

ITSPACE: Monotone Gaussian Optimal Transport Updates

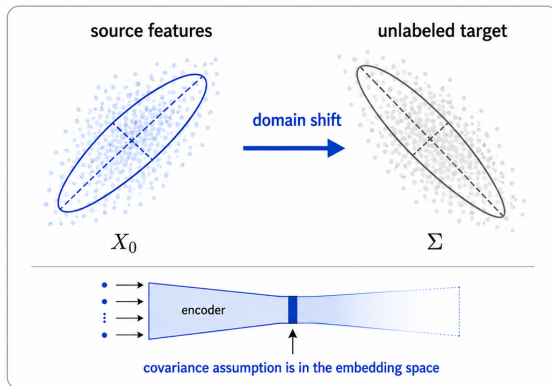
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Motivation: Why Few-step Covariance Updates?



short update loop

$$X_0 \rightarrow X_1 \rightarrow \cdots \rightarrow X_K$$

$$K \text{ small, } r \ll d$$

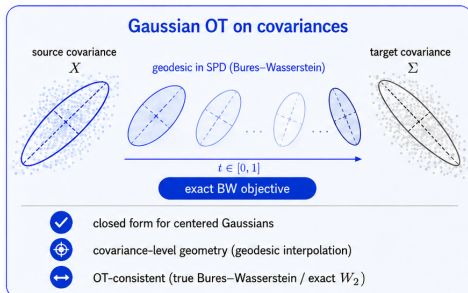
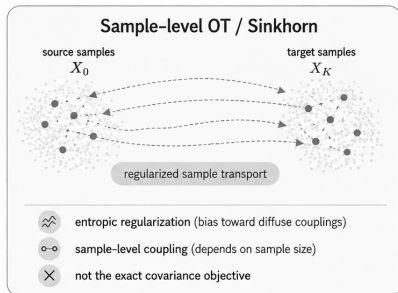
downstream module uses X_k

- 1 $X_k \geq 0$
- 2 $\text{rank}(X_k) \leq r$
- 3 useful progress at each step



Short-budget covariance adaptation needs intermediate iterates that are already usable.

Problem: Why Exact Gaussian OT?



For centered Gaussian covariances, exact W_2 is available in closed form.

$$W_2^2(X, \Sigma) = \text{tr}(X) + \text{tr}(\Sigma) - 2 \text{tr} \left((\Sigma^{1/2} X \Sigma^{1/2})^{1/2} \right)$$

1 PSD-valid

2 rank $\leq r$

3 K small



Goal: make useful progress on the true BW objective in a few rank-constrained steps.

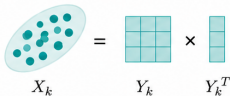
ITSPACE: Factorize, Certify, Update

1 Factorize

Represent covariance with low-rank factor

$$X_k = Y_k Y_k^T$$

$$Y_k \in \mathbb{R}^{d \times r}, r \ll d$$

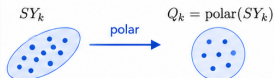


2 Certify (Polar)

Solve a nuclear-norm support problem to get optimal polar factor

$$S = \Sigma_+^{1/2}$$

$$Q_k = \text{polar}(SY_k)$$



Exact polar $\Rightarrow$ best alignment for the current subspace

3 Update

Closed-form proximal update on the factor

$$Y_{k+1} = (1 - \alpha)Y_k + \alpha SQ_k$$

$$\alpha \in (0, 1]$$

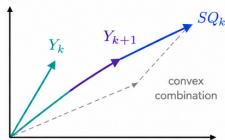


Closed-form factor update

$$Y_{k+1} = (1 - \alpha)Y_k + \alpha SQ_k$$

-  Y_k current factor
-  SQ_k optimally aligned factor in current subspace
-  Y_{k+1} updated factor (convex step)

Geometric intuition in factor space



We move from Y_k toward the best-aligned factor SQ_k by step size α .

Each step improves the true BW objective.



Takeaway: ITSPACE performs exact polar alignment in a low-rank subspace and then applies a simple closed-form update that provably decreases the true BW objective.

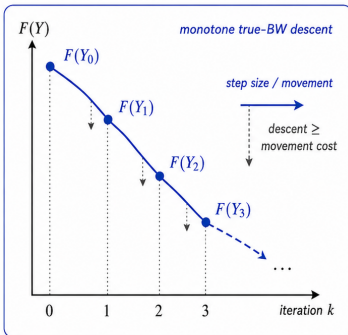
Guarantee: monotone descent of the true BW objective

Theorem 4.2: sufficient BW descent

$$F(Y_k) - F(Y_{k+1}) \geq \frac{1}{\alpha} \|Y_{k+1} - Y_k\|_F^2$$

$$\Rightarrow W_2^2(X_{k+1}, \Sigma_\star) \leq W_2^2(X_k, \Sigma_\star)$$

Under exact polar computation,
each step decreases the true BW objective.



PSD-valid iterates
 $\text{rank}(X_k) \leq r$

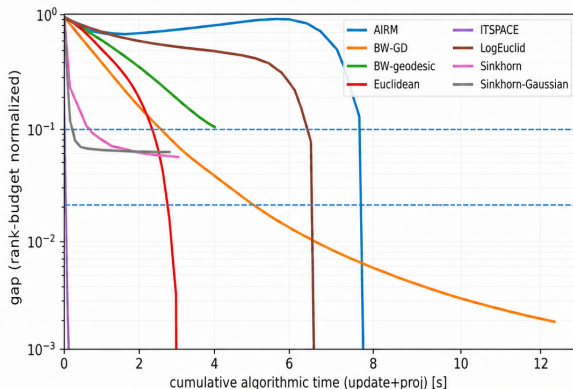


monotone true BW descent
under exact polar



finite-budget control
of cumulative movement

Few-step Low-rank Optimization Results



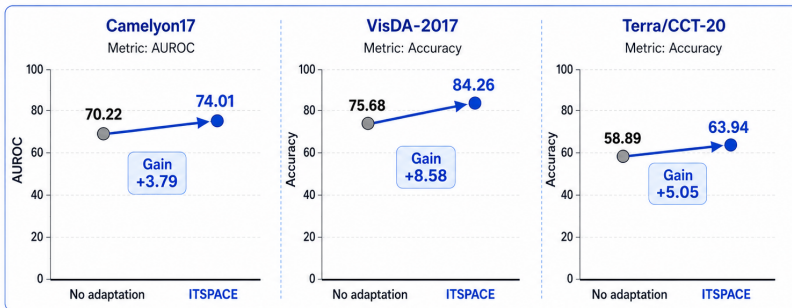
Time to reach gap ≤ 0.02

Dataset	ITSPACE (time)	BW-GD (time)	Speedup ($\times$)
Camelyon17	0.0575s	13.8s	239.7x
VisDA-2017	0.0550s	13.2s	239.8x
Terra/CCT-20	0.0369s	11.5s	310.8x

Under the same rank and step budget, **ITSPACE** reaches the near-floor BW gap in **tens of milliseconds**.

Downstream Task Results

CovDrift-MR: freeze the source head and adapt using unlabeled target moments.



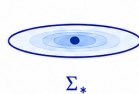
ITSPACE improves downstream performance using only unlabeled target moments.

ITSPACE at a glance

Source covariance



...



Target covariance

1

Exact
Gaussian OT

2

Low-rank
closed-form step

3

Monotone
BW descent

4

Practical
impact

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