Putting Chaos into Perspective: Evaluation of Statistical Test Suite Implementations on Isolated Sequences of Arbitrary Length

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Abstract: Randomness is ambiguously defined as the absence of structure, whereby reliable generation and evaluation thereof imposes a complex problem. Efforts have been made to quantify randomness by developing randomness test suites as aggregation of selected statistical methods. This study aims to evaluate caveats developers may encounter employing such methods, and compares the application of randomness test suites for arbitrary data to evaluate features of randomness. Therefore, an initial set of three open-source Python-based implementations of the NIST SP 800-22 test suite have been analyzed and compared. The results indicate no "one-size-fits-all" approach when assessing randomness; instead, it demonstrates how deviations between specification and implementation can lead to inaccurate results and erroneous conclusions about randomness.

1 INTRODUCTION

The concept of randomness is complex and counter-intuitive, as it is by its very definition the absence of structure or any predictability. Consider the following sentence as an introductory example: "A quick brown fox jumps over the lazy dog!" and the question of this 42 Byte isolated sequence being "random" or not. Given the human instinct, trained to look for patterns, probably none would consider this sequence to be "random". Nevertheless, common statistical methods and specialized test suites classify this sequence as such (as we will also show in Section 5). This problem raises the question of how such methods perform and for which application areas they are suitable besides the evaluation of random number generators.

A variety of statistical methods exist to evaluate randomness, which all have their own properties and limitations. Statistical methods are often combined into test suites to compensate for limitations by looking at multiple results more broadly. In principle, a sequence to be tested can represent any form of a data stream. This includes more or less structured data, such as TXT, DOC, PDF, over encrypted data, such as XOR, RC4, AES, up to "random" data generated by Pseudo (PRNG) or True Random Number Generators (TRNG). Knowledge of the data structure is required to be able to process data. Ultimately, it all comes down to a binary sequence as the only accurate representation for any given data stream in information systems, which may be considered chaos by humans unable to (efficiently) process binary data.

The Python programming language was the primary tool used in this project. Compared to C, Python is not the most efficient language, yet it has become a tool that has found great acceptance in many areas, as in the field of data science, where it is in no way inferior to its colleagues *R* or *Matlab*. Even embedded systems can benefit from this popularity by using a subset of the Python standard library, called *MicroPython*. Python has a large community that produces Free and Open Source Software (FOSS) on a daily basis. However, FOSS is not automatically a seal of quality. FOSS makes up a large share of the tools used daily in many different domains. Major projects have immense community support and are usually well maintained, but minor personal projects also exist. When browsing for tools, frameworks, or packages, users usually install blindly, using package managers, without looking at the code. Thus, one enjoys the benefit of a black-box that is easy to install, always at hand, and implements all the desired functions. Theory and practice are often far apart, and different implementations of the exact specification optimally have identical results, even though a different approach has been employed to reach a given state.

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1.1 Problem Statement

In a recent, yet unrelated, project using *Tensorflow* to work with machine learning (or pattern recognition), the assessment of randomness (or absence of any pattern) was required as a feature of the employed model. During this project, the question arose of how to collect and use this property from arbitrary data to improve the learning curve with measurement and to sort by the amount of "structure" supporting further development. A cursory glance at Github looking for randomness tests in Python revealed several projects implementing well-established randomness test-suites. However, the initially selected open-source implementation of a randomness test suite produced results that could only be described as "random" at the time, mainly due to the rather short sequences tested. Further comparisons and evaluations revealed noticeable differences in the results of different implementations of the same test suite. These findings raised fundamental questions about how developers should deal with these problems, so these points were pursued, deepened, and addressed in this work.

With this work, we want to provide the first indicators for developers on how to approach the problem of classifying an isolated sequences of arbitrary length. In this context, an isolated sequence is defined as any stream of bits, which is evaluated without any context besides the sequence length and "amount of structure" derived from statistical test results. While this paper focuses on comparing specific implementations to identify problem areas, it does not aim to evaluate the statistical methods but rather the difficulties developers face in implementing and using such.

1.2 Related Work

To the best of our knowledge, there are currently no publications dealing with the practical problems of evaluating the quality of open-source implementations of randomness test suites, focusing on the applications of diverse datasets and arbitrary length sequences to extract features of randomness.

Beside others, (Bastos et al., 2019; Parisot et al., 2021; Popereshnyak and Raichev, 2021) et al. focus on the originally intended application of randomness test suites to evaluate and select random number generators. (Zia et al., 2022; Poojari et al., 2021; Gao et al., 2022) et al. are trying to *design* new entropy sources focusing on the constraint Internet of Things (IoT). Others, are specialized in the evaluation of short sequences based on block cipher (Sulak et al., 2010), or specialized in the randomness of cryptographic function mappings (Kaminsky, 2019).

However, none of them question the way on *how* those evaluated randomness properties could be considered as a staggering feature. So with this work, we want to make the first steps towards addressing this gap, not from a purely mathematical or statistical but more of an "expert in other areas" point of view. This work focuses on applying (black box) statistical randomness test to extract features of randomness by "amount of structure". This work evaluates structure as the opposite of randomness and addresses how much data is required for an isolated sequence to detect structure and dissolve chaos, which may be provided to data type classifiers as features.

2 BACKGROUND

2.1 Randomness

The analogy of the "unbiased (fair) coin" is one attempt to describe randomness that is easy to follow. It assumes that elements can be generated in a sequence of evenly distributed values by tossing an unbiased coin with sides labeled with values "1" or "0". Thereby, each coin flip is independent of one another and has a probability of 50% of producing a "1" or "0" (Bassham et al., 2010). Consequently, such a sequence has no structure that allows for prediction or correlation. The concept of randomness may be rejected in philosophy and religion, where the concept of fate is believed in. In cryptography, on the other hand, there is no use for fate but in predictability and probability instead. Random data can be generated using random number generators (RNG), which come in two primary forms: Pseudo-RNG (PRNG) and True-RNG (TRNG) (or simply RNG). A TRNG gains randomness from non-deterministic physical phenomena such as the LavaRand (Cloudflare, 2017) or atmospheric noise (Haahr, 2018). PRNG uses a deterministic algorithm that is fed some input values, often defined by a seed value. These types of RNG are fast but can produce weak randomness if either the algorithm is weak, the seed is known, or if enough data has been collected so that the probability of predictability increases. Compared to TRNG, a PRNG does not generate randomness, but chaos, which a (non-linear) formula can model. Typically intersections of the two are used to create a usable Cryptographically Secure PRNG (CSPRNG) that uses physical phenomena to create a source pool with high entropy that serves as input to a robust algorithm that generates an arbitrary amount of random data that is unpredictable, no matter how much data was generated by the CSPRNG (Cloudflare, 2017).

2.2 Statistics

Statistical tests are formulated to test the null hypothesis (H0) that a given test sequence is random, in conjunction with the alternative hypothesis (Ha) that the sequence is not random. For each applied test, a decision is derived that accepts or rejects the null hypothesis (Bassham et al., 2010). Since statistical methods have their strengths and weaknesses, different methods are combined in test suites, which are all unique in scope and application:

- *Diehard*: Published in 1996, this suite provides a battery of 12 statistical tests for measuring the quality of RNG. There is an improved variant called *Dieharder* in native C, which, i.a., extends the list of tests to 26. (Marsaglia, 1995; Robert G. Brown, 2003)
- *ENT*: Statistical test for command-line application released in 1998, which uses five tests to detect the basic characteristics of random sequences including Entropy, Chi-Square, and Arithmetic Mean. (Walker, 1998)
- *NIST SP 800-22*: Originally released in 2001, the NIST Special Publication 800-22 Rev. 1a provides 15 tests to evaluate the randomness of arbitrary long binary sequences. The publication is currently under review as of July 2021. (Bassham et al., 2010)
- *TestU01*: Software library implemented in ANSI C that offers a collection of 7 tests for the empirical statistical testing of uniform RNG. (L'Ecuyer and Simard, 2007)

3 RESEARCH DESIGN

This study evaluates the performance and quality of a given set of randomness test suite implementations through a quantitative and qualitative case study. Due to the reputation, the number of tests, and availability of implementations in Python, the National Institute of Standards and Technology's (NIST) Special Publication (SP) 800-22 (Bassham et al., 2010) was chosen for the one randomness test suite to be used here. This test suite provides the basis for all analyses, results, and conclusions drawn for arbitrary data and use cases. We do not evaluate the NIST SP 800-22 it-self, but open source implementations thereof. The NIST SP 800-22 contains a set of 15 statistical tests. The NIST recommends a minimum input sizes and additional prerequisites and conditions for each of these tests to ensure the reliability, which will become an important factor for our evaluation. Therefore, it has to be noted that only at an input size of 1 Mbit all 15 randomness tests forming the test suite may be included in the evaluation. The following list shows the NIST SP 800-22 test battery and their recommended minimum input size:

1.	Frequency (aka. Monobit) Test	100 bit
2.	Frequency within a Block Test	100 bit[1]
3.	Runs Test	100 bit
4.	Longest-Run-of-Ones in a Block	128 bit[1]
5.	Binary Matrix Rank Test	38,912 bit
6.	Discrete Fourier Transform Test	1,000 bit
7.	Non-overlapping Template Matching [2]	1 bit[1]
8.	Overlapping Template Matching	1,000,000 bit
9.	Maurer's "Universal Stat." Test	387,840 bit
10.	Linear Complexity Test	1,000,000 bit[1]
11.	Serial Test	1 bit[1]
12.	Approximate Entropy Test	1 bit[1]
13.	Cumulative Sums Test	100 bit
14.	Random Excursions Test	1,000,000 bit
15.	Random Excursions Variant Test	1,000,000 bit

4 METHODS

The general methodology consists of three phases:

1. Determining a variety of NIST SP 800-22 test suite implementations.
2. Generating appropriate datasets used for testing, validation and results.
3. Preparing a common interface and validation framework for automated tests.

4.1 Implementations

A set of three Python-based FOSS implementations has been selected. A naming convention for the implementations based on the authors' initials is hereafter introduced to have a uniform way of identification; also, a color pattern is used to ease the interpretation of the results and related graphs.

It is very important for us to emphasize that this analysis is in no way intended to criticize or belittle the listed implementations in any way. Providing FOSS is hard work, and any comments in this work should be considered constructive feedback and may be used to improve the implementation. Any claim we make has been validated to the best of our knowledge and may not be covered by intentional use cases.

[1] Additional eligibility checks apply

[2] Features non-deterministic characteristics

- DJ aka. **dj-on-github/sp800_22_tests** (Johnston, 2017) (114 stars, 29 forks): The earliest implementation in the list was created by David Johnston, Engineer at Intel and author of "Random Number Generators, Principles and Practices" (Johnston, 2018). This implementation is "simplistic" in terms of coding concepts.
- LP aka. **InsaneMonster/NistRng** (Pasqualini, 2019) (18 stars, 8 forks): This work by Luca Pasqualini (SAILab) from the University of Siena is inspired by the work of David Johnston. The implementation is the "most advanced" in terms of coding concepts and is available as *pip* package thus, it is the most convenient to use and was the starting point for this work.
- SA aka. **stevenang/randomness_testsuite** (Ang, 2018) (50 stars, 12 forks): The Independent in Comparison, implemented by Steven Kho Ang. This implementation is characterised by the provision of an additional graphical user interface.

4.2 Datasets

This work is not focused on evaluating a single source of data of a given length. Instead, results are acquired by feeding data to each implementation and validating the number of passed tests in relation to input length, which results in a two-dimensional representation per implementation with input length on the x-axis, and the sum of S-values or P-values on the y-axis. But there is also a z-axis, by means of different datasets, which are staggered by the amount of expected "structure". Employed datasets are large blobs with more than 100 MB of data of a common "language" from which at random a sample is extracted for a specific test run. The datasets are chosen to cover all interesting cases, not to focus on any specific scenario; therefore, the datasets are introduced without greater generation details. Depending on the generation process, employed datasets are categorized into classes: random, cipher, or encoding. Finally, the datasets are ordered as listed from expected "randomness" to "structure". Many different types of data may be, and have been, compared using our method. This list reflects only a small selection of data sets with noteworthy attributes spanning over the whole spectrum:

1. **RND:** "True" randomness acquired via *RANDOM.ORG* (Haahr, 2018) gained from atmospheric noise, as the epitome of randomness.
2. **DES:** Weak block cipher in ECB mode using a weak key to add structural distortion compared to other cipher-modes, generated with *OpenSSL*.
3. **ZIP:** File archive of the *aclImdb* (Maas et al., 2011) dataset to evaluate the amount of chaos introduced by compression.
4. **TXT:** English text consisting of printable-ASCII, based on a large movie review dataset (Maas et al., 2011), which is further used as basis for generation of the *DES*, and *ZIP* datasets.
5. **NUL:** Straight binary sequence of all zeros (Null-Bytes) which together with the all-ones sequence can be argued as the epitome of structure.

4.3 Framework

A custom framework has been developed to overcome considerable differences in how each implementation handles inputs and provides output. These differences make it cumbersome to operate and to compare the results manually. For this reason, a common interface was designed for all implementations, and wrapper functions were developed to enable large-scale automatic tests to be carried out. This interface was then embedded into custom applications based on *Jupyter* notebooks, providing the easy-to-use ability to benchmark, plot, and analyze implementation characteristics like quality and time. The open-source Python libraries *pandas* (McKinney et al., 2010; Pandas Development Team, 2020) and *matplotlib* (Hunter, 2007) were of priceless help here.

All randomness tests return one straightforward metric, namely the probability, or P-value in short, in the range of zero to one, which summarizes the strength of the evidence against the null hypothesis. Tests are then run against a decision rule based on a significance level of 10% for each test in the SP 800-22 test suite, which means that any input for which a test returns a P-value above the decision mark is considered to be random by passing the test, with a P-value of 1 stating perfect randomness. The result of this comparison is hereafter defined as S-Value (Success-Value). Some tests may have lower significance levels or additional checks for a positive S-Value. This work mainly focuses on S-Values as Key Performance Indicators (KPI) to ease comparisons over the whole spectrum, rather than gathering enough P-Values for generic P-Graphs. P-Values are suitable for evaluating data sources by generating vast amounts of data while being too volatile to evaluate isolated sequences, as can be seen in Figure 2.

The test spectrum covers different scenarios in which the test suite may be applied, including the number of tests, the quality of the results, and the calculation speed in relation to different data lengths to be tested. One would think the number of tests is always the same when using only the same test suite,

Randomness Tests	E	P-DJ	S-DJ	P-LP	S-LP	P-SA	S-SA
Monobit	True	0.16	True	0.16	True	0.16	True
Frequency Within Block	True	0.40	True	0.40	True	0.59	True
Runs	True	0.74	True	0.74	True	0.74	True
Longest Run Ones In A Block	True	0.80	True	0.36	True	0.77	True
Binary Matrix Rank	False	0.00	False	None	None	-1.00	False
Discrete Fourier Transformation	False	0.23	True	0.23	True	0.23	True
~~Non Overlapping Template Matching~~	True	0.49	True	0.95	True	1.00	True
Overlapping Template Matching	False	0.00	False	None	None	1.00	True
Maurers Universal	False	0.00	False	None	None	-1.00	False
Linear Complexity	False	0.00	False	None	None	-1.00	False
Serial	True	0.20	True	0.33	True	0.72	True
Approximate Entropy	True	0.10	True	0.10	True	1.00	True
Cumulative Sums	True	0.23	True	0.27	True	0.23	True
Random Excursion	False	0.00	False	0.61	False	0.59	False
Random Excursion Variant	False	0.00	False	1.28	False	0.34	False
Overall Results Summary	14	20%	8/14	32%	8/14	24%	9/14
Eligible Results Summary	7	37%	7/7	34%	7/7	60%	7/7

(a) 42B *Pangram* (*TXT* dataset) from the introductory Example.

Randomness Tests	E	P-DJ	S-DJ	P-LP	S-LP	P-SA	S-SA
Monobit	True	0.75	True	0.75	True	0.75	True
Frequency Within Block	True	0.09	True	0.09	True	0.50	True
Runs	True	0.20	True	0.20	True	0.20	True
Longest Run Ones In A Block	True	0.13	True	0.07	True	0.78	True
Binary Matrix Rank	False	0.00	False	None	None	-1.00	False
Discrete Fourier Transformation	False	0.28	True	0.28	True	0.28	True
~~Non Overlapping Template Matching~~	True	0.37	True	0.00	False	0.00	False
Overlapping Template Matching	False	0.00	False	None	None	1.00	True
Maurers Universal	False	0.00	False	None	None	-1.00	False
Linear Complexity	False	0.00	False	None	None	-1.00	False
Serial	True	0.52	True	0.64	True	0.37	True
Approximate Entropy	True	0.78	True	0.78	True	1.00	True
Cumulative Sums	True	0.67	True	0.72	True	0.67	True
Random Excursion	False	0.24	True	0.20	False	0.42	True
Random Excursion Variant	False	0.05	True	0.46	True	1.01	True
Overall Results Summary	14	26%	10/14	30%	9/14	28%	11/14
Eligible Results Summary	7	45%	7/7	46%	7/7	61%	7/7

(b) 42B Sample from the *RND* dataset.

Figure 1: [P]robability and [S]uccess Calculation for [E]ligible NIST SP 800-22 Tests.

yet not all tests are applicable for all input lengths or may have other preconditions, as shown in the list of the statistical tests involved. The input length is an essential factor, as different use cases rely on shorter or longer sequences of data, while the test suite itself is claimed to be applicable for an arbitrary length of data; a given implementation may score differently in some scenarios where the different length of sequences of the same data set are fed. Finally, the speed of calculation, which naturally increases with the number of tests and input length, is an important factor that is not always tolerable. The growth is linear with occasional jumps, depending on how many tests are effectively applied at a given length. For example, testing a 128 bit value takes less than a second but only runs reliably against 8 out of 15 tests. On the other hand, to perform all 15 tests reliably, a minimum length of about 1Mb is required, whereby such a run takes between one and three minutes (on high-performance hardware) depending on the implementation, as later discussed and shown in Table 1. It should be noted that some implementations do not respect the input size *recommendations* for all tests or do not label the result appropriately to differentiate between a failed and a non-eligible test. Non-eligible tests should then be treated as unreliable or advisory, if at all.

5 ANALYSIS

The selected implementations are analyzed using the previously defined framework and datasets. In order to conclude on the defined metrics and scenarios, the framework has been used to develop multiple applications in form of *Jupyter Notebooks*, which focus on *details*, average *quality*, and *time* for different datasets and input lengths. With each run of an application, a given dataset sample is fed to each implementation. Each run is repeated for an increasing range of sample length, starting at the same offset of the data source. Note that a sample would randomly start at a different offset for any following run, which allows evaluating how the implementations react to the same input, as it is fed with more data of the same sequence. The results are returned as *Pandas DataFrames* and are plotted for better visualization. The tools are not yet publicly available; however, we plan on releasing the Git repository as well as our entire datasets.

The manual analysis for isolated sequences is not straightforward. Figure 1a shows the results for the example pangram from the Introduction, a detailed example of a single test run is discussed to show what kind of values the randomness test suites return. Figure 1b on the other hand, shows the results for a sequence from the *RND* dataset of the same length. It is

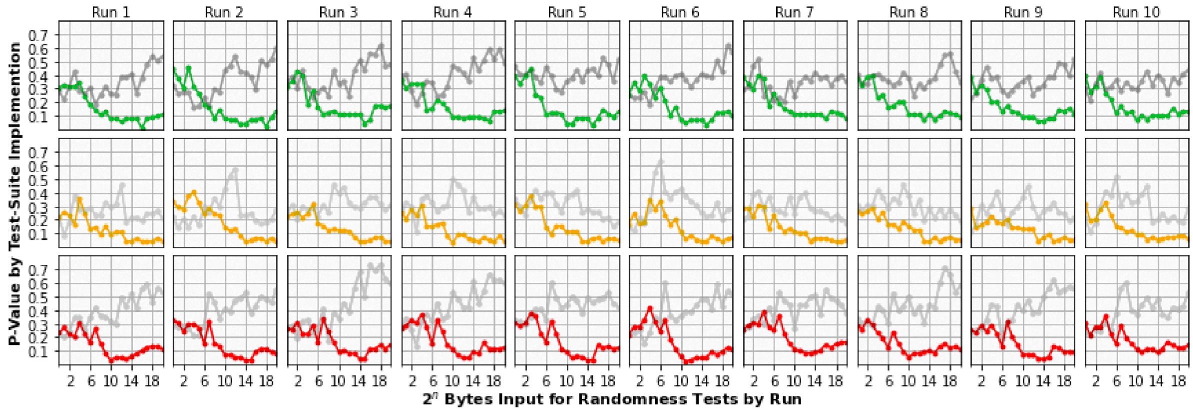

Figure 2: Example Results (P-Value) for the Datasets "TXT" and "RNG" (grey overlay) split by Run and Implementation.

intended to show that it is hard to conclude randomness, especially for short sequences. Note that these results are presented as they are returned from the actual implementations. Although the sum of the P-values is higher on average for 1b, which is not always true for other samples of the same dataset, all tests are passed for 1a too, so that both examples pass all eligible randomness tests. P-Values may vary largely, while S-Values are relatively constant. This fact is visualized in Figure 2, which shows the average results of P-Values for applied randomness tests for ten runs over the three different implementations. The resulting P-Values are used to average the test runs for Figures 4a and 4d in the Appendix. It is intended to show that the results of both datasets are similar for short sequences, then start to diverge with larger input sequences. Figure 2 reveals similar resulting curves for the "TXT" dataset, per run and implementation, while the curve of the "RND" dataset has no visible patterns. Note that, with increasing structure, the runs resulting curves feature correlate with a higher degree.

These detailed views are employed for manual analysis of anomalies within the other tools, which abstract or summarize these results per run instead of every test. Some implementations do not differentiate between zero and non-applicable (None) tests. Also, some implementations have slightly different criteria for eligibility that differ from the SP 800-22. Note that the *E* column denotes all eligible tests for the given sample data based on the *NIST Input Size Recommendation* (Bassham et al., 2010) and that the *Non-Overlapping Template Matching* test is not taken into consideration for the summary due to its non-deterministic characteristics. Besides the detailed view, the developed Notebook employs additional views for time and quality benchmarks, which will be introduced in the following chapter.

6 RESULTS

For all datasets introduced, benchmarks were performed on time, quality (S-Value), and accuracy (P-Value). The test results for *time* can be seen in Table 1. The results for *accuracy* and *quality* have been added to the Appendix as Figure 3 and 4, respectively. Each plot is the outcome of the average results for 100 runs with a maximum of 2^{20} Bytes input length, which required around 24 hours of calculation time on an 8-core (16-thread) Intel i9 CPU. The graphs show the average P-Values and S-Values for performed runs. Each benchmark run is performed for n steps using the input size of 2^n Bytes, where $n \in [0,20]$. The x-axis employs a logarithmic scale. 2^n may be considered a minimum, but smaller sequences are tested for completeness. Benchmark calculations were threaded to optimize processor performance and parallelize calculations. Note that the light-grey line and area in the quality and accuracy plots, denotes the maximum value that could be reliably achieved for a given input length. Optimally, the results should not exceed this line. The results show that the experiment was successful, yet many points were not as expected. The main observations, per implementation, are given in the following list:

- **DJ** : Overall good results in time and quality. The code leaves room for performance improvements. Weaker in the detection of "true" structure.
- **LP** : Decent quality but fails for input over 2^{13} Bytes and worst in time. Best in eligibility checks. Easiest to install and use. Scores have a small peak at 2^{16} Byte of input.
- **SA** : Decent quality, but the results are generally too high, yet the fastest in the set. Behaves strangely at 2^7 Byte of input where scores peak.

Table 1: Average Results of 10 Runs from 2^0 to 2^{20} Byte Inputs for Time Calculation.

n	2^n Byte	$8{\cdot}2^n$ Bit	DJ	LP	SA
0	1	8	189ms	4ms	420ms
1	2	16	179ms	8ms	428ms
2	4	32	181ms	8ms	438ms
3	8	64	185ms	14ms	441ms
4	16	128	170ms	20ms	450ms
5	32	256	170ms	30ms	460ms
6	64	512	190ms	60ms	460ms
7	128	1 Ki	200ms	100ms	500ms
8	256	2 Ki	240ms	200ms	550ms
9	512	4 Ki	320ms	380ms	640ms
10	1 Ki	8 Ki	440ms	740ms	820ms
11	2 Ki	16 Ki	700ms	1s 429ms	1s 159ms
12	4 Ki	32 Ki	1s 189ms	2s 890ms	1s 850ms
13	8 Ki	64 Ki	2s 319ms	5s 950ms	3s 250ms
14	16 Ki	128 Ki	4s 320ms	11s 570ms	5s 960ms
15	32 Ki	256 Ki	8s 439ms	22s 850ms	11s 119ms
16	64 Ki	512 Ki	17s 350ms	48s 299ms	22s 730ms
17	128 Ki	1 Mi	1m 29s 900ms	2m 59s 240ms	43s 840ms
18	256 Ki	2 Mi	2m 57s 569ms	5m 47s 069ms	1m 26s 409ms
19	512 Ki	4 Mi	5m 55s 860ms	11m 31s 600ms	2m 53s 530ms
20	1Mi	8Mi	12m 9s 179ms	23m 21s 910ms	5m 52s 930ms

Our preliminary results are highly context-dependent and require additional interpretation. Some of the statistical tests evaluate at bit, byte, or block level, which favor some structured or chaotic datasets. Also, the results for inputs smaller than 2^5 have hardly any significance. Finally, the number of ineligible and, therefore, unreliable tests distort the results. Full eligibility starts at $1Mbit$. Note the dip in the graphs as the length increases, which indicates the input length at which the algorithm can recognize structure within the chaos and starts to classify sequences as being not so random. As expected, the more structure attributed to the dataset, the further this dip shifts to the left. In this way, DES in ECB mode can be detected as no longer random, with a minimum sample size of about 2^{17} Byte.

Based on the results shown in Table 1, it can be seen that the implementations strongly differ in time consumed, where the fastest implementation for smaller input became the slowest by a factor of four for larger inputs. This fact is related to implementation differences, preliminary eligibility tests, and thus the number of tests that are only "unlocked" with larger input. Python may not be committed to performance, but the implementations would benefit from it, which could be achieved by multi-threading or by use of the Python libraries *NumPy* in combination with *Numba* just-in-time (jit) compilation to maximize parallel computing and efficiency. In addition, *Numba* also provides *CUDA* support for the use of *NVIDIA* Graphics Processing Units (GPU).

7 CONCLUSION

It can be concluded that the NIST SP 800-22 is only partially suited to extract features of randomness from isolated sequences and requires a lot of data to perform at full scale. For this, the calculations are too computationally intensive to be applied to larger data sets. Therefore, results for short sequences of 2^7 Bytes (1,024 bit) or less are hardly meaningful. We also could show that the compared implementations differ in results, although they implement the same specification, which should produce almost identical results, highlighting the importance for developers to be careful on selecting test suite implementations for evaluation of RNGs or similar.

Future Work will show how to incorporate the results into applications to acquire better randomness feature extraction by interpreting the relation between input length, dataset, and the actual P-Values (or even values of the tests internal state) to achieve better accuracy using only KPIs while respecting a given context. Until then, we mainly gain from these first results that developers looking for easy and reliable ways to check for the randomness of a given solution should be careful when interpreting the results of open-source implementations of randomness test suites. Always take them with reservations, when in doubt, use multiple different implementations or test suites to get a holistic picture.

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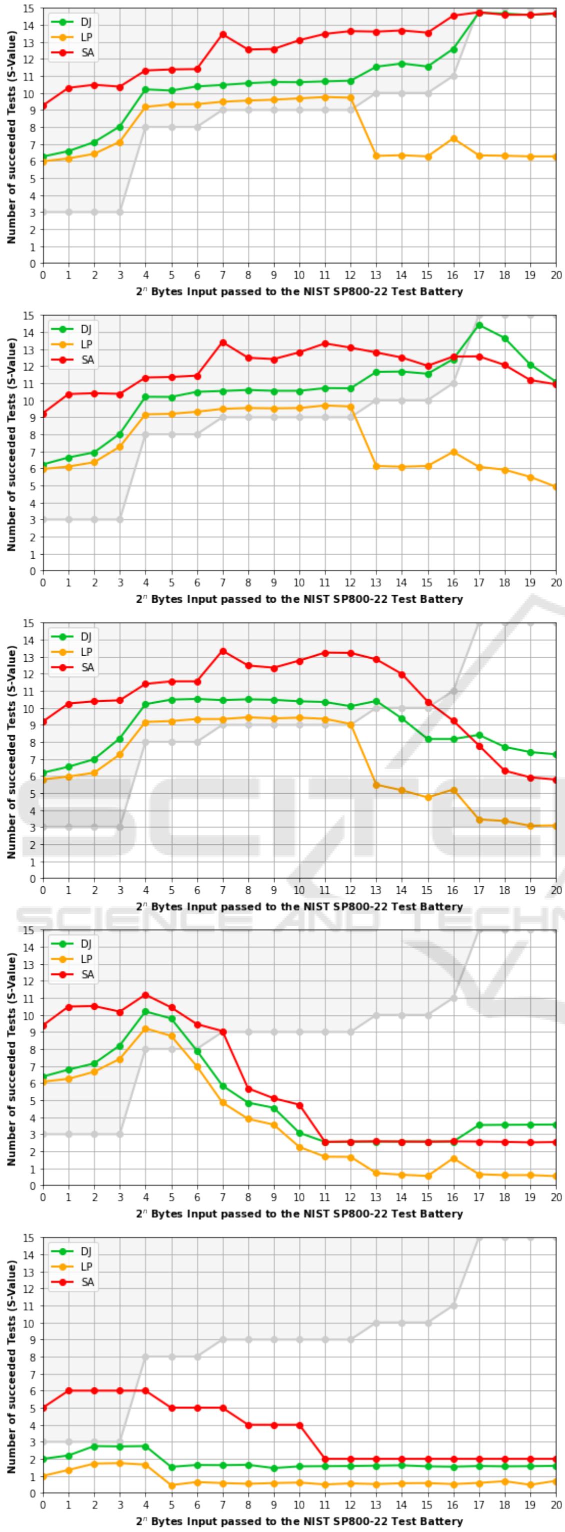
APPENDIX

Benchmark Environment

- **CPU**: i9-9980HK
- **macOS**: 12.1.1
- **Python**: 3.8.12
- **Jupyter-lab**: 3.2.1
- **Pandas**: 1.3.1
- **Matplotlib**: 3.3.4

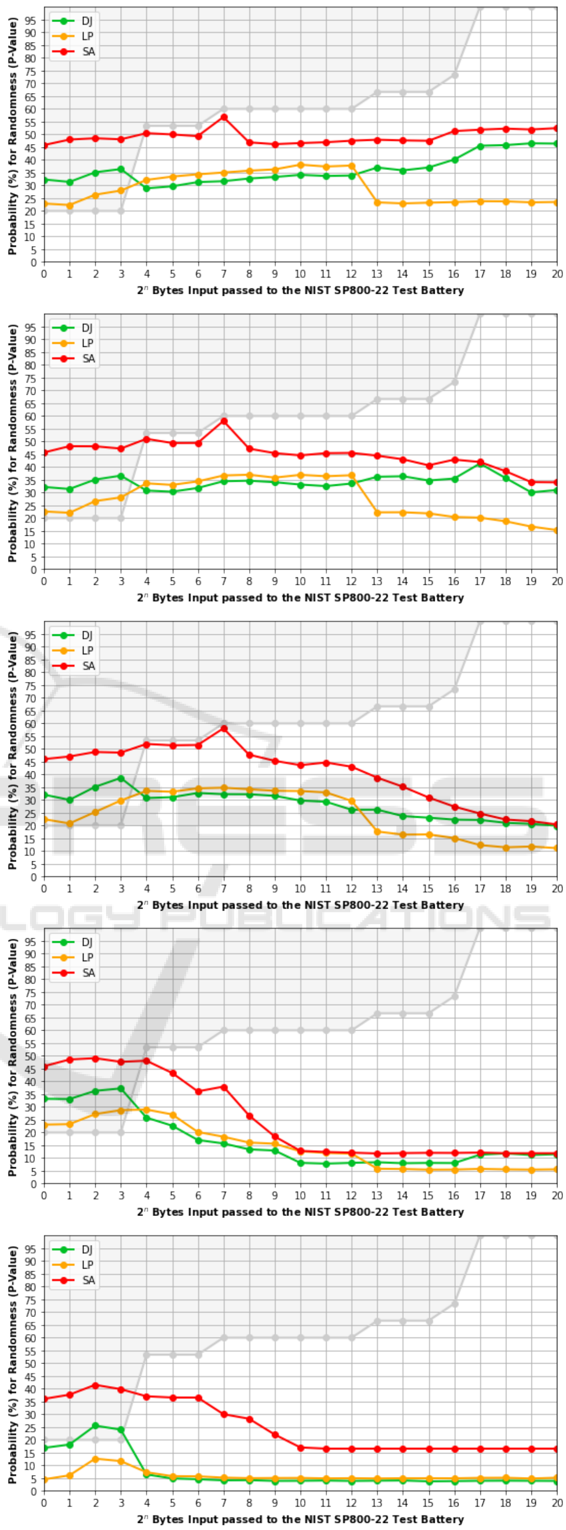
Benchmark Quality

See Figures 3 and 4.



(e) Results (S-Value) for Dataset "**NUL**".

Figure 3: Average **Succeeded Randomness tests** of 100 Runs per Dataset with Inputs of Length from 2^0 to 2^{20} Byte.



(e) Results (P-Value) for Dataset "**NUL**".

Figure 4: Average **Probability for Randomness** of 100 Runs per Dataset with Inputs of Length from 2^0 to 2^{20} Byte.