Robust Weighting and Matching Techniques for Causal Inference in Observational Studies with Continuous Treatment

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Contents

1 Introduction

Researchers are often left with observational studies to answer questions about causality. When confounders are present the task of infering causality can become arbitrarily complex. Propensity score methods [RR83], e.g. inverse probability weighting or matching, are popular methods to adjust for confounders. Usually these methods rely heavily on estimates of the true propensity score, which are known to suffer from model dependencies and misspecification [KS07]. This issue becomes more pressing when moving from binary to continuous treatment [HI05]. Therefore methods have been developed to directly target imbalances in the data [FHI18] [Hai12] [Zub15]. We take a closer look at [WZ19] and extend the analysis to settings with continuous treatment [VGC+20] [Tüb20].

2 Balancing Weights

2.1 Introduction

We work in the Rubin Causal Model.

We assume a sample of n units which is drawn from a population distribution.

In i.i.d. fashion.

We observe $(\mathbf{X}_i, T_i, Y_i)$, where $\mathbf{X}$ are covariates, T is the indicator if treatment has been received and Y is the observed outcome.

In the Rubin Causal Model we assume that for each unit the potential outcome exist, i.e. (Y_i^0, Y_i^1) where Y^1 stands for the potential outcome had the unit received treatment and Y^0 for the potential outcome had the unit received **no** treatment.

It is clear that $Y_i = Y_i^{T_i}$ i.e. we can observe only one of the potential outcomes.

Thus there is a connection to missing data problems.

This is the dilemma of causal inference.

On the population level it is possible to estimate both.

Usually the means of the potential outcomes are compared against each other.

In randomized trials this is a valid approach to causal inference.

In observational studies however the treatment assignment is not known and direct comparison can lead to systematically wrong results.

This phenomenon is called **confounding**.

To address the issue of confounding many methods have been proposed.

An intuitive way to think about potential outcomes is to think of a stochastic process $Y(\cdot)$ indexed over $\{0,1\}$. By observing Y_i we in fact sample from this process at random index T, i.e. from $Y(T)$. We have

$$\mathbf{E}[Y(T)] = \mathbf{E}[Y(1)|T=1]\mathbf{P}[T=1] + \mathbf{E}[Y(0)|T=0]\mathbf{P}[T=0]. \tag{2.1}$$

Suppose we observe $T=1$. Clearly we have

$$\mathbf{E}[Y(T)|T=1] = \mathbf{E}[Y(1)|T=1] \tag{2.2}$$

2.2 Estimating the Population Mean of Potential Outcomes

2.3 Application of Matrix Concentration Inequalities

Analysis of $\mathbf{E}[\max_{i\le r} \|\mathbf{A}_i\|^2]$

We have

$$\mathbf{A}_i := \frac{1}{r}\left(\frac{1-\pi_i}{\pi_i}\right)\mathbf{B}(X_i) \qquad \text{for } i \in \{1,\dots,r\}. \tag{2.3}$$

Since we take the maximum over a finite set it is attained for some $i^* \in \{1, \ldots, r\}$:

$$
\begin{aligned}
\mathbf{E}[\max_{i \le r} \|\mathbf{A}_i\|^2] &= \mathbf{E}[\|\mathbf{A}_{i^*}\|^2] \\
&= \frac{1}{r^2}\mathbf{E}\left[\left(\frac{1-\pi_{i^*}}{\pi_{i^*}}\right)^2 \|\mathbf{B}(X_{i^*})\|^2\right] \le \frac{1}{r^2}\mathbf{E}\left[\left(\frac{1-\pi_{i^*}}{\pi_{i^*}}\right)^4\right]^{\frac{1}{2}} \mathbf{E}[\|\mathbf{B}(X_{i^*})\|^4]^{\frac{1}{2}} \\
&\le \frac{K}{r^2}\sqrt{C_\pi C_{\mathbf{B}}}
\end{aligned}
\tag{2.4}
$$

In the last two steps we applied the Cauchy-Schwarz inequality and Assumption. Note that

$$
\sum_{i=1}^{r} \mathbf{E}[\|\mathbf{A}_i\|^2] \le \frac{K}{r}\sqrt{C_\pi C_{\mathbf{B}}} \tag{2.5}
$$

Assumption 2.1. *There exists $C_\pi \ge 1$ such that $\mathbf{E}\left[\left(\frac{1-\pi_i}{\pi_i}\right)^4\right] \le C_\pi$ for all $i \in \{1, \ldots, r\}$.*

Remark 2.1. *If we assume a logistic regression model for the propensity score it holds for some $\theta \in \mathbb{R}^N$ (N is the number of covariates)*

$$
\frac{1-\pi(X)}{\pi(X)} = \exp(-\theta X) \qquad \textit{and} \qquad \mathbf{E}\left[\left(\frac{1-\pi(X)}{\pi(X)}\right)^4\right] = \mathbf{E}[\exp(-4\theta X)] = M_X(-4\theta), \tag{2.6}
$$

where M_X is the momement-generating function of X. While the first quantity in (2.6) *may be unbounded when X has unbounded support, the latter quantity in* (2.6) *is still bounded for reasonable choices of X.* ♢

Assumption 2.2. *There exists $C_{\mathbf{B}} \ge 1$ such that $\mathbf{E}[\mathbf{B}_k(X_i)^4] \le C_{\mathbf{B}}$ for all $(k, i) \in \{1, \ldots, K\} \times \{1, \ldots, r\}$.*

Remark 2.2. *With Assumption we also get a bound on the fourth moment of $\|\mathbf{B}(X_i)\|$. Indeed, by the convexity of $x \mapsto x^2$, the monotonicity and linearity of the expectation it holds*

$$
\begin{aligned}
\mathbf{E}[\|\mathbf{B}(X_i)\|^4] &= \mathbf{E}\left[\left(\sum_{k=1}^{K} \mathbf{B}_k^2(X_i)\right)^2\right] = K^2\mathbf{E}\left[\left(\sum_{k=1}^{K} \frac{1}{K}\mathbf{B}_k^2(X_i)\right)^2\right] \le K^2\mathbf{E}\left[\sum_{k=1}^{K} \frac{1}{K}\mathbf{B}_k^4(X_i)\right] \\
&= K\sum_{k=1}^{K} \mathbf{E}\left[\mathbf{B}_k^4(X_i)\right] \le K^2 C_{\mathbf{B}}
\end{aligned}
\tag{2.7}
$$

♢

Analysis of $v(\mathbf{S})$

We use the fact that $\|\mathbf{A}\|_2 \le \|\mathbf{A}\|_F = \sqrt{\sum_{i,j} a_{ij}^2}$ It holds

$$
\sum_{i=1}^{r} \mathbf{E}[\mathbf{A}_i\mathbf{A}_i^\top] = \frac{1}{r^2}\sum_{i=1}^{r} \mathbf{E}\left[\left(\frac{1-\pi_i}{\pi_i}\right)^2 \mathbf{B}(X_i)\mathbf{B}(X_i)^\top\right] = \frac{1}{r^2}\left(\sum_{i=1}^{r} \mathbf{E}\left[\left(\frac{1-\pi_i}{\pi_i}\right)^2 B_k(X_i)B_l(X_i)\right]\right)_{1 \le k,l \le K} . \tag{2.8}
$$

Thus

$$
\begin{aligned}
&\left\| \sum_{i=1}^{r} \mathbf{E}[\mathbf{A}_i \mathbf{A}_i^\top] \right\|_2^2 \\
&\leq \left\| \sum_{i=1}^{r} \mathbf{E}[\mathbf{A}_i \mathbf{A}_i^\top] \right\|_F^2 = \frac{1}{r^4} \sum_{k,l=1}^{K} \left(\sum_{i=1}^{r} \mathbf{E}\left[\left(\frac{1-\pi_i}{\pi_i} \right)^2 B_k(X_i) B_l(X_i) \right] \right)^2 \\
&\leq \frac{1}{r^4} \sum_{k,l=1}^{K} \left(\sum_{i=1}^{r} \mathbf{E}\left[\left(\frac{1-\pi_i}{\pi_i} \right)^4 \right]^{\frac{1}{2}} \mathbf{E}[B_k(X_i)^4]^{\frac{1}{4}} \mathbf{E}[B_l(X_i)^4]^{\frac{1}{4}} \right)^2 \leq \left(\frac{K}{r} \right)^2 C_\pi C_B
\end{aligned}
\tag{2.9}
$$

On the other hand

$$
\begin{aligned}
\left\| \sum_{i=1}^{r} \mathbf{E}[\mathbf{A}_i^\top \mathbf{A}_i] \right\|_2 &= \sum_{i=1}^{r} \mathbf{E}[\mathbf{A}_i^\top \mathbf{A}_i] = \frac{1}{r^2} \sum_{i=1}^{r} \mathbf{E}\left[\left(\frac{1-\pi_i}{\pi_i} \right)^2 \|\mathbf{B}(X_i)\|_2^2 \right] \\
&\leq \frac{1}{r^2} \sum_{i=1}^{r} \mathbf{E}\left[\left(\frac{1-\pi_i}{\pi_i} \right)^4 \right]^{\frac{1}{2}} \mathbf{E}[\|\mathbf{B}(X_i)\|_2^4]^{\frac{1}{2}} \leq \frac{K}{r} \sqrt{C_\pi C_B}
\end{aligned}
\tag{2.10}
$$

It follows

$$
v(\mathbf{S}) \leq \frac{K}{r} \sqrt{C_\pi C_B} \tag{2.11}
$$

Thus we can apply Theorem 4.1 to get

$$
\mathbf{E}[\|\mathbf{S}\|_2] \leq \sqrt{2e \frac{K}{r} \sqrt{C_\pi C_B} \log(K+1)} + 4e \frac{\sqrt{K}}{r} \sqrt[4]{C_\pi C_B} \log(K+1) \leq 14 C_\pi C_B \sqrt{\frac{K \log(K+1)}{r}} \tag{2.12}
$$

3 Convex Analysis

3.1 Basic Notions

Excursively, we present some well known definitions and facts from convex analysis. For details, see, e.g., [MMN22].

A subset $C \subseteq \mathbb{R}^n$ is called **convex set**, if for all $x, y \in C$ and all $\lambda \in [0,1]$, we have $\lambda x + (1-\lambda)y \in C$. The Cartesian product of convex sets is convex. The intersection of a collection of convex sets is also convex. Given (not necessary convex) sets $\Omega, \Omega_1, \Omega_2 \subseteq \mathbb{R}^n$ and $\lambda \in \mathbb{R}$, define the **set addition** and **multiplication** by a real scalar as $\Omega_1 + \Omega_2 := \{x_1 + x_2 \colon x_1 \in \Omega_1, x_2 \in \Omega_2\}$ and $\lambda\Omega := \{\lambda x \colon x \in \Omega\}$. For convex sets the addition and multiplication by a real scalar are convex.

A mapping $A : \mathbb{R}^n \to \mathbb{R}^m$ is called **affine mapping** if there exist a linear mapping $L : \mathbb{R}^n \to \mathbb{R}^m$ and a vector $b \in \mathbb{R}^m$ such that $A(x) = L(x) + b$ for all $x \in \mathbb{R}^n$. The image and inverse image/preimage of convex sets under affine mappings are also convex.

3.2 Relative interiors

Definition 3.1. (Affine set and hull) *A set $A \subseteq \mathbb{R}^n$ is called **affine**, if*

$$\alpha x + (1-\alpha)y \in A \quad \text{for all } x, y \in A \text{ and } \alpha \in \mathbb{R}. \tag{3.1}$$

*The **affine hull** $\operatorname{aff}(\Omega)$ of a set $\Omega \subseteq \mathbb{R}^n$ is the smallest affine set that includes Ω.*

Definition 3.2. (Relative interior) *Let $\Omega \subseteq \mathbb{R}^n$. We define the **relative interior** of Ω by*

$$\operatorname{ri}(\Omega) := \{x \in \Omega \colon \text{there exists } \gamma > 0 \text{ such that } \mathrm{B}_\gamma(x) \cap \operatorname{aff}(\Omega) \in \Omega\}. \tag{3.2}$$

Proposition 3.1. *Let C be a non-empty convex set in $\mathbb{R}^n$. Then we get the representation*

$$\operatorname{ri}(C) = \{z \in C \colon \text{for all } x \in C \text{ there exists } t > 0 \text{ such that } z + t(z-x) \in C\}. \tag{3.3}$$

Proof. [Roc70, Theorem 6.4] □

Proposition 3.2. *Let $C_1 \subseteq \mathbb{R}^{n_1}$ and $C_2 \subseteq \mathbb{R}^{n_2}$ be two non-empty convex sets. Then it holds*

$$\operatorname{ri}(C_1 \times C_2) = \operatorname{ri}(C_1) \times \operatorname{ri}(C_2). \tag{3.4}$$

Proof. Let $(z_1, z_2) \in \operatorname{ri}(C_1 \times C_2)$. Then for all $(x_1, x_2) \in C_1 \times C_2$ there exists $t > 0$ such that

$$z_i + t(z_i - x_i) \in C_i \qquad \text{for } i \in \{1, 2\}. \tag{3.5}$$

This proves $\subseteq$. Suppose $z_1 \in \operatorname{ri}(C_1)$ and $z_2 \in \operatorname{ri}(C_2)$. Let $(x_1, x_2) \in C_1 \times C_2$ with corresponding $t_1, t_2 > 0$. If $t_1 = t_2$ everything is clear. W.l.o.g. assume $t_1 < t_2$. Define $\theta := \frac{t_1}{t_2} \in (0,1)$. By the convexity of C_2 it follows

$$z_2 + t_1(z_2 - x_2) = \theta(z_2 + t_2(z_2 - x_2)) + (1-\theta)z_2 \in C_2. \tag{3.6}$$

Thus $(z_1, z_2) \in \operatorname{ri}(C_1 \times C_2)$. This proves $\supseteq$ and equality. □

3.3 Convex Separation

Definition 3.3. *Let C_1 and C_2 be two non-empty convex sets in $\mathbb{R}^n$. A hyperplane H is said to **separate** C_1 and C_2 if C_1 is contained in one of the closed half-spaces associated with H and C_2 lies in the opposite closed half-space. It is said to separate C_1 and C_2 **properly** if C_1 and C_2 are not both actually contained in H itselef.*

Theorem 3.1. *Let C_1 and C_2 be two non-empty convex sets in $\mathbb{R}^n$. There exists a hyperplane separating C_1 and C_2 properly if and only if there exists a vector $b \in \mathbb{R}^n$ such that*

$$\sup_{x\in C_2} \langle x, b\rangle \leq \inf_{x\in C_1} \langle x, b\rangle \quad \textit{and} \quad \inf_{x\in C_2} \langle x, b\rangle < \sup_{x\in C_1} \langle x, b\rangle. \tag{3.7}$$

Proof. [Roc70, Theorem 11.1] □

Theorem 3.2. (Convex separation in finite dimension) *Let C_1 and C_2 be two non-empty convex sets in $\mathbb{R}^n$. Then C_1 and C_2 can be properly separated if and only if* $\operatorname{ri}(C_1) \cap \operatorname{ri}(C_2) = \emptyset$.

Proof. [Roc70, Theorem 11.3] □

Definition 3.4. (Support function intersection rule) (Support function) *Given a nonempty subset $\Omega \subseteq \mathbb{R}^n$ the **support function** $\sigma_\Omega : \mathbb{R}^n \to \overline{\mathbb{R}}$ of Ω is defined by*

$$\sigma_\Omega(x^*) := \sup_{x\in\Omega} \langle x^*, x\rangle \qquad \textit{for } x^* \in \mathbb{R}^n. \tag{3.8}$$

Theorem 3.3. *Let C_1 and C_2 be two non-empty convex sets in $\mathbb{R}^n$ with $\operatorname{ri}(C_1) \cap \operatorname{ri}(C_2) \neq \emptyset$. Then the support function of the intersection $C_1 \cap C_2$ is represented as*

$$(\sigma_{C_1\cap C_2})(x^*) = (\sigma_{C_1} \square \sigma_{C_2})(x^*) \qquad \textit{for all } x^* \in \mathbb{R}^n. \tag{3.9}$$

Furthermore, for any $x^* \in \operatorname{dom}(\sigma_{C_1\cap C_2})$ there exist dual elements $x_1^*, x_2^* \in \mathbb{R}^n$ such that $x^* = x_1^* + x_2^*$. and

$$(\sigma_{C_1\cap C_2})(x^*) = \sigma_{C_1}(x_1^*) + \sigma_{C_2}(x_2^*). \tag{3.10}$$

Proof. *[MMN22, Theorem 4.23]* We define

$$\Theta_1 := C_1 \times [0, \infty) \quad \text{and} \quad \Theta_2 := \{(x, \lambda) \in \mathbb{R}^n : x \in C_2 \text{ and } \lambda \leq \langle x^*, x\rangle - \alpha\}. \tag{3.11}$$

Clearly Θ_1 is convex by the convexity of C_1. Consider the affine function

$$\varphi : \mathbb{R}^{n+1} \to \mathbb{R}, \quad (x, \lambda) \mapsto \alpha - \langle x^*, x\rangle - \lambda. \tag{3.12}$$

It holds $\Theta_2 = \varphi^{-1}((-\infty, 0]) \cap (C_2 \times \mathbb{R})$. Thus, by the convexity of the sets $\varphi^{-1}((-\infty, 0])$ and C_2 it follows that Θ_2 is convex. We want to apply convex separation to Θ_1 and Θ_2. To this end we show $\operatorname{ri}(\Theta_1) \cap \operatorname{ri}(\Theta_2) = \emptyset$. First note that

$$\operatorname{ri}(\Theta_1) = \operatorname{ri}(C_1) \times \operatorname{ri}([0, \infty)) \subseteq \operatorname{ri}(C_1) \times (0, \infty). \tag{3.13}$$

Indeed, if $0 \in \mathrm{ri}([0,\infty))$ then there exists $t > 0$ such that $-tx \geq 0$ for some $x > 0$. A contradition. Furthermore

$$\mathrm{ri}(\Theta_2) \subseteq \{(x,\lambda) \in \mathbb{R}^n \colon x \in \mathrm{ri}(C_2) \text{ and } \lambda < \langle x^*, x\rangle - \alpha\}. \tag{3.14}$$

To see this, assume there is $(x,\lambda) \in \mathrm{ri}(\Theta_2)$ with $\lambda = \langle x^*, x\rangle - \alpha$. Then for some $(y,\mu) \in \Theta_2$ with $\mu < \langle x^*, y\rangle - \alpha$ there exists $t > 0$ such that $(x,\lambda) + t((x,\lambda) - (y,\mu)) \in \Theta_2$. It follows

$$0 \leq (1+t)(\langle x^*, x\rangle - \alpha - \lambda) + t(\mu - \langle x^*, y\rangle + \alpha) < 0, \tag{3.15}$$

a contradiction. The first inequality is due to $(x,\lambda) + t((x,\lambda) - (y,\mu)) \in \Theta_2$ and the second inequality due to $\mu < \langle x^*, y\rangle - \alpha$ and $\lambda = \langle x^*, x\rangle - \alpha$. But then $\mathrm{ri}(\Theta_1) \cap \mathrm{ri}(\Theta_2) = \emptyset$. Indeed, suppose that there exists $(x,\lambda) \in \mathrm{ri}(\Theta_1) \cap \mathrm{ri}(\Theta_2)$. Then it holds $\langle x^*, x\rangle - \alpha \leq 0$ and $\lambda > 0$ since $x \in \mathrm{ri}(C_1) \cap \mathrm{ri}(C_2) \subseteq C_1 \cap C_2$. On the other hand

$$0 < \lambda < \langle x^*, x\rangle - \alpha \leq 0, \tag{3.16}$$

a contradiction. □

Takeaways Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Ut purus elit, vestibulum ut, placerat ac, adipiscing vitae, felis. Curabitur dictum gravida mauris. Nam arcu libero, nonummy eget, consectetuer id, vulputate a, magna. Donec vehicula augue eu neque. Pellentesque habitant morbi tristique senectus et netus et malesuada fames ac turpis egestas. Mauris ut leo. Cras viverra metus rhoncus sem. Nulla et lectus vestibulum urna fringilla ultrices. Phasellus eu tellus sit amet tortor gravida placerat. Integer sapien est, iaculis in, pretium quis, viverra ac, nunc. Praesent eget sem vel leo ultrices bibendum. Aenean faucibus. Morbi dolor nulla, malesuada eu, pulvinar at, mollis ac, nulla. Curabitur auctor semper nulla. Donec varius orci eget risus. Duis nibh mi, congue eu, accumsan eleifend, sagittis quis, diam. Duis eget orci sit amet orci dignissim rutrum.

3.4 Relative Interior

Definition 3.5. *Let $\Omega \subseteq \mathbb{R}^n$. We define the* ***relative interior*** *of Ω by*

$$\mathrm{ri}(\Omega) := \{x \in \Omega \colon \textit{there exists } \gamma > 0 \textit{ such that } \mathrm{B}_\gamma(x) \cap \mathrm{aff}(\Omega) \in \Omega\}. \tag{3.17}$$

Next we collect some useful properties of relative interiors.

Theorem 3.4.

Theorem 3.5. *Let C be a non-empty convex set in $\mathbb{R}^n$. Then we get the representation*

(i) $\mathrm{ri}(C) = \{z \in C \colon \textit{for all } x \in C \textit{ there exists } t > 0 \textit{ such that } z + t(z-x) \in C\}$.

(ii) $\mathrm{cl}(C)$ *and* $\mathrm{ri}(C)$ *are convex sets.*

(iii) $\mathrm{cl}(\mathrm{ri}(C)) = \mathrm{cl}(C)$ *and* $\mathrm{ri}(\mathrm{cl}(C)) = \mathrm{ri}(C)$.

(iv) Suppose $\bigcap_{i\in I} C_i \neq \emptyset$ for a finite index set I. Then $\mathrm{ri}\left(\bigcap_{i\in I} C_i\right) = \bigcap_{i\in I} \mathrm{ri}(C_i)$.

(v) Let $L : \mathbb{R}^n \to \mathbb{R}^m$ be a linear mapping. Then $\mathrm{ri}(L(C)) = L(\mathrm{ri}(C))$. *If additionaly it holds* $L^{-1}(\mathrm{ri}(C)) \neq \emptyset$ *we have* $\mathrm{ri}(L^{-1}(C)) = L^{-1}(\mathrm{ri}(C))$.

(vi) $\mathrm{ri}(C_1 \times C_2) = \mathrm{ri}(C_1) \times \mathrm{ri}(C_2)$.

(vii) $\mathrm{ri}(C_1) \cap \mathrm{ri}(C_2) = \emptyset$ *if and only if* $0 \notin \mathrm{ri}(C_1 - C_2)$.

3.5 Conjugate Calculus

When studying different primal problems such as (**??**) we often turn to the dual instead. Therefore we need some reliable tools. Begin able to compute specific convex conjugates is one tool required.

Definition 3.6. (Convex conjugate) *Given a function* $f : \mathbb{R}^n \to \overline{\mathbb{R}}$ *, the* ***convex conjugate*** $f^* : \mathbb{R}^n \to \overline{\mathbb{R}}$ *of* f *is defined as*

$$f^*(x^*) := \sup_{x \in \mathbb{R}^n} (x^*)^T x - f(x) \tag{3.18}$$

Note that f in Definition 3.6 does not have to be convex. On the other hand, the convex conjugate is always convex:

Proposition 3.3. *Let* $f : \mathbb{R}^n \to (-\infty, \infty]$ *be a proper function. Then its convex conjugate* $f^* : \mathbb{R}^n \to (-\infty, \infty]$ *is convex.*

Definition 3.7. *Given a nonempty subset* $\Omega \subseteq \mathbb{R}^n$ *the* ***support function*** $\sigma_\Omega : \mathbb{R}^n \to \overline{\mathbb{R}}$ *of* Ω *is defined by*

$$\sigma_\Omega(x^*) := \sup_{x \in \Omega} \langle x^*, x \rangle \qquad \textit{for } x^* \in \mathbb{R}^n. \tag{3.19}$$

Lemma 3.1. *For any proper function* $f : \mathbb{R}^n \to \overline{\mathbb{R}}$ *we have*

$$f^*(x^*) = \sigma_{\mathrm{epi}(f)}(x^*, -1) \qquad \textit{for } x^* \in \mathbb{R}^n. \tag{3.20}$$

Proof. Let $x^* \in \mathbb{R}^n$ and $(x, \lambda) \in \mathrm{epi}(f)$. Then $x \in \mathrm{dom}(f)$ and $f(x) \leq \lambda$. Thus

$$\langle x^*, x \rangle - f(x) \geq \langle x^*, x \rangle - \lambda \qquad \text{for all } (x, \lambda) \in \mathrm{epi}(f). \tag{3.21}$$

On the other hand $(x, f(x)) \in \mathrm{epi}(f)$ for all $x \in \mathrm{dom}(f)$. It follows

$$\langle x^*, x \rangle - f(x) \leq \sup_{(x,\lambda) \in \mathrm{epi}(f)} \langle x^*, x \rangle - \lambda \qquad \text{for all } x \in \mathrm{dom}(f). \tag{3.22}$$

Taking the supremum in the last two displays yields

$$f^*(x^*) = \sup_{x \in \mathrm{dom}(f)} \langle x^*, x \rangle - f(x) = \sup_{(x,\lambda) \in \mathrm{epi}(f)} \langle x^*, x \rangle - \lambda \tag{3.23}$$

$$= \sup_{(x,\lambda) \in \mathrm{epi}(f)} \langle (x^*, -1), (x, \lambda) \rangle = \sigma_{\mathrm{epi}(f)}(x^*, -1). \tag{3.24}$$

□

Proposition 3.4.

Theorem 3.6. (Conjugate Chain Rule) *Let* $A : \mathbb{R}^m \to \mathbb{R}^n$ *be a linear map (matrix) and* $g : \mathbb{R}^n \to (-\infty, \infty]$ *a proper convex function. If* $Im(A) \cap ri(dom(g)) \neq \emptyset$ *it follows*

$$(g \circ A)^*(x^*) = \inf_{y^* \in (A^*)^{-1}(x^*)} g^*(y^*). \tag{3.25}$$

Furthermore, for any $x^* \in dom(g \circ A)^*$ *there exists* $y^* \in (A^*)^{-1}(x^*)$ *such that* $(g \circ A)^*(x^*) = g^*(y^*)$.

Definition 3.8. (Infimal convolution) *Given functions $f_i : \mathbb{R}^n \to (-\infty, \infty]$ for $i = 1, \dots, n$ the **infimal convolution** of these functions as defined as*

$$(f_1 \square \dots \square f_m)(x) := \inf_{\substack{x_i \in \mathbb{R}^n \\ \sum_{i=1}^m x_i = x}} \sum_{i=1}^m f_i(x_i) \tag{3.26}$$

Theorem 3.7. *Let $f, g : \mathbb{R}^n \to (-\infty, \infty]$ be proper convex functions and $ri(dom(f)) \cap ri(dom(g)) \neq \emptyset$. Then we have the conjugate sum rule*

$$(f+g)^*(x^*) = (f^* \square g^*)(x^*) \tag{3.27}$$

for all $x^* \in \mathbb{R}^n$. Moreover, the infimum in $(f^* \square g^*)(x^*)$ is attained, i.e., for any $x^* \in dom(f+g)^*$ there exists vectors x_1^*, x_2^* for which

$$(f+g)^*(x^*) = f^*(x_1^*) + g^*(x_2^*), \quad x^* = x_1^* + x_2^*. \tag{3.28}$$

Proof. Let $x^* \in \mathbb{R}^n$ and fix $x_1^*, x_2^* \in \mathbb{R}^n$ such that $x^* = x_1^* + x_2^*$. We get

$$\begin{aligned} f^*(x_1^*) + g^*(x_2^*) &= \sup_{x \in \mathbb{R}^n} \langle x_1^*, x \rangle - f(x) + \sup_{x \in \mathbb{R}^n} \langle x_2^*, x \rangle - g(x) \\ &\geq \sup_{x \in \mathbb{R}^n} \langle x_1^*, x \rangle - f(x) + \langle x_2^*, x \rangle - g(x) = \sup_{x \in \mathbb{R}^n} \langle x_1^* + x_2^*, x \rangle - (f(x) + g(x)) \\ &= \sup_{x \in \mathbb{R}^n} \langle x^*, x \rangle - (f+g)(x) = (f+g)^*(x^*) \end{aligned}$$

Taking the infimum over $x_1^*, x_2^* \in \mathbb{R}^n$ in the above display gives $(f^* \square g^*)(x^*) \geq (f+g)^*(x^*)$. Let us prove now $\leq$ under the condition $\mathrm{ri}\,(\mathrm{dom}(f)) \cap \mathrm{ri}\,(\mathrm{dom}(g)) \neq \emptyset$. The only case we need to consider is $(f+g)^*(x^*) < \infty$. Define two convex sets by

$$\Omega_1 := \left\{(x, \alpha, \beta) \in \mathbb{R}^{n+2} \colon \alpha \geq f(x)\right\} = \mathrm{epi}(f) \times \mathbb{R}, \tag{3.29}$$
$$\Omega_2 := \left\{(x, \alpha, \beta) \in \mathbb{R}^{n+2} \colon \beta \geq g(x)\right\}. \tag{3.30}$$

Similar to Lemma we get the representation

$$(f+g)^*(x^*) = \sigma_{\Omega_1 \cap \Omega_2}(x^*, -1, -1). \tag{3.31}$$

Indeed, the only thing we need to verify is $\mathrm{dom}(f) \cap \mathrm{dom}(g) = \mathrm{dom}(f+g)$. The inclusion $\subseteq$ is clear. Assume towards a contradiction that $(f+g)(x) < \infty$ and $f(x) = \infty$. Since $g(x) > -\infty$ it holds

$$\infty = \infty + g(x) = f(x) + g(x) = (f+g)(x) < \infty. \tag{3.32}$$

This is a contradiction. The same holds for f and g reversed. It follows the inclusion $\supseteq$ and equality. By the support function intersection rule there exist triples

$$(x_1^*, -\alpha_1, -\beta_1), (x_2^*, -\alpha_2, -\beta_2) \in \mathbb{R}^{n+2} \quad \text{such that} \quad (x^*, -1, -1) = (x_1^* + x_2^*, -(\alpha_1 + \alpha_2), -(\beta_1 + \beta_2)) \tag{3.33}$$

and

$$(f+g)^*(x^*) = \sigma_{\Omega_1 \cap \Omega_2}(x^*, -1, -1) = \sigma_{\Omega_1}(x_1^*, -\alpha_1, -\beta_1) + \sigma_{\Omega_2}(x_2^*, -\alpha_2, -\beta_2). \tag{3.34}$$

Next we show $\beta_1 = \alpha_2 = 0$. Suppose towards a contradiction that $\beta_1 \neq 0$. We fix $(\overline{x}, \overline{\alpha}) \in \mathrm{epi}(f)$. Then

$$\sigma_{\Omega_1}(x_1^*, -\alpha_1, -\beta_1) = \sup_{(x, \alpha, \beta) \in \mathrm{epi}(f) \times \mathbb{R}} \langle x^*, x \rangle - \alpha\alpha_1 - \beta\beta_1 \geq \sup_{\beta \in \mathbb{R}} \langle x^*, \overline{x} \rangle - \overline{\alpha}\alpha_1 - \beta\beta_1 = \infty. \tag{3.35}$$

This contradicts $(f+g)^*(x^*) < \infty$. In a similar fashion we can derive a contradiction for $\alpha_2 \neq 0$. Employing Lemma and taking into account the structures of the sets Ω_1 and Ω_2 this implies

$$(f+g)^*(x^*) = \sigma_{\Omega_1 \cap \Omega_2}(x^*, -1, -1) = \sigma_{\Omega_1}(x_1^*, -1, 0) + \sigma_{\Omega_2}(x_2^*, 0, -1) \tag{3.36}$$

$$= \sigma_{\mathrm{epi}(f)}(x_1^*, -1) + \sigma_{\mathrm{epi}(g)}(x_2^*, -1) = f^*(x_1^*) + g^*(x_2^*) \geq (f^* \Box g^*)(x^*). \tag{3.37}$$

This finishes the proof. □

4 Matrix Concentration Inequalities

Theorem 4.1. (Matrix Rosenthal-Pinelis) *Let* $\mathbf{A}_1, \ldots, \mathbf{A}_n$ *be independent, random matrices with dimension* $d_1 \times d_2$. *Introduce the random matrix*

$$\mathbf{S} := \sum_{k=1}^{n} \mathbf{A}_k.$$

Let $v(\mathbf{S})$ *be the matrix variance statistic of the sum:*

$$v(\mathbf{S}) := \left\|\mathbf{E}[\mathbf{S}\mathbf{S}^\top]\right\| \vee \left\|\mathbf{E}[\mathbf{S}^\top\mathbf{S}]\right\| = \left\|\sum_{k=1}^{n} \mathbf{E}[\mathbf{A}_k\mathbf{A}_k^\top]\right\| \vee \left\|\sum_{k=1}^{n} \mathbf{E}[\mathbf{A}_k^T\mathbf{A}_k]\right\|. \tag{4.1}$$

Then

$$\left(\mathbf{E}\left[\|\mathbf{S}\|^2\right]\right)^{\frac{1}{2}} \leq \sqrt{2ev(\mathbf{S})\log(d_1+d_2)} + 4e\left(\mathbf{E}[\max_{k\leq n}\|\mathbf{A}_k\|^2]\right)^{\frac{1}{2}}\log(d_1+d_2). \tag{4.2}$$

Remark 4.1. *Since* $\mathbf{E}[\|S\|] \leq \mathbf{E}[\|S\|^2]^{\frac{1}{2}}$ *by the Cauchy-Schwarz inequality, Theorem 4.1 also holds with* $\mathbf{E}[\|S\|]$ *on the left-hand side of* (4.2). *To obtain a tail bound we can employ the Markov inequality and Theorem 4.1:*

$$\begin{aligned}&\mathbf{P}[\,\|S\| \geq t]\\ &\quad\leq \frac{\mathbf{E}[\|S\|]}{t} \leq \frac{1}{t}\left(\sqrt{2ev(\mathbf{S})\log(d_1+d_2)} + 4e\left(\mathbf{E}[\max_{k\leq n}\|\mathbf{A}_k\|^2]\right)^{\frac{1}{2}}\log(d_1+d_2)\right) \quad \textit{for } t>0.\end{aligned} \tag{4.3}$$

It might be possible to improve the log *term employing an intrinsic dimension argument.* ♢

5 Empirical Processes

Let $(\Omega, \mathcal{A}, \mathbf{P})$ be a probability space and $(\mathcal{X}, \Sigma)$ a measurable space. Let $X_j : (\Omega, \mathcal{A}, \mathbf{P}) \to (\mathcal{X}, \Sigma)\,, j = 1, \ldots, n$ be independent and identically-distributed (i.i.d.) random variables with probability distribution $\mathbf{P}_X$ and $\mathcal{F}$ a family of measurable functions $f : (\mathcal{X}, \Sigma) \to (\mathbb{R}, \mathcal{B}(\mathbb{R}))$. Consider the map

$$f \mapsto G_n f := \sqrt{n} \left(\frac{1}{n} \sum_{i=1}^{n} f(X_i) - \mathbf{P}_X f \right), \tag{5.1}$$

where $\mathbf{P}_X f := \int_{\mathcal{X}} f \mathrm{d}\mathbf{P}_X$. We call $(G_n f)_{f \in \mathcal{F}}$ the empirical process indexed by $\mathcal{F}$. Furthermore

$$\|G_n f\|_{\mathcal{F}} := \sup_{f \in \mathcal{F}} |G_n f| \,. \tag{5.2}$$

Lemma 5.1. (Bernstein Inequality for Empirical Processes) *For any bounded, measurable function f it holds for all $t > 0$*

$$\mathbf{P}\left(|G_n f| > t\right) \leq 2 \exp\left(-\frac{1}{4} \frac{t^2}{\mathbf{P}_X(f^2) + t \|f\|_\infty / \sqrt{n}} \right) \tag{5.3}$$

Proof. By the Markov inequality it holds for all $\lambda > 0$

$$\mathbf{P}\left(G_n f > t\right) \leq e^{-\lambda t} \mathbf{E} \exp\left(\lambda G_n f\right) \tag{5.4}$$

□

Lemma 5.2. *For any finite class $\mathcal{F}$ of bounded, measurable, square-integrable functions, with $|\mathcal{F}|$ elements, it holds*

$$\mathbf{E}\, \|G_n f\|_{\mathcal{F}} \lesssim \max_{f \in \mathcal{F}} \frac{\|f\|_\infty}{\sqrt{n}} \log\left(1 + |\mathcal{F}|\right) + \max_{f \in \mathcal{F}} \|f\|_{\mathbf{P},2} \sqrt{\log\left(1 + |\mathcal{F}|\right)}. \tag{5.5}$$

6 Simple yet useful Calculations

Theorem 6.1. (Multivariate Taylor Theorem) *Let $f \in C^2(\mathbb{R}^n, \mathbb{R})$. Then for all $x, \Delta \in \mathbb{R}^n$ there exists $\xi \in [0,1]$ such that it holds*

$$\begin{aligned} f(x+\Delta) = f(x) + \sum_{i=1}^{n} \frac{\partial f(x)}{\partial x_i}\Delta_i + \sum_{\substack{i,j=1 \\ i\neq j}} \frac{\partial^2 f(x+\xi\Delta)}{\partial x_i \partial x_j}\Delta_i\Delta_j \\ + \frac{1}{2}\sum_{i=1}^{n} \frac{\partial^2 f(x+\xi\Delta)}{\partial x_i^2}\Delta_i^2 \end{aligned} \tag{6.1}$$

Corollary 6.1.1. *Let $f \in C^2(\mathbb{R})$. Then for all $a, x, \Delta \in \mathbb{R}^n$ there exist $\xi \in [0,1]$ such that it holds*

$$f(a^T(x+\Delta)) - f(a^T x) = f^{'}(a^T x)\, \Delta^T a + \frac{1}{2} f^{''}(a^T(x+\xi\Delta))\, \Delta^T A\ \Delta, \tag{6.2}$$

where $A := aa^T \in \mathbb{R}^{n\times n}$.

Proof. By the chain rule we have for all $a, x, \Delta \in \mathbb{R}^n$ and $\xi \in [0,1]$

$$\frac{\partial^2 f(a^T(x+\xi\Delta))}{\partial x_i \partial x_j} = f^{''}(a^T(x+\xi\Delta))\, a_i a_j. \tag{6.3}$$

Since $A := aa^T$ is symmetric we have

$$\Delta^T A\ \Delta = 2\sum_{\substack{i,j=1 \\ i\neq j}}^{n} a_i a_j \Delta_i \Delta_j + \sum_{i=1}^{n} a_i^2 \Delta_i^2. \tag{6.4}$$

Plugging (6.3) and (6.4) into (6.1) yields (6.2). □

Proposition 6.1. *For all $x, y \in \mathbb{R}$ it holds*

$$|x+y| - |x| \geq -|y| \tag{6.5}$$

Proof. Checking all 6 combinations of $x+y, x, y$ being nonnegative or negative yields the result. □

Notation Index

$\#A$ cardinality of the set A

$\mathbf{E}[X|Y]$ conditional expectation of the random variable X with respect to $\sigma(Y)$

$\mathbf{E}[X]$ expectation of the random variable X

$\mathbf{Var}[X]$ variance of the random variable X

$\overline{\mathbb{R}} = \mathbb{R} \cup \{+\infty\}$ extension of the real numbers

$\xrightarrow{\mathcal{D}}$ convergence of distributions

$\mathbf{P}$ generic probability measure

$\mathbf{P}_X = \mathbf{P} \circ X^{-1}$ distribution of the random variable X

$\mathbb{R}$ set of real numbers

$x \vee y, x \wedge y, x^+, x^-$ maximum, minimum, positive part, negative part of real numbers

$X \sim \mu$ the random variable has distribution μ

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