

Last section of 2.5

Backwards differentiation formulas

Last time we used the theorem

$$\sigma(w) = \frac{\rho(w)}{\log w} + O(|w-1|^p)$$

to find σ given a ρ that satisfies the root condition. This guarantees the method converges and then taking $p=s$ for an explicit method guarantees optimal order (or $p=s+1$ for an implicit method is also good).

Backwards differentiation formula solves for $\rho(w)$ given $\sigma(w)$:

$$\rho(w) = \log w \sigma(w) + O(|w-1|^{p+1})$$

where $\sigma(w) = \beta w^s$
↑
some constant...

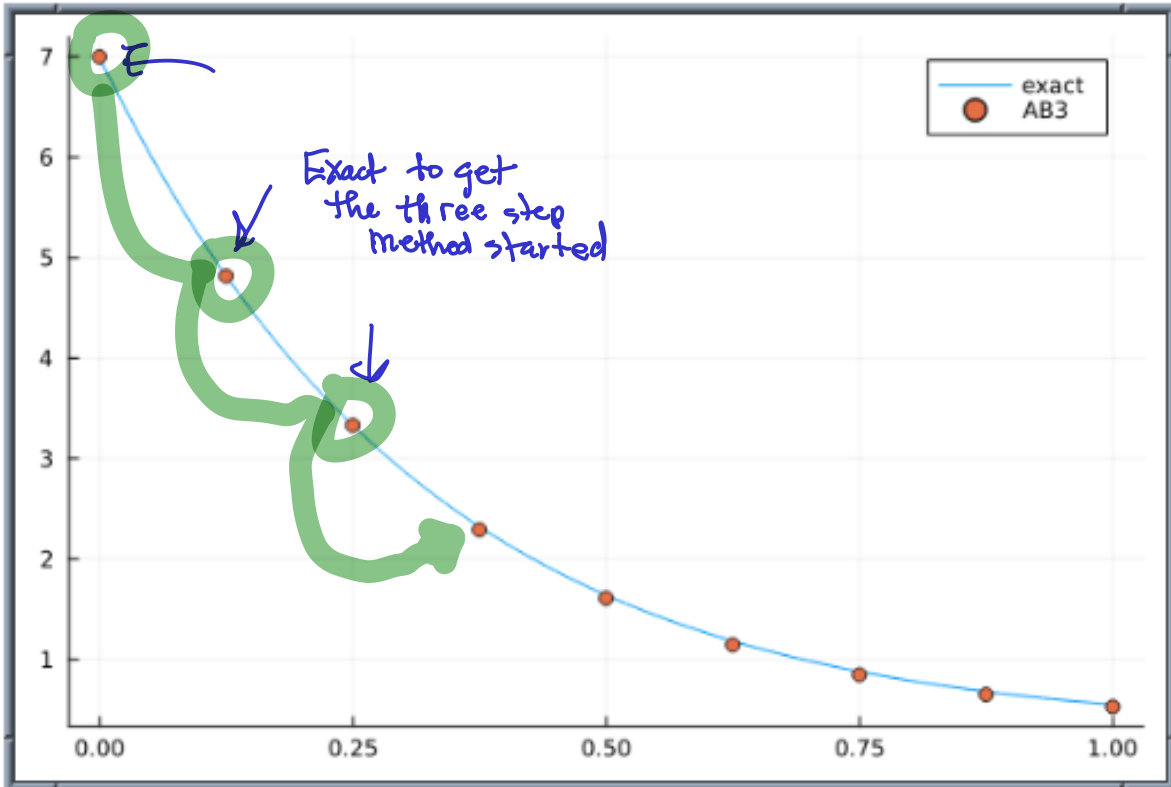
Note this is an implicit method since degree of σ is s and the same as ρ .

$$\sum_{m=0}^s a_m y_{n+m} = h \sum_{m=0}^s \beta_m f(t_{n+m}, y_{n+m}) \quad \text{where } n = 0, 1, \dots$$

BDF

$$\sum_{m=0}^s a_m y_{n+m} = h \beta f(t_{n+s}, y_{n+s})$$

↑
implicit on the RHS this increases stability for making rough approximations.
→ to be (discussed later)



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julia> rho(w)=w^(s-1)*(w-1) ← define ρ for AB method
rho (generic function with 1 method)

julia> t=Taylor1(s) ← Taylor series in t as 5 degree polynomials
1.0 t + 0(t^4)

julia> sigma=rho(t+1)/log(t+1) ← Create Taylor series expanded in
1.0 + 2.5 t + 1.9166666666666667 t^2 + 0(t^3)
    ← w = ξ + 1
    ← note its now O(|w-1|^3)

julia> z=evaluate(sigma,[t-1])[1]
0.41666666666666674 - 1.3333333333333335 t
+ 1.9166666666666667 t^2 + 0(t^3)
    ← shift back to the w variable...

julia> b=z.coeffs
3-element Vector{Float64}:
 0.41666666666666674  b₀ = b[1]
-1.3333333333333335  b₁ = b[2]
 1.9166666666666667  b₂ = b[3]

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