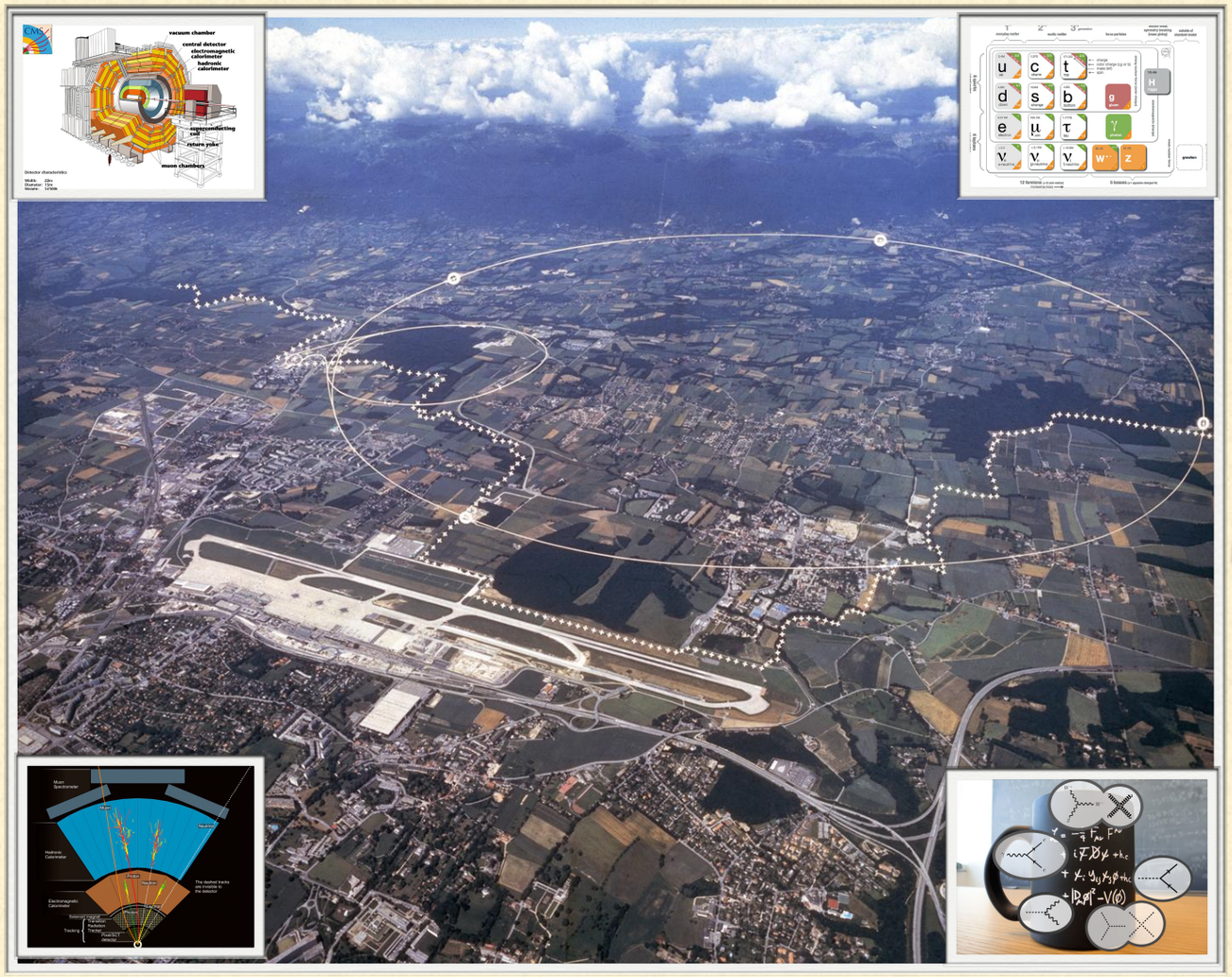
The AI/ML Driven Future of Particle Physics and Cosmology



Partha Konar
THEPH @ PRL

https://www.prl.res.in/~konar/

Partha Konar,
Monalisa Patra,
Sanmay Ganguly

<=========== 75 min ===========>

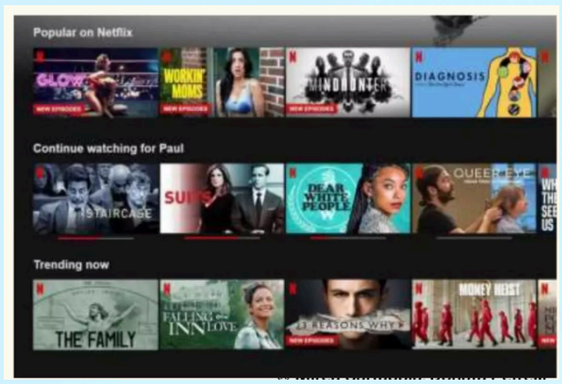
Centre for High Energy Physics

Frontiers of Particle Physics

August 9-11, 2024

While world is mesmerised with different impossibles
done with ML applications in our everyday life,

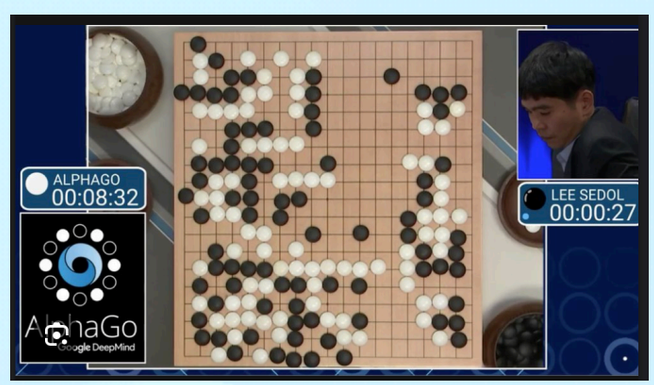
Content Recommendation



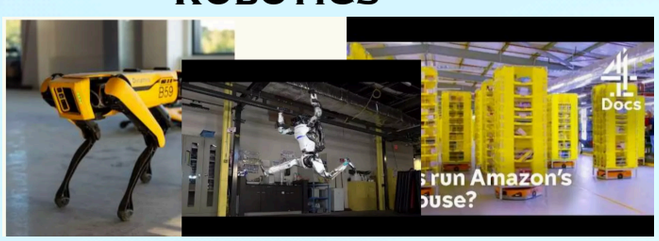
Self-driving Car

Face Recognition

Gaming



Robotics



Creativity Culture music

Virtual Assistance

Artificial Intelligence in Everyday Apps

Predictive Search

Object Detection

News Feed Relevance

Recommendations

Matching Algorithm

Smart Replies

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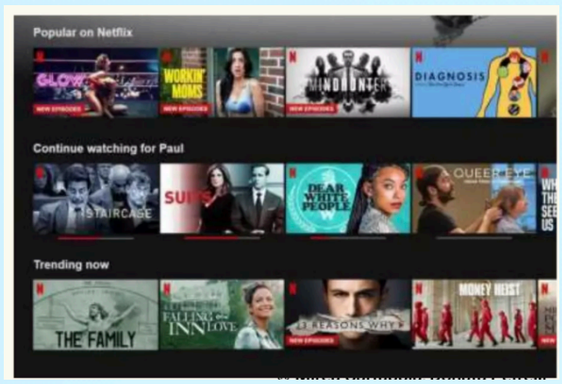

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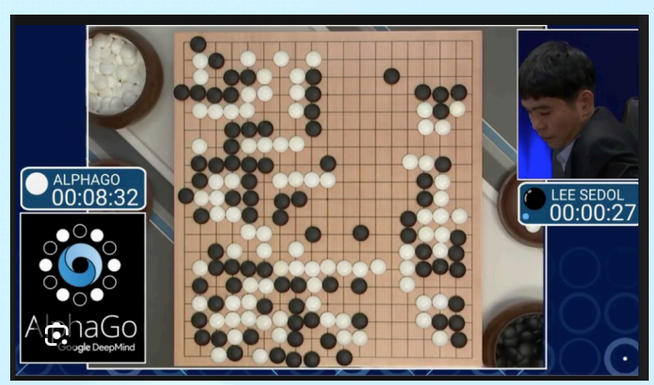

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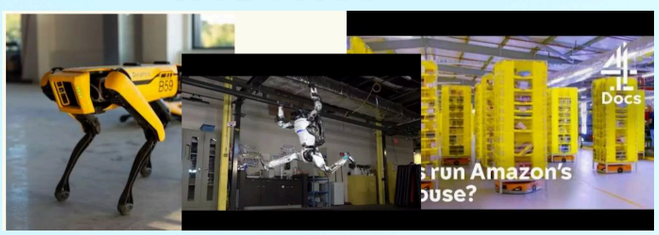

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including Healthcare, Medicine, Finance, Education services etc

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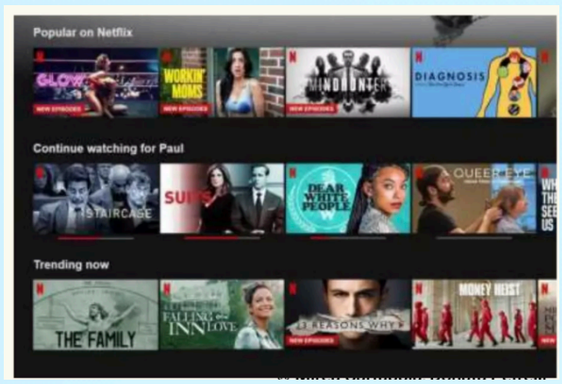

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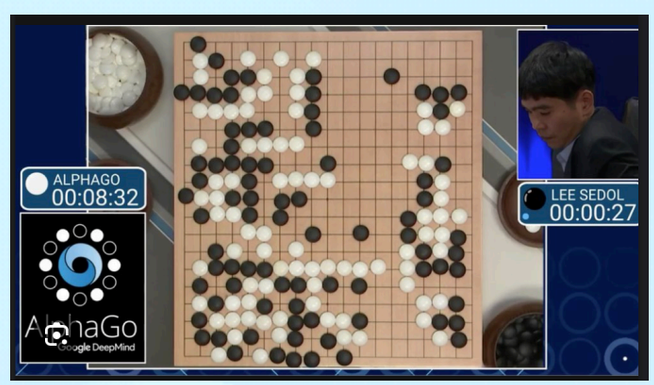

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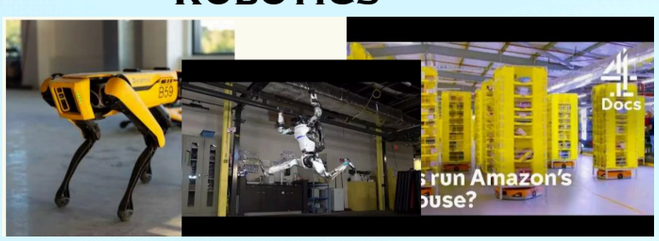

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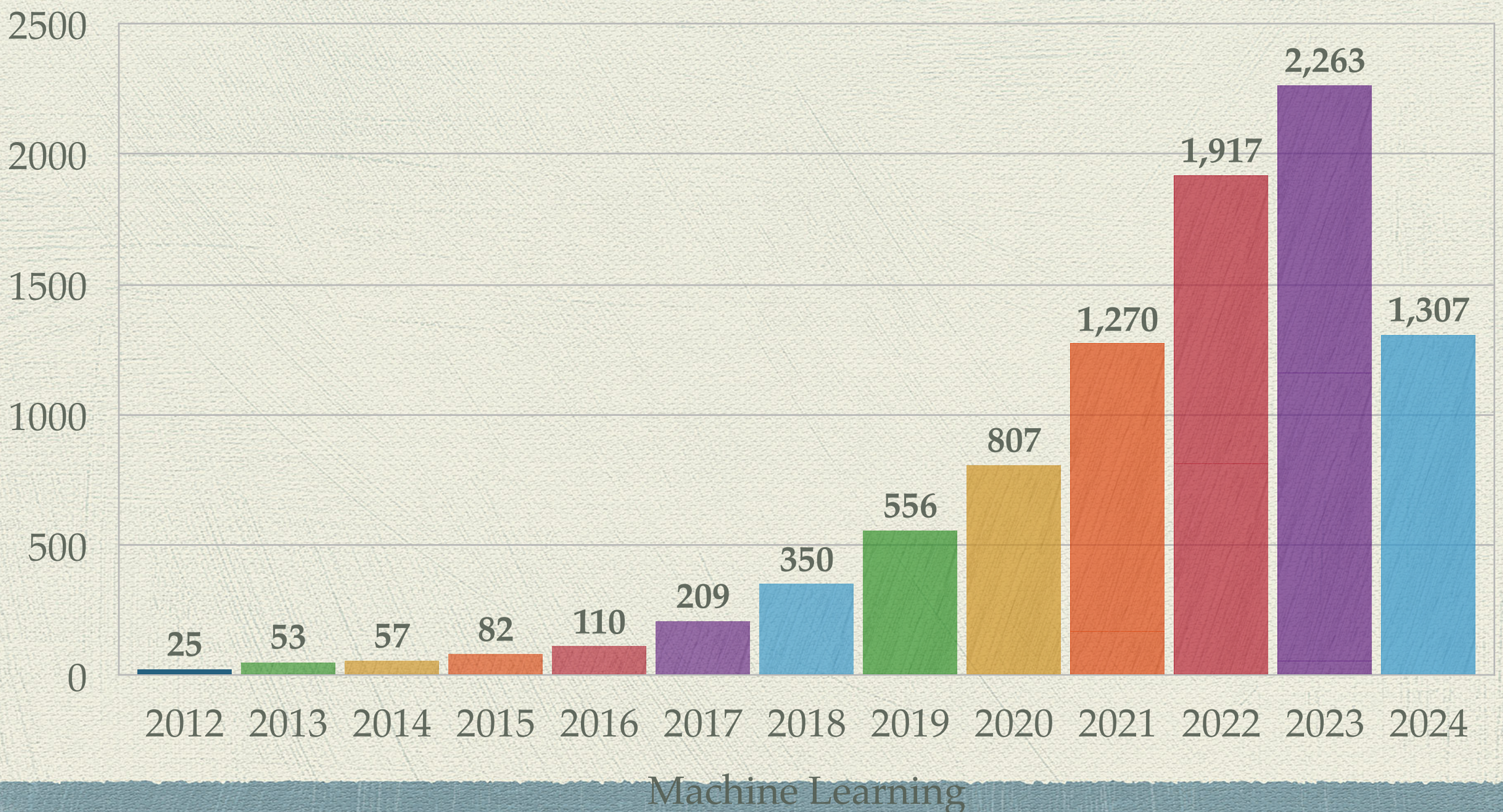
Several experimental results found their relevance — such scientific discoveries are ML driven


2500
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2012
2013
2014
2015
2016
2017
2018
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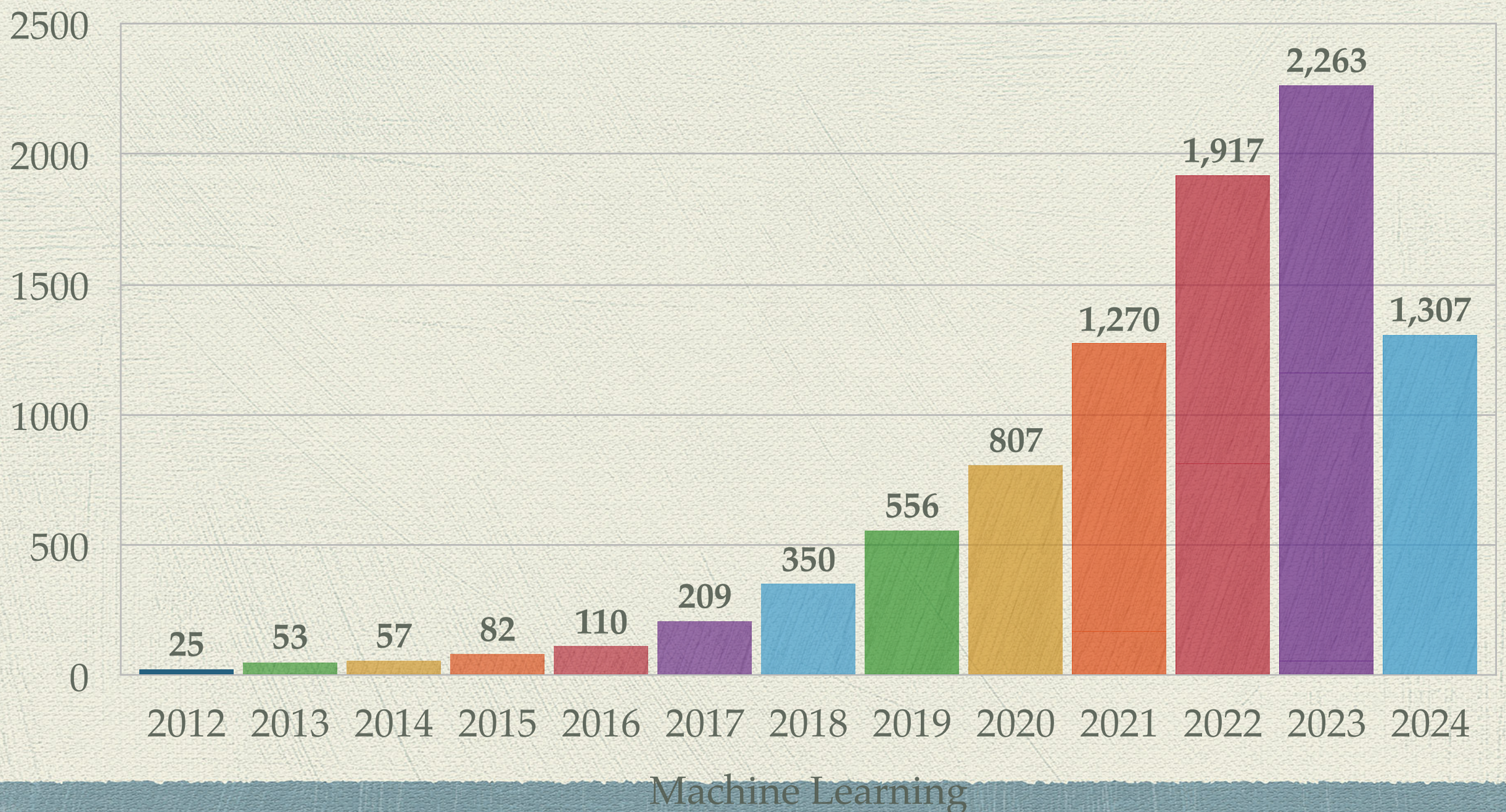
2021
2022
2023
2024
Machine Learning

- Inspire-HEP literatures with `machine learning'

2012 => 2024 : increased by 90 times



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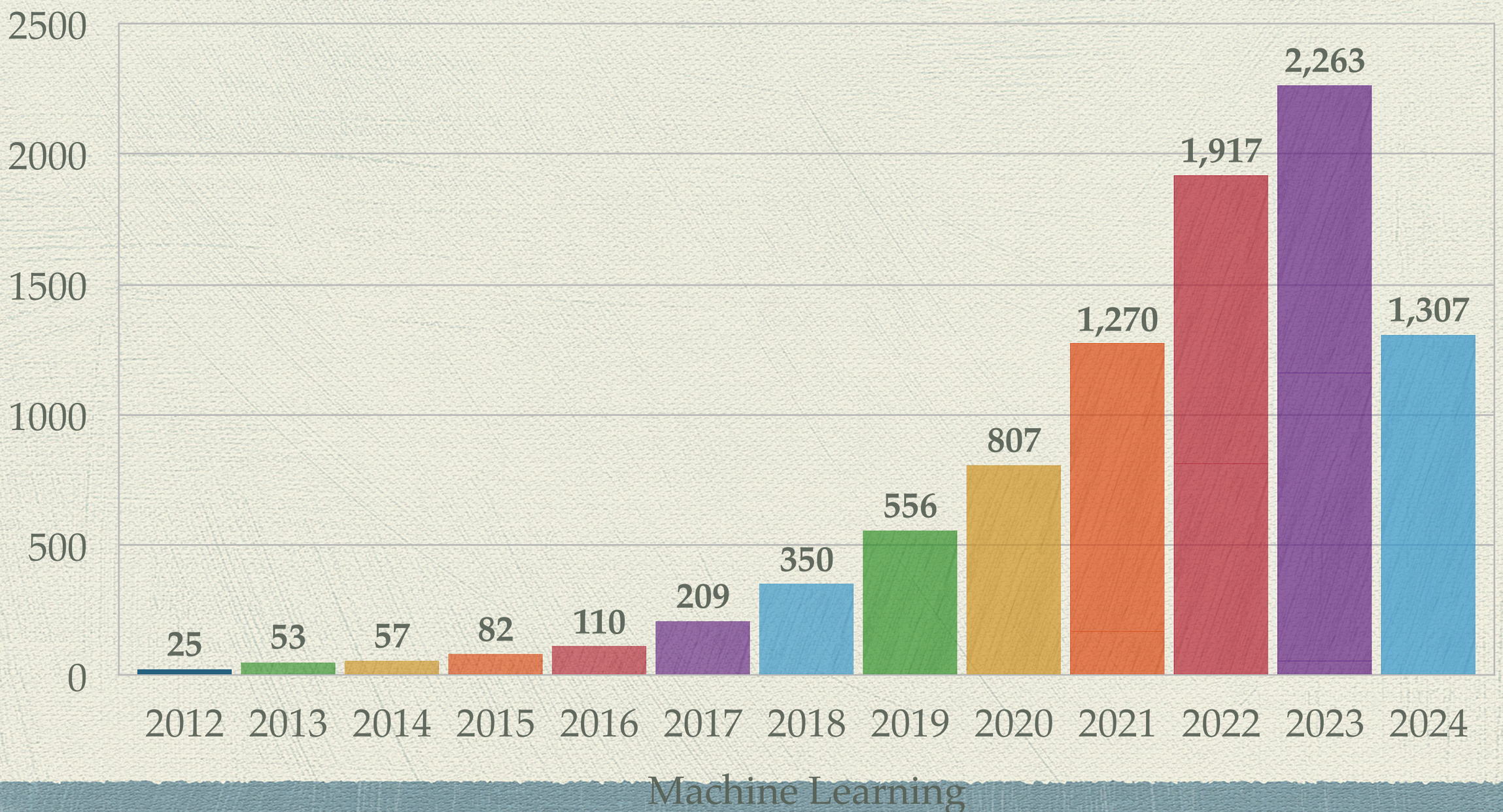
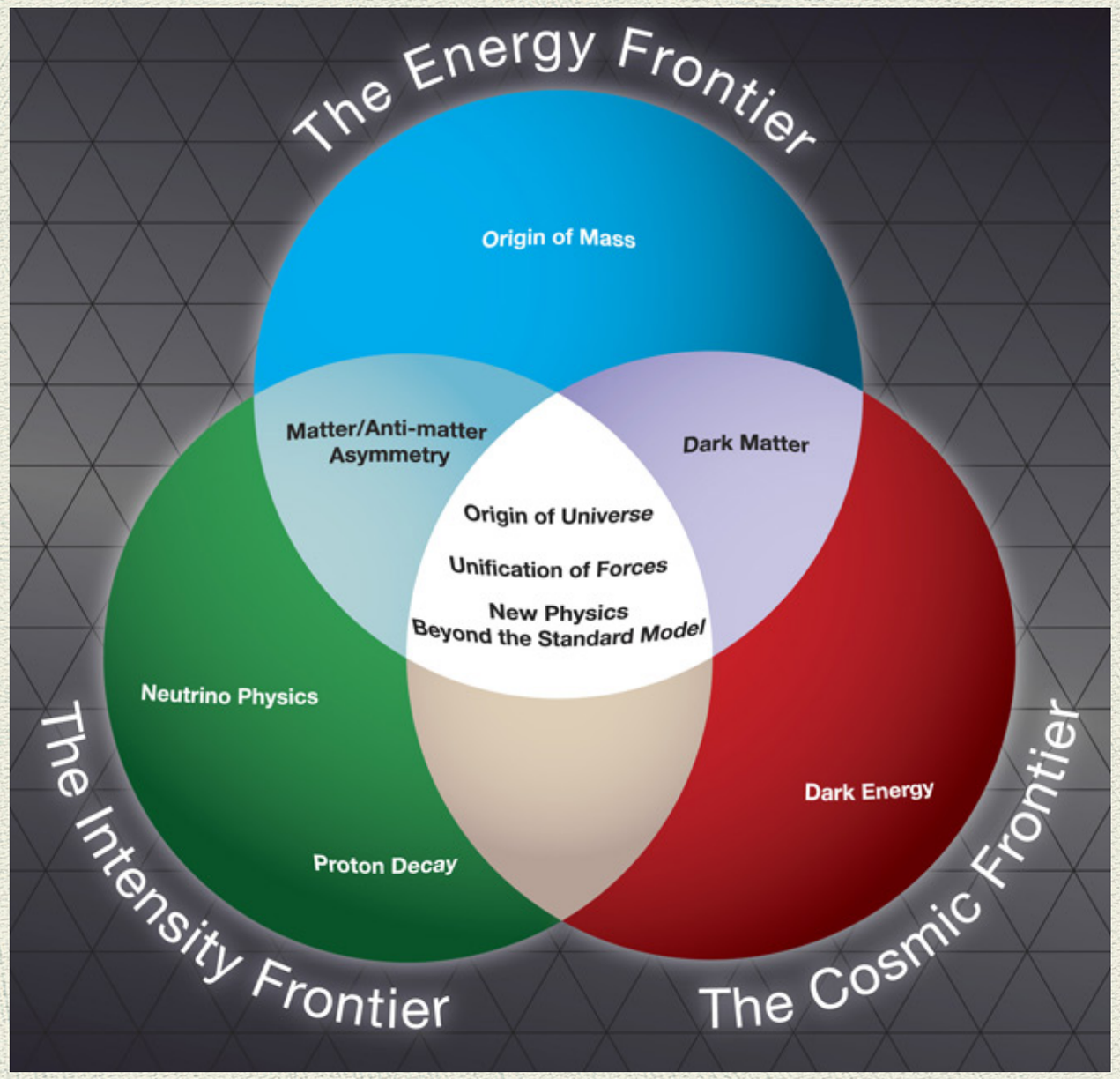
- **Whereas, SENSEX moved 17k=>74k — only 4.4 times!**



Particle Physics

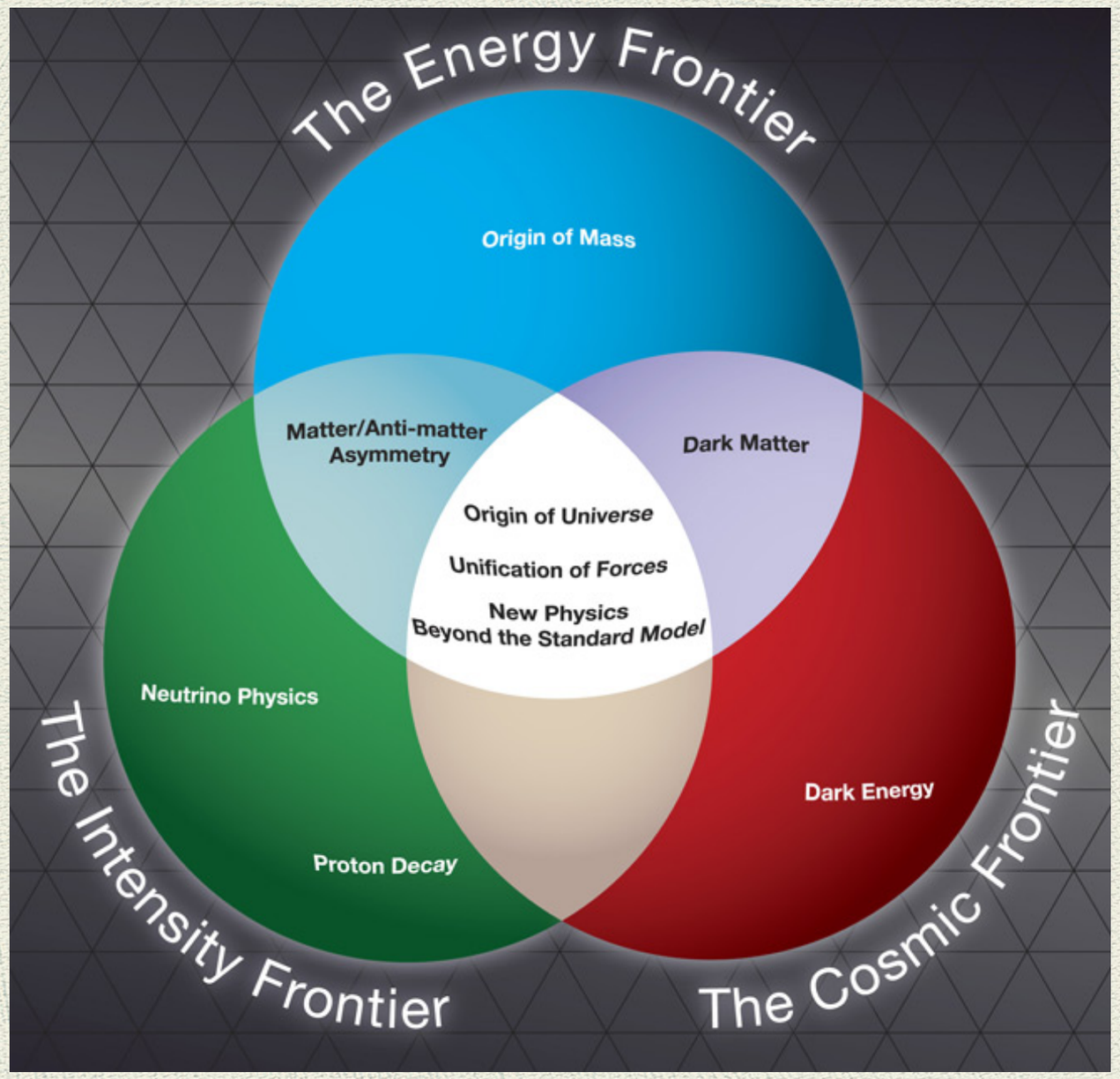


- 2210.05822 : The Future of High Energy Physics Software and Computing

Particle Physics

&

Computational Frontier



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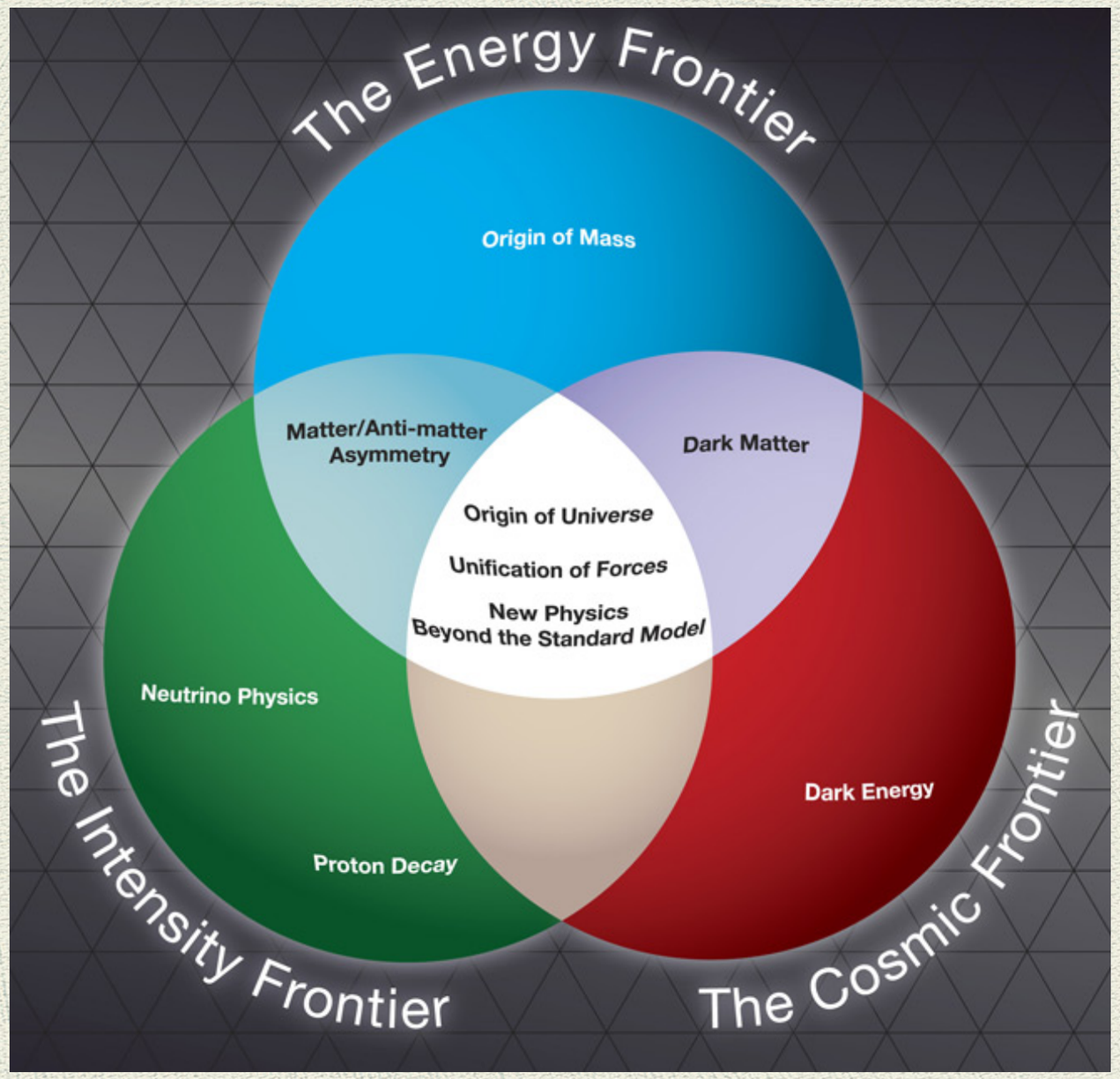

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Computational Frontier

- **Software and computing essentially present in all fronts**

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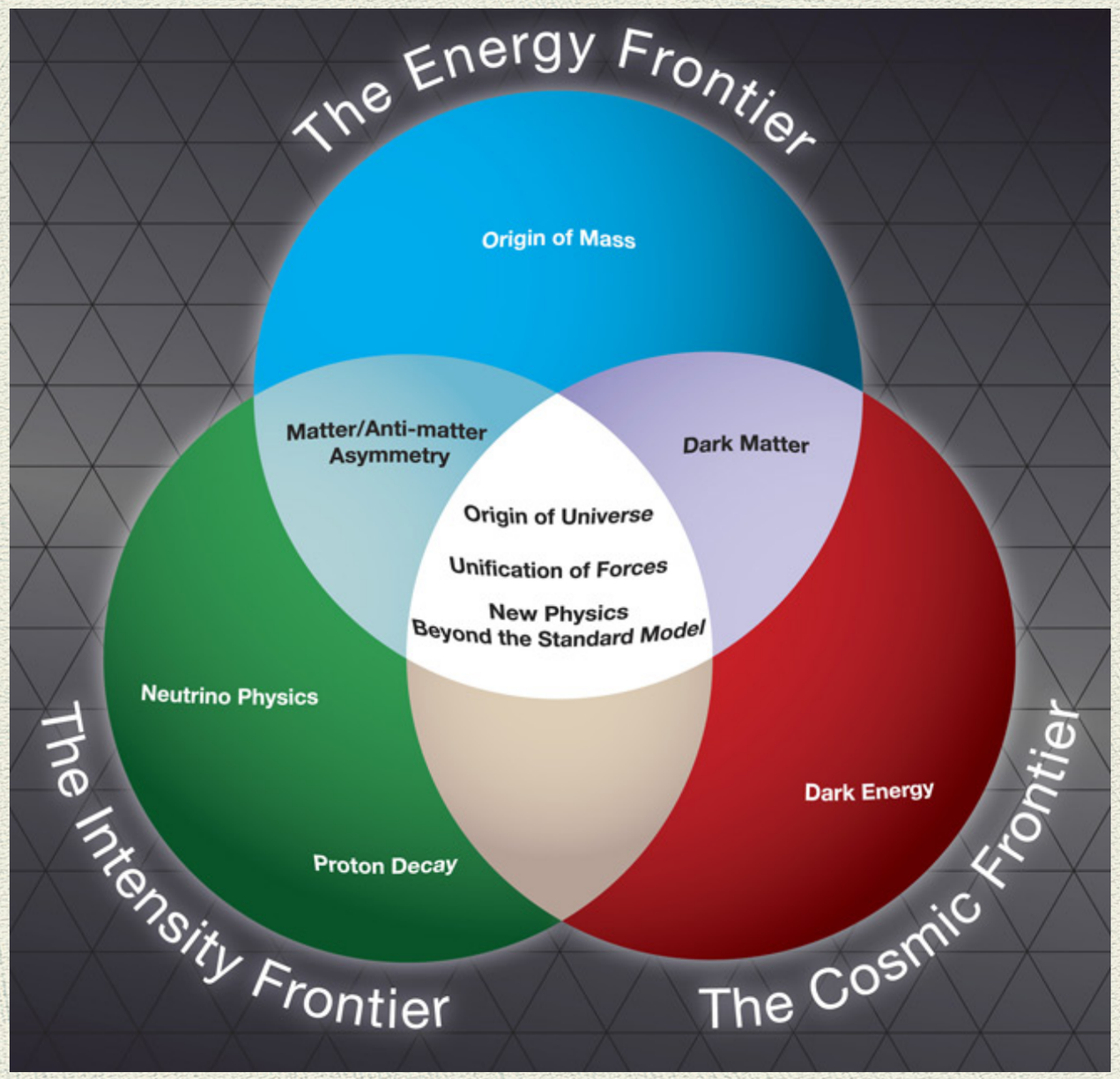
Particle Physics



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- Computing/methodological innovation

  => Full advantage of pristine data by state-of-the-art instruments

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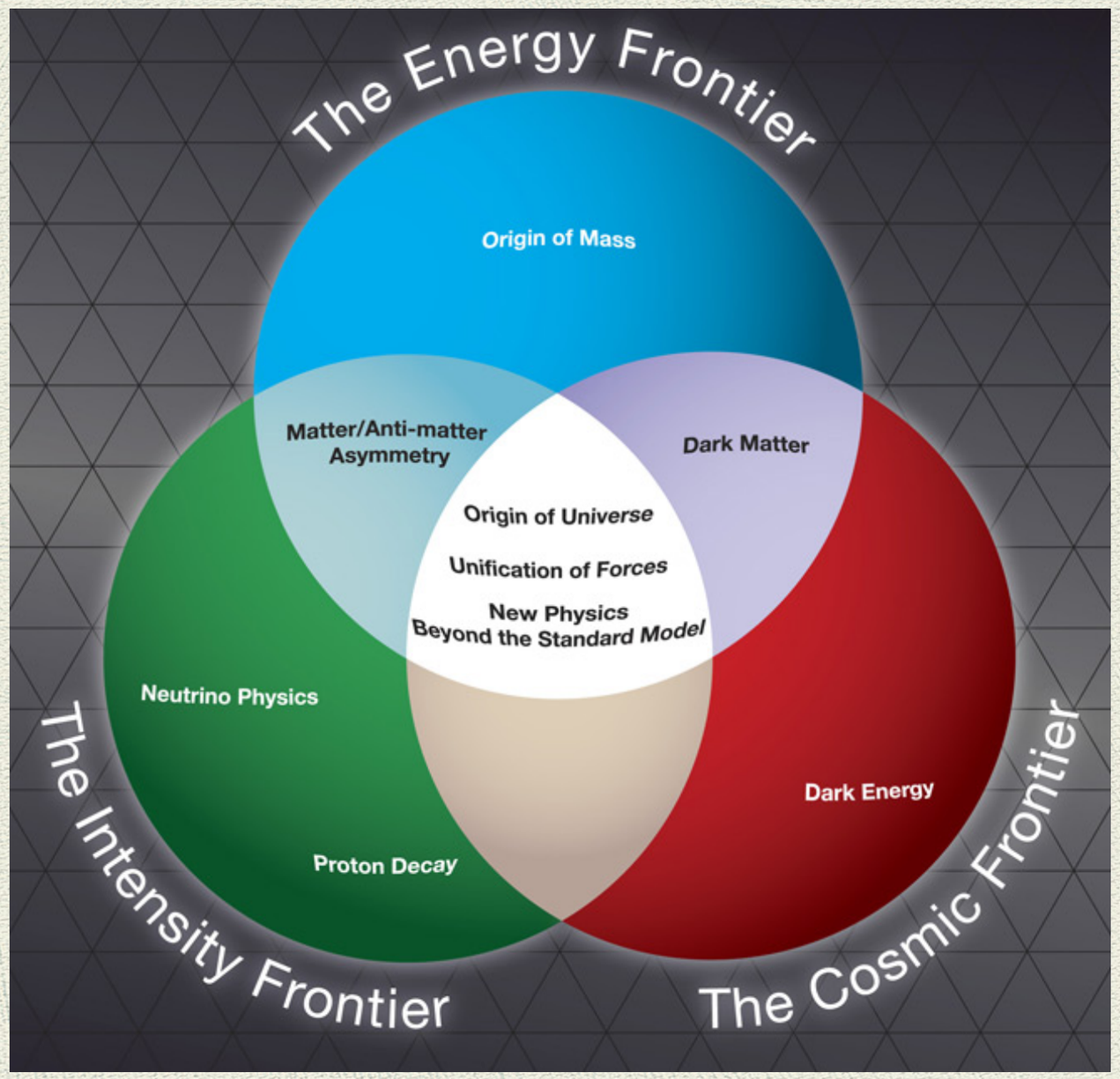

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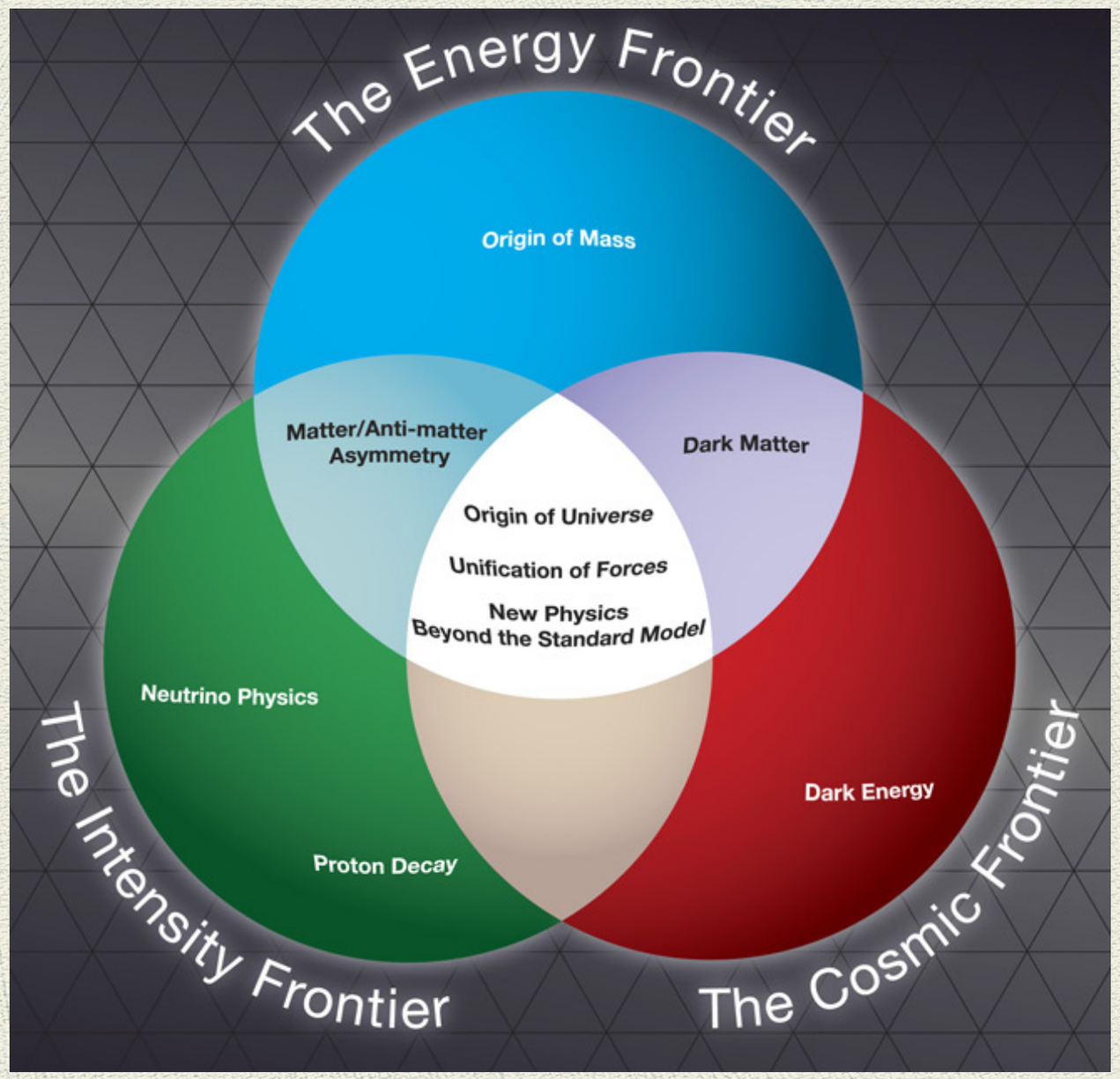

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- **[2/Top 10] most-cited papers of all time in particle physics — are software programs :**
  GEANT [Detector Simulation Toolkit]
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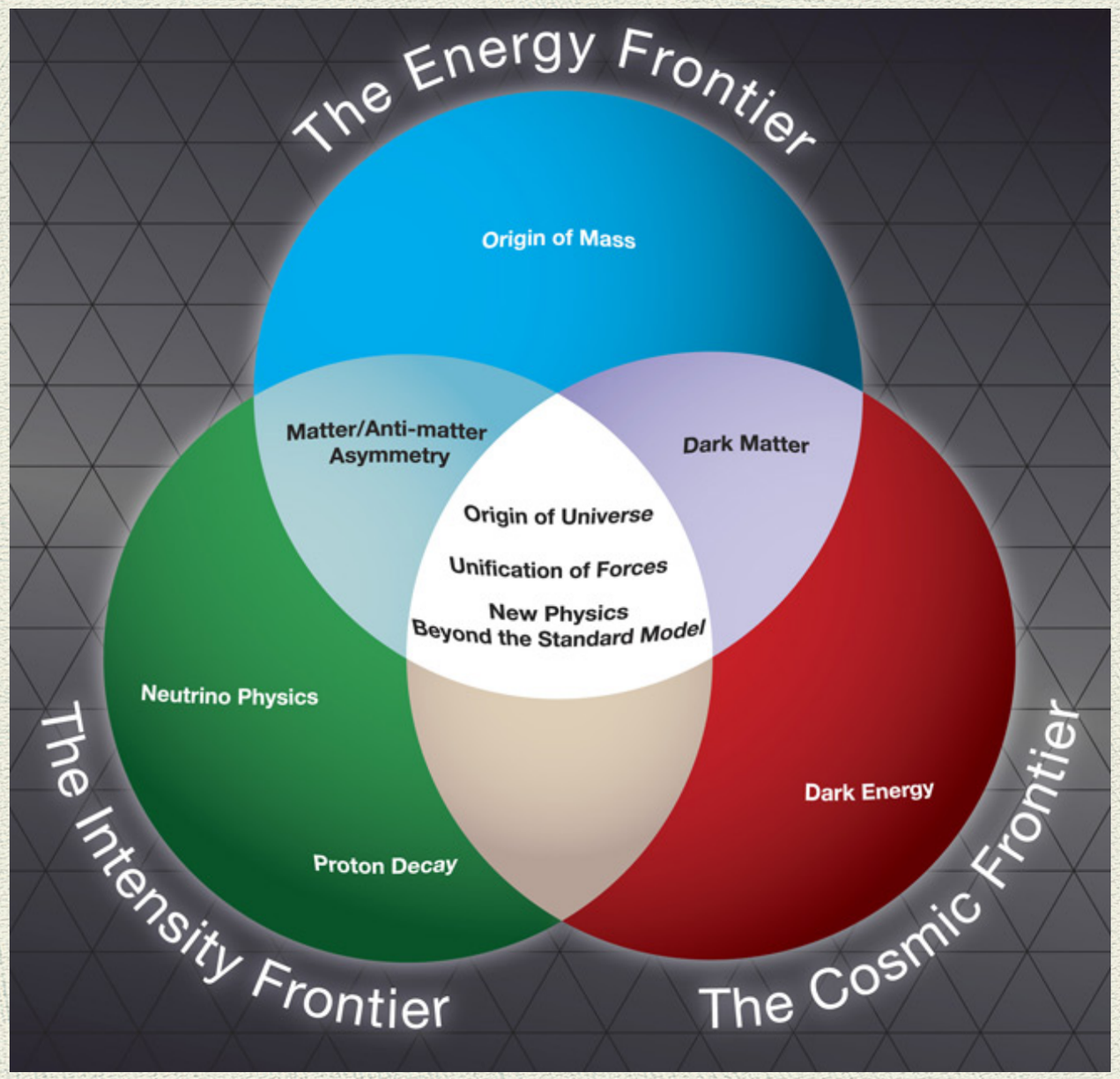

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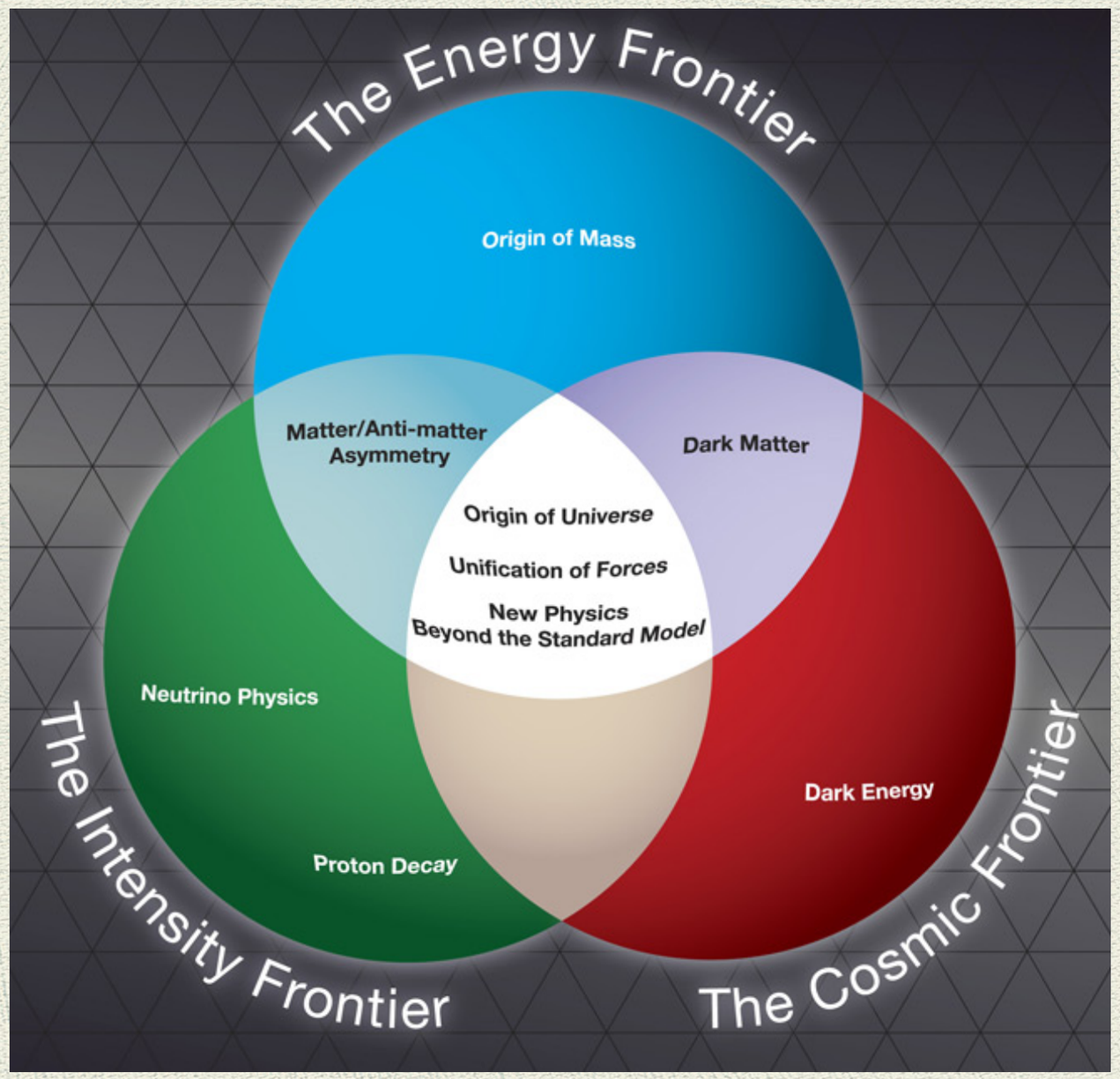

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- **[2/Top 10] most-cited papers of all time in particle physics — are software programs :**
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- Looking for new physics Beyond the Standard Model (BSM)

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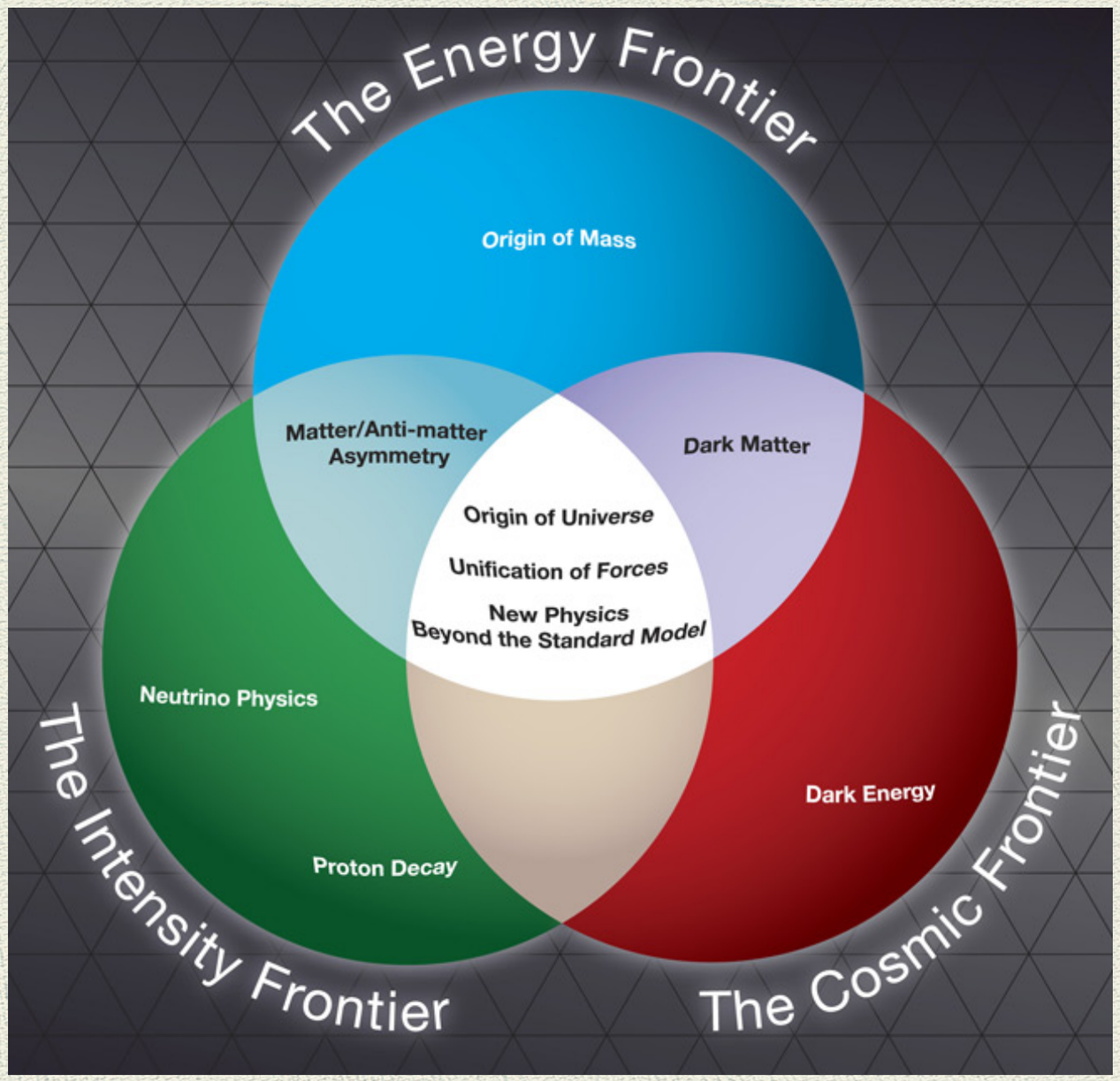
Particle Physics



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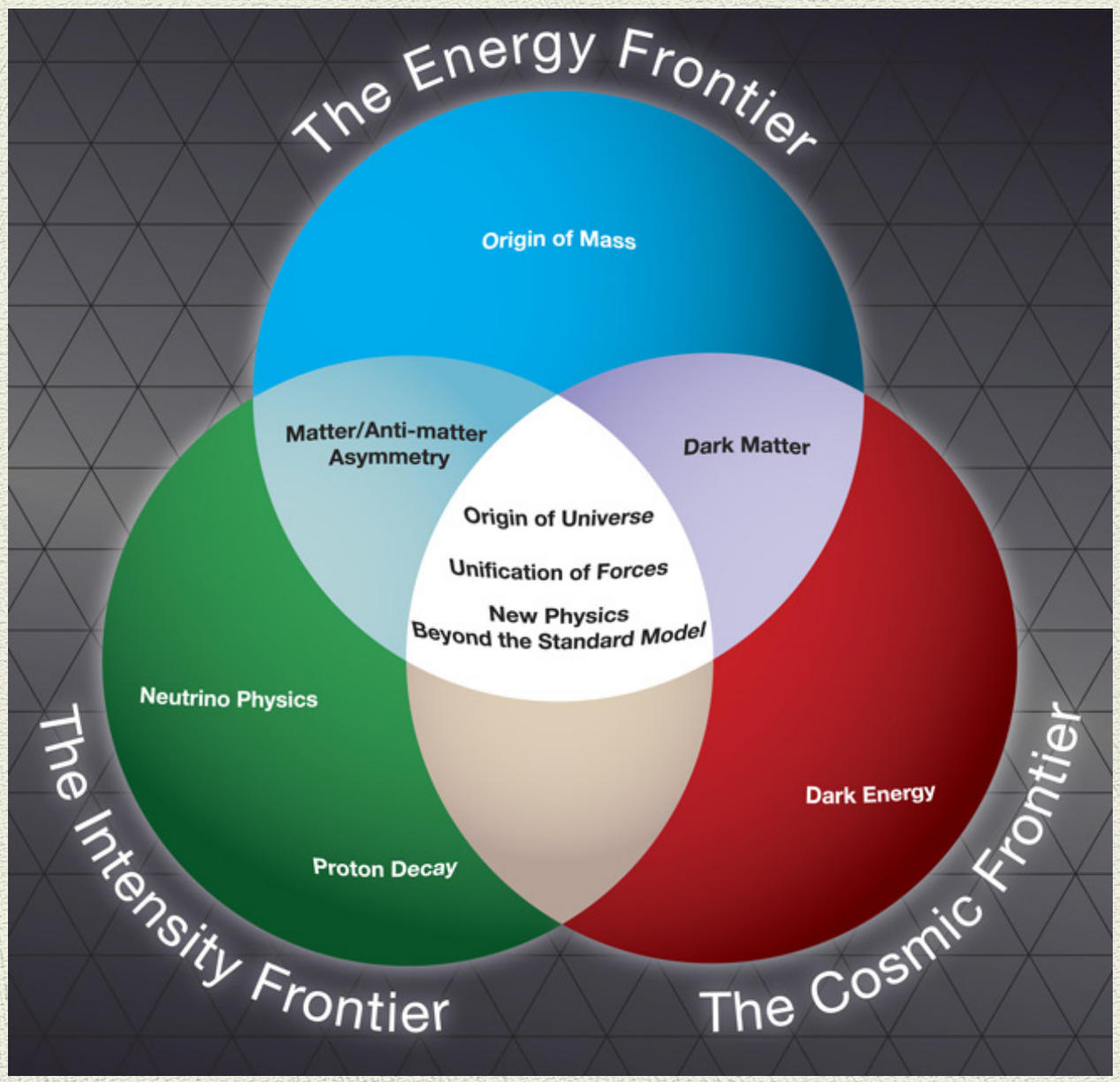

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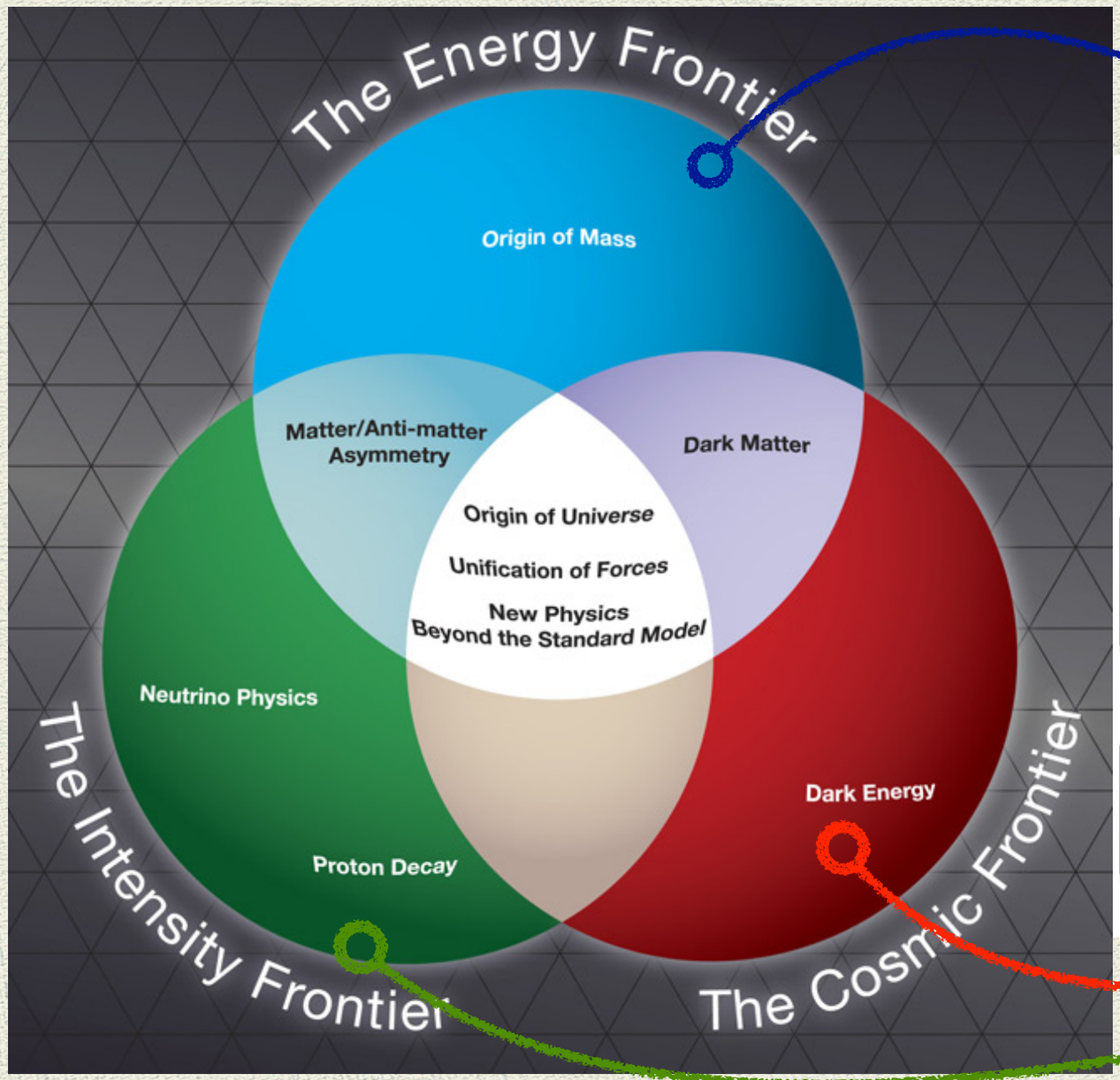
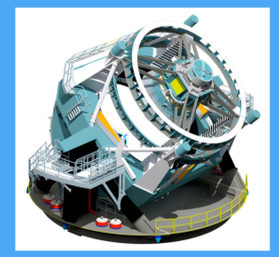
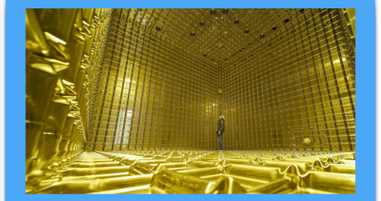


	High-Luminosity Large Hadron Collider	Vera Rubin	DUNE
			
	2020s - 2030s	Vera Rubin	2020s - 2030s
Edge	~MB / event (~200 collisions) 4 x 10^7 event / sec. (40 MHz) ~ 40 TB / sec. ~ 10^9 TB / year = **1 Zettabyte / yr**	1000 x 3.2 Gigapixel images / night 15 TB / night 20k alerts per minute	~ 6 GB / module 5.4 ms readout window ~ 10^8 TB / year = **100 EB / yr** SN trigger ~ 0.5 PB real time processing (1 trigger / month)
Offline	~99.98% of data are removed in real time (~10 kHz/40 MHz) ~10 years of running = **Exabytes of data** (per experiment)	~10 years of running **500 PB image database** 15 PB object database, 40 Billion sources	zero suppression + compression + trigger ~10 years of running **~ 400 PB of data**

- **2210.05822 : The Future of High Energy Physics Software and Computing**

MACHINE LEARNING

FOR HEP COMMUNITY

- Machine learning is not new for HEP community

- Used in low to high level experimental measurements with **track finding**, **calorimeter hit reconstruction**, **particle identification**, **energy/momenta reco**

- Multi Variate Analysis (**MVA**) & Boosted Decision Tree (**BDT**) used extensively on high level variables with primary focus as Classifier
  - **Significant contribution in Higgs discovery**

- **The emergence of modern deep learning era** greatly outperformed the previous state of arts in last one decade or so

- Driving forces -
  - **Advent of graphics processor (GPU) + Increased computing power**
  - **Large available data + Development of advanced ML architectures**

MACHINE LEARNING

AND .. GOING DEEPER

- Classification: Find faint signal against a large background
- Move into higher dimensional space —
  - ☑ Multivariate analysis with High Level Variables
  - ☑ Low Level Variables from detectors (number of dimensions very large)
- Find the Division Boundary in this higher dimensional space
  — Best possible [under-fitting?] but Trustworthy [over-fitting?] way
- Neural Networks based on interconnected nodes in layered structure
  — In analogy with brain neurones
  — Connects different input/ derived data
  — Involve free parameters (weight and bias) [inductive bias?]
  — Optimise “free parameters” using labeled data [Model]

MACHINE LEARNING

AND .. GOING DEEPER

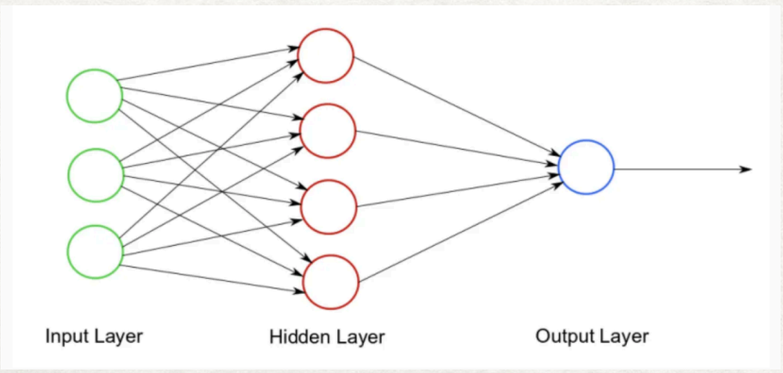
- Universal function approximation: NN with a single hidden layer can approximate any continuous function to any desired precision!

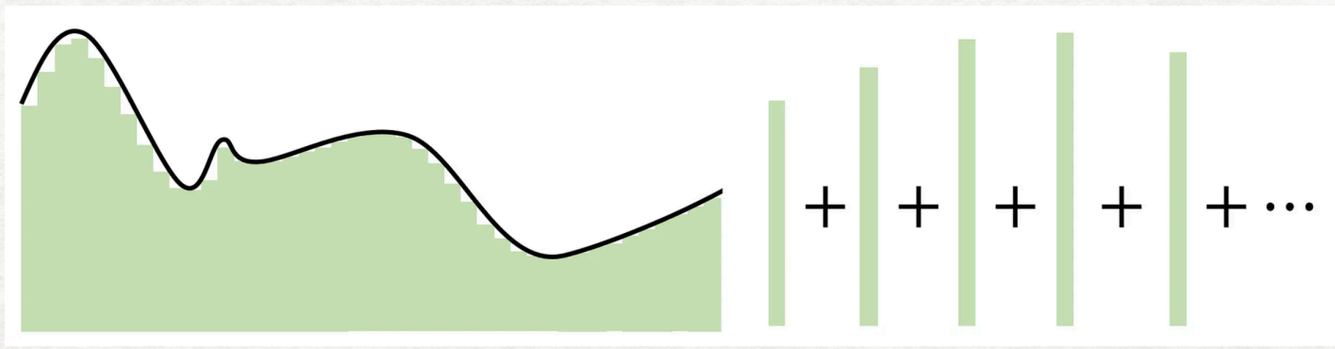
- Deep learning models with **multiple hidden layers** solves the need for infinitely large no of nodes in shallow NN

- Learning **scalable** with data - larger data for better performance

- Deep learning models are now capable of **extracting feature directly from low level data**

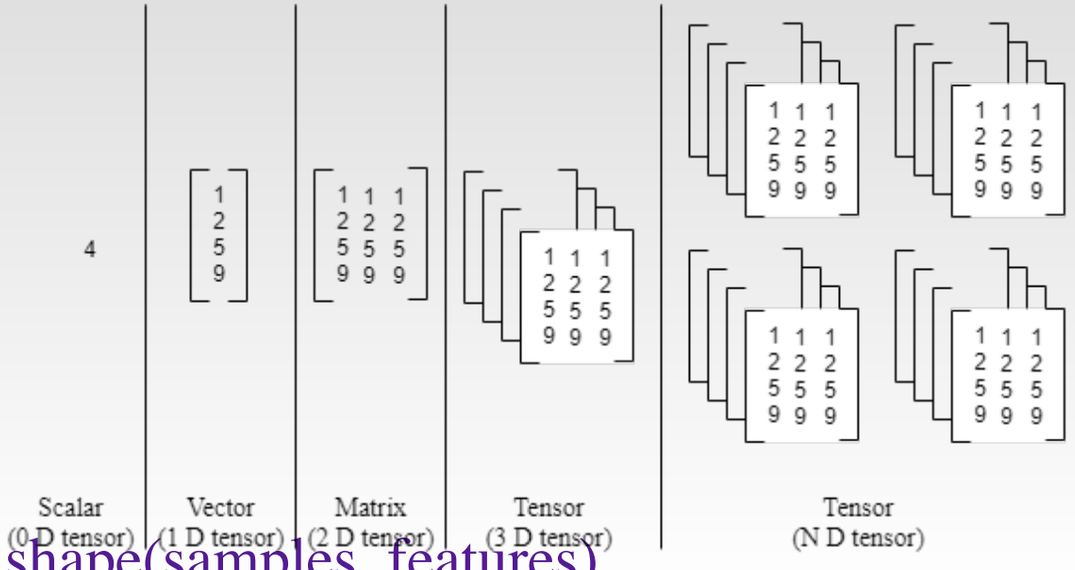
  — End for physics intuitive high level variables from domain experts?





Data Representation

✓ **Fundamental data structure:** Fixed-length Tensors (multi-dimensional arrays)



- **Vector data:** 2D tensor of shape(samples, features)
- **Time series data or sequence data:** 3D tensor of shape(samples, timesteps, features)
- **Images**: 4D tensor of shape(samples, channels, height, width)
  For a grayscale image: channel =1; For RGB image: channels = 3
- **Video**: It is a 5D tensor of shape(samples, frames, channel, height, width)

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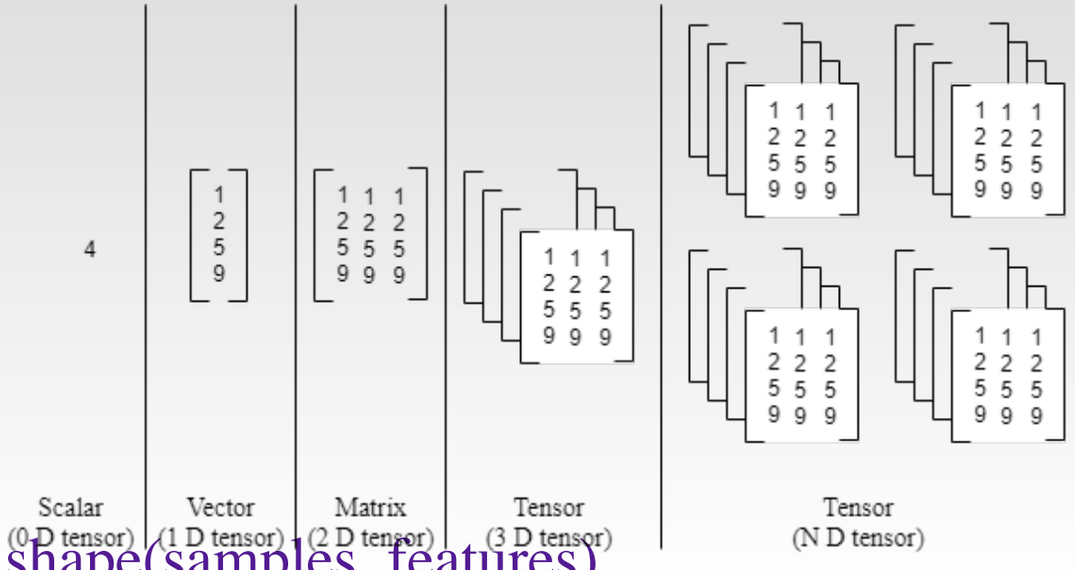

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✓ **Note : Euclidean spaces are isomorphic to** $x \in \mathbb{R}^n$; $\vec{x} = \{x_1, x_2, \ldots x_i \ldots x_n\}$
in a n-dimensional linear space

✓ **However some data does not map neatly into** $\mathbb{R}^n$ **=>** Graph Neural Networks seek to adapt existing ML to directly process non-Euclidean structured data as input

Data Representation

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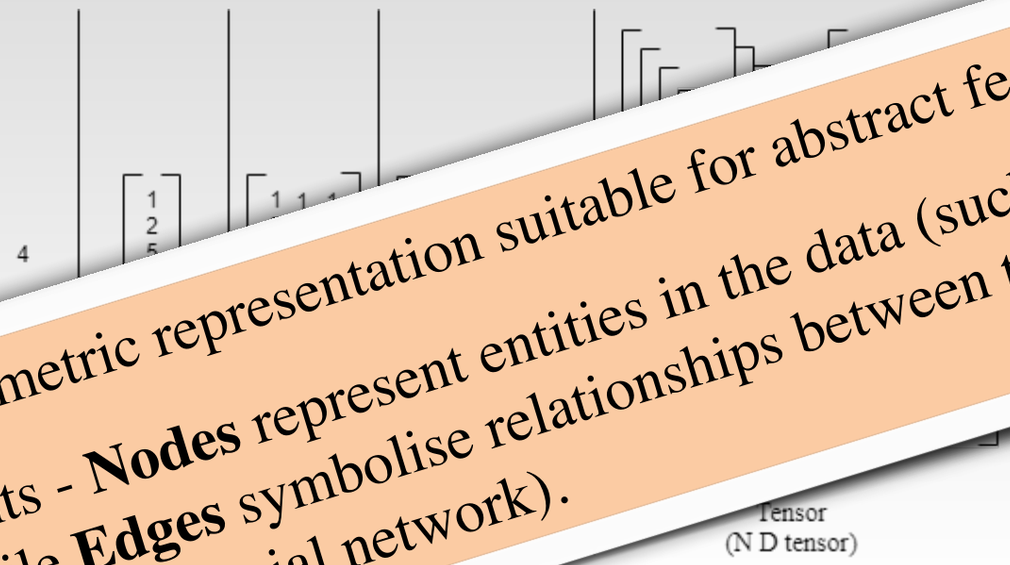

✓ **Point clouds:** A flexible geometric representation suitable for abstract features

✓ **Graphs:** Two basic elements - **Nodes** represent entities in the data (such as members of an online social network), while **Edges** symbolise relationships between those entities, (such as friendship between members of a social network).

- **Sequences**: 3D tensor of shape(samples, timesteps, features)
- **Images**: 4D tensor of shape(samples, channels, height, width)
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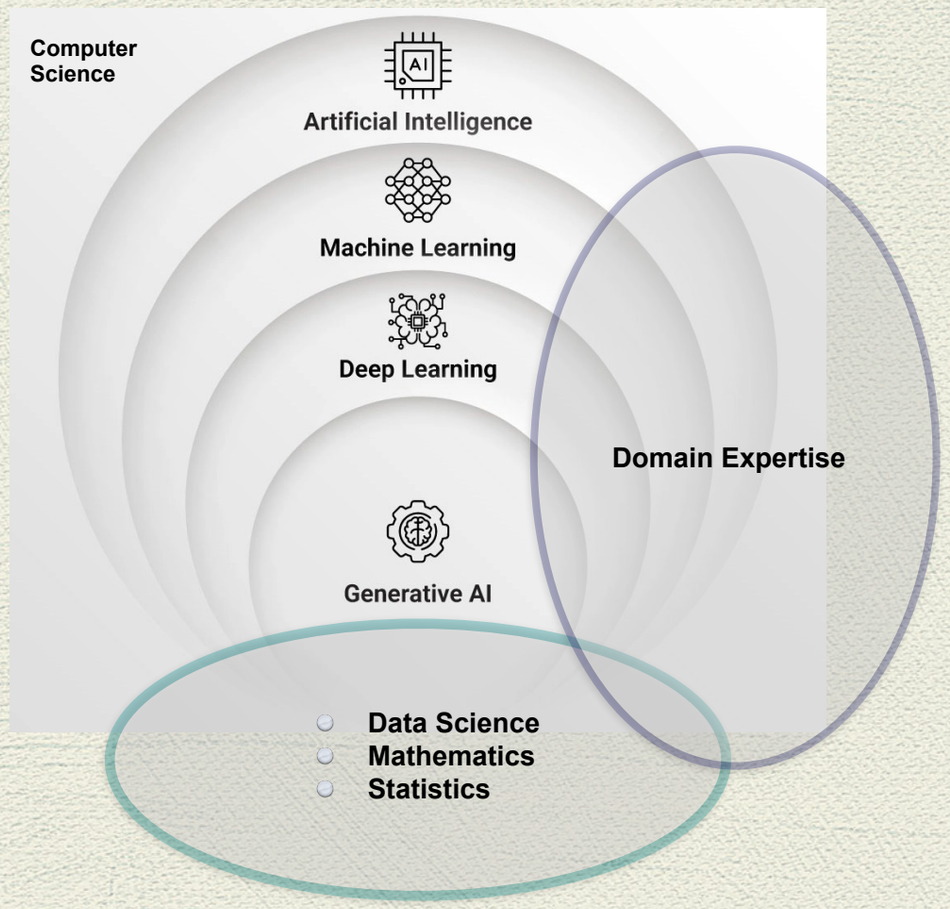
How ML works?


Computer Science
Artificial Intelligence
Machine Learning
Deep Learning
Generative AI
Domain Expertise
Data Science
Mathematics
Statistics

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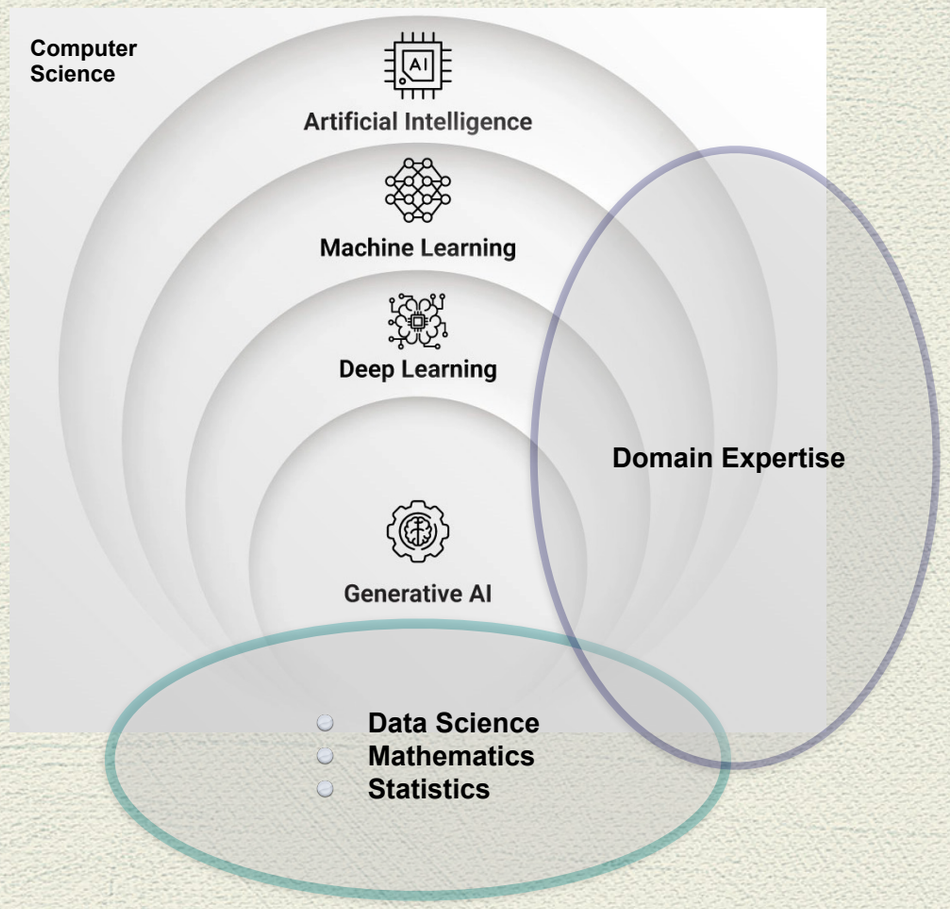
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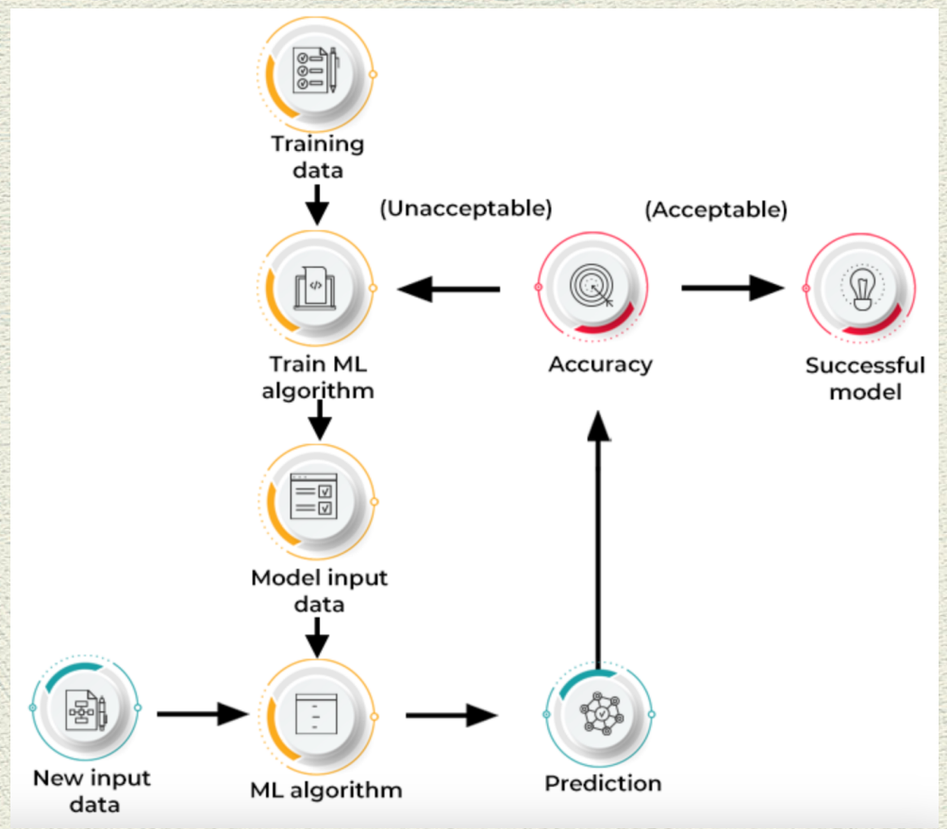
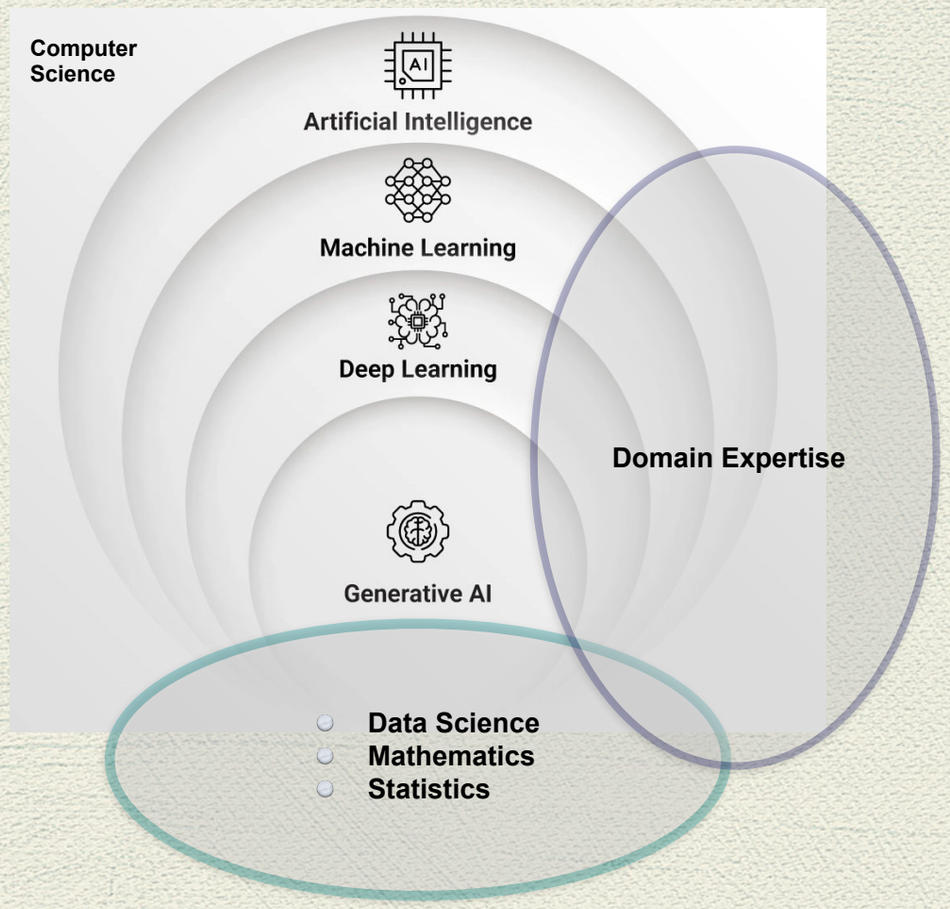
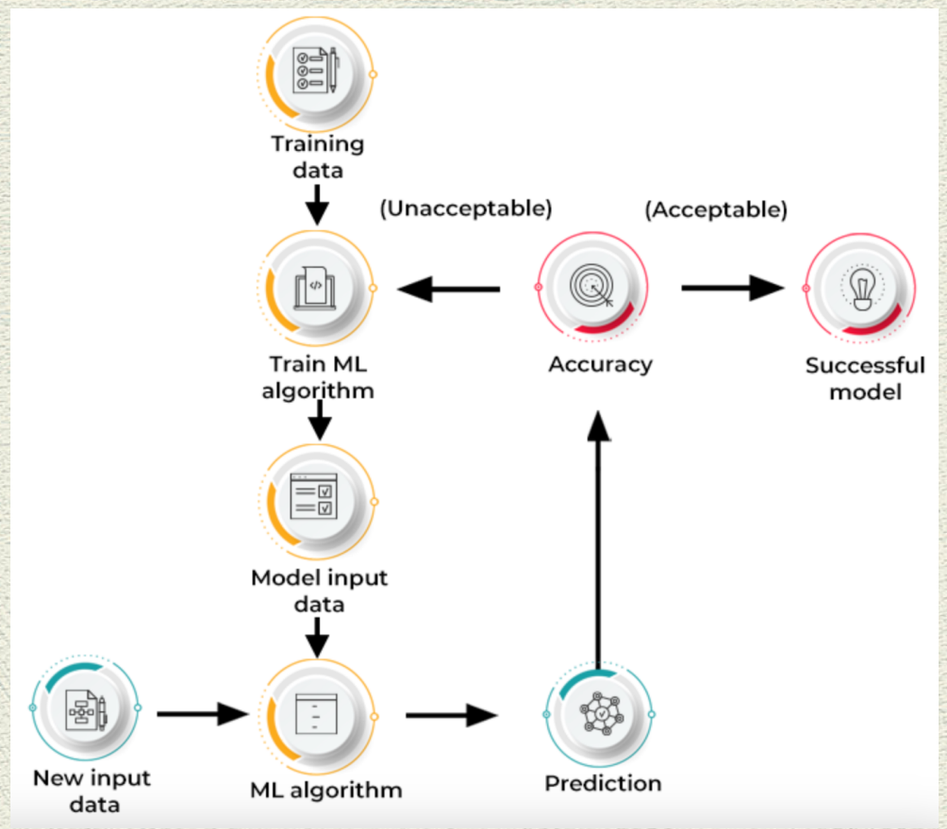

Training data
(Unacceptable)
(Acceptable)
Train ML algorithm
Accuracy
Successful model
Model input data
New input data
ML algorithm
Prediction

How ML works?





- **Decision boundary:** surface that divides multi-dim feature space into distinct groups of data points.
- **Training:** ML algorithm discovers the decision boundary
- **Testing**: Then uses to forecast the class of unseen data points.
- Key drivers for its growth

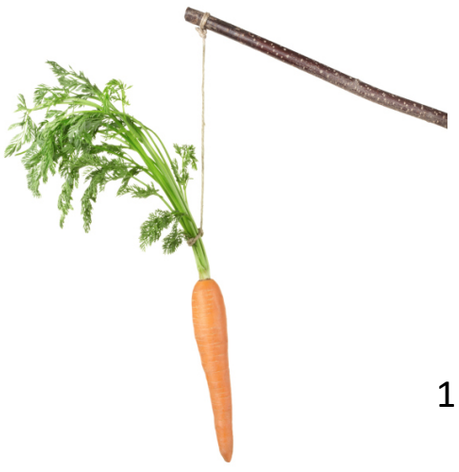
  — **Data, Algorithms & Hardware (graphics processing unit or GPU)**

Three Ways to Learn

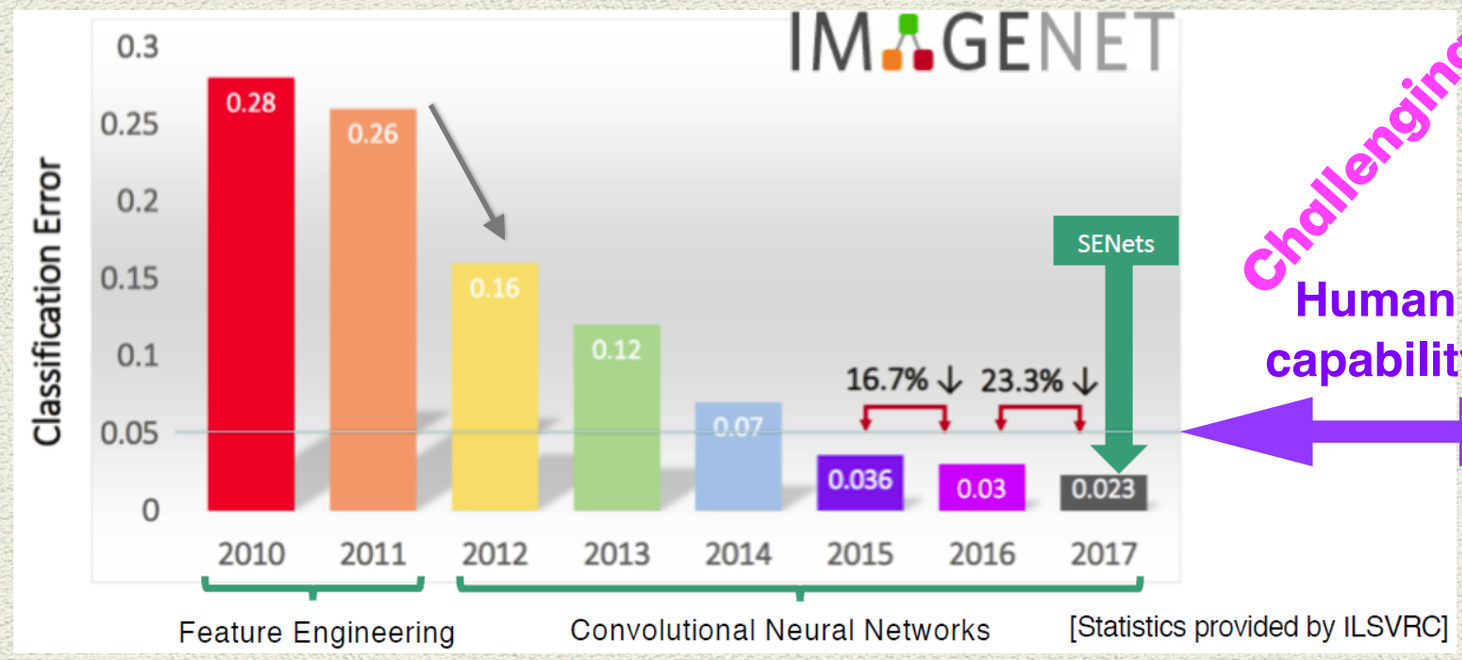
Supervised

Unsupervised

Reinforcement

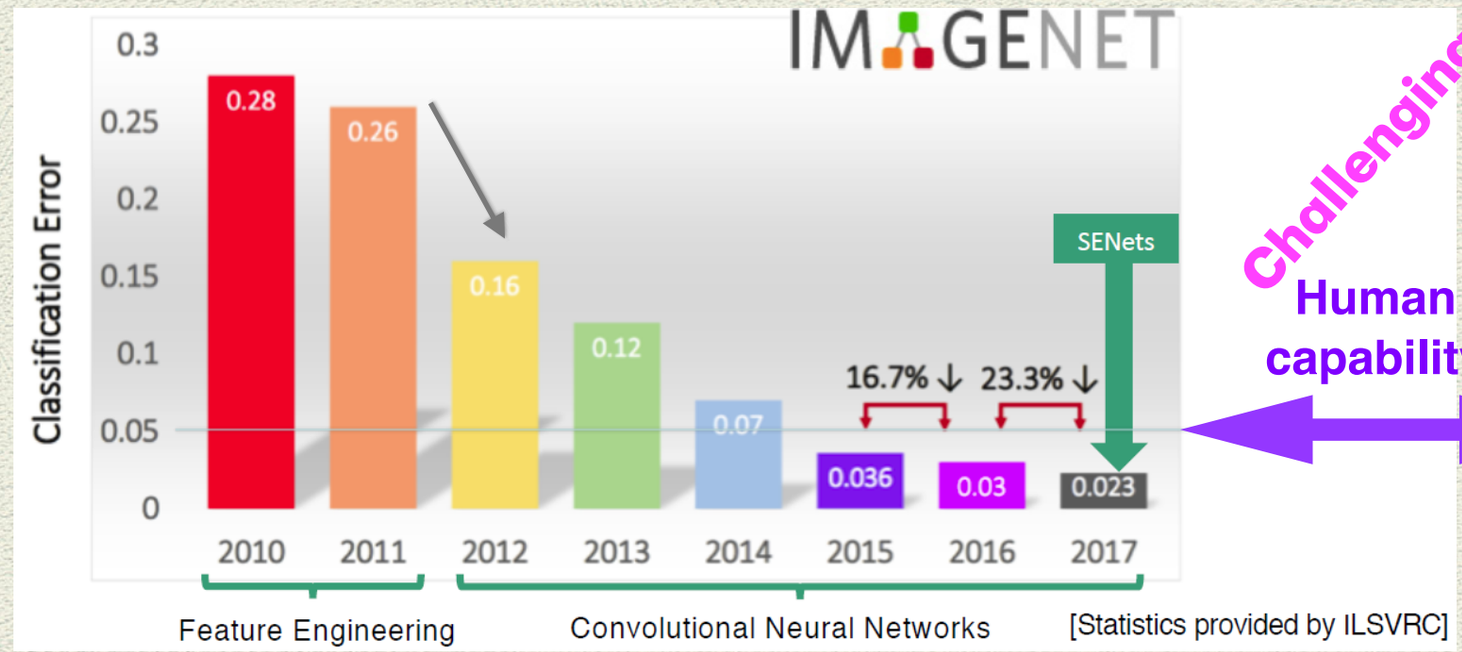


Progress of Deep Learning



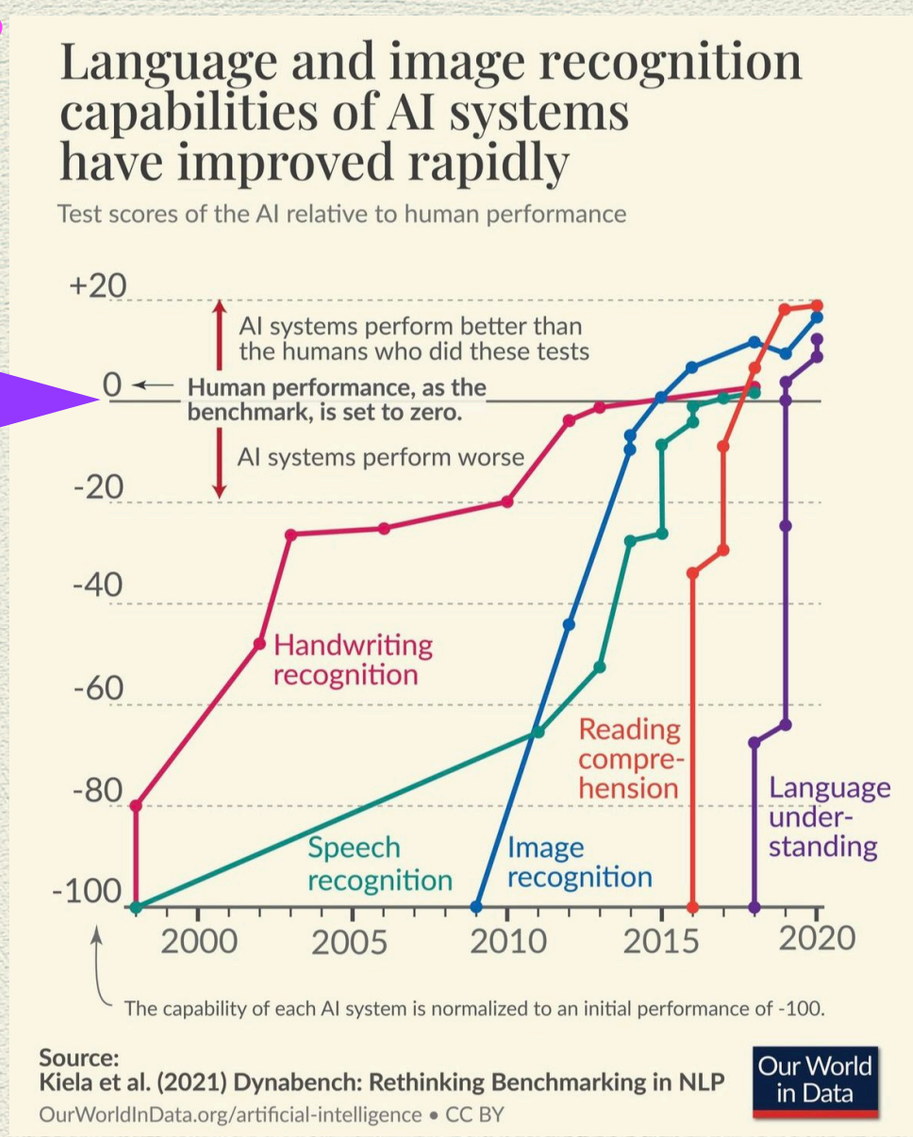
- ImageNet - Large Scale Visual Recognition Challenge (ILSVRC) held each year : largest contest in object recognition
- 2012 - AlexNet [Deep CNN by Alex Krizhevsky etal] ~ 15.4% error (2nd 26.2%!)]
- Since then, these competitions are consistently won by deep convolutional nets

Progress of Deep Learning



Challenging

Human capability



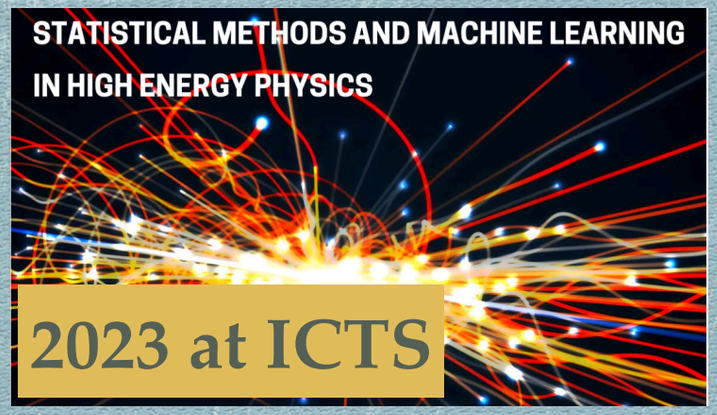
- ImageNet - Large Scale Visual Recognition Challenge (ILSVRC) held each year : largest contest in object recognition
- 2012 - AlexNet [Deep CNN by Alex Krizhevsky etal] ~ 15.4% error (2nd 26.2%!)]
- Since then, these competitions are consistently won by deep convolutional nets

- Imitate (defeat) human intelligence and capability in **visual perception, speech recognition, decision-making, language processing, and so on.**

DEEP MACHINE LEARNING

CATEGORY

Strategy	Representations	Targets / tagging	strategies
Classification	➡ Jet Image ➡ Event Image ➡ Sequence (Recurrent NN) ➡ Graph (Graph NN) ➡ Sets (Point cloud - Graph)	➡ Quarks vs gluons ➡ Boosted H / W / Z / Top tag ➡ New particles and models ➡ Particle tagging at detector ➡ Neutrino flavour	➡ Weak/ Semi/ Un-supervised ➡ Reinforcement Learning ➡ Quantum Machine Learn ➡ Feature Ranking ➡ Optimal Transport
Regression	➡ Parameter estimation ➡ Pileup mitigation ➡ Parton Distribution Func ➡ Symbolic Regression ➡ Function Approximation		
Generative models		➡ GANs ➡ Autoencoders ➡ Phase space generation ➡ Normalizing flows	
Anomaly detection			



Primarily for Students and PDFs working on using deep learning

Preparatory school (Online)
[June 12 - 23 2023]

Lecture + Tutorial
28 Aug - 04 Sep 2023

Workshop
5 - 8 Sep 2023

https://www.icts.res.in/program/ml4hep