Adapting learning models to distribution shifts with affine alignment

Antoine Collas - CMAP Retreat 2025
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1. Introduction to Domain Adaptation (DA)
2. Skada-Bench: Benchmarking Unsupervised DA methods
3. Joint shifts in (X, y) on manifolds: GOPSA

1. Introduction to Domain Adaptation (DA)

Supervised learning

Independent and identically distributed data:

$$\{(x_n, y_n)\}_{n=1}^{N} \sim \mathbb{P}(X, Y)$$

$x_n \in \mathcal{X}$, e.g. $\mathbb{R}^d$ and $y_n \in \mathcal{Y}$, e.g. $\{-1,1\}$ for binary classification

Goal: find a predictor $f : \mathcal{X} \mapsto \mathcal{Y}$ by empirical risk minimization

$$\min_{f \in \mathcal{F}} \left\{ \hat{R}(f) = \frac{1}{N} \sum_{n=1}^{N} \ell(y_n, f(x_n)) \right\}$$

with ℓ a loss function

Domain Adaptation (DA) Problem

Source domain ($\mathcal{S}$) and Target domain ($\mathcal{T}$) with

$$\mathbb{P}_{\mathcal{S}}(X, Y) \neq \mathbb{P}_{\mathcal{T}}(X, Y)$$

Source domain ($\mathcal{S}$): MNIST

2

8

Target domain ($\mathcal{T}$): SVHN

2

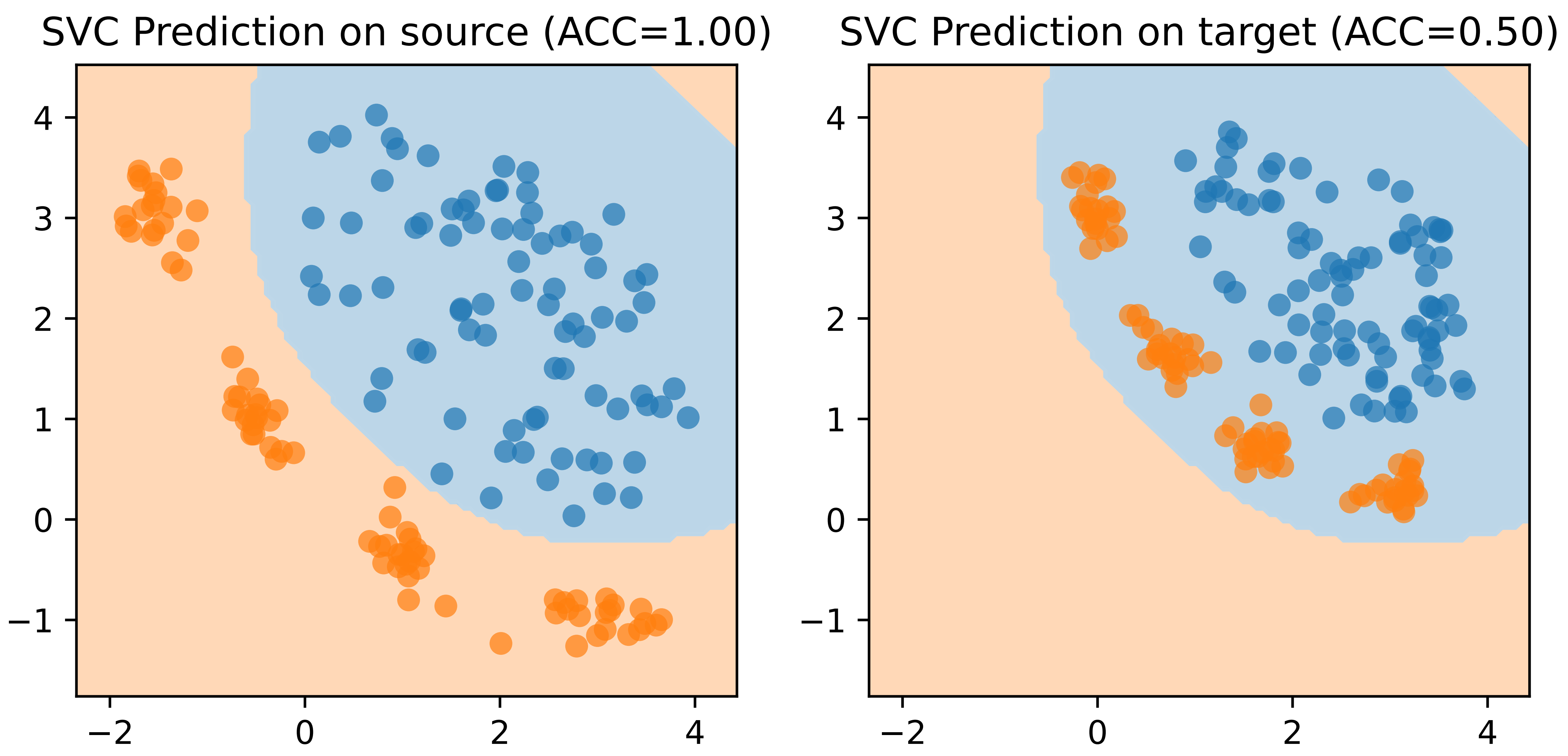
8

Domain Adaptation (DA) Problem

Source domain ($\mathcal{S}$) and Target domain ($\mathcal{T}$) with

$$\mathbb{P}_{\mathcal{S}}(X, Y) \neq \mathbb{P}_{\mathcal{T}}(X, Y)$$

Training on the source domain (classical empirical risk minimization):



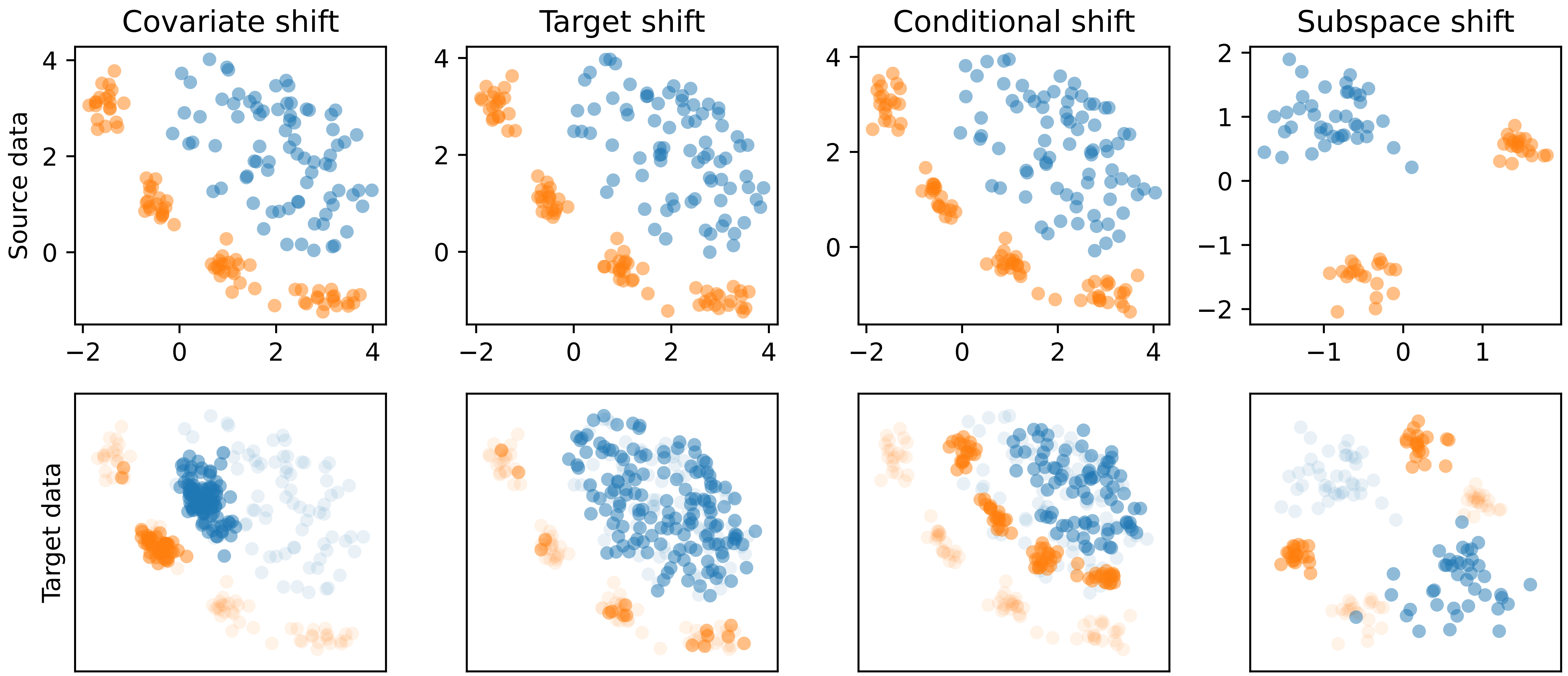
Simple shifts can lead to very bad classifications on the target domain!

Unsupervised DA Problem

Source domain is labeled: $\{(x_n, y_n)\}_{n=1}^{N^{\mathcal{S}}} \sim \mathbb{P}_{\mathcal{S}}(X, Y)$

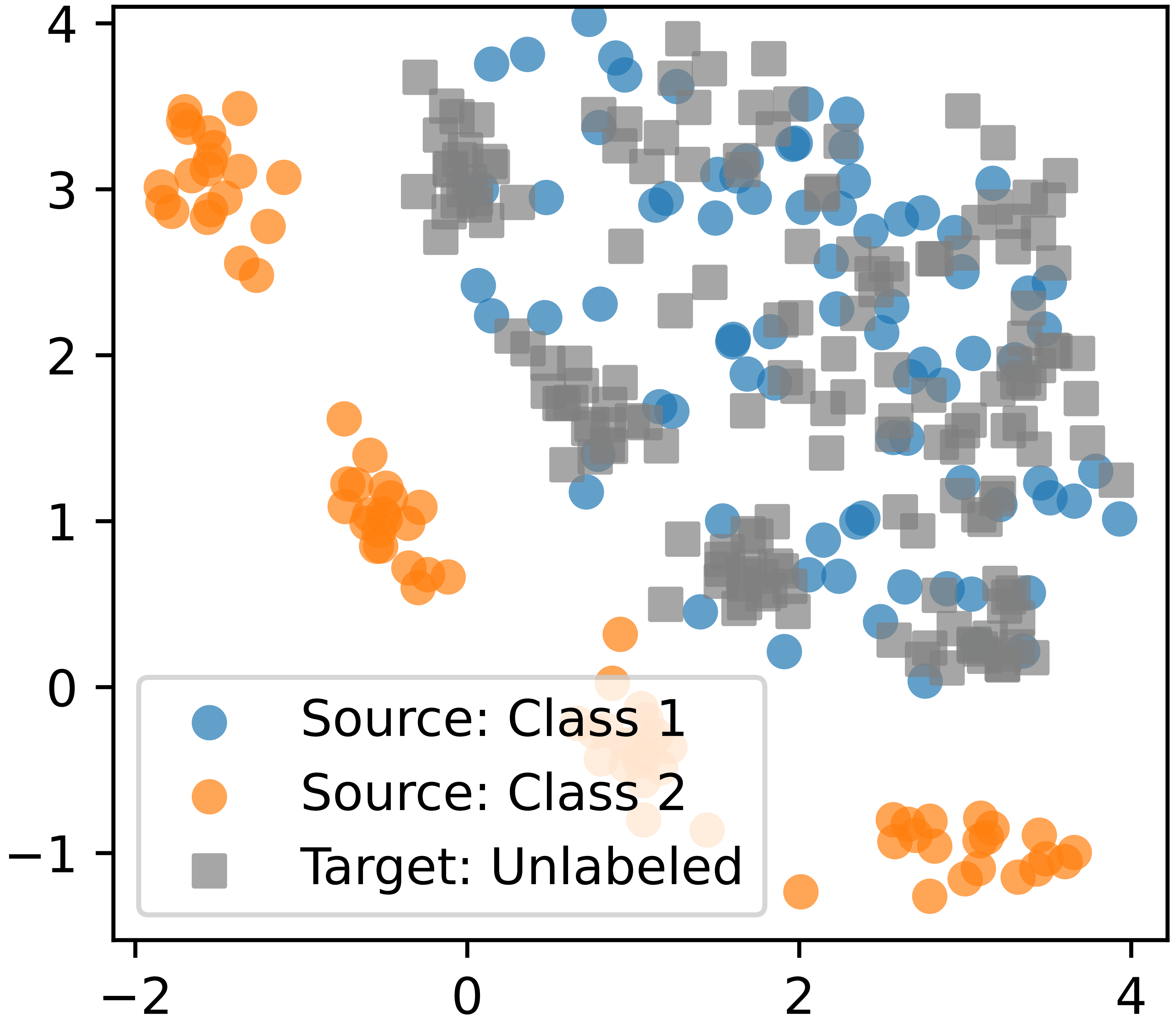
Target domain is unlabeled: $\{(x_n, \cdot\,)\}_{n=1}^{N^{\mathcal{T}}} \sim \mathbb{P}_{\mathcal{T}}(X, Y)$

Assumptions on the shift between $\mathbb{P}_{\mathcal{S}}(X, Y)$ and $\mathbb{P}_{\mathcal{T}}(X, Y)$:



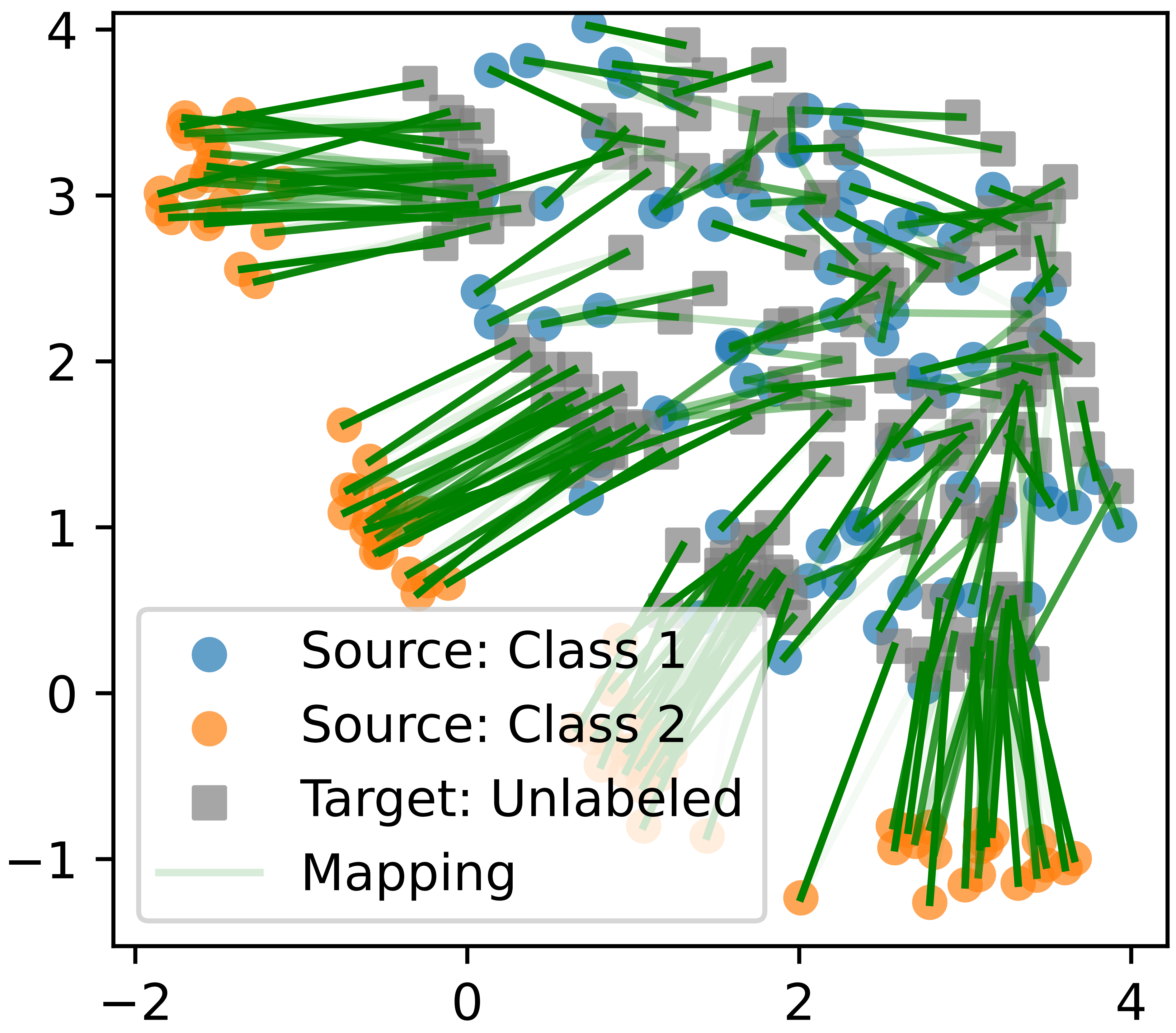
Toy Example: Mapping-Based UDA

Problem setting:



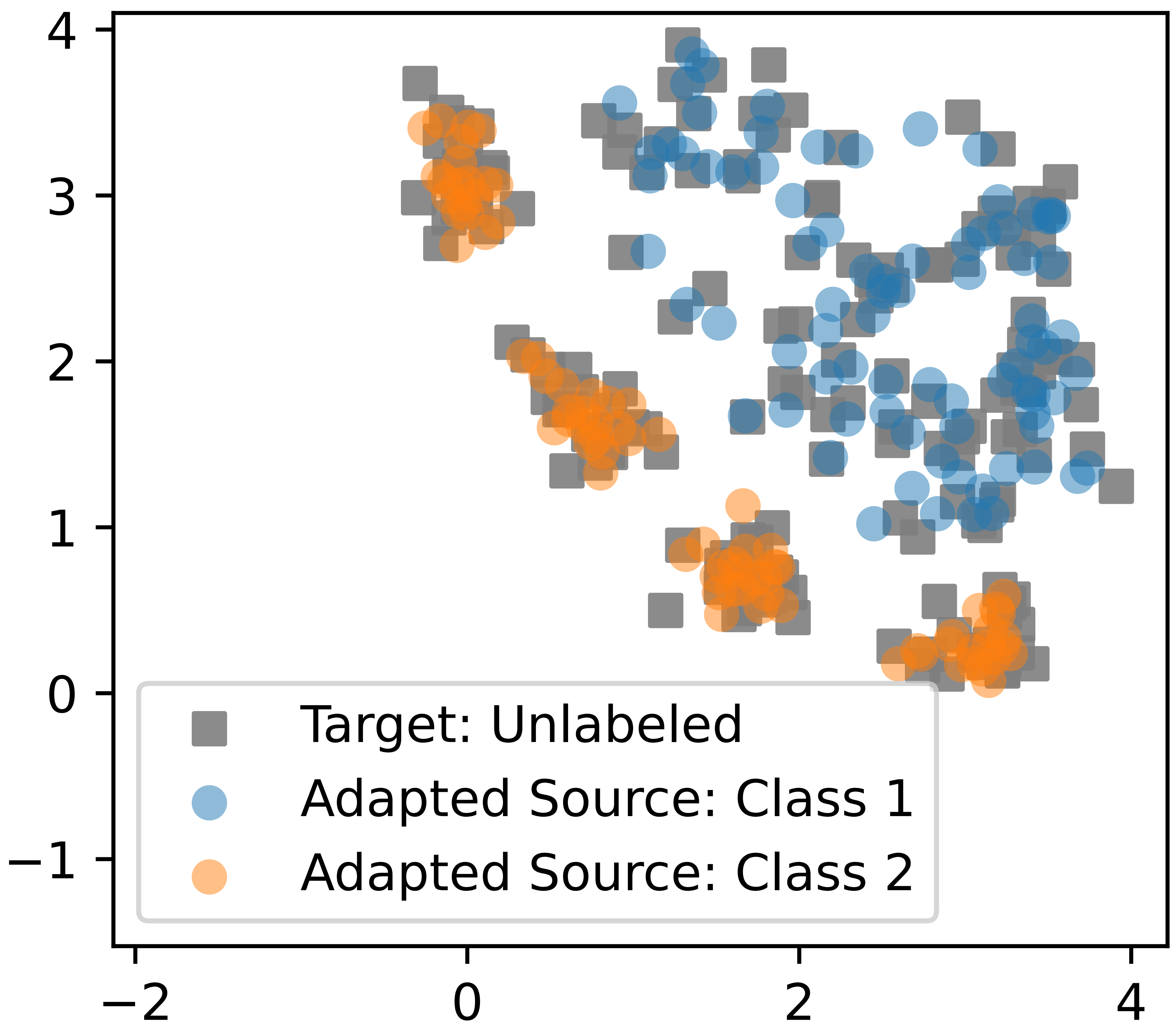
Toy Example: Mapping-Based UDA

Mapping computation:



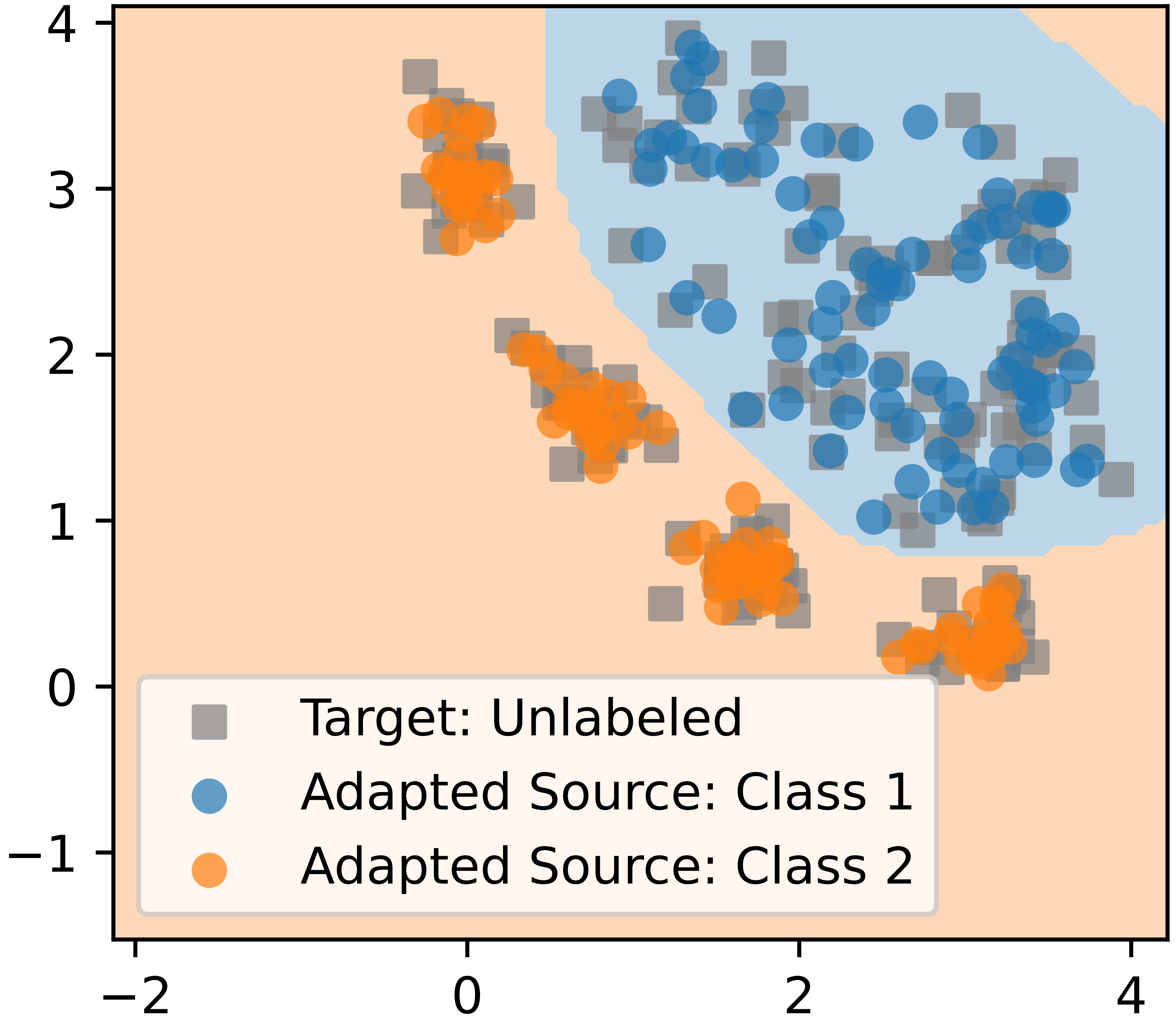
Toy Example: Mapping-Based UDA

Mapping application:



Toy Example: Mapping-Based UDA

Classifier fitting:



DA methods

Mapping:

$$f_{\text{DA}} = f \circ m$$

where m aligns source and target domains

m can be a normalization, subspace projection, optimal transport mapping, ...

Reweighting:

$$f_{\text{DA}} \in \arg\min_{f \in \mathcal{F}} \frac{1}{N_S} \sum_{n=1}^{N_S} w_i \ell\left(y_n, f(x_n)\right)$$

where w_i are importance weights depending on source and target domains

End-to-End Deep Learning:

Adversarial or discrepancy losses to align source and target distributions

Scikit-Adaptation: Skada

Python library for domain adaptation:

- Sklearn-like API with estimators (.fit, .predict, . . .), pipeline, grid search
- Shallow and Deep learning methods
- DA scorers to validate hyper-parameters without using target labels

https://github.com/scikit-adaptation/skada

2. SKADA-Bench: Benchmarking Unsupervised DA methods

Yanis Lalou*, Théo Gnassounou*, AC*, Antoine de Mathelin*, Oleksii Kachaiev, Ambroise Odonnat, Alexandre Gramfort, Thomas Moreau, Rémi Flamary

*Equal contribution

https://arxiv.org/abs/2407.11676

Motivation and setup

Evaluate DA methods across diverse modalities:

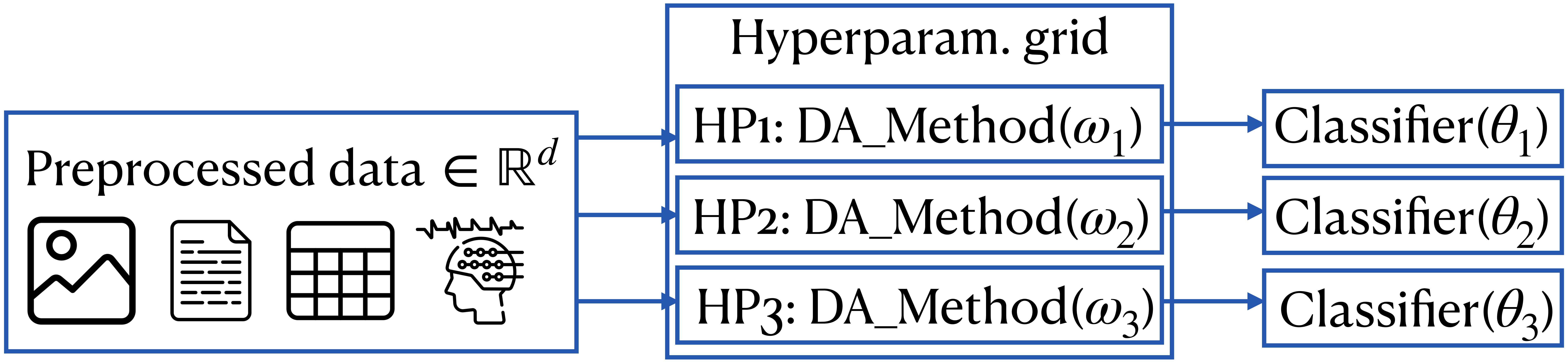
- 8 real-wold datasets of 4 modalities
- 4 synthetic datasets
- 51 adaptation pairs (source → target)
- 20 DA Methods
- 5-fold nested cross-validation
- built with Skada

https://github.com/scikit-adaptation/skada-bench

Dataset	Modality	Preprocessing
Office 31	CV	Decaff + PCA
Office Home	CV	ResNet + PCA
MNIST/USPS	CV	Vect + PCA
20 Newsgroup	NLP	LLM + PCA
Amazon Review	NLP	LLM + PCA
Mushrooms	Tabular	One Hot Encoding
Phishing	Tabular	None
BCI	Biosignals	Cov + TS

Pipeline

① Training: $\left(X^{\mathcal{S}}_{\text{train}}, y^{\mathcal{S}}_{\text{train}}, X^{\mathcal{T}}_{\text{train}}\right)$



Pipeline

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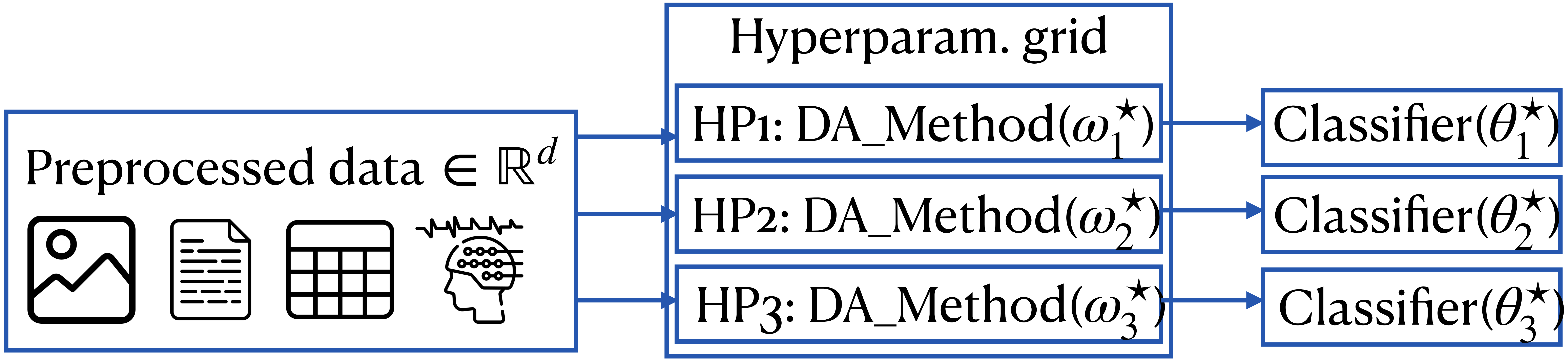
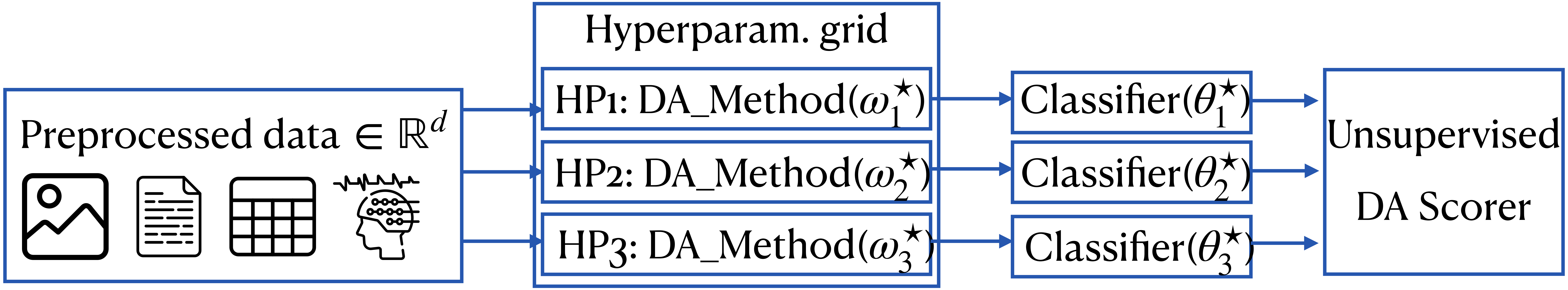


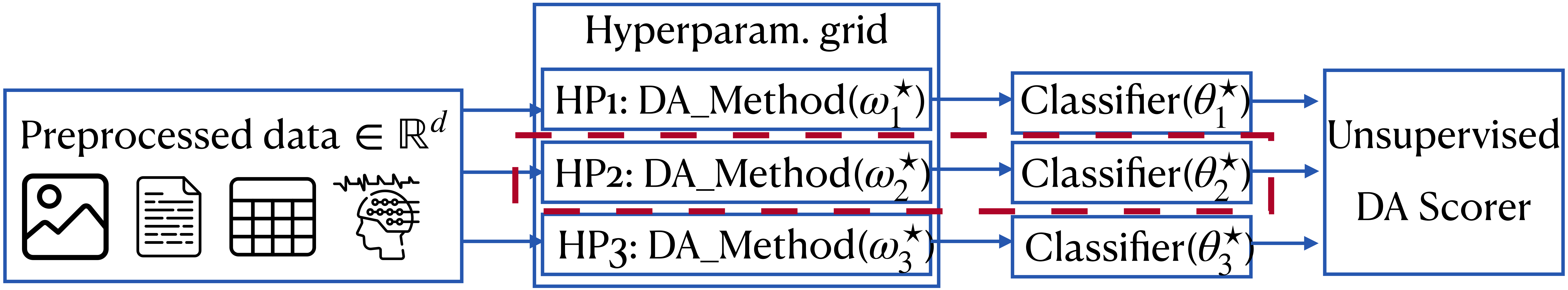
Pipeline

② Validation: $\left(X^{\mathcal{S}}_{\text{val}}, y^{\mathcal{S}}_{\text{val}}, X^{\mathcal{T}}_{\text{val}}\right)$



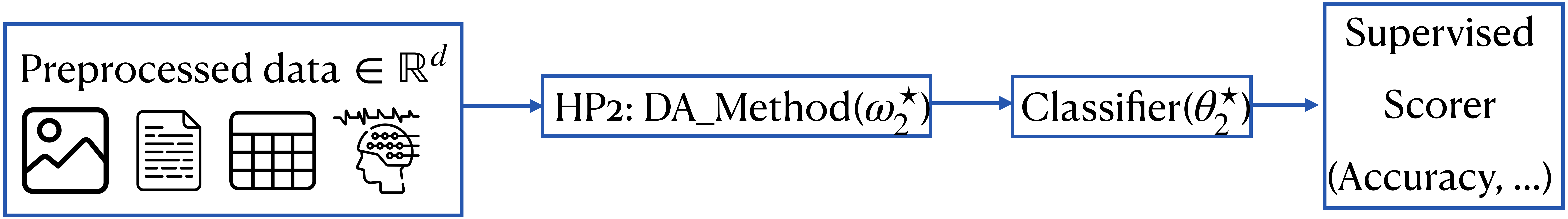
Pipeline

② Validation: $\left(X^{\mathcal{S}}_{\text{val}}, y^{\mathcal{S}}_{\text{val}}, X^{\mathcal{T}}_{\text{val}}\right)$



Pipeline

③ Evaluation: $\left(X^{\mathcal{T}}_{\text{test}}, y^{\mathcal{T}}_{\text{test}}\right)$



Realistic setup: no target labels for training, labels used only for benchmarking

Results

Adaptation

= gain

= loss

		Synthetic				Real									
		Cov. shift	Tar. shift	Cond. shift	Sub. shift	Office31	OfficeHome	MNIST/USPS	20NewsGroups	AmazonReview	Mushrooms	Phishing	BCI	Selected Scorer	Rank
	Train Src	0.88	0.85	0.66	0.19	0.65	0.56	0.54	0.59	0.7	0.72	0.91	0.55		10.66
	Train Tgt	0.92	0.93	0.82	0.98	0.89	0.8	0.96	1.0	0.73	1.0	0.97	0.64		1.55
Reweighting	Dens. RW	0.88	0.86	0.66	0.18	0.62	0.56	0.54	0.58	0.7	0.71	0.91	0.55	IW	12.20
	Disc. RW	0.85	0.83	0.71	0.18	0.63	0.54	0.5	0.6	0.68	0.75	0.91	0.56	CircV	8.75
	Gauss. RW	0.89	0.86	0.65	0.21	0.22	0.44	0.11	0.54	0.55	0.51	0.46	0.25	CircV	16.45
	KLIEP	0.88	0.86	0.66	0.19	0.65	0.56	0.54	0.6	0.69	0.72	0.91	0.55	CircV	10.56
	KMM	0.89	0.85	0.64	0.16	0.64	0.54	0.52	0.7	0.57	0.74	0.91	0.52	CircV	11.74
	NN RW	0.89	0.86	0.67	0.15	0.65	0.55	0.54	0.59	0.66	0.71	0.91	0.54	CircV	9.15
	MMDTarS	0.88	0.86	0.64	0.2	0.6	0.56	0.54	0.59	0.7	0.74	0.91	0.55	IW	10.81
Mapping	CORAL	0.74	0.7	0.76	0.18	0.65	0.57	0.62	0.73	0.7	0.72	0.92	0.62	CircV	5.08
	MapOT	0.72	0.57	0.82	0.02	0.6	0.51	0.61	0.76	0.68	0.63	0.84	0.47	PE	10.21
	EntOT	0.71	0.6	0.82	0.12	0.64	0.58	0.6	0.83	0.62	0.75	0.86	0.54	CircV	9.40
	ClassRegOT	0.74	0.58	0.81	0.11	NA	0.53	0.62	0.97	0.68	0.82	0.89	0.52	IW	8.25
	LinOT	0.73	0.73	0.76	0.18	0.66	0.57	0.64	0.82	0.7	0.76	0.91	0.61	CircV	4.06
	MMD-LS	0.78	0.72	0.76	0.56	0.65	0.56	0.55	0.97	0.63	0.85	NA	0.5	MixVal	8.22
Subspace	JPCA	0.88	0.85	0.66	0.15	0.62	0.48	0.51	0.77	0.69	0.78	0.9	0.54	PE	8.98
	SA	0.74	0.68	0.8	0.11	0.65	0.57	0.56	0.88	0.67	0.78	0.89	0.53	CircV	7.80
	TCA	0.52	0.47	0.51	0.62	0.04	0.02	0.07	0.61	0.61	0.49	0.48	0.26	DEV	17.58
	TSL	0.88	0.85	0.66	0.2	0.63	0.48	0.45	0.63	0.69	0.45	0.89	0.26	IW	15.09
Other	JDOT	0.72	0.58	0.82	0.13	0.6	0.42	0.59	0.79	0.67	0.65	0.79	0.47	IW	11.42
	OTLabelProp	0.72	0.59	0.8	0.07	0.66	0.56	0.62	0.86	0.67	0.64	0.86	0.5	CircV	10.01
	DASVM	0.89	0.86	0.65	0.15	NA	NA	NA	0.87	NA	0.83	0.85	NA	MixVal	7.29

Results

Adaptation

- (blue) = gain
- (pink) = loss

		Synthetic				Real									
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Affine Distribution Alignment Across Domains

CORAL (Correlation Alignment) [Sun et al., 2017]

Aligns second-order moments between source and target:

$$m(x) = \Sigma_{\mathcal{T}}^{\frac{1}{2}} \Sigma_{\mathcal{S}}^{-\frac{1}{2}} x, \qquad \arg\min_{A} \|A \Sigma_{\mathcal{S}} A^\top - \Sigma_{\mathcal{T}}\|_F^2$$

LinOT (Linear Optimal Transport) [Flamary et al., 2019]

Affine map minimizing transport cost between $\mathbb{P}_{\mathcal{S}} = \mathcal{N}(\mu_{\mathcal{S}}, \Sigma_{\mathcal{S}})$ and $\mathbb{P}_{\mathcal{T}} = \mathcal{N}(\mu_{\mathcal{T}}, \Sigma_{\mathcal{T}})$:

$$m(x) = Ax + b \quad \textbf{with} \quad A = \Sigma_{\mathcal{S}}^{-\frac{1}{2}} \left(\Sigma_{\mathcal{S}}^{\frac{1}{2}} \Sigma_{\mathcal{T}} \Sigma_{\mathcal{S}}^{\frac{1}{2}} \right)^{\frac{1}{2}} \Sigma_{\mathcal{S}}^{-\frac{1}{2}}, \quad b = \mu_{\mathcal{T}} - A\mu_{\mathcal{S}}$$

Normalization Across Domains

Many benefits:

- easy to code
- fast
- no need to access source and target data simultaneously
- no/few hyperparameters
- unsupervised: no target labels required

Normalization Across Domains

How to deal with ...?

- ...target shifts, i.e. joint shifts (X, y)?
- ...several source domains, i.e. multi-source adaptation?
- ...$\mathscr{X} = \mathscr{M}$, i.e. data on manifolds?

3. Joint shifts in (X, y) on manifolds: GOPSA

Apolline Mellot*, AC*, Sylvain Chevallier,
Alexandre Gramfort, Denis A. Engemann

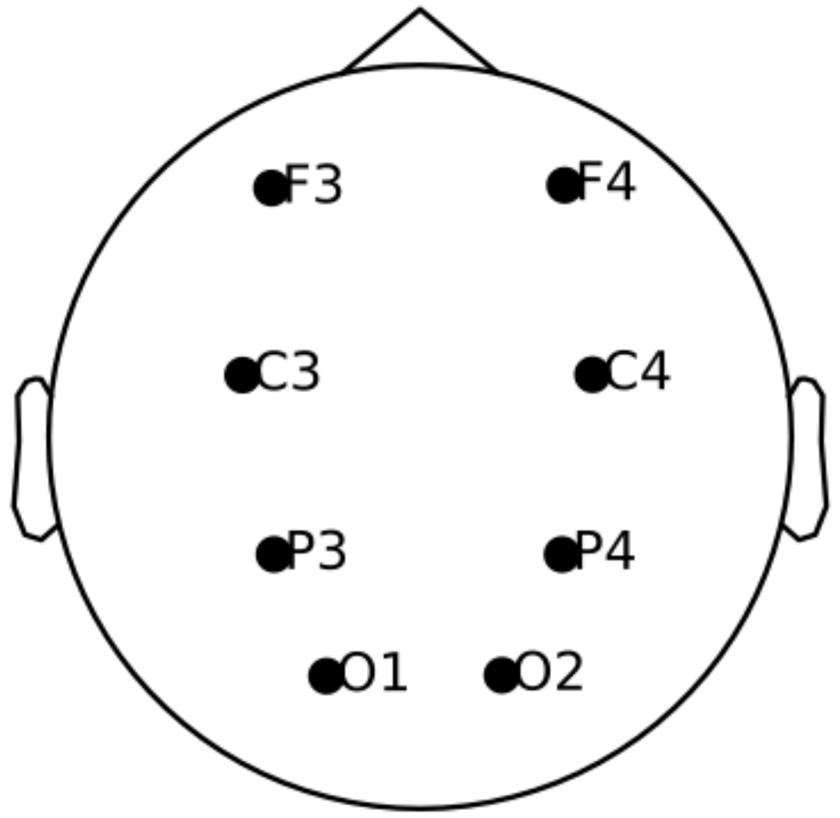
*Equal contribution

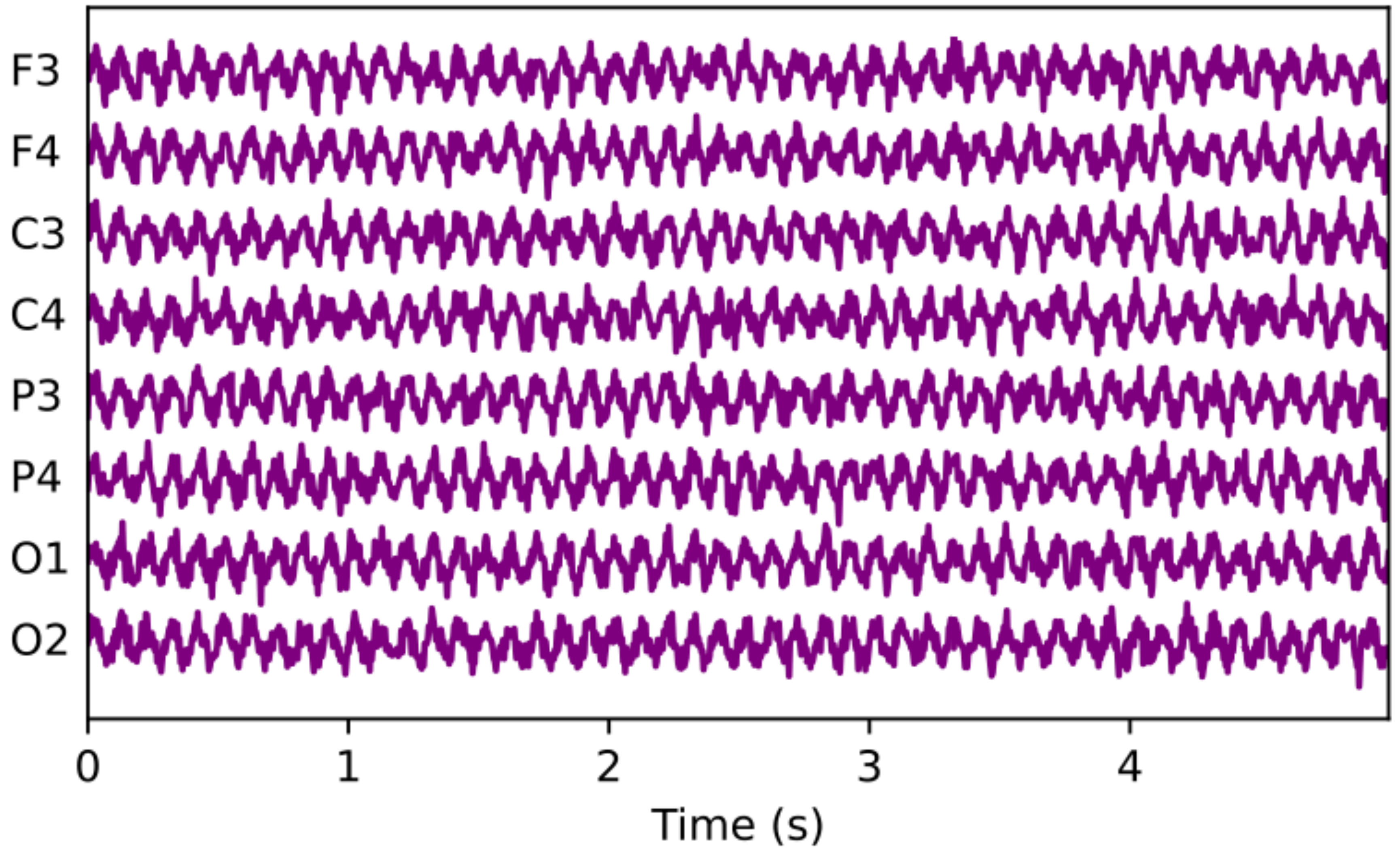
NeurIPS 2024, Spotlight

https://arxiv.org/abs/2407.03878

Machine learning on EEG data

Predicting an outcome from neural activity measured by EEG, a non-invasive technique that records brain signals from the scalp.



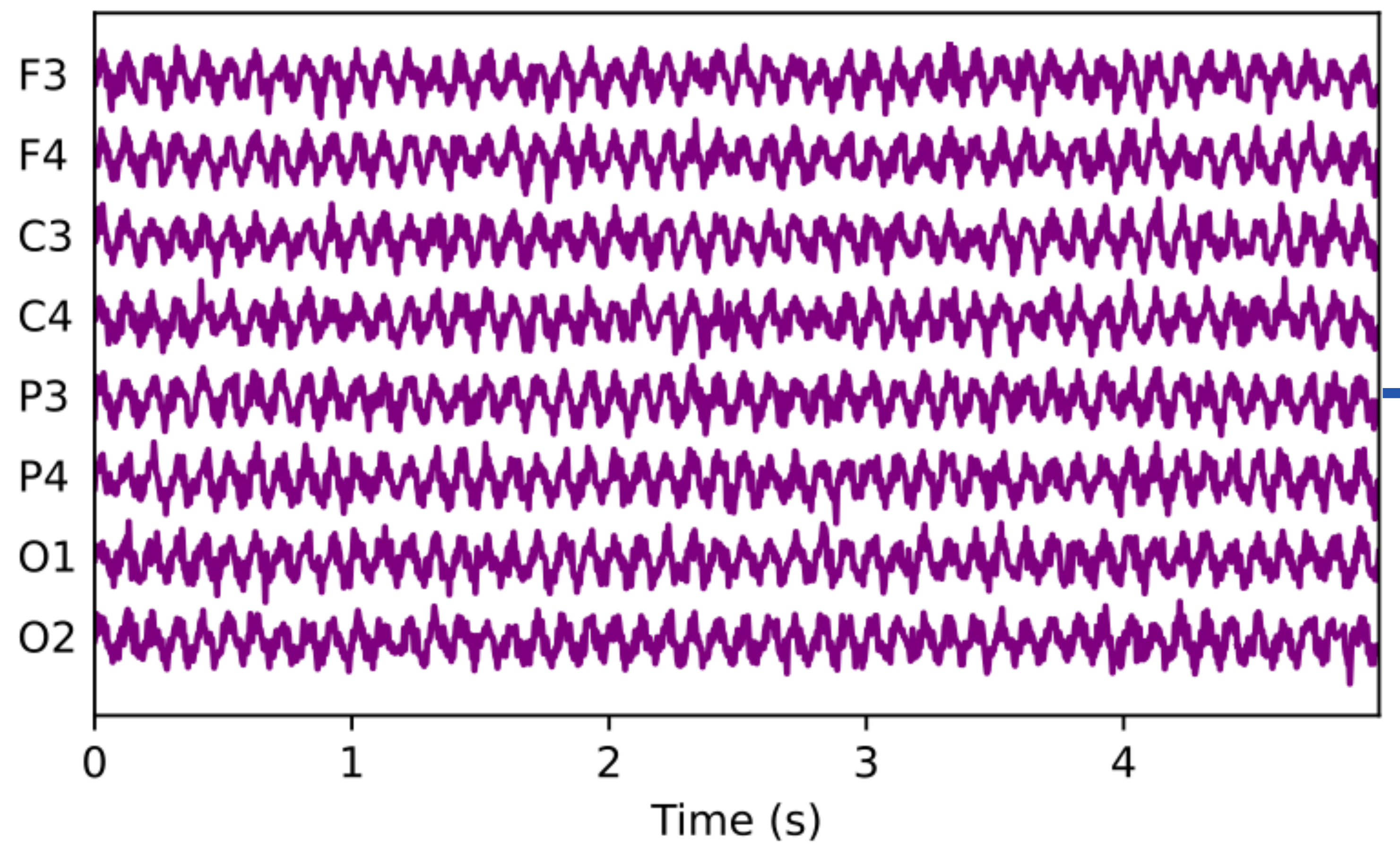


Applications:

sleep staging (awake, deep sleep, ...), brain-computer interface, biomarker regression, ...

Brain age: subject-level regression

1 time series = 1 subject



→ Co-spectrum matrix $\in \mathbb{S}_d^{++}$ → Tangent space features $\in \mathbb{R}^{\frac{d(d+1)}{2}}$ → Regression model → $\hat{y}$

Manifold-valued data

(Age estimation)

Brain age is a proxy for cognitive health and detects deviations from typical aging

Co-spectrum

Let $x_\ell \in \mathbb{R}^d$ be a stationary zero-mean time series

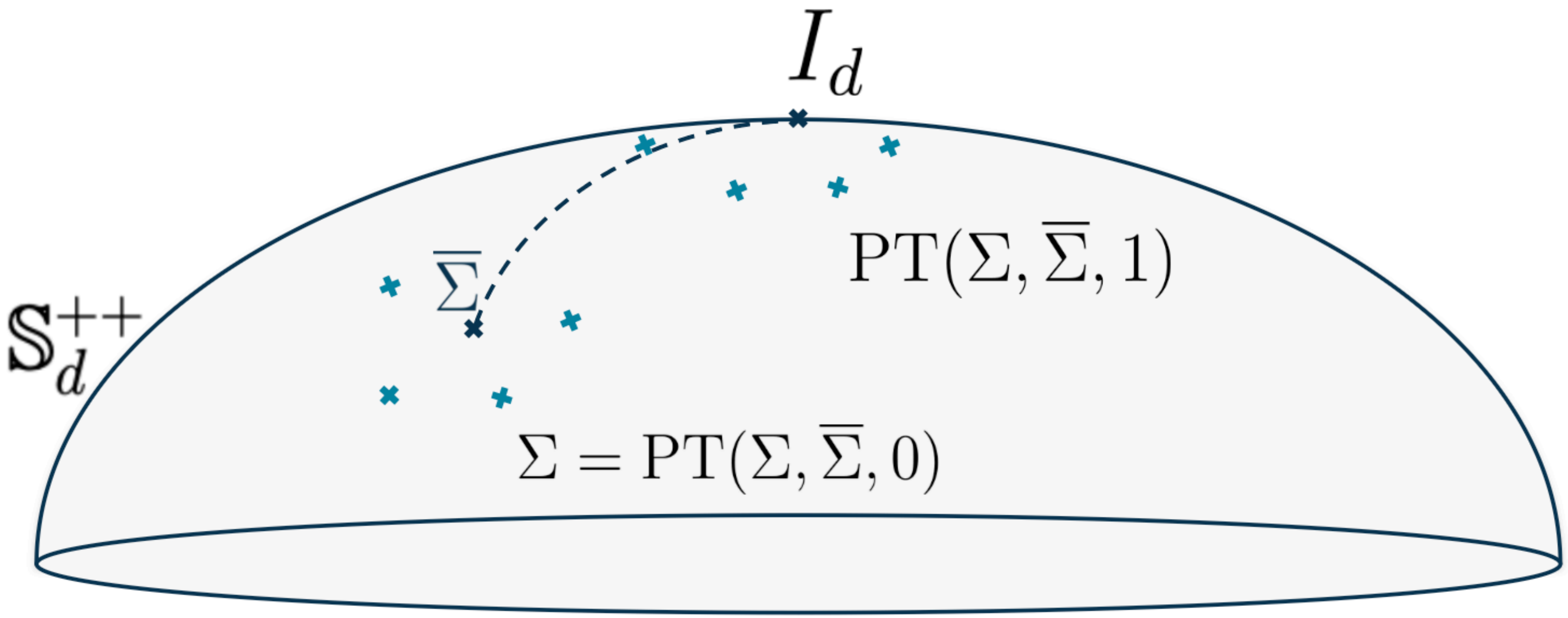
$$R(\tau) = \mathbb{E}\left[x_{\ell+\tau} x_\ell^\top\right] \in \mathbb{R}^{d\times d}$$

$$C(s) = \operatorname{Re}\left\{ \sum_{\tau=-\infty}^{\infty} e^{-i2\pi s\tau} R(\tau) \right\} \in \mathbb{S}_d^{++}$$

$[C(s_0), \ldots, C(s_{F-1})]$ represents the time-series and belongs to the manifold $(\mathbb{S}_d^{++})^F$

Regression on $\mathcal{S}_d^{++}$

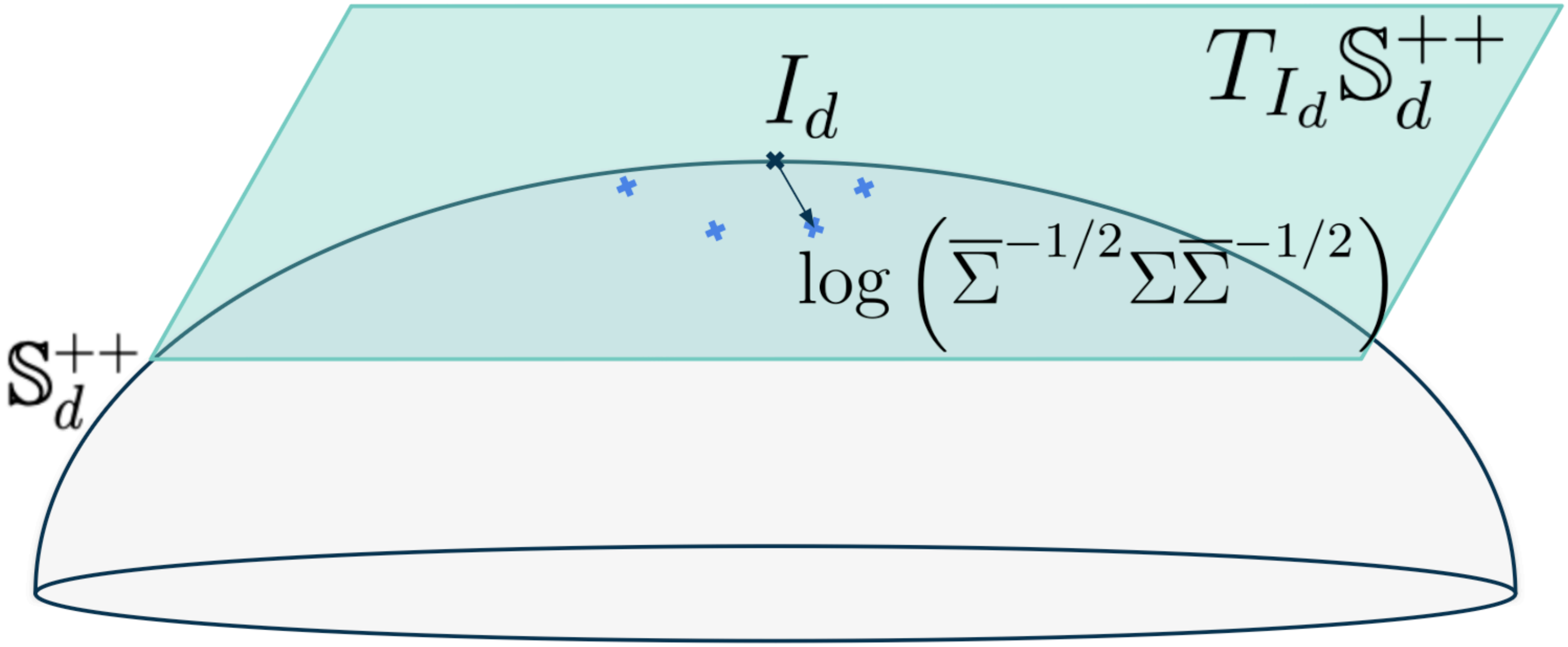
① Parallel transport moves Σ from $\bar{\Sigma}$ to I_d at $\alpha \in [0,1]$: $\mathrm{PT}(\Sigma, \bar{\Sigma}, \alpha) = \bar{\Sigma}^{-\alpha/2} \Sigma \bar{\Sigma}^{-\alpha/2}$



[Sabbagh, et al., 2019]

Regression on $\mathcal{S}_d^{++}$

② Riemannian logarithm of Σ at I_d



[Sabbagh, et al., 2019]

Regression on $\mathcal{S}_d^{++}$

③ Upper-triangular vectorization

$$\phi(\Sigma, \bar{\Sigma}) \triangleq \mathrm{uvec}\left(\log\left(\bar{\Sigma}^{-1/2}\Sigma\bar{\Sigma}^{-1/2}\right)\right) \in \mathbb{R}^{d(d+1)/2}$$

④ Regression

$$\hat{y} = \beta^\top \phi(\Sigma, \bar{\Sigma})$$

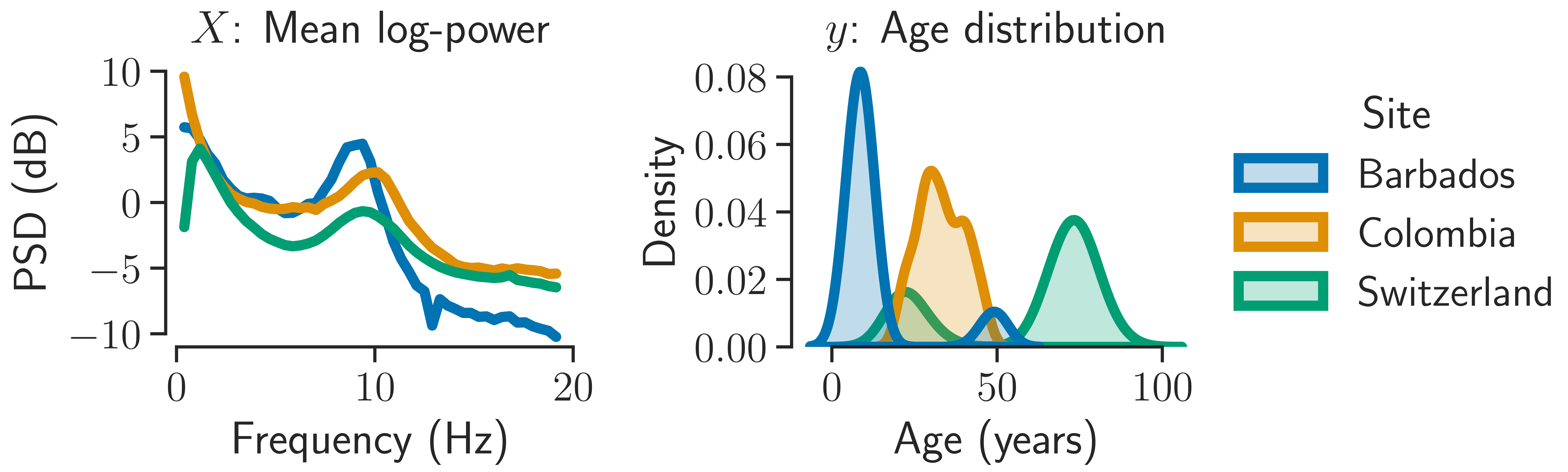
[Sabbagh, et al., 2019]

Data shifts in neuroscience

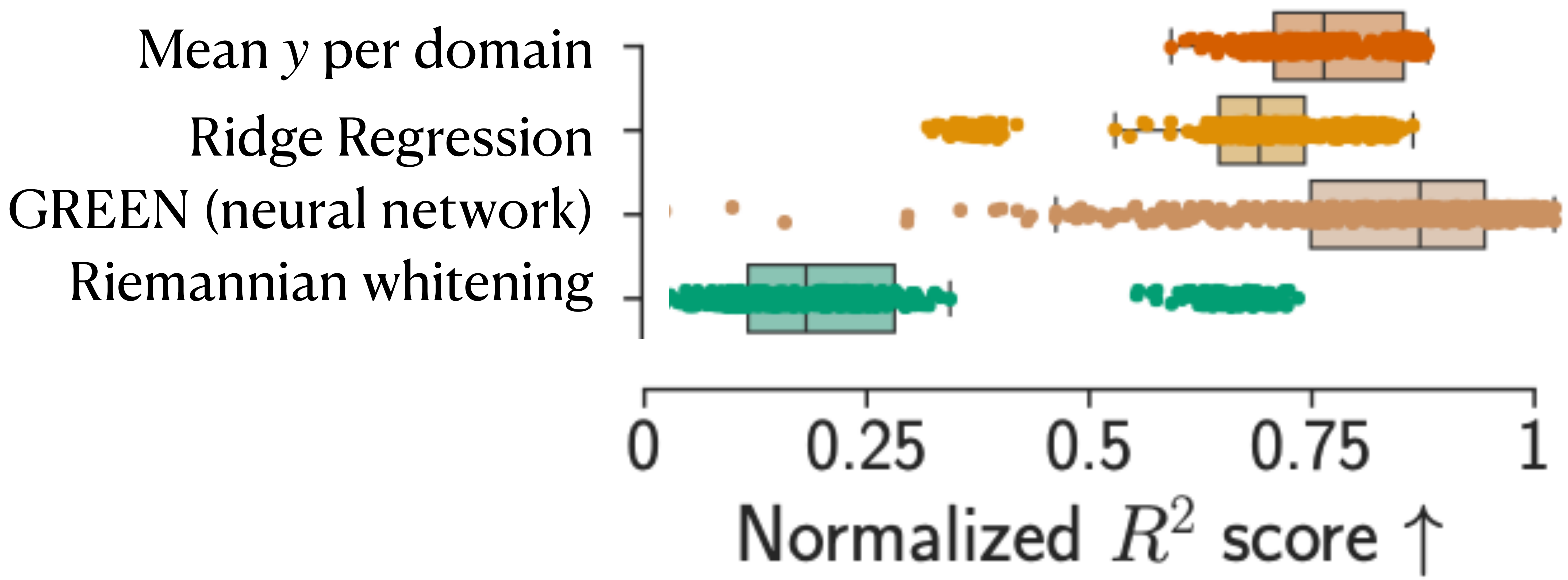
Sources of variability:

- population: age, gender, diseased or healthy, ...
- hardware and preprocessing: sensors, positions, sampling rates, ...
- task-related variability: tasks during recording, level of engagement, external stimuli, ...

HarMNqEEG dataset [Li et al., 2022]



Data shifts in neuroscience



GOPSA: Geodesic Optimization for Predictive Shift Adaptation

Setup:

K source domains: $\left\{(\Sigma_{k,n}, y_{k,n})\right\}_{n=1}^{N_k}$ for $k \in \{1,\ldots,K\}$ and $N_{\mathcal{S}} = \sum_{k=1}^{K} N_k$

One target domain: $\left\{\Sigma_{\mathcal{T},n}\right\}_{n=1}^{N_{\mathcal{T}}}, \bar{y}_{\mathcal{T}}$ (mean value)

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One target domain: $\left\{\Sigma_{\mathcal{T},n}\right\}_{n=1}^{N_{\mathcal{T}}}, \bar{y}_{\mathcal{T}}$ (mean value)

Learn the parallel transport $\alpha \in [0,1]$ per domain:

$$\phi(\Sigma, \bar{\Sigma}, \alpha) \triangleq \operatorname{uvec}\left(\log_{I_d}\left(\operatorname{PT}(\Sigma, \bar{\Sigma}, \alpha)\right)\right) = \operatorname{uvec}\left(\log\left(\bar{\Sigma}^{-\alpha/2}\Sigma\bar{\Sigma}^{-\alpha/2}\right)\right)$$

GOPSA: Geodesic Optimization for Predictive Shift Adaptation

Learnable source and target data matrices w.r.t. $\alpha_{\mathcal{S}} \in [0,1]^K$ and $\alpha_{\mathcal{T}}$:

$$Z_{\mathcal{S}}(\alpha_{\mathcal{S}}) \triangleq \left[\phi(\Sigma_{1,1}, \bar{\Sigma}_1, \alpha_1), \ \ldots, \phi(\Sigma_{K,N_K}, \bar{\Sigma}_K, \alpha_K)\right]^\top \in \mathbb{R}^{N_{\mathcal{S}} \times d(d+1)/2}$$

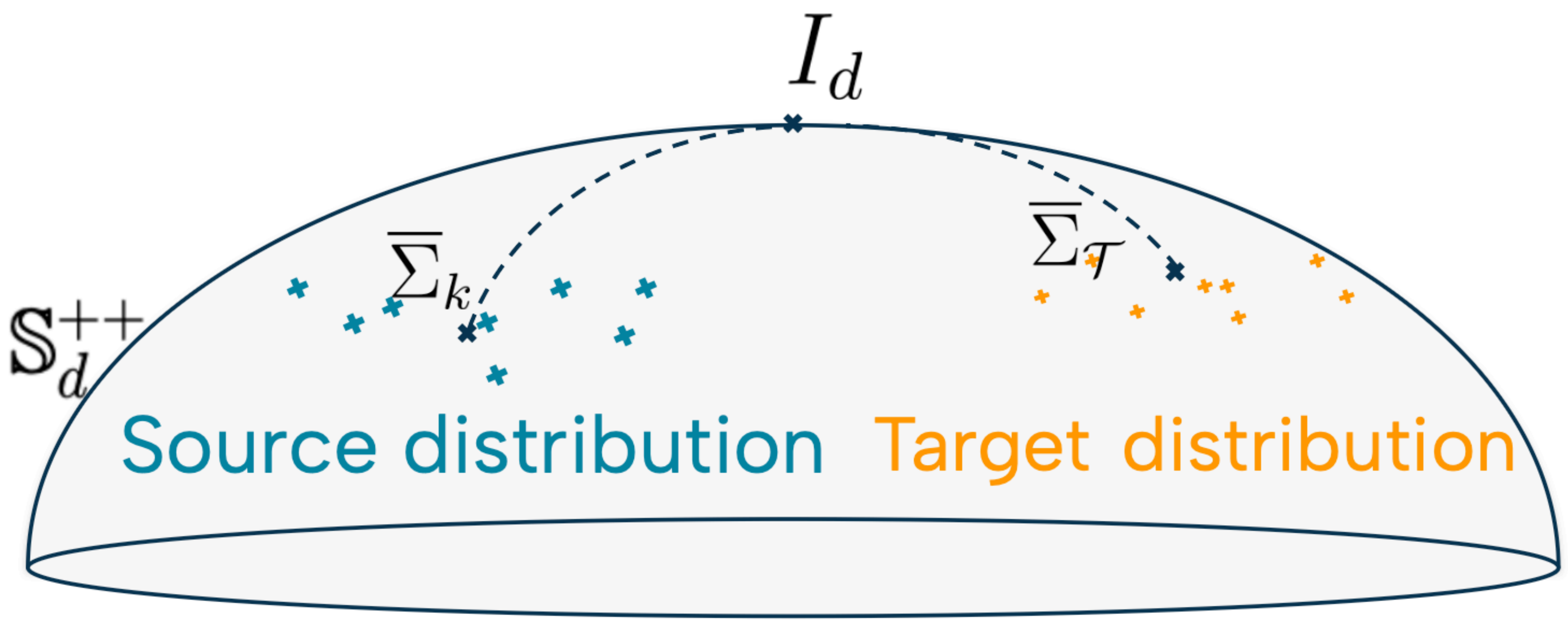
$$Z_{\mathcal{T}}(\alpha_{\mathcal{T}}) \triangleq \left[\phi(\Sigma_{\mathcal{T},1}, \bar{\Sigma}_{\mathcal{T}}, \alpha_{\mathcal{T}}), \ \ldots, \phi(\Sigma_{\mathcal{T},1}, \bar{\Sigma}_{\mathcal{T}}, \alpha_{\mathcal{T}})\right]^\top \in \mathbb{R}^{N_{\mathcal{T}} \times d(d+1)/2}$$

GOPSA: Geodesic Optimization for Predictive Shift Adaptation

Learnable source and target data matrices w.r.t. $\alpha_{\mathcal{S}} \in [0,1]^K$ and $\alpha_{\mathcal{T}}$:

$$Z_{\mathcal{S}}(\alpha_{\mathcal{S}}) \triangleq \left[\phi(\Sigma_{1,1}, \bar{\Sigma}_1, \alpha_1),\ \ldots, \phi(\Sigma_{K,N_K}, \bar{\Sigma}_K, \alpha_K)\right]^\top \in \mathbb{R}^{N_{\mathcal{S}} \times d(d+1)/2}$$

$$Z_{\mathcal{T}}(\alpha_{\mathcal{T}}) \triangleq \left[\phi(\Sigma_{\mathcal{T},1}, \bar{\Sigma}_{\mathcal{T}}, \alpha_{\mathcal{T}}),\ \ldots, \phi(\Sigma_{\mathcal{T},1}, \bar{\Sigma}_{\mathcal{T}}, \alpha_{\mathcal{T}})\right]^\top \in \mathbb{R}^{N_{\mathcal{T}} \times d(d+1)/2}$$

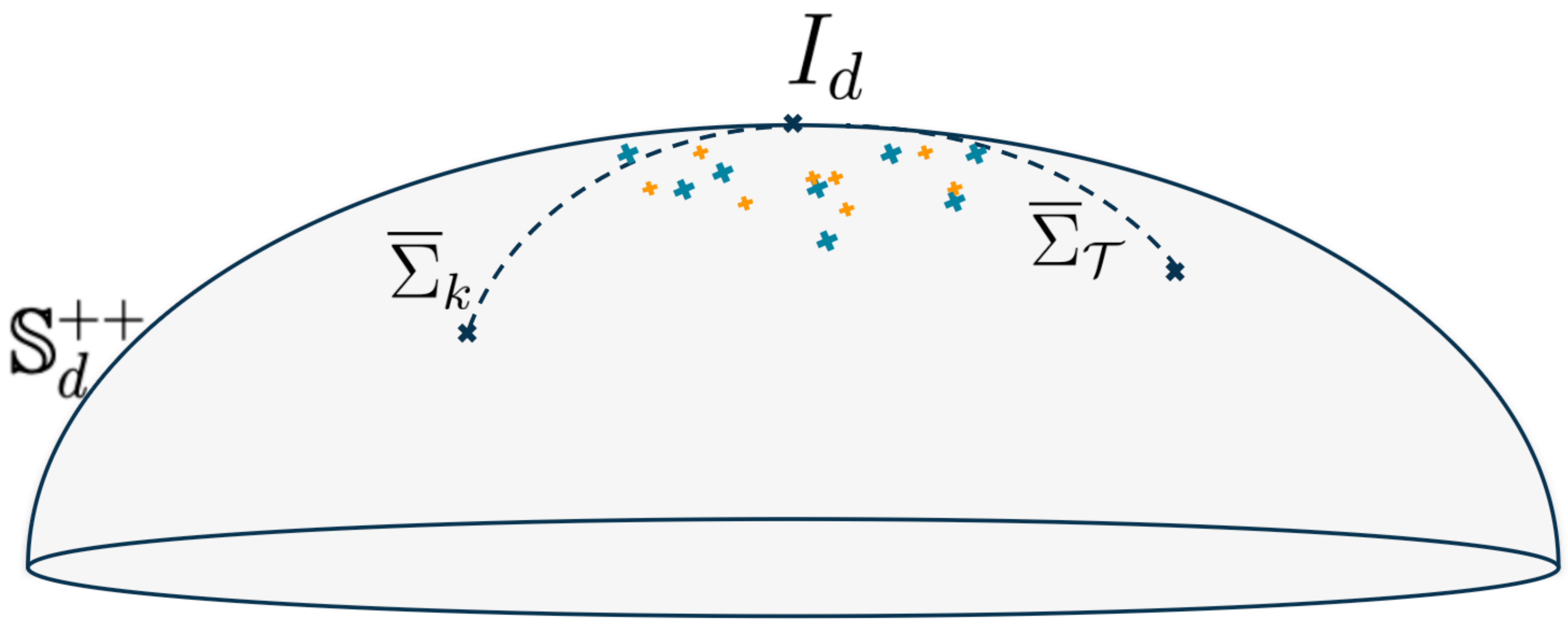


GOPSA: Geodesic Optimization for Predictive Shift Adaptation

Learnable source and target data matrices w.r.t. $\alpha_{\mathcal{S}} \in [0,1]^K$ and $\alpha_{\mathcal{T}}$:

$$Z_{\mathcal{S}}(\alpha_{\mathcal{S}}) \triangleq \left[\phi(\Sigma_{1,1}, \bar{\Sigma}_1, \alpha_1), \ \ldots, \phi(\Sigma_{K,N_K}, \bar{\Sigma}_K, \alpha_K)\right]^\top \in \mathbb{R}^{N_{\mathcal{S}} \times d(d+1)/2}$$

$$Z_{\mathcal{T}}(\alpha_{\mathcal{T}}) \triangleq \left[\phi(\Sigma_{\mathcal{T},1}, \bar{\Sigma}_{\mathcal{T}}, \alpha_{\mathcal{T}}), \ \ldots, \phi(\Sigma_{\mathcal{T},1}, \bar{\Sigma}_{\mathcal{T}}, \alpha_{\mathcal{T}})\right]^\top \in \mathbb{R}^{N_{\mathcal{T}} \times d(d+1)/2}$$



GOPSA: Geodesic Optimization for Predictive Shift Adaptation

Train-time:

$$\alpha^*_{\mathcal{S}} \triangleq \arg \min_{\alpha \in [0,1]^K} \left\| y_{\mathcal{S}} - Z_{\mathcal{S}}(\alpha)\, \beta^*_{\mathcal{S}}(\alpha) \right\|_2^2$$

subject to $\beta^*_{\mathcal{S}}(\alpha)$ is the ridge estimator

Test-time:

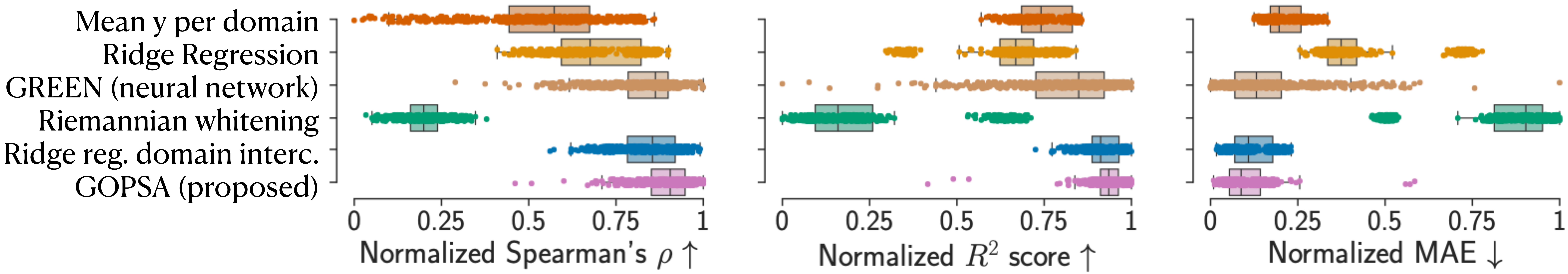
(Optimization) $$\alpha^*_{\mathcal{T}} \triangleq \arg \min_{\alpha \in [0,1]} \left(\bar{y}_{\mathcal{T}} - \text{mean}\left(Z_{\mathcal{T}}(\alpha) \beta^*_{\mathcal{S}}(\alpha^*_{\mathcal{S}}) \right) \right)^2$$

(Prediction) $$\hat{y}_{\mathcal{T}} \triangleq Z_{\mathcal{T}}(\alpha^*_{\mathcal{T}})\, \beta^*_{\mathcal{S}}(\alpha^*_{\mathcal{S}})$$

Evaluation

HarMNqEEG dataset [Li et al., 2022]

14 recording sites, 1500 human participants, random combination of source sites, single random target site



Conclusions

Benchmarks matter

→ Skada-Bench provides the first cross-modal, realistically-validated UDA benchmark

Back to basics: affine distribution alignment across domains

→ simple affine methods help reduce cross-domain error without labels

Joint shifts in (X, y) on manifolds

→ EEG data live on manifolds, yet we can design simple and efficient methods—such as GOPSA—that outperform more complex alternatives

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2. SKADA-Bench: Benchmarking Unsupervised Domain Adaptation Methods with Realistic Validation

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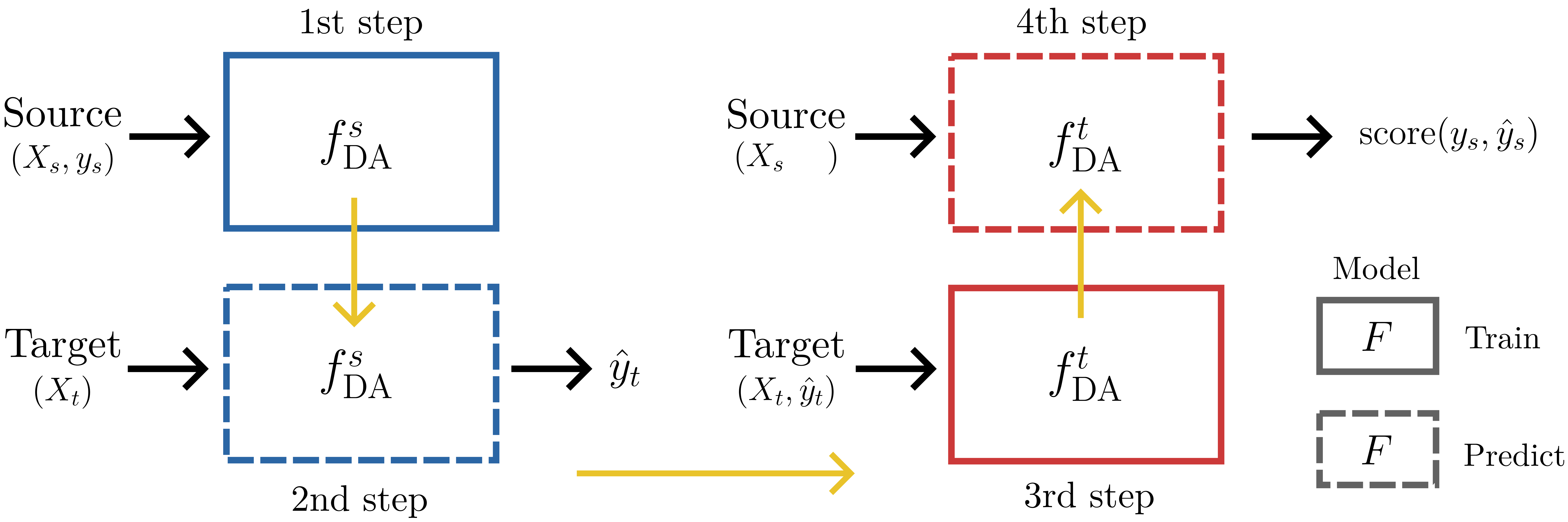
*Equal contribution

https://arxiv.org/abs/2407.11676

Datasets

Dataset	Modality	Preprocessing	Pairs of Adaptation	Classes	Samples	Features
Office 31	CV	Decaff + PCA	6	31	470 ± 350	100
Office Home	CV	ResNet + PCA	12	65	3897 ± 850	100
MNIST/USPS	CV	Vect + PCA	2	10	3000 / 10000	50
20 Newsgroup	NLP	LLM + PCA	6	2	3728 ± 174	50
Amazon Review	NLP	LLM + PCA	12	4	2000	50
Mushrooms	Tabular	One Hot Encoding	2	2	4062 ± 546	117
Phishing	Tabular	None	2	2	5527 ± 1734	30
BCI	Biosignals	Cov + TS	9	4	288	253

DA scorer: circular validation



3. Normalization for joint shifts in (X, y): GOPSA

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NeurIPS 2024, Spotlight

https://arxiv.org/abs/2407.03878

GOPSA: Geodesic Optimization for Predictive Shift Adaptation

Setup:

K source domains: $\left\{(\Sigma_{k,n}, y_{k,n})\right\}_{n=1}^{N_k}$ for $k \in \{1, \ldots, K\}$ and $N_{\mathcal{S}} = \sum_{k=1}^{K} N_k$

One target domain: $\left\{\Sigma_{\mathcal{T},n}\right\}_{n=1}^{N_{\mathcal{T}}}, \bar{y}_{\mathcal{T}}$ (mean value)

Learn the parallel transport $\alpha \in [0,1]$ per domain:

$$\phi(\Sigma, \bar{\Sigma}, \alpha) \triangleq \mathrm{uvec}\left(\log_{I_d}\left(\mathrm{PT}(\Sigma, \bar{\Sigma}, \alpha)\right)\right) = \mathrm{uvec}\left(\log\left(\bar{\Sigma}^{-\alpha/2}\Sigma\bar{\Sigma}^{-\alpha/2}\right)\right)$$

GOPSA: Geodesic Optimization for Predictive Shift Adaptation

Train-time:

$$\alpha^*_{\mathcal{S}} \triangleq \arg \min_{\alpha \in [0,1]^K} \left\| y_{\mathcal{S}} - Z_{\mathcal{S}}(\alpha)\, \beta^*_{\mathcal{S}}(\alpha) \right\|_2^2$$

$$\text{subject to} \quad \beta^*_{\mathcal{S}}(\alpha) \triangleq Z_{\mathcal{S}}(\alpha)^\top \left(\lambda I_N + Z_{\mathcal{S}}(\alpha) Z_{\mathcal{S}}(\alpha)^\top\right)^{-1} y_{\mathcal{S}}$$

Test-time:

$$\text{(Optimization)} \quad \alpha^*_{\mathcal{T}} \triangleq \arg \min_{\alpha \in [0,1]} \left(\bar{y}_{\mathcal{T}} - \frac{1}{N_{\mathcal{T}}} 1_{N_{\mathcal{T}}}^\top Z_{\mathcal{T}}(\alpha)\, \beta^*_{\mathcal{S}}(\alpha^*_{\mathcal{S}}) \right)^2$$

$$\text{(Prediction)} \quad \hat{y}_{\mathcal{T}} \triangleq Z_{\mathcal{T}}(\alpha^*_{\mathcal{T}})\, \beta^*_{\mathcal{S}}(\alpha^*_{\mathcal{S}})$$

GOPSA: Geodesic Optimization for Predictive Shift Adaptation

Train-time:

$$\alpha^*_{\mathcal{S}} \triangleq \arg \min_{\alpha \in [0,1]^K} \left\| y_{\mathcal{S}} - Z_{\mathcal{S}}(\alpha)\, \beta^*_{\mathcal{S}}(\alpha) \right\|_2^2$$

$$\text{subject to} \quad \beta^*_{\mathcal{S}}(\alpha) \triangleq Z_{\mathcal{S}}(\alpha)^\top \left(\lambda I_N + Z_{\mathcal{S}}(\alpha) Z_{\mathcal{S}}(\alpha)^\top \right)^{-1} y_{\mathcal{S}}$$

Test-time:

Assumption: $\bar{\Sigma}_{\mathcal{T}}, \bar{y}_{\mathcal{T}}$ are known

$$\text{(Optimization)} \quad \alpha^*_{\mathcal{T}} \triangleq \arg \min_{\alpha \in [0,1]} \left(\bar{y}_{\mathcal{T}} - \frac{1}{N_{\mathcal{T}}} 1_{N_{\mathcal{T}}}^\top Z_{\mathcal{T}}(\alpha)\, \beta^*_{\mathcal{S}}(\alpha^*_{\mathcal{S}}) \right)^2$$

$$\text{(Prediction)} \quad \hat{y}_{\mathcal{T}} \triangleq Z_{\mathcal{T}}(\alpha^*_{\mathcal{T}})\, \beta^*_{\mathcal{S}}(\alpha^*_{\mathcal{S}})$$