High-Dimensional Gaussian Sampling

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Problem Definition

Sampling from a d-dimensional Gaussian distribution $\mathcal{N}(\mu, \Sigma)$, where d may be large.

$$\pi(oldsymbol{ heta}) = rac{1}{(2\pi)^{d/2} ext{det}(oldsymbol{\Sigma})^{1/2}} \exp\left(-rac{1}{2}(oldsymbol{ heta} - oldsymbol{\mu})^{ op} oldsymbol{\Sigma}^{-1}(oldsymbol{ heta} - oldsymbol{\mu})
ight).$$

Covariance matrix ${f \Sigma}$ positive definite. Precision matrix ${f Q}={f \Sigma}^{-1}$ exists and also positive definite.

Vanilla Cholesky Sampler

Algorithm 1 Cholesky sampler

1: Set $\mathbf{C} = \operatorname{chol}(\mathbf{Q})$.

 $\triangleright \mathbf{Q} = \mathbf{C}\mathbf{C}^{\top}$

- 2: Draw $\mathbf{z} \sim \mathcal{N}(\mathbf{0}_d, \mathbf{I}_d)$.
- 3: Solve $\mathbf{C}^{\top}\mathbf{w} = \mathbf{z} \text{ w.r.t. } \mathbf{w}.$
- 4: return $\theta = \mu + w$.

Problem: computational cost $\Theta(d^3)$ and storage requirement $\Theta(d^2)$.

Better Solutions

- Square Root approximation: Approximate $\mathbf{Q}^{1/2}$.
- Conjugate Gradient: Solve a linear system w.r.t. **Q**.
- Matrix Splitting: A generation of Gibbs Sampler.
- Data Augmentation: Introduce auxiliary variable.

Improvement: computational cost $\mathcal{O}(d^2)$ and storage requirement $\Theta(d)$.

Guidelines to Choosing the Sampler

