



# Vectorization

1. Consider

$$\sum_{i=1}^m a_i b_i$$

- $a_i \in \mathbb{R}, b_i \in \mathbb{R}$
2. For Python and other softwares, the computation efficiency of using for-loops for summation is quite low
3. However, matrix calculation is very efficient
4. Thus, we use vectorization for the summation

# Vectorization

## 1. Vectorization result

$$\sum_{i=1}^m \color{red}{a_i} \color{blue}{b_i} = \color{red}{\mathbf{a}}^T \cdot \color{blue}{\mathbf{b}}$$

- $\color{red}{\mathbf{a}} = (\color{red}{a_1}, \dots, \color{red}{a_m})^T \in \mathbb{R}^{m \times 1}$
- $\color{blue}{\mathbf{b}} = (\color{blue}{b_1}, \dots, \color{blue}{b_m})^T \in \mathbb{R}^{m \times 1}$

# Vectorization

1. Example 1: Consider

$$\sum_{i=1}^m \textcolor{red}{a}_i$$

- $\textcolor{red}{a}_i \in \mathbb{R}$

2. Vectorization result

$$\sum_{i=1}^n \textcolor{red}{a}_i = \sum_{i=1}^n \textcolor{red}{a}_i \times \mathbf{1} = \mathbf{a}^T \cdot \mathbf{1} (= \mathbf{1}^T \cdot \mathbf{a})$$

- $\mathbf{a} = (\textcolor{red}{a}_1, \dots, \textcolor{red}{a}_m)^T \in \mathbb{R}^{m \times 1}$
- $\mathbf{1} = (1, \dots, 1)^T \in \mathbb{R}^{m \times 1}$ : a vector of 1's width length  $m$

# Vectorization

1. Example 2: Consider

$$\sum_{i=1}^m \color{red}{a_i} \color{blue}{b_i}$$

- $\color{red}{a_i} \in \mathbb{R}$ : a scalar, which may be 1
- $\color{blue}{b_i} \in \mathbb{R}^{k \times 1}$

2. Vectorization result

$$\sum_{i=1}^n \color{red}{a_i} \color{blue}{b_i} = \color{blue}{B} \cdot \color{red}{a}$$

- $\color{red}{a} = (\color{red}{a_1}, \dots, \color{red}{a_m})^T \in \mathbb{R}^{m \times 1}$
- $\color{blue}{B} = (\color{blue}{b_1}, \dots, \color{blue}{b_m}) \in \mathbb{R}^{k \times m}$

# Vectorization

1. Example 3: Consider

$$\sum_{i=1}^m \color{red}{a_i} \color{blue}{b_i}^\top$$

- $\color{red}{a_i} \in \mathbb{R}$ : a scalar, which may be 1
- $\color{blue}{b_i} \in \mathbb{R}^{k \times 1}$

2. Vectorization result

$$\sum_{i=1}^n \color{red}{a_i} \color{blue}{b_i} = \color{red}{a}^\top \cdot \color{blue}{B}$$

- $\color{red}{a} = (\color{red}{a_1}, \dots, \color{red}{a_m})^\top \in \mathbb{R}^{m \times 1}$
- $\color{blue}{B} = (\color{blue}{b_1}, \dots, \color{blue}{b_m})^\top \in \mathbb{R}^{m \times k}$