PopulAtion Parameter Averaging (PAPA)

Alexia Jolicoeur-Martineau, Emy Gervais, Kilian Fatras, Yan Zhang, Simon Lacoste-Julien

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Samsung Advanced
Institute of Technology
AI Lab Montreal

Structure

1. Leveraging a population of models
   - Ensembling
   - Weight averaging
2. PopulAtion Parameter Averaging (PAPA)
   - PAPA-all: occasionally replacing the weights by the average
   - PAPA: slowly pushing the weights toward the average
   - Why does averaging the weights of a population helps?
3. Results
4. Conclusion

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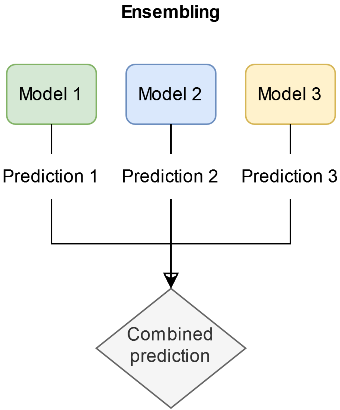

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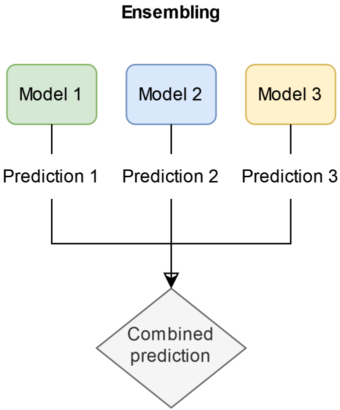

Ensembling: Combine the predictions of multiple models for a **massive boost in performance**

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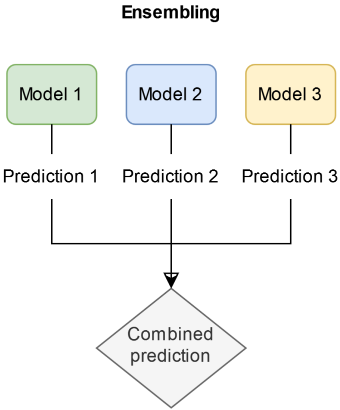

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Simplest form of ensembling: averaging the prediction of all models

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Although powerful ensembling has drawbacks:

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Solution: weight averaging

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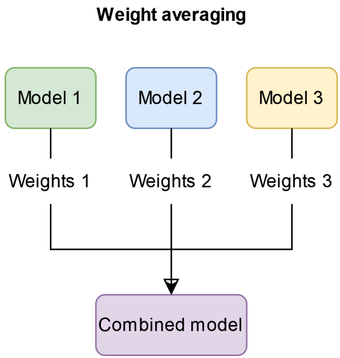

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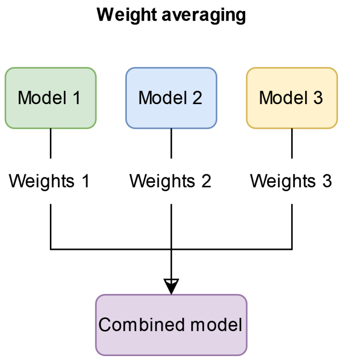

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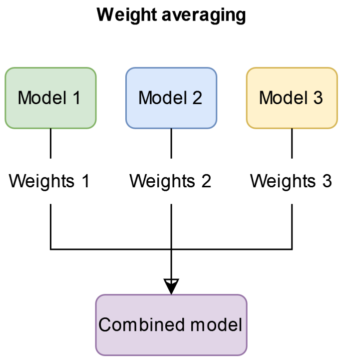

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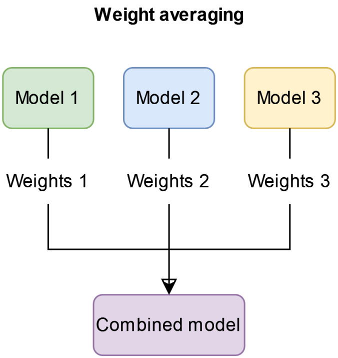

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Problem: Averaging does not work well in most scenarios

Question: Can we find a way to make it work well?

Permutation-alignment methods for better averaging

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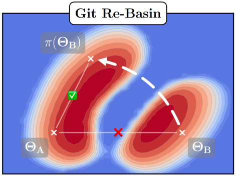

Figure 1: **Git Re-Basin merges models by teleporting solutions into a single basin.** Θ_B is permuted into functionally-equivalent $\pi(\Theta_B)$ so that it lies in the same basin as Θ_A.

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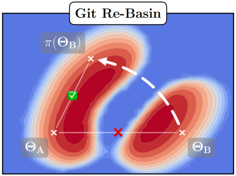

Figure 1: **Git Re-Basin merges models by teleporting solutions into a single basin.** Θ_B is permuted into functionally-equivalent $\pi(\Theta_B)$ so that it lies in the same basin as Θ_A.

Although powerful, permutation-alignment is not enough when averaging 3 models.

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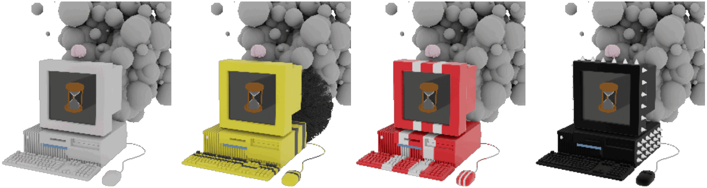
This is the key behind PAPA! We ensure during training that weights do not grow too dissimilar over time.

Overview

PAPA-all



4 networks (from 4 different random initializations) are trained independently on different data orderings, regularizations, and data-augmentations; each network learns slightly different features.

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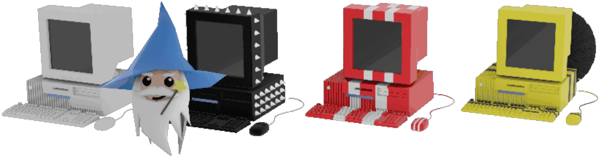
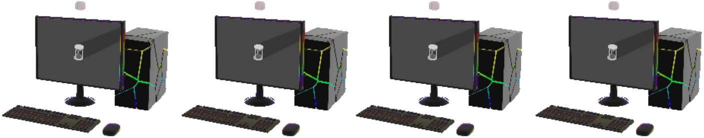


After K epochs, the 4 networks are combined through averaging to create a single averaged network that contains the features of each network and performs significantly better.

PAPA-all

The averaged network is duplicated to form the new population.

PAPA-all



The networks are trained independently again on different data ordering, regularizations, and data-augmentations.

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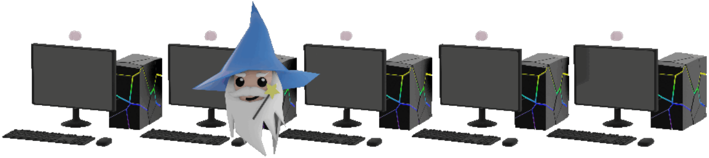

After k epochs, the networks are averaged again (and the process is repeated every k epochs until the end of training).

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By averaging occasionally, we gain in performance from averaging, but prevent misalignment due to dissimilar weights!

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Greedy soup: Greedy average of "meaningful" models

- Sort models in order of decreasing train (or valid) accuracy
- Soup = weights of the first model
- (For loop) Try adding the next model to the soup (averaging all models weights equally); if train accuracy improves, add it to the soup

REnormalizing Permuted Activations for Interpolation Repair (REPAIR)

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REPAIR makes the averaged network slightly **more performant** in PAPA

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Solution: At every SGD step, interpolate between current weights and population average:

$$_j \qquad _{papa} \; _j + (1 \qquad _{papa}) \, \bar{\ } ;$$

where $_{papa} = 0{:}999$, $_j$ is the weight of the j-th network, and $\bar{\ }$ is the population average of the weights.

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We can also interpret PAPA as amortizing $_{papa} = 0{:}999$ on many steps.
Example: CIFAR-10, averaging every 5 epochs, mini-batch of 64
$=) \quad _{papa} = {:}999^{(781 \text{ iterations } \; 5 \text{ epochs})} \quad 0{:}02$.

Visualizing the effect of PAPA variants

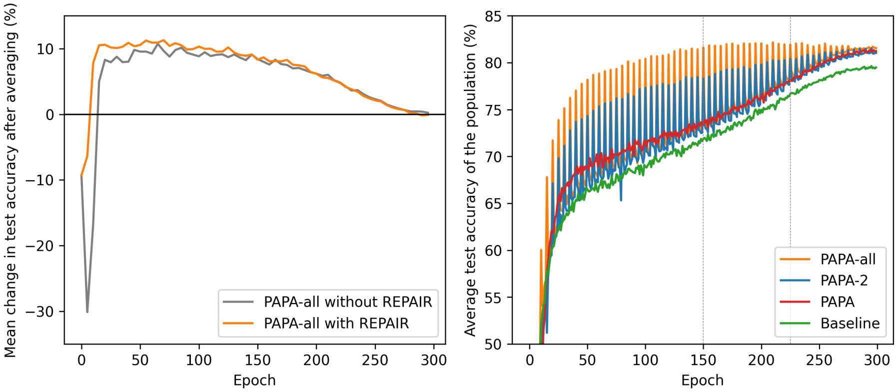

Figure: PAPA variants on CIFAR-100 when averaging every 5 epochs

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We demonstrate that:

- PAPA models share most of their features (proving feature mixing)
- Performance gain immediately after averaging (proving a benefit from feature mixing)

Thus, surprisingly, averaging weights also leads to averaging features in deep neural networks. More evidence exists in the permutation-alignment literature [Ainsworth et al., 2022].

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Conclusion: PAPA is an efficient way of parallelizing training length over multiple networks

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Future directions:

1. PAPA for large generative and language models
2. PAPA for continual learning
3. Better understand features propagation between networks in PAPA
4. Different weighting schemes to emphasize generalizable features

Samuel K Ainsworth, Jonathan Hayase, and Siddhartha Srinivasa. Git re-basin: Merging models modulo permutation symmetries. *arXiv preprint arXiv:2209.04836*, 2022.

Keller Jordan, Hanie Sedghi, Olga Saukh, Rahim Entezari, and Behnam Neyshabur. Repair: Renormalizing permuted activations for interpolation repair. *arXiv preprint arXiv:2211.08403*, 2022.

Mitchell Wortsman, Gabriel Ilharco, Samir Ya Gadre, Rebecca Roelofs, Raphael Gontijo-Lopes, Ari S Morcos, Hongseok Namkoong, Ali Farhadi, Yair Carmon, Simon Kornblith, and Ludwig Schmidt. Model soups: averaging weights of multiple fine-tuned models improves accuracy without increasing inference time. In Kamalika Chaudhuri, Stefanie Jegelka, Le Song, Csaba Szepesvari, Gang Niu, and Sivan Sabato, editors, *Proceedings of the 39th International Conference on Machine Learning*, volume 162 of *Proceedings of Machine Learning Research*, pages 23965–23998. PMLR, 17–23 Jul 2022. URL https://proceedings.mlr.press/v162/wortsman22a.html.