

# Computational practicum: Lecture 7

## Boundary value problems (BVPs): Shooting method, solve\_bvp function

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**Process  
Intelligence  
RESEARCH**

**Delft Institute of  
Applied Mathematics**

# Recap last lecture



## Boundary value problems (BVPs)

- BVPs have side constraints at more than one point.
- Boundary conditions define side constraints, e.g.,
  - Dirichlet boundary condition  $y = f$
  - Neumann boundary condition  $\frac{dy}{dx} = f$
  - ...

## Finite difference method

- Equation, e.g.,

$$\frac{d^2y}{dx^2} + \alpha \frac{dy}{dx} + y\beta = f(x)$$

- Finite difference equations for all nodes:

$$y_{i+1} \left( 1 + \frac{h}{2} \alpha \right) + y_i (h^2 \beta - 2) \\ + y_{i-1} \left( 1 - \frac{h}{2} \alpha \right) = h^2 f(x_i)$$

$$\forall i \in [1, N - 1]$$

$$y_0 = y_a, \quad y_N = y_b$$

# Learning goals of this lecture

After successfully completing this lecture, you are able to...

- explain numerical solution methods for boundary value problems (BVPs), namely:
  - finite difference method,
  - shooting method.
- implement the shooting method for boundary value problems (BVPs) from scratch.
- use Python libraries' built-in functions for numerical solution approaches to BVPs.

# Agenda

- **Boundary value problems (BVPs)**
  - Shooting method
    - a. Linear interpolation
    - b. Root-finding with secant method
  - *Solve\_bvp* function

# Agenda

- Boundary value problems (BVPs)
  - Shooting method
    - a. Linear interpolation
    - b. Root-finding with secant method
  - *Solve\_bvp* function

# An example boundary value problem (BVP)

- ODE

$$\frac{d^2y}{dx^2} = 4(y - x)$$

- Domain

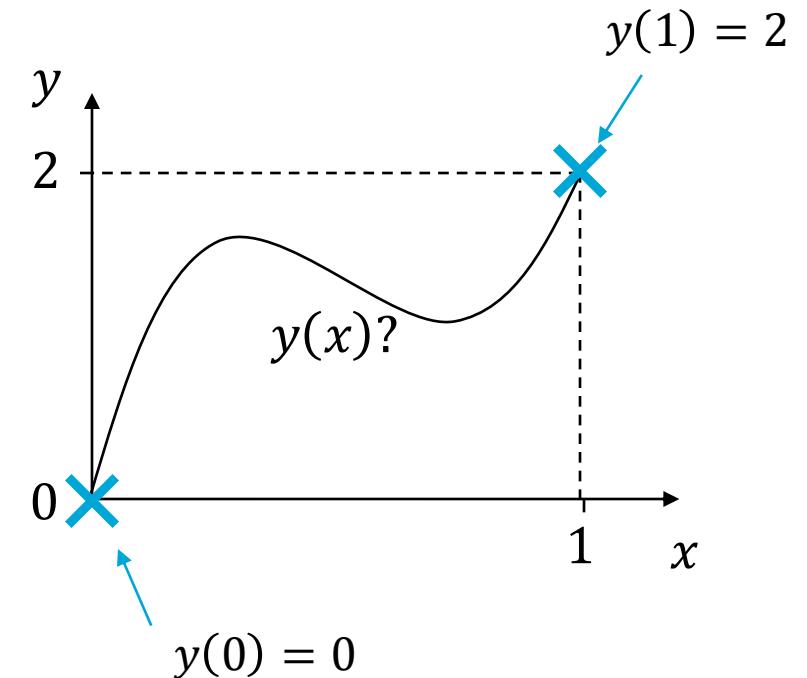
$$x \in [0,1]$$

- Boundary conditions

$$y(0) = 0, \quad y(1) = 2$$

- Let's try to interpret the BVP as an initial value problem (IVP)!

- The ODE is not 1<sup>st</sup> order!
- The ODE is non-autonomous but for the methods presented here, this is not a problem.



## RECAP

To solve an IVP, the ODE should be in a 1<sup>st</sup> order form, cf. lecture 5.

# Rewrite BVP in 1<sup>st</sup> order

- ODE

$$\frac{d^2y}{dx^2} = 4(y - x)$$

- Variable substitution

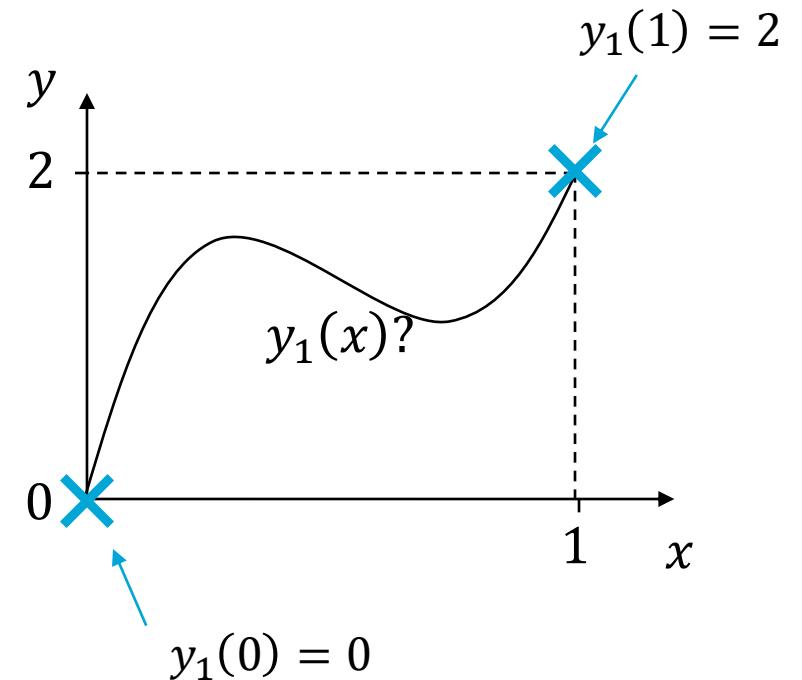
$$y_1 \equiv y, \quad y_2 \equiv \frac{dy_1}{dx}$$

- 1<sup>st</sup> order ODE system

$$\frac{dy_1}{dx} = y_2, \quad \frac{dy_2}{dx} = 4(y_1 - x)$$

- Initial conditions?

$$y_1(0) = 0, \quad y_2(0) = ?$$



There is no initial condition defined for  $y_2$ . We need the initial condition to apply the IVP methods.

# The shooting method

- 1<sup>st</sup> order ODE system

$$\frac{dy_1}{dx} = y_2, \quad \frac{dy_2}{dx} = 4(y_1 - x)$$

- Boundary conditions

$$y_1(0) = 0, \quad y_1(1) = 2$$

For now, ignore when solving the IVP

1. Make a (random) guess for the **initial** condition of  $y_2$ .

$$y_2(0) = \gamma_0 = 1$$

2. Solve the ODE system with the IVP methods from lecture 5, e.g., forward Euler method.
3. Evaluate the solution and **update** the guess  $\gamma$  for  $y_2(0)$  until  $y_1(1; \gamma) = 2$ .



For an IVP, all side constraints (“initial conditions”) need to be defined in one point. This point does not necessarily need to be the left domain boundary.

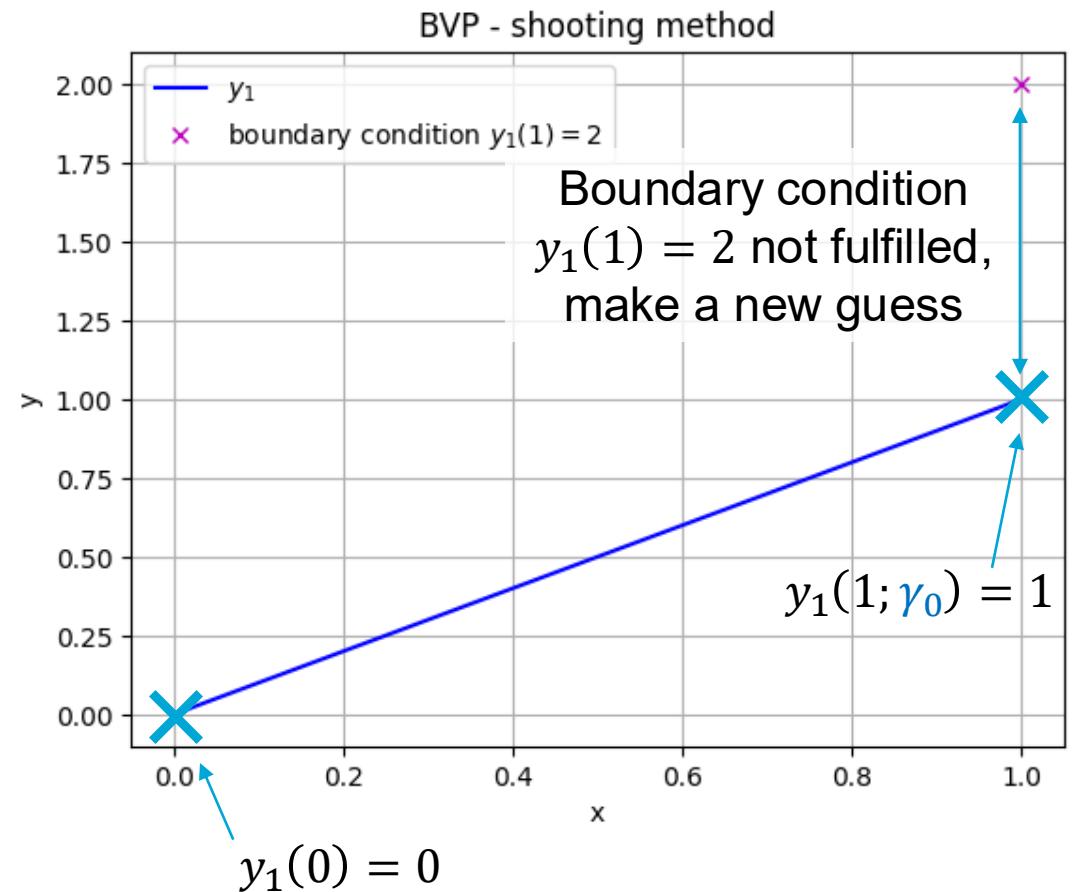
Greek letter gamma  $\gamma$ , not to be confused with Latin letter  $y$ .

# The shooting method

$$\frac{dy_1}{dx} = y_2, \quad \frac{dy_2}{dx} = 4(y_1 - x), \quad y_1(0) = 0$$

- First guess  $\gamma_0$

$$y_2(0) = \gamma_0 = 1$$



# The shooting method

$$\frac{dy_1}{dx} = y_2, \quad \frac{dy_2}{dx} = 4(y_1 - x), \quad y_1(0) = 0$$

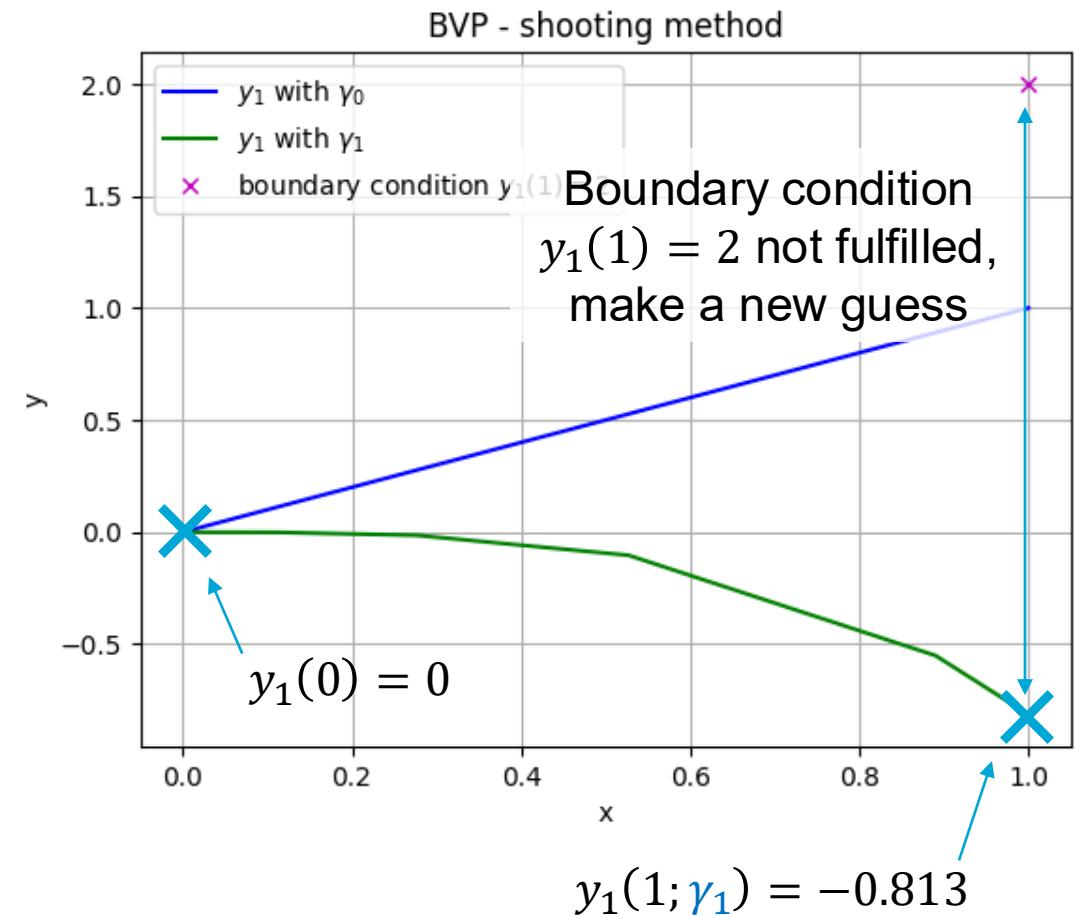
- First guess  $\gamma_0$

$$y_2(0) = \gamma_0 = 1$$

- Second guess  $\gamma_1$

$$y_2(0) = \gamma_1 = 0$$

We “shoot” from the start of the domain toward target. Then we repeat the shooting until we hit the target. Therefore, the method is called shooting method. :D



# The shooting method

$$\frac{dy_1}{dx} = y_2, \quad \frac{dy_2}{dx} = 4(y_1 - x), \quad y_1(0) = 0$$

- First guess  $\gamma_0$

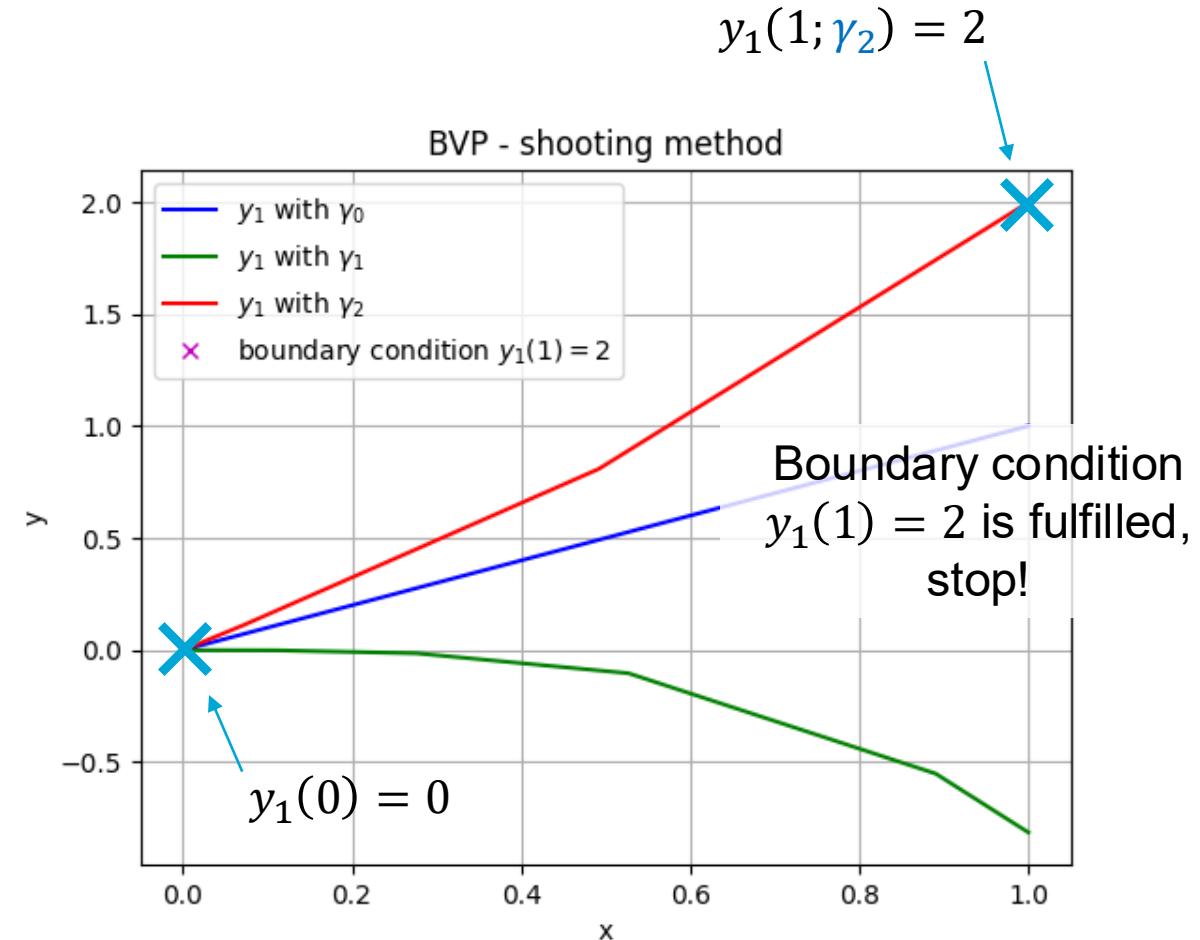
$$y_2(0) = \gamma_0 = 1$$

- Second guess  $\gamma_1$

$$y_2(0) = \gamma_1 = 0$$

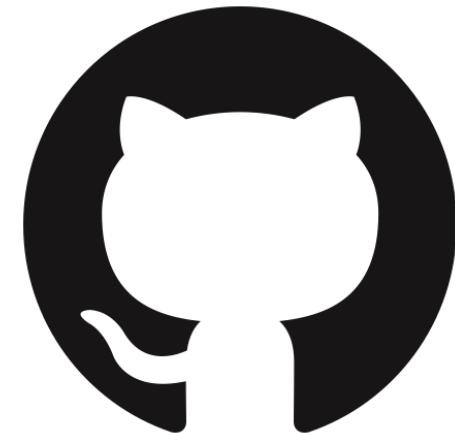
- Third guess  $\gamma_2$

$$y_2(0) = \gamma_2 = 1.55$$



# Live coding: Shooting method

- Open Colab: [Shooting method](#)



- Find more in the Github repository of the course: [https://github.com/process-intelligence-research/computational\\_practicum\\_lecture\\_coding/tree/main](https://github.com/process-intelligence-research/computational_practicum_lecture_coding/tree/main)

# The shooting method

$$\frac{dy_1}{dx} = y_2, \quad \frac{dy_2}{dx} = 4(y_1 - x), \quad y_1(0) = 0$$

- First guess  $\gamma_0$

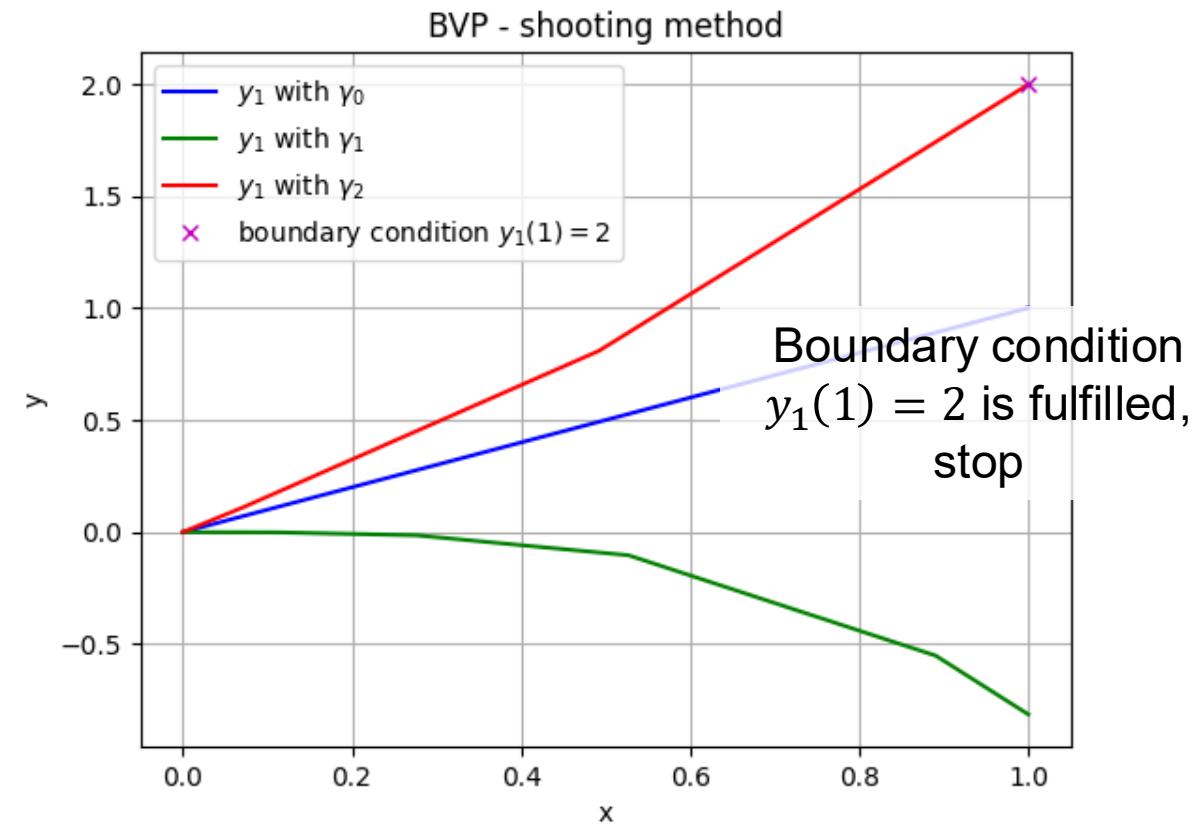
$$y_2(0) = \gamma_0 = 1$$

- Second guess  $\gamma_1$

$$y_2(0) = \gamma_1 = 0$$

- Third guess  $\gamma_2$

$$y_2(0) = \gamma_2 = 1.55$$



So far, we were randomly guessing the initial conditions. However, we want to make clever, strategic decisions on the initial conditions.

# Agenda

- Boundary value problems (BVPs)
  - Shooting method
    - a. Linear interpolation
    - b. Root-finding with secant method
  - *Solve\_bvp* function

# Updating guess: Linear interpolation

- Take two random guesses  $\gamma_0, \gamma_1$
- Compute next guess using linear interpolation between the previous two results. :

$$\frac{\Delta y_{10 \rightarrow 1}}{\Delta \gamma_{0 \rightarrow 1}} = \frac{\Delta y_{11 \rightarrow 2}}{\Delta \gamma_{1 \rightarrow 2}}$$

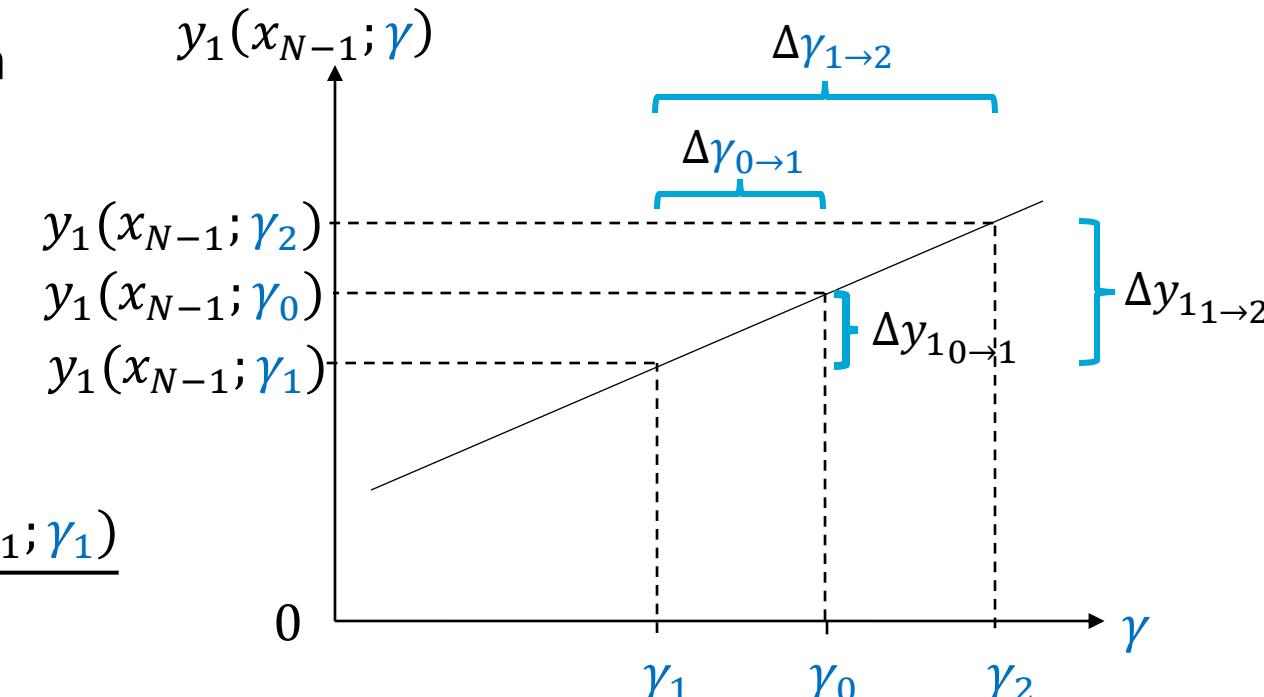
Solution of IVP at right boundary  $x_{N-1}$  using guess  $\gamma_1$

$$\frac{y_1(x_{N-1}; \gamma_1) - y_1(x_{N-1}; \gamma_0)}{\gamma_1 - \gamma_0} = \frac{y_1(x_{N-1}) - y_1(x_{N-1}; \gamma_1)}{\gamma_2 - \gamma_1}$$

Guess

$$\gamma_2 = \gamma_1 + (\gamma_1 - \gamma_0) \frac{y_1(x_{N-1}) - y_1(x_{N-1}; \gamma_1)}{y_1(x_{N-1}; \gamma_1) - y_1(x_{N-1}; \gamma_0)}$$

Boundary condition at right boundary  $x_{N-1}$ .



## NOTE

This is the general formula, in our example  $x_{N-1}$  is the right boundary index located at  $x = 1$ .

# Updating guess: Linear interpolation

- Take two random guesses  $\gamma_0, \gamma_1$
- Next guess,

$$\gamma_2 = \gamma_1 + (\gamma_1 - \gamma_0) \frac{y_1(x_{N-1}) - y_1(x_{N-1}; \gamma_1)}{y_1(x_{N-1}; \gamma_1) - y_1(x_{N-1}; \gamma_0)}$$

- For our example from the previous slides:

$$\gamma_2 = 0 + (0 - 1) \frac{2 - (-0.831)}{-0.831 - 1} = 1.55$$

- Linear interpolation directly yields correct guess for linear ODEs
  - In practice, the solution from the IVP solver  $y(1; \gamma_i)$  is not exact  
→ For bad guesses  $\gamma_0, \gamma_1$ , the next guess  $\gamma_2$  might be off
  - → Ideally, always use the root-finding using secant method.

# Agenda

- Boundary value problems (BVPs)
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    - a. Linear interpolation
    - b. Root-finding with secant method
  - *Solve\_bvp* function

# Updating guess: Root-finding with secant method

$$y_1(1; \gamma_0) = 1$$

$$y_1(1; \gamma_1) = -0.813$$

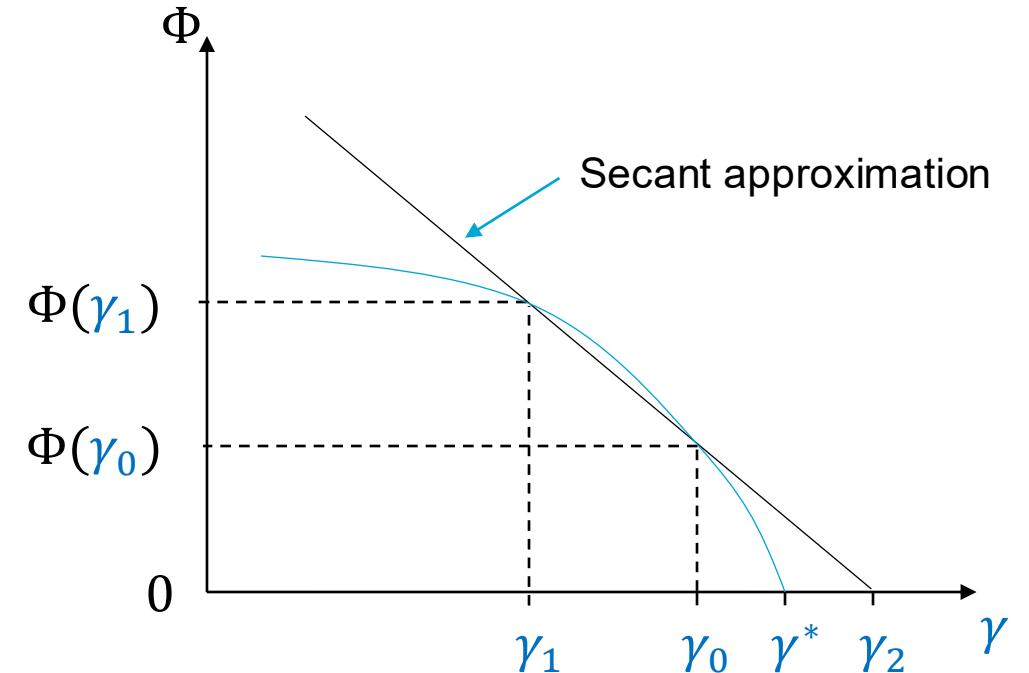
- Define a residual function measuring how far the boundary condition is from being satisfied:

$$\Phi(\gamma) = y_1(x_{N-1}; \gamma) - y_1(x_{N-1})$$

Boundary value we reach with our guess  $\gamma$

Actual boundary value, here = 2

- Objective:  $\min |\Phi(\gamma)|$
- Optimal solution:  $\Phi(\gamma^*) = 0$



## RECAP

Use a root finding algorithm to find the optimal solution (c.f., lecture 2)

# Optimal solution of the residual function

- Residual function

$$\Phi(\gamma_{i+1}) = y_1(x_{N-1}; \gamma_{i+1}) - y_1(x_{N-1})$$

- Taylor expansion

$$\Phi(\gamma_{i+1}) = \Phi(\gamma_i + \Delta\gamma) = \Phi(\gamma_i) + \frac{d\Phi}{d\gamma} \Big|_{\gamma_i} \Delta\gamma + \mathcal{O}(\Delta\gamma^2)$$

Current guess                      Changing the current guess

# Optimal solution of the residual function

- Residual function

$$\Phi(\gamma_{i+1}) = y_1(x_{N-1}; \gamma_{i+1}) - y_1(x_{N-1})$$

- Taylor expansion

$$\Phi(\gamma_{i+1}) = \Phi(\gamma_i + \Delta\gamma) = \Phi(\gamma_i) + \frac{d\Phi}{d\gamma} \Big|_{\gamma_i} \Delta\gamma + \mathcal{O}(\Delta\gamma^2)$$

- The correct initial guess is obtained if  $\Phi(\gamma) = 0$

$$0 = \Phi(\gamma_i) + \frac{d\Phi}{d\gamma} \Big|_{\gamma_i} \Delta\gamma + \mathcal{O}(\Delta\gamma^2)$$

# Optimal solution of the residual function

- Residual function

$$\Phi(\gamma_{i+1}) = y_1(x_{N-1}; \gamma_{i+1}) - y_1(x_{N-1})$$

- Taylor expansion

$$\Phi(\gamma_{i+1}) = \Phi(\gamma_i + \Delta\gamma) = \Phi(\gamma_i) + \frac{d\Phi}{d\gamma} \Big|_{\gamma_i} \Delta\gamma + \mathcal{O}(\Delta\gamma^2)$$

- The optimal value for  $\gamma$  satisfies  $\Phi(\gamma) = 0$ :

$$0 = \Phi(\gamma_i) + \frac{d\Phi}{d\gamma} \Big|_{\gamma_i} \Delta\gamma + \mathcal{O}(\Delta\gamma^2)$$

*rearrange,  
neglect  $\mathcal{O}(\Delta\gamma^2)$*

$$\Delta\gamma = -\frac{\Phi(\gamma_i)}{\frac{d\Phi}{d\gamma} \Big|_{\gamma_i}}$$

This is how we should  
change the current guess

# Optimal solution of the residual function

$$\Delta\gamma = - \frac{\Phi(\gamma_i)}{\left. \frac{d\Phi}{d\gamma} \right|_{\gamma_i}}$$

$$\Phi(\gamma) = y_1(x_{N-1}; \gamma) - y_1(x_{N-1})$$
$$\frac{d\Phi}{d\gamma} = \frac{dy_1(x_{N-1}; \gamma_i)}{d\gamma}$$

$$\Delta\gamma = - \frac{y_1(x_{N-1}; \gamma_i) - y_1(x_{N-1})}{\frac{dy_1(x_{N-1}; \gamma_i)}{d\gamma}}$$

Known values

Use previous guesses  
to estimate gradient

- Approximate the derivative numerically (backward difference)

$$\frac{dy_1(x_{N-1}; \gamma_i)}{d\gamma} = \frac{y_1(x_{N-1}; \gamma_i) - y_1(x_{N-1}; \gamma_{i-1})}{\gamma_i - \gamma_{i-1}}$$

$$\rightarrow \Delta\gamma = -(y_1(x_{N-1}; \gamma_i) - y_1(x_{N-1})) \cdot \frac{\gamma_i - \gamma_{i-1}}{y_1(x_{N-1}; \gamma_i) - y_1(x_{N-1}; \gamma_{i-1})}$$

# Optimal solution of the residual function

$$\Delta\gamma = \gamma_{i+1} - \gamma_i \rightarrow \gamma_{i+1} = \gamma_i - (y_1(x_{N-1}; \gamma_i) - y_1(x_{N-1})) \cdot \frac{\gamma_i - \gamma_{i-1}}{y_1(x_{N-1}; \gamma_i) - y_1(x_{N-1}; \gamma_{i-1})}$$

Yes, this is the same equation as for the linear interpolation. But it is derived differently, and we use it in an iterative approach.

- With

$$y_1(x_{N-1}; \gamma_0) = 1, \quad y_1(x_{N-1}; \gamma_1) = -0.813, \quad y_1(x_{N-1}) = 2, \quad \gamma_0 = 1, \quad \gamma_1 = 0$$

- Improve the guess

$$\gamma_2 = \gamma_1 + \Delta\gamma_1$$

$$\gamma_2 = 0 + 1 \cdot 1.55 = 1.55$$

# The shooting method residual function

Loop intuition:

Start:

- System of 1<sup>st</sup> order ODEs  $\frac{dy}{dx} = f(x, y)$
- Initial guesses  $y_0, y_1$
- Solve IVP with  $y_0, y_1 \rightarrow y_1(x_{N-1}; y_0), y_1(x_{N-1}; y_1)$



HINT: connect the dots

The shooting method solves IVPs. Hence, it inherits the stability (or instability) of the associated IVP solver (cf., lecture 5).

Check:

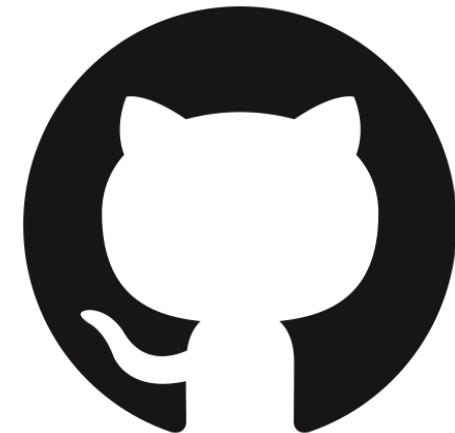
- $|\Phi| = |y_1(x_{N-1}; y_i) - y_1(x_{N-1})| \leq \epsilon$

Then:

- Compute  $y_{i+1} = y_i - (y_1(x_{N-1}; y_i) - y_1(x_{N-1})) \cdot \frac{y_i - y_{i-1}}{y_1(x_{N-1}; y_i) - y_1(x_{N-1}; y_{i-1})}$
- Solve IVP with  $y_{i+1} \rightarrow y_1(x_{N-1}; y_{i+1})$
- Set  $y_i = y_{i+1}, y_{i-1} = y_i$

# Live coding: Optimal shooting method

- Open Colab: [Optimal shooting](#)



- Find more in the Github repository of the course: [https://github.com/process-intelligence-research/computational\\_practicum\\_lecture\\_coding/tree/main](https://github.com/process-intelligence-research/computational_practicum_lecture_coding/tree/main)

# The shooting method for M equations

- Equations

$$\frac{dy_i}{dx} = f_i(x, y_1, y_2, \dots, y_M), \quad x \in [x_0, x_{N-1}], \quad i = 1, \dots, M$$

- Boundary conditions at  $x_{N-1}$  need to be replaced by boundary conditions at  $x_0$

$$y_j(x_{N-1}) = y_{j,N-1}, \quad j \subset i$$

- Initial guesses

$$y_j(x_0) = \gamma_0^j, \quad j \subset i$$

# The shooting method for M equations

- Equations

$$\frac{dy_i}{dx} = f_i(x, y_1, y_2, \dots, y_M), \quad x \in [x_0, x_{N-1}], \quad i = 1, \dots, M$$

- Improve the guesses

$$\Delta\boldsymbol{\gamma} = [\mathbf{J}(x_{N-1}, \boldsymbol{\gamma})]^{-1} \begin{pmatrix} y_{j[0]}(x_{N-1}; \boldsymbol{\gamma}_{j[0]}) \\ \dots \\ y_{j[-1]}(x_{N-1}; \boldsymbol{\gamma}_{j[-1]}) \end{pmatrix}$$

## RECAP

Jacobian known from  
Newton-Raphson method  
(c.f., lecture 2).

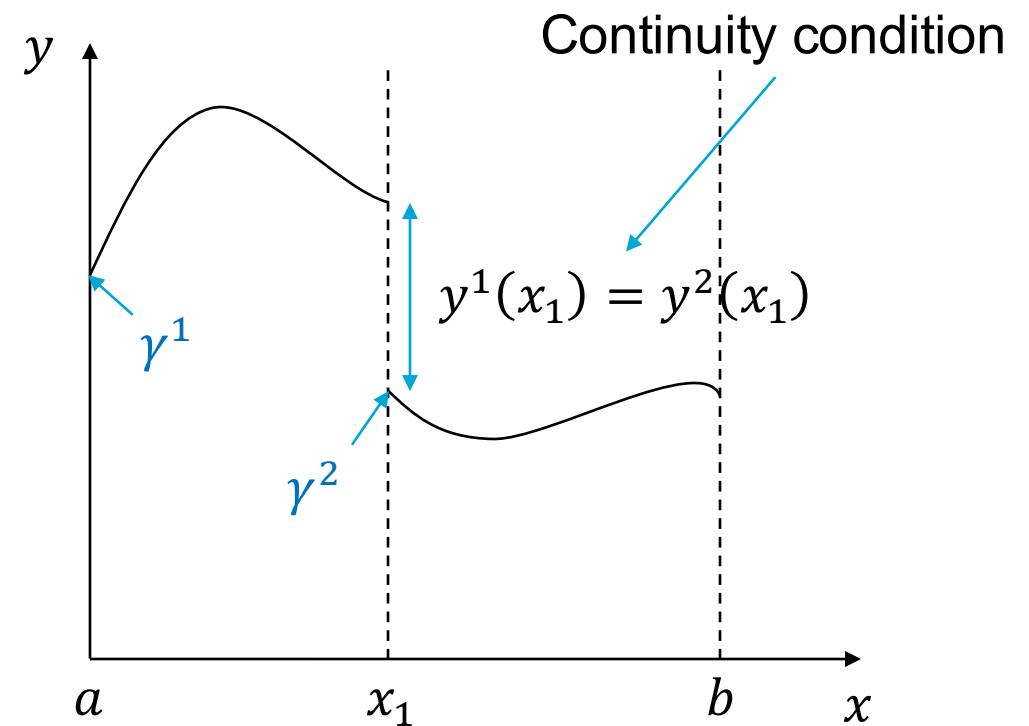
- With  $\mathbf{J}(x_{N-1}; \boldsymbol{\gamma})$  being the Jacobian

$$\mathbf{J}(x_{N-1}, \boldsymbol{\gamma}) = \begin{pmatrix} \frac{\partial y_{j[0]}}{\partial \boldsymbol{\gamma}_{j[0]}} & \dots & \frac{\partial y_{j[0]}}{\partial \boldsymbol{\gamma}_{j[-1]}} \\ \vdots & \ddots & \vdots \\ \frac{\partial y_{j[-1]}}{\partial \boldsymbol{\gamma}_{j[0]}} & \dots & \frac{\partial y_{j[-1]}}{\partial \boldsymbol{\gamma}_{j[-1]}} \end{pmatrix}$$

Approximated with previous  
guess, only exact for linear ODEs  
$$\frac{dy}{d\gamma} = \frac{y(x_{N-1}; \boldsymbol{\gamma}_i) - y(x_{N-1}; \boldsymbol{\gamma}_{i-1})}{\boldsymbol{\gamma}_i - \boldsymbol{\gamma}_{i-1}}$$

# The multiple shooting method

- Advanced shooting method.
- Breaks domain into sub-domains and solves IVP in each sub-domain.
- Add continuity and boundary conditions for each sub-domain.
- Advantages:
  - + Improved stability
  - + Parallelization
  - + More flexibility for initial guesses



# Finite differences vs. shooting method

## Finite difference method

- + ODE is solved only once.
- - Nonlinear ODEs require to solve a system of nonlinear equations.

## Shooting method

- + Solution of nonlinear equations is fairly straightforward.
- - ODE needs to be solved several times.



Choice depends on the problem.

# Agenda

- Boundary value problems (BVPs)
  - Shooting method
    - a. Linear interpolation
    - b. Secant method
  - *Solve\_bvp* function

# SciPy's *solve\_bvp*

- Uses the collocation method:
  - modification of the Multiple Shooting Method and the Finite Difference Method.
- Function arguments:
  - *fun*: Function containing the ODE system.
  - *bc*: Boundary conditions defined as a function.
  - *x*: Domain, must include domain boundaries.
  - *y*: Initial guess for function values.

Read the complete description of  
*solve\_bvp* ([link](#)) at home.

```
solve_bvp(fun, bc, x, y, p=None, S=None, fun_jac=None, bc_jac=None,  
tol=0.001, max_nodes=1000, verbose=0, bc_tol=None) [source]
```

Solve a boundary value problem for a system of ODEs.

This function numerically solves a first order system of ODEs subject to two-point boundary conditions:

```
dy / dx = f(x, y, p) + S * y / (x - a), a <= x <= b  
bc(y(a), y(b), p) = 0
```

Here *x* is a 1-D independent variable, *y(x)* is an *n*-D vector-valued function and *p* is a *k*-D vector of unknown parameters which is to be found along with *y(x)*. For the problem to be determined, there must be *n + k* boundary conditions, i.e., *bc* must be an *(n + k)*-D function.

The last singular term on the right-hand side of the system is optional. It is defined by an *n*-by-*n* matrix *S*, such that the solution must satisfy *S y(a) = 0*. This condition will be forced during iterations, so it must not contradict boundary conditions. See [2] for the explanation how this term is handled when solving BVPs numerically.

Problems in a complex domain can be solved as well. In this case, *y* and *p* are considered to be complex, and *f* and *bc* are assumed to be complex-valued functions, but *x* stays real. Note that *f* and *bc* must be complex differentiable (satisfy Cauchy-Riemann equations [4]), otherwise you should rewrite your problem for real and imaginary parts separately. To solve a problem in a complex domain, pass an initial guess for *y* with a complex data type (see below).

#### Parameters:

##### *fun* : callable

Right-hand side of the system. The calling signature is `fun(x, y)`, or `fun(x, y, p)` if parameters are present. All arguments are ndarray: `x` with shape (m,), `y` with shape (n, m), meaning that `y[:, i]` corresponds to `x[i]`, and `p` with shape (k,). The return value must be an array with shape (n, m) and with the same layout as `y`.

##### *bc* : callable

Function evaluating residuals of the boundary conditions. The calling signature is `bc(ya, yb)`, or `bc(ya, yb, p)` if parameters are present. All arguments are ndarray: `ya` and `yb` with shape (n,), and `p` with shape (k,). The return value must be an array with shape (n + k,).

# SciPy's *solve\_bvp*

- *fun*: Function containing the ODE system.

$$\frac{dy_1}{dx} = y_2, \quad \frac{dy_2}{dx} = 4(y_1 - x)$$

Annotations:

- $dydx[0]$  points to the first term of the first equation ( $\frac{dy_1}{dx}$ ).
- $y[1]$  points to the second term of the first equation ( $y_2$ ).
- $dydx[1]$  points to the right-hand side of the second equation ( $4(y_1 - x)$ ).

```
import numpy as np

def dy(x: np.ndarray, y: np.ndarray) -> np.ndarray:
    """First order ODEs from d2y/dx2=4(y-x).

    Args:
        x (np.ndarray): Grid points.
        y (np.ndarray): Function values.

    Returns:
        np.ndarray: Right hand-side of ODEs.
    """
    dydx = np.zeros(y.shape)
    dydx[0] = y[1]
    dydx[1] = 4*(y[0]-x)
    return dydx
```

- *bc*: Boundary conditions defined as a function.

$$0 = y_1(0), \quad 0 = y_1(1) - 2$$

Annotations:

- $[0]$  points to the value at  $x=0$  ( $y_1(0)$ ).
- $ya$  points to the value at  $x=1$  ( $y_1(1)$ ).
- $[0]$  points to the target value at  $x=1$  ( $-2$ ).
- $yb$  points to the target value at  $x=1$  ( $-2$ ).

```
import numpy as np

def my_bc(ya: np.ndarray, yb: np.ndarray) -> np.ndarray:
    """Residuals of the boundary conditions.

    Args:
        ya (np.ndarray): Function values at x0.
        yb (np.ndarray): Function values at x(N-1).

    Returns:
        np.ndarray: Residuals of boundary conditions.
    """
    return np.array([ya[0],yb[0]-2])
```

# SciPy's *solve\_bvp*

- Solve the BVP

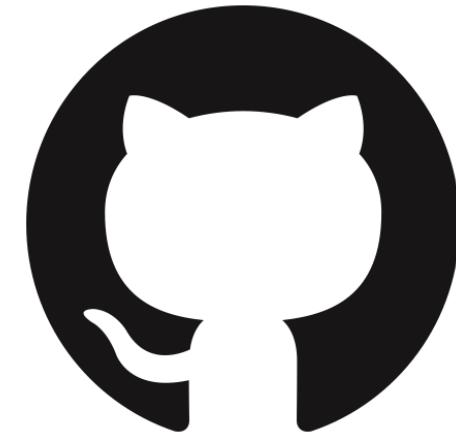
```
import scipy.integrate

x = np.linspace(0,1,101) # x grid points
y_guess = np.zeros((2,len(x))) # first guess, shape: no. dependent variables, no. grid points
bvp_result = scipy.integrate.solve_bvp(dy, my_bc, x, y_guess)
```

- *solve\_bvp* returns a tuple including, besides others:
  - *sol*: Polynomial approximation of the solution. This is a function that takes grid points as input.
  - *x*: Nodes of the final mesh (grid points inside solver).
  - *y*: Solution values at the mesh nodes.
- Note the difference between *sol* and *y*!

# Live coding: SciPy's *solve\_bvp()*

- Open Colab: [solve\\_bvp function](#)



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# Learning goals of this lecture

After successfully completing this lecture, you are able to...

- explain numerical solution methods for boundary value problems (BVPs), namely,
  - finite difference method,
  - shooting method.
- implement the shooting method for boundary value problems (BVPs) from scratch.
- use Python libraries' built-in functions for numerical solution approaches to BVPs.

# Thank you very much for your attention!

# Computer exam

- Computer exam has two parts: (i) a theory part and (ii) a practical programming part
- (i) The theory part consists of questions in ANS ([link](#))
- (ii) The programming part will be similar to the assignments
  - IDE: Anaconda Jupyter Notebook ([link](#))
  - Points given for solution format, e.g.,
    - Functions need to have type hints and descriptive docstrings
    - Plots need to have title, axis labels, legend (if more than two lines in one plot)
  - No autochecks provided
- Computer exam is closed book, but we provide
  - a cheat sheet with common Python commands (see Brightspace/Resources)
  - documentation for important build-in functions, e.g., *solve\_bvp* ([link](#)).

# Computer exam



Monday 03-01-2025  
09:00-12:00



CEG-Computer Room

# Practice exam

- We will publish solutions to the practice exam.
- Solving the assignments or practice exam can help you test your skills and knowledge level; however, you should not expect the questions of the final exams to be a simple repetition of questions from the assignments or practice exam. We expect students to be able to apply the learned theory and skills to a problem that they have not seen before.