

# Parallel Performance-Energy Predictive Modeling of Browsers: Case Study of Servo

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**Abstract**—Mozilla Research is developing Servo, a parallel web browser engine, to exploit the benefits of parallelism and concurrency in the web rendering pipeline. Although parallelization demonstrates speedups in displaying *pinterest.com*, the opposite is observed for *google.com*. The workload of a browser is dependent on the web page it is rendering. In many cases, the overhead of creating, deleting, and coordinating parallel work outweighs any of its benefits. In this paper, we model the relationship between key web page primitives and a web browser’s parallel performance using supervised learning. We discover a feature space that is representative of the parallelism available in a web page and characterize them using seven key features. Additionally, we consider energy usage trade-offs for different levels of performance improvements in our automated labeling algorithm. Such a model allows us to predict the degree of parallelism available in a web page and decide whether or not to render a web page in parallel. This is critical for improving the browser’s performance and minimizing its energy usage. We evaluate our model by using Servo’s layout stage as a case study. Experiments on a quad-core Intel Ivy Bridge (i7-3615QM) laptop show that we can improve performance and energy usage by up to 91.39% and 46.32% respectively on the 535 web pages considered in this study. Looking forward, we identify opportunities to apply this model to other stages of a browser’s architecture as well as other performance- and energy-critical devices.

## I. INTRODUCTION

For any particular browser, a heavier page will take longer to load than a lighter one will [15]. The workload of a web browser is dependent on the web page it is rendering. Additionally, with the meteoric rise of the Web’s popularity since the 1990s, web pages have become increasingly dynamic and graphically rich—their computational complexity is increasing. Hence, the page load times of web browsers have become a growing concern, especially when the user experience affects sales. A two-second delay in page load time during a transaction can result in abandonment rates of up to 87% [7]. Further challenging matters, an optimization that works well for one page may not work for another [29].

The concern of slow page load times is even more acute on mobile devices. Under the same wireless network, mobile devices load pages 3× slower than desktops, often taking more than 10 seconds [22]. As a result, mobile developers deploy their applications using low-level native frameworks (*e.g.* Android, iOS, etc. applications) instead of the high-level browser, which is usually the case for laptop developers. However, these applications are hard to port between phones, tablets, and

smart TVs, requiring the development and maintenance of a separate application for each platform. With a faster browser, the universal Web will become more viable for all platforms.

The web browser was not originally designed to handle the increased workload in today’s web pages while still delivering a responsive, flicker-free experience for users. Neither was its core architecture designed to take advantage of the multi-core parallelism available in today’s processors. An obvious way to solve the slow web browser problem is to build a parallel browser. Mozilla Research’s Servo [14] is a new web browser engine designed to improve both memory safety, through its use of the Rust [13] programming language, and responsiveness, by increasing concurrency, with the goal of enabling parallelism in *all* parts of the web rendering pipeline.

Currently, Servo (Section III) parallelizes its tasks for all web pages without considering their characteristics. However, if we naïvely attempt to parallelize all parts of the web rendering pipeline for all content, we will incur overheads from the use of hundreds to thousands of threads per web page. More importantly, we may also penalize very small workloads by increasing power usage or by delaying completion of tasks due to the overhead of coordinating parallel work. Thus, the challenge is to ensure fast and efficient page load times while preventing slowdowns caused by parallel overhead. We tackle this challenge by modeling, using accurate labels and supervised learning, the relationship between web page characteristics and the parallel performance of a web rendering engine and its energy usage within the *complete* execution of a browser. In this paper, we work with Servo since it is the only publicly available parallel browser currently. However, our modeling approach can easily extend to any parallel browser on any platform since our feature space is *blind* to the implementation of a web rendering engine.

Concretely, we model with seven web page features that represent the amount of parallelism available in the page. These features are oblivious to the implementation of a rendering engine. We correlate these features to the parallel performance in two stages of a parallel web rendering engine. The first stage, style application, is the process in which the engine determines the CSS styles that apply to the various HTML elements in a page. The second stage analyzed in this work is layout. During layout, the engine determines the final geometric positions of all of the HTML elements. We choose

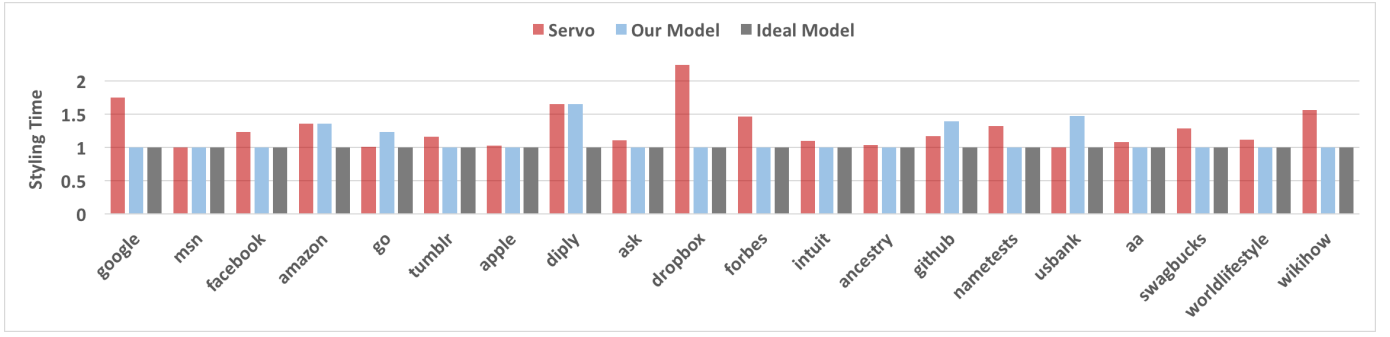


Fig. 1. Normalized styling times of Servo, Our Model and Ideal Model.

these two stages since they consume a significant portion of overall rendering time, especially for modern dynamic web pages. Internet Explorer and Safari spend 40-70% of their web page processing time, on an average, in the visual layout of the page [28].

We evaluate our model for Servo on a quad-core Intel Ivy Bridge using off-the-shelf supervised learning methods on 535 web pages. Even with heavy class-imbalance in our data set, we demonstrate strong accuracies, approaching 88%! Figure 1 depicts the styling times taken by Servo and our model against an optimal model (to which times are normalized) for the top 20 web pages in the Alexa Top 500 [3] list. *Ideal Model* represents the best time that is achieved using either 1, 2 or 4 threads (Section IV). *Our Model* represents the time taken using the number of threads suggested by our proposed model. *Servo* represents the time taken by 4 threads, the default number of threads that the Servo browser engine, unlike our model, spawns for the styling and layout stages on a quad-core processor. *Our Model* performs as well as the *Ideal Model* in most cases. We make three main contributions:

- (1) **Workload characterization** – The workload of a browser is dependent on the web page. We study and analyze the Document Object Model (DOM) [5] tree characteristics of a web page and use them to characterize the parallel workload of the rendering engine (Section II).
- (2) **Performance-energy labeling of web pages** – Considering performance speedups and energy usage “greenups,” [24] we label web pages into different categories using three cost models. To do so, we propose automated labeling algorithms for each cost model (Section V).
- (3) **Performance-energy modeling and prediction** – Using supervised learning, we construct, train and evaluate our proposed statistical inference models that capture the relationship between web page characteristics and the rendering engine’s performance and energy usage. Given the characteristics of a web page, we use the model to answer two key questions: (a) should we parallelize the styling and layout tasks for this web page? If so, (b) what is the degree of available parallelism for this web page? (Section VI)

## II. WEB PAGE CHARACTERIZATION

A wide variety of web pages exist in today’s World Wide Web. A web page can either contain minimal content with little to no images or text, or it could contain a wide variety of multimedia content including images and videos. The left-column of Figure 2 depicts the web pages of *google.com* and *ehow.com*, two contrasting instances that exemplify the variety of web pages that one comes across on a daily basis.

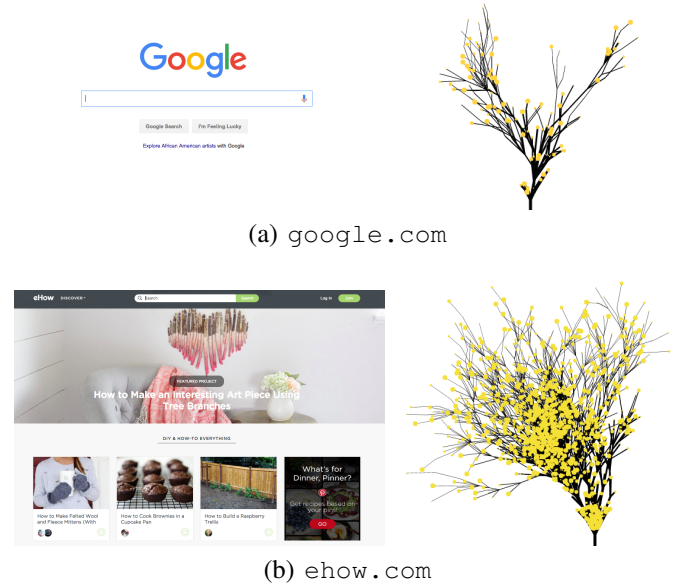


Fig. 2. Contrasting types of web pages (left) and the visualization of their DOM trees (right)

The right-column of the Figure 2 portrays a visual representation (created using Treeify [16]) of the DOM tree of the corresponding web pages. The DOM tree is an object representation of a web page’s HTML markup. Qualitatively, Figure 2 shows that simple web pages, like *google.com*, have relatively small DOM trees, low number of leaves, and are not as wide or deep. On the other hand, complex web pages, such as *ehow.com*, have relatively big trees, high number of leaves, and are much wider and deeper.

Browser-optimizations are primarily made in the style application stage since it is the most CPU-intensive of all

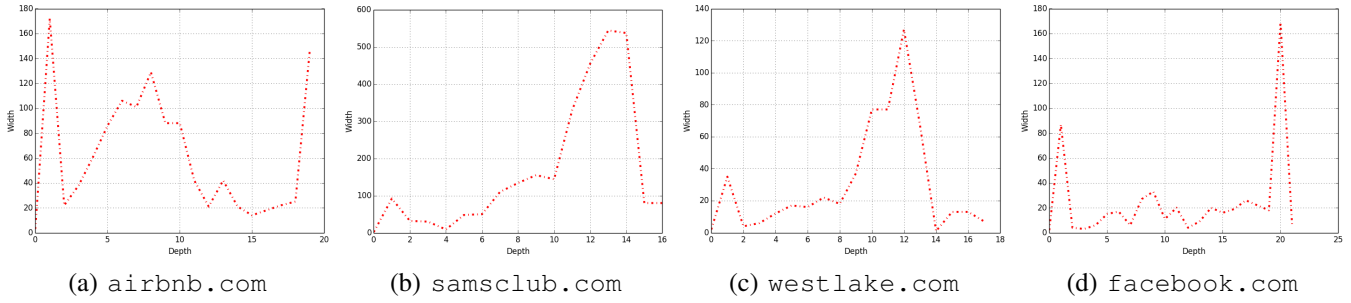


Fig. 3. Width Vs. Depth graphs of the DOM trees of different web pages (note that the scales of the axes are different).

stages [6]. It is during this stage that the DOM tree is traversed extensively to compute the styles for each element on the page. Naturally, a parallel browser would then optimize this stage using parallel tree traversals [28]. Hence, we identify DOM tree features that correlate strongly to the performance of these parallel tree traversals. Any amount of parallel speedup or slowdown would depend on the structure of the DOM tree. We intuitively choose the following set of nine characteristics to capture the properties of a web page and its DOM tree:

1. Total number of nodes in the DOM tree (**DOM-size**)
2. Total number of attributes in the HTML tags used to describe the web page (**attribute-count**)
3. Size of the web page’s HTML in bytes (**web-page-size**)
4. Number of levels in the DOM tree (**tree-depth**)
5. Number of leaves in the tree (**number-of-leaves**)
6. Average number of nodes at each level of the tree (**avg-tree-width**)
7. Largest number of nodes at a level of the tree (**max-tree-width**)
8. Ratio of max-tree-width to average-tree-width (**max-avg-width-ratio**)
9. Average work per level of the tree (**avg-work-per-level**)

Our intuition is that large<sup>1</sup> and wide trees observe higher speedups than small and narrow trees in parallel tree traversals (captured by **DOM-size** and **avg-tree-width**). In consecutive top-down and bottom-up parallel traversals (see Section III), trees with high number of leaves observe faster total traversal completion time (captured by **number-of-leaves**). Even amongst wide trees, those that don’t have abrupt changes in tree width, or are less deep, observe faster parallel traversals (captured by **tree-depth**, **max-avg-width-ratio**). **DOM-size** captures the total amount of work while **avg-work-per-level** ( $= \text{DOM-size} / \text{tree-depth}$ ) captures the average parallel work on the web page. **attribute-count**, and **web-page-size** capture the general information about a web page. Although we identify nine key features, from the results of the statistical correlation of these features to Servo’s parallel behavior, we choose only seven of them for the purpose of modeling with Servo (see Section VI).

<sup>1</sup>The values of the features lie on a continuous spectrum and so, we cannot assign discrete definition to descriptors such as “big,” “large,” “small,” “wide,” “narrow,” etc. For instance, defining **DOM-size** to be “big” if **DOM-size** > 150 wouldn’t be reasonable when **DOM-size** = 149.

To quantitatively analyze DOM trees, we plot the width of the trees at each of their depth-levels. In Figure 3, we do so for `airbnb.com`, `samsclub.com`, `westlake.com`, and `facebook.com`. Using these figures, we relate our intuition to observed data. `airbnb.com` and `samsclub.com` are examples of DOM tree structures that represent “good” levels of available parallelism. The **DOM-size** of `samsclub.com` is 2833 and hence, sufficient work is available. The **DOM-size** of `airbnb.com` is 1247 which is much smaller than that of `samsclub.com`. However, the DOM tree of `airbnb.com` has a high **avg-tree-width** of 62.3, a characteristic that favors parallelism. Our performance experiments show that `samsclub.com` achieves 1.48 $\times$  speedup with 2 threads and 2.12 $\times$  speedup with 4 threads. `airbnb.com` achieves speedups of 1.2 $\times$  and 1.43 $\times$  with 2 and 4 threads respectively which, although significant, are not as high as those of `samsclub.com` due to the lesser amount of available work. The DOM trees of `westlake.com` and `facebook.com` exemplify tree structures that represent “bad” candidates for parallelism. These trees have high widths only for a small number of depth levels. Hence, the **avg-tree-width** of these trees is small: 30.6 and 24.6 for `westlake.com` and `facebook.com` respectively. These trees don’t offer enough amount of work to keep multiple threads occupied. `westlake.com` shows slowdowns of 0.94 $\times$  and 0.74 $\times$  with 2 and 4 threads respectively. Similarly, `facebook.com` demonstrates slowdowns of 0.86 $\times$  and 0.81 $\times$  with 2 and 4 threads respectively.

### III. SERVO OVERVIEW

Servo [14] is a web browser engine that is being designed and developed by Mozilla Research. The goal of the Servo project is to design a browser architecture that employs inter- and intra-task parallelism while eliminating common sources of bugs and security vulnerabilities associated with incorrect memory management and data races. C++ is poorly suited to prevent these problems.

Hence, Servo is written in Rust [13], a new language designed, by Mozilla Research, specifically with Servo’s requirements in mind. Rust provides a task-parallel infrastructure and a strong type system that enforces memory safety and data-race freedom. The Servo project is creating both a full web browser, through the use of the purely HTML-based user interface BrowserHtml [4] and a solid, embeddable web

rendering engine. Although Servo was originally a research project, it was implemented with the goal of production-quality code and is in the process of shipping several of its components in the Firefox browser.

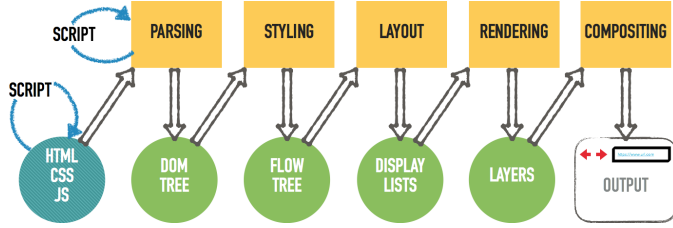


Fig. 4. Processing stages and intermediate representations in a browser engine. The circles represent data structures while the squares represent tasks.

The processing steps used by all browsers are very similar, as many parts of the interpretation of web content are defined by the standards from the World Wide Web Consortium (W3C) and Web Hypertext Application Technology Working Group (WHATWG). As such, the steps Servo uses in Figure 4 should be unsurprising to those familiar with the implementation of other modern browsers [6]. Due to space constraints, we describe only the phases relevant to this paper in detail. A more detailed description of these phases is available in one of our related papers [20].

#### A. Parsing HTML and CSS.

In a new navigation to a resource, whether from a click on a link, entry in the address bar, or programmatic navigation via JavaScript, the first step in loading a site is retrieving and parsing the HTML and/or CSS files. The HTML document is translated into a DOM tree, the data structure used by browser’s components to work with HTML elements. Each node of the DOM tree corresponds to an HTML element in the markup. The CSS file is loaded into style structures that will be used in *Styling*.

#### B. Styling

After constructing the DOM tree, Servo attaches styling information in the style structures to this tree. In this process, it constructs another tree called the *flow tree* which describes the layout of the DOM elements on the page in the correct order. However, the flow tree and the DOM tree don’t hold a one-to-one relation. For example, when a list item is styled to have an associated bullet, the bullet itself will be represented by a separate node in the flow tree even though it is not part of the DOM tree.

This stage contains the first step that is the subject of analysis in this paper. Servo executes *Styling* using parallel tree traversals, an approach similar to the one used by Meyerovich et al. [28]. Conceptually, styling, the first half of this step, is a trivially parallel process—each DOM-tree-node’s style can be determined at the same time as any other node’s. However, in order to prevent huge memory growth, Servo shares the concrete style structures that are associated with

multiple nodes, requiring communication between any parallel threads. The second half of this step is the construction of the flow tree.

#### C. Layout

The flow tree is then processed to first determine the final geometric positions of all of the elements and then to produce a set of *display list* items.

Determining these positions is the second step that is analyzed in this paper. In cases where no HTML elements prevent simultaneous evaluation (e.g. floated elements and mixed-direction writing modes), Servo performs consecutive top-down and bottom-up parallel tree traversals when determining the final positions of elements; the height of a parent node is dependent on the cumulative height of its children, and the widths of the children is dependent on the width of the parent. These traversals are executed incrementally and hence multiple individual passes occur before the end of a page-load. Figure 5 shows one parallel execution with four cores rendering *reddit.com*. Each colored rectangle corresponds to one of the four cores and surrounds the elements that were laid out on that core.

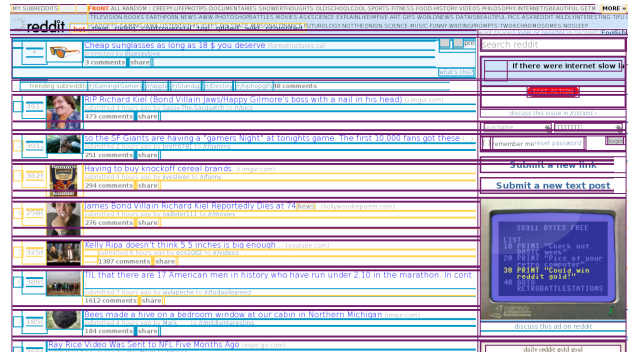


Fig. 5. Parallel layout on *reddit.com*. Different colors indicate that layout was performed by a different thread.

After final positions of the elements have been computed, the display list items are constructed. These list items are the actual graphical elements, text runs, etc. in their final on-screen positions. The order in which these elements are displayed is well-defined by the CSS standard [17].

#### D. Rendering and Compositing

Once all of the elements to appear on screen have been computed, these elements are *rendered*, or painted into memory buffers or directly to graphic-surfaces (*compositing*). In Servo, each of these buffers may be painted in parallel.

In Servo’s current implementation, a work-stealing scheduler is used to schedule the threads that are spawned (once) to perform the parallel tree traversals in the *Styling* and *Layout* stages. In the rest of the paper, we will use the term **Overall Layout** to refer to the *Styling* and *Layout* stages together and **Primary Layout** to refer to the *Layout* stage alone. Also, unless specified otherwise, we refer to *total* times of all the incremental layout passes performed for each stage.

#### IV. EXPERIMENTAL SETUP

The Web is extremely flexible and dynamic. Constantly changing network conditions can add a significant amount of variability in any testing that involves acquiring data directly from the Internet. Further, due to advertising networks, A/B testing, and rapidly changing site content, even consecutive requests can have significantly different workloads.

Hence, in order to achieve repeatable and reliable performance results with Servo, we use Google’s Web Page Replay [18] (WPR) to *record* and *replay* the HTTP content required for our tests. At a high level, WPR establishes local DNS and HTTP servers; the DNS server points to the local HTTP server. During *record*, the HTTP server acquires the requested content from the Internet and saves it to a local archive while serving the requesting client. During *replay*, the HTTP server serves all requests from the recorded archive. A 404 is served for any content that is not within the archive. We used WPR to first *record* the web pages in our sample set and then *replay* them during the experiments. The *replay* mode guarantees that Servo receives the same content every time it requests a particular web page. For our testing platform, we use a quad-core Intel i7-3615QM running OS X 10.9 with 8GB of RAM.

We collect our sample set from two sources: (1) Alexa Top 500 [3] web pages in the United States during January 2016, and (2) 2012 Fortune 1000 [1]. We initially started with 1000 web pages but these contained domain names that were either outdated or corresponded to server names and not actual web pages (e.g. `blogspot.com`, `t.co`). Also, some web pages caused runtime errors when Servo tried to load them since it is a work in progress. After filtering out all such web pages, we have a working set of 535 web pages.

For our performance testing, we use Servo’s internal profiling tool that spits out a CSV file containing user times of the *Styling* stage and also the *Primary Layout* stage. For our energy testing, we use Apple’s powermetrics [12] to capture processor power usage. In both the energy and timing experiments, we call Servo to open a web page and terminate it as soon as the *page load* is complete. Across all browsers, *page load* entails fully loading and parsing all resources, reflecting any changes through re-styling and layout. Servo goes a bit further in the automation harness and will also wait until any changes to the display list have been rendered into graphics buffers and until the in-view graphics buffers have been composited to the final surface. In the energy experiment, we allowed a sleep time of 10 seconds before each run of Servo to prevent incorrect energy measurements due to continuous processor usage.

Servo allows us to specify the number of threads to be spawned in the *Overall Layout* stage. Given that our platform is a quad-core, we used 1, 2, and 4 as the number of threads for each web page. Since Servo is still under development, we observe non-repeatable behavior. To account for repeatability, we run 5 trials with each thread number for each web page for both the performance and energy experiments. With 5

trials, the medians of the *median absolute deviations* (MAD) of all 1-, 2- and 4-thread executions are low: 6.76, 7.46, 7.49 respectively. The MAD is a robust measure of the variability of a data sample [26].

#### V. PERFORMANCE AND ENERGY AUTOMATED LABELING

In this section, we propose tunable, automated labeling algorithms that can be used with any web browser on any testing platform in order to classify web pages into different categories. Automated labeling eliminates the need for a domain expert to manually and accurately label data. Given the labels, a predictive model can be trained using supervised learning methods. For labeling, we consider three cost models:

1. **Performance** – Labels are based only on performance improvements from parallelization.
2. **Energy** – Labels are based only on energy usage increases from parallelization.
3. **Performance and Energy** – Labels are generated by considering both performance improvements and energy usage increases from parallelization.

Although we collected user times for both the *Styling* and *Primary Layout* stages on Servo, we focus our comparisons on the former for the following reasons – (1) The *Styling* stage works on the DOM tree while the *Primary Layout* stage works on the flow tree. Since we characterize web pages using the DOM tree, we expect *Styling* performance to correlate strongly to the tree characteristics. (2) The medians of total *Styling* time and total *Primary Layout* time as percentages of the *Overall Layout* time (single-thread execution) are 67.19% and 7.83%. Clearly, *Styling* time primarily defines *Overall Layout* time. Figure 6 shows these percentages for a sample of 40 randomly selected web pages.

Another interesting observation is that an individual, serial pass of *Primary Layout* ranges between 1 and 55 ms. This range is much smaller than the 1 to 320 ms range of an individual, serial *Styling* pass. Hence, parallelizing tree traversals for the *Primary Layout* stage will most likely result in poorer parallel performance due to thread communication and scheduling overheads. Our results validate this analysis. On average, the time taken by an individual, parallel pass for *Primary Layout* is 3.92 ms, 7.01 ms, and 9.82 ms with 1, 2, and 4 threads respectively. We also observe an increase in the average total times for *Primary Layout* with parallelization: 221.39 ms, 242.56 ms, 263.73 ms with 1, 2 and 4 threads respectively.

We compare the energy usage values of Servo in *Overall Layout* using 1, 2, and 4 threads. Although the data corresponds to the processor energy usage between the beginning and termination of Servo, these values are mainly affected by parallelization of *Overall Layout* because this stage constitutes the majority of the browser’s execution time. Powermetrics [12], or any external energy-profiling tool for that matter, doesn’t allow us to obtain measurements at the granularity of function-calls.



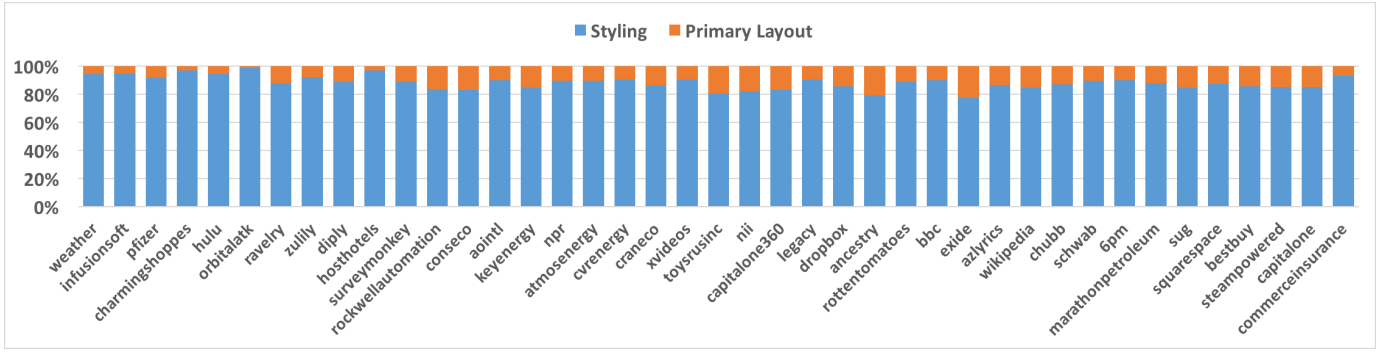


Fig. 6. Styling and Primary Layout time division in Overall Layout for a random sample of 40 web pages

### A. Performance Cost Model

In the *performance cost model*, we consider only parallel runtimes to appropriately label the web pages. Consider an arbitrary number of thread-configurations where each configuration uses  $t$  threads. The values of  $t$  are distinct. We first define the following terms.

- $x_t$  – time taken by  $t$  threads
- $t_{\text{serial}} = 1$  (serial execution)
- $p_t = x_{t_{\text{serial}}} / x_t$  (speedup)
- $p_t^{\max}$  – maximum value of  $p_t$
- $p_{\min}$  – minimum threshold that demarcates a significant speedup (to disregard measurement-noise)

The following steps describe the labeling process for a web page:

1. For each thread configuration, we compute its speedup with respect to serial execution.
2. Given all the  $p_t$  values for a web page, we calculate  $p_t^{\max}$ .
3. If  $p_t^{\max} > p_{\min}$ , we assign the web page label  $t$  where  $t$  corresponds to that of  $p_t^{\max}$ . Otherwise, we label the web page as  $t_{\text{serial}}$  since all other  $p_t$  values would be smaller than  $p_{\min}$ .

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#### Algorithm 1 Performance labeling of a web page

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##### Input:

- 1:  $N: \{t \mid t \text{ is number of threads in a configuration}\}$
- 2:  $P: \{p_t \mid p_t \text{ is speedup using } t \text{ threads, } \forall t \in N\}$
- 3:  $p_{\min}$ : minimum threshold for significant speedup

##### 4: **procedure** PERFORMANCE-LABELING

5:  $p_t^{\max} \leftarrow \text{maxReduce}(P)$

6: **if**  $p_t^{\max} > p_{\min}$  **then**

7:      $\text{label} \leftarrow t$

8: **else**

9:      $\text{label} \leftarrow t_{\text{serial}}$

**return** label

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Hence, if there are  $n$  thread-configurations, we have  $n$  possible labels. If a web page is labeled as  $t$ , it means that using  $t$  threads achieves the best performance for that web page. Note that these labels are *nominal* values. They only identify the category and don't represent the total number of thread-configuration or their order. Algorithm 1 formally

describes the classification of web page using the Performance Cost Model.

For our experimental testbed with 4 cores, we had three thread-configurations: 1 thread ( $t = 1$ ), 2 threads ( $t = 2$ ), and 4 threads ( $t = 4$ ). For a browser, where the running times are in the order of milliseconds, any amount of speedup would be significant. However, to account for noise in our measurements, we consider a 10% speedup to be significant. We attribute any speedup less than 10% to noise. Hence, we set the threshold value of  $p_{\min} = 1.1$ . Using Algorithm 1, the total number of web pages categorized into labels 1, 2, and 4 are 299 (55.88%), 49 (9.15%), and 187 (34.95%) respectively.

### B. Energy Cost Model

In the *energy cost model*, we consider only the energy usage values to label the web pages. The algorithm for labeling is the same as Algorithm 1. Instead of using speedup values, we consider greenup [24] (energy usage improvement) values. Let  $y_t$  represent the energy consumed by  $t$  threads. For each thread configuration, we compute its greenup,  $e_t$  with respect to serial execution ( $e_t = y_{t_{\text{serial}}} / y_t$ ).  $e_{\min}$  is the minimum threshold that demarcates a significant greenup.

Since our experimental platform is a laptop, we did not use the Energy Cost Model to classify our web pages. We will consider this model in the future for energy-critical mobile devices.

### C. Performance and Energy Cost Model

In the *performance and energy cost model*, we consider both timing and energy usage values to appropriately label the web pages. In cases where we can guarantee significant performance improvements through parallelization, we also need to consider increases in energy usage. Spawning more threads could result in higher energy usage especially if the parallel work scheduler is a power-hungry one such as a work-stealing scheduler (as is the case currently in Servo). Hence, we consider performance improvements through parallelization to be useful only if the corresponding energy usage is lesser than an assigned upper limit. We do so using a bucketing strategy described below.

Similar to the classification in the previous two cost models, we consider an arbitrary number of thread-configurations

where each configuration uses  $t$  threads. Each thread-configuration has a corresponding speedup,  $p_t$  and a greenup,  $e_t$ . In addition to the terminology defined in the previous two sub-sections, we define the following terms.

- $PET_t$  – *performance-energy tuple (PET)*,  $\{p_t, e_t\}$  which defines the speedup and greenup achieved using  $t$  threads.
- $X_j X_{j+1}$  – *PET bucket* to which a certain number of PETs belong.  $X_j$  and  $X_{j+1}$  represent speedup values and  $j \in \mathbb{N}$ . A PET,  $PET_t \in X_j X_{j+1}$  if  $X_j < p_t < X_{j+1}$ . One can define an arbitrary number of such buckets to categorize the tuples. Note that the value of  $X_1$  (lower limit of the first bucket) is always  $p_{\min}$ .
- $Y_j$  – *energy usage increase limit* (defined in terms of greenup) for a performance bucket  $X_j X_{j+1}$  where  $j \in \mathbb{N}$ .  $Y_j$  demarcates the tolerance of energy usage increase for all  $PET_t \in X_j X_{j+1}$ .

In this labeling, we perform the following steps for each web page:

1. We ignore all the values of  $p_t$  that are lower than  $p_{\min}$  and we define PET buckets based on design considerations.
2. If the filtering results in an empty set, we label the web page as  $t_{\text{serial}}$ . Otherwise, we organize the remaining speedups and greenups into PETs and assign them to the different PET buckets.
3. Starting from the bucket,  $j$  with the highest speedups,
  - a) We sort, in the descending order, the PETs w.r.t.  $p_t$  values.
  - b) We look at the PET with the highest speedup,  $p_t$  within this bucket and check to see if the energy usage of the speedup,  $e_t$  is less than the bucket's associated energy usage limit,  $Y_j$ . If the check isn't satisfied, we look at the next largest speedup in this bucket and repeat this step.
  - c) When all the speedups in a bucket have been unsatisfactorily checked, we look at the bucket with the next highest speedups and repeat the process. We do so until a speedup value satisfies the check against the energy usage increase limit.
4. If all the speedups don't satisfy the condition, we label the web page as  $t_{\text{serial}}$ . Otherwise, we label the web page as the value of  $t$  corresponding to the first speedup value that satisfies the condition.

Algorithm 2 formally describes the classification of the web pages using the Performance and Energy Cost Model.

For our case study with Servo, we had three thread-configurations: 1 thread ( $t = 1$ ), 2 threads ( $t = 2$ ), and 4 threads ( $t = 4$ ). We set the value of  $p_{\min} = 1.1$  (from Section V-A). Figure 7 depicts the histogram of Servo's  $p_2$  and  $p_4$  values along with their cumulative distribution functions (CDFs). The histogram shows that, out of the significant speedups (~40%), the half point lies roughly at 1.3. Thus, we used two performance buckets:  $X_1 X_2$  and  $X_2 X_3$  where  $X_1 = p_{\min}$ ,  $X_2 = 1.3$ , and  $X_3 = 12.87$  (the largest observed speedup). For the first bucket, we set the energy usage increase

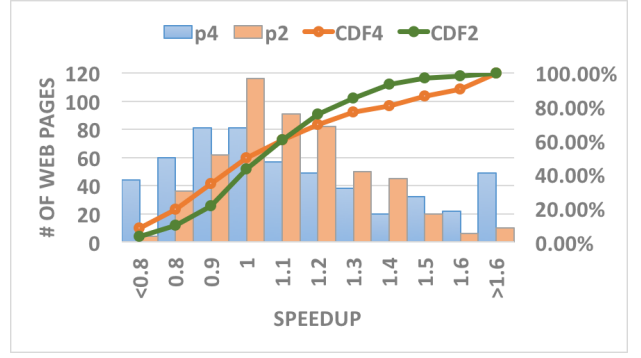


Fig. 7. Histogram of speedup values. The bin labels are upper limits.

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#### Algorithm 2 Performance-Energy labeling of a web page

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**Input:**

- 1:  $N$ :  $\{t \mid t \text{ is number of threads in a configuration}\}$
  - 2:  $PET$ :  $\{\{p_t, e_t\} \mid p_t \text{ is speedup using } t \text{ threads, } e_t \text{ is greenup using } t \text{ threads, } \forall t \in N\}$
  - 3:  $X$ :  $\{X_j X_{j+1} \mid X_j X_{j+1} \text{ is a performance bucket}\}$
  - 4:  $Y$ :  $\{Y_j \mid Y_j \text{ is energy usage increase limit for } X_j X_{j+1}, \forall X_j X_{j+1} \in X\}$
  - 5:  $p_{\min}$ : minimum threshold for significant speedup
  - 6: **procedure** PERFORMANCE-ENERGY-LABELING
  - 7:    $label \leftarrow t_{\text{serial}}$
  - 8:   **for**  $X_j X_{j+1} \in X$  **do** // highest  $j$  to lowest  $j$
  - 9:      $PET' \leftarrow \text{all } PET_t \in X_j X_{j+1}$
  - 10:      $PET'' \leftarrow \text{sortDescending}(PET' \text{ w.r.t } p_t)$
  - 11:     **for each**  $PET_t \in PET''$  **do**
  - 12:       **if**  $e_t > Y_j$  **then**
  - 13:          $label \leftarrow t$
  - 14:       **break**
  - 14:   **return**  $label$
- 

tolerance,  $Y_1 = 0.9^2$  since a 10% energy usage increase can make a noticeable difference in overall battery life of a laptop. For the second bucket we chose a tolerance,  $Y_2 = 0.85$  since an energy usage increase beyond 15% is not acceptable for any performance improvement. Using Algorithm 2, the total number of web pages categorized into labels 1, 2, and 4 are 317 (59.25%), 50 (9.34%), and 168 (31.40%) respectively.

#### VI. PERFORMANCE MODELING AND PREDICTION

Our aim is to model the relationship between a web page's characteristics and the parallel performance of the web rendering engine to perform styling and layout on that page. With such a model, given a new web page, a browser will be able to predict how much performance improvement the web page offers if it were to be rendered in parallel. The browser can then decide the number of threads it should use during *Overall Layout* for the given web page. If the browser observes slowdowns with parallelization, only a single thread will be used. Otherwise, the browser should spawn multiple threads. The

<sup>2</sup>These values can be tweaked based on design and device considerations. We choose these values for Servo on a quad-core Intel Ivy Bridge.

number of threads will depend on a statistically constructed model. When parallelization is beneficial, the browser should also consider energy usage values and check for tolerable amounts. Hence, our goal is to construct a predictive model that allows a browser to decide the number of threads it should use for its *Overall Layout* stage for any given web page by simply looking at the web page’s key characteristics.

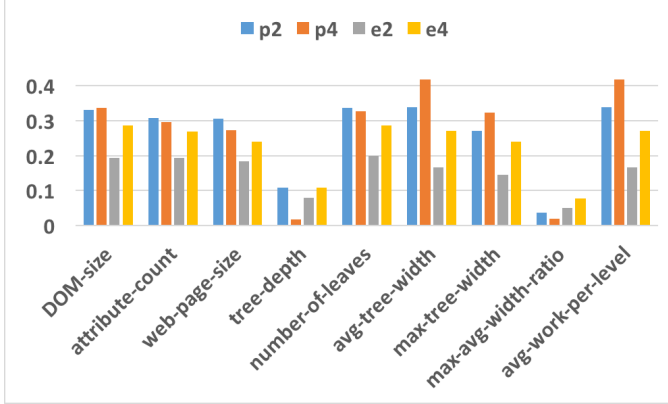


Fig. 8. Statistical correlation strengths:  $R$  values.

In this section, we construct and describe predictive models for Servo using off-the-shelf supervised learning methods on the Performance and Energy Cost Model (Section V-C). For each of the models, our predictive features are the characteristics of a web page that we describe in Section II. Since our features lie on different scales<sup>3</sup>, we use Normal Standardization<sup>4</sup> (using MATLAB’s `zscore` [11]) on our features to prevent one feature to dominate the other during learning. Figure 8 shows the correlation coefficient,  $R$  values between the nine features and the speedups and greenups observed with 2 ( $p_2$ ,  $e_2$  values) and 4 ( $p_4$ ,  $e_4$  values) threads. We see that a positive linear<sup>5</sup> relation exists between parallel benefits and the web page features. However, the true relationship between the predictors and results is unlikely to be strictly linear, as is evident from our modeling results. Also, we see that **tree-depth** and **max-avg-width-ratio**, by themselves, do not correlate strongly ( $< 0.1$ ) with the speedups and greenups observed in our dataset. However, when used in combination with other features, as in **avg-work-per-level**, we observe a stronger relationship. For our modeling, we choose the seven features predictor features that have  $R$  values greater than 0.1. The output for each of the models is one of the three labels: 1, 2, or 4 representing 1 thread, 2 threads, and 4 threads respectively. These response labels are *nominal* values.

Our data set has *heavy* class imbalance *i.e.* one label has many more observations than the other. For the performance and energy cost model, only 49 instances are labeled 2 while 299 and 187 are labeled 1 and 4 respectively. Also, the

predictor to observation ratio for our data set is quite small. Hence, we don’t face the issue of over-fitting.

To validate and test our models, we use *cross-validation* using a 90-10% training-testing ratio *i.e.* we divide our data set into 10 subsets. Using each of these 10 subsets as the testing set (55 samples) and the remaining data as the training set (480 samples), we train 10 models. For each of the models, we predict labels for their corresponding testing sets, which results in 10 model prediction accuracies. We consider the the mean and maximum of these 10 accuracies. When we are not able to use cross-validation, we use the *holdout-set* technique (again using a 90-10% training-testing ratio) wherein the data is divided into two sets: training and testing. We choose to use the cross-validation or holdout-set techniques because they result in true prediction error values and not “model errors” [2]. Additionally, they don’t rely on any parametric or theoretic assumptions about the data.

We experimented with the following supervised learning algorithms: Multinomial Logistic Regression (MNR), Ensemble Learning, and Neural Networks. We choose these three methods to capture non-linear relationships between web page characteristics and a rendering engine’s parallel performance.

**MNR:** In this multinomial logit model, the probability of each label for a web page is expressed as a non-linear function, using logit link functions of the predictor tree characteristics. We trained our model using MATLAB’s `mnrfit` [9] function. With a 90-10% training-test divide for cross-validation, we observe a mean and maximum accuracies of 72.22% and 87.27% respectively.

**Ensemble Learning:** For Ensemble Learning framework, the results of many models are combined together to generate the final prediction. For our data, we used the AdaBoostM2 (a variant of Adaptive Boosting for multi-class data) learning method on 100 simple Decision Tree learners and also on 100 Decision Trees with surrogate splits. We did so using MATLAB’s `fitensemble` [8] function. Using regular trees, with a 90-10% divide, we observe a mean accuracy of 71.12% and a maximum of 83.63%. Using trees with surrogate splits, we observe a mean accuracy of 69.44% and a maximum of 85.45%.

**Neural Networks.** Artificial Neural Networks consist of simple, connected elements. By training the weights of the connections between different elements, a large neural network can capture complex relationships between variables. For our data, we use a small neural network with 1 hidden layer containing 10 neurons. We do so using MATLAB’s `nprtool` [10]. Since MATLAB currently does not support cross-validation for its classifying neural network models, we use the holdout-set method to measure the accuracy of this model. We use 80% of the data for training, 10% for validation (which is essentially a part of training), and 10% for testing. The accuracy of this model on the testing set is 77.8%; the accuracy on all of the data is 71.61%. We attribute these lower (than those of MNR and Ensemble Learning) accuracies to the simplicity of the model and the lack of cross-validation. Figure 9 depicts the Receiver Operating Characteristic (ROC)

<sup>3</sup>*e.g.* the range of **DOM-size** is 8307 while that of **avg-tree-width** is 436

<sup>4</sup>The values of a feature are distributed according to its Normal distribution such that the mean of the feature is 0 and its standard deviation is 1.

<sup>5</sup>Statistical correlation measures the strength of only linear relationships between two variables.



curve<sup>6</sup> of this model on the three different sets.

The high accuracies of these off-the-shelf learning methods emphasize the effectiveness of our automated labeling algorithms. Instead of concentrating our efforts on tweaking the parameters of machine learning techniques to extract higher accuracies on our limited dataset, we demonstrate high accuracies by using *accurate* labeling algorithms that can be used on any dataset.

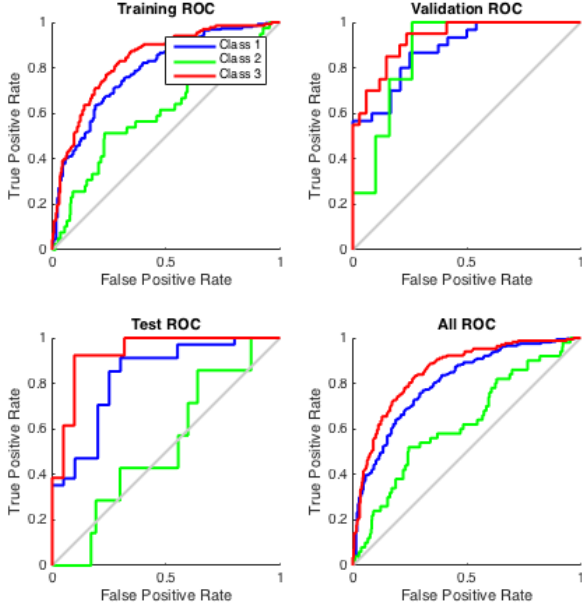


Fig. 9. ROC curve of the Neural Network Model (Class 1, 2 and 3 correspond to 1, 2, and 4 threads respectively)

**Limitations.** These accuracies, however, are not greater than 90%. Machine learning models have the potential to be highly accurate but are heavily dependent on a large amount of accurate training data. They behave as “black-boxes” with the true underlying relationships between variables remaining undiscovered to the user [19], [32], [33]. Our data for this case study is relatively small and is from a prototype; Servo is a project under development and is undergoing constant change. Many components of Servo haven’t been optimized for performance yet. Also, with multiple threads being spawned to exploit and explore concurrency in browser tasks, repeatability of executions is hard to acquire. Consequently, our data has a fair share of outliers—35% of the working set of web pages observes a MAD greater than 25. The class imbalance in our data is also an important factor that influences model accuracies since we don’t have an equal share of training data for each class.

Despite our limitations, we observe *confident* accuracy rates on each of these models. This fosters our intuition that the web page characteristics are indeed related to the parallel performance and energy usage of a browser and that the practical parallelism benefits can be predicted by

<sup>6</sup>The closer the line is to the left and top, the fewer false positives need to be accepted in order to get a high true positive rate.

considering these characteristics. The best performing model, MNR, compared to the current implementation of Servo, achieves a maximum of 91.39% performance savings (on [berkshirehathawayhs.com](http://berkshirehathawayhs.com)) and a maximum of 46.32% energy savings (on [starbucks.com](http://starbucks.com)).

## VII. RELATED WORK

Research on parallel browser-architectures and browser-tasks began only recently, starting in 2009. Although multi-core processors are ubiquitous today on both laptops and mobile devices, the browsers are yet to utilize their benefits. The growing concern of slow page load times, especially on mobile devices, and the unexploited parallelism benefits in commodity browsers are the primary motivations for this ongoing research. Below we outline existing research on parallelizing and analyzing browser-tasks.

**Browser Workload Characterization.** Gutierrez et al. [25] present characterization of an Android browser at the micro-architecture level using 11 web pages. Our approach, on the other hand, is agnostic to the platform on which a browser runs. Zhu et al. [35] correlate the web page variances to the difference in page load times and energy usage of the *serial* Firefox browser by characterizing the HTML and CSS elements of a web page. Our approach is similar to theirs: we consider only web page features to be predictive of a browser’s performance. However, we consider additional DOM tree features that are representative of the degree of *parallel* workload in a page.

**Browser Performance-Energy Analyses.** Thiagarajan et al. [30] present a breakdown of energy usage by the different elements, such as CSS and Javascript, of a serial browser. Additionally, they propose a few optimizations to improve the energy consumption of web browsers, such as re-organizing Javascript files or removing unnecessary CSS rules. Zhu et al. also focus on scheduling methods of heterogeneous systems to improve the energy efficiency of mobile processors. They evaluate benefits of a BIG.little heterogeneous system for a trade-off between performance and energy. However, both these projects are evaluated on serial browsers. Our work, on the other hand, analyzes performance and energy trade-offs for a *parallel* browser while remaining agnostic to the browser implementation and execution platform. To the best of our knowledge, this work is the first of its kind.

**Parallel Browsers.** In general, browsers use processes to isolate tabs and windows to enhance security. Gazelle [31] uses two processes per page while Chrome uses a process-per-page approach. This approach doesn’t exploit parallelism within the tasks. ZOomm [23] explores the challenges in managing concurrency in multi-core mobile-device browsers. This work exploits parallelism within the styling, image decoding and JavaScript tasks leaving layout as future work. Mai et al. [27] propose that browser developers should focus on parallelizing web pages rather than browser-tasks. They build Adrenaline, a server-client browser. Mozilla Research’s Servo, on the other hand, exploits both safety, particularly through its use of Rust, and parallelism between browser tasks and also within

the tasks themselves. So far, Servo has exploited parallelism its styling, layout and painting tasks, and is continuing to explore parallelism in other computational bottlenecks such as parsing. Servo is being developed for Android as well. More importantly, our work is not on parallelizing layout but is on predicting the degree of parallelism inherent in rendering a web page by considering the parallel performance and energy usage of a browser.

**Parallelizing Browser Tasks.** Several research projects on parallelizing browser-tasks such as styling [21], [28] and parsing [34] exist. Meyerovich et al. [28] introduce fast and parallel algorithms for CSS selector matching, layout solving and font rendering, and demonstrate speedups as high as  $80\times$ , using 16 threads, for six websites. However, they implement only a subset of CSS (without cascading) and evaluate their algorithm in isolation (not within a browser) without considering effects on energy usage. Servo adheres to the complete CSS specification and our work is modeled within the *complete* execution of a browser while considering energy usage constraints.

## VIII. CONCLUSION

The workload of a web rendering engine is dependent on the web page it is rendering; we confidently model the relationship between key web page features and the parallel performance of the rendering engine using simple supervised learning methods. Specifically, we characterize web pages using DOM tree features that correlate to the *Overall Layout* task but are blind to the rendering engine's implementation. We propose accurate and tunable automated labeling algorithms that categorize web pages into a user-defined number of classes. More importantly, our algorithm accounts for trade-offs between performance improvements and energy usage increases for multi-core processors. Using multinomial logit classification, ensemble learning, and simple neural networks, we demonstrate strong predictive model accuracies, achieving 87.27% with 535 web pages within the complete execution of a browser. On a laptop platform, our best performing model achieves performance and energy savings up to 91.39% and 46.32% respectively.

**Future Work.** The self-asserting results of this work motivate us to evaluate such a model on a mobile platform where performance and energy savings are expected to be more distinct and critical. Simultaneously, we would like to use advanced feature selection methods deployed by autoencoders and other deep learning methods to capture relationships, if any, that are not directly intuitive. Furthermore, we would like to acquire larger and more accurate data sets to improve model accuracies.

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