

Towards Dynamic Interleaving Optimizer

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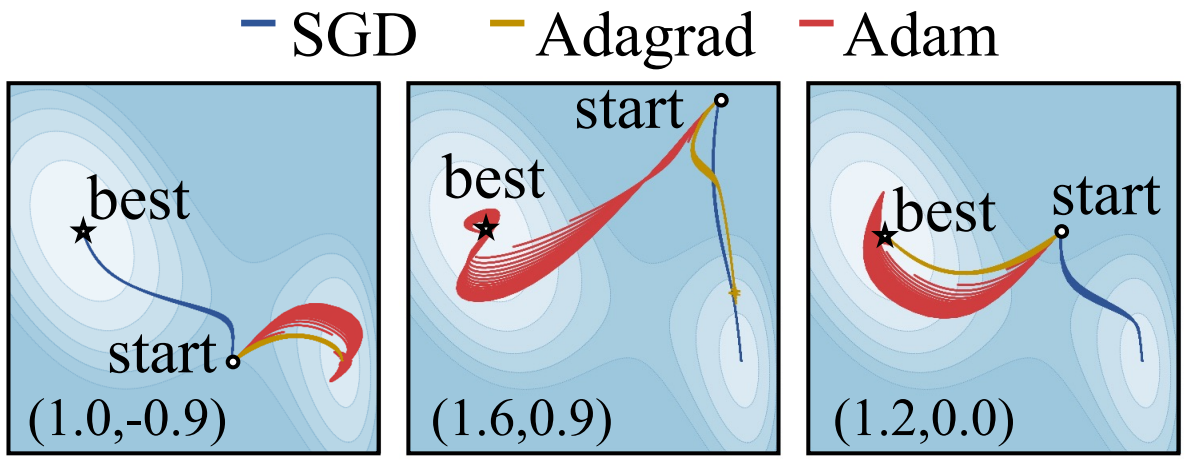
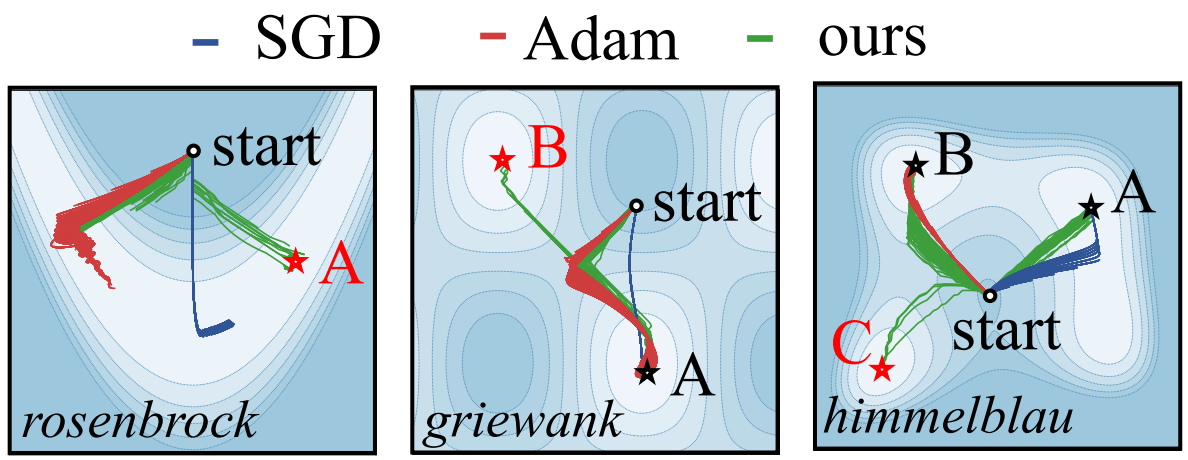
Motivation

- Different optimizers are suitable for different training states.
- Transitioning between optimizers during training can enhance both convergence speed and model generalization.
- We propose Dynamic Optimizer Interleaving Training (DOIT), a novel framework that adaptively selects the suitable optimizer during training.



Optimal optimizers vary across different initial states.



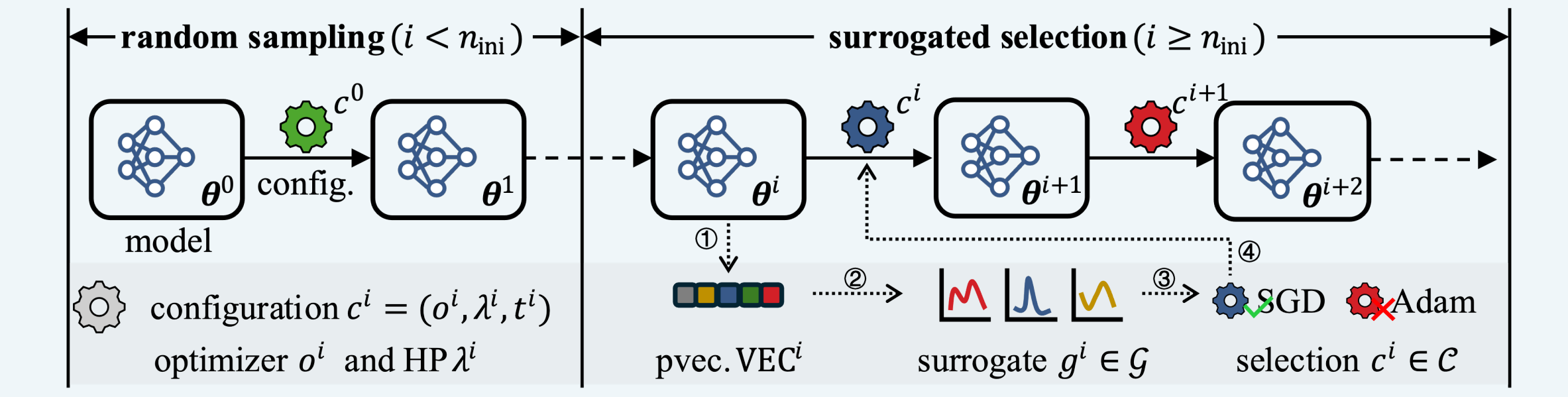
DOIT performs well across diverse parameter landscapes.

Our Method: surrogate model

- **Weighted random sampling:** collect diverse experience trajectories.
- **Surrogated selection:** predict performance of candidate optimizers.

  Input. Key model parameters VEC^i + HP λ^i.

  Output. Performance score $s = \tanh\big((\mu_\Delta + \Delta_{\mathrm{UPPER}} + \Delta_{\mathrm{LOWER}})/3 + \alpha\sigma_\Delta\big)$.



Training process of our proposed DOIT.

Our Method: acquisition function

- Consideration of variance.

$$ACQ(s_\mu, s_\sigma) = s_\mu + \alpha s_\sigma.$$

- Consideration of transferability.

$$ACQ(s_\mu, s_\sigma, \omega_t) = s_\mu + \alpha(1 - \omega_t)s_\sigma.$$

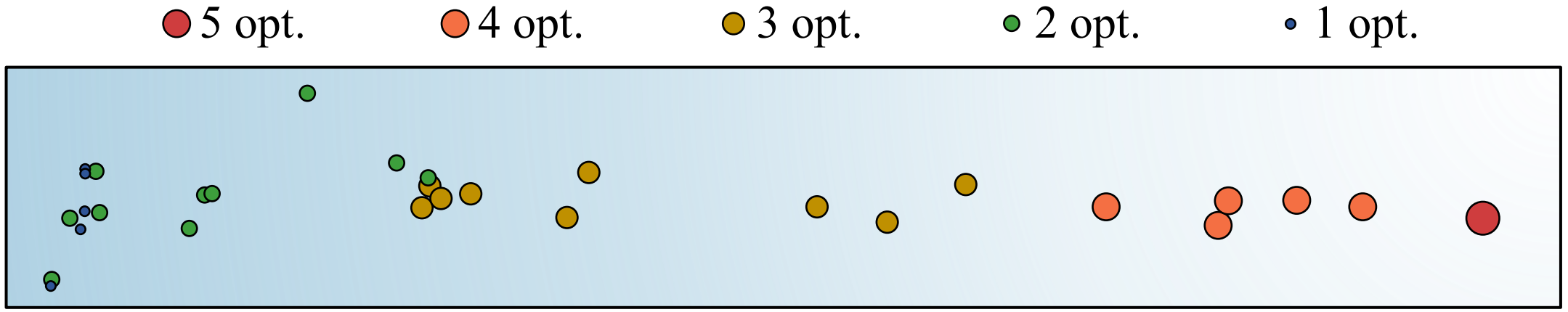
where ω_t is the transferability score.

- Consideration of training process.

$$e = \text{sigmoid}(s_\mu + \alpha(1 - 2^{-\lfloor i/n \rfloor} \cdot \omega_t)s_\sigma).$$

Our Method: surrogate model

- **Accuracy.** Achieving superior accuracy by unlocking novel optimization paths through multi-strategy synergy.



- **Time Cost.** predict performance of candidate optimizers.

	forward	gradient	optimizer	transferability	surrogate	acquisition
FLOPs	2.2×10^{16}	4.4×10^{16}	$0.2 \sim 2.0\times10^{13}$	2.2×10^{13}	5.3×10^{14}	1.0×10^{14}
Proportion	33.3%	66.7%	quite small	0.3‰	8.0‰	1.5‰

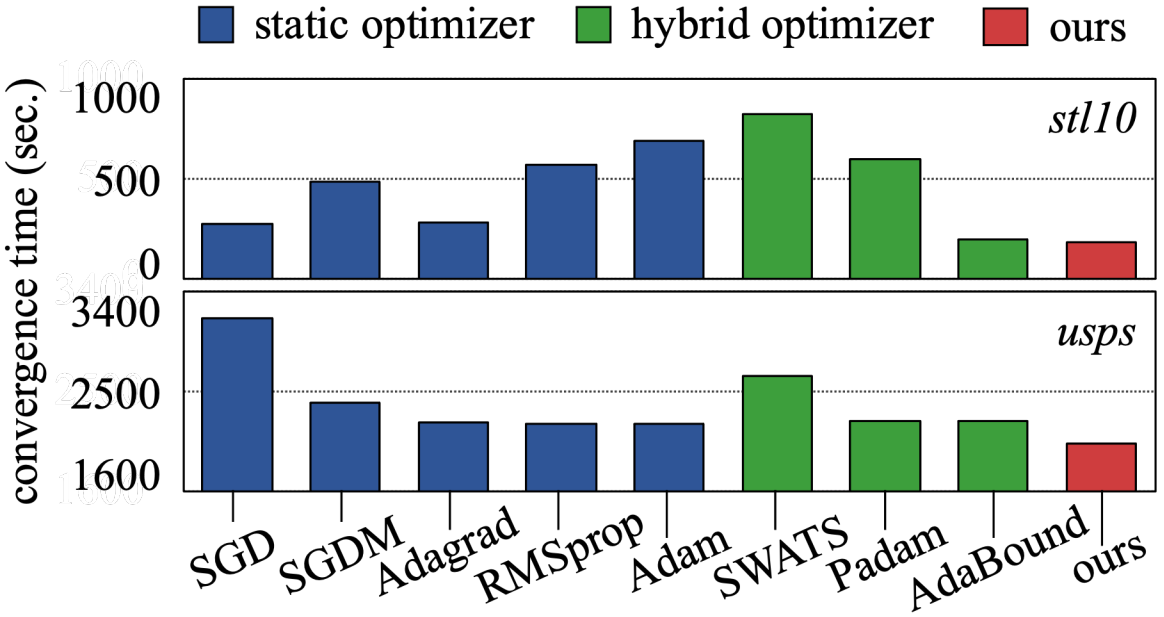
Experiment Results

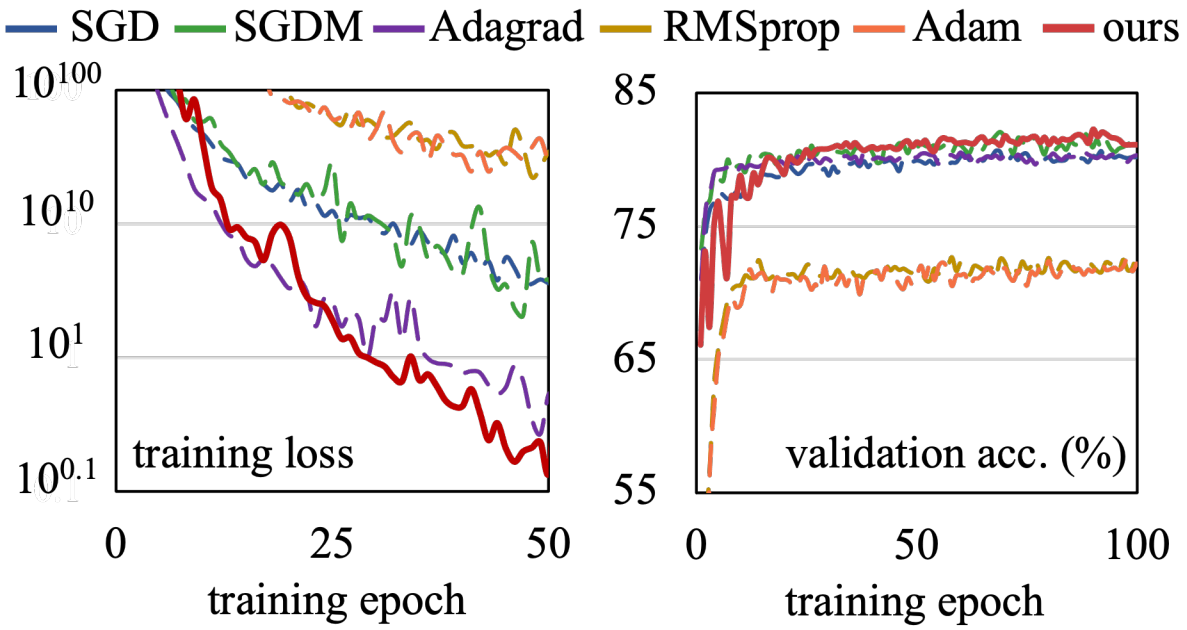
- Enhanced Accuracy & Stability.
  - 1%- 3% improvement across most benchmarks.
  - Lower variance, ensuring more robust training sessions.

	full training					PEFT			
	usps	mnist	stl10	cifar10	imagenet	usps	stl10	mrpc	qqp
SGD	97.46±0.70	99.50±0.04	97.83±0.22	97.53±0.03	78.73±0.38	94.42±0.21	97.75±0.16	85.21±0.35	82.13±0.52
SGDM	97.68±0.11	99.65±0.04	96.61±0.04	97.58±0.04	78.36±0.12	95.67±0.14	98.37±0.10	85.54±0.69	83.30±0.63
Adagrad	93.40±0.04	98.24±0.50	78.66±2.54	60.95±0.62	77.59±0.03	95.37±0.21	98.34±0.09	84.94±0.59	83.47±0.79
RMSprop	95.25±0.04	98.14±0.09	88.62±4.45	78.09±0.92	74.01±0.08	94.64±0.53	97.91±0.07	84.09±0.76	82.09±0.63
Adam	93.26±0.78	99.01±0.08	82.26±1.16	75.23±0.92	73.96±0.11	94.47±0.49	98.36±0.03	86.52±0.71	82.27±0.71
SWATS	94.00±1.23	98.73±0.13	88.03±0.44	66.15±4.74	76.93±0.19	95.12±0.21	98.38±0.10	86.27±0.62	80.79±0.81
Padam	97.58±0.11	99.66±0.04	90.81±0.06	96.03±0.03	77.47±0.16	95.72±0.42	98.38±0.10	80.64±0.32	73.04±0.91
AdaBound	87.64±0.84	97.54±0.13	86.33±2.39	70.91±4.35	75.93±0.13	95.42±0.11	98.30±0.14	68.38±0.59	78.64±0.49
ours	**97.81**±0.21	**99.71**±0.02	**98.21**±0.19	**98.04**±0.03	**79.98**±0.01	**96.12**±0.10	**99.01**±0.09	**87.99**±0.13	**85.57**±0.14

Experiment Results

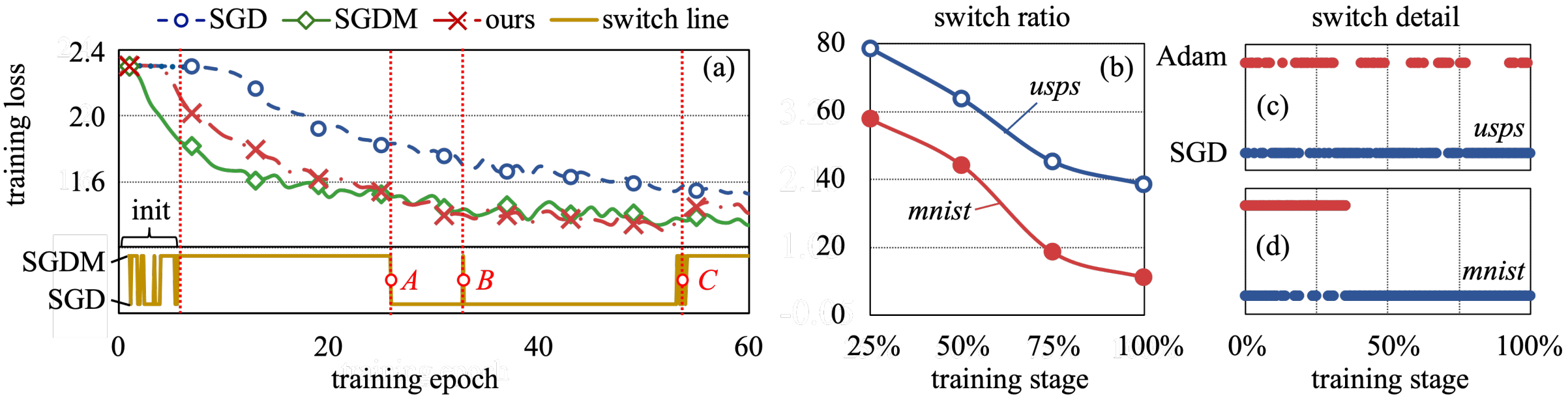
- Efficient Convergence.
  - Speedup in convergence with minimal computational overhead.





Selection Preference

- *As training progresses, the selection becomes more stable.*
- *In early phase, there is a tendency to select faster optimizers (e.g., Adam), later tends to select more stable optimizers (e.g., SGD).*
- *DOIT's selection preference is more apparent in a large dataset.*





THANKS !

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