ATISS: Autoregressive Transformers for Indoor Scene Synthesis

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https://nv-tlabs.github.io/ATISS
Can we learn a generative model of object arrangements trained for scene synthesis that can also perform a number of interactive scenarios with versatile user input?
Motivation

- Synthesis
- General Completion
- Object Suggestion
Existing scene synthesis methods impose unnatural constraints on the scene generation process because they represent scenes as ordered sequences of objects.

FastSynth, Ritchie et al. CVPR 2019

SceneFormer, Wang et al. ARXIV 2020
Existing scene synthesis methods impose unnatural constraints on the scene generation process because they represent scenes as ordered sequences of objects.

We pose scene synthesis as an unordered set generation problem.
Scene Parametrization

A scene comprises an unordered set of $M$ objects $\mathcal{O} = \{o_j\}_{j=1}^M$ and its floor shape $F$. 

![Diagram of a scene with unordered objects and a floor shape](image)
Scene Parametrization

A scene comprises an unordered set of $M$ objects $\mathcal{O} = \{o_j\}_{j=1}^M$ and its floor shape $\mathcal{F}$.

Each object $o_j = \{c_j, s_j, r_j, t_j\}$ is modelled with four random variables that describe their category, size, orientation and location.
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A scene comprises an **unordered set of** $M$ **objects** $\mathcal{O} = \{o_j\}_{j=1}^M$ and its **floor shape** $F$.

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Each object $o_j = \{c_j, s_j, r_j, t_j\}$ is modelled with four random variables that describe their category, size, orientation and location.

$$p_\theta(o_j | o_{<j}, F) = p_\theta(c_j | o_{<j}, F)p_\theta(t_j | c_j, o_{<j}, F)p_\theta(r_j | c_j, t_j, o_{<j}, F)p_\theta(s_j | c_j, t_j, r_j, o_{<j}, F)$$

Probability of generating $j$-th object
Scene Parametrization

A scene comprises an **unordered set of** $M$ **objects** $\mathcal{O} = \{o_j\}_{j=1}^M$ **and its floor shape** $F$.

The **likelihood** of generating a scene with any order is:

$$p_\theta(\mathcal{O}|F) = \sum_{\hat{\mathcal{O}} \in \pi(\mathcal{O})} \prod_{j \in \hat{\mathcal{O}}} p_\theta(o_j | o < j, F)$$

where $\pi(\mathcal{O})$ is a permutation function that computes the set of permutations of all objects $\mathcal{O}$ in the scene.
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Probability of generating $\mathcal{O}$ with any order

Probability of generating $\mathcal{O}$ with order $\hat{\mathcal{O}}$
Scene Parametrization

A scene comprises an unordered set of $M$ objects $\mathcal{O} = \{o_j\}^M_{j=1}$ and its floor shape $F$.

The likelihood of generating a scene with all orders is:

$$\hat{p}_\theta(\mathcal{O}|F) = \prod_{\hat{\mathcal{O}} \in \pi(\mathcal{O})} \prod_{j \in \hat{\mathcal{O}}} p_\theta(o_j | o_{<j}, F)$$

Probability of generating $\mathcal{O}$ with all orders

ATISS is trained to maximize the log-likelihood of all possible permutations of object arrangements in a collection of scenes.
Scene Parametrization

A scene comprises an unordered set of $M$ objects $\mathcal{O} = \{o_j\}_{j=1}^{M}$ and its floor shape $F$.

The log-likelihood of generating a scene with all orders is:

$$\log \hat{p}_\theta(\mathcal{O}|F) = \sum_{\hat{\mathcal{O}} \in \pi(\mathcal{O})} \sum_{j \in \hat{\mathcal{O}}} \log p_\theta(o_j | o_{<j}, F)$$

ATISS is trained to maximize the log-likelihood of all possible permutations of object arrangements in a collection of scenes.
Scene Generation

- **Layout encoder**: Computes a global feature representation for the floor.
- **Structure encoder**: Maps the j-th object to a per-object context embedding $C_j$.
- **Transformer encoder**: Takes $F$, $\{C_j\}_{M=1}^q$ and predicts the features $\hat{q}$ of the next object to be added in the scene.
- **Attribute extractor**: Predicts the object attributes of the next object.

$o_1$

$\vdots$

$o_M$
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Training Overview

- Randomly permute the \( M \) objects of a scene.
- Randomly select the first \( T \) objects to compute the context embedding \( C \).
- Conditioned on the \( C \) and \( F \), \( \text{ATISS} \) predicts the attribute distributions of the next object.
- \( \text{ATISS} \) is trained to maximize the log likelihood of the \( T + 1 \) object from the permuted set of objects.
Training Overview

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How well does it work?
Scene Synthesis

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Scene Synthesis

FID Score for Living rooms (↓)

- FastSynth: 61.67
- SceneFormer: 69.54
- Ours: 33.14

FID Score for Dining rooms (↓)

- FastSynth: 55.83
- SceneFormer: 67.04
- Ours: 29.23
Scene Synthesis

![Bar Chart for Living rooms](chart1)

![Bar Chart for Dining rooms](chart2)
Scene Synthesis

Classification Accuracy for Living rooms

- FastSynth: 0.945
- SceneFormer: 0.972
- Ours: 0.516

Classification Accuracy for Dining rooms

- FastSynth: 0.935
- SceneFormer: 0.941
- Ours: 0.477
Scene Synthesis

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Generalization Beyond Training Data

Scene Layout

FastSynth

SceneFormer

Ours
Scene Completion

Partial Scene

Completion 1

Completion 2
Scene Completion

FastSynth and SceneFormer can only generate objects in the order they were trained with. As a result, starting from partial scenes with less common objects, both models fail to generate plausible object arrangements.
Objects Suggestion

A user specifies a region of acceptable positions to place an object, marked as a red box and our model suggests suitable objects to be placed at this location. To perform this task, we compute the likelihood of an object conditioned on an arbitrary scene.
Failure Cases Correction

Our model identifies and corrects unnatural object arrangements in a scene. To identify such objects, our model computes the likelihood of each object conditioned on the other objects in the scene and objects with low likelihood are identified as problematic. For these objects a new location is sampled.
Generation Time

- At least $100 \times$ faster than the CNN-based FastSynth for all room types.
- At least $4 \times$ faster than the Transformer-based SceneFormer for all room types.
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Summary

- We propose ATISS a novel autoregressive model for unordered set generation.

  - Limitations:
    - The autoregressive generation of attributes need to follow a specific ordering.
    - Separate object retrieval module.
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Check out our project page for code and additional results!

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