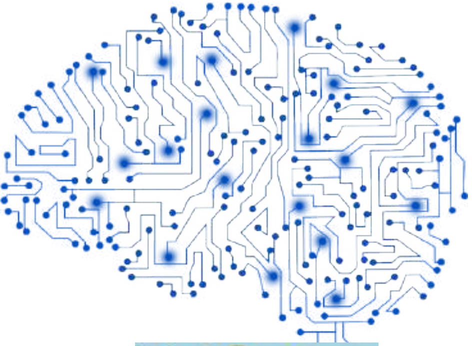
UNIVERSITY OF SURREY



Daniel Molina Cabrera

https://orcid.org/0000-0002-4175-2204

dmolinac@ugr.es

Evolution in Action: Bio-inspired Algorithms and Neuroevolution

DECSAI Universidad de Granada

DASCI Andalusian Research Institute in Data Science and Computational Intelligence

Financiado por la Unión Europea NextGenerationEU

GOBIERNO DE ESPAÑA | MINISTERIO PARA LA TRANSFORMACIÓN DIGITAL Y DE LA FUNCIÓN PÚBLICA | SECRETARÍA DE ESTADO DE DIGITALIZACIÓN E INTELIGENCIA ARTIFICIAL

Plan de Recuperación, Transformación y Resiliencia

España | digital 2026

UNIVERSIDAD DE GRANADA

UNIMORE UNIVERSITÀ DEGLI STUDI DI MODENA E REGGIO EMILIA

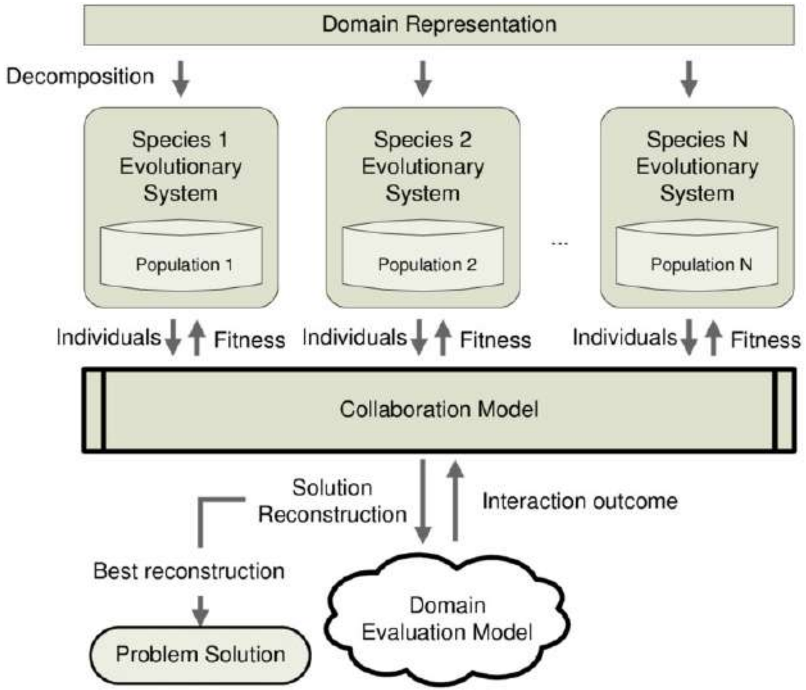
repsol

Be patient with my English

- Strong Spanish accent.
- Not used to British accent.

I hope we could have

COOPERATIVE COEVOLUTION



Available at

https://www.danimolina.net/talks/

About me

About me

- Senior Lecturer, Department Computer Science and AI, University of Granada, Spain.
- Researcher in Artificial Intelligence for 20 years.
- Inside the list of 2% more influencer researchers published by Stanford.

UNIVERSITAS · GRANATENSIS · 1531 ·
PLUS ULTRA

UNIVERSIDAD DE GRANADA

DECSAI
Universidad de Granada

DASCI
Andalusian Research Institute in Data Science and Computational Intelligence

University of Granada

UNIVERSIDAD
DE GRANADA

- More than 500 years.
- 56.000 students, one of the most important universities.
  - More than 3.200 international students.
  - 44% from other spanish cities.
- Considered 93º Best in Computer Science (Shangai Ranking).

Alhamba, in Granada

DASCI
Andalusian Research Institute
in Data Science and
Computational Intelligence

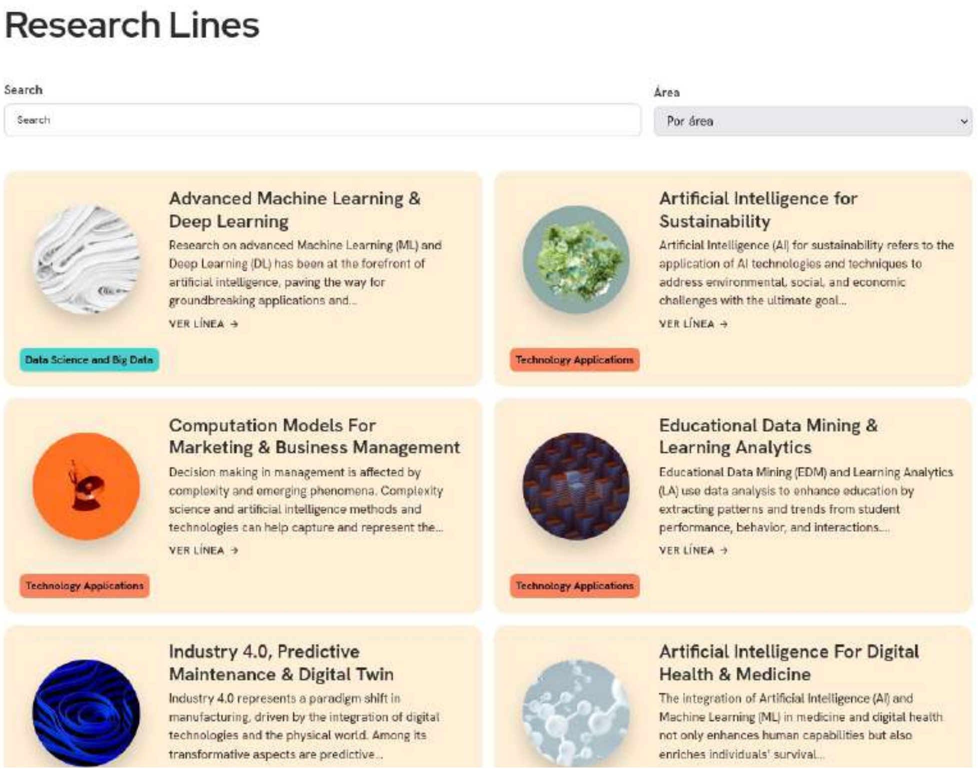
DaSCI

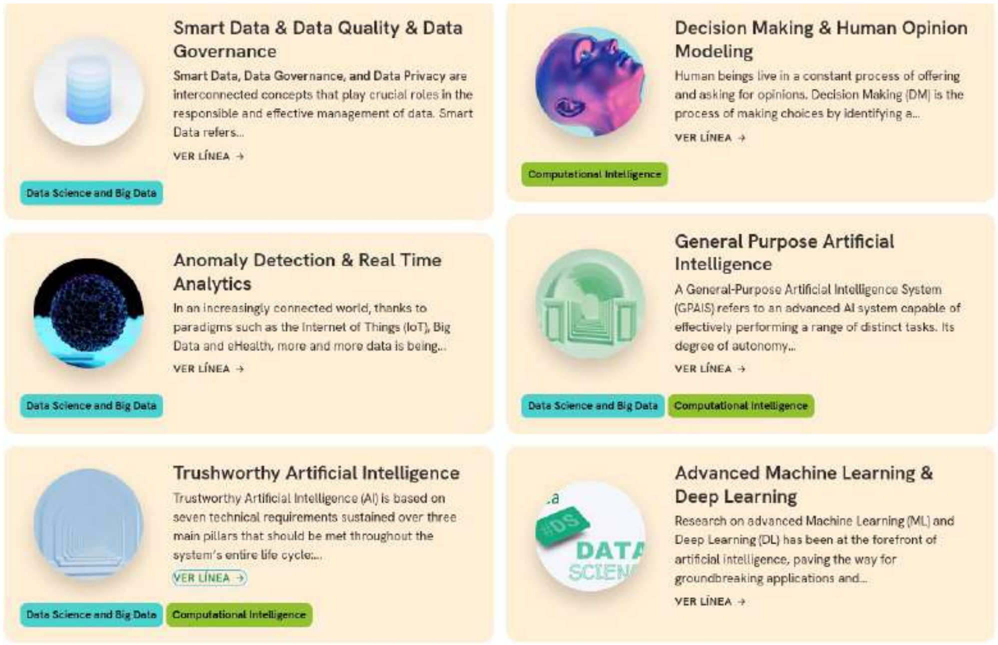
- Institution about AI research members of different Universities:
  - Granada.
  - Córdoba.
  - Jaén.

- Lead by the well-known research Paco Herrera.
- 82 doctors (16 professors) and many Phd students.

https://dasci.es/en/

DaSCI Research Lines



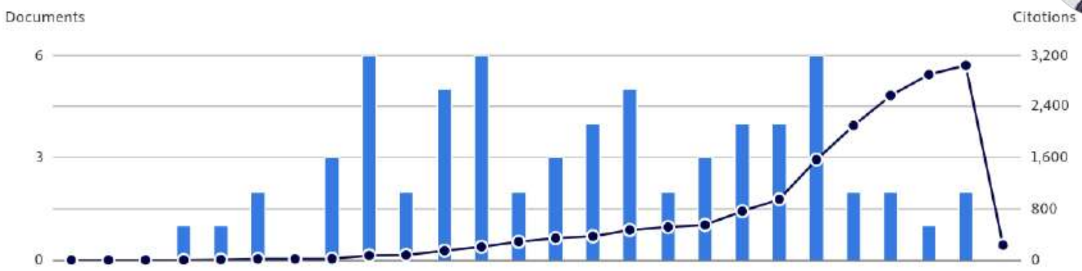


About me

- H-index: 28
- 42 Papers in International Journal.
- More than 16,000 citations in my papers (without self-citations).
- Ex-chair and co-chair of IEEE Task Force on Large Scale Global Optimization.
- Winner of two IEEE LSGO international competitions: 2010, 2018.
- Field-Weighted Citation: 9.85

Source: Scopus

About me



Sort by Cited by (highest)

	Documents	Year	<2001	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	Total
	Total		**0**	**0**	**0**	**0**	**1**	**7**	**18**	**20**	**21**	**70**	**79**	**146**	**205**	**286**	**340**	**370**	**469**	**513**	**547**	**17,208**
1	Explainable Artificial Intelligence (XAI): Co...	2020	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7,048
2	A practical tutorial on the use of nonpara...	2011	0	0	0	0	0	0	0	0	0	0	0	6	43	98	124	170	239	251	308	5,027
3	A study on the use of non-parametric tests ...	2009	0	0	0	0	0	0	0	0	1	10	32	66	68	86	93	95	84	134	121	1,578
4	Bio-inspired computation: Where we stand...	2019	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	536
5	A Tutorial On the design, experimentation ...	2021	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	322
6	Global and local real-coded genetic algori...	2008	0	0	0	0	0	0	0	0	3	10	10	12	16	8	20	12	26	20	18	266
7	Real-coded memetic algorithms with cross...	2004	0	0	0	0	1	7	12	11	8	27	21	19	28	20	21	11	19	6	10	264
8	A panoramic view and swot analysis of arti...	2021	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	192
9	Comprehensive Taxonomies of Nature- an...	2020	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	160
10	MA-SW-Chains: Memetic algorithm based ...	2010	0	0	0	0	0	0	0	0	0	0	1	5	2	9	10	7	9	15	18	160
11	Memetic algorithms for continuous optimi...	2010	0	0	0	0	0	0	0	0	0	0	1	6	17	18	22	10	11	6	8	135

About me

Instituto Andaluz Interuniversitario en Data Science and Computational Intelligence

- Projects with private companies:
  - GHENOVA Ingenieering.
  - REPSOL.
- AI courses:
  - National Military.
  - International teachers in AI (Arqus).
- IP National research project 120,000 € (2025-2027).
- Participate in 19 research projects.

About me

- Previous International research stays:
  - 3 months, Belgium, with Thomas Stuetze.
  - 3 months, Sweden, with Ning Xiong.
  - 1 month, Brasil, with Daniel Dos Santos.

Collaboration

45.7%
International collaboration
Percent of documents co-authored with researchers in other countries/regions

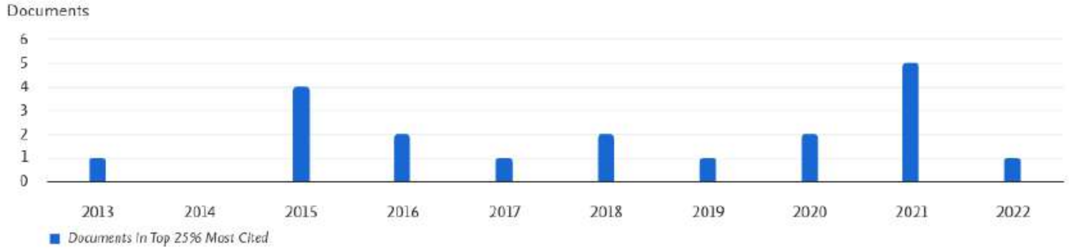
28.6%
Academic-Corporate collaboration
Percent of documents with both academic and corporate affiliations

Analyze author in SciVal ↗

Documents in top citation percentiles

59.4% (19 documents)
Percent of documents in the top 25% most cited documents worldwide

Analyze author in SciVal ↗



About me

Citations from many countries:

About me

- Teacher for 20 years.
- Computer Science:
  - Programming.
  - Web Developing.
  - Business Intelligence (Machine Learning).
  - Artificial Intelligence.
  - Metaheuristics.
- Master on Data Science (UGR).
- Many outreach talks about AI for responsible usage for teenages.

About me

- Free Software Advocate and Open Science
  - Papers in open repositories (arxiv, digibug).
  - Software of proposals in public repositories like Github.
  - General software available in public repositories like Github.
- Ex-director of Free Software Office at University of Cádiz.
- Many Technical Talks in Free Software Communities:
  - Pycon ES and Pycon Global.
  - JuliaCon.
  - Emacs Conf.

About me

- Advisor of 2 Finished Phd students:
  - Benjamin Lacroix, Marie Curie, about Bio-Inspired algorithm using Regions.
  - Javier Poyatos, about Neuroevolution (automatic pruning with EC).
- Current Phd students:
  - Irene Trigueros, about Distillation Knowledment (teacher-student).
  - Abel José Sánchez, about NAS using VGAE.
  - Karrar Aljammali, using ML for premature cognitive diseases.

My last Research Works

- Bio-Inspired Algorithms for real-world problems.
- GPAIS (Genetic Purpose Artificial Intelligence Systems)
- Critical Analysis of Bio-Inspired Algorithms.
- Neuro-evolution and NAS.

Optimization Concept

Optimize: Search the most efficient way to carry out a task

- **Scientific Context: Optimization is the process to search the best possible solution for a specific problem.**
- **Business:**
  - **Reducing the costs.**
  - **Improve client experience.**

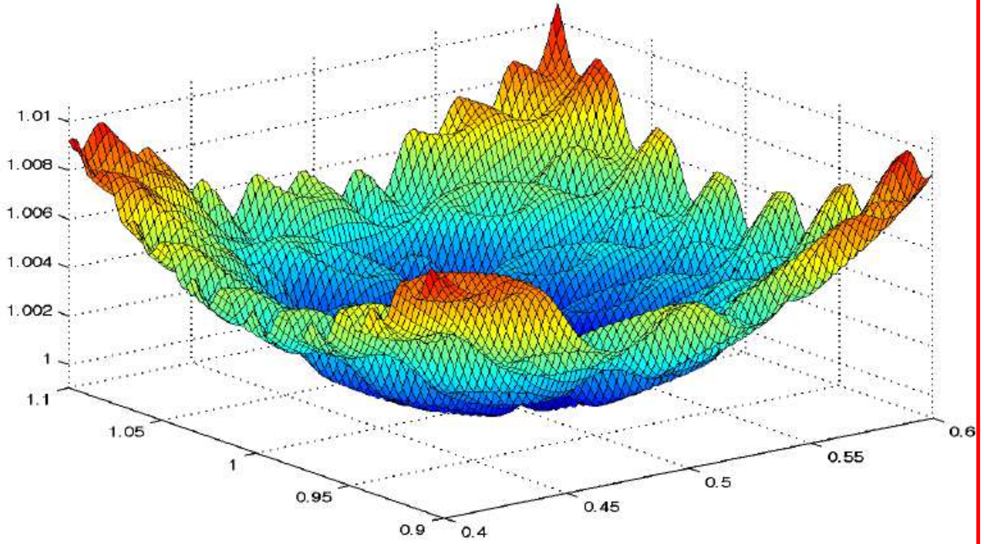
Optimization Problem

- Optimization
  - Many possible **solutions**, a **criterion** for valorate each one, and a **fitness function** to identify the best one.

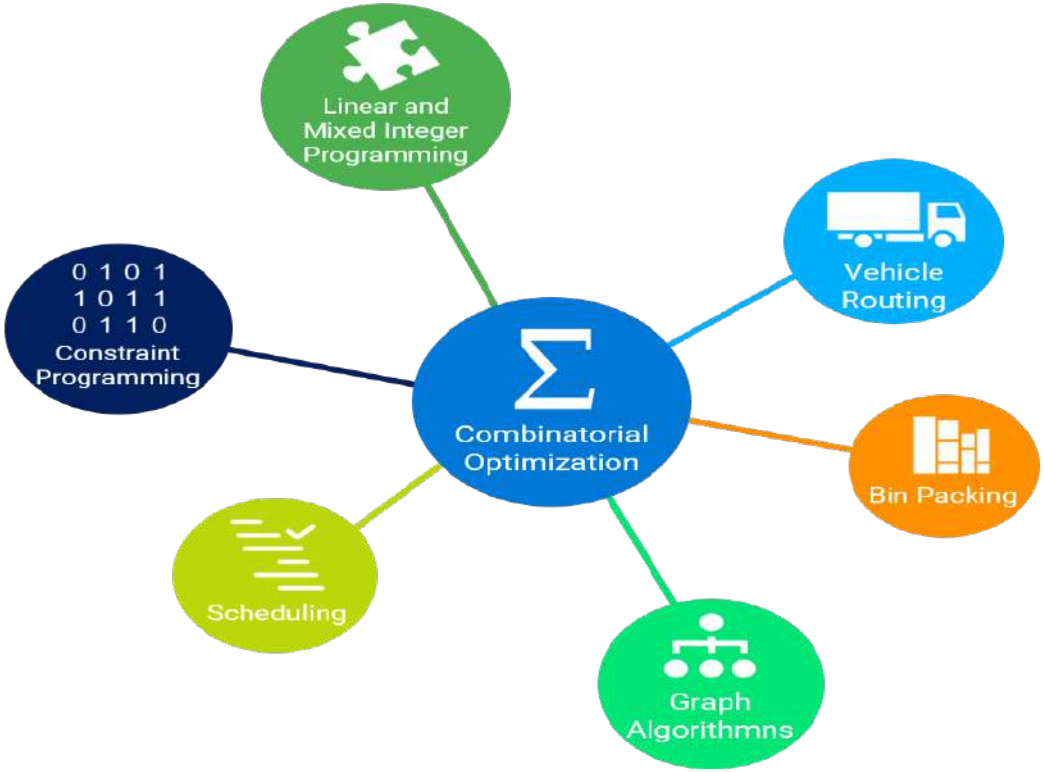
Different Problems

Combinatorial

Continuous Optimization



Combinatorial



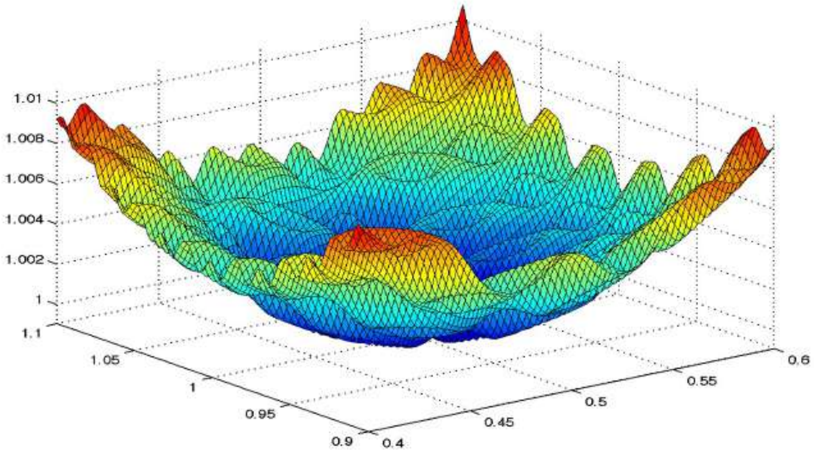
Continuous Optimization

- Optimize a range of real variables, each one with a range.

Global Optima $f(x^*) \leq f(x) \quad \forall x \in Domain$

Real-parameter Optimization $Domain \subseteq \Re^D$,

$$x^* = [x_1, x_2, \cdots, x_D]$$



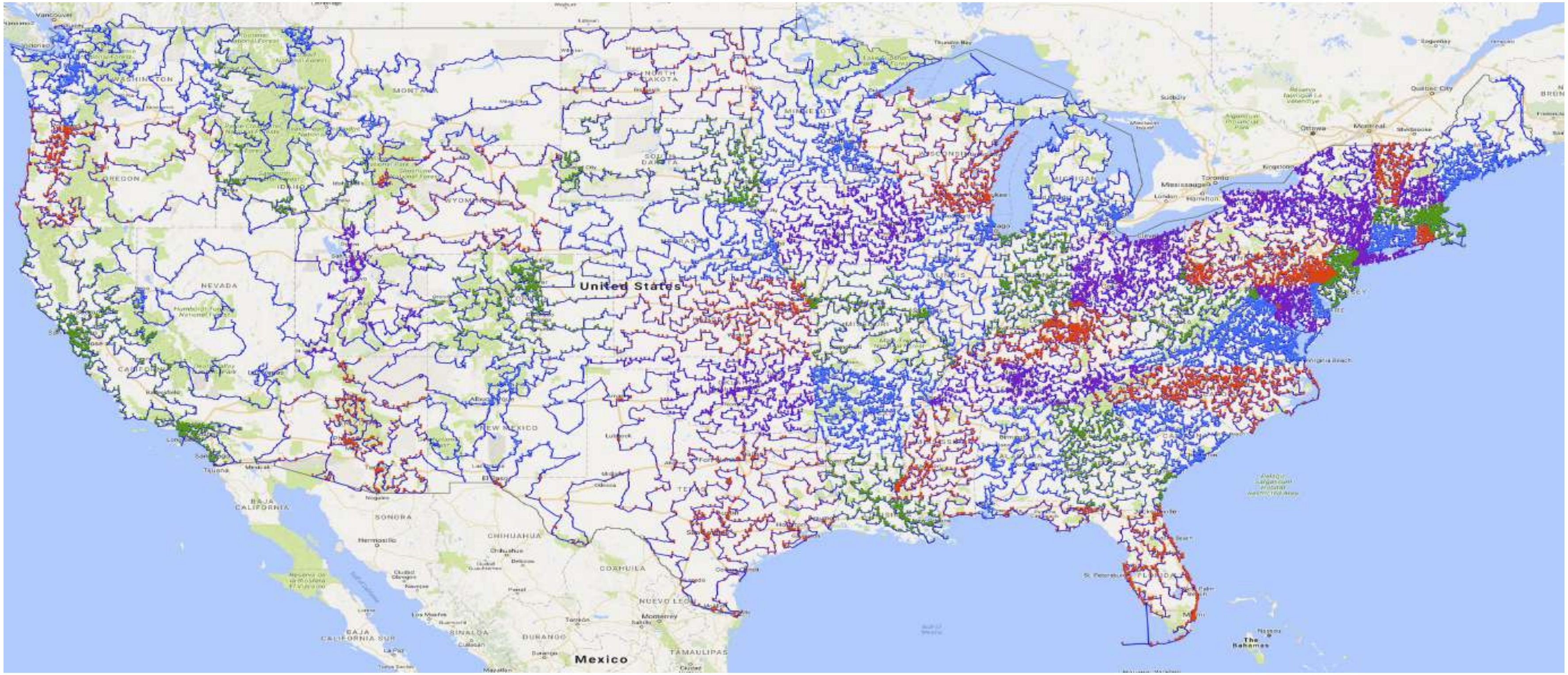
Non exact method, Why?

- There is not a clear way to find the optimum.
- It could be too expensive.
- Many time the fitness is obtained by a costly process (simulation, trainining, …).
- They could be be adequate for multi-objective problems/approaches.

Example Travelling Salesman Problem

- Find the shorter route crossing N towns.
- Each time for each town.
- Return to the original point.

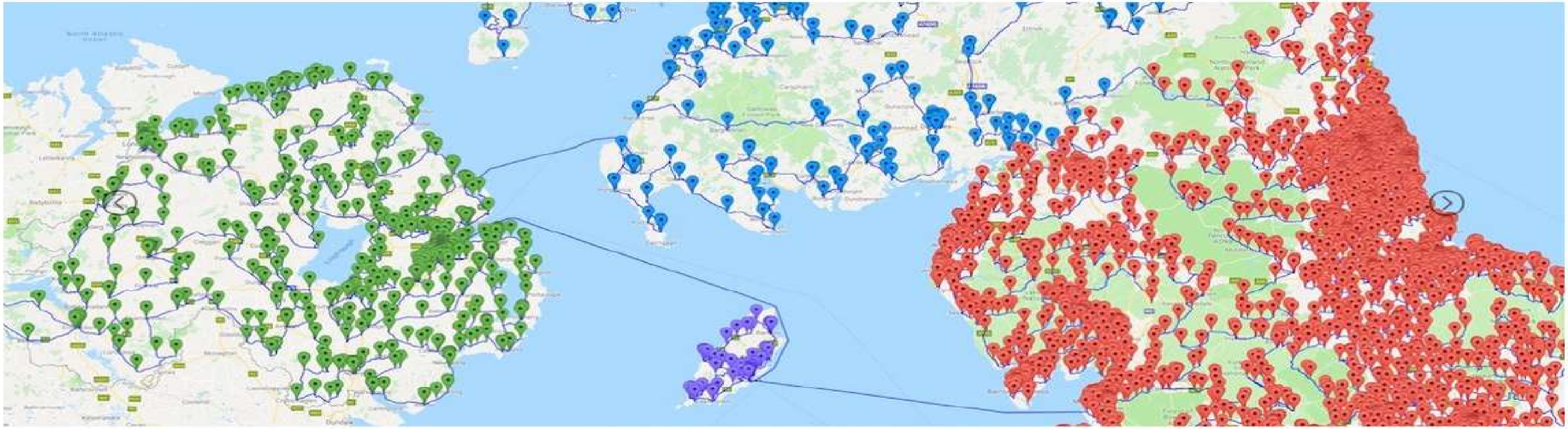
Example



Example

UK49687

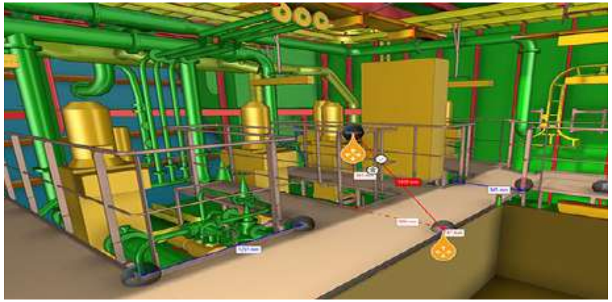
Shortest possible tour to nearly every pub in the United Kingdom.

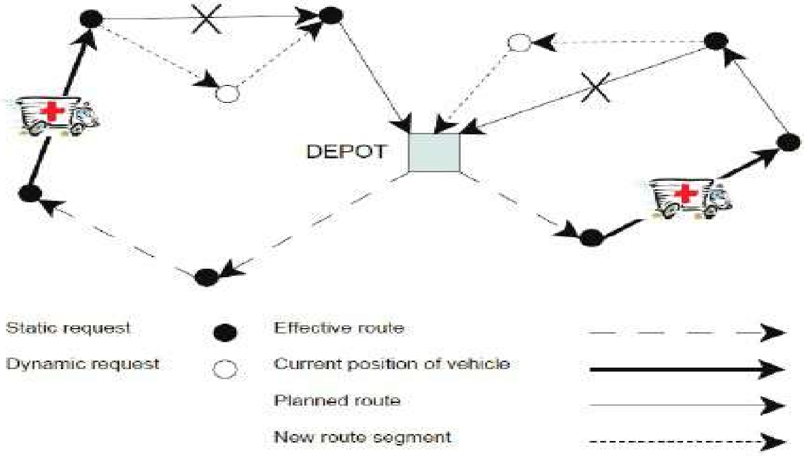


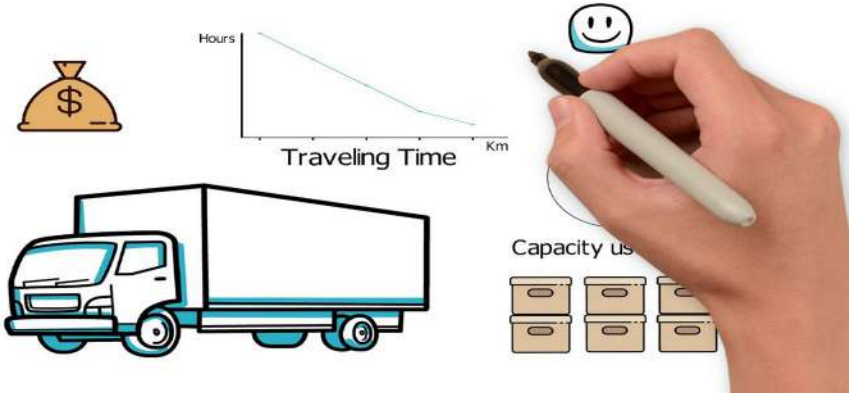
Optimal 49,687-stop pub crawl. Click.

Useful for

- Design chips.
- Aereal routes.
- Home or warehouse deliveries.







Times

Ciudades (N)	All combinations	Held-Karp Algorithm
10	2 second	0.1 second
11	22 secs	0.2 secs
14	13 hours	3 secs
16	200 days	11 secs
25	270000 years	4 hours
50	5 10^{50} years	58000 years

It is not affortable with exact algorithm

We need efficient algorithms!

Not the best but a good solution in reasonable time

Metaheuristics and Bio-Inspired

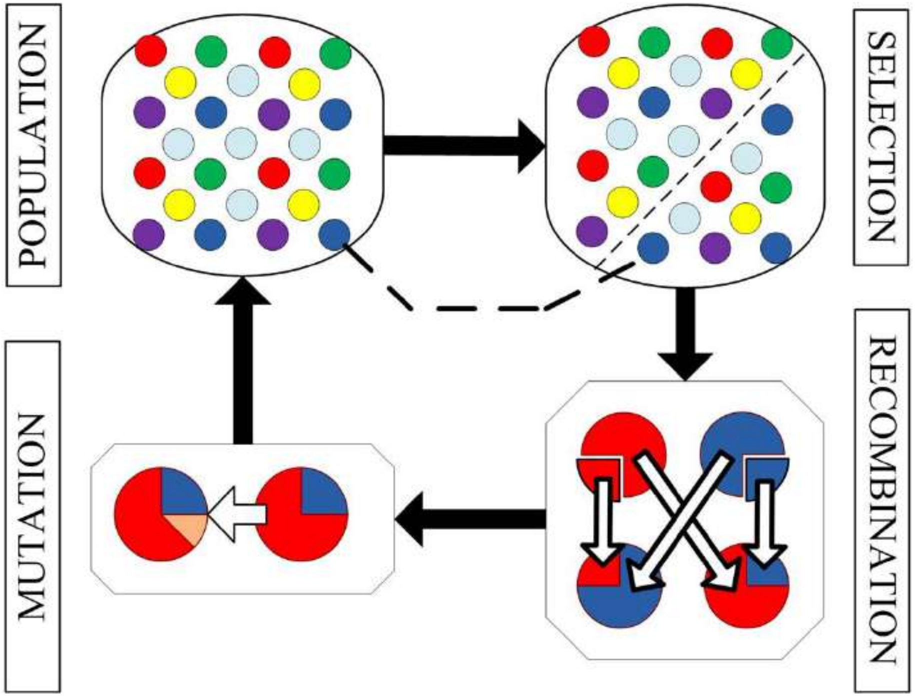
- Heuristic: Criterion for guiding the search, simple but without guarantees.
- Metaheuristics: Not exact algorithms that generate solution using heuristics (as that combining good solutions you could produce better ones).
- Bio-Inspired Algorithms: Inspired in Nature.
  - Genetic Algorithms, Particle Swarm Optimization, Whale, ...
- Evolutionary Algorithms: Keep a population of solutions that evolve keeping better solutions.

Advantages

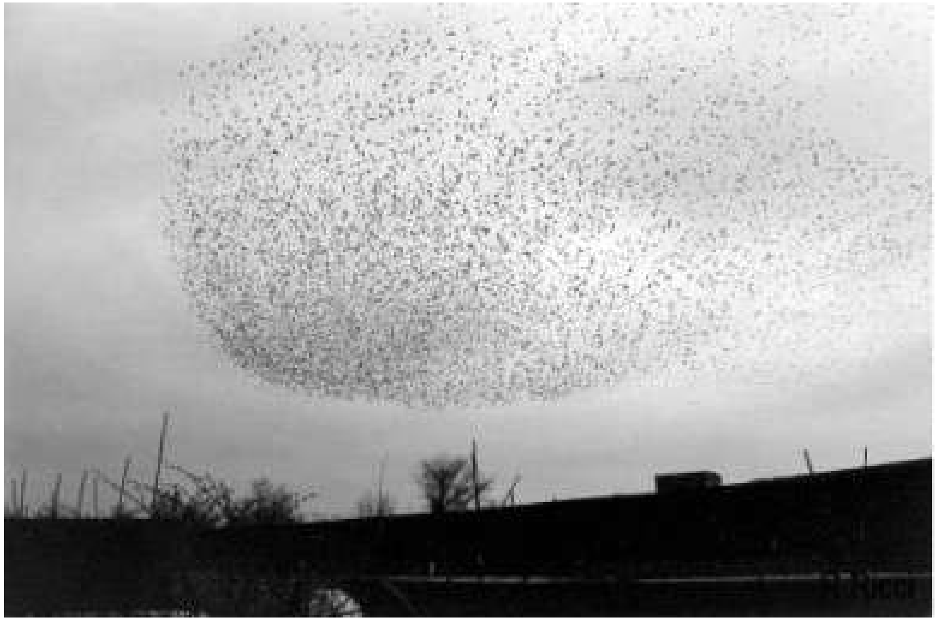
- No specific knowledgement of the problem.
  - » It can be helpful (using heuristics).
- No information of the problem:
  - » The function and their features (derivability, …) is uknown.
- It is only needed:
  - » Represent a solution, generate them.
  - » A fitness function to compare solutions between them.

Genetic Algorithms

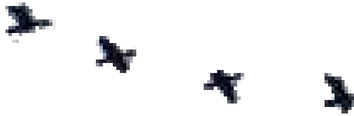
- Inspired in Evolution of Species.
- Use a population of solutions.
- Improve solutions mainly combining them.
- Simulate the natural process.
- Applied in many problems, including examples GHENOVA and Repsol.

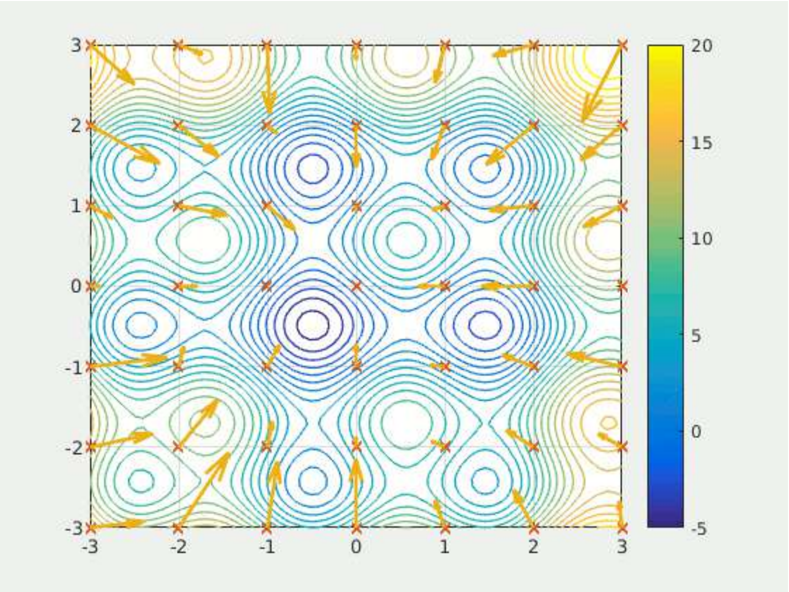


Bio-Inspired (Swarm)

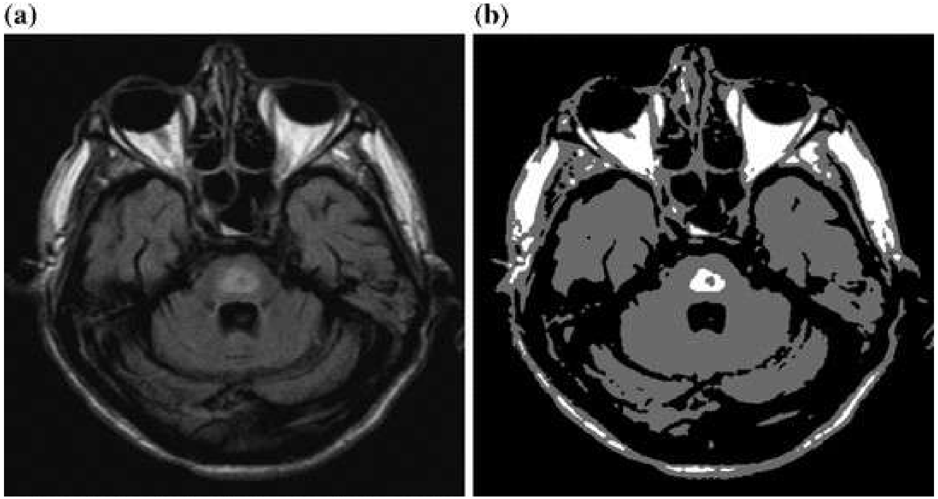


Example Particle Swarm Optimization



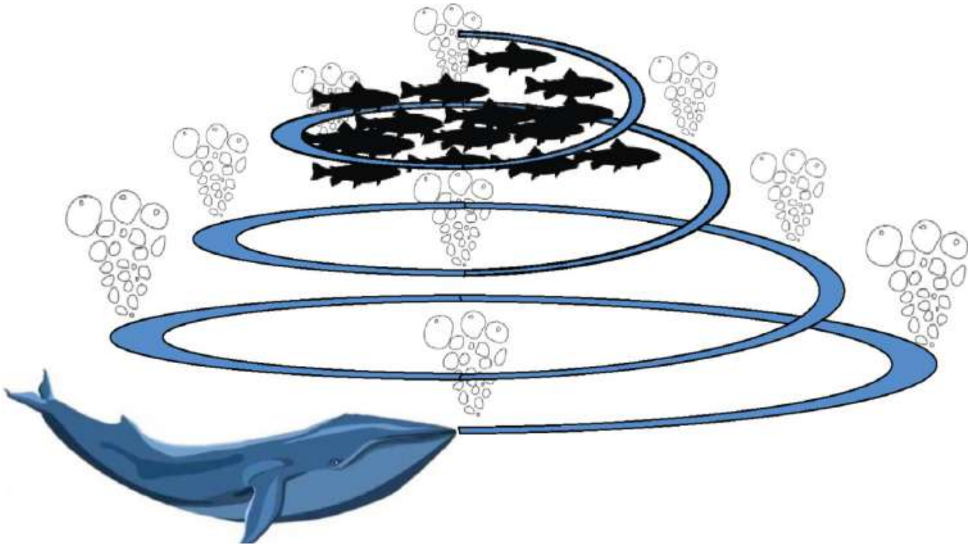


Automatic Segmentation

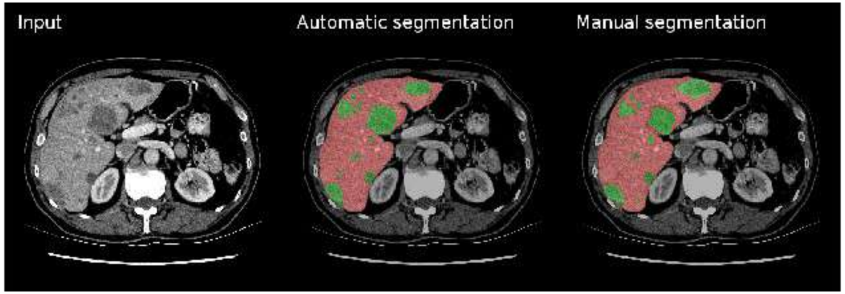


D. Mandal, A. Chatterjee, M. Maitra. Particle Swarm Optimization Based Fast Chan-Vese Algorithm for Medical Image Segmentation. Metaheuristics for Medicine and Biology, 44-74, 2017.

Bio-Inspired (Whale)



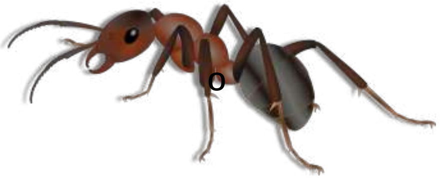
Real Applications



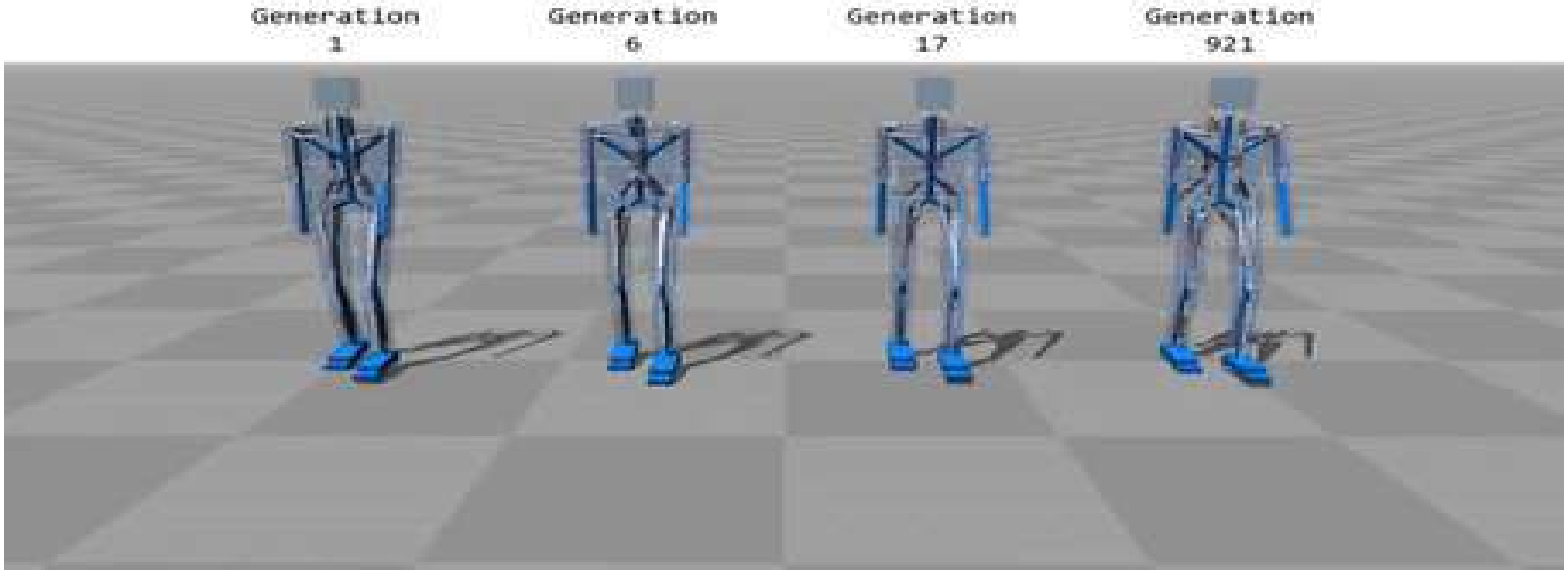
Many bio-Inspired models






Bio-Inspired and Robotics

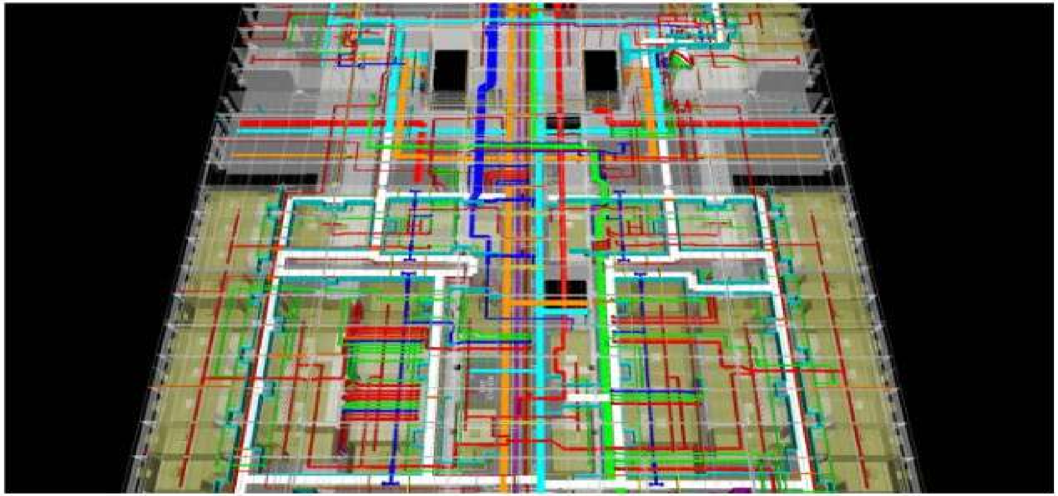


- It can be run with limited time:
- Better results with more resources.

Real-world Applications

Real-world Design problem

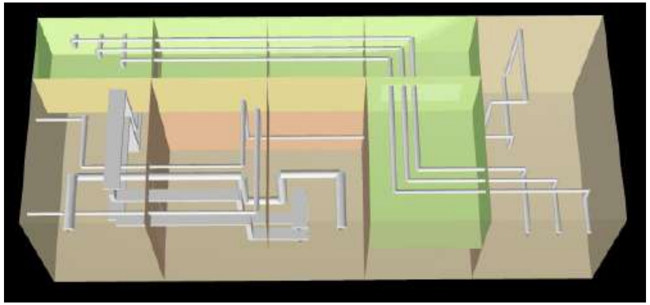
- Real application to automatically design the pipes in boats.



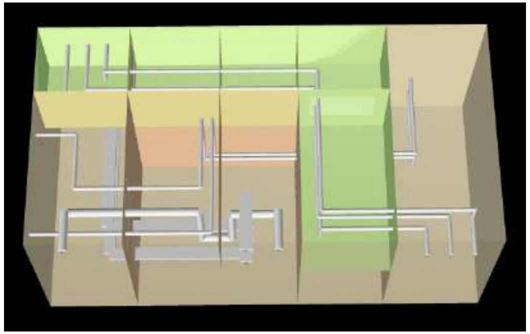
Dikjstra algorithm was used, but several parameters should be optimized

Real-world Design problem

Worse solution



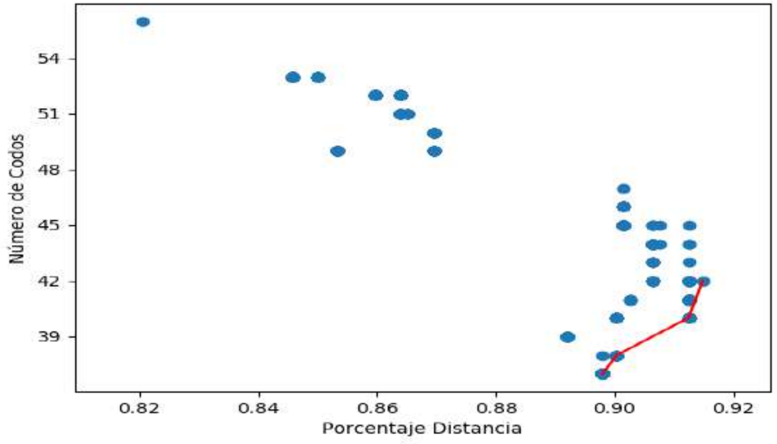
Best solution



- Automatic process that a expert validate.
- It depends on many real parameters (penalties).

Real-world Design problem

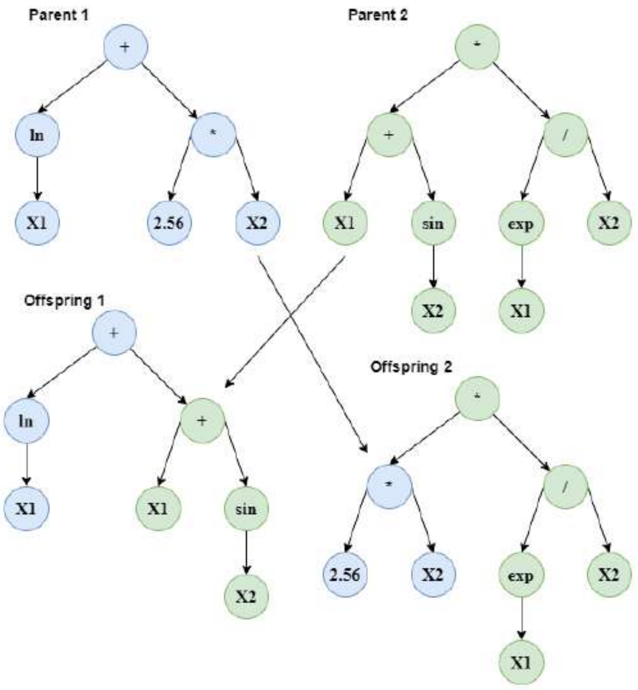
- Multiple objectives:
  - Reduce total distance of the pipes.
  - Reduce number of direction changes.
- Solved with modified NSGA-II (Genetic Algorithm Multi-objective)



Forecasting parameter in Engineering model

- Forecast an important parameter in complex chemical process.
- An interpretable model, not black-box one.
- Generate automatically equation to predict the parameter.
- Their expert can validate the solution.

Forecasting parameter in Engineering model



- We incorporate partial knowledgement.
- Details are confidentials.

Real-World Problem with Bio-Inspired Algorithm

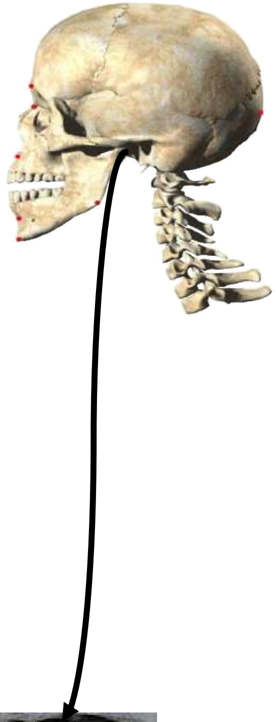
CSI: crime scene investigation

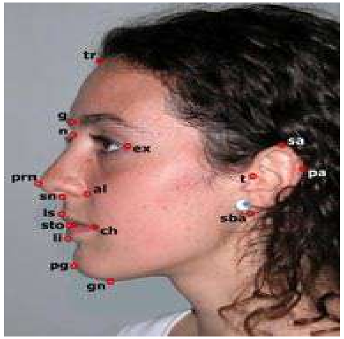
BONES

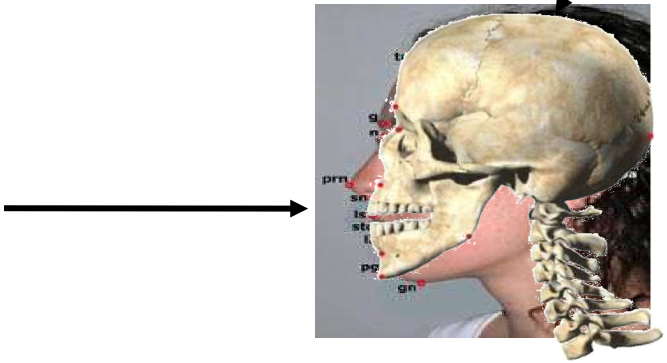
Missing People Identification

- We compare a photo with a 3-d representation of the skull.

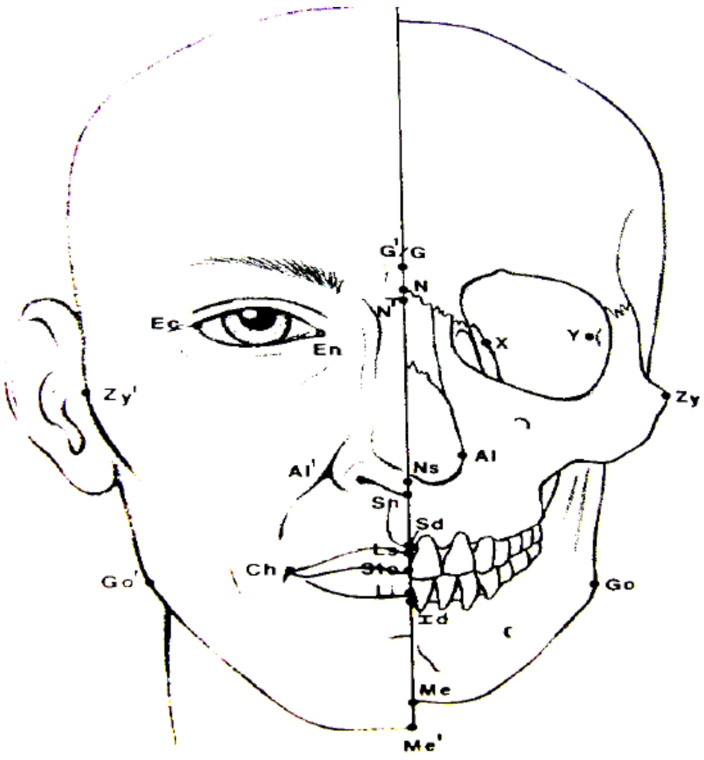
- It is a process usually done by an expert, very time-consuming

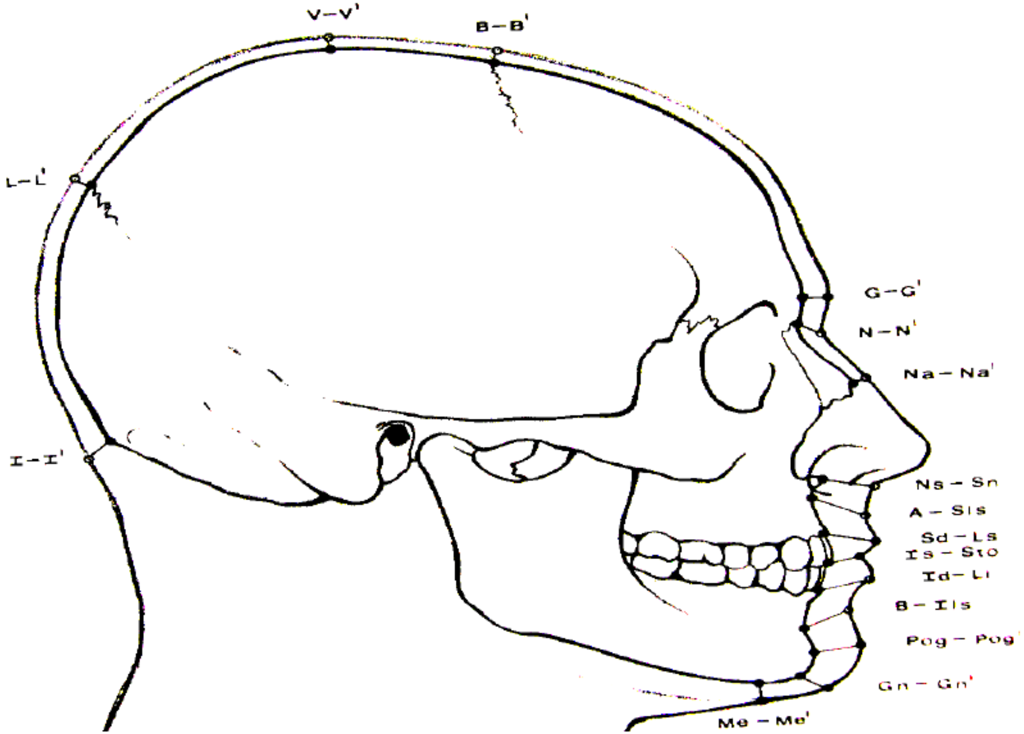






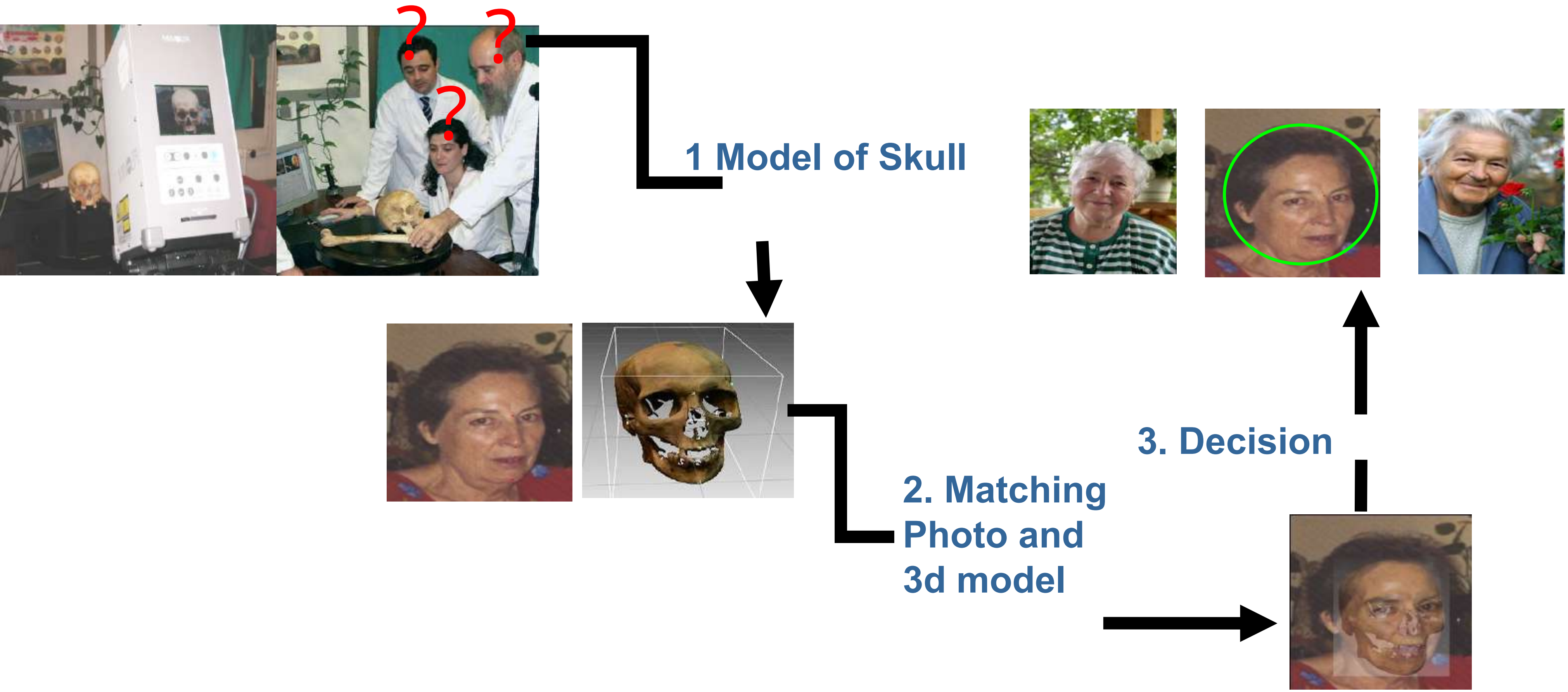
Missing People Identification





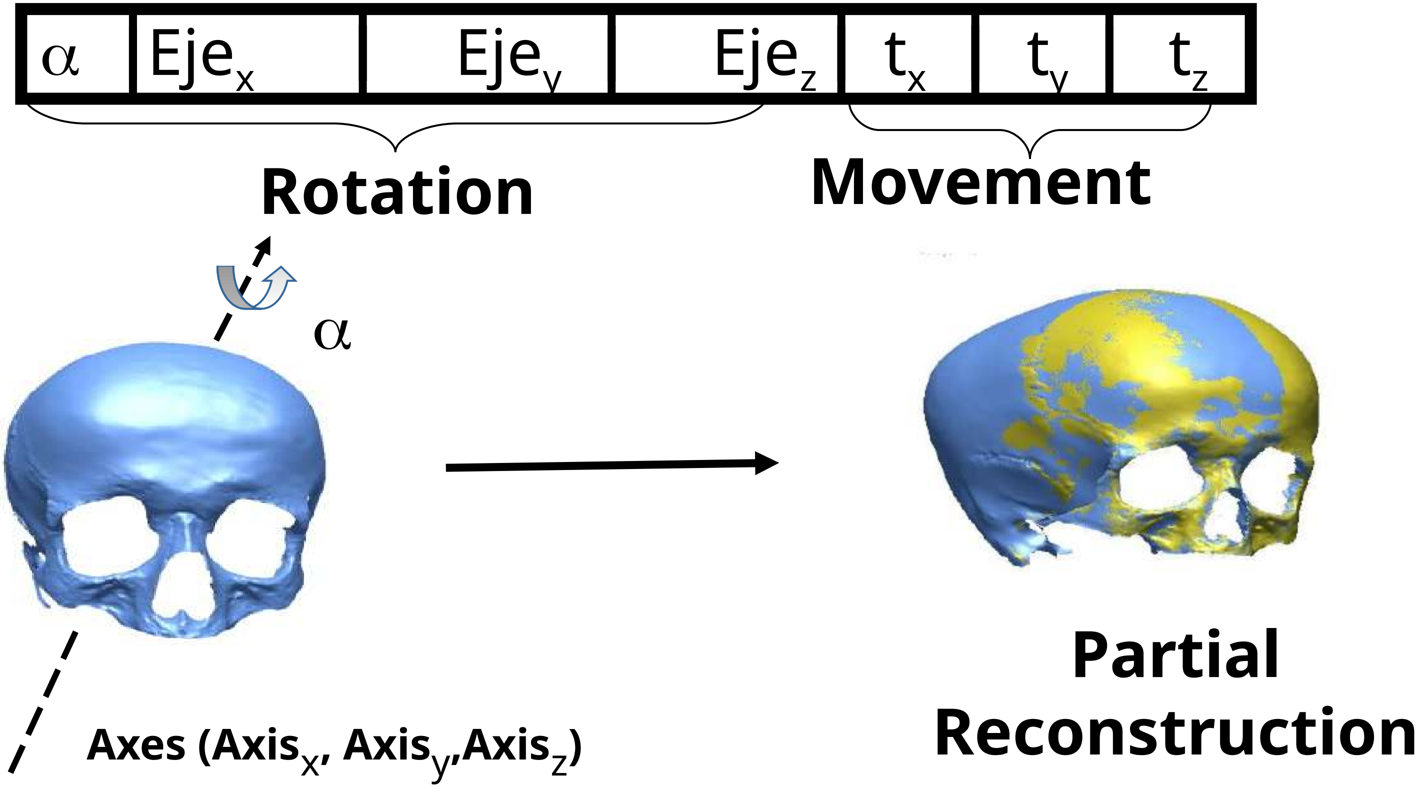
Correlation between specific points

Missing People Identification

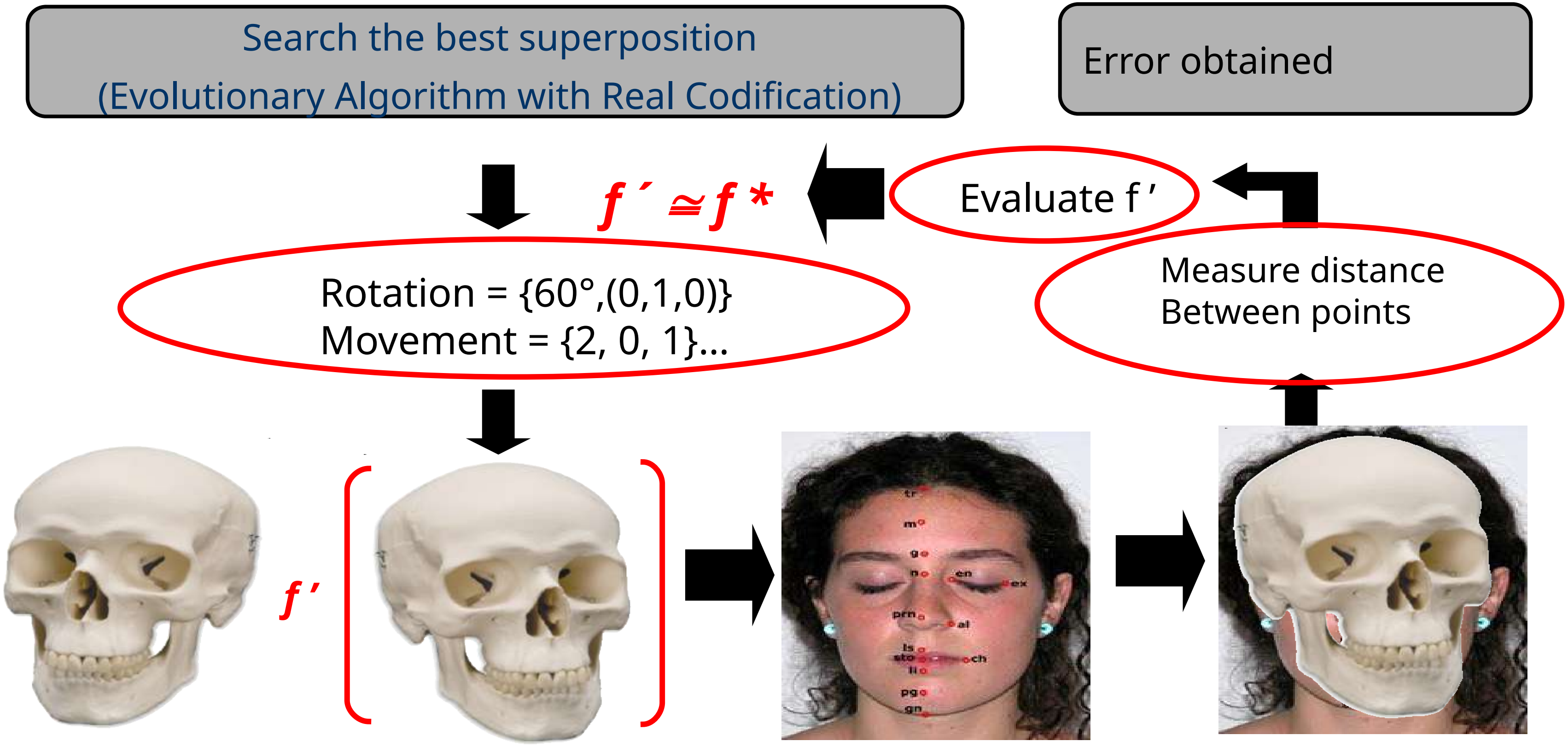


Missing People Identification

- Evolutionary Algorithm with real codification for the 3-d modelling.



Identificación Forense de Personas Desaparecidas



Identificación Forense de Personas Desaparecidas

Manual

Area deviation error: 34.70%

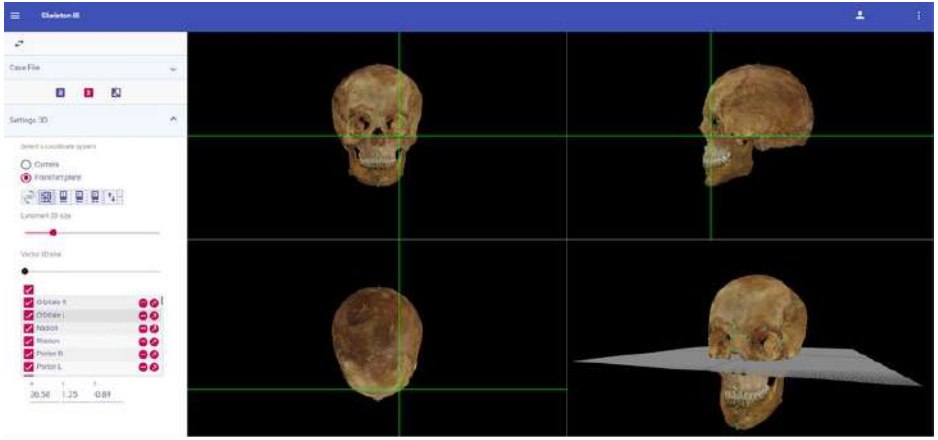
Several hours

Fuzzy AE

Area deviation error: 13.23%

2-4 minutos

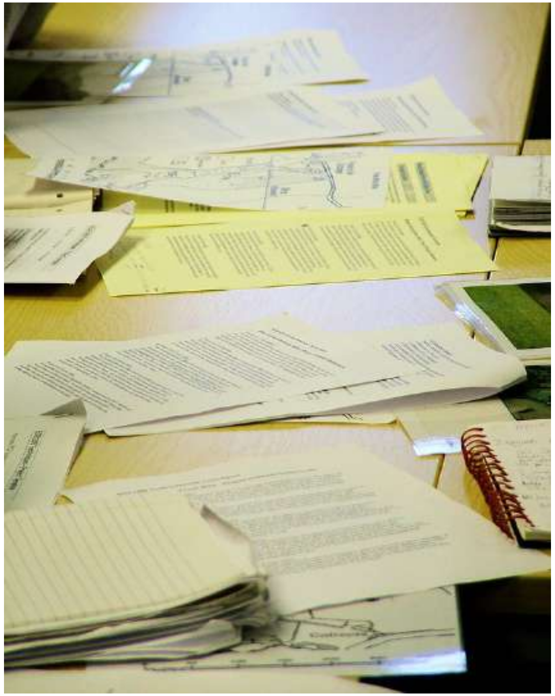
Business: skeleton-id



Gómez, O., Ibáñez, O., Valsecchi, A., Bermejo, E., Molina, D., & Cordón, O. (2020). Performance analysis of real-coded evolutionary algorithms under a computationally expensive optimization scenario: 3D–2D Comparative Radiography. Applied Soft Computing, 97, 106793. https://doi.org/10.1016/j.asoc.2020.106793

Review of research work

- Describe briefly papers.
- More focused on more relevant and/or recent ones.



Large-Scale Global Optimization

- Optimize a huge number of parameters (> 1k).
- Algorithms must be specific:
  - Huge domain search.
  - Few evaluations.
- Example: Optimize EEG processing (many parameters).

Large-Scale Global Optimization

- Paper:

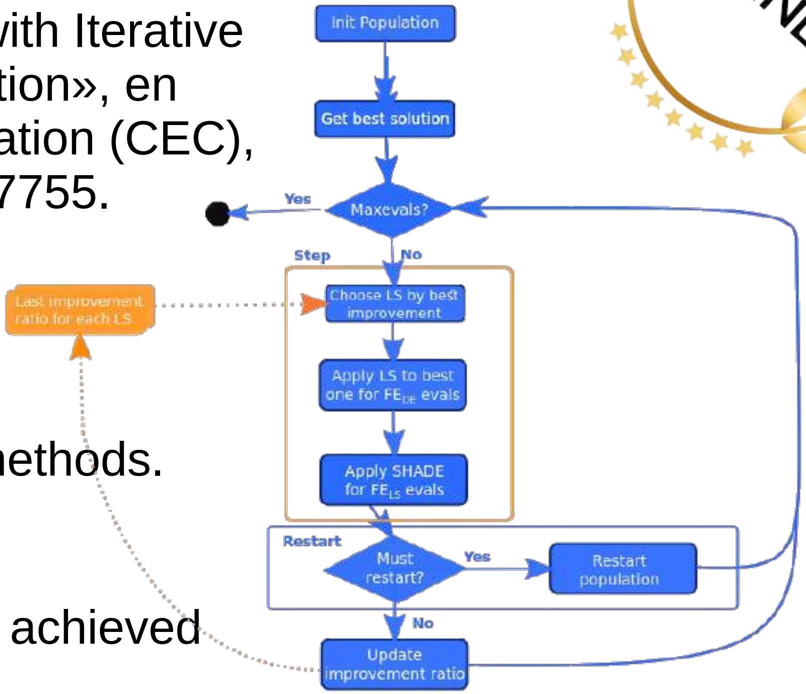
  D. Molina, M. Lozano, A. M. Sánchez, y F. Herrera, «Memetic algorithms based on local search chains for large scale continuous optimisation problems: MA-SSW-Chains», Soft Comput, vol. 15, n.º 11, pp. 2201-2220, nov. 2011, doi: 10.1007/s00500-010-0647-2.

- Summarize:
  - It applies a specific LS for many variables.
  - It is combined with LS chaining.

Large-Scale Global Optimization

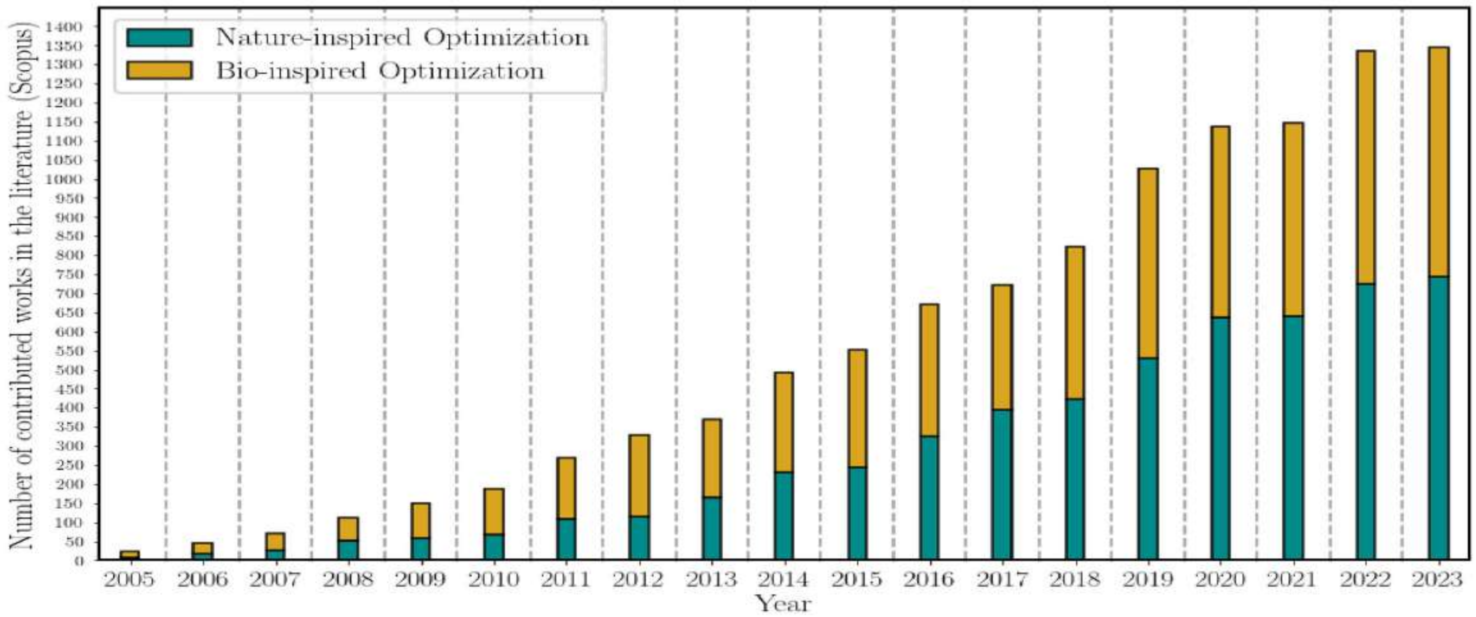
- Paper:

  D. Molina, A. LaTorre, y F. Herrera, «SHADE with Iterative Local Search for Large-Scale Global Optimization», en 2018 IEEE Congress on Evolutionary Computation (CEC), jul. 2018, pp. 1-8. doi: 10.1109/CEC.2018.8477755.



- Summarize:
  - It combines an adaptive DE with two LS methods.
  - The LS methods are complementary.
  - It applies always the LS method that have achieved more improvement ratio last time.

Bio-Inspiration proposals



Is it good, isn't it?

The best ones are the most recent?

D. Molina, J. Poyatos, J. D. Ser, S. García, A. Hussain, y F. Herrera, «Comprehensive Taxonomies of Nature- and Bio-inspired Optimization: Inspiration versus Algorithmic Behavior, Critical Analysis and Recommendations (from 2020 to 2024)», 17 de abril de 2024, arXiv: arXiv:2002.08136. doi: 10.48550/arXiv.2002.08136. -

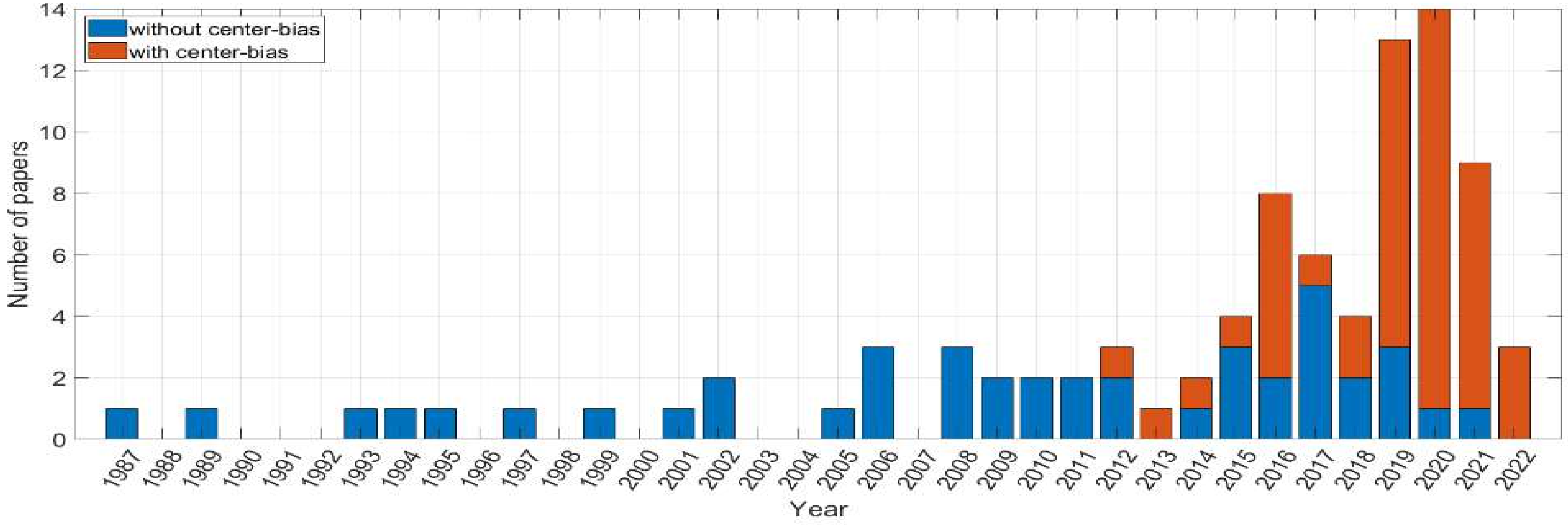
Sucess Paradox

Molina, D., Del Ser, J., Poyatos, J., & Herrera, F. (2025). The paradox of success in evolutionary and bioinspired optimization: Revisiting critical issues, key studies, and methodological pathways. Swarm and Evolutionary Computation, 98, 102063. https://doi.org/10.1016/j.swevo.2025.102063

No confidence in comparisons (which are the bests ones)

Algorithms over-estimate

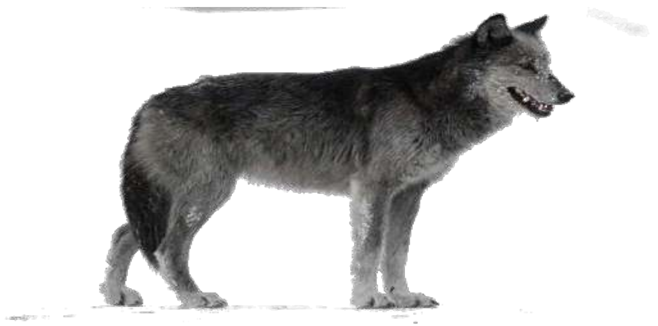
Jakub Kudela, The Evolutionary Computation Methods No One Should Use



J. Kudela, «The Evolutionary Computation Methods No One Should Use», 5 de enero de 2023, arXiv: arXiv:2301.01984. doi: 10.48550/arXiv.2301.01984.

Very well-known algorithms in that list

"butterfly" by davidyuweb is licensed under CC BY-NC 2.0.



"Origami Sailfish" by Ivan Svatko is licensed under CC BY-NC-ND 2.0

"Sky Bokeh with Dragonfly" by desertdutchman is licensed under CC BY 2.0.

A lot

Table 3: Considered algorithms and results.

Abbreviation	Method name	Year	Geomean	Abbreviation	Method name	Year	geomean
ABC [10]	Artificial Bee Colony	2008	1.29E+00	HC [15]	Hill Climbing	1993	1.13E+00
ACOR [16]	Ant Colony Optimization Continuous	2008	7.40E-01	HGS [17]	Hunger Games Search	2021	3.69E+06
AEO [18]	Artificial Ecosystem-based Optimization	2020	1.01E+07	HGSO [19]	Henry Gas Solubility Optimization	2019	8.07E+03
ALO [20]	Ant Lion Optimizer	2015	1.44E+00	HHO [21]	Harris Hawks Optimization	2019	1.62E+05
AO [22]	Aquila Optimization	2021	2.26E+05	HS [23]	Harmony Search	2001	9.97E-01
AOA [24]	Arithmetic Optimization Algorithm	2021	1.01E+10	IWO [25]	Invasive Weed Optimization	2006	1.88E+00
ArchOA [26]	Archimedes Optimization Algorithm	2021	3.75E+07	JA [27]	Jaya Algorithm	2016	1.19E+01
ASO [28]	Atom Search Optimization	2019	8.71E-01	KMA [29]	Komodo Mlipir Algorithm	2022	1.84E+05
BA [30]	Bat-inspired Algorithm	2010	1.44E+00	LCO [31]	Life Choice-based Optimization	2020	8.31E+07
BBO [32]	Biogeography-Based Optimization	2008	6.43E-01	MA [33]	Memetic Algorithm	1989	1.68E-03
BeesA [34]	Bees Algorithm	2006	1.16E+00	MFO [35]	Moth-Flame Optimization	2015	1.73E-01
BES [36]	Bald Eagle Search	2020	2.62E+08	MGO [37]	Mountain Gazelle Optimizer	2022	1.28E+01
BFO [38]	Bacterial Foraging Optimization	2002	9.66E-01	MPA [39]	Marine Predators Algorithm	2020	1.06E+02
BOA [40]	Butterfly Optimization Algorithm	2019	9.57E+05	MRFO [41]	Manta Ray Foraging Optimization	2020	6.40E+07
BRO [42]	Battle Royale Optimization	2021	2.59E+09	MSA [43]	Moth Search Algorithm	2018	8.37E+00
BSA [44]	Bird Swarm Algorithm	2016	1.09E+01	MVO [45]	Multi-Verse Optimizer	2016	1.75E+00
BSO [46]	Brain Storm Optimization	2011	7.85E+00	NMRA [47]	Naked Mole-Rat Algorithm	2019	5.65E+08
CA [48]	Culture Algorithm	2009	7.18E-01	NRO [49]	Nuclear Reaction Optimization	2019	2.30E+06
CEM [50]	Cross-Entropy Method	2005	1.33E+00	PFA [51]	Pathfinder Algorithm	2019	3.11E+08
CGO [52]	Chaos Game Optimization	2021	2.14E+07	PSO [53]	Particle Swarm Optimization	1995	9.70E-01
ChOA [54]	Chimp optimization algorithm	2020	3.89E+03	PSS [55]	Pareto-like Sequential Sampling	2021	1.77E+03
COA [56]	Coyote Optimization Algorithm	2018	4.00E+06	QSA [57]	Queuing Search Algorithm	2021	7.91E-01
CRO [58]	Coral Reefs Optimization	2014	9.69E-01	RKO [14]	Runge Kutta Optimizer	2021	7.36E+04
CSA [59]	Cuckoo Search Algorithm	2009	1.10E+00	SA [60]	Simulated Annealing	1987	8.95E-01
CSO [61]	Cat Swarm Optimization	2006	9.58E-01	SARO [62]	Search And Rescue Optimization	2019	2.27E+00
DE [11]	Differential Evolution	1997	9.66E-01	SBO [13]	Satin Bowerbird Optimizer	2017	3.95E+00
DandO [63]	Dandelion Optimizer	2022	3.59E+02	SCA [64]	Sine Cosine Algorithm	2016	1.18E+04
DO [65]	Dragonfly Optimization	2016	6.62E+02	SFO [66]	SailFish Optimizer	2019	2.57E+07
EFO [67]	Electromagnetic Field Optimization	2016	6.78E-01	SHO [68]	Spotted Hyena Optimizer	2017	1.31E+00
EHO [69]	Elephant Herding Optimization	2015	3.99E+03	SLO [70]	Sea Lion Optimization Algorithm	2019	2.83E+00
EO [71]	Equilibrium Optimizer	2020	4.65E+03	SMA [72]	Slime Mould Algorithm	2020	4.54E+06
EOA [73]	Earthworm Optimisation Algorithm	2018	2.55E+05	SRSR [74]	Swarm Robotics Search And Rescue	2017	2.03E+00
EP [75]	Evolutionary Programming	1999	1.43E+00	SSA [76]	Sparrow Search Algorithm	2020	2.61E+06
ES [77]	Evolution Strategies	2002	1.14E+00	SSDO [78]	Social Ski-Driver Optimization	2020	5.40E+08
FA [79]	Fireworks Algorithm	2010	1.34E+00	SSO [80]	Salp Swarm Optimization	2017	2.28E+01
FBIO [81]	Forensic-Based Investigation Optimization	2020	5.07E+06	SSpiderA [82]	Social Spider Algorithm	2015	1.12E+00
FFA [83]	Firefly Algorithm	2011	1.18E+00	STOA [84]	Sooty Tern Optimization Algorithm	2019	6.78E+04
FOA [85]	Fruit-fly Optimization Algorithm	2012	4.01E+00	TLO [86]	Teaching Learning-based Optimization	2012	3.19E+04
FPA [87]	Flower Pollination Algorithm	2012	9.74E-01	TPO [88]	Tree Physiology Optimization	2019	2.20E+01
GA [89]	Genetic Algorithm	1994	1.02E+00	TSA [90]	Tunicate Swarm Algorithm	2020	6.25E+06
GBO [91]	Gradient-Based Optimizer	2020	7.17E+07	TWO [92]	Tug of War Optimization	2017	9.69E-01
GCO [93]	Germinal Center Optimization	2018	1.02E+00	VCS [94]	Virus Colony Search	2016	2.90E+04
GOA [95]	Grasshopper Optimization Algorithm	2017	3.39E+00	WDO [96]	Wind Driven Optimization	2013	4.86E+01
GSKA [97]	Gaining Sharing Knowledge-based Algorithm	2020	4.51E-01	WHO [98]	Wildebeest Herd Optimization	2019	8.63E+02
GWO [99]	Grey Wolf Optimizer	2014	8.89E+05	WOA [100]	Whale Optimization Algorithm	2016	1.87E+03

Guideline for comparison

- Benchmark: standard to avoid bias, comparing previous winners.
- Right statistical comparisons.
- Analysis of the different components.
- Utility: Performance, efficiency, paralelism, ...

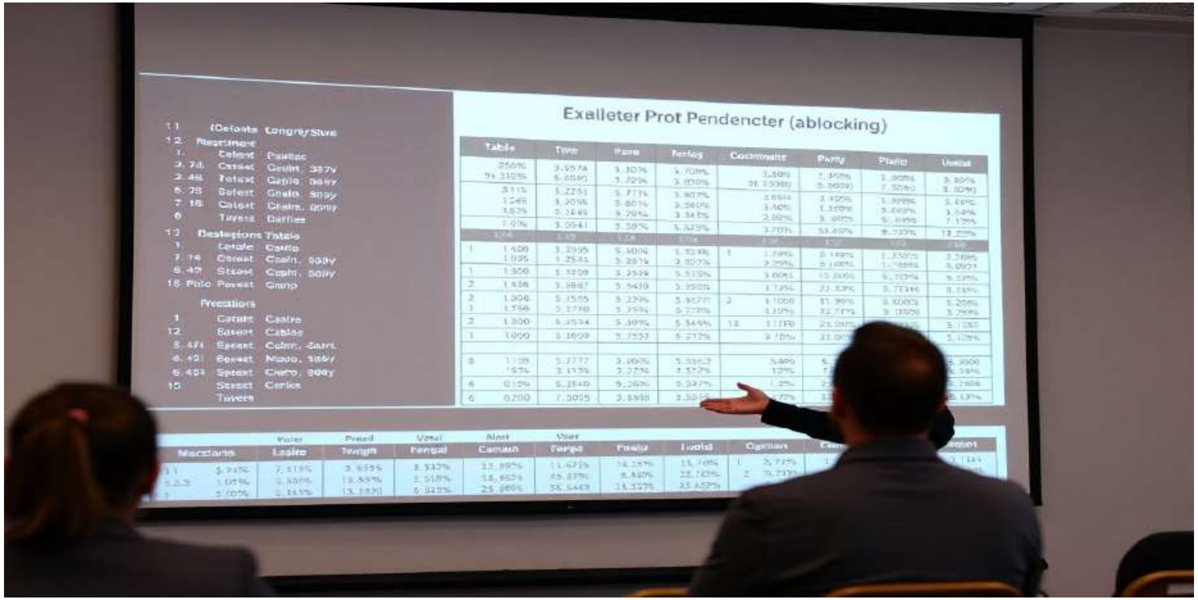
A. LaTorre, D. Molina, E. Osaba, J. Poyatos, J. Del Ser, y F. Herrera, «A prescription of methodological guidelines for comparing bio-inspired optimization algorithms», Swarm and Evolutionary Computation, vol. 67, p. 100973, dic. 2021, doi: 10.1016/j.swevo.2021.100973.

For real-world problems

- Priority: Constraints.
- Always validate and replicable.
- Performance is important, but also run in parallel.
- Results with different time/evaluations.
- Valorate the priorities of the real-world problem.

E. Osaba et al., «A Tutorial On the design, experimentation and application of metaheuristic algorithms to real-World optimization problems», Swarm and Evolutionary Computation, vol. 64, p. 100888, jul. 2021, doi: 10.1016/j.swevo.2021.100888.

Statistical treatment



García, S., Molina, D., Lozano, M., & Herrera, F. (2009). A study on the use of non-parametric tests for analyzing the evolutionary algorithms' behaviour: A case study on the CEC'2005 Special Session on Real Parameter Optimization. Journal of Heuristics, 15(6), 617-644. Scopus. https://doi.org/10.1007/s10732-008-9080-4

Bio-Inspired Algorithms

- Dual Taxonomy:

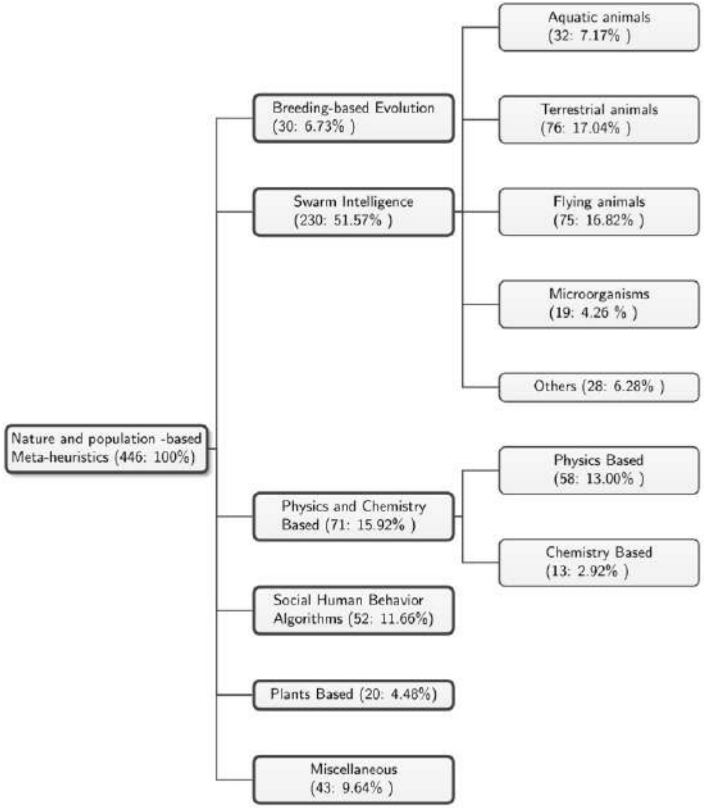
  J. Del Ser et al., «Bio-inspired computation: Where we stand and what’s next», Swarm and Evolutionary Computation, vol. 48, pp. 220-250, 2019, doi: 10.1016/j.swevo.2019.04.008.

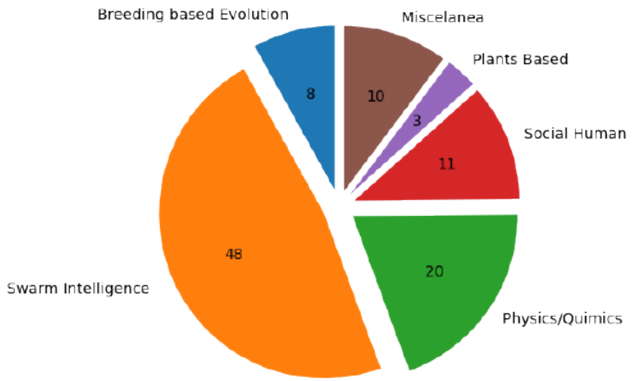
- Critical analysis and challenges:

  J. Del Ser et al., «Bio-inspired computation: Where we stand and what’s next», Swarm and Evolutionary Computation, vol. 48, pp. 220-250, 2019, doi: 10.1016/j.swevo.2019.04.008.

Taxonomía by Nature Inspiration

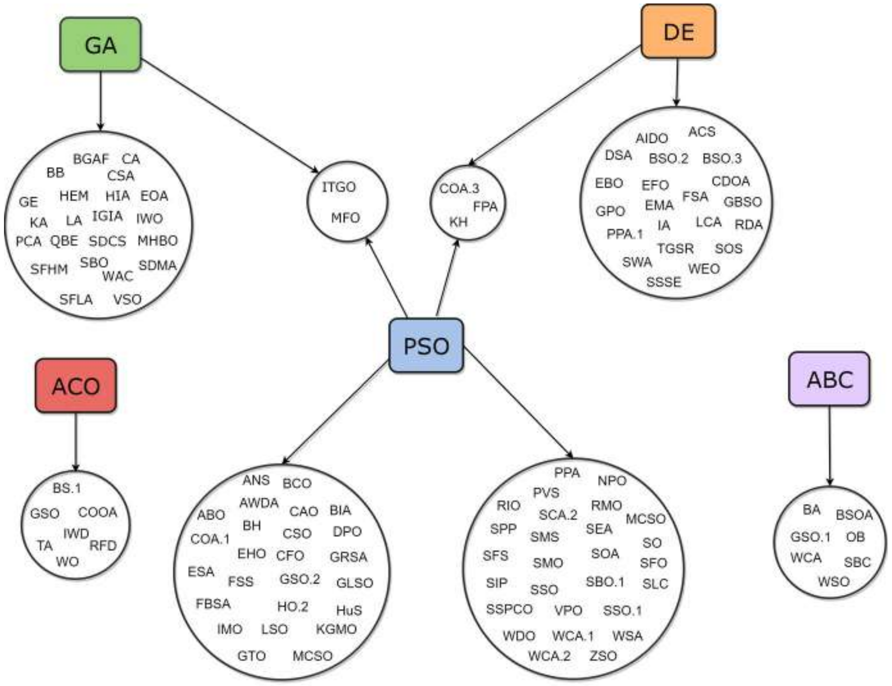
- Many proposals.
- Imbalance in topics.





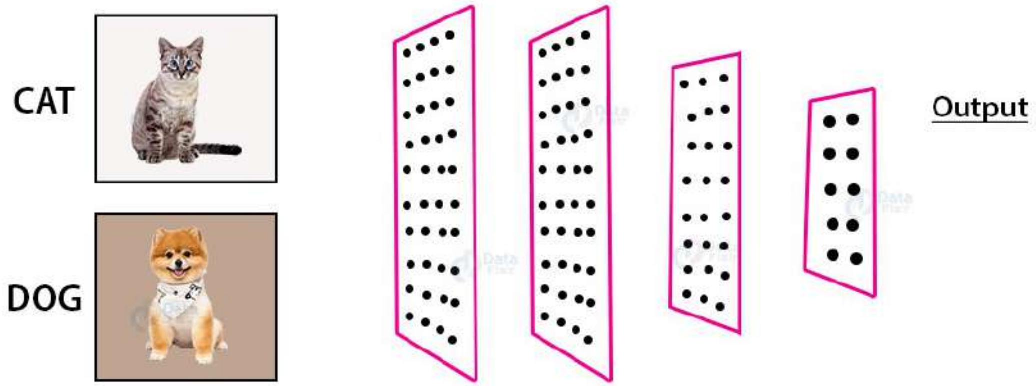
Taxonomy by behaviour

- Many proposals are actually very similar.
- Most of them too similar to PSO.
- It is required more diversity from an algorithmic point of view.

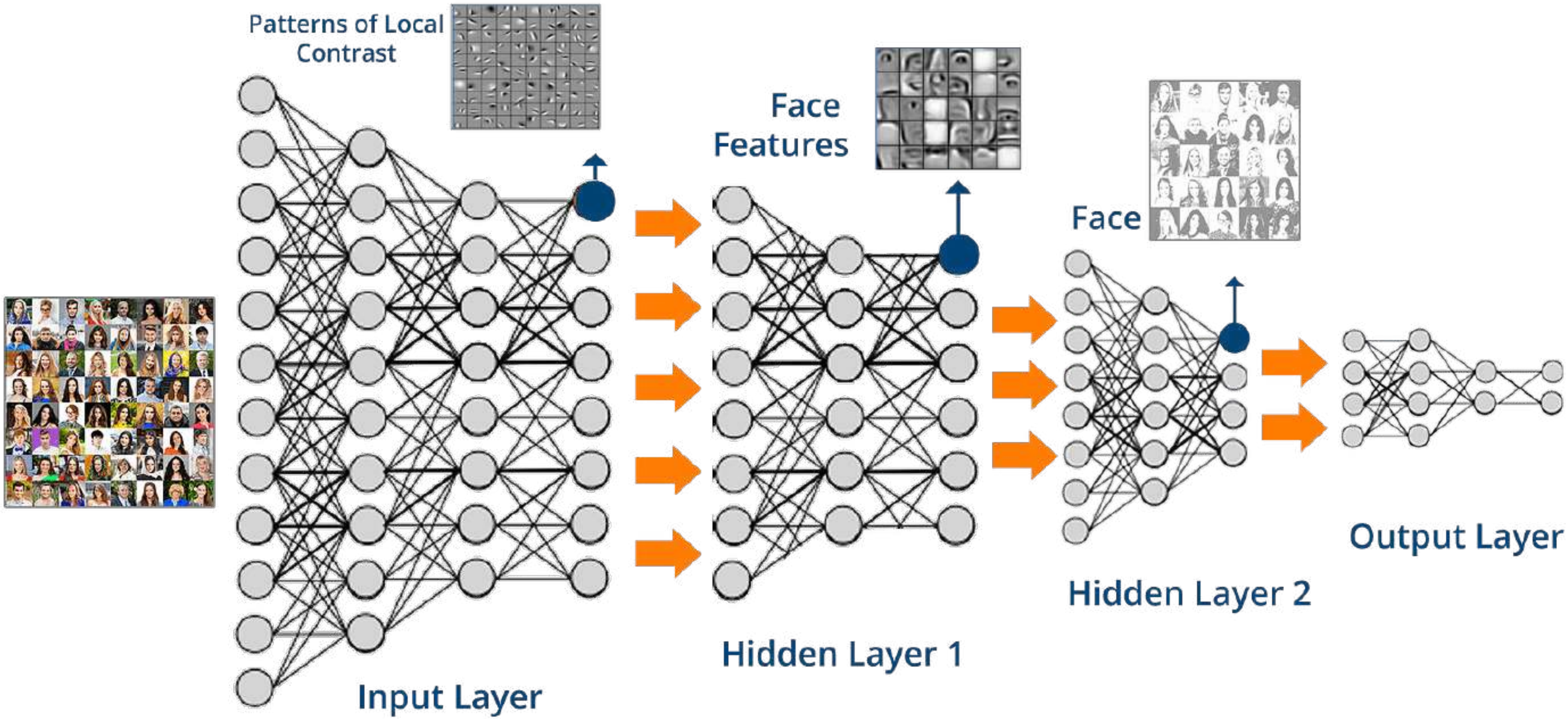


Neural Networks

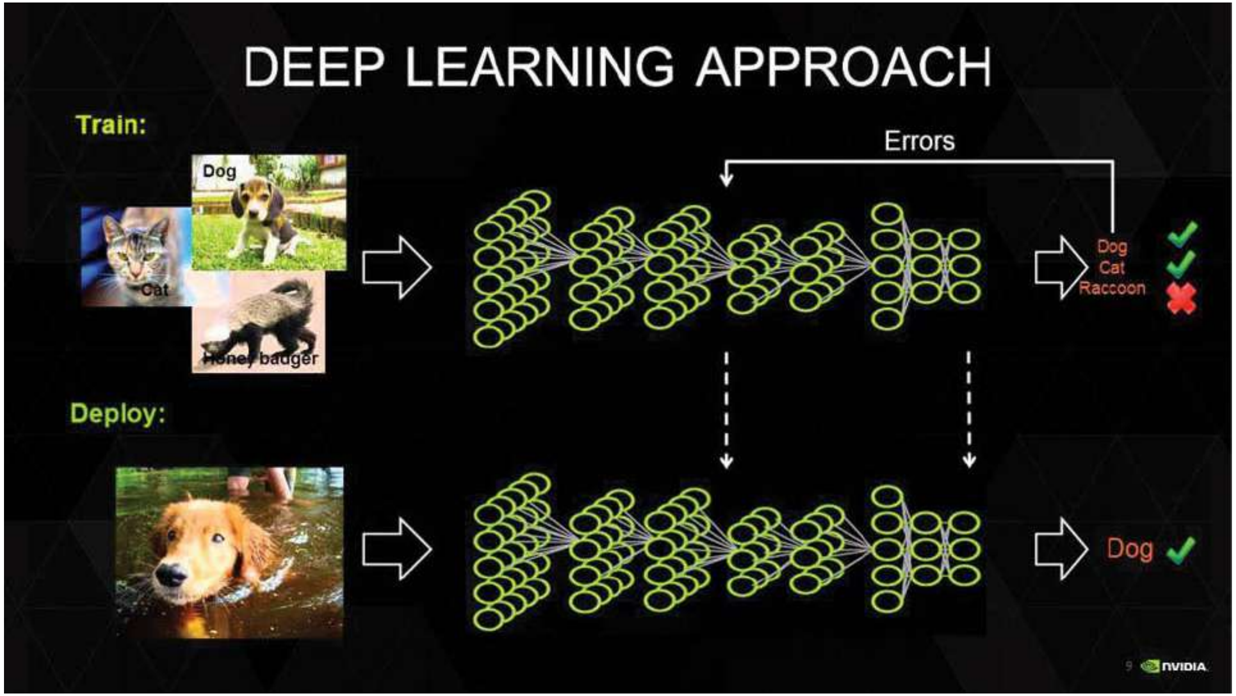
- They simulate neurons interconnected betwen them.
- Can process very nicely images (and signals).
- They requires to adjust their parameters (training/learning).



Deep Learning



Deep Learning



Evolutionary Deep Learning

A. D. Martinez et al., «Lights and shadows in Evolutionary Deep Learning: Taxonomy, critical methodological analysis, cases of study, learned lessons, recommendations and challenges», Information Fusion, vol. 67, pp. 161-194, mar. 2021, doi: 10.1016/j.inffus.2020.10.014.

- Review of the literature about le role of evolutionary algorithms for improving Deep Learning.
- Useful for get a snapshot of the literature.

Usage of Neuroevolution

- Automatically create a Neural Network for the problem.
- Simplify using the evolution the network for a specific problem.
- Search around many possible model the most adequate.

Generate Neural Network

- Each solution is a network.
- Networks are combined or mutated.
- First version: EvoDeep.
  - Good results but easily get too complex.

Martín, A., Lara-Cabrera, R., Fuentes-Hurtado, F., Naranjo, V., & Camacho, D. (2018). EvoDeep: A new evolutionary approach for automatic Deep Neural Networks parametrisation. Journal of Parallel and Distributed Computing, 117, 180-191. https://doi.org/10.1016/j.jpdc.2017.09.006

Our approach: Add complexity

- Optimize the parameters by a Local Search.
- In comparisons, prefer a network over other if:
  - It has better performance.
  - The difference is very small, and it has less complexity (size).
- NN increase in complexity, but not so quickly.

Results

Measure	EvoDeep	Proposal
acc_train	0.670	0.606
acc_val	0.470	**0.530**
acc_test	0.467	**0.524**
#Layers	6	6.6
#Params. (millions)	2.870	**0.337**
Time (min)	84.6	**88.73**

Dataset: CIFAR-10G (Gray)

Results

Measure	EvoDeep	Proposal
acc_train	0.959	0.925
acc_val	0.901	0.893
acc_test	0.898	0.887
#Layers	6.2	4.4
#Params. (millions)	2.006	**1.100**
Time (min)	105.8	**63**

Dataset: FashionMNIST

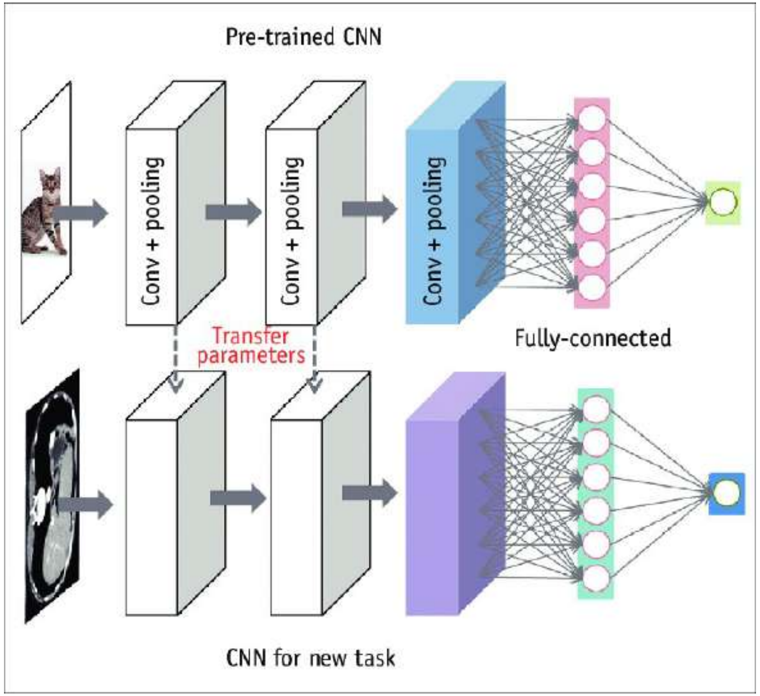
Results

- Reduce at half without significant improvement in FashionMNIST.
- In more complex dataset, it improve results with a 10% of original complexity.
- It still requires more work to be competitive.

Reduction of Network (Pruning)

- There are big models that are adapted to new problems.
- The model is not trained from scratch, it applies Transfer Learning.
- Maybe the model is very complex for the problem.

Transfer Learning



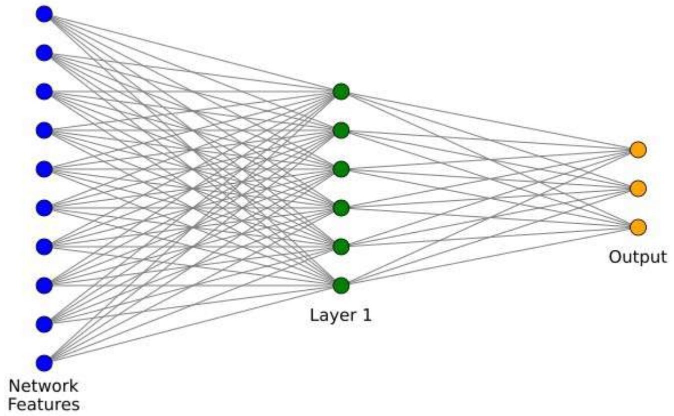
- Transfer Learning allows to reduce the training samples.
- Improve the results.
- Standard in the DL application.

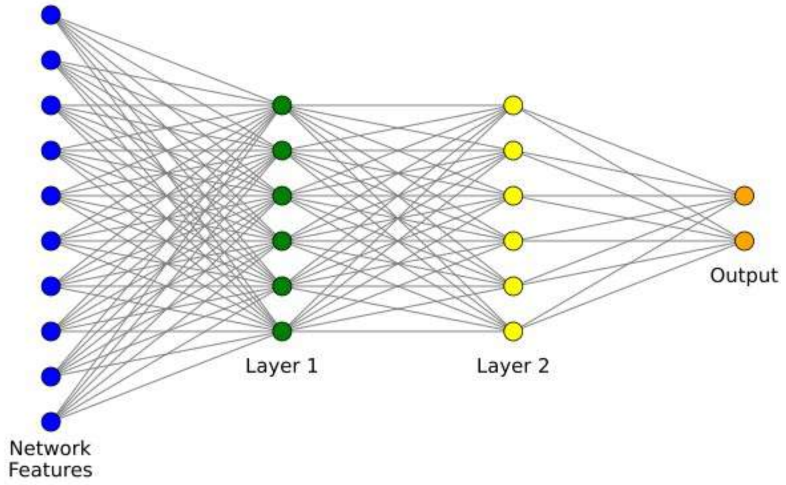
Neuro-evolution

- Transfer our expertise about bio-inspiration for improving neural networks, reducing them.
- First, we apply pruning, with some novelties:
  - Compatible with Transfer learning.
  - Improving interpretability.

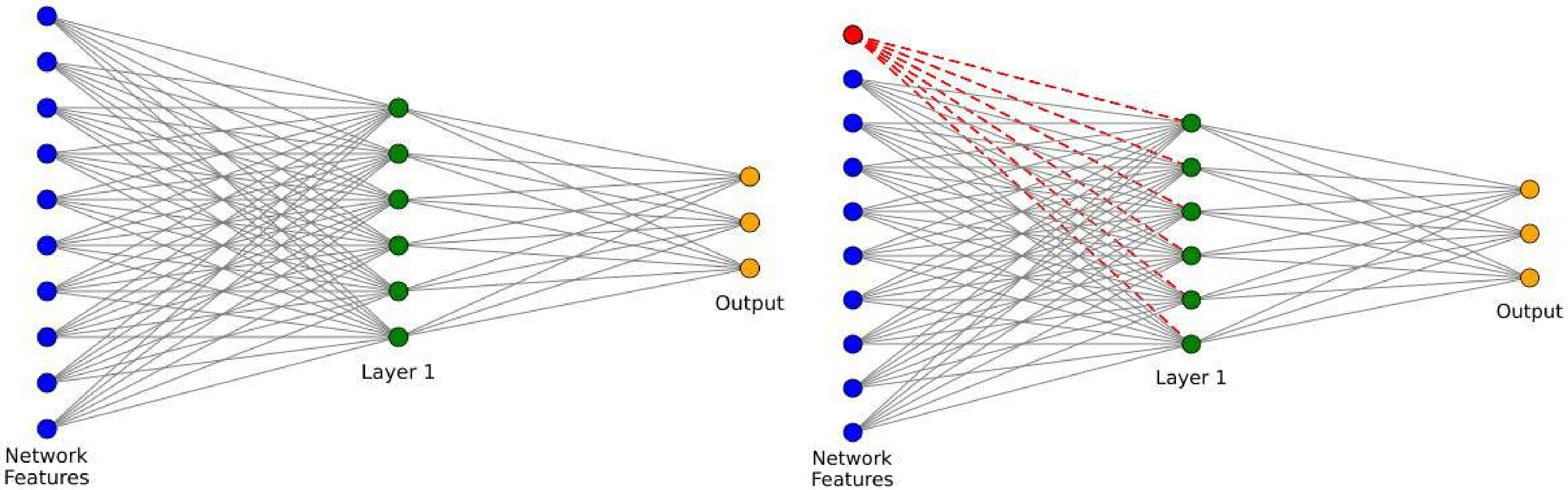
Pruning with Transfer Learning

J. Poyatos, D. Molina, A. D. Martinez, J. Del Ser, y F. Herrera, «EvoPruneDeepTL: An evolutionary pruning model for transfer learning based deep neural networks», Neural Networks, vol. 158, pp. 59-82, 2023, doi: 10.1016/j.neunet.2022.10.011.





Pruning with Transfer Learning



- Search using a GA the Neuron to prune (removing all output weights).

Pruning with Transfer Learning

Dataset	Measure	Not Pruned	Best Fixed	Feature Selection
SRSMAS	Accuracy	0.832	0.866	**0.884**
	% Active neur.	100	20	60
RPS	Accuracy	0.938	0.938	**0.985**
	% Active neur.	100	40	45
LEAVES	Accuracy	0.923	0.927	**0.943**
	% Active neur.	100	80	59
PAINTING	Accuracy	0.939	0.945	**0.958**
	% Active neur.	100	60	55
CATARACT	Accuracy	0.703	0.719	**0.747**
	% Active neur.	100	70	55
PLANTS	Accuracy	0.432	0.432	**0.472**
	% Active neur.	100	10	68

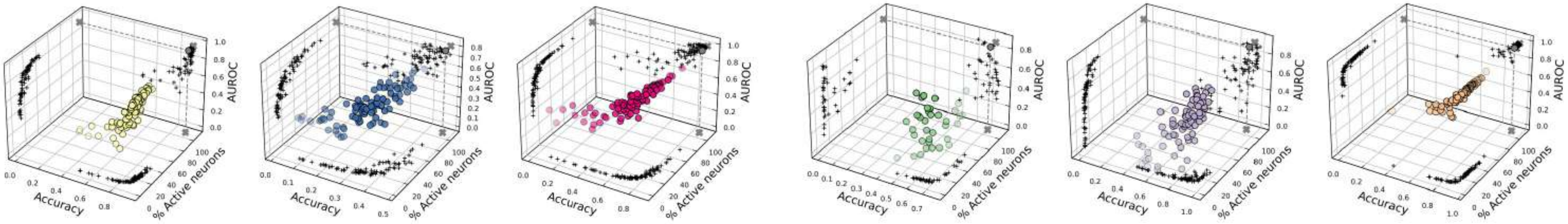
- It can improve the results removing features.
- It has sense: to ignore learned patterns that have not relation with the new problem.

Multi-objetive Pruning

- J. Poyatos, D. Molina, A. Martínez-Seras, J. Del Ser, y F. Herrera, «Multiobjective evolutionary pruning of Deep Neural Networks with Transfer Learning for improving their performance and robustness», Applied Soft Computing, vol. 147, 2023, doi: 10.1016/j.asoc.2023.110757.

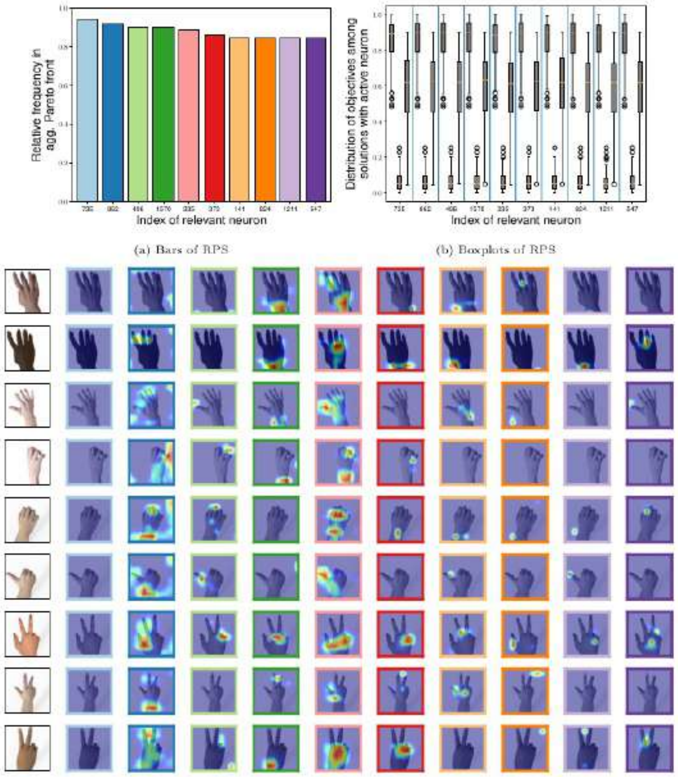
- Idea: To apply a multi-objective with tree criteria:
  - Accuracy.
  - Size (% neurons).
  - Robusness (AUROC using distribution output difference with other problem).

Multi-objetive Pruning



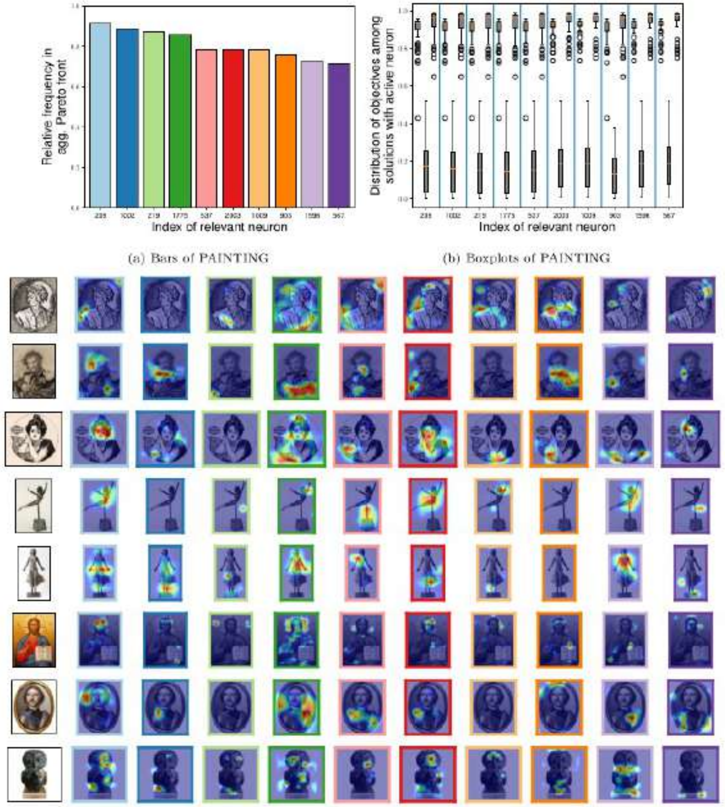
- There is a minimum size/complexity to improve results.
- The robustness criteria is less related with the size.

Multi-objetive Pruning



(a) Bars of RPS (b) Boxplots of RPS

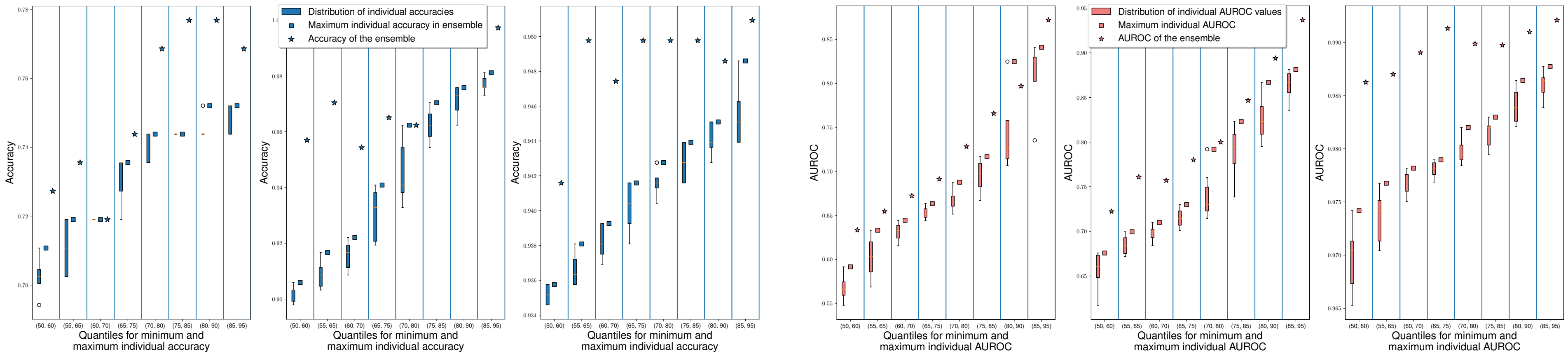
(c) Heatmaps of RPS



(a) Bars of PAINTING (b) Boxplots of PAINTING

(c) Heatmaps of PAINTING

Multi-objetive Pruning



- We build an Ensemble with better diverse solutions.
- It improve considering all criteria.

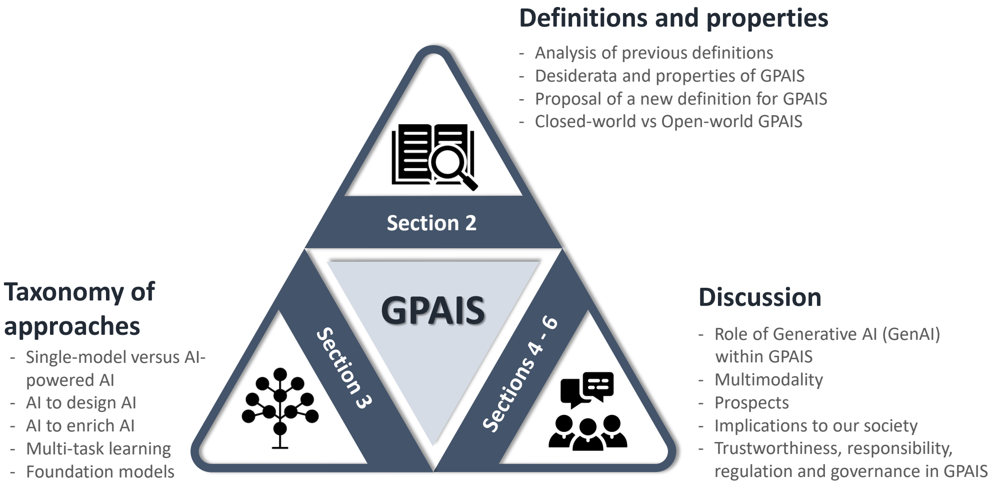
Explainable Artificial Intelligence

A. Barredo Arrieta et al., «Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI», Information Fusion, vol. 58, pp. 82-115, jun. 2020, doi: 10.1016/j.inffus.2019.12.012.

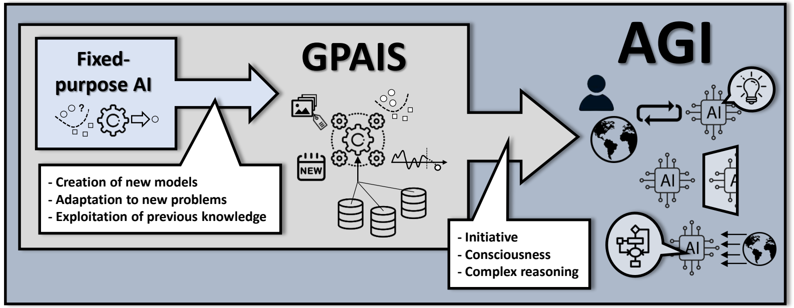
- Very useful for update about Explainable AI.
- AI must be explainable:
  - Detect/avoid discriminaiton.
  - Explaining decisions in several contexts.
- Very relevant in UE, new regulations.
- <u>We have several important projects about that topic, it is very important.</u>

Generic Purpose Artificial Intelligence Systems (GPAIS)

I. Triguero, D. Molina, J. Poyatos, J. Del Ser, y F. Herrera, «General Purpose Artificial Intelligence Systems (GPAIS): Properties, definition, taxonomy, societal implications and responsible governance», Information Fusion, vol. 103, 2024, doi: 10.1016/j.inffus.2023.102135.

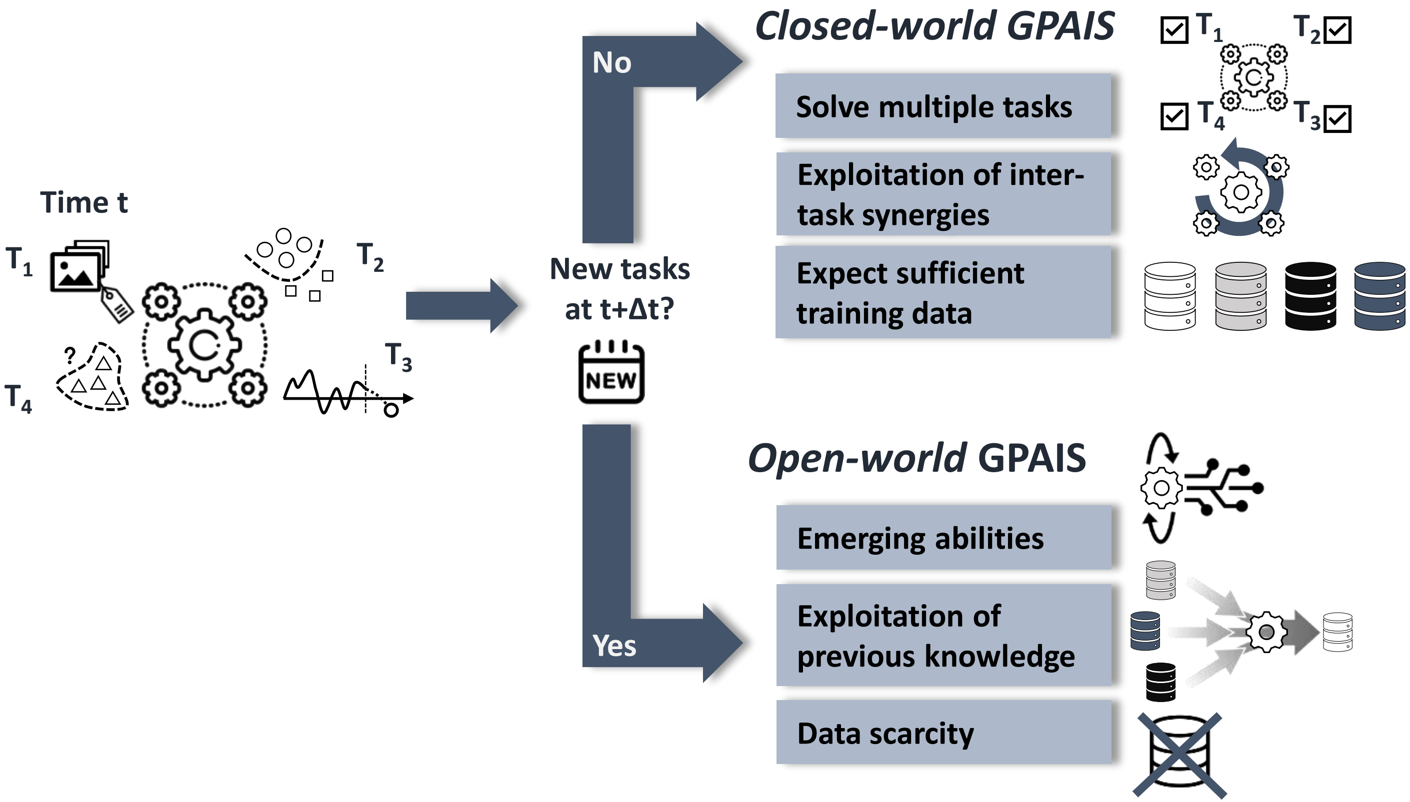


Generic Purpose Artificial Intelligence Systems (GPAIS)

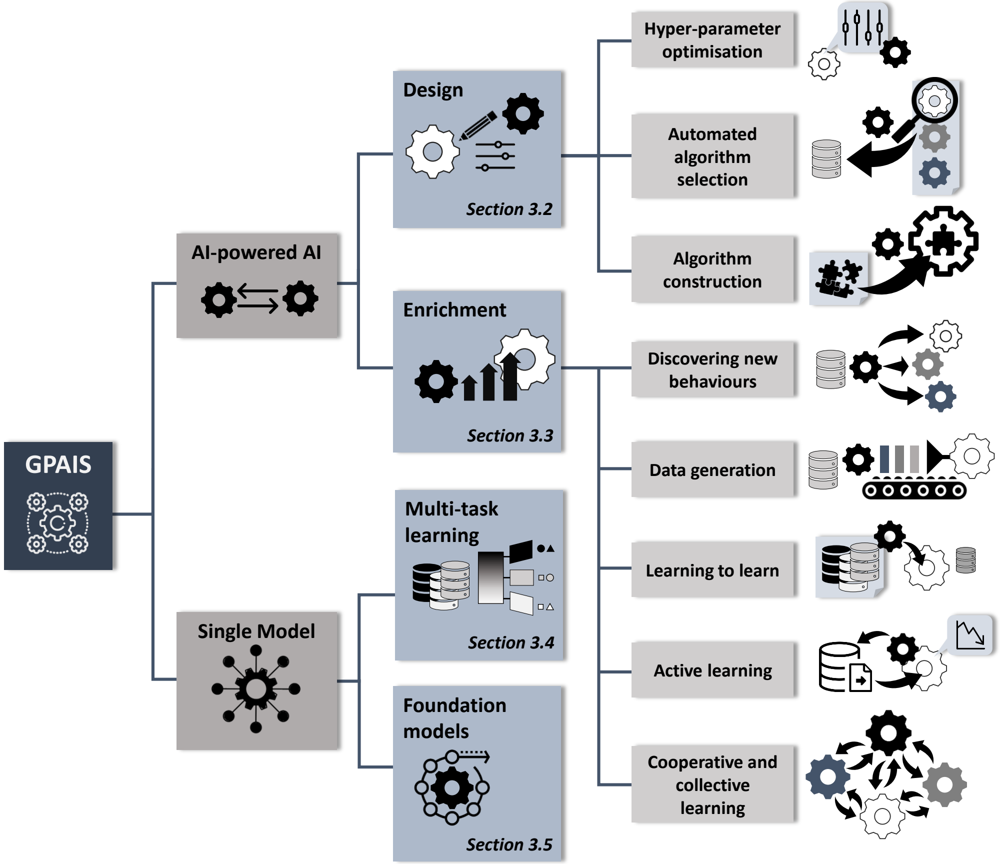


- We define GPAIS as a step toward an Artificial General Intelligence.
- We analyse generative models.
- Open-World and Close-World concepts.

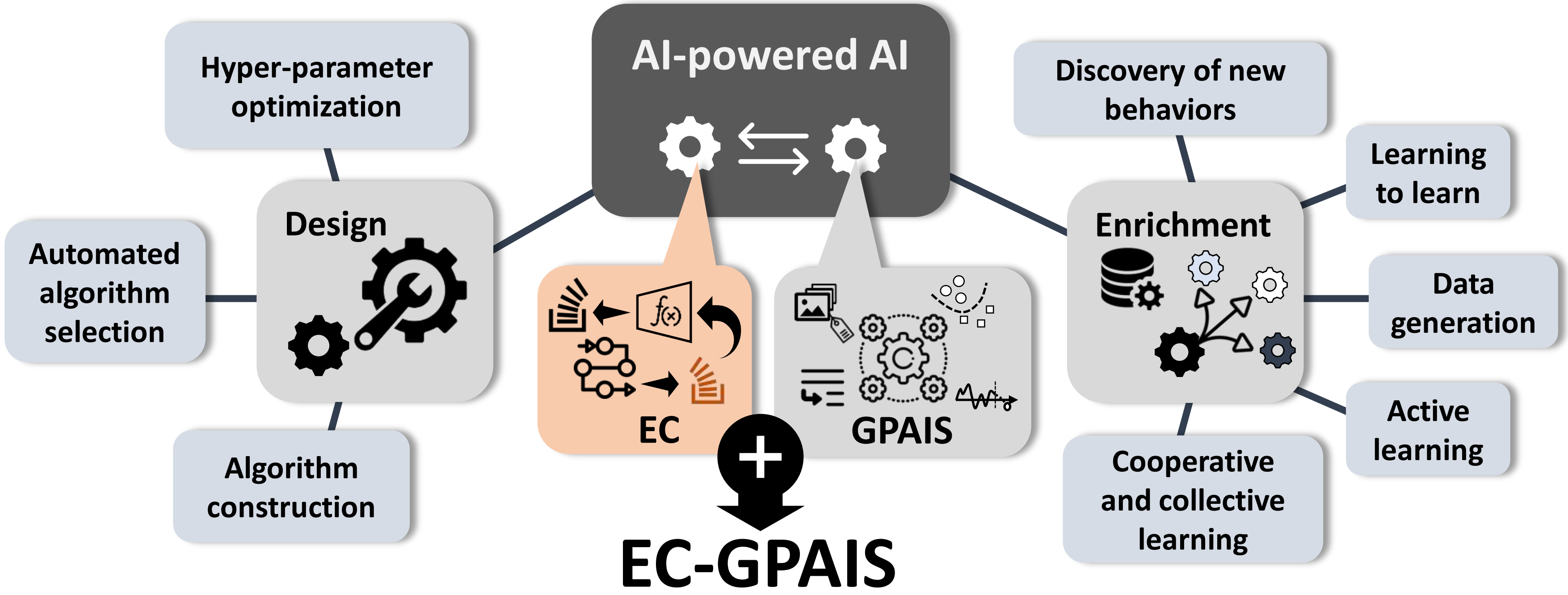
Generic Purpose Artificial Intelligence Systems (GPAIS)



Generic Purpose Artificial Intelligence Systems (GPAIS)

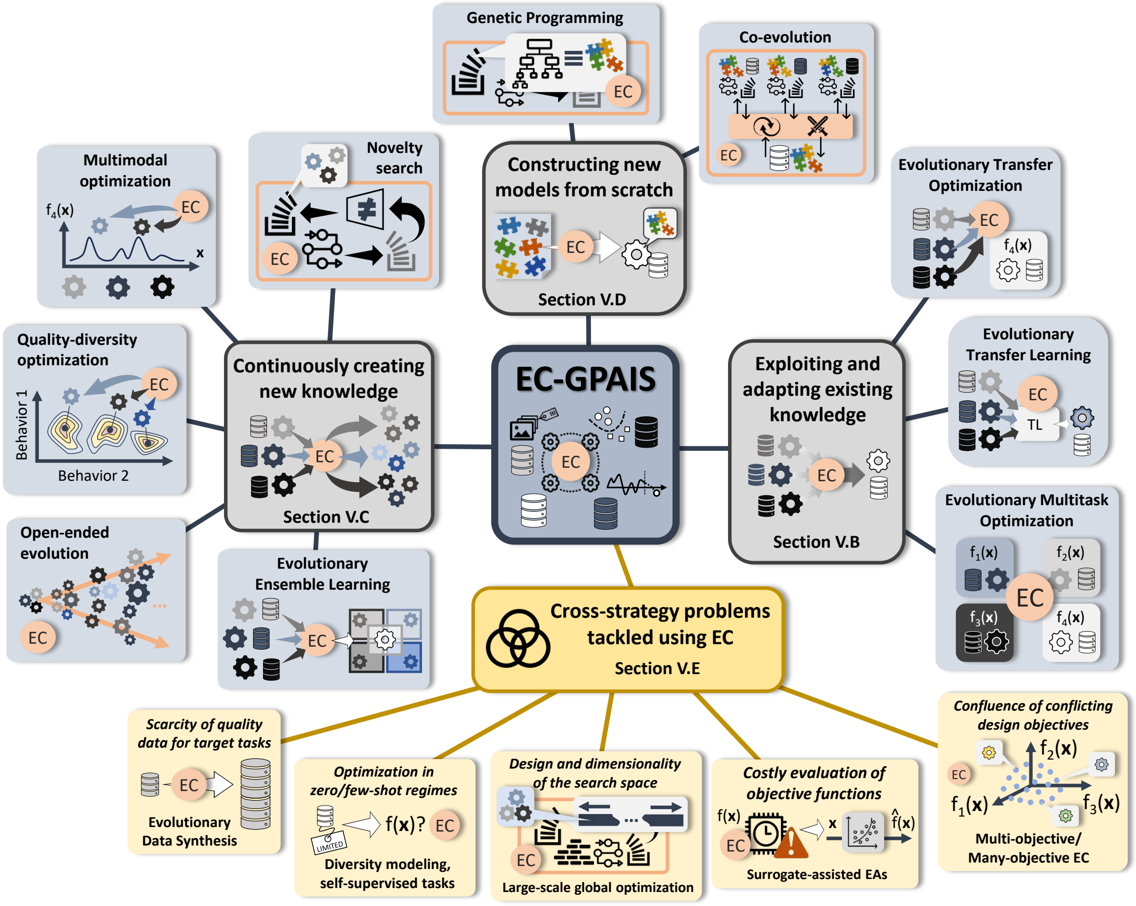


EC for GPAIS



D. Molina et al. «Evolutionary Computation for the Design and Enrichment of General-Purpose Artificial Intelligence Systems: Survey and Prospects», IEEE Transactions on Evolutionary Computation, pp. 1-1, 2025, doi: 10.1109/TEVC.2025.3530096.

Globally



EC-GPAIS
Constructing new models from scratch
Section V.D
Genetic Programming
Co-evolution
Continuously creating new knowledge
Section V.C
Multimodal optimization
Novelty search
Quality-diversity optimization
Behavior 1
Behavior 2
Open-ended evolution
Evolutionary Ensemble Learning
Exploiting and adapting existing knowledge
Section V.B
Evolutionary Transfer Optimization
Evolutionary Transfer Learning
TL
Evolutionary Multitask Optimization
Cross-strategy problems tackled using EC
Section V.E
Scarcity of quality data for target tasks
Evolutionary Data Synthesis
Optimization in zero/few-shot regimes
LIMITED
Diversity modeling, self-supervised tasks
Design and dimensionality of the search space
Large-scale global optimization
Costly evaluation of objective functions
Surrogate-assisted EAs
Confluence of conflicting design objectives
Multi-objective/ Many-objective EC
EC

My current Phd Students

- Irene Trigueros.
- Phd student about Distillation Knowledgment (DK).

- Abel José Sánchez.
- Phd student about Evolutionary NAS.

My current Phd Students

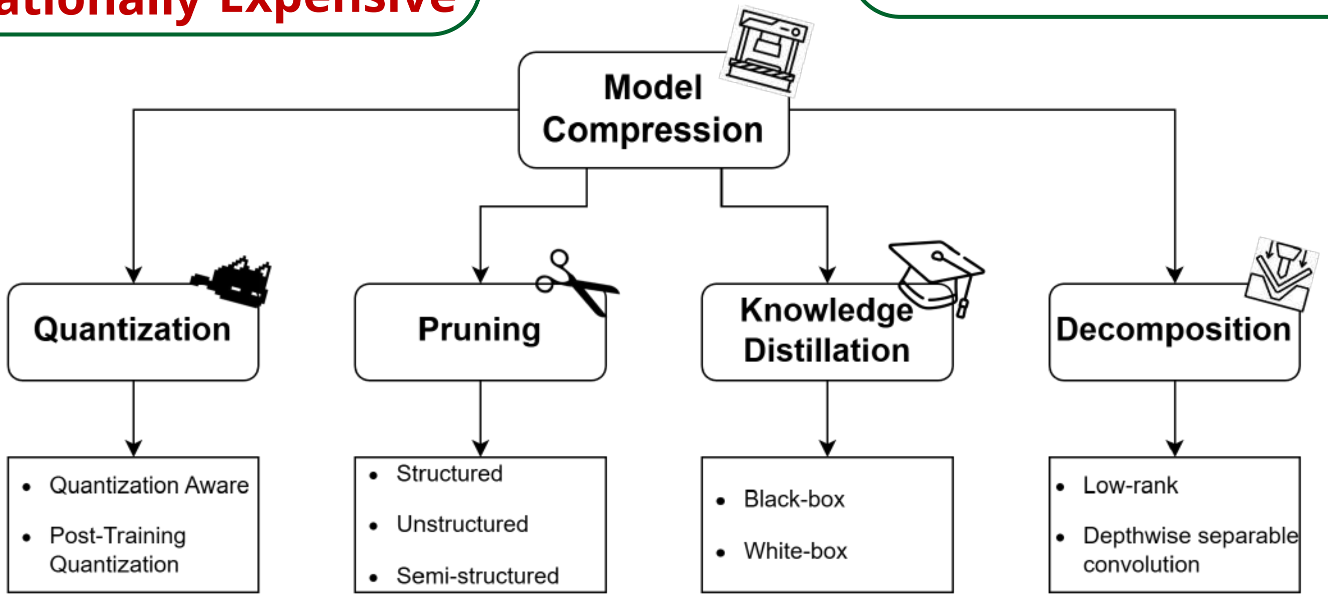
- Irene Trigueros.
- Phd student about Distillation Knowledgment (DK).

GPAIS

- Great results
- Great size → Computationally Expensive

Model Compression →

- Comparable results
- Smaller size → Less computationally expensive



1 Triguero, I., Molina, D., Poyatos, J., Del Ser, J., & Herrera, F. (2024). General Purpose Artificial Intelligence Systems (GPAIS): Properties, definition, taxonomy, societal implications and responsible governance. Information Fusion, 103, 102135

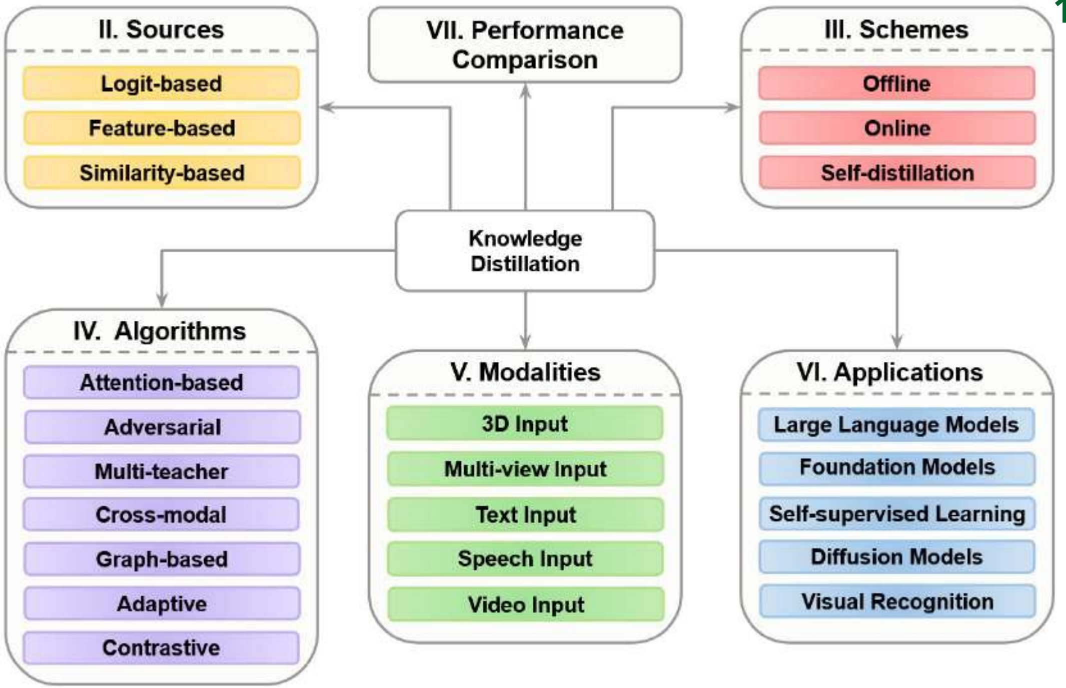
Teacher

- Great results
- Great size → Computationally Expensive

Knowledge Distillation

Student

- Learning from teacher
- Teacher-like behaviour

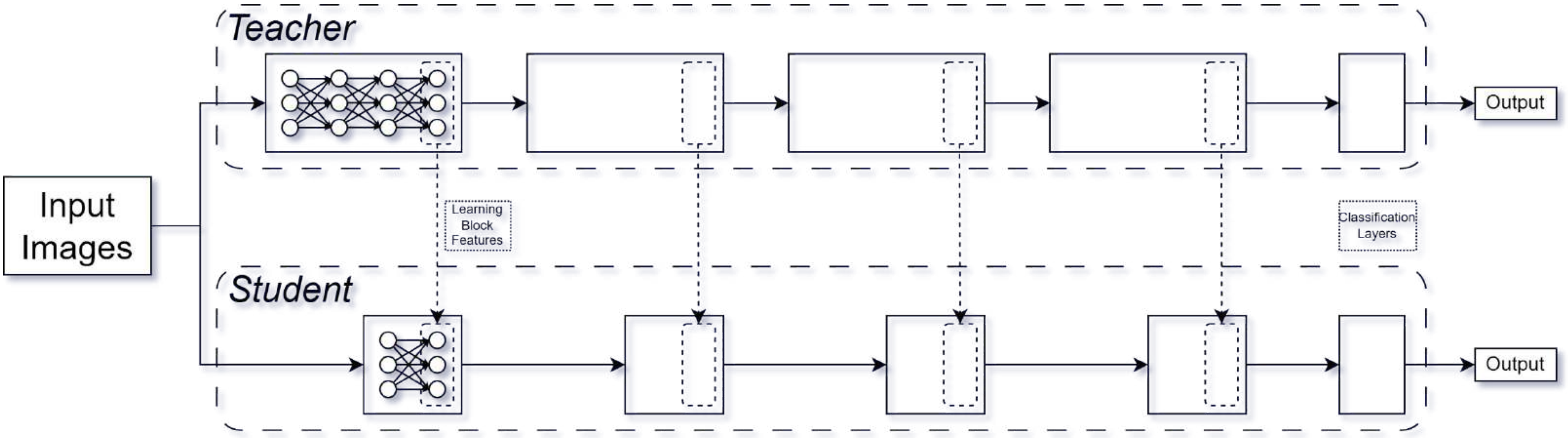


[1]

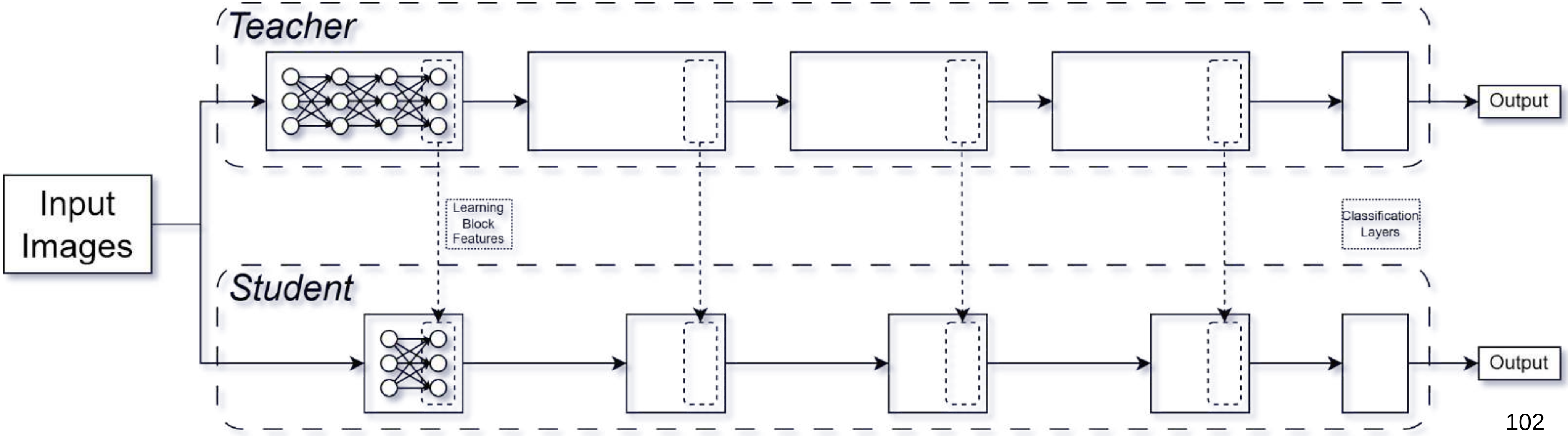
1 Mansourian, A. M., Ahmadi, R., Ghafouri, M., Babaei, A. M., Golezani, E. B., Ghamchi, Z. yasamani, Ramezanian, V., Taherian, A., Dinashi, K., Miri, A., & Kasaei, S. (2025). A Comprehensive Survey on Knowledge Distillation. Transactions on Machine Learning Research.

Learning by using intermediate features:

- ❑ Student achieves a better understanding of Teacher's behavior



- ❑ Fine-Tuned Teacher vs Not Fine-Tuned Teacher
- ❑ Fine-Tune whole Student vs Only train classification layers (after KD)
- ❑ Differences in using different number of blocks
- ❑ Introducing Explainability to feature-based KD



Several conclusions

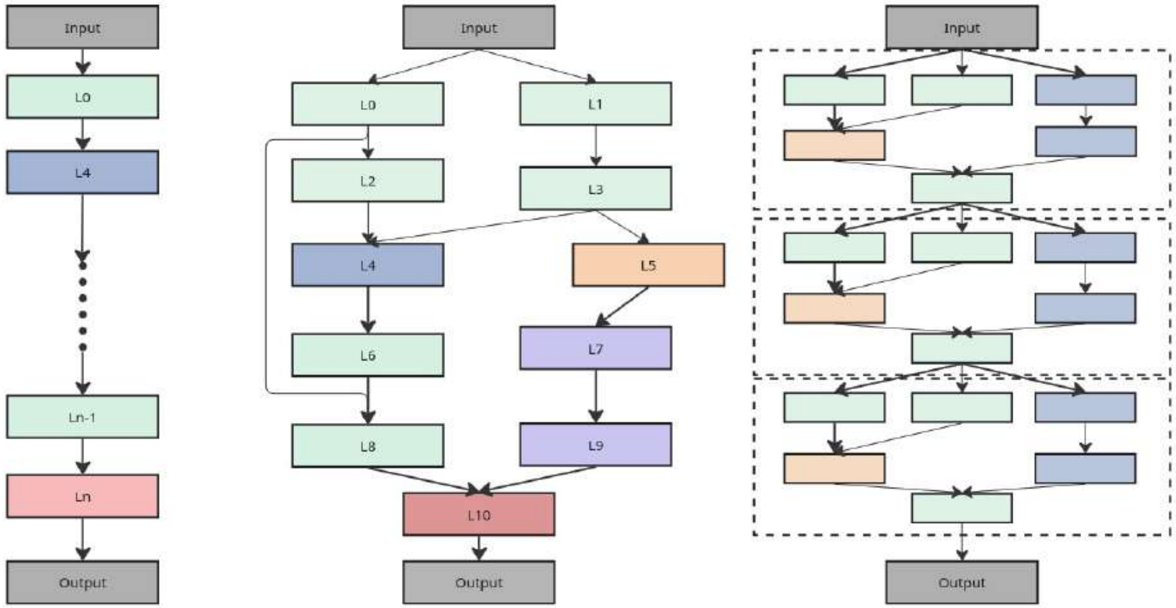
- DS with several blocks requires less data.
  - More risk of over-training (data augmentation?).
- It is better in time fine-tuning the student.
- We are studying the interpretabilidad of this model.
  - More differences in first blocks.

My current Phd Students

- Abel José Sánchez.
- Phd student about Evolutionary NAS.

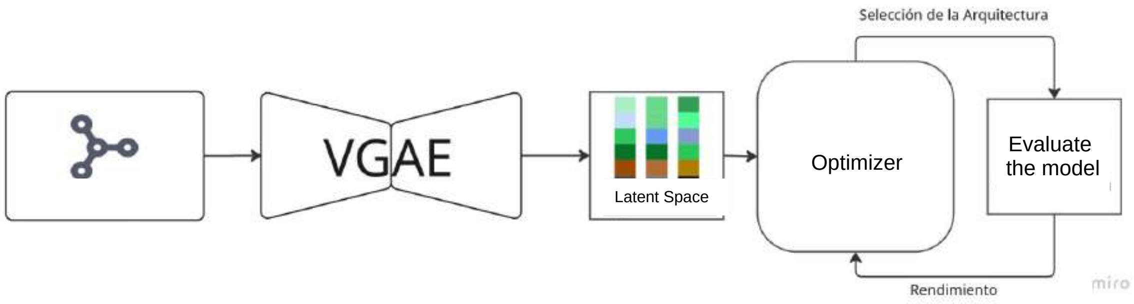
Network Arquitecture Search

- We search the best network model.



NAS with VGAE

- We transform the model space using a Variational Graph AutoEncoder.
- We apply the Evol. Algorithm in that space.



Gaps in NAS with VGAE

- Not realistic, benchmarks with many models and their performance.
- Huge domain search.
- How it can be applied for new dataset?

Automatically Filtering NN Models

Reduce Training Data

Surrogate techniques for reduce evaluations

Improve the EC search with few evaluations

¿Colaboramos/Collaborations?

Daniel Molina Cabrera
dmolinac@ugr.es