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Riemannian Hessians

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Optimization on manifolds, MATH 512 @ EPFL

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Let \mathcal{M} be a Riemannian manifold.

Let ∇ denote the (unique) Riemannian connection on \mathcal{M} .

Def.: Let $f: \mathcal{M} \rightarrow \mathbf{R}$ be smooth.

Its **Riemannian Hessian** at x is the linear map

$$\text{Hess}f(x): T_x\mathcal{M} \rightarrow T_x\mathcal{M}$$

defined by

$$\text{Hess}f(x)[u] = \nabla_u \text{grad}f.$$

Fact: $\text{Hess}f(x)$ is **symmetric**.

$\rightarrow \forall u, v \in T_x\mathcal{M} :$

$$\langle \text{Hess}f(x)[u], v \rangle_x = \langle \text{Hess}f(x)[v], u \rangle_x$$

\Rightarrow spectral theorem applies.

Example. Consider S^{d-1} as a Riemannian submanifold of \mathbf{R}^d .
 Let $f: \mathcal{M} \rightarrow \mathbf{R}$ be smooth on S^{d-1} , with extension \bar{f} .
 Compute $\text{Hess} f(x)$ in terms of \bar{f} .

$$T_x S^{d-1} = \{ v \in \mathbf{R}^d : x^T v = 0 \} ; \quad \text{Proj}_x(u) = u - (x^T u) x$$

$$\text{grad} f(x) = \text{Proj}_x(\text{grad} \bar{f}(x)) = \text{grad} \bar{f}(x) - (x^T \text{grad} \bar{f}(x)) x$$

Manopt: egrad2grad

$$\bar{G}(x) = \text{grad} \bar{f}(x) - (x^T \text{grad} \bar{f}(x)) x$$

$$D\bar{G}(x)[u] = \text{Hess} \bar{f}(x)[u] - (x^T \text{grad} \bar{f}(x)) u - (u^T \text{grad} \bar{f}(x) + x^T \text{Hess} \bar{f}(x) u) x$$

$$\text{Hess} f(x)[u] = \text{Proj}_x \left(D\bar{G}(x)[u] \right)$$

$$= \text{Proj}_x \left(\text{Hess} \bar{f}(x)[u] \right) - (x^T \text{grad} \bar{f}(x)) u.$$

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