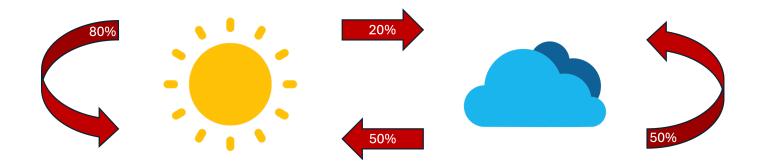
## Deep Learning for Computing Convergence Rates of Markov Chains

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NeurIPS 2024 Spotlight



#### **Example of a Markov Chain**



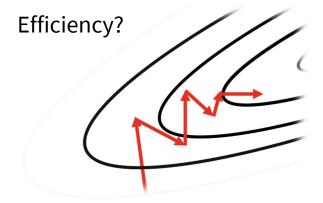
What is the percentage of sunny days in the long run?

$$P(X_n = \textcircled{P}) \bigoplus P(X_\infty = \textcircled{P}) = 5/7$$

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#### **Importance of Convergence Analysis**





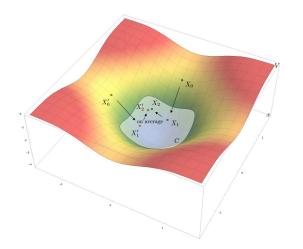
 $X_{n+1} = (X_n + S_{n+1} - A_{n+1})_+$ 

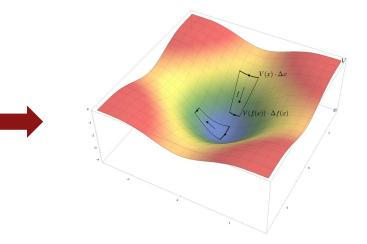
 $X_{n+1} = X_n - \alpha \nabla L(X_n, Z_{n+1})$ 

How fast does  $X_n$  converge to  $X_\infty$ ?

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#### **Convergence Analysis: Old and New**





#### Drift & Contraction, Hairer et al. (2011) $PV(x) = \mathbb{E}_x V(X_1) \le V(x) - U(x), \ x \notin C$ $W(P(y, \cdot), P(z, \cdot)) \le \alpha d(y, z), \ y, z \in C$

Contractive Drift (CD), Qu et al. (2023)  $KV(x) = \mathbb{E}_x Df(x)V(f(x)) \le V(x) - U(x)$  $Df(x) \approx \Delta f(x)/\Delta x, \quad X_{n+1} = f_{n+1}(X_n)$ 

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stochastic delay equations, Probability Theory and Related Fields 149(1), 223–259. Ou, Y., Blanchet, J. & Glynn, P. (2023), Computable bounds on convergence of Markov chains in Wasserstein distance, arXiv:2308.10341.

Hairer, M., Mattingly, J. C. & Scheutzow, M. (2011), Asymptotic coupling and a general form of Harris' theorem with applications to

## From Pen and Paper to Deep Learning

Q, Blanchet, Glynn (2024)



#### **Contractive Drift Equation (CDE)**

• Let  $X_{n+1} = f_{n+1}(X_n)$  be a Markov chain on  $\mathcal{X} \subset \mathbb{R}^d$ .

- If f is differentiable, then  $Df(x) = \|\nabla f(x)\|$ .
- CD is actually CDE:  $KV(x) = \mathbb{E}Df(x)V(f(x)) \bigoplus V(x) U(x)$ .

**Theorem.** Fix U and suppose that  $KW \leq W - U$  has a non-negative finite solution  $W_*$ . Then

$$V_*(x) \stackrel{\Delta}{=} \mathbb{E}_x \left[ \sum_{k=0}^{\infty} U(X_k) \prod_{l=1}^k Df_l(X_{l-1}) \right], \ x \in \mathcal{X}$$

is finite and satisfies  $KV_* = V_* - U$ . Furthermore, KV = V - U has at most one bounded solution.

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#### Why do we introduce CDE?

- Physics-informed neural networks (PINNs) solve a PDE by minimizing its integrated squared residual; see Raissi et al. (2019).
- The residual of a CDE is  $(X_0 \sim h)$

$$2l(\theta) = \int_{\mathcal{X}} (KV_{\theta}(x) - V_{\theta}(x) + U(x))^2 h(x) dx$$
$$= \mathbb{E} \left[ \mathbb{E} \left[ Df_1(X_0) V_{\theta}(f_1(X_0)) - V_{\theta}(X_0) + U(X_0) | X_0 \right] \right]^2$$

• Its derivative  $l'(\theta)$  is  $(f_1, f_{-1} \text{ iid})$ 

 $\mathbb{E}\left[\left[Df_{1}(X_{0})V_{\theta}(f_{1}(X_{0}))-V_{\theta}(X_{0})+U(X_{0})\right]\left[Df_{-1}(X_{0})V_{\theta}'(f_{-1}(X_{0}))-V_{\theta}'(X_{0})\right]\right],$ 

which leads to an unbiased gradient estimator.

#### Raissi, M., Perdikaris, P. & Karniadakis, G. E. (2019), Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations, Journal of Computational Physics 378, 686–707.

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#### **Deep Contractive Drift Calculator (DCDC)**

**Require:** Step-size  $\alpha$ , number of iterations T, neural network  $\{V_{\theta} : \theta \in \Theta\}$ , initialization  $\theta_0$ for  $t \in \{0, ..., T-1\}$  do sample  $(X_0, f_1, f_{-1})$ compute  $\hat{l'}(\theta_t)$  as  $[Df_1(X_0)V_{\theta_t}(f_1(X_0)) - V_{\theta_t}(X_0) + U(X_0)] [Df_{-1}(X_0)V'_{\theta_t}(f_{-1}(X_0)) - V'_{\theta_t}(X_0)]$ update  $\theta_{t+1} = \theta_t - \alpha \hat{l'}(\theta_t)$  (SGD or its variants) end for

convert  $V_{\theta_T}$  into a convergence bound

$$W(X_n, X_\infty) \le Cr^n, \ r = 1 - \inf U / \sup V, \ C = \frac{\mathbb{E} \|X_0 - X_1\| V(X_0 + \tilde{U}(X_1 - X_0))}{\inf U \cdot (\inf V / \sup V)}$$

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#### A Realistic SGD Example

- Data:  $(x_1, y_1), ..., (x_m, y_m) \in [-1/2, 1/2]^2 \times \{0, 1\}$
- Regularized logistic loss:

$$-\frac{1}{m}\sum_{i=1}^{m}(y_i\log p_i + (1-y_i)\log(1-p_i)) + \frac{\lambda}{2m} \|b\|^2, \ p_i = \sigma(b^{\top}x_i)$$

• SGD with step-size  $\alpha$  and batch-size  $\beta$ :

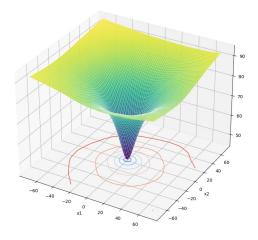
$$f(b) = b(1 - \lambda \alpha/m) + (\alpha/\beta) \sum_{i \in B} \left[ y_i - \sigma(b^\top x_i) \right] x_i$$

• 
$$m = 100, \lambda = 1, \alpha = 0.1, \beta = 10$$

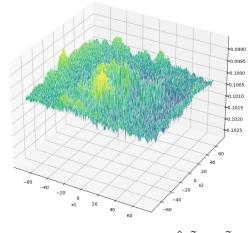
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#### A Realistic SGD Example

- A single-layer network with width 1000 and sigmoid activation
- $W(X_n, X_\infty) \le 8.1(1 1.07 \times 10^{-3})^n$



Learned solution of KV = V - 0.1



Estimated difference  $\hat{K}\tilde{V}-\tilde{V}$ 

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#### Takeaway

DCDC is just a start, the start of **computational** Markov chain convergence analysis.

# Thank you



https://quyanlin.github.io/

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