TriScale: A Framework Supporting Reproducible Performance Evaluations in Networking

Paper # 208, 12 pages body, 18 pages total

Code and live demo available at github.com/TriScale-Anon/triscale

ABSTRACT

When designing their performance evaluations, networking researchers often encounter questions such as: How long should a run be? How many runs to perform? How to account for the variability across multiple runs? Despite their best intentions, researchers often answer these questions differently, thus impairing the reproducibility of their evaluations and decreasing the confidence in their results.

To support networking researchers, we propose a *systematic methodology* that streamlines the design and analysis of performance evaluations. Our methodology first identifies the temporal characteristics of variability sources in networking experiments, and then applies rigorous statistical methods to derive performance results with *quantifiable confidence*, in spite of the inherent variability. We implement this methodology in a software framework called *TriScale*. For each performance metric, *TriScale* computes a variability score that estimates, with a desired confidence, how similar the results would be if the evaluation were repeated; in other words, *TriScale quantifies the reproducibility* of the performance evaluation. We apply *TriScale* to four diverse use cases (congestion control, wireless embedded systems, failure detection, video streaming), demonstrating that *TriScale* helps generalize and strengthen previously published results.

Improving the standards of reproducibility in networking is a crucial and complex challenge; with *TriScale*, we make an important contribution to this endeavor by providing a rationale and statistically sound experimental methodology.

1 INTRODUCTION

The ability to reproduce an experimental result is essential for making a scientifically sound claim. In networking research, reproducibility[1] is a well-recognized problem due to the *inherent variability of the experimental conditions*: The uncontrollable dynamics of real networks [26, 56] and the time-varying performance of hardware and software components [20, 54] cause major changes in the experimental conditions, making it difficult to reproduce results and quantitatively compare different solutions [13]. In addition, *differences in the methodology* used to design an experiment, process the measurements, and reason about the outcomes impair the ability to reproduce results and assess the validity of claims reported by other scientists. Without reproducibility, any performance evaluation is debatable at best.

Problem. To be reproducible, performance evaluations must account for the inherent variability of experiments—put simply, experiments must be repeated to have sufficient confidence in the results. To facilitate this, our community has put great efforts into developing testbeds [59] and data collection frameworks [79]. However, there is still no *systematic methodology* specifying how to design and analyze performance evaluations. The literature is currently limited to generic guidelines [14, 57, 66] and recommendations [43, 48, 60], which leave critical questions open *before* an experiment (*e.g.*, How many runs? How long should they be?) and *after* (*e.g.*, How to process the data and produce concise but accurate results?). Without a systematic methodology, scientists often design and analyze similar experiments in different ways, making them hardly comparable [21]. Yet, strong claims are being made ("Our system improves latency by 3×") while confidence is often discussed only in qualitative ways ("with high confidence"), if at all. Furthermore, it is unclear how to concretely assess whether a networking experiment is indeed reproducible. We argue that *a systematic methodology* can help resolving this situation.

Challenge. A methodology addressing the above problem should meet the following requirements.

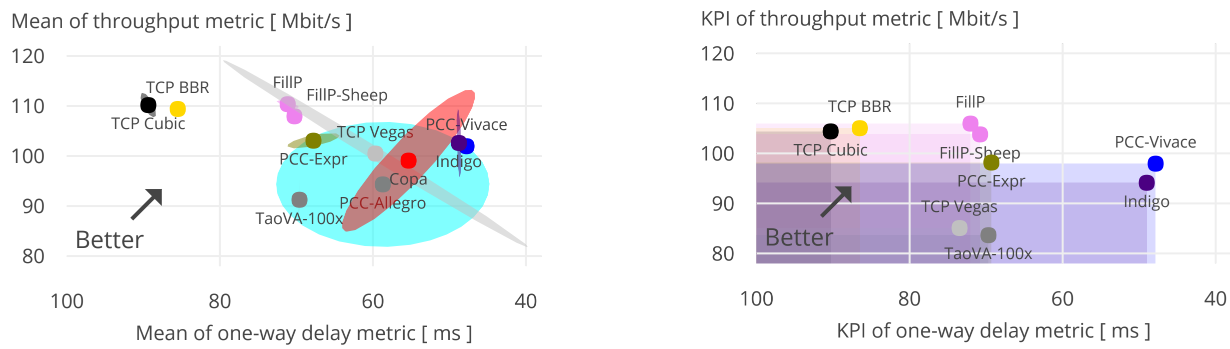
Rationality – The methodology must rationalize the experiment design by linking the design questions (*e.g.*, How many runs?) with the confidence in the performance claims.

Robustness – The methodology must be robust against the expectable variability of the experimental conditions. The data analysis must use statistics compatible with the nature of networking data and be able to quantify the performance variation expected shall the experiment be repeated.

Generality – The methodology must be applicable to a wide range of performance metrics, evaluation scenarios (emulator, testbed, real world), and network types (wired, wireless).

Conciseness – The methodology must describe the experimental design and the data analysis in a concise, yet unambiguous way to foster reproducibility while minimizing the use of highly treasured space in scientific papers.

[1]Different terminology is used to refer to different aspects of reproducible research [17, 62]. In this paper, we refer to reproducibility as the ability of different scientists to follow the steps described in published work, collect new data using the same tools, and eventually obtain the same results, within the margins of experimental error. This is sometimes called replicability [11].



(a) Data analysis with Pantheon [79] (reproduced). *Dots represent the mean performance across all runs; metrics are the mean throughput and 95th percentile of the one-way delay; ellipses represent the 1σ performance variation across all runs, where σ denotes the standard deviation.*

(b) Data analysis with *TriScale*. *Dots represent Key Performance Indicators (KPIs) across all runs: the 25th percentile of the throughput metric and the 75th percentile of the one-way delay metric (same metrics as in Fig. 1a). KPIs are estimated with 75% confidence. Shaded areas represent dominance regions:* scheme *A performs better than* scheme *B if the KPIs of B lies in the dominance region of A.*

Figure 1: Sample data from the congestion-control case study (§ 6.1). *The same data may be analyzed in different ways. Compared with Pantheon's analysis (Fig. 1a), TriScale's analysis allows for a more intuitive interpretation of the results (Fig. 1b): The performance of each scheme is reduced to a single point, TriScale's KPIs, which makes the comparison between the schemes unambiguous. These KPIs are not arbitrary: they are robust non-parametric statistics estimating, with a given confidence level, the expected performance if the experiment was repeated. Thus, TriScale's KPIs inherently account for the variability in the results.*

Contribution. We propose a systematic methodology to foster reproducibility and confidence in performance evaluations in networking. Our methodology is based on an analysis of the temporal characteristics of variability sources in networking experiments (§ 2.2). For each source, we identify appropriate statistical methods to derive performance results with *quantifiable confidence* (§ 3).

We implement this methodology in a software framework called *TriScale* (§ 4) and make it publicly available to the community [75]. We illustrate the benefits and generality of *TriScale* with case studies (§ 6) based on both testbeds and network emulation, and for four networking problems: congestion control, failure detection, wireless embedded systems, and video streaming. These examples show how the lack of methodology has led to erroneous or unfair comparisons between protocols or, conversely, how *TriScale* allows to generalize and strengthen previously published claims.

Existing works toward reproducible networking research focus mostly on data collection [59, 79]; *TriScale* complements these by providing the first concrete framework that guides researchers through the design of an experiment and the data analysis.

We strive to make this paper itself "reproducible": all data and source code are openly available [75]; most plots were created with *TriScale* and all are interactive, *i.e.*, they link to online versions allowing dynamic visualizations.

2 OVERVIEW OF *TRISCALE*

This section illustrates how *TriScale* improves the interpretation of experimental results with a concrete example (§ 2.1) then presents the core principles of the methodology (§ 2.2).

2.1 Shortcomings in the Data Analysis

Assume you are new to the field of congestion control and would like to understand the strengths and weaknesses of state-of-the-art schemes. Luckily, the community has developed useful tools like Pantheon [79], a data collection framework that facilitates comparisons between different schemes.

You are particularly interested in throughput and one-way delay of full-throttle flows, *i.e.*, flows whose performance is only limited due to congestion control. You start with one flow and evaluate performance using MahiMahi [58], an emulator integrated in Pantheon, following the same settings as in [79]: 10 runs of 30 seconds each. You collect data for the 17 congestion-control schemes available.

Pantheon helps you in collecting the data, not in their analysis or interpretation. Yet, none are trivial tasks. Consider, for example, the results shown in Fig. 1a (reproduced from [79]); the dots represent mean performance across all runs using mean throughput and 95th percentile of the one-way delay as metrics. Multiple questions arise:

(Q1) *Can the schemes be compared?* It appears that *TCP Vegas* performs better than, *e.g.*, *TaoVA-100x*. However, the ellipses capture the variability of the results across all runs; more precisely, they represent the 1σ variation across runs, where σ is the standard deviation. What can you then conclude about the actual performance of these schemes? Can you conclude anything if the ellipses are overlapping? For example, can you say that *TCP Vegas* performs better than *PCC-Expr*?

(Q2) *What is the confidence in the comparison?* Intuitively, the results of, *e.g.*, *PCC-Allegro*, which have a large variability, are less trustworthy than those of, *e.g.*, *FillP-Sheep*, for which the ellipse is hardly visible. But can you quantify the confidence in this result?

(Q3) *Is a runtime of 30 seconds sufficiently long to fairly compare the different schemes?*

These questions relate to the robustness and rationality requirements and are left unanswered by the data analysis shown in Fig. 1a. In fact, the analysis may suggest wrong interpretations. The ellipses are a two-dimensional representation of the standard deviation across the runs, suggesting that one can expect about 68% of the data points to fall in that region. However, this is correct *only if* the underlying distribution is normal, which is hardly ever true (§ 3).

Fig. 1b illustrates the *same data* analyzed with *TriScale*. The dots now represent *TriScale*'s Key Performance Indicators (KPIs). A KPI estimates a given percentile of a performance metric's underlying distribution (*i.e.*, the unknown distribution we would obtain with infinitely many samples) with a certain confidence. We use the same performance metrics: the mean throughput and 95th percentile of the one-way delay, for which we have 10 samples (one per run). Based on these 10 samples, *TriScale* estimates the *25th percentile* of the throughput metric (*higher* throughput is better) and the *75th percentile* of the one-way delay metric (*lower* delay is better). We choose a 75% confidence level for the estimation of both KPIs.[2] In other words, with a 75% confidence, 75% of the runs yield a performance that is as least as good as the KPI values (*i.e.*, equal or higher throughput and equal or lower one-way delay).

With this methodology (detailed in §§ 2.2 and 4), *TriScale* answers the three open questions mentioned previously:

(Q1) Since the KPIs are individual dots, we can unambiguously compare different schemes. Contrary to what Fig. 1a suggests, we observe in Fig. 1b that *TCP Vegas* is not generally better than *TaoVA-100x*, as each performs better in either delay or throughput; also, *PCC-Expr* performs strictly better than *TCP Vegas*.

(Q2) The confidence levels of the KPIs explicitly state how confident we are in the results we report.

(Q3) *TriScale* can check whether schemes have converged, *i.e.*, the metrics have reached stable values. We show in § 6.1 that many schemes do not reach a stable performance within 30 s, which is an aspect that needs be considered when estimating "long-term" performance.

Summary. Tools like Pantheon [79] support data collection, but leave the design of the experiments and the data analysis up to the researcher, leading to ambiguous interpretations and non-reproducible results. *TriScale* fills this gap.

2.2 Core Principles of *TriScale*

TriScale is a framework supporting the *design* and the *data analysis* of networking experiments (Fig. 2). Given the user's objectives (e.g., the KPI to analyze, the confidence level to reach), *TriScale* helps answering questions such as: How many runs should be done? How long should the runs be? and When to run them? Based on these answers, the user can then proceed with collecting the appropriate data. In the analysis phase, the user provides the raw data to *TriScale*, which then automatically produce expressive and easy-to-interpret performance reports together with variability scores.

In the following, we explain *TriScale*'s building blocks. We start by describing the three timescales (hence the name, ***Tri**Scale*) underlying the methodology, then describe how *TriScale* supports the experiment design and analysis.

Timescales. We structure *TriScale*'s methodology around three timescales: runs, series (of runs), and sequels (of series). These timescales intuitively capture the different sources of variability underlying network performance evaluation.

A *run* is one execution of an evaluation scenario (*e.g.*, a 30 s execution of *TCP BBR*); during a run, one measures some performance dimensions (*e.g.*, packet delay) which vary due to some sources of variability such as protocol dynamics and cross-traffic. The run performance is summarized with a *metric* (*e.g.*, 95th percentile). Depending on the scenario, one may want the metric to estimate long-term performance (*e.g.*, for "infinite" flows); the run should then be sufficiently long to let the metric value converge.

Typically, one does multiple runs to measure performance under different conditions; we call such a set of runs a *series* (*e.g.*, 100 runs within one week) from which we obtain a set of metric values (one per run). We summarize a series performance with a *key performance indicator (KPI)* that *estimates* the expected performance for any possible run in the time span of the series (*e.g.*, estimating the median of the metric distribution). The intuition is that, with a series of run, one randomly samples the distribution of possible experimental conditions, which allows to estimate the distribution of the performance metric of interest.

[2] We use a confidence level of 75% instead of the more common 95% because estimating the 25th and 75th percentiles with 95% confidence requires at least 11 data points (Eq. (3)), while Pantheon currently performs series of 10 runs. To compare *TriScale*'s and Pantheon's analysis methods, we chose to keep the same number of samples but use a lower confidence level.

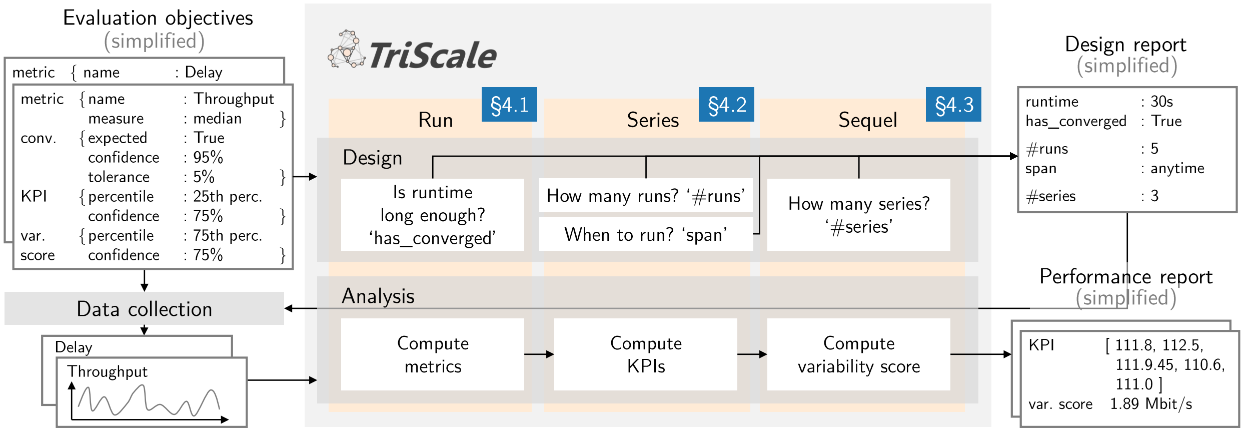


Figure 2: Overview of *TriScale*. *TriScale is a framework supporting the design and data analysis of networking experiments. TriScale assists the user in the design phase with a systematic methodology to answer important experiment design questions such as "How many runs?" and "How long should the runs be?". After the data has been collected, TriScale supports the user by automating the data analysis. The framework implements robust statistics that handle the intrinsic variability of experimental networking data and returns expressive performance reports as well as a variability score.*

In general, variability sources such as cross-traffic vary with a priori unknown time correlation; that is, the distribution of conditions sampled during a series may not be stationary, but time-varying. Therefore, to generalize the results, one should perform multiple series, which we call *sequels*. Intuitively, sequels allows to estimate the expected performance for any series (*e.g.*, the expected KPI for any week). Our method uses sequels to compute a *variability score* which serves to *quantify the reproducibility* of an experiment; *i.e.*, it defines a confidence interval for the expected results one would obtain shall new series of runs be performed.

TriScale divides the design and analysis pipelines based on the three timescales: runs, series, sequels.

Experiment design. The design phase starts with the definition of the evaluation objectives (Fig. 2, left). For each performance dimension, the user defines the metric, the convergence requirements, a KPI, and a variability score (§ 4). Given these inputs, *TriScale* derives the minimum number of runs (*#runs*) and series (*#series*) needed to compute the chosen KPIs and variability scores, thus answering the question how many runs to perform. Using data from test runs (or previous experiments), *TriScale* can assess whether the runtime appears long enough to let the metric value converge (*runtime*). Additionally, *TriScale* can make use of these test runs to identify time-dependent patterns in the experimental conditions (§ 4.6). This is important to understand the root cause of the statistical behavior of the measurements, and helps answering the question when the runs should be performed (*span*). Note that the congestion-control example presented previously uses network emulation; thus, there is no time dependency and it does not matter when the experiment is performed (*i.e.*, *span: anytime*). The design phase results in a report (Fig. 2, right) summarizing how to run the experiments. Based on this report, the user can then collect the raw data before starting with the analysis phase.

Data analysis. Once the experiment has been designed and the data collected, the raw data are passed to *TriScale* for a three-stage analysis, one per timescale. First, the raw data from one *run* is processed, *i.e.*, convergence is assessed and the performance metrics are computed. Then, *series* allow to account for the short-term variability in the experiments. This timescale leads to one number per series and per metric, *i.e.*, the KPI (§ 4.2). Finally, *sequels* are used to compute a *variability score* capturing the long-term variability in the KPIs. This timescale leads to one number per metric (§ 4.3).

Using *TriScale*. We implement *TriScale* as a Python module [75]. For each timescale, a dedicated function performs the corresponding test or analysis. The functions take as input raw data in the form of CSV file, Pandas DataFrames, or Python arrays; the outputs are returned and optionally saved as CSV files. These same functions also produce data visualizations such as those shown in Fig. 3 to 5.

The entire process is intuitive and easy-to-use. For a better impression of *TriScale*'s usability, an interactive demo is available and can be directly run in your web browser [5].

3 STATISTICS FOR REPRODUCIBILITY

This section briefly reviews classes of statistical approaches and motivates the choices of methods used by *TriScale* to handle the variability inherent to networking research.

Descriptive and predictive statistics. A statistic is a number computed from a data set using a mathematical formula; it can always be calculated and provides a factual description of the underlying data. This is referred to as a *descriptive statistic*. In addition, certain statistics have some *inference* power; that is, based on the collected data, one may infer the shape of the underlying data distribution, which is unknown. These are then referred to as *predictive statistics*.

Predictions are always uncertain and rely on certain hypotheses. If the hypotheses hold for the collected data, then the statistic estimates, with a quantifiable level of confidence, some property of the underlying distribution (*e.g.*, mean, median, etc.); one can then predict expected values of data samples that have not been collected. A common hypothesis for predictive statistics is that the collected data is *independent and identically distributed* (*i.i.d.*); informally, this means that the underlying distribution of the data does not change and that successive data samples are not correlated. It is also common to presume the *nature of the data distribution* (*e.g.*, normal or Poisson distribution). *E.g.*, one can estimate the mean μ and standard deviation σ of a distribution based on a data sample. If the underlying data distribution is normal (the hypothesis), we can infer that about 68% of all data points will be contained in $\mu \pm \sigma$ (the prediction). But if the distribution is *not normal*, the statistics μ and σ are *only descriptive*, *i.e.*, they do not predict the shape of the distribution.

Statistical methods. Two main classes of statistical approaches are hypothesis testing and estimation. *Hypothesis testing* consists in formulating a so-called null hypothesis, that the test aims to reject. Based on the collected data, one computes the probability, called the p-value, that the null hypothesis is correct. If the p-value is sufficiently low, the null hypothesis is rejected and considered proven incorrect. *E.g.*, the one-way ANOVA [8] is a common method to test for significant differences in the mean of multiple data samples. *Estimation* consists in computing confidence intervals (CIs) for a given parameter (*e.g.*, the mean of a distribution). A CI is always associated a confidence level (*e.g.*, a 95% CI) which is the probability that the interval includes the true value of the parameter. For example, $[a, b]$ is a 95% CI for the mean if the true mean value is between a and b with a probability $\geq$ 95%. These approaches are further categorized as *parametric*, when the nature of the underlying distribution is known, or *non-parametric*, when no assumption is made on the distribution's nature. *E.g.*, the Kruskal-Wallis test [7] is the non-parametric equivalent of the one-way ANOVA; the tests are similar but the first does not assume that the underlying distribution is normal. The central limit theorem [10] offers another alternative to handle unknown distributions, but it only allows to argue about the arithmetic mean.

Statistics for reproducibility in networking. Informally, reproducibility is the principle that the "same experiment" leads to the "same results". Assessing reproducibility entails predicting whether future data (*i.e.*, the results of a newly-performed experiment) will be the same as the known data (*i.e.*, the results of previous experiments): it is a prediction.

Literature reports that experimental data is rarely normal [54, 67] and hence recommends using *non-parametric* statistics. We should also consider *robust statistics*, *i.e.*, statistics not overly skewed by outliers, as these are common in networking data; *e.g.*, using median instead of mean. While hypothesis testing is commonly used, statisticians argue that the methods are misunderstood, misused [49], and are calling for a change in scientific practices [32, 77]. Hence, we favor *estimation* over hypothesis testing as CIs are more legible than p-values, easier to interpret. Furthermore, the level of confidence of an estimation only depends on the sample size, which is useful to guide the experimental design.

In 1936, Thompson introduced a method to compute non-parametric CIs for percentiles [74]. This approach is found in statistics [33] and computer science [50] textbooks, but it is barely used today ([18, 54, 67] are the few exceptions). As Thompson's method is well-suited to handle the variability of experimental networking data, we use it as the cornerstone of *TriScale*'s methodology (§ 4.5). In this work, we illustrate the potential of the approach (§ 6) and strive to facilitate its use by providing the necessary software support (§ 5).

4 DESIGNING *TRISCALE*

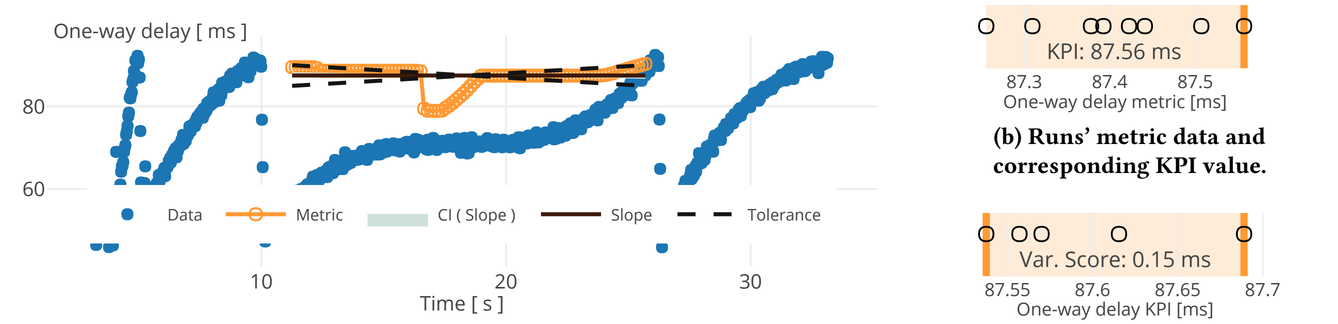
In this section, we first describe the data analysis performed by *TriScale* and how the analysis procedure is linked to the design of experiments (§ 4.1 to § 4.3). We then illustrate how the formalism introduced by *TriScale* allows to unambiguously describe an entire performance evaluation with only a handful of parameters (§ 4.4). Thereafter, we detail the robust and non-parametric statistical methods used by *TriScale* (§ 4.5), and discuss how the framework assists a user in deciding the required time span for a series of runs (§ 4.6). We finally show how *TriScale* helps assessing the reproducibility of experiments by computing a variability score (§ 4.7).

4.1 Runs and Metrics

TriScale metrics evaluate a performance dimension across one run. *E.g.*, a metric may be the mean throughput achieved by a congestion-control scheme over 30 s runtime of a full-throttle flow. Computing a metric takes the following inputs.

Inputs. - The metric *measure*; *e.g.*, mean, maximum, etc.
- The *convergence* requirements
{ expected : true/false ,
confidence : C (*default: 95%*) ,
tolerance : t (*default: 5%*) }
- The raw data of the run.

In general, any measure can be used. The current implementation of *TriScale* (§ 5) supports the arithmetic mean, the minimum, the maximum, and any percentile.



(a) Raw data (one-way delay) and metric (95th percentile). *Example run of TPC Cubic.*

(b) Runs' metric data and corresponding KPI value.

(c) Series' KPI data and corresponding variability score.

Figure 3: Example plots produced by *TriScale* during the data analysis. *Fig. 3a: computation of the metric (95th percentile on one-way delay) with convergence test (confidence 95%, tolerance 5%). Fig. 3b: computation of the KPI (75th percentile with 75% confidence). Fig. 3c: computation of the variability score (25-75th percentiles with 75% confidence). Sample data from the case study (§ 6) for TPC Cubic. Plots are produced by TriScale and are hyperlinks leading to a dynamic data visualization.*

Procedure. If the run is expected to converge, *TriScale* starts by performing a convergence test, whose purpose is to assess whether the metric has reached a "stable" value by the end of the run (and hence if it is a good estimate of the "long-running" performance). To test this, *TriScale* computes metric values over a sliding window of the raw data points. For each window, whose size is fixed to half of the data points, one metric value is computed, starting with the first half of the data. The window slides by a 100^{th} of the number of samples repeatedly until all data points are used, leading to a set of 100 metric values.*TriScale* performs its convergence test (detailed in § 4.5) on the metric values. This procedure tests the convergence of the *metric* (not the raw data) and damps the impact of transient behavior on the convergence test. If the test is passed, *TriScale* returns the median of metric values as run metric. If convergence is not expected, *TriScale* simply computes the run metric over the whole raw data.

Outputs. - The result of the convergence test (if any),
- The metric value for the run,
- Textual logs; plot of the input data and metric.

Link to the experiment design. The computation of metrics is linked to the definition of the *runtime*; *i.e.*, how long a run should be. If the evaluation scenario is terminating (*e.g.*, transmit 1 MB of data), the runtime must be long enough to complete the task. If the evaluation is "long-running" (*e.g.*, lifetime estimation), the runtime must be long enough for the metric (the energy consumption) to converge (convergence test details in § 4.5). *TriScale* can analyze experiments to estimate whether the runtime appears long enough (illustrated in § 6); *i.e.*, it can assess, with quantifiable confidence, that the metric values appear stable for a certain runtime. However, *TriScale* cannot *guarantee* that the runtime is long enough for a sound evaluation of "long-running" performance, as this requires context-specific knowledge.

4.2 Series and KPIs

TriScale's key performance indicators (KPIs) evaluate performance dimensions across a series of runs. Performing multiple runs allows to mitigate the inherent variability of the experimental conditions. KPIs capture this variability by estimating percentiles of the (unknown) metric distributions. Concretely, a *TriScale* KPI is a one-sided CI of one percentile; *e.g.*, a lower-bound for the 75th percentile of the throughput metric, estimated with a 95% confidence level.

Inputs. - The KPI definition,
{ percentile : p ,
confidence : C }
- The metric data from a series of runs.

Procedure. To compute the KPI (*i.e.*, to compute a CI for a given percentile), *TriScale* uses the Thompson's method (§ 4.5), which requires the input data to be *i.i.d.*. Thus, *TriScale* starts by performing an independence test (§ 4.5) on the metric data before computing the KPI.

Outputs. - The result of the independence test,
- The KPI value for the series of runs,
- Textual logs; plot of the metric data and its KPI.

Link to the experiment design. The computation of KPIs is linked to the definition of the number of runs in a series (*# runs*) and the series time span (*span*). The minimal number of runs in a series directly follows from the definition of the KPI, *i.e.*, the percentile to estimate p and the desired confidence level C (Eq. (3)). The series time span refers to the time interval used for scheduling the runs in a series (*i.e.*, when to run the experiment). This is important because networks often feature time-dependent conditions; for example, there may be systematically more cross-traffic during daytime than nighttime. Failing to consider such dependencies may bias the results and yield wrong conclusions. *TriScale* helps detecting such dependencies with a dedicated analysis function called "network profiling" (example in § 6).

4.3 Sequels and Variability Score

TriScale's variability score evaluates the variations of KPI values across repetitions of series of runs (*sequels*). Performing sequels allows to detect long-term variations of KPIs and ultimately quantify the reproducibility of an experiment.

Concretely, a variability score is a two-sided CI, *i.e.*, a symmetric pair of percentiles. For example, a 75% confidence interval is defined by the 25-75th percentiles of the delay KPIs from all sequels. Again, we attach a confidence value to the confidence interval, or equivalently, to the percentiles.

Inputs. - The variability score definition,
{ percentile : p (or 1-p),
confidence : C}
- The KPI values of each sequel.

Procedure. The procedure is the same as for the KPI: The Thompson's method requires the input data to be *i.i.d.* (§ 4.5), thus *TriScale* performs an independence test on the KPI data before computing the variability score.

Outputs. - The result of the independence test,
- The variability score value for the entire sequels,
- Textual logs; plot of the KPI data and corresponding variability score.

Link to the experiment design. The computation of the variability score is linked to the definition of the number of series (*#series*). The minimal number of series directly follows from the definition of the variability score; *i.e.*, the percentile to estimate p and the desired confidence level C (Eq. (3)).

4.4 Formalism Brings Conciseness

TriScale formalizes the definition of the evaluation objectives. For each performance dimension, the user defines a metric and convergence requirements (§ 4.1), a KPI (§ 4.2), and a variability score (§ 4.3). *TriScale* links these objectives with the experiment design, resulting in four additional parameters: the number of runs per series (*# runs*), the number of series (*# series*), the length of a run (*runtime*), and the time span of a series (*span*). Thanks to this formalism, *TriScale* meets the *conciseness* requirement: Altogether, these 12 parameters are sufficient to *formally describe the entire performance evaluation.* Since the data analysis in *TriScale* is automated and deterministic, documenting these parameters guarantees computational reproducibility (*i.e.*, the ability to recreate the results when all raw data are available [52]).

Table 1 shows a few examples of concrete parameter settings for typical networking evaluation objectives. For example, evaluating the latency of a real-time protocol requires high confidence levels for extreme percentiles. This quickly increases the number of runs that one must perform: *e.g.*, at least 90 for estimating the 95th percentile with 99% confidence; at least 299 for estimating the 99th percentile with 95% confidence. This illustrates that it is "easier" to increase the confidence level of an estimate than to estimate a more extreme percentile with the same confidence level. Note that both *#runs* and *#series* are only derived based on the definition of the KPI and variability score; these parameters are not influenced by the runtime or the time span of an experiment.

The second use case in Table 1 (bottom rows) illustrates two different perspectives on "averages", using delay as an example. If the metric is the median and the KPI the 90th percentile, one can conclude that 90% of the runs have a median delay equal or better than the KPI value. Conversely, if the metric is the 90th percentile and the KPI the median, one can conclude that, in half of the runs, the 90th percentile of the delay in the run is equal or better than the KPI. Both are "averages" but with different meanings and different requirements in terms of number of runs.

4.5 Statistics in *TriScale*

As discussed in § 3, networking performance evaluations should focus on statistics that are both *robust* (*i.e.*, tolerant to outliers) and *non-parametric* (*i.e.*, making no assumption about the nature of the data distribution). *TriScale* uses *three* carefully-chosen statistical methods. We first present the convergence test used in the computation of metrics (§ 4.1), which is based on the Theil-Sen linear regression [71, 73]. We then introduce the computation of confidence intervals using Thompson's method [74], which requires the data to be *i.i.d.*. *TriScale* checks empirically whether this assumption holds with an independence test, presented last.

Convergence test. When an evaluation aims to estimate the long-running performance (*i.e.*, the expected performance if the run would run "forever"), one must verify whether the runs are long enough to produce reliable estimates. To verify this, *TriScale* implements a convergence test based on the Theil-Sen linear regression [71, 73]. The approach computes the slope of the regression line as the median of all slopes between paired values. A $C\%$ confidence interval (CI) for the slope is defined as the interval containing the middle $C\%$ of slopes between single pairs. *TriScale* convergence test is passed if the $C\%$ CI for the regression is included in the tolerance value ($\pm\, t\%$). To test the convergence of a run, *TriScale* uses the confidence C and tolerance t parameters specified in the evaluation objectives (§ 2); C and t are set to 95% and 5% by default, respectively.

Such a test is sensitive to the scale of the input data. To remove this dependency, *TriScale* first maps the data to $[-1, 1]$ using a linear transformation; then performs the convergence test on the scaled data. Hence, the convergence test

Table 1: Exemplary evaluation parameters of typical networking use cases. * *TriScale returns the minimal number of runs (#runs) and series (#series) based on the definition of KPI and variability score, respectively.*

	Evaluation Objectives								Experiment Design			
Use case	Metric	Convergence			KPI		Var.Score					
	Measure	Exp.	Conf.	Tol.	Perc.	Conf.	Perc.	Conf.	#runs*	#series*	runtime	span
Latency of real-time protocol	max	True	95%	5%	95	95%	median	75%	59	3	Depend on networks and protocols	
					95	99%	75	75%	90	5		
					99	95%	median	90%	299	5		
Average delay	median	False	-	-	90	95%	median	90%	29	5		
	90th perc.				median	95%	median	90%	5	5		

becomes dimensionless and the same tolerance value can be used for different evaluations without introducing bias. An example of the Theil-Sen slope (brown, solid), its CI (light blue, solid), and tolerance (black, dashed) is shown in Fig. 3a.

Confidence intervals. *TriScale* defines KPIs (§ 4.2) and variability scores (§ 4.3) based on CIs for distribution percentiles, which can be computed using a robust and non-parametric approach due to Thompson [74], later shown to be valid for any independent samples of a continuous distribution [33].

Let us denote by P_p, the p-th percentile of a distribution and $\mathbb{P}(X)$ the probability of an event X. By definition, every data sample x is smaller than P_p with probability p (and larger with probability $1-p$). For a sorted list of *i.i.d.* samples x_i (where $i = 1..N$), the probability that P_p lies between two consecutive samples follows the binomial distribution [74]:

$$\mathbb{P}(x_k \leq P_p \leq x_{k+1}) = \binom{N}{k} p^k (1-p)^{N-k}, \quad k = 0..N \qquad (1)$$

where we assume $x_0 \rightarrow -\infty$ and $x_{N+1} \rightarrow \infty$. From this result, it follows that the probability of P_p being larger than any sample x_m ($1 \leq m \leq N$) can be computed as:

$$\mathbb{P}(x_m \leq P_p) = 1 - \sum_{k=0}^{m-1} \binom{N}{k} p^k (1-p)^{N-k} \qquad (2)$$

These probabilities are symmetric; that is, $\mathbb{P}(x_m \leq P_p) = \mathbb{P}(x_{N-m+1} \geq P_{1-p})$. Eq. (2) provides the upper- and lower-bounds required for computing the CIs. Furthermore, one can derive the minimal number of samples N to compute a CI for any percentile p with any confidence level C [67]:

$$Eq.\ (2) \quad \Rightarrow \quad N \geq \frac{\log(1-C)}{\log(1-p)} \qquad (3)$$

which defines the minimal number of runs and series required based on the definitions of the KPIs and variability scores. If the probability distribution is discrete, Eq. (2) becomes an inequality ($\mathbb{P}(x_m \leq P_p) \geq \dots$) providing a safe (*i.e.*, conservative) estimate of which sample x_m is the bound of the CI of interest [33].

This approach provides robust estimates for distribution percentiles and *does not make any assumption on the nature of the underlying distribution.* It does, however, require that the data samples are *i.i.d.*. *TriScale* checks whether this hypothesis holds using an independence test, described below.

Independence test. Estimating the percentile of a distribution requires often (if not always) that the samples are *i.i.d.* (§ 3); this is also the case for Thompson's method [74]. *TriScale* implements an empirical independence test to check whether we can safely treat the samples as *i.i.d.*. [3]

This independence test is applied to the metric data (resp. KPI data) before the computation of a KPI (resp. a variability score). This poses the particular challenge that the number of data samples may be very small (*e.g.*, 3 or 5 KPI values). *TriScale*'s independence test must therefore not be too strict.

The test is divided in two steps. First, *TriScale* tests whether the data appear *weakly stationary* (*i.e.*, no trend and constant autocorrelation structure [25]). *TriScale* verifies this empirically using its convergence test with a confidence of 50% and tolerance of 10%; these "loose" parameters are used to compensate for (very) small sample sizes. Second, *TriScale* computes the *sample autocorrelation coefficients*, denoted by $\widehat{\rho_k}$, which measure the linear dependency between values of a weakly stationary data series (where k is the lag between data points). A series of size N is *i.i.d.* with 95% probability if $|\widehat{\rho_k}| \leq 1.95/\sqrt{N}$ for $k \geq 1$ [25].

What if the tests fail? The user is responsible for designing the evaluation in such a way that the collected data will (likely) pass the tests. *TriScale* facilitates this by guiding the choice of runtime to pass the convergence test and informing about any network time dependencies (§ 4.6) to pass the independence test. Yet, the data may still be correlated or unstable, leading to failing tests (see examples in § 6). Even in such cases, the data still contain useful information. *TriScale* metrics, KPIs, or variability scores can be computed, however since the corresponding hypotheses do not hold, the statistics are *only descriptive* (§ 3); they do not predict the expected

[3] Generally, independence results from the experiment design. For networking experiments however, it is generally not possible to guarantee independence; *e.g.*, the experimental conditions cannot be fully controlled and may be correlated. In such cases, it is common to empirically check whether the data appear correlated. If the effective dependence between data samples is sufficiently low, it is considered safe to treat the samples as *i.i.d.*.

performance, and in particular they cannot (and should not be used to) assess the reproducibility of the experiment.

4.6 Network Profiling

TriScale assists the user in deciding on the time span for a series of runs, *i.e.*, the time interval containing all the runs of one series. This is important to avoid biasing the evaluation results with time dependencies in the experimental conditions. Indeed, it is common for real-world networks to exhibit periodic patterns. For example, there may be a lot more cross-traffic (*i.e.*, interference) at specific times. In the statistics literature, these patterns are called *seasonal components*. Neglecting these may bias experiments and lead to wrong conclusions, as we illustrate in § 6.

TriScale's network profiling functionality allows to compute the autocorrelation coefficients of link quality data (*e.g.*, [44]). Peaks in the autocorrelation plot suggest seasonal components in the network conditions (see Fig. 5), which helps detecting (sometimes unexpected) time dependencies. To avoid biasing the results, the span of a series of runs should be chosen as a multiple of the seasonal components.

4.7 Assessing Reproducibility

Reproducibility refers to the ability of obtaining "the same" results when performing "the same" experiment. In statistics, such property can be investigated using *equivalence testing* [49], which checks whether the values of some parameter of interest (*e.g.*, the median) obtained for different samples are sufficiently close to be considered "the same". Unfortunately, there is no general way to define "sufficiently close"; one must define in advance a threshold for the equivalence test based on expertise. Then, how to assess reproducibility of networking experiments? How to design a "reproducibility test" that fairly adapts to different networking contexts and metrics? After several failed attempts, we conclude that defining a generic threshold for equivalence testing in networking might not be possible. But it may not be necessary.

We argue that the most important is to confidently estimate the variability of the results, which *TriScale* computes with its variability score (§ 4.3). This score *quantifies reproducibility*: the larger the score, the less reproducible the results are (example in § B.1). Shall a binary cut between "reproducible" and "not reproducible" be desired, a threshold can be set based on the variability score; *e.g.*, "Results are said reproducible when the variability score is less than 20 Mbps." Such a threshold can only be context-specific; thus, deciding on threshold values relates more to benchmarking and hence goes beyond the scope of *TriScale* (see discussion in § 7).

5 IMPLEMENTATION AND SCALABILITY

5.1 All-Included Software Package

One obstacle to the adoption of non-parametric statistics is their lack of support in current scientific libraries; in particular, we had to implement the computation of CI using Thompson's method. We implemented *TriScale* as a Python module including all necessary functions to apply the methodology. *TriScale*'s API contains one function for each timescale of the data analysis, with docstrings containing detailed information about each function's usage. The module also includes support tools such as functions producing visualizations; *TriScale* uses Plotly [4] to create interactive plots in which one can zoom in and out in the plots, toggle the visibility of individual traces, read data values on hover, etc. Most plots in this paper have been produced using *TriScale* and all are "clickable": figures are hyperlinks leading to dynamic versions of the plots. Our implementation is open source [75][4] and we use Binder [45] to provide an interactive demo of *TriScale* that runs directly in your web browser [5].

5.2 Scalability of *TriScale* Data Analysis

We evaluate the scalability of *TriScale* with respect to its computation time; *i.e.*, we analyze how the time for the data analysis scales with increasing input sizes. To this end, we only consider the time required for performing computations, and exclude other outputs such as logs and plots (*e.g.*, Fig. 3a). Please refer to § A for more details.

Conclusion. The computation time for the data analysis in *TriScale* scales linearly with the input size (Table 2): it is fast (less than 1 s for one million data points on a commodity laptop) and negligible compared to the data collection time.

6 *TRISCALE* IN ACTION

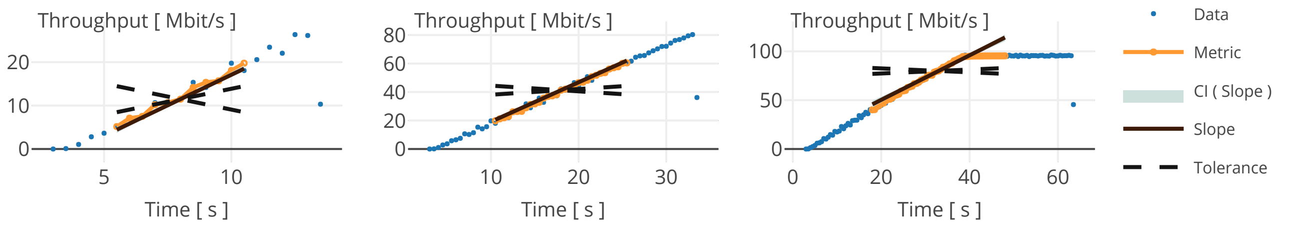
We present four case studies illustrating some performance evaluation shortcomings addressed by *TriScale*, and show how *TriScale* enables to generalize performance claims with a quantifiable confidence. Further details on these case studies (*e.g.*, data sources, additional plots) are available in § B.

6.1 Congestion Control

This case study shows that, for estimating long-running performance, it is important to carefully set the length of runs (the runtime) and verify whether performance appears to have converged for the system under evaluation.

We continue the evaluation introduced in § 2.1, which compares congestion-control schemes using Pantheon [79]. Assume we are now interested in *long-running flows*; that is, our goal is to estimate the performance one would obtain

[4]The repository is currently anonymous for double-blind review. Everything will be packaged and published on PyPI shall the paper be accepted.



(a) 10 s runtime **(b) 30 s runtime** **(c) 60 s runtime**

Figure 4: Egress throughput of the *LEDBAT* congestion-control scheme in MahiMahi [58]. *A runtime of 30 s is clearly not sufficient for LEDBAT's throughput to converge (Fig. 4b). The scheme does converge eventually (Fig. 4c), but even with 60 s runtime, TriScale's convergence test fails: the impact of the start-up phase is too important. See § B.1 for further details.*

if the flows ran "forever". *TriScale*'s convergence test (§ 4.1) checks whether the length of a run appears long-enough to provide a robust estimate. Since all schemes are different, it is hard to know a priori the minimum runtime for which the schemes actually converge; therefore we test runtimes from 10 to 60 s and check when the schemes pass the test.

For a runtime of 30 s (the one used by Pantheon maintainers [3]), only 11 out of 17 schemes pass the test (*i.e.*, converge) most of the times. Three schemes (*i.e.*, *Verus*, *PCC-Allegro*, *Copa*) only converge in less than half of the runs (see § B.1), whereas *QUIC Cubic*, *TPC Vegas*, and *LEDBAT never* pass the test, even with a runtime of 60 s. Fig. 4 details the case of *LEDBAT*: the inner working of the scheme causes the throughput to ramp-up in the first 38 s of runtime and then converge to about 92 Mbps. For this reason, if one uses a runtime of 30 s without checking for convergence, the computed mean throughput is about 40 Mbps, which is a totally wrong estimation of *LEDBAT*'s long-running throughput.

Conclusion. *TriScale*'s convergence test checks whether the runtime of an experiment appears to be sufficiently long to produce a robust estimation of the long-running performance. A failing convergence test warns a user about the need to increase the runtime or to take other measures (*e.g.*, pruning the start-up time in the raw data) in order to avoid wrong conclusions (as shown with LEDBAT in Fig. 4).

6.2 Wireless Embedded Systems

This case study shows the importance of choosing the time span for a series of runs. In particular, if there are strong temporal patterns in the experimental conditions, one may derive wrong results despite using a high confidence level.

We run a simple evaluation of Glossy [36], a low-power wireless protocol based on synchronous transmissions [81]. A key parameter of Glossy is the number of retransmissions, called N. We are hence interested in investigating the impact of two values of N on the reliability of Glossy, measured as the packet reception ratio (PRR). We define our KPI as the

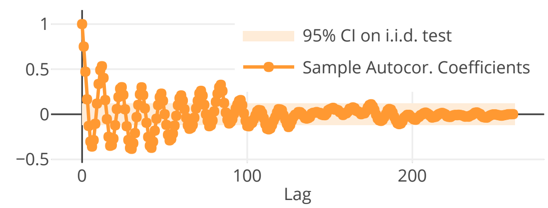


Figure 5: Autocorrelation plot for the wireless link quality on FlockLab [51], based on the raw data collected by the testbed maintainers [44]. *The dataset contains one test every two hours. The first peak at lag 12 (i.e., 24h) reveals the daily seasonal component. The data also show another at lag 84; which corresponds to one week. Indeed, there is less interference in the weekends than on weekdays: this creates a weekly seasonal component. Data from August 2019.*

median PRR with 95% confidence level (details in § B.2). We collect data using the FlockLab testbed [51], which is located in an office building where we expect more interference during daytime than nighttime. Thus, for each value of N, we perform a series of 24 runs scheduled randomly within one day. Computing the KPI leads to a PRR of 88% and 84% for $N = 1$ and $N = 2$, respectively; in other words, it appears that doing two retransmissions instead of one reduces reliability.

TriScale's network profiling function (§ 4.6) provides additional insights. The experiment leads to this (incorrect) conclusion because we neglected a weekly seasonal component, revealed by Fig. 5: there is more interference on weekdays than weekends. To account for this dependency, we repeat the experiment but extend the span to one week, which leads to KPI values of 80% and 88% for N=1 and N=2 respectively, matching our expectations about Glossy's performance.

Conclusion. Using a high confidence level is not enough to avoid drawing wrong conclusions. Real networks exhibit short-term variations that are unpredictable and often unavoidable. This is why it is important to perform multiple runs in a series. Moreover, there may also be systematic patterns, *i.e.*, times with consistently more or less interference.

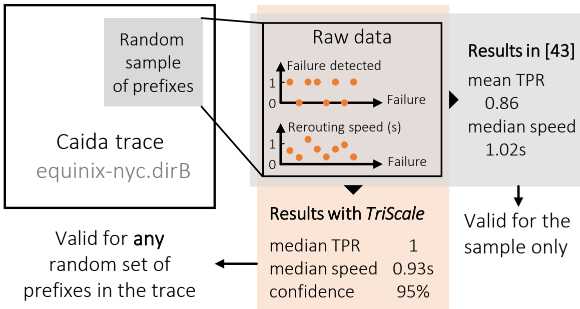


Figure 6: Using data from a sample of prefixes, *TriScale* allows to generalize and derive performance estimates for any random set of samples from the same Caida trace [27]. *See § B.3 for further details.*

Knowing about and accounting for these patterns is important to ensure fairness when comparing protocols: the span of a series should be long enough such that it does not matter when the series starts (*e.g.*, a weekend or a weekday).

6.3 Failure Detection

This case study illustrates how the methodology of *TriScale* allows to generalize performance claims for larger sets of input parameters based on a (relatively small) sample.

We focus on Blink [42], an algorithm that detects failures and reroutes traffic directly in the data plane. The authors evaluated the system performance in terms of true positive rate (TPR, *i.e.*, the fraction of failures successfully detected) and of time taken to reroute the traffic based on 15 internet traces [27, 29] containing data for thousands of prefixes. A subset of prefixes were randomly selected, based on which synthetic traces including artificial failures were generated.

Using *TriScale*, we can generalize the results: for each trace, the evaluation of Blink on one prefix can be seen as a *TriScale* run. Since the prefixes are randomly selected from a fixed set, runs are *i.i.d.* and we can use *TriScale*'s KPI to derive the expected performance of Blink for any set of prefixes (Fig. 6). § B.3 provides more details about Blink's analysis using *TriScale*: we can claim with 95% confidence that, for at least 50% of prefixes, Blink always detects link failures (TPR= 1) and reroutes traffic within 1 s of less (Fig. 8).

Conclusion. *TriScale*'s methodology can handle any source of performance variability as long as the variability source can be reasonably modelled by a stationary distribution. This allows to generalize performance claims for evaluations based on network emulation: one can randomly select input traces or system parameters, and derive the expected performance of any other random set. However, the stationarity assumption cannot be always guaranteed (*e.g.*, for cross-traffic over the internet) which is why *TriScale* includes an empirical independence test (§ 4.5).

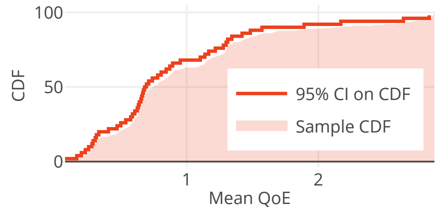


Figure 7: A CDF and its 95% CI, computed by *TriScale*. *Original CDF reproduced from [53]. The CI provides a lower-bound on the expected performance for any other random set of input traces generated in a similar way. See § B.4 for details.*

6.4 Video Streaming

This case study shows that the methodology of *TriScale* is compatible with common data reporting practices in networking, such as cumulative density functions (CDF).

For video streaming research, performance is often measured using the quality of experience (QoE) for the user as metric. The latter is used to compare state-of-the-art adaptive bitrate algorithms such as RobustMPC [80] or Pensieve [53]. Since QoE typically varies a lot, CDFs are often used to give a more global view on the performance of an algorithm. For example, Fig. 7 (shades) shows the CDF achieved by Pensieve over a static set of synthetic network traces (reproduced from [53], see § B.4). However, CDFs are no different from other metrics: what is the confidence in the result? How much would it vary with a different set of traces?

A CDF is a representation of all percentiles of a given distribution. Hence, *TriScale* can be directly used to estimate an *entire CDF* by computing a large set of KPIs. For example, Fig. 7 (solid line) shows the 95% CI for the 2th to the 98th percentile, which provides a lower-bound on the expected performance. Hence, one can claim that, for *any* set of traces that would be generated/obtained similarly, the QoE of an algorithm is better than the CI CDF with 95% confidence.

Conclusion. Thanks to the use of percentiles as KPI, *TriScale* is agnostic to the choice of metric and handles any source of variability that can be modelled as a stationary distribution.

7 DISCUSSION AND FUTURE WORK

Data collection. *TriScale* is not responsible for the execution of networking experiments: it does not perform the data collection. Frameworks such as Pantheon [79] are specialized in data collection; other examples include low-power wireless testbeds [51, 68, 69] and networking facilities [16, 34, 59]. *TriScale* can be integrated into these frameworks to create a fully-automated experimentation chain and build full-fledged benchmarking infrastructures [21].

Human-in-the-loop. *TriScale* automates the data analysis and implements tests that verify whether the required hypotheses hold. When such tests fail, it is up to the user to critically assess the reason (*e.g.*, the need for a longer runtime of *LEDBAT* illustrated in § 6.1), and derive the corresponding countermeasure (*e.g.*, pruning the start-up time in the raw data or re-running the experiments accordingly).

Ranking solutions. *TriScale* compares performance, but it does not rank. The evaluation results are always relative to a specific network or evaluation scenario. It is not trivial to generalize and claim that a solution A is better than a solution B. This problem relates to benchmarking and multi-objective optimization, which goes beyond the scope of *TriScale*.

Community guidelines. *TriScale* formalizes evaluation objectives (§ 4.4), but it does not dictate the parameters to use. Similarly, *TriScale* quantifies the variability of an experiment (§ 4.3), but it does not conclude whether it is reproducible (§ 4.7). *TriScale* provides a framework to describe evaluations and analyze the data in a consistent and statistically sound manner. It is now up to the networking communities to set their own standards, parameters to use, and acceptable requirements; as done in other disciplines [38].

8 RELATED WORK

The reproducibility of experiments and comparability of results are cornerstones of the scientific method. In recent years, several studies have highlighted the inability of scientists from various disciplines to reproduce their own experimental results [15, 61], often due to sloppy research protocols and faulty statistical analysis [20, 22, 67]. This is a problem in computer science as well [31, 76], where experiments are seldom reproducible and artifacts rarely shared.

Promoting reproducibility. To address this "reproducibility crisis" [15], many efforts aiming to incentivize a rigorous experimentation have gained momentum in computer science, including *e.g.*, ACM's badging system for publications [11]. Especially in the networking community – challenged by the need to carry out experiments on dynamic and uncontrollable conditions [26, 56] – several workshops [13, 24, 40], surveys [37], and guidelines [14, 48, 57, 66] have raised awareness on the reproducibility problem and promoted better experimentation practices. This large body of work mostly offers *qualitative* statements on how an experiment should be performed and documented. Such statements emphasize, *e.g.*, the need to carefully choose when and how often to sample data [14], or suggest which methodology to adopt during performance evaluations [48]. However, there is no guarantee that following these recommendations leads to reproducible results, nor is there a concrete way to assess whether an experiment can be considered reproducible.

In contrast, *TriScale* provides scientists with *quantitative* answers about how to concretely perform an experiment, *e.g.*, how many runs should be performed and how long they should be; answers derived by following a clear experimental methodology grounded on robust non-parametric statistics. Moreover, *TriScale* offers a way to assess and compare the reproducibility of experimental results by computing unambiguous performance indicators and variability scores.

Supporting reproducibility. A large number of experimental facilities and tools have been developed to aid scientists in carrying out reproducible networking studies [59]. Testbeds such as EmuLab [78] and FlexLab [64], as well as emulation tools such as MiniNet [41], enable the creation of artificial network conditions using a given specification or passively-observed traffic. Emulated conditions offer a more controlled environment than experiments with real-world traffic (*e.g.*, by transmitting data over the Internet [19, 30], cloud [23, 34], or wireless interfaces [12, 39, 55]). Still, they suffer from performance variability caused by the underlying hardware and software components, which hampers reproducibility [54]. To overcome these problems, several solutions have been proposed [35]: *e.g.*, revisiting OS libraries [72], using virtualization [41, 46, 47], adaptable profiles [65], and fault patterns [1]. Other tools have been developed to support mobility experiments [16, 28], maximize the repeatability of interference generation [70], and enable researchers to consistently evaluate congestion-control schemes [79].

While all aforementioned tools aim to improve reproducibility *during* the experiments, *TriScale* assists researchers *before* and *after* their execution. It does so by informing about the number and length of runs necessary to reach a given level of confidence, as well as by computing a score quantifying the variability of the results. Hence, *TriScale* complements the existing body of literature promoting and enhancing reproducibility in networking research.

In a prior workshop paper [63], we have argued that a well-defined methodology specifying how to plan, execute, and report on experimental results is of paramount importance for the networking community: *TriScale* is the concrete realization of this early vision into a tangible framework.

9 CONCLUSIONS

A consistent methodology for the design and analysis of networking experiments is crucial for a more rigorous and reproducible scientific activity. *TriScale* is the first concrete work in this direction: it implements a methodology grounded on non-parametric statistics into a framework that aids scientists in designing experiments and automating the data analysis. *TriScale* ultimately improves the legibility of results and helps quantifying the reproducibility of experiments.

We hope that *TriScale*'s open availability and usability [5, 75] will foster better experimentation practices in the short term for the networking community at large. The quest towards fully-reproducible networking experiments remains open, but we believe *TriScale* represents a first stepping stone towards an accepted standard for experimental evaluations.

This work does not raise any ethical issues.

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A DETAILS ON THE SCALABILITY EVALUATION

This appendix provides additional information about the evaluation of *TriScale*'s scalability presented in § 5.2. We perform the evaluation using a Jupyter notebook[5] (*i.e.*, an open-source web-based interactive computational environment to create and share documents containing live code, equations, visualizations, and text) that is available in the *TriScale* repository [75]. Such evaluation, which we run on a commodity laptop, yields the results summarized in Table 2.

Results – Metrics. The data shows two modes in the execution time of the *analysis_metric*() function: a step increase, followed by a slow linear increase. This can be easily explained: The more computationally expensive part of *analysis_metric*() is the convergence test, which includes the Theil-Sen regression (§ 4.5). The latter works by computing the slopes between all pairs of points and returns the median slope value; thus, the regression scales with $O(n^2)$.

However, *TriScale* does not perform the regression on the input data directly. Instead, *TriScale* divides the input data in chunks. For each chunk, a metric value is computed, leading to a new data series of metric values. The purpose of the convergence test is to verify that these metric values have converged; thus *TriScale* executes the Theil-Sen regression on this new data series. The Theil-Sen regression does not require many samples for producing a reliable result; a few tens of data points are often considered sufficient [9]. Thus, we can cap the size of metric data series (*TriScale* caps it to 100 values – § 4.1), which bounds the execution time of the Theil-Sen regression. Ultimately, this allows the *analysis_metric*() function to scale very well with the sample size.

The linear increase for a large number of raw samples is due to the computation of the metric on increasingly large chunks. The more complex the metric is, the longer the execution time. In this evaluation, a percentile is used as metric, which is computed efficiently with NumPy [2].

Overall, running *analysis_metric*() takes about 1 s for up to one million data points. The data collection time depends on the networking experiment, but it is unlikely that many experiments would produce much more than a million of data points per second. Thus, we conclude that the computation time of the *analysis_metric*() function is negligible for networking experiments.

Results – KPIs. The data shows a clear linear correlation between the sample size and the execution time of the *analysis_kpi*() function, which is not surprising: most computations are related to the determination of the confidence interval using Thompson's method, which is an iterative process through the ordered data samples [74].

Table 2: Scalability evaluation. *TriScale data analysis is fast and scales well with increasing input sizes. The most time-consuming element is the convergence test (§ 4.5) which is performed before the computation of metrics. Still, it generally takes less than one second for inputs (i.e., the number of raw measurements in a run) of up to one million data points.*

Computation of	Input size	Execution time (approx.)
Metrics	1000	20 ms
	10'000	50 ms
	1 M	1 s
KPIs and Variability scores	100	10 ms
	1000	100 ms

The input size for the KPI computation is the number of series one performs for an experiment. Our results show it takes less than 100 ms for an input size of 1000; we thus conclude that the computation time of the *analysis_kpi*() function is negligible for networking experiments.

Results - Variability scores. Unsurprisingly, the data is very similar as for *analysis_kpi*(): The two functions essentially perform the same computations. They only differ in the generation of outputs (logs and plots). Since the outputs are not considered in this scalability evaluation, we obtain very similar results for both functions. Thus, we conclude that the computation time of the *analysis_variability*() function is negligible for networking experiments.

B DETAILS ON CASE STUDIES

This appendix provides details on the four case studies presented in § 6; in particular, it details each evaluation scenario and how we have obtained the data. All case studies are performed using Jupyter notebooks, which are available in the *TriScale* repository [75].

B.1 Congestion Control

Reproducing the case study. The entire case study is described in detail in a Jupyter notebook[6] which is available in the *TriScale* repository [75].

Evaluation scenario. This case study compares the performance of 17 congestion-control schemes using Pantheon [79]. We evaluate the throughput and one-way delay of full-throttle flows, *i.e.*, stable flows whose only throttling/limiting factor is the congestion control. For a fair comparison between the schemes, we use the MahiMahi emulator [58] (integrated in Pantheon) and focus on a single flow scenario. We use only

[5] triscale_scalability.ipynb

[6] casestudy_congestion-control.ipynb

the calibrated path from AWS California to Mexico, provided by Pantheon.[7]

Data collection. We build the Pantheon toolchain from the source code provided by the authors[8] and test all schemes locally based on the aforementioned emulated network. We only modify the authors' code to save the throughput and delay raw data, such that we can do the analysis of runs using *TriScale*. We perform two sets of experiments with always 10 runs per series:

- A set of 5 series with a runtime of 30 s.
- A set of series with a runtime of 10, 20, 40, 50, and 60 s, respectively (one of each).

The data we collected are available on Zenodo [6].

B.2 Wireless Embedded Systems

Reproducing the case study. The entire case study is described in detail in a Jupyter notebook[9] which is available in the *TriScale* repository [75].

Evaluation scenario. We run a simple evaluation of Glossy [36], a low-power wireless protocol which includes as parameter the number of retransmissions of each packet, called N. We investigate the impact of two values of N on the reliability of Glossy, measured as the packet reception ratio (PRR). During one communication round, every node in the network initiates in turn a Glossy flood and all the other nodes log whether they successfully received the packet. This is repeated with for $N = \{1, 2\}$. In addition,

- The evaluation runs on TelosB motes[10] (26 nodes).
- The motes use radio frequency channel 22 (2.46 GHz, which largely overlaps with Wi-Fi traffic).
- The payload size is set to 64 bytes.

Data collection. We perform the experiments using the FlockLab testbed [51].[11] For both settings of the number of retransmissions N, we perform 24 randomly scheduled tests per day during 7 consecutive days. The data we collected are available on Zenodo [6].

B.3 Failure Detection

Reproducing the case study. The entire case study is described in detail in a Jupyter notebook[12] which is available in the *TriScale* repository [75].

Evaluation scenario. This case study re-uses one of the evaluation scenarios from the original Blink paper (§6.1 in [42]). It considers 15 publicly available real Internet traces [27, 29]. For each trace, 30 prefixes are randomly selected among those that contain sufficiently many active flows. For each prefix, the characteristics of the traffic are extracted and used to run simulations where traffic sources generate flows exhibiting the same distribution of parameters than the one extracted from the real traces. Artificial failures are introduced in the simulation, which Blink tries to detect. Blink is compared against two baseline strategies.

- *All flows*, which monitors up to 10k flows for each prefix and reroutes if at least 32 of them sees retransmissions within the same time window. This strategy provides an upper-bound on Blink's ability to reroute upon actual failures but ignores memory constraints.
- *Infinite Timeout*, which is a variant of Blink where flows are only evicted when they terminate (with a FIN packet) and never because of the flow eviction timeout. This strategy tests the effectiveness of Blink's flow eviction policy.

Data collection. The authors of Blink kindly provided the data they collected for the original paper [42]. The data are now available on Zenodo [6].

Evaluation objectives. Each prefix is used to generate five failure scenarios, based on which we compute two metrics: (i) the true positive rate (TPR), *i.e.*, the ratio of failures that Blink successfully detects (out of 5); (ii) the median rerouting speed, *i.e.*, the time Blink takes to reroute traffic once it detects the failure. For both metrics, we use the 95% CI on the median as KPI, computed over the set of prefixes for each Internet trace.

Results. Blink achieves a TPR KPI of one for all the Internet traces, with a rerouting speed ranging between 0.5 to 1 s (Fig. 8). Hence, we can claim with 95% confidence that these are the minimal performance expected for Blink for any random set of prefixes within each of the Internet trace.

B.4 Video Streaming

Reproducing the case study. The entire case study is described in detail in a Jupyter notebook[13] which is available in the *TriScale* repository [75].

Evaluation scenario. This case study re-uses one of the evaluation scenarios from the original Pensieve paper (§5.2 in [53]). Specifically, it compares Pensieve against pre-existing adaptive bitrate algorithms using different quality of experience (QoE) metrics. The comparison is performed using the MahiMahi [58] network emulator by replaying a set of synthetic traces generated from real-world broadband datasets. We consider the set of traces generated from the

[7] pantheon.stanford.edu/result/6539/
[8] github.com/StanfordSNR/pantheon
[9] casestudy_glossy.ipynb
[10] www.advanticsys.com/shop/mtmcm5000msp-p-14.html
[11] flocklab.ethz.ch
[12] casestudy_failure-detection.ipynb
[13] casestudy_video-streaming.ipynb

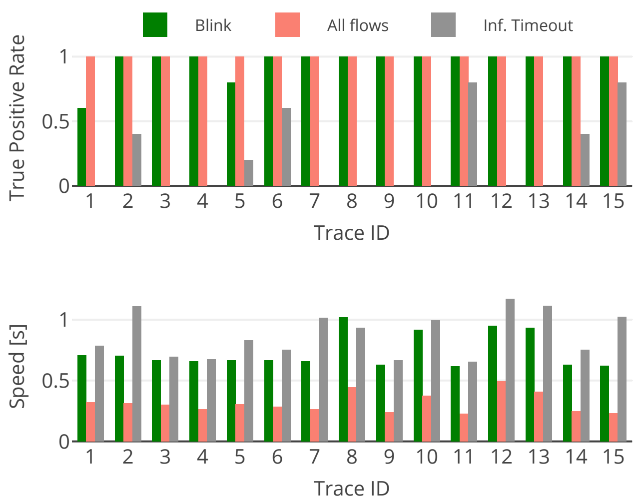

Figure 8: KPIs for Blink's performance evaluation. *95% CI on the median. Internet trace IDs listed in [42], §E.*

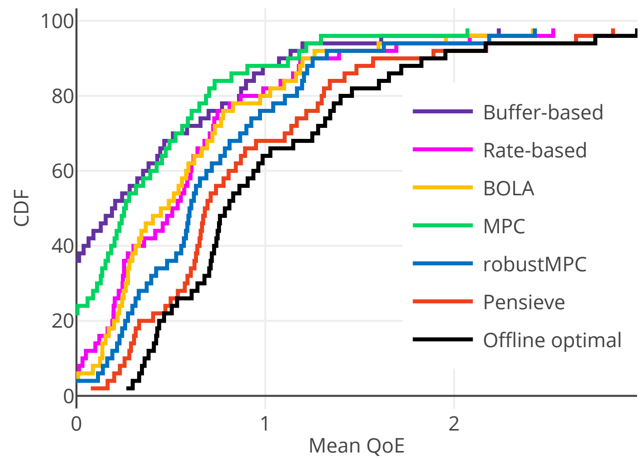

Figure 9: 95% CI on the CDF of various adaptive bitrate algorithms.

FCC dataset;[14] these traces were created by the Pensieve authors by concatenating randomly selected traces from the "Web browsing" category in the August 2016 collection. There are multiple definitions of QoE: we consider the "linear" one (see [53] for details).

Data collection. The authors of Pensieve were not able to provide the data they collected for the original paper [53]. Consequently, we retrieved the QoE data directly from the paper plots using a web-based application.[15] The data we retrieved are available on Zenodo [6].

Evaluation objectives. From the QoE metric values, we compute the 95% CI (lower-bound) for the $\{2, 4, 6 \ldots 98\}$th percentiles, based on which we obtain a 95% CI for the entire CDF of QoE for the different algorithms.

Results. Fig. 9 shows the 95% CI CDFs computed for the linear QoE metric. The 95% CI are relatively close to the empirical CDFs, as illustrated in Fig. 7, which shows both the empirical CDF and its 95% CI for Pensieve (the same applies to all algorithms).

[14] Federal Communications Commission. https://www.fcc.gov/reports-research/reports/

[15] apps.automeris.io/wpd/