Working with Evolutionary Algorithms

Chapter 14

Issues considered

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

Experimentation

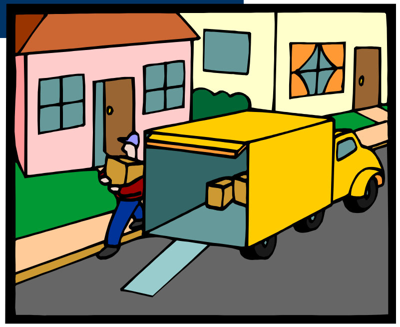
- Has a goal or goals
- Involves algorithm design and implementation
- Needs problem(s) to run the algorithm(s) on
- Amounts to running the algorithm(s) on the problem(s)
- Delivers measurement data, the results
- Is concluded with evaluating the results in the light of the given goal(s)
- Is often documented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

EA experimentation

- EA objectives determined by problem context:
- Design (engineering) problems – single ‘good’ solution required.
- Control (optimization) problems – requiring many ‘good’ yet ‘timely’ solutions.

Example: Production Perspective

- Optimizing Internet shopping delivery routes



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

Example: Design Perspective

- Optimizing 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 an EA's goals

- Design perspective:

  find a very good solution at least once

- Production perspective:

  find a good solution at almost every run

- Academic perspective:

  must meet scientific standards

These perspectives have very different implications when evaluating EA results.

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: initialization method
- Decide how to stop: termination criterion

Test problems for experimental comparisons

- Use problem instances from an academic repository
- Use randomly generated problem instances
- Use real life problem instances

Test problems for experimental comparisons

- 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

- 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?
  - Can the results be generalized ? (Is the tricky GA applicable for other problems? Which ones?)

Getting Problem Instances 1

- Testing on real data
- Advantages:
  - Results are application oriented
- Disadvantages
  - 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://people.brunel.ac.uk/~mastjjb/jeb/info.html
  - UCI Machine Learning Repository
    http://archive.ics.uci.edu/ml/
  - Advantage:
  - Tried and tested 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
- Advantage:
  - Allow systematic investigation of an objective function parameter range
  - 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 competition limits
  - 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

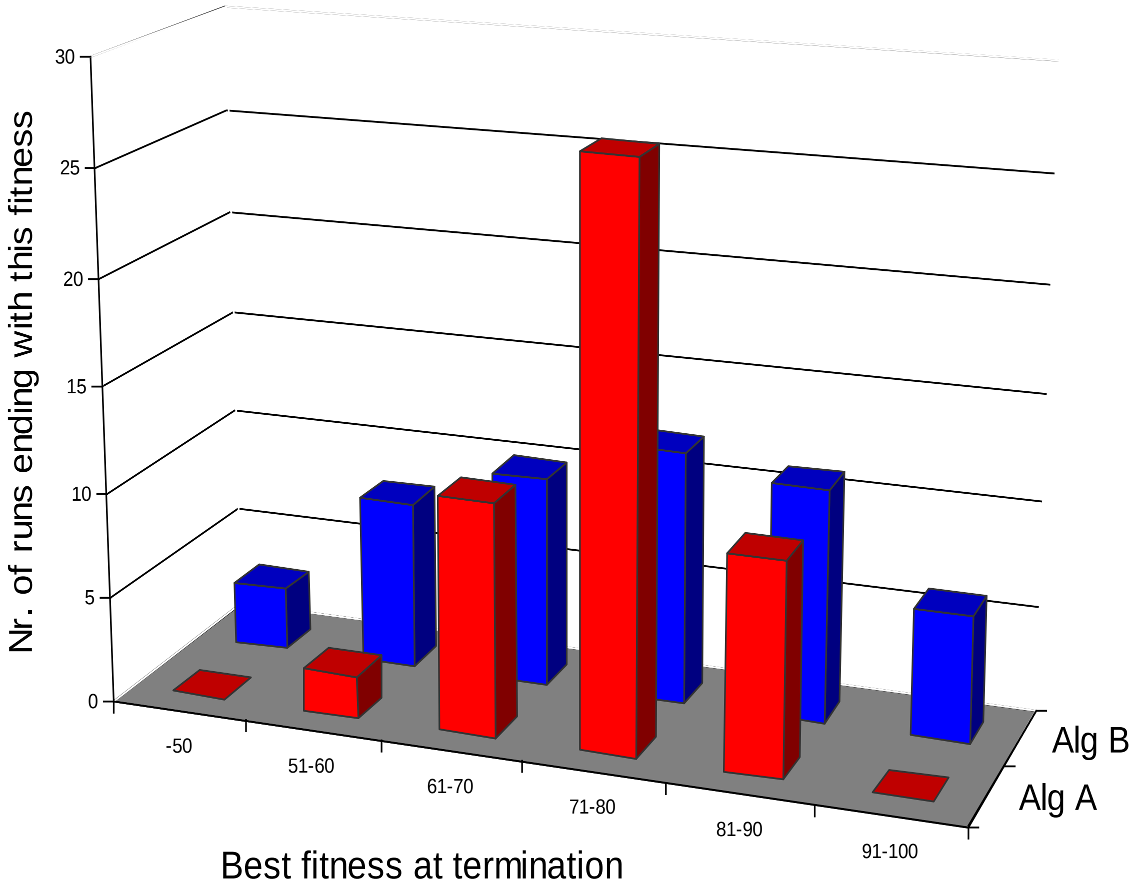
- No. of generated points in the search space
  = no. of fitness evaluations
  (don’t use no. of generations!)
- AES: average no. of evaluations to solution
- SR: success rate = % of runs finding a solution (individual with acceptabe quality / fitness)
- MBF: mean best fitness at termination, i.e., best 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

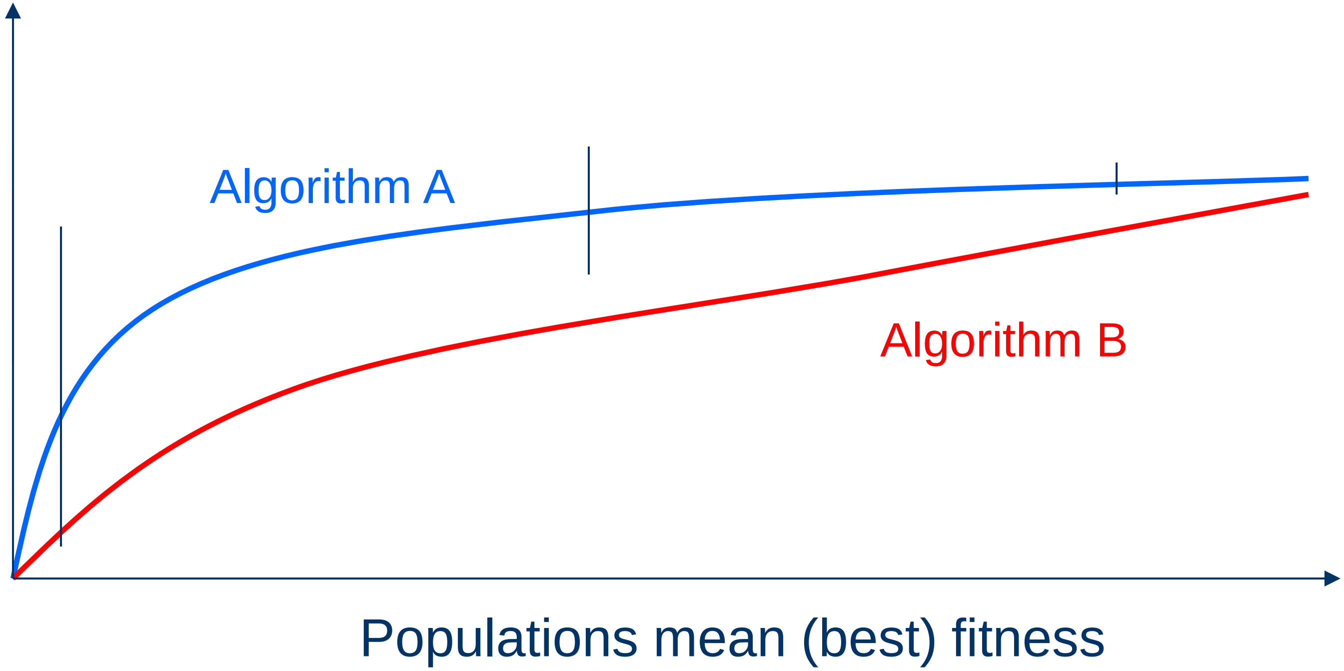
- Basic rule: use the same computational limit for each competitor
- Allow each EA the same no. of evaluations, but
  - Beware of hidden labour, e.g. in heuristic mutation operators
  - Beware of possibly fewer evaluations by smart operators
- EA vs. heuristic: allow the same no. of steps:
  - Defining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

Example: off-line performance measure evaluation

Which algorith is better?
Why?
When?

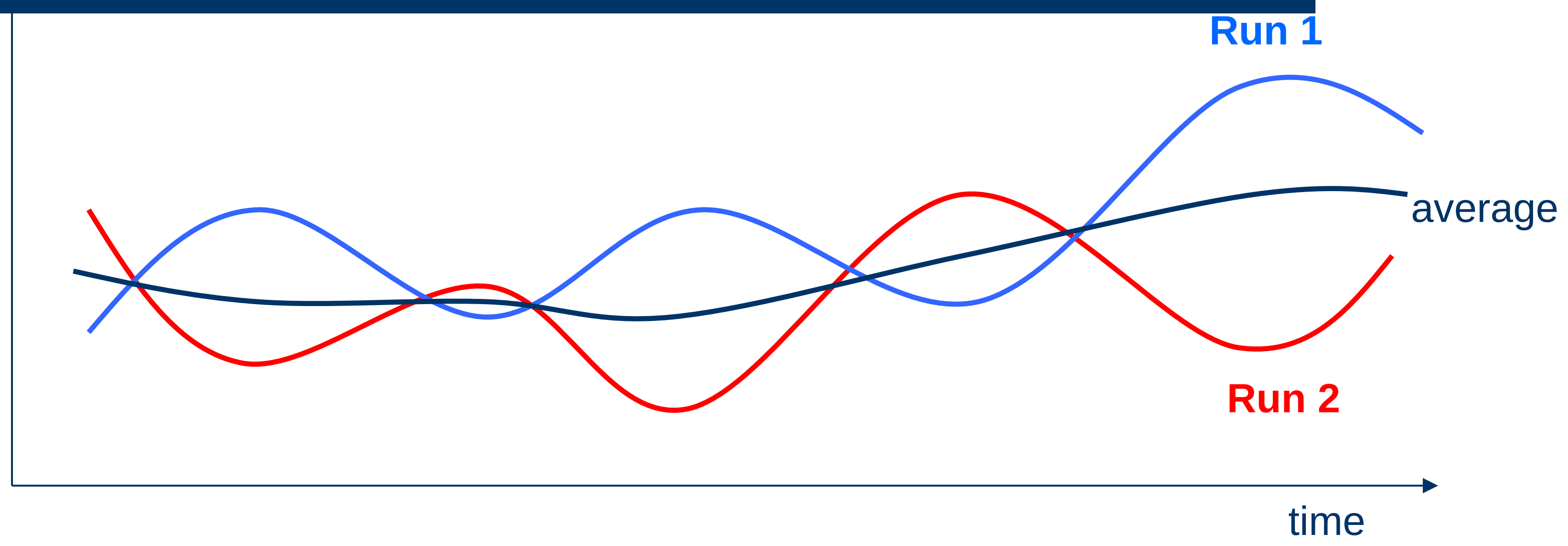


Example: on-line performance measure evaluation



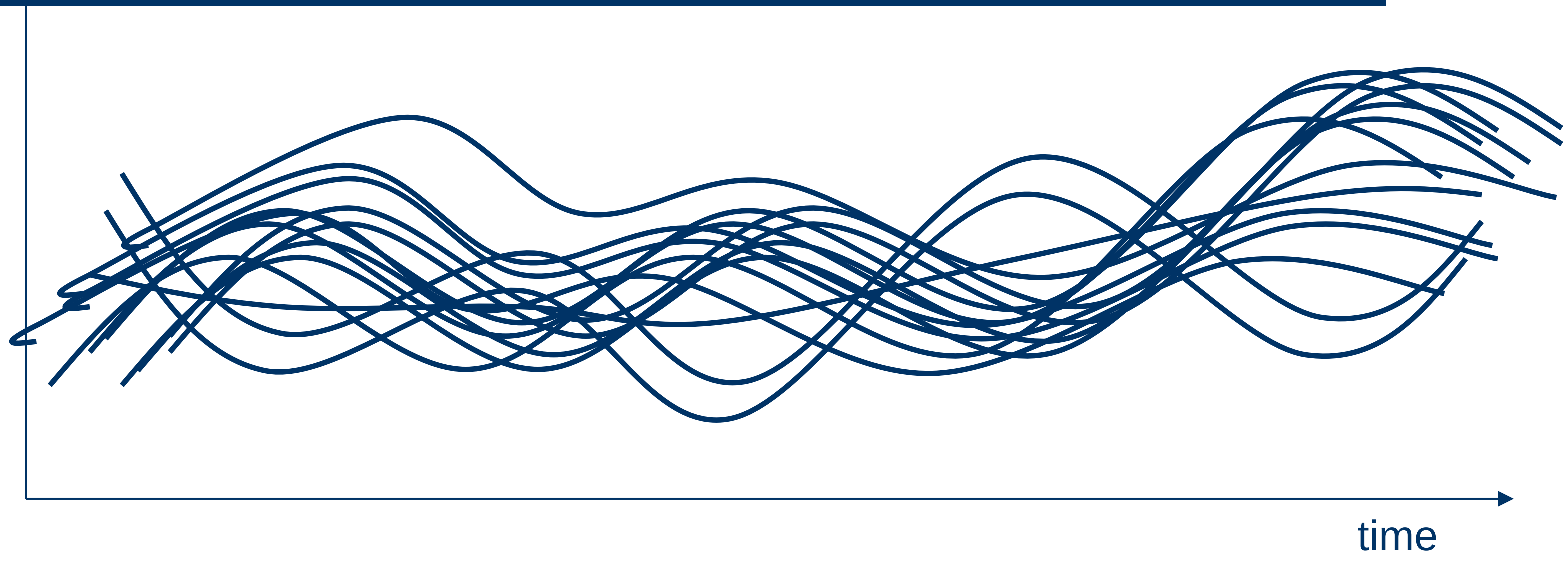
Which algorith is better? Why? When?

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**	

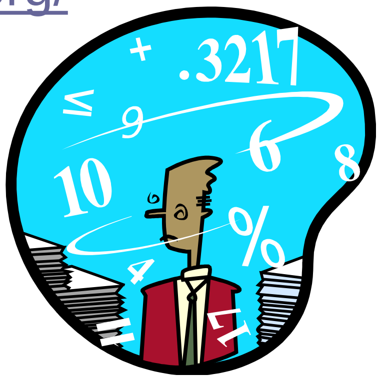
- Standard deviations supply additional info
- T-test (and alike) indicate the chance that the values came from the same underlying distribution (difference is due to random effetcs) E.g. with 7% chance in this example.

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.
  - KS-test (Kolmogorov-Smirnov), Kruskal-Wallis

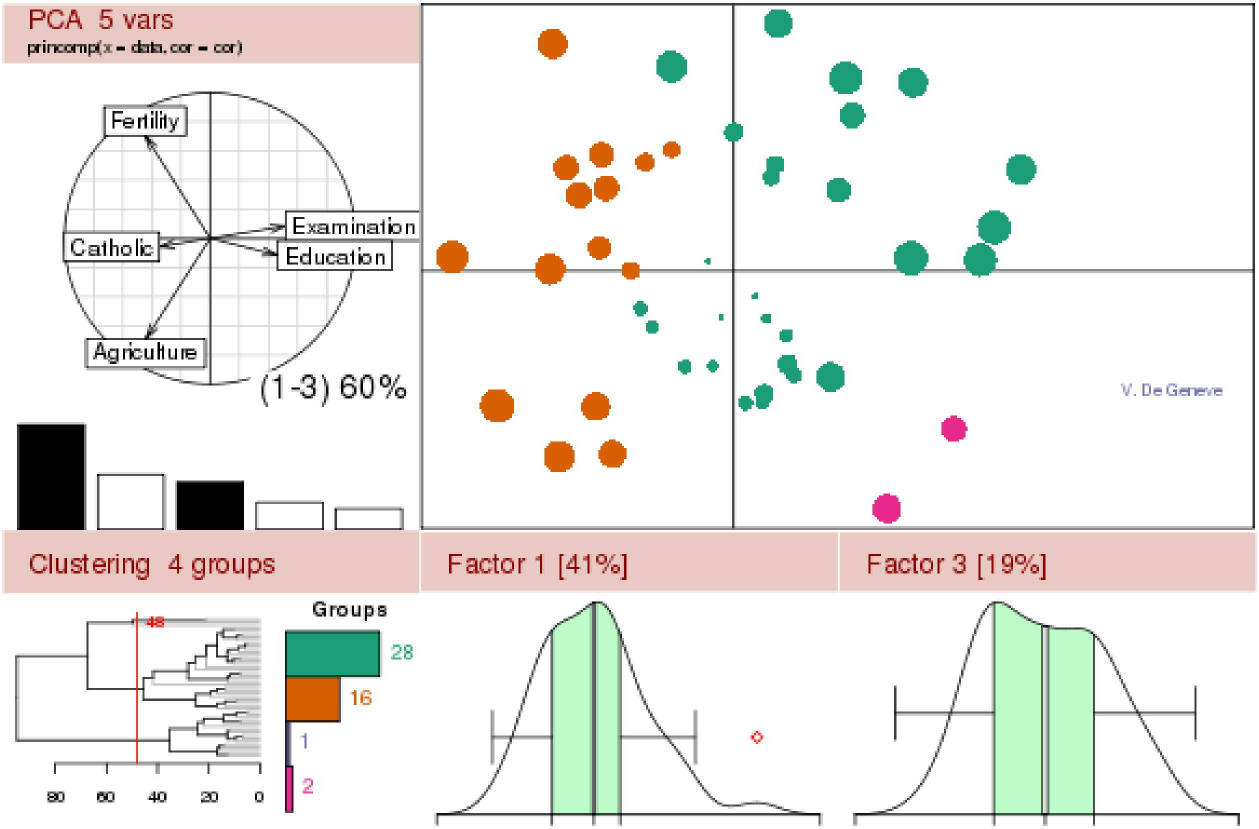
Statistical Resources

- 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/



Statistical Resources – cont'ed

- R - http://www.r-project.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)
- Present results well (figures, graphs, tables, …)
- Watch the scope of your claims
- Aim at generalizable results
- Publish code for reproducibility of results (if applicable)