

Computational Intelligence

Master in Artificial Intelligence

2016-17

Lluís A. Belanche

belanche@cs.upc.edu

Extra: tips for doing experimental work





Experimentation

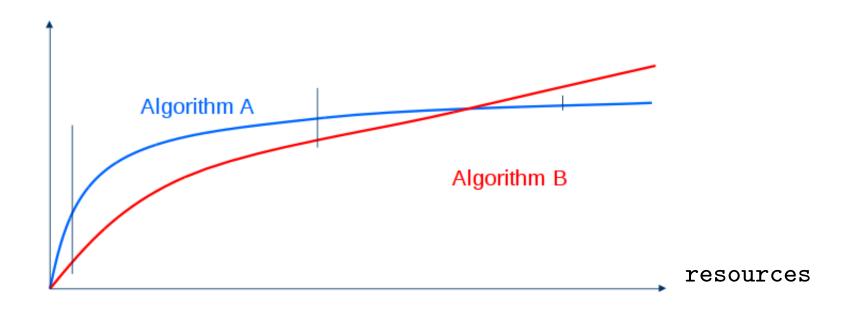
- 1. Has a goal(s) and conjecture(s) about the expected results
- 2. Involves algorithm design and implementation
- 3. Needs problems/data to run the algorithm on
- 4. Needs establishing what is variable and what is held fixed
- 5. Needs running the algorithm(s) on the problem(s) and collect the results
- Needs evaluating the results in the light of the given goal(s) and conjectures

Tips for doing experimental work Possible goals

- Get a good solution for a given problem
- Show that an algorithm is applicable to a problem or class thereof
- Show that an algorithm is better than another one in some respect
- Find "optimal" setup for parameters of a given algorithm
- Understand algorithm behavior:
 - how it scales up with problem size
 - how it performs under extreme conditions
 - → how performance is influenced by parameters (criticality)

Example 1

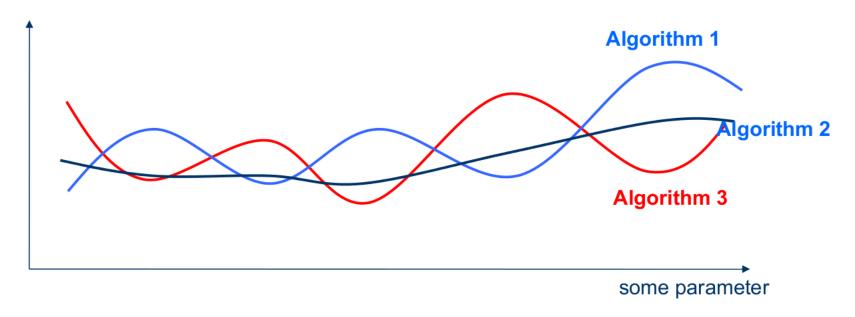
performance



Which algorithm is better?

Example 2

performance



What kind of algorithm we wanted?

- 1. very good in very specific situations
- 2. fairly good on average

Hallmarks of good scientific work

- Clear statement of target problem, goals and scope
- Large enough tests (number, difficulty, representativeness)
- Statistical analysis of results
- Reproducibility
- Insightful discussion of the results
- Conclusions: what have we achieved, what have we learned, whys and why nots, strenghts and limitations
- Future work: open problems, avenues for future investigation

Using real vs. synthetic problems/data

Advantages well-chosen problems (coming from real-world), comparison to previous work

Disadvantages not owner, might miss important absent information, problem feasibility?

Advantages allow systematic comparison: repetitions, sizes, hardness, ...; can target very specific issues; can be shared

Disadvantages not the "real thing"; might be too simplistic/hard; hidden biases?

never draw any conclusion from a single run!

- perform sufficient number of independent runs
- use statistical measures (means, standard errors)
- use statistical tests to assess reliability of conclusions (t-test, F-test, Wilcoxon, ...)

always do a fair competition!

- use same amount of resources for the competitors
- use same performance measures

Bad example

I invented a "Cool Super Algorithm" (CSA) for problem X

- I showed it really "works" by running it against a "standard" solution
- I chose a bunch of 10 problems (rather randomly)
- I run the two methods once (I invested 10 times more time in tuning mine)
- I found that my CSA was "better" on 7 problems, "equal" on 1, and "worse" on 2

I wrote everything down in a paper and got it published!

Bad example

Ask yourself ...

- 1. How relevant are these results? (honest, trustable, reproducible, representative, ...)
- 2. What is the scope of my claims? (and what are my claims ...)
- 3. Why do I get the 7 successes (and why these 2 failures)? Is there a common explanation?
- 4. What did I learned from this work? What will others learn?

Good example

I invented a new algorithm/variation "Quasi New Algorithm" (QNA) for problem X; then I ...

- Looked in the literature and selected 3 other methods and a baseline heuristic for problem X
- Asked myself when/why is my QNA better than any/some of these
- Found/designed a problem generator for problems of the X type with two parameters:
 - *n* (problem size)
 - k (problem-specific indicator: e.g., hardness)

Good example

- 1. Selected some values for k and some for n (with some criterion)
- 2. Generated 100 problem instances for each combination
- 3. Executed all methods on each instance
- 4. Recorded all performance measures (accuracies, CPU times, ...)
- 5. Put my program code and the instances on the Web \rightarrow facilitate reproducing my results \rightarrow further research (and learned a lot about problem X and its solvers)

Good example

- 1. Arranged results "in 3D": (n,k,performance)
- 2. Assessed statistical significance of results
- 3. Found the *niche* for my QNA: "Weak in ____ cases, strong in ____ cases, comparable otherwise."
 - Thereby I answered the -when- question
- 4. Analyzed the specific features and the niches of each algorithm, thus answering the -why- question
- 5. Achieved generalizable results, or at least claims with well-identified scope based on solid data