

The Golden Subspace: Where Efficiency Meets Generalization in Continual Test-Time Adaptation

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Abstract

*Continual Test-Time Adaptation (CTTA) aims to enable models to adapt online to unlabeled data streams under distribution shift without accessing source data. Existing CTTA methods face an efficiency–generalization trade-off: updating more parameters improves adaptation but severely reduces online inference efficiency. An ideal solution is to achieve comparable adaptation with minimal feature updates; we call this minimal subspace the golden subspace. We prove its existence in a single-step adaptation setting and show that it coincides with the row space of the pre-trained classifier. To enable online maintenance of this subspace, we introduce the sample-wise Average Gradient Outer Product (AGOP) as an efficient proxy for estimating the classifier weights without retraining. Building on these insights, we propose **Guided Online Low-rank Directional adaptation (GOLD)**, which uses a lightweight adapter to project features onto the golden subspace and learns a compact scaling vector while the subspace is dynamically updated via AGOP. Extensive experiments on classification and segmentation benchmarks, including autonomous-driving scenarios, demonstrate that GOLD attains superior efficiency, stability, and overall performance. Our code is available at <https://github.com/AIGNLAI/GOLD>.*

1. Introduction

In real-world applications, models are often required to perform inference under continuously shifting data distributions [4, 13, 19], such as weather and illumination changes in autonomous driving, scene variations in video stream analysis, and device heterogeneity in medical imaging [17, 47, 48]. These scenarios demand models that can adapt online during test time to unknown and gradually changing target domains, without re-accessing source

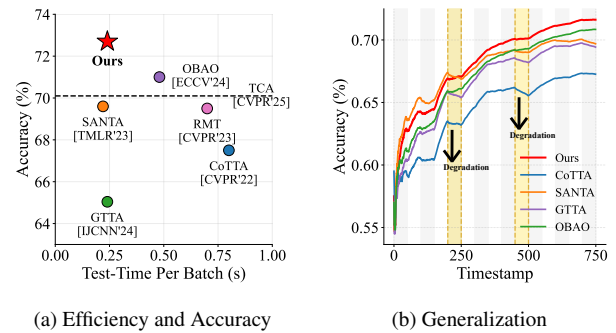


Figure 1. Results on the CIFAR100-C dataset. **Left:** performance–efficiency distribution of evaluated methods (TCA [31] is closed-source and shown as a line). **Right:** accuracy over the continuous test-time adaptation process; shaded background bands indicate periods of domain shift. In the **golden-shaded** intervals, prior methods exhibit significant performance degradation, whereas our method maintains generalization.

data or performing offline retraining. This problem setting, known as **Continual Test-Time Adaptation (CTTA)**, aims to enable models to maintain robust performance in dynamic environments [10, 34, 42]. In practical deployments, CT TA faces a trade-off between efficiency and generalization: better generalization typically requires more complex models and more intensive computation, reducing run-time efficiency. Existing approaches typically update model parameters at test time using self-supervised objectives, entropy minimization, or adaptive batch-normalization statistics [5, 25]. While such updates can provide short-term gains, they substantially increase computational cost and tend to amplify pseudo-label noise and induce parameter drift, undermining the generalization of the continual adaptation process and ultimately degrading long-term performance [8, 38, 44]. As shown in Fig. 1b, when a new domain arrives, existing methods fail to adapt quickly and exhibit sudden performance degradation, indicating an inability to

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preserve generalization during adaptation.

Ideally, our goal is to achieve the desired change in model output within the feature subspace (to ensure generalization) while keeping the update magnitude minimal (to ensure efficiency). We define this subspace as the **Golden Subspace**. We first consider a single-step adaptation scenario, derive its analytical formulation, and verify the existence of the golden subspace. Our analysis reveals that this subspace is essentially composed of the row-space of the classifier weights, which can be obtained via eigenvalue decomposition of the classifier weight matrix. **However**, a new challenge arises: the classifier weights encode predominantly source-domain information, and continuously updating them at test time reintroduces the same problems of high computational cost and structural degradation. **We therefore ask:** how can the classifier be endowed with target-domain information without retraining its weight?

Motivated by recent advances on Average Gradient Outer Product (AGOP) representations [1–3, 28, 37], we find that AGOP computed from high-confidence samples provides a faithful online proxy for the classifier’s parameter inner-product structure. Specifically, the golden subspace estimated via AGOP converges over time to the subspace obtained by single-step least-norm adaptation, which guarantees that models built on this estimator retain **strong generalization**. Empirically, AGOP matrices exhibit low effective rank, implying that the golden subspace is low-rank in practice and therefore amenable to highly **efficient** online maintenance and adaptation.

Building on these insights, we propose **Guided Online Low-rank Directional adaptation (GOLD)**, a method for efficient continuous test-time adaptation. GOLD maintains a lightweight matrix, which is initialized from the classifier weight inner-products and is updated online using the AGOP computed from high-confidence test samples. We periodically perform an eigendecomposition of it to extract the current low-rank *golden subspace*. Features from a frozen backbone are projected onto this subspace, and a compact scaling vector is learned to re-scale the projected coordinates for adaptation. This design introduces only a small number of external parameters and updates a very limited internal parameter subset, thereby intrinsically constraining parameter drift while providing sufficient capacity to refine outputs. As shown in Figure 1, GOLD attains the best performance with minimal adaptation cost (Figure 1a) and preserves high generalization ability across domain shifts (Figure 1b).

Our main contributions are summarized as follows:

- We formalize the *golden subspace* as the minimal feature-update subspace induced by the classifier and show that it admits a low-rank characterization. We further develop an AGOP-based online estimator that tracks this subspace during test-time adaptation.

- We introduce GOLD, a source-free online adaptation framework that projects features onto the golden subspace and learns a lightweight scaling vector. GOLD achieves efficient adaptation with minimal updates.
- Extensive experiments on **classification** and **segmentation** benchmarks demonstrate that GOLD achieves SOTA performance with a minimal computational footprint.

2. Related Work

Continual Test-Time Adaptation (CTTA) [14, 24] extends test-time adaptation to dynamic environments [20, 21], where a source model must adapt continuously to a stream of unlabeled and non-stationary target data without revisiting source samples [27, 30].

The pioneering CoTTA [42] introduced a teacher student framework with weight averaging and stochastic weight restoration to alleviate error accumulation and forgetting. Building on this idea, PETAL [5] proposed a data-driven parameter recovery mechanism that regularizes model updates toward the source parameter configuration to enhance robustness. RMT [11] and SANTA [6] enforced feature-level consistency with the source model through contrastive objectives, while DSS [44] improved reliability by filtering unsafe pseudo-labels during adaptation. More recently, TCA [31] maintained inter-class stability by preserving topological consistency among class representations during domain shifts. Despite these advances, most existing methods still rely on global or feature-level updates of the entire network [9, 39, 52], which inevitably leads to a trade-off between efficiency and generalization.

3. Preliminary

3.1. Problem Definition

We study the CTCTA setting [23, 45], where a model $f_\theta = h_\psi \circ g_\phi$ is pretrained on a labeled source domain $\mathcal{D}_{\text{src}} = \{(x_i^{\text{src}}, y_i^{\text{src}})\}_{i=1}^{N_{\text{src}}}$ and deployed to an unlabeled target data stream $\mathcal{D}_T = \{\mathcal{X}_1, \mathcal{X}_2, \dots, \mathcal{X}_T\}$. Each batch $\mathcal{X}_t = \{x_i^{(t)}\}_{i=1}^{N_t}$ is drawn from a target distribution $p_t(x)$ that may evolve over time, i.e., $p_t(x) \neq p_{t+1}(x)$.

During deployment, the model encounters the data stream sequentially. At each step t , it receives the current batch $\mathcal{X}_t$, produces predictions $\hat{y}^{(t)} = g_{\theta_t}(\mathcal{X}_t)$, and performs online adaptation using only the current unlabeled data, without any access to the source domain or previous target samples.

Two key factors determine the practicality of such continual adaptation: **efficiency** and **generalization**. For example, in autonomous driving systems, the model must adapt rapidly and robustly within a limited time window to ensure reliable perception and decision-making under shifting environments.

3.2. Does the Golden Subspace Exist?

An ideal *golden subspace* achieves the required change in model outputs (ensuring generalization) while minimizing the amount of training (ensuring efficiency). **We first consider a simple yet insightful single-step adaptation case.**

Given a frozen pretrained classifier $W \in \mathbb{R}^{C \times L}$ placed on top of a feature extractor. Let the pre-adaptation features for a test batch be $F \in \mathbb{R}^{B \times L}$, and suppose we aim to realize a desired output correction $\Delta Y \in \mathbb{R}^{B \times C}$ after adaptation. Seeking the smallest feature-space change (in Frobenius norm) that achieves this correction leads to the least-norm solution

$$\Delta F^* = \Delta Y (W^\top)^\dagger, \quad (1)$$

where $(\cdot)^\dagger$ denotes the Moore–Penrose pseudoinverse.

This algebraic relation directly leads to a rank constraint:

$$\text{rank}(\Delta F^*) \leq \text{rank}((W^\top)^\dagger) = \text{rank}(W^\top W). \quad (2)$$

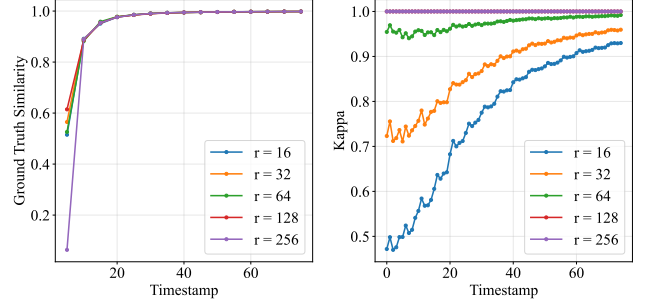
This implies that the rank of the golden subspace is constrained by the rank of the classifier weights, making it inherently low-rank. In neural networks, the number of classes is typically small, so the rank of W is bounded by the number of classes. This means that only a few classifier-related directions are sufficient to modify the model’s predictions for an entire batch, without the need to explore arbitrary high-dimensional perturbations.

To further interpret this result, consider the singular value decomposition $W^\top = V \Sigma U^\top$. Substituting into Equation (1) gives $\Delta F^* = V \Sigma^\dagger U^\top \Delta Y$, showing that the golden subspace is restricted to the subspace spanned by the principal eigenvectors of the classifier. The classifier implicitly defines a set of directions in the feature space to which the output is most sensitive.

This observation confirms the **existence** of the previously proposed golden subspace. It suggests that we can obtain the golden subspace by performing *eigenvalue decomposition* on the classifier weights. Such a constraint naturally reduces the risk of error amplification caused by noisy pseudo-labels, mitigates catastrophic forgetting by preventing uncontrolled parameter drift, and ultimately leads to a more efficient CTTA process.

3.3. How to Update the Golden Subspace?

While Equation (1) shows that the golden subspace lies in $\text{span}(W^\top)$, this fact alone is insufficient in the CTTA setting. The matrix W encodes a global weight configuration learned on the source domain, whereas the target-domain sample distribution, class confidences, and noise evolve over time. **Hence the key question is how to update the golden subspace online at test time so that it**



(a) Similarity of golden subspace between AGOP and ground truth. (b) Cumulative spectral energy $\kappa(k)$ of AGOP.

Figure 2. (a) Alignment between AGOP-derived subspace and source-derived ground-truth subspace as testing progresses. AGOP rapidly converges and remains highly aligned. (b) AGOP spectrum cumulative energy: the top 64–128 eigenvectors capture over 99% of the energy, indicating strong low-rank concentration.

reflects target-domain semantics. Retraining the classifier weights is impractical and inefficient, and accumulated errors can destroy the weight structure. Therefore, we require an **estimator** that dynamically maintains the golden subspace without retraining W , allowing it to implicitly incorporate target-domain information.

We note that, as observed in [36], for a well-trained neural network $\hat{f}$ the spectral structure of a layer’s weight matrix is closely related to an averaged outer-product of per-sample feature gradients. In particular, for layer l and its i -th weight matrix $W_i^{(l)}$ one can write

$$W_i^{(l)\top} W_i^{(l)} \propto \left(\frac{1}{n} \sum_{p=1}^n \sum_{j=1}^m \nabla_{u_{ij}^{(l)}} \hat{f}(x^{(p)}) \nabla_{u_{ij}^{(l)}} \hat{f}(x^{(p)})^\top \right)^\alpha,$$

where n denotes the number of training samples, m indexes the relevant input subunits (e.g. spatial locations or feature channels) feeding into the l -th layer, and $u_{ij}^{(l)}$ is the j -th input/pre-activation to that layer for unit i . The exponent α is typically taken to be around 1/2 in empirical studies.

Under the CTTA setting, a **key difference** is that we cannot obtain the labels, so we choose to use pseudo-labels from high-confidence samples for calculation. To verify the feasibility of this approach, we maintain an online AGOP estimator and perform eigenvalue decomposition to obtain an estimated single-step golden subspace. The ground-truth golden subspace is directly computed based on the definition in Equation (1). As shown in Figure 2a, we visualize the temporal evolution of similarity between the AGOP-derived subspace and the true golden subspace. Although the AGOP estimation initially performs poorly after initialization, it quickly converges above **0.8** and eventually stabilizes above **0.98**. This behavior demonstrates that AGOP serves as an effective estimator of the golden subspace, ensuring **strong generalization** capability for our method.

To quantify the low-rank nature of the golden subspace, we measure the cumulative spectral energy $\kappa(k) = \frac{\sum_{i=1}^k \lambda_i}{\sum_{i=1}^L \lambda_i}$, where $\{\lambda_i\}$ are the eigenvalues of G in descending order. The curve in Figure 2b shows that more than 99% of the spectral energy of G is captured by only 64–128 eigenvectors, confirming a strong low-rank concentration. This empirical fact justifies guiding continual adaptation with a low-dimensional subspace: doing so **reduces computational cost** while tightly controlling representational drift.

Finally, we observe that using a moderately low rank yields the best trade-off in practice: lower ranks lead to faster convergence and more efficient adaptation (as seen in Figure 2a), but an overly small rank fails to cover all important directions (Figure 2b). Accordingly, all experiments in this work use a moderate subspace dimensionality of 64.

4. Methodology

Based on the above analysis, we reach two key insights: 1) the golden subspace indeed exists and can be directly obtained via eigendecomposition of the classifier weights; 2) the AGOP computed from test samples provides a powerful approximation of the classifier weight dynamics without retraining. Building on these findings, we propose Guided Online Low-rank Directional adaptation (**GOLD**), as illustrated in Figure 3.

GOLD maintains a lightweight auxiliary matrix G_t , initialized from the inner-products of classifier weights and updated online using AGOP computed from high-confidence test samples. For each test batch, GOLD operates in two stages: in the **adapt stage**, backbone features are projected onto the golden subspace and refined via a compact scaling vector S for lightweight feature adaptation; in the **update stage**, the golden subspace is continually maintained through AGOP from confident samples, while the scaling vector S is optimized via self-training and prototype-based contrastive losses, enabling stable and source-free continual adaptation.

4.1. Pretraining and Prototype Extraction

We first pretrain a base model $f_\theta = h_\psi \circ g_\phi$ on the labeled source dataset $\mathcal{D}_{\text{src}} = \{(x_i^{\text{src}}, y_i^{\text{src}})\}_{i=1}^{N_{\text{src}}}$ using standard supervised losses (e.g., cross-entropy). After convergence the learned parameters $\theta^* = (\phi^*, \psi^*)$ induce a discriminative feature space $\mathbb{R}^L$ in which samples of the same class form compact clusters. The pretrained feature extractor g_{ϕ^*} is then frozen for subsequent test-time adaptation. For each class $c \in \{1, \dots, C\}$ we compute a class prototype as the mean embedding of all source examples of that class:

$$P_c = \frac{1}{|\mathcal{I}_c|} \sum_{i \in \mathcal{I}_c} g_{\phi^*}(x_i^{\text{src}}) \in \mathbb{R}^L, \quad \mathcal{I}_c = \{i \mid y_i^{\text{src}} = c\}.$$

All class prototypes are collected into the prototype matrix $P = [P_1, P_2, \dots, P_C]^\top \in \mathbb{R}^{C \times L}$. The matrix P serves as a set of *semantic anchors*, namely, class-level reference points that preserve the source-domain semantic geometry. During deployment, we never access source samples. Instead, we only retain the pre-computed class prototypes extracted offline before adaptation, which serve as fixed semantic anchors throughout test-time adaptation.

4.2. Subspace Projection and Adaptive Rescaling

For the t -th test batch we denote the input batch by $x_t \in \mathbb{R}^{B \times \cdot}$ and write the extracted features as $F_t = g_{\phi^*}(x_t) \in \mathbb{R}^{B \times L}$, so that each row $f \in \mathbb{R}^L$ of F_t corresponds to one example in the batch. We introduce a subspace projection matrix $V_t \in \mathbb{R}^{L \times r}$ and a scaling vector $S_t \in \mathbb{R}^r$. The r columns of V_t form a basis for a low-dimensional subspace of $\mathbb{R}^L$, and S_t specifies element-wise modulation of the coordinates in that subspace.

Given a single feature $f \in \mathbb{R}^L$, we first project it onto the *golden subspace* by

$$u = V_t^\top f \in \mathbb{R}^r,$$

then apply an element-wise rescaling of the projected coordinates,

$$\tilde{u} = (1 + S_t) \odot u \in \mathbb{R}^r,$$

where $\odot$ denotes the Hadamard (element-wise) product and $1 \in \mathbb{R}^r$ is the all-ones vector so that $S_t = 0$ yields the identity transform. The modulated coordinates are mapped back to the original feature space and added to the original feature in a residual manner:

$$\mathcal{A}(f) = f + V_t(\tilde{u} - u) = f + V_t(S_t \odot (V_t^\top f)).$$

This residual form preserves the original feature when $S_t = 0$, which helps stabilize adaptation.

Applied to the whole batch $F_t \in \mathbb{R}^{B \times L}$, we obtain

$$F_t^{\text{adapt}} = F_t + (S_t \odot (F_t V_t)) V_t^\top.$$

At this stage we obtain adapted features for prediction. How should we update the adapter’s subspace and the scaling vector? Guided by the derivation in Section 3.2, we propose an AGOP-based projection update in Section 4.3 and a scaling-vector update driven by self-training and prototype-based contrastive losses in Section 4.4.

4.3. AGOP-based Subspace Projection Update

Subspace projection aims to identify the directions in feature space that most require adaptation. Following the analysis in Section 3.2, we initialize an auxiliary matrix $G_0 = W^\top W$, which reflects the global geometry of the source classifier. To enable adaptation under shifting target domains, we then update this matrix online using the AGOP

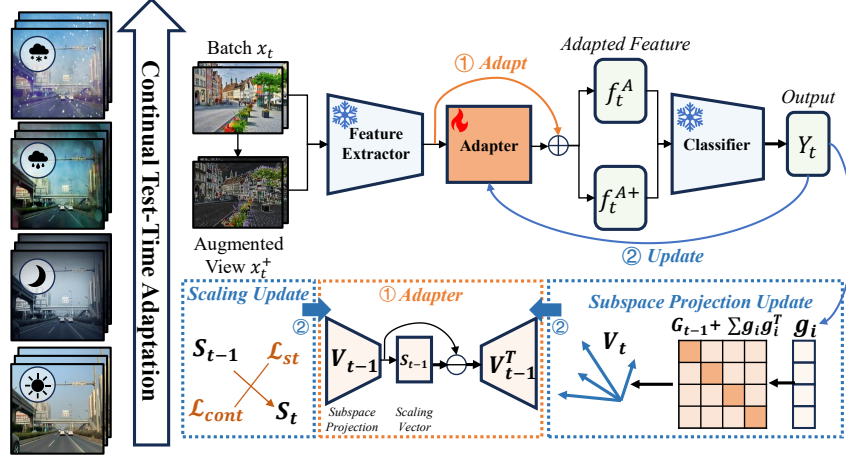


Figure 3. Overview of GOLD: it maintains an online AGOP estimator, from which the top- r eigenvectors V_t are extracted via eigendecomposition to form the golden subspace. A residual low-rank adapter of rank r is then applied to learn a lightweight scaling vector S_t . Meanwhile, a combination of self-training loss and prototype-based contrastive loss provides stable supervision.

computed from current high-confidence samples. This online refinement allows the subspace to gradually incorporate target-domain information without retraining the classifier, ensuring that adaptation remains both efficient and stable.

For the current test batch x_t we extract features and compute logits on the adapted features:

$$F_t = g_{\phi^*}(x_t) \in \mathbb{R}^{B \times L}, \quad Y_t = h_{\psi}(\mathcal{A}(F_t)) \in \mathbb{R}^{B \times C}.$$

For each sample i in the current batch, let

$$p_{t,i} = \max_c \text{Softmax}(Y_t)_{i,c},$$

denote its maximum predicted probability. We then select the high-confidence subset

$$\mathcal{M}_t = \{i \in [B] \mid p_{t,i} \geq \tau\},$$

where τ is a confidence threshold.

For each $i \in \mathcal{M}_t$ we form a gradient surrogate given by the gradient of the top logit with respect to the feature:

$$g_i = \nabla_{f_i} \left(\max_c h_{\psi}(f_i)_c \right) \in \mathbb{R}^L,$$

where f_i may be taken as the detached (pre-adaptation) feature to avoid unnecessary graph propagation.

The per-batch AGOP is constructed as

$$\widehat{G}_t^{(b)} = \frac{1}{|\mathcal{M}_t|} \sum_{i \in \mathcal{M}_t} g_i g_i^{\top} \in \mathbb{R}^{L \times L},$$

Batch contributions are aggregated online via an exponential moving average:

$$G_t = (1 - \alpha)G_{t-1} + \alpha \widehat{G}_t^{(b)},$$

where $\alpha \in (0, 1]$ controls the update rate.

Every T_{eig} batches we perform a symmetric eigendecomposition of G_t to extract the dominant subspace:

$$G_t = Q\Lambda Q^{\top}, \quad \Lambda = \text{diag}(\lambda_1, \dots, \lambda_L),$$

and select the top- r eigenvectors to form the subspace basis

$$V_t = [v_1, \dots, v_r] \in \mathbb{R}^{L \times r}.$$

V_t thus denotes the low-rank subspace to which the adapter is restricted, enabling effective adaptation while substantially reducing parameter and computational overhead.

4.4. Scaling-Vector Update

To provide more reliable supervision for updating the scaling vector, we follow recent CTTA works [26, 51, 53] and adopt an EMA teacher model. Let the student logits for the current batch be $Y_t = h_{\psi}(\mathcal{A}(g_{\phi^*}(x_t)))$ and let the teacher logits be $Y_t^{\text{ema}} = h_{\psi}^{\text{ema}}(g_{\phi^*}(x_t))$. We also denote by $Y_t^+ = h_{\psi}(\mathcal{A}(F_t^+))$ the logits computed on an augmented view x_t^+ of the same batch. Using both the original and an augmented view encourages the model to produce predictions that are invariant to realistic input perturbations and thus reduces overfitting to spurious features.

Self-training consistency loss. The EMA teacher provides a stable target for both the original and augmented views. We use a SCE (Symmetric Cross Entropy) loss [43]:

$$\mathcal{L}_{\text{st}} = \frac{1}{2} \text{SCE}(Y_t, Y_t^{\text{ema}}) + \frac{1}{2} \text{SCE}(Y_t^+, Y_t^{\text{ema}}).$$

Intuitively, the first term enforces that the student prediction on the original image matches the stable EMA target, while the second term enforces that an augmented view produces

Table 1. Online classification error rates (%) on CIFAR10-C, CIFAR100-C, and ImageNet-C under the CTTA setting. All methods are evaluated online at severity level 5, with our method’s results averaged over 5 independent runs. The best performance for each corruption type is highlighted in **bold** and the next best is underlined.

	Method	Gau.	shot	imp.	def.	glass	mot.	zoom	snow	fro.	fog	bri.	con.	ela.	pix.	jpeg	Mean
CIFAR10-C	TENT [40]	24.8	20.6	28.6	14.4	31.1	16.5	14.1	19.1	18.6	18.6	12.2	20.3	25.7	20.8	24.9	20.7
	Ada [7]	29.1	22.5	30.0	14.0	32.7	14.1	12.0	16.6	14.9	14.4	8.1	10.0	21.9	17.7	20.0	18.5
	CoTTA [42]	24.3	21.3	26.6	11.6	27.6	<u>12.2</u>	10.3	14.8	14.1	12.4	7.6	10.6	18.3	13.4	17.3	16.2
	RMT [11]	24.0	20.4	25.6	12.6	25.4	14.2	12.2	15.4	15.1	14.1	10.3	13.7	17.1	13.5	16.0	16.7
	DSS [44]	24.1	21.3	25.4	11.7	26.9	<u>12.2</u>	10.5	14.5	14.1	12.5	7.8	10.8	18.0	13.1	17.3	16.0
	EATA [32]	24.2	19.1	27.6	12.5	29.2	14.2	12.0	16.3	15.1	15.1	8.9	13.5	21.2	16.4	21.9	17.9
	SAR [33]	28.3	25.9	35.7	12.6	34.7	13.8	11.9	17.4	17.5	14.8	8.1	12.9	23.5	19.5	27.2	20.3
	BeCoTTA [22]	22.9	19.1	26.9	<u>10.2</u>	27.5	12.7	10.4	14.7	14.3	12.4	7.2	<u>9.4</u>	20.9	15.2	20.2	16.3
	SANTA [6]	23.9	20.1	28.0	11.6	27.4	12.6	10.2	14.1	13.2	12.2	7.6	10.3	19.1	13.3	18.5	16.1
	OBAO [53]	<u>22.2</u>	<u>18.3</u>	<u>25.0</u>	10.7	<u>24.7</u>	11.6	<u>10.0</u>	<u>12.9</u>	<u>12.7</u>	<u>10.9</u>	7.7	9.6	<u>15.7</u>	<u>11.4</u>	<u>15.2</u>	<u>14.6</u>
	GOLD	21.4	18.1	24.5	10.0	24.4	11.6	9.9	12.5	12.3	10.5	<u>7.5</u>	8.9	15.3	10.5	14.9	14.1
CIFAR100-C	TENT [40]	37.2	35.8	41.7	37.9	51.2	48.3	48.5	58.4	63.7	71.1	70.4	82.3	88.0	88.5	90.4	60.9
	Ada [7]	42.3	36.8	38.6	27.7	40.1	29.1	27.5	32.9	30.7	38.2	25.9	28.3	33.9	33.3	36.2	33.4
	CoTTA [42]	40.1	37.7	39.7	26.9	38.0	27.9	26.4	32.8	31.8	40.3	24.7	26.9	32.5	28.3	33.5	32.5
	RMT [11]	40.5	36.1	36.3	27.7	33.9	28.5	26.4	29.0	29.0	32.5	25.1	27.4	28.2	<u>26.3</u>	29.3	30.4
	DSS [44]	39.7	36.0	37.2	26.3	35.6	27.5	25.2	31.4	30.0	37.8	24.2	26.0	30.0	<u>26.3</u>	31.3	30.9
	EATA [32]	37.2	33.0	35.9	27.7	38.1	29.4	27.1	32.8	32.7	36.1	27.0	29.4	33.8	29.5	38.2	32.5
	SAR [33]	40.5	34.8	37.1	25.6	37.2	28.0	25.5	31.9	30.9	35.8	25.2	27.8	31.8	29.0	37.2	31.9
	BeCoTTA [22]	42.1	38.0	42.2	30.2	42.9	31.7	29.8	35.1	33.9	38.5	27.9	32.0	36.7	31.6	39.9	35.5
	SANTA [6]	36.6	<u>33.2</u>	<u>35.1</u>	<u>25.9</u>	34.9	27.7	25.4	29.5	29.9	33.1	<u>23.6</u>	26.7	31.9	27.5	35.2	30.4
	OBAO [53]	38.8	35.0	36.6	26.7	<u>33.4</u>	27.4	25.0	<u>28.6</u>	<u>28.0</u>	<u>31.2</u>	24.1	25.1	<u>27.5</u>	25.4	<u>29.1</u>	<u>29.5</u>
	GOLD	<u>37.1</u>	34.0	35.5	26.1	32.2	26.7	24.8	27.1	27.0	29.5	23.5	<u>25.2</u>	26.8	24.6	28.3	28.6
ImageNet-C	TENT [40]	81.6	74.6	72.7	77.6	73.8	65.5	55.3	61.6	63.0	51.7	38.2	72.1	50.8	47.4	53.3	62.6
	Ada [7]	82.9	80.9	78.4	81.4	78.7	72.9	64.0	63.5	64.5	53.5	38.4	66.7	54.6	49.4	53.0	65.5
	CoTTA [42]	84.7	82.1	80.6	81.3	79.0	68.6	57.5	60.3	60.5	48.3	36.6	66.1	47.3	41.2	46.0	62.7
	RMT [11]	80.2	76.4	74.5	77.1	74.4	66.2	57.6	57.0	<u>59.1</u>	48.0	39.1	<u>60.6</u>	47.3	42.5	43.4	60.2
	DSS [44]	82.3	78.4	76.7	81.9	77.8	66.9	60.9	50.8	60.9	47.7	35.4	69.0	47.5	40.9	46.2	62.2
	EATA [32]	<u>75.7</u>	66.7	65.4	<u>74.1</u>	69.2	64.2	57.5	63.0	62.8	53.4	41.3	64.0	50.5	47.2	50.0	60.4
	SAR [33]	82.0	74.0	71.9	77.4	73.6	66.1	56.2	61.3	63.1	51.2	37.1	69.0	49.8	46.0	51.2	62.0
	BeCoTTA [22]	84.1	74.3	72.2	77.4	71.9	<u>63.4</u>	<u>55.1</u>	57.2	61.2	50.7	36.4	66.1	49.2	45.6	48.4	60.9
	SANTA [6]	74.1	72.9	71.6	75.7	74.1	64.2	55.5	<u>55.6</u>	62.9	46.6	34.1	69.9	50.6	44.3	48.5	60.1
	OBAO [53]	78.5	75.3	73.0	75.7	73.1	64.5	56.0	55.8	58.1	<u>47.6</u>	40.5	60.1	47.4	43.9	<u>45.8</u>	<u>59.6</u>
	GOLD	76.6	<u>72.4</u>	<u>70.9</u>	73.3	<u>71.4</u>	62.2	54.9	57.7	60.3	48.5	38.7	61.8	48.6	45.3	47.8	59.3

the same stable prediction. These terms improve robustness and reduce confirmation bias from noisy pseudo-labels.

Prototype-based contrastive loss. To further anchor adapted features to source semantics, we form a prototype-based contrastive objective. For each sample i we find the nearest source prototype $k(i)$ by cosine similarity. Using the triplet $[P_{k(i)}, f_i, f_i^+]$ (where f_i^+ is the feature of the augmented view), we encourage both the original and augmented features to align with the chosen prototype while being separated from other prototypes. A practical instantiation uses an InfoNCE-style loss [35, 41] averaged over the two views:

$$\mathcal{L}_{\text{cont}} = -\frac{1}{2|\mathcal{B}|} \sum_{i \in \mathcal{B}} \left[\log \frac{\exp(\text{sim}(f_i, P_{k(i)})/\kappa)}{\sum_c \exp(\text{sim}(f_i, P_c)/\kappa)} + \log \frac{\exp(\text{sim}(f_i^+, P_{k(i)})/\kappa)}{\sum_c \exp(\text{sim}(f_i^+, P_c)/\kappa)} \right],$$

where $\text{sim}(u, v) = \frac{u^\top v}{\|u\| \|v\|}$ is cosine similarity, $\kappa > 0$ is a temperature, and $\mathcal{B}$ denotes the set of samples used for contrastive supervision. This loss pulls both views toward the same source prototype and discourages drifting away from source semantics; using the augmented view in the pair improves invariance to input transformations.

Total loss and online update. The overall objective combines the self-training term and the prototype contrastive term (weighted by tunable coefficients):

$$\mathcal{L} = \lambda_{\text{trg}} \mathcal{L}_{\text{st}} + \lambda_{\text{cont}} \mathcal{L}_{\text{cont}}.$$

We perform a **single gradient step** on the scaling vector S_t and a small set of batch-norm parameters θ .

5. Experiment

We evaluate the performance of GOLD on both image classification and semantic segmentation tasks, while also as-

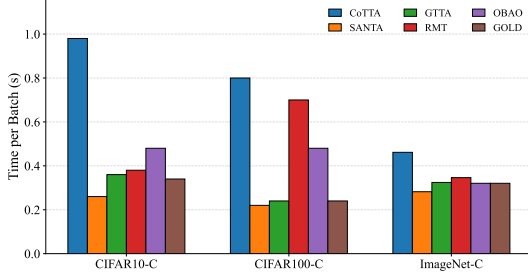


Figure 4. Comparison of method efficiency. The vertical axis shows the time required for each method to perform adaptation and prediction in each test batch.

sessing its adaptation efficiency. *Additional experiments presented in the supplementary material* include parameter robustness analysis, performance across different batch sizes, and additional factors.

5.1. Dataset and Settings

Following [31, 42], we evaluate GOLD on CIFAR10-C, CIFAR100-C, and ImageNet-C [16], which are standard robustness benchmarks containing 15 corruption types at severity levels 1–5. We use the clean training sets of CIFAR10, CIFAR100, and ImageNet [18] as source domains, and their corrupted counterparts as target domains. The model adapts sequentially to all 15 corruption types at severity level 5 in an online manner without domain change notification. For each corruption, we use 10,000 images for the CIFAR-based datasets and 5,000 for ImageNet-C.

We strictly adhere to the CTTA protocol without accessing any source data. Our method is compared against both established and state-of-the-art CTTA approaches, all evaluated online under the same conditions. For all datasets, we use the maximum corruption severity level of 5. Model predictions are generated before adapting to the current test stream. Following CoTTA, we employ standard pre-trained models as our source models: WideResNet-28 [49] for CIFAR10-C, ResNeXt-29 [46] for CIFAR100-C, and ResNet-50 [15] for ImageNet-C. Comprehensive descriptions of baseline methods and implementation details are provided in the supplementary material.

5.2. Main Results

Table 1 presents the classification error rates (lower is better) of various methods under the CTTA setting on three benchmark datasets, all evaluated at the highest corruption severity level 5. Our proposed GOLD establishes state-of-the-art performance across all benchmarks, demonstrating consistent effectiveness in handling diverse corruption types. On CIFAR10-C, GOLD achieves a mean error rate of 14.1%, outperforming all competing methods and demonstrating particularly strong results on geometri-

Table 2. Ablation studies of two components (G_t and S_t) on the CIFAR10-C, CIFAR100-C, and ImageNet-C datasets.

$W^T W$ init	AGOP	$\mathcal{L}_{\text{cont}}$	CIFAR10-C	CIFAR100-C	ImageNet-C
-	-	-	16.24	29.87	62.45
✓	-	-	15.11	29.15	60.24
✓	-	✓	14.64	28.63	60.01
✓	✓	-	15.06	28.77	59.87
-	✓	✓	14.32	28.61	59.52
✓	✓	✓	14.12	28.56	59.32

cally challenging corruptions like defocus blur and motion blur. The advantage is more pronounced on CIFAR100-C, where GOLD substantially surpasses CoTTA and TENT, indicating superior capability in handling fine-grained classification tasks. For ImageNet-C, GOLD maintains this competitive edge with the best overall performance, showing consistent robustness across datasets of varying scales. These results collectively validate GOLD’s effectiveness in diverse continuous test-time adaptation scenarios.

As shown in Table 2, we conduct an ablation study to investigate the effects of golden subspace estimation and loss components. For subspace construction, we compare three variants: (1) without subspace projection, (2) using the eigendecomposition of $W^T W$ for initialization (as motivated by Equation (1)), and (3) employing the proposed AGOP-based online update. The results demonstrate that subspace projection effectively suppresses excessive parameter updates and stabilizes adaptation. Using the eigenspace of $W^T W$ as a naive initialization validates our theoretical insight and serves as a fast, stable warm start for adaptation. Furthermore, the AGOP-based online update continuously refines the golden subspace, enabling the model to dynamically align with evolving domain statistics and achieve superior long-term performance. For the scaling-vector update, we also evaluate the impact of the contrastive loss $\mathcal{L}_{\text{cont}}$, which further enhances model robustness and helps preserve the source-domain semantic structure, effectively mitigating feature drift during continual adaptation.

Figure 4 shows the per-batch processing time of different methods across various benchmarks. Even as the test data becomes more challenging, GOLD consistently maintains an average runtime around **0.25** seconds, which is comparable to the fastest existing method SANTA [6], while achieving substantially better performance.

5.3. Experiments on Segmentation CTTA

Under the CarlaTTA benchmark [29], a synthetic dataset built on the CARLA simulator [12] for evaluating gradual test-time adaptation in urban scene segmentation, we simulate five types of continuously evolving and unknown real-world environmental conditions. These include: *day2night* (day to night), *clear2fog* (clear to foggy), *clear2rain* (clear to rainy), *dynamic* (combined varying conditions), and *highway* (transition from urban to highway scenes, which

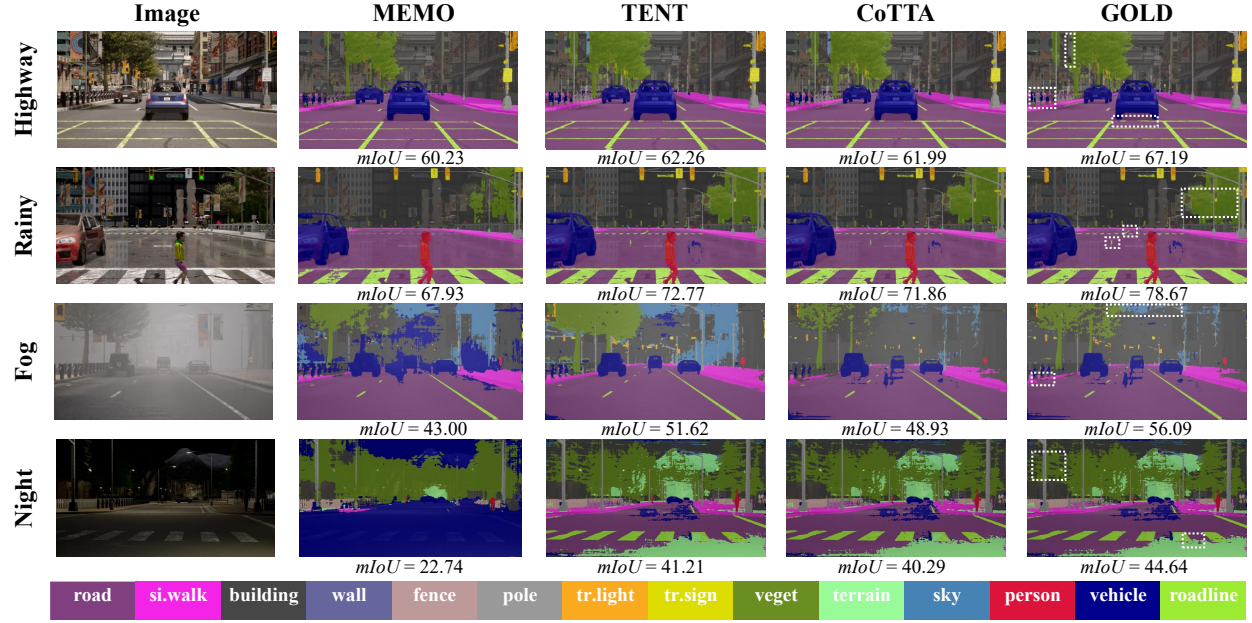


Figure 5. A visual comparison of segmentation results from different adaptive methods on the CarlaTTA sequence is presented. White boxes indicate areas where GOLD has made progress, and magnified images are shown in the supplementary material.

also introduces label distribution shift). The objective of this experiment is to assess the model’s online adaptation capability under these complex and continuously changing driving scenarios. Evaluation is performed by computing the **mean Intersection-over-Union** (mIoU) over the entire test sequence. *Detailed experimental configurations are provided in the supplementary material.*

Quantitative results are presented in Table 3. Compared with strong baselines including Source, MEMO, TENT, and CoTTA, our proposed GOLD method achieves competitive performance across all five domain shift scenarios. Specifically, GOLD obtains the highest mIoU on three sequences: *day2night*, *clear2fog*, and *highway*. Notably, on the challenging *highway* sequence which involves both covariate and label distribution shifts, GOLD outperforms all other methods by a clear margin. While CoTTA shows strong results on *highway*, GOLD achieves a further improvement of 0.7%. These results demonstrate that GOLD, as a lightweight approach, achieves performance comparable to CoTTA while being more computationally efficient.

Visual comparisons are provided in Figure 5, which showcases segmentation examples under different adaptation methods. GOLD captures fine-grained details that previous methods fail to recover. For instance, in the *highway* scenario, GOLD accurately identifies road markings partially occluded by vehicle shadows, while in the *clear2rain* sequence it preserves lane boundaries even under heavy rain streaks. Moreover, in adverse visibility conditions such as *clear2fog* and *day2night*, GOLD exhibits improved recog-

Table 3. Quantitative results of semantic segmentation under gradual domain shifts on CarlaTTA. We report mIoU (%) on five test sequences. Best results are in **bold**, second best are underlined.

	day2night	clear2fog	clear2rain	dynamic	highway
Source	58.4	52.8	71.8	46.2	24.7
MEMO [50]	61.0	55.1	<u>71.6</u>	36.7	23.6
TENT [40]	<u>61.5</u>	56.0	70.9	50.8	32.8
CoTTA [42]	61.4	56.8	70.7	46.3	<u>33.8</u>
GOLD	61.8	57.1	71.0	<u>48.9</u>	34.5

nition of distant scene structures and stable segmentation quality. This advantage arises from the AGOP-guided adaptation process, which rapidly aligns feature representations along important gradient directions, enabling the model to perform fast and effective updates without overfitting transient noise. Consequently, GOLD achieves more reliable adaptation to evolving visual domains while preserving the underlying semantic structure of the scene.

6. Conclusion

We presented GOLD, a source-free CTTA framework that performs adaptation through structured feature updates within a low-rank golden subspace. By combining an online AGOP-based subspace estimate with a lightweight scaling adapter, GOLD achieves a strong balance between adaptation efficiency and robustness across classification and segmentation benchmarks. We hope this perspective motivates future work on structure-aware online adaptation beyond global parameter updates.

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