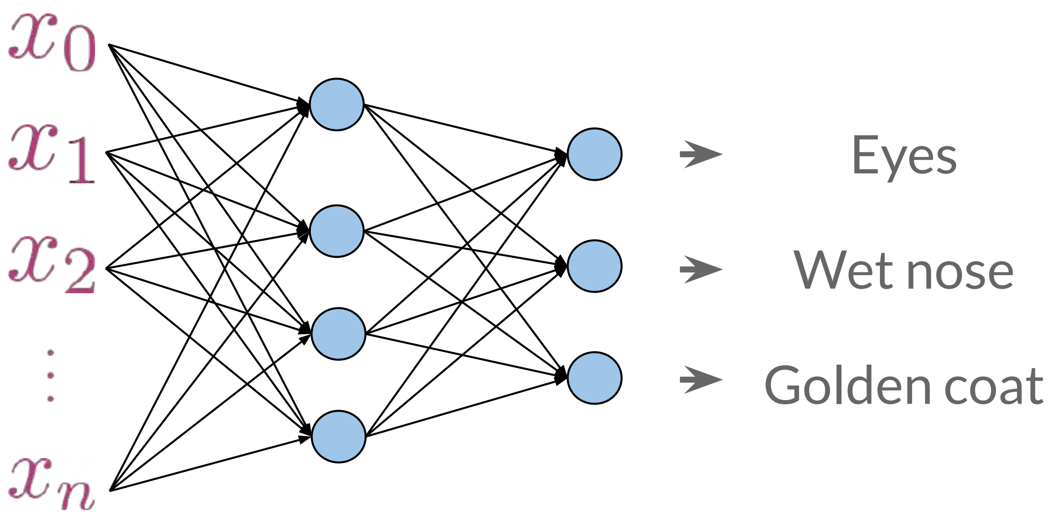
Feature Extraction

Outline

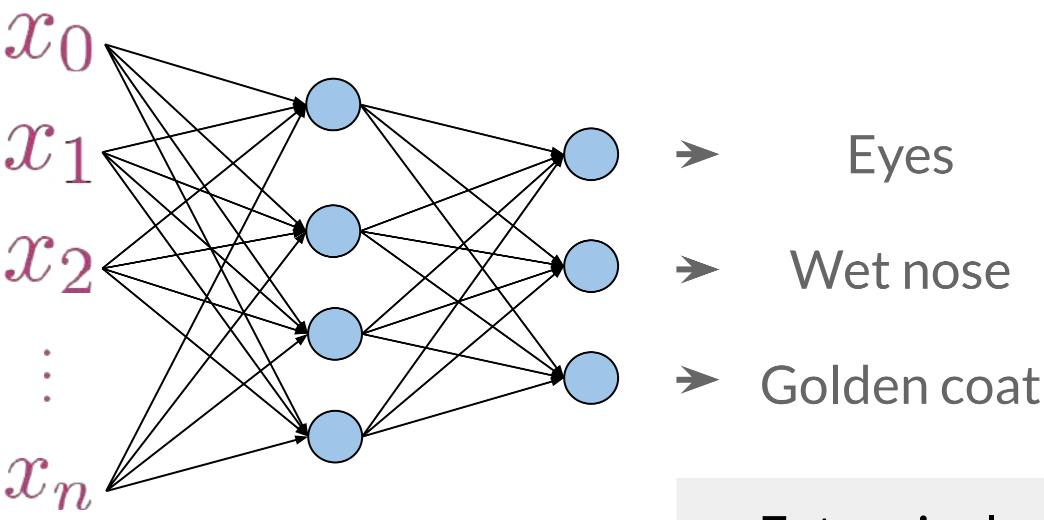
- Feature extraction using pre-trained classifiers
- ImageNet dataset



Classifier → Feature Extractor

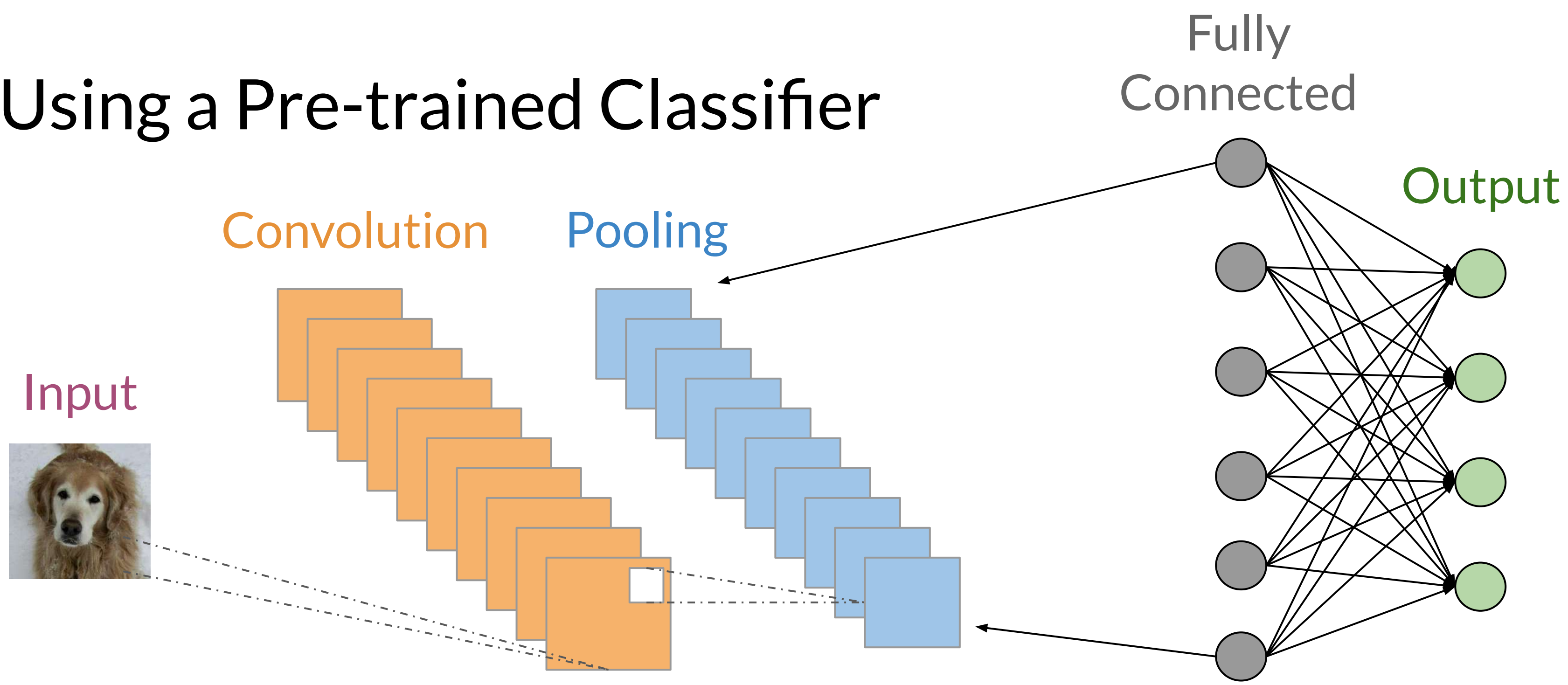


Classifier → Feature Extractor

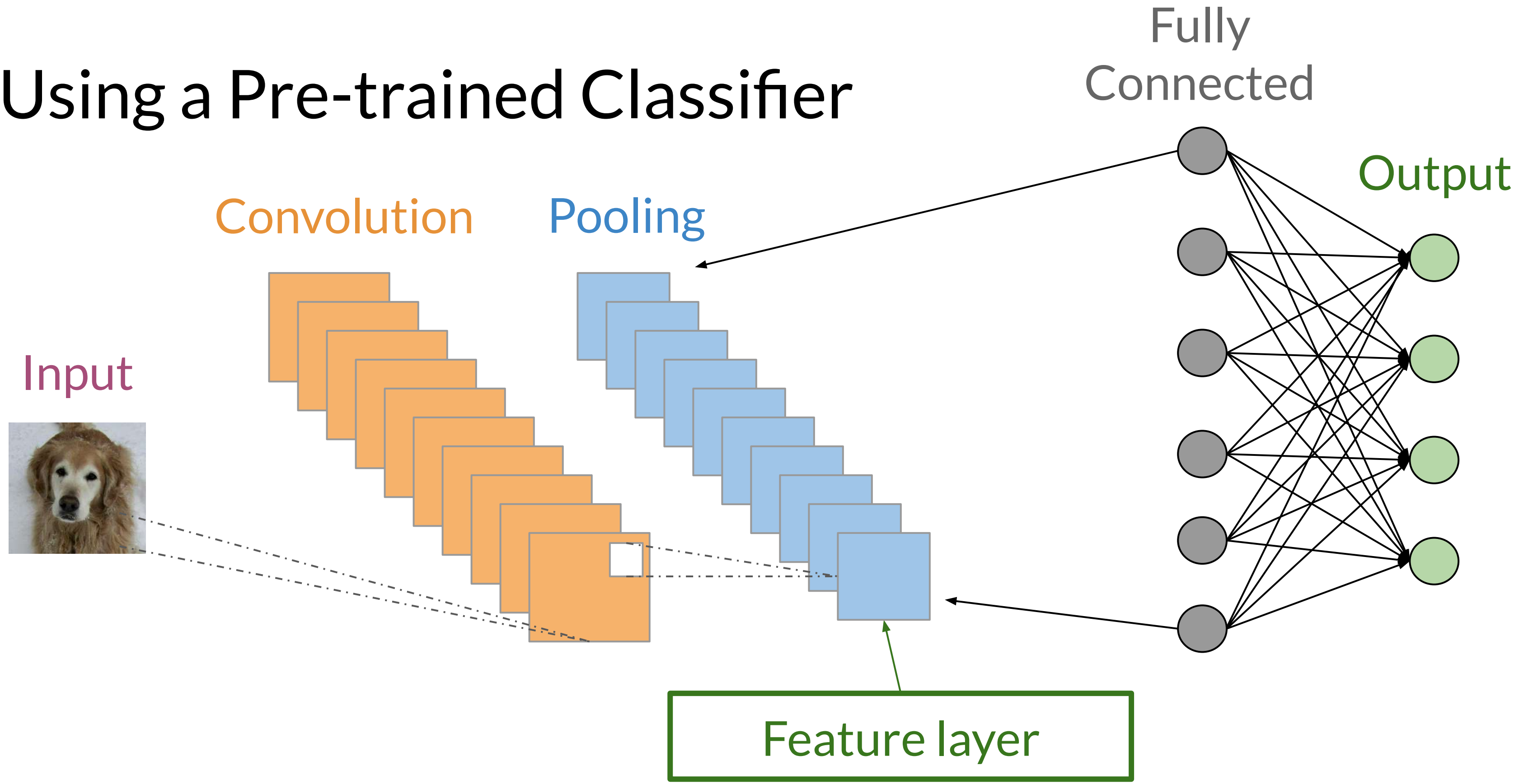


Extensively pre-trained classifiers available to use

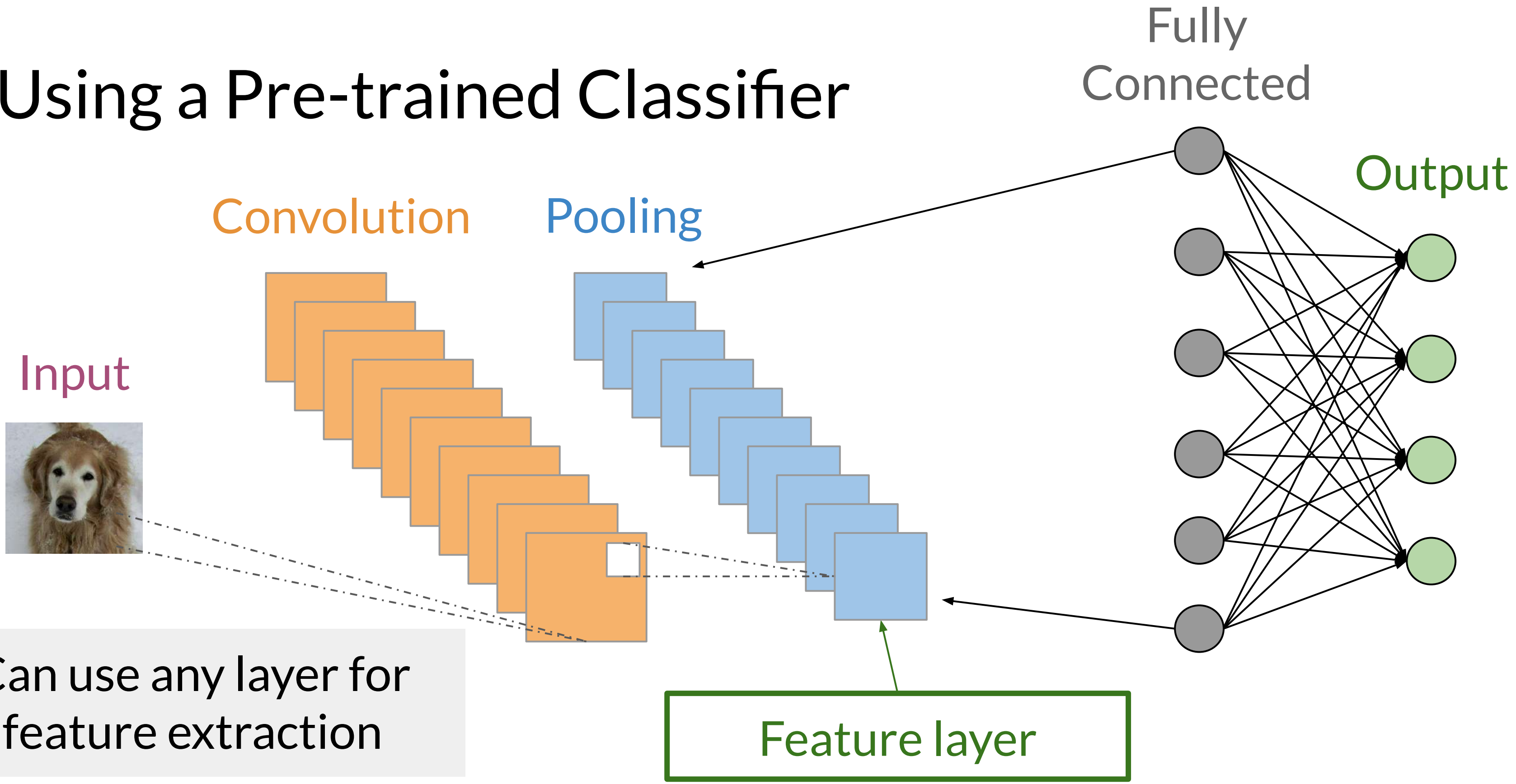
Using a Pre-trained Classifier



Using a Pre-trained Classifier



Using a Pre-trained Classifier



Can use any layer for feature extraction

ImageNet

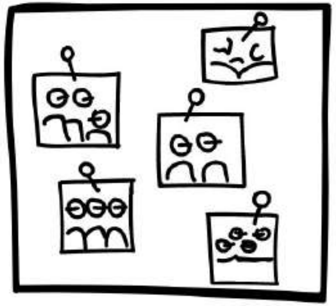
© 2016 Stanford Vision Lab

ImageNet Attributes

- > 14 million images
- > 20,000 categories

Summary

- Classifiers can be used as feature extractors by cutting the network at earlier layers
- The last pooling layer is most commonly used for feature extraction
- Best to use classifiers that have been trained on large datasets—ImageNet



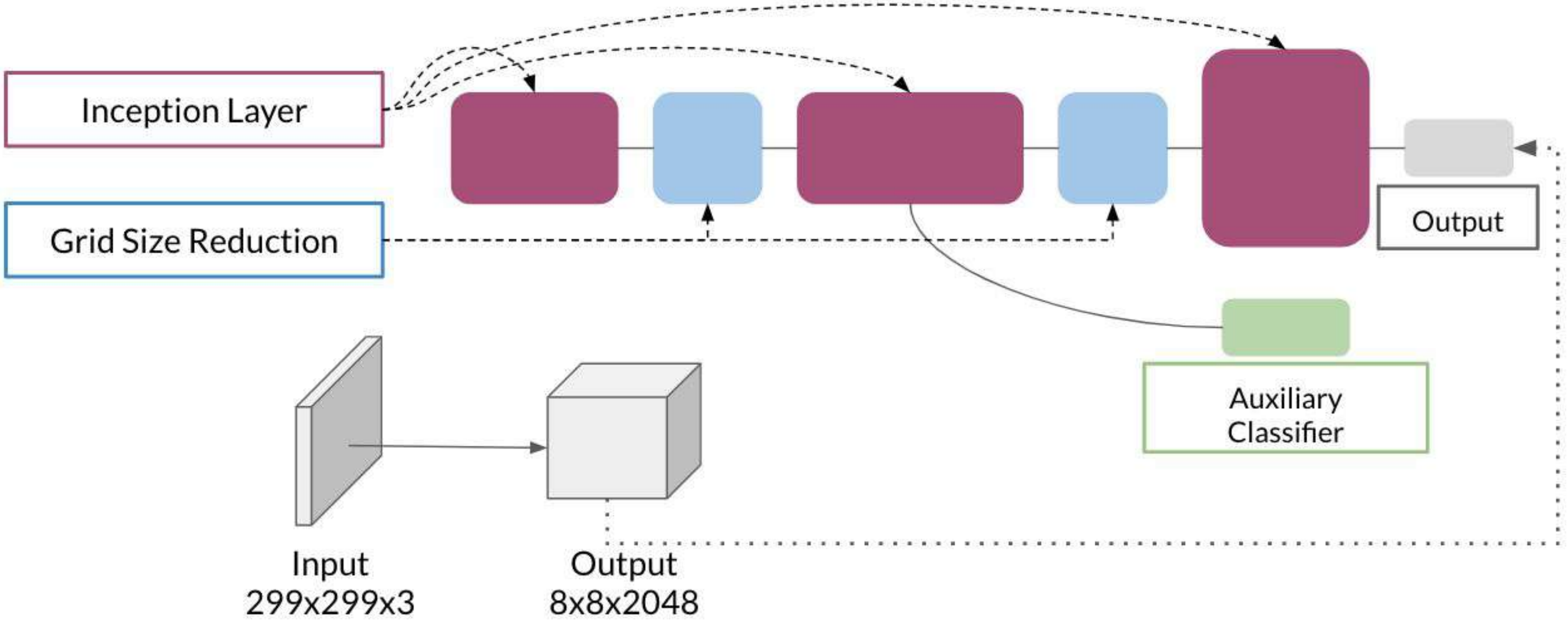
deeplearning.ai

Inception-v3 and Embeddings

Outline

- Inception-v3 architecture
- Comparing extracted feature embeddings

Inception-v3 Architecture



Based on: https://medium.com/@sh.tsang/review-inception-v3-1st-runner-up-image-classification-in-ilsvrc-2015-17915421f77c

Embeddings

Inception-v3

2 eyes,
2 droopy ears,
1 nose, ...

Embeddings

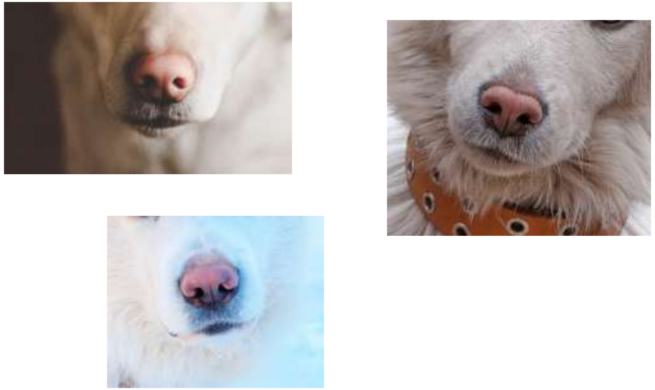
Inception-v3

2 eyes,
2 droopy ears,
1 nose, ...

= $\phi(x)$

Embedding of x

Comparing Embeddings



Fake

Comparing Embeddings



Fake



Real

Summary

- Commonly used feature extractor: Inception-v3 classifier, which is pre-trained on ImageNet, with the output layer cut off
- These features are called embeddings
- Compare embeddings to get the feature distance

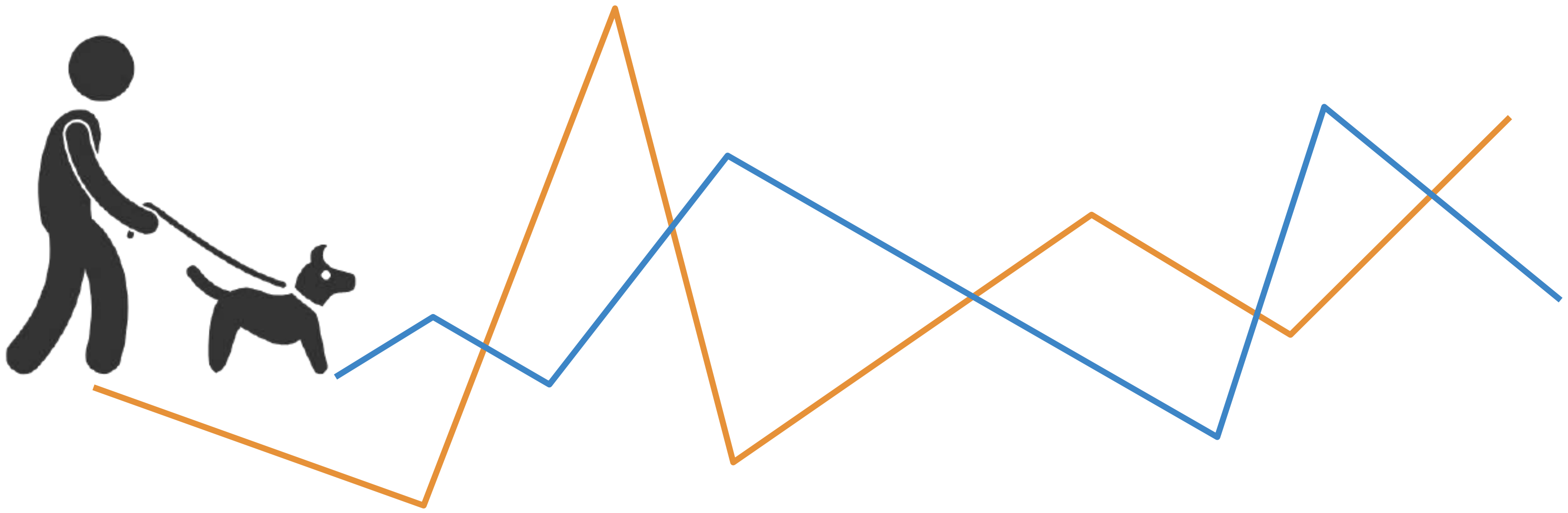
deeplearning.ai

Fréchet Inception Distance (FID)

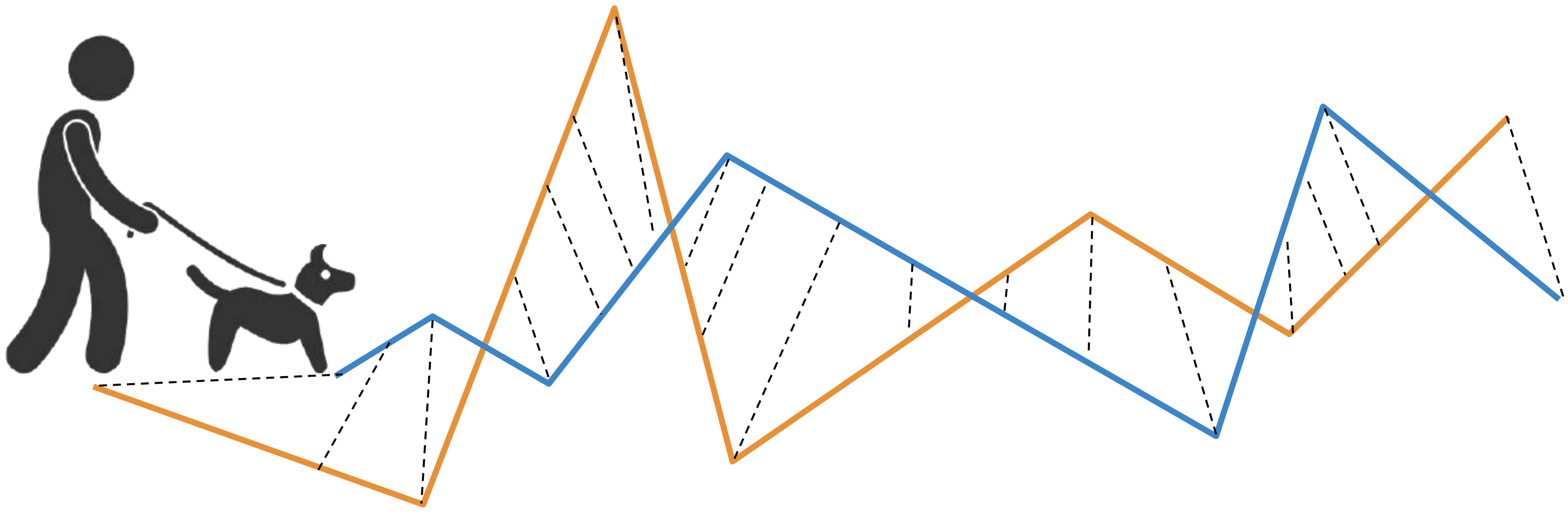
Outline

- Fréchet distance
- Evaluation method: Fréchet Inception Distance (FID)
- FID shortcomings

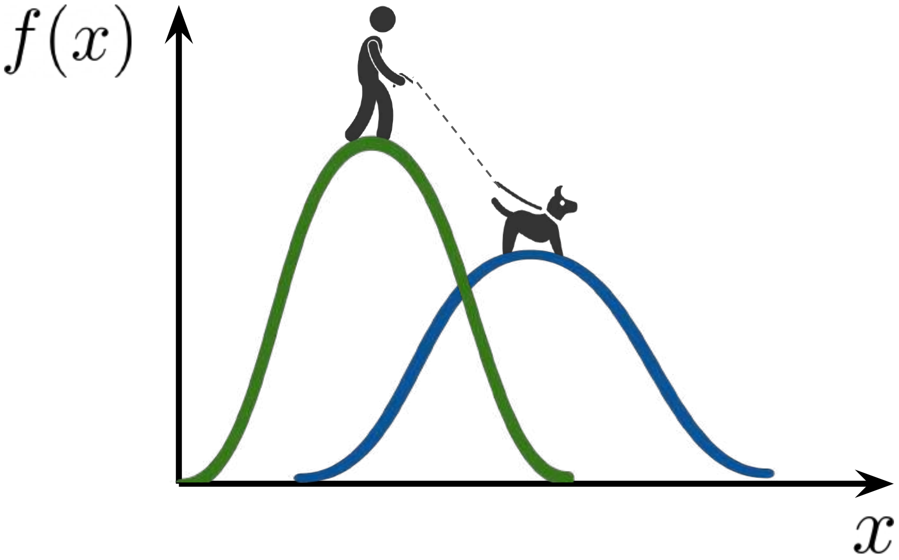
Fréchet Distance



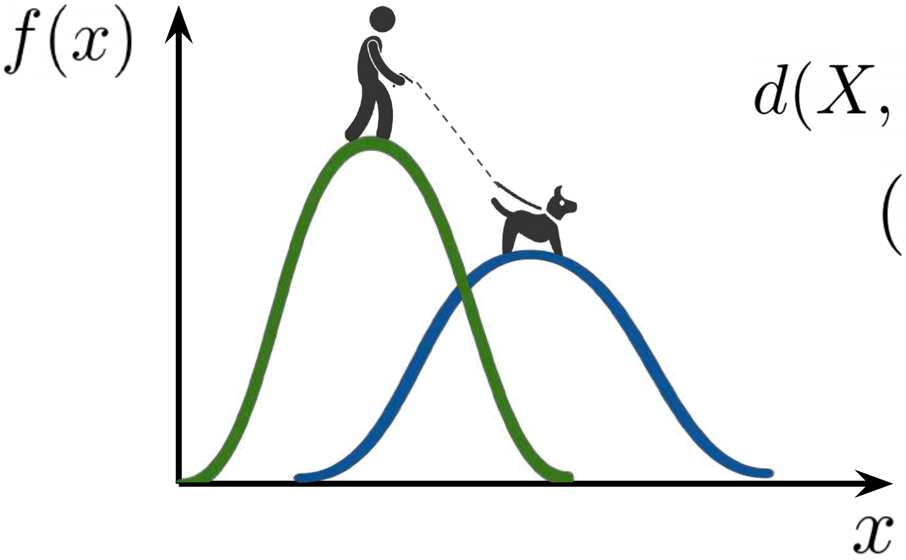
Fréchet Distance



Fréchet Distance Between Normal Distributions

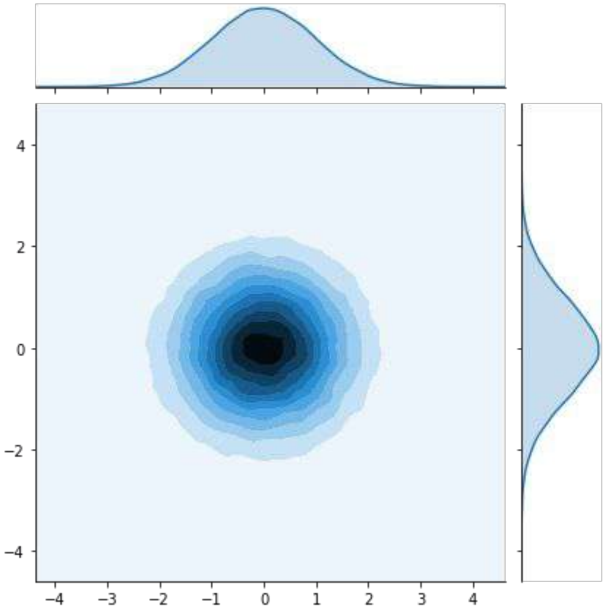


Fréchet Distance Between Normal Distributions

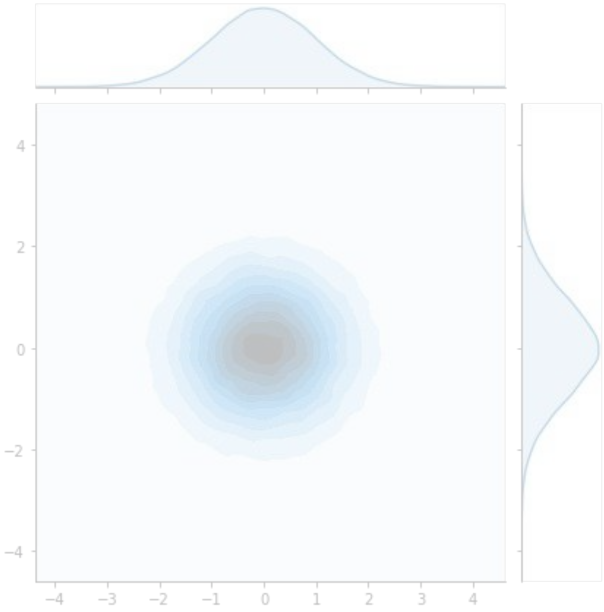


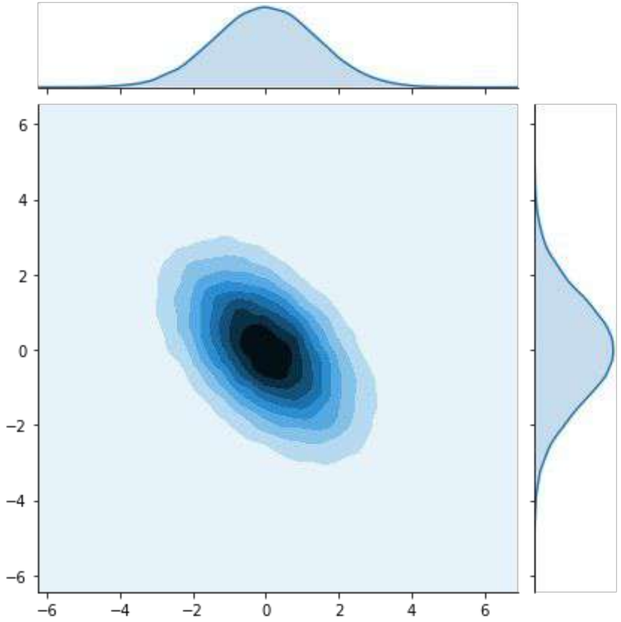
$$d(X,Y) = \underbrace{(\mu_X - \mu_Y)^2}_{\text{Mean}} + \underbrace{(\sigma_X - \sigma_Y)^2}_{\text{Standard deviation}}$$

Multivariate Normal Distributions

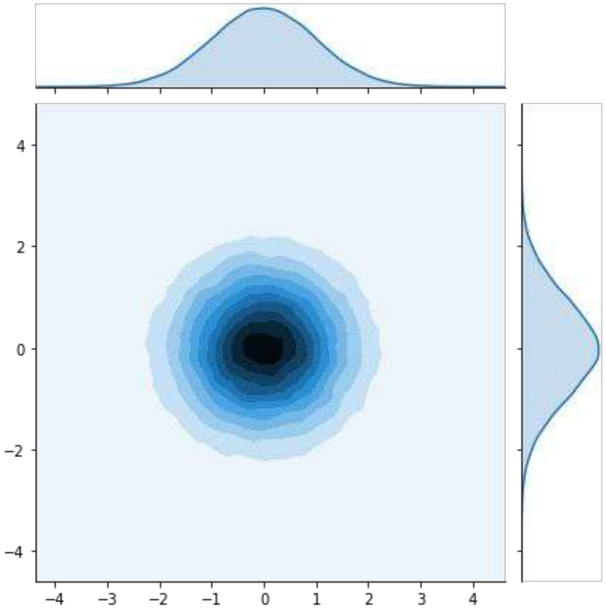


Multivariate Normal Distributions





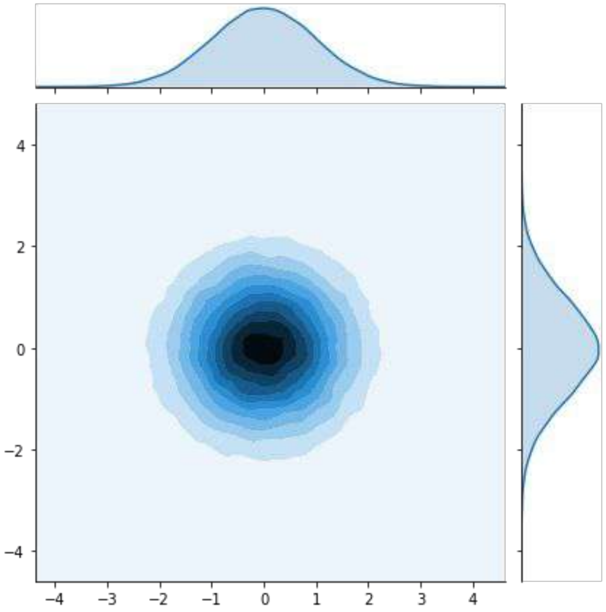
Multivariate Normal Distributions



$$\Sigma = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$$

Covariance matrix

Multivariate Normal Distributions



0's everywhere but the diagonal = all dimensions are *independent*

$$\Sigma = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$$

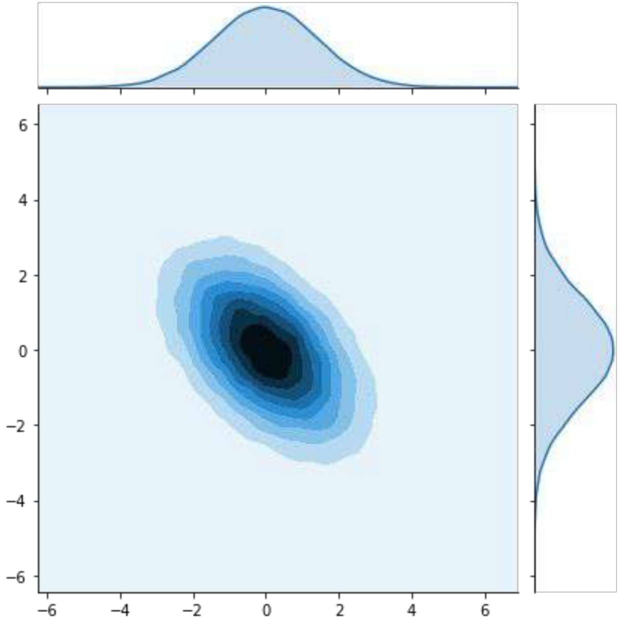
Covariance matrix

Multivariate Normal Distributions

Non-0's not on the diagonal = dimensions covary

$$\Sigma = \begin{pmatrix} 2 & -1 \\ -1 & 2 \end{pmatrix}$$

Covariance matrix



Multivariate Normal Fréchet Distance

Univariate Normal Fréchet Distance =

$$(\mu_X - \mu_Y)^2 + (\sigma_X - \sigma_Y)^2$$

Multivariate Normal Fréchet Distance =

$$\|\mu_X - \mu_Y\|^2 + \mathrm{Tr}\left(\Sigma_X + \Sigma_Y - 2\sqrt{\Sigma_X \Sigma_Y}\right)$$

Multivariate Normal Fréchet Distance

Univariate Normal Fréchet Distance =

$$(\mu_X - \mu_Y)^2 + (\sigma_X - \sigma_Y)^2$$

Multivariate Normal Fréchet Distance =

$$||\mu_X - \mu_Y||^2 + \mathrm{Tr}\left(\Sigma_X + \Sigma_Y - 2\sqrt{\Sigma_X \Sigma_Y}\right)$$

Multivariate Normal Fréchet Distance

Univariate Normal Fréchet Distance = $\boxed{(\sigma_X^2 + \sigma_Y^2 - 2\sigma_X\sigma_Y)}$

$$(\mu_X - \mu_Y)^2 + \boxed{(\sigma_X - \sigma_Y)^2}$$

Multivariate Normal Fréchet Distance =

$$\|\mu_X - \mu_Y\|^2 + \mathrm{Tr}\left(\Sigma_X + \Sigma_Y - 2\sqrt{\Sigma_X \Sigma_Y}\right)$$

Multivariate Normal Fréchet Distance

Univariate Normal Fréchet Distance =

$$(\mu_X - \mu_Y)^2 + (\sigma_X^2 + \sigma_Y^2 - 2\sigma_X\sigma_Y)$$

Multivariate Normal Fréchet Distance =

$$\|\mu_X - \mu_Y\|^2 + \mathrm{Tr}\left(\Sigma_X + \Sigma_Y - 2\sqrt{\Sigma_X\Sigma_Y}\right)$$

Fréchet Inception Distance (FID)

$$\mathrm{FID} = \|\mu_X - \mu_Y\|^2 + \mathrm{Tr}\left(\Sigma_X + \Sigma_Y - 2\sqrt{\Sigma_X \Sigma_Y}\right)$$

Real and fake embeddings are two **multivariate** normal distributions

Fréchet Inception Distance (FID)

Lower FID = closer distributions

$$\text{FID} = \|\mu_X - \mu_Y\|^2 + \text{Tr}\left(\Sigma_X + \Sigma_Y - 2\sqrt{\Sigma_X \Sigma_Y}\right)$$

Real and fake embeddings are two **multivariate** normal distributions

Fréchet Inception Distance (FID)

Lower FID = closer distributions

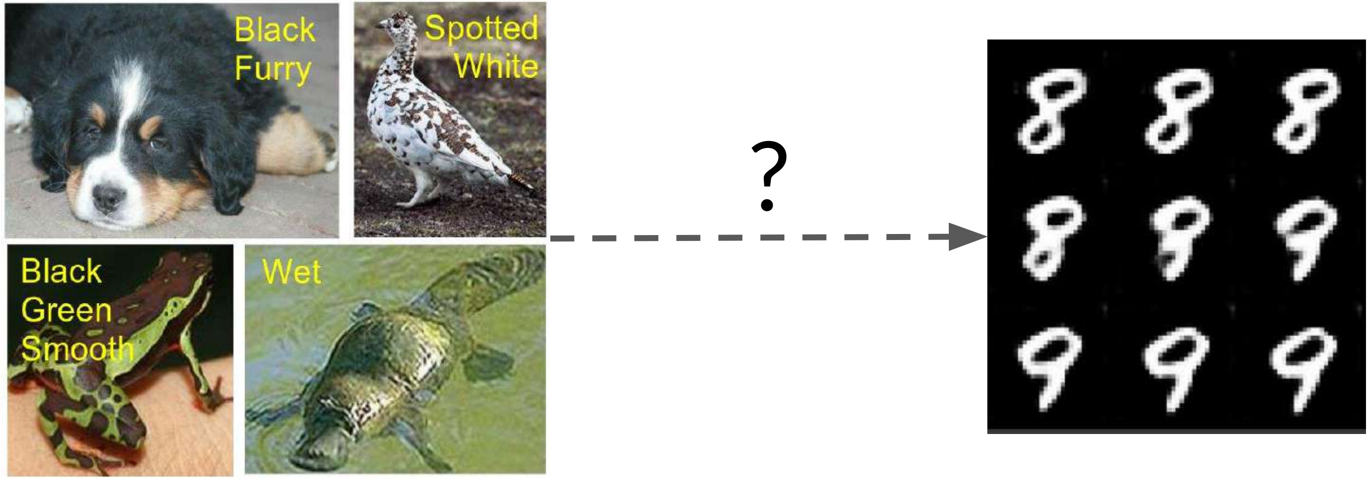
$$\text{FID} = \|\mu_X - \mu_Y\|^2 + \text{Tr}\left(\Sigma_X + \Sigma_Y - 2\sqrt{\Sigma_X \Sigma_Y}\right)$$

Real and fake embeddings are two **multivariate** normal distributions

Use *large sample size* to reduce noise

Shortcomings of FID

- Uses pre-trained Inception model, which may not capture all features



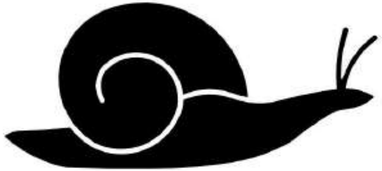
Shortcomings of FID

- Uses pre-trained Inception model, which may not capture all features
- Needs a large sample size

© 2016 Stanford Vision Lab

Shortcomings of FID

- Uses pre-trained Inception model, which may not capture all features
- Needs a large sample size
- Slow to run

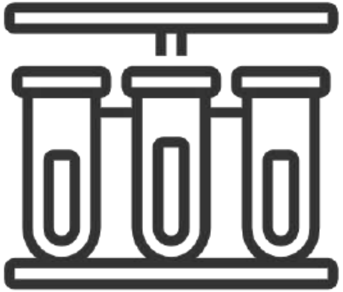


Shortcomings of FID

- Uses pre-trained Inception model, which may not capture all features
- Needs a large sample size
- Slow to run
- Limited statistics used: only mean and covariance

Summary

- FID calculates the difference between reals and fakes
- FID uses the Inception model and multivariate normal Fréchet distance
- Sample size needs to be large for FID to work well



deeplearning.ai

Inception Score

Outline

- Another evaluation metric: Inception Score (IS)
  - Intuition, notation, shortcomings

Inception Model Classification

Fake

0.30 Cat

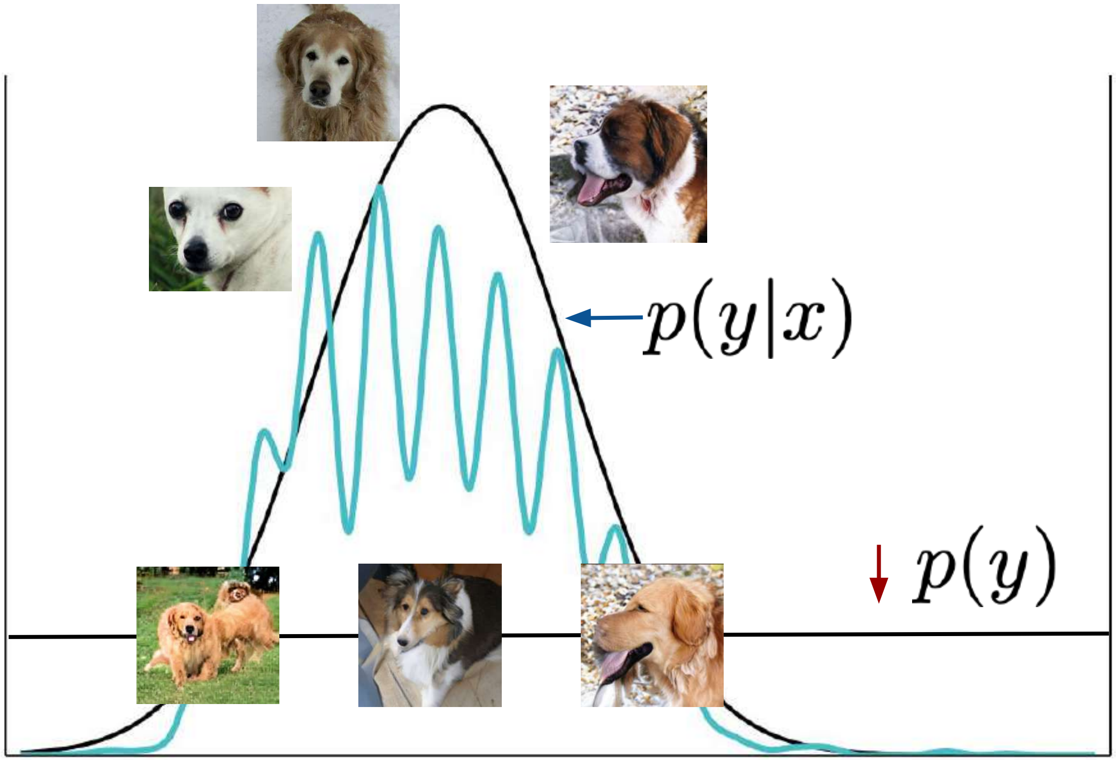
0.60 Dog

0.10 Bird

Entropy

Fidelity
(high entropy) →

Diversity
(low entropy) →



KL Divergence

$$D_{KL}(p(y|x)\|p(y)) = p(y|x)\log\left(\frac{p(y|x)}{p(y)}\right)$$

Conditional distribution (fidelity)

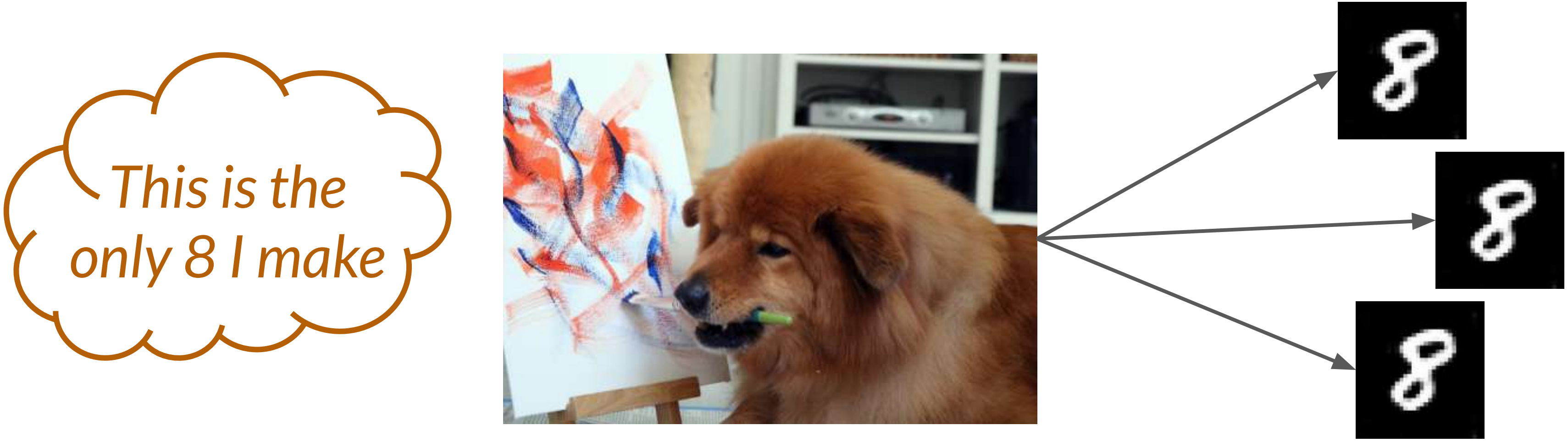
Marginal distribution (diversity)

Inception Score (IS)

$$\mathrm{IS} = \exp(\mathbb{E}_{x \sim p_\varepsilon} \underbrace{D_{KL}(p(y \mid x) \| p(y))}_{\text{KL Divergence}})$$

Shortcomings of IS

- Can be exploited or gamed
    - Generate one realistic image of each class



Shortcomings of IS

- Can be exploited or gamed
  - Generate one realistic image of each class
- Only looks at fake images
  - No comparison to real images

$$p(y|x) \qquad p(y)$$

Shortcomings of IS

- Can be exploited or gamed
  - Generate one realistic image of each class
- Only looks at fake images
  - No comparison to real images
- Can miss useful features
  - ImageNet isn't everything

Summary

- Inception Score tries to capture fidelity & diversity
- Inception Score has many shortcomings
    - Can be gamed too easily
    - Only looks at fake images, not reals
    - ImageNet doesn't teach a model all features
- Worse than Fréchet Inception Distance

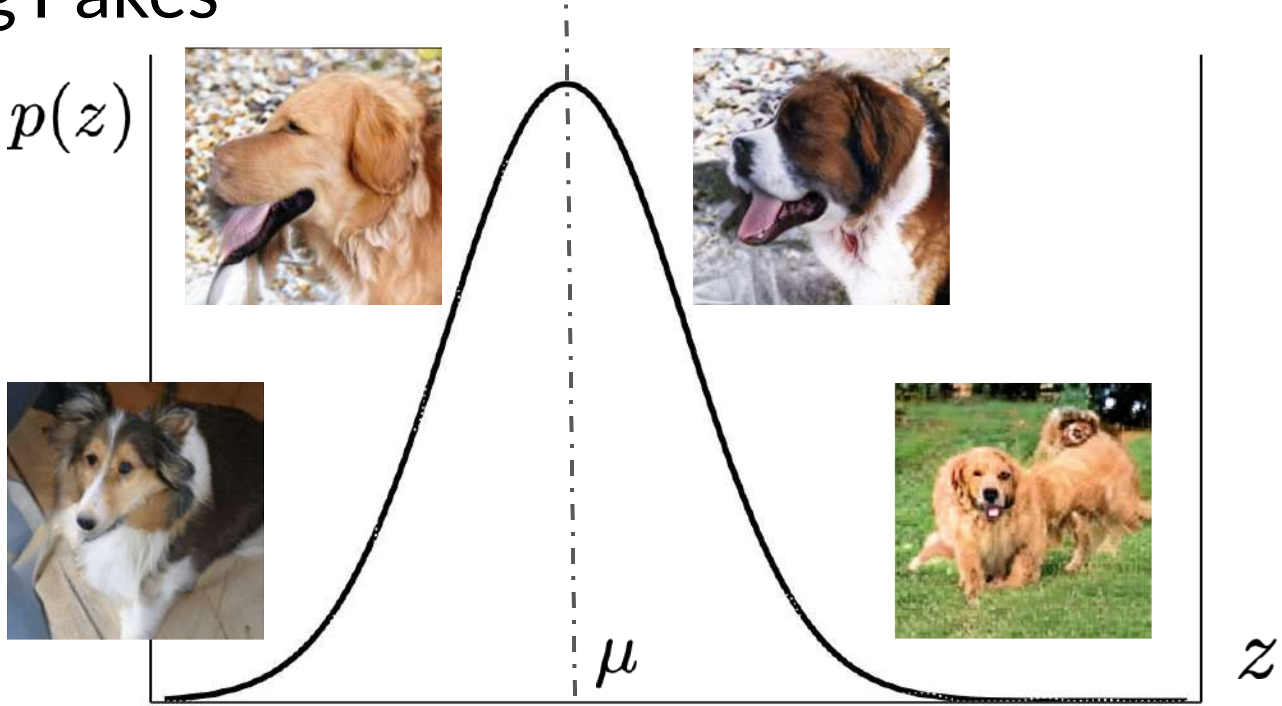
deeplearning.ai

Sampling and Truncation

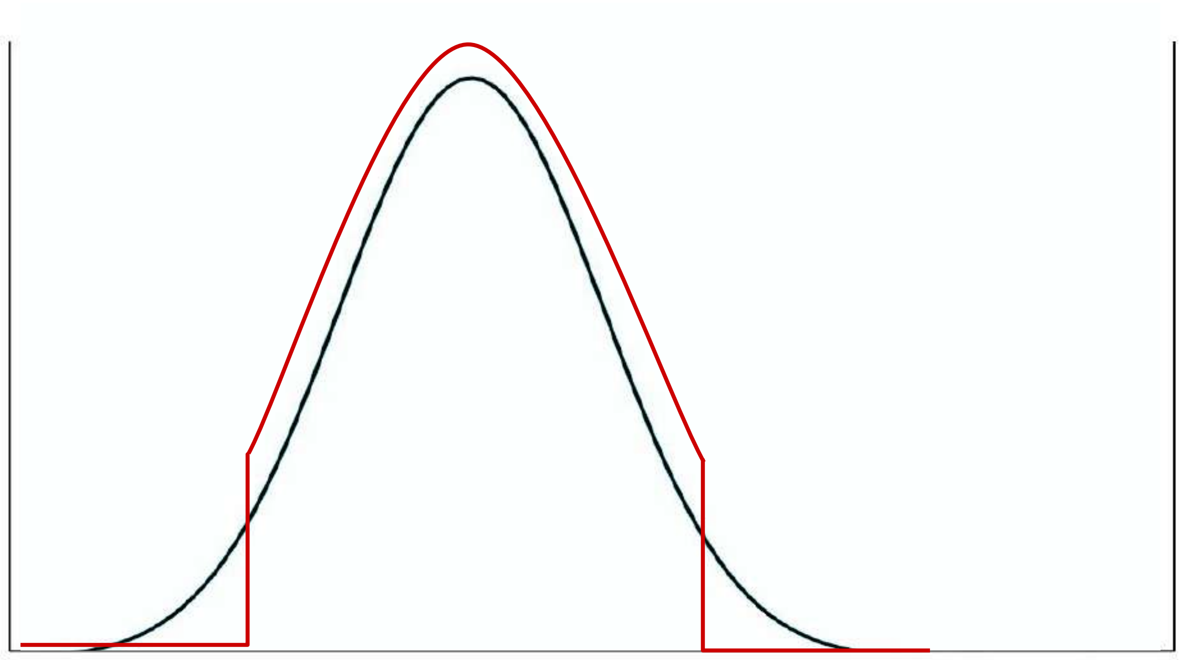
Outline

- Sampling reals vs. fakes
- The truncation trick
- HYPE!

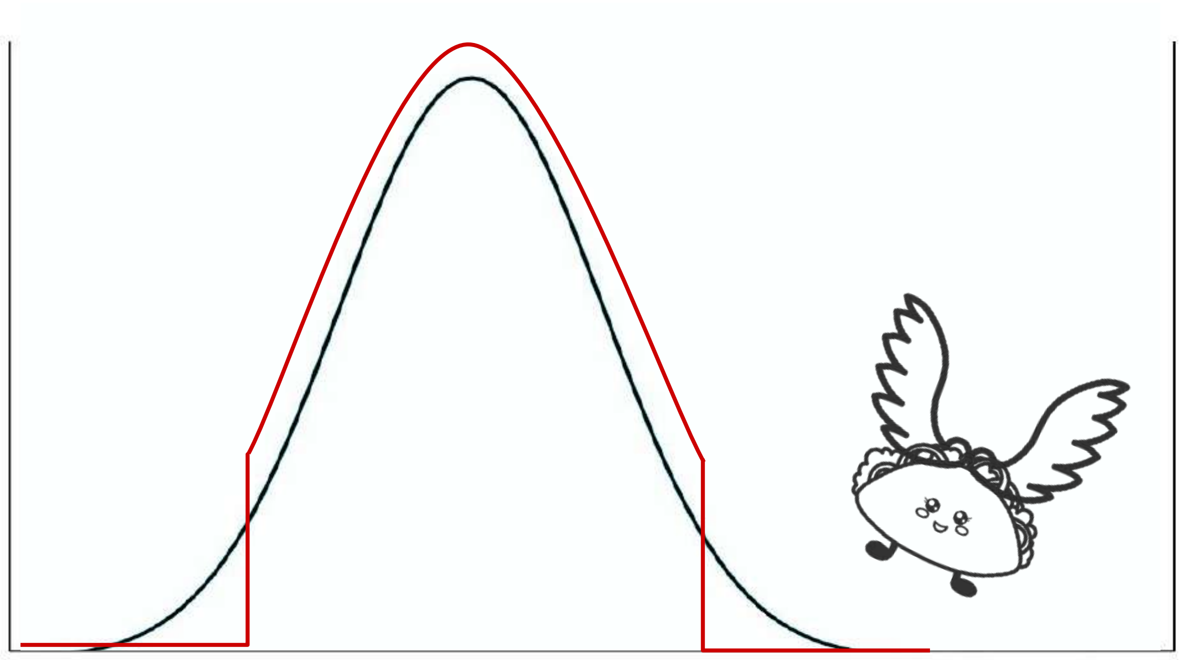
Sampling Fakes



Truncation Trick



Truncation Trick



HYPE and Human Evaluation

- Crowdsourced evaluation from Amazon Mechanical Turk
- $\text{HYPE}_{\text{time}}$ measures time-limited perceptual thresholds
- HYPE_{∞} measures error rate on a percentage of images
- Ultimately, evaluation depends on the type of downstream task

Available from: https://arxiv.org/abs/1904.01121

Summary

- Fakes are sampled using the training or prior distribution of z
- Truncate more for higher fidelity, lower diversity
- Human evaluation is still necessary for sampling

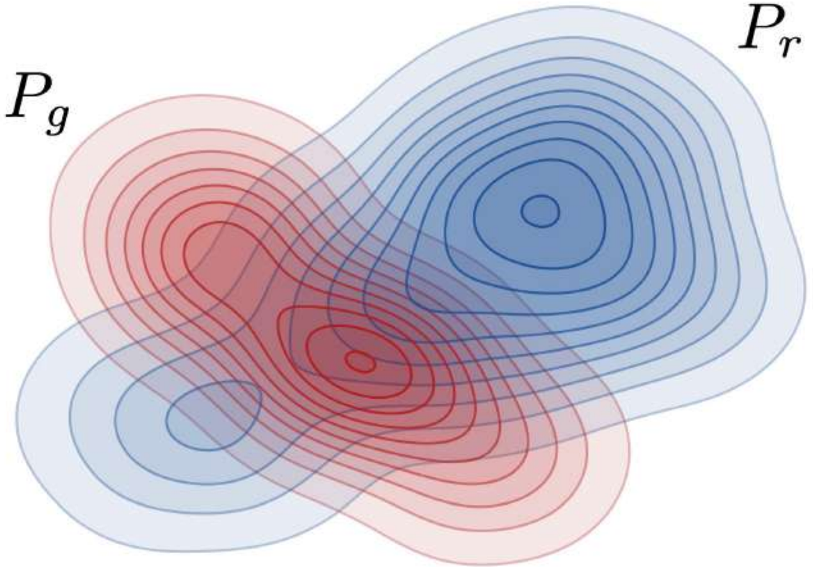
Precision and Recall

deeplearning.ai

Outline

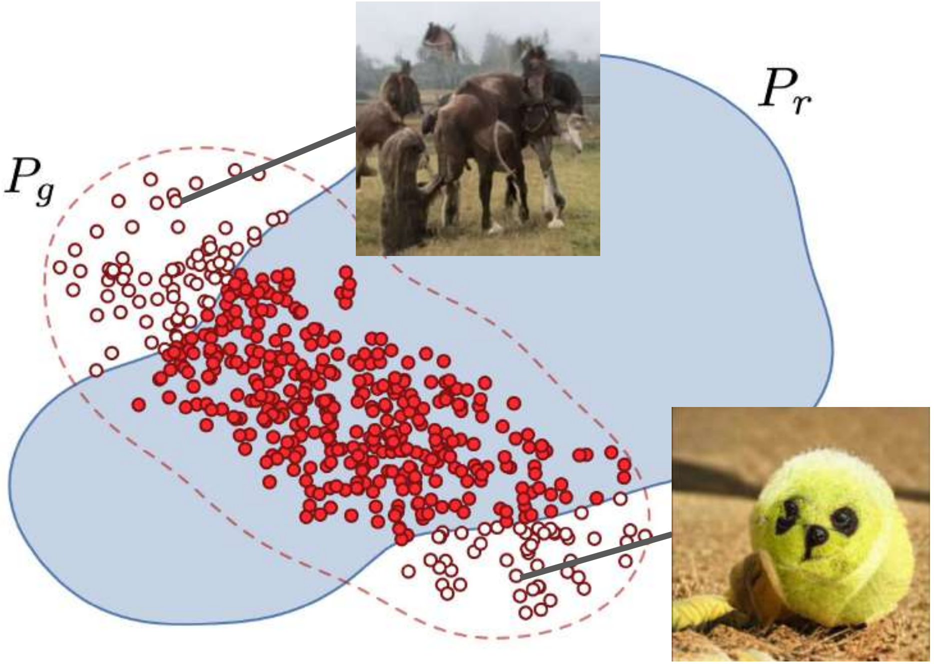
- Precision and recall in GANs evaluation
- Relating precision and recall to fidelity and diversity

Precision and Recall



Available at: https://arxiv.org/abs/1904.06991

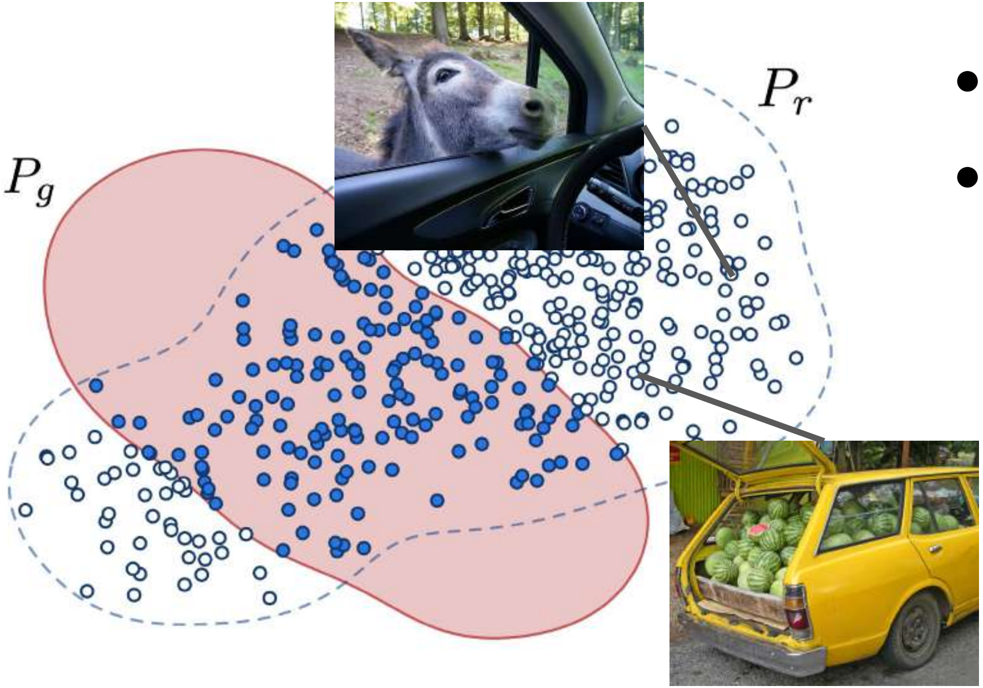
Precision



- Relates to fidelity
- Looks at overlap between reals and fakes, over how much extra gunk the generator produces (non-overlap red)

Diagram available at: https://arxiv.org/abs/1904.06991; Tennis dog available at: https://arxiv.org/abs/1809.11096

Recall



- Relates to diversity
- Looks at overlap between reals and fakes, over all the reals that the generator cannot model (non-overlap blue)

Diagram available at: https://arxiv.org/abs/1904.06991

Summary

- Precision is to fidelity as to recall is to diversity
- Models tend to be better at recall
- Use truncation trick to improve precision