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第5回 スーパーコンピュータ「不老」
2024年10月2日（水）13:30～17:05＠名古屋大学情報基盤センター2F　演習室

超多ケース弾塑性シミュレーションによる3D生成AIの訓練と精度検証

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Acknowledgment

- **Supercomputer “Fugaku” research project (hp220249)**
  - ―Capacity computing of elasto-plastic dynamics of component structures for next-generation automobile design and its probabilistic deep generative models
  - ―2022/10/01 – present
  - ―Research representative: Koji Nishiguchi, Nagoya University
  - ―Participating institutions:

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TOYOTA
SUZUKI
FUJITSU
RIKEN
R-CCS
RIKEN Center for Computational Science
TOHOKU UNIVERSITY
Tokyo Tech
UNIVERSITY OF YAMANASHI

- **JSPS科研費24K14968により購入したスーパーコンピュータ「不老」の計算資源**

Outline

1. **Background and objective**
2. 3D dataset generation by supercomputer Fugaku
3. 3D generative AI incorporating structural dynamics
4. Performance verification of trained AI
5. Concluding remarks

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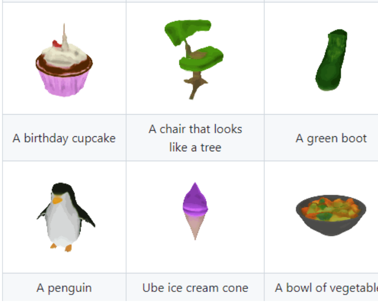
Recent studies of 3D generative AI

- From 2022 onwards, not only **2D generative AI** but also **3D generative AI** have been emerging one after another.
  - —The number of datasets for 3D shapes is much smaller than that for natural language and images.
  - —No dataset that can be applied to structural mechanics has been proposed.

Model name	Release date	Research group	3D representation	Model architecture	Data set	Number of 3D data
Shap-E	May 2023	OpenAI	Implicit function	Transformer-based diffusion model	ShapeNet（3D）, WebImageText（2D）	Several millions
Point-E	December 2022	OpenAI	3D point cloud	Transformer-based diffusion model	ShapeNet（3D）, WebImageText（2D）	Several millions
Magic3D	November 2022	NVIDIA	3D mesh	NeRF, diffusion model	COCO（2D）, ImageNet（2D）	None
DreamFusion	September 2022	Google, UCB	Implicit function	NeRF, diffusion model	COCO（2D）, ImageNet（2D）	None

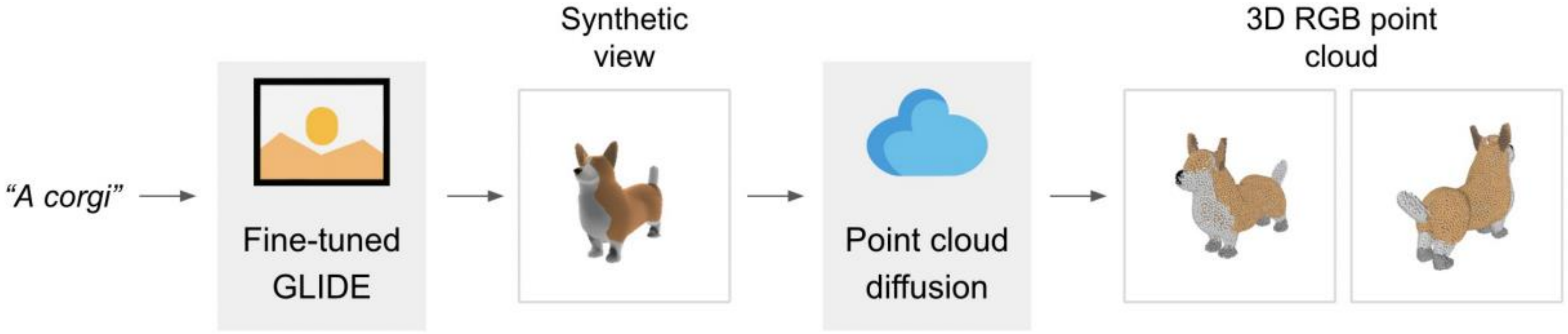


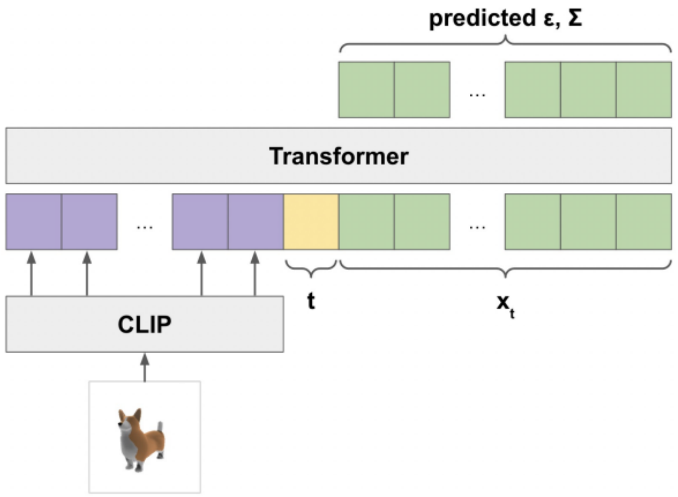
Shap-E

Magic3D

Lack of 3D datasets

- CLIP is used to compensate for the lack of 3D datasets.
  - —Point-E (OpenAI, December 2022)
    - ➢https://arxiv.org/pdf/2212.08751.pdf





Industrial impact of giga-casting

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https://thelastdriverlicenseholder.com/2022/04/20/tesla-revenue-grows-81-percent-in-q1-2022/

https://lowcarb.style/2022/08/23/tesla-gigapress-giga-texas/

Shock-absorbing structure (Tesla)

Giga-press (Tesla)

- In 2020: Tesla started using gigacasting for "Model Y“ of the rear body.
  —**30% weight reduction, 40% manufacturing cost reduction**
- In 2022: Chinese BEV companies (NIO and Xpeng) and Volvo has also decided to adopt it.
- In 2023: Toyota Motor Corporation has also decided to adopt it.
- **Difficult to find optimal structure for shock-absorbing**

Objective

Innovating vehicle structure with a giant aluminum die-casting

30% weight reduction
40% manufacturing cost reduction

Giga-press (Tesla)

3D generative AI (Parameter-to-3D model) for nonlinear structural design

Magic3D （NVIDIA, 2022）

Shap-E （OpenAI, 2023）

Rapid performance improvement of 3D generative AI

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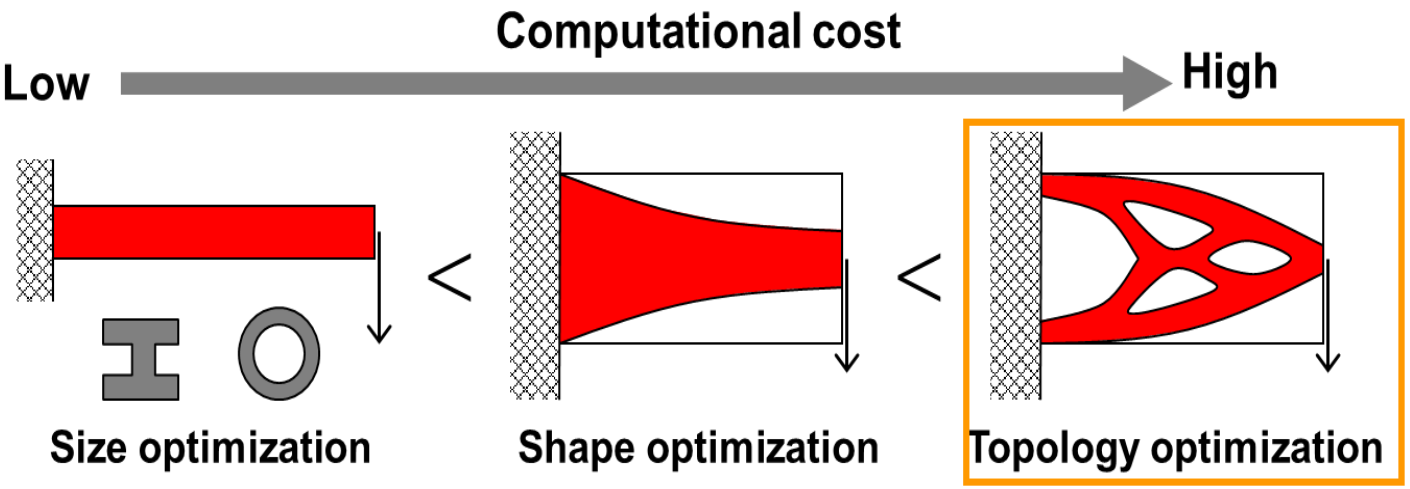
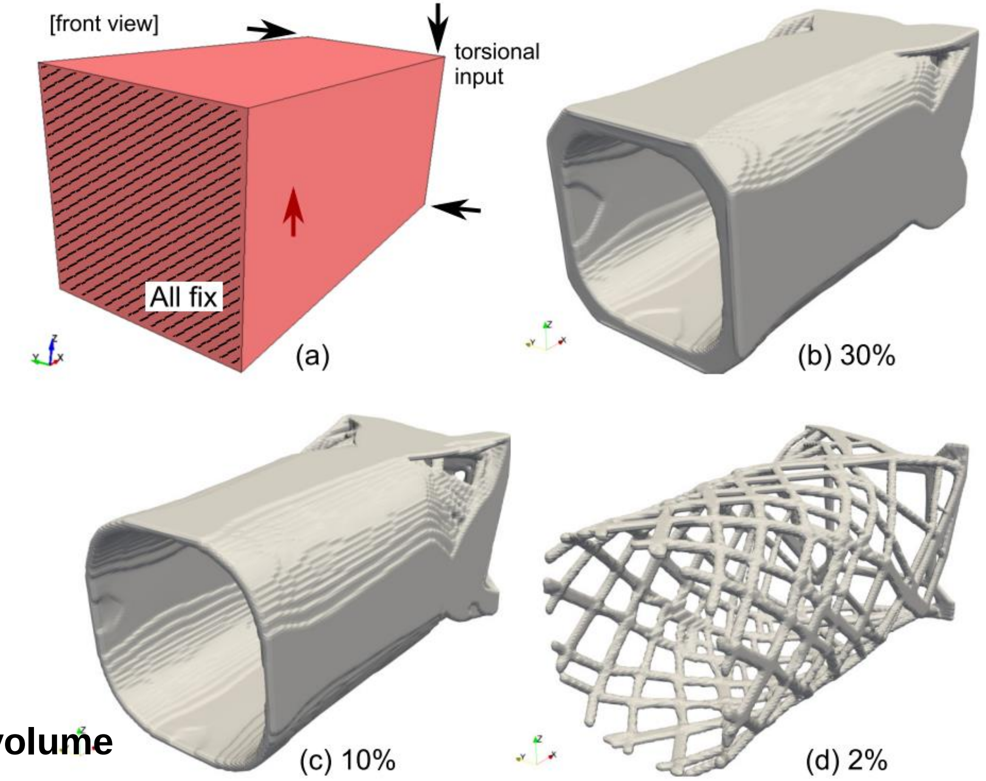
Structure for feasibility study: crash box

https://www3.nhk.or.jp/nhkworld/en/ondemand/video/2015315/

Many-case topology optimization

- Methods to find the best distribution of material for a given domain and boundary conditions
  - ➢Linear (static, small deformation) problems: established
  - ➢Nonlinear (crash) problems: not established yet

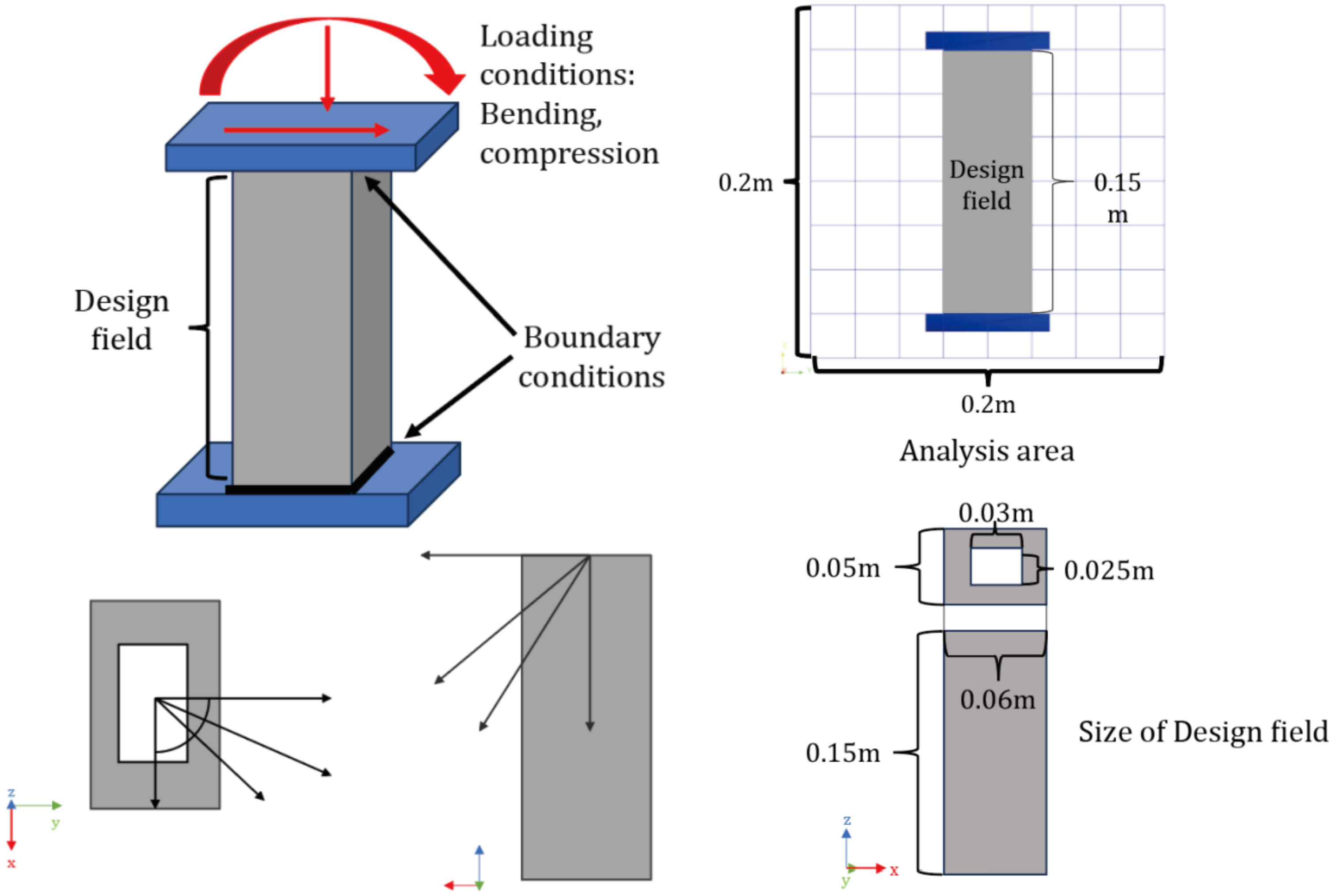




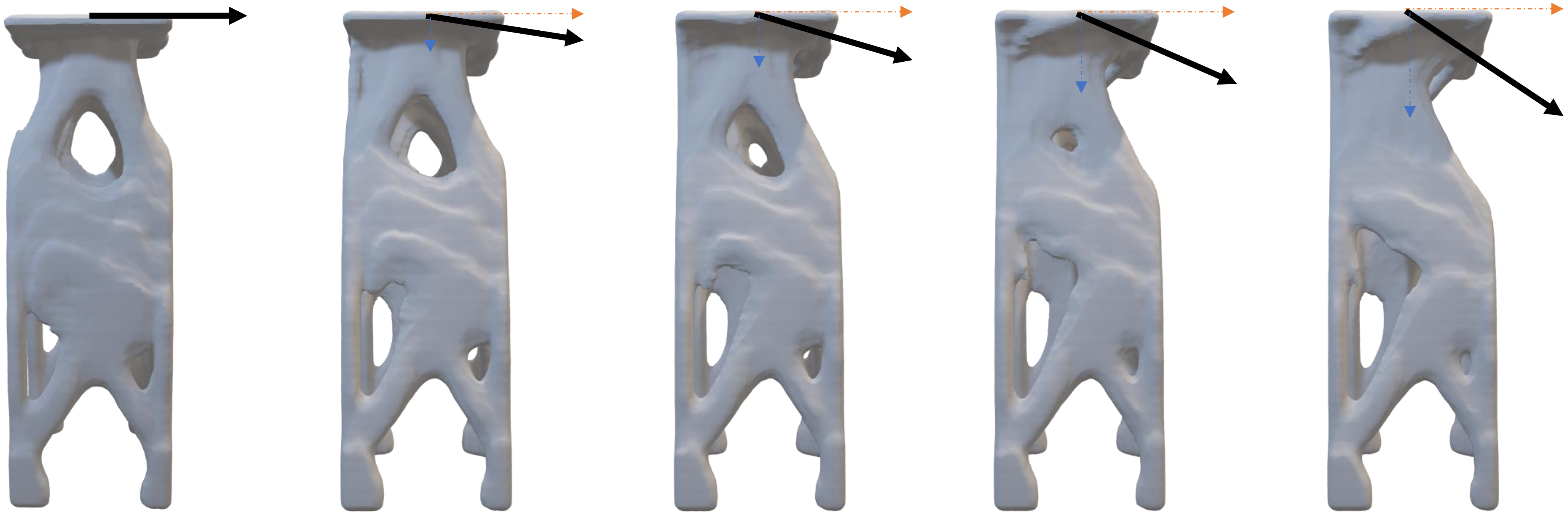
Different topologies can be obtained by changing volume constraints. (Yuji Wada, 2023)

Many-case topology optimization

- By changing the direction of loading, we generated **10114 cases** of structural topology.
  - —2,097,152 cell mesh
  - —16 nodes of Fugaku (64rank×8threads)
  - —30 min for each case



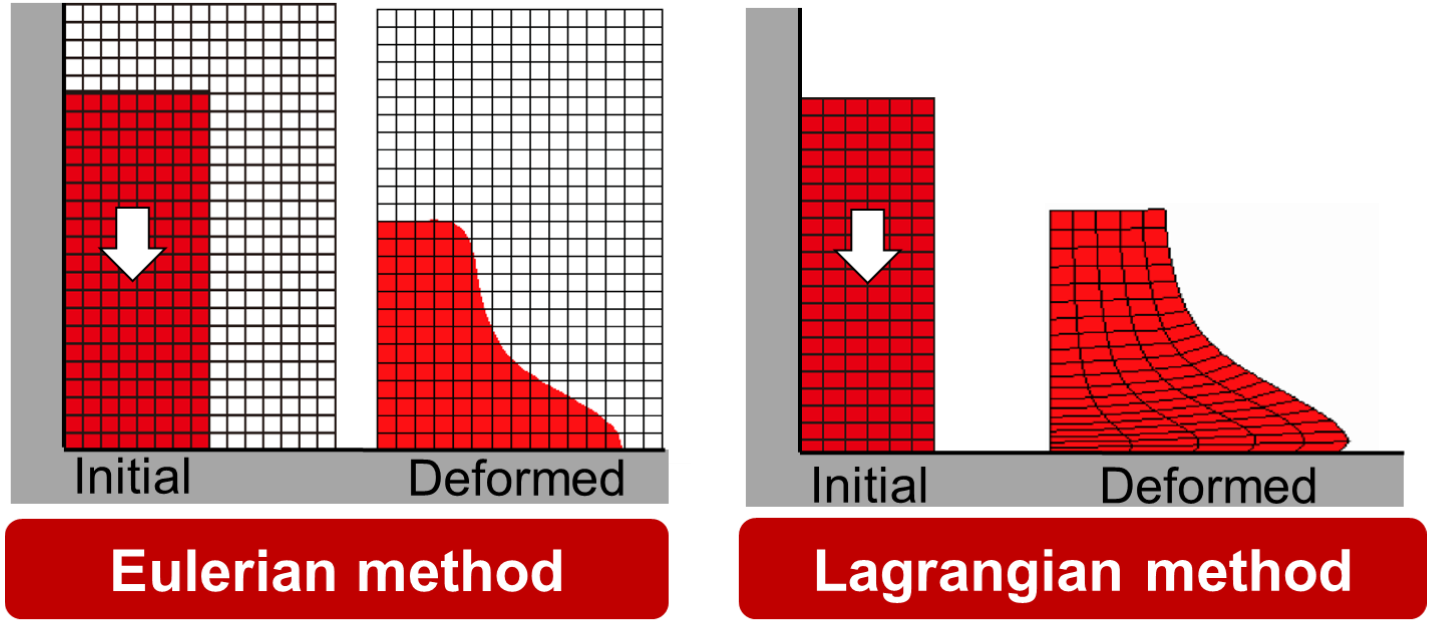
Many-case topology optimization



Many-case crash simulation

Eulerian finite volume method*

- Automatic and quick mesh generation
- Robust computation for large deformation
- **To get shock-absorbing energy (parameter)**



*K. Nishiguchi, et al. "Eulerian elastoplastic simulation of vehicle structures by building-cube method on supercomputer Fugaku." Proceedings of the International Conference on High Performance Computing in Asia-Pacific Region. 2024.

Many-case crash simulation

- By performing an elastoplastic crash simulation on **10114 cases**, we obtained the **shock-absorbing energy** of each case.

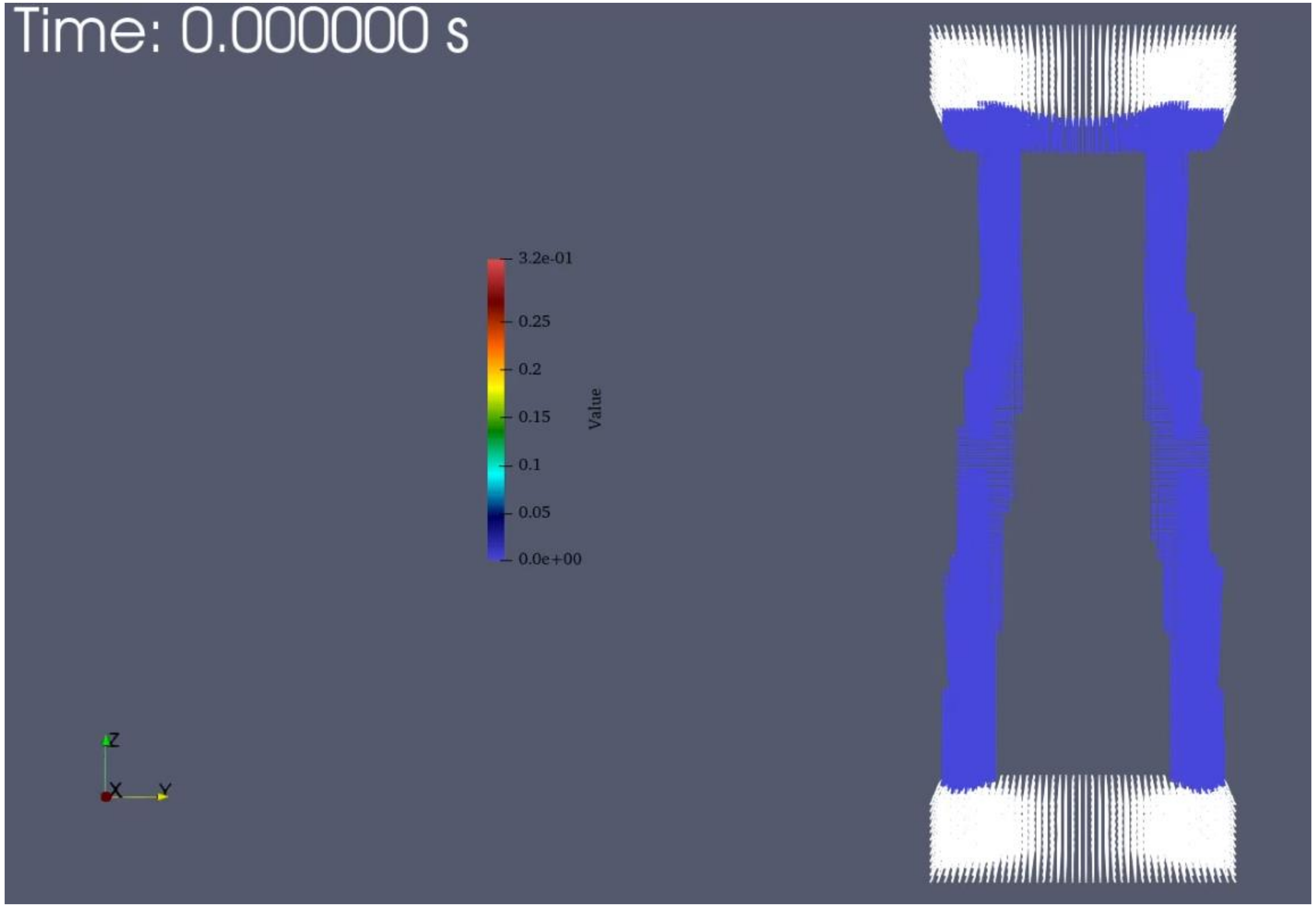
—4,194,304 cell mesh

—32 nodes of Fugaku

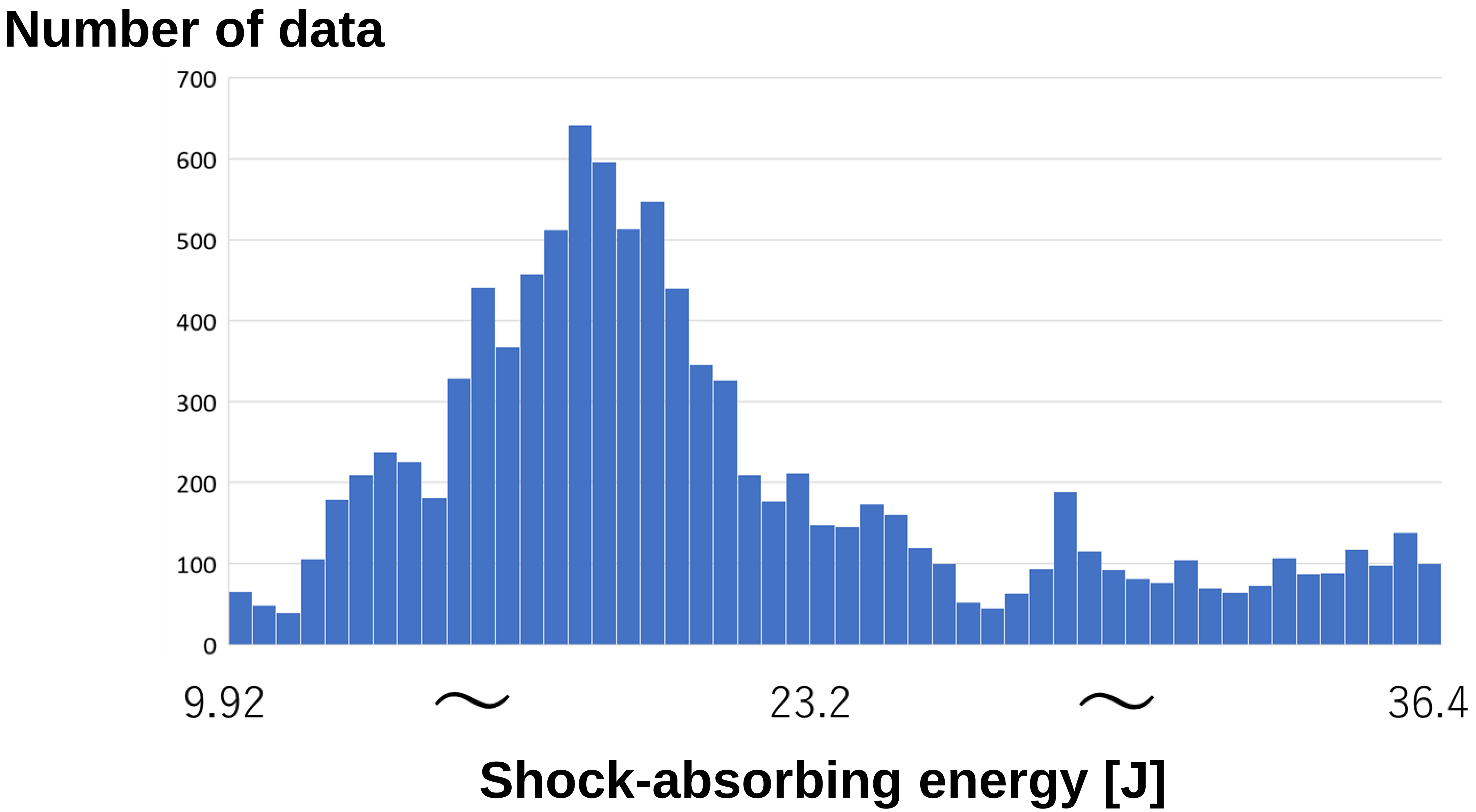
(128 rank × 8 threads,

1024 cores) for each

—2.5 hour for each case



Histogram of shock-absorbing energy



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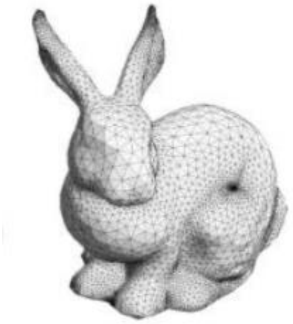
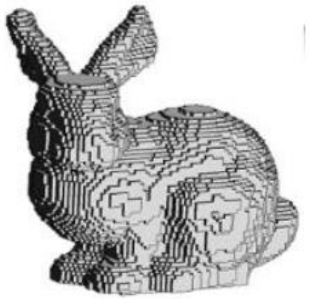
3Dデータ表現

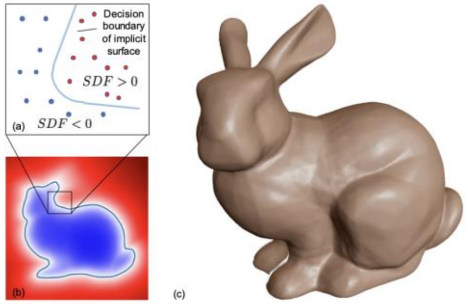
点群



メッシュ



ボクセル



Neural Field

	点群	メッシュ	ボクセル	Neural Field
メモリ	△	△	×	○
滑らかな表面	×	○	△	○
描画速度	○	△	○	△
3D表現の複雑さ	○	△	○	◎

https://cameronrwolfe.substack.com/p/3d-generative-modeling-with-deepsdf

Neural Fieldによる3Dデータ表現

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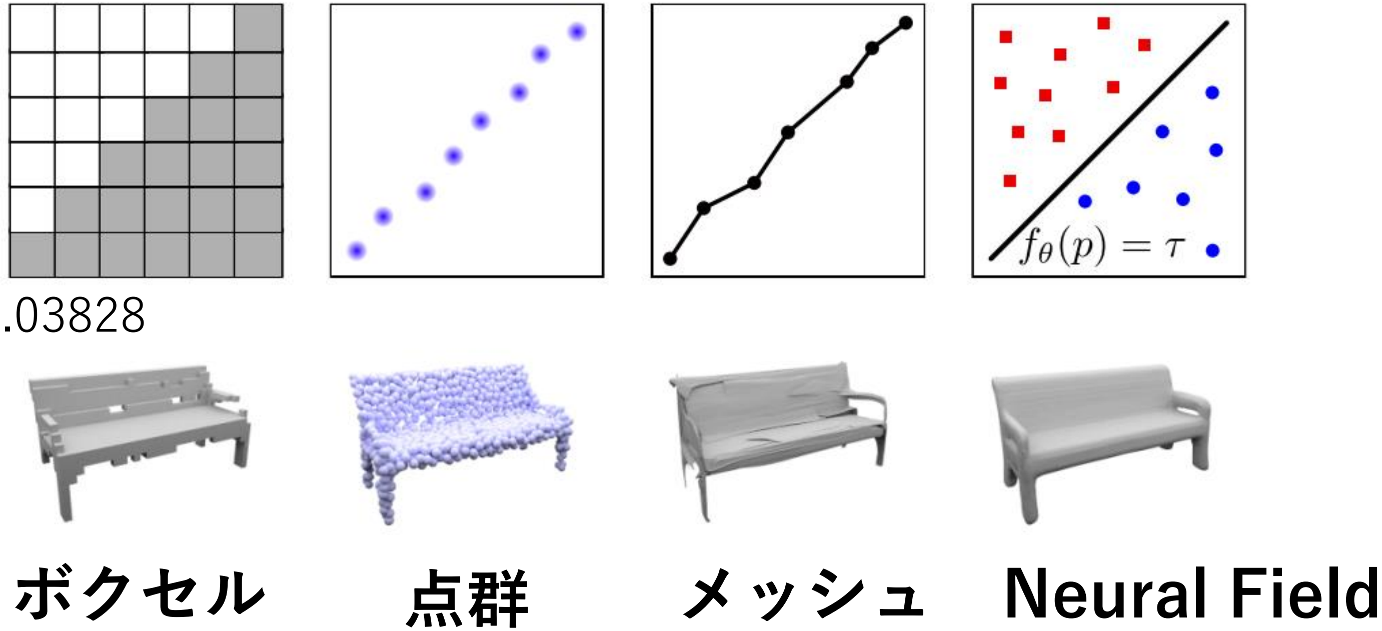
- 3D形状の陰関数をニューラルネットワークで近似するアプローチ
- メモリ消費量が少ない
- 3D表現の柔軟性
  —任意の解像度，トポロジーが表現できる
  —表現できる3D情報の精細さ ∝ NN の表現力 ≒ パラメータ数
- 深層学習で取り扱いやすい
  —3D形状を含めて，すべてニューラルネットワークで生成AIを構成できる



https://arxiv.org/pdf/1812.03828

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Neural Fieldによる3Dデータ表現

- 近年，コンピュータ・ビジョンやコンピューター グラフィックスの領域では主流の手法の一つになっている

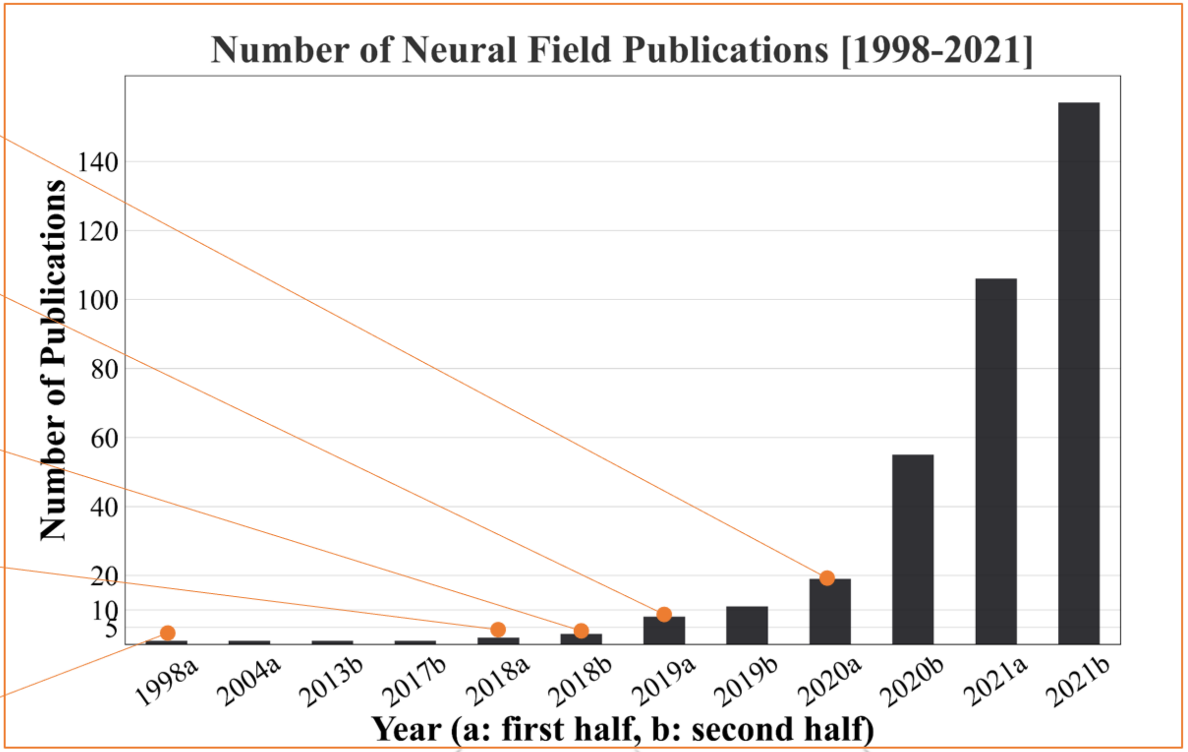
NeRF

DeepSDF
PIFu

Occupancy Networks, IM-NET

AtlasNet

Approximating Reflectance Functions using Neural Networks



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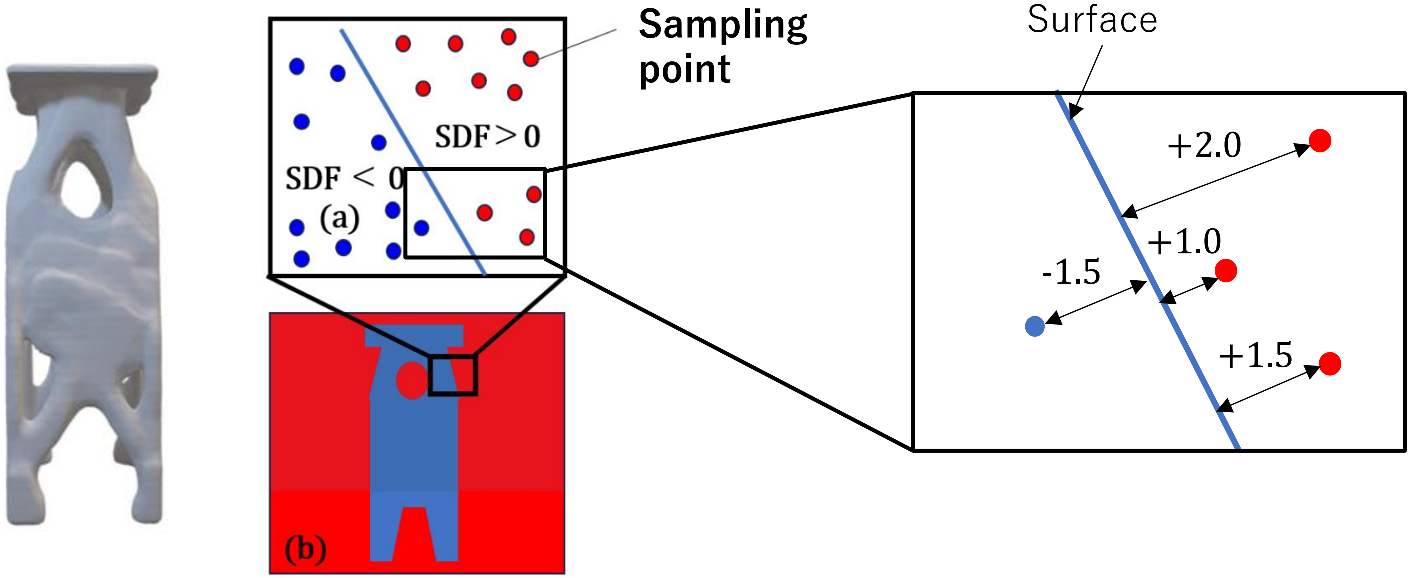
DeepSDF

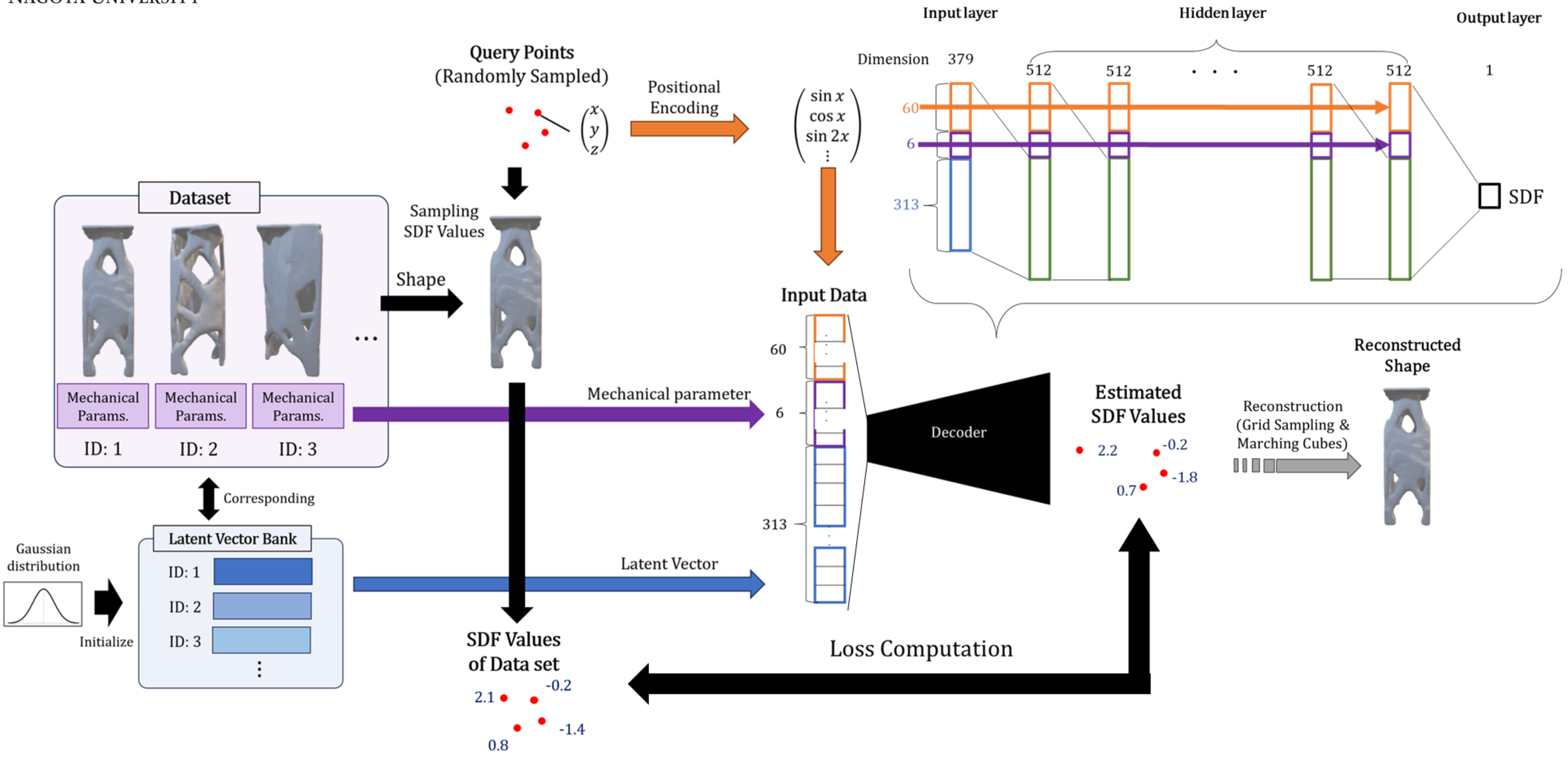
Jeong Joon Park, Peter Florence, Julian Straub, Richard Newcombe, Steven Lovegrove; Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2019, pp. 165-174

- Define the SDF value (shortest distance from the surface) at sample points in space.
- Represent a 3D shape as a vector using the coordinates of sample points and SDF values.



No.	SDF	Coordinates of sample point		
[1	+2.0	$x1$	$y1$	$z1$]
[2	+1.0	$x2$	$y2$	$z2$]
[3	+1.5	$x3$	$y3$	$z3$]
[4	+2.0	$x4$	$y4$	$z4$]

DeepSDF incorporating structural dynamics



Positional Encoding

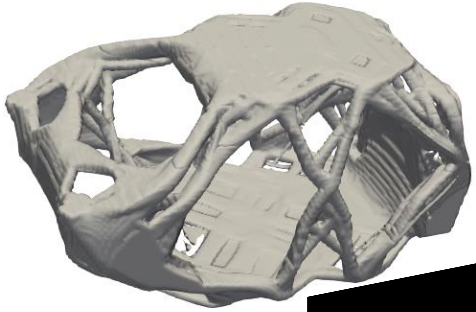
- We introduced **positional encoding** to improve the reconstruction accuracy for complex shapes.

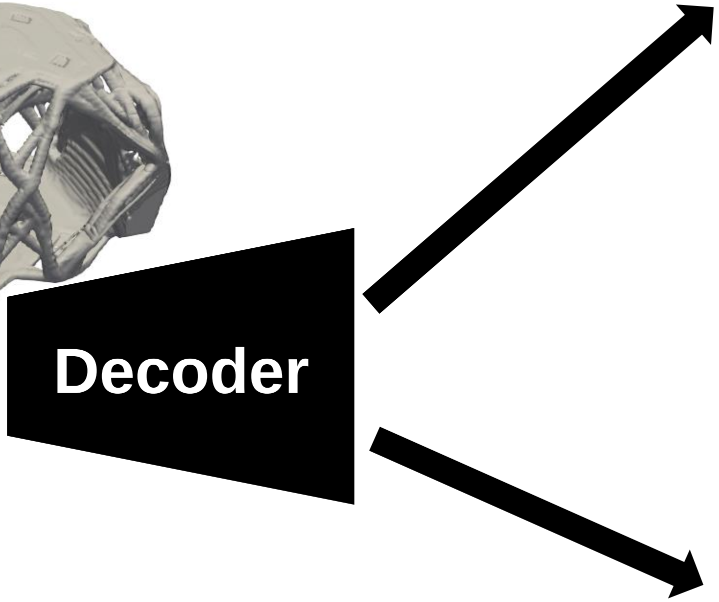
$$\phi(\boldsymbol{x}) = \begin{pmatrix} \sin(2^0 x) \\ \cos(2^0 x) \\ \vdots \\ \sin(2^9 x) \\ \cos(2^9 x) \\ \sin(2^0 y) \\ \cos(2^0 y) \\ \vdots \\ \sin(2^9 y) \\ \cos(2^9 y) \\ \sin(2^0 z) \\ \cos(2^0 z) \\ \vdots \\ \sin(2^9 z) \\ \cos(2^9 z) \end{pmatrix}$$

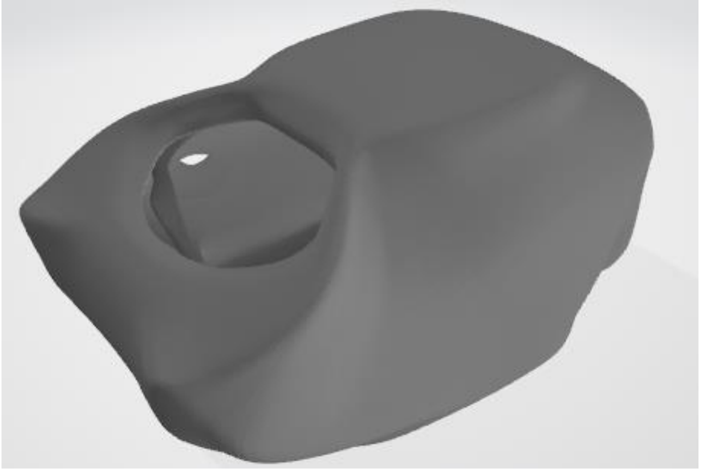
$$\phi : \mathbb{R}^3 \to \mathbb{R}^{60}$$

$$\boldsymbol{x} = (x, y, z)^T$$

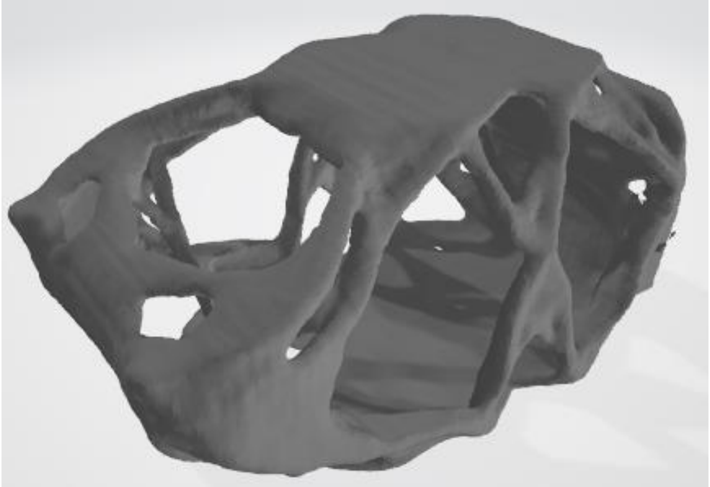
3D shapes for training







Original



With positional encoding

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Generalization performance for 3D shape

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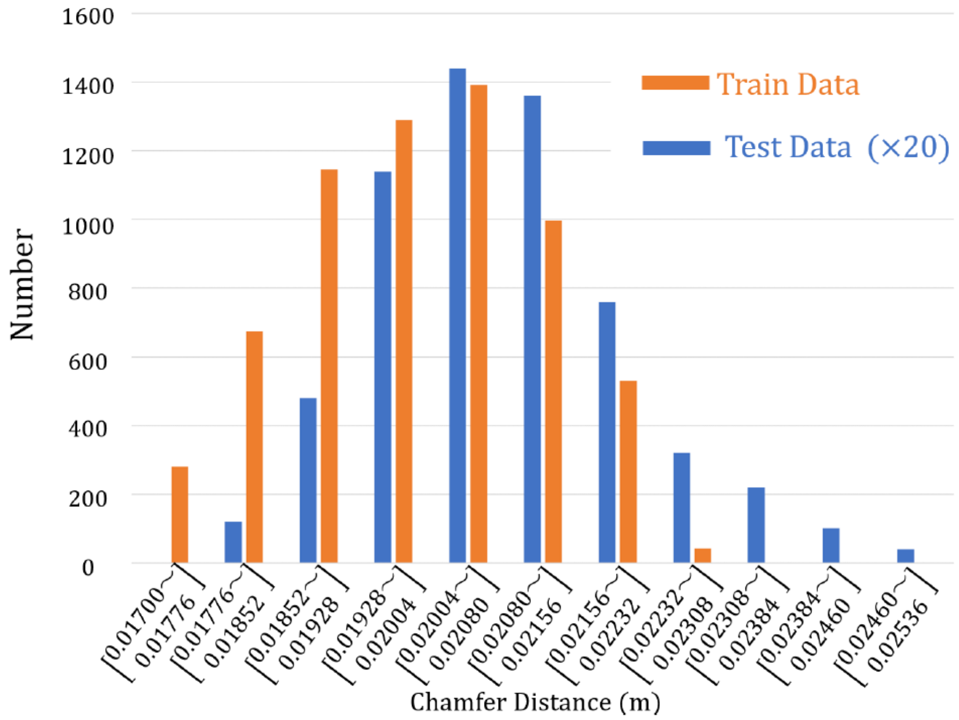
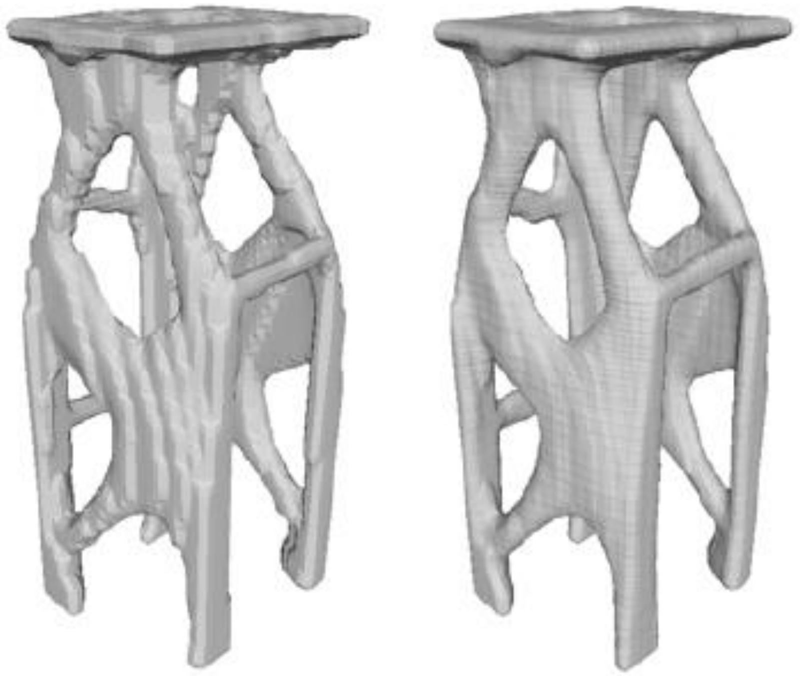
- How well 3D generative AI can produce data that is similar to the true data distribution, especially for unseen (test) shape.
- The trained generative AI demonstrates generalization performance for 3D shape generation.
  —The 3D generation error for the test data is almost the same as the 3D generation error for the training data.

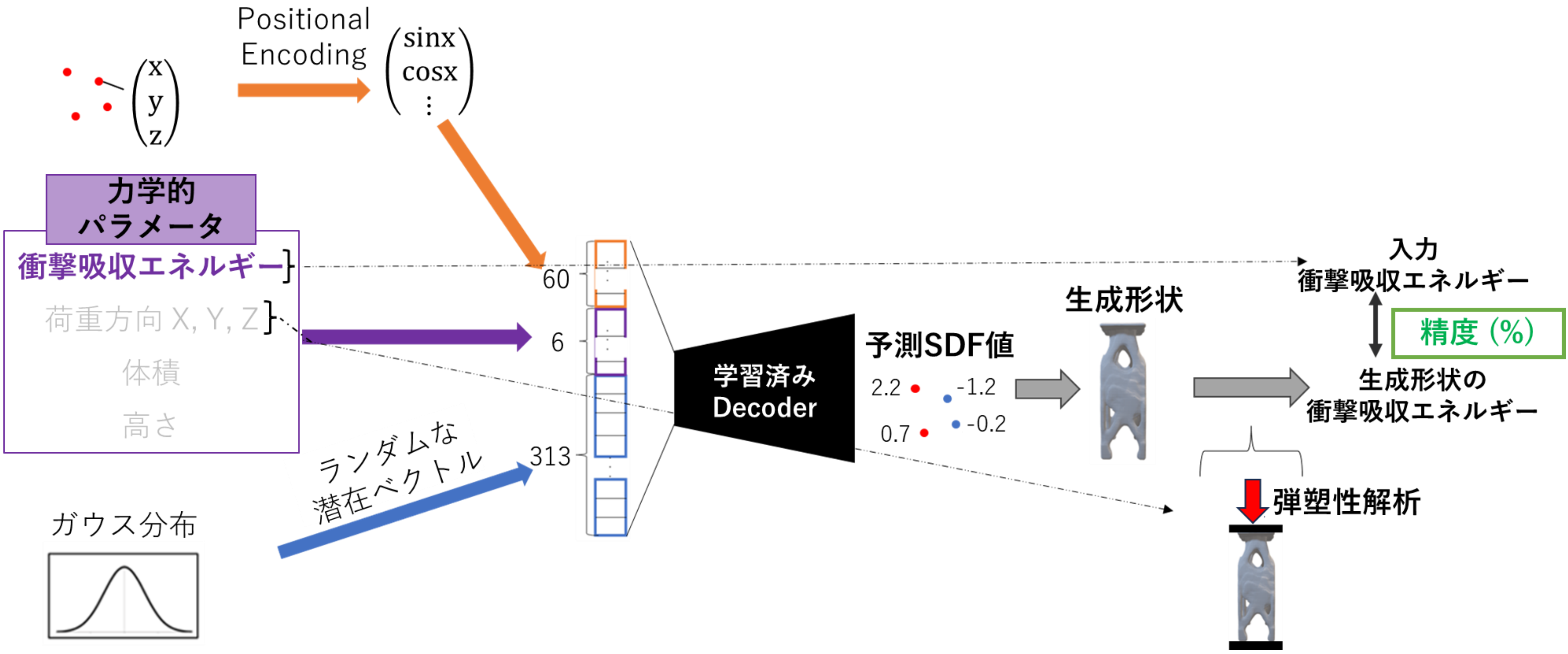


$$CD(X,Y) = \frac{1}{|X|}\sum_{x\in X}\min_{y\in Y}\|x-y\| + \frac{1}{|Y|}\sum_{y\in Y}\min_{x\in X}\|x-y\|$$



Unseen shape **Generated shape**

Parameter-to-3Dタスクの精度検証流れ



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Parameter-to-3D taskの具体例

- 指定した**力学的パラメータを満足する3D形状をさまざまな形状でランダムに生成**できた.
- 既往の逆解析手法（トポロジー最適化など）にはない**「生成AIならでは」の特長**.

入力値

（**衝撃吸収エネルギー**，荷重方向，体積，高さ）
（**12.5J**, X:0.0, Y:0.0, Z:-1.0, 16.9cm^3, 15.0cm）

↓

訓練済モデル

↓

衝撃吸収エネルギー：	12.7J	12.2J	13.1J	13.8J	13.0J
精度：	(98.5 %)	(98.0%)	(95.4%)	(90.6%)	(93.0%)

Accuracy verification of parameter-to-3D tasks

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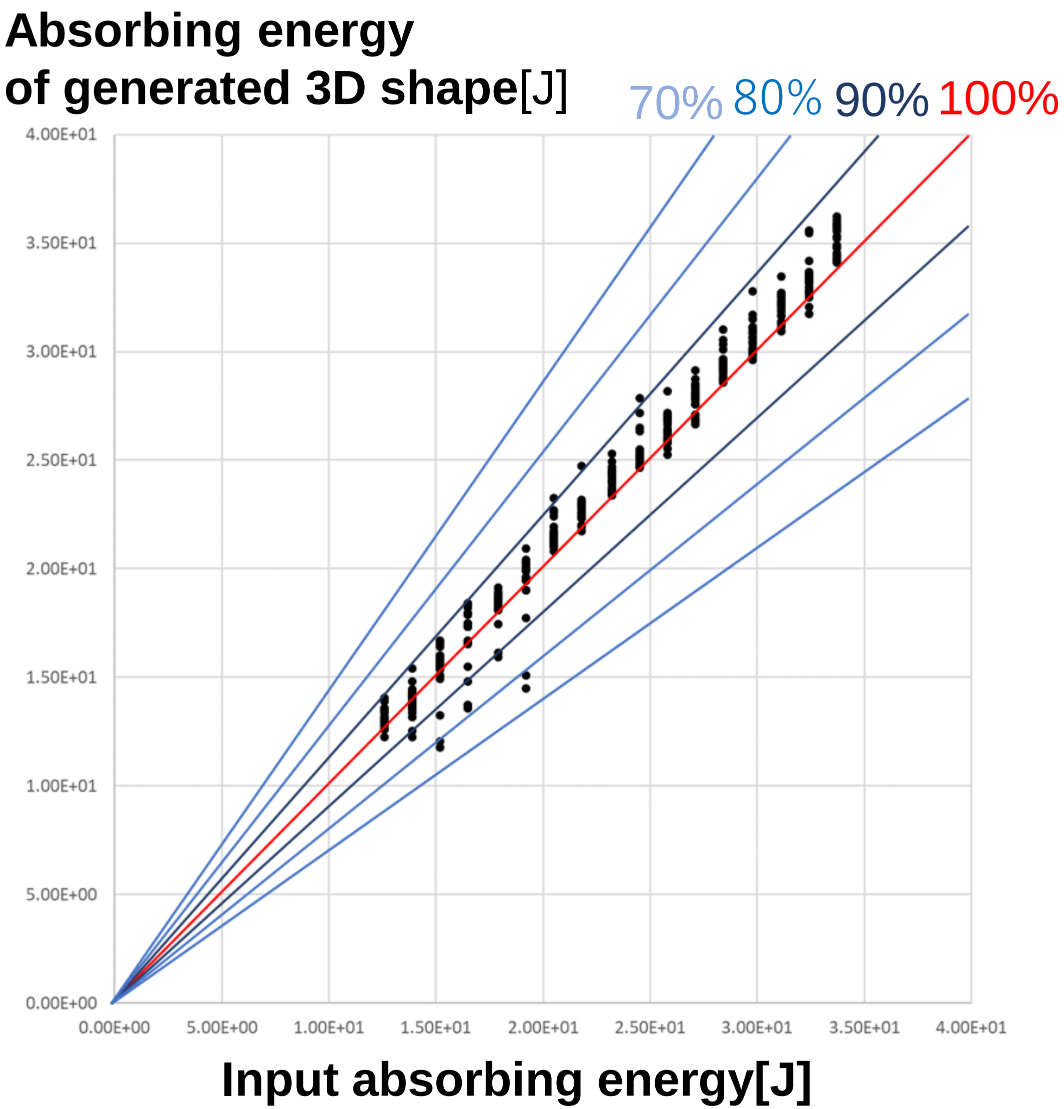
- Generated 340 shapes
  - —17 cases with strain energy ranging from 12.6J to 33.7J
  - —Generated 20 shapes each
  - —Computed the strain energy of the generated shape using Eulerian method

Number of data	340
Average accuracy	**95.7%**
Median accuracy	**96.5%**
Average error	0.68J
Median error	0.74J



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Summary

- We have proposed **3D generative AI** incorporating **structural dynamics**, based on DeepSDF.
  - — We generated **10114 datasets of paired 3D shapes and structural dynamics parameters** using the supercomputer "Fugaku" with linear topology optimization and Eulerian method.
  - —We confirmed that the **trained 3D generative AI** can generate 3D shapes that satisfy the input parameters with **a median accuracy of 96.5%**.
- The proposed 3D generative AI presents new possibilities for structural design methodologies.

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Future work

- **Large-scale training of 3D generation AI**
  - —To create a dataset including **millions of paired 3D shapes** and their corresponding **mechanical parameters**.
  - —Distributed parallel learning of 3D generation AI.
- **To develop a 3D generative model for thin-walled structures**