Sample as You Infer: Predictive Coding With Langevin Dynamics

*Umais Zahid, Qinghai Guo, Zafeirios Fountas**

Huawei Technologies R&D, London, UK

*email: *zafeirios.fountas@huawei.com*

Introduction

Predictive Coding (PC) is a compelling framework for understanding perception and learning in the brain. It employs hierarchical latent Gaussian generative models with complex, non-linear conditional parameterizations.

However, standard **PC** implementations often suffer from computational inefficiencies and lack of robustness, limiting their practical applicability in training unsupervised deep generative models on complex datasets.

We present **Langevin Predictive Coding (LPC)**, a novel algorithm which extends the **PC** framework using techniques from gradient-based Markov Chain Monte Carlo for training deep generative models.

Key idea: Inject Gaussian noise into predictive coding inference, reframing it as amortized Langevin sampling.

Key Contributions

- **LPC** is a version of **PC** with relatively small modifications that results in clearly better performance than variational autoencoders (**VAEs).**
- The use of Langevin Sampling + an amortised posterior aligns perfectly with a combination of *System 1* and *System 2* thinking in the brain.
- The injection of simple Gaussian noise has interesting implications for the nature and value of noise in the brain and potential implementation of **LPC** on naturally noisy analog chips.

Methods

Gaussian Noise Injection: Transforms standard **PC** inference into Langevin sampling, enabling principled posterior exploration.

ELBO Optimization: Utilizes Langevin samples to compute gradients for a tight evidence lower bound, improving model parameter optimization.

Amortized Warm-Starts: Trains an inference network to provide better initial states, enhancing Langevin chain mixing time.

Adaptive Preconditioning: Uses a lightweight diagonal preconditioning matrix inspired by Adam optimizer to enhance robustness to Langevin step size variations.

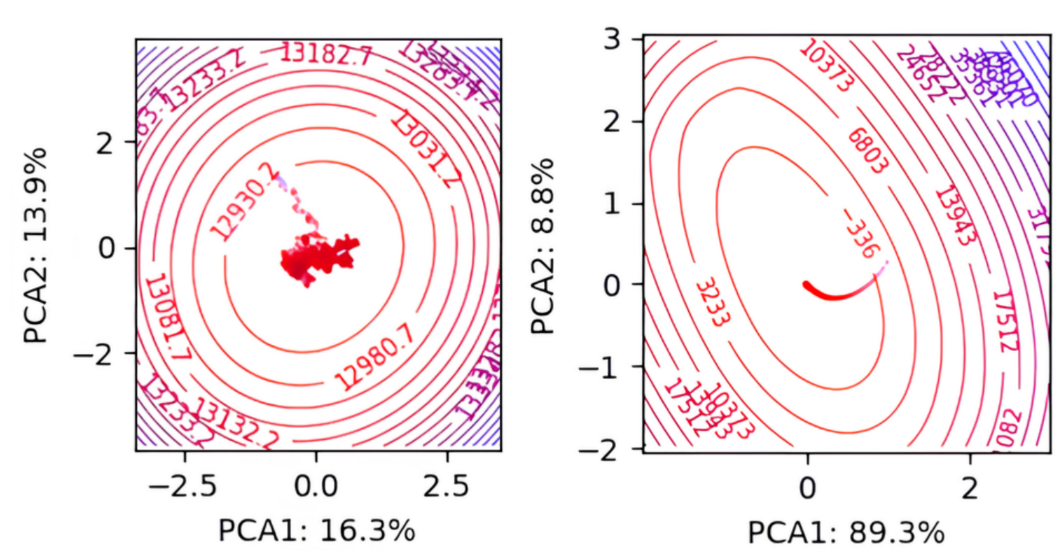


Figure: Projection of high-dimensional latent state trajectories under standard **PC** inference (right), and **LPC** sampling (left), using normalised PCA trajectories. **LPC** results in principled exploration of the posterior.

Discussion

LPC suggests a functional role for neuronal noise in brain-encoded probabilistic models.

Future directions:

- Hierarchical stochastic variable models
- Automatic Markov chain convergence criteria
- Underdamped Langevin dynamics for faster convergence
- **LPC** application to discrete variables
- Advanced approx. inference models for improved warm-starts

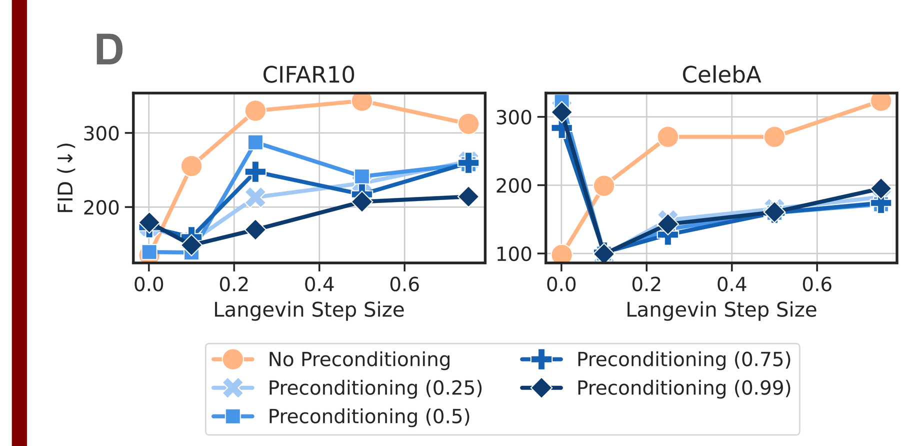
Results

LPC models matched or exceeded the sample quality, diversity, & data coverage of **VAE** models trained for over 3 times as many iterations, while converging in a fraction of the time (see **A** and **C** below).

A

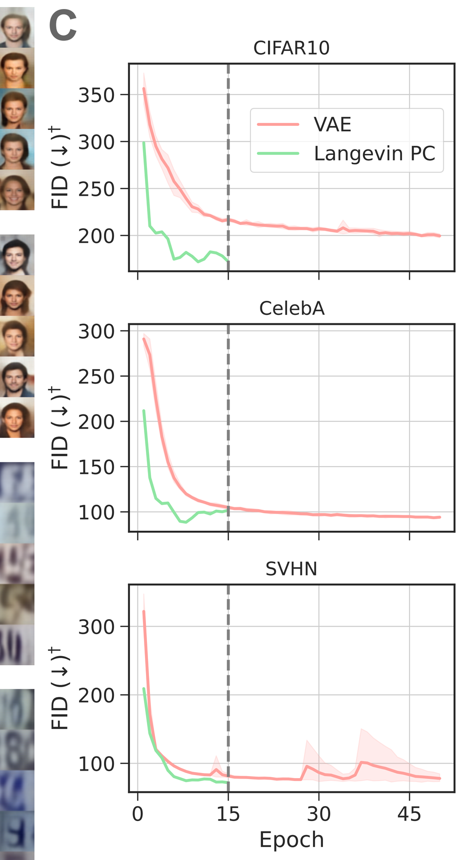
	Dataset	FID (↓)	Density (↑)	Coverage (↑)
LPC 15 epochs	CelebA	97.49	**0.54**	**0.13**
	SVHN	**39.64**	0.33	0.42
	CIFAR10	**113.29**	**0.63**	**0.13**
VAE 15 epochs	CelebA	90.63	0.10	0.08
	SVHN	53.88	0.60	0.39
	CIFAR10	183.21	0.06	0.03
VAE 50 epochs	CelebA	**82.09**	0.16	0.12
	SVHN	44.76	**0.65**	**0.48**
	CIFAR10	145.87	0.14	0.06

D



B

C



Samples from **LPC** exhibit sharper, clearer quality compared to prototypical blurriness observed in **VAE** samples (see samples in **B**).

Encoder training with reverse KL and Jeffrey's divergence yields significantly better performance than using no warm-starts.

Proposed preconditioning substantially increases model robustness to large Langevin step sizes across CIFAR-10, SVHN, & CelebA (see **D**).

Conclusions

LPC demonstrates superior performance compared to traditional **VAEs** while maintaining a strong connection to neurobiological plausibility.

This success suggests that neuronal noise may play a key functional role in facilitating learning in probabilistic models encoded by the brain.

It opens new perspectives on stochastic computations beyond simple noise or variability, potentially advancing both AI and neuroscience.