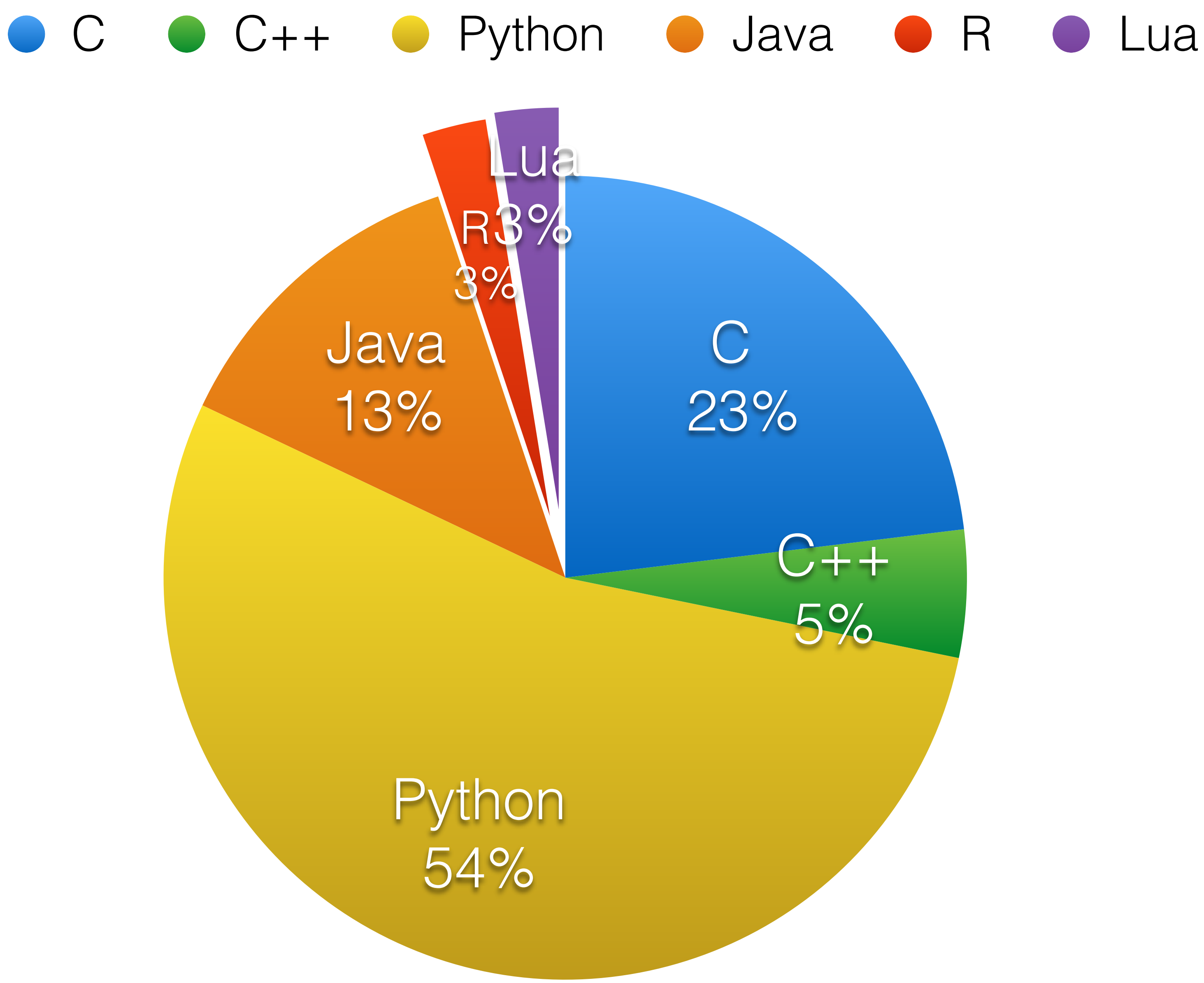
Introduction to SBSE (2/2)

Shin Yoo

CS454, Autumn 2018, School of Computing, KAIST

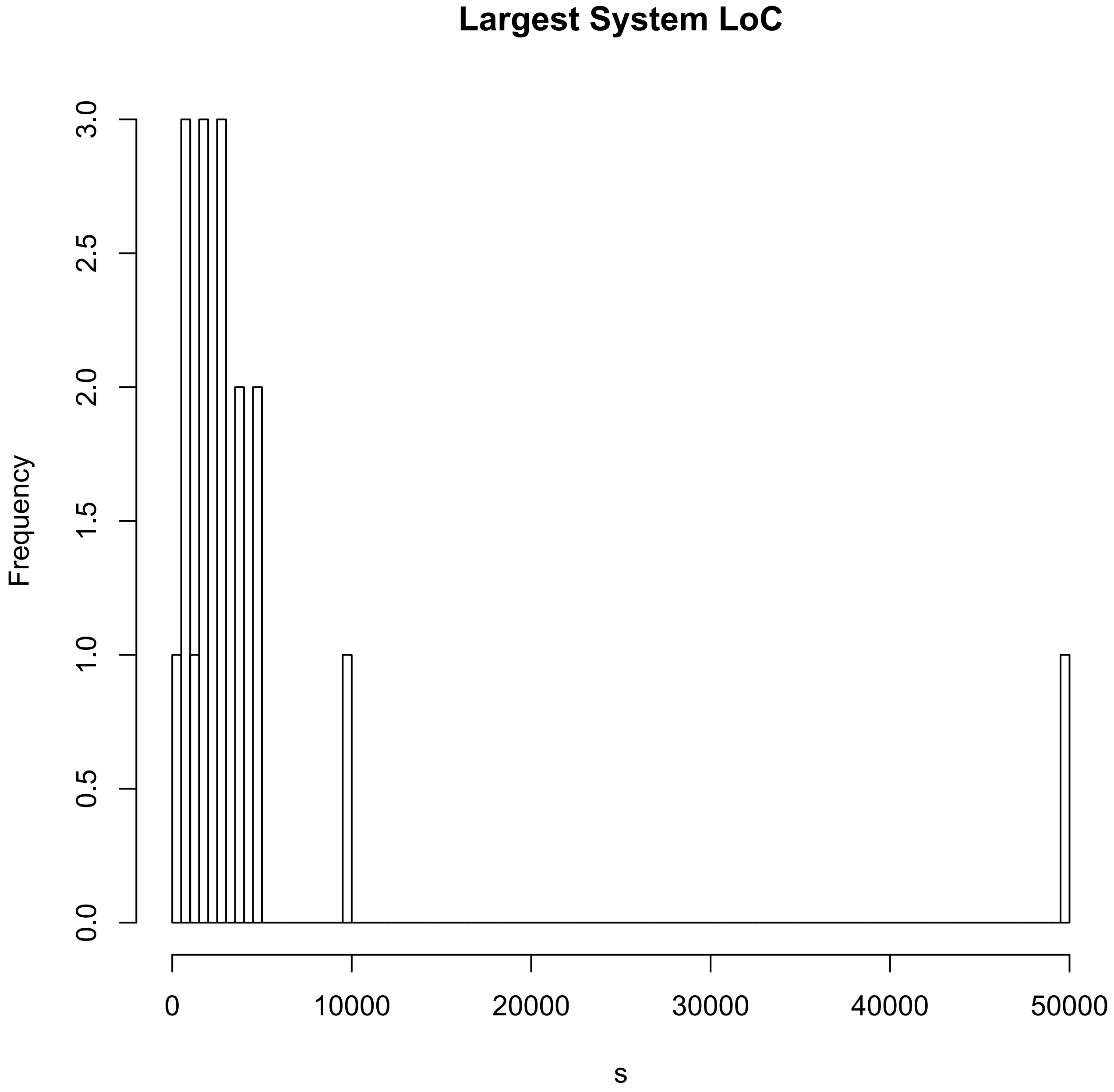
Favourite Language

- C: first language
- Java: OOP, easy to write
- Python: easy, quick to write, lots of libraries, intuitive



Largest System

- Median: ~3,000 lines
- Outliers
  - 1M LoC!
  - Pintos :)



Testing

- “manual”, “crash”, **“no testing”**
- “unit test”, “JUnit”
- “tests given by Pintos”

(meta)heuristic

- Algorithms most people heard about: greedy, dynamic programming

- Mixed: genetic algorithm

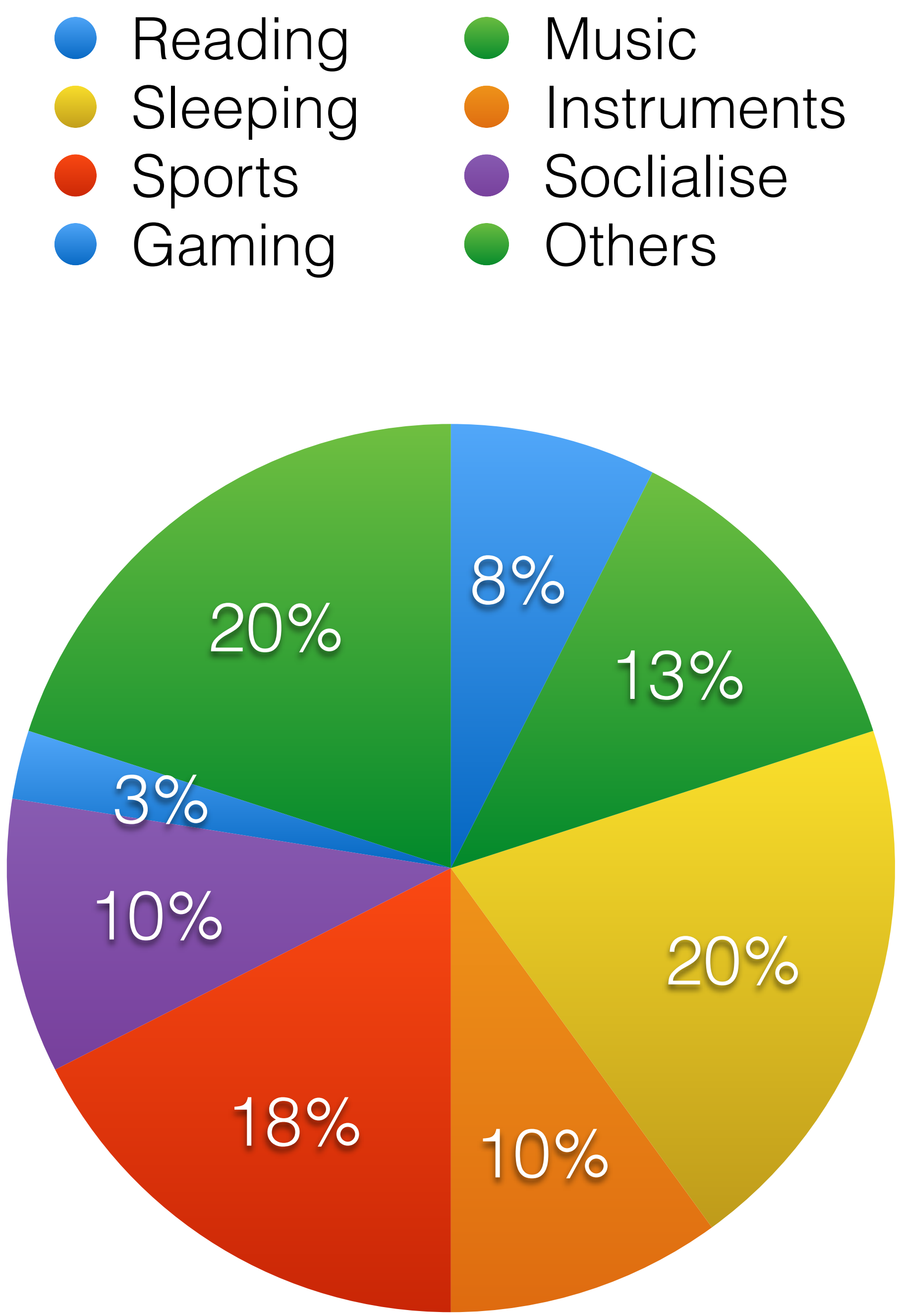
- Comparatively unknown: genetic programming

Things we want to automate

- Testing
- Compiling/building process
- Debugging, correcting trivial errors

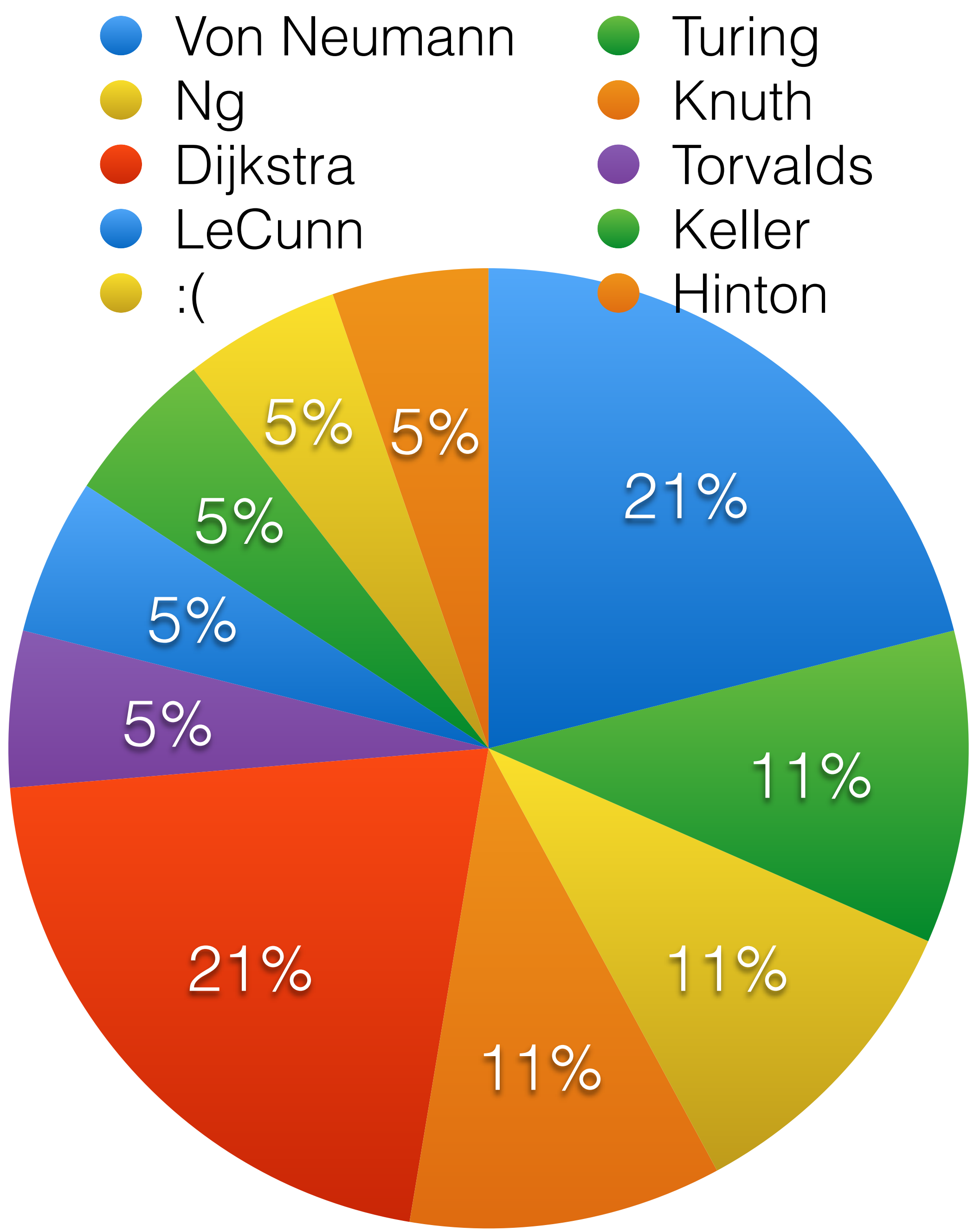
Away from keyboard

- I don’g believe gaming accounting only for 3% :p
- Others include:
    - “Delete & restart” (hmm)
    - “Research algorithms” (hmmmmm)
    - away from keyboard -> “get close with smartphone” (!)

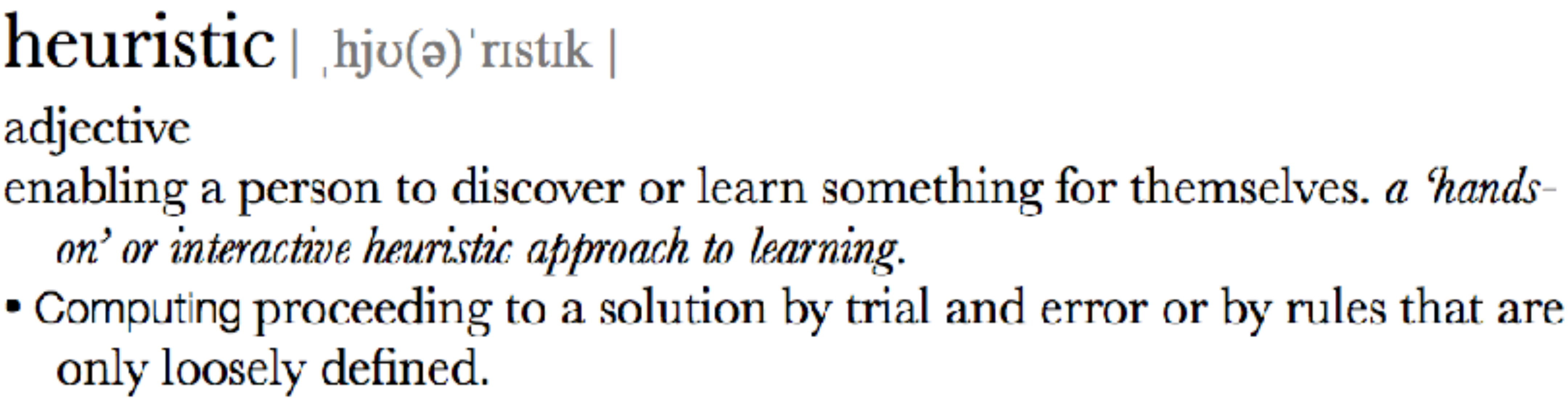


Favourite Computer Scientist

- Go, Deep Learning!
    - Ng, Hinton, LeCunn
- Jim Keller is probably more of an EE engineer :)
- :(??



Let’s start with terms.

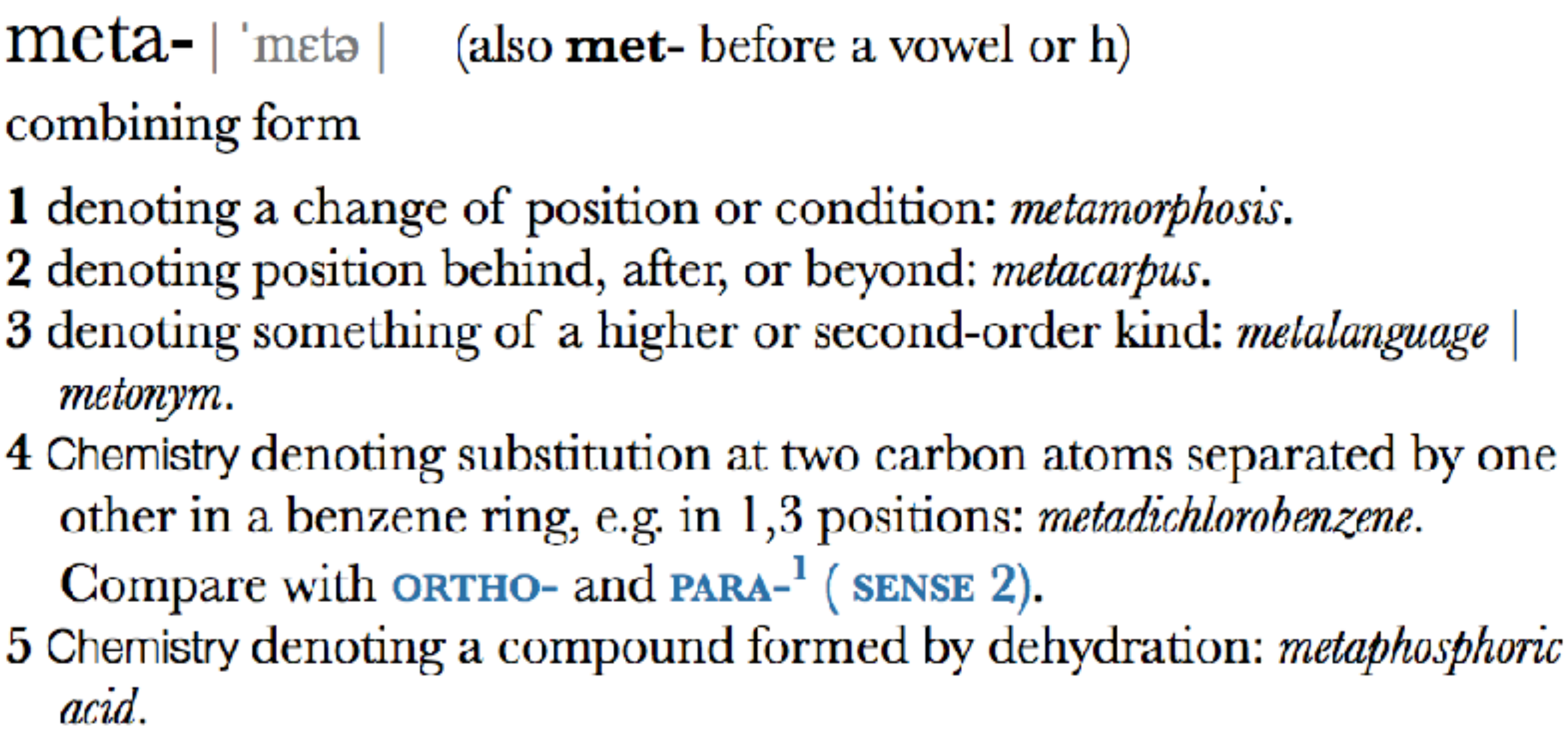


heuristic | ˌhjʊ(ə)ˈrɪstɪk |

adjective

enabling a person to discover or learn something for themselves. *a 'hands-on' or interactive heuristic approach to learning.*

- Computing proceeding to a solution by trial and error or by rules that are only loosely defined.



meta- | ˈmɛtə | (also **met-** before a vowel or h)

combining form

1 denoting a change of position or condition: *metamorphosis*.

2 denoting position behind, after, or beyond: *metacarpus*.

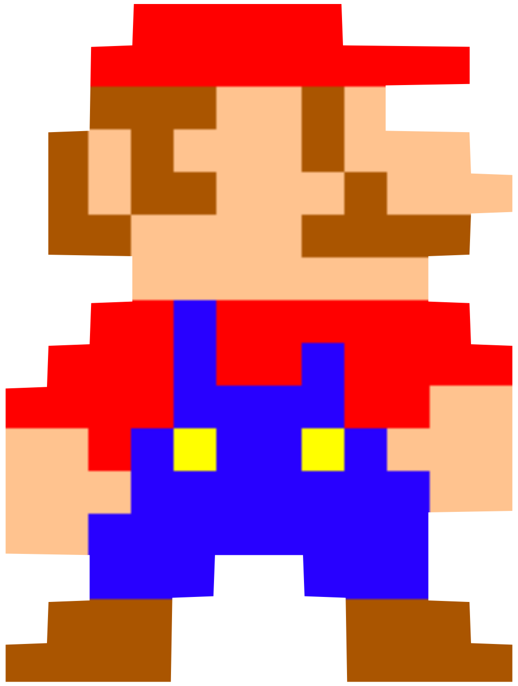
3 denoting something of a higher or second-order kind: *metalanguage* | *metonym*.

4 Chemistry denoting substitution at two carbon atoms separated by one other in a benzene ring, e.g. in 1,3 positions: *metadichlorobenzene*. Compare with ORTHO- and PARA-^{1} (SENSE 2).

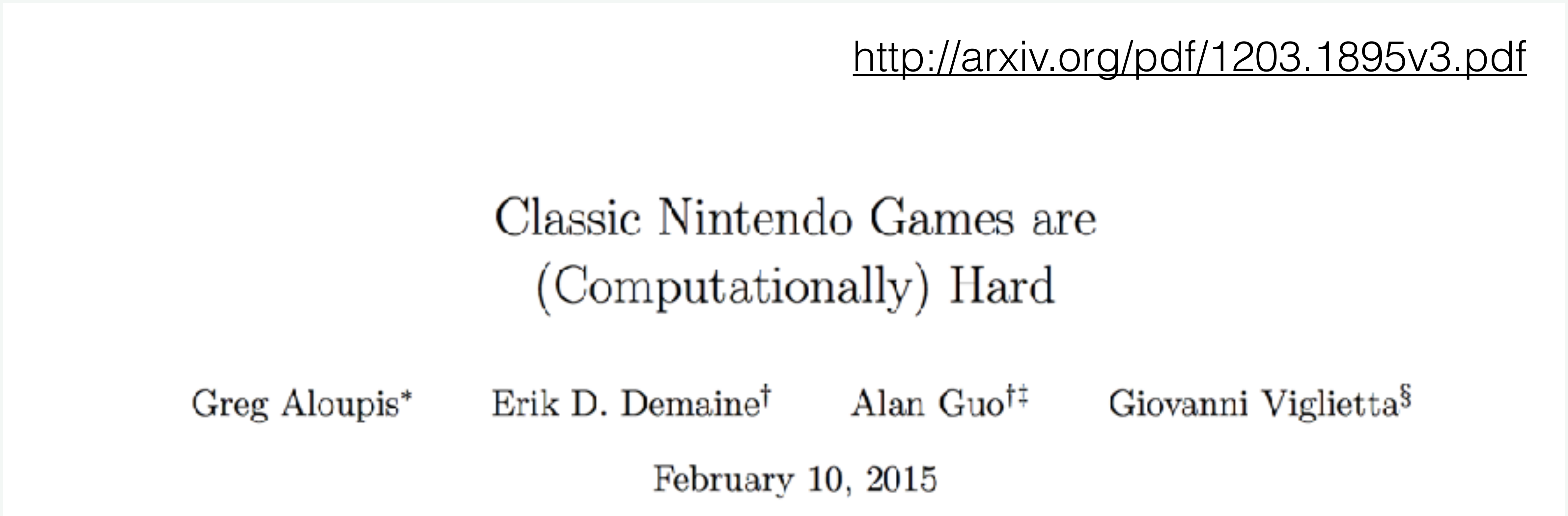
5 Chemistry denoting a compound formed by dehydration: *metaphosphoric acid*.

Meta-heuristic

- Strategies that guide the search of the acceptable solution
- Approximate and usually non-deterministic
- Not problem specific
- Smart trial and error



Let’s play Super Mario Bros.



http://arxiv.org/pdf/1203.1895v3.pdf

Classic Nintendo Games are (Computationally) Hard

Greg Aloupis[*] Erik D. Demaine[†] Alan Guo[†‡] Giovanni Viglietta[§]

February 10, 2015

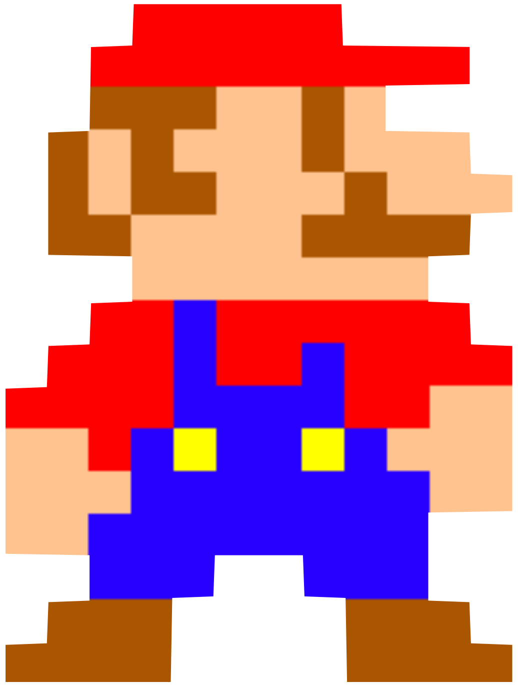
Player A

- Read the game manual to see which button does what.

- Google the level map and get familiar with it.

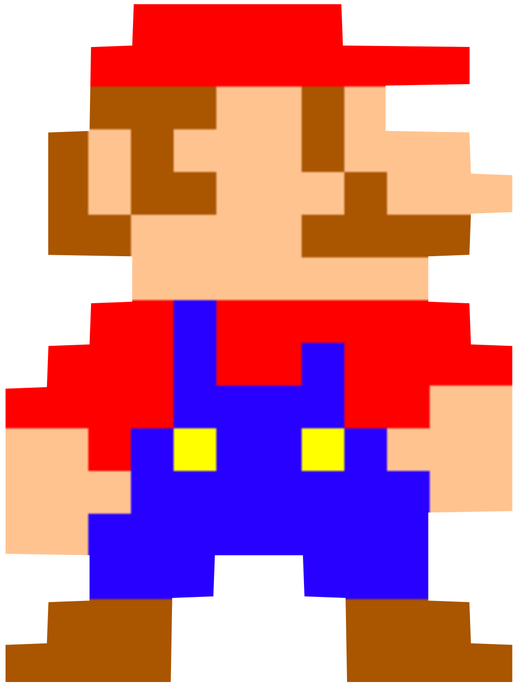
- Carefully, very carefully, plan when to press each button, for how long.

- Grab the controller and execute the plan.



Player B

- Grab the controller.
- Play.
- Die.
- Repeat until level is cleared.



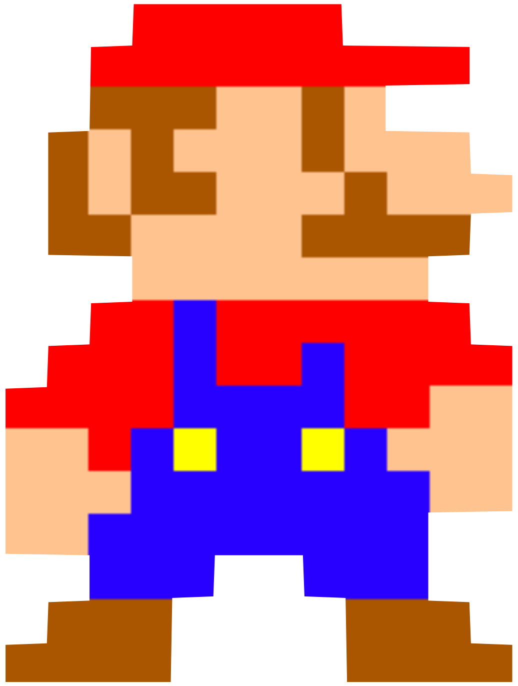
Intelligence lies in how differently you die next time.

Mario analogy goes a long way

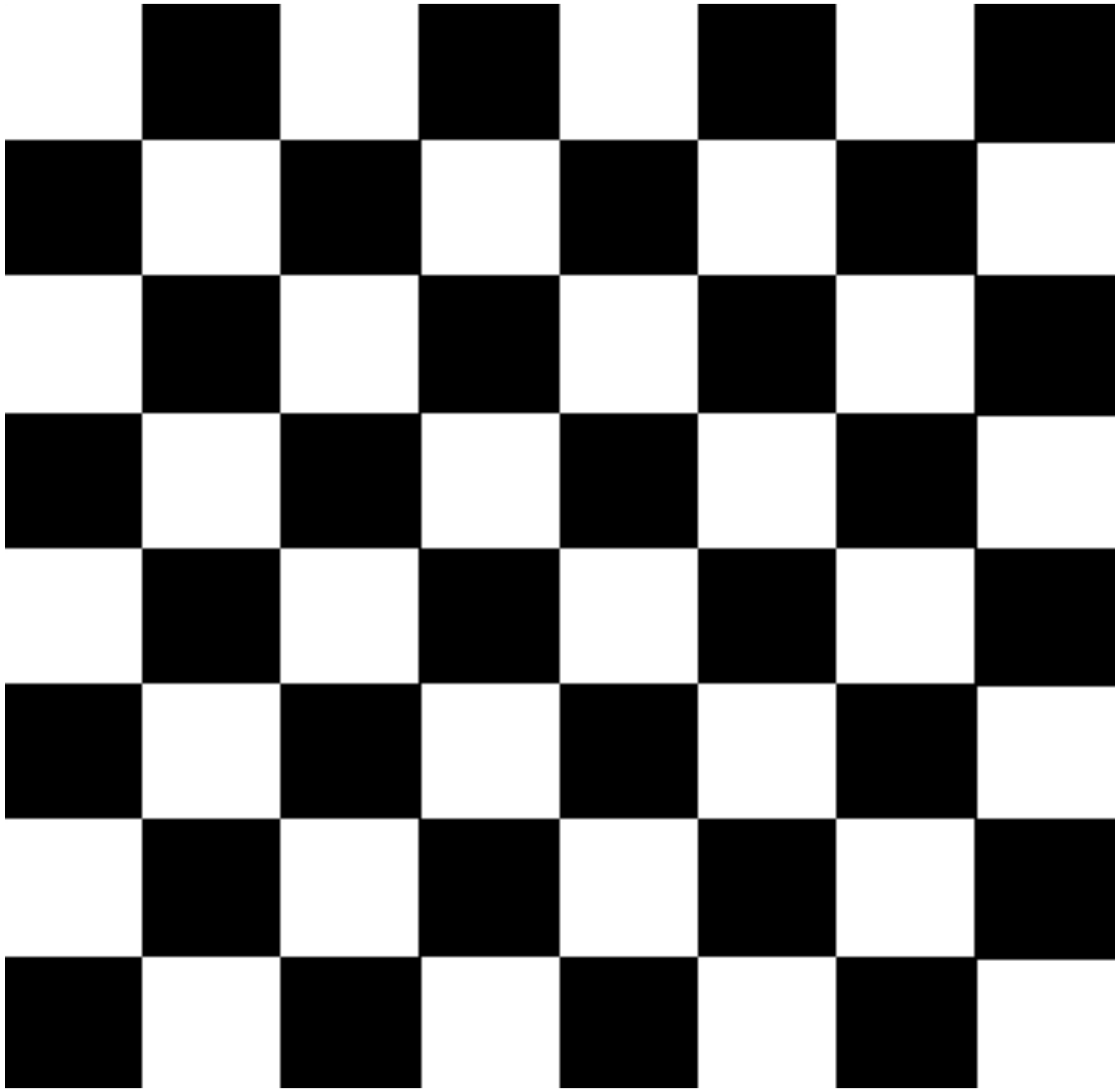
- You make small changes to your last attempt (“okay, I will press A slightly later this time”).

- You combine different bits of solutions (“Okay, jump over here, but then later do not jump over there”).

- You accidentally discover new parts of the map (“Oops, how did I find this secret passage?”)

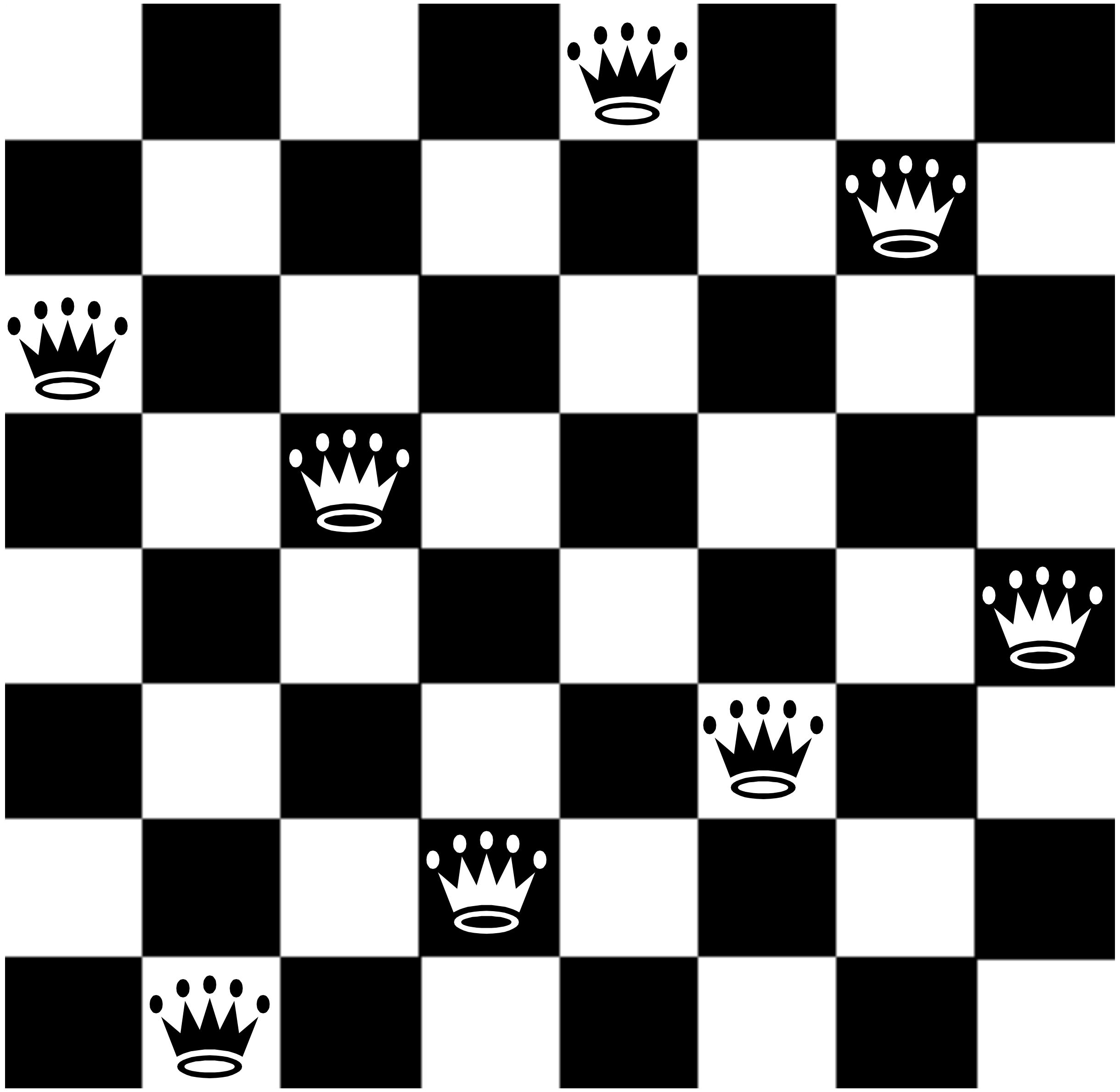


Eight Queens Problem



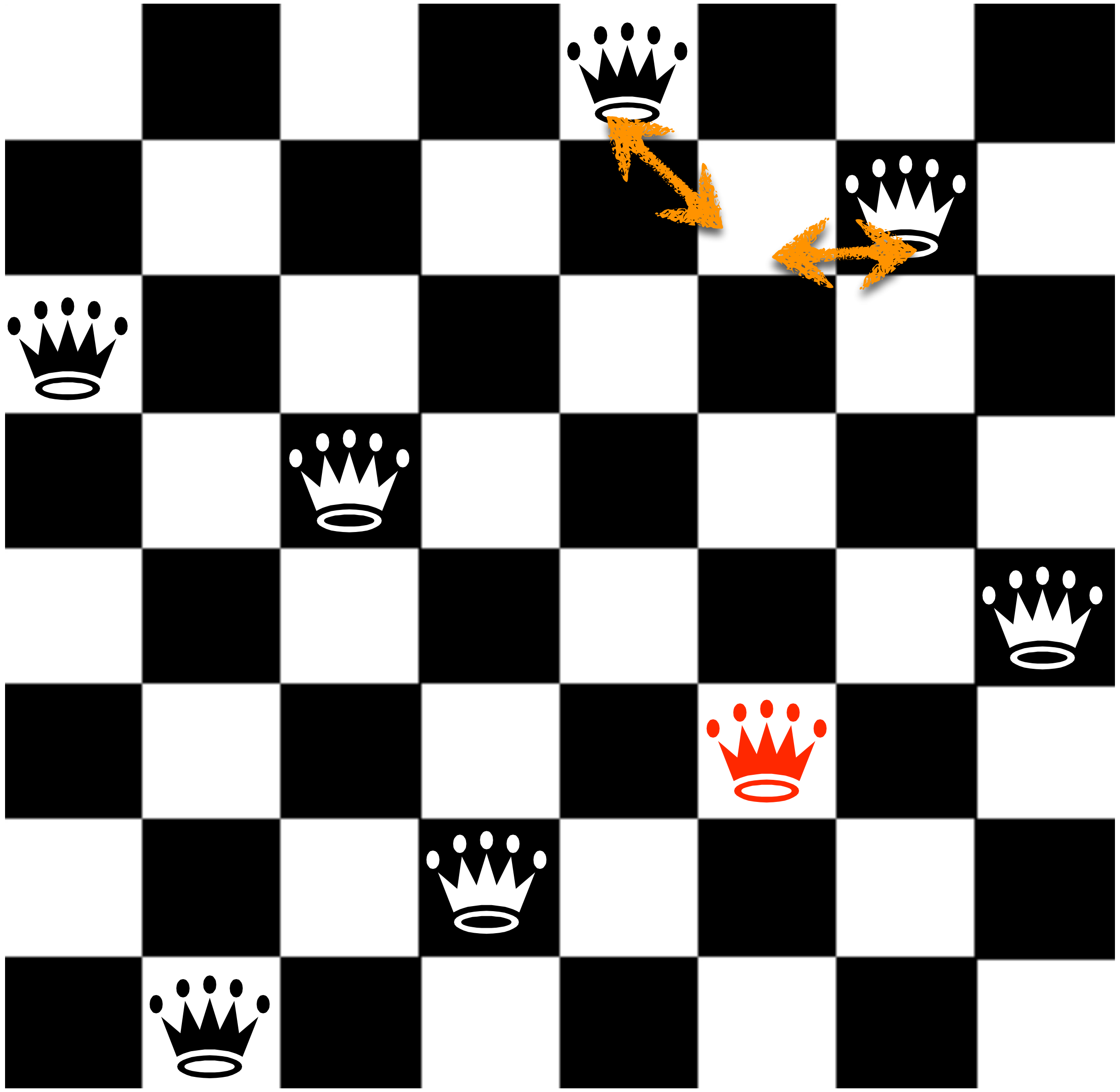
Place 8 queens on a chessboard so that no pair attacks each other.

Eight Queens Problem



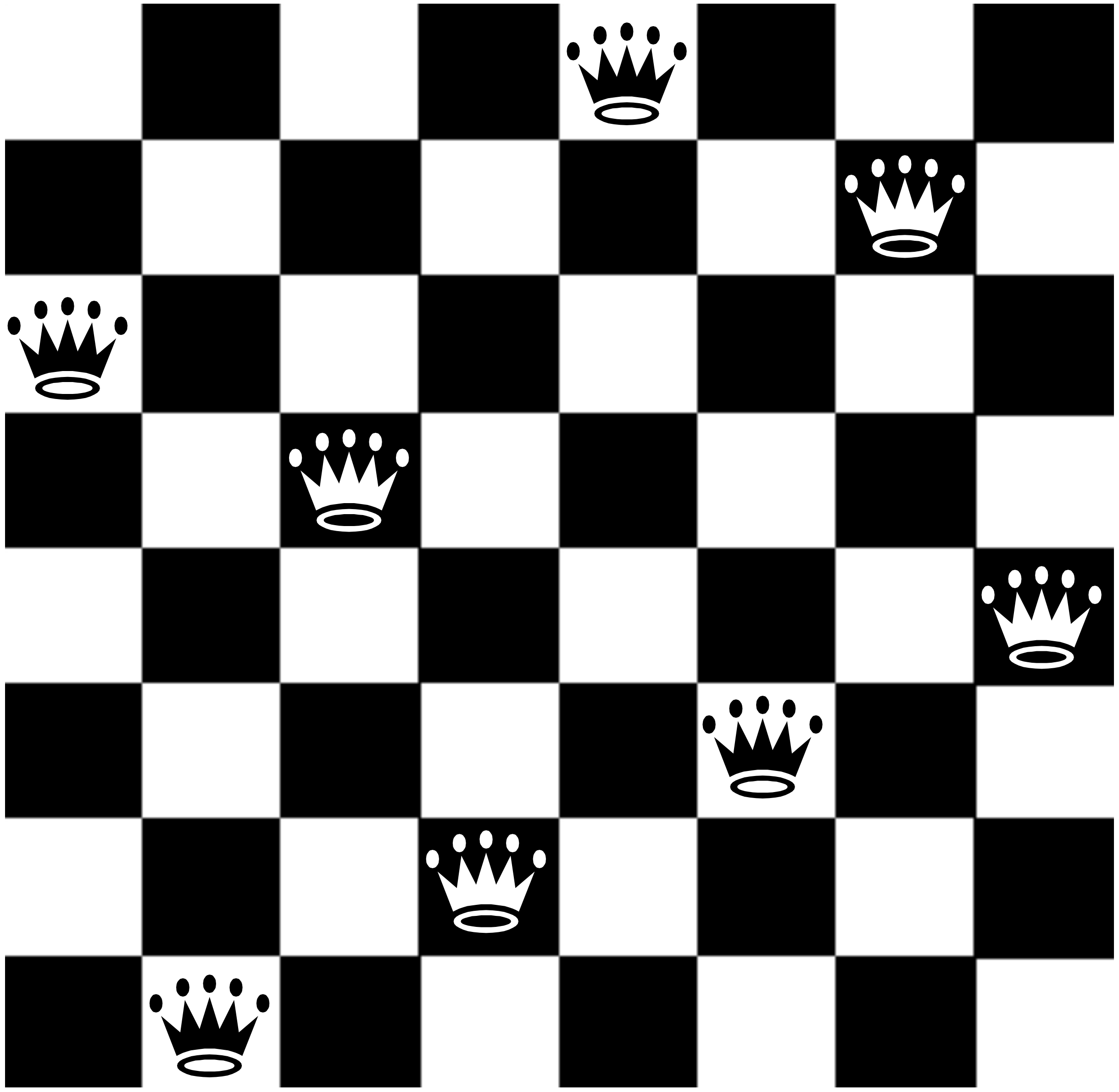
Perfect solution: score 0

Eight Queens Problem

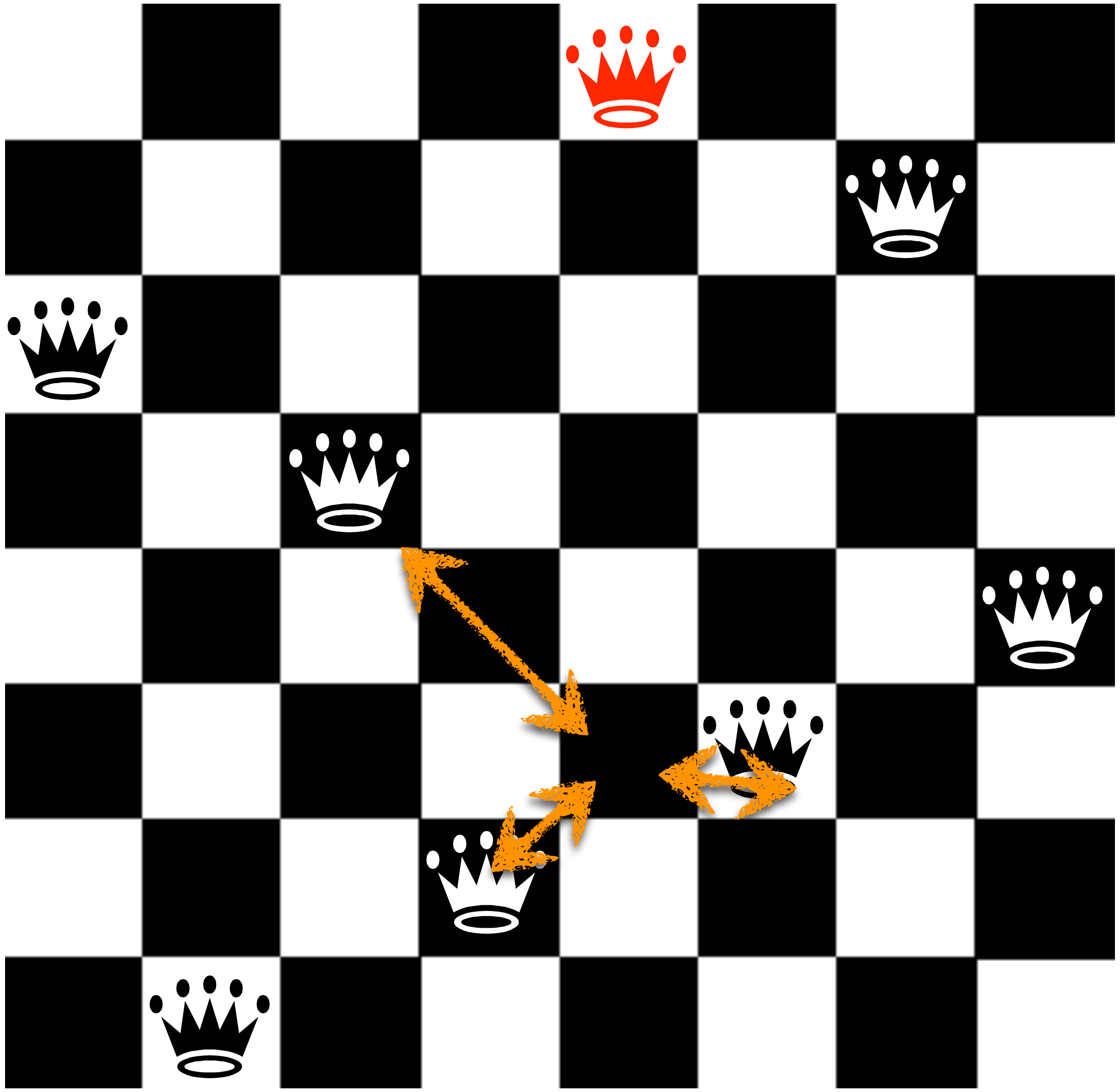


Two attacks: score -2

Eight Queens Problem



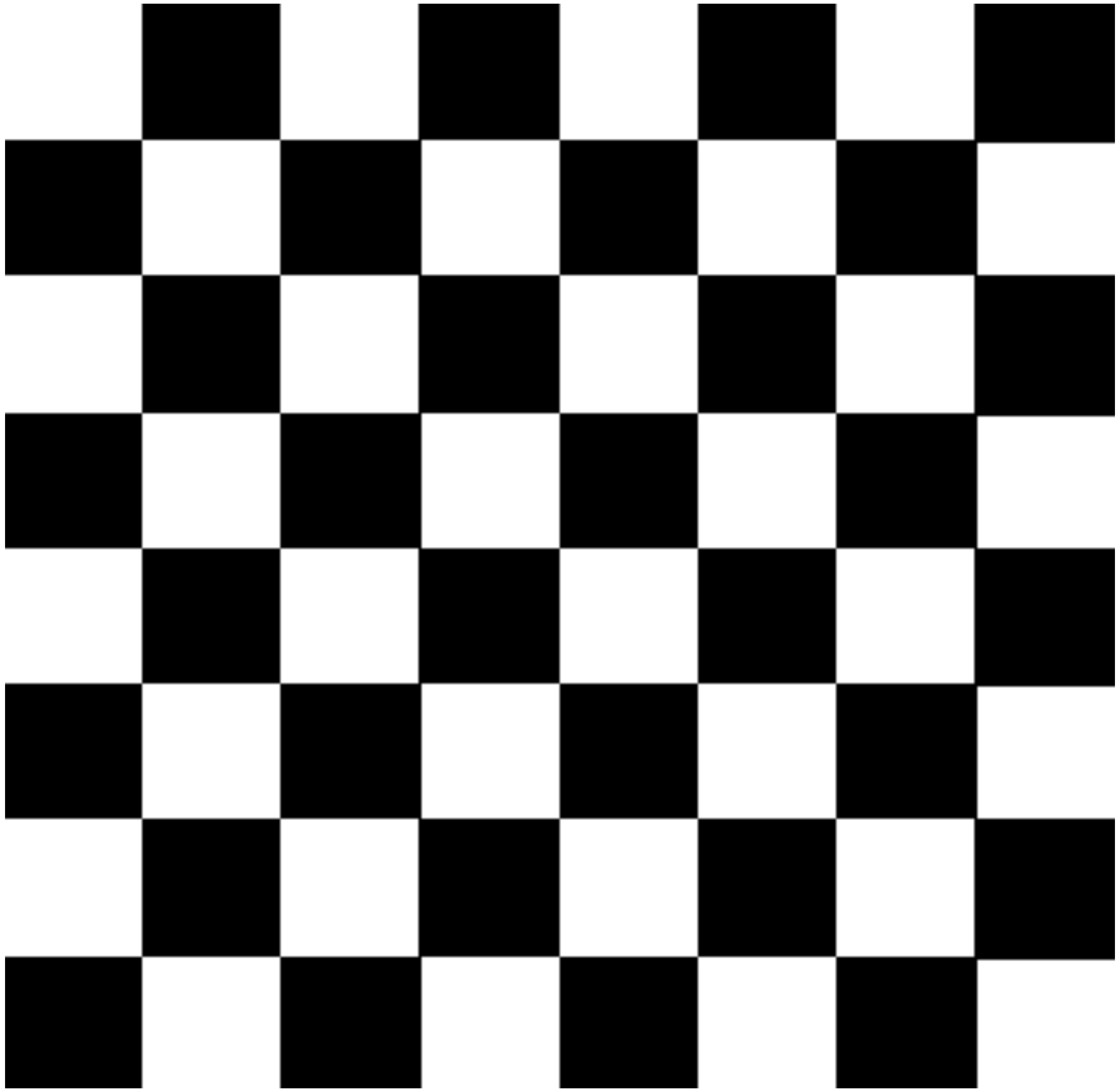
Eight Queens Problem



Three attacks: score -3

Two Approaches

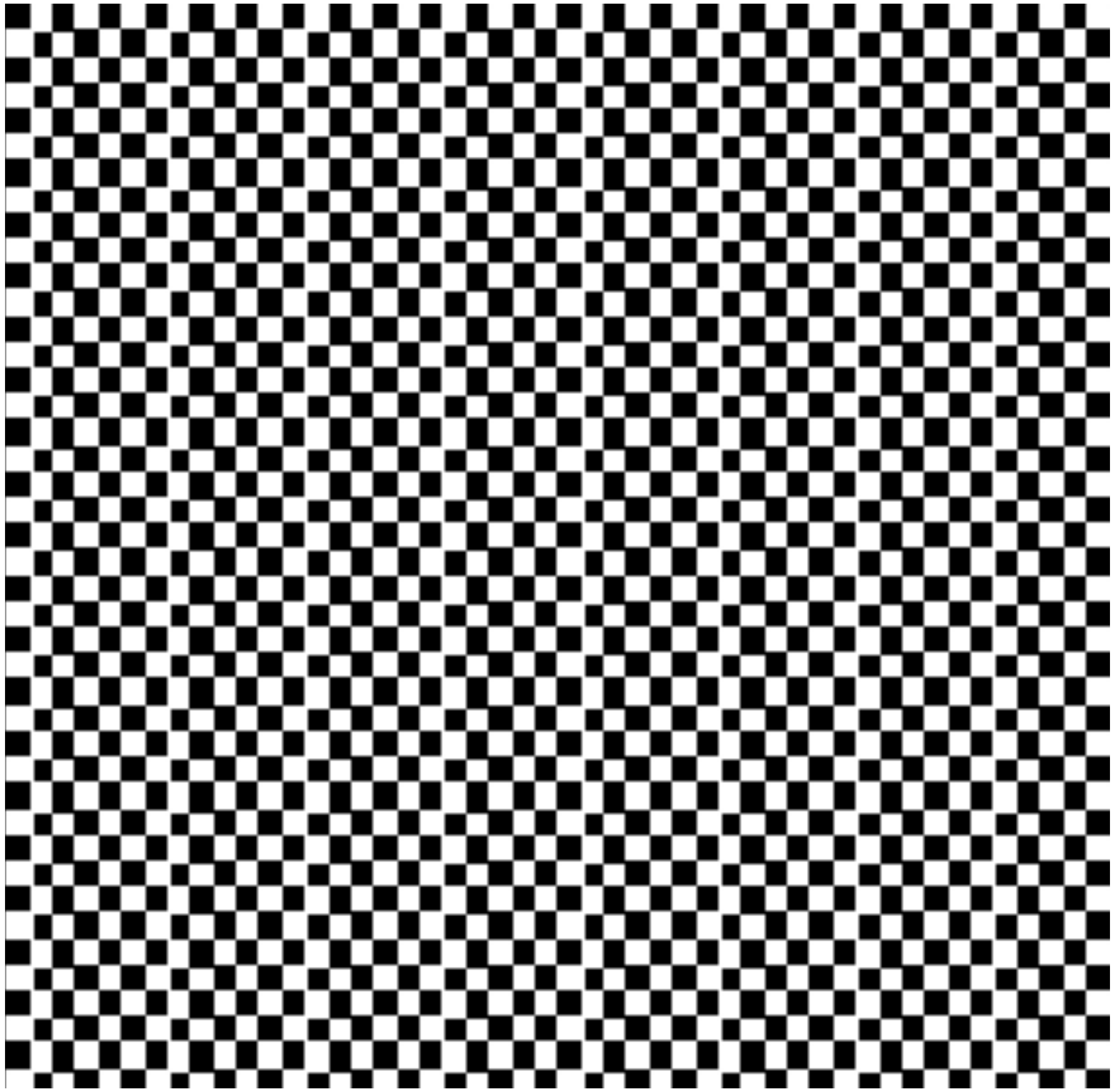
Build an algorithm that produces a solution to the problem by placing one piece at a time



Build an algorithm that compares two solutions to the problem; try different solutions, keep the better one, until you solve the problem

Does it scale?

44 Queens Problem



Place 44 Queens on the board with no attack.

10^{12} Queens Problem

Place 10^{12} Queens on the board with no attack.

Trial and Error

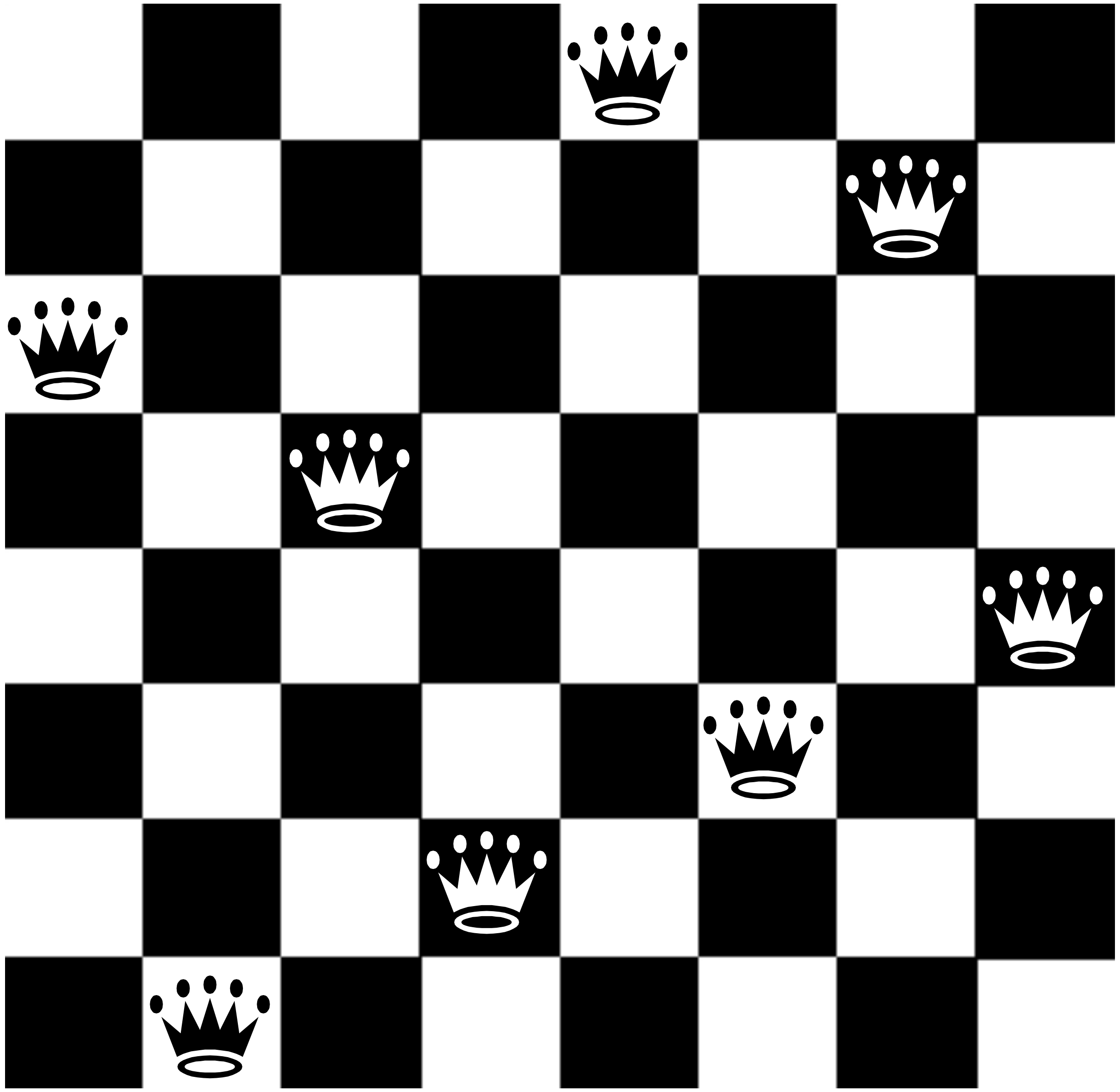
- Abundance of computational resources means many domains are adopting (knowingly or not) a similar approach.
  - Corpus-based NLP
  - Go (the only competitive AI players are based on Monte-Carlo Method)
  - Many application of machine learning

Key Ingredients

- **What** are we going to try this time? (representation)
- How is it **different** from what we tried before? (operators)
- **How well** did we do this time? (fitness/objective function)
- Minor (but critical) ingredients: constraints

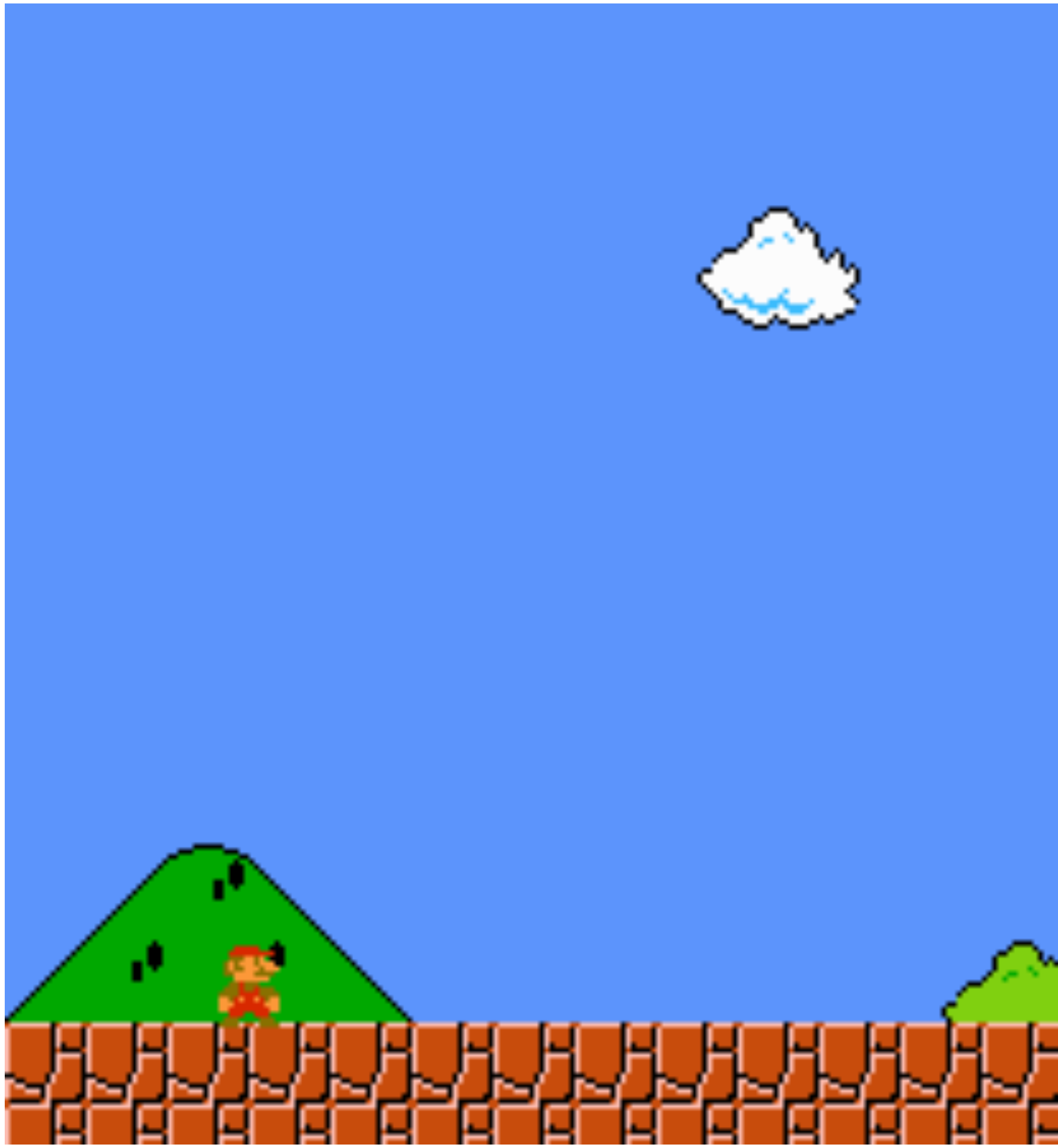
8 Queens Problem

- Representation: 8 by 8 matrix
- Operators: generate one valid board position from the current position, following the rule about Queen's movement
- Fitness function: number of attacks (to be minimised)



Super Mario Bros.

- Representation: a list of `(button, start_time, end_time)`
- Operators: change `button` type in one tuple, increase/decrease `start_time` or `end_time`
- Fitness function: the distance you travelled without dying



Universal Viewpoint

- There are many algorithms in computational intelligence; you do need to learn individual algorithms in detail.

- However, I also want to communicate a frame of thinking, not only individual algorithms.

- The tuple of (representation, operators, fitness function) can be a universal platform to understand different classes of algorithms.

- We will revisit individual algorithms, using this tuples.

Design dictates solution

- Incorrect representation: what happens if we use **`(button, pressed_time)`** instead?

- Using wrong operators: what happens if we decrease/increase **`start_time`** and **`end_time`** by 5 seconds?

- Missing constraints: what happens if we swap the order of two tuples?

- Measuring the wrong fitness: what happens if we use the time elapsed until death? Or the final score?

Exploitation vs. Exploration

- Exploitation: if a candidate solution looks promising, optimisation should focus on that particular direction. However,

- Exploration: unexplored solution space may contain something *much better*.

- How to balance these two is critical to all learning/ optimisation algorithms.

Machines are Dumb and Lazy

- Like human, they will do the minimum work that passes your criteria, i.e. design of the optimisation problem.

- Not because of their work ethic, but because of the fact that, usually, minimum work is the easiest to find solution.

Case Study: GenProg

- GenProg uses stochastic optimisation to modify existing faulty software code, until it passes all tests.
- We can only tell it to try until it passes all tests, not until the program is correct.

GOODNESS, YOU'RE FILTHY. INTO THE TUB WITH YOU.
I OBEY THE LETTER OF THE LAW, IF NOT THE SPIRIT.
LET'S HEAR SOME WATER RUNNING!
NUTS.

Anecdotes borrowed from Wes Weimer's SSBSE 2013 Keynote: https://www.cs.virginia.edu/~weimer/p/weimer-ssbse2013.pdf

Things GenProg Did…

- **`nullhttpd`**: test case for POST function failed; GenProg removed the entire functionality.

- **`sort`**: test required output to be sorted; GenProg's fix was to always output an empty set.

- Tests compared **`output.txt`** to **`correct_output.txt`**; GenProg deleted **`correct_output.txt`** and printed nothing.

Current State of the Art

- Low hanging fruits almost gone: “I applied algorithm X to problem Y” no longer counts.

- Metric-based optimisation (where fitness equals an existing SE metric) is starting to be criticised. Compare the following two papers:

    - M. Harman and J. Clark. **Metrics are fitness functions too**. In 10th International Software Metrics Symposium (METRICS 2004), pages 58–69, Los Alamitos, California, USA, Sept. **2004**. IEEE Computer Society Press.

    - C. Simons, J. Singer, and D. R. White. **Search-based refactoring: Metrics are not enough**. In M. Barros and Y. Labiche, editors, Search-Based Software Engineering, volume 9275 of Lecture Notes in Computer Science, pages 47–61. Springer International Publishing, **2015**.

How to do better?

- Try to learn from human engineers more.
- Eventually, solutions from SBSE should be adopted because humans accept it, **not** because the fitness value is above an arbitrary cut-off point X.
- Turing-test as fitness function!

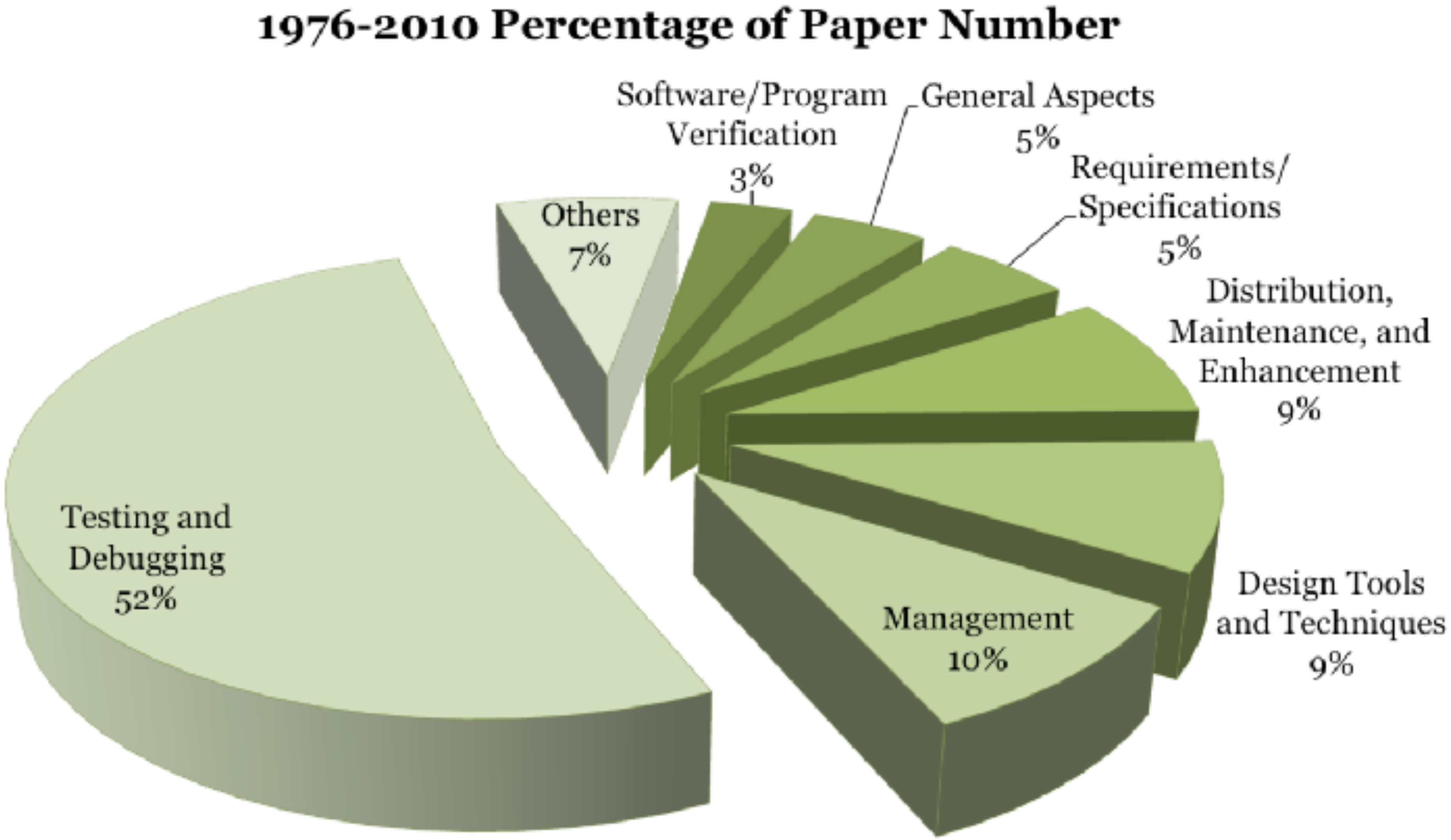
Expected Learning Outcome

- **Understand** basic metaheuristic algorithms; learn how to **implement** and **adapt** one to a given problem.

- **Embrace** metaheuristic optimisation as a valid tool for software engineers.

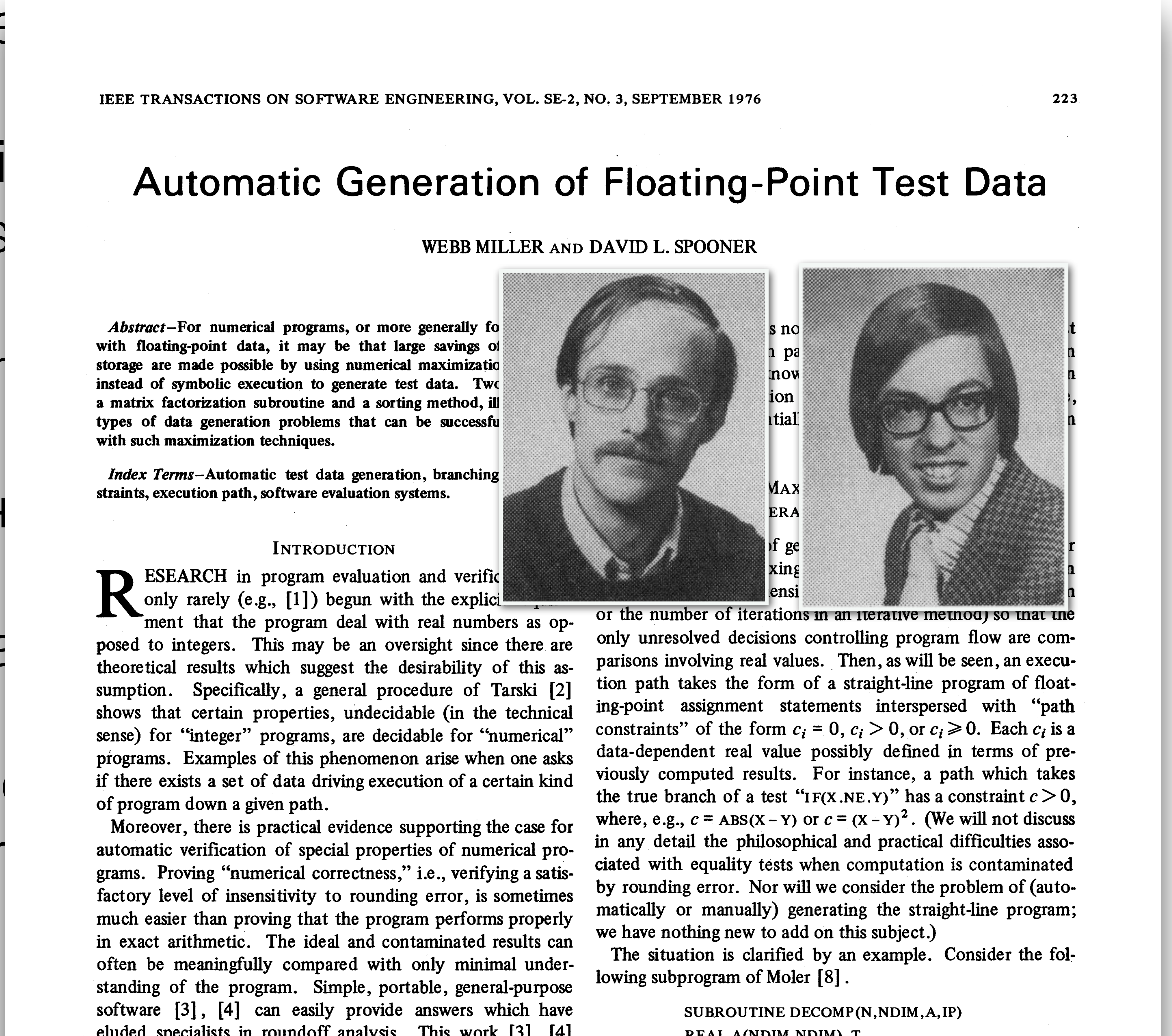
- Gain knowledge of the **literature**; learn **case studies** for various software development lifecycle stages.

Problem Domains



Structural Testing

- Take CS453 Automate
- Intuitively: define the i structural coverage; s
  - Symbolic executio
  - Dynamic analysis +
- Either way, huge adva
  - Clearly defined fitn on achieving cover



IEEE TRANSACTIONS ON SOFTWARE ENGINEERING, VOL. SE-2, NO. 3, SEPTEMBER 1976 223

Automatic Generation of Floating-Point Test Data

WEBB MILLER AND DAVID L. SPOONER

Abstract—For numerical programs, or more generally fo with floating-point data, it may be that large savings of storage are made possible by using numerical maximizatio instead of symbolic execution to generate test data. Two a matrix factorization subroutine and a sorting method, ill types of data generation problems that can be successfu with such maximization techniques.

Index Terms—Automatic test data generation, branching straints, execution path, software evaluation systems.

INTRODUCTION

RESEARCH in program evaluation and verific only rarely (e.g., [1]) begun with the explici ment that the program deal with real numbers as opposed to integers. This may be an oversight since there are theoretical results which suggest the desirability of this assumption. Specifically, a general procedure of Tarski [2] shows that certain properties, undecidable (in the technical sense) for "integer" programs, are decidable for "numerical" programs. Examples of this phenomenon arise when one asks if there exists a set of data driving execution of a certain kind of program down a given path.

Moreover, there is practical evidence supporting the case for automatic verification of special properties of numerical programs. Proving "numerical correctness," i.e., verifying a satisfactory level of insensitivity to rounding error, is sometimes much easier than proving that the program performs properly in exact arithmetic. The ideal and contaminated results can often be meaningfully compared with only minimal understanding of the program. Simple, portable, general-purpose software [3], [4] can easily provide answers which have eluded specialists in roundoff analysis. This work [3], [4]

or the number of iterations in an iterative method) so that the only unresolved decisions controlling program flow are comparisons involving real values. Then, as will be seen, an execution path takes the form of a straight-line program of floating-point assignment statements interspersed with "path constraints" of the form $c_i = 0$, $c_i > 0$, or $c_i \geqslant 0$. Each c_i is a data-dependent real value possibly defined in terms of previously computed results. For instance, a path which takes the true branch of a test "IF(X.NE.Y)" has a constraint $c > 0$, where, e.g., $c = \text{ABS}(X - Y)$ or $c = (X - Y)^2$. (We will not discuss in any detail the philosophical and practical difficulties associated with equality tests when computation is contaminated by rounding error. Nor will we consider the problem of (automatically or manually) generating the straight-line program; we have nothing new to add on this subject.)

The situation is clarified by an example. Consider the following subprogram of Moler [8].

```
SUBROUTINE DECOMP(N,NDIM,A,IP)
REAL A(NDIM,NDIM), T
```

Oracle Problem

- Coverage is not enough: “was the last execution **correct**?”
- Test oracle tells you whether the observed execution was correct or not
- Formal specification can serve as one; manual inspection by human can serve as one. But how do we automatically generate oracles?
- We want to test the code; we automatically generate test from the code; we want to check whether the test passed; we automatically generate test oracle from the co… wait a minute!
- This is a very hard problem; one which the state of the art does not know how to solve.

Testing non-functional properties

- Worst-Case Execution Time Analysis: strictly necessary for certain embedded systems (e.g. airbag controller), very hard to do statically; genetic algorithm has been very successful.
    - J. Wegener and M. Grochtmann. Verifying timing constraints of real-time systems by means of evolutionary testing. Real-Time Systems, 15(3): 275 – 298, 1998.

Requirements Engineering

- Next Release Problem: given cost and benefit (expected revenue) for each features, what is the best subset of features to be released for budget B?
    - 0-1 Knapsack (NP-complete)
    - But release decisions are more political than NP-complete.
- Sensitivity Analysis: requirements data are usually estimates; which estimation will have the largest impact on the project, if it is off by X%?

Project Management & Planning

- Quantitatively simulate and measure the communication overhead (linear? logarithmic?)
- Robust planning: search for the tradeoff between overrun risk, project duration, and amount of overtime assignment

Design/architecture/ refactoring

- Cluster software models to achieve certain structural properties (cohesion/coupling).

- Ironically, SBSE has also been used to analyse refactoring metrics: metric A and B both claim that they measure the same concept - optimising for A resulted in worse value of B, and vice versa :)

Genetic Improvement

- Given a source code, can we automatically improve its non-functional properties (such as speed)?

- Genetic Programming has been successfully applied to make genome-sequencing software 70 times faster. 70!

    - W. Langdon and M. Harman. Optimizing existing software with genetic programming. Transactions on Evolutionary Computation, 19(1):118–135, 2015.

- Evolve a specialised version of MiniSAT solver for problem classes.

    - J. Petke, M. Harman, W. B. Langdon, and W. Weimer. Using genetic improvement and code transplants to specialise a C++ program to a problem class. In proceedings of the 17th European Conference on Genetic Programming, volume 8599 of LNCS, pages 137–149. Springer, 2014.

Code Transplantation

- Software X has feature A, which you want to have in software Y. Can we automatically extract and transplant feature A from X to Y?
    - E. T. Barr, M. Harman, Y. Jia, A. Marginean, and J. Petke. Automated software transplantation. In Proceedings of the 2015 International Symposium on Software Testing and Analysis, ISSTA 2015, pages 257–269.

Summary

- Key ingredients to SBSE: representation, operators, fitness function.

- Design dictates solutions.

- Applications across all software development lifecycle activities, and beyond.

SBSE Repository

- http://crestweb.cs.ucl.ac.uk/resources/sbse_repository/