Leveraging Website Popularity Differences to Identify Performance Anomalies

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***Abstract*—Web performance anomalies (*e.g.* time periods when metrics like page load time are abnormally high) have significant impact on user experience and revenues of web service providers. Existing methods to automatically detect web performance anomalies focus on popular websites (*e.g.* with tens of thousands of visits per minute). Across a wider diversity of websites, however, the number of visits per hour varies enormously, and some sites will only have few visits per hour. Low rates of visits create measurement gaps and noise that prevent the use of existing methods. This paper develops WMF, a web performance anomaly detection method applicable across a range of websites with highly variable measurement volume. To demonstrate our method, we leverage data from a website monitoring company, which allows us to leverage cross-site measurements. WMF uses matrix factorization to mine patterns that emerge from a subset of the websites to "fill in" missing data on other websites. Our validation using both a controlled website and synthetic anomalies shows that WMF's F1-score is more than double that of the state-of-the-art method. We then apply WMF to three months of web performance measurements to shed light on performance anomalies across a variety of 125 small to medium websites.**

***Index Terms*—anomaly detection, data analysis, web performance measurement, matrix factorization**

I. Introduction

As more and more of our society and daily lives migrate online (from shopping to entertainment and work to mostly everything under the current pandemic), web performance becomes ever more crucial. Slow web load times can have significant impact on the revenues of online businesses, as users give up on browsing due to temporary performance degradations [1]. For example, Google reports that "increasing web search latency from 100 ms to 400 ms reduces the daily number of searches per user by 0.2% to 0.6%" [2] and a one second delay in page load time would cost Amazon an estimate of $1.6 billion in annual sales [3]. As such, website administrators spend significant effort to optimize the performance of their webpages—a task that requires accurate and efficient methods to detect and diagnose poor web performance.

Web performance monitoring and diagnosis have thus received considerable attention from research and industry. A number of efforts have focused on designing metrics to capture webpage performance (for example, Page Load Time, Above-The-Fold-Time [4], or SpeedIndex [5]) and understanding how these metrics relate to the user quality of experience [6], [7], [8]. Webpages are often instrumented to passively collect at least some of these metrics. In some cases, websites contract third-party companies such as Dynatrace [9], Pingdom [10], IP-Label [11], or Akamai [12] to monitor the performance of their websites on their behalf. An important task for such services is detecting *web performance anomalies* — abnormally high values of, for instance, page load time (PLT).

Unfortunately, however, both website administrators and third-party monitoring services lack effective tools to automatically detect the rare occurrences of web performance anomalies within the many visits to a website. To date, methods for web performance anomaly detection have focused on search response times [13], [14]. Such methods are designed for very popular websites (*e.g.* for Bing and Baidu, with tens to hundreds of thousands of visits per minute). However, when using passive measurement for more general-purpose websites, a significant challenge arises due to the Zipfian distribution of overall popularity. Across a collection of websites, usually a small number of sites will account for most visits and a vast majority of sites will be less popular [15]. This problem is compounded by the fact that measurement of site performance is expensive, and in many cases only a small sample of visits to a site can be instrumented and measured.

This highly variable quantity of performance measurements available across websites causes severe problems for traditional anomaly detection methods. First, anomaly detection for general purpose websites must deal with *measurement gaps* – time periods with no measurements. These gaps can happen because when a less-popular website takes sampled measurements, there can be periods where none of the visits are sampled. Second, low numbers of measurements increase the effect of *measurement noise*. For example, during a certain period, page load time may increase simply because the lower number of measurements happen to include many users who have a poor cellular connection.

On the other hand, the performance of websites is often measured by third parties. In this setting we observe that there is an opportunity to overcome challenges due to variable data volume by looking *across* websites. That is, we propose to "borrow from strength" using measurements of many websites simultaneously to overcome the challenges of spare per-site data. In this paper, we use this insight to develop a web performance anomaly detection method that overcomes the challenges of highly variable measurement volume. To demonstrate our method, we leverage data collected by a web performance monitoring company (presented in Sec. III). Our method can learn patterns from a subset of websites to help "fill in" the missing data on other websites. The method we develop in Sec. IV, called WMF for *Web Matrix Factorization*, leverages matrix factorization and the dataset's low dimensionality to identify both normal web performance and performance anomalies. We validate WMF in a controlled live setting where we are able to induce network delay to a server, as well as by injecting synthetic anomalies in the dataset (Sec. V). Our results discussed in Sec. VI show that WMF achieves a recall of about 0.9 and a precision of about 0.98 in controlled experiments. Precision and recall are lower in the evaluation with synthetic anomalies, because the dataset contains anomalies that we have not introduced, but WMF's F1 score is more than double that of state-of-the-art time series methods for anomaly detection of web performance [13]. This result confirms that it is non-trivial to adapt existing methods developed for popular websites to work on less popular sites.

We then apply WMF to detect anomalies on three months of web performance measurements across 125 websites (Sec. VII). This analysis sheds light on web performance anomalies in a heterogeneous set of small to medium websites. Only 56 out of the 125 websites experience any web performance anomaly during our study. Most anomalies are short (lasting less than one hour), but we detect a few events that last for more than ten hours. We also show that some websites had at least one anomaly every five days on average. We conclude that an automated web anomaly detection tool such as WMF can assist web administrators or third-party monitoring companies to quickly detect anomalous events despite the challenges posed by heterogeneous measurement volume across websites.

II. Background

In this paper, we are concerned with *web performance anomalies,* by which we mean abnormally poor (*i.e.* high) values of one of the web performance metrics (for instance, PLT). Because web and Internet measurements in general are noisy, a single outlier measurement is usually not significant enough to a website operator to merit a response. Hence, in this paper we focus on anomalies that last tens of minutes and that affect a considerable fraction of users.

A number of techniques have been proposed in the literature for anomaly detection of web measurements, and more generally, network measurements. We divide existing methods into *temporal* and *spatio-temporal* approaches.

Temporal methods. The most common way to study temporal data is to build a time series model of measurements in aggregated form (*e.g.* average or median of measurements in a time bin). Deviations from model predictions can then be used to identify anomalous time points. In this category we find Seasonal-Trend Decomposition using Loess (STL) [16] methods, which split the time series into three signals: the trend, the seasonal, and the residual components. The latter is normally analyzed to detect anomalies. In the domain of web performance measurements, the Week-over-Week (WoW) method relies on STL to detect anomalies on Search Response Time measurements performed on a major web search provider [13]. Other temporal approaches for anomaly detection are based on Autoregressive Integrated Moving Average (ARIMA) [17], [18], [19] and Exponential Smoothing [20] (with Holt-Winters seasonal method [21] being the most common), where historical values are used to forecast the next value of a time series, and anomaly detection is built on top of values far from the outcome of the model. Finally, neural networks methods such as LSTM Autoencoder [22], [23] can be used to detect anomalies, where the model is trained with a set of 'normal' data and then tries to reproduce the rest of the dataset. A degradation in the accuracy of the reconstructed signal means an anomaly is present.

A key concern when using time series analysis methods is the need for reliable values for every time bin. Whenever a time bin has no data one generally must interpolate the missing values. Errors in this estimation of the missing values will compromise the accuracy of the anomaly detection process on the known values. In our setting where many websites have low measurement volumes and can have many missing values, this becomes a critical issue.

Spatio-temporal methods. Spatio-temporal methods are commonly adopted in case of high dimensional datasets with timeseries measurements performed on different entities or at different locations. These techniques not only analyze the temporal relation of the signals in the datasets, but they also exploit the correlation among the different signals. A popular technique is Principal Component Analysis (PCA), which performs a linear mapping of the data to a lower dimensional space so as to represent the data using fewer components that describe the majority of the variance of the entire dataset. The low-rank representation of the dataset typically captures the 'normal' behavior, and deviations (residuals) from the low-rank representation allow identification of anomalies. PCA has been broadly used for anomaly detection, for instance in wide-area communication networks [24], [25], datacenter services [26], and social network activity [27]. A generalization of PCA to tensor factorization has been also adopted for anomaly detection [28].

However, as a data analysis technique, PCA has a limitation similar to time-series methods in that it cannot be used directly on data with missing values. An alternative to PCA that can build a model of data with missing values is *low rank matrix factorization,* also termed *matrix completion* [29], [30], [31]. A number of efficient algorithms have been developed for this problem [32], [33], [34]. Like PCA, matrix factorization seeks to find linear relations among the different signals in order to describe the majority of the data with a low rank matrix. However, it is designed to operate on matrices with missing data, and importantly, it can construct predictions of the missing data based on the low-rank approximation.

As noted above, a central challenge of working with website data is that there is an enormous variation in measurement volume across sites, as well as time periods with no sampled visits. This leads to many cases of missing data in our measurement matrices. It is thus very hard to build either time series or PCA models on such data (and such methods perform poorly, as we show below). Hence in this paper we adopt low-rank matrix factorization and adapt it to the problem of anomaly detection (described in detail in Sec. IV). While this general methodology has appeared in one prior work [35], to our knowledge this is the first work to apply it to anomaly detection problems in networking, and the first to recognize its power for addressing the data challenges presented by highly-variable website popularity.

III. Dataset

Overview. The primary dataset we use in this paper is collected by ip-label, a company that sells both passive and active website performance monitoring solutions. Ip-label embeds Javascript code in the webpages of its customers to measure web performance via the Navigation Timing API. Measurements are collected within the user's browser, then exported to a database maintained by the company. Website operators pay the monitoring service based on both the number of requests monitored and the number of metrics logged. To reduce costs, website operators often select a subset of webpages and visits to monitor, and collect only a few of the metrics available from the Navigation Timing API.

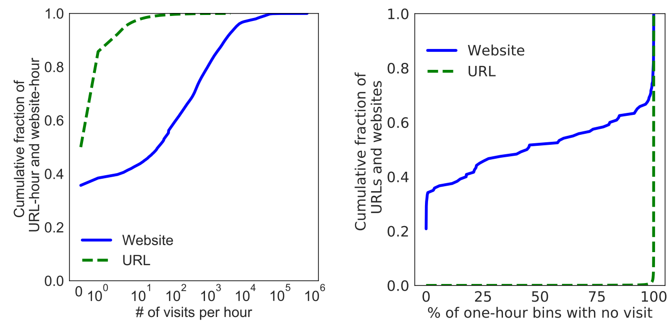
Our study relies on the dataset collected on 125 websites from July 29 to October 27, 2019 (mostly websites of private companies with few e-commerce and public institutions). Users access these sites from 235 countries across all continents, but 78% of the accesses come from Europe and 18% from Asia. We use the term *visit* to refer to a user accessing a webpage (or URL) within a website. The passive monitoring solution logs web performance of visits to a monitored website together with meta-data about the client's device.

The metrics captured are shown in Table 1. While space does not permit detailed definition of these metrics, they are for the most part standard or customized versions of standard web performance metrics. We made a more detailed descriptions available online [36].

Metric	#Websites	#Visits
Customized Page Load Time	94	233M
Time To Interactive	51	166M
DOM Completion Time	45	79M
Object Response Time	43	75M
Page Processing Time	43	74M
First Byte Received	43	63M
Connection Time	42	23M
DNS Response Time	39	16M

TABLE 1— Web performance metrics in the dataset. *#Websites* indicates how many websites report measurements for the given metric, while *#Visits* reports the number of visits that trigger a measurement for a given metric.

Variability of measurement volume. As described in Sec. II, prior methods for web anomaly detection were developed and evaluated for highly-popular websites such as Bing [13] (∼270k visits per minute worldwide [37]) and Baidu [14] (∼10k visits per minute). The websites in the dataset presented in the previous section, however, show a large range of measurement intensities. Fig. 1(a) shows the cumulative distribution function of the number of measurements per URL and per website in one-hour bins. We see that a vast majority of URLs have very few measurements per one-hour bin: over 50% of bins have no measurements, and less than 20% have more than one measurement in a time bin.



(a)— Number of measurements per hour. **(b)—** Percentage of one-hour bins with no measurements.

Fig. 1— Aggregation by time (hourly representation) and space (by URL or by website) of visits triggering web performance measurements.

We can improve the per-bin counts by aggregating measurements of all monitored URLs within the same website, which helps somewhat reducing the fraction of bins with no measurements to less than 40%. Even when we aggregate all visits to different URLs of the same website, Fig. 1(b) shows that for almost 50% of websites, at least half of their one-hour bins still have no measurements.

The nature of this data illustrates the challenges of anomaly detection across general-purpose websites. First, even when aggregating measurements in fairly large, one-hour time bins, a significant fraction of bins still have no data. Second, the number of measurements per hour is often small, which makes the statistics less stable. For example, the average PLT may vary significantly between time bins because users visit from poorer connections or devices. We note that previous work [13] has actually filtered out users accessing from mobile devices to eliminate some variation in metrics, but for our problem such an approach would reduce even further the number of data points for analysis.

Data representation choices. To address the challenges just presented, we adopt a number of strategies. First, we implement a binning strategy that aggregates measurements in one-hour time bins, which trades off time granularity for improved statistical properties. Second, we aggregate measurements from multiple URLs in each bin. Because content and page structure across URLs can vary considerably, we normalize measurements at a per-URL level to zero-mean and unit variance. Since normalization is performed across all time bins, this means that anomalies still stand out, but differences on the URL level are overcome.

Next, we consider how to summarize the samples in each bin. Prior work has generally summarized samples using the mean. However, due to the frequently limited measurement volume, the mean can be heavily influenced by single measurements. Further, our problem definition seeks to find anomalies that affect a significant fraction of visits. Hence we instead use percentile summaries; we find empirically that the 75th percentile captures well fluctuations in web performance even in bins with few measurements, so we adopt that metric. We made the evaluation of other aggregation metrics available online [36].

A final strategy we use to maximize the amount of data available for anomaly detection is to combine samples of multiple web performance metrics within the same matrix. Had we only considered a single metric, we would be discarding a significant fraction of available data. For example, even Customized Page Load Time, which is the most popular metric in the dataset (Table 1), is measured in only approximately 80% of visits. In addition, different metrics help capture different types of anomalies. For example, First Byte Received is more sensitive to high delays, whereas Customized Page Load Time is also going to increase under losses. This leads to one time series per web performance metric collected for each of the monitored website. Given that we normalize values of individual metrics so that distributions per metric have zero-mean and unit-variance, it is therefore reasonable to analyze time series of multiple metrics together in the same matrix.

Notation. Summing up, for each website and performance metric pair, we create a time series of the hourly 75th percentile of measurements. We obtain 425 time series, which we represent into an $n \times m$ matrix, $\mathbb{M}$. A row, i, corresponds to a time bin and a column, j, to a (website, performance metric) pair. The element (i, j) is the 75th percentile of the measurements of the (website, performance metric) pair, j, during the time bin, i. The dimensions of $\mathbb{M}$ depend on the dataset. In our case, $m = 425$ and $n = 2184$, which corresponds to three months of measurements. In a long running system, we expect to select n time bins in a sliding window fashion. Note that for the methods we discuss in the next section to work, we need to consider at least a few months of data to capture any weekly patterns in the dataset.

IV. Method

Given web performance of multiple websites over time represented in $\mathbb{M}$, our goal is to identify web performance anomalies – cells of $\mathbb{M}$ (*i.e.* a specific web performance metric for a specific website at a specific time) with abnormally high values. Note that the one-hour bins we use to aggregate web performance samples ensure that we focus on significant anomalies that affect a large fraction of visits during the hour.

Applying standard anomaly detection methods to $\mathbb{M}$ is challenging given the large number of empty cells (46% of the cells in $\mathbb{M}$ are empty). As described in Sec. II, matrix factorization is capable of constructing a low-rank matrix

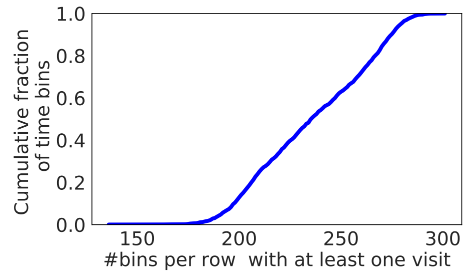


Fig. 2— Number of cells in $\mathbb{M}$ with at least one visit per one-hour time bin.

approximation even when there are many missing values. If a matrix has a low-rank approximation, $\mathbb{M}_L$, we can use this approximation to describe the 'normal' component of the data. The difference between the original matrix and the low-rank approximation represents the residual component, $\mathbb{M}_R$, which contains the anomalous part of the data. This section first evaluates our assumptions, then it presents our method, which we call WMF for Web Matrix Factorization, to compute $\mathbb{M}_L$ and to detect anomalies using $\mathbb{M}_R$.

A. Assumptions

Our method is fundamentally spatio-temporal, meaning that we identify the normal website performance from patterns found in the entire $\mathbb{M}$. The intuition is that factors such as the daily and weekly pattern of user access, common cloud providers, or shared network paths create partial correlation across websites. If we find these inter-dependencies (despite the large amount of missing data) we can use measurements of other websites to evaluate whether at a particular time bin the performance measurements of a given website are anomalous or not. This approach requires that in a given time when one website has no visits (*i.e.* a cell in $\mathbb{M}$ is empty) other websites have visits, and that there exist linear dependencies between the performance of different websites (*i.e.* that we can approximate $\mathbb{M}$ with a low rank representation). We evaluate these two assumptions before presenting our method to estimate the normal form of $\mathbb{M}$.

Websites can learn from one another. In every time bin in the dataset, there are at least 136 out of 425 website-metric pairs with at least one visit. At the same time, each row contains at least 125 empty cells (Fig. 2). Our method uses the fact that websites with no measurements at a given time can potentially rely on the data from other websites with visits to help reconstruct their 'normal' signal.

Low-rank representation of $\mathbb{M}$. The rank of a matrix indicates the number of linearly independent columns of the matrix. If $\mathbb{M}$ can be approximated with a matrix of rank lower than the number of columns, it means that there are linear dependencies among some of the columns of $\mathbb{M}$. This approximation allows to separate the normal pattern (captured in the low-rank approximation) from the anomalous pattern.

For a partially observed matrix A, we denote the set of known values in A as Ω. Given a matrix A in which only

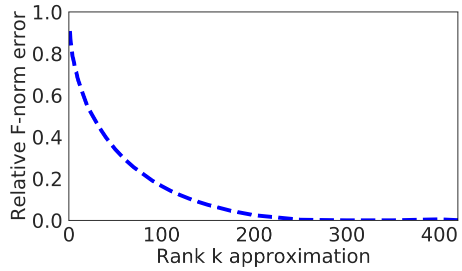


Fig. 3— Rank reduction: relative F-norm error of rank k approximations of $\mathbb{M}$.

the entries Ω are observed, we denote the error of using B to approximate A as

$$\|(A - B)_{\Omega}\|_F^2 = \sum_{(i,j)\in\Omega} (a_{ij} - b_{ij})^2.$$

To approximate an $n \times m$ matrix A via a low rank matrix, we seek to find factors U and V, such that U is $n \times k$, V is $m \times k$, and the rank k approximation of A is UV^T. This leads to the following minimization objective:

$$\min_{U,V} \left\|\left(\mathbb{M} - UV^T\right)_{\Omega}\right\|_F^2 + \lambda \left(\|U\|_F^2 + \|V\|_F^2\right), \qquad (1)$$

where Ω is the set of observable entries, U and V are the factor matrices and λ is a regularization parameter for U and V to avoid overfitting (with $\|X\|_F^2 = \sum_{ij} x_{ij}^2$).

To solve Eq. (1) for a given k and λ, we use an algorithm based on alternating least squares (ALS) [34]. The algorithm alternates between finding the best U and V in order to achieve the minimization objective. In practice, the ALS algorithm is fast and robust; it is known to typically converge quickly to a good rank k matrix UV^T for approximating $\mathbb{M}$.

To illustrate that a low-rank approximation is appropriate for our data, we plot in Fig. 3 the relative error of each rank k estimate of $\mathbb{M}$ (*i.e.* $\|(\mathbb{M} - UV^T)_{\Omega}\|_F^2 / \|\mathbb{M}_{\Omega}\|_F^2$). We see that the error rapidly decreases with k and reaches zero at approximately $k = 250$. This figure shows that we can indeed approximate the full 425-column matrix $\mathbb{M}$ with only 20% error using a matrix of rank between 70 and 100 (and that the 125 websites are not completely independent).

B. Estimation of the normal component

Different techniques exist in the literature for the estimation of the normal low rank component of a matrix. We evaluate ALS [34], SVD [38], PCA and LMaFit [32]. We do not report results for lack of space, but we observe that ALS achieves the highest F1 score; we hence apply ALS in WMF. We explore different settings for ALS and finally set $\lambda = 0.25$ and $k = 70$ because they achieve the maximum F1 scores for anomaly detection. We report the full evaluation online [36]. Note that these settings are not chosen to find the smallest error when representing $\mathbb{M}$ (as shown in Fig. 3), but rather to provide the best representation of the normal form of $\mathbb{M}$ for anomaly detection.

C. Anomaly detection

We next estimate the anomalous component, $\mathbb{M}_R$. Given the original matrix $\mathbb{M}$ with the per-hour average of all the web performance metrics for each website, and its low-rank approximation, $\mathbb{M}_L$, we compute the difference between $\mathbb{M}$ and $\mathbb{M}_L$. Note that $\mathbb{M}_L$ has no missing values thanks to the ALS method that fills in the missing values in such a way to preserve the structure of the low-rank approximation. When a cell in $\mathbb{M}$ is empty, however, we ignore it while calculating the difference, because there were no measured visits to the site at that time. The resulting matrix $\mathbb{M}_R$ indicates the extent of the anomalous component for each website-metric at every one-hour time bin. We then use $\mathbb{M}_R$ to detect anomalies.

Anomalies on a website appear in a single column of $\mathbb{M}$, or at most in few of them if the website collects measurements for other metrics and the same inefficiency impacts more than one metric. To detect such anomalies, we identify "large" residual values in $\mathbb{M}_R$. Anomalies in $\mathbb{M}$ are by definition far from the normal values and thus should not appear in $\mathbb{M}_L$, but only in the residual component matrix, $\mathbb{M}_R$. We label cells in $\mathbb{M}_R$ as anomalous if they are larger than a threshold, τ. We find that τ = 99.9th percentile of the values in $\mathbb{M}_R$ achieves the highest F1 score for our dataset.

D. Running time

We report here the running time of the analysis and break it down at each step. With an Intel(R) Xeon(R) Gold 6150 with 8 cores at 2.70GHz and a 2184 x 425 matrix (corresponding to three months of data), computing $\mathbb{M}_L$ and $\mathbb{M}_R$ takes on average 2 min and 26 sec. The second step of the analysis, detecting the anomaly given the residual matrix, requires instead on average 0.6 sec. The entire analysis is implemented in Python. An interesting avenue of future work is to optimize the implementation for real-time anomaly detection.

V. Validation setup

The evaluation of any anomaly detection method is challenging due to the lack of ground truth, *i.e.* time bins that contain known anomalies and others that are known not to contain any anomalies. We rely on two approaches to validate WMF: controlled experiments and synthetic anomalies. This section describes our validation method, evaluation metrics, and the baseline method we compare against.

A. Controlled website

Monitored website. We host a website on a server in our lab instrumented with the same web monitoring software used to collect the dataset described in Sec. III. We instrument five of the pages of the website. Three of the webpages have only static content (with varying size). The other two pages have, in addition, content retrieved by Javascript code from other web services (*e.g.* Google maps, weather forecast widget, etc). Normally the website experiences very light load, with on average less than 2-3 visits per hour.

Injected anomalies. We introduce network delay, d, on the server hosting the website to later verify whether our method can detect the time bins with these issues as anomalies.[1] We use Linux *tc* to periodically increase the delay of the outgoing traffic by either 500 ms or 1 s. We pick these values of delay increase to reflect values previously found to affect user experience [2], [39]. We introduce each network issue for 30 minutes, on average every 6 hours (with a Poisson process determining the start time). Given that our time bins are one hour long, we choose anomaly durations of 30 minutes to challenge our method, since issues that last more than one hour will be easier to detect (as they affect all samples in a bin). At the same time, our goal is to detect anomalies that last for sufficient time for human intervention, so 30 minutes is reasonable in this respect. We repeat each experiment 100 times, from July 29 to September 20, 2019 ($\sim$25 days for each type of injected anomaly).

Visits. Normally, our website has a small number of visits as it is mostly used for experimentation. To ensure that we have measurements during injected anomalies, we use two laptops connected to one residential and one lab WiFi to visit the website every five minutes on average during the two-month experiment. These automated visits bring the total number of visits to the website to $\sim$30 per hour, which is still low. To reduce the impact of browser caching, we use incognito-mode navigation, and before every visit we restart the browser.

B. Synthetic anomalies

We introduce synthetic anomalies in $\mathbb{M}$ to evaluate the method in a larger variety of settings. Our goal is to introduce realistic synthetic anomalies, where a single underlying issue (in our case, network delay) affects the web performance of multiple visits. We rely on the controlled website discussed in the previous section to build a regression model per web-page that captures the relationship between increased network delays and web performance degradation. We then apply this model to insert web performance anomalies in $\mathbb{M}$.

Injected anomalies. To introduce anomalies, we select a website and time bin and then increase the web performance of all samples in the corresponding cell of $\mathbb{M}$. We then re-run the per-url normalization process and recompute $\mathbb{M}$ (as described in Sec. IV). In particular, we evaluate with additional network delay, d, equal to 500ms, 1s, and 2s. For each d, we randomly pick 0.1% of cells in $\mathbb{M}$ among those with measurements to inject anomalies. To test the sensitivity of WMF to anomaly duration, we also inject anomalies with different durations.

C. Evaluation metrics

We rely on precision, recall, and F1-score to evaluate the accuracy of our anomaly detection method. These metrics are standard for detection problems with class imbalance (in our case, the number of anomalous cells is significantly smaller than that of normal cells).

Definition of true and false positives. The challenge in our case is to define what we consider as true positive (TP) and false positive (FP). Even when we inject anomalies in the controlled website scenario or synthetically in $\mathbb{M}$, we still have no complete ground truth. Visits to our controlled website may have suffered real issues that we have not introduced, and the dataset we use for introducing synthetic anomalies may likely contain real anomalies as well. These real anomalies appear as FP in our results. We consider a TP when our method correctly identifies a cell with an injected anomaly as anomalous. In the controlled website scenario, an injected anomaly may span two time bins. We consider a TP if the method detects at least one of the two time bins as anomalous. We are conservative and consider all other detected anomalies as FP.

Manual inspection of false positives. To evaluate the effect of real anomalies on the results we present, we manually inspect each website-metric time series and report cells that look anomalous, *i.e.*, a single large spike in the time series, or a group of consecutive bins with unusually high values. We then report additional values for precision and recall, which we label $M.I.$ for Manual Inspection. In this case, if the method detects any of the manually reported anomalies, we do not count it as FP nor as TP. Note that we select only the cells that look the most anomalous. There are still cells that may be rightfully detected by the method but are not manually labeled as anomalous. Out of $\sim$500k non empty cells, we only label 1,849 as anomalous (less than 0.4% of the entire dataset).

Controlled website. One issue with the controlled experiments is that we regularly introduce anomalies, and hence the anomalies may become part of the normal behavior. To avoid this bias, we conduct the evaluation in multiple steps each considering only few anomalies at a time (ignoring visits performed when the other anomalies we introduce occur).

D. Baseline

We compare our method with the state of the art time series method for anomaly detection of web performance, Week-over-Week (WoW) [13] (Section II). WoW assumes that there are no empty time bins. To apply it to our dataset, we use linear interpolation on each per-column time series whenever there are no measurements during a one-hour bin. Given an empty bin at row i and column j of $\mathbb{M}$, we estimate $\mathbb{M}[i,j]$ as $\mathbb{M}[a,j] + (\mathbb{M}[b,j] - \mathbb{M}[a,j]) \times \frac{(i-a)}{(b-a)}$, where a and b indicate the closest non empty bins to i for column j, respectively before and after i. WoW is designed for high volume of measurements and the authors filter out visits from mobile devices to reduce the variability of the measurements. In our already sparse dataset, mobile devices represents 52% of the visits. Thus, we keep these measurements.

VI. Validation Results

To evaluate the accuracy of WMF, we use both the controlled experiments and the synthetic anomalies described in the previous section. We run WMF against the three-month dataset. Although we omit results for shorter time windows, F1 score stabilizes for time windows of least two months.

Detection accuracy depends on anomaly duration and severity. We first evaluate the effect of anomaly duration and

[1] We also evaluated the effect of packet loss, but our experiments show that even 30% packet loss had minimal impact on web performance. Hence, we omit the results based on packet loss.

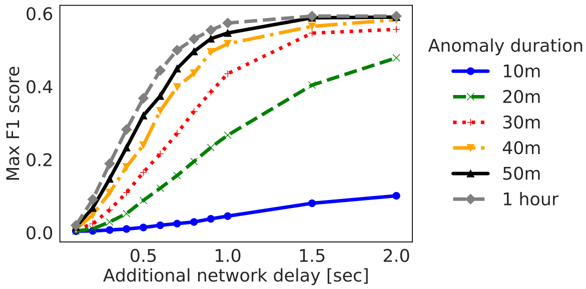


Fig. 4— Effect of anomaly duration and severity on WMF's maximum F1 score.

severity on the accuracy of our method. For this we rely on injecting synthetic anomalies. Intuitively, anomalies that last for a long time and that significantly increase performance metrics should be easier to detect.

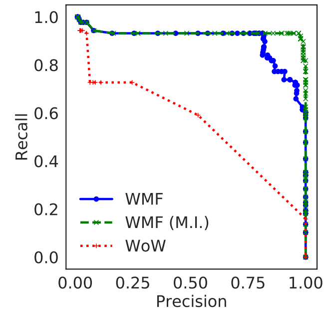
Fig. 4 shows that WMF's performance increases with the severity of the anomaly, *i.e.*, additional network delay, as well as with the duration of the anomaly (in minutes). Note that these numbers would be higher in practice, because our dataset contains true anomalies that our evaluation process is forced to treat as false alarms. Anomalies of short duration (30-40 minutes or less) are hard to detect because our measurement time bins are 60 minutes in length. When the added network delay is less than about 500 ms, detection is difficult overall; on the other hand, when the additional network delay is 1 s and more, F1 scores improve even for relatively short anomalies. We conclude that an additional network delay of 1 s represents an interesting performance region, and we focus on that next.

Precision and recall of WMF versus WoW. Focusing on the case of one-second network delay, we study the accuracy of WMF in more detail, and further compare it to that of WoW. In this case, we also use results from the controlled setting, and manually correct some of the false alarms in the analysis.

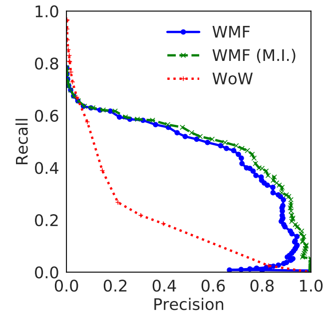
Fig. 5(a) presents the precision-recall curve of WMF and WoW for controlled anomalies, and Fig. 5(b) presents corresponding results for synthetic anomalies. The results show that WMF considerably outperforms WoW, for both controlled and synthetic anomalies. Even without manually correcting for the anomalies already present in the dataset (blue curve), WMF is capable of achieving impressive precision and recall (above 80% for both metrics at the same time). When we manually inspect and remove anomalies that are already present in the data, WMF performs even better and can achieve above 90% in precision and recall at the same time.

In Fig. 5(b), results span many different websites, which affects detection performance. Comparing the two plots, we see that synthetically injected delays appear to be more difficult to detect, but that WMF still strongly outperforms WoW. Further, we see that even across many diverse websites, WMF can achieve a good level of accuracy, with operating points that are above 50% in both precision and recall simultaneously.

Detection accuracy depends on the number of empty cells. One of the motivations behind the design of WMF is the need to handle websites with many empty measurement bins. Hence, we examine the effect of the number of empty bins on WMF's accuracy. We consider the synthetic anomalies scenario with 1 s additional network delay and we filter out columns based on the number of empty bins. Fig. 6 shows the maximum F1 score of WMF and WoW, when the maximum tolerated percentage of empty bins varies between 0% (only columns with no empty bins) and 100% (all the columns of matrix $\mathbb{M}$). The figure shows that, while F1 scores decrease as sites have more empty measurement bins, the performance of WoW is consistently lower than that of WMF. Further, the figure shows that even when considering columns with many empty bins (right side of the figure), WMF still achieves a high F1 score (around 0.6). Finally, the presence in the dataset of real anomalies not synthetically generated prevents achieving an F1 score closer to one.



(a)— Controlled website with 1 s extra delay.



(b)— Synthetic anomaly equivalent to 1 s extra delay.

Fig. 5— Comparison of WMF and WoW.

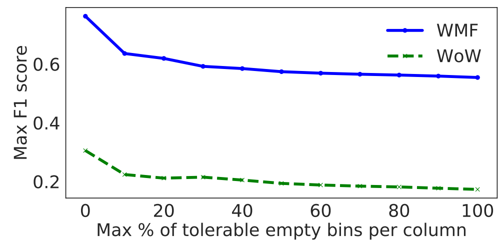


Fig. 6— Effect of percentage of empty bins on the detection accuracy.

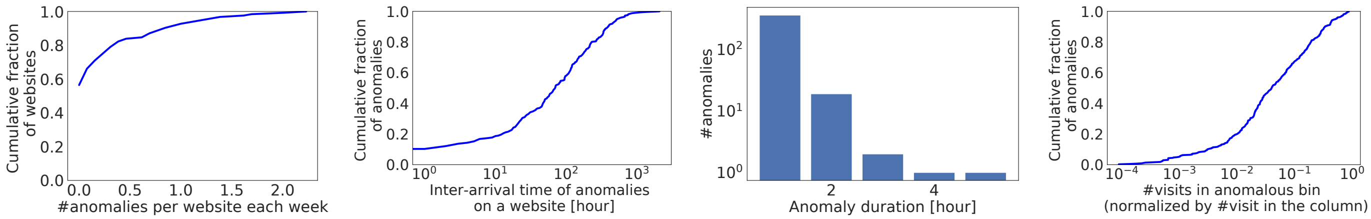
VII. Web Anomalies in the Wild

In this section, we characterize the anomalies WMF detects on the three-month dataset described in Sec. III (without any controlled or synthetic anomalies). We first present the overall characteristics of these anomalies, then we conduct a more detailed analysis of a few anomalous events.

A. Overview

WMF detects a total of 502 anomalies during the three-month measurement period, when using a threshold τ equal to the 99.9th percentile of $\mathbb{M}_R$.

Anomaly frequency. Fig. 7(a) presents the average number of anomalies per week on each website. Approximately 60%



(a)— Frequency of the anomalies: average number of anomalies on each website per week.

(b)— Inter-arrival time of anomalies on a website. 20% of the anomalies are consecutive or within 10 hours of each other.

(c)— Anomaly duration (in hours).

(d)— Normalized number of visits in the anomalous bin. The number of visits decreases when there is an anomaly.

Fig. 7— Anomalies over a 3-months period among 125 websites.

of websites experience no anomaly during the three months of our study. In fact, the 502 anomalies we detect concentrate on only 56 out of the 125 websites. In particular, three websites experience at least one anomaly every five days. We also study the inter-arrival time of anomalies on a given website in Fig. 7(b). We see that 20% of anomalies happen within ten hours or less of the previous anomaly. In those cases, it is likely that a single underlying issue lasts for several hours, but WMF may have only detected anomalies in a few of the bins (we will show one such example anomaly in the next section). Overall, this result suggests that the majority of anomalies in the dataset are isolated and short-term events – for instance, transient network congestion, a misconfiguration of the internal routing of a CDN, or a server overload caused by a spike in requests.

We compare the characteristics of the websites with and without anomalies, but found no particular factor that explains why a given website in the dataset experiences more anomalies. We analyze the number of empty bins in a website's data and the average number of visits, but neither has an effect. Other factors may have an impact on the frequency of anomalies on a website, such as the complexity of the pages, as well as the optimization and the distribution of the resources across different servers. Unfortunately, we have no information about the back-end of the web services and part of the URL's are hidden, which prevents us from accessing all the webpages and develop further our analysis in this direction.

Anomaly duration. We group consecutive anomalous bins together into individual anomalous events to infer anomaly duration in Fig. 7(c). Consistent with the results in Fig. 7(b), the large majority of anomalies has a duration of one hour, which is the minimum size we can identify due to our bins. A few anomalous events, however, last for four or five hours.

Website load and anomalies. One possible cause of anomalies can be website overload. We study the relationship between website load in terms of number of visits during the anomaly versus typical number of visits in Fig. 7(d). We use min-max normalization to bring the number of visits in the anomalous bins between 0 (minimum number of visits reported in the column) and 1 (maximum number of visits). We see that in the majority of the cases, the anomalous bins have a smaller number of visits compared to the normal trend for the website. This result indicates that users may momentarily leave the website when performance degrades.

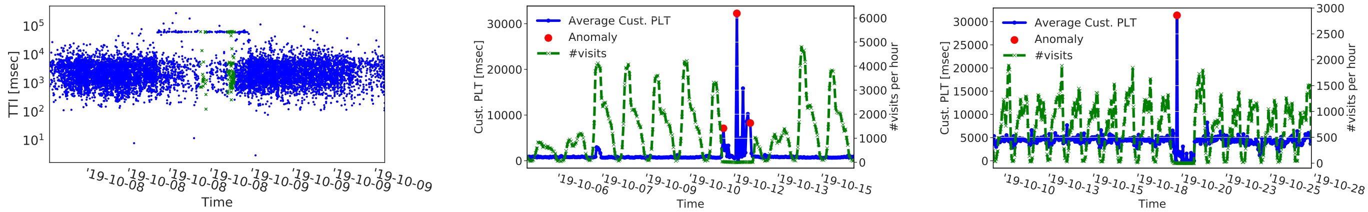
B. Analysis of anomalous events

Among the 502 anomalies WMF detects, we select four example events to study in more detail. We pick the most severe anomalies to allow analyzing their possible causes without the need for feedback from the operators of the websites.

Anomalous event#1, 13 hours of anomalous visits. On the 8th of October 2019, WMF detects two anomalies on a Chinese website within a five-hour time interval. We report in Fig. 8(a) the Time To Interactive of visits to this website over the two days that include the detections. For a period of 13 hours, a fraction of the visits reports TTI values higher than 60 seconds, which increases by a factor of ten the number of visits that normally reach such a high value. This behavior does not correspond to any daily or weekly pattern. Furthermore, we noticed that the majority of these anomalous TTI values fall within a relatively small time interval, between 62 and 70 seconds, which could be a symptom of timeouts expiring. We do not have any information about the back-end of the website, but we speculate that a problem affecting one of the servers hosting the website (or managing a specific resource) is behind this decrease in performance and possibly timeouts on some of the visits.

Anomalous event #2, national holiday. Fig. 8(b) shows the time series of the Customized Page Load Time of a Spanish website, overlaid with the per-hour number of visits to the website. WMF detects three anomalies within 22 hours, on the 11th of October (highlighted with red dots in the figure). A sudden drop in the number of visits appears at the beginning of the detection period and lasts for 27 hours. While this shift corresponds to no daily or weekly pattern, the 11th of October is a national holiday's eve in Spain, thus most likely the drop in visits is related to this festivity. We believe that the drop is caused by either a change in people's behavior during the holiday, or, by a maintenance scheduled on that day on the infrastructure of the webserver.

Anomalous event #3, WMF detects an anomaly on website likely to be down. Fig. 8(c) shows the time series of the



(a)— Anomalous event #1: TTI reported by each visit over two days, with green dots indicating the visits labeled as anomalous by WMF.

(b)— Anomalous event #2: sudden drop of visits during a national holiday.

(c)— Anomalous event #3: website is likely do be down for one day.

Fig. 8— Examples of major anomalies WMF detects.

Customized Page Load Time reported by a commercial Italian website, overlaid with the number of visits. WMF reports an anomaly on the 20th of October on this website. Looking at the number of visits in that period, we see that the website experienced a significant problem and had the number of visits reducing to almost zero for 24 hours. Not having direct information from the administrators of the web service, we can only speculate that the website was most likely down for most of the day and the few users may have hit caches on the Internet or on their own devices, executing thus the Javascript code that performs the measurements even if the main website was not accessible. Note that measurement results are uploaded directly to the monitoring company, not to the website.

Anomalous event #4, WMF detects a problem on a specific page. WMF detects on a Chinese website two consecutive anomalous bins with Object Response Time (ORT) bins higher than 5 seconds on the 28th of August. Among visits with high ORT, 98% are to a single page, which normally has an average ORT of 0.9 seconds. Considering all the visits within the two anomalous hours, the page covers 50% of the visits, while normally it covers about $\sim$9%. We do not have access to the webpage, but we speculate that the page contains objects not present in other pages of the website and that users experienced problems in accessing these specific objects of the page, likely caused by the spike in the requests to the page itself. The company providing us with the dataset performs active measurements targeting the website and confirms a partial problem with the same website on the same day. Unfortunately, they store logs for limited period of time so we do not have further details.

VIII. Conclusion

We presented WMF, a web performance anomaly detection method that addresses the challenge raised by passive measurement across a wide range of general-purpose websites. Although individual websites may have few or no measurements at certain times, WMF leverages data from other websites to identify normal behavior (for example, daily and weekly patterns) and to detect abnormal web performance. WMF relies on normalization and aggregation of measurements of different webpages of a given website to increase the number of samples in individual time bins. WMF further leverages matrix factorization and a low rank representation of the sparse dataset of web performance measurements to estimate the anomalous component of the performance of a website.

We validated WMF on a dataset of web performance measurements performed on 125 websites over a period of three months, with more than 290 million visits. In the controlled experiments on a single website, WMF achieved over 90% precision and recall. In the analysis of synthetic anomalies introduced in the dataset, the precision and recall were lower (as the dataset contains additional, unidentified anomalies); however WMF's F1 score was double that of state-of-the-art time series method. Finally, we characterized the anomalies in the dataset and showed that anomalies are often short, but that some anomalies can last for up to five hours and that some websites suffer from at least one anomaly every five days on average. Our case studies of four anomalous events illustrated that WMF can identify anomalous events with diverse characteristics. We conclude that WMF offers a valuable strategy that may be used by website administrators and third-party web monitoring companies to detect anomalies across the heterogeneous landscape of general-purpose websites.

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