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Towards Minimizing Feature Drift in Model Merging: Layer-wise Task Vector Fusion for Adaptive Knowledge Integration

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The Thirty-ninth Annual Conference on Neural Information Processing Systems

Content



Introduction

- Model Merging
- Baseline: Task Arithmetic

Method

- Knowledge Conflict
- LOT Merging

Experiment

Model Merging



Definition

Consider a pretrained model W_{pre} and a set of finetuned models $\{W_i\}_{i=1}^k$ with corresponding downstream tasks $\{D_i\}_{i=1}^k$.

Our goal is to merge all K models into a unified model W_{mtl} **without redundant retraining**. The unified model W_{mtl} should **perform well on all downstream tasks**.

Baseline: Task Arithmetic



Task Arithmetic: Considering a pretrained model W_{pre} and a set of finetuned models $\{W_i\}_{i=1}^k$ with corresponding downstream tasks $\{D_i\}_{i=1}^k$, the task vectors $\{T_i\}_{i=1}^k$ are defined as $T_i = W_i - W_0$.

Task vectors can be applied to W_{pre} with a scaling term λ , i.e., $W_{mtl} = W_{pre} + \alpha \sum_i T_i$, which allows to control the behavior of the edited model via simple arithmetic operations on task vectors.

Knowledge Conflict



Definition (for task arithmetic): the increase in task-specific loss incurred by merging.

For a given task k , associated with the loss function $\mathcal{L}_k(\cdot)$, the knowledge conflict during merging is quantified as:

$$\Delta\mathcal{L}_k = \mathcal{L}_k(W_{mtl}) - \mathcal{L}_k(W_k)$$

Isolating Knowledge Conflict



Theorem 4.4 (An Upper Bound on Knowledge Conflict):

Suppose that within the range of model merging, the function of layer l is γ_l -Lipschitz continuous with respect to its input, and the loss function L is β -Lipschitz continuous with respect to the final output of the network. Then, the knowledge conflict follows:

$$|\Delta \mathcal{L}_k| \leq \beta \sum_{l=1}^L \left(\prod_{m=l+1}^L \gamma_m \right) \|\Delta f_k^l\|$$

Objective

We propose to mitigate knowledge conflict by minimizing the **feature drift** for each layer:

$$T^{l^*} = \arg \min_{T^l} \sum_{k=1}^K \|\Delta f_k^l\|^2 = \arg \min_{T^l} \sum_{k=1}^K \|f_k^l(W_{\text{pre}} + T^l) - f_k^l(W_k)\|^2$$

For Linear Weights



Suppose $W^l \in \mathbb{R}^{d_l \times d_{l+1}}$ corresponds to the weight of a linear layer, which transforms features through matrix multiplication $f_k^l(W) = X_k^l W^l$ with pre-collected input X_k^l .

The objective becomes:

$$\begin{aligned} T^{l*} &= \arg \min_{T^l} \sum_{k=1}^K \|X_k^l(W_{\text{pre}}^l + T^l) - X_k^l(W_k^l)\|_F^2 \\ &= \arg \min_{T^l} \sum_{k=1}^K \|X_k^l(T^l - T_k^l)\|_F^2 = \arg \min_{T^l} \sum_{k=1}^K \text{trace}((T^l - T_k^l)^\top X_k^l{}^\top X_k^l(T^l - T_k^l)) \end{aligned}$$

This defines a convex quadratic optimization problem. Consequently, the optimal solution T^{l*} can be derived in closed form as follows :

$$T^{l*} = \left(\sum_k X_k^l{}^\top X_k^l \right)^\dagger \sum_k X_k^l{}^\top X_k^l T_k^l$$

Analysis: Why $T^{l*} = \left(\sum_k X_k^l{}^\top X_k^l \right)^\dagger \sum_k X_k^l{}^\top X_k^l T_k^l$ Work?



Consider SVD on input features $X_k^l = U_k^l \Sigma_k^l V_k^l{}^\top$.

Ideal case, where for any $k \neq j$, $V_k^l{}^\top V_j^l = 0$. Then, T^{l*} simplifies to:

$$T^{l*}_{\text{ideal}} = \left(\sum_k V_k^l \Sigma_k^l{}^2 V_k^l{}^\top \right)^\dagger \sum_k V_k^l \Sigma_k^l{}^2 V_k^l{}^\top T_k^l = \sum_k \left(V_k^l \Sigma_k^l{}^2 V_k^l{}^\top \right)^\dagger \sum_k V_k^l \Sigma_k^l{}^2 V_k^l{}^\top T_k^l = \sum_k V_k^l V_k^l{}^\top T_k^l.$$

There is no conflict in this case

$$\begin{aligned} \sum_{k=1}^K \|X_k^l (T^{l*}_{\text{ideal}} - T_k^l)\|_F^2 &= \sum_{k=1}^K \|U_k^l \Sigma_k^l V_k^l{}^\top \left(\sum_j V_j^l V_j^l{}^\top T_j^l - T_k^l \right)\|_F^2 \\ &= \sum_{k=1}^K \|U_k^l \Sigma_k^l V_k^l{}^\top V_k^l V_k^l{}^\top T_k^l - U_k^l \Sigma_k^l V_k^l{}^\top T_k^l\|_F^2 = 0 \end{aligned}$$

Analysis: Why $T^{l*} = \left(\sum_k X_k^l{}^\top X_k^l \right)^\dagger \sum_k X_k^l{}^\top X_k^l T_k^l$ Work?



Consider SVD on input features $X_k^l = U_k^l \Sigma_k^l V_k^{l\top}$.

Worst case, where for any k , $V_k^l = V^l$. Then, T^{l*} simplifies to:

$$\begin{aligned} T_{\text{worst}}^{l*} &= \left(\sum_k V^l \Sigma_k^{l^2} V^{l\top} \right)^\dagger \sum_k V^l \Sigma_k^{l^2} V^{l\top} T_k^l \\ &= V^l \left(\sum_k \Sigma_k^{l^2} \right)^\dagger V^{l\top} \sum_k V^l \Sigma_k^{l^2} V^{l\top} T_k^l = \sum_k \left(\underbrace{V^l \left(\sum_k \Sigma_k^{l^2} \right)^\dagger \Sigma_k^{l^2} V^{l\top}}_{\text{Normalized Weight}} T_k^l \right) \end{aligned}$$

Experiments



Method	SUN397	Cars	RESISC45	EuroSAT	SVHN	GTSRB	MNIST	DTD	Avg Acc	#best
<i>Basic baseline methods</i>										
Pre-trained	62.3	59.7	60.7	45.5	31.4	32.6	48.5	43.8	48.0	-
Individual	75.3	77.7	96.1	99.7	97.5	98.7	99.7	79.4	90.5	-
Traditional MTL	73.9	74.4	93.9	98.2	95.8	98.9	99.5	77.9	88.9	-
<i>Training-free methods</i>										
Weight Averaging	65.3	63.4	71.4	71.7	64.2	52.8	87.5	50.1	65.8	0
Fisher Merging	68.6	69.2	70.7	66.4	72.9	51.1	87.9	59.9	68.3	2
RegMean	65.3	63.5	75.6	78.6	78.1	67.4	93.7	52.0	71.8	0
Task Arithmetic	55.2	54.9	66.7	78.9	80.2	69.7	97.3	50.4	69.1	0
Ties-Merging	59.8	58.6	70.7	79.7	86.2	72.1	98.3	54.2	72.4	0
TATR	62.7	59.3	72.3	82.3	80.5	72.6	97.0	55.4	72.8	0
Ties-Merging & TATR	66.3	65.9	75.9	79.4	79.9	68.1	96.2	54.8	73.3	0
Consensus Merging	65.7	63.6	76.5	77.2	81.7	70.3	97.0	57.1	73.6	0
AWD Merging	63.5	61.9	72.6	84.9	85.1	79.1	98.1	56.7	75.2	0
PCB Merging	63.8	62.0	77.1	80.6	87.5	78.5	98.7	58.4	75.8	1
CAT Merging	68.1	65.4	80.5	89.5	85.5	78.5	98.6	60.7	78.3	0
LOT Merging (ours)	67.7	67.5	85.7	94.9	93.4	89.8	98.7	63.6	82.7	6

Experiments



Method	SUN397	Cars	RESISC45	EuroSAT	SVHN	GTSRB	MNIST	DTD	Avg Acc	#best
<i>Basic baseline methods</i>										
Pre-trained	66.8	77.7	71.0	59.9	58.4	50.5	76.3	55.3	64.5	-
Individual	82.3	92.4	97.4	100.0	98.1	99.2	99.7	84.1	94.2	-
Traditional MTL	80.8	90.6	96.3	96.3	97.6	99.1	99.6	84.4	93.5	-
<i>Training-free methods</i>										
Weight Averaging	72.1	81.6	82.6	91.9	78.2	70.7	97.1	62.8	79.6	0
Fisher Merging	69.2	88.6	87.5	93.5	80.6	74.8	93.3	70.0	82.2	1
RegMean	73.3	81.8	86.1	97.0	88.0	84.2	98.5	60.8	83.7	0
Task Arithmetic	73.9	82.1	86.6	94.1	87.9	86.7	98.9	65.6	84.5	0
Ties-Merging	76.5	85.0	89.3	95.7	90.3	83.3	99.0	68.8	86.0	0
TATR	74.6	83.7	87.6	93.7	88.6	88.1	99.0	66.8	85.3	0
Ties-Merging & TATR	76.3	85.3	88.8	94.4	90.8	88.7	99.2	68.8	86.5	0
Consensus Merging	75.0	84.3	89.4	95.6	88.3	82.4	98.9	68.0	85.2	0
AWD Merging	76.2	85.4	88.7	96.1	92.4	92.3	99.3	69.4	87.5	0
PCB Merging	76.2	86.0	89.6	95.9	89.9	92.3	99.2	71.4	87.6	0
CAT Merging	78.7	88.5	91.1	96.3	91.3	95.7	99.4	75.7	89.6	2
LOT Merging (ours)	76.7	88.6	91.7	98.7	97.1	95.7	99.5	76.4	90.5	7

Experiments



Method	COCO Caption	Flickr30k Caption	Textcaps	OKVQA	TextVQA	ScienceQA	#best
Metric	CIDEr	CIDEr	CIDEr	Accuracy	Accuracy	Accuracy	
Pre-trained	0.07	0.03	0.05	42.80	21.08	40.50	-
Individual	1.17	0.65	0.65	50.84	29.79	76.89	-
Task Arithmetic	0.86	0.50	0.39	17.71	0.49	40.10	0
Ties-Merging	0.53	0.27	0.22	27.95	0.57	40.35	0
TATR	0.46	0.31	0.21	28.30	14.74	42.98	0
PCB Merging	0.71	0.52	0.30	36.04	1.88	43.01	0
CAT Merging	0.91	0.53	0.36	44.07	19.69	46.36	2
LOT Merging (ours)	0.91	0.54	0.44	38.35	20.82	48.24	5

THANKS FOR WATCHING

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