

From Least Squares to Monge-Ampère

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Goals

- 1 Show that 'textbook' techniques, such as least-squares, still have applications nowadays.
- 2 Provide an example where 'things can go wrong'.
- 3 Talk about a very important partial differential equation in the field of *fully nonlinear elliptic equations*.



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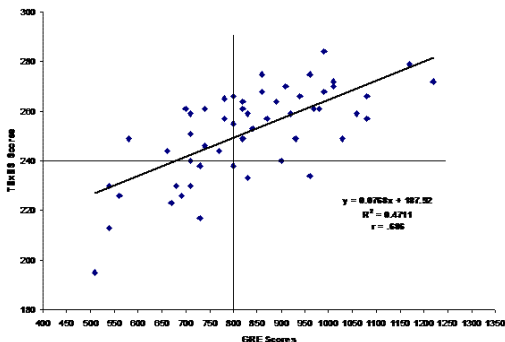


Outline

- Least Squares Methods and Approximation Theory
- The Monge-Ampère Equation
- Numerical Solution of the Monge-Ampère Equation
 - Domain Decomposition
 - Least Squares Formulation
 - A Collocation Method
- Numerical Results
- Conclusions, Perspectives and Other Examples



Starting with Statistics...



For $(x_i, y_i)_{i=1}^N$ given, find the line $y = ax + b$ satisfying

$$\min_{a,b} \sum_{i=1}^N (y_i - (ax_i + b))^2.$$

Linear Regression

Best line to approximate a cloud of point

For $(x_i, y_i)_{i=1}^N$ given, find the line $y = ax + b$ satisfying

$$\min_{a,b} \sum_{i=1}^N (y_i - (ax_i + b))^2.$$

Answer

$$a = \frac{N \sum_{i=1}^N x_i y_i - \left(\sum_{i=1}^N x_i \right) \left(\sum_{i=1}^N y_i \right)}{N \left(\sum_{i=1}^N x_i^2 \right) - \left(\sum_{i=1}^N x_i \right)^2},$$

$$b = \frac{\left(\sum_{i=1}^N y_i \right) - a \left(\sum_{i=1}^N x_i \right)}{N}.$$



Approximation of Functions

Problem

For a given function $f \in C^0[a, b]$, find the best polynomial of degree one $P_1(x)$ that approximates the function f on the interval $[a, b]$

Answer: Find the polynomial function $P_1(x)$ that minimizes the distance between f and P_1

$$\min_{P_1 \in \mathbb{P}_1} d(P_1, f).$$

Question: Choice of the distance function?



Distance Function

- L^∞ -norm:

$$\min_{a_0, a_1} \max_{x \in [a, b]} |f(x) - (a_0 + a_1 x)|.$$

This is called a **min-max** problem.

- L^1 -norm:

$$\min_{a_0, a_1} \int_a^b |f(x) - (a_0 + a_1 x)| dx.$$

Problem: Non-differentiable function.

- L^2 -norm:

$$\min_{a_0, a_1} \int_a^b (f(x) - (a_0 + a_1 x))^2 dx.$$

Least-squares problem.



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Least-squares problem.



Approximation of Functions by Polynomials

Problem

For a given function $f \in C^0[a, b]$, find the best polynomial of degree n , $P_n(x)$, that approximates the function f on the interval $[a, b]$. Since $P_n(x) = \sum_{k=0}^n a_k x^k$, the least squares approach is:

$$\min_{a_0, \dots, a_n} \int_a^b \left(f(x) - \sum_{k=0}^n a_k x^k \right)^2 dx = \min_{P_n \in \mathbb{P}_n} \|f - P_n\|_{L^2(a,b)}^2.$$



Normal Equations

The normal equations form the system

$$\frac{\partial}{\partial a_j} \|f - P_n\|_{L^2(a,b)}^2 = 0, \quad j = 0, \dots, n$$

In that case:

$$\sum_{i=0}^n a_i \int_a^b x^{i+j} dx = \int_a^b f x^j dx, \quad j = 0, \dots, n$$



Approximation of Functions by a Subspace

Let $\{\phi_1, \dots, \phi_n\}$ be a linearly independent family of functions in $C^0[a, b]$. Let

$$V = \text{span}\{\phi_1, \dots, \phi_n\} \subset C^0[a, b], \quad \dim V = n.$$

Problem

For a given function $f \in C^0[a, b]$, find the best function $g \in V$, that approximates the function f on the interval $[a, b]$. This function minimizes the distance between f and g :

$$\min_{g \in V} d(P_1, f).$$



Least-Squares approximations

- For instance, the **least squares problem** reads:

$$\min_{g \in V} \int_a^b (f(x) - g(x))^2 dx = \min_{g \in V} \int_a^b \left(f(x) - \sum_{k=1}^n a_k \phi_k(x) \right)^2 dx.$$

- The normal equations read:

$$\sum_{k=1}^n a_k \int_a^b \phi_k(x) \phi_j(x) dx = \int_a^b f(x) \phi_j(x) dx, \quad j = 1, \dots, n.$$

This system may be **diagonal** if the basis functions are **orthogonal**.



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Questions

- Choice of the subspace V ? What are the basis functions ϕ_k ?
- Choice of the distance d ? What objective function to minimize?



Dirichlet Problem for the Monge-Ampère Equation

Let $\Omega \subset \mathbb{R}^2$ bounded, smooth, convex. Consider $f \in L^1(\Omega)$, $f > 0$, and $g \in H^{3/2}(\partial\Omega)$.

Find $\psi \in H^2(\Omega)$ satisfying

$$\begin{cases} \det \mathbf{D}^2\psi = f & \text{in } \Omega, \\ \psi = g & \text{on } \Gamma = \partial\Omega. \end{cases}$$

$$\text{where } \mathbf{D}^2\psi = \begin{pmatrix} \frac{\partial^2\psi}{\partial x^2} & \frac{\partial^2\psi}{\partial x\partial y} \\ \frac{\partial^2\psi}{\partial x\partial y} & \frac{\partial^2\psi}{\partial y^2} \end{pmatrix}.$$

$$f > 0 \Rightarrow \psi \text{ convex.}$$



Applications and Interpretation

- "Monge-Ampère equation is in implicit nonlinear elliptic PDEs, the equivalent to the Laplace equation in linear elliptic PDEs".
- Many other applications: Geometry, optimal design of antenna arrays, front formation in meteorology, semigeostrophic flow (slow flows under rotation and stratification), reflector design (scattering field), compressible gas dynamics, etc.
- Optimal transportation problem (Monge problem).

[Caffarelli, Cabre AMS, 1995], [Gutierrez, 2001], [Caffarelli, Milman, 1997].



Optimal Transportation Problem

Discrete case

Given two sets of k points in \mathbb{R}^n : X_1, \dots, X_k and Y_1, \dots, Y_k , find a mapping of X_k onto Y_j , i.e., among all one-to-one functions $Y(X_k)$ that minimizes some transportation costs, for instance,

$$C = \frac{1}{2} \sum_k |Y(X_k) - X_k|^2.$$

Continuous case

Find an (admissible) map $Y(X)$, linking two probability densities, that minimizes some cost.

In that case, $Y(X) = \nabla\varphi$, where φ is a convex potential that satisfies the Monge-Ampère equation.



Existence and Regularity of Solutions

- When $f \in L^1(\Omega)$, $f > 0$, and $g \in H^{3/2}(\partial\Omega)$, it makes sense to look for a **convex** solution $\psi \in H^2(\Omega)$.
- The solution is not necessarily unique (actually at most two solutions).
- The smoothness of the data does not imply the smoothness of the solution. In particular, when the domain Ω is **not strictly convex**, there is no classical solution (even for f , g and $\partial\Omega$ smooth).

For instance, if $\Omega = (0, 1)^2$, $f = 1$, and $g = 0$, there is no classical solutions $\psi \in C^2(\Omega)$.

Indeed, $\psi = 0$ on the boundary, implies that both the product $\frac{\partial^2 \psi}{\partial x^2} \frac{\partial^2 \psi}{\partial y^2}$ and the cross derivative $\frac{\partial^2 \psi}{\partial x \partial y}$ vanish at the boundary. Which implies that $\det D^2 \psi$ is strictly smaller than one in a neighborhood of Γ .



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Viscosity Solutions

For conservation laws:

Find u^ε satisfying

$$\begin{cases} -\varepsilon \frac{\partial^2 u^\varepsilon}{\partial x^2} + \frac{\partial u^\varepsilon}{\partial t} + u^\varepsilon \frac{\partial u^\varepsilon}{\partial x} = 0 & \text{in } \mathbb{R} \times (0, \infty), \\ u^\varepsilon = g & \text{on } \mathbb{R} \times \{t = 0\}. \end{cases}$$

For Hamilton-Jacobi equations:

Find u^ε satisfying

$$\begin{cases} -\varepsilon \Delta u^\varepsilon + \frac{\partial u^\varepsilon}{\partial t} + H(\nabla u^\varepsilon, t) = 0 & \text{in } \mathbb{R}^n \times (0, \infty), \\ u^\varepsilon = g & \text{on } \mathbb{R}^n \times \{t = 0\}. \end{cases}$$

[L. C. Evans, AMS, 2002]



Viscosity Solutions

- **Moment methods** [Feng, Neilan, 2007]:

Find ψ^ε satisfying

$$\begin{cases} -\varepsilon \Delta^2 \psi^\varepsilon + \det \mathbf{D}^2 \psi^\varepsilon = f & \text{in } \Omega, \\ \psi^\varepsilon = g & \text{on } \Gamma = \partial\Omega, \\ \Delta^2 \psi^\varepsilon = \varepsilon^2, & \text{on } \Gamma = \partial\Omega \end{cases}$$

- We have [Feng, 2009]

$$\lim_{\varepsilon \rightarrow 0} \psi^\varepsilon = \psi.$$

- **Finite element approximation.** There are positive constants C , α and β such that

$$\|\psi^\varepsilon - \psi\| \leq Ch^\alpha \frac{1}{\varepsilon^\beta}.$$



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Least-Squares Methods

- Introduction of a distance function:

$$\inf_{\varphi \in V_g} J(\varphi),$$

where

$$V_g = \{\varphi \in H^2(\Omega), \varphi = g\},$$

and

$$J(\varphi) = \begin{cases} \frac{1}{2} \int_{\Omega} |\det \mathbf{D}^2\varphi - f|^2 dx, & \text{if } \det \mathbf{D}^2\varphi - f \in L^2(\Omega), \\ +\infty, & \text{otherwise} \end{cases}$$

- Numerical solution with operator-splitting methods and finite elements [Dean, Glowinski, CMAME, 2006].



Least-Squares Methods (2)

- Introduction of a variational principle:

$$\inf_{\varphi \in E_{fg}} \frac{1}{2} \int_{\Omega} |\Delta \varphi|^2 dx,$$

where

$$E_{fg} = \{ \varphi \in H^2(\Omega), \varphi = g \text{ on } \Gamma, \det \mathbf{D}^2 \varphi = f \}.$$

- Numerical solution with penalization, augmented Lagrangian methods and finite elements [Dean, Glowinski, CMAME, 2006].



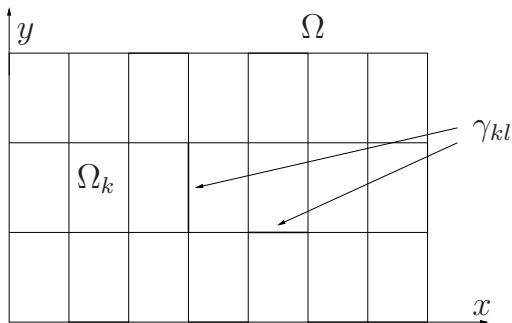
As we have seen, if we want to use *least-squares* methods, we have many choices for

- The subspace V of approximations;
- The distance (objective function) to minimize.

Let us describe another least-squares approach, a little bit less classical...



Domain Decomposition



The domain Ω is divided into K non-overlapping sub-domains Ω_k , $k = 1, \dots, K$, such that

$$\bigcup_{k=1}^K \overline{\Omega_k} = \overline{\Omega}, \quad \Omega_k \cap \Omega_j = \emptyset \text{ if } j \neq k.$$



Choice of the Subspace

- When looking for *convex solutions*, a convex polynomial function of degree two is associated to each sub-domain Ω_k , namely

$$\psi_k(x, y) = \frac{\sqrt{f_k}}{2} (x^2 + y^2) + \alpha_k x + \beta_k y + \gamma_k,$$

where α_k, β_k and γ_k are unknown real coefficients, and $f_k \simeq f|_{\Omega_k}$, e.g.

$$f_k = \frac{\int_{\Omega_k} f(x, y) dx dy}{\int_{\Omega_k} dx dy},$$

- Note that $\det \mathbf{D}^2 \psi_k = f_k$ in Ω_k .



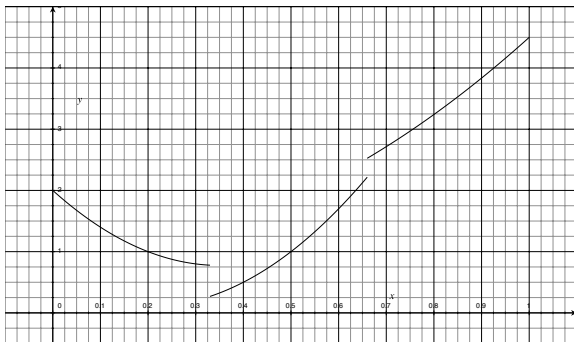
Choice of the Subspace

$$V = \left\{ \begin{array}{l} \varphi \in L^2(\Omega), \varphi|_{\Omega_k} \in \mathbb{P}_2, \\ \varphi(x, y)|_{\Omega_k} = \frac{\sqrt{f_k}}{2} (x^2 + y^2) + \alpha_k x + \beta_k y + \gamma_k, \\ \overline{\bigcup_{k=1}^K \Omega_k} = \bar{\Omega}, \end{array} \right\}$$



Choice of the Objective Function

One dimensional case:



Remember

We are looking for $\psi \in H^2(\Omega)$. In two dimensions, this corresponds to *nearly* $C^1(\Omega)$ -functions.



Objective Function

$$\min_{\alpha, \beta, \gamma \in \mathbb{R}^K} J(\alpha, \beta, \gamma),$$

where

$$\begin{aligned} J(\alpha, \beta, \gamma) = & \frac{1}{2} \sum_{1 \leq k, l \leq K} \int_{\gamma_{kl}} |\psi_k(x, y) - \psi_l(x, y)|^2 dS \\ & + \frac{1}{2} \sum_{1 \leq k \leq K} \int_{\partial\Omega_k \cap \Gamma} |\psi_k(x, y) - g(x, y)|^2 dS \\ & + \frac{r}{2} \sum_{1 \leq k, l \leq K} \int_{\gamma_{kl}} \left| \frac{\partial \psi_k}{\partial n_k}(x, y) + \frac{\partial \psi_l}{\partial n_l}(x, y) \right|^2 dS, \end{aligned}$$

where $\alpha = (\alpha_k)_{k=1}^K$, $\beta = (\beta_k)_{k=1}^K$ and $\gamma = (\gamma_k)_{k=1}^K$, and $r > 0$.



Alternative choice

$$\begin{aligned}
J(\alpha, \beta, \gamma) &= \frac{1}{2} \sum_{1 \leq k, l \leq K} \int_{\gamma_{kl}} |\psi_k(x, y) - \psi_l(x, y)| dS \\
&+ \frac{1}{2} \sum_{1 \leq k \leq K} \int_{\partial\Omega_k \cap \Gamma} |\psi_k(x, y) - g(x, y)| dS \\
&+ \frac{r}{2} \sum_{1 \leq k, l \leq K} \int_{\gamma_{kl}} \left| \frac{\partial\psi_k}{\partial n_k}(x, y) + \frac{\partial\psi_l}{\partial n_l}(x, y) \right| dS.
\end{aligned}$$



The Case of a Rectangle

Consider $\Omega = (0, a) \times (0, b)$, l, J given, and $h_x = a/l$, $h_y = b/J$. For $i = 1, \dots, l$ and $j = 1, \dots, J$, we consider the sub-domain $\Omega_{ij} = ((i-1)h_x, ih_x) \times ((j-1)h_y, jh_y)$ (such that $\overline{\Omega} = \overline{\bigcup_{ij} \Omega_{ij}}$), and the polynomial ψ_{ij} defined by

$$\psi_{ij}(x, y) = \frac{\sqrt{f_{ij}}}{2} (x^2 + y^2) + \alpha_{ij}x + \beta_{ij}y + \gamma_{ij}.$$



A Collocation Method

- Approximate each integral numerically in

$$\begin{aligned}
 J(\alpha, \beta, \gamma) &= \frac{1}{2} \sum_{1 \leq k, l \leq K} \int_{\gamma_{kl}} |\psi_k(x, y) - \psi_l(x, y)|^2 dS \\
 &+ \frac{1}{2} \sum_{1 \leq k \leq K} \int_{\partial\Omega_k \cap \Gamma} |\psi_k(x, y) - g(x, y)|^2 dS \\
 &+ \frac{r}{2} \sum_{1 \leq k, l \leq K} \int_{\gamma_{kl}} \left| \frac{\partial\psi_k}{\partial n_k}(x, y) + \frac{\partial\psi_l}{\partial n_l}(x, y) \right|^2 dS,
 \end{aligned}$$

- Numerical integration with **Gauss-Legendre points**

$$\int_a^b g(x) dx \simeq \sum_{k=1}^n \omega_k g(x_k).$$

Numerical integration is exact (if n large enough, *i.e.* $n = 3$)!

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System of Equations

Matching of Boundary conditions:

$$\alpha_{i1}x_{ki} + \gamma_{i1} = g_{x,ki1} - \frac{\sqrt{f_{i1}}}{2}x_{ki}^2, \quad k = 1, n, \quad i = 1, I.$$

$$\alpha_{iJ}x_{ki} + \beta_{iJ}b + \gamma_{iJ} = g_{x,ki2} - \frac{\sqrt{f_{iJ}}}{2}(x_{ki}^2 + b^2), \quad k = 1, n, \quad i = 1, I.$$

$$\beta_{1j}y_{kj} + \gamma_{1j} = g_{y,k1j} - \frac{\sqrt{f_{1j}}}{2}y_{kj}^2, \quad k = 1, n, \quad j = 1, J.$$

$$\alpha_{Ij}a + \beta_{Ij}y_{kj} + \gamma_{Ij} = g_{y,k2j} - \frac{\sqrt{f_{Ij}}}{2}(a^2 + y_{kj}^2), \quad k = 1, n, \quad j = 1, J.$$



System of Equations (2)

Matching of the solution on interior interfaces:

$$(\alpha_{ij+1} - \alpha_{ij})x_{ki} + (\beta_{ij+1} - \beta_{ij})(jh_y) + (\gamma_{ij+1} - \gamma_{ij}) = \frac{1}{2} (\sqrt{f_{ij}} - \sqrt{f_{ij+1}}) (x_{ki}^2 + (jh_y)^2), \quad k = 1, n, j = 1, J - 1, i = 1, l.$$

$$(\alpha_{i+1j} - \alpha_{ij})(ih_x) + (\beta_{i+1j} - \beta_{ij})y_{kj} + (\gamma_{i+1j} - \gamma_{ij}) = \frac{1}{2} (\sqrt{f_{ij}} - \sqrt{f_{i+1j}}) ((ih_x)^2 + y_{kj}^2), \quad k = 1, n, j = 1, J, i = 1, l - 1.$$

Matching of the normal derivatives on interior interfaces:

$$r\beta_{ij+1} - r\beta_{ij} = r (\sqrt{f_{ij}} - \sqrt{f_{ij+1}}) (jh_y), \quad j = 1, J - 1, i = 1, l.$$

$$r\alpha_{i+1j} - r\alpha_{ij} = r (\sqrt{f_{ij}} - \sqrt{f_{i+1j}}) (ih_x), \quad j = 1, \dots, J, i = 1, l - 1$$

Conclusion

$3IJ$ unknowns

$2n(I + J) + n[I(J - 1) + J(I - 1)] + I(J - 1) + J(I - 1)$ equations

Over-determined system!

$$\mathbf{Ax} = \mathbf{b}.$$

The matrix \mathbf{A} is of full column rank. The solution of an over-determined system is addressed by the **normal equations**:

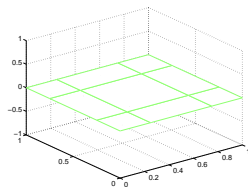
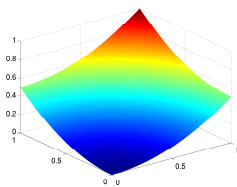
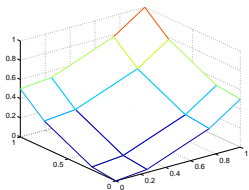
$$\mathbf{A}^T \mathbf{Ax} = \mathbf{A}^T \mathbf{b}.$$



Validation Example

$$\psi(x, y) = \frac{1}{2} (x^2 + y^2), \quad (x, y) \in \Omega.$$

i.e. $f(x, y) = 1$, and $g(x, y) = \frac{1}{2} (x^2 + y^2)$.



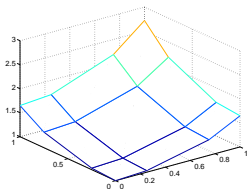
Approximation is exact! ($\alpha = \beta = \gamma = 0$)



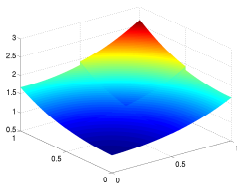
Exponential Example

$$\psi(x, y) = e^{\frac{1}{2}(x^2+y^2)}, \quad (x, y) \in \Omega.$$

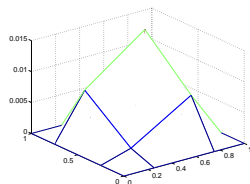
i.e. $f(x, y) = (1 + (x^2 + y^2)) e^{(x^2+y^2)}$, $g(x, y) = e^{\frac{1}{2}(x^2+y^2)}$.



Exact



Approximation



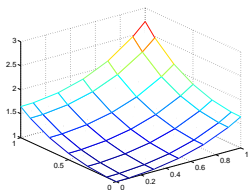
Error



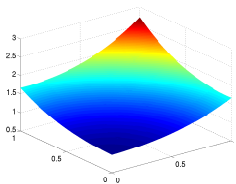
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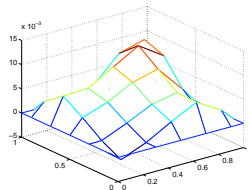
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Exact



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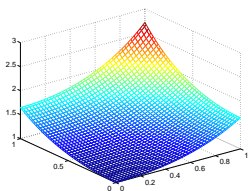
Error



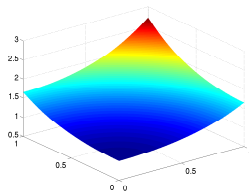
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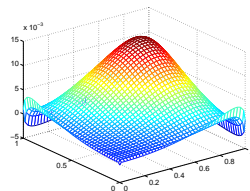
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Exact



Approximation

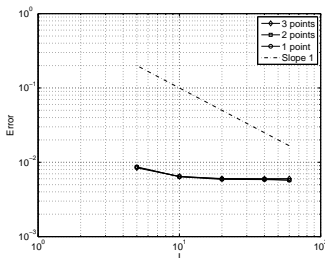


Error

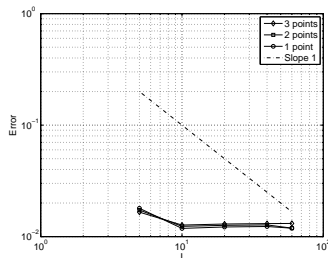


Convergence of Approximations

$I = J$	$\ \psi_h - \psi\ _{L^2(\Omega)}$	$\ \psi_h - \psi\ _{L^\infty(\Omega)}$
5	8.405588e-03	1.656257e-02
10	6.439176e-03	1.268631e-02
20	6.045698e-03	1.296824e-02
50	6.030157e-03	1.311007e-02



L^2 -norm



L^∞ -norm



A Second Example

$$\psi(x, y) = \frac{(2\sqrt{x^2 + y^2})^{3/2}}{3}, \quad (x, y) \in \Omega.$$

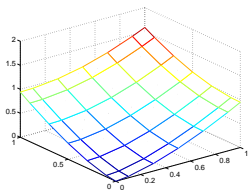
i.e. $f(x, y) = \frac{1}{\sqrt{x^2 + y^2}}, \quad g(x, y) = \frac{(2\sqrt{x^2 + y^2})^{3/2}}{3}.$

$I = J$	$\ \psi_h - \psi\ _{L^2(\Omega)}$	$\ \psi_h - \psi\ _{L^\infty(\Omega)}$
5	9.319363e-03	3.242689e-02
10	6.628609e-03	2.319420e-02
20	6.116831e-03	1.483774e-02
50	6.113496e-03	1.115342e-02

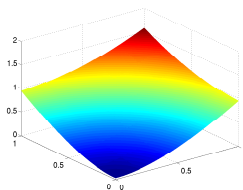


A Second Example (Results)

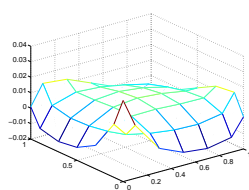
$$I = 5/I = 50$$



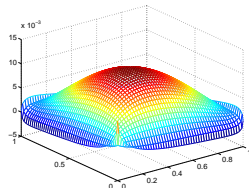
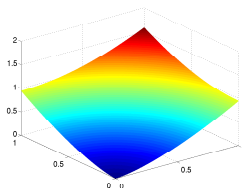
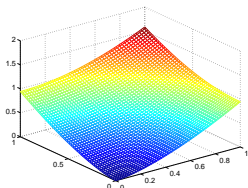
Exact



Approximation

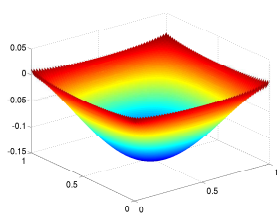
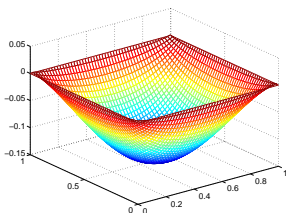
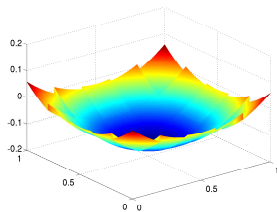
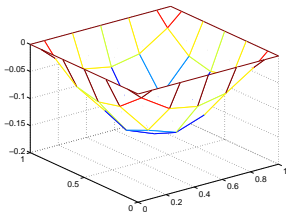


Error

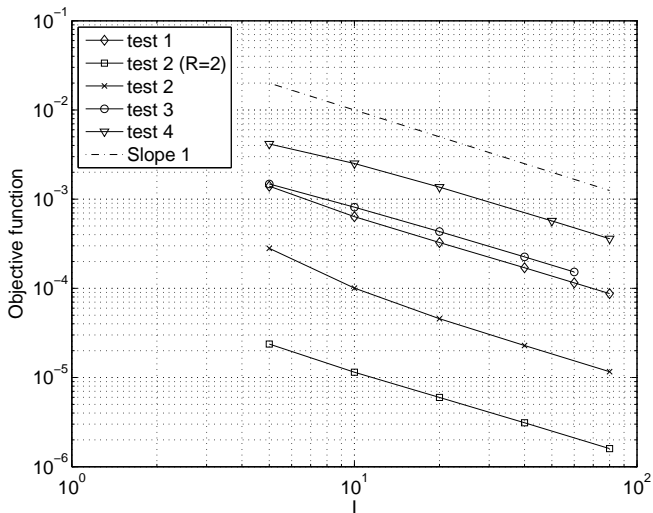


Example with No Smooth Solution

$$f(x, y) = 1, \quad g(x, y) = 0.$$



Decrease of Objective Function



Conclusions

- The distance decreases to zero when the number of sub-domains increases. In some sense, the approximation gets better.
- The error between approximation and exact functions **stagnates**. In some sense, the approximation does not get better.

- The sequence of subspaces V does not converge to $H^2(\Omega)$ when we increase the number of sub-domains. This is a **lack of density**.
- However the method does converge to some function, which is the **best approximation** of ψ in V (some projection of ψ on V).



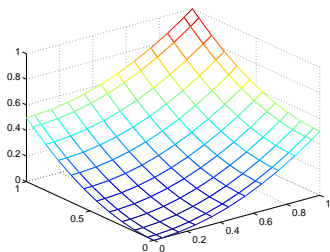
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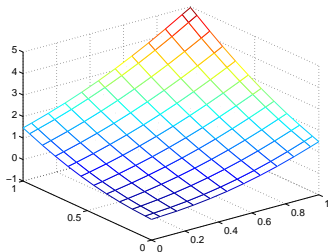
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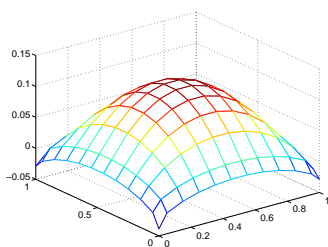
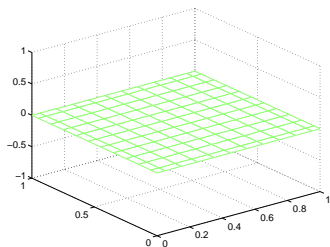
Influence of the Eigenvalues of the Hessian



$$\psi(x, y) = \frac{1}{2} (x^2 + y^2)$$



$$\psi(x, y) = \frac{1}{2} (x^2 + y^2 + 2xy)$$



Remedy?

Expand the approximation subspace!

$$\psi_k(x, y) = \frac{\sqrt{f_k}}{2} (a_k x^2 + 2b_k xy + c_k y^2) + \alpha_k x + \beta_k y + \gamma_k,$$

with α_k , β_k and γ_k as before, and a_k , b_k and c_k verifying

$$a_k b_k - c_k^2 = 1.$$

Justification: Local second order Taylor expansion ψ .



Other Examples

- Find $\mathbf{u} \in (H^1(\Omega) \cap L^\infty(\Omega))^2$ satisfying

$$\nabla \cdot \mathbf{u} = f (\in L^1(\Omega))$$

$$\min_{\mathbf{u} \in \mathbf{S}_f} \frac{1}{2} \int_{\Omega} |\nabla \mathbf{v}|^2 dx + g \|\mathbf{v}\|_{\infty}$$

$$\mathbf{S}_f = \{ \mathbf{v} \in (H^1(\Omega) \cap L^\infty(\Omega))^2, \nabla \cdot \mathbf{u} = f \}.$$



Other Examples

- Find the best constants in Sobolev injections:

$$\|\varphi\|_{L^\infty(\Omega)} \leq C \|\varphi\|_{H^2(\Omega)}, \quad \forall \varphi \in H^2(\Omega) \cap H_0^1(\Omega), \quad \Omega \text{ convex}.$$

$$\sup_{\varphi \in \Sigma} \|\varphi\|_{L^\infty(\Omega)},$$

$$\Sigma = \left\{ \psi \in H^2(\Omega) \cap H_0^1(\Omega), \|\Delta\psi\|_{L^2(\Omega)} = 1 \right\}.$$



Other Examples

- Numerical simulation involving non-smooth operators:

$$\frac{\partial u}{\partial t} + \partial I_K(u) \ni f$$

$$K = \{v \in H_0^1(\Omega), |\nabla v| \leq 1, v \geq u_0\}.$$

$$I_K(v) = \begin{cases} 0, & \text{if } v \in K, \\ +\infty, & \text{if } v \notin K, \end{cases}$$



