Experimentation with Evolutionary Computing

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with special thanks to Ben Paechter

Issues considered

- Experiment design
- Algorithm design
- Test problems
- Measurements and statistics
- Some tips and summary

Experimentation

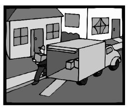
- Has a goal or goals
- Involves algorithm design and implementation
- Needs problem(s) to run the algorithm(s) on
- Amounts to running the algorithm(s) on the problem(s)
- Delivers measurement data, the results
- Is concluded with evaluating the results in the light of the given goal(s)
- Is often documented (see tutorial on paper writing)

Goals for experimentation

- Get a good solution for a given problem
- Show that EC is applicable in a (new) problem domain
- Show that *my_EA* is better than *benchmark_EA*
- Show that EAs outperform traditional algorithms (sic!)
- Find best setup for parameters of a given algorithm
- Understand algorithm behavior (e.g. pop dynamics)
- See how an EA scales-up with problem size
- See how performance is influenced by parameters
  - of the problem
  - of the algorithm
- …

Example: Production Perspective

- Optimising Internet shopping delivery route



  - Different destinations each day
  - Limited time to run algorithm each day
  - Must *always* be *reasonably* good route in limited time

Example: Design Perspective

- Optimising spending on improvements to national road network

–Total cost: billions of Euro
–Computing costs negligible
–Six months to run algorithm on hundreds computers
–Many runs possible
–Must produce *very* good result just *once*

Perspectives of goals

- Design perspective:
  find a very good solution at least once
- Production perspective:
  find a good solution at almost every run

also

- Publication perspective:
  must meet scientific standards (huh?)
- Application perspective:
  good enough is good enough (verification!)

These perspectives have very different implications on evaluating the results (yet often left implicit)

Algorithm design

- Design a representation
- Design a way of mapping a genotype to a phenotype
- Design a way of evaluating an individual
- Design suitable mutation operator(s)
- Design suitable recombination operator(s)
- Decide how to select individuals to be parents
- Decide how to select individuals for the next generation (how to manage the population)
- Decide how to start: initialisation method
- Decide how to stop: termination criterion

Algorithm design (cont'd)

For a detailed treatment see Ben Paechter's lecture from the 2001 Summer School:

http://evonet.dcs.napier.ac.uk/summerschool2001/problems.html

Test problems

- 5 DeJong functions
- 25 "hard" objective functions
- Frequently encountered or otherwise important variants of given practical problem
- Selection from recognized benchmark problem repository ("challenging" by being NP--- ?!)
- Problem instances made by random generator

Choice has severe implications on

- generalizability and
- scope of the results

Bad example

- I invented "tricky mutation"
- Showed that it is a good idea by:
  - Running standard (?) GA and tricky GA
  - On 10 objective functions from the literature
  - Finding tricky GA better on 7, equal on 1, worse on 2 cases
- I wrote it down in a paper
- And it got published!
- Q: what did I learned from this experience?
- Q: is this good work?

Bad example (cont'd)

- What did I (my readers) did not learn:
  - How relevant are these results (test functions)?
  - What is the scope of claims about the superiority of the tricky GA?
  - Is there a property distinguishing the 7 good and the 2 bad functions?
  - Are my results generalizable? (Is the tricky GA applicable for other problems? Which ones?)

Getting Problem Instances 1

- Testing on real data
- Advantages:
  - Results could be considered as very relevant viewed from the application domain (data supplier)
- Disadvantages
  - Can be over-complicated
  - Can be few available sets of real data
  - May be commercial sensitive – difficult to publish and to allow others to compare
  - Results are hard to generalize

Getting Problem Instances 2

- Standard data sets in problem repositories, e.g.:
  - OR-Library
    http://www.ms.ic.ac.uk/info.html
  - UCI Machine Learning Repository
    www.ics.uci.edu/~mlearn/MLRepository.html
- Advantage:
  - Well-chosen problems and instances (hopefully)
  - Much other work on these → results comparable
- Disadvantage:
  - Not real – might miss crucial aspect
  - Algorithms get tuned for popular test suites

Getting Problem Instances 3

- Problem instance generators produce simulated data for given parameters, e.g.:
  - GA/EA Repository of Test Problem Generators
    http://www.cs.uwyo.edu/~wspears/generators.html
- Advantage:
  - Allow very systematic comparisons for they
    - can produce many instances with the same characteristics
    - enable gradual traversion of a range of characteristics (hardness)
  - Can be shared allowing comparisons with other researchers
- Disadvantage
  - Not real – might miss crucial aspect
  - Given generator might have hidden bias

Basic rules of experimentation

- EAs are stochastic →
  never draw any conclusion from a single run
  - perform sufficient number of independent runs
  - use statistical measures (averages, standard deviations)
  - use statistical tests to assess reliability of conclusions
- EA experimentation is about comparison →
  always do a fair competition
  - use the same amount of resources for the competitors
  - try different comp. limits (to coop with turtle/hare effect)
  - use the same performance measures

Things to Measure

Many different ways. Examples:

- Average result in given time
- Average time for given result
- Proportion of runs within % of target
- Best result over *n* runs
- Amount of computing required to reach target in given time with % confidence
- …

What time units do we use?

- Elapsed time?
  - Depends on computer, network, etc…
- CPU Time?
  - Depends on skill of programmer, implementation, etc…
- Generations?
  - Difficult to compare when parameters like population size change
- Evaluations?
  - Evaluation time could depend on algorithm, e.g. direct vs. indirect representation

Measures

- Performance measures (off-line)
  - Efficiency (alg. speed)
    - CPU time
    - No. of steps, i.e., generated points in the search space
  - Effectivity (alg. quality)
    - Success rate
    - Solution quality at termination
- "Working" measures (on-line)
  - Population distribution (genotypic)
  - Fitness distribution (phenotypic)
  - Improvements per time unit or per genetic operator
  - …

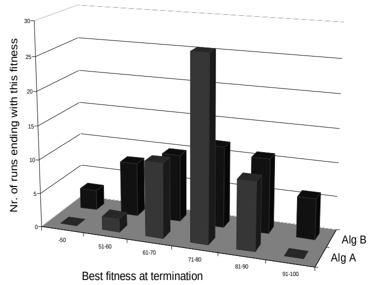
Performance measures

- No. of generated points in the search space = no. of fitness evaluations (don't use no. of generations!)
- AES: average no. of evaluations to solution
- SR: success rate = % of runs finding a solution (individual with acceptabe quality / fitness)
- MBF: mean best fitness at termination, i.e., best per run, mean over a set of runs
- SR $\neq$ MBF
  - Low SR, high MBF: good approximizer (more time helps?)
  - High SR, low MBF: "Murphy" algorithm

Fair experiments

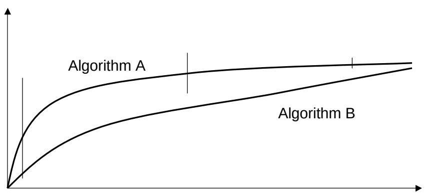
- Basic rule: use the same computational limit for each competitor
- Allow each EA the same no. of evaluations, but
  - Beware of hidden labour, e.g. in heuristic mutation operators
  - Beware of possibly fewer evaluations by smart operators
- EA vs. heuristic: allow the same no. of steps:
  - Defining "step" is crucial, might imply bias!
  - Scale-up comparisons eliminate this bias

Example: off-line performance measure evaluation



Which algorith is better? Why? When?

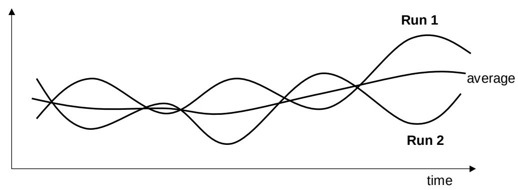
Example: on-line performance measure evaluation



Populations mean (best) fitness

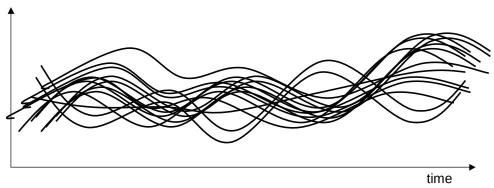
Which algorith is better? Why? When?

Example: averaging on-line measures



Averaging can "choke" interesting onformation

Example: overlaying on-line measures



Overlay of curves can lead to very “cloudy” figures

Statistical Comparisons and Significance

- Algorithms are stochastic
- Results have element of “luck”
- Sometimes can get away with less rigour – e.g. parameter tuning
- For scientific papers where a claim is made: “Newbie recombination is better ran uniform crossover”, need to show statistical significance of comparisons

Example

Trial	Old Method	New Method
1	500	657
2	600	543
3	556	654
4	573	565
5	420	654
6	590	712
7	700	456
8	472	564
9	534	675
10	512	643
Average	545.7	612.3

Is the new method better?

Example (cont’d)

Trial	Old Method	New Method
1	500	657
2	600	543
3	556	654
4	573	565
5	420	654
6	590	712
7	700	456
8	472	564
9	534	675
10	512	643
Average	545.7	612.3
SD	73.5962635	73.5473317
T-test	**0.07080798**	

- Standard deviations supply additional info
- T-test (and alike) indicate the chance that the values came from the same underlying distribution (difference is due to random effetcs) E.g. with 7% chance in this example.

Statistical tests

- T-test assummes:
  - Data taken from continuous interval or close approximation
  - Normal distribution
  - Similar variances for too few data points
  - Similar sized groups of data points
- Other tests:
  - Wilcoxon – preferred to t-test where numbers are small or distribution is not known.
  - F-test – tests if two samples have different variances.

Statistical Resources

- http://fonsg3.let.uva.nl/Service/Statistics.html
- http://department.obg.cuhk.edu.hk/ResearchSupport/
- http://faculty.vassar.edu/lowry/webtext.html
- Microsoft Excel
- http://www.octave.org/

Better example: problem setting

- I invented myEA for problem X
- Looked and found 3 other EAs and a traditional benchmark heuristic for problem X in the literature
- Asked myself when and why is myEA better

Better example: experiments

- Found/made problem instance generator for problem X with 2 parameters:
  - *n* (problem size)
  - *k* (some problem specific indicator)
- Selected 5 values for *k* and 5 values for *n*
- Generated 100 problem instances for all combinations
- Executed all alg's on each instance 100 times (benchmark was also stochastic)
- Recorded AES, SR, MBF values w/ same comp. limit (AES for benchmark?)
- Put my program code and the instances on the Web

Better example: evaluation

- Arranged results "in 3D" (*n,k*) + performance (with special attention to the effect of *n*, as for scale-up)
- Assessed statistical significance of results
- Found the niche for my_EA:
  - Weak in … cases, strong in - - - cases, comparable otherwise
  - Thereby I answered the "when question"
- Analyzed the specific features and the niches of each algorithm thus answering the "why question"
- Learned a lot about problem X and its solvers
- Achieved generalizable results, or at least claims with well-identified scope based on solid data
- Facilitated reproducing my results → further research

Some tips

- Be organized
- Decide what you want
- Define appropriate measures
- Choose test problems carefully
- Make an experiment plan (estimate time when possible)
- Perform sufficient number of runs
- Keep all experimental data (never throw away anything)
- Use good statistics ("standard" tools from Web, MS)
- Present results well (figures, graphs, tables, …)
- Watch the scope of your claims
- Aim at generalizable results
- Publish code for reproducibility of results (if applicable)

Summary

- Experimental methodology in EC is weak
  - Lack of strong selection pressure for publications
  - Laziness (seniors), copycat behavior (novices)
- Not much learning from other fields actively using better methodology, e.g.,
  - machine learning (training-test instances)
  - social sciences! (statistics)
- Not much effort into
  - better methodologies
  - better test suites
  - reproducible results (code standardization)
- Much room for improvement: do it!