KI DELTA LEARNING
Scalable AI for Automated Driving

# On the Frequency Bias of Generative Models

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WP 2.2
WP 2.3

## Use-Case in Delta Learning

Training neural networks on generated data promises better generalization to unseen domains. The preferred tool for generating synthetic data that matches the statistics of real-world data is GANs. However, state-of-the-art GANs yet struggle to achieve this goal entirely. In particular, recent literature reports an elevated amount of high frequencies in spectral statistics, making it straightforward to distinguish real from fake images.

## Technical Problem

Is there a frequency bias that prevents learning high frequencies in existing GAN models? This is a non-trivial question as GAN training involves two players where architectures for both the generator and discriminator, loss functions, as well as the dataset statistics can all affect the outcome.

## Technical Solution

To narrow down potential factors, we develop isolated testbeds for both the generator (G) and discriminator (D). Then, we extend our findings to state-of-the-art GANs on large-scale datasets.

### Generator Testbed

- G: PGAN, D: None
- Data: 10 images + 10 latents
- Loss: pixelwise L2 loss
- Examining: upsampling schemes

### Discriminator Testbed

- G, Learnable Tensor, D: PGAN
- Data: 10 images + 10 labels
- Loss: adversarial loss + R1
- Examining: downsampling schemes, spectral discriminator

## Evaluation

Figure 1 and 2 summarize the main findings.

### Generator Testbed

- Bilinear and NN upsampling bias G towards little high-frequency content
- Zero insertion and reshaping is prone to producing checkerboard artifacts
- Suitable loss functions can reduce the artifacts

### Discriminator Testbed

- D can detect high frequencies but struggles with low magnitudes
- All commonly used downsampling operations can impair the training signal quality (see Figure 3)

### Full GAN Training

- Results are well aligned with finding of the testbeds
- Spectral discriminators (SD) can partially close the gap of spectral discrepancies. However, an SD can impair image fidelity (see Figure 3).

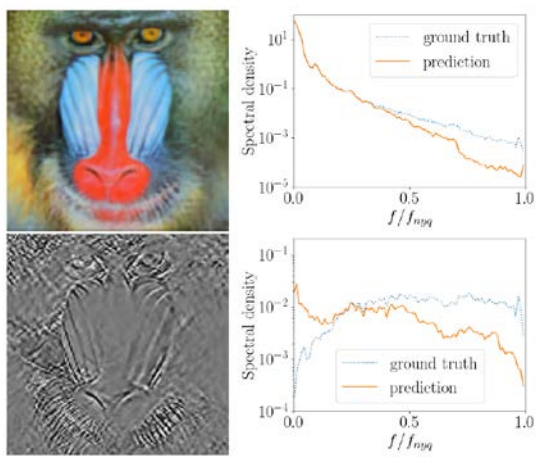


*Figure 1: **Spectral Properties of G**. Bilinear upsampling biases G towards generating data with little high-frequency content.*

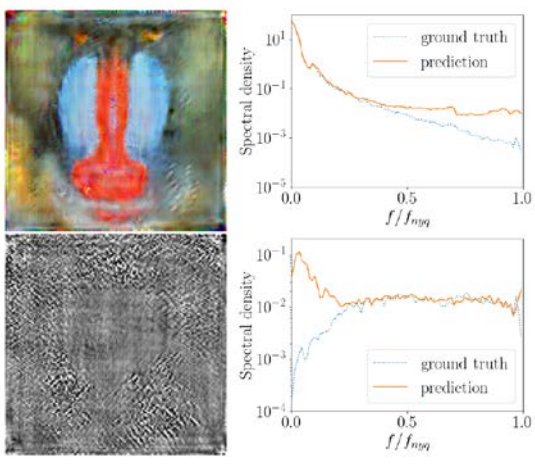


*Figure 2: **Spectral Properties of D**. D provides better guidance for frequencies with high magnitude.*

*Figure 3: Reconstruction by D. Using downsamping in D leads to large deviation from the ground truth.*

Networks

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