Distributed Momentum for Byzantine-resilient Stochastic Gradient Descent

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Abstract

Byzantine-resilient Stochastic Gradient Descent (SGD) aims at shielding model training from *Byzantine faults*, be they ill-labeled training datapoints, software/hardware bugs, or malicious worker nodes in a distributed setting. Two recent attacks have been challenging state-of-the-art defenses though, often successfully precluding the model from even fitting the training set. The main identified weakness of current defenses is their requirement of a sufficiently low *variance-norm* ratio for the stochastic gradients. We propose a practical method which, despite increasing the variance, reduces the *variance-norm* ratio, mitigating the identified weakness. We assess the effectiveness of our method over 736 different training configurations, comprising the 2 state-of-the-art attacks and 6 defenses. For confidence and reproducibility purposes, each configuration is run 5 times, with seeds 1 to 5, totalling 3680 runs. In our experiments, when the attack is effective enough to decrease the highest observed top-1 cross-accuracy by at least 20% compared to the *unattacked* run, our technique systematically increases back the highest observed accuracy, and is able to recover at least 20% in more than 60% of the cases.

1 Introduction

Stochastic Gradient Descent (SGD) is one of the main driving forces behind the successes of machine learning. Scaling SGD can mean aggregating more but inevitably less well-sanitized data, and distributing the training over several machines, making SGD even more vulnerable to *Byzantine faults*: corrupted/malicious training datapoints, software bugs, etc. Many *Byzantine-resilient* techniques have been proposed to keep SGD safer from these faults, e.g. Alistarh et al. (2018); Damaskinos et al. (2018); Yang & Bajwa (2019b); TianXiang et al. (2019); Bernstein et al. (2019); Yang & Bajwa (2019a); Yang et al. (2019); Rajput et al. (2019); Muñoz-González et al. (2019). These techniques mainly use the same adversarial model (Figure 2): a central, trusted parameter server distributing gradient computations to several workers, a minority of which is controlled by an adversary and can submit arbitrary gradients.

Two families of defense techniques can be distinguished. The first employs *redundancy* schemes, inspired by coding theory. This approach has strong resilience guarantees, but its requirement to share data between workers makes this approach unsuitable for several classes of applications, e.g. when data cannot be shared for privacy, scalability or legal reasons. The second family uses *statistically-robust* aggregation schemes, and is the focus of this paper. The underlying idea is simple. At each training step, the server aggregates the stochastic gradients computed by the workers into one gradient, using a function called a Byzantine-resilient *Gradient Aggregation Rule* (GAR). These statistically-robust GARs are designed to produce at each step a gradient that is expected to decrease the loss.

Intuitively, one can think of this second family as different formulations of the multivariate median. In particular, if the non-Byzantine gradients were all equal at each step, any different (adversarial) gradient would be rejected by each of these medians, and no attack would succeed. But due to their stochastic nature, the non-Byzantine gradients are different: their *variance* is strictly positive. Formal guarantees on any given statistically-robust GAR typically require that the *variance-norm* ratio, the ratio between the *variance* of the non-Byzantine gradients and the *norm* of the *expected* non-Byzantine gradient, remains below a

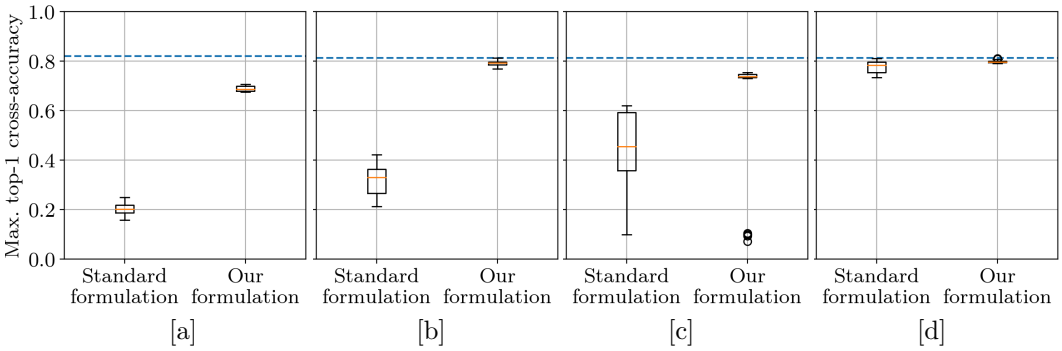

Figure 1: We report on the highest measured top-1 cross-accuracy while training under either of the two studied, state-of-the-art attacks. [a, b]: a convolutional model (Section 4.1) for CIFAR-10 under the attack from Baruch et al. (2019), and [c, d]: a fully connected model for Fashion-MNIST (Xiao et al., 2017) under the attack from Xie et al. (2019a). Roughly half the workers implements the attack in [a, c], and a quarter does in [b, d]; see Section 4.1. Each experiment is run 5 times. The dotted blue line is the median of the maximum top-1 cross-accuracy of the 5 runs without attack, and the boxes aggregate the maximum top-1 cross-accuracies obtained under attack with each 5 runs of the 6 studied defenses. Over 736 different combinations of attacks, defenses, datasets, etc (totalling of 3680 runs), our method consistently obtain at least similar, if not substantially *better performances* (lower minimal loss, higher maximal top-1 cross-accuracy) than the standard formulation. Notably, our formulation obtains these results with no additional computational complexity.

certain constant (constant which depends on the GAR itself and fixed hyperparameters). Intuitively, this notion of *variance-norm* ratio can be comprehended quite analogously to the inverse of the *signal-to-noise* ratio (i.e. the *"noise-to-signal"* ratio) in signal processing.

However, Baruch et al. (2019) noted that an attack could send gradients that are close to non-Byzantine *outlier* gradients, building an apparent majority of gradients that could be sufficiently far from the expected non-Byzantine gradient to *increase* the loss. This can happen against most statistically-robust GARs in practice, as the *variance-norm* ratio is often *too* large for them. Two recent attacks (Baruch et al., 2019; Xie et al., 2019a) were able to exploit this fact to substantially hamper the training process (which our experiments confirm).

The work presented here aims at (substantially) improving the resilience of statistically robust GARs "also in practice", by reducing the *variance-norm* ratio of the gradients received by the server. We do that by taking advantage of an old technique normally used for acceleration: momentum. This technique is regularly applied at the server, but instead we propose to confer it upon each distributed worker, effectively making the Byzantine-resilient GAR aggregate *accumulated* gradients. Crucially, there is no computational complexity attached to our reformulation: it only *reorders* operations in existing (distributed) algorithms.

Contributions. Our main contributions can be summarized as follows:

- A reformulation of classical/Nesterov *momentum* which can significantly improve the effectiveness (Figure 1) of any statistically-robust *Gradient Aggregation Rule* (GAR). We formally analyze the impact of our reformulation on the *variance-norm* ratio of the aggregated gradients, ratio on which the studied GARs assume an upper bound.
- An extensive and reproducible[1] set of experiments substantiating the effectiveness of our reformulation of momentum in improving existing defenses against state-of-the-art attacks.

Paper Organization. Section 2 provides the necessary background. Section 3 presents our distributed momentum scheme and provides some intuitions on its effects. Formal developments of these intuitions are given in the appendix. Section 4 describes our experimental settings in details, before presenting and analysing some of our experimental results. The appendix reports on the entirety of our experiments, and details how they can be reproduced (in one command, graphs included). Section 5 discusses related and future work.

[1]Namely: $736 \times 5 = 3680$ seeded runs, and one single script to reproduce all of our results.

2 Background

2.1 Byzantine Distributed SGD

Stochastic Gradient Descent (SGD). We consider the classical problem of optimizing a non-convex, differentiable loss function $Q : \mathbb{R}^d \to \mathbb{R}$, where $Q(\theta_t) \triangleq \mathbb{E}_{x \sim \mathcal{D}}[q(\theta_t, x)]$ for a fixed data distribution $\mathcal{D}$. Ideally, we seek θ^* such that $\theta^* = \arg\min_\theta (Q(\theta))$.

We employ *mini-batch SGD* optimization. Starting from initial parameter $\theta_0 \in \mathbb{R}^d$, at every step $t \geq 0$, b *samples* $\left(x_t^{(1)} \ldots x_t^{(b)}\right)$ are sampled from $\mathcal{D}$ to estimate one *stochastic gradient* $g_t \triangleq \frac{1}{b} \sum_{k=1}^{b} \nabla q\left(\theta_t, x_t^{(k)}\right) \approx \nabla Q(\theta_t)$. This stochastic gradient is then used to update the *parameters* θ_t, with: $\theta_{t+1} = \theta_t - \alpha_t \, g_t$. The sequence $\alpha_t > 0$ is called the *learning rate*.

Classical and Nesterov momentum One field-tested amendment to mini-batch SGD is *classical momentum* (Polyak, 1964), where each gradient keeps an exponentially-decreasing effect on every subsequent update. Formally: $\theta_{t+1} = \theta_t - \alpha_t \sum_{u=0}^{t} \mu^{t-u} g_u$, with $0 < \mu < 1$.

Nesterov (1983) proposed another revision. Noting v_t the *velocity vector*, $v_0 = 0$, formally:

$$v_{t+1} = \mu \, v_t + \frac{1}{b} \sum_{k=1}^{b} \nabla q\left(\theta_t - \alpha_t \, v_t, x_t^{(k)}\right)$$
$$\theta_{t+1} = \theta_t - \alpha_t \, v_{t+1}$$

Compared to classical momentum, the gradient is estimated at $\theta_t - \alpha_t \, v_t$ instead of θ_t.

Distributed SGD with Byzantine workers. We follow the parameter server model (Li et al., 2014): one single process (the *parameter server*) holding the parameter vector $\theta_t \in \mathbb{R}^d$, and n other (the *workers*) estimating gradients. Among these n workers, up to $f < n$ are said *Byzantine*, i.e. adversarial. Unlike the other $n - f$ *honest* workers, these f *Byzantine* workers can submit arbitrary gradients (Figure 2).

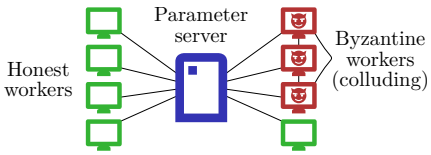

Figure 2: A parameter server setup with $n = 8$ workers, among which $f = 3$ are *Byzantine* (i.e., adversarial) workers. A black line represents a bidirectional communication channel.

At each step t, the parameter server receives n different gradients $g_t^{(1)} \ldots g_t^{(n)}$, among which f are arbitrary (submitted by the Byzantine workers). So the update equation becomes: $\theta_{t+1} = \theta_t - \alpha_t \, G_t$, where:

$$G_t \triangleq \sum_{u=0}^{t} \mu^{t-u} F\left(g_u^{(1)}, \ldots, g_u^{(n)}\right) \tag{1}$$

Function F is called a *Gradient Aggregation Rule* (GAR). In non-Byzantine settings, averaging is used; formally: $F\left(g_t^{(1)}, \ldots, g_t^{(n)}\right) = \frac{1}{n} \sum_{i=1}^{n} g_t^{(i)}$. In the presence of Byzantine workers, a more robust aggregation is performed with a *Byzantine-resilient* GAR. Sections 2.2 and 2.3 respectively describe the 6 existing GARs and 2 attacks studied in this paper.

Adversarial Model. The goal of the adversary is to impede the learning process, which is defined as the maximization of the loss Q or, more judiciously for the image *classification tasks* tackled in this paper, as the minimization[2] of the model's top-1 cross-accuracy. The adversary cannot directly overwrite θ_t at the parameter server. The adversary only submits f arbitrary gradients to the server per step, via the f Byzantine workers it controls[3]. We assume an omniscient adversary. In particular, the adversary knows the GAR used by the parameter server and, at each step, the adversary can generate Byzantine gradients dependent on the honest gradients submitted at the same step and any previous step.

[2]Exempli gratia, with 10 classes, the worst possible final accuracy is 0.1.
[3]Said otherwise, the f Byzantine workers can collude.

2.2 Byzantine-resilient GARs

We briefly present below the 6 studied GARs. A more formal presentation, along with the theoretical guarantees of some of these GARs, is provided in the appendix (Section A). Let n be the number of gradients the parameter server received from the n workers (Figure 2), and let f be the maximum number of Byzantine gradients the GAR must be able to tolerate.

Median (Yin et al., 2018). The coordinate-wise median of the n received gradients.

Krum (Blanchard et al., 2017). Each received gradient is assigned a score. The score of gradient x is the sum of the squared ℓ_2-distances between x and the $n-f-2$ closest gradients to x. The aggregated gradient is then the arithmetic mean of the $n-f-2$ gradients with the smallest scores. This variant is called *Multi-Krum* in the original paper.

Trimmed Mean (Yin et al., 2018). The coordinate-wise trimmed-mean of the n received gradients. The *trimmed-mean* of a vector of n values is the arithmetic mean, after the f smallest and the f largest values have been discarded, of the remaining values.

Phocas (Xie et al., 2018b). The coordinate-wise arithmetic mean of the $n-f$ closest values to the coordinate-wise trimmed-mean.

MeaMed (Xie et al., 2018a). Same as *Phocas*, but with median replacing trimmed-mean.

Bulyan (El-Mhamdi et al., 2018). This is a *composite* aggregation rule that iterates on another GAR in a first selection phase. *Bulyan* uses *Krum*, so this first phase selects $n-2f-2$ gradients, at each iteration removing the highest scoring gradient. The aggregated gradient is the coordinate-wise arithmetic mean of the $n-4f-2$ closest values to the (coordinate-wise) median of the selected gradients.

2.3 Studied Attacks

The two state-of-the-art attacks, that recently appeared in the literature, follow the same core principle. Let $\varepsilon \in \mathbb{R}_{\geq 0}$ be a non-negative factor, and $a_t \in \mathbb{R}^d$ an *attack vector* which value depends on the actual attack used (see below for possible values of a_t). At each step t, each of the f Byzantine workers submits the same Byzantine gradient: $\overline{g_t} + \varepsilon\, a_t$, where $\overline{g_t}$ is an approximation of the real gradient $\nabla Q\left(\theta_t\right)$ at step t. The value of ε is fixed (see below).

A Little is Enough (Baruch et al., 2019). In this attack, each Byzantine worker submits $\overline{g_t} + \varepsilon\, a_t$, with $a_t \triangleq -\sigma_t$ the opposite of the coordinate-wise standard deviation of the honest gradient distribution $\mathcal{G}_t$. Our experiments use $\varepsilon = 1.5$, as proposed by the original paper.

Fall of Empires (Xie et al., 2019a). Each Byzantine worker submits $(1-\varepsilon)\,\overline{g_t}$, i.e., $a_t \triangleq -\overline{g_t}$. The original paper tested $\epsilon \in \{-10, -1, 0, 0.1, 0.2, 0.5, 1, 10, 100\}$, our experiments use[4] $\varepsilon = 1.1$, corresponding in the notation of the original paper to $\epsilon \triangleq -\left(1-\varepsilon\right) = -\left(1-1.1\right) = 0.1$.

3 Momentum at the Workers

Intuitively, the Byzantine-resilient GARs (Section 2.2) rely on the honest gradients being sufficiently *clumped* (formalized in e.g. Equation 3 and Equation 4). In the edge case where every honest gradient is equal (i.e. no stochastic noise), no attack can affect the learning: there is by assumption a strict majority of identical honest gradients. On the contrary when the honest gradients are "spread", i.e. their variance is *large enough* compared to their norms, the attack vectors can form a majority by relying on a few outlier (but honest) gradients (Baruch et al., 2019), and so substantially influence the aggregated gradient.

Momentum makes the parameters θ_t travel down the loss function with *inertia*, accumulating both the *real* gradient $\nabla Q\left(t\right)$ and the *error* (i.e. here, the *stochastic noise*) $g_t - \nabla Q\left(t\right)$. Intuitively, the accumulation of *errors* grows at a moderate rate, as past errors can be partially compensated by future ones. But when consecutive $\nabla Q\left(t\right)$ have sufficiently low solid angles, past real gradients do not compensate future real gradients: the *norm* of G_t can grow "faster" (for each new step) than its *variance*, mitigating the potential impact of an attack.

[4]This factor made this attack consistently successful in the original paper.

3.1 Formulation

From the formulation of *momentum SGD* in a distributed setting (Equation 1):

$$G_t \triangleq \sum_{u=0}^{t} \mu^{t-u} F\left(g_u^{(1)}, \ldots, g_u^{(n)}\right)$$

we instead confer the momentum computation on the workers:

$$G_t \triangleq F\Bigg(\underbrace{\sum_{u=0}^{t} \mu^{t-u} g_u^{(1)}}_{G_t^{(1)}}, \ldots, \underbrace{\sum_{u=0}^{t} \mu^{t-u} g_u^{(n)}}_{G_t^{(n)}}\Bigg) \tag{2}$$

Notations. In the remaining of this paper, we call the original formulation *(momentum) at the server*, and the proposed, revised formulation *(momentum) at the worker(s)*. The quantities $G_t^{(1)} \ldots G_t^{(n)}$ will be called the *submitted gradients* (at step t). At step t, the *variance-norm* ratio is computed on the honest subset of: $g_t^{(1)} \ldots g_t^{(n)}$, if momentum at the server is employed, otherwise $G_t^{(1)} \ldots G_t^{(n)}$, if momentum at the workers is used instead.

Formal analysis. The formal analysis of the impact of our technique on the *variance-norm* ratio of the aggregated gradients is available in the appendix, Section B.2.

4 Experiments

Our experiments cover 2 models, 4 datasets, the 6 studied defenses under each of the 2 state-of-the-art attacks[5], different fractions of Byzantine workers (either *half* or *a quarter*), using Nestorov instead of classical momentum, plus unattacked settings where each worker is honest and the GAR is mere *averaging*. Since our theoretical results (Section B.1) suggest that smaller learning rates may reduce the *variance-norm* ratio, two learning rate schedules (an *optimal* and a *smaller* one) are also tested. For reproducibility and confidence in the empirical benefits of our reformulation, we test every combination of the hyperparameters mentioned above, and each combination is repeated 5 times with fixed *seeds* 1 to 5 (totally 3680 runs).

The tools we developed to implement our reformulation captures $\sim$20 metrics, including the evolution of the average loss, top-1 cross-accuracy and *variance-norm* ratio of the submitted gradients. In this section and Section D, we specifically report on these 3 metrics.

4.1 Experimental Setup

We use a compact notation to define the models: L(#outputs) for a fully-connected linear layer, R for ReLU activation, S for log-softmax, C(#channels) for a fully-connected 2D-convolutional layer (kernel size 3, padding 1, stride 1), M for 2D-maxpool (kernel size 2), B for batch-normalization, and D for dropout (with fixed probability 0.25).

We use the models from respectively Baruch et al. (2019) and Xie et al. (2019a):

	Fully connected	***Convolutional***
Model	(784)-L(100)-R-L(10)-R-S	(3, 32×32)-C(64)-R-B-C(64)-R-B-M-D- -C(128)-R-B-C(128)-R-B-M-D- -L(128)-R-D-L(10)-S
Datasets	MNIST, Fashion MNIST (83 samples/gradient)	CIFAR-10, CIFAR-100 (50 samples/gradient)
#workers	$n = 51 \quad f \in \{24, 12\}$	$n = 25 \quad f \in \{11, 5\}$

For model training, we use the *negative log likelihood* loss and respectively 10^{-4} and 10^{-2} ℓ_2-regularization for the *fully connected* and *convolutional* models. We also clip gradients, en-

[5]To the best of our knowledge, putting aside simple attacks (e.g. sending attack gradients sampled from a Gaussian distribution) tested in each defense papers, no other attack has been published.

suring their norms remain respectively below 2 and 5 for the *fully connected* and *convolutional* models. Regarding evaluation, we use the *top-1 cross-accuracy* over the whole test set.

Datasets are pre-processed before training. MNIST receives the same pre-processing as in Baruch et al. (2019): an input image normalization with mean 0.1307 and standard deviation 0.3081. Fashion MNIST, CIFAR-10 and CIFAR-100 are all expanded with horizontally flipped images. For both CIFAR-10 and CIFAR-100, a per-channel normalization with means 0.4914, 0.4822, 0.4465 and standard deviations 0.2023, 0.1994, 0.2010 (Liu, 2019) has been applied.

We denote by f the number of Byzantine workers either to the maximum for which *Krum* can be used (roughly an half: $f = \lfloor \frac{n-3}{2} \rfloor$), or the maximum for *Bulyan* (roughly a quarter, $f = \lfloor \frac{n-3}{4} \rfloor$). The attack factors ε_t (Section 2.3) are set to constants proposed in the literature, namely $\varepsilon_t = 1.5$ for Baruch et al. (2019) and $\varepsilon_t = 1.1$ for Xie et al. (2019a). We also experiment two different learning rates. The first and largest is selected so as to maximize the *performance* (highest final cross-accuracy and accuracy gain per step) of the model trained without Byzantine workers. The second and smallest is chosen so as to minimize the *performance loss* under attack, without substantially impacting the final accuracy when trained without Byzantine workers. The *fully connected* and *convolutional* models are trained respectively with $\mu = 0.9$ and $\mu = 0.99$. These values were obtained by trial and error, to maximize the accuracy gain per step when there is no attack.

Reproducibility. Particular care has been taken to make our results reproducible. Each of the 5 runs per experiment are respectively seeded with seed 1 to 5. For instance, this implies that two experiments with same seed and same model also starts with the same parameters θ_0. To further reduce the sources of non-determinism, the CuDNN backend is configured in deterministic mode (our experiments ran on two *GeForce GTX 1080 Ti*) with benchmark mode turned off. We also used *log-softmax + nll loss*, which is equal to *softmax + cross-entropy loss*, but with improved numerical stability on PyTorch. We provide our code along with a script reproducing *all* of our results, both the experiments and the graphs, in one command. Details, including software and hardware dependencies, are available in the appendix.

4.2 Experimental Results

This section reports on the evolution of the average loss, top-1 cross-accuracy and *variance-norm* ratio of the submitted gradients. Section D in the appendix includes all our results.

One first important remark is that our new formulation either obtain similar, or (subtantially) increased maximum top-1 cross-accuracy measured, compared to the standard formulation in the exact same settings. Namely, in only 4 pairs of runs (0.23% of all the tested pairs) did our formulation lead to a decreased maximum top-1 cross-accuracy. Also, these decreases were only observed with the *fully connected* model, using *Krum* against Xie et al. (2019a), and for each of these 4 runs using any of the 4 other seeds made the decrease disappear.

In all our experiments, we observe a strong correlation between higher top-1 cross-accuracies and lower average losses; e.g. see Figure 4. The two state-of-the-art attacks decreased the accuracy by at least 20%, compared to the unattacked case (see "No attack" in Figure 3), in 25.80% and 70.80% of the runs with respectively the *fully connected* and *convolutional* models.

Focusing on the *convolutional* model, when roughly *an half* of the workers are Byzantine, both attacks actually succeed in decreasing the accuracy by at least 20% in 100% of our runs. Our technique manages to recover at least 10% and 20% in respectively 79.75% and 49.25% of these runs. When roughly *a quarter* of the workers are Byzantine, the attacks decrease the accuracy by at least 20% in 46.46% of our runs. Our technique then manages to recover at least 20% in 95.07% of these runs. Figure 3 shows a fraction of these runs.

Technically, our reformulation aims at reducing the *variance-norm* ratio of the aggregated gradients. Intuitively, this ratio is expected to increase as the loss decreases; more correctly as the norm of the gradient decreases. For instance, Figure 5 displays the *variance-norm* ratios of *Trimmed Mean* and *Bulyan* using the same settings as in Figure 4. At least before the final cross-accuracies are reached, our technique consistently decreases the *variance-norm* ratio of the aggregated gradients. Also, we consistently observed in the experiments that reducing the learning rate indeed reduces the *variance-norm* ratio (e.g. Figure 5, $t \geq 1500$).

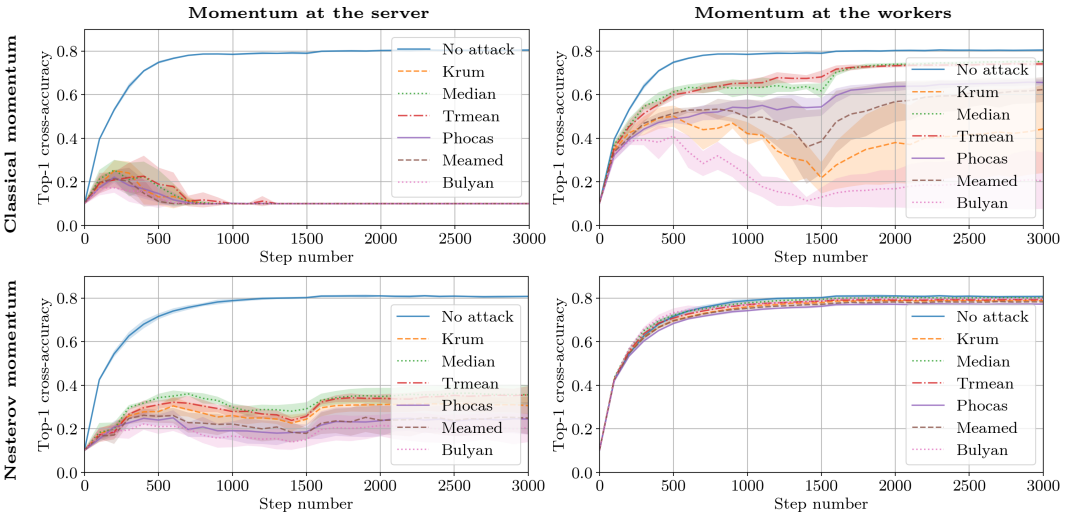

Figure 3: CIFAR-10 and the *convolutional* model (Section 4.1), with $n = 25$, $f = 5$ and $\alpha_t = 0.01$ if $t < 1500$ else $\alpha_t = 0.001$, under attack from (Baruch et al., 2019). Each line and colored surface correspond to respectively the average and standard deviation of the top-1 cross-accuracy over 5 seeded runs. Only two parameters change between graphs: where momentum is computed (*at the server* or *at the workers*), and which flavor of momentum is employed.

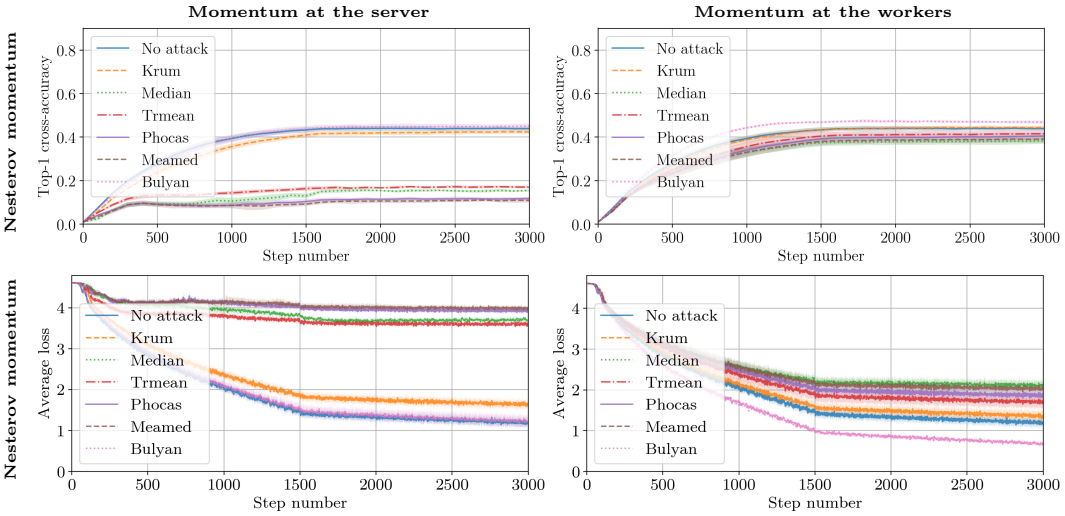

Figure 4: Accuracy and average loss, CIFAR-100 and the *convolutional* model, with $n = 25$, $f = 5$ and $\alpha_t = 0.01$ if $t < 1500$ else $\alpha_t = 0.001$, under attack from (Xie et al., 2019a).

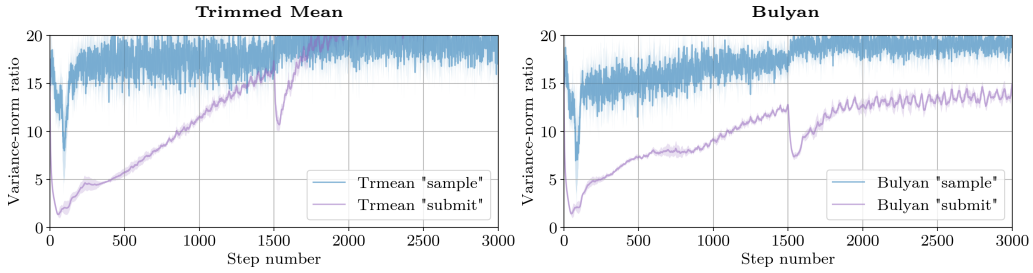

Figure 5: Same settings as in Figure 4, *variance-norm* ratios of *Trimmed Mean* and *Bulyan* with *momentum at the workers*. "sample" corresponds to the *variance-norm* ratio of the sampled gradients, and "submit" to the *variance-norm* ratio of the *submitted gradients*.

5 Related and future work

Alternative Byzantine-resilient Approaches. The Byzantine abstraction is a very general fault model that has long been studied in distributed computing (Lamport et al., 1982). The standard, golden solution for Byzantine fault tolerance is the *state machine replication* approach (Schneider, 1990). This approach is however based on *replication*, which is known to be unsuitable for distributed machine learning and stochastic gradient descent.

Chen et al. (2018) was the first Byzantine-resilient mechanism based on a *redundancy* scheme rather than statistical robustness. While the proposed mechanism is not vulnerable to the attacks discussed in this paper, it induces (due to the redundancy) substantial computational costs compared to statistically-robust techniques. Rajput et al. (2019) combines Chen et al. (2018) with statistically-robust GARs into a *hybrid* system, and achieves an improved aggregation time. Under the requirements of both redundancy-based schemes and statistically-robust GARs, Rajput et al. (2019) can significantly decrease the voting power of the adversary, and can consequently also deflect attacks in these cases. Xie et al. (2019b), and its follow-up (Xie, 2019), introduced the concept of *suspicion-based* fault-tolerance: the parameter server uses the loss of each received gradient to assign it a score. The lowest scoring gradients are then filtered-out, and the remaining gradients are averaged and used to update the model.

Momentum-based Variance Reduction. Our algorithm is different from Cutkosky & Orabona (2019), as instead of reducing the variance of the gradients, we actually *increase* it (Equation 6). What we seek to reduce is the *variance-norm* ratio, which is the key quantity for any Byzantine-resilient GAR approximating a high-dimensional median, e.g. *Krum*, *Median*, as well as Yang & Bajwa (2019b;a); Chen et al. (2017); Muñoz-González et al. (2019)[6]. Some of the ideas introduced in Cutkosky & Orabona (2019) could nevertheless help further improve Byzantine resilience. For instance, introducing an adaptive learning rate which decreases depending on the curvature of the parameter trajectory is an appealing approach to further reduce the *variance-norm* ratio (Equation 8). The computation of momentum *at the workers* has also been used in the literature for the purpose of *gradient compression* (Lin et al., 2018). These techniques are nevertheless not (meant to be) Byzantine-resilient.

Future Work. The theoretical condition to reduce the *variance-norm* ratio of the submitted gradients (compared to the *variance-norm* ratio of the sampled gradients at the same step), in Section B.2, shows that momentum at the workers is a double-edged sword. The problem is that s_t can become negative: the norm of the momentum gradient would then be *decreased*, increasing the *variance-norm* ratio. While the ability to cross narrow, local minima is recognized as an accelerator (Goh, 2017), for the purpose of Byzantine-resilience we want to ensure momentum at the workers does not increase the *variance-norm* ratio (compared to the *variance-norm* ratio of the sampled gradients at the same step). The theoretical condition for this purpose is given in Equation 7. One simple amendment would then be to use momentum at the workers when Equation 7 is satisfied, and fallback to computing it at the server otherwise. Also, a more complex, possible future approach could be to dynamically adapt the momentum factor μ, decreasing it as the curvature increases.

Asynchronous SGD. We focused in this work on the synchronous setting, which received most of the attention in the Byzantine-resilient literature. Yet, we do not see any issue that would prevent our work from being applied in asynchronous settings. Specifically, combining our idea with a filtering scheme such as *Kardam* (Damaskinos et al., 2018) is in principle possible, as this filter and momentum commute. However, further analysis of the interplay between the dynamics of stale gradients and the dynamics of momentum remain necessary.

Byzantine Servers. While most of the research on Byzantine-resilience gradient descent has focused on the workers' side, assuming a reliable server, recent efforts have started tackling Byzantine servers (El-Mhamdi et al., 2020). Our reduction of the *variance-norm* ratio strengthens the gradient aggregation phase, which is necessary whether we deal with Byzantine workers or Byzantine servers. An interesting open question is whether the dynamics of momentum could positively affect the model drift between different parameter servers in a Byzantine context. Any quantitative answer to this question could enable the use of our method in fully decentralised Byzantine resilient gradient descent.

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A Studied defenses

To assess the positive impact of our method, we deploy 2 state-of-the-art attacks against 6 Byzantine-resilient *Gradient Aggregation Rules* (GAR).

In this section, we formally present the theoretical guarantee the defenses studied in this paper provide, along with a more formal description for some of these defenses.

These GARs are *Byzantine-resilient*, a notion first introduced by Blanchard et al. (2017) under the name (α, f)-Byzantine-resilience. When used within its operating assumptions, a Byzantine-resilient GAR guarantees *convergence* even in an adversarial setting.

Definition 1. Let $(\alpha, f) \in \left[0..\frac{\pi}{2}\right[\times [0..n]$, with n the total number of workers. Without loss of generality, let $g_t^{(1)} \dots g_t^{(n-f)} \sim \mathcal{G}_t$ be $n-f$ independent, "honest" gradients following the same distribution $\mathcal{G}_t$, and let $g_t^{(n-f+1)} \dots g_t^{(n)} \in \left(\mathbb{R}^d\right)^f$ be arbitrary gradients, each possibly dependent on $\mathcal{G}_t$ and the "honest" gradients. A GAR F is said (α, f)-Byzantine resilient iff:

$$g_t \triangleq F\left(g_t^{(1)}, \dots, g_t^{(n)}\right)$$

satisfies:

1. $\left\langle \mathbb{E}\, g_t, \mathbb{E}\, g_t^{(1)} \right\rangle \geq (1 - \sin\alpha) \cdot \left\| \mathbb{E}\, g_t^{(1)} \right\| > 0$
2. $\forall r \in \{2, 3, 4\}$, $\mathbb{E}\left\|g_t\right\|^r$ is bounded above by a linear combination of the terms $\mathbb{E}\left\|g_t^{(1)}\right\|^{r_1} \dots \mathbb{E}\left\|g_t^{(1)}\right\|^{r_k}$, with $(k, r_1 \dots r_k) \in \left(\mathbb{N}^*\right)^{k+1}$ and $r_1 + \dots + r_k = r$.

A.1 Krum (Blanchard et al., 2017)

Let $(f, m) \in \mathbb{N}^2$, with $n \geq 2f + 3$ and $1 \leq m \leq n - f - 2$.

Krum works by assigning a score to each input gradient. The score of $g_t^{(i)}$ is the sum of the distances between $g_t^{(i)}$ and its $n - f - 2$ closest neighbor gradients. *Krum* outputs the arithmetic mean of the m smallest–scoring gradients[7].

In our experiments, we set m to its maximum: $n - f - 2$.

To be proven (α, f)-Byzantine resilient, besides the standard convergence conditions in non-convex optimization (Bottou, 1998), *Krum* requires the honest gradients' variance $\mathbb{E}\left\|\mathcal{G}_t - \mathbb{E}\,\mathcal{G}_t\right\|^2$ to be bounded above as follows:

$$2 \cdot \kappa(n, f) \cdot \mathbb{E}\left\|\mathcal{G}_t - \mathbb{E}\,\mathcal{G}_t\right\|^2 < \left\|\mathbb{E}\,\mathcal{G}_t\right\|^2 \tag{3}$$

$$\text{with:} \qquad \kappa(n, f) \triangleq n - f + \frac{f\,(n-f-2) + f^2\,(n-f-1)}{n-2f-2}$$

A.2 Median (Yin et al., 2018)

Let $f \in \mathbb{N}$ with $n \geq 2f + 1$.

[7]The original paper called the GAR *Multi-Krum* when $m > 1$.

Median computes the coordinate-wise median of the input gradients $g_t^{(1)} \dots g_t^{(n)}$. Formally for the real-valued median:

$$\text{median}\left(x_1 \dots x_n\right) \triangleq \underset{x \in \mathbb{R}}{\arg\min} \sum_{i=1}^{n} |x_i - x|$$

And so, formally for the coordinate–wise *Median*:

$$\text{Median}\left(g_t^{(1)} \dots g_t^{(n)}\right) \triangleq \begin{pmatrix} \text{median}\left(g_t^{(1)}[1] \dots g_t^{(n)}[1]\right) \\ \vdots \\ \text{median}\left(g_t^{(1)}[d] \dots g_t^{(n)}[d]\right) \end{pmatrix}$$

The condition of (α, f)-Byzantine resilience is:

$$(n-f) \cdot \mathbb{E}\left\|\mathcal{G}_t - \mathbb{E}\,\mathcal{G}_t\right\|^2 < \left\|\mathbb{E}\,\mathcal{G}_t\right\|^2 \tag{4}$$

A.3 Bulyan (El-Mhamdi et al., 2018)

Bulyan uses another Byzantine-resilient GAR to aggregate the input gradients. In the remaining of this paper we will consider Bulyan of *Krum*, that we will simply call *Bulyan*.

Let $(f, m) \in \mathbb{N}^2$, with $n \geq 4f + 3$ and $1 \leq m \leq n - f - 2$.

Bulyan first selects $n - 2f - 2$ gradients by iterating $n - 2f - 2$ times over *Krum*, each time removing the highest scoring gradient from the input gradient set. From these $n - 2f - 2 \geq 2f + 1$ selected gradients, *Bulyan* outputs the coordinate-wise average of the $n - 4f - 2 \geq 1$ closest coordinate values to the coordinate-wise median.

The theoretical requirements for the (α, f)-Byzantine resilience of *Bulyan* are the same as the ones of *Krum*.

B Momentum at the Workers

B.1 Formulation

From the formulation of *momentum SGD* in a distributed setting (Equation 1):

$$G_t \triangleq \sum_{u=0}^{t} \mu^{t-u} F\left(g_u^{(1)}, \dots, g_u^{(n)}\right)$$

we instead confer the momentum computation on the workers:

$$G_t \triangleq F\Bigg(\underbrace{\sum_{u=0}^{t} \mu^{t-u} g_u^{(1)}}_{G_t^{(1)}}, \dots, \underbrace{\sum_{u=0}^{t} \mu^{t-u} g_u^{(n)}}_{G_t^{(n)}}\Bigg) \tag{5}$$

B.2 Effects

We compare the *variance-norm* ratio of the non-Byzantine subset of the sampled gradients $g_t^{(1)} \dots g_t^{(n)}$ against the *variance-norm* ratio of the non-Byzantine subset of the submitted gradients $G_t^{(1)} \dots G_t^{(n)}$ when *classical* momentum is computed *at the workers*.

We denote by $\mathbb{E}\,\mathcal{G}_t \triangleq \nabla Q\left(\theta_t\right)$ the "real" gradient at step t.

Let $\lambda_t \triangleq \|\mathbb{E}\,\mathcal{G}_t\| > 0$ be the real gradient's norm at step t[8].

Let $\sigma_t \triangleq \sqrt{\mathbb{E}\left\|\mathcal{G}_t - \mathbb{E}\,\mathcal{G}_t\right\|^2}$ be the standard deviation of the real gradient at step t. The

[8] In this analysis, the expectations are by default conditioned on the past randomness (all what happened up to step t) from the $(n-f) \cdot b$ data-points sampled, at each past step, by the $(n-f)$ honest workers to estimate their respective gradients.

variance-norm ratio of the non-Byzantine subset of the sampled gradients at step t is:

$$r_t^{(s)} \triangleq \frac{{\sigma_t}^2}{{\lambda_t}^2}$$

We will now compute the *variance-norm* ratio of the non-Byzantine subset of the submitted gradients. Let $G_t^{(i)}$, with $G_{-1}^{(i)} \triangleq 0$, be the gradient sent by any honest worker i at step t, i.e.:

$$G_t^{(i)} \triangleq \sum_{u=0}^{t} \mu^{t-u} g_u^{(i)}$$

The numerator of the *variance-norm* ratio is, for any two honest worker identifiers $i \neq j$:

$$\begin{aligned}
&\mathbb{E}\left\|G_t^{(i)} - G_t^{(j)}\right\|^2 \\
&= \mathbb{E}\left\|g_t^{(i)} + \mu\, G_{t-1}^{(i)} - g_t^{(j)} - \mu\, G_{t-1}^{(j)}\right\|^2 \\
&= \mathbb{E}\left\|g_t^{(i)} - g_t^{(j)}\right\|^2 + \mu^2\, \mathbb{E}\left\|G_{t-1}^{(i)} - G_{t-1}^{(j)}\right\|^2 + \underbrace{2\,\mu \left(\underbrace{\mathbb{E}\, g_t^{(i)} - \mathbb{E}\, g_t^{(j)}}_{=\mathbb{E}\,\mathcal{G}_t - \mathbb{E}\,\mathcal{G}_t}\right) \cdot \left(\mathbb{E}\, G_{t-1}^{(i)} - \mathbb{E}\, G_{t-1}^{(j)}\right)}_{=0} \\
&= \mathbb{E}\left\|g_t^{(i)} - g_t^{(j)}\right\|^2 + \mu^2\, \mathbb{E}\left\|G_{t-1}^{(i)} - G_{t-1}^{(j)}\right\|^2 \\
&= 2\,{\sigma_t}^2 + \mu^2 \left(2\,{\sigma_{t-1}}^2 + \mu^2 \left(2\,{\sigma_{t-2}}^2 + \mu^2 \left(...\right)\right)\right) \\
&= 2 \sum_{u=0}^{t} \mu^{2(t-u)} {\sigma_u}^2 \qquad (6) \\
&= 2\, \mathbb{E}\left\|G_t^{(i)} - \mathbb{E}\, G_t^{(i)}\right\|^2
\end{aligned}$$

And the denominator of the *variance-norm* ratio is:

$$\begin{aligned}
&\left\|\mathbb{E}\, G_t^{(i)}\right\|^2 = \left\|\mathbb{E}\, g_t^{(i)} + \mu\, \mathbb{E}\, G_{t-1}^{(i)}\right\|^2 \\
&= \left\|\mathbb{E}\, g_t^{(i)}\right\|^2 + 2\,\mu\, \mathbb{E}\, g_t^{(i)} \cdot \mathbb{E}\, G_{t-1}^{(i)} + \mu^2 \left\|\mathbb{E}\, G_{t-1}^{(i)}\right\|^2 \\
&= {\lambda_t}^2 + 2\,\mu\, \mathbb{E}\, g_t^{(i)} \cdot \left(\mathbb{E}\, g_{t-1}^{(i)} + \mu \left(\mathbb{E}\, g_{t-2}^{(i)} + \mu\, \left(...\right)\right)\right) \\
&\quad + \mu^2 \left({\lambda_{t-1}}^2 + 2\,\mu\, \mathbb{E}\, g_{t-1}^{(i)} \cdot \left(\mathbb{E}\, g_{t-2}^{(i)} + \mu\, \left(...\right)\right)\right. \\
&\qquad \left. + \mu^2\, \mathbb{E}\left\|G_{t-2}^{(i)}\right\|^2\right) \\
&= \sum_{u=0}^{t} \mu^{2(t-u)} \left({\lambda_u}^2 + 2 \sum_{v=0}^{u-1} \mu^{u-v} \underbrace{\mathbb{E}\, g_u^{(i)} \cdot \mathbb{E}\, g_v^{(i)}}_{=\mathbb{E}\,\mathcal{G}_u \cdot \mathbb{E}\,\mathcal{G}_v}\right)
\end{aligned}$$

Thus, assuming honest gradients $\mathbb{E}\, G_t^{(i)}$ do not become null:

$$r_t^{(w)} \triangleq \frac{{\Omega_t}^2}{{\Lambda_t}^2} = \frac{\sum_{u=0}^{t} \mu^{2(t-u)} {\sigma_u}^2}{\sum_{u=0}^{t} \mu^{2(t-u)} \left({\lambda_u}^2 + s_u\right)}$$

where the expected "straightness" of the gradient trajectory at step u is defined by:

$$s_u \triangleq 2 \sum_{v=0}^{u-1} \mu^{u-v}\, \mathbb{E}\,\mathcal{G}_u \cdot \mathbb{E}\,\mathcal{G}_v$$

s_u quantifies what is intuitively the *curvature* of the gradient trajectory. Straight trajectories can make s_u grow up to $(1-\mu)^{-1} > 1$ times the expected squared-norm of the honest gradients, while highly "curved" trajectories (e.g. close to a local minimum) can make s_u negative.

This observation stresses that this formulation of momentum can sometimes be harmful for the purpose of Byzantine resilience. We measured s_u for every step $u > 0$ in our experiments, and we always observed that this quantity is positive and increases for a short window of (dozen) steps (depending on α_t), and then oscillates between positive and negative values. While the empirical impact (decreased or cancelled loss in accuracy) is concrete, we believe there is room for further improvements, as discussed in Section 5.

The purpose of using momentum at the workers is to reduce the *variance-norm* ratio $r_t^{(w)}$, compared to $r_t^{(s)}$. Since $g_0^{(i)} = G_0^{(i)}$, we verify that $r_0^{(u)} = r_0^{(w)}$. Then, $\forall t > 0$:

$$\begin{aligned} r_t^{(w)} \leq r_t^{(s)} &\Leftrightarrow \frac{{\sigma_t}^2 + \mu^2 {\Omega_{t-1}}^2}{{\lambda_t}^2 + s_t + \mu^2 {\Lambda_{t-1}}^2} \leq \frac{{\sigma_t}^2}{{\lambda_t}^2} \\ &\Leftrightarrow \mu^2 {\Omega_{t-1}}^2 {\lambda_t}^2 \leq \left(s_t + \mu^2 {\Lambda_{t-1}}^2\right) {\sigma_t}^2 \\ &\Leftrightarrow s_t \geq \mu^2 {\Lambda_{t-1}}^2 \left(\frac{r_{t-1}^{(w)}}{r_t^{(s)}} - 1\right) \end{aligned} \tag{7}$$

The condition for decreasing $r_t^{(w)}$ can be obtained similarly:

$$r_t^{(w)} \leq r_{t-1}^{(w)} \Leftrightarrow s_t \geq {\lambda_t}^2 \left(\frac{r_t^{(s)}}{r_{t-1}^{(w)}} - 1\right)$$

To study the impact of a lower learning rate α_t on s_t, we will assume that the real gradient ∇Q is l-Lipschitz. Namely:

$$\forall (t,u) \in \mathbb{N}^2, u < t, \left\|\mathbb{E}\,\mathcal{G}_t - \mathbb{E}\,\mathcal{G}_u\right\|^2 \leq l^2 \left\|\theta_t - \theta_u\right\| \leq l^2 \left\|\sum_{v=u}^{t-1} \alpha_v\, G_v\right\|$$

Then, $\forall (t,u) \in \mathbb{N}^2, u < t$, we can rewrite:

$$\left\|\mathbb{E}\,\mathcal{G}_t - \mathbb{E}\,\mathcal{G}_u\right\|^2 = \underbrace{\left\|\mathbb{E}\,\mathcal{G}_t\right\|^2}_{{\lambda_t}^2} + \underbrace{\left\|\mathbb{E}\,\mathcal{G}_u\right\|^2}_{{\lambda_u}^2} - 2\,\mathbb{E}\,\mathcal{G}_t \cdot \mathbb{E}\,\mathcal{G}_u$$

And finally, we can lower-bound s_t as:

$$\begin{aligned} &\sum_{u=0}^{t-1} \mu^{t-u} \left\|\mathbb{E}\,\mathcal{G}_t - \mathbb{E}\,\mathcal{G}_u\right\|^2 \\ &= \sum_{u=0}^{t-1} \mu^{t-u} \left({\lambda_t}^2 + {\lambda_u}^2\right) - \underbrace{2 \sum_{u=0}^{t-1} \mu^{t-u}\, \mathbb{E}\,\mathcal{G}_t \cdot \mathbb{E}\,\mathcal{G}_u}_{s_t} \\ &\leq \sum_{u=0}^{t-1} \mu^{t-u}\, l^2 \left\|\sum_{v=u}^{t-1} \alpha_v\, G_v\right\| \\ \Leftrightarrow s_t &\geq \sum_{u=0}^{t-1} \mu^{t-u} \left({\lambda_t}^2 + {\lambda_u}^2 - l^2 \left\|\sum_{v=u}^{t-1} \alpha_v\, G_v\right\|\right) \\ &\geq \frac{1-\mu^t}{1-\mu} {\lambda_t}^2 + \sum_{u=0}^{t-1} \mu^{t-u} \left({\lambda_u}^2 - l^2 \left\|\sum_{v=u}^{t-1} \alpha_v\, G_v\right\|\right) \end{aligned} \tag{8}$$

When the real gradient ∇Q is (locally) Lipschitz continuous, reducing the learning rate α_t can suffice to ensure s_t satisfies the conditions laid above for decreasing the *variance-norm* ratio $r_t^{(w)}$; the purpose of momentum at the workers. Importantly this last lower bound, namely Equation 8, sets how the practitioner should choose two hyperparameters, μ and α_t, for the purpose of Byzantine-resilience. Basically, and as long as it does not harm the training without adversary, μ should be set *as high* and α_t *as low* as possible.

C Reproducing the results

At this point you should have been provided with a ZIP file containing our code contribution.

C.1 Dependencies

Software dependencies. Python 3.7.3 has been used to run our scripts. Besides the standard libraries associated with Python 3.7.3, our scripts also depend on:

Library	Version
numpy	1.19.1
torch	1.6.0
torchvision	0.7.0
pandas	1.1.0
matplotlib	3.0.2
tqdm	4.40.2
PIL	7.2.0

Library	Version
six	1.15.0
pytz	2020.1
dateutil	2.8.1
pyparsing	2.2.0
cycler	0.10.0
kiwisolver	1.0.1
cffi	1.13.2

We list below the OS on which our scripts have been tested:

- Debian 10 (GNU/Linux 4.19.0-11-amd64)
- Ubuntu 18.04.3 LTS (GNU/Linux 4.15.0-58 x86_64)

Hardware dependencies. We list below the hardware components used:

- 1 Intel(R) Core(TM) i7-8700K CPU @ 3.70GHz
- 2 Nvidia GeForce GTX 1080 Ti
- 64 GB of RAM

C.2 Command

Our results are reproducible in one command. In the root directory of the ZIP file:

```
$ python3 reproduce.py
```

On our hardware, reproducing the results takes a bit less than a week. Please be aware this script will require non-negligible disk space: 2.1 GB of run data, and 132 MB of graphs.

D More experimental results

For every pair model-dataset, the following parameters vary:

- Which attack: (Baruch et al., 2019) or (Xie et al., 2019a)
- Which defense: *Krum*, *Median*, *Trimmed Mean*, *Phocas*, *MeaMed*, or *Bulyan*
- How many Byzantine workers (*an half* or *a quarter*)
- Where momentum is computed (*server* or *workers*)
- Which flavor of momentum is used (*classical* or *Nesterov*)
- Which learning rate is used (*larger* or *smaller*)

Every possible combination is tested[9], leading to a total of 736 different experiment setups. Each setup is tested 5 times, each run with a fixed seed from 1 to 5, enabling verbatim reproduction of our results[10]. In this specific section, we report on the evolution of the average and standard deviation of the *top-1 cross-accuracy* for every tested setup.

The results regarding the top-1 cross-accuracy are layed out by "blocks" of 4 experiment setups presenting the same model, dataset, learning rate schedule, number of Byzantine workers and attack. These results are presented from Figure 6 to Figure 37.

[9] Along with baselines using *averaging* without attack.

[10] Despite our best efforts, there may still exist minor sources of non-determinism, like race-conditions in the evaluation of certain functions (e.g., parallel additions) in a GPU. Nevertheless we believe these should not affect the results in any significant way.

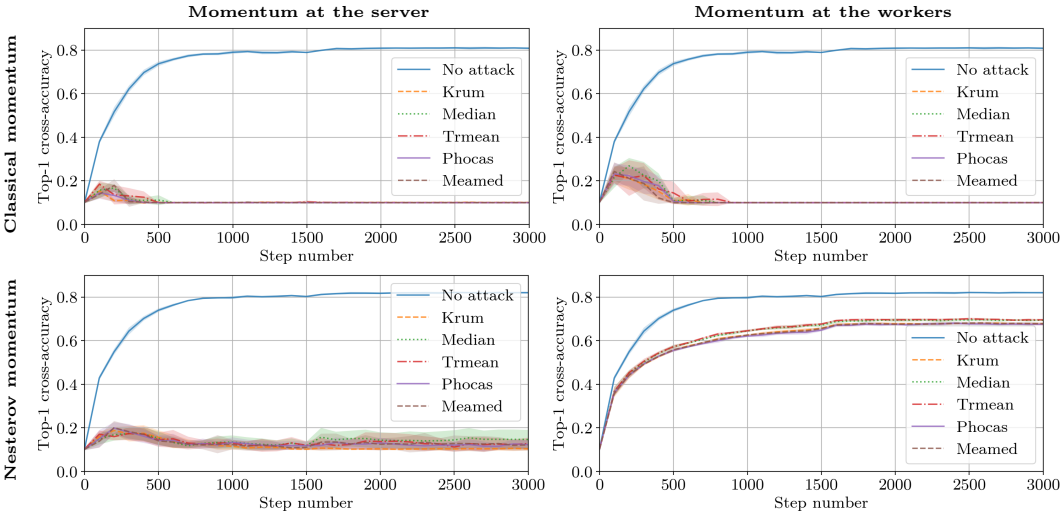

Figure 6: CIFAR-10 dataset and *convolutional* model, with $n = 25$, $f = 11$ and $\alpha_t = 0.01$ if $t < 1500$ else $\alpha_t = 0.001$, under attack from Baruch et al. (2019).

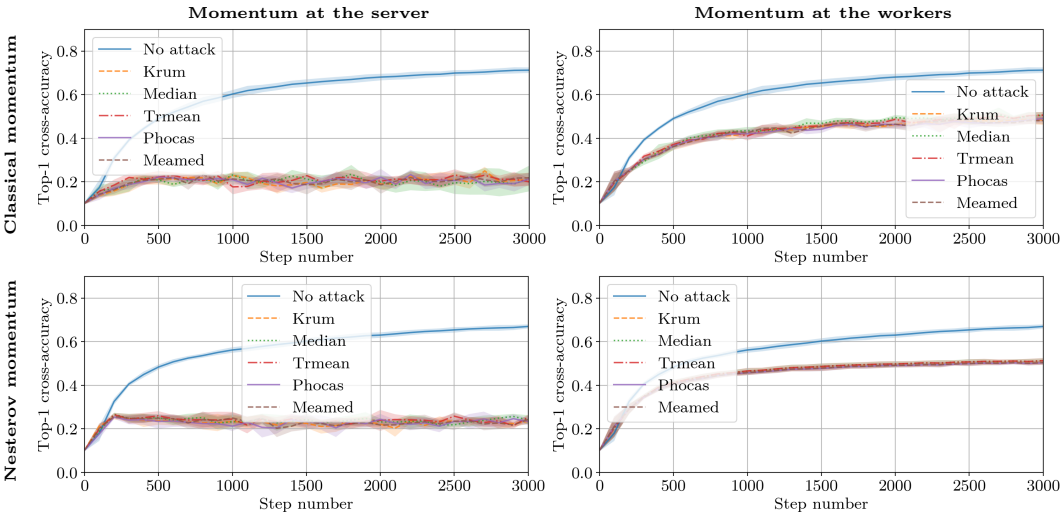

Figure 7: CIFAR-10 dataset and *convolutional* model, with $n = 25$, $f = 11$ and $\alpha_t = 0.001$, under attack from Baruch et al. (2019).

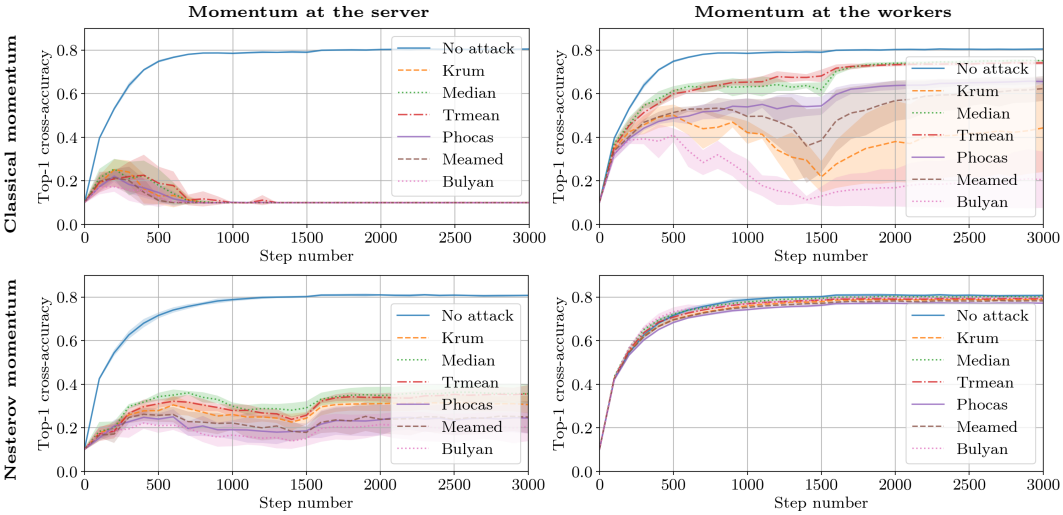

Figure 8: CIFAR-10 dataset and *convolutional* model, with $n = 25$, $f = 5$ and $\alpha_t = 0.01$ if $t < 1500$ else $\alpha_t = 0.001$, under attack from Baruch et al. (2019).

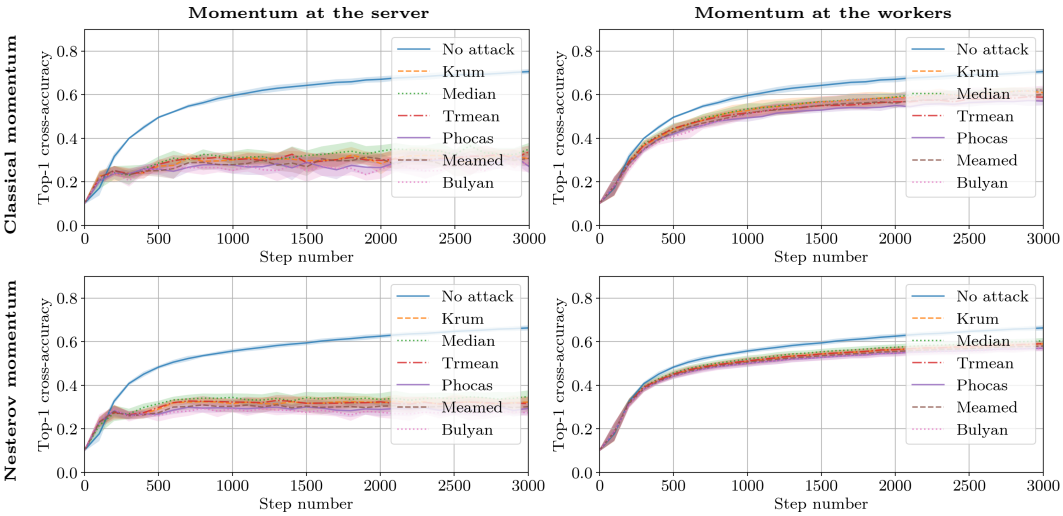

Figure 9: CIFAR-10 dataset and *convolutional* model, with $n = 25$, $f = 5$ and $\alpha_t = 0.001$, under attack from Baruch et al. (2019).

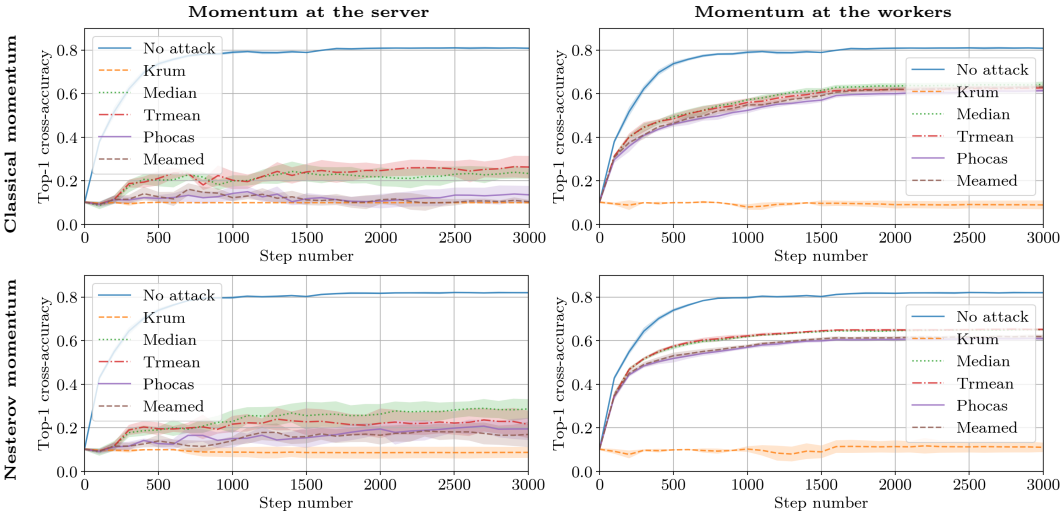

Figure 10: CIFAR-10 dataset and *convolutional* model, with $n = 25$, $f = 11$ and $\alpha_t = 0.01$ if $t < 1500$ else $\alpha_t = 0.001$, under attack from Xie et al. (2019a).

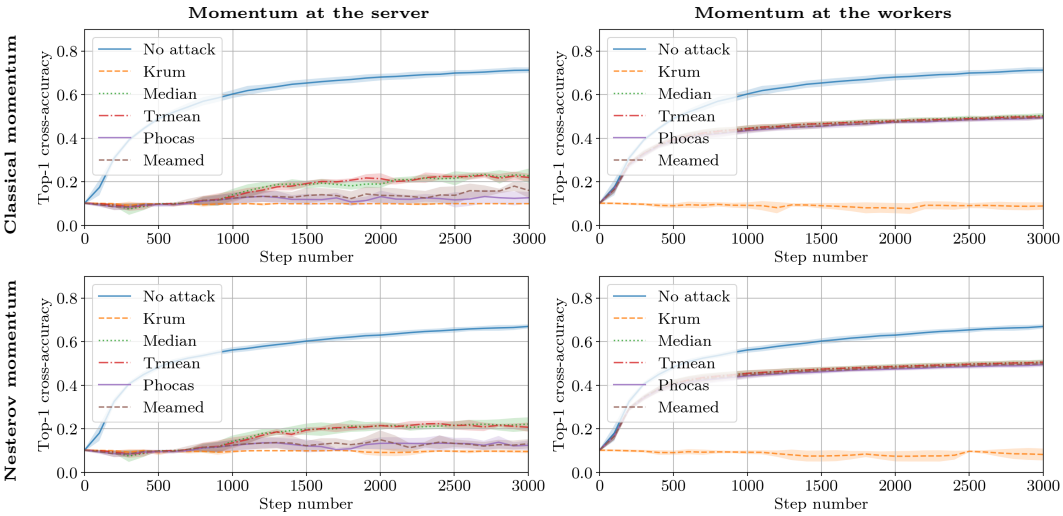

Figure 11: CIFAR-10 dataset and *convolutional* model, with $n = 25$, $f = 11$ and $\alpha_t = 0.001$, under attack from Xie et al. (2019a).

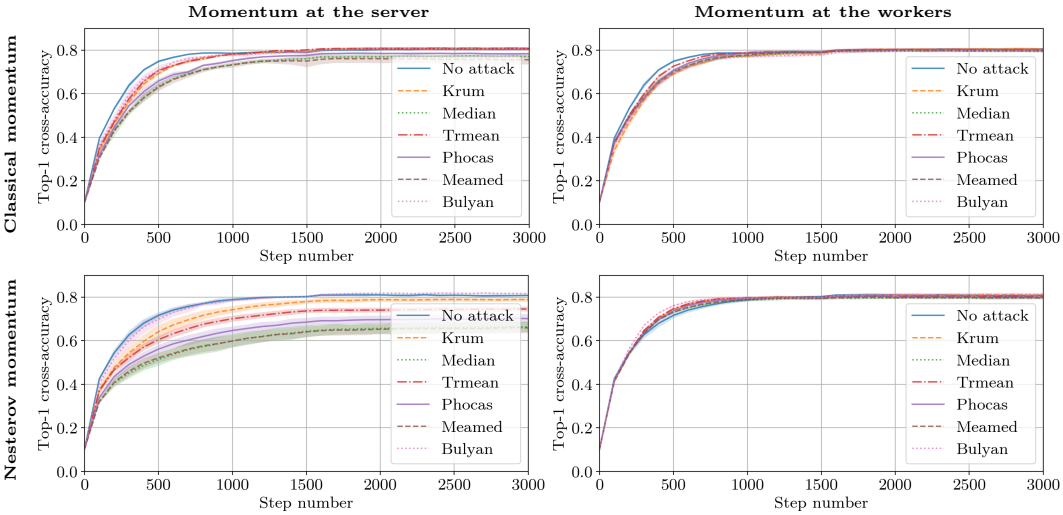

Figure 12: CIFAR-10 dataset and *convolutional* model, with $n = 25$, $f = 5$ and $\alpha_t = 0.01$ if $t < 1500$ else $\alpha_t = 0.001$, under attack from Xie et al. (2019a).

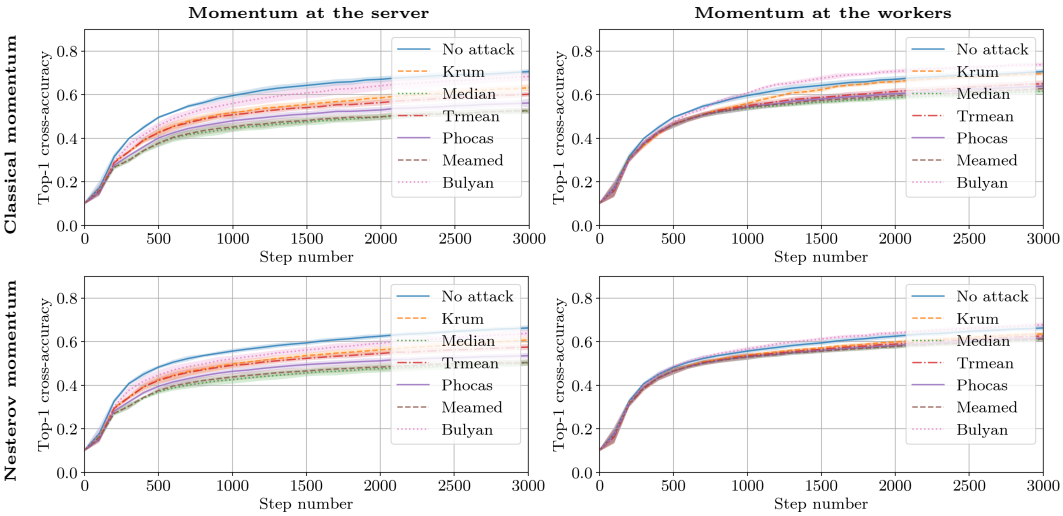

Figure 13: CIFAR-10 dataset and *convolutional* model, with $n = 25$, $f = 5$ and $\alpha_t = 0.001$, under attack from Xie et al. (2019a).

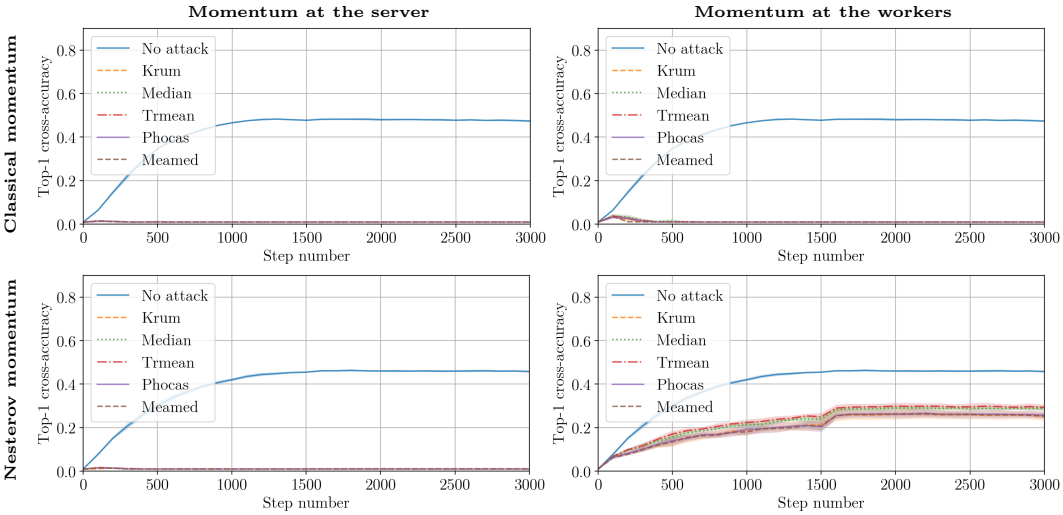

Figure 14: CIFAR-100 dataset and *convolutional* model, with $n = 25$, $f = 11$ and $\alpha_t = 0.01$ if $t < 1500$ else $\alpha_t = 0.001$, under attack from Baruch et al. (2019).

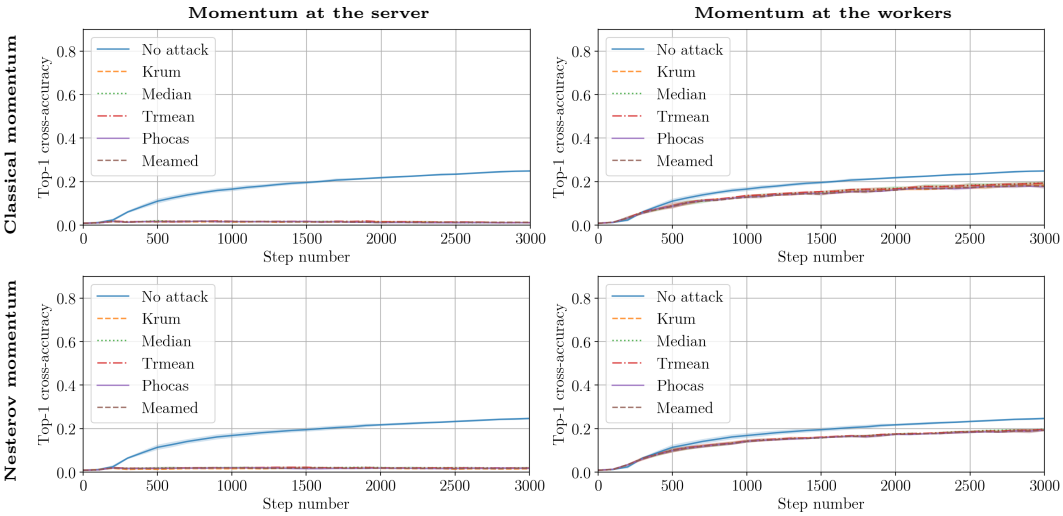

Figure 15: CIFAR-100 dataset and *convolutional* model, with $n = 25$, $f = 11$ and $\alpha_t = 0.001$, under attack from Baruch et al. (2019).

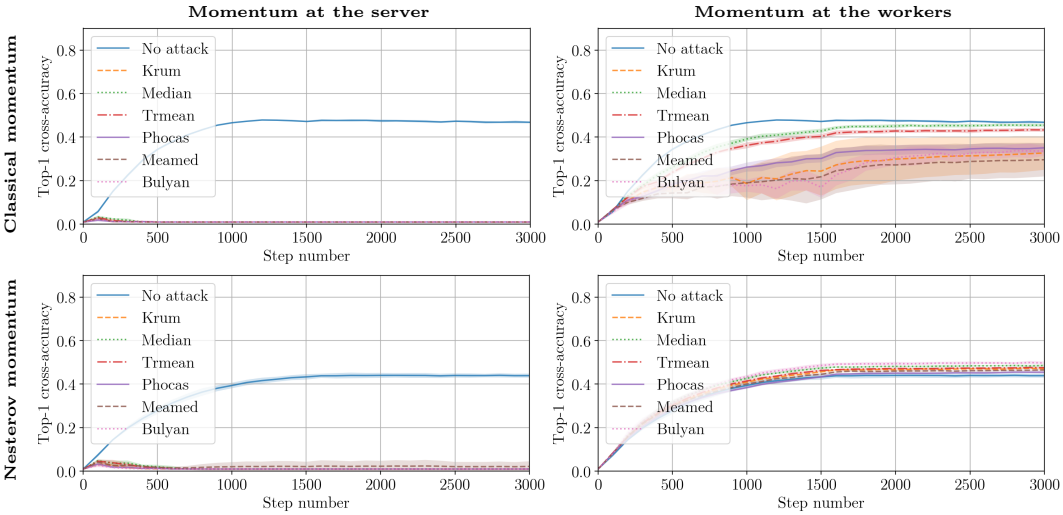

Figure 16: CIFAR-100 dataset and *convolutional* model, with $n = 25$, $f = 5$ and $\alpha_t = 0.01$ if $t < 1500$ else $\alpha_t = 0.001$, under attack from Baruch et al. (2019).

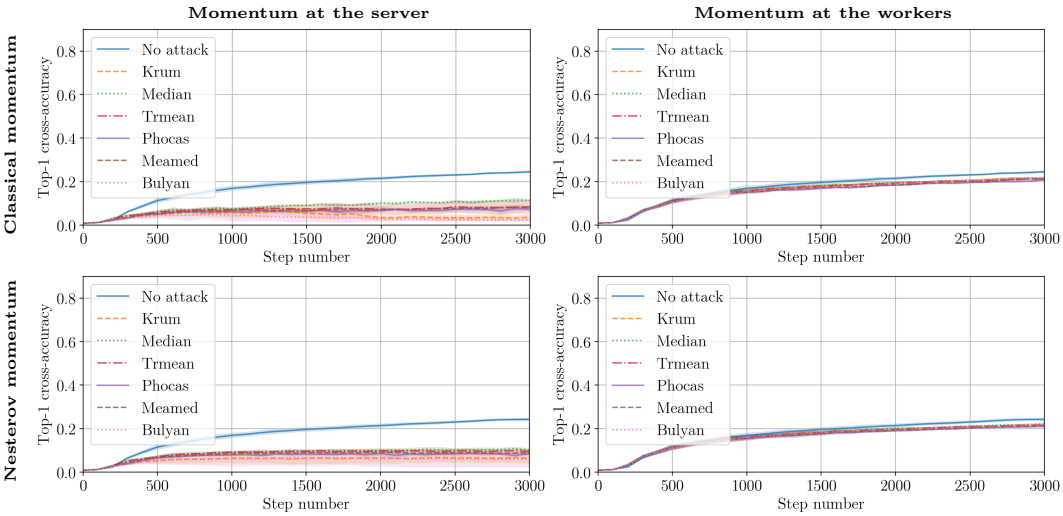

Figure 17: CIFAR-100 dataset and *convolutional* model, with $n = 25$, $f = 5$ and $\alpha_t = 0.001$, under attack from Baruch et al. (2019).

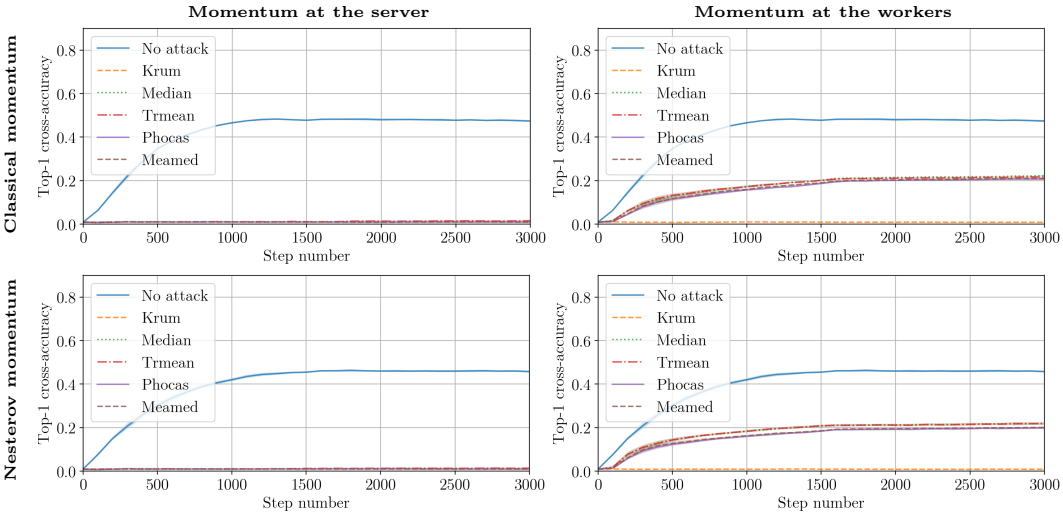

Figure 18: CIFAR-100 dataset and *convolutional* model, with $n = 25$, $f = 11$ and $\alpha_t = 0.01$ if $t < 1500$ else $\alpha_t = 0.001$, under attack from Xie et al. (2019a).

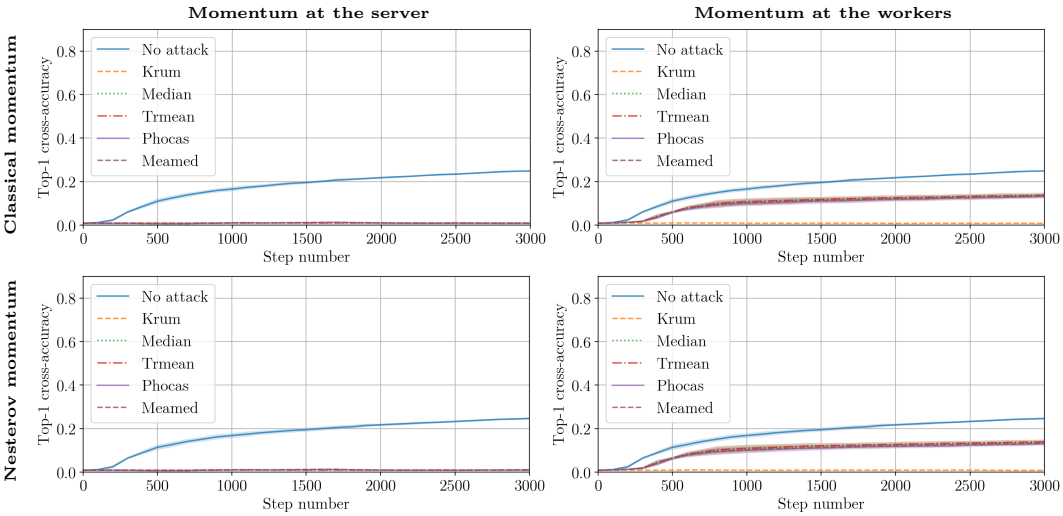

Figure 19: CIFAR-100 dataset and *convolutional* model, with $n = 25$, $f = 11$ and $\alpha_t = 0.001$, under attack from Xie et al. (2019a).

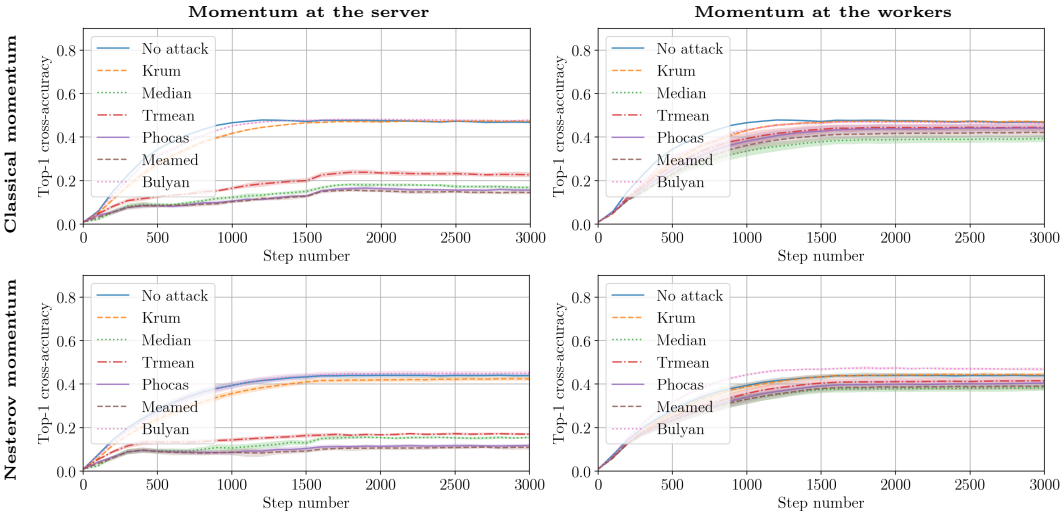

Figure 20: CIFAR-100 dataset and *convolutional* model, with $n = 25$, $f = 5$ and $\alpha_t = 0.01$ if $t < 1500$ else $\alpha_t = 0.001$, under attack from Xie et al. (2019a).

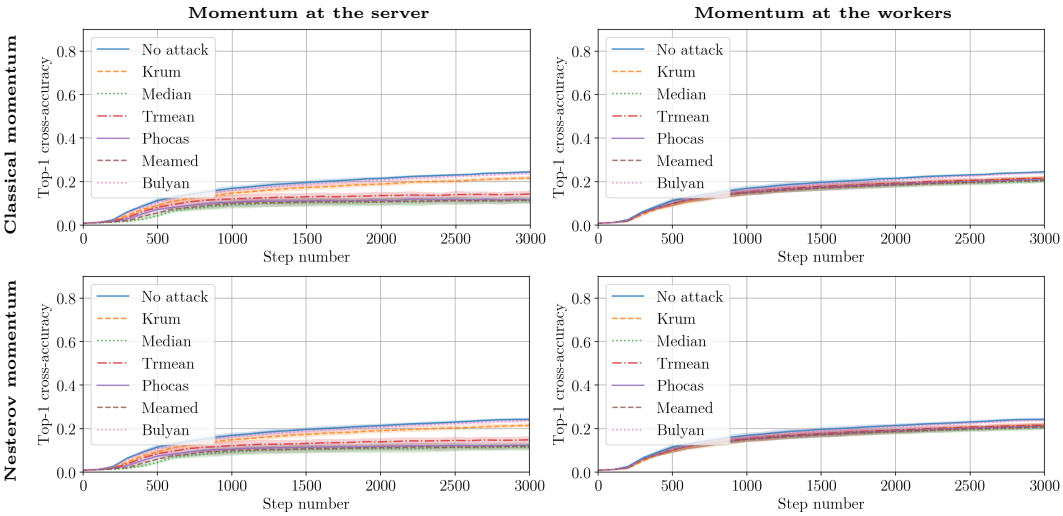

Figure 21: CIFAR-100 dataset and *convolutional* model, with $n = 25$, $f = 5$ and $\alpha_t = 0.001$, under attack from Xie et al. (2019a).

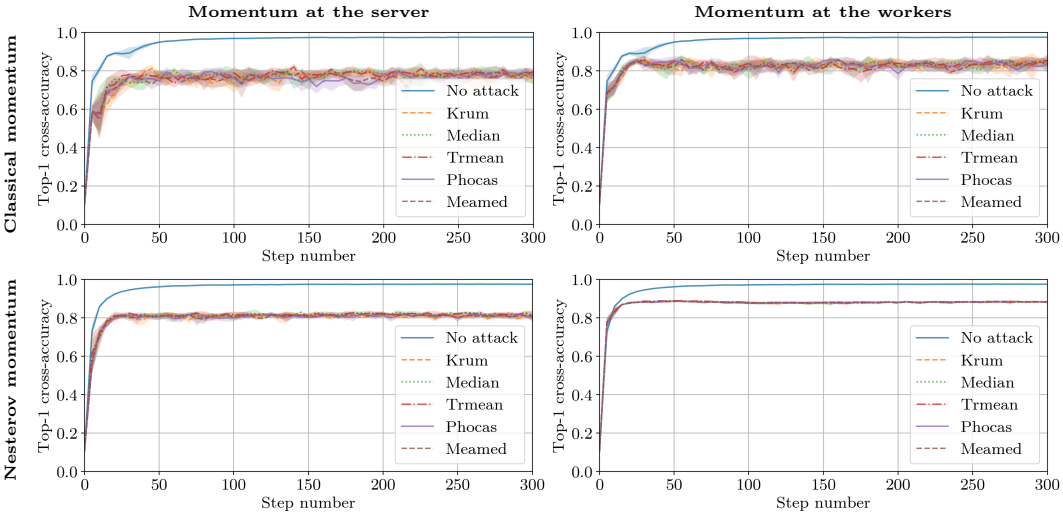

Figure 22: MNIST dataset and *fully connected* model, with $n = 51$, $f = 24$ and $\alpha_t = 0.5$, under attack from Baruch et al. (2019).

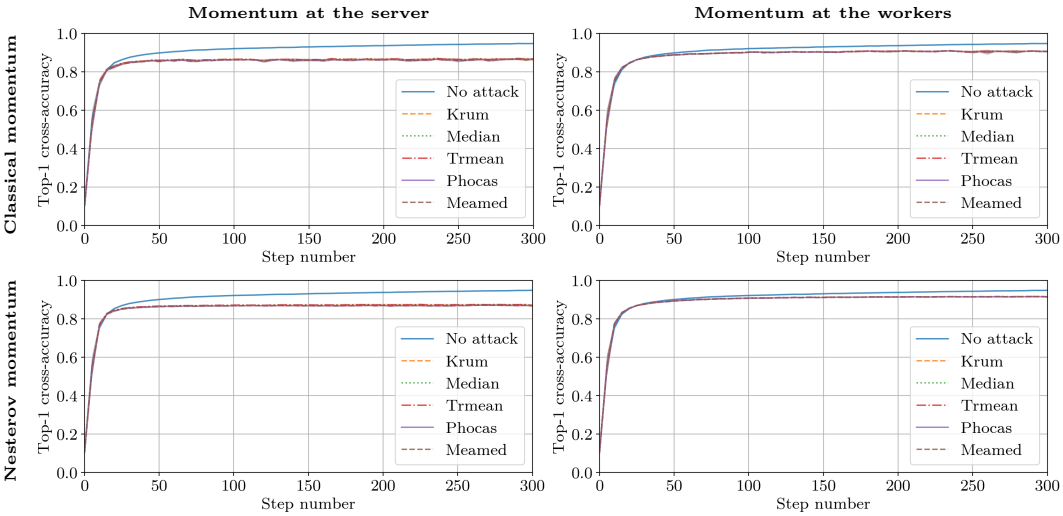

Figure 23: MNIST dataset and *fully connected* model, with $n = 51$, $f = 24$ and $\alpha_t = 0.02$, under attack from Baruch et al. (2019).

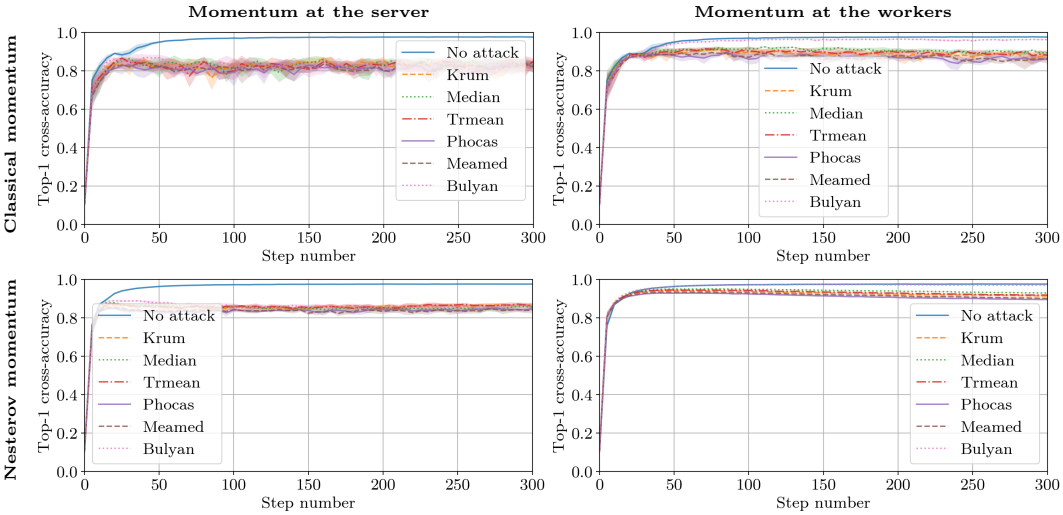

Figure 24: MNIST dataset and *fully connected* model, with $n = 51$, $f = 12$ and $\alpha_t = 0.5$, under attack from Baruch et al. (2019).

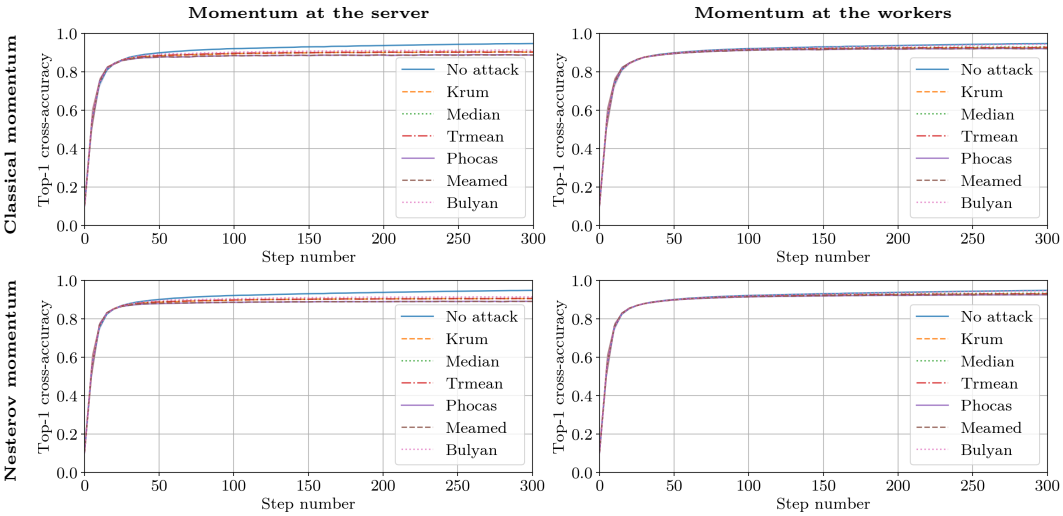

Figure 25: MNIST dataset and *fully connected* model, with $n = 51$, $f = 12$ and $\alpha_t = 0.02$, under attack from Baruch et al. (2019).

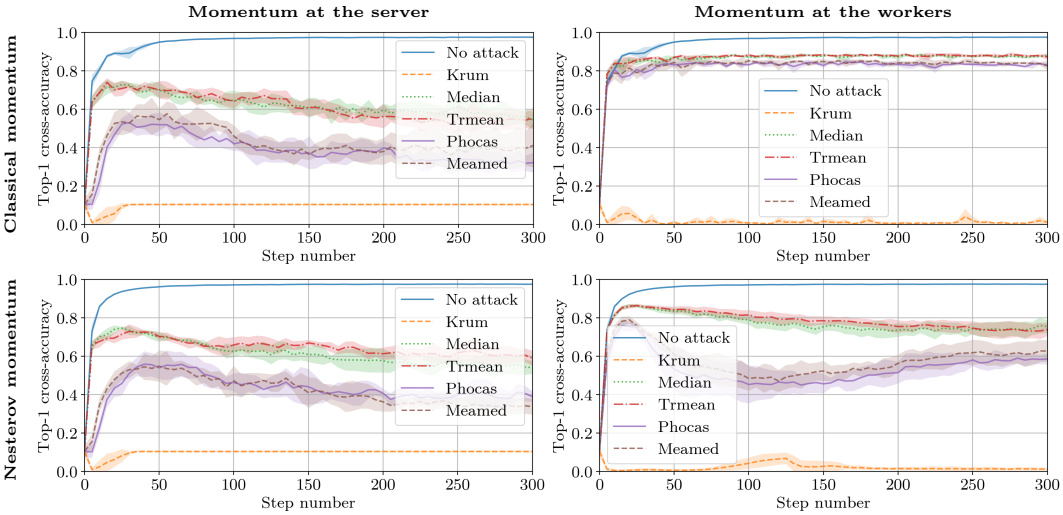

Figure 26: MNIST dataset and *fully connected* model, with $n = 51$, $f = 24$ and $\alpha_t = 0.5$, under attack from Xie et al. (2019a).

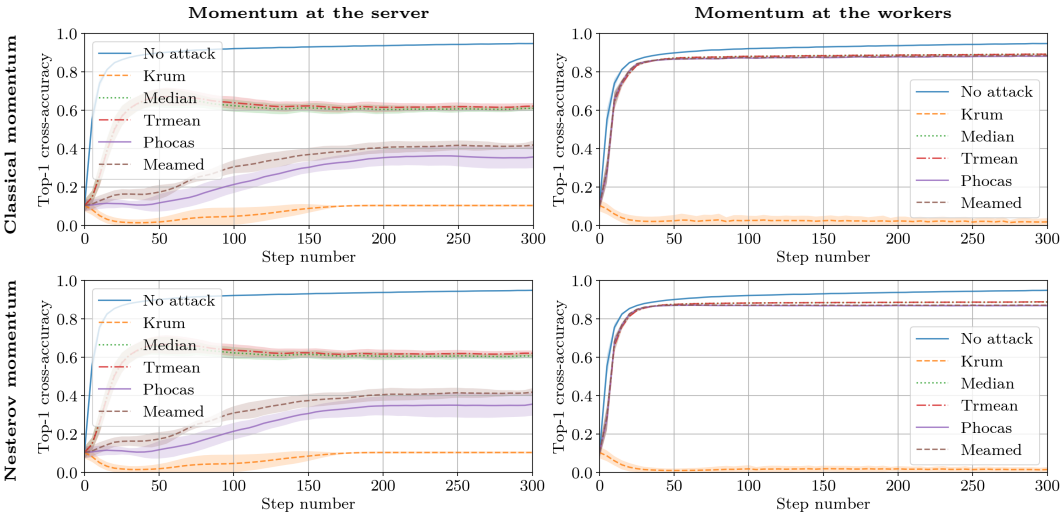

Figure 27: MNIST dataset and *fully connected* model, with $n = 51$, $f = 24$ and $\alpha_t = 0.02$, under attack from Xie et al. (2019a).

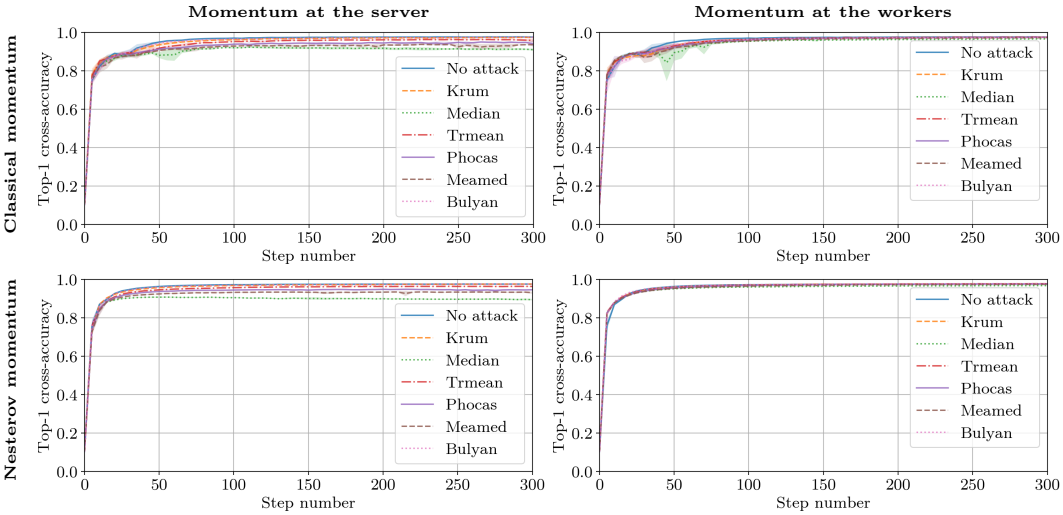

Figure 28: MNIST dataset and *fully connected* model, with $n = 51$, $f = 12$ and $\alpha_t = 0.5$, under attack from Xie et al. (2019a).

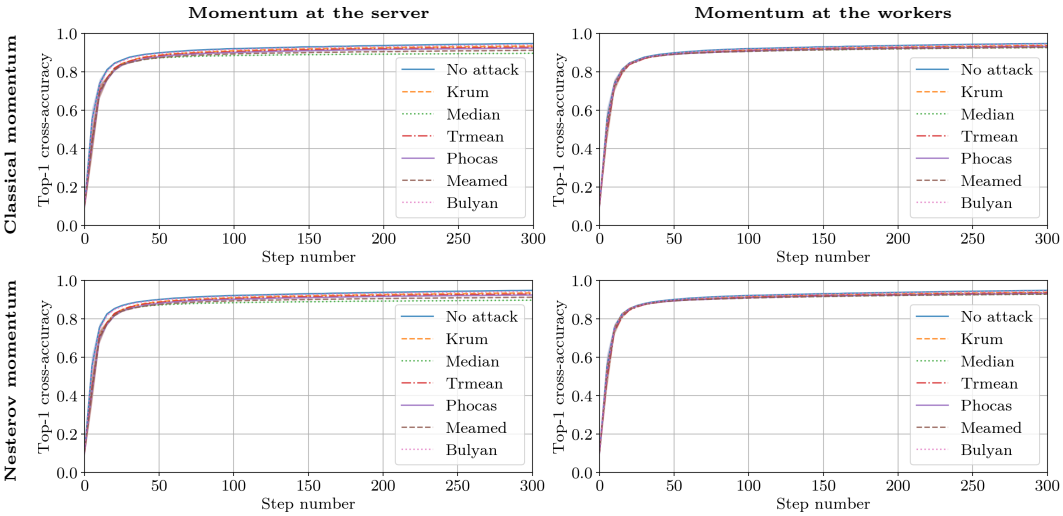

Figure 29: MNIST dataset and *fully connected* model, with $n = 51$, $f = 12$ and $\alpha_t = 0.02$, under attack from Xie et al. (2019a).

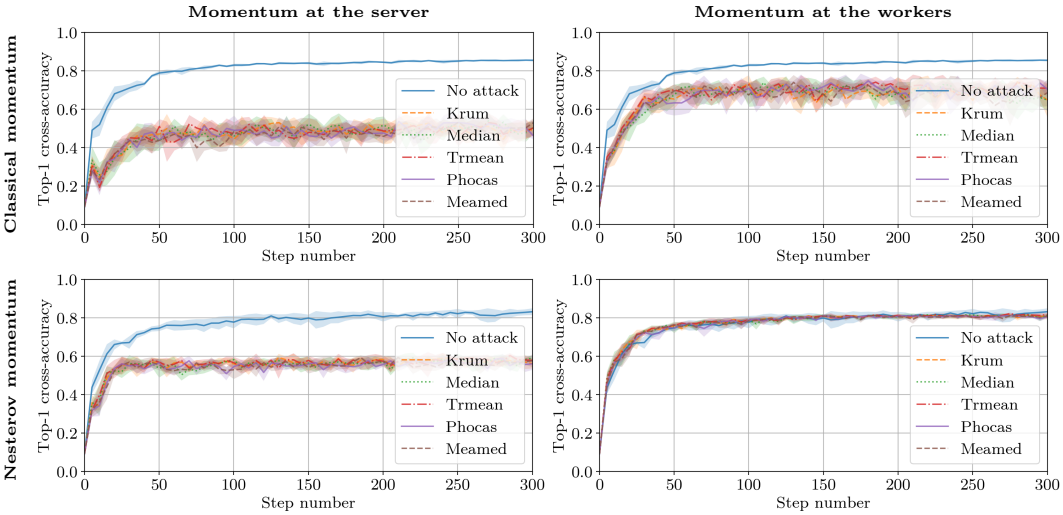

Figure 30: Fashion MNIST dataset and *fully connected* model, with $n = 51$, $f = 24$ and $\alpha_t = 0.5$, under attack from Baruch et al. (2019).

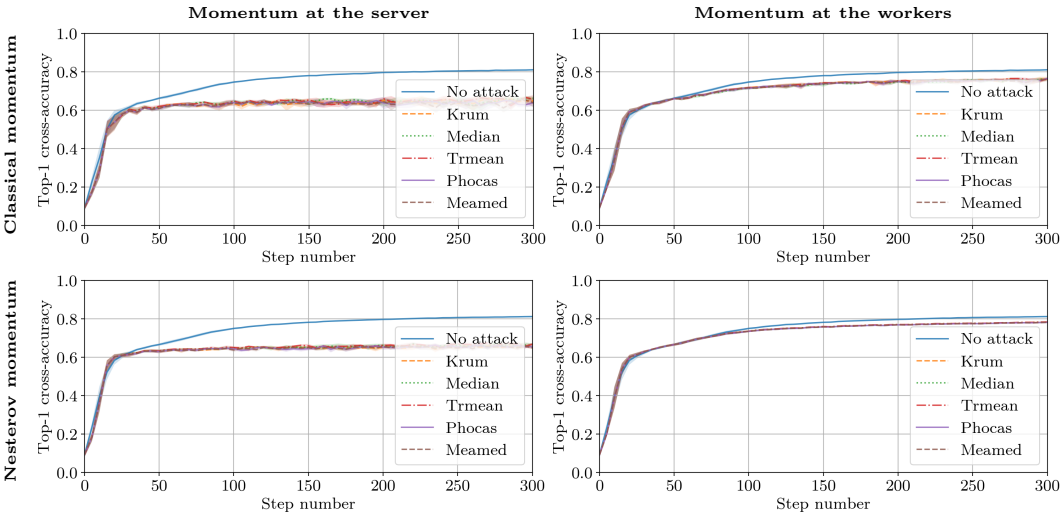

Figure 31: Fashion MNIST dataset and *fully connected* model, with $n = 51$, $f = 24$ and $\alpha_t = 0.02$, under attack from Baruch et al. (2019).

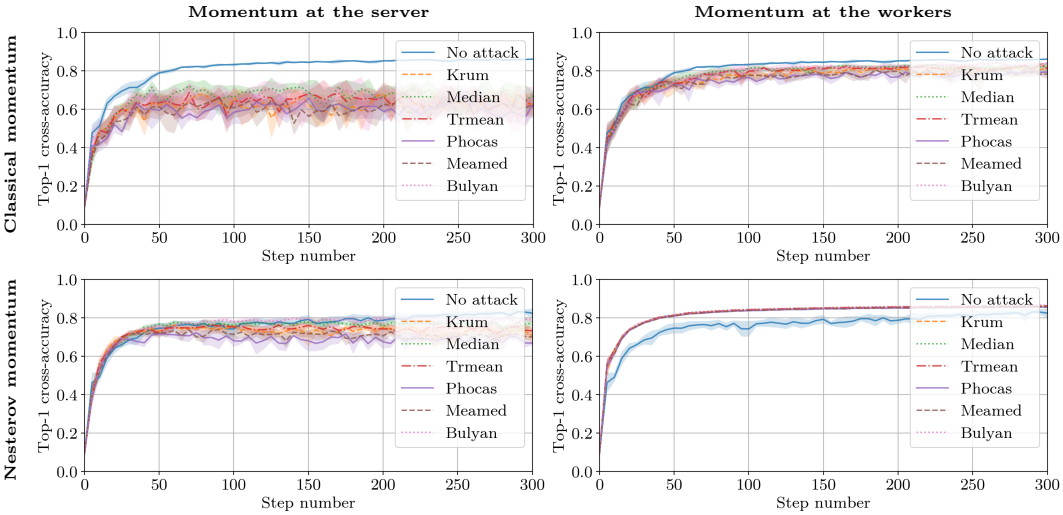

Figure 32: Fashion MNIST dataset and *fully connected* model, with $n = 51$, $f = 12$ and $\alpha_t = 0.5$, under attack from Baruch et al. (2019).

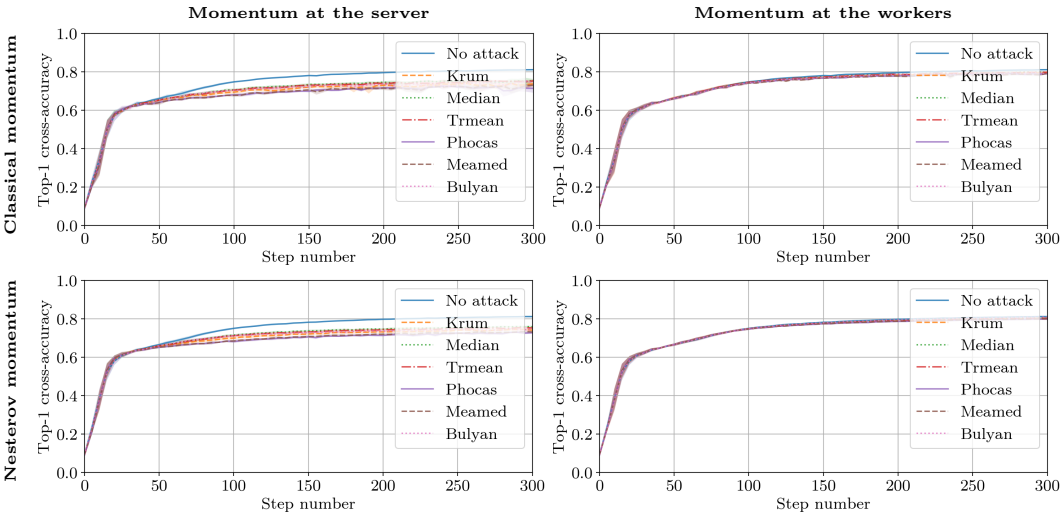

Figure 33: Fashion MNIST dataset and *fully connected* model, with $n = 51$, $f = 12$ and $\alpha_t = 0.02$, under attack from Baruch et al. (2019).

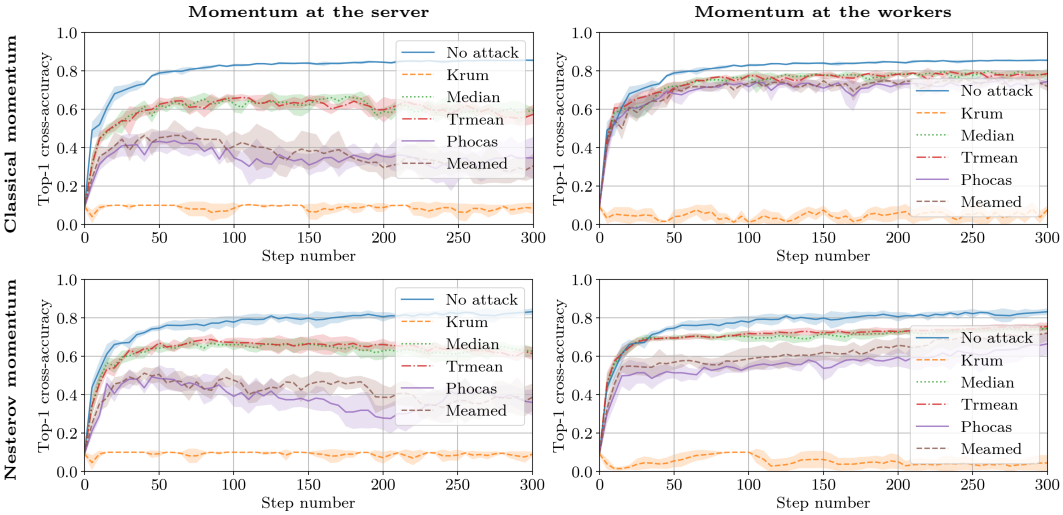

Figure 34: Fashion MNIST dataset and *fully connected* model, with $n = 51$, $f = 24$ and $\alpha_t = 0.5$, under attack from Xie et al. (2019a).

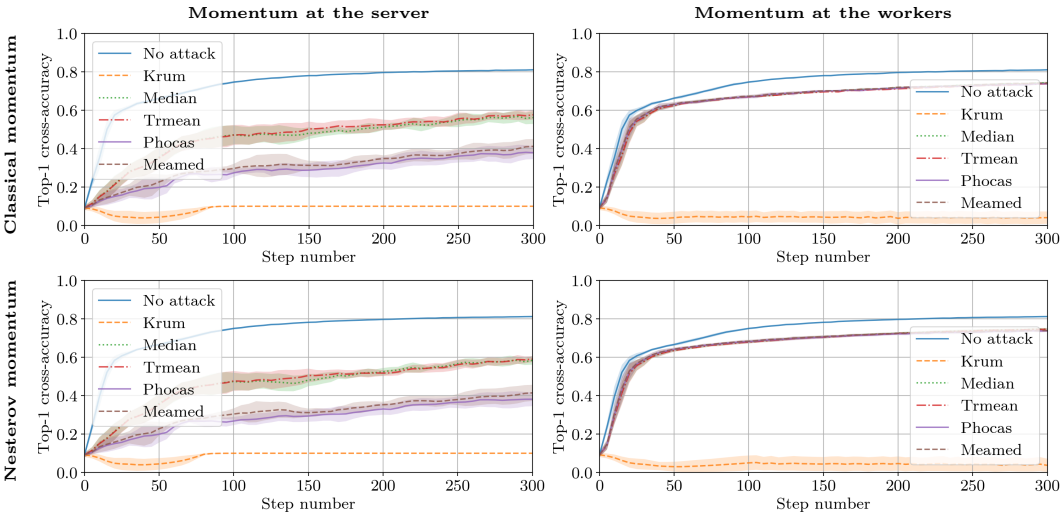

Figure 35: Fashion MNIST dataset and *fully connected* model, with $n = 51$, $f = 24$ and $\alpha_t = 0.02$, under attack from Xie et al. (2019a).

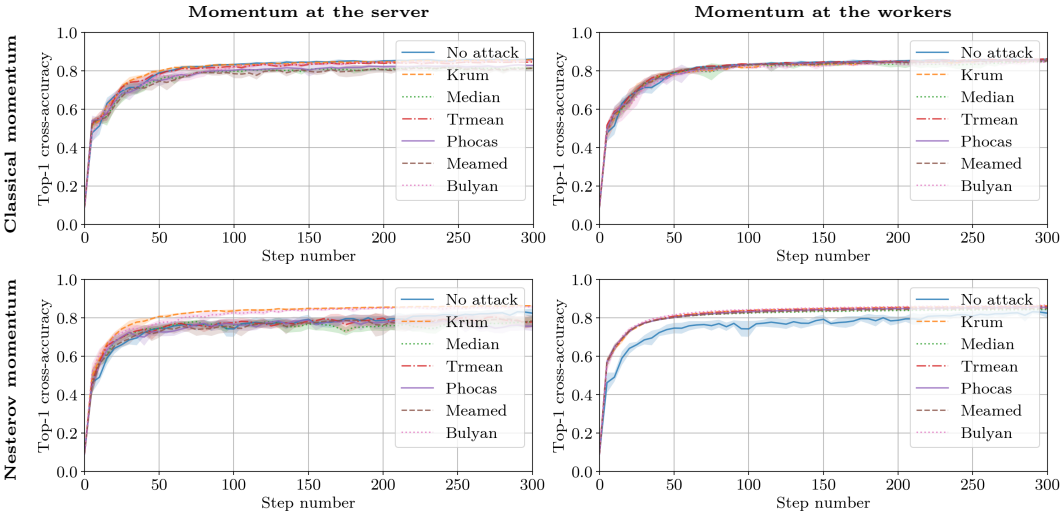

Figure 36: Fashion MNIST dataset and *fully connected* model, with $n = 51$, $f = 12$ and $\alpha_t = 0.5$, under attack from Xie et al. (2019a).

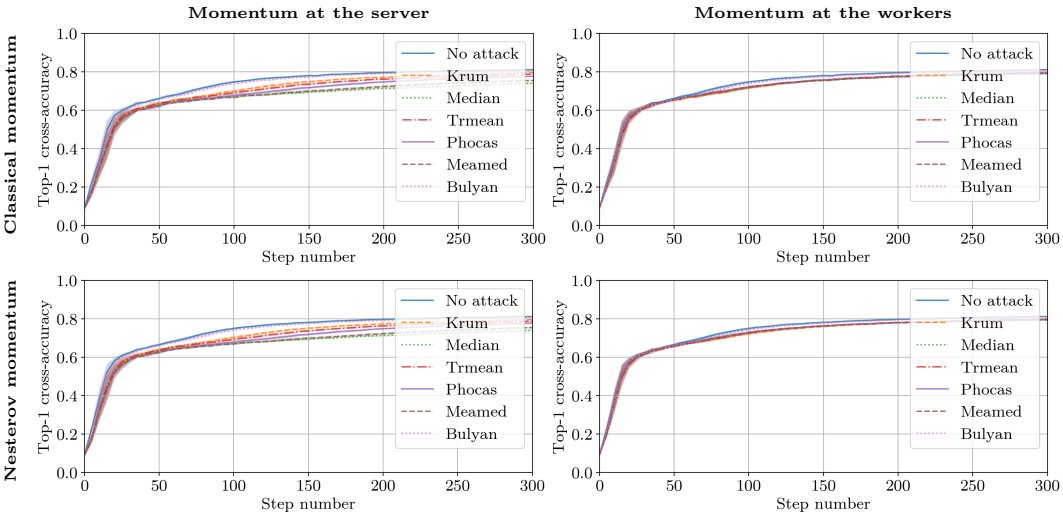

Figure 37: Fashion MNIST dataset and *fully connected* model, with $n = 51$, $f = 12$ and $\alpha_t = 0.02$, under attack from Xie et al. (2019a).