

A Supplementary Material

We provide here proofs of all the results from the main text.

Proof of Theorem 1

Proof. We will prove the result by contradiction.

Suppose there is some $\hat{e} \in E$ such that the optimal solution assigns $J^+(\hat{e}) > 0$ and $J^-(\hat{e}) > 0$. Then we note that

$$a \triangleq \min\{J^+(\hat{e}), J^-(\hat{e})\} > 0.$$

Consider an alternate solution $(\tilde{J}^+, \tilde{J}^-)$ such that $\forall e \in E$,

$$\tilde{J}^+(e) = \begin{cases} J^+(e) - a & \text{if } e = \hat{e} \\ J^+(e) & \text{if } e \in E \setminus \{\hat{e}\} \end{cases},$$

$$\tilde{J}^-(e) = \begin{cases} J^-(e) - a & \text{if } e = \hat{e} \\ J^-(e) & \text{if } e \in E \setminus \{\hat{e}\} \end{cases}.$$

Clearly, $(\tilde{J}^+, \tilde{J}^-)$ is feasible for (1). Moreover, it achieves a lower value of the objective than the optimal solution (J^+, J^-) . Therefore, (J^+, J^-) cannot be optimal. \square

Proof of Theorem 2

Proof. We introduce non-negative Lagrangian vectors α and β , respectively, for the constraints $Ft \preceq c$ and $-c \preceq Ft$. We consider the terms in the objective that depend on t

$$g(t) = t^\top(\rho_1 - \rho_0) + \alpha^\top(Ft - c) - \beta^\top(Ft + c).$$

The gradient $\nabla g(t)$ must vanish at optimality, so

$$\rho_1^* - \rho_0 + F^\top(\alpha - \beta) = \mathbf{0}.$$

The first part of the theorem follows immediately by defining $\eta = \beta - \alpha$. A closer look at (1) reveals that $\eta = J^- - J^+$ is, in fact, the net flow along the edges e^- from (1).

Now, we prove the second part. By definition, in order for an edge e to be active, at least one of e^+ and e^- must be active, i.e., we must have $J^+(e) + J^-(e) > 0$. On the other hand, Theorem 1 implies that at least one of $J^+(e)$ and $J^-(e)$ is 0 for each $e \in E$ in the optimal solution. Combining these facts, we have that for any active edge e , exactly one of e^+ and e^- is active, i.e., exactly one of the inequalities $J^+(e) > 0$ and $J^-(e) > 0$ must hold. This immediately implies, by complementary slackness, that exactly one of $\alpha(e)$ or $\beta(e)$ is 0. Thus, for any active edge e , either the lower bound or the upper bound on $Ft^*(e)$ in the constraints $-c(e) \leq Ft^*(e) \leq c(e)$ must become tight. Therefore, we must have $Ft^*(e) \in \{\pm c(e)\}$. \square

Proof of Theorem 3

Proof. Note that since at least one coordinate of ϵ is strictly greater than 0, the feasible region is non-empty, and consequently, a unique projection exists. We introduce variables $\alpha \in \mathbb{R}$ and $\beta \in \mathbb{R}_+^d$, and form the Lagrangian

$$L(x, \alpha, \beta) = \frac{1}{2} \|x - y\|^2 - \alpha((x \odot \epsilon)^\top \mathbf{1} - 1) - \beta^\top(x \odot \epsilon).$$

We now write the KKT conditions for the optimal solution x . For each $j \in [d]$, we must have

$$\begin{aligned} x_j - y_j - \alpha \epsilon_j - \beta_j \epsilon_j &= 0 \\ \epsilon_j x_j &\geq 0 \\ \beta_j &\geq 0 \\ \epsilon_j x_j \beta_j &= 0. \end{aligned}$$

Additionally,
$$\sum_{j=1}^d \epsilon_j x_j = 1.$$

Clearly, for $j \in [d] \triangleq \{1, 2, \dots, d\}$, $\epsilon_j = 0 \implies x_j = y_j$. Therefore, without loss of generality we assume in the rest of the proof that $\epsilon_j > 0$ for all j . Then we can immediately simplify the KKT conditions to

$$x_j - y_j - \alpha\epsilon_j - \beta_j\epsilon_j = 0 \quad (10)$$

$$x_j \geq 0 \quad (11)$$

$$\beta_j \geq 0 \quad (12)$$

$$x_j\beta_j = 0 \quad (13)$$

$$\sum_{j=1}^d \epsilon_j x_j = 1 \quad (14)$$

We note that $x_j > 0 \xrightarrow{(13)} \beta_j = 0 \xrightarrow{(10)} y_j + \alpha\epsilon_j > 0 \xrightarrow{\epsilon_j > 0} y_j/\epsilon_j > -\alpha$, whereas

$$x_j = 0 \xrightarrow{(10)} y_j + \alpha\epsilon_j = -\beta_j\epsilon_j \xrightarrow[\epsilon_j > 0]{(12)} y_j + \alpha\epsilon_j \leq 0 \xrightarrow{\epsilon_j > 0} y_j/\epsilon_j \leq -\alpha.$$

This shows that the zero coordinates x_j correspond to smaller values of y_j/ϵ_j . Thus, we can sort the indices j in non-increasing order based on the ratio y_j/ϵ_j , reorder x according to the sorted indices, and find an index $\ell \in [d]$ such that $x_j > 0$ for $j \in [\ell]$ and 0 for $\ell < j \leq d$. Without loss of generality, we therefore assume that

$$x_1 \geq x_2 \dots \geq x_\ell > 0 = x_{\ell+1} \dots = x_d, \text{ and} \\ y_1/\epsilon_1 \geq y_2/\epsilon_2 \dots \geq y_\ell/\epsilon_\ell. \quad (15)$$

We then have from (14) that

$$1 = \sum_{j=1}^d \epsilon_j x_j = \sum_{j=1}^{\ell} \epsilon_j x_j = \sum_{j=1}^{\ell} \epsilon_j (y_j + \alpha\epsilon_j) \\ \implies \alpha = \frac{1 - \sum_{j=1}^{\ell} \epsilon_j y_j}{\sum_{j=1}^{\ell} \epsilon_j^2}. \quad (16)$$

Thus, our task essentially boils down to finding the number of positive coordinates ℓ . We now show that

$$\ell = \max \left\{ j \in [d] \mid y_j + \epsilon_j \frac{(1 - \sum_{i=1}^j \epsilon_i y_i)}{\sum_{i=1}^j \epsilon_i^2} > 0 \right\}.$$

First consider $j < \ell$. Then $y_j/\epsilon_j > -\alpha$ for $j \in [j]$. Noting that $\epsilon_j > 0$ for all j and using (16), we must have

$$y_j + \epsilon_j \frac{(1 - \sum_{i=1}^j \epsilon_i y_i)}{\sum_{i=1}^j \epsilon_i^2} \\ = \frac{\epsilon_j}{\sum_{i=1}^j \epsilon_i^2} \left(y_j \frac{\sum_{i=1}^j \epsilon_i^2}{\epsilon_j} + 1 - \sum_{i=1}^j \epsilon_i y_i \right)$$

which has the same sign as

$$y_j \frac{\sum_{i=1}^j \epsilon_i^2}{\epsilon_j} + 1 - \sum_{i=1}^j \epsilon_i y_i \\ = y_j \frac{\sum_{i=1}^j \epsilon_i^2}{\epsilon_j} + \sum_{i=j+1}^{\ell} \epsilon_i y_i + 1 - \sum_{i=1}^{\ell} \epsilon_i y_i \\ = y_j \frac{\sum_{i=1}^j \epsilon_i^2}{\epsilon_j} + \sum_{i=j+1}^{\ell} \epsilon_i y_i + \alpha \sum_{i=1}^{\ell} \epsilon_i^2 \\ = \left(\frac{y_j}{\epsilon_j} + \alpha \right) \sum_{i=1}^j \epsilon_i^2 + \sum_{i=j+1}^{\ell} \epsilon_i^2 \left(\frac{y_i}{\epsilon_i} + \alpha \right) \\ > 0.$$

Now consider $j = \ell$. Since $y_\ell/\epsilon_\ell > -\alpha$ and $\epsilon_\ell > 0$, we have $y_\ell + \alpha\epsilon_\ell > 0$. Thus

$$\begin{aligned} y_j + \epsilon_j \frac{(1 - \sum_{i=1}^j \epsilon_i y_i)}{\sum_{i=1}^j \epsilon_i^2} &= y_\ell + \epsilon_\ell \frac{(1 - \sum_{i=1}^\ell \epsilon_i y_i)}{\sum_{i=1}^\ell \epsilon_i^2} \\ &= y_\ell + \alpha\epsilon_\ell > 0. \end{aligned}$$

Finally, we consider $\ell < j \leq d$. We note that

$$\begin{aligned} &y_j + \epsilon_j \frac{(1 - \sum_{i=1}^j \epsilon_i y_i)}{\sum_{i=1}^j \epsilon_i^2} \\ &= \frac{\epsilon_j}{\sum_{i=1}^j \epsilon_i^2} \left(y_j \frac{\sum_{i=1}^j \epsilon_i^2}{\epsilon_j} + 1 - \sum_{i=1}^j \epsilon_i y_i \right), \end{aligned}$$

which has the same sign as

$$\begin{aligned} &y_j \frac{\sum_{i=1}^j \epsilon_i^2}{\epsilon_j} + 1 - \sum_{i=1}^j \epsilon_i y_i \\ &= y_j \frac{\sum_{i=1}^j \epsilon_i^2}{\epsilon_j} + 1 - \sum_{i=1}^\ell \epsilon_i y_i - \sum_{i=\ell+1}^j \epsilon_i y_i \\ &= y_j \frac{\sum_{i=1}^j \epsilon_i^2}{\epsilon_j} + \alpha \sum_{i=1}^\ell \epsilon_i^2 - \sum_{i=\ell+1}^j \epsilon_i y_i \\ &= \left(\frac{y_j}{\epsilon_j} + \alpha \right) \sum_{i=1}^\ell \epsilon_i^2 + \sum_{i=\ell+1}^j \epsilon_i^2 \left(\frac{y_j}{\epsilon_j} - \frac{y_i}{\epsilon_i} \right), \\ &\leq 0, \end{aligned}$$

by leveraging the sorted property in (15) and the fact that $y_j/\epsilon_j \leq -\alpha$ for $j \in [\ell]$.

Therefore, we have shown that $y_j + \epsilon_j \frac{(1 - \sum_{i=1}^j \epsilon_i y_i)}{\sum_{i=1}^j \epsilon_i^2} > 0$ for all $j \in [\ell]$, and at most 0 for $\ell < j \leq d$. Algorithm 1 implements this procedure, and that proves its correctness. The $O(d \log d)$ time complexity is due to the cost of sorting the indices $j \in [d]$ based on y_j/ϵ_j . \square

Proof of Theorem 4

Proof. Recall the formulation (6):

$$\min_{\substack{\epsilon \in \mathcal{E}_k \\ \tilde{\rho}_1 \odot \epsilon \in \Delta(V)}} \max_{t \in \mathcal{T}_{F,c}} \underbrace{t^\top (\tilde{\rho}_1 \odot \epsilon - \rho_0) + \frac{\lambda}{2} \|\tilde{\rho}_1\|^2}_{\phi(\epsilon, t, \tilde{\rho}_1)}.$$

Making the constraints \mathcal{E}_k explicit, we get

$$\min_{\substack{\epsilon \in \{0,1\}^{|V|} \\ \epsilon^\top \mathbf{1} \leq k}} \left(\min_{\substack{\tilde{\rho}_1 \in \mathbb{R}^{|V|} \\ \tilde{\rho}_1 \odot \epsilon \in \Delta(V)}} \max_{t \in \mathcal{T}_{F,c}} \phi(\epsilon, t, \tilde{\rho}_1) \right). \quad (17)$$

Note that for any fixed ϵ (a) $\{\tilde{\rho}_1 \in \mathbb{R}^{|V|} \mid (\tilde{\rho}_1 \odot \epsilon) \in \Delta(V)\}$ is convex, and $\mathcal{T}_{F,c}$ is convex and compact, (b) $\phi(\epsilon, t, \tilde{\rho}_1)$ is continuous, and (c) for every fixed t , $\phi(\epsilon, t, \cdot)$ is convex in $\tilde{\rho}_1$; while for every fixed $\tilde{\rho}_1$, $\phi(\epsilon, \cdot, \tilde{\rho}_1)$ is linear (thus concave) in t . Therefore, invoking the Sion's minimax theorem [60], we can swap the order of min and max within the parentheses in (17), and obtain

$$\min_{\substack{\epsilon \in \{0,1\}^{|V|} \\ \epsilon^\top \mathbf{1} \leq k}} \left(\max_{t \in \mathcal{T}_{F,c}} \min_{\substack{\tilde{\rho}_1 \in \mathbb{R}^{|V|} \\ \tilde{\rho}_1 \odot \epsilon \in \Delta(V)}} \phi(\epsilon, t, \tilde{\rho}_1) \right). \quad (18)$$

We introduce Lagrangian variables $\nu \in \mathbb{R}_+^{|V|}$ and $\zeta \in \mathbb{R}$, respectively, for the simplex constraints (a) $\mathbf{0} \preceq \tilde{\rho}_1 \odot \epsilon$ and (b) $(\tilde{\rho}_1 \odot \epsilon)^\top \mathbf{1} = 1$ to get

$$\Phi(\epsilon, t, \tilde{\rho}_1, \nu, \zeta) \triangleq \phi(\epsilon, t, \tilde{\rho}_1) + \zeta((\tilde{\rho}_1 \odot \epsilon)^\top \mathbf{1} - 1) - \nu^\top (\tilde{\rho}_1 \odot \epsilon) . \quad (19)$$

Applying the optimality conditions, we note for any fixed pair (ϵ, t) , the corresponding optimal $\tilde{\rho}_1$ must satisfy

$$\partial_{\tilde{\rho}_1} \Phi(\epsilon, t, \tilde{\rho}_1, \nu, \zeta) = \mathbf{0} ,$$

whereby

$$\tilde{\rho}_1 = - \left(\frac{(t - \nu) \odot \epsilon + \zeta \epsilon}{\lambda} \right) . \quad (20)$$

Plugging in $\tilde{\rho}_1$ from (20) into (19), we thus have the following equivalent dual formulation for (18)

$$\min_{\substack{\epsilon \in \{0,1\}^{|V|} \\ \epsilon^\top \mathbf{1} \leq k}} \max_{t \in \mathcal{T}_{F,c}} \max_{\nu \in \mathbb{R}_+^{|V|}, \zeta \in \mathbb{R}} \mathcal{M}(\epsilon, t, \nu, \zeta) ,$$

where

$$\mathcal{M}(\epsilon, t, \nu, \zeta) = \frac{-1}{2\lambda} \|(t - \nu + \zeta \mathbf{1}) \odot \epsilon\|^2 - t^\top \rho_0 - \zeta . \quad (21)$$

Invoking the first order convex optimality condition for constrained optimization, the $\hat{\epsilon}$ obtained from relaxation of (6) is optimal if and only if

$$\mathbf{0} \in \left\{ \underbrace{\partial_\epsilon \max_{t \in \mathcal{T}_{F,c}} \max_{\nu \in \mathbb{R}_+^{|V|}, \zeta \in \mathbb{R}} \mathcal{M}(\epsilon, t, \nu, \zeta)}_{(A)} + \mathbb{N} \right\} , \quad (22)$$

where \mathbb{N} is the normal cone of the relaxed constraints

$$\tilde{\mathcal{E}}_k = \left\{ \epsilon \in [0, 1]^{|V|} \mid \epsilon^\top \mathbf{1} \leq k \right\} .$$

Now we note that for any vector x , we can write $x \odot \epsilon = D(\epsilon)x$, where $D(\epsilon)$ is the diagonal matrix corresponding to ϵ . Also, since $\epsilon \in \{0, 1\}^{|V|}$, we get $D(\epsilon)^\top D(\epsilon) = D(\epsilon)$. Thus, for any x , we have

$$\|x \odot \epsilon\|^2 = \|D(\epsilon)x\|^2 = (D(\epsilon)x)^\top D(\epsilon)x = x^\top D(\epsilon)^\top D(\epsilon)x = x^\top D(\epsilon)x .$$

In particular, we can simplify $\|(t - \nu + \zeta \mathbf{1}) \odot \epsilon\|^2$ in (21) when we set x to $t - \nu + \zeta \mathbf{1}$. The theorem statement then follows immediately from (22) by representing \mathbb{N} at the integral point $\hat{\epsilon}^*$ and leveraging the non-negative dual parameter associated with the constraint $\epsilon^\top \mathbf{1} \leq k$. \square

Proof of Theorem 5

Proof. We will use the shorthand $\tilde{\rho}_{1v}$ for $\tilde{\rho}_1(v)$, and likewise for indexing t, ν , and ϵ . Using (20),

$$\tilde{\rho}_1 = - \left(\frac{(t - \nu) \odot \epsilon + \zeta \epsilon}{\lambda} \right) = - \left(\frac{t - \nu + \zeta \mathbf{1}}{\lambda} \right) \odot \epsilon .$$

Therefore,

$$\tilde{\rho}_1 \odot \epsilon = - \left(\frac{t - \nu + \zeta \mathbf{1}}{\lambda} \right) \odot \epsilon \odot \epsilon = - \left(\frac{t - \nu + \zeta \mathbf{1}}{\lambda} \right) \odot \epsilon = \tilde{\rho}_1 , \quad (23)$$

since $\epsilon \in \{0, 1\}^{|V|}$. We write one of the KKT conditions for optimality

$$\tilde{\rho}_1 \odot \epsilon \odot \nu = \tilde{\rho}_1 \odot \nu = \mathbf{0} .$$

We consider the different cases. Note that for $v \in V$, using (23), we have

$$\tilde{\rho}_{1v} > 0 \implies \nu_v = 0 \implies \tilde{\rho}_{1v} = - \frac{(t_v + \zeta)\epsilon_v}{\lambda} , \quad (24)$$

and

$$\tilde{\rho}_{1v} = 0 \implies (t_v - \nu_v + \zeta)\epsilon_v = 0 \implies \nu_v \epsilon_v = (t_v + \zeta)\epsilon_v. \quad (25)$$

But since $\nu_v \geq 0$, and $\epsilon_v \in \{0, 1\}$, we note that $\nu_v \epsilon_v \geq 0$. Then, by (25), we have

$$\nu_v \epsilon_v \geq 0 \implies -\frac{(t_v + \zeta)\epsilon_v}{\lambda} \leq 0 = \tilde{\rho}_{1v}. \quad (26)$$

Combining (24) and (26), we can write

$$\tilde{\rho}_{1v} = \max \left\{ -\frac{(t_v + \zeta)\epsilon_v}{\lambda}, 0 \right\} = \frac{\epsilon_v}{\lambda} \max \{ -(t_v + \zeta), 0 \}, \quad (27)$$

since $\epsilon_v \geq 0$ for all $v \in V$ and $\lambda > 0$. Therefore, we get $\tilde{\rho}_1 = \frac{\epsilon}{\lambda} \odot r_+$, where $r = -(t + \zeta \mathbf{1})$, and r_+ is computed by setting the negative coordinates of r to 0.

Moreover, since $\tilde{\rho}_1 \odot \nu = \mathbf{0}$, we can eliminate ν from (19) and write (17) as

$$\min_{\epsilon \in \mathcal{E}_k} \max_{t \in \mathcal{T}_{F,c}} \max_{\zeta \in \mathbb{R}} t^\top (\tilde{\rho}_1 - \rho_0) + \frac{\lambda}{2} \|\tilde{\rho}_1\|^2 + \zeta (\tilde{\rho}_1^\top \mathbf{1} - 1)$$

Substituting for $\tilde{\rho}_1$ from (27), we obtain the following equivalent problem

$$\begin{aligned} \min_{\epsilon \in \mathcal{E}_k} \max_{t \in \mathcal{T}_{F,c}} \max_{\zeta \in \mathbb{R}} & -\frac{r^\top}{\lambda} (\epsilon \odot r_+) + \frac{1}{2\lambda} r_+^\top (\epsilon \odot r_+) - t^\top \rho_0 - \zeta, \\ & = \min_{\epsilon \in \mathcal{E}_k} \max_{t \in \mathcal{T}_{F,c}} \max_{\zeta \in \mathbb{R}} \frac{-1}{2\lambda} \epsilon^\top (r_+ \odot (2r - r_+)) - t^\top \rho_0 - \zeta, \end{aligned}$$

which can be written as

$$\begin{aligned} & \min_{\epsilon \in \mathcal{E}_k} \max_{t \in \mathcal{T}_{F,c}} \max_{\zeta \in \mathbb{R}} -\frac{1}{2\lambda} \sum_{v:r_v \geq 0} \epsilon_v r_v^2 - t^\top \rho_0 - \zeta \\ = & \min_{\epsilon \in \mathcal{E}_k} \max_{t \in \mathcal{T}_{F,c}} \max_{\zeta \in \mathbb{R}} -\frac{1}{2\lambda} \sum_{v:t_v \leq -\zeta} \epsilon_v r_v^2 - t^\top \rho_0 - \zeta \\ = & \min_{\epsilon \in \mathcal{E}_k} \max_{t \in \mathcal{T}_{F,c}} \max_{\zeta \in \mathbb{R}} -\frac{1}{2\lambda} \sum_{v:t_v \leq -\zeta} \epsilon_v (t_v + \zeta)^2 - t^\top \rho_0 - \zeta \\ = & \min_{\epsilon \in \mathcal{E}_k} \max_{t \in \mathcal{T}_{F,c}} \max_{\zeta \in \mathbb{R}} -\frac{1}{2\lambda} \sum_{v:t_v \leq -\zeta} (\epsilon_v (t_v + \zeta)^2 + 2\lambda t_v \rho_{0,v}) - \sum_{v:t_v > -\zeta} t_v \rho_{0,v} - \zeta. \end{aligned}$$

□