What We Talk About When We Talk About Evolutionary Computation

Giovanni Squillero
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What is EA?

https://github.com/squillero/10k/

september 2022 **version 1.2**

2

What We
When We
Evolution
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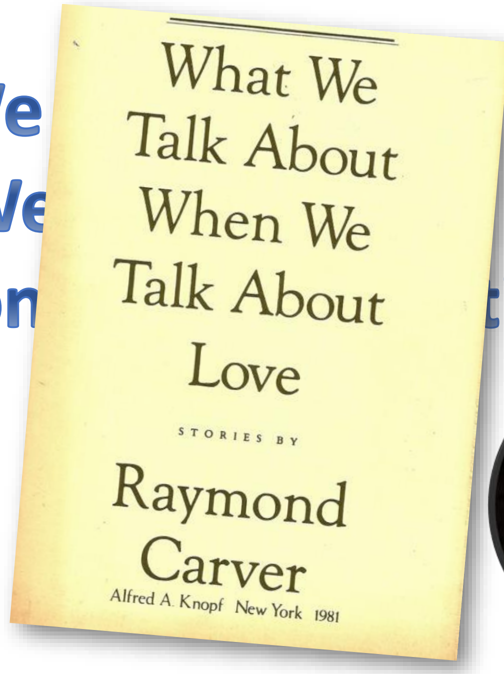

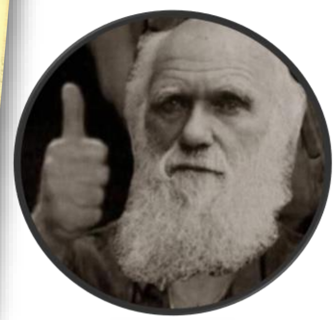

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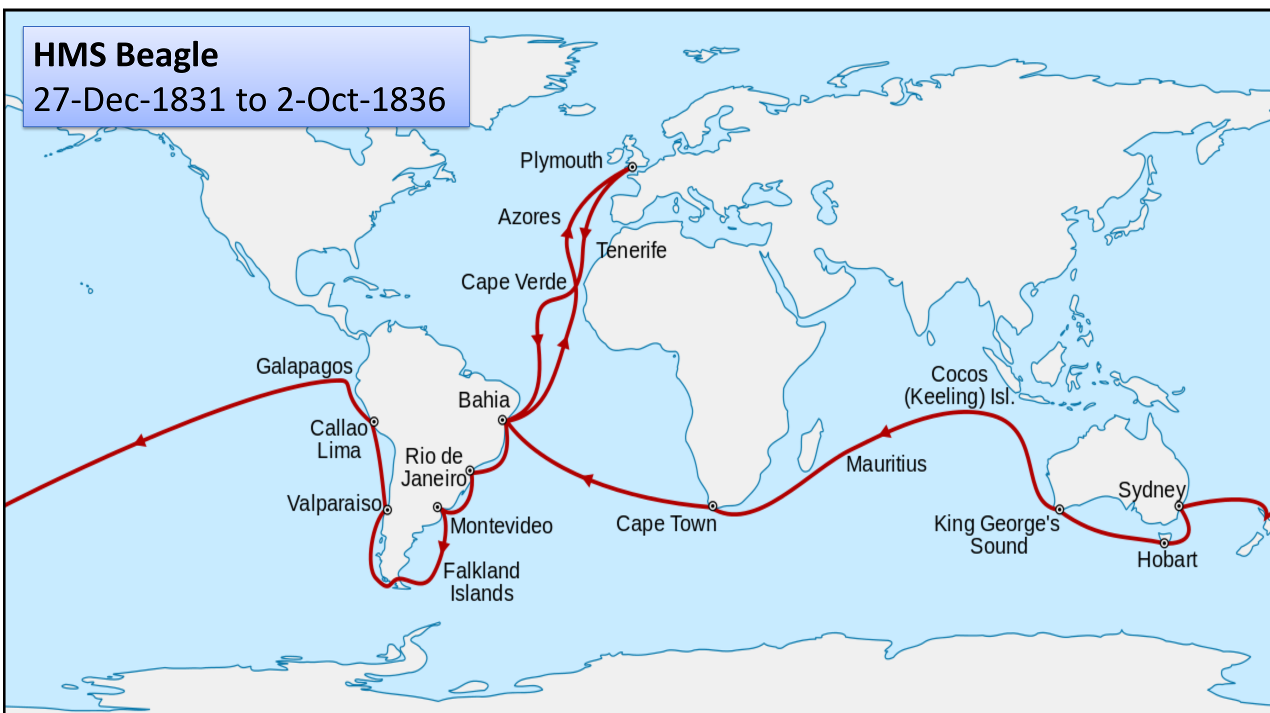
HMS Beagle
27-Dec-1831 to 2-Oct-1836



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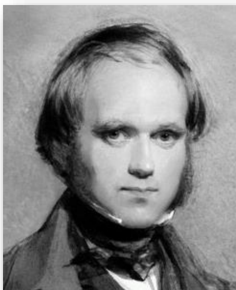
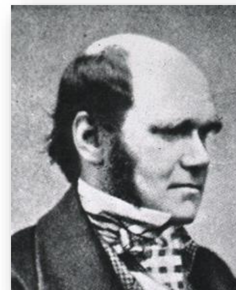
Charles Robert Darwin



1831-36



1859

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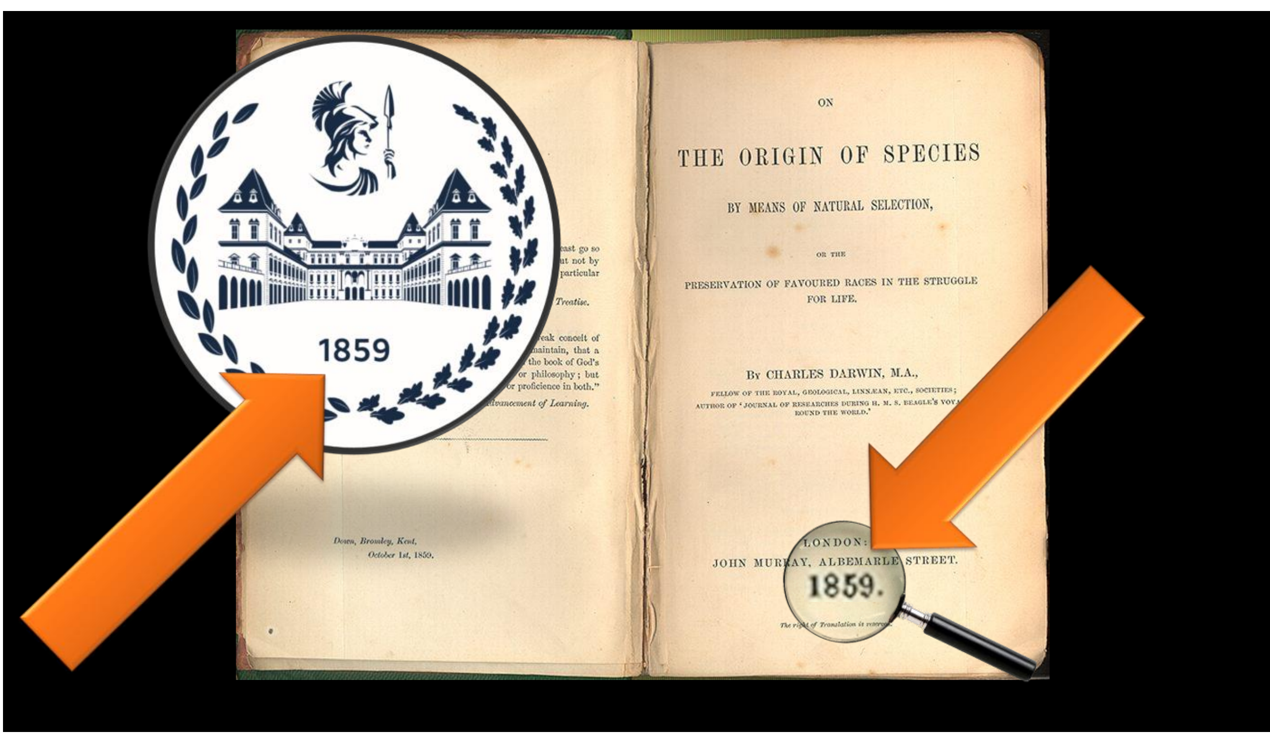

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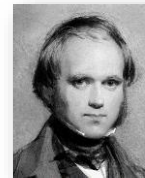
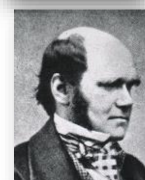
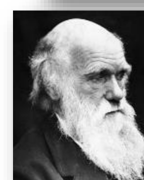
Charles Robert Darwin

- **1809**: Charles Robert Darwin born in Shrewsbury
- **1831–1836**: Voyage of the Beagle
- **1842–1846**: Three volumes of geological observations (formation of atoll & reef)
- **1851–1854**: Four volumes on barnacles
- **1859**: *On the Origin of Species*
- **1862–1881**: Many publications on botanic (mainly orchids), studies on variations of domestic plants and animals …
- **1871**: *The Descent of Man, and Selection in Relation to Sex*
- **1882**: Died in Downe

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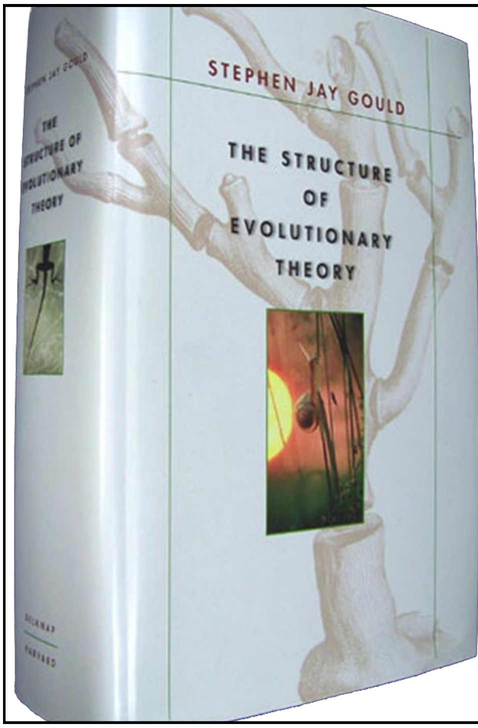

Suggested Reading

Stephen Jay Gould

The structure of evolutionary theory

Hardcover: 1,433 pages

Belknap Press: Harvard University Press (March 21, 2002)

6.8 x 3 x 10 inches, 4.3 pounds

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From Biology to Computer Science

- The **accumulation** of **tiny variations**
- Evolutions is a sequence of **two** contributions
  - Variations (mostly **random**)
  - Selection (mostly **deterministic**)
- In evolution, changes are not **designed**

  …but merely **evaluated**

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From Biology to Computer Science

- The **accumulation** of **tiny variations**
- Evolutions is a sequence of **two** contributions
  – Variations (mostly **random**)
  – Selection (mostly **deterministic**)
- In evolution, changes are not **designed**
  …but merely **evaluated**
- Evolution is **not** a **random** process
  … though random variability *"afford materials"*

From Biology to Computer Science

- Evolution is **not** an **optimization** process
- Evolution does **not** have a **goal**
- Evolution does **not** favor **strength**
- Evolution does **not** favor **intelligence**

From Biology to Computer Science

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- Evolution does **not** favor **intelligence**

However…

- When all variations are accumulated in **one** specific **direction** the final outcome may look like the product of an **intelligent design**!

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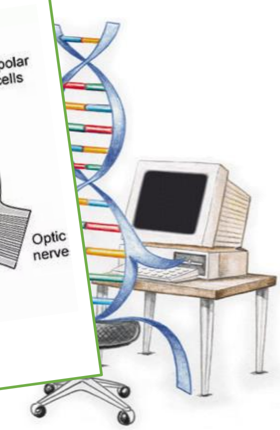
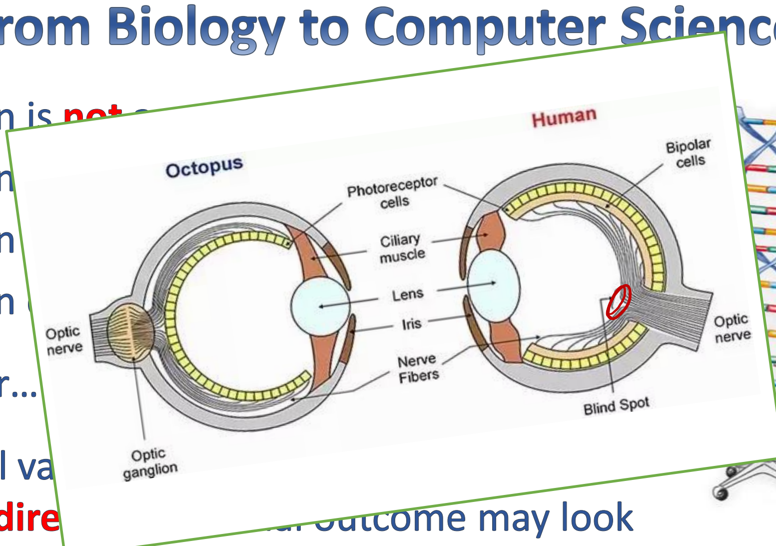
From Biology to Computer Science

- Evolution is **not** a
- Evolution
- Evolution
- Evolution

However…

- When all va specific **dire** outcome may look like the product of an **intelligent design**!





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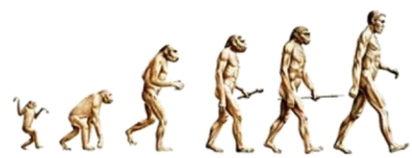
Summary

- Introduction
- **What is an EA**
- Classical Paradigms
- How they work, why they fail
- Evolutionary Computation vs. Machine Learning



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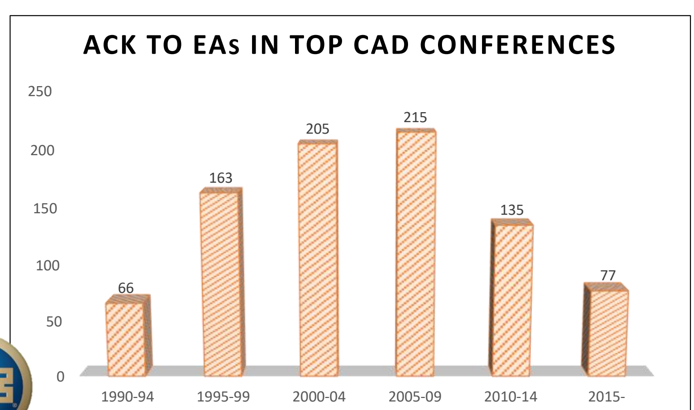
Evolutionary Algorithm

- A **generic population-based metaheuristic** optimization algorithm that uses some mechanisms **vaguely inspired** by biological evolution
  - – Embryonic research: 50s
  - – Working prototypes: 60s
  - – Research: since 80s
  - – Real use: since 90s



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Evolutionary Algorithm

- Candidate solution → Individual
- Set of candidate solutions → Population
- Ability to solve the problem → Fitness
- Sequence of steps → Generations

Individual

- Encode a potential solution for the problem. E.g.,
  - A list of real numbers
  - A sequence of cities
  - A bit string
  - A path out of a maze
  - An analog circuit
  - A weighted multi graph
  - …

Population

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Parent Selection

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Genetic operators

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Offspring (new individuals)

24

Evaluation

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Survival Selection

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27

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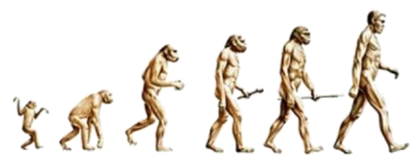

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"Classical" Paradigms

- Genetic Algorithm (**GA**)
  - John H. Holland
- Evolution Strategies (**ES**)
  - Ingo Rechenberg & Hans-Paul Schwefel
- Evolutionary Programming (**EP**)
  - Lawrence J. Fogel
- Genetic Programming (**GP**)
  - John R. Koza

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More EAs (incomplete list)

- **Swarm** Intelligence
  - Make an effective behavior emerge out of (partially coordinated) simple agents (e.g., **ants**, **bees**, **wasps**, …)
- Population-less (a.k.a., **E**stimation of **D**istribution **A**lgorithms)
  - Substitute the set of individuals with its statistical parameters
- Real-value optimization
  - **D**ifferential **E**volution
  - **CMA**-ES

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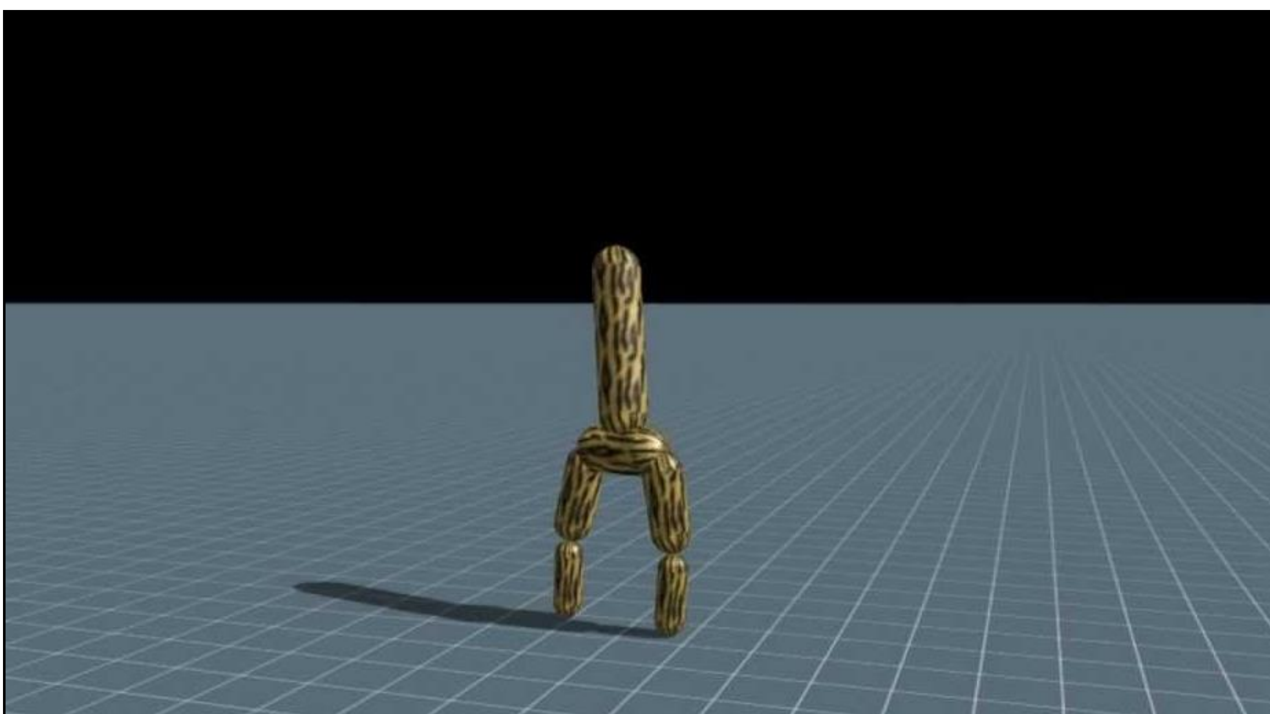

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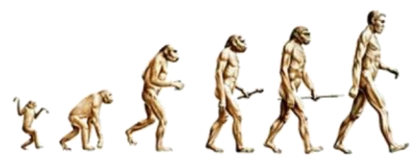

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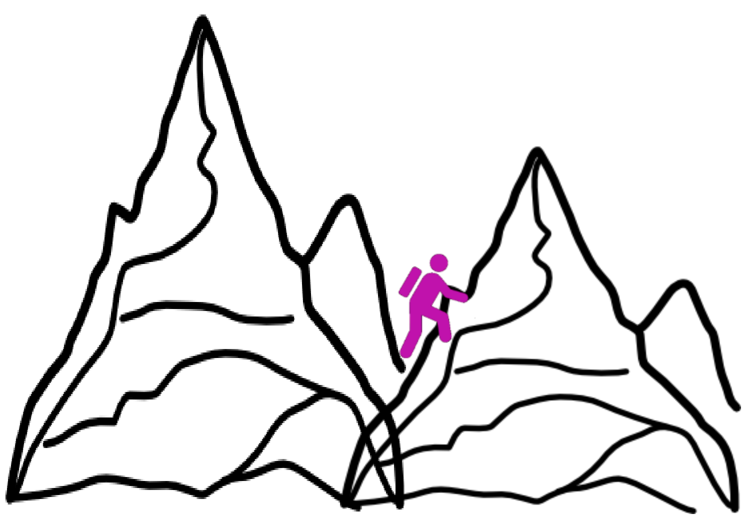
Hill climber



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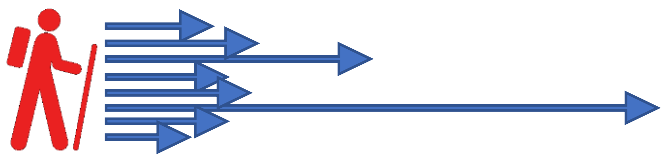
EA: Variable step size



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EA: Population based

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Inheritance

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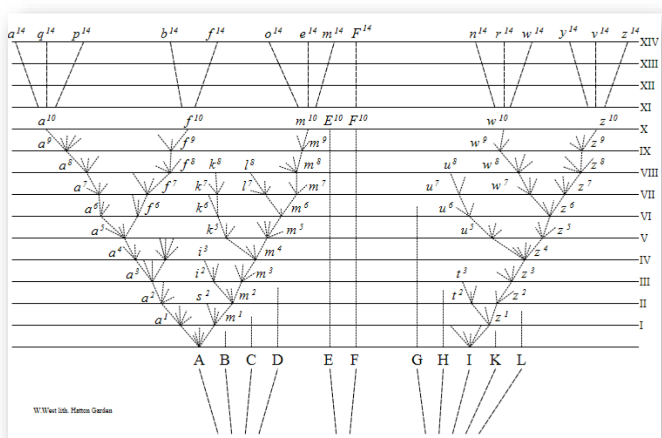
Natural Evolution

- **Fitness**
- **Genotype**
- **Phenotype**



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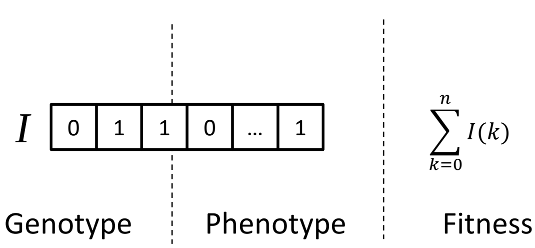
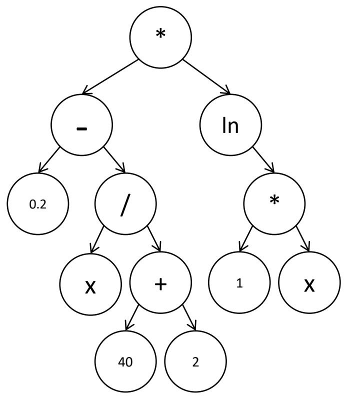
Levels in EC

- **Fitness**: how well the candidate solution is able to solve the target problem
- **Genotype**: the internal representation of the individual, i.e., what is directly manipulated by genetic operators
- **Phenotype**: the candidate solution that is encoded in the genotype
  - the intermediate form in which the genotype needs to be transformed into for evaluating fitness
  - if genotype can be directly evaluated: genotype and phenotype coincide

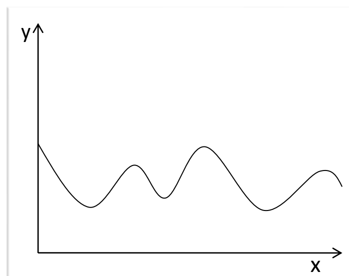
Levels in EC



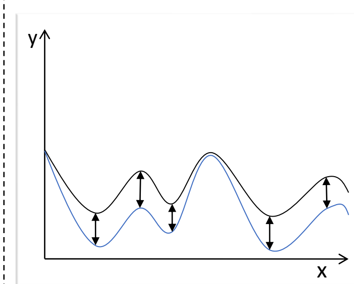
Levels in EC



$$f(x) = \left(0.2 - \frac{x}{42}\right) \cdot \ln(x)$$

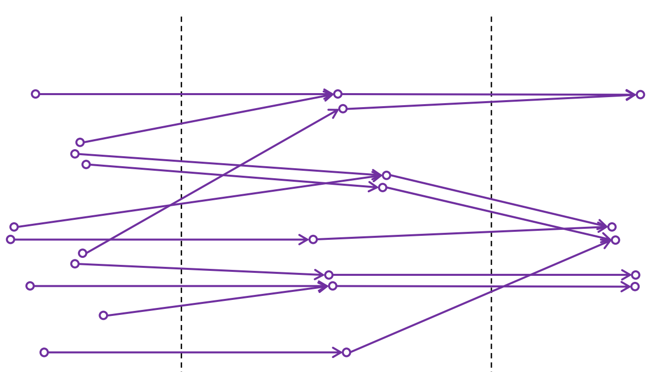


Fitness $\approx \int_{x=0}^{E} |f(x) - g(x)|$



Genotype | Phenotype | Fitness

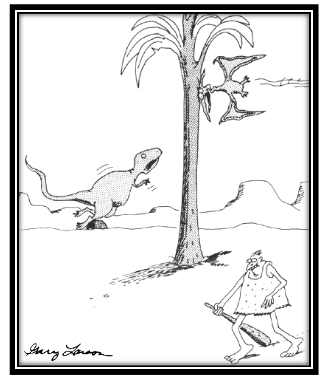
Indirect Mappings



Genotype | Phenotype | Fitness

Importance of mappings

- **Small** differences should bring **small** differences in the fitness (**locality**)



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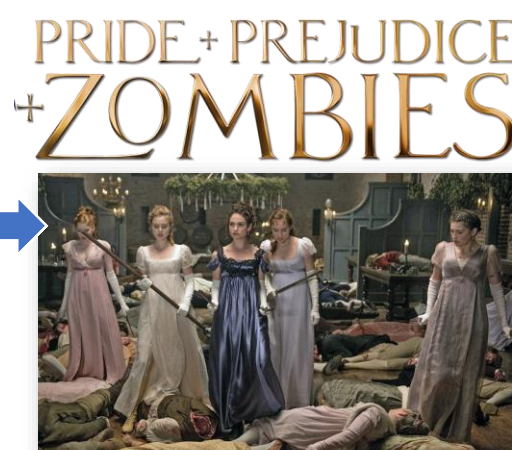
Importance of encoding

- **Genetic** operators should make sense at **phenotype** level

Austen

Romero



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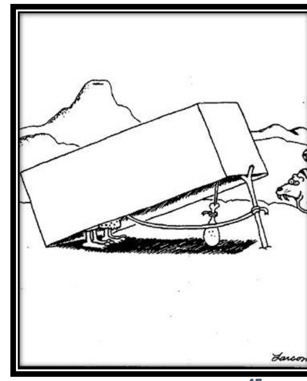
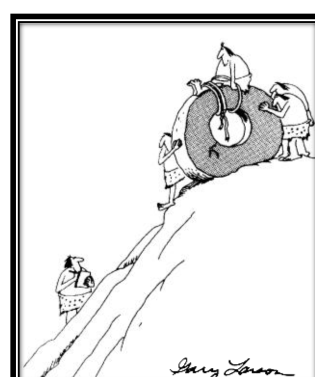
Importance of fitness

- **Differential survivals**



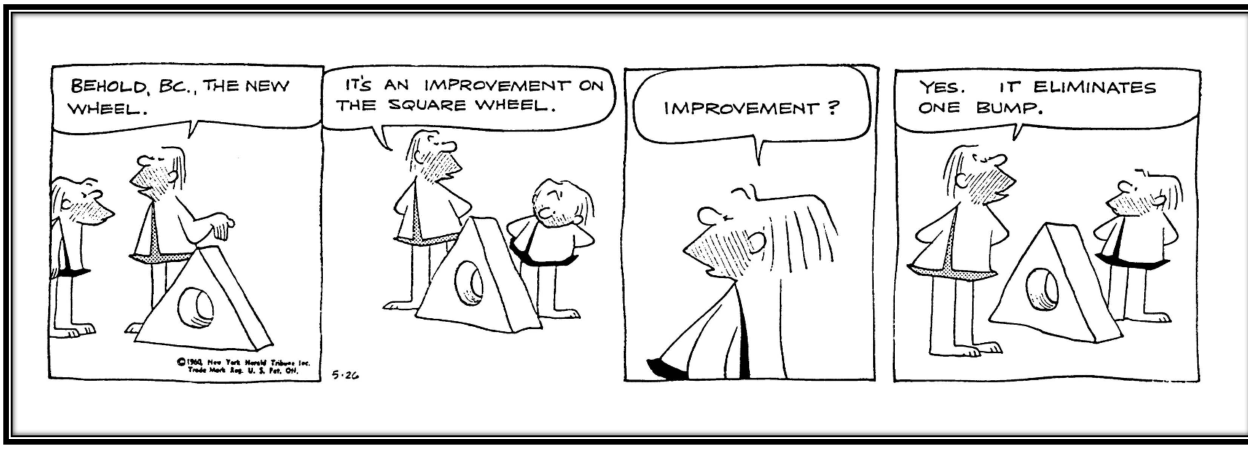
Importance of fitness

- **Differential survivals**
- **Each** single **difference** must bring an **advantage** over others



Importance of fitness

- The fitness must reflect your **true** goal



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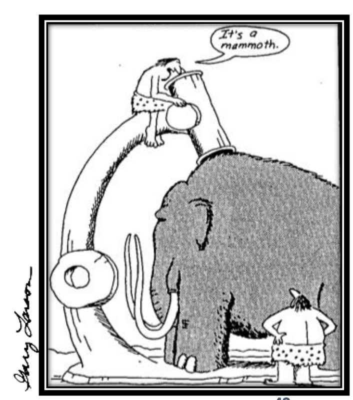
Exploration **vs.** Exploitation

- **Recombination**
  - **Mixes** together two or more solutions to create the offspring
  - Associated with the idea of exploration
- **Mutation**
  - Performs a (usually small) **change** in an individual
  - Associated with the idea of exploitation



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Exploration vs. Exploitation

- When all parents are very similar, the effectiveness of recombination is limited
- The ability to explore remote parts of the search space is impaired
- "**Conventional wisdom** suggests that increasing diversity should be generally beneficial"

Exploration vs. Exploitation

- When all parents are very similar, the effectiveness of recombination is limited

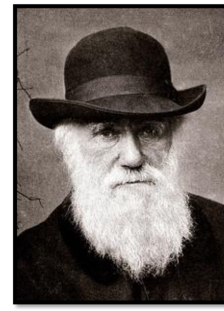
what is the definition of "similar"?

- The ability to explore remote parts of the search space is impaired

and the definition of "diversity"?

- "**Conventional wisdom** suggests that increasing diversity should be generally beneficial"

Divergence of character



- "**Great diversity** of forms in nature"
- "The principle, which I have designated by this term, is of **high importance**, and explains, as I believe, several important facts"
  - "The principle of divergence causes **differences**, at first barely appreciable, to **steadily** to **increase**, and the breeds to diverge in character, both from each other and from their common parent"
  - "The varying descendants of each species try to occupy as many and as **different places** as possible in the **economy of nature**"

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Premature convergence

- I.e., the tendency of an algorithm to **converge** towards a point where it was **not supposed to converge** to in the first place
- Probably an oxymoron
- **General inability** to exploit environmental niches
- Holland's "**Lack of speciation**"
- **Endemic problem** of EAs

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Divergence of character

- “The basic point of the principle of divergence is **simplicity itself**: the more the coinhabitants of an area differ from each other in their ecological requirements, the less they will compete with each other; therefore natural selection will tend to favor any variation toward greater divergence.“

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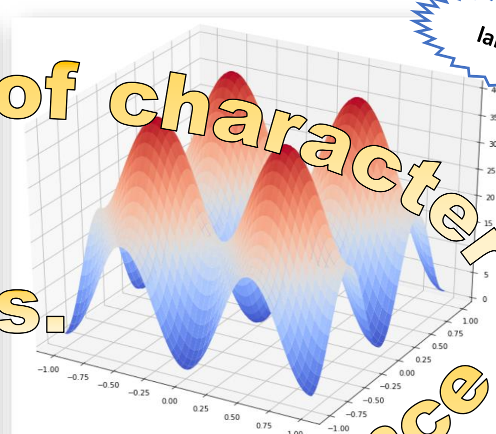
Environment vs. Fitness function

ecosystem

environment

landscape



divergence of character

vs.

premature convergence

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Promoting Diversity in EA

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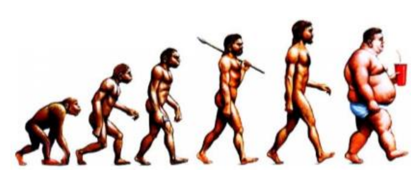

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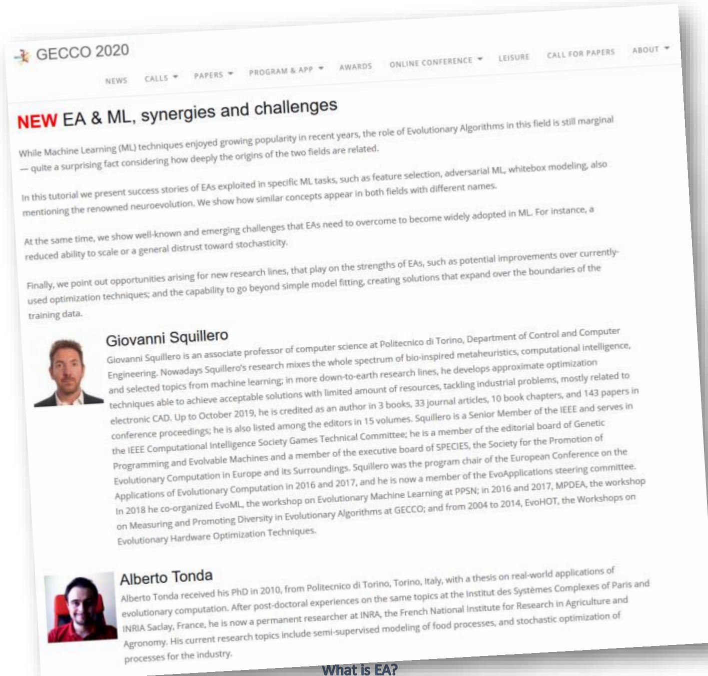

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NEW EA & ML, synergies and challenges

While Machine Learning (ML) techniques enjoyed growing popularity in recent years, the role of Evolutionary Algorithms in this field is still marginal — quite a surprising fact considering how deeply the origins of the two fields are related.

In this tutorial we present success stories of EAs exploited in specific ML tasks, such as feature selection, adversarial ML, whitebox modeling, also mentioning the renowned neuroevolution. We show how similar concepts appear in both fields with different names.

At the same time, we show well-known and emerging challenges that EAs need to overcome to become widely adopted in ML. For instance, a reduced ability to scale or a general distrust toward stochasticity.

Finally, we point out opportunities arising for new research lines, that play on the strengths of EAs, such as potential improvements over currently-used optimization techniques; and the capability to go beyond simple model fitting, creating solutions that expand over the boundaries of the training data.

Giovanni Squillero

Giovanni Squillero is an associate professor of computer science at Politecnico di Torino, Department of Control and Computer Engineering. Nowadays Squillero's research mixes the whole spectrum of bio-inspired metaheuristics, computational intelligence, and selected topics from machine learning; in more down-to-earth research lines, he develops approximate optimization techniques able to achieve acceptable solutions with limited amount of resources, tackling industrial problems, mostly related to electronic CAD. Up to October 2019, he is credited as an author in 3 books, 33 journal articles, 10 book chapters, and 143 papers in conference proceedings; he is also listed among the editors in 15 volumes. Squillero is a Senior Member of the IEEE and serves in the IEEE Computational Intelligence Society Games Technical Committee; he is a member of the editorial board of Genetic Programming and Evolvable Machines and a member of the executive board of SPECIES, the Society for the Promotion of Evolutionary Computation in Europe and its Surroundings. Squillero was the program chair of the European Conference on the Applications of Evolutionary Computation in 2016 and 2017, and he is now a member of the EvoApplications steering committee. In 2018 he co-organized EvoML, the workshop on Evolutionary Machine Learning at PPSN; in 2016 and 2017, MPDEA, the workshop on Measuring and Promoting Diversity in Evolutionary Algorithms at GECCO; and from 2004 to 2014, EvoHOT, the Workshops on Evolutionary Hardware Optimization Techniques.

Alberto Tonda

Alberto Tonda received his PhD in 2010, from Politecnico di Torino, Torino, Italy, with a thesis on real-world applications of evolutionary computation. After post-doctoral experiences on the same topics at the Institut des Systèmes Complexes of Paris and INRIA Saclay, France, he is now a permanent researcher at INRA, the French National Institute for Research in Agriculture and Agronomy. His current research topics include semi-supervised modeling of food processes, and stochastic optimization of processes for the industry.

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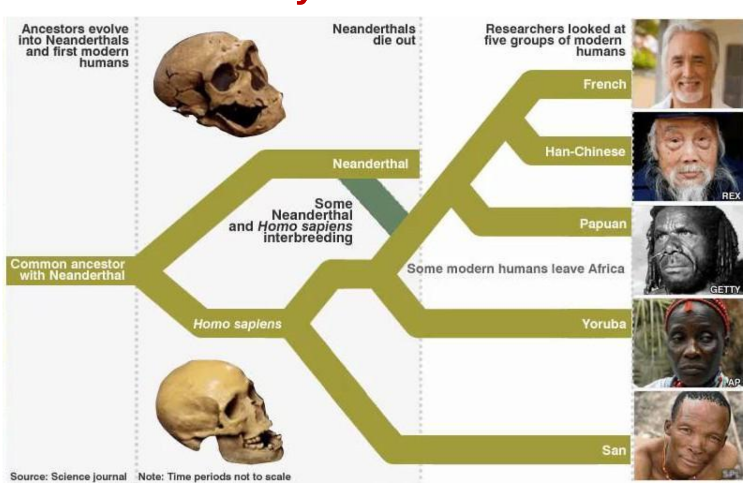
A common origin?
Shared themes and crossways?



Green, Richard E., et al. "A draft sequence of the Neandertal genome." *science* 328.5979 (2010): 710-722.

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A common origin?

- Both ML and EC scholars point to the **very same** paper as the **starting point** of their fields:
  - Turing AM. Computing "Machinery and Intelligence". *Mind*. 1950 Oct 1;LIX(236):433–60
- The **term** "Machine Learning" was popularized by Arthur Samuel in a paper describing an **evolutionary approach** for playing checkers
  - Samuel AL. *Some Studies in Machine Learning Using the Game of Checkers*. *IBM Journal of Research and Development*. 1959 Jul;3(3):210–29.
- Seminal works in EC explicitly refer to the "Machine Learning" keyword
  - E.g., Goldberg DE, Holland JH. "Genetic Algorithms and Machine Learning". *Machine Learning*. 1988 Oct 1;3(2):95–9
  - Goldberg DE. *Genetic Algorithms in Search, Optimization and Machine Learning*. 1st ed. USA: Addison-Wesley Longman Publishing Co., Inc.; 1989. 372 p.

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Shared themes and crossways

- Learning without the need of human expertise
- DeepMind's AlphaZero
  - "Mastering chess and shogi **by self-play** with a general reinforcement learning algorithm"
- Fogel's Blondie24
  - "Evolving neural networks to play checkers **without relying on expert knowledge**"
- "Overlapping subsquares" vs. "Convolutional neural network"

Silver D, Hubert T, Schrittwieser J, Antonoglou I, Lai M, Guez A, et al. "Mastering chess and shogi by self-play with a general reinforcement learning algorithm". arXiv:171201815 [cs]. 2017 Dec.

Chellapilla K, Fogel DB. "Evolving neural networks to play checkers without relying on expert knowledge". IEEE Transactions on Neural Networks. 1999 Nov;10(6):1382–91.

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Shared themes and crossways

- Some boosting methods creates an ensemble of learners, **removing** points that have been **already solved** and **focusing** on the **remaining ones**
- Some EAs that target the creation of multiple populations for cumulatively solving a problem **remove** the part of the problem that have been **already solved** and **focus** on the **remaining ones**

Hansen, 2009. *Benchmarking a BI-Population CMA-ES on the BBOB-2009 Function Testbed*. GECCO'09

Freund, Y., & Schapire, R. E. 1995. *A decision-theoretic generalization of on-line learning and an application to boosting*. Springer, Berlin, Heidelberg.

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Shared themes and crossways

- **Reinforcement Learning** in ML is important and likely to play a pivotal role in the future
  - AlphaZero can be described as "a generic **reinforcement learning** algorithm"
  - Deep Reinforcement Learning (DRL) and Deep **Q-Networks** (DQNs) were demonstrated able to achieve impressive results
  - Multi-Agent RL (MARL) and Multi-Agent Deep RL (MADRL) are emerging techniques to handle problems where **multiple agents** need to communicate and cooperate
- **Reinforcement Learning** did play a pivotal role in EC
  - Holland's Learning Classifier Systems (LCS) are rule-based systems able to evolve and generalize set of **q-Learning-like** rules
  - Cooperative Coevolution is a well-known technique in EC to handle problems where **multiple agents** need to communicate and cooperate

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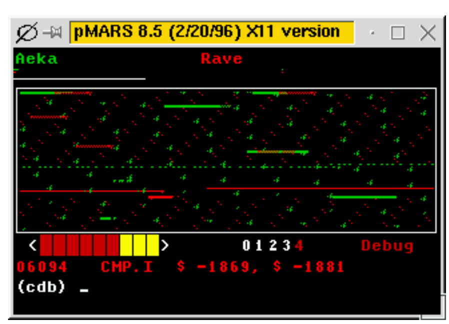
Shared themes and crossways

- Reinforcement Learning shares similarities with Co-evolution
  - In (Deep) RL, agents are trained on data, play against each other
  - Their games generate new data, that is then used to train the agents even more
  - In modern applications, agents are deep NNs, that replace the classical tables
- (Competitive) Co-evolution for games
  - Each individual in the population represents a different style of play
  - Individuals play against each other, obtaining a relative fitness score
  - The “learning” is modeled as the individuals’ genome
  - Successful individuals “hand down” part of their style of play to children

Shared themes and crossways

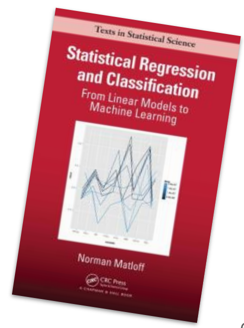
- Example of competitive co-evolution for games: Core Wars
  - A player in the game is a program in Redcode (similar to assembly)
  - Player and opponent are executed one line at a time, alternatively
  - Objective of the game is to force opponent to execute a non-valid instruction
  - Using competitive co-evolution, a Redcode program (WhiteNoise) was created
  - WhiteNoise was the champion of a competitive hill for months



Corno, F., Sánchez, E., & Squillero, G. (2005). *Evolving assembly programs: how games help microprocessor validation*. IEEE Transactions on Evolutionary Computation, 9(6), 695-706.

Shared themes and crossways

- Genetic Programming has been used for **Symbolic Regression** since the 1990s
- **Regression** is a popular application in modern ML



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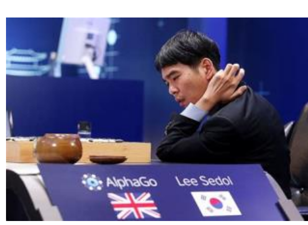
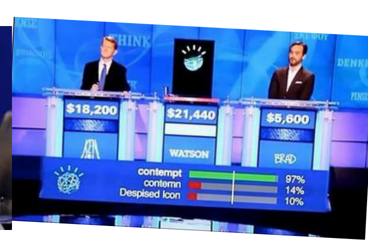
Popular moments in AI / ML

- **1997**: DeepBlue defeated then-reigning world chess champion Garry Kasparov in a six-game match
- **2011**: Watson defeated two renowned champions at Jeopardy
- **2016**: AlphaGo sealed 4-1 victory over Go grandmaster Lee Sedol





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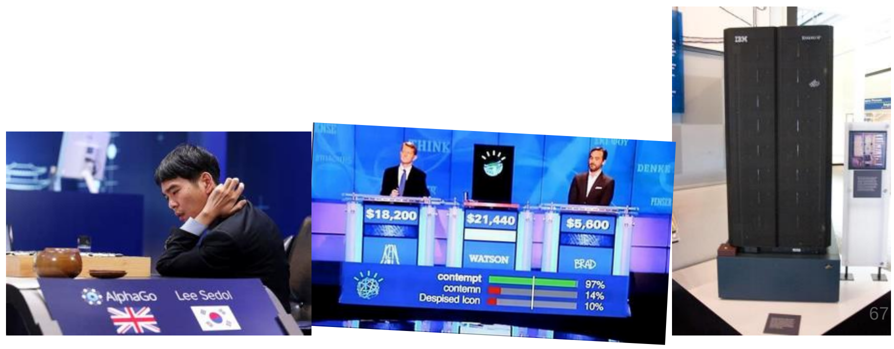
Popular moments in AI / ML

- **1997**: DeepBlue defeated then-reigning world chess champion Garry Kasparov in a six-game match
- **2011**: Watson defeated two renowned champions at Jeopardy
- **2012**: AlexNet achieved an astonishing top-5 error of 15.3% in ImageNet Large Scale Visual Recognition Competition
- **2016**: AlphaGo sealed 4-1 victory over Go grandmaster Lee Sedol



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Popular moments in EC

- **1964**: Der Spiegel published an article on using Evolutionary Computation for solving aerodynamic problems
- **2017**: Facebook admits using an evolutionary tool for uncovering critical software bugs

Werkes — Proust an eine Bekannte: „Odette de Crécy (eine seiner Romanfiguren) ist nicht nur nicht Sie, sondern genau das Gegenteil von Ihnen" — sowie vom qualvollen Kampf um die endgültige Edition der „Recherche", den Proust unter Schmerzen und Atemnot vom Bett aus führen mußte, arbeitsfähig nur durch Koffeintabletten, getrieben von Todesangst und von Furcht, die Veröffentlichung des Werkes nicht mehr zu erleben oder den „endlosen Wälzer" (Proust) überhaupt nicht vollenden zu können.

Als sich nach Erscheinen der ersten Bände unerwarteter Erfolg einstellte — für den zweiten Band erhielt Proust 1919 den Prix Goncourt —, lebte der Moribunde für kurze Zeit noch einmal auf. Er ging wieder aus, meistens nachts, und dinierte im Hotel Ritz, wo er totenbleich, mit fiebrigen Augen erschien, in einem hochbeleganten, aber derangierten Abendanzug, aus dessen Jackett wär-

FORSCHUNG

AERODYNAMIK

Zickzack nach Darwin

Der Eingebung und oftmals auch glücklichem Zufall verdanken Generationen von Flugzeugtechnikern zukunftweisende Lösungen. Aber ein Student der Technischen Universität in West-Berlin möchte den Fortschritt kalkulabel machen: Er fand für das Roulette-Spiel der Flugzeugingenieure ein System.

Zahllose aufwendige Versuchsreihen in mietshausgroßen Windkanälen, deren Bau Millionen Dollar kostet und in denen Mammut-Flügelräder leichte Brise ebenso wie heulenden Orkan oder mehrfach schallschnelle Luftströme erzeugen können, sind bei den großen Flugzeugfirmen nötig, um für ein neues

Student **Rechenberg**, Lehrer **Wille***: Roulette in der Hochschule

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