Consider an input space $X = \mathbb{R}^n$. Suppose you have two scalar-valued constraints, h_1 and h_2 , which are satisfied if $h_i = 0$.

$$h_1(\mathbf{x}) \quad J_{h_1}(\mathbf{x}) = \nabla_{h_1}^T(\mathbf{x}) = \begin{bmatrix} \frac{\partial h_1}{\partial x_1} & \frac{\partial h_1}{\partial x_2} & \dots & \frac{\partial h_1}{\partial x_n} \end{bmatrix}$$
$$h_2(\mathbf{x}) \quad J_{h_2}(\mathbf{x}) = \nabla_{h_2}^T(\mathbf{x}) = \begin{bmatrix} \frac{\partial h_2}{\partial x_1} & \frac{\partial h_2}{\partial x_2} & \dots & \frac{\partial h_2}{\partial x_n} \end{bmatrix}$$

We want to combine these into one constraint, and then use Newton's method to project an input point \mathbf{x}_{in} onto the combined constraint.

One option is to stack the constraints into a vector-valued constraint function:

$$\mathbf{h}(\mathbf{x}) = \left[\begin{array}{c} h_1(\mathbf{x}) \\ h_2(\mathbf{x}) \end{array} \right]$$

Then, apply Newton's method directly on h:

$$\begin{aligned} \mathbf{h}_{\mathbf{p}}(\mathbf{x}) &= \mathbf{h}(\mathbf{p}) + J_{\mathbf{h}}(\mathbf{p}) \left(\mathbf{x} - \mathbf{p}\right) = \mathbf{0} \\ \mathbf{x} &= \mathbf{p} - J_{\mathbf{h}}^{\dagger}(\mathbf{p}) \, \mathbf{h}(\mathbf{p}) \end{aligned}$$

with J^{\dagger} a left-inverse of J.

Alternatively, we could consider various ways of representing our constraint as a scalar-valued function $s(\mathbf{x})$. One common way is to use the ℓ^2 norm:

$$\begin{split} s(\mathbf{x}) &= ||\mathbf{h}(\mathbf{x})||\\ J_s(\mathbf{x}) &= \nabla_s^T(\mathbf{x}) = \frac{\mathbf{h}^T(\mathbf{x})}{||\mathbf{h}(\mathbf{x})||} J_{\mathbf{h}}(\mathbf{x}) \end{split}$$

Applying Newton's method to **s** yields:

$$\mathbf{x} = \mathbf{p} - \frac{1}{||\nabla_s(\mathbf{x})||^2} J_{\mathbf{h}}^T(\mathbf{p}) \, \mathbf{h}(\mathbf{x})$$

In other words, scalarizing the constraint using the ℓ^2 norm is equivalent to a Jacobian-transpose approach to root-finding.