Topology Tools
for
Explainable and Green Artificial Intelligence

Rocio Gonzalez-Diaz
rogodi@us.es

Sixth EACA International School on Computer Algebra and its Applications

SANTIAGO DE COMPOSTELA, JULY 18-21, 2023

Topology Tools for Explainable and Green Artificial Intelligence (topology inside REXASI-PRO)

Topology Tools
for
Explainable and Green Artificial Intelligence

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- Context: Green and Explainable artificial intelligence (REXASI-PRO)
- Computational topology tools: Persistent homology, barcodes, distance bottleneck, simplicial maps, Persistence modules, morphisms between persistence modules
- Partial matchings between barcodes
- Simplicial maps neural networks

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https://www.slido.com/

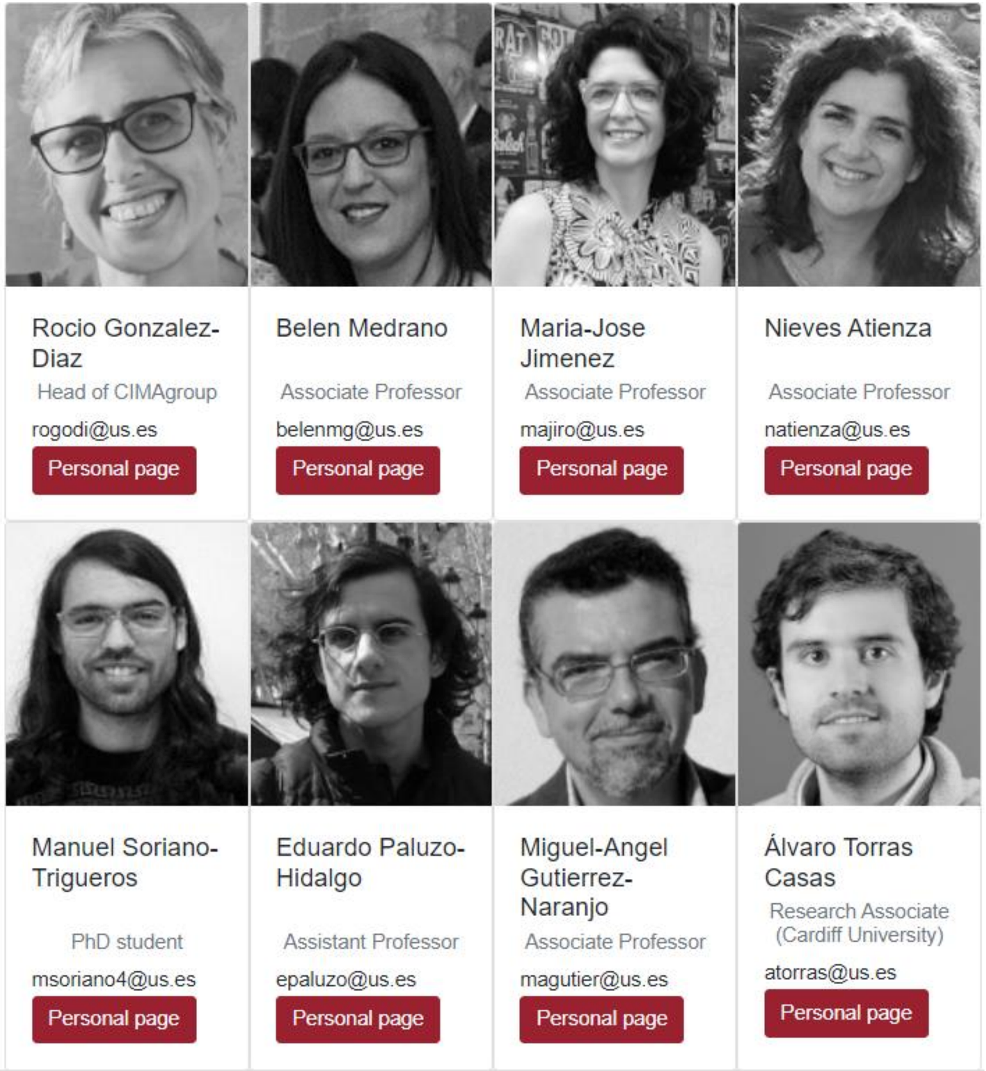
#7058060

https://colab.research.google.com/

Combinatorial Image Analysis group

CIMAGROUP Sevilla, Spain

http://grupo.us.es/cimagroup



Javier Perera Lago
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Topology Tools
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- Computational topology tools: Persistent homology, barcodes, distance bottleneck, simplicial maps, Persistence modules, morphisms between persistence modules
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REXASI-PRO | Reliable & eXplAinable Swarm Intelligence for People with Reduced mObility

HORIZON EUROPE | CALL HORIZON-CL4-2021-HUMAN-01-01

Verifiable robustness, energy efficiency and transparency for Trustworthy AI: Scientific excellence boosting industrial competitiveness

Type of action: RIA – Innovation Action

Proposal Budget € million: 4 (100% for all)

European Commission

https://rexasi-pro.spindoxlabs.com/

Twitter: @REXASI-PRO

https://www.linkedin.com/company/rexasi-pro

REXASI PRO

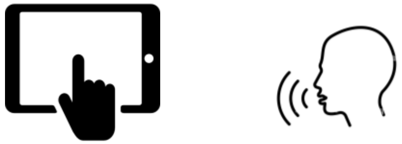
GOAL:

To design a novel safe secure ethical green and explainable framework to develop an Artificial Swarm Intelligence solution for people with reduce mobility.

The framework will make a trustworthy collaboration among an orchestrator and a swarm formed by autonomous wheelchairs and flying robots.

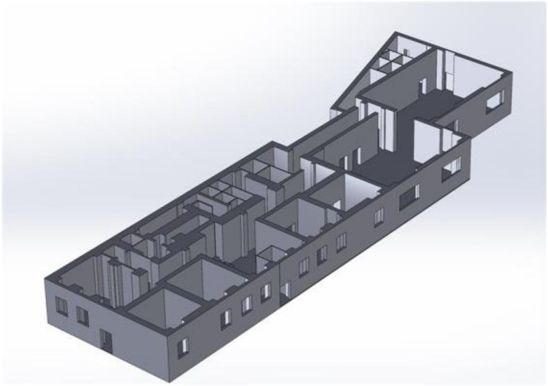
REXASI

PRO



Fleet of intelligent wheelchairs

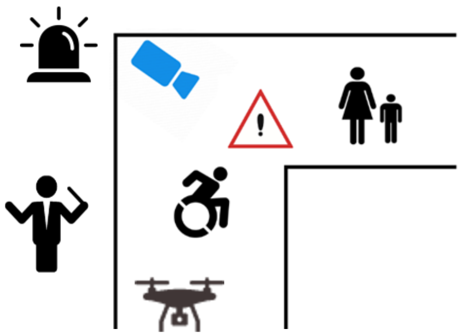
equipped with sensors to support the user with **safe driving** (braking, automatic collision avoidance or evasion) and **autonomous navigation**



Fleet of indoor drones

NO pilot, **NO** GPS(GNSS), **NO** radio communication and **NO** light

Produce high detail 3D digital models of underground infrastructure: **fast, accurate** and **SAFE**



Use Case

Navigation in crowded environment

AI for Autonomous Wheelchair in different real-time scenarios:
1)Safety Assistant;
2) Driving Assistant;
3) Route Assistant;
4) Social Navigation.
New trustable social navigation approaches will be developed.

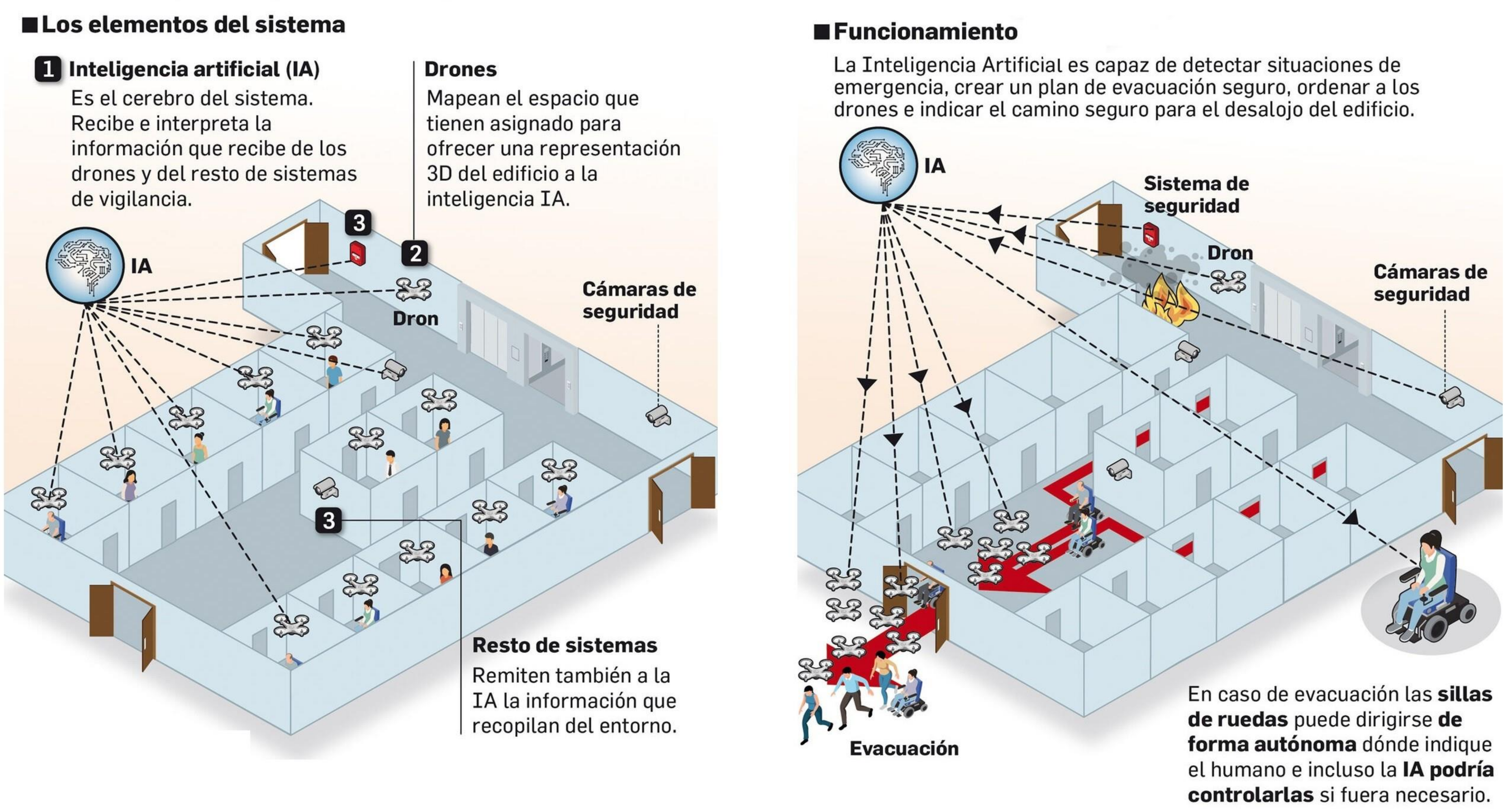
Flying robot mapping

Flying robots capable of flying autonomously in an indoor/underground environment and generating a map of the building that would be latter used by the wheelchair.
The flying robot will collaborate with an orchestrator with optimal consumption of time and energy.

Collaborative Navigation

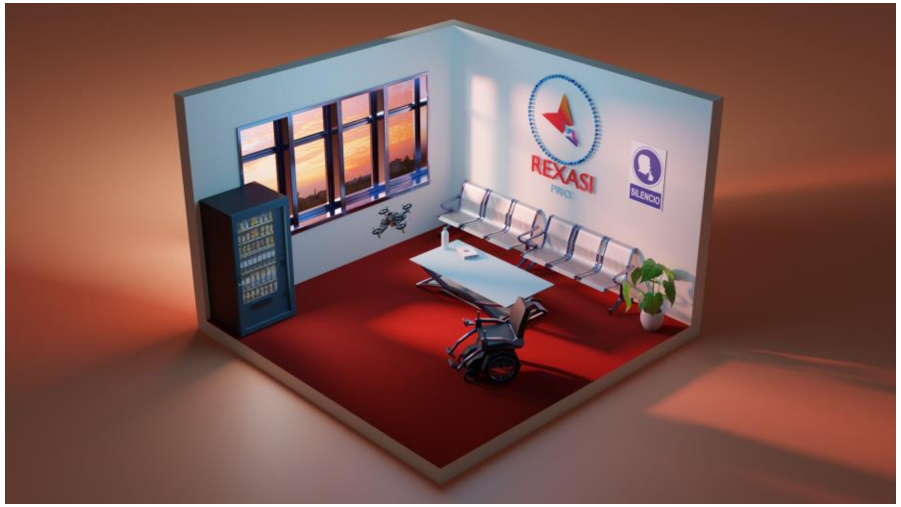
Mixed collaborative indoor environment where the swarm communicate with each other in emergency cases.
The swarm would include the wheelchairs, the flying robots, the orchestrator, and intelligent cameras for people detection and crowd monitoring.

REXASI-PRO | Reliable & eXplAinable Swarm Intelligence for People with Reduced mObility



https://www.diariodesevilla.es/sevilla/universidad-sevilla-us-inteligencia-artificial-ia_0_1795322279.html

REXASI-PRO | Reliable & eXplAinable Swarm Intelligence for People with Reduced mObility



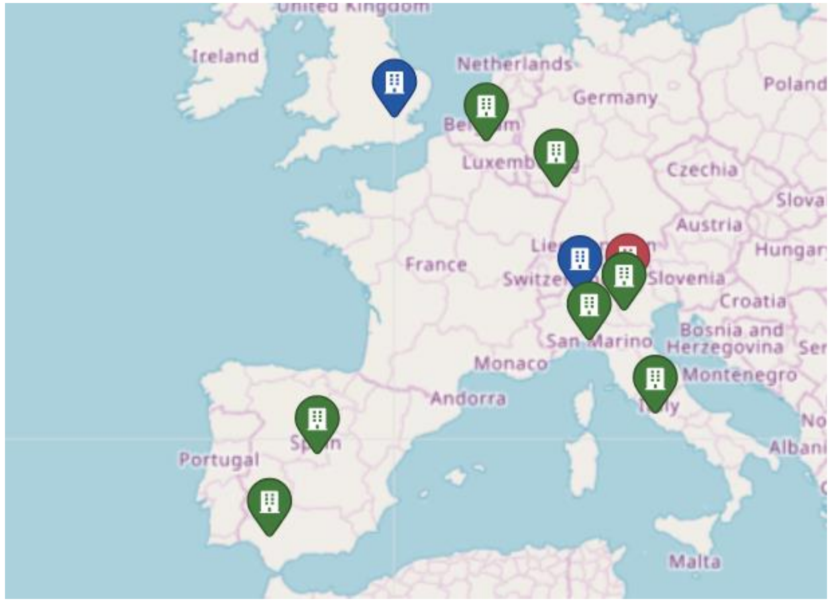
Trabajos realizados por alumnos de la asignatura Modelado y Visualización Gráfica (MVG 2022/2023)

https://twitter.com/REXASIPRO_EU

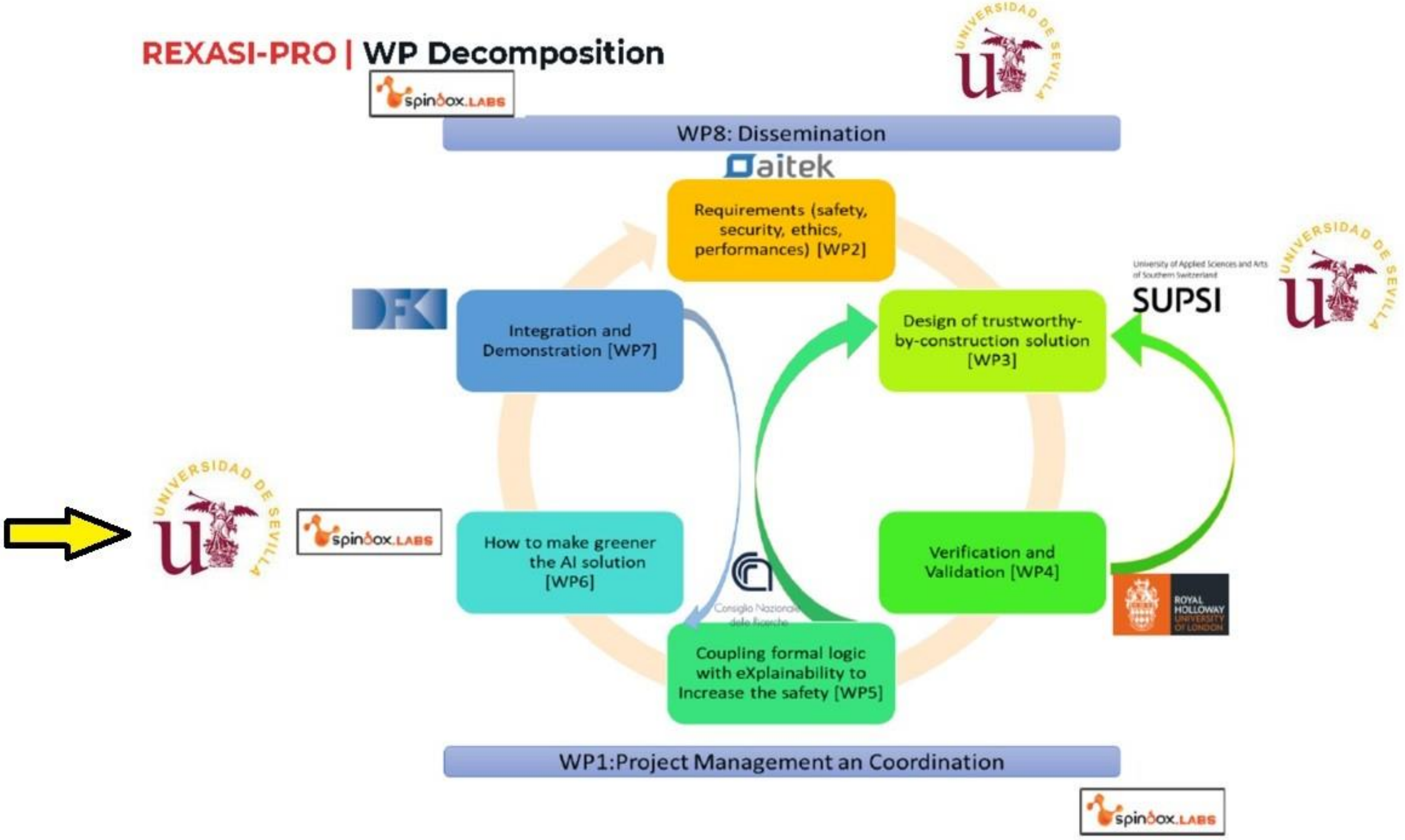
REXASI-PRO | Reliable & eXplAinable Swarm Intelligence for People with Reduced mObility

Consortium

SPINDOX LABS srl | IT - Coordinator	+
CNR | IT (explainability)	+
DFKI | DE (wheelchairs)	+
V-RESEARCH | NL (secure by design)	+
AITEK SPA | IT (safety)	+
KCL | UK (verification)	+
USE | ES (green and explainability)	+
HOVERING SOLUTIONS | ES (drones)	+
EURONET | BE (business plan)	+
SUPSI | CH (trustable social navigation)	+
SCUOLA DI ROBOTICA | IT (ethics)	+



https://cordis.europa.eu/project/id/101070028


REXASI-PRO | WP Decomposition
WP8: Dissemination
aitek
Requirements (safety, security, ethics, performances) [WP2]
Integration and Demonstration [WP7]
Design of trustworthy-by-construction solution [WP3]
University of Applied Sciences and Arts of Southern Switzerland
SUPSI
How to make greener the AI solution [WP6]
Verification and Validation [WP4]
Coupling formal logic with eXplainability to Increase the safety [WP5]
ROYAL HOLLOWAY UNIVERSITY OF LONDON
WP1:Project Management an Coordination

Our goals within REXASI-PRO

Main goal

Use computational topology to design new methods to achieve **explainable and green artificial intelligence models.**

Specific Goals

1. Topology-aware reduce the input dataset.
2. Build explainable models based on topology.
3. Simplify the model preserving its learning capacity.
4. Create synthetic samples that can quickly train a model.

Artificial intelligence

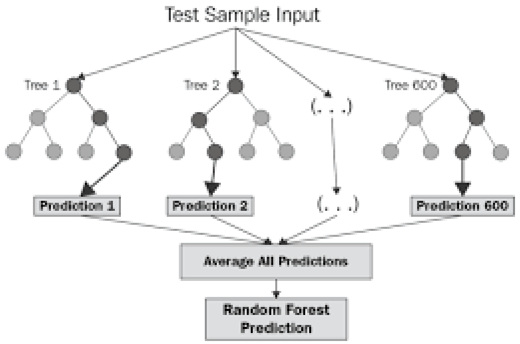
Aim: machines that can "think and act" humanly and rationally

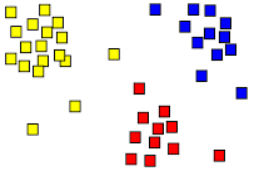
Building blocks: ML models

Machine learning

Aim: automatically identify patterns and make predictions or decisions based on the input data.

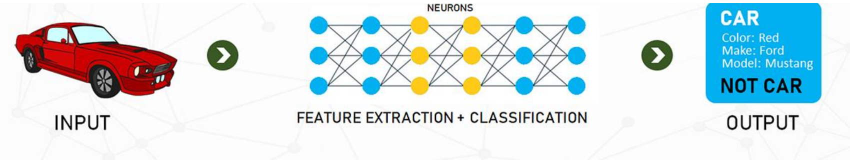
Examples: Decision trees, random forest, clustering, **neural networks**





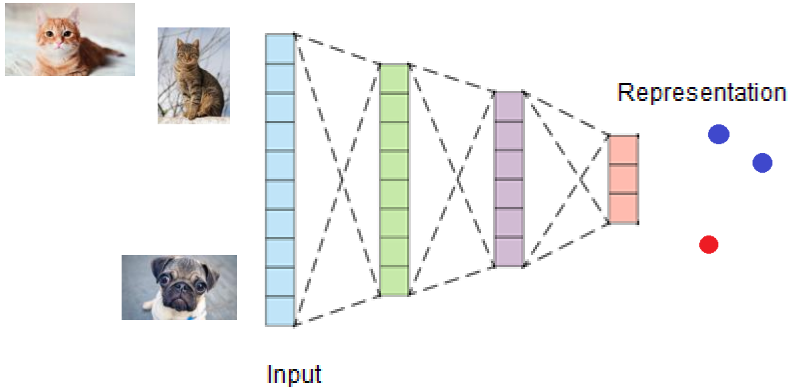
Deep learning

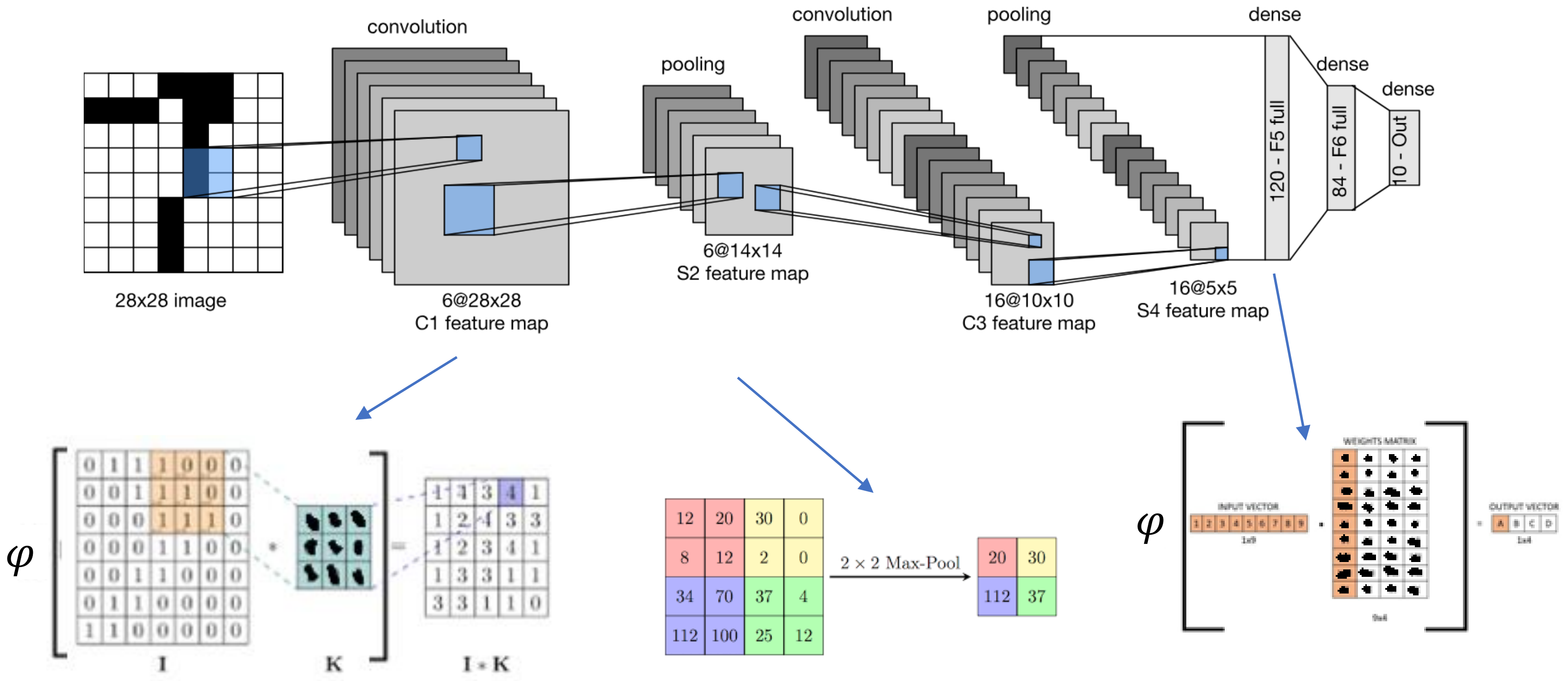
Aim: to learn representations of data

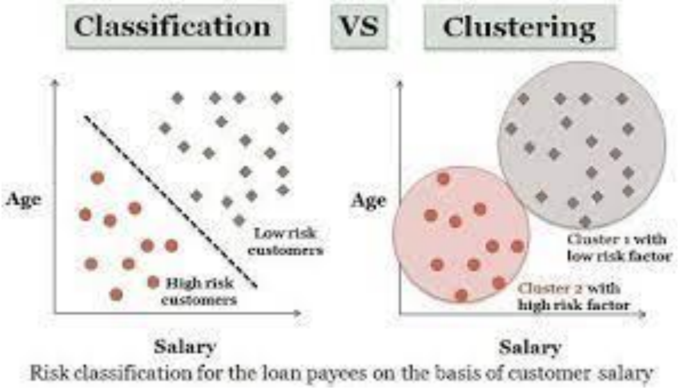


https://www.ibm.com/cloud/blog/ai-vs-machine-learning-vs-deep-learning-vs-neural-networks

Deep learning models: LeNet, AlexNet, ResNet, autoencoders, large language models, etc

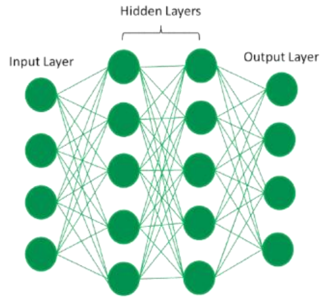




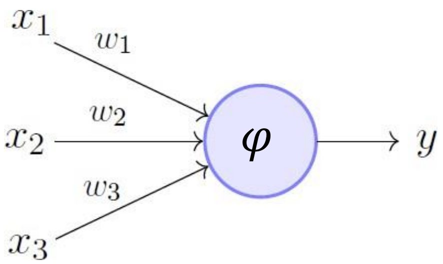


Deep learning models: **representation+classification**

Deep learning $\subset$ Neural networks

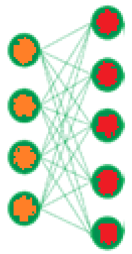


Hidden neuron



$$y = \varphi(\sum \omega_i \, x_i + b)$$

Layer



$$\boldsymbol{y} = \boldsymbol{\varphi}(W \, \boldsymbol{x} + B)$$

Input: $\boldsymbol{a} = (a_1, \dots, a_n)$

Activation function φ

Output layer (for regression): $\mathbf{b} = (b_1, \dots, b_k)$

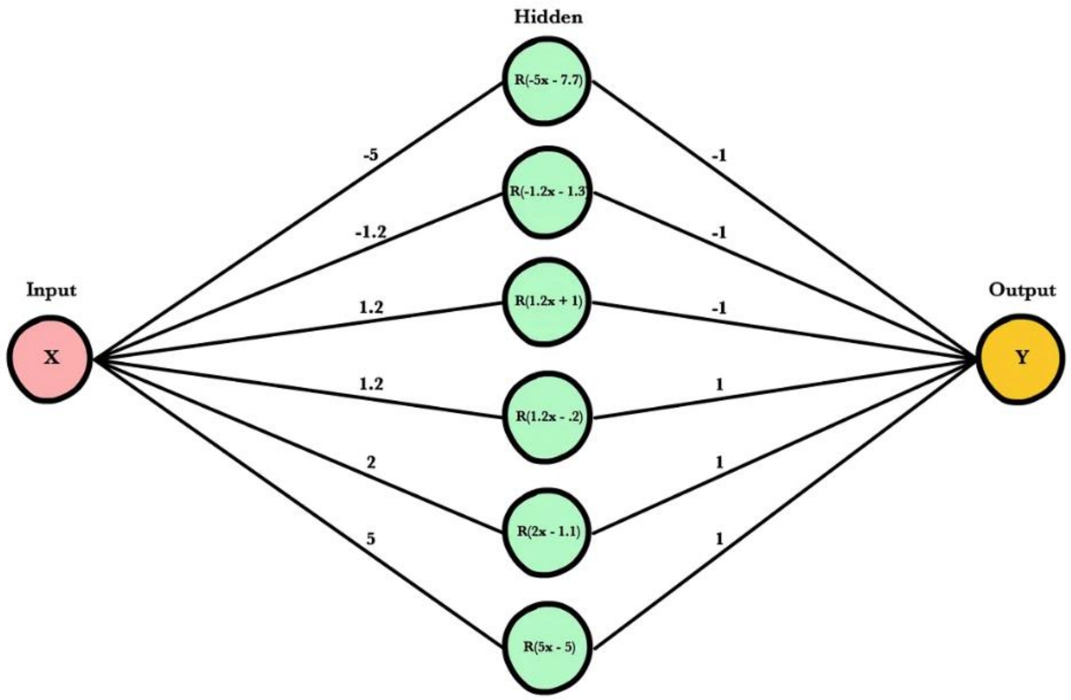
Output layer (for classification): $softmax(\mathbf{b}) = (p_1, \dots, p_k)$

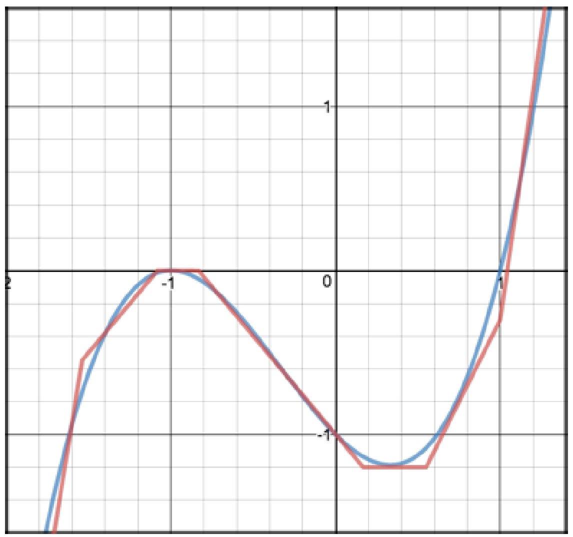
$$softmax \ : \mathbb{R}^K \to [0,1]^K$$

$$softmax \ (\mathbf{z})_j = \frac{e^{z_j}}{\sum_{k=1}^{K} e^{z_k}} \qquad j = 1, \dots, K.$$

Hornik, K., et al.Multilayer feedforward networks are universal approximators. Neural Networks 2, 5 (1989), 359 – 366

Theorem (Universal Approximation Theorem) *Let A be any compact subset of $\mathbb{R}^n$ and let $C(A)$ be the space of real-valued continuous functions on A. Then, given any $\epsilon > 0$ and any function $g \in C(A)$, there exists a multi-layer feed-forward network $\mathcal{N} : \mathbb{R}^n \to \mathbb{R}$ approximating g, that is, $||g - \mathcal{N}|| < \epsilon$.*





$$n_1(x) = Relu(-5x - 7.7)$$
$$n_2(x) = Relu(-1.2x - 1.3)$$
$$n_3(x) = Relu(1.2x + 1)$$
$$n_4(x) = Relu(1.2x - .2)$$
$$n_5(x) = Relu(2x - 1.1)$$
$$n_6(x) = Relu(5x - 5)$$

$$Z(x) = -n_1(x) - n_2(x) - n_3(x) + n_4(x) + n_5(x) + n_6(x)$$

https://towardsdatascience.com/can-neural-networks-really-learn-any-function-65e106617fc6

Training neural networks Input data $\{\boldsymbol{x} \in R^n$ with expected output value $\boldsymbol{y} \in R^k\}$.

1. Set an architecture: number of layers, number of neurons in each layer, activation functions, connections (CNN, full connected), output layers (regression, classification, **learning rate**, **stop condition**),…

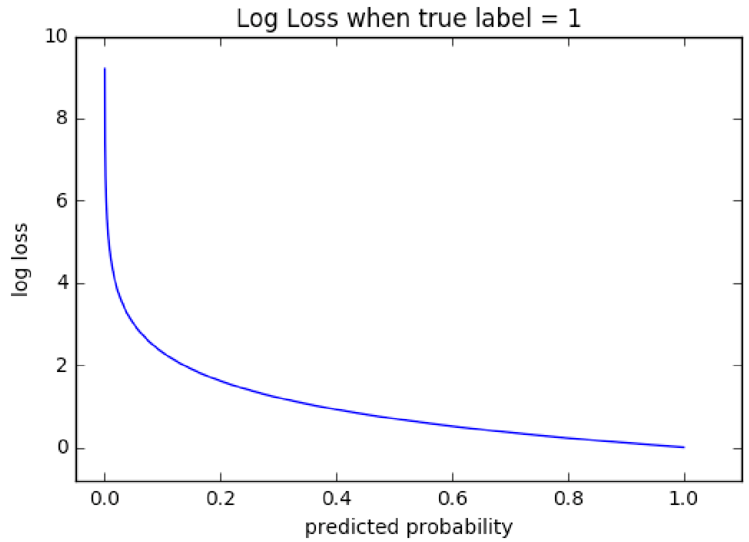
2. Initiate the weights (usually randomly). Compute the output $\hat{\boldsymbol{y}} \in R^k$ of an input value $\boldsymbol{x} \in R^n$

3. Select a loss function $\boldsymbol{E}$: for example $\mathrm{MSE}(\boldsymbol{y}, \hat{\boldsymbol{y}}) = \frac{1}{k}\sum(y_i - \hat{y}_i)$ for regression or cross-entropy loss for classification $\mathrm{LogLoss}(\boldsymbol{y}, \hat{\boldsymbol{y}}) = -\sum y_i \log(\hat{y}_i)$

4. Adjust the weights using a learning method such that back propagation:

$$\Delta\omega_{ij} = -\eta \frac{\partial E}{\partial \omega_{ij}}(\boldsymbol{y}, \hat{\boldsymbol{y}})$$

ω_{ij} changes in a way that E always decreases.



Repeat the process until the stop condition is satisfied.

Our goals within REXASI-PRO

Main goal

Use computational topology to design new methods to achieve **explainable and green artificial intelligence models.**

Specific Goals

1. Topology-aware reduce the input dataset.
2. Build explainable models based on topology.
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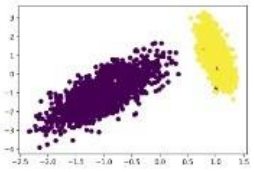
4. Create synthetic samples that can quickly train a model.

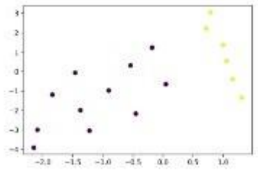
Our goals within REXASI-PRO

1. Topology-aware reduce the input dataset.

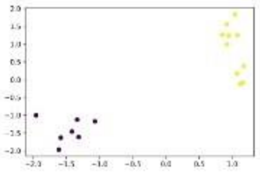
Topology-based representative datasets to reduce neural network training resources. Neural Computing and Applications, 1-17 (2022)



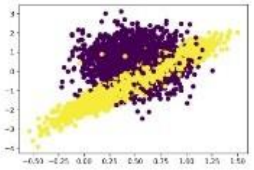
(a) (Synthetic) case 1: original dataset



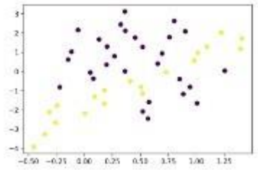
(b) (Synthetic) case 1: representative dataset



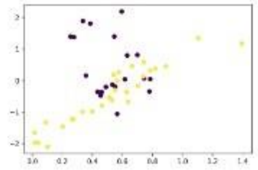
(c) (Synthetic) case 1: random dataset



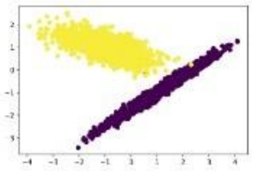
(d) (Synthetic) case 2: original dataset



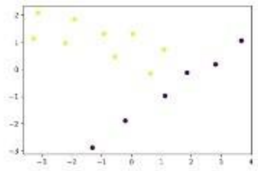
(e) (Synthetic) case 2: representative dataset



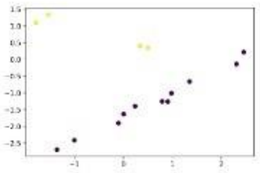
(f) (Synthetic) case 2: random dataset



(g) (Synthetic) case 3: original dataset

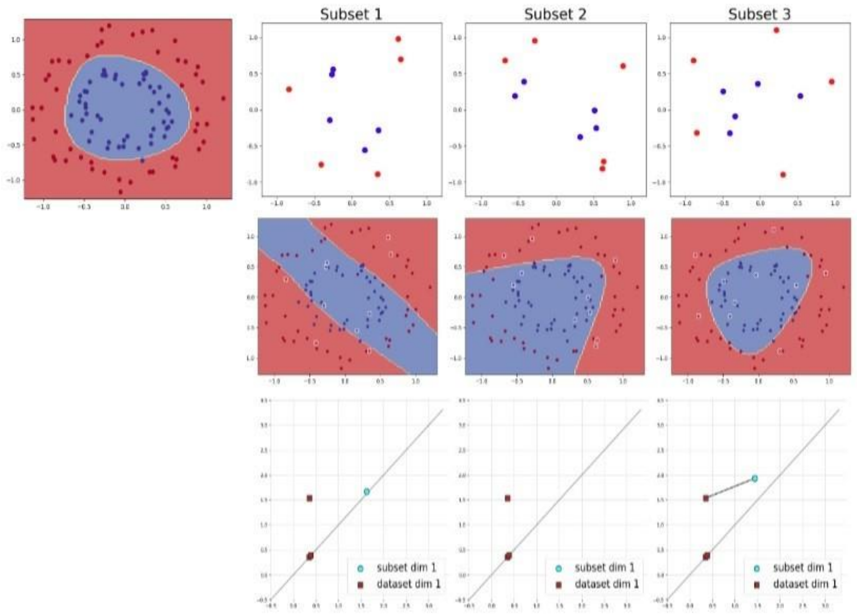


(h) (Synthetic) case 3: representative dataset



(i) (Synthetic) case 3: random dataset

TOPOLOGICAL DATA QUALITY



A Topological Approach to Measuring Training Data Quality. Arxiv (2023)

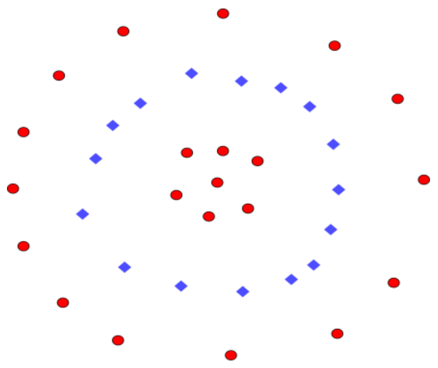
REXASI-PRO | Reliable & eXplAinable Swarm Intelligence for People with Reduced mObility

Our goals within REXASI-PRO

2. Build explainable models based on topology.

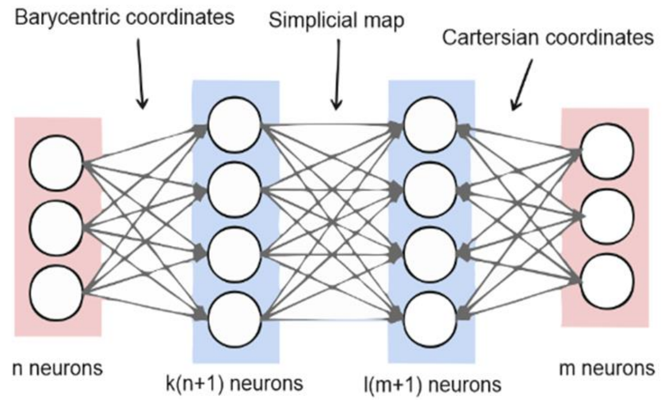
Two-hidden-layer feed-forward networks are universal approximators: A constructive approach. Neural Networks 131, 29-3 (2020)

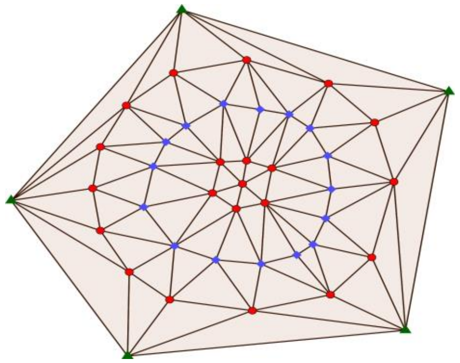
Input data P

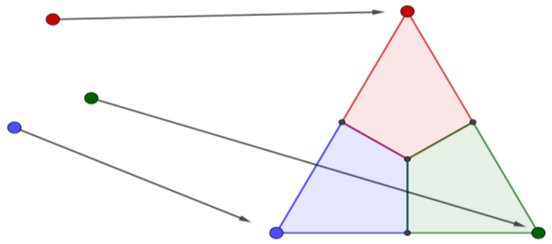


Simplicial map neural network ($SMNN$)

N_φ







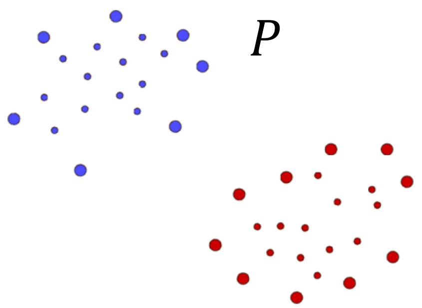
N_φ correctly classifies P

Simplicial map $|K| \xrightarrow{\varphi} |L|$

Simplicial-Map Neural Networks Robust to Adversarial Examples. Mathematics 9 (2), 169 (2021)

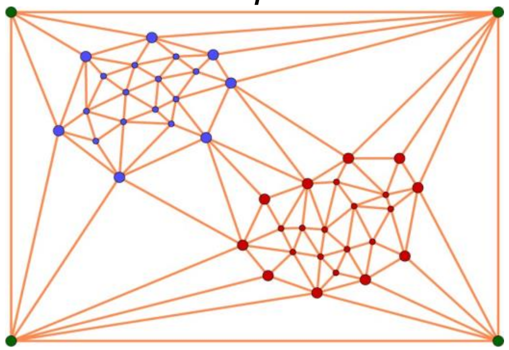
Our goals within REXASI-PRO

3. Simplify the model preserving its learning capacity.

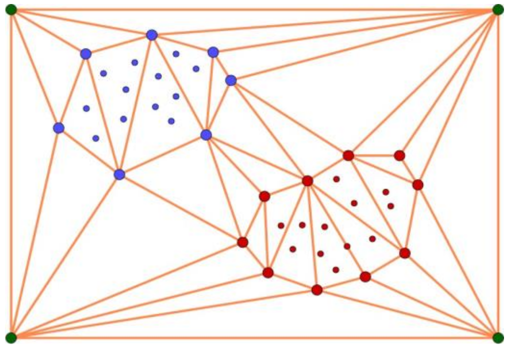


P

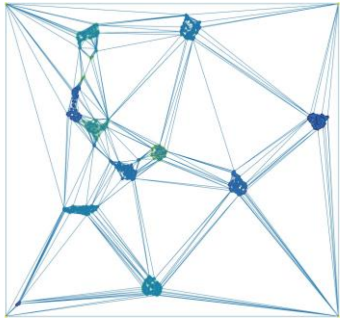
N_{φ}



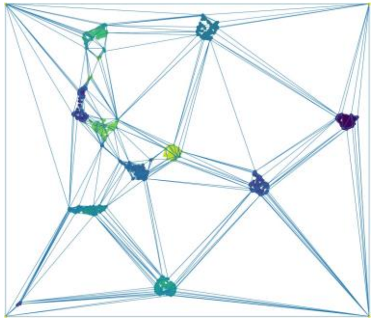
$N_{\tilde{\varphi}}$



Both N_{φ} and $N_{\tilde{\varphi}}$ correctly classify P



N_{φ}



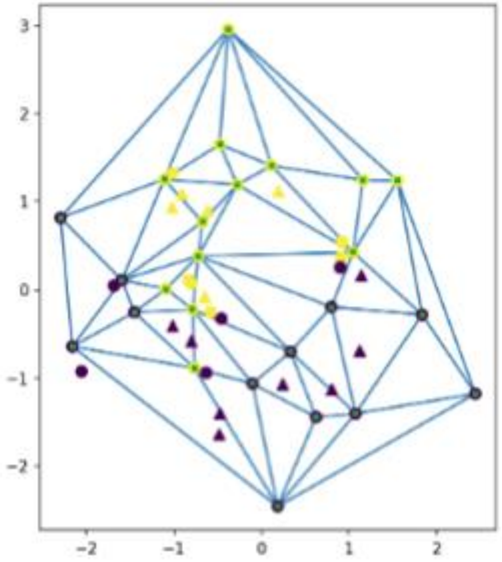
$N_{\tilde{\varphi}}$

	Dataset Size	2-Simplices
Original	1801	3596
Reduced	604	305

Optimizing the Simplicial-Map Neural Network Architecture. Journal of Imaging 7 (9), 173 (2021)

Our goals within REXASI-PRO

4. Create synthetic samples that can quickly train a model.



Explainability in Simplicial Map Neural Networks. Arxiv (2023)

Our goals within REXASI-PRO

New open position!!!

https://investigacion.us.es/investigacion/contratos-personal

Referencia: INV-IND-09-2023-I-015.

Relación de contratos convocados: 1.

Convocatoria: Convocatoria Indefinidos (IND) Septiembre 2023.

Dicho proyecto/ayuda/programa financiará el contrato por un período previsto desde **01/12/2023** hasta el **30/09/2025** (fecha fin del proyecto/ayuda/programa).

La actividad del presente contrato se desarrollará en el marco de una línea de investigación « *Computational Topology for Green Artificial Intelligence*», conforme a lo establecido en la convocatoria del proceso selectivo.

La dedicación será de **37,5 horas** semanales que se distribuirán conforme a la siguiente jornada laboral: **De lunes a viernes de 8:00 a 15:30.**

Retribuciones

El sueldo bruto mensual que percibirá el contratado ascenderá a **1.935,45** euros. En dicha retribución se encuentra incluido el prorrateo o parte proporcional de las pagas extras y cuotas a la seguridad social.

Links

http://grupo.us.es/cimagroup

https://rexasi-pro.spindoxlabs.com/

https://www.deeplearningbook.org/

https://www.deep-mind.org/2023/03/26/the-universal-approximation-theorem/

https://cs.nyu.edu/~mohri/mlbook/

http://neuralnetworksanddeeplearning.com/

https://playground.tensorflow.org/

https://colab.research.google.com/github/google/eng-edu/blob/main/ml/cc/exercises/intro_to_neural_nets.ipynb

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