Lecture 18: Newton's method vs. gradient descent

Ciaran Evans

Feedback summary

Thanks for feedback on the course! A brief summary of responses:

- Overall pace of the course about right
- Challenge assignments and extended practice questions working well – we'll continue those
- Overall workload a bit high
 - Change to 2 projects, not 3
- ► HW 4 too hard
- Deadlines overwhelming preference for evening deadlines. I'll change that going forward
- Project 1: most people expected to use extension days. So:
 - Formal deadline moved to after Spring break
 - Ideally everyone is able to submit before break, but this gives you a few extra days if needed!

Previously

Gradient descent:

$$\mathbf{x}^{(k+1)} = \mathbf{x}^{(k)} - \alpha_k \nabla f(\mathbf{x}^{(k)})$$

Newton's method:

$$\mathbf{x}^{(k+1)} = \mathbf{x}^{(k)} - \alpha_k(\mathbf{H}_f(\mathbf{x}^{(k)}))^{-1} \nabla f(\mathbf{x}^{(k)})$$

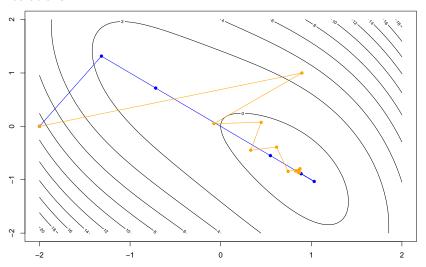
Today:

- Brief comparison between the two methods
- Which one gets used in practice?

Previously

Newton's method (blue): 7 iterations

Gradient descent with backtracking line search (orange): 27 iterations



Some properties of gradient descent

Question: What are some properties we have shown/observed about gradient descent?

Some properties of gradient descent

- ► The direction $\nabla f(\mathbf{x})$ is the direction of *steepest descent* (minimizes directional derivative)
- If α_k is chosen via exact line search, $\nabla f(\mathbf{x}^{(k+1)}) \perp \nabla f(\mathbf{x}^{(k)})$ (zig-zag pattern)
- Gradient descent takes many iterations in long, narrow valleys; scaling matters

Some properties of Newton's method

Gradient descent:

- ► The direction $-\nabla f(\mathbf{x})$ is the direction of *steepest descent* (minimizes directional derivative)
- ▶ If α_k is chosen via exact line search, $\nabla f(\mathbf{x}^{(k+1)}) \perp \nabla f(\mathbf{x}^{(k)})$ (zig-zag pattern)
- Gradient descent takes many iterations in long, narrow valleys; scaling matters

Newton's method:

- ► $-(\mathbf{H}_f(\mathbf{x}))^{-1}\nabla f(\mathbf{x})$ is a descent direction (directional derivative is negative)
- Not forced to take zig-zag steps
- Less susceptible to scaling issue

 $-(\mathbf{H}_f(\mathbf{x}))^{-1}\nabla f(\mathbf{x})$ is a descent direction

Claim: Let **u** be a unit vector in the direction of $-(\mathbf{H}_f(\mathbf{x}))^{-1}\nabla f(\mathbf{x})$. Then $D_{\mathbf{u}}f(\mathbf{x}) < 0$ if \mathbf{H}_f is a **positive definite** matrix

Definition (positive definite): $\mathbf{H}_f(\mathbf{x})$ is a positive definite matrix if for all vectors $\mathbf{v} \neq 0$,

$$\mathbf{v}^T \mathbf{H}_f(\mathbf{x}) \mathbf{v} > 0$$

- ► Fact: If $H_f(x)$ is positive definite for all x, then f is a **convex** function
- ▶ Fact: If $H_f(x)$ is positive definite, then $(H_f(x))^{-1}$ is positive definite

$$-(\mathbf{H}_f(\mathbf{x}))^{-1}\nabla f(\mathbf{x})$$
 is a descent direction

Claim: Let ${\bf u}$ be a unit vector in the direction of $-({\bf H}_f({\bf x}))^{-1}\nabla f({\bf x})$. Then $D_{\bf u}f({\bf x})<0$ if ${\bf H}_f$ is a **positive definite** matrix

Definition (positive definite): $\mathbf{H}_f(\mathbf{x})$ is a positive definite matrix if for all vectors $\mathbf{v} \neq 0$,

$$\mathbf{v}^T \mathbf{H}_f(\mathbf{x}) \mathbf{v} > 0$$

Proof of claim:

What actually gets used in practice? A broad generalization

Classical statistics: (parametric models with moderate size) Newton's method

- Generalized linear models: Fisher scoring (Newton's method with Fisher info), often calculated with iteratively re-weighted least squares (IRLS)
- ► Generalized estimating equations
- Nonlinear least squares: Gauss-Newton (variant of Newton's method)

Modern statistical learning: (large models with *many* parameters) Gradient descent

- ▶ Basic gradient descent and line search are not commonly used with large models
- Variations (stochastic gradient descent, momentum, subgradient methods, etc) are standard