

# Gibbs Sampling of Continuous Potentials on a Quantum Computer

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# Motivation

**Problem.** Given an ‘energy’ function  $E : \mathbb{R}^d \rightarrow \mathbb{R}$ , generate samples from the corresponding Gibbs distribution

$$p(x) = \frac{e^{-\beta E(x)}}{Z_\beta}$$

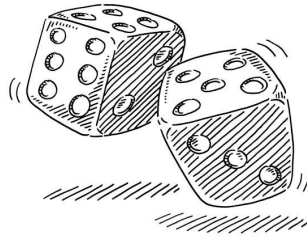


image source: istockphoto.com

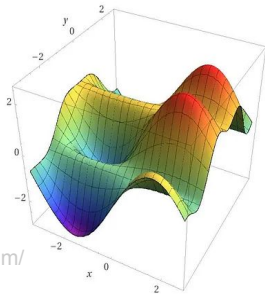
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**Applications.**

Optimization



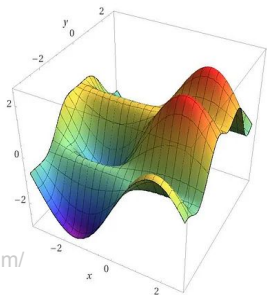
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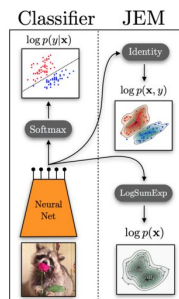
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**Applications.**

Optimization



<https://wikipedia.com/>



Training EBMs

<https://medium.com/>

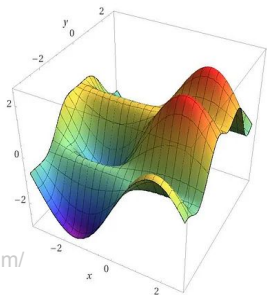
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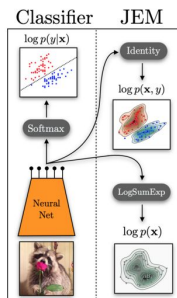
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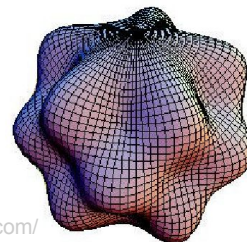
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Training EBMs

Counting



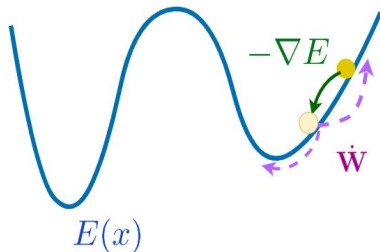
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# Results

Method	Potential type	Sampling complexity	Mean estimation complexity
Our work	non-convex periodic	$\tilde{O}(\kappa_{E/2} e^{\Delta/2} d^7)$	$\tilde{O}(\kappa_{E/2} e^{\Delta/2} d^7 \Delta_f \varepsilon^{-1})$
Rejection sampling	non-convex	$O(e^\Delta)$	$O(e^\Delta \Delta_f^2 \varepsilon^{-2})$
Our work	Morse and periodic	$\tilde{O}(\lambda^{-2} e^{\Delta/2} d^7)$	$\tilde{O}(\lambda^{-2} e^{\Delta/2} d^7 \Delta_f \varepsilon^{-1})$
[LE20]	Morse and periodic	$\tilde{O}(\lambda^{-4} L^4 d^3 \varepsilon^{-2})$	$\tilde{O}(\lambda^{-4} L^4 d^3 \Delta_f^2 \varepsilon^{-4})$
[DCWY18]	convex	$\tilde{O}(L^2 d^3 \varepsilon^{-2})$	$\tilde{O}(L^2 d^3 \Delta_f^2 \varepsilon^{-4})$
[CLL <sup>+</sup> 22]	strongly convex	$\tilde{O}(\mu^{-1/2} L^{1/2} d)$	$\tilde{O}(\mu^{-1/2} L^{1/2} d \Delta_f \varepsilon^{-1})$
[LST20]	strongly convex	$\tilde{O}(\mu^{-1} L d)$	$\tilde{O}(\mu^{-1} L d \Delta_f^2 \varepsilon^{-2})$

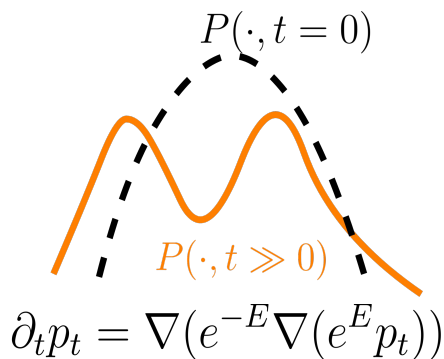
# Techniques: main idea

SDE  
Langevin dynamics  
Good for classical computers



$$dX_t = -\nabla E(X_t) + \sqrt{2} dW_t$$

PDE  
Fokker–Planck equation  
Good for quantum computers



- Due to recent quantum algorithms, we can efficiently solve differential equations over exponentially many points [CPO21]
- Normalization constant comes at the cost of post-selection  $\rightarrow$  relates to mixing time!

# Techniques: interpolation

**Theorem.** We can quantumly interpolate

$N$  point discretization  $\mapsto e^{\Omega(N)}$  point discretization

with **poly(N)** gate complexity.



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$f$  is (semi)-**analytic**  $\iff \frac{|\widehat{f}|^2}{\|\widehat{f}\|^2}$  is a **sub-exp** distribution

**Thank You!**