GreenAI

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Introduction

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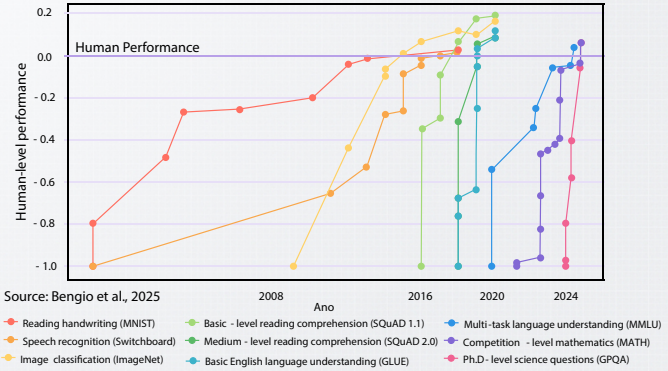
- Deep learning drives unprecedented progress in various cognitive tasks and serves as the powerhouse for learning patterns from data
  - Modern models match or even surpass human performance[1]



[1] Bengio et al. *International Scientific Report on the Safety of Advanced AI*, 2025

Advances in Deep Learning

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- Three factors drive the advance of Deep Learning
  - Algorithm innovation (predictive models)
  - Data
  - Hardware (amount of computing available)

- Algorithm innovation $\times$ data $\times$ hardware
  - The availability of large and well-curated datasets benefits the predictive ability of models
  - The need for massive computing exposes shortcomings of current algorithms
  - To avoid performance overhead, large datasets require high-capacity hardware

Energy Consumption

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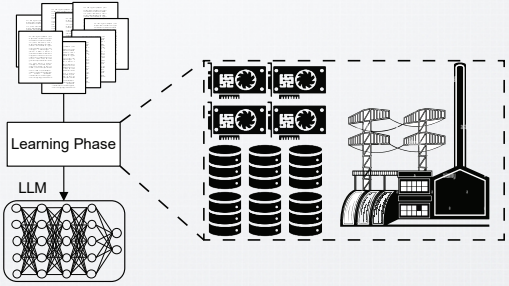
- There is a growing demand for energy to power AI workloads
  - Microsoft recently signed a deal to purchase the next 20 years of energy generated by reopening a nuclear power plant[1]
  - Energy providers are extending the life of aging fossil fuel plants to keep up with demand[1]



Modelo (#Params)	#Exec.	Equiv. CO2	Equi. Água (1 pessoa)
<1B	20	gallons of gasoline	3 months
1B	227	40× NY ↔ SF	1 year
7B	375	150 oil barrels	2 years, 7 month

[1] Morrison et al. *Holistically Evaluating the Environmental Impact of Creating Language Models.* ICLR, 2025

Financial Cost

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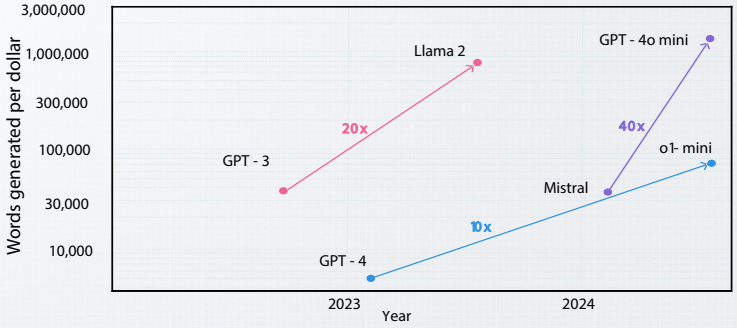
- Modern models are more efficient in terms of inference per cost[1]
- The largest model providers are producing up to a hundred billion tokens per day[2]



[1] Bengio et al. *International Scientific Report on the Safety of Advanced AI*, 2025

[2] Morrison et al. *Holistically Evaluating the Environmental Impact of Creating Language Models.* ICLR, 2025

Financial Cost

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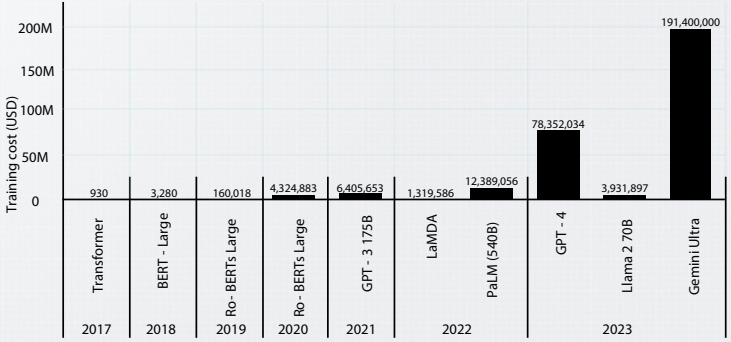
- The development of state-of-the-art models requires enormous financial investment[1]
- Few companies can afford to train models at such a high cost[1]



[1] Bengio et al. *International Scientific Report on the Safety of Advanced AI*, 2025

Notable Models by Sector

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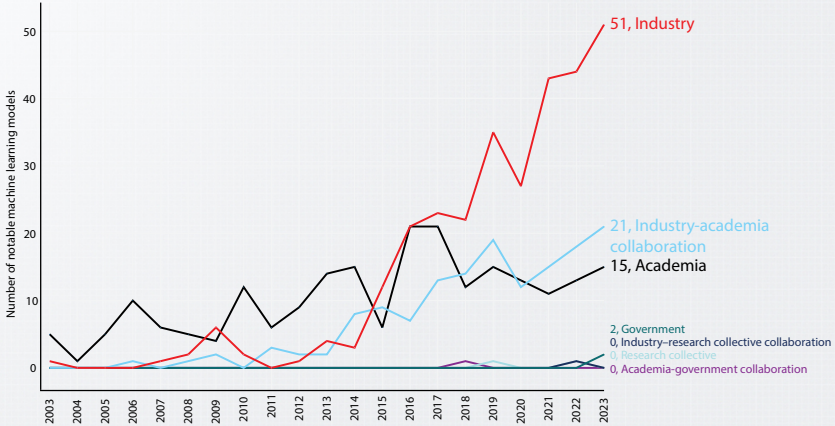
- Companies typically have more access to computational resources than academic institutions[1]



[1] Maslej et al. *Artificial Intelligence Index Report*, 2024

GreenAI Metrics

GreenAI

- CO_2-eq. footprint[1] = Energy Consumption $\times$ Carbon Energy Efficiency
  - Energy Consumption (kWh): W*hours/1000
  - Carbon Energy Efficiency: CO_2 emissions per kWh (Default value 0.432)

- Since other gases have a warming effect, the standard measure describes how much warming a given amount of gas causes, expressed in CO_2-equivalents

- User-friendly toolkits
  - (Deep learning-specific)[1] https://mlco2.github.io/impact/
  - (LLM-specific)[2] https://github.com/SotaroKaneda/MLCarbon
  - (General Purpose)[3] http://calculator.green-algorithms.org/

Lacoste et al. *Quantifying the carbon emissions of machine learning.* NeurIPS, 2019

Faiz et al. *LLMCarbon: Modeling the End-to-End Carbon Footprint of Large Language Models.* ICLR, 2024

Lannelongue et al. *Green Algorithms: Quantifying the Carbon Footprint of Computation.* Advanced Science, 2021

Environmental Impact of Inference

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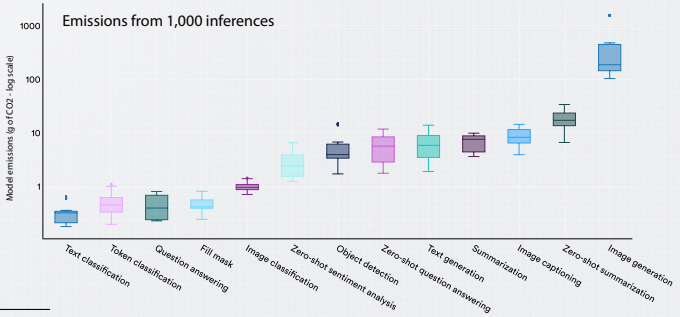
- Models requiring more computation often have larger environmental footprints[1]
- While the emissions from inference may be relatively low, the total impact can surpass that of training when models are queried thousands, if not millions, of times daily



[1] Morrison et al. *Holistically Evaluating the Environmental Impact of Creating Language Models.* ICLR, 2025

Challenges

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- A major challenge in evaluating the environmental impacts of AI models is a lack of transparency about emissions

- The environmental impact of vital pieces of all model development pipelines is still unknown[1] (embodied emissions)
  - GPUs manufacturing
  - **Data center construction**

[1] Morrison et al. *Holistically Evaluating the Environmental Impact of Creating Language Models.* ICLR, 2025

Positive Side of Large Models

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- The community widely acknowledges the environmental costs of developing AI systems

- AI can help promote environmental sustainability

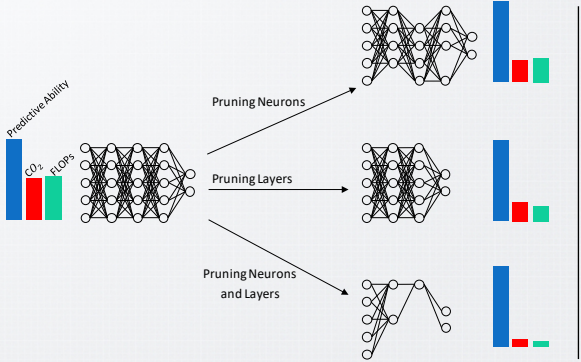
Use Case	AI Contribution
Management of thermal energy storage systems	Anticipating thermal energy needs and managing thermal energy storage systems
Agriculture	Identifying and eliminating pests in commercial harvests
Enhancing urban air quality	Forecasting and predicting air quality in urban cities
Predicting extreme events	Early identification of extreme storm tide events

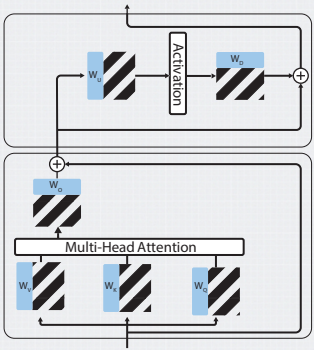
Research Projects

Compression of Deep Models

Research Projects

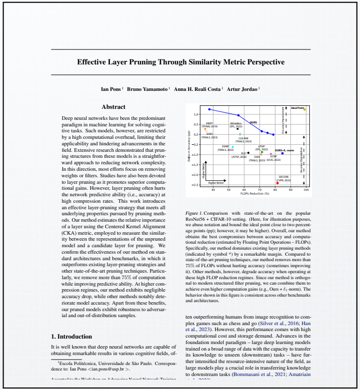
- Pruning strategies remove structures from neural networks
- *How to identify unimportant structures?*

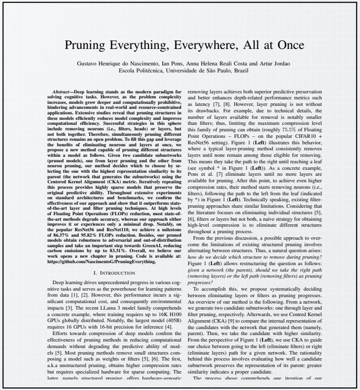


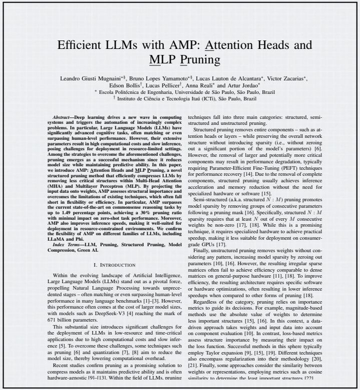


Compression of Deep Models

Research Projects







Pons et al. *Effective Layer Pruning Through Similarity Metric Perspective*. ICPR (Oral) and ICML Workshops, 2024

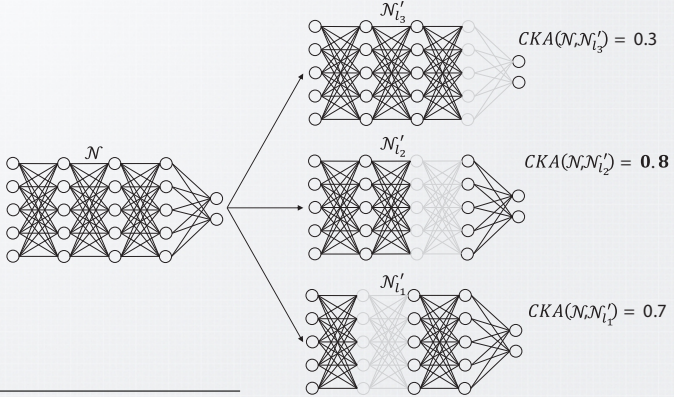
Nascimento et al. *Pruning Everything, Everywhere, All at Once*. IJCNN, 2025

Mugnain et al. *Efficient LLMs with AMP: Attention Heads and MLP Pruning*. IJCNN, 2025

Compression of Deep Models

Research Projects

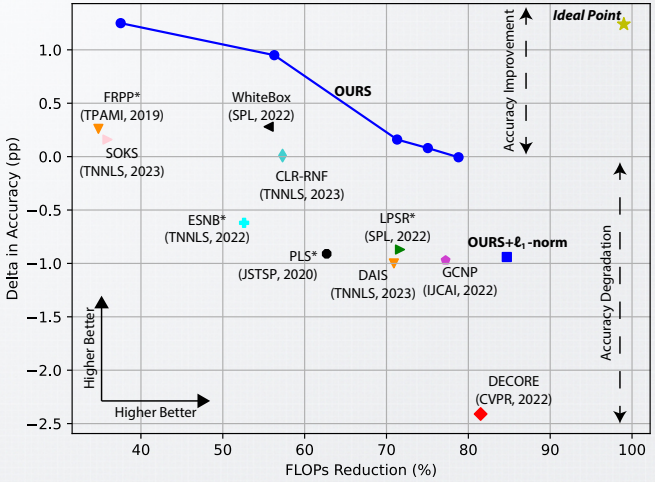
- *We showed that similar representations between a dense (unpruned) network and its optimal pruning candidate indicate lower relative importance, thus capturing underlying properties exhibited by layers and preventing model collapse*



[0]Pons et al. *Effective Layer Pruning Through Similarity Metric Perspective*. ICPR (Oral) and ICML Workshops, 2024

Compression of Deep Models

Research Projects

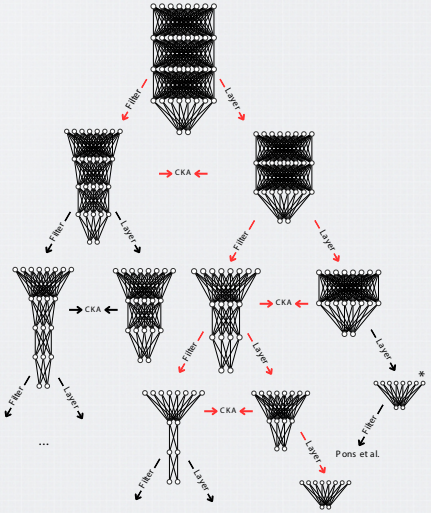


Pons et al. *Effective Layer Pruning Through Similarity Metric Perspective*. ICPR (Oral) and ICML Workshops, 2024

Compression of Deep Models

Research Projects

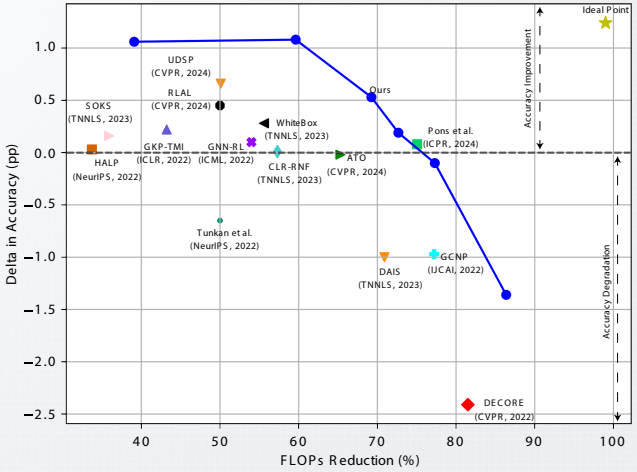
- *Given two candidate subnetworks, one from layer pruning and the other from filter pruning, we can effectively decide which to choose by selecting the one with the highest representation similarity to its parent*



Nascimento et al. *Pruning Everything, Everywhere, All at Once*. IJCNN, 2025

Compression of Deep Models

Research Projects

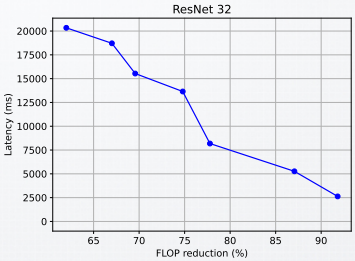


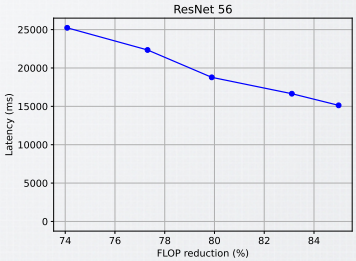
Nascimento et al. *Pruning Everything, Everywhere, All at Once*. IJCNN, 2025

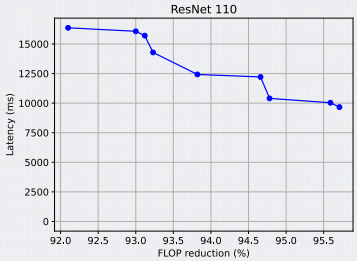
Compression of Deep Models

Research Projects

- Effectiveness on a resource-constrained device
  - ESP32





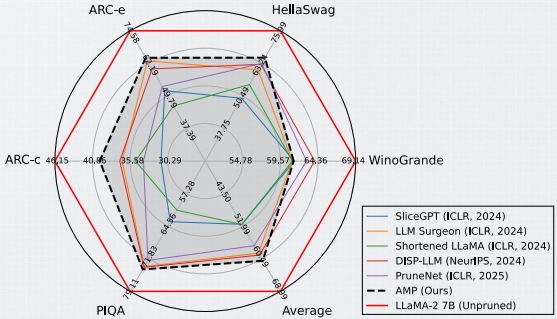


Nascimento et al. *Pruning Everything, Everywhere, All at Once*. IJCNN, 2025

Compression of Deep Models

Research Projects

- *We effectively estimate the importance of internal components in LLMs by projecting input data onto the weights, thereby quantifying their importance to the final representation. Consequently, removing components with the lowest contributions results in models that are lighter, faster, and maintain their predictive capacity*



Compression of Deep Models

Research Projects

- Short demo: https://github.com/c2d-usp/Efficient-LLMs-with-AMP

Compression Ratio	Method	WinoGrande	HellaSwag	ARC-e	ARC-c	PIQA	Avg. ↑
0%	LLaMA 7B	69.85	76.21	72.81	44.71	79.16	68.55
20%	LLM Pruner (NeurIPS, 2023)	61.33	65.34	59.18	37.12	75.57	59.71
	LLM Pruner (+ fine-tuning) (NeurIPS, 2023)	65.11	68.11	63.43	37.88	76.44	62.19
	Shortened LLaMA (ICLR, 2024)	**68.82**	69.82	64.06	39.93	74.65	63.46
	DISP-LLM (NeurIPS, 2024)	64.72	68.39	64.81	37.12	76.66	62.34
	PruneNet (ICLR, 2025)	62.12	65.40	64.65	36.52	75.51	60.82
	AMP (Ours)	63.93	**70.34**	**69.82**	**41.38**	**77.15**	**64.52**
0%	LLaMA-2 7B	69.14	75.99	74.58	46.15	79.11	68.99
30%	SliceGPT (ICLR, 2024)	61.33	49.62	51.77	31.23	63.55	51.50
	LLM Surgeon (ICLR, 2024)	61.09	60.72	63.09	36.69	73.56	59.03
	Shortened LLaMA (ICLR, 2024) (‡)	61.09	54.97	45.96	34.81	60.99	51.56
	DISP-LLM (NeurIPS, 2024)	**63.93**	62.87	60.1	37.03	73.72	59.53
	PruneNet (ICLR, 2025)	61.09	58.30	53.20	32.94	71.11	55.33
	PruneNet (+ fine-tuning) (ICLR, 2025)	62.90	63.21	53.37	33.70	72.20	57.08
	AMP (Ours)	61.25	**65.47**	**64.31**	**39.85**	**74.21**	**61.02**

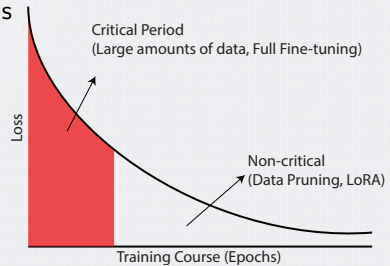
Mugnain et al. *Efficient LLMs with AMP: Attention Heads and MLP Pruning.* IJCNN, 2025

Efficient Training – Critical Periods

Research Projects

- Critical Learning Periods comprise an important phenomenon involving deep learning[1][2]
  - Early epochs play a decisive role in the success of many training recipes

- *How to identify critical periods during the course of training?*
  - Given calls for more efficient training in the era of foundation models, answering this question yields notable gains



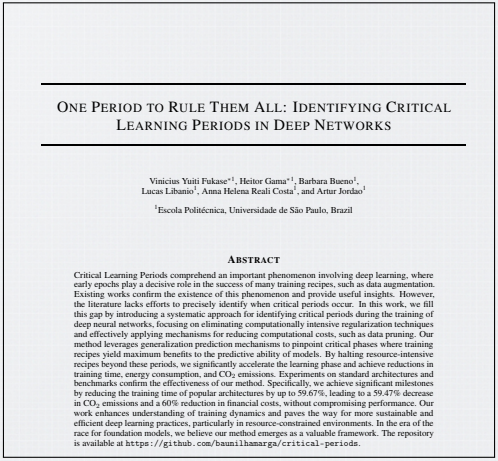
[1] Golatkar et al. *Time Matters in Regularizing Deep Networks: Weight Decay and Data Augmentation Affect Early Learning Dynamics, Matter Little Near Convergence.* NeurIPS, 2019

[2] Achille et al. *Critical Learning Periods in Deep Networks.* ICLR, 2019

Efficient Training – Critical Periods

Research Projects

- *Throughout the course of training, a simple generalization estimation enables successful identifying when the critical period emerges*



ONE PERIOD TO RULE THEM ALL: IDENTIFYING CRITICAL LEARNING PERIODS IN DEEP NETWORKS

Vinicius Yuiti Fukase*[1], Heitor Gama*[1], Barbara Bueno[1], Lucas Libanio[1], Anna Helena Reali Costa[1], and Artur Jordao[1]

[1]Escola Politécnica, Universidade de São Paulo, Brazil

ABSTRACT

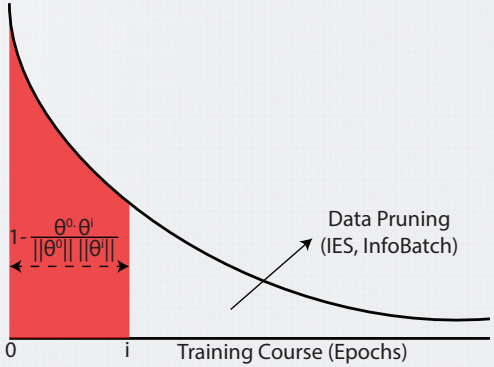
Critical Learning Periods comprehend an important phenomenon involving deep learning, where early epochs play a decisive role in the success of many training recipes, such as data augmentation. Existing works confirm the existence of this phenomenon and provide useful insights. However, the literature lacks efforts to precisely identify when critical periods occur. In this work, we fill this gap by introducing a systematic approach for identifying critical periods during the training of deep neural networks, focusing on eliminating computationally intensive regularization techniques and effectively applying mechanisms for reducing computational costs, such as data pruning. Our method leverages generalization prediction mechanisms to pinpoint critical phases where training recipes yield maximum benefits to the predictive ability of models. By halting resource-intensive recipes beyond these periods, we significantly accelerate the learning phase and achieve reductions in training time, energy consumption, and CO_2 emissions. Experiments on standard architectures and benchmarks confirm the effectiveness of our method. Specifically, we achieve significant milestones by reducing the training time of popular architectures by up to 59.67%, leading to a 59.47% decrease in CO_2 emissions and a 60% reduction in financial costs, without compromising performance. Our work enhances understanding of training dynamics and paves the way for more sustainable and efficient deep learning practices, particularly in resource-constrained environments. In the era of the race for foundation models, we believe our method emerges as a valuable framework. The repository is available at `https://github.com/baunilhamarga/critical-periods`.

Fukase et al. *One Period to Rule Them All: Identifying Critical Learning Periods in Deep Networks.* ArXiv, 2025

Efficient Training – Critical Periods

Research Projects

- Layer rotation[1]: $1 - \frac{\theta^{\mathbf{0}} \cdot \theta^{\mathbf{i}}}{||\theta^{\mathbf{0}}|| \, ||\theta^{\mathbf{i}}||}$
  - θ^0 indicates the initially randomized weights
  - θ^i indicates weights at epoch i



[1] Carbonnelle et al. *Layer rotation: a surprisingly simple indicator of generalization in deep networks?* ICML, 2019

Efficient Training – Critical Periods

Research Projects

- Setup
  - Original: Data pruning method by Yuan et al.[1] (without critical period)
  - Ours: Data pruning after critical period
  - Baseline: Standard training using full data

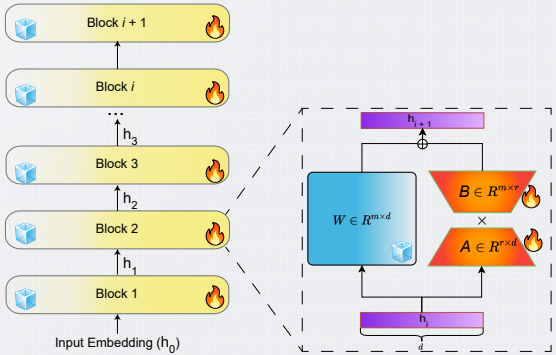
	Dataset	CIFAR-10			CIFAR-100		
	Architecture	ResNet18	ResNet50	VGG16	ResNet34	ResNet101	DenseNet121
IES[1]	Data pruning	0.9469	0.9464	0.9312	0.7747	0.7799	0.7912
	Ours	0.9489	0.9474	**0.9331**	**0.7754**	0.7788	**0.7930**
	Baseline	**0.9504**	**0.9488**	0.9329	0.7752	**0.7815**	0.7907

[1] Yuan et al. *Instance-dependent Early Stopping* ICLR, 2025

Parameter Efficient Fine-Tuning

Research Projects

- LoRA[1] constitutes an important technique in the age of large models
  - It allows the exploration of the capacity of these models for specialized tasks with efficient fine-tuning
  - $W + \Delta W \approx W + BA$
- *Are all LoRA modules necessary?*

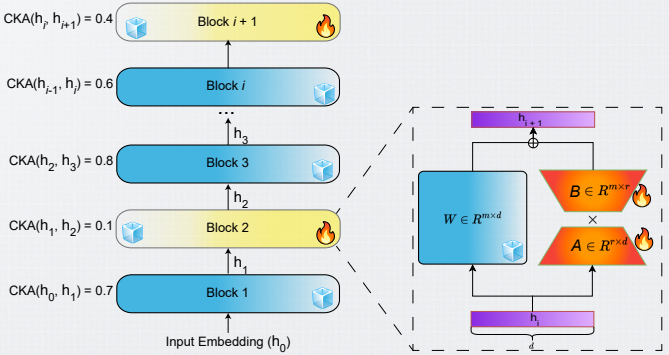


[1] Hu et al. *LoRA: Low-Rank Adaptation of Large Language Models.* ICLR, 2022

Parameter Efficient Fine-Tuning

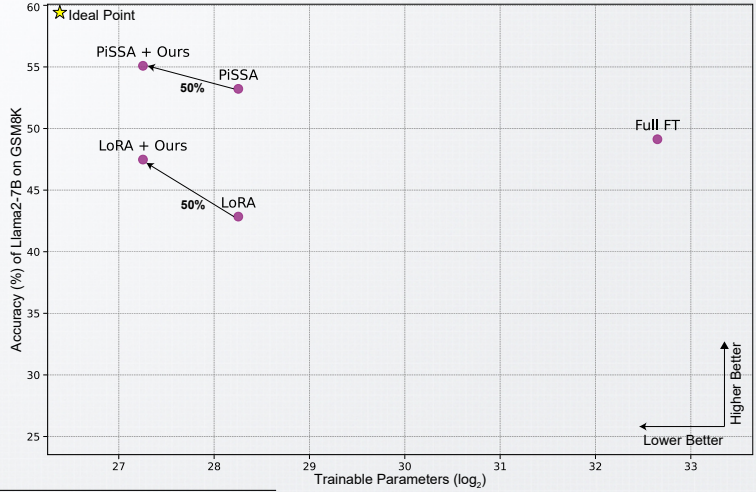
Research Projects

- *Given a LLM and a task, we can effectively choose a subset of n transformer blocks to fine-tune by measuring their participation on the construction of internal representations. We quantify this relevance to the task by assessing the similarity between the input and output representations of a block*



Parameter Efficient Fine-Tuning

Research Projects



[1] Hu et al. *LoRA: Low-Rank Adaptation of Large Language Models.* ICLR, 2022

[2] Meng et al. *PiSSA: Principal Singular Values and Singular Vectors Adaptation of Large Language Models.* NeurIPS, 2024

Parameter Efficient Fine-Tuning

Research Projects

Model	Params	Strategy	GSM8K	MATH	HumanEval	MBPP
LLaMA 2-7B	6738M	Full FT	49.13±0.21	7.29±0.22	21.20±0.30	35.59±0.25
	320M	LoRA	42.85±0.12	5.50±0.33	18.35±0.31	35.50±0.14
	320M	PiSSA	53.22±0.55	7.47±0.34	21.92±0.38	37.24±0.63
	159M	LoRA + Ours	47.48±1.29	5.90±0.25	22.77±1.56	34.26±2.23
	159M	PiSSA + Ours	**55.09±1.14**	**8.28±0.33**	**24.60±0.69**	**40.86±1.50**
Mistral-7B	7240M	Full FT	69.91±0.25	18.64±0.35	45.31±0.14	51.46±0.13
	335M	LoRA	69.50±0.42	20.08±0.20	43.78±0.34	58.46±0.37
	335M	PiSSA	**73.31±0.23**	**23.12±0.52**	46.88±0.25	**62.55±0.58**
	167M	LoRA + Ours	72.63±0.08	20.69±0.13	50.00±1.58	62.43±0.55
	167M	PiSSA + Ours	73.29±0.84	21.56±0.23	**50.20±4.09**	60.57±1.59
Gemma-7B	8540M	Full FT	72.09±0.32	22.71±0.34	47.02±0.27	55.67±0.50
	400M	LoRA	75.11±0.64	30.41±0.48	53.70±0.23	65.58±0.29
	400M	PiSSA	**77.78±0.32**	**31.33±0.33**	**54.31±0.28**	**66.17±0.43**
	200M	LoRA + Ours	73.54±0.66	28.39±0.43	49.80±2.50	65.00±0.66
	200M	PiSSA + Ours	73.76±0.50	27.38±0.53	51.03±3.67	61.80±0.53