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Test-time Assessment of a Model's Performance on Unseen Domains via Optimal Transport

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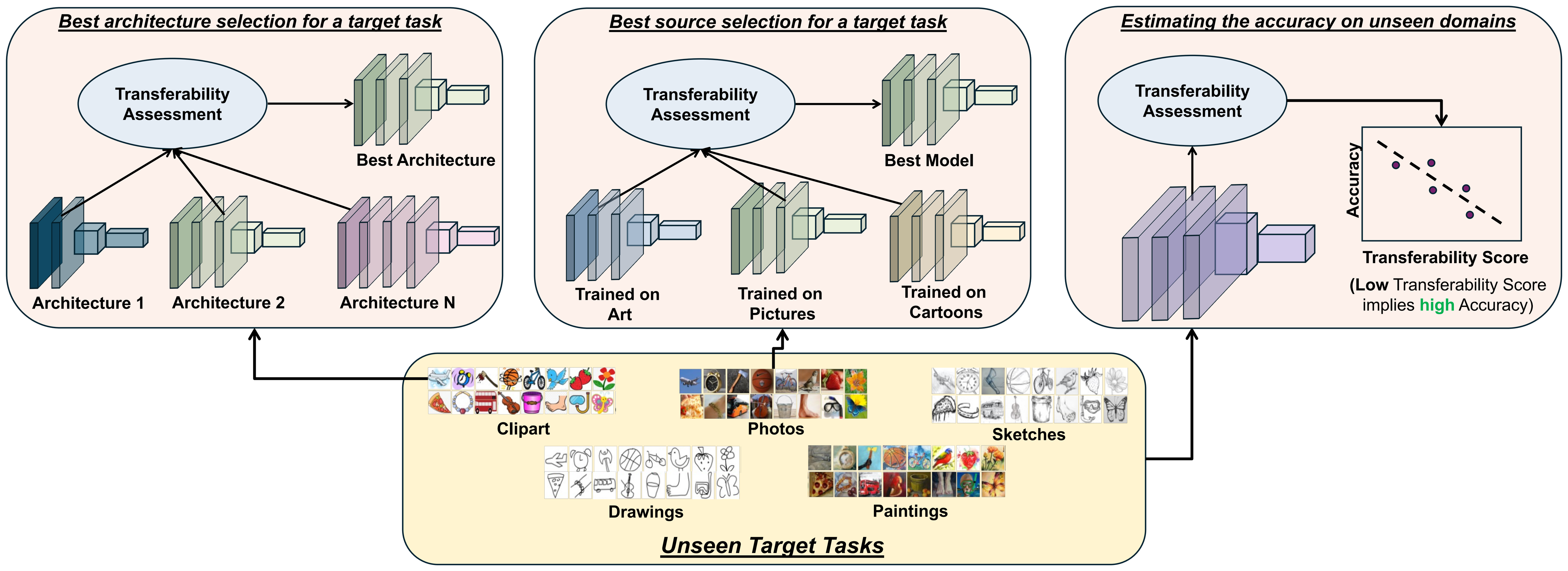
Motivation

- A model's performance on in-distribution data is a poor indicator of its performance on data from unseen domains (a.k.a. transferability).
- Metrics that can assess a model's performance without labels can be used for gauging their performance at test time.
- Such metrics can be used to select the best pre-trained model for an unseen domain or can assess model's performance on different unseen domains.

Contributions

- We propose TETOT, for assessing the transferability of classification models to unseen domains.
- TETOT is efficiently computable using unlabeled target data and requires only a small number of samples/statistics from the source domain.
- TETOT produces a better correlation with transferability compared to the popular entropy-based metric on practical problems.

Test-time Estimation of Transferability via Optimal Transport (TETOT)



Def. 1. (Transferability): Transferability of a model trained on the source domain S to an unseen target domain T is measured as the model's accuracy on T i.e.,

$$\mathbb{E}_{(x,y)\in P_T(x,y)}[\boldsymbol{accuracy}(\boldsymbol{h}(\boldsymbol{g}(\boldsymbol{x})),\boldsymbol{y})],$$

where $g: \mathcal{X} \to \mathcal{Z}$ is the encoder and $h: \mathcal{Z} \to \mathcal{Y}$ is the classifier.

Def. 2. (Base distance): The base distance c is defined as

$$\boldsymbol{c}((\boldsymbol{x_S},\boldsymbol{y_S}),(\boldsymbol{x_T},\hat{\boldsymbol{y}}_{\boldsymbol{T}})) \coloneqq \boldsymbol{c_{features}}(\boldsymbol{x_S},\boldsymbol{x_T}) + \boldsymbol{\lambda}\cdot \boldsymbol{c_{labels}}(\boldsymbol{y_S},\hat{\boldsymbol{y}}_{\boldsymbol{T}}).$$

Def. 3. (TETOT): TETOT is defined as

$$\boldsymbol{OT_c}(\boldsymbol{P_S},\boldsymbol{P_T}) \coloneqq \inf_{\pi\in\Pi(P_S,P_T)} \mathbb{E}_{\boldsymbol{\pi}}[\boldsymbol{c}((\boldsymbol{x_S},\boldsymbol{y_S}),(\boldsymbol{x_T},\hat{\boldsymbol{y}}_{\boldsymbol{T}}))],$$

where P_S/P_T is the distribution of S/T and c is the base distance.

Algorithm to compute TETOT

\# Select samples from S and T.
Randomly sample m samples, $(x_S^i, y_S^i) \sim \mathcal{D}_S$
Randomly sample n samples, $(x_T^j) \sim \mathcal{D}_T$

\# Compute pairwise cost.
for $i = 1,\dots,m$ and $j = 1,\dots,n$ **do**
$c_{features}^{ij} \coloneqq \|g(x_S^i) - g(x_T^j)\|_2$
$c_{labels}^{ij} \coloneqq \|y_S^i - h(g(x_T^j))\|_2$

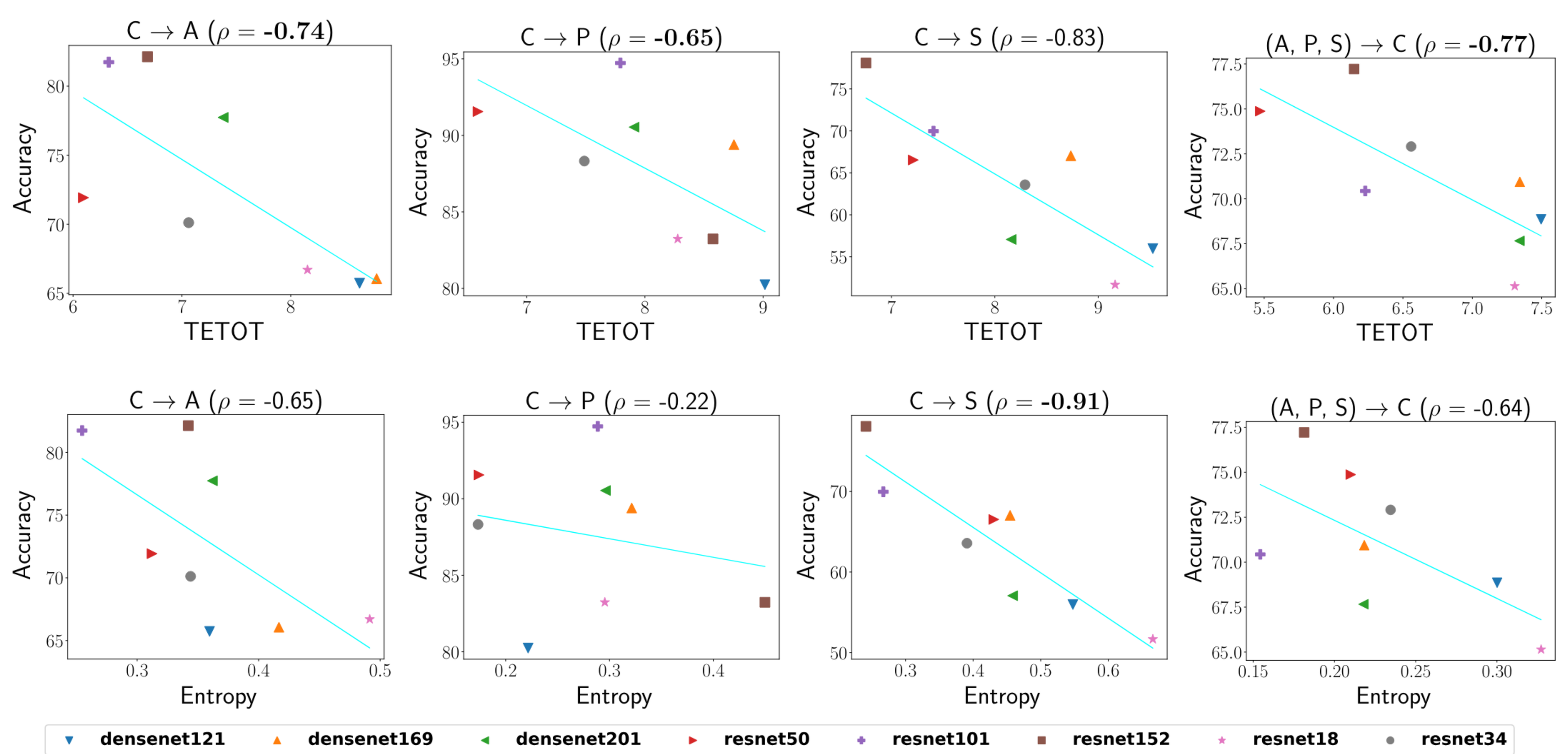
$c \coloneqq c_{features} + \lambda \cdot c_{labels}$

$$\boldsymbol{TETOT} \coloneqq min_{\pi\in\Pi(P_S,P_T)} \sum_{i,j} \pi^{ij}\cdot c^{ij}$$

$$s.t. \sum_j \pi^{ij} = \frac{1}{m}\ \forall i, \sum_i \pi^{ij} = \frac{1}{n}\ \forall j$$

Key Results

Best architecture selection for a target task

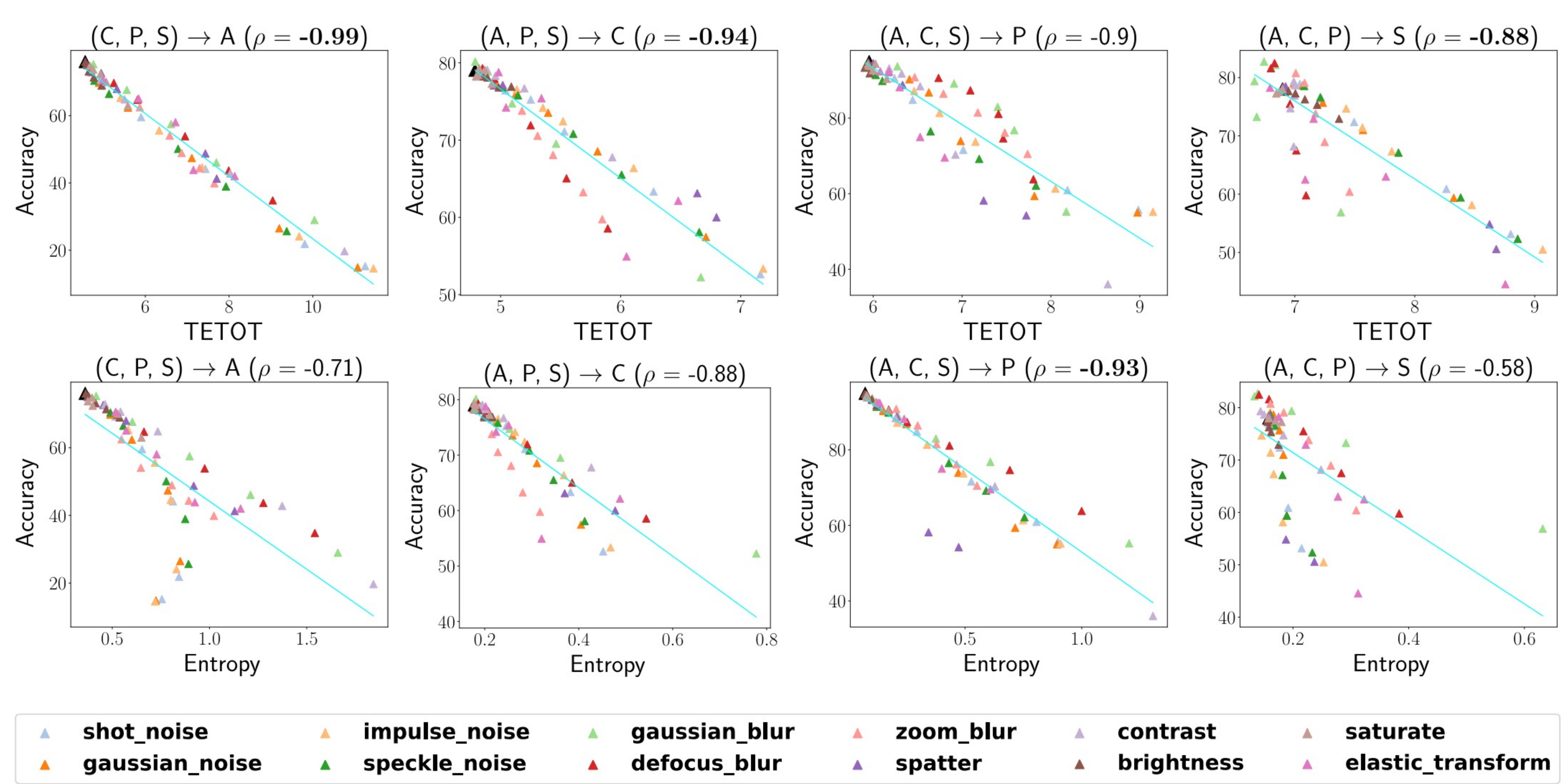


Dataset	Entropy	TETOT
PACS	-0.40	**-0.62**
VLCS	-0.29	**-0.40**
Average	-0.35	**-0.51**

Best source selection for a target task

Dataset	Entropy	TETOT
PACS	-0.47	**-0.94**
VLCS	-0.58	**-0.92**
Average	-0.53	**-0.93**

Correlation of transferability with TETOT



Dataset	Entropy	TETOT
PACS	-0.39	**-0.93**
VLCS	-0.34	**-0.80**
Average	-0.36	**-0.86**

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