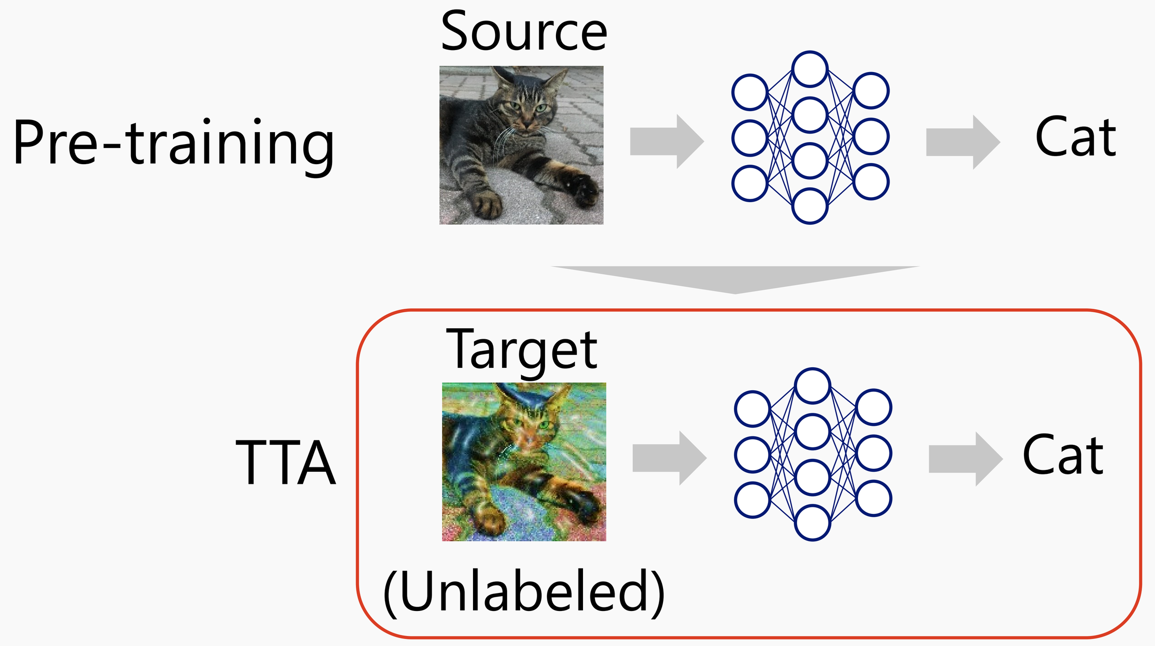
Test-time Adaptation for Regression by Subspace Alignment

Kazuki Adachi*, Shin'ya Yamaguchi*†, and Atsutoshi Kumagai*
*NTT †Kyoto University

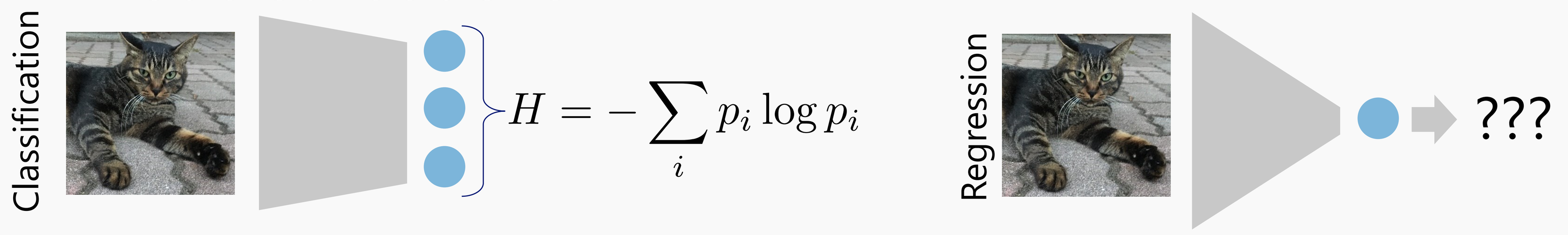
Test-time Adaptation (TTA)

- Adapts a pre-trained model to the target domain <u>with unlabeled target data</u>
- <u>Does not access the source data</u>

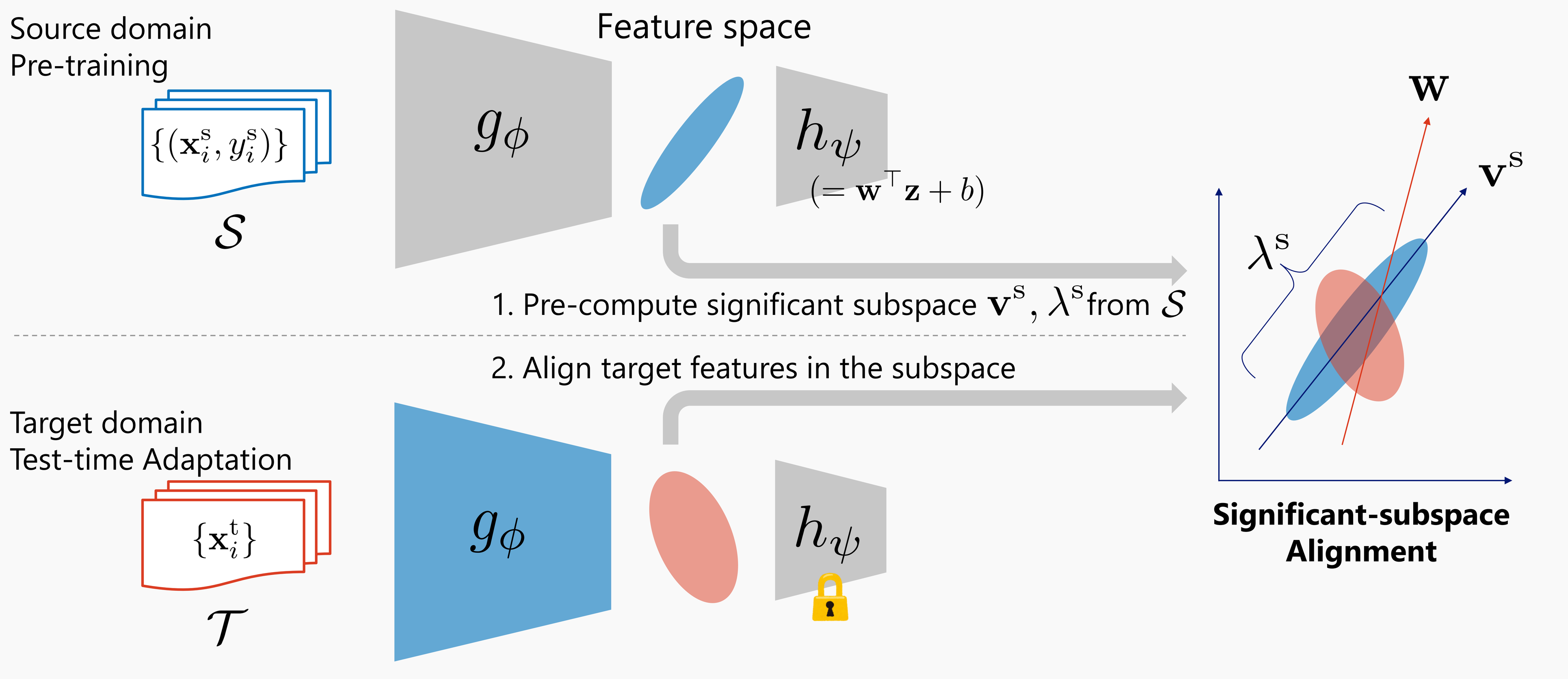


TTA for Regression

- TTA for regression has not been explored because existing TTA methods typically focus on classification using entropy minimization
- <u>Entropy cannot be computed for regression models</u>
  - ➢ Regression models output single scalar values, not distributions



Proposed Method



- <u>Basic Idea: Feature Alignment</u>
  - ➢ Aligns the target feature mean and variance with pre-computed source statistics
  - ➢ **Problem**: <u>Alignment in the entire feature space is inefficient in regression</u>
    - – Features are less diverse than classification [1]
    - – **Features are distributed only in a small subspace** (Tab. 1)
- <u>Subspace Detection</u>
  - ➢ Detects the source feature subspace significant to the output using PCA
- <u>Dimension Weighting</u>
  - ➢ Weights the subspace dimensions based on the significance to the output

[1] Zhang et al., Improving Deep Regression with Ordinal Entropy. ICLR 2023.

Experiment

- <u>Subspace Dimensions</u>
  - ➢ Smaller than appearance (2048 dims.) in regression
  - ➢ **Entire feature alignment is ineffective**

Table 1. Number of feature dimensions

Dataset	#Valid dims.	#Subspace dims.
SVHN	353	14
UTKFace	2041	76
Biwi Kinect (Male, Pitch)	677	33
Biwi Kinect (Male, Yaw)	735	12
Biwi Kinect (Male, Roll)	640	39
Biwi Kinect (Female, Pitch)	699	40
Biwi Kinect (Female, Yaw)	823	34
Biwi Kinect (Female, Roll)	704	49

- <u>Regression Performance</u>
  - ➢ **Our SSA outperformed existing classification TTA baselines**

Table 2. SVHN-MNIST

Method	R^2	RMSE
Source	$0.406_{\pm 0.00}$	$2.232_{\pm 0.00}$
DANN	$0.307_{\pm 0.09}$	$2.406_{\pm 0.16}$
TTT	$0.288_{\pm 0.02}$	$2.443_{\pm 0.03}$
BN-adapt	$0.396_{\pm 0.00}$	$2.251_{\pm 0.01}$
Prototype	$0.491_{\pm 0.00}$	$2.065_{\pm 0.01}$
FR	$0.369_{\pm 0.01}$	$2.300_{\pm 0.02}$
SSA (ours)	$\mathbf{0.511}_{\pm \mathbf{0.03}}$	$\mathbf{2.024}_{\pm \mathbf{0.06}}$

Table 3. R^2 on UTKFace (age prediction)

Method	Defocus blur	Motion blur	Zoom blur	Contrast	Elastic transform	Jpeg comp.	Pixelate	Gaussian noise	Impulse noise	Shot noise	Brightness	Fog	Snow	Mean
Source	0.410	0.159	0.658	−3.906	0.711	0.069	0.595	−2.536	−2.539	−2.522	0.661	−0.029	−0.544	−0.678
DANN	0.512	0.586	0.637	−0.720	0.729	0.698	0.807	−4.341	−3.114	−3.744	0.590	−0.131	−0.425	−0.609
TTT	0.748	0.761	0.773	0.778	0.826	0.772	0.861	0.525	0.532	0.477	0.775	0.397	0.493	0.671
BN-Adapt	0.727	0.759	0.763	0.702	0.826	0.778	0.850	0.510	0.510	0.446	0.790	0.392	0.452	0.654
Prototype	−1.003	−1.020	−1.016	−0.719	−0.967	−0.908	−0.974	−0.514	−0.512	−0.512	−1.004	−0.823	−0.822	−0.830
FR	0.794	**0.839**	0.849	0.756	**0.899**	0.825	**0.946**	0.509	0.522	0.458	0.861	0.408	0.428	0.700
SSA (ours)	**0.803**	**0.839**	**0.851**	**0.792**	**0.899**	**0.829**	0.943	**0.580**	**0.592**	**0.560**	**0.863**	**0.440**	**0.517**	**0.731**