Multi-step Online Unsupervised Domain Adaptation

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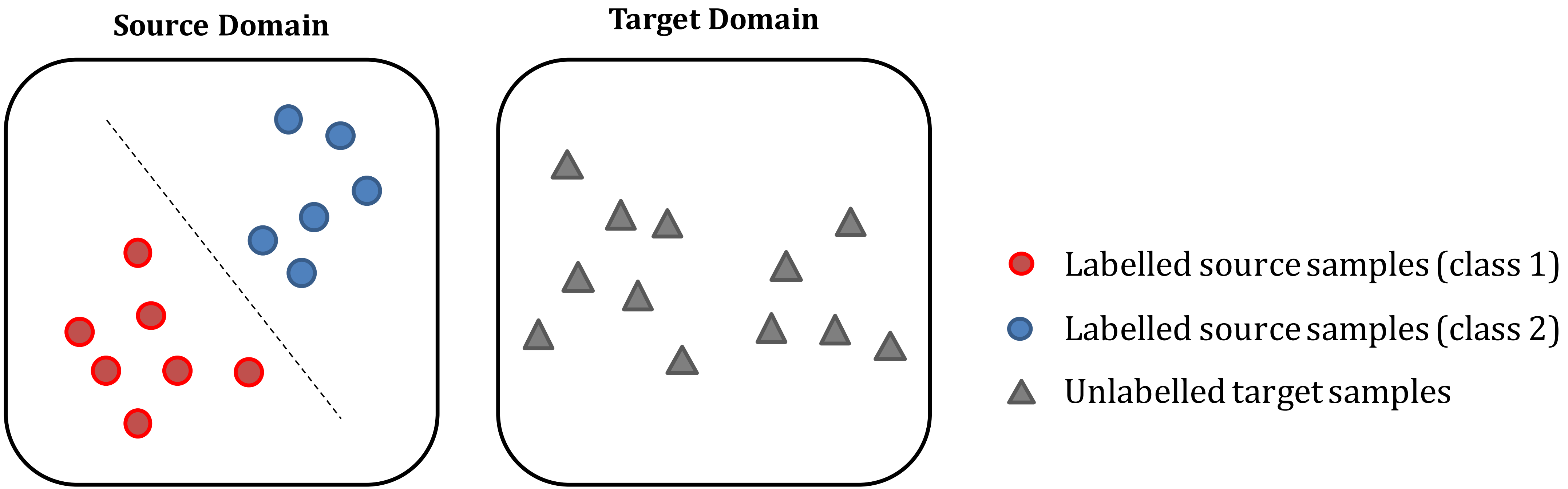
Outline

- Introduction
- Main steps of proposed method
  - Subspace Representation
  - Averaging Mean-target Subspace
  - Domain Adaptation
  - Recursive Feedback
- Experimental Results
- Conclusion

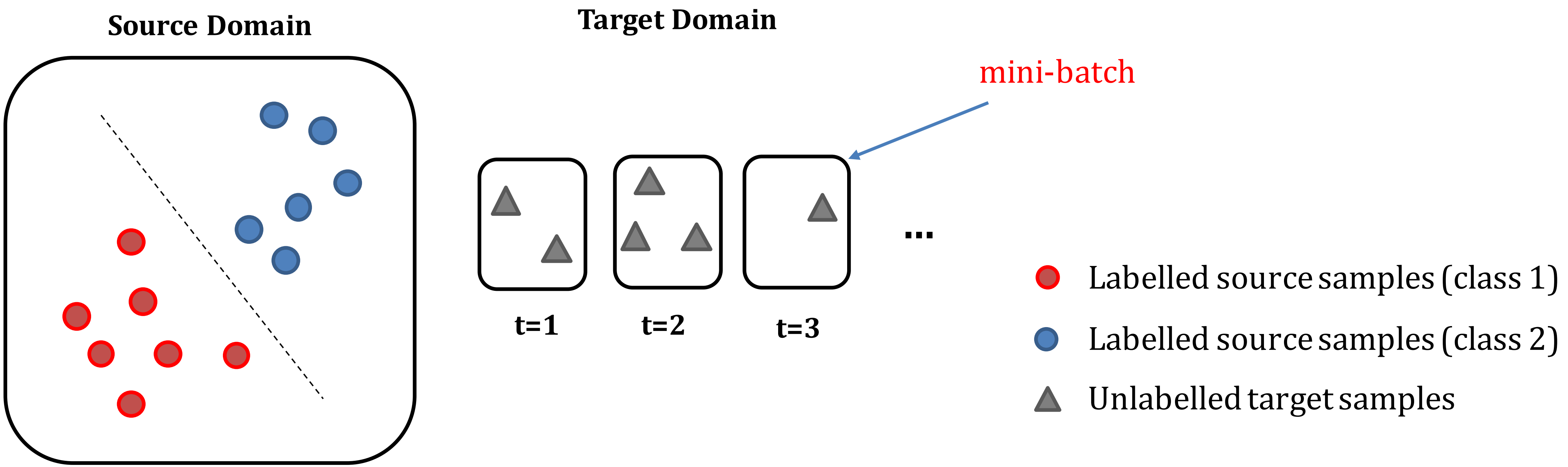
Introduction

Unsupervised Domain Adaptation (UDA)



- Unsupervised Domain Adaptation (UDA) transfers the knowledge from the labelled source domain to the unlabelled target domain
- Source and target samples are in batch

Online Unsupervised Domain Adaptation (OUDA)

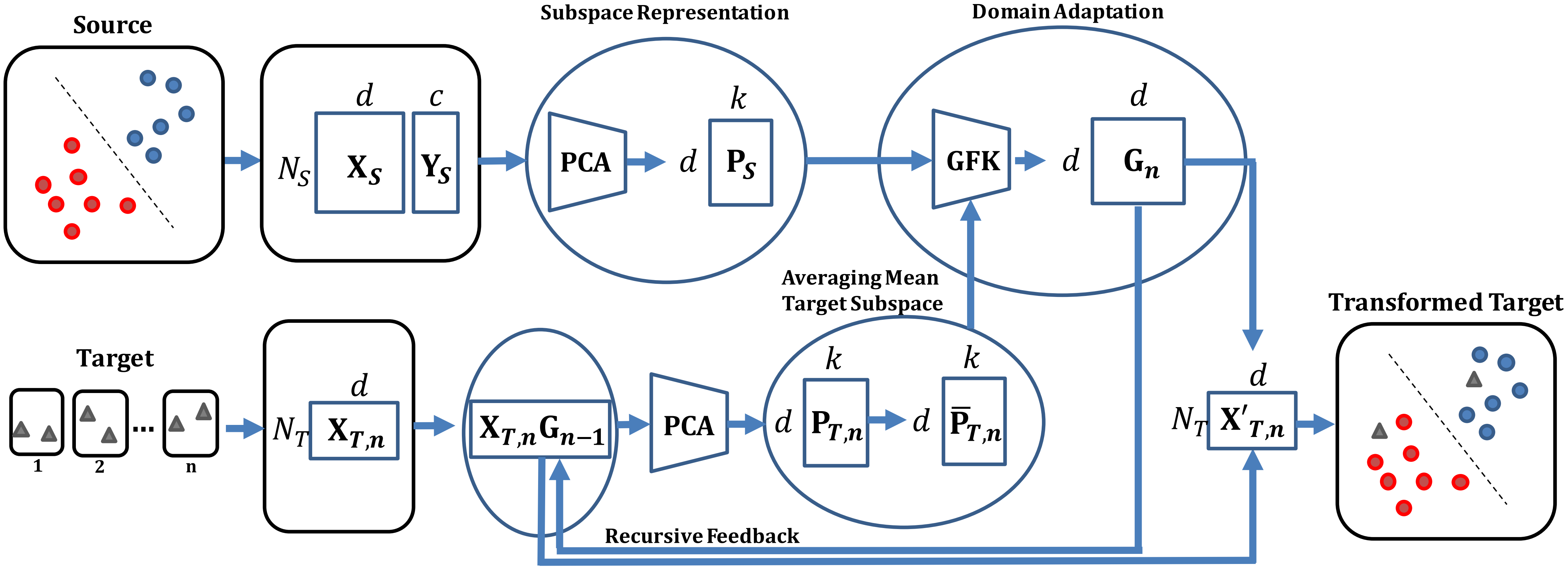


- Online Unsupervised Domain Adaptation (OUDA) is a more challenging problem than a traditional UDA problem
- Target samples arrive in online fashion (each mini-batch)

Main Steps of Proposed Method

- Subspace Representation
- Averaging Mean-target Subspace
- Domain Adaptation
- Recursive Feedback

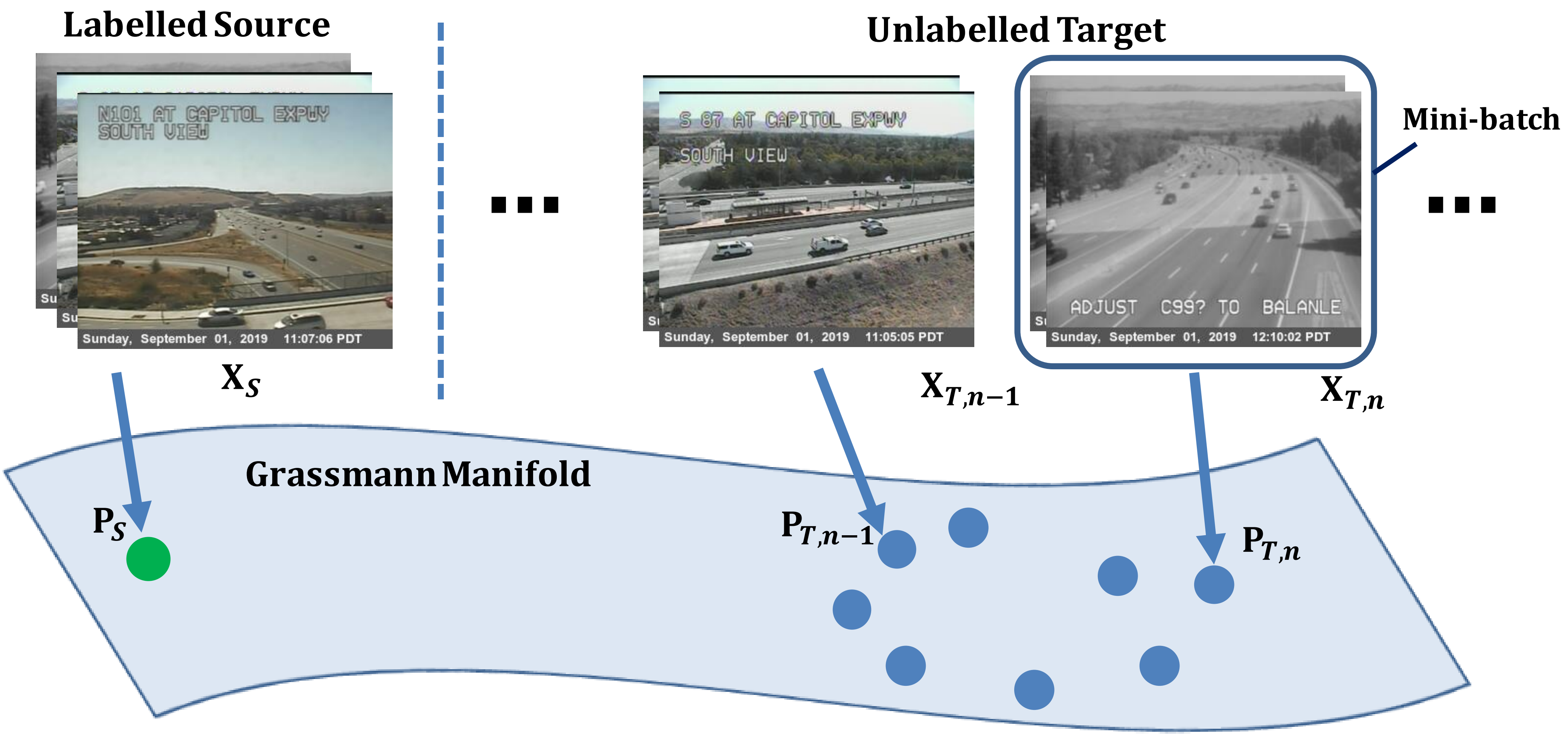
Overall Procedure



Each Step of the Proposed Framework

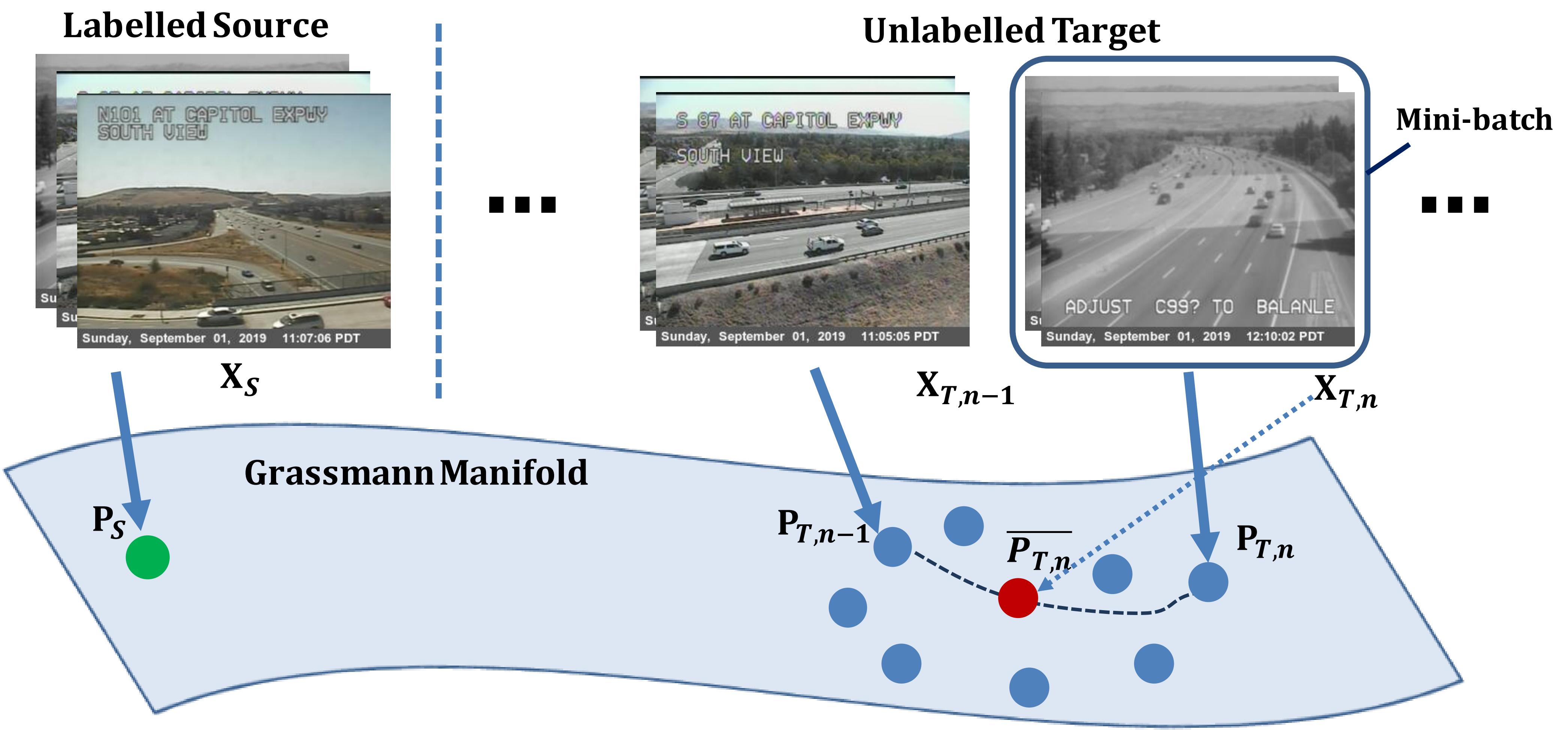
1. Subspace Representation

Subspace Representation



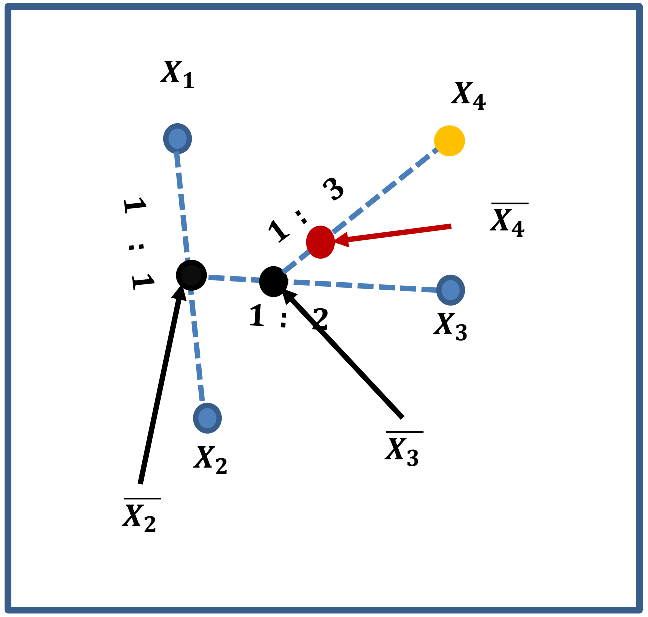
2. Averaging Mean-target Subspace

Averaging Mean-target Subspace



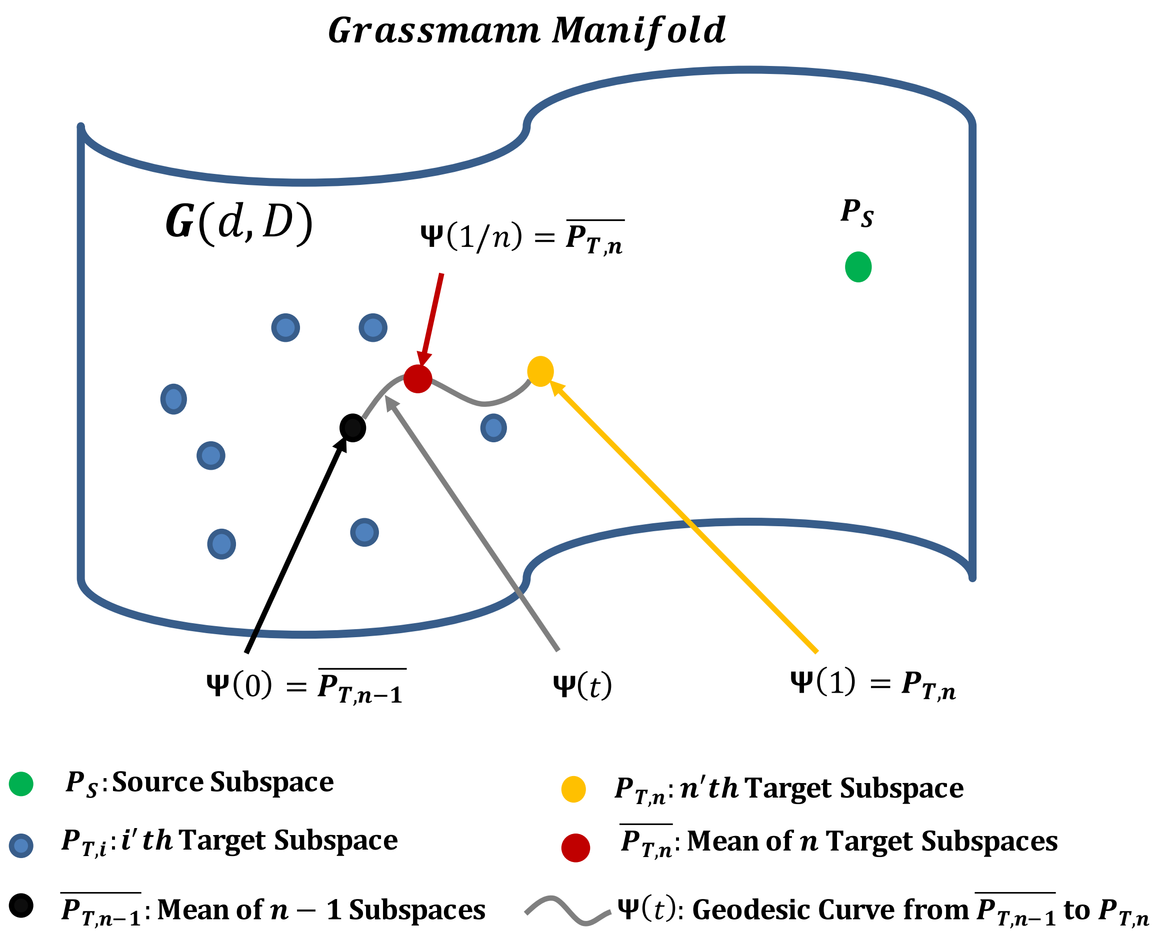
Mean Point on a Euclidean Space

Euclidean Space



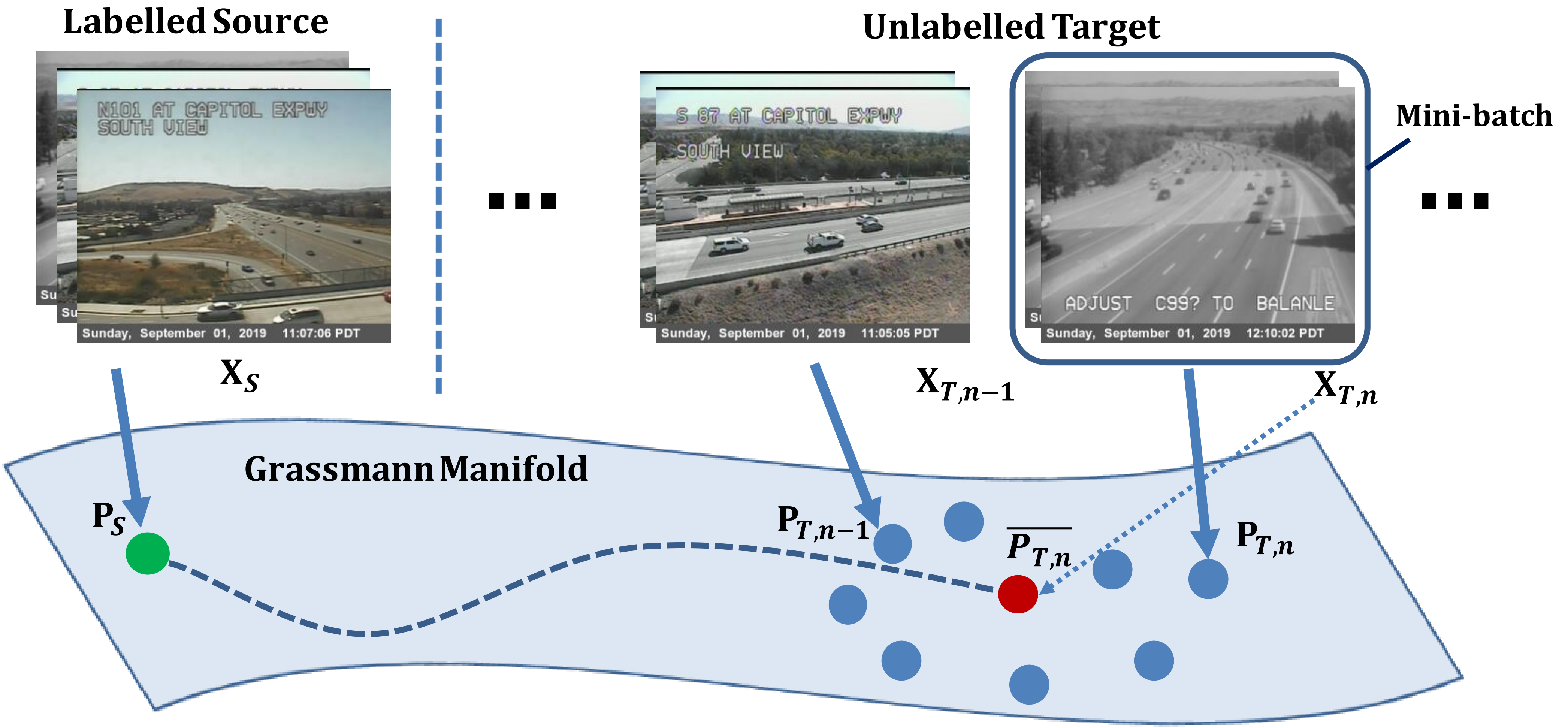
$$\overline{X_n} = \frac{(n-1)\overline{X_{n-1}} + X_n}{n}$$

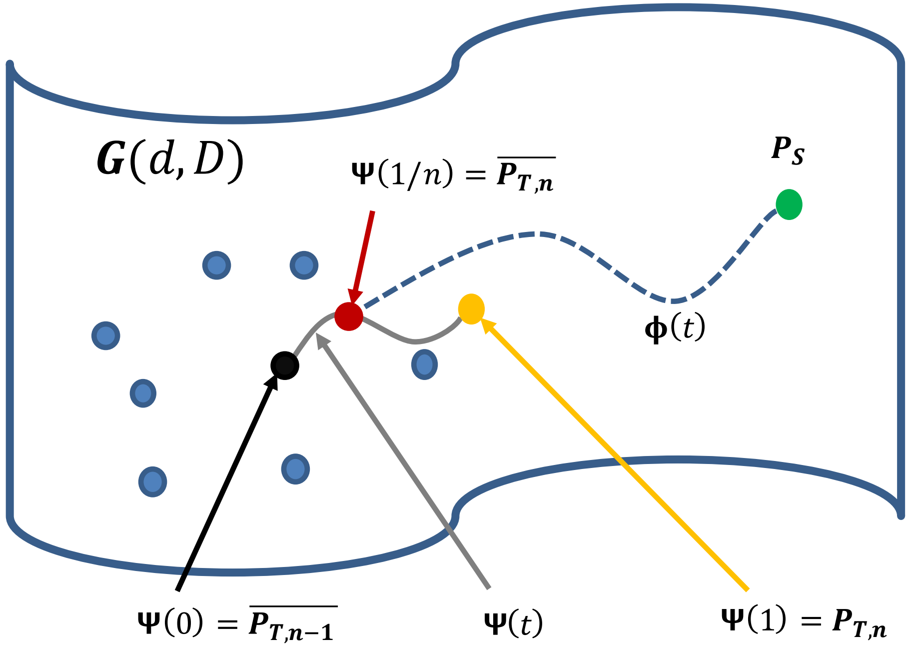
Mean Subspace on a Grassmann Manifold



- $\boldsymbol{\Psi}(0) = \overline{\boldsymbol{P}_{\boldsymbol{T},\boldsymbol{n}-\boldsymbol{1}}}$
- $\boldsymbol{\Psi}(1) = \boldsymbol{P}_{\boldsymbol{T},\boldsymbol{n}}$
- $\boldsymbol{\Psi}(1/n) = \overline{\boldsymbol{P}_{\boldsymbol{T},\boldsymbol{n}}}$

3. Domain Adaptation


Labelled Source
N101 AT CAPITOL EXPWY
SOUTH VIEW
Sunday, September 01, 2019 11:07:06 PDT
X_S
Unlabelled Target
S 87 AT CAPITOL EXPWY
SOUTH VIEW
Sunday, September 01, 2019 11:05:05 PDT
$X_{T,n-1}$
Mini-batch
ADJUST C99? TO BALANLE
Sunday, September 01, 2019 12:10:02 PDT
$X_{T,n}$
Grassmann Manifold
P_S
$P_{T,n-1}$
$\overline{P_{T,n}}$
$P_{T,n}$

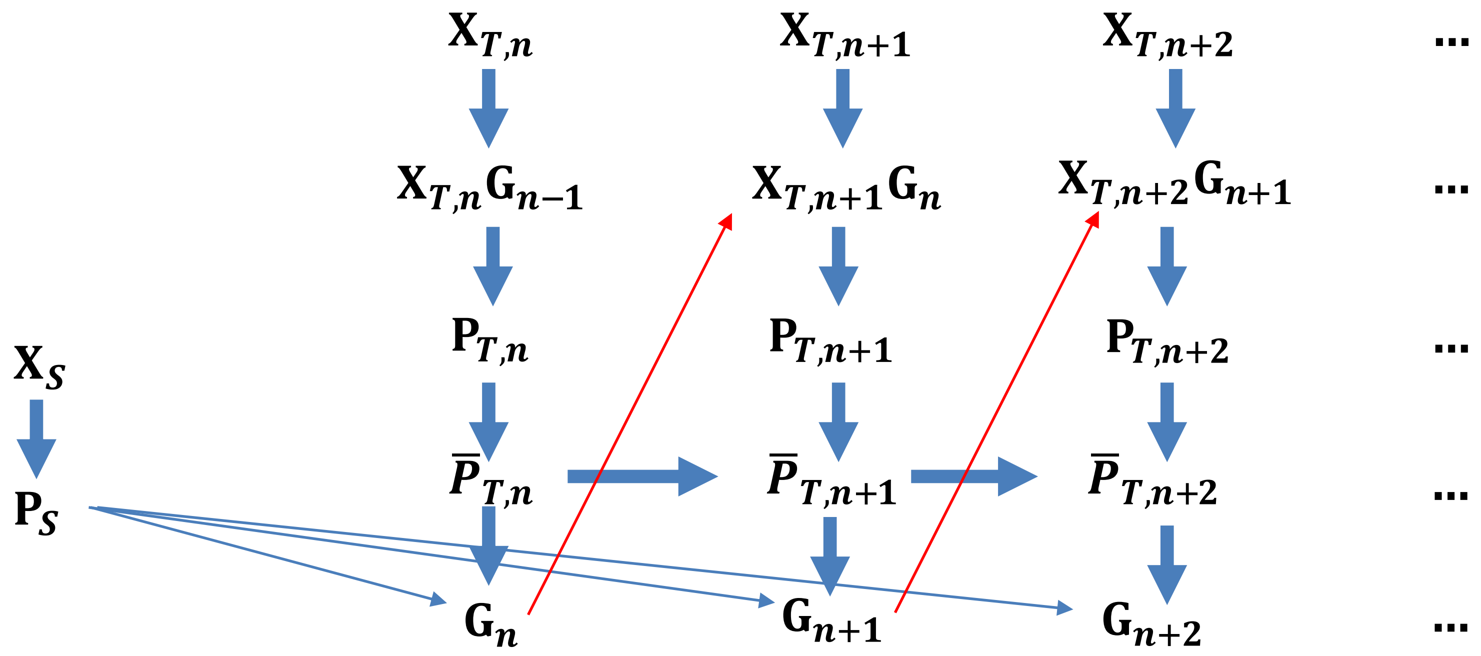


- Transformation matrix $\boldsymbol{G}_n$ from the target domain to the source domain using the Geodesic Flow Kernel (GFK)

- $\boldsymbol{G}_n = \int_0^1 \boldsymbol{\phi}(\alpha)\boldsymbol{\phi}(\alpha)^T$

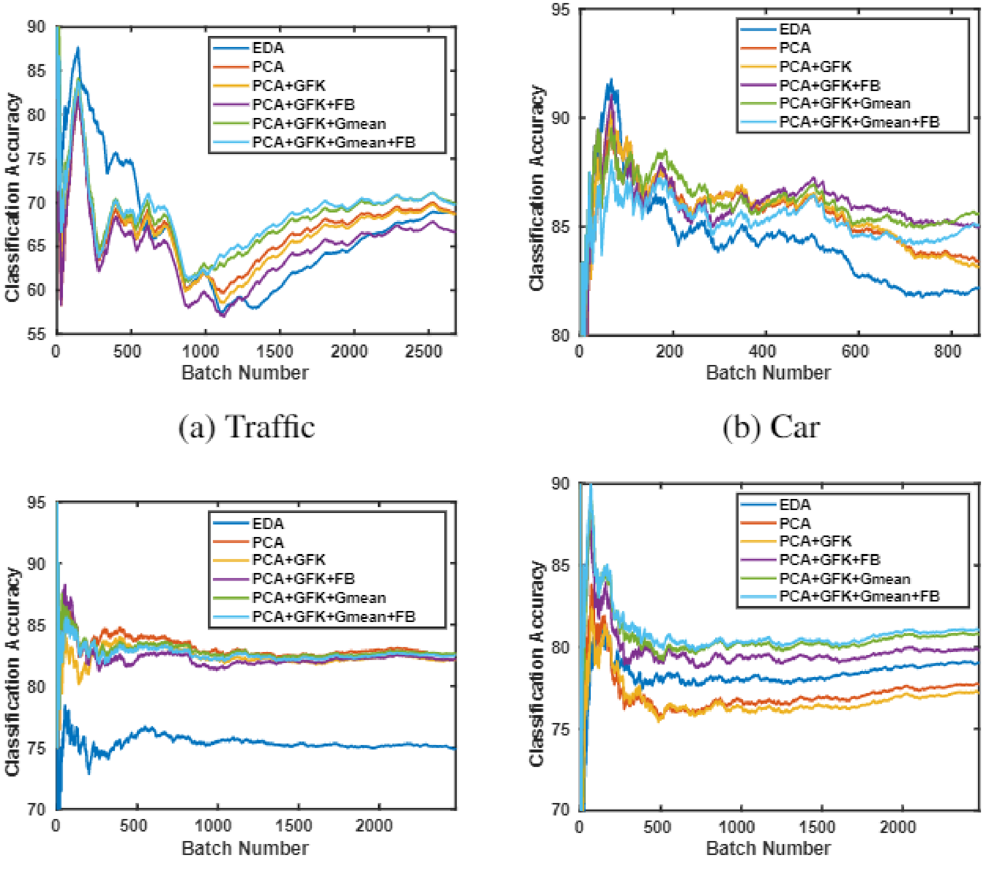
4. Recursive Feedback

Recursive Feedback



- Based on the computed transformation matrix $\boldsymbol{G_n}$, modify the (n+1)th target mini-batch $\boldsymbol{X_{T,n+1}}$ to $\boldsymbol{X_{T,n+1}^{pre}} = \boldsymbol{X_{T,n+1}G_n}$ before subspace representation step.

Experimental Results



(a) Traffic (b) Car

(c) Waveform21 (d) Waveform40

Fig. 4: Accuracy of the previous method (EDA) and variants of the proposed method.

Table 1: Accuracy (%) of Various Methods(Vanilla AE)

Method	Classifier	Traffic	Car	Waveform21	Waveform40
CMA+GFK	KNN	63.22	82.50	72.48	66.85
	SVM	68.87	82.73	69.15	68.77
CMA+SA	KNN	41.33	56.45	33.19	33.09
	SVM	41.33	56.45	33.84	33.05
EDA	ISSL	69.00	82.59	74.65	79.66
PCA	KNN	63.05	82.50	71.07	66.08
	SVM	68.85	83.31	82.55	77.74
PCA+GFK	KNN	64.02	82.44	70.55	65.76
	SVM	68.71	83.08	82.10	77.23
PCA+GFK+FB	KNN	61.77	81.28	72.65	66.85
	SVM	66.67	84.88	82.18	79.86
PCA+GFK+Gmean	KNN	56.42	82.73	72.22	67.11
	SVM	**69.94**	**85.52**	**82.69**	80.79
PCA+GFK+Gmean+FB	KNN	57.03	82.44	72.38	67.90
	SVM	69.77	85.00	82.51	**81.07**

Table 2: Comparison of Computation Time (sec)

Method	Traffic	Car	Waveform21	Waveform40
EDA	105.7	2545	22.32	23.42
Proposed method	57.45	5503	3.188	4.410

Conclusion

- We proposed a multi-step framework to solve the OUDA problem.
- We incrementally computed the mean-target subspace on a Grassmann manifold.
- Our method outperformed the previous OUDA methods in terms of classification accuracy and computation time.