

# CaloChallenge: A Proposal

David Shih

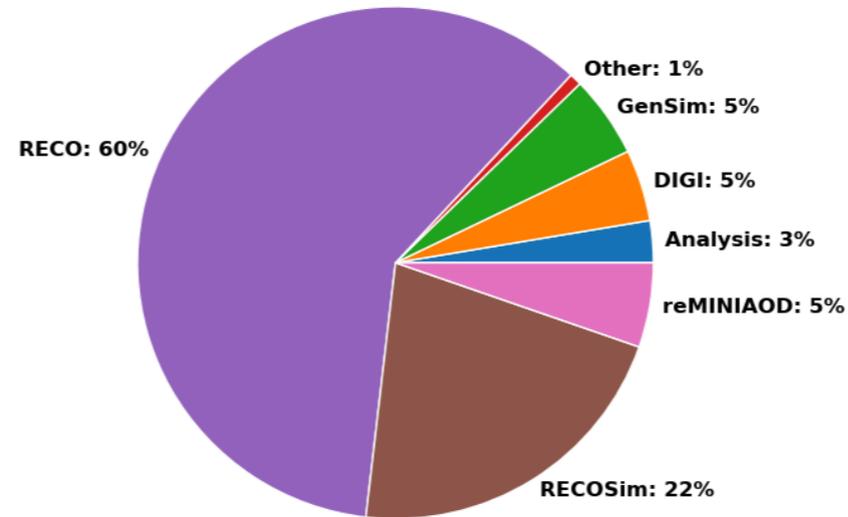
on behalf of Michele Fauci Giannelli, Gregor Kasieczka,  
Ben Nachman & Dalilia Salamani

ML4Jets 2021

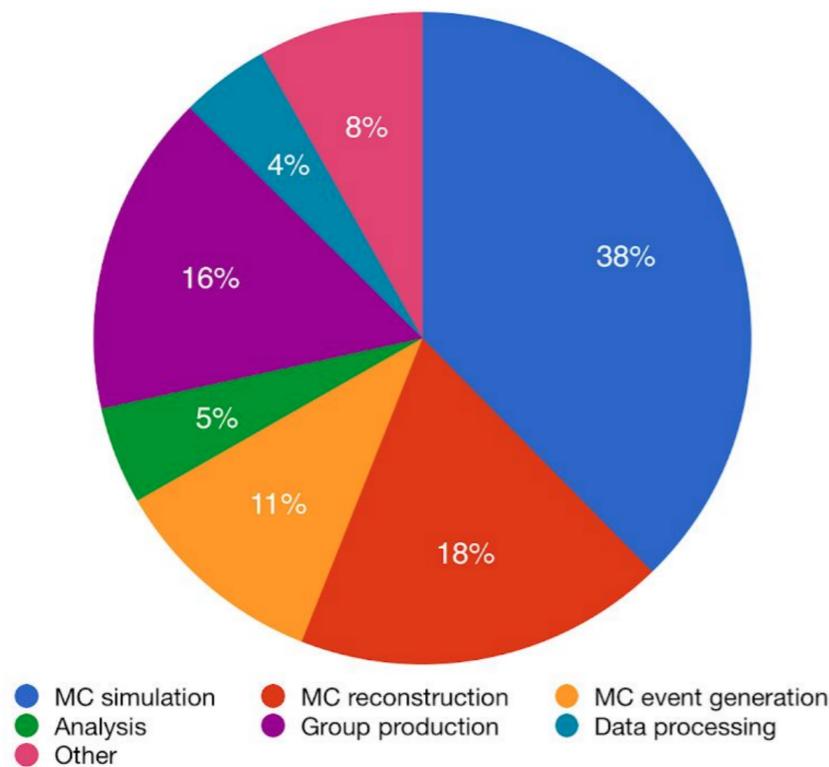


# Detector Simulation is Expensive

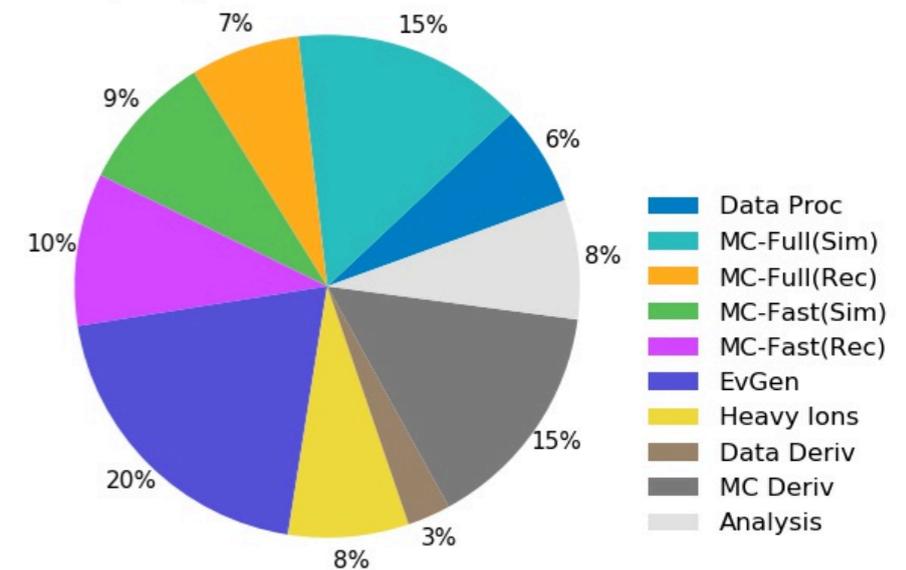
**CMS Public**  
Total CPU HL-LHC fractions  
2020 estimates



Wall clock consumption per workflow



**ATLAS Preliminary**  
2020 Computing Model -CPU: 2030: Baseline

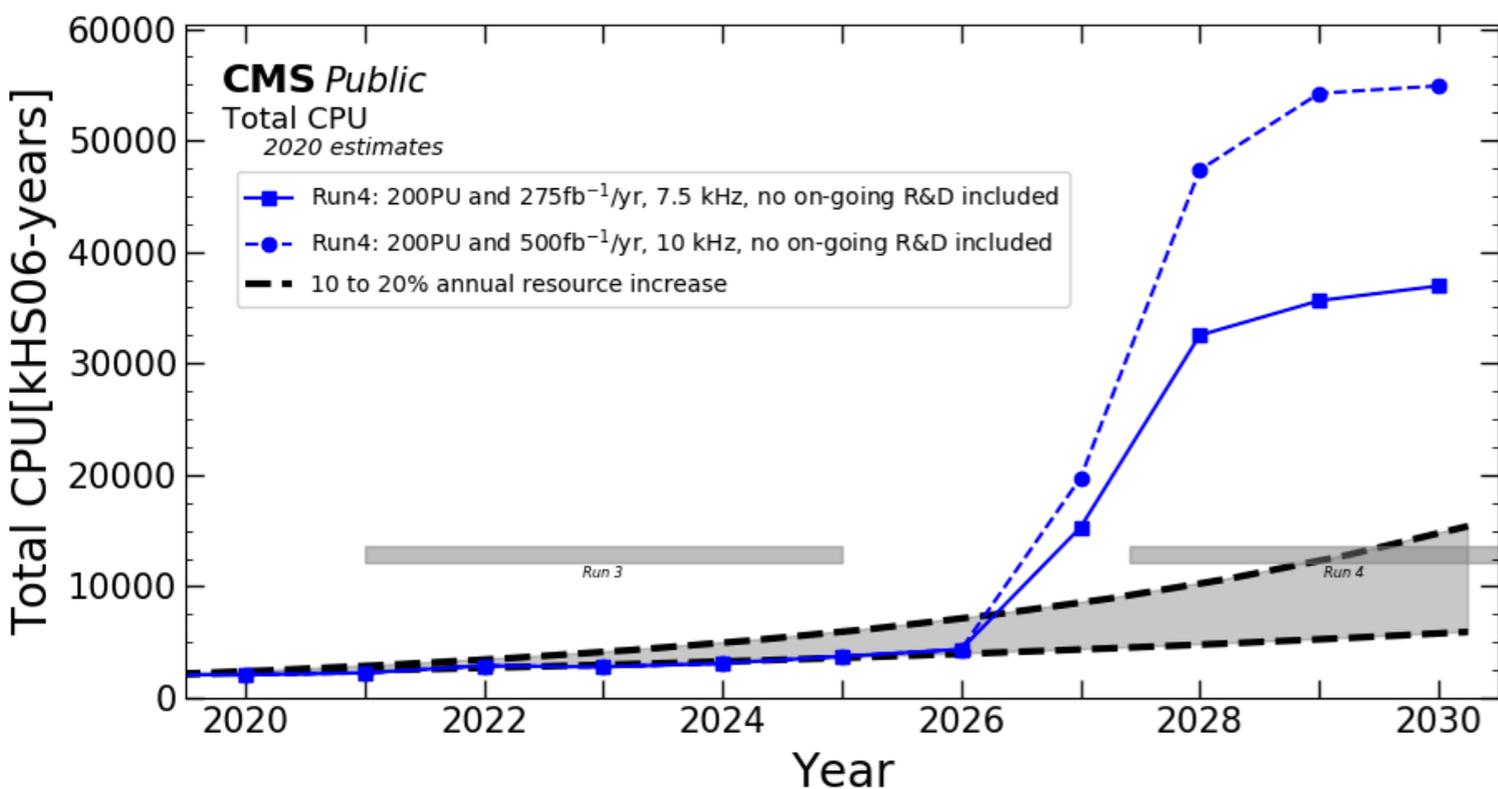


CERN-LHCC-2020-015

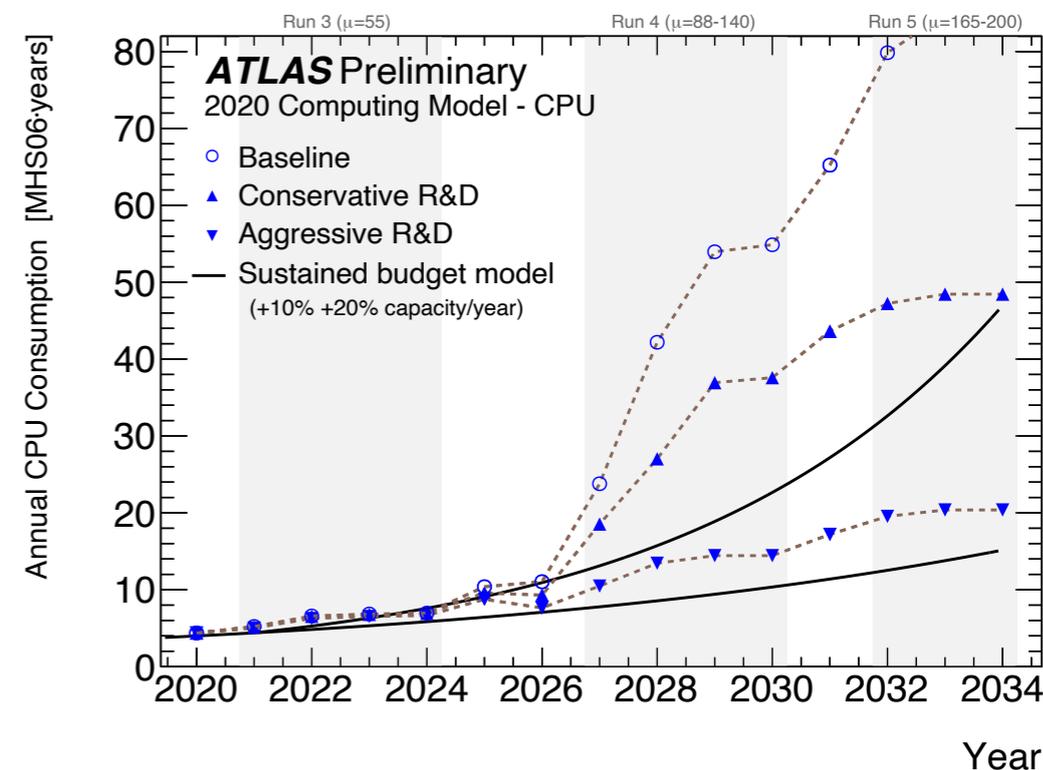
<https://twiki.cern.ch/twiki/bin/view/CMSPublic/CMSOfflineComputingResults>

<https://twiki.cern.ch/twiki/bin/view/AtlasPublic/ComputingandSoftwarePublicResults>

# Without major R&D, computing needs at HL-LHC will far outstrip available resources



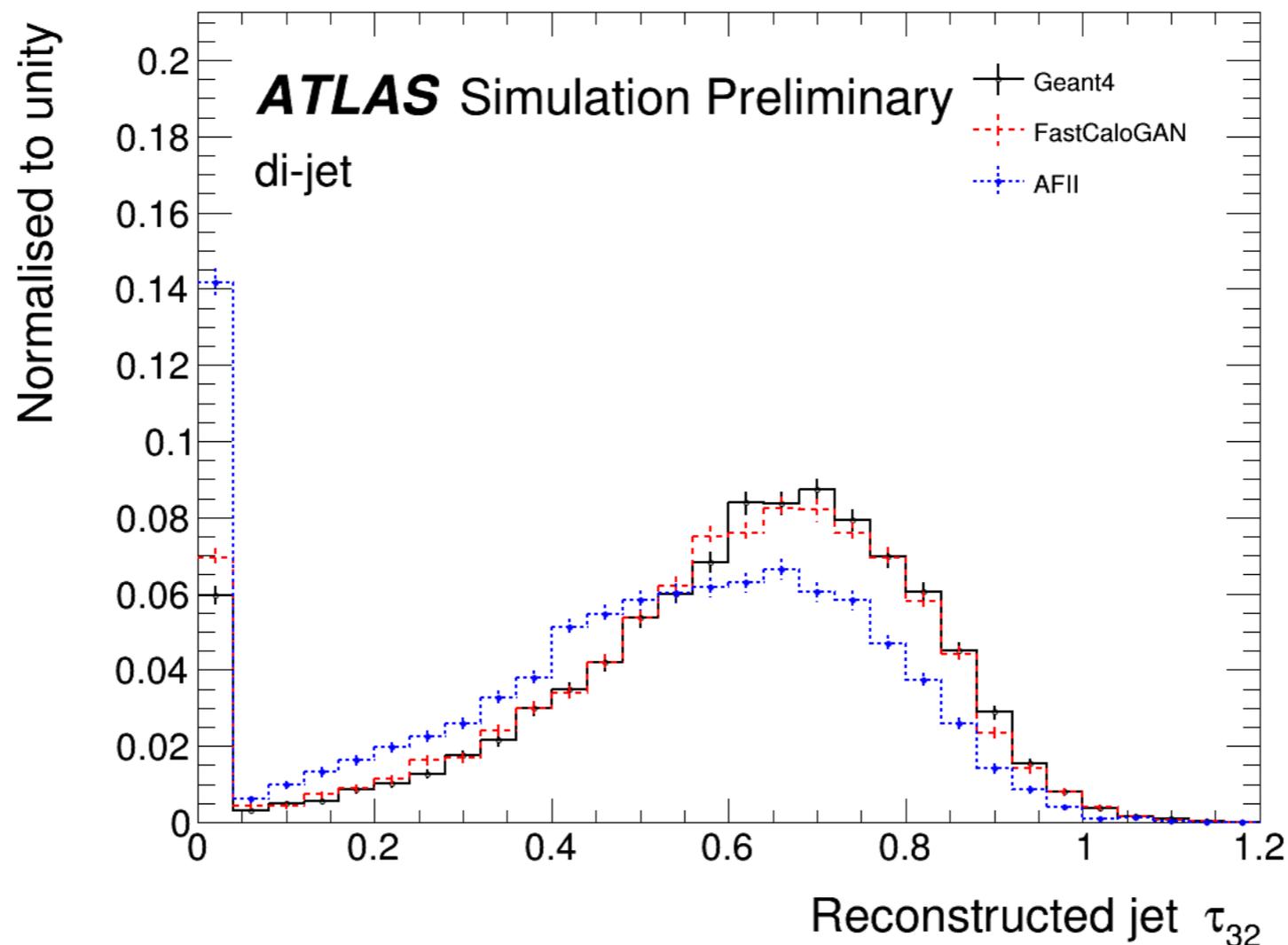
There is a major need for fast and accurate alternatives to GEANT4 calorimeter simulation!



# Fast CaloSim with Deep Learning

Actually, regardless of computing resources, there is a lot of potential for improving fast calorimeter simulation with deep learning

from [ATL-SOFT-PUB-2020-006](#)



# Fast CaloSim with Deep Learning

	Classification	Datasets	Regression, Calibration, and Fast	Simulation and Generative Models
14:00	<b>CaloFlow: Fast and Accurate Generation of Calorimeter S...</b> <i>Dr Claudius Krause</i>			<b>Machine learning based Particle Flow algorithm and appl...</b> <i>Sanmay Ganguly</i>
	<b>Multi-detector geometery modeling and Geant4 Integration</b> <i>Dallia Salamani</i>			<b>Using Machine Learning for Heavy-Ion Jet <math>p_{\text{T}}</math> R...</b> <i>Hannah Bossi</i>
	<b>Angular Conditioning of Deep Generative Models for Fast...</b> <i>Peter McKeown</i>			<b>Learning Uncertainties the Frequentist Way: Calibration ...</b> <i>Rikab Gambhir</i>
15:00	<b>Fast and Accurate Electromagnetic and Hadronic Shower...</b> <i>Engin Eren</i>			<b>ML in jet physics beyond classification</b> <i>CMS Collaboration</i> 15:00 - 15:20
	<b>AtFast3: The next generation of fast simulation in ATLAS</b> <i>Joshua Falco Beirer</i>			<b>Pileup mitigation in CMS</b> <i>CMS Collaboration</i> 15:20 - 15:40
	<b>Fast Simulation of Jets with VAEs</b> <i>Mary Touranakou</i> 15:40 - 16:00			<b>Lightweight Jet Reconstruction as an Object Detection T...</b> <i>Adrian Alan Pol</i>
16:00	<b>Foundations of a Fast, Data-Driven, Machine-Learned Sim...</b> <i>Jessica N. Howard et al.</i>			<b>Measurement of Muon Energy From Radiative Losses in ...</b> <i>Giles Chatham Strong</i>
	<b>Particle Cloud Generation with Message Passing GANs</b> <i>Raghav Kansal</i>			<b>Deep learning jet modifications in heavy-ion collisions</b> <i>Dr Yilun Du</i>
	<b>White Box AI for parton shower development</b> <i>Felix Ringer</i> 16:40 - 17:00			<b>Matrix Element Calculations on the GPU</b> <i>Joshua Isaacson</i> 16:40 - 17:00
17:00	<b>How to GAN Event Unweighting</b> <i>Mr Mathias Backes</i> 17:00 - 17:20			<b>Jet Identification in L1 Trigger at HL-LHC based on DNN i...</b> <i>Dr Andre Sznajder</i>
	<b>Sparse Data Generation with Convolutional VAE</b> <i>Breno Orzari</i>			<b>OnlineFlow: Trigger Free Analysis Using Online Learned ...</b> <i>Sascha Daniel Diefenbacher</i>
	<b>Super-Resolution for QCD and Top Jets</b>			<i>Lukas Blecher</i> 17:40 - 18:00

**A lot of exciting work on this topic!**

# Existing approaches

Many different approaches have been tried for fast GEANT4 emulation with deep learning:

- GANs  
[Paganini, de Oliveira & Nachman 1712.10321](#)  
[Belayneh et al 1912.06794](#)
- WGANs  
[Erdmann et al 1802.03325, 1807.01954](#)  
[ATL-SOFT-PUB-2018-001, ATL-SOFT-PUB-2020-006](#)
- Bib-AE  
[Buhmann et al 2005.05334, 2102.12491](#)
- VAEs  
[ATL-SOFT-PUB-2018-001](#)
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[Krause & DS 2106.05285](#)
- ... plus many others that focus on other generative modeling tasks, e.g. jet images, cf [HEP-ML living review](#)

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But for the most part, each study uses its own dataset, making it hard to benchmark and compare different approaches

# Proposal

A community challenge, based on a common dataset, for developing and benchmarking different approaches to fast calorimeter simulation

Modeled after:

- Top tagging community study  
*Kasieczka, Plehn (eds) et al* [<https://arxiv.org/abs/1902.09914>]
- LHC Olympics 2020  
*Kasieczka, Nachman & DS (eds) et al* [<https://arxiv.org/abs/2101.08320>]

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  - Realistic resolution
  - Multiple particles (eg  $e^+$  and  $\pi^+$ )
  - Voxels and cells?

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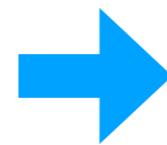
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  - Maybe just the central eta slice of the detector?

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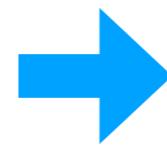


Something like the dataset used  
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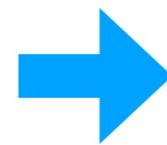


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- Something which outside ML people could also participate in



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# Metrics

Challenge should have clearly defined metrics from the outset (and not too many).

Some ideas include:

- Ultimate classifier metric: classifier between real and generated samples  
see Krause & DS [<https://arxiv.org/abs/2106.05285>]
- Histograms
- Average Images
- Nearest Neighbor Tests
- Other metrics (Frechet distance, Wasserstein Distance...)  
see Kansal et al [<https://arxiv.org/abs/2106.11535>]
- Training time
- Evaluation time
- Memory usage

# Timeline

Dataset in: ~ 2-3 months

Challenge duration: ~ 1 year

Results deadline: ~ 1 month before ML4Jets2022

Presentation of results at ML4Jets2022

**Community input welcome!!**