Still doing evolutionary algorithms with Perl

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Abstract

Algorithm::Evolutionary (A::E from now on) was introduced in 2002, after a talk in YAPC::EU in München. 7 years later, A::E is in its 0.67 version (past its "number of the beast" 0.666), and has been used extensively, to the point of being the foundation of much of the (computer) science being done by our research group (and, admittedly, not many others). All is not done, however; now A::E is being integrated with POE so that evolutionary algorithms (EAs) can be combined with all kinds of servers and used in client, servers, and anything in between. In this companion to the talk I will explain what evolutionary algorithms are, what they are being used for, how to do them with Perl (using these or other fine modules found in CPAN) and what evolutionary algorithms can do for Perl at large.

1 Don’t talk no evolution, I believe in intelligent design!

Right-on, buddy, but while you’re at it think about this very simple experiment. You’ve probably never done a chili con carne, right? Well, if you
Table 1: Scores given by Y. O. Ure family to the set of chili con carne recipes.

| Stew # | Score |
|--------|-------|
| 0      | 43    |
| 1      | 94    |
| 2      | 3     |
| 3      | 77    |
| 4      | 82    |
| 5      | 88    |
| 6      | 21    |
| 7      | 97    |
| 8      | 41    |
| 9      | 31    |

really believe in that you might have. OK, then go to your nearest hardware store and buy ten (yes, 10) cast-iron pots, plus a notepad. Grab a ten-fire kitchen (that’s a bit more difficult, but, hey, this is a thought experiment, right?) and put to cook ten chili’s con carne with different ingredients. Here you put a bit more chili, there a bit more carne, and up there a bit more con. Note down carefully all you’ve done to all of them; you’ll end up with ten different recipes for chili con carne. Bring down your (extended) family, and sit them down to eat, giving a score to each one of your recipes. You’ll end up with something like what we show in table 1. Well, right there you have pretty mean chili’s con carne. And you don’t even need to do them all in a row, you can treat your (extended) family 10 days in sequence until they stop remembering the good old times when they ate something different to chili con carne. At any rate, since you have the recipes for all of them, you decide to convert #2, #6, and, for good measure, #9 to biofuels, and try new ones.

What can you do to make improvements in existing recipes for #1 and #7, which were received with cheers and loud burps (actually, the score had to be given in burps)? You pick a few quantities in the recipe for one of them, and randomly mix it with the other. Let’s say one of them was a bit overcooked, and the other had a pinch more of cumin and secret ingredient X\(^1\). You create recipe #10 which is both overcooked, has ingredient X and a cumin bonus track. It would be like breeding boiling pots of chili, but without the pot and with extra chili. That’s one way of improving your already excellent recipe, but you don’t know in advance whether you’re going to obtain a better result.

\(^1\)That would be cough syrup, but don’t tell anyone
But there are more. While your aunt Fred (a particularly extravagant member of your family nobody really wants to talk extensively about) was tasting #4, she said

This one is excellent, if only it had a bit more chorizo!

She’s partial to chorizo, this aunt Fred. Which is why you take the recipe for number 4, and write down “4 chorizo links” instead of the previous 2. That’s a bit like when Peter Parker mutated into Spiderman when bitten by radioactive spider, right? You insert a small mutation in the recipe to create a new one.

And you do this over and over, you generate new recipes via small changes and mixing what seems to be good (or simply feels right) of old recipes, and, lo and behold, out comes intelligent life, sorry, a whole family with a serious case of heartburn.

2 Nature inspired optimization

Natural evolution works a bit like that [1], with the DNA acting as the chili recipes, and Nature itself working as your family (yes, your aunt Fred too, never heard about platypus?). Only it is a bit misleading to think that Nature actually optimizes species: it adapts and builds on what already exists, but species are not in the path to perfection same way as CPAN is not more perfect now than it was ten years ago[2].

However, searching the space of all possible chili recipes in this fashion actually takes you to better and better recipes in time. Even if not every time you make a change you obtain a better chili, the whole set of stews improves each generation, by the simple procedure of removing the worst and building on the best, the same way species in Nature adapt and change, creating new ones.

That is the basic idea behind evolutionary algorithms: incrementally improving known solutions to problems by creating recipes for them (which might be bit strings or more complicated data structures, like program trees), giving them an score (which is called fitness in EA parlance), eliminate those with the lowest fitness, and create new ones via changes (mutation) and interchanges (crossover) of existing solutions.

This kind of method was the one proposed by Holland [2], Hans-Paul Schwefel [3] and eventually Goldberg [4], who was one of the first that applied what were then called genetic algorithms to engineering optimization

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[1] Only it actually is
problems. Nowadays, evolutionary algorithms comprise a whole family of algorithms including Genetic Programming [5, 6] and Evolution Strategies [7], but their main differences are on the specific representation they use for problem solutions (program trees, floating point vectors, cellular automata) and the operators they apply to them; all of them boil down (like chili) to the same pattern of solutions improved (or not) via crossover and mutation in a population.

3 Evolving camels

Despite this flexibility, there are not many libraries that implement evolutionary algorithms in Perl (for a review on evolutionary algorithms in Perl, and a tutorial of the first versions of A::E, see [8]); most published modules deal with genetic programming (hereafter GP) in Perl, due to the fact that it is an interpreted language, and it is very easy to evaluate expressions and statements from a program (or script). The first (as claimed by the author) paper published on the subject seems to be one by Baldi et al. [9], but the source code itself was not published, and no hypothesis can be done on its features. From that moment on, there are several papers that describe Perl implementation of evolutionary algorithms: Kunken [10] described an application that evolves words that “look as if they were English”, or fake English words, by trying to evolve them using the same letter pattern that English uses. The same application is also mentioned by Zlatanov in [11], who implements a genetic programming system, with source code available, to solve the same problem.

From then on, there are several papers about doing genetic programming [6] in Perl: the first one was written by Murray and Williams [12], which, despite its title, actually describes a genetic programming system, similar to another mentioned in the PerlMonks site [13] (a meeting place for practitioners). Several other introductions to genetic algorithms with code have been published in the same place [14, 15], but the first mention to a module that implements a canonical genetic algorithm was done in [16]. This module, called Algorithm::Genetic, cannot be easily extended or adapted to new paradigms, since it is a single file with all data structures and algorithms used already built-in into the file. McCallum [17] has also presented a system called PerlGP, used specifically in the context of bioinformatics, which has extensive facilities, including a database back-end for serialization, and its main advantage is that it uses as a programming language for doing GP in Perl itself. Its main drawback is its specificity: it is not intended for general evolutionary computation, and most data structures and methods are geared
towards GP. A later attempt is Algorithm::Evolve [?], which is well designed, and quite easily extensible. Unfortunately, its development stopped in 2003, and cannot be easily extended to include representations different from the two default ones provided. Math::ES [?] comes approximately from the same date, and is not intended as a general-purpose evolutionary computation library, but rather designed for implementing the above mentioned Evolution Strategies. This library if also frozen in the state it was in 2003.

The most complete (apart from the one presented in this paper) and peculiar implementation of evolutionary algorithms in Perl was called myBeasties [18] and eventually became a module called AI::GP. This system implements different kinds of objects, that can be evolved in many possible ways; there’s a language that describes these transformations. It is an interesting system, but its extensibility is not so strong, and the learning curve is also somewhat steep, since it involves learning a new language apart from Perl itself. It is mainly used for evolving Perl scripts, the same way that Genetic Programming evolves Lisp functions, not intended for the implementation of a general evolutionary computation program, which implies also learning structures unfamiliar for the EA practitioner.

On the other hand, one of the most recent is AI::Genetic::Pro, which has recently entered version 0.34. The main objective of this module [19] is to optimize speed through coding the most critical parts in C, through the Perl interface called XS that allows this. In fact, initial tests show that it is several times slower than A::E, with extensibility being also sacrificed through the use of this XS API. The other one is Math::Evol [?], which, as a differentiating trait, takes into account constraints in search to guide evolution. It is mainly intended for straightforward optimization problems, not as an extensible framework. The user has to supply a set of problemspecific functions. However, this one is still in development so who knows what its future will be.

The majority of those systems do not make use Perl’s capabilities to implement an object-oriented library, easily adaptable and expandable, which have been two of the objectives A::E’s designers had in mind. This, and the fact that the quality of the Perl programmer are laziness, impatience and hubris, make up for the fact that I keep on developing this library instead of paying some attention to the others (which I should).

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3See equivalent programs at our CVS server: [http://opeal.cvs.sourceforge.net/viewvc/opeal/Algorithm-Evo ai-genetic-pro.pl and bitflip.pl](http://opeal.cvs.sourceforge.net/viewvc/opeal/Algorithm-Evo ai-genetic-pro.pl and bitflip.pl)
4 Using A::E

Right behind making chili, one of the biggest problems in engineering today is to place dots within sets of rectangles. It’s probably not very well known outside the rectangle engineering community, but whenever you build a city in the clouds, optimally cover pole-dancing poles within shoe boxes, or bake marshmallows, finding where the dot has to precisely be is essential. But no worries, here’s the Perl program (split in Figures 1 and 2) that does exactly that by making use of the excellent Algorithm::RectanglesContainingDot module by Salvador Fandiño.

This is a kind of minimal program to use an evolutionary algorithm. The first part is devoted to generate a set of random rectangles, and then a closure is declared as a fitness function, which counts within how many rectangles the dot is in; it uses the decode function, which converts the binary representation the individual member of the population into an array of numbers, which are then used to compute how many rectangles contain those dots. Besides closures, classes can also be used to implement fitness functions; in that case the object must respond to the apply method, returning the fitness. In this case (as in many others) this function is the one that will be maximized: we will generate a population of dots, and evolve one that is in as many rectangles as possible.

The population we start from is generated next: it is a purely random population, composed of bit-strings with randomly generated bits.

After that, a couple of operators are generated (already in Figure 2 as said in section 1), we need two kind of operations: mutation (here declared as $m) and crossover ($c here). The declaration of these operators includes the frequency with which they will be used. Priority, or rate, is 1 for mutation and 9 for crossover: that means that 90% of the new individuals will be generated by crossover (combining the bitstrings of two individuals), and the rest by mutation. Priorities are transformed to probabilities in runtime whenever operators are applied, that way, operator rates can be changed in runtime and new operators can easily be added to them.

These operators are used to define the $generation object, which processes a single generation, destroying the 10% worst (that’s the 0.1 in $selection_rate), and substituting it by the offspring of the rest. After that, the population is evaluated; this could be done faster by map( $_->evaluate( $fitness ), @pop ).

The algorithm itself is a simple business: apply the generation object until a dot in all rectangles is found (not very likely) or until the maximum number of generations has been reached. This usually happens in as few as 25 generations, but it might take a few more than that. The whole business
use Algorithm::RectanglesContainingDot;
use Time::HiRes qw( gettimeofday tv_interval);
use Algorithm::Evolutionary qw( Individual::BitString Op::Easy Op::Bitflip Op::Crossover );

my $alg = Algorithm::RectanglesContainingDot->new;
my $num_rects = shift || 25;
my $arena_side = shift || 10;
my $dot_x = shift || 5;
my $dot_y = shift || 5;
my $bits = shift || 32;
my $popSize = shift || 64;  # Population size
my $numGens = shift || 50;  # Max number of generations
my $selection_rate = shift || 0.2;

# Generate random rectangles
for my $i (0 .. $num_rects) {
    my $x0 = rand( $arena_side );
    my $y0 = rand( $arena_side );
    $alg->add_rectangle("rectangle_$i", $x0, $y0, $x0+$arena_side, $y0+$arena_side);
}

# Declare fitness function
my $fitness = sub {
    my $individual = shift;
    my ( $dot_x, $dot_y ) = $individual->decode($bits/2, 0, $arena_side);
    my @contained_in = $alg->rectangles_containing_dot($dot_x, $dot_y);
    return scalar @contained_in;
};

# Initial population
my @pop;
for (0 .. $popSize) {
    my $indi = Algorithm::Evolutionary::Individual::BitString->new($bits);
    push( @pop, $indi );
}

Figure 1: find_dot_in_rectangles.pl tries to find the position where the dot would be inside a maximal amount of rectangles. This program is available from our CVS server: http://opeal.cvs.sourceforge.net/viewvc/opeal/Algorithm-Evolutionary/examples/find_dot_in_rectangles.pl
Continues in Figure 2
# Variation operators

my $m = Algorithm::Evolutionary::Op::Bitflip->new; # Rate = 1
my $c = Algorithm::Evolutionary::Op::Crossover->new(2, 9); # Rate = 9

my $generation = Algorithm::Evolutionary::Op::Easy->new( $fitness,
    $selection_rate, [$m, $c] );
my $inicioTiempo = [gettimeofday()];

for ( @pop ) {
    if ( !defined $_[>Fitness() ) {
        my $this_fitness = $fitness->($_);
        $_[>Fitness( $this_fitness );
    }
}

# Start Evolutionary Algorithm

my $contador=0;

do {
    $generation->apply( \@pop );
    print "$contador : ", $pop[0]->asString(), "n" ;
$contador++;
} while( ($contador < $numGens)
    && ($pop[0]->Fitness() < $num_rects));

print "Best is:n	r ", $pop[0]->asString(), " Fitness:
", $pop[0]->Fitness(), "n";
print "n
ntime: ", tv_interval( $inicioTiempo ) , "n";

Figure 2: (Continues in Figure [1]) find_dot_in_rectangles.pl tries to find the position where the dot would be inside a maximal amount of rectangles (2nd part). This program is available from our CVS server:

http://opeal.cvs.sourceforge.net/viewvc/opeal/Algorithm-Evolutionary/examples/find_dot_in_rectangulars.pl
takes less than one second in my computer.

5 Now with POE

As soon as you want to integrate an evolutionary algorithm with anything else, from a standalone daemon to a existing web server, or simulate parallel systems (which you might be interested in if you want to know what happens when you split the population in two islands, but don’t care much about what's the actual time improvement) it will be necessary to include it in an event loop system such as POE \[20\]. Initially, we did this a bit by hand \[21\], but then we decided to create a POE component that handled evolutionary algorithms: POE::Component::Algorithm::Evolutionary, which besides being one of the CPAN modules with the longest name, handles genetic populations as POE sessions, allowing them to proceed evolutively alongside each other, and communicate in several possible ways. For instance, the program shown in Figure 3 would be a fraction of a program\[4\] just like the one shown in Figure 3.

In Figure 3 two sessions or nodes are created, each one of them running a separate evolutionary algorithm. Nothing much seems to happen here, but after each step of the algorithm, a single individual is sent from one of the nodes to the other, in a island-hopping way. This is the default way of operation of the island model evolutionary algorithm \[22\]: each node is running its own population and, from time to time, they interchange some individuals. It might get a bit more complicated, depending on who you send, who you chose to receive, and what you do with them\[5\], but it boils down to that: islands, and a boat to send things between them. For the time being, it uses POE’s own post mechanism for posting (that is why it’s called POEtic), but more mechanisms are intended in the future, starting with SOAP and following with anything else that can be easily integrated with it (XMPP, anyone?)

6 Don’t ask what evolutionary algorithms can do for you

Well, actually, you can. EAs can be used for search and optimization, so you can search and optimize whatever you want. For instance, you can

\[4\] Which is actually in http://search.cpan.org/~merelo/POE-Component-Algorithm-Evolutionary-0.2.1/lib

\[5\] Check, for instance, our interesting multikulti algorithm \[23\], which sends the most different instead of the best
use POE qw(Component::Algorithm::Evolutionary::Island::POEtic);

#Stuff here
my $generation = Algorithm::Evolutionary::Op::CanonicalGA->new($rr, $selection_rate, [$m, $c]);
my $gterm = new Algorithm::Evolutionary::Op::GenerationalTerm 10;

my @nodes = qw(node_1 node_2);
my %sessions;
for my $n (@nodes)
{
    my @nodes_here = grep($ne $n, @nodes);
    $sessions{$n} = POE::Component::Algorithm::Evolutionary::Island::POEtic->new(Fitness => $rr,
    Creator => $creator,
    Single_Step => $generation,
    Terminator => $gterm,
    Alias => $n,
    Peers => \
    @nodes_here);
}

$poe_kernel->run();

Figure 3: Fraction of an evolutionary algorithm as a POE component.
search for the solution to the Mastermind game [24] with the help of the Games::Mastermind, search for the best parameters to train a neural net using MachineLearning::NeuralNetwork or evolve English-sounding words after analyzing text corpora using Text::NGrams or suchlike. Perl is fast enough, even more so if you try to optimize the interpreter for speed and if you try to optimize as much as possible the areas where the application spends the most time: fitness evaluation and application of evolutionary operators (mutation, crossover).

Of course, you can use it not only for playing, but also for research: evolving a new data structure needs only 3 new classes: the one for representing the data structure, which might even come for free if it is amenable to be used inside Algorithm::Evolutionary::Individual::Any, and a mutation and crossover. You can use hashes, vectors, B-Trees, even hairier data structures, provided you know how to change them incrementally and combine them. Remember that each change need not be for the better: it is the population that improves on average, not each individual, X-Men style.

With respect to A::E itself, I will continue to develop it for the foreseeable future; of course, some help will always be appreciated. Maybe a bit more of profiling is needed to identify bottlenecks; a bit has been done, but not in all possible situations. Bugs are mostly under control, but I haven’t tested for coverage, so maybe some will arise in the future. Best practices [?] are also generally followed, but I’m not keen on renaming variables or modules pre-2005 to this convention. It will have to be done, eventually, I guess.

Finally, I know there’s no decent library out there without a shining and singing GUI. This will be done eventually. Until then, no version 1.0.

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6A forthcoming paper compares the performance of this and other Java library, finding out that, precisely in this area, they are comparable and, in some cases, Perl might even be the winner.

7These are only those that are current now, but there have been many more of them since 2002.
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