## Dimension-reduced Interior Point Method

Discussion 6

September 8, 2022

## Accelerate computation of negative curvature

$$\nabla_{\mathbf{x}\mathbf{x}}^2 \varphi(\mathbf{x}) = -\frac{\rho \nabla f(\mathbf{x}) \nabla f(\mathbf{x})}{f(\mathbf{x})^2} + \frac{\rho \mathbf{A}^{\top} \mathbf{A}}{f(\mathbf{x})} + \mathbf{X}^{-2}.$$

## Observations

- $\nabla f(\mathbf{x}) \nabla f(\mathbf{x})^{\top}$  is dense and specially treated
- Customized Lanczos solver behaves 100x more efficient than direct eigen-decomposition
- Works fine for problems up to  $10^{-3}$  accuracy
- For higher accuracy, Lanczos might be unstable

The spectrum of  $\nabla^2$  is increasingly worse when optimization proceeds

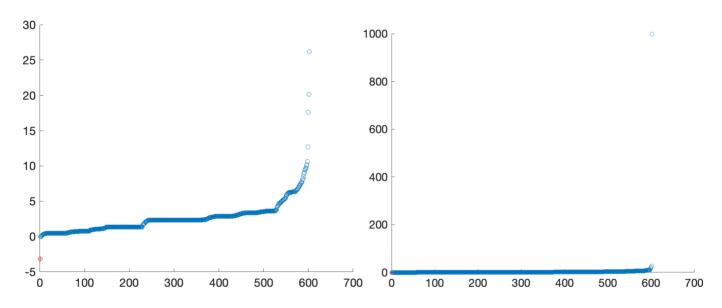


Figure 1. Spectrum at the beginning/at the end, ploted in relative scale

Left: min  $-9.36\times10^5$ , max  $2.24\times10^{11}$ . Right: min  $-3.18\times10^5$ , max  $1.26\times10^{14}$ 

The positive eigen-value of the potential function increases and makes negative hard to find.

$$\nabla^2_{\mathbf{x}\mathbf{x}}\varphi(\mathbf{x}) = -\frac{\rho\nabla f(\mathbf{x})\nabla f(\mathbf{x})}{f(\mathbf{x})^2}^\top + \frac{\rho\mathbf{A}^\top\mathbf{A}}{f(\mathbf{x})} + \mathbf{X}^{-2}.$$

$$\min_{\mathbf{v}} \langle \mathbf{v}, \nabla^2 \mathbf{v} \rangle$$
  
subject to  $\mathbf{e}^\top \mathbf{v} = 0$   
 $\|\mathbf{v}\| = 1$ 

An alternative is to use scaled Hessian

$$\begin{aligned} \min_{\mathbf{v}} & \langle \mathbf{v}, \mathbf{X} \nabla^2 \mathbf{X} \mathbf{v} \rangle \\ \text{subject to} & \mathbf{e}^\top \mathbf{X} \mathbf{v} = 0 \\ & \|\mathbf{v}\| = 1 \end{aligned}$$

and the scaled Hessian is

$$-\frac{\rho \mathbf{X} \nabla f(\mathbf{x}) \nabla f(\mathbf{x})^{\top} \mathbf{X}}{f(\mathbf{x})^2} + \frac{\rho \mathbf{X} \mathbf{A}^{\top} \mathbf{A} \mathbf{X}}{f(\mathbf{x})} + \mathbf{I}.$$

$$\nabla_{\mathbf{x}\mathbf{x}}^{2}\varphi(\mathbf{x}) = -\frac{\rho\nabla f(\mathbf{x})\nabla f(\mathbf{x})}{f(\mathbf{x})^{2}}^{\top} + \frac{\rho\mathbf{A}^{\top}\mathbf{A}}{f(\mathbf{x})} + \mathbf{X}^{-2}$$

- The scaled direction makes spectrum more balanced
- Another way is to do diagonal scaling  $\operatorname{diag}(\nabla^2_{\mathbf{x}\mathbf{x}}\varphi(\mathbf{x}))$
- Both solving LPs to  $10^{-4}$  to  $10^{-5}$  (but accurate eigen computation gives  $10^{-7}$  to  $10^{-8}$ )

## More attempts include

Method	Accuracy
Lanczos	$10^{-4}$
Lanczos + scaling (+ re-orthorgonalization)	$10^{-4} \sim 10^{-5}$
Shifted inverse power method	$10^{-5}$ (solve linear system)
Full eigen-decomposition	$10^{-7} \sim 10^{-8}$

Table 1. Current attempts

The spectrum of  $abla^2$  is increasingly worse when optimization proceeds

$$\nabla_{\mathbf{x}\mathbf{x}}^2 \varphi(\mathbf{x}) = -\frac{\rho \nabla f(\mathbf{x}) \nabla f(\mathbf{x})^{\top}}{f(\mathbf{x})^2} + \frac{\rho \mathbf{A}^{\top} \mathbf{A}}{f(\mathbf{x})} + \mathbf{X}^{-2}.$$

Intuition:  $\arg\min_{i}^{k} \{x_i\}$  is **not likely** to contribute to negative curvature.

- Use  ${\bf X}^{-2}$  to predict the support of curvature  ${\bf v}$
- Truncate  $\alpha$  percent of the Hessian by  ${\bf X}^{-2}$
- Reducing complexity and hardness to evaluate Hessian

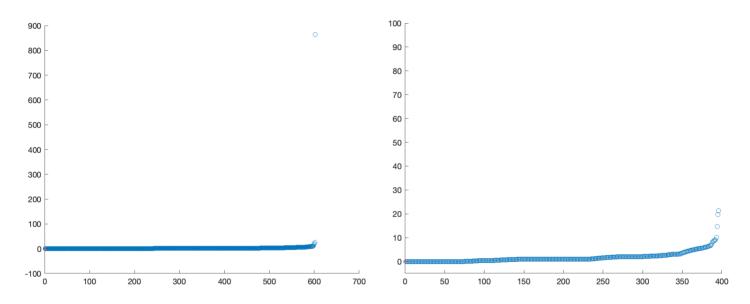


Figure 2. Spectrum of reduced support truncating 50% of dimension

- Retain negative curvature in general
- Need more tuning

$$\nabla^2 = -\frac{\rho \nabla f(\mathbf{x}) \nabla f(\mathbf{x})}{f(\mathbf{x})^2}^\top + \frac{\rho \mathbf{A}^\top \mathbf{A}}{f(\mathbf{x})} + \mathbf{X}^{-2}.$$

$$\min_{\mathbf{v}} \langle \mathbf{v}, \nabla^2 \mathbf{v} \rangle$$
  
subject to  $\mathbf{e}^\top \mathbf{v} = 0$   
 $\|\mathbf{v}\| = 1$ 

- The customization greatly accelerate computation
   100x faster at the beginning
- The spectrum of Hessian is not well-distributed Lanczos stagnates since  $\lambda_1(\nabla^2) \gg \lambda_{n-k}(\nabla^2)$ , for k of interest
- Necessary to look for a method that uses the prior knowledge to accelerate
  We know that there exists exactly one negative eigen-value
  (Now experimenting on FEAST contour method)