Modeling browser-based distributed evolutionary computation systems

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Abstract

From the era of big science we are back to the “do it yourself”, where you do not have any money to buy clusters or subscribe to grids but still have algorithms that crave many computing nodes and need them to measure scalability. Fortunately, this coincides with the era of big data, cloud computing, and browsers that include JavaScript virtual machines. Those are the reasons why this paper will focus on two different aspects of volunteer or freeriding computing: first, the pragmatic: where to find those resources, which ones can be used, what kind of support you have to give them; and then, the theoretical: how evolutionary algorithms can be adapted to an environment in which nodes come and go, have different computing capabilities and operate in complete asynchrony of each other. We will examine the setup needed to create a very simple distributed evolutionary algorithm using JavaScript and then find a model of how users react to it by collecting data from several experiments featuring different classical benchmark functions.

1 Introduction

The world has computational resources in spades. Most of them do not belong to you or your lab. That does not mean you cannot use them. The problem is how.

Most theory in parallel computing has been devoted to predict and optimize the performance in systems where the number of nodes, their connections, and the time every one is dedicating to the computation is known in advance. However, even if Big Science is not really over and it is slated to come back, the era of Citizen Science already started a few years ago (with SETI@home [2] and then BOINC [1]) and it offers a vast amount of computational resources to be used, if only you know how to attract them. But there is a challenge: knowing, or at least having a ballpark, of how your algorithm is going to perform in this
uncertain environment, where none of the factors is known: neither the number
of nodes, through how they are connected, to how long are they going to be
focused on doing what you want them to. That is why some effort is needed to
first understand the dynamics of the decision to participate in an experiment
that requires you to click on a link and then stay for a while looking at the
screen (or just leave it there running).

Besides, since Amazon started selling EC2 several years ago, reliable and
scalable computing resources are also available for a low price and on demand.
Recently, Google has also refurbished its offering lowering their prices. This
means that the conjunction of free or low-cost cloud computing engines, vol-
unteer computing systems and untapped capability of desktop systems can be
used for creating massive, or at least potentially massive, distributed computing
experiments. These experiments can be easily created using open-source repos-
itory sites like GitHub\(^1\) and deployed automatically to Platform as a Service
(PaaS) products such as Heroku\(^2\) or OpenShift\(^3\).

In general, any volunteer computing experiment will have to be made “in
the open”. The fact that somebody is giving you, basically for free, computing
resources, means that the scientist using them has to give back. The base-
line is releasing the source code used: all volunteer computing platforms, from
SETI@home on, have done it. The opposite is probably the reason why many
companies like PopularPower\[^4\] have folded or others like CrowdProcess have
decided to turn their product to in-house computation: there must be a mutual
relationship of trust among the scientist and the person that is running his/her
code in the browser. As it has been mentioned in the early stages of what was
then called desktop grid computing\[^3\], in fact CPU cycle selling might not make
economic sense since there are not so much demand for it and supply is quite
high. However, while potential supply is in fact huge, actual supply will depend
on the person holding it willing to actually allocate it to a particular company
selling it or a particular experiment needing it, not to mention the fact that
the experiment actually has to draw the attention of the supplier. That is why
trust is essential, and using free software might not be enough: Openness has
to progress from open source code to open science: releasing all data obtained
in the experiment in a repository such as GitHub, mentioned above, and even
allowing real-time access to experimental data to users.

Another possible reason of the failure of former companies to create a for-
profit desktop grid might be the lack of a way to predict what is going to be that
supply in a particular moment. It is impossible to predict, in advance, to know
how many persons are going to visit a particular website. Even if you pull all the
resources you have and they lie across continents and time zones, the number
of cycles apportioned to a particular experiment will depend not only on the
users lending their web real state to the experiments (which is usually the case
for cycle brokerage companies) but especially to users going to a web site and
spending some time on them. Even if it is theoretically impossible to predict

\(^{1}\)\text{http://www.github.com}
\(^{2}\)\text{https://www.heroku.com/}
\(^{3}\)\text{https://www.openshift.com/}

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to a high precision what happens, it is in practice possible to approximate the number of visits in a site, at least in a particular one, using time series. But in the short term and using a more general model, there is still need to model the behavior of users, so that more factors can be added to the model other than the time series. This user behavior, of course, presupposes that you are respecting their anonymity and privacy (not using cookies, for instance) and that you are respecting the open approach mentioned above. All computation can be done without the knowledge of the user [19], but this would work against openness that would, curiously enough, result in a huge decrease of the future performance of any experiment you might want to perform.

These are best practices that have been followed in the experiments in this paper, that first presents the first versions of a platform for distributed evolutionary algorithms (EAs) using the browser and a free (as in free beer) backend, and second, shows the result from a statistical point of view in order to put the basis for a model of the metacomputer obtained by joining all volunteers and the free backend used for the experiment. This is not an exhaustive or complete exploration of the possibilities of this kind of computation, but it is enough to present the free software used to perform the experiments and will allow us to describe, in general, the behavior of the users as well as the performance achieved on the experiments done so far, which should show some advantage over doing the same kind of experiments locally using available resources.

The rest of the paper is organized as follows: next we will present the state of the art in volunteer computing and its modelization. We will proceed to describe the experimental setup in Section 3, some preliminary results in Section 4 and finally we will present our conclusions in Section 5 along with future lines of work.

2 State of the art

Using the web as a resource for distributed, or plainly user based, evolutionary computation has a long history since JavaScript was introduced as a browser-based language in 1997 and even before, when other procedures, including Flash animations, VBScript, ActiveX or Java applets were used. Java was pointed out in [33] as a “language for internet”, providing some advantages such as multi-architecture compatibility or security mechanisms. In that work, Soares et al. describe JET, a system that supports the execution of parallel applications over the Internet. This system has a comprehensive statistics support, allowing its use for science, unlike the other systems compared in that paper.

However, Java (and all the other technologies) is not universal in the sense than an extra component, namely, the Java virtual machine, has to be installed in the browser. JavaScript [12] was introduced in 1997 as a browser-embedded language and has, since then, become a set of standards [10] for the language, its components and future versions that have been widely adopted by the industry and also by scientists, who used them for creating a non-distributed EA on the browser as early as 1998 [30].
The potential for volunteer computing using browsers was realized later on [32] as well as the potential for mischief of users with code in their hands [31]. However, these early efforts by Sarmenta once again used Java and not JavaScript, making this effort less universal. JavaScript can be used either for unwitting [19] or volunteer [20, 24] distributed evolutionary computation and it has been used ever since by several authors, including more recent efforts [7, 8, 14] that even used the client’s GPU [9]. Many other researchers have used Java [6] and others have gone away from the server-based paradigm to embrace peer to peer systems [18, 34]. These computing platforms avoid single points of failure (the server) but, since they need a certain amount of infrastructure installed to start, the threshold to join them is much lower.

There have been relatively few efforts to analyze what is the performance that can be obtained from these volunteer computing efforts. There was some attempt initially to dodge the issue by making the algorithm adaptive to the kind of resources allotted to it [26], which is actually not such a big problem in algorithms such as the EA that can easily be parallelized via population splitting or farming out evaluations to all the nodes available. Lately, several approaches have focused on the fault-tolerance of volunteer algorithms [15] which can, of course, be studied in a more general distributed computing context [29] or including it in a more general study of performance of the EA itself [17]. But the raw material of volunteer computing, number of users and the time spent in the computation in browser-based volunteer computing experiments, have only been studied in a limited way in [17] on the basis of a single run. Studies using volunteer computing platforms such as SETI@home [16] found out that the Weibull, log-normal and Gamma distribution modeled quite well the availability of resources in several clusters of that framework; the shape of those distributions is a skewed bell with more resources in the low areas than in the high areas: there are many users that give a small amount of cycles, while there are just a few that give many cycles. This is in concordance with the results obtained in [23].

As far as we know, this paper presents the only experiment that uses computational resources that are as dissimilar as smartphones and powerful laptops or desktop computers in a research center. The methodology used to gather resources and the algorithms used will be described next.

3 Methodology

In order to test the volunteer computing environment, a presentation describing a low cost volunteer computing environment was created. This presentation was actually delivered in several conferences [4]. During the conference, it was revealed to the persons attending it that they were participating in the experiment. The same procedure was used when trying to gather users in social networks: a description of the container (the presentation) and disclosure of its purpose.

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4Names withheld for the double blind review
The upper right corner of the presentation shows the progress of the evolution. It stops when the solution has been reached.

Above the experiment, from the point of view of the user, has been described. What it is actually running is an island model [27] in every browser that uses the server as a shuttle to transfer individuals from one browser to another in what can be eventually a fully connected topology; however, all connections take place between the browser and the server. This deals with several problems. The connection is stateless: islands connect to the server to send and receive a single individual but there is no task balancing: all islands start clicking on an URL and finish when they browse off to the next page. Fault tolerance is implicit, in the sense that no island has information that cannot be, or generated, somewhere else, although if the server fails the experiment results might be lost. All operation is asynchronous, with islands entering and leaving the experiment all of their own.

We will next explain its different parts from the point of view of the architecture itself and the algorithm that it is actually running. First, we will describe the client code and next, in subsection 3.2 the server architecture and where it is hosted.

3.1 Volunteer distributed evolutionary computation in the browser

As stated above, the evolutionary algorithms run mainly in the browser. The problem run is a multimodal problem called \( l\)-trap, which has been used extensively as a benchmark for evolutionary algorithms [11, 28]. This function counts the number of bits in a sequence of \( l \) and assigns the local maximum if it has got 0 bits and the global maximum to \( l \) bits. The fitness goes down to a trap as you increase the number of bits, that is why it creates a rugged fitness landscape that is difficult to surmount for evolutionary algorithms. Its difficulty is increased as the number of traps concatenated grows, so that in some cases it might need millions of evaluations to find the solution. In our case we have used several values, from 30 to 50 traps, although we were not so much focused on finding the solution (or the fastest way of finding it) but on creating an experiment that could last for a certain amount of time, around one hour, so that there would be a chance for having many users checkout out the page and contributing cycles to it.

This fitness is implemented as part of the Nodeo evolutionary algorithm library written in node.js, a server-based implementation of JavaScript. However, since it is going to be run on the browser, a procedure called “browserification” must be applied to it so that it can run, without modifications, in any browser. The main difference between JavaScript on the browser and node.js is the way they load the external libraries. The algorithm used a population of 256 individuals, random initialization, a canonical evolutionary algorithm with an elite of 2 individuals and crossover and then mutation applied to all the population pool, that was generated using 2-individual tournament selection. Once again, the particular evolutionary algorithm used is not so important, since we were
rather focused on the user behavior, although it is quite clear that the selective pressure of the algorithm will have an impact in its performance and will play for or against its asynchrony in many different and complex ways [25].

The initial code was only modified to represent the fitness in a chart (that uses the chart.js JavaScript library) so that the user has a visual feedback of what is going on. The migration part is also added: after every 100 generations, a single individual is sent to the server and another request is made to the server of a single and random individual. This makes the procedure less greedy, and also decreases the probability of getting the same individual that was sent some generations back. These two operations are made in fire and forget style, that is, without any error checking, so that if the server is down, or indeed if the algorithm is run locally, it is not interrupted and continues operation until the solution is found, a string with all ones.

As a summary, the only thing needed to run an evolutionary algorithm in the browser is to add migration functions. To make the operation of the algorithm independent of them is a plus, because it makes the local algorithm more fault-tolerant. The algorithm running on every browser has the same parameters and starts from a random population when the page is loaded.

3.2 Server side

The server was also written using node.js and the express.js module and has three REST [5] functions, that is, three functions that can be accessed from any client, including the browser, via a request encoded in an URL and a standard HTTP command. These functions are

- **GET random** returns a random, non-evaluated individual, from the pool. The pool is just an array containing chromosomes, that is initialized at the beginning of the experiment.
- **PUT one** puts a single individual in the pool. In REST conventions, PUT is used to create a resource, that is why it is used, in this case, to add a new individual to the pool.
- **GET log** returns the experiment log so far. It is used by the researcher to gather data, and as a transparency measure so that anyone can use it.

In fact, the program includes more logic to serve the static pages that contain the talk in which it is included and the JavaScript/CSS code also, but it all amounts to a small amount of code. This code can be deployed, in principle, in any server running node.js, but for the purposes of this experiment Heroku, a Platform as a Service with a free tier, has been chosen. It could be also be deployed, with small or no modification, to OpenShift or other similar PaaS. Far from being a freeriding way, using free or very low cost servers can be a sustainable way of performing massive distributed evolutionary computation experiments [21, 22].

Having the pages and the server in the same domain allows to work in default Ajax mode, that does not allow cross-site requests. However, these can also be
disabled if needed. In this case, every domain holds a single experiment, there is no multi-tenancy of experiments, so its management is quite simple.

When the experiment is finished, that is, the solution has been found, the server is restarted using command line tools provided by Heroku. Every experiment was first done during the talk and then announced in Twitter several times until enough data was gathered.

As indicated in the introduction, every part of the experiment and data gathered have been released as free software in the GitHub repository [https://github.com/JJ/idc-keynote](https://github.com/JJ/idc-keynote). These results will be analyzed in the next section.

4 Results

The litmus test that all experiments should pass, that is, that they work and found the solution, passed. In fact, the first version of the algorithm (until January 2015) used too much memory on the browser, which crashed after a while running. A total of 7 experiments were done with this version. After January, a new version of the evolutionary algorithm with non-cached fitness was used which did not crash the browser and was thus allowed to run as much time as needed. That was the version used in a lightning talk at the beginning of February. A total of 10 experiments were made with this second version. In the first version, finding the solution took a few minutes. The second needed around 20 minutes. In the logs used, it was not checked that the algorithm had found the solution, but in most cases it had. More systematic experimentation would have to wait until the next version, since in this first one we were looking for some kind of systematicity in the behavior of users and the experimental apparatus is the minimum possible to have it running.

![Figure 1: Histogram of number of different IPs in an experiment](image)

(a) First experiment

(b) Second experiment

The fact that it run correctly during a massive lightning talk means that this setup is a valid, no-cost, platform for massive evolutionary algorithms. There were several ways of introducing it: during a talk, telling the audience to visit the web that was posted in the first slide, and after the talk, inserting the URL in a tweet with a brief explanation and several tweets more indicating what it
was about and what it did. If any question arose, it was answered as fast as possible. In the first experiment, the median number of different IPs was 18, with a maximum of 28 and a minimum of 6. In the second, the median was 12.5 with a maximum of 19 and a minimum of 8. The histogram of different IPs in each experiment is shown in figure 1. Probably the most remarkable thing is that a cluster of 6 computers can, as a minimum, be gathered for a distributed computing experiment by just announcing it as a tweet, but the fact that we can obtain more than a dozen computers in more than half the cases is also remarkable, and goes to prove the excess of computing resources that people, willingly, lend to a simple experiment.

![Figure 1: Histogram of different IPs](image1.png)

(a) First experiment, run 3
(b) Second experiment, run 7

Figure 2: IPs and the number of PUTs (one every \( n \) generations, 50 in the first experiment, 100 in the second experiment) they did, sorted. These correspond to the runs in each batch of experiments with the max number of different IPs. Please note the algorithmic scale in the \( x \) axis.

Not all users contribute in the same way. The distribution for the runs in each experiment with the most IPs is shown in Figure 2 which chooses the experiment with the most number of uses and ranks, tops to down, every IP with the number of PUTs (which should be multiplied by the number of generations per PUT, 50 in the first case, 100 in the second, although at this point it is not important, since all nodes in the experiment do it after the same number of generations) contributed to the experiment. We can observe in both cases a power law, something already observed by [23] and which implies that there is a fixed proportion between the number of cycles (generations) contributed by the first and that contributed by the second which is roughly the same as the one between the second and third. Note also that, since the experiment is hosted in a PaaS, the IPs listed are anonymous, with a 10 always as the first number.

At any rate, this exponential trend in the first posts breaks down after a number of IPs. That could be due to several possible factors: persons checking the web for just an instant, late comers, or very slow computers that are not able to lend more cycles to the simulation. The first IP in both cases contributes on the order of a hundred PUTs, that is, several thousands generations and several hundred thousands evaluations, which, once again, is quite remarkable for such a simple experiment announced by an ephemeral tweet. It should be noted that, since the speed in the browser virtual machines (Chrome, mainly,
but also Firefox) is as fast as the node.js version, a parallel version does not add overhead to the single-browser version, which, as mentioned above, can run in an independent way: a second browser always adds to the first, even if the total number of evaluations and the time needed will not speed up in the same way. However, even taking into account the stochastic nature of a single evolutionary algorithm, what we are going to find is a high dispersion of the times needed to reach a solution, which are plotted in Figure 3 against the number of IPs. There is a wide range of durations, although there is no clear decrease of the time needed as the number of IPs used increase. However, we will have to investigate further the speedups achieved and if these are algorithmic or due to the particular asynchronous and web-based implementation. Figure 4 might help understand the kind of raw material we are using: It plots a histogram of the time needed by all experiments to process 100 generations, 25600 evaluations and the associated evolutionary genetics. The vast majority of browsers processes it in less than 3 seconds (logarithm(time) ¡ 0.5, which is equivalent to 3.16). However, it is interesting to note that there are some intervals that go up to the thousands of seconds, for which we cannot really offer an explanation, other than the user leaving the page and returning after a while. However, 75% of the cases take less than 4 seconds, which is thus a statistical measure of the kind of performance we can expect from clients for this type of problem. We can also conclude that 75%, or a majority, will be in the fastest tier, although there will be a small amount of them that will be quite slow and will probably be impossible to accommodate in the distributed computing experiment.
Figure 4: Histogram of the time between two PUTs for all the experiments in the second batch. The x axis is logarithmic and bin size is 0.5, which means that the first bin contains all intervals of less than 3 seconds.

5 Conclusion

In this paper we have presented our experience on using browser-based computing applied to the design of evolutionary algorithms. In the spirit of Open Science, we have released all material related to the experiment, including this paper. Experiments have been performed at several times of the day and announced in Twitter or during a live presentation about distributed computation using the browser.

What we conclude from these computers is that the nature of the performance, which is due to the number of persons deciding to participate in the experiment, is not totally random. There are at least lower bounds we can count on: several computers (as few as six) can almost always be relied on, and in some cases up to 30 can participate in a single experiment. However, it is not clear how all these computers contribute to the overall performance in terms of time, although all experiments were performed until a solution was found. Most computers participating in the experiment are in the same performance tier, although a small percentage of them (which will be around 25%) are quite slow.

The evolutionary algorithm programmed in this way can easily accommodate all kinds of browsers. However, we are using an homogeneous configuration for all of them, which might not be the best from an algorithmic point of view; a random parameter setting like the one used by [13] could offer better results, since we do not know in advance what is the performance of the nodes. More systematic experimentation is also needed, specially using different kind of problems, including more complex problems in which the fitness function is heavier and takes longer to be processed. However, the main intention of this paper, which was to prove that distributed evolutionary computation could be done
efficiently in a volunteer/free environment, has been sufficiently proved.

There are many issues involved in using these resources: from adapting current algorithms so that they match this environment to check which EA configuration works the best in it, or creating a framework that can use it easily. But the main challenge is that asking people to contribute resources implies that you are opening your science to society and you have to give something in return: you have to adopt a set of best practices that have come to be known as Open Science, because “Give, and it shall be given unto you”, you will get as much back from society as you give to it opening your science and explaining it to the public. This, among other things, means that popularity will become directly performance of the metacomputer you create by attracting more users. And this interplay between the social network itself (popularity in Twitter, people attending to the conference and interested in following the slides in their computer) is another, very interesting, venue to explore in the future.

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