Mechanistic Interpretability for Vision Models Optimization

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Course: **Computer Vision**
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Outline:

→ Motivation and problem statement

→ Related work and gaps

→ Method: Mechanistic Pruning with ACDC

→ Dataset and Task Definition

→ Experimental Setup

→ Results and Analysis

→ Conclusion and Future Work

Problem Statement:

ViTs deliver top-tier accuracy but their fully-connected attention graphs contain millions of redundant edges and heads.

This makes them computationally expensive...
Especially for edge devices.

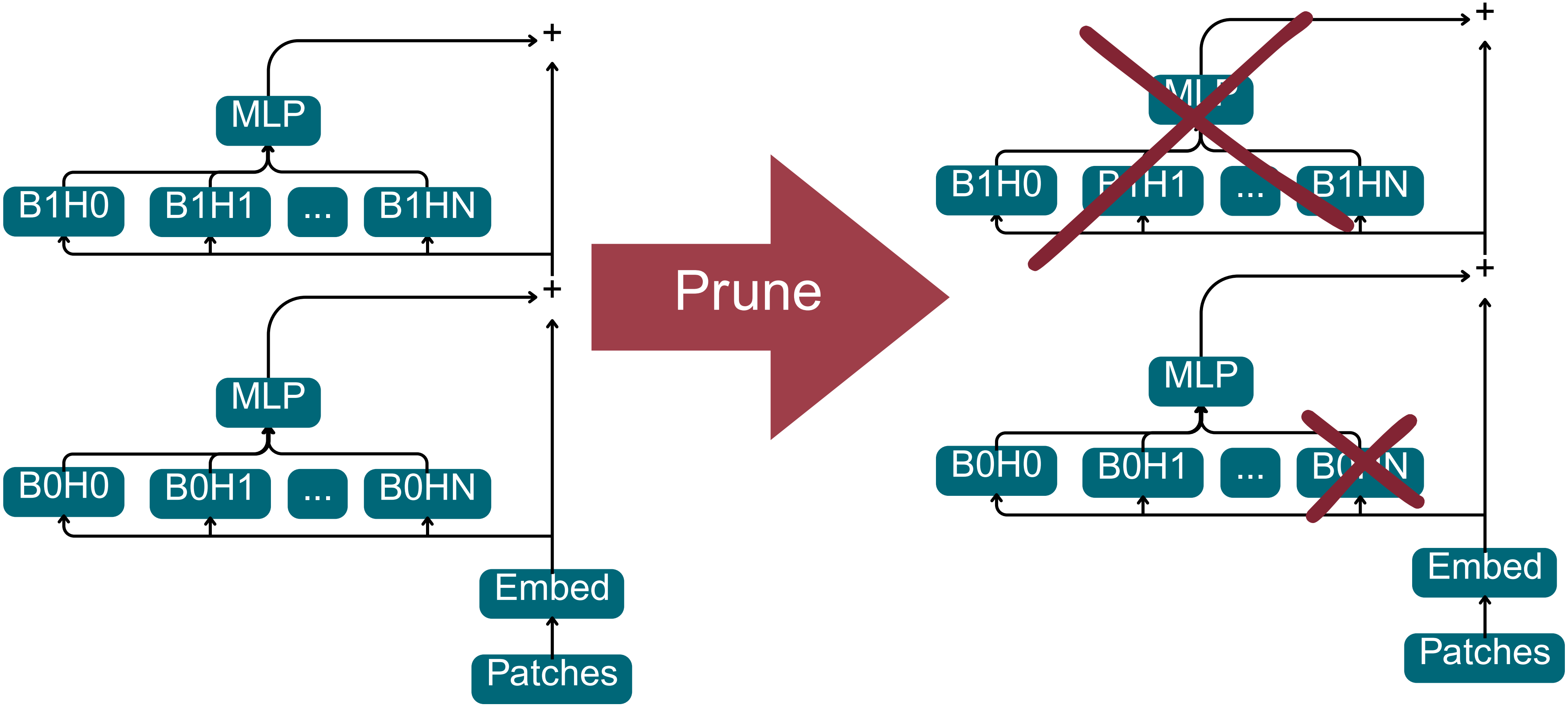
We need an automated way to discover and remove super-fluous internal edges ahead of deployment, yielding a sparse, hardware-friendly ViT that preserves task accuracy.

State of the art:

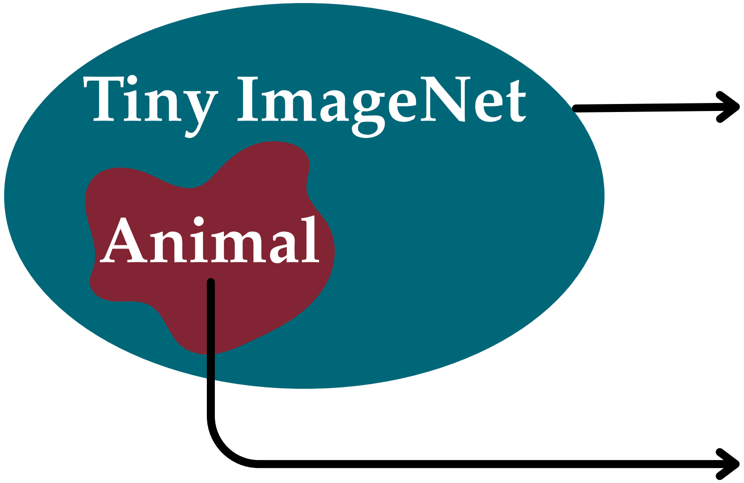
- Static Circuit Discovery:
  ACDC | Edge-Pruning (NeurIPS 24)
- Dynamic Token Pruning:
  MADTP, Zero-TPrune
- Efficient Architectures:
  SpectFormer-H-L, CRATE-α-L, EfficientViT
- Quantisation & Binarisation:
  BHViT, DeepCompress-ViT, Joint Prune-Quant (CVPR 25)
- Parameter-Efficient FT:
  Serial-LoRA, NOLA
- Fast Attention Kernels:
  FlashAttention-3

Proposed method:

By pruning a ViT trained on a more complicated task
We can obtain a more efficient ViT



Dataset:



- 100.000 64x64 images
- 200 classes

- 58 animal classes

ACDC TASK: 6 coarse animal classes

Acquatic | Reptiles | Arthropods
Birds | Mammals | Marine Life

Experimental Setup (1)

Train the ViT to recognize the 58 fine classes

ViT architecture:

- Patch size: 8
- Hidden size: 64
- Blocks: 6
- Attention heads: 8

Data transformations:

- RandAugment
- Horizontal flip
- Random erasing: 25%

Trainer parameters:

- Dropout: 0.2
- Criterion: Soft CrossEntropy
- Optimizer: AdamW
- Mixup + CutMix
- LR: 3e-4
- WarmUp: 20 epochs
- Cosine annealing
- Patience: 50 epochs

Experimental Setup (2)

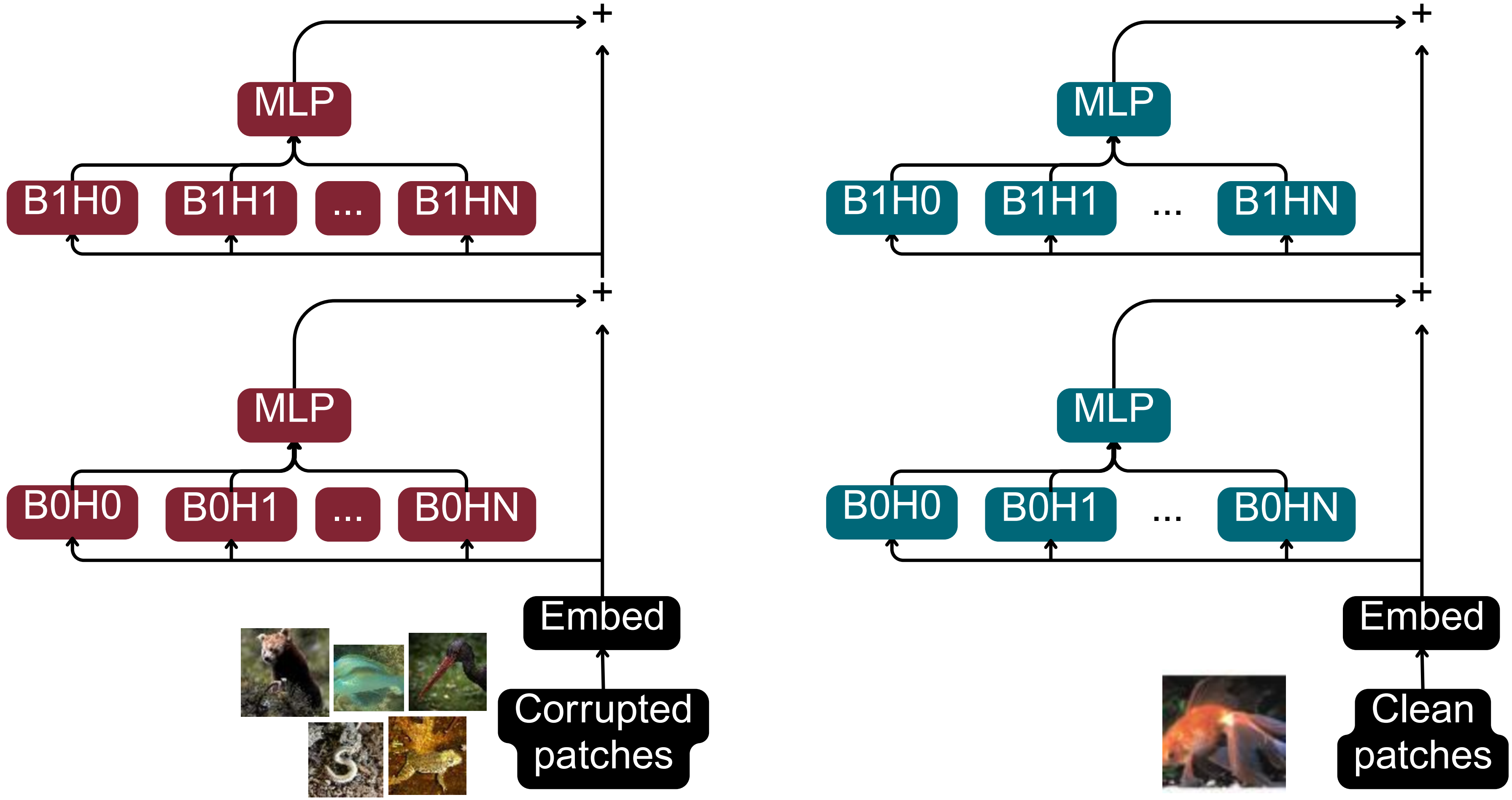
ACDC (1):

For each sample Get one "bad" sample (negative) from each of the other classes

Experimental Setup (2)

ACDC (2):

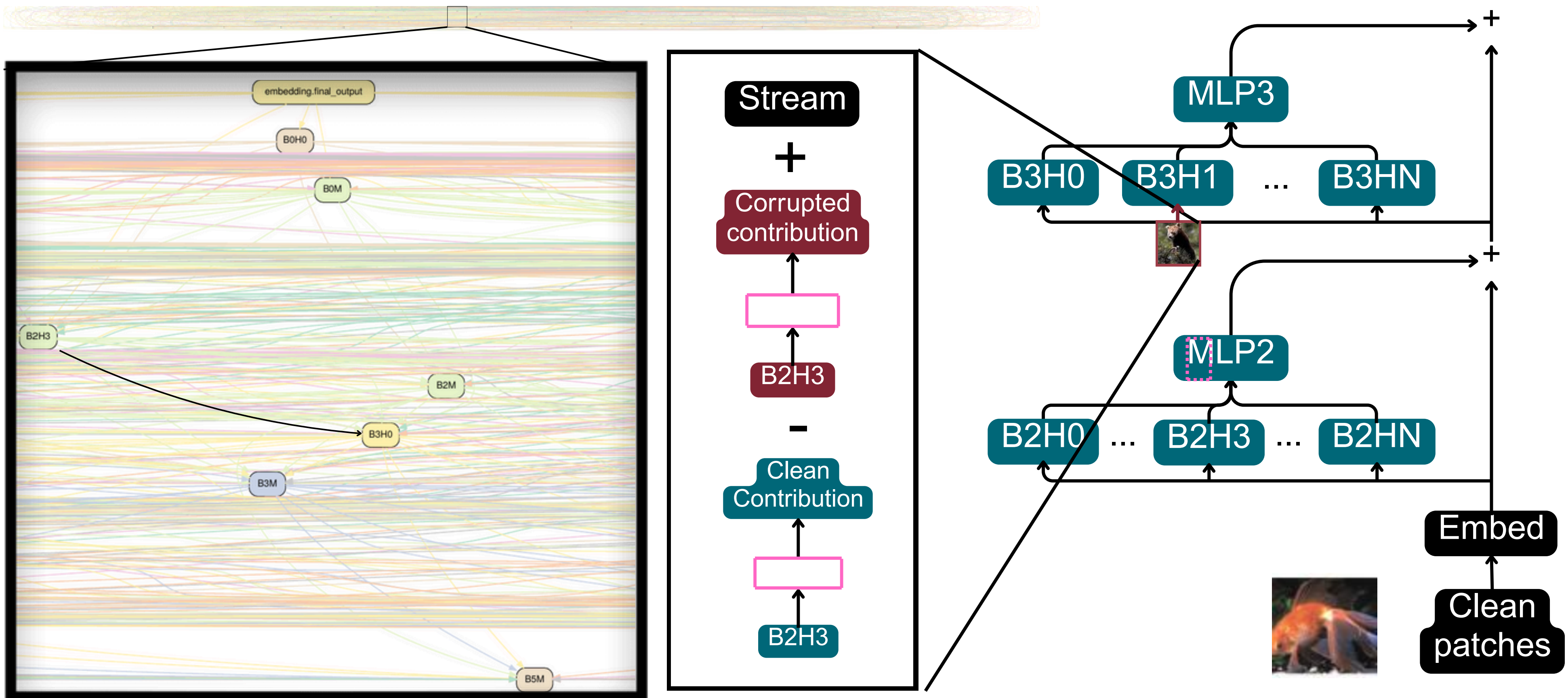
Cache all activations



Experimental Setup (2)

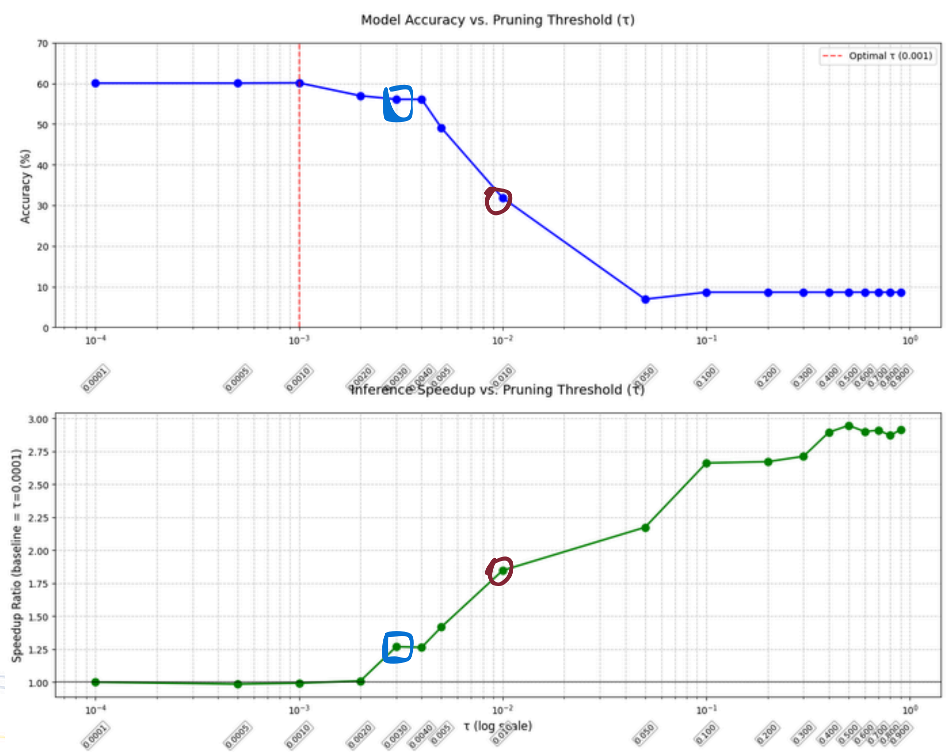
ACDC (3):

- Test each edge changing the input stream in input to the dest node
- If the average KL-Divergenge over train dataset between clean logits is less than τ, Prune the edge



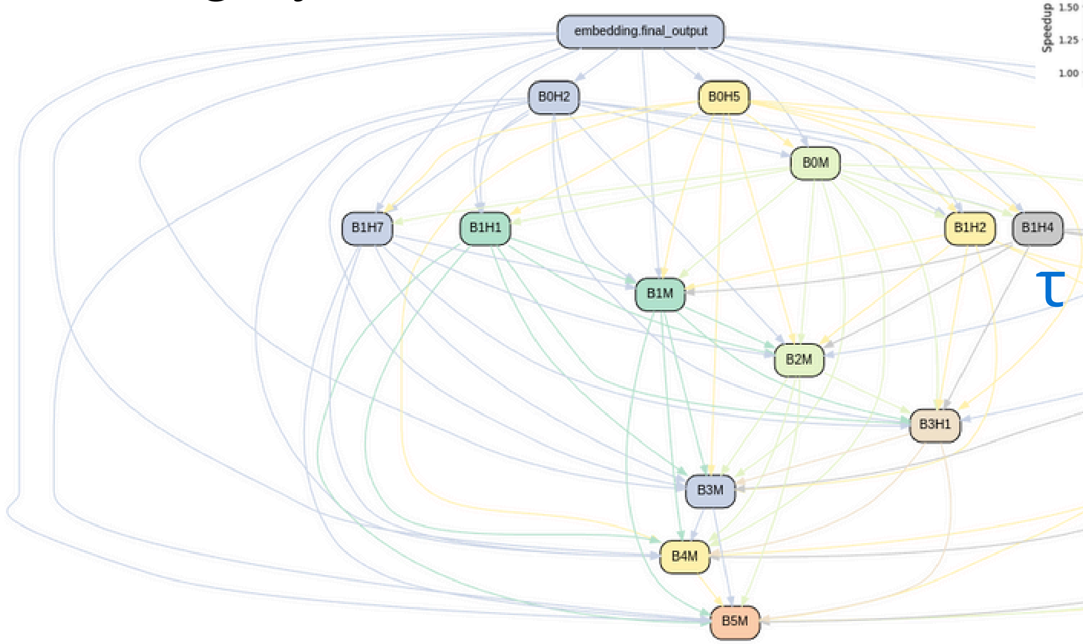
Model Evaluation (1)

Inference time and accuracy over τ



τ = 0.01:

- ACDC pruned 94% of edges and 41 unused attention heads
- 50% accuracy decrease
- Roughly 2 times faster on CPU

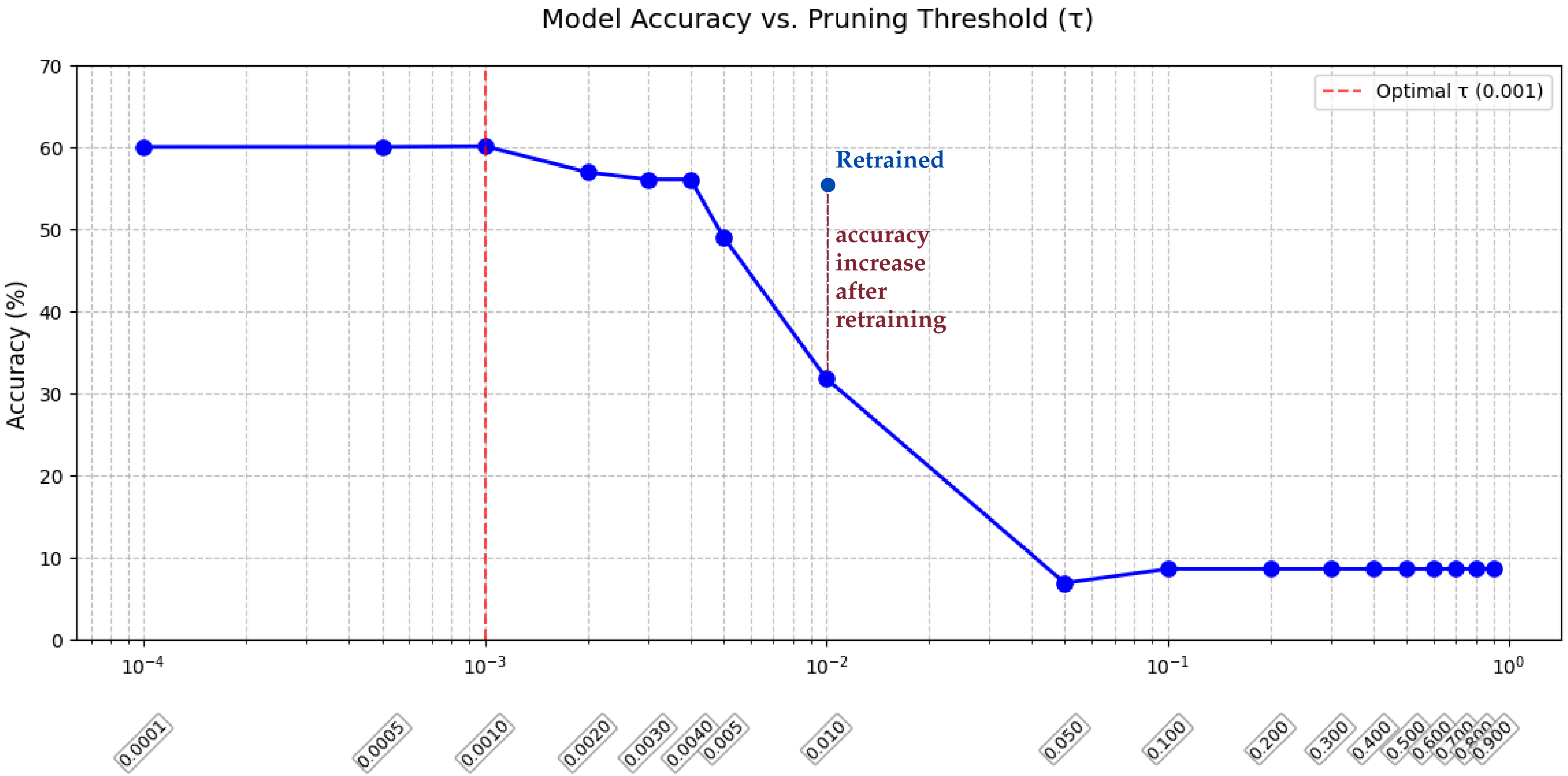


τ = 0.003:

- ACDC pruned 57% of edges
- pruned 18 unused heads
- 9% accuracy decrease
- 25% speedup

Model Evaluation (2)

Accuracy on coarse classes after re initialization and training of the pruned ViT on the 58 fine labels



Conclusions:

- Mechanistic interpretability allows to squeeze performances from existing models
- 2 times speed increase and only 9% decrease of performances on CPU

Future work

- Create a prunable ViT architecture that scales well on GPU
- Benchmark performances on GPU

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References

Miller et al. (2024). **Transformer Circuit Evaluation Metrics Are Not Robust.**
Conference on Language Modeling.

Conmy et al. (2023). **Towards Automated Circuit Discovery for Mechanistic Interpretability.**
NeurIPS. arXiv:2304.14997 [cs.LG].

Elhage, et al. (2021) "**A Mathematical Framework for Transformer Circuits**", Transformer Circuits Thread.

Matt Nguyen. (2024). "**Building a Vision Transformer Model from Scratch.**" Medium.

Yuechun (Ethan) Gu (2024) "**Fine-Tuning Vision Transformer (ViT) on Tiny ImageNet Dataset**"