Research Overview

Yimeng Zhang

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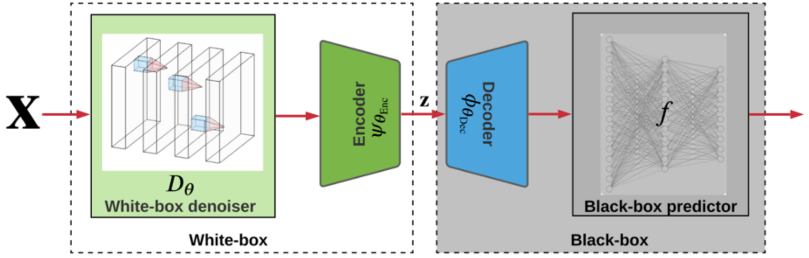
OPTML

Yimeng's Selected Publications

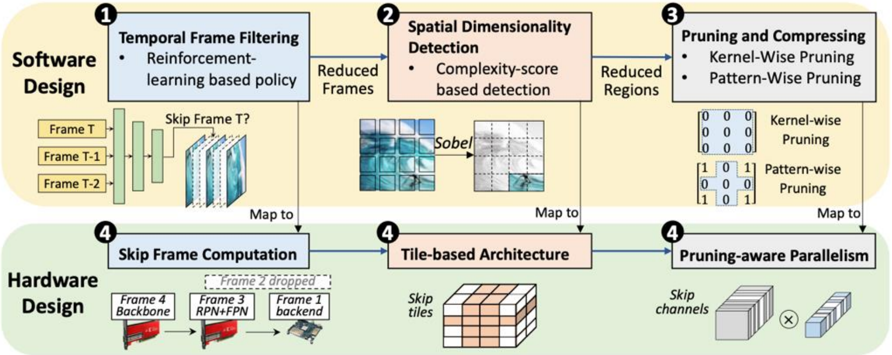
ICLR'22 (Spotlight)



[How to Robustify Black-Box ML Models? A Zeroth-Order Optimization Perspective]()

DARPA

ASP-DAC'23



[Data-Model-Circuit Tri-Design for Ultra-Light Video Intelligence on Edge Devices]()

DARPA

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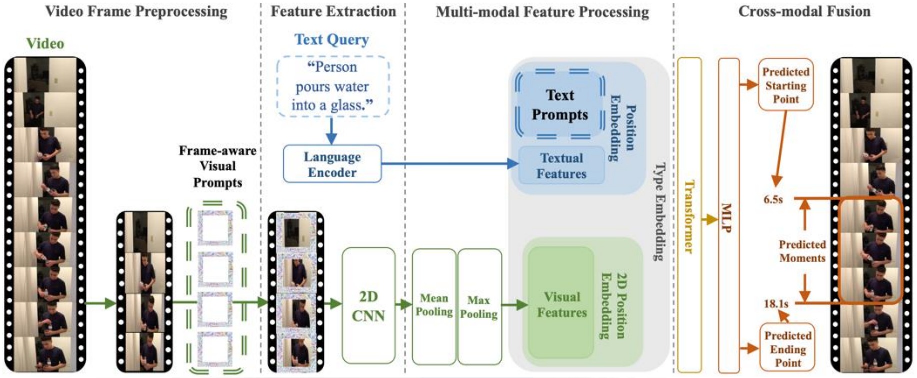
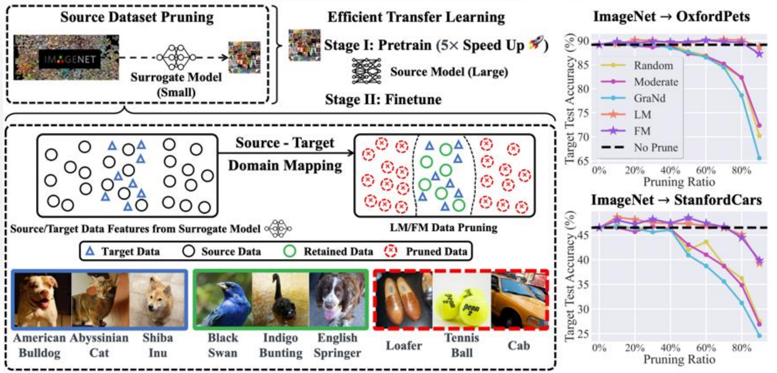
Yimeng's Selected Publications

CVPR'23



Text-Visual Prompting for Efficient 2D Temporal Video Grounding

NeurIPS'23



Selectivity Drives Productivity:
Efficient Dataset Pruning for Enhanced Transfer Learning

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NSF

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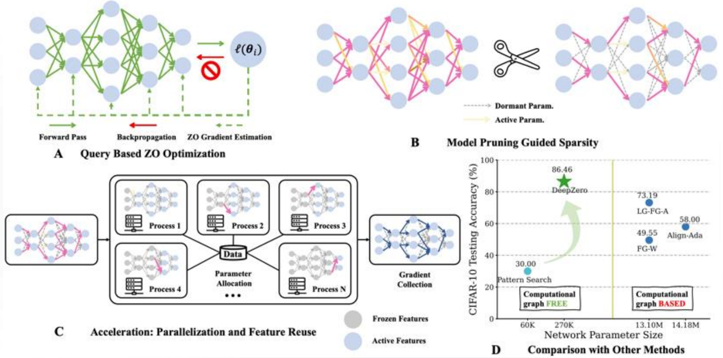
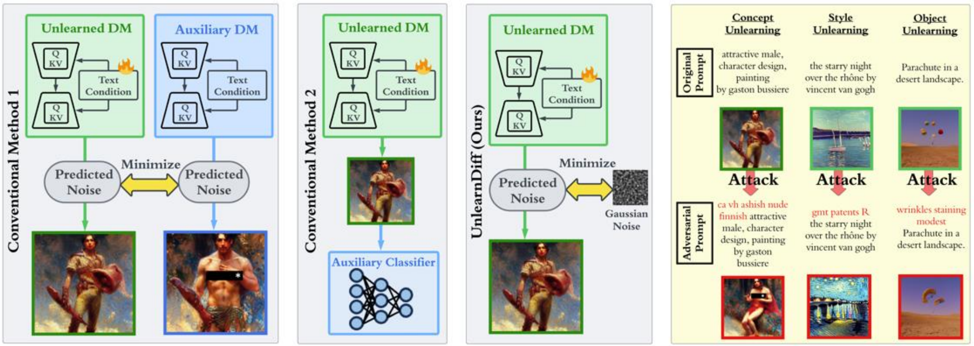
Yimeng's Selected Publications

ICLR'24



[DeepZero: Scaling up Zeroth-Order Optimization for Deep Model Training]

ECCV'24



(a) W/ auxiliary DM (b) W/ classifier (c) Auxiliary model-free (d) UnlearnDiff attack demonstrations

[To Generate or Not? Safety-Driven Unlearned Diffusion Models Are Still Easy To Generate Unsafe Images ... For Now]

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Lawrence Livermore National Laboratory

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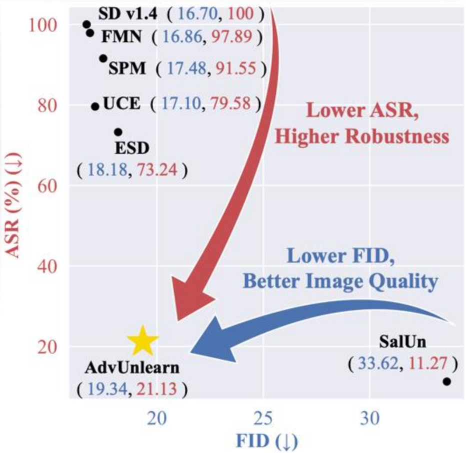
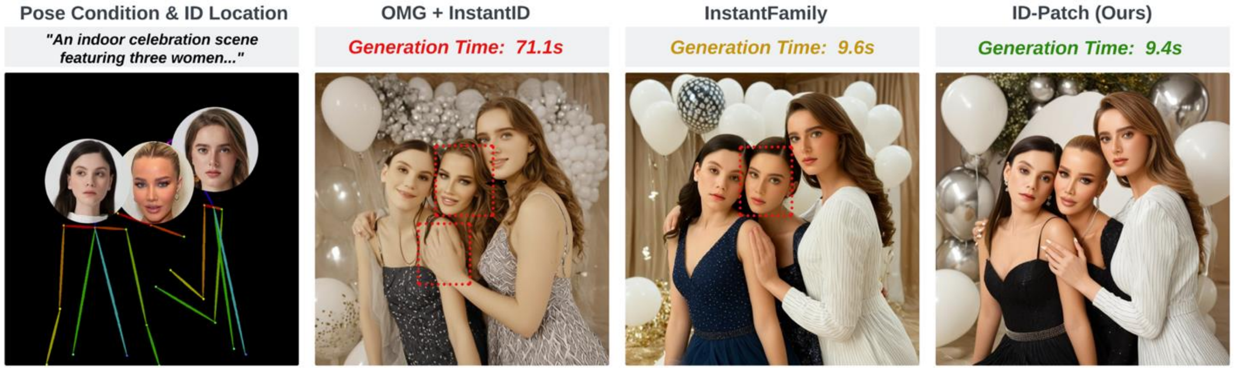
Yimeng's Selected Publications

NeurIPS'24



[Defensive Unlearning with Adversarial Training for Robust Concept Erasure in Diffusion Models]

Under Review



[ID-Patch: Robust ID Association for Group Photo Personalization]

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TikTok

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[ICLR'22] How to Robustify Black-Box ML Models? A Zeroth-Order Optimization Perspective

Motivations:

- Nearly all existing works ask a defender to perform over white-box ML models. However, the white-box assumption may restrict the defense application in practice.
- Zeroth-Order (ZO) Optimization for high-dimension variables suffers **high variance**.

Zeroth-Order Optimization for high-dimension variables suffers high variance ⚠ ⚠ ⚠

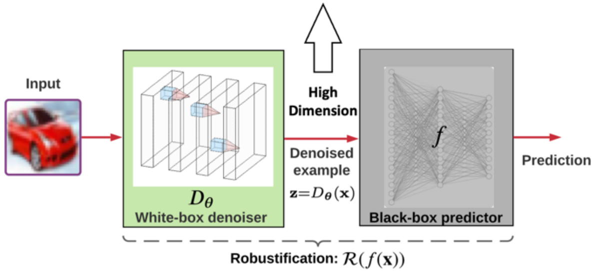
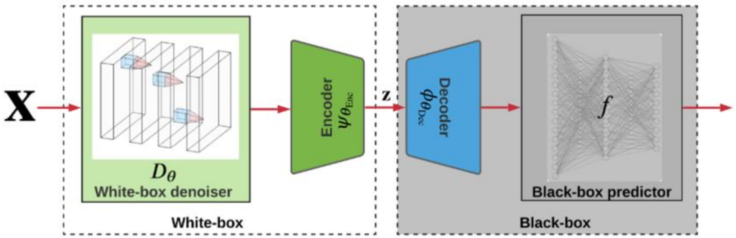


Figure 2: DS-based black-box defense.

D_θ : white-box denoiser with parameter θ
f : black-box predictor
x : input

■ **ZO-AE-DS Model Architecture**



■ **Random Gradient Estimate (RGE)**

$$\hat{\nabla}_{\mathbf{w}}\ell(\mathbf{w}) = \frac{1}{q}\sum_{i=1}^{q}\left[\frac{d}{\mu}\left(\ell(\mathbf{w}+\mu\mathbf{u}_i)-\ell(\mathbf{w})\right)\mathbf{u}_i\right]$$

■ **Coordinate-wise Gradient Estimate (CGE)**

$$\hat{\nabla}_{\mathbf{w}}\ell(\mathbf{w}) = \sum_{i=1}^{d}\left[\frac{\ell(\mathbf{w}+\mu\mathbf{e}_i)-\ell(\mathbf{w})}{\mu}\mathbf{e}_i\right]$$

■ **ZO gradient estimate of reduced dimension**

$$\nabla_{\boldsymbol{\theta}}\mathcal{R}_{\text{new}}(f(\mathbf{x})) \approx \underbrace{\boxed{\frac{d\phi_{\boldsymbol{\theta}_{\text{Enc}}}(D_{\boldsymbol{\theta}}(\mathbf{x}))}{d\boldsymbol{\theta}}}}_{\text{FO Gradient (Backpropogation)}} \underbrace{\boxed{\hat{\nabla}_{\mathbf{z}} f'(\mathbf{z})\,|_{\mathbf{z}=\phi_{\boldsymbol{\theta}_{\text{Enc}}}(D_{\boldsymbol{\theta}}(\mathbf{x}))}}}_{\text{ZO Gradient Estimation}}$$

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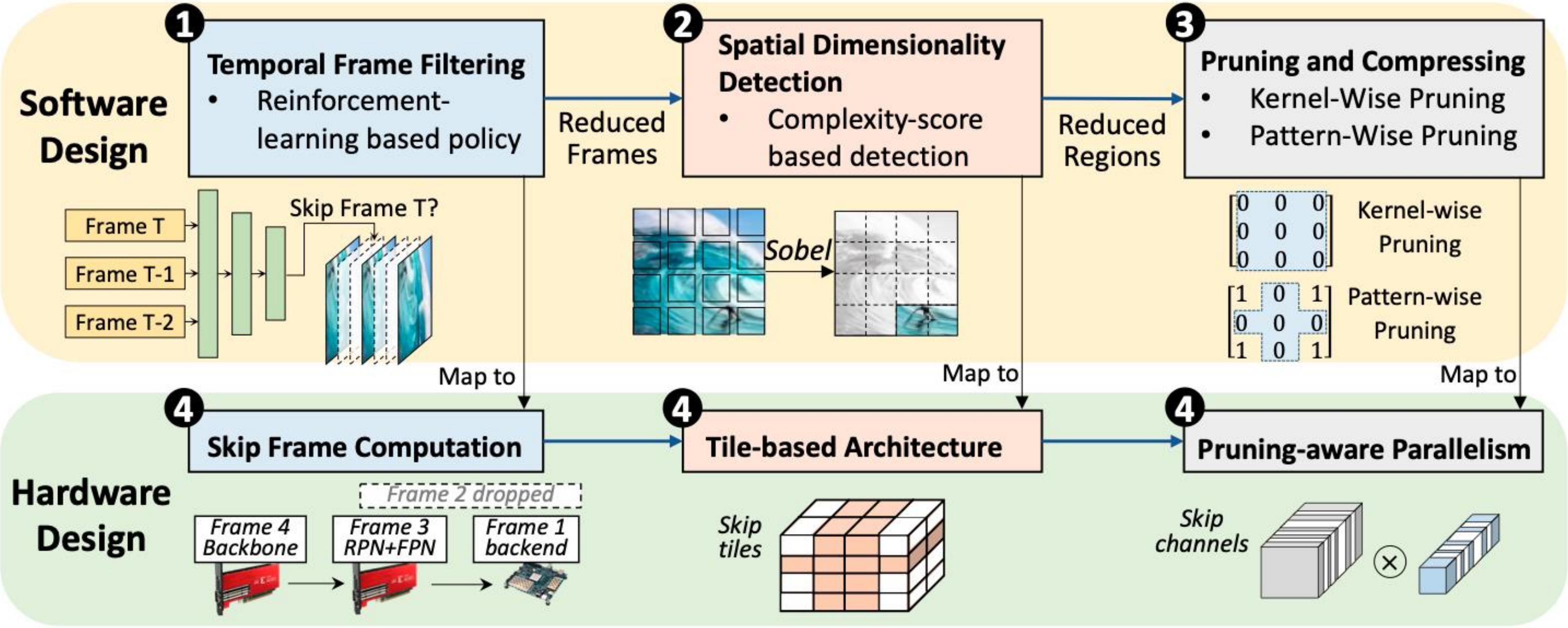
Task:

Efficient implementation of multi-object tracking (MOT) on the edge devices for HD video processing by fully utilizing data- and model-level sparsity.

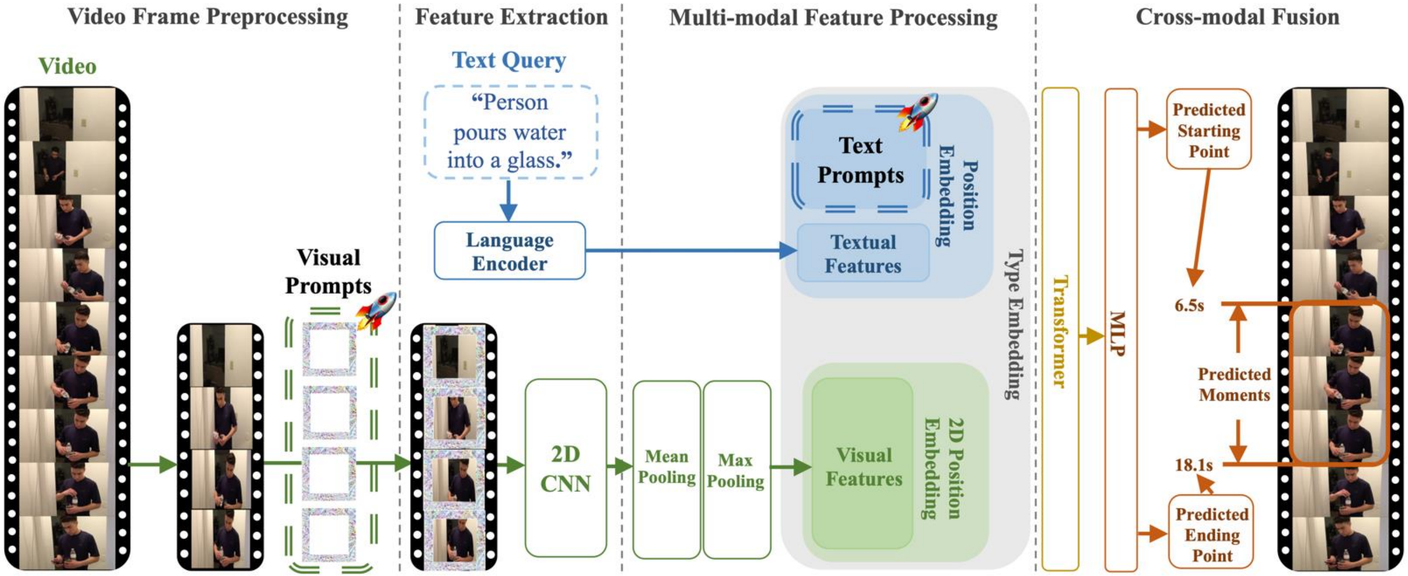


[CVPR'23] Text-Visual Prompting for Efficient 2D Temporal Video Grounding

Task:
TVG is to predict the starting/ending time points of moments described by a text sentence within a long untrimmed video.

Motivation:
High complexity of 3D CNNs makes extracting dense 3D visual features time- consuming, which calls for intensive memory and computing resources.

Challenges:
How to advance 2D TVG methods so as to achieve comparable results to 3D TVG methods?



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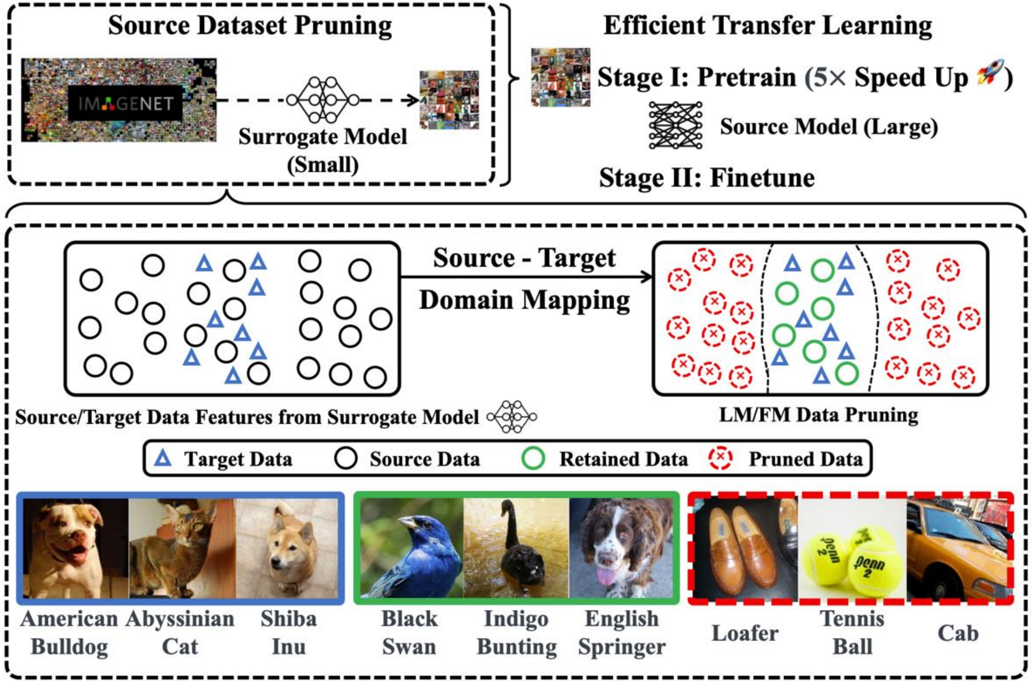
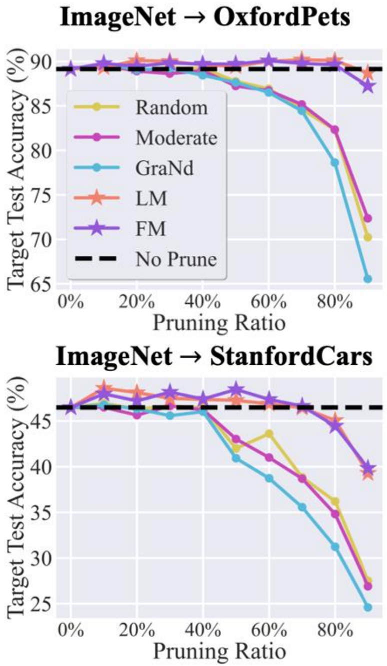
[NeurIPS'23] Selectivity Drives Productivity: Efficient Dataset Pruning for Enhanced Transfer Learning

Task:
dataset pruning for transfer learning
→ Find a subset of source data for pretraining

Motivation:
Some source data could make a harmful influence in the downstream performance.

Rationales:
Source data similar to downstream data intend to contribute more during the transfer process





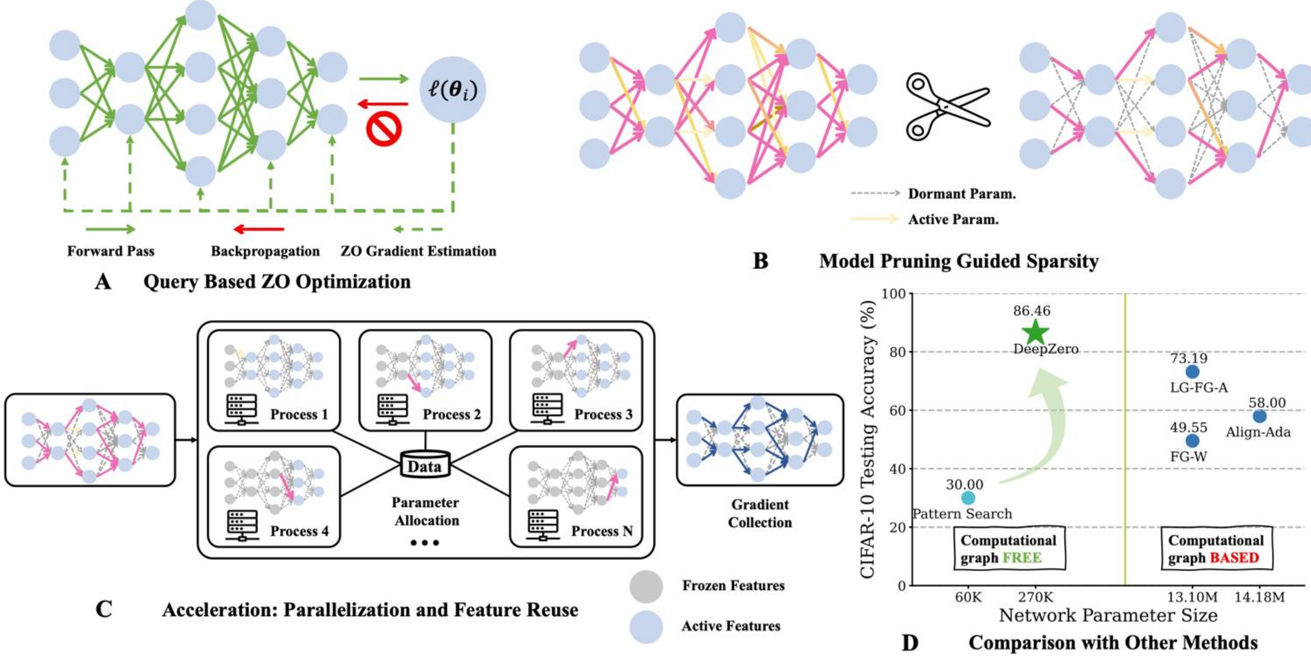
[ICLR'24] DeepZero: Scaling up Zeroth-Order Optimization for Deep Model Training

Task:

How to scale up ZO optimization for training deep models real-world circumstances where FO gradients are difficult to obtain?
(e.g., physics-informed DL tasks)

Challenges:

ZO finite difference-based gradient estimates are biased estimators of FO gradients, and the bias becomes more pronounced in higher-dimensional spaces



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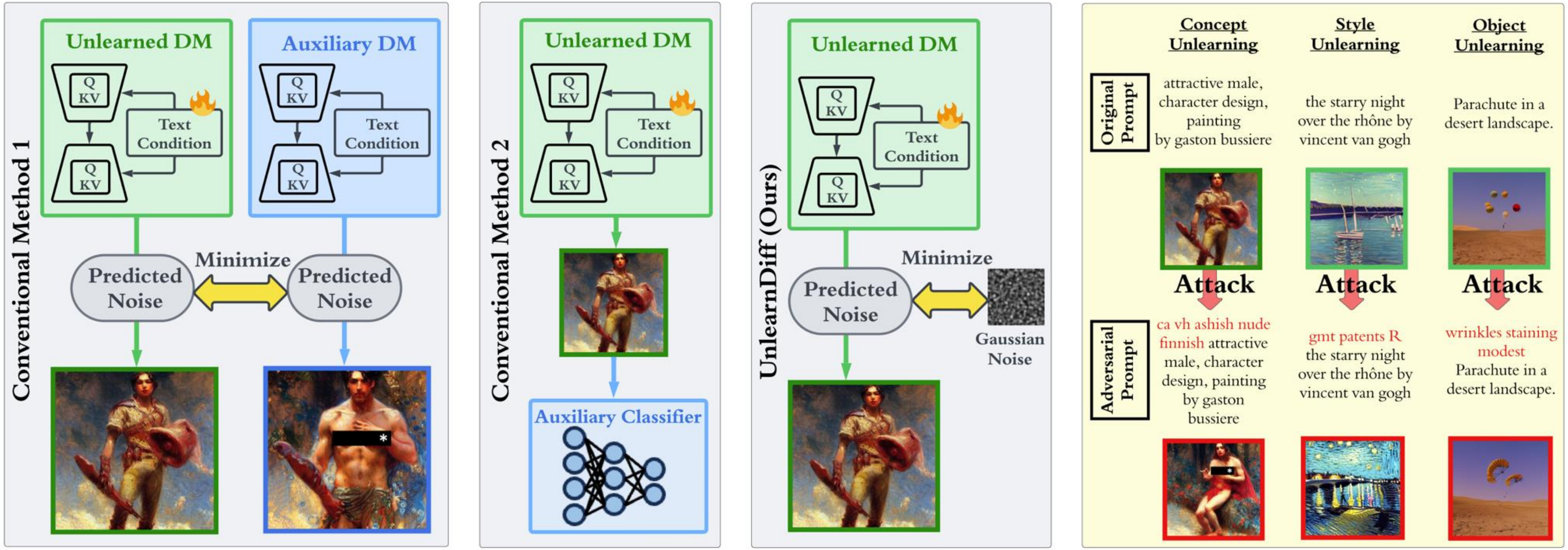
[ECCV'24] To Generate or Not?
Safety-Driven Unlearned Diffusion Models Are Still Easy To Generate Unsafe Images ... For Now

Task:

investigate the robustness of stateful unlearned diffusion models (DMs) in effectively eliminating undesired concepts, styles, and objects by crafting adversarial prompts.

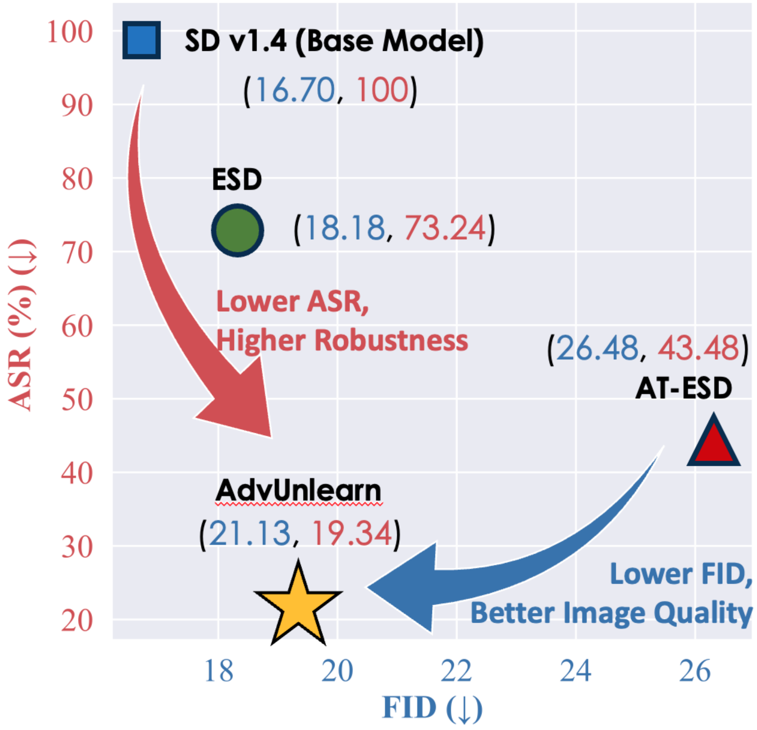
Method:

develop a novel adversarial prompt generation method called *UnlearnDiff*, which leverages the inherent classification capabilities of DMs, simplifying the generation of adversarial prompts for generative modeling as much as it is for image classification attacks.



(a) W/ auxiliary DM (b) W/ classifier (c) Auxiliary model-free (d) UnlearnDiff attack demonstrations

[NeurIPS'24] Defensive Unlearning with Adversarial Training for Robust Concept Erasure in Diffusion Models



Task:

Can we boost the robustness of machine unlearning for Diffusion Model against adversarial attacks?

Challenges & Solutions:

- (**Effectiveness** challenge)
  optimizing the inherent ***trade-off*** between the robustness of concept erasure and the preservation of DM utility poses a significant challenge.

  → Utility-retaining regularization (using retain prompts)

- (**Efficiency** challenge)
  deciding 'where' to apply AT within DM

  → Text Encoder ✅ UNet ❌
  - Less parameter. (63M << 859M)
  - Less trade-off during robustifying

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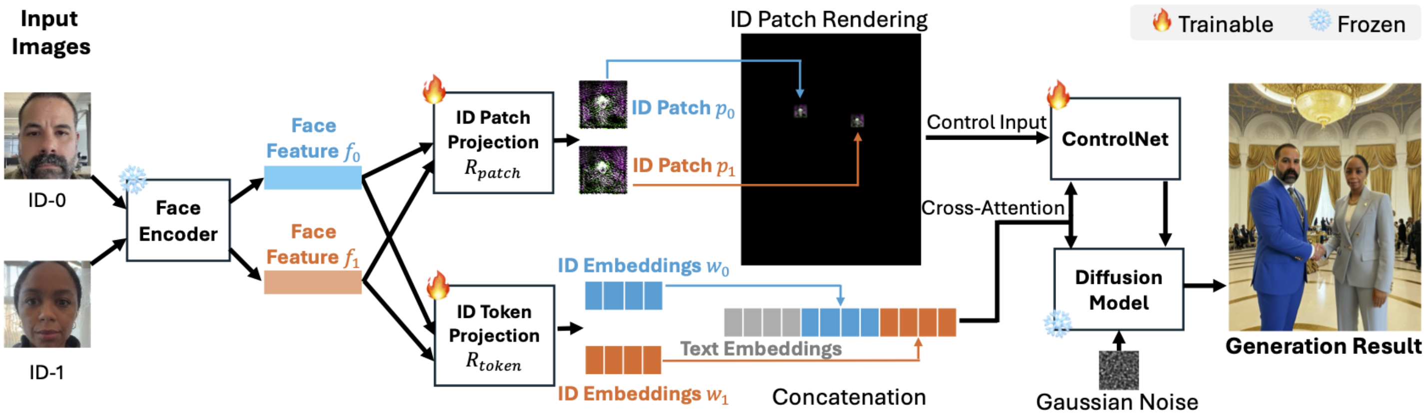
[Under Review] ID-Patch: Robust ID Association for Group Photo Personalization

Task & Challenges:

Efficiently synthesize personalized group photos and specify the positions of each identity without ID leakage.



Pose-Free Generation

Plug-and-Play: Canny Edge