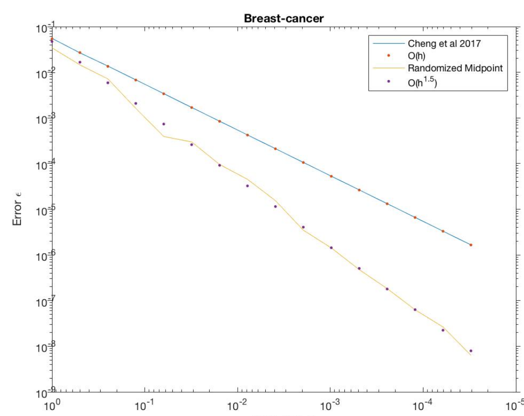
We sincerely appreciate the time and the efforts the reviewers invested in reading our paper and providing valuable feedback. We would like to emphasize again the main contribution of our paper. In our paper, we developed a general framework for simulating stochastic differential equations(SDE). We illustrated the usefulness of our framework on the sampling problem and obtained a significantly better result than numerous previous results without making any extra assumptions. We believe that there are many other applications of our framework and that our paper is among the top accepted papers.

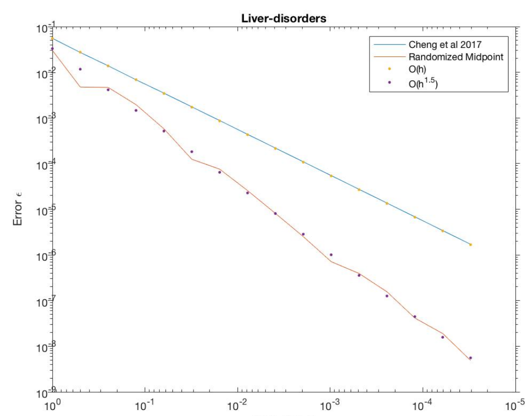
To Reviewer 1: Thanks for the citations and the correction you provided. In our final submission, we will cite [4] and compare the runtime of our algorithm with [2], which achieves $O\left(\frac{\kappa^{1.5}}{\epsilon}+\kappa^2\right)$ runtime and improves the result of [1]. We will also correct all the items mentioned in SPECIFIC REMARKS/TYPOS. However, we still prefer using $O(1)$ instead of explicit numerical constants because we believe numerical constants will distract readers from the key contributions.

To Reviewer 2: The problem studied in our paper, sampling from log-concave distributions, is an essential tool for Bayesian inference. It also has many other applications such as volume computation and bandit optimization. (We mentioned the applications in the first paragraph.) We will make the application of our algorithm more explicit in our final submission. We will also include an experiment section in our final submission, which shows the performance of algorithm on real-world datasets. The preliminary results are attached.

To Reviewer 3: We will make a distinction between a Markov process and its discretization in our final submission. We will make sure that everything is defined properly before used and polish the statement of our theorems. Thanks for suggesting we evaluate the ϵ dependence of our paper via experiment. We will include an experiment section in our final submission which will analyze the performance of our algorithm on real-world datasets. The preliminary results are attached. The result shows that the bound $\epsilon^{2/3}$ we obtained is in fact tight even for real-world example and is an improvement over [1].

To All: We attach the preliminary result of our experiments here. In our experiment, we compare the algorithm from our paper with the one from [1]. In our final submission, we will compare our algorithm with more algorithms. We test the algorithms on the liver-disorders dataset and the breast-cancer dataset from UCL machine learning repository[3]. For both datasets, we sample from the problem $f(x)=\frac{\lambda}{2}\left\|x\right\|^2+\frac{1}{m}\sum_{i=1}^{m}\log\left(\exp\left(-y_i a_i^T x\right)+1\right)$,where λ is the regularization parameters (We set it to be 10^{-2}), y_i is the label, a_i is the input and m is the number of inputs. Our results show that the ϵ dependence analysis of our algorithm and that of [1] are both tight.





References

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[2] Arnak S Dalalyan and Lionel Riou-Durand. On sampling from a log-concave density using kinetic Langevin diffusions. *arXiv preprint arXiv:1807.09382*, 2018.

[3] Dheeru Dua and Casey Graff. UCI machine learning repository, 2017.

[4] Alain Durmus, Szymon Majewski, and Blazej Miasojedow. Analysis of langevin monte carlo via convex optimization. *Journal of Machine Learning Research*, 20(73):1–46, 2019.