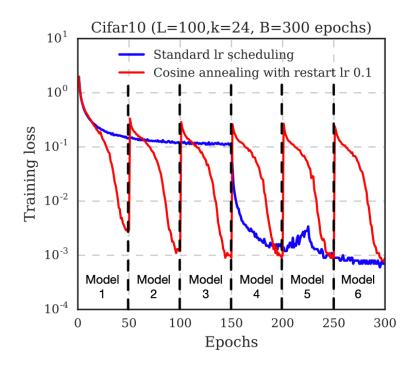
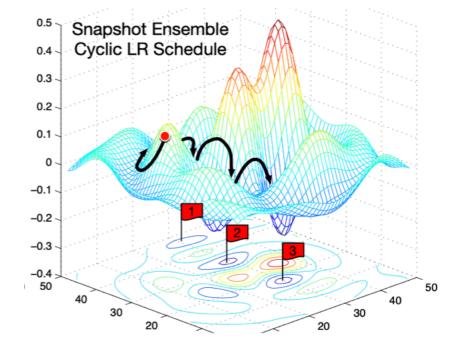
Analysis of Neural Networks Internal Representations During Transfer Learning

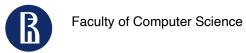
Gritsaev Timofei Grigorievich under Ildus Sadrtdinov supervision

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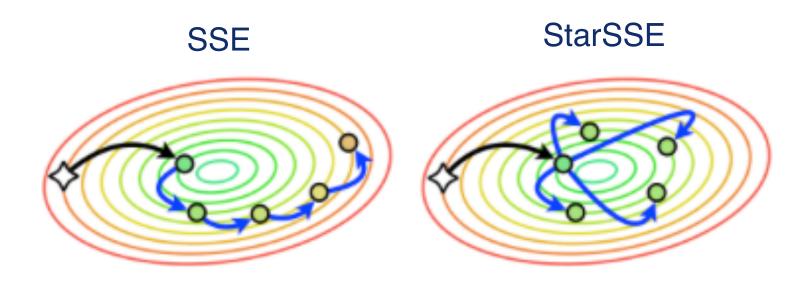
SNAPSHOT ENSEMBLES (SSE): TRAIN 1, GET M FOR FREE







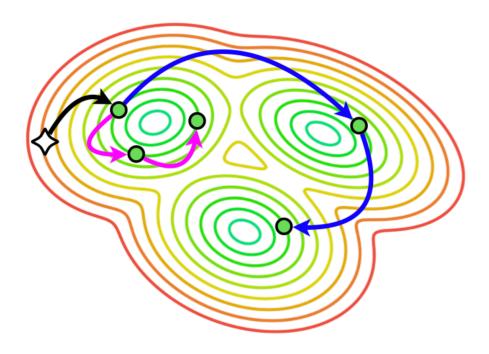
"To Stay or Not to Stay in the Pre-train Basin: Insights on Ensembling in Transfer Learning"





More local vs Semi-local

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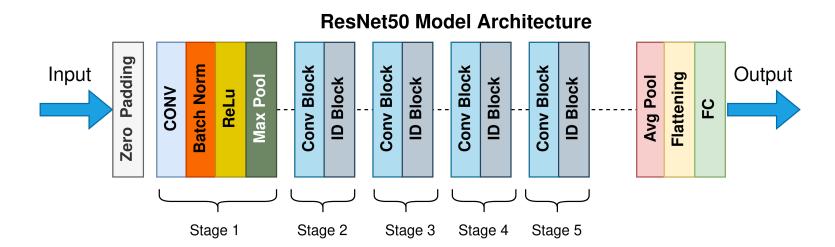
Methodology

- ResNet50
- CIFAR-100
- Following the protocol from
 "To Stay or Not to Stay in the Pre-train Basin: Insights on Ensembling in Transfer Learning"

Analysis of Neural Networks Internal

Representations During Transfer

Learning

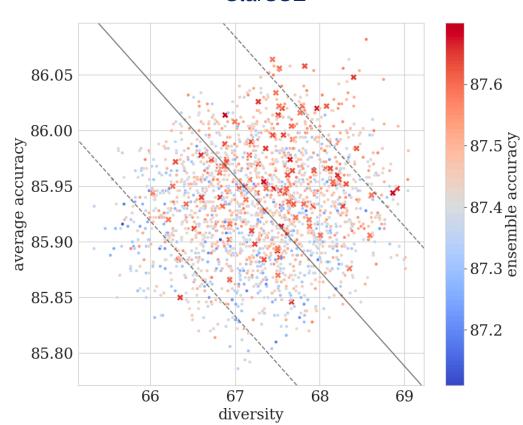




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Average accuracy, diversity, ensemble accuracy



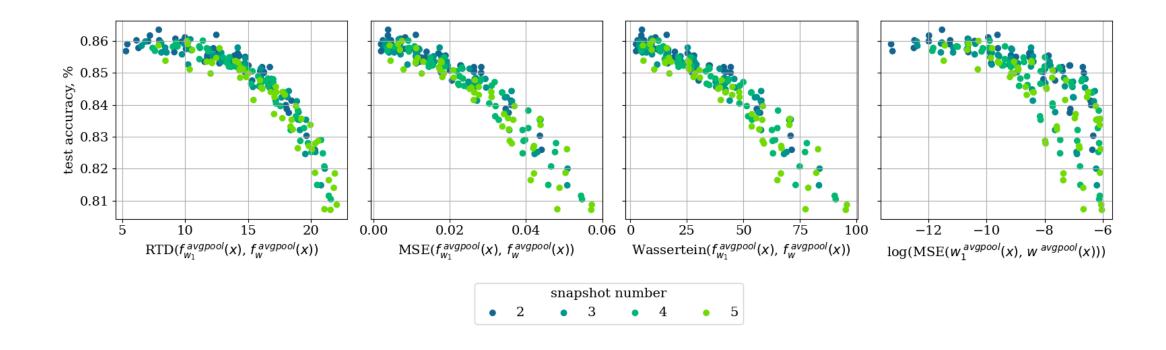


Algorithm		worst 5%	best 5%
	avg.acc.	85.91±0.04	85.95±0.05
StarSSE	div.	67.11 ± 0.78	$67.44{\scriptstyle\pm0.6}$
	ens. acc.	87.24 ± 0.03	87.62±0.03



SSE regularization motivation

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Regularized SSE results

Learning

Algorithm	avg. acc.	div.	ens. acc.	
SSE	85.52 ± 0.34	$71.57{\scriptstyle\pm5.94}$	87.11±0.06	
StarSSE	$85.88{\scriptstyle\pm0.25}$	$68.12{\scriptstyle\pm1.15}$	87.41 ±0.12	
SSE-RTD	85.71 ± 0.07	68.04 ± 5.78	87.36±0.09	
SSE-MSE	85.81 ± 0.221	$67.62{\scriptstyle\pm5.95}$	$87.37{\scriptstyle\pm0.02}$	

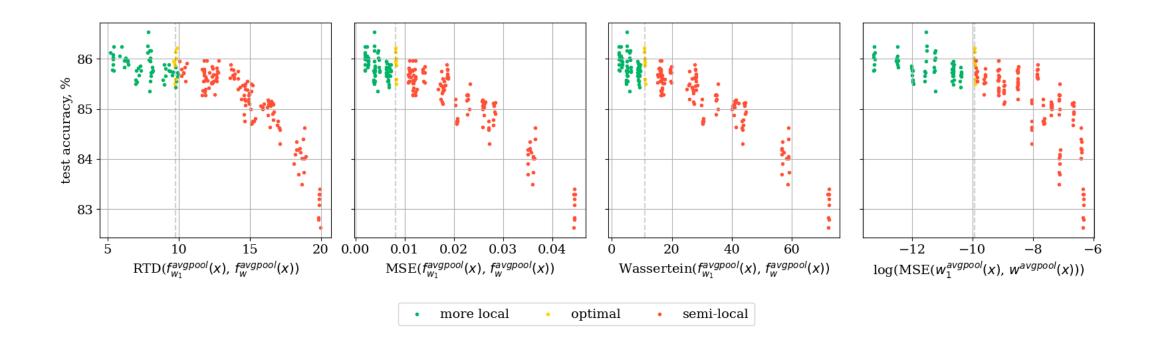


Analysis of StarSSE internal representations

Learning

Analysis of Neural Networks Internal

Representations During Transfer



Pairwise diversity

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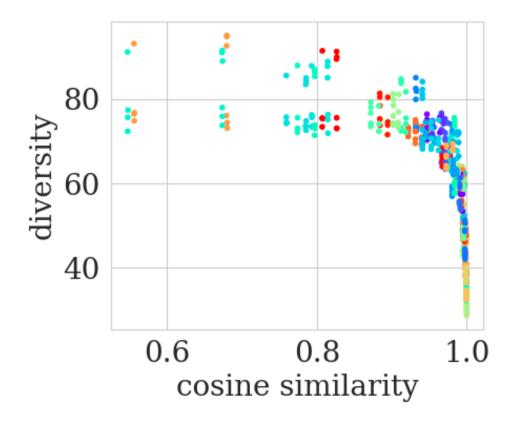
Random ensemble

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	I	II	III	IV	V
Ι	0.0	73.26	70.83	69.58	70.76
\mathbf{II}	73.26	0.0	70.93	72.06	74.49
III	70.83	70.93	0.0	71.07	71.14
IV	69.58	72.06	71.07	0.0	71.57
\mathbf{V}	70.76	73.26 0.0 70.93 72.06 74.49	71.14	71.57	0.0



StarSSE—WO



Analysis of Neural Networks Internal

Representations During Transfer

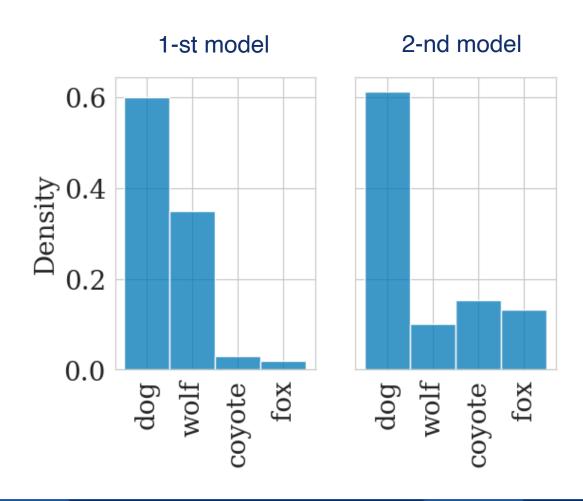
Learning

Analysis of Neural Networks Internal

Representations During Transfer

Learning

StarSSE—CE



The modifications of StarSSE results

Algorithm	avg. acc.	div.	ens. acc.
SSE	85.52 ± 0.34	$71.57{\scriptstyle\pm5.94}$	87.11±0.06
StarSSE	85.88 ± 0.25	$68.12{\scriptstyle\pm1.15}$	87.41 ±0.12
StarSSE-WO	85.83 ± 0.24	$67.31{\scriptstyle\pm1.77}$	87.4 ± 0.16
StarSSE-CE (2)	85.4 ± 0.49	$75.21{\scriptstyle\pm3.79}$	87.44 ± 0.2



StarSSE with Parameter efficient Fine-tuning (PeFt)

Learning

Analysis of Neural Networks Internal

Representations During Transfer

ResNet50 Model Architecture Padding Block **Block** Block **Batch Norm Conv Block** Input Output Flattening Block Block Max Pool Block Block **Avg Pool** CONV ReLu Conv Conv \Box Zero Stage 1 Stage 2 Stage 3 Stage 5 Stage 4



StarSSE with PeFt results

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Algorithm	avg. acc.	div.	ens. acc.
StarSSE	85.88 ± 0.25	$68.12{\scriptstyle\pm1.15}$	87.41 ±0.12
StarSSE (1) x0.74 time		$71.37{\scriptstyle\pm2.02}$	87.26±0.06
StarSSE (2) x0.6 time	85.94 ± 0.225	60.94 ± 1.25	87.1 ± 0.14
StarSSE (3) x0.55 time	86.01 ± 0.195	17.38 ± 1.02	$86.09{\scriptstyle\pm0.22}$

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Conclusion

- Individual quality and diversity are the key
- Increasing StarSSE individual quality reduces ensemble performance
- Increasing StarSSE diversity corrupts individual models, but it is possible

Analysis of Neural Networks Internal

Representations During Transfer

Learning

• StarSSE is the best algorithm, gives the best diversity with insignificant individual quality decrease