Domain Adaptation for Regression under Monotonic Causal Shift

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InfoSci

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Domain **A**daptation under monotonic causal shift via **S**urrogate **D**omain **E**stimation (**DASDE**)

[Keywords]

Monotonic Causal Shift, Data Augmentation, Multi-Domain Adaptation, Regression for Tabular Dataset

INTRODUCTION

[Index]

1. Monotonic Covariate Shift
2. Data Augmentation

Monotonic Causal Shift

Traditional Domain Shift

- Covariate Shift

$$P(Y_S|X_S) = P(Y_T|X_T) \ \ and \ P(X_S) \neq P(X_T)$$

"Unseen/Biased Data Problem"

- Concept Shift

$$P(Y_S|X_S) \neq P(Y_T|X_T) \ \ and \ P(X_S) = P(X_T) \quad [X \rightarrow Y]$$

$$P(X_S|Y_S) \neq P(X_T|Y_T) \ \ and \ P(Y_S) = P(Y_T) \quad [Y \rightarrow X]$$

"Fixed Input & Shift Output"

$\{X_S, Y_S\}$: *Source Domain*, $\{X_T, Y_T\}$: *Target Domain*

Monotonic Causal Shift

	Sensor A	Sensor B
CJ	190	183
DH	180	?
YJ	170	177

100% CI : (177, 183)

$$P(X_T) = P\big(\Phi(X_S)\big) \ and \ P(X_T|Y_T) = P(\Phi(X_S)|Y_S)$$

$$and \ \ if \ \ X_i > X_k \ \ \text{then} \ \ \Phi(X_i) > \Phi(X_k)$$

$\Phi(.)$: *Shift Function*

"Sensor : Replacement Effect"

"Image : Light Reflection/Shadow Effect"

Data Augmentation

Traditional Data Augmentation

- **Image Data** Bi-Direction Graph

  Mirroring / Random Cropping

  Rotation / Local Wrapping

  Shearing / Color Shifting

- **Noise Injection** Robustness

  Random Masking

- **Generative Model**

Monotonic Transformation

"Monotonic Causal Shift Characteristic"

↓

"Monotonic Feature Augmentation"

↓

1. **Robust to Shift Situation**
2. **Fast Adaptation to Shifted Domain**

RELATED WORKS

[Index]

1. Monotonic Neural Network
2. Multi-Domain Adaptation

Monotonic Neural Networks

Monotonic NN Structure

[Paper Info]

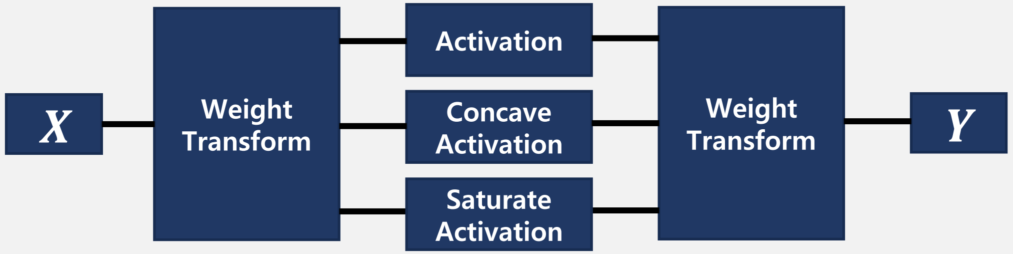
- Constrained Monotonic Neural Networks, 2023, ICML

[MAIN IDEA]

- **Weight Transformation Function** : Embedding to $[0, \infty)$
- **Concave Activation Function** : $-f(-x)$ ($f(x)$: activation function)
- **Saturate Activation Function** :

$$\begin{cases} f(x+1) - f(1) & (if\ x < 0) \\ -f(-x+1) + f(1) & (otherwise) \end{cases}$$

- **Monotonic NN Architecture**



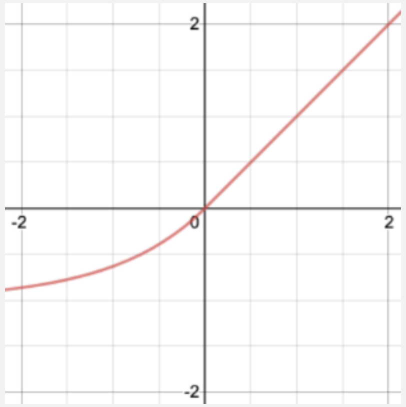
Monotonic Function

[Paper Info]

- Fast And Accurate Deep Network Learning by Exponential Linear Units (ELUs), 2016, ICLR

[MAIN IDEA]

- **No Dead Neuron** : $\forall x \ \ f'(x) > 0$
- **Smooth and Strong Monotonic Increasing Function**
- **Fast Convergence**



$$ELU(x) = \begin{cases} x & (if\ x > 0) \\ e^x - 1 & (otherwise) \end{cases}$$

Multi-Domain Adaptation

DARC

[Paper Info]

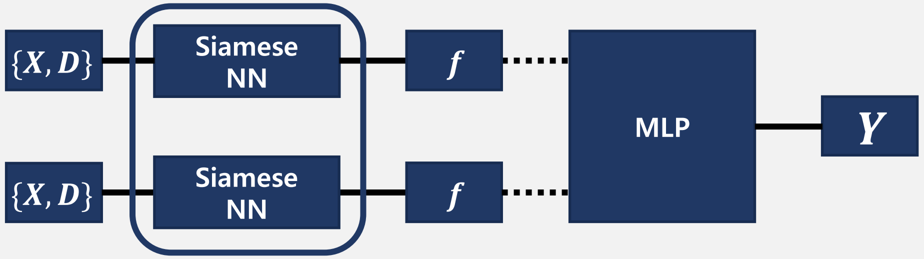
- Multi-domain adaptation for regression under conditional distribution shift, 2023, Expert Systems With Applications

[MAIN IDEA]

- **Domain Labeling** : One-Hot Encoding
- **Shame Network** : Feature & Domain → Shared Feature
- **Conditional Distribution Matching** :

$$\text{minimize } \left| |f_i - f_k| - |y_i - y_k| \right| \qquad f : shared\ feature$$

- **DARC Architecture**



MAML

[Paper Info]

- Model-Agnostic Meta-Learning for Fast Adaptation of Deep Networks, 2017, ICML
- Online Meta-Learning, 2019, ICML

[MAIN IDEA]

- **Meta-Parent Model** : Shared Feature
- **Domain-Specific Child Model** : Domain Specific Feature
- **Fast Few-Shot Learning** :

1. Child Model : Initial weight = Parent Model
2. Child Model update weight using their Domain
3. Parent Model update weight

→ minimize $\sum_{n_D} Child\_Error_k$ $\quad n_D$: # of Domain

Loop (1 ~ 3)

4. Use Parent Model as Initial Weight

PROPOSED METHOD

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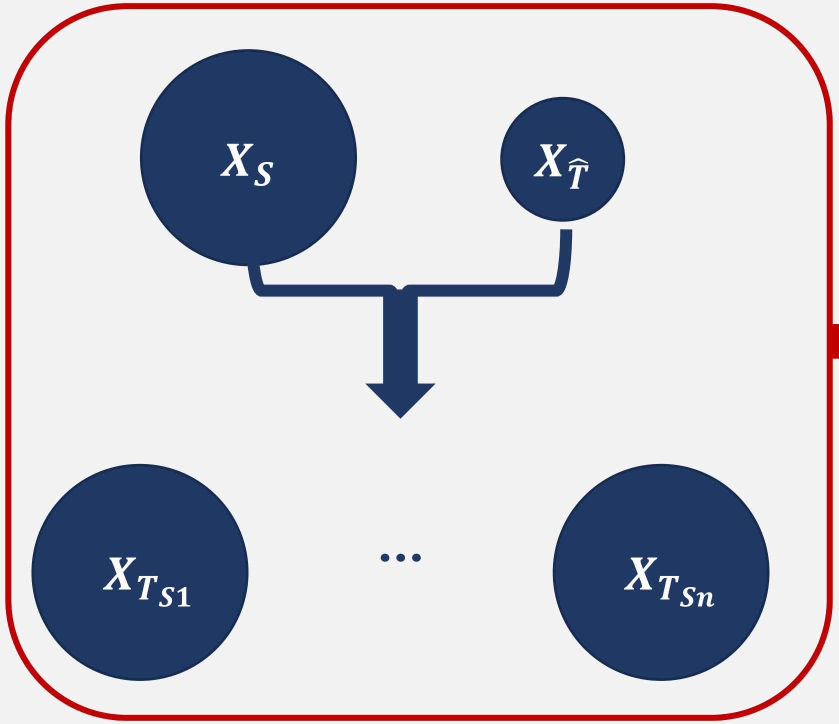
1. Full Architecture
2. Surrogate Domain Estimation

Full Architecture

① SDE

Surrogate Domain Estimation



X_S : *Source Domain Input*

$X_{\hat{T}}$: *Known Target Domain Input*

X_{T_S} : *Surrogate Domain Input*

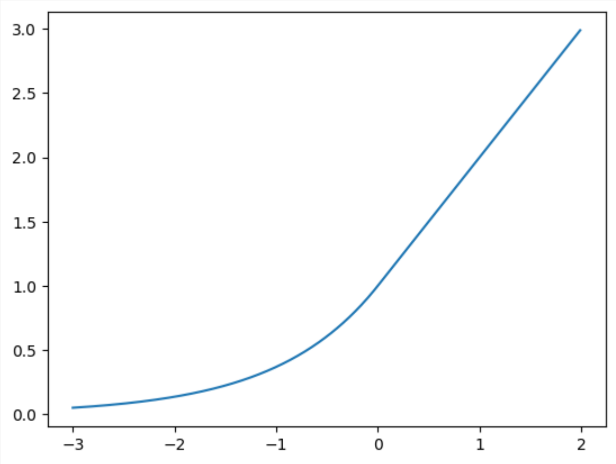
② apply DARC/MAML

Multi-Domain Adaptation

Surrogate Domain Estimation (SDE)

Modified Exponential Linear Units (MELU)

$$MELU(x) = \begin{cases} e^{x} & (if\ x < 0) \\ x + 1 & (otherwise) \end{cases}$$

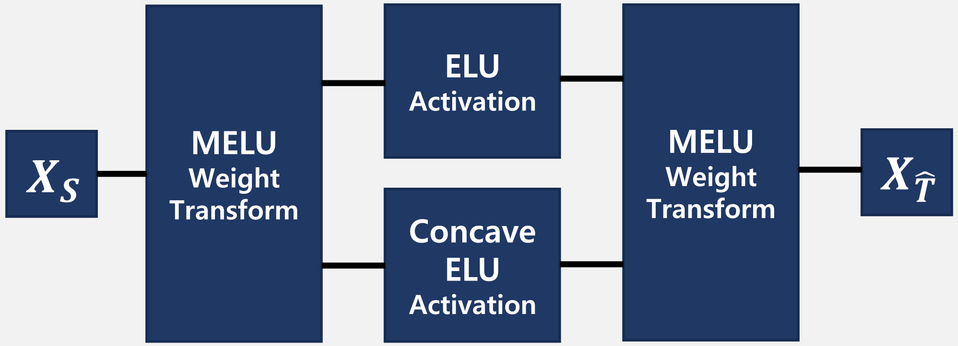


- **Fast Convergence** : ELU Characteristic
- **Computation Cost**

  : high when x<0, but low when x>0

Surrogate Domain Estimation (SDE)

"Estimate Monotonic Causal Shift Function"



X_S : *Source Domain Input*
$X_{\hat{T}}$: *Known Target Domain Input*

- **MELU Weight & ELU based Activation Function**
- **Shift Function** : Source Domain → Target Domain
- **Strong Monotonicity** : $\forall x \quad f'(x) > 0$
- **Available to Explain Convex/Concave Function**

EXPERIMENTS

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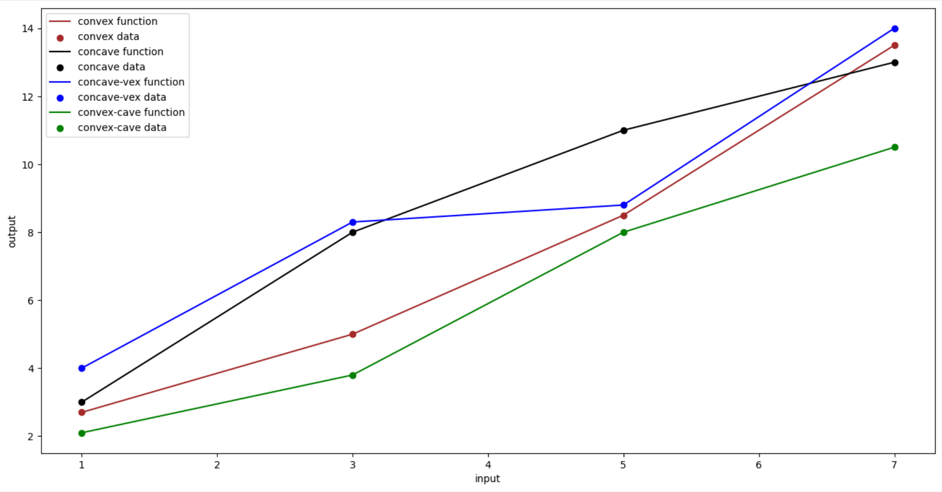
1. Monotonic Structure Experiment
2. DA Experiment Setting
3. Result & Conclusion

Monotonic Structure Experiment - Setting

[Dataset]



- 4 kinds of Function Setting(4 Shot Learning)

  : Convex, Concave, Concave-Convex, Convex-Concave

- Learning Rate : 0.01, NN Structure : 1-10-10-1

[Comparison]

Weight Transformation Function

- MELU $min(1, e^{w}) + max(1, w+1)$
- SOFTPLUS $log(1 + e^{w})$
- ABS $|w|$
- SQUARE w^2
- SQRT $\sqrt{|w|}$

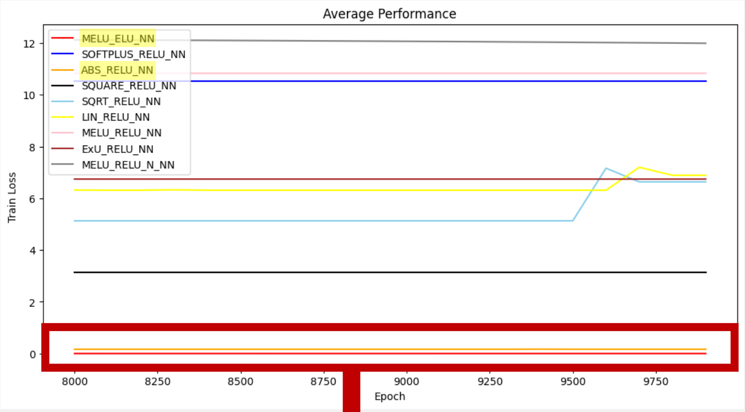
Activation Function

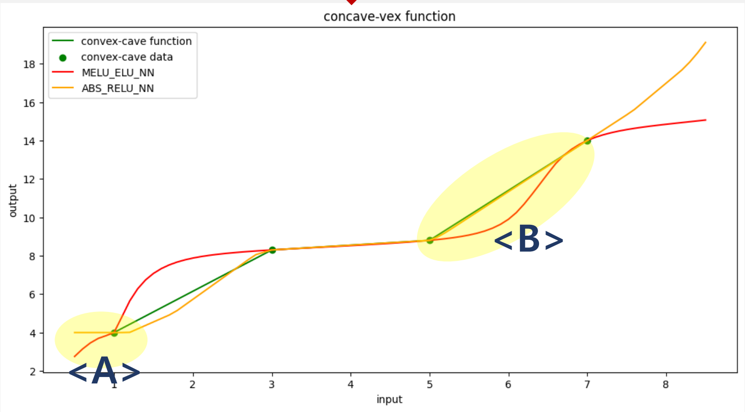
- ELU & Concaved ELU($-ELU(-x)$)
- ReLU & Concaved ReLU($-ReLU(-x)$)
- Saturated ReLU

$$\begin{cases} ReLU(x+1) - 1 & (if\ x < 0) \\ -ReLU(-x+1) + 1 & (otherwise) \end{cases}$$

Monotonic Structure Experiment - Result

[Result] 4 Experiments (4 dataset x 1)





[Conclusion]

1. **Fast & Stable Train Structure**

   : MELU with ELU & Concave ELU

   : ABS with ReLU & Concave ReLU

2. **Strong Monotonicity**

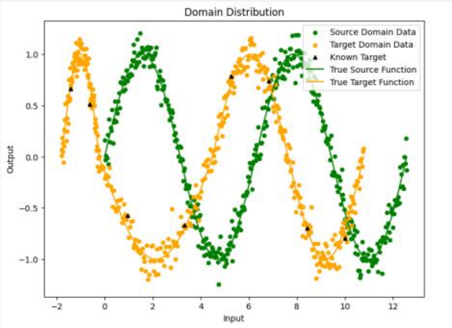
   : MELU with ELU & Concave ELU <A>

3. **Smooth Estimation**

   : MELU with ELU & Concave ELU <B>

DA Experiment - Setting

[Dataset]



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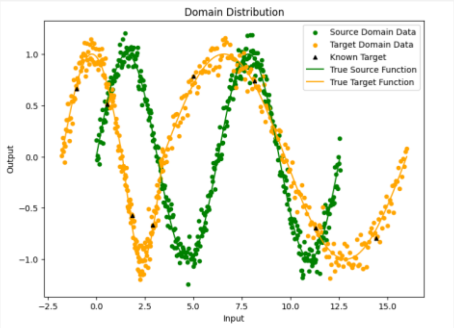

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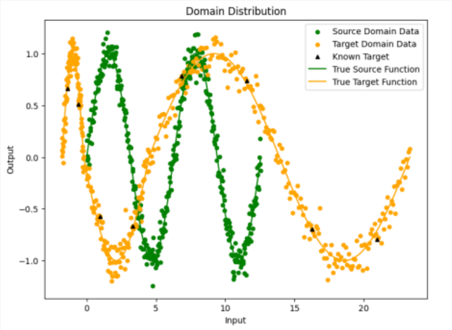

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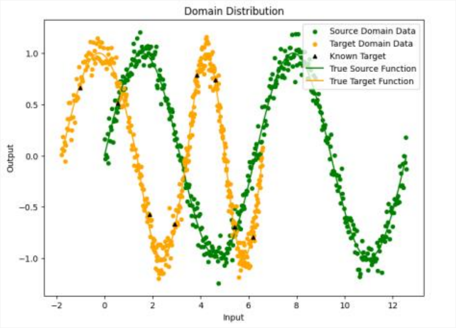


(d)

<Source Dataset>

$$P(X_S) \sim Unif(0, 4\pi)$$

$$P(Y_S|X_S) \sim N(sin(X_S), 0.1)$$

$$n_S = 400$$

<Target Dataset>

$$P(X_T) = P(\Phi(X_S))$$

$$P(Y_T) = P(Y_T)$$

$$P(X_T|Y_T) = P(\Phi(X_S)|Y_S)$$

$$n_T = 400, \qquad n_{\hat{T}} = 8$$

n_S : # of Source Domain Data, $\{X_S, Y_S\}$: Source Domain

n_T : # of Target Domain Data, $\{X_T, Y_T\}$: Target Domain

$n_{\hat{T}}$: # of Known Target Domain Data, $\Phi(.)$: Shift Function

DA Experiment – Surrogate Domain Estimation

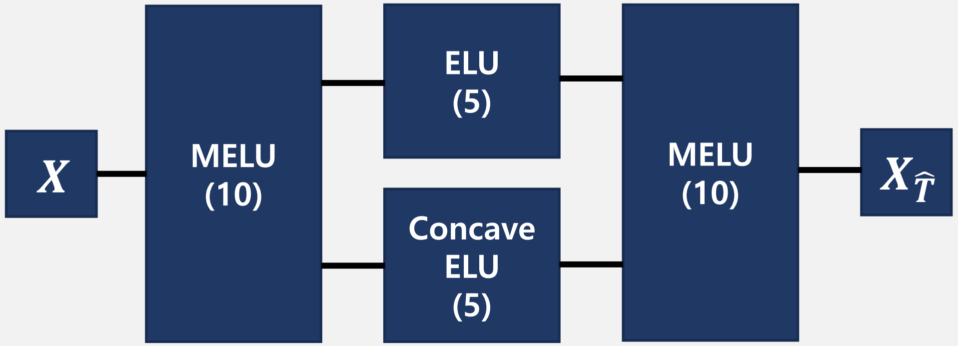
[Surrogate Domain Estimator]

Architecture

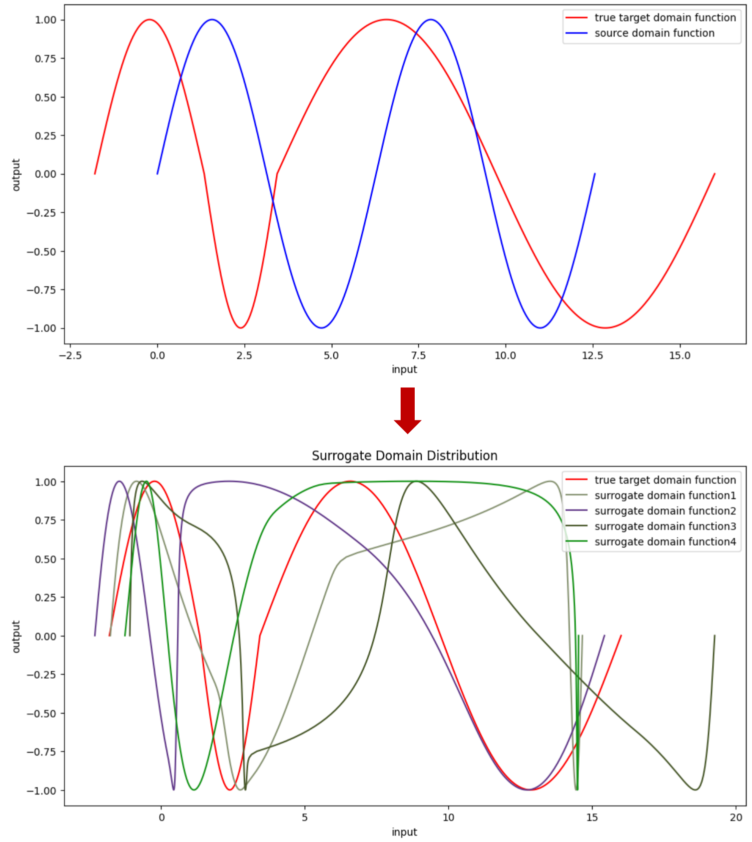
- Input : $X \sim P(X_S)$ [Random Sampling & Sorting]
- Output : $X_{\hat{T}}$ [Known Target Domain Input & Sorting]
- Structure

  weight : MELU

  activation function : ELU & Concave ELU



[Result] 4 Surrogate Domain Estimation



DA Experiment – Multi-Domain Adaptation

MAML-SDE

Meta-Learning Architecture

- Input : $\{X_S, X_{T_{S1}}, X_{T_{S2}}, X_{T_{S3}}, X_{T_{S4}}\}$ [X_{T_S} : Surrogate Domain]
- Output : $\{Y_S, Y_S, Y_S, Y_S, Y_S\}$
- Structure iterative update Child & Meta-Model

    (Child-Model) initial weight : Meta-Model

    (Meta-Model) Val_Error_{Child} → update

Inference Architecture

- Input : $X_{\hat{T}}$
- Output : $Y_{\hat{T}}$
- Structure

    initial weight : Meta-Model

DARC-SDE

Latent Transformation Architecture

- Input : $\{X_S, X_{T_{S1}}, X_{T_{S2}}, X_{T_{S3}}, X_{T_{S4}}, X_{\hat{T}}\}$ **+ Domain Label**
- Output : $\{F_S, F_{T_{S1}}, F_{T_{S2}}, F_{T_{S3}}, F_{T_{S4}}, F_{\hat{T}}\}$ [F: Shared Feature]
- Structure

    Siamese Neural Network

Inference Architecture

- Input : $\{F_S, F_{T_{S1}}, F_{T_{S2}}, F_{T_{S3}}, F_{T_{S4}}, F_{\hat{T}}\}$
- Output : $\{Y_S, Y_S, Y_S, Y_S, Y_S, Y_{\hat{T}}\}$
- Structure

    MLP Structure

DA Experiment – Comparison Method

DEFAULT SETTING

Few-Shot Learning Architecture

- Input : $X_{\hat{T}}$ - Output : $Y_{\hat{T}}$
- Structure

initial weight : MLP Training on $\{X_S, Y_S\}$

Only Target Domain Architecture

- Input : $X_{\hat{T}}$ - Output : $Y_{\hat{T}}$
- Structure

MLP Structure

DARC

Latent Transformation Architecture

- Input : $\{X_S, X_{\hat{T}}\}$ + **Domain Label**
- Output : $\{F_S, F_{\hat{T}}\}$ [F: Shared Feature]
- Structure

Siamese Neural Networks

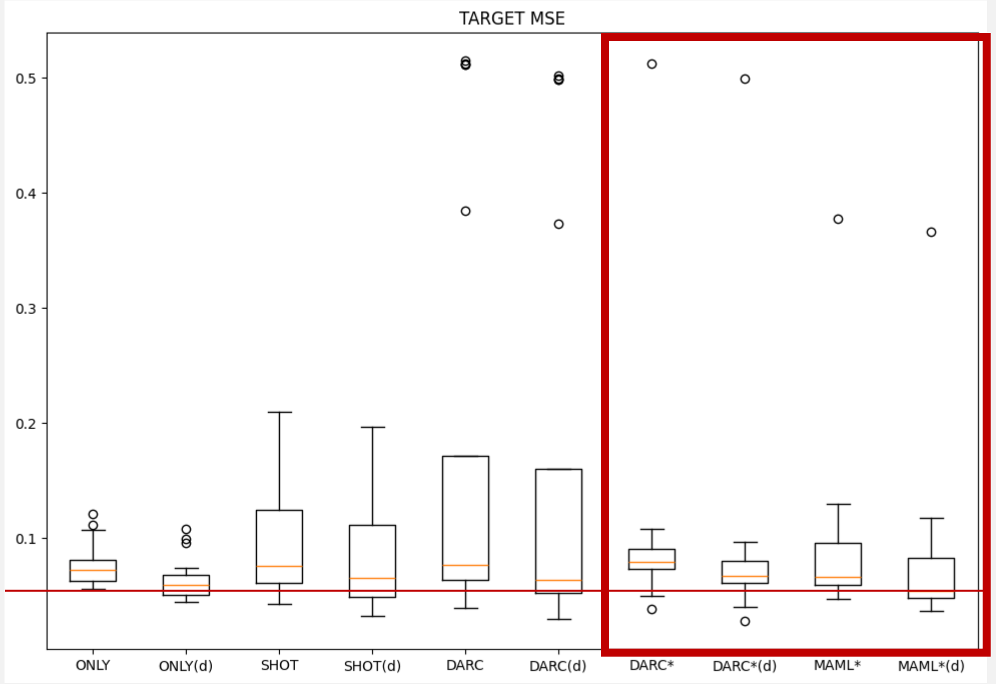
Inference Architecture

- Input : $\{F_S, F_{\hat{T}}\}$
- Output : $\{Y_S, Y_{\hat{T}}\}$
- Structure

MLP Structure

Result & Conclusion

[Result] 20 Experiments (4 dataset x 5)



0.072	0.059	0.076	0.065	0.076	0.063	0.079	0.067	**0.066**	**0.054**

ONLY : Only Target Domain, SHOT : Few-Shot Learning

* : applying SDE method, (d) : denoised MSE

[Conclusion]

1. **MAML-SDE show high Performance**

   : Median Performance (MSE 0.066, MSE(d) 0.054)

2. **DARC → DARC-SDE**

   : Lower Variance (Std(d) 0.186 → 0.098)

   : Lower Median Performance (MSE(d) 0.063 → 0.067)

3. **MAML/DARC is not suitable under Monotonic Causal Shift**

   [vs Only Target Domain Performance]

   : Low Performance & Stable (DARC, DARC-SDE)

   : High Performance & Unstable (MAML-SDE)

   ∵ DARC & MAML : Concept Shift(+Covariate Shift)

Domain **A**daptation under monotonic causal shift via **C**ausal **D**istribution **T**ransformation (**DACDT**)

[Keywords]

Monotonic Causal Shift, Restore Function, Domain Transformation, Regression for Tabular Dataset

INTRODUCTION

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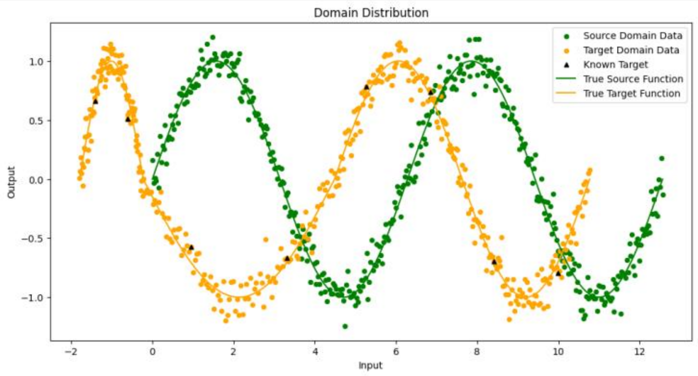
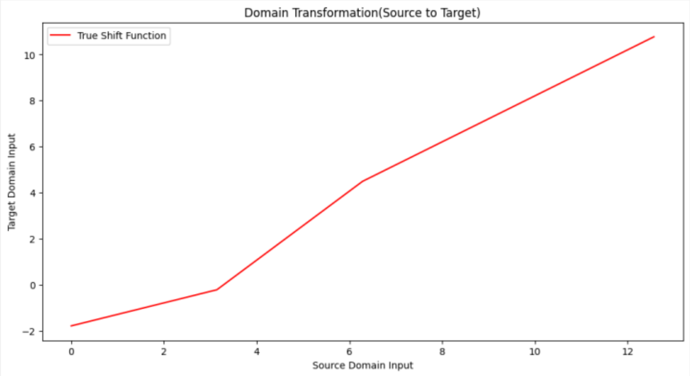
Monotonic Causal Shift Function

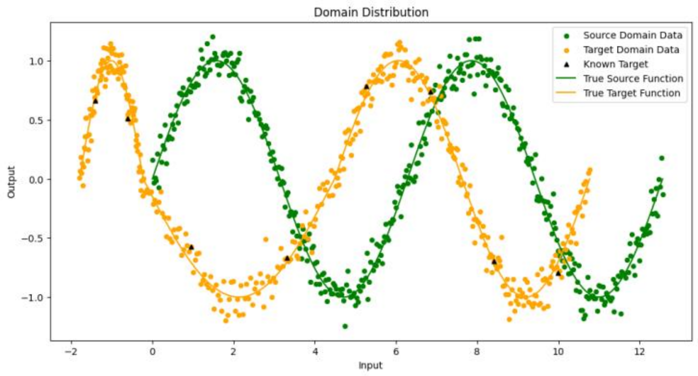
Data Perspective	Shift Function Perspective



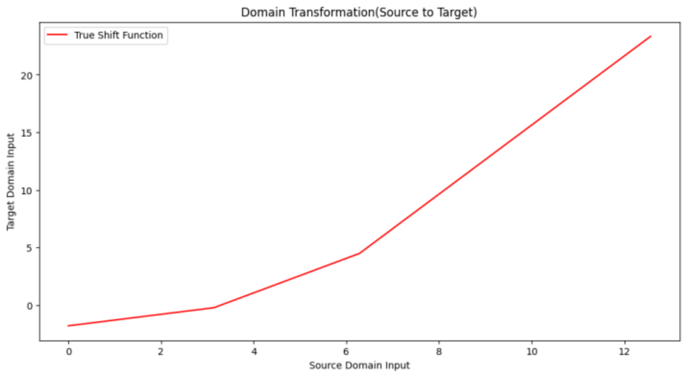
(a)



(a)



(c)



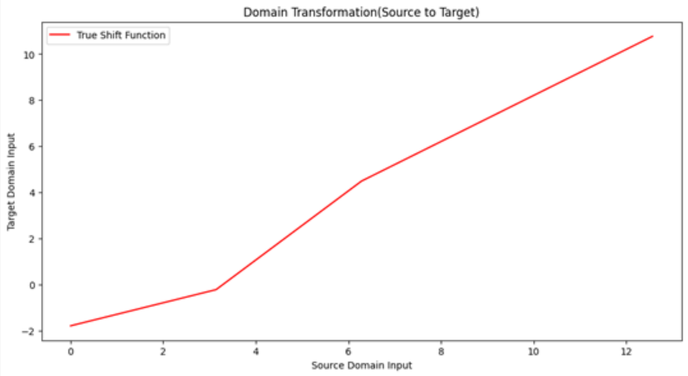
(c)

Restore Function

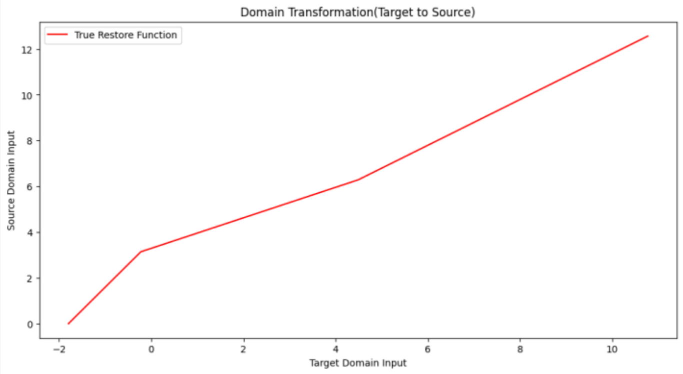
Shift Function

Inverse Function!!

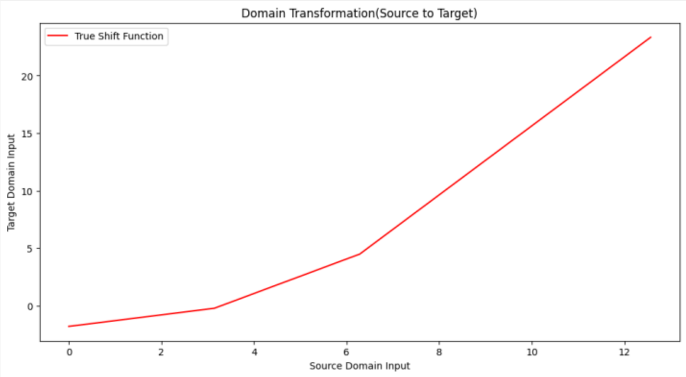
Restore Function



(a)



(a)



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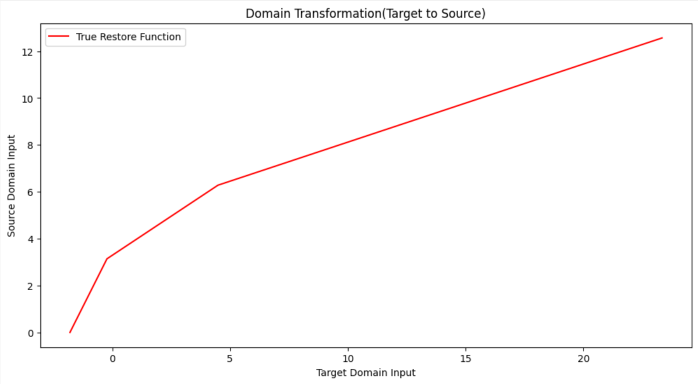

(c)

PROPOSED METHOD

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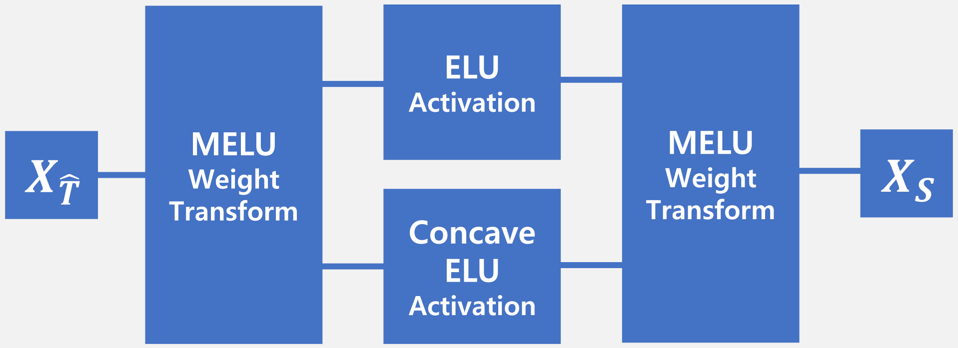
Full Architecture

[Restore Model Architecture]

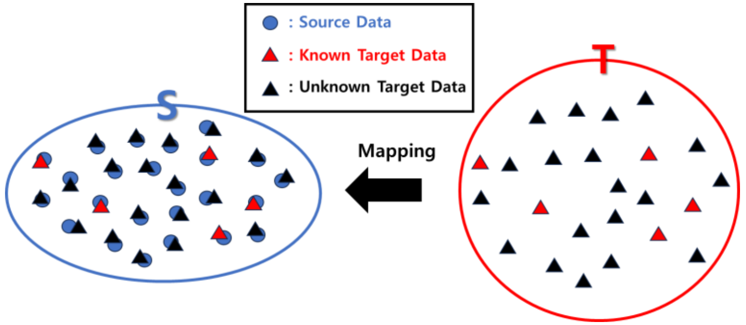
"Monotonic Neural Network"



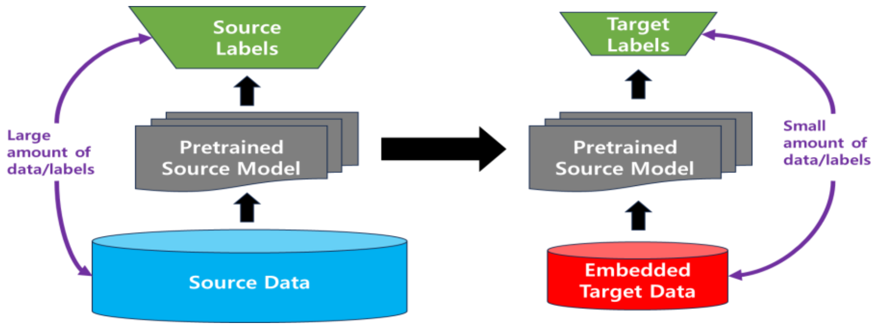
$X_{\hat{T}}$: *Known Target Domain Input*
X_S : *Source Domain Input*

[Use Cases]

① Restore Function Estimation

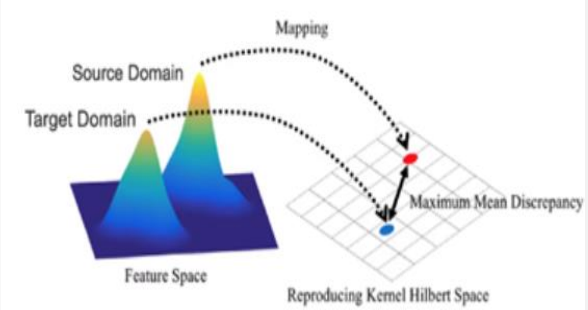


② Use Source Function to Inference



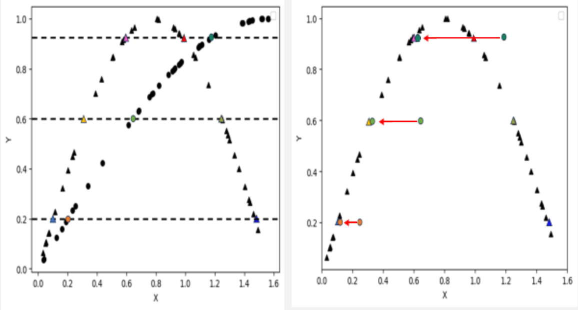
Causal Distribution Transformation

Maximum **M**ean **D**iscrepancy (**MMD**)	**N**eighborhood **S**imilarity (**NS**)



"Marginal Distribution"

$$\|P(X_S) - P\left(\Phi^{-1}(X_{\hat{T}})\right)\|$$



"Causal Distribution"

$$\|P(X_S|Y_S) - P\left(\Phi^{-1}(X_{\hat{T}})|Y_{\hat{T}}\right)\|$$

$$L_{MMD} = \max_m \left(\left\| \frac{1}{n^S} \sum_{j=1}^{n^S} \varphi_m(x_i^s) - \frac{1}{n^{\hat{T}}} \sum_{j=1}^{n^{\hat{T}}} \varphi_m\left(x_j^{\hat{T}}\right) \right\|^2 \right)$$

n^S : # of Source Domain Data, x^S : Source Domain Input

$n^{\hat{T}}$: # of Known Target Domain Data, $x^{\hat{T}}$: Known Target Domain Input

$\varphi(.)$: RKHS embedding function, $\Phi^{-1}(.)$: Restore Function

$$L_{ns} = \frac{1}{n^{\hat{T}}} \sum_{i=1}^{n^{\hat{T}}} \left| x_{\hat{j}}^S - \Phi^{-1}\left(x_i^{\hat{T}}\right) \right|_2$$

$$\left(\hat{j} = \arg\min_j \left| x_{(j)}^S - \Phi^{-1}\left(x_i^{\hat{T}}\right)\right|_2 + \left| y_{(j)}^S - y_i^{\hat{T}} \right|\right)$$

$$\left\{ x_{(1)}^S, x_{(2)}^S, \cdots, x_{(k)}^S \;\middle|\; \left| y_{(1)}^S - y_i^{\hat{T}} \right| < \cdots < \left| y_{(k)}^S - y_i^{\hat{T}} \right| \right\}$$

n^S : # of Source Domain Data, $\{x^S, y^S\}$: Source Domain

$n^{\hat{T}}$: # of Known Target Domain Data, $\{x^S, y^S\}$: Known Target Domain

k : # of neighbor candidates, $\Phi^{-1}(.)$: Restore Function

EXPERIMENTS

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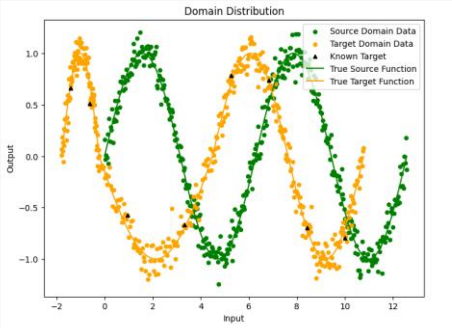
DA Experiment - Setting

[Dataset]



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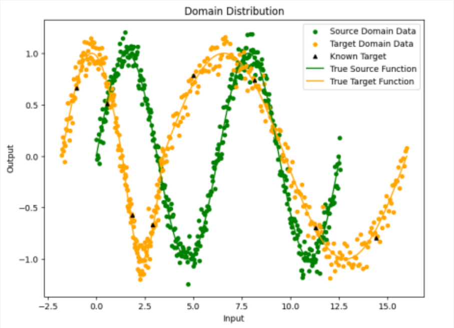

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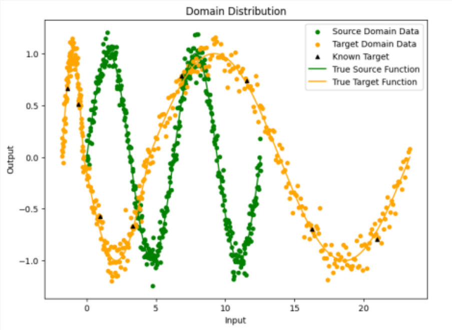

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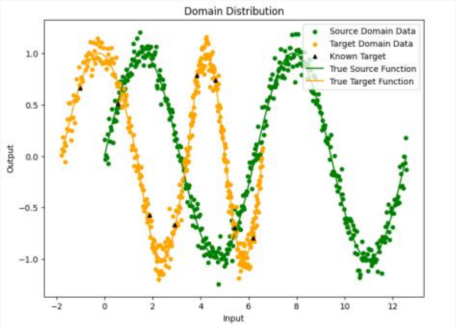


(d)

<Source Dataset>

$$P(X_S) \sim Unif(0, 4\pi)$$

$$P(Y_S|X_S) \sim N(sin(X_S), 0.1)$$

$$n_S = 400$$

<Target Dataset>

$$P(X_T) = P\big(\Phi(X_T)\big)$$

$$P(Y_T) = P(Y_T)$$

$$P(X_T|Y_T) = P(\Phi(X_S)|Y_S)$$

$$n_T = 400, \qquad n_{\hat{T}} = 8$$

n_S : # of Source Domain Data, $\{X_S, Y_S\}$: Source Domain

n_T : # of Target Domain Data, $\{X_T, Y_T\}$: Target Domain

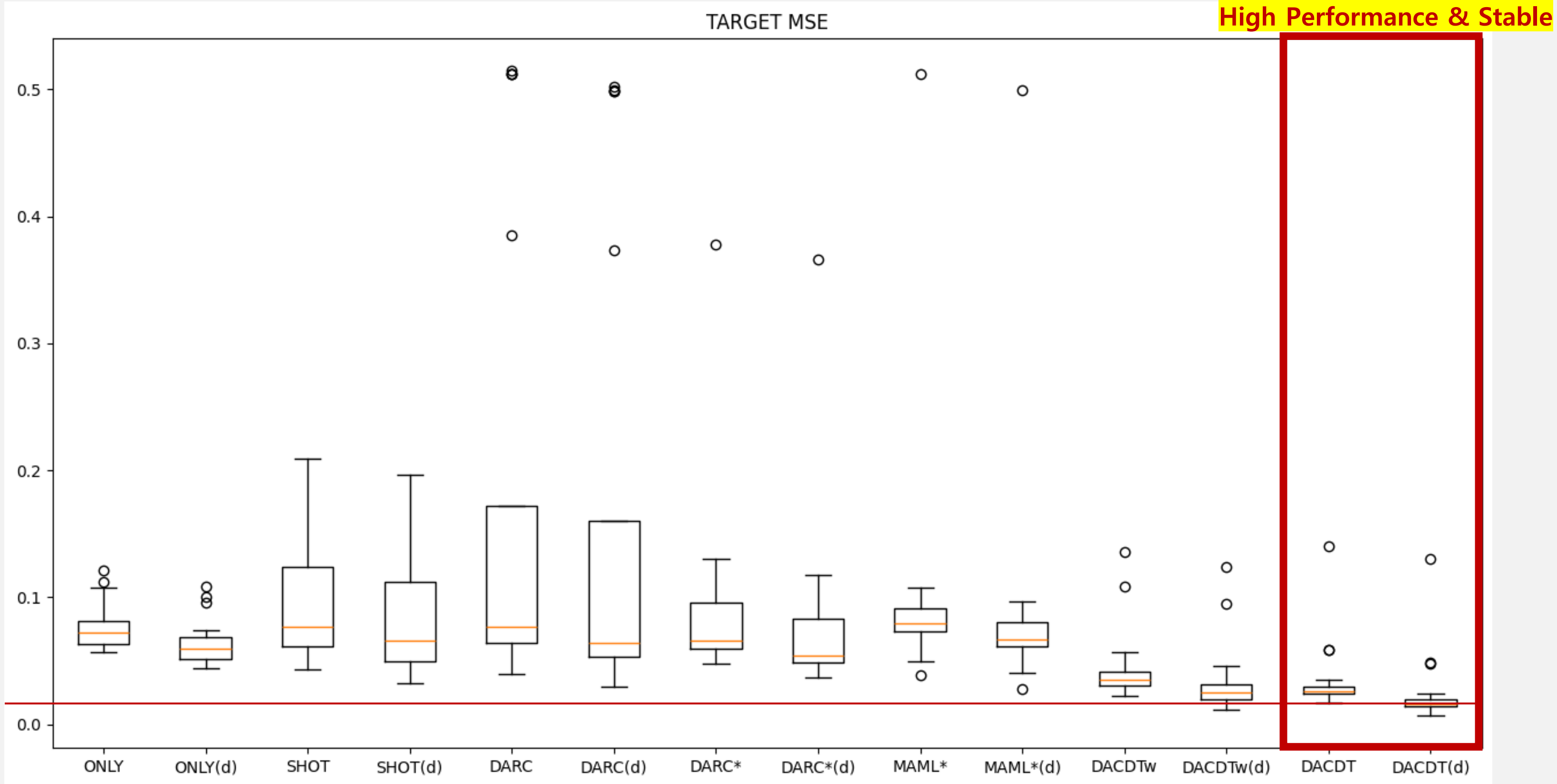
$n_{\hat{T}}$: # of Known Target Domain Data, $\Phi(.)$: Shift Function

DA Experiment – DA Method

Proposed Method (DACDT)	Comparison Method
Restore Model Architecture - Input : $X_{\hat{T}}$ - Output : X_S - Structure weight : MELU activation function : ELU & Concave ELU Loss function : $L_{MMD} + L_{NS}$ **Inference Model Architecture** - Input : X_S - Output : Y_S - Structure MLP Structure	**- Only Target Domain** **- Few-Shot Learning** **- DARC** **- DARC-SDE** **- MAML-SDE** **- DACDT with MLP Restore Model**

Result

[Result] 20 Experiments (4 dataset x 5)



ONLY	ONLY(d)	SHOT	SHOT(d)	DARC	DARC(d)	DARC*	DARC*(d)	MAML*	MAML*(d)	DACDTw	DACDTw(d)	DACDT	DACDT(d)
0.072	0.059	0.076	0.065	0.076	0.063	0.079	0.067	0.066	0.054	0.034	0.024	**0.026**	**0.015**

ONLY : Only Target Domain, SHOT : Few-Shot Learning, * : applying SDE method, (d) : denoised MSE, DACDTw : DACDT with MLP Restore Model

CONCLUSION

Conclusion

[Contribution]

- **Novel Problem Definition**

  : Monotonic Causal Shift

- **Tabular Data Augmentation**

  : Surrogate Domain Estimation

- **Efficient Monotonic Unit**

  : MELU

- **Achieve High Performance**

  : DACDT

[Future Works]

- **More Complex Experiments**

  : n-dim Toy Data Experiments

  with non-shift and shift feature

  : Real Dataset Experiments

- **Meta-Restore Model**

  : SDE + MAML → Estimate Initial Weight

- **Explainable Causal Shift Detection**

  : Identity Function Similarity

Thank You

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