

# 1D Root Finding



# Part II Roadmap

- Part I – Linear Algebra (units 1-12)  $Ac = b$
  - Part II – Optimization (units 13-20)
    - (units 13-16) Optimization -> Nonlinear Equations -> 1D roots/minima
    - (units 17-18) Computing/Avoiding Derivatives
    - (unit 19) Hack 1.0: "I give up"  $H = I$  and  $J$  is mostly 0 (descent methods)
    - (unit 20) Hack 2.0: "It's an ODE!?" (adaptive learning rate and momentum)
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- ```
graph TD; P1[Part I - Linear Algebra (units 1-12) Ac = b]; P2[Part II - Optimization (units 13-20)]; P2 -- linearize --> P1; P1 -- line search --> T[1D roots/minima]; T --- The[Theory]; P2 --> M[Methods]; M --- H1["(unit 19) Hack 1.0: 'I give up' H = I and J is mostly 0 (descent methods)"]; M --- H2["(unit 20) Hack 2.0: 'It's an ODE!?' (adaptive learning rate and momentum)"];
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# Fixed Point Iteration

- Find roots of  $g(t)$ , i.e. where  $g(t) = 0$
- Let  $\hat{g}(t) = g(t) + t$  and iterate  $t^{q+1} = \hat{g}(t^q)$  until convergence
- A converged  $t^*$  satisfies  $t^* = \hat{g}(t^*) = g(t^*) + t^*$  implying that  $g(t^*) = 0$
- Converges when:  $|g'(t^*)| < 1$ , the initial guess is close enough to  $t^*$ , and  $g$  is sufficiently smooth
- $e^{q+1} = t^{q+1} - t^* = \hat{g}(t^q) - \hat{g}(t^*) = g'(\hat{t})(t^q - t^*) = g'(\hat{t})e^q$  for some  $\hat{t}$  between  $t^{q+1}$  and  $t^*$  (by the Mean Value Theorem)
- When all  $g'(\hat{t})$  have  $|g'(\hat{t})| \leq C < 1$ , then  $|e^q| \leq C^q |e^0|$  proves convergence



# Convergence Rate

- Consider  $\|e^{q+1}\| \leq C\|e^q\|^p$  as  $q \rightarrow \infty$  where  $C \geq 0$ 
  - When  $p = 1$ ,  $C < 1$  is required and the convergence rate is linear
  - When  $p > 1$ , the convergence rate is superlinear
  - When  $p = 2$ , the convergence rate is quadratic
- Statements only apply asymptotically (once convergence is happening)
- Might converge to a different non-desired root (when other roots are present)
- Solving  $g(t) = 0$  may only approximate the problem being solved, so it's not clear how accurate the root finder needs to be anyways



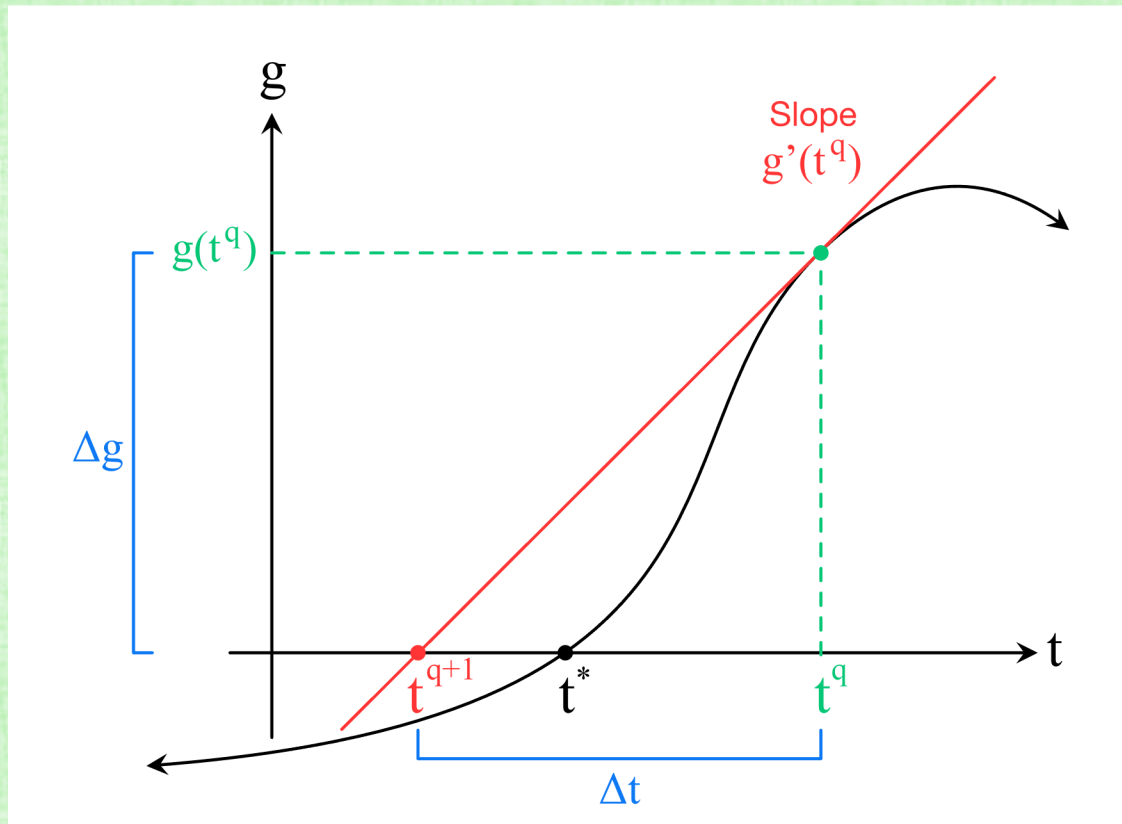
# 1D Newton's Method

- Solve  $g'(t^q)\Delta t = -g(t^q)$  and update  $t^{q+1} = t^q + \Delta t = t^q - \frac{g(t^q)}{g'(t^q)}$
- Stop when  $|g(t^q)| < \epsilon$ , which implies  $|t^{q+1} - t^q| < \frac{\epsilon}{|g'(t^q)|}$ 
  - Thus, poorly conditioned when  $g'(t^*)$  is small
  - Especially problematic for repeated roots where  $g'(t^*) = 0$
- Quadratic convergence rate ( $p = 2$ ), when not degenerate
- Requires computing  $g$  and  $g'$  every iteration; but, computing derivatives isn't always straightforward/cheap (see units 17/18 on Computing/Avoiding Derivatives)



# 1D Newton's Method

•  $t^{q+1} = t^q - \frac{g(t^q)}{g'(t^q)}$  or alternatively  $g'(t^q) = \frac{g(t^q) - 0}{t^q - t^{q+1}} = \frac{\Delta g}{\Delta t}$





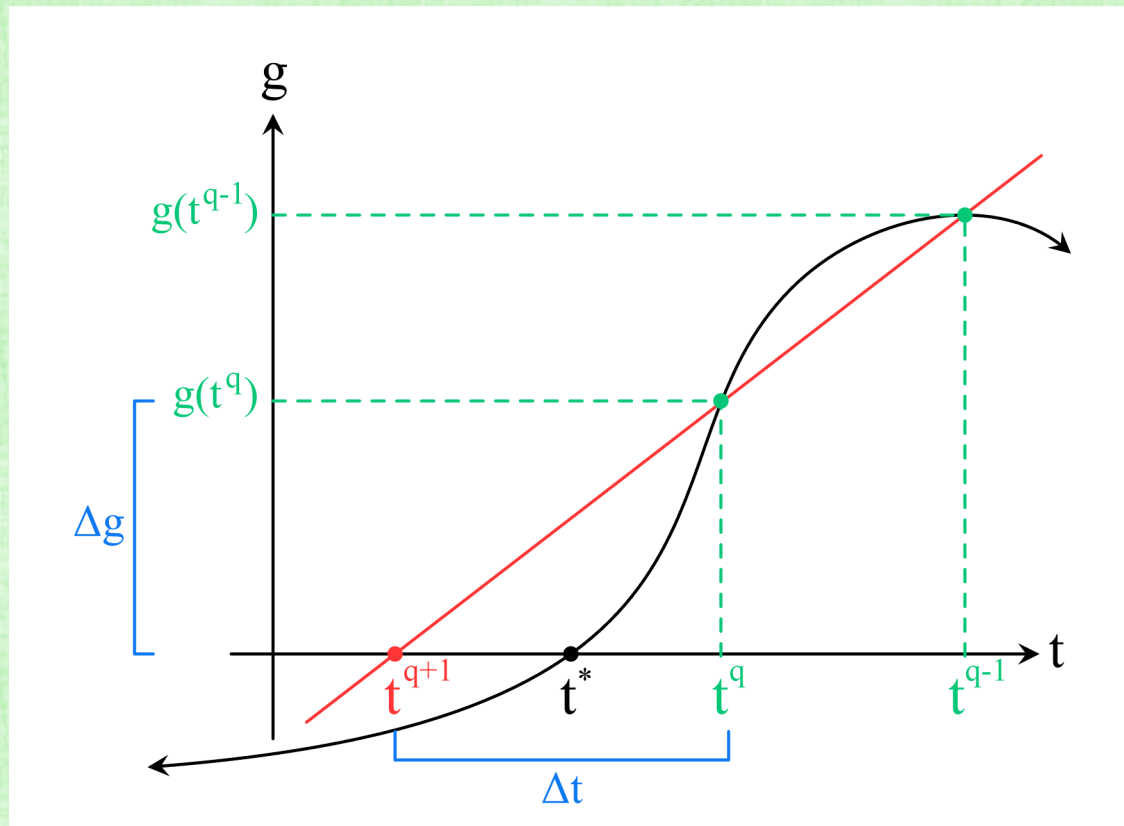
# Secant Method

- Replace  $g'(t^q)$  in Newton's method with an estimate (a few choices for this)
- The standard approach draws a line through previous iterates
- Estimate  $g'(t^q) \approx \frac{g(t^q) - g(t^{q-1})}{t^q - t^{q-1}}$
- Then  $t^{q+1} = t^q - g(t^q) \frac{t^q - t^{q-1}}{g(t^q) - g(t^{q-1})}$
- Superlinear convergence rate with  $p \approx 1.618$ , when not degenerate
- Typically/often faster than Newton, since  $g'$  is not needed and only a few extra iterations are required to obtain the same accuracy (for a reasonable accuracy)



# Secant Method

- $t^{q+1} = t^q - g(t^q) \frac{t^q - t^{q-1}}{g(t^q) - g(t^{q-1})}$  based on  $g'(t^q) \approx \frac{g(t^q) - g(t^{q-1})}{t^q - t^{q-1}}$





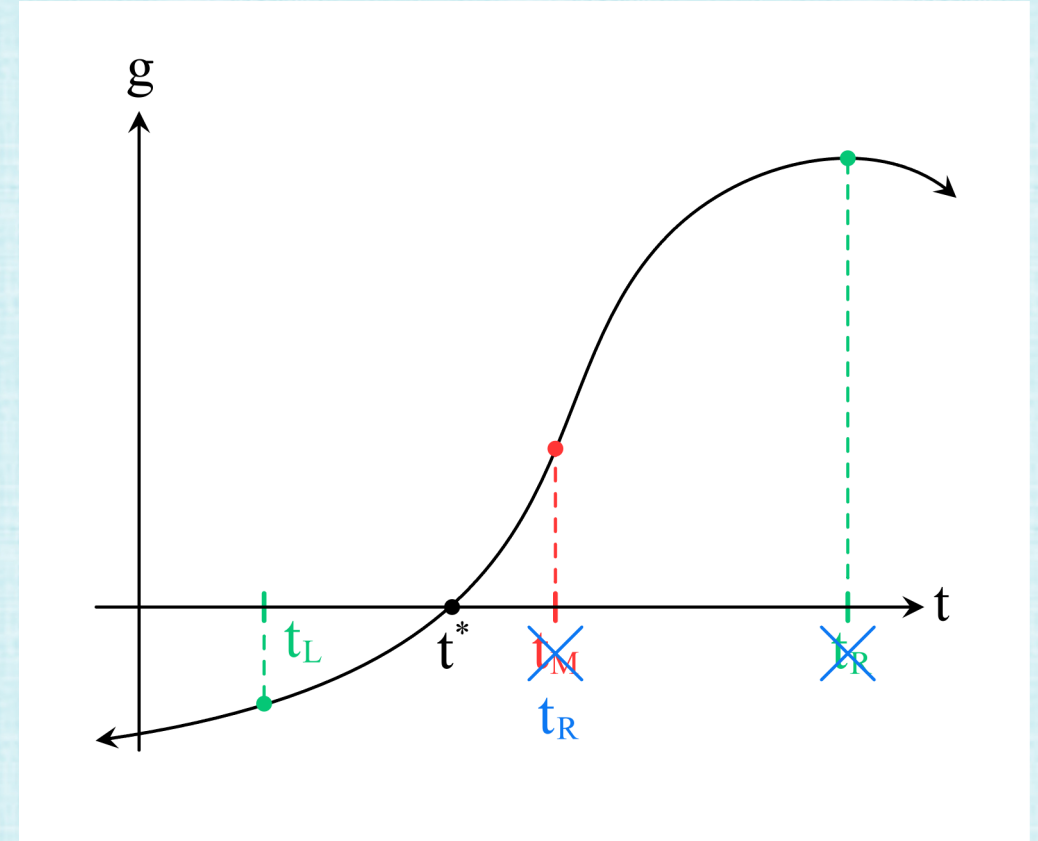
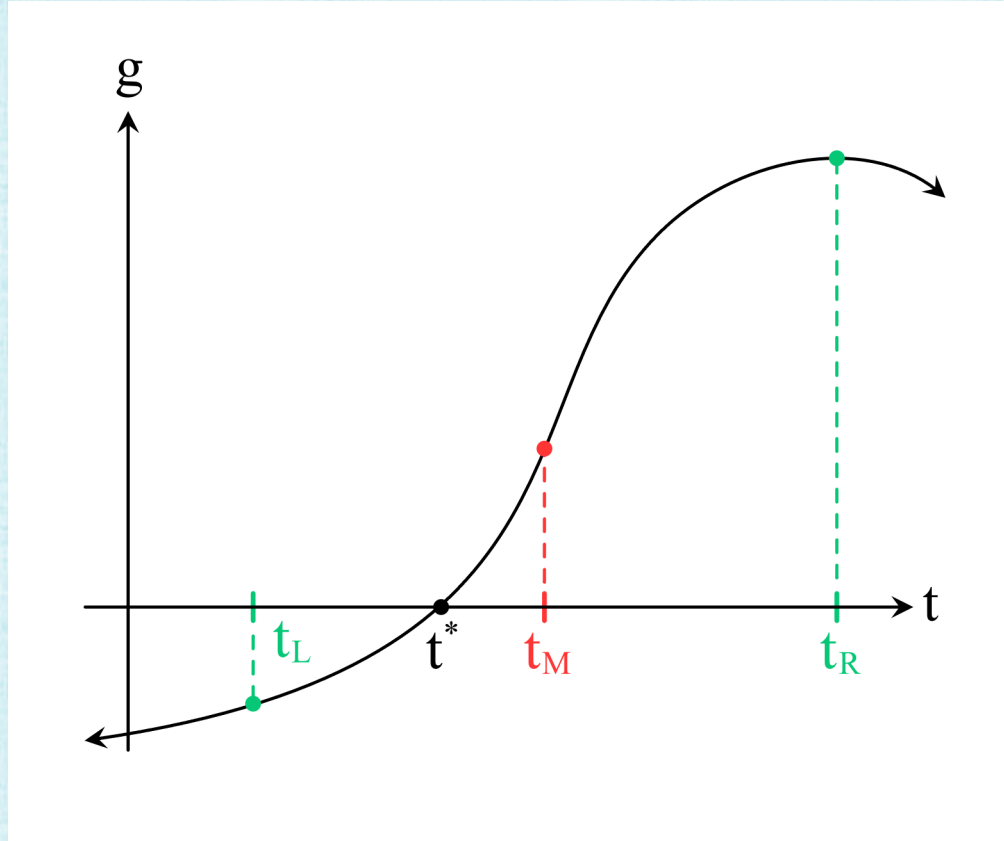
# Bisection Method

- If  $g(t_L)g(t_R) < 0$ , then (assuming continuity) the sign change indicates a root in the interval  $[t_L, t_R]$
- Let  $t_M = \frac{t_L + t_R}{2}$ ,
  - If  $g(t_L)g(t_M) < 0$ , set  $t_R = t_M$
  - Otherwise, set  $t_L = t_M$  knowing that  $g(t_R)g(t_M) < 0$  is true
- Iterate until  $t_R - t_L < \epsilon$
- Guaranteed to converge to a root in the interval (unlike Newton/Secant)
- The interval shrinks in size by a factor of two each iteration; so, linear convergence rate ( $p = 1$ ) with  $C = \frac{1}{2}$



# Bisection Method

- If  $g(t_L)g(t_M) < 0$ , set  $t_R = t_M$ ; otherwise, set  $t_L = t_M$





# Mixed Methods

- Given an interval with a root indicated by  $g(t_L)g(t_R) < 0$
- Iterate with Newton/Secant as long as the iterates stay inside the interval
  - When iteration attempts to leave the interval, use prior iterates to shrink the interval as much as possible (while still guaranteeing a root)
- If Newton/Secant attempt to leave the current interval, instead use Bisection to continue shrinking the interval
- Leverages the speed of Newton/Secant, while still guaranteeing convergence via Bisection
- Many/various strategies exist



# Function/Derivative Requirements

- All methods require evaluation of the function  $g$
- Newton also requires the derivative  $g'$  (as do mixed methods using Newton)



# Useful Derivatives

- $\frac{\partial}{\partial t} c^{q+1}(t) = \Delta c^q$ , since  $c^{q+1}(t) = c^q + t\Delta c^q$
- $\frac{\partial}{\partial t} F(c^{q+1}(t)) = J_F(c^{q+1}(t))\Delta c^q$  and  $\frac{\partial}{\partial t} F^T(c^{q+1}(t)) = (\Delta c^q)^T J_F^T(c^{q+1}(t))$ 
  - $\frac{\partial}{\partial t} F_i(c^{q+1}(t)) = (J_F)_i(c^{q+1}(t)) \Delta c^q$  where the  $F_i(c^{q+1}(t))$  are the scalar row entries of  $F(c^{q+1}(t))$
- Scalar  $\hat{f}(c^{q+1}(t))$  has system  $J_{\hat{f}}^T(c^{q+1}(t)) = 0$  for critical points
- $\frac{\partial}{\partial t} J_{\hat{f}}^T(c^{q+1}(t)) = H_{\hat{f}}^T(c^{q+1}(t))\Delta c^q$  and  $\frac{\partial}{\partial t} J_{\hat{f}}(c^{q+1}(t)) = (\Delta c^q)^T H_{\hat{f}}(c^{q+1}(t))$ 
  - $\frac{\partial}{\partial t} (J_{\hat{f}}^T)_i(c^{q+1}(t)) = (H_{\hat{f}}^T)_i(c^{q+1}(t))\Delta c^q$



## Recall: Line Search (Unit 14)

- Given the linearization errors in  $F'(c^q)\Delta c^q = (\beta - 1)F(c^q)$ , the resulting  $\Delta c^q$  can lead to a poor estimate for  $c^{q+1}$  via  $c^{q+1} = c^q + \Delta c^q$
- Instead,  $\Delta c^q$  is often just used as a search direction, i.e.  $c^{q+1} = c^q + \alpha^q \Delta c^q$
- The 1D (parameterized) line  $c^{q+1}(\alpha) = c^q + \alpha \Delta c^q$  is the new domain
- Find an  $\alpha$  with  $F(c^{q+1}(\alpha)) = 0$  simultaneously for all equations
- Safe Set methods restrict  $\alpha$  in various ways, e.g.  $0 \leq \alpha \leq 1$



# Recall: Line Search (Unit 14)

- Since  $F$  is vector valued, consider  $g(\alpha) = F(c^{q+1}(\alpha))^T F(c^{q+1}(\alpha)) = 0$
- Since  $g(\alpha) \geq 0$ , solutions to  $F(c^{q+1}(\alpha)) = 0$  are minima of  $g(\alpha)$
- $g(\alpha)$  might be strictly positive (with no  $g(\alpha) = 0$ ), but minimizing  $g(\alpha)$  might still help to make progress towards an  $\alpha$  with  $F(c^{q+1}(\alpha)) = 0$
  
- Option 1: find simultaneous **roots** of the vector valued  $F(c^{q+1}(\alpha)) = 0$
- Option 2: find **roots** of or minimize  $g(\alpha) = \frac{1}{2} F^T(c^{q+1}(\alpha)) F(c^{q+1}(\alpha))$ , to find or make progress towards an  $\alpha$  with  $F(c^{q+1}(\alpha)) = 0$



# Nonlinear Systems Problems

- Solve  $J_F(c^q)\Delta c^q = (\beta - 1)F(c^q)$  for  $\Delta c^q$  and use  $c^{q+1}(t) = c^q + t\Delta c^q$  in  $F(c^{q+1}(t)) = 0$
- Option 1: find simultaneous (for all  $i$ ) **roots** for all the  $g_i(t) = F_i(c^{q+1}(t)) = 0$ 
  - Here,  $g'_i(t) = (J_F)_i(c^{q+1}(t))\Delta c^q$
- Option 2: find **roots** of  $g(t) = \frac{1}{2}F^T(c^{q+1}(t))F(c^{q+1}(t)) = 0$ 
  - Here,  $g'(t) = \frac{1}{2}F^T(c^{q+1}(t))J_F(c^{q+1}(t))\Delta c^q + \frac{1}{2}(\Delta c^q)^T J_F^T(c^{q+1}(t))F(c^{q+1}(t))$
  - Since both terms are scalars,  $g'(t) = F^T(c^{q+1}(t))J_F(c^{q+1}(t))\Delta c^q$



# Recall: Optimization Problems (Unit 14)

- Minimize the scalar cost function  $\hat{f}(c)$  by finding the critical points where  $\nabla \hat{f}(c) = J_{\hat{f}}^T(c) = F(c) = 0$
- $F'(c^q)\Delta c^q = (\beta - 1)F(c^q)$  gives the search direction (as usual)
- Here,  $F'(c) = J_F(c) = H_{\hat{f}}^T(c)$
- So, solve  $H_{\hat{f}}^T(c^q)\Delta c^q = (\beta - 1)J_{\hat{f}}^T(c^q)$  to find the search direction  $\Delta c^q$
- Option 1: find simultaneous **roots** of the vector valued  $J_{\hat{f}}^T(c^{q+1}(\alpha)) = 0$ , which are critical points of  $\hat{f}(c)$
- Option 2: find **roots** of or minimize  $g(\alpha) = \frac{1}{2}J_{\hat{f}}(c^{q+1}(\alpha))J_{\hat{f}}^T(c^{q+1}(\alpha))$ , to find or make progress towards critical points of  $\hat{f}(c)$
- Option 3: minimize  $\hat{f}(c^{q+1}(\alpha))$  directly



# Optimization Problems

- Solve  $H_{\hat{f}}^T(c^q)\Delta c^q = (\beta - 1)J_{\hat{f}}^T(c^q)$  for  $\Delta c^q$  and use  $c^{q+1}(t) = c^q + t\Delta c^q$  in  $J_{\hat{f}}^T(c^{q+1}(t)) = 0$
- Option 1: find simultaneous (for all  $i$ ) **roots** for all the  $g_i(t) = (J_{\hat{f}}^T)_i(c^{q+1}(t)) = 0$  to find the critical points of  $\hat{f}(c)$ 
  - Here,  $g'_i(t) = (H_{\hat{f}}^T)_i(c^{q+1}(t))\Delta c^q$
- Option 2: find **roots** of  $g(t) = \frac{1}{2}J_{\hat{f}}(c^{q+1}(t))J_{\hat{f}}^T(c^{q+1}(t)) = 0$  to find or make progress towards critical points of  $\hat{f}(c)$ 
  - Here,  $g'(t) = \frac{1}{2}J_{\hat{f}}(c^{q+1}(t))H_{\hat{f}}^T(c^{q+1}(t))\Delta c^q + \frac{1}{2}(\Delta c^q)^T H_{\hat{f}}(c^{q+1}(t))J_{\hat{f}}^T(c^{q+1}(t))$
  - Since both terms are scalars,  $g'(t) = J_{\hat{f}}(c^{q+1}(t))H_{\hat{f}}^T(c^{q+1}(t))\Delta c^q$
- Option 3: **minimize**  $\hat{f}(c^{q+1}(t))$  directly (see **unit 16**)