

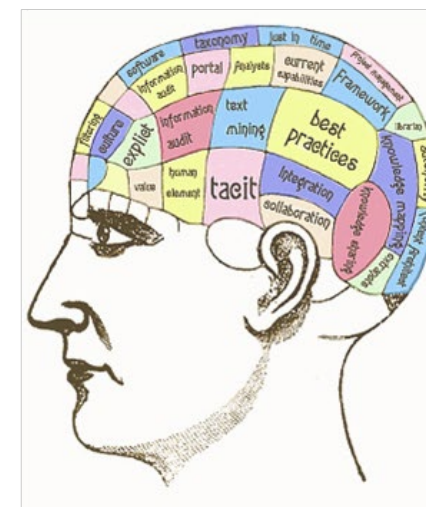
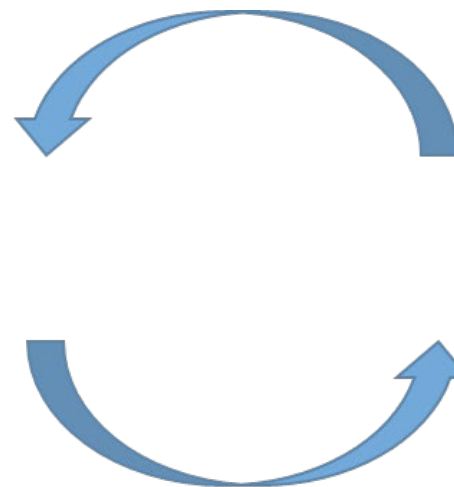
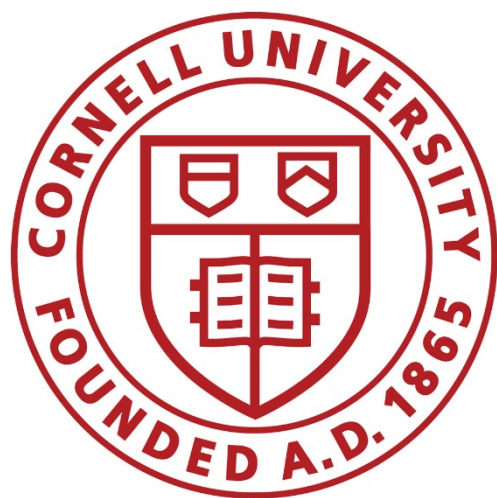


Human-Machine Symbiotic Design of Complex Systems

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NSF EDSE Workshop

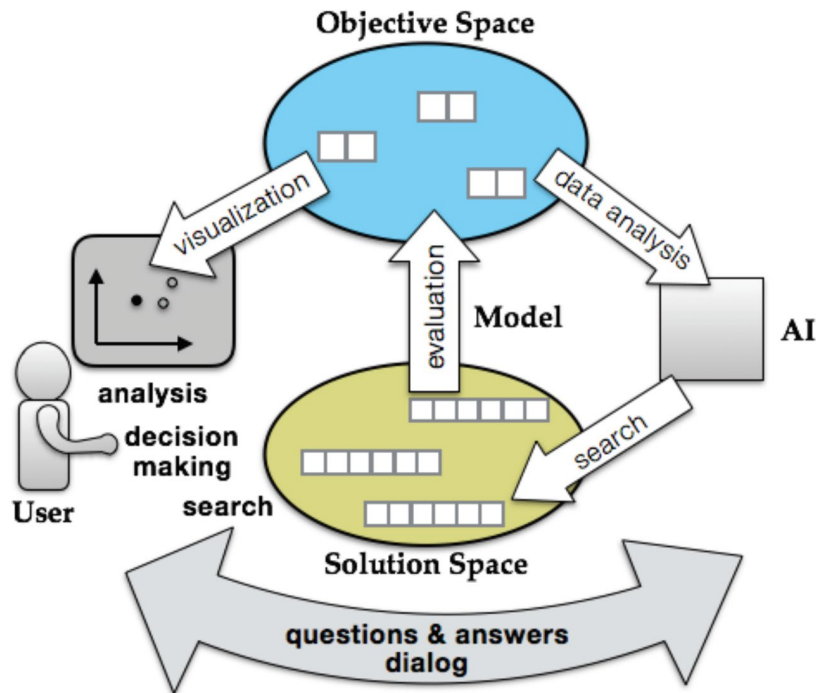
October 8 2019



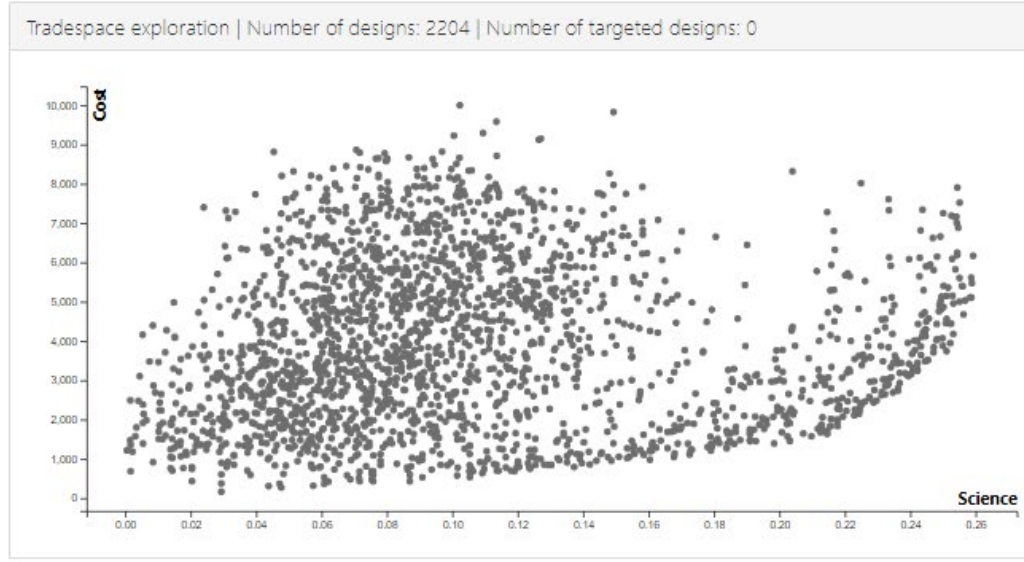
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Human-machine collaborative design space exploration



Daphne What do you think of design D1580?



Answers

The advice I have for design d1580 is:

- **Expert:** Cumulative spacecraft data rate in orbit SSO-800-SSO-PM is too high: 0.21. Try removing an instrument.
- **Expert:** Cumulative spacecraft data rate in orbit SSO-600-SSO-AM is too high: 0.14. Try removing an instrument.
- **Expert:** Cumulative spacecraft data rate in orbit LEO-600-polar-NA is too high: 0.17. Try removing an instrument.
- **Expert:** Instrument CLAR_ERB should not be in orbit SSO-800-SSO-DD.
- **Expert:** Instrument GACM_SWIR should not

Human-machine collaborative design space exploration

Objective 1: Multiple agents and role allocation

- New roles (functionality and level of initiative) for design assistants (e.g., “Explorer” role)
- Effect of number of agents and role-to-agent allocation
- Effect of allowing agents to converse with each other
- **Measures:** design quality and diversity, designer learning, dialog structure, trust

Objective 2: Intent inference and anticipation

- Model and infer human intent in DSE using dynamic Bayes nets
- Model and infer agent optimal action (e.g., suggest design, criticize design) using MDP and reinforcement learning

Knowledge- and data-driven design of mechanical meta-materials

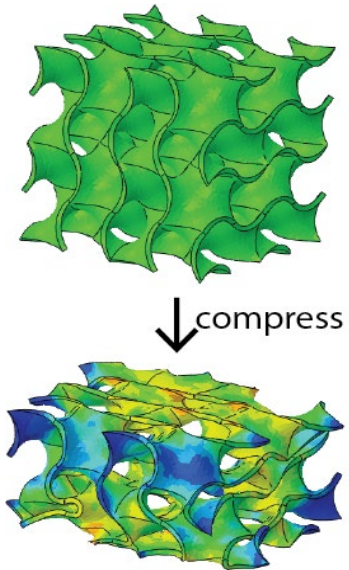
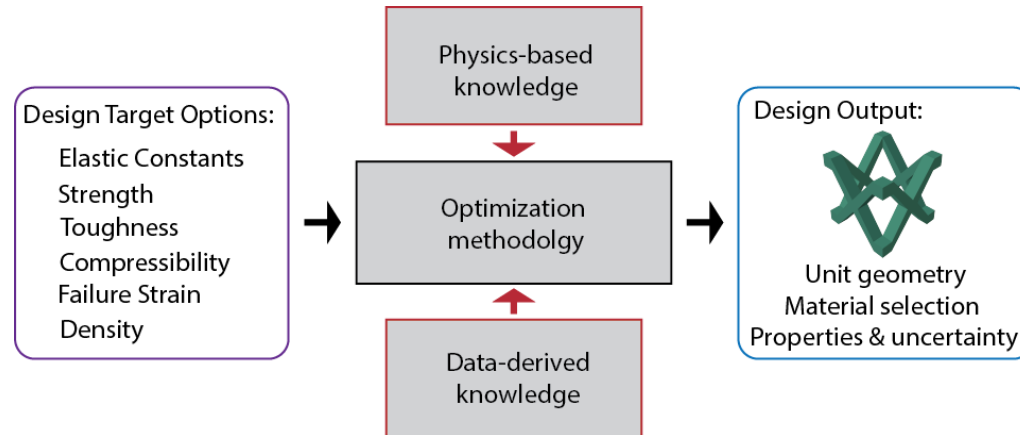


Figure 7. Gyroid before and after 50% strain. Contour shows Mises stress.

- **Scope:** 3D-printed lattice and minimum energy surface materials



Research Objectives

1. Derive physics-based low computational cost models and design heuristics
2. Derive low computational cost surrogate models
3. Develop and evaluate strategies to combine expert knowledge and data-driven approaches to improve design space exploration

Expert knowledge:

- Physics laws
- Heuristics
- Beliefs

Combining expert knowledge and data in design of mechanical meta-materials

Evaluate various strategies in benchmark and real-world problems and provide guidelines about when to use them

while not converged do:

$f_i \leftarrow \text{SelectModel}(x_i; M)$

$y_i \leftarrow \text{ApplyModel}(x_i; f_i)$

$O_i \leftarrow \text{SelectOperator}(x_i; S)$

$x_i \leftarrow \text{ApplyOperator}(x_i; O_i)$

Model selection

- Pool of models (physics-based model, FEA simulation, surrogate model, or human-as-model)
- Screening and clustering
- Select model w/highest expected accuracy in region
- Weighted average, w_0 = beliefs, update with data

Operator selection

- Pool of operators (domain-independent, based on heuristics, physics laws, learned from data, or human-as-operator)
- Bandit-based adaptive operator selection