NITO: Neural Implicit Fields for Resolution-free and Domain-Adaptable Topology Optimization

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Abstract

Structural topology optimization plays a crucial role in engineering by determining the optimal material layout within a design space to maximize performance under given constraints. We introduce Neural Implicit Topology Optimization (NITO), a deep learning regression approach to accelerate topology optimization tasks. We demonstrate that, compared to state-of-the-art diffusion models, NITO generates structures that are under 15% as structurally sub-optimal and does so ten times faster. Furthermore, we show that NITO is entirely resolution-free and domain-agnostic, offering a more scalable solution than the current fixed-resolution and domain-specific diffusion models. To achieve this state-of-the-art performance NITO combines three key innovations. First, we introduce the Boundary Point Order-Invariant MLP (BPOM), which represents boundary conditions in a sparse and domain-agnostic manner, allowing NITO to train on variable conditioning, domain shapes, and mesh resolutions. Second, we adopt a neural implicit field representation, which allows NITO to synthesize topologies of any shape or resolution. Finally, we propose an inference-time refinement step using a few steps of gradient-based optimization to enable NITO to achieve results comparable to direct optimization methods. These three innovations empower NITO with a precision and versatility that is currently unparalleled among competing deep learning approaches for topology optimization. Code & Data: https://github.com/ahnobari/NITO_Public

1 Introduction

Deep learning methods have established a near-uncontested dominance in a variety of generative problems, such as image and text synthesis (Rombach et al., 2022; Achiam et al., 2023). In engineering-related design synthesis tasks, despite a wealth of promising exploratory work (Regenwetter et al., 2022; Song et al., 2023; Hu et al., 2024; Wu et al., 2021), the performance of such models remains highly contested. Design synthesis is a particularly challenging problem for statistical models (Regenwetter et al., 2023). This is in part due to the nonlinearities between 'feature space' and 'performance space' – very similar designs may have extreme discrepancy in performance. Additionally, design constraints (which may be safety-critical) cause difficult-to-learn gaps in the distributional support of the design space. For these reasons, direct optimization of design parameters has classically been preferred since many optimization algorithms efficiently navigate complex constraints and objectives (Boyd & Vandenberghe, 2004).

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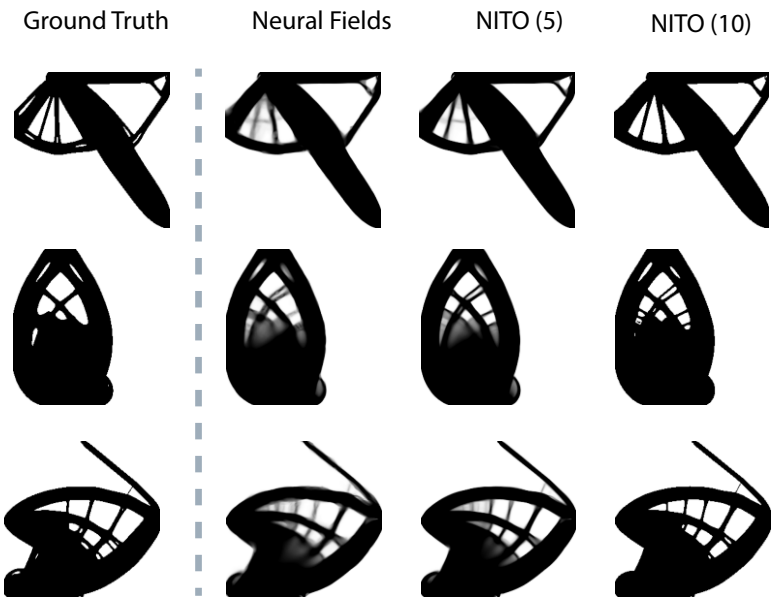

Figure 1: NITO framework. Left: Ground truth obtained using SIMP. Second Column: Output of neural fields. Right Columns: the NITO framework output leveraging a few steps (5 and 10 steps) of optimization. NITO rapidly generates high-quality, constraint-satisfying topologies.

The numerous challenges of successful design synthesis using deep learning and the relative success of direct optimization is exemplified by a prominent and frequently-occuring design problem known as structural topology optimization. Structural topology optimization (TO) aims to allocate a finite amount of material within a designated space to maximize structural stiffness, known as compliance minimization. However, depending on the specific engineering application, other performance goals like heat transfer might also be considered. A popular TO method is the Solid Isotropic Material with Penalization method (Bendsøe & Kikuchi, 1988; Rozvany et al., 1992) (SIMP). While methods such as SIMP are powerful engineering tools, they struggle with computational cost when solving large-scale problems due to their iterative nature and expensive per-step computations (Sigmund & Maute, 2013).

In recent years, many works have investigated the prospect of tackling topology optimization problems using machine learning (Regenwetter et al., 2022; Shin et al., 2023). Many of these are methods for direct topology synthesis, which are often trained on a dataset of optimized topologies while conditioned on the corresponding boundary conditions (force loads and support locations) that yielded each optimized topology (Nie et al., 2021b; Mazé & Ahmed, 2023; Giannone et al., 2023; Giannone & Ahmed, 2023; Hu et al., 2024). The main justification for these approaches is significant time savings compared to TO solvers like SIMP. This could allow designers to run TO in real time during an interative design process, remedying frequent pain-points of current direct-optimization TO users (Saadi & Yang, 2023).

Despite early success, deep learning issues have struggled with several issues. One of these is generalizability, which is critical for their application to real-world TO problems, which are almost always unique. These real TO problems feature one-of-a-kind load and support locations, allow material placement in a specific domain shape and aspect ratio, and require a particular level of detail (i.e., mesh resolution). Most existing deep learning methods discretize the physical domain into pixels or voxels to leverage a convolutional neural networks (CNN) as their basic building block (Mazé & Ahmed, 2023; Giannone & Ahmed, 2023; Giannone et al., 2023; Nie et al., 2021b; Hu et al., 2024). This limits their generation capabilities to a specific resolution and shape (such as a square domain). Thus, applying the problem to a new resolution or aspect ratio necessitates an entirely new dataset and model.

In addition to their generalizability issues, pure data-driven approaches typically do not generate optimal topologies compared to classic iterative optimizers like SIMP, despite being faster (Woldseth et al., 2022). This is primarily attributable to the fact that data-driven models typically focus on density estimation and remain agnostic to the physics of a given problem. To address this, researchers often try to incorporate the physics into their model. These approaches typically rely on physical fields (or approximations) as a representation of the boundary condition constraints of the underlying problems (Mazé & Ahmed, 2023; Giannone & Ahmed, 2023; Giannone et al., 2023; Nie et al., 2021b; Chen et al., 2023; Hu et al., 2024). These physical fields are represented as images to be handled by CNNs. Not only is this approach computationally expensive, particularly for high dimensionality, but it further exacerbates the lack of generalizability across problems and domains. These non-generalizabile ML-based TO methods are essentially unable to solve new problems and commonly receive criticism from the computational structural engineering community (Woldseth et al., 2022).

In this work, we take a stride toward overcoming key generalizability and optimality shortcombings of ML-based TO. To avoid the generalizability pitfall of CNN-based generative schemes, we propose an approach based on neural implicit fields that can be applied to physical domains of any size, shape, and resolution. We also propose a generalizable scheme for representing sparse boundary conditions in numerical physics domains, eliminating the need for computationally expensive and domain-limiting physical field calculations, previously thought to be crucial for constraint representation (Chen et al., 2023). Instead, we show that our computationally- and memory-efficient scheme is capable of representing sparse boundary conditions effectively, without loss of performance. To address optimality issues, we propose to couple our deep learning approach with a few steps of direct optimization to refine generated topologies during inference. Our approach outperforms the state-of-the-art in ML-based direct topology synthesis by more than 80% in key performance metrics while running 2.5-50 times faster.

Contributions:

1. We introduce a novel framework for TO called "Neural Implicit Topology Optimizer (NITO)," a model capable of generating near-optimal topologies. NITO achieves domain- and resolution-agnosticism through its use of neural inplicit fields and our novel "Boundary Point Order-Invariant MLP (BPOM)," It achieves state-of-the-art performance through its use of few-step optimization-based refinement during inference.

2. NITO is resolution-free and domain-agnostic during both training and inference. We show in our experiments that NITO can be trained on multiple resolutions and domain shapes simultaneously and can generate topologies across a variety of resolutions, overcoming a major shortcoming of prior works.

3. We empirically show that NITO is an effective framework, producing topologies with up to 80% lower compliance errors than SOTA learning-based models, while requiring an order of magnitude fewer parameters, allowing 2.5-50x faster interence. These performance metrics are consistent across a variety of resolutions, despite maintaining the same architecture and number of parameters.

4. We implement a new SIMP optimizer for minimum compliance TO. Compared to solvers used to generate existing datasets, our new optimizer produces topologies that are on average 3% lower in compliance, yielding a dataset comprised of significantly more optimal topologies. Our optimizer runs up to 6x faster than widely-used Python implementations. We also introduce a high-quality dataset and improved versions of state-of-the-art models.

2 Background

This section will provide background information on topology optimization and neural implicit fields. We introduce previous work using neural fields for optimal topology generation in this section and review existing work using deep learning for TO in the Appendix.

2.1 Structural Topology Optimization

In structural applications, TO often aims to minimize compliance (structural deformation) given a set of forces and supports (Liu & Tovar, 2014). Fig. 2 illustrates the common structural TO problem formulation, in

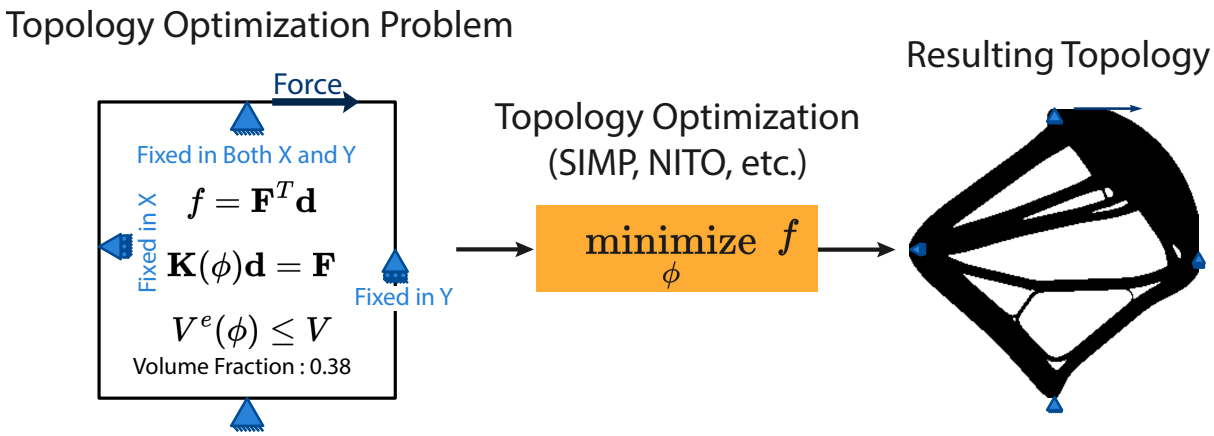

Figure 2: Topology Optimization. Given a domain, boundary conditions, loads, and volume fraction, TO aims to find the design variables ϕ that maximize performance (such as minimizing compliance f), fulfilling all the prescribed constraints and respecting the underlying physics (Static equilibrium).

which a set of forces and supports are specified, along with a target folume fracton. TO finds a topology that minimizes compliance under these conditons. A prominent technique in TO is the Solid Isotropic Material with Penalization (SIMP) method, introduced by Bendsøe (1989). This method models material properties through a density field, where the density value signifies the amount of material in a specific region. The optimization iteratively simulates the system to evaluate the objective, and then adjusts the density field based on the gradient of the objective score for the field. Mathematically, we represent the density distribution as $\rho(\phi)$, where ϕ is a set of design variables, each representing a value within the problem domain Ω. The optimization task is structured as follows:

$$\begin{aligned} \min_{\phi} \quad & f = \mathbf{F}^T\mathbf{d} \\ \text{s. t.} \quad & \mathbf{K}(\phi)\mathbf{d} = \mathbf{F} \\ & \textstyle\sum_{e\in\Omega} \rho^e(\phi)v^e \leq V \\ & \phi_{\min} \leq \phi_i \leq \phi_{\max} \quad \forall i \in \Omega \end{aligned} \tag{1}$$

The objective is to minimize the compliance $\mathbf{F}^T\mathbf{d}$. $\mathbf{F}$ is the load tensor and $\mathbf{d}$ the nodal displacement derived from $\mathbf{K}(\phi)\mathbf{d} = \mathbf{F}$, where $\mathbf{K}(\phi)$ is the stiffness matrix contingent on the design variables ϕ. The constraint $\sum_{e\in\Omega} \rho^e(\phi)v^e \leq V$ ensures the total volume does not exceed a maximum limit V (often expressed as a fraction of the domain volume). The optimization seeks design variables within specified bounds ($\phi_{\min}$ and $\phi_{\max}$) for every element i in the domain Ω. By allowing continuous variation of design variables between 0 and 1, this formulation supports gradient-based optimization. Nonetheless, the expensive finite element simulation (solving $\mathbf{K}(\phi)\mathbf{d} = \mathbf{F}$) at each iteration creates significant computational cost. Notably, solving the linear system of the equations scales cubically ($O(n^3)$) with the number of nodes.

2.2 Deep Learning For Topology Optimization

The limitations associated with conventional optimization have motivated a significant body of work around deep learning approaches for topology optimization (TO). These approaches have been discussed in detail in dedicated reviews (Woldseth et al., 2022; Shin et al., 2023). Most relevant to our work are other methods that perform the task in an end-to-end manner, meaning they take constraints and boundary conditions as input and produce near-optimal topologies to minimize compliance (Oh et al., 2019; Sharpe & Seepersad, 2019; Parrott et al., 2022). For example, Yu et al. (2019) proposes an auto-encoding GAN approach that uses an autoencoder for topology generation and a GAN for super-resolution which is applied simultaneously. Rawat & Shen (2019) and Li et al. (2019) take a similar approach but use GANs for both initial generation and super-resolution. This is while Sharpe & Seepersad (2019), Nie et al. (2021a), and Behzadi & Ilieş (2021) propose directly generating topologies using conditional GANs and Wang et al. (2021b) introduce U-Net-based architectures for TO. More recently, researchers have looked at using implicit neural fields to

generate topologies. Specifically, Hu et al. (2024) use implicit neural representations to produce topologies in their approach called IF-TONIR. In their approach, however, the authors use stress and strain fields for their representations of boundary conditions which rely on CNNs and somewhat reduce the generalizability of the implicit neural fields' versatility.

Conditioning on Physics Fields: Most of the recent state-of-the-art approaches (Mazé & Ahmed, 2023; Nie et al., 2021b; Chen et al., 2023) have adopted a conditioning method in which the boundary conditions of TO problems are represented through physical fields such as stress and strain energy. Although these fields are typically simulation-derived, kernel-based approximations have also been proposed to reduce cost (Giannone & Ahmed, 2023). Regardless, this field-based conditioning approach is essential for these models to generate high-performing topologies. Problematically, field-based conditioning has only successfully been handled by CNN models, which prevent the model from being applied to any new problem with different domain shape or resolution than the training data.

Diffusion-based Topology Optimization: New methods that utilize diffusion models have recently achieved significant performance improvements over the aforementioned methods (Mazé & Ahmed, 2023; Giannone & Ahmed, 2023; Giannone et al., 2023). Mazé & Ahmed (2023) were the first to do so and demonstrated that diffusion models are significantly better than GANs at optimal topology generation. They also showed that introducing guidance based on a regression model for predicting compliance and a classifier trained to identify floating material significantly improves the performance of such models. Like iterative optimization, however, diffusion models are slow, requiring the models to be run as many as 1000 times to generate a sample. This puts their value into question when the time savings are not notable compared to the optimizer itself. Giannone et al. (2023) propose aligning the diffusion models denoising with the optimizer's intermediate designs as a way to reduce the number of iterations needed for the diffusion model and show that they can indeed reduce the number of sampling steps significantly.

Despite the upsides of the best-performing models which are diffusion-based, they lack speed and are all based around CNNs, which means that they treat the problem as images. Furthermore, the mechanism they use for conditioning based on boundary conditions is field-based, meaning these methods compute some physical or energy field to represent the boundary conditions of the problem, treat these fields as images, and employ CNN-based architectures to handle them. This method introduces two limitations. These models generate images instead of density fields, restricting them to a specific problem domain and resolution (e.g. a square-shaped domain treated as 64x64 images) and making them unsuitable for different domain shapes and resolutions. Additionally, the use of image-based fields for boundary conditions further narrows their generalizability. This approach fails to capture boundary conditions in their raw form, limiting applicability to problems with boundary conditions defined for the exact domain they are trained on and excluding problems with irregular boundary conditions.

2.3 Implicit Neural Fields

A neural field is a field that is partially or fully defined by a neural network (Xie et al., 2022). This neural network takes some form of coordinate representation in space $\mathbf{x} \in \mathbb{R}^n$ as input and outputs a set of values (i.e. a measure of the desired field) $\Phi(\mathbf{x}) \in \mathbb{R}^m$:

$$\tilde{\Phi}(\mathbf{x}) = f_\Theta(\mathbf{x}) \tag{2}$$

where f_Θ is the neural network function given parameters Θ. These neural fields have proven effective in representing audio (Du et al., 2021), images (Skorokhodov et al., 2021; Sitzmann et al., 2020), videos (Yu et al., 2022), 3d objects (Park et al., 2019), 3D scenes (Mildenhall et al., 2020), and many more applications (see the review by Xie et al. (2022) for a more comprehensive picture). It has also been shown that neural implicit representations can be directly optimized using gradient-based optimizers similar to SIMP to represent the optimal topology for any given problem (Zehnder et al., 2021; Joglekar et al., 2023; Chandrasekhar & Suresh, 2021), which shows that these implicit neural representations are indeed capable of generating density fields that represent *individual* optimal topologies. Compared to existing work, which representes one individual topology per neural field, we propose a conditional implicit neural field approach that generates *different* optimal topologies based on conditions (i.e., volume, loads, supports).

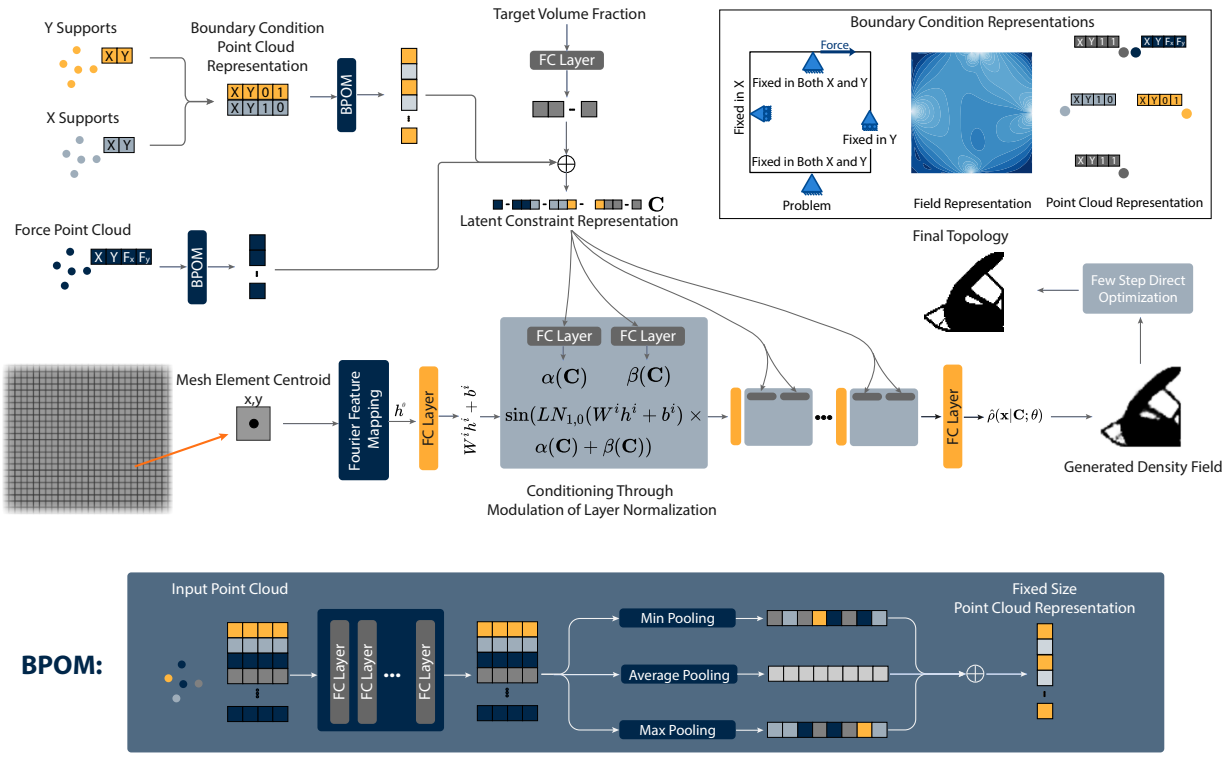

Figure 3: The NITO framework for topology optimization: Boundary conditions processed as point clouds using BPOM; neural field conditioned on these representations by modulating layer normalization based on latent constraint representation to predict optimal density field; predicted field refined through direct optimization steps. Top-right: Point cloud boundary conditions (right) vs. field-based representations like stress fields (middle), given a TO problem (left). Point clouds offer generalizable, memory-efficient boundary condition representation, unlike expensive, domain-limiting iterative FEA method.

3 Methodology

We introduce NITO: Neural Implicit Topology Optimization. Unlike the majority of existing deep learning approaches in TO, NITO effortlessly generalizes across different solution domains and problem resolutions. NITO also achieves a more effective balance of speed and optimality than existing approachs. To enable these achievements, NITO combines three key innovations. First is the neural field-based topology representation that affords much of NITO's flexibility. Second is the Boundary Point Order-invariant MLP (BPOM) which is the second ingredient in NITO's domain- and resolution-agnosticism. NITO's third and final component is a few-step optimization-based refinement of topologies during inference, allowing NITO to rapidly generate solutions that rival the highly-optimal structures generated by direct optimization methods. This section discusses these key three innovations in detail. A detailed schematic of how the NITO framework operates is shown in Figure 3.

3.1 Implicit Topology Representation using Neural Fields

The spatial density distribution used in SIMP is highly compatible with neural fields. We denote as $\rho(\mathbf{x})$, where $\mathbf{x}$ is the coordinate of a given point in space and $\rho(\mathbf{x})$ is the density of material in that part of space. Since we need to learn a conditional distribution based on the boundary conditions and volume ratio for a given problem, we learn:

$$\hat{\rho}(\mathbf{x}|\mathbf{C};\theta) = f_\theta(\mathbf{x}, \mathbf{C}), \tag{3}$$

where f denotes the neural field function which is defined by the neural network architecture and $\mathbf{C}$ is a condition vector that includes information about the domain shape, boundary conditions, and desired volume ratio. In practice, this density field is desired to have a density of exactly 0 or 1 at any point, representing

where material should or should not be placed. As such, the density fields that are generated by the SIMP optimizer for a given problem have binary values.

In practice, it is more practical to formulate the problem as the probability of material being placed at any given coordinate. As such, the formulation of the objective can be written as:

$$\begin{aligned}\mathcal{L}(\theta) = -\,&\mathbb{E}_{\mathbf{x},\mathbf{C}}\left[\rho(\mathbf{x}|\mathbf{C})\log f_\theta(\mathbf{x},\mathbf{C})\right.\\ &\left.+(1-\rho(\mathbf{x}|\mathbf{C}))\log(1-f_\theta(\mathbf{x},\mathbf{C}))\right]\end{aligned} \tag{4}$$

where $\rho(\mathbf{x}|\mathbf{C})$ is the probability of material existing at $\mathbf{x}$, which in this case is the same as the output of the SIMP optimizer.

We implement our neural fields using simple multi-layer perceptrons (MLPs) with SIREN (Sitzmann et al., 2020) layers which apply sine activation functions to the output of each layer. Since neural fields tend to ignore higher-frequency features (Tancik et al., 2020), we apply Fourier feature mapping to the input coordinates of the model to mitigate this issue.

3.2 Latent Constraint Representation using Boundary Point Order-invariant MLP (BPOM)

Having discussed the neural field implementation, we now consider boundary conditions in discretized domains, as seen in TO problems. In particular, we discuss how arbitrary discrete boundary conditions can condition generative models in a sparse and generalizable way. This is particularly important for large domains, where defining constraints over grids is computationally cumbersome and memory-expensive.

In most existing studies, authors only considered simple input-only conditioning, which is prone to be ignored by the model (Perez et al., 2017). We suspect this tendency of models to ignore sparse input conditions explains the singular popularity of the rigid field-based conditioning discussed in Sec. 2.2, despite its lack of generalizability. In this paper, we instead propose a simple and effective condition representation model that leverages more advanced conditioning methods to incorporate conditioning information. This allows our model to train on simple and generalizable point-cloud-based conditions, expanding its applicability to various domains and resolutions.

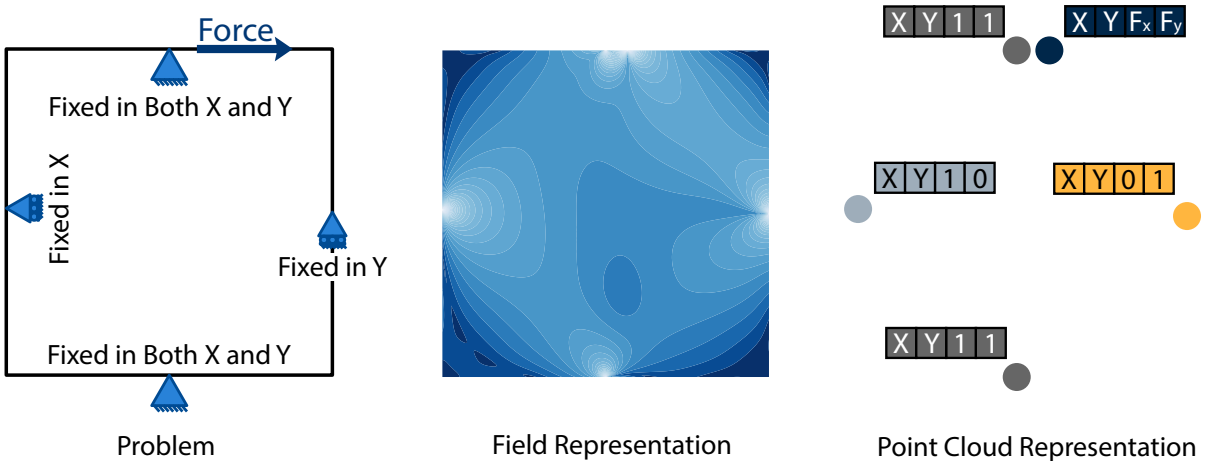

Figure 4: Comparison of field-based (middle), and point-cloud-based (right) representations, given a TO problem (left). Unlike the expensive and domain-limiting iterative FEA method, the point clouds offer a generalizable and memory efficient, representation of the boundary conditions.

Constraints as Point Clouds: In our approach, we represent TO boundary conditions as point clouds, which are agnostic to the problem domain and solution resolution. In all problems, conditioning is based on loads, displacement constraints, and volume fraction (see Figure 4). Since a problem may have arbitrarily many loads or boundary conditions, we need a mechanism that can take all loads and boundary conditions for a problem and reduce them to a single latent representation. To do this, we treat these sparse conditions as a set of two point clouds – one for loads, and another for supports (see Figures 3 and 4). Then we process

each point cloud using ResP Layers proposed by Ma et al. (2022) in their point cloud model, PointMLP. However, unlike PointMLP, we removed the geometric affine module (as proposed by the authors for complex point cloud geometries) due to the simpler geometric nature of our sparse boundary condition point clouds.

Order-Invariant Aggregation: Since the point clouds can have any size, we take the output of the point cloud model and perform order-invariant pooling to reduce every point cloud into one single vector representing the boundary conditions. We do this by computing minimum, maximum, and average pooling and concatenating the three pooling results. In the end, the three point clouds are each reduced and then concatenated into one vector. We call this boundary condition representation Boundary Point Order-Invariant MLP (BPOM) and we show that this representation works just as well as physical fields. Finally, for the volume fraction condition (which is always a single floating point value), we use a single fully-connected layer and concatenate its output to the BPOM outputs of the boundary condition point clouds.

Feature-wise Linear Modulation: Next, we discuss how the condition vector is fed into the neural fields model. Neural fields possess the capability to assimilate prior behaviors and exhibit generalization to novel fields through conditioning on a latent variable $\mathbf{C}$, which encapsulates the characteristics of a field. Specifically, this includes the boundary conditions and the volume ratio in our problem. Perez et al. (2017) propose Feature-wise Linear Modulation (FiLM) which applies conditioning by modulating the outputs of the different layers of the model. The conditioning mechanism includes two networks $\alpha(\mathbf{C})$ and $\beta(\mathbf{C})$, which predict a multiplicative and additive adjustment to the outputs of each layer. Our implementation is inspired by similar mechanisms built around normalization layers such as adaptive instance normalization (AdaIN) (Huang & Belongie, 2017). Instead of modulating the outputs of each layer, we apply layer normalization and modulate the scale and shift of the layer norm for each feature of the layer output. Our neural field can be described as:

$$f_\theta(\mathbf{x}, \mathbf{C}) = f^{(L)} \circ f^{(L-1)} \circ \cdots \circ f^{(0)}(\mathbf{x}, \mathbf{C})) \tag{5}$$

where $f^{(i)}$ for $i \in \{1, 2, ..., L-1\}$ indicates the function applied at each layer of the neural field except the first and last layer. Each layer in the model takes a hidden state $h^{(i)}$ as input and performs a linear transformation and layer normalization with modulation based on the condition vector:

$$f^i(h^i, \mathbf{C}) = \sin(LN_{1,0}(W^i h^i + b^i) \times \alpha(\mathbf{C}) + \beta(\mathbf{C})), \tag{6}$$

where $LN_{1,0}$ is layer normalization with scale 1 and shift zero and α and β are fully-connected (FC) layers that determine the feature-wise scale and shift based on the condition inputs.

BPOM allows NITO to generalize to any domain shape and TO problem as long as that information is contained in the condition latent representation $\mathbf{C}$.

3.3 High-quality Solutions using Optimization-Based Refinement

Despite the success of generative models and other deep learning techniques for TO, we observe that the performance of these models always lags behind the optimization baseline. To address this, we follow an optimization-based refinement approach proposed by Giannone et al. (2023) who suggest applying a few steps (5-10) of SIMP optimization to topologies synthesized by deep learning models during inference (compared to 200-500 iterations for full optimization). This allows SIMP to rapidly hone in on more accurate structures for the given boundary conditions using near-optimal generated topologies as a starting point. To ensure that the optimization itself is performed optimally, we implement the SIMP method based on the latest research on TO (Wang et al., 2021a) and use this solver for our experiments and training. This optimization-based refinement represents the third and final key innovation of our NITO framework.

3.4 Training and Model Details

The training of the conditional neural implicit model is performed in 3 stages. In the first stage, we perform training by sampling points of a 16x16 grid (i.e., we sample points in space that each belong to one of the 16x16 divisions in space for the unit square domain). Furthermore, when sampling, if the material exists in a given sampling grid we randomly choose a point with material rather than picking points that are void. The first stage of training is carried out for 20 epochs. In the second stage we sample on a 32x32 grid for 20 epochs. Finally we we train for 10 more epochs, sampling on a 32x32 grid but rather than preferring material

points, we sample completely randomly. We use AdamW optimizer with a starting learning rate of 10^{-4} which is reduced on a cosine annealing schedule to be reduced at the end of each epoch to reach 5×10^{-6} at the final epoch. The learning rate is stepped at the end of each epoch.

In our implementation, we use 8 layers of size 1024 for the neural fields and use 4 layers of size 256 for the three point cloud models (one for applied force and one for constraints in each x and y direction). Although intermediate layers of the neural fields model use the aforementioned FiLM activations, the final layer's activation function is a simple sigmoid. Further details can be found in our code.

4 Experiments

In this section, we present an assortment of experiments to compare the performance of NITO to existing state-of-the-art models in the literature. With these experiments, we provide compelling evidence that NITO is a scalable, resolution-free and domain-adaptable paradigm that outperforms convolution-based methodologies with a significantly smaller parameter count. We further demonstrate that NITO can generate constraint-satisfying, high-performance topologies much faster than a state-of-the-art SIMP optimizer, while merging the power of deep learning models as an efficient first stage, and the precision and guarantees of optimization as a reliable second stage. For more experiments, discussion, and visualization, we refer the reader to the Appendix.

4.1 Experimental Details

Before presenting the results, we will first discuss key experimental details.

Dataset and Solver: We create a dataset comprised of various domain shapes and resolutions using a custom SIMP optimizer leveraging recent advancements in iterative TO (Wang et al., 2021a). Noting that much of the previous data-driven TO work uses datasets generated by ToPy (Hunter et al., 2017), which lacks these recent TO advancements and is much slower than our solver, our dataset is larger and more optimal than those used in previous works. We then used this new and faster solver to generate a new dataset with mixed resolution and shapes. To allow for comparison to prior works, we re-created the 64x64 dataset from Mazé & Ahmed (2023) with our solver, finding significant improvements in optimality. We additionally created high-resolution 256x256 data. Finally, we also generated 64x32, 64x48, and 64x16 data, to test NITO's ability to handle mixed domain shapes (something prior works cannot handle). We include loading conditions, boundary conditions, volume fractions, and stress and strain energy fields in our dataset. A total of 199,000 samples can be found in our dataset including 48,000 64x64 samples, 61,000 256x256 samples, and 30,000 samples of 16x64, 32x64, and 48x64 each. For each resolution, 1,000 samples are used for testing. To keep results consistent with prior works we use the exact same 1,000 test samples in the 64x64 subset as prior works have used. For fairness in comparison, we retrained the TopoDiff model (Mazé & Ahmed, 2023) (the best-performing model in literature) on our new re-optimized dataset (64x64 and 256x256 only), while also acknowledging the original performance metrics reported by the authors. Further details on the dataset and solver are included in the Appendix.

Evaluation Metrics: We evaluate the models in terms of performance (i.e., minimum compliance) and constraint satisfaction. First, to measure how well the models perform in compliance minimization, we measure compliance error (CE), which is calculated by subtracting the compliance of a generated sample from the compliance of the SIMP-optimized solution for the corresponding problem, then normalizing by the SIMP-optimized compliance value. Since mean compliance error tends to be dominated by just a few samples, we report mean and median compliance error. We also report median volume fraction error (VFE), which quantifies the absolute error between the generated topology's actual volume fraction and the target volume fraction for the given problem. Beyond these base performance metrics, we quantify inference time. The speed of the SIMP optimizer is also benchmarked for comparison. We remove outlying samples, which have extremely high compliance errors (above 1000%) due to models failing to place material in locations where the load is applied. We do this for all models including other SOTA models that we compare against, as is common practice in prior works (Mazé & Ahmed, 2023; Giannone et al., 2023; Nie et al., 2021b).

Setup: We train NITO for 50 epochs in four different scenarios: (1) We train on topologies with a resolution of 64x64. (2) We train on 256x256 topologies. (3) We train on both 64x64 and 256x256 datasets simultaneously to demonstrate resolution-free generalizability. (4) We train on all 64x64, 256x256, 64x48, 64x32, and 64x16

datasets to demonstrate the generalizability of our approach across both resolution and domain shapes. To compare our approach to the state of the art, we also train TopoDiff on the 64x64 in the manner the original authors did (Mazé & Ahmed, 2023). TopoDiff is currently state-of-the-art in literature (Giannone et al., 2023). Training a diffusion model like TopoDiff on large images of size 256x256 is computationally expensive. Despite this, we train TopoDiff on the 256x256 dataset for 500,000 steps and report the results, however, we do not train TopoDiff with guidance (which, as demonstrated in the original work (Mazé & Ahmed, 2023) and corroborated by our experiments, does not lead to any significant improvement in performances).

4.2 Performance Comparison to State of The Art

Table 1: Quantitative evaluation on 64x64 datasets (All models only trained on 64x64 data). All TopoDiff variants are re-trained on optimized topologies obtained using our improved optimizer. *TopologyGAN and cDDPM results from Mazé & Ahmed (2023) and Giannone et al. (2023). w/ G: using a classifier and regression guidance. CE: Compliance Error. VFE: Volume Fraction Error. NITO achieves SOTA performance on topology optimization in terms of compliance and volume fraction error.

Model	Refinement Steps	CE % Mean	CE % Median	VFE % Mean
TopologyGAN*	-	48.51	2.06	11.87
cDDPM*	-	60.79	3.15	1.72
TopoDiff	-	3.23	0.45	1.14
TopoDiff w/ G	-	2.59	0.49	1.18
NITO (ours)	-	8.13	**0.47**	1.40
NITO (ours)	5	**0.30**	**0.12**	**0.40**
NITO (ours)	10	**0.17**	**0.071**	**0.25**

Table 2: Quantitative Evaluation on 256x256 datasets (All models are only trained on 256x256 data). The columns are the same as Table 1. NITO is effective at generating topologies with high performance irrespective of the considered problem resolution. On the other hand, the performance of TopoDiff has degraded so much that NITO outperforms it even without a refinement step.

Model	Refinement Steps	CE % Mean	CE % Median	VFE % Mean
TopoDiff	-	16.62	0.59	2.92
NITO (ours)	-	9.178	0.96	1.52
NITO (ours)	5	**0.25**	**0.09**	**0.34**
NITO (ours)	10	**0.033**	**0.012**	**0.128**

In Table 1 we present a quantitative evaluation of SOTA models for topology optimization on the commonly-tested 64x64 resolution. Mean compliance error results are on average much higher than median results due to a small number of samples having extreme compliance. TopologyGAN and cDDPM show higher values in CE % Mean and VFE % Mean compared to other models. TopologyGAN is consistent with prior benchmarks of the model and cDDPM is a naive conditioning of diffusion models, which struggles to perform well in such a complex problem. A vanilla neural fields model without optimization does not perform as well as TopoDiff in mean compliance error, but performs similarlarly in median compliance error and volume fraction errors. Unambiguously though, Table 1 demonstrates that our NITO framework achieves a significant leap in performance compared to the SOTA. Neural fields start with average compliance errors of more than double TopoDiff. However, after even 5 steps of direct optimization, NITO outperforms TopoDiff and other methods by a large margin. When taking 10 steps of refinement using direct optimization, NITO finds solutions that are on average only 0.1% more compliant than the solutions yielded by 500 steps of optimization.

Next, we proceed to test NITO and TopoDiff on the much more challenging dataset of 256x256 topologies. Table 2 presents the results of this study for NITO and TopoDiff (the leading SOTA approach). In this case, we train TopoDiff with a larger model size to allow for effective learning on the 256x256 images. Despite this, we see a significant performance degradation of TopoDiff with increased resolution. This performance decrease is so severe that the NITO outperforms TopoDiff in most metrics even without a refinement step (highlighted in green in table 2). With refinement, NITO achieves results on par with or slightly better than the 64x64 tests, all while using the same model size, architecture, and training. This illustrates that NITO scales effectively to higher resolutions without performance degradation.

4.3 Topology Refinement Across Baselines

Table 3: In this table, we consider the effects of few-step direct optimization to topologies generated by TopoDiff. While direct optimization significantly improves the topologies generated by the neural field, it only slightly improves topologies generated by TopoDiff.

Model	Refinement Steps	CE % Mean	CE % Median	VFE % Mean
TopoDiff	-	3.23 (-)	0.45 (-)	1.14 (-)
TopoDiff	5	3.55 (+9.91%)	0.42 (-6.67%)	0.67 (-41.2%)
TopoDiff	10	1.38 (-57.3%)	0.33 (-26.7%)	0.45 (-60.5%)
TopoDiff w/ G	-	2.59 (-)	0.49 (-)	1.18 (-)
TopoDiff w/ G	5	2.24 (-13.5%)	0.44 (-10.2%)	0.69 (-41.5%)
TopoDiff w/ G	10	1.05 (-59.5%)	0.32 (-34.7%)	0.45 (-61.9%)
NITO (ours)	-	8.13 (-)	0.47 (-)	1.40 (-)
NITO (ours)	5	**0.30 (-96.3%)**	**0.12 (-74.5%)**	**0.40 (-71.4%)**
NITO (ours)	10	**0.17 (-97.9%)**	**0.071(-84.9%)**	**0.25 (-82.1%)**

NITO uses a few steps of optimization to refine generated topologies. In this section, we consider the performance of SOTA models, should they be subjected to the same few-step refinement using optimization. Table 3 indicates that optimization of topologies generated by TopoDiff yields a much smaller performance boost compared to NITO and even reduces performance in some cases. After just 5 iterations of refinement, NITO outperforms all variants of TopoDiff tested (including TopoDiff with 10 iterations). NITO's lead continues to grow with more refinement steps. Visual examination suggests that while TopoDiff-generated topologies are detailed, topologies generated by the neural field tend to be slightly more blurry (see Fig. 1). Therefore, we hypothesize that Topodiff finds crisp locally-optimal solutions, while NITO, despite being a much smaller model and not using FEA-based physical fields, finds less locally-optimal solutions that lie closer to a stronger 'global' optimum. This suggests that NITO is more robust, generalizable, and efficient.

4.4 Inference Speed & Efficiency

Speed is one of the key benefits of ML-based TO over direct optimization. In Table 4 we present a comparative analysis showing that NITO is significantly faster than both iterative TO methods and competing generative models in inference time. For the 64x64 and 256x256 data respectively, resolution, NITO is 83% and 63% faster than the fastest state-of-the-art model DOM (Giannone et al., 2023), and 97% and 96% faster than our fast SIMP implementation (which itself is up to 6x faster than existing implementations). Thus, in addition to generating superior topologies, NITO's speed and efficiency is orders of magnitude faster than the SOTA.

Table 4 also highlights the number of parameters each model uses in their architecture. NITO can be trained on both image resolutions with the same number of parameters, 22 million, achieving SOTA performance, while CNN-based models have to be made larger and still face significant performance degradation. This is further evidence of NITO's efficiency and scalability. We train NITO for both 64x64 and 256x256 resolution for the same number of steps while sampling the same number of points for each batch during training, which means that the model trains roughly for the same amount of time and with the same memory requirements. In fact a single consumer GPU (we use an RTX 4090) is enough to train NITO. On the contrary, diffusion models like TopoDiff or DOM must grow to match larger resolutions and therefore require more memory and

Table 4: Average inference time for different problem resolutions. We include 10 SIMP iterations when computing NITO inference time. NITO is resolution-free, i.e. we can leverage the same small model for 64x64, 256x256, and any intermediate resolution. These times are measured using an RTX 4090 GPU and an Intel Core i9-13900K CPU. We run the SIMP optimizer for 300 iterations.

	64x64 Resolution		256x256 Resolution	
Model	Parameters (M)	Inference (s)	Parameters (M)	Inference (s)
TopoDiff	121	1.86	553	10.81
TopoDiff w/ G	239	4.79	1092	22.04
DOM	121	0.82	553	7.82
SIMP (Hunter et al., 2017)	-	18.12	-	316.02
SIMP (our implementation)	-	3.45	-	69.45
NITO (No Ref.) (ours)	**22**	**0.005**	**22**	**0.16**
NITO (ours)	**22**	0.14	**22**	2.88

time to run and train. For resolutions above 256x256 or 3D TO problems, these frameworks can be impractical to train or run for most practitioners. In contrast, NITO is built to generalize to different domains/resolutions without issue, allowing for practical training of large problems with consumer-level computational resources. In the following, we specifically showcase the versatility of NITO when handling different domains.

4.5 Resolution-Free and Cross-Domain Generalization

	Training Data											
	64x64			256x256			64x64 & 256x256			All Data		
Testing Data	CE Mean	CE Med.	VFE Mean	CE Mean	CE Med.	VFE Mean	CE Mean	CE Med.	VFE Mean	CE Mean	CE Med.	VFE Mean
64x64	0.17	0.071	0.25	0.27	0.11	0.30	0.22	0.072	0.29	0.22	0.074	0.31
256x256	0.058	0.016	0.13	0.033	0.012	0.128	0.048	0.027	0.14	0.066	0.032	0.14
64x48	-	-	-	-	-	-	-	-	-	0.43	0.20	0.35
64x32	-	-	-	-	-	-	-	-	-	0.90	0.20	0.41
64x16	-	-	-	-	-	-	-	-	-	1.16	0.14	0.72

Table 5: Quantitative evaluation of NITO trained on mixed resolution and aspect ratio data using 10 steps of refinement. **All metrics are reported as percentages**. The results show that NITO trained on mixed-resolution and mixed-shape data performs well across different resolutions and shapes.

To showcase NITO's ability to generalize across multiple resolutions and physical domains, we present results for different training configurations of NITO and its performance on different domains and resolutions. These results are presented in detail in Table 5. We see that the model simultaneously trained on data of all resolutions and aspect ratios performs on par and better than other SOTA models on both the 256x256 data and the 64x64 data while also effectively handling the non-square configurations in the dataset. This illustrates NITO's resolution-free and domain-adaptable nature. It can be trained on multiple domains and perform well on all of them. Similarly, NITO can train on one resolution and be applied to problems at a new resolution. This capability is demonstrated by testing NITO models trained on 64x64 data with 256x256 resolution tasks, and vice versa. Remarkably, NITO's performance is consistent across resolutions and shapes: it performs similarly when trained on lower-resolution data compared to higher or mixed-resolution data, and likewise when tested on higher-resolution or lower-resolution problems. This underscores NITO's exceptional adaptability, indicating that its architecture not only supports training across multiple domains but also facilitates the transfer of learning from one domain to another, provided the problems share related distributions. This ability signifies a critical advantage of such frameworks—the potential to train on cost-effective low-resolution data and immediately apply or quickly fine-tune the models for higher resolutions.

5 Conclusion & Limitations

In this paper, we introduce Neural Implicit Topology Optimization (NITO), a novel resolution-free and domain-agnostic deep learning framework for topology optimization. Using a neural implicit field representation and our Boundary Point Order-Invariant MLP (BPOM) to represent boundary conditions, NITO can be effortlessly trained and deployed on mixed domain shapes and resolutions. Thanks to its few-step optimization-based refinement, NITO significantly outperforms state-of-the-art models in topology optimality across multiple resolutions and domains. Notably, NITO is much faster and has significantly fewer parameters than previous state of the art models. As such, NITO offers a solution to high-dimensional problems that were previously insurmountable with CNN-based methods. Furthermore, NITO's scalability and generalizability offer a robust foundation for future models in topology optimization and other physics-based problems.

Limitations: While NITO presents significant advancements in topology optimization, it is not without shortcomings. Firstly, NITO is not a generative model, which means that the outputs of NITO are deterministic and not diverse for a given set of constraints. This limits NITO's ability to generate solutions that enable exploration of the design space. This characteristic could potentially hinder NITO's efficacy in addressing problems outside its training distribution, given the lack of a generative mechanism that enhances performance in entirely new tasks (See the Appendix for a broader discussion). Future work could be devoted to addressing this matter, potentially by leveraging recent advances in generative frameworks for neural implicit fields (You et al., 2023; Kosiorek et al., 2021). In addition, NITO generates topologies that lack sufficient detail before refinement, making it heavily reliant on its refinement step. Future improvements could aim to refine NITO's training procedures and architecture to reduce the reliance on direct optimization.

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A Additional Experiments

Here we will discuss some further experiments and discuss some limitations of our approach.

Table 6: Quantiative Evaluation on out-of-distribution 64x64 datasets. w/ G: using a classifier and/or regression guidance. FS-SIMP: Few-Steps of optimization. CE: Compliance Error. VFE: Volume Fraction Error.

Model	Train Res.	FS-SIMP	CE % Mean	CE % Median	VFE % Mean	VFE % Median
`out-of-distro`						
NeuralField	64	-	73.24	12.81	8.12	6.87
TopoDiff	64	-	8.57	1.14	1.14	0.97
TopoDiff w/ G	64	-	**7.79**	1.26	1.21	1.00
TopoDiff	64	5	6.20	1.07	0.93	0.55
TopoDiff w/ G	64	5	**5.44**	1.05	0.89	0.55
NITO (ours)	64	5	9.33	2.37	2.22	1.32
TopoDiff	64	10	2.91	0.71	0.64	0.33
TopoDiff w/ G	64	10	2.25	0.71	0.63	0.35
NITO (ours)	64	10	6.38	1.43	1.55	0.85

A.1 Out of Distribution Experiments

Something that should be looked at when it comes to these models is their performance generalizability to problems that are very different from the distribution of data used for training. To do this we test the performance of different models on an out-of-distribution test set for the 64x64 dataset. These results are presented in Table 6 for TopoDiff and NITO. As it can be seen NITO's performance has significantly deteriorated on out-of-distribution data. This can be attributed to two matters. The first and most impactful is the nature of these models. TopoDiff generalizes better when it comes to these out-of-distribution tests given the fact that the model is generative in nature. This allows TopoDiff to handle out-of-distribution conditions better. To understand this we can look at generative models as a sort of retrieval approach, which allows the models to generate detailed and high-quality samples by finding the most similar topologies from the training data even when faced with very different inputs. On the other hand, NITO is a deterministic model that learns to map specific boundary conditions to near-optimal density fields. This makes it rather challenging for models like NITO when it comes to generating topologies for unseen and very different inputs since the mapping is a deterministic one. This highlights the importance of future work focusing on transforming our framework to be generative, which should be possible since many works have shown implicit neural approaches can be made generative (You et al., 2023). The second potential reason contributing to TopoDiff's better performance on out-of-distribution samples is the use of physics-based fields for conditioning. This is because mapping stress fields to topologies makes it easier to handle very different boundary conditions since the stress fields may still be similar to samples in the dataset. However, this creates the kind of limitation that we discussed before, as such it is better to focus on making more robust generative schemes rather than using physical fields.

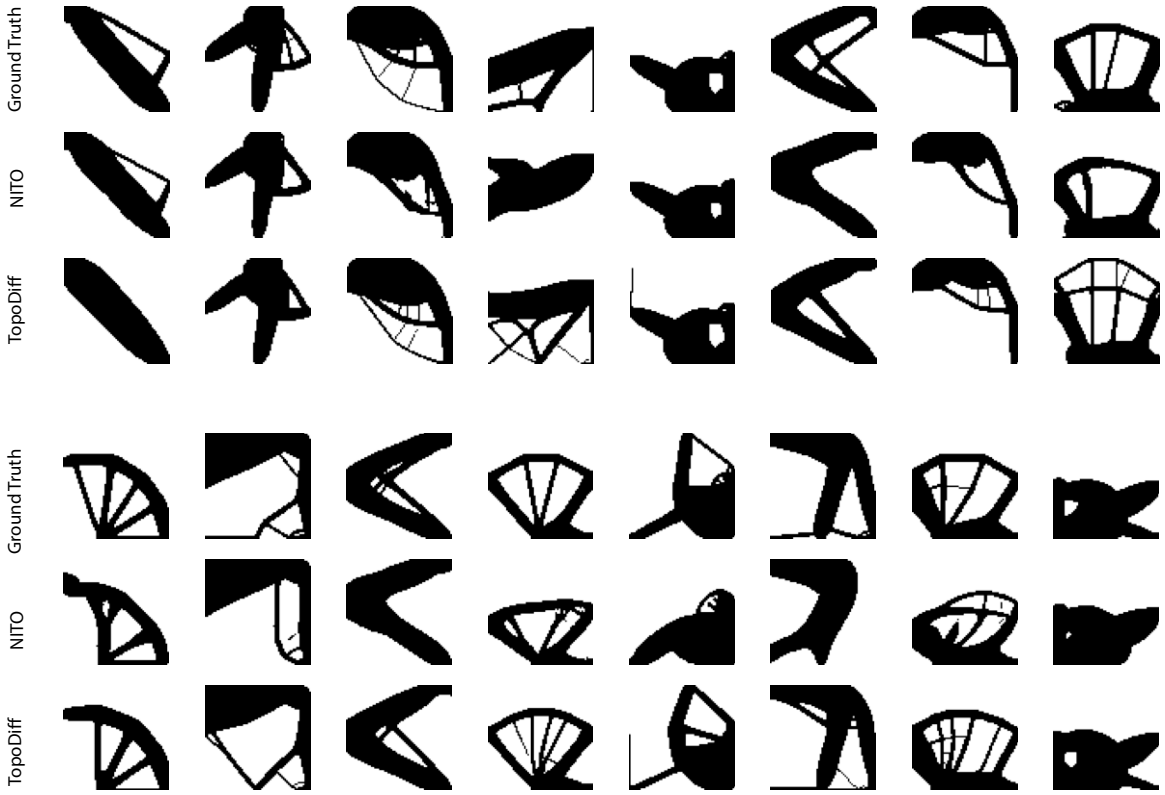

Figure 5: Visual comparison of samples generated for the out-of-distribution test. Each row is labeled. Ground truth samples are SIMP-optimized samples.

A.2 Further Examination Of Results & Outperforming The Optimizer

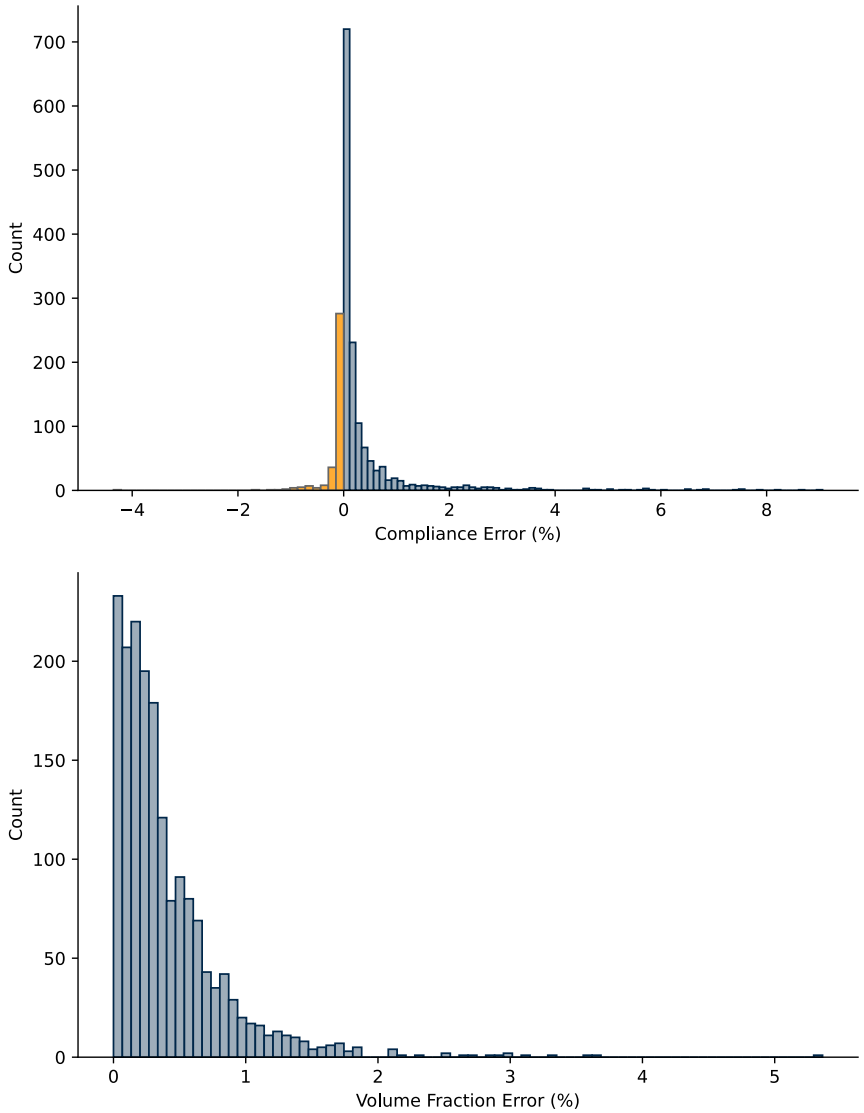

Figure 6: Distributions of volume fraction error (Bottom) and Compliance Error(Top). We see that NITO is capable of out-performing SIMP 19% of the time as highlighted by yellow in the negative compliance errors (meaning better than SIMP) on the top histogram. This data is for the 64x64 test set.

In Figure 6, we show the distribution of compliance error and volume fraction error for NITO on the 64x64 dataset. We see that the majority of volume fraction error is below 1% and a small number of high error samples skew the average. Similarly, we see that the majority of the compliance errors for NITO are below 1% as well. Most notably, we observe that on 19.2% of the samples in the test set NITO actually outperforms SIMP as indicated by the negative compliance errors visible on the histogram. This is a rather interesting outcome where NITO is capable of doing better than the optimizer that the training data came from. In Figure 24, we visualize a few instances of this phenomenon. It can be seen that in some problems NITO actually comes up with a different solution which as it happens out-performs SIMP, while in other instances the topologies are very similar and NITO has adjusted some of the finer details and redistributed the material differently to achieve better performance.

Figure 7: Example topologies where NITO outperforms SIMP. It can be seen that in some instances NITO finds very different topologies that outperform SIMP and in some instances, NITO has removed some details and redistributed the material in a way that has improved performance.

B Visualizations

Here we will provide a set of different visualizations for each test case.

B.1 Direct Optimization Visualization

In this section we provide some visualizations, demonstrating the effect of direct optimization on neural field-generated density fields. The main objective here is to showcase the importance and effectiveness of a few steps of direct optimization on the generated samples which completes the NITO framework. As can be seen in Figures 8 and 9, neural fields tend to have some smoothing and averaging in areas of high detail in the topology, which makes the baseline performance of neural fields worse. With only a small number of direct optimization iterations, however, we see that NITO can resolve the complex details effectively, showcasing why direct optimization is a crucial aspect of our framework.

In contrast, when we look at the effect of direct optimization on TopoDiff (Figures 10 and 11) we see that in cases where the details predicted by TopoDiff are accurate, the optimizer does not provide much benefit, and when TopoDiff has not generated the correct details the generated topology is far from optimal which means that few steps of optimization do not provide significant benefits.

Figure 8: Visualization of the effect of direct optimization on samples generated by neural fields. The first column of each set of images shows the ground truth, the next column shows the raw predictions from neural fields, and the two columns that follow show the effects of 5 and 10 steps of direct optimization on the samples respectively. These samples are from the 64x64 test set.

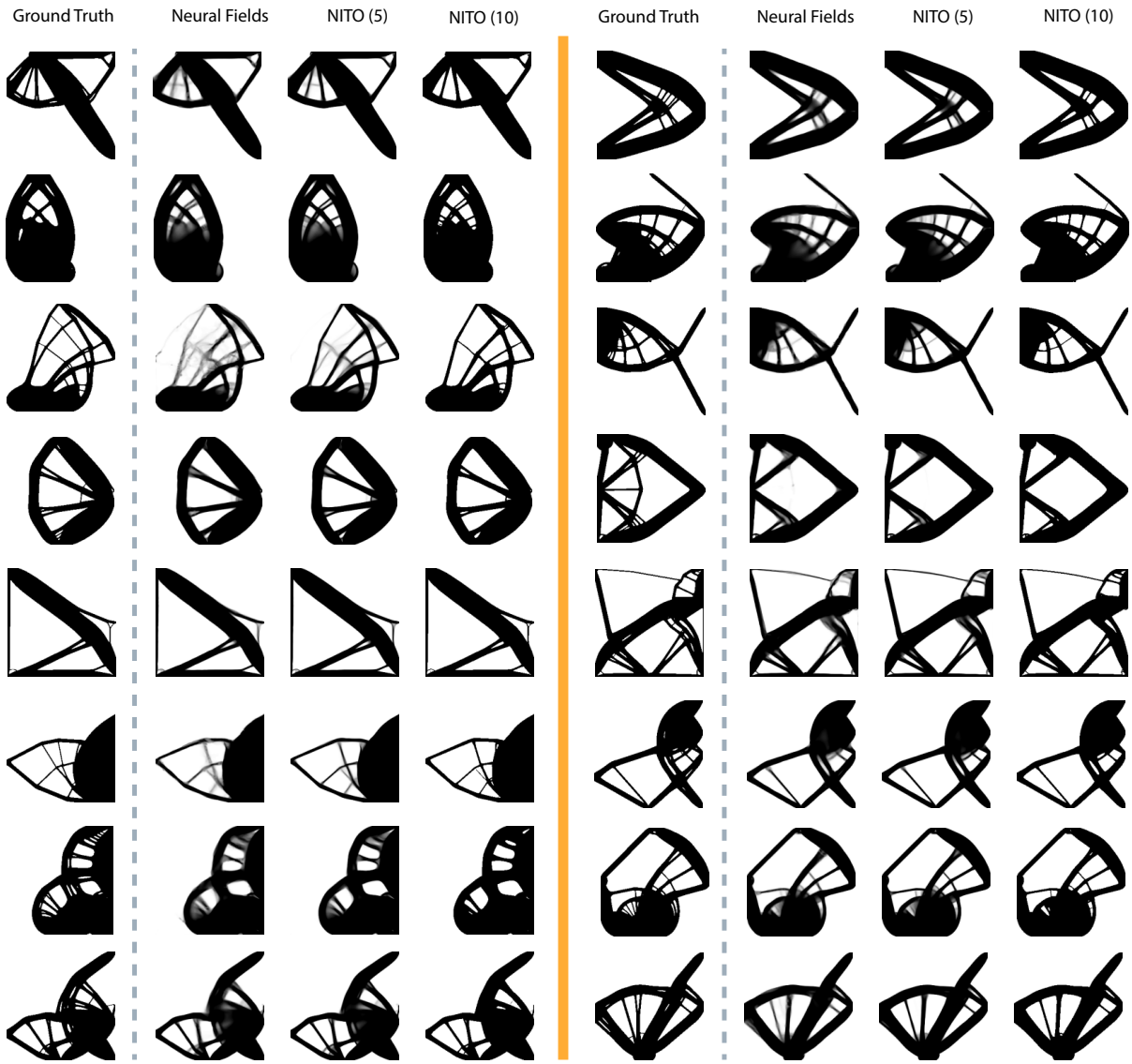

Figure 9: Visualization of the effect of direct optimization on samples generated by neural fields. The first column of each set of images shows the ground truth, the next column shows the raw predictions from neural fields, and the two columns that follow show the effects of 5 and 10 steps of direct optimization on the samples respectively. These samples are from the 256x256 test set.

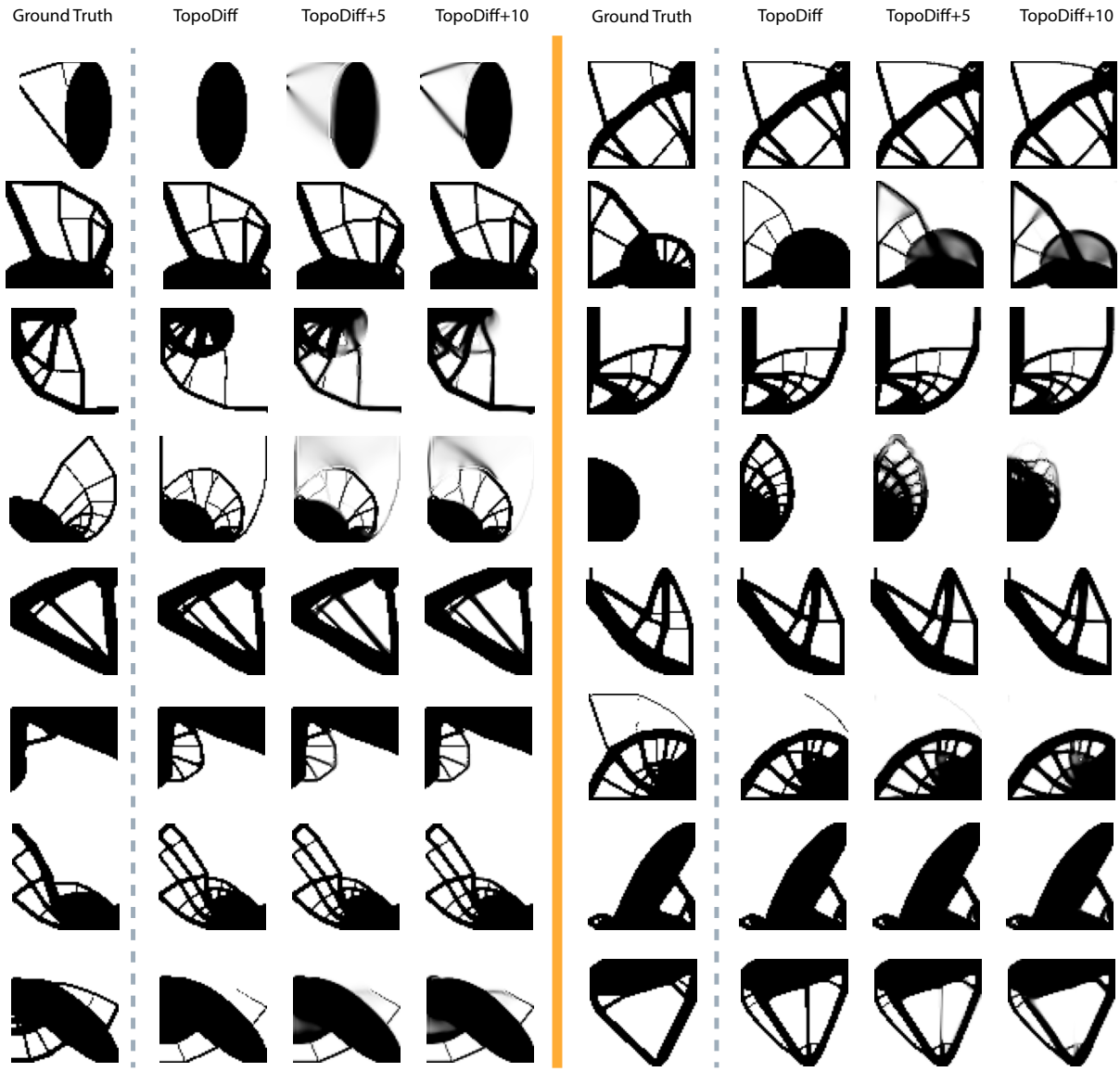

Figure 10: Visualization of the effect of direct optimization on samples generated by TopoDiff. The first column of each set of images shows the ground truth, the next column shows the samples generated by TopoDiff, and the two columns that follow show the effects of 5 and 10 steps of direct optimization on the samples respectively. These samples are from the 64x64 test set.

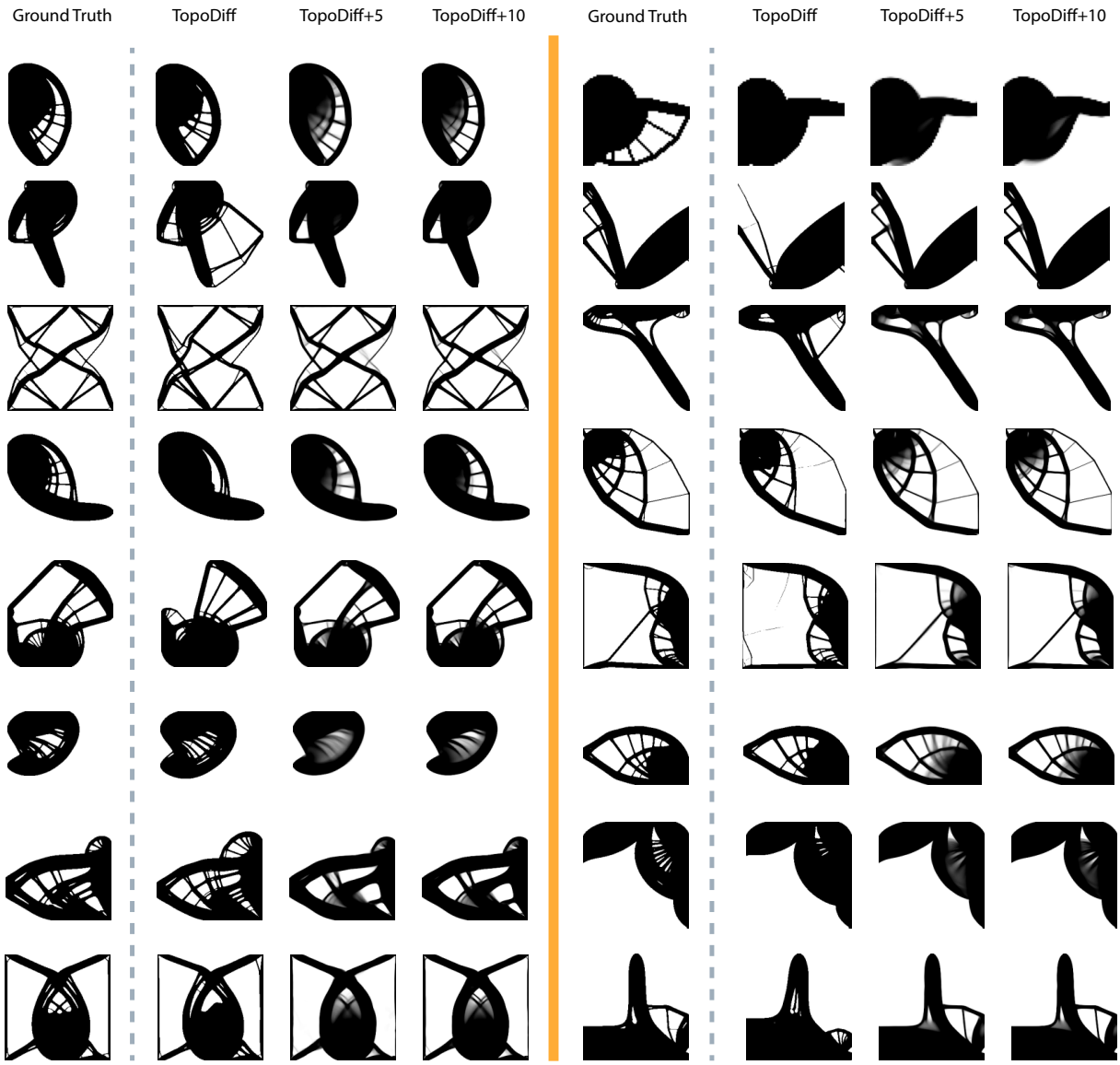

Figure 11: Visualization of the effect of direct optimization on samples generated by TopoDiff. The first column of each set of images shows the ground truth, the next column shows the samples generated by TopoDiff, and the two columns that follow show the effects of 5 and 10 steps of direct optimization on the samples respectively. These samples are from the 256x256 test set.

B.2 Generated Samples Visualizations

In this section, we provide visualizations of samples predicted by different configurations of our model on different problems.

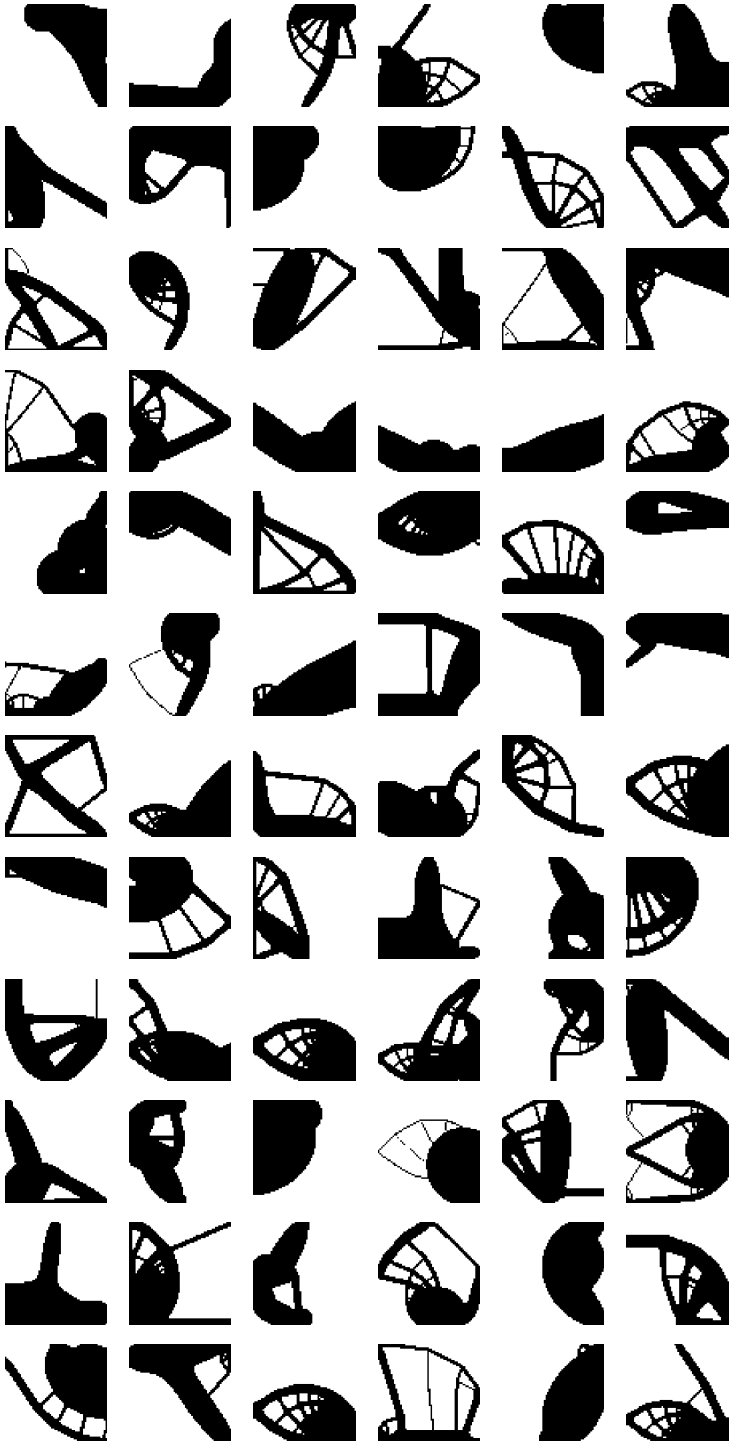

Figure 12: Ground truth images from the 64x64 SIMP datasets. Images that follow visualize NITO generated samples for the same problems.

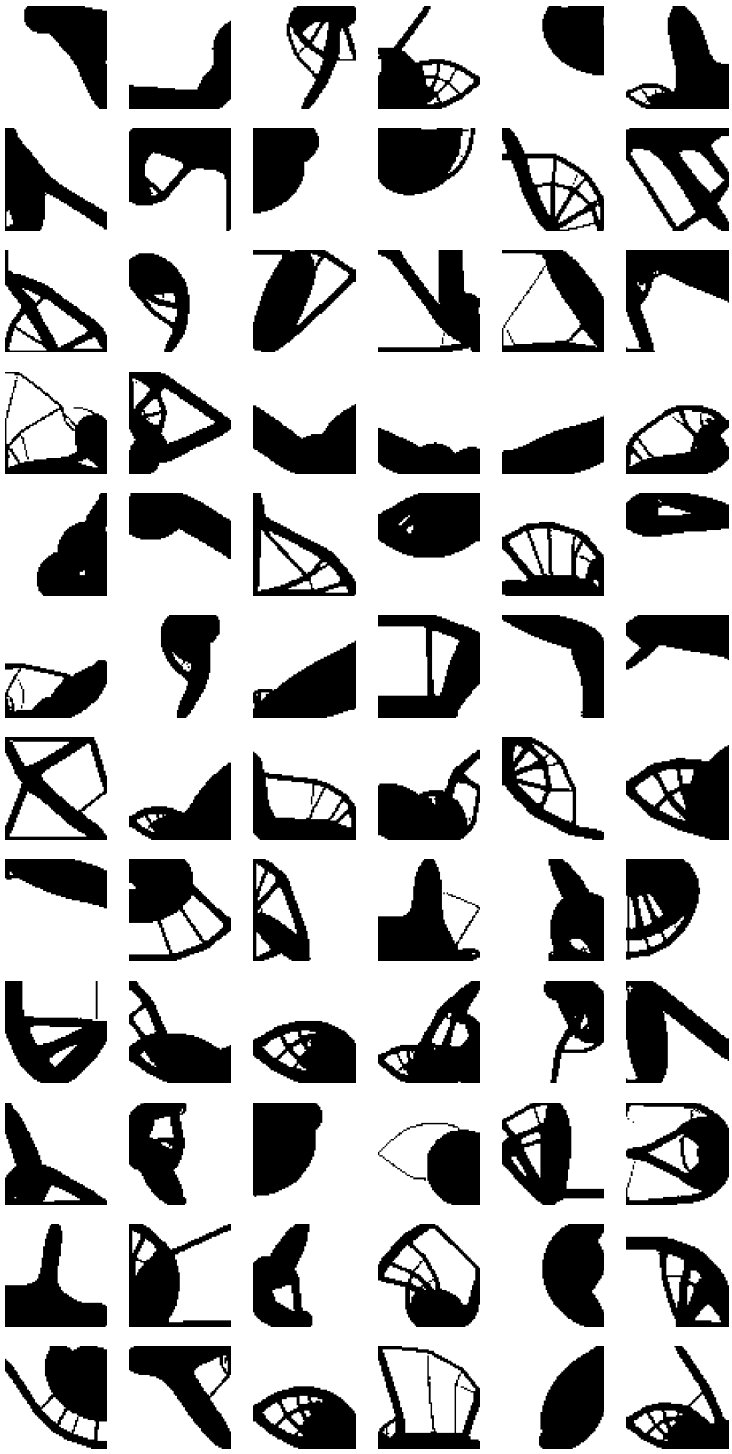

Figure 13: NITO generated topologies using a model trained on 64x64. Tested on the 64x64 data.

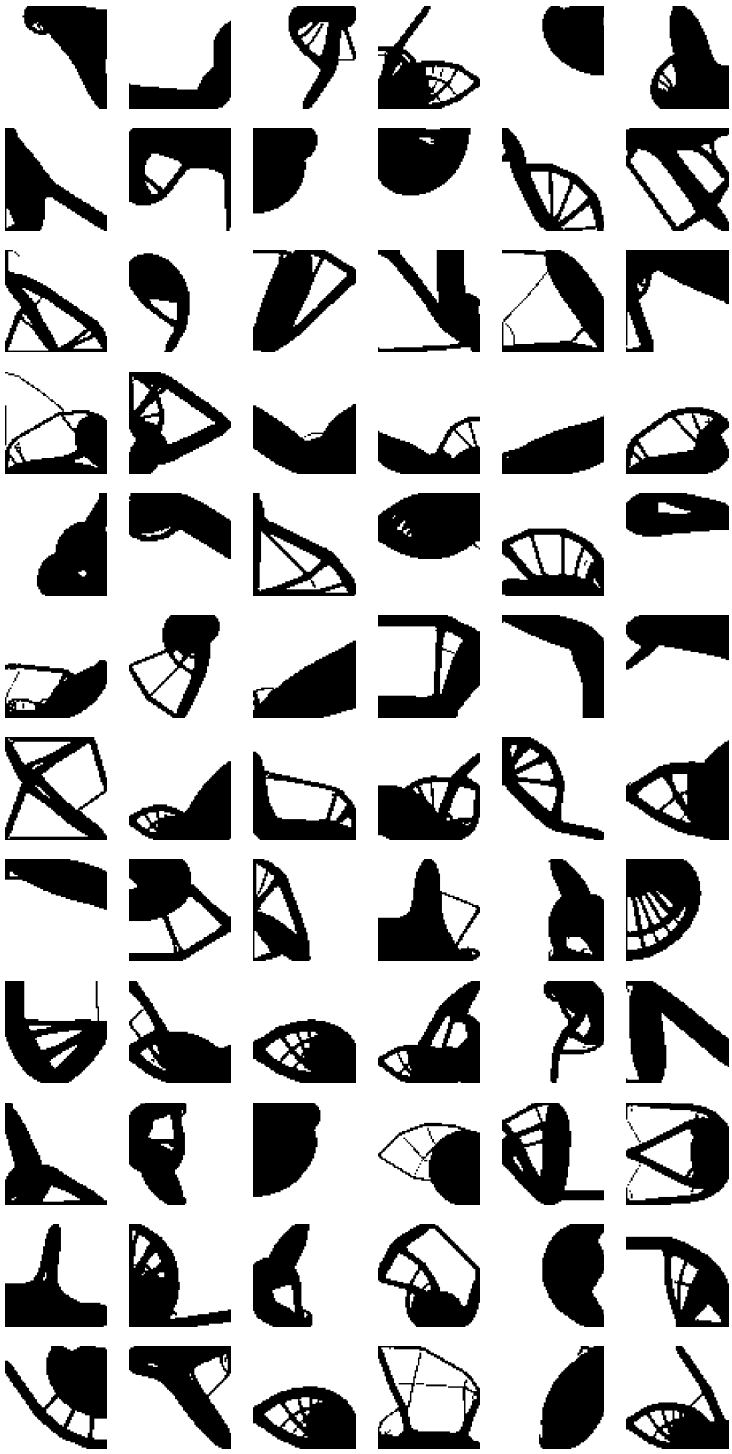

Figure 14: NITO generated topologies using a model trained on 256x256. Tested on the 64x64 data.

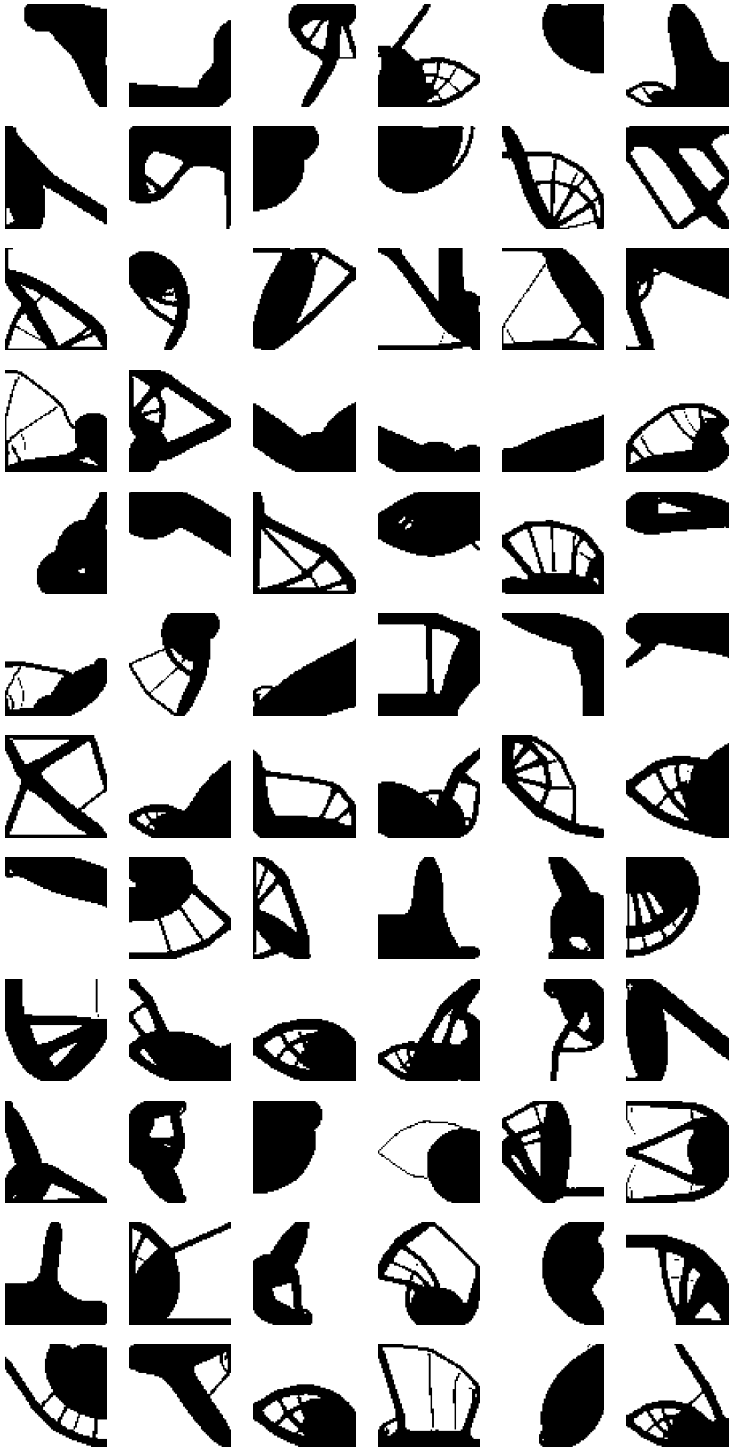

Figure 15: NITO generated topologies using a model trained on both 64x64 and 256x256. Tested on the 64x64 data.

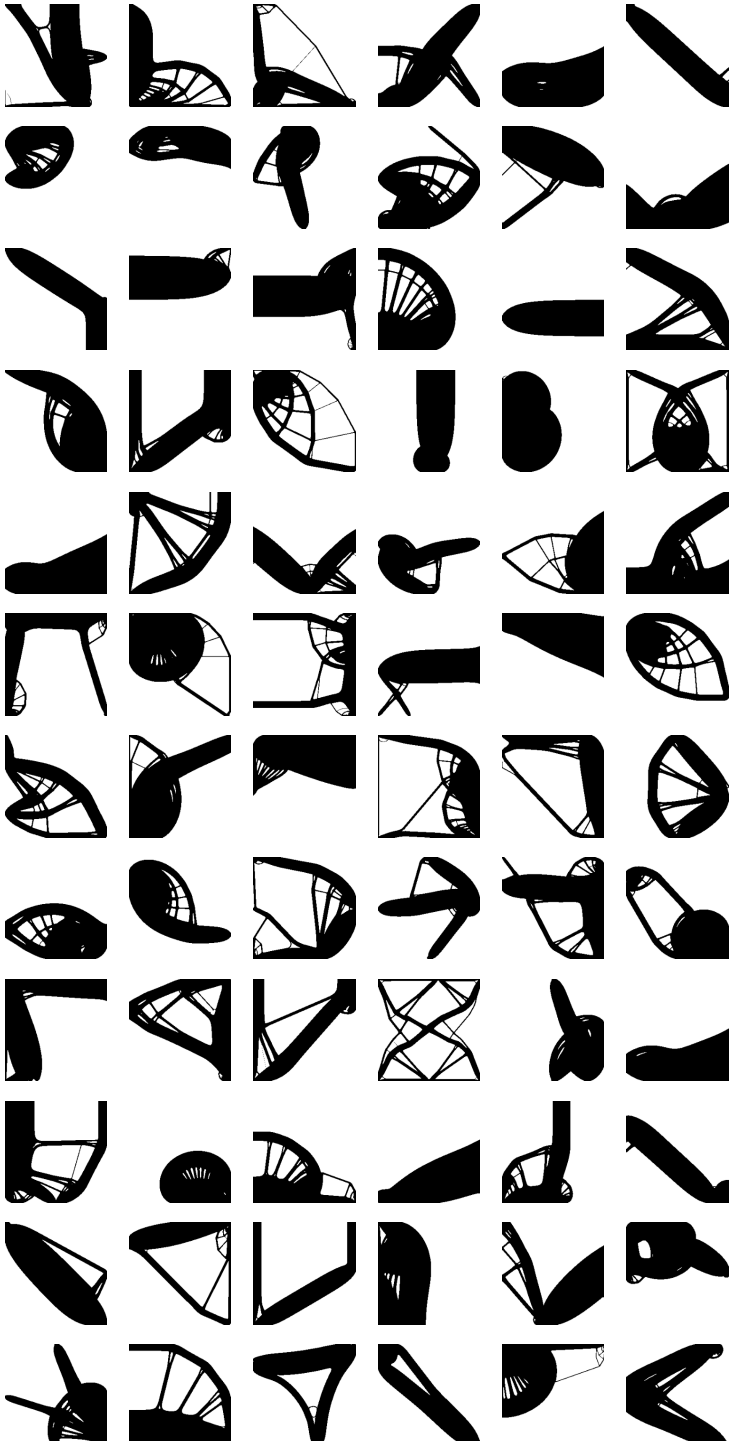

Figure 16: Ground truth images from the 256x256 SIMP datasets. Images that follow visualize NITO generated samples for the same problems.

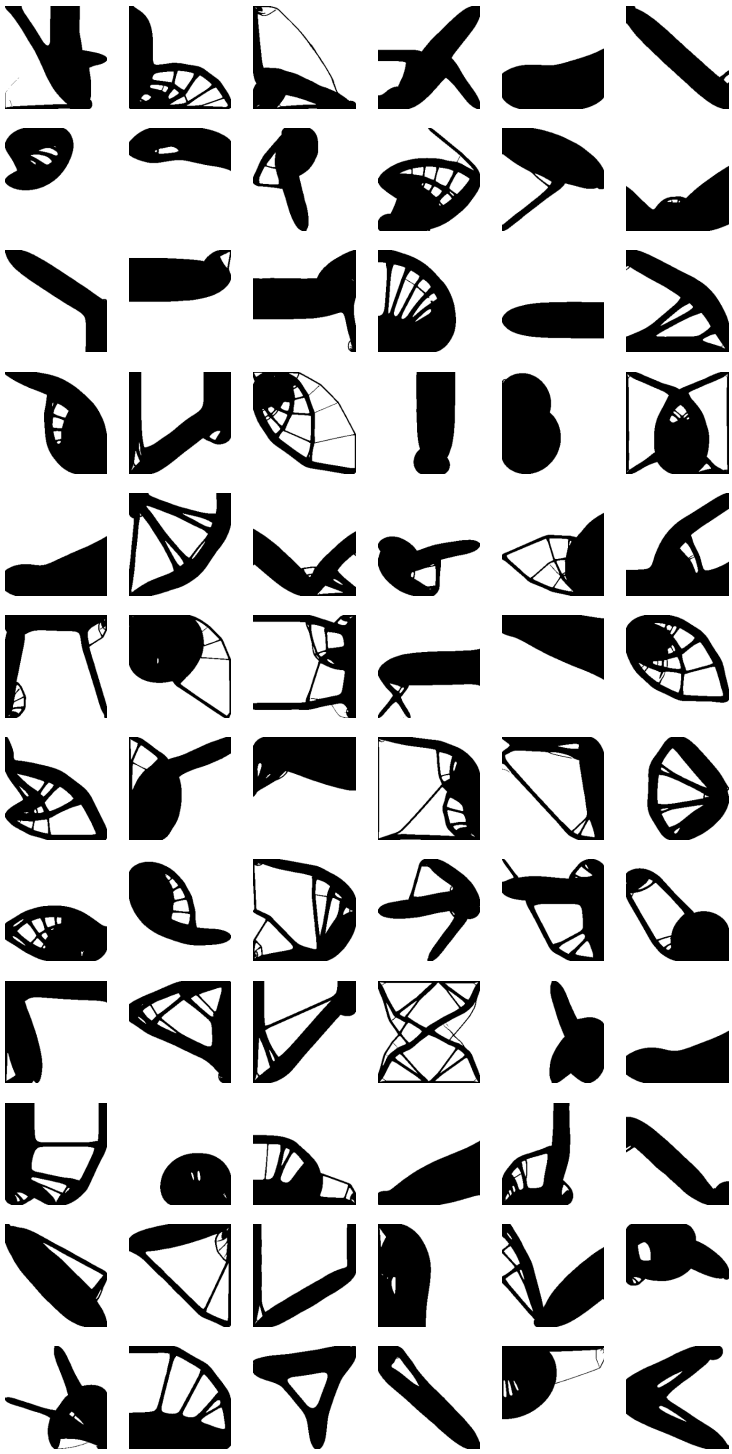

Figure 17: NITO generated topologies using a model trained on 256x256. Tested on the 256x256 data.

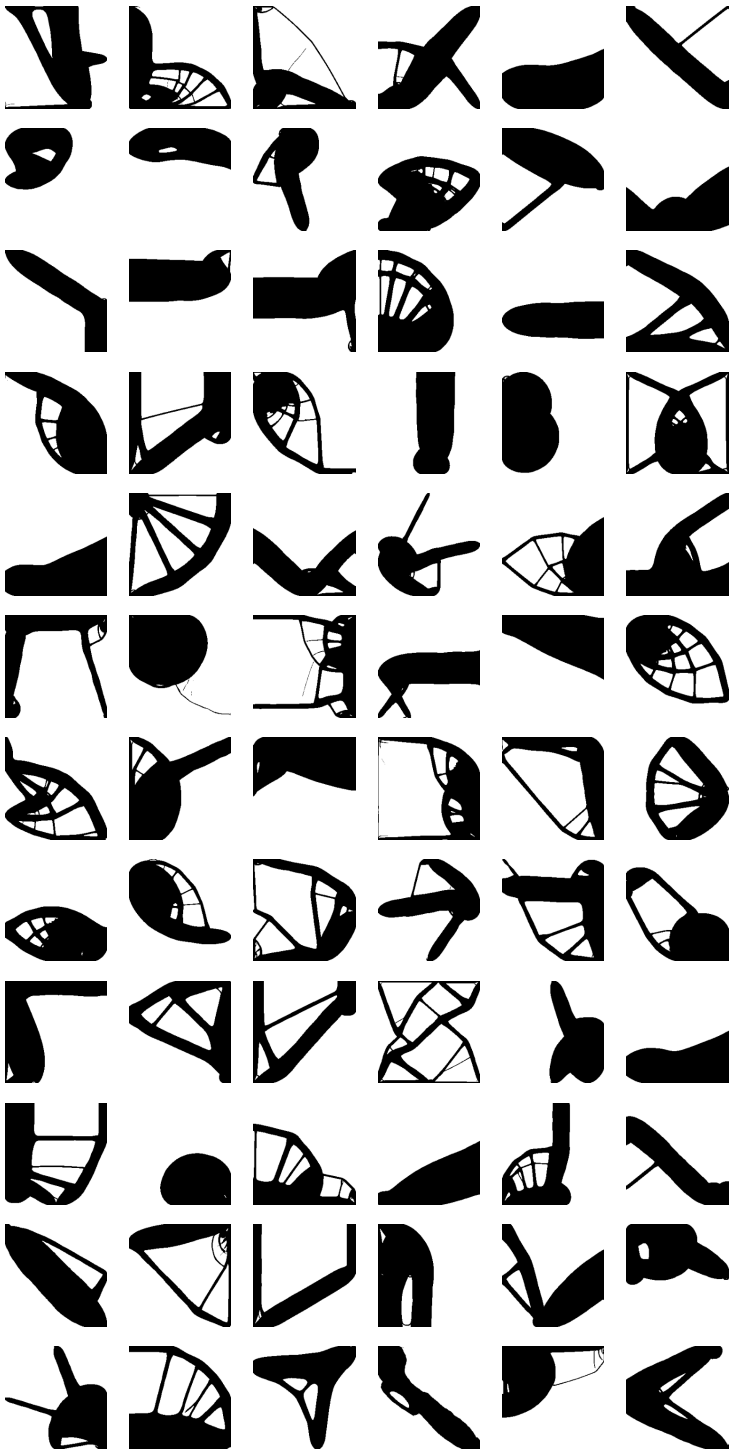

Figure 18: NITO generated topologies using a model trained on 64x64. Tested on the 256x256 data.

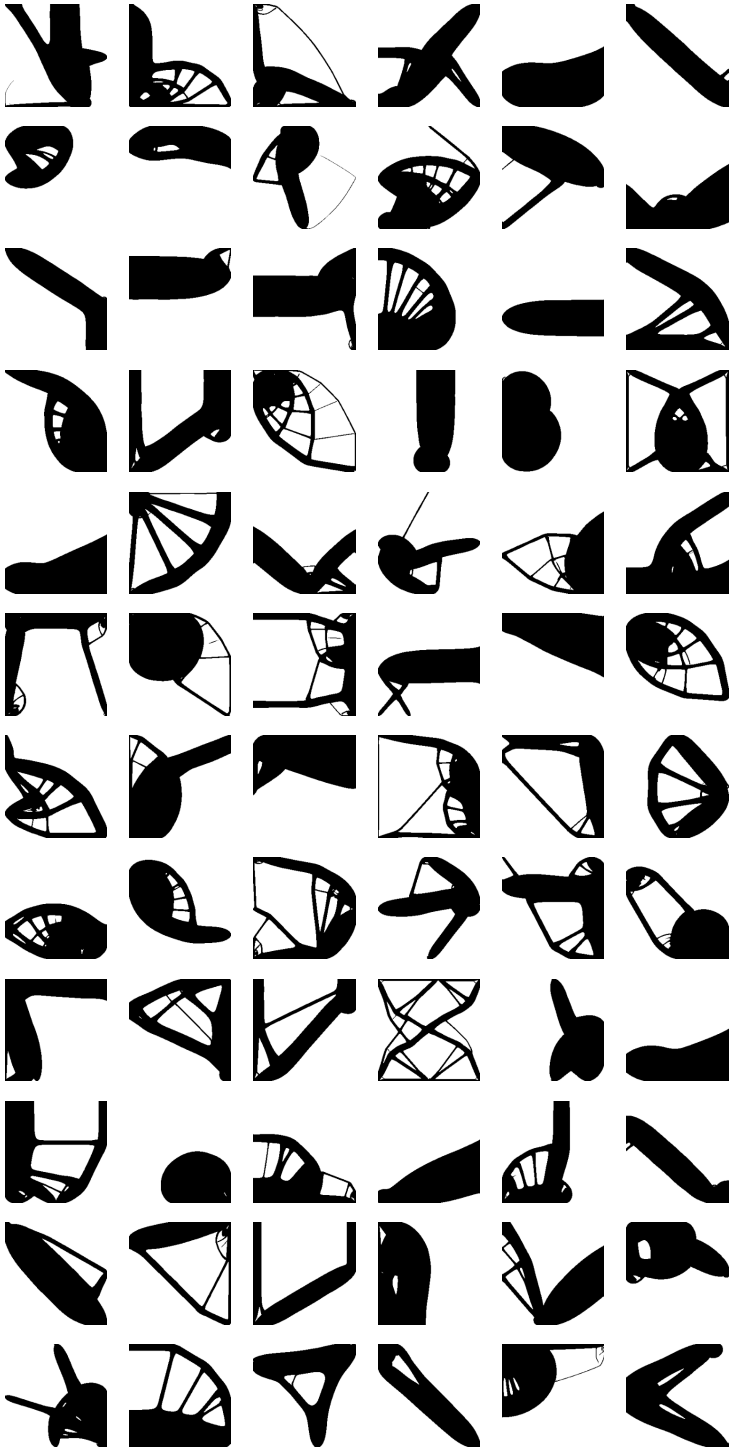

Figure 19: NITO generated topologies using a model trained on both 64x64 and 256x256. Tested on the 256x256 data.

C Dataset & Optimizer Details

Our experiments use a dataset of SIMP-optimized topologies in a unit square domain with a size of 64x64 and 256x256 and rectangular domains with different aspect rations including 64x48, 64x32, and 64x16. For each topology in the dataset information about the loading condition, boundary condition, and volume fraction, are included. Furthermore, we include the stress and strain energy fields. Our dataset is similar to the one proposed by Mazé & Ahmed (2023), however, we noted that the dataset used in prior works has been generated using an older version of SIMP, namely ToPy (Hunter et al., 2017).

This solver, although a robust implementation of SIMP, does not implement the latest improvements to the SIMP algorithm and uses a slower solver, which causes two issues. Firstly, the topologies that are used in the dataset proposed by Mazé & Ahmed (2023) are lower-performing topologies in comparison to what the latest solvers produce, hence possibly overestimating the performance of these models in some cases. Secondly, the SIMP method itself that prior studies compared their inference time with did not use the fastest solvers, making those comparisons also somewhat inaccurate. To ensure that this is not the case in our studies we implement the SIMP optimizer from scratch in Python (The code for which will be publicly available), which performs the optimization using the latest and fastest implementation of the SIMP algorithm as far as the authors are aware (Wang et al., 2021a).

As such we re-create the 64x64 dataset proposed by Mazé & Ahmed (2023) using our solvers and find that the resulting topologies using our method are significantly better performing in comparison to the prior datasets used by many other works of research (Giannone et al., 2023; Giannone & Ahmed, 2023; Mazé & Ahmed, 2023; Nie et al., 2021b). Given this, it is safe to assume that the performance of the models in prior studies that compare to the inferior dataset may have been overestimated while also training models on lower-performance samoples. However, to allow for a fair comparison we retrain the best-performing model in the literature TopoDiff (Mazé & Ahmed, 2023) on our new dataset and rerun their experiments on this new dataset. However, we report the performance of other models as the original authors measured them overestimated or otherwise.

The 64x64 dataset includes 48,000 training samples and 1,000 test samples which we use for testing our models. The 256x256 dataset includes 60,000 training samples and 1,800 samples for testing and the other three domains have 29,000 samples each with 1,000 test samples each. The figures that follow visualize some of the training samples for each dataset. In the following figures, we include figures showing samples from all datasets.

Figure 20: Random samples from the 64x64 dataset. Green arrows show the locations and directions of the loads applied in each problem. Blue triangles indicate points that are constrained in x and red triangles indicate points that are constrained in y.

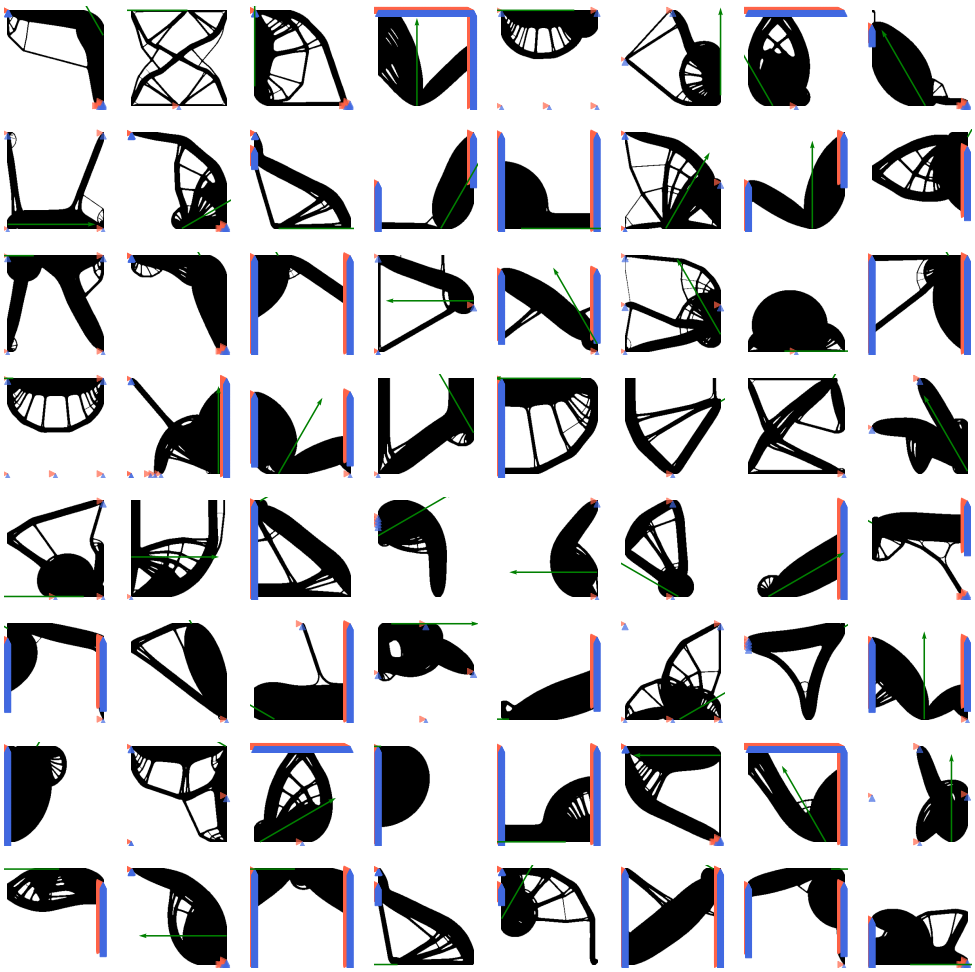

Figure 21: Random samples from the 256x256 dataset. Green arrows show the locations and directions of the loads applied in each problem. Blue triangles indicate points that are constrained in x and red triangles indicate points that are constrained in y.

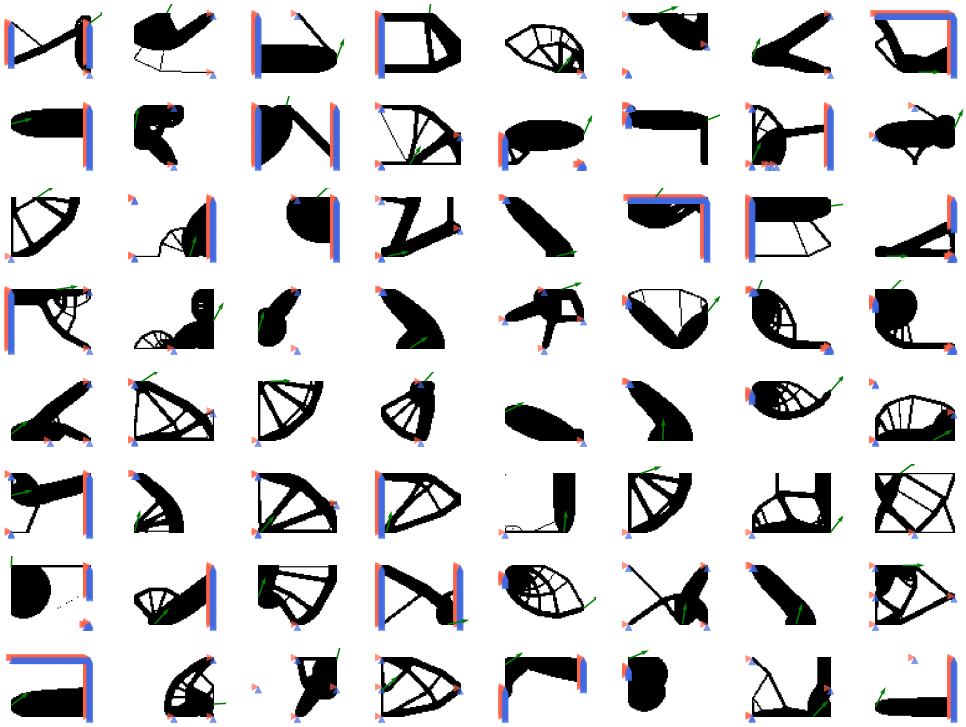

Figure 22: Random samples from the 64x48 dataset. Green arrows show the locations and directions of the loads applied in each problem. Blue triangles indicate points that are constrained in x and red triangles indicate points that are constrained in y.

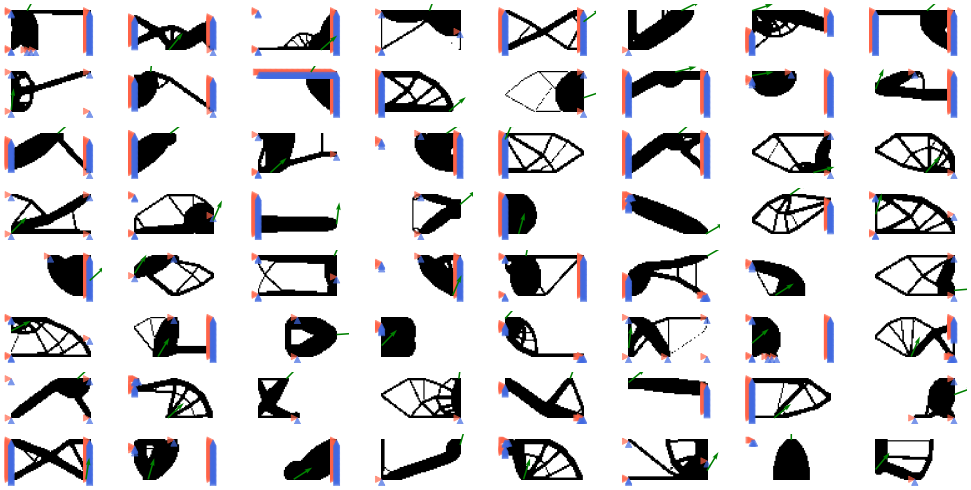

Figure 23: Random samples from the 64x32 dataset. Green arrows show the locations and directions of the loads applied in each problem. Blue triangles indicate points that are constrained in x and red triangles indicate points that are constrained in y.

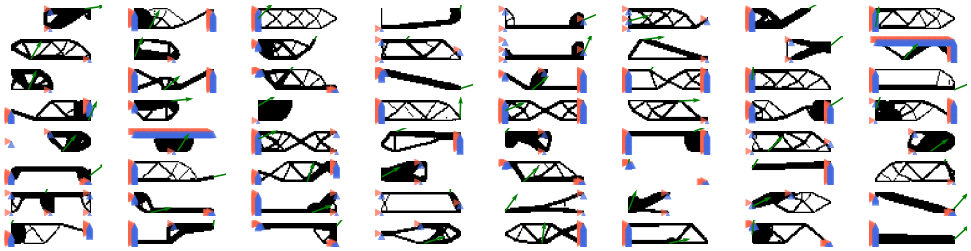

Figure 24: Random samples from the 64x16 dataset. Green arrows show the locations and directions of the loads applied in each problem. Blue triangles indicate points that are constrained in x and red triangles indicate points that are constrained in y.