

Inference

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COMP 64101 – Reasoning and Learning under Uncertainty
Lecture 2



Topics: Variational Inference (VI)

“I know it’s Tuesday. It’s a good day for math!”

Max Mintz

- What is VI? (Murphy, 2023, § 10.1)
- Gradient-based VI (Murphy, 2023, § 10.2)
 - Blackbox VI (Murphy, 2023, § 10.2.3)
- Coordinate Ascent VI (Murphy, 2023, § 10.3)
 - Variational Bayes (Murphy, 2023, § 10.3.3)
- More VI Goodies (Murphy, 2023, § 10.4 – 10.7)

Topics: Monte Carlo (MC) Methods

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- MC integration (Murphy, 2023, § 11.2)
- Importance Sampling (Murphy, 2023, § 11.5)
- Rao-Blackwellization (Murphy, 2023, § 11.6.2)

Topics: Markov Chain Monte Carlo (MCMC)

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- Metropolis-Hastings Algorithm (Murphy, 2023, § 12.2)
- Gibbs Sampling (Murphy, 2023, § 12.3)
- Hamiltonian MC (Murphy, 2023, § 12.5.3 – 12.5.4)
- MCMC Convergence (Murphy, 2023, § 12.6)

What is VI?

- **Variational Inference (VI)** reduces posterior inference to optimization
- Consider a model with unknown (latent) variables z , known variables x , and fixed parameters θ

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- **Variational Inference (VI)** reduces posterior inference to optimization
- Consider a model with unknown (latent) variables z , known variables x , and fixed parameters θ

- Prior: $p(\theta)$

- Likelihood: $p_\theta(x | z)$

- (Unnormalized) Joint: $p_\theta(x, z) = p_\theta(x | z)p_\theta(z)$

- Posterior:

$$p_\theta(z | x) = \frac{p_\theta(x, z)}{\underbrace{p_\theta(x)}_{=\int p_\theta(x, z) dz, \text{ intractable}}}$$

- Need to approximate the posterior!

What is VI?

- We approximate the posterior by the distribution $q(z)$ that minimizes the loss

$$q^* = \arg \min_{q \in \mathcal{Q}} D_{KL}(q(z) \| p_\theta(z | x)) \quad (1)$$

- In practice, we pick a parametric family \mathcal{Q} ; call ψ its **variational parameters**
- (1) can be rewritten as

$$\begin{aligned} \psi^* &= \arg \min_{\psi} D_{KL}(q_{\psi}(z) \| p_\theta(z | x)) \\ &= \arg \min_{\psi} \mathbb{E}_{q_{\psi}(z)} \left[\log q_{\psi}(z) - \log \left(\frac{p_\theta(x | z)p_\theta(z)}{p_\theta(x)} \right) \right] \\ &= \arg \min_{\psi} \underbrace{\mathbb{E}_{q_{\psi}(z)} [\log q_{\psi}(z) - \log p_\theta(x | z) - \log p_\theta(z)]}_{=: \mathcal{L}(\theta, \psi | x)} + \underbrace{\log p_\theta(x)}_{\text{intract. but } \perp \!\!\! \perp \psi} \end{aligned}$$

ELBO

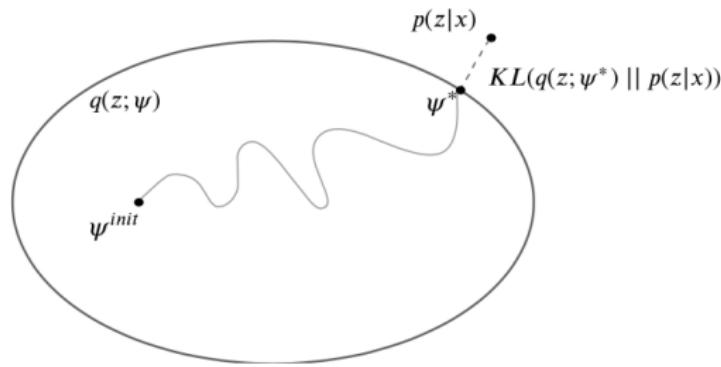
- So, we want to minimize the variational free energy

$$\mathcal{L}(\theta, \psi | x) := \mathbb{E}_{q_\psi(z)} [\log q_\psi(z) - \log p_\theta(x, z)]$$

- Or equivalently, maximize the evidence lower bound (ELBO)

$$\mathcal{L}(\theta, \psi | x) := -\mathcal{L}(\theta, \psi | x) = \mathbb{E}_{q_\psi(z)} [-\log q_\psi(z) + \log p_\theta(x, z)]$$

- $\mathcal{L}(\theta, \psi | x) \leq \log p_\theta(x)$, the evidence



ELBO Interpretation

- $\underbrace{\mathcal{L}(\theta, \psi | x)}_{\text{ELBO}} = \underbrace{\mathbb{E}_{q_\psi(z)} [\log p_\theta(x, z)]}_{\text{expected log joint}} + \underbrace{H(q_\psi(z))}_{\text{entropy}}$
 - Second term encourages the posterior to be maximum entropy; first encourages it to be a joint MAP configuration

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$$\begin{aligned}\underbrace{\mathcal{L}(\theta, \psi | x)}_{\text{ELBO}} &= \mathbb{E}_{q_\psi(z)} [\log p_\theta(x | z) + \log p_\theta(z) - \log q_\psi(z)] \\ &= \underbrace{\mathbb{E}_{q_\psi(z)} [\log p_\theta(x | z)]}_{\text{expected log likelihood}} - \underbrace{D_{KL}(q_\psi(z) \| p_\theta(z))}_{\text{KL from posterior to prior}}\end{aligned}$$

- The KL term acts like a regularizer, preventing the posterior from diverging too much from the prior

Choosing the Form of the Variational Posterior

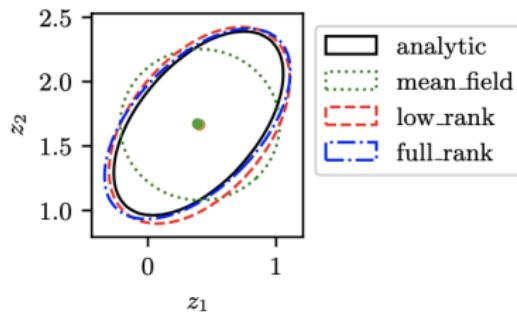
- **Fixed-form VI:** pick a convenient functional form (e.g. multivariate Gaussian) and optimize ELBO using gradient-based methods
- **Free-form VI:** make the **mean field assumption** that the posterior factorizes as $q_{\psi}(z) = \prod_{j=1}^J q_j(z_j)$
 - $q_j(z_j) \equiv q_{\psi_j}(z_j)$ is the posterior over the j -th group of variables
 - No need to specify the functional form for each q_j
 - Optimal distributional form derived by maximizing the ELBO wrt each group of variational parameters one at a time
 - In a coordinate ascent manner

Multivariate Normal Example

- Unknown mean, known covariance matrix
- Exact posterior can be computed analytically: Multivariate Normal conjugate prior

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- If q uses a **full covariance matrix**, it matches the exact posterior; intractable in high dimensions
- If q uses a **diagonal covariance matrix** (mean field approximation): the approximation is over confident
 - Mode-seeking nature of minimizing $D_{KL}(q||p)$
- If q uses a **rank-1 plus diagonal approximation**: better approximation; can be computed efficiently

Parameter Estimation

- If the model parameters θ are not known, can we estimate them?
- Maximizing the likelihood of the dataset $D = \{x_n\}_{n=1}^N$ in the presence of latent variables $\{z_n\}_{n=1}^N$,

$$p(D, \{z_n\} \mid \theta) = \prod_{n=1}^N p(z_n \mid \theta)p(x_n \mid z_n, \theta)$$

- Since the latent variables z_n are hidden, we must marginalize them out to get the log marginal likelihood

$$\log p(x_n \mid \theta) = \log \left[\underbrace{\int p(x_n \mid z_n, \theta)p(z_n \mid \theta)dz_n}_{\text{intractable: normalization constant of the exact posterior}} \right]$$

Parameter Estimation

- ELBO is a lower bound on this, $\mathcal{L}(\theta, \psi_n | x_n) \leq \log p(x_n | \theta)$
- Optimize the model parameters by maximizing

$$\mathcal{L}(\theta, \{\psi_n\} | D) := \sum_{n=1}^N \mathcal{L}(\theta, \psi_n | x_n) \leq \log p(D | \theta)$$

- **Variational EM algorithm** (Murphy, 2023, § 6.5.6.1): alternate between
 - Maximizing the ELBO wrt the variational parameters $\{\psi_n\}$ in the E step, to give us $q_{\psi_n}(z_n)$
 - Maximizing the ELBO (using the new ψ_n) wrt the model parameters θ in the M step
 - Faster alternative: **Stochastic VI** (Murphy, 2023, § 10.1.4)

Gradient-Based VI

- Choose convenient form for $q_\psi(z)$, e.g. Gaussian for continuous z , or product of Categoricals for discrete z
- Optimize the ELBO using gradient based methods
- **Stochastic Gradient Descend (SGD)**: Suppose we have a way of computing an unbiased estimate g_t of the gradient of the ELBO, i.e.

$$\mathbb{E}(g_t) = \nabla_{\theta} \mathcal{L}(\theta, \psi \mid x)|_{\theta_t}$$

- Then, we can use it in a gradient descent procedure

$$\theta_{t+1} = \theta_t - \eta_t g_t,$$

where η_t is the **learning rate** or step size (Murphy, 2023, § 6.3.1.1)

- Same for the gradient wrt ψ

Gradient wrt Generative Parameters $\nabla_{\theta}\mathcal{L}(\theta, \psi \mid x)$

- Easy to compute: push gradients inside the expectation, and use a single Monte Carlo sample

$$\begin{aligned}\nabla_{\theta}\mathcal{L}(\theta, \psi \mid x) &= \nabla_{\theta}\mathbb{E}_{q_{\psi}(z)}[-\log q_{\psi}(z) + \log p_{\theta}(x, z)] \\ &= \mathbb{E}_{q_{\psi}(z)}[\nabla_{\theta}(-\log q_{\psi}(z) + \log p_{\theta}(x, z))] \\ &\approx \mathbb{E}_{q_{\psi}(z)}[\nabla_{\theta} \log p_{\theta}(x, z^s)], \quad z^s \sim q_{\psi}(z)\end{aligned}$$

- This is an unbiased estimate of the gradient, so can be used with SGD

Gradient wrt Inference Parameters $\nabla_{\psi}\mathcal{L}(\theta, \psi \mid x)$

- Harder to compute: we cannot push gradients inside the expectation.
[Reparametrized VI \(RVI\)](#)
- Rewrite $z \sim q_{\psi}(z)$ as differentiable (and invertible) transformation h of $\epsilon \sim p(\epsilon)$, does not depend on ψ , i.e. $z = h(\psi, x, \epsilon)$
 - E.g. $z \sim \mathcal{N}(\mu, \text{diag}(\sigma)) \iff z = \mu + \epsilon \odot \sigma, \quad \epsilon \sim \mathcal{N}(0, I)$

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 - E.g. $z \sim \mathcal{N}(\mu, \text{diag}(\sigma)) \iff z = \mu + \epsilon \odot \sigma, \quad \epsilon \sim \mathcal{N}(0, I)$
- Then, $\mathbb{E}_{q_{\psi}(z)}[f(z)] = \mathbb{E}_{p(\epsilon)}[f(z)], \quad z = h(\psi, x, \epsilon)$
 - Where $f(z) \equiv f_{\theta, \psi}(z) = \log p_{\theta}(x, z) - \log q_{\psi}(z)$

Gradient wrt Inference Parameters $\nabla_{\psi}\mathcal{L}(\theta, \psi \mid x)$

- Hence

$$\begin{aligned}\nabla_{\psi}\mathcal{L}(\theta, \psi \mid x) &= \nabla_{\psi}\mathbb{E}_{q_{\psi}(z)}[f(z)] = \nabla_{\psi}\mathbb{E}_{p(\epsilon)}[f(z)] = \mathbb{E}_{p(\epsilon)}[\nabla_{\psi}f(z)] \\ &\approx \mathbb{E}_{p(\epsilon)}[\nabla_{\psi}f(h(\psi, x, \epsilon^s))], \quad \epsilon^s \sim p(\epsilon)\end{aligned}$$

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- This is an unbiased estimate of the gradient, so can be used with SGD
- Since we are now working with ϵ , need to use the change of variables formula

$$\log q_{\psi}(z) = \log p(\epsilon) - \log \left| \det \left(\frac{\partial z}{\partial \epsilon} \right) \right|$$

- $\partial z / \partial \epsilon$ is the Jacobian, i.e. the matrix of all its first-order partial derivatives
- We design transformation $z = h(\psi, x, \epsilon)$ s.t. this Jacobian is tractable to compute
- Examples: (Murphy, 2023, § 10.2.1)

Blackbox VI (BBVI)

- Suppose we can evaluate $\ell(\psi, z) := -\log q_\psi(z) + \log p_\theta(x, z)$ pointwise, but may not be able to take gradients of it
- To estimate the gradient of the ELBO, we use the [score function estimator](#). Write the ELBO as

$$\mathcal{L}(\theta, \psi \mid x) = \mathbb{E}_{q_\psi(z)}[\ell(\psi, z)] = \mathbb{E}_{q_\psi(z)}[-\log q_\psi(z) + \log p_\theta(x, z)]$$

- From [\(Murphy, 2023, Eq. \(6.58\)\)](#),

$$\nabla_\psi \mathcal{L}(\theta, \psi \mid x) = \mathbb{E}_{q_\psi(z)} [\ell(\psi, z) \nabla_\psi \log q_\psi(z)]$$

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$$\nabla_\psi \mathcal{L}(\theta, \psi \mid x) = \mathbb{E}_{q_\psi(z)} [\ell(\psi, z) \nabla_\psi \log q_\psi(z)]$$

- Compute a **Monte Carlo** approximation to this

$$\widehat{\nabla_\psi \mathcal{L}(\theta, \psi \mid x)} \Big|_{\psi_t} = \frac{1}{S} \sum_{s=1}^S \ell(\psi, z^s) \nabla_\psi \log q_\psi(z^s) \Big|_{\psi_t},$$
$$z^1, \dots, z^S \sim q_\psi(z)$$

- This is an unbiased estimate of the gradient, so can be used with SGD

Coordinate Ascent VI (CAVI)

- Mean field approximation in VI: assume that all latent variables are independent, $q_\psi(z) = \prod_{j=1}^J q_j(z_j) \equiv \prod_{j=1}^J q_{\psi_j}(z_j)$
 - J is the number of hidden variables
 - ψ_j are the variational parameters for the j -th distribution
- From previous slides, the ELBO becomes

$$\mathcal{L}(\theta, \psi | x) = \int q_\psi(z) \log p_\theta(x, z) dz + \sum_{j=1}^J H(q_j)$$

- First term decomposes according to Markov properties of the model
- This allows us to use a coordinate ascent optimization scheme to estimate each ψ_j
 - Optimize $\mathcal{L}(\theta, \psi | x)$ wrt each q_j , one at a time, keeping others fixed
 - Convergence is guaranteed since the bound is concave wrt each of the factors q_j
 - Functional form of the q_j 's need not be specified in advance: determined by the form of the log joint
- CAVI algorithm: (Murphy, 2023, Algorithm 10.4)

Variational Bayes

- Bayesian modeling: treat the parameters θ as latent variables
- Goal: approximate parameter posterior $p(\theta | D) \propto p(\theta)p(D | \theta)$
- No latent variables except for the shared global parameters,
 $p(\theta, D) = p(\theta) \prod_{n=1}^N p(x_n | \theta)$
- Fit the variational posterior by maximizing the ELBO

$$\mathcal{L}(\theta, \psi | D) = \mathbb{E}_{q_{\psi_\theta}(\theta)}[\log p(\theta, D)] + H(q_{\psi_\theta}(\theta))$$

- Assume the variational posterior factorizes as $q_{\psi_\theta}(\theta) = \prod_{j=1}^J q_{\psi_{\theta_j}}(\theta_j)$
- Update each ψ_{θ_j} via CAVI (Murphy, 2023, Algorithm 10.4)
 - Examples: (Murphy, 2023, § 10.3.4)
 - Of possible interest: Variational Bayes EM (Murphy, 2023, § 10.3.5 – 10.3.6)

More VI Goodies

- Improve tightness of ELBO lower bound – reducing KL of our posterior approximation – if we use more flexible posterior families
 - Optimizing within more flexible families may be slower, and can incur statistical error if the sample size is low (Murphy, 2023, § 10.4)

More VI Goodies

- Improve tightness of ELBO lower bound – reducing KL of our posterior approximation – if we use more flexible posterior families
 - Optimizing within more flexible families may be slower, and can incur statistical error if the sample size is low ([Murphy, 2023, § 10.4](#))
- Improve quality of posterior approximation: optimize q wrt a bound that is a tighter approximation to the log marginal likelihood compared to ELBO ([Murphy, 2023, § 10.5](#))

More VI Goodies

- Problem with lower bound maximization (standard VI): minimizing $D_{KL}(q\|p)$, which induces zero-forcing behavior
- This means that $q(z | x)$ tends to be too compact (over-confident), to avoid the situation in which $q(z | x) > 0$ but $p(z | x) = 0$,
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 - Would incur infinite KL penalty
- Zero-forcing can be desirable for multi-modal posteriors (e.g. mixture models); not so reasonable for unimodal posteriors
- Avoid this problem: minimize $D_{KL}(p\|q)$, which is zero-avoiding
- Result in broad posteriors, which avoids overconfidence
- **Expectation propagation:** local approximation to $D_{KL}(p\|q)$ (Murphy, 2023, § 10.7)

VI for Imprecise Probabilities

Cella and Martin (2024) are the first who study VI in the context of Inferential Models. If interested, we can work together on this!

Monte Carlo Methods

- Monte Carlo methods are a stochastic approach to solving numerical integration problems



Monte Carlo Integration

- Integration of interest

$$\mathbb{E}[\varphi(x)] = \int_{\mathbb{R}^n} \varphi(x) \pi(x) dx$$

- $\varphi : \mathbb{R}^n \rightarrow \mathbb{R}^m$
- $\pi(x)$ is the target distribution, often a posterior

- Approximate it via Monte Carlo integration

$$\mathbb{E}[\varphi(x)] \approx \frac{1}{N_s} \sum_{n=1}^{N_s} \varphi(x_n), \quad x_1, \dots, x_{N_s} \sim \pi(x)$$

- The function is only evaluated in places where there is non-negligible probability
- Not need to uniformly cover the entire space
- Accuracy is independent of the dimensionality of x ; only depends on the number of samples N_s

Sampling from the Target Distribution

- How to sample from $\pi(x)$?
- One possible method: **Rejection Sampling** (Murphy, 2023, § 11.4)
 - Drawbacks in high dimensions (Murphy, 2023, § 11.4.4)
- A better one: **Importance Sampling** (Murphy, 2023, § 11.5)
- In general, it is difficult to sample from $\pi(x)$
 - Sample from a proposal distribution $q(x)$
 - Adjust for this inaccuracy by associating weights with each sample
 - We end up with a weighted MC approximation

$$\mathbb{E}[\varphi(x)] \approx \sum_{n=1}^{N_s} W_n \varphi(x_n)$$

Direct Importance Sampling

- We can evaluate the normalized target distribution $\pi(x)$, but we cannot sample from it
- Instead, we sample from the proposal $q(x)$,

$$\mathbb{E}_\pi[\varphi(x)] = \int_{\mathbb{R}^n} \varphi(x) \pi(x) dx = \int_{\mathbb{R}^n} \varphi(x) \frac{\pi(x)}{q(x)} q(x) dx = \mathbb{E}_q \left[\varphi(x) \frac{\pi(x)}{q(x)} \right]$$

- **Require:** $\text{supp}(q) \supseteq \text{supp}(\pi)$

Direct Importance Sampling

- Sample $x_1, \dots, x_{N_s} \sim q(x)$; then,

$$\mathbb{E}[\varphi(x)] \approx \frac{1}{N_s} \sum_{n=1}^{N_s} \underbrace{\frac{\pi(x_n)}{q(x_n)}}_{=: \tilde{w}_n, \text{ importance weights}} \varphi(x_n)$$

- Unbiased estimate of the true mean $\mathbb{E}[\varphi(x)]$

- From slide 20, $W_n = \frac{\tilde{w}_n}{N_s} = \frac{\pi(x_n)}{N_s \cdot q(x_n)}$

Self-Normalized Importance Sampling

- We can only evaluate the unnormalized target distribution
 $\tilde{\gamma}(x) = Z\pi(x)$, $Z = \int_{\mathbb{R}^n} \tilde{\gamma}(x)dx$
- E.g. $\pi(\textcolor{red}{x}) = p(\theta | y)$, $\tilde{\gamma}(\textcolor{red}{x}) = p(\theta, y)$, and $Z = p(y)$
- **Self-normalized importance sampling:** key idea also approximate normalization constant Z with importance sampling
- Resulting estimate is a ratio of two estimates: biased
 - However as $N_s \rightarrow \infty$, the bias goes to zero, under some weak assumptions

Self-Normalized Importance Sampling

- Sample $x_1, \dots, x_{N_s} \sim q(x)$; then,

$$\begin{aligned}\mathbb{E}[\varphi(x)] &= \int_{\mathbb{R}^n} \varphi(x) \pi(x) dx = \frac{\int_{\mathbb{R}^n} \varphi(x) \tilde{\gamma}(x) dx}{\int_{\mathbb{R}^n} \tilde{\gamma}(x) dx} \\ &= \frac{\int_{\mathbb{R}^n} \left[\frac{\tilde{\gamma}(x)}{q(x)} \varphi(x) \right] q(x) dx}{\int_{\mathbb{R}^n} \left[\frac{\tilde{\gamma}(x)}{q(x)} \right] q(x) dx} \approx \frac{\frac{1}{N_s} \sum_{n=1}^{N_s} \tilde{w}_n \varphi(x_n)}{\frac{1}{N_s} \sum_{n=1}^{N_s} \tilde{w}_n},\end{aligned}$$

where $\tilde{w}_n = \tilde{\gamma}(x_n)/q(x_n)$

- From slide 20, $\mathbb{E}[\varphi(x)] \approx \sum_{n=1}^{N_s} W_n \varphi(x_n)$, and $W_n = \frac{\tilde{w}_n}{\sum_{n'=1}^{N_s} \tilde{w}_{n'}}$
- Approximation to the normalization constant: $Z \approx \frac{1}{N_s} \sum_{n=1}^{N_s} \tilde{w}_n =: \hat{Z}$

Choosing the Proposal

- Performance of importance sampling depends crucially on quality of proposal distribution q
- We need $\text{supp}(q) \supseteq \text{supp}(\pi)$, but we do not want $\text{supp}(q)$ to be “too large”
- $\text{supp}(q)$ should also take into account properties of the target function φ as well
- However, usually the target function φ is unknown or ignored
 - Try to find a “generally useful” approximation to the target
 - One way to come up with a good proposal is to [learn one](#), by [optimizing the ELBO](#)

Controlling Monte Carlo Variance

- The standard error in a Monte Carlo estimate is $\mathcal{O}(1/\sqrt{S})$
 - $S \leq N_s$ is the number of (independent) samples
- It may take many samples to reduce the variance to a sufficiently small value
- Rao and Blackwell come to the rescue!



Rao-Blackwellization

- Consider two rv's, Θ and X ; we want to estimate $\bar{f} = \mathbb{E}[f(\Theta, X)]$
- Naïve MC approx: $\hat{f}_{MC} = \frac{1}{S} \sum_{s=1}^S f(\Theta_s, X_s)$,
 $(\Theta_1, X_1), \dots, (\Theta_S, X_S) \sim p(\Theta, X)$ i.i.d.
 - Unbiased, but may have high variance
- Suppose we can analytically marginalize out X , provided we know Θ ,
i.e., we can tractably compute

$$f_\Theta(\theta_s) = \int_{\mathbb{R}^n} f(\theta_s, X) p(X | \theta_s) dX = \mathbb{E}[f(\Theta, X) | \Theta = \theta_s]$$

- Rao-Blackwellized estimator: $\hat{f}_{RB} = \frac{1}{S} \sum_{s=1}^S f_\Theta(\theta_s)$,
 $\theta_1, \dots, \theta_S \sim p(\Theta)$
- \hat{f}_{RB} is unbiased, and has lower variance than \hat{f}_{MC}
 - We are now sampling in a reduced dimensional space

Markov Chain Monte Carlo

- Popular method for sampling from high-dimensional distributions
- Construct a **Markov chain** on the state space \mathcal{X} whose stationary distribution is the target density $\pi(x)$ of interest, e.g. posterior
- Perform a random walk on the state space so that the fraction of time we spend in each state x is proportional to $\pi(x)$
- Initial samples from the chain do not come from the stationary distribution: discarded
 - **Mixing time**: time it takes to reach stationarity



Metropolis-Hastings Algorithm

- MH Algorithm: (Murphy, 2023, Algorithm 12.1)
- At each step, we propose to move from the current state x to a new state x' w.p. $q(x' | x)$
 - q is the **proposal distribution**
 - Common proposal distributions: (Murphy, 2023, § 12.3)
 - Good proposal design depends on the form of target distribution $\pi(x)$
- The user is free to use any kind of proposal they want, subject to $\text{supp}(\pi) \subseteq \cup_{x \in \mathcal{X}} \text{supp}(q(\cdot | x))$
 - q is valid if it “covers” the support of the target π : MH flexible method
- Having proposed a move to x' , decide whether to accept this proposal, or to reject it
 - The long-term fraction of time spent in each state is $\propto \pi(x)$
- If the proposal is accepted, the new state is x' , otherwise same as the current state x (repeat the sample)

MH Algorithm: Symmetric Proposal

- Proposal is symmetric: $q(x' | x) = q(x | x')$
- Acceptance probability: $A = \min\left(1, \frac{\pi(x')}{\pi(x)}\right)$
- If x' is more probable than x , we move there, since $\pi(x')/\pi(x) > 1$
- If x' is less probable, we may still move there anyway, depending on the relative probabilities
- Instead of greedily moving to only more probable states, we occasionally allow “downhill” moves to less probable states
- This procedure ensures that the fraction of time we spend in each state x is equal to $\pi(x)$ (Murphy, 2023, § 12.2.2)

MH Algorithm: Asymmetric Proposal

- Proposal is asymmetric: $q(x' | x) \neq q(x | x')$
- Need Hastings correction

$$A = \min(1, \alpha), \quad \alpha = \frac{\pi(x')q(x | x')}{\pi(x)q(x' | x)} = \frac{\pi(x')/q(x' | x)}{\pi(x)/q(x | x')}$$

- Correction needed: the proposal distribution itself (rather than just the target distribution) might favor certain states
- When evaluating α , we only need to know the target density up to a normalization constant

$$\pi(x) = \frac{1}{Z} \tilde{\pi}(x) \implies \alpha = \frac{(\tilde{\pi}(x')/Z)q(x | x')}{(\tilde{\pi}(x)/Z)q(x' | x)} = \frac{\tilde{\pi}(x')q(x | x')}{\tilde{\pi}(x)q(x' | x)}$$

- We can sample from π even if Z is unknown

Stochastic MH

Very active line of research still nowadays, see e.g. **Bieringer et al. (2023)**

Gibbs Sampling

- Problems with MH: (i) need to choose the proposal distribution, (ii) acceptance rate may be low
- **Gibbs Sampling**: MH method exploiting conditional independence to automatically create a good proposal; acceptance probability 1 (Murphy, 2023, Eq.'s (12.21), (12.22))

Gibbs Sampling: Algorithm

- We begin with some initial value $x^{(0)} = (x_1^{(0)}, x_2^{(0)}, x_3^{(0)})$ sampled from a joint distribution p on \mathbb{R}^3
- We want the next sample $x^{(1)}$
- To do so, for each component $x_j^{(1)}$, we condition on $x^{(1)}$'s components up to $x_{j-1}^{(1)}$
 - Thereafter condition on $x^{(0)}$'s components, starting from $x_{j+1}^{(0)}$ until $x_3^{(0)}$

$$x_1^{(1)} \sim p(x_1 | x_2^{(0)}, x_3^{(0)})$$

$$x_2^{(1)} \sim p(x_2 | x_1^{(1)}, x_3^{(0)})$$

$$x_3^{(1)} \sim p(x_3 | x_1^{(1)}, x_2^{(1)})$$

- This immediately generalizes to \mathbb{R}^D , $D > 3$ and $x^{(s)}$, $s > 1$
- $p(x_j | x_{-j}^{(s)})$ is called the **full conditional** for variable j

Gibbs Sampling as a Special Case of MH

- Gibbs sampling is a special case of MH where we use a sequence of proposals of the form

$$q_j(x' \mid x) = p(x'_j \mid x_{-j}) \mathbb{I}(x'_{-j} = x_{-j})$$

- We move to a new state where x_j is sampled from its full conditional, but x_{-j} is left unchanged
- The fact that the acceptance rate is 100% does not necessarily mean that Gibbs will converge rapidly
 - Only updates one coordinate at a time
- If we can group together correlated variables, then we can sample them as a group: help mixing (**Murphy, 2023, § 12.3**)

Metropolis Within Gibbs

- What should we do if we cannot sample from full conditional?
- To sample $x_j^{(s+1)} \sim p(x_j | x_{1:j-1}^{(s+1)}, x_{j+1:D}^{(s)})$, we
 - Propose $x'_j \sim q(x'_j | x_j^{(s)})$
 - Compute acceptance probability $A_j = \min(1, \alpha_j)$,

$$\alpha_j = \frac{p(x_{1:j-1}^{(s+1)}, \textcolor{red}{x'_j}, x_{j+1:D}^{(s)})/q(\textcolor{red}{x'_j} | \textcolor{blue}{x_j^{(s)}})}{p(x_{1:j-1}^{(s+1)}, \textcolor{blue}{x_j^{(s)}}, x_{j+1:D}^{(s)})/q(\textcolor{blue}{x_j^{(s)}} | \textcolor{red}{x'_j})}$$

- Sample $u \sim \mathcal{U}(0, 1)$, and set

$$x_j^{(s+1)} = \begin{cases} x'_j & \text{if } u < A_j \\ x_j^{(s)} & \text{if } u \geq A_j \end{cases}$$

Hamiltonian Monte Carlo (HMC)

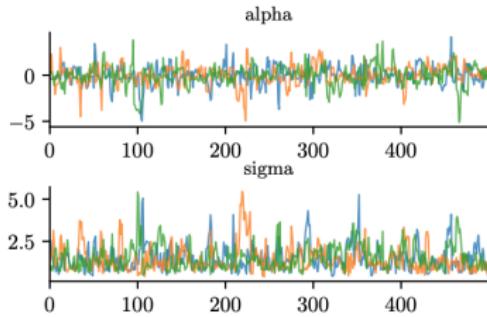
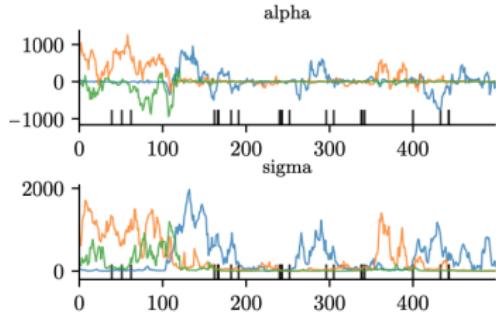
- Many MCMC algorithms perform poorly in high dimensional spaces, because they rely on a form of random search based on local perturbations
- Hamiltonian Monte Carlo leverages gradient information to guide the local moves
 - Important in applications
- Algorithm: (Murphy, 2023, § 12.5.3)
- Tuning: (Murphy, 2023, § 12.5.4)
- Implementation: BlackJAX

MCMC Convergence

- We start MCMC from an arbitrary initial state
- The samples will be coming from the chain's stationary distribution π only when the chain has “forgotten” where it started from
- **Mixing time:** amount of time it takes to enter the stationary distribution
- Samples collected before the chain has reached its stationary distribution do not come from π , and are usually thrown away
- **Burn-in phase:** initial period, whose samples will be ignored

MCMC Convergence Diagnostic

- Assessing if the method has converged:
 - Run multiple chains (typically 3 or 4) from very different overdispersed starting points
 - Trace plot: plot the samples of some quantity of interest
 - E.g. value of a certain component of the state vector, or some event such as the value taking on an extreme value
- If the chain has mixed, it should have “forgotten” where it started from
 - Trace plots should converge to the same distribution, and thus overlap with each other



MCMC Convergence Diagnostic

- MCMC lets us draw samples from a target distribution (assuming it has converged), but the samples are not independent
 - We may need to draw a lot of them to get a reliable estimate
- How to compute the **effective sample size** from a set of (possibly correlated) samples: (**Murphy, 2023, § 12.6.3**)
- How to improve the speed of convergence: (**Murphy, 2023, § 12.6.4**)

References

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