Natasha 2 (Allen-zhu)

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Problem

Online stochastic nonconvex optimization

$$\min_{x \in \mathbb{R}^d} \left\{ f(x) \stackrel{\text{def}}{=} \mathbb{E}_i[f_i(x)] = \frac{1}{n} \sum_{i=1}^n f_i(x) \right\}$$

- Need to avoid saddle points
 - Random Perturbation
 - Is there another strategy?

Use the Hessian (kind of)!

• When at saddle, take negative curvature direction



Figure 1: Local minimum (left), saddle point (right) and its negative-curvature direction.

 Use Oja's Algorithm to find this direction, which empirically takes roughly twice the time of a gradient computation

Algorithm specified

Very similar to SVRG and repeatSVRG

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Algorithm 2 an informal version of Natasha2(f, y_0, \varepsilon, \delta)
Input: function f(x) satisfying Problem (5.1), starting vector y_0, target accuracy \varepsilon > 0 and \delta > 0.
 1: for k \leftarrow 0 to \infty do
           Apply Oja's algorithm to find minEV v of \nabla^2 f(y_k).
          if v \in \mathbb{R}^d is found s.t. v^{\top} \nabla^2 f(y_k) v \leq -\frac{\delta}{2} then
               y_{k+1} \leftarrow y_k \pm \frac{\delta}{L_2} v where the sign is random.
 4:
                                                                                                                \diamond it satisfies \nabla^2 f(y_k) \succeq -\delta \mathbf{I}
           else
  5:
                F(x) = F^k(x) \stackrel{\text{def}}{=} f(x) + L(\max\{0, ||x - y_k|| - \frac{\delta}{L_0}\})^2.
               y_{k+1} \leftarrow \mathtt{Natasha1.5}(F, y_k, \varepsilon^{-2}, 1, \varepsilon^{4/3}/\delta^{1/3})
                Break the for loop if have performed \Theta(\frac{\delta^{1/3}}{\epsilon^{4/3}}) first-order steps.
 8:
           end if
 9:
10: end for
11: return y_k.
```

Guarantees

- What's the weird stuff? Additive terms, reusing previous iterates in the additive terms
 - Natasha 1.5: to bound approximation error, to make it nice
 - Natasha 2: to ensure that $grad(F) \sim 0 => grad(f) \sim 0$, to make it nice

Theorem 2 (informal). Under (A1), (A2) and (A4), Natasha2 outputs a point x^{out} with

$$\|\nabla f(x^{\mathsf{out}})\| \le \varepsilon \quad and \quad \nabla^2 f(x^{\mathsf{out}}) \succeq -\delta \mathbf{I}$$

in gradient complexity¹²

$$T = \widetilde{O}\left(\frac{1}{\delta^5} + \frac{1}{\delta \varepsilon^3} + \frac{1}{\varepsilon^{3.25}}\right) ,$$

if we hide L, L_2 , Δ_f , and \mathcal{V} in the big-O notion.