

# Approximate Solution to Inverse Problems for Elliptic Equations

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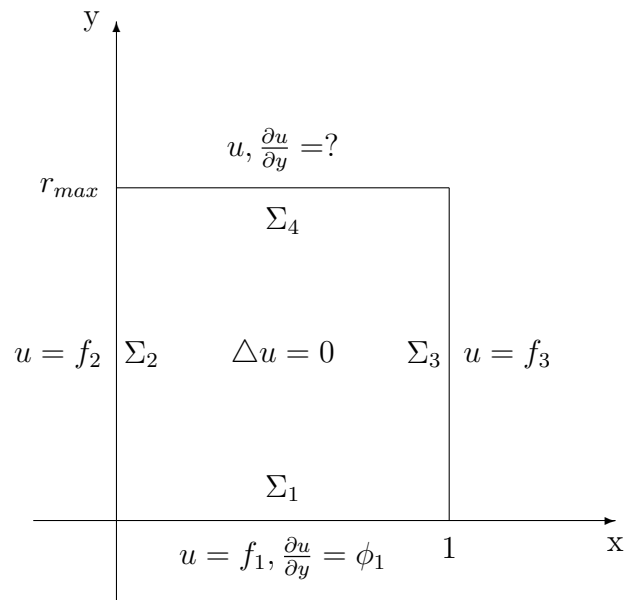
Minisymposium ”Inverse Probleme und Inkorrektheits–Phänomene”

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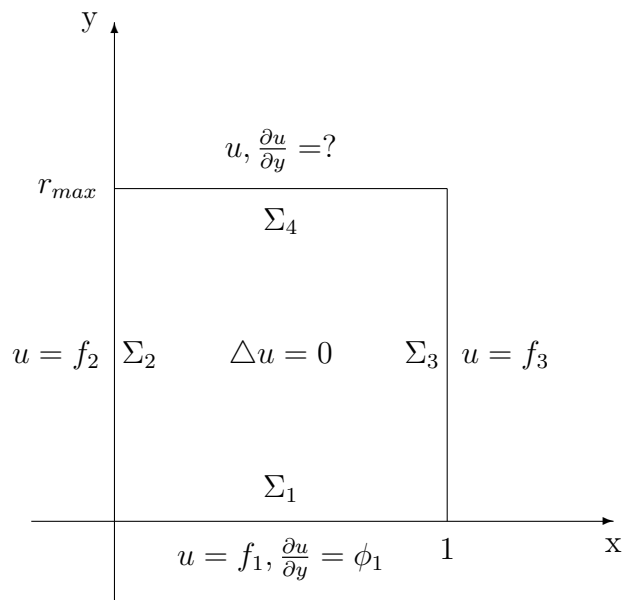
• PROBLEM SETTINGS

Cauchy–Problem  
for Laplace’s Equation (CPLE)



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Hadamard Example (1923)

$$\Delta u = 0 ,$$

$$u(x, 0) = 0 ,$$

$$\frac{\partial u}{\partial y}(x, 0) = \frac{1}{n} \sin(n\pi x) =: g_n , \quad x \in (0, 1)$$

$$u(0, y) = u(1, y) = 0 , \quad 0 \leq y \leq 1$$

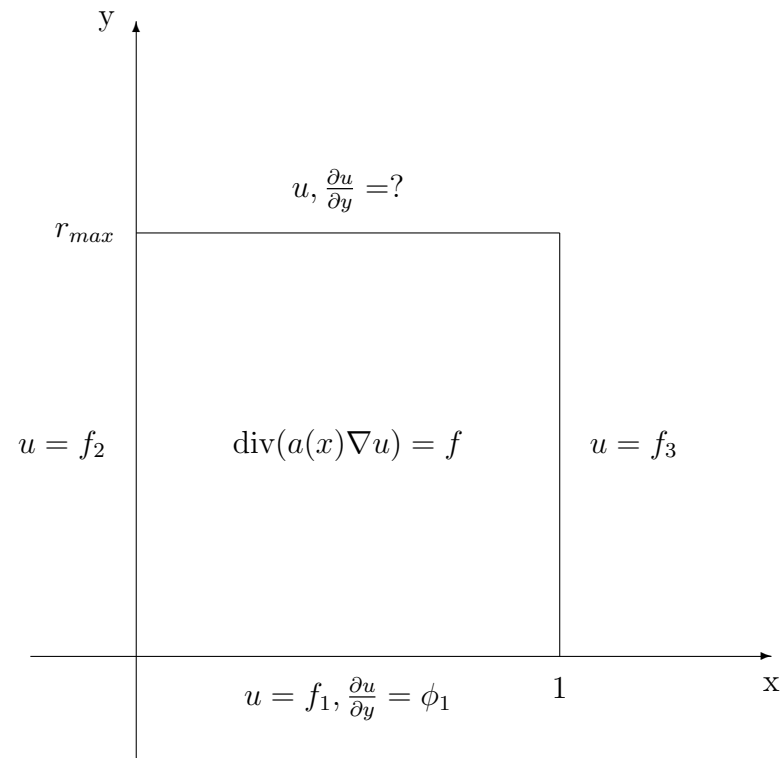
$$\implies u_n(x, y) = (n\pi)^{-2} \sin(n\pi x) \sinh(n\pi y) ,$$

$$(x, y) \in [0, 1] \times [0, 1]$$

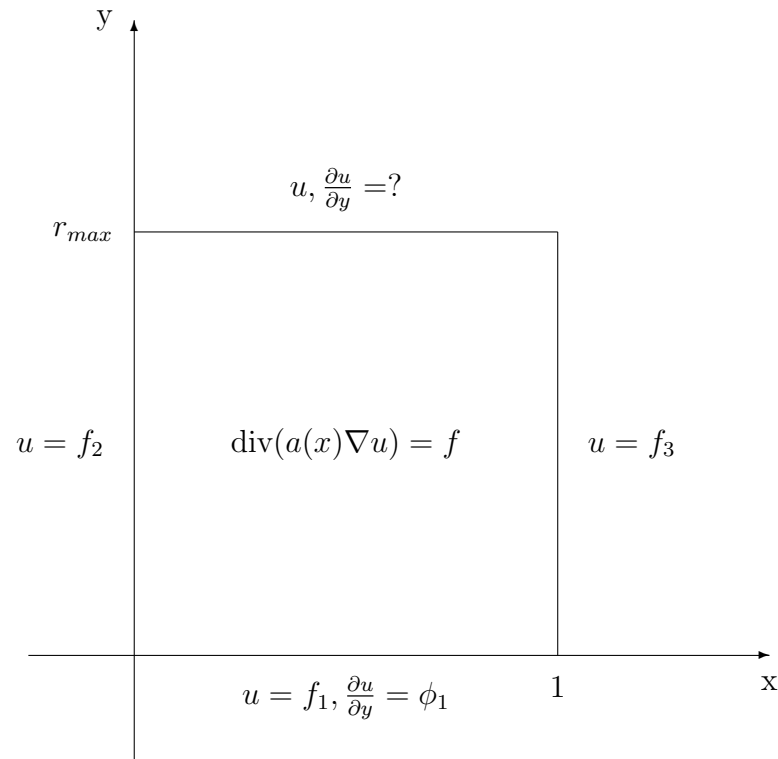
Illposed:  $g_n \rightarrow 0$ , but  $u_n(x, y) \rightarrow \infty$  ( $n \rightarrow \infty$ )  
for any  $y > 0$

**Lit.:** Lavrentiev ('56), Payne ('60ff), Han ('82), Falk ('90),  
M. Kubo ('94), Kabanikhin + Karchevsky ('95),  
Fayazov + Lavrentiev ('95) and many others.

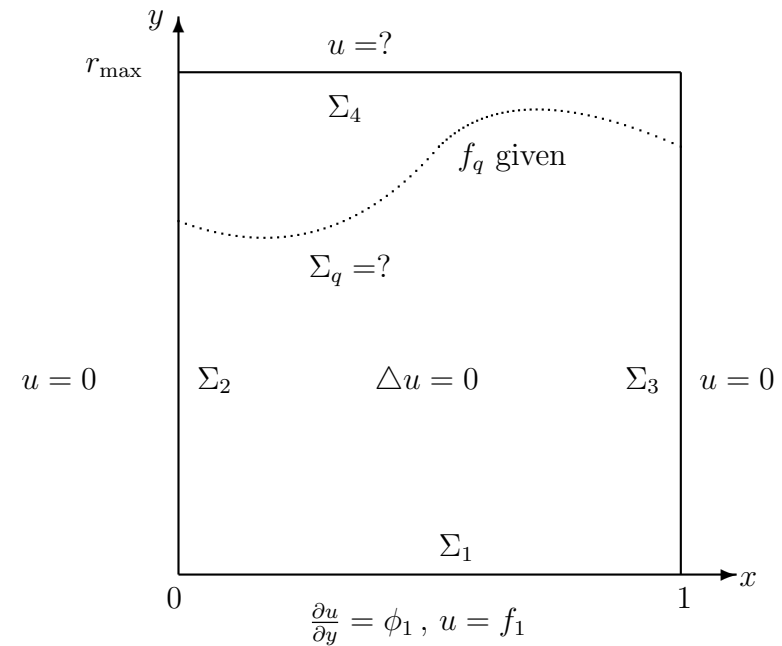
## Cauchy–Problem for more general elliptic equations



### Cauchy–Problem for more general elliptic equations



### Shape Optimization Problem



## Remarks

- All three problems are illposed.
- $f, f_1, f_2, f_3$  can be set to zero in the Cauchy-Problem for more general elliptic equations. Note:  $a = a(x)$ .
- The shape optimization problem needs the solution of the Cauchy-Problem beforehand.

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## Applications

- Medicine: Electrocardiology
- Geology: Gravimetric search of resources
- Steel production: Thickness of furnace wall
- Stationary Inverse Heat Conduction Problems



## • METHOD OF LINES APPROXIMATION

$$x_i = ih, \quad i = 0, \dots, N$$

$$\Delta_h u(x_i, y) = \frac{\partial^2 u}{\partial y^2}(x_i, y) + \frac{u_{i-1} - 2u_i + u_{i+1}}{h^2}$$

$$u(x_i, \cdot) \approx u_i, \quad \frac{\partial^2 u}{\partial y^2}(x_i, \cdot) \approx u_i''$$

$$U = (u_1, \dots, u_{N-1})$$

$$\Delta_h \mathbf{u} = \mathbf{0} \iff \mathbf{U}'' + \mathbf{A}U = \mathbf{0}$$

with

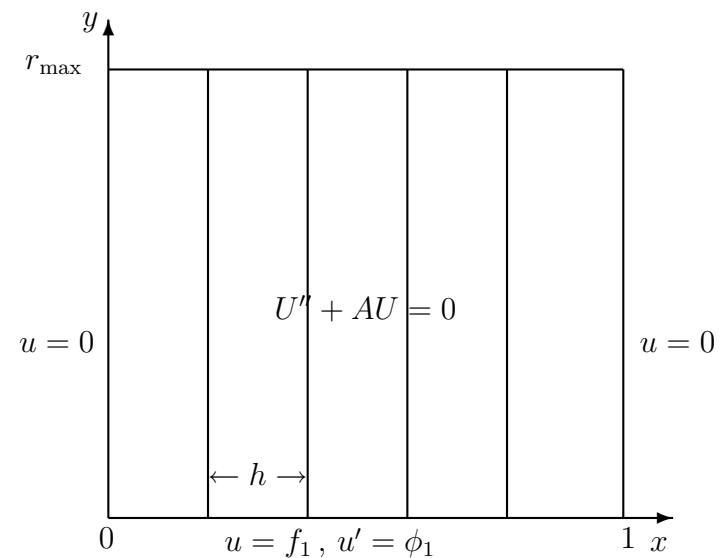
$$A := \frac{1}{h^2} \begin{pmatrix} -2 & 1 & 0 & \dots & 0 & 0 & 0 \\ 1 & -2 & 1 & \dots & 0 & 0 & 0 \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ 0 & 0 & 0 & \dots & 1 & -2 & 1 \\ 0 & 0 & 0 & \dots & 0 & 1 & -2 \end{pmatrix}$$

$$\in \mathbb{R}^{N-1, N-1}$$

Boundary Conditions:

$$u_i(0) = f_1(x_i), \quad u_i'(0) = \phi_1(x_i),$$

$$i = 1, \dots, N-1$$



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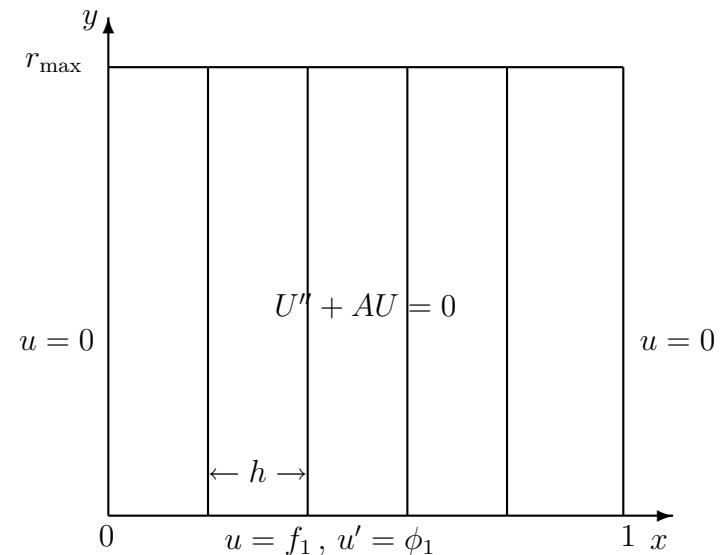
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$$u_i(0) = f_1(x_i), \quad u_i'(0) = \phi_1(x_i),$$

$$i = 1, \dots, N - 1$$



The above system can be decoupled, since eigenvalues and eigenvectors of  $A$  are known.

$$\begin{aligned}
 & U'' + AU = 0 \\
 \iff & WU'' + WAU = 0 \\
 \iff & WU'' + \underbrace{WAW^{-1}}_{=D} WU = 0 \\
 \iff & (WU)'' + D(WU) = 0 \\
 \stackrel{V:=WU}{\iff} & V'' + DV = 0, \quad V = (v_1, \dots, v_{N-1})^\top \\
 \iff & v_i'' + \lambda_i v_i = 0, \quad i = 1, \dots, N-1
 \end{aligned}$$

$\lambda_i =$  eigenvalues,  $D = \text{diag}(\lambda_i)$ ,

$W = (w_1 | \dots | w_{N-1})$  eigenvectors of  $A$  (orthogonal)

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$$\implies v_k(y) = \xi_k \exp(\sqrt{-\lambda_k} y) + \eta_k \exp(-\sqrt{-\lambda_k} y), \quad k = 1, \dots, N-1$$

$$\implies \xi_k = \sqrt{\frac{h}{2}} \sum_{j=1}^{N-1} \left( \sin(kjh\pi) f_1(x_j) + \frac{h \sin(khj\pi)}{2 \sin(kh\frac{\pi}{2})} \phi_1(x_j) \right)$$

$$\eta_k = \sqrt{\frac{h}{2}} \sum_{j=1}^{N-1} \left( \sin(kjh\pi) f_1(x_j) - \frac{h \sin(khj\pi)}{2 \sin(kh\frac{\pi}{2})} \phi_1(x_j) \right)$$

$\implies$  solution  $U = (U_1, \dots, U_{N-1})$  of  $U'' + AU = 0$  :

$$\begin{aligned}
 u_i(y) &= (WV)_i(y) \\
 &= 2h \cdot \sum_{k=1}^{N-1} \left( \sin(ikh\pi) \left( \cosh(\sqrt{-\lambda_k}y) \sum_{j=1}^{N-1} \sin(kjh\pi) f_1(x_j) \right. \right. \\
 &\quad \left. \left. + \frac{h}{2 \sin(kh\frac{\pi}{2})} \sinh(\sqrt{-\lambda_k}y) \sum_{j=1}^{N-1} \sin(kjh\pi) \phi_1(x_j) \right) \right)
 \end{aligned}$$

**Remarks:**

1) The CPLG is solved by  $u(x, y) = \sum_{k=1}^{\infty} g_k(x, y)$  with

$$g_k(x, y) = 2 \sin(k\pi x) \left( (f_1(\cdot), \sin(k\pi \cdot))_{L_2} \cosh(k\pi y) + \frac{(\phi_1(\cdot), \sin(k\pi \cdot))_{L_2}}{k\pi} \sinh(k\pi y) \right)$$

provided the series converges.

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2) The method of lines approximation is still illposed on every line.

3) The CPLE is conditionally well-posed if data  $f_1, \phi_1 \in D_M$  (data with *bounded frequencies*), where

$$D_M = \left\{ \phi \in C^1(0, 1) \mid \phi(0) = \phi(1) = 0, \int_0^1 \sin(k\pi t) \phi(t) dt = 0, k > M \right\}$$

Solution:

$$u(x, y) = \sum_{k=1}^M \left( 2 \sin(k\pi x) \left( (f_1(\cdot), \sin(k\pi \cdot))_{L_2} \cosh(k\pi y) + \frac{(\phi_1(\cdot), \sin(k\pi \cdot))_{L_2}}{k\pi} \sinh(k\pi y) \right) \right)$$



#### 4) Data spaces

$$D : = \{ \phi \in C^1[0, 1] \mid \phi(0) = \phi(1) = 0 \}$$

$$D_M : = \left\{ \phi \in D \mid \int_0^1 \sin(k\pi t) \phi(t) dt = 0, k > M \right\}$$

$$D_M^h : = \left\{ \Phi \in \mathbb{R}^{N-1} \mid \sum_{j=1}^{n-1} \sin(k\pi jh) \Phi_j = 0, N > k > M \right\} \quad (N > M)$$

where  $\Phi := (\phi(h), \dots, \phi((N-1)h))^\top$ ,  $\phi \in D$ .

*Projection*  $P_M : \mathbb{R}^{N-1} \longrightarrow D_M^h$

$$(P_M \Phi)_j = \sum_{k=1}^M \left( 2h \sum_{\ell=1}^{N-1} \Phi_\ell \sin(k\pi \ell h) \right) \sin(k\pi jh)$$

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$\implies$  Fourier coeff. of  $\phi \in D_M$  are finite sums,

$$\int_0^1 \phi(t) \sin(k\pi t) dt = h \sum_{j=1}^{N-1} \sin(k\pi jh) \Phi_j$$

$\forall M, N, k \in \mathbb{N}, M < N, k < N, f \in D_M$ .

- **CONVERGENCE AND ERROR ESTIMATES**

(in case of data with bounded frequencies; assume  $N > M(h = 1/M)$ ):

If  $f_1, \phi_1 \in D_M$  then  $|u(x_i, y) - u_i(y)| = O(h^2) \quad (h \rightarrow 0)$ .

For perturbed data  $\|f_1 - f_1^\varepsilon\|_\infty = O(\varepsilon), \|\phi_1 - \phi_1^\varepsilon\|_\infty = O(\varepsilon)$ :

$$\begin{aligned} |u(x_i, y) - u_{i,\varepsilon}^*(y)| &\leq \frac{M^4 \pi^3 y}{12} \exp(M\pi y) (\|f_1\|_{L_1} + \|\phi_1\|_{L_1}) h^2 + \frac{4M^2(M+1)}{\sqrt{2}} \exp(\pi M y) \varepsilon \\ &= O(h^2 + \varepsilon), \end{aligned}$$

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where  $u_{i,\varepsilon}^*$  is the semidiscrete solution belonging to data, which are perturbed and projected onto  $D_M$  afterwards, i.e.  $F_{1,\varepsilon}^* = P_M F_{1,\varepsilon}, \Phi_{1,\varepsilon}^* = P_M \Phi_{1,\varepsilon}$ ,

$$\begin{aligned} u_{i,\varepsilon}^* &= 2h \sum_{k=1}^M \sin(ikh\pi) \cosh(\sqrt{-\lambda_k} y) \sum_{j=1}^{N-1} \sin(kjh\pi) (F_{1,\varepsilon}^*)_j \\ &+ h^2 \sum_{k=1}^M \left( \frac{\sin(ikh\pi)}{\sin(kh\frac{\pi}{2})} \sinh(\sqrt{-\lambda_k} y) \sum_{j=1}^{N-1} \sin(kjh\pi) (\Phi_{1,\varepsilon}^*)_j \right). \end{aligned}$$

• **CASE: BOUNDED SOLUTION** (on  $\Sigma_4$ )

**Stability Theorem:** If  $u \in C^2(\text{int}(\Omega)) \cap C(\Omega)$  s.t.

$$\Delta u(x, y) = 0 \quad \text{in} \quad \text{int}(\Omega)$$

$$u = 0 \quad \text{on} \quad \Sigma_1 \cup \Sigma_2 \cup \Sigma_3 \quad (\text{i.e. } f_1 = f_2 = f_3 = 0)$$

$$\frac{\partial u}{\partial y}(x) = \phi_1(x) \quad \text{on} \quad \Sigma_1$$

$$\|u\|_{L_2(\Sigma_4)} \leq E. \quad (*)$$

Then

$$\|u(\cdot, y)\|_{L_2} \leq R_1 \|\phi_1\|_{L_2}^{1 - \frac{y}{r_{max}}} E^{\frac{y}{r_{max}}}$$

for all  $y \in [0, r_{max}]$ , with  $R_1 = \max(r_{max}, 1)$ .

**Remarks:**

- 1) The proof uses *logarithmic convexity* of  $s(y) = \|u(\cdot, y)\|_{L_2}^2 / y^2$ , i.e.  $\ln(s)$  convex.
- 2) CPLE is conditionally wellposed in this case.

## Approximability:

**Projection** (orth.)  $P_M : D \longrightarrow D_M$  satisfies

$$\|\phi_1 - P_M \phi_1\|_{L_2(\Sigma_1)} \leq \frac{E}{r_{max}^2 (1 - \exp(-4\pi r_{max}))} \cdot \frac{M}{\exp(M\pi r_{max})},$$

provided

$$(*) : \|u\|_{L_2(\Sigma_u)} \leq E,$$

holds.

**Assume**  $f_1 = 0$ ,  $\|\phi_1 - \phi_1^\varepsilon\|_\infty = 0(\varepsilon)$ . Then ...

## Error estimates:

$$\begin{aligned} & \| (u - \overline{(u_\varepsilon^*)_h})(\cdot, y) \|_{L_2} \\ & \leq C_1(r_{max}) E \cdot \left( \frac{M}{\exp(M\pi r_{max})} \right)^{1 - \frac{y}{r_{max}}} \end{aligned}$$

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 & + C_2(y) \frac{2}{\pi^2} \frac{\sinh(M\pi y)}{M} \varepsilon \\
 & + \frac{M^4 \pi^3 y}{12} \exp(M\pi y) \| (\phi_1)_\varepsilon^* \|_{L_1} h^2 \quad \forall y \in [0, r_{max}].
 \end{aligned}$$

where

$$\begin{aligned}
 \overline{(u_\varepsilon^*)_h}(x, y) &= \sum_{k=1}^M \left( 2h \sum_{j=1}^{N-1} \sin(k\pi jh) u_{j,\varepsilon}^*(y) \right) \sin(k\pi x) \\
 &= \text{continuation of } (u_{1,\varepsilon}^*(y), \dots, u_{N-1,\varepsilon}^*(y))^\top \text{ in } D_M \\
 u_{i,\varepsilon}^*(y) &= \text{solution on } i\text{-th line with data } P_M \phi_1^\varepsilon.
 \end{aligned}$$

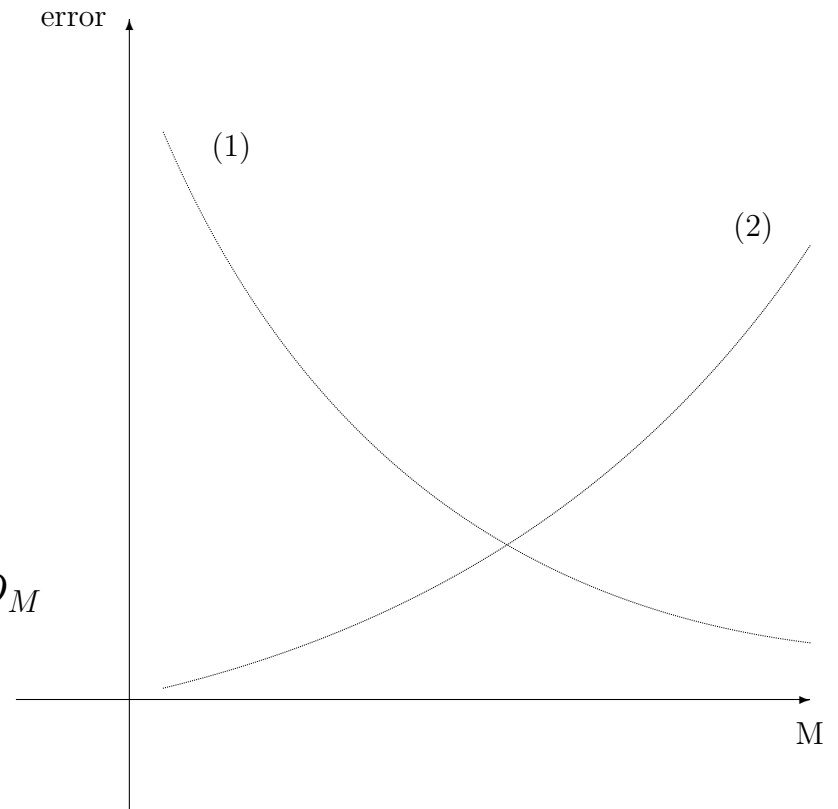


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(1) projection error, (2) data error;  $\varepsilon, h$  fixed

## Optimal Convergence:

If  $M = \left\lceil \frac{\ln 1/\varepsilon}{\pi r_{\max}} \right\rceil$  and  $h = \sqrt{\varepsilon}$ , then

$$\begin{aligned}
 \|(u - \overline{(u_\varepsilon^*)_h})(\cdot, y)\|_{L_2} &\leq C_1(r_{\max})E \cdot \left( \frac{\varepsilon \cdot \ln\left(\frac{1}{\varepsilon}\right)}{\pi r_{\max}} + \varepsilon \right)^{1 - \frac{y}{r_{\max}}} \\
 &+ 2C_2(y) \exp(\pi y) r_{\max} \frac{\varepsilon^{1 - \frac{y}{r_{\max}}}}{\ln\left(\frac{1}{\varepsilon}\right)} \\
 &+ \frac{y}{12\pi} \|(\phi_1)_\varepsilon^*\|_{L_1} \frac{\left(\ln\left(\frac{1}{\varepsilon}\right) + \pi r_{\max}\right)^4 \cdot \exp(\pi y) \cdot \varepsilon^{1 - \frac{y}{r_{\max}}}}{r_{\max}^4} \longrightarrow 0 \quad (\varepsilon \rightarrow 0)
 \end{aligned}$$

- **MORE GENERAL SITUATION:**  $\operatorname{div}(a(x)\nabla u) = 0$   
(Assumptions:  $0 < r_a \leq a(x) \leq R_a, |a'(x)| \leq R'_a$ )

### Same program:

- Method of lines approximation  
Difficulty: Eigenvalues, -vectors are not explicitly known
- Analyse discrete Sturm-Liouville-Eigenvalue Problem  
(convergence of eigenvalues and eigenvectors)
- Use logarithmic convexity etc.

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(convergence of eigenvalues and eigenvectors)
- Use logarithmic convexity etc.

**Similar results** as for CPLE w.r.t.  $(v_h, w_h)_{0,a} = h \sum_{j \in \mathbb{Z}} a(x_j) v_h(x_j) w_h(x_j);$

use projection  $P_M$  onto  $D_M$  also w.r.t.  $(\cdot, \cdot)_{0,a}$

**Convergence:** For  $M = \left\lceil \ln(1/\varepsilon) / (\pi r_{\max} \sqrt{\frac{R_a}{r_a}}) \right\rceil$ ,  $h = \sqrt{\varepsilon}$

$$\begin{aligned} \|u - \overline{u_{\varepsilon,h}^*}\|_a &\leq CE \left( \frac{\frac{r_a}{\varepsilon R_a} \ln\left(\frac{1}{\varepsilon}\right)}{\pi r_{\max} \sqrt{\frac{R_a}{r_a}}} + \varepsilon \frac{r_a}{R_a} \right)^{1 - \frac{y}{r_{\max}}} \\ &+ \frac{R_a^2 r_{\max} C(y) \exp\left(\sqrt{\frac{R_a}{r_a}} \pi y\right)}{r_a} \cdot \frac{\varepsilon^{1 - \frac{y}{r_{\max}}}}{\ln\left(\frac{1}{\varepsilon}\right)} \\ &+ C \varepsilon^{1 - \frac{y}{r_{\max}}} \ln\left(\frac{1}{\varepsilon}\right) \longrightarrow 0 \quad (\varepsilon \rightarrow 0) \end{aligned}$$

- Numerical results for Cauchy Problem (Hadamard's example):  $a = \text{const.}$

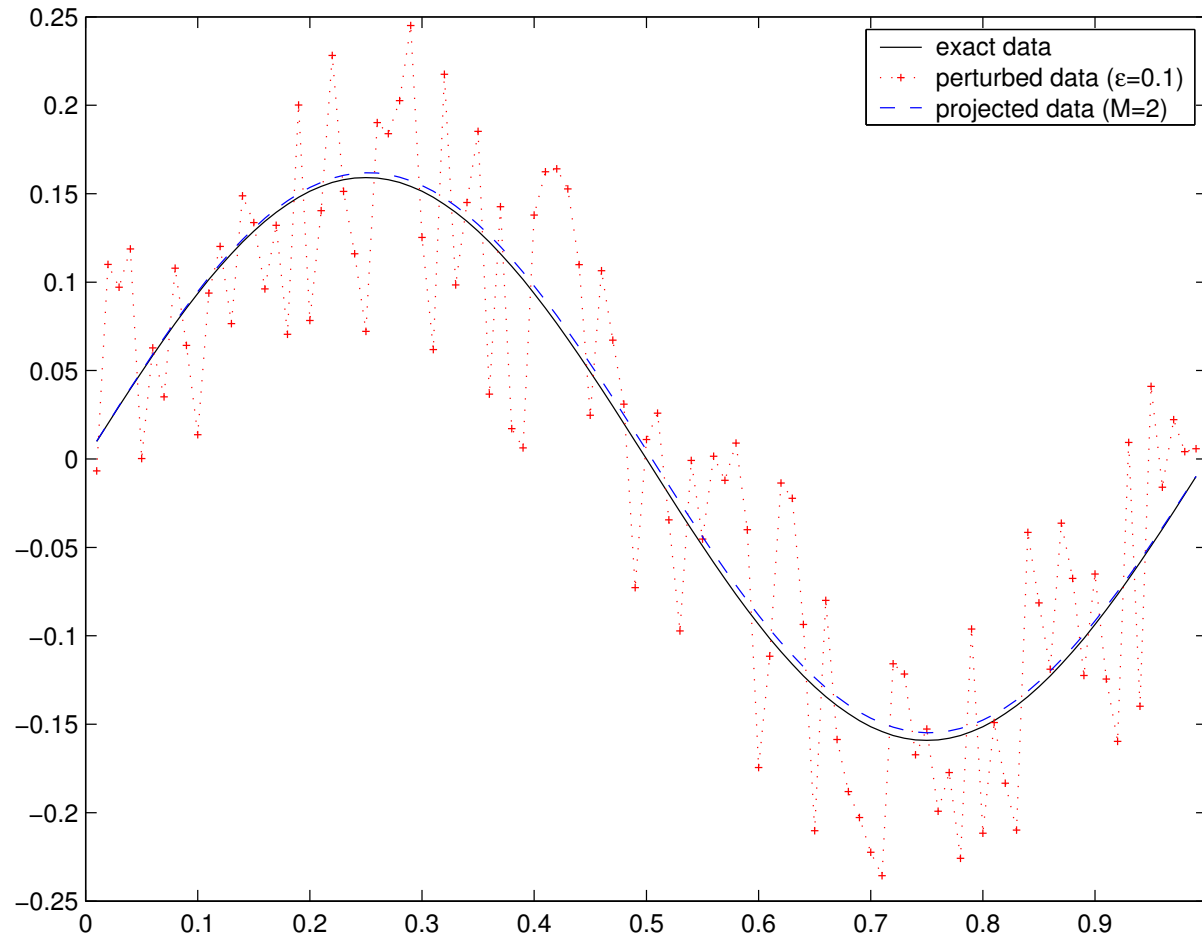


Figure 1: Projected data  $\Phi_1$  (from Hadamard Example) at  $y = 0$  onto  $D_M$  with  $\epsilon = 0.1$ ,  $h = \frac{1}{100}$ ,  $m = 2$ ,  $M = 2$

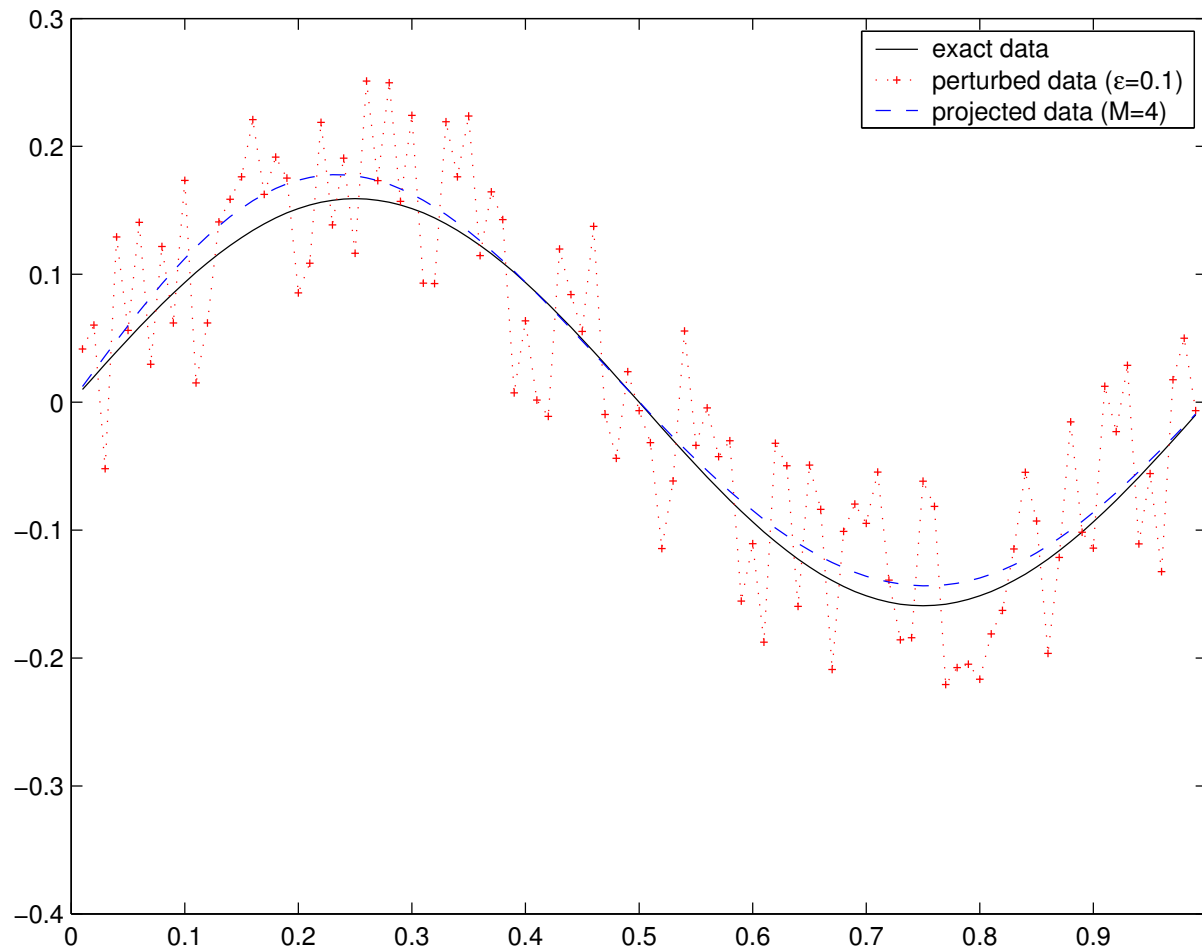


Figure 2: same as Fig. 1 with  $M = 4$

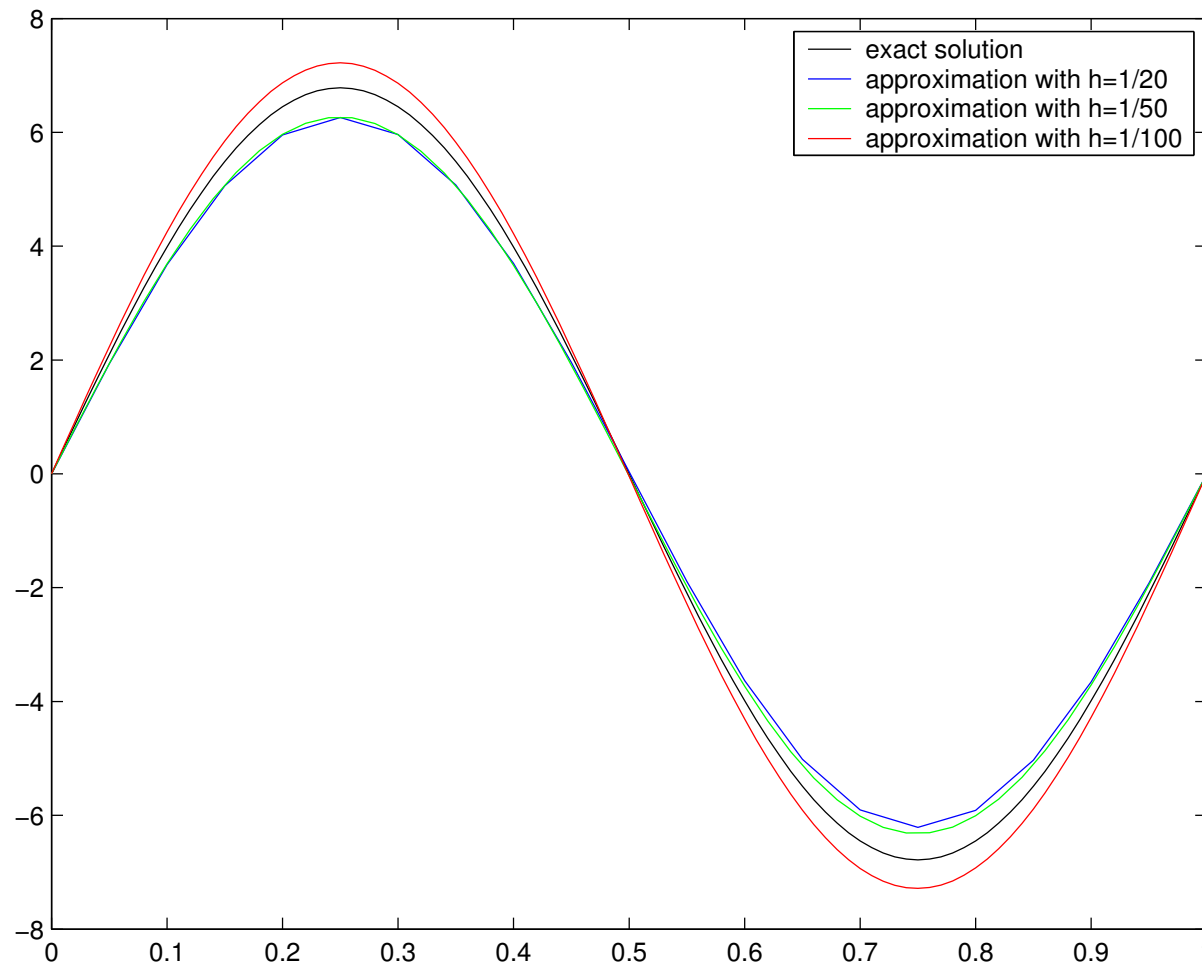


Figure 3: Solution and line method approximations of Hadamard Example at  $y = 1$  for  $\varepsilon = 0.1$ ,  $m = 2$ ,  $M = 2$  and different  $h$ 's



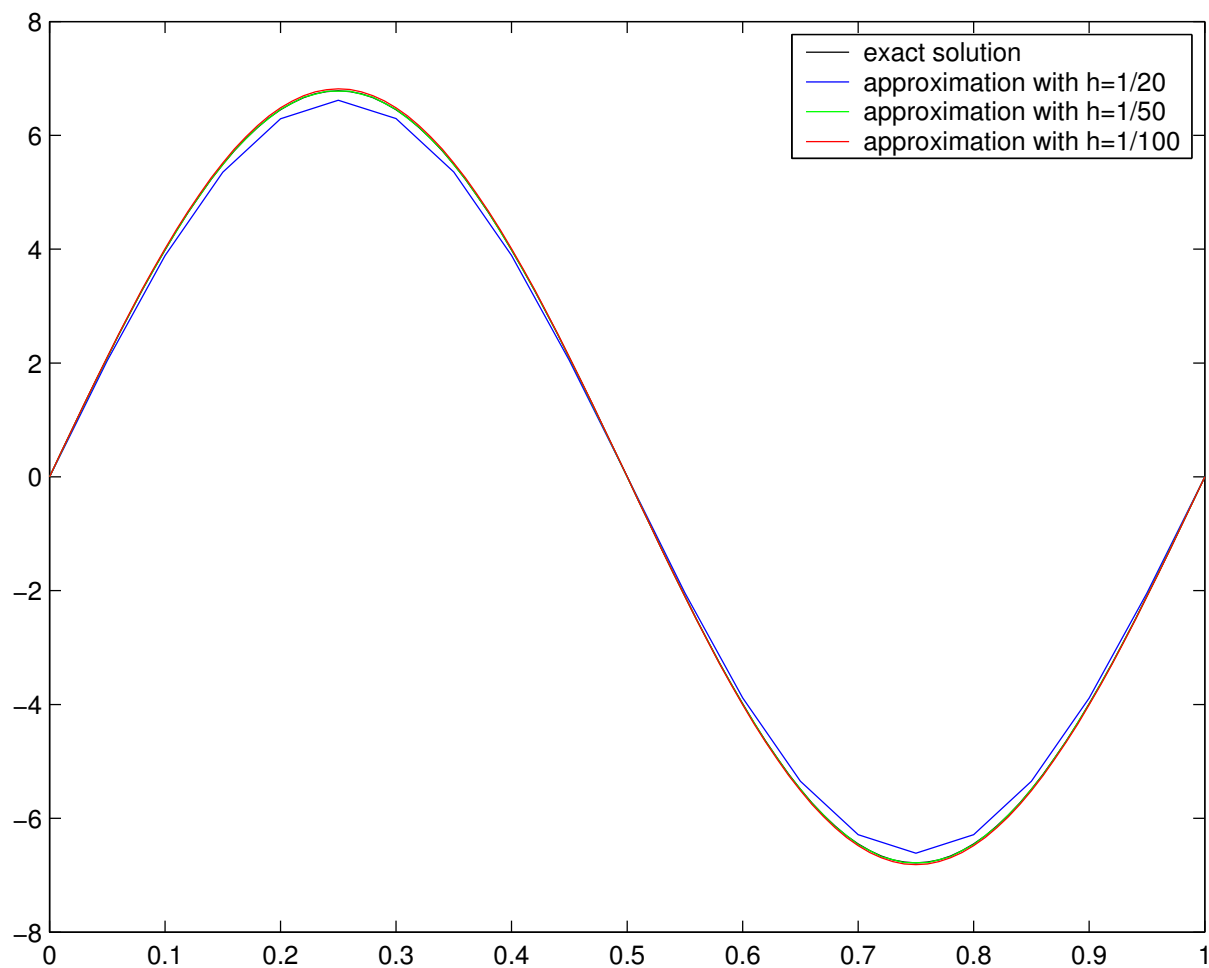


Figure 4: same as Fig. 3 with  $\varepsilon = 10^{-2}$

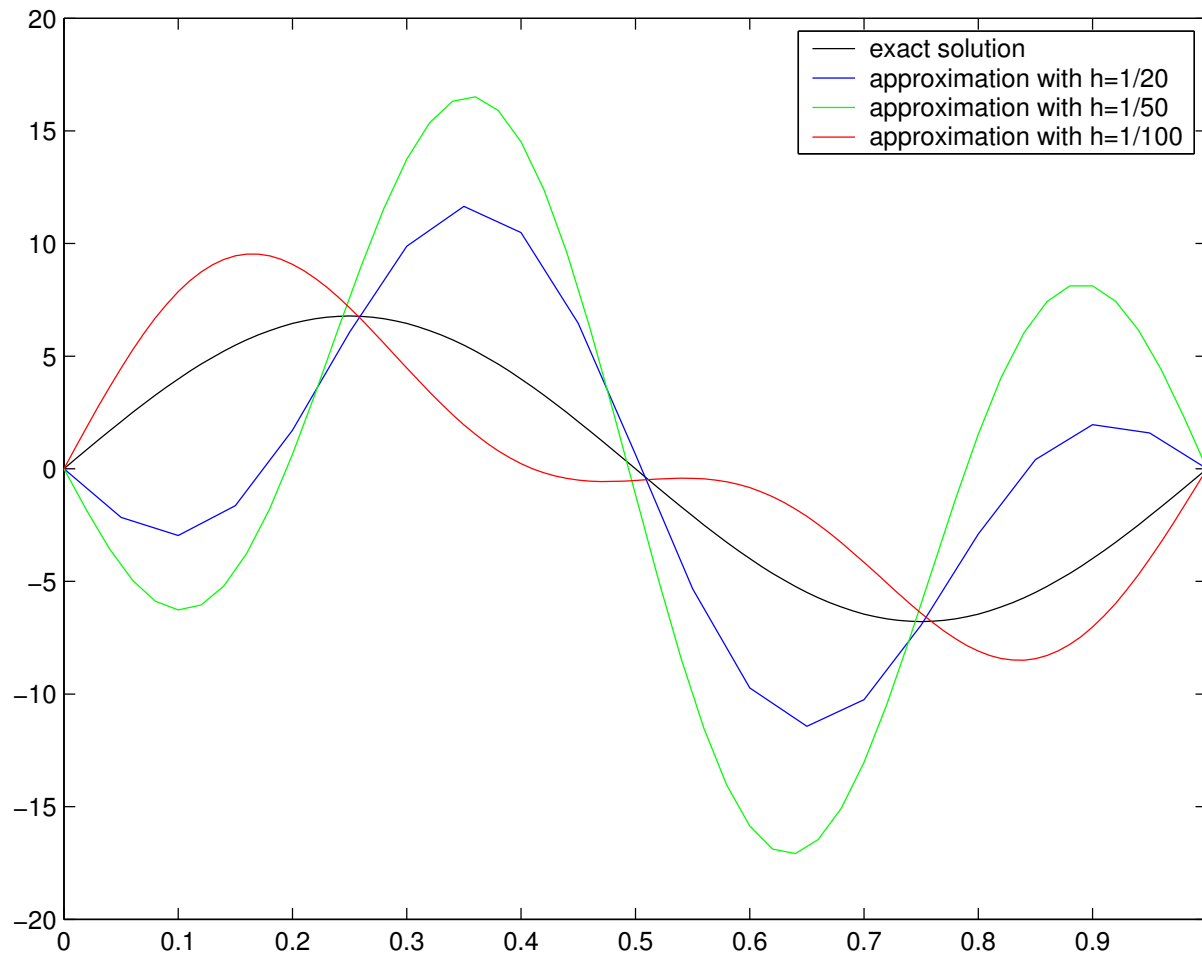


Figure 5: Solution and line method approximations of Hadamard Example at  $y = 1$  for  $\varepsilon = 10^{-2}$ ,  $m = 2$ ,  $M = 4$  and different  $h$ 's

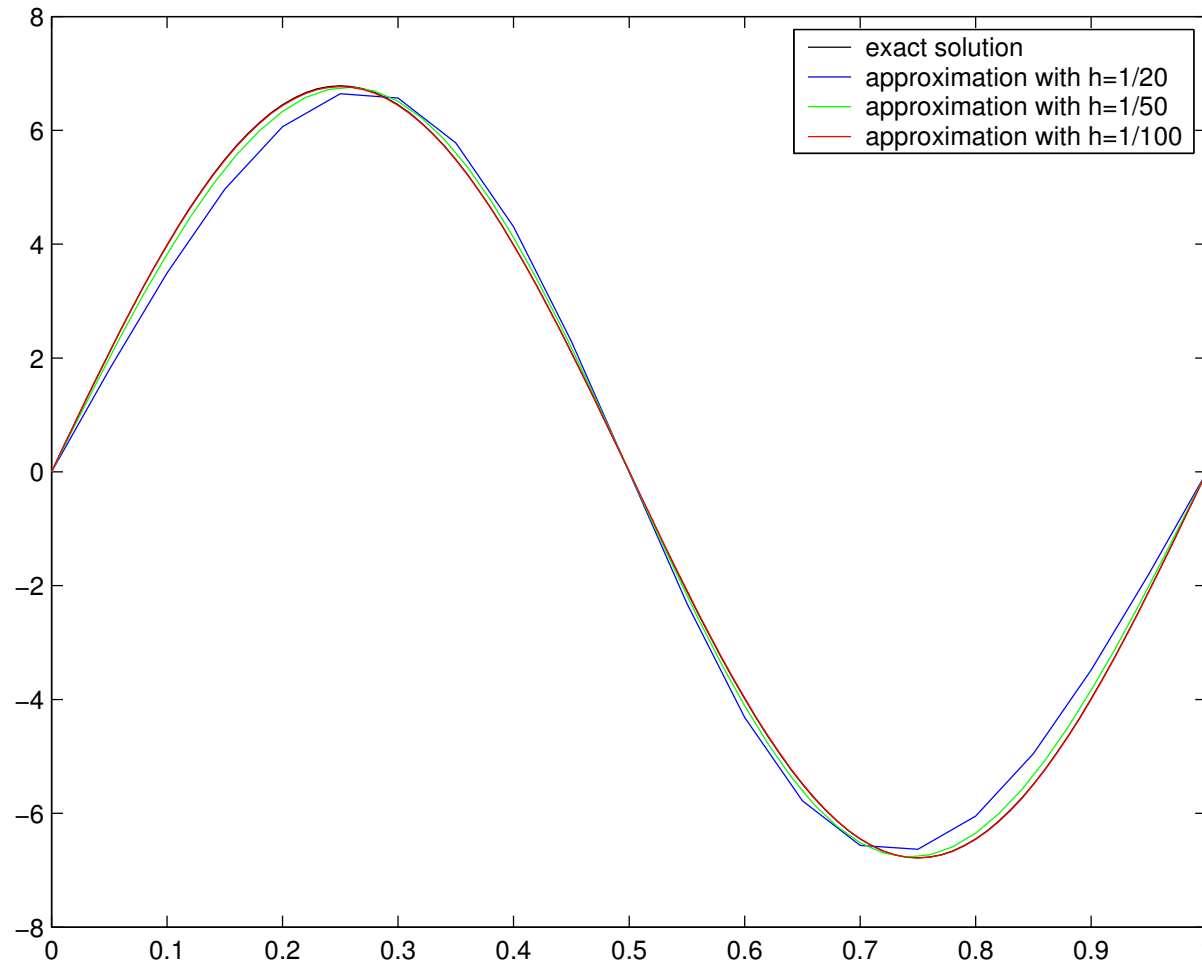


Figure 6: same as Fig. 5 with  $\varepsilon = 10^{-4}$  (Note:  $\varepsilon \approx 1/\exp M$ )

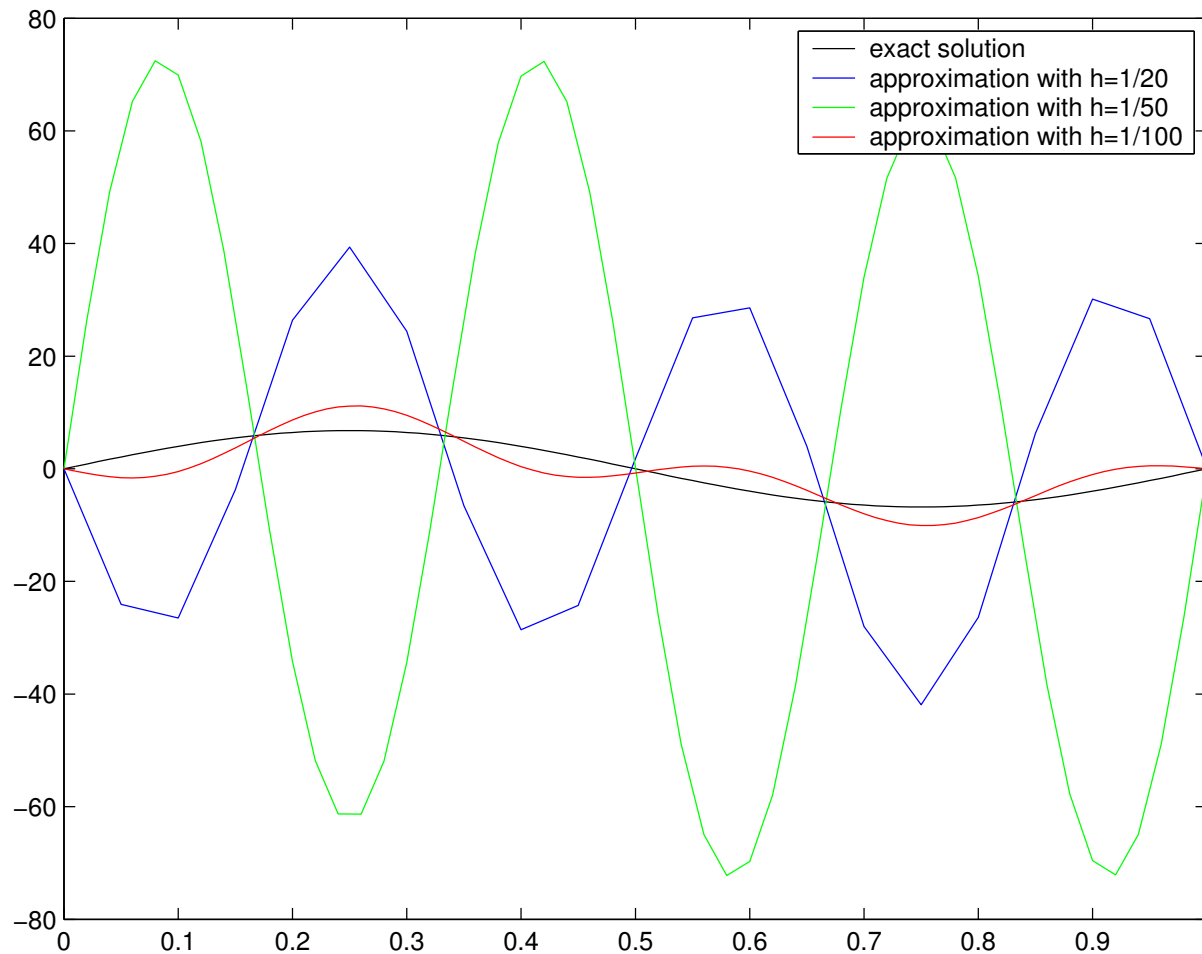


Figure 7: Solution and line method approximations of Hadamard Example at  $y = 1$  for  $\varepsilon = 10^{-4}$ ,  $m = 2$ ,  $M = 6$  and different  $h$ 's

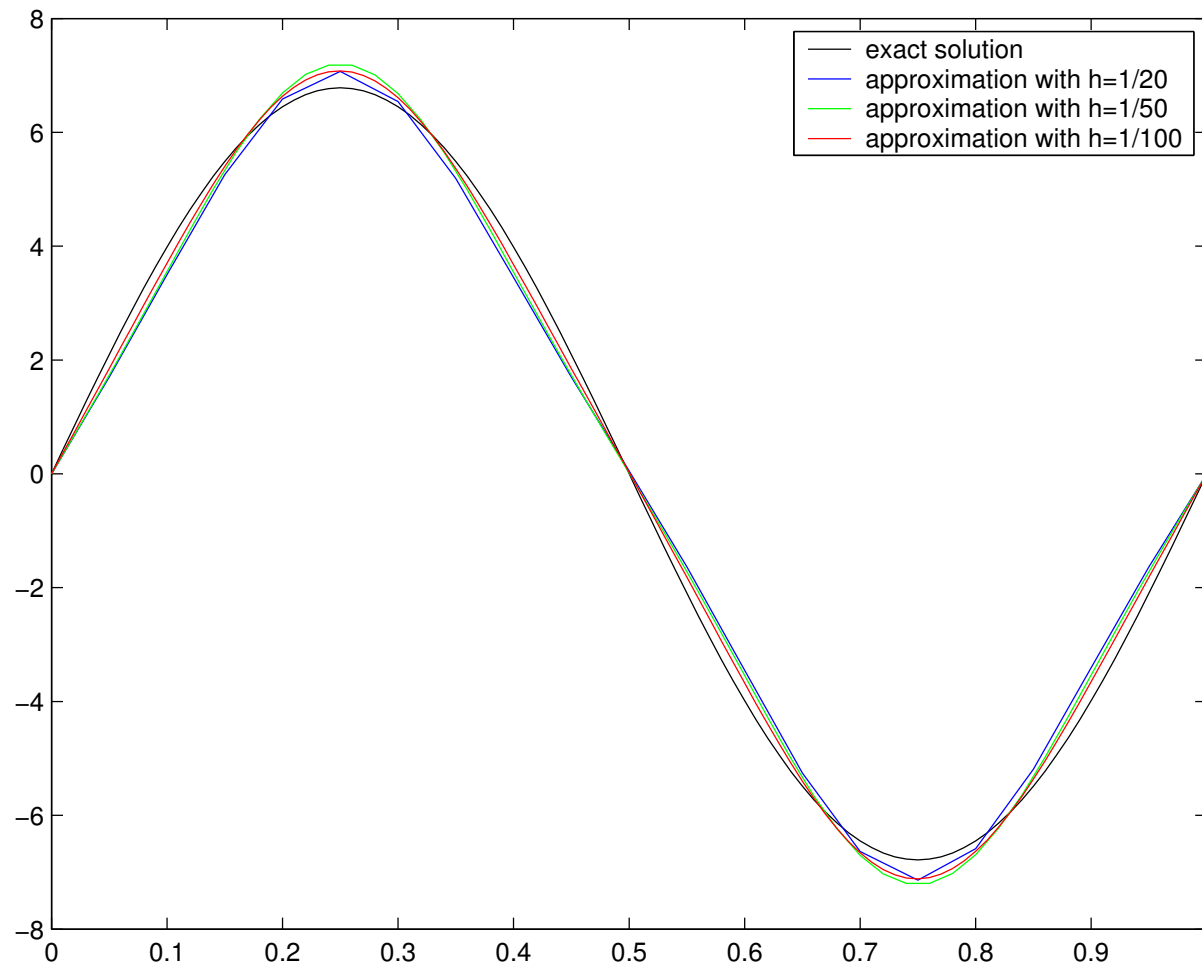


Figure 8: same as Fig. 7 with  $\varepsilon = 10^{-6}$

- Numerical results for Cauchy-Problem:  $a(x) = x + 1$

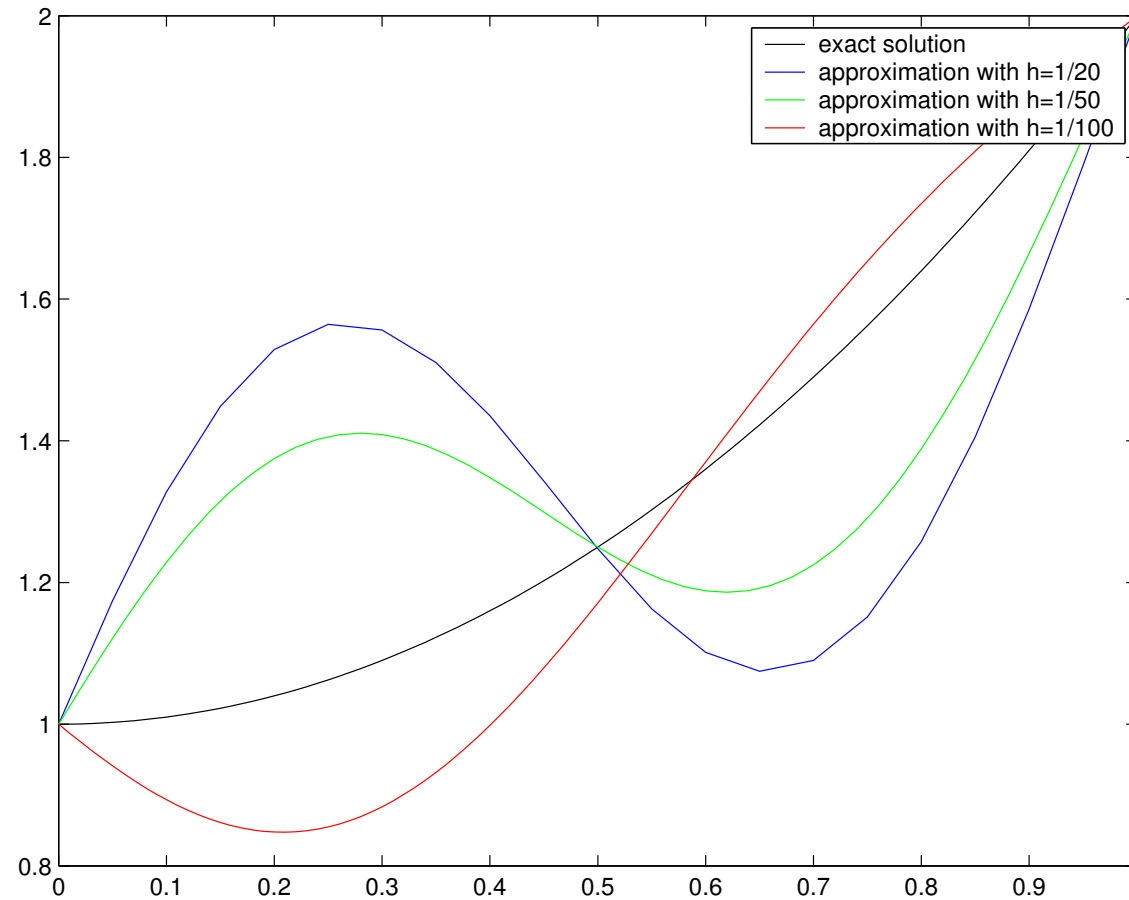


Figure 9: Solution  $u = x^2 + y^2$  and line method approximations in case of  $a(x) = x + 1$  at  $y = 1$  for  $\varepsilon = 10^{-1}$ ,  $M = 2$ , different  $h$ 's (and  $\bar{h} = \frac{1}{200}$ )

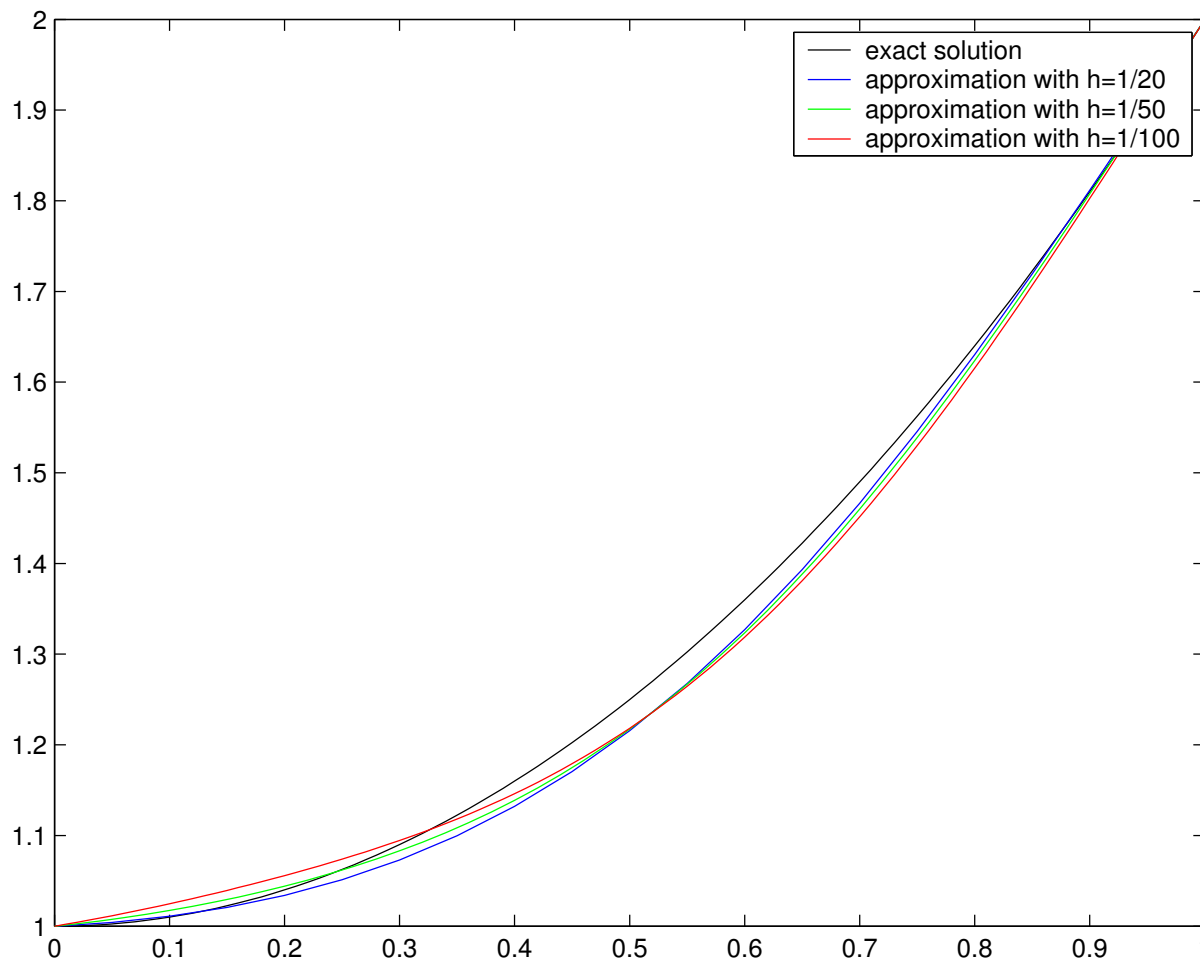


Figure 10: same as Fig. 9 with  $\varepsilon = 10^{-3}$

## Conclusions for Cauchy problem:

When the 2-d domain is a rectangle, or can be transformed to a rectangle, then

- the method of lines is a computable, efficient and convergent approximation scheme;
- the regularization parameter  $M$  (i.e. dimension of data space) can be chosen – and computed – in an optimal way depending on the magnitude  $\varepsilon$  of data perturbations, the bound  $E$  on the unknown part of the boundary, and the mesh width  $h$ .
- The general case  $\nabla(a(x)\nabla u) = 0$  can be treated similarly.



- Numerical results for shape optimization

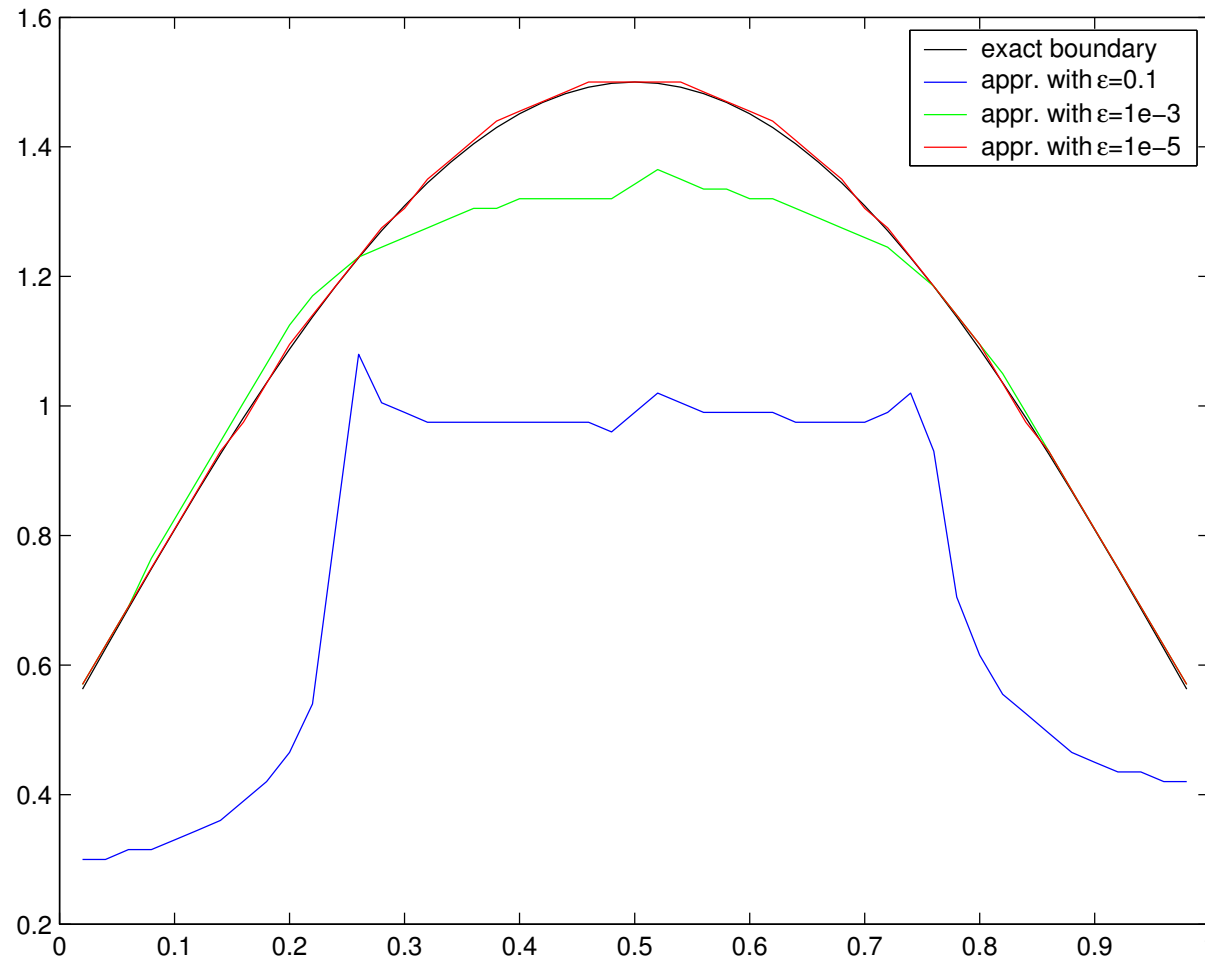


Figure 11: Solution of Hadamard example and approximation of shape identification with  $m = 2$ ,  $M = 4$ ,  $h = \frac{1}{50}$  and different  $\epsilon$ 's (exact form of shape  $\frac{1}{2} + \sin \pi x$ )

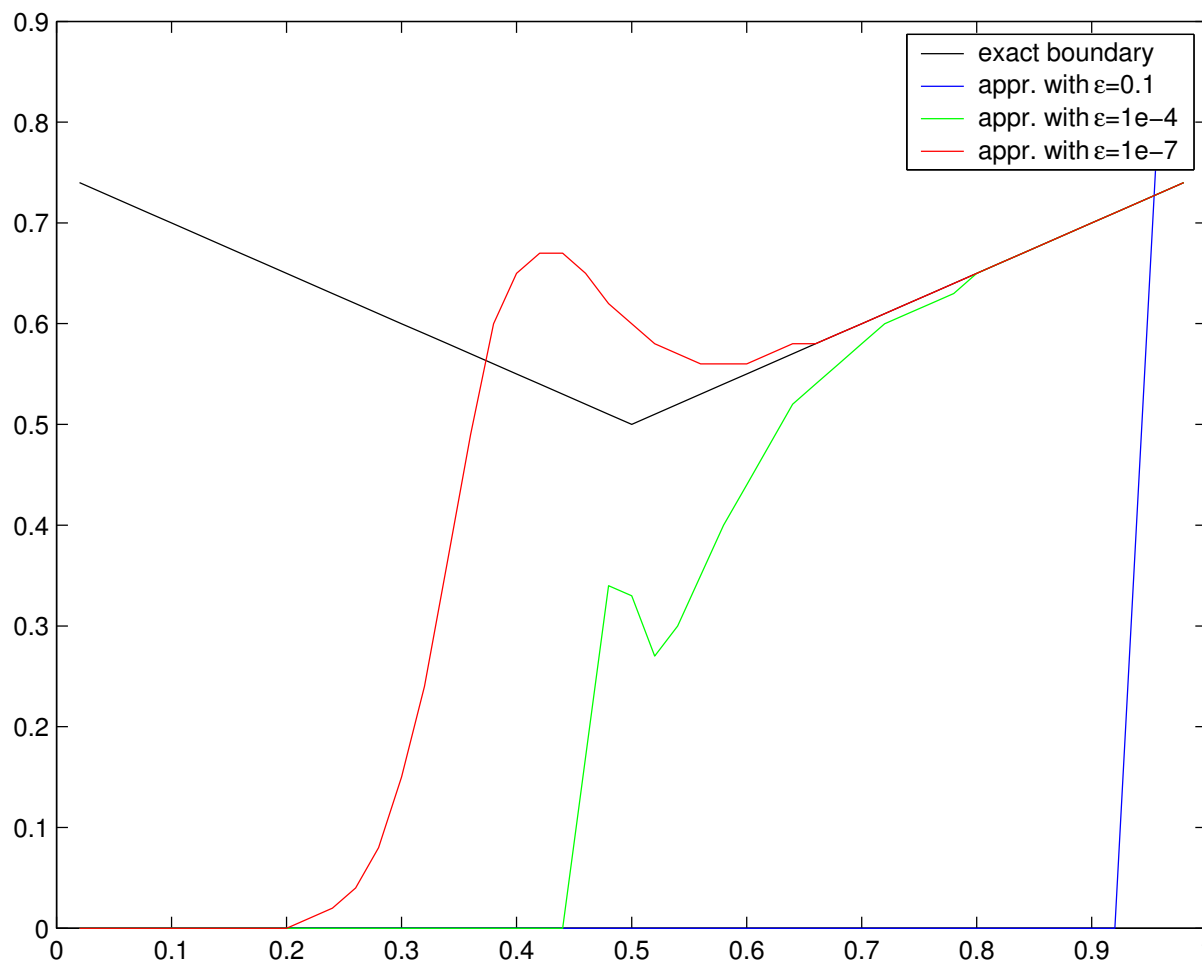


Figure 12: same as Fig. 11 (solution  $u = x^{10}y^{10}$ , exact shape  $\frac{1}{2}(1 + |\frac{1}{2} - x|)$ )