AIエージェント時代の構造設計支援

3D生成AIとシミュレーションによる3D生成・探索ループ

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Outline

1. **Background and Objective**
2. 3D Generative Model
3. Learning and Shape Exploration from Limited Manufacturing Data
4. Toward AI agentic loop design
5. Discussion and Open Questions

Rapid Progress & Challenges in Generative AI

- Generative AI is rapidly advancing in text, image, and 3D generation

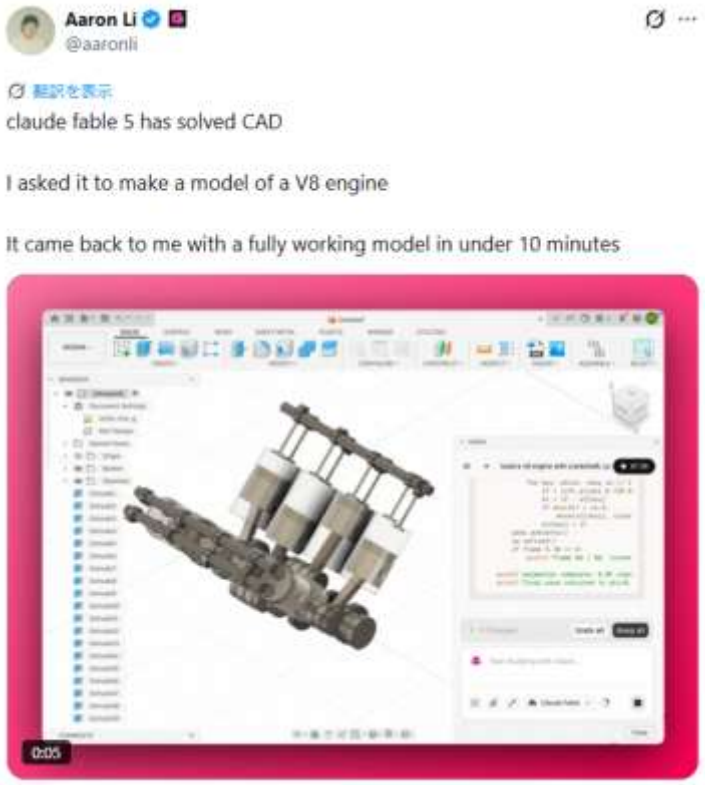
Model name	Release date	Research group	3D representation	Model architecture	Data set	Number of 3D data
Shap-E	May 2023	OpenAI	Implicit function	Transformer-based diffusion model	ShapeNet（3D）, WebImageText（2D）	Several millions
Point-E	December 2022	OpenAI	3D point cloud	Transformer-based diffusion model	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

Progress in Neural CAD (Text-to-CAD) / AI-Agent-Based CAD

- Neural CAD (Text-to-CAD) / AI-Agent-Based CADが進展し，「CADの線を描く」こと自体は自動化できつつある.



https://x.com/aaronli/status/2064876123109089742

Rapid Progress & Challenges in Generative AI

- **Limitations of current 3D Generative AI in Engineering**
  - **—Lack of Physics-Awareness**

    Primarily trained on 2D image datasets, ignoring physical laws in 3D geometries.
  - **—Shortage of Datasets**

    Extreme shortage of paired datasets containing both 3D geometries and their physical properties.
  - **—Ambiguity of "Text-to-3D“**

    Relying on natural language (text prompts) is inherently ambiguous and unsuitable for rigorous engineering design.

Objective: A Novel "Parameter-to-3D" Approach

- **Concept**
  —Generating 3D geometries directly from mechanical performance requirements.

- **Proposed Model**
  —Developing a 3D generative model capable of accurately encoding physical quantities for structural design.

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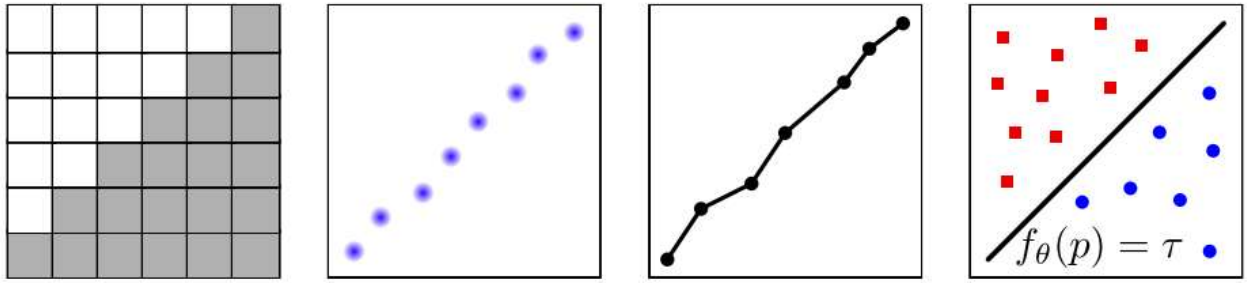
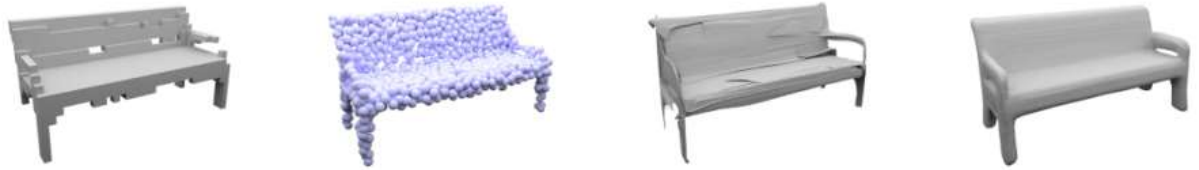
3D Data Representation Using Neural Fields

- **Memory-efficient**
- **Flexibility in 3D representation**
  - —Capable of representing arbitrary resolutions and topologies
  - —The precision of representable 3D information ∝ Representation capacity of the neural network ≒ Number of parameters
- **Scaling laws may hold for 3D generative models as well as LLM**



https://arxiv.org/pdf/1812.03828

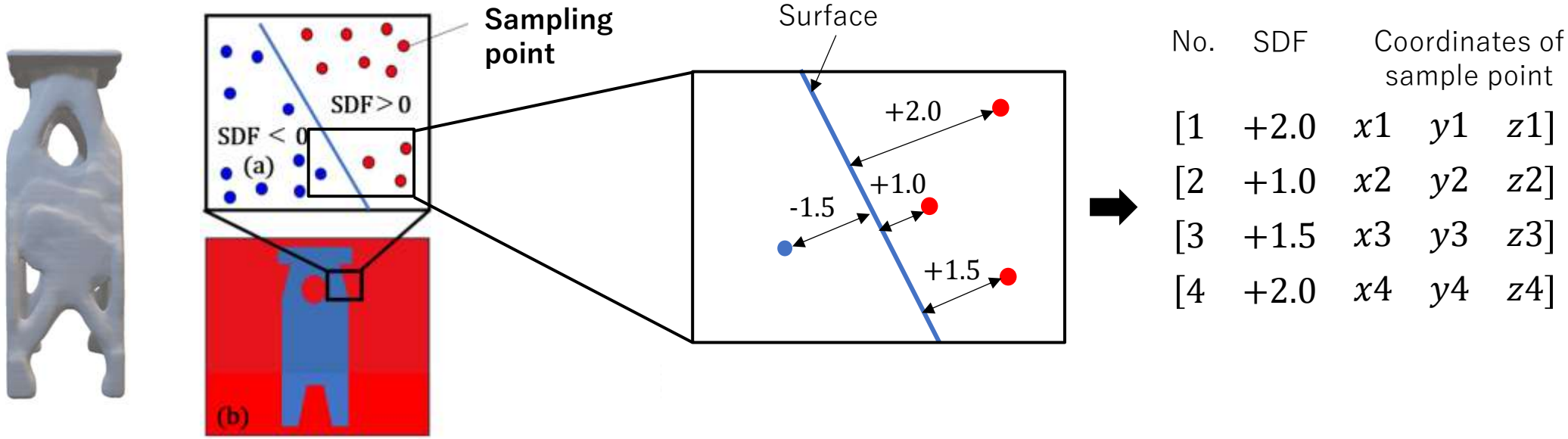


Voxel **Point clouds** **mesh** **Neural Field**

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

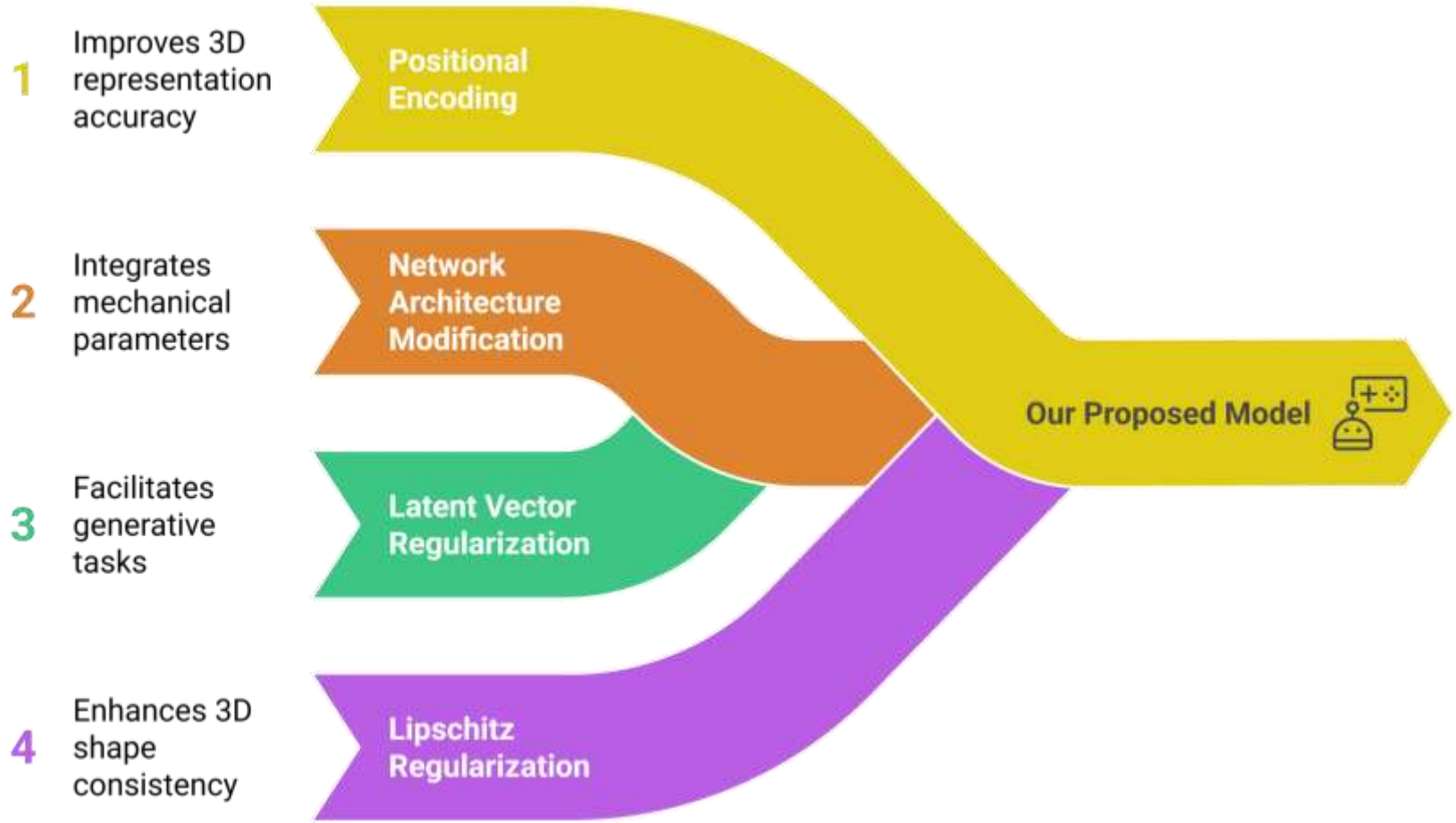
- Deep learning-based implicit representation method for 3D shapes using Signed Distance Functions (SDF).
  - —Represent a 3D shape as a vector using the coordinates of sample points and SDF values.



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	$x4$	$y4$	$z4$]

Our Proposed Generative Model based on DeepSDF

- The core technologies of this generative model are currently protected by multiple pending PCT applications by Nagoya University.



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製造業データは「1件」が高価

LLM・画像生成AI

- 公開データを広く収集できる
- データ形式が比較的標準化されている
- サンプル作成の追加コストが低い
- 巨大な汎用データセットを前提にしやすい

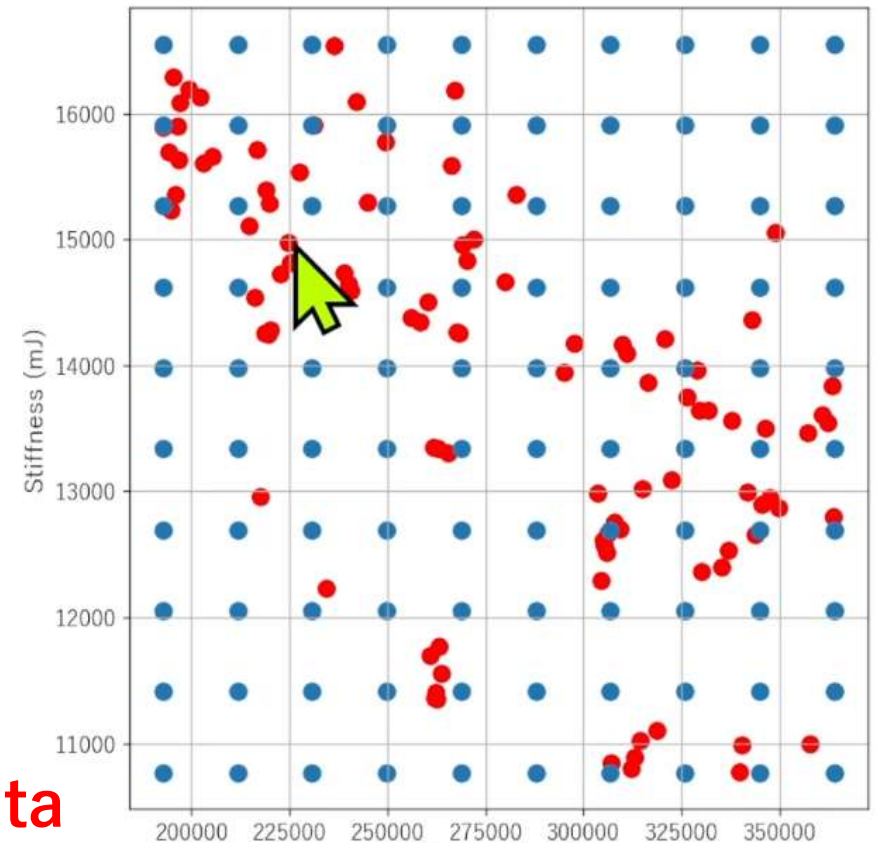
製造業の実験・CAEデータ

- CAD・解析条件は機密情報である
- 設計・メッシュ・解析・確認が必要
- 座標系・単位・履歴が不均一
- 不採用案や失敗データが残りにくい

製造業の3D生成AIは、少量・機密・不均一なデータを前提に設計する必要がある

Parameter-to-3D Task (Aircraft Engine Mounting Bracket)

- Generates 3D shapes instantly from target performance metrics and runs smoothly on a consumer-grade RTX 4000-series GPU.
- Capable of learning from limited datasets of around 50 samples.
- Multi-fidelity Simulation-in-the loop process assisted by AI agent



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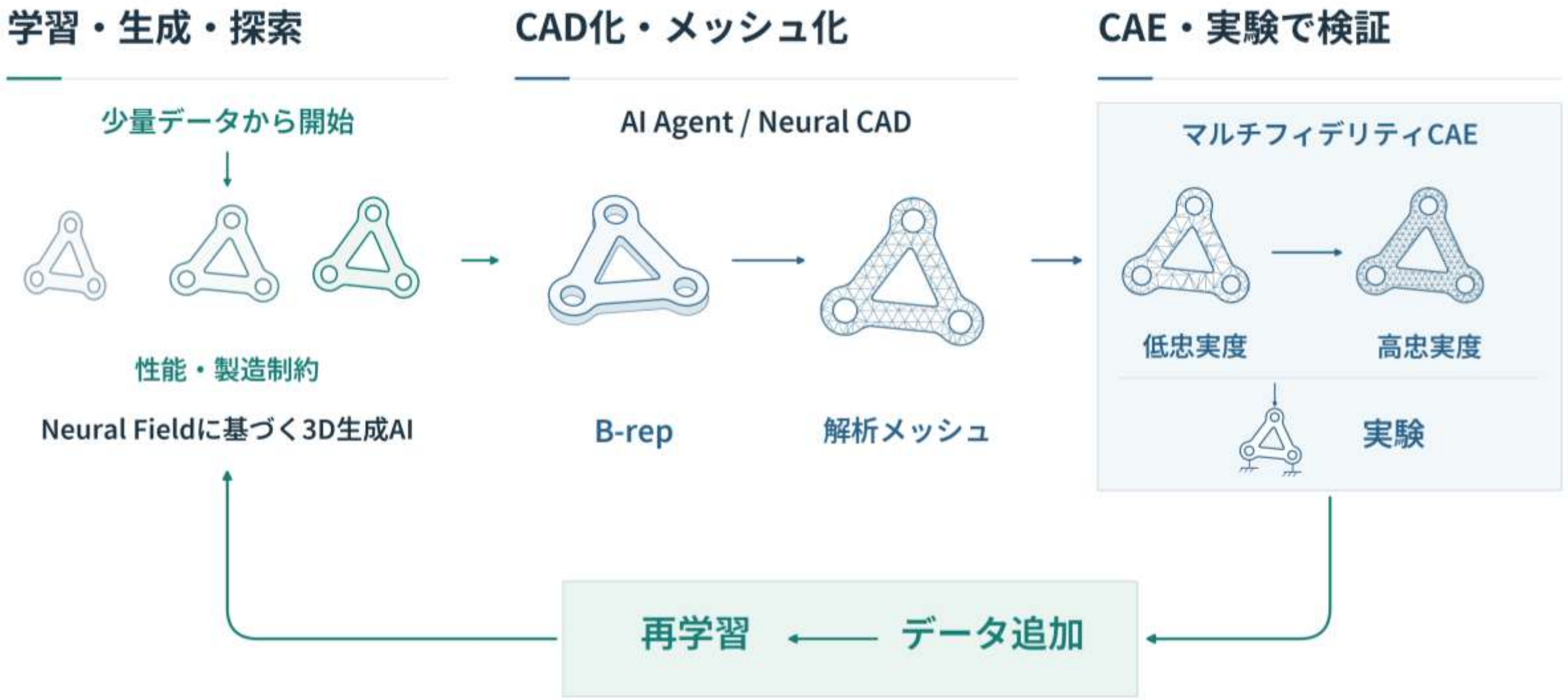
まとめ：AI agentic loop design



学術研究と社会実装を繋ぐ産学連携

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Open Questions

- How can we build shared & non-confidential benchmark problems for physics-aware 3D generative AI?
- How should we define mechanical validity for generated designs?
- How do we integrate foundation models (LLM), simulation, and engineering workflows?

Acknowledgment

- **Supercomputer “Fugaku” research project (hp220249)**
  - —Principal Investigator: **Koji Nishiguchi (Nagoya Univ./RIKEN)**
  - —Capacity computing of elasto-plastic dynamics of component structures for next-generation automobile design and its probabilistic deep generative models
  - —2022/10/01 – present
- **Supercomputer “Fugaku” research project (hp240296)**
  - —Principal Investigator: **Koji Nishiguchi (Nagoya Univ./RIKEN)**
  - —Uncertainty quantification through multi-case elasto-plastic simulation of gigantic die-cast structure considering porosity
  - —2024/10/01 – present
- **JST / Nagoya University, FY2024 GAP Fund Program Step 1**
  - —Principal Investigator: **Koji Nishiguchi (Nagoya Univ./RIKEN)**
  - —Virtual testing and automated structural design enabled by 3D generative AI
- **Ministry of Economy, Trade and Industry (METI) / Japan Patent Office (JPO), iAca Program: Startup Creation Support**