

AN UNSUPERVISED 3D NEURAL METHOD FOR WORLD-TO-WORLD TRANSLATION ARUN MALLYA, SENIOR RESEARCH SCIENTIST





Unsupervised 3D Neural Rendering of Minecraft Worlds (oral presentation)







2D image-to-image translation

• We have amazing technologies that produce photorealistic outputs given Microsoft Paint-like inputs!





2D image-to-image translation

- We have amazing technologies that produce photorealistic outputs given Microsoft Paint-like inputs!
- Trained in a supervised fashion using millions of (segmentation map, real image) pairs
- Plug: https://www.nvidia.com/en-us/studio/canvas/ is free and publicly available!





What about 3D content creation?

AND expensive Fancy and complicated tools











- Requires years of experience
- Lots of time and money
- Great for professionals!
- But big barrier to entry for most people

Is there an easier way?



- YES!
- Even kids can make 3D models!





Its digital counterpart





World-to-world translation

- GANcraft extends the task of 2D image-to-image translation to 3D
- It translates an input 3D world to another view-consistent 3D world
- Our work focuses on converting Minecraft-style semantically-labeled block worlds to realistic-looking worlds, without paired supervision







Creating photorealistic 3D worlds is challenging

• 2D landscape images are widely available on the internet



• But what about paired 3D and 2D image data?

GANcraft converts voxel worlds to reality!





High-resolution results 1024 x 2048 pixels, 30 fps





GANcraft generalizes to new worlds with significant label distribution shifts - desert

GANcraft generalizes to new worlds with significant label distribution shifts - **snow**

GANcraft generalizes to new worlds with unique input geometry – valleys and arches

Style interpolation GANcraft can render worlds with different style-conditioning images

The "Why don't you just use im2im translation?" Question aka Comparison with baselines

MUNIT (ECCV'18)

Flickering - generates one image at a time, with no memory of past Mismatch between segmentation label and texture due to unsupervised training

SPADE (CVPR'19)

Flickering - generates one image at a time, with no memory of past

wc-vid2vid (ECCV'20)

View consistent, but fails for large motions due to incremental inpainting Does not refine blocky geometry

NSVF-W (NeurIPS'20, CVPR'21)

View consistent, but dull unrealistic outputs due to lack of GAN loss Single-stage rendering, difficult to scale up

GANcraft (ours)

Our full model: view consistent, vivid colors, more realistic Implicitly refines blocky geometry to learn fine details

GANcraft (ours) MUNIT (ECCV'18) SPADE (CVPR'19) wc-vid2vid (ECCV'20) NSVF-W (NeurIPS'20, CVPR'21)

Failure cases

Some regions look blocky due to underlying input geometry

Certain scene-style combinations don't work well

GANcraft details

• We want to render the semantically-labeled voxel world (as in Minecraft) as a realistic-looking world

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60% desert, 30% forest, 10% water

5% desert, 50% forest, 30% water, ...

- We want to render the semantically-labeled voxel world (as in Minecraft) as a realistic-looking world
- There is no paired data mapping Minecraft segmentations to real images
- Label, geometry and camera pose distribution between Minecraft scenes and real images is very different
- Solution: pseudo-ground truths, and adversarial training

We are given a semantically-labeled voxel world as input

We sample random camera locations

and project the voxel world to obtain segmentation maps

These segmentation maps are fed to a pretrained image-to-image translation network to obtain pseudo-ground truths

Such pseudo-ground truths are not guaranteed to be 3D consistent, but our method is designed to be robust to such noisy training data

Why bother with Pseudo-ground truth?

- Enables us to use pixel-wise losses such as the L₁, L₂, and the VGG Perceptual loss!
- Why not simply use a GAN loss?

Pseudo-ground truth significantly improves the quality

GANcraft without using pseudo-ground truth

GANcraft with pseudo-ground truth

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- Enables us to use pixel-wise losses such as the L₁, L₂, and the VGG Perceptual loss!
- Why not simply use a GAN loss?
- Truth hurts, but just GAN losses may not be enough for complicated tasks

We sample a camera location, obtain the segmentation map, and generate the pseudo-ground truth

We sample N points from voxels along the ray, trilinearly interpolate the corner features and pass them through a per-sample MLP, and blend them to obtain image pixel features

We pass the image pixel features to a CNN and generate an output image

Both the MLP and the CNN are conditioned on the style of the pseudo-ground truth image

The style encoder explains away the view-inconsistency of pseudo-ground truth image

We apply a GAN loss, VGG-19 perceptual loss, and pixel-wise losses between the output and pseudo-ground truth

We also apply a GAN loss between the output and real images to improve realism

Additional Details

Neural sky dome

A neural sky dome located at infinitely far away catches the residual transmittance.

Two-stage renderer improves scalability

GANcraft only uses 24 samples per ray in the volumetric rendering stage – noisy feature map

Two-stage renderer improves scalability

GANcraft only uses 24 samples per ray in the volumetric rendering stage – noisy feature map WHY?? NeRF uses over a 100!

- NeRF applies L₂ loss per pixel only
- We need to produce the whole image (not just a subset) to apply perceptual and GAN losses

Two-stage renderer improves scalability

GANcraft only uses 24 samples per ray in the volumetric rendering stage – noisy feature map The CNN aggregates information within local patches and removes noise The CNN is more flops-efficient than the radiance field MLP due to fewer number of evaluations Need small CNN to preserve view-consistency!

Two-stage renderer improves quality

One-stage (MLP only)

Two-stage (MLP + CNN)

Two-stage rendering pipeline produces images with better detail under the same computation and memory budget

Please refer to the main paper for further details and quantitative results Website: <u>https://nvlabs.github.io/GANcraft/</u> Code available at <u>https://github.com/nvlabs/imaginaire/</u>

