生成AIで拓く
ものづくりの民主化と自動化

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- 専門分野：**計算力学（非線形構造解析，構造-流体連成問題，高性能計算）**
- 経歴：
  - ―1985年：広島県広島市生まれ
  - ―2004年～2010年：広島大学 工学部（建設・環境系）と修士課程
  - ―2011年～2015年：広島大学 博士課程
  - ―2010年～2016年：日東電工株式会社 研究開発本部
    - ✓工場実習0.5年，CAEに関わる研究開発（3.5年），新規事業開発（２年）
  - ―2016年～2020年：理化学研究所 計算科学研究センター
    - ✓特別研究員，スパコン「京」PJ，スパコン「富岳」PJの研究
  - ―2020年～2023年：名古屋大学 大学院工学研究科 土木工学専攻 講師
  - ―2023年～現在：名古屋大学 大学院工学研究科 土木工学専攻 准教授
    - ✓客員：理化学研究所，神戸大学，山梨大学

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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

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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

Recent studies of 3D generative AI

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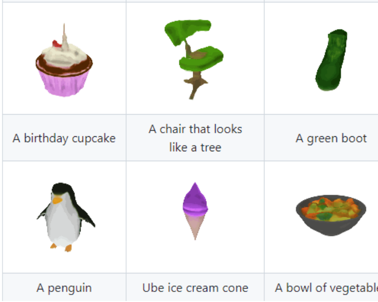
- From 2022 onwards, not only **2D generative AI** but also **3D generative AI** have been emerging one after another.
  - —The number of datasets for 3D shapes is much smaller than that for natural language and images.
  - —No dataset that can be applied to structural mechanics has been proposed.

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

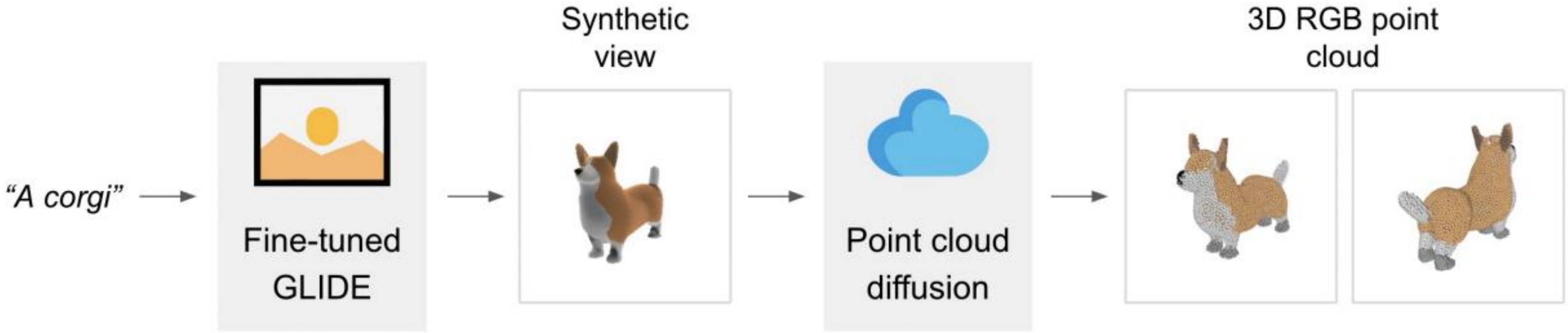


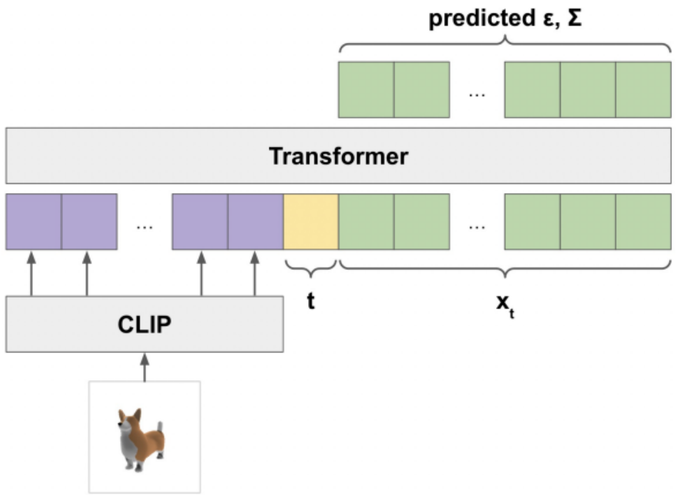
Shap-E

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

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

Shock-absorbing structure (Tesla)

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

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

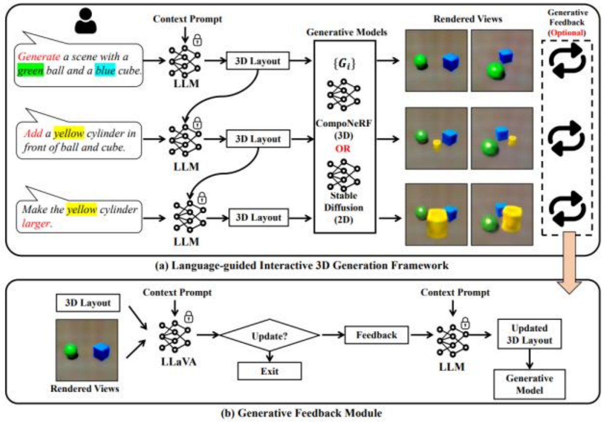
Final goal

- **Automation and democratization of structural design**

Human feedback by Non-experts

Designer **Marketer**

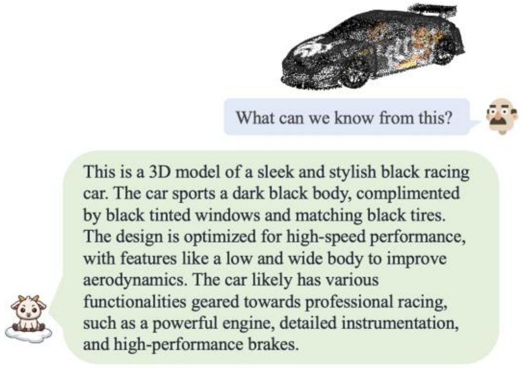
Text-to-parameter model
(LLMs as Parameter Interpreter)



Natural language → Mechanical parameters → 3D structure → Natural language → Human feedback → Natural language

Paramter-to-3D model

3D-to-text model
(LLMs to understand 3D structure)



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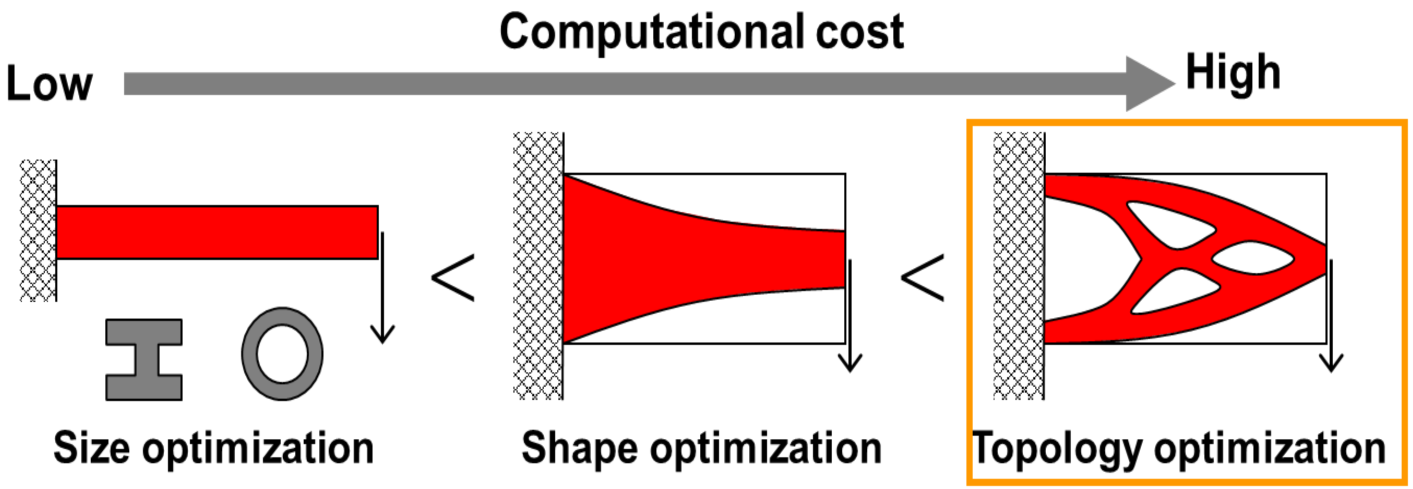
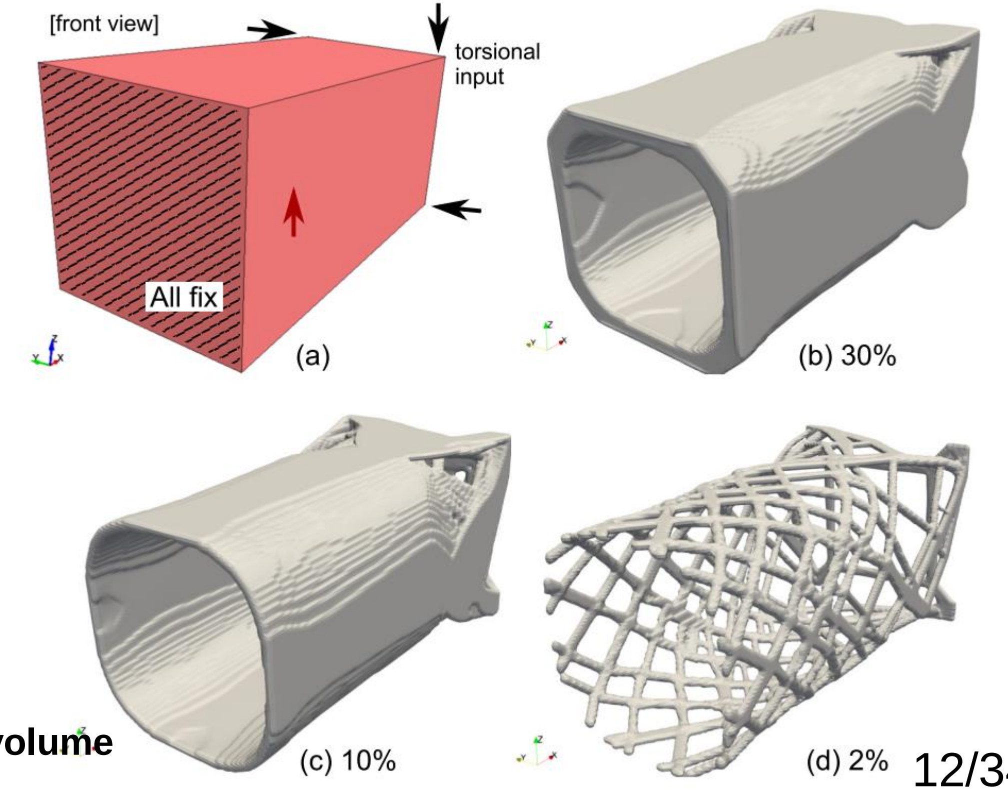
Structure for feasibility study: crash box

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

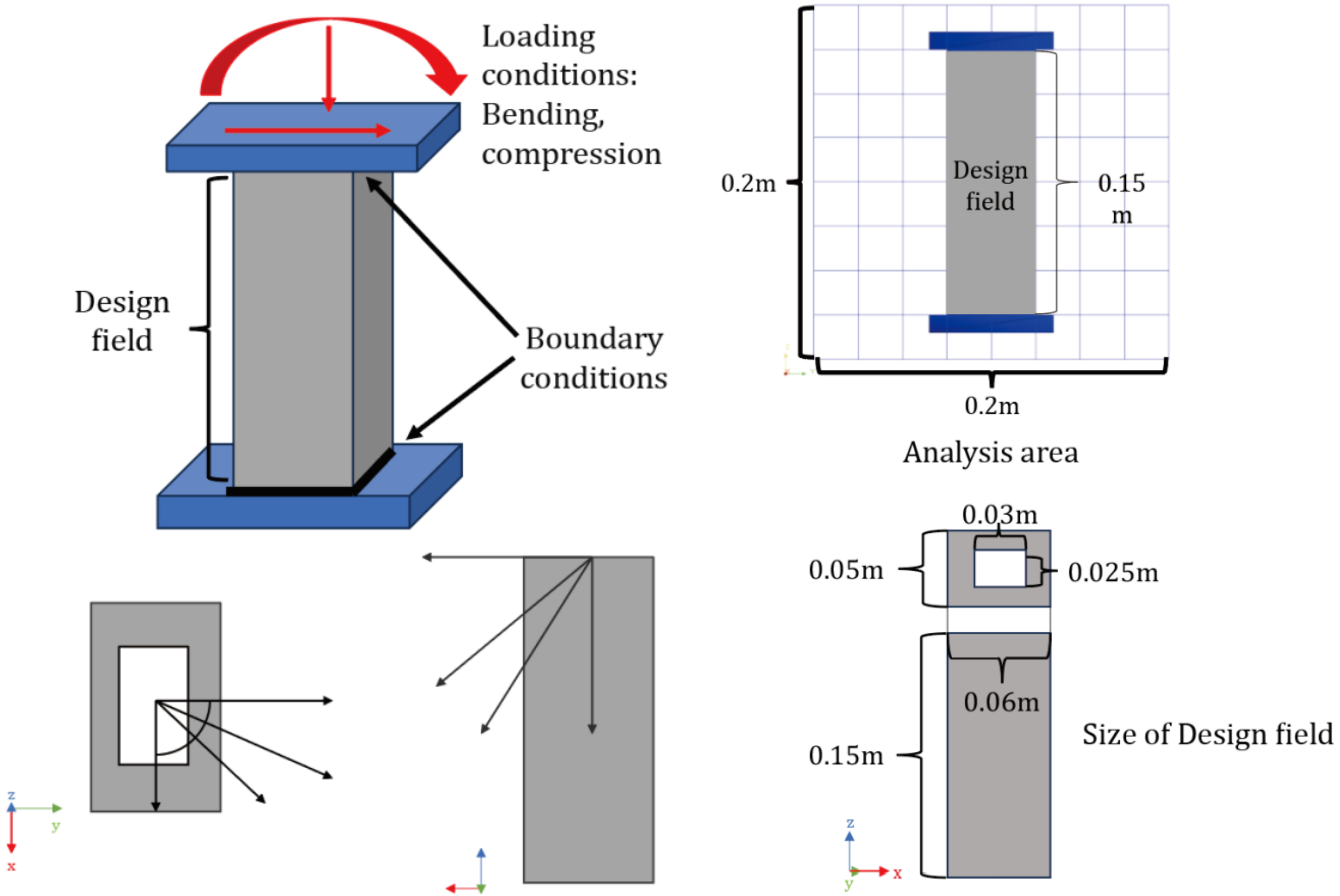




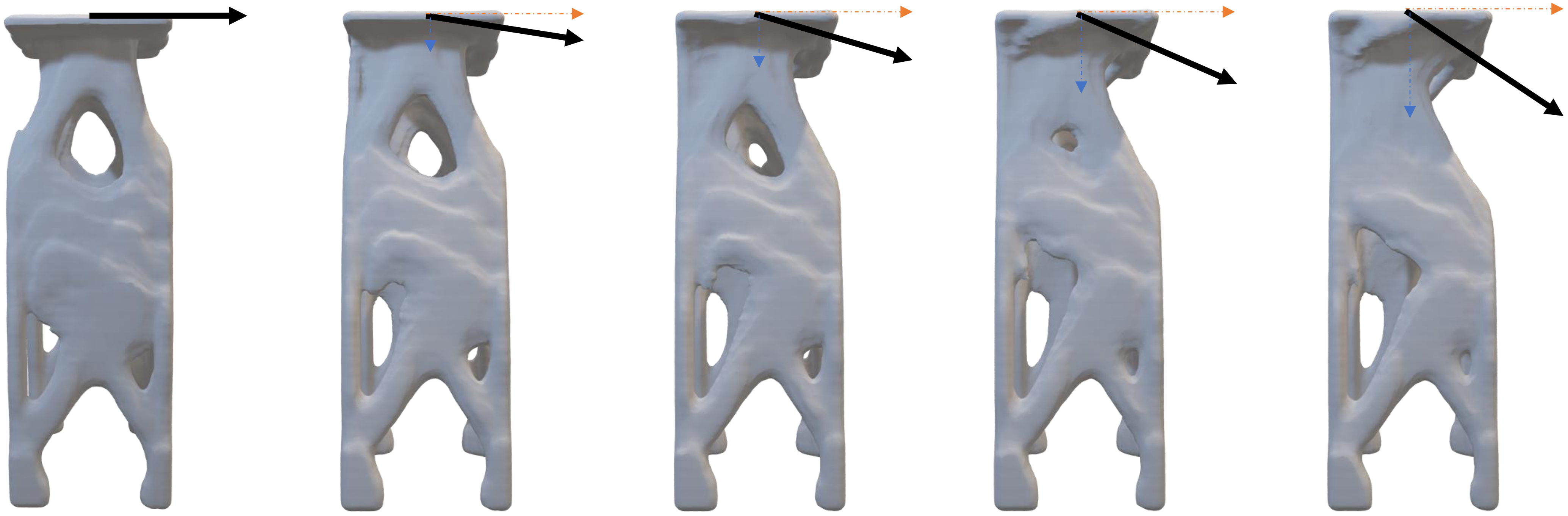
Different topologies can be obtained by changing volume constraints. (Yuji Wada, 2023)

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



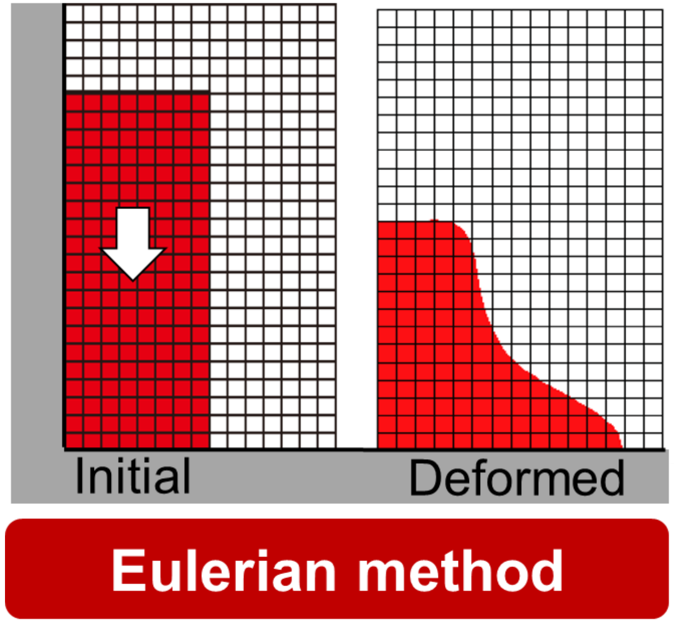
Many-case topology optimization

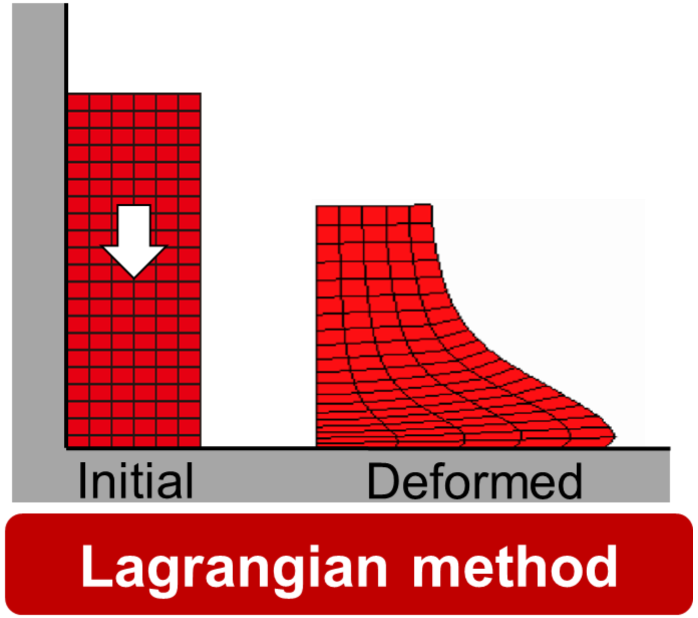


Many-case crash simulation

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.

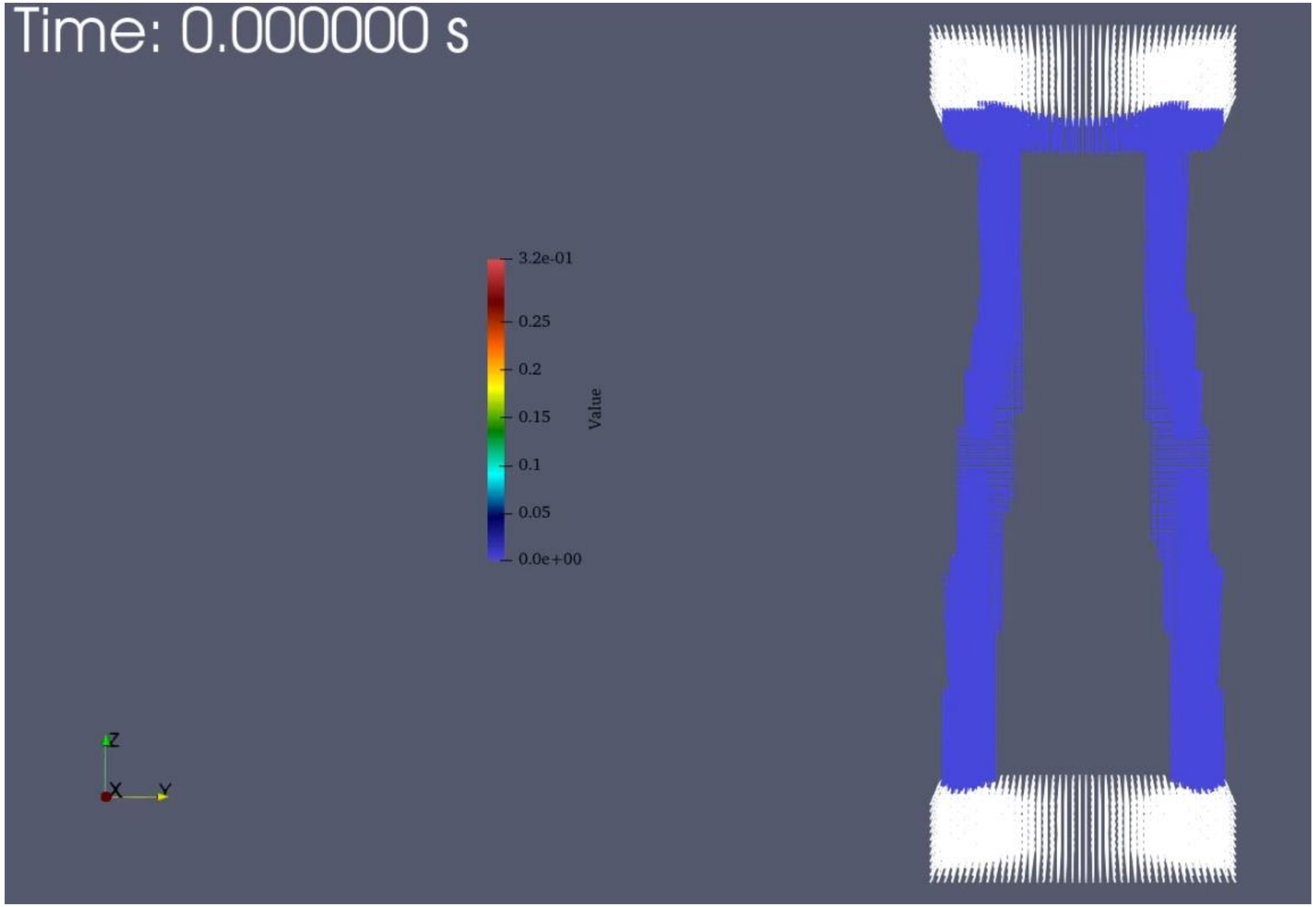
Many-case crash simulation

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

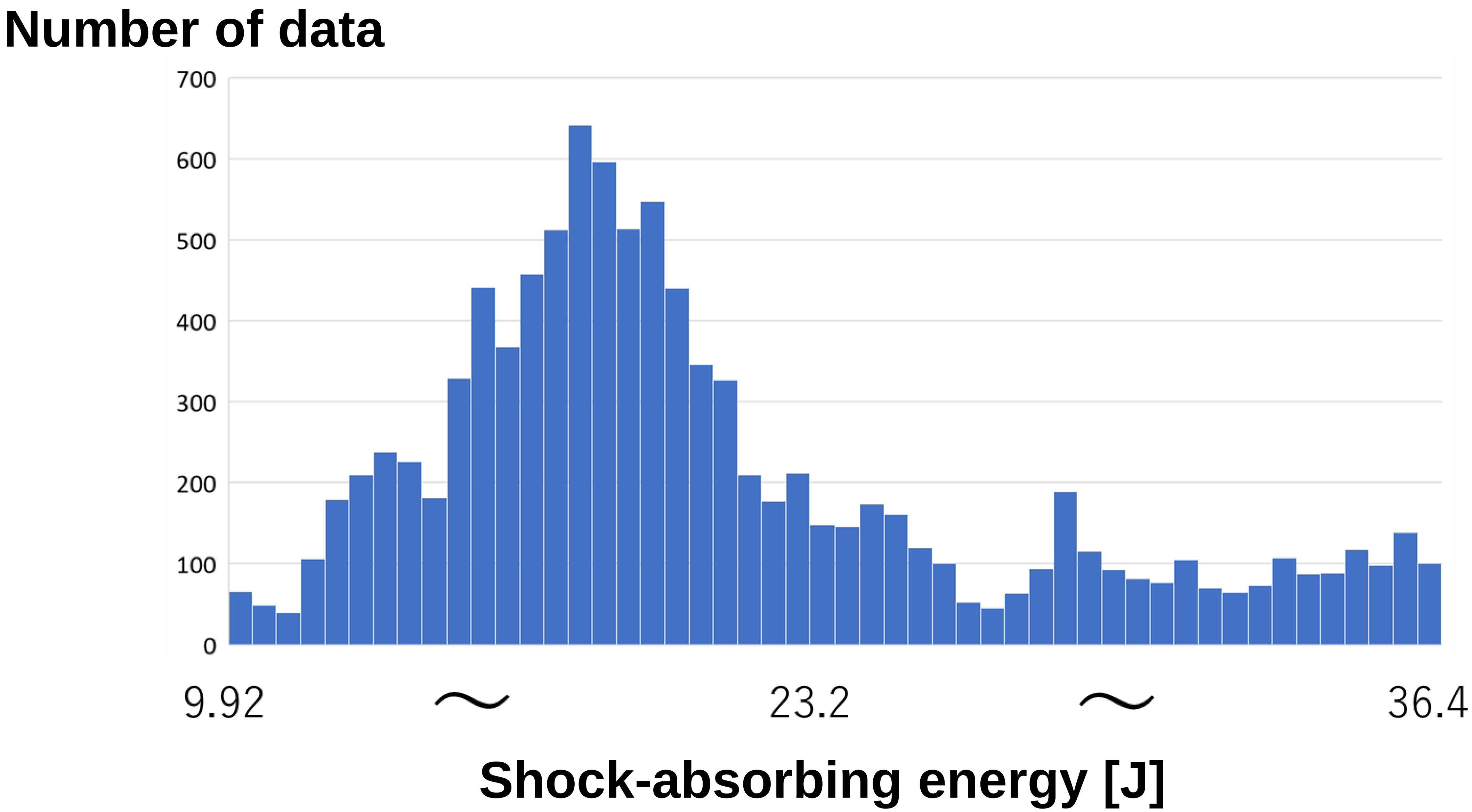
—4,194,304 cell mesh

—32 nodes of Fugaku
(128 rank × 8 threads, 1024 cores) for each

—2.5 hour for each case



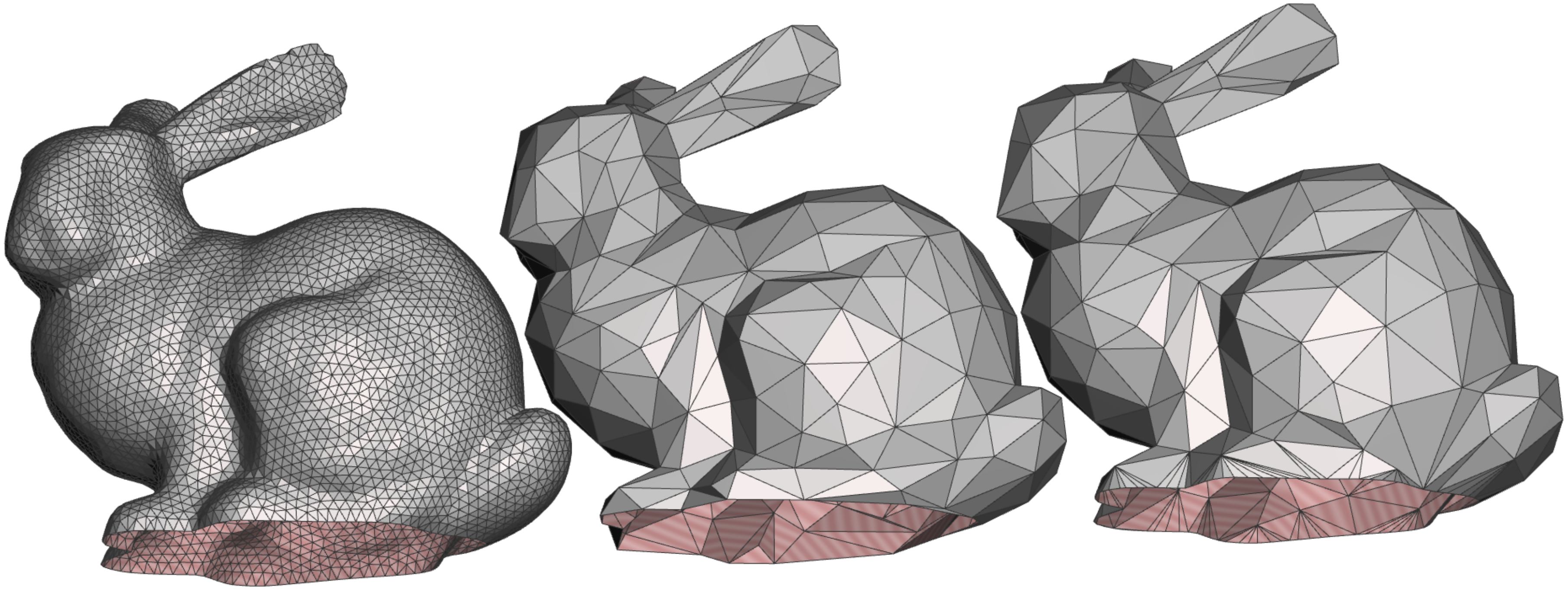
Histogram of shock-absorbing energy



Outline

メッシュによる3Dデータ表現

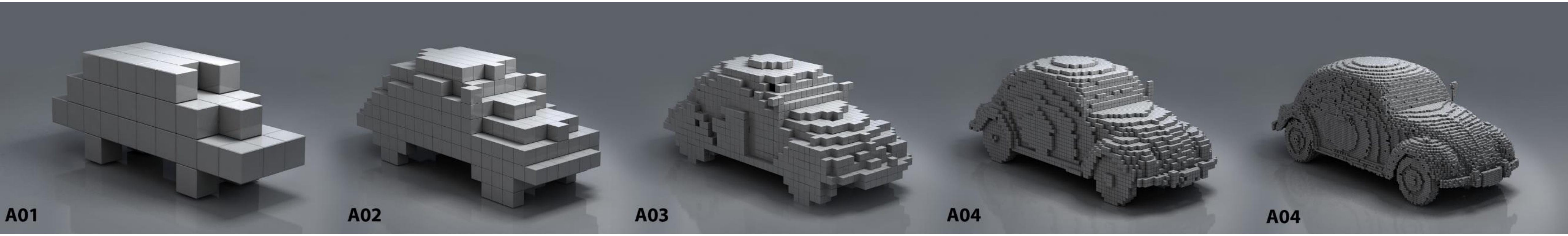
- CAEなどで広く使用され，メモリ消費は比較的少ない．
- 高品質なメッシュ生成にはノウハウや労力が必要な場合が多く，大量のデータセット作成は難しい．
- 深層学習でメッシュのグラフ構造を扱うのは容易ではない．



https://www.gradientspace.com/tutorials/2017/8/30/mesh-simplification

ボクセルによる3Dデータ表現

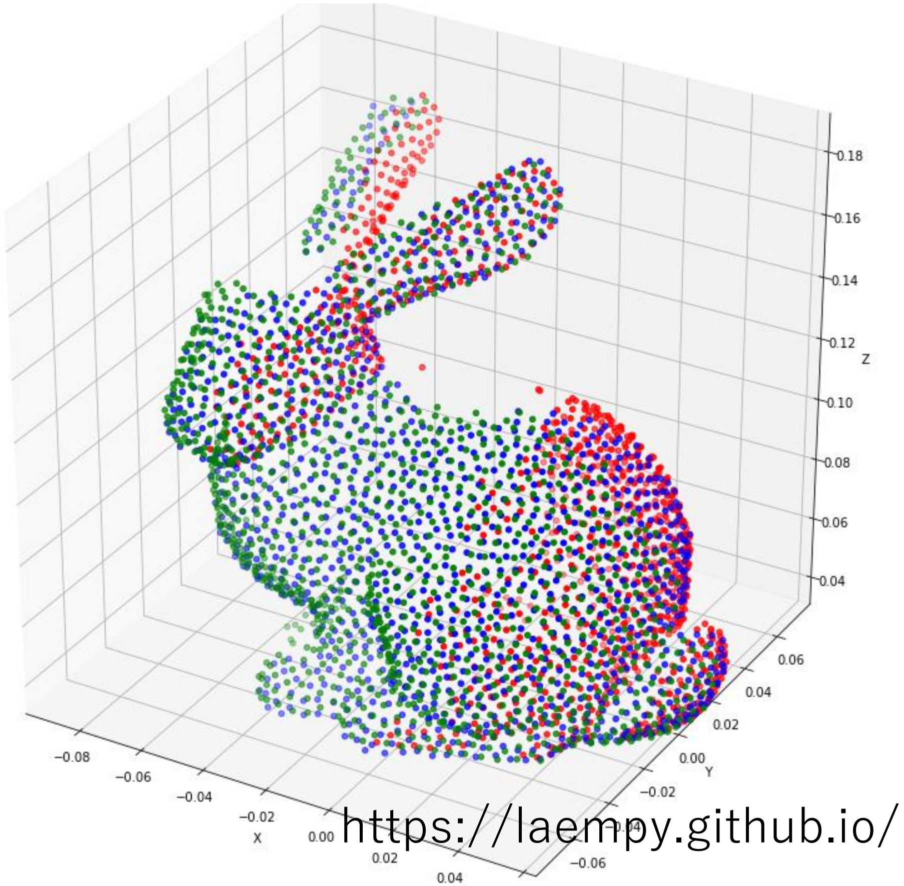
- 画像を認識·生成する方法論 (CNN等) を活用しやすい.
- メモリ消費量が非常に大きい.
  - —GPUスパコンで超並列分散学習を行えば扱えないこともないが，現在の3D生成AIでは主流のアプローチではない.



http://www.bilderzucht.de/blog/3d-pixel-voxel/

点群による3Dデータ表現

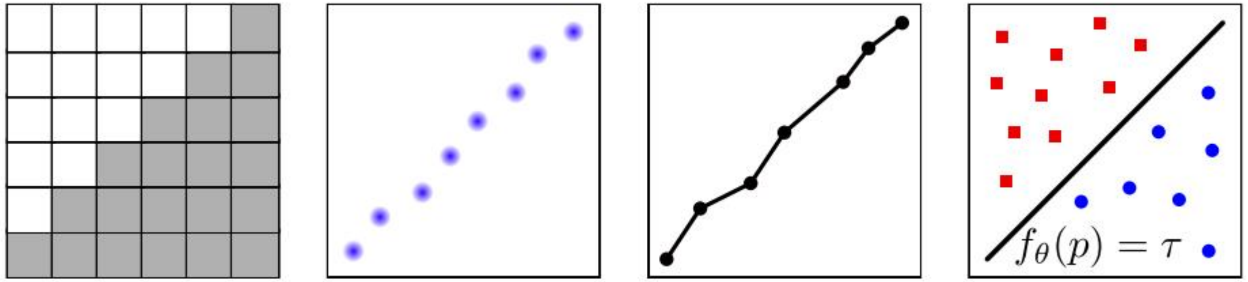
- ボクセルよりメモリ消費量は少ない
- 面を表現できない →界面の物理量を反映しにくい.
- 深層学習で扱うのがやや難しい.



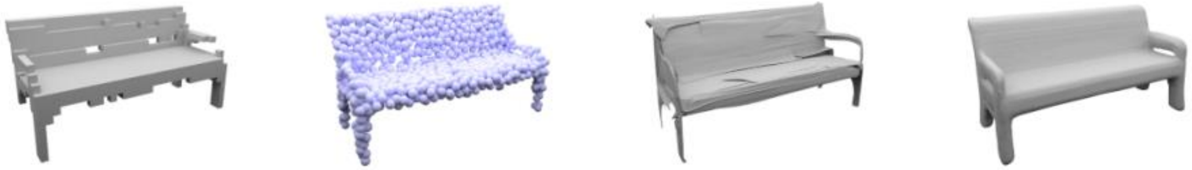
https://laempy.github.io/pyoints/tutorials/icp.html

Neural Fieldによる3Dデータ表現

- 3D形状自体をニューラルネットワークで表現するアプローチ
- 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



ボクセル　**点群**　**メッシュ**　**Neural Field**

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

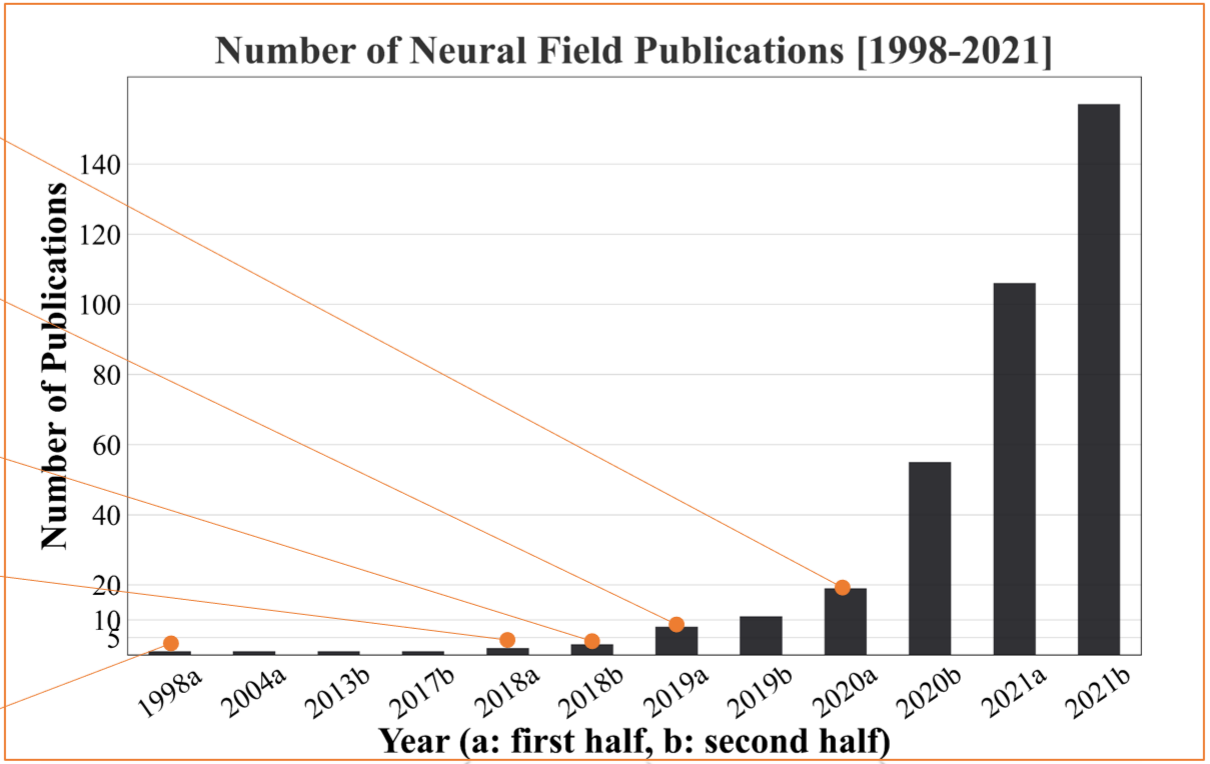
NeRF

DeepSDF
PIFu

Occupancy Networks, IM-NET

AtlasNet

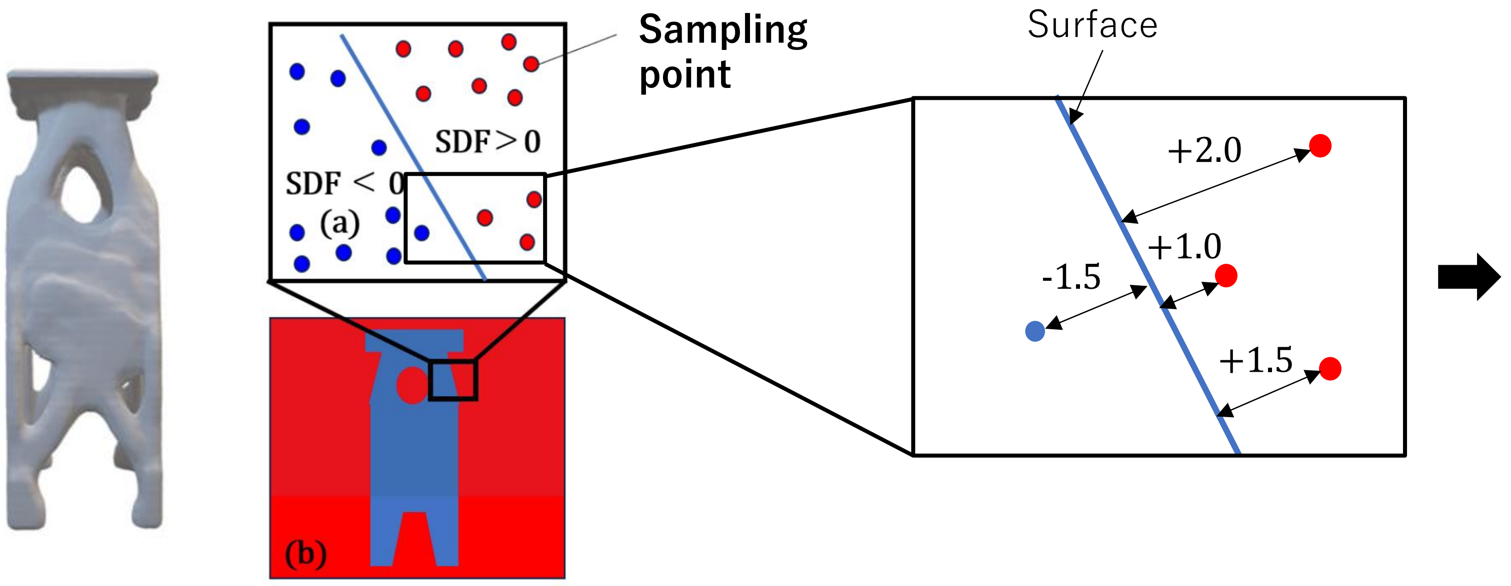
Approximating Reflectance Functions using Neural Networks



DeepSDF

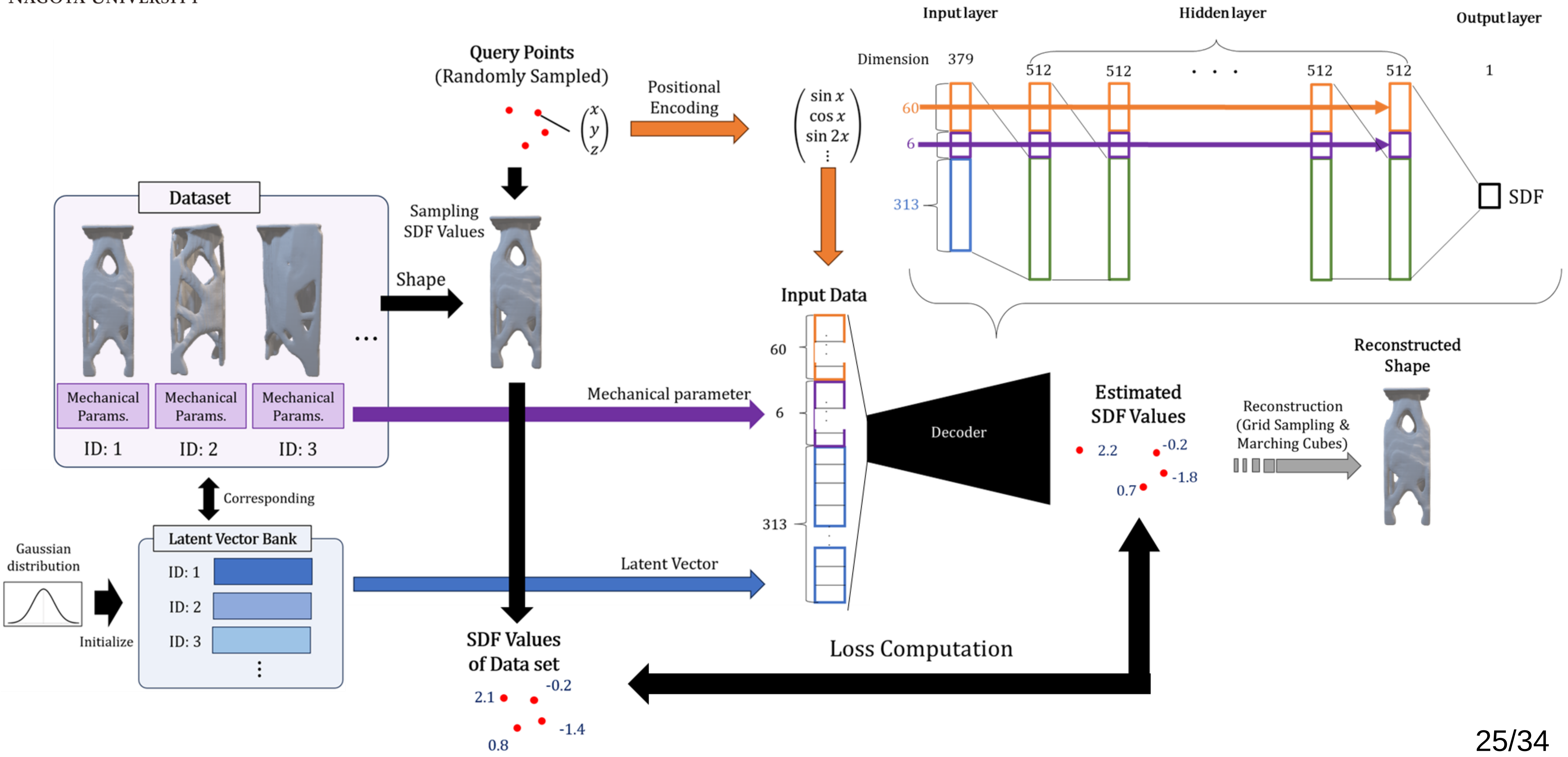
Jeong Joon Park, Peter Florence, Julian Straub, Richard Newcombe, Steven Lovegrove; Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2019, pp. 165-174

- 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

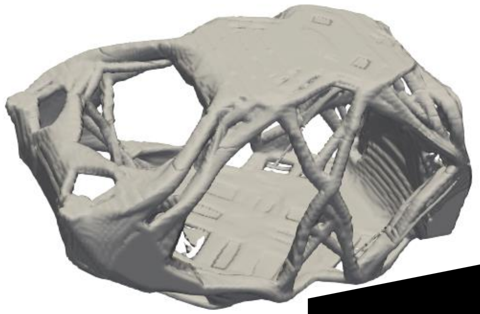
- We introduced **positional encoding** to improve the reconstruction accuracy for complex shapes.

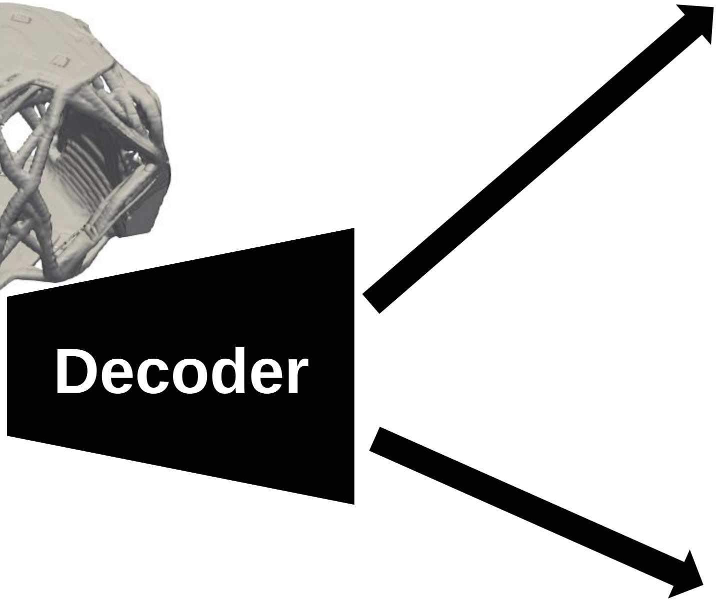
$$\phi(\boldsymbol{x}) = \begin{pmatrix} \sin\left(2^0 x\right) \\ \cos\left(2^0 x\right) \\ \vdots \\ \sin\left(2^9 x\right) \\ \cos\left(2^9 x\right) \\ \sin\left(2^0 y\right) \\ \cos\left(2^0 y\right) \\ \vdots \\ \sin\left(2^9 y\right) \\ \cos\left(2^9 y\right) \\ \sin\left(2^0 z\right) \\ \cos\left(2^0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

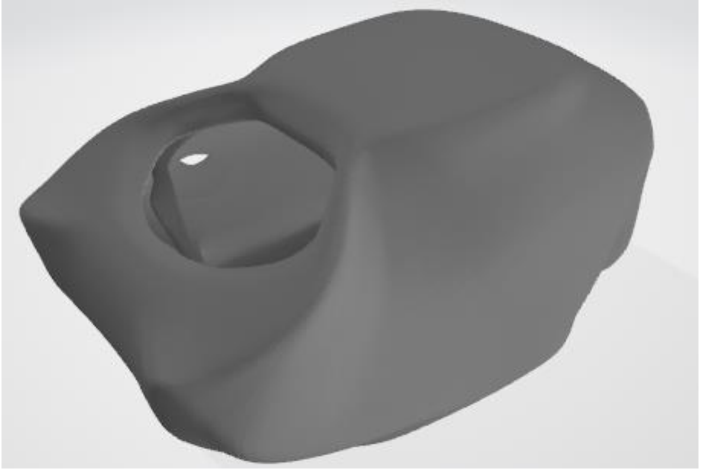
$$\phi : \mathbb{R}^3 \to \mathbb{R}^{60}$$

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

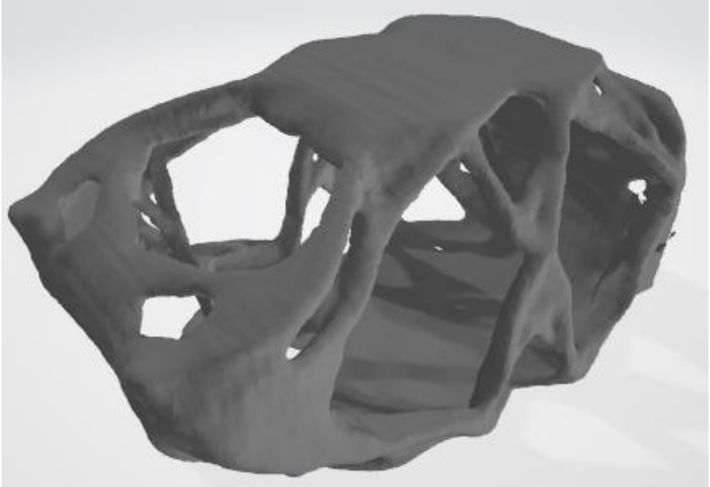
3D shapes for training







Original



With positional encoding

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Accuracy verification of parameter-to-3D tasks

We succeeded in randomly generating 3D shapes with various pattern topologies that satisfy the input parameters.

Input parameters

（Absorbing energy, load direction, volume, height）

（**12.6J**, X:0.0, Y:0.0, Z:-1.0, 16.9cm^3, 15.0cm）

Trained 3D AI

Energy	**12.7J**	**12.2J**	**13.1J**	**13.8J**	**13.0J**
Accuracy	**（98.0%）**	**（98.5%）**	**（95.4%）**	**（90.6%）**	**（93.0%）**

Accuracy verification of parameter-to-3D tasks

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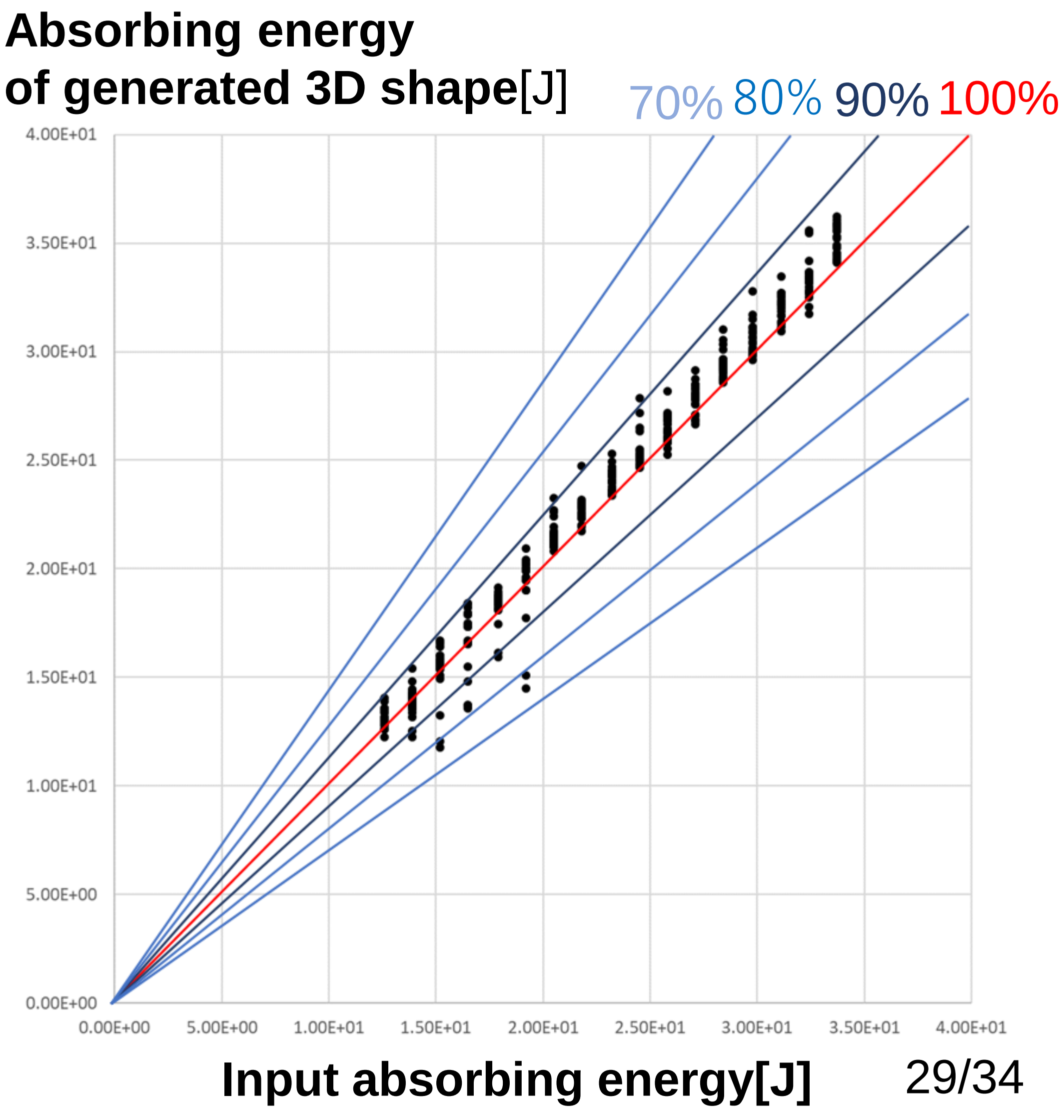
- Generated 340 shapes
  - —17 cases with strain energy ranging from 12.6J to 33.7J
  - —Generated 20 shapes each
  - —Computed the strain energy of the generated shape using Eulerian method

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.

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**

AI for Manufacturing：日本の勝ち筋は？

- **生成AIを「ユーザとして使う」だけでなく「つくる側」の取り組みも急務**
  - 生成AIの性能向上は今も続いており，未だその性能限界が見えていない．
  - 「つかう側」の議論も大事だが，我が国も産官学で，生成AIを「つくる側」の取組みを，できることから今すぐ始めるべき．
- **ものづくりの3D生成AIは世界的にも進んでいない**
  - ChatGPT等はまだ序章にすぎず，現在，AGIと呼ばれる汎用的AIに加えて，各領域に特化した生成AIの研究開発が進んでいる．特に創薬・医療・マテリアル・インフォマティクスなどデータセットが豊富にある領域.
  - 機械/土木/建築分野は大規模データセットが整備されていない領域であり，3D生成AIの研究は世界的にも進んでいない.
- **日本の勝ち筋は**
  - 機械/土木/建築分野領域では，スパコンでデータセット自体を作り出すことに加えて，競争領域と協調領域を線引きした上で，各社が協調してデータセット整備（各社ごとにデータはバラバラ）を進めることが欧米勢に勝つためには必要.
  - 日本の法規制は他国に比べて生成AI開発に有利

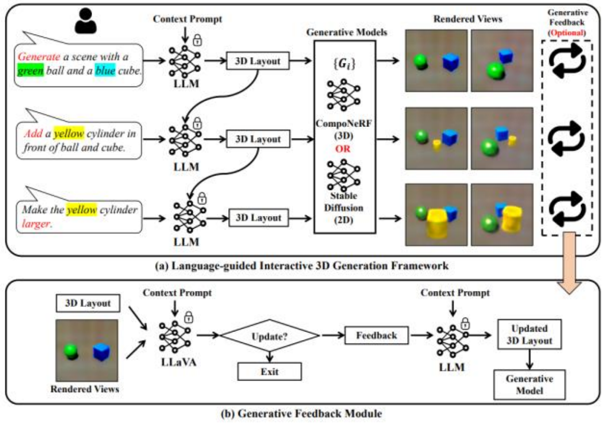
Final goal

- **Automation and democratization of structural design**

Human feedback by Non-experts

Designer **Marketer**

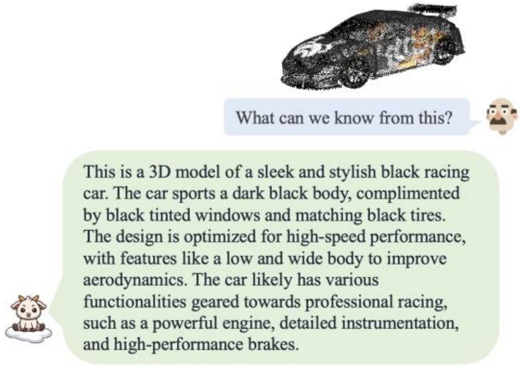
Text-to-parameter model
(LLMs as Parameter Interpreter)



Natural language → Mechanical parameters → 3D structure → Natural language → Human feedback → Natural language

Paramter-to-3D model

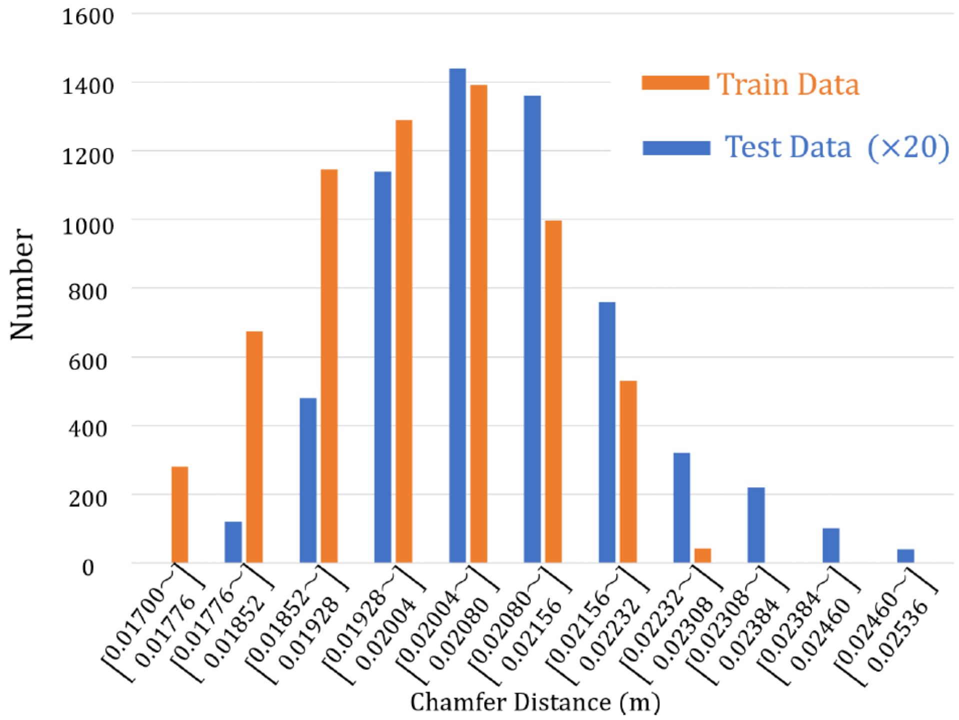
3D-to-text model
(LLMs to understand 3D structure)



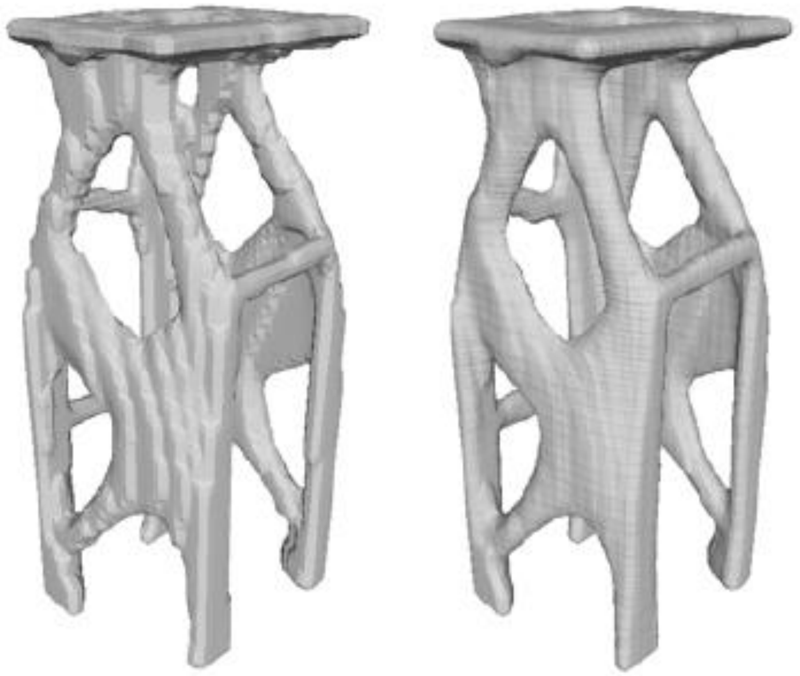
補足資料

Generalization performance for 3D shape

- 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