BART-Lagrangian [BART-L]

When Transformers Write Particle Physics Lagrangians

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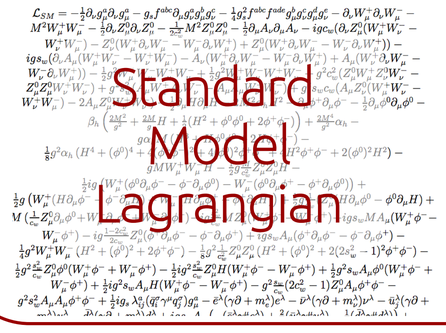
Based on work done in [1]

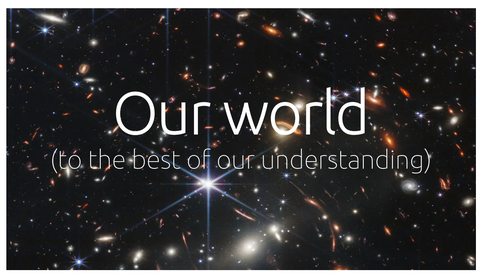
Can Transformers write Lagrangians?

YES!

Try it out yourself!

In particle physics, the Lagrangian serves as the fundamental mathematical object from which all interactions and predictions of a theory are derived. For example:





How does it work?

Natural Langauge : Never Gonna Give You Up ...

Lagrangians : $D_\mu \Phi^\dagger D^\mu \Phi + m^2 \Phi^\dagger \Phi + \lambda \Phi^\dagger \Phi \Phi^\dagger \Phi + \lambda' \Phi \Phi'' \Phi''' + i \Psi^\dagger_L \bar{\sigma}^\mu D_\mu \Psi_L \ldots$

Data Generation

Given the symmetries and particle content, one can write the symmetry conserving Lagrangian

Fields → AutoEFT [2] → Lagrangians

Model Task

Transformers works great with natural language, it should work great for a physicist's Language too!

Tokenized Fields → BART-L → Tokenized Lagrangians

Bidirectional and Auto-Regressive Transformer - Lagrangians

Example Tokenization Scheme

Object	Tokens
$\phi(\mathbf{3}, \mathbf{2}, -1/3)$	FIELD, SPIN, 0, SU3, -, 3, SU2, 2, U1, -, 1, /, 3, ID3
$\psi_L(\bar{\mathbf{1}}, \mathbf{3}, 0)$	FIELD, SPIN, 1, /, 2, SU2, 3, HEL, 1, /, 2, ID9
$\phi^\dagger(\mathbf{1}, \mathbf{1}, 7/5)$	FIELD, SPIN, 0, U1, 7, /, 5, DAGGER, ID7
$D_\mu^{(SU(2),U(1))}$	DERIVATIVE, SU2, U1, ID4
$D_\mu^{(SU(3),SU(2),U(1))}$	DERIVATIVE, SU3, SU2, U1, ID1
∂_μ	DERIVATIVE, ID5
$\bar{\sigma}^\mu$	SIGMA_BAR, ID2
$g^{\mu\nu}$	LORENTZ, ID6, ID4
ϵ^{ab}	SU2, ID0, ID7

Term : $\lambda\, \phi\, \phi^\dagger\, \Phi\, \Phi^\dagger$

Information	Tokens
λ	
$\phi(\mathbf{3}, \mathbf{2}, 6)$	FIELD, SPIN, 0, SU3, 3, SU2, 3, U1, 6, ID5
$\phi^\dagger(\bar{\mathbf{3}}, \mathbf{2}, -6)$	FIELD, SPIN, 0, SU3, -, 3, SU2, 3, U1, -, 6, DAGGER, ID7
$\Phi(\bar{\mathbf{3}}, \mathbf{1}, -7/2)$	FIELD, SPIN, 0, SU3, -, 3, U1, -, 7, /, 2, ID8
$\Phi^\dagger(\mathbf{3}, \mathbf{1}, 7/2)$	FIELD, SPIN, 0, SU3, 3, U1, 7, /, 2, DAGGER, ID2
	CONTRACTIONS
$\epsilon^{a_1 b_2 c_2}\ \phi_{a_1}\ \phi^\dagger_{b_1 b_2}\ \Phi_{c_1 c_2}\ \Phi^\dagger_{d_1}$	SU3, ID5, ID7, ID8
$\epsilon^{b_1 c_1 d_1}\ \phi_{a_1}\ \phi^\dagger_{b_1 b_2}\ \Phi_{c_1 c_2}\ \Phi^\dagger_{d_1}$	SU3, ID7, ID8, ID2
$\epsilon^{a_1 b_1}\ \phi_{a_1 a_2}\ \phi^\dagger_{b_1 b_2}\ \Phi\ \Phi^\dagger$	SU2, ID5, ID7
$\epsilon^{a_2 b_2}\ \phi_{a_1 a_2}\ \phi^\dagger_{b_1 b_2}\ \Phi\ \Phi^\dagger$	SU2, ID5, ID7

But why?

It's all about what comes next!

"What you did is a solved problem!"

BSM Extension Recommender

(Ongoing)

Known Fields & Extra Fields Requirement → BART-L+ → BSM Extension

Possible Directions

Lagrangian Autocomplete: Incomplete Lagrangian → AI → Complete Lagrangian

Symmetry Finder: Particle Content → AI → Lagrangian w/ Extra Symmetry

Symmetry Restoration: Symmetry Broken Lagrangian → AI → Symmetry Restored Lagrangian

Direct Data BSM Inference :
Large Language Model → pictures to words
Large Lagrangian Model → experimental data to Lagrangians

Experimental Data! → AI → Beyond Standard Model Lagrangian

Foundational model for *all* of particle physics : It must incorporate symbolic expressions - the language we use to describe and make sense of the universe – as a modality

Numerical Data ← Foundation models → Symbolic Language

Performance : How good is it?

Accuracy ≥90%

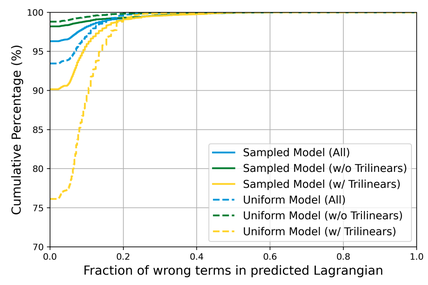
(Percentage of Dataset with $S_{Lagrangian} = 1$)

	Sampled Model	Uniform Model
Sampled Dataset	93.4%	89.9%
Uniform Dataset	90.5%	96.6%
Merged Dataset	92.0%	93.2%

$$S_{Lagrangian} = \frac{N^{Terms}_{Correct} - N^{Terms}_{Extra}}{N^{Terms}_{Expected}}$$

Tend to miss Yukawa Terms due to lack of Lagrangians involving many Yukawa Terms in training data (Solvable!)

Examples	Best $S_{Lagrangian}$
Lepton Sector	1
Quark Sector	1
Higgs + Leptons	1
Higgs + Quarks	0.86
Standard Model	0.77
2HDM	0.81
Georgi-Machacek	0.90
RPV-MSSM LLE	1
RPV-MSSM UDD	0.88
RPV-MSSM LQD	0.78

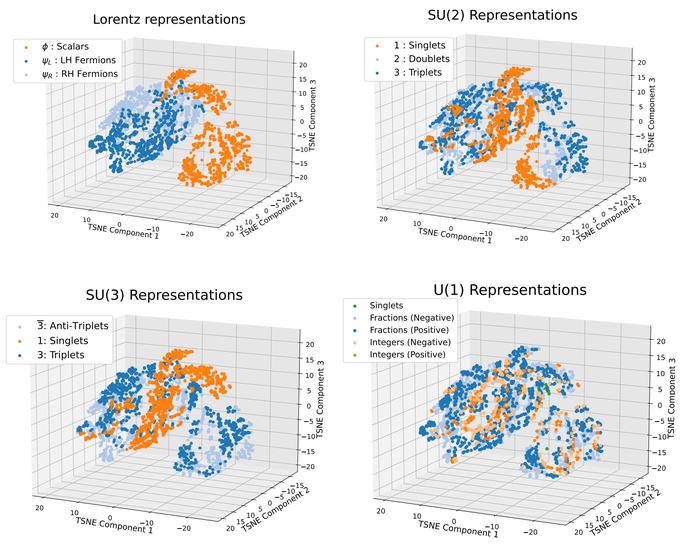


Embedding Analysis : What did it learn?

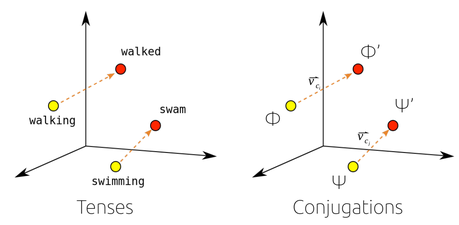
Symmetries!

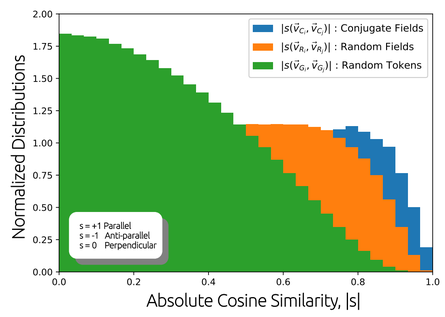
Despite being trained only to generate Lagrangians, the model has learned symmetry representations and conjugation transformations!

Field Embeddings



Vector Offset Method

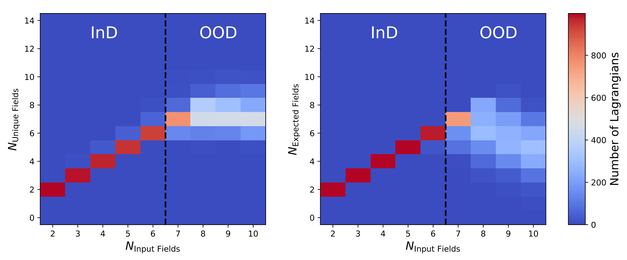




Out-of-Distribution (OOD) : Can it work with...

...more fields? YES! But it can't count properly

In-Distribution (Train) : ≤6 Fields
Out-of-Distribution (Test) : 7-10 Fields

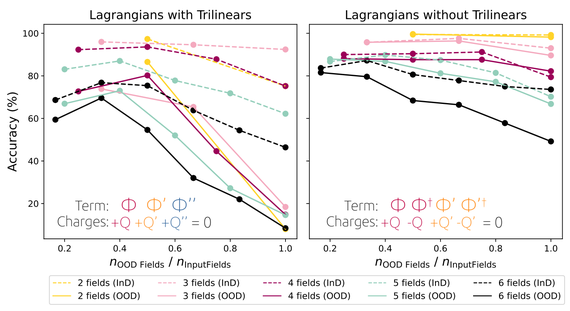


It knows there should be more fields in the Lagrangian, but it doesn't know how many (plateau at ~7)

BART's bidirectional encoder are known to struggle with contextual counting tasks [3]

...non-minimal charges? YES! But it can't do arithmetic

In-Distribution (Train) : Q = ½, 2, -7/2, ...
Out-of-Distribution (Test) : Q = 2/4, 6/2, 3/9, ...



It struggles with Lagrangians involving Trilinears because arithmetic is required for charge conservation in Trilinear terms while it's just pattern recognition for others!

Text-based encoding schemes for numbers are prone to take advantage of spurious correlations in the data [4]

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References

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3) S. Golkar, A. Bietti, M. Pettee, M. Eickenberg, M. Cranmer, K. Hirashima, G. Krawezik, N. Lourie, M. McCabe, R. Morel et al., Contextual counting: A mechanistic study of transformers on a quantitative task, arXiv preprint arXiv:2406.02585 (2024).
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