Domain Adaptation for Time Series Under Feature and Label Shifts

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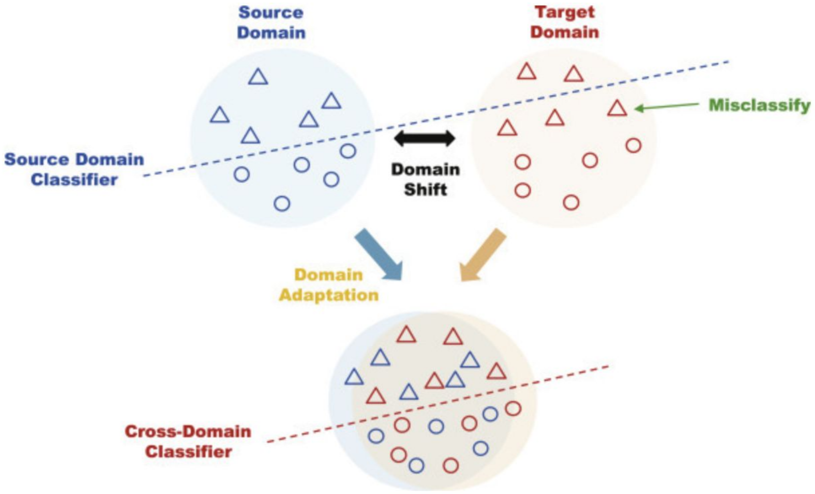
INTRODUCTION

Unsupervised domain adaptation (UDA)

: enables the transfer of models trained on source domains to unlabeled target domains



INTRODUCTION

Unsupervised domain adaptation (UDA)

: enables the transfer of models trained on source domains to unlabeled target domains

- **Feature shifts**

  : in the time and frequency representations

- **Label shifts**

  : label distributions of tasks in the source and target domains can differ significantly, posing difficulties in addressing label shifts and recognizing labels unique to the target domain

INTRODUCTION

What makes DA difficult?

to achieve robustness to domain shifts, model must learn highly generalizable features; however,

“Private Labels”

: classes that exist in the target domain but not in the source domain

→ In UDA, a model must generalize across domains when labels from the target domain are not available during training

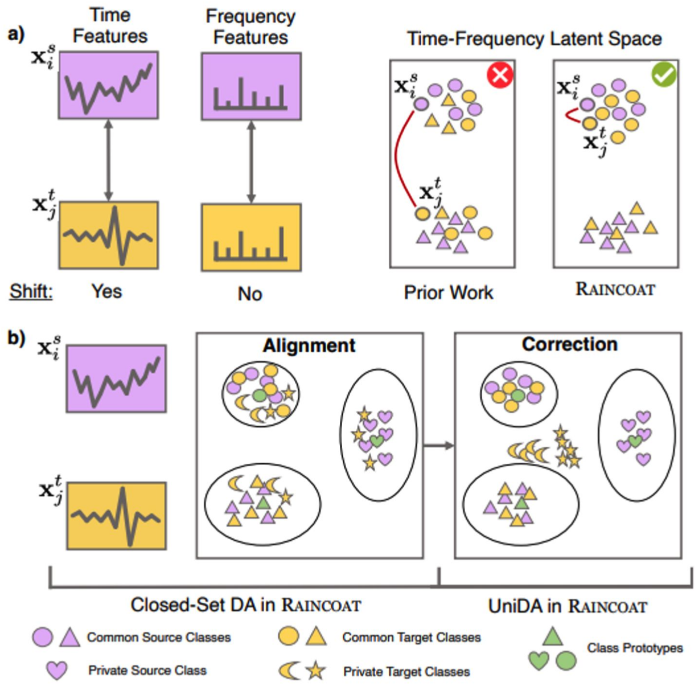
INTRODUCTION

Unsupervised domain adaptation (UDA)

Methods needed

1) produce generalizable representations robust to feature and label shifts

2) expand the scope of existing DA methods by supporting both closed-set and universal DA



INTRODUCTION

What makes DA difficult in “time-series”?

1) Domain shifts can occur in both the time and frequency features of time series

: shift that highly perturbs time features while frequency features are relatively unchanged, or vice versa may occur

2) Short cut learning

(leading to limited poor performance on data unseen during training)

OVERVIEW

RAINCOAT

f**R**equency-augmented **AlI**g**N**-then-**C**orrect for d**O**main **A**daptation for **T**ime series

: a novel domain adaptation method for time series data that can handle both feature and label shifts

- the first to address both closed-set and universal domain adaptation for time series

- has the unique capability of handling feature and label shifts

METHODS

Notation

- **Dataset** (source, target) :

$$\mathcal{D}^s = \{(\mathbf{x}_i^s, y_i^s)\}_{i=1}^{n_s} \qquad \mathcal{D}^t = \{(\mathbf{x}_i^t)\}_{i=1}^{n_t}$$

- **Label Sets** : $\mathcal{C}^s$ and $\mathcal{C}^t$

- **Sample distributions :**

$$\mathcal{D}^s \sim p_s(\mathbf{x}^s, y^s) \text{ and } \mathcal{D}^t \sim p_t(\mathbf{x}^t, y^t)$$

OVERVIEW

Domain shifts

feature shift

occurs when marginal probability distributions of x differ :

$p_s(\mathbf{x}) \neq p_t(\mathbf{x})$

while conditional probability distributions remain constant :

$p_s(y|\mathbf{x}) = p_t(y|\mathbf{x})$

▼ Property

feature shifts may occur in both time and frequency spectra

label shift

occurs when marginal probability distributions of y differ :

$p_s(y) \neq p_t(y)$

OVERVIEW

1) Closed-set Domain Adaptation

$$\mathcal{C}^s = \mathcal{C}^t$$

train a classifier f on Ds such that ***f*** generalizes to Dt

⇒ In real-world application?

Private labels in either the source or target domain may exist!

$$\bar{\mathcal{C}}^s = \mathcal{C}^s \backslash \mathcal{C}^t \qquad \bar{\mathcal{C}}^t = \mathcal{C}^t \backslash \mathcal{C}^s \qquad \mathcal{C}^{s,t} = \mathcal{C}^s \cap \mathcal{C}^t$$

OVERVIEW

2) UniDA (universal)

$$\bar{\mathcal{C}}^s = \mathcal{C}^s \backslash \mathcal{C}^t \qquad \bar{\mathcal{C}}^t = \mathcal{C}^t \backslash \mathcal{C}^s \qquad \mathcal{C}^{s,t} = \mathcal{C}^s \cap \mathcal{C}^t$$

- train a classifier f on Ds such that ***f*** generalizes to Dt
- identify samples in private target classes, as unknown samples

$$\mathbf{x}_i \sim \mathcal{D}^t[\bar{\mathcal{C}}^t]$$

METHODS

RAINCOAT

: an unsupervised method for closed set and universal domain adaptation in time series

- **time-frequency encoding**
- **feature alignment**
- **unknown sample detection**
- **training and inference**

consist of three modules :

time-frequency encoder G_{TF}, classifier H , decoder U_{TF}

Time-Frequency Feature Encoder

: RAINCOAT encodes both time and frequency features in its representations

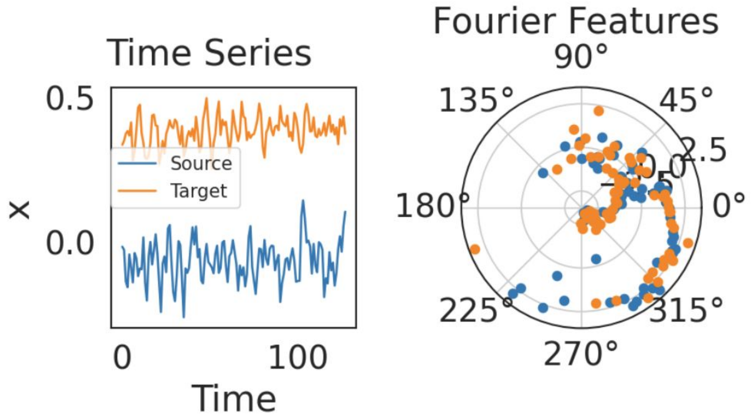
- source: $\mathbf{e}^s_{\mathrm{F},i}$ and $\mathbf{e}^s_{\mathrm{T},i}$
- target: $\mathbf{e}^t_{\mathrm{F},i}$ and $\mathbf{e}^t_{\mathrm{T},i}$

"frequency shift"

: another type of feature shift

$$(p_s(y|DFT(\mathbf{x}^s)) = p_t(y|DFT(\mathbf{x}^t)))$$

$$(p(DFT(\mathbf{x}^s)) \neq p(DFT(\mathbf{x}^t)))$$



METHODS

Time-Frequency Feature Encoder

STEPS

1) smooth : $\mathbf{x}_i = \mathrm{Smooth}(\mathbf{x}_i)$
2) DFT : $\mathbf{v}_i = \mathrm{DFT}(\mathbf{x}_i)$
3) convolution : $\tilde{\mathbf{v}}_i = \mathbf{B} * \mathbf{v}_i$
4) Transform : $\mathbf{a}_i, \mathbf{p}_i \leftarrow \tilde{\mathbf{v}}_i$
5) Extract : $\mathbf{e}_{\mathrm{F},i} = [\mathbf{a}_i; \mathbf{p}_i]$

latent representation $\mathbf{z}_i$: concatenation of frequency and time features $[\mathbf{e}_{\mathrm{F},i}; \mathbf{e}_{\mathrm{T},i}]$

METHODS

Correction Step in RAINCOAT

correction step helps reduce negative transfer by rejecting target unknown samples $\mathbf{x}_i \sim \mathcal{D}^t[\bar{\mathcal{C}}^t]$

HOW?

update the encoder GTF and decoder UTF by solving a reconstruction task on target samples (minimizing reconstruction loss)

* target features (before/ after) : $\mathbf{z}^t_{a,i}$ and $\mathbf{z}^t_{c,i}$

RESULT

target features of common samples $\mathbf{x}^t \sim \mathcal{D}^t[\mathcal{C}^{s,t}]$ should change less in the latent space than those of unknown samples

METHODS

Inference : Detect Target Private Samples

detects target unknown samples by determining the movement of target features before and after the correction step

feature vector $\mathbf{z}_i^t$: input to classifier ***H***, which consists of prototypes for each class ***W***= $[\mathbf{w}_1, \mathbf{w}_2, \cdots, \mathbf{w}_C]$

⇒ distance : $d(\mathbf{z}_i^t, \mathbf{w}_c)$

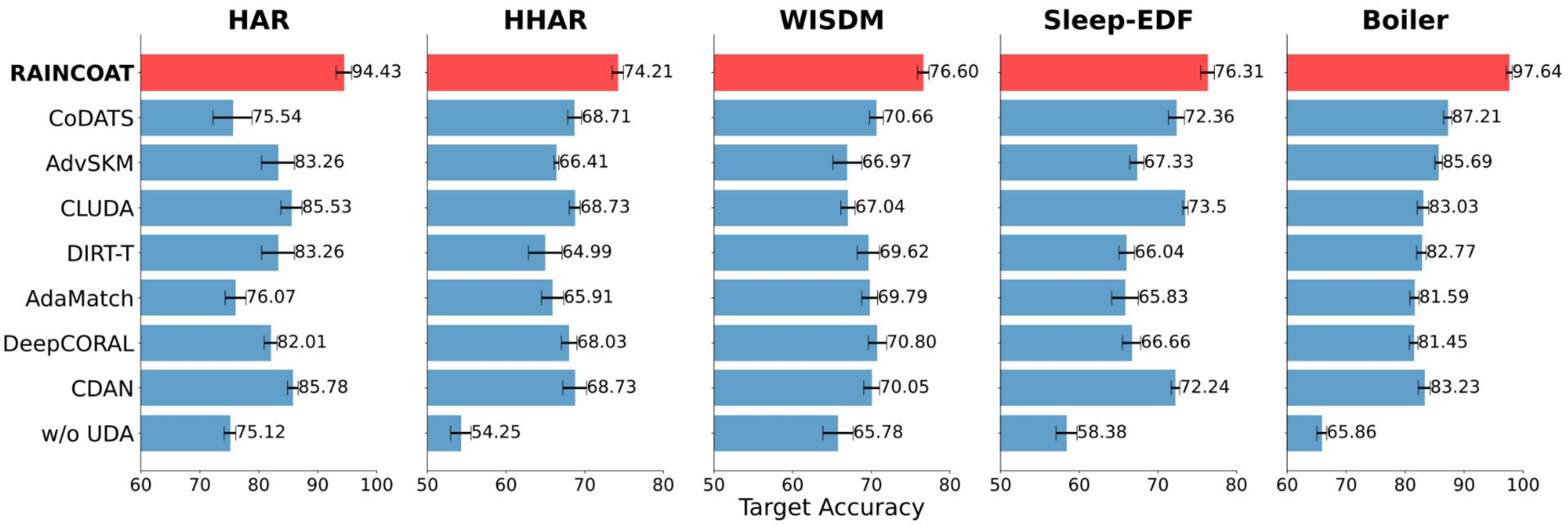
RESULT

difference of target features' distance to the assigned prototype before and after correction :

$$d_i^{ac} = |d(\mathbf{z}_{a,i}^t, \mathbf{w}_c) - d(\mathbf{z}_{c,i}^t, \mathbf{w}_c)|$$

EXPERIMENTS

for closed-set DA



EXPERIMENTS

for UNIDA

Source ↦ Target	UAN	DANCE	OVANet	UniOT	RAINCOAT
WISDM 3 ↦ 2	0	0	0.07	0.11	**0.51**
WISDM 3 ↦ 7	0	0	0.2	0.22	**0.52**
WISDM 13 ↦ 15	0	0.14	0.33	0.36	**0.50**
WISDM 14 ↦ 19	0.24	0.28	0.31	0.28	**0.55**
WISDM 27 ↦ 28	0.07	0.07	0.23	0.35	**0.59**
WISDM 1 ↦ 0	0.41	0.39	0.38	0.40	**0.43**
WISDM 1 ↦ 3	0.46	0.49	0.45	0.43	**0.51**
WISDM 10 ↦ 11	0	0	0.34	0.41	**0.53**
WISDM 22 ↦ 17	0.13	0	0.32	0.41	**0.52**
WISDM 27 ↦ 15	0.43	0.51	0.46	0.52	**0.57**
WISDM Avg	0.17	0.19	0.31	0.35	**0.52**
WISDM Std of Avg	0.04	0.05	0.04	0.05	**0.04**
W→H 4 ↦ 0	0	0.14	0.15	0.19	**0.49**
W→H 5 ↦ 1	0.24	0.22	0.25	0.28	**0.53**
W→H 6 ↦ 2	0.14	0.12	0.20	0.25	**0.55**
W→H 7 ↦ 3	0	0.15	0.04	0.14	**0.51**
W→H 17 ↦ 4	0.35	0.28	0.41	0.45	**0.57**
W→H 18 ↦ 5	0.20	0.27	0.29	0.32	**0.47**
W→H 19 ↦ 6	0.19	0.22	0.25	0.28	**0.51**
W→H 20 ↦ 7	0.11	0.17	0.35	0.41	**0.49**
W→H 23 ↦ 8	0.21	0.28	0.47	0.51	**0.57**
W→H Avg	0.16	0.21	0.24	0.28	**0.52**
W→H Std of Avg	0.03	0.02	0.03	0.02	**0.02**
H→W 0 ↦ 4	0.23	0.28	0.33	0.37	**0.45**
H→W 1 ↦ 5	0.19	0.31	0.38	0.42	**0.47**
H→W 2 ↦ 6	0.04	0.17	0.23	0.29	**0.39**
H→W 3 ↦ 7	0.25	0.32	0.34	0.40	**0.42**
H→W 4 ↦ 17	0.31	0.39	0.41	0.40	**0.51**
H→W 5 ↦ 18	0.28	0.34	0.37	0.36	**0.48**
H→W 6 ↦ 19	0.42	0.42	0.46	0.47	**0.49**
H→W 7 ↦ 20	0.39	0.41	0.41	0.44	**0.52**
H→W 8 ↦ 23	0.19	0.28	0.32	0.35	**0.46**
H→W Avg	0.26	0.32	0.36	0.39	**0.47**
H→W Std of Avg	0.05	0.05	0.03	0.04	**0.03**

Higher H-score is better. Best performance is indicated in bold.