

## 15.084J Recitation Handout 2

### Second Week in a Nutshell:

- Newton's Method
- When Newton's Method Fails
- Rates of Convergence
- Quadratic Forms
- Eigenvectors/Eigenvalues/Decompositions

New notation:  $Q$  is positive semidefinite is written as  $Q \succeq 0$  (and similarly for positive definite, and negative (semi-)definite).

New definition:  $M$  is orthonormal if  $M^{-1} = M^t$ ; the rows/columns of  $M$  have norm 1 and are perpendicular.

$\gamma$  is an eigenvalue with eigenvector  $x$  of a matrix  $M$  if  $Mx = \gamma x$

### Newton's Method

We can find the solution to a quadratic problem in closed form. Since everything looks quadratic if you squint hard enough, find a quadratic approximation to your problem at a given point, then jump to a new (and presumably better) point which is the minimum of the approximation.

More formally, do a taylor expansion of your function at point  $x^k$ ...  $f(x) \approx f(x^k) + \nabla f(x^k)^t(x - x^k) + \frac{1}{2}(x - x^k)^t H(x^k)(x - x^k)$ . Then you can minimize this in closed form to get  $x^{k+1} = x^k - H(x^k)^{-1} \nabla f(x^k)$ . You can generalize this by doing a line search in the given direction, or moving some multiple of that distance.

### When Does Newton's Method Fail

- You can't use the method if you can't get gradients and Hessians easily.
- The step is undefined if the Hessian is non-invertable – the function is essentially flat in some direction at the current point
- The method is finding where the gradient is zero – might be a maximum!
- The Hessian must not change too fast (if it does, quadratic approximation is bad)
- The starting point must be “near” an optimum, and you generally don't know how to test for that
- In its current form, it doesn't deal with constraints (though we will later see versions that do)

### Rates of Convergence

If we have a sequence  $x^k$  converging to  $\bar{x}$ , we say it has *linear* convergence if  $\lim \frac{x^{k+1} - \bar{x}}{x^k - \bar{x}} = \delta < 1$  This means it takes a constant number of iterations to add each significant figure of accuracy.

It has *quadratic* convergence if  $\lim \frac{(x^{k+1} - \bar{x})^2}{(x^k - \bar{x})^2} = \delta < 1$  This means it takes a constant number of iterations to double the significant figures of accuracy.

Newton's method has quadratic convergence once it is sufficiently close to a minimum or maximum.

### Quadratic Forms

A quadratic form is a function  $f(x) = x^t Q x + c^t x + d$

Fun facts about quadratic forms:

- You can assume without loss of generality that  $Q$  is symmetric
- For minimizing/maximizing, you can assume wolog that  $d$  is zero
- The gradient is  $Qx + c$
- The Hessian is  $Q$
- The quadratic is convex when  $Q \succeq 0$ ; concave when  $Q \preceq 0$

Facts about matrices:

- If  $Q$  is real and symmetric, all of its eigenvalues are real, and its eigenvectors are orthogonal
- Thus, you can factor it into  $Q = RDR$  where  $D$  is the diagonal matrix of eigenvalues, and  $R$  is an orthonormal matrix of eigenvectors.
- If  $Q \succeq 0$ , its eigenvalues are nonnegative; if  $Q \succ 0$  its eigenvalues are positive; if  $Q \prec 0$  its eigenvalues are negative, and if  $Q \preceq 0$  its eigenvalues are nonpositive.
- If  $Q$  is symmetric, then  $Q \succeq 0$  and nonsingular if and only if  $Q \succ 0$ .
- If  $Q \succeq 0$  then any principal submatrix of  $Q$  is  $\succeq 0$  (and similarly for  $\succ$ ,  $\prec$ , and  $\preceq$ )
- If  $Q \succ 0$ , then  $M = \begin{bmatrix} Q & c \\ c^t & b \end{bmatrix}$  has  $M \succ 0$  iff  $b > c^t Q^{-1} c$