

LEAPing Forward

A tour through an open-source
evolutionary algorithm toolkit

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LEAPing Forward

I will share aspects of ongoing work developing an open-source, python-based evolutionary algorithm (EA) toolkit.

I will cover details that will hopefully be useful to other python users.

What is an Evolutionary Algorithm?

- Biologically inspired
- Populations of individuals that represent posed solutions
- Selected parents beget offspring
- Offspring are incrementally different from their parents
 - via mutation
 - and possibly crossover
- “Survival of the fittest” culls inferior individuals
- Over time the population converges on viable solutions

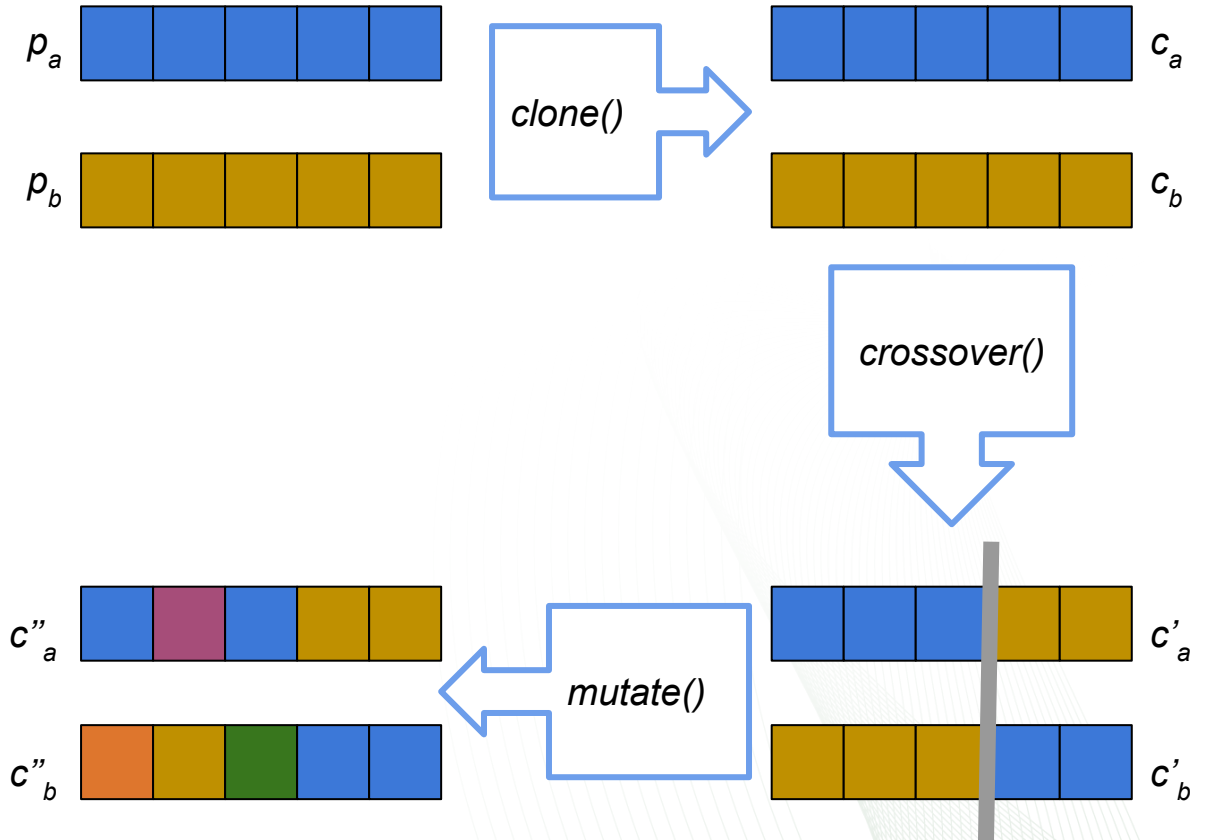


(Public Domain image from <https://www.flickr.com/photos/dennism2/>)

General Evolutionary Algorithm

1. make initial population *main()*
2. evaluate them
3. current pop \leftarrow initial population
4. while not done:
 - a. offspring \leftarrow *breed*(current pop)
 - b. evaluate offspring
 - c. current pop \leftarrow *cull*(current pop, offspring)

1. $C \leftarrow \{\}$
2. while *size*(C) < desired kids: *breed()*
 - a. $\{p_a, p_b\} \leftarrow \text{select}(P_i)$
 - b. $\{c_a, c_b\} \leftarrow \text{clone}(p_a, p_b)$
 - c. $\{c'_a, c'_b\} \leftarrow \text{crossover}(c_a, c_b)$
 - d. $c''_a \leftarrow \text{mutate}(c'_a)$
 - e. $c''_b \leftarrow \text{mutate}(c'_b)$
 - f. append $\{c''_a, c''_b\}$ to C
3. return C



LEAP — a python-based open source EA toolkit

Ideally would like an available open-source EA solution.

- Library for Evolutionary Algorithms in Python (LEAP)
 - Thanks to Dr. Jeff Bassett of GMU
- Initially written in 2004 (!)
 - Python 2.4 was the most recent version that year
- Has been maintained, but suffers from a little bit-rot
- Had a unique pipeline-like architecture that was ripe for refactoring to take advantage of some modern python constructs
 - Closures
 - Generators
 - Functional programming

smallLEAP as sandbox for LEAP refactoring

GitLab Projects Groups Activity Milestones Snippets

Mark Coletti / smallLEAP · Details

smallLEAP
Project ID: 8932314
Unstar 2 Fork 0 Clone

Add license 172 Commits 16 Branches 0 Tags 1 MB Files

This is a sandbox to try out new ideas for Library for Evolutionary Algorithms in Python (LEAP).

develop
smallleap / +
History Find file Web IDE

Should always explicitly check for None fix.
Mark Coletti authored 6 days ago
b6897b63

README Add CHANGELOG Add CONTRIBUTING Enable Auto DevOps Add Kubernetes cluster Set up CI/CD

Name	Last commit	Last update
contrib	Cleaned up example LSF script.	1 week ago
etc	Added environment file for standard development environm...	2 months ago
examples	Added clone functionality to examples.	2 weeks ago
smallLEAP	Should always explicitly check for None fix.	6 days ago
.gitignore	git ignores dask scratch directory	2 weeks ago
MANIFEST.in		

Jump right into the weeds

Let's look at *some* of smallLEAPs implementation and design details. Even though you may not have an interest in EAs, there may be some facets of smallLEAP that could be applicable to your python work.

Toolz is a useful 3rd party python package.

<https://github.com/pytoolz/toolz>

<https://toolz.readthedocs.io/en/latest/>

It provides three categories of tools:

- Tools for iterators
- Tools for functional programming
- Tools for dictionaries

If you're familiar with the *nix style text processing pipeline:

```
grep newacronym acronyms.tex | awk '{print $1}' | egrep -o '[a-z]{4}' | sed -e 's/{///' -e 's/}///'
```

alcc

dice

dsge

gdal

glcm

lulc

ccsi

`toolz.functoolz.pipe()` serves a similar purpose

`toolz.functoolz.pipe(data, *funcs)`

- pipe data through a function sequence

```
>>> double = lambda i: 2 * i
```

```
>>> pipe(3, double, str)
```

```
'6'
```

(<https://toolz.readthedocs.io/en/latest/api.html#toolz.functoolz.pipe>)

From a certain perspective, an EA is a pipeline of data

1. The **initial data** is the set of prospective **parents**
2. Selected **parents** move down the pipe
3. They are **cloned** and passed down the pipe
4. Those **clones** are **mutated** and may go through **crossover** and passed down the pipe
5. The **children** are **evaluated** and passed down the pipe
6. Process is repeated until a set number of **children** are **pooled**, and then passed down the pipe
7. **Survivors** are **culled** to become prospective **parents** for the next generation

toolz.pipe() facilitates implementing an EA

```
# This will loop until we've exhausted our budget of generations, or there
# has been no difference between successive sets of parents.
while all([max_gen(), not my_no_change(parent_population)]):
    new_parents = toolz.pipe(
        parent_population,
        smallLEAP.selection.tournament_select_generator, # return best of two randomly selected parents
        smallLEAP.reproduction.clone_generator, # clone them so we don't damage original parent
        functools.partial(smallLEAP.reproduction.bit_flip_mutation_generator, # binary bit flip mutation
                           probability=0.2),
        problem.evaluate_generator, # figure out fitness of new kid
        functools.partial(smallLEAP.reproduction.create_pool, size=20), # collect a pool of 20 offspring
        functools.partial(smallLEAP.selection.truncate, # pick only the best of parents *and* offspring
                           second_population=parent_population,
                           size=len(parent_population)))

    parent_population = new_parents
```


Using generators for selecting parents biased by fitness

```
def tournament_selection(population, k=2):  
    """ return best of drawn k samples  
  
    defaults to "binary tournament" with k = 2  
  
    Note that random.sample() samples *without replacement*, which means  
    that selected individuals are guaranteed to be unique. This may not  
    be what you want; if so, consider random.choices(), instead.  
    """  
    choices = random.sample(population, k)  
  
    return max(choices)|  
  
def tournament_select_generator(population, k = 2):  
    """ Selects the best individual from k individuals randomly selected from  
        the given population  
    """  
    while True:  
        yield tournament_selection(population, k)
```

Generator to pass a clone down the pipeline

```
def clone_generator(next_individual):  
    """ generator version of individual.clone()  
  
    :param next_individual: iterator for next individual to be cloned  
    :return: copy of next_individual  
    """  
    while True:  
        yield next(next_individual).clone()
```

More use of generators to implement mutation

```
def binary_flip_mutation(individual, probability):  
    """ return a copy of individual with with individual.sequence bits flipped  
        based on probability  
    """  
    def flip(gene):  
        if random.random() < probability:  
            return (gene + 1) % 2  
        else:  
            return gene  
  
    individual.encoding.sequence = [flip(gene) for gene in individual.encoding.sequence]  
  
    return individual  
  
def bit_flip_mutation_generator(next_individual, probability=0.1):  
    """ Generator for mutating an individual and passing it down the line  
    """  
    while True:  
        yield binary_flip_mutation(next(next_individual), probability)
```


Generator function for evaluating individuals as needed

```
def evaluate_generator(next_individual):  
    """ Evaluates the next individual in the pipeline and passes them along.  
    """  
    while True:  
        individual = next(next_individual)  
        individual.evaluate()  
        yield individual
```


create_pool() pulls offspring from upstream as needed

```
def create_pool(next_individual, size):  
    """ 'Sink' for creating `size` individuals from preceding pipeline source.  
  
    Allows for "pooling" individuals to be processed by next pipeline  
    operator. Typically used to collect offspring from preceding set of  
    selection and birth operators, but could also be used to, say, "pool"  
    individuals to be passed to an EDA as a training set.  
    """  
    return [next(next_individual) for _ in range(size)]
```

toolz.itertoolz.topk() and itertools.chain()

```
def truncate(population, size, second_population=None):  
    """ return the `size` best individuals from the given population  
  
    second_population is an optional population that is "blended" with the  
    first for truncation purposes, and is usually used to allow parents  
    and offspring to compete.  
    """  
    if second_population is not None:  
        return toolz.itertoolz.topk(size, itertools.chain(population,  
                                                            second_population))  
    else:  
        return toolz.itertoolz.topk(size, population)
```

Using function closures to impose max generations

```
def countdown(limit):  
    """ Used to countdown to zero.  
  
    Repeated invocations will return True until limit reached, then  
    False is returned. Used for determining maximum generations to run.  
  
    countdown.count() returns current count  
    """  
    curr = limit  
  
    def count():  
        return curr  
  
    def do_countdown():  
        nonlocal curr  
        curr -= 1  
        if curr < 0:  
            return False  
        else:  
            return True  
  
    do_countdown.count = count  
  
    return do_countdown
```


Expanded example

```
# run for a maximum of 8 generations
max_gen = smallLEAP.halt.countdown(8)

# run until two successive generations produce identical parents
my_no_change = smallLEAP.halt.no_change()

# write offspring to this CSV file
my_csv_probe = smallLEAP.probes.population_probe('offspring.csv')

# This will loop until we've exhausted our budget of generations, or there
# has been no difference between successive sets of parents.
while all([max_gen(), not my_no_change(parent_population)]):
    new_parents = toolz.pipe(
        parent_population,
        smallLEAP.selection.tournament_select_generator,
        smallLEAP.reproduction.clone_generator,
        functools.partial(smallLEAP.reproduction.uniform_recombination_generator,
                           p_swap=0.5),
        functools.partial(smallLEAP.reproduction.bit_flip_mutation_generator,
                           probability=0.2),
        problem.evaluate_generator,
        functools.partial(smallLEAP.reproduction.create_pool, size=20),
        my_csv_probe, # snapshot of offspring before survival op
        functools.partial(smallLEAP.selection.truncate,
                           second_population=parent_population,
                           size=len(parent_population)))

    print('new parents:', [_ for _ in new_parents])

    parent_population = new_parents
```


Highlights

- Exposed to functional- and iterator-oriented packages
 - functools — <https://docs.python.org/3.6/library/functools.html>
 - itertools — <https://docs.python.org/3.6/library/itertools.html>
 - toolz — <https://github.com/pytoolz/toolz>
- Can use iterators to de-couple functionality for enhanced flexibility
- Usefulness of closures and generators
- SmallLEAP is on gitlab
 - Private repo, ask to be brought in after creating a gitlab.com account
 - <https://gitlab.com/mcoletti/smallleap>
 - Eventually will become LEAP 2.0

Thank you.

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This presentation is at: <https://goo.gl/Z6312P>

