

Lesson 3

Boundary Value Problems for ODEs

3.2 Shooting Method

3.3 Finite Difference Method

3.4 Variational Methods



Boundary Value Problems: Variational Methods



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with boundary conditions

$$u(a) = \alpha, \quad u(b) = \beta.$$



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We seek the solution of the form

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where $\varphi_i(t)$ are basis functions defined on $[a, b]$ and y is an n -vector of parameters to be determined.



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The residual $r(t, y) := v''(t, y) - f(t, v(t, y), v'(t, y))$ measures how well the approximation satisfies the ODE. For an exact approximation, that is, $u(t) = v(t, y)$, we have $r(t, y) = 0$.

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- Collocation Method



Boundary Value Problems: Variational Methods



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In addition, we also enforce the boundary condition at the end-points:

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This yields a system of n algebraic equations in n unknowns. This may be linear or non-linear depending on whether f is linear or non-linear.





In particular, for the approximation space consisting of polynomials of degree $n - 1$ or less (i.e., \mathcal{P}_{n-1}), we have

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where the Lagrange basis, given by

$$\ell_i(t) = \frac{\prod_{k=1, k \neq i}^n (t - t_k)}{\prod_{k=1, k \neq i}^n (t_i - t_k)} \in \mathcal{P}_{n-1}$$

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is used. Then the collocation method yields the following system of algebraic equations: $Ay = F(y)$ where

$$Ay = \begin{bmatrix} \ell_1(t_1) & \ell_2(t_1) & \cdots & \ell_n(t_1) \\ \ell_1''(t_2) & \ell_2''(t_2) & & \\ \vdots & \vdots & \ddots & \vdots \\ & & & \ell_{n-1}''(t_{n-1}) & \ell_n''(t_{n-1}) \\ \ell_1(t_n) & \cdots & & \ell_{n-1}(t_n) & \ell_n(t_n) \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_{n-1} \\ y_n \end{bmatrix}, \quad F(y) = \begin{bmatrix} \alpha \\ f\left(t_2, \sum_{i=1}^n y_i \ell_i(t_2), \sum_{i=1}^n y_i \ell_i'(t_2)\right) \\ \vdots \\ f\left(t_{n-1}, \sum_{i=1}^n y_i \ell_i(t_{n-1}), \sum_{i=1}^n y_i \ell_i'(t_{n-1})\right) \\ \beta \end{bmatrix}.$$

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The Newton iterations take the form $y^{(m+1)} = y^{(m)} - (A - F'(y^{(m)}))^{-1} (Ay^{(m)} - F(y^{(m)}))$.



Example

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- Least Squares Method



Boundary Value Problems: Variational Methods



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Toward this, consider the functional $F: \mathbb{R}^n \rightarrow \mathbb{R}$ given by

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This yields a system of algebraic equations

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In particular, for the linear problem with $f(t, u, v) = f(t)$, we have

$$\sum_{j=1}^n y_j \langle \varphi_j'', \varphi_i'' \rangle = \langle f, \varphi_i'' \rangle,$$

a symmetric system.

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3.3 Finite Difference Method

3.4 Variational Methods

- Galerkin Method





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$$-\sum_{j=1}^n y_j \langle \varphi_j', \varphi_i' \rangle = \langle f, \varphi_i \rangle, \quad i = 1, \dots, n.$$



Example

Consider the two-point BVP

$$\begin{aligned}u'' &= 6t, & 0 < t < 1, \\u(0) &= 0, & u(1) = 1.\end{aligned}$$

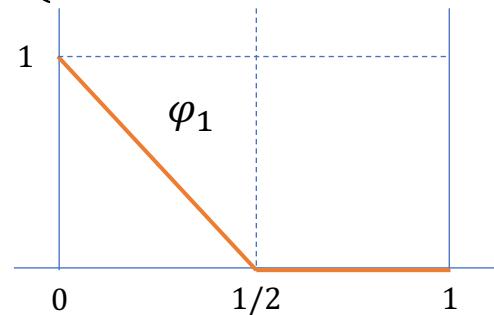
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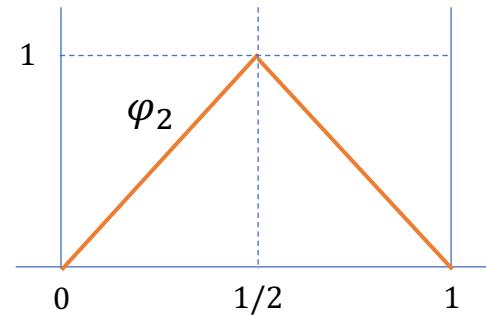
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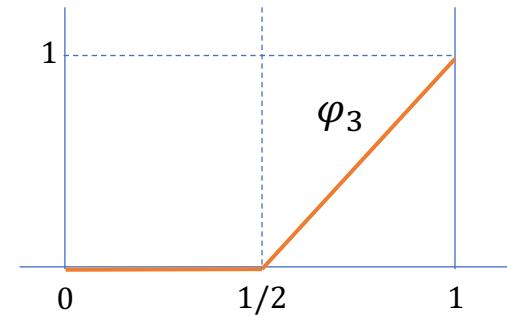
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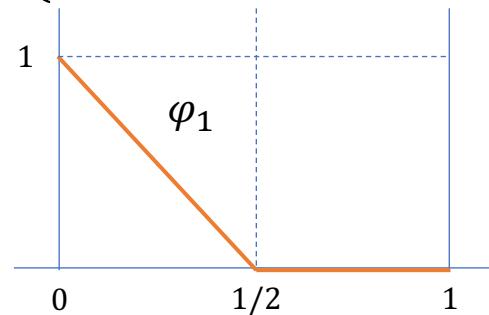
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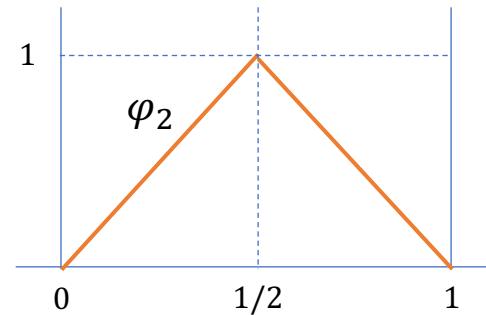
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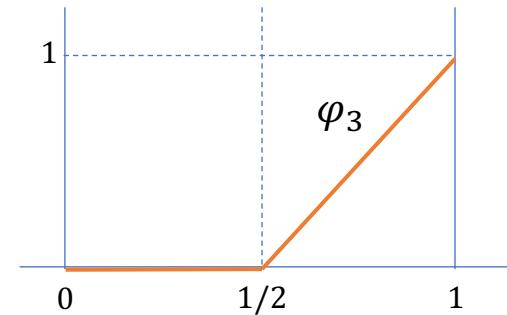
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Lesson 3

Boundary Value Problems for ODEs

3.2 Shooting Method

3.3 Finite Difference Method

3.4 Variational Methods

- Convergence Analysis for Galerkin Method





For analyzing the computational error in the Galerkin method, note that the solution u to the boundary value problem

$$\begin{aligned} u'' &= f(t), & a < t < b, \\ u(a) &= 0, & u(b) = 0, \end{aligned}$$

and any function of the form

$$v(t, x) = \sum_{i=1}^n x_i \varphi_i(t),$$

with $\varphi_i(a) = \varphi_i(b) = 0$, satisfies

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Thus, for any $z \in \mathbb{R}^n$, we have

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Define the H^1 norm $\|\cdot\|_{H^1}$ on $C_0^1([a, b]) = \{w \in C^1([a, b]): w(a) = w(b) = 0\}$ as

$$\|w\|_{H^1}^2 := \|w\|_{L^2}^2 + \|w'\|_{L^2}^2$$

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$$\|\nu(\cdot, y) - \nu(\cdot, z)\|_{H^1}^2 \leq (1 + c^2(b-a)^2) \int_a^b (\nu'(t, y) - \nu'(t, z))^2 dt$$

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Now,

$$\|u - v(\cdot, y)\|_{H^1} \leq \|u - v(\cdot, z)\|_{H^1} + \|v(\cdot, z) - v(\cdot, y)\|_{H^1} \leq (2 + c^2(b - a)^2) \|u - v(\cdot, z)\|_{H^1}.$$

As $z \in \mathbb{R}^n$ is arbitrary, we conclude that

$$\|u - v(\cdot, y)\|_{H^1} \leq (2 + c^2(b - a)^2) \inf_{z \in \mathbb{R}^n} \|u - v(\cdot, z)\|_{H^1}$$

Therefore,

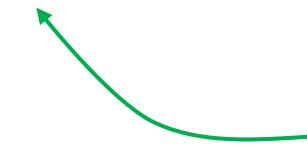
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Best approximation
of u by functions in
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For piecewise linear elements, we have

$$\inf_{z \in \mathbb{R}^n} \|u - v(\cdot, z)\|_{H^1} \leq Ch \|u''\|_{L^2}$$

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As $z \in \mathbb{R}^n$ is arbitrary, we conclude that

$$\|u - v(\cdot, y)\|_{H^1} \leq (2 + c^2(b - a)^2) \inf_{z \in \mathbb{R}^n} \|u - v(\cdot, z)\|_{H^1}$$

For piecewise linear elements, we have

$$\inf_{z \in \mathbb{R}^n} \|u - v(\cdot, z)\|_{H^1} \leq Ch \|u''\|_{L^2}$$

and, more generally, for elements of degree r , we have an estimate

$$\inf_{z \in \mathbb{R}^n} \|u - v(\cdot, z)\|_{H^1} \leq Ch^r \|u\|_{H^{r+1}}$$

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