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Evaluation

Outline

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

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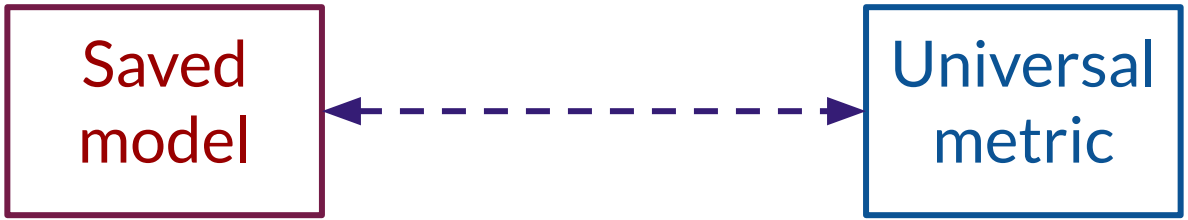
Why is evaluating GANs hard?



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Why is evaluating GANs hard?

Classifier

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Why is evaluating GANs hard?

Classifier

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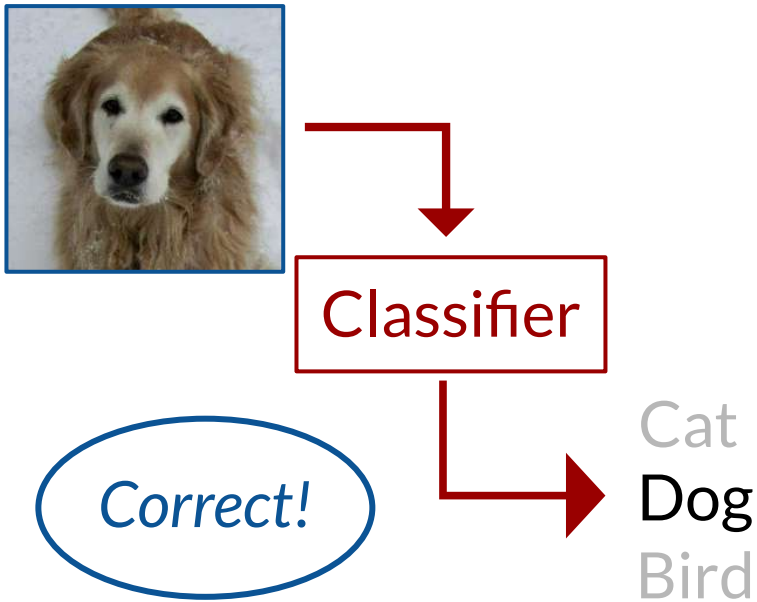
Why is evaluating GANs hard?



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Why is evaluating GANs hard?

Classifier

Cat
Dog
Bird

Correct!

GAN

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Why is evaluating GANs hard?

Classifier

Cat
Dog
Bird

Correct!

GAN

deeplearning.ai

Why is evaluating GANs hard?

Classifier

Correct!

Cat
Dog
Bird

GAN

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Why is evaluating GANs hard?

Classifier

Cat
Dog
Bird

Correct!

GAN

Uh… looks real?

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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

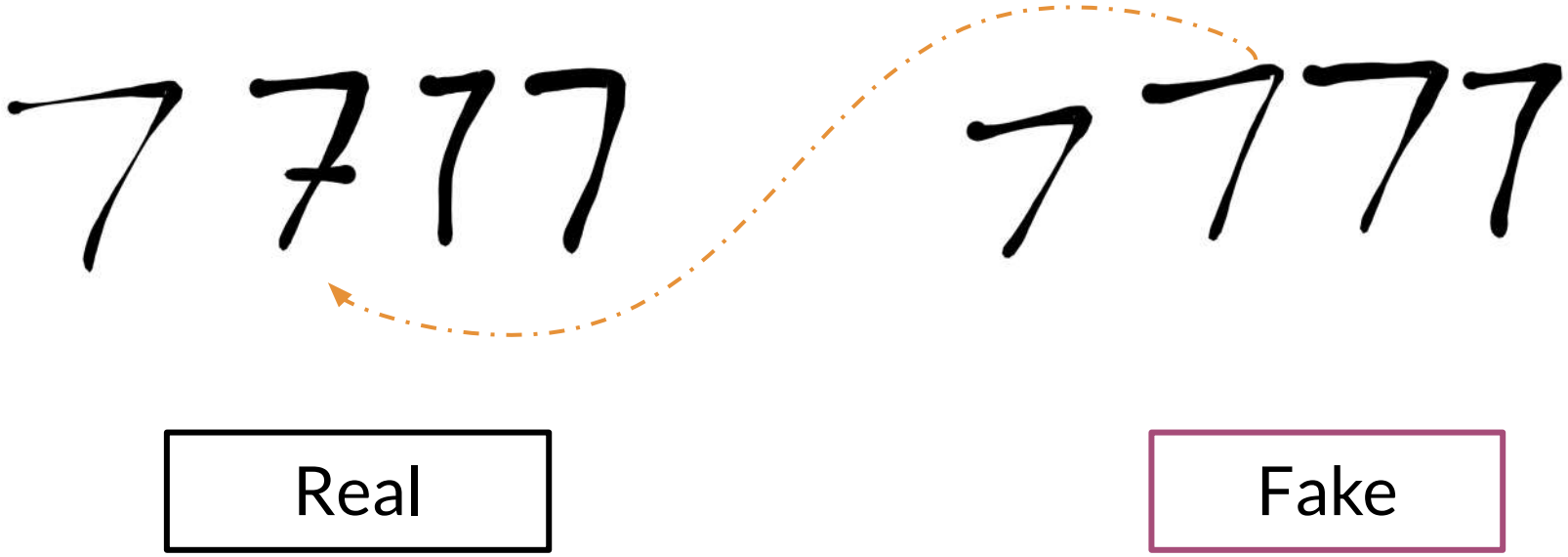
(Left) Available at: https://github.com/NVlabs/stylegan

Fidelity

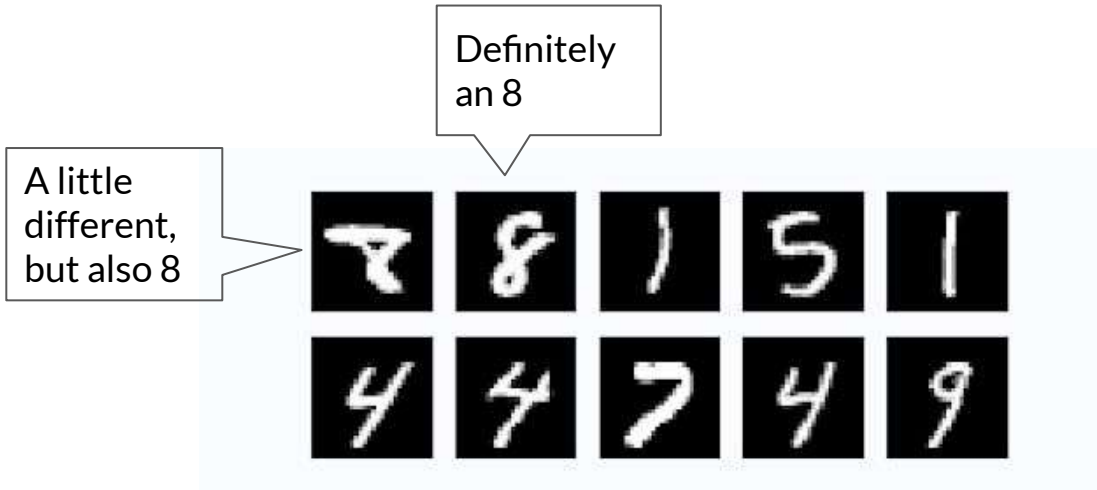
Fidelity

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

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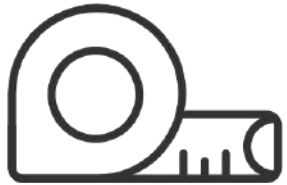
Comparing Images

Outline

- Pixel distance
- Feature distance



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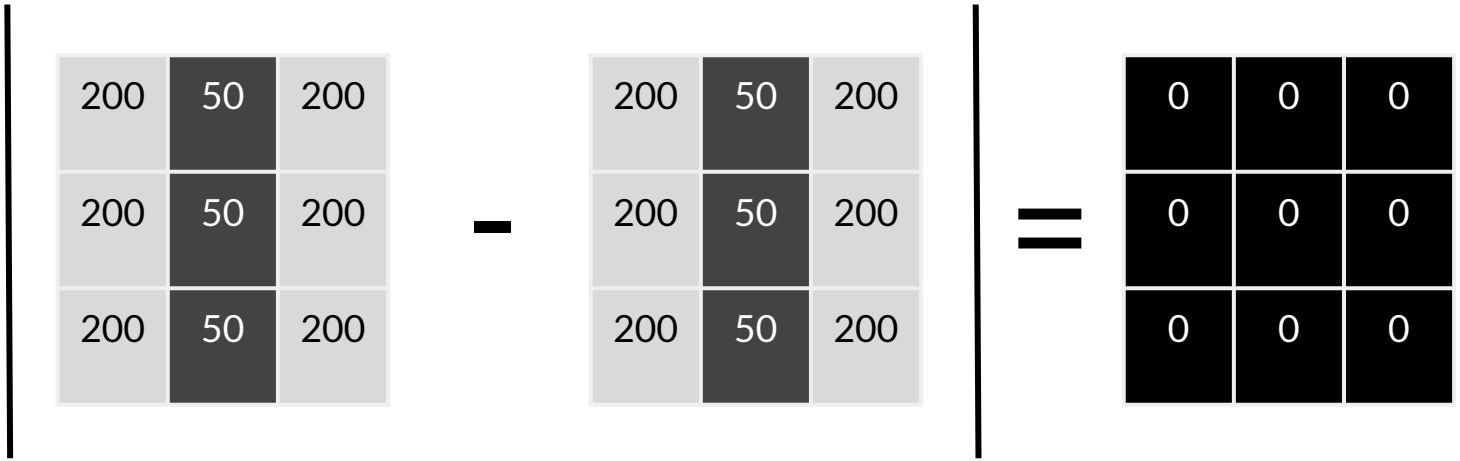
Pixel Distance



Real

Fake

Absolute difference

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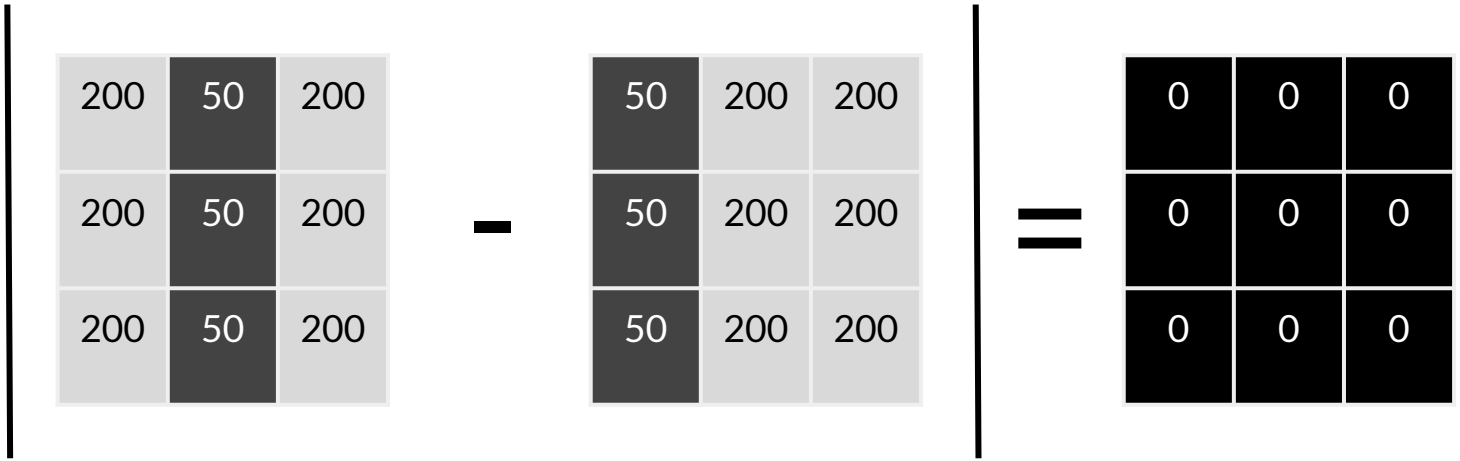
Pixel Distance



Real

Fake

Absolute difference

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Feature Distance

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Feature Distance

Real

Fake

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Feature Distance

Real

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

Fake

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

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Feature Distance

Real

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

Fake

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

Compare features!

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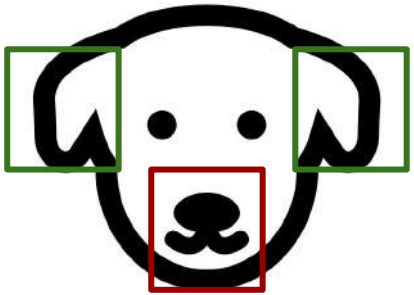
Summary

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



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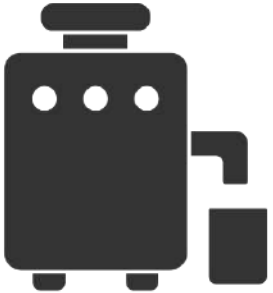
Feature Extraction

Outline

- Feature extraction using pre-trained classifiers
- ImageNet dataset



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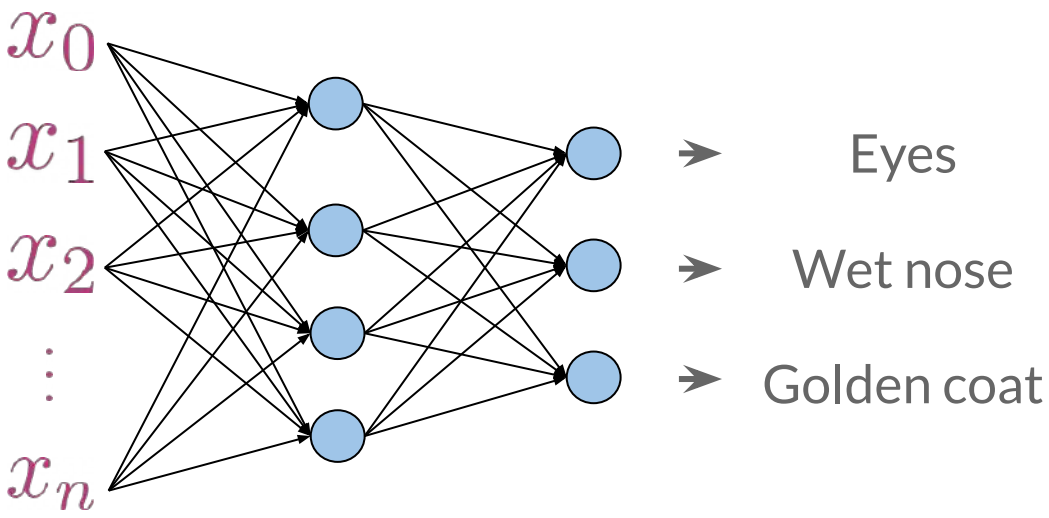
Classifier → Feature Extractor



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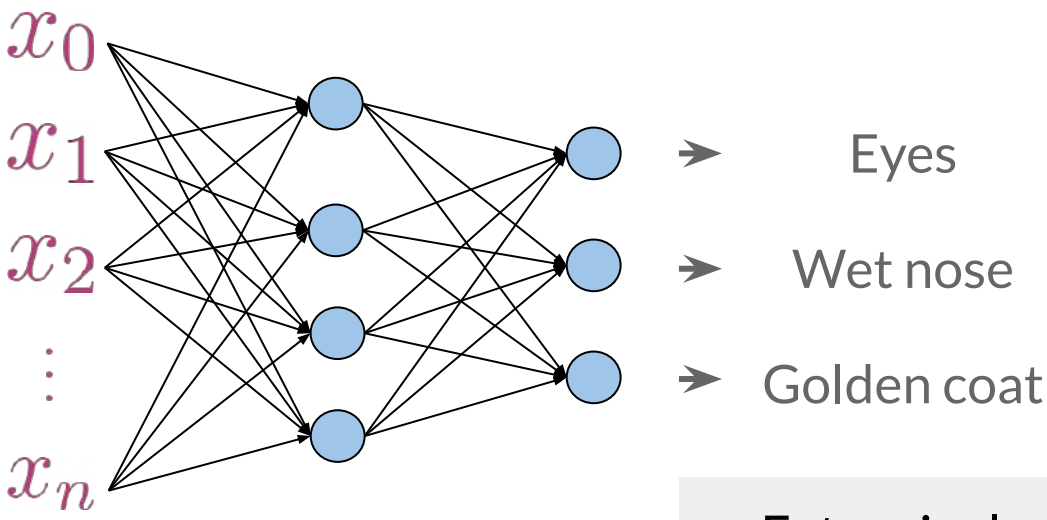
Classifier → Feature Extractor



Extensively pre-trained classifiers available to use

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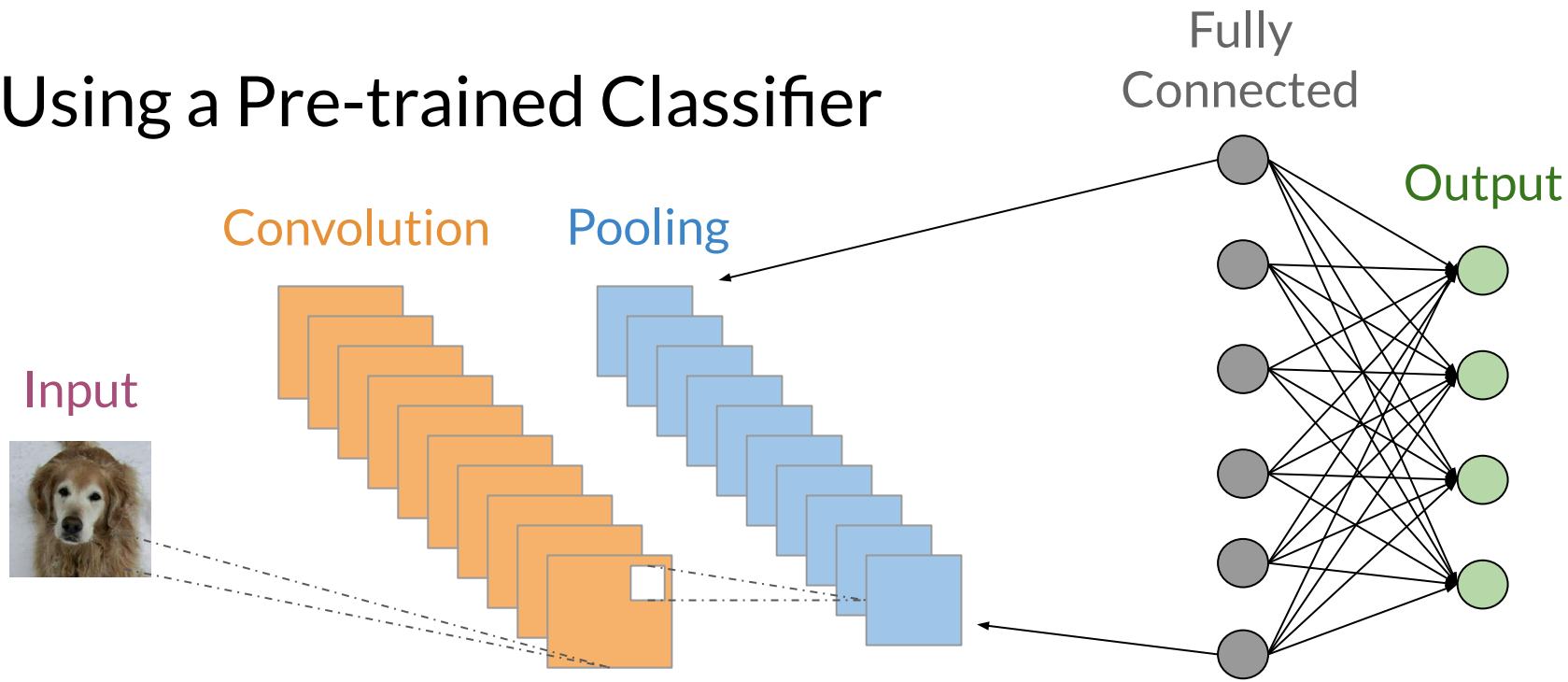
Using a Pre-trained Classifier



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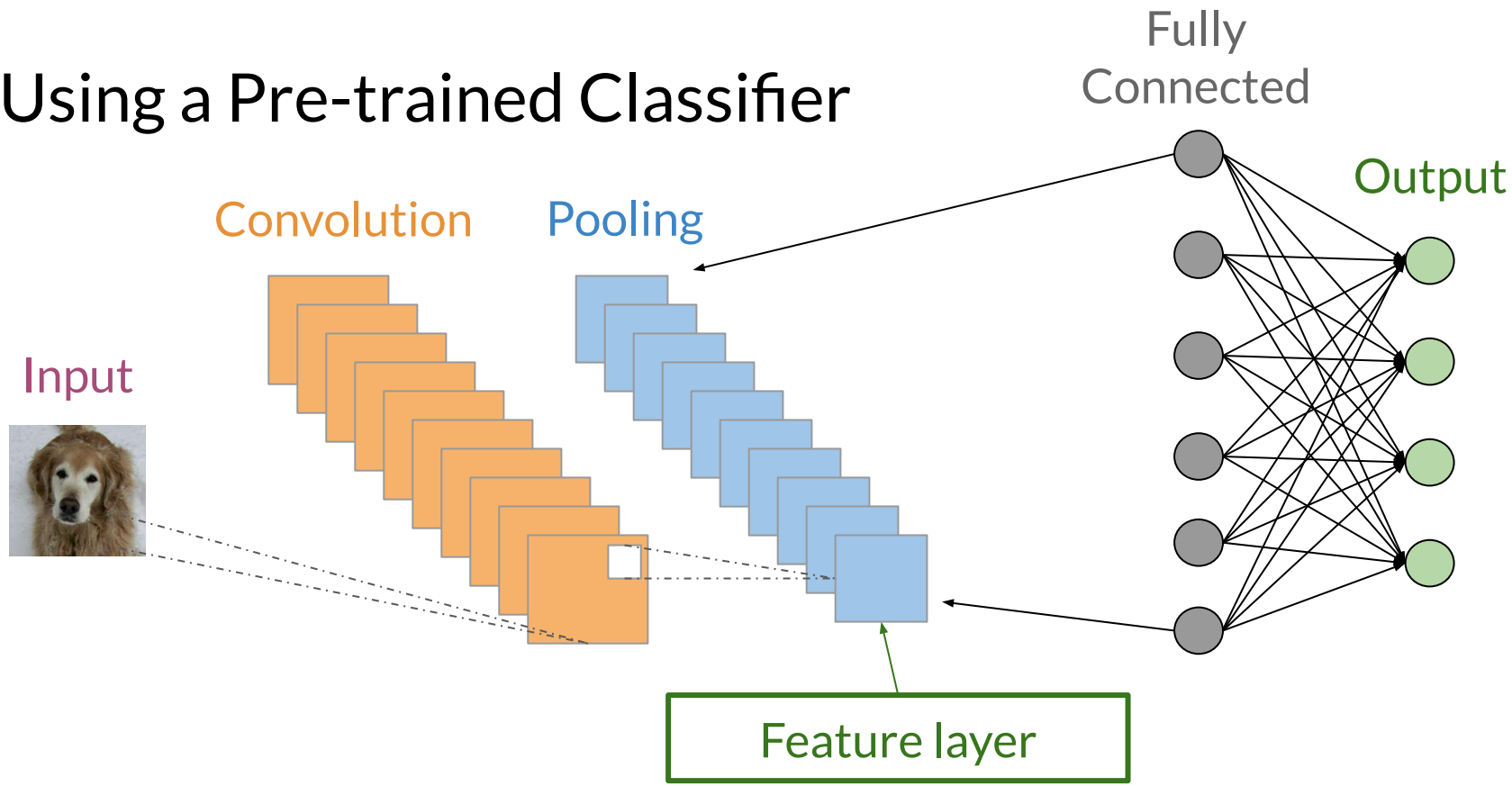
Using a Pre-trained Classifier



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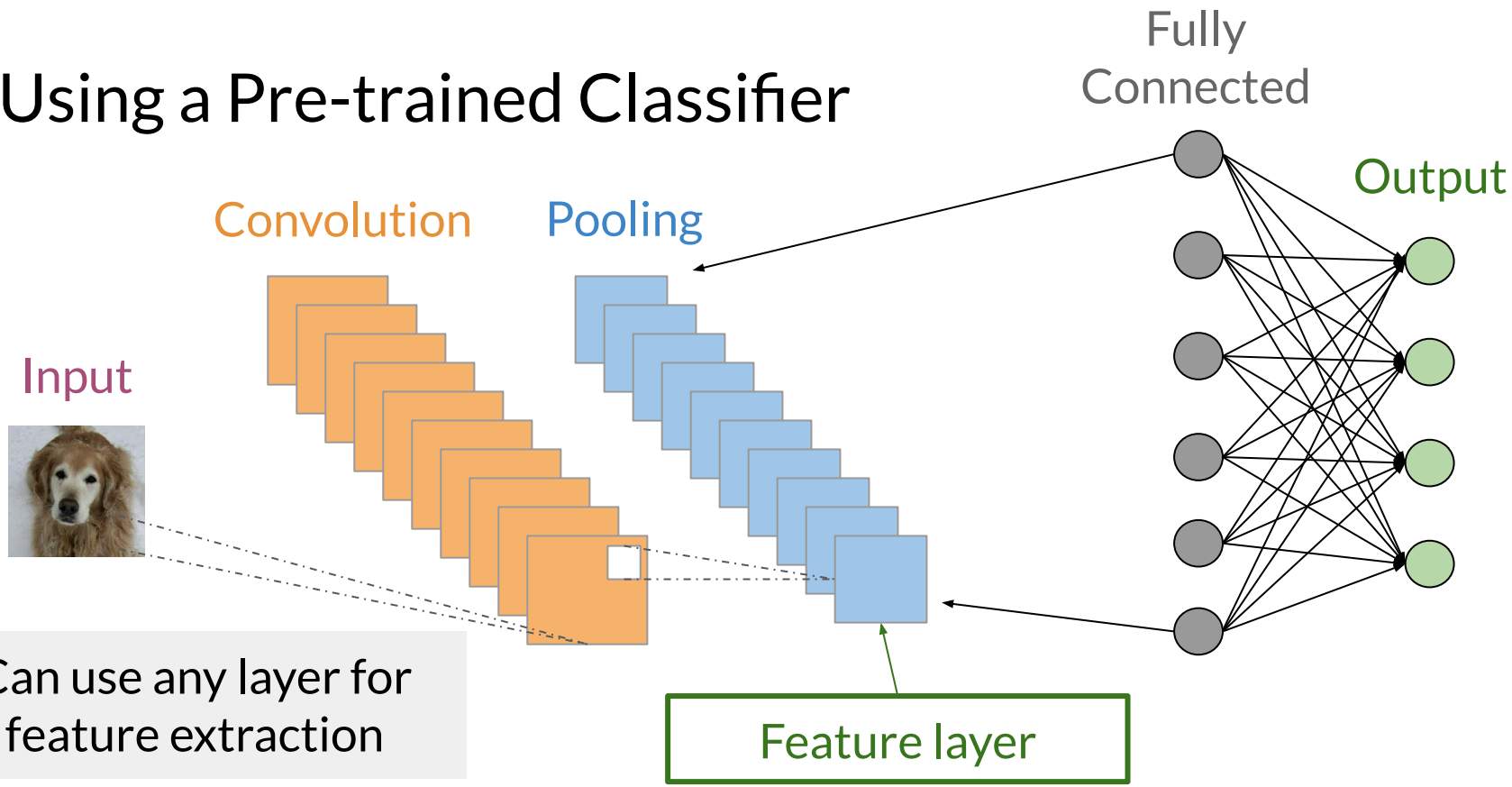
Using a Pre-trained Classifier



Can use any layer for feature extraction

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ImageNet

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ImageNet Attributes

- > 14 million images
- > 20,000 categories

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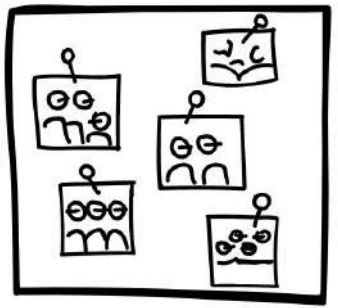
Summary

- 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



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Inception-v3 and Embeddings

Outline

- Inception-v3 architecture
- Comparing extracted feature embeddings

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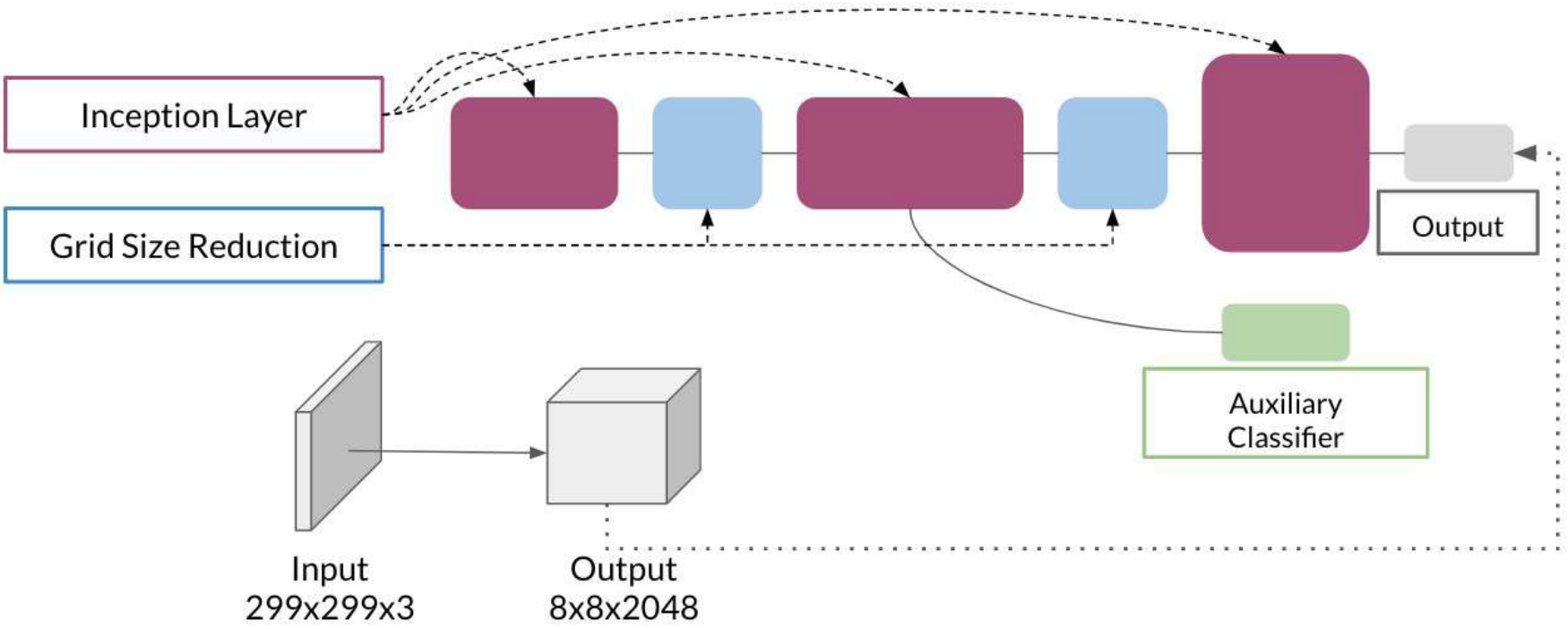
Inception-v3 Architecture



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

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Embeddings

Inception-v3

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

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Embeddings

Inception-v3

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

= $\phi(x)$

Embedding of x

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Comparing Embeddings

Fake

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Comparing Embeddings

Fake

Real

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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

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Fréchet Inception Distance (FID)

Outline

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

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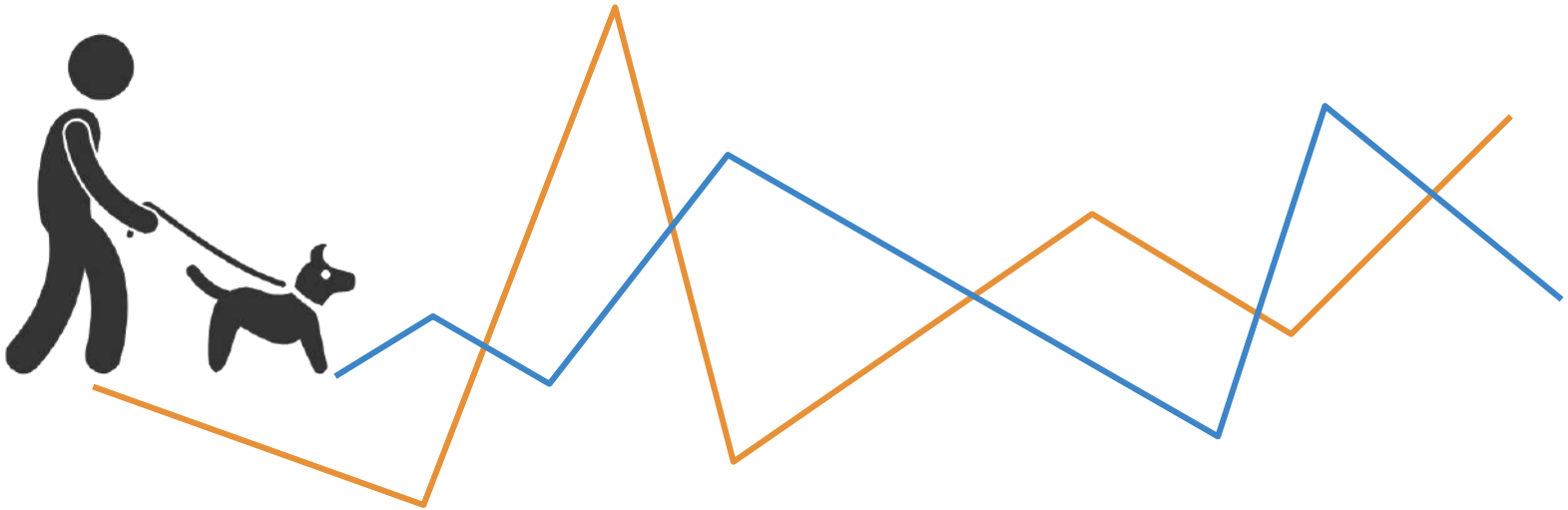
Fréchet Distance



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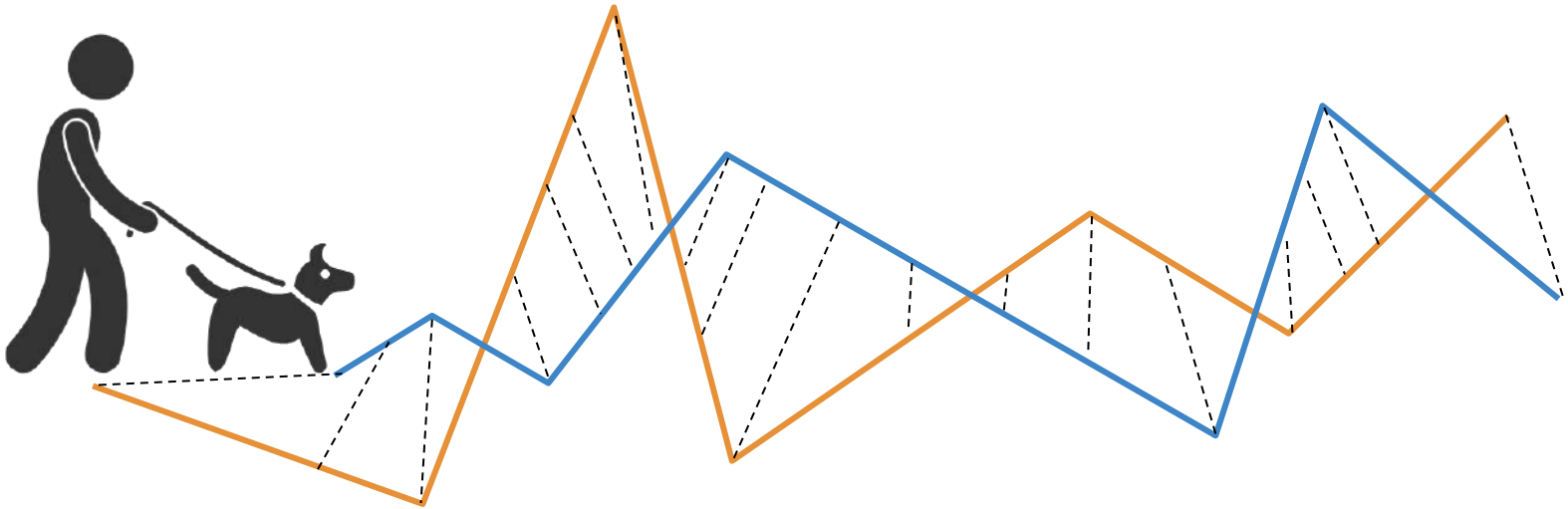
Fréchet Distance



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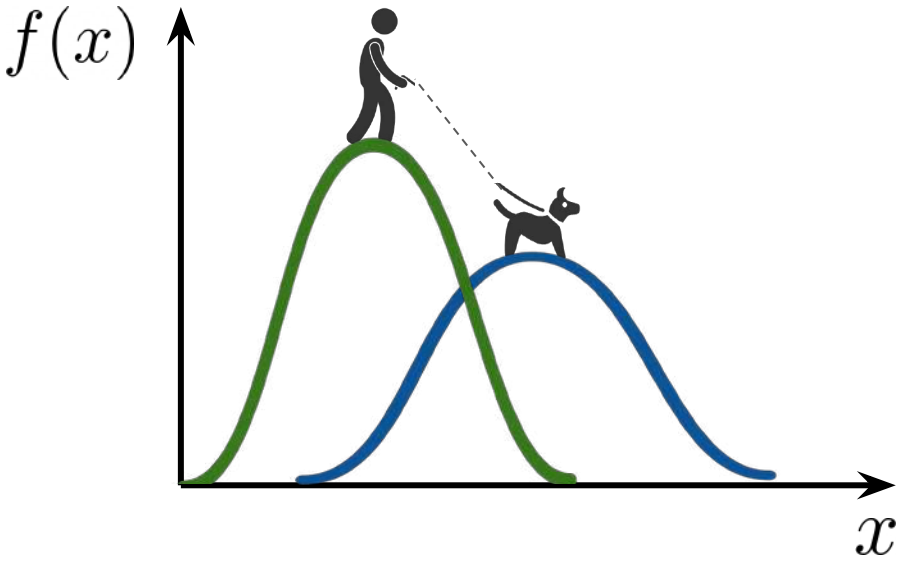
Fréchet Distance Between Normal Distributions



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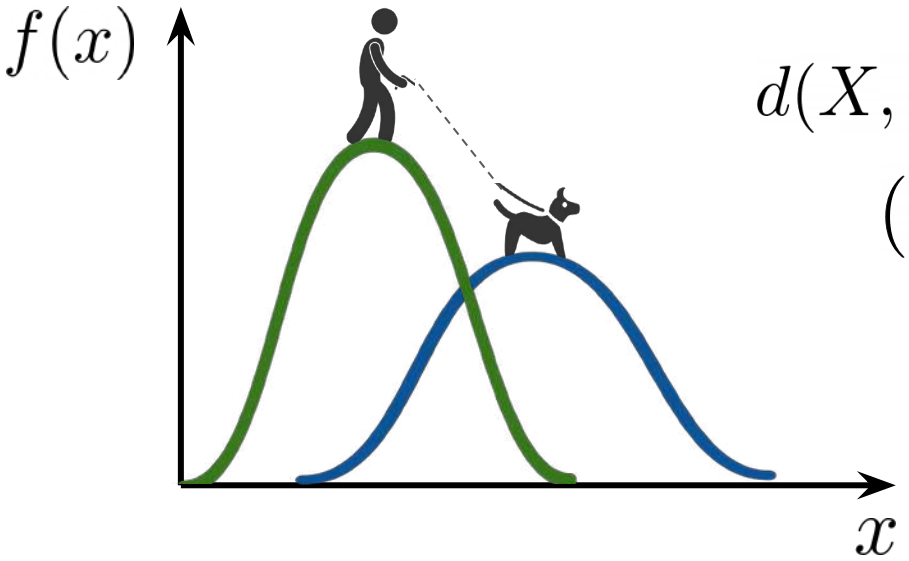
Fréchet Distance Between Normal Distributions



$$d(X,Y) = (\mu_X - \mu_Y)^2 + (\sigma_X - \sigma_Y)^2$$

Mean

Standard deviation

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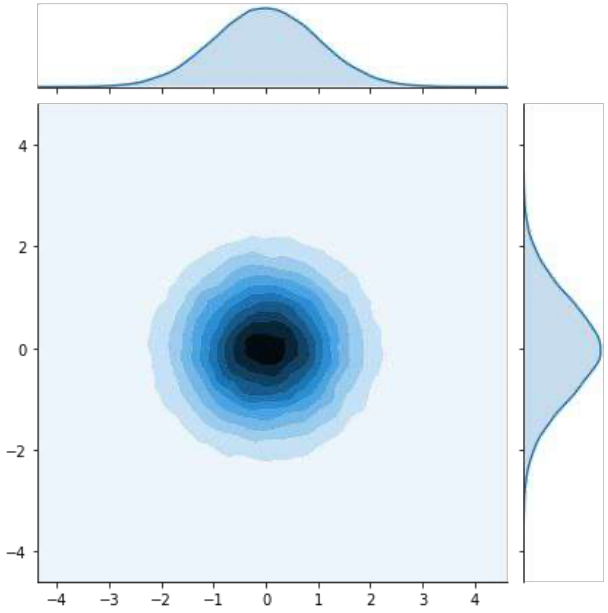
Multivariate Normal Distributions



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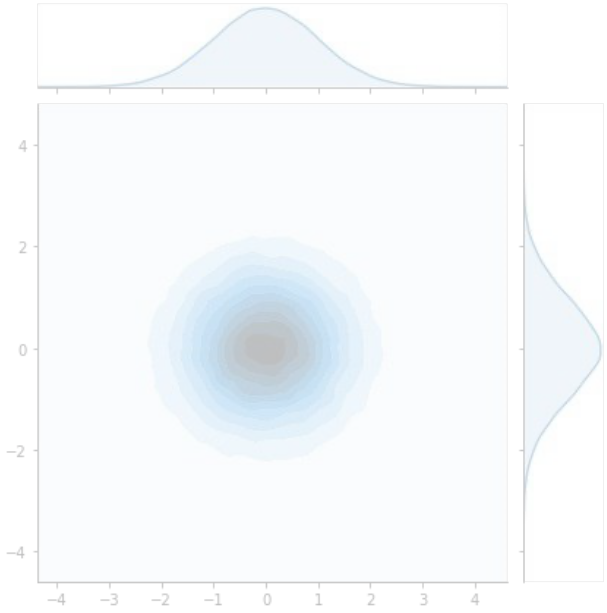
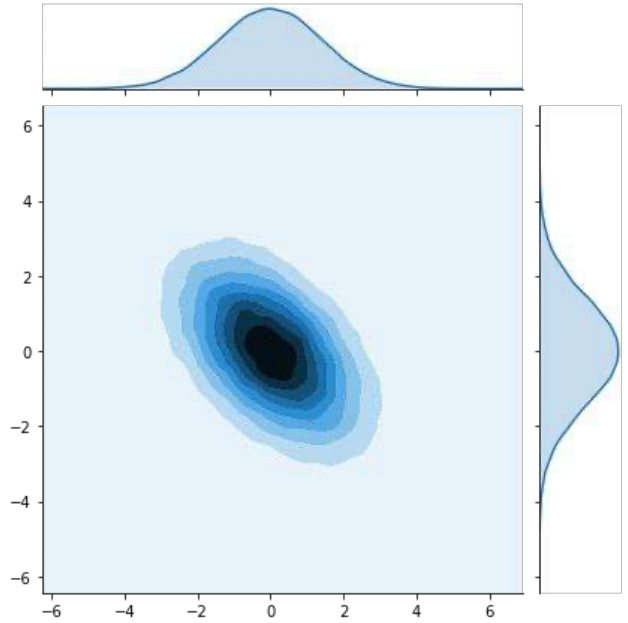
Multivariate Normal Distributions





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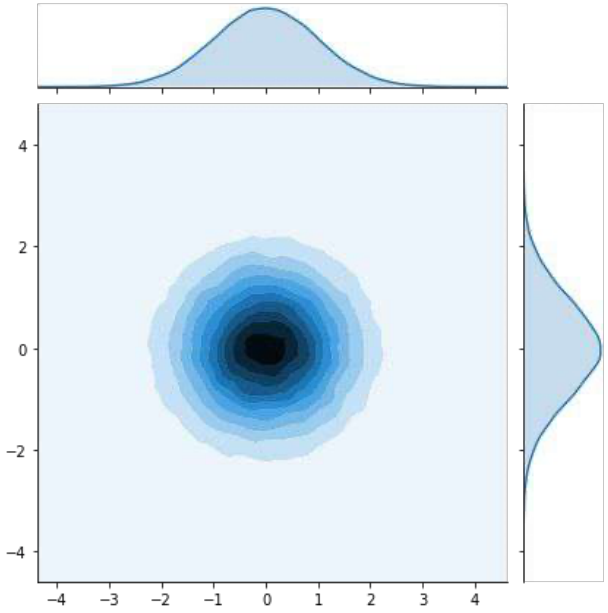
Multivariate Normal Distributions



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

Covariance matrix

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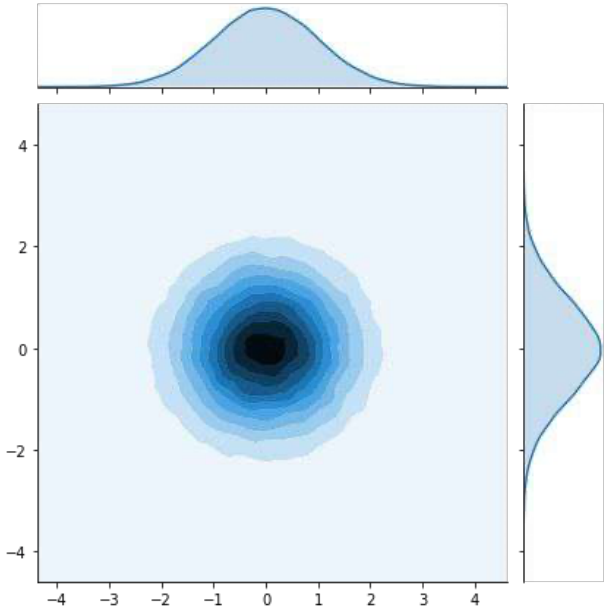
Multivariate Normal Distributions



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

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

Covariance matrix

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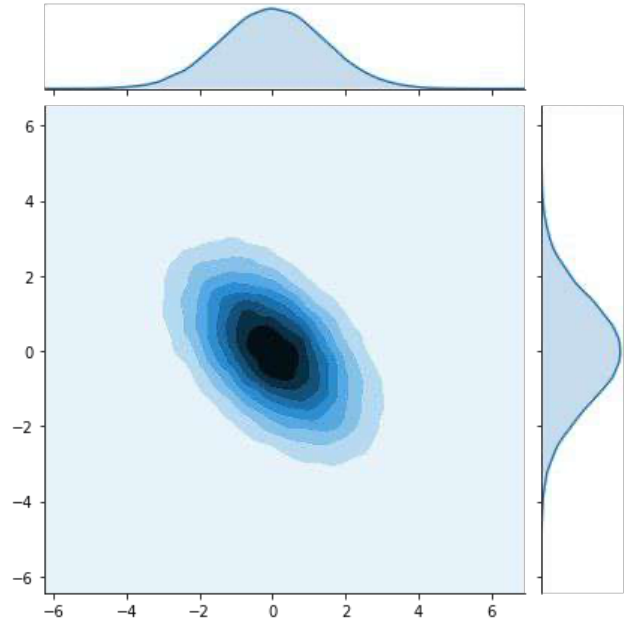
Multivariate Normal Distributions

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

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

Covariance matrix



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Multivariate Normal Fréchet Distance

Univariate Normal Fréchet Distance =

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

Multivariate Normal Fréchet Distance =

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

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Multivariate Normal Fréchet Distance

Univariate Normal Fréchet Distance =

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

Multivariate Normal Fréchet Distance =

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

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Multivariate Normal Fréchet Distance

Univariate Normal Fréchet Distance = $(\mu_X - \mu_Y)^2 + (\sigma_X - \sigma_Y)^2 + (\sigma_X^2 + \sigma_Y^2 - 2\sigma_X\sigma_Y)$

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

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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 =

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

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Fréchet Inception Distance (FID)

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

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

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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

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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

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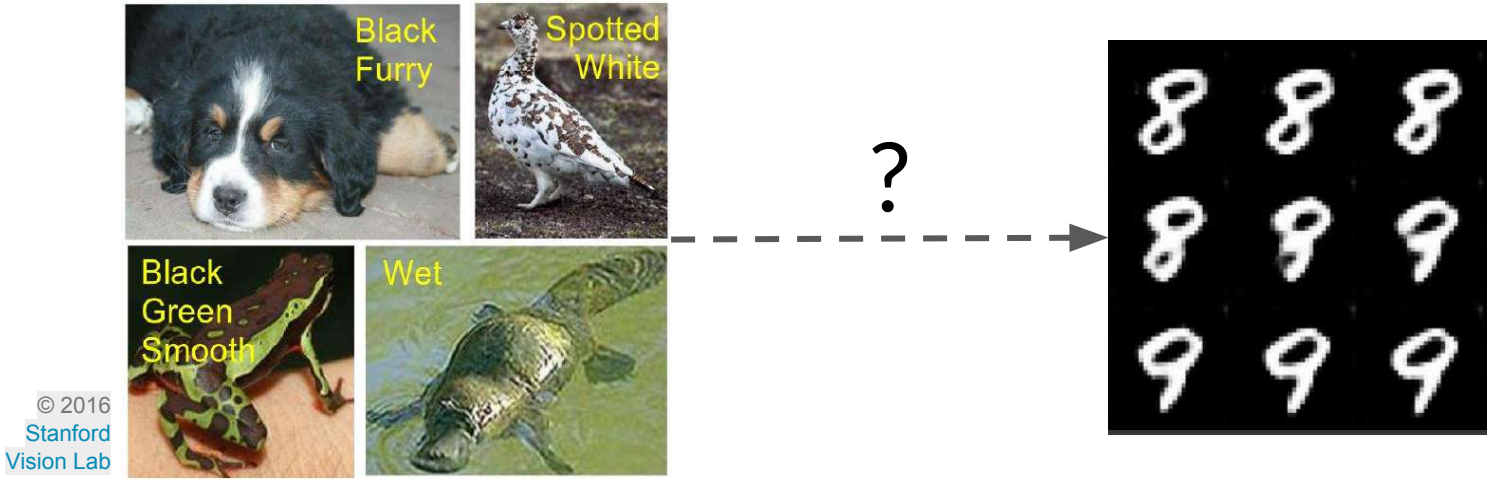
Shortcomings of FID

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



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Shortcomings of FID

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

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Shortcomings of FID

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

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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

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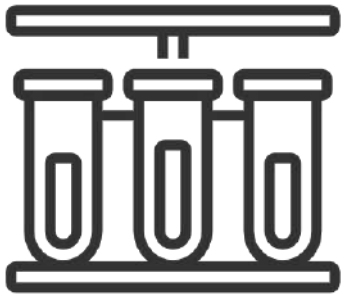
Summary

- 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



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Inception Score

Outline

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

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Inception Model Classification

0.30 Cat

0.60 Dog

0.10 Bird

Fake

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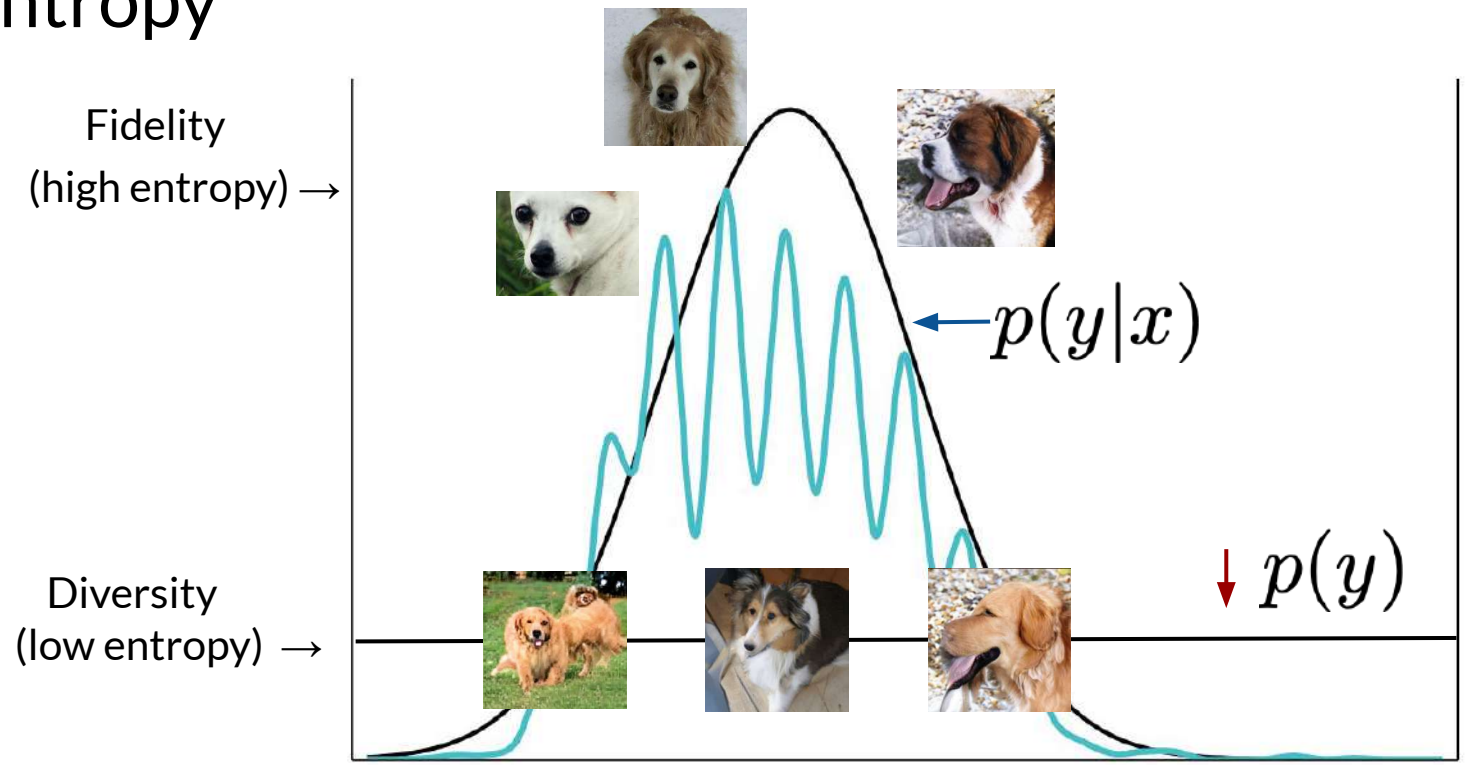
Entropy



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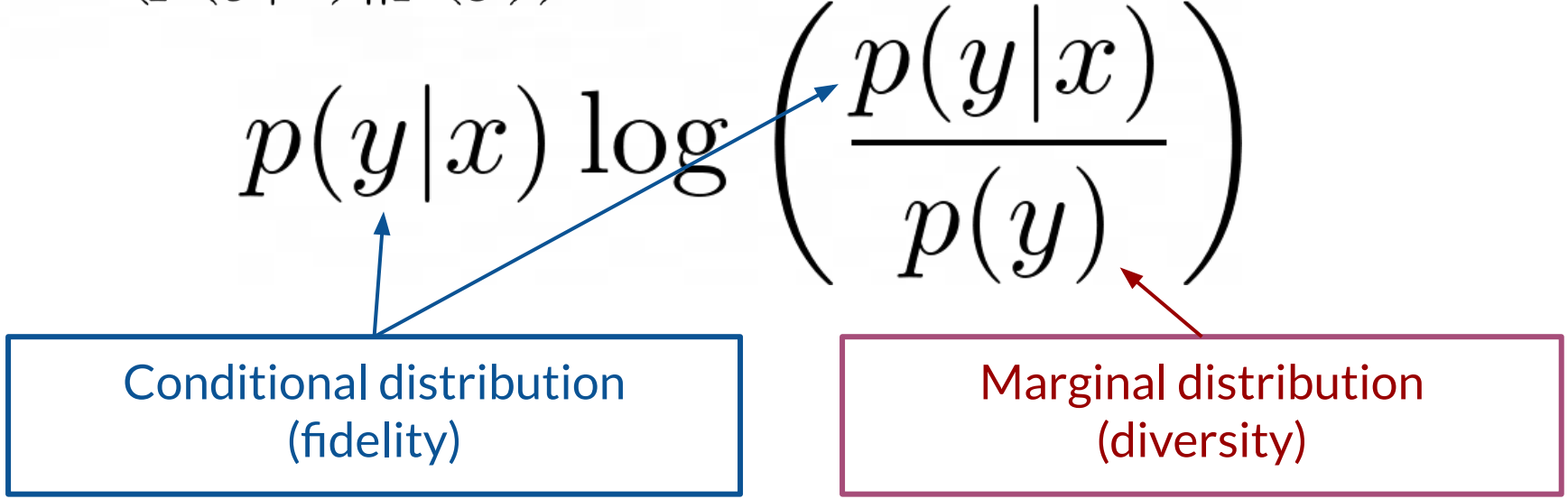
KL Divergence

$$D_{KL}(p(y|x)\|p(y)) =$$

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



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Inception Score (IS)

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

KL Divergence

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Shortcomings of IS

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

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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

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

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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

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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

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Sampling and Truncation

Outline

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

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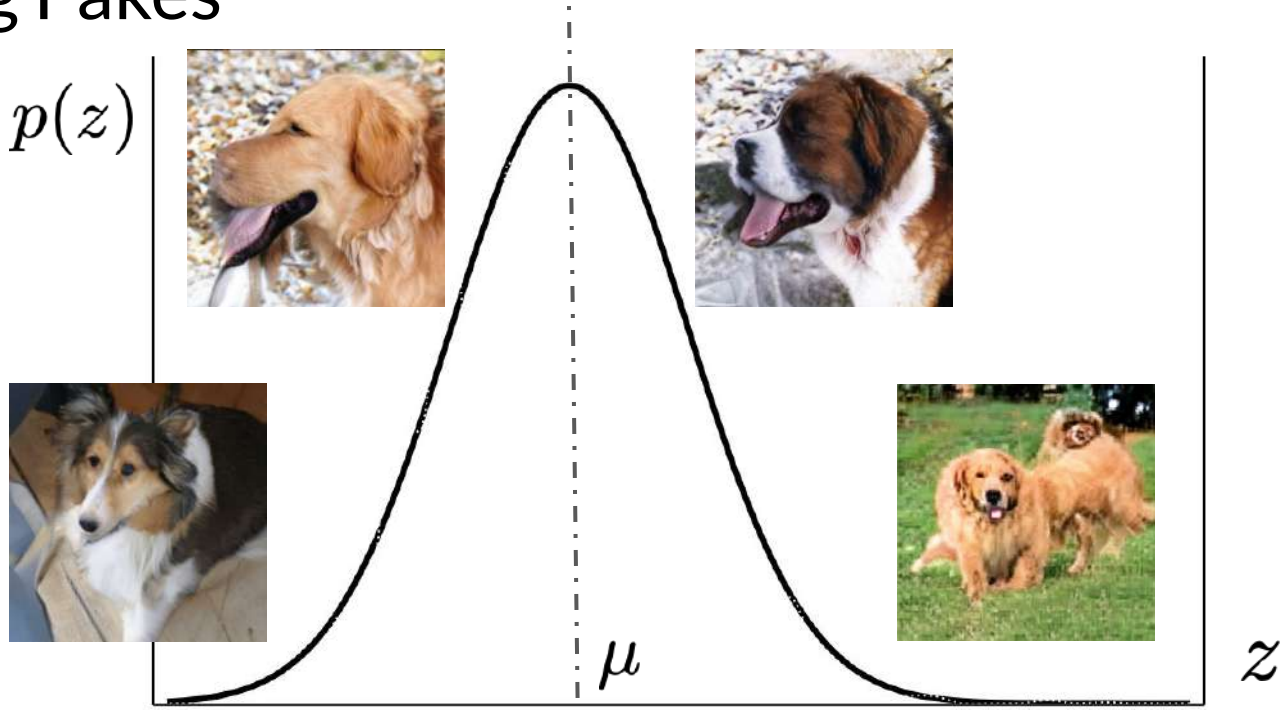
Sampling Fakes



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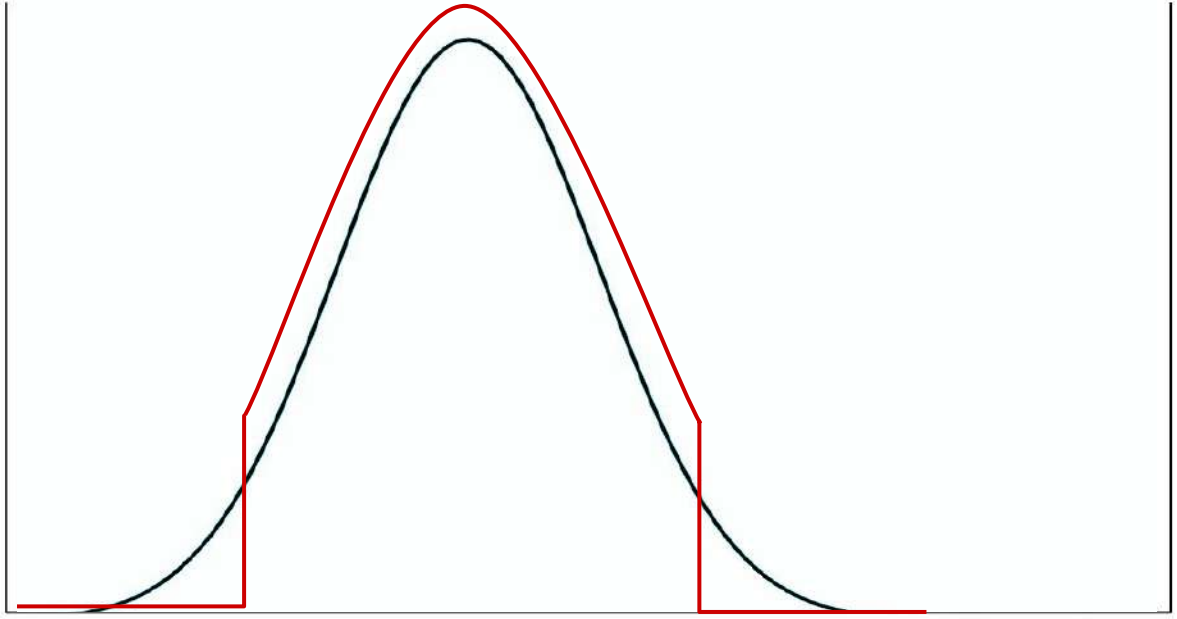
Truncation Trick



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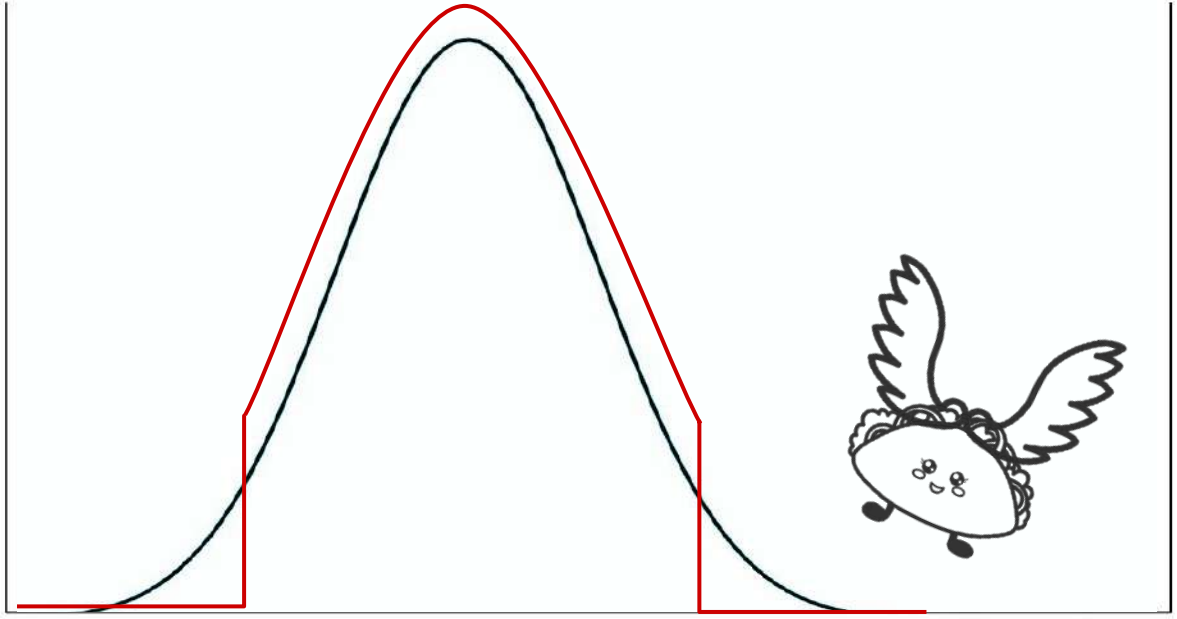
Truncation Trick



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HYPE and Human Evaluation

- Crowdsourced evaluation from Amazon Mechanical Turk
- $HYPE_{time}$ measures time-limited perceptual thresholds
- $HYPE_{\infty}$ 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

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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

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Precision and Recall

Outline

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

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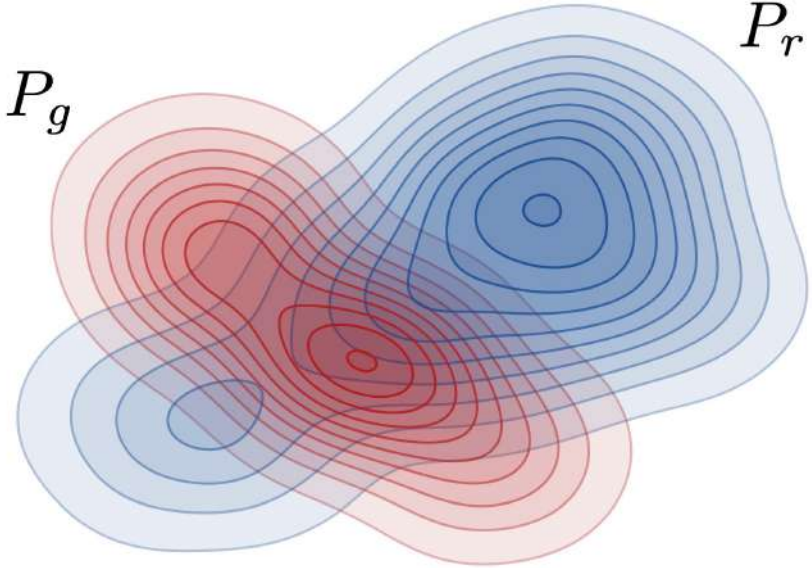
Precision and Recall



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

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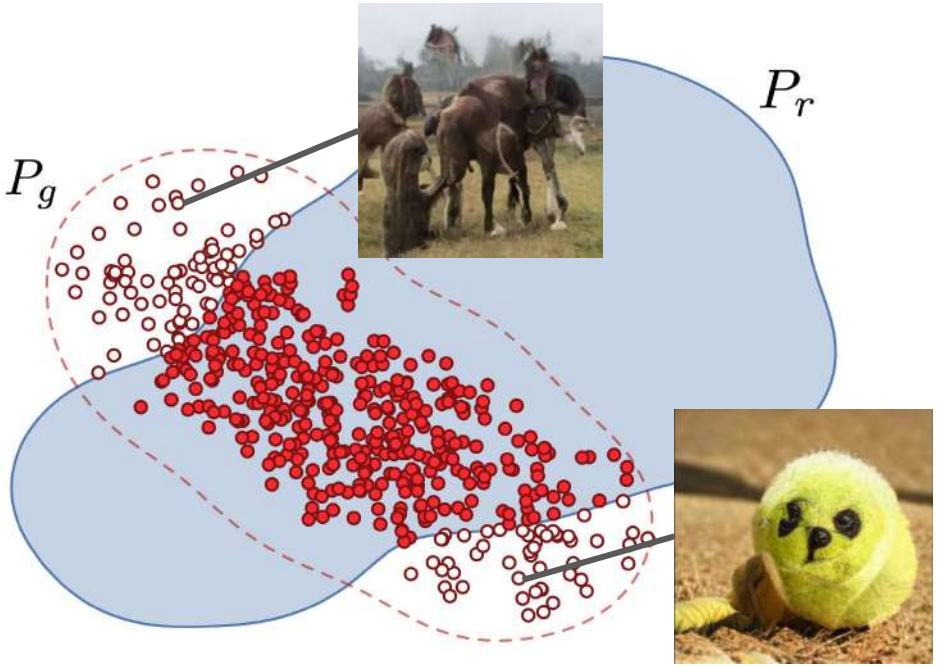
Precision



- 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

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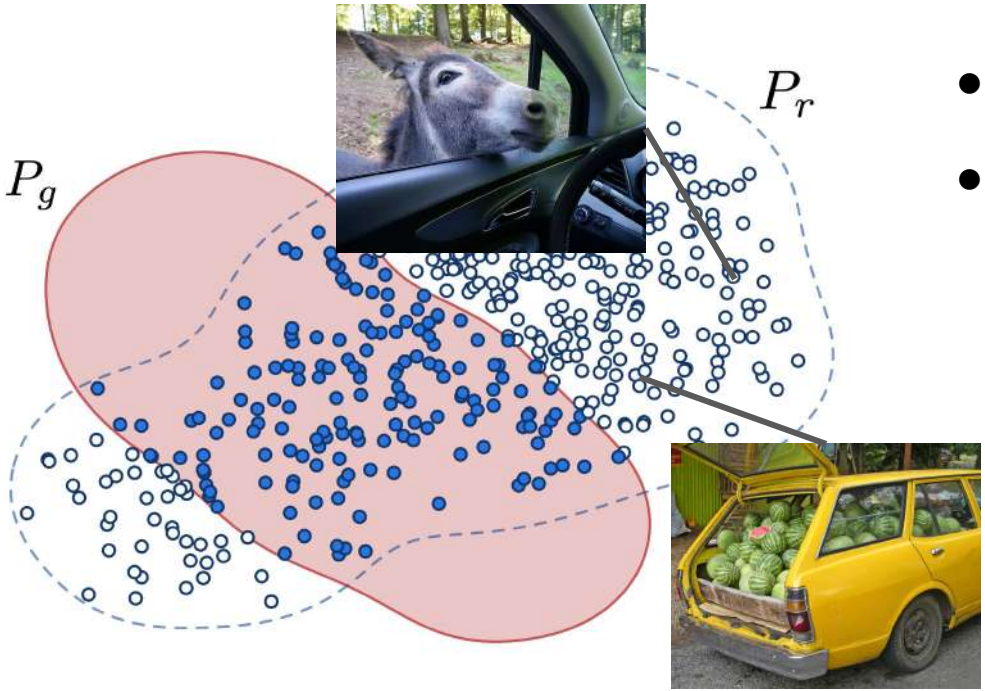
Recall



- 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

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Summary

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

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