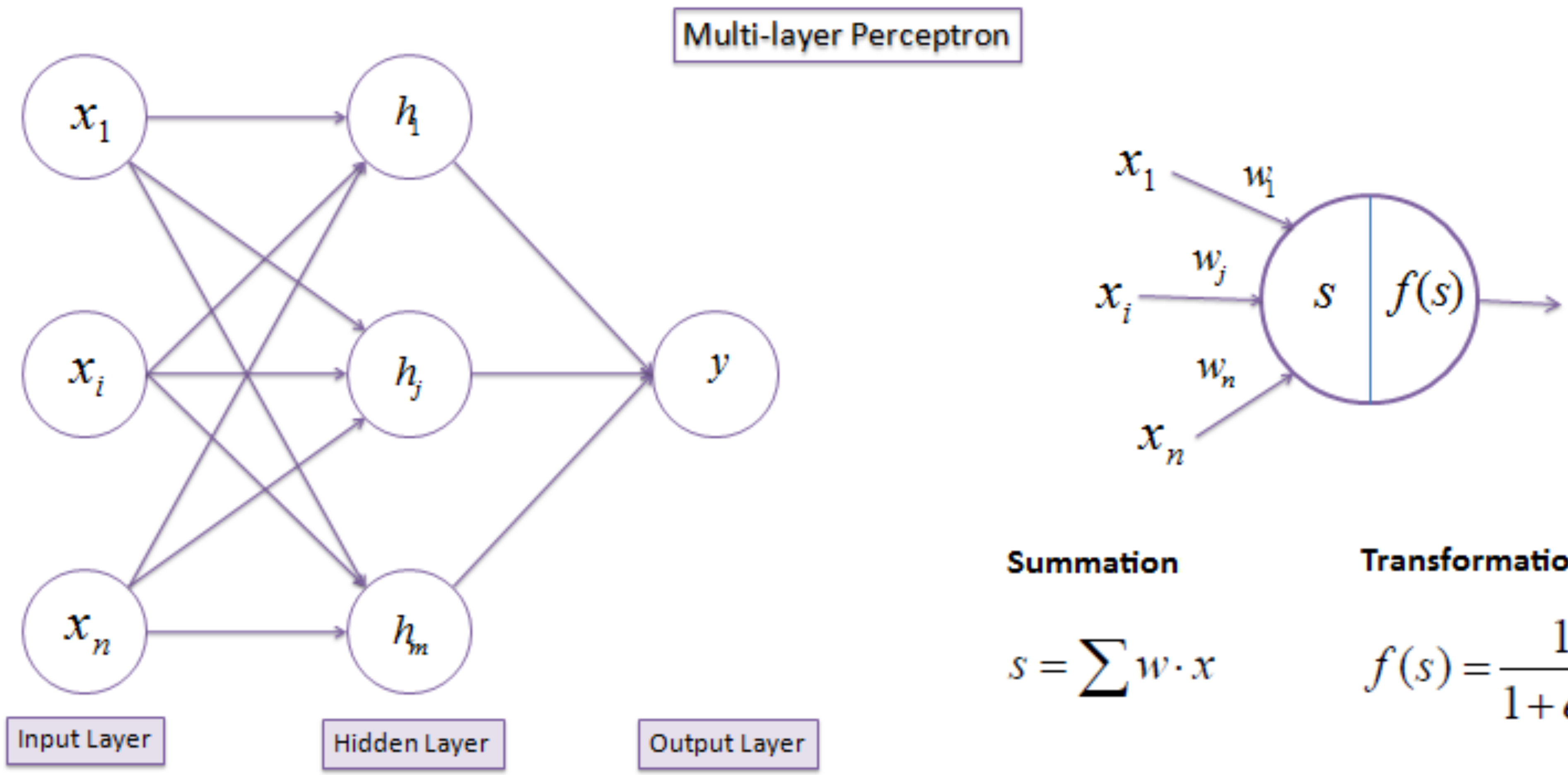
Analysis of Ground Patterns with a Deep Neural Network to Improve Gamma/Hadron Discrimination

Filipe Assunção, João Correia, Rúben Conceição, Mário Pimenta, Bernardo Tomé,
Nuno Lourenço, Penousal Machado

fga@dei.uc.pt — http://cdv.dei.uc.pt

ARTIFICIAL NEURAL NETWORKS



Summation

$$s = \sum w \cdot x$$

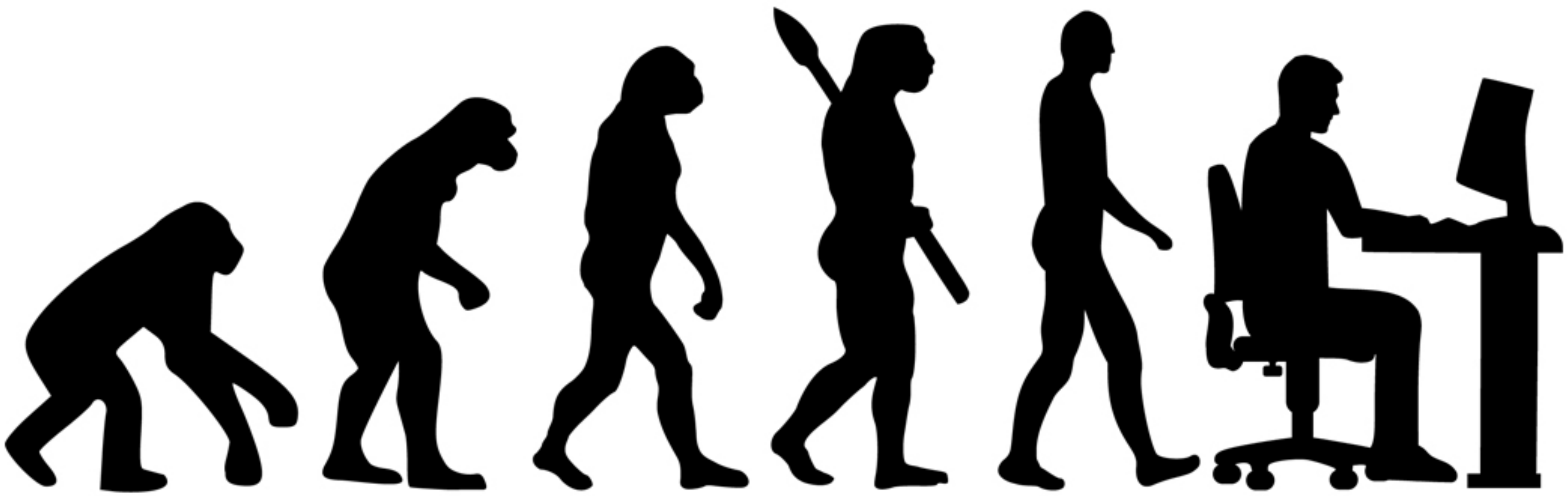
Transformation

$$f(s) = \frac{1}{1 + e^{-s}}$$

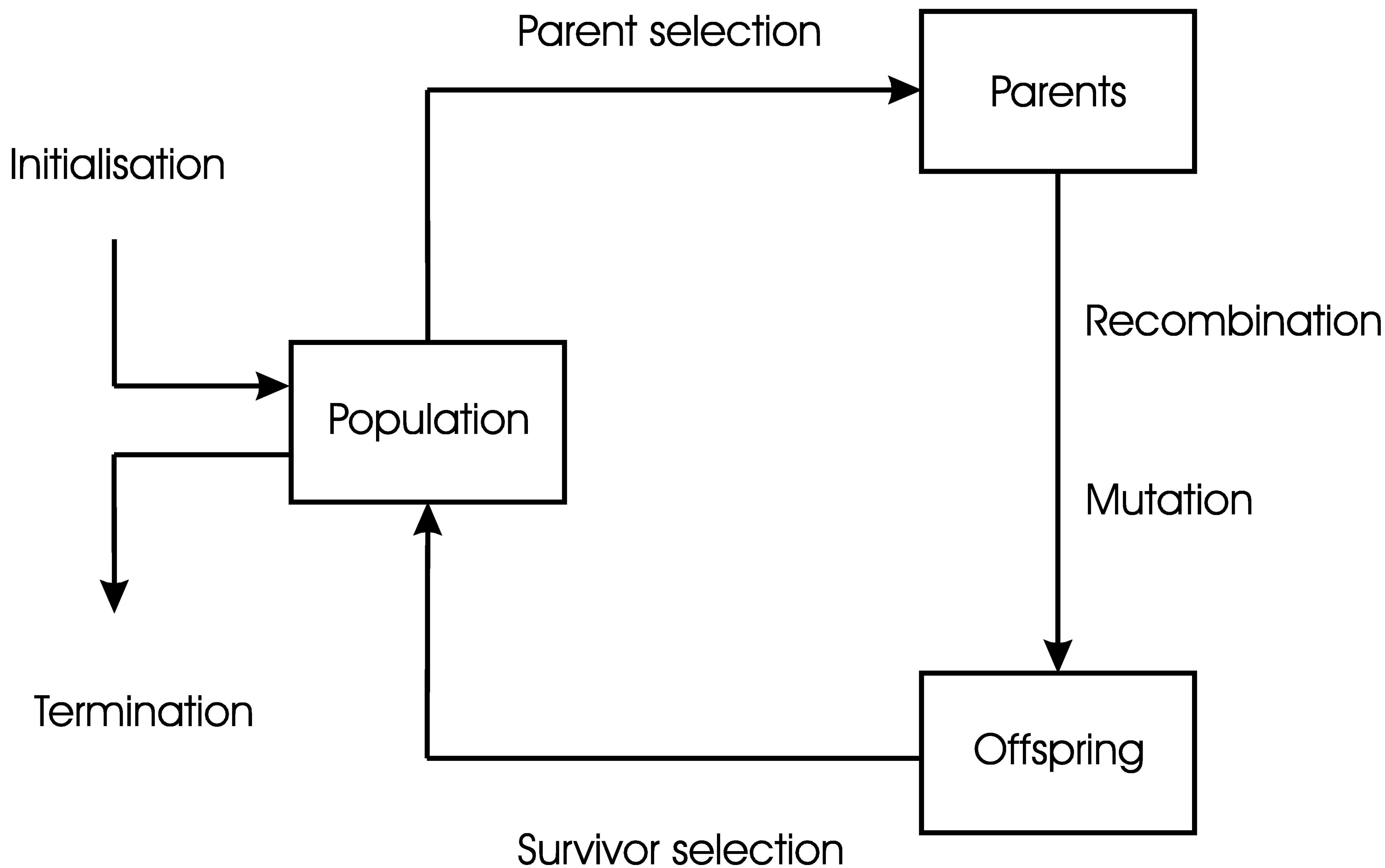
DEEP ARTIFICIAL NEURAL NETWORKS

- Artificial Neural Networks on steroids: with more layers
- E.g., a MLP with more than two hidden layers.

EVOLUTIONARY COMPUTATION



EVOLUTIONARY COMPUTATION



NEUROEVOLUTION

- Application of EC to optimise Artificial Neural Networks:
  - Topology;
  - Learning strategy;
  - Topology and learning strategy.

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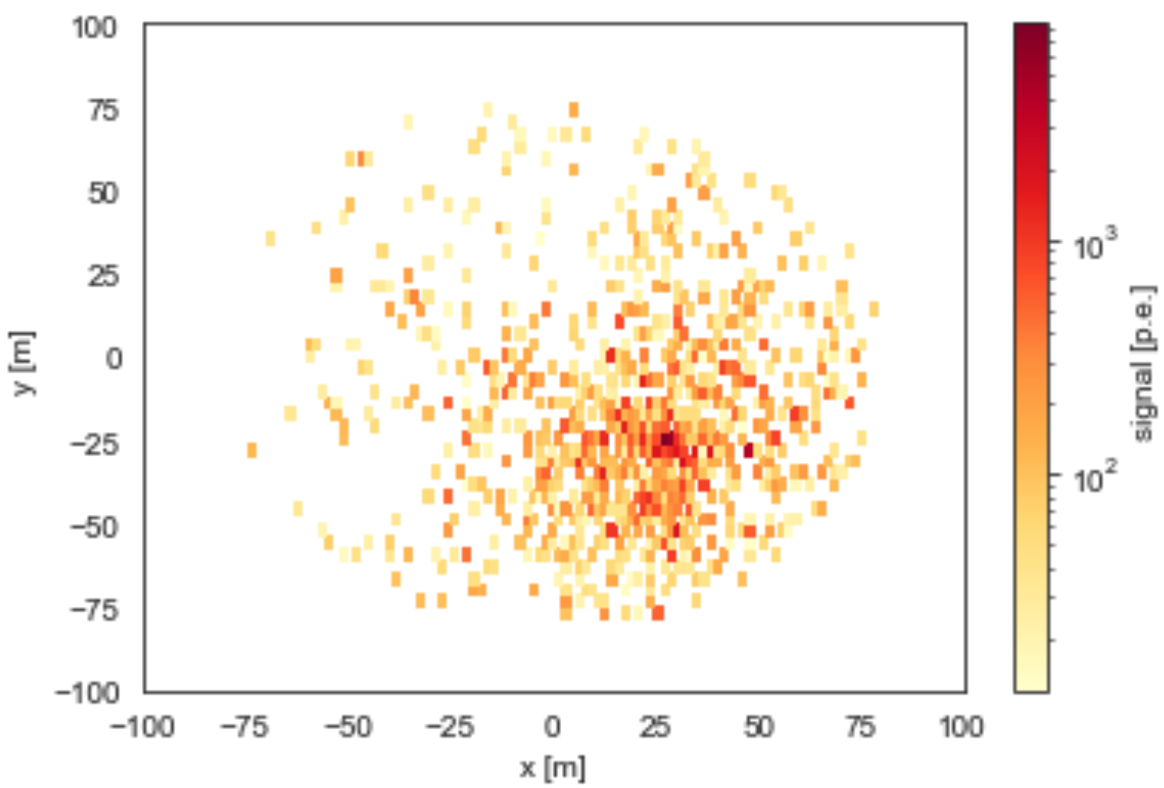
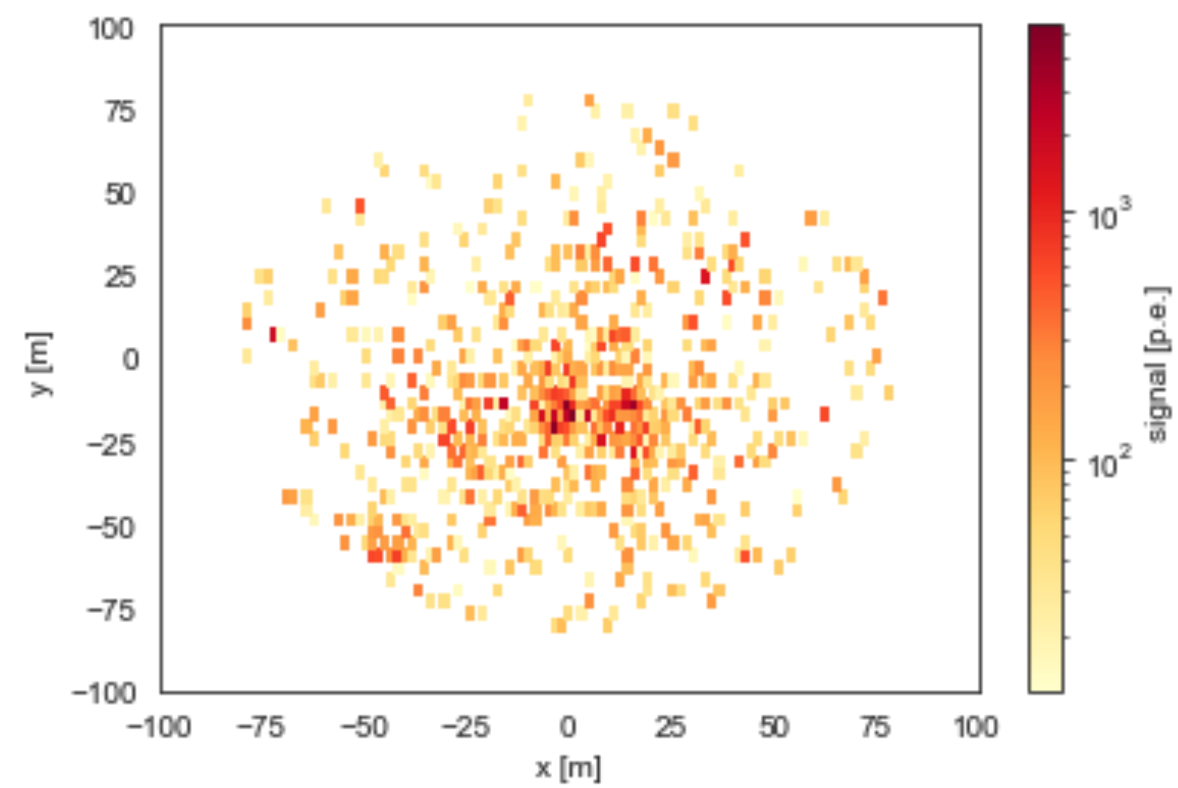
    - Topology;
    - Learning strategy;
    - Topology and learning strategy.
- The population encodes ANNs;
- The fitness measures the performance of each individual in the problem at hand.

GAMMA/HADRON SHOWERS GROUND IMPACT PATTERNS

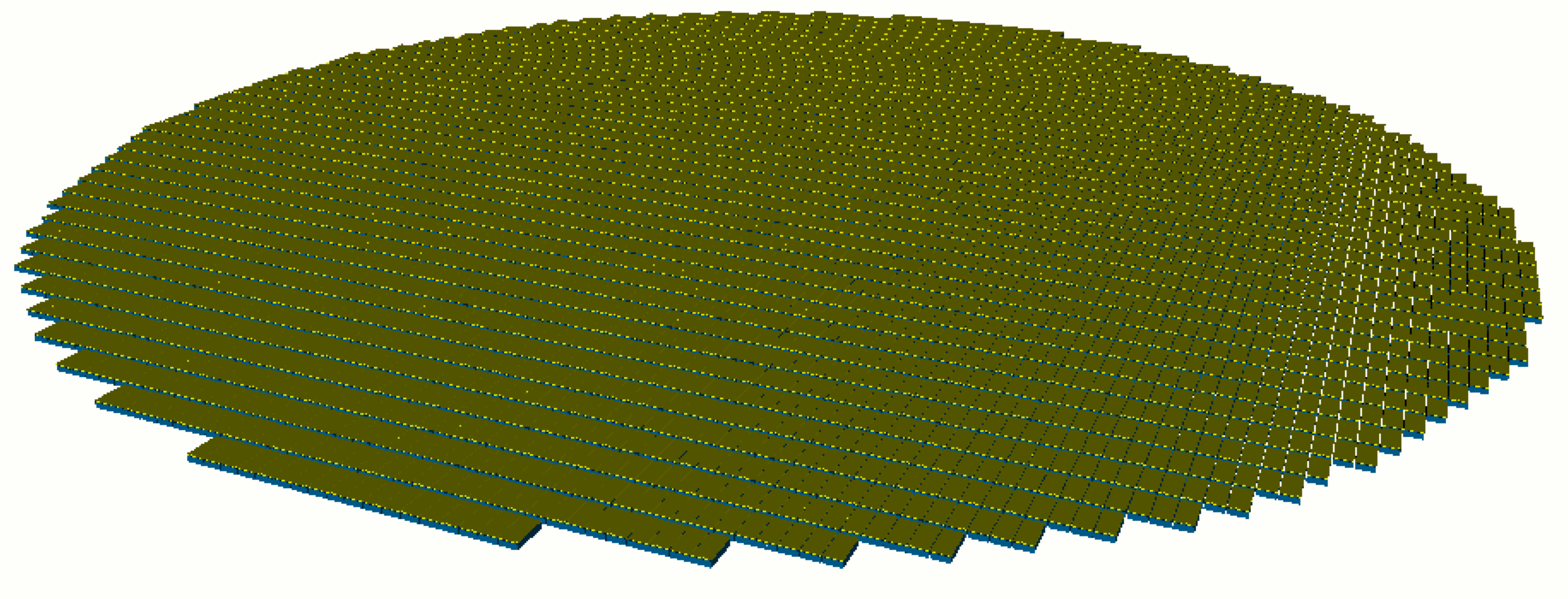
Gamma



Proton

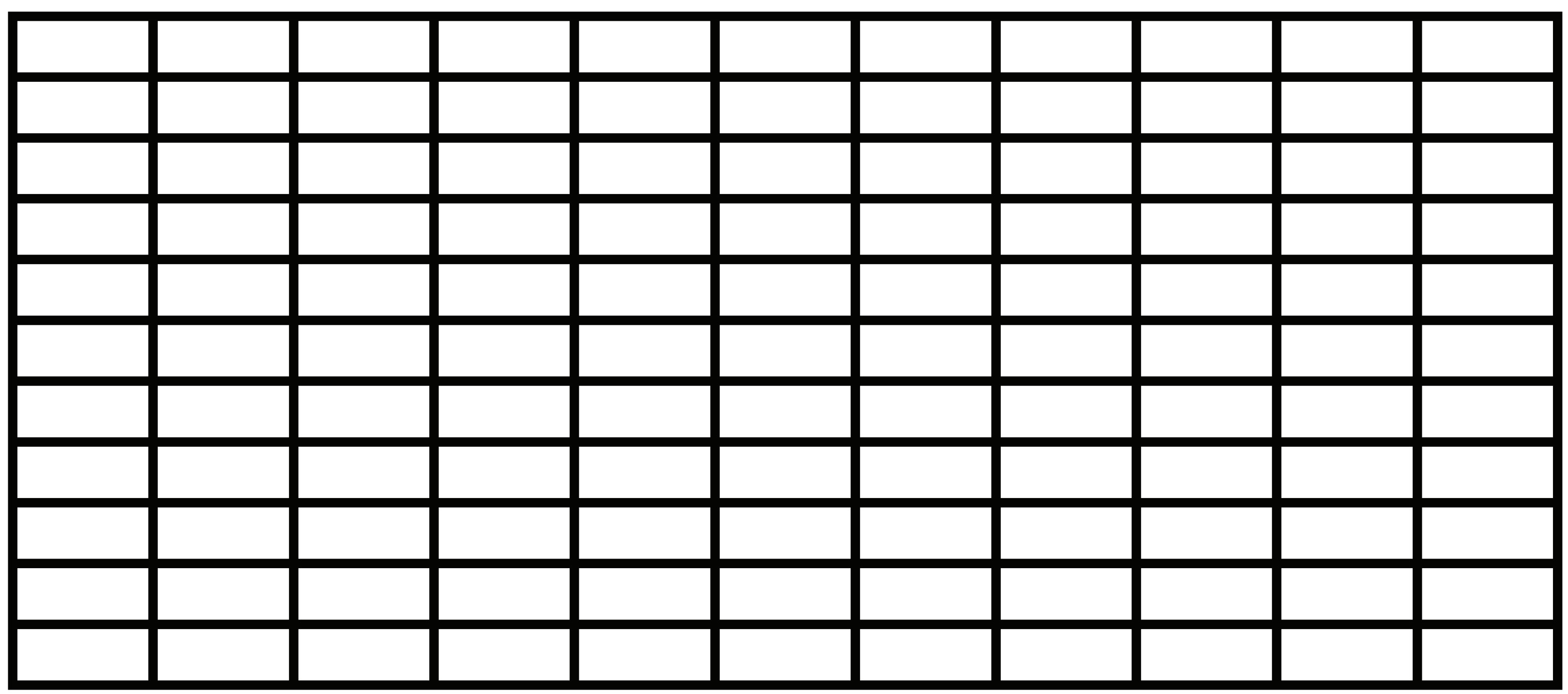


DATA



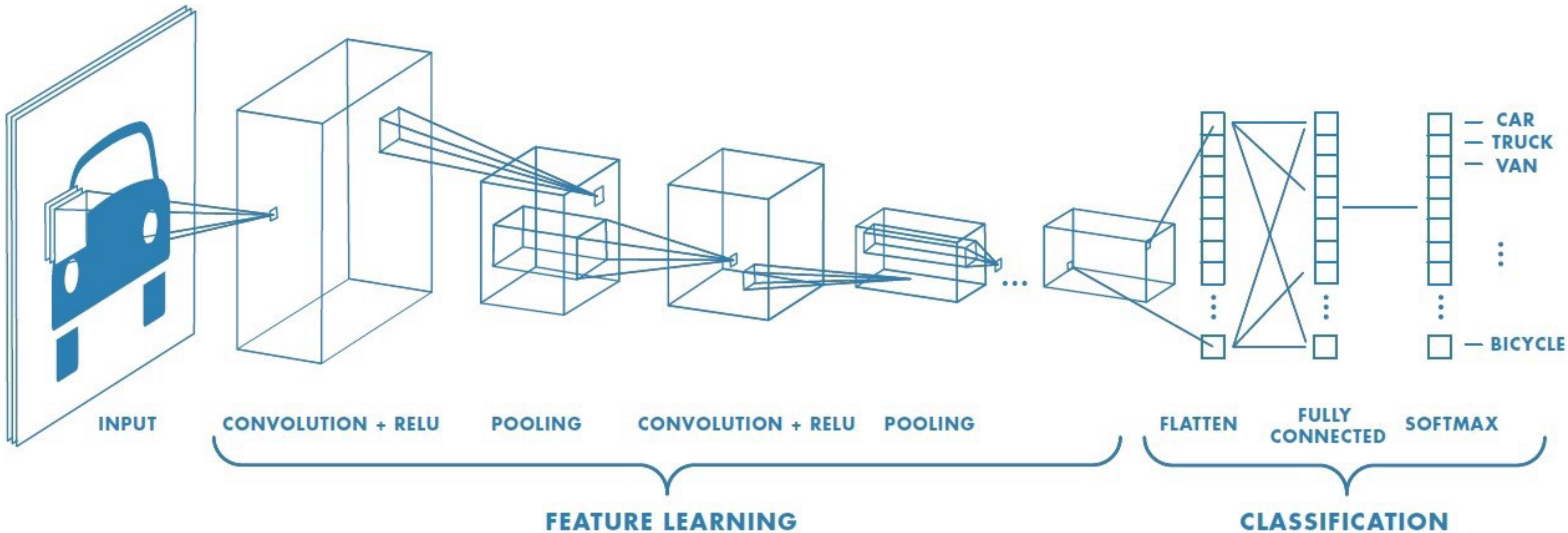
DATA

45

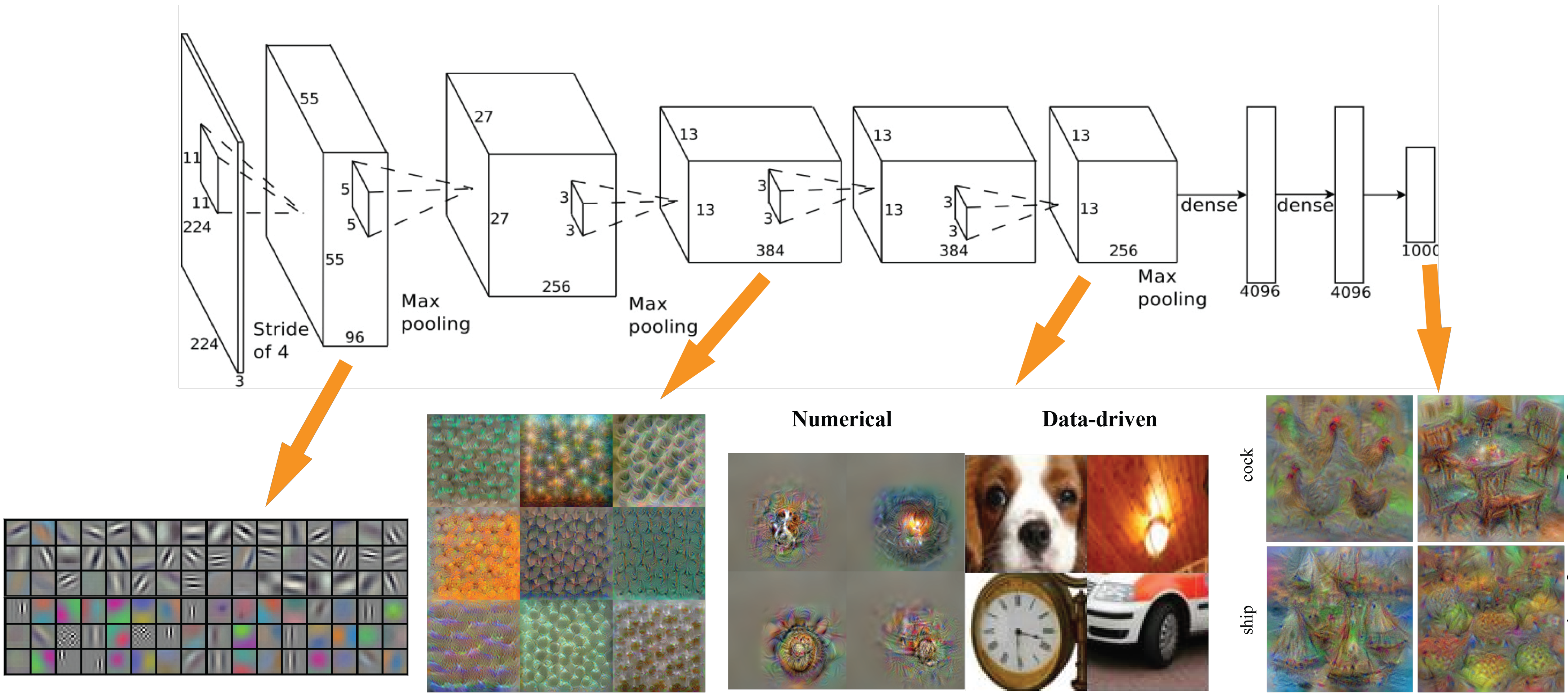


100

CONVOLUTIONAL NEURAL NETWORKS



CONVOLUTIONAL NEURAL NETWORKS



Conv 1: Edge+Blob

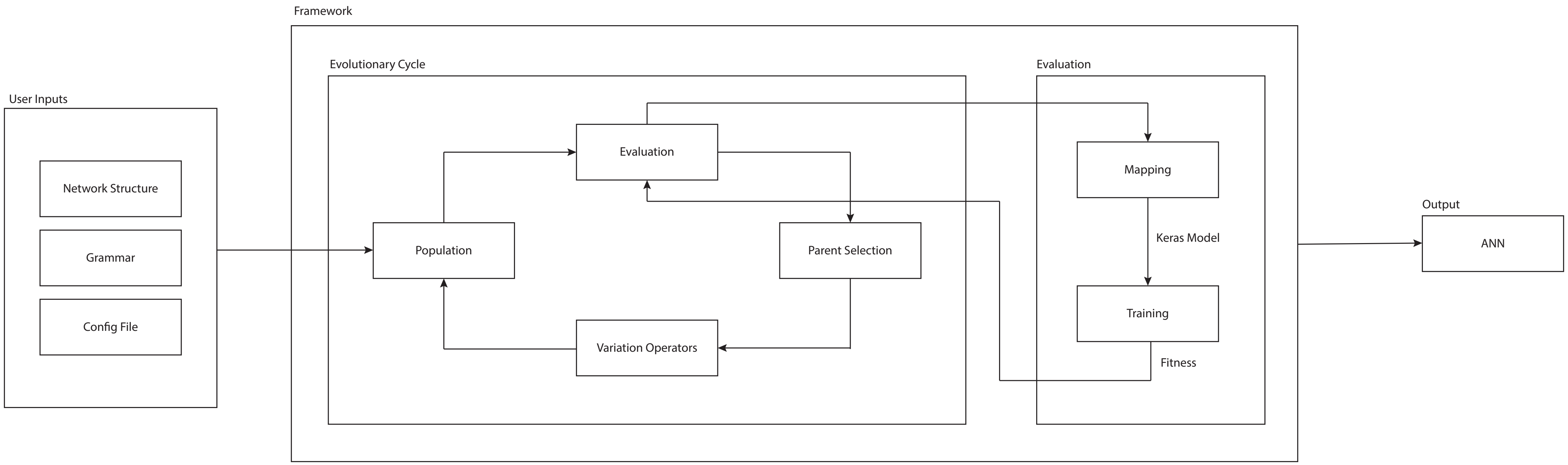
Conv 3: Texture

Conv 5: Object Parts

Fc8: Object Classes

EVOLUTION OF CONVOLUTIONAL NEURAL NETWORKS FOR GAMMA/HADRON DISCRIMINATION

DENSER



http://cdv.dei.uc.pt/denser

GRAMMAR EXAMPLE

<features>	::=	<convolution> | <convolution>	(1)
		| <pooling> | <pooling>	(2)
		| <dropout> | <batch-norm>	(3)
<convolution>	::=	layer:conv [num-filters,int,1,32,256]	(4)
		[filter-shape,int,1,2,5] [stride,int,1,1,3]	(5)
		<padding> <activation> <bias>	(6)
<batch-norm>	::=	layer:batch-norm	(7)
<pooling>	::=	<pool-type> [kernel-size,int,1,2,5]	(8)
		[stride,int,1,1,3] <padding>	(9)
<pool-type>	::=	layer:pool-avg | layer:pool-max	(10)
<padding>	::=	padding:same | padding:valid	(11)
<classification>	::=	<fully-connected> | <dropout>	(12)
<fully-connected>	::=	layer:fc <activation>	(13)
		[num-units,int,1,128,2048 <bias>	(14)
<dropout>	::=	layer:dropput [rate,float,1,0,0.7]	(15)
<activation>	::=	act:linear | act:relu | act:sigmoid	(16)
<bias>	::=	bias:True | bias:False	(17)
<softmax>	::=	layer:fc act:softmax num-units:2 bias:True	(18)
<learning>	::=	<bp> <stop> [batch_size,int,1,50,300]	(19)
		| <rmsprop> <stop> [batch_size,int,1,50,300]	(20)
		| <adam> <stop> [batch_size,int,1,50,300]	(21)
<bp>	::=	learning:gradient-descent [lr,float,1,0.0001,0.1]	(22)
		[momentum,float,1,0.68,0.99]	(23)
		[decay,float,1,0.000001,0.001] <nesterov>	(24)
<nesterov>	::=	nesterov:True | nesterov:False	(25)
<adam>	::=	learning:adam [lr,float,1,0.0001,0.1]	(26)
		[beta1,float,1,0.5,1] [beta2,float,1,0.5,1]	(27)
		[decay,float,1,0.000001,0.001]	(28)
<rmsprop>	::=	learning:rmsprop [lr,float,1,0.0001,0.1]	(29)
		[rho,float,1,0.5,1] [decay,float,1,0.000001,0.001]	(30)
<stop>	::=	[early_stop,int,1,5,20]	(31)

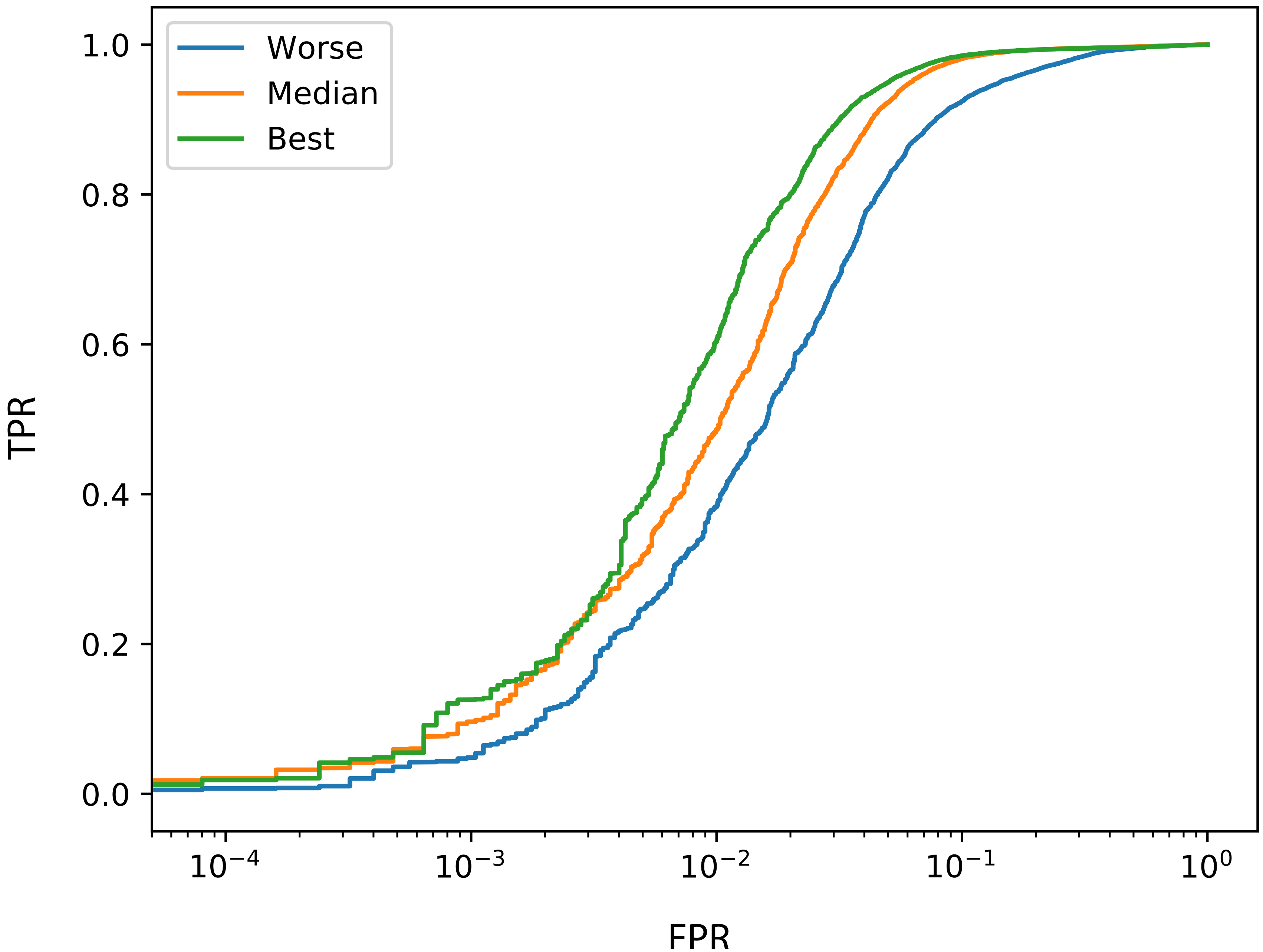
FITNESS

$$\text{fitness(ind)} = max\left(\frac{\text{TPR(x)}}{\sqrt{\text{FPR(x)}}}\right)$$

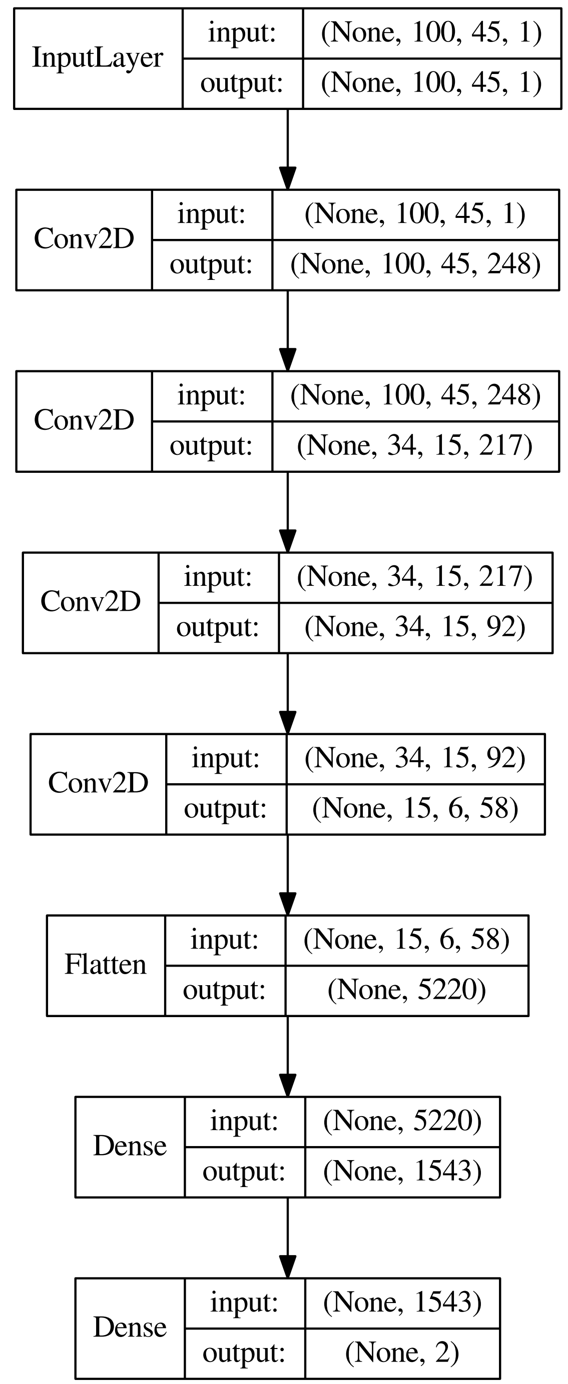
TPR - True Positive Rate = signal (gamma)

FPR - False Positive Rate = background (proton)

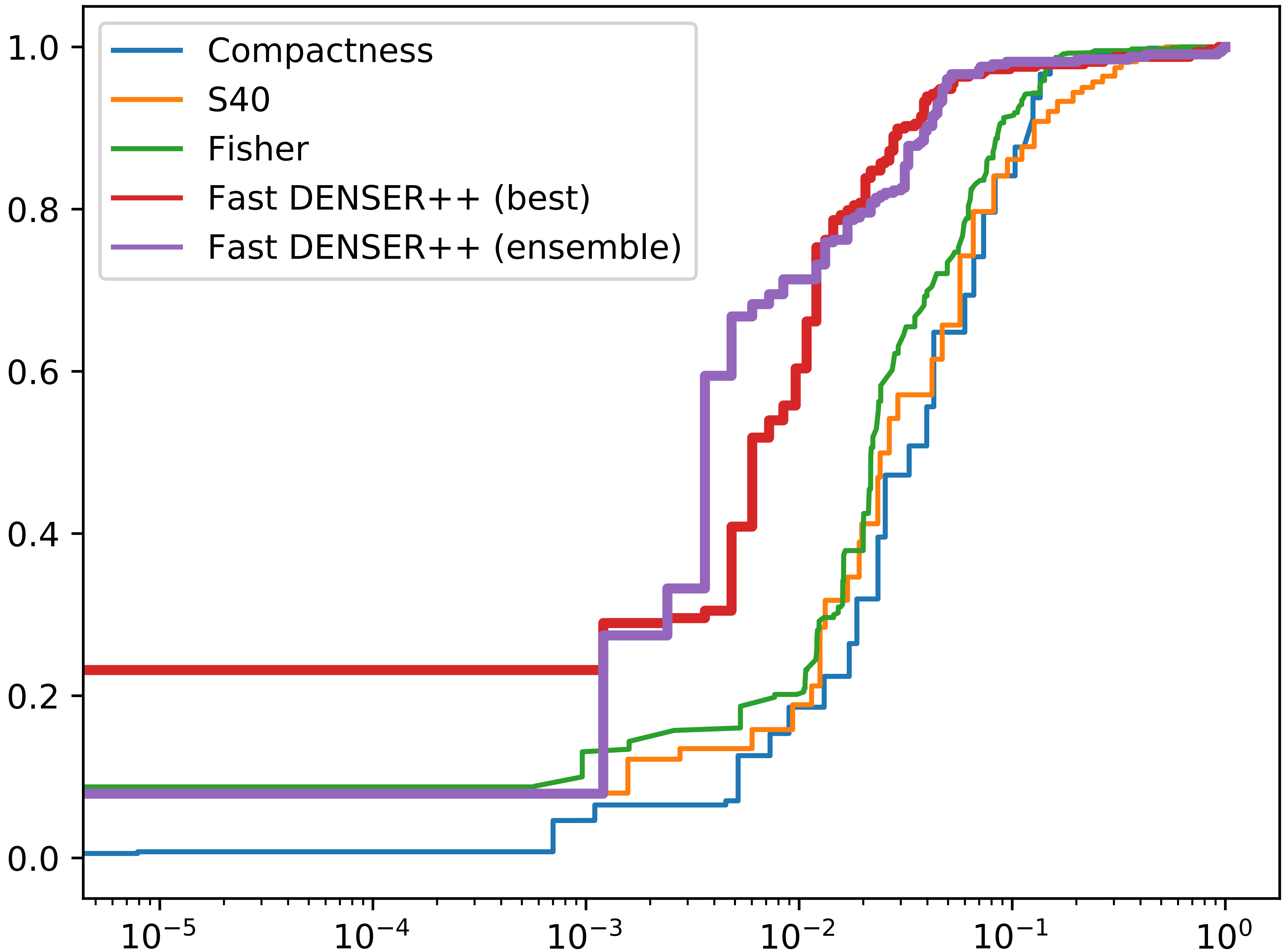
EVOLUTIONARY RESULTS ROC CURVES



FITTEST NETWORK TOPOLOGY



RESULTS


Compactness
S40
Fisher
Fast DENSER++ (best)
Fast DENSER++ (ensemble)
1.0
0.8
0.6
0.4
0.2
0.0
10^{-5}
10^{-4}
10^{-3}
10^{-2}
10^{-1}
10^{0}

RESULTS

- $E_{rec} \sim 1\,\mathrm{TeV}$
- Improvement by a factor of 2

ROAD AHEAD

- Physics:
  - Search networks for different primary energies;
  - Study the impact of the detector configuration (shape of the cells, and size of the grid).

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  - Search networks for different primary energies;
  - Study the impact of the detector configuration (shape of the cells, and size of the grid).
- Evolution:
  - Multi-objective to incorporate the size and number of trainable parameters of the networks.

PUBLICATIONS

- Assunção, F., Correia, J., Conceição, R., Pimenta, M., Tomé, B., Lourenço, N. and Machado, P., 2019. Automatic Design of Artificial Neural Networks for Gamma-Ray Detection. arXiv preprint arXiv:1905.03532.
(submitted to IEEE Access)

CISUC

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COMPUTATIONAL DESIGN & VISUALIZATION LAB.

UNIVERSIDADE D COIMBRA

FCT Fundação para a Ciência e a Tecnologia

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