

Lipschitz stability of least-squares problems regularized by functions with \mathcal{C}^2 -cone reducible conjugates

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The 26th Midwest Optimization Meeting
University of Waterloo

(Based on the joint work with Y. Cui (UC), T. Hoheisel (MU), and D. Sun (HKPU))

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A particular situation in different areas of engineering and science is that one has the observation $y_0 = \Phi x_0$ via a known (or random) linear operator $\Phi : \mathbb{R}^n \rightarrow \mathbb{R}^m$ ($m \ll n$) and an unknown vector $x_0 \in \mathbb{R}^n$. To recover x_0 , we have to solve

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Let's generate some random data:

$$x_0 \in [-1, 1]^{250} \quad \text{with} \quad \text{nnz}(x_0) = 25 \quad \text{and} \quad \Phi \in \mathbb{R}^{100 \times 250}.$$

Solving (1) by the least-square method or the projection method:

$$\text{(LS)} \quad \min_{x \in \mathbb{R}^{250}} \|\Phi x - y_0\|^2 \quad \text{or} \quad \text{(PM)} \quad \min_{x \in \mathbb{R}^{250}} \|x\|_2 \quad \text{subject to} \quad \Phi x = y_0$$

gives us the same solution

$$x_{LS} = \Phi^\dagger y_0 \quad \text{with} \quad \text{nnz}(x_{LS}) = 250 \quad \text{and} \quad \|x_{LS} - x_0\| \approx 2.9.$$

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Solving the (ℓ_1) problem

$$(\ell_1) \quad \min_{x \in \mathbb{R}^{250}} \|x\|_1 \quad \text{subject to} \quad \Phi x = y_0$$

gives us $\text{nnz}(\bar{x}) = 25$ and $\|\bar{x} - x_0\| \approx 10^{-14}$, and recovers exactly x_0 .

When there is some error/noise in the observation y_0 , i.e., our observation y satisfies

$$\|\Phi x_0 - y\| \leq \delta = 0.001 \quad \text{for some } \delta > 0.$$

Solving the least square problem gives us x_δ with

$$\text{nnz}(x_\delta) = 250 \quad \text{and} \quad \|x_\delta - x_0\| \approx 2.6.$$

As we want to recover a sparse vector, adding the ℓ_1 norm to the least square course is helpful:

$$\min_{x \in \mathbb{R}^n} \frac{1}{2} \|Ax - b\|^2 + \mu \|x\|_1. \quad (2)$$

With $\mu = \delta$, its optimal solution \bar{x}_μ satisfies

$$\text{nnz}(\bar{x}_\mu) = 31 \quad \text{and} \quad \|\bar{x}_\mu - x_0\| \approx 0.009.$$

If x_0 has low-complexity (e.g., sparsity, group-sparsity, or low-rank) and $y \approx \Phi x_0$, we solve

$$(P(y, \mu) \quad \min_{x \in \mathbb{R}^n} \quad \frac{1}{2\mu} \|\Phi x - y\|^2 + g(x), \quad (3)$$

where $\mu > 0$, $y \in \mathbb{R}^m$, and $g: \mathbb{R}^n \rightarrow \mathbb{R}$ is a convex regularizer (ℓ_1 norm, ℓ_1/ℓ_2 norm, nuclear norm, etc).

- μ is called the tuning parameter.
- y is also another parameter.

We are interested in studying stability and sensitivity of the solution mapping:

$$S(y, \mu) := \operatorname{argmin} \left\{ \frac{1}{2\mu} \|\Phi x - y\|^2 + g(x) \mid x \in \mathbb{R}^n \right\}. \quad (4)$$

- [Vaiter et al 2017] showed that $S(y, \mu)$ is a *differentiable* function around $(\bar{y}, \bar{\mu}) \in \mathbb{R}^m \times \mathbb{R}_{++}$ under the **nondegeneracy condition** (ND):

$$-\frac{1}{\mu} \Phi^*(\Phi \bar{x} - \bar{y}) \in \text{ri } \partial g(\bar{x}) \quad \text{with} \quad \bar{x} = S(\bar{y}, \mu) \quad (5)$$

together with **another second-order condition**.

- When $g = \|\cdot\|_1$, without the (ND) condition, [Bolte et al 2021] showed that if $S(y, \mu)$ is **Lipschitz continuous** around $(\bar{y}, \bar{\mu})$, then it is **path differentiable** and its conservative Jacobian at $(\bar{y}, \bar{\mu})$ is computable.

- When $g = \|\cdot\|_1$, [Berk-Brugiapaglia-Hoheisel 2023] shows that the Tibshirani's condition [Tibshirani 2013] is a **sufficient condition** for Lipschitz stability of $S(y, b)$.
- [N. 2024] obtained **full characterizations** for Lipschitz stability of this solution mapping for different classes of $g(x)$.

The common point of these papers is: they are **heavy in second-order analysis!**

Lipschitz stability and second-order analysis

The solution mapping S is Lipschitz continuous around $(\bar{y}, \bar{\mu})$ provided that

$$\|\Phi w\|^2 + \inf\{\langle z, w \rangle \mid z \in \partial^2 g(\bar{x}|\bar{v})(w)\} > 0 \quad \text{for any } w \neq 0, \quad (6)$$

where $\bar{x} \in S(\bar{y}, \bar{\mu})$, $\bar{v} := -\frac{1}{\bar{\mu}}\Phi^*(\Phi\bar{x} - \bar{y}) \in \partial g(\bar{x})$, and $\partial^2 g(\bar{x}|\bar{v})(w)$ is the **generalized Hessian** of g [Mordukhovich 1992] due to the theory of **blue stability** [Levy-Poliquin-Rockafellar 2000].

$\partial^2 g(\bar{x}|\bar{v}) : \mathbb{R}^n \rightrightarrows \mathbb{R}^n$ is a **second-order structure** and it could be **very hard** to compute it, e.g., g is the nuclear norm.

Our question was: “Can we surpass the computation of second-order structures and obtain simple conditions for Lipschitz stability?”

Our approach via the dual problem

The dual problem of (3) reads

$$\min_{z \in \mathbb{R}^m} \quad \frac{\mu}{2} \|z\|^2 - \langle z, y \rangle + g^*(\Phi^* z),$$

or equivalently

$$(D(y, \mu)) \quad \min_{z \in \mathbb{R}^m} \quad \frac{\mu}{2} \|z\|^2 - \langle z, y \rangle + t \quad \text{subject to} \quad (\Phi^* z, t) \in \text{epi } g^*. \quad (7)$$

The key observation: This problem has a unique solution and TFAE:

- x solves problem $P(y, \mu)$;
- $(z, g^*(\Phi^* z))$ solves problem $(D(y, \mu))$ and $(x, -1)$ is the corresponding Lagrange multiplier of the constrained optimization problem (7).

Lipschitz stability of the Lagrange system reminds us about Robinson's strong regularity [Robinson 1980]!

Constrained Optimization Problems and Robinson's Strong Regularity

Consider the parametric optimization problem

$$\text{OPT}(p) : \min_{x \in \mathbb{R}^n} \varphi(x, p) \quad \text{subject to} \quad G(x, p) \in \Theta, \quad (8)$$

where $\Theta \subset \mathbb{R}^m$ is a closed and convex set, $\varphi : \mathbb{R}^n \times \mathbb{R}^d \rightarrow \mathbb{R}$ and $G : \mathbb{R}^n \times \mathbb{R}^d \rightarrow \mathbb{R}^m$ are **twice continuously differentiable** functions.

The *Lagrangian* of problem $\text{OPT}(p)$ is $\mathcal{L} : \mathbb{R}^n \times \mathbb{R}^d \times \mathbb{R}^m \rightarrow \mathbb{R}$ given by

$$\mathcal{L}(x, p, \lambda) := \varphi(x, p) + \langle \lambda, G(x, p) \rangle \quad \text{for} \quad (x, p, \lambda) \in \mathbb{R}^n \times \mathbb{R}^d \times \mathbb{R}^m.$$

A feasible point $x \in \mathbb{R}^n$ is called a **stationary** point of $\text{OPT}(p)$ if there exists a *Lagrange multiplier* $\lambda \in \mathbb{R}^m$ satisfying

$$0 = \nabla_x \mathcal{L}(x, p, \lambda) \quad \text{and} \quad \lambda \in N_{\Theta}(G(x, p)).$$

The Lagrange system can be written as a generalized equation

$$\text{GE}(p) : 0 \in \begin{pmatrix} \nabla_x \varphi(x, p) + \mathcal{J}_x G(x, p)^* \lambda \\ -G(x, p) \end{pmatrix} + \begin{pmatrix} 0 \\ N_{\Theta}^{-1}(\lambda) \end{pmatrix}. \quad (9)$$

Let $H : \mathbb{R}^d \rightrightarrows \mathbb{R}^n \times \mathbb{R}^m$ be its *solution mapping*. [Robinson 1980] showed that this mapping has a **single-valued and Lipschitz continuous localization** around some \bar{p} for some $(\bar{x}, \bar{\lambda}) \in H(\bar{p})$ if its linearized system

$$\delta \in \begin{pmatrix} 0 \\ -G(\bar{x}, \bar{p}) \end{pmatrix} + \begin{pmatrix} \nabla_{xx}^2 \mathcal{L}(\bar{x}, \bar{p}, \bar{\lambda})(x - \bar{x}) + \mathcal{J}_x G(\bar{x}, \bar{p})^* (\lambda - \bar{\lambda}) \\ -\mathcal{J}_x G(\bar{x}, \bar{p})(x - \bar{x}) \end{pmatrix} + \begin{pmatrix} 0 \\ N_{\Theta}^{-1}(\lambda) \end{pmatrix} \quad (10)$$

does around $(0, 0) \in \mathbb{R}^n \times \mathbb{R}^m$ for $(\bar{x}, \bar{\lambda})$. Lipschitz stability of this linearized system is known as **Robinson's strong regularity** at (\bar{x}, \bar{p}) for the corresponding Lagrange multiplier $\bar{\lambda}$.

Characterizations of Robinson's strong regularity

- For nonlinear programming (NP)

$$\min \varphi(x, p) \quad \text{subject to} \quad G(x, p) \in -\mathbb{R}_+^m$$

[Robinson 1980] showed that strong regularity occurs at (\bar{x}, \bar{p}) for $\bar{\lambda}$ if

- The **linear independence constraint qualification** holds at (\bar{x}, \bar{p}) , i.e., $\{\nabla_x G_i(\bar{x}, \bar{p})\}_{i \in I}$ are linearly independent with $I := \{i \mid G_i(\bar{x}, \bar{p}) = 0\}$.
- The **strong second-order sufficient condition** (SSOSC) holds

$$\langle \nabla_{xx}^2 \mathcal{L}(\bar{x}, \bar{p}, \bar{\lambda}) w, w \rangle > 0 \quad \text{whenever} \quad \langle \nabla_x G_i(\bar{x}, \bar{p}), w \rangle = 0 \quad \text{with} \quad \bar{\lambda}_i > 0. \quad (11)$$

- [Bonnans-Ramirez 2005] extended it to second-order cone programming (SOCP).
- [Sun 2006] generalized the result to semidefinite programming when $\Theta = -\mathbb{S}_+^n$.

\mathcal{C}^2 -reducible cone programming

Back to our dual problem:

$$(D(y, \mu)) \quad \min_{z \in \mathbb{R}^m} \quad \frac{\mu}{2} \|z\|^2 - \langle z, y \rangle + t \quad \text{subject to} \quad (\Phi^* z, t) \in \Theta := \text{epi } g^*.$$

This is a constrained problem, but it is neither NP, SOCP, nor SDP!

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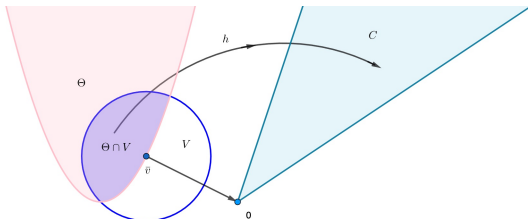
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[Mordukhovich-N.-Rockafellar 2017] obtained full characterization of Robinson's strong regularity for \mathcal{C}^2 -cone reducible programming [Bonnans-Shapiro 2000].

Definition 1 (\mathcal{C}^2 -cone reducible sets)

A closed convex set $\Theta \subset \mathbb{R}^m$ is said to be \mathcal{C}^2 -cone reducible at $\bar{v} \in \Theta$ if there exist a neighborhood V of \bar{v} , a **pointed, closed, convex cone** C in \mathbb{R}^q , and a \mathcal{C}^2 -smooth mapping $h: V \rightarrow \mathbb{R}^q$ such that $h(\bar{v}) = 0$, $\mathcal{J}h(\bar{v})$ is **surjective**, and that $\Theta \cap V = \{v \in V \mid h(v) \in C\}$.

We say Θ is \mathcal{C}^2 -cone reducible if it is \mathcal{C}^2 -cone reducible at any $\bar{v} \in \Theta$.



- Polyhedral sets, the positive semi-definite cone, the second-order cone are \mathcal{C}^2 -cone reducible.

[Mordukhovich-N.-Rockafellar 2017] showed that Robinson's strong regularity occurs around (\bar{x}, \bar{p}) for $\bar{\lambda}$ if and only if

- The following **constraint nondegeneracy condition** holds

$$\text{Ker } \mathcal{J}_x G(\bar{x}, \bar{p})^* \cap \text{span} N_{\Theta}(G(\bar{x}, \bar{p})) = \{0\}. \quad (12)$$

- A **Generalized Strong Second-order Sufficient Condition** (GSSOSC) holds.

Back to the dual problem again:

$$(D(y, \mu)) \quad \min_{z \in \mathbb{R}^m} \quad \frac{\mu}{2} \|z\|^2 - \langle z, y \rangle + t \quad \text{subject to} \quad (\Phi^* z, t) \in \Theta := \text{epi } g^*.$$

To apply [Mordukhovich-N.-Rockafellar 2017], we need $\Theta := \text{epi } g^*$ to be \mathcal{C}^2 -cone reducible.

- All convex piecewise linear functions g have \mathcal{C}^2 -cone reducible $\text{epi } g^*$, e.g., ℓ_1 norm, ℓ_∞ norm, 1-D total variation (semi)norm $\|Dx\|_1$, 2-D anisotropic total variation (semi)norm, ...
- The ℓ_1/ℓ_2 norm.
- Support function $g(x) = \sigma_C(x) = \sup\{\langle v, x \rangle \mid v \in C\}$ with closed convex set $C \subset \mathbb{R}^n$, when C is \mathcal{C}^2 -cone reducible.
- The nuclear norm and many spectral functions.

When applying [Mordukhovich-N.-Rockafellar 2017] to the dual problems

$$(D(y, \mu)) \quad \min_{z \in \mathbb{R}^m} \quad \frac{\mu}{2} \|z\|^2 - \langle z, y \rangle + t \quad \text{subject to} \quad (\Phi^* z, t) \in \Theta := \text{epi } g^*,$$

we showed that

- The GSSOSC is free!

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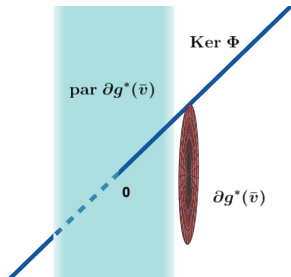
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we showed that

- The GSSOSC is free!
- The constraint nondegeneracy condition turns to

$$\text{Ker } \Phi \cap \text{par } \partial g^*(\bar{v}) = \{0\} \quad \text{with} \quad \bar{v} := \frac{1}{\bar{\mu}} \Phi^*(\Phi \bar{x} - \bar{y}), \quad (13)$$

where $\text{par } \partial g^*(\bar{v})$ is the **parallel space** of $\partial g^*(\bar{v})$.



Theorem 2 (Sufficient condition for Lipschitz stability)

Let \bar{x} be a solution of $P(\bar{y}, \bar{\mu})$ with $(\bar{y}, \bar{\mu}) \in \mathbb{R}^m \times \mathbb{R}_{++}$ and suppose that $\text{epi } g^*$ is \mathcal{C}^2 -cone reducible. If

$$\text{Ker } \Phi \cap \text{par } \partial g^*(\bar{v}) = \{0\},$$

then $S(y, \mu)$ is *single-valued and Lipschitz continuous* around $(\bar{y}, \bar{\mu})$.

- Although our approach is based on second-order analysis, this is a **first-order** condition for Lipschitz stability. It is very simple to check.
- It does NOT need the nondegeneracy condition $\bar{v} \in \text{ri } \partial g(\bar{x})$.

Is it a necessary condition?

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Let \bar{x} be a solution of $P(\bar{y}, \bar{\mu})$ with $(\bar{y}, \bar{\mu}) \in \mathbb{R}^m \times \mathbb{R}_{++}$ and suppose that $\text{epi } g^*$ is C^2 -cone reducible. If

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Theorem 3 (Necessary condition for single-valuedness)

Let \bar{x} be a solution of $P(\bar{y}, \bar{\mu})$ with $(\bar{y}, \bar{\mu}) \in \mathbb{R}^m \times \mathbb{R}_{++}$. If $S(y, \mu)$ is *single-valued* around $(\bar{y}, \bar{\mu})$, then

$$\text{Ker } \Phi \cap \text{par } \partial g^*(\bar{v}) = \{0\}.$$

Corollary 4 (Full characterization of Lipschitz stability)

Let \bar{x} be a solution of $P(\bar{y}, \bar{\mu})$ with $(\bar{y}, \bar{\mu}) \in \mathbb{R}^m \times \mathbb{R}_{++}$ and suppose that $\text{epi } g^*$ is \mathcal{C}^2 -cone reducible. TFAE:

- (i) $S(y, \mu)$ is *single-valued* around $(\bar{y}, \bar{\mu})$.
- (ii) $\text{Ker } \Phi \cap \text{par } \partial g^*(\bar{v}) = \{0\}$.
- (iii) $S(y, \mu)$ is *single-valued* and *Lipschitz continuous* around $(\bar{y}, \bar{\mu})$.

Proof. [(i) \Rightarrow (ii) \Rightarrow (iii) \Rightarrow (i)]. □

- Recover quickly the results in [Berk-Brugiapaglia-Hoheisel 2023] for ℓ_1 norm and ℓ_1/ℓ_2 and nuclear norms in [N. 2024].

No \mathcal{C}^2 -cone reducibility?

Example 5 (No Lipschitz-stability without \mathcal{C}^2 -cone reducibility)

Consider the following problem

$$(P(y)) \quad \min_{x \in \mathbb{R}^2} \quad \frac{1}{2} [(x_1 - x_2 - y_1)^2 + (x_1 - x_2 - y_2)^2] + \frac{1}{4} (x_1^4 + x_2^4).$$

With $\bar{y} = (0, 0)$, $\bar{x} = (0, 0)$ is an optimal solution. Moreover, $(y_1^{\frac{1}{3}}, y_1^{\frac{1}{3}}) \in S(y_1, y_1)$ is **NOT** Lipschitz continuous around $(0, 0)$. With $g(x) = \frac{1}{4}(x_1^4 + x_2^4)$, we have

$$g^*(v) = \frac{3}{4} \left(v_1^{\frac{4}{3}} + v_2^{\frac{4}{3}} \right) \quad \text{and} \quad \partial g^*(\bar{v}) = \{(0, 0)\} \quad \text{with} \quad \bar{v} = (0, 0).$$

Obviously, $\text{Ker } \Phi \cap \text{par } \partial g^*(\bar{v}) = \{0\}$ and $\text{epi } g^*$ is **not** \mathcal{C}^2 -cone reducible.

Some important functions may be not \mathcal{C}^2 -cone reducible:

- Convex piecewise linear-quadratic functions.
- Composite functions such as the 2-D anisotropic total variation (semi)norm $\|D^* x\|_{1,2}$ and the lifted nuclear norm $\|D^* X\|_*$ for some linear operators D^* .

With Nondegeneracy Condition

Corollary 6 (Lipschitz stability under Nondegeneracy Condition)

Let \bar{x} be a solution of $P(\bar{y}, \bar{\mu})$ with $(\bar{y}, \bar{\mu}) \in \mathbb{R}^m \times \mathbb{R}_{++}$ and suppose that $\text{epi } g^*$ is \mathcal{C}^2 -cone reducible. Suppose further that the *dual* nondegeneracy condition

$$\bar{x} \in \text{ri } \partial g^*(\bar{v}). \quad (14)$$

TFAE:

- (i) \bar{x} is the *unique solution* of $P(\bar{y}, \bar{\mu})$
- (ii) $S(y, \mu)$ is *single-valued* around $(\bar{y}, \bar{\mu})$.
- (iii) $S(y, \mu)$ is *single-valued* and *Lipschitz continuous* around $(\bar{y}, \bar{\mu})$.

- The dual ND condition (14) and the (primal) ND condition $\bar{v} \in \text{ri } \partial g(\bar{x})$ are equivalent in many frameworks.
- Under the primal ND condition, [Lewis and Zhang 13] established the equivalence between strong solutions and tilt-stable solutions.

Full stability

In this section, we study the following optimization problem

$$P(\bar{p}) \quad \min_{x \in \mathbb{R}^n} \quad f(x, \bar{p}) + g(x), \quad (15)$$

where $f : \mathbb{R}^n \times \mathbb{R}^d \rightarrow \mathbb{R}$ and $g : \mathbb{R}^n \rightarrow \mathbb{R} \cup \{+\infty\}$ are closed, proper, convex functions. Moreover, f is \mathcal{C}^2 differentiable.

Definition 7 (Full stability and tilt stability)

The point \bar{x} is called a **fully stable** optimal solution of problem (15) if there exists $\gamma > 0$ such that the solution map

$$M_\gamma(v, p) := \operatorname{argmin} \{f(x, p) + g(x) - \langle v, x \rangle \mid x \in \mathbb{B}_\gamma(\bar{x})\} \quad \text{for } (v, p) \in \mathbb{R}^n \times \mathbb{R}^d \quad (16)$$

is **Lipschitz continuous** around $(0, \bar{p}) \in \mathbb{R}^n \times \mathbb{R}^d$ with $M_\gamma(0, \bar{p}) = \bar{x}$.

The point \bar{x} is called a **tilt stable** optimal solution of problem (15) if the mapping $M_\gamma(\cdot, \bar{p})$ is Lipschitz continuous around $0 \in \mathbb{R}^n$ with $M_\gamma(0, \bar{p}) = \bar{x}$.

\bar{x} is a **fully stable optimal solution** of problem (15) **iff** it is fully stable for

$$\min_{x \in \mathbb{R}^n} \frac{1}{2} \langle \nabla_{xx}^2 f(\bar{x}, \bar{p})(x - \bar{x}), x - \bar{x} \rangle + \langle \nabla_x f(\bar{x}, \bar{p}), x - \bar{x} \rangle + f(\bar{x}, \bar{p}) + g(x).$$

Theorem 8 (Characterization of full stability)

Suppose that \bar{x} is an optimal solution of problem (15) and that the function g^* is C^2 -cone reducible at $\bar{v} = -\nabla_x f(\bar{x}, \bar{p}) \in \partial g(\bar{x})$. Then the following are equivalent:

- (i) \bar{x} is a fully stable optimal solution of problem (15).
- (ii) \bar{x} is a tilt stable optimal solution of problem (15).
- (iii) $\text{Ker } \nabla_{xx}^2 f(\bar{x}, \bar{p}) \cap \text{par } \partial g^*(\bar{v}) = \{0\}$.
- (i) $\text{Ker } \nabla_{xx}^2 f(\bar{x}, \bar{p}) \cap \text{Ker } \partial^2 g(\bar{x}, \bar{v}) = \{0\}$.

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Do we have

$$\text{Ker } \partial^2 g(\bar{x}, \bar{v}) = \text{par } \partial g^*(\bar{v})?$$

So far, we have

$$\text{span} [\text{Ker } \partial^2 g(\bar{x}, \bar{v})] = \text{par } \partial g^*(\bar{v}).$$

This formula is very useful in second-order variational analysis especially for the **chain rule** of composite function $g \circ G$ when G is a \mathcal{C}^2 differentiable functions:

- $\delta_{\Theta} \circ G$ for constrained optimization problems, where δ_{Θ} is the indicator function.
- convex regularizers: isotopic total variation (semi) norm $\|D^* x\|_{1,2}$ and lifted nuclear norm $\|D^* X\|_*$.

In this work, we obtain

- A first-order simple characterization for Lipschitz stability of least-square problems.
- A first-order simple characterization for full/tilt stability of convex problems.

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We are working on some directions:

- Sensitivity analysis for our optimal solution mapping when it is single-valued and Lipschitz continuous.
- Extending these results to composite/constrained problems and variational systems.
- Using $\text{span}[\text{Ker } \partial^2 g(\bar{x}, \bar{v})] = \text{par } \partial g^*(\bar{v})$ to derive chain rule of second-order structures.

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