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Codeless Web Testing using Selenium and Machine Learning

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Abstract: Complexity of web systems lead to development processes always more tough to test. Testing phases are crucial in software and system engineering and are known to be very costly. While automated testing methods appear to take over the role of the human testers, the issues of reliability and the capability of the testing method still need to be solved. In our paper, we focus on the automation of functional tests of websites. A single web page may contain a huge set of important functionalities leading to the execution of critical web service operations. Besides, testing all of these functionalities implemented in a web page service is highly complex. Two current popular research areas for automation web-based testing are Codeless Functional Test Automation and Machine Learning/Artificial Intelligence (ML/AI) in test automation. We therefore define and implement a framework to figure out how to automate the web service product under test, the machine can detect or predict the change and adapt those changes to suitable generic test cases. In our work, we examine on Selenium and the benefits of using machine learning in automated web application testing.


1 INTRODUCTION

Software systems and their complexity distributed through diverse components, sometimes virtualized using different platforms (e.g., XaaS) (Patel et al., 2016), lead to development processes always more complicated to test. However, testing phases are crucial in software and system engineering (Kassab et al., 2017). They are known as very costly necessitating resources (including time and people) spent to prepare testing architectures, test case scenarios and their execution. That cost is estimated to be between 40% and 80% of the total cost of the service/system development (Heusser and Kulkarni, 2018). While automated testing methods appear to take over the role of the human testers, the issues of reliability and the capability of the testing method still need to be solved. In our paper, we focus on the functional tests of websites. A single web page may contain a huge set of important functionalities leading to the execution of critical web service operations. Besides, testing all of these functionalities implemented in a web page service is highly complex. For that purpose, several automation tools are available to help the testers and to facilitate the execution of testing processes (Hynninen et al., 2018; Raulamo-Jurvanen et al., 2019). Among

them, we may cite the well known and adopted tools in the industry: Selenium and OpenScript. Recently, it has been shown that Selenium (Selenium, 2020) is very efficient for testing applications which are browser based (Jain and Rajnish, 2018). It runs specific tests on diverse installed browsers and return results, alerting you to failures in browsers as they crop up.

However, automated web-based testing tools like Selenium still have major drawbacks. Indeed, tests have to be repetitive and require resources and a lot of maintenance. A very small change or modification in the content of a web page may cause a test fail. Furthermore, many tests scripts are manually handled which increases the costs and time for testing (Shariff et al., 2019; Ameer-Boulifa et al., 2019). Researchers and industrials are studying and defining optimized approaches to deal with this challenge. Two current popular research areas for automation web-based testing are Codeless Functional Test Automation and Machine Learning/Artificial Intelligence (ML/AI) in test automation. In here, algorithms are defined and implemented to figure out how to automate the software/web service product under test, the machine can detect or predict the change and adapt those changes to the suitable test cases. Thanks to codeless testing, testers can drastically reduce the cost of test automation creation, test execution, and maintenance. In our

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work, we examine on Selenium and the benefits of using machine learning in automated web application testing. The motivation is to utilize the selenium framework in the world of automated testing and utilize a machine learning approach for codeless testing, enabling to test multiple functional web pages without using code.

The main contributions of our paper are:

- Defining a framework named “codeless testing” by combining Selenium and machine learning technique,
- Implementing and applying our framework to run generic test cases in order to test the functionality *search* that is present in multiple web pages,
- Through our experiment results, we show that the success of generic test cases may help to contribute in decreasing implementation and maintenance costs of automated tests of functional browser based applications.

Finally, our paper is organized as it follows. In Section 2, we present the state of the art about automated codeless testing techniques and tools. Then in Section 3, we depict the basis used in our paper. Our ML based web testing framework is defined in the Section 4 and evaluated in the Section 5 in which relevant experimental results are presented. We conclude and give perspectives in Section 6.

2 RELATED WORKS

In the literature, there are several papers introducing approaches for automation web-based applications testing by applying machine learning techniques (RJ Bhojan, 2019) (Rosenfeld et al., 2018) (Nguyen et al., 2018) (Joshi, 2016). Although we got inspired of these works, none of them has proposed novel codeless web service testing. With the same observation, codeless testing approaches have been recently proposed. We may cite (Isha and Revathi, 2019) in which the authors proposed an automated API testing tool in providing a GUI with support for codeless testing. However, they do not intend to use any learning techniques that could improve their work and the problematic we are tackling in our paper. We may note the same lack in (Brueckmann et al., 2017). Though the technique proposed is not entirely codeless, the authors proposed a framework to implement a simple business process by integrating existing services in a mashup with codeless engineering processes. However, they still do not integrate any learning techniques.

Moreover, in the market area, many start-up companies with several tools have entered the market recently, all with the promise of solving the coding skill conundrum. While no-code or low-code concepts become a trend (following the recent Google patent (Arkadyev, 2017)), companies such as Salesforce promote plug-and-play offers. Some testing tools such as Testcraft¹, Ranorex², Tricentis³, Leapwork⁴, etc. advertise that they can provide this functionality by building a user-friendly UI on top of the code layer and also enabling switching between two modes. The companies promote that testers can still write scripts and receive detailed feedback but skip the coding part. However, when it comes to test automation, an issue is often raised on how codeless is being interpreted. Moreover, none of these codeless testing tools proposed by those companies are open-source.

In our approach, we cope with these above mentioned issues by defining a machine learning based approach for codeless web automation testing.

3 BASICS

3.1 Selenium

Selenium (Selenium, 2020) is a suite of automation testing techniques and tools which allows the testers to run the tests directly on the target browser, drive the interactions on the required web pages and rerun them without any manual inputs. Selenium has become very popular among testers because of the various advantages it offers. With its advent in 2004, Selenium made the life of automation testers easier, highly improved the testing time, costs, detected failures and is now a favorite tool for many automation testers. Selenium was invented with the introduction of a basic tool named as JavaScriptTestRunner, by Jason Huggins at ThoughtWorks to test their internal Time and Expenses application. Now it has gained popularity among software testers and developers as an open-source portable automation testing framework. Nowadays, Selenium is currently used in production in many large companies as Netflix, Google, HubSpot, Fitbit, and more. According to (Enlyft, 2020), there are 42,159 companies that use Selenium, taking 26.83% market share in software testing tool (see Figure 1).

The primary reason behind such overwhelming

¹<https://www.testcraft.io/>

²<https://www.ranorex.com/>

³<https://www.tricentis.com/>

⁴<https://www.leapwork.com/>

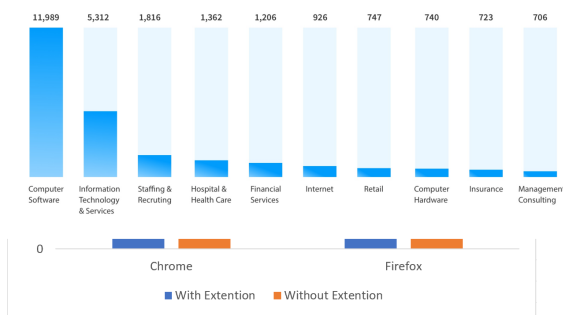


Figure 1: Selenium used by company size.

popularity of Selenium is that it is open source. This not only helps keep the costs in check but also ensures that companies are using a tool that will get continually updated. Other reasons include the multi-dimensional flexibility that it offers in terms of scripting languages, operating systems, browsers, and integration with other tools. This widens the scale of reach and test coverage, enabling enterprises to deliver a web application that is highly reliable and functional. Selenium test scripts can be written in Java, Python, C#, PHP, Ruby, Perl and .Net. This allows a large number of testers to easily use it without any language barriers. It can be carried out on Windows, MacOS, and Linux, using any browsers out of Mozilla Firefox, Internet Explorer, Chrome, Safari, and Opera. This enables a thorough cross browser compatibility testing with strong environment support.

Selenium suite includes three major components (Figure 2), each tool has its own approach for automation testing. The testers or developers can choose tools out of it depending upon the testing requirements.

- *Selenium IDE.*

Selenium IDE, earlier known as Selenium recorder, is a tool used to record, edit, debug and replay functional tests. Selenium IDE is implemented as an extension to the Chrome browser and add-on in Firefox browser. With Selenium IDE plugin, the testers can do simple record-and-playback of interactions with the browser, they can also export tests in any of the supported programming languages like Ruby, Java, PHP, Javascript, etc.

- *Selenium Grid.*

Selenium Grid allows the testers to run parallel automated tests on multiple machines and browsers at the same time. The main function of this tool is to save time. If the test suite is large, the testers can use Selenium Grid to reduce the time running. Considering how scripts normally run slow on a browser, using performance-

improving techniques such as parallel testing can help with the problem. Testers can also use it to test one application in different browsers in parallel, when one machine is running Firefox, the other Chrome, and so on. Testers can also create different configurations with Grid, combining different versions of browsers and operating systems. Needless to say that when used in large production environments, Grid is a huge time-saver.

- *Selenium Webdriver.*

Selenium Webdriver (which is also known as Selenium 2.0 or 3.0 currently version) is an enhanced version of Selenium RC and the most used tool. Selenium Webdriver is by far the most important component of Selenium Suite. It provides a programming interface to create and execute automation scripts. It accepts commands via client API and sends them to browsers. Selenium WebDriver allows testers to choose a programming language of their choice to create test scripts. Test scripts are written in order to identify web elements on web pages and then desired actions are performed on those elements. Selenium Webdriver currently supports most popular browsers (Chrome, Firefox, Opera, etc.). Every browser has different drivers to run tests. In our "codeless testing framework", we use Selenium Webdriver to conduct the automated tests on multiple popular web browsers.

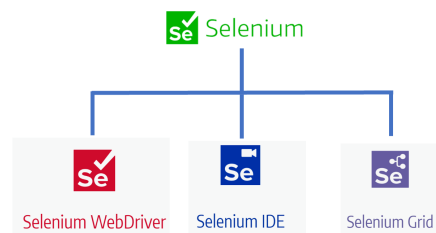


Figure 2: Selenium suite components.

3.2 Codeless Testing

Despite the advantages above listed, Selenium still has limitations. The most challenge of using Selenium in automation testing is steep learning curve. Testers require high technical skills to accurately design and maintain test automation. Maintenance including modifications and updating Selenium test code in an efficient way is a very common problem in automated test. The impact of the changes occur in the web page or application under test could suffer during its development. Changes or modifications from web User Interface (UI) or from its structure to its elements or its attributes could make the whole

test suites collapse. For that purpose, one of automated testing trends, namely *Codeless Testing*, was introduced to try resolving those issues.

Codeless Testing for web services refers to the methodology which utilizes a generic test case to test multiple websites. This approach allows any tester without deep programming knowledge to perform tests. Organizations started adapting tools and approaches to simplify test automation and empower team members who lacked sophisticated programming skills. Codeless tools were originally meant to help the tester avoid the hours of programming that are usually necessary to get the most out of testing logic. While their objective was to address programming complexity, most tools in the market adapted a no-code approach by avoiding the code, but not really addressing the logical complexity in testing. A common misconception is that codeless test automation tools should completely avoid code. We believe this is actually a disservice, as very soon users will start hitting roadblocks. Testing requirements are typically as vast as application development. It is hard to believe that all testing requirements could be addressed with some canned, pre-packaged solution. Some level of logic development flexibility is required, but in a way so that the user does not get bogged down by the syntactical complexities. Note that, though the name codeless testing, it does not mean it is completely code free. While a tester can generate most of the tests code free, certain tests may still need some coding. Testers can use codeless testing for keeping up with the deployment needs.

3.3 Support Vector Machines

A support vector machine (SVM) (Vapnik and Vapnik, 1998) is a linear classifier defined by a separating hyperplane that determines the decision surface for the classification. Given a training set (supervised learning), the SVM algorithm finds a hyperplane to classify new data. Consider a binary classification problem, with a training dataset composed of pairs $(\mathbf{x}_1, y_1), \dots, (\mathbf{x}_l, y_l)$, where each vector $\mathbf{x}_i \in R^n$ and $y_i \in \{-1, +1\}$. The SVM classifier model is a hyperplane that separates the training data in two sets corresponding to the desired classes. Equation (1) defines a separating hyperplane

$$f(\mathbf{x}) = \mathbf{w}^T \mathbf{x} + b = 0 \quad (1)$$

where $\mathbf{w} \in R^n$ and $b \in R$ are parameters that control the function. Function f gives the signed distance between a point \mathbf{x} and the separating hyperplane. A point \mathbf{x} is assigned to the positive class if $f(\mathbf{x}) \geq 0$, and otherwise to the negative class. The SVM algorithm computes a hyperplane that maximizes the

distance between the data points on either side, this distance is called *margin*. SVMs can be modeled as the solution of the optimization problem given by (2), this problem maximizes the margin between training points.

$$\min_{\mathbf{w}, b} \frac{1}{2} \|\mathbf{w}\|^2 \quad (2)$$

$$\text{subject to: } y_i(\mathbf{w}^T \mathbf{x}_i + b) \geq 1, i = 1, \dots, l$$

All training examples label -1 are on one side of the hyperplane and all training examples label 1 are on the other side. Not all the samples of the training data are used to determine the hyperplane, only a subset of the training samples contribute to the definition of the classifier. The data points used in the algorithm to maximize the margin are called *support vectors*.

4 A ML-BASED WEB TESTING FRAMEWORK

The architecture overview of our codeless testing framework is illustrated in Figure 3.

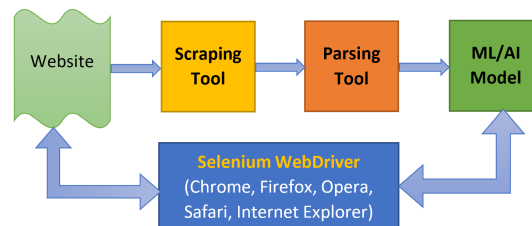


Figure 3: Our architecture of codeless testing framework.

As mentioned in the previous sections, our framework is combined of Selenium and a machine learning algorithm. It is composed by four main components.

- **Selenium Webdriver Component.**

This is the major module, it plays a role as an engine to drive the browser for automating website and for testing. As referring in Figure 2, Selenium Webdriver (web, 2020) is the core module of our testing framework. Selenium WebDriver plays as a browser automation framework that accepts commands and sends them to a browser. It is implemented through a browser-specific driver. It controls the browser by directly communicating with it. The flexibility that Selenium Webdriver provides is almost unmatched in the test automation world.

- **Scraping Data Component.**

We implemented our scraping tool in Python. Besides, we utilize BeautifulSoup (Richardson, 2020) as a web scraping library to pull data out of DOM in HTML or XML format.

- **Processing Data Component.**

This component has a role to process the data after pulling from HTML DOM file, its main goal is to clean up and extract the useful data, then transform the cleaned data to the next stage for training.

- **SVM Model.**

A machine learning model to recognise and/or predict the *search* element pattern which appears in HTML data of testing website.

4.1 Scraping and Processing Web Data

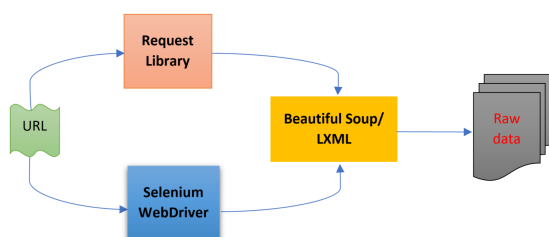


Figure 4: The structure of our scraping tool.

The general architecture of our scraping tool is showed in Figure 4. Its main target is exactly as its name - to collect HTML data and their position in the DOM tree from the website which is driven by Selenium Webdriver. We use both Selenium Webdriver and Request library to send a HTTP request to the URL of the webpage we want to access. We discover that some websites with heavy render JavaScript will not response to the request module. Also, some websites can detect the request is performed in an automated way (not by human browsing but expected to be a bot) by their tool, it will deny to establish the connection. Selenium Webdriver works fine with almost all major websites, however the speed is recorded as very slow since Selenium needs to open the real browsers to perform tasks. Moreover, using different browsers (Chrome, Firefox, Opera, etc.) may lead to obtain different behaviours of navigation websites. For example, some websites are optimized for Chrome but not Firefox or vice versa, or some website may crash down on Microsoft Edge browser. Therefore, we use both modules Selenium Webdriver and Request library (Pypi, 2020) to ensure that our scraping tool can adapt with most of the websites to collect as most as data it can. First, using request library for speeding up the test, if a request fails, then Selenium Webdriver will easily detect it. Moreover, each website has its different DOM structure, thousands of websites will have thousands of DOM structures, therefore it is a challenge process to retrieve in an automated way the data from multiple of websites con-

currently. Nevertheless, our scraping tool enables to scrape and collect variety of websites. Our scraping tool follows two tasks:

1. Query the website using requests or Selenium WebDriver and return its HTML content.
2. Using BeautifulSoup (Richardson, 2020) and LXML (LXML, 2020) libraries to go through the HTML structure of each website, parse HTML content and extract the expected data useful to tested the targeted functionality embedded in the website.

4.2 Our SVM Model

In considering that web HTML elements are keep changing dynamically in both structure and attribute values, it is a very challenging task to adapt test suites with the websites changes. In our proposed framework, the objective of SVM model is to recognize the pattern of web elements corresponding to the *search* box in each website as illustrated in Figure 5. Specifically, the SVM model will learn the HTML structure of each website, in case of any modification in terms of web elements, the SVM model will find the similar pattern of HTML web and adjust its model according to the changes.

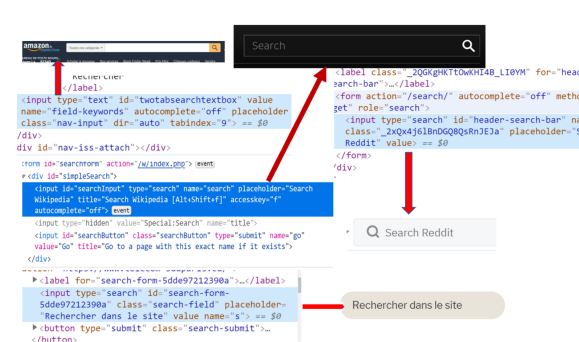


Figure 5: SVM model detects search box pattern.

For the next testing step, if the website has changed, the SVM model detects its changes and guides the Selenium code to adapt automatically with it. In this case, the test code will not be broken and can be reused. More specifically, the goal of the SVM is to train a model that assigns new unseen web elements into a particular category. It achieves this by creating a linear partition of the feature space into two categories. In each website, structured data is extracted for each HTML element, they have to be turned into proper feature vectors. We use SVM model to recognize the relevant feature of each web element corresponding to its density and apply in the feature importance property of our model. Many features and preprocessing steps are performed as part

of our cross-validation process, and we kept the ones yielding best performance and moved them in the final model. Feature importance gives a score for each feature attribute, the higher of the score, the more important or more relevant of the feature is. Therefore, the weight for each element attribute is assigned according to its frequency and informative ranking.

4.3 Data Collection and Analysis

In order to have the dataset for our training SVM model, we need to gather the large amount of data. By using the scraping tool described above, we are successful to retrieve the data from the list of 5000 websites provided by the Alexa database. This database contains more than one million URLs on top ranking of Alexa (Helme, 2020). Our tool can scrape any website that has the search functionality, it pulls down all the web elements corresponding to the search box.

However, these elements are collected as raw data in an undesired format, unorganized, and extremely large. Furthermore, these elements may be different from one page to another. We need, for further steps, to use the processing tool to enhance the data quality and, related to our experiments, in particular to extract the elements linked to the search box (our testing purpose).

The main steps for preprocessing data are formatting and cleaning. Data cleaning is applied to remove messy data, duplicate data and manage missing values. Formatting is required to ensure that all variables within the same attribute are consistently written. Once structured data is extracted for each HTML element, they have to be turned into proper feature vectors.

After this preprocessing phase, vectors with relevant features is obtained, our training dataset is built. For that purpose, an important task of labelling is then performed to classify our vectors depending on the structure of the "search box". We labeled 1000 webpages to provide three classes according to the three cases detailed in Section 5.1. From this training dataset, an SVM model has been obtained as above explained.

5 EXPERIMENTAL STUDIES AND RESULTS

5.1 Use Case Studies

To test our codeless testing framework, our experiences focus on testing the search-functionality of

websites. To be concrete, let us follow the following scenario: if the users want to use Google to search for the term Codeless Testing, they normally open their favourite browser, let say Chrome, to navigate to the website of Google. After the official site of Google page fully loaded, the users need to locate the search box, then type the search term Codeless Testing. All of this manual steps performed by human can be completely replaced those steps by our codeless testing framework. However, although these steps can be indeed easily automated for this scenario, our codeless testing approach intends to make it generic enough to test the *search* functionality on diverse websites. By analyzing the multiple search activities on various websites, we group the *search* scenario in three use cases:

- *Case 1 (Traditional Search)*: we call it traditional because the search box is appeared directly in the website interface, the user can easily locate it and enter the search query. We studied that 80-90% search websites are designed in this case 1 (Fig. 6). For example: google, youtube, yahoo, amazon, etc.

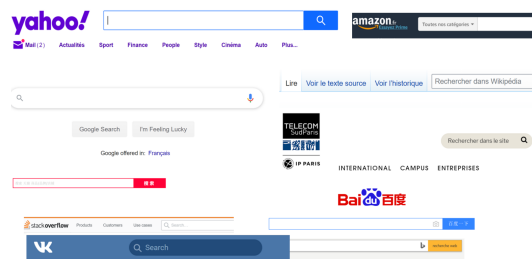


Figure 6: Case 1 search type: traditional search.

- *Case 2 (Hidden Bar Search)*: The search bar is hidden, the users are required extra step by clicking the search button to activate/open the search bar. Once the search bar appears, the user can enter his search query (Fig. 7).

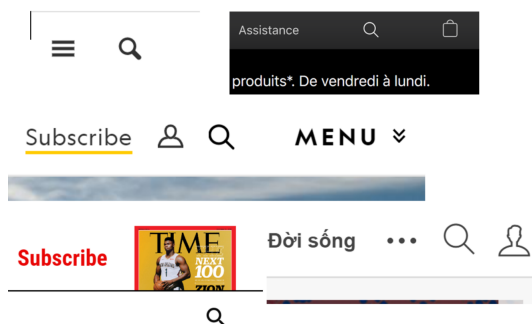


Figure 7: Case 2 search type: hidden search box.

- *Case 3 (Pattern/Condition Search)*: the websites have many filters/criteria for search, the users

must select the right criteria to proceed. For instance, some hotel or housing websites only allow users to select the special search key in their pattern database (region, type of house, size of house, price, number of rooms, etc.). Furthermore, particular websites only allow the users to perform the search on specify content provided in their database. If the users type a random search query, or the query does not correspond to a specific form, nothing is returned (Fig. 8).

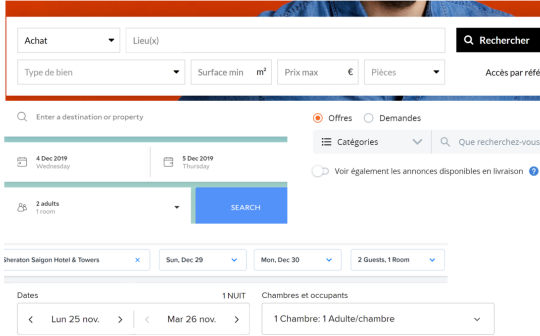


Figure 8: Case 3 search type: filters/criteria search.

In order to test the search functionality in a website, we defined three verdicts within our generic test case: *pass*, *fail*, *error*, as it follows.

- The test is considered as **pass** if a browser has fully loaded the website, the “search term” is entered in the search box, the website returns the answer corresponding to the “search term”.
- The test is considered as **fail** if the browser was unable to load the website under test and to navigate to the search box.
- The test is considered as **error** if the website under test does not contain any search box or does not have the search functionality in its services.

Based on these verdicts and the three above mentioned use cases, we define other verdicts as it follows:

- When entering “search term” in the search box of the webpage under test, “search term” has to appear into the targeted search box, if not, we deliver the verdict *fail*.
- The targeted search box has to accept any type of query as input (number, text, special characters, etc.). If not, we deliver the verdict *error*.
- We do not consider webpages where there are condition/limit/boundary/criteria for the input search (case 3 as described above). In this case, we deliver the verdict *error*.

- If a website requires more than a step rather than type search term (case 3), we deliver the verdict *error*.
- A website has to provide the response for the search term. If an answer belonging to the class “no result found or nothing found” is returned, we deliver the verdict *pass*.

5.2 Experiments Setup

In the experiment phase, we test our framework on the dataset as described in Section 5.3.1.

Testbed.

- OS: x86-64 Microsoft Windows 10 Pro, version 10.0.18363, Build 18363
 - Processor: Intel Core i7-7500U CPU @ 2.70GHzx2
 - Memory: 16GB
 - SSD: 512GB
 - Dataset:
 - Metadata: 1.3 Mb in csv format. 1000 rows x 7 columns
 - Training set: 70% metadata in npy format (numpy array)
 - Test set: 20% metadata in npy format (numpy array).
- From this training dataset, our tool processed the SVM model in average 7 minutes using the dependencies below mentioned.
- Browsers are detailed in the Table 1

Table 1: Browser Version.

Chrome	78.0.3904.70 (64-bit)
Firefox	70.0 (64-bit)
Opera	76.0.3809.132
Internet Explorer	11.418.18362
Microsoft Edge	44.18362.387.0 Build 18362

Project Tools.

In order to run the experiments, we setup our system environment as in the following:

- Python 3.6.8,
- Dependencies: Keras/Tensorflow, scikit-learn: core platform to analyse/process data and training SVM model,
- Libraries: Selenium, Request HTTP, Beautiful Soup, LXML,
- Jupyter Notebook App: online web-based platform to visualize the data.

5.3 Results and Discussions

5.3.1 Automation Testing against Multiple Websites

To evaluate the efficiency of our framework, we conducted the tests using a generic test case through 1000 websites chosen randomly on the list of Alexa described above. First, the learning approach has been processed. A sample of raw data with 10 features has been scraped (Fig. 9).

```

1 url,name,placeholder,class,id,aria-label,title,tabindex,role,accesskey
2 google.com,q,NA,glFyf gsfi,NA,Rech.,Rechercher,NA,combobox,NA
3 facebook.com,custom_gender,Genre (Facultatif),inputtext_58mg_5dba_2ph
4 youtube.com,search_query,NA,NA,search,NA,NA,0,NA,NA
5 twitter.com,NA,Recherche d'un quartier ou d'une ville,GeoSearch-queryInp
6 microsoft.com,q,Rechercher sur Microsoft.com,NA,cli_shellHeaderSearchInp
7 amazon.com,field-keywords,,nav-input_twotabsearchtextbox,NA,NA,19,NA,NA
8 linkedin.com,firstName,First Name,search-input_firstName,NA,NA,NA,NA,NA
9 tmall.com,q,NA,NA,mq,NA,NA,NA,NA,5
10 instagram.com,fullName,NA,2hVTZ_pexuQ_zyHYF,NA,Full Name,NA,NA,NA,NA
11 wikipedia.org,search,NA,NA,searchInput,NA,NA,NA,NA,F
12 apple.com,NA,Search apple,ac-gn-searchform-input,ac-gn-searchform-in
13 yahoo.com,p,NA,Pos(a) T(0) Start(0) Bd Bdc($searchBdr) Bxsh(n) Fz(18px)
14 taobao.com,q, 蘑菇街,NA,mq,NA,请输入搜索文字,NA,NA,5
15 yelp.com,find_desc,"burgers, barbers, spas, plombiers...",pseudo-input_fi
16 adobe.com,q,search,,sAYT-input,NA,Search,,NA,NA,NA,NA,NA
17 wikipedia.com,search,NA,NA,searchInput,NA,NA,NA,NA,F
    
```

Figure 9: Sample of raw data.

The preprocessing phase and specifically the cleaning step allowed to obtain the seven features and one thousand lines of our training dataset. An illustration of these lines are presented in the Fig. 10.

```

3 twitter.com None Recherche d'un quartier ou d'une ville ... None None placeholder
4 microsoft.com q Recherche sur Microsoft.com ... cli_shellHeaderSearchInput search expanded none
5 amazon.com field-keywords ... twotabsearchtextbox none none
...
1380 newsw.co.uk tp None None None none none
1381 qantax.com query Search ... all_search_2 none none
1382 mangareader.net None None search none none
1384 lucas.com keywords Find courses, information, and more ... keywords none none
[1385 rows x 7 columns]
    
```

Figure 10: Training dataset sample.

Our testing search functionality has been implemented in Selenium, the testing results are showed in the table below (Table 2).

Table 2: Testing against 1000 web sites.

	Pass	Fail	Error
Chrome	48%	18%	34%
Firefox	57%	16%	27%
Opera	47%	12%	41%
Internet Explorer	9%	19%	72%
Microsoft Edge	17%	19%	64%

First, we may be surprised by the number of fail and error verdicts. Nevertheless, the high percentage of results getting error does not mean that our framework is defective. After analysis, we noted that it is due to the fact that we did the test on 1000 websites chosen randomly. Therefore, there are websites that do not have the search functionality. From Table 2, we can see that Internet Explorer and Microsoft Edge perform the worst. It makes sense since Microsoft

has stopped support for Internet Explorer. Microsoft Edge is replaced as the main and fast browser for the Windows OS. However, the Selenium Webdriver for Microsoft Edge is not fully supported and still under development. We encountered that Internet Explorer and Microsoft Edge crashed when testing more than 20 websites concurrently.

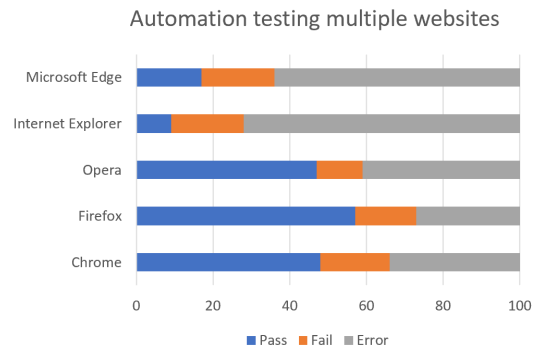


Figure 11: Automation testing against multiple web sites.

Through our experimental results for automation testing the search functionality showed in Figure 11, Firefox performs the best in terms of pass cases. Chrome is the best browser to handle the verdicts error. We experienced that Chrome is a good choice when testing the websites which are rendered heavily with JavaScript, while Firefox still suffers for those sites. Opera is fairly good in our test. We were also surprised with the performance of Opera considered that it is not as popular as Chrome and Firefox.

5.3.2 Testing with Extension (Add-on)

During our experiments, we noticed that our tests were interrupted if a pop-up windows suddenly appears during the test. The pop-up can be of any type (advertisement, data privacy, etc.) but the main met one was the pop-up which requires to accept the term and privacy when browsing the website as seen in Figure 12. Without clicking the accept button, there is no way to browse the website further. Considering that the test is running automated under Selenium code, there is no interference by manual hand to click the accept button. Therefore, the tests were most of the time broken when facing with pop-up windows.

In order to solve this problem, we decided to add a blocking pop-up extension to the browsers. This led to a trade-off, adding this extension allows to test pop-up websites, but in return, the test speeds decreased. The reason is that we modified our Selenium scripts in order to detect such pop-up windows and then to add such an extension when it occurs. Therefore, the webdriver had to trigger automatically the extension

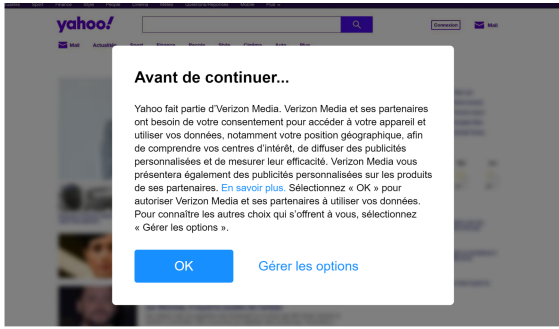


Figure 12: Pop-up blocks the browser in Yahoo website.

in the targeted browser, reducing at the same time the performance of our tests (in terms of response time - obtained verdicts).

For the experiments, we chose two extensions below due to their efficiency in blocking pop-up windows, there are more than 10 millions users using those extensions:

- *Ublock*: (ubl, 2020) is a free and open-source, cross-platform browser extension for content-filtering, including ad-blocking.
- *I dont care about cookie*: (Kladnik, 2020) This browser extension removes cookie warnings from almost all websites and saves thousands of unnecessary clicks, very useful for our codeless testing approach.

Since the above extensions are only fully supported for Chrome and Firefox, the experiments in this section were only run on these two browsers. The tests were run on 20 random websites concurrently on each browser in two modes: with extension and without extension. The Table 3 and Fig. 13 illustrate our results.

Table 3: Verdict results when testing with/without extensions.

	With Extension			Without Extension		
	Pass	Fail	Error	Pass	Fail	Error
Chrome	12	2	6	9	5	6
Firefox	11	3	6	9	5	6

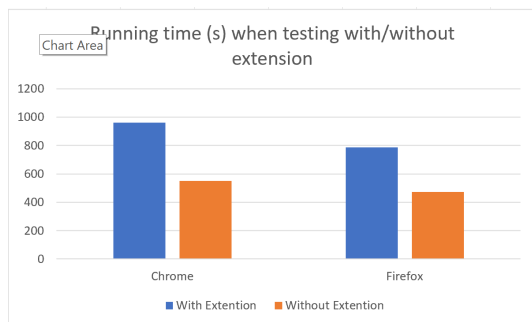


Figure 13: Running time with extensions testing.

Within Table 3, we can note that using extension to block the pop-up is very effective during the tests. It helps to enhance the *pass* case and reduce the *fail* one. However, the running time when executing the tests with addons is reduced (Fig. 13). We also note that Firefox is more efficient than Chrome in terms of time performance in both cases (with and without extensions).

6 CONCLUSION AND PERSPECTIVES

In this paper, we proposed a framework to test multiple websites in an automation way. The approach is able to use a generic test case to test a single functionality through multiple websites by leveraging machine learning technique and selenium on web element locators. Our technique can adapt dynamically to the changes of the website. This framework called “codeless testing automation” aims to help the tester in reducing the time and efforts that are commonly spent to change or modify the test codes. In our experiments, we focus on testing the *search* functionality of a web service. The test scenario is the following: using our framework, without modify the test code, the framework must be able to test the search functionality of multiple websites. Note that the categorization of websites is not a matter, the framework enable to check with any website. From the experiments, the results show that our framework can be efficient to perform the automation testing with most of standard websites by using the generic test case without rewriting the test code into Selenium.

From this work, we intend several perspectives. First, we have to tackle all the use cases mentioned in our paper and in particular the third case in which constraints are given on the search functionality. Furthermore, we aim at testing several behaviors at the same time. This aspect will need another testing architecture to consider the huge amount of data needed to be trained and analysed through our framework. Besides, we expect to propose APIs and generic test scripts to the community in order to assess our technique on diverse functional tests. This is will lead to interesting and relevant comparisons with other approaches. Finally, other learning techniques such as neural based mechanisms are studied.

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