AI for Nuclear Physics

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Impact and strategic value to the Laboratory's mission

AI & ML having large impact in a diverse array of science

Astrophysics



AstroCLIP: single, versatile model that can embed both galaxy images and spectra into a shared, physically meaningful latent space

Medical research



Fluid dynamics



	T = 0	T = 20	T = 40	T = 60	T = 80	T = 100
True	-	-	-	-	-	
FLUID- OPT125m	-		-	-	-	-
FLUID- OPT2.7b				-		-
DilResNet	-	-	-			Condition
GAT2Conv	-		-	-		-
MeshGraph Nets	-	-	-		-	

FLUID-LLM: a novel framework combining pretrained LLMs with spatiotemporal-aware encoding to predict unsteady fluid dynamics

The goal is to build expertise that utilizes artificial intelligence technologies, including Large Language Models, to realize the full potential of JLab domain data and to accelerate the lab's scientific program.

We will establish a new core capability in Foundation Models/LLMs/LLMs for NP



Level of innovation

Aim 1: R&D of data tokenization and embedding models



- Data collection
- Tokenization & simulation DB
- Develop embedding model

Work cannot be carried out under existing grants - only LDRD



Aim 2: R&D on updating open-source LLMs GPT models, including evaluation



- Additional pretraining of open-source LLMs & evaluation
- Systematic analysis of latent space

Outcomes:

- Well-placed for future data
- Embed into JLab community
- Disseminate research through seminars/workshops enable new use cases

Aim 3: R&D on using structured data for the fine tuning of data downstream applications



LLMs for PDFs



LLMs for JLab experimental data



- Task-specific fine-tuning
- Tune LLM & validate

Milestones

				FY24 FY25		;	-		
Aims	Objective number	Milestone	H1	H2	H1	H2			
	LQCD Milestone 1	Collect observables from spin-model simulations as numeric source for embedding model; Begin formulation of Self-Learning Monte Carlo (SLMC) is the two-dimension O(4) sigma model utilizing Self-Attention transformer; Renormalization Group flow of 2D O(4) nonlinear sigma models via Self-Attention transformers; Utilizing established training codes, characterize potential performance improvements for SLMC compared to established meth	ods						
1	PDF Milestone 1	Collect all the data available at LHAPDF; Generate PDF data for all the PDF s using the LHAPDF interpolation software across a dense grid in x and Q2 alor with their corresponding 1-sigma confidence bands; Design suitable tokenizati scheme that integrates the info file of the PDF sets, the associated arxiv docum and the PDF data; Train and validate the embedding models using the tokenizati LHAPDF corpus data.	ets g on ient d						
	JED Milestone 1	Simulate eP data using Pythia and generate a variety of phase space distribution Design suitable tokenization scheme that integrates the simulated event level data, the phase space distributions; Train and validate the embedding models; Collect real JLab data along with the associated publications and train and validate the embedding models.	ns;						
	Milestone 1	Identify and select research text and numeric data sources from the use cases							
	Milestone 2	The tokenized text and simulation data database from Milestone 1					Large Unlabeled JLab Corp	ous	
	Milestone 3	Develop a prototype of the embedding model.							
2	Milestone 1	Train the base, open-source LLMs in an unsupervised manner using JLab-spec unlabeled data, specifically, the vector database developed in Aim 1.	ific						
	Milestone 2	Carry out a systematic analysis of the latent space with existing tools.		\perp					
	Milestone 1	For the three use cases, develop the questions for the task-specific fine-tuning.							
3	Milestone 2	Tune the LLM and validate the data from Milestone 1.							
	Milestone 3	Evaluate the trained LLM from initial LLM and post-transfer learning. Evaluations will include accuracy, biases, training time, and generalizability.					Data Tokenization (1)	Nodel	
	1		1		i.	8		Task-Specific JLab LLM	3 Task fine tuning
Out	comes:								bedding Model
							Pretraining 2		Prepare a simulation for th
•	well-plac	ced for future data				Ba	se Model		Small LQCD Labeled Co
•	Embed in	ito JLab community			(Op	en-	Source LLM)		bedding Model
•	Dissemina	ate research through				J			Display the PDFs in the x
•					rin.	≻Ľ		Task-Specific	<numerical range=""> for the</numerical>
	seminars	/workshops - encourage			An		Domain Specific	JLAD LLIVI	following scales < list of cc
		Cases	TEVT	Embe	edding Mo	odel	(JLab LLM)		Small PDF Labeled Corp
				nlal	heled	Co	rous		edding Model
		Trair	ing via p	predi	icting m	asked	I values.	Task-Specific	List all the measurements (reaction < <i>reaction type</i> > a

Example: Training via [MASK] masked values.

Task-Specific

JLab LLM

reaction *<reaction type>* a

Small Experimental Data



Project team & responsibilities





Robert Edwards: Will oversee the project. Apply LLM methods to constructing

Nobuo Sato: Data encoding methods - connecting theory to expt. for PDF and

Kostas Orginos: AI/ML Simulation methods in Aim 1 for LQCD use case.

improved simulation methods in LQCD use case of Aim 1.

Theory Group:





Data Group:

JED use-case for year 1.

Diana McSpadden: Characterization of data encoding for all use cases. Will contribute to common year 1 milestones, and all year 2 milestones.



Postdoc:

TBD : Data and Theory Simulation analyst. Contribute to data-encoding of PDF & JLab Expt Data (JED) use cases. This 1.0 FTE could support two people.



Budget & justification

Different components under Aim 1 (1st year)

All team members share common milestones for Aims 2 & 3 (2nd year)

Team member	Role	Year 1	Year 2	Contribution
Robert Edwards	PI	20%	20%	Aim 1: LLM methods to construct improved simulation methods for LQCD
Diana McSpadden	Co-PI	40%	40%	Characterization of data encoding. Lead pre-training of LLMs & evaluation
Kostas Orginos	Co-PI	20%	0	AI/ML simulations in Aim 1. Common milestones in year 2
Nobuo Sato	Co-PI	5%	5%	Data encoding methods: theory-expt for PDF & Events use-case in Aim 1
TBD	Postdoc	100%	100%	Data & Theory simulation analyst

Budget	Total	FY24	FY25	FY26	
(\$K)	562	0	294	268	



Potential future funding (Beyond LDRD)

FOA:

- DOE/NP has plans to release in the fall an FOA on the topic "AI in Nuclear Physics"
- As understood, intention is for NP to build capability & utilize AI for range of topics
- Likely LLMs will be central to the call

Potential future directions for proposals:

- Application of Attention technologies for LGT simulations
- R&D for Foundational Models that integrate coherently all data from JLab for Expt.& Theory
- Development of AI Agents for Nuc. Theory research

Why us? Why now?

- Lab needs experience & capabilities
- Al or Die...



DOE Press Releases

Office of

CRITICAL AND EMERGING TECHNOLOGIES

- U.S. Department of Energy Announces \$18 Million to Advance Particle Accelerator Technologies and Workforce Training (March 2021)
- DOE Announces \$37 Million for Artificial Intelligence and Machine Learning at DOE Scientific User Facilities (August 2020)

NP Funding Opportunity Announcements & Awards Lists

- Data, Artificial Intelligence, and Machine Learning at Scientific User Facilities (LAB 20-2261 FOA), (Award List), 2020.
- Data Analytics for Autonomous Optimization and Control of Accelerators and Detectors (FOA-0002490), 2021.
- Artificial intelligence and Machine Learning for Autonomous Optimization and Control of Accelerators and Detectors (DE-FOA-0002875), 2023.







Example: Self-Attention Transformers

Accessing smaller lattice spacings critical to physics program. Critical slowing down - exponential growth in cost. Eliminated in a 2d fermionic model.

Attention: https://doi.org/10.48550/arXiv.1706.03762

Self-learning Monte Carlo with equivariant Transformer https://arxiv.org/pdf/2306.11527







Example: AstroCLIP

AstroCLIP https://doi.org/10.1093/mnras/stae1450



https://arxiv.org/html/2310.03024v2

Figure 1: Illustration of the *AstroCLIP* cross-modal training strategy. This approach consists of two steps. First, galaxy images and spectra are embedded separately by pretraining both an image and a spectrum encoder in a SSL setting. Then, these encoders are aligned using a cross-modal contrastive loss. Once aligned, these embeddings allow us to connect and compare cross-modal representations. Moreover, they possess physically meaningful high-level information which can be used for a variety of downstream tasks on which the model was neither trained nor fine-tuned.



Example: Med-PaLM

Med-PaLM

A large language model from Google Research, designed for the medical domain.

Singhal, K., Azizi, S., Tu, T. *et al.* Large language models encode clinical knowledge. *Nature* 620, 172–180 (2023). <u>https://doi.org/10.1038/s41586-023-06291-</u> <u>2</u>





Findings:

- · Devices: None.
- Lungs: No pneumothorax. No substantial pleural effusion. Lungs appear clear.
- Cardiomediastinal: Normal heart size. Mediastinal contours within normal limits.
- Other: No acute skeletal abnormality.

Impression:

No active disease seen in chest.



FLUID-LLM: Learning Computational Fluid Dynamics with Spatiotemporal-aware Large Language Models





The presentations of the FY25 LDRD proposals are scheduled for Friday, July 26, 2024, starting at 11:00 AM. The agenda is attached. Each presentation is scheduled for exactly 10 minutes, followed by 5 minutes of questions from the committee. Susan is creating an Indico page where you will need to upload your presentation by July 26 at 10:00 AM.

In addition to the project description, scope, and team, your presentations should address the following:

- Impact and strategic value to the Laboratory's mission
- Level of innovation
- Deliverables with corresponding timeline and milestones
- Budget and budget justification
- Potential future funding (Beyond LDRD)

The meeting will be in B207, and you will need to be there only for your presentation. Let me know if you have any questions.

