Generating Random Numbers with Network Data

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Abstract—

I. INTRODUCTION

A true random number is a range of possible value usually drawn statistically. Random values are used utilized by many applications, from OS-level functionality for stack pointer randomization, facilitating gaming, scientific computing and for computer security for cryptographic key generation.new citationsA true random number generator uses a physical phenomenon as a source for the generation of randomness like a little variation in the movement of your mouse or keystroke. On the other hand the pseudo random number generator uses algorithms, mathematical formulae or a precalculated table as source for the generation of randomness.Random.org is one of the example of true random number generator while linear congruential generator is of pseudo random number generator. Out of the many sources possible for the generation of random numbers, Linux being one of them due to its inbuilt PRNG, one of the major drawback would be the system running out entropy i.e a drop in the level of entropy. The linux system uses /dev/random and /dev/urandom for the generation of random numbers and both the interfaces behave differently in case of low entropy level. The dev/random blocks until the entropy level is high thus leading to delays and degrading the quality of services while the /dev/urandom does not block but the random data may not be suited for security related applications. Also the source of random number generator on linux is limited and may not be suitable for generation of large amount of random data. In this paper huge amount of random number were generated in linux, with the help of the network data. The entropy was processed using the network data that was captured instead of using the entropy of the operating system. This technique could be used as an additional source of Random Number Generator when a higher quantity of random numbers are needed for applications such as computer security. This is a feasible technique as every computer now-a-days comes equipped with a network Interface Card and the network data could prove to be a good source of random values.We also further analyzed the change in the sequence in case of an known attack that may have occurred on the network with the help of NIST test.

II. RELATED WORK

There has been a substantial amount of work on the generation of random numbers using modern devices such as cellular automata, and Multiple-mersenne twisters [CITATION NEEDED]. As well as the use of natural phenomenon to generate random numbers, some such techniques are discussed here. [**?**]

A. PRNG Linux system

Linux is one of the most popular operating system used in the world which serves as an operating system for a variety of applications and it provides a built in service for the generation of random numbers. The Linux RNG uses the kernel space for the generation of Random Numbers. It consist of three components, first which converts events into bits and is the key source for entropy. The second component is responsible for the addition of these bits to the generator pools and the third component applies three consecutive SHA-1 operations when the bits are read from the generator which in turn generates the output of the generator which is then feed back into the pool. The randomness generated is received in the form of a word i.e 32 bits. An account of the amount of physical randomness added into the pool is done with the help of counter which is calculated as a function of the different system events occurring. This counter value is denoted as entropy in case of Linux Random Number Generator.

B. Kernel level random number generator

Linux has a kernel-level random number generator and is abstracted as a 2-character device /dev/random and /dev/urandom. The former is a blocking random number generator, the latter is a non-blocking random number generator. [**?**], [**?**], [**?**]

1) Blocked random number generator: The application can read the random number values in the /dev/random internal entropy pool through the read () system call. The read () system call is blocked when the number of random numbers in the entropy pool is less

than the number of applications to read, the application is suspended.

2) Non-blocking random number generator: /dev/urandom is a non-blocking pseudo-random number generating program that can be supplied to any number of random numbers of the application at any time. When the application requires too many random numbers, the entropy pool cannot be updated in time, so its entropy will be reduced. Same with /dev/urandom, the application reads through the read () system call random number value. Qualitative Analysis of Kernel Level Random Number Generator Performance

The application must call the read () system call to get the random number from /dev/random or /dev/urandom, and the read () system call will cause the system context to switch. Visible, from the application's perspective, the random number generated delay includes not only the delay of the random number algorithm itself, but also the overhead of context switching, etc. For network security applications where the key translation is frequent, if the delay generated by the random number is large, the performance of the application will be degraded. Obviously, this is unacceptable for such applications.

C. Random Number Sources

In order to facilitate software debugging and performance measurements, Intel has built a timestamp counter in its Pentium processor and subsequent processors (TSC, Time Stamp Counter). TSC is a 64 bit hardware counter with a count of one for each processor clock cycle. Application can be non-privileged instructions RDTSC read TSC count value. Fast algorithm using TSC as a random number. Since the application can access TSC directly in user space, this allows fast algorithms to be implemented in user space.

SHA is widely used in cryptographic algorithms, key hash validation and the generation of random numbers. SHA cannot infer the input of SHA because of the irreversibility of the one-way hash function that cannot be based on the input of the existing random number inverse algorithm Subsequent random numbers, so the random number generated by SHA is unpredictable, ensuring that the generated random number is safe.

D. Mobile and IOT Devices

Random Number in Android is based on the Linux Random Number Generator. APRNG mainly consist of two parts the Entropy Mixer which is used to preserve the current state of /dev/urandom and the Secure Random Front end acts as current SHA1PRNG which is a current provider for cryptographically secure random numbers for Android OS. Initial algorithms proposed for the generation of randomness and which is currently being

utilized for IOS is the Yarrow RNG. Intel uses RDRAND instruction for entropy generation or for generation of random number The Intel Data Protection Technology is accessible through RDRAND and RDSEED which provide a wide range of statistical random numbers which do not require any additional libraries or operating system handling.

A more novel Sensor based approach for IOT and Mobile device is developed which uses noise in the sensor data as a source of Random number generator which produces a less computational overhead in comparison to the current Android Pseudo Random Generator. [?]

E. Virtual Machine

The paper about Not-So-Random Numbers in Virtualized Linux and the Whirlwind RNG by Yan Zhai mentions about how Linux operating system generates and how they attempt to harvest entropy form various hardware sources. A new Whirlwind approach is specified for generating secure randomness which is developed with a view to rectify the current problem with the existing VM reset vulnerabilities which reuses the internal state to develop random number which may not be very secure when used for cryptographic applications. [?]

III. HARVESTING ENTROPY

Although sources of entropy are frequently gathered by modern random number generators, there is not much information on how the harvested entropy foments useful random numbers. As was stated in the introduction the Linux random number generator does extract entropy from interrupts, disk accesses, keyboard input, and more, but not much is said on how the entropy is actually taken from these events.

One obvious metric to examine when attempting to extract entropy timing. For instance, when harvesting entropy from the keyboard, one possible method for doing so is the careful examination of the wait times between key presses. The slight variations in key presses may not be a *truly* random data source (I.e. the distribution may not be uniform), but there are many methods for transforming known distributions into uniform ones, one such method is the first of, what we claim, are three ways to harvest entropy from a random stream.

A. A Posteriori Coin-Flip

The principle behind this method of entropy harvesting relies on a known data set size. After the data is collected, the median value of the distribution is calculated. Since by definition the median is a measure of center, calculated as the middle element of the data set, exactly one half of the retrieved values will be above

the median and the other will be below. Obviously, this extends to the use of other measures of center, and even potentially trend models such as a Linear regression, ARMA and other forecasting techniques.

The A Posteriori Coin-Flip occurs after your entire data set has been collected and a valid trend seeking line (whether flat as with the mean or median, or sloped), begin at the first data point (this is the first coin-flip) if it lies above the calculated measure of center (MOC) record one, or heads as the result of the first coin-flip. Continue until all data points have been assigned a bit. This bitstring is an example of extracting entropy from a system if you are given knowledge about the data system ahead of time. Mathematically this notion can be expressed in the following way.

Definition 1 A Posteriori Coin-Flip

Given X such that $X = \{x_1, x_2, x_3, ..., x_n\}$

$$Q_2 = \{x | P(X > x) = P(X < x) = 0.5\}$$

$$R_\psi(x_i) = r_i = \begin{cases} 1 & x_i > Q_2 \\ 0 & x_i < Q_2 \end{cases}$$

Hence, the entropy is extracted into the binary value:
$$r_1 r_2 r_3 r_4 ... r_n$$

In this definition we are using the median as the MOC (represented by Q_2), however this can easily be replaced with any other MOC. As with any method there is a short pros and cons list for using the A Posteriori Coin-Flip. One obvious con of the definition in the manner we present it with a static MOC, as opposed to a dynamic MOC such as a time series ARMA model, there will tend to be an obvious correlation between values close together. Of course, the better the entropy source, the higher quality the harvested entropy will be. A Pro of using this method is that we can force a uniform distribution on the output string. A further benefit of using this method is that the MOC must only be calculated one time (after all of the data is collected)

A mathematical proof that this method (using the median) will harvest the maximum theoretical entropy is given here:

Proof A Posteriori Coin-Flip maximizes Shannon Entropy
Given a *supposedly* random sample

$$X = \{x_1 \in \mathbb{R}, x_2 \in \mathbb{R}, x_3 \in \mathbb{R}, ..., x_n \in \mathbb{R}\}$$

We define the random variable α in terms of the median (or second quartile) of X

$$\alpha : \mathbb{R} \to \mathbb{B}$$

$$P(\alpha = 0) = p_0(\alpha) = \frac{|\{x | x < Q_2(X)\}|}{|X|} = \frac{1}{2}$$

$$P(\alpha = 1) = p_1(\alpha) = \frac{|\{x | x > Q_2(X)\}|}{|X|} = \frac{1}{2}$$

The formula for the entropy of a string of Bernoulli trials (or a 'bitstring') is given:

$$H(p_0(b), p_1(b)) = -(p_0(b)\log_2(p_0(b)) + p_1(b)\log_2(p_1(b)))$$

We can maximize the Entropy function as so:

$$\nabla H(p_0, p_1) = \left(\frac{\partial H}{\partial p_0}, \frac{\partial H}{\partial p_1}\right) = \left(-\frac{\ln(p_0) + 1}{\ln(2)}, -\frac{\ln(p_1) + 1}{\ln(2)}\right)$$

Maximizing we find

$$\frac{-\ln(p_0) - 1}{\ln(2)} = 0 \implies \ln(p_0) = -1 \implies p_0 = \frac{1}{e}$$

$$\frac{-\ln(p_1) - 1}{\ln(2)} = 0 \implies \ln(p_1) = -1 \implies p_1 = \frac{1}{e}$$

This seemingly odd result is because there is an *inherent* dependence among these two values, expressed mathematically as $p_0 + p_1 = 1$, in our first maximization attempt, we neglected to account for the hard-restraint $p_0 + p_1 = 1$ In constraining the original optimization we have the following system:

$$\frac{-\ln(p_1) - 1}{\ln(2)} = 0 = \frac{-\ln(p_0) - 1}{\ln(2)}$$

$$p_1 = 1 - p_0$$

$$\frac{-\ln(1 - p_0) - 1}{\ln(2)} = \frac{-\ln(p_0) - 1}{\ln(2)} \implies 1 - p_0 = p_0$$

$$\implies p_0 = 0.5 \implies p_1 = 1 - 0.5 = 0.5$$

Because $p_0(\alpha) = p_1(\alpha) = 0.5$ by definition, we have maximized the entropy function for the constraint $p_1 + p_0 = 1$. ∎

Corollary 3.1: The author would like to note that the characterization of the bias in this formula is potentially a novel concept, and suggests that a more natural measurement of entropy extends by adding the factor $\left(\frac{1}{2} - \frac{1}{e}\right)$ to the probabilities p_0 and p_1 before using the original definition of the formula. (this will increase the maximum possible entropy in a string to $\frac{2}{e \cdot \log(2)}$ but it can be rescaled accordingly using simple ratios)

B. Extemporaneous Coin-Flip

As the name implies, the extemporaneous coin-flip occurs simultaneously as new data is available. The general procedure is very similar to that of the A Posteriori coin-flip, however in this method the measure of center is recomputed with every new sample that becomes available. In this method we start with an initial guess as to the measure of center (This could be a MOC from a previous entropy capture, or an educated guess, or simply the first value observed). As a side note, in both this and the A Priori Coin-Flip method, the first

random bit retrieved can and should be thrown away in certain circumstances.

As with the previous method, each time new data becomes available it is compared to the MOC and a bit is generated depending on whether the point lies above or below. Unlike the previous example, the MOC changes with every new data point available. in the following definition the chosen MOC is again the median, however again this can easily be replaced with whichever statistic is desired.

Definition 2 Extemporaneous Coin-Flip

Given a series of sets $X = \{X_1, X_2, X_3, ..., X_n\}$
Such that $X_1 \subset X_2 \subset X_3 \subset ... \subset X_n$
$\{\forall i \in \mathbb{N} | 0 < i \leq n\} \implies |X_i| + 1 = |X_{i-1}|$

Given an initial guess g_0 to serve as the MOC (before the first data point is collected) We can express our updating median as a function of data sets in the following manner.

$$Q_2(X_i) = \{x | P(X_i > x) = P(X_i < x) = 0.5\}$$

$$R_\phi(x_i) = r_i = \begin{cases} 1 & x_i > Q_2(X_i) \\ 0 & x_i < Q_2(X_i) \end{cases}$$

As with the previous definition the entropy generated can be utilized by the bitstream given by:

$$r_1 r_2 r_3 r_4 ... r_n$$

As with the A Posteriori method, there are some benefits, and draw backs to using this method for entropy extraction. In this method the measure of center must be recomputed with each subsequent data point gathered, this could waste valuable CPU cycles. The primary benefit of using this method is that after the new MOC is calculated, the old can be discarded, as well as the immediate discarding of all previous data, as it is analyzed simultaneously as it is gathered. This method is also easy to implement on systems where you would like to be constantly analyzing data (such as massive server banks connected to Muller-Geiger tubes and old fire detector parts).

C. A Priori Coin-Flip

The last of what we claim are three entropy extraction methodologies presented in this work we again require some guess or 'A priori' knowledge in order to effectively use the first bit as a truly random coin flip. This method is performed in exactly the same manner as the previous, with one key difference. In this method, the MOC that is used must determine the outcome of the coin-flip **before** it is updated with the new information. The new value must be used to update the MOC after the previous coin-flip, both the previous data value and previous MOC can be immediately discarded after the new MOC is generated. As it is essentially the same method as above simply time-lagged by one observation the definition is very similar with the difference highlighted below

Definition 3 A Priori Coin-Flip

Given a series of sets $X = \{X_1, X_2, X_3, ..., X_n\}$
Such that $X_1 \subset X_2 \subset X_3 \subset ... \subset X_n$
$\{\forall i \in \mathbb{N} | 0 \leq i \leq n\} \implies |X_i| + 1 = |X_{i-1}|$

Given an initial guess g_0 to serve as the MOC (before the first data point is collected) We can express our updating median as a function of data sets in the following manner.

$$Q_2(X_i) = \begin{cases} \{x | P(X_i > x) = P(X_i < x) = 0.5\} & i \neq 1 \\ g_0 & i = 0 \end{cases}$$

$$R_\pi(x_i) = r_i = \begin{cases} 1 & x_i > Q_2(X_{i-1}) \\ 0 & x_i < Q_2(X_{i-1}) \end{cases}$$

The entropy is in the bit string:

$$r_1 r_2 r_3 r_4 ... r_n$$

Corollary 3.2: This method can easily be extended ad inf. by using MOC's from more than one observation in the past, then updating with a lag value greater than one.

Corollary 3.3: When using certain methods for the MOC, such as forecasting models for time series, prior data must be kept for the recalculation of the MOC, however, a sliding window could also be used in this case to save memory.

Many of the pros and cons for using this method correspond with what was said about the Extemporaneous Coin-Flip. In this method, unlike the last, the new MOC does not need to be calculated before the result of the next coin-flip can be determined. This is a great method to use when events are rare, and there is a long wait time before the next observation. When using this method in the given scenario, the wait time can be used as compute time for the updated MOC.

It is essential to note that in all of the above methods the entropy extracted from the random stream should not be used directly (I.e. do not directly use the bit strings calculated as your random values), they should instead be used as inputs to pseudo-random number generators, conglomerated with multiple other sources of entropy with a mixing function, or as we will further explore in

this work use pseudo-random functions such as cryptographic primitives like hash functions and HMACs (potentially even using the random value a key in a keyed HMAC). One could even potentially use a good compression algorithm to produce a valuable random number.

IV. Harvesting Entropy from Network Timing Data

In this section we attempt to harvest entropy from an real-life random stream, that almost any modern computer has access to. We propose the harvesting of entropy from simple packet capture data. This notion extends much further than the manner in which it is presented here, and can be applied to far more sophisticated broadcast data (I.e. low band AM, Snow on television). In this case, we take a very clearly deliberate and logical approach to extracting entropy.

We briefly mentioned in the last section that a straight-forward approach to extracting entropy from a random stream is to investigate the timings of the events. In this specific application we examine the timing data for packets using a standard packet capture tool (Wire-shark). Once a given packet capture was completed we computed the retrieved entropy bit strings using the A Posteriori method described in the previous section.

With our packet capture results, timing data was given in terms of seconds (with 5 digits of significance). As each time was initially reported in the elapsed time since the beginning of the capture, we first needed to subtract each next arrival time from the prior arrival time. In this manner each of the packets received would be assigned a time delta, (or in other words, the time stamp of the packet received after the current packet minus the current packet's time stamp. We can formally define this in the following manner.

Definition 4 Harvesting Entropy from Packet Timing Data

let t_i represent the ith time stamp given in seconds, since the beginning of the packet capture.

$$\delta_i = t_{i+1} - t_i$$

Note that this necessarily excludes the generation of the terminal δ_i (because t_{i+1} has not been observed yet). Suppose that in a given packet capture, n packets are captured, then

$$\Delta = \{\delta_1, \delta_2, .., \delta_{n-1}\}$$

We can then define a probability space over the set Δ

$$P(\overline{\Delta} < x) = \frac{|\{\delta_i \in \Delta | \delta_i < x\}|}{|\Delta|}$$

$$Q_2 = \{\delta | P(\overline{\Delta} < \delta) = P(\overline{\Delta} > \delta) = 0.5\}$$

We then simply perform the A Posteriori Coin-Flip discussed in the previous section

$$R_\psi(\delta_i) = r_i = \begin{cases} 1 & \delta_i > Q_2 \\ 0 & \delta_i < Q_2 \end{cases}$$

V. Results

Packet captures of sizes ranging from 5000-50000 packets were run at three different times, and over multiple networks on three different operating systems (Mac OSX, Windows 10, Ubuntu Linux 16.10).

Fig. 1. Packet Timings in Various OS

A very quick inspection of the plots reveals that there is temporal correlation in the data at this point, however, we are not worried about the quality of the random

numbers produced at this stage in their creation. As was stated in Section III, we are not going to simply use the produced value, we are more likely to use the gathered entropy to seed a deterministic pseudorandom generator.

We leave it to future work to perform more sophisticated trend modeling, in this analysis we will simply be using the median to decide the outcome of the A Posteriori Coin-Flip. The medians were calculated and nine different entropic bit strings were collected.

VI. ANALYSIS

In our analysis we will simply be using the Linux utility ENT, created at Fourmilabs, which reports several statistics on the entropy contained, temporal correlations, even quality of randomness (Monte Carlo simulation of Pi). In the following paragraphs we will briefly examine and discuss the use of each of the statistics that are calculated using ENT, as well as presenting a table of the results for the entropic strings that were generated using the A Posteriori Coin-Flip method on our nine packet capture timing Data vectors.

The first metric reported by ENT is its name-sake: entropy. For all intents and purposes we can think of this measure as a rough estimate as to how much information is actually contained within a bitstring. The metric of entropy was defined by Claude Shannon in his seminal work *A Mathematical Theory of Communication*. The formula he gives for approximating the entropy of a bit string is defined as:

Definition Shannon Entropy (as applied to bitstrings)
The Shannon Entropy of a bitstring is quantified in terms of the information inherently contained by the string. The derivation of this formula is very simple and intuitive. Shannon entropy is defined as:

$$H(X) = -\sum_{i=1}^{n} p_i \log_2(p_i)$$

In a bitstring, there are two possible outcomes, either a one or a zero. Hence there are only two probabilities to deal with, $p_0 = P(\overline{X} = 0)$ and $p_1 = P(\overline{X} = 1)$ for random variable $\overline{X}$, which is distri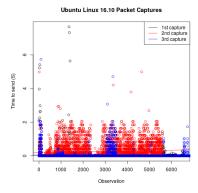buted according to the relative frequency distribution for bits contained within the random string $X = x_1 x_2 x_3 .. x_n$. In this way, the entropy is calculated in a very similar manner to that of the way which it is extracted in the A Posteriori Coin-Flip, where we must have retrieved all information before we can provide an accurate estimate. Once we have collected all of the data, and calculated $\{p_0, p_1\}$ we can calculate the entropy of the bit string directly as:

$$H(X) = -[p_1 \log_2(p_1) + p_0 \log_2(p_0)]$$

Corollary 6.1: The authors suggest the use of an iterative distribution update, or prior distribution update when harvesting random data from a continuous string. In the same manner as the iteratively updating MOC in the Extemporaneous, and A Priori Coin-Flip methods.

The entropy is reported in terms of a measurement of the amount of 'bits' of information contained in a specific character, in the case of a random bit string it reports the 'bits' per bit. Hence in the *ideal* case we would see entropy approaching 1.0 (or subsequently, the number of bits used to encode the symbol)

The second statistic reported on by ENT is the optimum compression ratio. Note that, this is calculated directly from the entropy estimate. We also would like to note that because of this, it may not take more useful and modern compression techniques into account and is simply a theoretical value. The statistic is reported in relation to compression on bytes, as well as the compression for the value as a bit string. Again, thanks to Claude Shannon, a theoretical maximum value for the optimum compression ratio was quantized in terms of the entropy of the string to be compressed.

Definition Shannon's Source Coding Theorem
This theorem simply states that the length of the optimally compressed string is directly related to the entropy contained over the entire string, Note that this is not the ratio of entropy per symbol as it is reported by ent, it is technically equivalent to the entropy ratio reported by ent multiplied by the length of the string in symbols. Mathematically the bound on the minimum length of a compressed string is given as:

$$L_c < H(X) + \frac{1}{N}$$

Where L_c is the minimum length of the compressed string X of length N. The Compression ratio then simply becomes:

$$C = \frac{L_u - L_c}{L_u}$$

Where L_u and L_c are the uncompressed and compressed string lengths. Ideally, the entropy ratio is close to one bit per bit, and therefore there the difference $L_u - L_c$ will approach zero, causing the compression ratio to become zero. The theoretical nature of this calculation does not apply to different compression methods, such as run-length encoding.

The next statistical result reported on by ent are the results of a chi-squared(χ^2) test for randomness. The χ^2-test was first proposed by Karl Pearson, an extremely prolific statistician out of London England. As with any statistical hypothesis test this test is formulated by examining collected data through the use of a deterministic function of said data known as a statistic. The statistic, or test-statistic, is then compared to a critical point on the **Known Distribution** of test-statistics to ascertain

whether or not a specific hypothesis should be rejected. In this way, it is similar to the Coin-Flip methods described above, however the MOC would correspond to the critical-value on the distribution of test-statistics. The key contribution of Pearson to this particular test was his proof that a test statistic (deterministic function of the data) would be distributed (in the theoretical case) according to a parameterized distribution known as the χ^2 distribution (so named as the square of the sum of normally distributed random variables follows this distribution). The χ^2 distribution is a parameterized distribution, meaning that the deterministic function providing its probability density function (PDF) is dependent on a value supplied in the instantiation of the distribution. The required value for the χ^2 distribution is given the symbol κ and known as the "degrees of freedom". Degrees of freedom are so called, because when special conditions are met, they can be calculated indirectly as a function of how much data was collected, however it should be noted that this is simply an estimate, as was proven in Kendall's Advanced theory of Statistics.

In the case of the χ^2 test, it was shown that the sum of the squared differences in frequencies between that of an observed distribution, and that of a theoretical distribution divided by the theoretical distribution, for each discretized observation bin will follow a χ^2 distribution with degrees of freedom calculated by use of the number of observation bins n, and the number of co-variates used to specify the theoretical distribution p. Again due to Shannon, it was speculated that if data were to be truly random, it would be pulled from a Uniform distribution, with two parameters (a which is the first observation,b which is the last observation). Therefore, to use the proposed test for randomness, the theoretical distribution that will be used is the uniform distribution. Hence a χ^2 test for randomness can be mathematically formulated in the following way:

Definition Chi-Square test for Randomness
Given a set of **discrete** observations $X = x_1, x_2, x_3, ..., x_n$, we wish to show:

$$(\overline{X} : X \to X) \sim U[x_1, x_n]$$

The random variable $\overline{X}$ defined as a mapping of data points to themselves in the measure space is distributed sufficiently close to, or far away from the given uniform distribution.

$$H_0 : \overline{X} \sim U[x_1, x_n]$$

$$H_1 : \overline{X} \sim \Lambda$$

Where Λ is an unknown distribution. A significance level α, denoting the point of the critical value (I.e. which determines *how similar* the frequencies must be

to **not reject the null hypothesis**) is chosen. A standard value is $\alpha = 0.05$. Calculating the test statistic, and determining the critical point on the appropriate χ^2 distribution as shown here:

$$c_p = \{x | P(\chi^2(\kappa) < x) = \alpha = 0.05\}$$

$$\chi^2 = \sum_{i=1}^{n} \frac{(O_i - T_i)^2}{T_i}$$

$$\kappa = n - (p + 1)$$

Note that the definition of how many bins exist depends strongly on the manner in which a random string is analyzed. In ent, for instance, when running in byte mode, there are $2^8 = 256$ bins, whereas when analyzing in bit mode, there are only two bins, one and zero.

Remark The ent results also report the tail probability ('it will exceed this value less than X percent of the time'). This value is also known as the p-value, if the p-value is greater than our significance level α then we fail to reject the possibility that the data does indeed come from a random distribution.

Fourmilabs, the creator of ent, suggests the following interpretations for χ^2 test results.

TABLE I
χ^2 P-VALUE INTERPRETATIONS

p-value	Interpretation
p-val > 99%	Almost certainly not random.
99% < p-val > 95%	The sequence is suspect.
95% < p-val > 90%	The sequence is almost suspect.
90% < p-val > 10%	The sequence is good.
10% < p-val > 5%	The sequence is almost suspect.
5% < p-val > 1%	The sequence is suspect.
p-val < 1%	Almost certainly not random.

The next parameter reported by ent is the arithmetic mean of the data, depending on whether you specify byte or bit mode in ent, this will produce an average of the binary numbers encoded in a single byte (0-255) or, simply the bits present in the file. It is calculated simply by summing every value, and dividing by the number of values present. We could further use the calculated mean as a test-statistic in a student's t-test, however it is sufficient to simply compare to the ideal means 0.5, and 127.5 for bits and bytes respectively.

In another test, the ent suite reports the monte-carlo simulation value for pi. In the monte Carlo simulation for pi, the value of pi is approximated using a technique whereby a circle is inscribed into a square, such that pi can be calculated as a ratio of the area inside the square and outside the circle, to the area inside the circle. Then taking advantage of the fact that if the points calculated are truly random, then they should fall in a fairly unifrom

way on the image (once scaled), such that the ratio of points outside the circle to the ratio on the inside allows us to gain an approximation of pi.

The Serial Correlation of a value is the last of the statistics that are reported on by ENT. ENT reports this value suing an algorithm that was printed in Pseudo-Numerical Algorithms by Donald Knuth. [CITATION NEEDED] The algorithm is dependent on the ordering of numbers, it takes

TABLE II
PURE ENTROPIC STRING ENT RESULTS

	Entropy		Arithmetic Mean		Serial Correlation		Compression		
	bits/byte	bits/bit	by byte	by bit	by byte	by bit	size (b)	comp. size (b)	ratio (%)
Windows 10									
Capture 1	6.666783	0.999995	126.5384	0.4986	-0.104782	0.207267	2200	2200	0
Capture 2	7.196086	1.000000	125.5073	0.4998	0.083004	0.209302	5504	5504	0
Capture 3	7.362089	1.000000	126.5384	0.4997	0.374569	0.232915	11472	11472	0
Mac OS X 12.10									
Capture 1	7.198828	1.000000	125.7977	0.5000	0.326609	0.070809	5536	5536	0
Capture 2	7.229747	1.000000	126.3883	0.5000	0.249999	0.119658	6552	6552	0
Capture 3	3.843544	0.980664	71.4336	0.4183	0.397400	0.018324	11680	11563	1
Ubuntu Linux 16.10									
Capture 1	7.229747	1.000000	126.3883	0.5000	0.249999	0.119658	6552	6552	0
Capture 2	6.973394	0.999999	127.8026	0.4993	0.313810	0.307581	5592	5592	0
Capture 3	5.304753	1.000000	128.1367	0.5001	-0.003104	0.682508	50080	50080	0
Averages									
Linux	6.503	1.0	127.4	0.4998	0.188971	0.3699	-	-	0
Mac	6.091	0.9936	107.87	0.4728	0.3247	0.06960	-	-	0.3333
PC	7.075	1.0	126.2	0.4994	0.11760	0.2165	-	-	0
Reference									
Hotbits	7.916369	0.999995	128.7873	0.4987	0.031555	0.000973	16320	16320	0
Ideal	8.0	1.0	127.5	0.5	0.0	0.0	-	-	0
Cross Platform Average	6.5563	0.997867	120.49	0.49067	0.21042367	0.21867	-	-	10

TABLE OF HASHED PACKET DATA ENT RESULTS (BY BITS)

	Operating.System	Hash	Size	Entropy	Chi.Sq.	Mean	MC.Pi	Serial.Correlation
1	Linux	bl2b	6656	0.999993	0.060096	0.498498	3.217391	-0.013230
2	Linux	bl2b	5632	0.999960	0.313210	0.503729	3.247863	-0.004317
3	Linux	bl2b	50176	0.999996	0.277503	0.498824	3.058373	0.004060
4	Windows	bl2b	2560	0.999901	0.351562	0.505859	3.396226	0.018615
5	Windows	bl2b	5632	0.999923	0.597301	0.505149	2.974359	0.008418
6	Windows	bl2b	11776	0.999970	0.490489	0.496773	3.134694	0.000638
7	Mac	bl2b	5632	0.999997	0.025568	0.498935	3.111111	-0.004266
8	Mac	bl2b	6656	0.999993	0.060096	0.498498	3.217391	-0.013230
9	Mac	bl2b	11776	0.999928	1.182405	0.494990	3.118367	-0.002139
10	Linux	bl2s	6656	0.999933	0.615385	0.504808	3.304348	0.023347
11	Linux	bl2s	5632	0.999974	0.205256	0.496982	3.145299	-0.008559
12	Linux	bl2s	50176	1.000000	0.006457	0.499821	3.196172	-0.000160
13	Windows	bl2s	2304	0.999783	0.694444	0.508681	3.000000	-0.022878
14	Windows	bl2s	5632	0.999977	0.181818	0.497159	3.145299	-0.003584
15	Windows	bl2s	11520	0.999996	0.068056	0.501215	3.116667	-0.016325
16	Mac	bl2s	5632	0.999956	0.343750	0.496094	3.179487	-0.011425
17	Mac	bl2s	6656	0.999933	0.615385	0.504808	3.304348	0.023347
18	Mac	bl2s	11776	0.999992	0.135870	0.498302	3.036735	0.013915
19	Linux	md5	6656	0.999850	1.384615	0.492788	3.275362	-0.005618
20	Linux	md5	5632	0.999994	0.045455	0.498580	3.247863	-0.004980
21	Linux	md5	50176	0.999944	3.928890	0.504424	3.123445	0.006220
22	Windows	md5	2304	0.999986	0.043403	0.502170	2.750000	-0.008700
23	Windows	md5	5504	0.999790	1.605378	0.491461	3.157895	-0.006107
24	Windows	md5	11520	0.999948	0.833681	0.495747	3.100000	-0.010490
25	Mac	md5	5632	0.999934	0.517756	0.495206	3.384615	0.030451
26	Mac	md5	6656	0.999850	1.384615	0.492788	3.275362	-0.005618
27	Mac	md5	11776	0.999962	0.628057	0.496349	3.102041	-0.003111
28	Linux	s1	6560	0.999846	1.404878	0.492683	3.264706	0.005885
29	Linux	s1	5600	0.999853	1.142857	0.507143	3.137931	-0.011635
30	Linux	s1	50080	0.999993	0.511182	0.498403	3.137105	0.001667
31	Windows	s1	2240	0.999917	0.257143	0.494643	3.217391	-0.005473
32	Windows	s1	5600	0.999860	1.086429	0.493036	3.206897	0.015523
33	Windows	s1	11520	0.999969	0.501389	0.503299	3.066667	-0.005599
34	Mac	s1	5600	0.999923	0.600714	0.505179	3.275862	-0.000822
35	Mac	s1	6560	0.999846	1.404878	0.492683	3.264706	0.005885
36	Mac	s1	11680	1.000000	0.003082	0.500257	3.209877	-0.001713
37	Linux	s2224	6720	0.999998	0.021429	0.500893	3.057143	0.011306
38	Linux	s2224	5600	0.999994	0.045714	0.498571	3.275862	-0.006437
39	Linux	s2224	50176	0.999959	2.817602	0.503747	3.154067	-0.002288
40	Windows	s2224	2240	0.999792	0.644643	0.491518	3.478261	-0.019936
41	Windows	s2224	5600	0.999830	1.320714	0.507679	2.724138	0.002622
42	Windows	s2224	11648	0.999808	3.099245	0.508156	3.123967	0.004886
43	Mac	s2224	5600	0.999845	1.200714	0.507321	2.931034	0.019790
44	Mac	s2224	6720	0.999998	0.021429	0.500893	3.057143	0.011306
45	Mac	s2224	11872	0.999976	0.389488	0.497136	3.206478	-0.012163
46	Linux	s2512	6656	0.999741	2.385216	0.490535	3.275362	-0.000358
47	Linux	s2512	5632	0.999971	0.230114	0.496804	3.589744	-0.005013
48	Linux	s2512	50176	0.999998	0.121253	0.500777	3.027751	-0.006858
49	Windows	s2512	2560	0.999841	0.564063	0.492578	3.245283	-0.001783
50	Windows	s2512	5632	0.999661	2.642756	0.510831	3.418803	-0.006865
51	Windows	s2512	11776	0.999970	0.490489	0.496773	3.069388	0.006412

52	Mac	s2512	5632	0.999847	1.193892	0.492720	3.008547	-0.011578
53	Mac	s2512	6656	0.999741	2.385216	0.490535	3.275362	-0.000358
54	Mac	s2512	11776	0.999904	1.570652	0.494226	3.232653	-0.002851
55	Linux	s256	6656	0.999896	0.961538	0.493990	3.159420	0.000457
56	Linux	s256	5632	0.999987	0.102273	0.497869	2.769231	-0.019195
57	Linux	s256	50176	0.999978	1.518176	0.497250	3.234450	-0.006408
58	Windows	s256	2304	0.999783	0.694444	0.491319	3.333333	0.004908
59	Windows	s256	5632	0.999715	2.227273	0.509943	3.076923	0.022341
60	Windows	s256	11520	0.999727	4.355556	0.509722	3.116667	-0.010799
61	Mac	s256	5632	0.999999	0.006392	0.499467	3.350427	-0.004263
62	Mac	s256	6656	0.999896	0.961538	0.493990	3.159420	0.000457
63	Mac	s256	11776	0.999880	1.961957	0.493546	3.151020	-0.005602
64	Linux	s3224	6720	0.999946	0.500595	0.504315	3.057143	0.013617
65	Linux	s3224	5600	0.999669	2.571429	0.489286	3.103448	0.019550
66	Linux	s3224	50176	0.999914	5.985013	0.494539	3.146411	-0.001953
67	Windows	s3224	2240	0.999998	0.007143	0.499107	3.652174	-0.017860
68	Windows	s3224	5600	0.999979	0.160714	0.502679	3.241379	-0.015029
69	Windows	s3224	11648	0.999936	1.038805	0.495278	3.206612	-0.006271
70	Mac	s3224	5600	0.999669	2.571429	0.510714	3.172414	0.007401
71	Mac	s3224	6720	0.999946	0.500595	0.504315	3.057143	0.013617
72	Mac	s3224	11872	0.999999	0.008423	0.499579	3.028340	0.003705
73	Linux	s3256	6656	0.999850	1.384615	0.507212	3.275362	-0.001410
74	Linux	s3256	5632	0.999980	0.159801	0.502663	2.905983	0.002102
75	Linux	s3256	50176	0.999988	0.829401	0.497967	3.211483	-0.006075
76	Windows	s3256	2304	0.999804	0.626736	0.491753	2.916667	-0.012428
77	Windows	s3256	5632	0.999980	0.159801	0.497337	2.632479	0.002813
78	Windows	s3256	11520	0.999978	0.355556	0.502778	2.900000	0.006219
79	Mac	s3256	5632	0.999934	0.517756	0.504794	3.145299	-0.029924
80	Mac	s3256	6656	0.999850	1.384615	0.507212	3.275362	-0.001410
81	Mac	s3256	11776	0.999983	0.285666	0.497537	3.248980	-0.010215
82	Linux	s3384	6912	1.000000	0.000579	0.500145	3.194444	0.017361
83	Linux	s3384	5760	0.999765	1.877778	0.490972	2.966667	-0.003105
84	Linux	s3384	50304	0.999958	2.900843	0.503797	3.171756	0.001612
85	Windows	s3384	2304	0.999893	0.340278	0.493924	3.500000	0.020689
86	Windows	s3384	5760	1.000000	0.000000	0.500000	3.266667	0.005556
87	Windows	s3384	11520	0.999996	0.068056	0.498785	3.300000	-0.018409
88	Mac	s3384	5760	0.999727	2.177778	0.490278	3.200000	0.004485
89	Mac	s3384	6912	1.000000	0.000579	0.500145	3.194444	0.017361
90	Mac	s3384	11904	0.999996	0.065860	0.498824	3.145161	0.001003
91	Linux	s3512	6656	0.999998	0.021635	0.500901	3.043478	0.007208
92	Linux	s3512	5632	0.999247	5.881392	0.516158	3.111111	0.011041
93	Linux	s3512	50176	0.999997	0.191406	0.499023	3.184689	0.001591
94	Windows	s3512	2560	0.999989	0.039062	0.501953	3.169811	-0.000015
95	Windows	s3512	5632	0.999974	0.205256	0.503018	3.111111	-0.000036
96	Windows	s3512	11776	1.000000	0.000340	0.499915	3.363265	-0.004755
97	Mac	s3512	5632	0.999967	0.256392	0.503374	3.247863	-0.005728
98	Mac	s3512	6656	0.999998	0.021635	0.500901	3.043478	0.007208
99	Mac	s3512	11776	0.999883	1.910666	0.506369	3.053061	-0.002540
100	Linux	s384	6912	0.999978	0.208912	0.502749	3.361111	-0.000030
101	Linux	s384	5760	0.999854	1.167361	0.507118	3.000000	-0.000203
102	Linux	s384	50304	0.999985	1.015347	0.497754	3.152672	0.010874
103	Windows	s384	2304	0.999760	0.765625	0.490885	3.333333	-0.009016
104	Windows	s384	5760	0.999893	0.850694	0.506076	2.800000	0.008187
105	Windows	s384	11520	0.999905	1.512500	0.494271	3.133333	0.006467

106	Mac	s384	5760	0.999993	0.056250	0.498437	3.133333	-0.002788
107	Mac	s384	6912	0.999978	0.208912	0.502749	3.361111	-0.000030
108	Mac	s384	11904	0.999999	0.008401	0.500420	3.080645	-0.008065
109	Linux	ske128	53248	0.999998	0.126277	0.500770	3.184851	-0.006388
110	Linux	ske128	45056	0.999986	0.852628	0.502175	3.087420	0.000070
111	Linux	ske128	401408	0.999993	3.671566	0.501512	3.097823	-0.002929
112	Windows	ske128	18432	0.999917	2.126953	0.505371	3.041667	-0.005975
113	Windows	ske128	44032	0.999998	0.093023	0.500727	3.097056	0.003450
114	Windows	ske128	92160	0.999999	0.117361	0.500564	3.104167	-0.003387
115	Mac	ske128	45056	0.999999	0.079901	0.500666	3.223881	-0.007726
116	Mac	ske128	53248	0.999998	0.126277	0.500770	3.184851	-0.006388
117	Mac	ske128	94208	0.999986	1.854662	0.502218	3.080530	-0.001463
118	Linux	ske256	53248	0.999989	0.844050	0.498009	3.065825	0.001036
119	Linux	ske256	45056	0.999984	1.016424	0.497625	3.159915	0.000421
120	Linux	ske256	401408	0.999996	2.000000	0.501116	3.106912	0.000324
121	Windows	ske256	18432	0.999915	2.170139	0.505425	3.166667	0.004874
122	Windows	ske256	45056	0.999998	0.096680	0.499268	3.070362	-0.002843
123	Windows	ske256	92160	0.999999	0.108507	0.499457	3.133333	-0.003039
124	Mac	ske256	45056	0.999976	1.523526	0.502907	3.113006	-0.001099
125	Mac	ske256	53248	0.999989	0.844050	0.498009	3.065825	0.001036
126	Mac	ske256	94208	0.999996	0.495245	0.498854	3.233435	-0.002680

TABLE OF HASHED PACKET DATA ENT RESULTS (BY BYTES)

	Operating.System	Hash	Size	Entropy	Chi.Sq.	Mean	MC.Pi	Serial.Correlation
1	Linux	bl2b	832	7.710039	300.307692	127.264423	3.217391	-0.018633
2	Linux	bl2b	704	7.702965	261.818182	126.428977	3.247863	0.014207
3	Linux	bl2b	6272	7.969971	254.938776	127.346301	3.058373	0.007395
4	Windows	bl2b	320	7.270584	291.200000	121.150000	3.396226	0.056477
5	Windows	bl2b	704	7.715849	242.181818	129.509943	2.974359	-0.069928
6	Windows	bl2b	1472	7.892107	212.869565	127.847826	3.134694	0.016110
7	Mac	bl2b	704	7.713464	267.636364	129.460227	3.111111	-0.042946
8	Mac	bl2b	832	7.710039	300.307692	127.264423	3.217391	-0.018633
9	Mac	bl2b	1472	7.876650	254.608696	127.368886	3.118367	0.004450
10	Linux	bl2s	832	7.773328	238.769231	125.485577	3.304348	0.040503
11	Linux	bl2s	704	7.738005	226.909091	127.433239	3.145299	0.006780
12	Linux	bl2s	6272	7.972498	240.000000	127.052136	3.196172	0.005147
13	Windows	bl2s	288	7.304656	238.222222	128.576389	3.000000	0.050329
14	Windows	bl2s	704	7.660487	285.818182	130.575284	3.145299	-0.025152
15	Windows	bl2s	1440	7.843532	293.688889	126.505556	3.116667	0.006463
16	Mac	bl2s	704	7.729896	233.454545	125.386364	3.179487	0.030814
17	Mac	bl2s	832	7.773328	238.769231	125.485577	3.304348	0.040503
18	Mac	bl2s	1472	7.877831	232.000000	129.487092	3.036735	-0.037924
19	Linux	md5	832	7.792125	225.230769	125.064904	3.275362	0.023621
20	Linux	md5	704	7.750837	219.636364	127.099432	3.247863	-0.018354
21	Linux	md5	6272	7.975274	214.938776	129.631696	3.123445	-0.000403
22	Windows	md5	288	7.269933	247.111111	126.934028	2.750000	-0.043805
23	Windows	md5	688	7.694080	280.186047	127.311047	3.157895	0.075736
24	Windows	md5	1440	7.861282	275.200000	125.158333	3.100000	0.013610
25	Mac	md5	704	7.682353	280.727273	125.585227	3.384615	-0.002881
26	Mac	md5	832	7.792125	225.230769	125.064904	3.275362	0.023621
27	Mac	md5	1472	7.872019	252.869565	127.814538	3.102041	-0.019107
28	Linux	s1	820	7.758565	248.956098	129.296341	3.264706	-0.013552
29	Linux	s1	700	7.783396	185.760000	129.557143	3.137931	-0.001530

30	Linux	s1	6260	7.975602	214.100958	127.829393	3.137105	-0.000585
31	Windows	s1	280	7.199130	270.400000	124.496429	3.217391	-0.066604
32	Windows	s1	700	7.709263	263.291429	127.067143	3.206897	0.042612
33	Windows	s1	1440	7.874314	250.311111	127.495139	3.066667	-0.002471
34	Mac	s1	700	7.728470	230.377143	128.402857	3.275862	0.015743
35	Mac	s1	820	7.758565	248.956098	129.296341	3.264706	-0.013552
36	Mac	s1	1460	7.872787	250.290411	125.832877	3.209877	0.026565
37	Linux	s2224	840	7.753958	260.800000	128.400000	3.057143	0.057046
38	Linux	s2224	700	7.742857	220.868571	128.710000	3.275862	0.015311
39	Linux	s2224	6272	7.973649	227.265306	127.926977	3.154067	0.006535
40	Windows	s2224	280	7.278507	241.142857	123.903571	3.478261	-0.043458
41	Windows	s2224	700	7.723549	234.765714	130.487143	2.724138	-0.064134
42	Windows	s2224	1456	7.865446	275.164835	131.181319	3.123967	0.003073
43	Mac	s2224	700	7.692566	272.068571	131.611429	2.931034	-0.034132
44	Mac	s2224	840	7.753958	260.800000	128.400000	3.057143	0.057046
45	Mac	s2224	1484	7.868655	257.628032	126.528976	3.206478	-0.004081
46	Linux	s2512	832	7.704390	306.461538	126.534856	3.275362	-0.029305
47	Linux	s2512	704	7.670309	297.454545	123.305398	3.589744	0.006054
48	Linux	s2512	6272	7.967540	278.530612	129.594228	3.027751	0.013194
49	Windows	s2512	320	7.334577	259.200000	125.846875	3.245283	0.032896
50	Windows	s2512	704	7.695319	257.454545	127.291193	3.418803	0.060673
51	Windows	s2512	1472	7.871521	248.347826	128.235054	3.069388	0.031987
52	Mac	s2512	704	7.698028	257.454545	127.694602	3.008547	0.006978
53	Mac	s2512	832	7.704390	306.461538	126.534856	3.275362	-0.029305
54	Mac	s2512	1472	7.891616	213.913043	128.177310	3.232653	0.022711
55	Linux	s256	832	7.779267	245.538462	126.610577	3.159420	-0.000649
56	Linux	s256	704	7.710811	245.090909	129.092330	2.769231	0.000002
57	Linux	s256	6272	7.971919	239.265306	126.325733	3.234450	-0.002037
58	Windows	s256	288	7.234864	264.888889	130.118056	3.333333	-0.047004
59	Windows	s256	704	7.683751	276.363636	129.930398	3.076923	-0.076702
60	Windows	s256	1440	7.880827	232.177778	132.816667	3.116667	-0.004271
61	Mac	s256	704	7.695856	273.454545	125.764205	3.350427	-0.022197
62	Mac	s256	832	7.779267	245.538462	126.610577	3.159420	-0.000649
63	Mac	s256	1472	7.878207	224.347826	124.204484	3.151020	-0.025419
64	Linux	s3224	840	7.778400	236.419048	128.988095	3.057143	0.013207
65	Linux	s3224	700	7.702655	259.634286	124.245714	3.103448	-0.044994
66	Linux	s3224	6272	7.967804	275.918367	125.329401	3.146411	-0.000142
67	Windows	s3224	280	7.242436	252.114286	123.835714	3.652174	-0.010893
68	Windows	s3224	700	7.739539	247.200000	129.010000	3.241379	0.020837
69	Windows	s3224	1456	7.859315	270.593407	126.365385	3.206612	0.008682
70	Mac	s3224	700	7.683715	265.485714	129.378571	3.172414	-0.002125
71	Mac	s3224	840	7.778400	236.419048	128.988095	3.057143	0.013207
72	Mac	s3224	1484	7.877415	241.067385	127.932615	3.028340	0.003752
73	Linux	s3256	832	7.753414	256.000000	128.602163	3.275362	0.048506
74	Linux	s3256	704	7.741961	224.000000	131.028409	2.905983	0.047420
75	Linux	s3256	6272	7.965849	289.632653	126.299107	3.211483	0.020687
76	Windows	s3256	288	7.234292	259.555556	128.000000	2.916667	0.061016
77	Windows	s3256	704	7.703964	264.727273	127.936080	2.632479	-0.005221
78	Windows	s3256	1440	7.866361	254.222222	130.946528	2.900000	0.025603
79	Mac	s3256	704	7.687196	277.818182	128.656250	3.145299	0.036072
80	Mac	s3256	832	7.753414	256.000000	128.602163	3.275362	0.048506
81	Mac	s3256	1472	7.855335	288.000000	128.259511	3.248980	0.038541
82	Linux	s3384	864	7.761851	254.814815	128.918981	3.194444	-0.015815
83	Linux	s3384	720	7.715698	252.800000	127.777778	2.966667	-0.041907

84	Linux	s3384	6288	7.972837	232.427481	128.986641	3.171756	0.004582
85	Windows	s3384	288	7.213459	282.666667	124.416667	3.500000	-0.015012
86	Windows	s3384	720	7.747280	223.644444	129.375000	3.266667	-0.042779
87	Windows	s3384	1440	7.859569	267.377778	127.314583	3.300000	-0.017518
88	Mac	s3384	720	7.763615	215.822222	124.181944	3.200000	-0.007164
89	Mac	s3384	864	7.761851	254.814815	128.918981	3.194444	-0.015815
90	Mac	s3384	1488	7.871211	258.236559	125.281586	3.145161	0.009742
91	Linux	s3512	832	7.766552	248.000000	128.135817	3.043478	0.021811
92	Linux	s3512	704	7.662472	268.363636	131.238636	3.111111	-0.052930
93	Linux	s3512	6272	7.971745	243.428571	126.980230	3.184689	-0.015177
94	Windows	s3512	320	7.396562	222.400000	123.125000	3.169811	-0.082289
95	Windows	s3512	704	7.731868	242.181818	130.046875	3.111111	-0.087689
96	Windows	s3512	1472	7.882993	233.043478	125.650136	3.363265	-0.028381
97	Mac	s3512	704	7.761054	214.545455	126.816761	3.247863	-0.022706
98	Mac	s3512	832	7.766552	248.000000	128.135817	3.043478	0.021811
99	Mac	s3512	1472	7.862705	269.913043	125.770380	3.053061	-0.044422
100	Linux	s384	864	7.773845	247.703704	128.181713	3.361111	-0.021854
101	Linux	s384	720	7.736049	244.977778	133.411111	3.000000	0.016837
102	Linux	s384	6288	7.968660	275.175573	126.286896	3.152672	-0.008539
103	Windows	s384	288	7.278580	254.222222	121.520833	3.333333	0.024395
104	Windows	s384	720	7.759210	215.822222	128.675000	2.800000	0.015283
105	Windows	s384	1440	7.873597	243.555556	127.036111	3.133333	0.026074
106	Mac	s384	720	7.672383	269.866667	126.418056	3.133333	-0.033970
107	Mac	s384	864	7.773845	247.703704	128.181713	3.361111	-0.021854
108	Mac	s384	1488	7.865237	265.462366	128.364919	3.080645	0.006206
109	Linux	ske128	6656	7.970905	265.846154	126.759465	3.184851	-0.000201
110	Linux	ske128	5632	7.967123	258.909091	127.199929	3.087420	0.014356
111	Linux	ske128	50176	7.996414	249.459184	128.226244	3.097823	0.003339
112	Windows	ske128	2304	7.916286	264.666667	128.543837	3.041667	-0.031410
113	Windows	ske128	5504	7.967025	251.534884	127.953852	3.097056	-0.010840
114	Windows	ske128	11520	7.982189	278.977778	127.773003	3.104167	-0.007903
115	Mac	ske128	5632	7.974622	200.090909	127.500888	3.223881	0.000357
116	Mac	ske128	6656	7.970905	265.846154	126.759465	3.184851	-0.000201
117	Mac	ske128	11776	7.983905	257.739130	127.984800	3.080530	-0.009015
118	Linux	ske256	6656	7.977339	207.000000	127.836088	3.065825	-0.004594
119	Linux	ske256	5632	7.964023	281.090909	125.890980	3.159915	0.010597
120	Linux	ske256	50176	7.996496	241.836735	127.928890	3.106912	0.003930
121	Windows	ske256	2304	7.919073	252.888889	127.405382	3.166667	0.007476
122	Windows	ske256	5632	7.967695	247.545455	128.561435	3.070362	0.008183
123	Windows	ske256	11520	7.983745	259.955556	127.478125	3.133333	-0.003942
124	Mac	ske256	5632	7.964904	271.000000	128.811435	3.113006	-0.023878
125	Mac	ske256	6656	7.977339	207.000000	127.836088	3.065825	-0.004594
126	Mac	ske256	11776	7.983456	265.000000	126.689963	3.233435	-0.003222