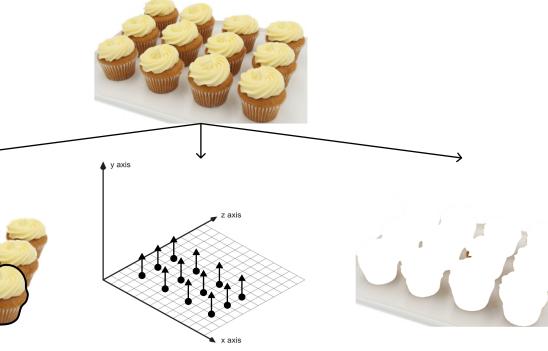


# SinLayout: Learning Generative 3D Scene Layouts from a Single Image

### **Research Overview**

- Scene = Objects + **Spatial Arrangement** + Background.
- While recent works pushed the boundary for modelling 3D objects, learning the 3D layout is underexplored.
- Allows us to generate **plausible and diverse** 3D scenes.



- Problem Setting:
  - -- Input: a single image (segmented) of multiple objects from the same category.
  - -- Goal: learn the objects' **3D layout distribution** (location + rotation) and generate similar scenes.
- Main Approach: Train a permutation-equivariant generator with a patch-based discriminator.
- Main Contributions:
  - -- Propose the task of learning explicit 3D scene layout from a single image of multiple similar instances.
  - -- Build a generative pipeline that fulfills this task.
  - -- Demonstrate effectiveness on Internet images with interpolation and extrapolation results.

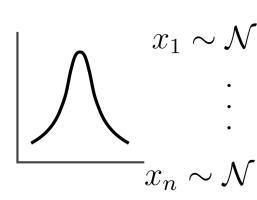
### **Datasets & Metrics**

- Dataset contains single-view **Internet images**.
- Segment the foreground objects (e.g. with SAM).





- Rely on **qualitative** judgements since we have no ground-truth 3D poses of objects.
- Implement camera walks, latent walks, and extrapolation to different number of instances.





**Real Image** w/ segmented instances

Input Image













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# Main Pipeline **Rotation Quaternions** 3D Location SET TRANSFORMER $x_1 \sim \mathcal{N}(0, I) - \mathsf{FC} \mathsf{In-Layer} imes$ $\longrightarrow (q_1^0, q_1^1, q_1^2, q_1^3)$ - FC Out-Layer $ightarrow (x_1, y_1, z_1)$ Add & Norm Feed-Forward kх Add & Norm Multi-Head - FC Out-Layer $\rightarrow$ $(x_n, y_n, z_n) \longrightarrow (q_n^0, q_n^1, q_n^2, q_n^3)$ $x_n \sim \mathcal{N}(0, I) - \mathsf{FC}$ In-Layer $\rightarrow$ Attention **Fake Patch Real Patch 3D RENDERING** Alpha Compose **Object 3D recovered from Image Discriminator** segmented instances + Auxiliary losses Results **Extrapolation to Different Number of Instances** Learned Generative Layouts 3D Camera Walk





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# **Technical Details**

• Wonder3D to obtain 3D object geometry from segmented instances. Mesh + layout = scene images.



• **2 Discriminators** with WGAN objective.



40% Crop

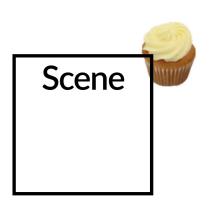


80% Crop

- Augmentation: Pose prediction + Random color background + Noise.
- Auxiliary Losses:







**2D Location Loss** 

Overlapping Loss

Off-scene Loss

## Analysis

- Learn **diverse** range of layouts from a single image.
- Novel views + Interpolation + Extrapolation abilities.
- **Disentanglement** between geometry and layout.

Layout transfer:



- Difficult to **quantitatively** evaluate the results.
- Single-view supervision  $\rightarrow$  other views can have slight irregularities.
- Extrapolation to different number of instances seems to be interpolating among object instances.
- Training is unstable & fails for more **complex scenes**.
- Extend the pipeline to real images of multiple **different** objects (e.g. indoor scenes).















