Retrieving and Ranking Relevant JavaScript Technologies from Web Repositories

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Summary

The selection of software technologies is an important but complex task. We consider developers of JavaScript (JS) applications, for whom the assessment of JS libraries has become difficult and time-consuming due to the growing number of technology options available. A common strategy is to browse software repositories via search engines (e.g., NPM, or Google), although it brings some problems. First, given a technology need, the engines might return a long list of results, which often causes information overload issues. Second, the results should be ranked according to criteria of interest for the developer. However, deciding how to weight these criteria to make a decision is not straightforward. In this work, we propose a two-phase approach for assisting developers to retrieve and rank JS technologies in a semi-automated fashion. The first-phase (ST-Retrieval) uses a meta-search technique for collecting JS technologies that meet the developer’s needs. The second-phase (called ST-Rank), relies on a machine learning technique to infer, based on criteria used by other projects in the Web, a ranking of the output of ST-Retrieval. We evaluated our approach with NPM and obtained satisfactory results in terms of the accuracy of the technologies retrieved and the order in which they were ranked.

KEYWORDS: JavaScript, Information overloading, Web repositories

1 INTRODUCTION

Software technologies are an essential part of current software development practices. The use of software technologies, such as libraries and frameworks, can greatly improve developers’ productivity. Nonetheless, an inappropriate technology selection can negatively affect the software product being built, and also the business goals of the organization[3]. In this context, the task of selecting a software technology that fulfills the specific needs of a development task is generally a complex and time-consuming decision-making process. One of the reasons for this complexity is the availability of a large number of software technologies in the market, in response to the growing demand from software companies. Keeping up-to-date with technological developments is challenging for developers.

In particular, this situation is very common in JavaScript (JS) development, as developers have to regularly search, evaluate and compare candidate JS libraries/frameworks for their applications. This process can be perceived by developers as “technological fatigue.” This phenomenon is due to the extensive number of JS technologies available in Web repositories, such as NPM[1](Node Package Manager), which promote reuse by lowering production costs and speeding up software delivery[2].

1 https://medium.com/@ericclemmons/javascript-fatigue-48d4011b6fc4
2 https://www.npmjs.com/
We argue that one of the reasons for JS technological fatigue is the lack of precision in the search engines for JS repositories. As a consequence, developers often resort to general-purpose search engines (e.g., Google or Bing) with the hope of having better results. However, the downside of such engines is that they tend to return long lists of documents, and then developers have to navigate within each result to find possible JS technologies. This leads to information overload issues. Furthermore, once the developer identifies a set of candidate technologies for her application, she must analyze each technology to decide which one better fits her needs. Normally, this decision is driven by features of the technology, such as: popularity in the community, or number of downloads, among others. Assigning weights to these features for comparison purposes is not straightforward. For instance, NPM uses the AHP (Analytic Hierarchy Process)\textsuperscript{3} technique to support comparisons of JS technologies.

The problem of information overload has been studied in various disciplines\textsuperscript{4}, and Web search engines are one of the main tools to face the problem\textsuperscript{5}. The usage of search engines for Web-based software repositories has received some attention in the literature, but there are still challenges for finding technologies being relevant to a particular development (or technological) need\textsuperscript{6}. Previous works on software technology selection have addressed the problem from different perspectives\textsuperscript{7,8,9,10}. Nonetheless, most works focus on the evaluation of candidate technologies based on specific characteristics, departing from a given group of technologies, and they leave aside the problem of searching for relevant candidates. In addition, the characteristics for decision making are often manually assessed by developers.

In this article, we propose an approach to assist developers in searching and ranking JS technologies. The approach works in two phases called ST-Retrieval and ST-Rank. Given a developer’s query expressing a JS technological need, ST-Retrieval applies a meta-search strategy\textsuperscript{12}, which combines the search results of both a JS-specific engine and general-purpose engines. Based on the technologies recovered by ST-Retrieval, ST-Rank generates a ranking of those technologies for the developer by means of a pair-wise learning to rank method. The ranking is based on an (automated) analysis of technology features extracted from JS projects on the Web (e.g., number of stars in the repository, number of releases in the last year, number of contributors, etc.). To assess the relevance of the projects, we employ a popularity metric called CDSel. CDSel measures the relationship between the number of projects in which the technology was selected and how popular are those projects.

We have evaluated the approach on the NPM repository for JS, using a predefined set of queries and 1000 popular projects from GitHub. For ST-Retrieval, our experiments reported an average precision improvement of 20\%, and we were able to recover a larger number of relevant JS technologies than using the default search engine provided by NPM. Regarding ST-Rank, we observed improvements of at least 20\% on average when compared to the default ranking strategy followed by NPM. Based on these initial results, our approach makes two contributions: (i) it can boost the performance of the NPM search system by leveraging on results provided by multiple search engines, and (ii) it helps developers by ranking first those technologies being widely used in the JS community.

The rest of the article is structured as follows. In Section\textsuperscript{2}, we provide a brief description of the software technology selection problem, along with a motivational scenario in JS development. In Section\textsuperscript{3}, we describe the two phases of the approach in detail. Section\textsuperscript{4} presents the evaluation of ST-Retrieval and ST-Rank, and discusses their pros and cons. Section\textsuperscript{5} covers related work. Finally, Section\textsuperscript{6} gives the conclusions and outlines future lines of work.

2 SOFTWARE TECHNOLOGY SELECTION

From a development perspective, the selection of software technologies has an influential role in both the development process and the quality of the final product\textsuperscript{13}. The successful application of a given technology (e.g., a JS package) means that its usage for a particular task produces a desired objective\textsuperscript{14}. This success also depends on contextual features (e.g., alignment between the developer’s requirement and the chosen package, maintenance of the package, type of license, or package usability, among others).

As a motivational example of the technology selection problem for JS development, let us consider a JS developer that needs to extract a barcode from an image, with the goal of automating a process for extracting codes from a series of image files. The application context for this functionality is a Web browser. Initially, she goes to the NPM package repository and submits the query "extract barcode from image" to its search engine, which returns only the package bytescout\textsuperscript{15} as output. Bytescout is a JS client for a cloud service of the same name. When reading about Bytescout, our developer finds out that it is a paid service and that the JS client is not open-source. Also, when she looks at the package description, NPM reports that Bytescout has been downloaded 40 times in the last month, which for a JS package might indicate that it is not very popular in the community. Let us assume that our developer is not convinced with these features, or they are not aligned with the standards of her project. However, bytescout is the only technology returned by NPM. In this context, our developer has several options, namely: (i) adopt the package despite her disagreement with its features, (ii) implement a solution from scratch to read the barcodes, (iii) try a modified query with the hope of getting more results from NPM, or (iv) use alternative information sources (e.g. Google, or NPMSearch, among other engines) to find alternative technologies. Let us suppose here that she goes for the third option and re-phrase the query as "barcode reader", which makes NPM return now\textsuperscript{3} https://bytescout.com/
16 results. After inspecting each result, our developer is still unconvinced of using any of the technologies, since they do not seem to be very popular nor receive enough maintenance. The scenario so far shows the current limitations of JS-specific search engines, like NPM.

Next, let us assume that our developer decides to go for the fourth option, and she submits the query "extract barcode from image javascript package" to Google (the last phrase intend to prevent Google form returning results for libraries in other languages). This query returns a list of Web pages, and our developer then inspects each page in order to check whether some JS technologies are mentioned. In doing so, she realizes that a technology called QuaggaJS\(^4\) is referenced in 3 results from the top-10 pages of the list. As she is not aware of this technology, she goes back to the NPM repository and finds that QuaggaJS is more popular than bytescout, it is open-source, and is well-maintained by the community. At this point, our developer can pick QuaggaJS for her development need, or keep looking for other technologies. This scenario illustrates the challenge of using general-purpose search engines for JS, but also the issues related to the comparison of technologies.

The bottom line of the example has two implications. First, the search and comparison of JS technologies should take advantage of different information sources. Second, the developer's manual analysis of technologies (e.g., by looking at Web sites) should be minimized, in the sense that semi-automated rankings could be created from criteria or feedback provided by other projects. Based on these ideas, we developed the ST-Retrieval and ST-Rank components of our approach.

3.1 APPROACH

For retrieving and ranking relevant JS technologies, we propose two-phase approach as shown in Figure 1. The first phase, called ST-Retrieval, takes a query given by the JS developer and returns a list of candidate technologies matching the query. The query is written in natural language and specifies a technological requirement (e.g. "extract barcode from image"). The goal of this phase is to leverage on various search engines. Afterwards, the second phase, called ST-Rank, is fed with the outputs of ST-Retrieval along with an application context\(^5\) (i.e. Web browser, Node.js, etc.) provided by the developer, and generates a ranking of JS technologies based on their relevance. The goal of this phase is to infer a ranking by "learning" from technology features and decisions made in other projects. To do so, a machine learning (ML) model is built. Each phase internally involves different steps. Gray boxes in the figure correspond to steps or artifacts provided at setup, while white boxes refer to steps performed every time a new query is entered by the developer.

3.1.1 ST-Retrieval

We model the search and retrieval of JS technologies as a meta-search problem.\(^6\) In meta-search, the original query is sent in parallel to a set of search engines, each one returning an ordered list of items that satisfy the query. The meta-search system combines all the lists into a new one that is expected to keep the "best" items of the individual lists.

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4\(https://serratus.github.io/quaggaJS/\)
5\(Since some technologies only work in a specific context, our approach needs to be informed of the application context in which the developer is going to apply the technology\)
The meta-search strategy for ST-Retrieval works in three steps (Figure 1), as follows. First, the input query is sent to both domain-specific engines (e.g., NPM) and general-purpose engines (e.g., Google, Bing). The domain-specific engines directly return a list of JS technologies. However, the general-purpose engines produce a list of Web pages, which might include names of JS technologies. Second, these Web pages are processed in order to extract a list of JS technologies. Third, the lists from each search engine are merged into one single list, which is passed on to the second phase.

The technical aspects of each step are explained below.

3.1.1 Process query
In this step, we aim at leveraging on the capabilities of existing search engines. Specifically, we use four engines, namely: NPM, NPMSearch, Google, and Bing. In general, the possible engines envisioned in our approach fall into two types: (i) domain-specific (DS), and (ii) general-purpose (GP). The former are especially designed for the search of JS technologies (NPM and NPMSearch), while the latter are often used for general queries (Google and Bing).

Both types of engines allow developers to enter queries in natural language. Developers’ queries can express functional or non-functional requirements that should be met by a JS technology. Stop-words (e.g., articles, pronouns, prepositions, etc.) that do not provide information to the search engine are removed from the query. For GP engines, it also augments the query to avoid results from other domains (e.g., technologies in a language incompatible with the project). Since we are retrieving JS technologies, the query is expanded with the suffix “javascript package”. Once the query was expanded, it is ready for execution in the corresponding engine. The result of this execution is a set of Web pages (or documents) in HTML, XML or JSON format.

3.1.2 Extract technologies
This step is concerned with obtaining the technologies named in the documents being returned by a query. Technologies are represented as a tuple \(<\text{name, repository-url, home-url, description}>\) where:

- \(\text{name}\): corresponds to the name of the technology in the repository (e.g., “quagga”).
- \(\text{repository-url}\): is the technology URL on the repository site (e.g., “https://www.npmjs.com/package/quagga”).
- \(\text{home-url}\): is the URL of the technology site (e.g., “https://serratus.github.io/quaggaJS/”).
- \(\text{description}\): is the description of the technology (e.g., “An advanced barcode-scanner written in JavaScript”).

On one hand, for DS engines, each result will map one-to-one with existing technologies in the repository via its \(\text{name}\) and \(\text{repository-url}\). On the other hand, for GP engines, the search results are Web documents, which might refer to zero, one or many technologies. For this reason, those names of the technologies should be recovered. This information extraction task can be seen as a Named Entity Recognition (NER) problem. NER aims at classifying entities found in a given text into predefined categories (e.g., people, organizations, places, time expressions, among others). In our work, the named entity category is “software technology”, and we employ a rule-based strategy for string-matching. By means of these rules, all the technologies whose name or address (home-url, repository-url) match the category are extracted.

This step requires a repository of JS technologies as input (Figure 1), which includes the information of the tuples. We generated this repository in advance via a process of Web crawling on the NPM site. Figure 2 shows an example of results and technologies obtained from the NPM and Google engines, along with their mappings for the query “extract barcode from image”. In the example, NPM returned a single result (bytescout) matching the name of a technology in the repository. Unlike NPM, Google returned an HTML document, whose text was parsed for matches of names or addresses of technologies. In particular, the technology name in the resulting page (QuaggaJS) did not match the technology name in the repository (quagga) but the address of the site did match (home-url, https://serratus.github.io/quaggaJS/).

3.1.3 Merge technology results
Based on the set of named technologies, this step creates an ordered list of technologies per search engine. For DS engines, the sorting function is straightforward, and each technology is assigned to the position of the result where it is named. For GP engines, a result can be related to many
named technologies. In this case, the sorting function is based on the order in which the technologies were named. If two technologies are named within the same result, the first one named will appear in the list before than the one named afterwards. For example, if the first result contains the text “You can use Quagga or Barcode-Reader” and the next result contains the text “You should use Bytescout”, then the candidates will be ordered as 1) Quagga, 2) Barcode-Reader, and 3) Bytescout.

After all search engines produced their individual lists, they are merged into a single list. In meta-search, this process is known as a ranking aggregation function\cite{12}. Aggregation functions can be classified into two main types\cite{12}: (i) those that use similarity scores returned by the search engine, and (ii) those that use ranking positions. When engines do not expose their similarity scores for their results, as in the cases of Google or Bing, ranking positions can be used instead. For this reason, we decided to use Borda Fuse in our approach. Borda Fuse is a positional aggregation function that is computationally simple to implement\cite{12}, and it performs well in the context of Web searching\cite{12}.

In the Borda Fuse method, each search engine is considered as a voter. Each voter presents a list of $n$ ordered candidates (i.e., technologies). For each list, the best first candidate receives $n$ points, the second candidate receives $n-1$ points, and so on. Then, the points awarded by the different voters are added and the candidates are ranked in descending order according to the total of points obtained. Table 1 shows an aggregation example using the Borda Fuse method. Each list gives a maximum of 4 points (equal to the maximum length of individual lists) and decreases by one to each position of the list, i.e. the second position gives 3 points, the third position gives 2 points, and the last position gives 1 point. The scores are added and a final list from highest to lowest scores is created. In our example, the most relevant results, quagga and bytescout, are in the top-ranked positions of the final list.

3.2 | ST-Rank

ST-Retrieval outputs a set of candidate technologies for the developer’s query. Since these technologies have the same goals, the developer has to scrutinize them to find the technology that best fulfills her needs. This analysis often involves indicators provided by the repository (e.g., the number of downloads, dependent projects, or contributors, among others) and also searching for developers’ opinions in blogs and forums. In this context,
ST-Rank assists developers to select the “best” technology by creating a ranking based on the choices made by other developers. The assistance consists of four steps (Figure 1), as follows. First, information about popular technologies used by other developers in open-source repositories is collected. Second, a dataset is created by taking into account the previous information and the application context of each technology (e.g., Web browser, Node.js, etc.). A training dataset is derived from the dataset, and we apply a supervised machine learning algorithm to build a ranking model for JS technologies. These three steps happen during the setup of the approach. At last, the machine learning model predicts a ranking for the technologies given by ST-Retrieval, according to the “patterns” inferred from the training dataset.

The technical aspects of each step are explained below.

3.2.1 Collect data
The input of this step is a group of popular open-source JS projects. We are interested in the dependencies of every project and their features. In NPM, these dependencies are in the `package.json` of each project.

The processing of each dependency involves three tasks. The first task is to look for alternatives to the technologies identified. For example, project Chart.js depends on moment, which is a library to manipulate dates (Figure 3). Thus, alternative technologies solving the same need are sought, such as date-fns and momentjs. We implemented this search by automatically scraping the website of NPMCompare. For a given technology, the website gives a list of related packages.

The second task is to assess the “popularity” of the dependency (or JS technology). To do so, we propose a metric called CDSel (Community Degree of Selection) for a technology. CDSel is intended to capture the relationship between the number of projects in which the technology was selected and the relevance of those projects. Let \( n \) be the number of reference projects, \( \text{rel}(P_i) \) the relevance of project \( i \), and \( s = 1 \) when the technology was selected in \( P_i \) (0 otherwise), then CDSel is computed as follows:

\[
CDSel = \sum_{i=1}^{n} s \times \frac{\text{rel}(P_i)}{\log_2(i+1)}
\]

The logarithm serves as an attenuating factor in the ranking, so as to produce a controlled reduction in the values of the metric. For example, in our dataset we obtained a CDSel value of 396.192 for moment, 15.646 for date-fns, and 1.791 for momentjs, which means that moment is most

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*(Since both the “reference projects” and their dependencies are JS projects themselves, for the sake of clarity we refer to the former as “projects” and to the latter as “technologies”)*

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10 https://www.npmjs.com/package/chart.js
11 https://www.npmjs.com/package/moment
12 https://www.npmjs.com/package/momentjs
13 https://www.npmjs.com/package/date-fns
14 https://www.npmjs.com/package/momentjs
15 https://npmcompare.com
often selected by relevant repositories than date-fns and momentjs (Figure 3). Regarding $rel(P_i)$, it is computed as follows:

$$rel(P_i) = z - (rankPosition(P_i))$$

where $z$ is the length of the ranking and $rankPosition(P_i)$ is the position in the ranking of project $(P_i)$. The ranking is based on the stars of each project in GitHub.

The third task is to access to the NPM and GitHub repositories for retrieving features that characterize each technology. We focus on features that can be used as criteria for decision making, such as: number of developers that maintain the technology, #daily downloads, or #dependencies, among others. More than 40 features are taken into account. It should be noticed that all the technologies are represented with the same set of features. It is up to the machine learning algorithm to decide which features are relevant. Our rationale is that, if a technology $T$ was chosen in a project (over other available options), then there should be a criterion over some technology features, upon which $T$ was considered more relevant than the other options. Thus, being able to learn the selection criteria depends on the features collected from the technologies.

3.2.2 Create dataset

This step assembles the dataset to be used for building the machine learning (ranking) model. We refer to this dataset as the training dataset (Figure 1), and it contains a set of training instances. A given training instance captures a pair of technologies. Initially, a training ranking is computed for each technology according to its CDSel value. In our example, moment will be ranked first since its CDSel value is higher than the CDSel value of date-fns and momentjs. Then, each technology is represented as a feature vector $[FT_1, FT_2, ..., FT_n]$ where $FT$ is a particular feature and $n$ is the total number of features. Each vector is normalized via feature scaling so that its values are between 0 and 1. For example, in Figure 3 vector (1, 10, 5) for moment becomes (1, 0.77, 1) after normalization.

At last, a set of training instances is created. Specifically, for each possible pair of technologies in a training ranking, a vector is created by concatenation of their normalized feature vectors. A label of 1 is added to this vector when the first technology is more relevant than the second one, or 0 otherwise. In our example, the pair (moment, date-fns) is labeled to 1 because moment is ranked before date-fns.

3.2.3 Build ML model

This step applies a "learning-to-rank" technique on the training instances of the dataset. A pairwise supervised variant is used, since the order of two given technologies is not affected by other technologies in the list. For example, moment is more relevant than date-fns regardless of other alternative technologies. Among the various learning-to-rank algorithms reported in the literature, we chose GBRank due to its effectiveness in Web search ranking. GBRank is based on a gradient boosting method for minimizing wrong preference predictions.

3.2.4 Rank technologies

Given two technologies, the ML model (above) is able to predict an order for them according to their relevance. Finally, this step takes all possible pairs of technologies (from the Merge technology results step) and runs them through the ML model, in order to generate a ranking. The pairs are filtered according to the application context defined by the JS developer. Those technologies being most relevant (i.e., popular) should be ranked first by the ML model.

4 EVALUATION

We performed an empirical evaluation of the ST-Retrieval and ST-Rank components using datasets sampled from JS projects. The following research questions were addressed:

- **RQ#1**: How does the performance of ST-Retrieval compare to that of existing search engines?
- **RQ#2**: What is the quality of the rankings proposed by ST-Rank with respect to the rankings from NPM and NPMCompare?

The experiments to answer RQ#1 and RQ#2 are reported in sub-sections 4.1 and 4.2 respectively.

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16 The full list of features can be found in the Supplementary Material zip file at https://bit.ly/2w9sOzV.
TABLE 2 Reference Queries.

| Queries                                                                 |
|------------------------------------------------------------------------|
| check valid email address                                            |
| download web videos                                                     |
| send sms                                                               |
| quick sort algorithm                                                   |
| filter adult content images                                            |
| user authentication                                                    |
| extract barcode from image                                            |
| convert data formats                                                   |
| download free music                                                    |
| convert typewritten image to text                                     |
| sentiment analysis                                                     |
| third party authentication                                             |
| convert text to speech                                                 |
| calculate word similarity                                              |
| translate english to spanish                                           |
| credit card validation                                                 |
| health tracker                                                         |
| captcha authentication                                                 |
| detect text language                                                   |
| rank aggregation algorithms                                            |
| mobile app framework                                                   |
| DOM manipulation utils                                                 |
| lightweight 3D graphic library                                        |
| mathematical functions                                                |
| scraper                                                                |

4.1 Evaluation of ST-Retrieval

The main goal is to determine whether the performance of ST-Retrieval for retrieving a set of JS technologies is better than the performance of DS and GP search engines.

4.1.1 Experimental Design and Operation

We used NPM as the basis for the evaluation, as NPM is the de-facto package repository for JS technologies. First, we downloaded the technology registry from the NPM repository. With this information, we built the repository of technologies (Figure 1) to a given date (08/28/17), as described in sub-section 3.1.2. Then, we asked two senior JS developers to record any search (i.e., queries) for technologies in NPM that they would make, during 2 weeks, in their normal projects. After filtering some of their search results (in order to remove very similar queries), we obtained a reference set of 25 queries (Table 2) representing a variety of technological needs. We ran ST-Retrieval 25 times on this set (once for each query) and stored the lists of outputted technologies. The length of the queries was selected as a normal distribution over the most usual length. The search engines were: NPM, NPMSearch, Google, and Bing. We also ran a retrieval effectiveness test for search engines.

During the Process query step, we only took into account the first 20 documents from the list of results. This was because users searching the Web (e.g., using Google) are very likely to consider only the first results. These documents were recorded in order each time we ran the step. As part of the Extract technologies step, we stored all the technologies identified. At the end, we retrieved a total of 2760 JS technologies (in general, multiple technologies were extracted from the documents returned by Google and Bing). Then, in order to establish a baseline, we asked 12 JS senior developers (different from the ones that produced the reference set of queries) to assess the technology results. Each developer was given all the technologies for a query in random order, and was asked to judge the technology relevance using a binary scale (yes/no). The developers did not know which search engine produced a particular result, and duplicate results (i.e. results returned by more than one engine) were presented to...
them only once. In particular, 11 developers analyzed the results of 2 queries and 1 developer analyzed the results of 3 queries. On average, each JS developer analyzed 230 technologies.

4.1.2 Metrics
Information Retrieval metrics were used for gauging performance such as: precision, recall, MAP (Mean Average Precision) and DCG (Discounted Cumulative Gain). We leveraged on the reference set of queries and the technology baseline described previously.

In our domain, precision is the ratio between the number of relevant technologies recovered and the total number of technologies recovered. The closer the precision value is to 1, the greater the number of relevant technologies recovered with ST-Retrieval. Recall is the ratio between the number of relevant technologies recovered and the total relevant technologies known. A recall of 1 indicates that all relevant technologies have been recovered. In addition, MAP measures, for a set of queries, the average precision for each query. MAP values close to 1 mean that the relevant technologies are within the top-ranked positions. At last, DCG measures the quality of rankings, in terms of the utility (gain) of a result based on its relevance and position in the ranking. DCG can be divided by the maximum value taken from among all the queries, and then, the values for each query can be averaged to measure the average quality of the rankings. This variant of DCG is called Normalized DCG (nDCG).

4.1.3 Analysis of Results
Recall and Precision were calculated in different positions of the ranking in order to establish the value of the metric in that position. In addition, the reported results are the arithmetic mean of the values for each query.

![Figure 4](https://via.placeholder.com/150)

**FIGURE 4** Hits, Precision, and Recall at K position (ST-Retrieval).

Figure 4 shows the results for the four search engines and the Borda Fuse function considering each position (k) of the ranking (k = 1, first position). The first chart shows the average number of hits (Hits). A result is said to be a hit if it is relevant to the query. The other charts show the results for Precision, and Recall. As it can be observed, ST-Retrieval presents high values in all positions for all the metrics. Google and NPM behave similarly to ST-Retrieval until around the third position. From that position on, ST-Retrieval exhibits a considerable improvement. We argue that this improvement is due to the aggregation of results, and also to the ability of Borda Fuse to find the global relevance of a result based on its position in the results relative to the different search engines. The maximum precision obtained by ST-Retrieval was 0.72 (8% increase when compared to the search engines) and the maximum recall was of 0.77 (34% more than the search engines). This difference in performance is also observed in the nDCG and MAP metrics for ranking quality metrics.

Table 3 shows the values for nDCG (nD) and MAP (M) for ranking sizes of 5, 10, and 20. Table 3 also shows the values of Hits (H) and Precision (P) in positions 5, 10, and 20, respectively. Interestingly, Borda Fuse shows the best performance along all positions. In the case of the search engines, NPM obtained the best results. For this reason, we compared Borda Fuse against NPM. For instance, NPM is outperformed by the BordaFuse technique in 19.06% (in average) for all positions in Hits. This means that around position 5 Borda Fuse is able to return one more relevant technology than NPM. Thus, the precision of NPM is outperformed by Borda Fuse by 19.06% (in average) over all positions.

Regarding the ranking quality, Borda Fuse obtained a nDCG of 22.04%, 20.5% and 25.9% higher than the same metric for NPM, for ranking lengths of 5, 10 and 20 respectively. When it comes to MAP, the improvements of Borda Fuse with respect to NPM were of 27.37%, 25.16%, and 21.78% for ranking lengths of 5, 10 and 20 respectively. The improvement in ranking quality can be related to the improvements in precision and recall. On one hand, by increasing the precision in the top-ranked positions, the relevant results near the top of the ranking increase and so do the values of nDCG and MAP (since both metrics reward results in the top-ranked positions). On the other hand, by increasing recall, the amount of relevant results that add up along the nDCG and MAP calculations also increases.
TABLE 3 Metrics for search engines (ST-Retrieval).

| Method/Metric | H@1  | H@5  | H@10 | H@20 | P@5  | P@10 | P@20 | nD(r=5) | nD(r=10) | nD(r=20) | M(r=5)  | M(r=10) | M(r=20) |
|---------------|------|------|------|------|------|------|------|--------|----------|----------|---------|---------|---------|
| NPM           | 0.600| 2.680| 4.760| 7.680| 0.536| 0.476| 0.384| 0.635  | 0.639    | 0.660    | 0.632   | 0.620   | 0.615   |
| NPMSearch     | 0.320| 1.240| 2.480| 4.280| 0.248| 0.248| 0.214| 0.322  | 0.333    | 0.361    | 0.348   | 0.336   | 0.325   |
| Google        | 0.640| 2.480| 3.480| 4.040| 0.496| 0.348| 0.202| 0.720  | 0.736    | 0.750    | 0.712   | 0.704   | 0.695   |
| Bing          | 0.560| 1.920| 2.280| 2.320| 0.384| 0.228| 0.116| 0.662  | 0.675    | 0.677    | 0.638   | 0.639   | 0.639   |
| BordaFuse     | 0.720| 3.240| 5.480| 9.400| 0.648| 0.548| 0.470| 0.775  | 0.770    | 0.831    | 0.805   | 0.776   | 0.749   |

After observing that the performance values of ST-Retrieval were higher than those of the search engines, we tested the statistical significance of the results using the non-parametric Wilcoxon Signed Rank Test [31] with a significance level $\alpha = 0.05$. We stated the null hypothesis ($H_{10}$) as: “The metric values from ST-Retrieval are equal to those from other search engines”. The alternative hypothesis ($H_{11}$) states that there is a difference between these metrics. Table 4 shows the p-values obtained for each metric (treatment) reported in Table 3 after running the tests. With the exception of the number of hits at first position (H@1), all p-value values are less than 0.05. This means that we can reject $H_{10}$ for all the metrics (except H@1), and conclude that the differences between ST-Retrieval and the existing search engines are statistically significant. Finally, we successfully answer RQ#1 by saying that ST-Retrieval does improve the search results.

TABLE 4 Comparison on the retrieval metrics using Wilcoxon signed rank test (ST-Retrieval).

| ST-Retrieval vs | H@1  | H@5  | H@10 | H@20 | P@5  | P@10 | P@20 | nD(r=5) | nD(r=10) | nD(r=20) | M(r=5)  | M(r=10) | M(r=20) |
|----------------|------|------|------|------|------|------|------|--------|----------|----------|---------|---------|---------|
| NPM            | .317 | <.001| <.001| <.001| <.001| <.001| <.001| <.05   | <.05     | <.05     | <.001   | <.001   | <.001   |
| NPMSearch      | <.05 | <.001| <.001| <.001| <.001| <.001| <.001| <.001  | <.001    | <.001    | <.001   | <.001   | <.001   |
| Google         | .317 | <.001| <.001| <.001| <.001| <.001| <.001| <.001  | <.001    | <.001    | <.001   | <.001   | <.001   |
| Bing           | .248 | <.001| <.001| <.001| <.001| <.001| <.001| <.001  | <.001    | <.001    | <.001   | <.001   | <.001   |

4.2 Evaluation of ST-Rank

The main goal is to determine whether ST-Rank improves the rankings generated by NPM.

4.2.1 Experimental Design and Operation

In order to obtain a “group of popular projects” for the Collect data step, we selected the top-1000 most popular projects according to GitHub, from the repository of technologies (Figure 1) used in the ST-Retrieval experiment. NPM and NPMCompare were employed for obtaining features and alternatives for each technology. In the Create dataset step, we then created around 250 training rankings of between 2 and 6 technologies each. In total, more than 1000 training instances were created [17].

To assess the rankings produced by ST-Rank, we defined a test set by randomly removing 20% of the training rankings (along with their training instances). Specifically, we shuffled the order of each training ranking. Then, we presented the technologies of each ranking to two senior JS developers and asked them to produce reference rankings by sorting the technologies in descending order of relevance [18]. The remaining 80% of the training instances were divided to perform a k-fold cross-validation [32] with $k = 5$, in order to train the ML model and find the best configuration of hyper-parameters for GBRank. Specifically, we used random search [33] to explore the possible values of the hyper-parameters, and the values close to the best random configuration achieved by a grid search [34] were applied. In the end, GBRank was run with parameters learning_rate = 0.004, max_depth = 50, min_samples_split = 50, and min_samples_leaf = 10.

For the application contexts, we manually classified the JS technologies based on their execution environment. We considered three possible environments, namely: (i) technologies running in a Web browser (Web), (ii) technologies to be used in the Node.js execution environment (Node), (iii) technologies to be used in the Node.js execution environment (Node).

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17 The training dataset can be found in the Supplementary Material zip file at https://bit.ly/2w9sOzV.
18 The reference rankings can be found in the Supplementary Material zip file at https://bit.ly/2w9sOzV.
and (iii) technologies that do not require a specific environment (No context). From these application contexts, we configured 5 possible scenarios, as follows: (i) All - the developer makes no distinction among application contexts (i.e. the three execution environments are considered), (ii) Web - the developer needs a technology for a Web browser (i.e. Web and No context are considered), (iii) Node - the developer needs a technology for Node.js (Node and No context are considered), (iv) OnlyWeb - the developer needs a technology specifically developed for the Web browser (only Web is considered), and (v) OnlyNode - the developer needs a technology specifically developed for Node.js (only Node is considered). Based on these scenarios, we need ST-Rank to classify the inputted technologies and the training rankings. Thus, we ran ST-Rank 5 times, once for each scenario. At last, we compared our results with the default ranking techniques supported by NPM and NPMCompare, which are the Analytic Hierarchy Process (AHP)\(^3\) and the Weighted Average Method (WAM)\(^3\), respectively.

### 4.2.2 Metrics

We use three metrics to evaluate the performance of the rankings, namely: MAP (see Section 4.1.2), SRCC (Spearman Rank Correlation Coefficient)\(^3\), and MRR (Mean Reciprocal Rank)\(^3\). SRCC measures the correlation between the rankings created by ST-Rank (and also by AHP and WAM) against the reference rankings created by the senior JS developers. In particular, we calculated SRCC for each ranking and then averaged them to obtain a value that summarizes the “stability” of each technique. MRR, in turn, evaluates if the highest-ranked items are relevant. The closer the MRR value is to 1, the greater the number of relevant technologies in the highest positions.

### 4.2.3 Analysis of Results

**TABLE 5** Ranking results for different scenarios (ST-Rank).

| Technique | All M@3 | M@5 | SRCC MRR | Web M@3 | M@5 | SRCC MRR | Node M@3 | M@5 | SRCC MRR | OnlyWeb M@3 | M@5 | SRCC MRR | OnlyNode M@3 | M@5 | SRCC MRR |
|-----------|---------|-----|----------|---------|-----|----------|----------|-----|----------|-------------|-----|----------|---------------|-----|----------|
| AHP       | 0.517   | 0.541 | 0.454    | 0.654   | 0.756 | 0.762    | 0.731    | 0.865| 0.541    | 0.365        | 0.667| 0.785    | 0.725         | 0.621| 0.880    |
| WAM       | 0.813   | 0.798 | 0.656    | 0.863   | 0.744 | 0.729    | 0.669    | 0.836| 0.793    | 0.928        | 0.878| 0.952    | 0.872         | 0.796| 0.750    |
| GBRank    | 0.925   | 0.914 | 0.788    | 0.915   | 0.910 | 0.864    | 0.835    | 0.942| 0.874    | 0.889        | 0.886| 0.932    | 0.952         | 0.962| 0.964    |

Table 5 shows the metric values for the scenarios. In the case of MAP, we computed it for different ranking lengths (M@3 and M@5 means MAP considers a ranking of 3 and 5 technologies respectively). The values in bold in the columns correspond to the best value for the metric along that column. As it can be observed, GBRank shows the best results for all the metrics. For example, for the All scenario, when considering MAP, GBRank outperforms AHP and WAM by around 44% and 12% respectively. Similarly, in the case SRCC, GBRank improves the values of AHP and WAM by around 42% and 17%. MRR shows smaller improvements of GBRank, 28% and 6% for AHP and WAM respectively. The differences between the techniques are similar for the other scenarios. On average, the improvements of ST-Rank over AHP and WAM are of 10%, 20% at least, and 5% for MAP, SRCC, and MRR, respectively. The smallest improvement was that of MRR, although this result was expected. MRR only takes into account the first element of the ranking. That is, if the first element of the reference ranking is in the first position of the ranking being evaluated, this ranking has a maximum value of MRR (although the other elements are disordered). However, in the problem of ranking of technologies, it is important that the other elements are also ordered. If for some reason (e.g., due to a technical limitation) the first technology cannot be used, the rest of the technologies should be as orderly as possible. This might happen if the JS developer needs to develop a proof-of-concept, and she should be able to find the right technology as quickly as possible.

**TABLE 6** Results of Wilcoxon signed rank test (ST-Rank).

| ST-Rank vs | M@3   | M@5   | SRCC  | MRR   |
|------------|-------|-------|-------|-------|
| AHP        | 4.41e^{-12} | 1.31e^{-13} | 2.35e^{-16} | 4.27e^{-12} |
| WAM        | 5.52e^{-05} | 1.01e^{-06} | 1.67e^{-10} | 5.79e^{-04} |

To analyze if the results are statistically significant, we tested the results using the non-parametric Wilcoxon Signed Rank Test with a significance level \( \alpha = 0.05 \). We stated the null hypothesis \( (H_{20}) \) as: “The metric values from ST-Rank are equal to those provided by the other techniques (i.e.
A threat to construct validity has to do with the queries (reference set) and technology searches (baseline) used in the experiments. We tried to rely on queries and searches being representative of real-world JS development. To this end, we extracted a dataset from the NPM repository using the public JS package registry. While we used only 25 queries, they returned 2760 JS technologies that were manually analyzed. Since the analysis of query results from search engines takes a substantial amount of time from experts, we preferred not to do a detailed query analysis and leave this for future work.

A threat to internal validity is the usage of Borda Fuse to order the list of technologies in ST-Retrieval, which might have biased the results, and also affected the outputs of ST-Rank. Alternative aggregation methods could return different orderings and should be explored in future works. Similarly, for ST-Rank we used a particular learning-to-rank technique, but other techniques could have led to different results.

Another threat is that the training rankings ST-Rank were based on the CDSel metric. This metric was chosen as a proxy for the popularity of JS packages, but it might not correctly represent the relevance of the packages for the community. Thus, a better validation of this metrics should be pursued.

To mitigate threats to external validity, we considered queries with different sizes, purposes and domains. However, our dataset might not be representative of all kinds of JS projects, and further experimentation and surveys of JS projects are necessary. Furthermore, the off-line evaluation showed that the computations of ST-Retrieval sometimes take a considerable time, which might be a problem in an online search engine. We have not consider yet the computation time of the search engines as a comparison factor.

### 5 RELATED WORK

Several approaches have been developed to support selection of software technologies. In general, these approaches are based on creating a list of technologies that are compared and presented to developers, so they can decide which ones to apply to their projects. Some works have focused on the evaluation of a set of pre-established candidate technologies and do not deal with the problem of searching/retrieving the technologies from (Web) repositories. For example, given a set of predefined candidates, Ernst et al. proposes a scorecard to help developers to select a given technology. The scorecard is based on performance, maintenance, and community criteria.

Software repositories are one of the main sources for search/retrieval of candidate technologies. However, existing repositories have not been very successful for this task, despite improvements in their underlying technology, such as the Web. One of the reasons is the performance of the search engines, which sometimes fail to produce the desired results. Based on the above, several works have tried to improve the search offered by the repositories. As far as we know, no works about meta-search targeted to software technologies have been proposed. However, there are a few works that bear similarities with our approach. Agora is a research prototype that intended to replace the idea of software repositories by creating a global database of JavaBeans and CORBA components, which was automatically generated and indexed. However, a major drawback was its reliance on the syntactic interface of JavaBeans and CORBA to carry out its search function. In addition, Agora did not use search engines for software repositories. Another recent work is Dolphin, which indexes open-source projects from version control repositories (e.g., OpenHub, SourceForge) and ranks them according to their influence in discussions of forum communities (e.g., StackOverflow, OSChina). Our main difference with this work is that Dolphin searches open-source code from version control repositories, while ST-Retrieval focuses on software released and stored in repositories (e.g., NPM). Another difference is that Dolphin does not use general-purpose search engines.

LibFinder is a search-based recommendation system for Java that uses multi-objective optimization to recommend software libraries, that combine GitHub and Maven repositories. However, it does not allow user queries to find technologies. Instead, it is based on the source code to recommend libraries that can replace pieces of source code made by hand. LibFinder does not use general-purpose search engines. Soliman et al. developed an approach to retrieve architectural design decisions and solution alternatives. The approach uses StackOverflow as an example of an online repository of architecture knowledge. However, this approach is based on a mapping between text and a “de-facto” ontology, and its applicability to other contexts is yet to be determined.

Regarding the order in which the technologies are created, there are works that address the problem from different perspectives. However, most of these works create ranking strategies manually, based on specific candidate characteristics. For example, Franch and Carvallo propose the adoption of a structured quality model to evaluate software packages. This model provides a taxonomy of software quality characteristics and
metrics to calculate its value for a given domain. Jadhav et al.\textsuperscript{13} classifies package ranking strategies into two groups, those using AHP and those using WAM. Then, an expert system is used. This approach is difficult to implement, since it depends on experts to construct rules in a manual fashion. Grande et al.\textsuperscript{10} define the selection problem as a multi-objective optimization problem and develop a framework for its treatment. They apply genetic algorithms to solve the multi-objective problem. One limitation of this approach is the creation and maintenance of the repository of technologies and their characteristics.

6 | CONCLUSIONS

In this article we proposed an approach targeted to JS technologies based on two complementary phases, called \textit{ST-Retrieval} and \textit{ST-Rank}. \textit{ST-Retrieval} helps developers to search and retrieve JS technologies using a meta-search strategy. \textit{ST-Rank} assists developers in ranking the candidate JS technologies identified by the previous phase. To achieve this goal, \textit{ST-Rank} uses a machine learning strategy that learns how to create rankings of technologies from previous choices made by the development community in popular open-source projects.

An initial evaluation of the approach using the NPM repository showed satisfactory results. In the case of \textit{ST-Retrieval}, precision and recall values of around 80\% were obtained, improving other search engines by approximately 20\%. Regarding \textit{ST-Rank}, improvements of around 5\% for MRR, 10\% for MAP, and 20\% for SRCC, were obtained in the ranking metrics. Despite these results, the approach still presents some drawbacks. First, the technology extraction function using string-matching in \textit{ST-Retrieval} can be expensive in computational terms. This might limit the application of the approach for online searching. For this reason, we will analyze the possibility of building an extraction function using other NER techniques and exploring their influence on the \textit{ST-Retrieval} results. Second the CDSel metric to measure the degree of selection of a technology in the community in \textit{ST-Rank} still needs further validation. Although reasonable results were obtained during the evaluations with CDSel using 1000 projects, considering alternative parameters in this metric can have an impact on the quality of the rankings.

As future work, in the case of \textit{ST-Retrieval}, we will apply aggregation functions other than Borda Fuse. In the case of \textit{ST-Rank}, we will explore alternatives to GBRank for the learning-to-rank task. In addition, we plan to conduct a study with subjects (JS developers as users of our approach) in order to corroborate our findings. Further work can extend our approach to technology repositories for other programming languages (e.g., Ruby, Python or Java, among others). Finally, following ideas of XAI (eXplainable AI)\textsuperscript{44}, it would be interesting to add support for generating explanations of the rankings, so that the comparison strategies are easier to understand by developers.

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How to cite this article: H. Vazquez, J.A. Diaz Pace, C. Marcos, and S. Vidal (2020), An Automated Machine Learning Approach for Retrieving and Ranking Relevant JavaScript Technologies from Web Repositories, Software Evolution and Process, 2017:00:1–6.