Stochastic Computational Electrostatics and Applications: Computing Capacitance

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Outline of the Talk

Monte Carlo Methods for PDEs

A Little History on Monte Carlo Methods for PDEs

Stochastic Methods to Solve Electrostatics Problems

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First Passage Probability is the Green's Function

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Important Computational Paradigm: Computing Capacitance

Computing Capacitance

Computing Capacitance Deterministically

Computing Capacitance Probabilistically

Capacitance as a Computational Paradigm

Biochemical Problems

Electrostatic Potential and Energy

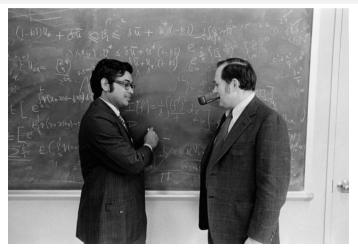
Walk-in-Subdomains

Monte Carlo Estimates

Conclusions



Thanks to My Probability Professors at Courant: Raghu Varadhan and Monroe Donsker





In Memoriam: Nikolai Simonov, 1956–2019





- Monte Carlo Methods for PDEs

A Little History on Monte Carlo Methods for PDEs

Early History of MCMs for PDEs

- 1. Courant, Friedrichs, and Lewy: Their pivotal 1928 paper has probabilistic interpretations and MC algorithms for linear elliptic and parabolic problems
- Fermi/Ulam/von Neumann: Atomic bomb calculations were done using Monte Carlo methods for neutron transport, their success inspired much post-War work especially in nuclear reactor design
- 3. Kac and Donsker: Used large deviation calculations to estimate eigenvalues of a linear Schrödinger equation
- 4. Forsythe and Leibler: Derived a MCM for solving special linear systems related to discrete elliptic PDE problems



Sampling Elliptic PDEs via Brownian motion

The First Passage (FP) Probability is the Green's Function

The canonical elliptic boundary value problem for electrostatics (one of Maxwell's equations):

$$\frac{1}{2}\Delta u(x) = 0, \quad x \in \Omega$$
$$u(x) = f(x), \quad x \in \partial \Omega$$

- Distribution of z is uniform on the sphere
- u(x) has mean-value property and harmonic
- Also, u(x) satisfies the boundary condition
 u(x) = E_x[f(X^x(t_{∂Ω}))]



First Passage Probability is the Green's Function

The First Passage (FP) Probability is the Green's Function

Reinterpreting as an average of the boundary values

$$u(x) = \int_{\partial\Omega} p(x, y) f(y) \, dy \tag{2}$$

Another representation in terms of an integral over the boundary

$$u(x) = \int_{\partial\Omega} \frac{\partial g(x, y)}{\partial \mathbf{n}} f(y) \, dy$$

g(x, y) – Green's function of the Dirichlet problem in Ω

$$\Rightarrow p(x,y) = rac{\partial g(x,y)}{\partial \mathbf{n}}$$



(4)

(3)

Walk on Spheres

'Walk on Spheres' (WOS) and 'Green's Function First Passage' (GFFP) Algorithms

Green's function is known

 \Longrightarrow direct simulation of exit points and computation of the solution through averaging boundary values

Green's function is unknown

 \implies simulation of exit points from standard subdomains of Ω , e.g. spheres

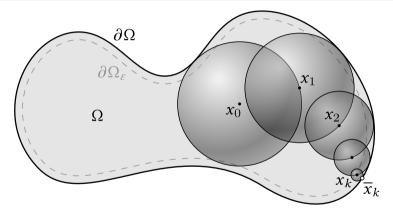
- \implies Markov chain of 'Walk on Spheres' (or GFFP algorithm) $x_0 = x, x_1, \dots, x_N$
- $x_i \rightarrow \partial \Omega$ and hits ε -shell is $N = O(|\ln(\varepsilon)|)$ steps

 x_N simulates exit point from Ω with $O(\varepsilon)$ accuracy



Walk on Spheres

The First Passage (FP) Probability is the Green's Function





Important Computational Paradigm: Computing Capacitance

Computing Permeability via Capacitance

- Hubbard and Douglas from NIST showed that the permeability of a porous medium is functionally related to the capacitance of a nonskew conductor
- Capacitance and permeability are proportionality constants
 - 1. Capacitance is the ratio of charge to voltage
 - 2. Permeability is the ratio of pressure gradient to flux
- Capacitance and permeability are completely determined by geometry
- The mathematical problems surrounding both are elliptic
 - 1. For capacitance it is the Laplace (a Maxwell) equation
 - 2. For permeability it is the Stokes equation for creeping flow



Stochastic Computational Electrostatics and Applications: Computing Capacitance

- Stochastic Methods to Solve Electrostatics Problems

Computing Capacitance

Computing Capacitance

- ► Recall that $C = \frac{Q}{u}$, if we hold the conductor, Ω , at unit potential u = 1, then C = total charge the conductor's surface, $\partial \Omega$
- The PDE system for the potential is

 $\Delta u = 0, \ x \notin \Omega; \quad u = 1, \ x \in \partial \Omega; \quad u \to 0 \ \text{as} \ |x| \to \infty$ (5)

lf we know the charge density, q on the conductor, Ω , then the total charge is just

$$\int_{\partial\Omega} q(s)\,ds$$

- Knowing u(x) gives us $q(x) = -\frac{1}{4\pi} \frac{\partial u}{\partial n}$
- Solving for capacitance requires computing the following for the solution to the above Laplace equation

$$Q = -rac{1}{4\pi}\int_{\partial\Omega}rac{\partial u(s)}{\partial n(s)}\,ds$$



Computing Capacitance

Computing Capacitance Deterministically

- The problem we are solving for capacitance the exterior problem, and so one must discretize based on the method of choice
 - 1. Boundary Element Method (BEM): Must discretize $\partial \Omega$
 - 2. Finite Element Method (FEM) or Finite Difference Method (FDM): Must discretize $\mathbb{R}^3 \setminus \Omega$
- Solve the exterior Laplace equation (5) for *u*
- Differentiate u on $\partial \Omega$
- Integrate to compute the total charge using equation (6)



Computing Capacitance

Computing Capacitance Probabilistically

The PDE system for the potential is

$$\Delta u = 0, \ x \notin \Omega; \quad u = 1, \ x \in \partial \Omega; \quad u \to 0 \ \text{as} \ |x| \to \infty$$

- ► Recall $u(\mathbf{x}) = \mathbb{E}_{\mathbf{x}}[f(X^{\mathbf{x}}(t_{\partial\Omega}))] = 1$, if the walker hits $\partial\Omega$, or 0, if the walker $\rightarrow \infty =$ probability of walker starting at \mathbf{x} hitting Ω before escaping to infinity
- Charge density is first passage measure on the exterior of Ω
- Construct a sphere, S(R), such that $\Omega \subset S(R)$
- Capacitance is C = R × P(t_{∂Ω} < ∞) = R × ∫_{∂S(R)} u(x)ds, where the starting point of the walk is chosen uniformly on the ∂S(R)
- Note, this definition is independent of R



Stochastic Computational Electrostatics and Applications: Computing Capacitance

Stochastic Methods to Solve Electrostatics Problems

Computing Capacitance

Porous Media: Complicated Interfaces





Capacitance as a Computational Paradigm

Capacitance as a Computational Paradigm

- We have found that the running time of these codes hinged on the efficiency of geometrical computations
- The probabilistic capacitance computation is key in
 - 1. Permeability computation via Hubbard-Douglas
 - 2. Many other electrostatics computations in areas of chemistry, computer science, physics, and materials science, including our own PBE computations
 - 3. In the ZENO code written for materials property computations at NIST
- We took the NIST ZENO code and analyzed it to determine areas for improvement



Capacitance as a Computational Paradigm

What is the Computational Geometric Problem?

- ZENO is named for the paradox, and getting close the boundary for producing approximate first-passage locations is done with the ZENO algorithm, which is WOS by another name
- The usual geometry in these problems is additive
- As mentioned above the primitive computation geometrically is given a query point, find the closest point to the boundary, and that is used as the radius to construct the WOS radius
- ► The usual ZENO problem is the so-called exterior problem, which is what is done in permeability: computing the probability of first-passage from ∞ using relative capacitance of a bounding sphere



Stochastic Computational Electrostatics and Applications: Computing Capacitance

Stochastic Methods to Solve Electrostatics Problems

Capacitance as a Computational Paradigm

Gridding vs. Hierarchical Decomposition

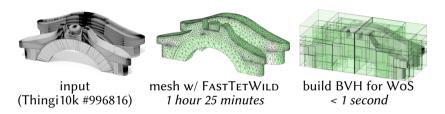


Figure: Gridding for FEM vs. Bounded Volume Hierarchy (BVH) for WOS Geometric Query



Capacitance as a Computational Paradigm

Mathematical Model: Molecular Geometry

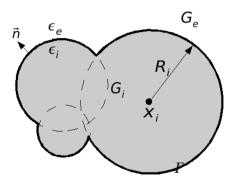


Figure: Biomolecule with dielectric ϵ_i and region region G_i is in solution with dielectric ϵ_e and region G_e . On the boundary of the biomolecule, electrostatic potential and normal component of dielectric displacement continue



Mathematical Model: Partial Differential Equations

Poisson equation for the electrostatic potential, Φ_i, and point charges, Q_m, inside a molecule (in CGS units):

$$\epsilon_i \Delta \Phi_i(x) + 4\pi \sum_{m=1}^M \mathcal{Q}_m \delta(x-x^{(m)}) = 0 \;,\; x\in \mathcal{G}_i$$

► For 1-1 salt (such as *NaCl*) Poisson-Boltzmann equation (PBE):

$$\Delta \Phi_{e}(x) - \kappa^{2} \sinh(\Phi_{e}(x)) = 0 \;,\; x \in G_{e} \;,$$

but we only consider the linearized PBE:

$$\Delta \Phi_{e}(x) - \kappa^2 \Phi_{e}(x) = 0 \;,\; x \in G_{e}$$

For one-surface model: continuity condition on the dielectric boundary

$$\Phi_i = \Phi_e \ , \ \epsilon_i \frac{\partial \Phi_i}{\partial n(y)} = \epsilon_e \frac{\partial \Phi_e}{\partial n(y)} \ , \ y \in \Gamma$$



Mathematical Model: Debye-Hückle Parameter

Dependence on salt in the Debye-Hückle parameter (units as per Kirkwood):

$$\kappa^2 = rac{8\pi N_A e^2 C_s}{\epsilon_e 1000 k_B T}, ext{ where }$$

- C_s concentration of ions (in moles)
- N_A Avogadro's number
- e elementary protonic charge
- \triangleright k_B Boltzmann's constant
- ϵ_e dielectric permittivity outside the molecule



Electrostatic Potential and Energy

Electrostatic Potential and Energy

• Point values of the potential: $\Phi(x) = \Phi_{rf}(x) + \Phi^{c}(x)$ Here, singular part of Φ :

$$\Phi^c(x) = \sum_{m=1}^M \frac{Q_m}{|x - x^{(m)}|}$$

Reaction field electrostatic free energy of a molecule is linear combination of point values of the regular part of the electrostatic potential:

$$W_{rf} = rac{1}{2} \sum_{m=1}^{M} \Phi_{rf}(x^{(m)}) Q_m \; ,$$

Electrostatic solvation free energy = difference between the energy for a molecule in solvent with a given salt concentration and the energy for the same molecule in vacuum:

$$\Delta G_{\textit{solv}}^{\textit{elec}} = \textit{W}_{\textit{rf}}(\epsilon_i, \epsilon_e, \kappa) - \textit{W}_{\textit{rf}}(\epsilon_i, 1, 0)$$



Electrostatic Potential and Energy

'Walk-on-Spheres' Algorithm

- Walk-on-spheres (WOS) algorithm for general domains with a regular boundary
- Define a Markov chain $\{x_i, i = 1, 2, ...\}$
- Set $x_0 = x^{(m)}$ for some $m, x_i = x_{i-1} + d_i \omega_i$, i = 1, 2, ..., where
 - 1. $d_i = d(x_{i-1})$ is distance from x_{i-1} to Γ
 - 2. $\{\omega_i\}$ is sequence of independent unit isotropic vectors
 - 3. x_i is the exit point from the ball, $B(x_{i-1}, d(x_{i-1}))$, for a Brownian motion starting at x_{i-1}
- > Outside the molecule, on every step, walk-on-spheres terminates with probability

$$1 - q(\kappa, d_i)$$
, where $q(\kappa, d_i) = rac{\kappa d_i}{\sinh(\kappa d_i)}$ to deal with LPBE



Walk-in-Subdomains

'Walk-on-Spheres' and 'Walk-in-Subdomains'

> For general domains, an efficient way to simulate exit points is a combination of

- 1. Inside the molecule: 'walk-in-subdomains'
- 2. Outside the molecule 'walk-on-spheres'

> The whole domain, G_i , is represented as a union of intersecting subdomains:

$$G_i = \bigcup_{m=1}^M G^m$$

- ▶ 'Walk-in-Subdomains': Simulate exit point separately in every *G^m*
 - 1. $x_0 = x, x_1, ..., x_N$ Markov chain, every x_{i+1} is an exit point from the corresponding subdomain for Brownian motion starting at x_i
 - 2. For spherical subdomains, $B(x_i^m, R_i^m)$, exit points are distributed in accordance with the Poisson kernel:

$$\frac{1}{4\pi R_i^m} \frac{|x_i - x_i^m|^2 - (R_i^m)^2}{|x_i - x_{i+1}|^3}$$



Walk-in-Subdomains

'Walk-on-Spheres' and 'Walk-in-Subdomains'

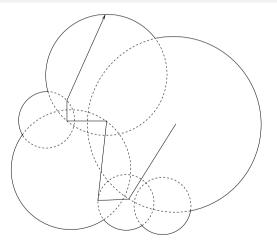


Figure: Walk in subdomains example



- Biochemical Problems
 - Monte Carlo Estimates

Monte Carlo Estimates

The estimate for the reaction-field potential point value:

$$\xi[\Phi_{rf}](x^{(m)}) = -\Phi^{c}(x_{1}^{*}) + \sum_{j=2}^{N_{ins}} F_{j}(\kappa) \left(\Phi^{c}(x_{j}^{ins}) - \Phi^{c}(x_{j,ins}^{*})\right)$$
(7)

- Here {x_{j,ins}} is a sequence of boundary points, after which the random walker moves inside the domain, G_i, to x_j^{ins}
- The estimate for the reaction-field energy:

$$\xi[W_{rf}] = \frac{1}{2} \sum_{m=1}^{M} Q_m \, \xi[\Phi_{rf}](x^{(m)})$$

(8)



Monte Carlo Estimates

Computational Results: 3 Truncated Arginine-Rich Peptides



Figure: PDB IDs: 1a4t, 1hji, 1qfq



Monte Carlo Estimates

Accuracy: Monte Carlo vs. Deterministic

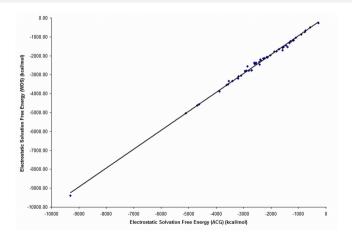


Figure: PDB IDs: 1a4t, 1hji, 1qfq



Conclusions

- Monte Carlo can be an efficient method for the numerical solution of PDEs as evidenced by
 - 1. Financial computing
 - 2. Numerous problems in electrostatics: mutual capacitance in EDA, biochemical electrostatics
 - 3. Numerous problems in computational materials: permeability, ZENO
- The computation of capacitance is a good model problem for computational investigation, capacitance is an important functional of geometry
 - 1. Computational geometry is the bottleneck that can be overcome with proper choice of data-structure/algorithm
 - 2. Allows for almost perfect parallelization, across cores and multicore nodes
- C++ version of ZENO uses SPRNG



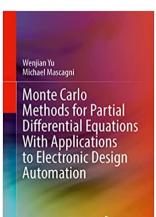
Future Work

- Continue work on biochemical electrostatics
- We expect to be able to improve all the codes we have developed
 - 1. Current C++ version of the WOS-PBE code:
 - https://zeno.nist.gov
- We want to have a WOS-based implementation of the capacitance code using CUDA on NVidia GPUs
 - 1. WOS is being used by computer graphics folks
 - 2. The geometric query in WOS is a generalization of the GPU-based geometry query in ray tracing
- Compare WOS capacitance extraction to:
 - 1. Deterministic methods (FEM, FDM, BEM)
 - 2. Machine learning methods



Conclusions

A Book Of Interest?



Springer



- Conclusions

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Conclusions

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