Diffusion Models Beat GANs on Topology Optimization

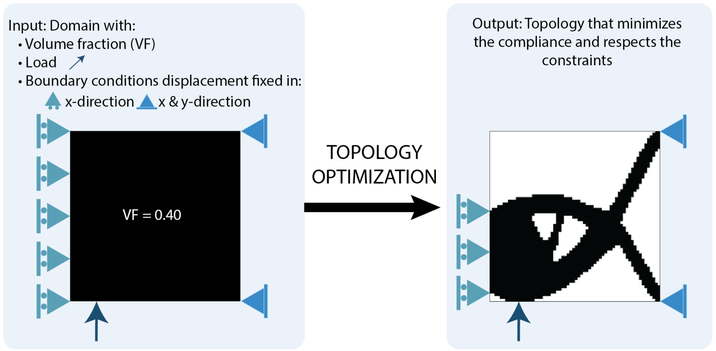
François Mazé[1], Faez Ahmed[1]
[1]Massachusetts Institute of Technology

DESIGN COMPUTATION & DIGITAL ENGINEERING LAB

Motivation

Topology Optimization (TO)

- Objective: **find the optimal physical structure under a set of constraints**



- **Key problem** in many engineering domains (aerospace, mechanical engineering…)
- Included in most design software (Autodesk, Solidworks…)

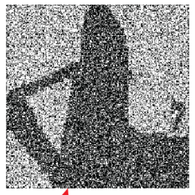
Problem & Questions

- **GANs: promising approach** to improve traditional TO methods (speed and local optima convergence)
- GANs face several issues:
  - Difficult to train
  - Limited generalization
  - Neglect physical objectives
- Hypothesis: Performance and manufacturability explicit guidance is needed
- **Question: Can diffusion models outperform GANs for TO?**

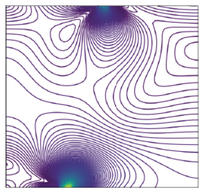
Example of unmanufacturable design generated by a GAN

Topology Optimization Dataset

- Main dataset: **33000 optimal topologies** for diverse combinations of input conditions
- Every data point contains:
  - Optimal topology
  - Physical fields
  - Raw constraints



x_t, l, v



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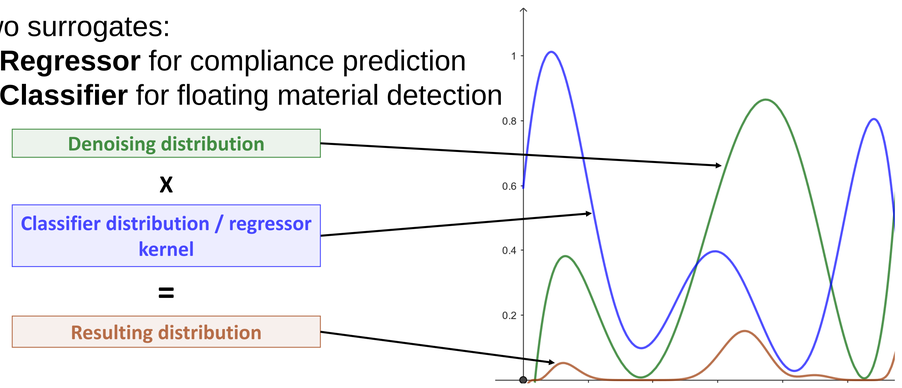
TopoDiff: A conditional guided diffusion model

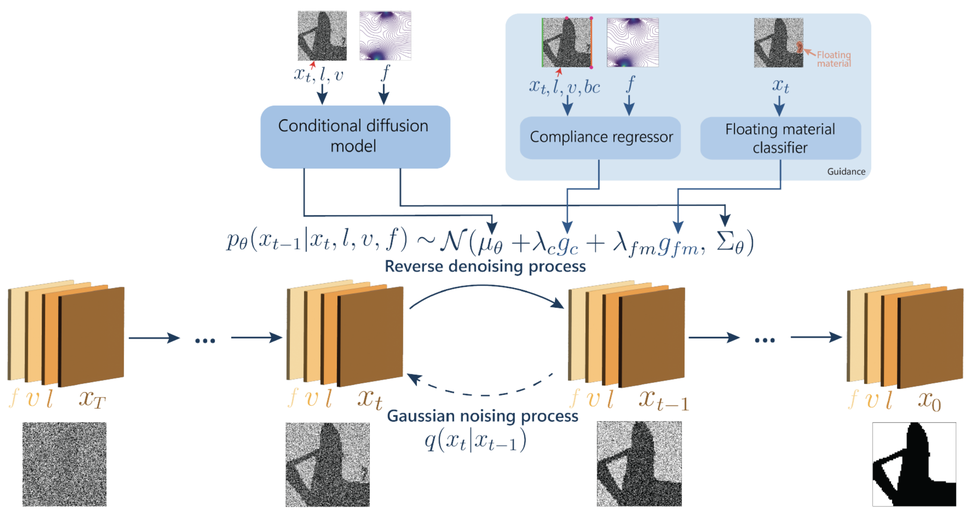
Conditional Diffusion Model

- Main architecture: **conditional diffusion model** with constraints passed as extra channels of the noisy input
- Denoising process: $p_\theta(x_{t-1}|x_t, l, v, f) \sim \mathcal{N}(\mu_\theta, \Sigma_\theta)$

Explicit Guidance Strategy

- Two surrogates:
  - **Regressor** for compliance prediction
  - **Classifier** for floating material detection





Results

- **Two-level test dataset**
- Level 1: **in-distribution** boundary conditions
- Level 2: **out-of-distribution** boundary conditions

TopoDiff outperforms state-of-art cGAN

	Level 1 test data		*Level 2* test data	
Model	TopologyGAN	Guided TopoDiff	TopologyGAN	Guided TopoDiff
Average CE (%)	48.51 +/- 16.38	**4.39** +/- 0.94	143.08 +/- 38.50	**18.40** +/- 5.88
Median CE (%)	2.06	**0.83**	6.82	**1.82**
Prop. of CE>30% (%)	10.11	**2.56**	24.10	**8.10**
Average VFE (%)	11.87 +/- 0.52	**1.85** +/- 0.03	14.31 +/- 0.75	**1.80 +/- 0.04**
Proportion of LV (%)	**0.00**	**0.00**	**0.00**	**0.00**
Proportion of FM (%)	46.78	**5.54**	67.90	**6.21**

- On out-of-distribution boundary conditions:

Compliance error: 7x reduction

Volume error: 8x reduction

Floating material: 11x reduction

Future Directions

- Reduce sampling time for diffusion models
- Remove dependency on mesh size
- Extend to 3D topology optimization

Conclusion

- **Diffusion models can also outperform GANs in engineering design applications**
- General diffusion-model-based framework to solve other physical optimization problems.

Paper, code, datasets…

decode.mit.edu/project/topodiff/