

## Problem

For  $G \subseteq \mathbb{R}^d$  and  $\varrho: G \rightarrow [0, \infty)$  we want to sample with respect to

$$\pi(A) = \frac{\int_A \varrho(x) dx}{\int_G \varrho(x) dx}, \quad A \subseteq G,$$

by the simple slice sampler.

Qualitative convergence results, see e.g. [1].

## Simple slice sampler

The simple slice sampler generates a Markov chain  $(X_n)_{n \in \mathbb{N}}$  as follows: Assume that  $X_n = x_n$ , then the next state  $X_{n+1} = x_{n+1}$  is generated by the following steps:

1. Draw  $T_n \sim \text{Unif}[0, \varrho(x_n)]$ , call the result  $t_n$ ;
2. Draw  $X_{n+1} \sim \text{Unif}(G(t_n))$ , call the result  $x_{n+1}$ .

## Notations and basics

- The level set of  $\varrho$  (of level  $t$ ):

$$G(t) := \{x \in G \mid \varrho(x) \geq t\}, \quad t \in [0, \|\varrho\|_\infty];$$

- The transition kernel of  $(X_n)_{n \in \mathbb{N}}$ :

$$U(x, A) = \frac{1}{\varrho(x)} \int_0^{\varrho(x)} \frac{\text{vol}_d(A \cap G(t))}{\text{vol}_d(G(t))} dt, \quad A \subseteq G;$$

- The transition kernel of  $(T_n)_{n \in \mathbb{N}}$ :

$$Q(t, B) = \frac{1}{\text{vol}_d(G(t))} \int_{G(t)} \frac{\text{vol}_1(B \cap [0, \varrho(x)])}{\varrho(x)} dx, \quad B \subseteq (0, \infty);$$

- The probability measure  $\mu$  on  $(0, \infty)$ :

$$\mu(B) := \frac{\int_B \text{vol}_d(G(s)) ds}{\int_0^\infty \text{vol}_d(G(t)) dt}, \quad B \subseteq (0, \infty);$$

- The Markov operators  $U$  and  $Q$ :

$$Uf(x) := \int_G f(y) U(x, dy), \quad Qg(t) := \int_0^\infty g(s) Q(t, ds).$$

## Spectral gap

The spectral gaps of  $U$  and  $Q$  are defined by

$$\text{gap}(U) := 1 - \|U - E_\pi\|_{L_2(\pi) \rightarrow L_2(\pi)}, \quad \text{gap}(Q) := 1 - \|Q - E_\mu\|_{L_2(\mu) \rightarrow L_2(\mu)}.$$

If  $\text{gap}(U) > 0$ , then

- $\|v U^n(\cdot) - \pi(\cdot)\|_{\text{TV}} \leq (1 - \text{gap}(U))^n \left\| \frac{dv}{d\pi} - 1 \right\|_2$ ;
- a CLT holds for the ergodic average for all  $f \in L_2(\pi)$ , see [2];
- there is a mean squared error bound for the ergodic average for  $f \in L_p(\pi)$ ,  $p > 2$ , see [3].

## Main tool: Wasserstein metric

- Wasserstein distance between two measures on  $G$ :

$$W(\mu, \nu) := \inf_{\gamma \in \Gamma(\mu, \nu)} \int_{G \times G} |x - y| d\gamma(x, y),$$

where  $\Gamma(\mu, \nu)$  is the set of all couplings of  $\mu$  and  $\nu$ ;

- By [4, Proposition 30] we have

$$W(U(x, \cdot), U(\tilde{x}, \cdot)) \leq \alpha |\tilde{x} - x|, \quad \forall x, \tilde{x} \in G \implies \text{gap}(U) \geq 1 - \alpha.$$

## Main results

**Theorem 1 (Natarovskii, Rudolf, 2018).** Let  $\varrho(x) = e^{-\varphi(|x|)}$ , where  $\varphi: [0, \infty) \rightarrow [0, \infty)$  satisfies the following conditions:

1.  $\varphi \in C^1[0, \infty)$ ,
2.  $\varphi'(0) \geq 0$  and  $\varphi'(s) > 0$  for all  $s > 0$ ,
3.  $\varphi'(s)$  is non-decreasing.

Then

$$W(U(x, \cdot), U(\tilde{x}, \cdot)) \leq \frac{d}{d+1} |\tilde{x} - x|, \quad \forall x, \tilde{x} \in G.$$

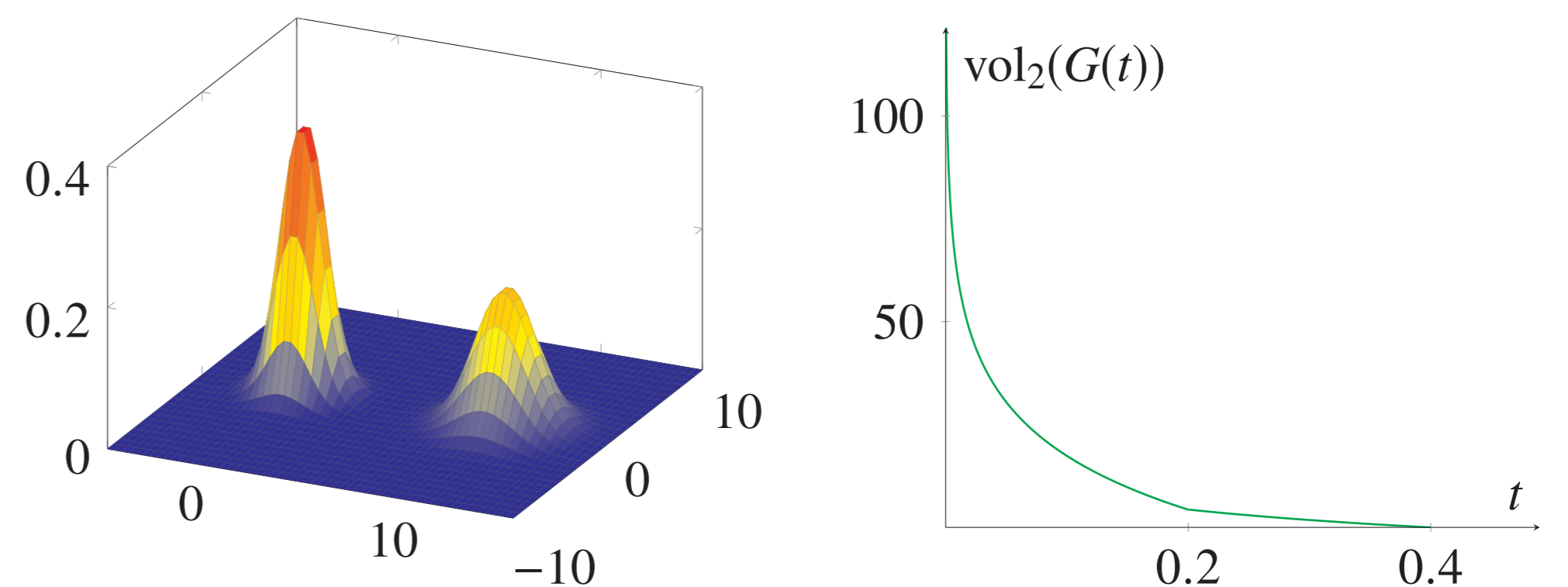
**Lemma 2 (Natarovskii, Rudolf, 2018).**  $\text{gap}(U) = \text{gap}(Q)$ .

**Theorem 3 (Natarovskii, Rudolf, 2018).** Let  $\varrho(x)$  be such that for some  $k \in \mathbb{N}$  the function  $\varphi(s) := -\log(\inf\{t : \text{vol}_d(G(t)) \leq \text{vol}_k(B_k) s^k\})$  satisfies conditions 1.-3. from Theorem 2. Then

$$\text{gap}(U) \geq 1 - \frac{k}{k+1} = \frac{1}{k+1}.$$

## Illustration of the technique

Let  $\varrho(x)$  be the maximum of two Gaussian densities:



Examples of densities with the same level-set function as  $\varrho(x)$ :

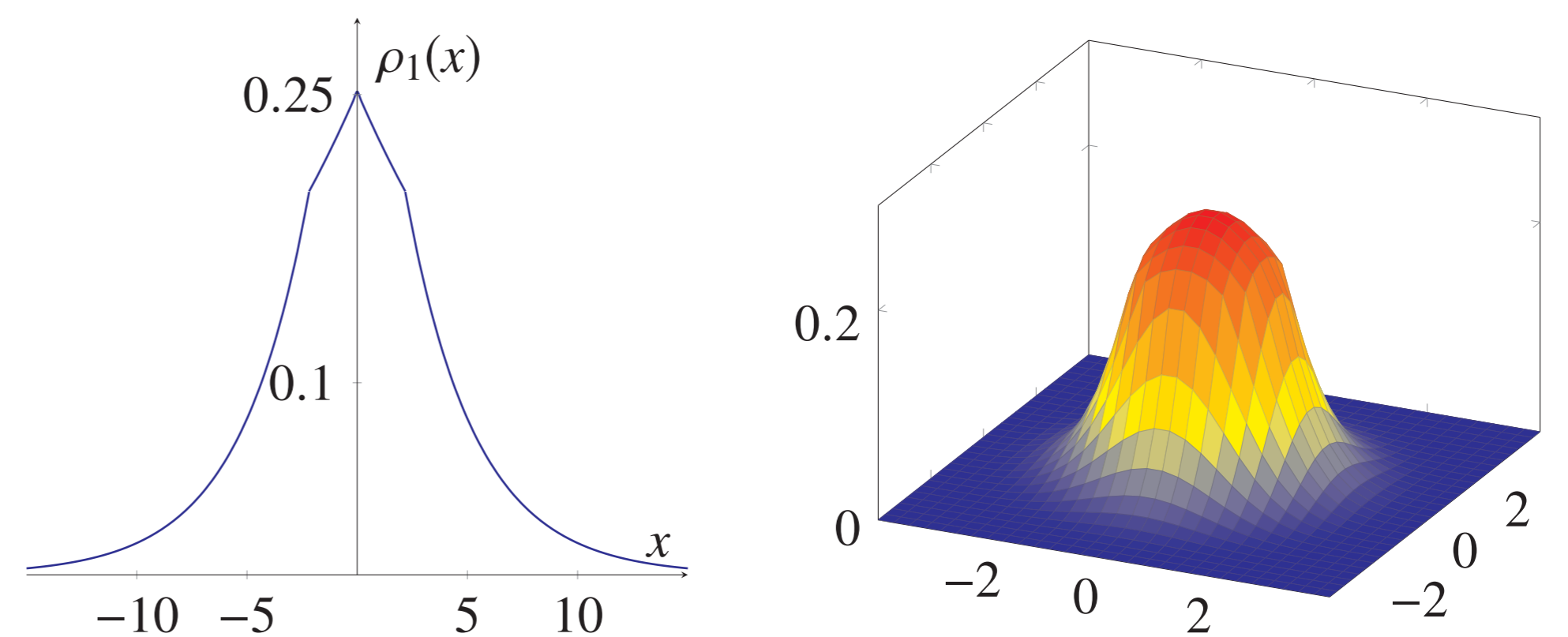


Figure: Density  $\varrho_1(x)$  in  $\mathbb{R}^1$

Figure: Density  $\varrho_2(x)$  in  $\mathbb{R}^2$

## Future research

- Weakening assumptions of Theorem 1;
- Spectral gap for elliptical slice sampling, see [5];
- Spectral gap for hybrid slice sampling, see [6].

## References

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