## Chapter 1. Optimization Overview

Page 22. About the gradient in Eq. (1.23),

$$\nabla f = \begin{bmatrix} \frac{\partial f}{\partial x_1} \\ \frac{\partial f}{\partial x_n} \\ \vdots \\ \frac{\partial f}{\partial x_n} \end{bmatrix}$$

where the second entry should be  $\partial f/\partial x_2$ .

## Chapter 2. Gradient Based Optimization

Page 48. About the gradient descent formula in Eq. (2.16a),

$$\mathbf{x}_{k+1} = \mathbf{x}_k - \gamma (\mathbf{A}\mathbf{x}_k - \mathbf{b})$$

should be

$$\mathbf{x}_{k+1} = \mathbf{x}_k - \gamma(\mathbf{A}\mathbf{x}_k + \mathbf{b})$$

## **Chapter 2. Gradient Based Optimization**

Page 50. About the gradient descent update in Eq. (2.19),

$$\mathbf{x}_{k+1} = \mathbf{x}_k - \gamma \nabla f(\mathbf{x}_k) + \frac{\beta_k \mathbf{v}_k}{\mathbf{v}_{k+1}}$$
$$\mathbf{v}_{k+1} = \beta \mathbf{v}_k - \gamma \nabla f(\mathbf{x}_k)$$

where the hyper-parameter  $\beta_k$  should be  $\beta$ . In my mind, this equation could be simplified as follows,

$$\mathbf{v}_{k+1} = \beta \mathbf{v}_k - \gamma \nabla f(\mathbf{x}_k)$$
$$\mathbf{x}_{k+1} = \mathbf{x}_k + \mathbf{v}_{k+1}$$

## **Chapter 2. Gradient Based Optimization**

Page 51. Multiplying both sides by  $\Delta t^2$  and grouping terms, this simplifies as

$$m(\mathbf{x}_{k+1} - 2\mathbf{x}_k + \mathbf{x}_{k+1}) = -\Delta t^2 \nabla f(\mathbf{x}_k) - \frac{\mathbf{d}}{\Delta t}(\mathbf{x}_{k+1} - \mathbf{x}_k)$$

should be

$$m(\mathbf{x}_{k+1} - 2\mathbf{x}_k + \mathbf{x}_{k+1}) = -\Delta t^2 \nabla f(\mathbf{x}_k) - \delta \Delta t(\mathbf{x}_{k+1} - \mathbf{x}_k)$$

This typo also appears in the left-hand side:

$$(m + \mathbf{d}\Delta t)\mathbf{x}_{k+1} = \cdots$$

which should be

$$(m + \delta \Delta t)\mathbf{x}_{k+1} = \cdots$$