Covariance-aware Feature Alignment with Pre-computed Source Statistics for Test-time Adaptation

Session: TA.PA.2

Kazuki Adachi, Shin'ya Yamaguchi, and Atsutoshi Kumagai
NTT Computer and Data Science Laboratories

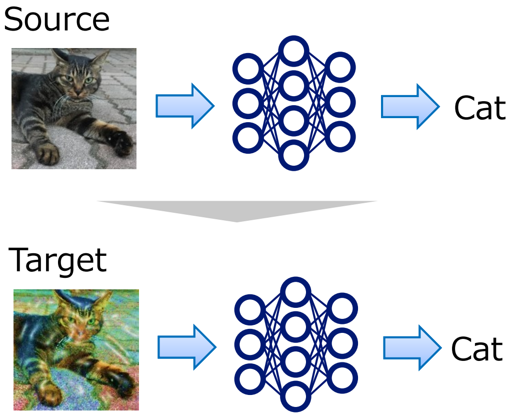
Background

- Deep neural networks degrade accuracy when the training and test distributions are different (a.k.a distribution shift)

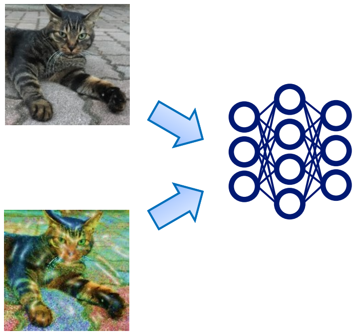
  - Distribution shift often occurs in the real world
    - e.g., weather, brightness, image quality, …
  - Adjusting data pre-processing by hand highly costs
  - <u>Retaining accuracy in the target domain is necessary</u>

Existing Approaches

- Fine-tuning
  - Re-trains models on data collected
    from the target domain
    after training on the source domain
  - Needs to make a new labeled dataset
    in the target domain



- Domain adaptation
  - Uses the datasets of both domains during training
    to learn invariant features
  - Does not require labels for the target dataset
  - Requires the both datasets simultaneously



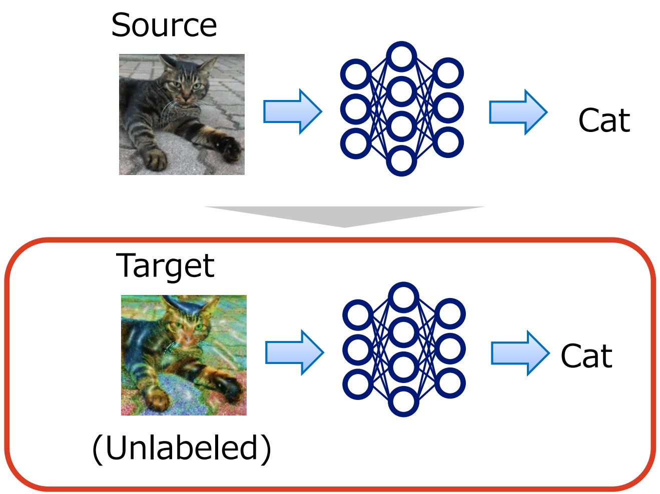
Problem

- Fine-tuning and domain adaptation are not suitable in some situations:
  - Annotation for target data highly costs
  - Obtaining target data in advance during the source-training phase can be difficult
  - Bringing the source data to the target domain can be prohibited
    - Security, privacy, or storage limitations

- Model adaptation with only target data is needed

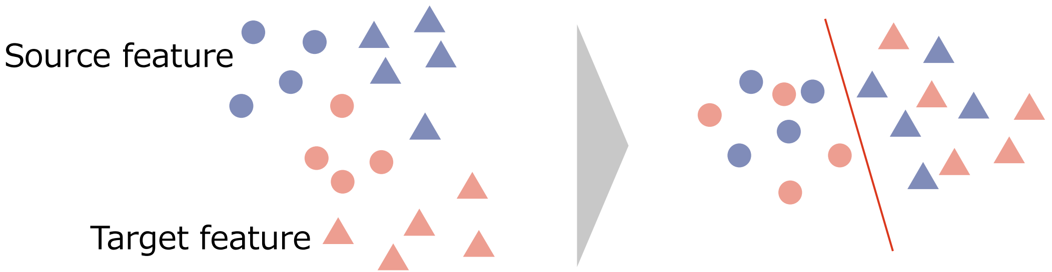
Test-time Adaptation (TTA)

- Given: a source-pretrained model
- Goal: adapt the model with unlabeled target data



Key Idea

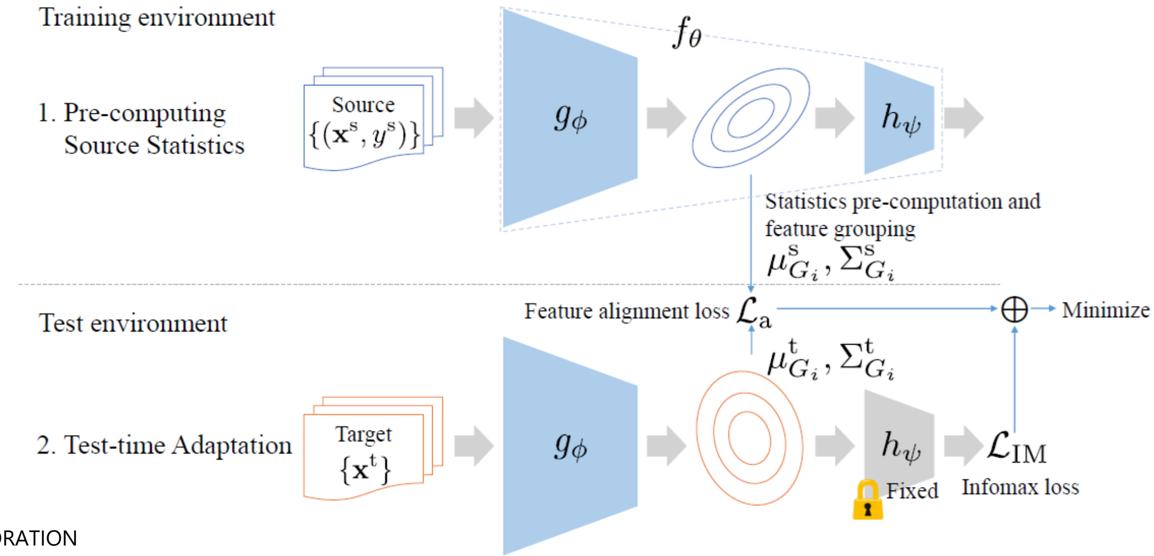
- Insight of domain adaptation:
  - Closing the source and target feature distributions is important to learn invariant features (feature alignment)



- Existing TTA methods mainly focus on refining model outputs
- Can we improve TTA by feature alignment?

Proposed Method

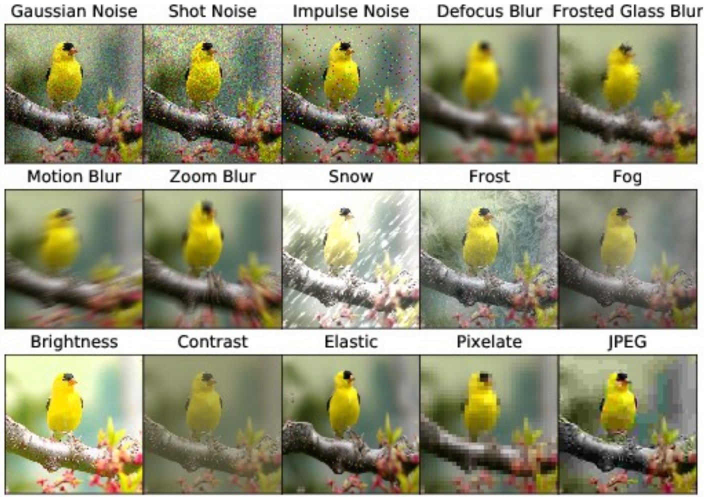
- Covariance-aware Feature Alignment (CAFe)
  - Pre-computes the statistics of source features in the source domain
  - Aligns the statistics of target features during TTA



Experiment

- Compare accuracy under distribution shifts

- Source data: ImageNet
- Target data: ImageNet-C
  - Corrupted ImageNet images in various ways
  - 15 corruptions × 5 levels of severity
- Model: ResNet-50



Result

- CAFe improved the accuracy especially when multiple types and severity levels of corruptions are mixed
- CAFe can adapt to more complex distribution shifts

Method	ImageNet-C Separated	ImageNet-C Severity-mixed	ImageNet-C All-mixed
Source	39.14	$39.43_{\pm 0.00}$	$39.16_{\pm 0.01}$
AdaBN [4]	$50.28_{\pm 0.02}$	$48.00_{\pm 0.17}$	$39.85_{\pm 0.18}$
T3A [9]	$39.05_{\pm 0.01}$	$39.28_{\pm 0.03}$	$37.46_{\pm 0.09}$
Tent [7]	$58.97_{\pm 0.03}$	$57.15_{\pm 0.05}$	$44.44_{\pm 0.22}$
BACS [8]	$57.01_{\pm 0.19}$	$55.05_{\pm 0.29}$	$33.07_{\pm 1.38}$
FR [21]	$53.54_{\pm 0.01}$	$50.38_{\pm 0.20}$	$40.52_{\pm 0.16}$
Infomax [23]	$60.20_{\pm 0.05}$	$57.52_{\pm 0.23}$	$46.52_{\pm 0.08}$
CAFe (w/o infomax)	$57.35_{\pm 0.02}$	$54.43_{\pm 0.14}$	$43.83_{\pm 0.16}$
CAFe (dimwise)	$\underline{60.29}_{\pm 0.08}$	$\underline{58.60}_{\pm 0.36}$	$\underline{47.19}_{\pm 0.24}$
CAFe	$\mathbf{60.77}_{\pm 0.09}$	$\mathbf{59.04}_{\pm 0.22}$	$\mathbf{48.55}_{\pm 0.26}$

Thank you for watching!

Poster: TA.PA.2