

## Software Objectives

To provide QMC software [1] that is:

- comprised of free open source tools
- designed for continuous development
- easy to use for non-experts
- a recognized standard

## The Integration Problem

### Original Form

$$\mu = \int_T g(t) \lambda(dt)$$

$g : T \rightarrow \mathbb{R}$  is original integrand

$\lambda$  is original measure

### Convenient Form

$$\mu = \int_X f(x) \rho(x) dx = \int_X f(x) \nu(dx)$$

$f : X \rightarrow \mathbb{R}$  is integrand after change of variables

$\nu$  is some well defined probability measure

$\rho : X \rightarrow T$  is the probability density

### (Quasi-)Monte Carlo Approximation

$$\hat{\mu}_n = a_n \sum_{i=1}^n f(x_i) w_i = \int_X f(x) \hat{\nu}(dx)$$

$\nu \approx \hat{\nu}_n = a_n \sum_{i=1}^n w_i \delta_{x_i}(\cdot)$  is discrete probability measure

The routine `integrate` accepts instances of concrete subclasses of four abstract classes that represent the integrand, original measure, discrete distribution associated with the sampling points, and stopping criterion.

### integrate

Given  $\epsilon > 0$ , find  $\hat{\mu}_n$  such that  $|\mu - \hat{\mu}_n| \leq \epsilon$

#### Arguments

- Function instance
- Measure instance
- Discrete Distribution instance
- Stopping Criteria instance

### Function

Specify and generate values  $f(x_i)$

#### Concrete Classes

- Keister functions [2]
- Asian call option's payoff

### Discrete Distribution, $\hat{\nu}$

Specify and generate  $a_n \sum_{i=1}^n w_i \delta_{x_i}(\cdot)$

#### Concrete Classes

- IID
- QMC (Lattice & Sobol) [3, 4]

### Stopping Criterion

Determine sample size,  $n$ , given  $\epsilon$

#### Concrete Classes

- Central limit theorem (IID)
- Mean Variance (Mesh)

### Measure, $\lambda$ and $\nu$

Specify the original measure and convenient probability measure

#### Implemented Functions

- Standard uniform
- Standard Gaussian
- IID zero-mean Gaussian
- Brownian motion

### Accumulate Data

Accumulate data required for the computation of the integral and the stopping criterion

## Results

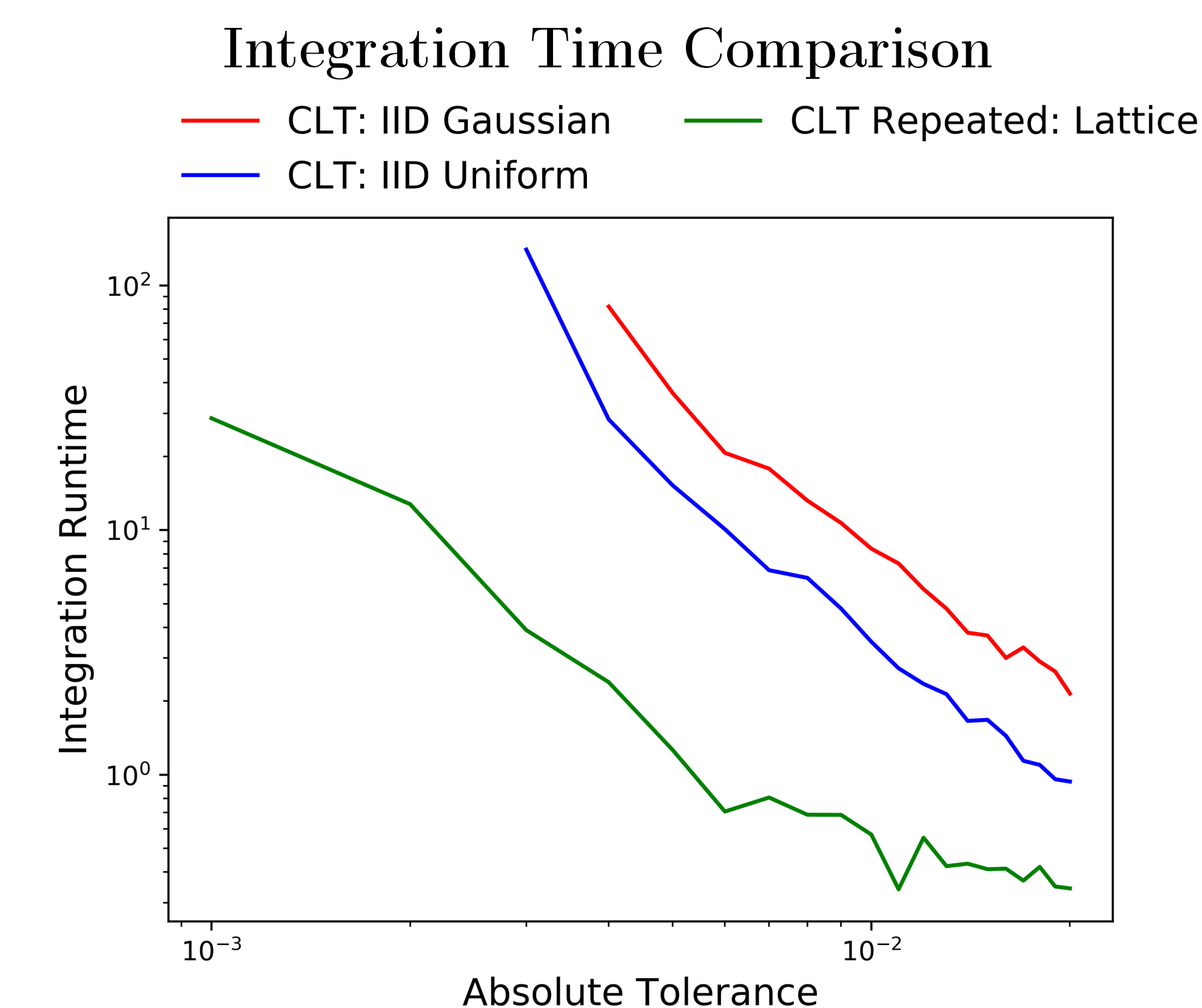


Figure 2: Multi-dimensional Asian call option integrated with respect to Brownian Motion. This figure can be easily reproduced by `Test_AbsTo1_RunTime.py` [1].

## Future Work

- Enhance tests, examples, and documentation
- Refine existing code. e.g. improve Sobol speed
- Bring in relevant algorithms from GAIL [5]
- Expand community of contributors

## References

- [1] F. J. Hickernell, S.-C. T. Choi, and A. Sorokin, "QMC Community Software." MATLAB and Python 3 software, 2019. Work in progress. <https://github.com/QMCSoftware/QMCSoftware>.
- [2] B. D. Keister, "Multidimensional quadrature algorithms," *Computers in Physics*, vol. 10, no. 2, pp. 119–128, 1996.
- [3] F. Y. Kuo and D. Nuyens, "Application of quasi-Monte Carlo methods to elliptic PDEs with random diffusion coefficients: a survey of analysis and implementation," *Foundations of Computational Mathematics*, vol. 16, no. 6, pp. 1631–1696, 2016.
- [4] D. Nuyens, "The magic point shop of QMC point generators and generating vectors." MATLAB and Python software, 2018. <https://people.cs.kuleuven.be/dirk.nuyens/qmc-generators>.
- [5] S.-C. T. Choi, Y. Ding, F. J. Hickernell, L. Jiang, L. A. Jiménez Rugama, D. Li, R. Jagadeeswaran, X. Tong, K. Zhang, Y. Zhang, and X. Zhou, "GAIL: Guaranteed Automatic Integration Library (versions 1.0–2.3)." MATLAB software, 2013–2019. [http://gailgithub.github.io/GAIL\\_Dev/](http://gailgithub.github.io/GAIL_Dev/).

Listing 1: Essential code for estimating the Keister integral in the first subplot of Figure 1.

```
d = 2
stopObj = CLTStopping(nInit=16,
                      absTol=.5)
measureObj = measure().\
    IIDMeanGaussian(dimension=[d],
                    variance=[.5])
distribObj = IIDDistribution(
    trueD=measure().stdGaussian(
        dimension=[d]))
sol, out = integrate(KeisterFun(),
                    measureObj, distribObj, stopObj)
```

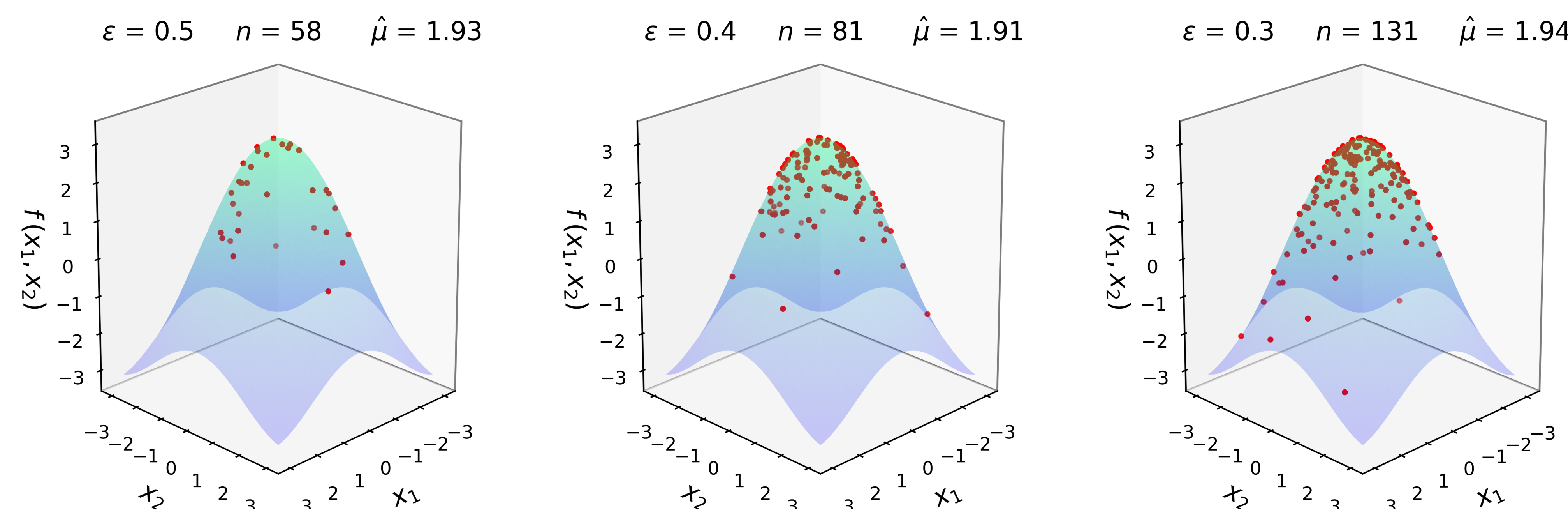


Figure 1: Reducing tolerance automatically results in more samples and better approximations of the Keister integral [2],  $\int_{\mathbb{R}^d} \pi^{d/2} \cos(\|\mathbf{t}\|) \frac{\exp(-\|\mathbf{t}\|^2/2)}{\pi^{d/2}} d\mathbf{t} = \int_{\mathbb{R}^d} \pi^{d/2} \cos(\|\mathbf{x}\|/\sqrt{2}) \frac{\exp(-\|\mathbf{x}\|^2/2)}{(2\pi)^{d/2}} d\mathbf{x} \approx 1.80819$  with  $d = 2$  and where  $\Phi$  is the standard normal cumulative distribution function. This figure is reproducible by `Test_3D_Point_Distribution.py` [1].