## A Sinkhorn-Newton method for entropic optimal transport Christian Clason<sup>†</sup> Dirk Lorenz\* Benedikt Wirth\* Christoph Brauer\*

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# **Entropically regularized optimal transport**

We consider the entropically regularized Kantorovich problem of optimal mass transport between two given probability measures  $\mu \in \mathbb{R}^M$  and  $\nu \in \mathbb{R}^N$ , with non-negative cost  $c \in \mathbb{R}^{M \times N}$  and regularization strength  $\gamma > 0$ ,

$$\begin{array}{ll} \inf_{\pi \in \mathbb{R}^{M \times N}} & \langle c, \pi \rangle + \gamma \langle \pi, \log \pi - \mathbb{1} \rangle \\ \text{s.t.} & \pi \mathbb{1} = \mu \\ & \pi^{\top} \mathbb{1} = \nu, \end{array} \tag{P}$$

# Dual problem

By Fenchel-Rockafellar duality, the primal problem (P) is associated with the dual problem

$$\sup_{\alpha \in \mathbb{R}^{M}, \ \beta \in \mathbb{R}^{N}} - \langle \mu, \alpha \rangle - \langle \nu, \beta \rangle - \gamma \langle e^{-\frac{c}{\gamma}}, e^{-\frac{\alpha \mathbf{1}^{\top} + \mathbf{1}\beta^{\top}}{\gamma}} \rangle, \quad (D)$$

where the exponential function is applied componentwise to the

where  $\mathbf{1}$  and  $\mathbb{1}$  denote vectors and matrices of all ones.

**Optimality conditions** 

The primal and the dual problems are connected via the optimality conditions

$$\pi = K \odot e^{-\frac{\alpha \mathbf{1}^{\top} + \mathbf{1}\beta^{\top}}{\gamma}}$$
(1)  

$$\mu = e^{-\frac{\alpha}{\gamma}} \odot K e^{-\frac{\beta}{\gamma}}$$
(2)  

$$\nu = e^{-\frac{\beta}{\gamma}} \odot K^{\top} e^{-\frac{\alpha}{\gamma}}.$$
(3)

- The first condition implies that the optimal transport plan  $\pi$  is the componentwise product of K and a low-rank matrix induced by the dual variables  $\alpha$  and  $\beta$ .
- The second and third conditions are the constraints of (P) with  $\pi$ replaced by the right-hand side of (1).

- respective matrices.
- In the following, we abbreviate  $K := e^{-\frac{c}{\gamma}} \in \mathbb{R}^{M \times N}$  and use the symbol  $\odot$  to denote the Hadamard product.

# Newton step

Our approach is to solve (2) and (3) simultaneously by applying Newton's method to the function

$$G(\alpha,\beta) \coloneqq \begin{pmatrix} \mu - e^{-\frac{\alpha}{\gamma}} \odot K e^{-\frac{\beta}{\gamma}} \\ \nu - e^{-\frac{\beta}{\gamma}} \odot K^{\top} e^{-\frac{\alpha}{\gamma}} \end{pmatrix}.$$
 (4)

The associated Newton step can be written in the form of

$$\frac{1}{\gamma} \begin{bmatrix} \text{Diag}(\pi \mathbf{1}) & \pi \\ \pi^{\top} & \text{Diag}(\pi^{\top} \mathbf{1}) \end{bmatrix} \begin{pmatrix} \delta \alpha \\ \delta \beta \end{pmatrix} = -\underbrace{\begin{pmatrix} \mu - \pi \mathbf{1} \\ \nu - \pi^{\top} \mathbf{1} \end{pmatrix}}_{=G(\alpha,\beta)}, \quad (5)$$

where (1) is used to simplify both  $G(\alpha, \beta)$  and  $DG(\alpha, \beta)$ .

## Properties

- For  $\alpha, \beta > -\infty$ ,  $DG(\alpha, \beta)$  is symmetric positive semi-definite, and its kernel is  $ker(DG(\alpha, \beta)) =$ span  $\{\begin{pmatrix} -1 \\ 1 \end{pmatrix}\}$ . Hence, we can use a (preconditioned) conjugate gradient method to solve (5), which operates on the orthogonal complement of the kernel as long as the initial point satisfies  $\sum_i \alpha_i^0 = \sum_j \beta_j^0.$
- A cheap diagonal preconditioner is provided by  $DG(\alpha, \beta)$  without the off-diagonal blocks.
- If the initial point  $(\alpha^0, \beta^0)$  is chosen sufficiently close to a solution of (2)-(3) and if the optimal transport plan satisfies  $\pi \geq \varepsilon \mathbb{1}$  for some  $\varepsilon > 0$ , then the Newton iteration converges quadratically.
- After a substitution, a Sinkhorn-Knopp step approximates (5) by neglecting the off-diagonal

### **Numerical Experiments**

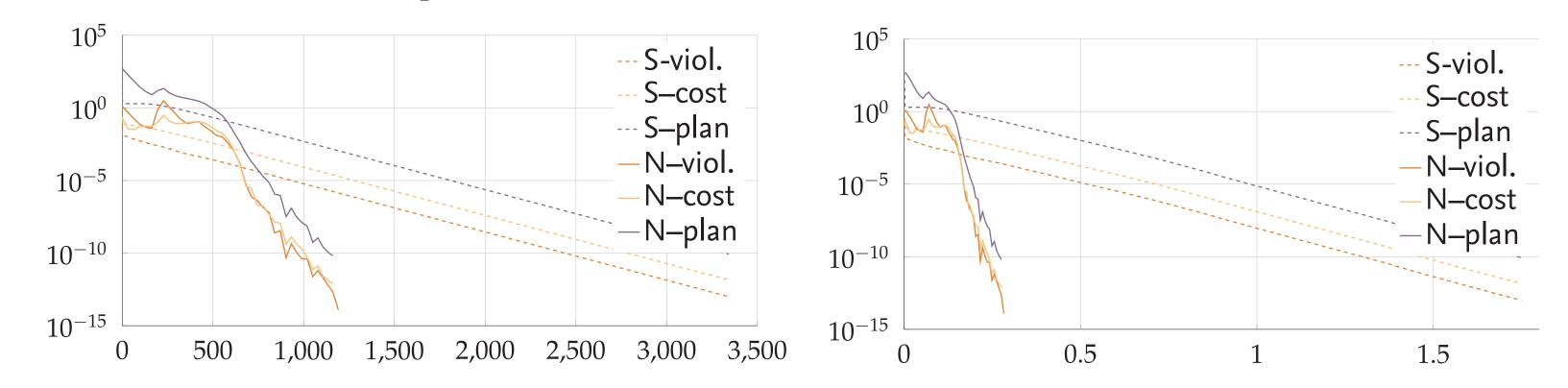
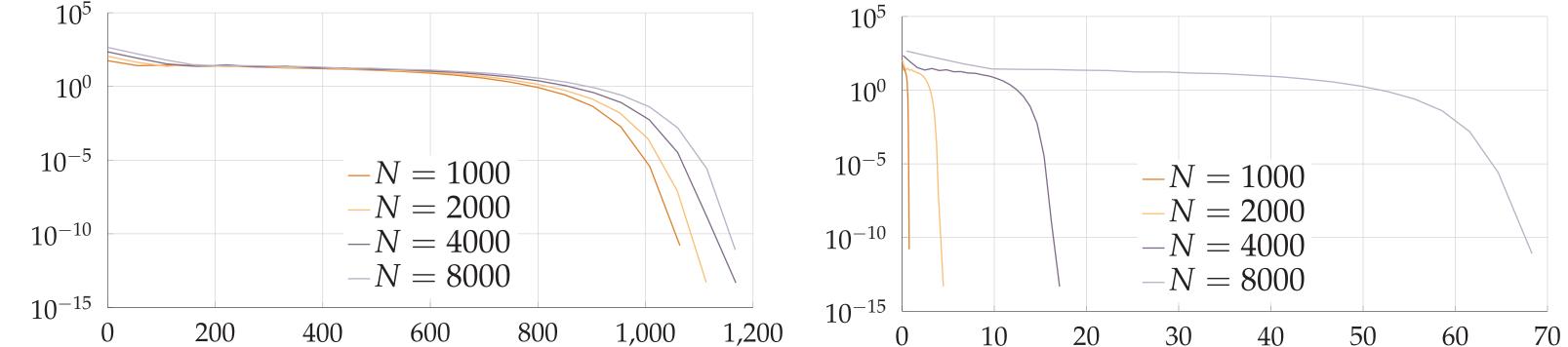


Figure 1: Exemplary performance of Sinkhorn (S) and Newton (N) iterations measured by constraint violation (viol.), distance to optimal transport costs (cost) and distance to optimal transport plan (plan). Left: Erros over CG iterations. Right: Errors over run time in seconds.



blocks of  $DG(\alpha, \beta)$  and solving separately for both variables.

Figure 2: Convergence behavior of Newton for different mesh sizes N (with M = N), measured by constraint violation. Left: Errors over CG iterations. Right: Errors over run time in seconds.

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