UTS

ÓBUDAI EGYETEM
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IEEE
23rd International Symposium on Computational Intelligence and Informatics
(IEEE CINTI 2023)

Evolutionary Computation for Intelligent Data Analytics

Key Applications in Engineering

Amir H Gandomi

Professor of Data Science at University of Technology Sydney
Distinguished Professor at Óbuda University, Budapest

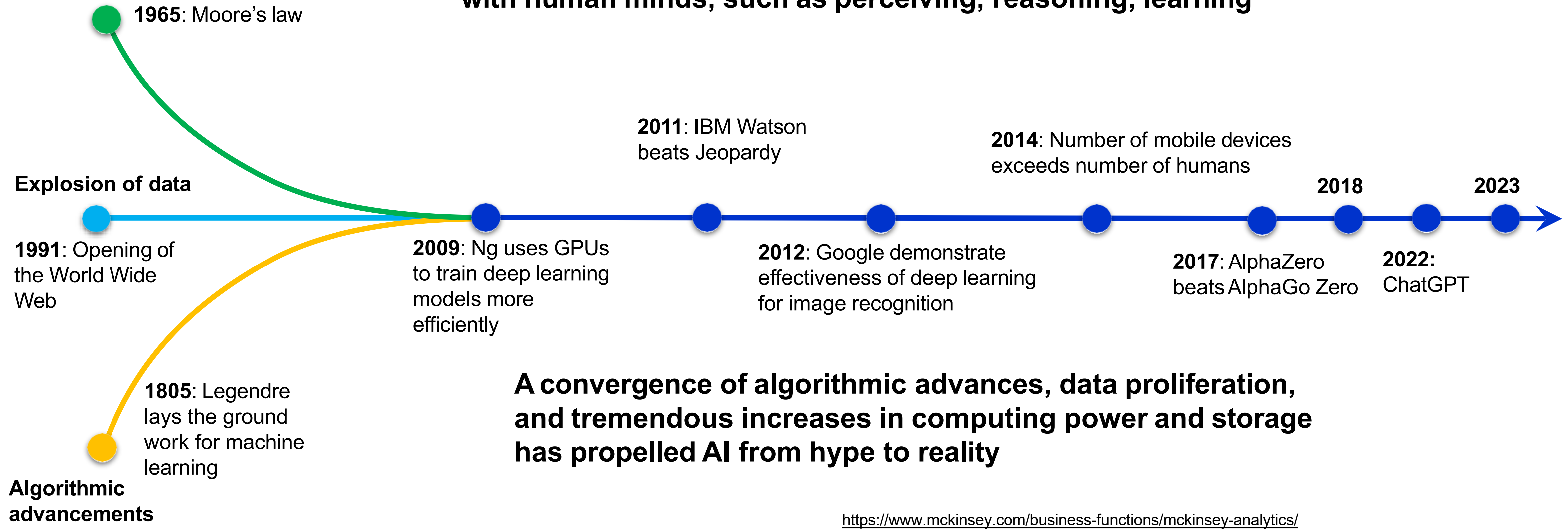
BOSCH

Robert Bosch Engineering company, Budapest, Hungary
20 November, 2023

AI in Action – An overview

What is Artificial Intelligence (AI) ?

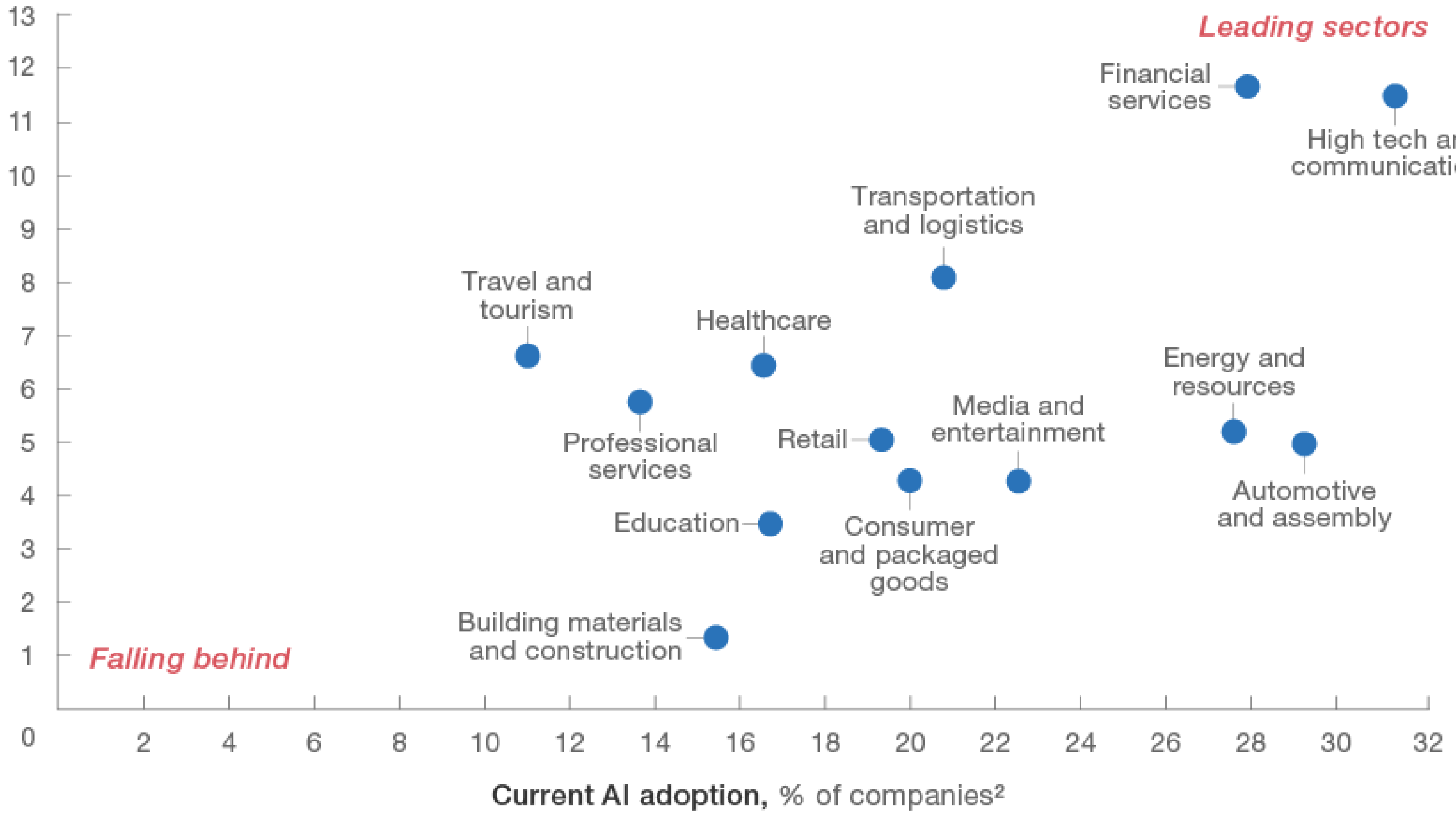
AI: The ability of a machine to perform cognitive functions we associate with human minds, such as perceiving, reasoning, learning



A convergence of algorithmic advances, data proliferation, and tremendous increases in computing power and storage has propelled AI from hype to reality

https://www.mckinsey.com/business-functions/mckinsey-analytics/

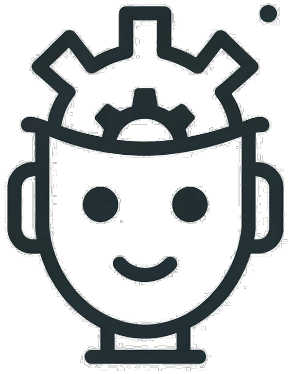
Leaders in the adoption of artificial intelligence also intend to invest more in the near future compared with laggards.



[1]Estimated average, weighted by company size; demand trajectory based on midpoint of range selected by survey respondent.
[2]Adopting 1 or more AI technologies at scale or in business core; weighted by company size.
Source: McKinsey Global Institute AI adoption and use survey; McKinsey Global Institute analysis

How we use AI in Action

Prediction
- **Classification**
- **Regression**
- **Clustering**
- **etc**



AI tools

ANN, **EI**, FL

Optimization
- **Cost**
- **Quality**
- **Time**
- **Risk**
- **Reliability, etc**

Automation
- **Decision making**
- **Smart systems**
- **Robotics**

Mechanical Engineerin g

Smart Cities

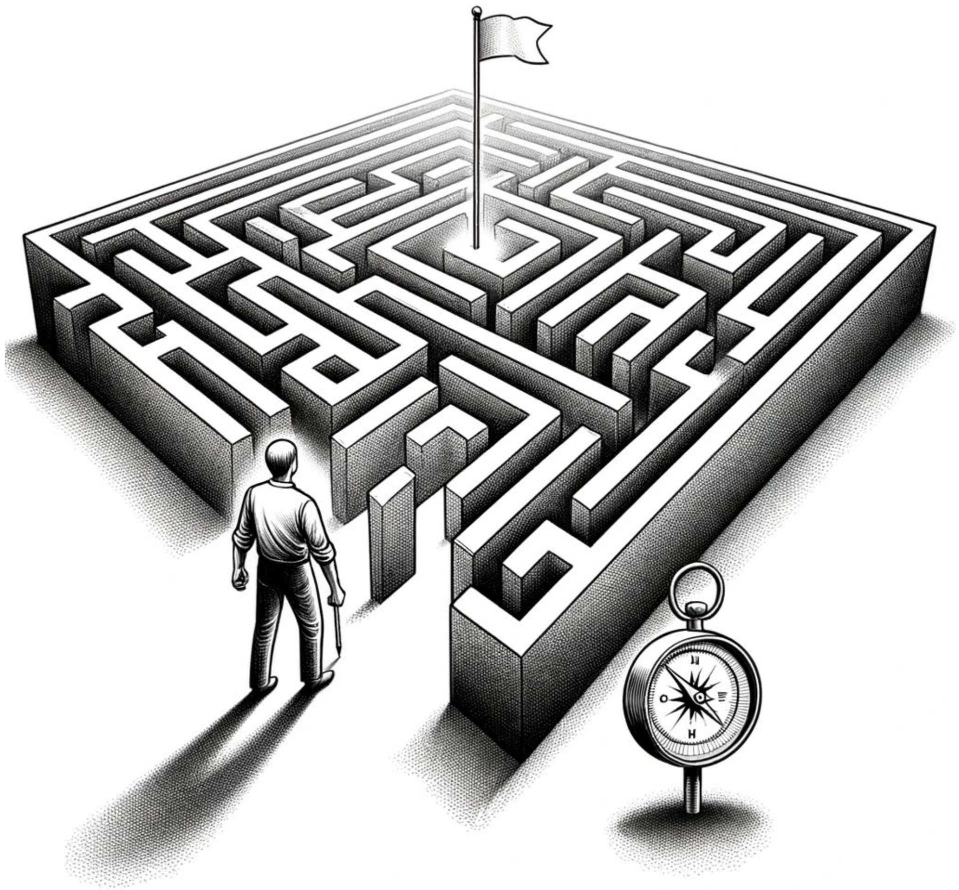
Civil Infrastructu res

Structural Health Monitoring

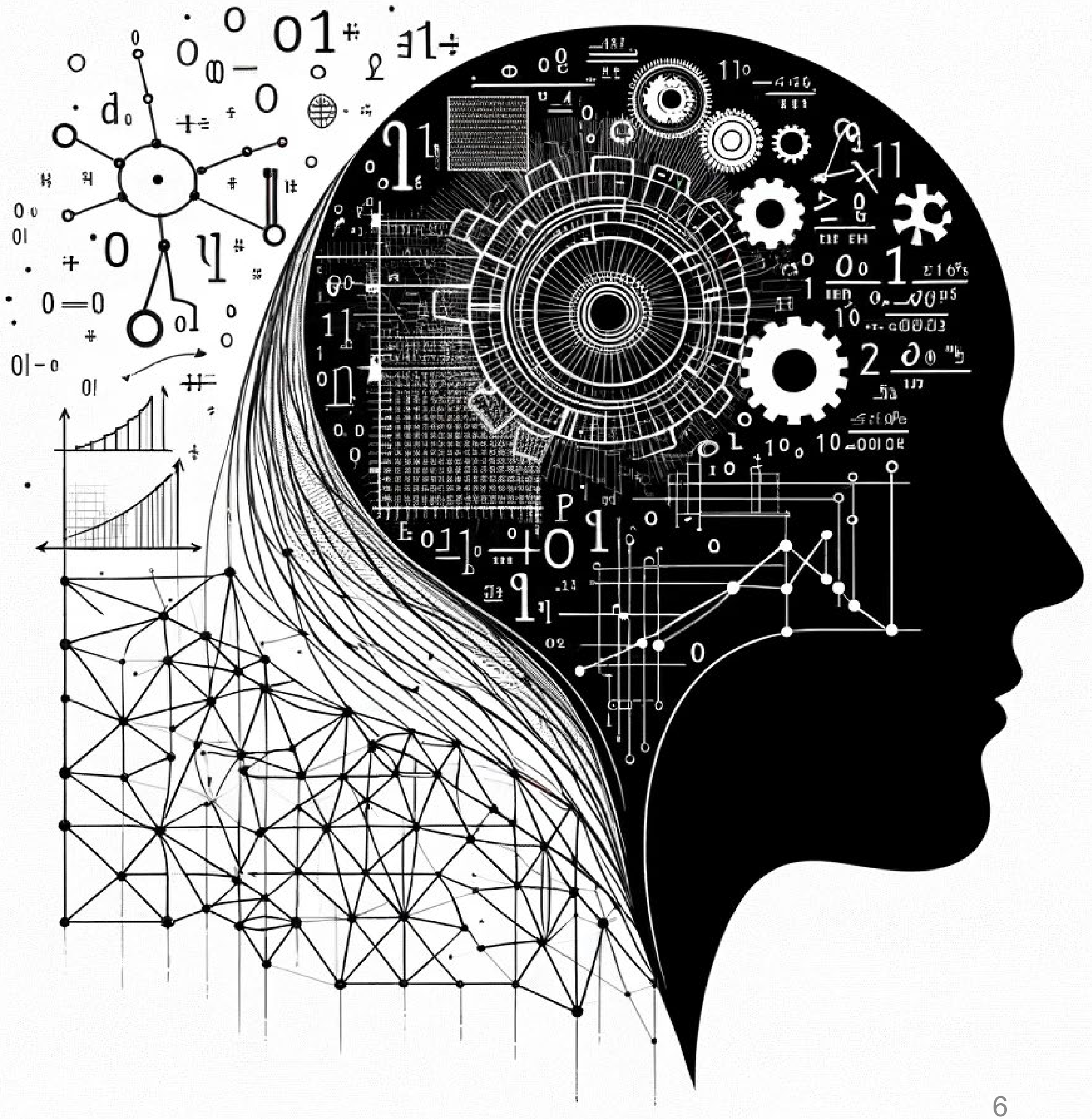
Outlines

Evolutionary Intelligence in Engineering

- Modelling
- Optimization
- Monitoring

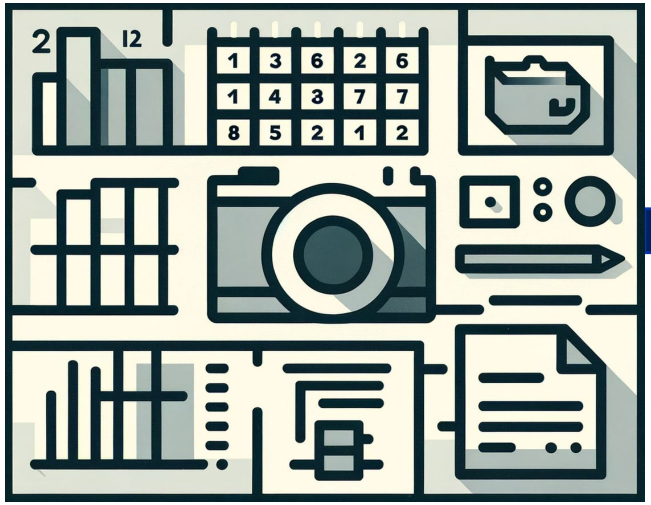


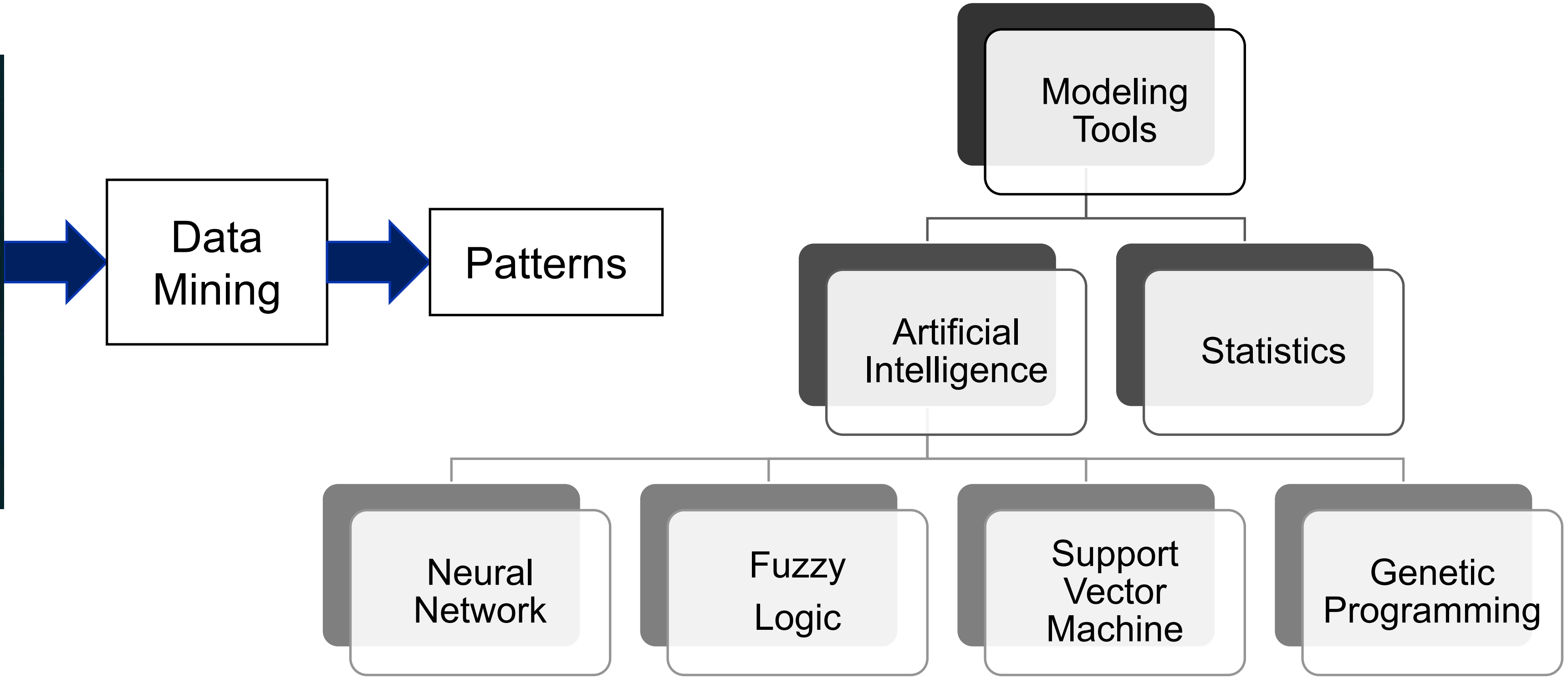
AI/EI for Engineering Modelling



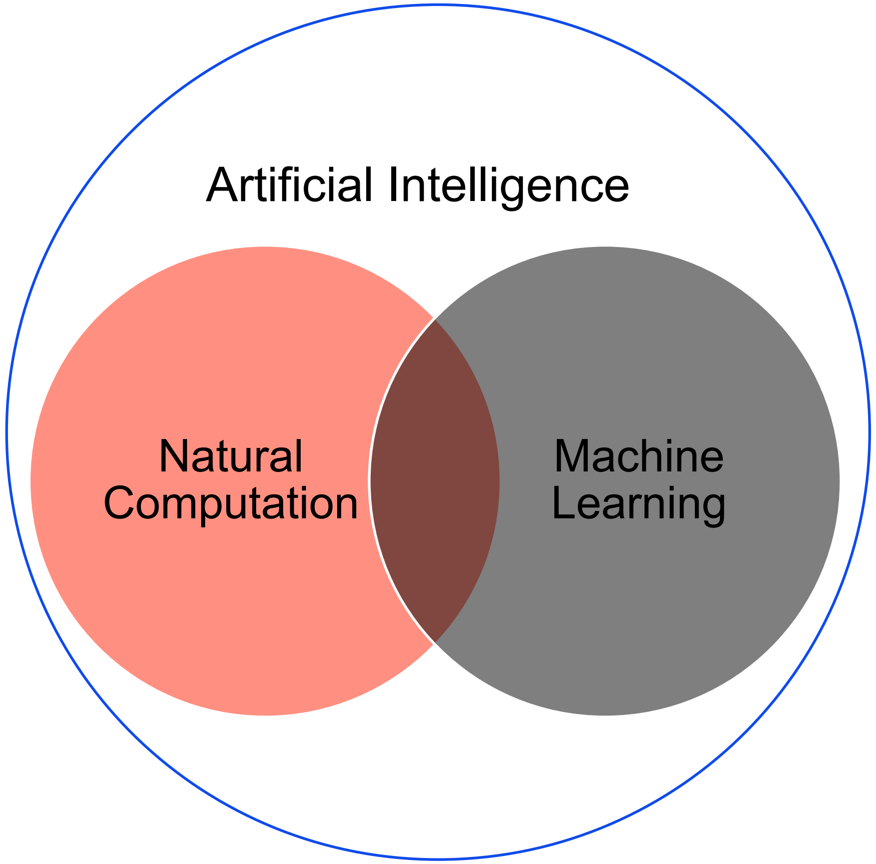
AI-based Data-Driven based Modelling Tools

- Discovering patterns





AI-based Predictive Data Analytic Tools



Look deep into nature, and then you will understand everything better

Albert Einstein

Nature is the source of all true knowledge.

Leonardo da Vinci

Telikani A., Tahmassebi, A.H., Banzhaf, W., Gandomi, A.H.*, “Evolutionary Machine Learning: A Survey" ACM Computing Surveys, ACM, 54(8), 11-50, 2021.

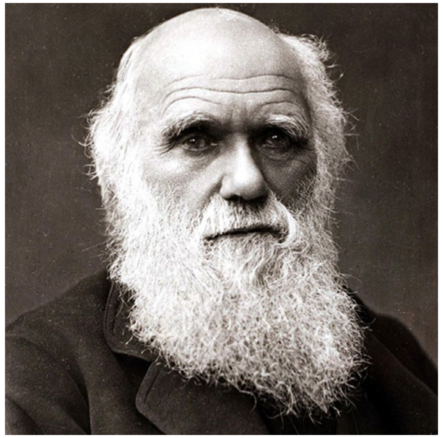
Evolution

Evolution Philosophy

Jalal-Din M. Rumi (Mevlâna)

13th Century

“I died as a mineral and became a plant,
I died as plant and rose to animal,
I died as animal and I was Man.”



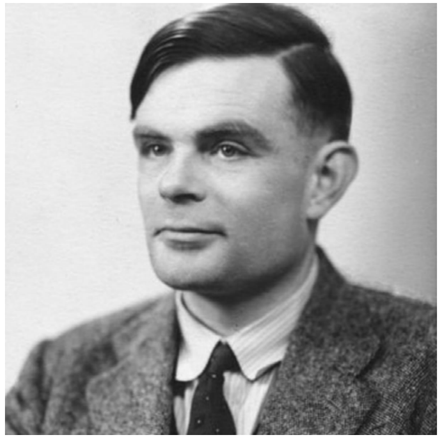
Theory of Evolution

based on Natural Selection

Charles R. Darwin

1859

“On the Origin of Species”



Evolutionary Search & Learning

Alan M. Turing

1950

“...there is the genetic or evolutionary search by which a combination of genes is looked for, the criterion being the survival value”

What is Genetic Programming

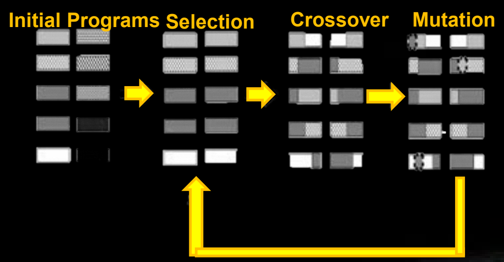
A Software with Evolution as the programmer!

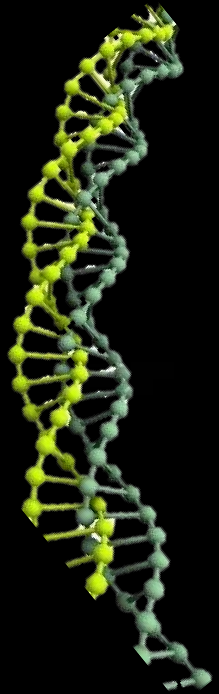
- Many problems can be solved by genetic programing!

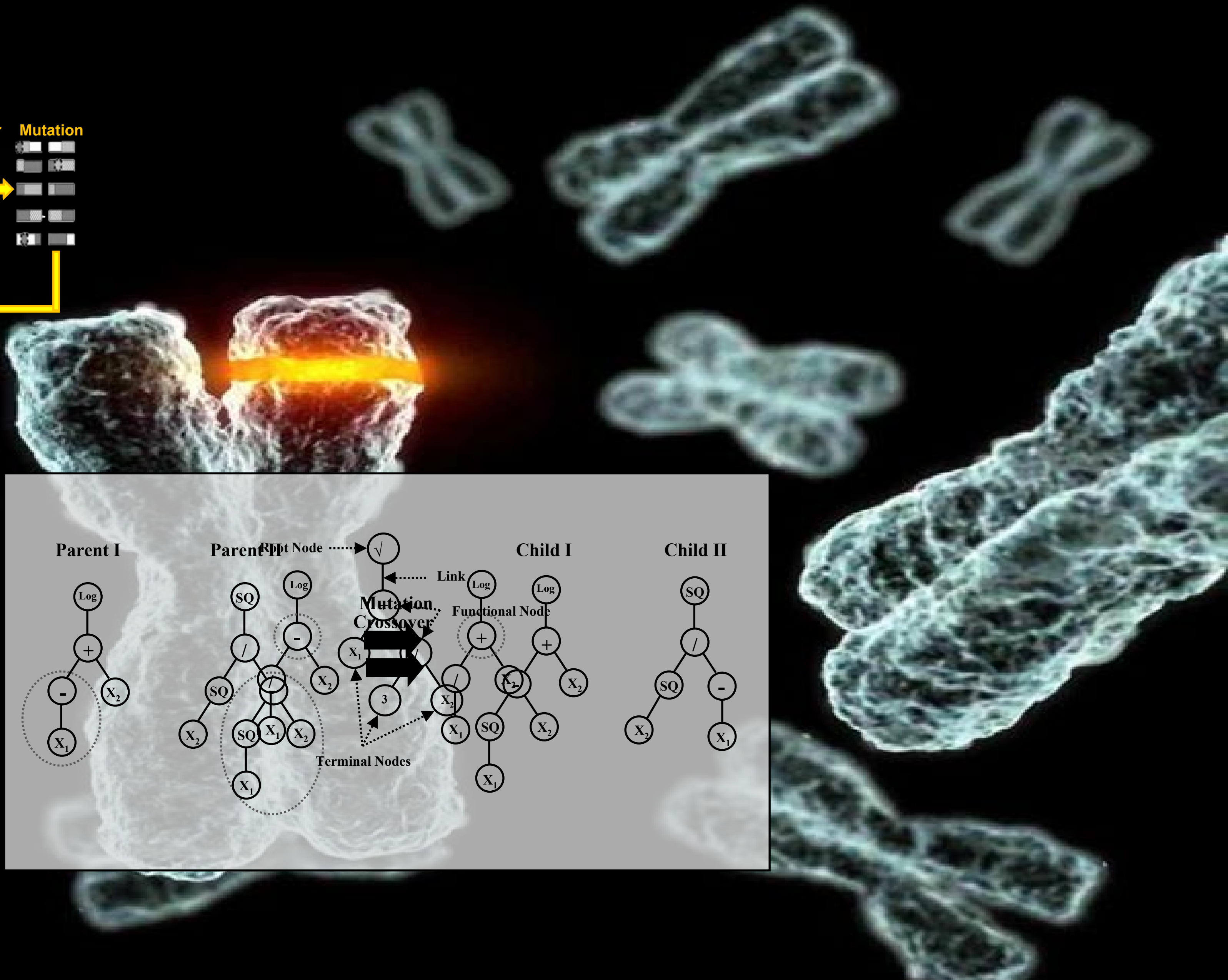
- Most popular for predictive data analytics

Reference:

Gandomi, Amir H., et al. *Handbook of genetic programming applications*. Cham: Springer, 2015.

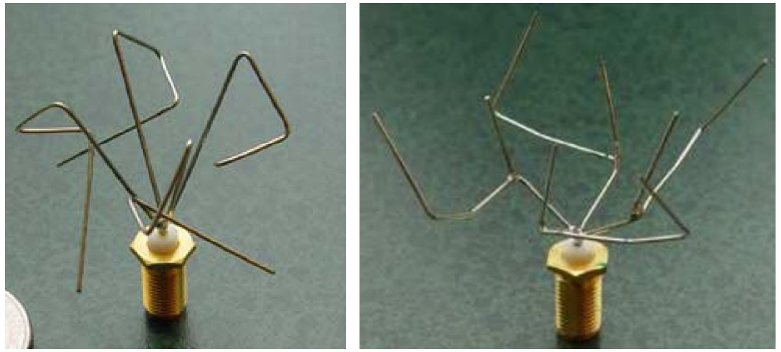

Initial Programs
Selection
Crossover
Mutation




Parent I
Parent II
Root Node
Link
Mutation
Crossover
Functional Node
Terminal Nodes
Child I
Child II

Finding the Model Structure

NASA Communication antennas
On the ST-5 mission (2006)

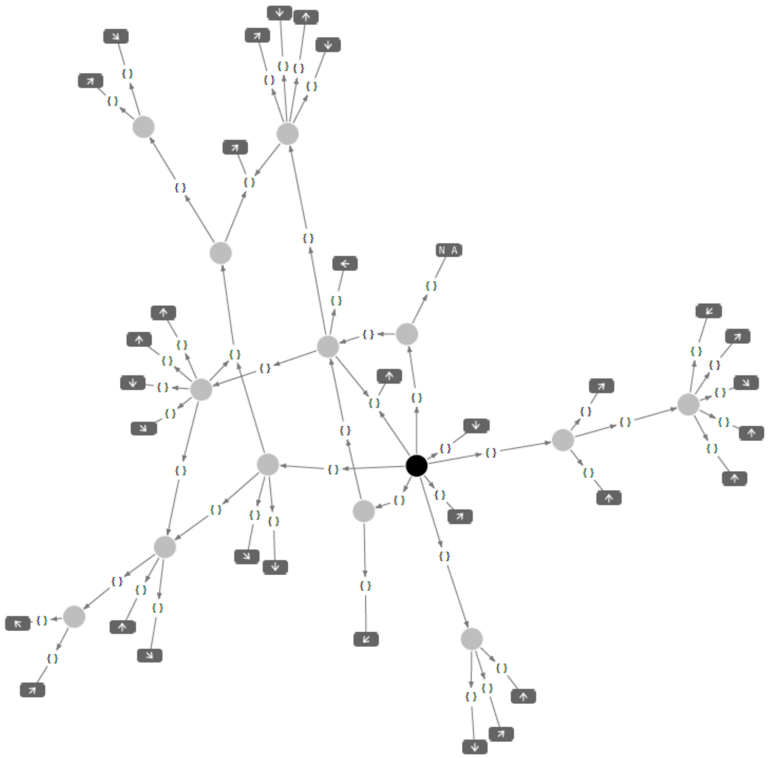


Jason D. Lohn, Gregory S. Hornby and Derek S. Linden, "Human-competitive evolved antennas", Artificial Intelligence for Engineering Design, Analysis and Manufacturing, volume 22, issue 3, pages 235–247 (2008).

In Genetic Programming:

- The Structure is found via Evolution
- Pre-defined structure is not required
- Distinguished feature from other machine learning methods
- It can model the behaviour without any prior assumptions

Simplicity and Explainability



Kelly, Stephen, and Malcolm I. Heywood. "Emergent tangled graph representations for Atari game playing agents." In European Conference on Genetic Programming, pp. 64-79. Springer, Cham, 2017.

MIT Technology Review

Intelligent Machines

Evolutionary algorithm outperforms deep-learning machines at video games

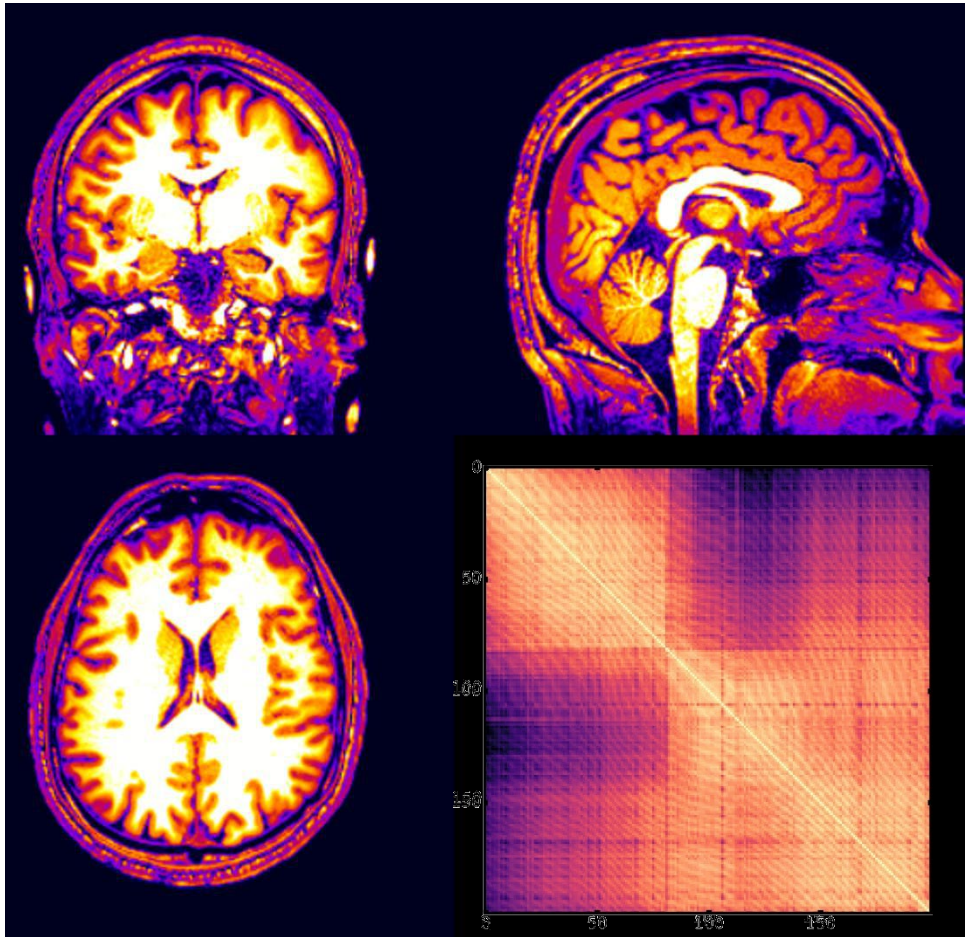
Neural networks have garnered all the headlines, but a much more powerful approach is waiting in the wings.

by Emerging Technology from the arXiv   July 18, 2018

With all the excitement over neural networks and deep-learning

Wilson, D. G., Cussat-Blanc, S., Luga, H., and Miller, J. F. Evolving simple programs for playing atari games. In Proceedings of the Genetic and Evolutionary Computation Conference. ACM, (2018).

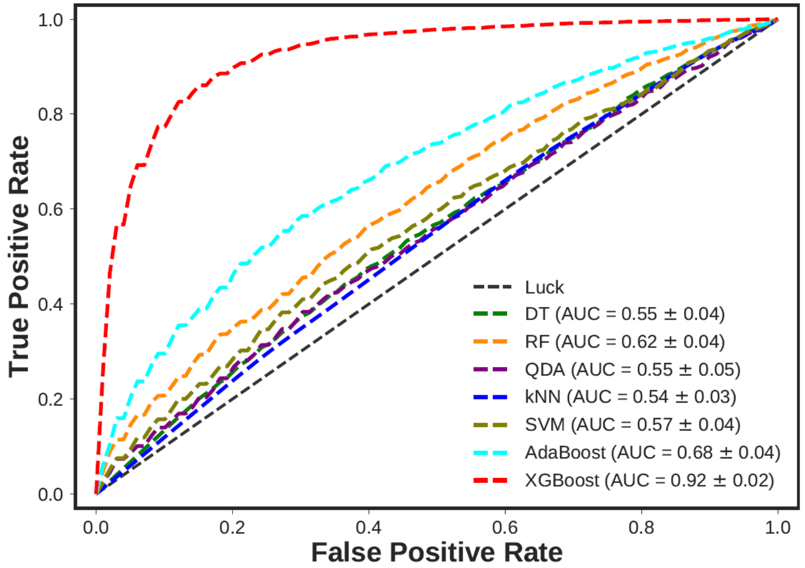
Inherently Making the Selections!



After cleaning data

Feature selection

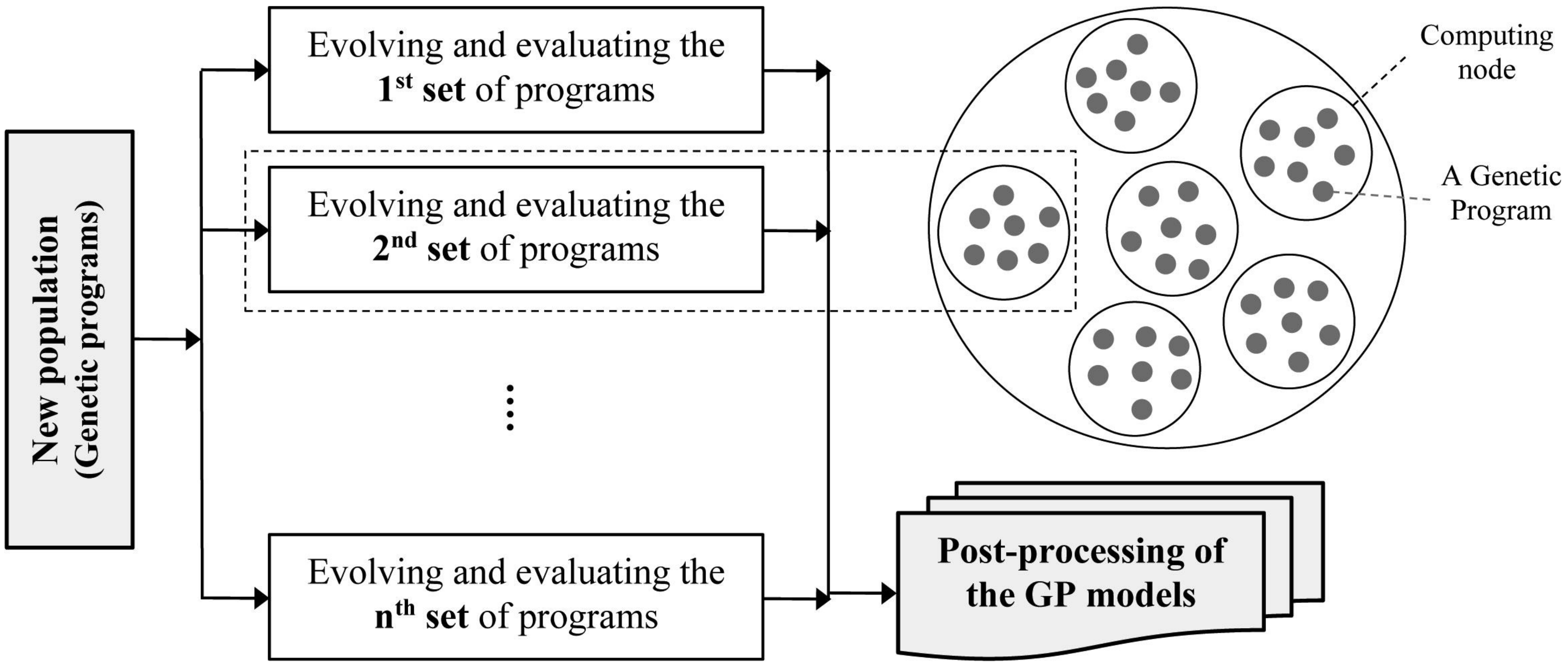
Model selection



Tahmassebi, A. Gandomi A.H., et al. (2018) "Deep Learning in Medical Imaging: fMRI Big Data Analysis via Convolutional Neural Networks" Proceedings of PEARC18, ACM.

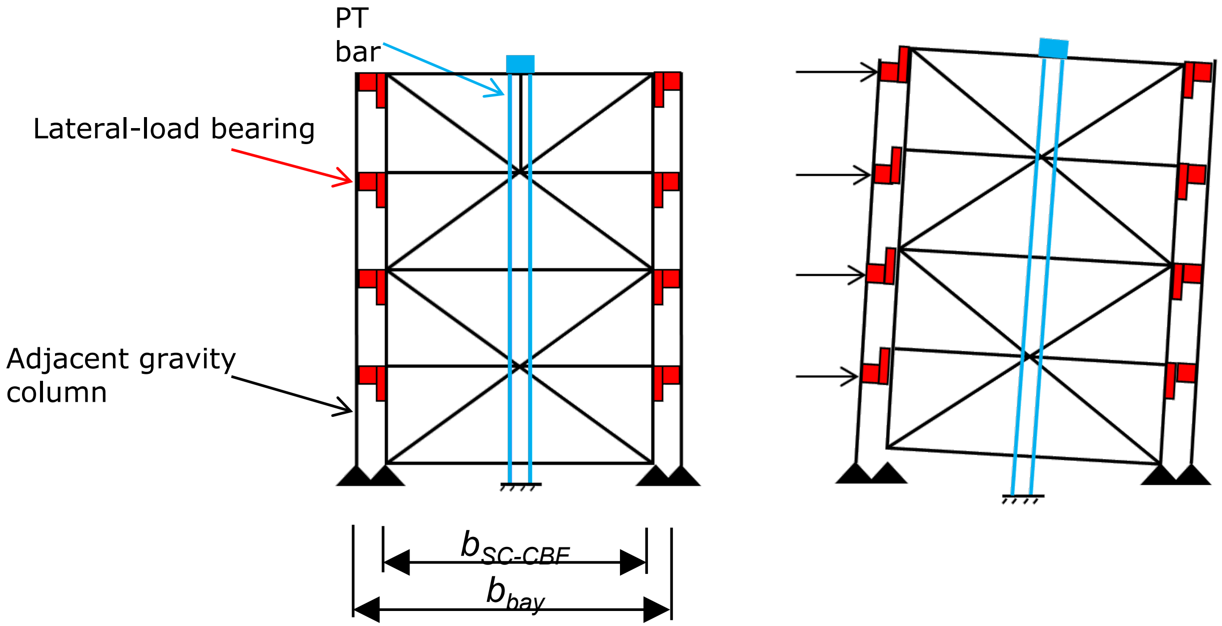
"Optimized Naive-Bayes and Decision Tree Approaches for fMRI Smoking Cessation Classification" Complexity, Wiley.

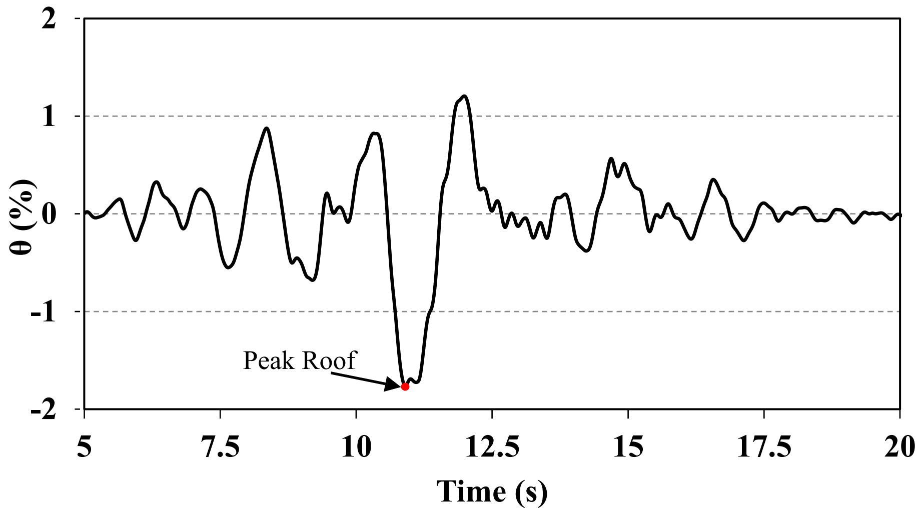
Parallel Processing in Genetic Programming



Gharehbaghi, S., Gandomi, M., Plevris, V. and Gandomi, A.H., 2021. Prediction of seismic damage spectra using computational intelligence methods. Computers & Structures, 253, p.106584.

Ex. I.1: Response of Self-Centering Concentrically Braced Frames





Gandomi A.H., "Seismic Response Formulation of Self-Centering Concentrically Braced Frames Using Genetic Programming" 2014 IEEE Symposium on Computational Intelligence, Orlando, FL, December 9-12, 2014.

Ex. I.1: Formulation of each Record's Response

θ = f(Structural Design, Intensity Measures)

Intensity Measures:

IM
Elastic spectral acceleration
Elastic spectral acceleration
Elastic spectral velocity
Elastic spectral displacement
Peak ground acceleration
Peak ground velocity
Peak ground displacement
Cumulative absolute velocity
Cumulative absolute displacement
Arias intensity
Velocity intensity
Root mean square acceleration
Characteristic intensity
Strong ground motion duration

Structural Design:

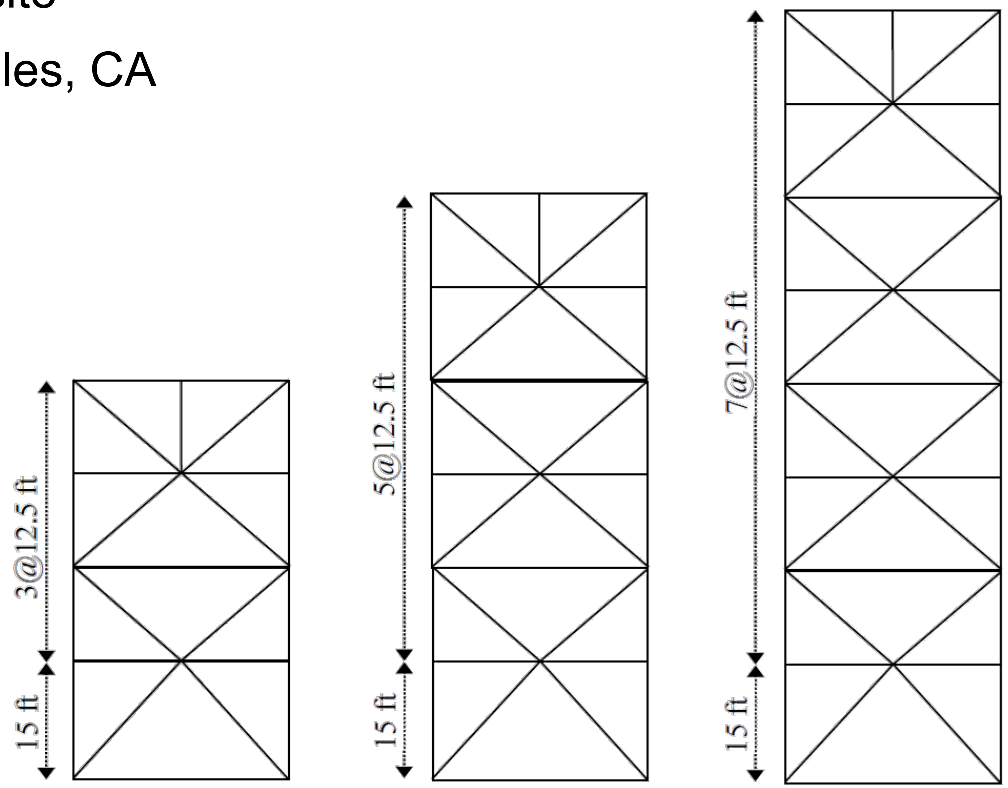
Geometrical		Mechanical	
b, ft (m)	*h, ft (m)*	F_y *, ksi (MPa)*	μ
22.5 (6.9)	52.5 (16)	36 (248)	0.30
30 (9.1)	77.5 (23.6)	50 (345)	0.45
40 (12.2)	102.5 (31.2)	60 (414)	0.60

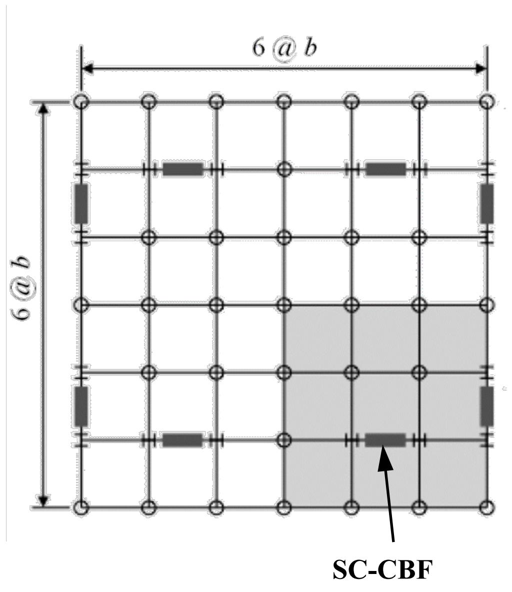
SC-CBF Parameters

Office buildings

Stiff soil site

Los Angeles, CA

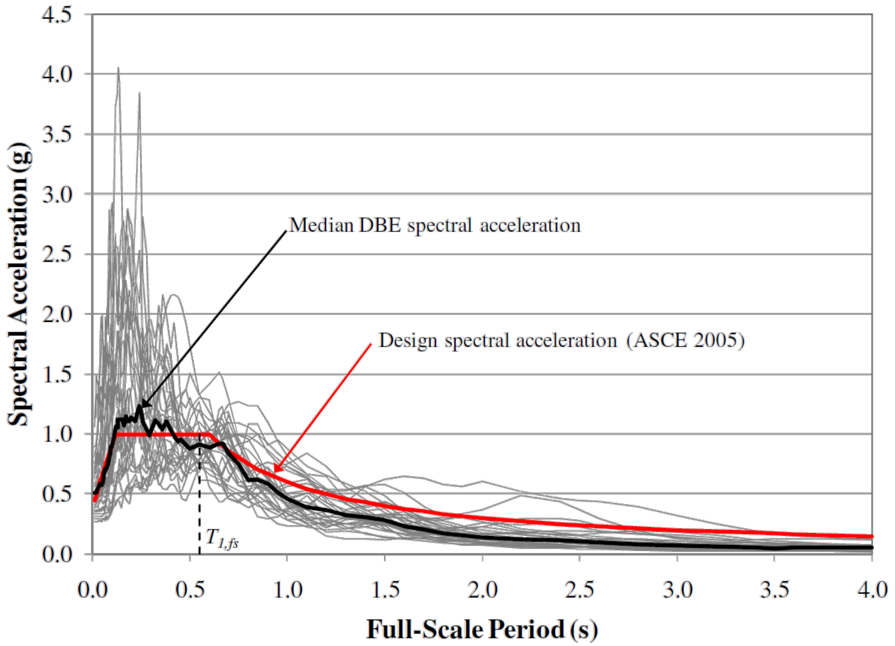




Nonlinear Dynamic Analysis

1) 75 SC-CBF System are designed
2) 30 earthquake records in DBE level
3) 140 ground motion records used in the FEMA SAC Steel Project

Area	FOE	DBE	MCE
Los Angeles, CA	20	20	20
Boston, MA	X	20	20
Seattle, WA	X	20	20



Feature Selection: Evolutionary Coefficient

- Best correlation coefficient (R)!
- R: linear relationship

$$R_e = \frac{\sum_{i=1}^{n}\left(y_i - \overline{y_i}\right)\left(f_{j,GP}\left(x_{ij}\right) - \overline{f_{j,GP}\left(x_{ij}\right)}\right)}{\sqrt{\sum_{i=1}^{n}\left(y_i - \overline{y_i}\right)^2 \sum_{i=1}^{n}\left(f_{j,GP}\left(x_{ij}\right) - \overline{f_{j,GP}\left(x_{ij}\right)}\right)^2}}$$

- $f_{j,GP}$: Transformed and correlated x_j

Gandomi A.H., "Seismic Response Formulation of Self-Centering Concentrically Braced Frames Using Genetic Programming" 2014 IEEE Symposium on Computational Intelligence, Orlando, FL, December 9-12, 2014.

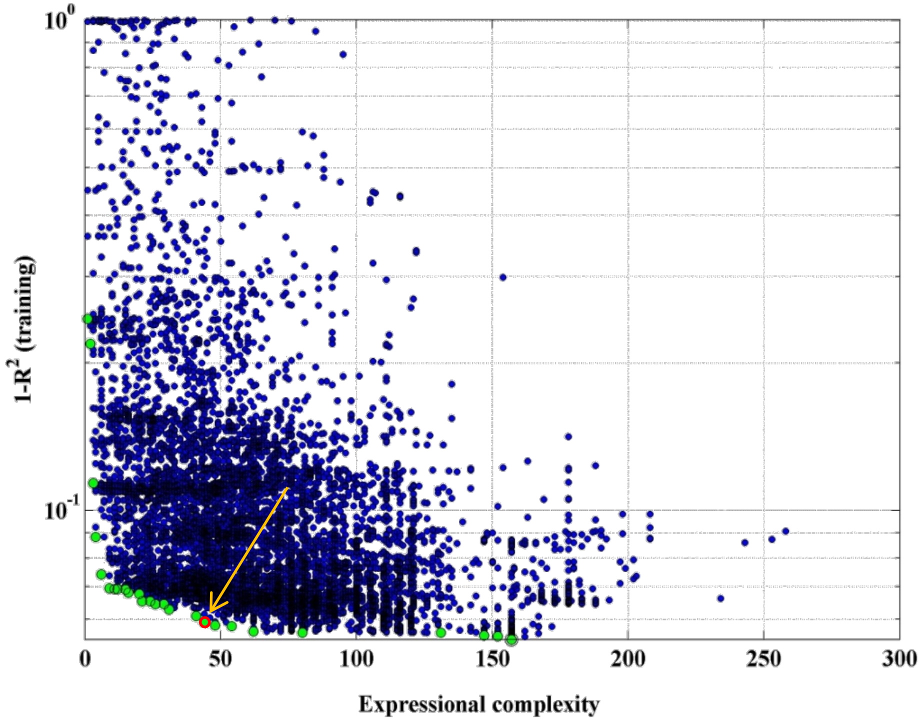
Feature Selection: Evolutionary Coefficient

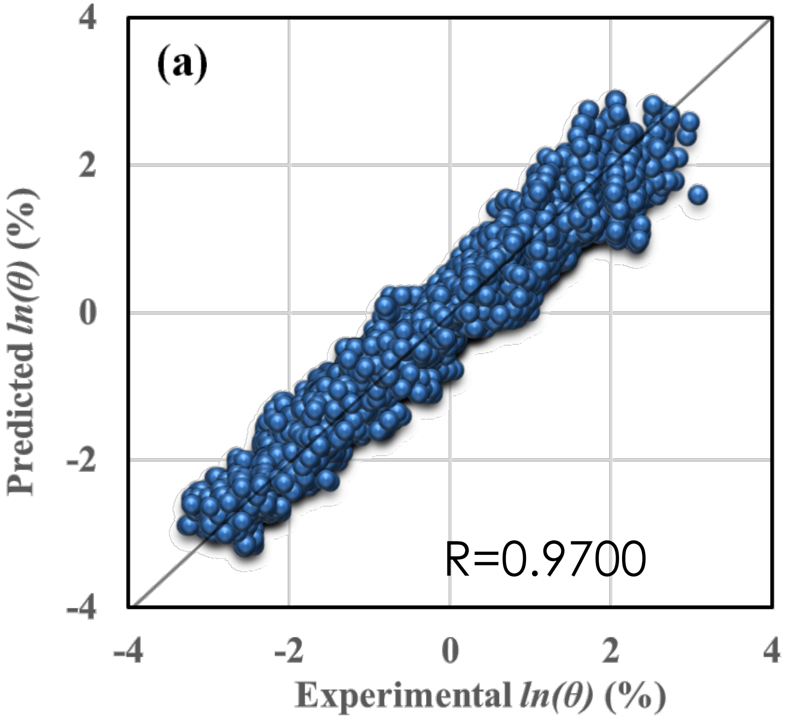
IM	Symbol	R^2	R_e^2	↑ (%)	Rank
Elastic spectral acceleration	$S_a(T)$	0.5589	0.7975	42.7	3
Elastic spectral acceleration	$S_a(2T)$	0.6709	0.8680	29.4	2
Elastic spectral velocity	S_v	0.5560	0.7938	42.8	4
Elastic spectral displacement	S_d	0.5147	0.7761	50.8	5
Peak ground acceleration	PGA	0.4190	0.5359	27.9	10
Peak ground velocity	PGV	0.7765	0.9022	16.2	1
Peak ground displacement	PGD	0.5181	0.7222	39.4	6
Cumulative absolute velocity	CAV	0.1890	0.5694	201.3	11
Cumulative absolute displacement	CAD	0.4036	0.6729	66.7	7
Arias intensity	I_A	0.1461	0.6612	352.6	8
Velocity intensity	I_v	0.4233	0.6454	52.5	9
Root mean square acceleration	A_{rms}	0.2858	0.3235	13.2	13
Characteristic intensity	I_c	0.2053	0.3305	61.0	12
Strong ground motion duration	T_D	0.0216	0.0881	307.9	14

Formulation of each Record's Response

Multi-Objective Strategy

$$Ln(\theta) = 25.9PGV + 0.615\ln\left|\tanh\left(2S_a(T)\right)\left(S_a(2T) + \left(\frac{h}{b}\right)^2\right)\sqrt{F_y}\right| - 1.08$$



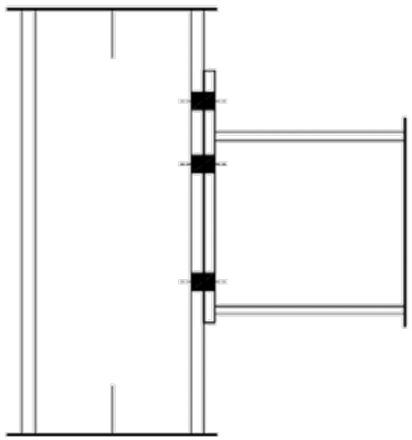


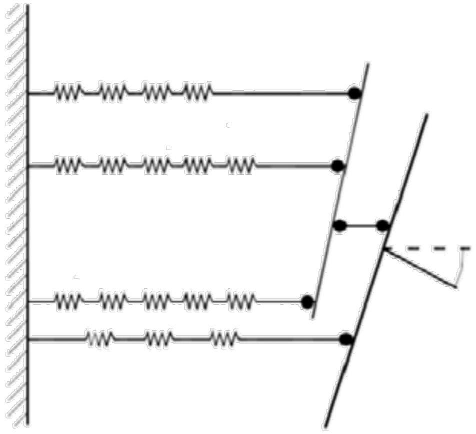
Gandomi, Amir H., and David Roke. "A Multi-Objective Evolutionary Framework for Formulation of Nonlinear Structural Systems." *IEEE Transactions on Industrial Informatics,* 18 (9), 5795 – 5803, 2022.

Team Solution: Steel Semi-Rigid Joints

Prediction

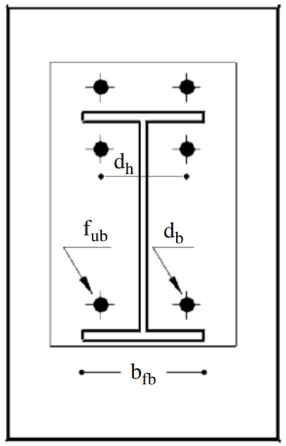
- flexural resistance
- initial rotation stiffness

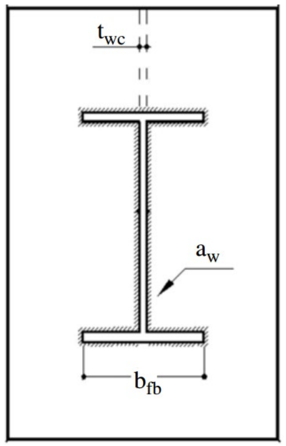


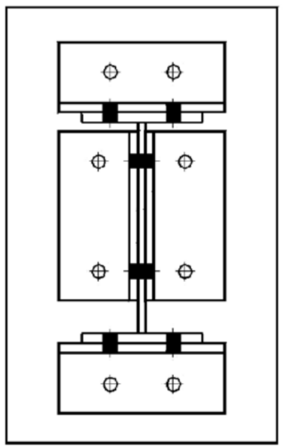


Joint types

- Extended endplate joint
- Welded joint
- Bolted angle joint







Gandomi et al. “Behavior Appraisal of Steel Semi-Rigid Joints Using Linear Genetic Programming.” *Journal of Constructional Steel Research, Elsevier,* 65: 1738-1750, 2009.

Team GP Solution

Performance statistics of models for flexural resistance prediction for all element test data

Type of Joint	LGP (single solution)				LGP (team solution)				EC3				GP/SA		
	R	MAE	MSE		R	MAE	MSE		R	MAE	MSE		R	MAE	MSE
Bolted Endplate Joint	**0.9986**	8.5496	**123.68**		0.9975	**5.9564**	183.88		0.9604	29.516	3019.2		0.9793	15.45	2035.1
Welded Joint	0.9819	22.06	1073.5		**0.988**	**18.55**	**674.77**		0.9169	54.09	6636.1		0.9761	20.75	1333.6
Bolted Joints with Angles	0.9918	3.2328	25.82		**0.9964**	**2.6267**	**12.72**		0.964	11.85	193.69		0.9846	4.56	46.7

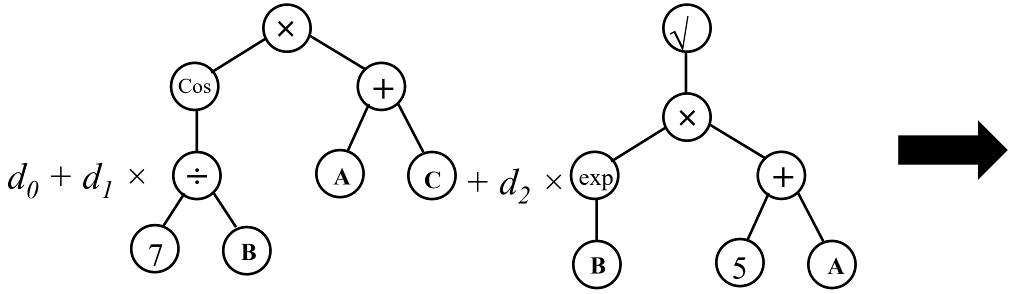
Performance statistics of models for initial rotation stiffness prediction for all element test data

Type of Joint	LGP (single solution)				LGP (team solution)				EC3				GP/SA		
	R	MAE	MSE		R	MAE	MSE		R	MAE	MSE		R	MAE	MSE
Bolted Endplate Joint	0.9969	3.2788	59.11		**0.9985**	**2.041**	**29.28**		0.9778	17.041	663.42		0.9836	3.62	313.51
Welded Joint	0.9734	9.9467	201.14		**0.9735**	**9.347**	**165.04**		0.9455	32.36	2340.9		0.949	10.25	314.09
Bolted Joints with Angles	0.9901	1.88	5.5		**0.9923**	**1.7272**	**4.95**		0.9271	6.1606	63.58		0.9784	1.31	11.7

Gandomi et al. “Behavior Appraisal of Steel Semi-Rigid Joints Using Linear Genetic Programming.” *Journal of Constructional Steel Research, Elsevier,* 65: 1738-1750, 2009.

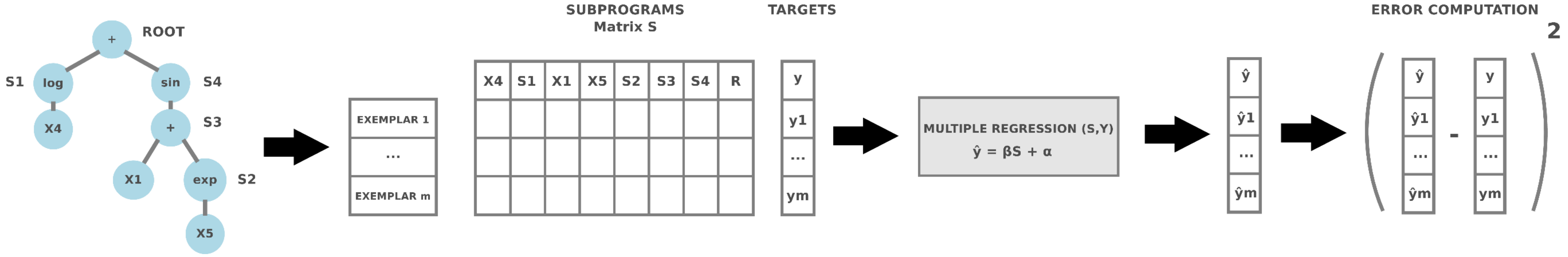
Multiple Regression in GP

Multi-Gene Symbolic regression (Searson et al. 2010)



$$Y = d_0 + d_1(A + C)Cos\left(\frac{7}{B}\right) + d_2\sqrt{(5 + A)e^B}$$

Multiple Regression Genetic Programming (Arnaldo et al. 2014)



Hybrid GP for Concrete Creep Prediction

$$\hat{J}(t,t_0) = d_0 + d_1G_1 + d_2G_2 + d_3G_3$$

$$G_1 = \left(\frac{w}{c}\right) \cdot \frac{\ln\left(t_e + 2.46\right)}{f_c'}$$

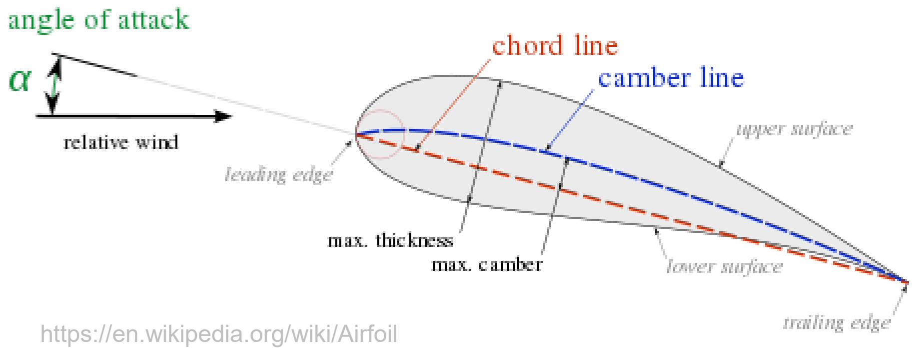
$$G_2 = \ln\left[\left(\frac{w}{c}\right)\sqrt{t_0}\right]$$

$$G_3 = \left(\frac{f_c' \cdot t_0}{h^2}\right)^2$$

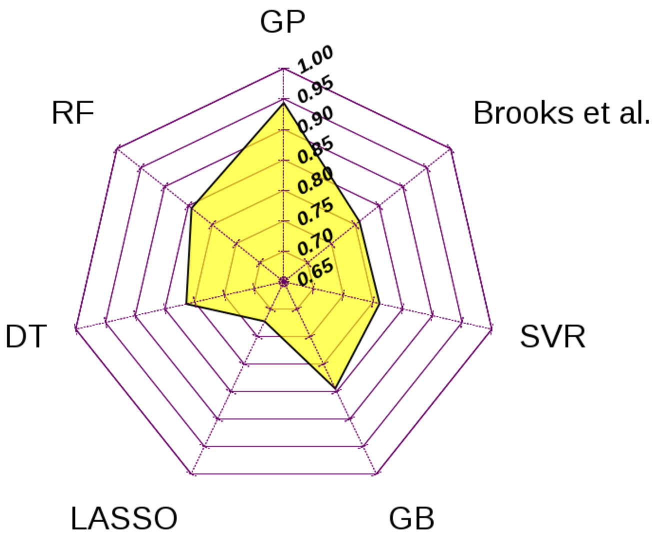
Model	Number of Variables.	Accuracy measure					
		R^2	RRMSE	ρ	V_{CEB}	F_{CEB}	M_{CEB}
G-C	5	0.83	0.37	0.19	0.37	61.7	1.63
Bažant-Baweja B3	10	0.56	0.62	0.35	0.59	55.7	2.10
CEB-FIB MC90	5	0.62	0.55	0.31	0.54	67.4	1.73
GL2000	6	0.48	0.69	0.41	0.65	57.9	2.22

Gandomi et al., "Genetic Programming for Experimental Big-Data Mining: A Case Study on Concrete Creep Formulation." Automation in Construction, Elsevier, 70, 89–97, 2016.

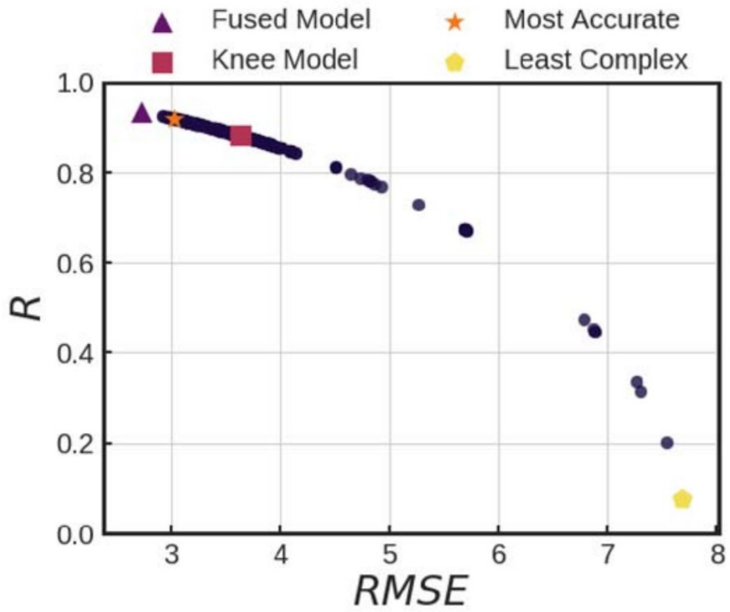
Fused GP for Airfoil Self-Noise Prediction

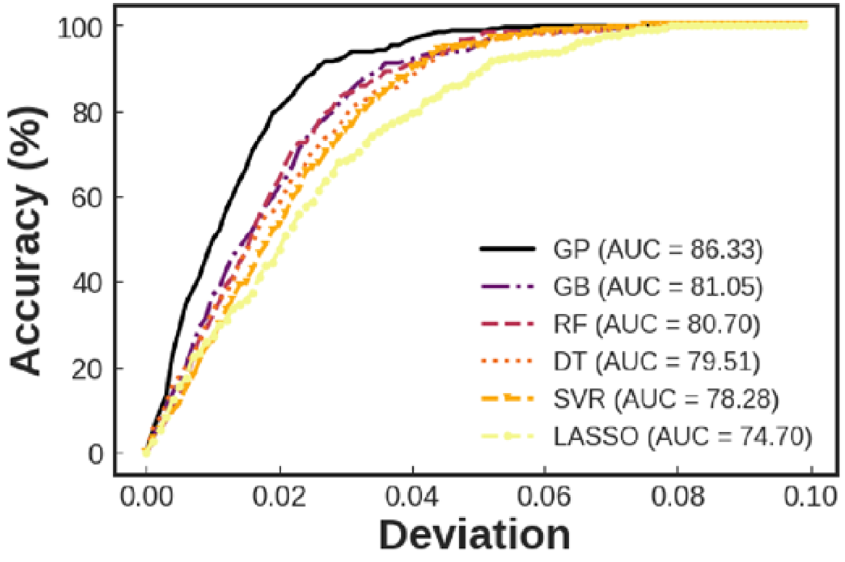


https://en.wikipedia.org/wiki/Airfoil



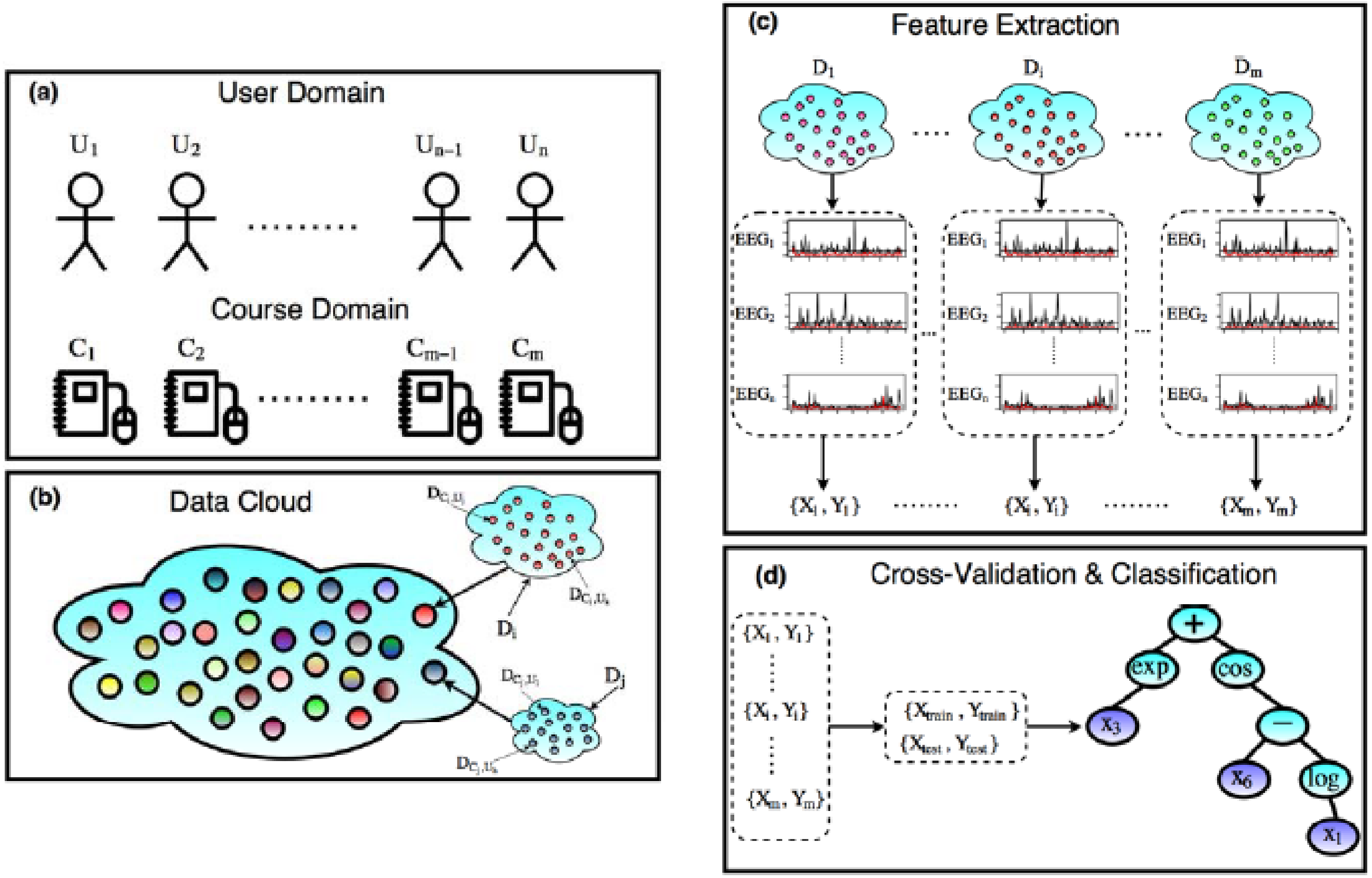
Fusing GP Models by Adaptive Regression by Mixing (ARM) Algorithm

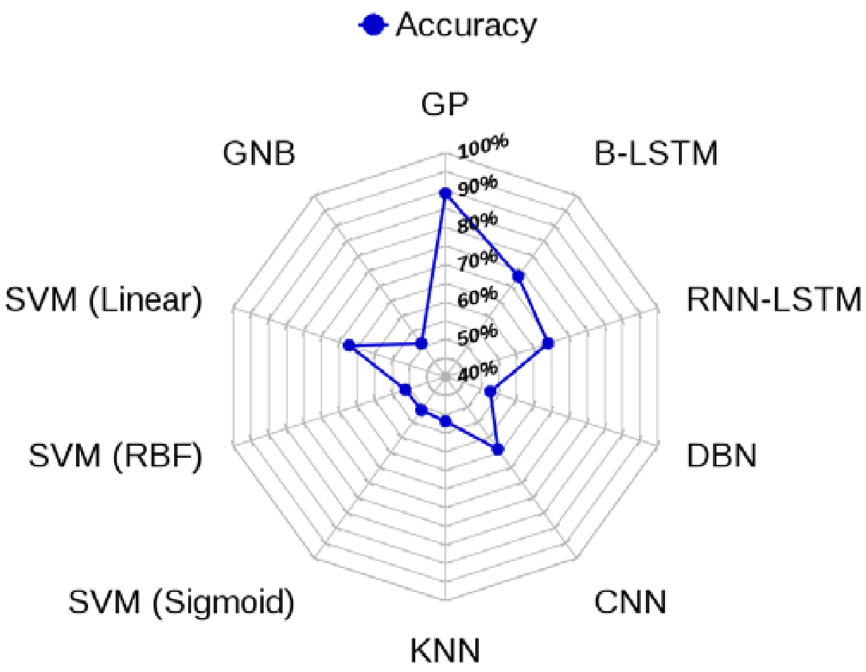




Tahmassebi, Amirhessam, Amir H. Gandomi, and Anke Meyer-Baese. "A Pareto front based evolutionary model for airfoil self-noise prediction." In 2018 IEEE Congress on Evolutionary Computation (CEC), pp. 1-8. IEEE, 2018.

MOOC Performance Modelling using EEG Data





Tahmassebi, Amirhessam, Amir H. Gandomi, and Anke Meyer-Baese. "An Evolutionary Online Framework for MOOC Performance Using EEG Data." In 2018 IEEE Congress on Evolutionary Computation (CEC), pp. 1-8. IEEE, 2018.

BIG DATA

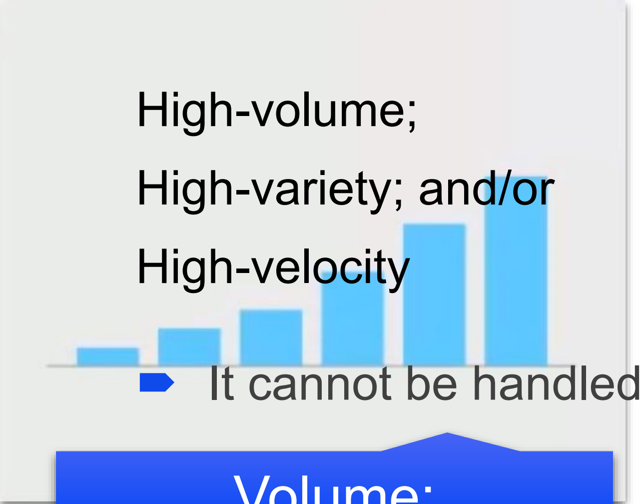
3Vs

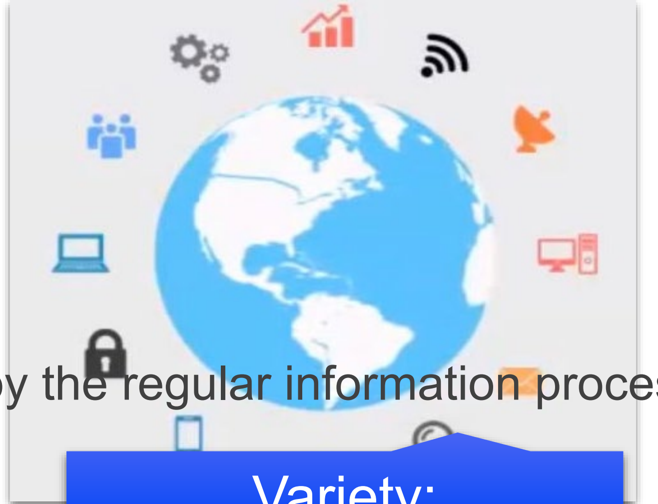
High-volume;

High-variety; and/or

High-velocity

- It cannot be handled by the regular information processing





Volume:
Size

Variety:
Complexity

Velocity:
Rate of growth

- Big data techniques: cost-effective and innovative

Why BIG DATA?

>200 million

4 million

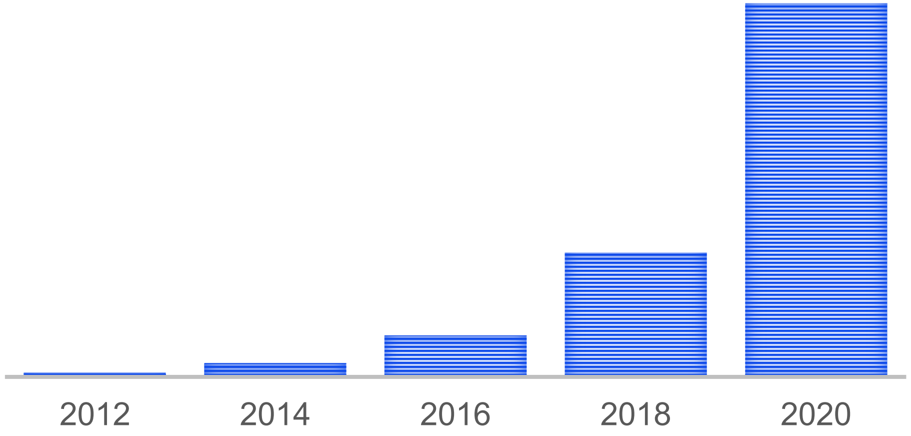
350,000

3.8 million

500 hours

How much data?

Moore's law



https://skai.io, https://www.brandwatch.com, https://www.dsayce.com, https://prosperitymedia.com.au/

Genetic Programming for Big Data Analytics (Current)

Divide-and-conquer

- find an efficient and systematic divide-and-conquer strategy, such as information theory
- structure initializations for GP

GP development

- extend GP with a multi-gene structure
- couple GP with other machine learning and/or regression analysis
- extend traditional evolutionary operators and define new operator(s) for the newly developed GP

Multi-stage genetic programming

Multi-Stage Genetic Programming

```
Begin
  Y = f(X)
  for i = 1: n (n is the number of inputs)
    Input = x_i
    Output = Y
    % Run GP for f_i(x_i)
    Randomly generate initial population
 ->  Access fitness of population
    if (The termination or convergence conditions are not satisfied)
      Select individual based on fitness
      Make random changes (Crossover, Mutation, etc.)
      Go to
    end if
    Y = Y − f_i(x_i)
  end for i
  Input = X (x_1, x_2, ..., x_n)
  Output = Y
  % Run GP for f_int(X)
  Randomly generate initial population
-> Access fitness of population
  if (The termination or convergence conditions are not satisfied)
    Select individual based on fitness
    Make random changes (Crossover, Mutation, etc.)
    Go to
  end if
  f(X)_MSGP = Σ_{j=1}^{n} f_j(x_j) + f_int(X)
end
```

$$f(X) = f_1(x_1) + f_2(x_2) + \cdots + f_n(x_n) + f_{int}(X) = \sum_{i=1}^{n} f_i(x_i) + f_{int}(X)$$

$$f_2(x_2) = f(X) - f_1(x_1)$$

$$f_3(x_3) = f(X) - f_1(x_1) - f_2(x_2)$$

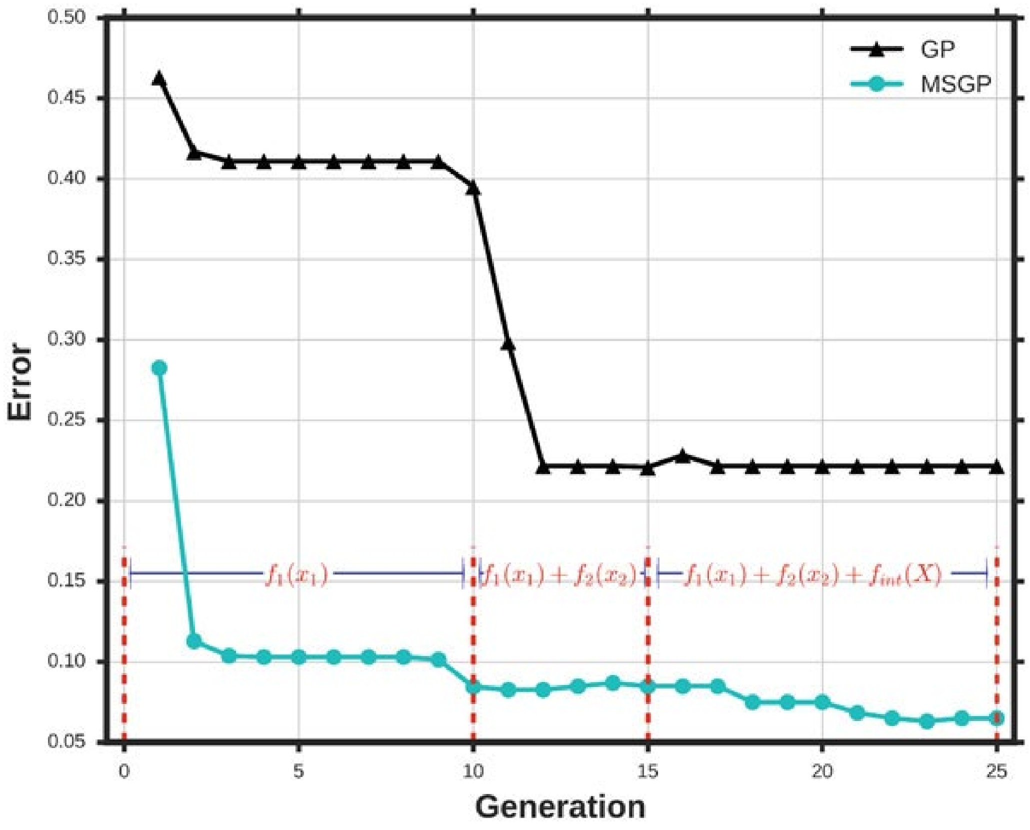
$$\vdots$$

$$f_n(x_n) = f(X) - f_1(x_1) - f_2(x_2) - \cdots - f_{n-1}(x_{n-1})$$

$$f_{int}(X) = f(X) - \sum_{i=1}^{n} f_i(x_i)$$

Gandomi A.H., Alavi A.H., “Multi-Stage Genetic Programming: A New Strategy to Nonlinear System Modeling.” Information Sciences, Elsevier, 181(23): 5227-5239, 2011.

MSGP for Big Data



Tahmassebi, A. and Gandomi, A.H., 2018. Genetic programming based on error decomposition: A big data approach. In *Genetic Programming Theory and Practice XV*(pp. 135-147). Springer, Cham.

MSGP for Classification: Soil Liquefaction modelling

Stage 1:

$$F_1 = \cos((\arctan(((q_c^2 + 8.372)/(q_c - 8.372)))^2))^3$$

Stage 2:

$$F_2 = (-R_f + 1.393)/(R_f + (5.281/R_f))$$

Stage 3:

$$F_3 = \sin\left(-8.297\sigma_v'^2 + -6.012 - \sigma_v'\right)/ - 8.297$$

Stage 4:

$$F_4 == ((\arctan(\cos((\sigma_v^3)))^2)(\arctan(\cos(\sigma_v))^3))$$

Stage 5:

$$F_5 = \arctan(\arctan(\arctan(((0.0102 - 0.1011/a_{\max}) + 0.466)))$$

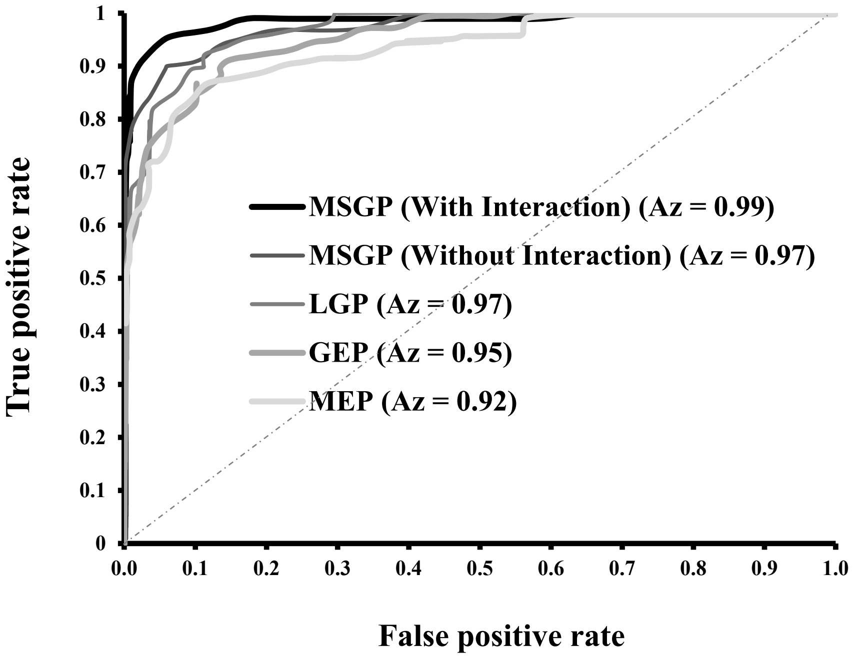
Stage 6:

$$F_6 = 0.034 \sin\left(\left(\left(M_w^2\right) - (1.589 - M_w)\right)\right)$$

Stage 7 (interaction):

$$F_{\text{int}} = (\cos((((((\cos(M_w)a_{\max})(1.534 - M_w + 5.936)) \exp(M_w))^3)/a_{\max}))/(M_w - 1.534))$$

Figure: ROC curves

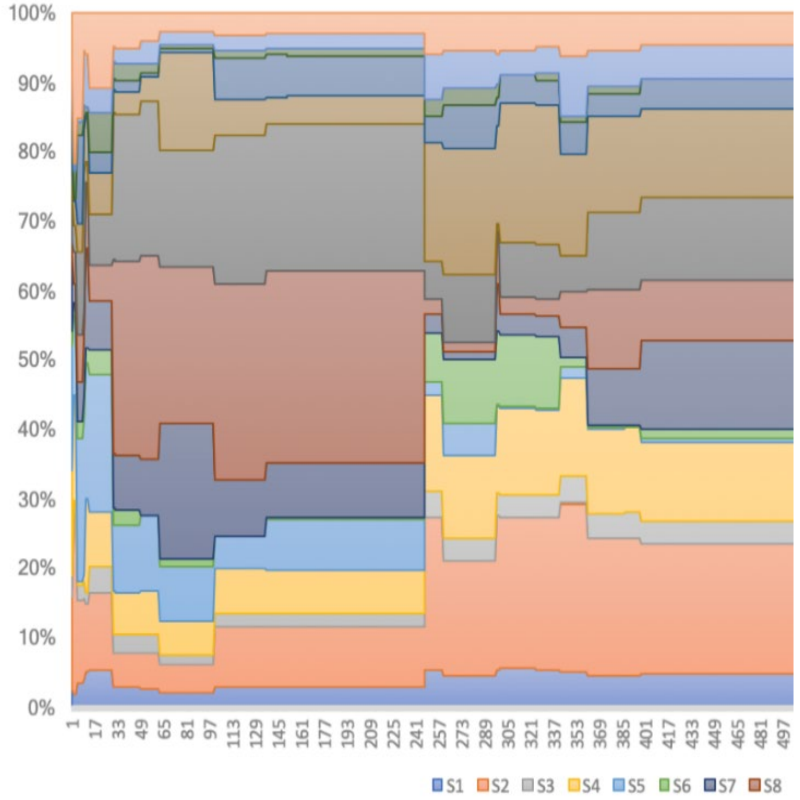


Gandomi A.H., Alavi A.H., "Multi-Stage Genetic Programming: A New Strategy to Nonlinear System Modeling." Information Sciences, Elsevier, 181(23): 5227-5239, 2011.

Advancing Genetic Programming via Information Theory

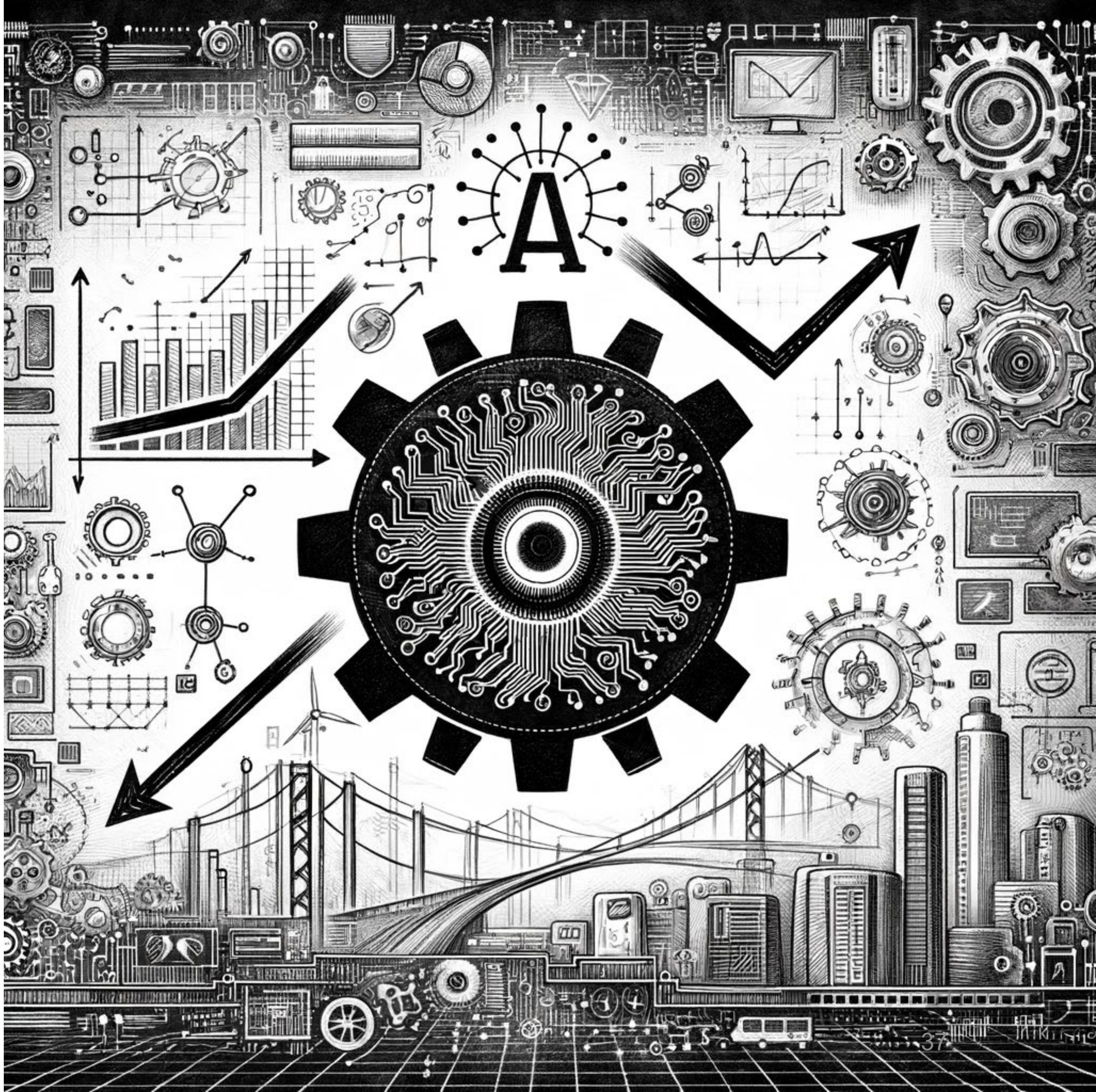
$$\begin{pmatrix} G_{11} & G_{21} & \cdots & G_{n1} \\ \vdots & & \ddots & \vdots \\ G_{1m} & & \cdots & G_{nm} \end{pmatrix} \times \begin{pmatrix} \beta_{11} & \beta_{12} & \cdots & \beta_{1m} \\ \vdots & & \ddots & \vdots \\ \beta_{n1} & \beta_{n2} & \cdots & \beta_{nm} \end{pmatrix} + \begin{pmatrix} \beta_{01} \\ \vdots \\ \beta_{0m} \end{pmatrix} = \begin{pmatrix} y_1^{pr} \\ \vdots \\ y_m^{pr} \end{pmatrix}$$

Population size	Method	WIR	WIW
1,000	MR	0.1012	0.0992
	GP	0.1084	0.1048
	RRGP	0.1012	0.1094
	MRGP-TC	0.1172	0.0958
	MRGP-SumT	0.1115	0.0959
	MRGP-MDL	0.1120	0.0960
	MRGP-SMDL	0.1347	0.0961
100	MRGP-TC	0.1085	0.0961
	MRGP-SumT	0.1076	0.0963
	MRGP-MDL	0.1030	0.0964
	MRGP-SMDL	0.1080	0.0968
	Proposed GP	**0.0617**	**0.0664**

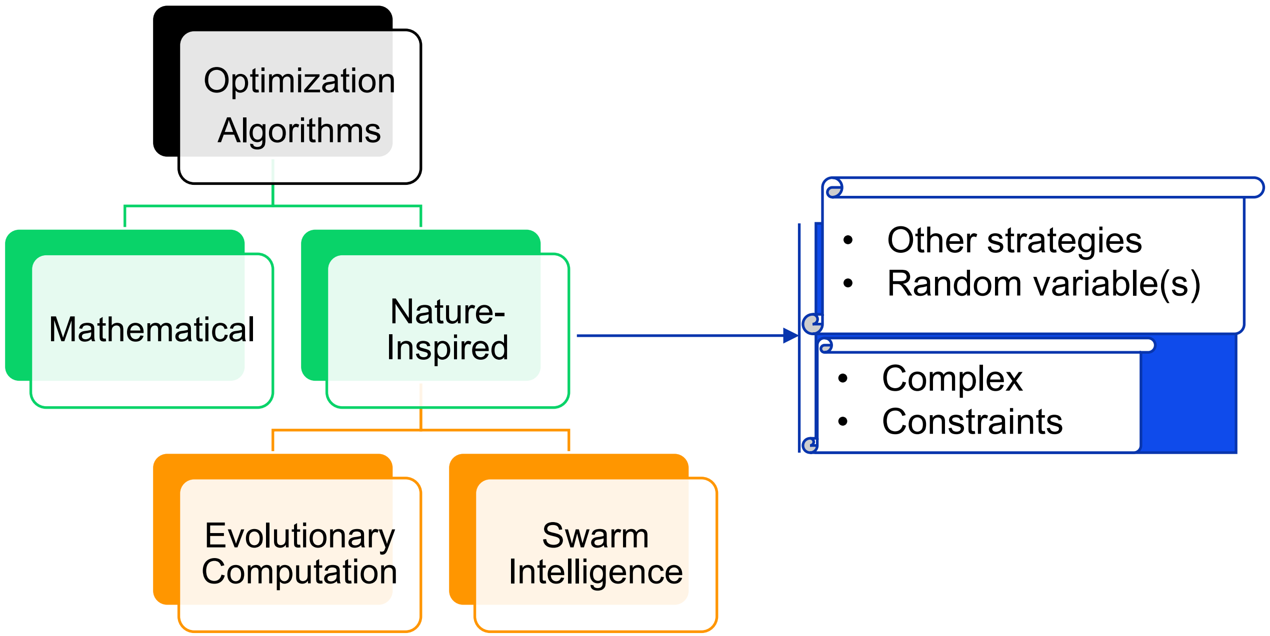


Grin, A.V. and Gandomi, A.H., 2021, June. Advancing Genetic Programming via Information Theory. In 2021 IEEE Congress on Evolutionary Computation (CEC) (pp. 1991-1998). IEEE.

AI/EI for
Engineering Optimization



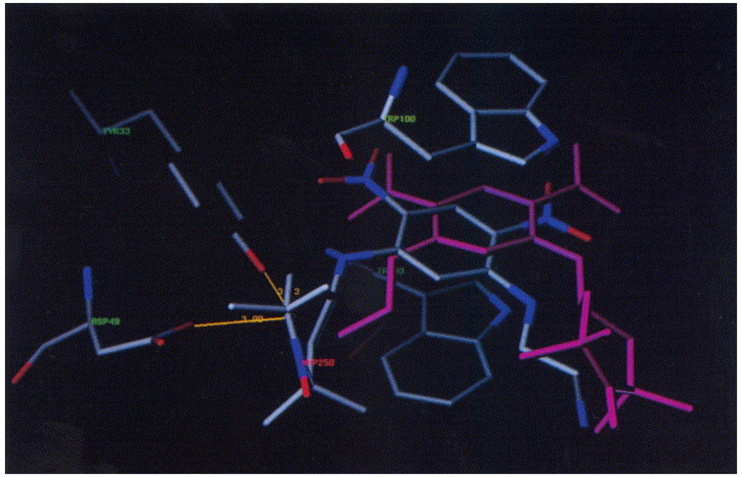
Optimization Algorithms



EC in Real-World Problems

Boeing Turbine geometry of 777 GE engine Design:

Charles W. Petit, “Touched by nature: putting evolution to work on the assembly line.” US News & World Report, volume 125, issue 4, pages 43–45 (1998).



Merck Pharmaceutical discovered first clinically-approved antiviral drug for HIV:

Jones G, Willett P, Glen RC, Leach AR, Taylor R (1997) Development and validation of a genetic algorithm for flexible docking. J Mol Biol 267: 727–748.

& so many other companies.

amazon

Google Brain

Uber

BMW

Oral-B

Traditional Algorithms:

- Genetic Algorithm (GA)
- Simulated Annealing (SA)
- Particle Swarm Optimization (PSO)

Recent Algorithms:

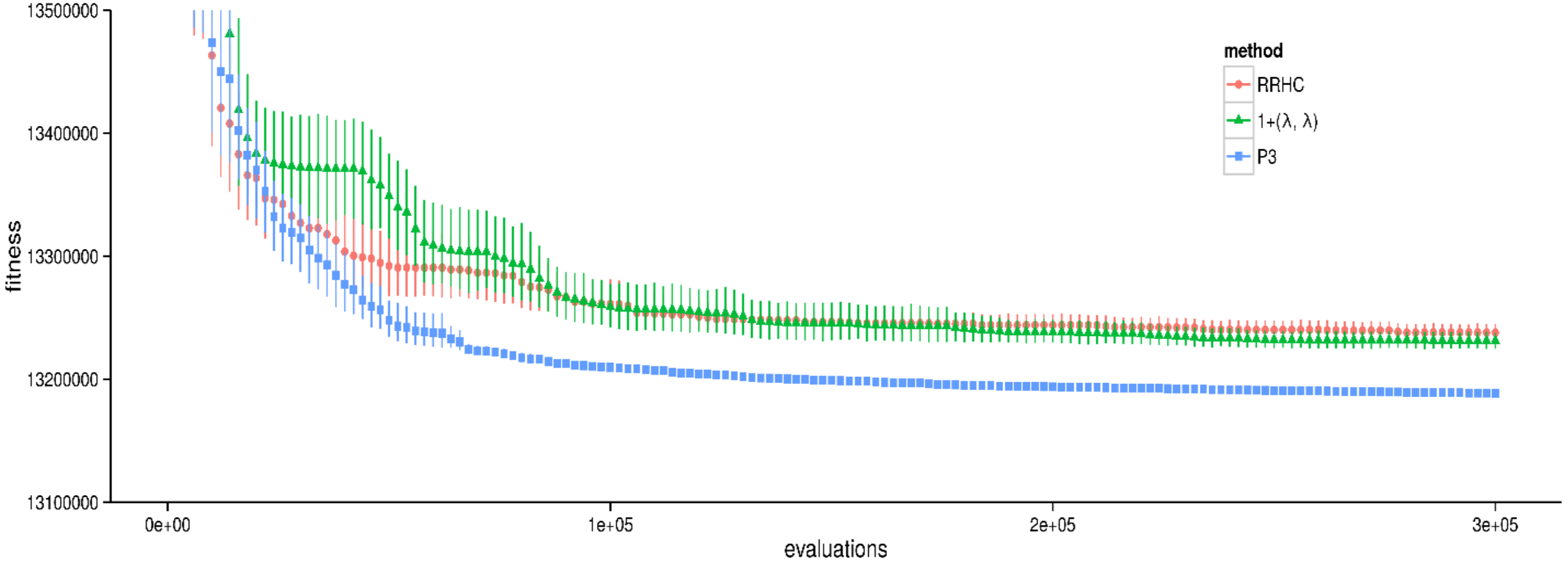
- Hunger Games Search (HGS)
- Reptile Search Algorithm (RSA)
- Colony Predation Algorithm (CPA)
- Runge Kutta based Algorithm (RUN)
- Material Generation Algorithm (MGA)
- Arithmetic Optimization Algorithm (AOA)
- Quantum-based Avian Navigation Algorithm (QANA)

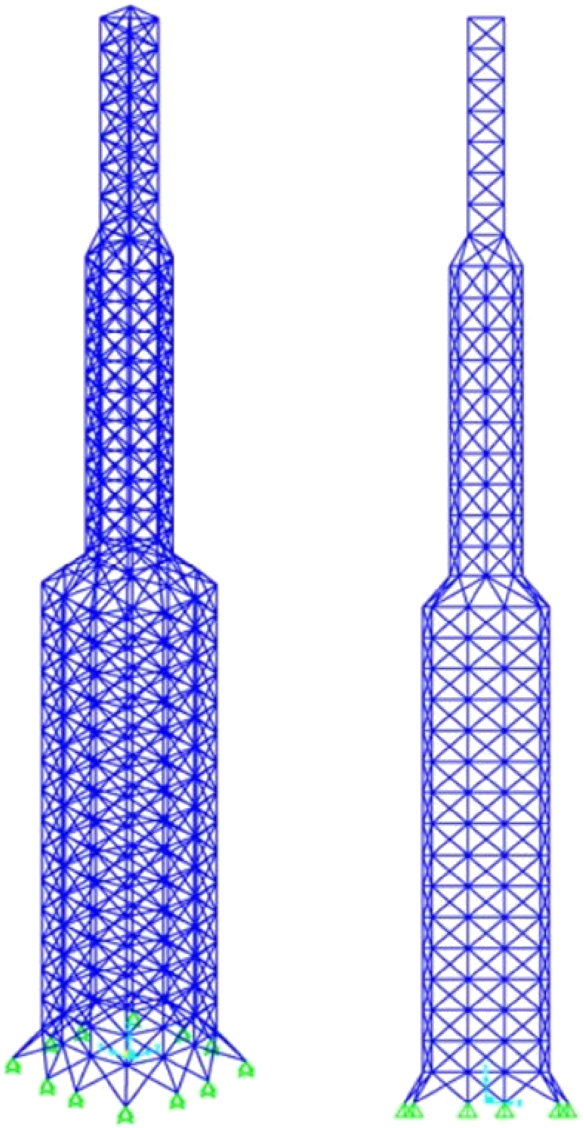
Elsevier – IFAC Best Theory Paper Award in EAAI from 2020-2022

- Aquila Optimizer (AO)
- Krill Herd Algorithm (KH)
- Fire Hawk Optimizer (FHO)
- Salp Swarm Algorithm (SSA)
- Interior Search Algorithm (ISA)
- Prairie Dog Optimization (PDO)
- Marine Predators Algorithm (MPA)
- Partial Reinforcement Optimizer (PRO)

Complex Systems: 35-Storey Space Tower

1262 members and 936 degrees of freedom





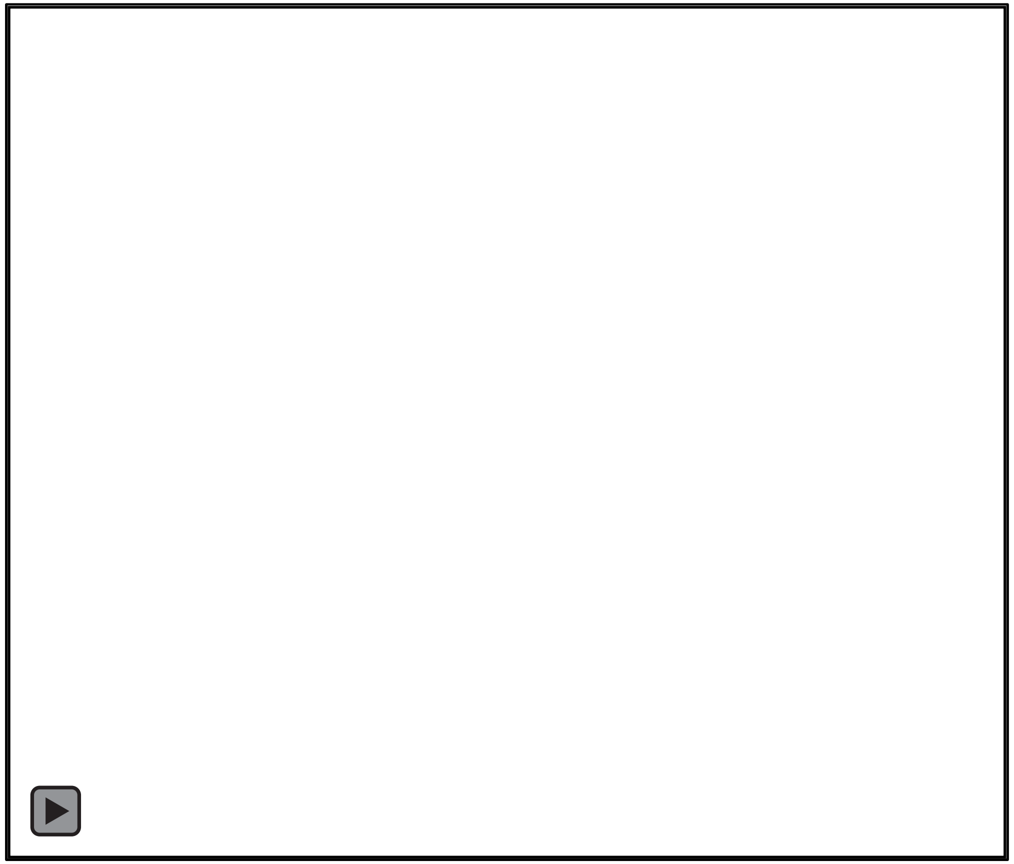
Gandomi, A. H., & Goldman, B. W. Parameter-less population pyramid for large-scale tower optimization. Expert Systems with Applications, 96, 175-184, 2018.

Many Objective Evolutionary Optimization

- 18 evolutionary many-objective algorithms are compared against well-known combinatorial problems!

- knapsack problem,
- traveling salesman problem,
- quadratic assignment problem

- 3, 5, and 10 objectives problems are tested

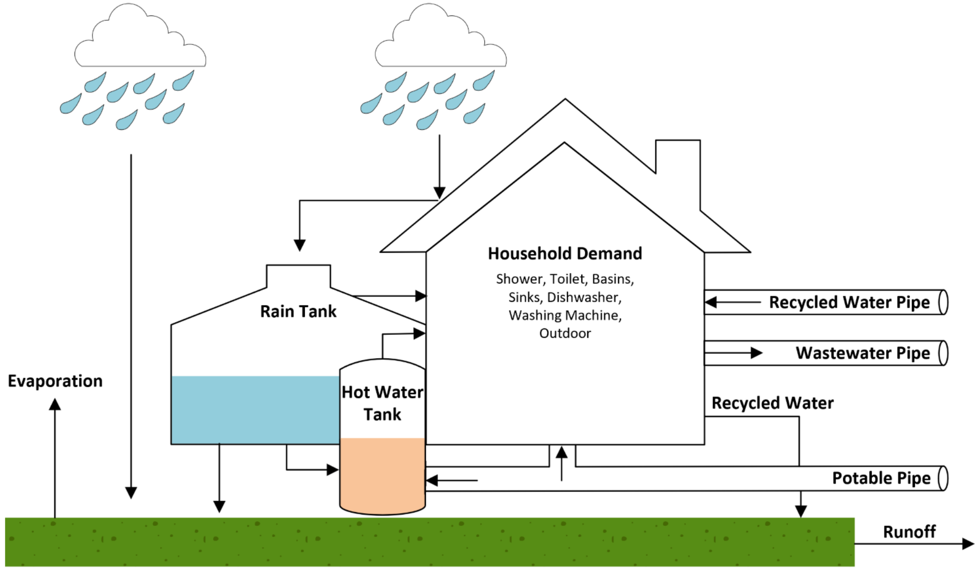


Behmanesh, R., Rahimi, I. and Gandomi, A.H., 2021. Evolutionary many-objective algorithms for combinatorial optimization problems: a comparative study. Archives of Computational Methods in Engineering, 28(2), pp.673-688.

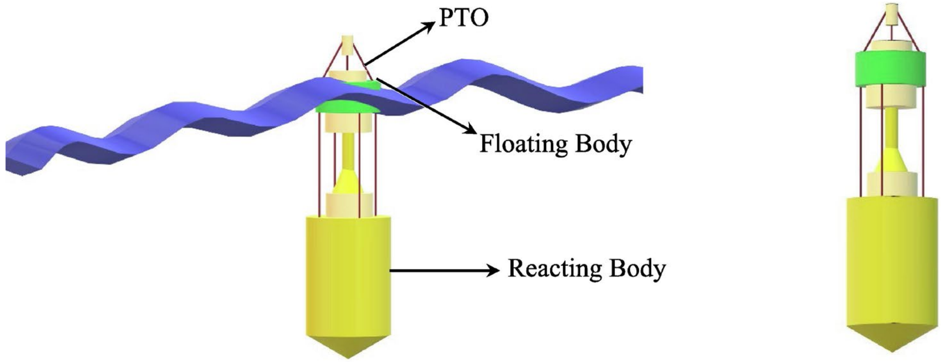
EMO for Water and Environmental Problems

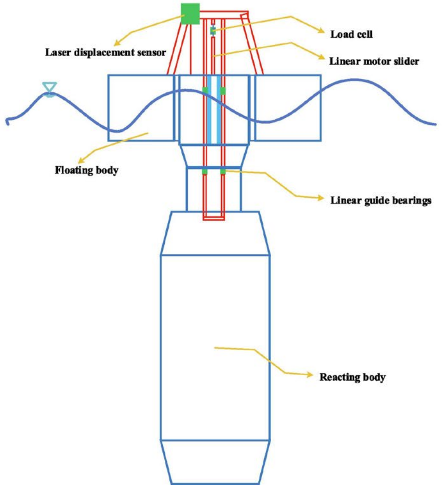
Optimisation of Local Integrated Water Management System. Objectives:

- mean daily piped potable water,
- mean daily site run-off,
- mean daily nominal costs.



Several studies on multi-objective optimization of wave energy converters (locations, layouts, shapes, etc).





EI for Combating COVID-19

XPRIZE-Cognizant Pandemic Challenge

F1: daily new cases
F2: stringency of planned interventions

UTS team:
I led team **Kangaroos** in this competition
Our team used

- ML to build models
- EMO to optimize the objectives

Results:

- We were the only team from Australia to reach the final
- We end up as a top-ten team
- We became one of the Honourable Mention Winners

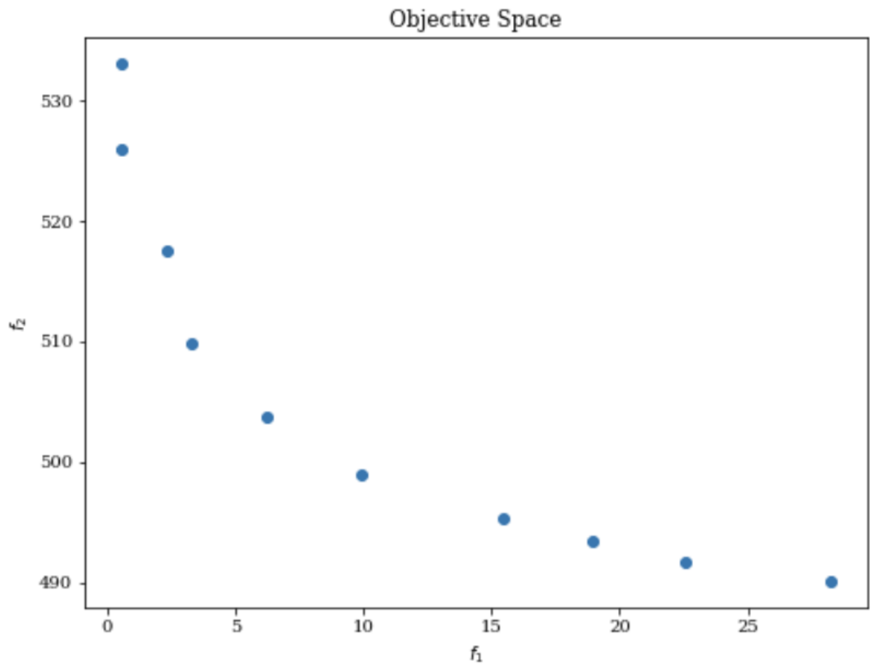


Figure 1. Sample Pareto Front for Canada

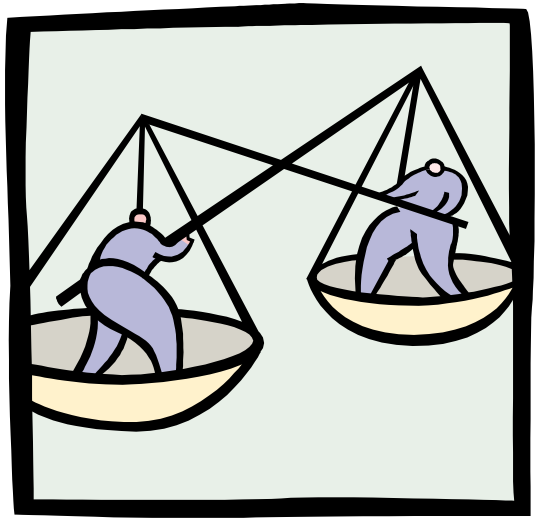
https://www.bloomberg.com/press-releases/2021-03-09/xprize-and-cognizant-announce-grand-prize-winners-in-pandemic-response-challenge-to-restart-economies-around-the-world

Customization in Optimization

AI-based Algorithms

- PROs
  - Derivative-free
  - Global
  - -- Flexible

- CONs
  - Slow



- Heuristic
  - More efficient
    - Convergence
    - Speed

Domain Knowledge

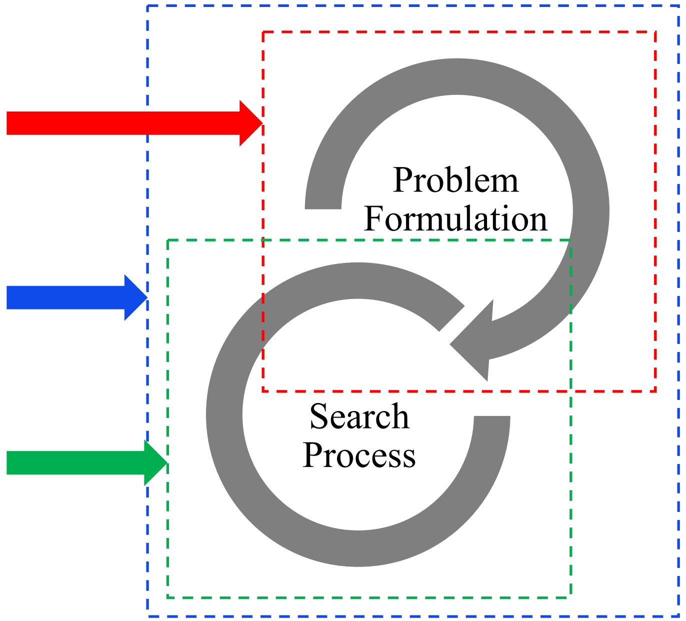
Possible Knowledge

Expert Knowledge

Information and Mathematical Theories

Engineering Principles

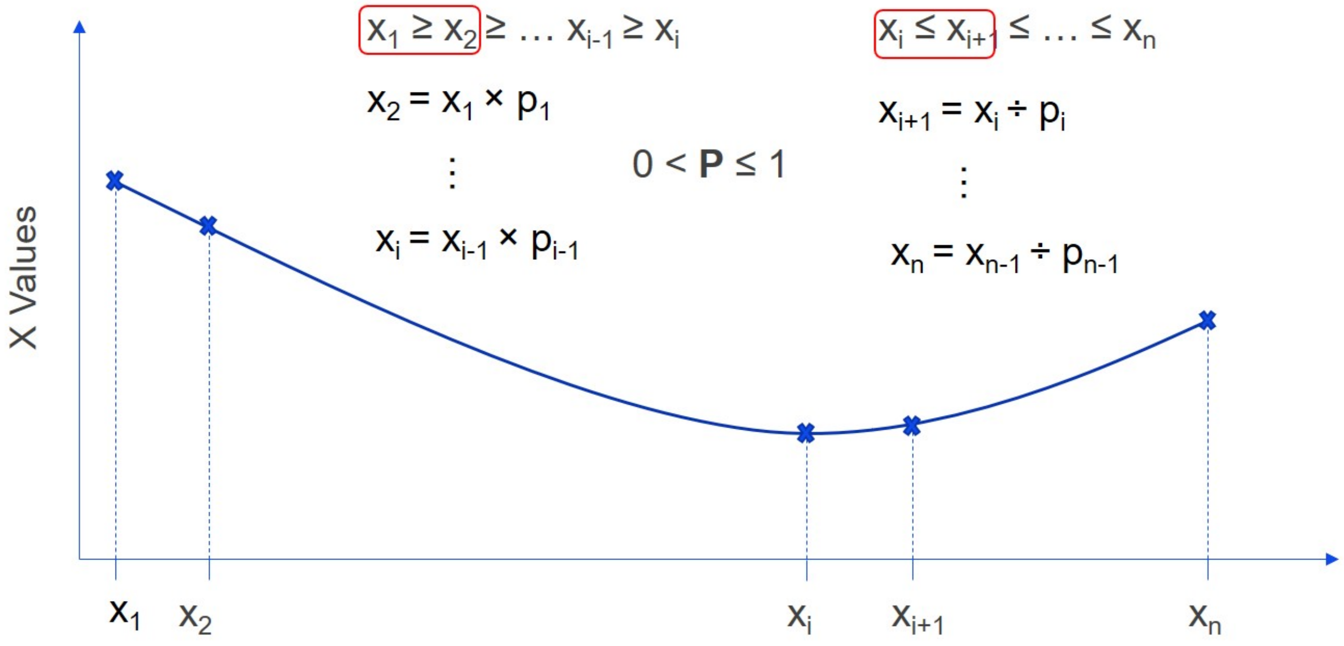
Scientific Concepts



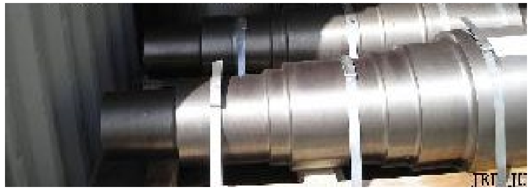
Tutorial (most recent):

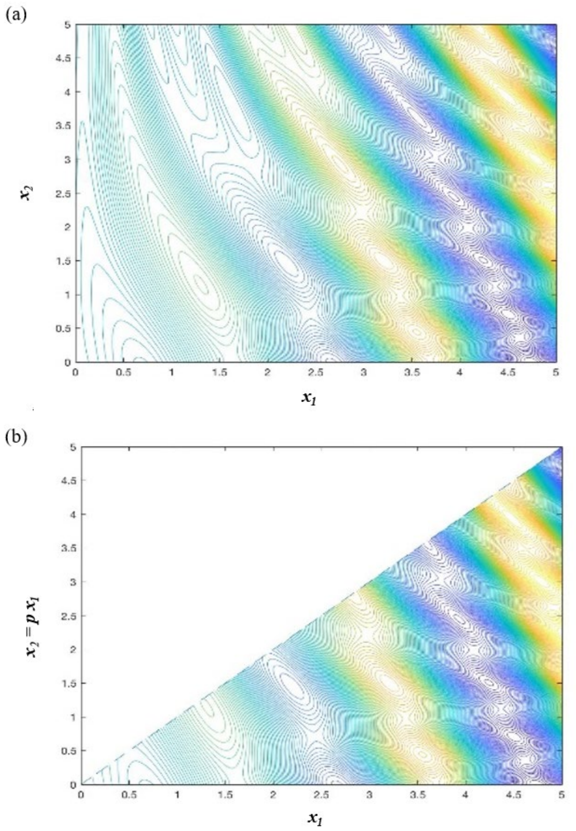
Gandomi, A.H., (2022) ACM GECCO 2022# embedding knowledge into optimization process. In *Proceedings of the Genetic and Evolutionary Computation Conference Companion, ACM* (pp. 922-936). DOI 10.1145/3520304.3533641

Semi-Independent Variables (SIV)



$\mathbf{X} \rightarrow x_1, \mathbf{P}$





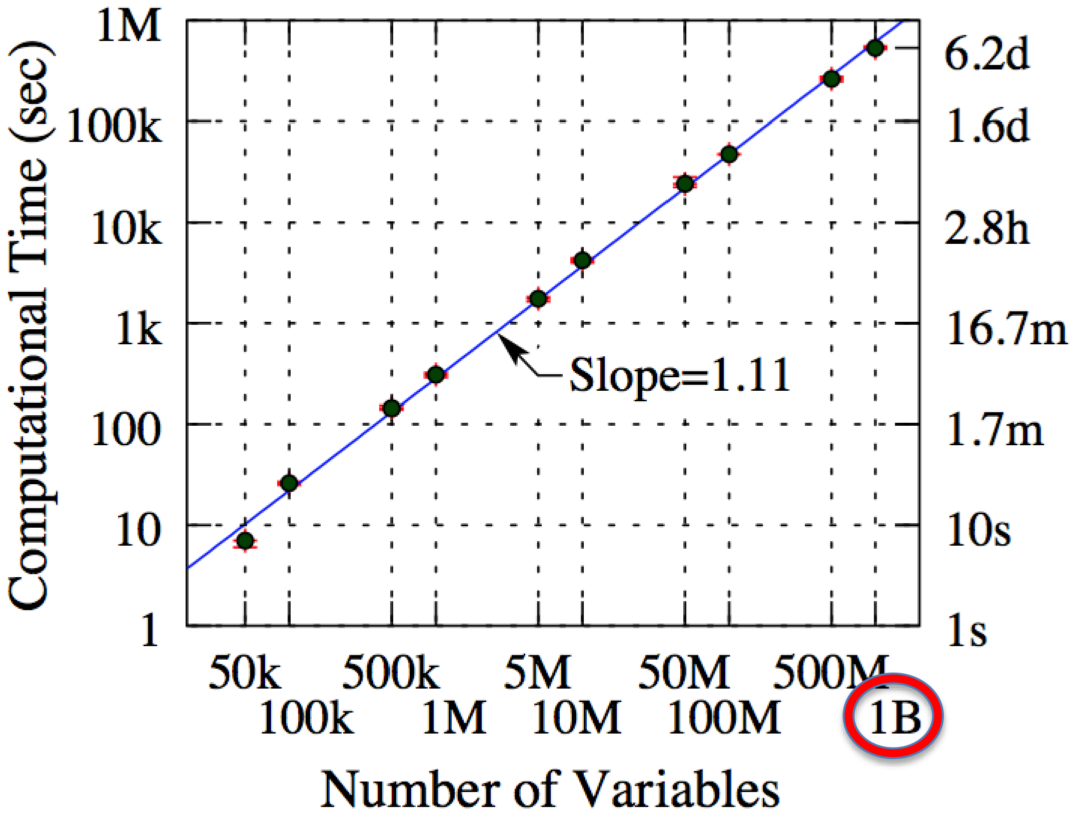
$$Reduction\ ratio = 2^N$$
$$N: number\ of\ SIVs$$

Gandomi, A.H., Deb, K., Averill, R.C., Rahnamayan, S. and Omidvar, M.N., 2018. Using Semi-independent Variables to Enhance Optimization Search. *Expert Systems with Applications*. 120, 279-297, 2019.

Billion Variable Problem Solved using EAs

Resource allocation Problem:

- Casting scheduling
- Multi-knapsack problem is NP-hard
- Discrete Variables
- Pop. Size: 60 for all problems

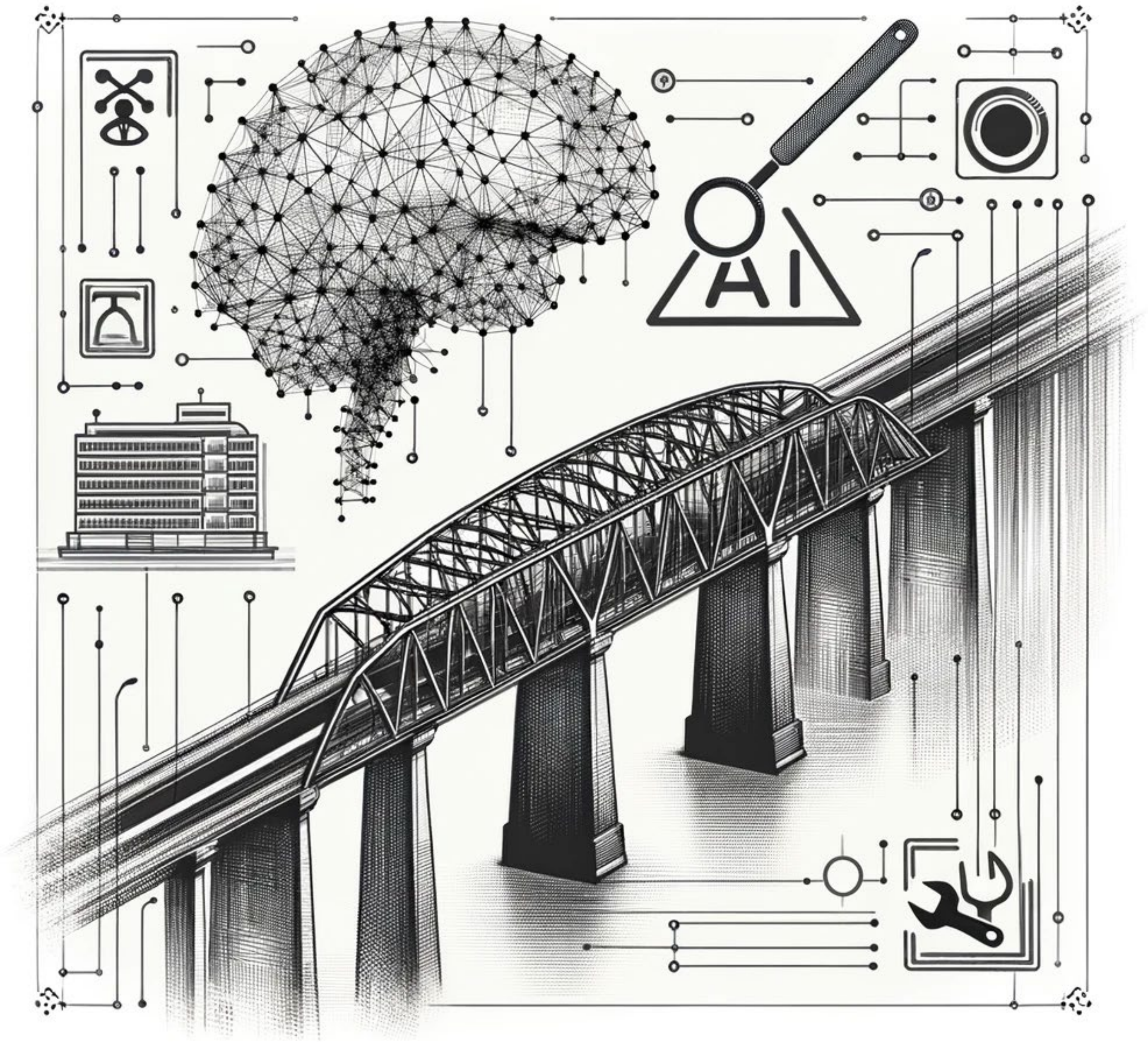


How much is a Billion?

•4GBytes for a solution, 240GB RAM for a population

Deb, K. and Myburgh, C., 2017. A population-based fast algorithm for a billion-dimensional resource allocation problem with integer variables. European Journal of Operational Research, 261(2), pp.460-474.

AI for Engineering Monitoring and Maintenance



Structural Health Monitoring

Sungsoo Bridge, Seoul (1994)

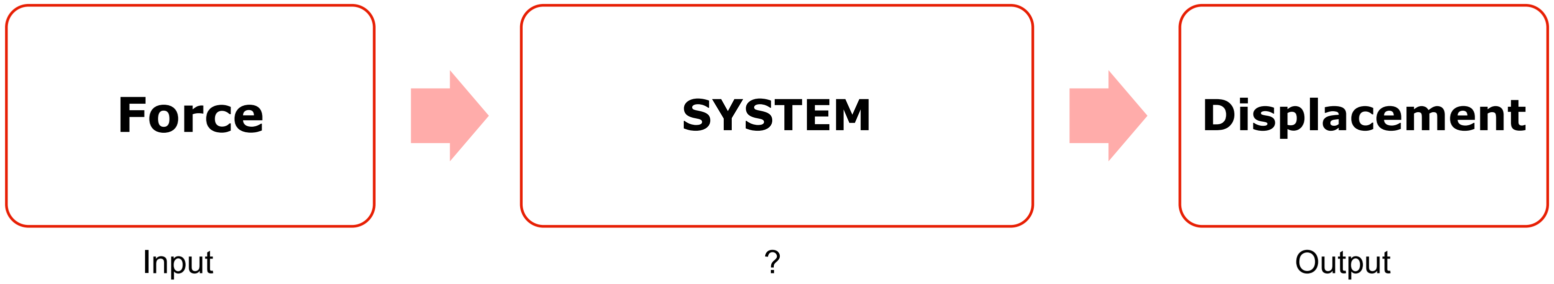
Kobe Earthquake (1995)

San Francisco-Oakland Bridge (1989)

Highway Bridge, Minnesota (2007)

Inverse Analysis

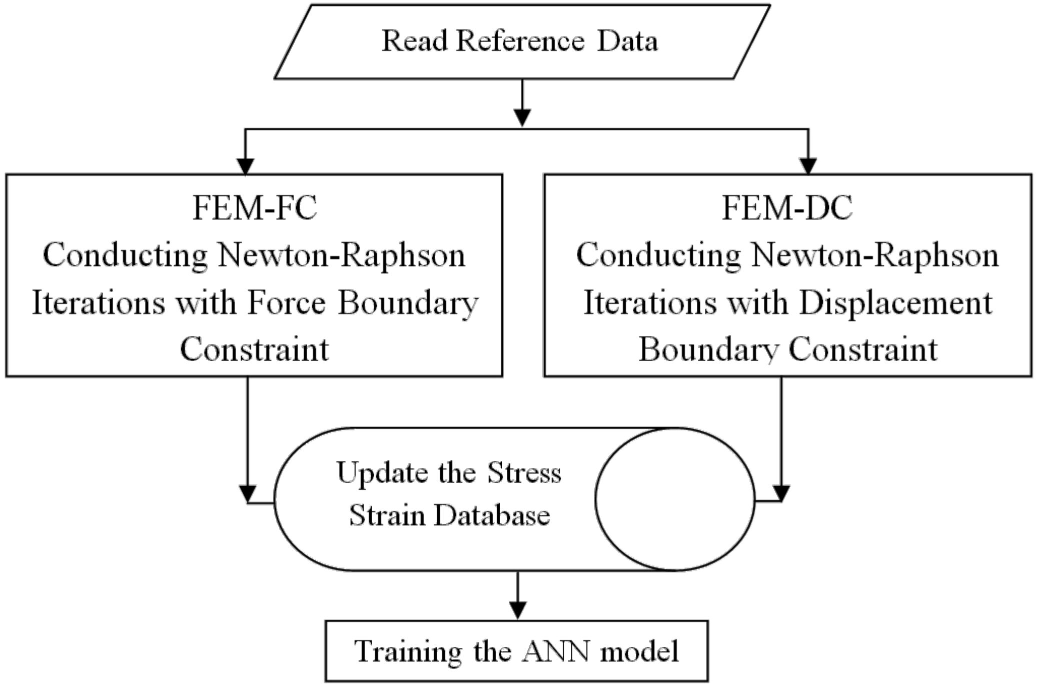
Inverse Problem of Engineering Systems



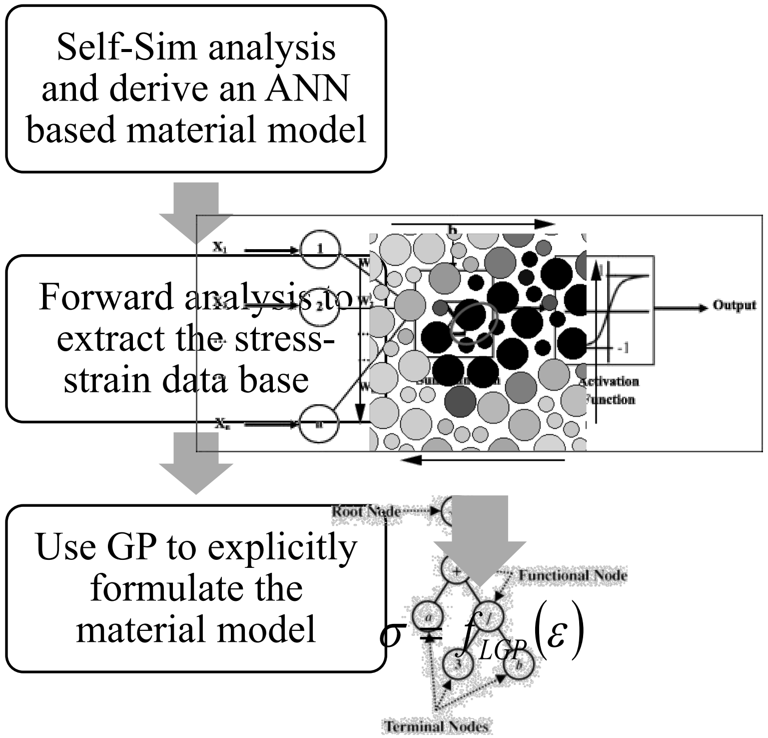
As the system properties are usually unknown we need to do the inverse analysis

We need to have the Model (F.E. Model)

Coupled Self-Sim & GP

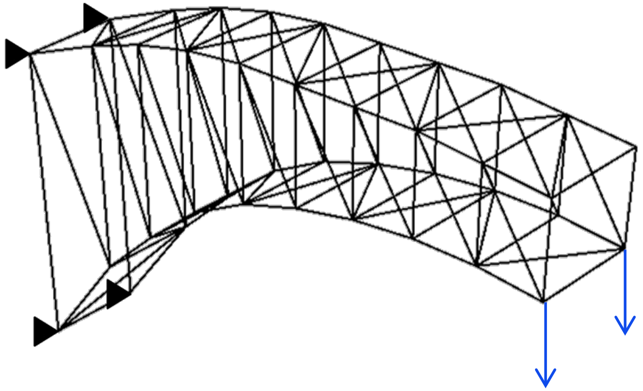


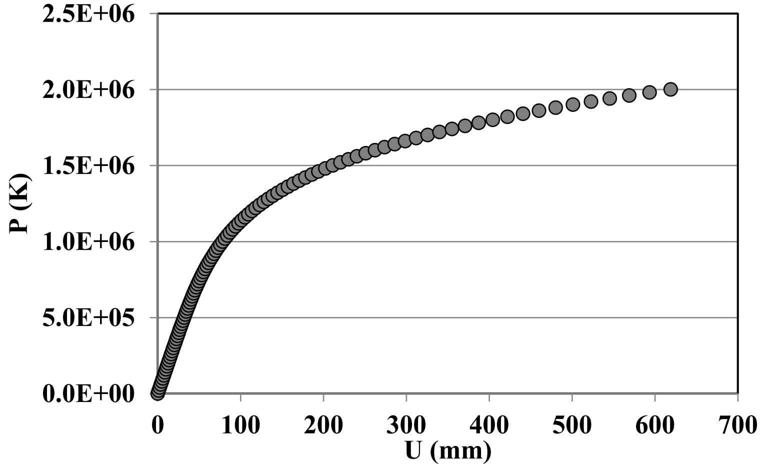
Ghaboussi, J., Pecknold, D.A., Zhang, M. and Haj-Ali, R.M., 1998. Autoprogressive training of neural network constitutive models. *International Journal for Numerical Methods in Engineering*, *42*(1), pp.105-126.



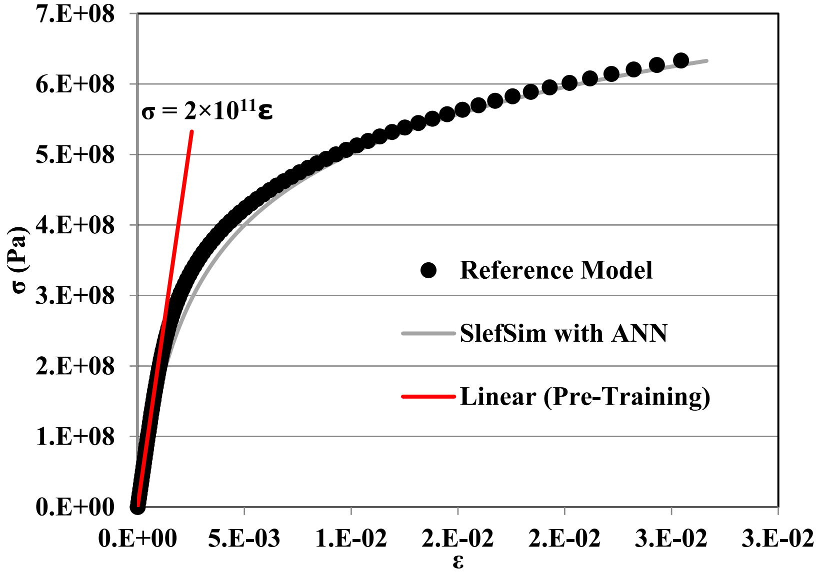
Gandomi A.H., Yun G.J., “Coupled SelfSim and genetic programming for non-linear material constitutive modelling.” Inverse Problems in Science and Engineering, 23(7), 2015

Case Study: 112 bar Space Truss

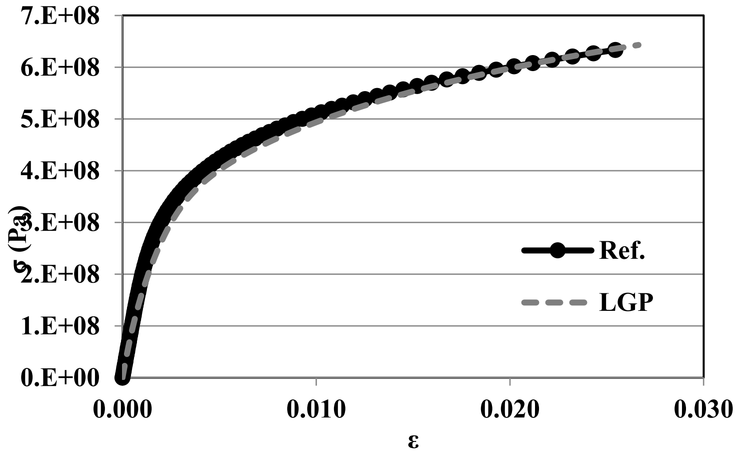




GP-based Constitutive Model

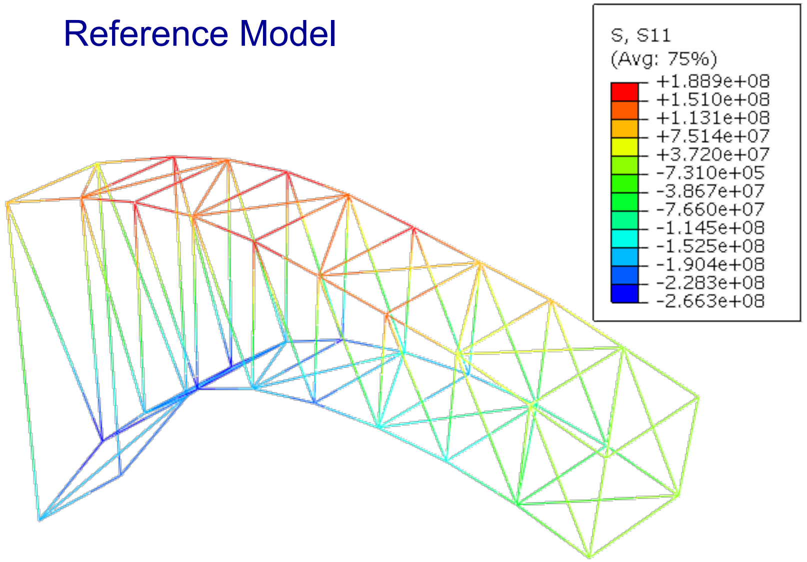


f[1]=f[2]=f[3]=f[4]=f[5]= f[6]=f[7]=f[8]= 0;
f[0]=v[0];
l0: f[0]*=8;
l1: f[0]=sqrt(f[0]);
f[1]-=f[0];
l2: f[0]-=0.25;
l3: f[0]*=f[0];
f[1]+=f[0];
l4: f[1]+=f[0];
f[0]+=f[1];
l5: f[0]=fabs(f[0]);
f[0]-=f[1];
l6: f[1]-=f[0];
f[0]*=f[0];
l7: f[0]*=f[0];
f[0]+=f[1];
l8:
l9:
return f[0];
}

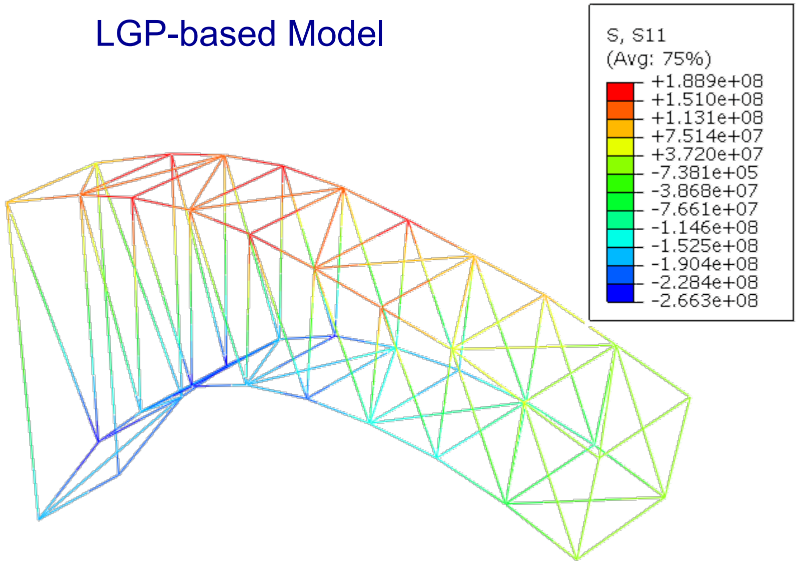


Forward FE simulation using GP-based constitutive model

Reference Model

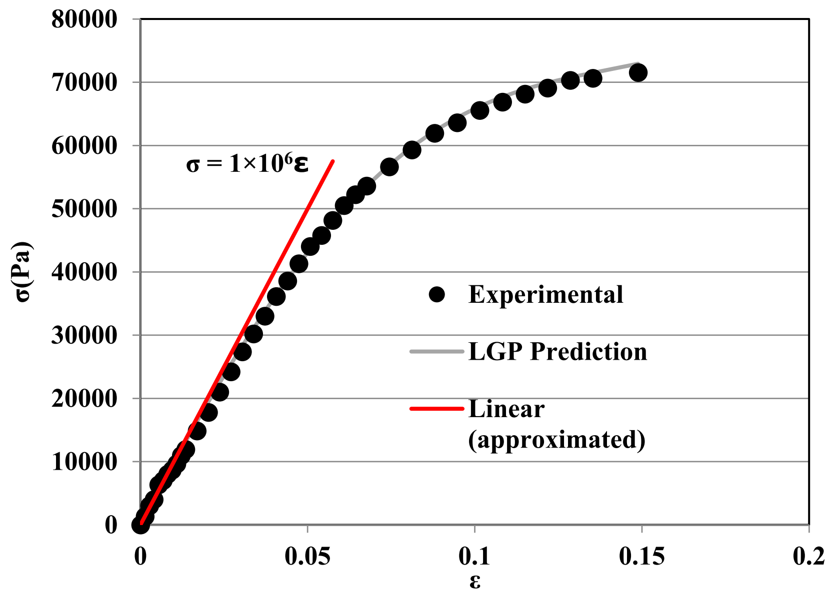


LGP-based Model

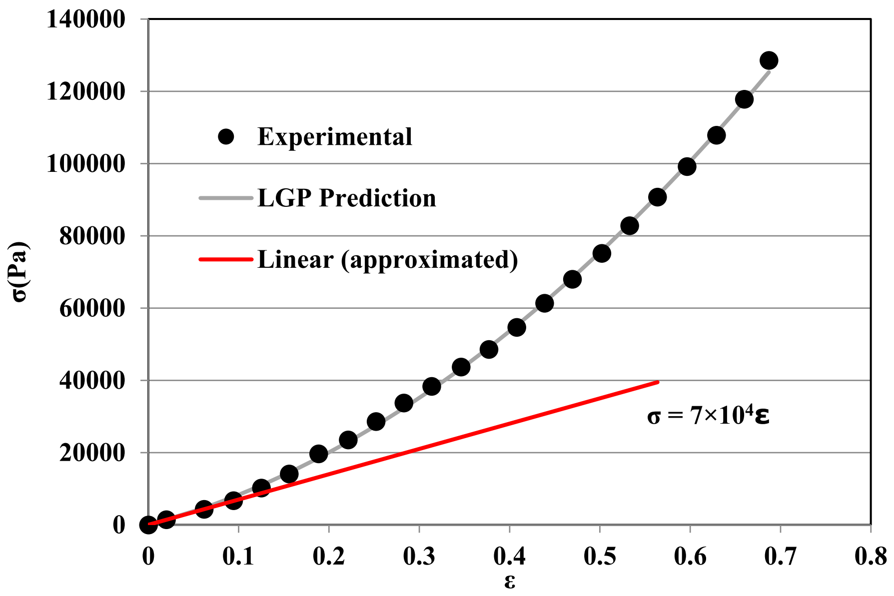


Other Cases

- Soil Modelling



- Aortic Modelling



Yun G.J., Gandomi A.H., "Coupled selfsim and genetic programming for non-linear material constitutive modeling" In Proceedings of the Joint Conference of the Engineering Mechanics Institute and 11th ASCE Joint Specialty Conference on Probabilistic Mechanics and Structural Reliability, Notre Dame, IN, Paper ID. 657, 2012.

EI is only one of the AI tools!

AI methodologies/Tools:

- Machine Learning
- Deep Learning
- Natural Language Processing
- Computer Vision
- Predictive Analytics
- Evolutionary Intelligence
- Fuzzy Logic
- Expert Systems
- Robotics
- Signal Processing

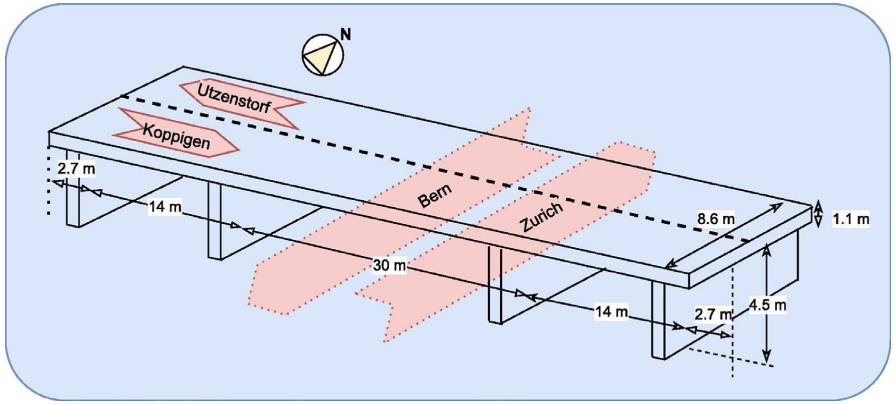
Mousavi, M., Taskhiri, M.S. and Gandomi, A.H., 2023. Standing tree health assessment using contact–ultrasonic testing and machine learning. *Computers and Electronics in Agriculture*, *209*, p.107816.

Other studies!

Using other AI based tools such as the following SHM studies:

- Assessment of standing trees and wooden poles using contact–ultrasonic testing and machine learning and convolutional neural network!

- Combining advanced signal processing (VMD and Johansen cointegration) and machine learning approaches for structural health monitoring!



Mousavi, M. and Gandomi, A.H., 2021. Prediction error of Johansen cointegration residuals for structural health monitoring. *Mechanical Systems and Signal Processing*, *160*, p.107847.

AI Impacts in Engineering

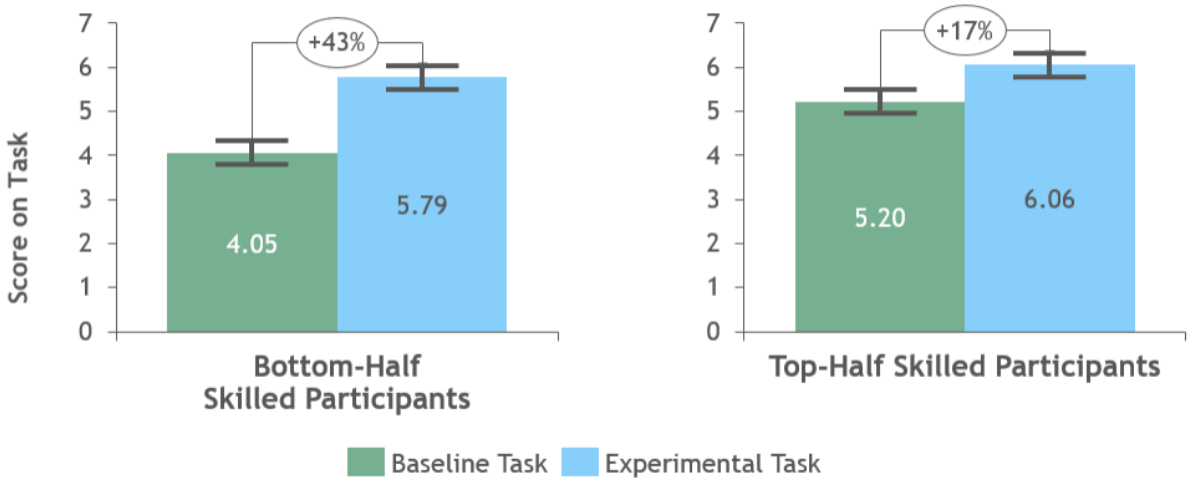
- **Enhanced Design and Simulation**
- **Predictive Maintenance**
- **Improved Efficiency and Automation**
- **Quality Control**
- **Risk Assessment**
- **Resource Optimization**
- **Smart Infrastructure**
- **Environmental Impact**
- **Supply Chain and Logistics**
- **Customization**
- **Safety Enhancements**
- **Data Management and Decision Making**
- **Intelligent Monitoring Systems**
- **Workforce Transformation**
- **Research and Development**

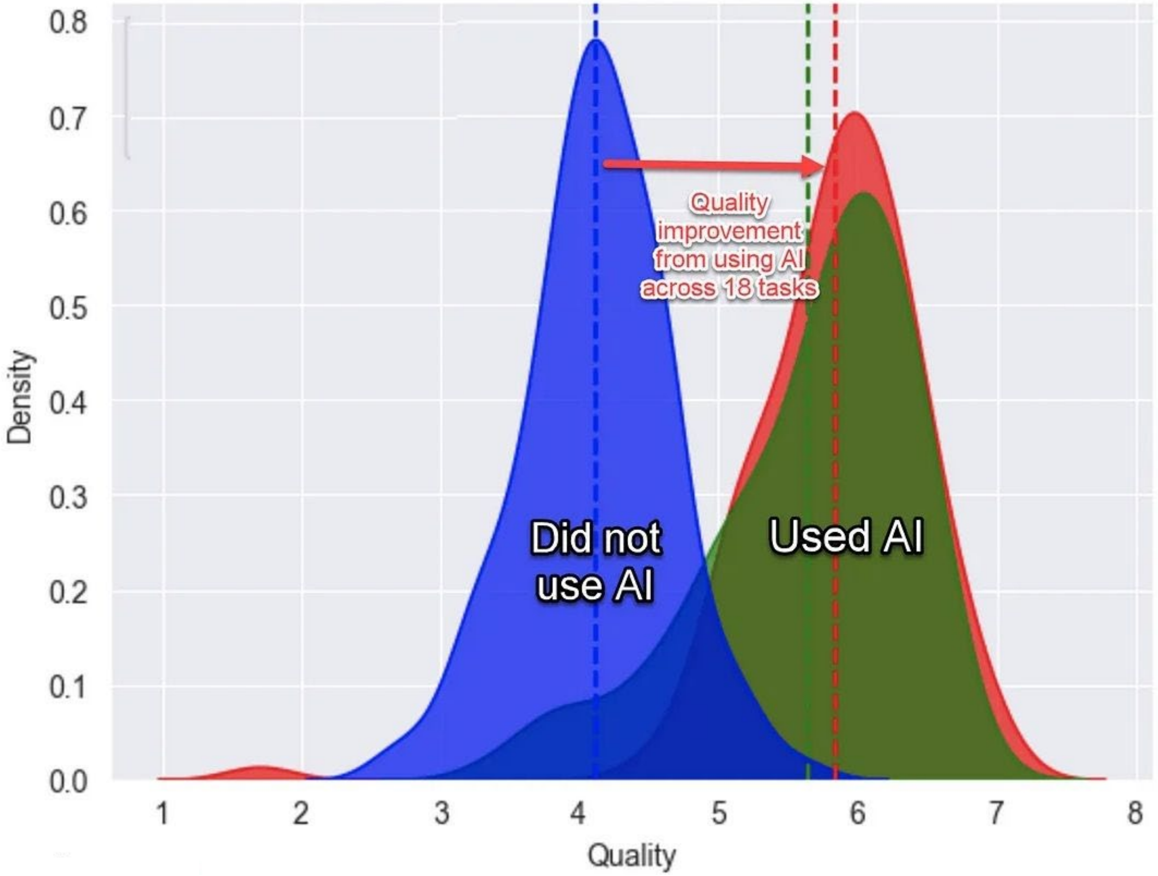
Effect of AI in Performance

25+% increase in speed,

40+% improvement in output quality, **and**

12+% more tasks completed





Dell'Acqua, et al., Navigating the Jagged Technological Frontier: Field Experimental Evidence of the Effects of AI on Knowledge Worker Productivity and Quality (September 15, 2023). Harvard Business School Technology & Operations Mgt. Unit Working Paper No. 24-013

ÓBUDAI EGYETEM
ÓBUDA UNIVERSITY

IEEE
23rd International Symposium on Computational Intelligence and Informatics
(IEEE CINTI 2023)
Óbuda University, Budapest, Hungary

Thank you!

Amir H Gandomi

Professor of Data Science at University of Technology Sydney
Distinguished Professor at Óbuda University, Budapest

Robert Bosch Engineering company, Budapest, Hungary
20 November, 2023