



# ENOT: Expectile Regularization for Fast and Accurate Training of Neural Optimal Transport

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$$OT(\alpha, \beta) = \inf_{T: T\#\alpha=\beta} \int_{\mathcal{X}} c(x, T(x)) d\alpha(x)$$

In **dual formulation** we optimize sum of Kantorovich potentials  $f$  and  $g$

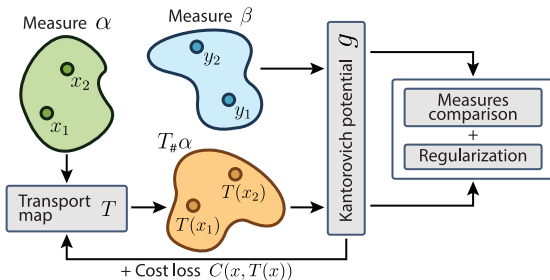
$$\sup_{f \in L_1(\alpha), g \in L_1(\beta)} \left[ \mathbb{E}_{\alpha}[f(\mathbf{x})] + \mathbb{E}_{\beta}[g(\mathbf{y})] \right]$$

under condition (c-conjugate dependence)

$$f(\mathbf{x}) = \min_{\mathbf{y}} \{c(\mathbf{x}, \mathbf{y}) - g(\mathbf{y})\}$$

$$g(\mathbf{y}) = \min_{\mathbf{x}} \{c(\mathbf{x}, \mathbf{y}) - f(\mathbf{x})\}$$

c-conjugate transformation requires computationally intensive fine-tuning

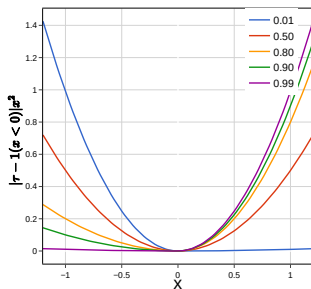


$$\max_g \mathbb{E}_\beta[g(\mathbf{y})] - \mathbb{E}_\alpha[g(T(\mathbf{x}))]$$

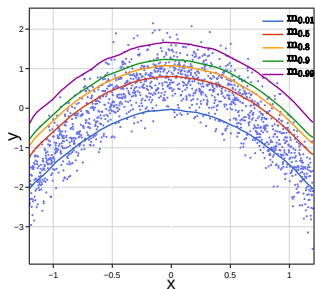
$$\min_T \mathbb{E}_\alpha[c(\mathbf{x}, T(\mathbf{x}))] - \mathbb{E}_\alpha[g(T(\mathbf{x}))]$$

Computationally fast but unstable training

Expectile loss function



Expectiles of cond. distribution



$$\min_f \mathbb{E} \mathcal{L}_\tau [f(\mathbf{x}) - y], \quad \mathcal{L}_\tau[\mathbf{x}] = |\tau - \mathbb{I}(\mathbf{x} < 0)| \mathbf{x}^2$$

Particularly when  $\tau \rightarrow 1$ :

$$f(\mathbf{x}) \rightarrow \max \text{supp. } y|\mathbf{x}$$

Desired regularization terms

$$\min_f \mathbb{E} \left[ f(\mathbf{x}) - \min_y \{c(\mathbf{x}, y) - g(y)\} \right]^2$$

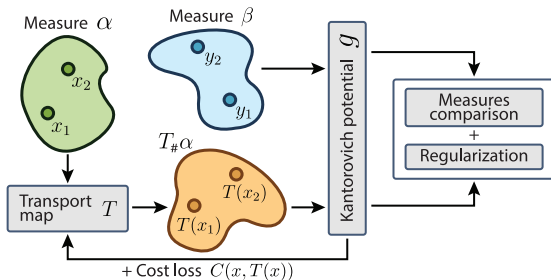
$$\min_g \mathbb{E} \left[ g(y) - \min_x \{c(\mathbf{x}, y) - f(\mathbf{x})\} \right]^2$$

expressed as the expectile regression problem

$$\min_{f, g} \mathbb{E} \mathcal{L}_\tau [f(\mathbf{x}) - c(\mathbf{x}, y) + g(y)]$$

Optimize sum of Kantorovich potentials  $f$  and  $g$  with expectile regularization

$$\begin{aligned} \sup_{f \in L_1(\alpha), g \in L_1(\beta)} & \left[ \mathbb{E}_\alpha [f(\mathbf{x})] + \mathbb{E}_\beta [g(y)] \right] \\ & - \lambda \mathbb{E} \mathcal{L}_\tau [f(\mathbf{x}) + g(y) - c(\mathbf{x}, y)] \end{aligned}$$



In practical implementation replace  $f(\mathbf{x})$  with  $\min_T \{c(\mathbf{x}, T(\mathbf{x})) - g(T(\mathbf{x}))\}$

$$\max_g \mathbb{E}_\beta[g(\mathbf{y})] - \mathbb{E}_\alpha[g(T(\mathbf{x}))] - \lambda \mathbb{E} \mathcal{L}_\tau [c(\mathbf{x}, T(\mathbf{x})) - g(T(\mathbf{x})) + g(\mathbf{y}) - c(\mathbf{x}, \mathbf{y})]$$

$$\min_T \mathbb{E}_\alpha [c(\mathbf{x}, T(\mathbf{x}))] - \mathbb{E}_\alpha [g(T(\mathbf{x}))]$$

Method	Conjugate	$D = 64$	$D = 128$	$D = 256$
W2-Cycle	None	7.2	2.0	2.7
MM-Objective	None	8.1	2.2	2.6
MM-R-Objective	None	10.1	3.2	2.7
Monge Gap	None	$7.99 \pm 0.19$	$9.1 \pm 0.29$	$9.41 \pm 0.21$
W2OT-Cycle	None	> 100	> 100	> 100
W2OT-Objective	None	> 100	> 100	> 100
W2OT-Cycle	L-BFGS	> 100	> 100	> 100
W2OT-Objective	L-BFGS	$2.08 \pm 0.40$	$0.67 \pm 0.05$	$0.59 \pm 0.04$
W2OT-Regression	L-BFGS	$2.08 \pm 0.39$	$0.67 \pm 0.05$	$0.65 \pm 0.07$
W2OT-Cycle	Adam	> 100	> 100	> 100
W2OT-Objective	Adam	$2.21 \pm 0.32$	$0.77 \pm 0.05$	$0.66 \pm 0.07$
W2OT-Regression	Adam	$2.37 \pm 0.46$	$0.77 \pm 0.06$	$0.75 \pm 0.09$
<b>ENOT (Ours)</b>	None	$0.56 \pm 0.03$	$0.3 \pm 0.01$	$0.51 \pm 0.02$
$\mathcal{L}_2^{\text{UV}}$ Metric				
ENOT Time	None	16 min	21 min	21 min
W2OT-Objective Time	L-BFGS	397 min	571 min	1028 min



Task and image size	CycleGAN	StarGAN	Extr. OT	Ker. OT	ENOT
Handbags $\Rightarrow$ Shoes 128	23.4	22.36	27.10	26.7	19.19
FFHQ $\Rightarrow$ Comics 128	-	-	20.95	20.81	17.11
CelebA(f) $\Rightarrow$ Anime 64	20.8	22.40	14.65	18.28	13.12
CelebA(f) $\Rightarrow$ Anime 128	-	-	19.44	21.96	18.85

FID Metric



$$\lambda \mathbb{E} \mathcal{L}_\tau [c(\mathbf{x}, T(\mathbf{x})) - g(T(\mathbf{x})) + g(\mathbf{y}) - c(\mathbf{x}, \mathbf{y})]$$

### ■ Theoretical Guarantees:

- Unbiased estimation when  $\tau \rightarrow 1$ ,
- Forces potential  $g$  to be  $c$ -concave

### ■ Empirical Advantages:

- 3-10x faster convergence,
- Improved stability,
- No extensive hyperparameters tuning ( $\lambda$  and  $\tau$ )

### ■ Applications:

- Various cost functions beyond W2 distance



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