EBERHARD KARLS TÜBINGEN

Abstract

Natural gradient descent uses the Fisher information matrix to adapt to the geometry. Several works advocate for the empirical Fisher approximation and draw connections between second-order methods and heuristics like Adam. We show that this approximation does not capture the problem geometry.

Natural Gradient Descent

Goal: learn the conditional distribution $y \mid x$;

 $\mathcal{L}(\theta) = -\sum_{n} \log p_{\theta}(y_n | x_n)$

Natural Gradient Descent: preconditioned gradient update with the Fisher information F,

$$\theta_{t+1} = \theta_t - F(\theta_t)^{-1} \nabla \mathcal{L}(\theta_t)$$

The landscape of Fisher matrices

The Fisher of the joint $p_{\theta}(x, y) = p(x)p_{\theta}(y|x)$ is

 $N\mathbb{E}_{p(x)}\mathbb{E}_{p_{\theta}(y|x)}\left[\nabla \log p_{\theta}(y|x)\nabla \log p_{\theta}(y|x)^{\top}\right]$

If p(x) is unknown, the Fisher of the conditional $p_{\theta}(y|x_n)$ (empirical x_n) also works;

 $\sum_{n} \mathbb{E}_{p_{\theta}(y|x_{n})} \left[\nabla \log p_{\theta}(y|x_{n}) \nabla \log p_{\theta}(y|x_{n})^{\top} \right]$

But the empirical Fisher approximaton uses the empirical y_n ;

$$\nabla \log p_{\theta}(y_n | x_n) \nabla \log p_{\theta}(y_n |$$

Limitations of the empirical Fisher approximation for natural gradient descent Frederik Kunstner, Lukas Balles, Philipp Hennig



- geometry

 \blacktriangleright EF should \approx Fisher at the minimum if model is well-specified and there is enough data \implies hard to check in advance.



► The problem is ill conditioned; Gradient descent struggles and natural gradients adapt to the

► EF distorts direction and magnitude; large gradient \implies small update small gradient \implies large update

Small update when gradient is large \implies step-size tuning is hard

Even if tuned, direction might fail; can be opposite of natural gradient

Large models can help; more likely to be well-specified but also need more data