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U.S. DEPARTMENT OF ENERGY
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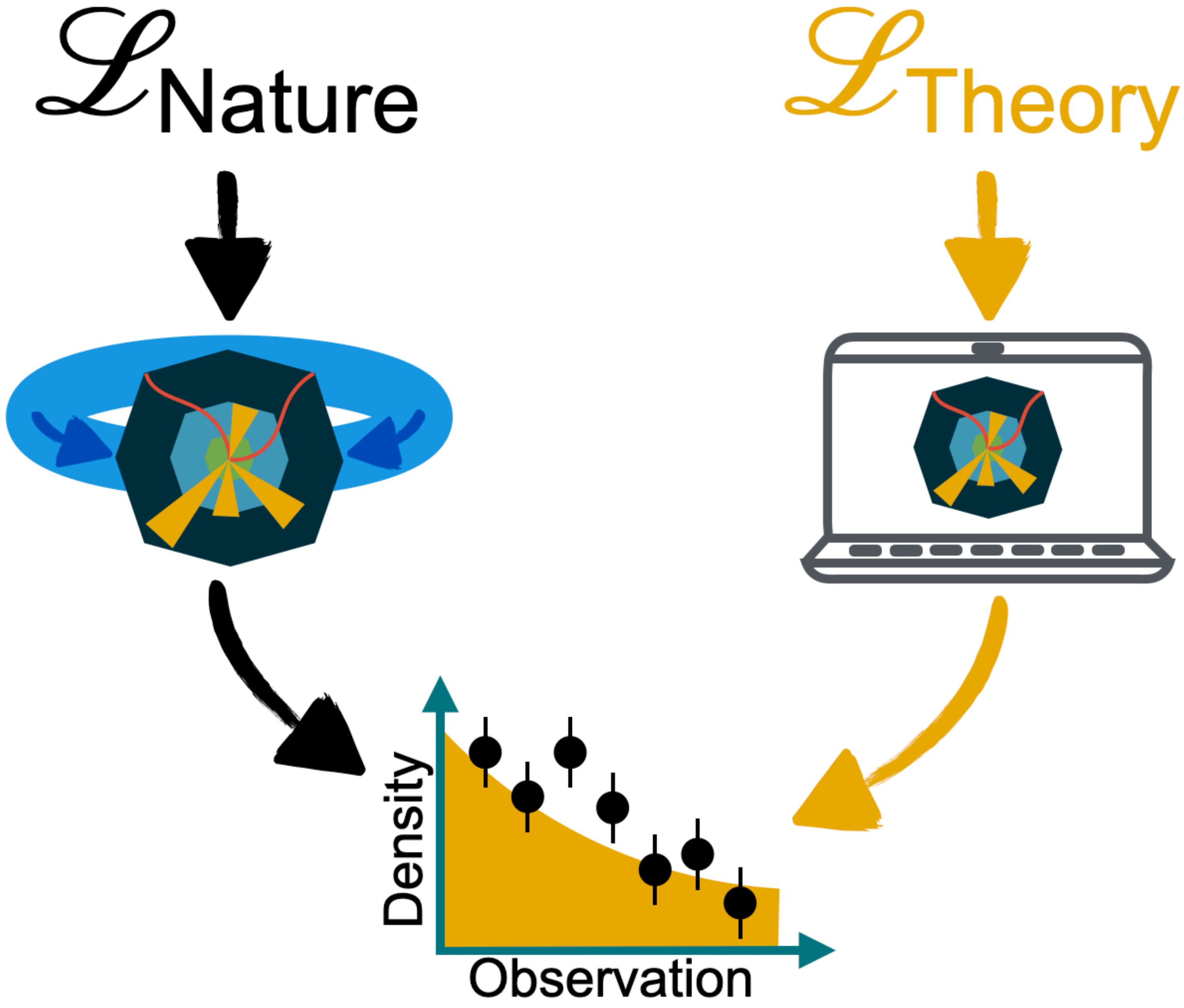
Machine Learning for HEP Data Analysis

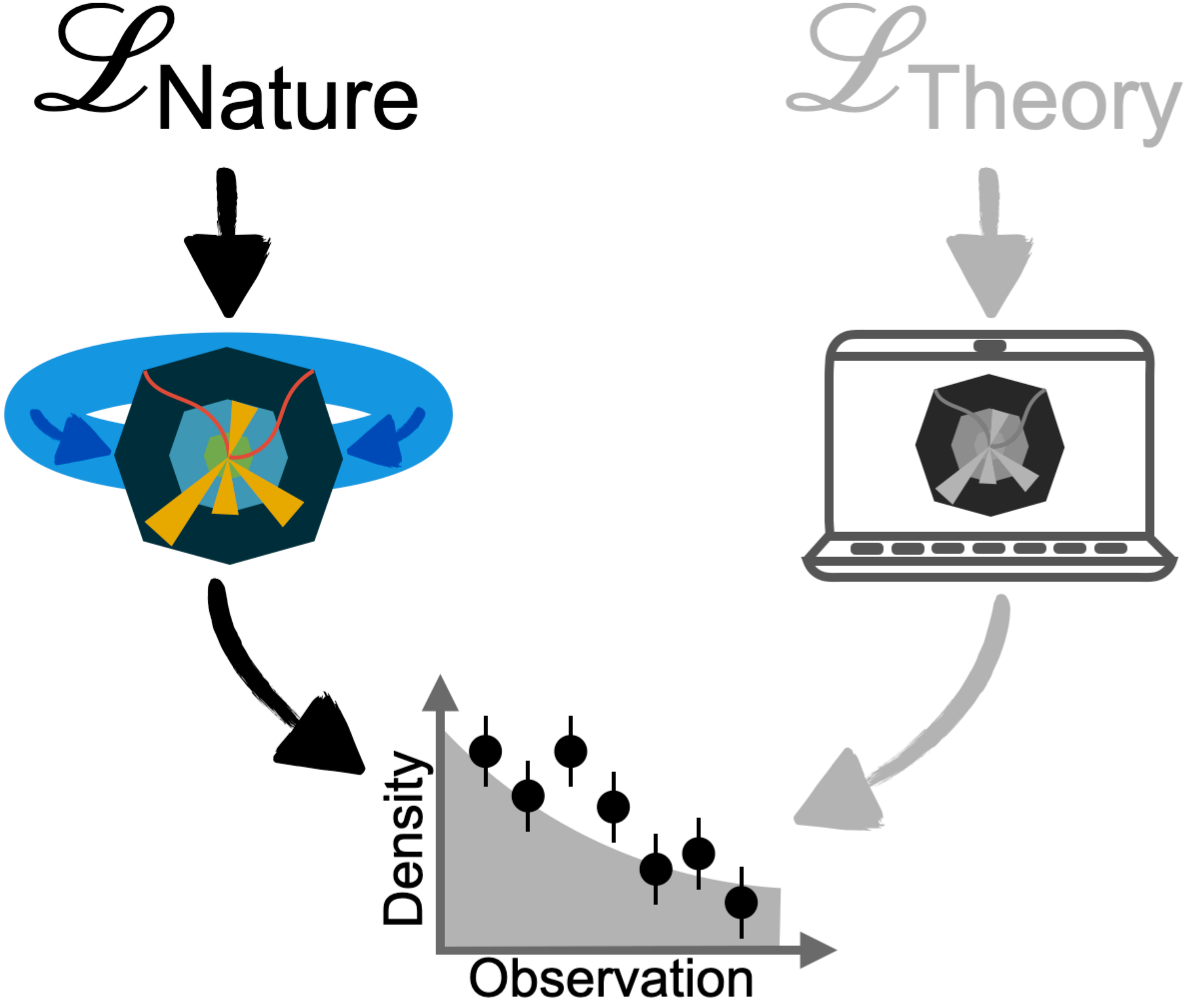
Dennis Noll

FCC Week 2024

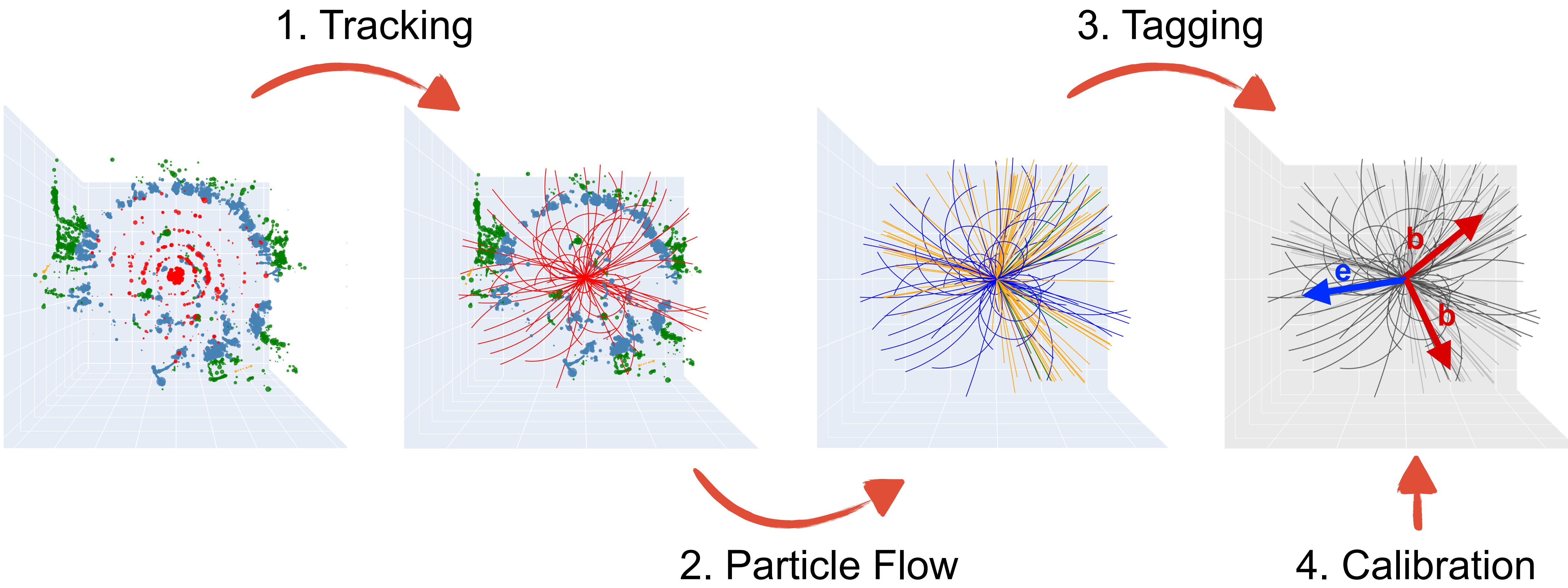
June 13, 2024



Inspired by [1]


$\mathcal{L}_{\text{Nature}}$
$\mathcal{L}_{\text{Theory}}$
Density
Observation

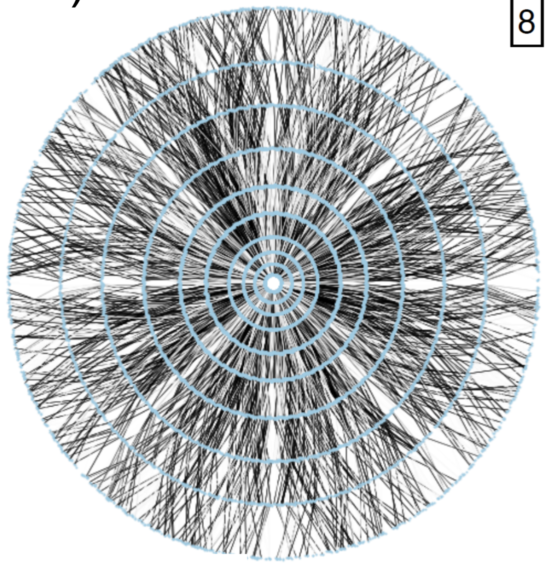
Introduction - Experiment [2]

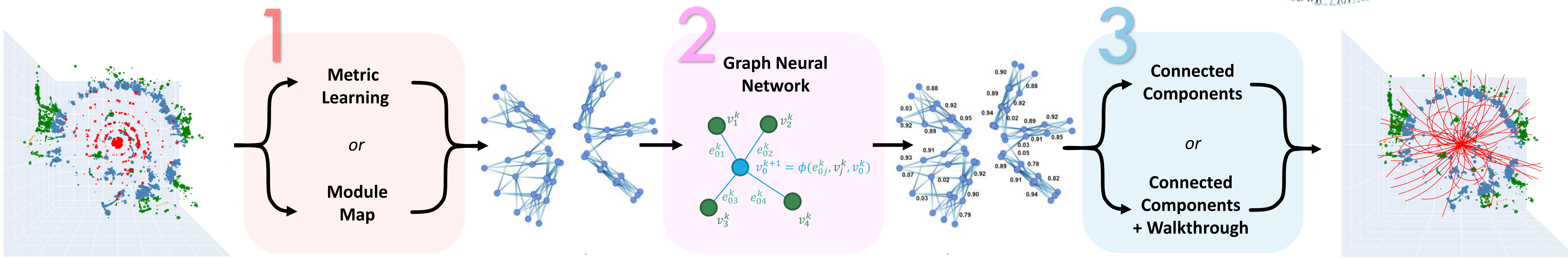


Experiment - 1. Tracking [3]

- Charged particles leave hist in tracker along their path (up to ~5000 per event)
- Turn tracker hits into tracks with graph-based ML
- Using ExaTrkX algorithm:
  1. Construct graph of hits
  2. Label graph edges
  3. Segment graph into tracks

[8]

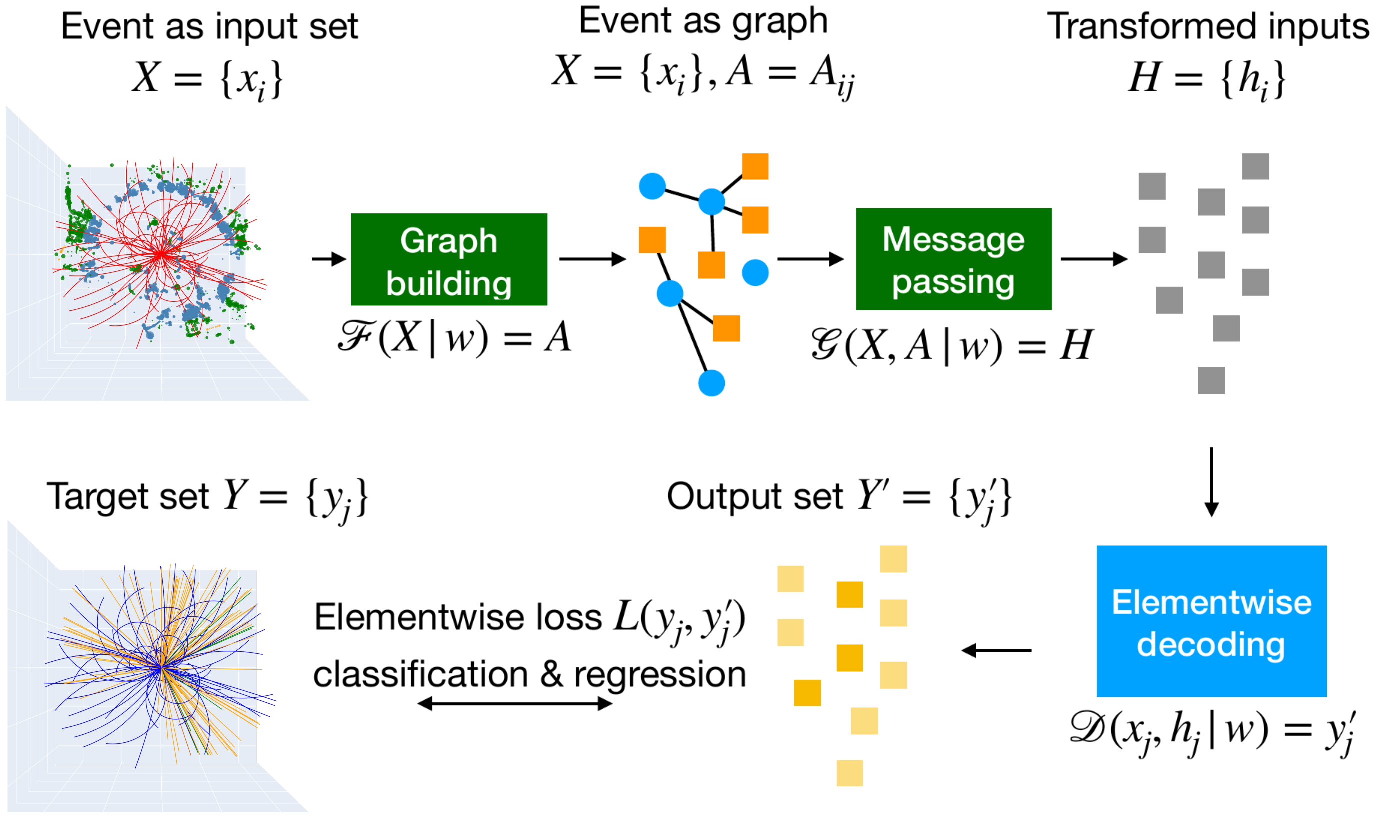




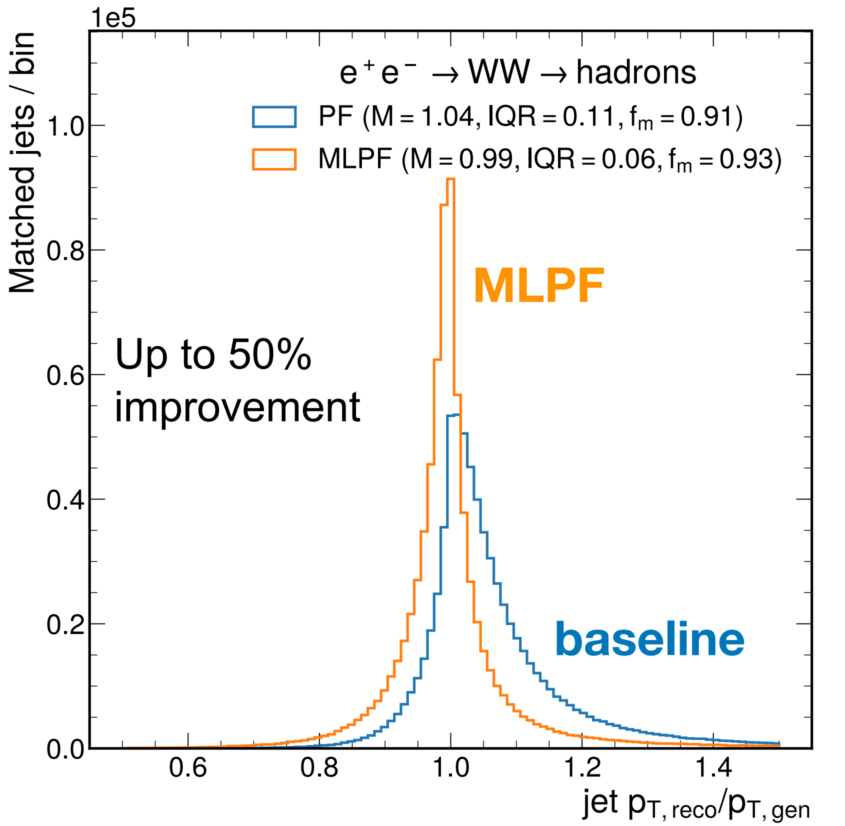
Experiment - 2. Particle Flow [2,4]

- Turn tracks and calorimenter clusters into particles
- Use granular detector layout optimally
- Different graph-based approaches ML approaches exist (MLPF, HGPflow, …)

MLPF Method

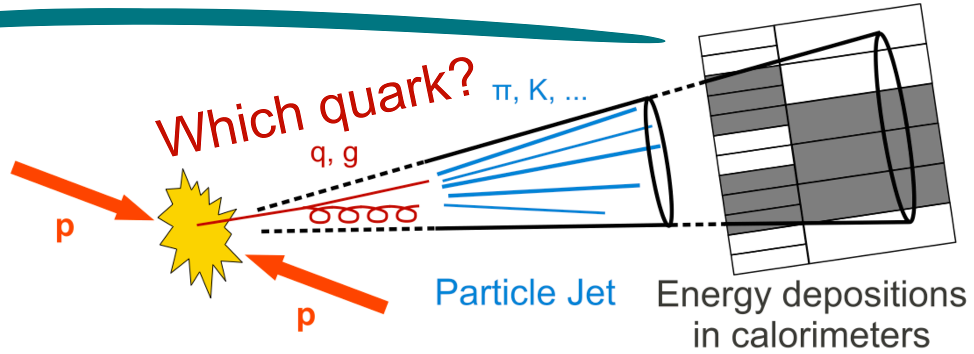


MLPF Result

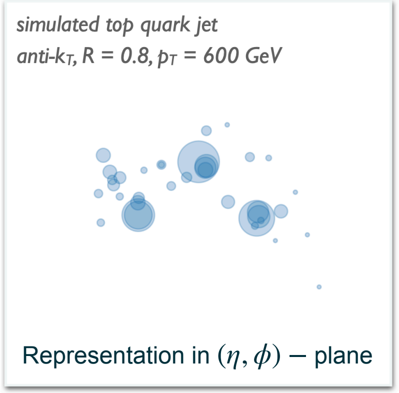


Experiment - 3. Tagging [5]

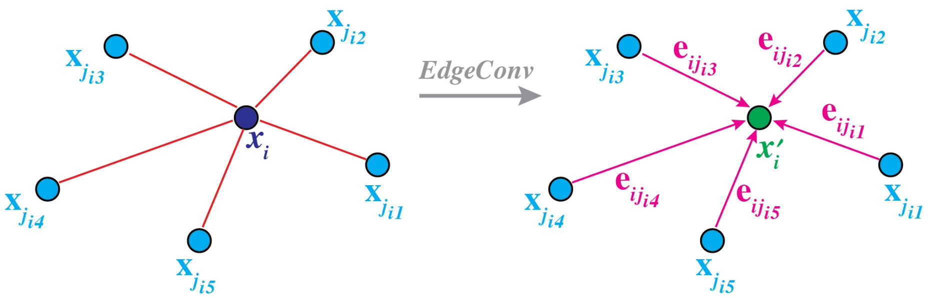
- Quarks from the hard interaction initiate jets in the detector
- Determine which type of quark initiated the jet (tagging)

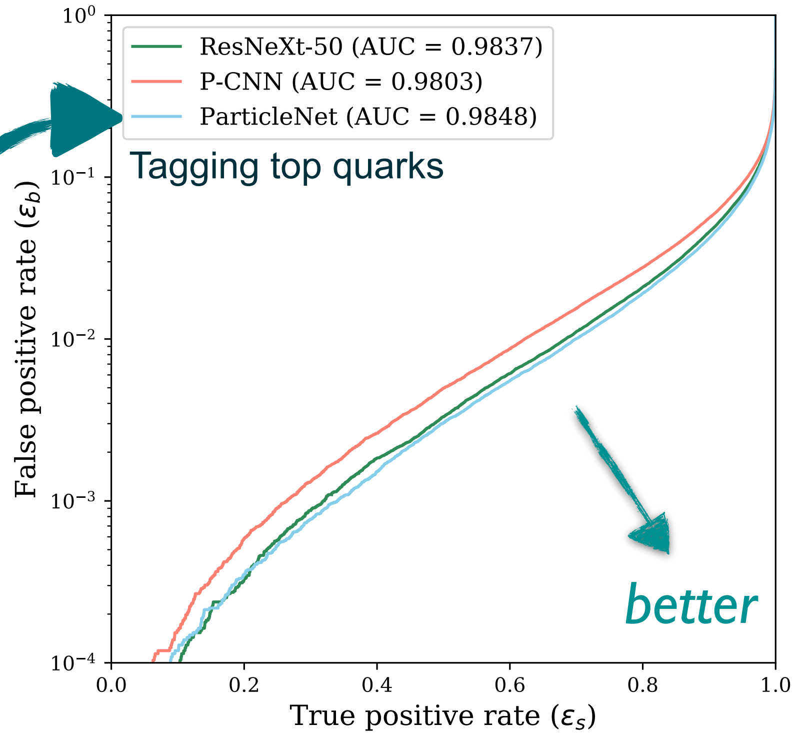


Jet as Point Cloud



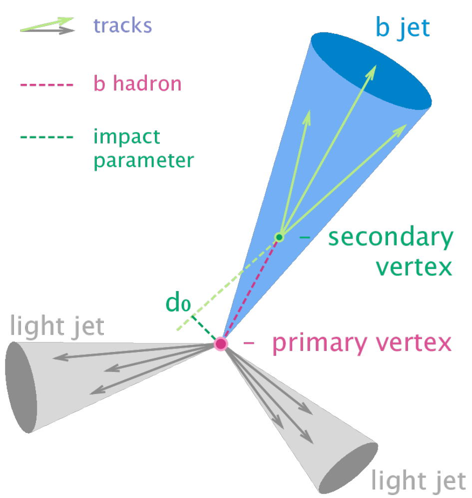
ParticleNet



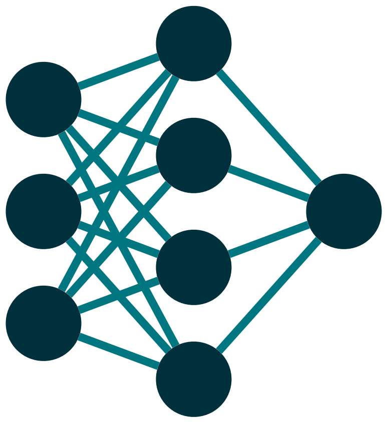


Experiment - 4. Calibration [6]

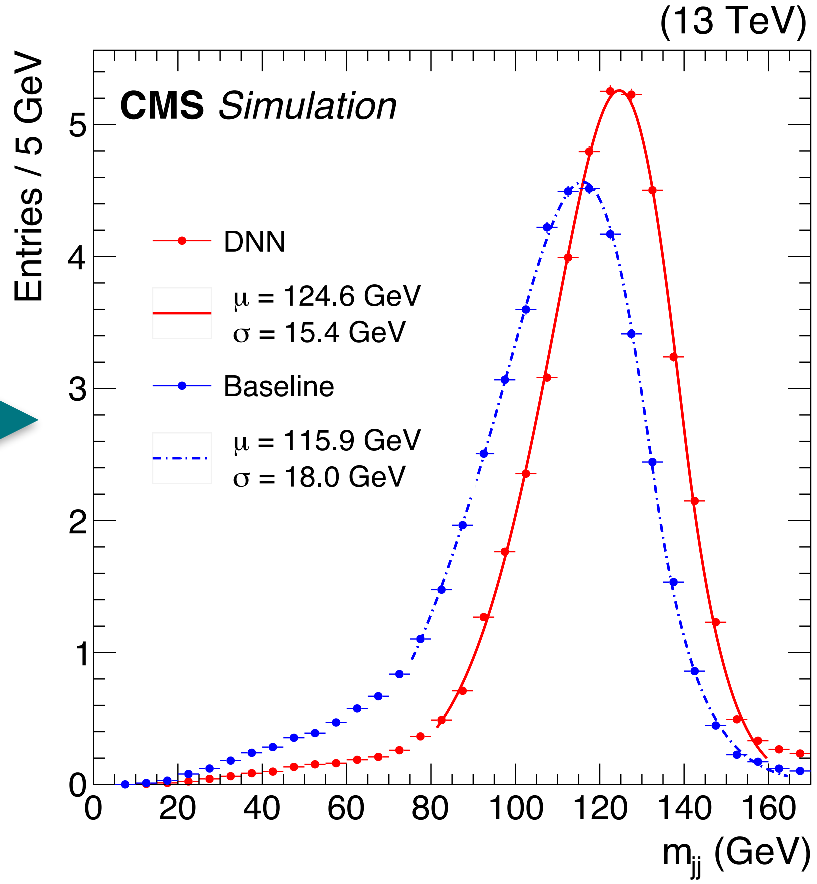
- Jets from b-quarks have large invisible (neutrino) contribution
- Calibrate the momentum of the jets with feed forward DNN regression
- Improved di-jet resolution by ~15% compared to baseline



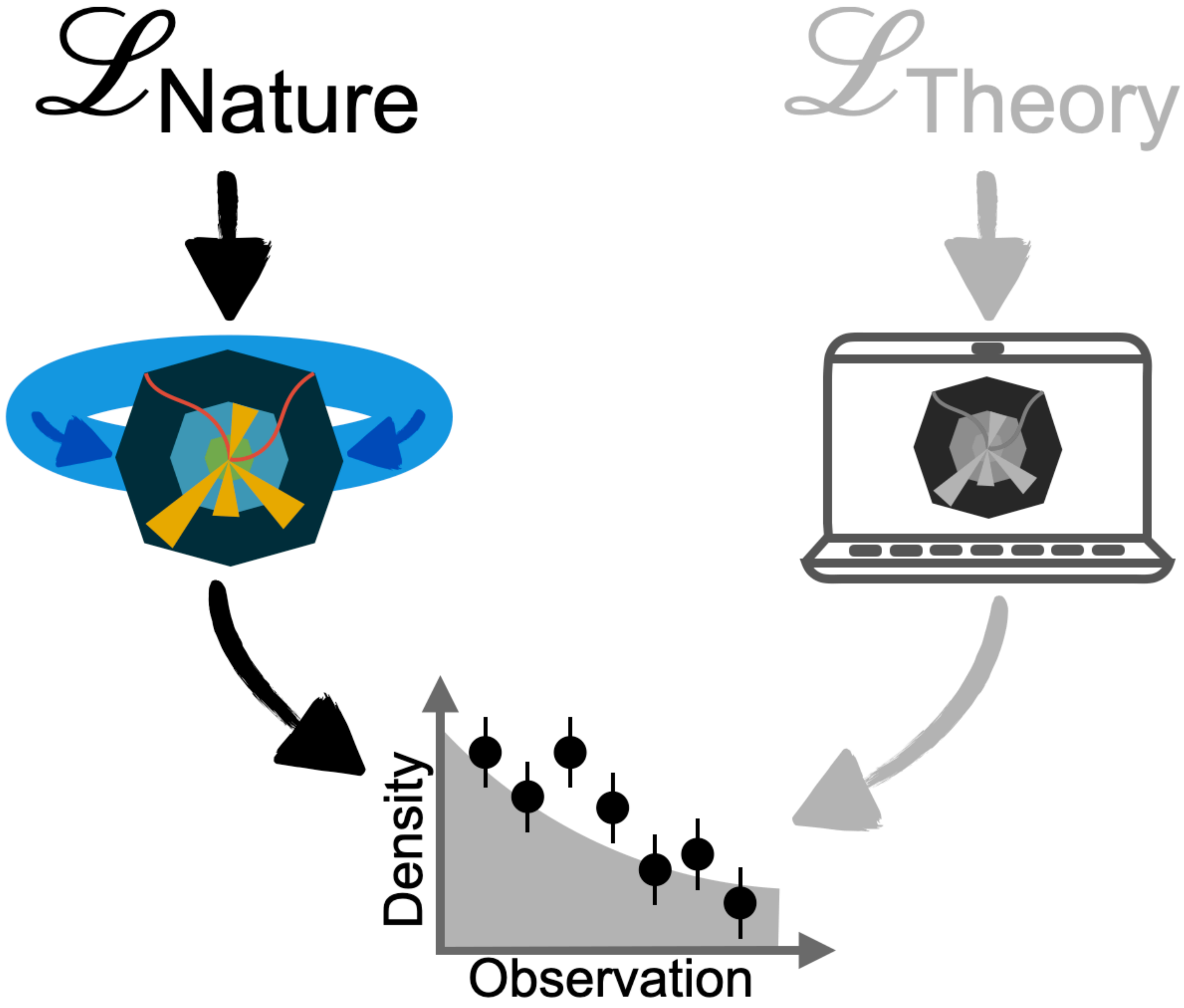
- Jet kinematics
- Jet composition
- PU info



$$\frac{p_{T,true}}{p_{T,reco}}$$



Experiment:
- Tracking
- MLPF
- Tagging
- Calibration



Experiment:
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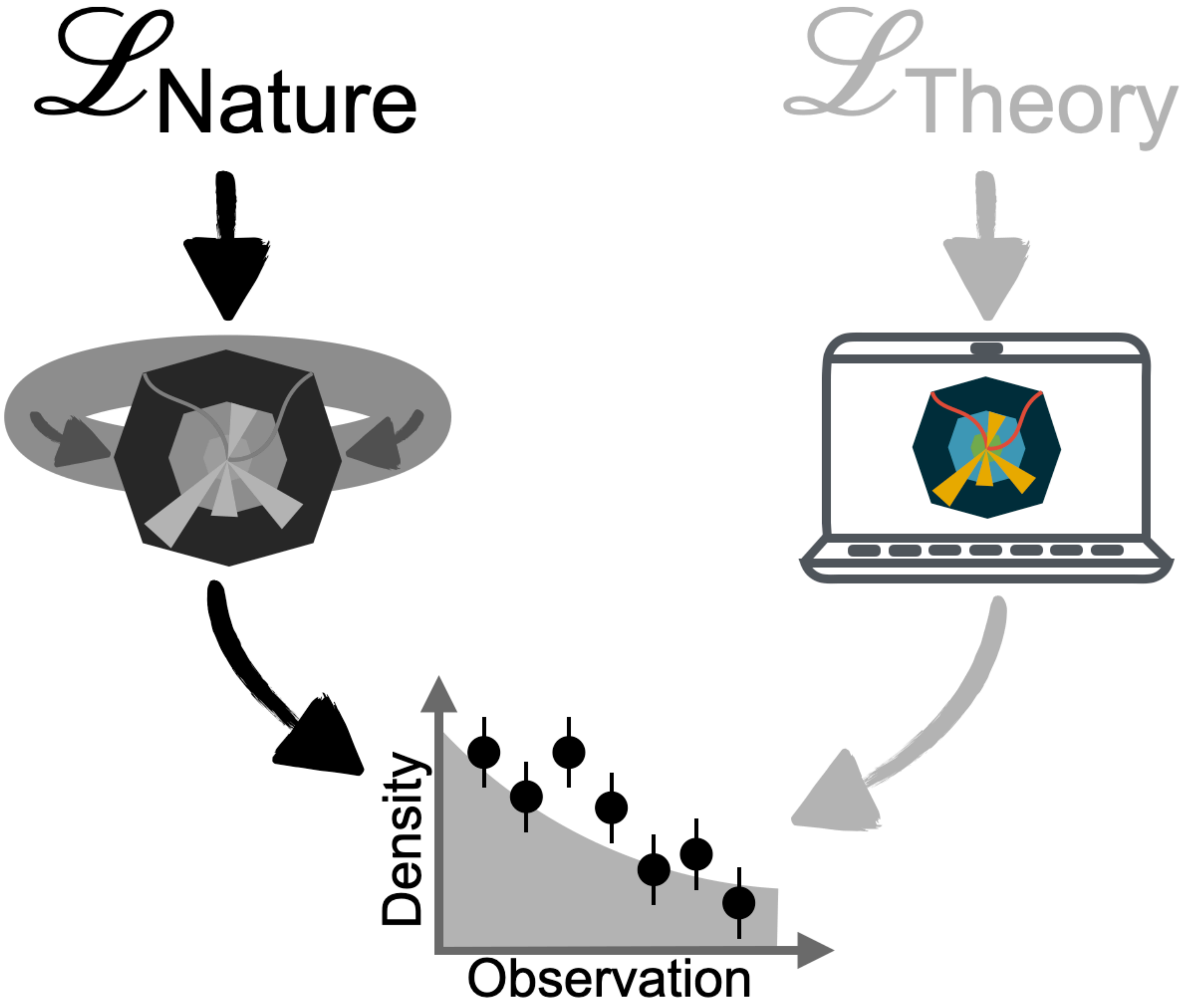
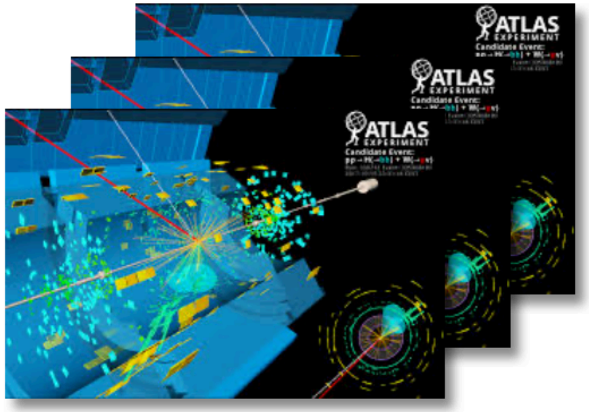


Simulation - Introduction [1]

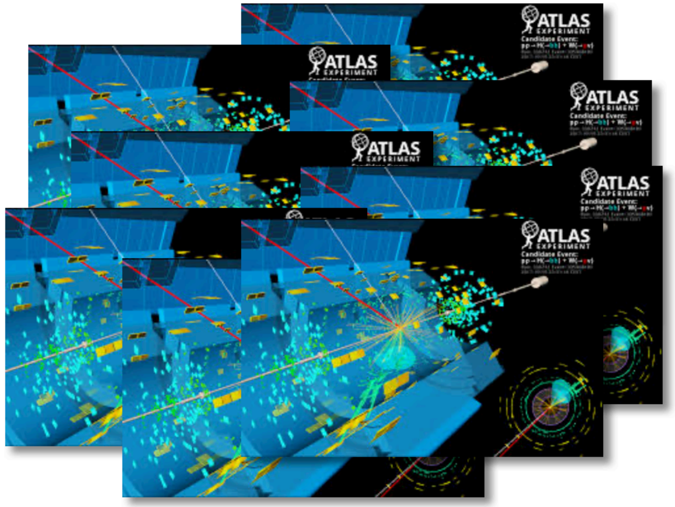
- Experiments spend significant computing budget on simulations
- Can make simulations much more efficient using ML
- **Simulations have different levels (full detector vs. particles), data types, complexities, …**



Simulation /
Recorded Data

Generative
Model

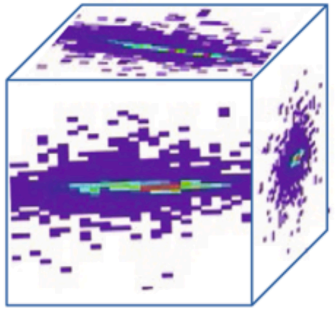
- GANs
- Variational AEs
- Normalizing Flows
- Diffusion Models
- …

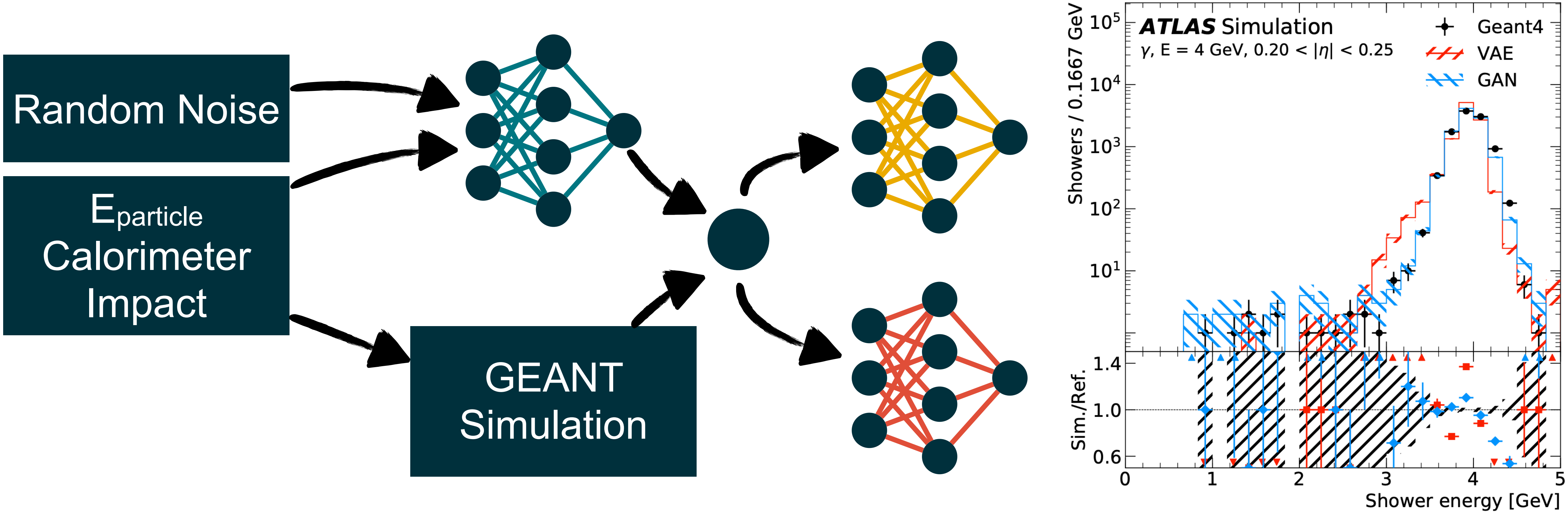


Oversampled

Simulation - Detector Level (Showers) [7]

- Simulate regular spatial shower profiles with ML
- Using generative adversarial networks (GANs)
- Parametrized by particle energy, calorimeter configuration, impact point
- Three networks: Generator, Critic, Energy Critic

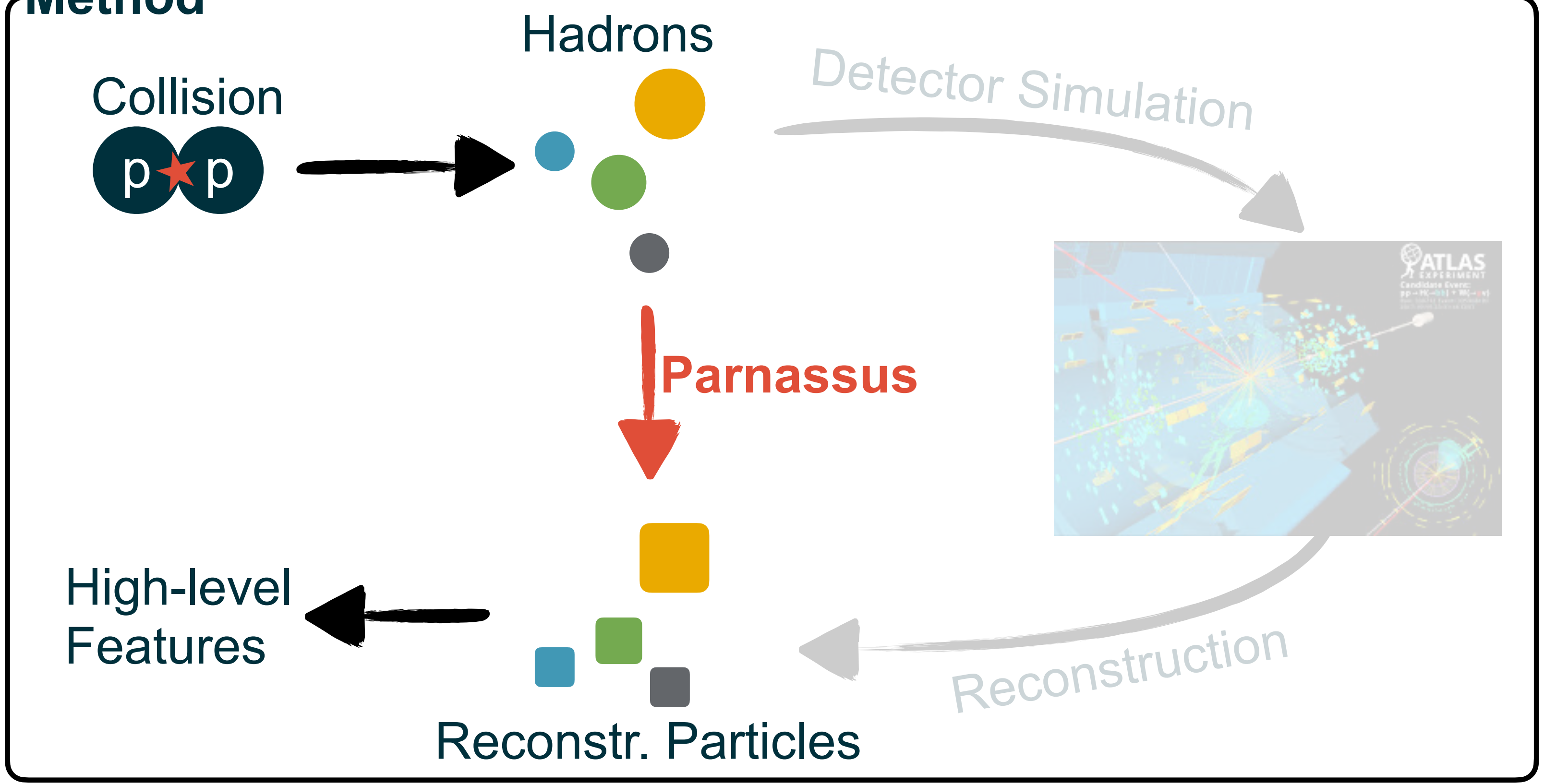




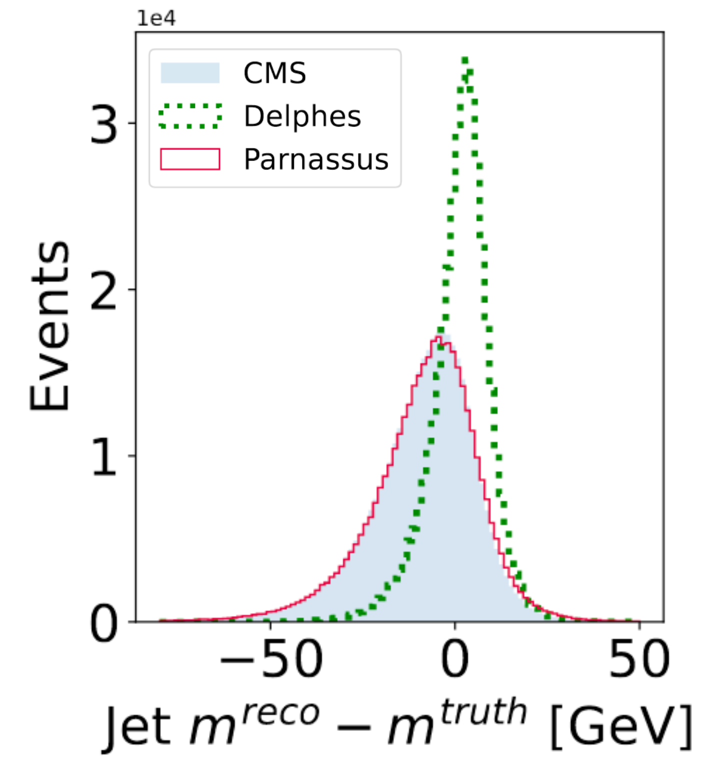
Simulation - Particle Level [8]

- Skip detector simulation and directly model reconstructed particles
- New ML method **Parnassus** [8]:
  - Normalizing Flow with Neural Ordinary Differential Equations
  - Transformer architecture (particle relations)

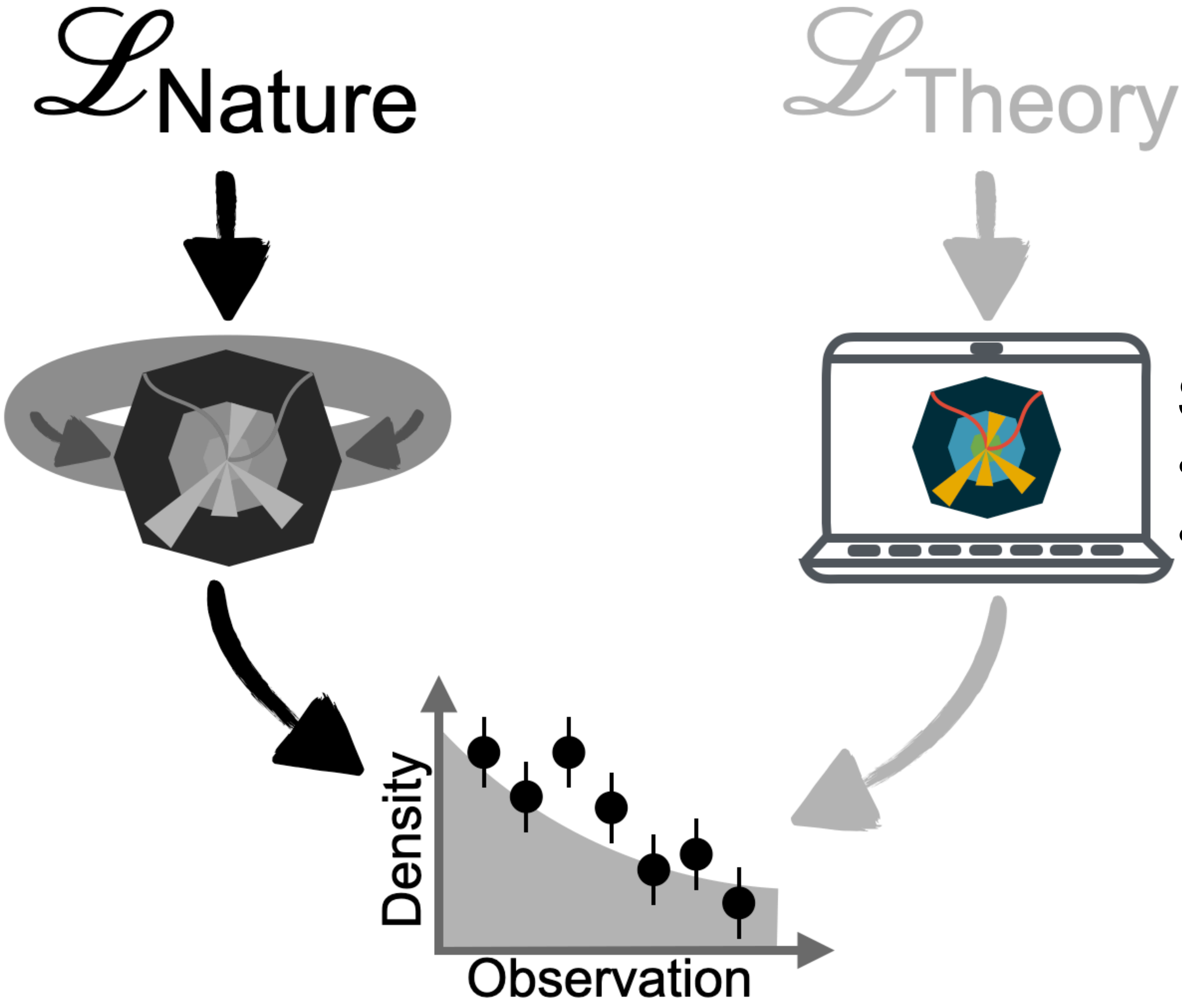
Method



Results



Experiment:
- Tracking
- MLPF
- Tagging
- Calibration



Simulation:
- Shower-level
- Particle-level

Experiment:
- Tracking
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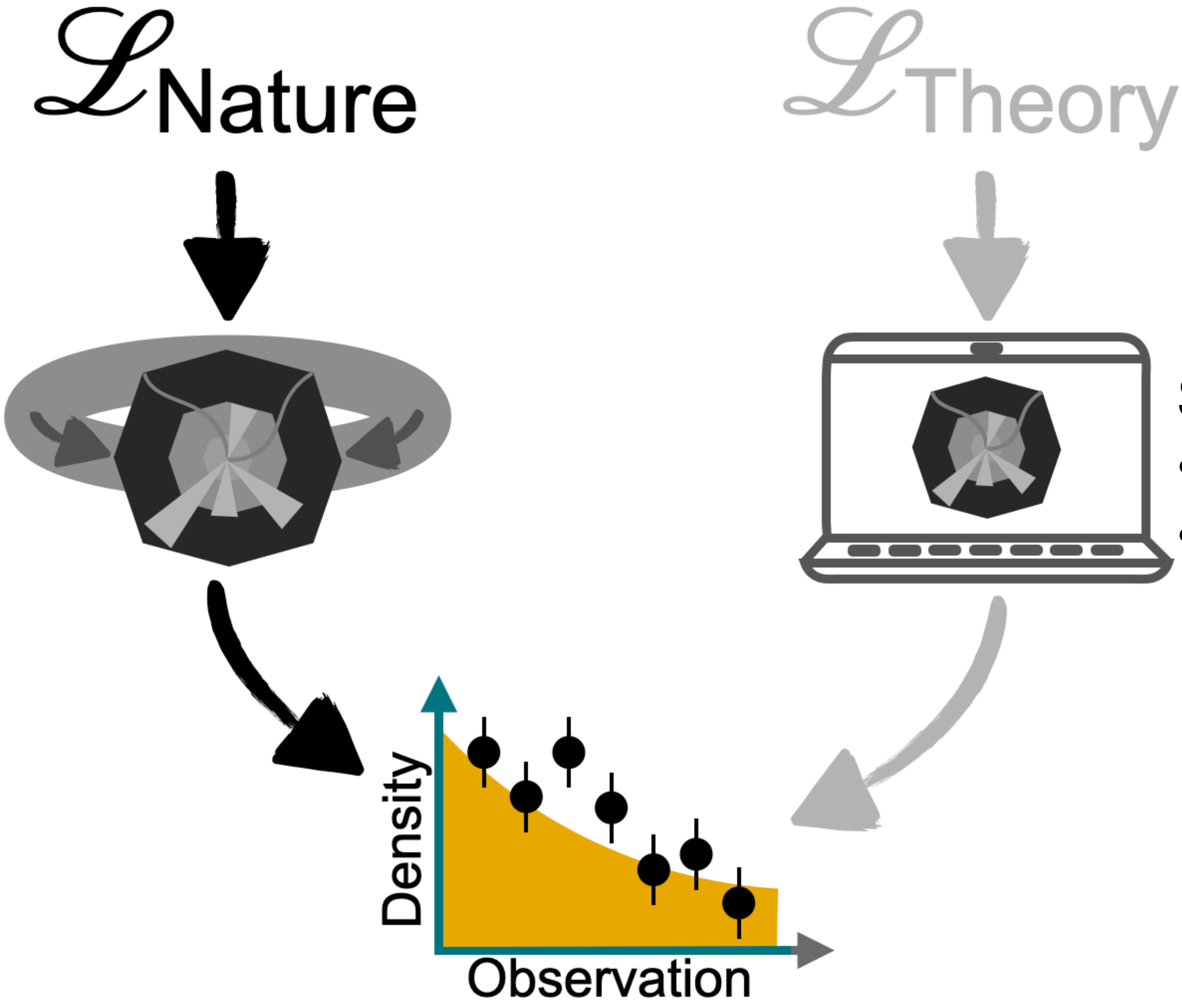
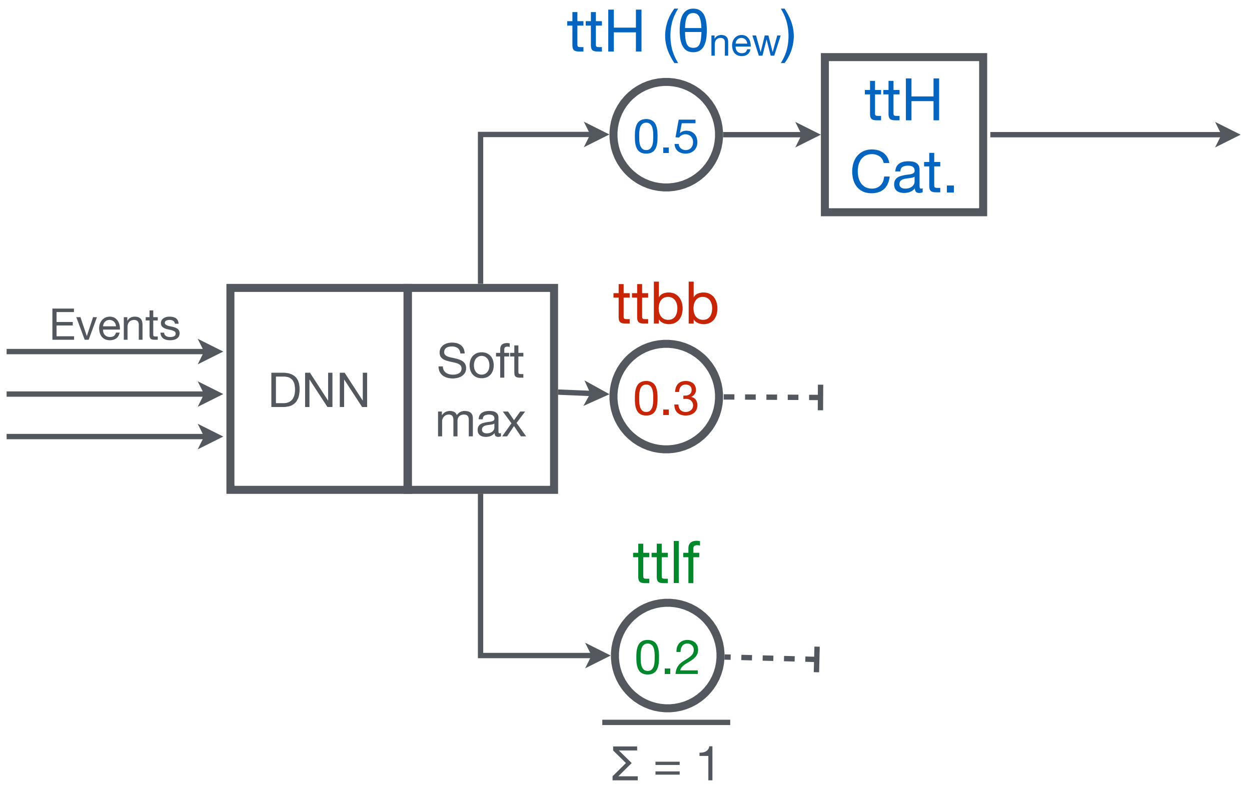
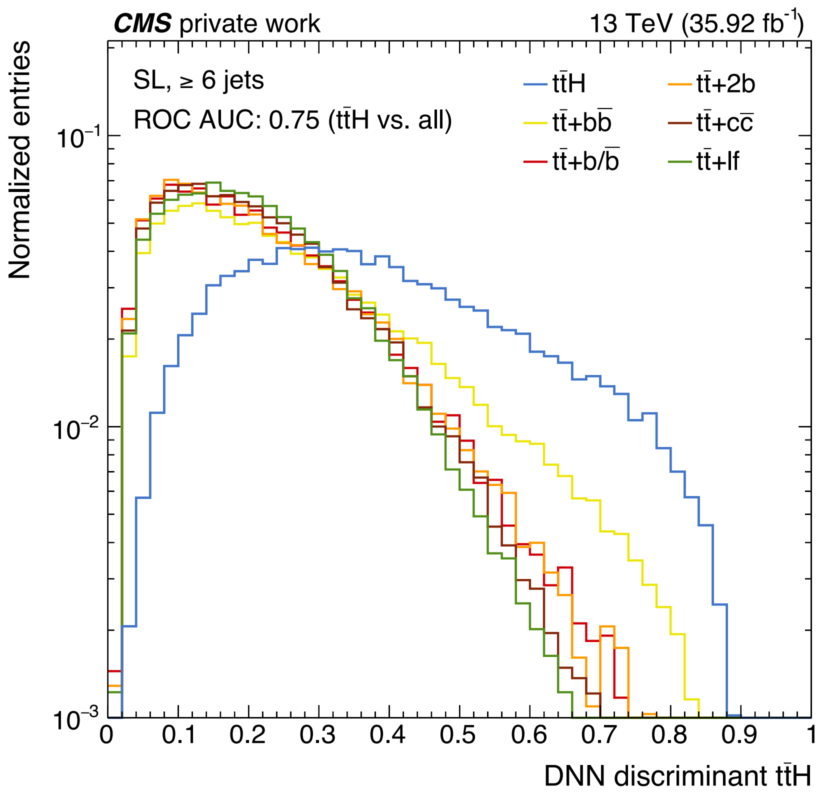


Simulation:
- Shower-level
- Particle-level

Regular Analysis [9]

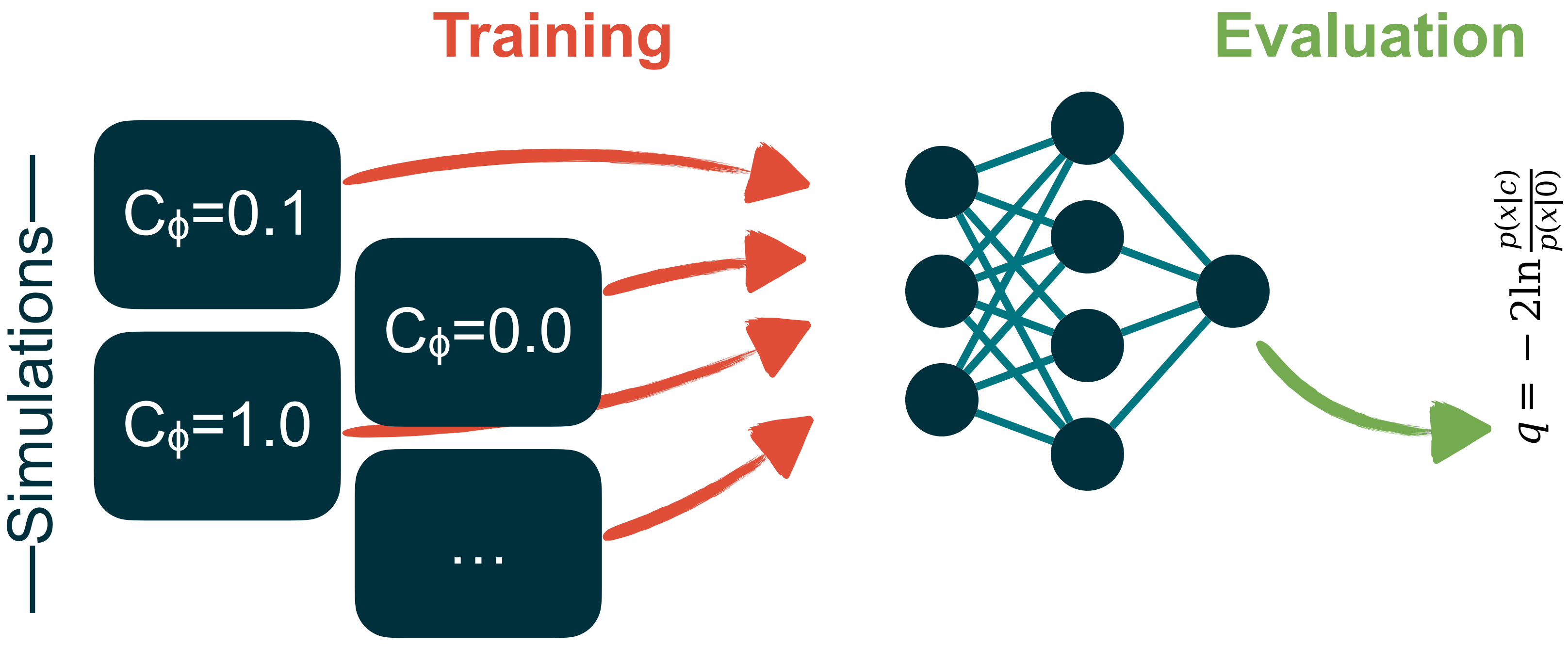
- Challenge: Decrease dimensionality of data (x) but keep physics information
- Optimal feature is probability of a new model $p(x|\theta_{new})$ vs $p(x|\theta_{old})$
- Multi-class classification trained with categorical cross-entropy (e.g. ttH measurement)

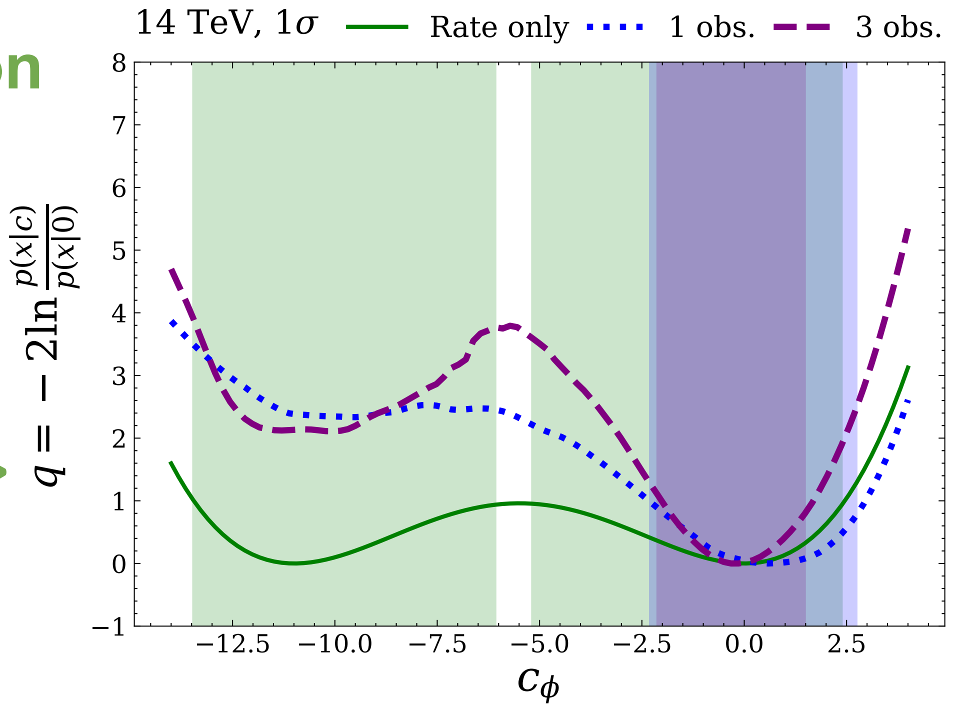




Simulation-Based Inference (SBI) [10,11]

- Techniques to directly infer p(θ|x) without using summary statistics / histograms
- Train networks to directly model likelihood ratio:
  - Trained via simple classification (e.g. $p(x|\theta_{BSM}) / p(x|\theta_{SM})$)
  - DNN can use low or high-dimensional data x





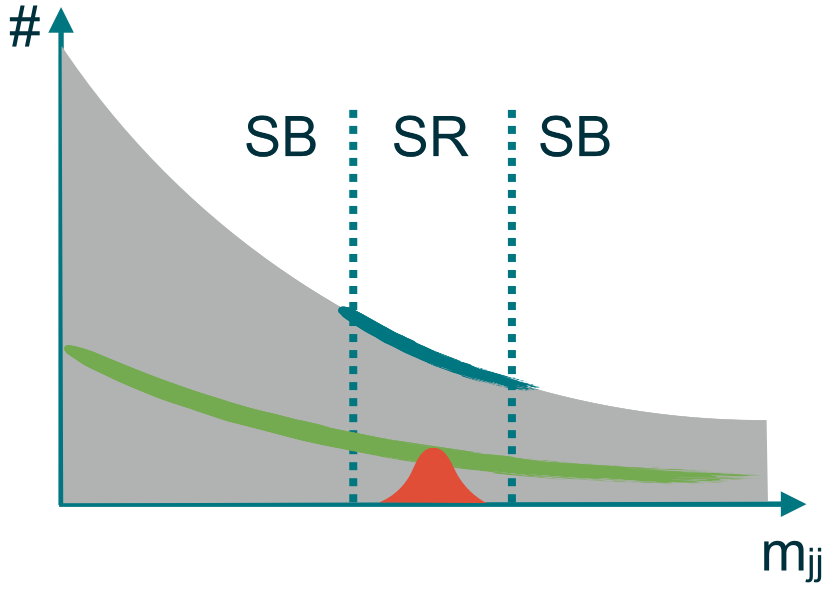
Anomaly Detection (AD) [12,13]

- Search for BSM in a model agnostic way
- Let machine figure out:
  - Interesting parts of phase space
  - How to look at them

2 Approaches	Assumption	Drawback
Unsupervised ML	Signal is rare	Not universal [14]
Weakly Supervised ML	Signal is peak	Need Bkg. Est.

Weakly Supervised AD in a Nutshell:

1. Define SR/SB
2. ML Bkg. Estimate
3. ML Class. ■ vs. ■
4. Bump Hunt



$\mathcal{L}_{\text{Nature}}$ $\mathcal{L}_{\text{Theory}}$

Experiment:
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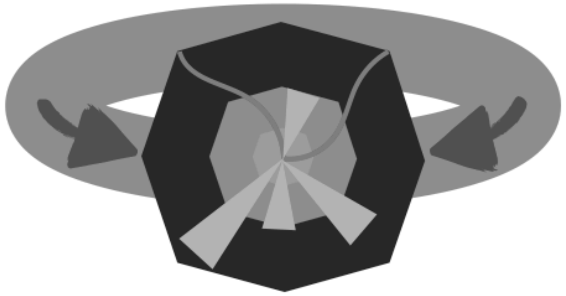
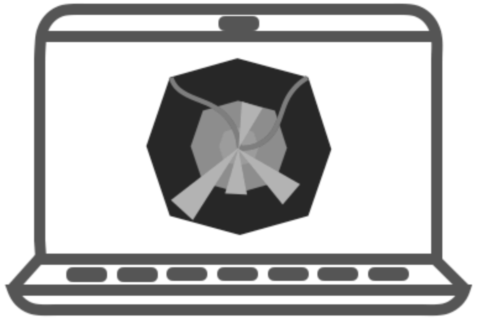
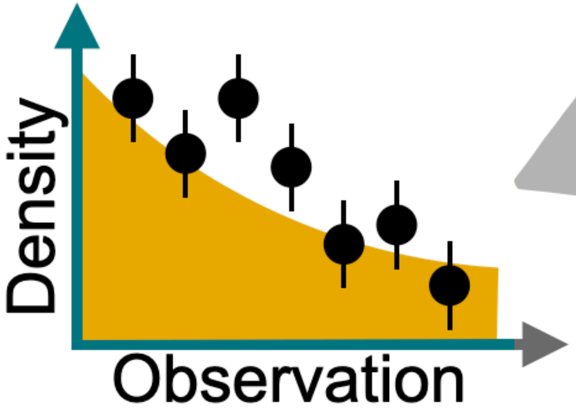




Simulation:
- Shower-level
- Particle-level

Comparison:
- Classification
- SBI
- AD



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Experiment:
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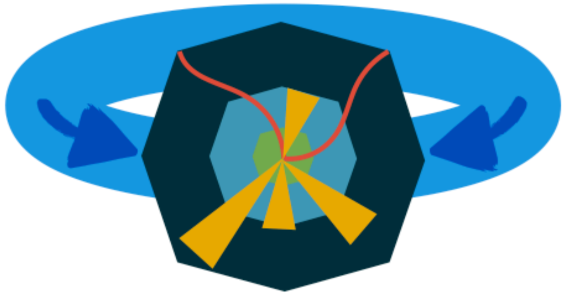

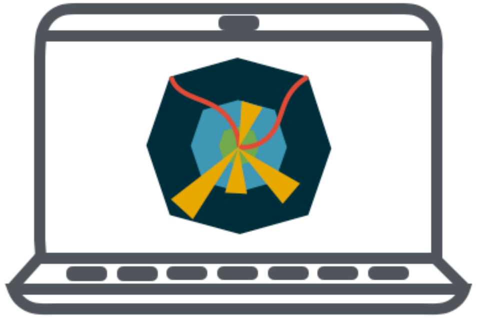

Simulation:
- Shower-level
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Comparison:
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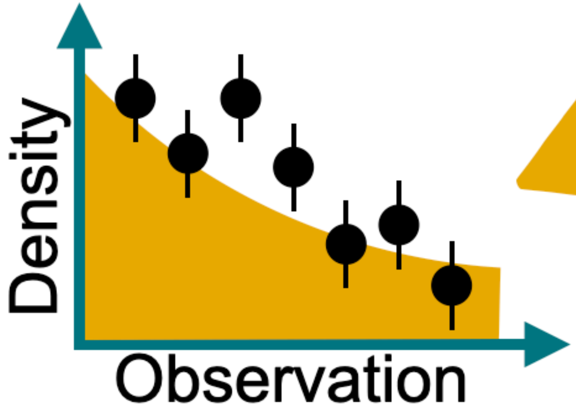
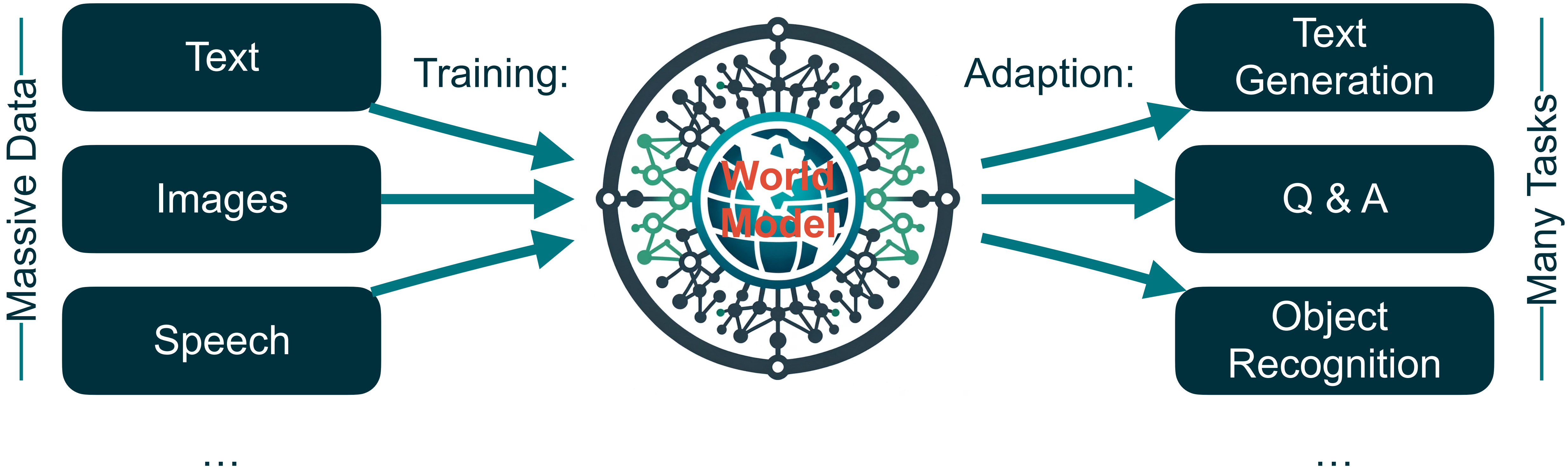
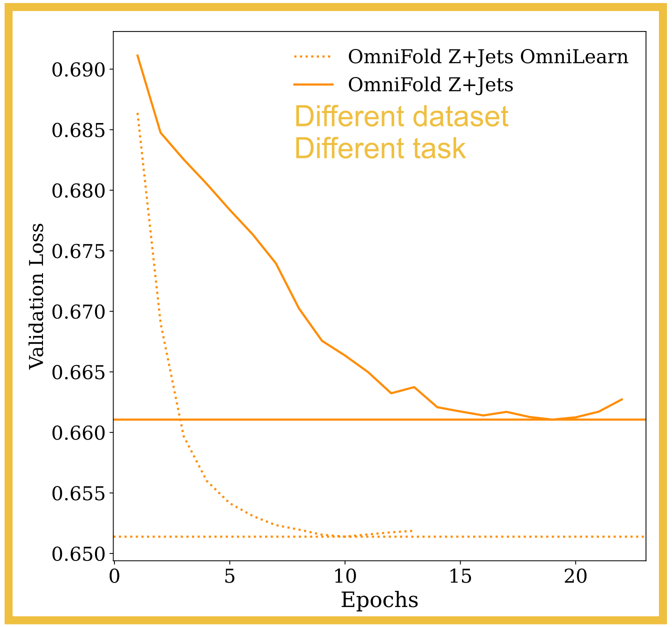


Foundation Models (Motivation) [15]



Foundation Models (Physics - OmniLearn) [16]

- OmniLearn:
  - Train foundation model for many jet-related tasks
  - Transformer model with Graph-attention networks
- Learns general World (Jet) Model
- Adaption better and more cost-efficient than training from scratch



Experiment:
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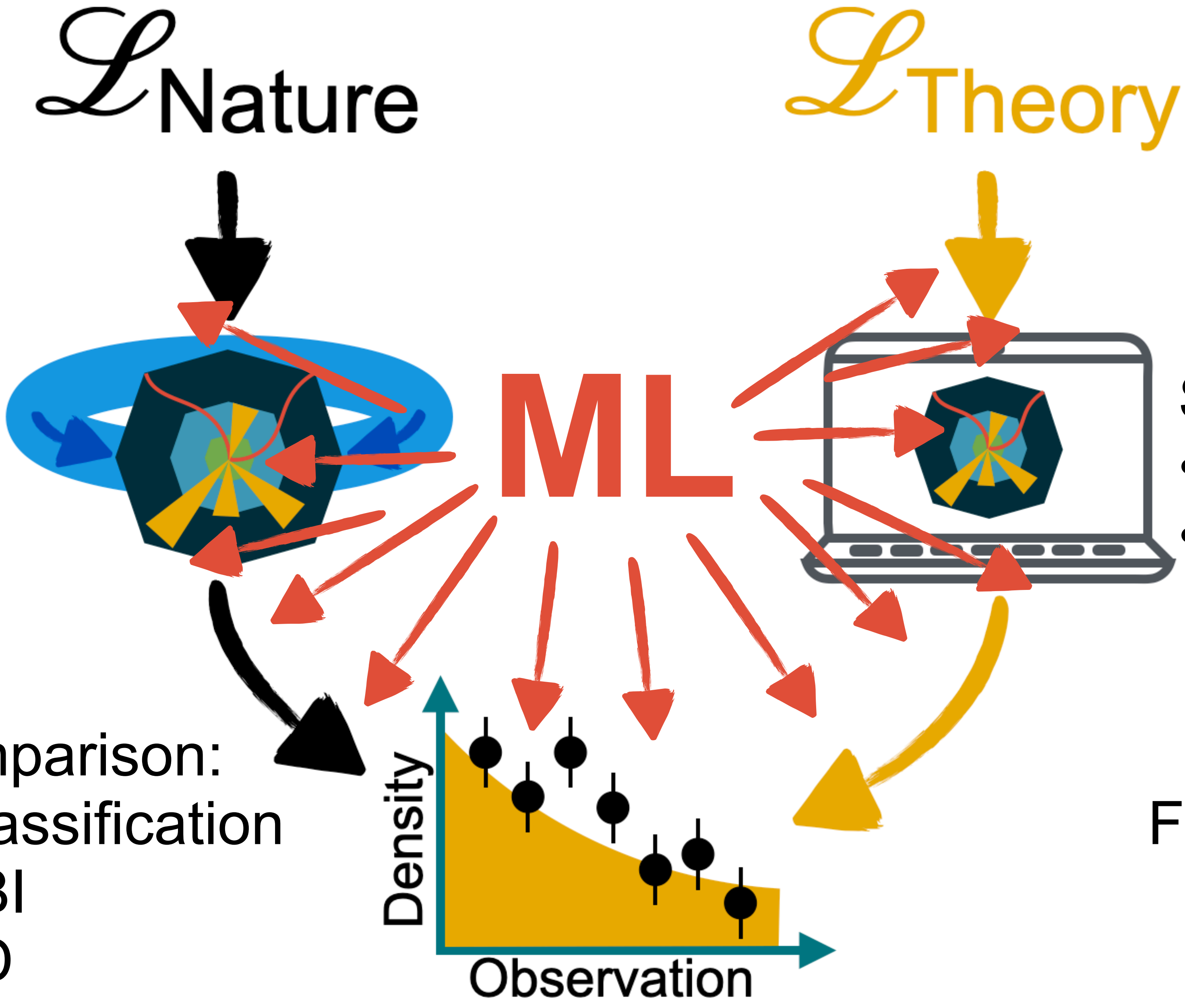

Simulation:
- Shower-level
- Particle-level

Comparison:
- Classification
- SBI
- AD

Foundation Models

Contact

- First year postdoc at Berkeley Lab
- Since >7 years working in data analysis for CERN experiments

- **Physics**: Higgs, Anomaly Detection
- **Deep Learning**: Supervised, Unsupervised, Reinforcement
- **Computing**: Fast O(TB) Data Processing & Computing Pipelines

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Citations

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