— ICML 2026

Unifying Stacking and Cascading for Efficient Ensemble Inference

LazyStack

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— THE PROBLEM

Ensembles are accurate — but you pay for every model

Combining many models lifts accuracy. But running all of them on every input is expensive, and models differ wildly in cost.

Within a single ensemble, the most expensive model can cost **3–11×** the cheapest (vision), **17×** (LLMs), or even more on tabular tasks.

The two levers, in tension

Accuracy ↑ wants *more* models

Cost ↓ wants *fewer* models

Most inputs are easy and need just one or two. A few are hard and need the whole ensemble.

— EXISTING APPROACH · 1

Stacking — run all models, fuse their predictions

input · leopard

MobileNetV2 8.2 ms	→ jaguar	0.38
ResNet-18 12.4 ms	→ leopard	0.52
EfficientNet-B0 15.1 ms	→ leopard	0.71
ResNet-50 21.3 ms	→ tiger	0.46
EfficientNet-B4 28.7 ms	→ leopard	0.88
ViT-B/16 30.5 ms	→ leopard	0.83

→

meta-learner

↓

leopard

`cost = 116.2 ms`

Accurate: the meta-learner exploits agreement and per-model reliability. **But you pay the full cost on every input.**

— EXISTING APPROACH · 2

Cascading — exit on single-model confidence (or fall through)

EASY INPUT · EXITS AT MODEL 2

easy input · sunflower

MobileNetV2	~~sunflower~~	0.72	< θ
ResNet-18	**sunflower**	0.91	EXIT ✓
EfficientNet-B0	—	0.00	—
ResNet-50	—	0.00	—
EfficientNet-B4	—	0.00	—

prediction: **sunflower** ✓ — 20.6 ms

HARD INPUT · FALLS THROUGH

hard input · leopard

MobileNetV2	~~jaguar~~	0.38	< θ
ResNet-18	~~leopard~~	0.52	< θ
EfficientNet-B0	~~leopard~~	0.71	< θ
ResNet-50	~~tiger~~	0.46	< θ
EfficientNet-B4	**leopard**	0.83	no exit

prediction: **leopard** ✓ — 85.7 ms · full!

Easy inputs exit early on a single confident model. On **hard** inputs no single model crosses θ — the cascade runs *everything* (full ensemble cost), and earlier predictions are still thrown away.

— THE GAP

No method learns both the order and the aggregation

METHOD	EXECUTION ORDER	AGGREGATION ACROSS MODELS
Cost Cascade	cheapest-first heuristic	none — last model only
ABC	accuracy-order heuristic	fixed averaging
FrugalGPT	cost-order heuristic	none — quality judge
RouteLLM	routes to one model	none — no sequence
LazyStack	**learned (MDP) ✓**	**learned (substacker) ✓**

— OUR IDEA · LAZYSTACK

Progressive stacking — same hard input, earlier exit

same hard input · leopard

MobileNetV2 8.2 ms	THIS MODEL → **jaguar** 0.38	SUBSTACKER · ALL SO FAR	agg 0.38
ResNet-18 12.4 ms	THIS MODEL → **leopard** 0.52	SUBSTACKER · ALL SO FAR	agg 0.61
EfficientNet-B0 15.1 ms	THIS MODEL → **leopard** 0.71	SUBSTACKER · ALL SO FAR	EXIT ✓

+ 2 idle ResNet-50 · EfficientNet-B4 — never run

decision uses
aggregated conf

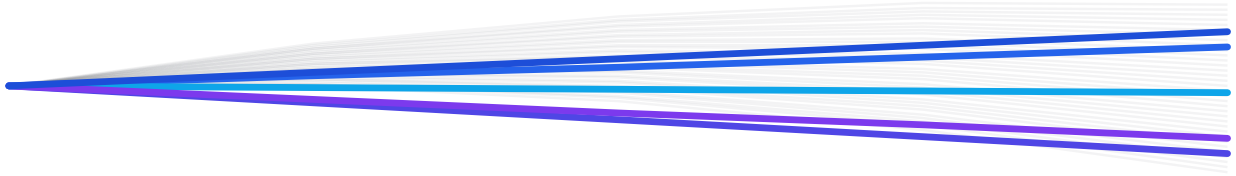
leopard

cost = 35.7 ms

A learned **substacker** re-aggregates *all* predictions so far. Three models — none individually confident — together exceed θ. Exit in **35.7 ms** instead of the cascade's full 85.7 ms.

— WHY IT'S TRACTABLE

Samples concentrate on a few execution paths



Out of 2^k possible orderings, just a handful are taken in practice.

Across every benchmark we tested, the top 3–8 trajectories already cover 95%+ of inputs. We only need to learn aggregators for those paths — not all 2^k.

how it works

— METHOD

Two offline stages, one online loop.

— OVERVIEW

Discover order → learn aggregators → exit early

OFFLINE · 1

Trajectory Discovery

An **MDP** learns which model to run next and when to stop — discovering the trajectories that matter.

OFFLINE · 2

Prefix Meta-Learning

Train lightweight **substackers** for the **prefixes** of those trajectories — not all 2^k subsets.

ONLINE

Early-Exit Inference

Follow the policy, aggregate with the matching substacker, **exit** once confident.

— STAGE 1 · OFFLINE

Trajectory discovery as an MDP

State `(E, h, k)`

executed-set **E** · entropy bin **h** · last predicted class **k**

Actions

`EXEC(Mⱼ)` run a model · `STOP`

Reward

$\beta \cdot \mathbb{1}[\text{correct}] - \Sigma\ \text{cost}$

Pay per model run; get paid for being right. Solved by **value iteration**.

Roll out the policy → keep the top trajectories (each ≥ 2% of inputs).

— WHAT THE MDP LEARNS

The cheapest model first is not optimal

Cheapest-first (cost cascade) — **70.6 ms**

MobileNetV2	ResNet-18	ResNet-50	EfficientNet-B4
8.2 ms	12.4 ms	21.3 ms	28.7 ms
			EXIT ✓

LazyStack (MDP-discovered) — **36.4 ms**

EfficientNet-B0	ResNet-50	ViT-B/16	EfficientNet-B4
15.1 ms	21.3 ms	30.5 ms	28.7 ms
	EXIT ✓		

total cost to a confident answer

The MDP discovers that a **costlier but more confident** first model can be cheaper overall.

Higher confidence triggers an earlier exit, more than paying back the extra cost. No cheapest-first heuristic finds this.

— STAGE 2 · OFFLINE

Train aggregators only for the prefixes that occur

2^k

all subsets — intractable

→

$O(k)$

prefixes of discovered trajectories

A trajectory $[M_2, M_5, M_1]$ contributes prefixes $[M_2]$, $[M_2, M_5]$, $[M_2, M_5, M_1]$.

Trajectories **share prefixes** → only **~12–18** substackers in practice.

— TWO VARIANTS

Specialized substackers, or one masked stacker

LAZYSTACK-SUB

One MLP per prefix

Input = concatenated probs of executed models.

+0.23–0.33% accuracy (specialization)

14–22 stacker artifacts (8–12 MB total).

vs

LAZYSTACK-MASK

One shared MLP + binary mask

Unexecuted slots zero-filled; a mask says which ran.

up to 79.6× on NSL-KDD · simpler deploy

A single model artifact to ship.

— ONLINE · INFERENCE

Run, aggregate, exit when confident

input · leopard

ResNet-50
21.3 ms
→ tiger
0.46

EfficientNet-B0
15.1 ms
→ leopard
0.71

EfficientNet-B4
28.7 ms
→ leopard
0.88

+ 3 idle ResNet-18 · MobileNetV2 · ViT-B/16 — never run

`exit · 3/6 models · prediction leopard · aggregated 0.88`

Illustrative input. θ is calibrated on validation to retain ~97% of full-ensemble accuracy.

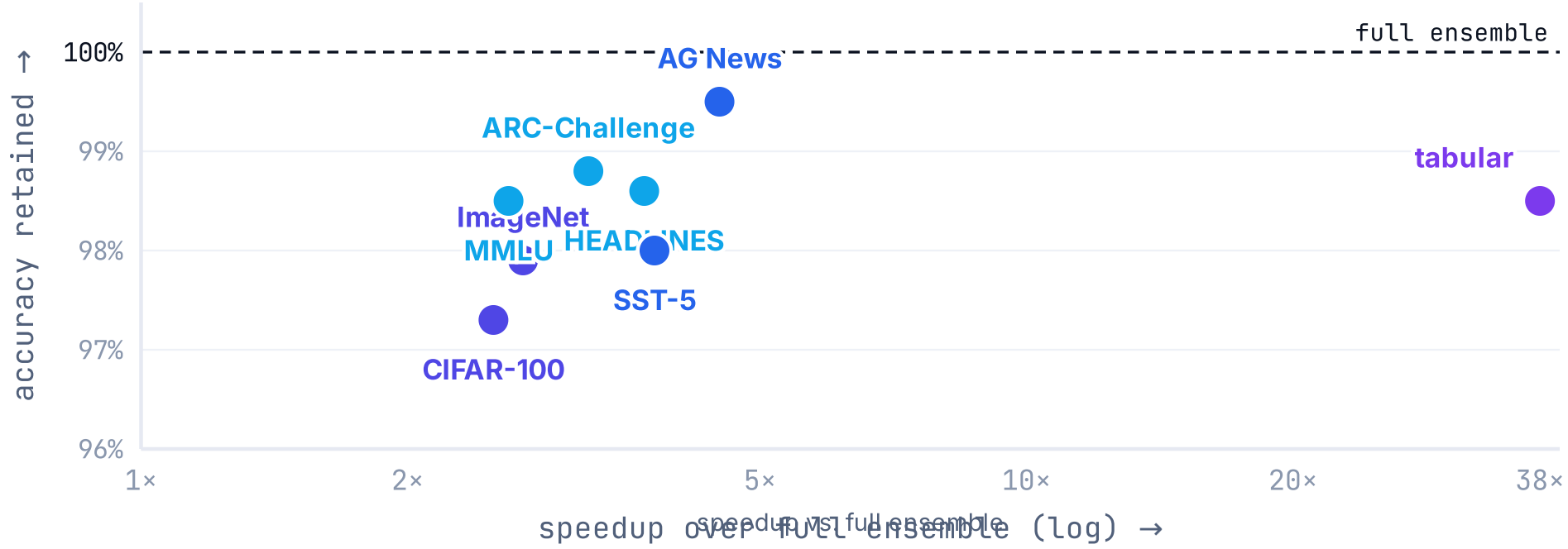
does it work

— EVALUATION

8 datasets, 4 domains. Vision · tabular · text · LLM routing.

— OVERVIEW · 8 BENCHMARKS

97%+ of full-ensemble accuracy across every benchmark

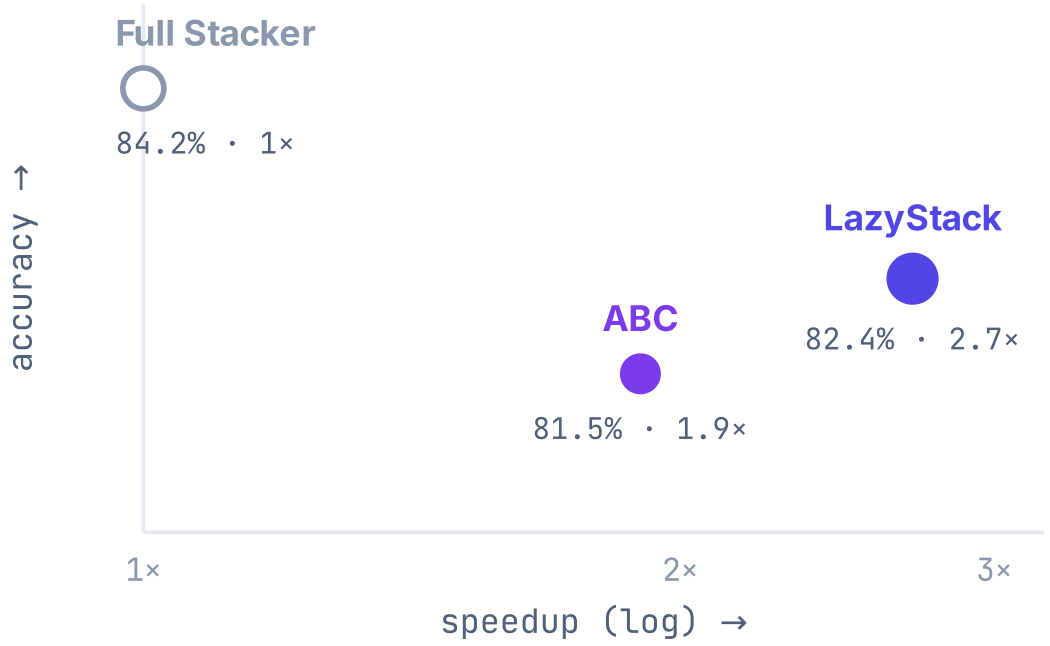


vision · LLM routing · text · tabular

Every benchmark retains 97%+ of full-ensemble accuracy while using only ~2–3 models per input on average. Speedup ranges from 2.5× on many-class vision to 38× on tabular (cost ratio 65×).

SPOTLIGHT · IMAGENET-1K

More accurate than the baseline, near the full ensemble



LazyStack: **82.4%** at 2.7× — beats ABC on both axes.

The full ensemble caps at 84.2% (1×). LazyStack keeps almost all of it while running ~2.7 of 8 models per image.

SAME IDEA · LLM ROUTING

Stop at the smallest model that's confident

ARC-CHALLENGE

A candle in a sealed jar of CO_2 goes out almost immediately. Which best explains why?

A. fuel ran out

B. jar absorbed heat

C. no O_2 to combust

D. CO_2 reflected light

Qwen2.5-7B 48 ms	→ **A**	0.43
LLaMA-3.1-8B 52 ms	→ **C**	0.61
Qwen2.5-32B 180 ms	→ **C**	0.82
LLaMA-3.1-70B 820 ms	→ —	0.00
Qwen2.5-72B 890 ms	→ —	0.00

exit · 3/5 models · prediction **C** · aggregated 0.82

Illustrative cascade. Two large 70B+ models stay idle; the substacker exits at 280 ms instead of running the full ~2 s ensemble.

— GENERALITY

The pattern holds across every domain

DATASET	DOMAIN	LAZYSTACK	FULL STACKER	SPEEDUP
ImageNet-1K	vision	82.4%	84.2%	2.7×
CIFAR-100	vision	75.9%	78.0%	2.5×
MMLU	LLM routing	77.2%	—	2.6×
ARC-Challenge	LLM routing	88.2%	—	3.2×
HEADLINES	LLM routing	64.3%	—	3.7×
AG News	text	95.3%	95.8%	4.5×
SST-5	text	87.4%	89.2%	3.8×
NSL-KDD	tabular	76.8%	78.0%	38×

LLM Full Stacker numbers omitted; paper reports 97%+ retention at 2.6–3.9× speedup. Speedups for LLMs are relative to always-70B.

— STRONG CLAIM

Black-box LazyStack matches a white-box method

IMAGENET · MATCHED SPEEDUP	ACCESS	ACC	SPEEDUP
Gatekeeper ($M_2 \rightarrow M_8$)	white-box	81.6%	2.7×
LazyStack	**black-box**	**82.4%**	**2.7×**

CIFAR-100: 75.9% vs 75.8% at comparable speed.

At the same speedup, LazyStack beats Gatekeeper by **+0.8%** — despite Gatekeeper having white-box access to fine-tune internals.

LazyStack sees only output probabilities. Black-box access is not a handicap on vision.

ABLATION · IMAGENET

Both learned components are essential — and superadditive

Remove either and speedup drops; remove both and you collapse to running the whole ensemble. Same pattern across MMLU, AG News, and the tabular task.

— TAKEAWAYS

Run the ensemble lazily

1. Progressive stacking turns ensemble accuracy into cascade cost.
2. Samples concentrate on a few trajectories — so learning is tractable.
3. Works black-box across vision, text, tabular, and LLM routing.

Honest limits

- Needs labeled validation data.
- State space $O(2^N \cdot B \cdot C)$ → function approximation past ~15 models.
- Many classes spread confidence thin → smaller speedups.
- Generative LLM tasks remain open.