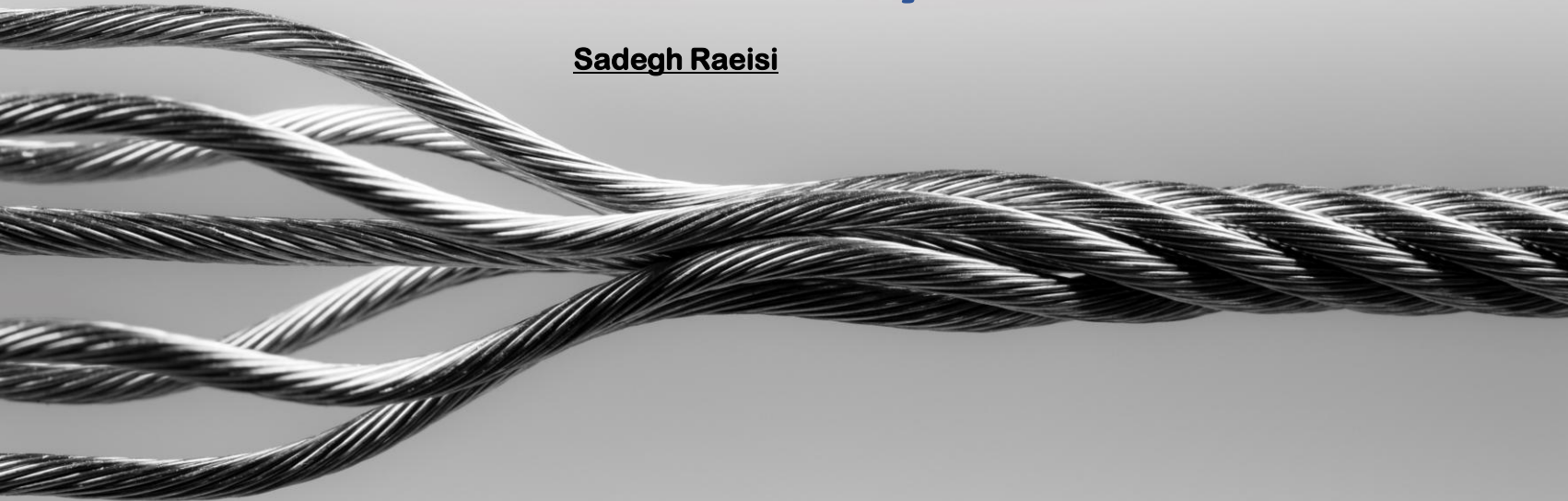


ML in Physics

Sadegh Raeisi



Outline



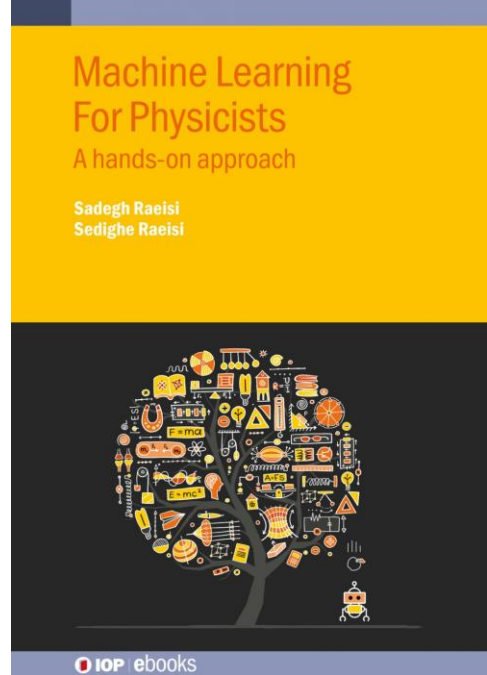
ML in science

ML in Physics

ML in my research

Some resources

https://github.com/sraeisi/MachineLearning_Physics



ML in Science: Protein Folding

nature

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[nature](#) > [articles](#) > [article](#)

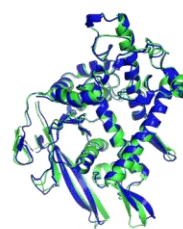
Article | [Open Access](#) | Published: 15 July 2021

Highly accurate protein structure prediction with AlphaFold

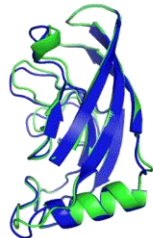
John Jumper , Richard Evans, [...] Demis Hassabis 

Nature **596**, 583–589 (2021) | [Cite this article](#)

336k Accesses | **2765** Altmetric | [Metrics](#)



T1037 / 6vr4
90.7 GDT
(RNA polymerase domain)

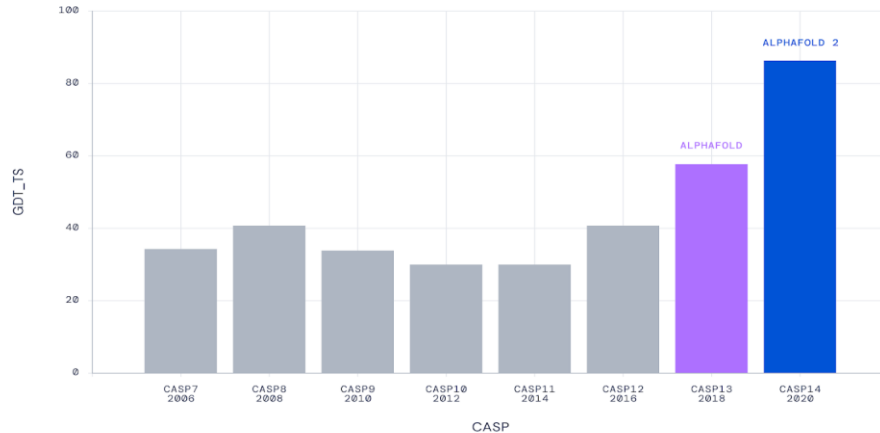


T1049 / 6y4f
93.3 GDT
(adhesin tip)

● Experimental result
● Computational prediction

ML in Science: Protein Folding

Median Free-Modelling Accuracy



ML in Science: Drug discovery

nature biomedical engineering

nature communication nature reviews gastroenterology

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nature > nature biomedical engineering > articles > article

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nature > nature reviews gastroenterology & hepatology > r

Article | [Open Access](#) | Published: 12 July 2021

Artificial intelligence for protective therapy in

Debashis Sahoo , Lee Swanson, Ibrahim M. Rama F. Pranadinata, Courtney Tindle, MacL Sandborn, Soumita Das  & Pradipta Ghos

Nature Communications **12**, Article number

5285 Accesses | 157 Altmetric | [Metrics](#)

Review Article | Published: 03 January 2020

Harnessing big ‘omics’ data and in hepatocellular carcinoma


Bin Chen , Lana Garmire, Diego F. Calvisi, Mei-Sze Chua, Rol

Nature Reviews Gastroenterology & Hepatology **17**, 238–251 (

4354 Accesses | 24 Citations | 48 Altmetric | [Metrics](#)

Article | Published: 15 April 2021

Optimization of therapeutic antibodies by predicting antigen specificity from antibody sequence via deep learning

Derek M. Mason, Simon Friedensohn, Cédric R. Weber, Christian Jordi, Bastian Wagner, Simon M. Meng, Roy A. Ehling, Lucia Bonati, Jan Dahinden, Pablo Gainza, Bruno E. Correia & Sai T. Reddy 

Nature Biomedical Engineering **5**, 600–612 (2021) | [Cite this article](#)

4788 Accesses | 2 Citations | 145 Altmetric | [Metrics](#)

ML in Science: Mathematics

NewScientist

Volume 242, Issue 3228, 4 May 2019, Page 9

News & Technology

Machine learning

Google's AI mathematician

Leah Crane

Artificial intelligence trained by google
learns to prove 1200 theorems.

HOList: An Environment for Machine Learning of Higher-Order Theorem Proving

Kshitij Bansal, Sarah M. Loos, Markus N. Rabe, Christian Szegedy, Stewart Wilcox

We present an environment, benchmark, and deep learning driven automated theorem prover for higher-order logic. Higher-order interactive theorem provers enable the formalization of arbitrary mathematical theories and thereby present an interesting, open-ended challenge for deep learning. We provide an open-source framework based on the HOL Light theorem prover that can be used as a reinforcement learning environment. HOL Light comes with a broad coverage of basic mathematical theorems on calculus and the formal proof of the Kepler conjecture, from which we derive a challenging benchmark for automated reasoning. We also present a deep reinforcement learning driven automated theorem prover, DeepHOL, with strong initial results on this benchmark.

Comments: Accepted at ICML 2019

Subjects: **Logic in Computer Science (cs.LO)**; Artificial Intelligence (cs.AI); Machine Learning (cs.LG)

Cite as: [arXiv:1904.03241](https://arxiv.org/abs/1904.03241) [cs.LO]

(or [arXiv:1904.03241v3](https://arxiv.org/abs/1904.03241v3) [cs.LO] for this version)

[\[1904.03241\]](https://arxiv.org/abs/1904.03241) [HOList: An Environment
for Machine Learning of Higher-Order
Theorem Proving \(arxiv.org\)](https://arxiv.org/abs/1904.03241)

ML in Science: writing books

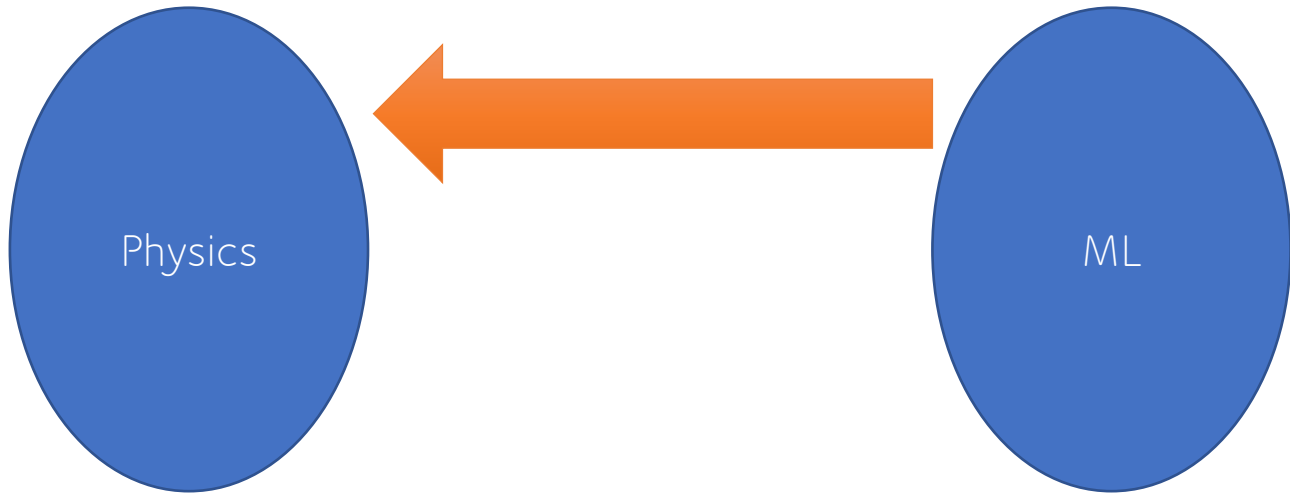
Lithium-Ion Batteries

A Machine-Generated Summary of
Current Research

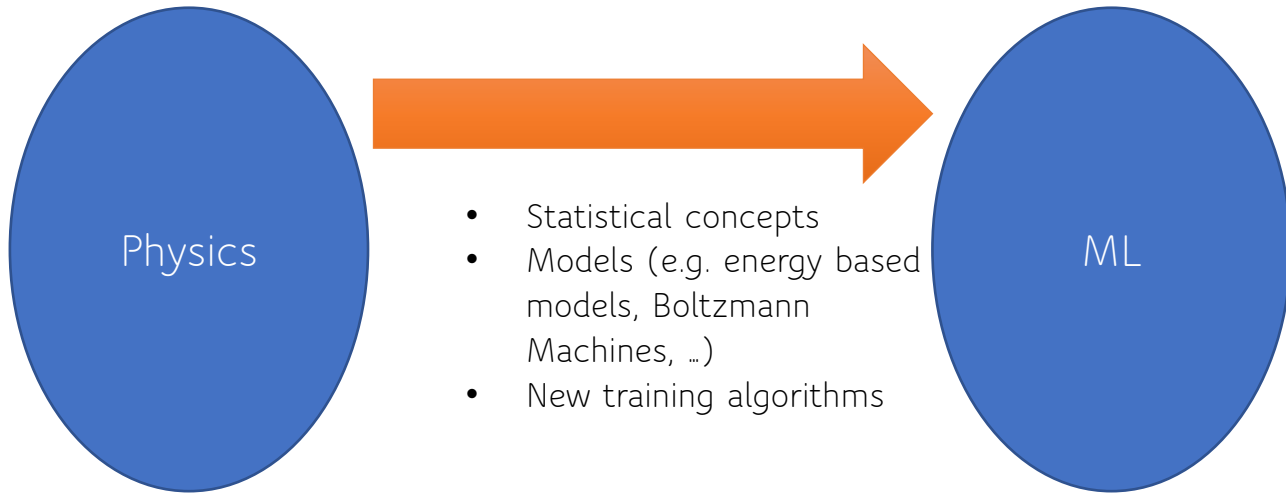
Can machines replace scientists?

What are the key aspects that cannot be replaced?

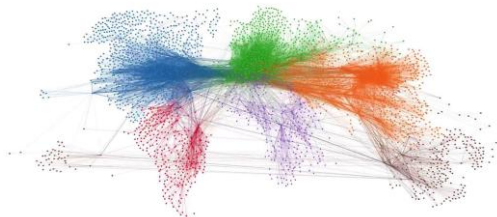
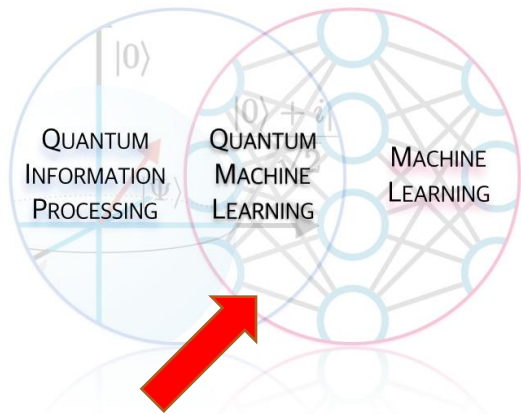
ML in Physics



ML in Physics



Some of my works

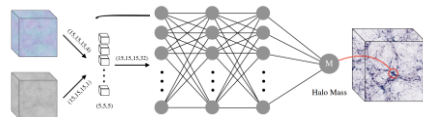


complex networks

Fake news detection

Information spreading

Collaboration with Dr. Ghanbarnejad



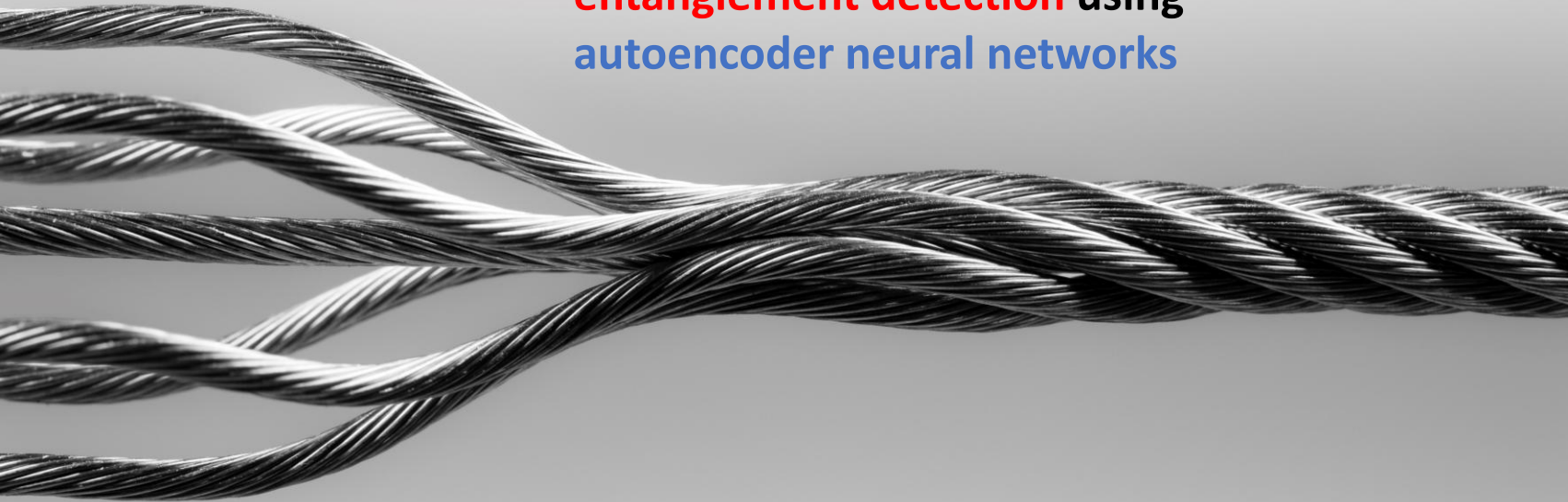
Cosmology: Structure formation
Collaboration with Dr. Baghran

Classification of variable stars
Collaboration with Dr. Rahvar

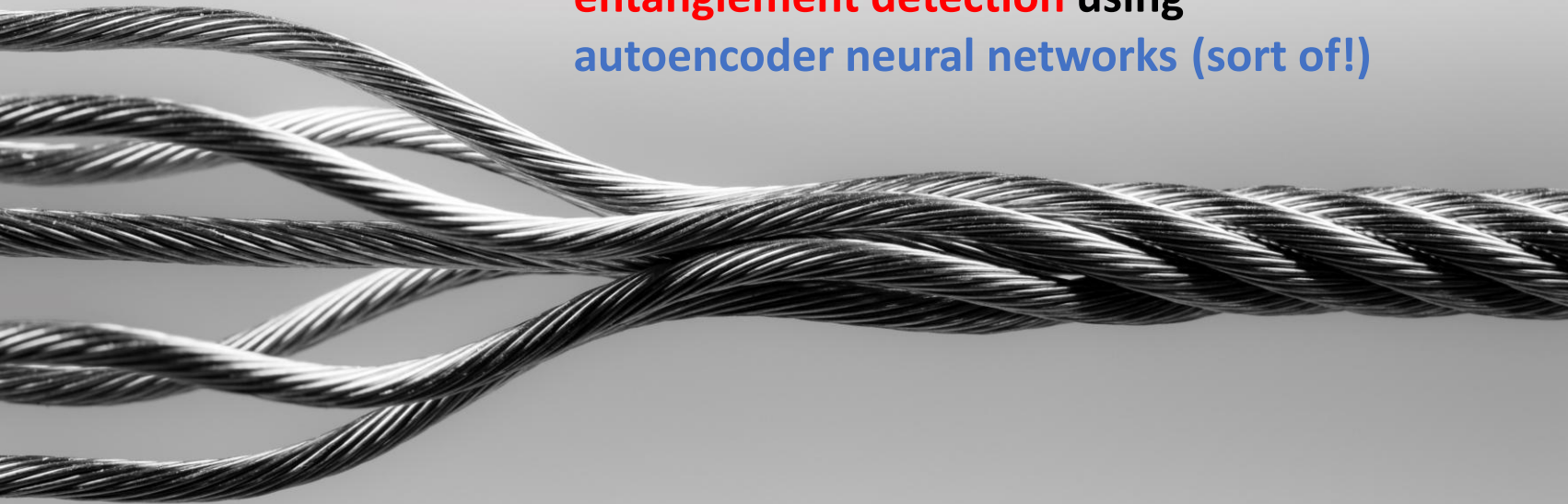
[Quantum Machine Learning: Path to a Better Artificial Intelligence? - QML](#)

Silva, F., and L. da F. Costa. "Visualizing Complex Networks (CDT-5)." *Costa's Didactic Texts-CDTs* (2018).

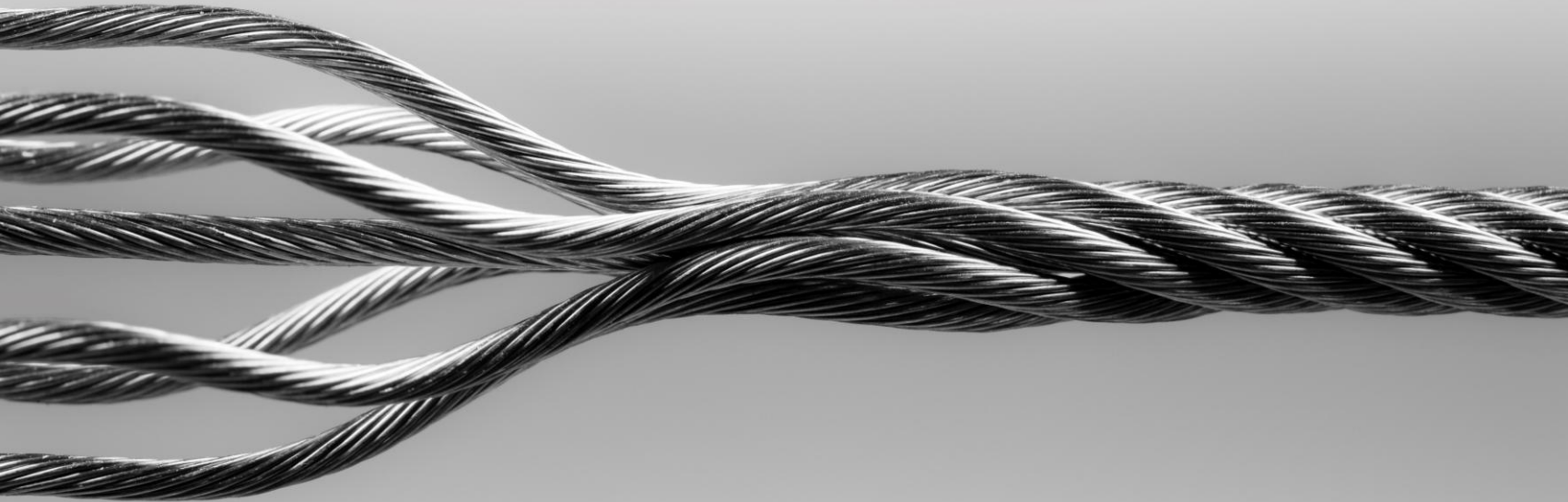
Finding semi-optimal measurements for
entanglement detection using
autoencoder neural networks



Finding semi-optimal measurements for
entanglement detection using
autoencoder neural networks (sort of!)



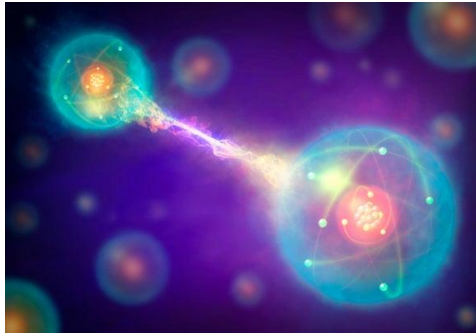
What should I measure in the lab?



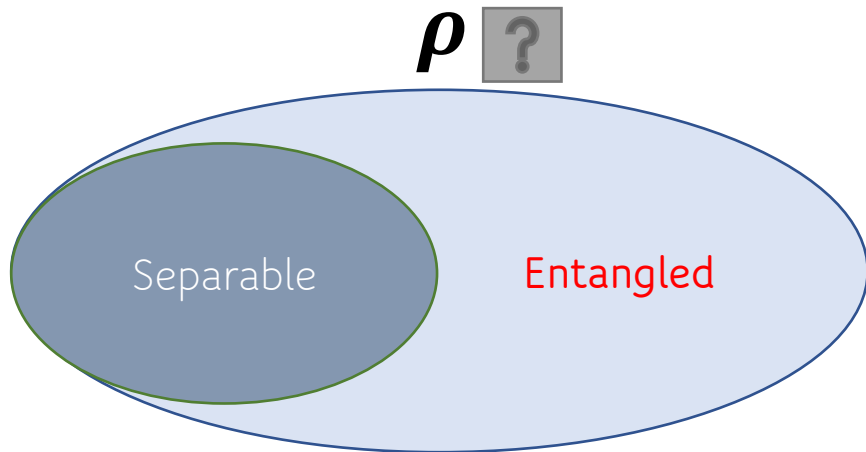
Quantum States



Entanglement is a **MAGIC** property
that is of interest in many
Quant. Tech.



Entanglement



Entanglement Detection

ρ 

15 measurements are
needed to decide!
(for the smallest case)

Problem:

15 measurement is too many!!

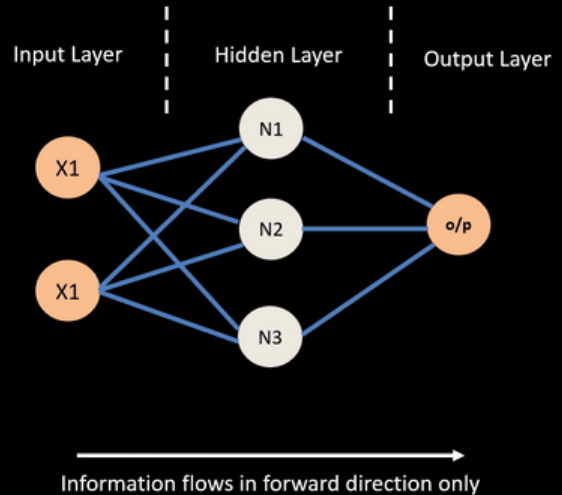
Can we do it with fewer measurements?

Problem:

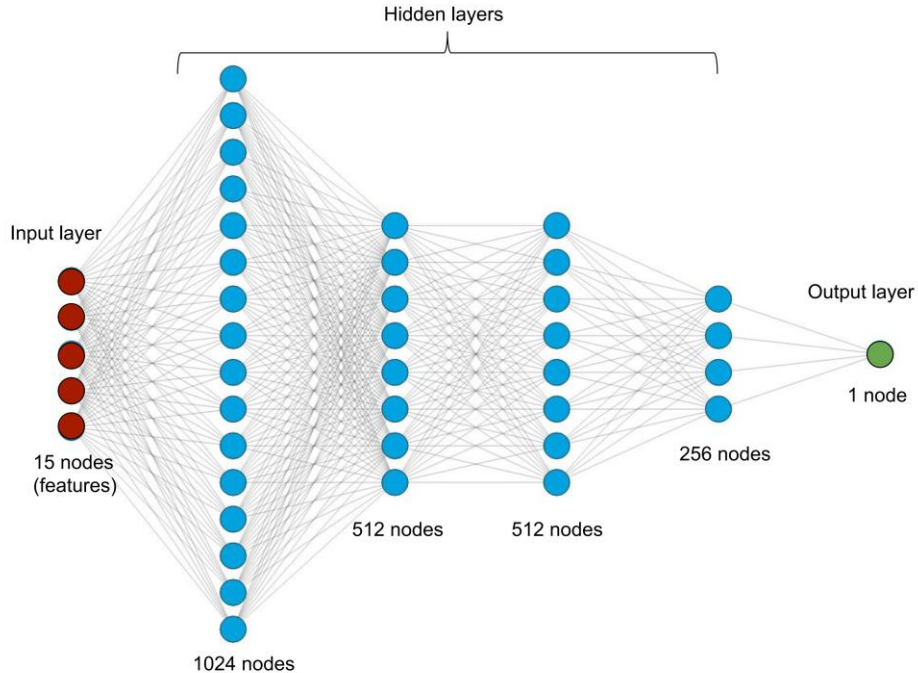
Which measurements are
most informative
for
Entanglement detection?

Autoencoder Neural Network

Neural Network

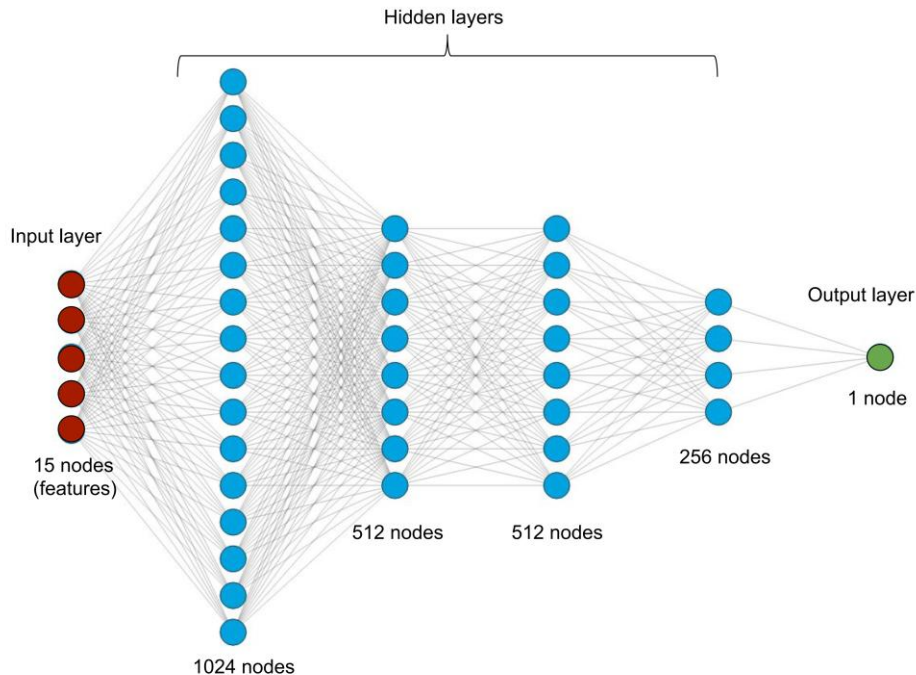


Neural Network for entanglement

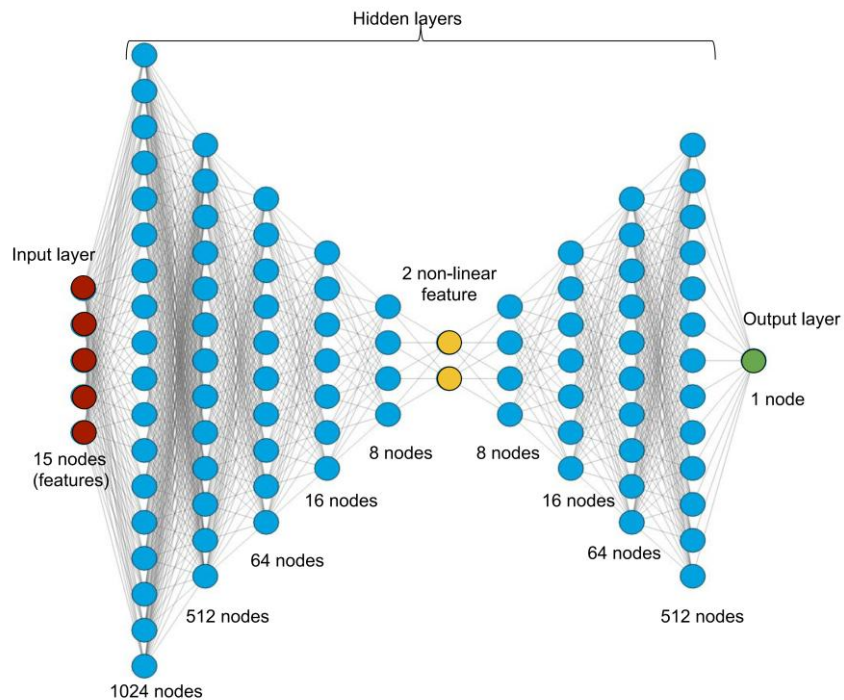


Neural Network for entanglement

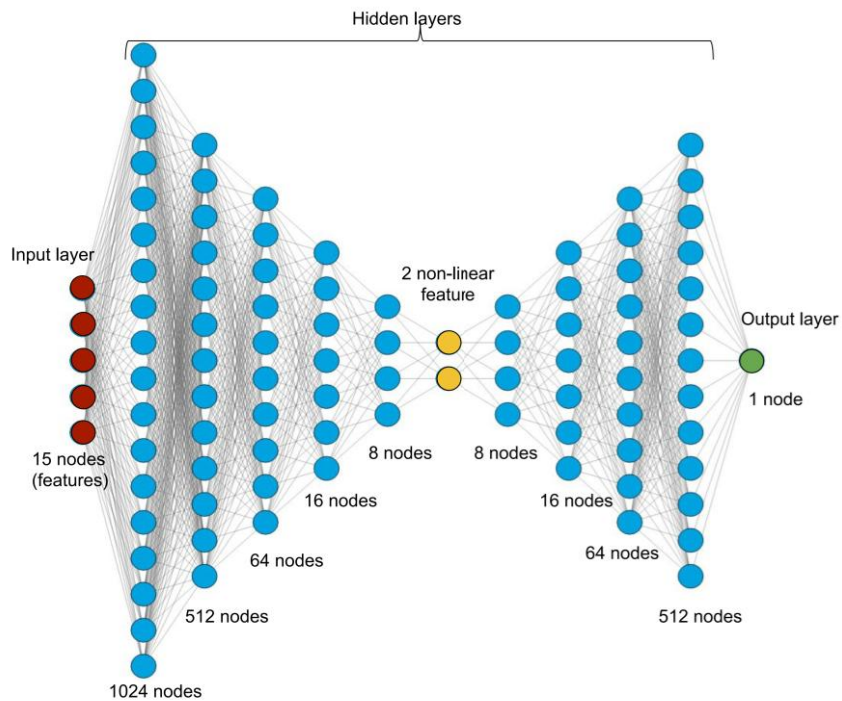
99.7% Accuracy



Autoencoder NN

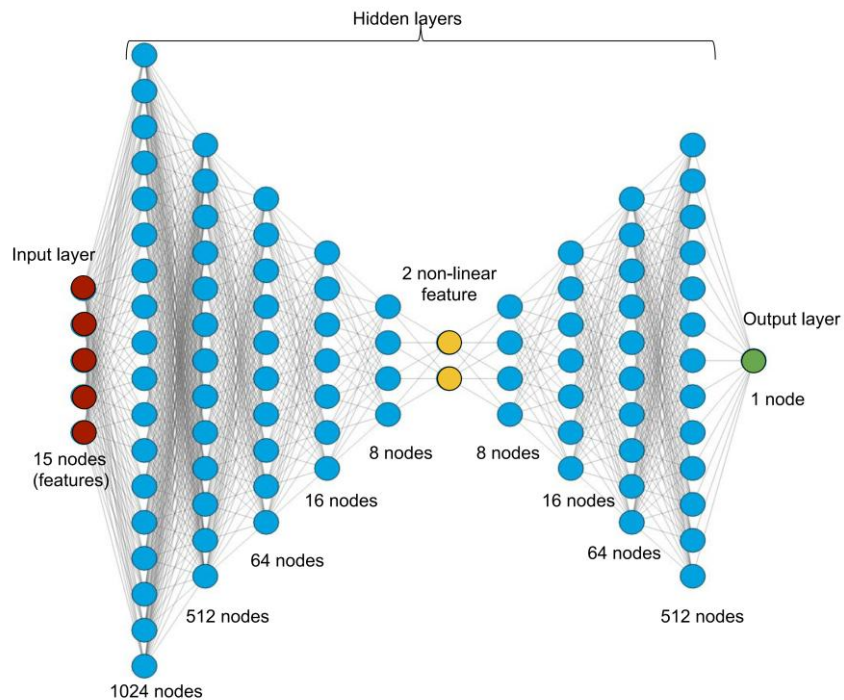


Autoencoder NN



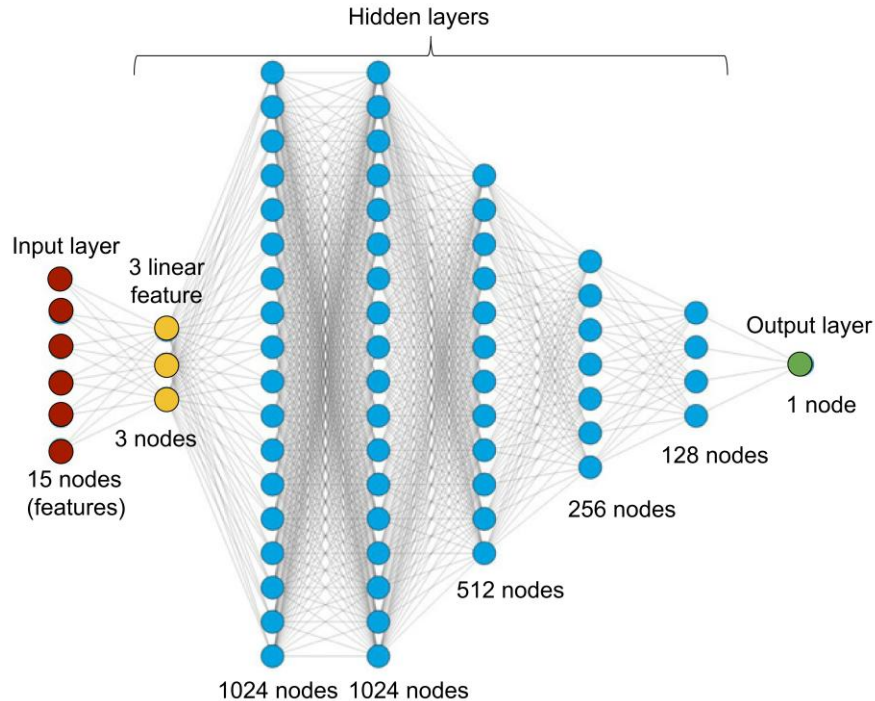
Autoencoder NN

99% Accuracy

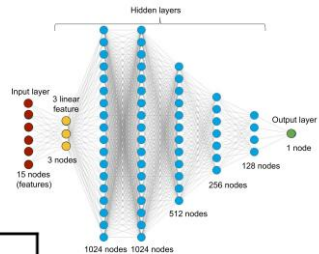
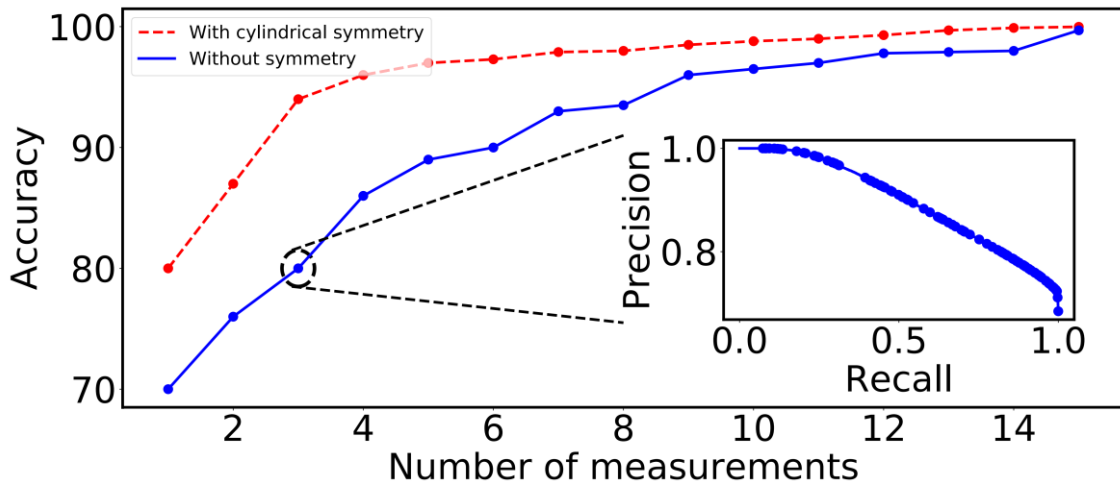


Autoencoder NN: Linear Measurements

80% Accuracy

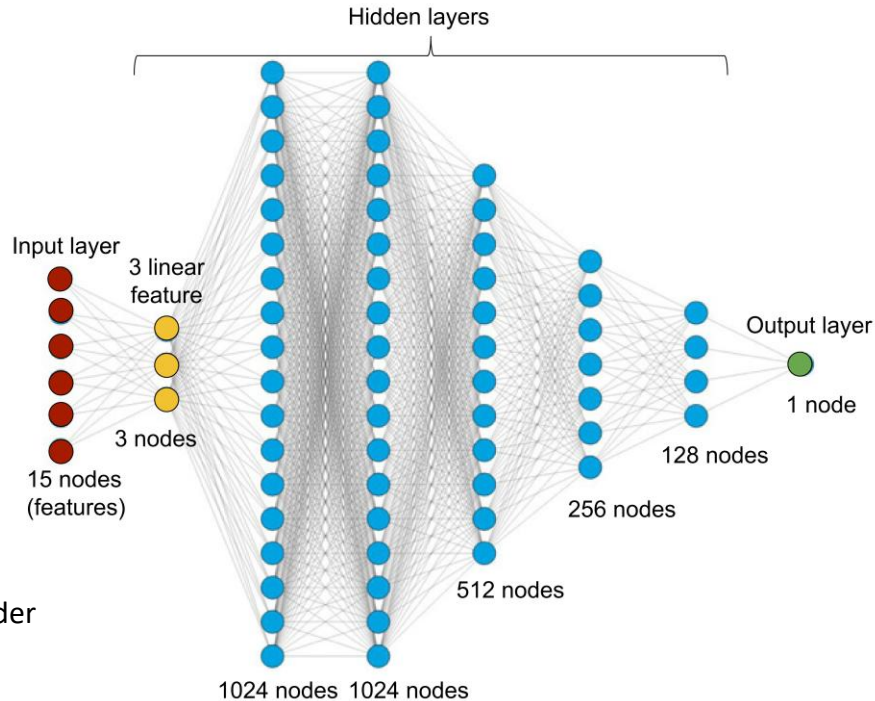


Results



Conclusion

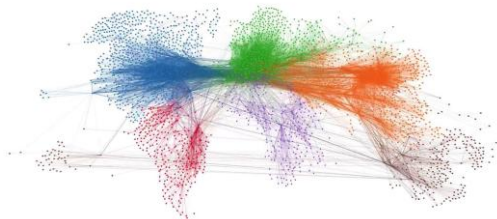
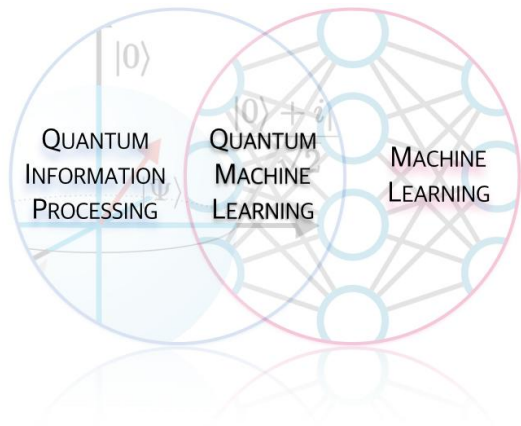
Model	Accuracy
All 15 measurements	99.7%
2 non-linear measurements	99 %
3 linear measurements	80%
4 linear measurements (cyl. symmetry)	99%
3 linear measurements (cyl. symmetry)	96 %
2 linear measurements (cyl. symmetry)	93 %
1 linear measurement (cyl. symmetry)	90 %



M. Yosefpor, M. R. Mostaan, **S. Raeisi** "Finding Semi-optimal Measurements for Entanglement Detection Using Autoencoder Neural Networks", *Quantum Sci. Technol.* 5 045006 (2020)

<https://doi.org/10.1088/2058-9565/aba34c>

Some of my works

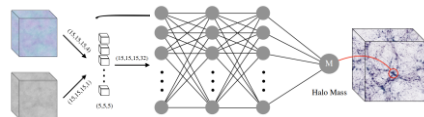


complex networks

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[Quantum Machine Learning: Path to a Better Artificial Intelligence? - QML](#)

Silva, F., and L. da F. Costa. "Visualizing Complex Networks (CDT-5)." *Costa's Didactic Texts-CDTs* (2018).

Some resources

https://github.com/sraeisi/MachineLearning_Physics

Machine Learning For Physicists

A hands-on approach

Sadegh Raeisi
Sedighe Raeisi



IOP ebooks

<https://store.ioppublishing.org/page/detail/Machine-Learning-For-Physicists//?k=9780750349550>