CCA Project

Neural Networks Performance for Generating Standard Random Distributions

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May 27, 2024

SCIENCES SORBONNE UNIVERSITÉ

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Introduction

Methodology

Methodology

Understanding Mathematical Concepts

Understanding Mathematical Concepts

What questions did we ask ourselves?

- What is a random variable?
- How do we define probability distributions?
- Why are these concepts important in simulations?
- How do random number generators work?

Random variables

Random variable

A real random variable (resp. a random vector) on Ω is an application $X : \Omega \to \mathbb{R}$ (resp. $\Omega \to \mathbb{R}^m$) such that for any open interval I of $\mathbb{R}$ (resp. an open box in $\mathbb{R}^m$) $X^{-1}(I)$ is a event (so in $\mathcal{B}$).

Probability Distributions

- **Threshold-based Generation:**
  - Bernoulli Distribution
- **Summation of Trials:**
  - Binomial Distribution
- **Transform Methods:**
  - Chi-Squared Distribution (Box-Muller transform)
  - Exponential Distribution (Inverse transform sampling)
- **Rejection Sampling:**
  - Poisson Distribution

How Do Random Number Generators Work?

- **Sequential Generation:**
  - Uses a seed to initialize
  - Generates a deterministic sequence
- **Linear Congruential Generators (LCG):**
  - Commonly used method
  - Formula: $X_n = (aX_{n-1} + c) \mod m$
- **Then used in Advanced Methods:**
  - Inverse Transform Sampling
  - Rejection Sampling
  - Box-Muller Transform

Methodology

Implementation

In Python

- **Why Python?**
  - Simplicity and readability
  - Extensive libraries available
- **Libraries Used:**
  - NumPy
  - PyTorch
- **Development Process:**
  - Used built-in functions for initial implementation
  - Coded our own generators for comparison

In C

- **Why C?**
  - Improved performance and efficiency
  - Low-level memory control
  - Preparing for GAN implementations with CUDA/C++
- **Translation Process:**
  - Translate algorithms from Python to C
  - Optimize for performance in C

Re-coding with the Professor's RNG

- **Integration of Professor's RNG:**
  - Adapted RNGs provided by the professor
  - Ensured compatibility with our code
- **Optimization:**
  - Fine-tuned algorithms using these RNGs
  - Enhanced performance and accuracy

What are GANs?

Generative Adversarial Networks (GANs)

- **Concept:**
  - Introduced by Ian Goodfellow in 2014
  - Composed of two neural networks: the **Generator** and the **Discriminator**
- **Generator:**
  - Generates new data instances
  - Learns to create data that mimics real data
- **Discriminator:**
  - Evaluates the authenticity of the data
  - Distinguishes between real and generated data
- **Applications:**
  - Image generation, Data augmentation, Anomaly detection ...

Results

Results

Comparison of Execution Times

On CPU — Built-in Python functions : NumPy vs PyTorch

$n\_sample = 1,000,000$ $p = 0.5$ Distribution simulated with built-in functions	Numpy with a 'for' loop	Numpy without a 'for' loop	Pytorch
Bernoulli	0.80000s	0.02087s	0.02651s
Binomial ($n = 100$)	0.81285s	0.08303s	0.22444s
Exponential ($\lambda = 2$)	0.60388s	0.01727s	0.06846s
Poisson rejection ($\mu = 5$)	0.8195s	0.13516s	0.19474s
Chi-squared (d = 10)	0.68824s	0.16115s	0.23700s
Normal	0.85456s	0.05965s	0.01545s

On CPU — With our custom generators in Python using Numpy and Pytorch

$n\_sample = 1,000,000$ $p = 0.5$ Distribution simulated	Custom generators using NumPy	Custom generator using PyTorch
Bernoulli ($n = 100$)	0.02893s	0.05091s
Binomiale with Bernoulli ($n = 100$)	1.22517s	1.46297s
Binomiale without Bernoulli	1.87530s	
Exponentielle ($\lambda = 2$)	3.62260s	0.10872s
Poisson rejection ($\mu = 5$)	11.88620s	3.66399s
Chi-squared (d = 10)	0.16001s	1.19594s
Compound Poisson	3.48699s	2.73748s
Noncentral chi-squared	8.63048s	

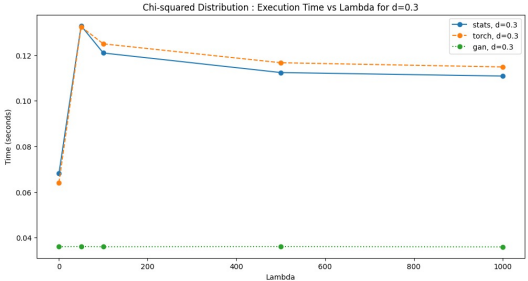
On CPU — With our custom generators in C/C++ using built-in rand() and our RNG

$n\_sample = 1,000,000$ $p = 0.5$ Distribution simulated	using built-in rand() function in C	using our RNG in C++
Bernoulli	0.08834s	0.09479s
Binomial with Bernoulli ($n = 100$)	2.11896s	0.06306s
Binomial without Bernoulli ($n = 100$)	2.75088s	1.30529s
Exponential ($\lambda = 2$)	0.05505s	0.08671s
Poisson rejection ($\mu = 5$)	0.266195s	0.01859s
Chi-squared (d = 10)	0.79669s	0.10384s

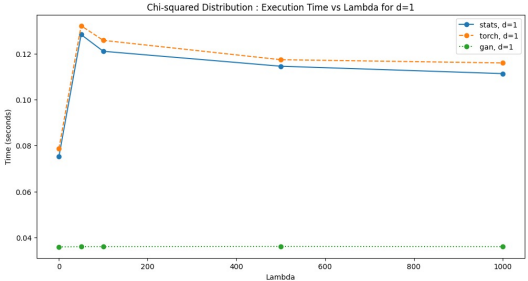
On GPU — With our custom generators using PyTorch in Python and our RNG in CUDA

$n\_sample = 1,000,000$ $p = 0.5$ Distribution simulated	in Python using PyTorch	our RNG in C using CUDA
Bernoulli	0.00054s	0.000703s
Binomial with Bernoulli ($n = 100$)	0.00052s	0.000582s
Exponential ($\lambda = 2$)	0.00036	0.000058s
Chi-squared (d = 10)	0.00568s	0.000099s
Poisson distribution ($\mu = 5$)	0.01825s	0.000202
Compound Poisson Distribution	0.019852s	

GAN — Chi-squared distribution varying Degrees of Freedom

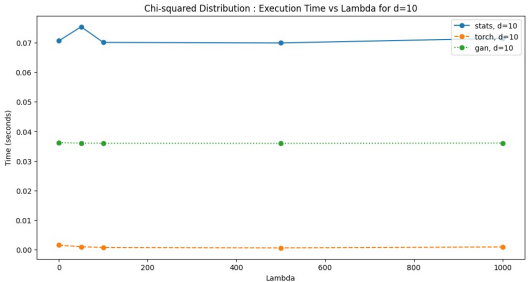


Degree of freedoms = 0.3

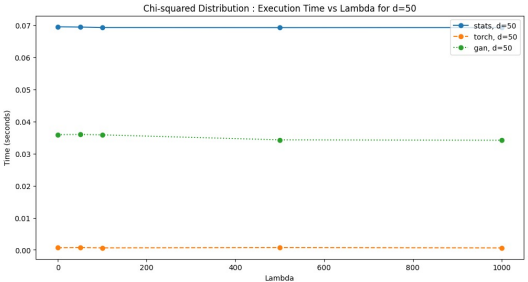


Degree of freedoms = 1

GAN — Chi-squared distribution varying Degrees of Freedom

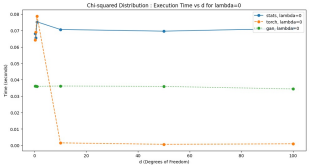


Degree of freedoms = 10

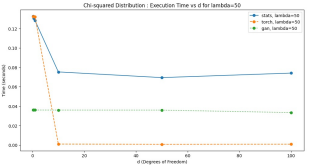


Degree of freedoms = 50

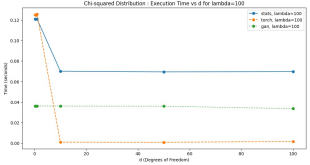
GAN — Chi-squared distribution varying Lambda



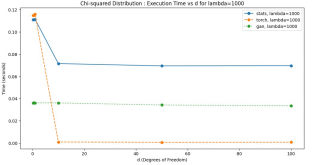
$\lambda = 0$



$\lambda = 50$

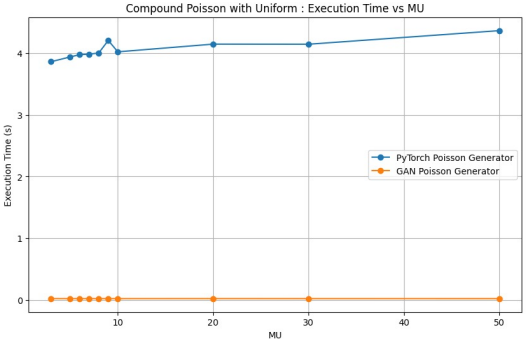


$\lambda = 100$

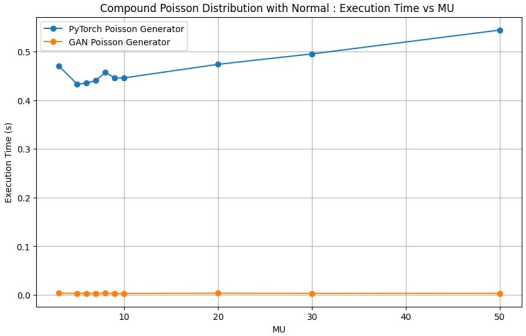


$\lambda = 1000$

GAN — Compound Poisson distribution with Uniform vs with Normal

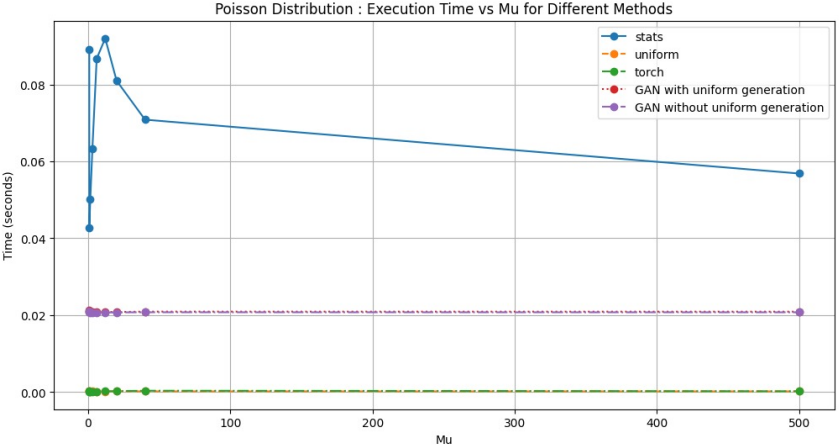


Compound Poisson with Uniform



Compound Poisson with Normal

GAN — Poisson distribution using various methods



Results

Defects and Improvements

Defects and Improvements

- **Identified Defects:**
  - Inconsistent performance across different distributions
  - All our GANs are slower than our parallelized GPU code
  - Lack of certain functions that we couldn't implement
- **Potential Improvements:**
  - Enhance parallelization
  - Optimize GAN training for better performance
  - Conduct more extensive benchmarking across varied hardware
  - Explore hybrid models combining traditional methods with GANs

Conclusion

Thank You For Your Attention