Surpassing Nuclear Fuel Designer Intelligence by Accelerating an AI Agent’s Optimization Strategy

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To combat climate change, nuclear energy must be made much more economic.

- Nuclear Power is the largest source of Carbon Free Energy in the United States
- Yet its economic viability is challenged in markets that do not reward emission-free reliable sources of electricity
- Nuclear reactor core design is a significant factor constraining the maintenance and development of reactors

AI methods accelerate the search for optimal designs, but simulation still poses a bottleneck.

- Since the 1960s, nuclear fuel designers have relied on engineering experience and human intelligence when choosing several attributes to meet complex safety objectives.
- Recent research has produced a reinforcement learning (RL) approach to tackle the multi-objective, combinatorial problem of optimizing reactor core design.
- This process consists of an AI agent that learns optimal reactor core designs by driving licensed nuclear safety tools (Seurin et al 2022).

Our multi-task deep learning model predicts three safety parameters normally obtained via slower simulation tools

- Convolutional Neural Networks (CNNs) have shown remarkable success in discovering prominent patterns in multi dimensional image data.
- We leverage CNNs for latent representation learning of nuclear reactor core patterns.
- By tuning a deep neural architecture, we encourage the network to learn a shared set of latent features from the input that helps predict our outputs.

Full optimization with physics simulation takes a week. Deep learning brings this down to a day.

- Montgomery Dropout technique allows model to be sampled for an uncertainty distribution.
- During agent training, UQ will decide when surrogate predictions are too uncertain.
- In these per core pattern cases, full simulation with licensed nuclear tools will be utilized instead.

Surrogate modelling is 84% faster than physics simulation codes during RL agent training.

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Acknowledgements

We would like to thank the MIT Summer Research Program for supporting this research.