

Machine Learning at the Edge for Real Time Data Processing

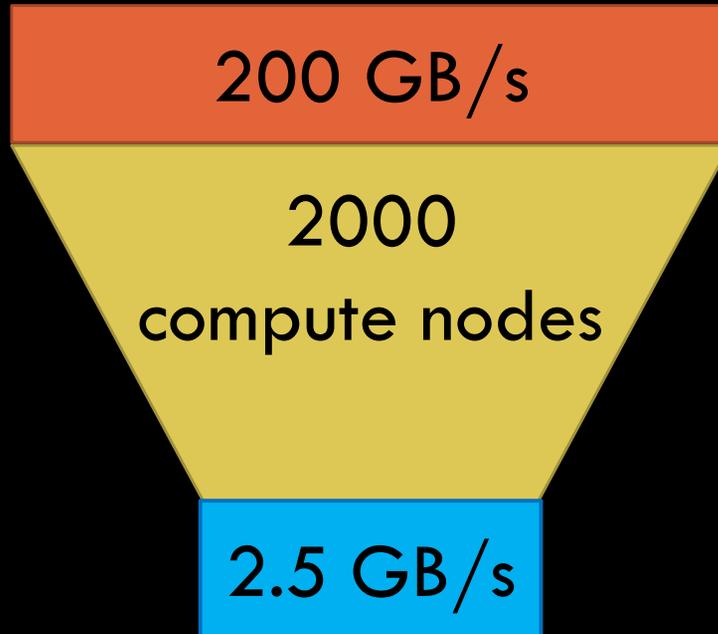
Audrey Corbeil Therrien

October 2020



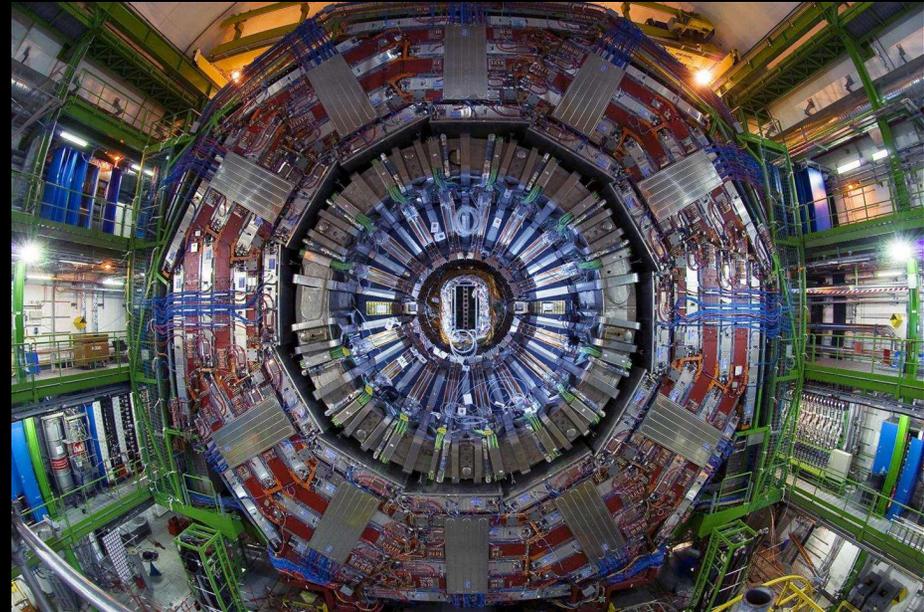
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Why do we need Real-Time ML



Source : Hegeman, J. (2018)

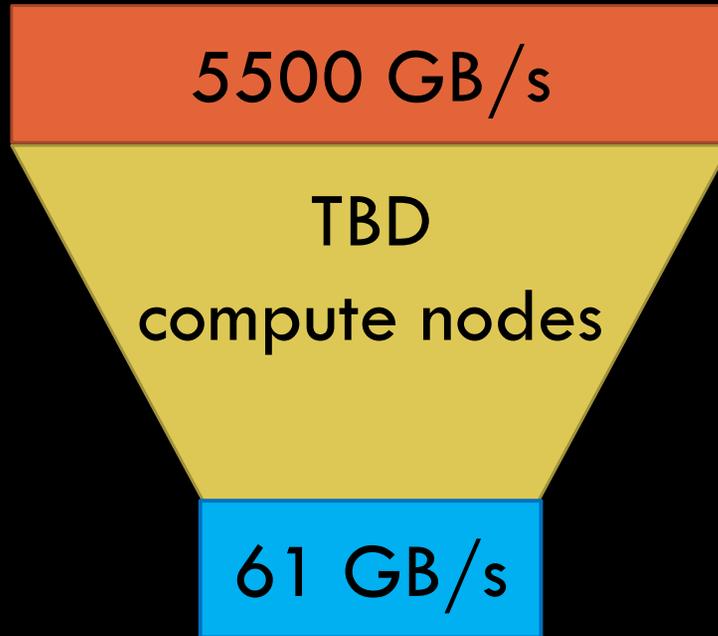
LARGE HADRON COLLIDER



Credit : CERN

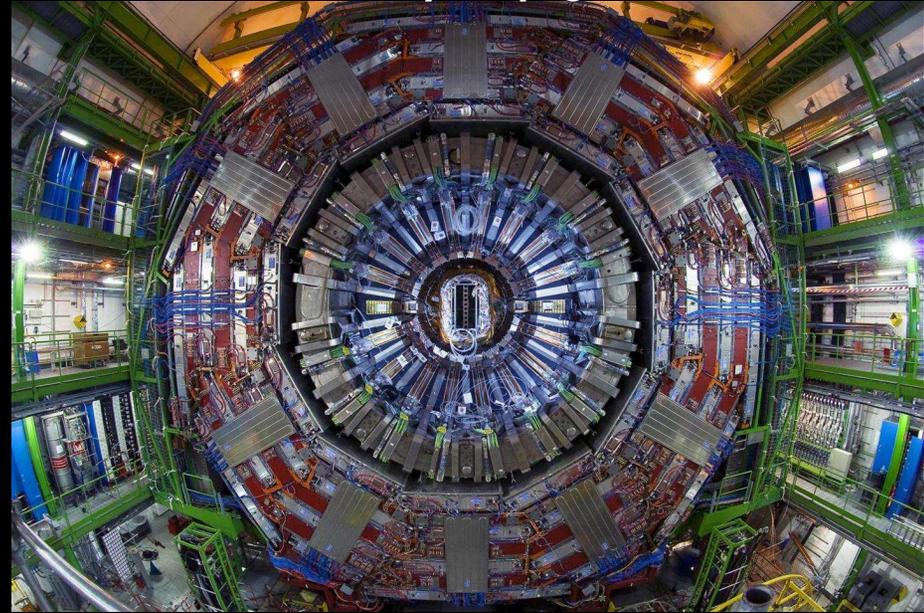
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Why do we need Real-Time ML



Source : Hegeman, J. (2018)

Hi-Luminosity Upgrade



Credit : CERN

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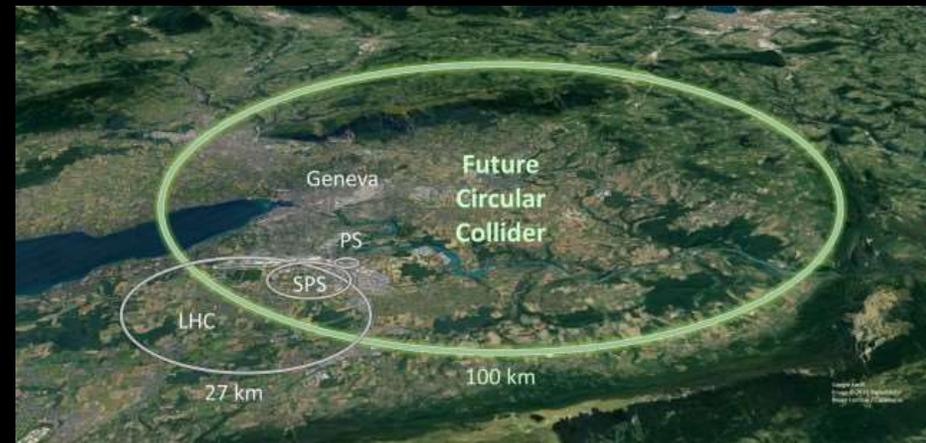
Why do we need Real-Time ML

2 000 000 GB/s

2 MW

TBD
Compute nodes

FUTURE CIRCULAR COLLIDER



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Why do we need Real-Time ML

LINAC Coherent Light Source



20 to 1200 GB/s

- Assuming 1 TB/s, 12 hour shift, nonstop
- 43 200 TB per shift – 56 years of 4K movies
- 1.3 M\$/month of storage costs created every shift

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What is Machine Learning?

What is Machine Learning

Traditional programming

Input

+

Program

=

Output

Machine Learning

Input

+

Output

=

Program

3!T

What is ML?

Hardware

CookieBox

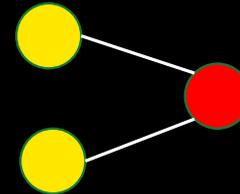
Pitfalls

Conclusion

What is Machine Learning



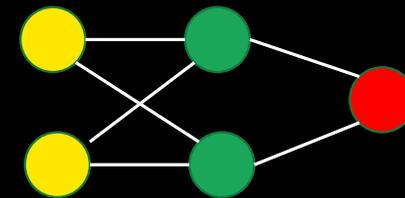
Decision Trees



Perceptron



Random Forest



FeedForward

What is Machine Learning

What is ML?

Hardware

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Pitfalls

Conclusion

Convolutional neural network

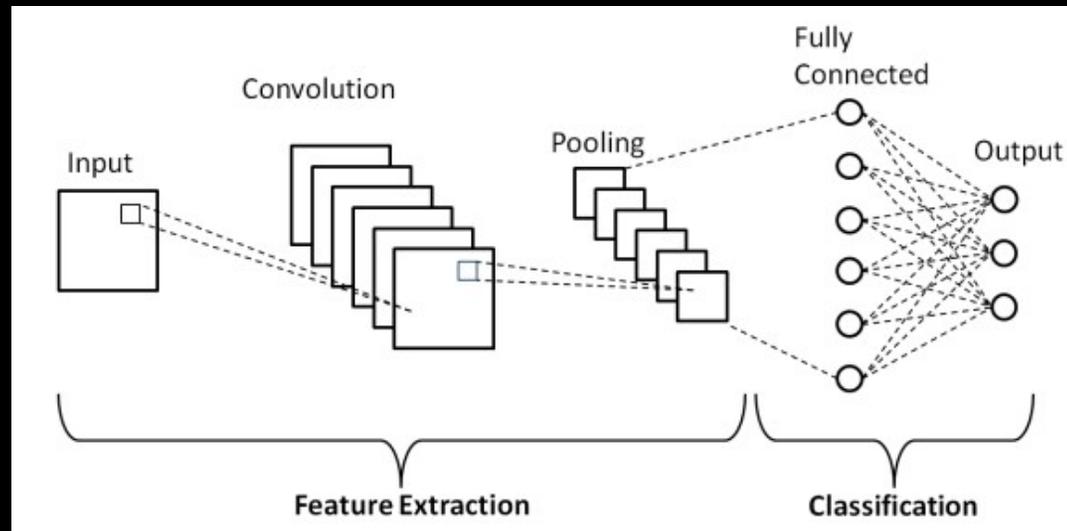


Image
recognition

What is ML?

Hardware

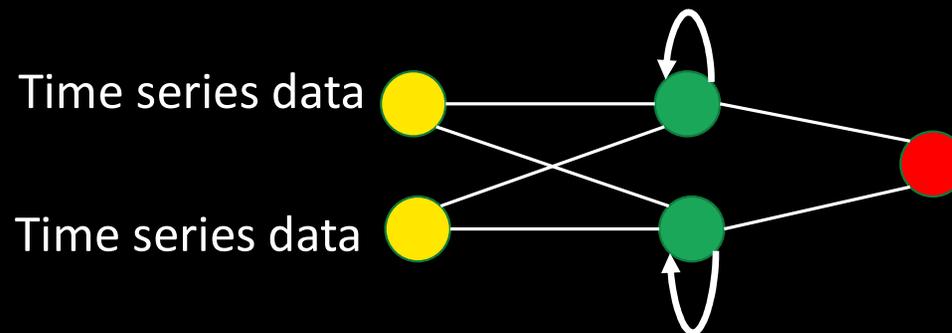
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Pitfalls

Conclusion

What is Machine Learning

Recurrent Neural Network



What is Machine Learning

What is ML?

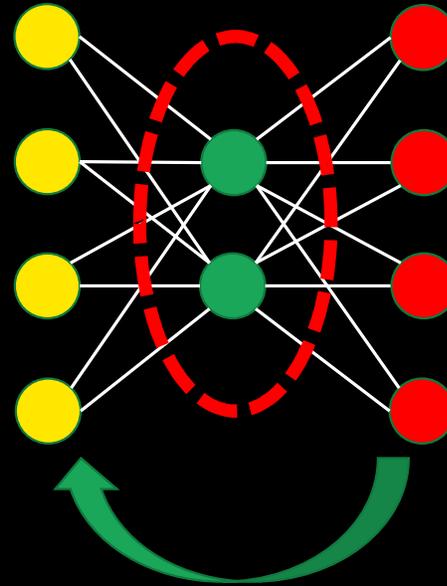
Hardware

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Pitfalls

Conclusion

Autoencoders



Data compression
Feature extraction

What is ML?

Hardware

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Pitfalls

Conclusion

Benefits of ML

Recognizing patterns

Recognizing
anomalies

Non linear regression
→ reconstruction

Benefits of ML

Faster more flexible
programming

Lower computational
burden

Fast inference
Low latency decision

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Hardware

3!T

What is ML?

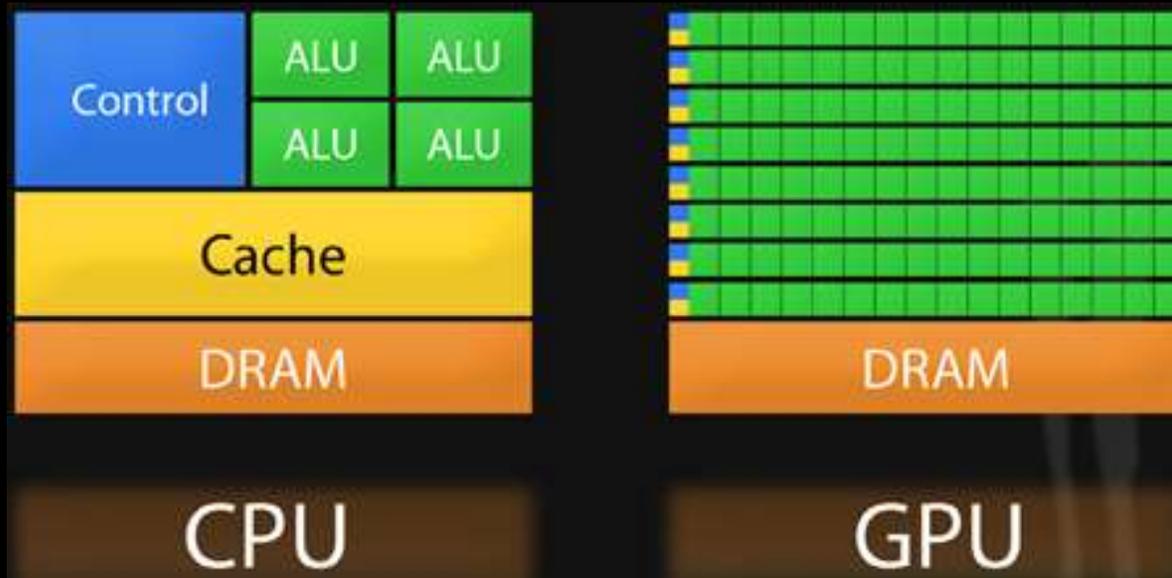
Hardware

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Pitfalls

Conclusion

ML Hardware - GPU



Thousands of ALU

Highly parallel

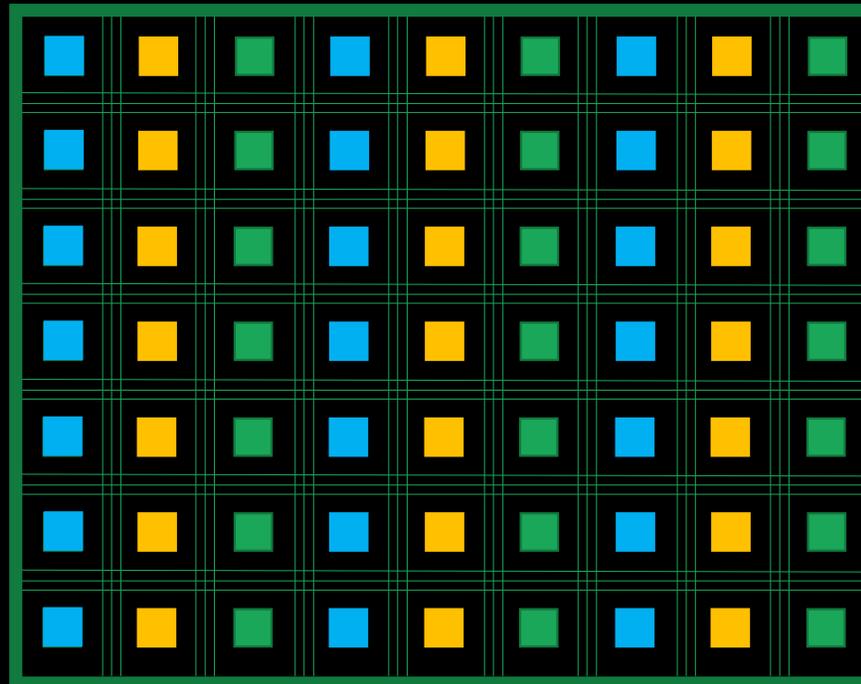
Batch oriented

Host CPU

Power

Size

ML Hardware - FPGA



■ Logic
■ Memory
■ Digital signal processing slices

Reconfigurable

Efficient

I/O capacity

Programming

Limited clock

Limited resources

What is ML?

Hardware

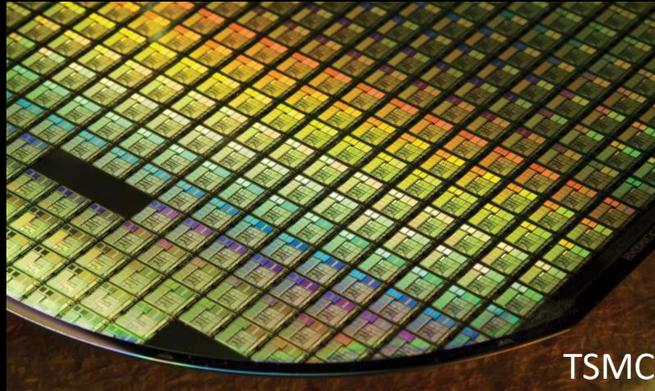
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Pitfalls

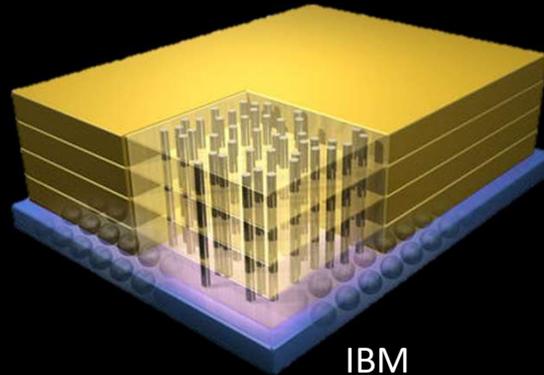
Conclusion

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ML Hardware - ASIC



TSMC



IBM

What is ML?

Hardware

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Pitfalls

Conclusion

Efficient++

Custom I/O

3DIC

Reconfigurable

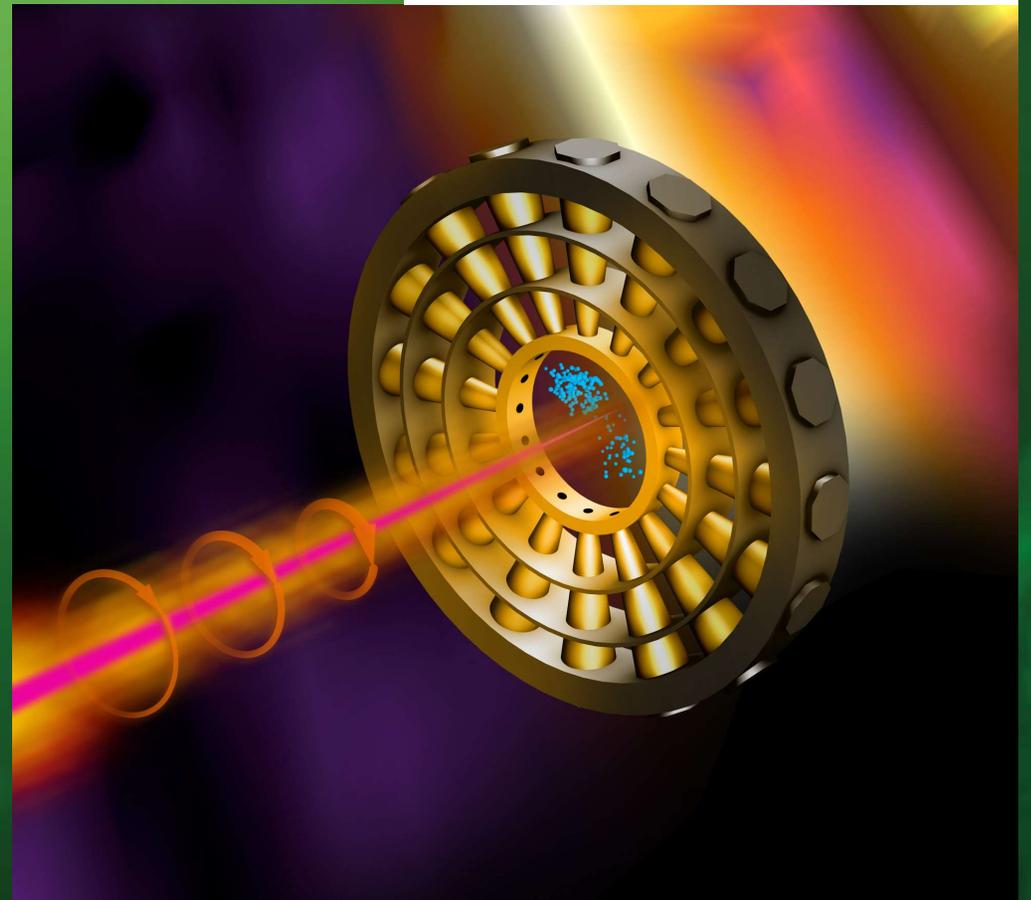
Expensive

Long design cycle

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Proof of concept



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What is ML?

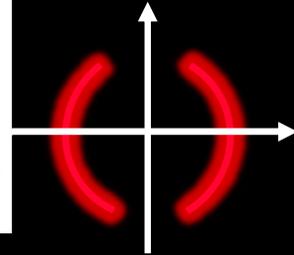
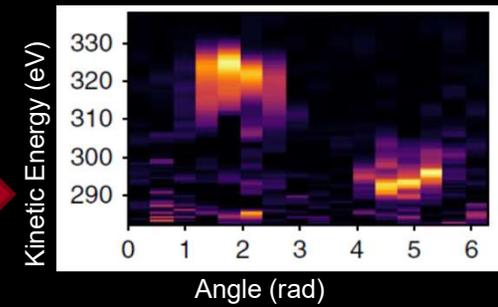
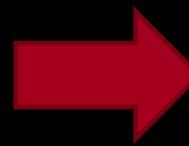
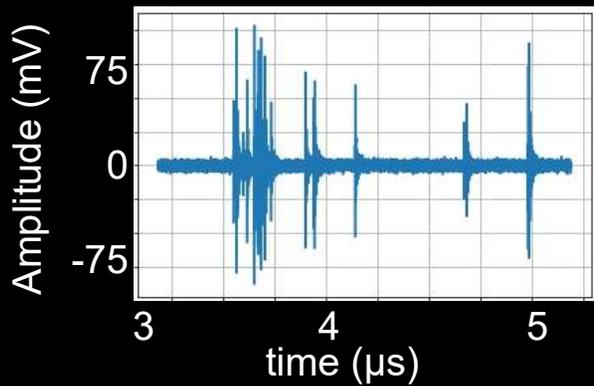
Hardware

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Pitfalls

Conclusion

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Complex reconstruction

N. Hartmann et al., Nature Photonics, 2018

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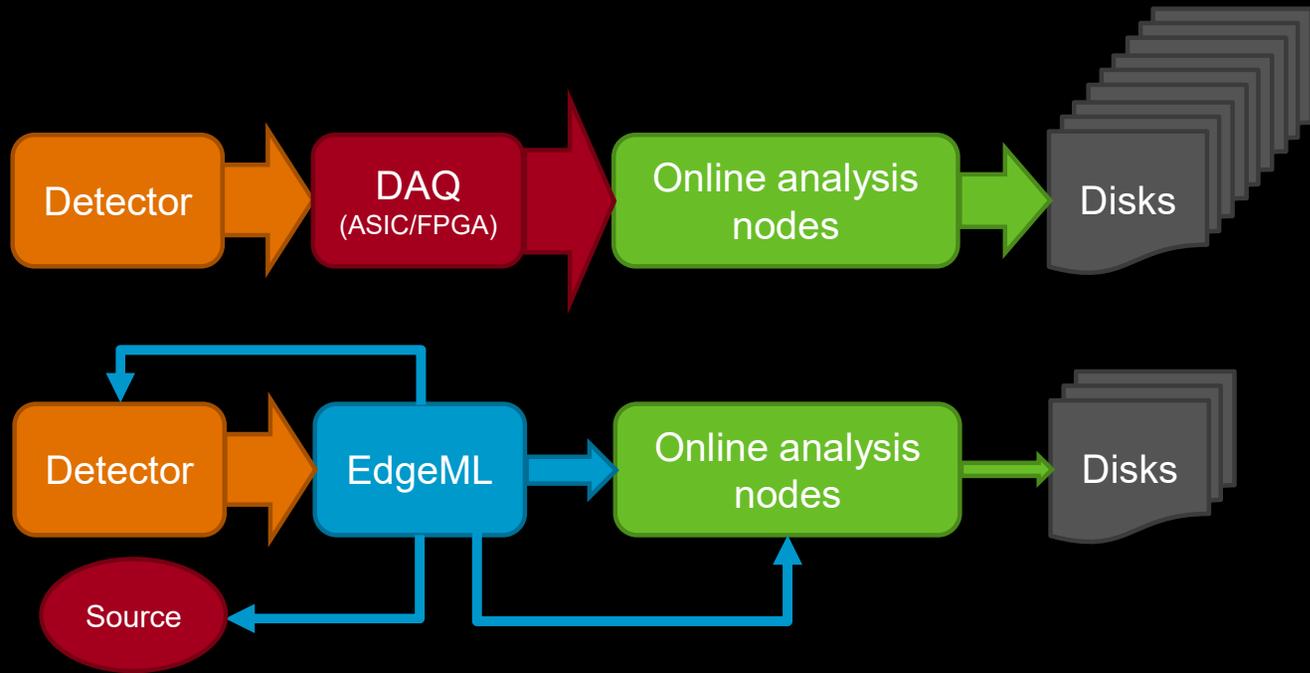
What is ML?

Hardware

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Pitfalls

Conclusion



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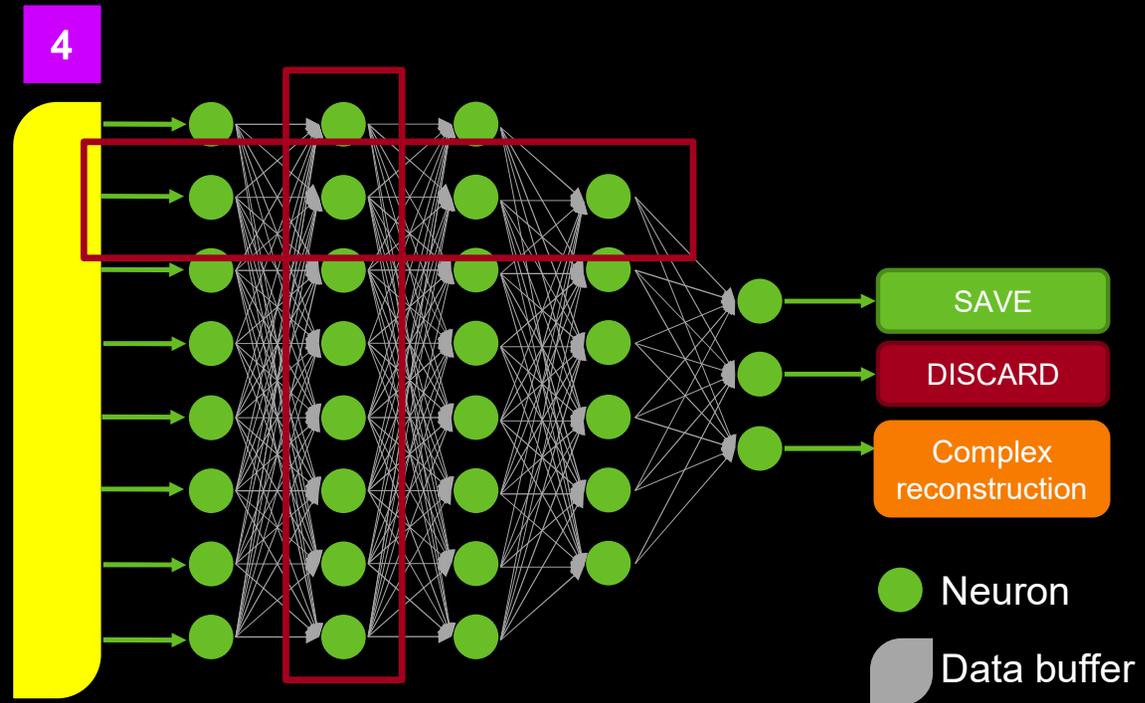
What is ML?

Hardware

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Pitfalls

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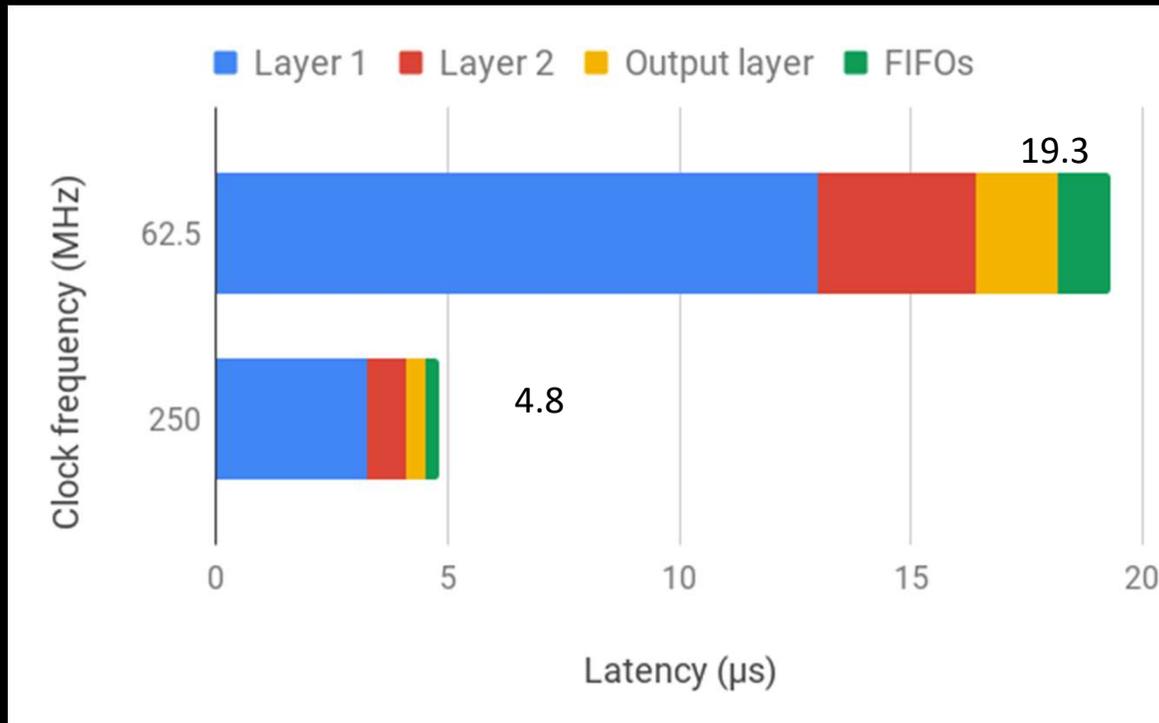
What is ML?

Hardware

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Pitfalls

Conclusion



Layer 1 : 800 inputs
 Layer 2 : 200 inputs
 Output Layer : 100 inputs

Maximum theoretical throughput R :

$$R = \frac{1}{\text{MAX}(\text{layer latency})}$$

R (62,5 MHz) = 77 kHz

R (250 MHz) = 308 kHz

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What is ML?

Hardware

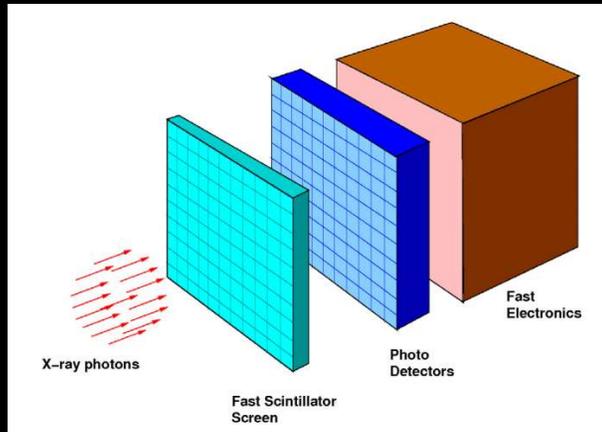
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Conclusion

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Other projects



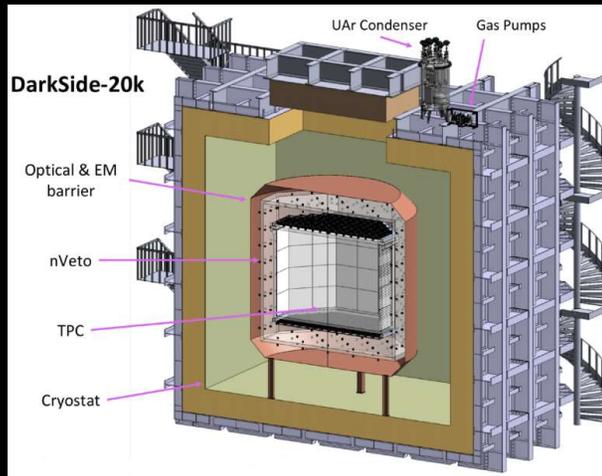
Billion-pixel camera for X-ray applications

Hu, C. et al, 2019

doi.org/10.1016/j.nima.2019.06.011



~2GB per image



Liquid Argon detectors for dark matter search

Global Argon Dark Matter Collaboration

CPAD2019

~1.2 GB/s

DS20K Veto system

Other projects

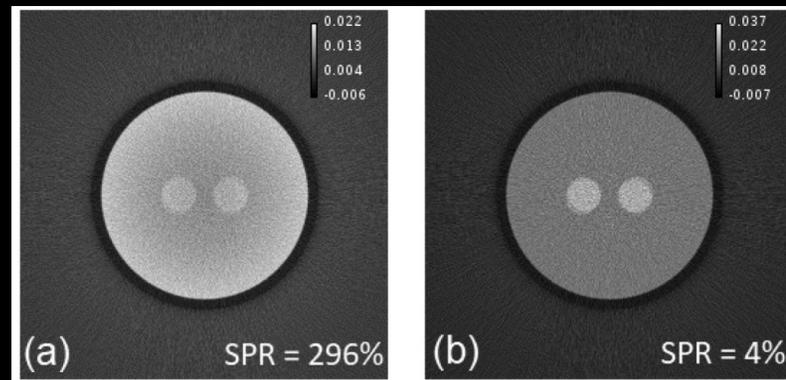
What is ML?

Hardware

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Conclusion



Time of Flight Computed Tomography

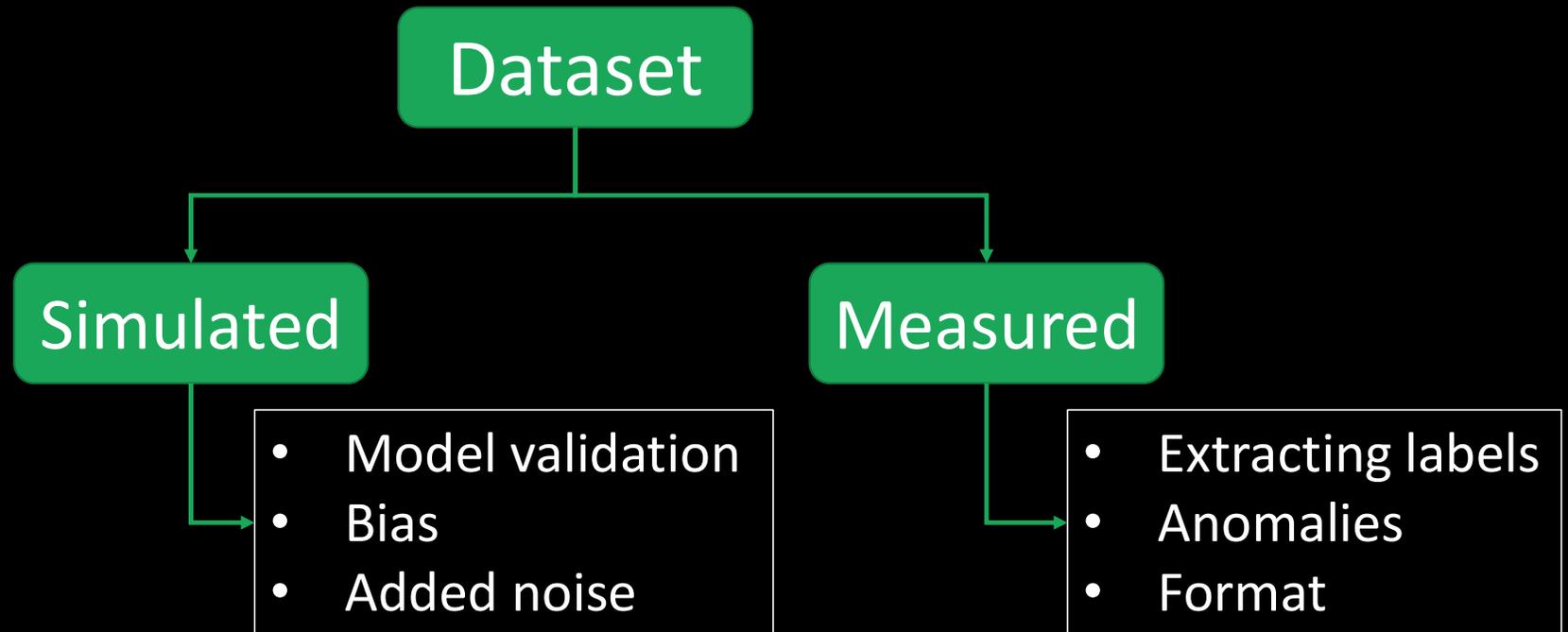
Rossignol, J. et al. 2020
doi.org/10.1088/1361-6560/ab78bf

~120 TB/s
14x14 cm²

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Pitfalls

Training Datasets

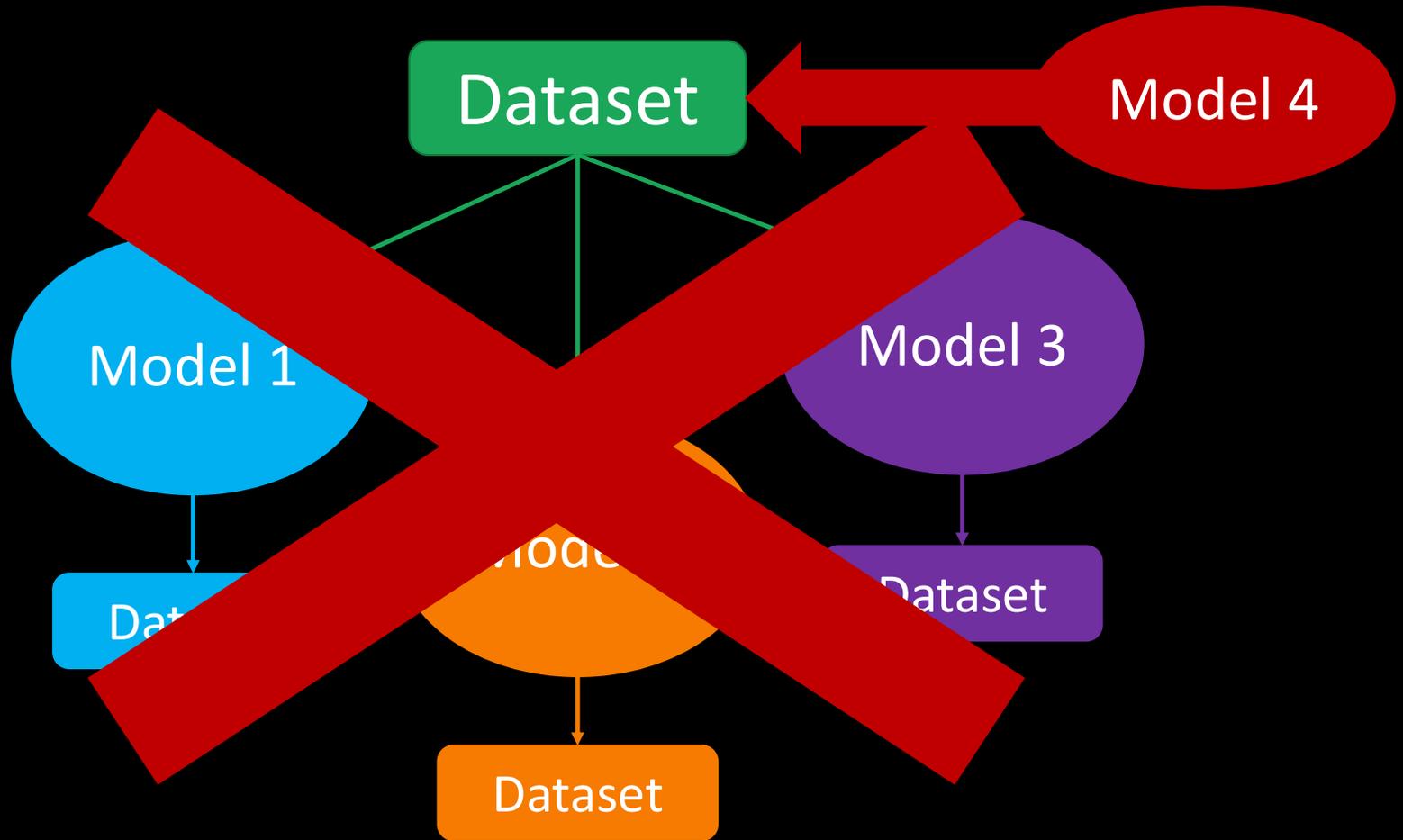


User endorsement

How do we convince the users of the instruments that the machine learning inference gives them accurate information?

- Validation
- Interpretation
- Uncertainty measurement
 - Raw data sampling

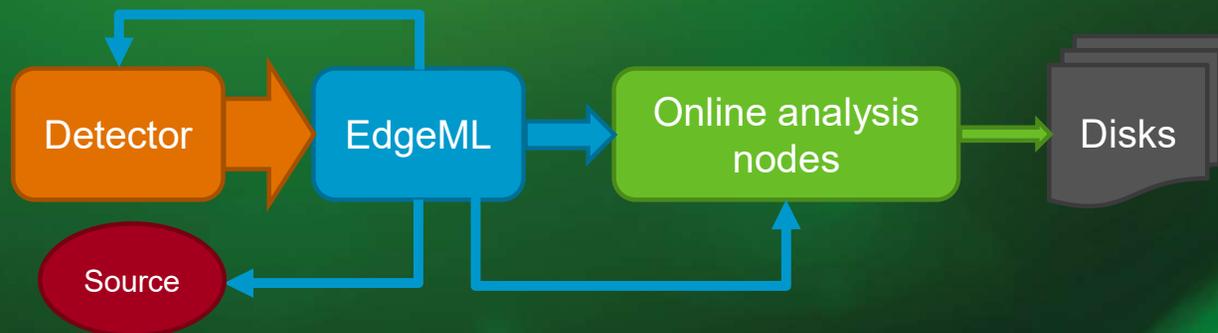
Data and model provenance



Conclusion

Edge Machine Learning is key to exploit the full potential of new high rate detectors and will accelerate critical discoveries...

...but we have a lot of work to do!



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