Numerical Analysis & Scientific Computing II

Lesson 2 Initial Value Problems

- 2.2 Stability
- 2.3 Euler's method
- 2.4 Implicit method
 - Trapezoidal method



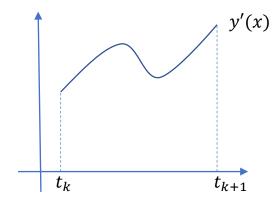


How do we obtain a higher-order method?



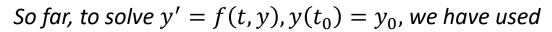
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So far, to solve
$$y'=f(t,y), y(t_0)=y_0$$
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$$y(t_{k+1})=y(t_k)+\int_{t_k}^{t_{k+1}}y'(s)ds$$



Initial Value Problems: Implicit Methods

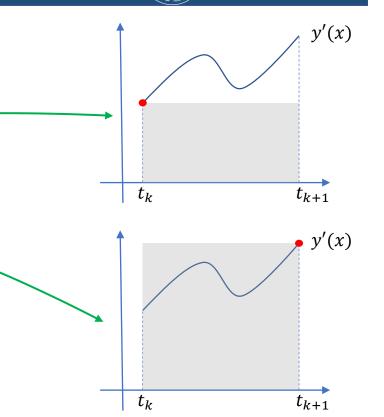
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Initial Value Problems: Implicit Methods

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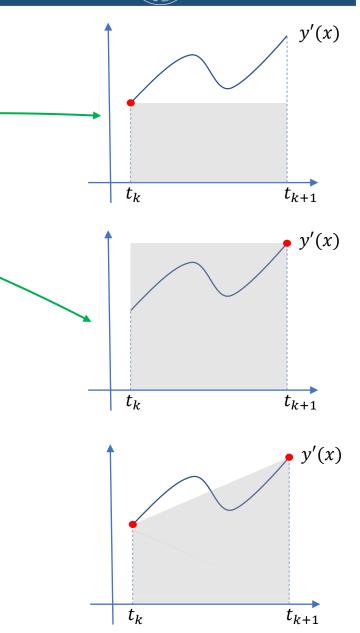
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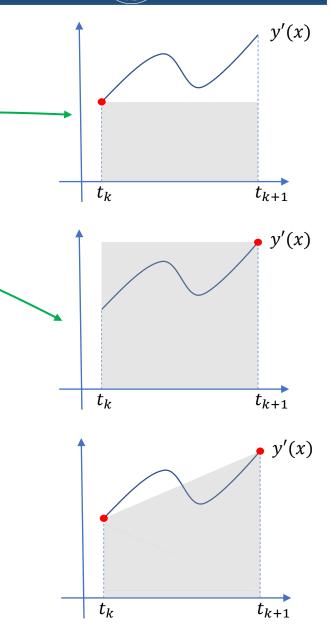
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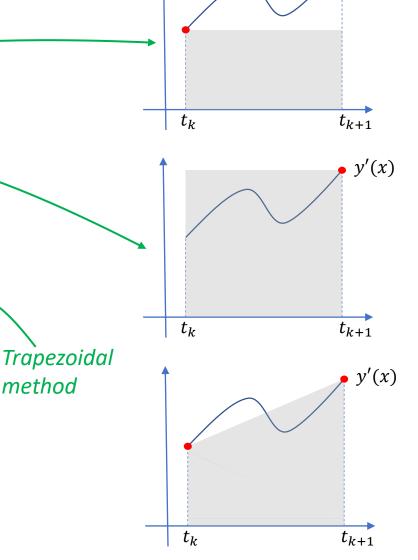
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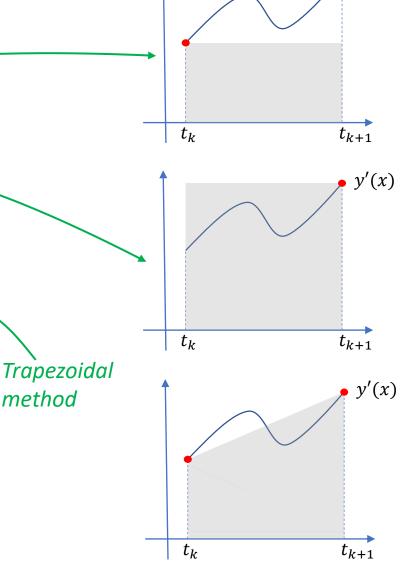
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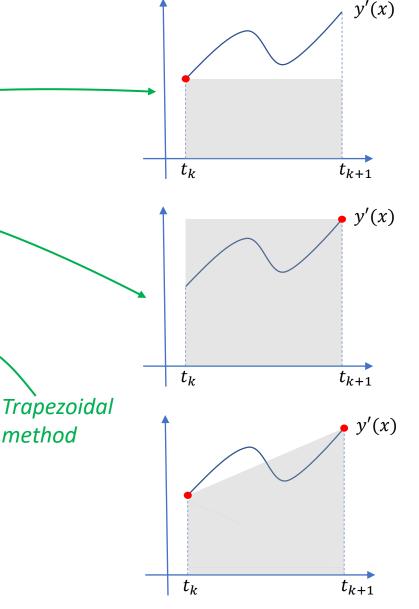
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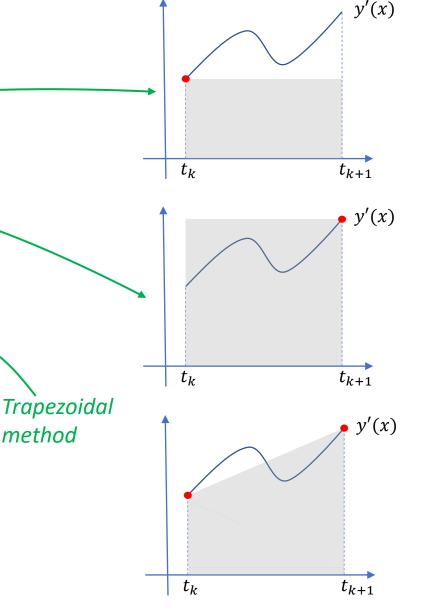
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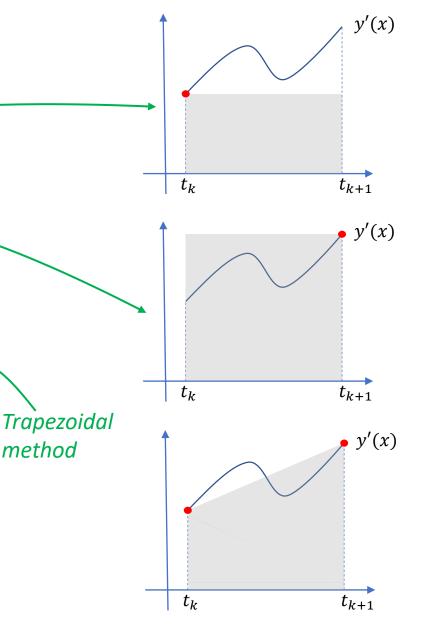
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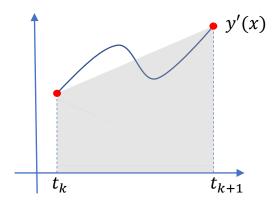
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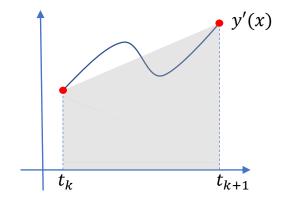
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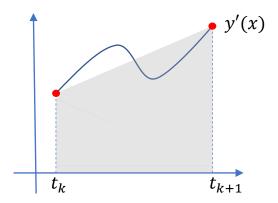
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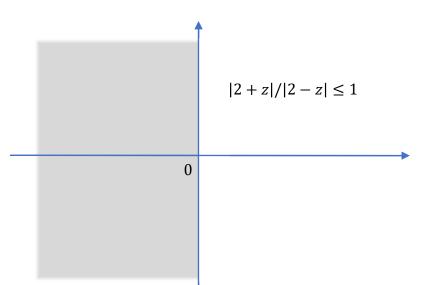
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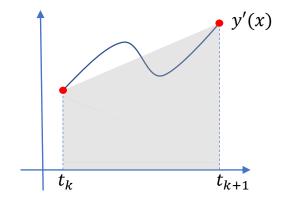
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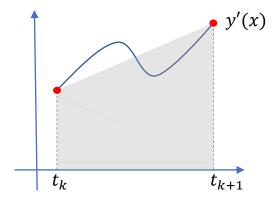
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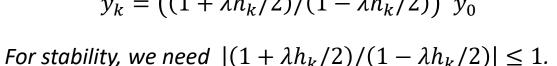
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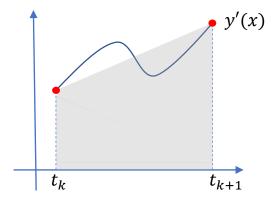
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$$\begin{split} \ell_{k+1} &= y(t_k) + h_k \big(f(t_k, y(t_k)) + f(t_{k+1}, y(t_{k+1})) \big) / 2 - y(t_{k+1}) \\ &= h_k \big(f(t_k, y(t_k)) + f(t_{k+1}, y(t_{k+1})) \big) / 2 - (y(t_{k+1}) - y(t_k)) / 2 + \big(y(t_k) - y(t_{k+1}) \big) / 2 \\ &= h_k \big(f(t_k, y(t_k)) + f(t_{k+1}, y(t_{k+1})) \big) / 2 - \big(h_k y'(t_k) + h_k^2 y''(t_k) / 2 + O(h_k^3) \big) / 2 \\ &+ \Big(-h_k y'(t_{k+1}) + h_k^2 y''(t_{k+1}) / 2 + O(h_k^3) \Big) / 2 \end{split}$$





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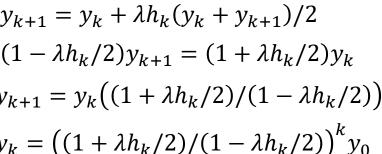
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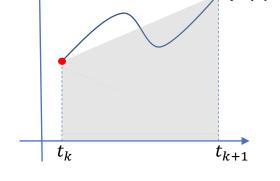
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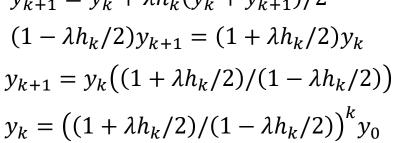
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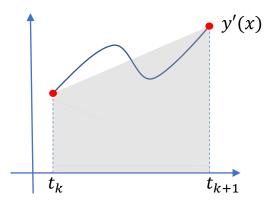
For order of accuracy, we look at the local error

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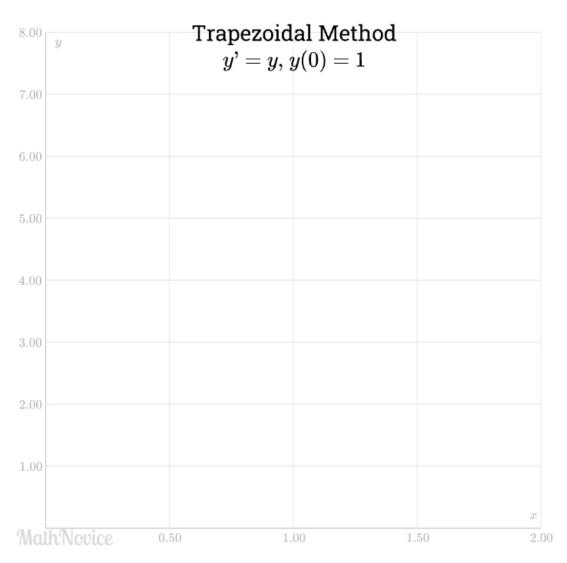
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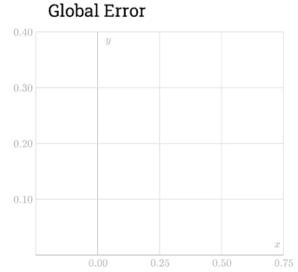
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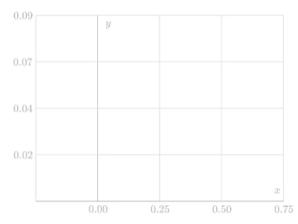
second-order accurate!





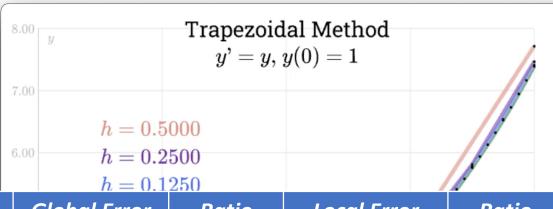


Max Local Error

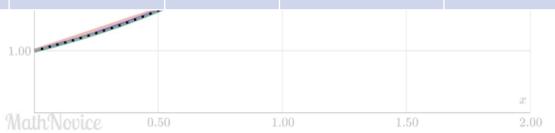


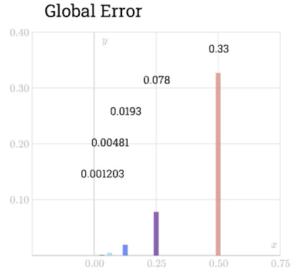
Source: https://www.youtube.com/watch?v=kcgtbXgDNE8





R = 0.1250		<i># 10</i>		
h	Global Error	Ratio	Local Error	Ratio
1/2	0.33	4.23	0.08	8.00
1/4	0.078	4.04	0.010	8.33
1/8	0.0193	4.01	0.0012	8.00
1/16	0.00481	4.00	0.00015	7.90
1/32	0.001203	_	0.000019	_





Max Local Error



Numerical Analysis & Scientific Computing II

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- 2.4 Implicit method
- 2.5 Stiffness





Example

Consider the following IVP, y' = f(t, y), $y(0) = y_0$, where

$$y = \begin{bmatrix} y_1 \\ y_2 \end{bmatrix}$$
, $f(t, y) = \begin{bmatrix} -1 & 0 \\ 0 & -100 \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \end{bmatrix}$, and $y_0 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$.

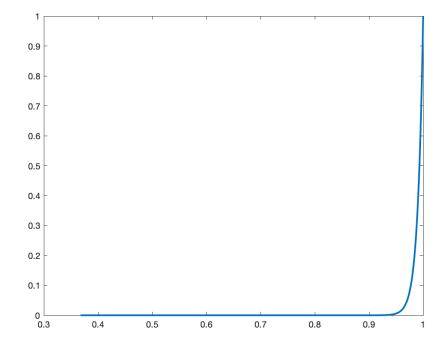


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Exact solution



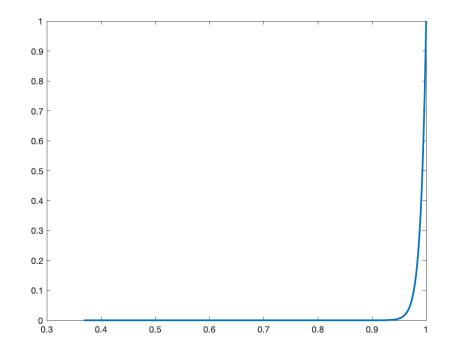


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Exact solution



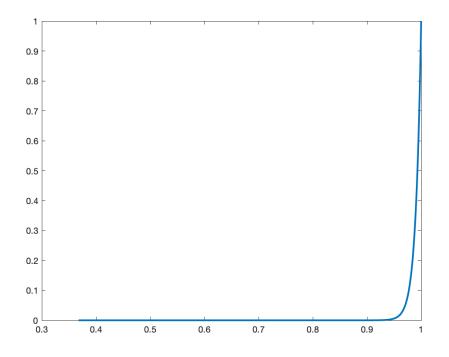


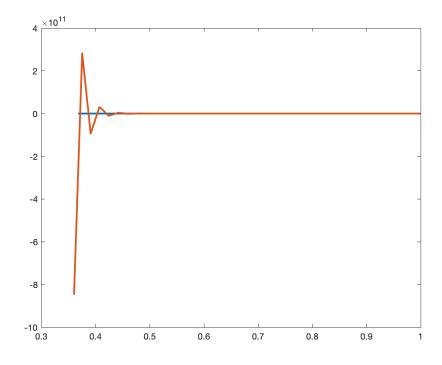
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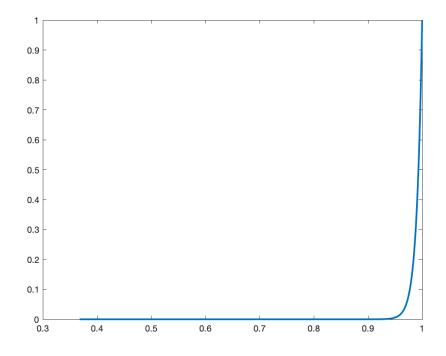


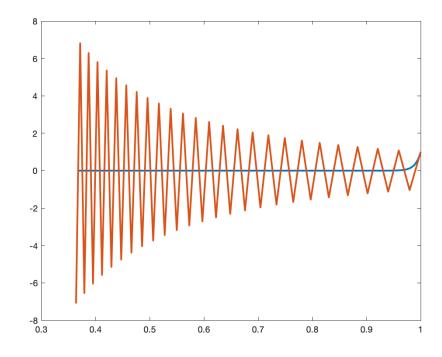
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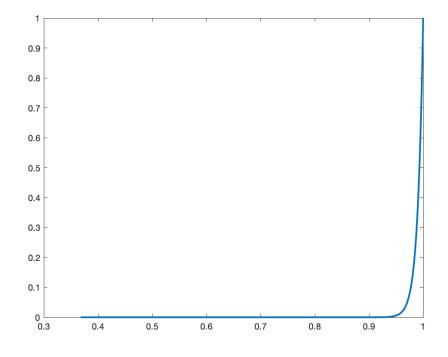


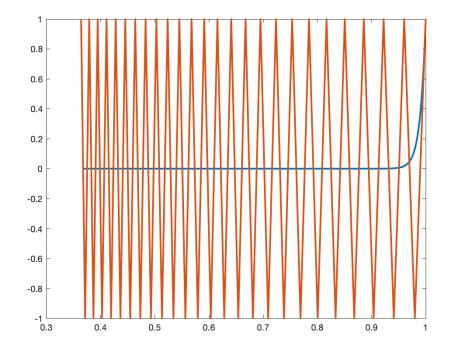
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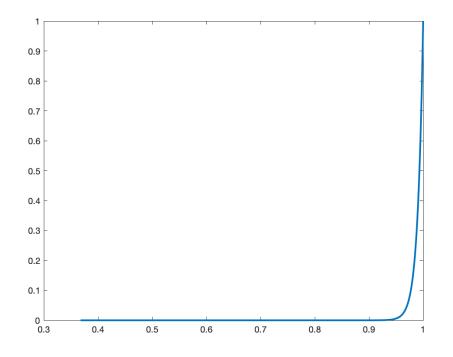


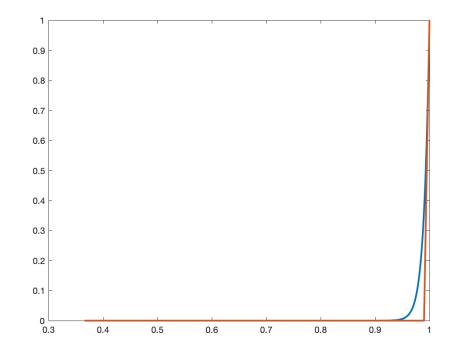
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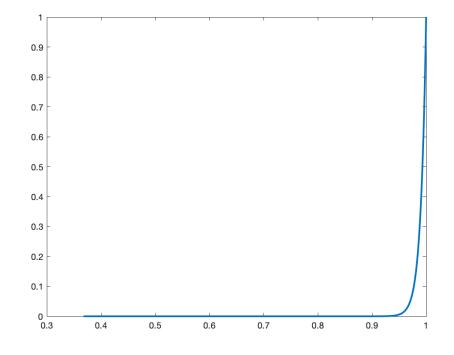


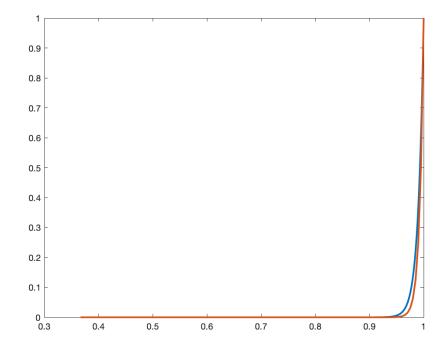
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The more severe restriction $h \le 0.02$ is primarily due to the second equation $y_2' = -100y_2$ which governs the component that varies much more rapidly than the first component y_1 .



Stiffness

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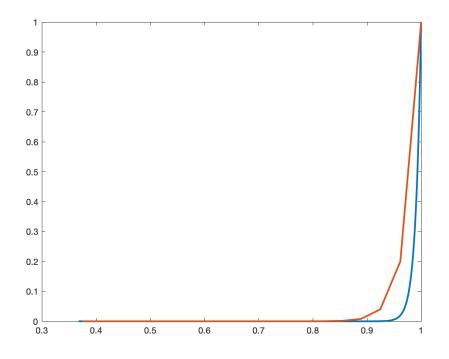


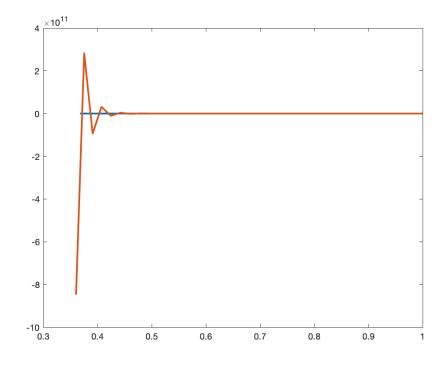
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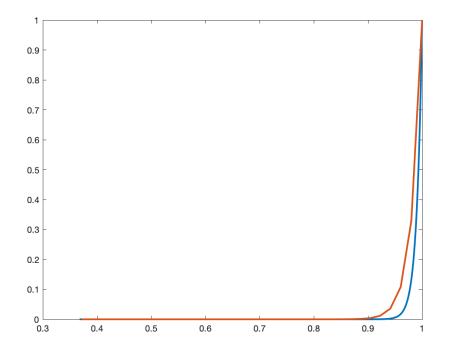


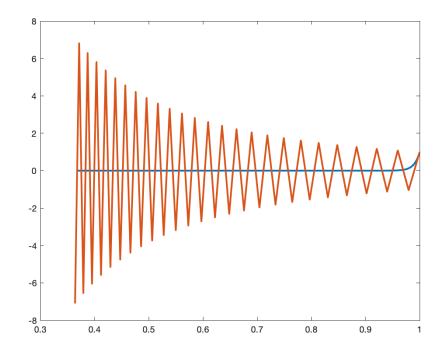
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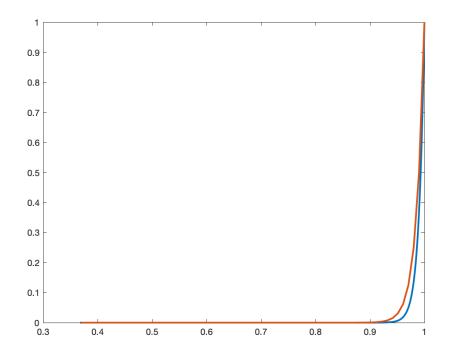


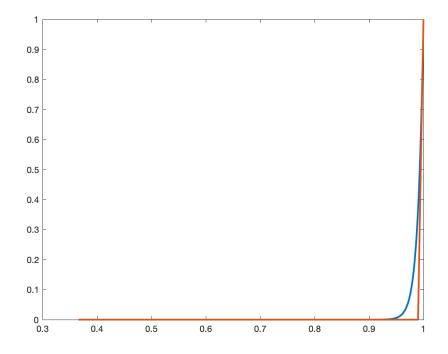
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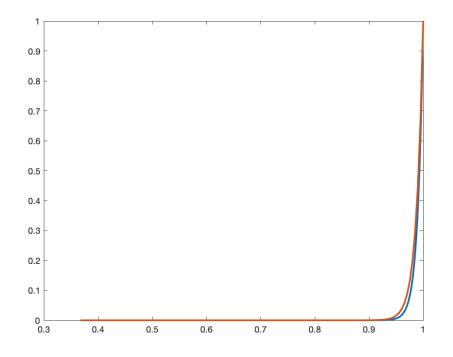


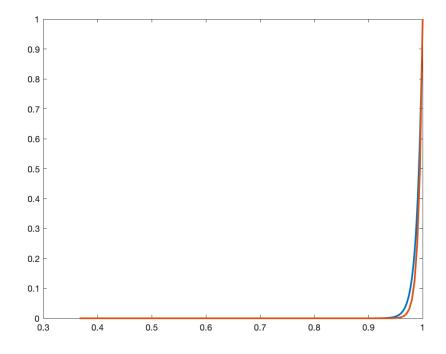
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Therefore, implicit methods are required for stiff ODEs. Thus, a nonlinear (generally) equation must be solved at each step. For fixed point iterations to converge, step size h must be small which defeats the purpose of using implicit method at the first place. As a result, Newton's method or its variants are used.