

Lagrangian Relaxation

NanoCad Tutorial 4/17/2012

Lagrangian Relaxation

- Suppose that

$$\text{minimize } f(x), \text{ subject to } f_i(x) \leq 0$$

Is difficult to solve

- However, suppose that

$$\text{minimize } f(x) + f_i(x)$$

Is easy

- Then consider Lagrangian Relaxation

Lagrangian Relaxation

- Idea: Optimize the Lagrangian of

$$\text{minimize } f(x), \text{ subject to } f_i(x) \leq 0$$

Which is:

$$L(x, \lambda) = f(x) + \sum_i \lambda_i f_i(x)$$

- Finally, instead of solving:

$$\text{minimize } f(x), \text{ subject to } f_i(x) \leq 0$$

Solve

$$\max_{\lambda} \min_x (L(x, \lambda))$$

Lagrangian Relaxation Details

- Details

$$\max_{\lambda} \min_x (L(x, \lambda))$$

Has two optimizations (min x, max lambda)

- This is only good if min x is very efficient

- When are

$$\max_{\lambda} \min_x (L(x, \lambda))$$

minimize $f(x)$, subject to $f_i(x) \leq 0$

Equivalent?

- Sufficient – convex and strictly feasible; Necessary: ?

Everett's Theorem

Everett's Theorem Let us start with a very elementary observation. Suppose we have maximized $L(\cdot, u)$ for a certain u , and thus obtained an optimal x_u , together with its constraint-value $c(x_u) \in \mathbb{R}^m$; set $g_u := -c(x_u)$ and take an arbitrary $x \in \mathcal{X}$ such that $c(x) = -g_u$. By definition, $L(x, u) \leq L(x_u, u)$, which can be written

$$f(x) \leq f(x_u) - u^\top c(x_u) + u^\top c(x) = f(x_u). \quad (23)$$

This is a useful result for approximate resolutions of (1):

Theorem 12 (Everett) *With the notation above, x_u solves the following perturbation of (1):*

$$\max f(x), \quad x \in \mathcal{X}, \quad c(x) = -g_u. \quad \square$$

Examples

- Integer Programming

$$\min \sum_{i,j=1}^n Q_{ij} x_i x_j = x^\top Q x, \quad x_i^2 = 1, \quad i = 1, \dots, n.$$

becomes

$$L(x, u) = x^\top Q x - \sum_{i=1}^n u_i (x_i^2 - 1) = x^\top (Q - D(u)) x + e^\top u;$$

which is just

$$\max e^\top u, \quad \text{subject to } Q - D(u) \succcurlyeq 0.$$

Gate Sizing (Network Optimization Problem)

$$\begin{aligned}
 &\text{minimize} && \sum_g p_g w_g \\
 &\text{Subject to} && t_{a(g)} + d_i(g, w) \leq t_{a(g')} \text{ for } g' \in \text{fanout}(g) \\
 &&& t_j \leq T_{\max}
 \end{aligned}$$

$$\begin{aligned}
 L(w, t_a, \lambda) = & \sum_{g \in \mathcal{G}} p_g w_g \\
 & + \sum_g \sum_{g' \in \text{fo}(g)} \lambda_{g,g'} (t_{a(g)} + d(g, w) - t_{a(g')}) \\
 & + \sum_{g \in \text{PO}} \lambda_g (t_{a(g)} - T_{\max}).
 \end{aligned}$$

Gate Sizing

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 L(w, t_a, \lambda) &= \sum_{g \in \mathcal{G}} p_g w_g \\
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 &+ \sum_{g \in \text{PO}} \lambda_g (t_{a(g)} - T_{\max}).
 \end{aligned}$$

$$\begin{aligned}
 L(w, t_a, \lambda) &= \sum_{g \in \mathcal{G}} \left(\sum_{g'' \in \text{fo}(g)} \lambda_{g,g''} - \sum_{g' \in \text{fi}(g)} \lambda_{g',g} \right) \cdot t_{a(g)} \\
 &+ \sum_{g \in \mathcal{G}} p_g w_g + \left(\sum_{g \in \text{PO}} \lambda_g \right) \cdot T_{\max} \\
 &+ \sum_g \left(\sum_{g' \in \text{fo}(g)} \lambda_{g,g'} \right) d(g, w)
 \end{aligned}$$

Gate Sizing

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 & + \sum_g \left(\sum_{g' \in \text{fo}(g)} \lambda_{g, g'} \right) d(g, w) \\
 & + \left(\sum_{g \in \text{PO}} \lambda_g \right) \cdot T_{\max}.
 \end{aligned}$$

$$\max_{\lambda \geq 0} \left\{ \min_{t_a, w_{\min} \leq w \leq w_{\max}} \{L(w, t_a, \lambda)\} \right\}.$$

Gate Sizing

- Minimizing over w

$$\begin{aligned} L(w, t_a, \lambda) = & \sum_{g \in \mathcal{G}} p_g w_g \\ & + \sum_g \left(\sum_{g' \in \text{fo}(g)} \lambda_{g,g'} \right) d(g, w) \\ & + \left(\sum_{g \in \text{PO}} \lambda_g \right) \cdot T_{\max}. \end{aligned}$$

Is very fast. Method iterates between minimizing over w and maximizing over λ

Summary

- Difficult problems may benefit from Lagrangian Relaxation
 - Problems where minimizing with constraint in objective is easy
- Useful in network flow problems, combinatorial problems
- Can also be used to generate theoretical bounds