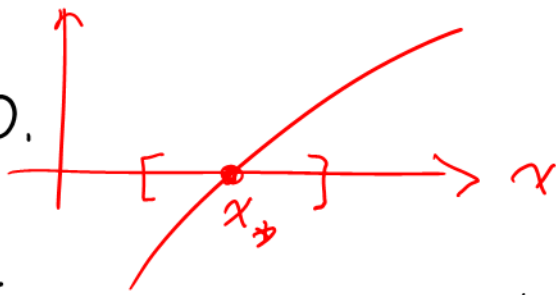


Back to "local analysis"

Consider a function $f(x)$ in a small nghd of a zero x_* :

Assume $f'(x_*) > 0$.

& f smooth.



In a suff'ly small nghd of x_* ,

f will be very nearly a linear function. So, let's consider it's

approximation $\tilde{f}(x) = \alpha(x - x_*)$

$$\alpha = \tilde{f}'(x_*)$$

Consider the fixed pt. iteration:

$$x_{k+1} = x_k - \lambda \tilde{f}(x_k) \quad (**)$$

(**) is called a "relaxation" & λ a "relaxation parameter." For our

approximation, $\tilde{g}(x) = x - \lambda \alpha (x - x_*)$

$$\tilde{g}'(x) = (1 - \lambda \alpha)$$

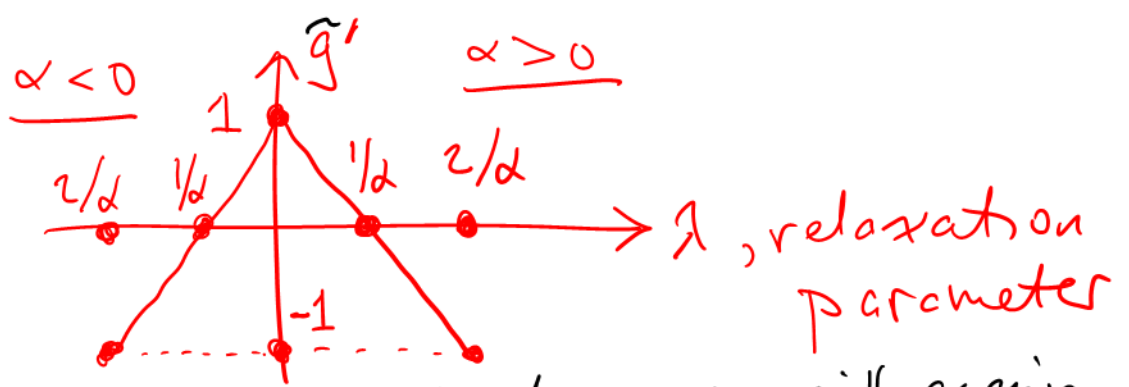
\tilde{g} will be a contraction if $|1 - \lambda \alpha| < 1$

$$\Rightarrow -1 < 1 - \lambda \alpha < 1$$

$$\alpha > 0, \text{ so must take } \lambda > 0. \Rightarrow -2 < -\lambda \alpha < 0$$

$$\Rightarrow 2 > \lambda \alpha > 0$$

$$\begin{array}{c} \text{or} \\ 0 < \lambda < 2/\alpha \end{array}$$



What if $\alpha < 0$? For contraction we will again have

$$-2 < -\lambda\alpha < 0$$

which can be satisfied only by taking $\lambda < 0$ (i.e. to get $-\lambda\alpha < 0$)

or since $\alpha < 0$: $\frac{2}{\alpha} < \lambda < 0$ | Q: what is the "optimal" choice for λ ? $\lambda = \frac{1}{\alpha}$
 Conv. in $\underline{1}$ itr!

So, here is the theorem about relaxations (slightly incorrect in the text)

Consider a continuously differentiable ftn $f(x)$ with $f(x_*) = 0$ & $f'(x_*) > 0$ ($f'(x_*) < 0$)

[only need smoothness in a neighborhood of x_*].

and consider the relaxation fixed point

$$\text{iteration } x_{k+1} = x_k - \lambda f(x_k) = g_\lambda(x_k)$$

Thm For $f'(x_*) > 0$ [$f'(x_*) < 0$],

$\exists \lambda_* > 0$ [$\lambda_* < 0$] & $\delta > 0$ s.t.

$x_k \rightarrow x_*$ for any $0 < \lambda \leq \lambda_*$ [$\lambda_* \leq \lambda < 0$]
 with $x_0 \in [x_* - \delta, x_* + \delta]$.

Pf. Assume $f'(x_*) = \alpha > 0$. Continuous f'
 $\Rightarrow \exists \delta > 0$ s.t. $f'(x) > \frac{1}{2}\alpha \forall |x - x_*| < \delta$.

Let $M =$ upper bd on f' in this interval
so that $M > \frac{1}{2}\alpha$. Hence:

$$-M \leq -f'(x) \leq -\frac{1}{2}\alpha$$

& for any $\lambda > 0$

$$1 - \lambda M \leq 1 - \lambda f'(x) \leq 1 - \frac{1}{2}\lambda\alpha$$

Choose, because why not, λ_* s.t.

$$-v = 1 - \lambda_* M \leq 1 - \lambda_* f'(x) \leq 1 - \frac{1}{2}\lambda_*\alpha = v > 0$$

$$\Rightarrow -1 + \lambda_* M = 1 - \frac{1}{2}\lambda_*\alpha$$

$$\Rightarrow \lambda_* (M + \frac{1}{2}\alpha) = 2 \Rightarrow \boxed{\lambda_* = \frac{4}{\alpha + 2M} > 0}$$

or. $v = \lambda M - 1$

$$= \frac{4M - \alpha - 2M}{\alpha + 2M} = \frac{2M - \alpha}{2M + \alpha} < 1$$

$$\Rightarrow |g'_{\lambda_*}(x)| < 1 \quad \forall |x - x_*| \leq \delta$$

And moreover, for any $\lambda > \lambda_* \leq \lambda_*$

$$|g'_{\lambda}(x)| < 1 \quad \forall |x - x_*| < \delta$$

Apply Thm 1.5 of book.

Works the same way for $f'(x_*) < 0$.

Newton's Method

What if instead we consider

$$x_{k+1} = x_k - \lambda(x_k) f(x_k)$$

$$g(x) = x - \lambda(x) f(x)$$

$$g'(x) = 1 - \lambda'(x) f(x) - \lambda(x) f'(x)$$

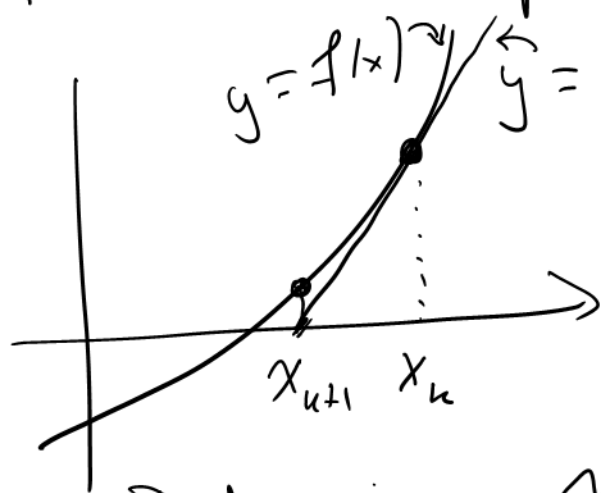
$$g'(x_*) = 1 - \lambda(x_*) f'(x_*)$$

If $\lambda(x_k) = \frac{1}{f'(x_k)}$, we will have the smallest absolute $|g'(x_*)| = 0$

$$x_{k+1} = x_k - f(x_k) / f'(x_k)$$

is Newton's Method.

Another interpretation:



$= M(x; x_k)$
is the tangent line approximation to f at $x = x_k$.

Determine x_{k+1} by condition

$$M(x_{k+1}; x_k) = 0 \quad \text{N.M.}$$

$$\Rightarrow f(x_k) + f'(x_k)(x_{k+1} - x_k) = 0$$

Back of the envelope "local analysis of N.M.
Let $f(x_*) = 0$ and $f'(x_*) \neq 0$ assume f has a
continuous 2nd derivative in its nghd.

Consider x_k in the nghd of x_*

$$f(x_*) = f(x_k) + f'(x_k)(x_* - x_k) \\ + \frac{1}{2} f''(\eta_k)(x_* - x_k)^2$$

where η_k lies between x_k and x_* , by

Taylor's Thm w. Remainder.

$$\text{So, } f(x_*) + f'(x_k)(x_* - x_k) + \frac{1}{2} f''(\eta_k)(x_* - x_k)^2 \\ = 0$$

$$\Rightarrow (x_* - x_k) + \frac{f(x_k)}{f'(x_k)} = - \frac{f''(\eta_k)}{2 f'(x_k)} (x_* - x_k)^2$$

$$\cancel{x_*} - \cancel{x_k} = (x_* - x_{k+1}) \quad \text{Assuming } f'(x_k) \neq 0$$

$$|x_* - x_{k+1}| = \left| \frac{f''(\eta_k)}{2 f'(x_k)} \right| |x_* - x_k|^2 \\ = C_k |x_* - x_k|^2$$