

# Improving Deep Learning by Exploiting Synthetic Images



**Dr. Manuel Castillo-Cara**  
[www.manuelcastillo.eu](http://www.manuelcastillo.eu)

Departamento de Inteligencia Artificial  
Escuela Técnica Superior de Ingeniería Informática  
Universidad Nacional de Educación a Distancia (UNED)



# Preliminar

- Improving Deep Learning by Exploiting Synthetic Images © 2024 by Manuel Castillo-Cara is licensed under Attribution-NonCommercial 4.0 International





# Índice

- Equipo de trabajo
- Datos tabulares
- Arquitecturas neuronales
- Fundamentos de imágenes sintéticas
- Métodos de transformación
- Métodos paramétricos
- Métodos no paramétricos
- Arquitecturas con imágenes sintéticas
- Casos de uso

# Equipo de trabajo

ETS de  
Ingeniería  
Informática



UNED



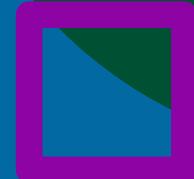
# Instituciones desarrolladoras



Universidad  
Rey Juan Carlos

# Datos tabulares

ETS de  
Ingeniería  
Informática



UNED



# Regression vs. Classification

	A	B	C	D	E	F	G	H	I	
1	preg	plas	pres	skin	insu	mass	pedi	age	class	
2	1	85	66	29	0	26.6	351	31	tested_negative	
3	5	116	74	0	0	25.6	201	30	tested_negative	
4	10	115	0	0	0	35.3	134	29	tested_negative	
5	4	110	92	0	0	37.6	191	30	tested_negative	
6	10	139	80	0	0	27.1	1441	57	tested_negative	
7	8	99	84	0	0	35.4	388	50	tested_negative	
8	5	117	92	0	0	34.1	337	38	tested_negative	
9	5	109	75	26	0	36	546	60	tested_negative	

	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	class
2	0.00632	18.231		0	538	6575	65.2	4.09	1	296	15.3	396.9	4.98	24
3	0.02731	0.707		0	469	6421	78.9	4.9671	2	242	17.8	396.9	9.14	21.6
4	0.02729	0.707		0	469	7185	61.1	4.9671	2	242	17.8	392.83	4.03	34.7
5	0.03237	0.218		0	458	6998	45.8	6.0622	3	222	18.7	394.63	2.94	33.4
6	0.06905	0.218		0	458	7147	54.2	6.0622	3	222	18.7	396.9	5.33	36.2
7	0.02985	0.218		0	458	6.43	58.7	6.0622	3	222	18.7	394.12	5.21	28.7



# Regression vs. Classification

	A	B	C	D	E	F	G	H	I	
1	preg	plas	pres	skin	insu	mass	pedi	age	class	
2	1	85	66	29	0	26.6	351	31	tested_negative	
3	5	116	74	0	0	25.6	201	30	tested_negative	
4	10	115	0	0	0	35.3	134	29	tested_negative	
5	4	110	92	0	0	37.6	191	30	tested_negative	
6	10	139	80	0	0	27.1	1441	57	tested_negative	
7	8	99	84	0	0	35.4	388	50	tested_negative	
8	5	117	92	0	0	34.1	337	38	tested_negative	
9	5	109	75	26	0	36	546	60	tested_negative	

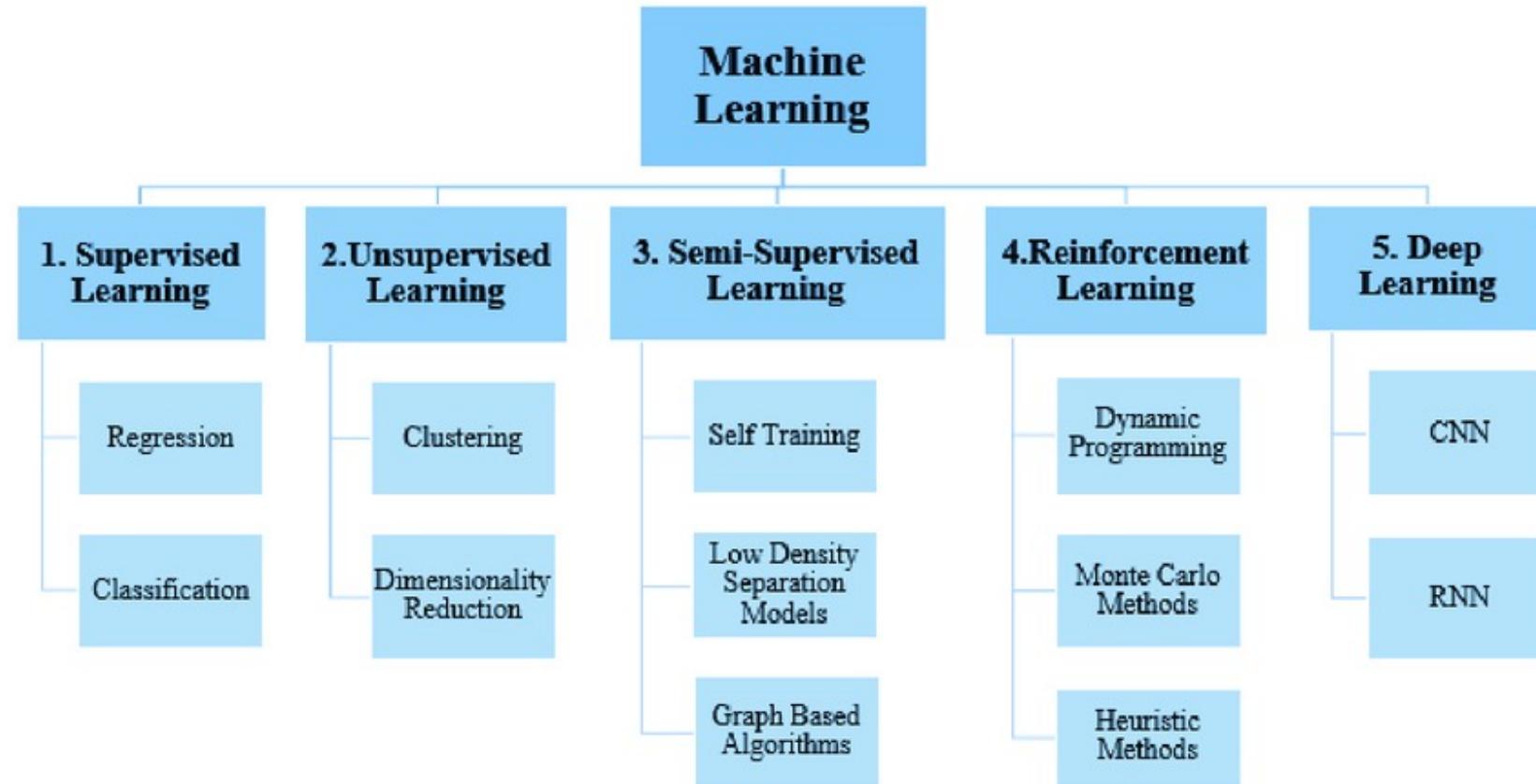
Classification

Regression

	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	class
2	0.00632	18.231		0	538	6575	65.2	4.09	1	296	15.3	396.9	4.98	24
3	0.02731	0.707		0	469	6421	78.9	4.9671	2	242	17.8	396.9	9.14	21.6
4	0.02729	0.707		0	469	7185	61.1	4.9671	2	242	17.8	392.83	4.03	34.7
5	0.03237	0.218		0	458	6998	45.8	6.0622	3	222	18.7	394.63	2.94	33.4
6	0.06905	0.218		0	458	7147	54.2	6.0622	3	222	18.7	396.9	5.33	36.2
7	0.02985	0.218		0	458	6.43	58.7	6.0622	3	222	18.7	394.12	5.21	28.7

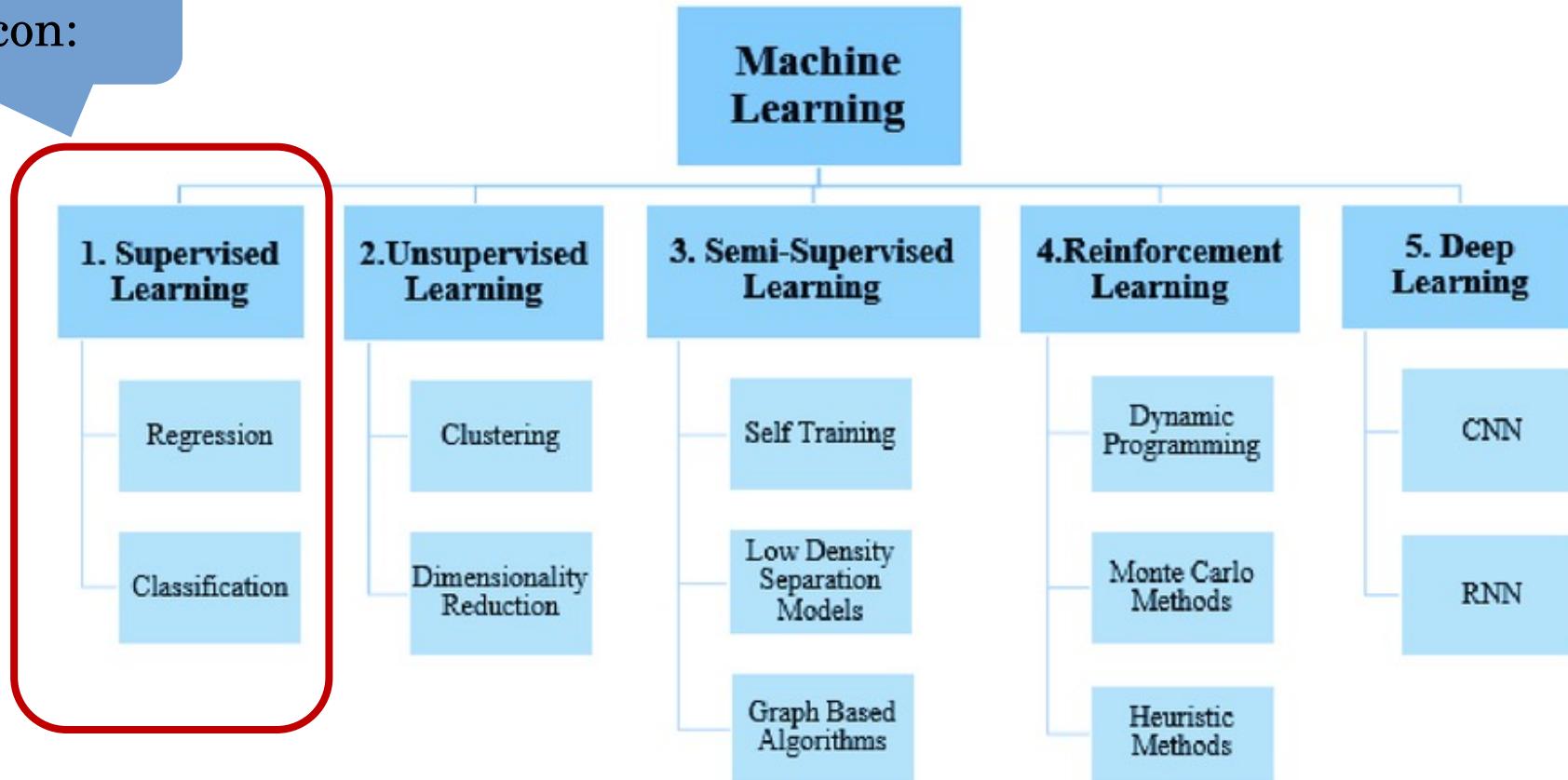


# Machine Learning



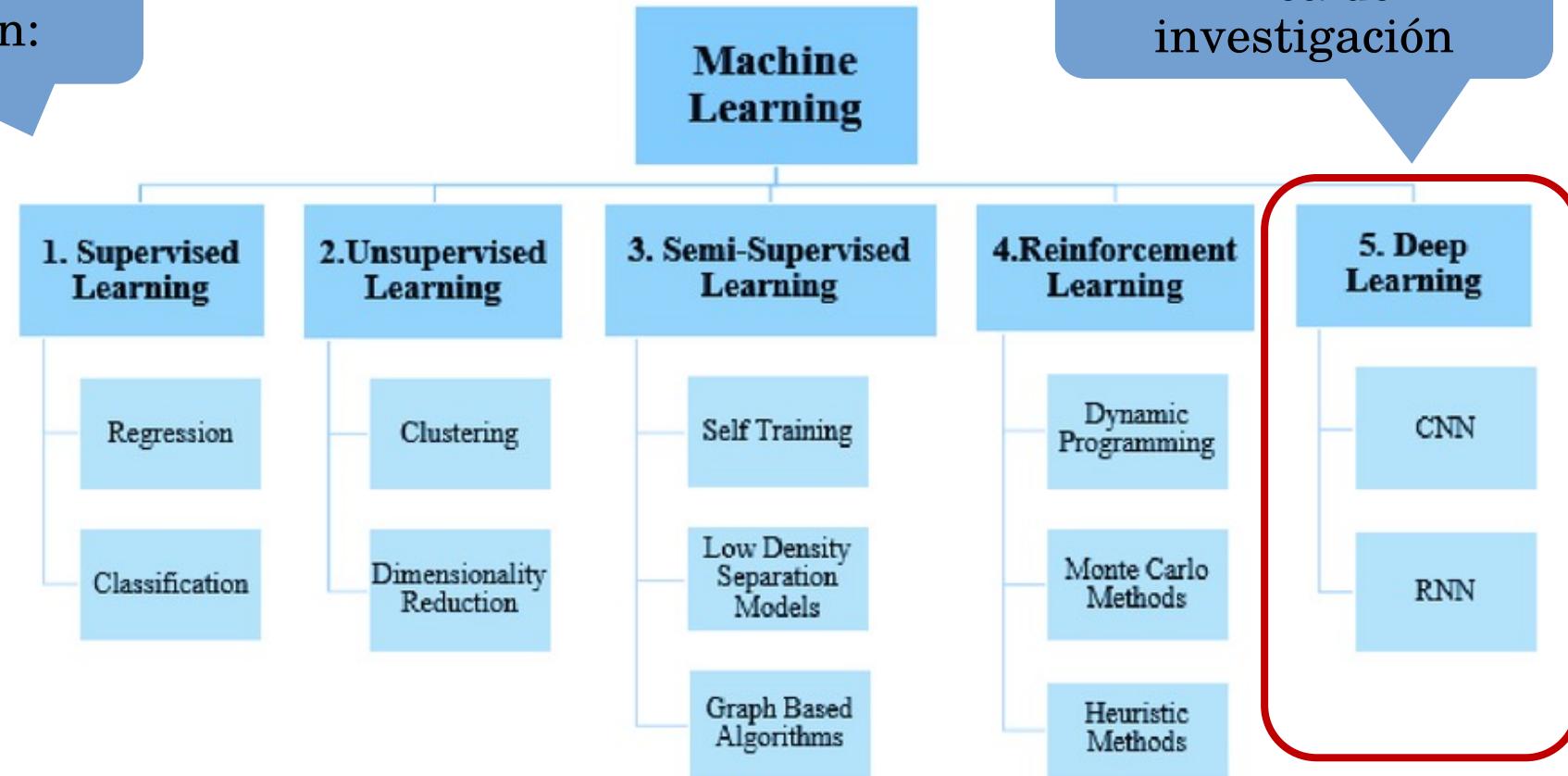
# Machine Learning

Normalmente se resuelven con:



# Machine Learning

Normalmente se resuelven con:



Pero hay una nueva línea de investigación

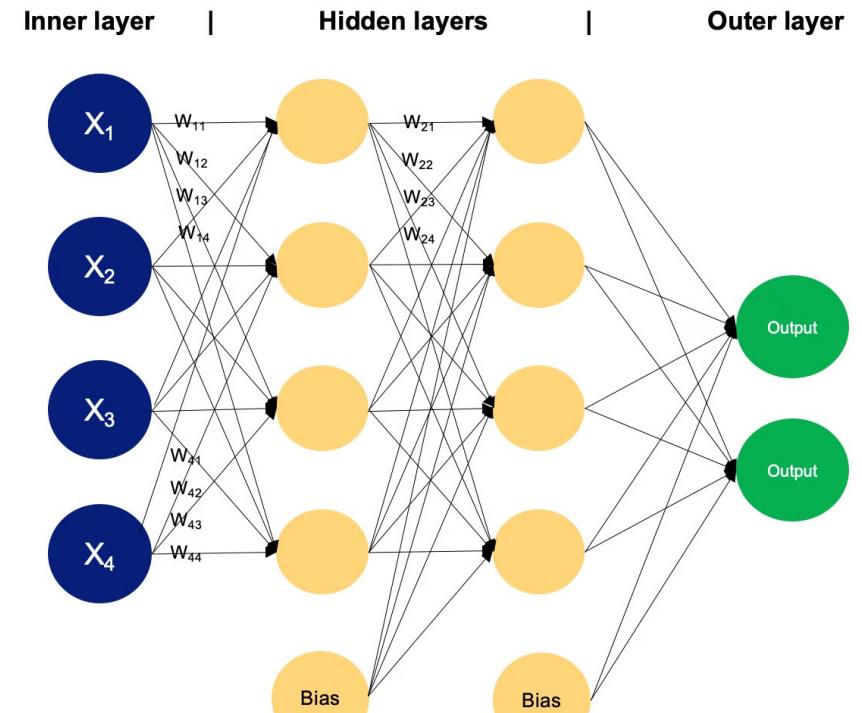
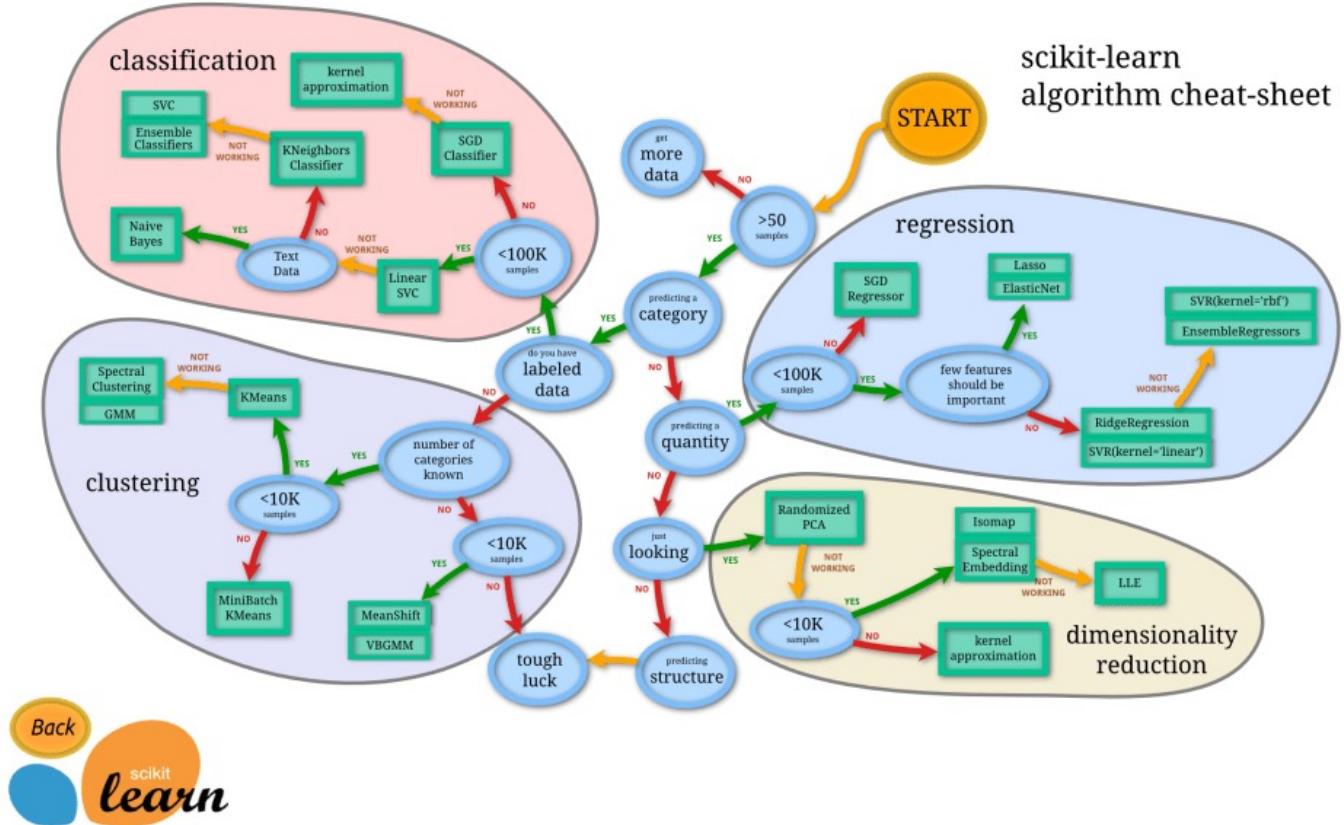
# \Arquitecturas neuronales

ETS de  
Ingeniería  
Informática

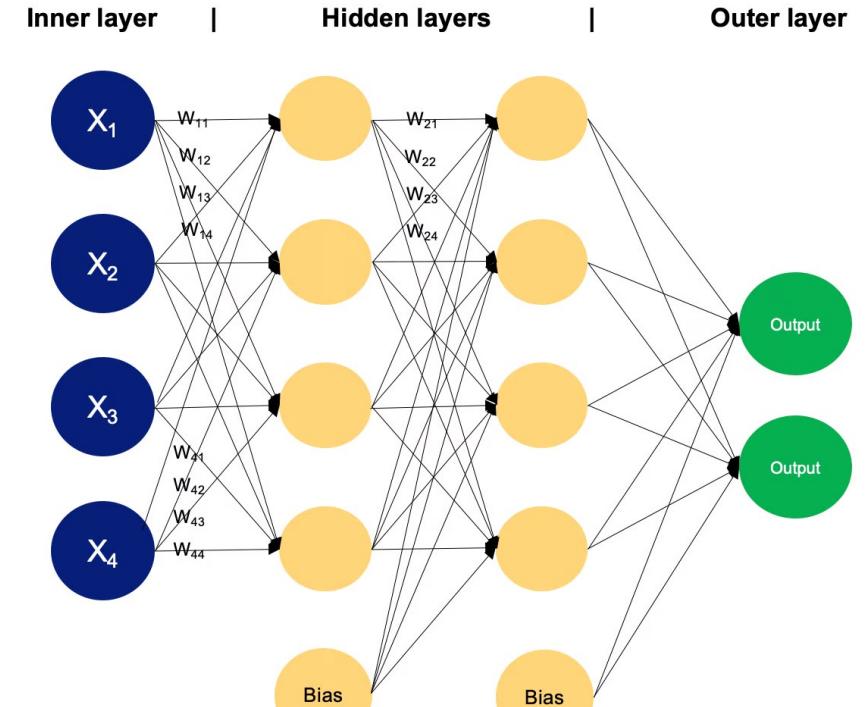
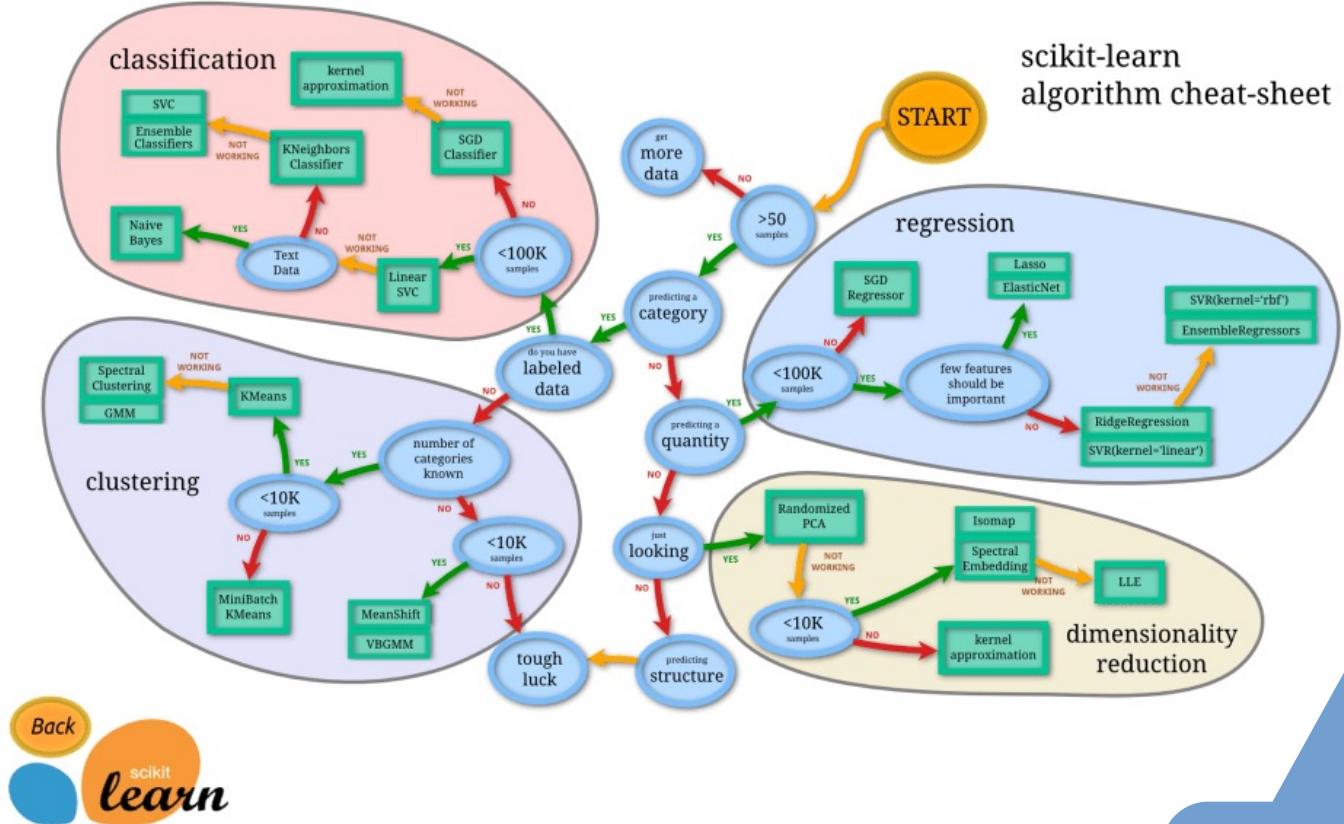


UNED

# Algoritmos clásicos Vs. Multilayer Perceptrón

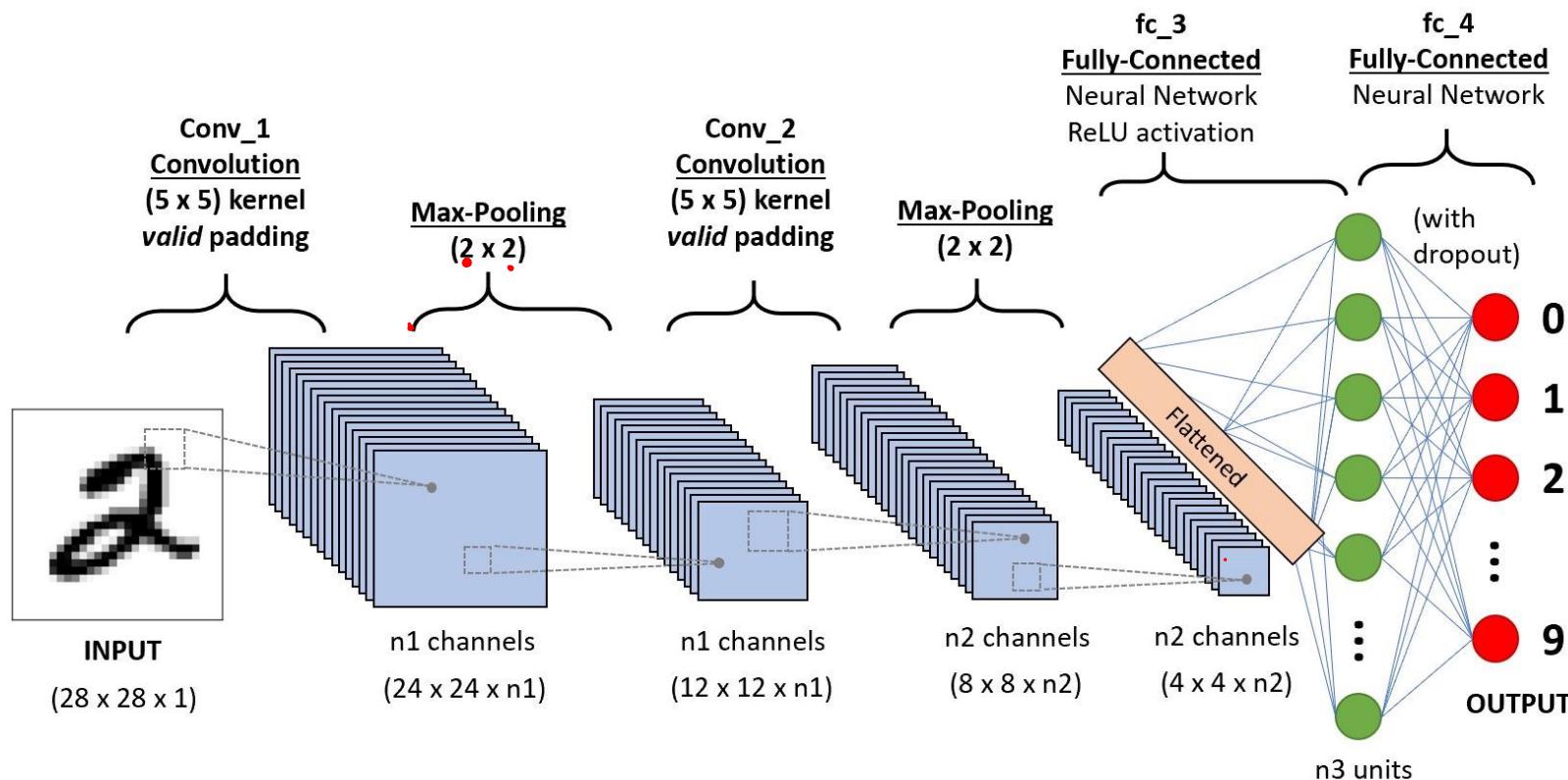


# Algoritmos clásicos Vs. Multilayer Perceptrón



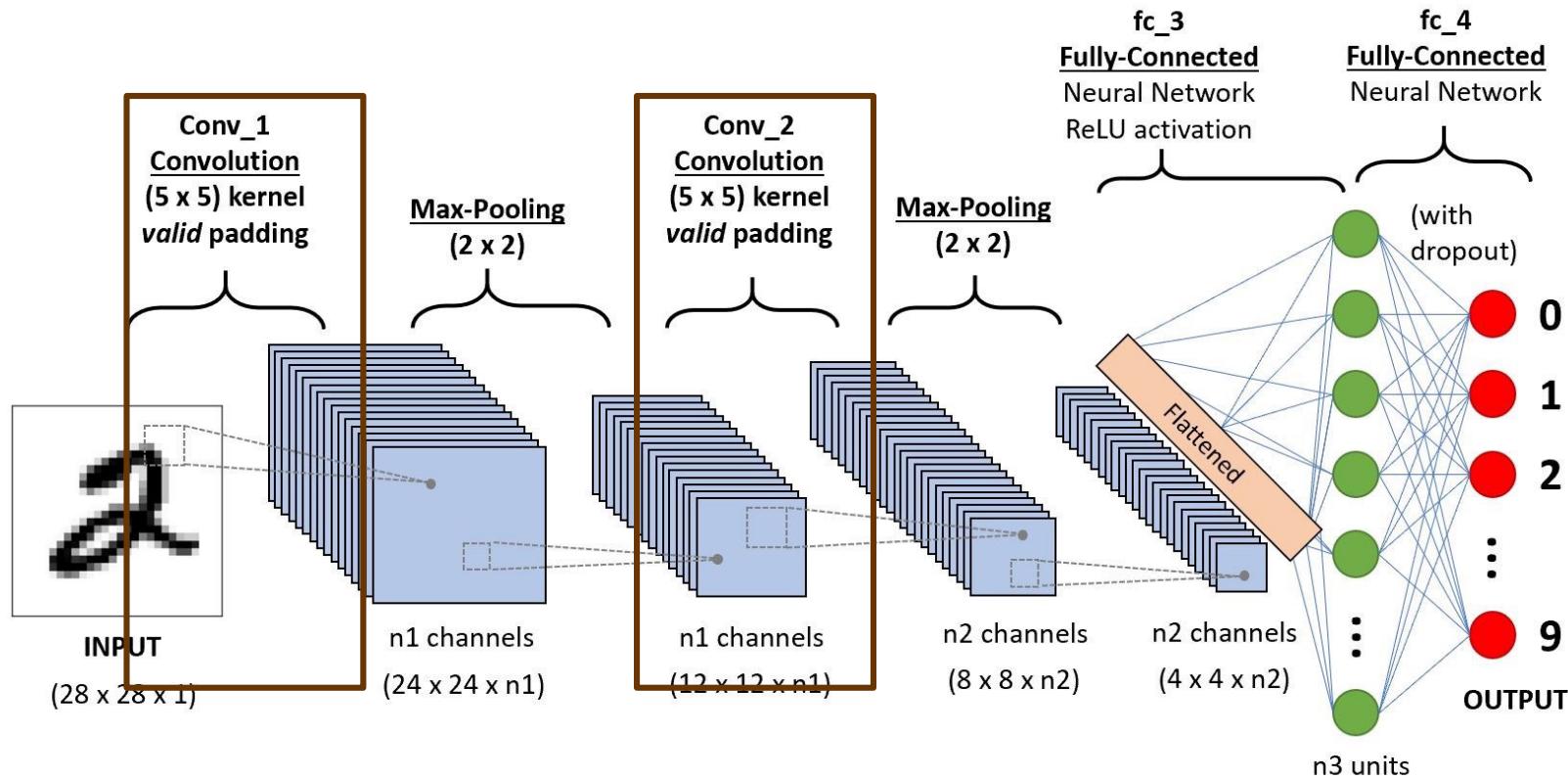
¡Para datos tabulares!

# Redes Neuronales Convolucionales



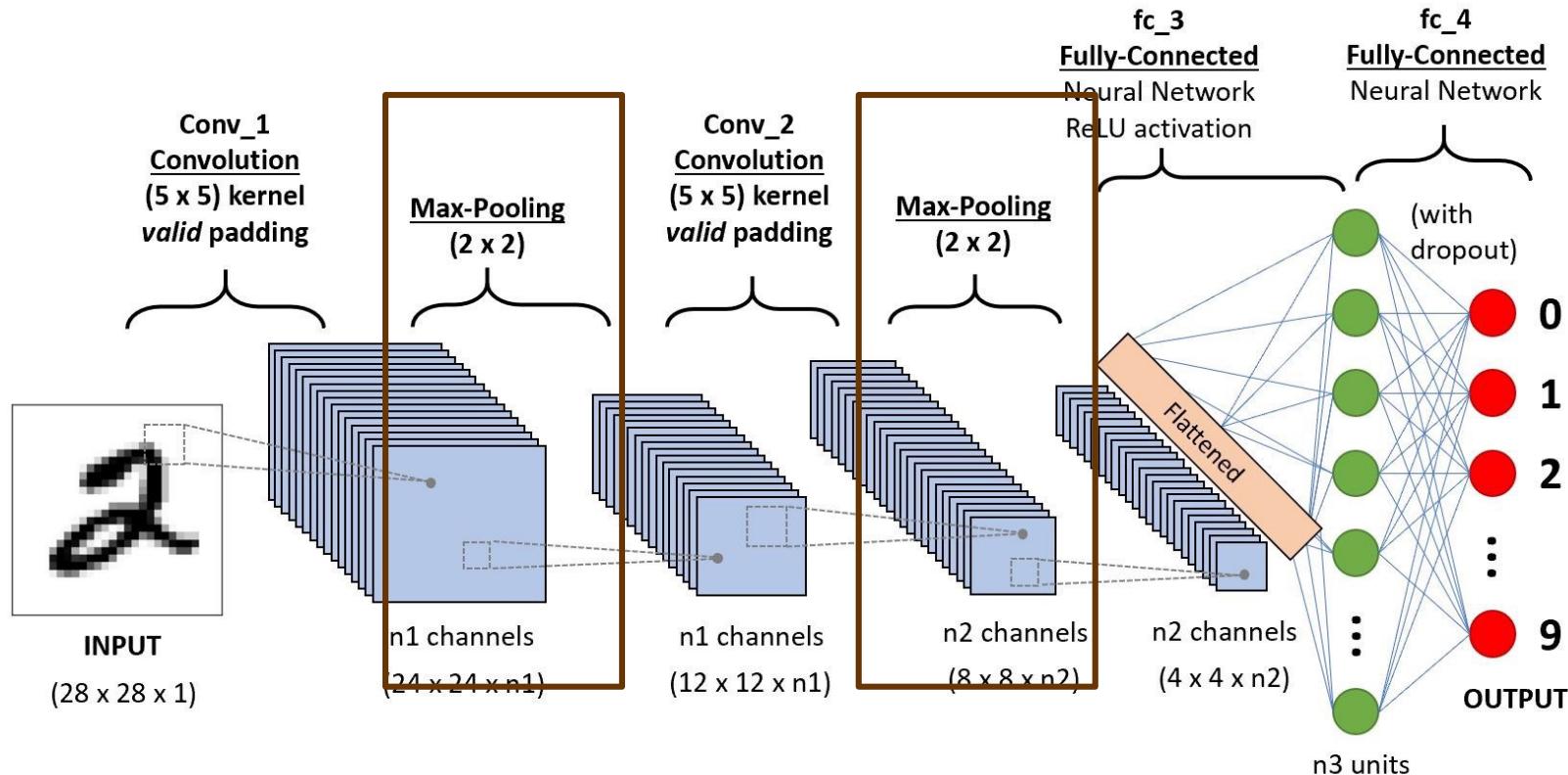
# Redes Neuronales Convolucionales

## Capas convolucionales



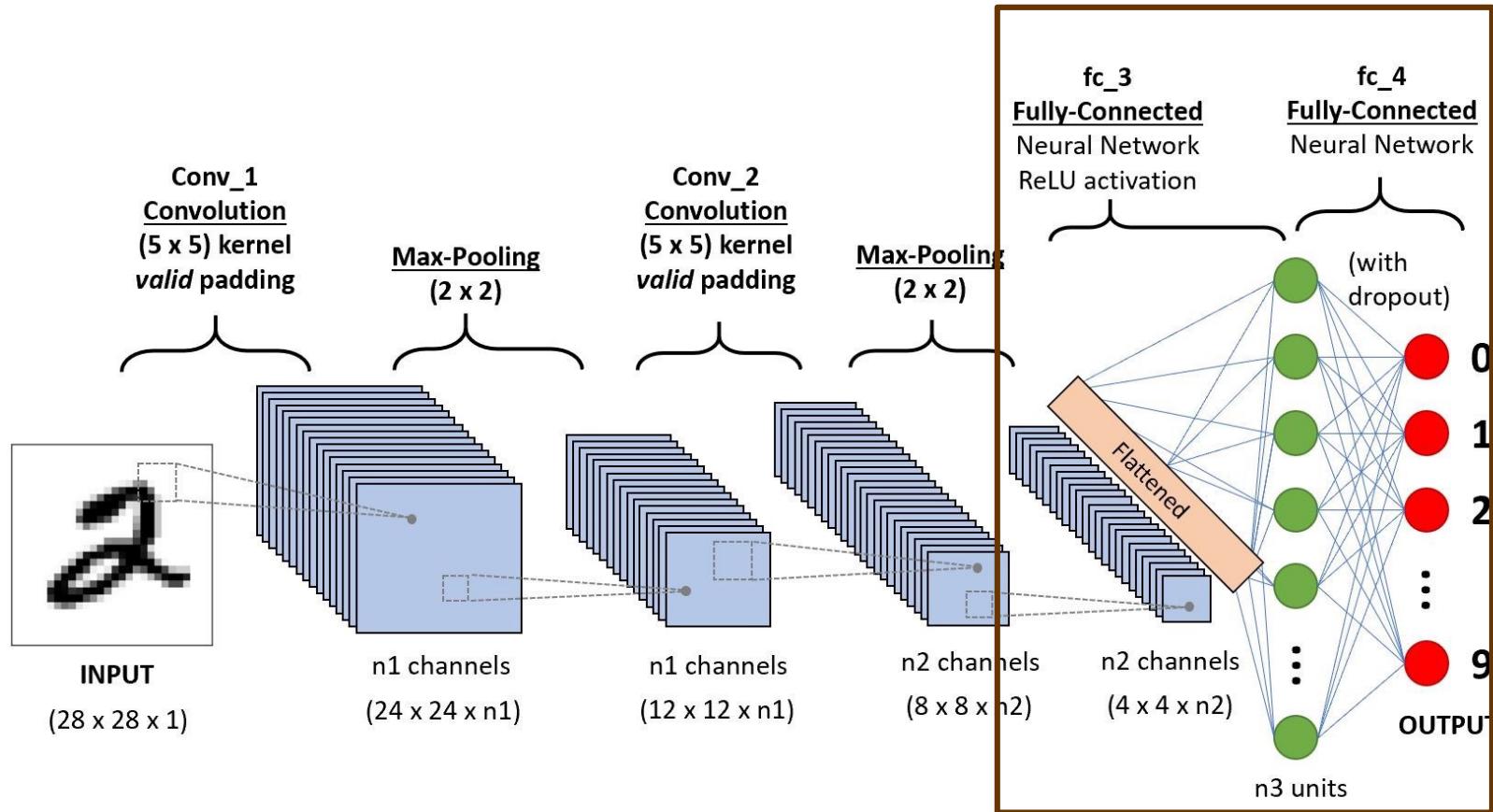
# Redes Neuronales Convolucionales

## Capas de agrupación (*pooling*)



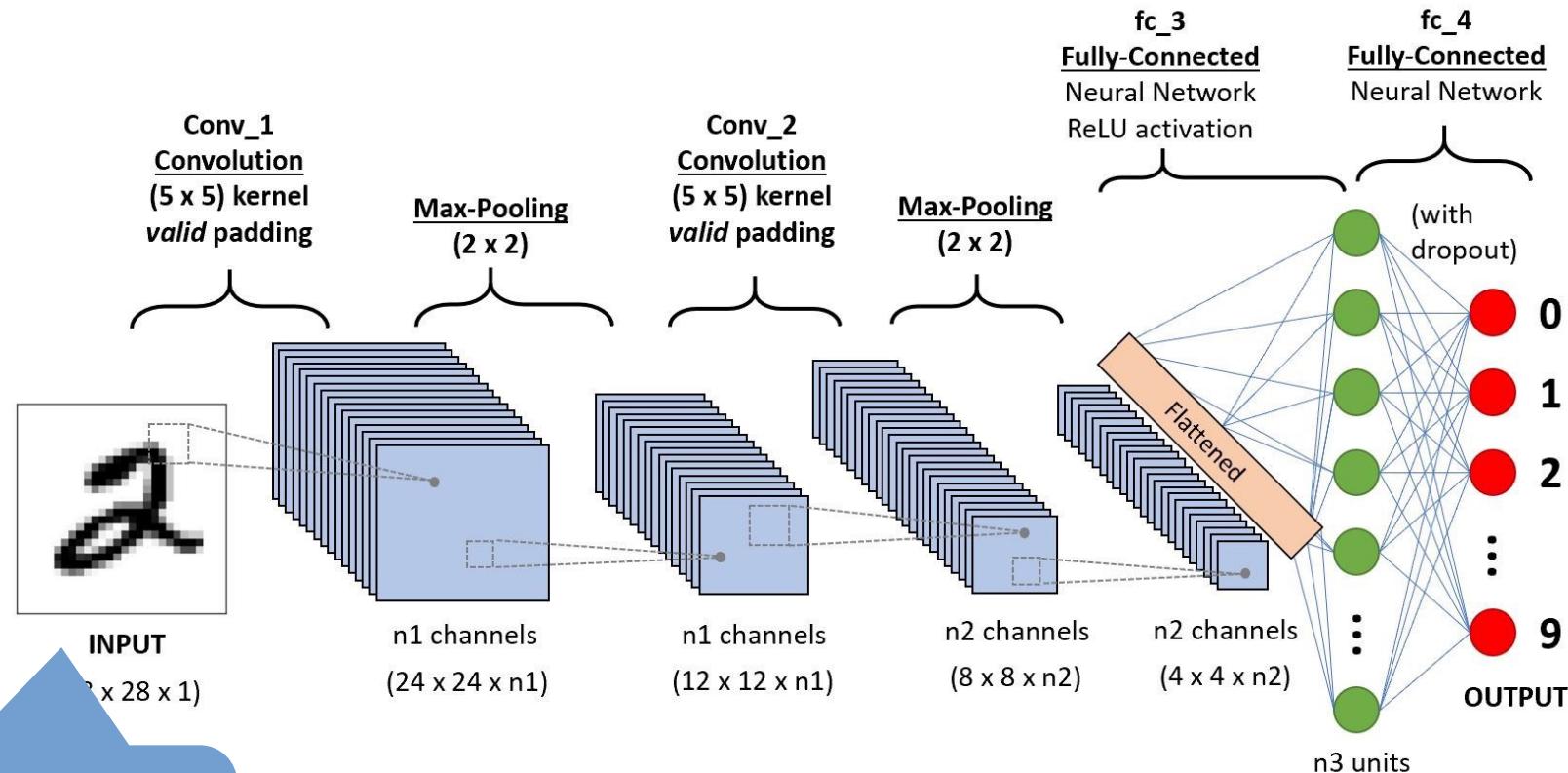
# Redes Neuronales Convolucionales

## Capas completamente conectadas



# Redes Neuronales Convolucionales

## Capas completamente conectadas



¡Para imágenes!



# Vision Transformer (ViT)



¡Para imágenes!

# / Fundamentos de imágenes sintéticas

ETS de  
Ingeniería  
Informática



UNED

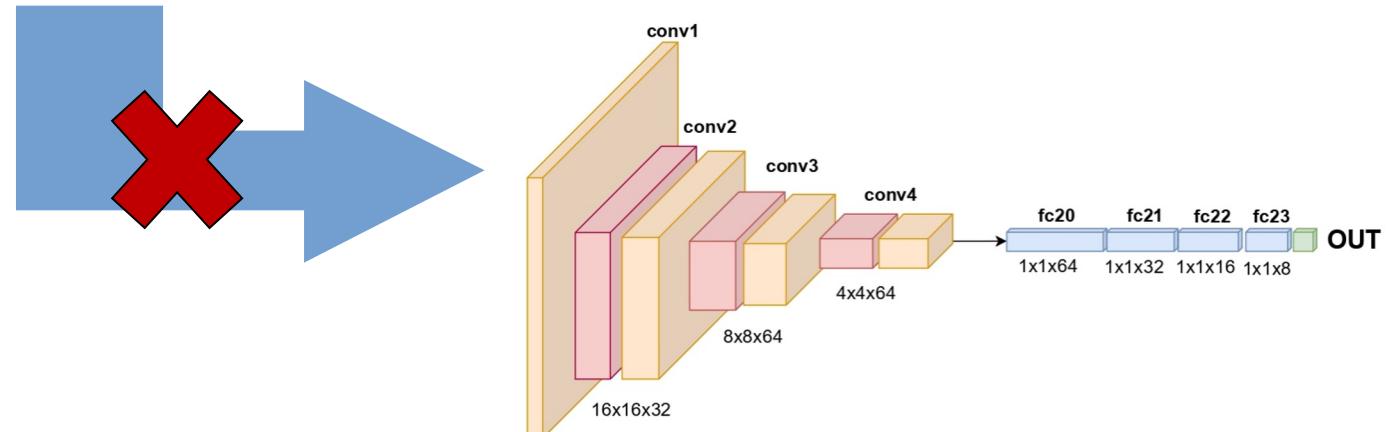


# Transformación de datos

Be07	Be08	Be09	Be10	Be11	Sector
-65	-61	-74	-73	-67	1
-60	-57	-83	-62	-69	2
-66	-70	-78	-63	-73	3
...	...	...	...	...	...
-58	-66	-71	-73	-69	14
-60	-62	-73	-69	-57	15

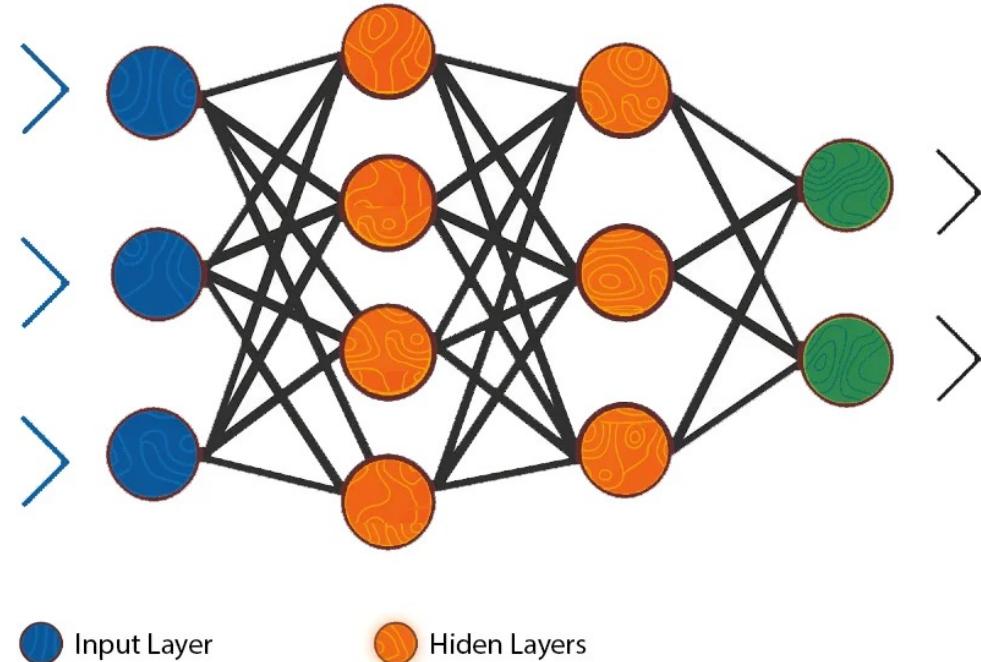
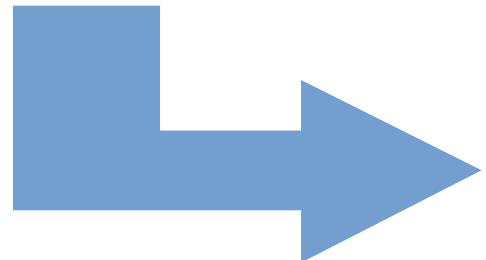
# Transformación de datos

Be07	Be08	Be09	Be10	Be11	Sector
-65	-61	-74	-73	-67	1
-60	-57	-83	-62	-69	2
-66	-70	-78	-63	-73	3
...	...	...	...	...	...
-58	-66	-71	-73	-69	14
-60	-62	-73	-69	-57	15



# Transformación de datos

Be07	Be08	Be09	Be10	Be11	Sector
-65	-61	-74	-73	-67	1
-60	-57	-83	-62	-69	2
-66	-70	-78	-63	-73	3
...	...	...	...	...	...
-58	-66	-71	-73	-69	14
-60	-62	-73	-69	-57	15



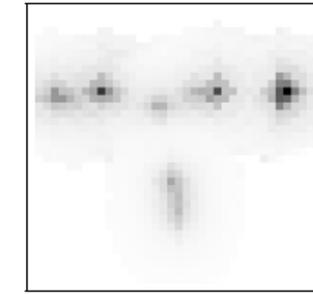
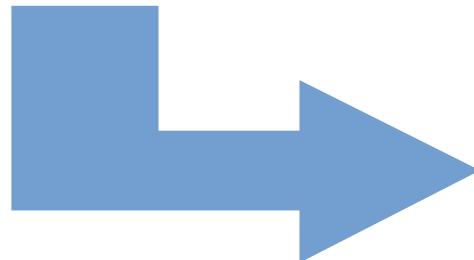


# Transformación de datos

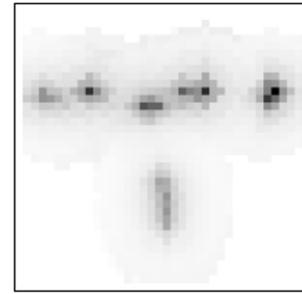
Be07	Be08	Be09	Be10	Be11	Sector
-65	-61	-74	-73	-67	1
-60	-57	-83	-62	-69	2
-66	-70	-78	-63	-73	3
...	...	...	...	...	...
-58	-66	-71	-73	-69	14
-60	-62	-73	-69	-57	15

# Transformación de datos

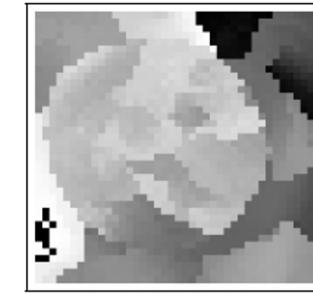
Be07	Be08	Be09	Be10	Be11	Sector
-65	-61	-74	-73	-67	1
-60	-57	-83	-62	-69	2
-66	-70	-78	-63	-73	3
...	...	...	...	...	...
-58	-66	-71	-73	-69	14
-60	-62	-73	-69	-57	15



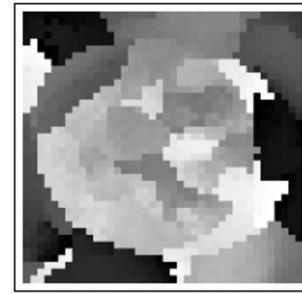
(a) TINTO - Sample 1.



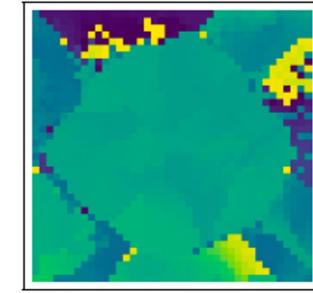
(b) TINTO - Sample 50,000.



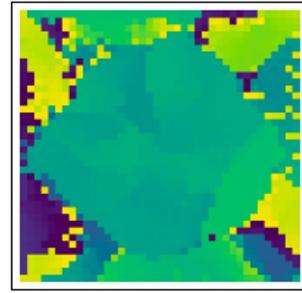
(c) IGTD - Sample 1.



(d) IGTD - Sample 50,000.

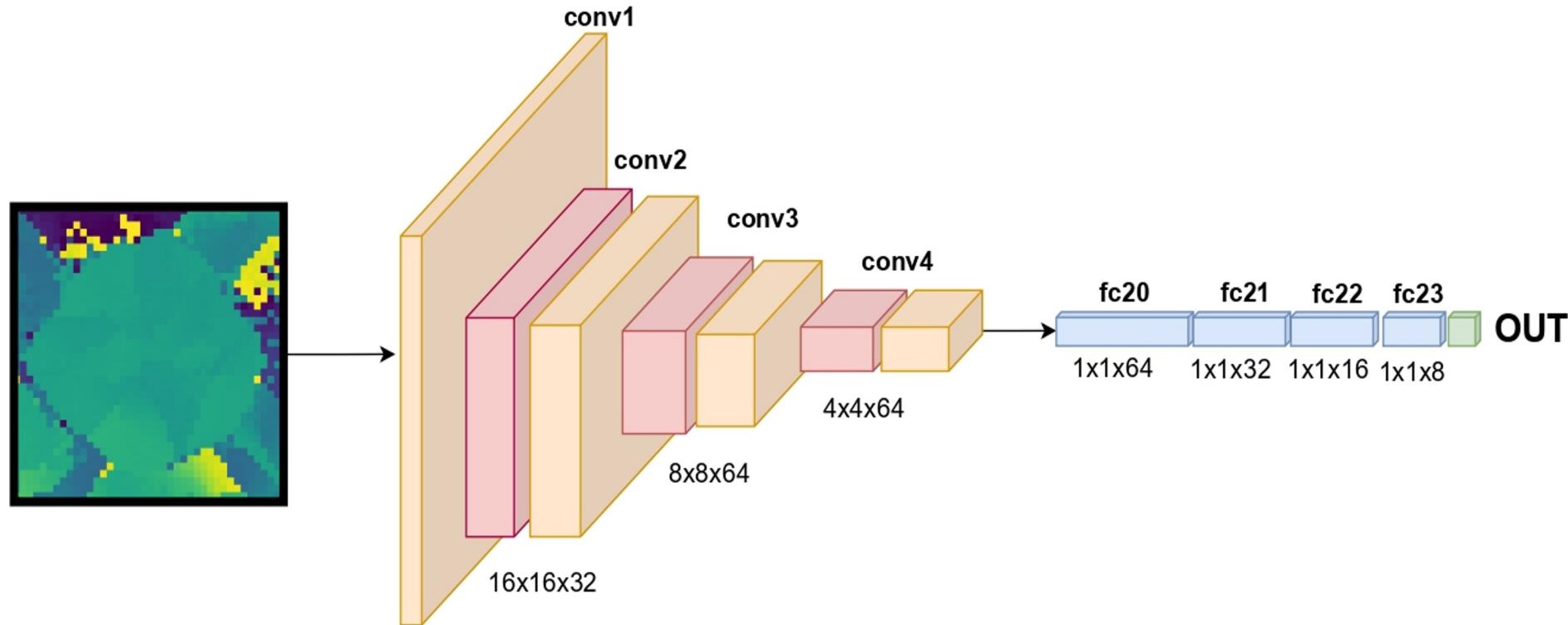


(e) REFINED - Sample 1.

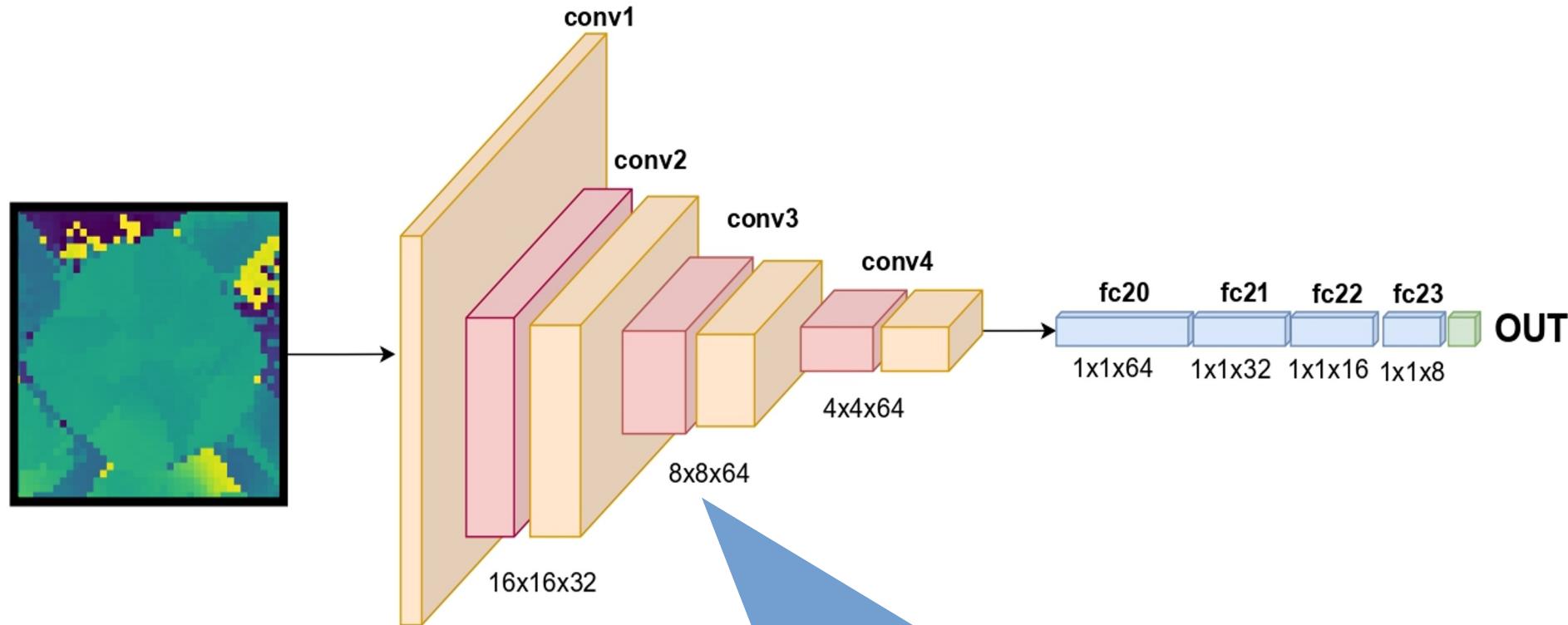


(f) REFINED - Sample 50,000.

# CNN Puras



# CNN Puras



Pero no solamente  
CNNs

# Métodos de transformación

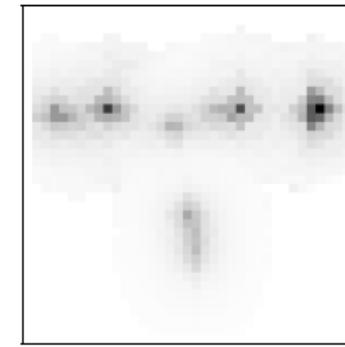
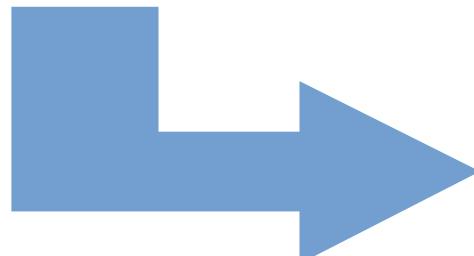
ETS de  
Ingeniería  
Informática



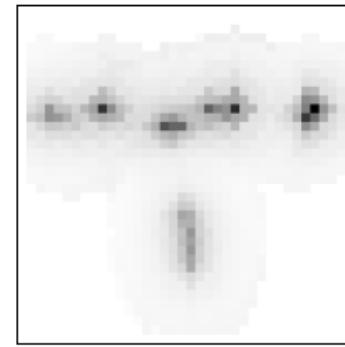
UNED

# Transformación de datos

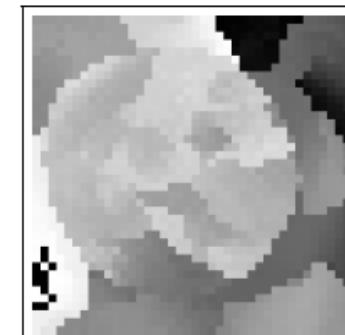
Be07	Be08	Be09	Be10	Be11	Sector
-65	-61	-74	-73	-67	1
-60	-57	-83	-62	-69	2
-66	-70	-78	-63	-73	3
...	...	...	...	...	...
-58	-66	-71	-73	-69	14
-60	-62	-73	-69	-57	15



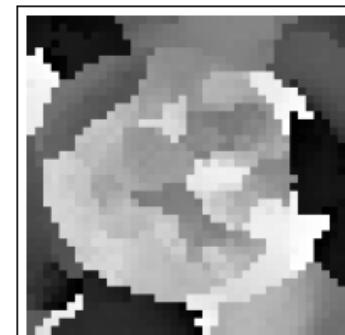
(a) TINTO - Sample 1.



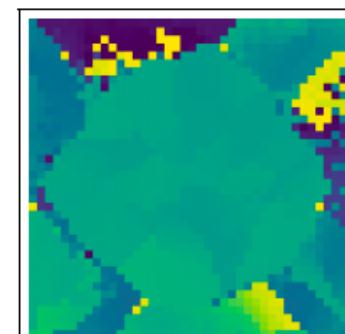
(b) TINTO - Sample 50,000.



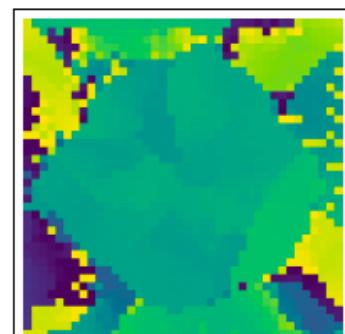
(c) IGTD - Sample 1.



(d) IGTD - Sample 50,000.

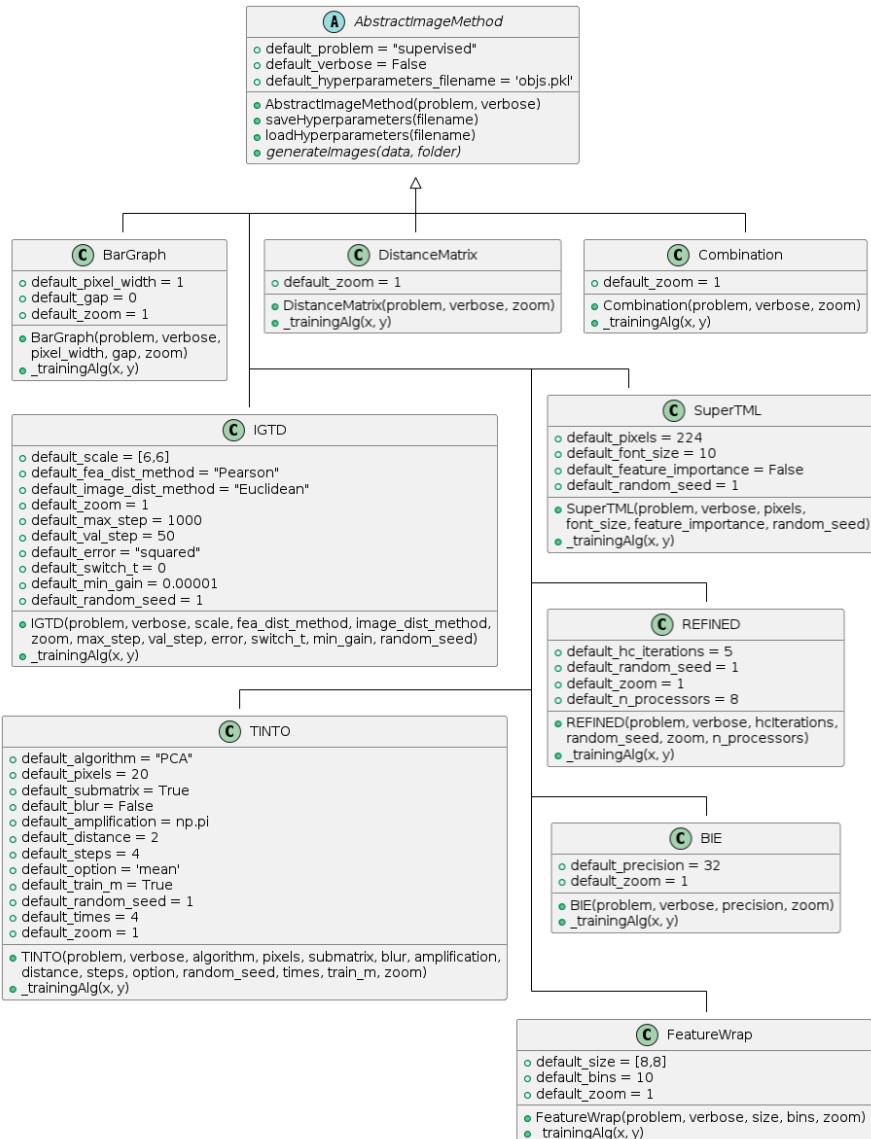


(e) REFINED - Sample 1.

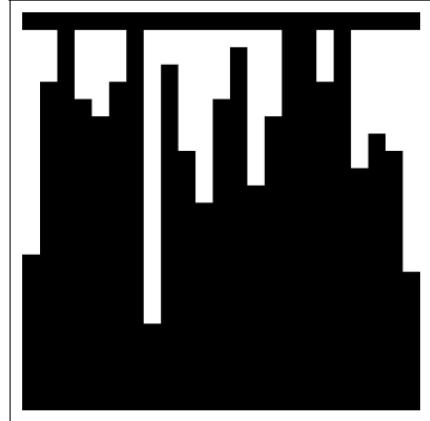


(f) REFINED - Sample 50,000.

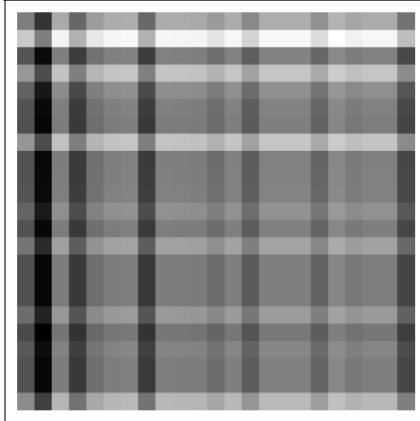
# Métodos de transformación



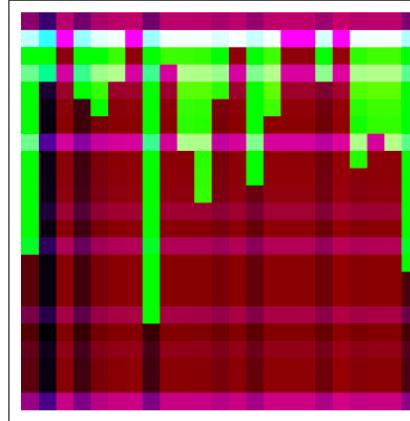
# Métodos de transformación



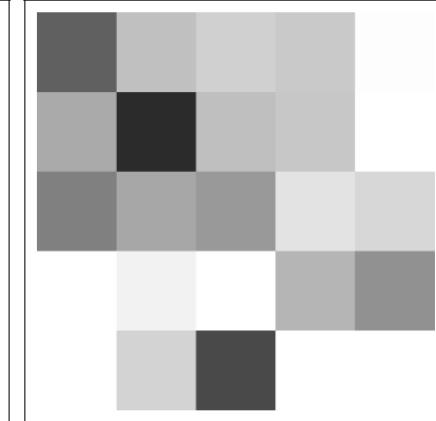
BarGraph



DistanceMatrix



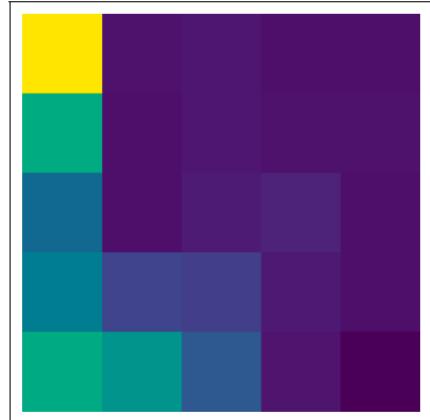
Combination



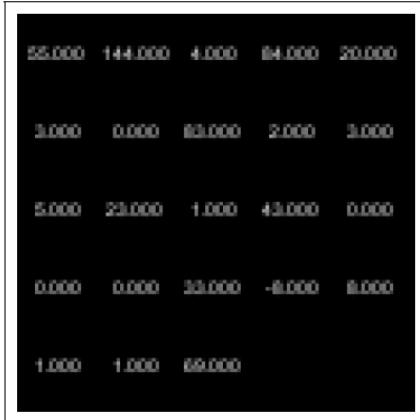
IGTD



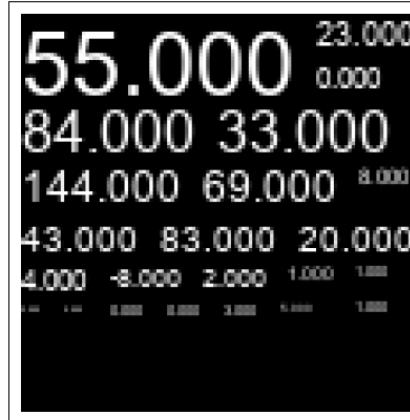
BIE



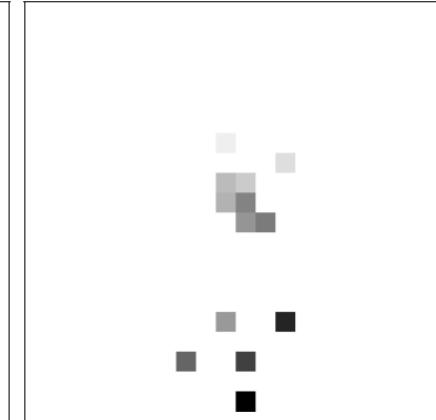
REFINED



SuperTML-EF



SuperTML-VF



TINTO



Feature Wrap

Problema de  
investigación  
abierto

ETS de  
Ingeniería  
Informática



UNED



# Problema de investigación abierto

- Kadra et al. nombró datasets como “*last unconquered castle*” para modelos basados en Deep Neural Networks (DNN).
- La adaptación de las DNN a Datos Tabulares (TD) para tareas de inferencia o generación de datos sigue siendo un **gran desafío**.



# Problema de investigación abierto

- Kadra et al. nombró datasets como “***last unconquered castle***” para modelos basados en Deep Neural Networks (DNN).
- La adaptación de las DNN a Datos Tabulares (TD) para tareas de inferencia o generación de datos sigue siendo un **gran desafío**.
- Vadim Borísov et al. hacen un benchmark de diferentes métodos/datasets entre ensembles vs. DNN y **ganar los ensembles**. De hecho, afirman:
  - “El progreso de la investigación sobre modelos competitivos de aprendizaje profundo para datos tabulares **se está estancando**”.
  - “Es un **área de investigación abierta**”.



# Problema de investigación abierto

- [Kadra et al.](#) nombró datasets como “***last unconquered castle***” para modelos basados en Deep Neural Networks (DNN).
- La adaptación de las DNN a Datos Tabulares (TD) para tareas de inferencia o generación de datos sigue siendo un **gran desafío**.
- [Vadim Borísov et al.](#) hacen un benchmark de diferentes métodos/datasets entre ensembles vs. DNN y **ganar los ensembles**. De hecho, afirman:
  - “El progreso de la investigación sobre modelos competitivos de aprendizaje profundo para datos tabulares **se está estancando**”.
  - “Es un **área de investigación abierta**”.
- [Shwartz Ziv & Armon](#) en su artículo “*Tabular data: Deep learning is not all you need*”, compararon enfoques de DNN vs. árbol de decisión de aumento de gradiente (GBDT). **Los GBDT cuestionaron los DNN**, lo que concluyeron que el modelado de datos tabulares utilizando DNN sigue siendo un **problema de investigación abierto**.



# Problema de investigación abierto

- Kadra et al. nombró datasets como “***last unconquered castle***” para modelos basados en Deep Neural Networks (DNN).
- La adaptación de las DNN a Datos Tabulares (TD) para tareas de inferencia o generación de datos sigue siendo un **gran desafío**.
- Vadim Borísov et al. hacen un benchmark de diferentes métodos/datasets entre ensembles vs. DNN y **ganan los ensembles**. De hecho, afirman:
  - “El progreso de la investigación sobre modelos competitivos de aprendizaje profundo para datos tabulares **se está estancando**”.
  - “Es un **área de investigación abierta**”.
- Shwartz Ziv & Armon en su artículo “*Tabular data: Deep learning is not all you need*”, compararon enfoques de DNN vs. árbol de decisión de aumento de gradiente (GBDT). **Los GBDT cuestionaron los DNN**, lo que concluyeron que el modelado de datos tabulares utilizando DNN sigue siendo un **problema de investigación abierto**.
- Las implementaciones exitosas de aplicaciones basadas en datos requieren resolver varias tareas, entre las cuales identificamos **3 desafíos centrales: (1) Inferencia; (2) Generación de datos; y (3) Interpretabilidad**.
  - La **tarea más crucial es la inferencia**, que se ocupa de hacer predicciones basadas en observaciones pasadas.

# Métodos no paramétricos

ETS de  
Ingeniería  
Informática



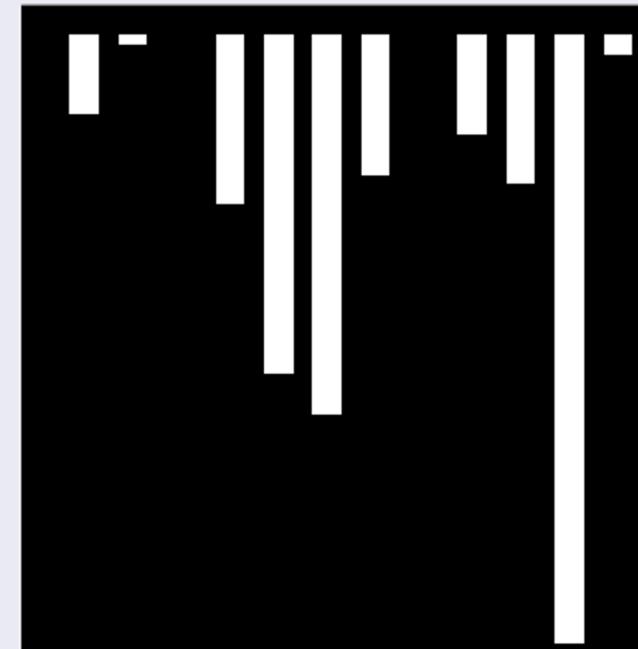
UNED

# BarGraph

BarGraph

INPUT

0.00632 18.00 2.31 0 0.538 6.575 65.20 4.09 1 296.0 15.3 396 4.98



OUPUT

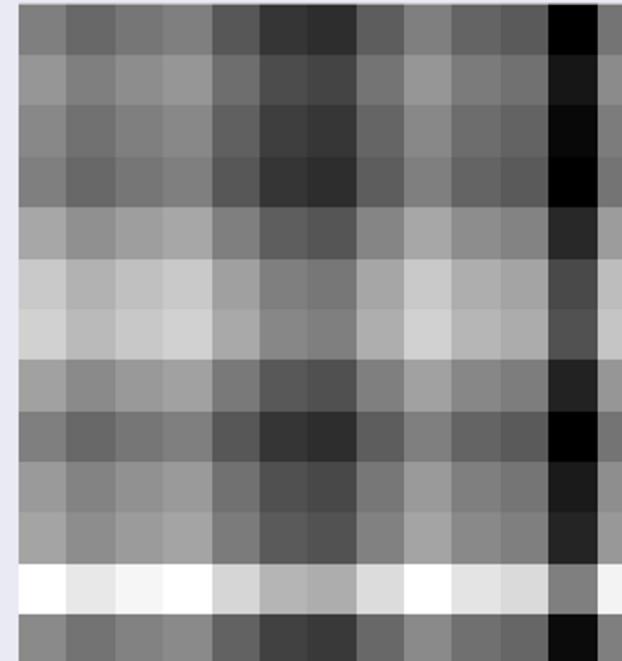


# DistanceMatrix

DistanceMatrix

INPUT

0.00632	18.00	2.31	0	0.538	6.575	65.20	4.09	1	296.0	15.3	396	4.98
---------	-------	------	---	-------	-------	-------	------	---	-------	------	-----	------



OUPUT

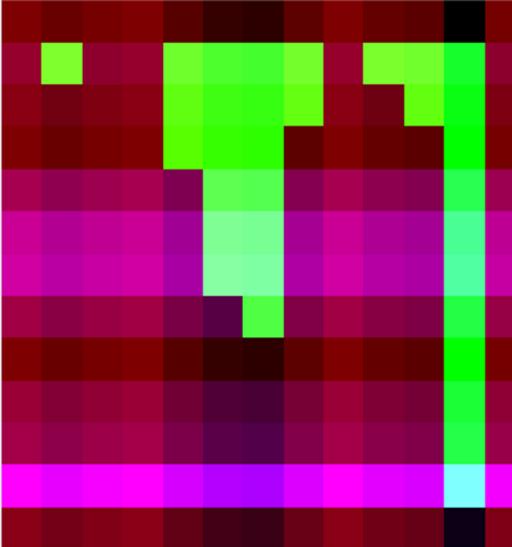
# Combination

Combination

INPUT

0.00632	18.00	2.31	0	0.538	6.575	65.20	4.09	1	296.0	15.3	396	4.98
---------	-------	------	---	-------	-------	-------	------	---	-------	------	-----	------

OUTPUT





# SuperTML

SuperTML

INPUT

0.00632	18.00	2.31	0	0.538	6.575	65.20	4.09	1	296.0	15.3	396	4.98
---------	-------	------	---	-------	-------	-------	------	---	-------	------	-----	------

0.006	18.000	2.310	0.000
0.538	6.575	65.200	4.090
1.000	296.000	15.300	396.900
4.980			

OUPUT



# FeatureWrap

FeatureWrap

INPUT

0.00632	18.00	2.31	0	0.538	6.575	65.20	4.09	1	296.0	15.3	396	4.98
---------	-------	------	---	-------	-------	-------	------	---	-------	------	-----	------



OUPUT

# Binary Image Encoding

BIE

INPUT

0.00632 18.00 2.31 0 0.538 6.575 65.20 4.09 1 296.0 15.3 396 4.98

OUPUT

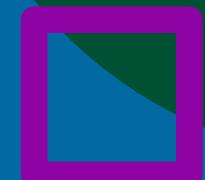




# Métodos paramétricos



ETS de  
Ingeniería  
Informática



UNED

# TINTO

TINTO

INPUT

0.00632	18.00	2.31	0	0.538	6.575	65.20	4.09	1	296.0	15.3	396	4.98
---------	-------	------	---	-------	-------	-------	------	---	-------	------	-----	------

OUTPUT



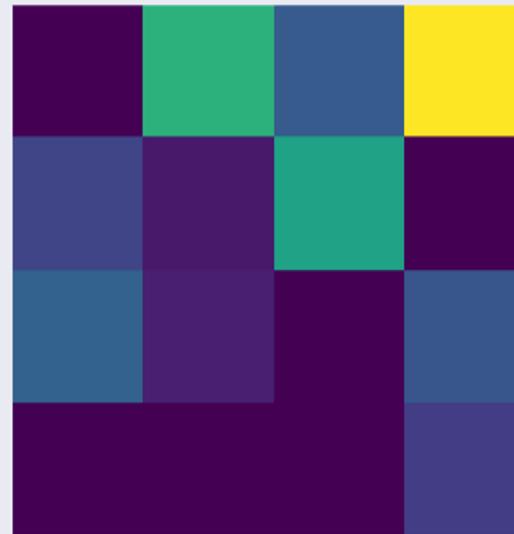
# REFINED

REFINED

INPUT

0.00632	18.00	2.31	0	0.538	6.575	65.20	4.09	1	296.0	15.3	396	4.98
---------	-------	------	---	-------	-------	-------	------	---	-------	------	-----	------

OUTPUT



IGTD

INPUT

0.00632	18.00	2.31	0	0.538	6.575	65.20	4.09	1	296.0	15.3	396	4.98
---------	-------	------	---	-------	-------	-------	------	---	-------	------	-----	------

OUTPUT

A 4x4 grid of colored squares. The colors transition through various shades of gray and black. The top-left square is white, followed by a light gray, a medium gray, and a dark gray. The bottom-left square is white, followed by a light gray, a medium gray, and a black square in the bottom-right corner.

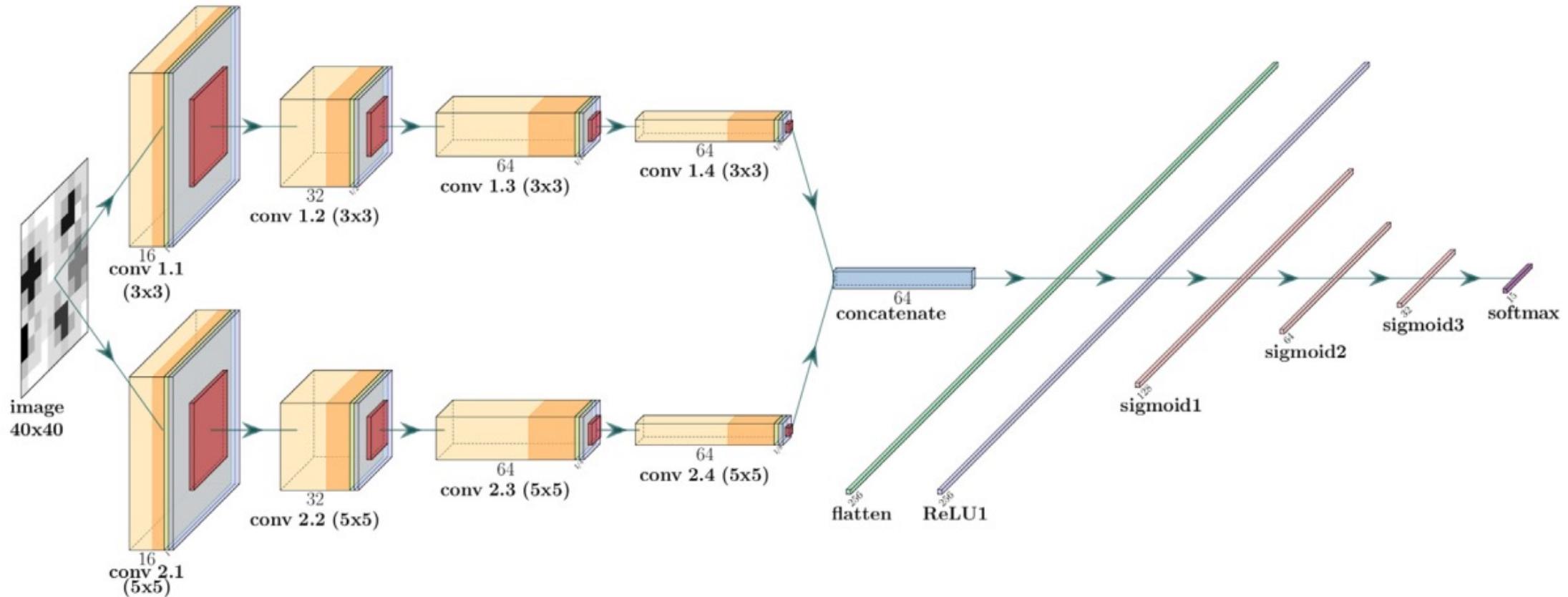
# Arquitecturas con imágenes sintéticas

ETS de  
Ingeniería  
Informática

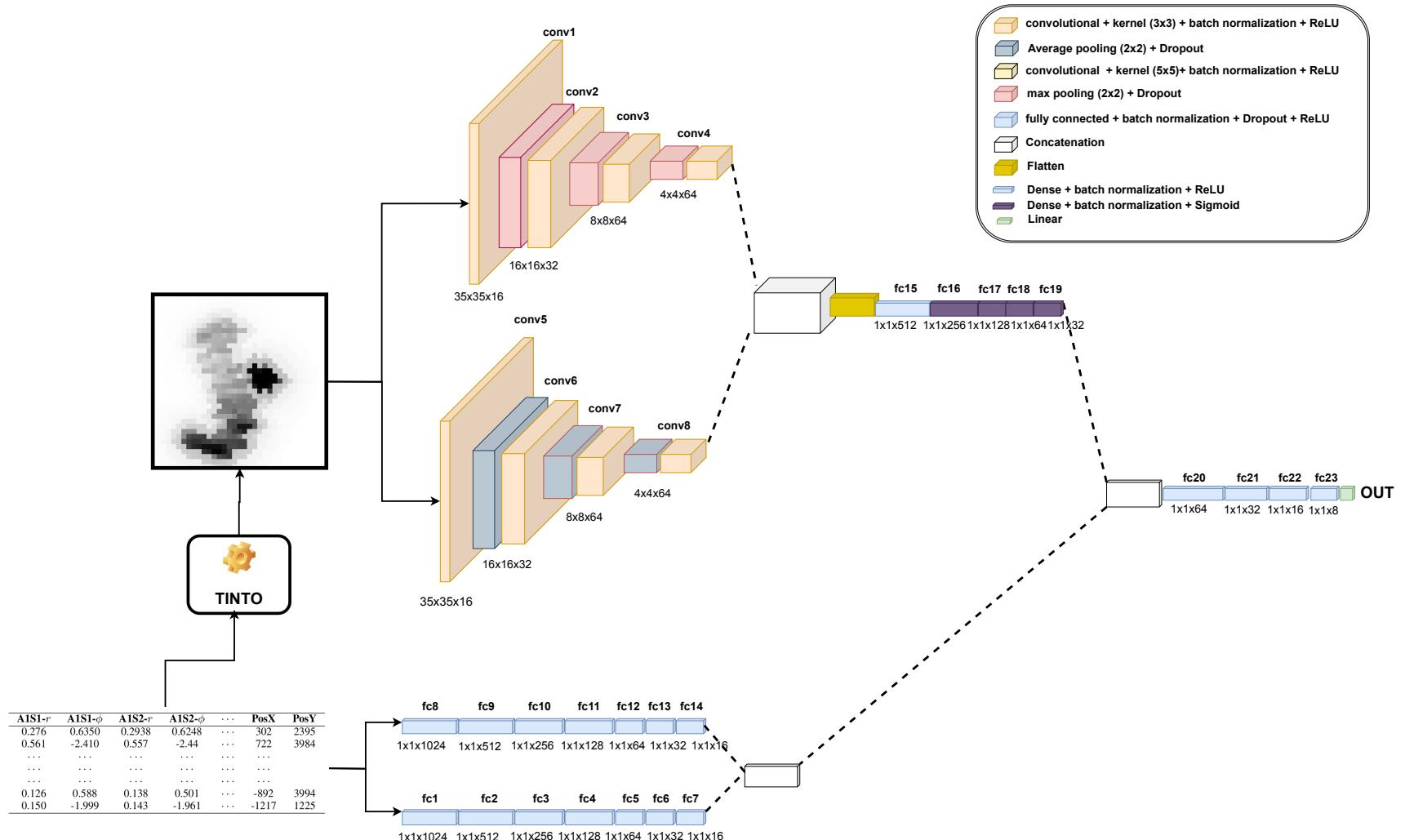


UNED

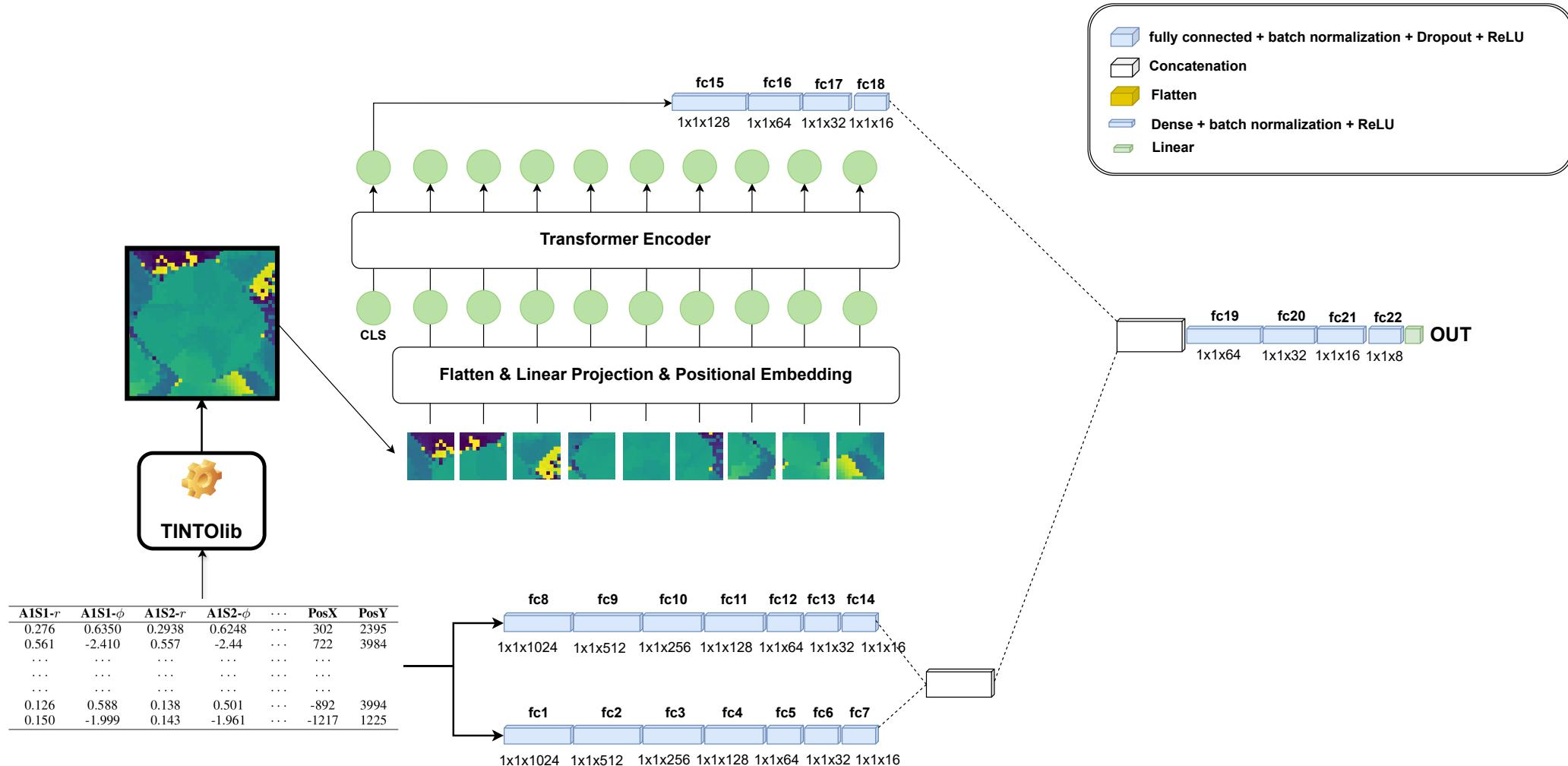
# CNN



# HyNN



# HyViT



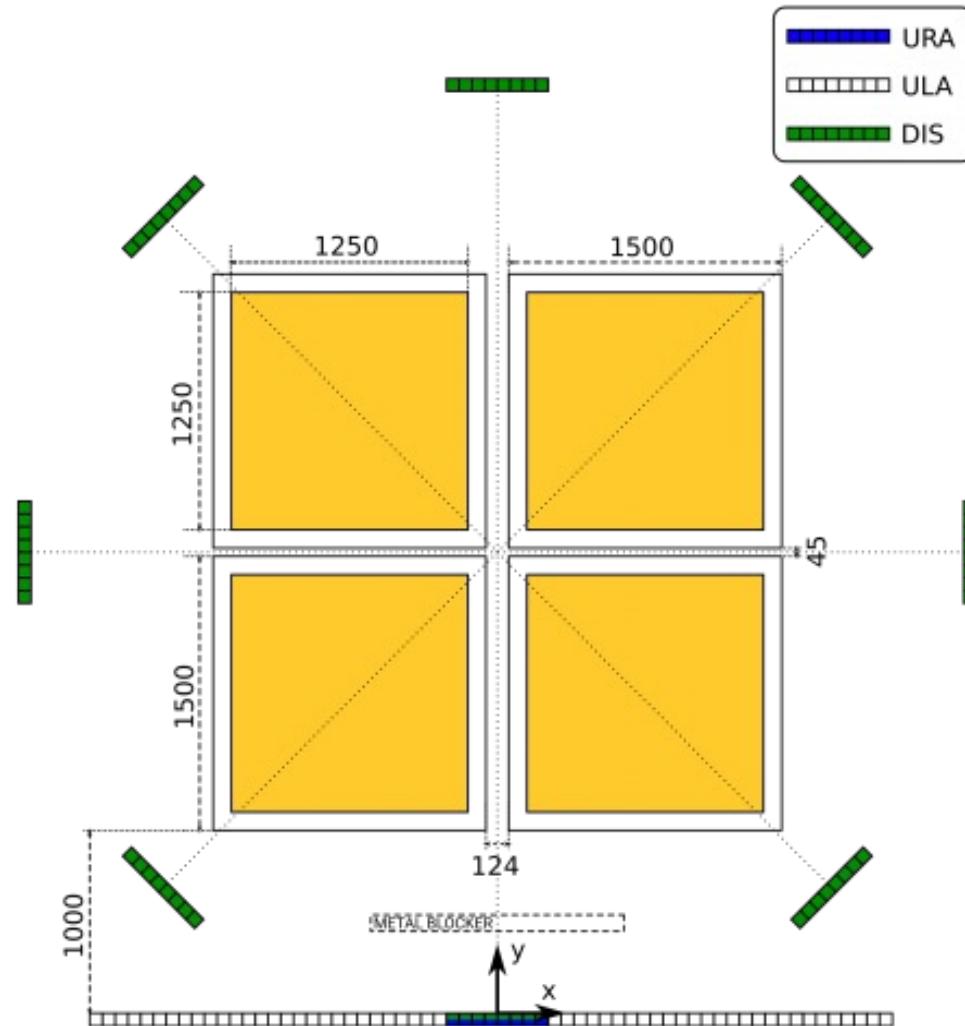
# ‘Caso de uso: Localización en interiores con MIMO

ETS de  
Ingeniería  
Informática



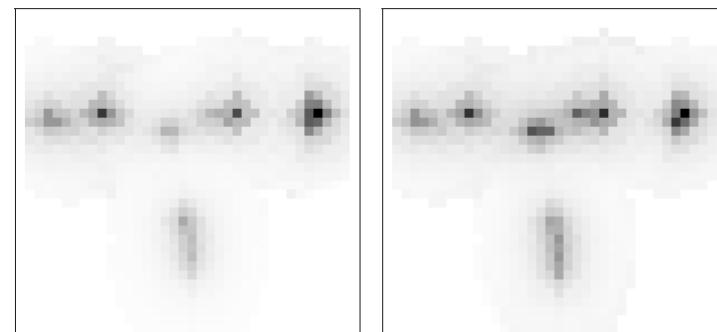
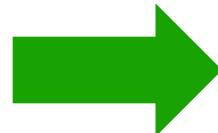
UNED

# Escenario

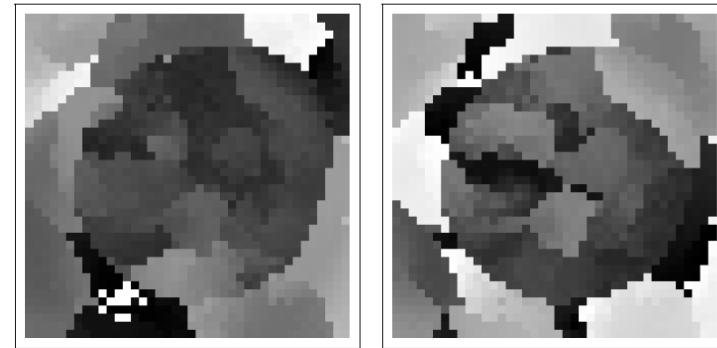


# Imágenes sintéticas

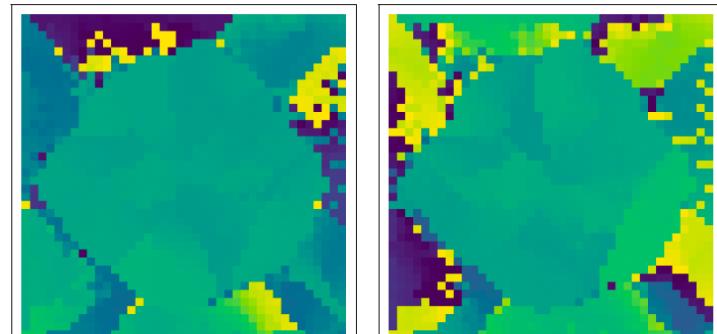
<b>A1C1-<i>m</i></b>	<b>A1C1-<math>\phi</math></b>	<b>A1C2-<i>m</i></b>	<b>A1C2-<math>\phi</math></b>	...	<b>PosX</b>	<b>PosY</b>
0.276	0.6350	0.2938	0.6248	...	302	2395
0.561	-2.410	0.557	-2.44	...	722	3984
...	...	...	...	...	...	...
...	...	...	...	...	...	...
...	...	...	...	...	...	...
0.126	0.588	0.138	0.501	...	-892	3994
0.150	-1.999	0.143	-1.961	...	-1217	1225



(a) DIS - TINTO - Sample 1. (b) DIS - TINTO - Sample 50,000.



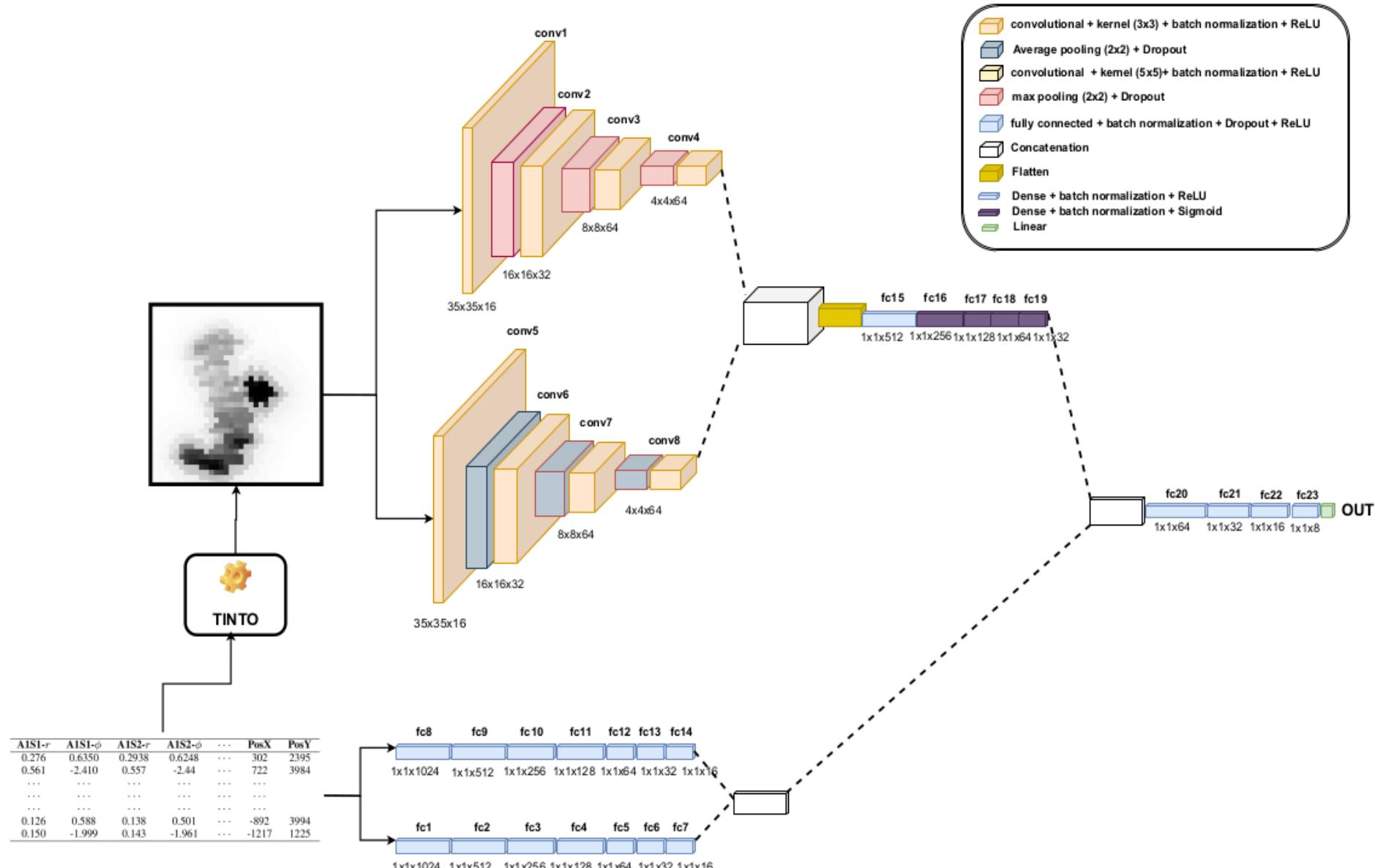
(c) DIS - IGTD - Sample 1. (d) DIS - IGTD - Sample 50,000.



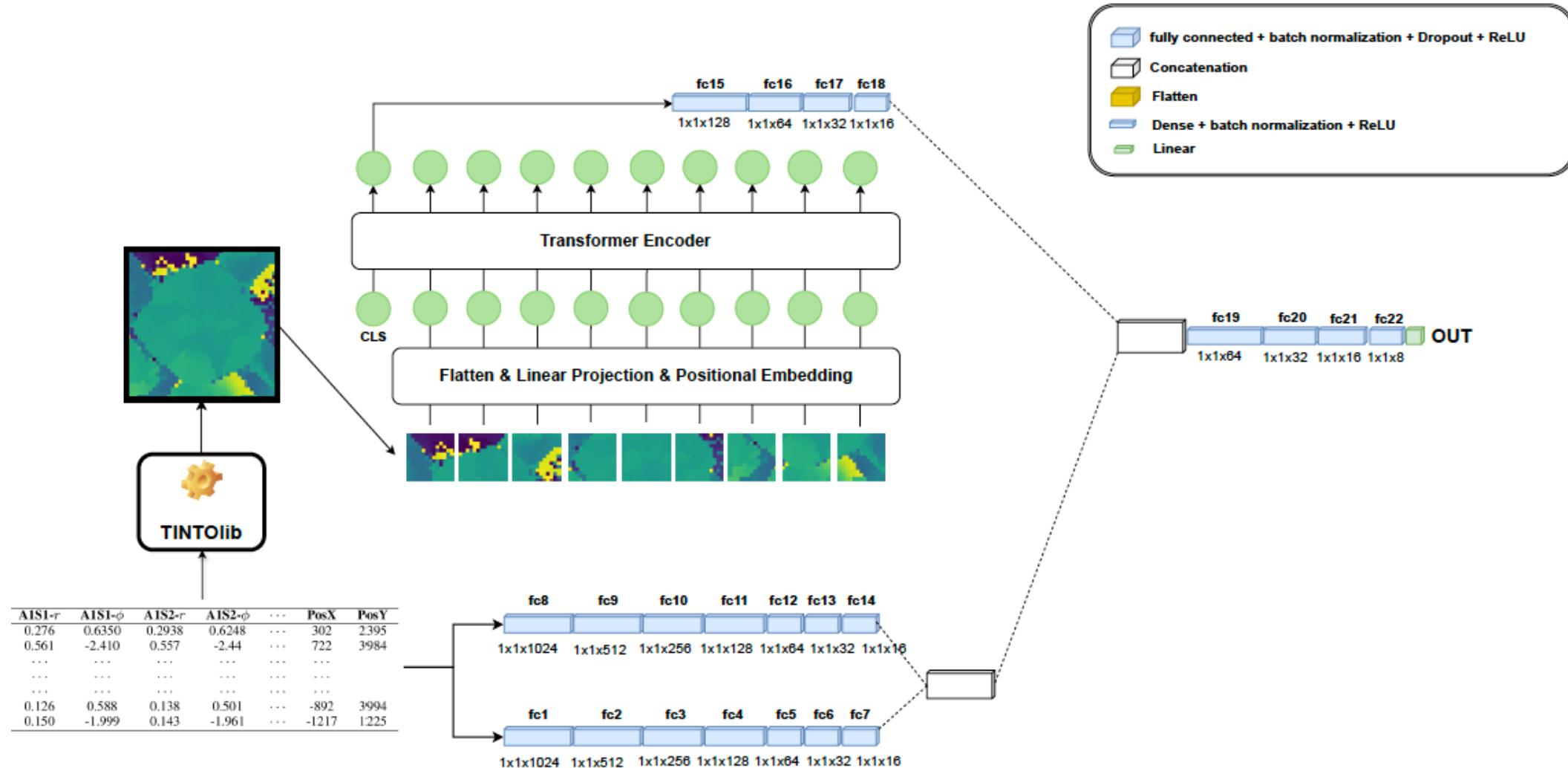
(e) DIS - REFINED - Sample 1. (f) DIS - REFINED - Sample 50,000.

**Figure 3.** Synthetic image samples generated by TINTOlib for different samples in 8 antennas DIS scenario.

# HyNN → CNN+MLP



# HyViT → ViT+MLP



# Baseline Results

**Table 2.** RMSE (in mm) in validation (Val) and test split. Best results are shown in bold.

Algorithm	PosX		PosY	
	Val	Test	Val	Test
BR	226.05	225.00	251.43	255.54
ET	163.15	161.65	180.00	185.70
HGB	194.10	194.97	236.55	236.46
KNN	<b>110.50</b>	<b>110.54</b>	<b>133.70</b>	<b>140.16</b>
LiR	383.05	386.95	432.83	439.10
MLP	179.80	178.82	326.11	334.76
RF	226.09	225.18	251.37	255.62
RCV	383.04	386.94	432.80	439.06
XGB	178.41	180.03	202.45	201.66
LGB	194.14	194.15	231.19	232.89



# Hybrid Neural Networks Results

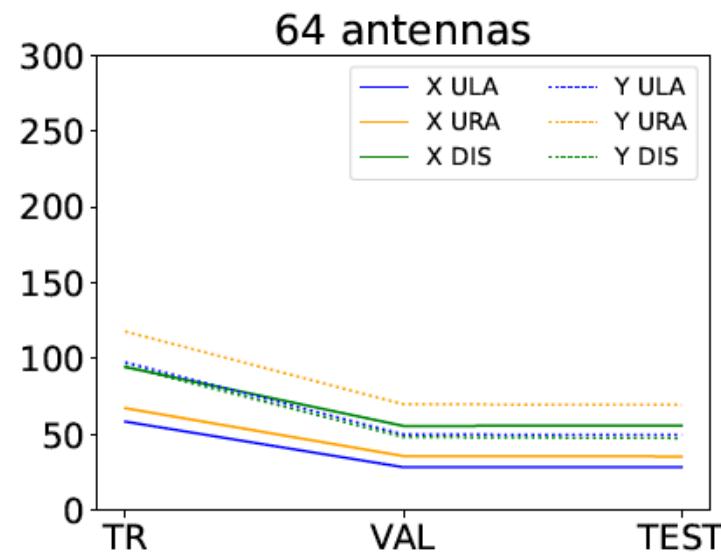
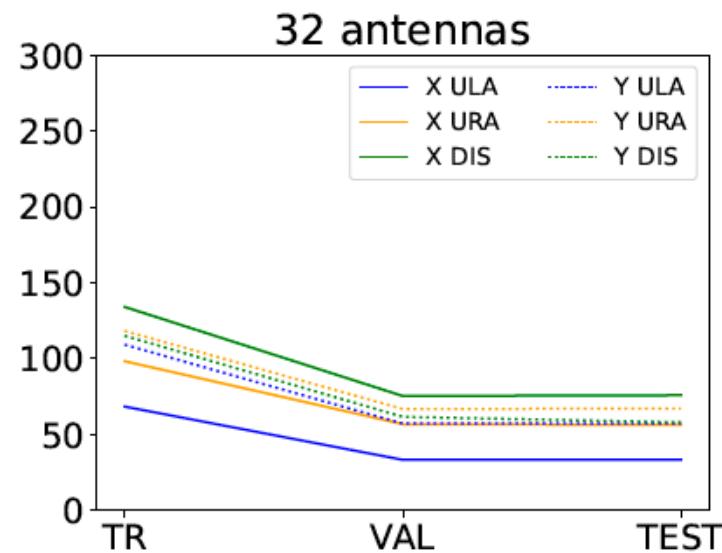
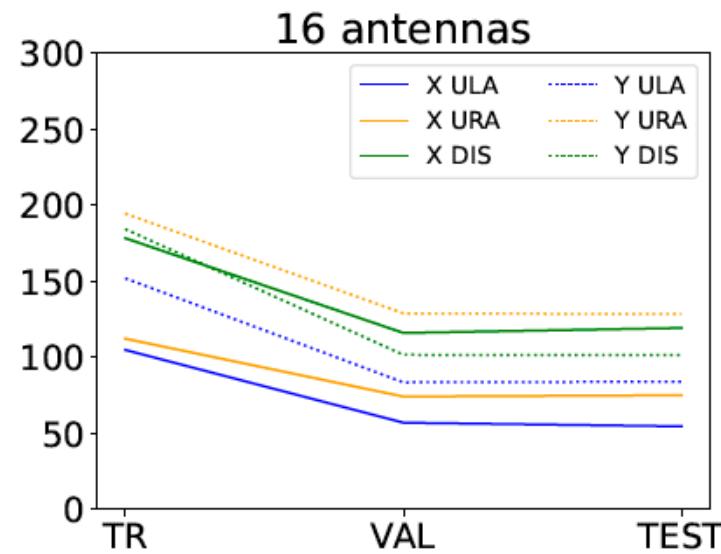
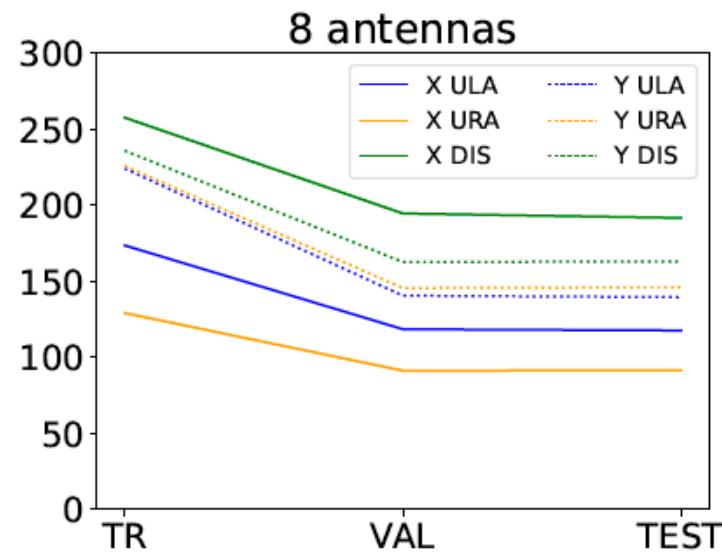
**Table 2.** RMSE (in mm) in validation (Val) and test split. Best results are shown in bold.

Algorithm	PosX		PosY	
	Val	Test	Val	Test
BR	226.05	225.00	251.43	255.54
ET	163.15	161.65	180.00	185.70
HGB	194.10	194.97	236.55	236.46
KNN	<b>110.50</b>	<b>110.54</b>	<b>133.70</b>	<b>140.16</b>
LiR	383.05	386.95	432.83	439.10
MLP	179.80	178.82	326.11	334.76
RF	226.09	225.18	251.37	255.62
RCV	383.04	386.94	432.80	439.06
XGB	178.41	180.03	202.45	201.66
LGB	194.14	194.15	231.19	232.89

**Table 3.** RMSE (in mm) for the different HyNNs architectures and HyViT in Validation (Val) and test. Best results are shown in bold.

Position	Model	TINTO		IGTD		REFINED	
		Val	Test	Val	Test	Val	Test
PosX	HyCNN	187.10	188.10	92.8	92.21	105.69	105.38
	HyTNN	178.28	179.25	119.59	119.62	115.90	114.98
	HyTTNN	181.96	184.19	179.01	180.05	193.56	196.09
	HyGTNN	176.71	176.43	173.42	174.20	173.38	174.02
	HyViT	<b>103.27</b>	<b>104.17</b>	<b>46.57</b>	<b>45.77</b>	<b>41.38</b>	<b>41.84</b>
PosY	HyCNN	152.19	151.94	101.01	99.45	115.40	114.69
	HyTNN	143.10	143.29	95.95	95.83	112.27	112.02
	HyTTNN	151.35	151.97	155.35	154.12	147.22	146.01
	HyGTNN	155.06	153.40	154.68	154.50	157.10	155.39
	HyViT	<b>121.77</b>	<b>123.90</b>	<b>70.84</b>	<b>68.93</b>	<b>90.11</b>	<b>90.56</b>

# Inferencia



Más  
información

ETS de  
Ingeniería  
Informática



UNED



# Más información

- Documentación oficial de TINTOlib:  
<https://tintolib.readthedocs.io/en/latest/>
- TINTOlib Crash Course: [https://github.com/oeg-upm/TINTOlib-Crash\\_Course](https://github.com/oeg-upm/TINTOlib-Crash_Course)
- Librería TINTOlib en PyPI: <https://pypi.org/project/TINTOlib/>
- GitHub con el código de TINTOlib: <https://github.com/oeg-upm/TINTOlib>
- GitHub con el código de TINTO: <https://github.com/oeg-upm/TINTO>
- Artículo sobre TINTO y su aplicación en indoor localization. Incluye la definición formal matemática: <https://doi.org/10.1016/j.inffus.2022.10.011>
- Artículo sobre TINTO: <https://doi.org/10.1016/j.softx.2023.101391>



# ¡Gracias!



**Dr. Manuel Castillo-Cara**  
[www.manuelcastillo.eu](http://www.manuelcastillo.eu)

Departamento de Inteligencia Artificial  
Escuela Técnica Superior de Ingeniería Informática  
Universidad Nacional de Educación a Distancia (UNED)