

3. What's difficult to apply AD

1. svd

(1) Complex derivative

Natural way:

$$df = \frac{\partial f}{\partial z} dz + \frac{\partial f}{\partial z^*} dz^*$$

When f is a real value function, it's easy to get that df is real as well, that is to say:

$$df = \frac{1}{2}(u'_x - iu'_y)dz + c.c$$

(2) Complex gradient

How define complex gradient for a function? Denote a complex linear function:

$$\nabla_z f(z) = R(z) + iI(z)$$

When $f(z) = u(z)$, we hope that the complex gradient is the direction of the fastest increase of u , which is to say:

$$\nabla u(z) = u'_x + iu'_y$$

Now we consider analytic functions:

$$\begin{aligned}\nabla f(z) &= \nabla u(z) + i\nabla v(z) \\ &= u'_x + iu'_y + i(v'_x + iv'_y) \\ &= u'_x + iu'_y + i(-u'_y + iu'_x) = 0\end{aligned}$$

So we can define $\nabla f(z)$ on $\mathbb{H}(\mathbb{C})$ as

$$\nabla f(z) = k \frac{\partial f}{\partial z^*}$$

And consider $\nabla u(z)$ we get $k = 2$.

Continue this to all complex function, we get:

$$\nabla f(z) = 2 \frac{\partial f}{\partial z^*}$$

Specifically, when $f(z)$ is a real value function, we have:

$$\nabla f(z) = 2 \left(\frac{\partial f}{\partial z} \right)^*$$

(3) Complex derivative of on \mathbb{C}^n

When $f : \mathbb{C}^n \rightarrow \mathbb{C}$, we can define its complex derivative on \mathbb{C}^n as:

$$\frac{\partial f}{\partial Z} = \left(\frac{\partial f}{\partial z_i} \right)_{1 \leq i \leq n}$$

$$\nabla f(Z) = 2 \left(\frac{\partial f}{\partial z_i^*} \right)_{1 \leq i \leq n}$$

Here we have clear that for

$$Z = (z_{ij})_{1 \leq i \leq n, 1 \leq j \leq m}$$

We define $\frac{\partial f}{\partial Z}$ as:

$$\left(\frac{\partial f}{\partial z_{ij}} \right)_{ij}$$

But not

$$\left(\frac{\partial f}{\partial z_{ji}} \right)_{ij}$$

This also means that if Z is a column (row) vector, $\frac{\partial f}{\partial Z}$ is also a row (column) vector.

(4) Introduction to AD for svd

Denote

$$\bar{A} = \frac{\partial Loss}{\partial A}$$

Assume that $L(A)$ is a real gauge loss function. Gauge means for a svd composition

$$A = USV^\dagger$$

$$Loss(A) = Loss(U, S, V)$$

has nothing with the choose of U, V .

And assume that A is a matrix has no zero or same eigenvalue.

Then we have:

$$dLoss = \text{Tr}(\bar{A}^T dA + c.c)$$

$$\implies \nabla f(A) = 2(\bar{A})^* = 2(A_s + A_J + A_K + A_O)^*$$

$$A_s^* = U(\bar{S})^* V^\dagger$$

$$A_J^* = U(J^* + J^T) S V^\dagger$$

$$A_K^* = U S (K^* + K^T) V^\dagger$$

$$A_O^* = \frac{1}{2} U S^{-1} (O - O^\dagger) V^\dagger$$

$$J = F \circ (U^T \bar{U})$$

$$K = F \circ (V^T \bar{V})$$

$$O = I \circ (V^T \bar{V})$$

$$F = \frac{1}{s_j^2 - s_i^2} \chi_{i \neq j}$$

In formulas above, \circ is:

$$(a_{ij})_{n \times n} \circ (b_{ij})_{n \times n} = (a_{ij} b_{ij})_{n \times n}$$

I is identity matrix.

(5) Theoretical validation of method effectiveness.

(a) Gauge freedom

Arbitrary given

$$\text{diag}\{e^{i\theta_1}, \dots, e^{i\theta_m}\}, V = [v_1, \dots, v_m]$$

$$\implies V \text{diag} = [\dots, e^{i\theta_m} v_m]$$

$$\implies \|\text{Bary}(v_m e^{i\theta_m}) - A\|_2^2 = \|\text{Bary}(v_m) - A\|_2^2 = Loss$$

(b) Different eigenvalues

In practice, input green function values take some noise and therefore we can assume that all submatrices of L without zero eigenvalues are non-singular with probability 1.

(c) non-zero eigenvalues

Denote size of L is $N \times N$ and size of L_{sub} is $(N - m) \times m$.

For equation:

$$L_{sub} w = G_{sub}$$

In practice, G_{sub} has noise so if $m \leq N/2$ and not full column rank, this equation has no solution with probability 1.

So if $m \leq N/2$, we can think that L_{sub} is full column and therefore has no zero eigenvalue.