CS545: Gradient Descent Chuck Anderson

Gradient Descent
Parabola
Examples in R

# CS545: Gradient Descent

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#### Outline

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Gradient Descent Parabola Examples in R

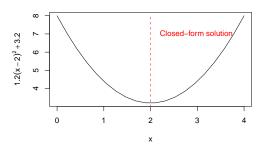
 Yep. Take derivative, set equal to zero, and try to solve for x.

$$f(x) = 1.2(x-2)^{2} + 3.2$$

$$\frac{df(x)}{dx} = 1.2(2)(x-2) = 2.4(x-2)$$

$$\frac{df(x)}{dx} = 0 = 2.4(x-2)$$

$$x = 2$$



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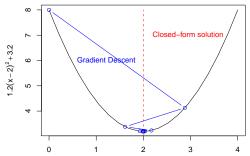


- Start at some x value, use derivative at that value to tell us which way to move, and repeat. Gradient descent.
- $oldsymbol{
  ho}$  is factor of derivative to control how far to go

$$\frac{df(x)}{dx} = 2.4(x-2)$$

$$x(0) = 0 \text{ (for example)}$$

$$x(n) = x(n-1) - \rho 2.4(x-2)$$



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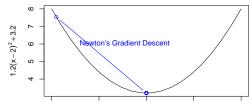
$$\frac{df(x)}{dx} = f' = 2.4(x - 2)$$
$$\frac{d^2f(x)}{dx^2} = f'' = 2.4$$

 and use Newton's method (see the Wikipedia entry for "Newton's method")

$$x(n) = x(n-1) - \frac{f'}{f''}$$

$$x(n) = x(n-1) - \frac{2.4(x-2)}{2.4}$$

$$x(n) = x(n-1) - (x-2)$$



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- If the function is not a parabola, what can we do? Cannot solve directly for x. Can still do gradient descent. Can we always use Newton's method?
- No. Reason 1: If x has 1000 components, the second derivative (Hessian) is a  $1000 \times 1000$  matrix. May be too big.
- Reason 2: If not a parabola the second derivative information may lead you very far away. When?

 Say we have picked a direction, p, to go. Rather than compute the second derivative in that direction, we can approximate it using two first derivative values.

$$f''(x)p \approx \frac{f'(x+\alpha p)-f'(x)}{\alpha}$$
 for  $0 < \alpha << 1$ 

• In practice, Moller found he had to modify this by adding  $\lambda p$  where  $\lambda$  is set to a value for which the resulting approximated second derivative is well behaved.

$$f''(x)p pprox rac{f'(x+lpha p)-f'(x)}{lpha} + \lambda p, ext{ for } 0 < lpha << 1$$

This gives us a way to scale the step size.

- Now, how about that direction? How do we decide that?
- Moller uses conjugate gradients. (See the wikipedia entry for "conjugate gradient")
- The conjugate gradient direction is based on the previous direction and the current gradient.

## Parabola Example

```
f <- function(x) {
    1.2 * (x-2)^2 + 3.2 }

grad <- function(x) {
    1.2 * 2 * (x-2)
}

secondGrad <- function(x) {
    2.4
```

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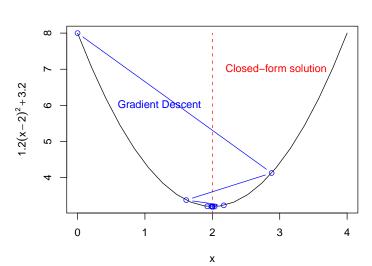
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### Steepest Descent

```
\times s < - seq(0,4,len=20)
plot(xs, f(xs), type="l", xlab="x", ylab=expression(1.2(x-2)^2 +3.2))
\#\#\# df/dx = 2.4(x-2)
### df/dx = 0 - - - > 0 = 2.4x - 4.8 - - - > x = 2
lines (c (2,2), c (3,8), col="red", lty=2)
text (2.1,7, "Closed-form solution", col="red", pos=4)
### gradient descent
x < -0.1
xtrace < - x
ftrace <- f(x)
stepFactor <- 0.6 ### try larger and smaller values (0.8 and 0.01)
for (step in 1:100) {
  x < -x - stepFactor * grad(x)
  xtrace < - c(xtrace,x)
  ftrace < - c(ftrace, f(x))
lines (xtrace, ftrace, type="b",col="blue")
text (0.5,6, "Gradient Descent", col="blue", pos=4)
```

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## Steepest Descent with gradientDescents.R

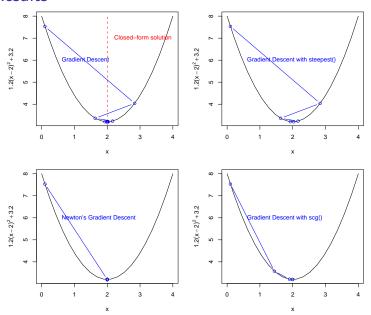
```
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```

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# With Scaled Conjugate Gradient from gradientDescents.R

```
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```

#### Results



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