LANDSCAPE GENERATION IN PROLOGUE WITH PYSHEDS AND ML



PROLOGUE: GO WAYBACK!

- Go Wayback! Is our survival game, releasing in summer 2025
- Realistic depiction of landscape inspired by Saxon Switzerland (real world data, augmented by our tech art team)
- Punishing, deadly environment
- Each run has a fresh 64km² chunk of land
- Land must be generated on a players' GPU in seconds



Image credit: playtesters GLORIOUSPURPOSE & Nerdvous





GENERATIVE MACHINE LEARNING: 10,000 BOWLS OF SLOP

- ML models are capable
- However:
 - They are not creative
 - They don't want to explore
 - They are black boxes without levers



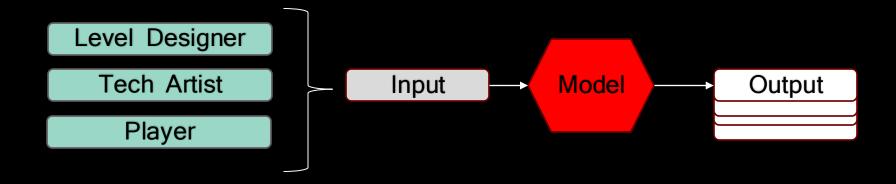






GUIDED GENERATION

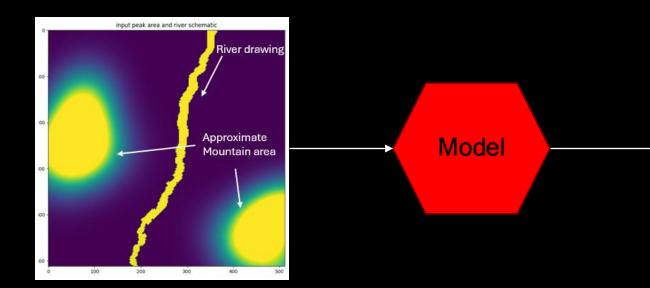
- The guided generation principle:
 - People are creative
 - ML is scalable
- Design ML models to work with creative people
- Each interesting idea leads to many interesting outputs



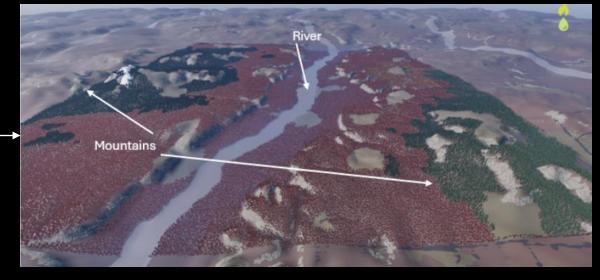


PROLOGUE: GUIDED GENERATION

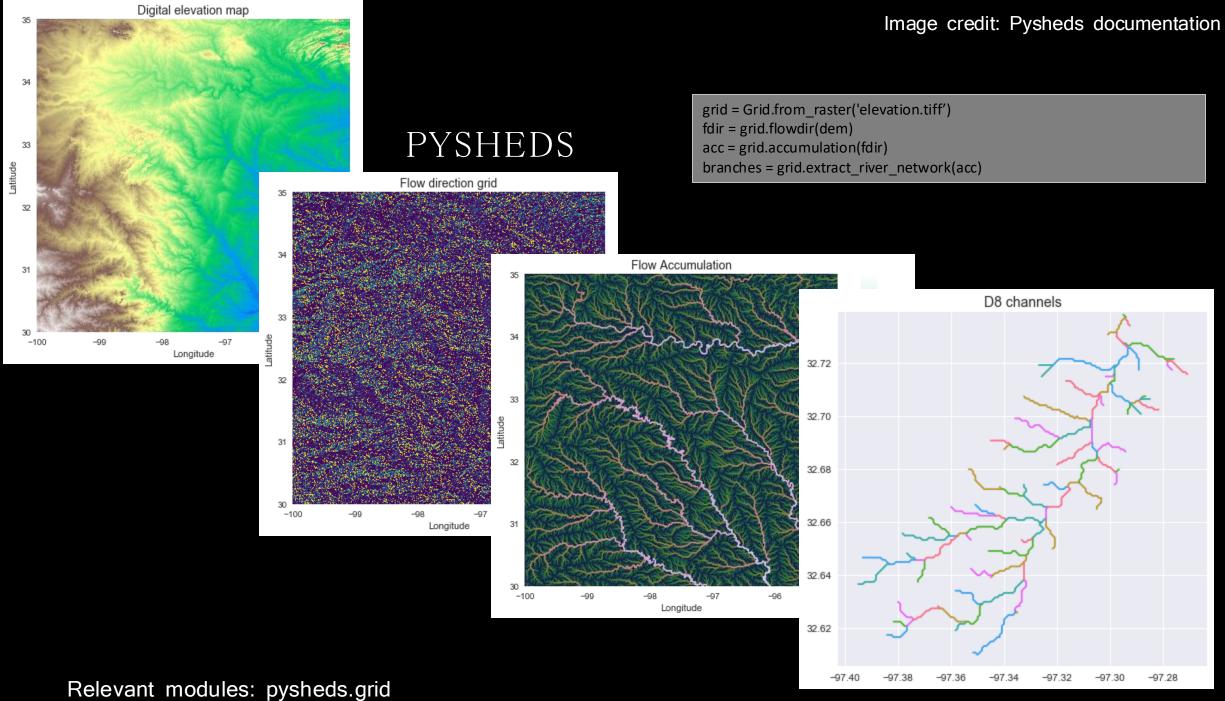
- Elevation and water are important gameplay features
- Artists draws a river and mountain area sketch
- ML generates heightmaps from these sketches
- ML provides 4m per pixel heightmap



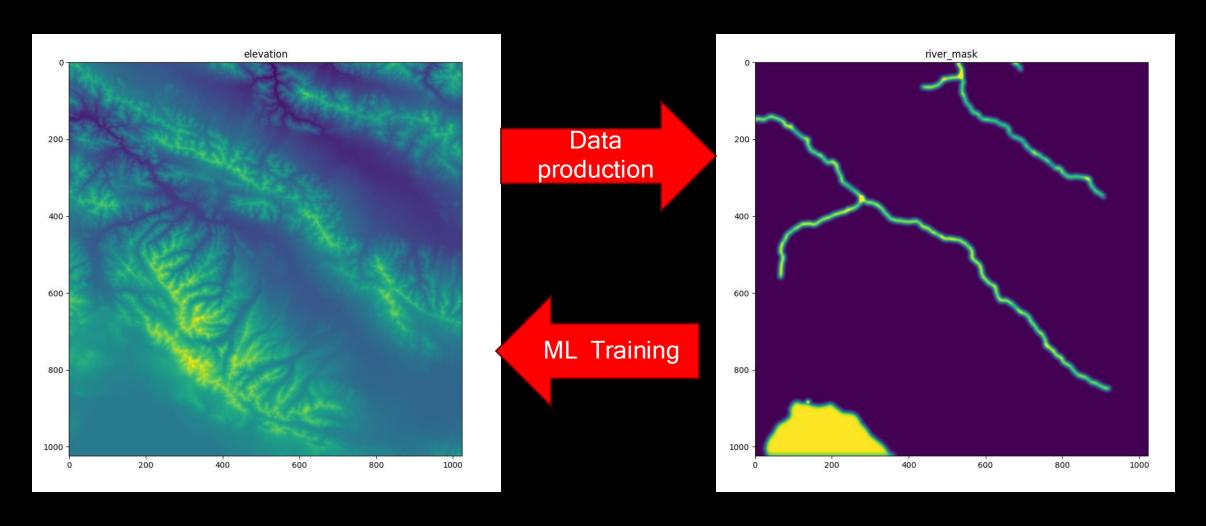


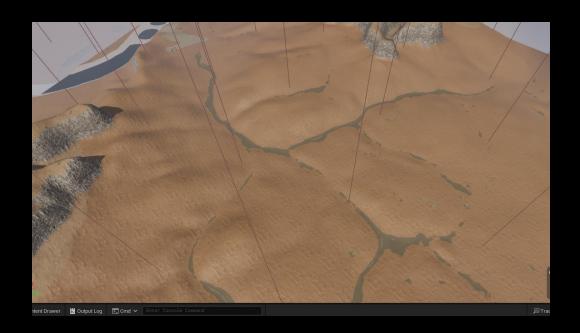


PYSHEDS: FINDING RIVERSIN HEIGHTMAPS



PYSHEDS





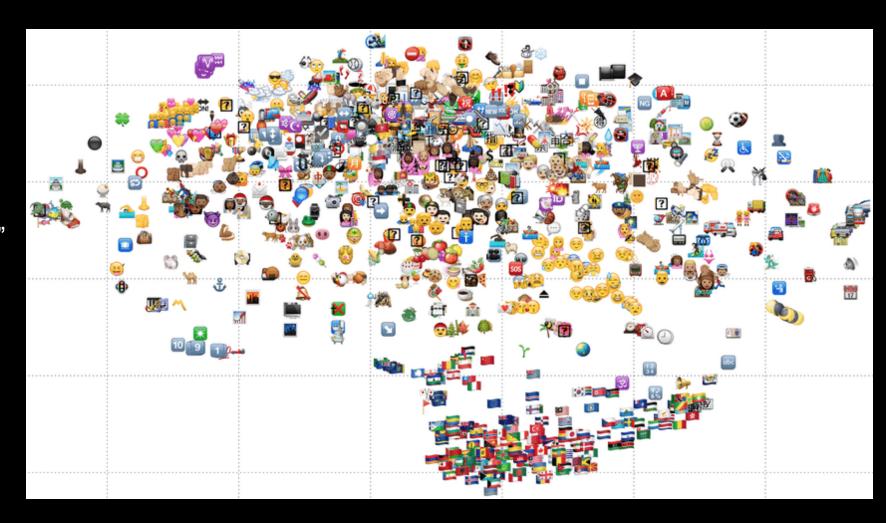


TORCH/DIFFUSERS: MAKING A LATENT SPACE OF LANDSCAPES



LATENT SPACE

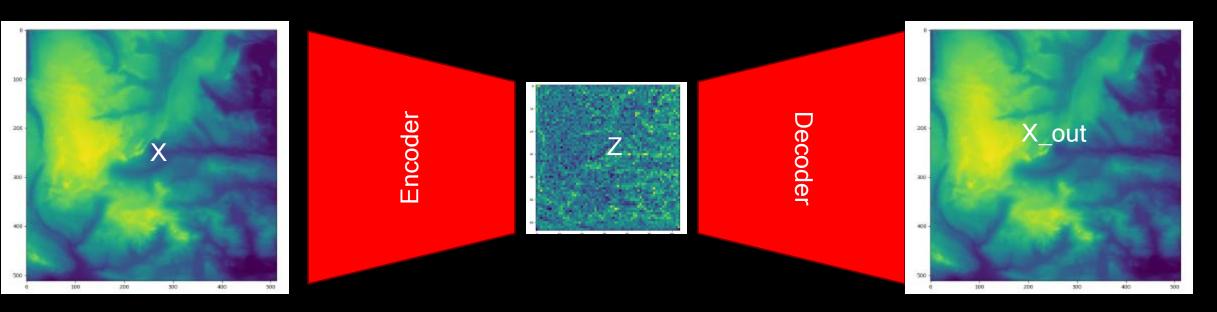
- Latent space:
 - ML trained
 - Compressed
 - Semantic "instructions"



LANDSCAPE LATENT SPACE

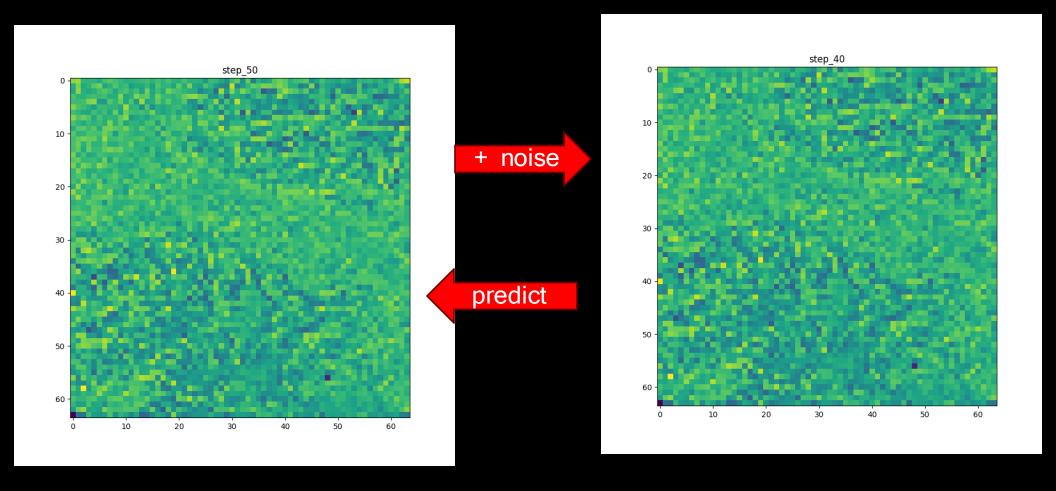
- #training
 vae = AutoencoderKL()
 Z = vae.encode(X)
- X_out = vae.decode(Z)
 Optimize(loss(X_out, X))

- Variational Autoencoder
- 512*512 -> 4*64*64 = 16x compressed
- Y,Z dims: ~spatial, X dim: ~instruction

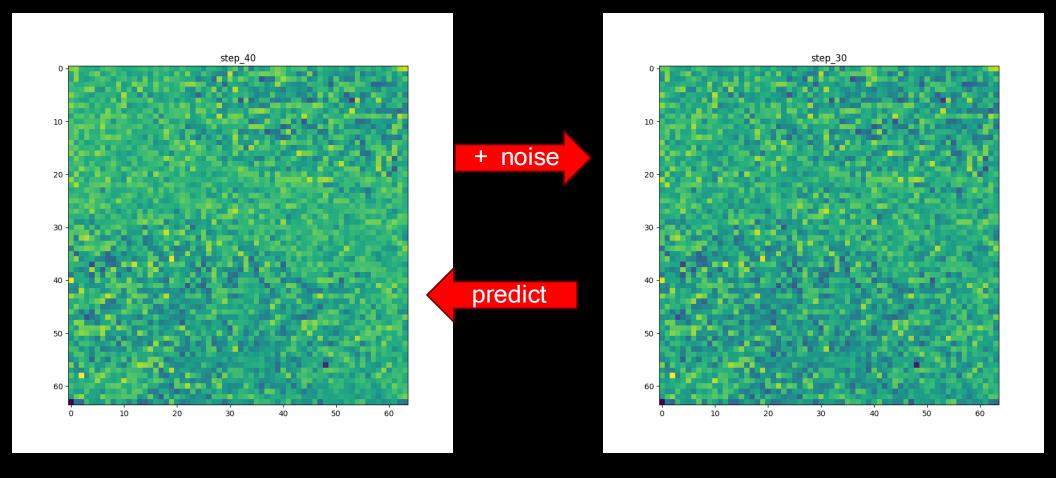


Relevant modules: diffusers.AutoencoderKL, torch

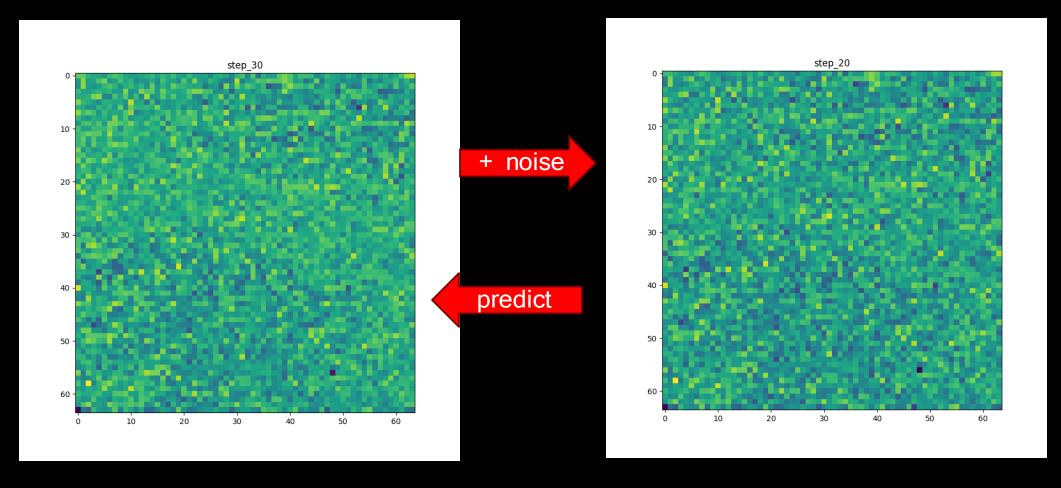
data production
X_i+1 = X_i + noise_i+1 * np.random.randn(X_i.shape)
model training/inference
X_i = model(X_i+1, step=i+1)



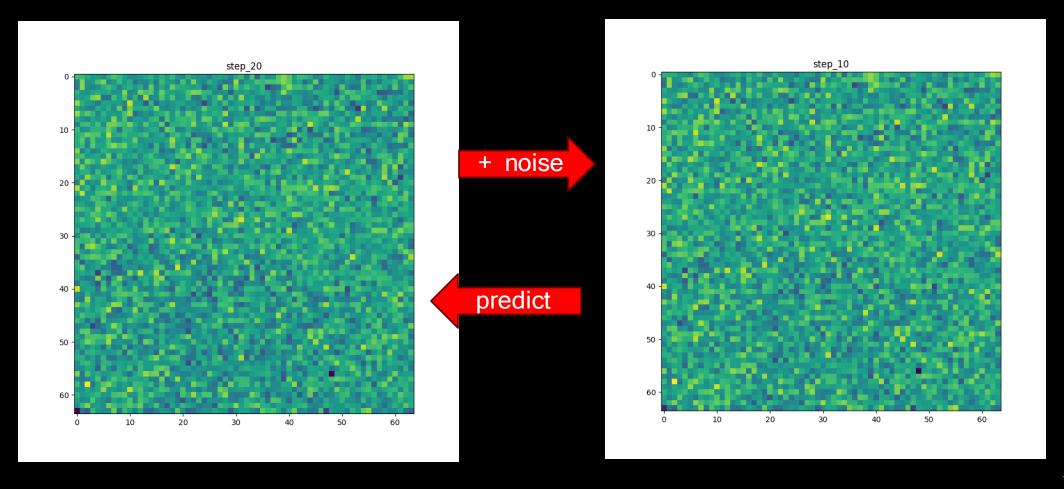
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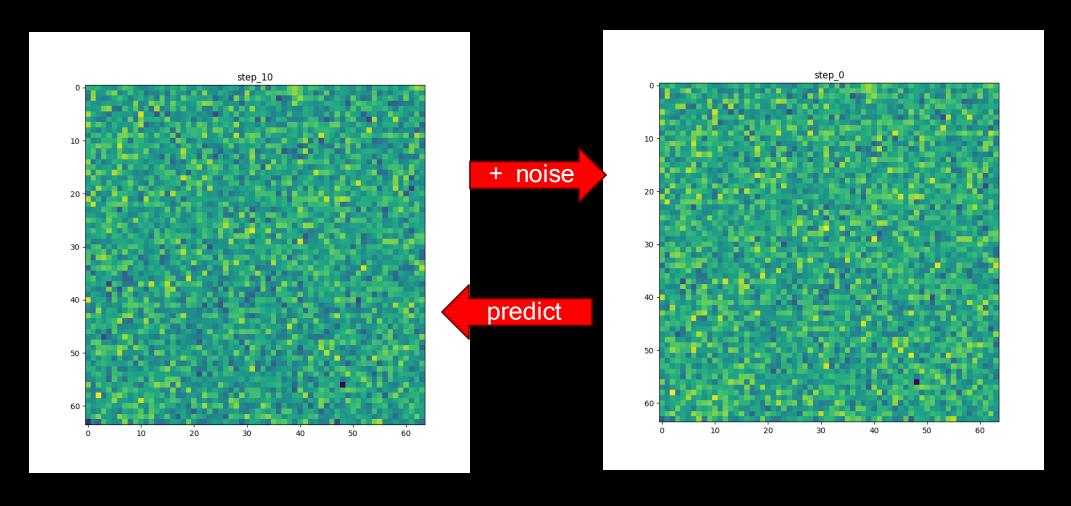
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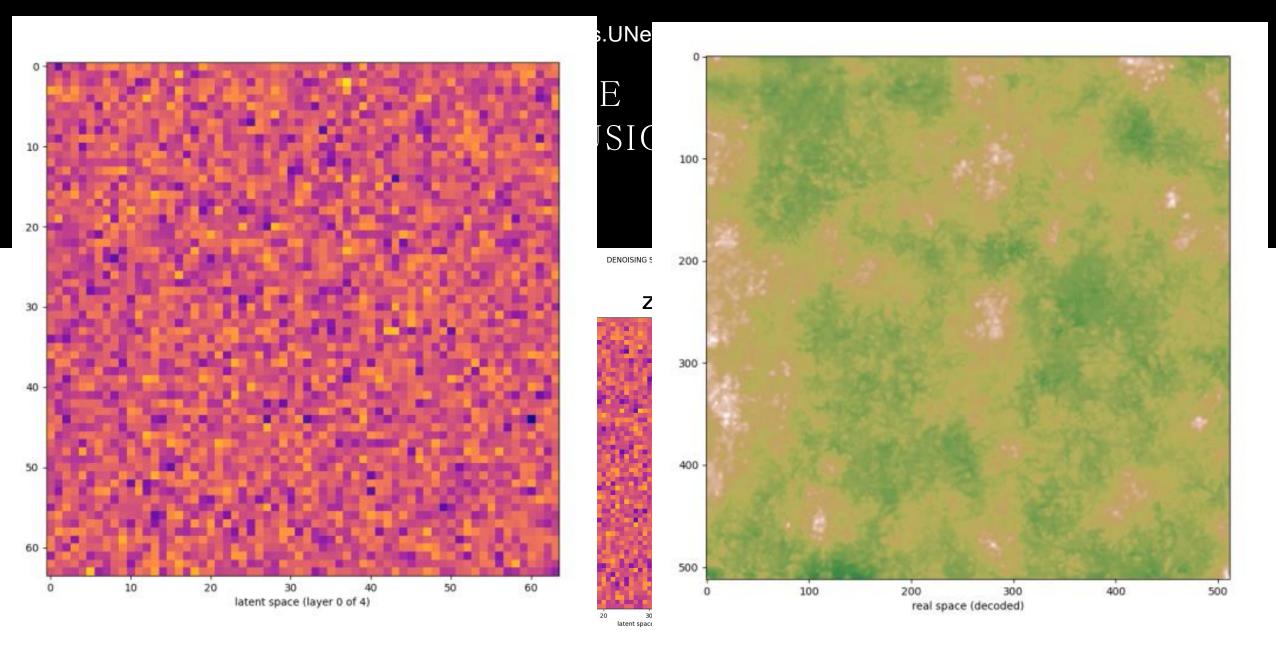


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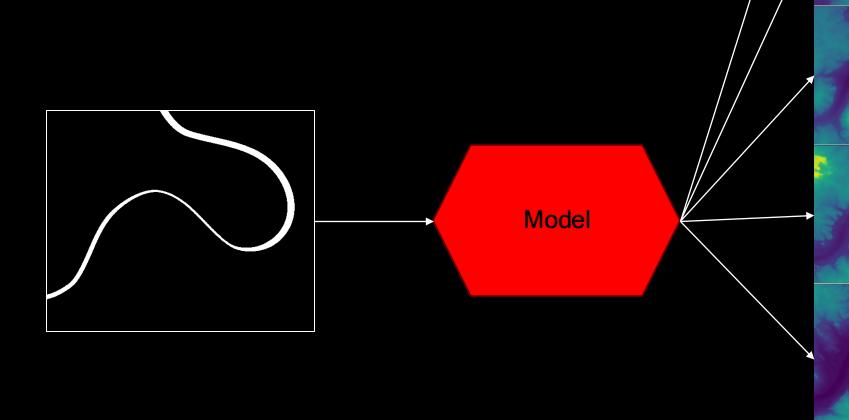
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```







Landscapes are interesting, playable but diverse



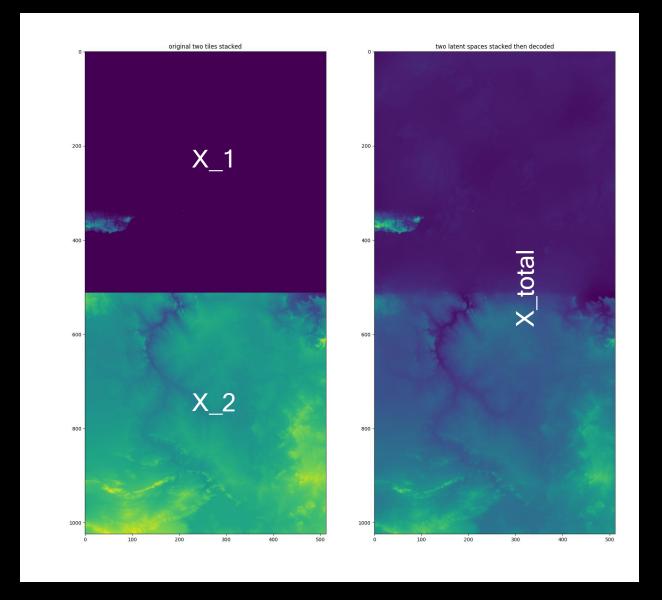


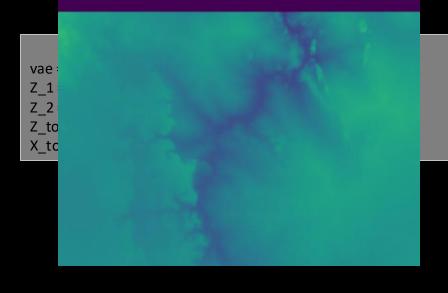


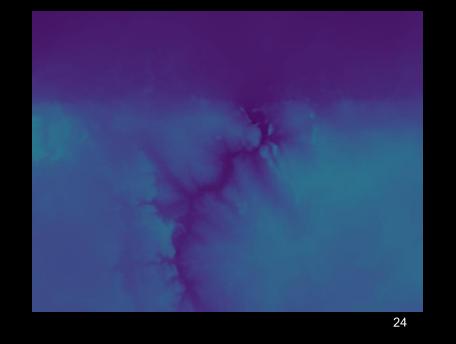
NEXT STEPS: LATENT SPACE EXPLORATION



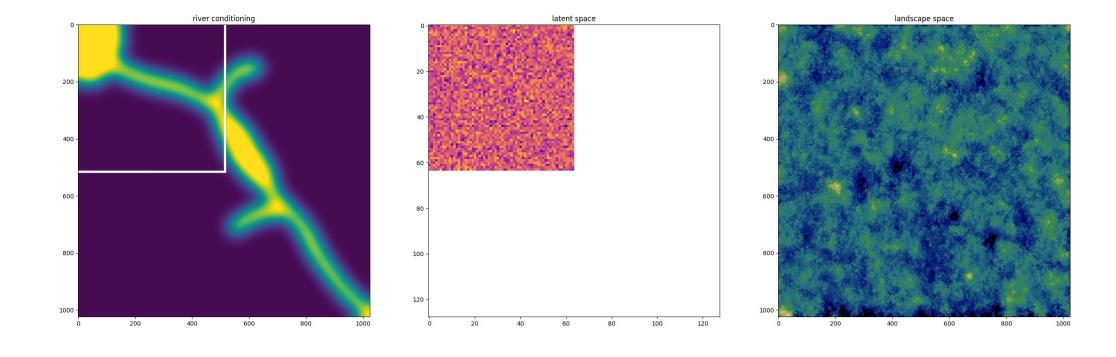
NAÏVE STACKING OF LATENTS

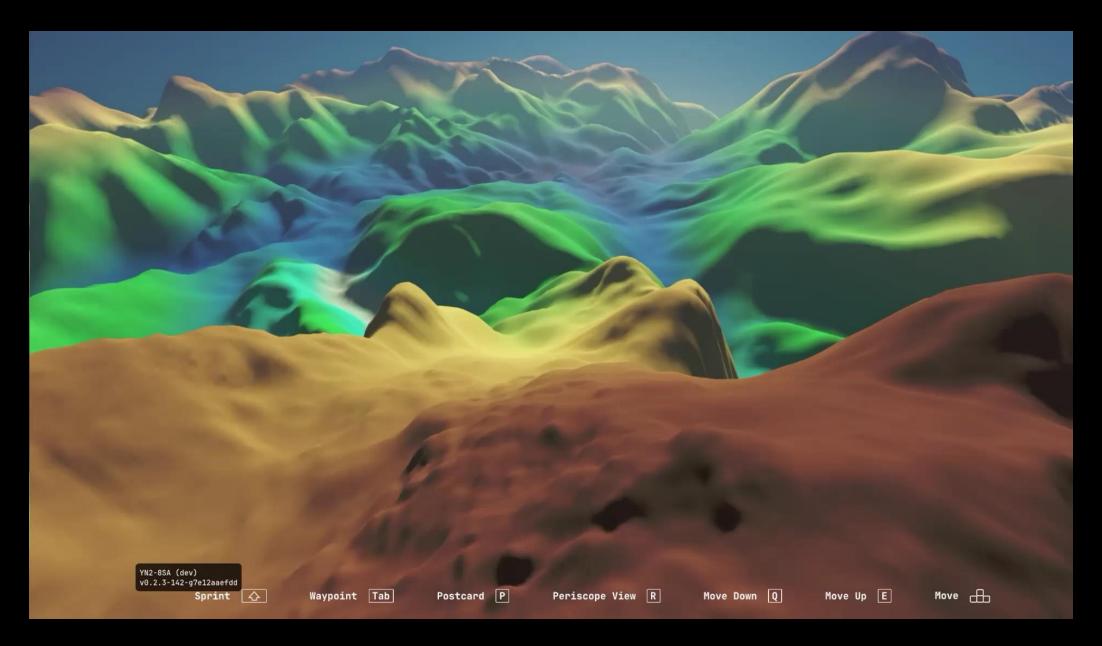






LATENT TILING

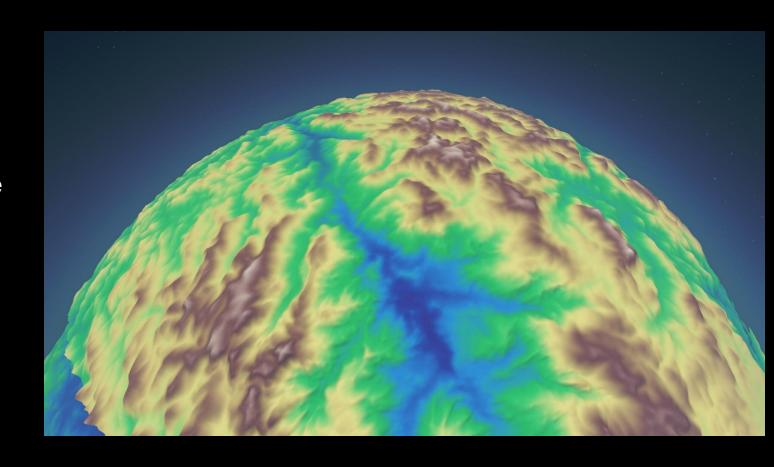




FROM 64KM2 TO THE WORLD

Open questions

- How do we scale this to planets?
- Can we force a VAE to be local?
- At what scale does it make sense to:
 - swap to real space
 - swap to procedural generation



THANKS, AND WE'RE HIRING!

- MLOps Engineer
- Interns
- Speculative applications
- Apply online or chat to me or Eddie about it!

https://playerunknownproductions.net/careers

