



Research article

Cardinality-constrained maximal predictability portfolios with an ℓ_2 regularization

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Appendix

Appendix A Proof of Theorem 1

For convenience, we additionally impose the redundant upper-bound constraints $y_n \leq M$ ($n \in \mathcal{N}$) on Problem (2.12), where M is chosen sufficiently large so that these upper-bound constraints are inactive at an optimal solution.

The Lagrange function of Problem (2.12) is represented as follows:

$$\begin{aligned} & \mathcal{L}(y, v, u; \phi, \psi, b, \pi, \xi, s) \\ & : = \frac{1}{2\gamma} \mathbf{y}^\top \mathbf{y} + \mathbf{v}^\top \mathbf{v} - \phi^\top (\mathbf{v} - \mathbf{E}\mathbf{y}) - \psi^\top (\mathbf{u} - \mathbf{R}\mathbf{y}) \\ & \quad - b(\tilde{\mathbf{r}}^\top \mathbf{y} - \rho \mathbf{1}^\top \mathbf{y}) - \pi^\top \mathbf{y} - \xi^\top (\mathbf{M}\mathbf{1} - \mathbf{y}) - s(\mathbf{u}^\top \mathbf{u} - 1), \end{aligned} \tag{A.1}$$

where

$$b \geq 0, \quad \pi \geq \mathbf{0}, \quad \xi \geq \mathbf{0}, \quad \phi \in \mathbb{R}^T, \quad \psi \in \mathbb{R}^T, \quad s \in \mathbb{R}$$

are Lagrange multipliers and $\mathbf{1}$ denotes the all-ones vector of appropriate dimension. Then, the dual problem associated with Problem (2.12) is represented as follows:

$$\max_{\phi, \psi, b, \pi, \xi, s} \min_{y, v, u} \mathcal{L}(y, v, u; \phi, \psi, b, \pi, \xi, s). \tag{A.2}$$

We focus on the inner minimization problem:

$$\min_{y,v,u} \mathcal{L}(y, v, u; \phi, \psi, b, \pi, \xi, s). \quad (\text{A.3})$$

Because the objective function of Problem (A.3) is differentiable, the following optimality conditions are satisfied:

$$\nabla_y = \frac{1}{\gamma} \mathbf{y} - (-\mathbf{E}^\top \phi - \mathbf{R}^\top \psi + b(\tilde{\mathbf{r}} - \rho \mathbf{1}) + \pi - \xi) = 0, \quad (\text{A.4a})$$

$$\nabla_v = 2v - \phi = 0, \quad (\text{A.4b})$$

$$\nabla_u = -\psi - 2su = 0. \quad (\text{A.4c})$$

According to (A.4), Problem (A.2) can be represented using the following objective function:

$$-\frac{\gamma}{2} \mathbf{w}^\top \mathbf{w} - \frac{\phi^\top \phi}{4} + s - \mathbf{M} \mathbf{1}^\top \xi, \quad (\text{A.5})$$

where $\mathbf{w} \in \mathbb{R}^N$ is defined by

$$\mathbf{w} = -\mathbf{E}^\top \phi + 2s\mathbf{R}^\top \mathbf{u} + b(\tilde{\mathbf{r}} - \rho \mathbf{1}) + \pi - \xi. \quad (\text{A.6})$$

Then, from (A.4a) and (A.6), we obtain

$$\mathbf{y} = \gamma \mathbf{w}.$$

As $\gamma > 0$ and $\mathbf{y} \geq \mathbf{0}$ in (2.7), it follows that $\mathbf{w} \geq \mathbf{0}$.

Moreover, the equality in (A.6) with $\pi \geq \mathbf{0}$ is equivalent to

$$\mathbf{w} \geq -\mathbf{E}^\top \phi + 2s\mathbf{R}^\top \mathbf{u} + b(\tilde{\mathbf{r}} - \rho \mathbf{1}) - \xi. \quad (\text{A.7})$$

Indeed, if (A.6) holds for some $\pi \geq \mathbf{0}$, then (A.7) immediately follows. Conversely, if (A.7) holds, then one can obtain

$$\pi = \mathbf{w} + \mathbf{E}^\top \phi - 2s\mathbf{R}^\top \mathbf{u} - b(\tilde{\mathbf{r}} - \rho \mathbf{1}) + \xi,$$

which satisfies $\pi \geq \mathbf{0}$ and recovers (A.6). Hence, π can be eliminated from the dual formulation.

Thus, Problem (A.2) can be represented as follows:

$$\left| \begin{array}{ll} \max_{\mathbf{w}, \phi, s, b, \xi} \min_u & -\frac{\gamma}{2} \mathbf{w}^\top \mathbf{w} - \frac{\phi^\top \phi}{4} + s - \mathbf{M} \mathbf{1}^\top \xi \\ \text{s.t.} & \mathbf{w} \geq -\mathbf{E}^\top \phi + 2s\mathbf{R}^\top \mathbf{u} + b(\tilde{\mathbf{r}} - \rho \mathbf{1}) - \xi, \\ & \mathbf{w} \geq \mathbf{0}, \quad \xi \geq \mathbf{0}, \quad b \geq 0. \end{array} \right. \quad (\text{A.8})$$

By the assumption that M is sufficiently large, the upper-bound constraints $y_n \leq M$ ($n \in \mathcal{N}$) are inactive at an optimal solution of Problem (2.12). Therefore, by the complementary slackness condition,

$$\xi_n(M - y_n) = 0 \quad (n \in \mathcal{N})$$

and $M - y_n > 0$, which imply

$$\xi_n = 0 \quad (n \in \mathcal{N}).$$

Hence, $\xi = \mathbf{0}$, and Problem (A.8) reduces to

$$\left| \begin{array}{ll} \max_{\mathbf{w}, \phi, s, b} \min_u & -\frac{\gamma}{2} \mathbf{w}^\top \mathbf{w} - \frac{\phi^\top \phi}{4} + s \\ \text{s.t.} & \mathbf{w} \geq -\mathbf{E}^\top \phi + 2s\mathbf{R}^\top \mathbf{u} + b(\tilde{\mathbf{r}} - \rho \mathbf{1}), \\ & \mathbf{w} \geq \mathbf{0}, \quad b \geq 0. \end{array} \right. \quad (\text{A.9})$$

□

Appendix B Proof of Theorem 2

We assume that M is chosen sufficiently large so that the upper-bound constraints $y_n \leq M$ ($n \in \mathcal{N}(z)$) are inactive at an optimal solution of Problem (2.30), as in (2.7).

The Lagrange function of Problem (2.30) is formulated as follows:

$$\begin{aligned} & \bar{\mathcal{L}}(y_z, v, u; \phi, \psi, b, \pi, \xi, s) \\ & : = \frac{1}{2\gamma} y_z^\top y_z + v^\top v - \phi^\top (v - E_z y_z) - \psi^\top (u - R_z y_z) \\ & \quad - b(\tilde{r}_z^\top y_z - \rho \mathbf{1}^\top y_z) - \pi^\top y_z - \xi^\top (M\mathbf{1} - y_z) - s(u^\top u^*(z) - 1), \end{aligned} \quad (\text{B.1})$$

where

$$b \geq 0, \quad \pi \geq \mathbf{0}, \quad \xi \geq \mathbf{0}, \quad \phi \in \mathbb{R}^T, \quad \psi \in \mathbb{R}^T, \quad s \in \mathbb{R}$$

are Lagrange multipliers. Then, the dual problem associated with Problem (2.30) is given by

$$\max_{\phi, \psi, b, \pi, \xi, s} \min_{y_z, v, u} \bar{\mathcal{L}}(y_z, v, u; \phi, \psi, b, \pi, \xi, s). \quad (\text{B.2})$$

We focus on the inner minimization problem:

$$\min_{y_z, v, u} \bar{\mathcal{L}}(y_z, v, u; \phi, \psi, b, \pi, \xi, s). \quad (\text{B.3})$$

Because the objective function of Problem (B.3) is differentiable and convex, the following optimality conditions are satisfied:

$$\nabla_{y_z} = \frac{1}{\gamma} y_z - (-E_z^\top \phi - R_z^\top \psi + b(\tilde{r}_z - \rho \mathbf{1}) + \pi - \xi) = 0, \quad (\text{B.4a})$$

$$\nabla_v = 2v - \phi = 0, \quad (\text{B.4b})$$

$$\nabla_u = -\psi - 2su^*(z) = 0. \quad (\text{B.4c})$$

According to (B.4), Problem (B.2) can be reformulated using the following objective function:

$$-\frac{\gamma}{2} w_z^\top w_z - \frac{\phi^\top \phi}{4} + s - M\mathbf{1}^\top \xi, \quad (\text{B.5})$$

where

$$w_z = (w_n \mid z_n = 1) \in \mathbb{R}^{|\mathcal{N}(z)|}$$

is defined by

$$w_z = -E_z^\top \phi + 2sR_z^\top u^*(z) + b(\tilde{r}_z - \rho \mathbf{1}) + \pi - \xi. \quad (\text{B.6})$$

Then, from (B.4a) and (B.6), we obtain

$$y_z = \gamma w_z.$$

As $\gamma > 0$ and $y_z \geq \mathbf{0}$ in (2.28), it follows that $w_z \geq \mathbf{0}$.

Moreover, the equality in (B.6) with $\pi \geq \mathbf{0}$ is equivalent to

$$w_z \geq -E_z^\top \phi + 2sR_z^\top u^*(z) + b(\tilde{r}_z - \rho \mathbf{1}) - \xi. \quad (\text{B.7})$$

Indeed, if (B.6) holds for some $\boldsymbol{\pi} \geq \mathbf{0}$, then (B.7) immediately follows. Conversely, if (B.7) holds, then one can obtain

$$\boldsymbol{\pi} = \mathbf{w}_z + \mathbf{E}_z^\top \boldsymbol{\phi} - 2s\mathbf{R}_z^\top \mathbf{u}^*(z) - b(\tilde{\mathbf{r}}_z - \rho\mathbf{1}) + \boldsymbol{\xi},$$

which satisfies $\boldsymbol{\pi} \geq \mathbf{0}$ and recovers (B.6). Hence, $\boldsymbol{\pi}$ can be eliminated from the dual formulation.

Thus, Problem (B.2) can be reformulated as

$$\left\{ \begin{array}{l} \max_{\mathbf{w}_z, \boldsymbol{\phi}, s, b, \boldsymbol{\xi}} \quad -\frac{\gamma}{2} \mathbf{w}_z^\top \mathbf{w}_z - \frac{\boldsymbol{\phi}^\top \boldsymbol{\phi}}{4} + s - \mathbf{M}\mathbf{1}^\top \boldsymbol{\xi} \\ \text{s.t.} \quad \mathbf{w}_z \geq -\mathbf{E}_z^\top \boldsymbol{\phi} + 2s\mathbf{R}_z^\top \mathbf{u}^*(z) + b(\tilde{\mathbf{r}}_z - \rho\mathbf{1}) - \boldsymbol{\xi}, \\ \mathbf{w}_z \geq \mathbf{0}, \quad \boldsymbol{\xi} \geq \mathbf{0}, \quad b \geq 0. \end{array} \right. \quad (\text{B.8})$$

By the assumption that M is sufficiently large, the upper-bound constraints $y_n \leq M$ ($n \in \mathcal{N}(z)$) are inactive at an optimal solution of Problem (2.30). Therefore, by the complementary slackness condition,

$$\xi_n(M - y_n) = 0 \quad (n \in \mathcal{N}(z))$$

and $M - y_n > 0$, which imply

$$\xi_n = 0 \quad (n \in \mathcal{N}(z)).$$

Hence, $\boldsymbol{\xi} = \mathbf{0}$, and Problem (B.8) reduces to

$$\left\{ \begin{array}{l} \max_{\mathbf{w}_z, \boldsymbol{\phi}, s, b} \quad -\frac{\gamma}{2} \mathbf{w}_z^\top \mathbf{w}_z - \frac{\boldsymbol{\phi}^\top \boldsymbol{\phi}}{4} + s \\ \text{s.t.} \quad \mathbf{w}_z \geq -\mathbf{E}_z^\top \boldsymbol{\phi} + 2s\mathbf{R}_z^\top \mathbf{u}^*(z) + b(\tilde{\mathbf{r}}_z - \rho\mathbf{1}), \\ \mathbf{w}_z \geq \mathbf{0}, \quad b \geq 0. \end{array} \right. \quad (\text{B.9})$$

□

Appendix C Proof of Proposition 1

First, the normalization preserves the descent argument used in Proposition 3.2 of [20]. Because the additional term $\frac{1}{2\gamma} \mathbf{y}_z^\top \mathbf{y}_z$ is quadratic, the regularized objective consists only of quadratic terms.

$$\frac{1}{2\gamma} (\mathbf{y}_z^k)^\top \mathbf{y}_z^k + (\mathbf{v}^k)^\top \mathbf{v}^k = \frac{1}{(\hat{\mathbf{u}}^k)^\top \hat{\mathbf{u}}^k} \left(\frac{1}{2\gamma} (\hat{\mathbf{y}}_z^k)^\top \hat{\mathbf{y}}_z^k + (\hat{\mathbf{v}}^k)^\top \hat{\mathbf{v}}^k \right).$$

Therefore, under the same normalization step as in [20], the regularized objective satisfies the same scaling relation, and hence the same descent inequality as in Proposition 3.2 of [20] follows.

Second, the boundedness of the NL iterates follows immediately from the boundedness of \mathcal{Y}_z , which has already been established in the existence argument for Problem (2.29). As $\mathbf{y}_z^k \in \mathcal{Y}_z$ for all k , the sequence $\{\mathbf{y}_z^k\}$ is bounded, and thus so are $\{\mathbf{u}^k\}$ and $\{\mathbf{v}^k\}$ because $\mathbf{u}^k = \mathbf{R}_z \mathbf{y}_z^k$ and $\mathbf{v}^k = \mathbf{E}_z \mathbf{y}_z^k$.

Finally, when $\varepsilon = 0$, every accumulation point satisfies the KKT conditions of Problem (2.29). The proof follows Proposition 3.3 of [20] with only minor modifications. In particular, from the first-order optimality conditions in a similar manner to Appendix B; see (B.4a)–(B.4c), the stationarity condition with respect to \mathbf{y}_z can be written as follows, where the multipliers $\boldsymbol{\pi}$ and $\boldsymbol{\xi}$ are retained to make the stationarity condition explicit, and $\mathbf{u}^*(z)$ is replaced by the variable \mathbf{u} :

$$\frac{1}{\gamma} \mathbf{y}_z = -2\mathbf{E}_z^\top \mathbf{v} + 2s\mathbf{R}_z^\top \mathbf{u} + b(\tilde{\mathbf{r}}_z - \rho\mathbf{1}) + \boldsymbol{\pi} - \boldsymbol{\xi}.$$

Here, the ℓ_2 regularization contributes the additional term $\gamma^{-1}\mathbf{y}_z$. Thus, every accumulation point satisfies the KKT conditions of Problem (2.29).

Therefore, the generated sequence is bounded, and every accumulation point satisfies the KKT conditions of Problem (2.29) when $\epsilon = 0$.

□

Appendix D Additional results of algorithm performance

Table 1 gives the optimal objective values for $(N, K, S) = (25, 3, 3)$. The objective values on all seven instances increase with a decrease in γ .

Table 1. Each optimal objective value with $(N, K, S) = (25, 3, 3)$.

$\gamma \setminus$ Instance	1	2	3	4	5	6	7
$\frac{0.01}{\sqrt{N}}$	204.69	219.52	226.22	235.51	240.41	262.48	262.41
$\frac{0.1}{\sqrt{N}}$	21.35	22.78	23.47	24.44	24.87	27.11	27.09
$\frac{1}{\sqrt{N}}$	3.01	3.1	3.2	3.33	3.32	3.57	3.53
$\frac{10}{\sqrt{N}}$	1.16	1.13	1.17	1.22	1.15	1.21	1.17
$\frac{100}{\sqrt{N}}$	0.85	0.91	0.91	0.96	0.9	0.9	0.88

Appendix E Investment performance for $N = 200$

Table 2 shows that for $N = 200$, where overfitting is limited, the unregularized case ($\gamma = \infty$) yields the best out-of-sample performance.

Table 2. Investment performance with $(N, K) = (200, 6)$.

S	Metric\(γ	$\frac{0.01}{\sqrt{N}}$	$\frac{0.1}{\sqrt{N}}$	$\frac{1}{\sqrt{N}}$	$\frac{5}{\sqrt{N}}$	$\frac{10}{\sqrt{N}}$	$\frac{100}{\sqrt{N}}$	∞
10	$\mu R^2(\mathbf{x})(\%)$	10.1	10.93	14.17	21.74	27.14	39.94	42.22
	Return(%)	25.67	16.85	21.64	21.69	25.37	16.22	24.38
	Risk(%)	28.62	19.96	19.09	20.89	24.98	17.37	21.24
	SR	0.9	0.84	1.13	1.04	1.02	0.93	1.15
	UR(%)	2.9	1.53	1.67	1.77	2.56	1.22	2.28
20	$\mu R^2(\mathbf{x})(\%)$	9.71	10.93	13.08	18.49	28.83	39.67	42.25
	Return(%)	22.55	18.66	19.94	21.53	20.49	16.07	24.16
	Risk(%)	24.12	19.18	19.24	19.65	21.38	16.91	21.23
	SR	0.93	0.97	1.04	1.1	0.96	0.95	1.14
	UR(%)	2.26	1.32	1.42	1.59	1.8	1.19	2.26
30	$\mu R^2(\mathbf{x})(\%)$	9.63	10.37	12.4	17.98	27.19	39.63	42.25
	Return(%)	21.69	18.5	17.78	20.7	20.36	16.14	24.16
	Risk(%)	23.01	19.14	19.18	18.6	20.9	16.88	21.23
	SR	0.94	0.97	0.93	1.11	0.97	0.96	1.14
	UR(%)	2.08	1.28	1.2	1.42	1.69	1.18	2.26



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