

## 7. Root finding II: Newton method

## Summary of last lecture

- Iterative algorithms:

$$x_{n+1} = g(x_n)$$

- If an iteration converges to  $x^*$  then  $x^* = g(x^*)$
- $x^*$  solves the equation  $x = g(x)$
- $x^*$  solves root-finding problem  $f(x) = g(x) - x = 0$
- *Sufficient* condition for existence + stability of fixed point:  
 $|g'(x)| < k < 1$  for all  $x$  in an interval

## Goals for today

- Rate of convergence
- Data analysis
- Constructing fixed-point methods to solve equations
- Newton method

## Convergence to a fixed point

- Assume there is a fixed point  $x^*$
- Let's look at the distance  $\delta_n := x_n - x^*$

# Convergence to a fixed point

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- Let's look at the distance  $\delta_n := x_n - x^*$
- We have

$$\begin{aligned}\delta_{n+1} &= x_{n+1} - x^* \\ &= g(x_n) - x^* \\ &= g(x^* + \delta_n) - x^* \\ &\simeq g(x^*) + g'(x^*) \delta_n - x^* && \text{Taylor} \\ &\simeq \delta_n g'(x^*) && \text{since } g(x^*) = x^*\end{aligned}$$

## Convergence to a fixed point II

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- $|\delta_n| \rightarrow 0$  if  $|\alpha| < 1$       **stable** fixed point
- $|\delta_n| \rightarrow \infty$  if  $|\alpha| > 1$       **unstable** fixed point



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  - What does the speed of convergence mean?
- 
- The speed of convergence tells us **how good the approximation algorithm is**
  - An algorithm that *converges faster* does *less work* to solve the problem

## Collaboration I: Data analysis using logarithms

### Data analysis using logarithms

Suppose we have data pairs  $(x_i, y_i)$ .

- 1 On a semi-log graph, with a logarithmic scale for  $y$ , what are the variables we're plotting?
- 2 If we see a straight line on a semi-log graph, how are these new variables related?
- 3 So what is the relationship between the original variables  $x$  and  $y$ ?
- 4 Repeat this if instead we have a straight line on a log-log graph, i.e. with logarithmic axes in both  $x$  and  $y$ .

## Data analysis: Semi-log graphs

- Suppose we have some data that “look exponential”
- I.e. points  $(x_i, y_i)$  that we *think* satisfy

$$y \sim \exp(-\alpha x)$$

- How could we become “more confident” about this by plotting the data in a different way?

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- How could we become “more confident” about this by plotting the data in a different way?
- Plot the data with a logarithmic axis in the  $y$  direction
- Effectively we are plotting  $\log(y_i)$  against  $x_i$

## Data analysis: Semi-log graphs II

- If plotting  $\log(y_i)$  against  $x_i$  gives a straight line then

$$\log(y_i) \sim -Ax_i + B$$

for some constants  $A$  and  $B$

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- So

$$y_i \sim \exp(B - Ax_i) = C \exp(-Ax_i)$$



## Data analysis: Log-log graphs

- Suppose we have some data that “decay but not fast enough to be exponential”
- Suppose we plot the data with logarithmic axes in the  $x$  and  $y$  directions
- What can we conclude if we find a straight line?

## Data analysis: Log-log graphs

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- What can we conclude if we find a straight line?

$$\log(y_i) \sim -\alpha \log(x_i) + \beta$$

- So

$$y_i \sim \exp[\beta - \alpha \log(x_i) + \beta] = Cx_i^{-\alpha}$$

– a **power law**

## Cobweb diagrams

- A nice visualisation of fixed-point iteration is given by **cobweb diagrams**
- We can think of the fixed-point iteration  $x_{n+1} = g(x_n)$  as the two successive operations

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- So we plot a trajectory that visits the points  $(x_n, g(x_n))$  and  $(x_{n+1}, x_{n+1})$
- We see how the condition  $|\text{derivative}| < 1$  leads to convergence

## Constructing a useful iteration

- Given a root-finding problem  $f(x) = 0$  to solve
- How can we *construct* a  $g$  such that the iteration  $x_{n+1} = g(x_n)$  converges to a root of  $h$ ?

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- How can we *construct* a  $g$  such that the iteration  $x_{n+1} = g(x_n)$  converges to a root of  $h$ ?
- We know that *if* it converges to  $x^*$ , then  $x^* = g(x^*)$
- So we need to rearrange  $f(x) = 0$  into  $g(x) = x$

## Constructing a useful iteration II

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- One possibility is  $g(x) = f(x) + x$



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for *any*  $\phi$ !

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for *any*  $\phi$ !

- We need  $|g(x^*)| < 1$  at the fixed point
- This is tricky: *we don't know where the fixed point is*

## Towards the Newton method

- So far we have seen that the convergence in fixed-point iterations has  $\delta_{n+1} \simeq \alpha \delta_n$
- Thus the convergence is exponential
- How could we try to *accelerate* convergence?

## Towards the Newton method

- So far we have seen that the convergence in fixed-point iterations has  $\delta_{n+1} \simeq \alpha \delta_n$
- Thus the convergence is exponential
- How could we try to *accelerate* convergence?
- Look at the cobweb plot
- What would happen if  $g'(x^*) = 0$ ?

## Collaboration: A special fixed-point iteration

### A special fixed-point iteration

Let's look for roots of  $f$ , i.e.  $x^*$  such that  $f(x^*) = 0$ .

Define  $g(x) := x - \phi(x)f(x)$  and look for fixed points of  $g$ .

If we impose  $g'(x^*) = 0$ , what should  $\phi$  satisfy?

## Newton method as a fixed-point iteration

- Let's look for a fixed-point algorithm to solve  $f(x) = 0$
- Define  $g(x) := x - \phi(x)f(x)$   
where  $\phi$  is as-yet unknown

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where  $\phi$  is as-yet unknown
- Let's *impose* that  $g'(x^*) = 0$  at the root  $f(x^*) = 0$ , in other words at the fixed point  $g(x^*) = x^*$

## Newton method as a fixed-point iteration II

- We have  $g(x) := x - \phi(x)f(x)$
- So  $g'(x) = 1 - \phi'(x)f(x) - \phi(x)f'(x)$
- So  $g'(x^*) = 1 - \phi(x^*)f'(x^*) = 0$  since  $\phi'(x^*) = 0$



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- So  $g'(x^*) = 1 - \phi(x^*)f'(x^*) = 0$  since  $\phi'(x^*) = 0$
- So we must take  $\phi(x^*) = \frac{1}{f'(x^*)}$
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- So we must take  $\phi(x^*) = \frac{1}{f'(x^*)}$
- Take  $\phi(x) := \frac{1}{f'(x)}$
- This gives the **Newton method**:

$$g(x) := x - \frac{\phi(x)}{\phi'(x)}$$

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- Impose  $f(x_0 + \delta) = 0$
- Taylor to first order:

$$f(x_0) + f'(x_0) \delta \simeq 0$$

- So  $\delta = -f(x_0)/f'(x_0)$
- And  $x_1 = x_0 - \frac{f(x_0)}{f'(x_0)}$

# Newton method

- The Newton method is a *general* method to try to find a root for *any* function  $f$ :

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$$x_{n+1} = x_n - \frac{f(x_n)}{f'(x_n)}$$

- Iteration with  $g(x) = x - f(x)/f'(x)$
- Sufficiently close to a root, it converges *very fast*
- But it *may fail to converge*!
- The Babylonian algorithm is a special case



# Convergence of Newton method

- There are known conditions for Newton to converge:
  - Smale  $\alpha$  theory
  - Radii polynomials
- Interval Newton method: Use interval arithmetic to guarantee convergence

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then the iteration is of **order**  $\alpha$

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- $\delta_{n+1} \sim \delta_n^\alpha$  as  $n \rightarrow \infty$
- $\alpha = 1$ : “**linear**” convergence
- $\alpha = 2$ : “**quadratic**” convergence

# Summary

- Rate of convergence
- Some data analysis
- Newton method:
  - General fixed-point method to solve  $f(x) = 0$