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Progressive Decoupling of Linkages in Optimization with Elicitable Convexity

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An Optimization Model for Promoting Decomposition

Problem

minimize $\sum_{j=1}^{q} f_j(x_j) + g\Big(\sum_{j=1}^{q} F_j(x_j)\Big)$ over $(x_1, \ldots, x_q) \in S$

Ingredients: for this presentation

- mappings $F_j : \boldsymbol{R}^{n_j} \to \boldsymbol{R}^m$, just $\mathcal{C}^1$ or $\mathcal{C}^2$ for $j = 1, \ldots, q$,
- functions $f_j : \boldsymbol{R}^{n_j} \to (-\infty, \infty]$, just lsc for $j = 1, \ldots, q$,
- function $g : \boldsymbol{R}^m \to (-\infty, \infty]$, lsc, convex, pos. homogeneous
- subspace $S \subset \boldsymbol{R}^n = \boldsymbol{R}^{n_1} \times \cdots \times \boldsymbol{R}^{n_q}$ with complement $S^\perp$

Challenge

solve this by a scheme which breaks computations down into subproblems in separate indices j that bypass the S constraint

Territory Covered by this Formulation

$$\text{minimize } \sum_{j=1}^{q} f_j(x_j) + g\Big(\sum_{j=1}^{q} F_j(x_j) \Big) \text{ over } (x_1, \ldots, x_q) \in S$$

Specializations of the coupling term:

- $g(u) = \delta_K(u)$ for a closed convex cone K for a constraint
- $g(u) = ||u|| =$ some norm for regularization term

pos. homogeneity of g can be dropped with some adjustments

Specializations of the coupling space:

- S gives application-dependent linear relations among the x_j's
- $S = \{(x_1, \ldots, x_q) \,|\, x_1 = \cdots = x_q\}$, for the splitting version
- S taken to be all of R^n (thereby "dropping out"), $S^\perp = \{0\}$

Specializatins to convex optimization:

- f_j convex and $F_j = A_j$ affine
- f_j and F_j convex and g nondecreasing among others

Reformulation to Liberate Underlying Separability

Expansion Lemma

$$g\big(\textstyle\sum_{j=1}^{q} F_j(x_j)\big) \leq \alpha \quad \Longleftrightarrow \quad \exists\, u_j \in \boldsymbol{R}^m \text{ for } j = 1, \ldots, q$$

$$\text{such that } \textstyle\sum_{j=1}^{q} u_j = 0 \text{ and } \textstyle\sum_{j=1}^{q} g\big(F_j(x_j) + u_j\big) \leq \alpha$$

Extended coupling space: now in $\boldsymbol{R}^n \times [\boldsymbol{R}^m]^q$

$$\overline{S} = \big\{(x_1, \ldots, x_q, u_1, \ldots, u_q) \,\big|\, (x_1, \ldots, x_q) \in S,\ \textstyle\sum_{j=1}^{q} u_j = 0\big\},$$

$$\overline{S}^{\perp} = \big\{(v_1, \ldots, v_q, y_1, \ldots, y_q) \,\big|\, (v_1, \ldots, v_q) \in S^{\perp},\ y_1 = \cdots = y_q\big\}$$

Expanded problem (equivalent)

$$\min \textstyle\sum_{j=1}^{q} \big[\, f_j(x_j) + g(F_j(x_j) + u_j) \,\big] \text{ over } (x_1, \ldots, x_q, u_1, \ldots, u_q) \in \overline{S}$$

$\longrightarrow$ **separability achieved in the objective:**

$$\varphi(x_1, \ldots, x_q, u_1, \ldots, u_q) = \varphi_1(x_1, u_1) + \cdots + \varphi_q(x_q, u_q)$$

Linkage Problems in Terms of Subgradients

Goal: minimize some lsc function f over some subspace S
to be applied later to minimizing φ on $\overline{S}$ as above

First-order condition for local optimality

$$\bar{w} \in S \;\text{ and }\; \exists\, \bar{z} \in \partial f(\bar{w}) \;\text{ such that }\; \bar{z} \in S^{\perp}$$

Regular subgradients: notation $\bar{z} \in \widehat{\partial} f(\bar{w})$

$$f(w) \geq f(\bar{w}) + \bar{z}\cdot(w - \bar{w}) + o(||w - \bar{w}||)$$

General subgradients: notation $\bar{z} \in \partial f(\bar{w})$

$$\exists\, z^{\nu} \to \bar{z} \text{ with } z^{\nu} \in \widehat{\partial} f(w^{\nu}),\; w^{\nu} \to \bar{w},\; f(w^{\nu}) \to f(\bar{w})$$

Convex case: general = regular = convex subgradients
Smooth case: general = regular = classical gradients

Linkage problem — for given f and S

$$\text{find a pair } (\bar{w}, \bar{z}) \in [\operatorname{gph} \partial f] \cap [S \times S^{\perp}]$$

Second-order Sufficiency via Virtual Convexity

Key observation: in terms of $e =$ "elicitation" parameter ≥ 0,
$d_S(w) =$ distance of w from the subspace S

minimizing f on S $\longleftrightarrow$ minimizing $f_e = f + \frac{e}{2} d_S^2$ on S

First-order optimality is thereby unaffected:

$\bar{z} \in \partial f(\bar{w}) \iff \bar{z} \in \partial f_e(\bar{w})$ when $\bar{w} \in S$ and $\bar{z} \in S^\perp$

Variational second-order sufficient condition: in addition,
for e high enough, f_e is variationally convex at $(\bar{w}, \bar{z})$, meaning

$\exists\, \varepsilon > 0$, open convex nbhd $W \times Z$ of $(\bar{w}, \bar{z})$, and lsc convex $h \leq f_e$ on W such that $\operatorname{gph} \partial h$ coincides in $W \times Z$ with

$$\operatorname{gph} T_{e,\varepsilon} = \left\{ (w, z) \in \operatorname{gph} \partial f_e \,\middle|\, f_e(w) \leq f_e(\bar{w}) + \varepsilon \right\}$$

and, on that common set, furthermore $h(w) = f_e(w)$

Strong version: the function $h \leq f_e$ is strongly convex

Sufficiency in the Convex and Smooth Cases

Convex example

for convex f, the variational condition is superfluous

the first-order condition already guarantees global optimality

Smooth example: $f \in \mathcal{C}^2$ with gradient $\nabla f(\bar{w})$, hessian $\nabla^2 f(\bar{w})$

- the first-order condition reduces to:

  $\bar{w} \in S$, and the gradient $\bar{z} = \nabla f(\bar{w})$ is $\perp S$

- the second-order condition in strong form reduces to:

  $\nabla^2 f(\bar{w})$ is positive definite relative to S

$\longrightarrow$ these are the standard sufficient conditions for a local min

Progressive Decoupling of Linkages (Rock. 2018)

for determining $(\bar{w}, \bar{z}) \in [\mathrm{gph}\,\partial f] \cap [S \times S^{\perp}]$

Algorithm with parameters $r > e \geq 0$, generating $\{(w^k, z^k)\}_{k=1}^{\infty}$

In iteration k, having $w^k \in S$ and $z^k \in S^{\perp}$, get

$$\widehat{w}^k = (\mathrm{local?})\,\mathrm{argmin}_w \left\{ f(w) - z^k \cdot w + \tfrac{r}{2}||w - w^k||^2 \right\}$$

Update by $\quad w^{k+1} = \mathrm{proj}_S\, \widehat{w}^k, \qquad z^{k+1} = z^k - (r - e)[\widehat{w}^k - w^{k+1}]$

Convergence Theorem

Convex case: converges globally from any initial (w^0, z^0)

General case: if $(\bar{w}, \bar{z})$ satisfies the sufficient condition at elicitation level e, then $\exists$ nbhd $W \times Z$ of $(\bar{w}, \bar{z})$ such that, if $(w^0, z^0) \in W \times Z$, the generated sequence stays in $W \times Z$ with $\widehat{w}^k$ = unique local minimizer on W, and it converges to to some solution $(\widetilde{w}, \widetilde{z})$ such that $\widetilde{w} \in$ argmin of f on $W \cap S$

Underpinnings of the Progressive Decoupling Algorithm

- exploits properties of max monotonicity of set-valued mappings
- derives from the proximal point algorithm of Rock. (1976)
- extends the partial inverse method of Spingarn (1983)
- extends the proximal point localization of Pennanen (2002)

Criterion for local max monotonicity — Rock. (2018)

The variational sufficiency condition $\Longrightarrow$ the mapping

$T_{e,\varepsilon}$ having its graph $= \{(w,z) \in \operatorname{gph} \partial f_e \,|\, f_e(w) \le f_e(\bar{w}) + \varepsilon\}$

is locally **max monotone** around $(\bar{w}, \bar{z})$, and moreover is **equivalent** to that when $\bar{z}$ is a **regular** subgradient of f at $\bar{w}$

$\Longrightarrow$ **the proximal point algorithm can operate locally**

as long as the initial (w^0, z^0) is near enough to $(\bar{w}, \bar{z})$

Application to the Expanded Programming Model

minimize $\varphi(x_1,\ldots,x_q,u_1,\ldots,u_q) = \sum_{j=1}^q \varphi_j(x_j,u_j)$ over $\overline{S}$

$$\text{where } \varphi_j(x_j,u_j) \;=\; f_j(x_j) + g\big(F_j(x_j)+u_j\big)$$

$$\overline{S} = \big\{(x_1,\ldots,x_q,u_1,\ldots,u_q)\,\big|\,(x_1,\ldots,x_q)\in S,\;\; \textstyle\sum_{j=1}^q u_j = 0\big\},$$

$$\overline{S}^\perp = \big\{(v_1,\ldots,v_q,y_1,\ldots,y_q)\,\big|\,(v_1,\ldots,v_q)\in S^\perp,\; y_1=\cdots=y_q\big\}$$

Algorithm elements in this specialization:

$w^k = (x_1^k,\ldots,x_q^k,u_1^k,\ldots,u_q^k)$ for $(x_1^k,\ldots,x_q^k)\in S$, $\sum_{j=1}^q u_j^k = 0$,

$z^k = (v_1^k,\ldots,v_q^k,y^k,\ldots,y^k)$ for $(v_1^k,\ldots,v_q^k)\in S^\perp$

Decomposition property from liberated separability

The step in which the algorithm determines $\widehat{w}^k$ breakes down for $j=1.\ldots,q$ to calculating: $(\widehat{x}_j^k,\widehat{u}_j^k) =$ (local?)argmin of

$$\varphi_j^k(x_j,u_j) = \varphi_j(x_j,u_j) - (v_j^k,y^k)\cdot(x_j,u_j) + \tfrac{r}{2}||(x_j,u_j)-(x_j^k,u_j^k)||^2$$

Resulting Procedure — Full Form

Algorithm (with parameters $r > e \geq 0$)

In iteration k, having $(x_1^k, \dots, x_q^k) \in S$ and $(v_1^k, \dots, v_q^k) \in S^\perp$ along with y^k and $(u_1^k, \dots, u_q^k)$ such that $\sum_{j=1}^q u_j^k = 0$,

determine $(\widehat{x}_j^k, \widehat{u}_j^k)$ for $j = 1, \dots, q$ as the (local?) minimizer of
$f_j(x_j) + g(F_j(x_j) + u_j) - v_j^k \cdot x_j - y^k \cdot u_j + \frac{r}{2}||x_j - x_j^k||^2 + \frac{r}{2}||u_j - u_j^k||^2$

Then let $\widehat{u}^k = \frac{1}{q} \sum_{j=1}^q \widehat{u}_j^k$ and update by

$$(x_1^{k+1}, \dots, x_q^{k+1}) = \mathrm{proj}_S(\widehat{x}_j^k, \dots, \widehat{x}_j^k), \qquad u_j^{k+1} = u_j^k - \widehat{u}^k$$
$$v_j^{k+1} = v_j^k - (r-e)[\widehat{x}_j^k - x_j^{k+1}], \qquad y^{k+1} = y^k - (r-e)\widehat{u}^k$$

Convergence: global in the convex case, and moreover local in the nonconvex case as long as the algorithm starts near enough to a solution where the second-order variational sufficiency condition is satisfied at level e of the elicitation parameter

Bringing in Augmented Lagrangians

Consider auxiliary subproblems:

minimize $f_j(x_j) + g(F_j^k(x_j))$ in x_j where $F_j^k(x_j) = F_j(x_j) + u_j^k$

Dualization: g is lsc convex pos.homog., so its conjugate is
$g^* = \delta_Y$ (indicator) for some closed convex set $Y \subset R^m$

Examples: $g = \delta_K$ for cone K yields Y = polar cone K^*
$g = ||\cdot||_p$ yields Y = unit ball for dual norm $||\cdot||_q$

Lagrangians: $L_j^k(x_j, y) = f_j(x_j) + y{\cdot}F_j^k(x_j) - \delta_Y(y)$

Augmented Lagrangians (with parameter $r > 0$):

$$L_{j,r}^k(x_j, y) = f_j(x_j) + y{\cdot}F_j^k(x_j) + \frac{r}{2}||F_j^k(x_j)||^2 - \frac{1}{2r}d_Y^2\left(y + rF_j^k(x_j)\right)$$
$$= f_j(x_j) + \min_{u_j}\left\{g(F_j(x_j) + u_j) - y{\cdot}u_j + \frac{r}{2}||u_j - u_j^k||^2\right\}$$

Observation: this min arises in the algorithm for $y = y^k$
$\longrightarrow$ and then $\widehat{u}_j^k$, the argmin, equals $-\nabla_y L_{j,r}^k(x_j, y^k)$

Resulting Procedure with Augmented Lagrangians

Decomposition algorithm in condensed form

From $(x_1^k, \ldots, x_q^k) \in S$, $(v_1^k, \ldots, v_q^k) \in S^\perp$, $\sum_{j=1}^q u_j^k = 0$, y^k, get

$$\widehat{x}_j^k = \text{(local)}\,\mathrm{argmin}_{x_j}\left\{ L_{j,r}^k(x_j, y^k) - v_j^k \cdot x_j + \frac{r}{2}||x_j - x_j^k||^2 \right\}$$

and update by $\quad (x_1^{k+1}, \ldots, x_q^{k+1}) = \mathrm{proj}_S(\widehat{x}_1^k, \ldots, \widehat{x}_q^k),$

$$v_j^{k+1} = v_j^k - (r-e)[\widehat{x}_j^k - x_j^{k+1}], \qquad \widehat{u}_j^k = -\nabla_y L_{j,r}^k(x_j^{k+1}, y^k),$$

$$\widehat{u}^k = \frac{1}{q}\sum_{j=1}^q \widehat{u}_j^k, \qquad u_j^{k+1} = u_j^k - \widehat{u}^k, \qquad y^{k+1} = y^k - (r-e)\widehat{u}^k$$

Note: a convenient formula for the gradient is often available

Connection with the new second-order local optimality criterion

The variational sufficiency condition holds for a solution with elements $\bar{x}_j$, $\bar{v}_j$, $\bar{u}_j$, $\bar{y}$, with respect to an elicitation level e if and only if there are neighborhoods $X_j \times Y_j$ of $(\bar{x}_j, \bar{y})$ such that the iterations have $L_{j,r}^k(x_j, y)$ convex-concave on $X_j \times Y_j$

References

[1] R.T. Rockafellar (2018) "Progressive decoupling of linkages in optimization and variational inequalities with elicitable convexity or monotonicity," accepted for publication.

[2] R.T. Rockafellar (2018) "Variational convexity and local monotonicity of subgradient mappings," accepted for publication.

[3] R.T. Rockafellar (2018) "Variational second-order sufficiency, generalized augmented Lagrangians and local duality in optimization," soon to be available.

downloads: **sites.math.washington.edu/~rtr/mypage.html**