# LLM MERGING



## **Model Merging using Geometric Median of Task Vectors**

**NEURAL INFORMATION** PROCESSING SYSTEMS

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#### MODEL MERGING

- Model merging or model fusion, combines the parameters of multiple models with unique strengths into a single, unified model.
- Unlike ensemble methods, which require high memory and processing power, model merging consolidates knowledge into one streamlined model, reducing computational costs, memory usage, and latency.
- This efficient technique enhances generalization across tasks and is ideal for resource-constrained or low-latency environments, as it does not require access to the original training data or extensive computation and training.



#### TASK VECTOR

The vector encodes the information related to the task that the fine-tuned model learned. For example, if the fine-tuned model learns to summarize text, the task vector would represent "text summarization ability."

$$
\tau_t = \theta_t^{\rm ft} - \theta_{\rm pre}.
$$



#### LORA , PEFT

LORA/PEFT reduces the number of parameters that need to be updated during fine-tuning, making the process of finetuning faster and more memory-efficient, while maintaining performance on downstream tasks.

$$
W' = W + \Delta W
$$

$$
\Delta W = BA
$$



#### GEOMETRIC MEDIAN

The geometric median is a point in multidimensional space that minimizes the sum of distances to a set of given points.



Mathematically, given a set of points  $X = \{x_1, x_2, \dots, x_n\}$  in Euclidean space  $\mathbb{R}^d$ , the geometric median  $M$  is the point that minimizes the sum of Euclidean distances to the given points:

$$
M = \arg\min_{y \in \mathbb{R}^d} \sum_{i=1}^n \|y - x_i\|
$$
 (1)

where:

- $\bullet$  *M* is the geometric median (the point to be found).
- $||y x_i||$  denotes the Euclidean distance between point y and  $x_i$ .

### METHOD

- In our approach, the fine-tuned LLM's we used had 23 encoder blocks and 23 decoder blocks, and each encoder or decoder block has LoRA  $A \in \mathbb{R}^{16 \times 2048}$ and  $B \in \mathbb{R}^{2048 \times 16}$ 
	- $\Delta W = BA$  is the corresponding task vector of a given fine-tuned LLM for a given encoder/decoder block ( parameter matrix of the  $W \in \mathbb{R}^{2048 \times 2048}$
	- **We flatten all these task vector matrices to a high dimensional vector**   $\mathbb{R}^{1\times 4194304}$  and then find the geometric median of all these flattened **vectors treating each of these vectors as a point in multidimensional space to get a "net task vector" for that block which is finally added to the corresponding block in the pretrained base LLM after reshaping to**  the original size  $\mathbb{R}^{2048\times2048}$  of block's parameter.
	- We are finding the geometric median , so that our model is able to optimally perform in all the tasks.

# WEISZFELD **ITERATIVE**

The Weiszfeld algorithm is an iterative method used to compute the geometric median of a set of points in multi-dimensional space.

**Algorithm 1** Weiszfeld Algorithm for Minimizing  $f(x) = \sum_{i=1}^{n} w_i ||x - p_i||$ 

**Input:** Points  $p_i \in \mathbb{R}^d$ ,  $i = 1, ..., n$ , with optional weights  $w_i > 0$ . Initial guess  $x^{(0)} \in \mathbb{R}^d$ .

- 1:  $k \leftarrow 0$
- $2:$  repeat
- if  $x^{(k)} \neq p_i$  for all  $i \in \{1, \ldots, n\}$  then  $3:$
- Compute the weighted average:  $4:$

$$
x^{(k+1)} \leftarrow \frac{\sum_{i=1}^{n} \frac{w_i}{\|x^{(k)} - p_i\|} p_i}{\sum_{i=1}^{n} \frac{w_i}{\|x^{(k)} - p_i\|}}
$$

else  $5:$ 

- Apply a small perturbation to avoid division by zero.  $6:$
- $7:$ end if

 $8:$  $k \leftarrow k+1$ 

9: until convergence (i.e., 
$$
||x^{(k+1)} - x^{(k)}|| < \epsilon
$$
 for a small  $\epsilon$ )

**Output:** Geometric median  $x^{(k+1)}$ .

$$
\begin{array}{c}\n\text{WEISZFELD}\n\\ \n\text{ITERATIVE}\n\\ \n\min_{x} \left\{ f(x) = \sum_{i=1}^{m} \omega_i ||x - a_i|| \right\} \n\end{array}
$$

Let  $x^*$  be the optimal solution of problem (FW). If  $x^* \notin A$ , then

$$
\nabla f(x^*) = \sum_{i=1}^m \omega_i \frac{x^* - a_i}{\|x^* - a_i\|} = 0.
$$

The optimal solution can be expressed as:

$$
x^* = \frac{\sum_{i=1}^m \omega_i a_i / \|x^* - a_i\|}{\sum_{i=1}^m \omega_i / \|x^* - a_i\|}
$$

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or in operator form:

 $x^* = T(x^*),$ 

where the operator  $T: \mathbb{R}^d \setminus A \to \mathbb{R}^d$  is defined by:

$$
T(x) := \frac{\sum_{i=1}^{m} \omega_i a_i / \|x - a_i\|}{\sum_{i=1}^{m} \omega_i / \|x - a_i\|}
$$

### RESULTS



The table compares the performance of merging various number of models using two methods: GeoMed, which computes the geometric median of task vectors, and WeightAvg, a baseline method that computes the average of all task vectors.



Table 2: List of Finetuned Models Used to obtain results of table 1



Table 3: As shown in Table 2, several finetuned models were used for various tasks such as Text Classification, Question Answering, and Sentence Similarity etc.

# THANKS