Interactive Visualization of Website Performance

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Abstract— Any delay in the performance of the website tends to cause user frustration. Therefore, analysis of website performance is crucial to users, more importantly to the website owners. We propose an improved visual analysis of website performance by comparing their performance metrics affecting time. These metrics are Speed index, Load time, Fully loaded, First Byte, Start Render, Document complete and DOM Elements. A low value of these metrics signifies better performance. In this paper, we introduce a visual analytics tool to the user to visually explore different statistical relationships between their website and the performance metrics, and also visually explore their website performance against top 100 websites. The tool comprises of several visuals which analyze statistical distribution of the websites and compares the performance metrics of interest against a benchmark. This comparison provides a useful and detailed analysis of the performance lag, as a result, mitigating the frustration of a user who is suffering from any delay or performance issues. Lastly, we recommend using our visualization tool for predicting these critical performance metrics and motivate the design of an appropriate predictive model for this purpose. This predictive model can enhance the user experience in visualizing the website performance. Moreover, this would also enable them to troubleshoot any performance issues more rapidly.

Index Terms—Speed index, Load time, Fully loaded, First Byte, Start Render, Document Complete, DOM Elements

1 Introduction

Users expect fast and reliable online experience. Any delay or lag in the performance leads to user frustration. Testing and visualizing website performance is critical to test the stability and speed of the websites. It helps the user to analyze the performance of the website in unpredictable situations. Previous work in the relevant area has focused more on providing website rankings based on load time, speed and requests [13]. An improved interactive visual analytics method to analyze the website performance by comparing performance metrics affecting time, can provide an elaborate analysis of the website performance issues.The comparison of these metrics through different visualization views provides flexibility to the user to analyze the performance results of their choice, moreover, help them fix the issues they are facing with their website performance more rapidly.

We must understand that website ranking and performance analysis are crucial to users, as they analyze how effectively the website of their interests perform in comparison to others. By visualizing the website performance against a benchmark, the users can understand where their website is lagging in terms of performance. The performance metrics such as Speed index, load time, Document complete time, DOM, First Byte and start render are the crucial metrics comparing the performance of the websites, which we would discuss in detail later in this paper. With the help of different visualization views - Bar Ranking view, Histogram view, Density view and Table view, users engagement in resolving the performance issues of their website increases, thus, providing them an improved overview of the performance issues their website is facing. The visual exploration of the performance metrics of the users website of interest against a benchmark can help them analyze the improvement required in performance.

In this paper, we introduce a visual analytics tool to the user to explore different statistical relationships between their website and the performance metrics, and also visually explore their website performance against top 100 websites. In the next section, we discuss the background of the relevant work and how our tool is novel from the past work. Before moving forward with our design process, we discuss in depth the problem we are aiming to solve and understand the dataset used in our study. Further, we propose our design process and the design requirements to support the visual exploration.Next, we discuss the significance and the capabilities of our designed visualization tool, interactive features it offers, and the additional features we aim to provide for improved performance. After the design discussion, we present our implementation details. And finally, we discuss our initial effort to create a predictive model for the motivation of a useful usage scenario of this work. We conclude the paper with a discussion of the future scope of this work.

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2 Literature Survey

The development of our work builds from the research of previous study in website performance visualization. Most of the relevant work has focused on developing a website performance testing tool to analyze the performance of websites through waterfall charts, reports, or by providing numerical results to the users [5]. However, the novelty of our work lies in providing detailed statistical visuals to the users to analyze the distribution of the websites existing in a certain range of performance metrics and comparing their website performance against the average performance.

In evaluating website performance, sophisticated evaluation models and improvement analysis methods have been developed. In a particular work, complex decision-making trails are used to assess the interdependency between the evaluation parameters [32]. Another work [17] also contributed to Web performance by comparing page load speed of websites using state-of-the-art Website speed test services and provided a recommendation to optimize website performance. Although all of these work provides useful results of website performance quantitatively, there is no flavor of visualization and therefore is not much useful in terms of interactive visualization of the Website performance.

Analysis of e-commerce websites also relates to our work. In one of the study, a multi-criteria satisfaction analysis (MUSA) method is used to rank six usability attributes in eight Greek E-tourism websites [27]. Another study performs tests to measure the quality of e-government websites of five Asian countries through web diagnostic tools. They develop a linear weight model (LWM), analytical hierarchy process (AHP), fuzzy analytical hierarchy process (FAHP) and a hybrid model to find out the best e-government website [22]. Similar to this work, comparison of Asian airline websites was performed using a non-parametric test having sophisticated models[23]. Another research extending this work conducts tests to examine the quality of the e-government website of five Asian countries through web diagnostic tool [25]. In all of these work, the focus is more on the development of complex analytical models to analyze the performance and less on the visualization aspect. They do not provide interactive solutions which can be applied in the visual analytical field for the better visualization of the performance through a tool, which is our focus in this paper.

Another work aims to evaluate CVB websites to assess website performance by measuring the customer friendliness, usability, and technical functions, content of the information displayed by creating Spatial maps. They visualized overall CVB website performance using ArcMap v.9.2 GIS software. They obtained a structural pattern of CVB website performance using Structural Equation Modeling (SEM) [30]. Our Visual Analytics tool also aims to assess website performance, however, our methodology is different from this work as our visualization views target to provide performance analysis using an improved and easy to interact visual design by comparing crucial performance metrics affecting time.

Many of the previous academic research work focused on analyzing website performance by developing ranking lists [19]. One of these studies throws light on the reliability of the website ranking lists based on the performance [26]. They provide a comparison of the similarities and differences among the publicly available websites to find out the reliability. They also discuss the search engine results to evaluate website performance through ranking. Another study makes an effort to analyze the limitations of the ranking lists generated by website performance analysis [29]. The authors compare four main rankings used in recent studies in terms of their agreement with each other, stability, representation bias and potential impact on research cases. They illustrate unique ways to manipulate the rankings and bend research results to their will and demonstrate that the research community should exercise more caution when selecting and using these rankings. Research on the relationship between interactive functions such as Online Two-way Communication, Customization, Content Variety, and Interactive Job Search and web page rankings also focus on rankings and their relationships but does not focus on the performance aspect of the websites or visual exploration of the website performance. Another work proposes a complex multilevel adaptive aggregation method for the Markov chain to model web page rankings [21]. Comparison of PageRank to an idealized web surfer and efficient computation of PageRank for a large number of websites was another study performed to analyze how PageRank can be applied to user navigation [28]. Although these studies aim to find out the website performance though rankings, the visualization approach to analyze the website performance for the problem is not defined in these academic work.

Apart from the academic research performed in analyzing the performance of the websites, currently there are several businesses using web analytics tools to provide an analysis of the performance of the websites and to some extent visualize their performance. PerfTool [8] is an open source tool that collects the information from a client website and displays the information. The tool displays information about web pages, their score, HTML errors, and ways to fix performance issues. Dotcom monitor [11] is another tool which provides web page speed testing from different locations. This tool also presents individual reports for a waterfall breakdown analysis of the performance. Another useful tool for website load time analysis is Sucuri load time tester [7], which provides a global rating to a website from A-F by measuring the fully loaded time of the website. Google page speed insights [12], is also a very popular tool to measure the half load time and the full load time of the website, presents the results in an attractive manner. It ranks the website out of 100, on the basis of which website is categorized into good, needs work and poor. Yahoo came up with an alternative tool to Google page speed insights by developing Yslow [3] which analyses the web page and shows its performance with respect to Yahoo rules. Another website speed test tool is Pingdom speed test [15] provides a report of the results in four sections - waterfall chart, performance grade, page analysis, and history. Further adding to this list, Pagelocity [4] is another such tool which offers a special approach to website performance testing. It provides a score to a website out of 100 but also includes factors such as social media, Search Engine Optimization, resources, and code. Although all of these web analytics tools makes an effort to visually explore few of the performance metrics like speed or load time, we aim to explore all the crucial time- related metrics to analyze the performance in our study. Also, none of these web analytics provides a detailed statistical visual analysis of the websites and analyzes the lag in performance through visualization views, which we aim to provide through our design.

We would discuss the visualization problems in a few more relevant work later in the paper, after proposing our visual design and present a comparison between them. The study of background work throws light on the importance of the contribution of our work in providing a detailed statistical analysis of website performance and comparison of the website performance using the critical metrics. Thus, signifying that the interactive views depicting the website performance and comparison with a benchmark performance are helpful to analyze the performance of the website by businesses and website owners.

3 Understanding The Problem and the Data

3.1 An Illustration

We provide an example to explain the importance of the visualization of website performance. Imagine a bunch of customers trying to make a purchase from their favorite shopping website, and they are experiencing a slow website performance during that time. If the issue persists even for a small duration of time, they will most likely switch to a competitor's website for their purchase. However, if the user has to make the purchase from that specific website only, then the user has no choice but to wait for the issue to get resolved. Instead, with the help of an interactive website performance visualization tool, the users can analyze the performance issues themselves. They can have an analysis of the different views of their favorite website and the performance metric values to analyze the issues they are facing. The visualization of the prediction of the optimal performance from the actual performance of the website, can further reduce their frustration and help them to analyze the issue in detail. This can also be used by the website owners to get an overview of the issues in performance while they are operating their websites so that they can come up quickly with a troubleshooting mechanism for the same.

3.2 Problem Discussion

Most of the research work in website visualization and analytics has focused on the load testing of the websites, to find out how much load or number of users a particular website can handle. They have also focused on developing a ranking of the websites based on the number of web page searches [19]. Few web analytics tools have contributed in visualizing the performance of websites through their load times, speed index and other critical metrics. Online web page testing tools like WebpageTest [5] do provide some sense of visualization of these metrics, but these are limited to having waterfall views and are not interactive. Therefore, a more improved interactive experience is required by the users and the website owners to analyze the performance of the websites and their performance metrics more effectively. This would enable the website owners to understand which of the metrics are performing low or high, and adjust them to provide a good experience to the users.

3.3 Proposed Solution

The solution provided by our Visual Analytics tool is an improved solution as it provides an interactive dashboard to the users and website owners to analyze the performance. The dashboard consists of different types of statistical plots and views for the customers to closely review the relationships between the websites and their metrics and understand the most critical parameter of interest affecting the performance. The view also provides a side-by side comparison of the user's websites against mean performance of the performance metric. Our effort to show a predictive model also motivates improved user interaction for modifying the performance of the websites depending on the predictions observed. Therefore, the main contribution of this work is to introduce an improved visual system to analyze users websites against most popular website performance through an interactive interface.

3.4 Understanding the Dataset

There are two datasets we require for our study - one is users website data and the other is benchmark dataset which would be used for comparing the users data. We would discuss the data collection process for both.

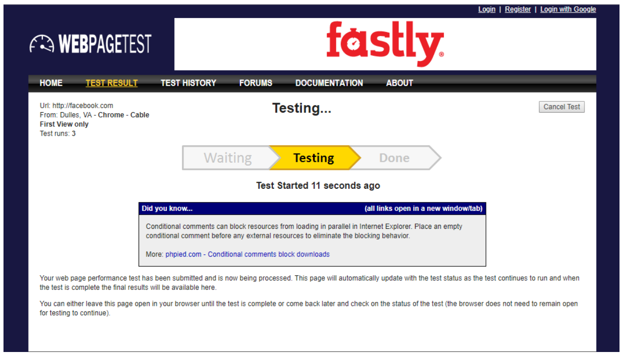

Fig. 1. WebPagetest data collection process [5]

For our first dataset, we collected data from the top performing websites. For this purpose, we extracted the dataset for the top 100 website ranking list provided by Alexa [10]. Webpagetest, a web tool provides a list of performance metrics values for any website entered by the user [5]. We automated the process of retrieving this data from WebPagetest API and collected the data of the performance metrics for these 100 websites. This data can be used as a standard for comparison of the users website of interest. Figure 1 shows a how WebPagetest collects data when we want to perform the data collection automatically for our analysis. Next, the data which is collected had to be normalized to bring them into the same scale. This normalization would help our visual encodings and perform our visualization tasks. The normalized data is ready to be used a benchmark for comparing the users website dataset.

The second dataset collected is the performance metrics for a single test website provided by the user. Similar to the first dataset collection, we automate the process of collecting this data from WebPagetest. The collected data is then saved to a Django model [9], which uses the power of relational databases to save the data provided by the user. The model makes the process of data collection very efficient by saving the website data collected from WebPagetest in a table. If the user inputs a website already stored in the database, then it retrieves the data from the table, otherwise saves the data by collecting data from WebPagetest.

4 Design Process

Once we understand the problem and the dataset, our next goal was to frame the design process. This design process would discuss the various stages of our design methodology to solve the intended problem.

The first stage was to understand the key design requirements of our visual analytics tool. In the second stage, depending on our design requirements, we divided our design tasks into 3 stages - Back-end, User Interface and the integration of the back-end with the User Interface. For each task, the key design requirements were analyzed.

Next, we started with the back-end design as it was crucial to be developed first to make progress in the other design processes. Data collection of the standard websites performance parameters and the user website from WebpageTest and Django Model was a part of back-end design. Parallelly, we started with the design of the visuals. Analyzing which type of visualization for this dataset can be most useful to the user, was a crucial part of this design process.

Once we identified the most useful visualization design, the next design stage was the Integration of the back-end with the front-end to complete the prototype design. With the help of this design process framework, we prioritized our different design tasks and understood the sequence of each of the design tasks involved to create our tool.

5 Visual Analysis Design

A key stage in our design process is the design of the visualization tasks in the tool, and to understand the usefulness of these visualizations to the user. We designed a template for the intended visualization tasks possible in our visual analytics tool. Before discussing the components of the Visual system, it is important to understand the significance of the proposed visuals, to get a complete insight into the purpose of our design.

5.1 Significance of the Design Choices

User engagement in resolving the performance issues of their website increases with the help of different visualization views. By engaging themselves and analyzing the performance lag of their websites, they can get an improved insight of the issues they are facing with their website. Also, the visual exploration of the performance metrics of the users website of interest against a benchmark can help them analyze the improvement required in performance. Each of these visuals is significant in increasing the understanding of the user of the website performance. The different statistical distribution of the websites for a certain range of performance metrics is more clear with these visuals, and it helps them analyze the crucial statistics about the websites.

As mentioned before, selection of these visuals was a key stage in our design process. For the appropriate selection of these visuals in our design, we needed to understand which visual analysis can be most useful to the user using our dataset . We initiated our work by plotting basic Scatter plots for our initial study. We found that visuals showing Scatter plots of the website against their performance metric were not of much use to a user. Showing a large number of data points for the 100 websites in a single scatter plot proved difficult for visual analysis, as the user has to scroll over the entire plot to analyze the website of their interest. Also, plotting multiple scatter plots for a website and each of their performance metrics would have created visual clutter.

Next, we tried working with categorical plots, which also did not serve useful for our design as the criteria and idea to group the websites into a specific category was unclear. For our design, we decided to provide the users the web performance analysis using web page statistics in an interactive fashion. For this purpose, our selection of visuals - Bar Ranking, Histogram, and Density view fits well into our design criteria, which is the reason for their selection in our design process.

5.2 Components

After understanding the significance of the visual design, we now discuss different components of our visual system.

The User Interface was designed to have a dashboard having different views of the statistical relationships and comparison of the two datasets. The tool running on a server displays different views for the websites and their performance metrics.The welcome page is the first component in our visualization tool which the users interact with. When the application runs, the user is directed to this welcome page. They are presented with a form, where they need to enter a website of their choice. They are also asked to enter their user credentials, but these are not mandatory. Once the user enters a website, the server collects all performance metrics for that website, as discussed previously in the dataset collection. Next, the user can switch to different visualization views to analyze their website performance. The views on the Dashboard are the Bar Ranking view, Histogram view, Density view, and Table view. Each view plays a significant role in making the user understand their website performance. Now, we shall discuss each of the visualization views in detail.

5.2.1 Bar Ranking view

The Bar Ranking view provides a comparison of the average performance of the website and the website of the user. It provides a side by side comparison of their performance metrics - Load time, Start render, First byte, Speed index and Document complete.

To understand the importance and usefulness of this view, we first need to discuss the definition of these metrics. Then we can conclude whether high or low values are better for each performance parameter of the website.

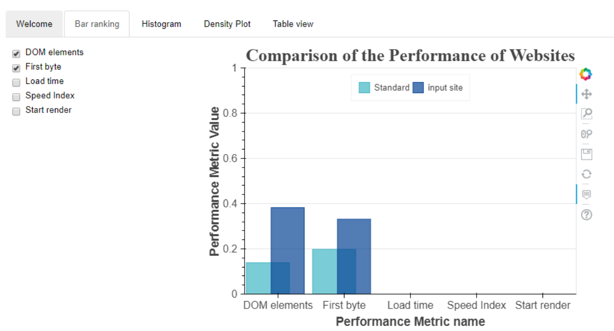

Fig. 2. Bar Ranking view

Beginning with Document complete, it is the point where the browser loading starts and when all the static contents of the page have been loaded. Fully loaded is different than Document complete as it is the point when after the loading of the browser when all static, as well as dynamic elements, have been loaded. Speed index signifies how rapidly the visual elements of the web page appears. First Byte, as the name indicates is the time taken until the first byte of the base web page is received by the browser. Start render is the time between the start of the initial navigation to the web page and the first non-white content displayed on the browser. A web page is basically a document which is either displayed as HTML source or in the browser [14]. Lastly, DOM elements stands for the Document Object Model which means formatting of the HTML page. For example, it could be different elements of the web page such as HTML, DIV and body element. It consists of different elements of a Document in a formatted fashion. More is the size of the DOM tree, more is the time taken for the website load, affecting website performance. Therefore, size of DOM tree also affects time [6].

To understand the usefulness of this view completely, we must know whether the website requires a high or low value of each performance metric. Intuitively, the user always demand less time for loading websites or for performing any tasks during their online experience. Therefore, the user would require a low value of speed index, fully loaded, document complete, DOM, First byte and start render time, for the best performance of their website.

We analyze the test website provided by the user against the top 100 websites in this view. A lower value of each performance metric signifies that the website has a good performance. A higher value of any metric would denote that the websites performance is low on such a metric. There are two bars in this view, one shows the performance of the input website of the user and other shows the mean performance of all the websites. Lower the value, better is the performance of the website. If the input site bar is higher than the mean value, it indicates that there improvement required for that particular metric for the input website. On the other hand, if the value of the input website metric is lower than the mean value, it suggests that the website is performing well for that performance metric. Therefore, this view is useful to the user to analyze how much improvement is needed to make the performance of the websites better than the standard performance. Figure 2 shows the bar ranking view of our tool.

Further, we observe interesting results in this particular view. The visualization shows low values for most of the performance metrics for websites having top rankings. We observed there some critical performance metrics for each website which makes it perform better. For example - considering Facebook has the highest ranking among all websites, our tool displays few critical performance metrics which made this website the top website among all. This information can be very crucial for website owners to understand which is the strongest performance metric for their website and which metrics needs improvement.

There are several interactive features in this view. The user can select or de-select the website parameter of the choice to see the filtered results on the view. This feature can be helpful when the user wants to focus and visualize only specific critical metrics from the list. Currently, we considered only five performance metrics for our evaluation, however, in the future if we would like to compare the performance for a huge number of metrics, these check boxes can be very helpful to the user to visualize only a specific data. Another interesting interaction offered by this view is muting the color of the bars by clicking on their legends.This feature could be helpful as the user can easily switch to single bar view instead of side-by-side view.

5.2.2 Histogram view

To have a color-coded distribution of the websites with respect to their metrics, we constructed a Histogram view. Figure 3 shows the Histogram view. We developed a color-coded histogram view of each website and their performance metrics. This view would enable the user to understand their overall distribution of the websites falling in a certain range. The normalized parameter values falling between the range 0 to 1 are divided into bins or classes. The area of the histogram signifies the number of websites having their performance within that bin width.

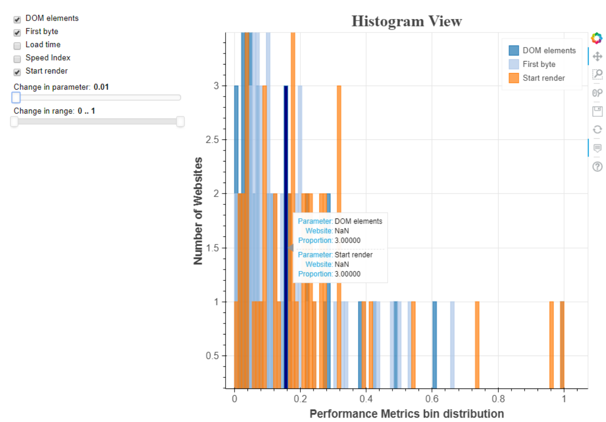

Fig. 3. Histogram view

This visual is helpful to analyze web performance. The user can visualize their website of interest lying in this distribution, which informs them the range of metrics and number of websites performing in the same range as their website. It gives them an indication of the performance of their websites against other websites. For more detailed information about their website and other websites falling in the same range in the selected bin, the users can select the metrics of interest through checkboxes to know the proportion of these metrics.

For generating this visualization, the first step was to read the raw data and normalize it to plot this histogram view. Then we analyze the data by calculating the mean, standard deviation, min, max, 25 percent, 50 percent, and 75 percent. Once we know these values for each of the metrics, we decide our range and bin width to create the histogram.

This view is interactive as the user can select or de-select a specific performance metric check boxes. Once they select or de-select the check boxes, the plot is updated with the visuals showing the data of those check boxes which are active. The slide bars adjusting the range of performance metrics and bin width makes the view more interactive. Also, when we hover over any bar in the histogram, we would find the values of the performance metric for those number of websites.

5.2.3 Density view

The density view aims to provide the relative likelihood percentage of number of websites in each performance metric range. It finds the Kernel density estimation [33], which aims to estimate the probability density function for that value of that metric, therefore, each interval of the curve specifies the number of websites having a percentage of the probability distribution of that performance metric. In other words, we provide Kernel Density estimation of the performance metrics through this density visualization view. The peak value of any metric indicates that the likelihood percentage of those number of websites are more in that specific range of the metric values. Figure 4 shows the density view of our tool.

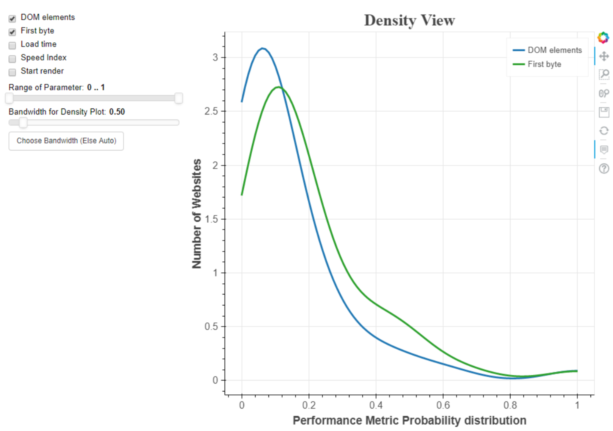

Fig. 4. Density view

This density view is different and significant as compared to Histogram view as the bin width can be adjusted to visualize and picture their probability distribution better in density view, especially for continuous data. The bandwidth adjustment interactive feature in this view further helps in providing an estimation of the bandwidth to the user to aim for better performance and peak probability distributions in the curve. The bandwidth scale can also be modified by the user and the user can click on the choose bandwidth button to reload the new values. Also, each of the metrics is color-coded to distinguish between their probability density curve easily. The user would have an interactive interface to select or de-select any of the metrics from the tool bar provided in the side.

5.2.4 Table view

This view is an additional view for the user if the user wishes to analyze the list of the metrics and their mean performance for the top 100 websites. This visualization is provided for the users who would like to investigate more about the particular values of the data points in the form of a table.

Welcome | Bar ranking | Histogram | Density Plot | Table view

#	Performance Parameter	Average Performance
0	DOM elements	0.1386673533451194
1	First byte	0.1982231452636294
2	Load time	0.17544931599754254
3	Speed Index	0.2296435782463032
4	Start render	0.2174657534247791

Fig. 5. Table view

The table is currently shows the performance parameter name and their mean performance value. Further, another column displaying the value of the metric for the website entered by the user, to perform a side-by-side comparison of the values in a table could be more helpful. This view would help the user in analyzing, how much lag or improvement is required against the average performance of each metric for the website of their interest through numerical figures. The table view has a feature to sort its columns in increasing or decreasing order. Figure 5 shows the Table view of our Visual Analytics tool.

5.3 Integrated View

Although these visuals independently help analyze important relationships between the performance metrics against standard performance and insight about their distribution in terms of their performance metrics, an overall visualization view would be more helpful to the user. This unified view on a single screen comprising of links for each of these views can make the design more compact and interactive. The user can visualize the view of their choice in detail with the help of these links. We further aim to provide a more compact design to the user as an extension of this work to have these multiple views on a single screen, which would be more user-friendly.

5.4 Interactive Features

Our visualization views have several interactive features which enhances user engagement. We would be discussing few of the interactive features common to all the views.

Users can visualize the values of the metrics by hovering over the point of interest. The tool allows to hover over the parameters of interests and display their value on the Interface. Figure 6 shows the hovering interaction feature.

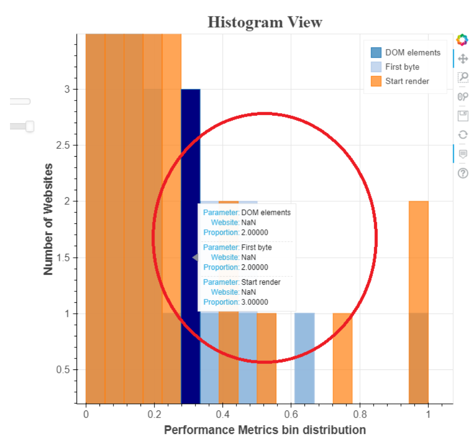

Fig. 6. Hovering interaction

Sometimes, users wish to enlarge the visuals to explore detailed information. For this purpose, the user can use the box zoom feature in our tool to select a box on the interface and zoom the plot to investigate more in detail. Figure 7 shows the box zoom feature.

Another useful interaction offered by this tool is the resetting feature which enables the user to reset the view to its original state so that the user can go back to the previous visuals after box zoom. The reset feature will plot the visuals in the original state. Figure 8 shows the reset feature available in the tool.

Further, the visualization tool contains a save functionality where the users can save their plots of interest in their local machine. The save features save the visual shown on the screen to a PNG file in the user's local machine. This feature is useful to the user if the user wants to save interesting plots and results obtained from this tool for their research or study.

Apart from these useful interactive features, we added a widget to change the value and change of the metrics in range to update the visuals on the respective views by sliding the slide bars. We also added

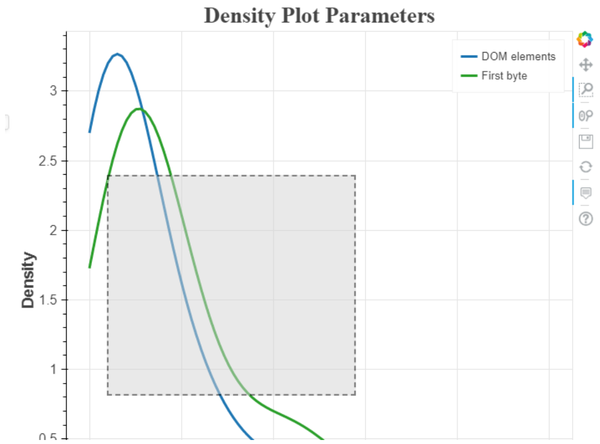

Fig. 7. Box zoom interaction

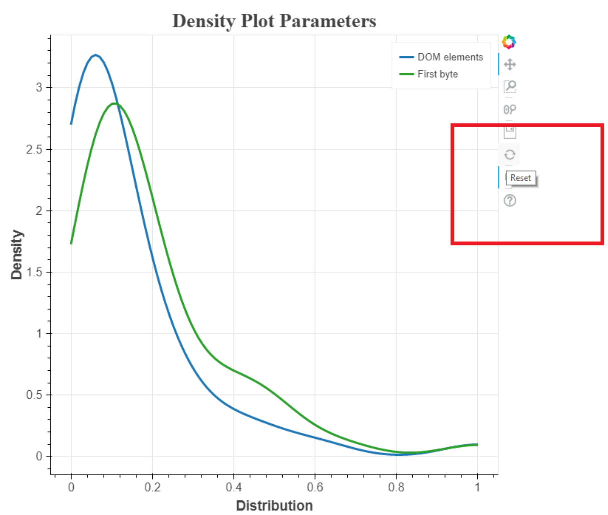

Fig. 8. Reset Interactive feature

a checkbox to select and de-select the metrics of interest for visualization. Figure 9 shows the interactive slide bars and checkbox designed for the user in the tool.

5.5 Comparison with other Visual Designs

We also compared our visuals with other relevant work and observed their differences and similarities with our work. This process helped us to be aware of the strengths of our tool and the improvements needed in the design. We would be discussing few of these studies to understand the significance of our visual design.

One of the relevant work developed visualization views to analyze website usability [18]. They created a predictive visualization model called Information Scent, which simulated users to uncover patterns and deficiencies in information accessibility. They developed a visualization prototype to illustrate enhancement of web usage analysis using visualization methods. Their visualizing views focus on visualizing website evolution using time tube view, visualizing significant traffic routes by first extracting important paths, and building a predictive model of user paths. Our visualization views are different from this work as it aims focuses on statistical analysis and comparison of the website performance metrics against benchmark to enhance website performance analysis. Our visual design also motivates a predictive model to improve the user experience in the analysis process.

We also studied a web analytics system design using a computer-implemented method for visualization of website analytics overlaid upon the source website. The visualization analyses website usage

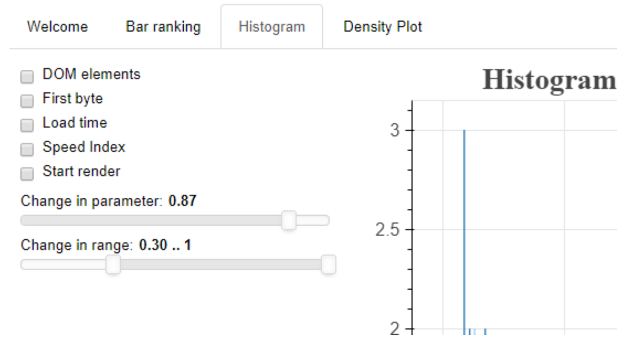

Fig. 9. Slide bars and Checkbox Interactive feature

data, generates website statistics similar to our study, however, provides interactive graphical reports over the website for visualizing the results. The interactive graphical reports include reporting elements positioned over website elements. The reporting elements are independent of any variations in the size and shape of the display window [16].

Study of Social Dynamics on Wikipedia to visualize the overall conflict pattern between a group of users for the visual analysis of opinion groups and rapid interactive exploration is another contribution in the Web page analysis. They constructed Revert Graph, a visual analytics tool having such capability. Our Visual Analytics tool focuses on the visual analysis of a single user, not a group of users, however, the interactive exploration features offered is having similarity with our proposed interactive features in the visuals [31].

6 Implementation Details

As a first step in our implementation , we collected data for the top 100 Alexa websites using WebPagetest. The development of the prototype was initiated by automating the collection process using a JavaScript program. Moreover, the script processes the result from WebPagetest and saved it into a CSV file for further analysis. After back-end development, our main task was to integrate the back-end with the UI to complete the prototype.

Different ideas for implementation evolved while developing the prototype. Initially, we created interactive views from our processed data solely through the Bokeh [1] server. While the server runs, the user gets directed to a dashboard, which has various views for the purpose of visualization. The Welcome view, Histogram view, Density view, and Bar ranking view and Table view are the views currently available to the user. The user is prompted to enter a website name to test its performance against other Alexa websites and to analyze the statistical relationships between the website and their performance parameters. Once the user enters a website name, the server calls the back-end script to collect performance parameters of that website from WebPagetest. Next, the data collected from the server is saved in a CSV/JSON format file for further processing to create or update the visualization views. After the views for that website are generated, the user can switch to different views to analyze the website performance.

Our aim was to collect data from the server and save it in a CSV/JSON format file to process it for our visualization tasks. Although Bokeh server was very helpful in collecting the data for the website entered by the user for producing the visualization views, saving the data collected to a JSON/ CSV file was a bit of a challenge. For this purpose, we used Django - a high-level Python web framework which is used for producing web applications. Through Django, a form was created on the dashboard to enable the user to enter their credentials and the website name which they wanted to test. The user credentials are not a required field; however, the website name is a required field in this form. The Django model, which uses the power of relational databases to store data served helpful to retrieve the data of the websites from the database table. After entering the required website name from the user, the model helps in retrieving the website parameters from the database, if it is not present already. If the website is present, the user is prompted with a message that the website data is already loaded in the database.

7 Recommendation

Based on the design of our visualization tool, we suggest a recommendation to use this tool for predicting the critical performance metrics.This prediction can provide a better insight to the user of how much improvement is needed in their website performance.

```
                            OLS Regression Results
==============================================================================
Dep. Variable:            Speed Index   R-squared:                       0.666
Model:                            OLS   Adj. R-squared:                  0.643
Method:                 Least Squares   F-statistic:                     29.88
Date:                Thu, 15 Nov 2018   Prob (F-statistic):           8.78e-11
Time:                        19:43:27   Log-Likelihood:                -426.54
No. Observations:                  49   AIC:                             861.1
Df Residuals:                      45   BIC:                             868.6
Df Model:                           3
Covariance Type:            nonrobust
to hide ============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         879.4862    546.778      1.608      0.115    -221.782    1980.754
Start render    0.6519      0.143      4.563      0.000       0.364       0.940
Load time       0.2088      0.030      7.046      0.000       0.149       0.268
First byte     -0.1717      0.842     -0.204      0.839      -1.868       1.525
==============================================================================
Omnibus:                        5.052   Durbin-Watson:                   2.016
Prob(Omnibus):                  0.080   Jarque-Bera (JB):                4.798
Skew:                           0.363   Prob(JB):                       0.0908
Kurtosis:                       4.350   Cond. No.                     2.62e+04
==============================================================================
```

Fig. 10. OLS Regression Results for our predictive model

Our initial efforts in this predictive modeling motivate us to research for more suitable models for this dataset and perform a comparison of the prediction results to evaluate the models performance. For our initial study, we use the normalized dataset to have a uniform scaling of the data points, which can enable us to perform useful machine learning analysis like regression. We performed Multiple Regression [20] modeling to understand the relationship between the dependent variable and the independent variables in our predictive model. To start with the predictive modeling process, We build a hypothesis to estimate the speed index based on the other performance metrics. By changing the number of independent variables, we estimate the correlations between the different performance metrics. Further, using Ordinary Least Squares (OLS) [2], which is a statistical technique to minimize the error between the predicted and the actual values, we tried to estimate the model accuracy based on the R^2 value. The accuracy of model predictions increases as and when R^2 value reaches close to 1. For the model estimating speed index on the basis of Start Render, Load time and First byte, we obtained R^2 value of 0.66. The results of the prediction model are shown in Figure 10.

Although the results of this analysis are currently not significantly useful for this particular model, our prediction analysis motivates us to find an appropriate relationship between the dependent and independent variables and future research for an accurate model for such a prediction [24]. Future scope of this work aims to perform predictive modeling of the performance metric estimation for different websites. The extension of the work along this line will help the users more in understanding the website performance prediction for improvement.

8 Conclusion

In this paper, we aim to develop a visual analytics tool to analyze website performance against top 100 websites of Alexa. Previous work to analyze the websites have focused more on providing web rankings data to users and less on providing interactive plots to show their performance over critical performance parameters. We aim to provide interactive views to the user through our visualization tool to enable the users and website owners to be aware of the strengths and improvements required for their website of interest. We discuss the design approach to design the tool and their various components. Lastly, we discuss the different components of our visualization tool and their capabilities. The significance of the Histogram, Density and Bar Comparison and Table view and their interactive features are discussed in detail.Finally, we present our initial efforts in creating a predictive model for providing useful predictions to the user to improve their website performance. We recommend researching more predictive models and compare them against this model to evaluate their accuracy in predictions.

9 Future Work

The future scope of this work is to add more interactive views to this tool to analyze new relationships between the websites and their performance parameters. This would enable the user to have a greater insight of their website performance. Another area of improvement could be extending our intial work in making this tool adaptive by showing predictions and improvement required through a suitable machine learning model to get the optimal performance of the website. Based on our current template design provided by our tool, we plan to integrate prediction model views to the UI in future.

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