

- You can skip sections 5.3, 5.4 (regula-falsi and fixed-point iteration)
- So far we have focused on <u>linear equations</u>.
 This is because we can <u>solve</u> these equations in a finite number of steps!

 $\mathbf{A}\mathbf{x} = \mathbf{b}$ is solved in (N^3) steps!

- Example: suppose we are trying to fit some reaction rate data as a function of T.
- If we have a single irreversible reaction:

$$k = a e^{-E_a/k_BT}$$

a: pre-exponential factor

E_a: activation energy

k_B: Boltzmann's constant

- If we have a series of measured reaction rates
 k_i(T_i) we can solve for a and E_a using <u>linear</u>
 regression.
- Transform equation: $\ln k = \ln a E_a/k_B (1/T)$ b $x_1 x_2$
- So find the **x** that minimizes norm($\mathbf{Ax} \mathbf{b}$)², where $\mathbf{b} = (\ln k_1; \ln k_2; ...; \ln k_n)$ and $\mathbf{A} = (1, 1/T_1; 1, 1/T_2; ...; 1, 1/T_n).$

- So we know how to solve that. Suppose now we have a more complex problem in which a substance can follow 2 reaction pathways.
- In this case:

$$k = a_1 e^{-E_{a1}/kT} + a_2 e^{-E_{a2}/kT}$$

- You can't linearize this!
- We can still set it up as a least squares problem...

So we still find the x that minimizes

norm
$$(k_i - k(T_i))^2 = S(\mathbf{x}),$$

where $\mathbf{x} = (a_1; E_{a_1}; a_2; E_{a_2}).$

• We can determine the minimum by requiring dS(x)/dx = 0: 4 equations with 4 unknowns.

• But this is a <u>nonlinear problem</u>.

- Nonlinear problems are <u>nasty</u> because:
 - It may not have a unique solution!
 You may have multiple roots, local minima, etc.
 For linear problems (non-singular) you are guaranteed a unique solution!
 - 2. For linear systems, you can solve it in a finite number of steps $(O(n^3))$.

For nonlinear problems there is <u>no</u> guarantee – sometimes algorithms will fail to converge on <u>any</u> solution!

- Let's focus on the problem f(x) = 0
 (we'll generalize this to the system f(x) = 0 later)
- Let x^* satisfy $f(x^*) = 0$
- We will say that x' "solves" f(x)=0 if:
 |f(x')| ~ 0 or |x' x*| ~ 0
 - (~0 means less than some set tolerance)
- We need this dual definition because f(x) may have a steep slope near x*.

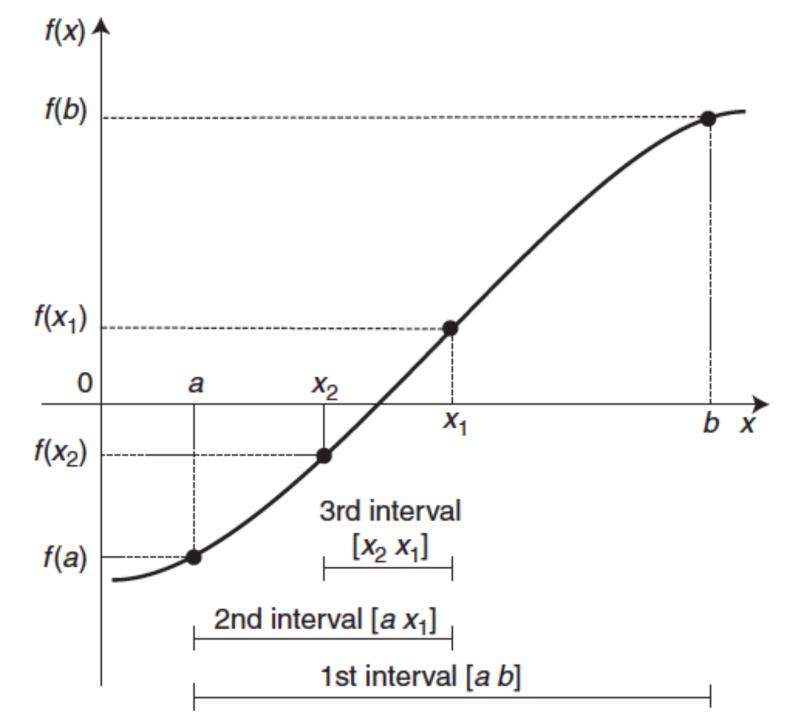
The approaches to solving f(x) = 0 are <u>iterative</u>
 we obtain a series (sequence) of approximations to the solution:

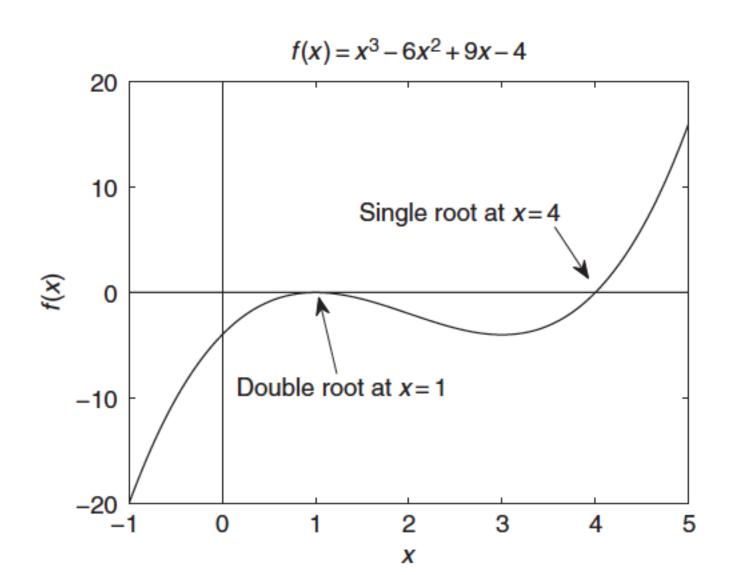
$$X_1, X_2, X_3, ..., X_n$$

which hopefully converges on x*!

- How do we do this?
- The simplest approach is the method of bisection.

- Suppose f(x) is <u>continuous</u> over the interval x~[a,b] <u>and</u> that f(a)f(b) < 0.
- Then we know that there is at least one root in this interval!
- We can get within some interval of x* in a finite number of steps!
- We divide the interval in half and test to see which is satisfied:
 - f(a)f(m) < 0 or f(m)f(b) < 0, where m = (a+b)/2
- We just keep the half with the root!





- How fast does this converge?
- Each iteration divides the interval in <u>half</u>, the midpoint is an estimate of x*, thus

$$|m-x^*|$$

is cut in half (approximately) at each iteration.

 The error is less than 10⁻⁷ of the original interval after about 24 iterations.

- Let's take e_i as the error at the ith iteration (e.g., m – x*).
- Then for bisection, $|e_{i+1}|/|e_i| \sim \frac{1}{2}$ on average.
- In general, a method is said to converge at a rate <u>r</u> if:

$$limit(i -> inf) |e_{i+1}|/|e_i|^r = c$$

In general, |e_i| << 1 so we want r to be <u>large</u>
 (>1) and c to be small.

- If c is too large the method won't converge!
- If r=1 the method is linear
- If r=2 the method is <u>quadratic</u>
- If r>1 the method is <u>superlinear</u>

• For bisection, r=1 (linear convergence).

Q1: Is the following model "linear"? Meaning, can it be formulated as a linear regression?

$$y = a \cdot e^{-kt}$$

- A. Yes
- B. No

Q2: How many model parameters does this model have?

$$y = a \cdot e^{-kt}$$

- A. 1
- B. 2
- C. 3
- D. 4

Q3: How about the following model. Is it "linear"? Can it be formulated as a linear regression?

$$y = a_1 \cdot e^{-k_1 t} + a_2 \cdot e^{-k_2 t}$$

- A. Yes
- B. No

Q4: Okay, so we must use <u>nonlinear regression</u> to fit this model to a data set. So how many <u>model parameters</u> does it have?

$$y = a_1 \cdot e^{-k_1 t} + a_2 \cdot e^{-k_2 t}$$

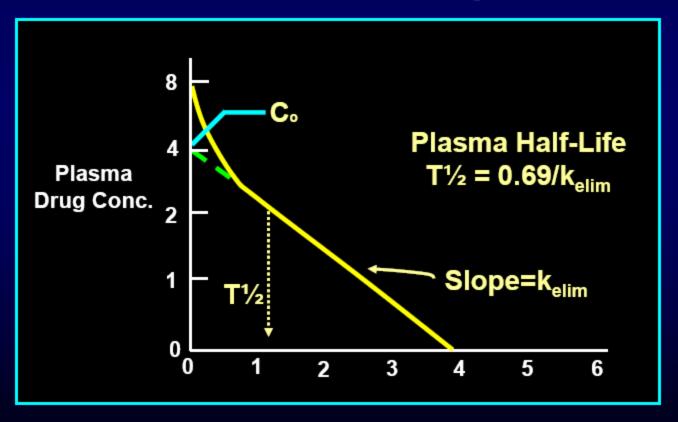
- A. 1
- B. 2
- C. 3
- D. 4
- E. 5

A. The Single Compartment Model of drug distribution assumes that the drug distributes evenly throughout a single homogeneous space in the body. While this is obviously an over-simplification, it often allows us to predict the general pharmacokinetic properties of the drug sufficiently well for clinical use.



B. The Apparent Volume of Distribution (V_d) of this single compartment can be estimated by dividing the intravenously administered dose by the initial blood concentration (C_o):

$$V_d = IV Dose / C_o$$



Simple Compartmental Model (lumped)

Absorption

R or ko

Body

Elimination

 $\mathbf{k_1}$

1st order absorption: $\frac{dA}{dt} = -k_0 A$ $\frac{dE}{dt} = k_1 B$ $\frac{dB}{dt} = k_0 A - k_1 B$

$$\frac{dA}{dt} = -k_0 A$$

$$\left| \frac{dE}{dt} = k_{\scriptscriptstyle 1} B \right|$$

$$\frac{dB}{dt} = k_{\scriptscriptstyle 0} A - k_{\scriptscriptstyle 1} B$$

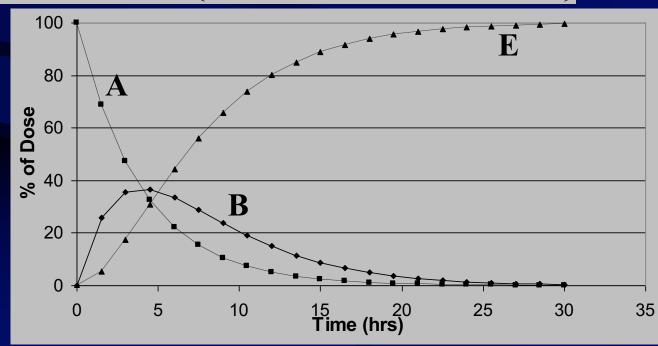
Solution:
$$A(t) = A_0 \exp(-k_0 t)$$

$$B(t) = \frac{k_{0}A_{0}}{k_{1}-k_{0}} = [\exp(-k_{0}t) - \exp(k_{1}t)]$$

$$B(t) = \frac{k_{0}A_{0}}{k_{1} - k_{0}} = \left[\exp(-k_{0}t) - \exp(k_{1}t)\right]$$

$$E(t) = A_{0} - A(t) - B(t) = A_{0} \left\{1 - \left(\frac{1}{k_{1} - k_{0}}\right) \left[k_{1} \exp(-k_{0}t) - k_{0} \exp(-k_{1}t)\right]\right\}$$

 $IC's:A(o)=A_0$ B(0) = 0E(o)=0



Simple Compartmental Model (lumped)

