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ICCV
OCT 19-23, 2025
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PEFTDiff: Diffusion-Guided Transferability Estimation for Parameter-Efficient Fine-Tuning

Prafful Kumar Khoba[1,2], Zijian Wang[2], Chetan Arora[1], Mahsa Baktashmotlagh[2]

[1]Indian Institute of Technology Delhi, [2]The University of Queensland

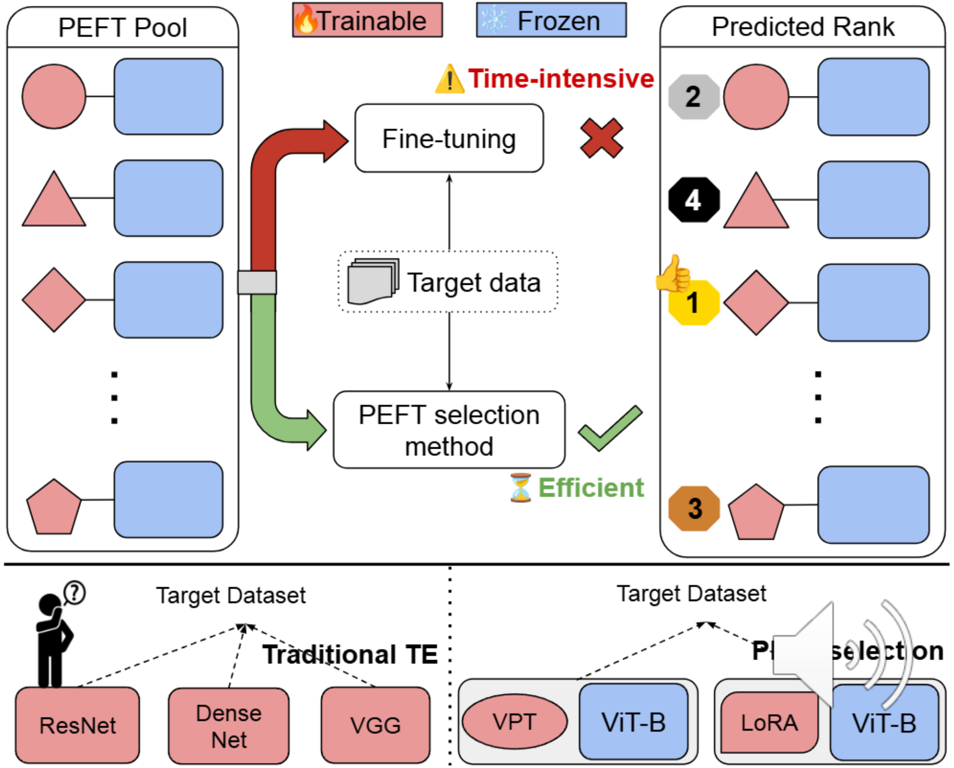
Motivation

Keywords:

1. PEFT: Parameter-Efficient Fine-Tuning
2. Transfer Learning
3. Transferability estimation: Metrics that predicts the adaptability of a pre-trained model on downstream dataset with minimal computation cost.

Motivation:

Given the increasing number of PEFT techniques, selecting the most suitable one for a given task is a nontrivial challenge.



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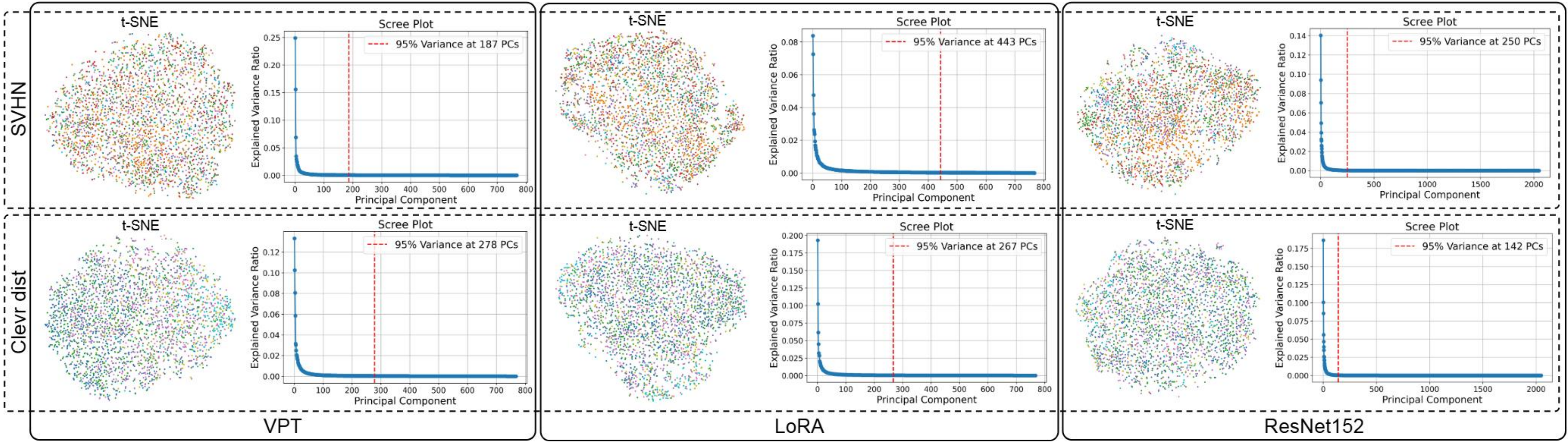
Uncovering why Previous TE does not work



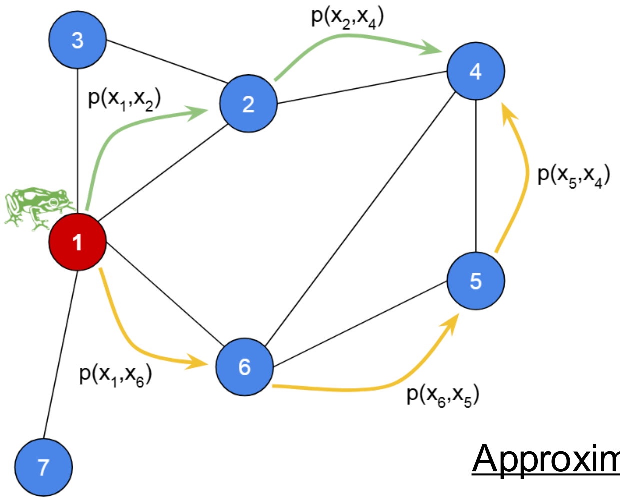
ResNet152 embeddings require significantly fewer principal components **(approximately 7%)** to retain 95% of the variance, indicating a simpler geometric structure. In contrast, PEFT embeddings exhibit substantially higher complexity, requiring **30–50%** of principal components to achieve the same variance retention.

How to overcome it

- To address these challenges, we propose a diffusion-based approach that leverages diffusion processes to model feature relationship.
- Diffusion maps (introduced by Coifman and Lafon, 2006) is a non-linear technique. It transforms the data according to parameters of its underlying geometry.

Diffusion Maps and Diffusion distance

Diffusion map construct a graph, based on representation of the features, where nodes represent data points and edges encode transition probabilities based on distance between the nodes.



Connectivity $$k(z_i, z_j) = \exp\left(\frac{-\|z_i - z_j\|^2}{\sigma^2}\right)$$

Apply K-NN to Sparsify $K_{ij} = k(z_i, z_j).$

Transition Matrix $$P = D^{-1}K\,, \quad D_{ii} = \sum_j K_{ij}$$

t-step in the diffusion space $$P^t = P \cdot P \cdots P \quad (t \text{ times})$$

Diffusion Distance $$D_t^2(z_i, z_j) = \sum_{u \in z} |p_t(z_i, u) - p_t(z_j, u)|^2$$

Approximating Diffusion Distance $$D_t^2(z_i, z_j) \approx \sum_{l=1}^{c} (\lambda_l^t)^2 \left(\phi_l(z_i) - \phi_l(z_j)\right)^2$$

PEFT selection score

The **goal** is to assess how well a PEFT method preserves intra-class compactness and inter-class separability compared to a frozen backbone.

- A negative change in intra-score indicates that PEFT technique has improved intra-class compactness.
- A positive change in inter-score suggests that the PEFT technique has increased inter-class separation.

Intra-class Score

$$S_t(C_k) = \frac{1}{|C_k|} \sum_{z_i \in C_k} D_t^2(z_i, \mu_{C_k})$$

Inter-class Score

$$S_t(C_k, C_l) = D_t^2(\mu_{C_k}, \mu_{C_l})$$

$$\Delta S_t^{\text{intra}} = S_t^{\text{intra}}(P_{\text{PEFT}_i}) - S_t^{\text{intra}}(P_{\text{backbone}})$$

$$\Delta S_t^{\text{inter}} = S_t^{\text{inter}}(P_{\text{PEFT}_i}) - S_t^{\text{inter}}(P_{\text{backbone}})$$

PEFT selection score

$$S_{\text{PEFT}_i} = \hat{\Delta S}_t^{\text{inter}} + \hat{\Delta S}_t^{\text{intra}}$$

Experiment Setup

- Dataset: Visual Task Adaptation Benchmark (VTAB) contains **19 datasets** that can be categorized into **Natural, Specialized** and **Structured**
- PEFT Pool: Keeping ViT-B16 as backbone, we curate a diverse pool of **9** PEFT techniques. This includes addition-based methods such as **Adapter, Convpass, Convpass Attention**, and **Visual Prompt Tuning**, which introduce minimal trainable layers or tokens to the model. From the partial-based category, we incorporate **BitFit, LoRA, Fact-TK, and Fact-TT**, which selectively modify parameters while keeping most of the model frozen. Finally, we include **NOAH** from unified-based methods, which combines multiple fine-tuning strategies into a single framework.
- Ground Truth Ranking: Established by fine-tuning each pre-trained PEFT (trained on ImageNet) on the VTAB-1k benchmark.
- Correlation Measurement: We use weighted Kendall's τ_w , where **Larger τ_w indicates better correlation** and better metric.

Performance Comparison (T_w)

Dataset	Cal101	Cifar	DTD	OxF	OxP	SVHN	Sun	PatchC	Euro	Resisc	DR	Avg. Nat	Avg. Spec
$\mathcal{N}$LEEP[25]	-0.496	0.022	0.384	-0.820	-0.365	-0.135	0.276	-0.367	-0.556	-0.177	0.328	-0.162	-0.193
NCTI[34]	0.146	-0.245	0.551	0.431	-0.771	0.487	0.225	-0.101	0.381	0.680	0.195	0.118	0.289
SFDA[31]	-0.068	-0.051	0.512	0.509	-0.544	0.515	0.210	-0.224	0.381	0.510	0.258	0.155	0.231
LogME[37]	0.404	-0.099	0.692	-0.336	-0.274	0.469	0.371	-0.224	0.591	**0.787**	0.307	0.175	0.365
Ours	**0.551**	**0.866**	**0.712**	**0.692**	**0.274**	**0.884**	**0.441**	**0.576**	**0.763**	0.396	**0.498**	**0.631**	**0.558**

Natural Datasets (Cal101 – Sun)

Specialized Datasets (PatchC – DR)

Analysis

- Performs best for all the dataset in Natural category.
- Performs best for 3 out of 4 in Specialized category.
- On an average, our metric performs better than Traditional TE metric for both Natural and Specialized datasets.

Performance Comparison (T_w)

Dataset	ClevC	ClevD	DmLab	Kitti	DspL	DspO	SNazi	SNelev	Avg. Str	Overall Avg.
$\mathcal{N}$LEEP[25]	0.434	0.232	**0.702**	-0.136	0.638	0.113	**0.826**	-0.194	0.327	0.037
NCTI[34]	0.439	0.123	0.461	-0.193	0.198	0.194	0.682	0.052	0.245	0.207
SFDA[31]	0.349	-0.013	0.328	NaN	0.035	0.472	0.682	0.006	0.266	0.215
LogME[37]	**0.535**	0.025	0.328	**0.531**	0.528	**0.763**	0.682	-0.265	0.391	0.306
Ours	0.230	**0.404**	0.471	0.212	**0.916**	0.402	0.275	**0.266**	**0.397**	**0.517**

Structured Datasets

Analysis

- On an average, our metric performs better than Traditional TE metric for both Structured datasets.
- Overall, in all the three categories, our metric performs the best which shows the efficacy of our diffusion-based metric.

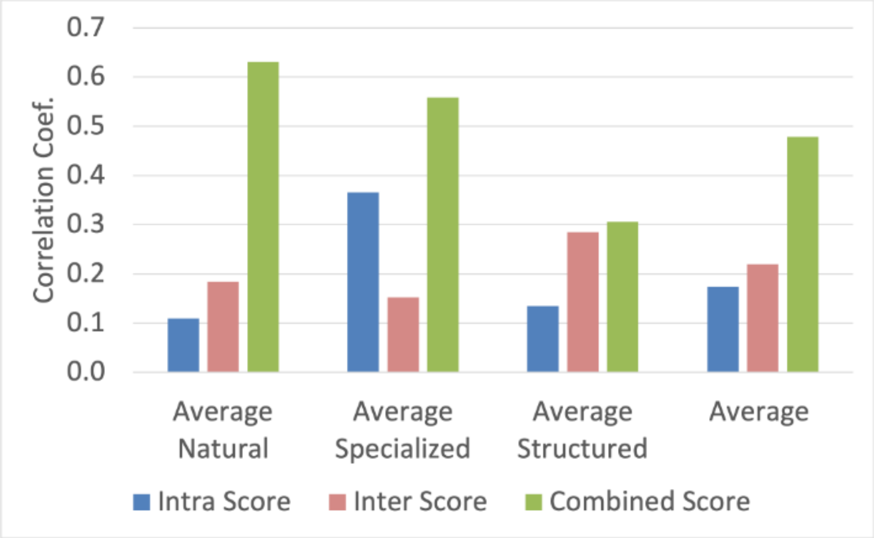
Method	Average Improvement
NLEEP	1297.29%
NCTI	149.75%
SFDA	140.46%
LogME	68.95%

Ablation study

The final PEFT selection score is derived from both intra-class and inter-class diffusion distances.

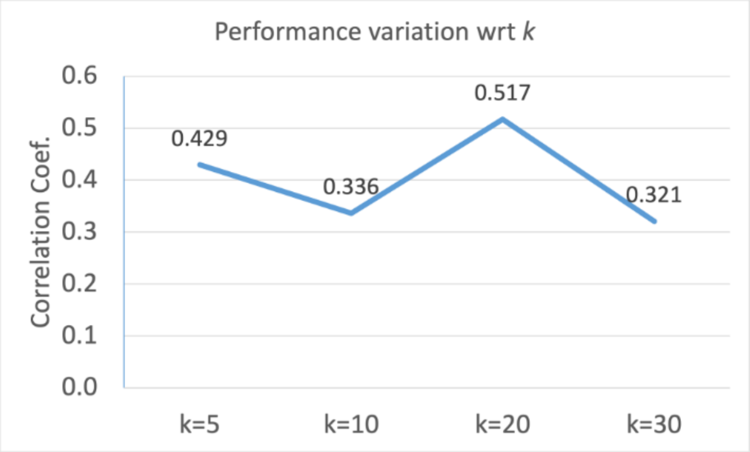
Intra-class diffusion score alone: **Tw = 0.174**
Inter-class diffusion score alone: **Tw = 0.22**
Combined/ Final diffusion score: **Tw = 0.517**

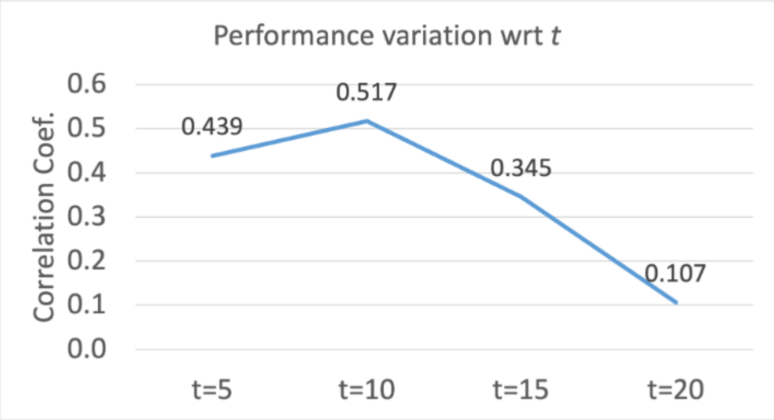
Both intra and inter-class scores are essential for accurate PEFT ranking.

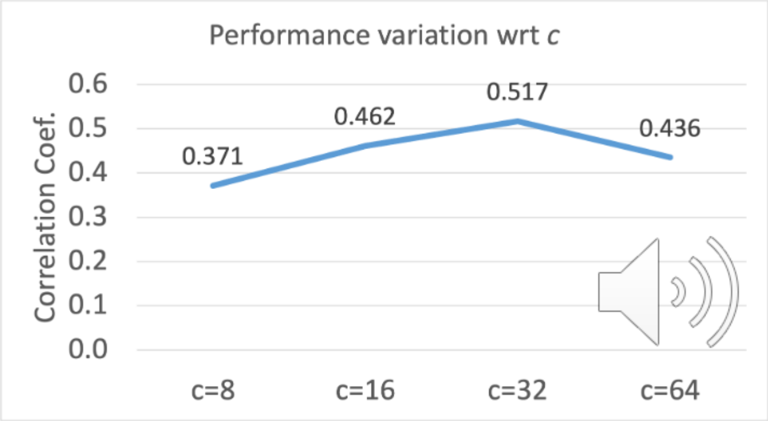


Hyper-parameter analysis

- To find the best hyper-parameter, we do a grid search for each of the hyper-parameter, while keeping the other fixed.
- For example, to isolate the effect of t, we fix the optimal values of k and c and vary t.

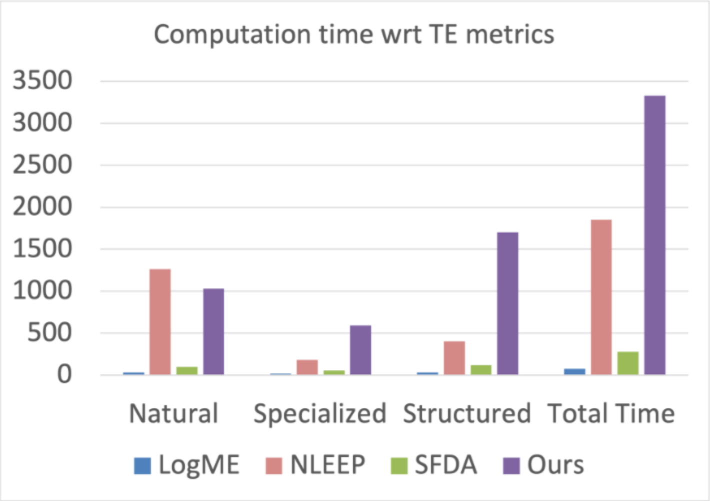






Time complexity

- Our method exhibits the highest computational cost among the evaluated metrics, except for the Natural category, where it is lower than NLEEP.
- A key advantage of our method is its substantial computational savings compared to full fine-tuning of PEFT techniques.
- This demonstrates that while our method is more computationally demanding than some transferability estimation baselines, it remains highly efficient compared to exhaustive fine-tuning, making it a practical and scalable alternative for PEFT selection.



Dataset Categories	Ours (min)	PEFT Fine-tuning (min)	Speed-up
Natural	17.18	3748.5	218.23×
Specialized	9.87	2106	213[illegible]0×
Structured	28.39	5220	1[illegible]5×
Total Time	55.44	11074.5	199.77×

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Thank you !!