Guidepost: Target-Oriented Few-shot Transferring via Measuring Task Similarity

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Problem Definition

Few-shot Task: Fast Adaptation to the target task from the trained weight from auxiliary dataset.

FSL Definition:

Training Dataset: $\{S_i^{tr}, Q_i^{tr}\}_{i=0}^{M} \sim D^{tr}$.

Validation Dataset: $\{S_i^{v}, Q_i^{v}\}_{i=0}^{N} \sim D^{val}$.

Test Dataset: $\{S_i^{ts}, Q_i^{ts}\}_{i=0}^{T} \sim D^{ts}$.

S_i^*: C-way K-shot. (K = 1, 5, 20…)

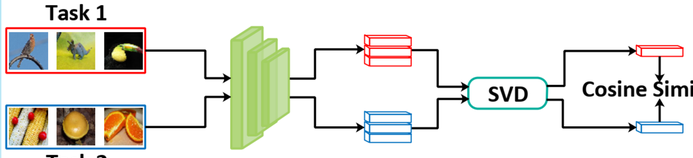
Q_i^*: C-way L-shot. (L > K)

FSL Pipeline: Training the model with D^{tr}, and fast adaptation with S_i^{ts}. Finally test on Q_i^{ts}.

Key Contributions

- We propose a task-level learn-to-learn mechanism to implicitly learn the task similarities with the proposed task descriptor and develop a target-oriented few-shot learner named Guidepost.
- A new FSL benchmark is proposed to satisfy realistic needs, and we empirically observe that representative FSL models fail to perform well.
- We evaluate Guidepost according to two aspects: domain adaptation and few-shot learning. Extensive experiments demonstrate that Guidepost outperforms its baselines on multiple benchmarks, which verifies the superiority of the target-oriented property.

Task Descriptor



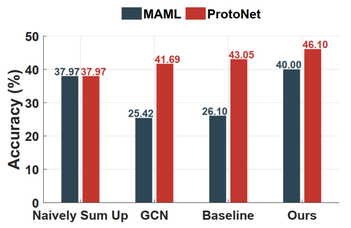
Motivation: Task descriptor should be representative for a task and is essential for learning task similarity.

Task Descriptor:

$T_{dp} = U\bar{P}_{N\times D}$ $\quad U,S,V = SVD(\bar{P}_{N\times D})$

$\bar{P}_{N\times D} = P_{N\times D} - P_{1\times D}$ $\quad P_{N\times D} = \mathcal{C}_{\varphi}(T)$

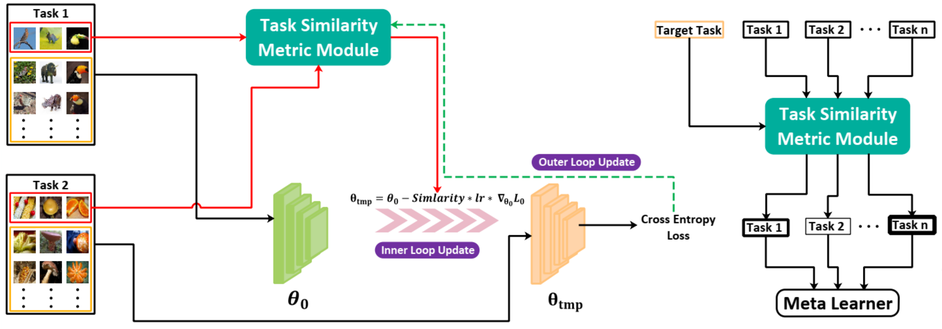
Leverage SVD to extract primary components shared by all categories



(a) The comparison of different task descriptor.

Our task descriptor shows superiority compared to others.

Guidepost: Target-oriented Meta Training



Stage 1: Task-level learn to learn mechanism

Stage 2: Target-oriented Meta Training

Inner Loop: $\phi_{tmp} \leftarrow \phi_i - \alpha\omega \nabla_{\phi_i} \mathcal{L}_{\mathcal{T}_i}(S_i, f_{\phi_i})$

Weight assigned by the task similarity module

Outer Loop: $\phi_{i+1} \leftarrow \phi_i - \beta \nabla_{\phi_i} \mathcal{L}_{\mathcal{T}_i}(Q_i, f_{\phi_{tmp}})$

Goal: Learning a task similarity module via a modulated bi-level optimization.

Inner Loop:

$$\theta_{tmp} = \theta_0 - Sim * lr_{in} * \nabla_{\theta_0}\mathcal{L}_0$$

Similarity assigned by the task similarity module

Outer Loop:

$$\varphi \leftarrow \varphi - lr_{ou} * \nabla_{\varphi}\mathcal{L}_1$$

Only task similarity module is updatable

Main Results on FSL Benchmarks

Table 1: Comprehensive 1 on 1 domain adaptation experiment results. 'FT' represents the model is fine-tuned by target 1-shot labeled sample. The bold one represents rank first. 'Guidepost-M' is the MAML version of Guidepost.

Accuracy (%)	2→1	2→3	2→4	2→5	2→6	1→3	1→4	1→5	1→6	3→4	3→5	3→6	4→5	4→6	5→6	Ave.
CNN	80.22	80.22	64.81	79.64	82.53	75.15	67.60	81.26	79.30	60.45	80.31	82.48	69.74	62.20	77.53	74.90
CNN_FT	79.34	75.82	64.63	79.75	83.16	74.10	67.78	81.82	**80.34**	60.45	80.31	82.38	67.11	63.56	81.02	74.77
EI	82.70	81.79	65.83	79.42	84.72	70.75	64.72	76.40	76.64	62.89	79.47	82.01	72.09	65.02	78.52	74.86
EI_FT	75.33	73.28	67.25	76.01	85.77	74.40	63.07	77.91	75.91	56.01	83.22	78.94	54.59	62.15	79.25	72.21
MatNet	78.54	75.52	**73.52**	75.17	85.74	76.49	68.32	80.86	76.70	63.02	84.15	83.32	68.81	67.82	**87.29**	76.35
HDA	84.66	83.71	69.97	82.77	84.70	**76.50**	70.23	85.09	78.56	54.86	86.00	83.33	78.91	81.18	72.38	78.17
PACL	75.40	79.31	72.00	79.65	82.21	72.31	**70.82**	**86.94**	80.11	65.82	**88.76**	**84.53**	**86.29**	66.95	80.53	78.11
RFNet	60.37	45.78	50.62	67.23	62.86	47.83	58.33	66.55	56.04	43.92	62.84	56.51	55.84	45.35	58.68	55.92
MetaSense	85.57	87.01	68.99	87.02	87.80	67.69	60.45	65.60	73.21	65.24	80.76	81.18	78.91	78.57	81.26	76.85
MetaSense_FT	85.57	87.16	68.81	87.02	87.75	70.97	60.54	68.46	74.94	65.24	80.76	82.01	78.91	78.73	81.33	77.27
Guidepost-M	**86.62**	**88.51**	69.86	**87.55**	**88.01**	71.64	60.28	72.37	74.54	**65.94**	81.82	81.88	80.98	**81.75**	82.38	**78.28**

miniImageNet

Accuracy (%)	1	2	3	4	5	6	7	8	9	10	Ave.
MAML	26.24	26.21	30.88	26.68	26.51	29.28	28.81	26.88	26.54	28.41	27.64
Guidepost + MAML	26.30	26.91	31.68	28.14	27.95	29.62	29.24	28.35	26.58	28.54	**28.33**
ProtoNet.5	21.53	23.48	35.59	12.71	23.38	20.07	24.57	17.29	21.58	23.55	22.38
ProtoNet.30	15.98	21.08	33.27	11.64	23.23	19.72	28.83	15.46	22.39	21.52	21.31
Guidepost + ProtoNet.5	24.37	26.91	23.54	22.80	27.05	23.37	23.81	23.81	21.80	25.11	**24.26**
RENet	23.56	23.29	25.56	24.59	21.95	24.25	26.64	23.84	23.82	25.58	24.31
Guidepost + RENet	24.05	24.53	26.38	25.52	22.03	24.03	27.37	23.16	23.65	26.35	**24.68**

CUB200

Accuracy (%)	1	2	3	4	5	6	7	8	9	10	Ave.
MAML	21.38	26.10	41.69	46.44	47.80	48.81	45.42	45.42	39.31	44.75	40.71
Guidepost + MAML	45.86	40.00	46.44	46.78	47.80	52.20	54.24	51.53	47.93	48.14	**45.75**
ProtoNet.5	47.93	43.05	35.59	24.07	44.07	42.37	51.86	46.44	17.24	41.69	39.43
ProtoNet.30	22.41	22.03	31.19	41.69	47.46	26.10	54.58	44.07	32.41	23.73	34.57
Guidepost + ProtoNet.5	46.55	46.10	44.07	44.41	45.76	49.49	46.78	50.17	47.59	48.47	**46.94**
RENet	24.32	23.58	26.04	23.53	22.33	23.32	27.82	25.10	24.23	27.49	24.78
Guidepost + RENet	47.92	49.26	44.44	50.00	49.26	50.37	48.52	42.96	44.15	41.48	**46.84**

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