

Circumventing Compactness in Conditional-Moment Optimal Transport Duality

A Perturbation Approach

Louis L. Chen¹ **Jake Roth**² Johannes O. Royset³

March 21, 2026

¹Operations Research, Naval Postgraduate School.

²Industrial and Systems Engineering, University of Minnesota.

³Industrial and Systems Engineering, University of Southern California.

Recent work in DRO

DRO problem for uncertain U taking values in \mathcal{U} :

$$\inf_{x \in \mathcal{X}} \text{UQ}(x) := \sup_{\mu \in \mathcal{A}(\hat{\mu})} \mathbb{E}_{\mu}[f(x, U)] \quad (\text{DRO})$$

Popular ambiguity sets / models:

Wasserstein / OT [MK18; BM19; ZYG24; GK23; ASD26]

$$\sup_{\gamma \in \mathcal{P}(\mathcal{U} \times \mathcal{U})} \mathbb{E}_{\gamma}[f(U)] : \mathbb{E}_{\gamma}[d(\hat{U}, U)] \leq \rho, \quad \pi_1 \gamma = \hat{\mu}$$

“influence how *values* behave”

Recent work in DRO

DRO problem for uncertain U taking values in \mathcal{U} :

$$\inf_{x \in \mathcal{X}} \text{UQ}(x) := \sup_{\mu \in \mathcal{A}(\hat{\mu})} \mathbb{E}_{\mu}[f(x, U)] \quad (\text{DRO})$$

Popular ambiguity sets / models:

ϕ -divergence [BT07; BL15; AH21]

$$\sup_{\mu \in \mathcal{P}(\mathcal{U})} \mathbb{E}_{\mu}[f(U)] : \mathbb{D}_{\phi}(\hat{\mu}, \mu) \leq \rho$$

“influence how *weights* behave”

Recent work in DRO

DRO problem for uncertain U taking values in \mathcal{U} :

$$\inf_{x \in \mathcal{X}} \text{UQ}(x) := \sup_{\mu \in \mathcal{A}(\hat{\mu})} \mathbb{E}_{\mu}[f(x, U)] \quad (\text{DRO})$$

Popular ambiguity sets / models:

Sinkhorn [WGX25; WM23; Dap+23; YZL25]

$$\sup_{\gamma \in \mathcal{P}(\mathcal{U} \times \mathcal{U})} \mathbb{E}_{\gamma}[f(U)] : \mathbb{E}_{\gamma}[d(\hat{U}, U)] + \beta \mathbb{D}(\gamma, \hat{\eta} \otimes \eta) \leq \rho, \quad \pi_1 \gamma = \hat{\mu}$$

“interpolate between OT and ϕ -divergence”

Recent work in DRO

DRO problem for uncertain U taking values in \mathcal{U} :

$$\inf_{x \in \mathcal{X}} \text{UQ}(x) := \sup_{\mu \in \mathcal{A}(\hat{\mu})} \mathbb{E}_{\mu}[f(x, U)] \quad (\text{DRO})$$

Popular ambiguity sets / models:

Unified model: CM-OT [Bla+25] handles each

$$\sup_{\mu \in \mathcal{P}(\mathcal{U})} \mathbb{E}_{\mu}[f(U)] : \mathbb{M}(\hat{\mu}, \mu) \leq \rho$$

“influence how *values* and *weights* behave”

CM-OT discrepancy $\mathbb{M}(\hat{\mu}, \mu)$ [Bla+25]

- ▶ Space: $\mathcal{U} = \mathcal{V} \times \mathcal{W}$ of values and weights;
- ▶ Objective $f : \mathcal{U} \rightarrow \overline{\mathbb{R}}$ (dropping dependence on “ x ”);
- ▶ CM-OT discrepancy

$$\mathbb{M}_h(\hat{\mu}, \mu) := \left\{ \begin{array}{ll} \text{infimum} & \mathbb{E}_\gamma[c(\hat{V}, \hat{W}; V, W)] \\ \gamma \in \Gamma(\hat{\mu}, \mu) & \\ \text{s. t.} & A\gamma = 0 \in L^1, \hat{\nu}\text{-a.s.} \end{array} \right\}$$

- ▶ Primal UQ

$$(P) : \sup_{\mu \in \mathcal{P}(\mathcal{U})} \mathbb{E}_\mu[f] : \mathbb{M}(\hat{\mu}, \mu) \leq \rho$$

CM-OT duality

Upper bounds for (P):

$$(P) = \sup_{\mu \in \mathcal{P}(\mathcal{U})} \left\{ \mathbb{E}_{\mu}[f] : \mathbb{M}(\hat{\mu}, \mu) \leq \rho \right\}$$

CM-OT duality

Upper bounds for (P):

$$(P) = \sup_{\mu \in \mathcal{P}(\mathcal{U})} \left\{ \mathbb{E}_{\mu}[f] : \inf_{\gamma \in \Gamma(\hat{\mu}, \mu)} \sup_{\psi \in \Psi} \{ \mathbb{E}_{\gamma}[c] + \langle \psi, A\gamma \rangle \} \leq \rho \right\}$$

CM-OT duality

Upper bounds for (P):

$$(P) \leq \sup_{\mu \in \mathcal{P}(\mathcal{U})} \left\{ \mathbb{E}_{\mu}[f] : \sup_{\psi \in \Psi} \inf_{\gamma \in \Gamma(\hat{\mu}, \mu)} \{ \mathbb{E}_{\gamma}[c] + \langle \psi, A\gamma \rangle \} \leq \rho \right\}$$

CM-OT duality

Upper bounds for (P):

$$(P) \leq \sup_{\mu \in \mathcal{P}(\mathcal{U})} \left\{ \inf_{\lambda \geq 0} \left\{ \mathbb{E}_{\mu}[f] + \lambda \left(\rho - \sup_{\psi \in \Psi} \inf_{\gamma \in \Gamma(\hat{\mu}, \mu)} \{ \mathbb{E}_{\gamma}[c] + \langle \psi, A\gamma \rangle \} \right) \right\} \right\}$$

CM-OT duality

Upper bounds for (P):

$$(P) \leq \inf_{\lambda \geq 0} \sup_{\mu \in \mathcal{P}(\mathcal{U})} \left\{ \mathbb{E}_{\mu}[f] + \lambda \left(\rho - \sup_{\psi \in \Psi} \inf_{\gamma \in \Gamma(\hat{\mu}, \mu)} \{ \mathbb{E}_{\gamma}[c] + \langle \psi, A\gamma \rangle \} \right) \right\}$$

CM-OT duality

Upper bounds for (P):

$$(P) \leq \inf_{\substack{\lambda \geq 0 \\ \psi \in \Psi}} \lambda \rho + \sup_{\gamma \in \Gamma_{\hat{\mu}}} \mathbb{E}_{\gamma} \left[f(U) - \psi(\hat{V}) \cdot (W - h(\hat{V})) - \lambda c(\hat{U}; U) \right] : (D_{\Psi})$$

CM-OT duality

Upper bounds for (P):

$$(P) \leq \inf_{\substack{\lambda \geq 0 \\ \psi \in \Psi}} \lambda \rho + \sup_{\gamma \in \Gamma_{\hat{\mu}}} \mathbb{E}_{\gamma} \left[f(U) - \psi(\hat{V}) \cdot (W - h(\hat{V})) - \lambda c(\hat{U}; U) \right] : (D_{\Psi})$$

$$\leq \inf_{\substack{\lambda \geq 0 \\ \psi \in \Psi}} \lambda \rho + \mathbb{E}_{\hat{\mu}} \left[\sup_{u \in \mathcal{U}} f(u) - \psi(\hat{V}) \cdot (w - h(\hat{V})) - \lambda c(\hat{U}; u) \right] : (D_{\Psi} + IP)$$

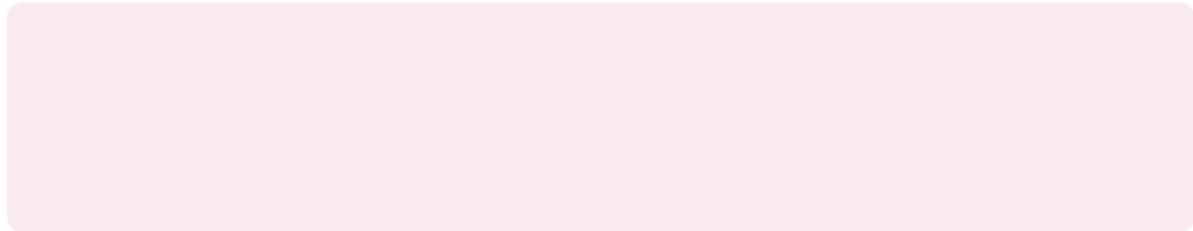
CM-OT duality

Upper bounds for (P):

$$(P) \leq \inf_{\substack{\lambda \geq 0 \\ \psi \in \Psi}} \lambda \rho + \sup_{\gamma \in \Gamma_{\hat{\mu}}} \mathbb{E}_{\gamma} \left[f(U) - \psi(\hat{V}) \cdot (W - h(\hat{V})) - \lambda c(\hat{U}; U) \right] : (D_{\Psi})$$

$$\leq \inf_{\substack{\lambda \geq 0 \\ \psi \in \Psi}} \lambda \rho + \mathbb{E}_{\hat{\mu}} \left[\sup_{u \in \mathcal{U}} f(u) - \psi(\hat{V}) \cdot (w - h(\hat{V})) - \lambda c(\hat{U}; u) \right] : (D_{\Psi} + IP)$$

CM-OT duality [(P) = (D_Ψ + IP)]:



CM-OT duality

Upper bounds for (P):

$$\begin{aligned} (P) &\leq \inf_{\substack{\lambda \geq 0 \\ \psi \in \Psi}} \lambda \rho + \sup_{\gamma \in \Gamma_{\hat{\mu}}} \mathbb{E}_{\gamma} \left[f(U) - \psi(\hat{V}) \cdot (W - h(\hat{V})) - \lambda c(\hat{U}; U) \right] : (D_{\Psi}) \\ &\leq \inf_{\substack{\lambda \geq 0 \\ \psi \in \Psi}} \lambda \rho + \mathbb{E}_{\hat{\mu}} \left[\sup_{u \in \mathcal{U}} f(u) - \psi(\hat{V}) \cdot (w - h(\hat{V})) - \lambda c(\hat{U}; u) \right] : (D_{\Psi} + IP) \end{aligned}$$

CM-OT duality [(P) = (D_Ψ + IP)]:

I. [(P) = (D_Ψ)] zero duality gap; and

CM-OT duality

Upper bounds for (P):

$$\begin{aligned} (P) &\leq \inf_{\substack{\lambda \geq 0 \\ \psi \in \Psi}} \lambda \rho + \sup_{\gamma \in \Gamma_{\hat{\mu}}} \mathbb{E}_{\gamma} \left[f(U) - \psi(\hat{V}) \cdot (W - h(\hat{V})) - \lambda c(\hat{U}; U) \right] : (D_{\Psi}) \\ &\leq \inf_{\substack{\lambda \geq 0 \\ \psi \in \Psi}} \lambda \rho + \mathbb{E}_{\hat{\mu}} \left[\sup_{u \in \mathcal{U}} f(u) - \psi(\hat{V}) \cdot (w - h(\hat{V})) - \lambda c(\hat{U}; u) \right] : (D_{\Psi} + IP) \end{aligned}$$

CM-OT duality [(P) = (D_Ψ + IP)]:

- I. [(P) = (D_Ψ)] zero duality gap; and
- II. [(D_Ψ) = (D_Ψ + IP)] Interchangeability Principle (IP) [Roc74; ZYG24].

When \mathcal{U} is compact

Space of multipliers $\Psi = \mathcal{C}_b(\mathcal{V})$: Dual to compactly supported measures

Zero duality gap: Sion minimax for interchanging $\sup_{\gamma \in \Gamma_{\hat{\mu}}} \inf_{\lambda \geq 0, \psi \in \Psi}$

IP: Ensures existence of a solution map for IP

when \mathcal{U} is not compact... (e.g., $\hat{\mu}$ is Gaussian)

CM-OT duality fails in general: $[(P) \neq (D_{\Psi})]$ for **unbounded f**

Our results: when \mathcal{U} is not compact

Theorem 1 (Zero gap: $(P) = (D_{L^\infty})$)

If f is bounded above; c is bounded below; and two assumptions (pointwise correction and strict feasibility) hold; then $(P) = (D_{L^\infty})$.

Proof idea: use characterization of “zero gap” in perturbation duality

Theorem 2 (IP: $(D_{L^\infty}) = (D_{C_b} + IP)$)

If in addition: f is usc; c is lsc; and \mathcal{V} is Polish and \mathcal{W} is bounded; then $(D_{L^\infty}) = (D_{C_b} + IP)$.

Proof idea: Lusin's theorem + Tietze extension theorem

Perturbation approach when \mathcal{U} is not compact

Look for **perturbation** assumptions:

1. What if we have a strictly feasible measure μ^0 ?

Can be helpful for existence of λ for perturbed budget constraints

$$\mathbb{M}(\hat{\mu}, \mu) \leq \rho + \tau$$

Not enough...

2. What if we could **perturb** the CM constraint rhs h up/down?

Could we “correct” any failures of the CM constraint?

Perturbation argument I: closedness goal

Starting point:

$$(P) \geq (P') \quad \left\{ \begin{array}{l} \sup_{\gamma \in \Gamma_{\hat{\mu}}} \mathbb{E}_{\gamma}[f] \\ \text{s. t.} \quad \mathbb{E}_{\gamma}[c] \leq \rho, \\ \mathbb{E}_{\gamma}[W | \hat{V}] - h(\hat{V}) = 0, \hat{\nu}\text{-a.s.} \end{array} \right\}$$

Perturbation argument I: closedness goal

Starting point:

$$p(\tau, \theta) = \left\{ \begin{array}{l} \sup_{\gamma \in \Gamma_{\hat{\mu}}} \mathbb{E}_{\gamma}[f] \\ \text{s. t.} \quad \mathbb{E}_{\gamma}[c] \leq \rho + \tau, \\ \mathbb{E}_{\gamma}[W | \hat{V}] - h(\hat{V}) = \theta, \hat{\nu}\text{-a.s.} \end{array} \right\}$$

Goal: Show [Roc70; Pon80; ET99; Zal02]

$$(D) \equiv (\text{cl } p)(0, 0) \equiv \limsup_{(\tau, \theta) \rightarrow 0} p(\tau, \theta) \leq p(0, 0) \equiv (P). \quad (*)$$

Perturbation argument II: sequences

Main question: How do nearby solutions to nearby problems $p(\tau, \theta)$ relate to the unperturbed problem $p(0, 0)$?

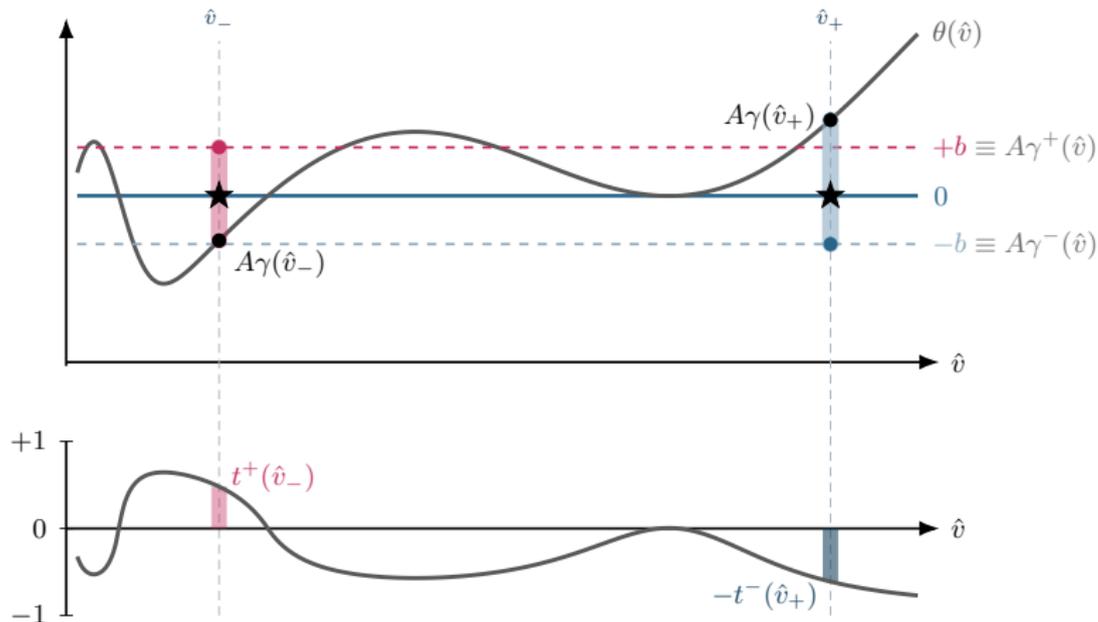
$$\limsup_{(\tau, \theta) \rightarrow 0} p(\tau, \theta) \leq p(0, 0) \quad (*)$$

Step 1: there exists $\{\tau_r, \theta_r\}_{r=1}^{\infty} \subseteq \mathbb{R} \times L^1$ s.t. $(\tau_r, \theta_r) \rightarrow 0$ $p(\tau_r, \theta_r) > -\infty$

Step 2: leverage *pointwise correction*

Step 3: leverage *strict feasibility*

Assumption: pointwise correction



Discussion

- ▶ Assumptions in earlier works *implied* that f, c were bounded over $\mathcal{W} \times \mathcal{V}$ and \mathcal{W} ;
- ▶ *Strict feasibility* holds if ρ is replaced with $\rho + \epsilon$ for any $\epsilon > 0$;
- ▶ *Pointwise correction* holds if c, f are Lipschitz continuous;
- ▶ In Theorems 1 and 2, neither primal nor dual attainment is guaranteed; see arXiv (uploaded and processing!) for counterexamples.

Questions? Thanks!

Draft: [arXiv:2603.20503](https://arxiv.org/abs/2603.20503)

References I

- [AH21] Rohit Agrawal and Thibaut Horel. “Optimal Bounds between f -Divergences and Integral Probability Metrics.” In: *J. of Mach. Learn. Res.* 22 (2021).
- [ASD26] Liviu Aolaritei, Soroosh Shafiee, and Florian Dörfler. “Wasserstein distributionally robust estimation in high dimensions: Performance analysis and optimal hyperparameter tuning.” In: *Math. Prog.* (2026).
- [BL15] Güzin Bayraksan and David K. Love. “Data-Driven Stochastic Programming Using ϕ -Divergences.” In: *INFORMS TutORials in Oper. Res.* (2015).
- [Bla+25] J. Blanchet et al. *Unifying Distributionally Robust Optimization via Optimal Transport Theory*. [arXiv:2308.05414](https://arxiv.org/abs/2308.05414). 2025.
- [BM19] José Blanchet and Karthyek Murthy. “Quantifying Distributional Model Risk Via Optimal Transport.” In: *Math. Oper. Res.* 44.2 (2019).

References II

- [BT07] Aharon Ben-Tal and Marc Teboulle. “An Old-New Concept of Convex Risk Measures: The Optimized Certainty Equivalent.” In: *Mathematical Finance* 17.3 (2007), pp. 449–476.
- [Dap+23] Charles Dapogny et al. “Entropy-regularized Wasserstein distributionally robust shape and topology optimization.” In: *Structural and Multidisciplinary Optim.* 66.42 (2023).
- [ET99] I. Ekeland and R. Témam. *Convex Analysis and Variational Problems*. SIAM, 1999.
- [GK23] R. Gao and A. Kleywegt. “Distributionally Robust Stochastic Optimization with Wasserstein Distance.” In: *Math. Oper. Res.* 48.2 (2023).
- [MK18] Peyman Mohajerin Esfahani and Daniel Kuhn. “Data-driven distributionally robust optimization using the Wasserstein metric: Performance guarantees and tractable reformulations.” In: *Math. Prog.* 171.1–2 (2018).
- [Pon80] J. Ponstein. *Approaches to the Theory of Optimization*. Cambridge University Press, 1980.

References III

- [Roc70] R. T. Rockafellar. *Convex Analysis*. Vol. 11. Princeton University Press, 1970.
- [Roc74] R T Rockafellar. *Conjugate Duality and Optimization*. Conference Board of Math. Sciences Series, SIAM Publications, 1974.
- [WGX25] Jie Wang, Rui Gao, and Yao Xie. “Sinkhorn Distributionally Robust Optimization.” In: *Oper. Res.* (Oct. 2025).
- [WM23] Franck Iutzeler Waïss Azizian and Jérôme Malick. “Regularization for Wasserstein distributionally robust optimization.” In: *ESAIM: Control, Optimisation and Calculus of Variations* 29.33 (2023).
- [YZL25] Yufeng Yang, Yi Zhou, and Zhaosong Lu. *Nested Stochastic Algorithm for Generalized Sinkhorn distance-Regularized Distributionally Robust Optimization*. 2503.22923. 2025.
- [Zal02] C. Zalinescu. *Convex Analysis in General Vector Spaces*. World Scientific, 2002.

References IV

- [ZYG24] L. Zhang, J. Yang, and R. Gao. “A Short and General Duality Proof for Wasserstein Distributionally Robust Optimization.” In: *Oper. Res.* 73.4 (2024).

Appendices

When does *pointwise correction* hold?

Suppose:

- ▶ *strict feasibility* holds: $\gamma^0 : \mathbb{E}_{\gamma^0}[c] < \rho$ and $A\gamma^0 = 0$;
- ▶ $h(\hat{V}) \pm \beta \in \mathcal{W}$
- ▶ c is L -Lipschitz in $(\hat{v}, \hat{w}; v, \cdot)$

Then:

- ▶ γ^0 is nearly good enough
- ▶ if f are continuous in the w -component, then we can trade-off slack in the transport budget to perturb γ^0 's w -component up/down slightly to $h \pm b$
- ▶ and if $f > -\infty$

Unbounded f

Suppose: $\mathcal{V} := \mathbb{R}$ $\mathcal{W} := \mathbb{R}_+$ $f(v, w) := v \cdot (w - 1)$, $h(\hat{V}) \equiv 1$, $\rho > 0$, $c(\hat{v}, \hat{w}; v, w)$ take value $+\infty$ if $v \neq \hat{v}$ and zero otherwise.

Also let $\hat{\nu}$ be any probability distribution on \mathcal{V} that is not essentially bounded above, i.e., $\hat{\nu}(\hat{V} > t) > 0$ for every $t \in \mathbb{R}$, and let $\hat{\mu} := \hat{\nu} \otimes \delta_1$ be the product measure of $\hat{\nu}$ with the point-mass on 1.

Finally let $\Psi := L^\infty(\hat{\nu})$.

Then $0 = (P) < (D_\Psi) = +\infty$.