REPLACING PERLIN NOISE WITH AI

Hyper-Realistic, Fast, and Infinite

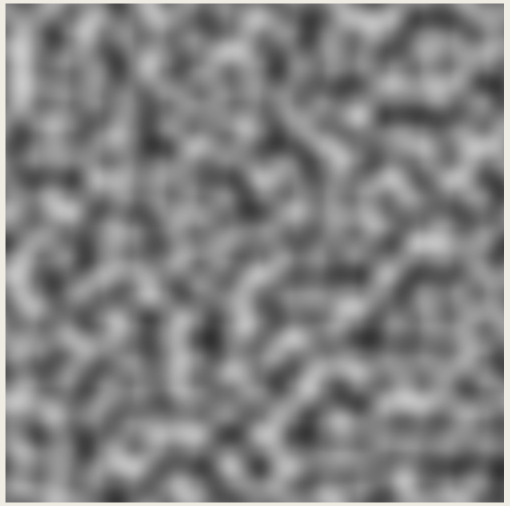
What is Perlin Noise?

1. A Classic Procedural Tool

Developed in the 1980s by Ken Perlin, Perlin noise is a smooth, pseudo-random function used to generate natural-looking textures and terrain in computer graphics and games.

2. Why It's Popular

- Simple and fast to compute
- Seamless and tileable
- Looks "organic"
- Often used for procedural terrain



Often stacked to create variety

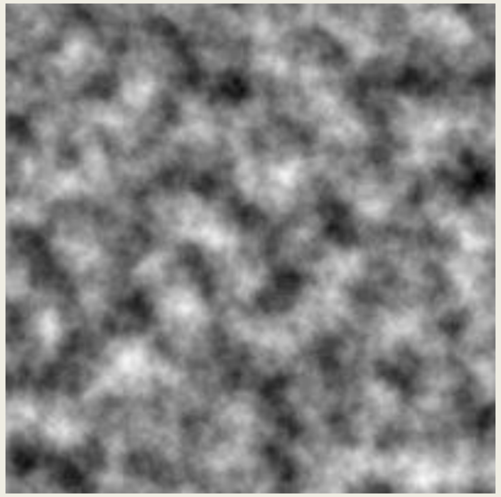
Why Procedural Terrain Matters

- **Games:** Infinite, procedural worlds (e.g Minecraft, Terraria, No Man's Sky, etc.)
- **Simulations:** Terrain needed for physics, pathfinding, climate, etc.
- **GIS / Digital Twins:** Scalable Earth Models for research or urban planning

The Problem with Perlin Noise

Traditional Noise

- Blobby, repetitive patterns
- Unscaled (values between 0 and 1)
- **Boring, even with post-processing**



Real Terrain

- Varied, multi-scale details
- Realistic, wide-ranging elevations
- **Awesome out of the box**

My Goal

Generate infinite, realistic terrain in real time.

Requirements:

- Fast enough for interactive use
- Infinitely tileable
- Consistent: Given a seed and position, the elevation is always the same, no matter what order generation occurs
- Realistic

Key Challenges

- Precision: Real terrain ranges in elevation from -10,000m to 10,000m. Diffusion models and GANs will struggle to obtain ~1m accuracy.
- Scalability: Tiling diffusion models has been done before, but extending that to infinite domains is complex.
- Efficiency: Diffusion models are slow. They become *massively* slower when tiling.
- Quality: Most terrain looks boring. We want to bias our model to prefer generating interesting terrain.

Precision Issues

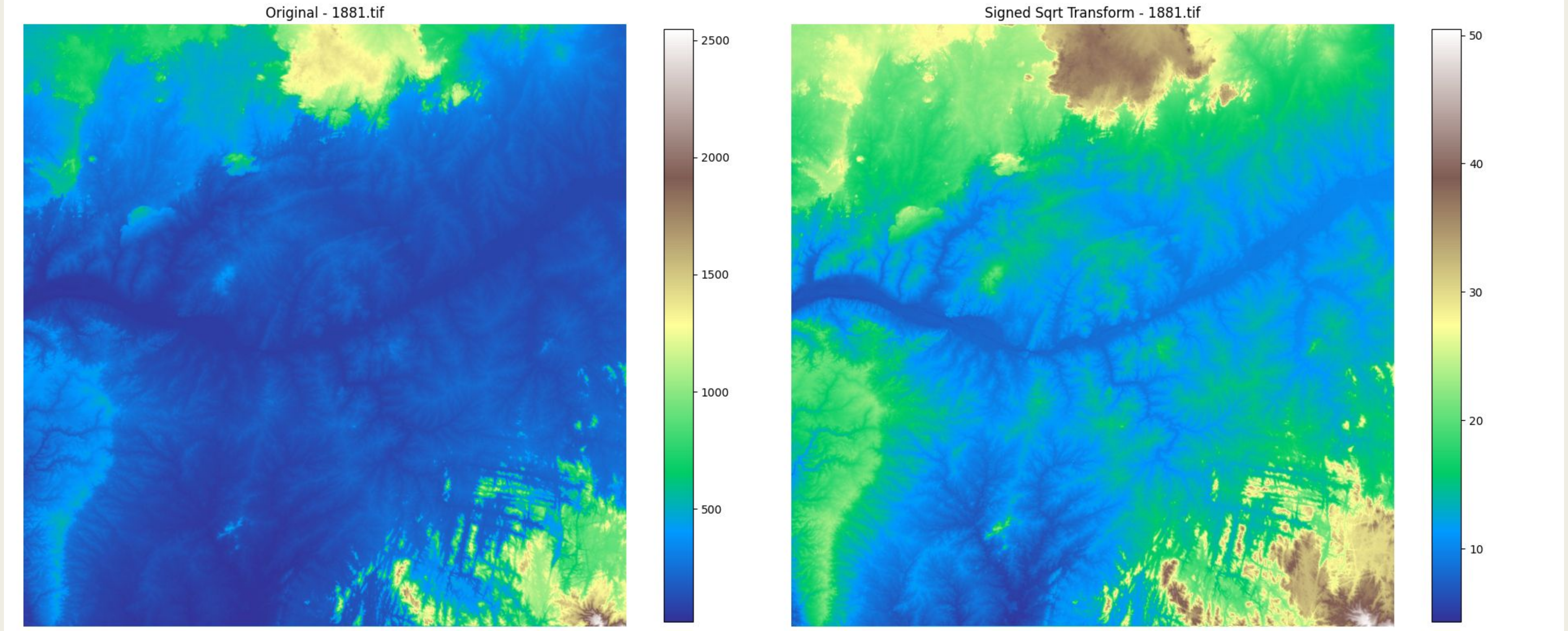
- Elevation data spans from -10,000m to 10,000m
- When normalized to have mean=0 and std=1, a 0.01 error is magnified to a 30m elevation error.
- Small features like ~50m hills are visually important to humans, but represent <1% of elevation range, and are largely treated as noise by models.
- A shoreline is the difference between -1m and 1m. Imperceptible to models, but critical for humans.

Solution (Part 1)
Laplacian Encodings

- Decompose elevation into:
  - *Low frequency: Global shape, larger stdev*
  - *High frequency: Local details, smaller stdev*
- Solves error magnification issues:
  - *Noise in low frequency -> Removed by deleting high frequency component*
  - *Noise in high frequency -> Smaller value range, not amplified as much*
- How?
  - *Low frequency map generated by resizing image and blurring*
    - Resize from 512x512 to 64x64
    - Blur image. I use sigma=5.
  - *High frequency map generated by taking difference between original heightmap and low frequency map*
    - Low-freq map is resized back to 512x512 first. Bilinear interpolation works fine.

Solution (Part 2)
Signed-Sqrt Transform

- Apply f(x) = sign(x) * sqrt(abs(x))
  - *Can invert with f(x) = sign(x) * x^2*
- Expands low-lying features
  - *0-100m now covers ~10% of elevation range, so the model can dedicate more capacity to subtle but visually important terrain.*
- Decouples mean and variance
  - *Before, variance in a crop was strongly tied to it's mean elevation. Now, variance is more uniformly distributed.*
- Improves shorelines
  - *Before, -1m to 1m was imperceptible. Now, its ~2% of the total elevation range. Enough for models to represent clean coastlines.*


Original - 1881.tif
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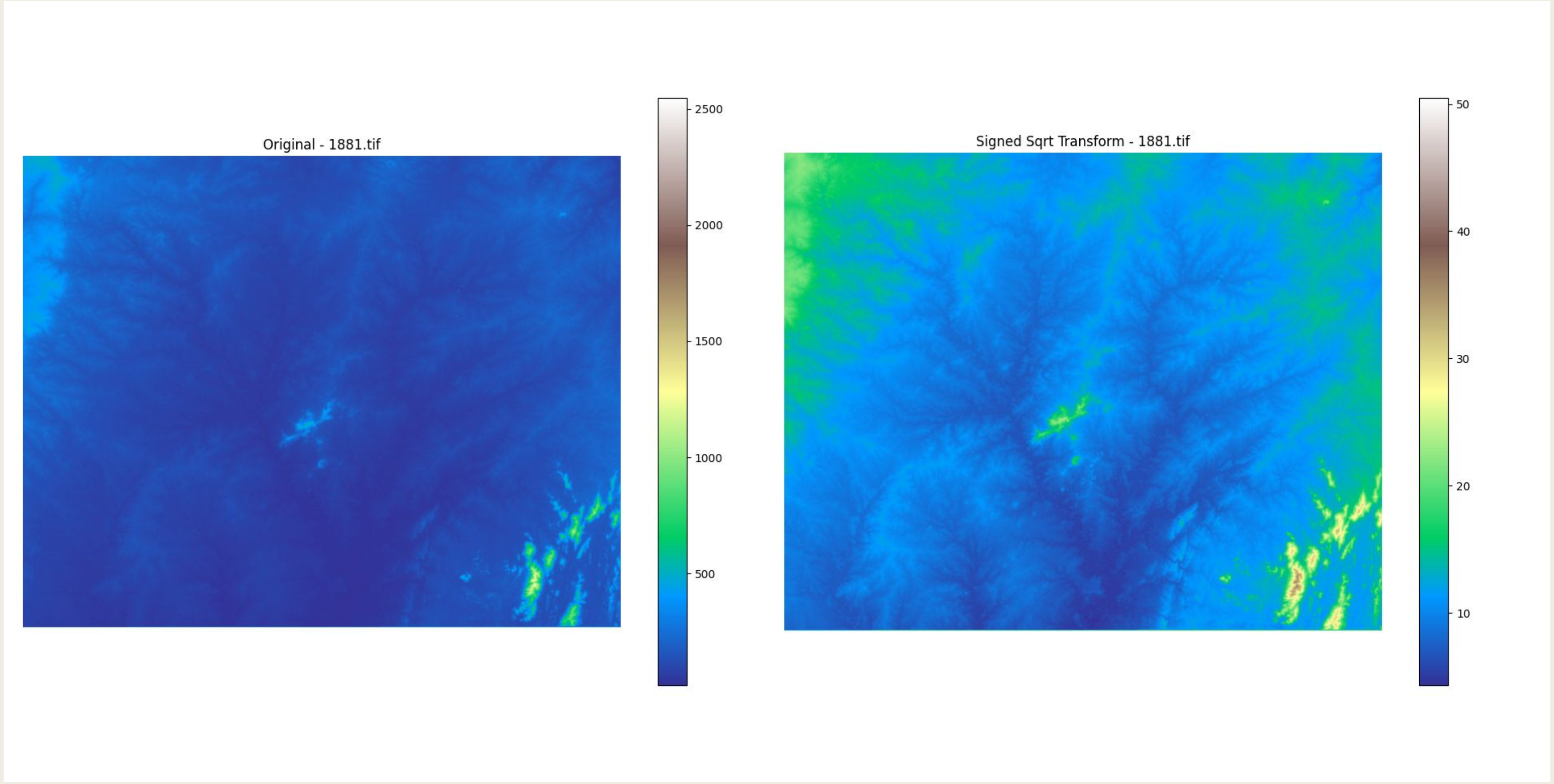
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Scalability

Problem: We don’t want one patch of land, we want an entire planet.

Solution: **Multi-Diffusion**

- Key Idea: Train a model to predict the noise of patches of images. During inference, combine all predictions into one large prediction, covering the full image.
  - Overlap in tiles is necessary: This is how the models ”collaborate”
  - Mismatched predictions in overlapping regions are solved by taking the average
    - Even better: Take a weighted average. Predictions close to the center of a region weighted > predictions near the edge.
- Can we extend this to infinity? **Yes. With difficulty.** To denoise a tile to step x, need all surrounding tiles to have been denoised to step x-1.
  - Has a cascading effect: To generate one tile in 30 steps, need to call diffusion model **10,000 times.** We will come back to this problem.

Getting Multi-Diffusion to work in unbounded spaces was complicated. I wrote a small library to help.

Infinite Tensors:

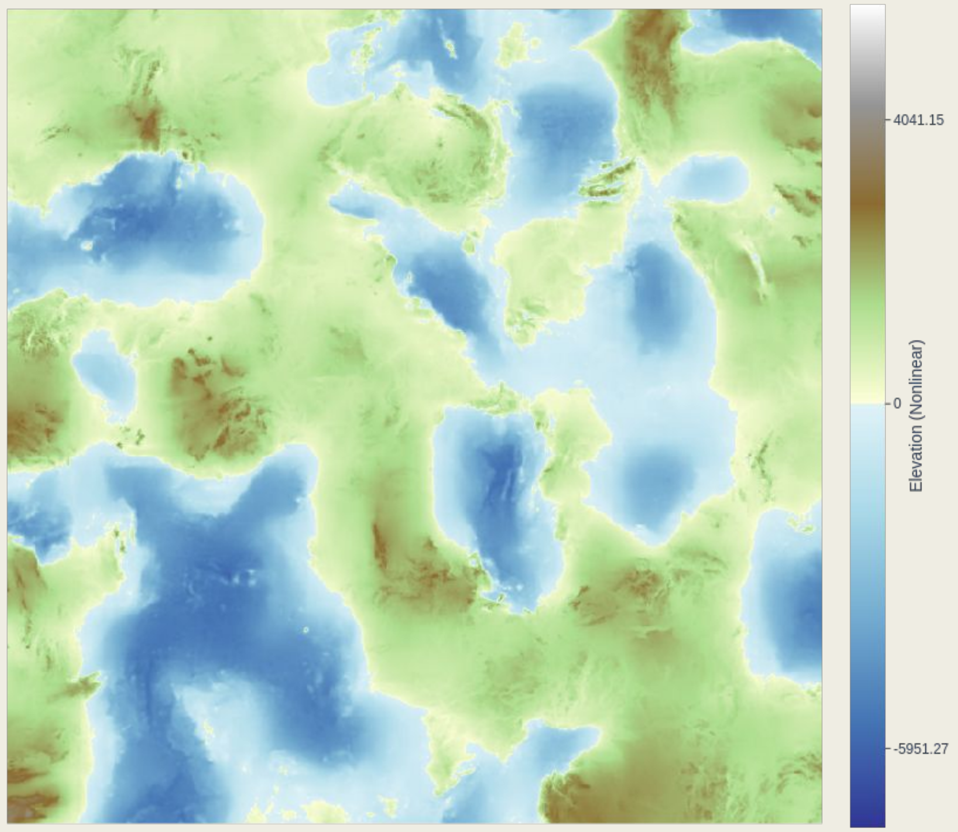
- Divides infinite dimensions into chunks (tiles)
  - Works just like a normal tensor, but some dimensions can be ‘None’ (Infinite)
  - Tiles are stored in memory or on disk
- Processes data in windows using any provided function (e.g diffusion model)
- Manages dependencies between tensors
  - Can generate new infinite tensors as products of any number of other infinite tensors (and other arguments)
- Automatically cleans up unused tiles to conserve memory/disk

Problem: When tiling with diffusion model, terrain statistics are off.

Real terrain range: -10000m to 10000m
Generated terrain (Left): -6000m to 4000m

Extreme values extraordinarily rare: Why?

Core Idea: When generating one tile, the mean elevation of the output is highly correlated with the mean of the initial noise (call this mean noise for short)



Early prototype of diffusion tiling

What about two adjacent tiles?

Can be a mismatch:

- One tile has very positive mean noise
- One tile has a very negative mean noise

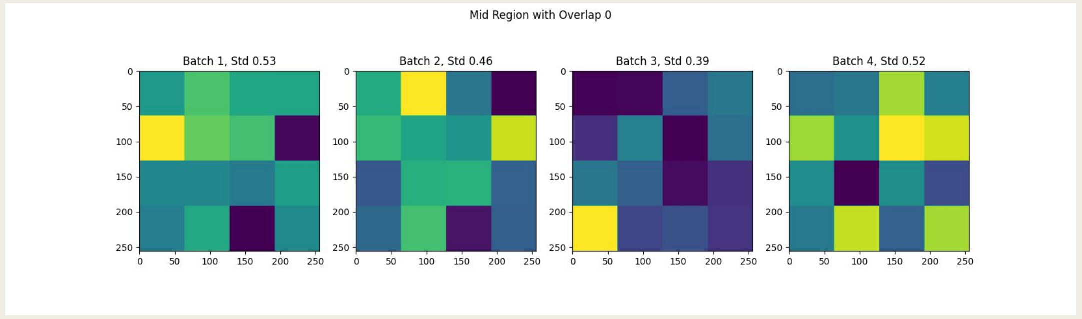
One tile tries to generate Mt Everest, the other wants to generate the Mariana Trench.

What about the overlapping region?

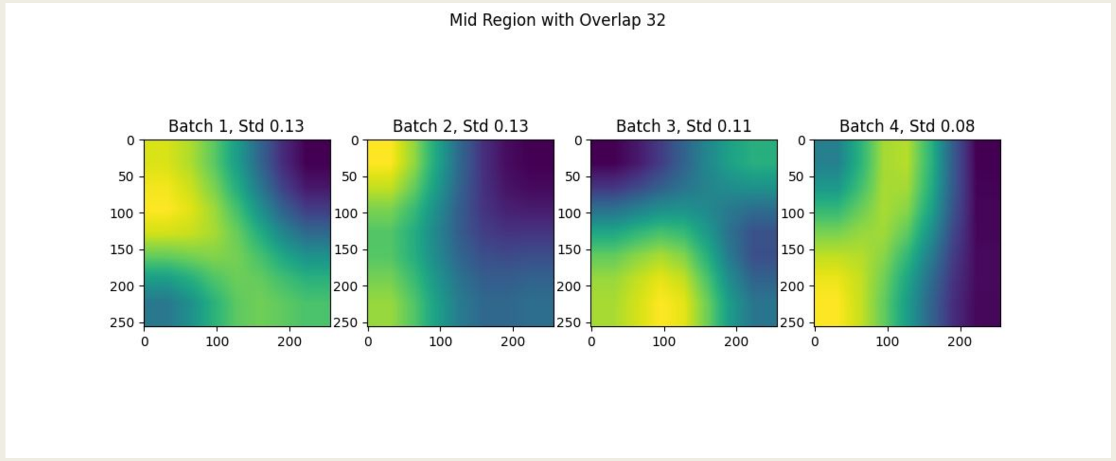
- Has to be a transition somewhere (e.g a shoreline)
- But you can't have Mt Everest that close to a shore; nor can you have the Mariana Trench next to a shore
- Eventually: Diffusion paths compromise. Both features are muted, and we end up with a small mountain and small trench, or nothing at all.
- In practice: Extremely unlikely a high-elevation tile will be surrounded by other high-elevation tiles. So extreme tiles tend to be muted.

Toy Example

Generating without overlap: Std = 0.5



Generating with overlap: Std = 0.1



Solution:
Condition diffusion models on mean elevation

Now adjacent tiles are aligned.

But how do we get the mean elevation of a tile before generation?

- Train a GAN on small (e.g 12x12), ultra-low resolution (~16km pixels) patches of the world
  - *Small resolution makes the model incredibly fast*
- Remove padding from the model to make it translation invariant
  - *Allows for native infinite generation*
- Use R3GAN (recent work) to maximize quality and stability.
- Negligible performance impact.

Efficiency

Problem: 10,000 diffusion steps to generate one tile is way too much.
Solution: Consistency models

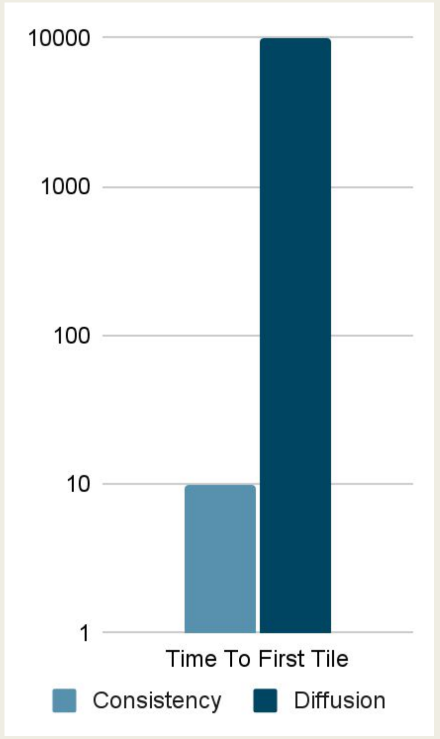
What is a consistency model?

- A recent family of models for fast generative sampling
  - *Same architecture and data as diffusion models*
- Requires only 1 or 2 steps to generate images, not 30.
- Learns to generate images directly by minimizing the difference in the predicted image between two timesteps

Why do we need this?

- Generating 1 tile with diffusion models: 10,000 calls
- Generating 1 tile with 2-step consistency models: 10 calls
- When generation is unbounded, a 15x speedup becomes more like 1000x.

Issue: Discrete CMs magnify FID by 2-3x



Continuous Consistency Models (sCM)

- Consistency models can be made continuous
  - Avoids discretization errors
  - Prone to training instability - **not good in practice**
- **Until *Lu et al.* proposes a fix for training instability (The sCM paper)**
  - FID now increases by just 10% for 2-step CMs

I wrote the **first public implementation** of the sCM paper

- Adapted it for use in terrain diffusion
- Terrain is now **high quality** and **generates in real-time**.

Quality

Problem: Most terrain is boring
Solution: Bias the model towards generating high-quality terrain

- Want to rate terrain on 1-5 scale
  - *1 indicates terrain is boring – flat, not a lot going on*
  - *5 indicates terrain is crazy cool – grand canyon, the Andes, etc.*
- Terrain data is stored in ~4096x4096 tiles at 90m resolution, or 368x368km.
  - *Very large scale. Not worried about individual mountains or lakes, but entire mountain ranges, canyons, and small countries.*
- Start by rating ~100 tiles manually
- Gather some simple features: Take FFT, bin by distance from center, use mean power as feature
  - *power = log(abs(fft))*
  - *Good metric for how varied terrain is*
- Add in stdev, mean elev, 1/stdev, log(stdev), etc.
- Linear regression on manual ratings is surprisingly accurate! $R^2 = 0.8$
- **During training, add extra weight to samples with high ratings**
  - *I chose to pick a random rating, then pick a random tile with that rating*

References

T. Karras, M. Aittala, J. Lehtinen, J. Hellsten, T. Aila, and S. Laine, “Analyzing and Improving the Training Dynamics of Diffusion Models,” 2023, *arXiv*. doi: 10.48550/ARXIV.2312.02696.

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K. Perlin, “Improving noise,” *ACM Trans. Graph.*, vol. 21, no. 3, pp. 681–682, July 2002, doi: 10.1145/566654.566636.

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O. Bar-Tal, L. Yariv, Y. Lipman, and T. Dekel, “MultiDiffusion: Fusing Diffusion Paths for Controlled Image Generation,” 2023, *arXiv*. doi: 10.48550/ARXIV.2302.08113.

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C. Lu and Y. Song, “Simplifying, Stabilizing and Scaling Continuous-Time Consistency Models,” 2024, *arXiv*. doi: 10.48550/ARXIV.2410.11081.