The Datatype of Loss Landscapes

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0. Loss Landscapes

What is the natural setting for a stochastic gradient-based optimizer such as SGD? A typical implementation might have this pseudocode:

```
Weight learn(Data^N X, Weight w_0, float(*l)(Data, Weight), int E) {
    Weight w = w_0;
    for (int e = 0; e ≠ E; e = e + 1) {
        shuffle(X);
        for (Data x: X) {
            Covector g = ∇_w l(x, w);
            w = exp_w(−transpose(g));
        }
    }
    return w;
}
```

We thus see that the key ingredients are

- a probability space X of data;
- a manifold W of weights that is equipped with
- a Riemannian (inverse) metric $\texttt{transpose} : T^*W \to TW$ to turn covectors into vectors (the learning rate is part of this data) that in turn induces
- the flow $\exp : TW \to W$ to update along a vector; and
- a loss function $l : X \times W \to \mathbb{R}$.

One wishes for W to be metrically complete, for $w \mapsto l(x, w)$ to be smooth for all x, and for each random variable $\nabla_w^a \nabla_w^b \cdots \nabla_w^z l(x, w)$ to be subgaussian for all w. In this case, let us call the listed data (X, W, l) a **loss landscape**. Traditionally, W has been either curved according to a Fisher metric or else flat. The purpose of this note is to unify and clarify these and all other reasonable possibilities.

Let us write $\langle f(x) \rangle$ for the expectation of $f(x)$, and let us notate derivatives such as $\nabla_w^a \nabla_w^a \nabla_w^b \nabla_w^c l(x, w)$ by parenthesized sequences of indices such as $(aabc)$. By subgaussianity, every grammatical expression of $\langle\rangle$s and $()$s has a finite value. For example, we may consider the **hessian** $H = \langle (ab) \rangle$ or the **covariance** $C = \langle (a)(b) \rangle - \langle (a) \rangle \langle (b) \rangle$. Though both H and C are symmetric 2-tensors on TW, their meanings greatly differ. For instance, H scales linearly with l while C scales quadratically. Table 0 makes such scalings vivid by imagining that the loss has units of dollars.

1. Germs

2. Taylor Expansion in the Metric

DIMENSIONS	length^{-2}	length^{-1}	length^{0}	length^{1}
dollars^{-1}			learning rate	gas mileage
dollars^{0}	metric		$\boxed{\text{unitless}}$	weight update
dollars^{1}	hessian	gradient	loss	
dollars^{2}	covariance		trace covariance	

Table 0: This table indicates the scaling properties of selected objects so that the reader may orient her intuition for dimensional analysis. Many interesting objects are left unlisted: for instance, the variance $\langle ()() \rangle - \langle () \rangle \langle () \rangle$ of the loss would inhabit the trace-covariance's cell, and the intensity $\langle (a) \rangle \langle (a) \rangle$ of the mean gradient would inhabit the covariance's cell.

3. Geometry as Prior

4. Example: The Valley of Death