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ALGORITMOS EVOLUTIVOS I (CURSADO)

DOCENTE DEL CURSO

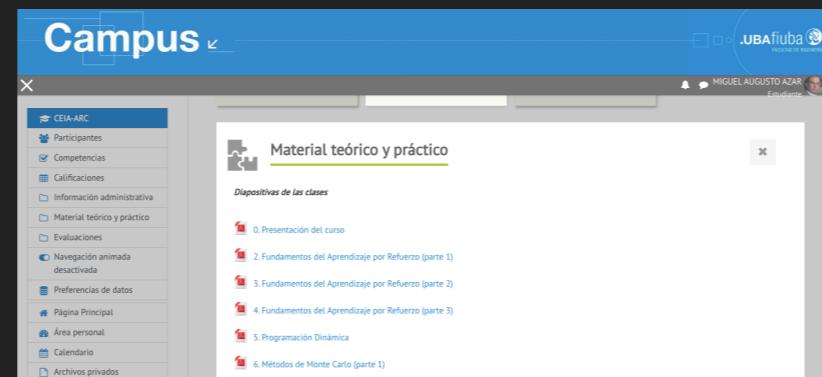
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- ▶ Ingeniero en Informática
- ▶ Especialista en Docencia Superior
- ▶ Docente e investigador
- ▶ Email: augusto.azar@gmail.com o mazar@fi.uba.ar

RECURSOS VIRTUALES

- ▶ Campus virtual

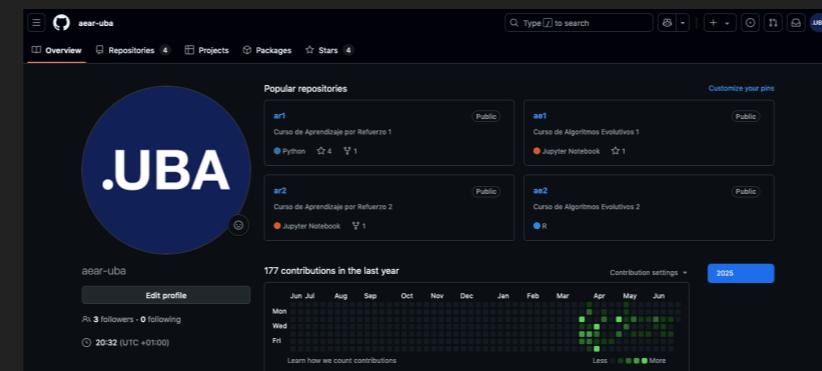
<https://campusposgrado.fi.uba.ar/course/view.php?id=420>

Automatriculación: ae1==2025



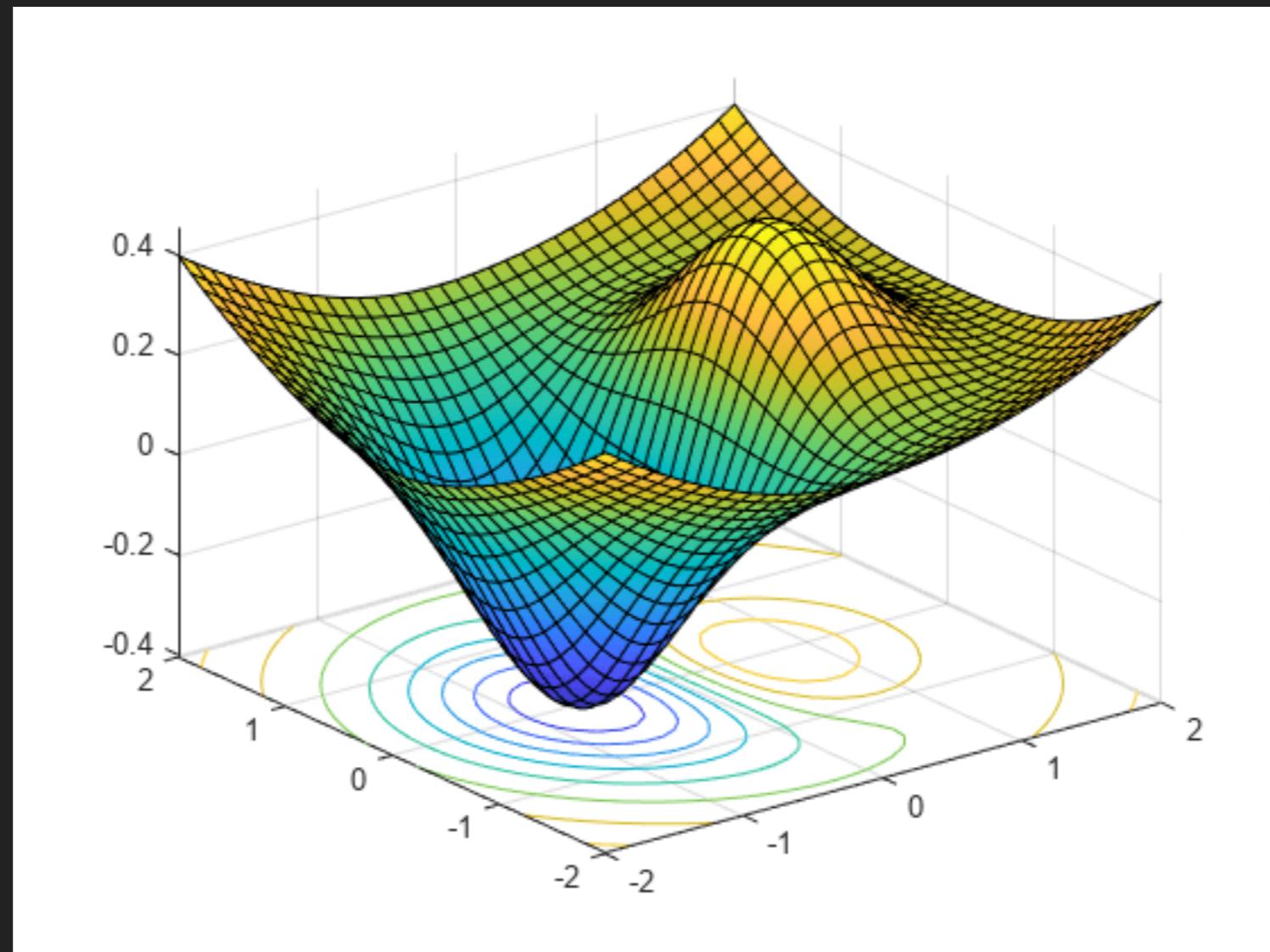
- ▶ Repositorio

<https://github.com/aear-uba/ae1/tree/main/2025b5/>



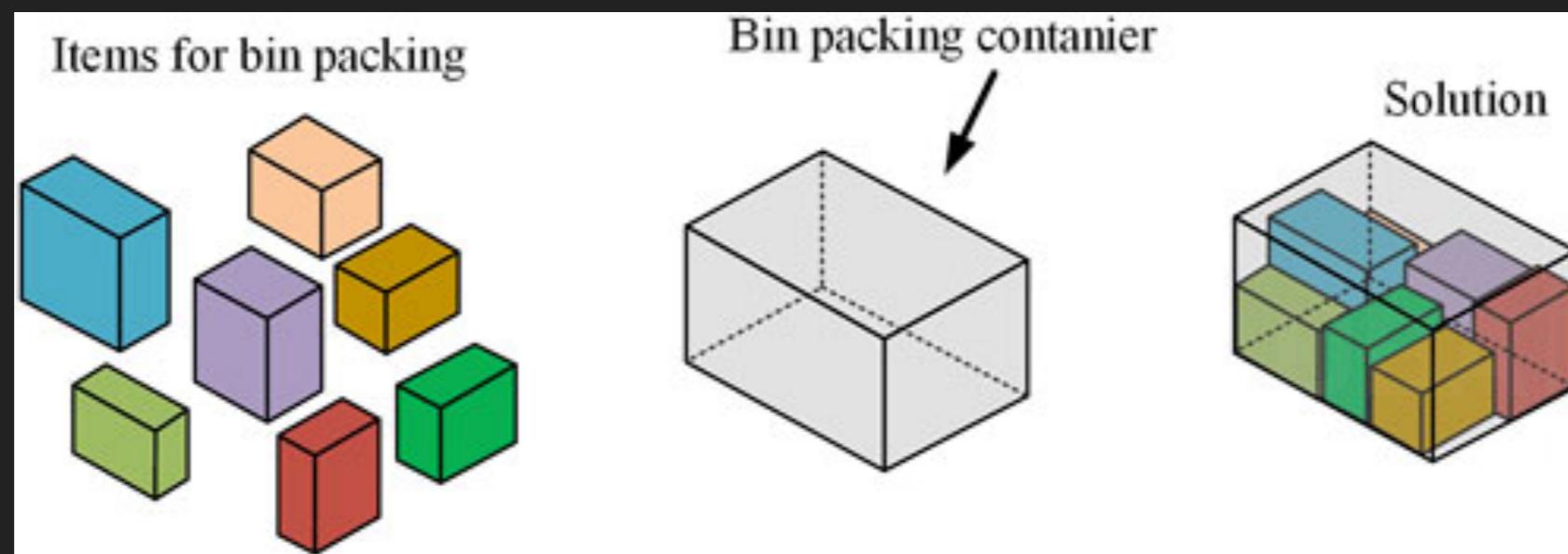
¿DE QUE SE TRATA ALGORITMOS EVOLUTIVOS I?

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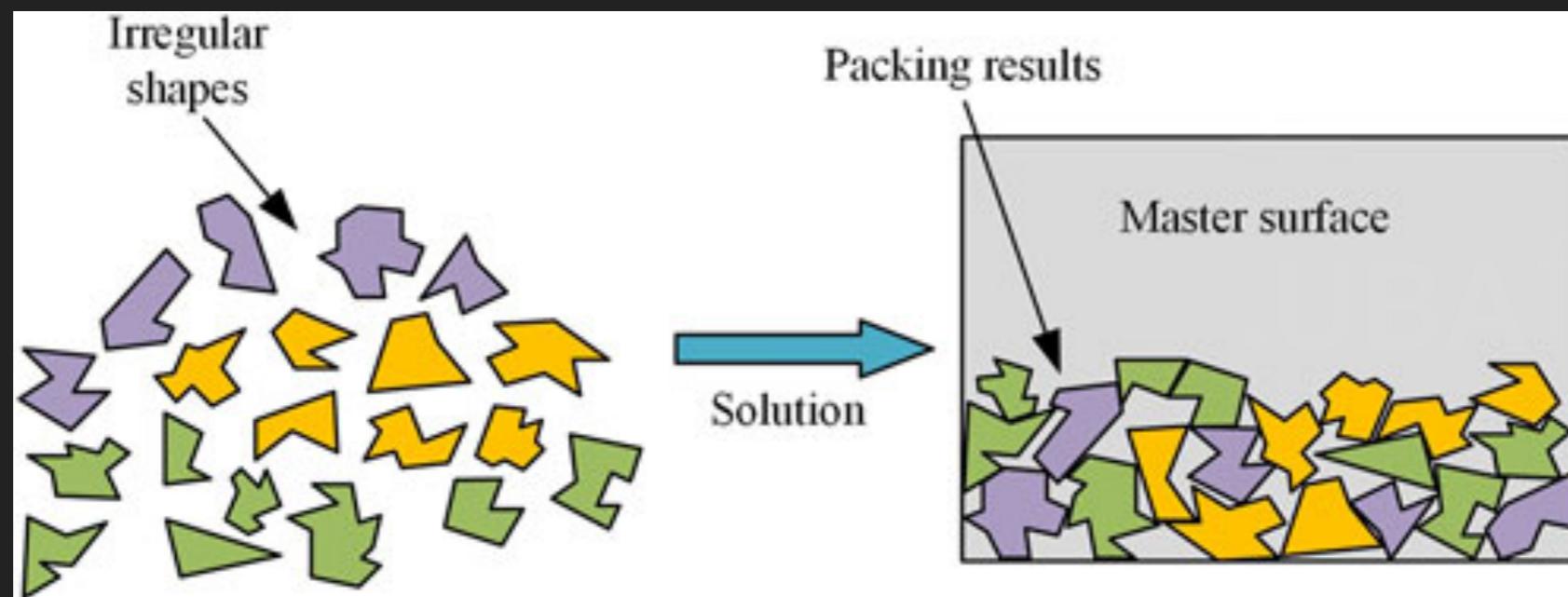
- ▶ Artículos a embalar en un contenedor



- ▶ 3D bin packing problem (set packing)

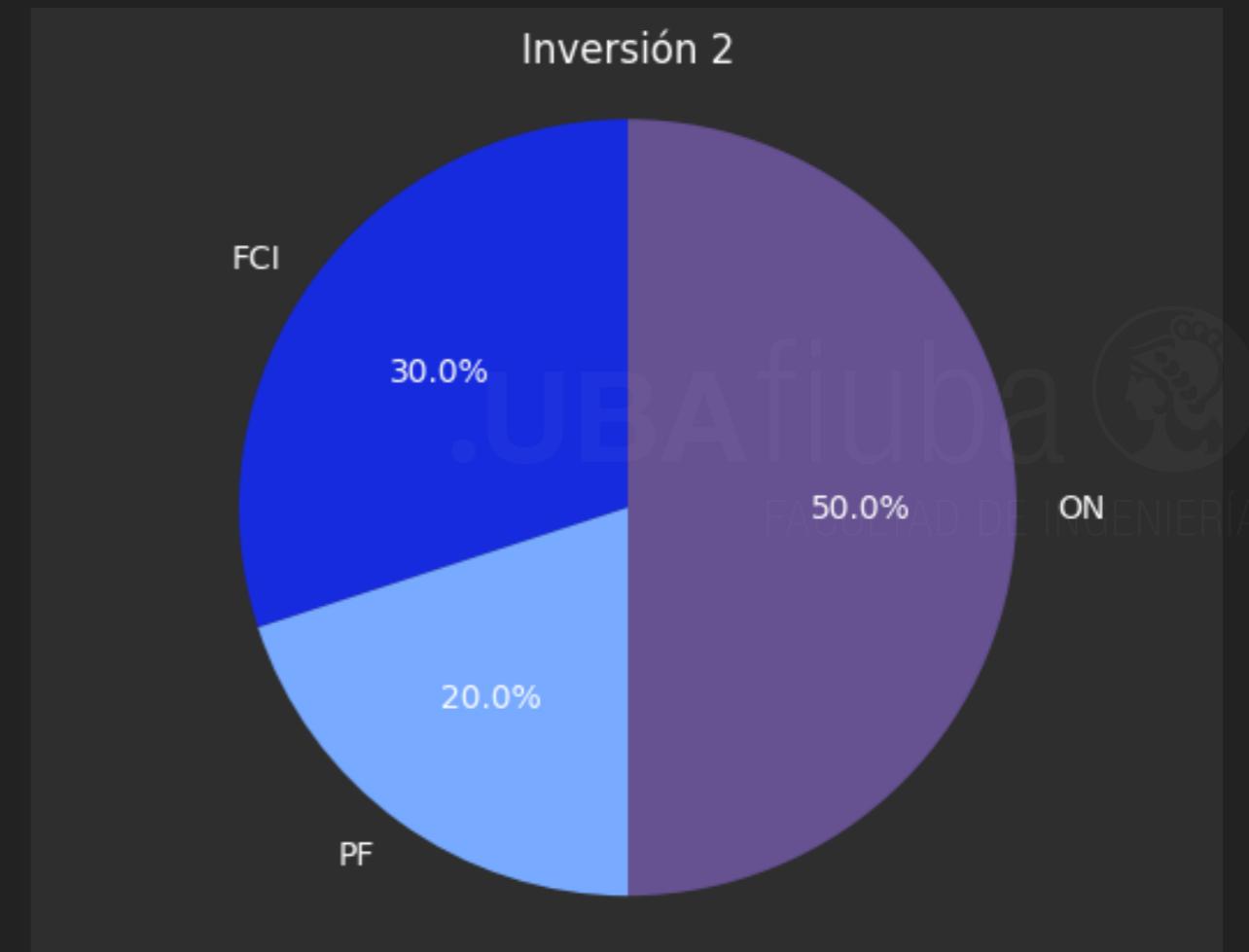
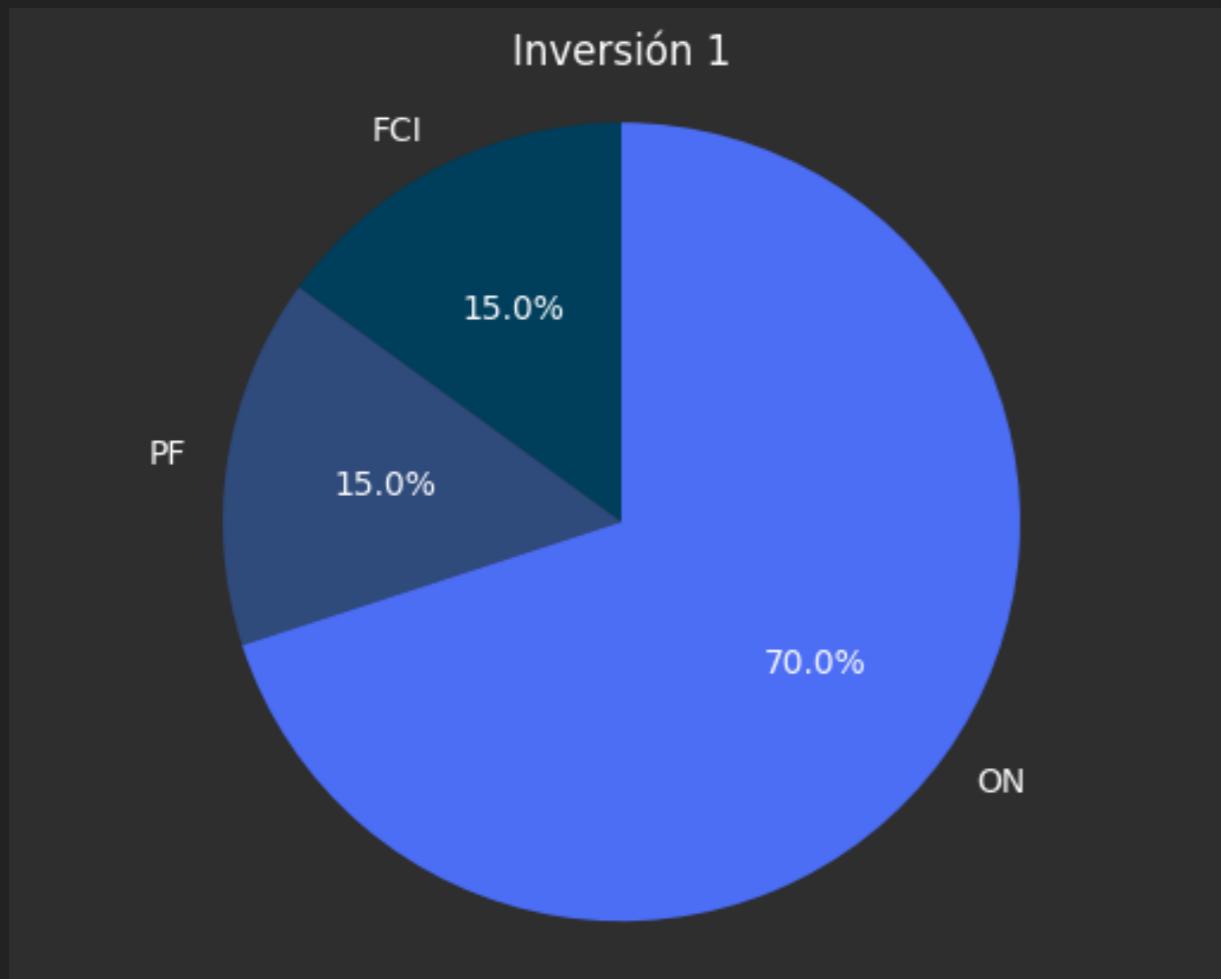
¿DE QUE SE TRATA ALGORITMOS EVOLUTIVOS I?

- ▶ Tela en una fábrica de prendas



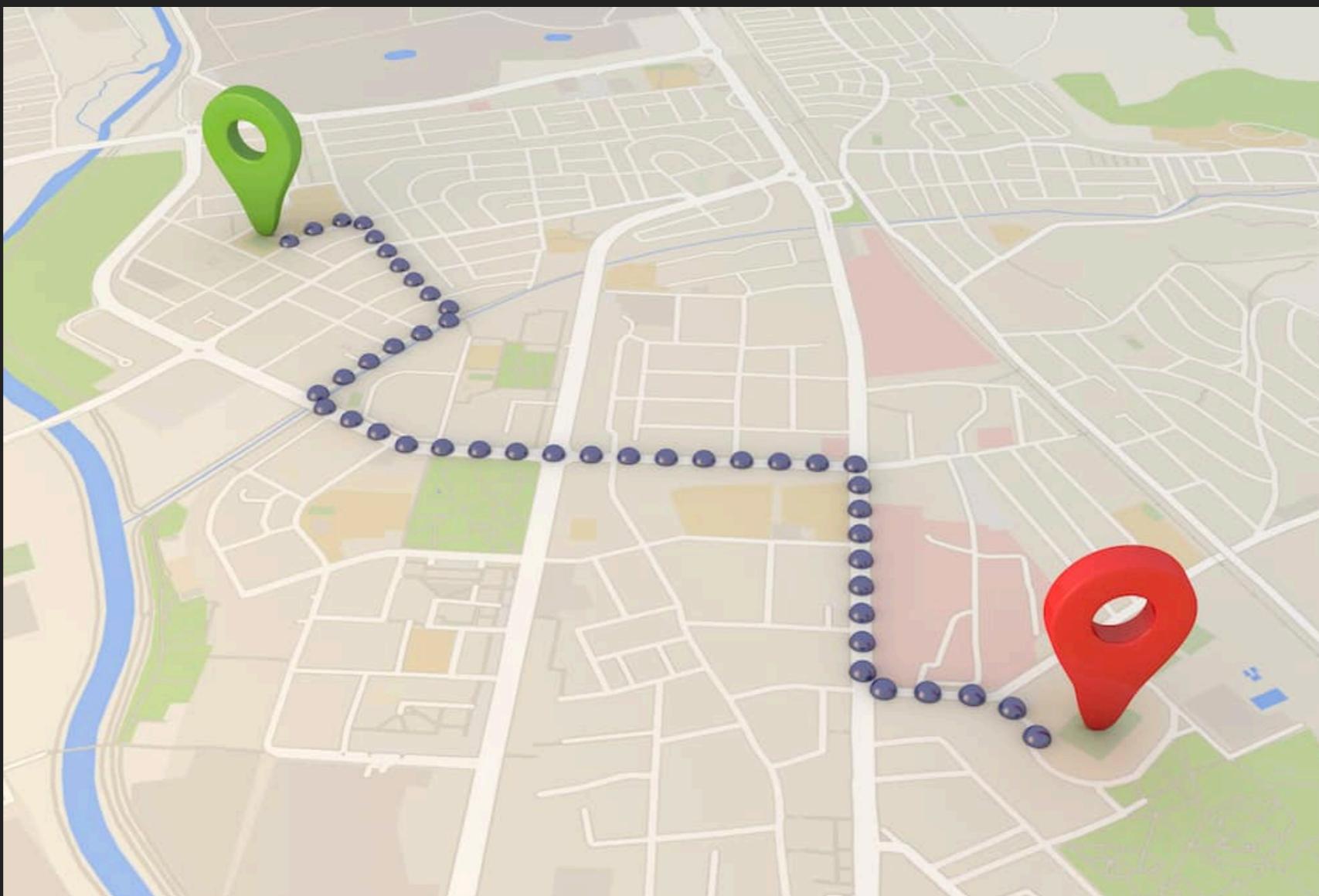
¿DE QUE SE TRATA ALGORITMOS EVOLUTIVOS I?

- ▶ Optimización de un portfolio de inversión



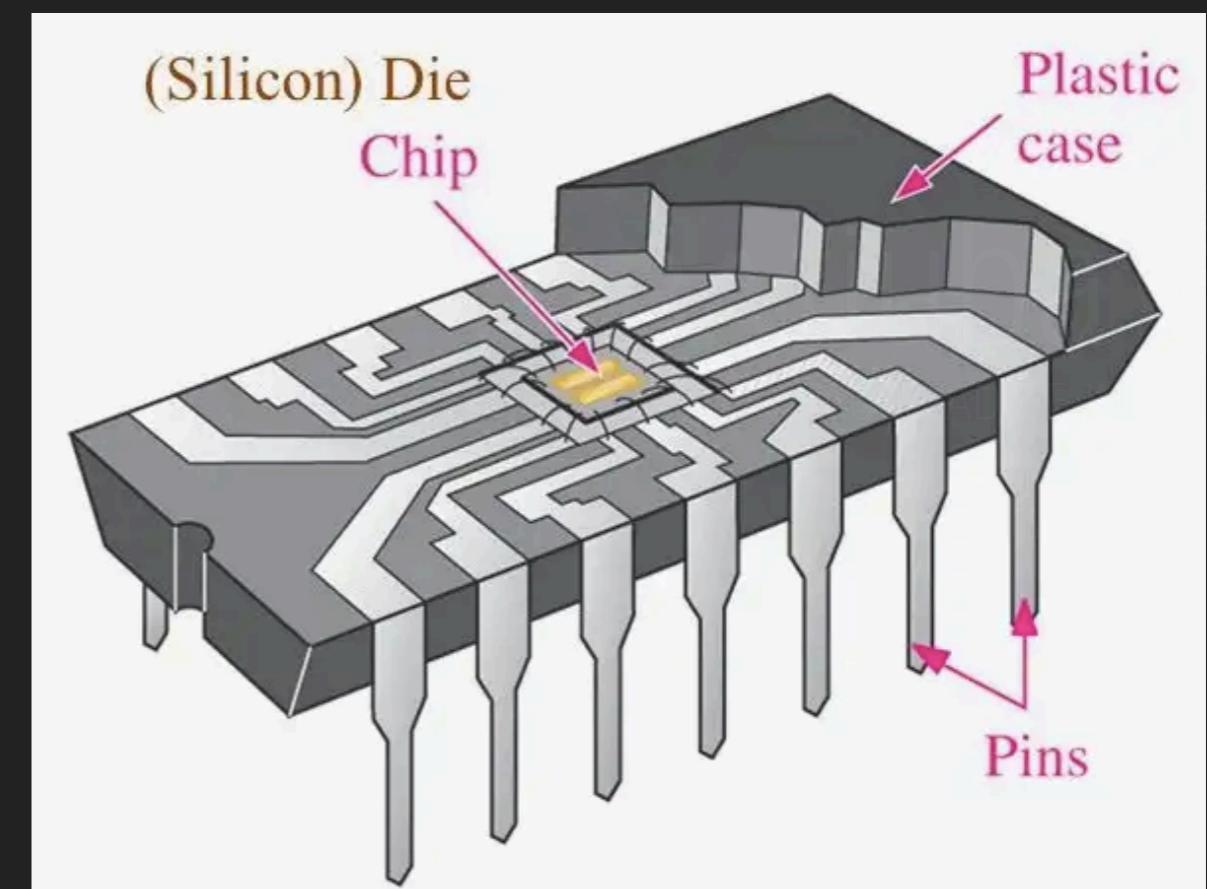
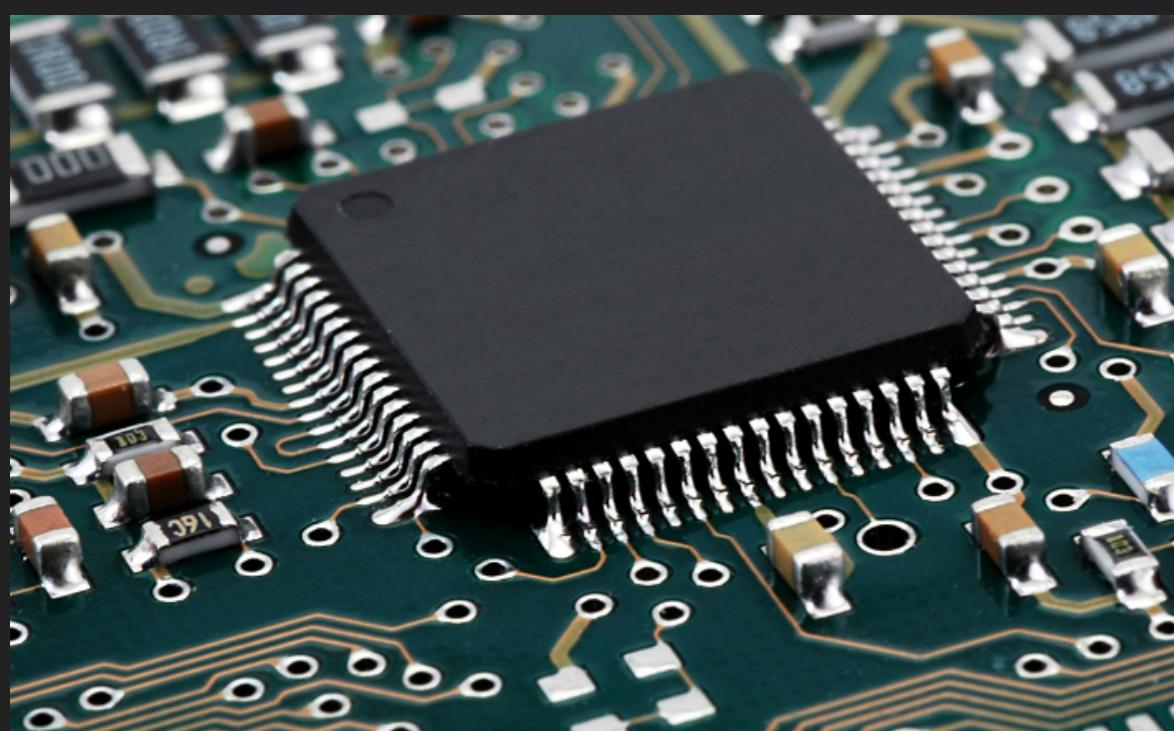
¿DE QUE SE TRATA ALGORITMOS EVOLUTIVOS I?

- ▶ Transporte



¿DE QUE SE TRATA ALGORITMOS EVOLUTIVOS I?

- ▶ Diseño de **circuitos integrados VLSI** (Very Large Scale Integration)



¿DE QUE SE TRATA ALGORITMOS EVOLUTIVOS I?

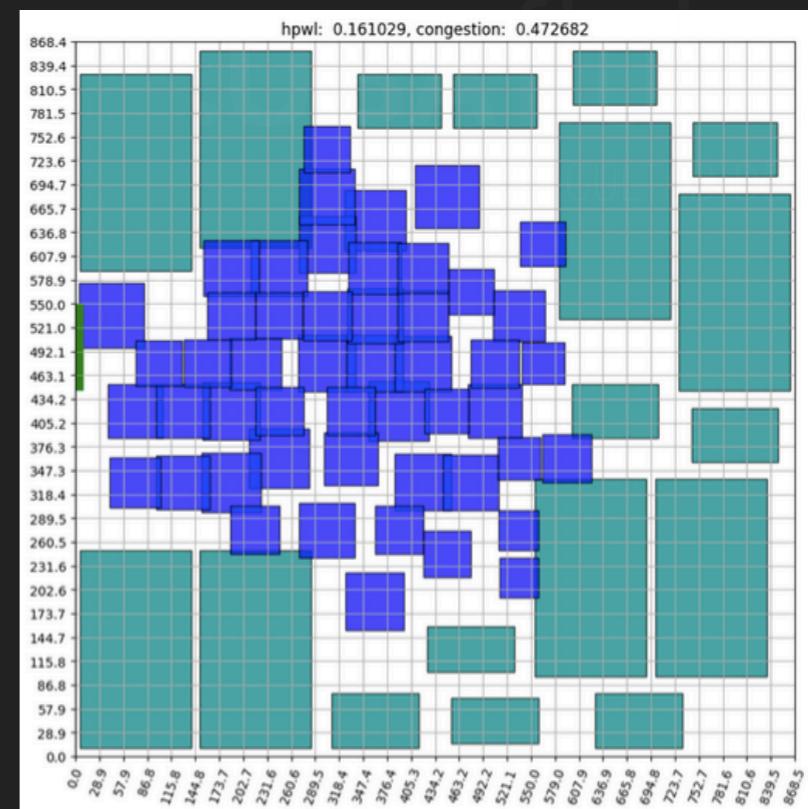
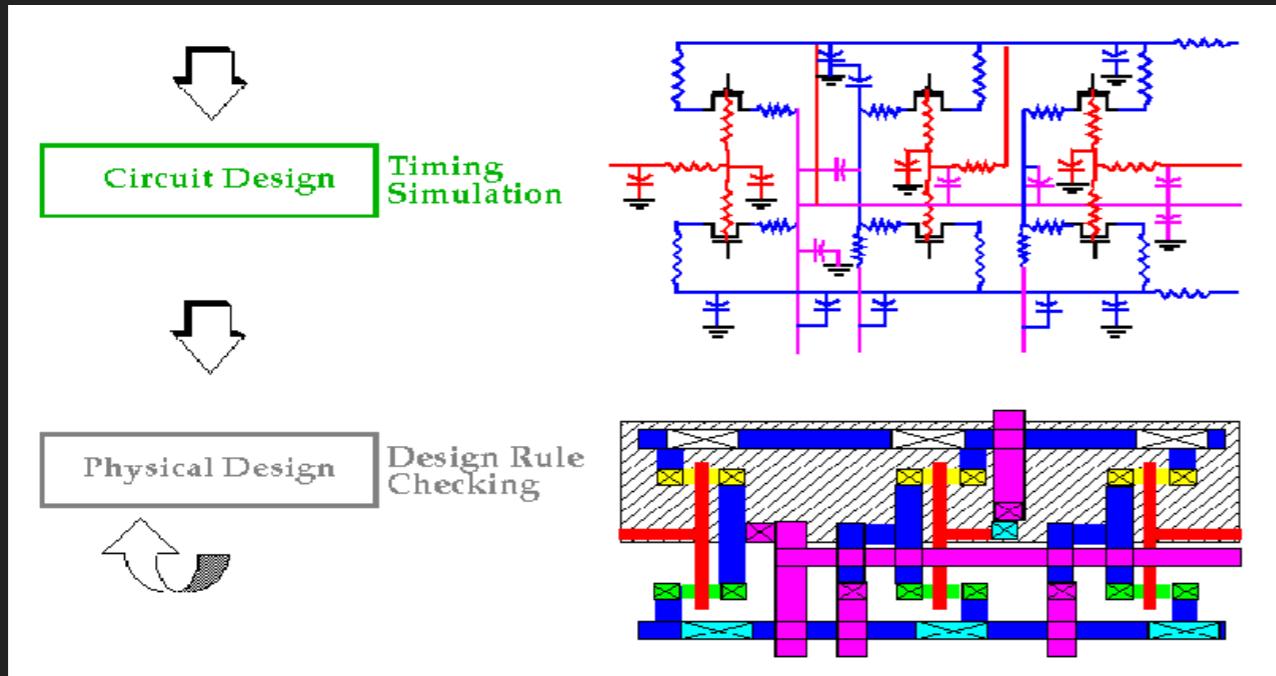
- ▶ Diseño de circuitos integrados VLSI (Very Large Scale Integration):

✓ Routing (enrutamiento de conexiones)

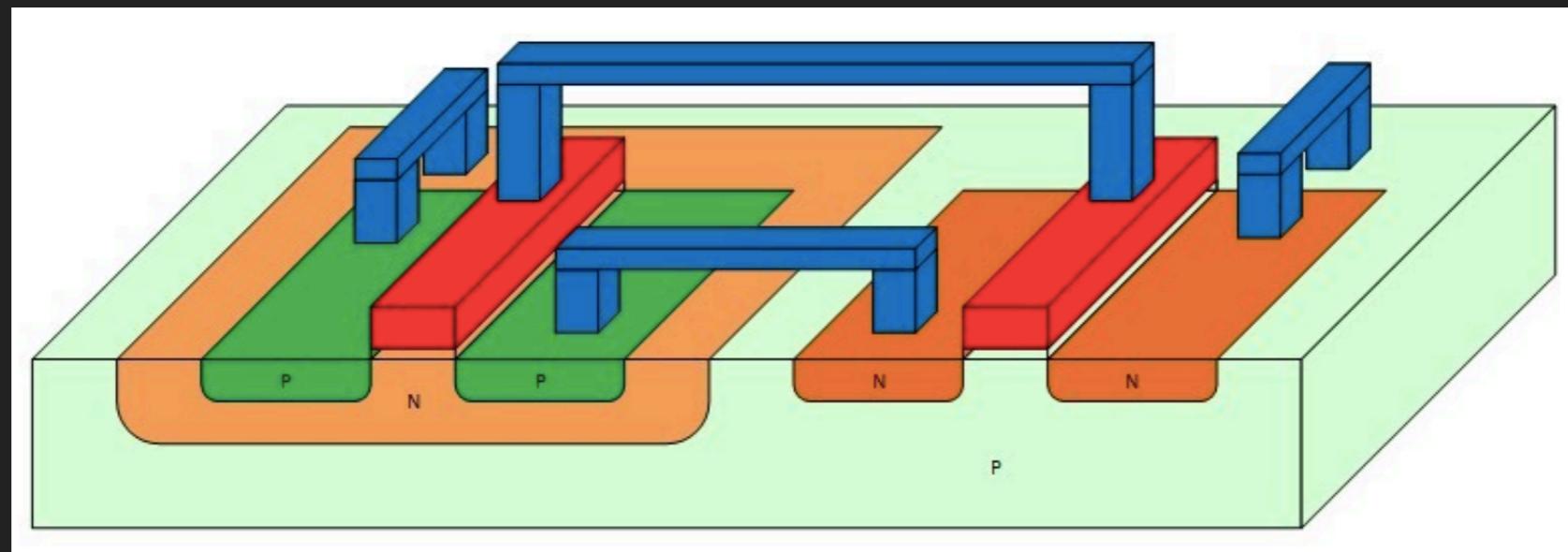
→ Interconexión, max. performance, min. Interferencia, min. longitud "cableado".

✓ Placement (colocación de componentes macros y clústers)

→ Floorplanning y PPA

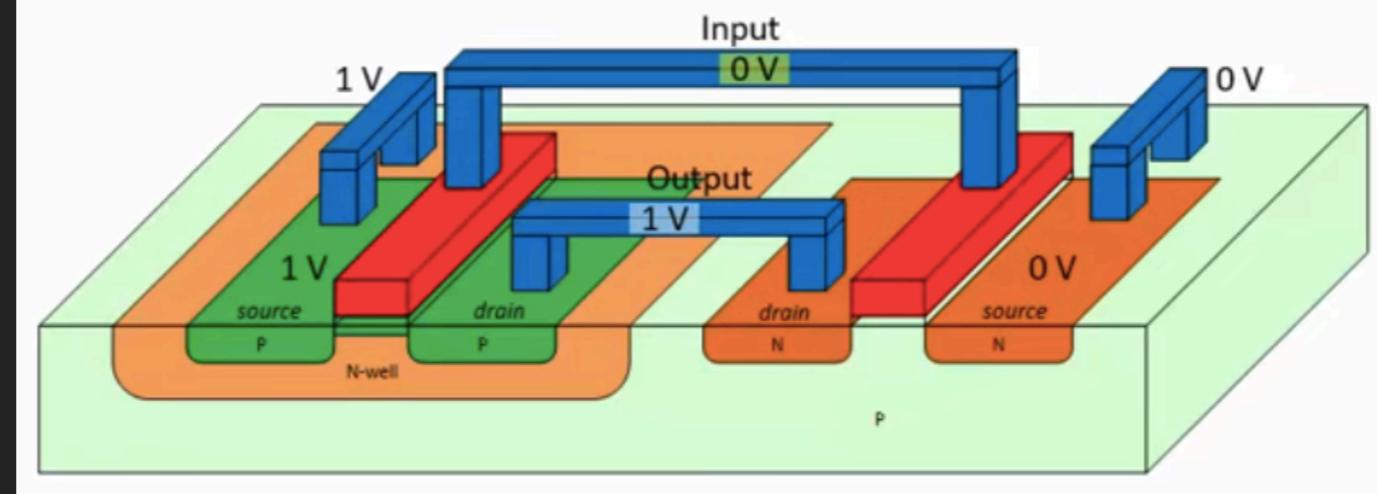


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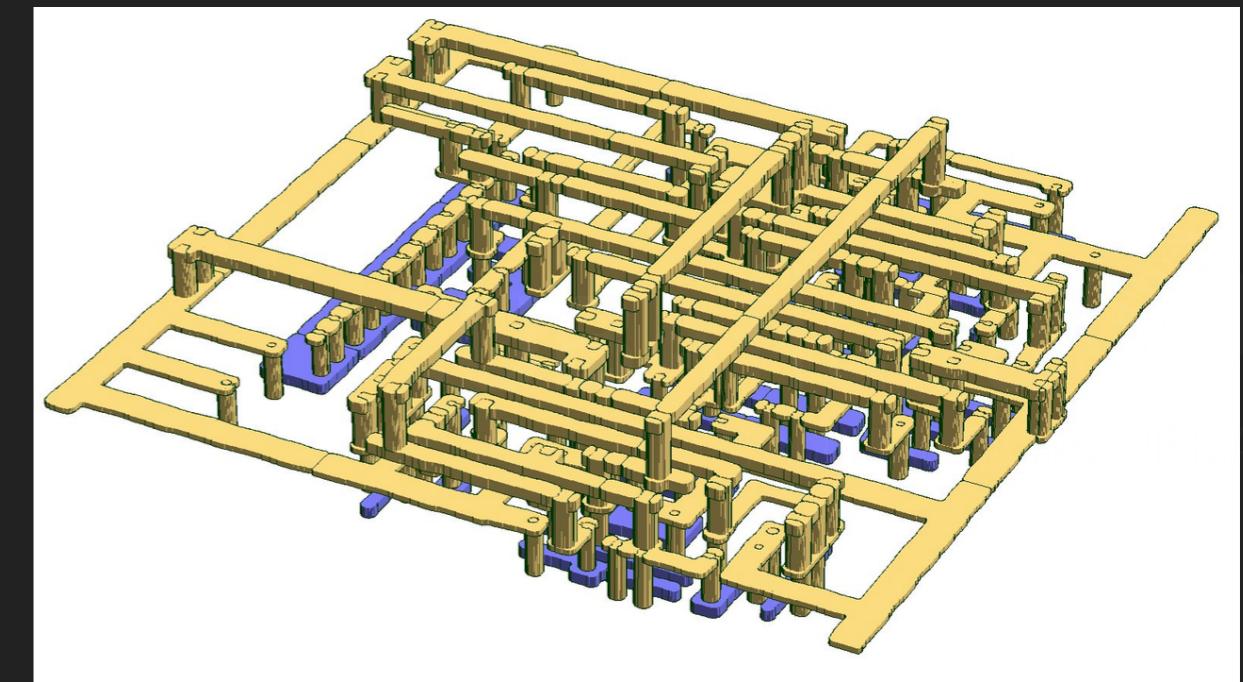
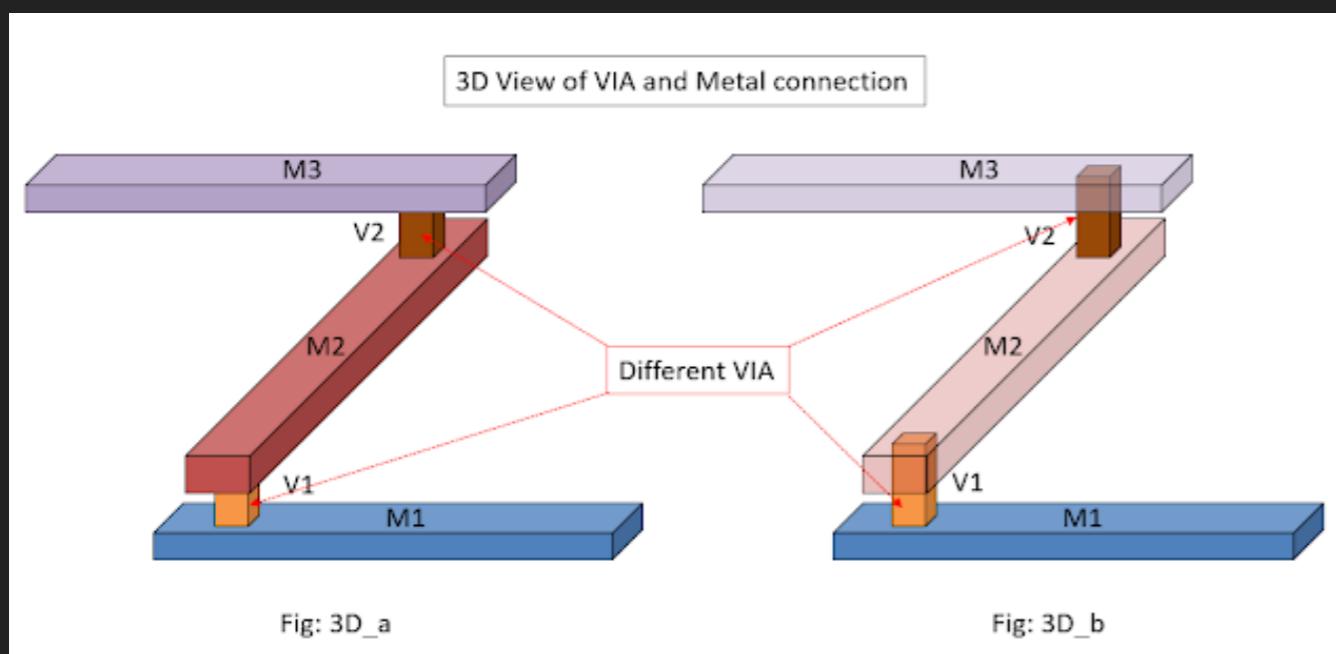


CMOS Technology: Inverter

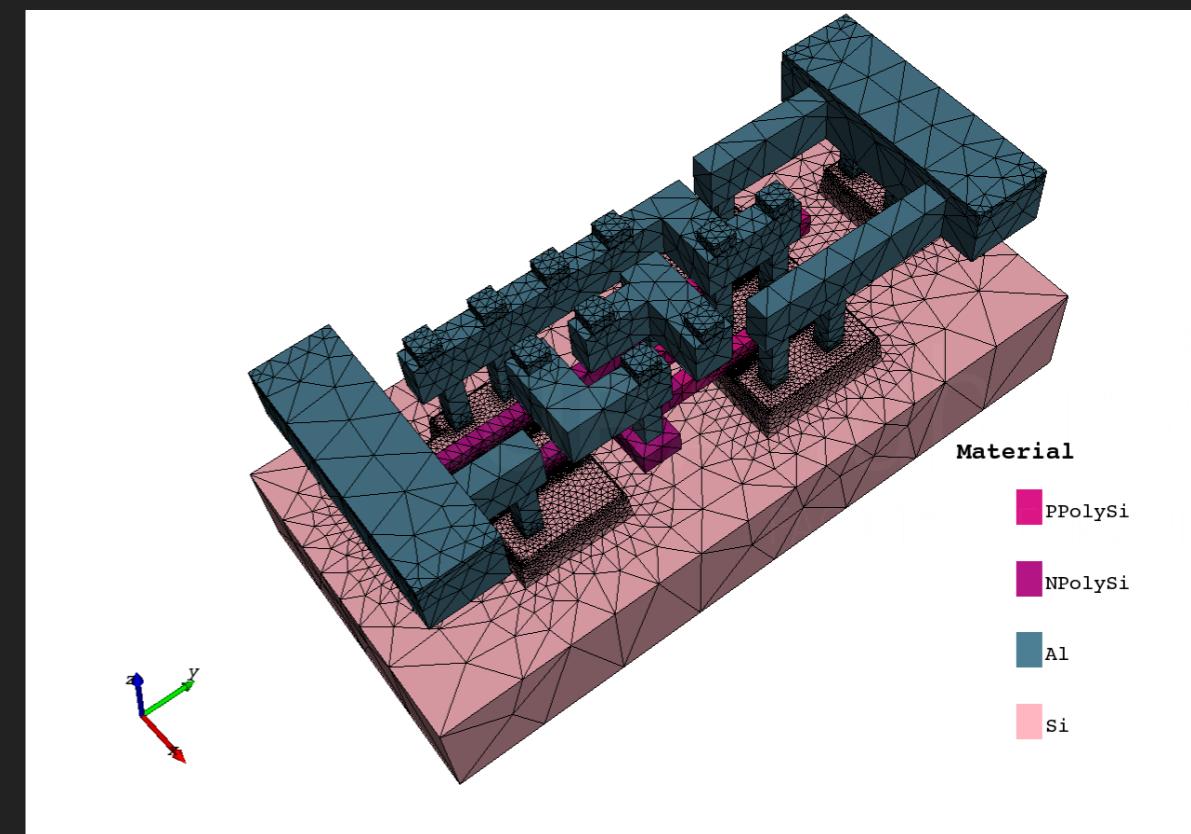
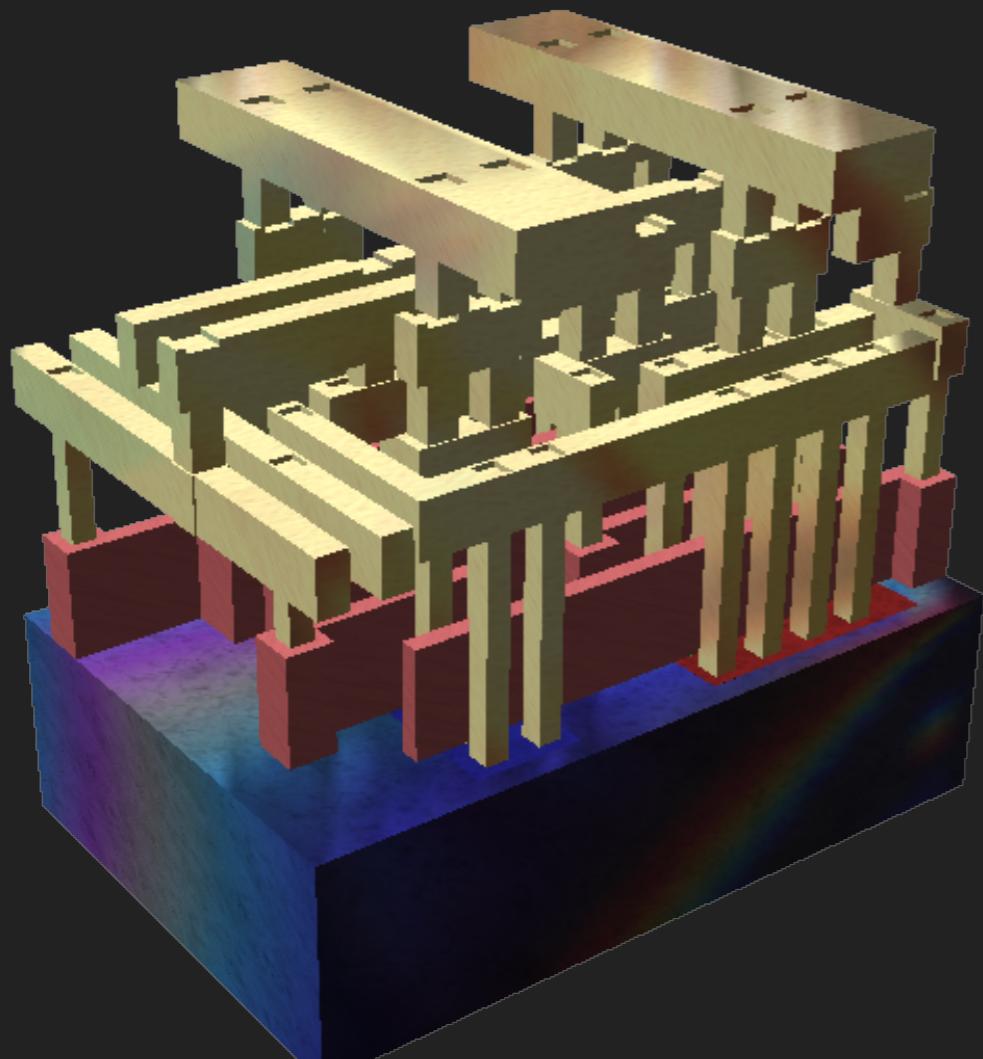
- Input 0: PMOS on, NMOS off, output = 1



¿DE QUE SE TRATA ALGORITMOS EVOLUTIVOS I?

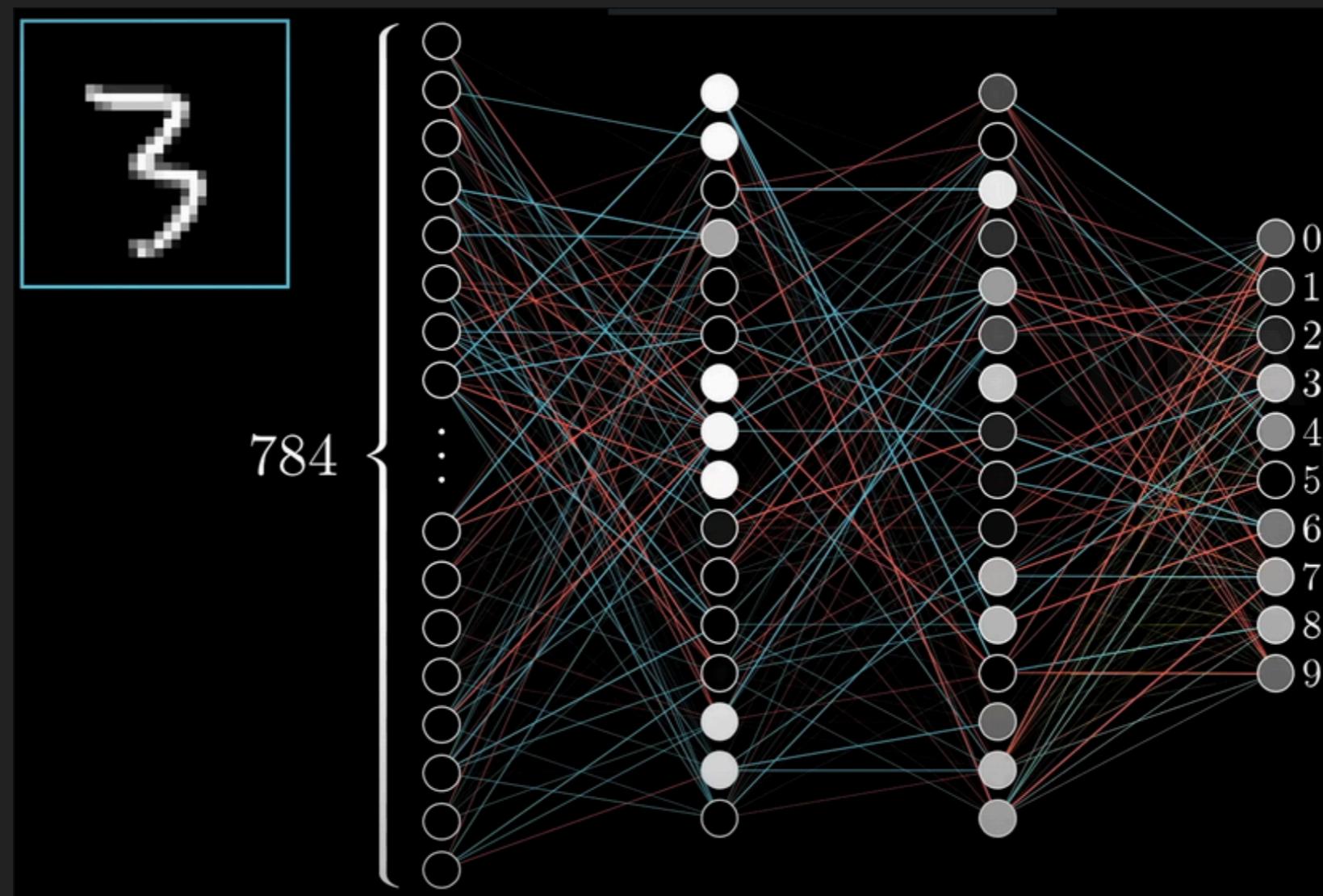


¿DE QUE SE TRATA ALGORITMOS EVOLUTIVOS I?



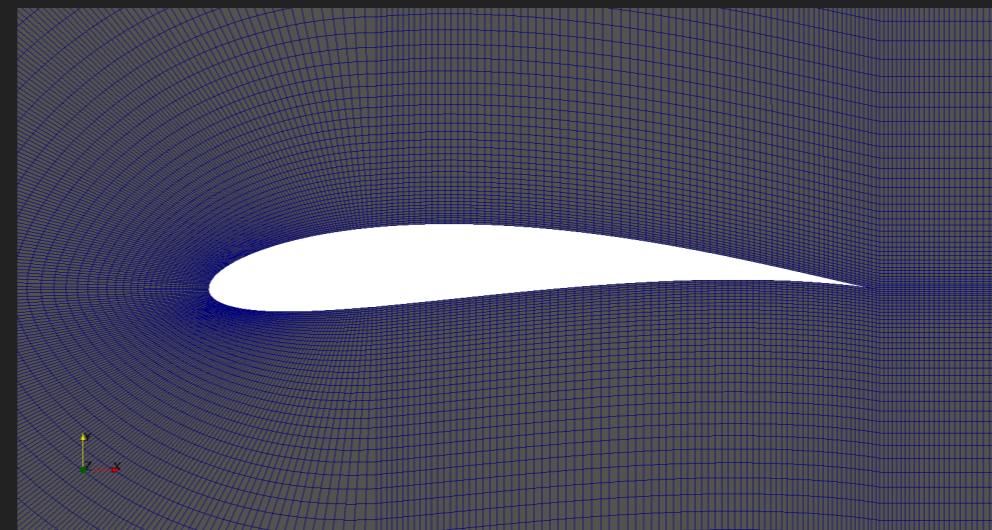
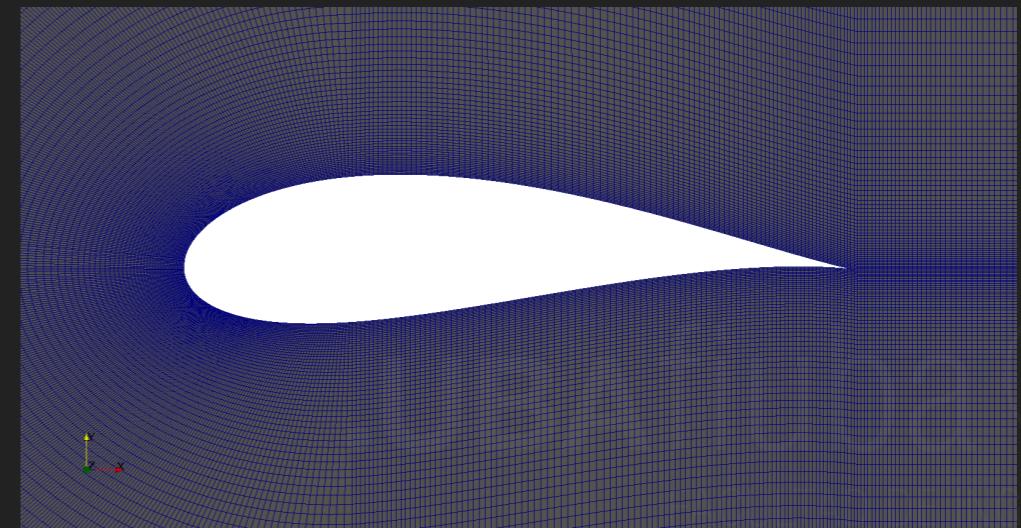
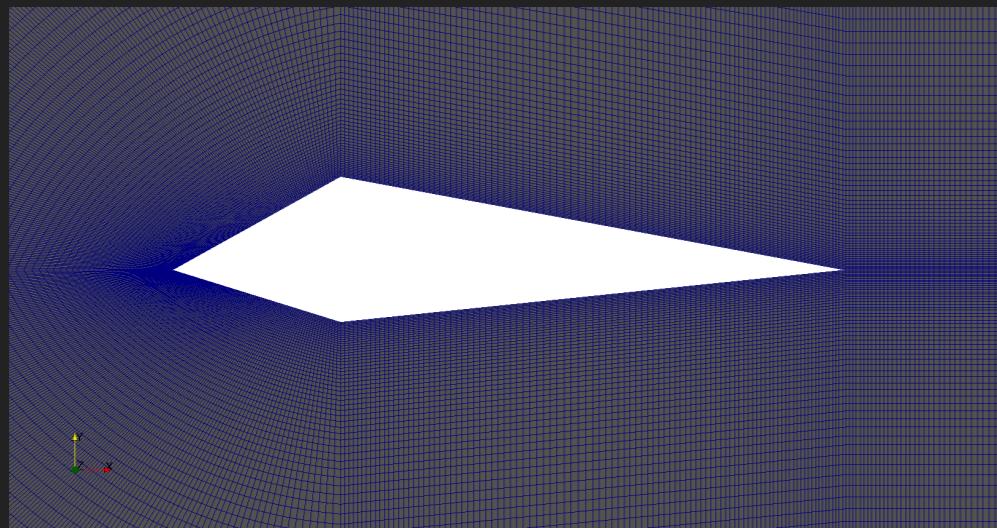
¿DE QUE SE TRATA ALGORITMOS EVOLUTIVOS I?

- ▶ Optimización de hiperparámetros en DNN



¿DE QUE SE TRATA ALGORITMOS EVOLUTIVOS I?

- ▶ Diseño óptimo de aerodinámica en vehículos terrestres, aéreos o navales.



¿DE QUE SE TRATA ALGORITMOS EVOLUTIVOS I?

- ▶ Generador evolutivo de nuevas variantes del mecanismo de atención
- ▶ ASI-ARCH (Framework)
- ▶ “Momento AlphaGo para el Descubrimiento de Arquitecturas de Modelos” (Liu et al., 2025)

The screenshot shows the abstract page of a research paper titled "AlphaGo Moment for Model Architecture Discovery". The page includes the logos for ASI and SII-GAIR, author names (Yixiu Liu, Yang Nan, Weixian Xu, Xiangkun Hu, Lyumannshan Ye, Zhen Qin, Pengfei Liu), institutional affiliations, and links to the SII-GAIR/ASI-Arch Model Gallery. The abstract discusses the limitations of traditional Neural Architecture Search (NAS) and how ASI-ARCH overcomes them by enabling AI to conduct its own architectural innovation through an end-to-end scientific research process.

18074v1 [cs.AI] 24 Jul 2025



¿DE QUE SE TRATA ALGORITMOS EVOLUTIVOS I?

► Argumento:

- ✓ La **investigación en IA** está **limitada** por la **capacidad cognitiva humana** → cuello de botella en el desarrollo de nuevas arquitecturas de LLMs.

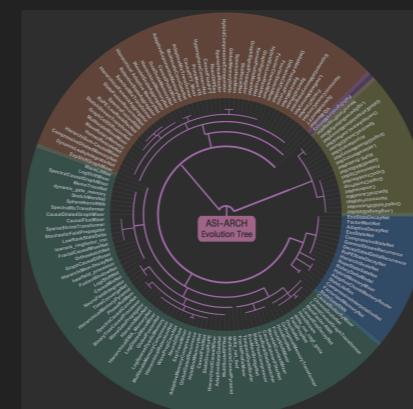
► Propuesta:

Diseñar un framework que:

- ✓ genera hipótesis de nuevas arquitecturas
- ✓ las implementa en código
- ✓ entrena los modelos y
- ✓ valida su desempeño empíricamente de forma automática.

► Resultado:

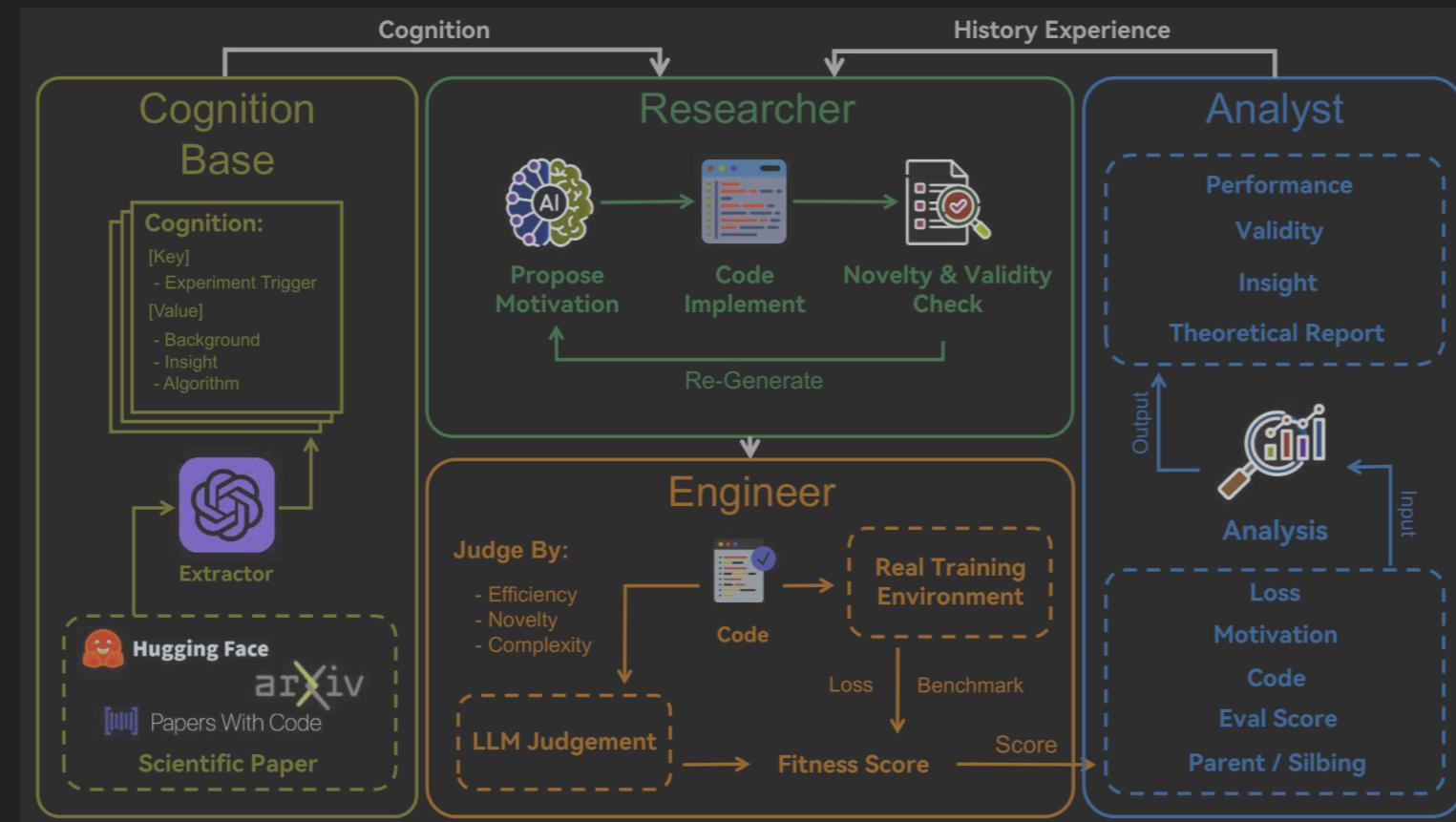
- ✓ Creó 106 arquitecturas de atención lineal.



¿DE QUE SE TRATA ALGORITMOS EVOLUTIVOS I?

▶ Función Fitness:

$$\text{Fitness} = \frac{1}{3} [\sigma(\Delta_{\text{loss}}) + \sigma(\Delta_{\text{benchmark}}) + \text{LLM}_{\text{judge}}]$$



¿DE QUE SE TRATA ALGORITMOS EVOLUTIVOS I?

- ▶ “Generación de ejemplos antagónicos mediante la exploración del espacio latente de redes generativas antagónicas” (Clare et al., 2023)
- ▶ Usa un Algoritmo Genético para buscar vectores latentes (semillas óptimas) que produzcan imágenes que engañen al clasificador.



Generating Adversarial Examples through Latent Space Exploration of Generative Adversarial Networks

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ABSTRACT
Artificial Neural Networks are vulnerable to adversarial examples, malicious inputs that aim to subvert neural networks' outputs. Generative Adversarial Networks (GANs) are generative models capable of generating data that follows the training data distribution. We explore the hypothesis of using the latent space of the trained GAN to find adversarial examples. We test the adversarial examples on external classifiers trained on the same training data. Thus, we propose a framework for Generating adversarial exAmpleS through latent Space Exploration (GLASSE). A Genetic Algorithm evolves latent vectors as individuals and uses a trained GAN to generate examples to maximise a target activation value of the discriminator network. After the evolutionary process, an external classifier trained on the same dataset evaluates whether it is adversarial. The results indicate that we can optimise the objective and find adversarial examples. We tested the generated examples with models from the adversarial learning literature, showing that 82% on average of the generated examples resulted in successful attacks. We show a t-SNE analysis of the examples, showcasing that generated adversarial examples are blended in the cluster of each belonging class and visually similar to the training dataset examples, showcasing the viability of the proposed approach.

1 INTRODUCTION
Adversarial examples are created to attack the machine learning model, causing it to misclassify with high confidence. Typically, these examples are created from the modification of existing data, from the testing or training, with only small perturbations and mostly imperceptible. The interest in adversarial examples rises from the fact that even state-of-the-art deep neural networks (DNNs) are vulnerable to such manipulations [16]. The topic of adversarial attacks and defences is widespread and can help us understand the model's assurance, security and generalization. Studying the attacks to understand better the vulnerability and weakness of DNNs is essential to develop a defensive strategy for more robust models. For this purpose, many algorithms have been proposed to create adversarial examples, such as the fast gradient sign method [11], the backward pass differentiable approximation [1], the AdvGAN method [18] and the GreedyFool method [8].

Generative Adversarial Networks (GANs) can generate synthetic but convincing images following a given training dataset distribution. GANs are composed of two models: a generator and a discriminator. During training, the interplay between the generator and discriminator allows the generator to learn how to generate realistic examples that the discriminator classifies as belonging to the training dataset [10]. With a GAN trained with a dataset of multiple classes, it is hard to precisely control the appearance (e.g. class) of the examples being generated. In contrast, a Conditional GAN offers the opportunity to condition the generator to produce examples from a given class [14].

CCS CONCEPTS
• Computing methodologies → Genetic algorithms; Generative and developmental approaches.

TEMAS Y TÉCNICAS A ABORDAR EN EL CURSO



TEMAS Y TÉCNICAS A ABORDAR EN EL CURSO

- ▶ Conceptualización de términos utilizados en AE
- ▶ Algoritmos Genéticos (**GA**)
- ▶ Optimización por Enjambre de Partículas (**PSO**)
- ▶ Optimización basada en Enseñanza Aprendizaje (**TLBO**)
- ▶ Optimización basada en Colonia de Hormigas (**ACO**)
- ▶ Búsqueda Tabú (**TS**)
- ▶ Hiperheurísticas

CURSADO

- ▶ Parte 1 (~ 80 min.)
- ▶ Break (~ 10-20 min.)
- ▶ Parte 2 (~ 80 min.)

EVALUACIÓN

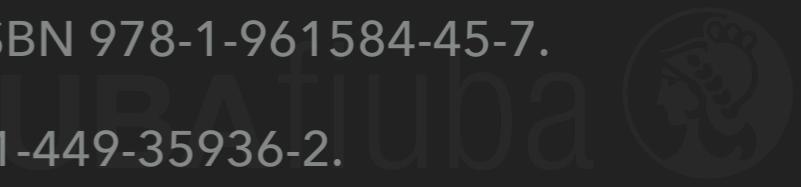
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FACULTAD DE INGENIERÍA

EVALUACIÓN

- ▶ Se aprueba la materia implementando **1 desafío práctico** presentado en forma:
 - ✓ Individual.
 - ✓ Grupal (hasta 4 integrantes).
- ▶ La entrega consta de:
 - ✓ Informe explicativo de al menos 3 carillas (.pdf).
 - ✓ Código fuente en Python (.py, .ipynb, etc.) transcripto parcialmente en el informe y completo en un repositorio (el enlace al repositorio debe proporcionarse en el informe).
- ▶ La modalidad de entrega se realizará:
 - ✓ Durante la cursada o al final subiendo el .pdf al campus de la FIUBA.
 - ✓ Sin exposición en la última clase.
- ▶ Los desafíos son abiertos. El estudiante o el grupo elige un caso de uso según una o varias de las técnicas de Algoritmos Evolutivos vistas durante la cursada y elabora el desafío práctico.

REFERENCIAS BIBLIOGRÁFICAS Y WEB (I)

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- ▶ Coello Coello, C. A., "Use of a self-adaptive penalty approach for engineering optimization problems", Elsevier Science, Computers in Industry 41, 2000, pp. 113-127.
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- ▶ Engelbrecht, A. P., "Fundamentals of Computational Swarm Intelligence", John Wiley & Sons Ltd, England, 2005.
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- ▶ López, J. (2013). Optimización multiobjetivo: aplicaciones a problemas del mundo real. Buenos Aires, Argentina, Universidad Nacional de la Plata.
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REFERENCIAS BIBLIOGRÁFICAS Y WEB (IV)

- ▶ <https://www.youtube.com/watch?v=oSrUsM0hoPs> CMOS Tech: NMOS and PMOS Transistors in CMOS Inverter (3-D View)
- ▶ <https://www.youtube.com/watch?v=1Lad28K3Xi0> CMOS Fabrication Process (Animation)
- ▶ <https://www.makinarocks.ai/en/application-specific-integrated-circuit-asic-floorplan-automation-part-ii/>
- ▶ Liu, Y., Nan, Y., Xu, W., Hu, X., Ye, L., Qin, Z., & Liu, P. (2025). Alphago moment for model architecture discovery. arXiv preprint arXiv:2507.18074.
- ▶ Clare, L., & Correia, J. (2023, July). Generating adversarial examples through latent space exploration of generative adversarial networks. In Proceedings of the Companion Conference on Genetic and Evolutionary Computation (pp. 1760-1767).