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Modeling Nuclear Physics Data with Novel Artificial Intelligence Approaches

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- **Physics background**
  - state-of-the-art models;
  - problems;

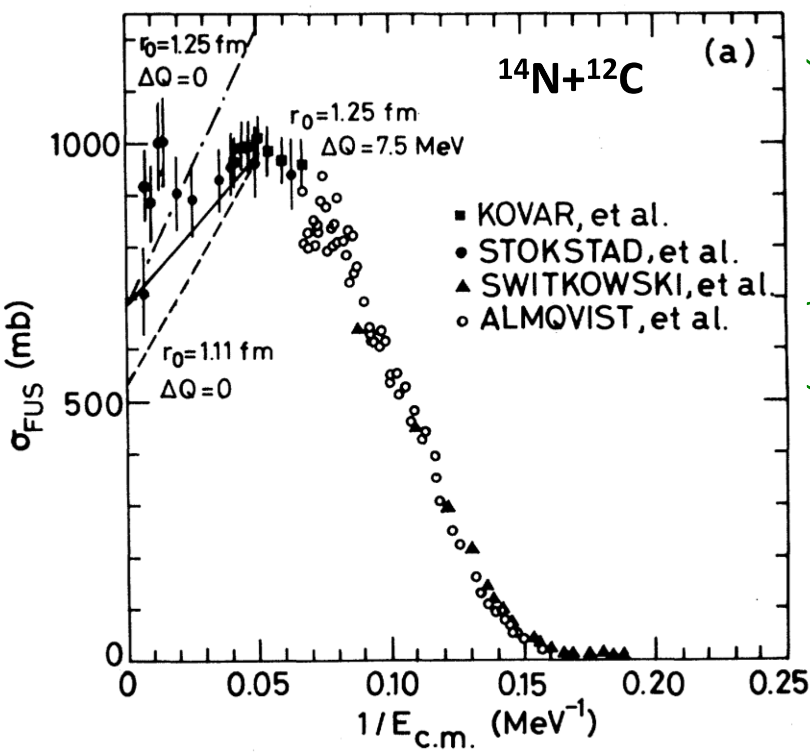
- **Dataset and approach**
  - Nuclear Reaction Video (NRV) Project;

- **Methods: Brain Project**
  - genetic programming: population, crossover, fitness;
  - parallel and distributed implementation;
  - neural networks;
  - data modeling;

- **Results**
  - comparisons with the literature;
  - conclusions and perspectives.

Heavy-ion fusion cross section at energies above-barrier

Different, complementary, experimental methods can be effectively used to estimate the yield of evaporation residues (gamma-ray analysis, time-of-flight and magnetic spectrometers, charged particle detection with telescope arrays) → heavy-ion fusion cross section from the Coulomb barrier to the onset of multi-fragmentation →
See e.g. *P. Frobrich, Phys. Rep. 116 (1984) 337*.



From S.M. Lee, T. Matsuse and A. Arima Phys. Rev. Lett. 45 (1980) 165

Models for the description of fusion cross section between heavy-ions.

- **Microscopical approaches**: Time-Dependent Hartree Fock (TDHF); Molecular dynamics;
- **Macroscopic models**: critical distance models, limitation to the compound nucleus model (empirical nuclear potentials from semi-classical considerations);
- **Empirical models**: starting from nuclear reaction theory and then optimizing to the experimental data.

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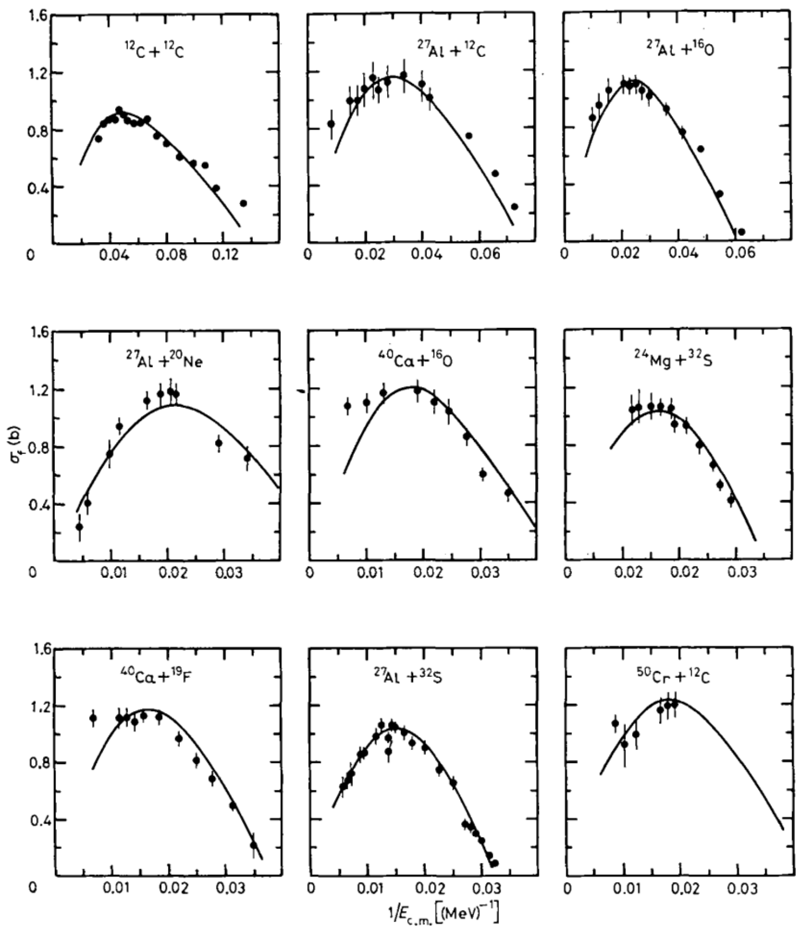
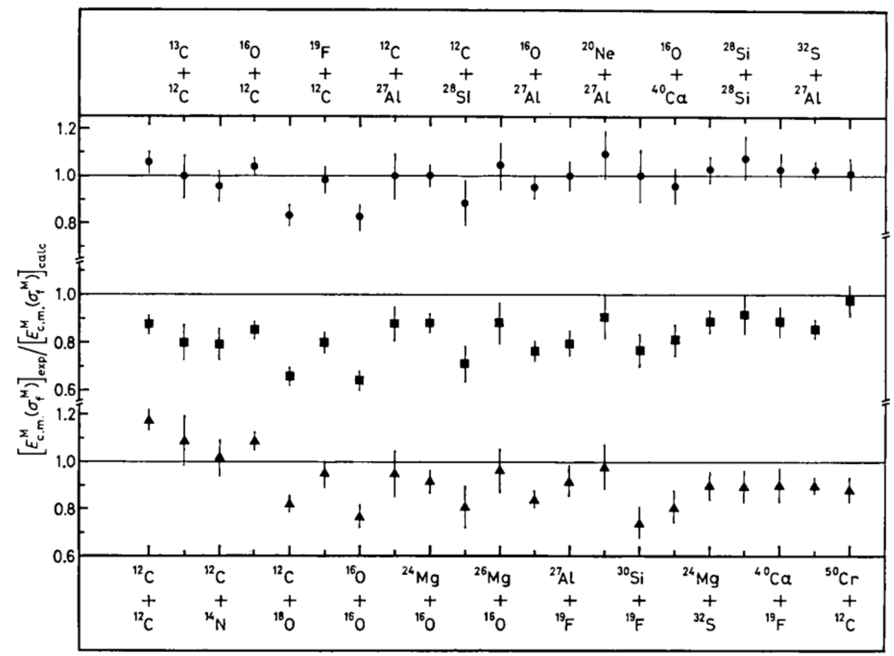
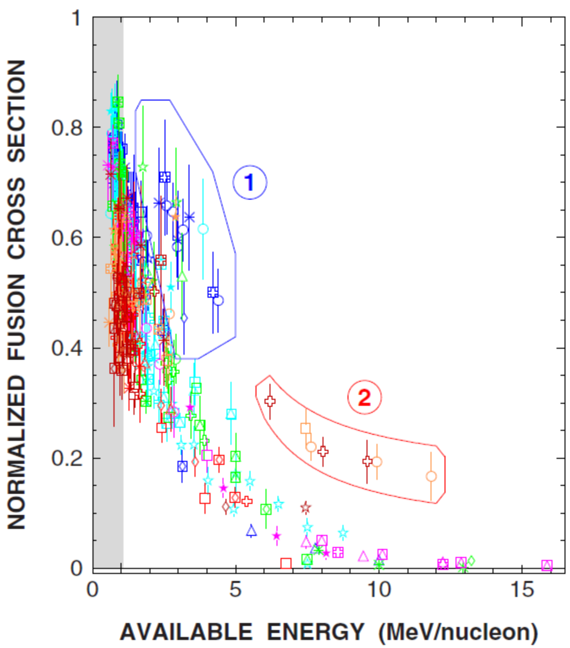
Previous data-driven (*phenomenological*) approaches, see e.g. *Porto F and Sambataro S 1984 Nuov. Cim.* ***83*** *339* → *good description of data around the maxima of the cross section* → *few datasets in Region III (high energies) and Region I (close to the Coulomb barrier).*

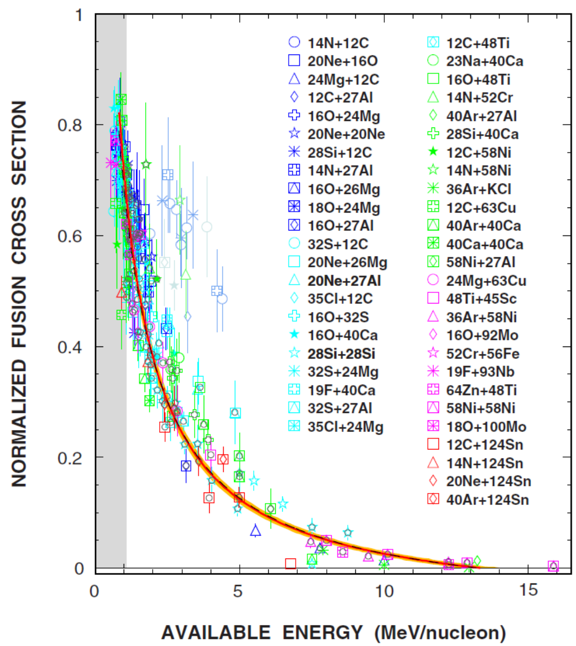




More recently → systematic study of Region III shows discrepancies for some of the systems → further investigation on both experiment and theory is required!

from P. Eudes et al., Phys. Rev. C 90 (2014) 034609.





Fusion cross section in Region III → disagreement with the prediction of state-of-the-art for some collision systems such as:

$^{28}Si+^{12}C$
$^{12}C+^{27}Al$
$^{48}Ti+^{40}Ca$
$^{16}O+^{40}Ca$
$^{14}N+^{12}C$
$^{14}N+^{14}N$
$^{14}N+^{27}Al$
$^{14}N+^{52}Cr$
$^{14}N+^{58}Ni$

State-of-the-art artificial intelligence approaches can serve to help describing the cross section between heavy-ions in a broad energy range!

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About 50 years of systematics (see e.g. *Nuclear Reactions Video: Karpov A et al., 2017 Nucl. Instrum. Meth. Phys. Res. A 859 112; Zagrebaev V et al.*, 1999 NRV web knowledge base on low-energy nuclear physics URL http://nrv.jinr.ru/ for a complete database) → Possibility to derive new **data-driven** models for the description of the fusion cross section between heavy-ions in Regions I-III.

Experimental data on HI fusion cross sections

Experimental data on
fusion
elastic scattering
evaporation residue

Specify fusion reaction (at least one item) Z_1 A_1 + Z_2 A_2 Search

or choose it from the list Go

(Quite recently we started to fill the database. We are very far from finish...)
Show all accumulated data

Ordered by **P-T combination,** compound nucleus, time of publication

(access to the source may be restricted by owner!)

^{3}He + ^{58}Ni	-> ^{61}Zn	(EvR)	E.F. Aguilera, E. Martinez-Quiroz, R. Chavez-Gonzalez et al.,	Physical Review, C **87** (2013) 14613
^{3}He + ^{167}Er	-> ^{170}Yb	(EvR)	S. Gil, R. Vandenbosch, A. Charlop et al.,	Physical Review, C **43** (1991) 701
^{3}He + ^{181}Ta	-> ^{184}Re	(FF)	F. D. Becchetti, K. H. Hicks, C. A. Fields et al.,	Physical Review, C **28** (1983) 1217
^{3}He + ^{197}Au	-> ^{200}Tl	(FF)	F. D. Becchetti, K. H. Hicks, C. A. Fields et al.,	Physical Review, C **28** (1983) 1217
^{3}He + ^{209}Bi	-> ^{212}At	(FF)	F. D. Becchetti, K. H. Hicks, C. A. Fields et al.,	Physical Review, C **28** (1983) 1217
^{3}He + ^{232}Th	-> ^{235}U	(FF)	F. D. Becchetti, K. H. Hicks, C. A. Fields et al.,	Physical Review, C **28** (1983) 1217
^{4}He + ^{40}Ca	-> ^{44}Ti	(EvR)	K.A. Eberhard, Ch. Appel, R. Bangert et al.,	Physical Review Letters, **43** (1979) 107
^{4}He + ^{44}Ca	-> ^{48}Ti	(EvR)	K.A. Eberhard, Ch. Appel, R. Bangert et al.,	Physical Review Letters, **43** (1979) 107
^{4}He + ^{63}Cu	-> ^{67}Ga	(EvR)	A. Navin, V. Tripathi, Y. Blumenfeld et al.,	Physical Review, C **70** (2004) 44601
^{4}He + ^{65}Cu	-> ^{69}Ga	(EvR)	A. Navin, V. Tripathi, Y. Blumenfeld et al.,	Physical Review, C **70** (2004) 44601
^{4}He + ^{64}Zn	-> ^{68}Ge	(X-rays from EC of EvR)	M Fisichella, V Scuderi, A Di Pietro et al.,	Journal of Physics, **282** (2011) 012014
^{4}He + ^{64}Zn	-> ^{68}Ge	(EvR)	V. Scuderi, A. Di Pietro, P. Figuera et al.,	Physical Review, C **84** (2011) 64604
^{4}He + ^{64}Zn	-> ^{68}Ge	(EvR)	A. Di Pietro, P. Figuera, V. Scuderi et al.,	Physics of Atomic Nuclei, **69** (2006) 1366
^{4}He + ^{93}Nb	-> ^{97}Tc	(EvR)	C. S. Palshetkar, S. Santra, A Chatterjee, K. Ramachandran, Shital Tha,	Physical Review, C**82** (2010) 044608
^{4}He + ^{107}Ag	-> ^{111}In	(FF)	A. Buttkewitz, H. H. Duhm, F. Goldenbaum et al.,	Physical Review, C **80** (2009) 37603
^{4}He + ^{139}La	-> ^{143}Pr	(FF)	A. Buttkewitz, H. H. Duhm, F. Goldenbaum et al.,	Physical Review, C **80** (2009) 37603
^{4}He + ^{154}Sm	-> ^{158}Gd	(EvR)	S. Gil, R. Vandenbosch, A. J. Lazzarini et al.,	Physical Review, C **31** (1985) 1752
^{4}He + ^{162}Dy	-> ^{166}Er	(EvR)	R. Broda, M. Ishihara, B. Herskind et al.,	Nuclear Physics, **A 248** (1975) 356
^{4}He + ^{165}Ho	-> ^{169}Tm	(FF)	A. Buttkewitz, H. H. Duhm, F. Goldenbaum et al.,	Physical Review, C **80** (2009) 37603
^{4}He + ^{166}Er	-> ^{170}Yb	(EvR)	S. Gil, R. Vandenbosch, A. Charlop et al.,	Physical Review, C **43** (1991) 701
^{4}He + ^{188}Os	-> ^{192}Pt	(EvR)	A. Navin, V. Tripathi, Y. Blumenfeld et al.,	Physical Review, C **70** (2004) 44601
^{4}He + ^{192}Os	-> ^{196}Pt	(EvR)	A. Navin, V. Tripathi, Y. Blumenfeld et al.,	Physical Review, C **70** (2004) 44601
^{4}He + ^{197}Au	-> ^{201}Tl	(FF)	D. L. Uhl, T. L. McDaniel, J. W. Cobble,	Physical Review, C **4** (1971) 1357
^{4}He + ^{197}Au	-> ^{201}Tl	(FF)	J. Ralarosy, M. Debeauvais, G. Remy et al.,	Physical Review, C **8** (1973) 2372
^{4}He + ^{197}Au	-> ^{201}Tl	(FF)	J. Gindler, H. Munzel, J. Buschmann et al.,	Nuclear Physics, **A 145** (1970) 337
^{4}He + ^{197}Au	-> ^{201}Tl	(EvR)	H. E. Kurz, E. W. Jasper, K. Fischer et al.,	Nuclear Physics, **A 168** (1971) 129
^{4}He + ^{197}Au	-> ^{201}Tl	(FF)	A. Buttkewitz, H. H. Duhm, F. Goldenbaum et al.,	Physical Review, C **80** (2009) 37603
^{4}He + ^{197}Au	-> ^{201}Tl	(FF)	J.R. Huizenga, R. Chaudhry, R. Vandenbosch,	Physical Review, **126** (1962) 210
^{4}He + ^{203}Tl	-> ^{207}Bi	(FF)	J.R. Huizenga, R. Chaudhry, R. Vandenbosch,	Physical Review, **126** (1962) 210
^{4}He + ^{205}Tl	-> ^{209}Bi	(FF)	J.R. Huizenga, R. Chaudhry, R. Vandenbosch,	Physical Review, **126** (1962) 210
^{4}He + ^{206}Pb	-> ^{210}Po	(FF)	J.R. Huizenga, R. Chaudhry, R. Vandenbosch,	Physical Review, **126** (1962) 210
^{4}He + ^{207}Pb	-> ^{211}Po	(FF)	J. Ralarosy, M. Debeauvais, G. Remy et al.,	Physical Review, C **8** (1973) 2372
^{4}He + ^{208}Pb	-> ^{212}Po	(alpha-decay of EvR)	S.M. Lukyanov, Yu.E. Penionzhkevich, R.A. Astabatian et al.,	Physics Letters, **B 670** (2009) 321
^{4}He + ^{209}Bi	-> ^{213}At	(FF)	W. G. Meyer, V. E. Viola, Jr., R. G. Clark et al.,	Physical Review, C **20** (1979) 1716
^{4}He + ^{209}Bi	-> ^{213}At	(FF)	D. L. Uhl, T. L. McDaniel, J. W. Cobble,	Physical Review, C **4** (1971) 1357
^{4}He + ^{209}Bi	-> ^{213}At	(FF)	J. Ralarosy, M. Debeauvais, G. Remy et al.,	Physical Review, C **8** (1973) 2372
^{4}He + ^{209}Bi	-> ^{213}At	(FF)	Yu.E. Penionzhkevich, Yu.A. Muzychka, S.M. Lukyanov et al.,	European Physical Journal, **A 13** (2002) 123
^{4}He + ^{209}Bi	-> ^{213}At	(FF)	A.S. Fomichev, I. David, Z. Dlouhy et al.,	Zeitschrift fur Physik, **351** (1995) 129
^{4}He + ^{209}Bi	-> ^{213}At	(FF)	J. Gindler, H. Munzel, J. Buschmann et al.,	Nuclear Physics, **A 145** (1970) 337
^{4}He + ^{209}Bi	-> ^{213}At	(FF)	J.R. Huizenga, R. Chaudhry, R. Vandenbosch,	Physical Review, **126** (1962) 210
^{4}He + ^{232}Th	-> ^{236}U	(FF)	J. Ralarosy, M. Debeauvais, G. Remy et al.,	Physical Review, C **8** (1973) 2372
^{4}He + ^{233}U	-> ^{237}Pu	(FF)	W. G. Meyer, V. E. Viola, Jr., R. G. Clark et al.,	Physical Review, C **20** (1979) 1716
^{4}He + ^{233}U	-> ^{237}Pu	(FF)	H. Freiesleben, J. R. Huizenga,	Nuclear Physics, **A 224** (1974) 503
^{4}He + ^{233}U	-> ^{237}Pu	(FF)	J. Gindler, H. Munzel, J. Buschmann et al.,	Nuclear Physics, **A 145** (1970) 337

Approach: *supervised learning* using ***symbolic regression*** algorithms.

Novelties:

- Deriving mathematical expressions to describe the data → support to theories and models attempting to predict the fusion cross section between heavy-ions;
- Comprehensive analysis of large amount of nuclear data → universal model for the description of the entire dataset;
- Advanced feature selection → allows to inspect the dependence on several variables (including nuclear structure variables).

Major challenges:

- The amplitude of the cross section varies even by several orders of magnitude with the energy;
- Experimental errors associated to each individual data point differ by several orders of magnitude for each data point;
- Resulting models must have physical boundaries and extrapolation capabilities.

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Dataset used for model derivation → about 4500 experimental data points.

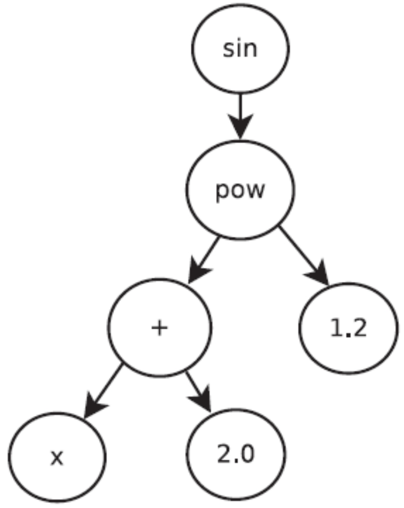
- Learning dataset: $Z_p Z_t < 250$ → light-to-medium mass nuclei.
- Testing dataset 1: $Z_p Z_t \geq 250$ → heavy systems (test the extrapolation towards heavy systems).
- Testing dataset 2: $Z_p Z_t < 250$ → some of the lighter systems.

Symbol	Description
$\frac{1}{E_{cm}}$	inverse of the collision center-of-mass energy (MeV)
Z_1	charge of the projectile
Z_2	charge of the target
A_1	mass of the projectile
A_2	mass of the target
J_1	spin of the projectile
J_2	spin of the target
π_1	parity of the projectile (1 for positive parity, −1 for negative parity)
π_2	parity of the target (1 for positive parity, −1 for negative parity)
μ_1	magnetic dipole momentum of the projectile (μ_N)
μ_2	magnetic dipole momentum of the target (μ_N)
$\langle r^2 \rangle_1$	rms charge radius of the projectile (fm)
$\langle r^2 \rangle_2$	rms charge radius of the target (fm)
Q-value	fusion Q-value (MeV)
S_α	α separation energy of the compound nucleus (MeV)
$S_{\alpha 1}$	α separation energy of the projectile
$S_{\alpha 2}$	α separation energy of the target
S_{n1}	one-neutron separation energy of the projectile
S_{n2}	one-neutron separation energy of the target
S_{p_1}	one-proton separation energy of the projectile
S_{p_2}	one-neutron separation energy of the target
S_{2n1}	two-neutron separation energy of the projectile
S_{2n2}	two-neutron separation energy of the target
S_{2p_2}	two-proton separation energy of the projectile
S_{2p_2}	two-neutron separation energy of the target

Brain Project – a neural-genetic tool for the formal modeling of data

Exploits a novel hybridization of genetic programming and artificial neural network → the task is that of symbolic regression. Genetic part → foresees the evolution of tree-like structures representing mathematical expressions → deals with the global search for the maximum of a suitable fitness function; Neural part → deals with the local search for the minimum of the error when the genetic part has identified a good maximum of the fitness function.

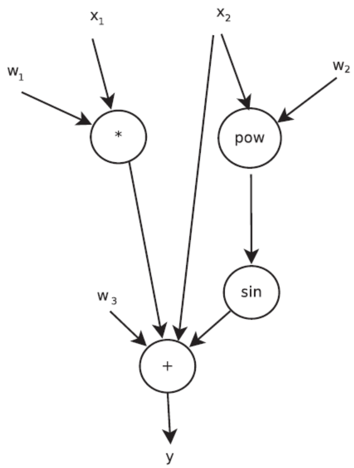
Russo M 2016 Swarm Evo. Comput. ***27*** *145*
Russo M 2020 Soft Comput. ***24*** *16885–16894*



Genetic evolution of tree-like structures representing mathematical expressions

+

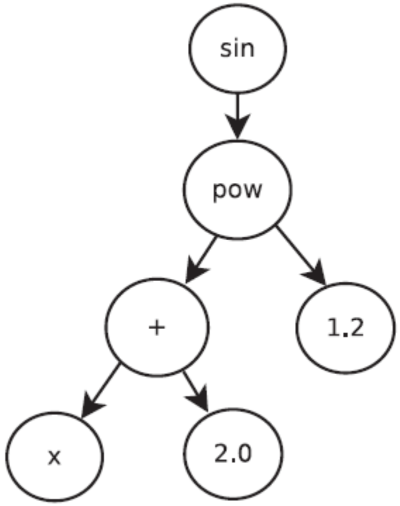
$$y = 2.5 * x_1 + \sin(x_2^{3.8}) + x_2 + 1.5$$



Artificial neural networks to optimize the constants (gradient descent technique)

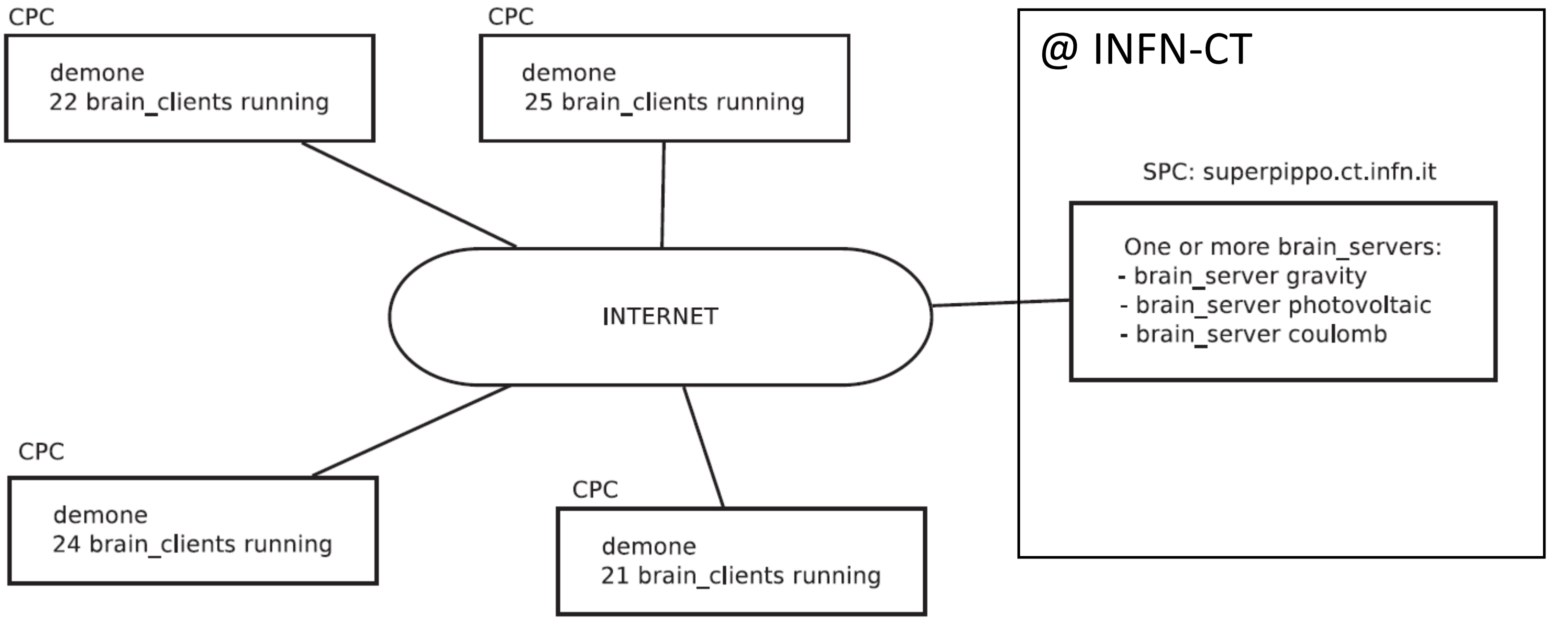
Brain Project: *genetic part* uses genetic → a programming technique that exploits concepts derived from the natural selection (Darwinian Theory of Evolution) to solve optimization problems.

See e.g. *John R. Koza, Genetic Programming – On the Programming of Computers by Means of Natural Selection, A Bradford Book – The MIT Press (Cambridge, Massachussets; London, England)*



1. Generate an initial population of random trees representing possible solutions to the SR problem being studied;
2. Evaluate each possible solution and assign it a fitness value f_{fit};
3. Create a new population of trees starting from the previous population using some evolutionary operators, e.g. copy, crossover, mutation, selection and heuristic operators;
4. Return to step two until the termination criterion is met.

Key «ingredients»:
- crossover;
- fitness;
- mutation;
- populations/migration.



from Russo M 2016 Swarm Evo. Comput. ***27*** *145*

Fitness function → is the function to maximize → it suitably contains the prediction error and a term related to the complexity of the model and/or feature costs.

to tune the desired trade-off between accuracy and complexity

$$f_{\text{fit}} = 100.0 * \frac{f_e u(f_e) + \alpha f_n u(f_n)}{1+\alpha} e^{f_e(1-u(f_e))} e^{f_n(1-u(f_n))}$$

$$f_e = \frac{e_{\max} - e}{e_{\max}}$$

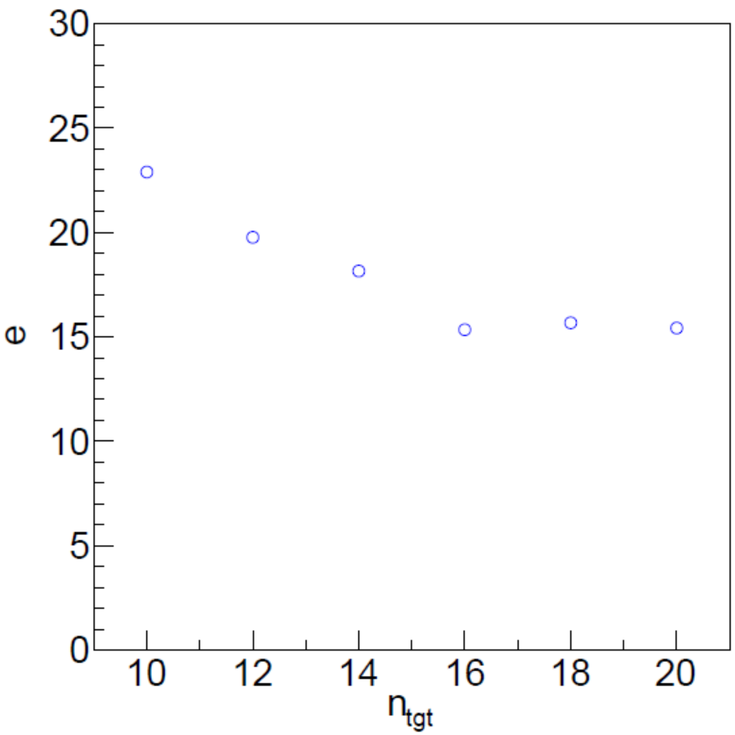
related to the accuracy of the model

$$e = 100 \sqrt{\sum_{o=1}^{N_o} \sum_{p=1}^{N_p} \frac{\left(w\_pat_p w\_out_o (y^d_{op} - y^c_{op})\right)^2}{N_o N p_{eq}}}$$

$$f_n = \frac{n_{\max} - n}{n_{\max} - 1}$$

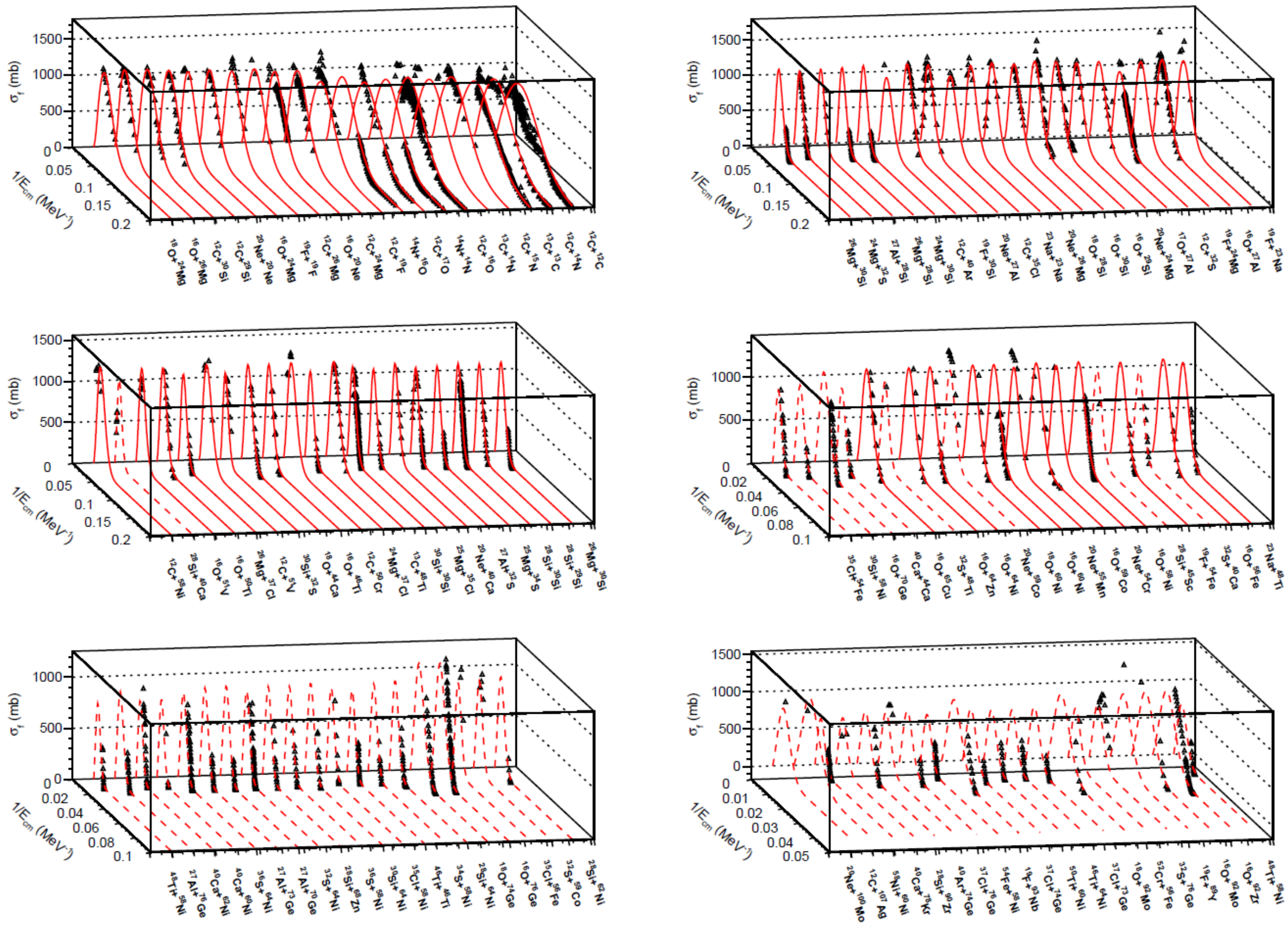
related to the complexity of the model

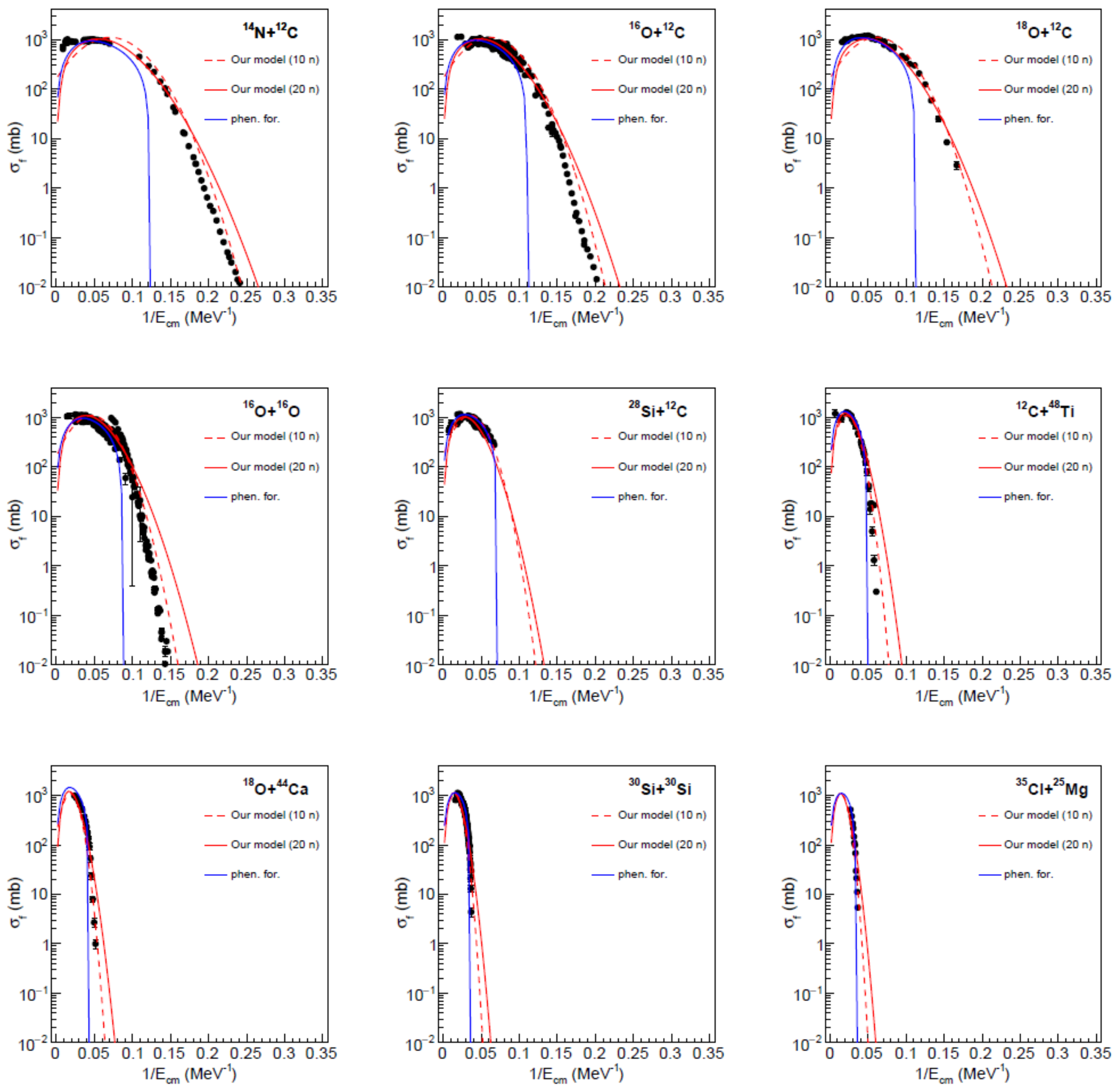
$f_{fit} = f_{fit} \cdot e^{\frac{n_{tgt}-n}{n_{tgt}}}$ → required to reach a predefined, target, number of nodes. Brain Project usually tries to optimize the error with a given number of nodes → interesting to more easily tune the complexity of the desired model.



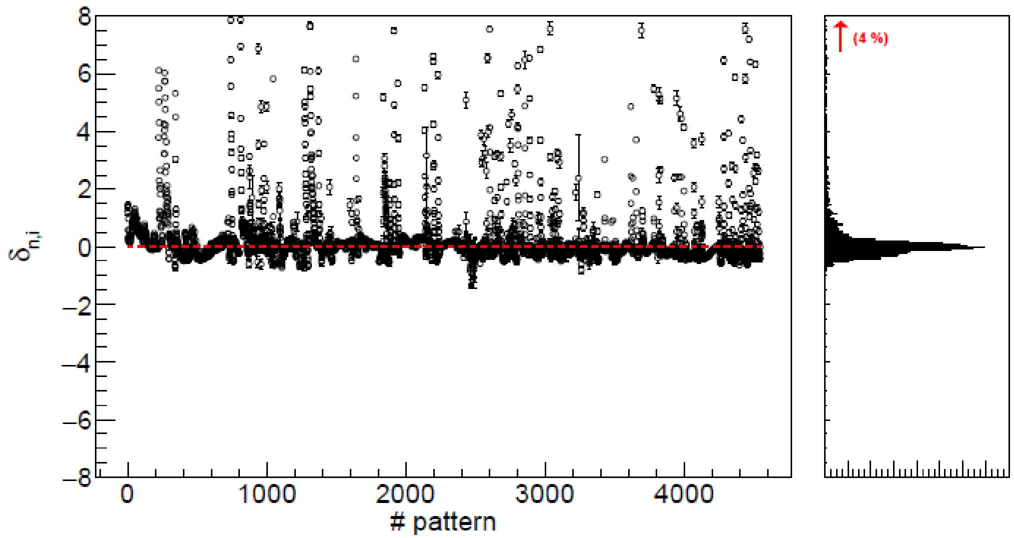
$$\sigma_{fus}^{(n_{tgt}=10)}(E_{cm}) = 1102 \cdot \exp\left[-\left(1.39 - 0.469 \cdot Z_2 \cdot Z_1 \cdot \frac{1}{E_{cm}}\right)^2\right]$$

$$\sigma_{fus}^{(n_{tgt}=20)}(E_{cm}) = 144.5 \cdot \mathrm{erf}\left\{\exp\left[-\left(0.129 \cdot \frac{1}{E_{cm}} \cdot Z_1 \cdot (A_2 + \ln(S_{2n2}))\right)^2\right]\right\} \cdot \\ \cdot e^{\mathrm{erf}\left(102.3 \cdot \frac{1}{E_{cm}}\right)} \cdot Z_1 \cdot \frac{1}{E_{cm}} \cdot A_2$$


σ_f (mb)
$1/E_{cm}$ (MeV^{-1})



$^{14}N+^{12}C$
$^{16}O+^{12}C$
$^{18}O+^{12}C$
$^{16}O+^{16}O$
$^{28}Si+^{12}C$
$^{12}C+^{48}Ti$
$^{18}O+^{44}Ca$
$^{30}Si+^{30}Si$
$^{35}Cl+^{25}Mg$
Our model (10 n)
Our model (20 n)
phen. for.
σ_f (mb)
$1/E_{cm}$ (MeV^{-1})



8
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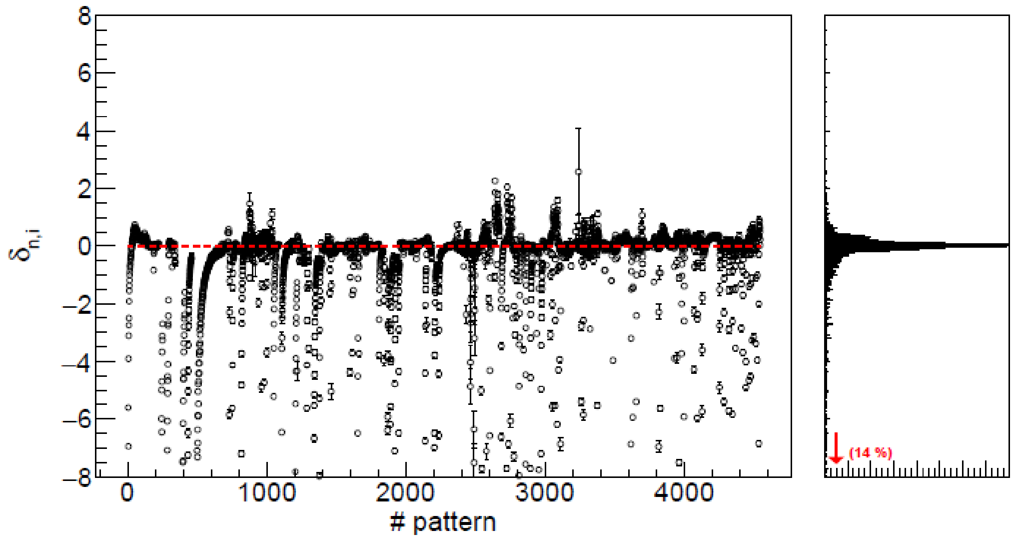

8
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pattern
(14 %)

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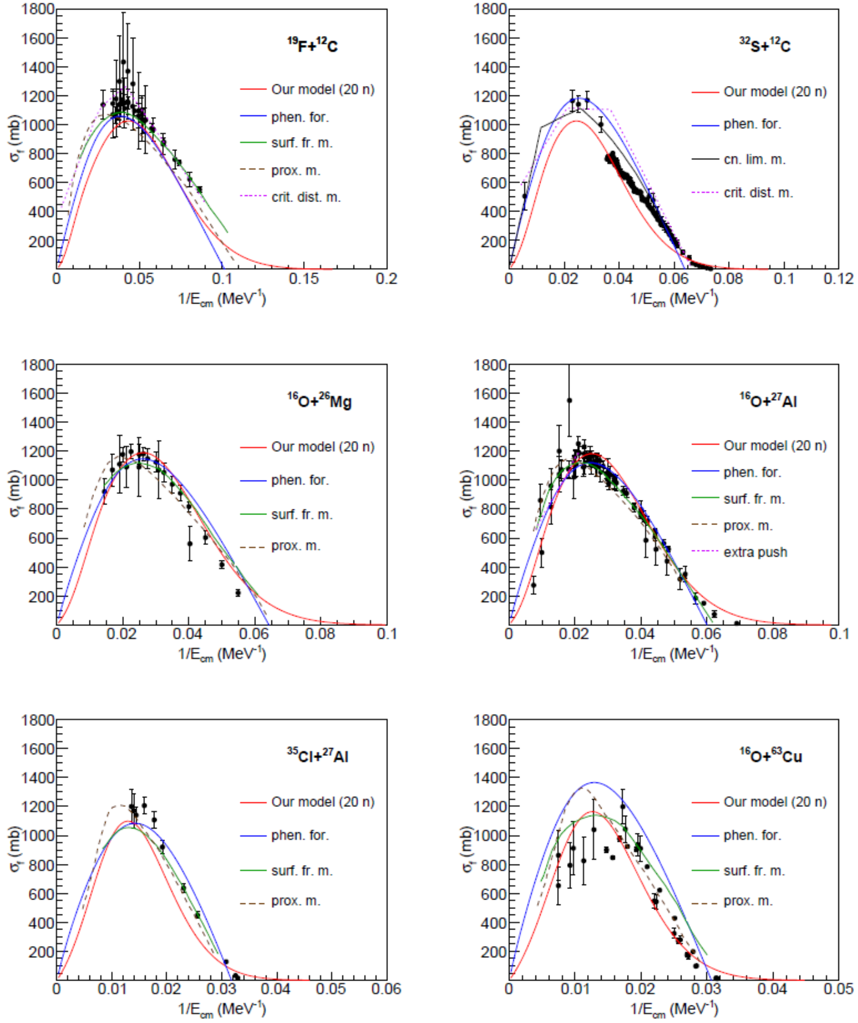
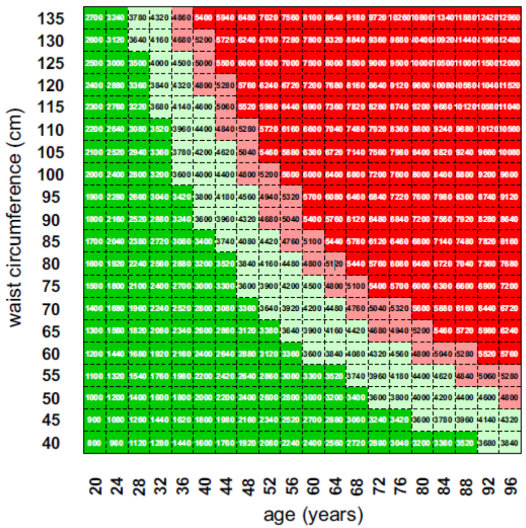
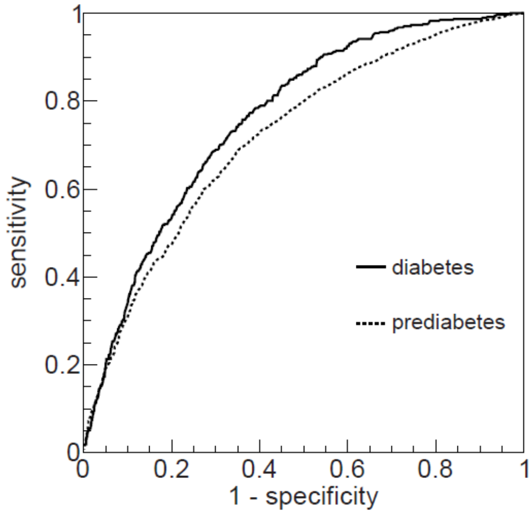


Daniele Dell'Aquila, Brunilde Gnoffo, Ivano Lombardo, Francesco Porto, Marco Russo, Modeling Heavy-Ion Fusion Cross Section Data via a Novel Artificial Intelligence Approach, arXiv:2203.10367, https://doi.org/10.48550/arXiv.2203.10367

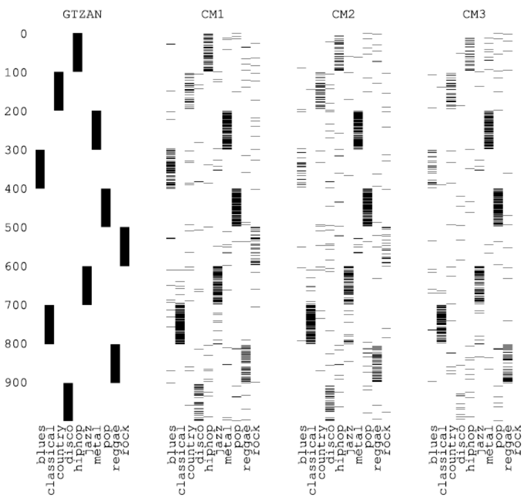
E. Buccheri, D. Dell'Aquila and M. Russo
Artificial intelligence in health data analysis: The Darwinian evolution theory suggests an extremely simple and zero-cost large-scale screening tool for prediabetes and type 2 diabetes, Diabetes Research and Clinical Practice **174** (2021) 108722.



E. Buccheri, D. Dell'Aquila and M. Russo
Stratified analysis of the age-related waist circumference cut-off model for the screening of dysglycemia at zero-cost, Obesity Medicine **31** (2022) 100398.



G. Campobello, D. Dell'Aquila and M. Russo, A. Segreto,
Neuro-genetic programming for multigenre classification of music content, Applied Soft Computing **94** (2020) 106488.



- Numerous datasets are curretly available in nuclear physics, taking advantage of several decades of sophisticated experimental investigations;
- NRV has collected fusion cross section data between heavy-ions → their overall description is still not completely understood by state-of-the-art models;
- Artificial intelligence techniques based on symbolic regression (which exploit genetic programming and artificial neural networks) can serve to effectively model even particularly complex datasets;
- Analytical formulation of the models → useful to spot funcitonal dependencies that can be exploited by theoretical models;
- Advanced feature selection → can serve to guide theoretical models towards the discovery of the dependence on key nuclear physics parameters;
- Many more datasets are yet to be modeled!