Searching for Strongly Coupled Dark Sectors with Unsupervised and Generative Learning

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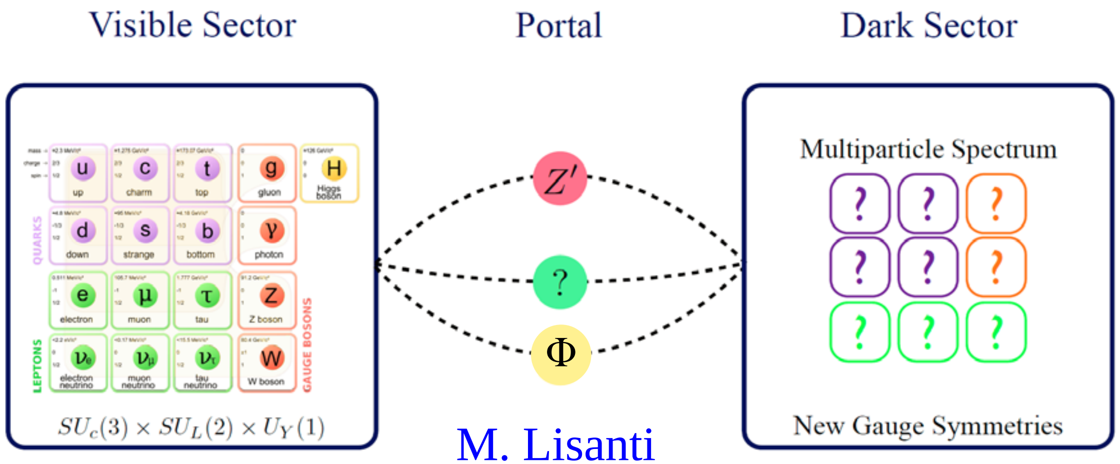
Strongly Coupled Dark Sectors



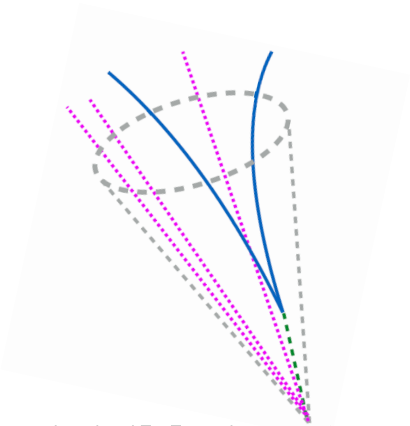
M. Lisanti

- Numerous sources of evidence that dark matter exists and behaves differently from visible matter
- But no direct experimental evidence of its nature
- What if DM is *hiding* in existing collider data?

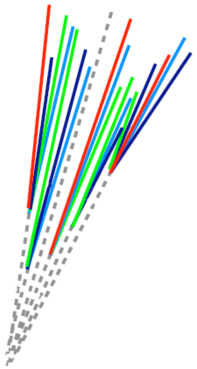
- Dark sector may consist of multiple species of particles interacting via new "dark QCD" force
- Analogous to SM: dark quarks, dark gluons, dark hadrons (stable and unstable)

- DM abundance arises from asymmetry mechanism → no annihilation
- DM interactions with ordinary matter highly suppressed → no direct detection

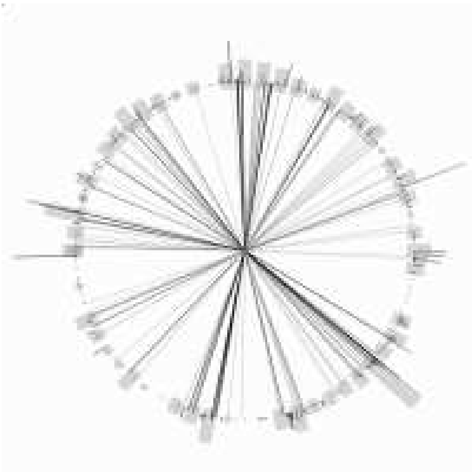
Phenomenology



Semivisible jets (SVJs)
mixture of stable and unstable dark hadrons
→ p_T^{miss} aligned with jets



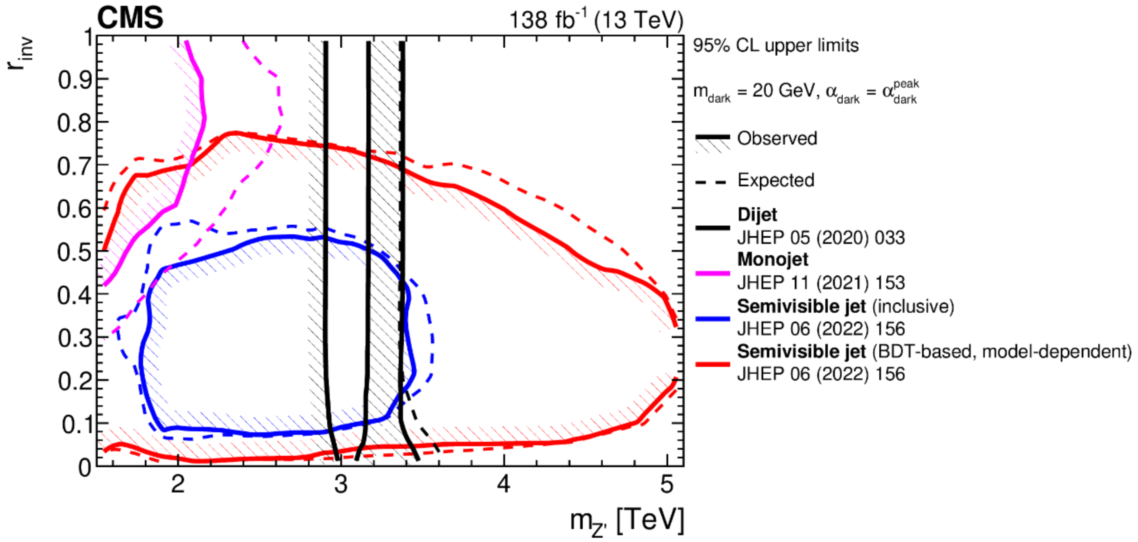
Emerging jets (EMJs)
dark hadrons decay after some lifetime
→ multiple displaced vertices within each jet

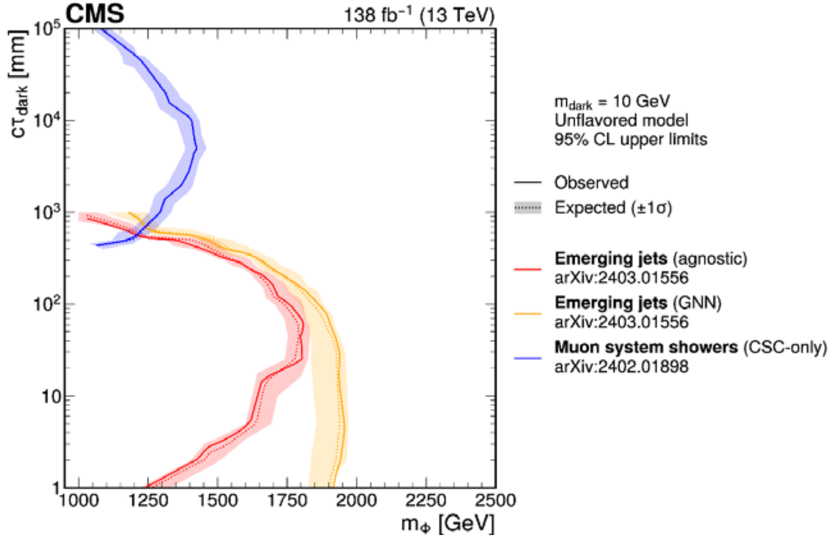


Soft unclustered energy patterns (SUEPs)
confining theory with large ‘t Hooft coupling, beyond QCD-like regime
→ spherical distribution of low-p_T tracks

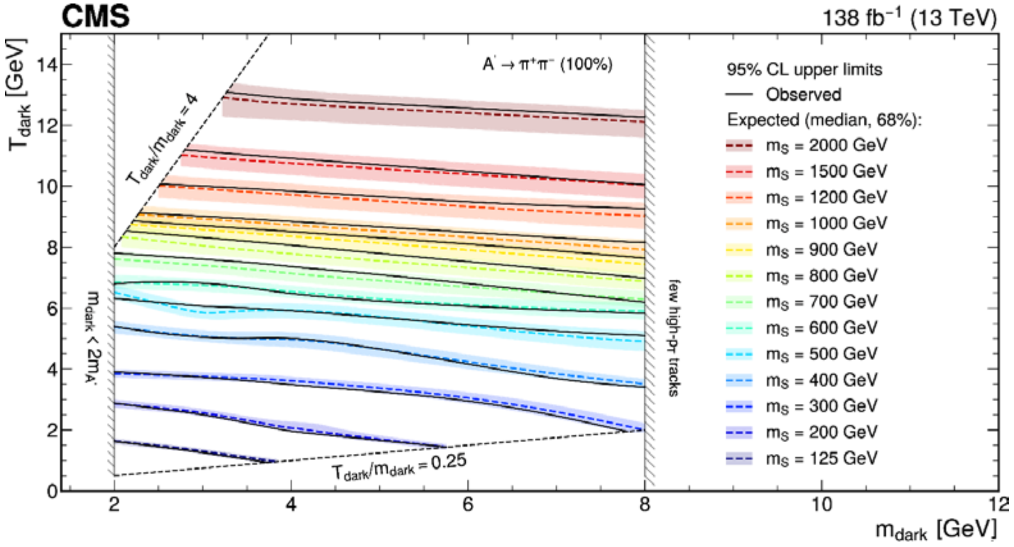
Latest Results

- CMS has executed *first searches* for all dark QCD phenomena using LHC Run 2 data





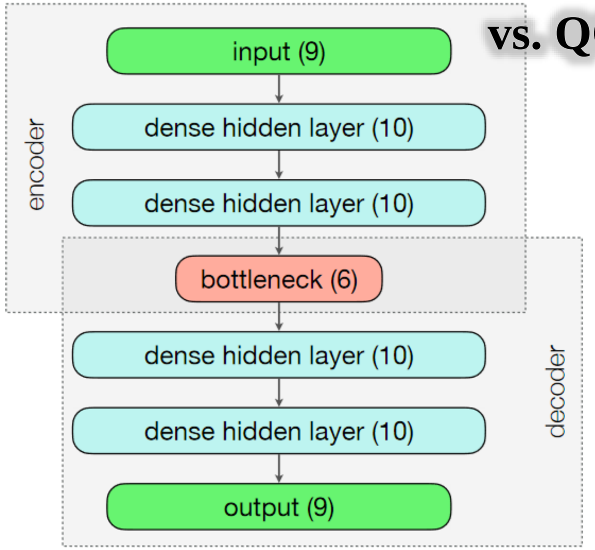
- *Complementarity* between existing strategies and new, dedicated searches



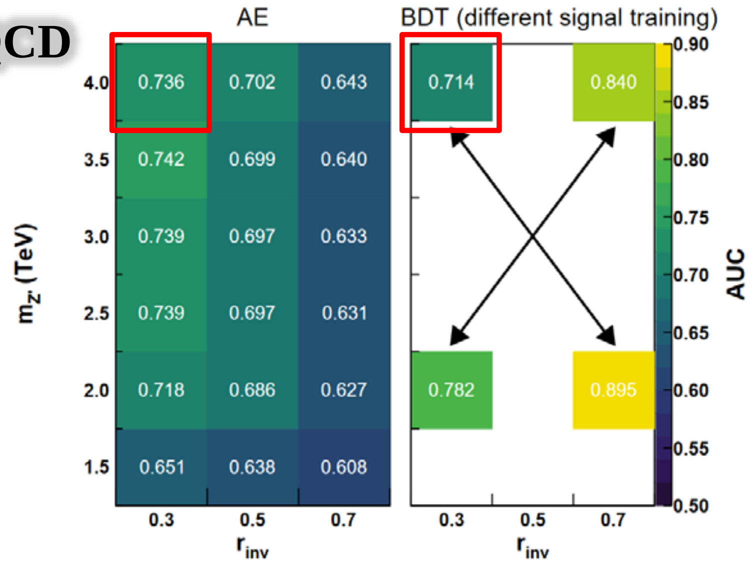
- *Supervised ML* to "tag" new kinds of jets:
  - Significantly increases sensitivity
  - Cost: model dependence

Autoencoders for Semivisible Jets

arXiv:2112.02864



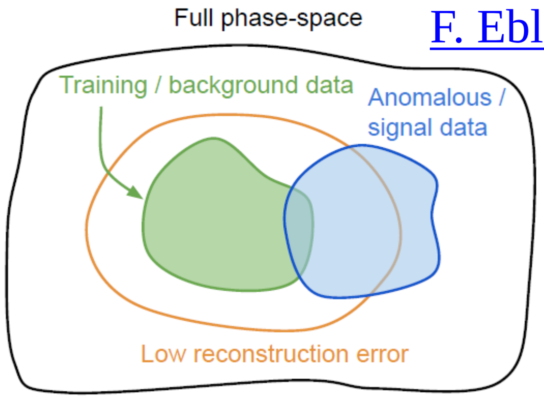
vs. QCD



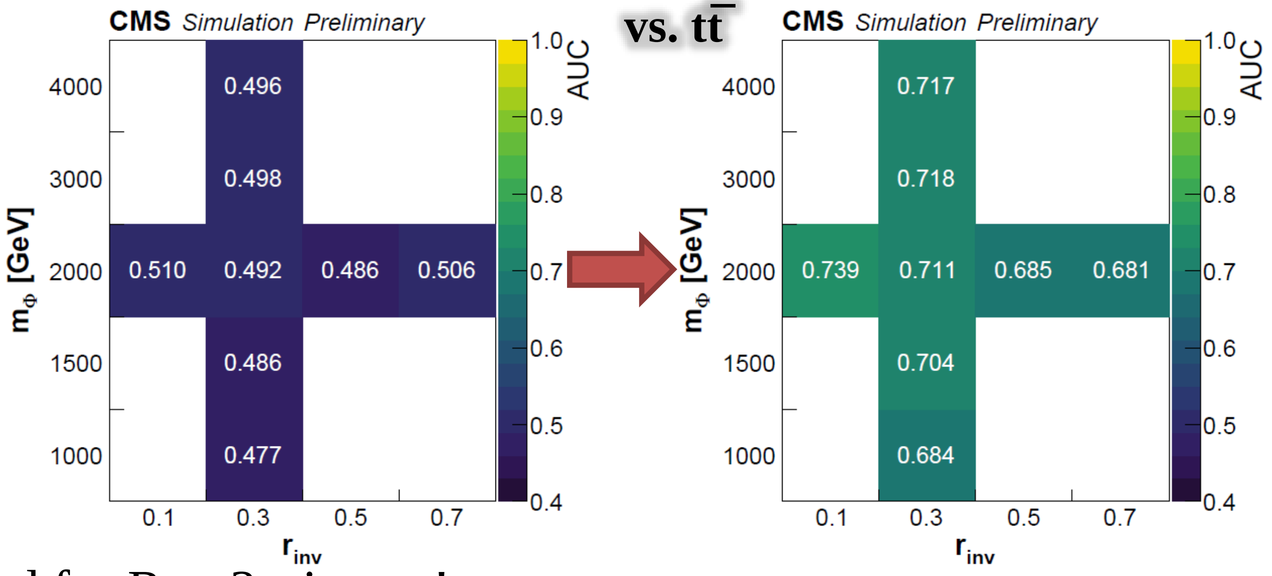
- Learn latent representation that can accurately reconstruct *background*
  - o Signal not used in training; identified later via high *reconstruction error*
- Autoencoder can *outperform* BDT on signals with different parameter values
- Works well against QCD background, but not $t\bar{t}$ … *complexity bias*

- Normalized autoencoder formalism:
  - o *Sample* from low-error space during training to prevent over-generalizing
- Use Energy Mover's Distance to choose best model (prevent mode collapse)

F. Eble



vs. $t\bar{t}$

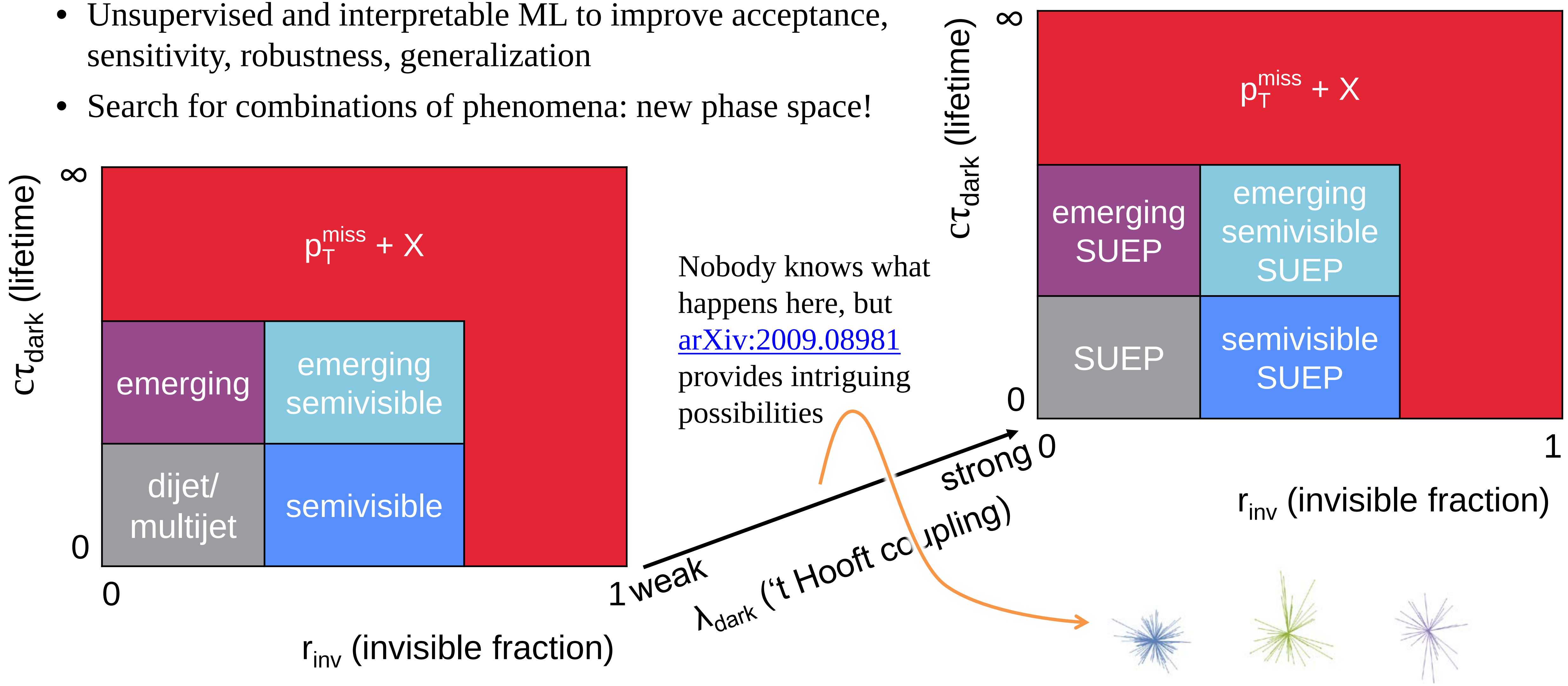


➢ Now being pursued for Run 3 triggers!

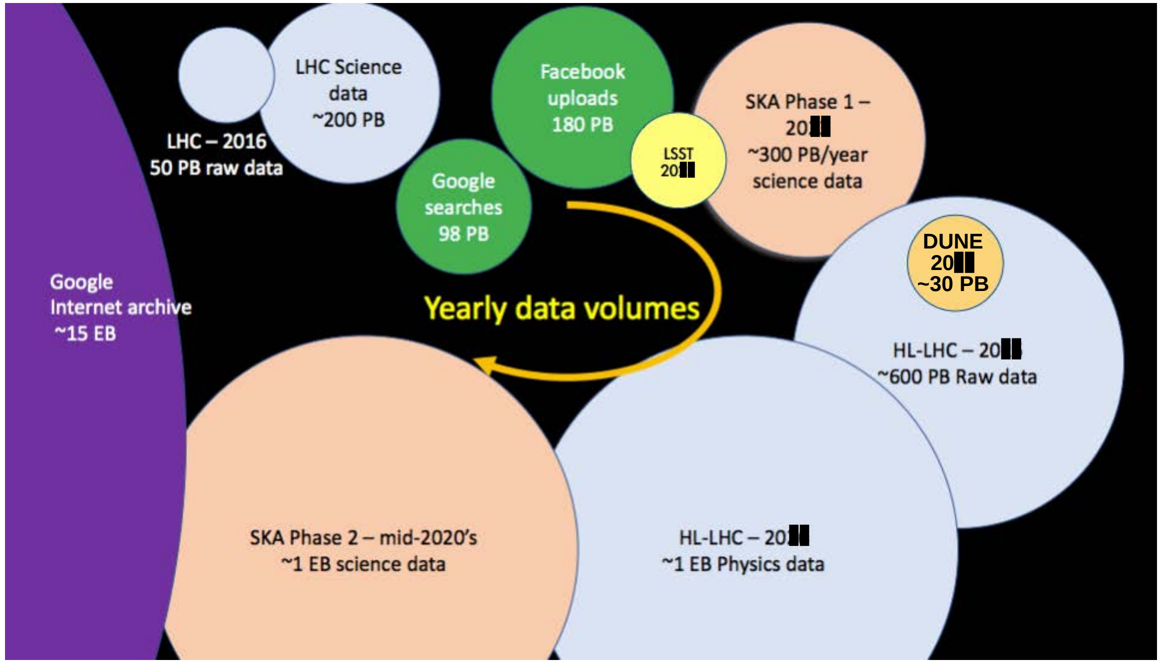
The Future of Dark QCD Searches

- Expand to more production modes (vector, scalar, bifundamental, Higgs, …)
- Unsupervised and interpretable ML to improve acceptance, sensitivity, robustness, generalization
- Search for combinations of phenomena: new phase space!

Nobody knows what happens here, but [arXiv:2009.08981](https://arxiv.org/abs/2009.08981) provides intriguing possibilities

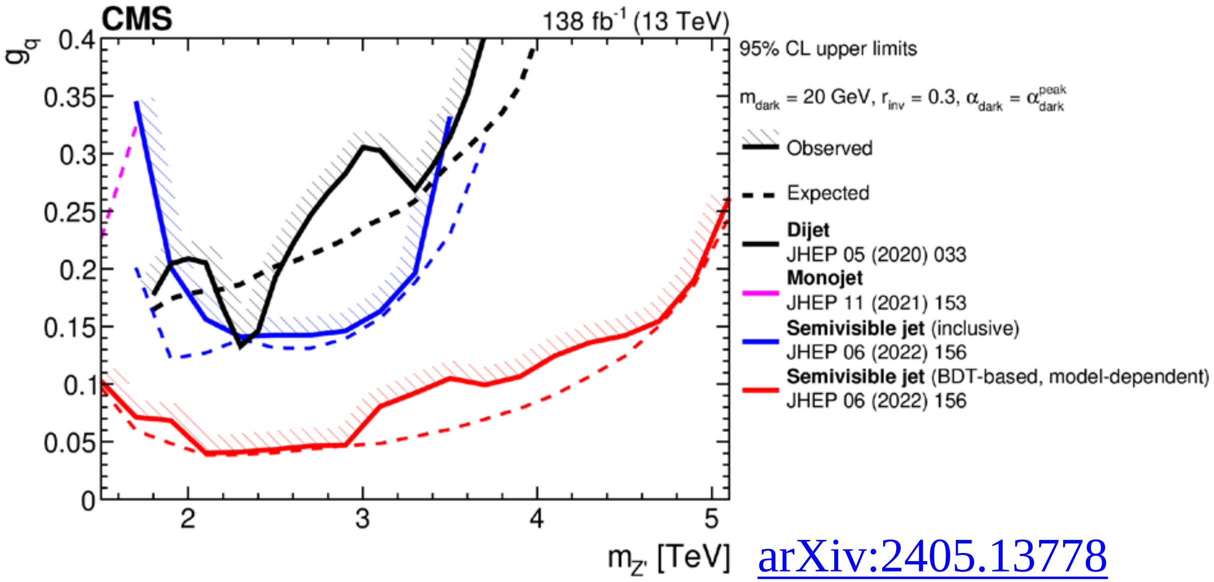


High-Luminosity Future



- *Challenges* to process, store, and analyze this upcoming flood of data
- Simulation is critical for analysis design and interpretation
  - o Will need to deliver more events with more complexity and more accuracy… while using *smaller fraction* of computing

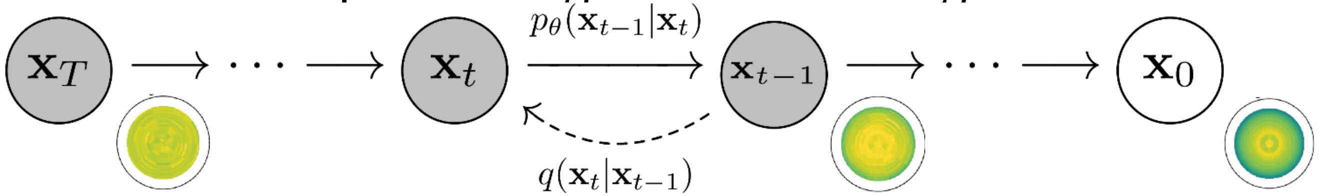
- A new precision era is imminent: HL-LHC, DUNE, LSST, SKA
  - o 10× or more data vs. existing experiments
- *Opportunities* for most precise measurements and discovery of rare processes
  - o Dark QCD w/ very weakly coupled mediators?
    - Models have dozens of parameters…



arXiv:2405.13778

ML For Simulation

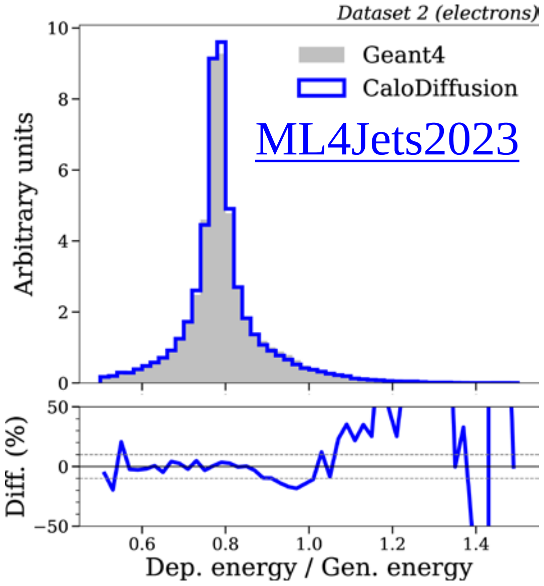
- CaloDiffusion ([arXiv:2308.03876]): current state-of-the-art model
  - o Adapt industry generative techniques to irregular calorimeter geometries



- Now the standard for comparison and a platform for further development: [arXiv:2401.13162], [arXiv:2406.12898]

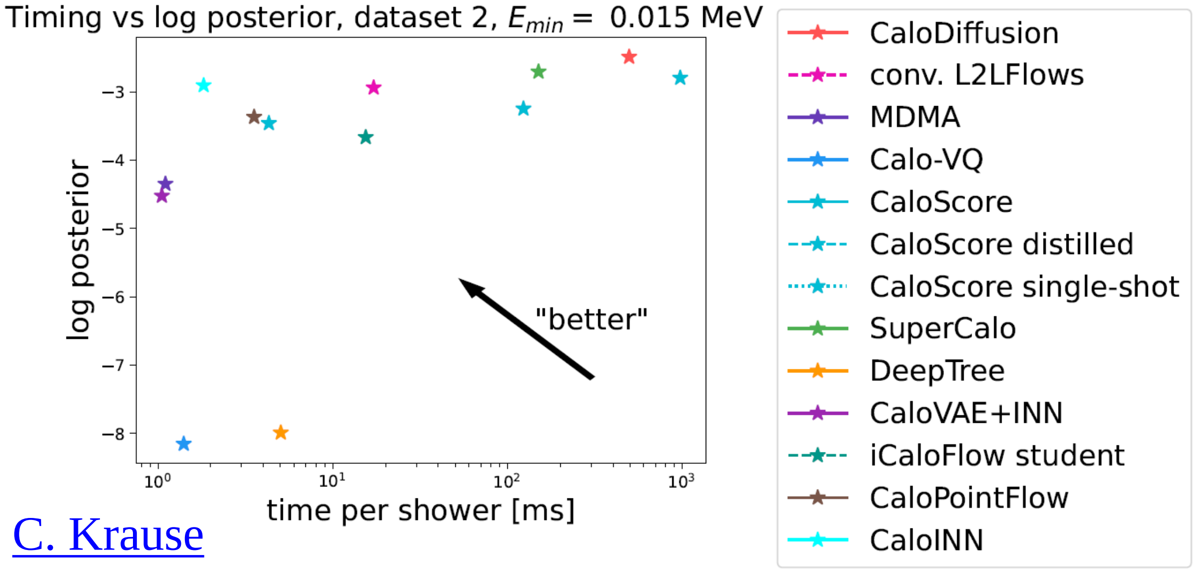
- Excellent agreement with full simulation even in difficult global quantities

➢ Most accurate entry in community challenge



[ML4Jets2023]

- Also in development: ML refinement of high-level variables
  - o Correct for any remaining inaccuracies
  - o "Perturbative" approach to detector simulation

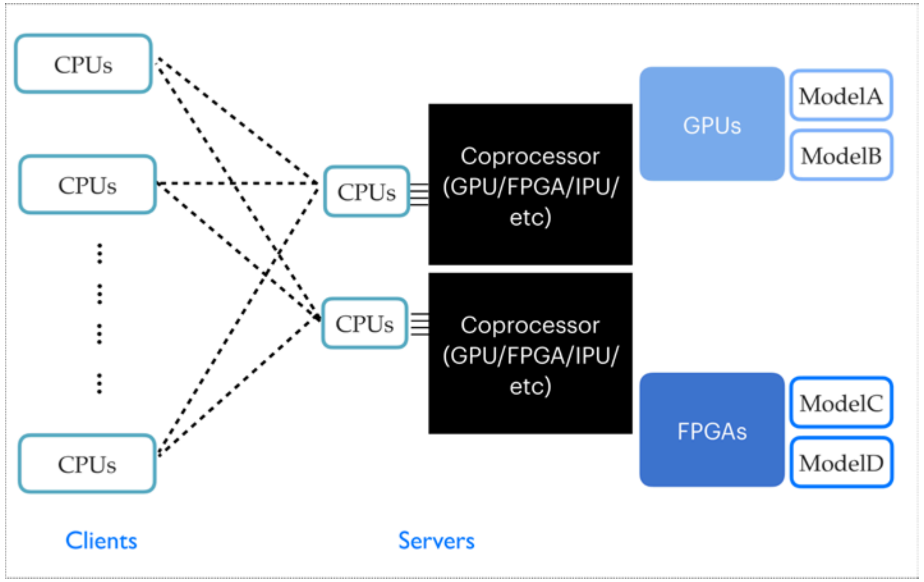


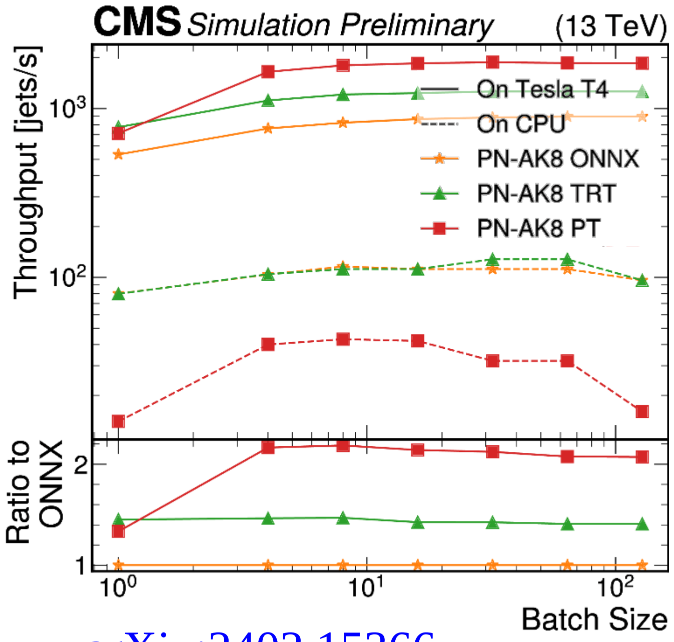
[C. Krause]

Computing for ML

- ML algorithms use a restricted set of operations (mostly matrix multiplications)
  - o Natural and easy to accelerate on specialized coprocessors
- *Most flexible* approach: inference as a service
  - o Abstract away specific computing elements: client makes request, server delivers
    - ▪ Use CPUs, GPUs, FPGAs, IPUs… with no code changes!
  - o Example: ~10× speedup in ParticleNet on GPU vs. CPU
    - ▪ Algorithm latency becomes essentially *invisible* with asynchronous calls in offline processing
    - ▪ Can batch *across events* for optimal GPU utilization → maximize throughput
  - o Similar 10× speedup in CaloDiffusion

➢ ML can *solve* high-luminosity challenges
  - o Result: *better, smarter, faster* physics

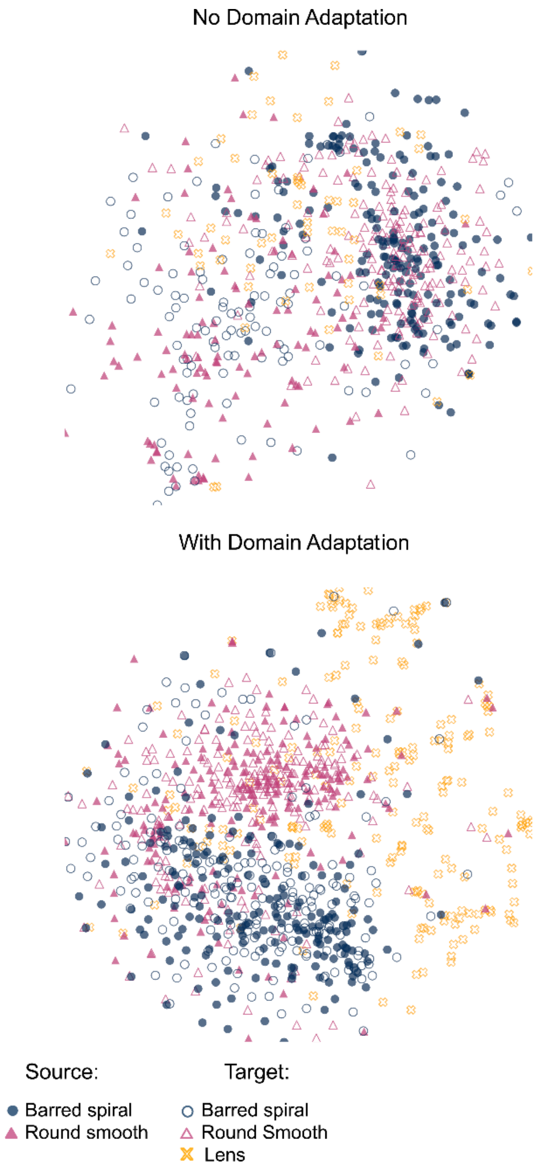




arXiv:2402.15366

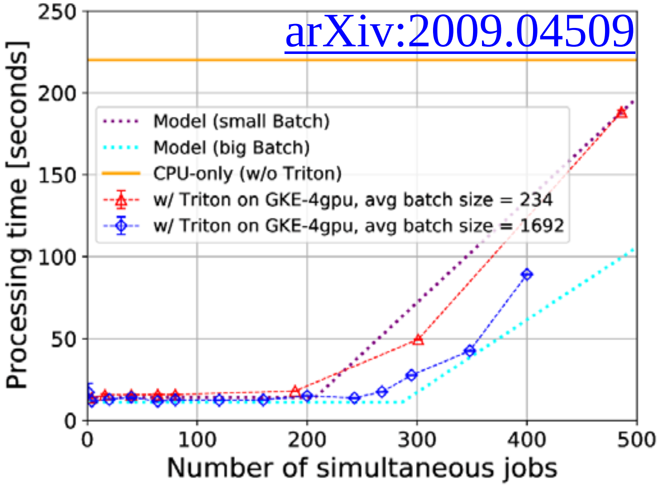
Beyond Colliders

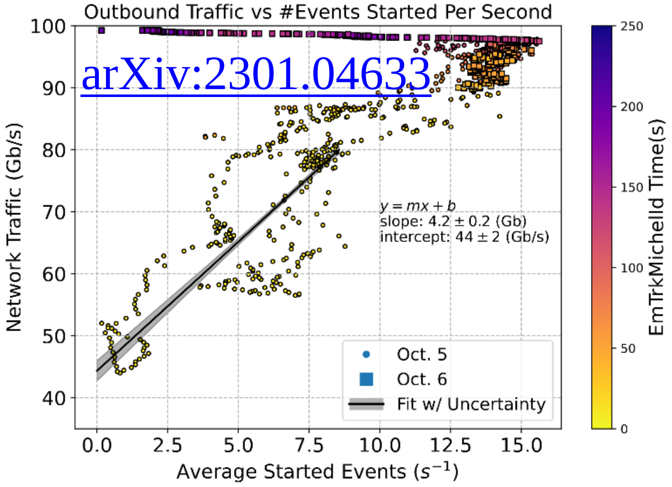
- Astrophysics:
  - o Goal: classify events (e.g. galaxy mergers)
  - o Multiple data sources, limited-accuracy simulation
    - ➢ Use semi-supervised *contrastive learning* (adaptive clustering + entropy separation)
  - o Domain adaptation improves performance and robustness
  - o Physically meaningful latent space
  - o Anomaly detection for unknown classes



arXiv:2302.02005

Neutrinos:
- o Inference as a service vital for large image classification algorithms
- o Algorithm level: 17× speedup using GPU
  - ▪ Analytical model of GPU saturation effects
- o Datacenter level: reprocess entire protoDUNE dataset in weeks instead of months
  - ▪ Mitigate network saturation via concurrency limits





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  - US CMS Collaboration and LHC Physics Center
  - International CMS collaboration at CERN
  - Dark QCD theorists, colleagues at other labs
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  - Industry partners: Nvidia, Microsoft, Google, Graphcore
  - My family, especially my wife, Titas

2024 US CMS Annual Collaboration Meeting (Princeton)

Backup

Publications

Dark QCD:
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