

Numerical Methods to Solve the Weighted Poisson Equation

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CSL Student Conference, Coordinated Science Laboratory, University of Illinois at Urbana-Champaign, February 2017

Classical Poisson equation

Physics

$-\Delta \phi = h$

 ϕ is the electric/gravitational potential

Stochastic Optimal Control

$$\phi = P\phi + h$$

 ϕ is the relative value function

Weighted Poisson equation and Problem statement

Weighted Poisson equation

$$-\frac{1}{\rho(x)}\nabla\cdot(\rho(x)\nabla\phi(x))=h(x)-\hat{h}$$

- $ho: \mathbb{R}^d
 ightarrow \mathbb{R}^+$ (prob. density)
- ▶ $h: \mathbb{R}^d \to \mathbb{R}$ (given function), $\hat{h}:=\int h(x)\rho(x)\,\mathrm{d}x$
- $ightharpoonup \phi: \mathbb{R}^d
 ightarrow \mathbb{R}$ (solution)

Input: $\{X^1, \dots, X^N\} \stackrel{\text{i.i.d}}{\sim} \rho$ **Output:** $\{\phi(X^1), ..., \phi(X^N)\}$

[R. S. Laugesen, et. al. SICON, (2015)]

Application: Classification

Feature vector: $X \in \mathbb{R}^d$

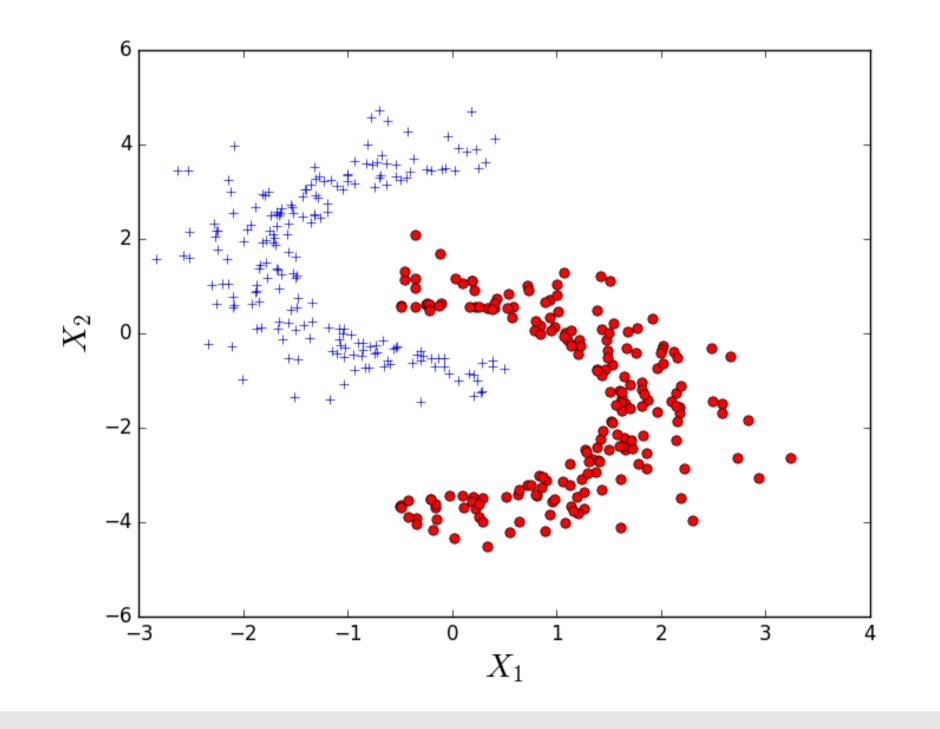
Label: $Y \in \{-1, 1\}$

Training data: $\{(X^1, Y^1), ..., (X^N, Y^N)\}$

Classifier: $\phi(x) = ?$

$$\min_{\phi \in \Phi} \ \mathsf{E} \left[\underbrace{\frac{1}{2} |\nabla \phi(X)|^2}_{\text{Begularizer}} \underbrace{-(\phi(X) - \hat{\phi})Y}_{\text{Loss function}} \right]$$

The minimizer solves the Poisson equation



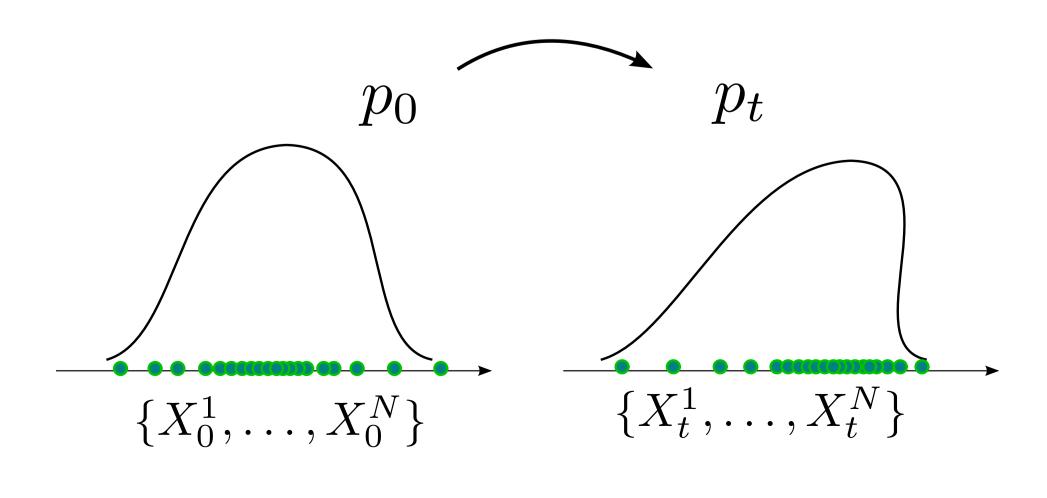
Application: Transporting densities

Input: $\{X_0^1, \ldots, X_0^N\} \stackrel{\text{i.i.d}}{\sim} p_0 \text{ (prior)}$

Output: $\{X_t^1, \dots, X_t^N\} \stackrel{\text{i.i.d}}{\sim} p_t$ (posterior)

$$\frac{\mathrm{d}X_t^i}{\mathrm{d}t} = \nabla \phi(X_t^i)$$

where ϕ solves the Poisson equation [T, Yang, et. al. Automatica, (2016)]



Two formulations, Two algorithms

$$\mathsf{E}[
abla \phi(X) \cdot
abla \psi(X)] = \mathsf{E}[\psi(X)(h(X) - \hat{h})] \quad \forall \psi \in H^1(\mathbb{R}^d, \rho)$$

Algorithm: (Galerkin)

- ► Select basis functions $\{\psi_1, \dots, \psi_M\}$
- Solve system of M linear equations

2) Semigroup formulation: (Stochastic viewpoint)

$$\phi = extbf{ extit{P}} \phi + ilde{ extit{h}}$$

where $P:=e^{\epsilon\Delta_{
ho}}$ and $ilde{h}:=\int_0^t e^{s\Delta_{
ho}}(h-\hat{h})\,\mathrm{d}s$

Algorithm: (kernel-based)

► Approximate *P* with a finite rank Markov operator

$$P\phi(x) pprox \sum_{i=1}^{N} k_{\epsilon}(x, X^{i})\phi(X^{i})$$

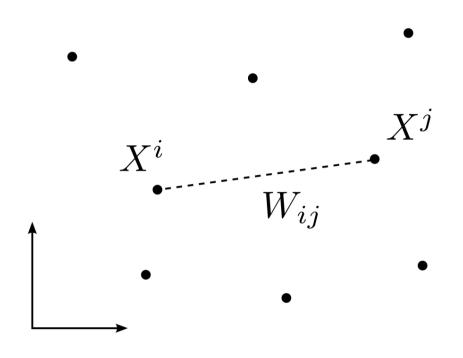
Solve the fixed point equation iteratively [Coifman, Lafon, 2006] [Hein, et. al. 2007]

1) Weak formulation: (PDE viewpoint)

$$\mathbb{E}[\nabla \phi(X) \cdot \nabla \psi(X)] = \mathbb{E}[\psi(X)(h(X) - \hat{h})] \quad \forall \psi \in H^1(\mathbb{R}^d, \rho)$$

error $\nabla \phi^{(M)}$

 $\nabla \phi$

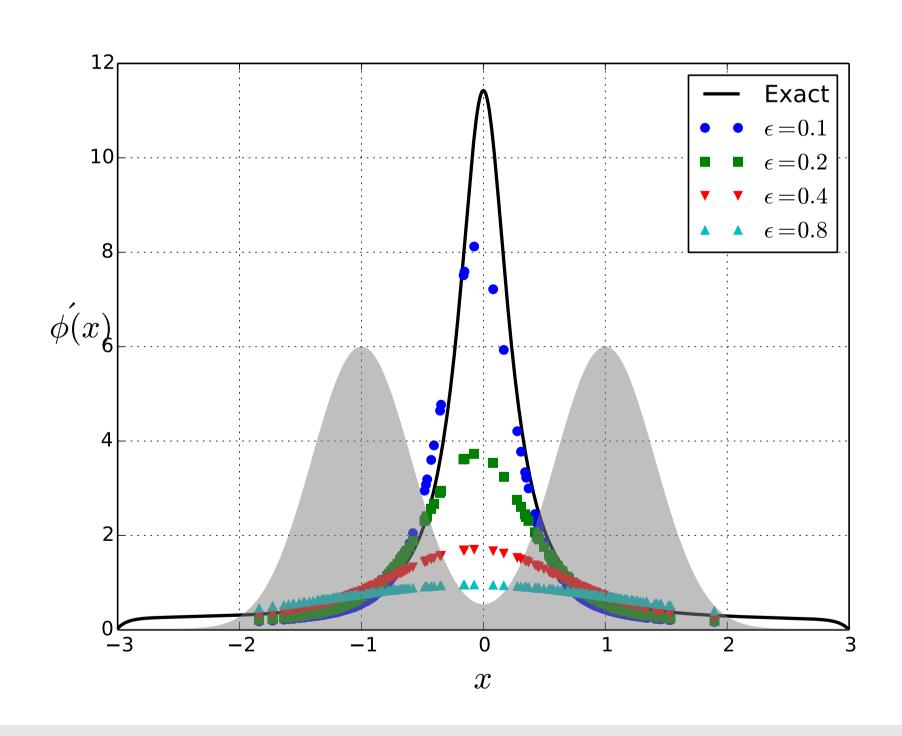


Numerical result

Galerkin Algorithm

Exact 1 modes ▼ ▼ 3 modes ▲ ▲ 5 modes $\phi(x)$

Kernel-based Algorithm



Error analysis

Galerkin Algorithm

Total error
$$\leq C \|h - \Pi_S h\|_{L^2} + \frac{1}{\sqrt{N}} \|h\|_{\infty} \sqrt{\sum_{m=1}^{N} \frac{1}{\lambda_m}}$$
Variance

Kernel-based Algorithm

Total error
$$\leq O(\epsilon) + O(\frac{1}{\epsilon^{1+d/4}\sqrt{N}})$$

Variance

Acknowledgement

Research supported by Computational Science and Engineering Fellowship, UIUC, 2016-2017