Statistical global modeling of β⁻-decay halflives systematics using Multilayer Feedforward Neural Networks and Support Vector Machines

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NUMBERS RULE THE UNIVERSE

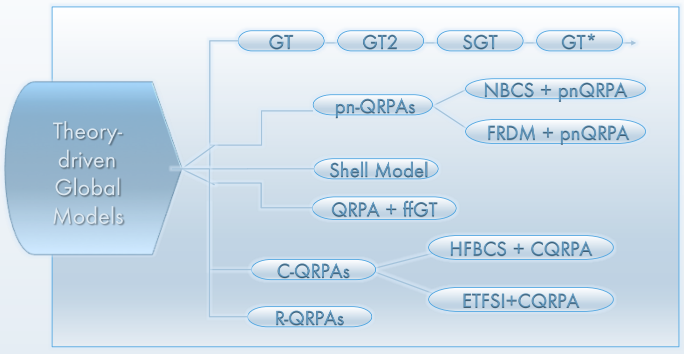
Abstract

Reliable estimates of β⁻-decay halflives for nuclei far from stability *are needed* by the experimental *exploration* of the nuclear landscape at existing and future radioactive ion-beam facilities and by ongoing major efforts in astrophysics towards understanding of supernova explosions, and the processes of nucleosynthesis, notably the **r-process**.

A constellation of *theory-driven*, macroscopic or semi-microscopic models has been developed during the last decades for generating β⁻*-decay* halflives. However, the predictive power of these **theory-thick** models is rather *limited.* The recent advances in **Artificial Intelligence** (AI) algorithms and in statistical learning theory, present on the other hand the opportunity to develop statistical, *data-driven* models of quantum systems exhibiting remarkable predictive power [1-3].

In this work, the beta-decay halflives problem is dealt as a nonlinear optimization problem, which is resolved in the statistical framework of machine learning. Continuing past similar approaches [3], we construct more sophisticated **Artificial Neural Network** (NN) and **Support Vector Regression Machine** (SVRM) [2] methods to global model the systematics of nuclei that decay 100% by the β⁻ mode in their ground states. The arising **large-scale** lifetime calculations generated by both types of machines are discussed and compared with the available experimental data [4], with previous results obtained with neural networks [3], as well as with estimates coming from traditional global nuclear models. Particular attention is paid on the estimates for exotic and halo nuclei and we focus to those nuclides that are involved in the **r-process nucleosynthesis**. It seems that both NNs and SVRVs demonstrate similar performance and that our statistical, ***theory-thin***, large-scale calculations can surpass the predictive performance of the best conventional global calculations.

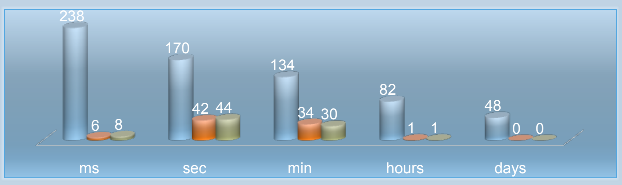
Main Theory-Thick Global Models



*Several models for determining β⁻ halflives have been proposed and applied over the years. One can mention the more phenomenological models based on **Gross Theory (GT)**, as well as models that employ the **pn Quasiparticle Random-Phase Approximation (pn-QRPA)** (in various versions) or **shell-model** calculations. The latest hybrid version of the RPA models developed by Möller and coworkers, combines the **pn-QRPA** model with the statistical **Gross Theory of ff-decay**. There are also some models in which the ground state of the parent nucleus is described by the **extended Thomas-Fermi plus Strutinsky integral method**, the **Hartree-Fock BCS**, or other density functional method (**DF**) and which use the **continuum QRPA (CQRPA)**. Recently relativistic pn-QRPA **(RQRPA)** models has been applied in the treatment of neutron-rich nuclei in the **N~50, N~82** and **Z~28** and **50** regions.*

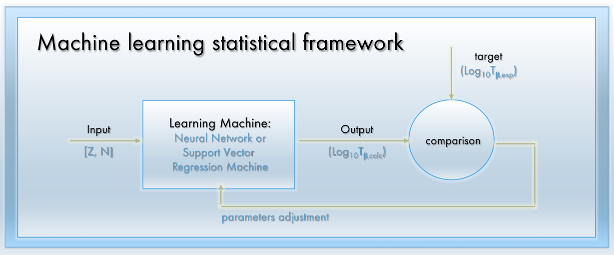
Data Sets For Theory-Thin Modeling

Database	NuSet-B		Half-life Range	Decay Mode
NuBase2003 [4]	**Cutoff**	10^6 s	0.15×10^{-2} s → ^{35}Na 0.20×10^{6}s → ^{247}Pu	100% β⁻



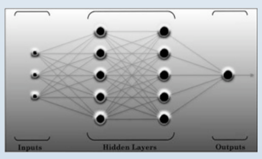
***NuSet-B** consists of **838** nuclides: **672 (~80%)** of them have been randomly chosen to train the machines (**learning set**), **83 (~10%)** to validate the learning procedure (**validation set**) and the remaining **83 (~10%)** to evaluate the accuracy of the prediction (**test set**).*

Machine Learning Procedure

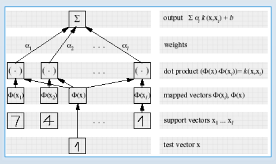


*The central idea of machine learning is that free parameters can be adjusted by minimizing the so-called "**cost function**" through a proper **training algorithm**, so that the machine responds to a desired behavior.*

NN & SVRM Learning Machines



Artificial Neural Network



Support Vector Regression

NNs are systems, consisting of interconnected dynamical units (neurons) that are typically arranged in a distinct layered topology.

SVRMs, which belong to the class of kernel methods, are systems based on the statistical VC theory.

Results

Comparison with the experimental data

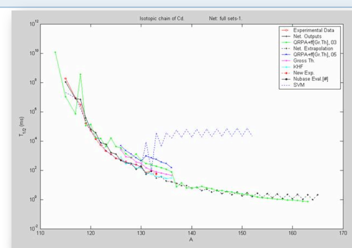
$$RMSE = \sqrt{\frac{1}{N}\sum_i \left(Log_{10} T_{\beta,calc}^{i} - Log_{10} T_{\beta,exp}^{i}\right)^2}$$

	Learning Set		Validation Set		Test Set	
Classes	**N**	**RMSE**	**N**	**RMSE**	**N**	**RMSE**
(a) Current NN Calculation						
EE	131	0.36	16	0.41	16	0.62
EO	179	0.38	22	0.44	22	0.39
OE	172	0.44	21	0.46	21	0.53
OO	190	0.52	24	0.42	24	0.33
Total	**672**	**0.41**	**83**	**0.44**	**83**	**0.51**
(b) Current SVR Calculation [2]						
EE	131	0.55	16	0.57	16	0.62
EO	179	0.41	22	0.42	22	0.51
OE	172	0.41	21	0.47	21	0.47
OO	190	0.52	24	0.40	24	0.52
Total	**672**	**0.47**	**83**	**0.46**	**83**	**0.53**
(c) Previous NN Calculation [3]						
Total	-	1.08	-	-	-	1.82

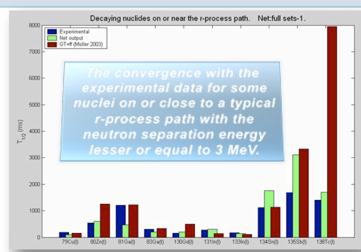
Fundamental Beta-Decay Question

To what extent do the nucleonic numbers determine the beta-decay halflife systematics of a nuclear system?

Figures - Comparisons



The subdivision of the sets in four parity classes can lead to spurious fluctuations. This favors the use of the NN model developed recently by means of the whole basis [1].



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