CaloTrilogy

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Toward a Breakthrough in One Step, E2E, Physics-Guided Shower Generation for Modern Calorimeter

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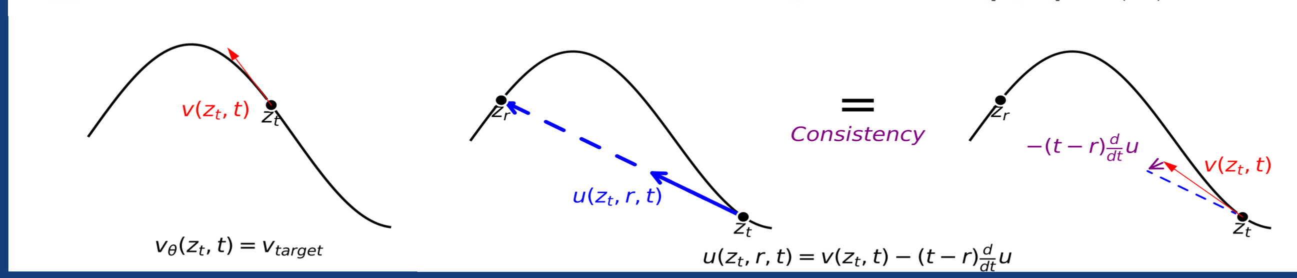
Intro

- Higher luminosity & pileup → rapidly growing MC demand.
- Calorimeter simulation dominates computing cost.
- Generative models (Flow, Diffusion, VAE) enable fast surrogates.
- High fidelity typically requires many steps → slow inference
- Goal: balance speed, memory, and physics fidelity for scalable deployment

MeanFlow

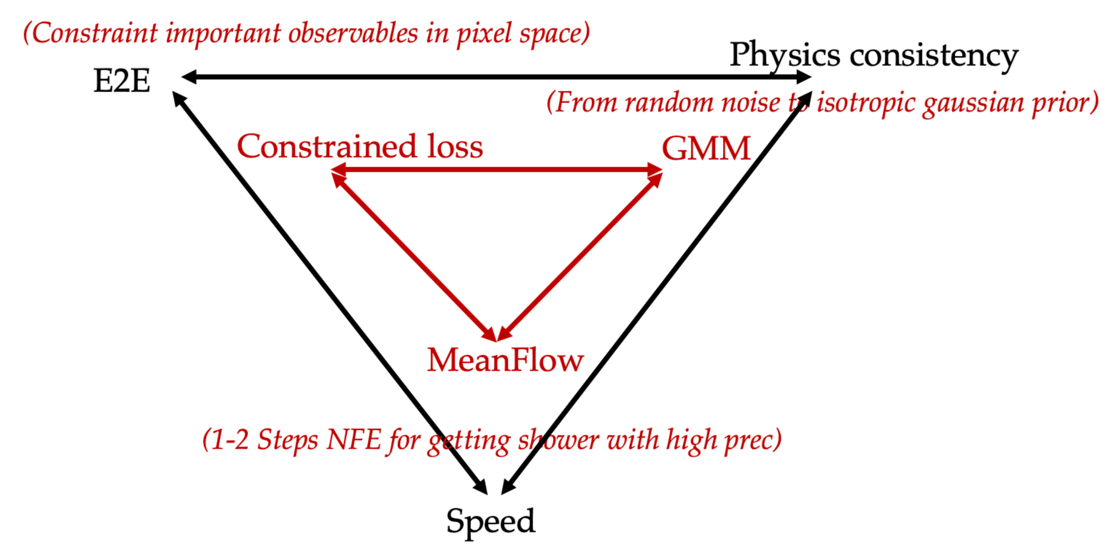
$$\frac{dx_t}{dt} = v(x_t, t), \quad \bar{v}(r,t) := \frac{1}{t-r}\int_r^t v(x_\tau, \tau)\, d\tau.$$

- the **local** truncation error per step is $\mathcal{O}(\Delta t^2)$,
- the **global** error over $[t_0, t_K]$ is $\mathcal{O}(\Delta t)$.



- Replace step-by-step integration of instantaneous flows with an average flow over the entire path.
- Make a "big jump" in trajectory space → high-fidelity in 1–2 steps instead of O(100).

Motivation



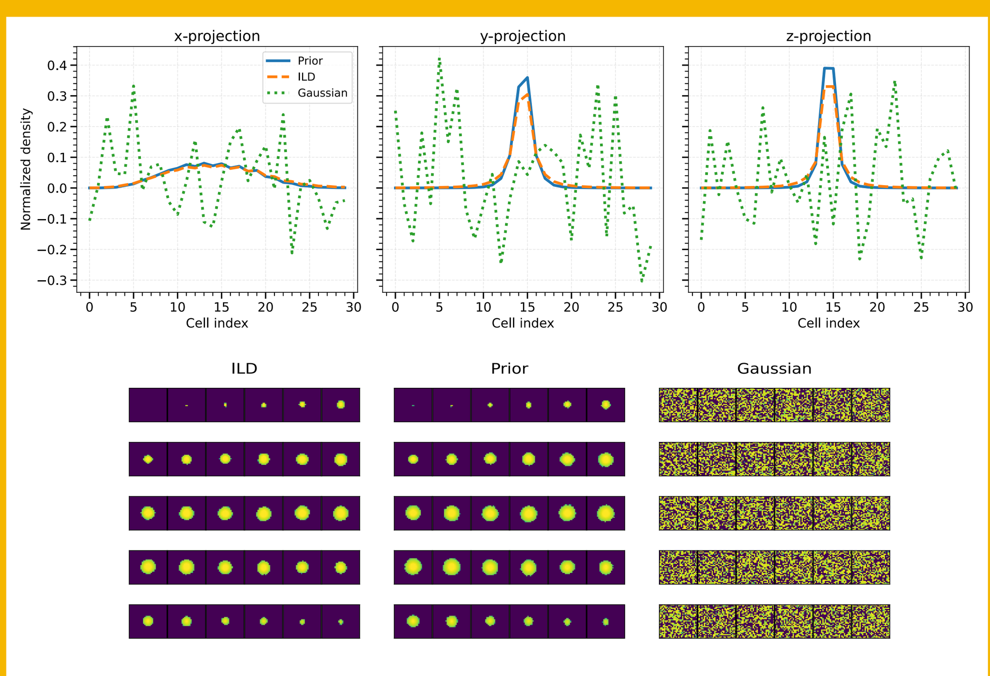
With satisfied performance, one model to do all?

GMM

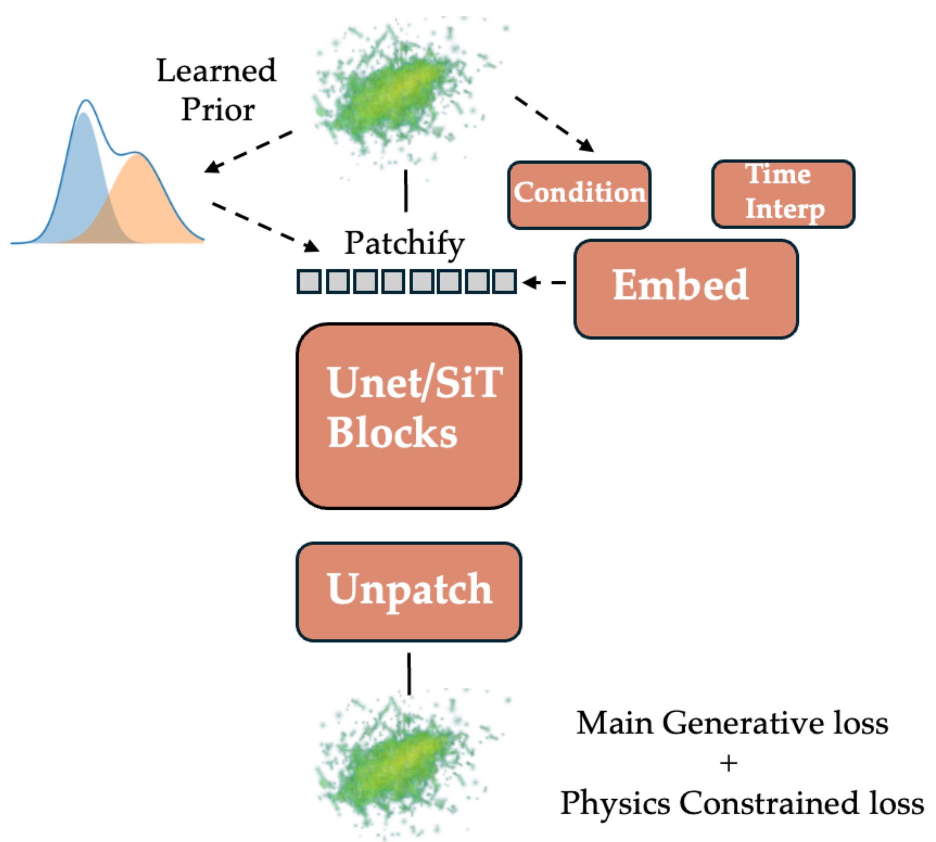
$$p(x \mid c) = \sum_{k=1}^{K} \pi_k(c)\, \mathcal{N}(x \mid \mu_k(c), \Sigma_k(c))$$

- K: number of components
- $\pi_k(c)$: weights ($\sum = 1$)
- $\mu_k(c) \in \mathbb{R}^D$: mean

- Fixed angle particle gun samples follows isotropic Gaussian like distribution.
- Shorter and easier pathfor MeanFlow.

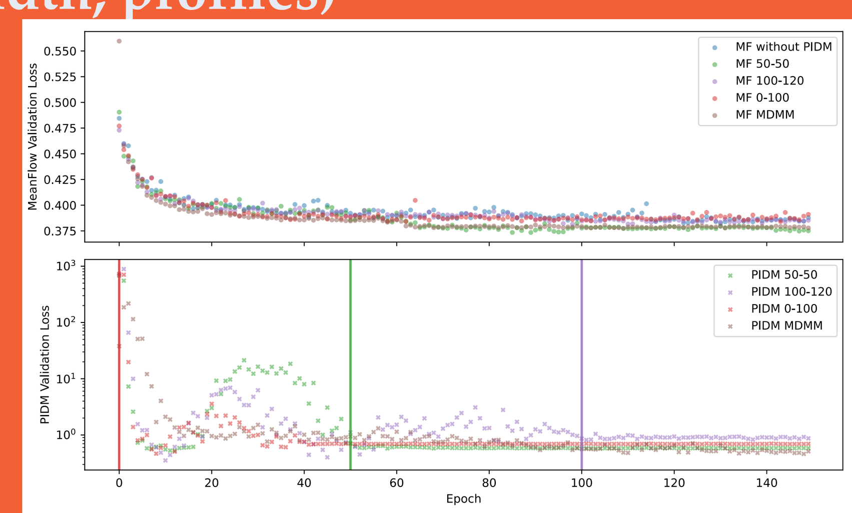


Archs



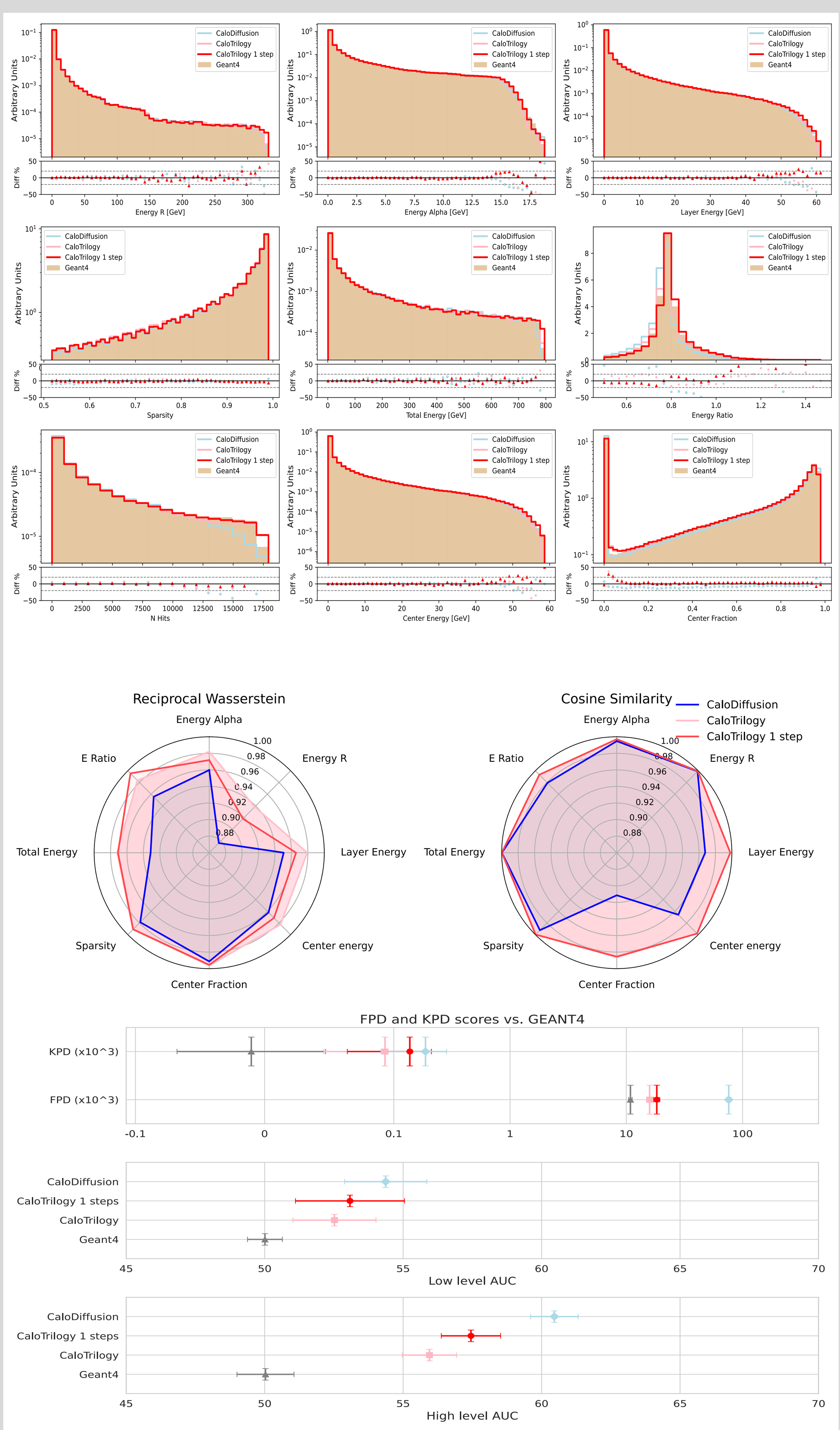
PI Loss

- Standard training (voxel-wise) does not explicitly constrain key observables.
- Existing approaches post-hoc norm (e.g. layerE), not fully generalizable.
- PI loss enforces desired observable → end-to-end, shared weights, and extensible (e.g. width, profiles)



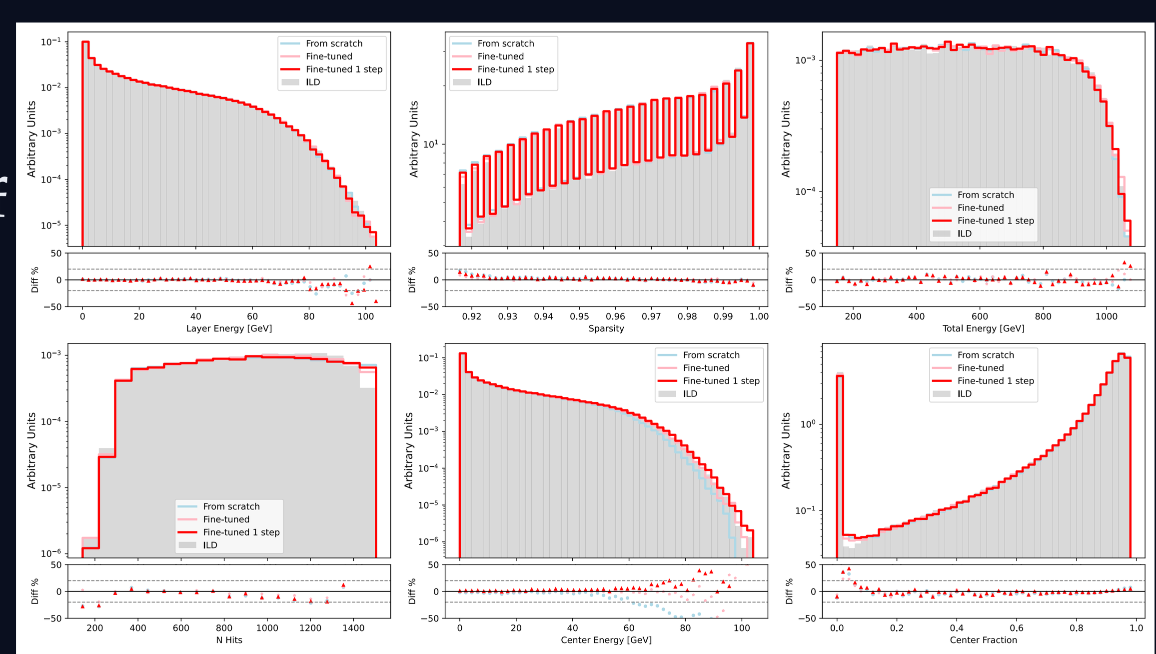
Results

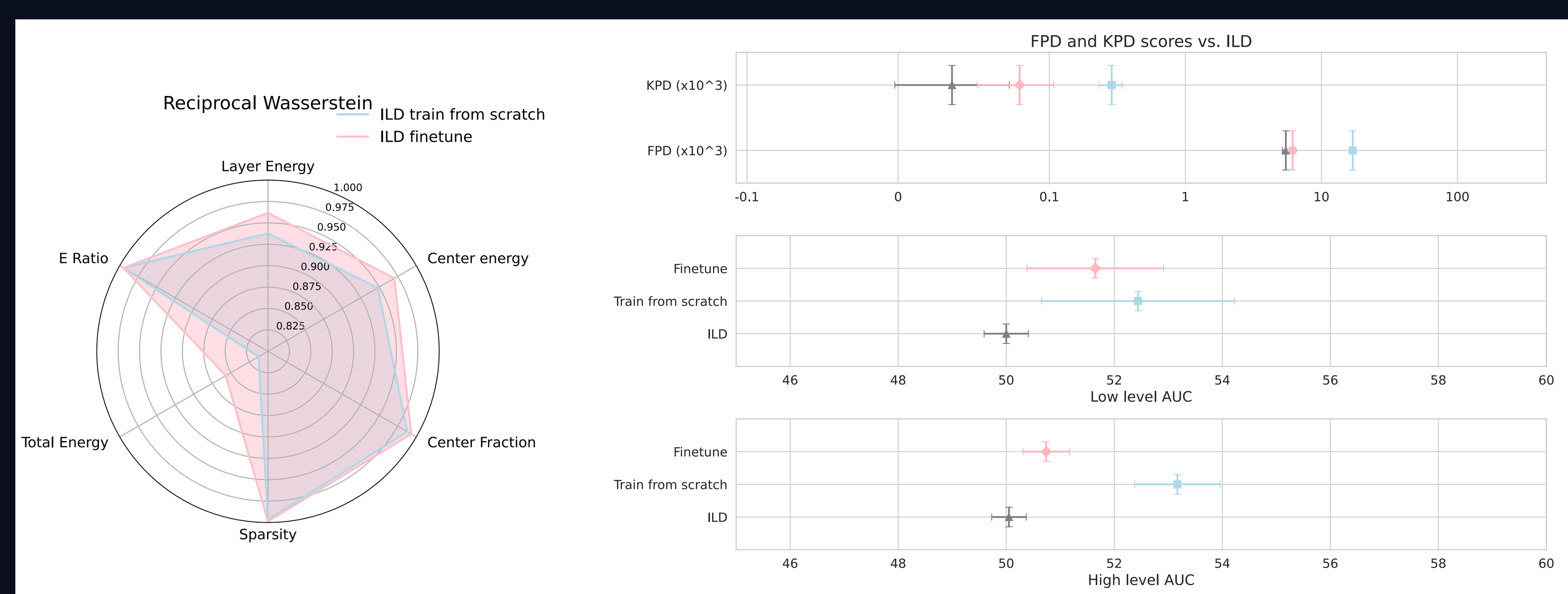
- Extensive validation across complementary metrics (binned histograms, Wasserstein distance, correlations such as FPD/AUC).
- Avoid reliance on any single metric → no metric bias in evaluation.
- Consistent improvements across most confirm model quality.



Fine-tuning in generative model

- Pretraining learns global shower structure across diverse conditions (energy, angles, materials).
- Fine-tuning specializes this knowledge to a target domain instead of relearning from scratch.
- Better inductive bias → improved sample quality, stability, and data efficiency.





Outlooks

- Scale to larger and more diverse datasets for improved generalization.
- Enhance structured priors (e.g. incorporating latent geometric information).
- Extend physics-informed constraints to richer and more complex observables.
- Explore fine-tuning strategies and linear or sparse architectures.

ArXiv coming soon ;)

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