## Noiseless recovery condition for the supremum norm

Proposition 1. Let $\beta \in \mathbb{R}^{p}$ where $\beta \neq 0$ and $I:=\left\{i \in[p]:\left|\beta_{i}\right|<\|\beta\|_{\infty}\right\}$. Let $\tilde{X}=\left(\tilde{X}_{1} \mid X_{I}\right)$ where

$$
\tilde{X}_{1}=\sum_{i \notin I} \operatorname{sign}\left(\beta_{i}\right) X_{i} .
$$

The following equivalence occurs

$$
\exists \lambda>0 \exists \hat{\beta} \in S_{X, \lambda\|\cdot\|}(X \beta) \text { such that } \hat{\beta} \stackrel{\|\cdot\|_{\infty}}{\sim} \beta \Leftrightarrow \tilde{X}^{\prime}\left(\tilde{X}^{\prime}\right)^{+} e_{1}=e_{1},
$$

where $e_{1}$ is a vector whose first component is 1 and remaining components are 0 .
Before giving the proof, we recall that the subdifferential of the $\ell_{\infty}$ norm at 0 is the unit ball of the $\ell_{1}$ norm and for $x \neq 0$ this subdifferential is equal to

$$
\begin{align*}
\partial_{\|\cdot\| \infty}(x) & =\left\{s \in \mathbb{R}^{p}:\|s\|_{1} \leq 1 \text { and } s^{\prime} x=\|x\|_{\infty}\right\} \\
& =\left\{s \in \mathbb{R}^{p}:\|s\|_{1}=1 \text { and }\left\{\begin{array}{ll}
s_{i} x_{i} \geq 0 & \text { if }\left|x_{i}\right|=\|x\|_{\infty} \\
s_{i}=0 & \text { otherwise }
\end{array}\right\} .\right. \tag{1}
\end{align*}
$$

Proof. $(\Longrightarrow)$ Let us assume that there exists $\lambda>0$ and $\hat{\beta} \in S_{X, \lambda\|\cdot\| \infty}(X \beta)$ such that $\hat{\beta} \stackrel{\|\cdot\|_{\infty}}{\sim} \beta$. Then the following property holds

$$
\begin{equation*}
\frac{1}{\lambda} X^{\prime}(X \beta-X \hat{\beta}) \in \partial_{\|\cdot\|_{\infty}}(\hat{\beta})=\partial_{\|\cdot\|_{\infty}}(\beta) . \tag{2}
\end{equation*}
$$

Let us set $c=\left(\|\beta\|_{\infty}, \beta_{I}\right)^{\prime}$ and $\hat{c}=\left(\|\hat{\beta}\|_{\infty}, \hat{\beta}_{I}\right)^{\prime}$. By construction $X \beta=\tilde{X} c$. Moreover, since $\partial_{\|\cdot\| \infty}(\beta)=$ $\partial_{\|\cdot\|_{\infty}}(\hat{\beta})$, we also have $X \hat{\beta}=\tilde{X} \hat{c}$. Consequently, according to (2), we have

$$
\frac{1}{\lambda} X^{\prime} \tilde{X}(c-\hat{c}) \in \partial_{\|\cdot\|_{\infty}}(\beta) .
$$

Given a subgradient $s \in \partial_{\|\cdot\| \infty}(\beta)$, according to (2), the following implications hold

$$
\left\{\begin{array}{ll}
\forall i \in I & X_{i}^{\prime} \tilde{X}(c-\hat{c}) \tilde{}=0 \\
\frac{1}{\lambda} \sum_{i \notin I} \operatorname{sign}\left(\beta_{i}\right) X_{i}^{\prime} \tilde{X}(c-\hat{c})=1
\end{array} \quad \Rightarrow \frac{1}{\lambda} \tilde{X}^{\prime} \tilde{X}(c-\hat{c})=e_{1} \Rightarrow \tilde{X}(c-\hat{c})=\lambda\left(\tilde{X}^{\prime}\right)^{+} e_{1} .\right.
$$

Using the last implication, one may deduce the following fact

$$
\frac{1}{\lambda} X^{\prime}(X \beta-X \hat{\beta})=\frac{1}{\lambda} X^{\prime} \tilde{X}(c-\hat{c})=X^{\prime}\left(\tilde{X}^{\prime}\right)^{+} e_{1} .
$$

Since $X^{\prime}\left(\tilde{X}^{\prime}\right)^{+} e_{1} \in \partial_{\|\cdot\|_{\infty}}(\beta)$, let us prove that $\tilde{X}^{\prime}\left(\tilde{X}^{\prime}\right)^{+} e_{1}=e_{1}$.

$$
X^{\prime}\left(\tilde{X}^{\prime}\right)^{+} e_{1} \in \partial_{\|\cdot\|_{\infty}}(\beta) \Rightarrow\left\{\begin{array}{l}
\forall i \in I X_{i}^{\prime}\left(\tilde{X}^{\prime}\right)^{+} e_{1}=0 \\
\sum_{i \notin I} \operatorname{sign}\left(\beta_{i}\right) X_{i}^{\prime}\left(\tilde{X}^{\prime}\right)^{+} e_{1}=X_{1}^{\prime}\left(\tilde{X}^{\prime}\right)^{+} e_{1}=1
\end{array} \quad \Rightarrow \tilde{X}^{\prime}\left(\tilde{X}^{\prime}\right)^{+} e_{1}=e_{1}\right.
$$

$(\Longleftarrow)$ Let us define $\hat{c}=c-\lambda \tilde{X}^{+}\left(\tilde{X}^{\prime}\right)^{+} e_{1}=\left(\hat{c}_{1}, \hat{c}_{-1}\right)^{\prime}$ (the first component is $\hat{c}_{1}$ and remaining components are $\hat{c}_{-1}$ ) and let us set $\hat{\beta}$ as follows

$$
\forall i \notin I \quad \hat{\beta}_{i}=\operatorname{sign}\left(\beta_{i}\right) \hat{c}_{1} \text { and } \hat{\beta}_{I}=\hat{c}_{-1} .
$$

Because $c_{1}=\|\beta\|_{\infty}$, then for $\lambda>0$ small enough, we have $\left\{i \in[p]:\left|\hat{\beta}_{i}\right|<\|\hat{\beta}\|_{\infty}\right\}=\{i \in[p]:$ $\left.\left|\beta_{i}\right|<\|\beta\|_{\infty}\right\}=I$ and for $i \notin I$ we have $\beta_{i} \hat{\beta}_{i}>0$. Consequently, for $\lambda$ small enough we have
$\partial_{\|\cdot\|_{\infty}}(\hat{\beta})=\partial_{\|\cdot\|_{\infty}}(\beta)$. Therefore, to conclude the proof, it is enough to show that $\hat{\beta} \in S_{X, \lambda\|\cdot\|_{\infty}}(X \beta)$, i.e. $\frac{1}{\lambda} X^{\prime}(X \beta-X \hat{\beta}) \in \partial_{\|\cdot\|_{\infty}}(\hat{\beta})$. Because $\operatorname{col}\left(\left(\tilde{X}^{\prime}\right)^{+}\right)=\operatorname{col}(\tilde{X})$ and since $\tilde{X} \tilde{X}^{+}$is the projection onto $\operatorname{col}(\tilde{X})$ we have the following equalities

$$
\frac{1}{\lambda} X^{\prime}(X \beta-X \hat{\beta})=\frac{1}{\lambda} X^{\prime}(\tilde{X} c-\tilde{X} \hat{c})=X^{\prime} \tilde{X} \tilde{X}^{+}\left(\tilde{X}^{\prime}\right)^{+} e_{1}=X^{\prime}\left(\tilde{X}^{\prime}\right)^{+} e_{1}
$$

Finally, let us prove that $X^{\prime}\left(\tilde{X}^{\prime}\right)^{+} e_{1} \in \partial_{\|\cdot\|_{\infty}}(\beta)$.

$$
\begin{aligned}
\tilde{X}^{\prime}\left(\tilde{X}^{\prime}\right)^{+} e_{1}=e_{1} & \Rightarrow\left\{\begin{array}{l}
X_{1}^{\prime}\left(\tilde{X}^{\prime}\right)^{+} e_{1}=1 \\
\forall i \in I X_{i}^{\prime}\left(\tilde{X}^{\prime}\right)^{+} e_{1}=0
\end{array}\right. \\
& \Rightarrow\left\{\begin{array}{l}
\sum_{i \notin I} \operatorname{sign}\left(\beta_{i}\right) X_{i}^{\prime}\left(\tilde{X}^{\prime}\right)^{+} e_{1}=1 \\
\forall i \in I X_{i}^{\prime}\left(\tilde{X}^{\prime}\right)^{+} e_{1}=0
\end{array} \Rightarrow X^{\prime}\left(\tilde{X}^{\prime}\right)^{+} e_{1} \in \partial_{\|\cdot\|_{\infty}}(\beta) .\right.
\end{aligned}
$$

Consequently, for $\lambda>0$ small enough, $\hat{\beta} \in S_{X, \lambda\|\cdot\|_{\infty}}(X \beta)$.

## Linear span of a pattern equivalent class

In Proposition 2 we prove that the linear span of a pattern equivalent class is equal to the model subspace as defined in Vaiter.

Proposition 2. Let $\phi(x)=\max \left\{u_{1}^{\prime} x \ldots, u_{l}^{\prime} x\right\}$ for some $u_{1}, \ldots, u_{l} \in \mathbb{R}^{p}$ be a convex function then

$$
\operatorname{lin}\left(C_{x}\right)=\overrightarrow{\partial \phi(x)} \perp
$$

The proof of Proposition 2 is mainly based on the following lemmas
Lemma 1. Let $P$ be the polyhedron $\left\{x \in \mathbb{R}^{p}: s_{1}^{\prime} x \leq r_{1}, \ldots, s_{n}^{\prime} x \leq r_{n}\right\}$ let $\bar{x} \in P$ and $\bar{I}:=\{i \in[n]$ : $\left.s_{i}^{\prime} \bar{x}=r_{i}\right\}$ then

$$
N_{P}(\bar{x})=\operatorname{cone}\left\{s_{i}\right\}_{i \in \bar{I}}
$$

The proof of Lemma 1 is given in Gruber (Proposition 14.1 page 250).
Lemma 2. Let $P$ be the polyhedron $\left\{x \in \mathbb{R}^{p}: s_{1}^{\prime} x \leq r_{1}, \ldots, s_{n}^{\prime} x \leq r_{n}\right\}$ let $\bar{x} \in P$ and $\bar{I}:=\{i \in[n]$ : $\left.s_{i}^{\prime} \bar{x}=r_{i}\right\}$ then

$$
\operatorname{lin}\left(N_{P}(\bar{x})\right)=\overrightarrow{\operatorname{aff}(F)^{\perp}}
$$

where $F$ is the smallest face of $P$ containing $\bar{x}$ :

$$
F=\left\{x \in P: s_{i}^{\prime} x=r_{i} \quad \forall i \in \bar{I}\right\}
$$

Proof. The face $F$ can be rewritten as the following polyhedron:

$$
F=\left\{x \in \mathbb{R}^{p}:\left\{\begin{array}{l}
s_{i}^{\prime} x \leq r_{i} \text { and }-s_{i}^{\prime} x \leq-r_{i} \quad \forall i \in \bar{I} \\
s_{i}^{\prime} x \leq r_{i} \quad \forall i \notin \bar{I}
\end{array}\right\} .\right.
$$

Consequently, according to Lemma 1, the following identity occurs.

$$
N_{F}(\bar{x})=\operatorname{cone}\left\{s_{i},-s_{i}: i \in \bar{I}\right\}=\operatorname{lin}\left\{s_{i}: i \in \bar{I}\right\}=\operatorname{lin}\left(\operatorname{cone}\left\{s_{i}: i \in \bar{I}\right\}\right)=\operatorname{lin}\left(N_{P}(\bar{x})\right)
$$

It remains to prove that $N_{F}(\bar{x})=\overrightarrow{\operatorname{aff}(F)}{ }^{\perp}$. Let $v \in \overrightarrow{\operatorname{aff}(F)}{ }^{\perp}$. Because $\overrightarrow{\operatorname{aff}(F)}=\operatorname{lin}\{w-\bar{x}: w \in F\}$ then for all $w \in F$ we have $v^{\prime}(w-\bar{x})=0$. Therefore, $v \in N_{F}(\bar{x})$. Conversely, let $v \in N_{F}(\bar{x})$. Because $\bar{x} \in \operatorname{ri}(\bar{F})$ then for $x \in F$ and $\delta \neq 0$ small enough $\bar{x}+\delta(x-\bar{x}) \in F$. Consequently,

$$
\begin{equation*}
v^{\prime}(\bar{x}+\delta(x-\bar{x})-\bar{x})=\delta v^{\prime}(x-\bar{x}) \leq 0 \tag{3}
\end{equation*}
$$

Taking $\delta$ arbitrarily small and positive (resp. negative) in (3) leads to $v^{\prime}(x-\bar{x}) \leq 0$ (resp. $v^{\prime}(x-\bar{x}) \geq 0$ ). Therefore, $v \in \overrightarrow{\operatorname{aff}(F)^{\perp}}$

Proof of Proposition 2. According to Theorem 4 (in main) we have $\operatorname{lin}\left(C_{x}\right)=\operatorname{lin}\left(\operatorname{ri}\left(N_{B^{*}}(\partial \phi(x))\right)\right)$, where $B^{*}$ is the polytope $\operatorname{conv}\left\{u_{1}, \ldots, u_{l}\right\}$. Since a linear space is closed one may deduce that $\left.N_{B^{*}}(\partial \phi(x))\right) \subset \operatorname{lin}\left(\operatorname{ri}\left(N_{B^{*}}(\partial \phi(x))\right)\right)$. Consequently, $\operatorname{lin}\left(\operatorname{ri}\left(N_{B^{*}}(\partial \phi(x))\right)\right)=\operatorname{lin}\left(N_{B^{*}}(\partial \phi(x))\right)$. Let $u \in \operatorname{ri}(\partial \phi(x))$. Because $\operatorname{lin}\left(N_{B^{*}}(\partial \phi(x))\right)=\operatorname{lin}\left(N_{B^{*}}(u)\right)$ (see e.g. Ewald page 16) and since $\partial \phi(x)$ is the smallest face of $B^{*}$ containing $u$ one may deduce, according to Lemma 1 , that $\operatorname{lin}\left(N_{B^{*}}(u)\right)=\overrightarrow{\partial \phi(x)} \perp$. Therefore $\operatorname{lin}\left(C_{x}\right)=\overrightarrow{\partial \phi(x)^{\perp}}$.

## Geometrical characterisation of the noiseless recovery condition

Theorem 1 we provides a geometrical characterisation of the noiseless recovery condition.
Theorem 1. Let pen be a polyhedral norm.
$\exists \lambda>0 \exists \hat{\beta} \in S_{X, \lambda \text { pen }}(X \beta), \hat{\beta} \stackrel{\text { pen }}{\sim} \beta \Leftrightarrow X^{\prime} X \operatorname{lin}\left(C_{\beta}\right) \cap \partial_{\text {pen }}(\beta) \neq \varnothing \Leftrightarrow X^{\prime} X \overrightarrow{\operatorname{aff}\left(\partial_{\text {pen }}(\beta)\right)^{\perp} \cap \partial_{\text {pen }}(\beta) \neq \varnothing . ~}$
Proof. According to Proposition 2, $\operatorname{lin}\left(C_{\beta}\right)=\overrightarrow{\operatorname{aff}\left(\partial_{\text {pen }}(\beta)\right)^{\perp}}$. Therefore $X^{\prime} X \operatorname{lin}\left(C_{\beta}\right) \cap \partial_{\text {pen }}(\beta) \neq \varnothing \Leftrightarrow$ $X^{\prime} X \overrightarrow{\operatorname{aff}\left(\partial_{\text {pen }}(\beta)\right)^{\perp} \cap \partial_{\text {pen }}(\beta) \neq \varnothing \text {. Let us prove the first equivalence }}$ $(\Longrightarrow):$ Let $\hat{\beta} \in S_{X, \lambda \text { pen }}(X \beta)$ such that $\hat{\beta} \stackrel{\text { pen }}{\sim} \beta$ then

$$
\frac{1}{\lambda} X^{\prime} X(\beta-\hat{\beta}) \in \partial_{\mathrm{pen}}(\beta)
$$

Since $\hat{\beta} \in C_{\beta}$ then $\frac{\beta-\hat{\beta}}{\lambda} \in \operatorname{lin}\left(C_{\beta}\right)$. Consequently,

$$
X^{\prime} X \operatorname{lin}\left(C_{\beta}\right) \cap \partial_{\text {pen }}(\beta) \neq \varnothing
$$

$(\Longleftarrow)$ : Let us assume that $\left.X^{\prime} X \operatorname{lin}\left(C_{\beta}\right)\right) \cap \partial_{\text {pen }}(\beta) \neq \varnothing$, i.e. there exists such $\left.z \in \operatorname{lin}\left(C_{\beta}\right)\right)$ such that $X^{\prime} X z \in \partial_{\text {pen }}(\beta)$. Let us set $\hat{\beta}=\beta-\lambda z$. Because, according to Proposition 3 (in main), $C_{\beta}$ is relatively open and because $z \in \operatorname{lin}\left(C_{\beta}\right)=\operatorname{aff}\left(C_{\beta}\right)$ (since 0 lies in the relative boundary of $C_{\beta}$ ), then for $\lambda$ small enough we have $\hat{\beta} \stackrel{\text { pen }}{\sim} \beta$. Consequently

$$
\frac{1}{\lambda} X^{\prime}(X \beta-X \hat{\beta})=X^{\prime} X z \in \partial_{\mathrm{pen}}(\hat{\beta})
$$

Therefore $\hat{\beta} \in S_{X, \lambda \text { pen }}(X \beta)$, which achieves the proof.

