



# Pruna AI

## Compression for Language Models



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Founder, President & Chief Scientist

# How Do People Use Deep Learning?

## Many Deep Learning Tasks



### Image

- Classification
- Object detection
- Gen. from text
- Segmentation
- ...



### Video

- Object tracking
- Gen. from text
- Gen. from image
- ...



### Audio

- Transcription
- Translation
- Gen. from text
- ...



### Text

- Question answering
- Summarization
- Classification
- ...



### Proteins

- Folding
- De novo Gen
- Property prediction
- ...

## Phases of Deep Learning Models

Development

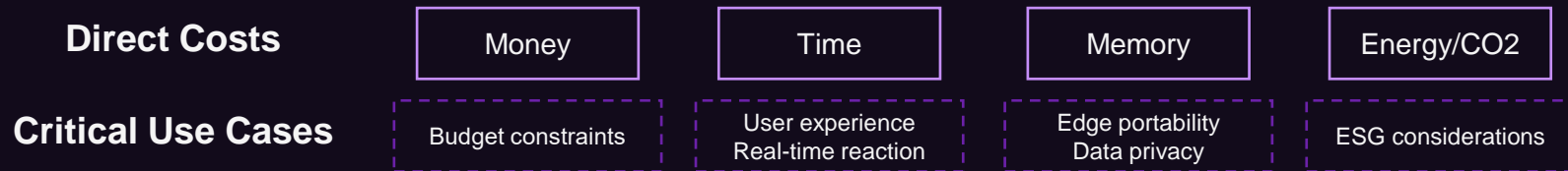
Training

Inference

80-90% of  
DL workload



# Why Do We Need Efficient Deep Learning?

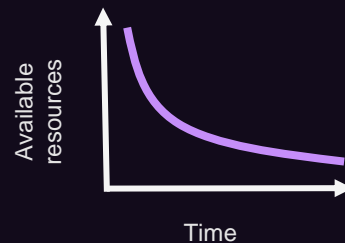
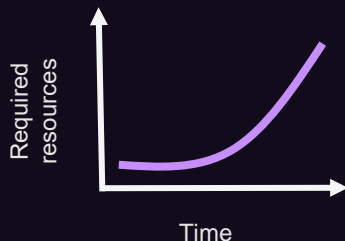


## What Are Good Efficiency Metrics?

Metrics are often correlated

Metrics can be contradictory

Metrics should measure **direct real-world costs**



[1] The efficiency misnomer, ICLR 2022

[2] Power Hungry Processing: Watts Driving the Cost of AI Deployment?

# How Does a Deep Learning Model Work?

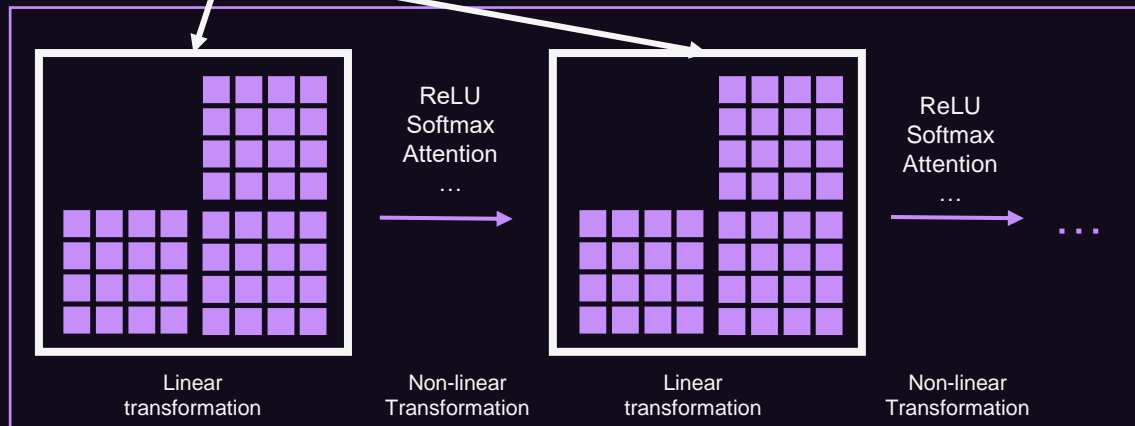
Input data

Output prediction

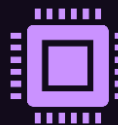


80-95% of  
DL workload

Model



Language



Hardware



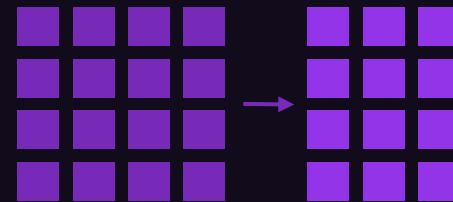
### Pruning



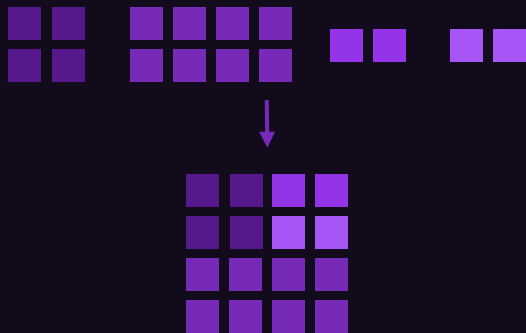
### Quantization



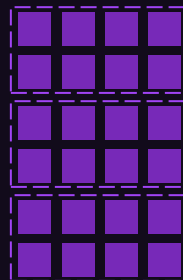
### Distillation



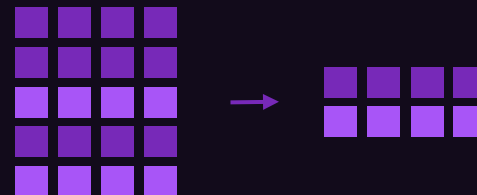
### Compilation



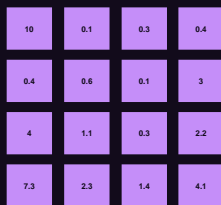
### Batching



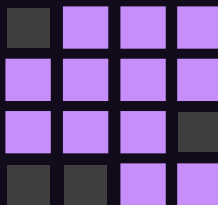
### Caching



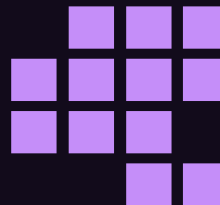
# How to Prune Deep Learning Models?



**Step 1**  
Score  
structures



**Step 2**  
Rank  
structures  
w.r.t. scores



**Step 3**  
Prune structures  
with lowest  
scores

- **What structure to prune?** Unstructured pruning, structured pruning, ...
- **How to score structures?** Random, magnitude, gradient, hessian
- **What sparsity to prune?** Homogeneous, heterogeneous
- **When to prune?** Before, during, after training

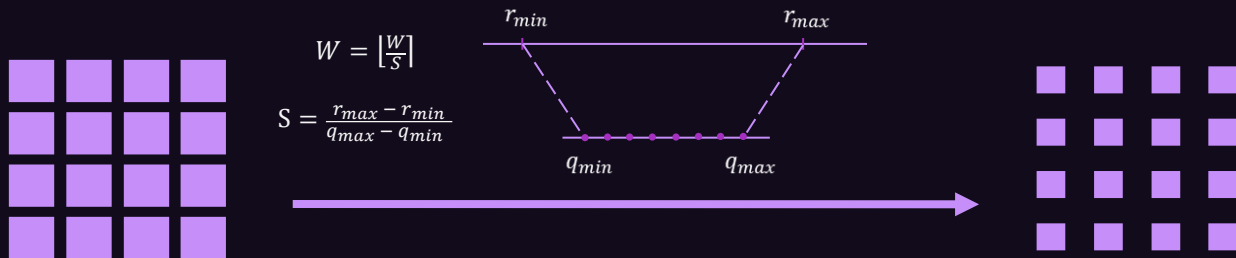


[1] Winning the Lottery Ahead of Time: Efficient Early Network Pruning. ICML 2022

[2] How Sparse Can We Prune A Deep Network: A Fundamental Limit Viewpoint

[3] Structurally Prune Anything: Any Architecture, Any Framework, Any Time.

# How to Quantize Deep Learning Models?



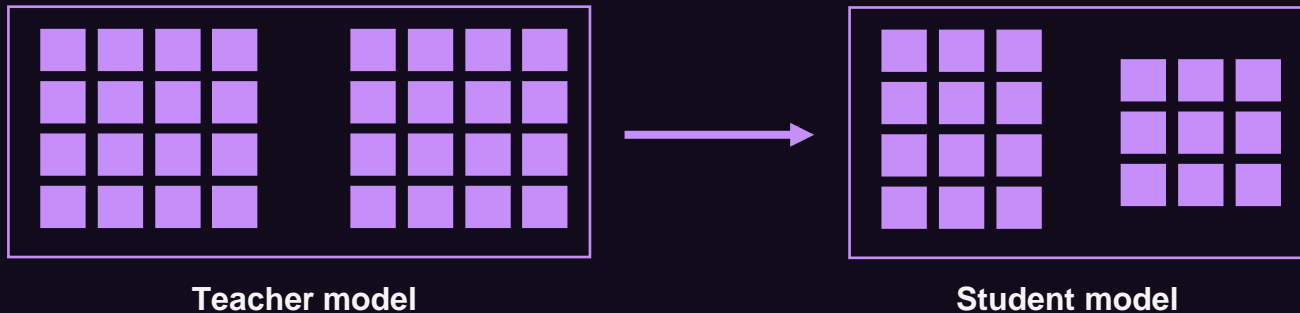
- **What structure to quantize?** Per tensor/channel/group/outliers, weight/activation
- **How to quantize structures?** Linear quantization, code books
- **What precision to quantize?** 16, 8, 4, 2, 1 bits
- **When to quantize?** Quantization-aware, post-training



[1] AWQ: Activation-aware Weight Quantization for LLM Compression and Acceleration. NeurIPS 2023

[2] GPTQ: Accurate Post-Training Quantization for Generative Pre-trained Transformers. ICLR 2023

# How to Distill Deep Learning Models?



- **What information to distill?** Response, feature, weights...
- **What model to distill into?** Architecture, size, precision
- **When to distill?** Offline, online



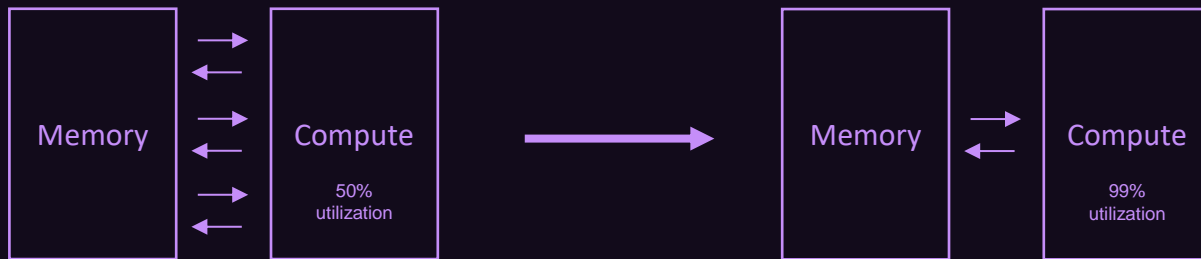
[1] Does Knowledge Distillation Really Work?. NeurIPS 2021

[2] Improved Knowledge Distillation via Teacher Assistant. AAAI 2019

[3] Fitnets: Hints for Thin Deep Nets. ICLR 2015



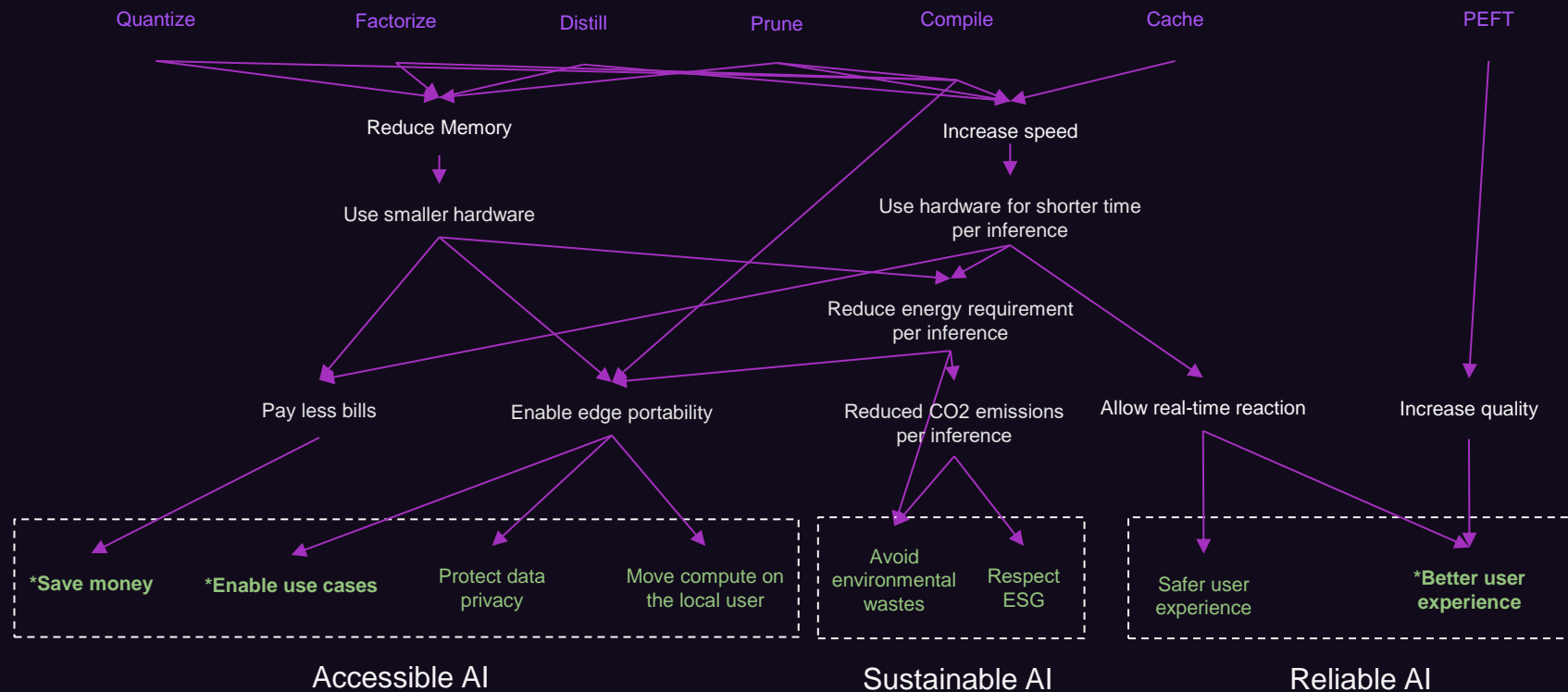
# How to Compile Deep Learning Models?



- **What structure to compile?** Linear/Attention/..., Fuse operators
- **What compilation backend/kernels to use?** CUDA, Triton, ARM, Custom backend
- **What hardware is supported by compilation?** CPU, GPU, others
- **How to compile?** Memory vs compute bound



# How Does Compression Benefit Deep Learning?



# How Well Does Compression Methods Work?

	Acc.	Speed	Mem.
Base	~75%	x1	x1
Prun.	~76%	x2	X0.5

ResNet50 - ImageNet

	Perpl.	Speed	Mem.
Base	~5.6	x1	x1
Quant.	~6.0	x2	X0.5

Llama 7B - WikiText

	Speed	Mem.
Base	x1	x1
Distill.	x2	X0.5

Stable Diffusion

- **Remark 1:** There are many, many, many other compression methods.
- **Remark 2:** Compression methods can be combined
- **Remark 3:** The best (combination of) compression methods depends on the final application setup (incl. architecture, hardware, data,...).

**Compression of DL model is complex!**



[1] Structurally Prune Anything: Any Architecture, Any Framework, Any Time.

[2] GPTQ: Accurate Post-Training Quantization for Generative Pre-trained Transformers. ICLR 2023

[3] SSD-1B. Segmind

# How Well Does Compression Methods Work?



Base



Pruna



# How Well Does Compression Methods Work?



Base

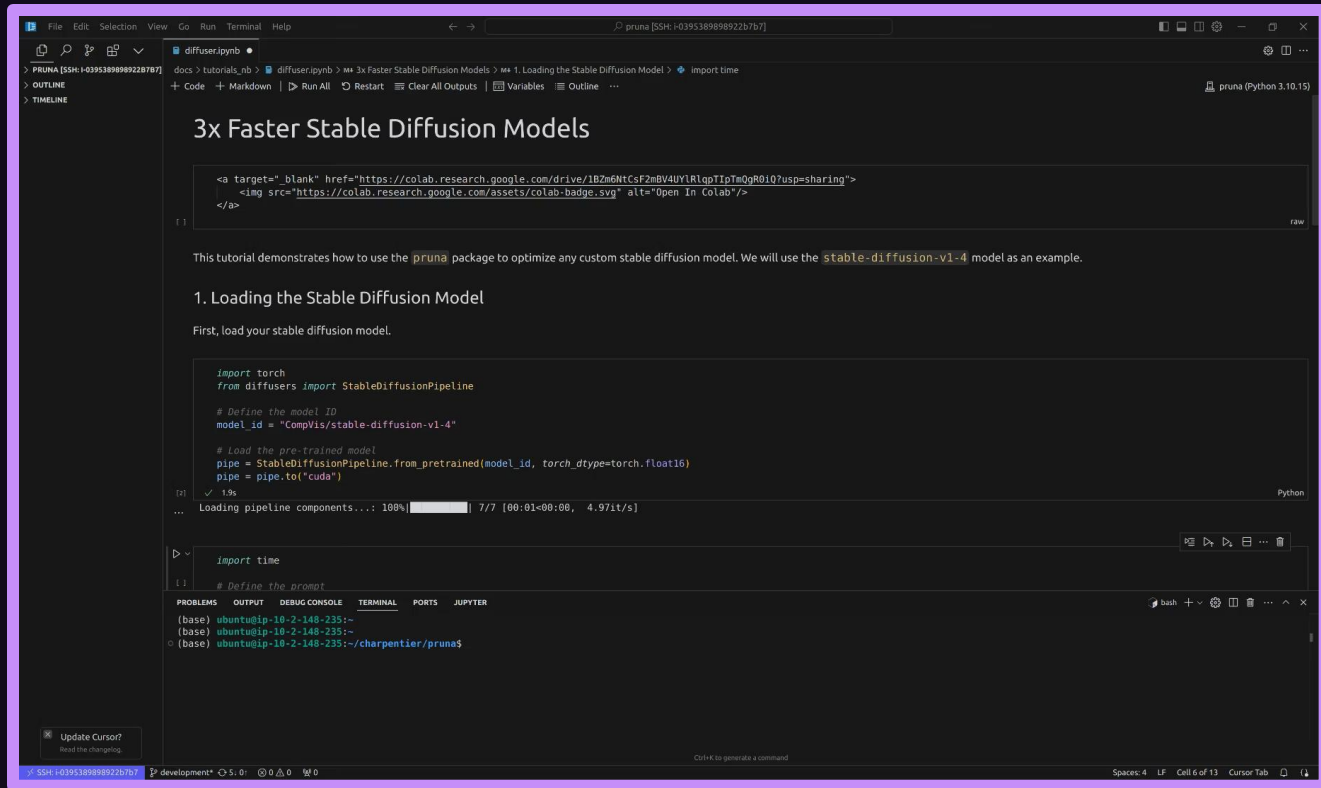


Pruna

Compression of DL model does not  
necessarily means quality loss!



# How to Compress Your Deep Learning Model?



```
diffuser.ipynb
> PRUNA [SSH: i439538989892257b7] docs > tutorials.nb > 3x Faster Stable Diffusion Models > 1. Loading the Stable Diffusion Model > import time
+ Code + Markdown | ▶ Run All | ⏮ Restart | 🧹 Clear All Outputs | 📄 Variables | 📖 Outline | ...
```

## 3x Faster Stable Diffusion Models

<https://colab.research.google.com/drive/1B7mFntCsF2mBV4UY1RlqTIpTm0pR0IQ?usp=sharing>

This tutorial demonstrates how to use the `pruna` package to optimize any custom stable diffusion model. We will use the `stable-diffusion-v1-4` model as an example.

### 1. Loading the Stable Diffusion Model

First, load your stable diffusion model.

```
import torch
from diffusers import StableDiffusionPipeline

# Define the model ID
model_id = "CompVis/stable-diffusion-v1-4"

# Load the pre-trained model
pipe = StableDiffusionPipeline.from_pretrained(model_id, torch_dtype=torch.float16)
pipe = pipe.to("cuda")
```

[1] ✓ 1.9s Python

... Loading pipeline components...: 100% [████████████████████] 7/7 [00:01:00:00, 4.97it/s]

```
import time

# Define the prompt
```

PROBLEMS OUTPUT DEBUG CONSOLE TERMINAL PORTS JUPYTER

(base) ubuntu@ip-10-2-148-235:~  
(base) ubuntu@ip-10-2-148-235:~  
(base) ubuntu@ip-10-2-148-235:~/charpentier/pruna\$

Update Cursor?  
Read the changelog

SSH: i439538989892257b7 development\* 0:0:0 0 0 0



# How to Compress Your Deep Learning Model?

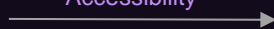
## Manual solution

1. Read & understand research papers.
2. Implement & test compression methods
3. Integrate compression methods for your specific model/hardware.
4. Test & evaluate all hyperparameters.
5. *Hopefully* get efficiency gains



Long research exploration

Accessibility

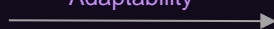


Easy-to-use compressions



Painful model/hardware debugging

Adaptability

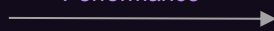


Model/hardware adaptability



Resources wasted/Impossible project

Performance



Reliable efficiency gains



**Try our 10,000+ smashed models on  
Hugging Face!**

