

#### **Quasi-Monte Carlo**

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#### **Overview**

- Why Monte Carlo anyways?
- Quasi-Monte Carlo and low discrepancy
- When to use Quasi-Monte Carlo
- Example
- Generating Halton sequences



## Why Monte Carlo?

- Traditional numerical integration uses regular grids to maximize accuracy:
  - Example:





## Why Monte Carlo?

- Traditional numerical integration has trouble in high dimensions the grids do not scale well:
  - Example:

$$\int_{x\in[0,1]^n} e^{Ax} dx$$

- Picking uniform points in the hypercube:
  - In 1 dimension (n=1), pick 5 uniform points
  - In 2 dimensions (n=2), pick  $5^2$ = 25 points
  - In 5 dimensions (n=5), pick  $5^5$ = 3125 points?!

#### Integration is difficult to do for n > 4 !



## Why Monte Carlo?

Monte Carlo estimates the integral using samples:
– Example:

$$\int_{x \in [0,1]^n} e^{Ax} dx \approx \sum_{i=1}^N e^{Ax_i}$$

• Use random samples  $x_i$  to estimate the integral

#### Accuracy is independent of the dimension!

Accuracy 
$$\propto \frac{1}{\sqrt{N}}$$



#### **Quasi-Monte Carlo**

- Combines the best parts of traditional numerical integration with best parts of Monte-Carlo
  - Regularity of traditional numerical integration
    - Points are more regular than monte-carlo points
  - Accuracy that is independent of dimension
    - Don't need a ton of grid points to get accurate results\*
- Accuracy is enhanced: Accuracy  $\propto \frac{1}{N}$



#### **Quasi-Monte Carlo: How?**

- Uses low discrepancy:
  - Increases the regularity of monte-carlo
  - Less 'clumping', 'whitespaces' -> less discrepancy





## **Example: Estimating Wafer Profit**





#### **Example: Estimating Wafer Profit**

Calculated Average Profit (tens of thousands of dollars) Dimensions: 2368

		5	10	15	20	25	30	35	40	45	50	10000
	MC	1.5430	1.5385	1.5375	1.5420	1.5419	1.5400	1.5411	1.5402	1.5403	1.5405	1.5405
	QMC	1.5360	1.5361	1.5368	1.5373	1.5376	1.5381	1.5387	1.5391	1.5396	1.5401	1.7170

#### Percentage Error (%) Dimensions: 2368

	5	10	15	20	25	30	35	40	45	50	10000
MC	0.1623	0.1298	0.1947	0.0974	0.0909	0.0325	0.0389	0.0195	0.0130	0	0
QMC	13.844	9.9555	8.0301	6.0237	5.2881	4.0893	3.1108	2.4045	2.1099	1.5655	0

#### QMC performs worse than MC!



## Why does QMC perform worse?

 Quasi-Monte Carlo suffers from the same problem as conventional integration: a minimum number of samples is needed to fill the space

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- The number of samples is proportional to 2<sup>n</sup>
  - For 1 dimension, approx 2 points
  - For 5 dimensions, approx 32 points
  - For 2000 dimensions, approx ∞ points





#### **Example QMC vs. MC**



In 25 dimensions, QMC is more accurate for 300+ samples



# Another pitfall – generating the correct dimension

- Cannot create higher dimension QMC sequences using lower dimension QMC sequences
  - Unlike pseudo-random
- What happens:





## **Generating Halton Sequences**

- Halton sequences are a type of low discrepancy sequence used for QMC
- Every Halton sequence, regardless of dimension, use prime number(s) for its base(s) (Halton1958)



## **Generating Halton Sequences**

• Express any integer n as the sum of the successive powers of radix R. That is,

-  $n = n_M n_{M-1} \dots n_2 n_1 n_0 = n_0 + n_1 R + n_2 R^2 + \dots + n_M R^M$ , where  $M = [log_R n]$ 

• a new fraction, *f*, between 0 and 1, is formed when all the powers of the radix are changed with their respective inverses. That is,

 $- f = f_{R}(n) = 0.n_{0} n_{1} n_{2}...n_{M} n_{M-1} = n_{0} R^{-1} + n_{1}R^{-2} + n_{2}R^{-3} + ... + n_{M}R^{-M-1}$ 

- To generate N numbers in K dimensions, use the kdimensional space
  - (n/N,  $f_{R1}(n)$ ,  $f_{R2}(n)$ , ...,  $f_{RK-1}(n)$ ),
  - where n = 1, 2, ..., N and R<sub>1</sub>, R<sub>2</sub>, ..., R<sub>k-1</sub> are the first k-1 primes.