

Ab initio theory towards reliable neutrinoless double beta decay nuclear matrix elements

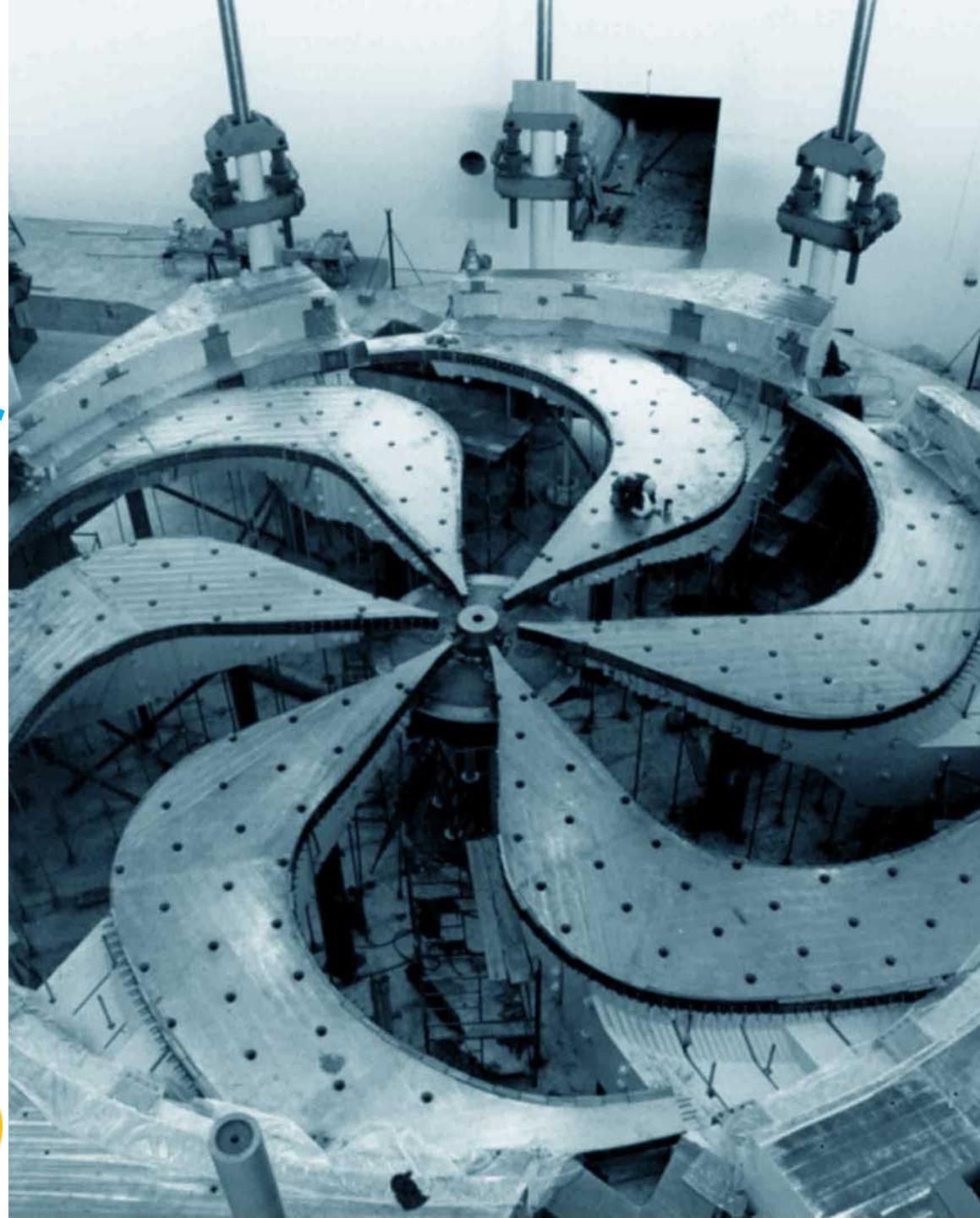
Antoine Belley

TRIUMF PAINT 2024

Collaborators: **Jack Pitcher**, Takayuki Miyagi,
Ragnar Stroberg, Jason Holt



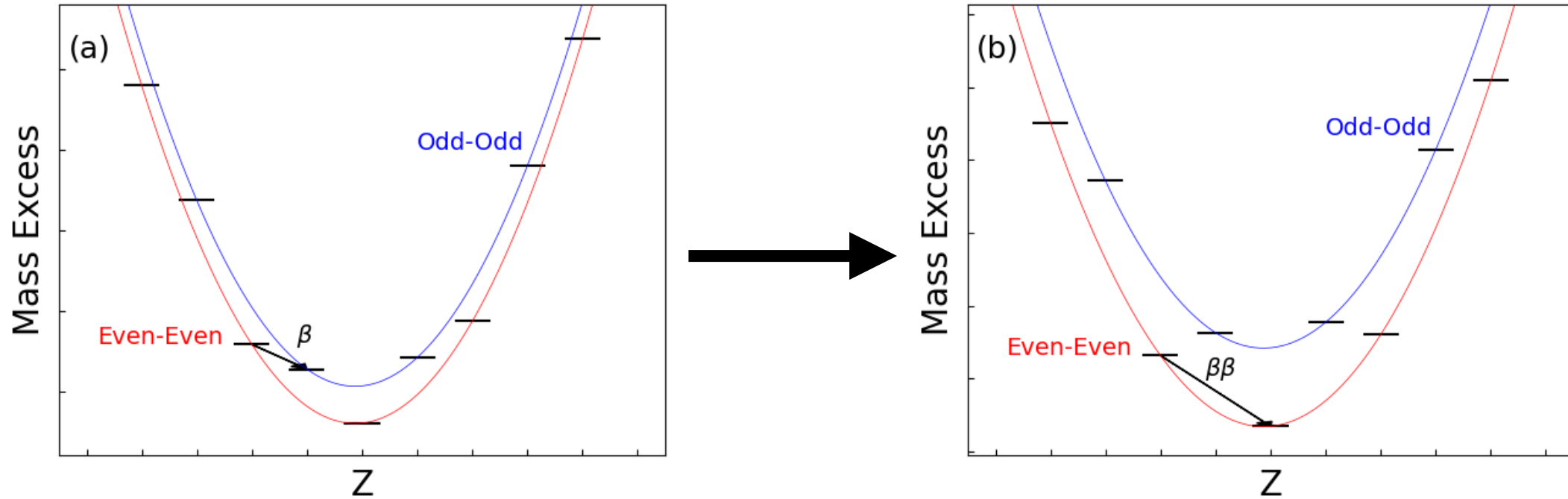
Arthur B. McDonald
Canadian Astroparticle Physics Research Institute



Second order weak process

2

Only possible when single beta decay is energetically forbidden (or strongly disadvantaged).



Decay	$2\nu\beta\beta$	$0\nu\beta\beta$
Diagram		
Half-life Formula	$[T_{1/2}^{2\nu}]^{-1} = G^{2\nu} M^{2\nu} ^2$	$[T_{1/2}^{0\nu}]^{-1} = G^{0\nu} M^{0\nu} ^2 \left(\frac{\langle m_{\beta\beta} \rangle}{m_e} \right)^2$
NME Formula	$M^{2\nu} \approx M_{GT}^{2\nu}$	$M^{0\nu} = M_{GT}^{0\nu} - \left(\frac{g_v}{g_a} \right)^2 M_F^{0\nu} + M_T^{0\nu} - 2g_{\nu\nu} M_{CT}^{0\nu}$
LNV	No	Yes!
Observed	Yes	No

*NME : Nuclear matrix elements

**LNV : Lepton number violation

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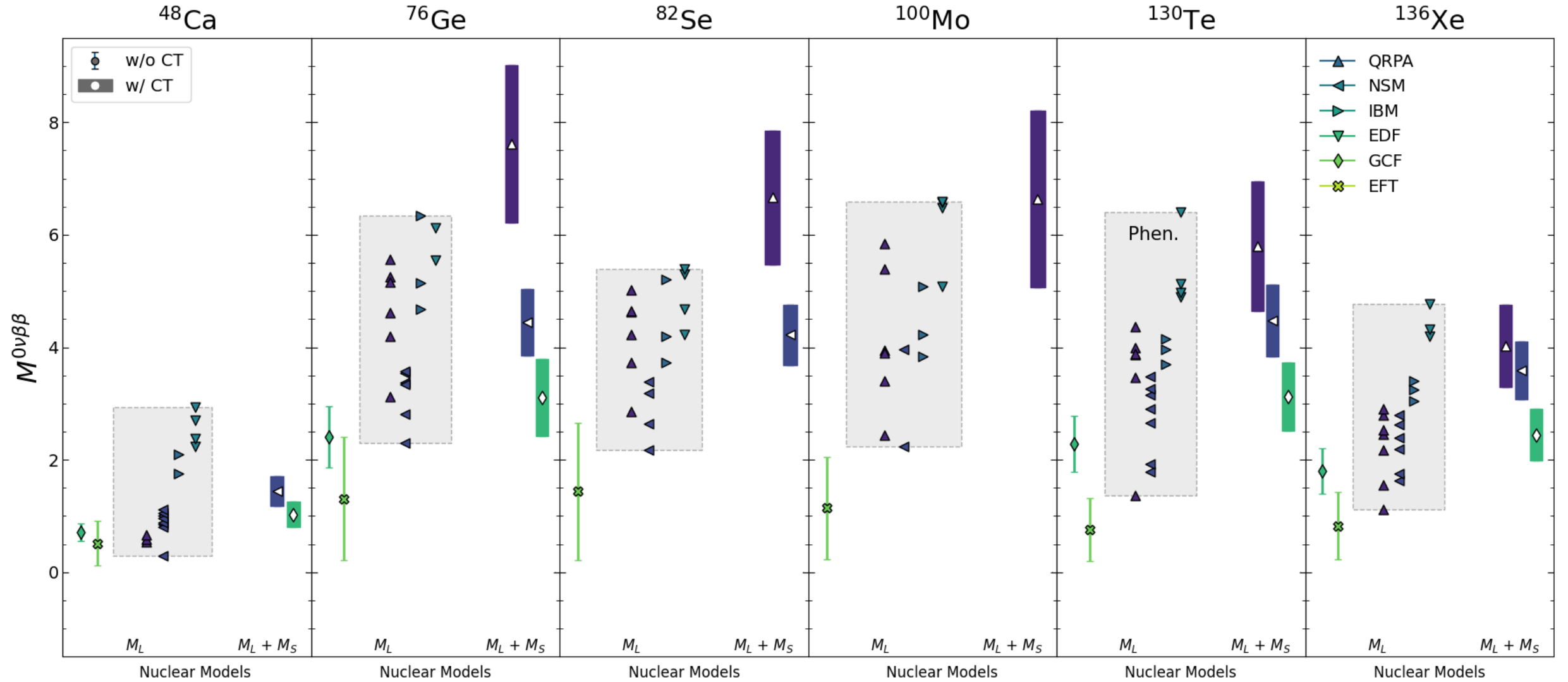
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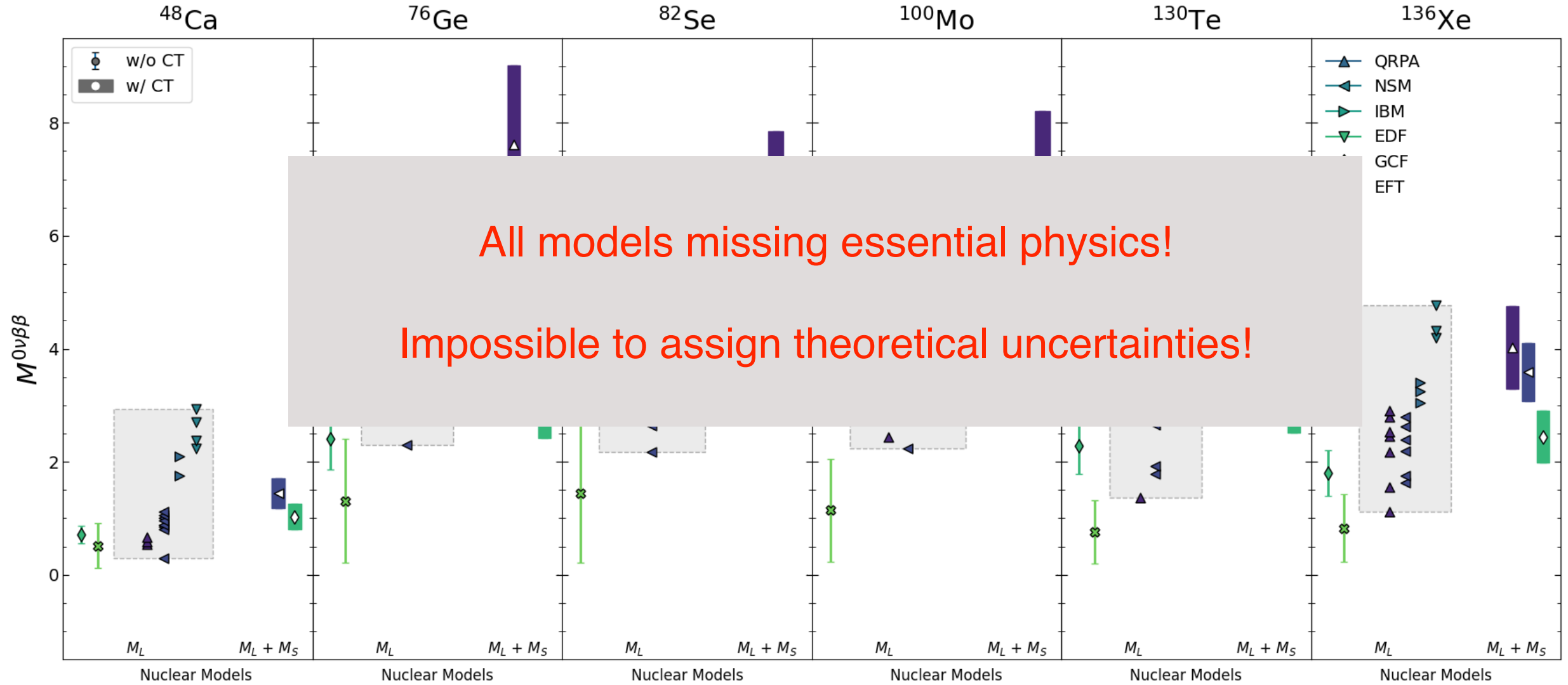
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Goal of the talk

Show how by using ab initio methods that rely on systematically improvable expansions, a coherent picture can be achieved for the NMEs.

List of challenges

- Obtaining a result:

$$NME = \langle \psi_f | O | \psi_i \rangle$$

- Obtaining a **reliable** result:

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 - Solving the nuclear many-body problem
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 - Uncertainty quantification

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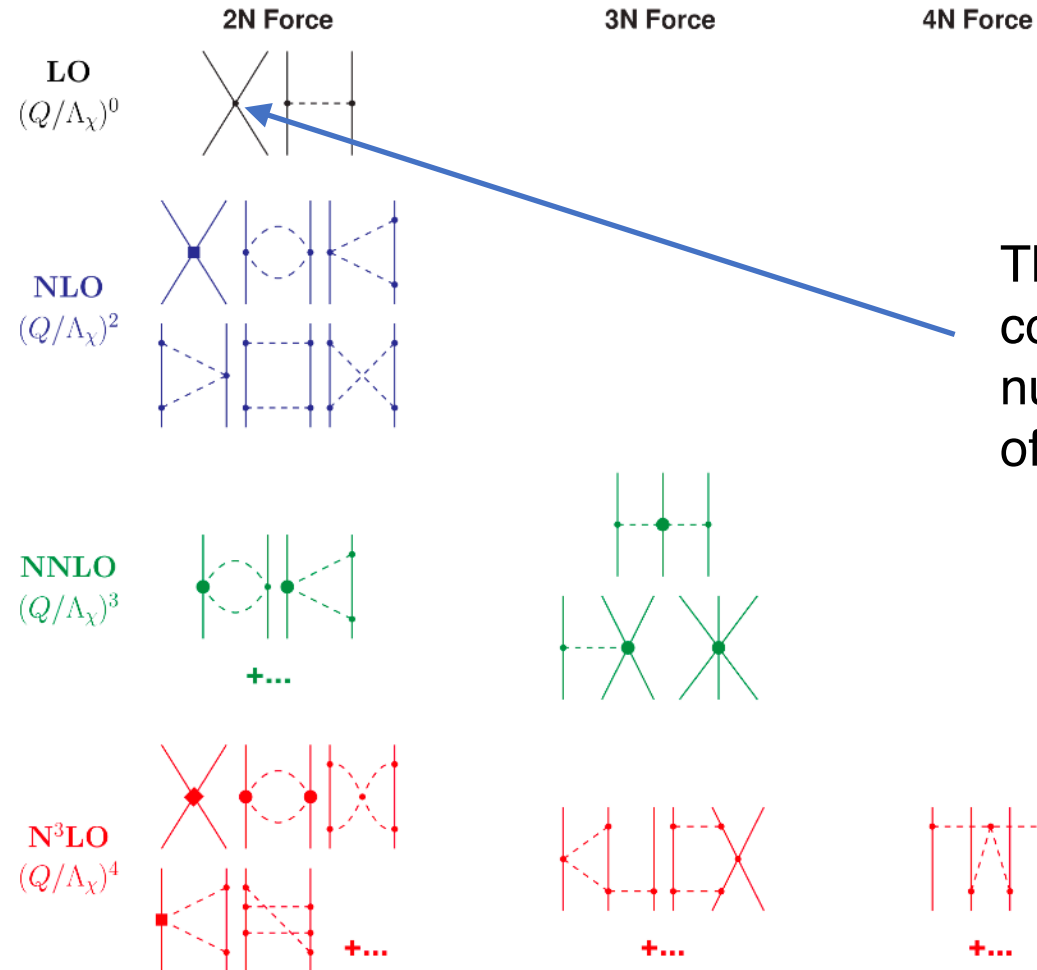
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- Deriving an expression for the nuclear potential (χ -EFT)
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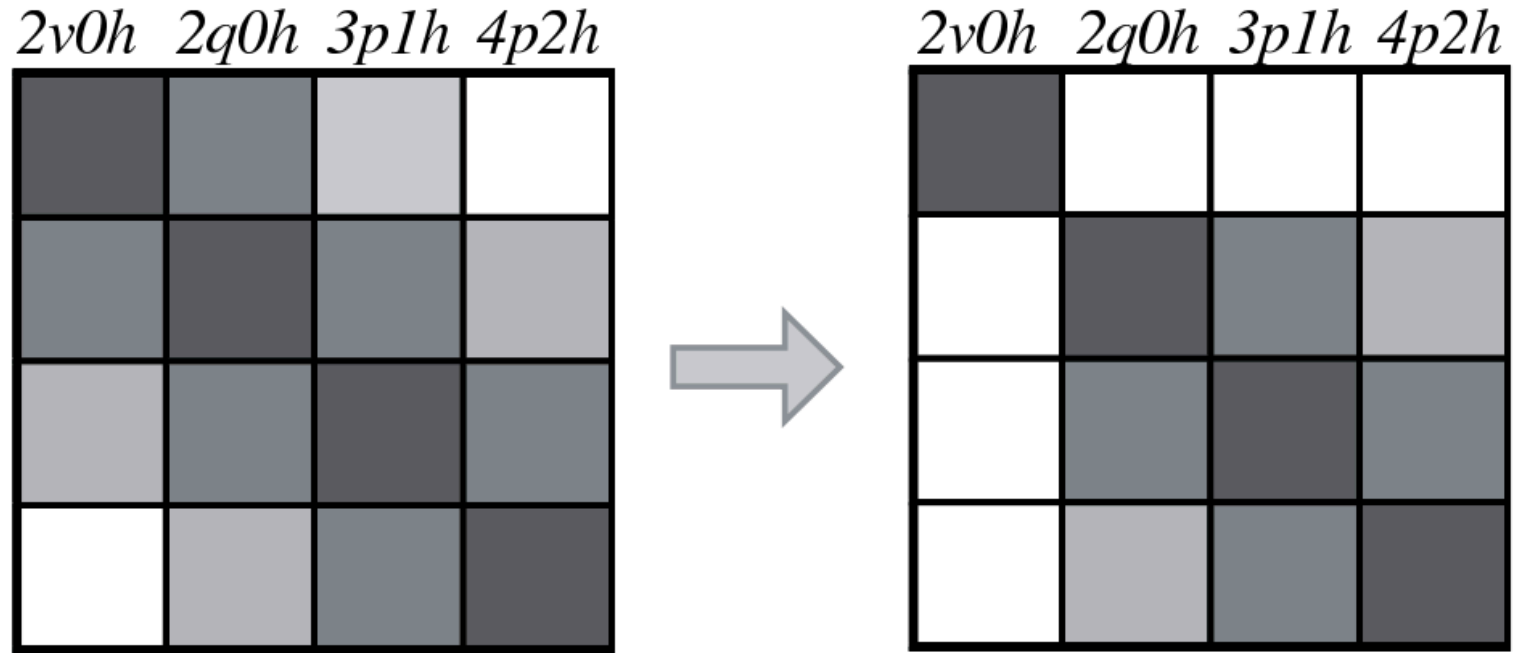
Expansion order by order of the nuclear forces

Reproduces symmetries of low-energy QCD using nucleons as fields and mesons as force carriers.



The different low energy coupling constants (LECs) are fitted to few nucleons data to absorb the effect of higher order terms

Valence-Space In Medium Similarity Renormalization Group



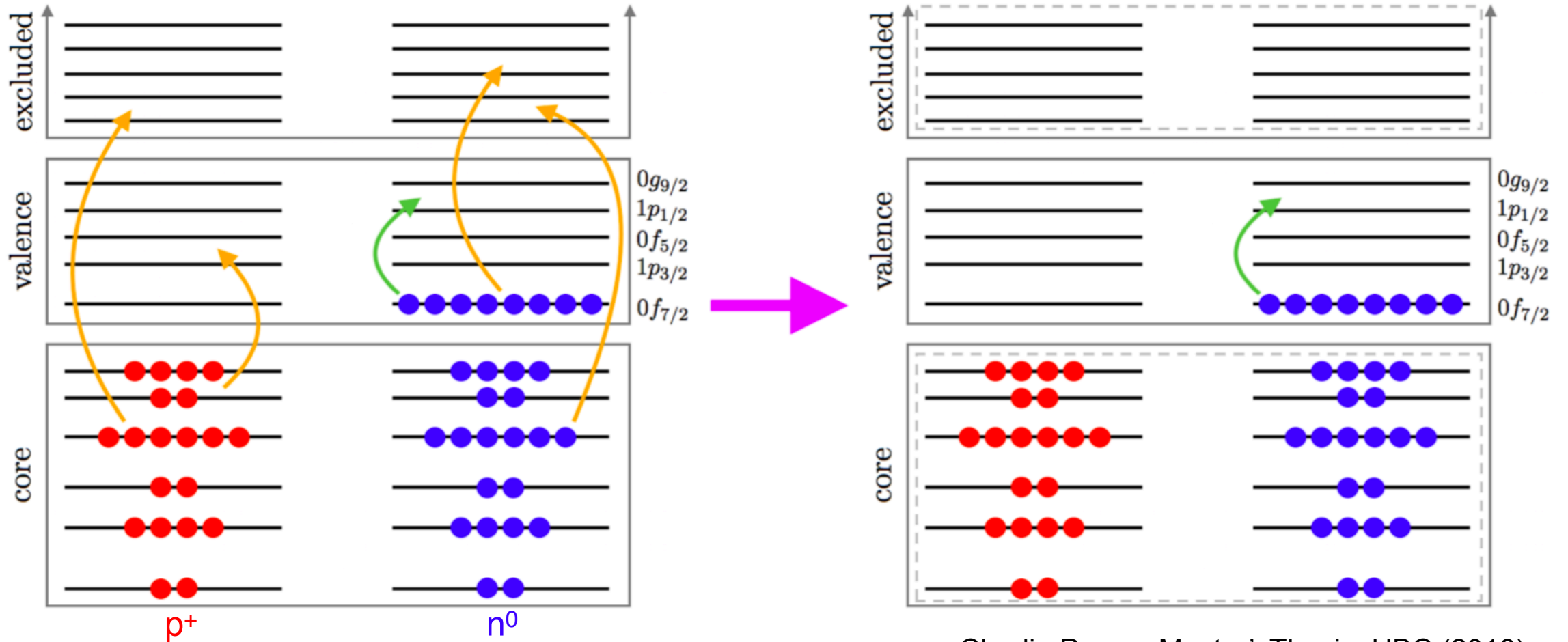
$$\hat{H}(0)$$



$$\hat{H}(s) = e^{\Omega(s)} \hat{H}(0) e^{-\Omega(s)}$$

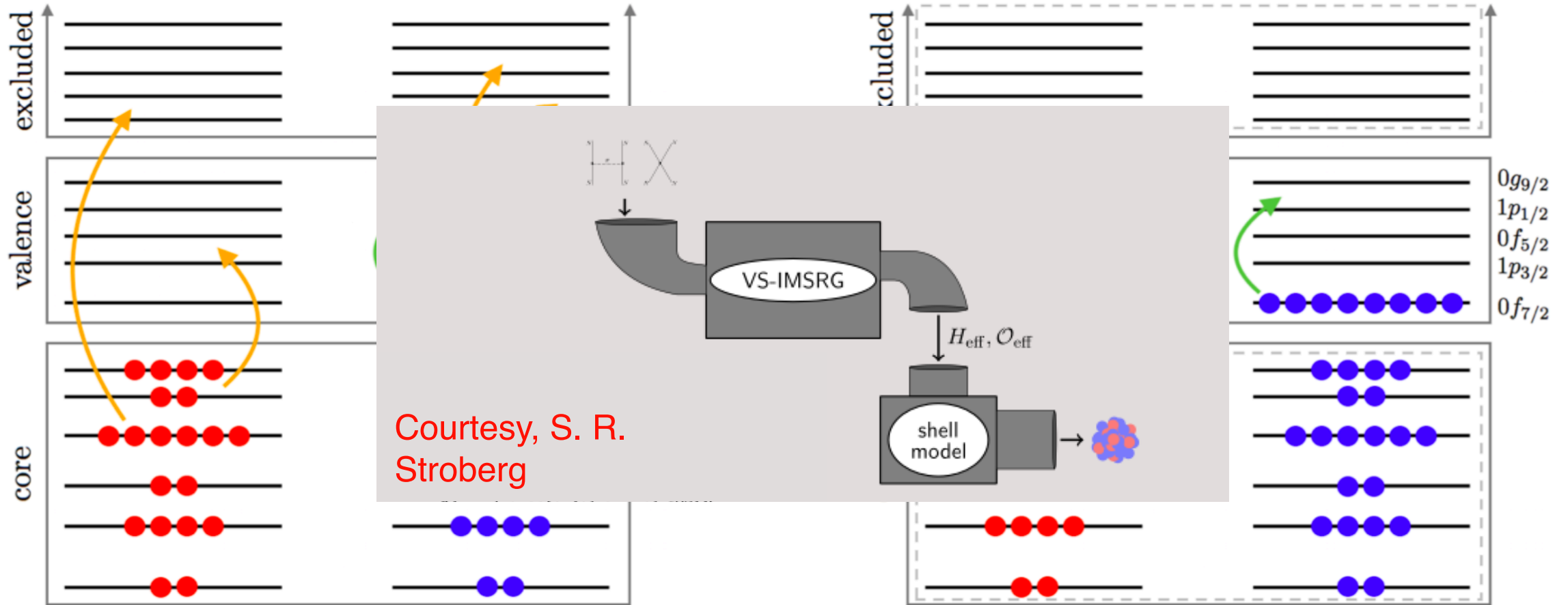
Tsukiyama et al., Phys. Rev. C **85**, 061304(R) (2012)

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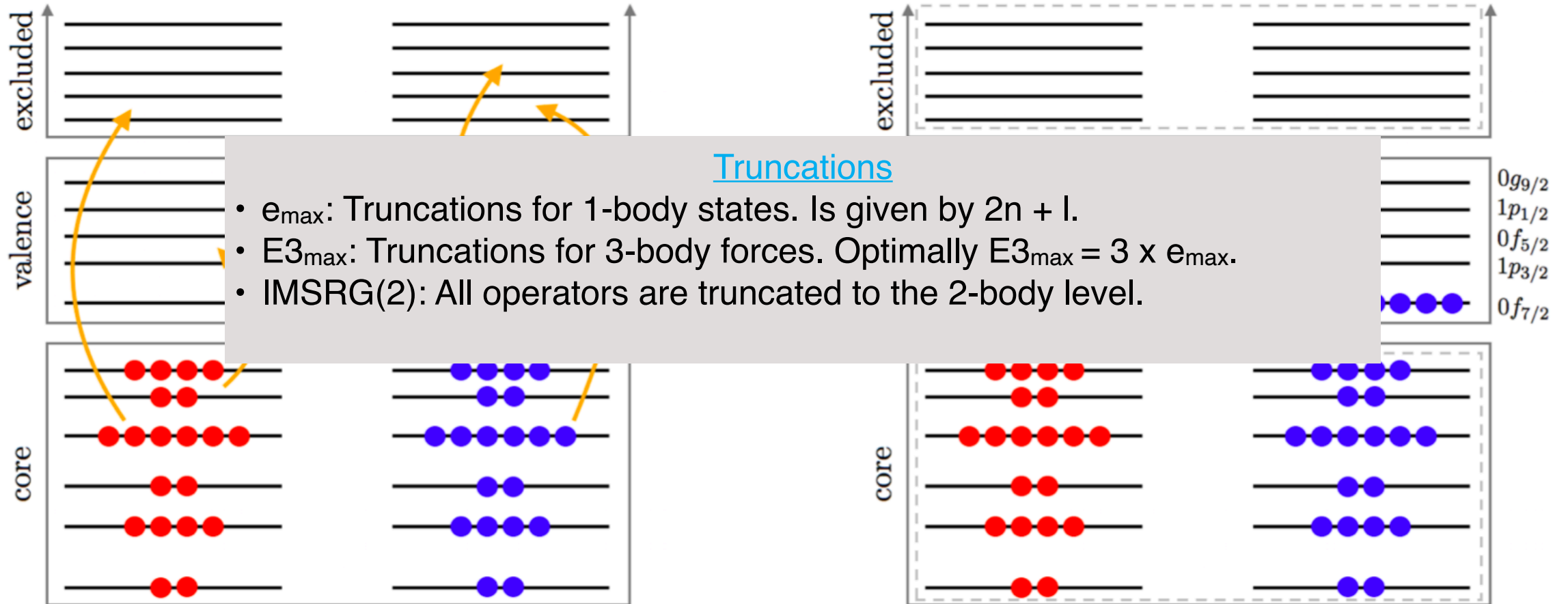
Charlie Payne, Master's Thesis, UBC (2018)

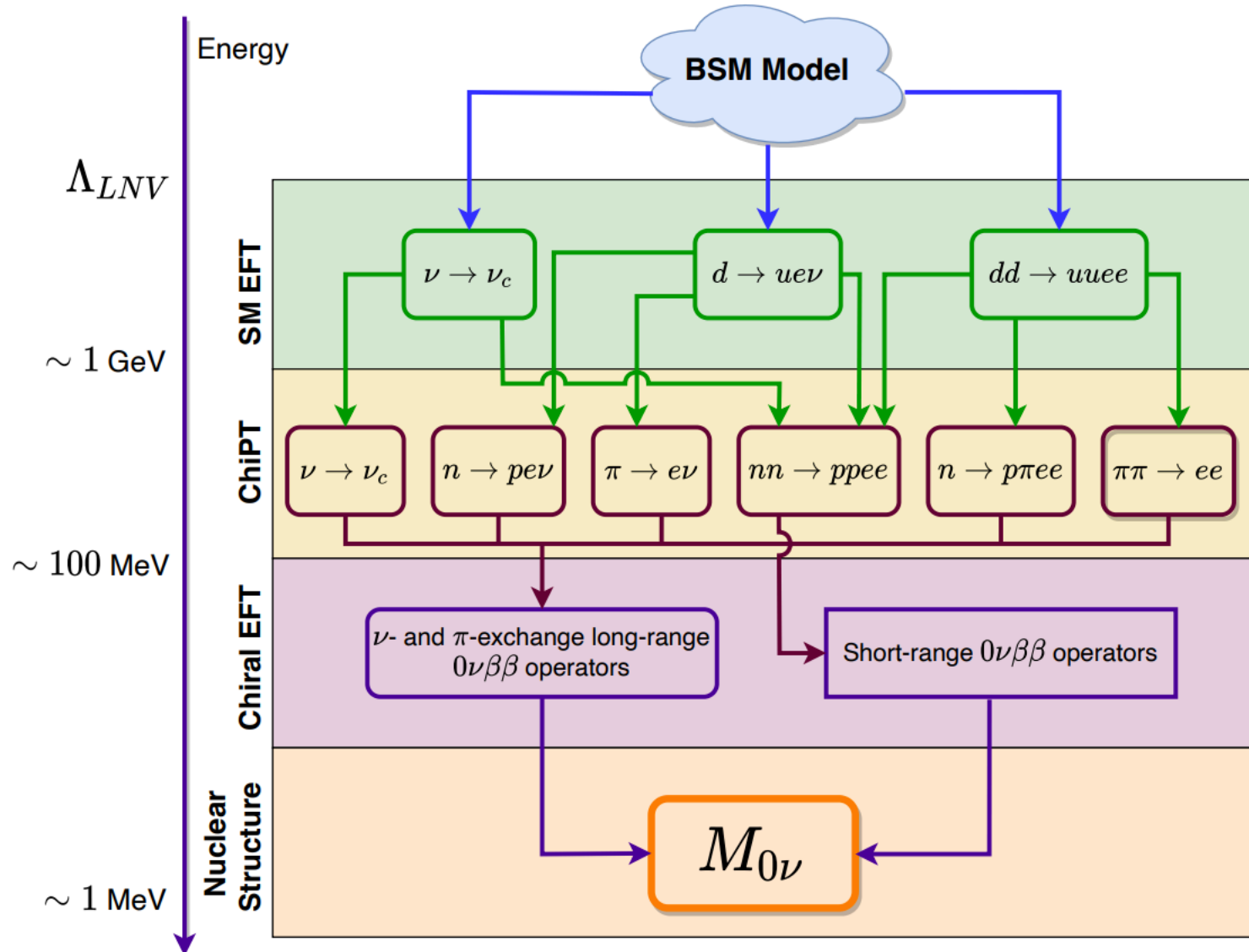
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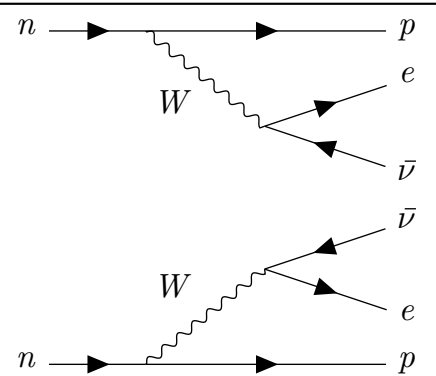
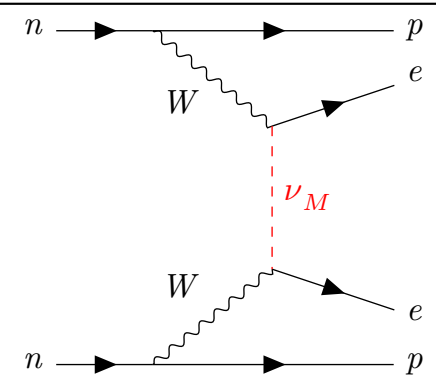


Courtesy, S. R. Stroberg

Valence-Space In Medium Similarity Renormalization Group





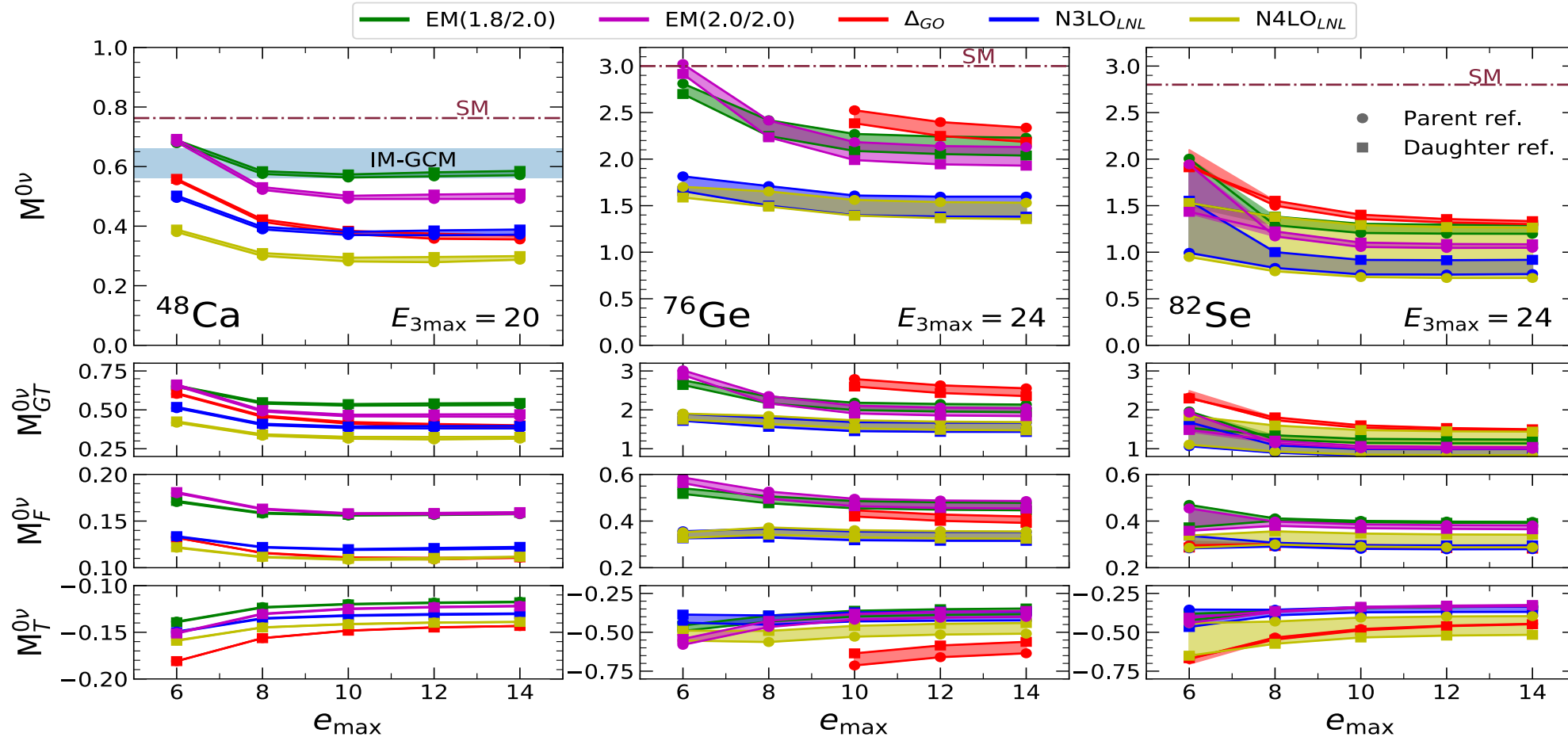
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Obtaining a result

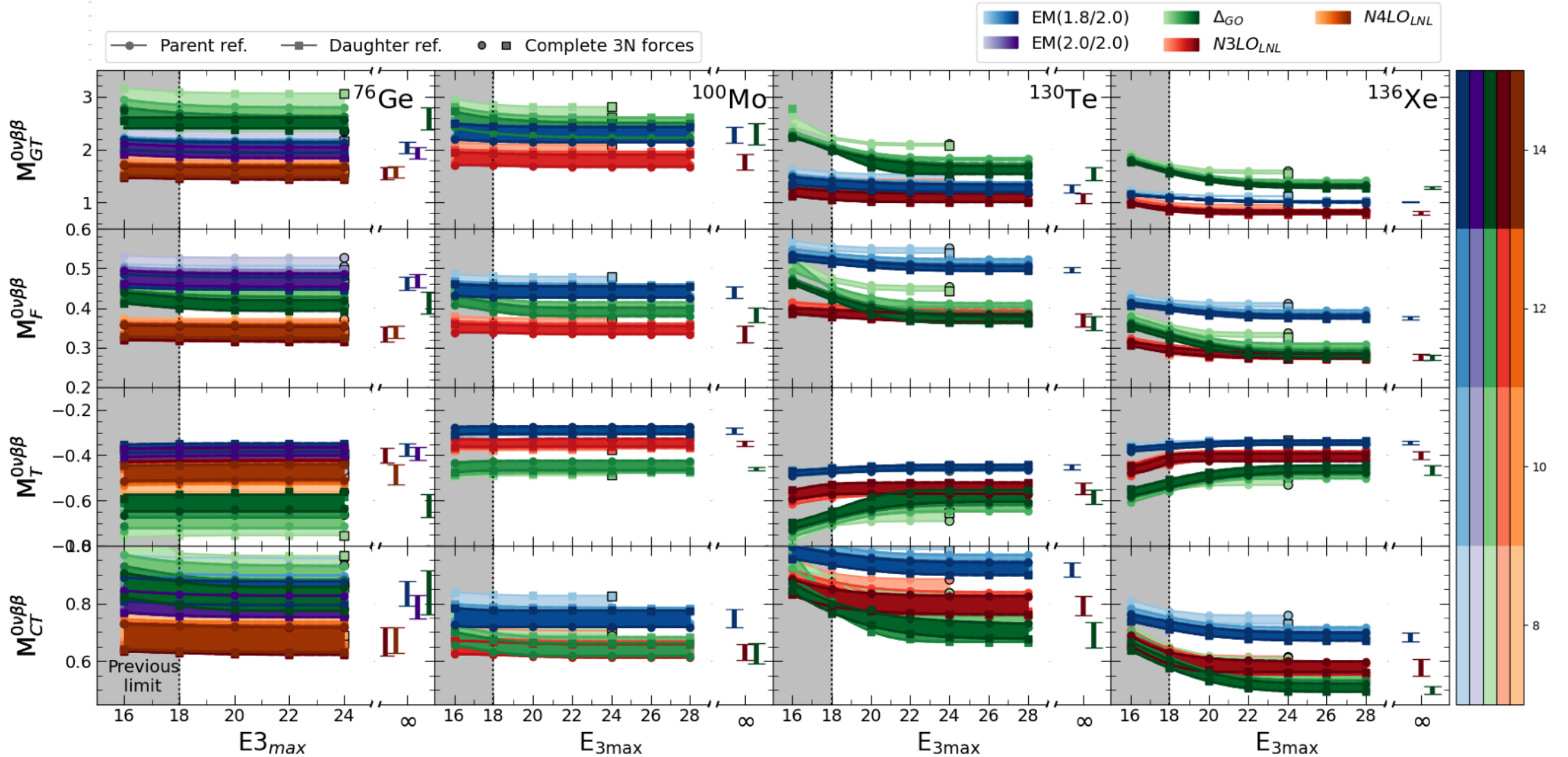
Results with 5 different input Hamiltonians to study uncertainty from interaction choice.

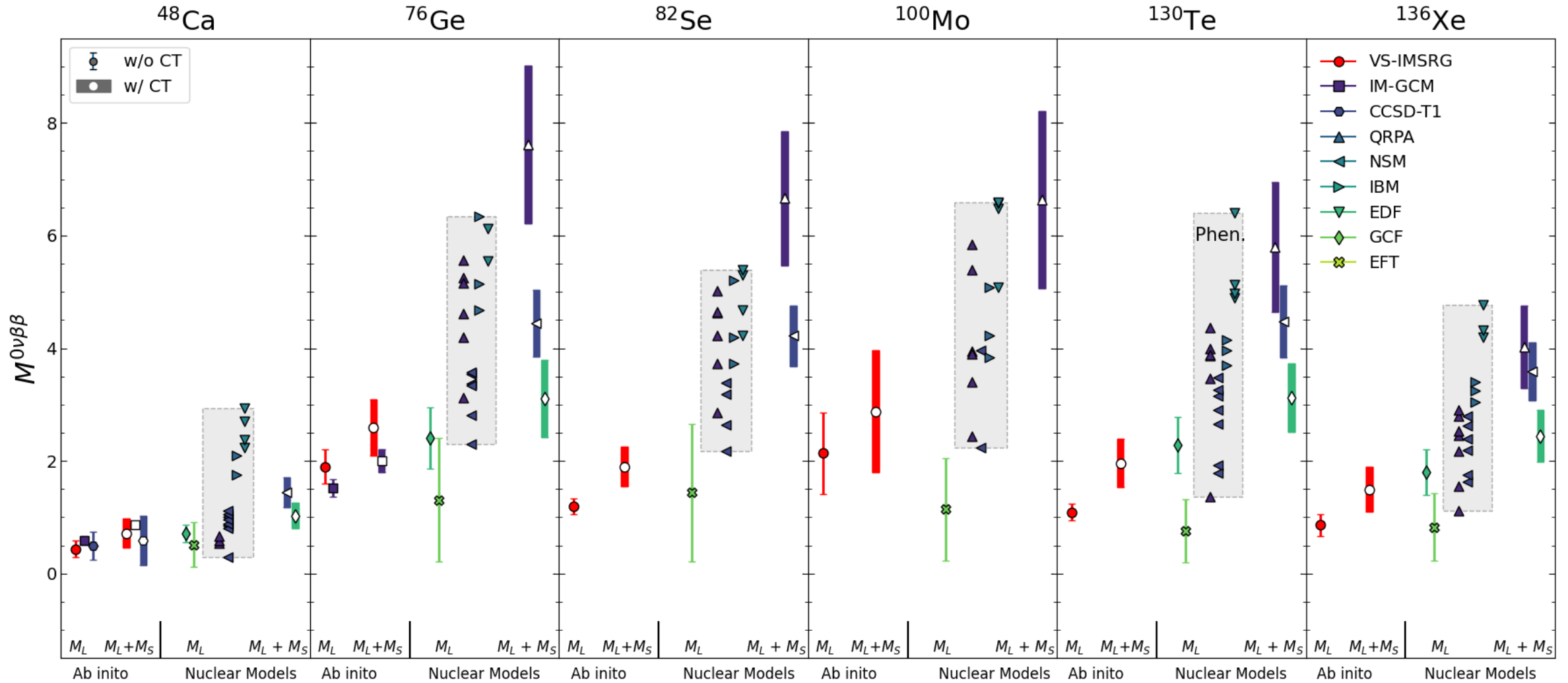


Things to add: valence-space variation, two-body currents, IMSRG(3), ...

^{100}Mo , ^{130}Te , ^{136}Xe : major players in global searches with Cupid, SNO+, CUORE and nEXO.

Increased $E_{3\text{max}}$ capabilities allow first converged ab initio calculations [EM1.8/2.0, Δ_{GO} , N3LO_{LNL}].²⁴





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 - **Uncertainty quantification**

Uncertainty Quantification

Recall that the nuclear potential depends on a set of LECs α :

$$M^{0\nu\beta\beta}(\alpha) = \langle \psi_f(\alpha) | O | \psi_i(\alpha) \rangle$$

that are fitted to NN and few nucleons data, i.e. each LEC has an uncertainty $\delta\alpha$ associated with it.

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How to propagate $\delta\alpha$ to $\delta M^{0\nu\beta\beta}$?

Bayesian statistics!

Value of the nuclear matrix elements (what we are interested in)

Different values obtained with different interactions/methods

Any other relevant information we have beforehand

$$\underbrace{prob(y | y_k, I)}_{\text{Posterior distribution}} \propto \underbrace{prob(y_k | y, I)}_{\text{Likelihood}} \times \underbrace{prob(y | I)}_{\text{Prior}}$$

Posterior distribution

Probability distribution for the final value given the data and our previous knowledge (what we want to obtain).

For finite samples, we use sampling/importance resampling to obtain the final PDF.

Likelihood

Probability that this sample gives a result that is representative of experimental values.

Chosen to be a multivariate normal centred at the experimental value for few observables we have data on (calibrating observables).

Prior

Assume a uniform prior for low energy constants of natural size. Then use history matching to remove implausible samples from the set. Assume each of the remaining samples to be as likely as the others.

We read $prob(A | B)$ as probability of A given B

1. Generate a set of LECs samples equally distributed in a reasonable range.
2. Using History Matching, reduce the number of samples in the set to “non-implausible” samples.
3. These “non-implausible” samples are now your prior and are taken to be equally probable.
4. Assign a likelihood to each sample by comparing their performance for certain calibrating observables. To give sensible estimate of the target observable, the calibrating observables should correlate with the target observable.
5. Resample the LECs a large number of times ($>10^6$) with probability of being sampled given by the likelihood of the sample (Sampling/Importance Resampling).
6. Evaluate the target observables with the resampled set to obtain a posterior predictive distribution.
7. Other sources of error can be sampled and added independently in the previous step. Those are taken to be normally distributed.

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The catch

Need to be able to compute the observables for all the non-implausible samples.

4. Assign a likelihood
To give sensible
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Due to the very large cost of many-body methods this becomes very quickly non-feasible as the number of samples grows.

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7. Other sources of error can be sampled and added independently in the previous step. Those are taken to be normally distributed.

- Idea behind Gaussian Process regressions is to assume that the distribution of the observable we want to fit is Gaussian:

$$f(\mathbf{x}) = \mathcal{N}(\mu, K(\mathbf{x}, \mathbf{x}))$$

where μ is a mean function and $K(\mathbf{x}, \mathbf{x})$ is the covariance matrix between the inputs.

- Want to infer the joint distribution of potentially unobserved Y^* points and the observed points Y . This can be done via a property of Gaussian distribution called Conditioning, i.e.:

$$P_{Y^*|Y} \sim \mathcal{N} \left(\mu_{Y^*}^* + \Sigma_{X^*X} \Sigma_{XX}^{-1} (Y - \mu_Y), \Sigma_{X^*X^*} - \Sigma_{X^*X} \Sigma_{XX}^{-1} \Sigma_{XX^*} \right).$$

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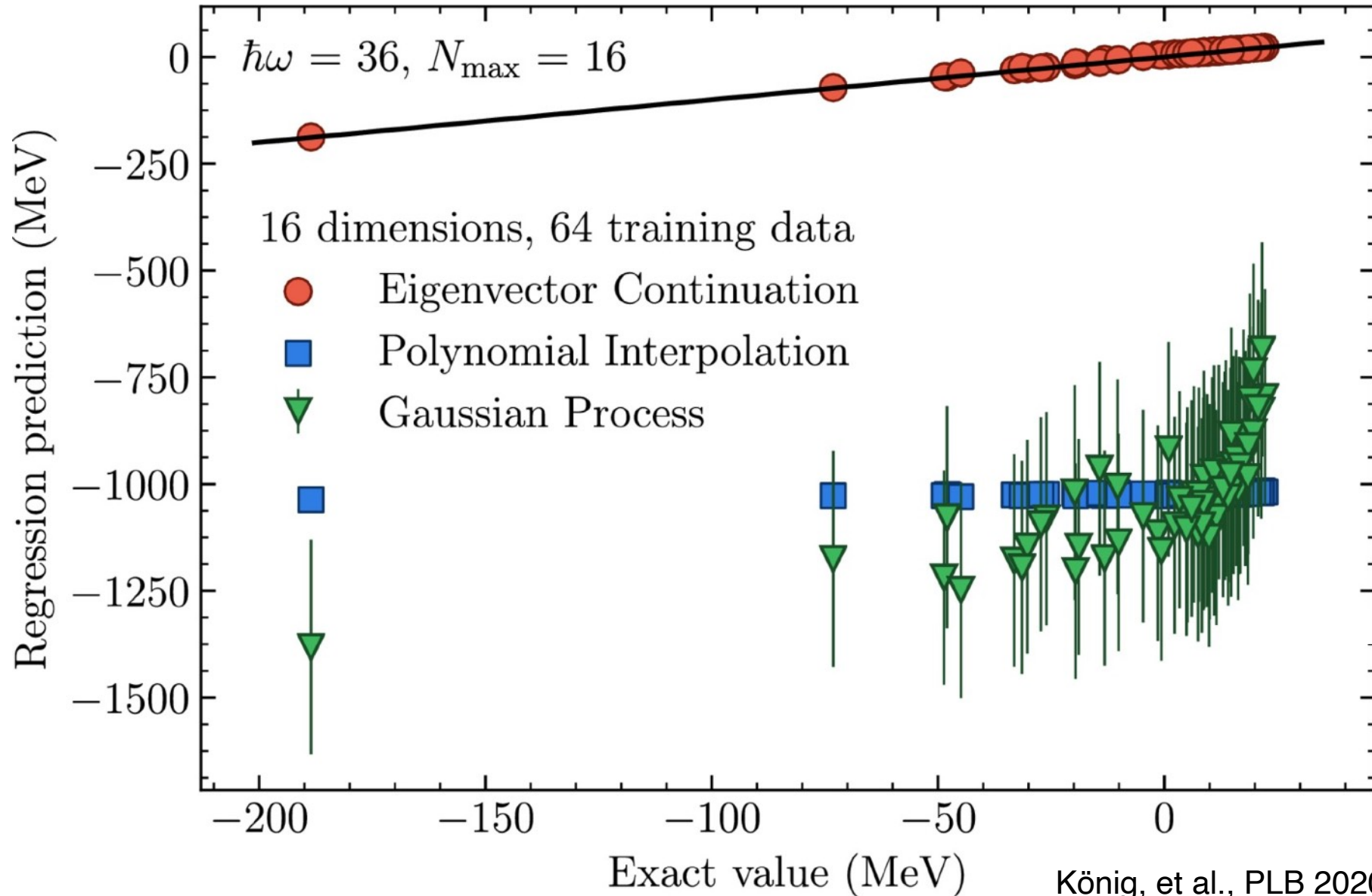
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Normalizing inputs

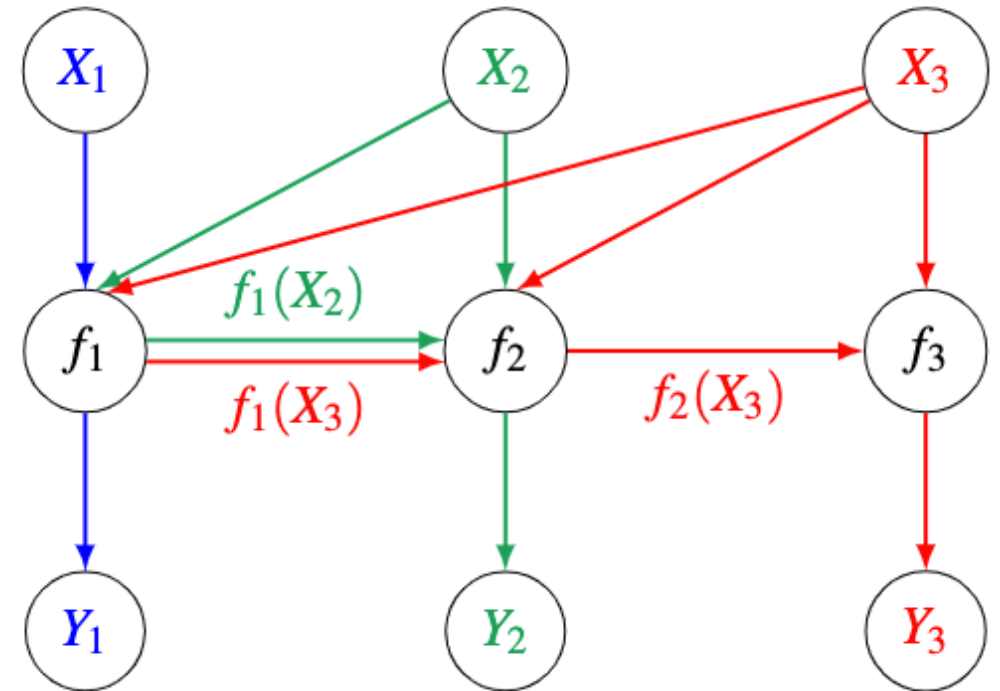
Only need to optimize hyperparameters of $K(\mathbf{x}, \mathbf{x})$!



- Multi-Tasks Gaussian Process: Uses multiple correlated outputs from the same inputs by defining the kernel as $K_{inputs} \otimes K_{outputs}$. This allows us to increase the number of data points without needing to do more expensive calculations.
- Multi-Fidelity Gaussian Process: Uses few data points of high fidelity (full IMSRG calculations) and many data points of low fidelity (e.g. Hartree-Fock results, lower e_{max}). The difference function is fitted by a Gaussian Process in order to predict the value of full calculations using the low fidelity data points. This assumes a linear scaling for between the low- and high-fidelity calculations.

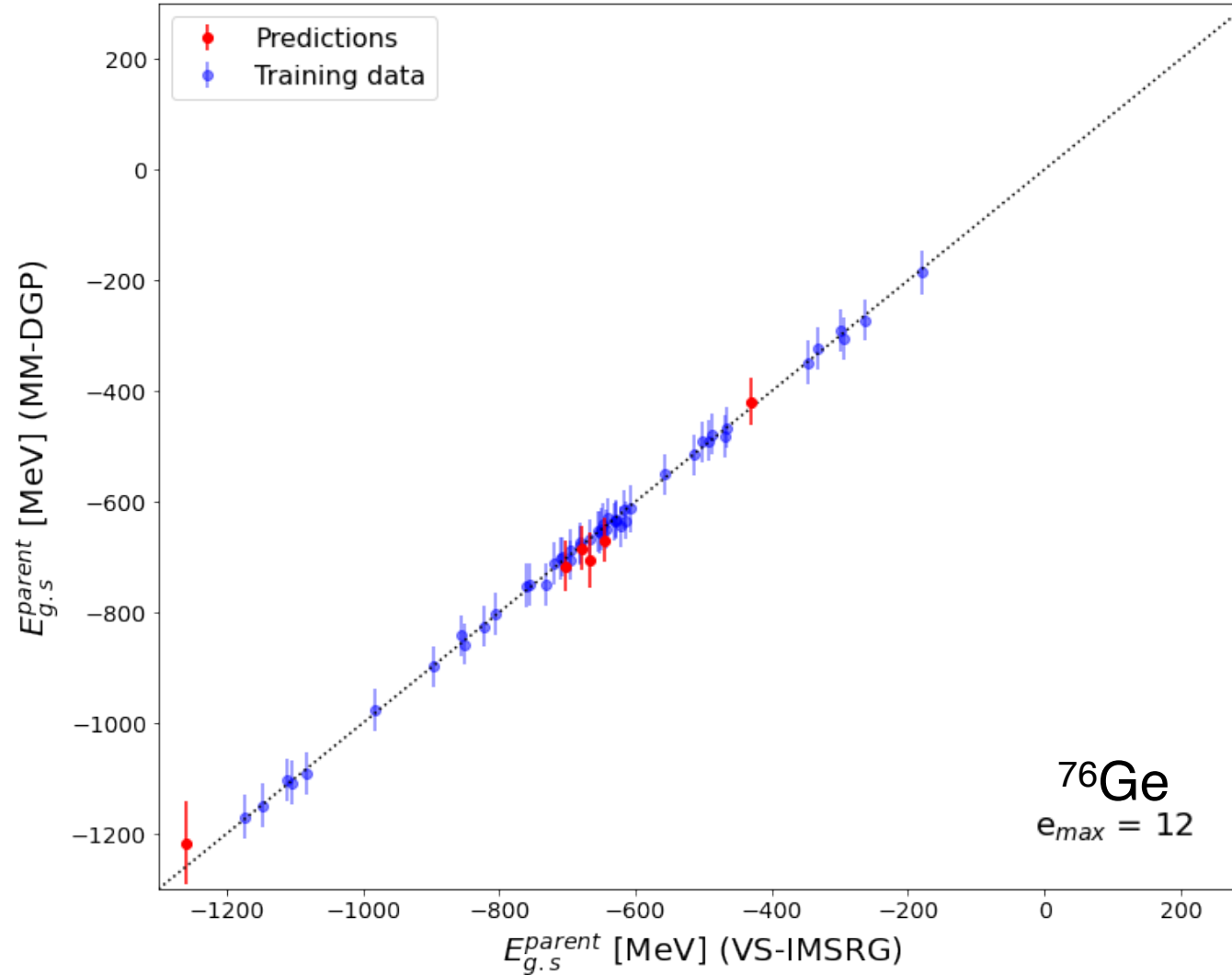
- When the relation between low-fidelity and high-fidelity data is complicated, the simple multi-fidelity approach does not produce good results.
- Deep Gaussian Processes [1] link multiple Gaussian Processes inside a architecture similar to neural network to improve results.
- This can be used to model the difference function between the low- and high-fidelity by including outputs of the previous fidelity as an input of higher fidelity by taking a kernel of the form:

$$K(\mathbf{x}, \mathbf{x}) = k(\mathbf{x}, \mathbf{x}) \cdot k(f_{prev}(\mathbf{x}), f_{prev}(\mathbf{x})) + k_{bias}(\mathbf{x}, \mathbf{x})$$
- This was developed for single-output Gaussian Processes and we have adapted it for multi-output case, creating the MM-DGP: **Multi-output Multi-fidelity Deep Gaussian Process**.



Using Δ -full chiral EFT interactions at N2LO:

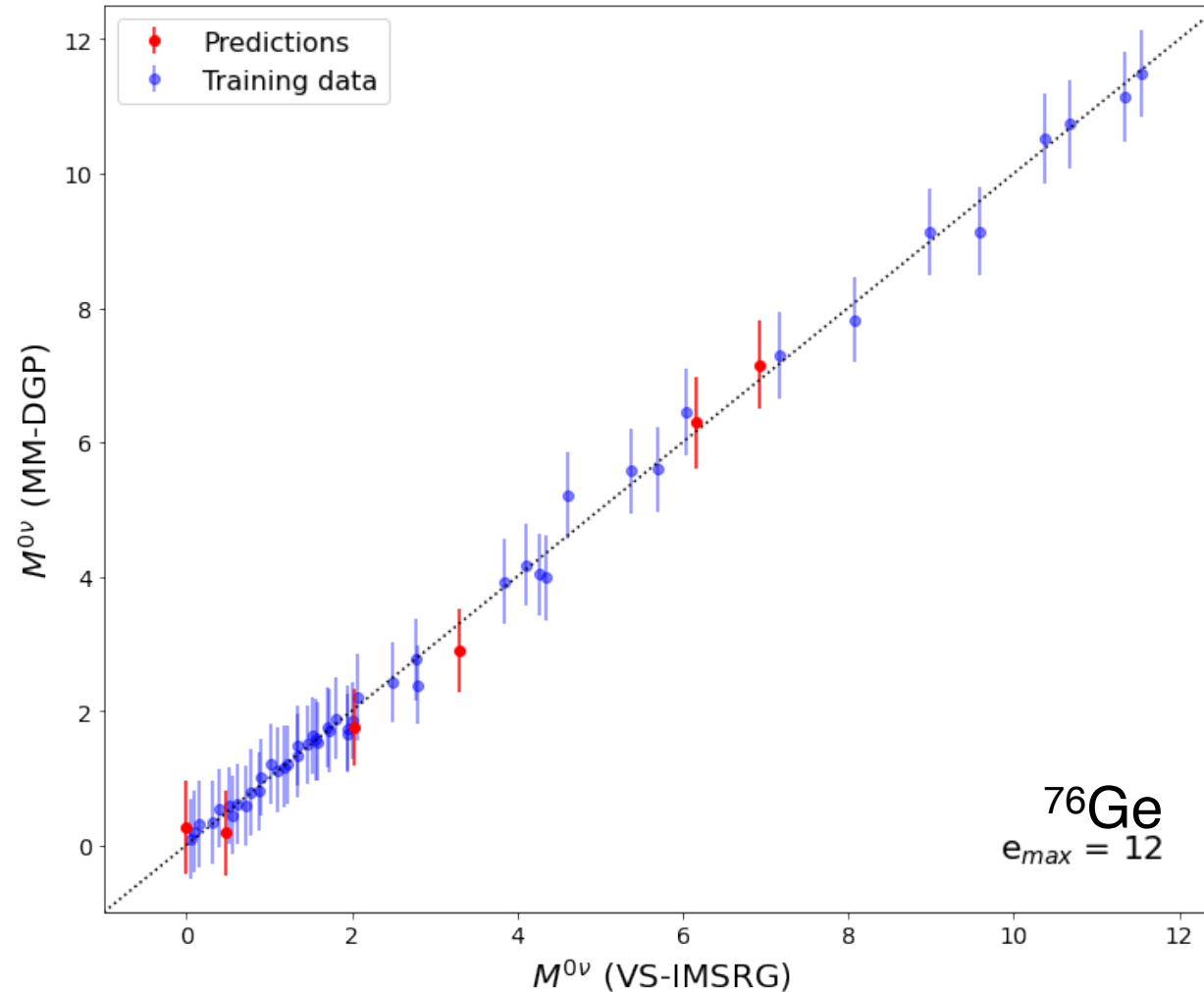
50 training points



Root Mean Square
Error = 11 MeV

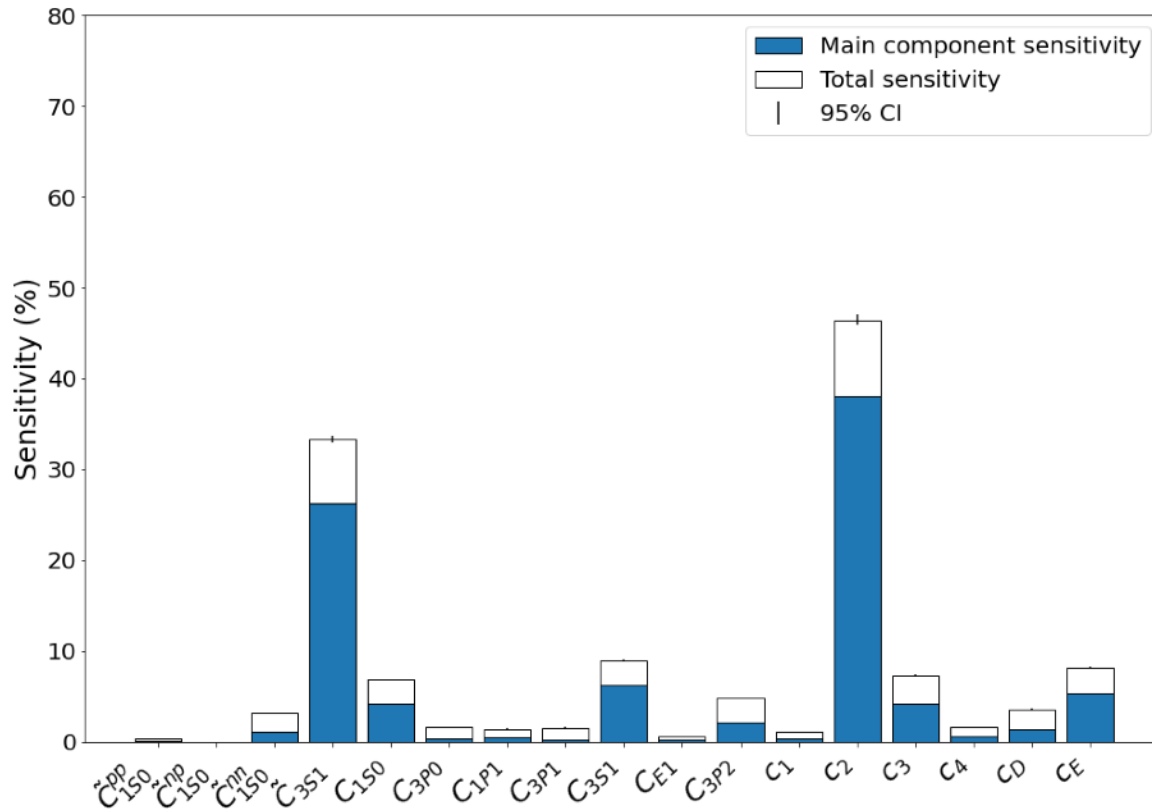
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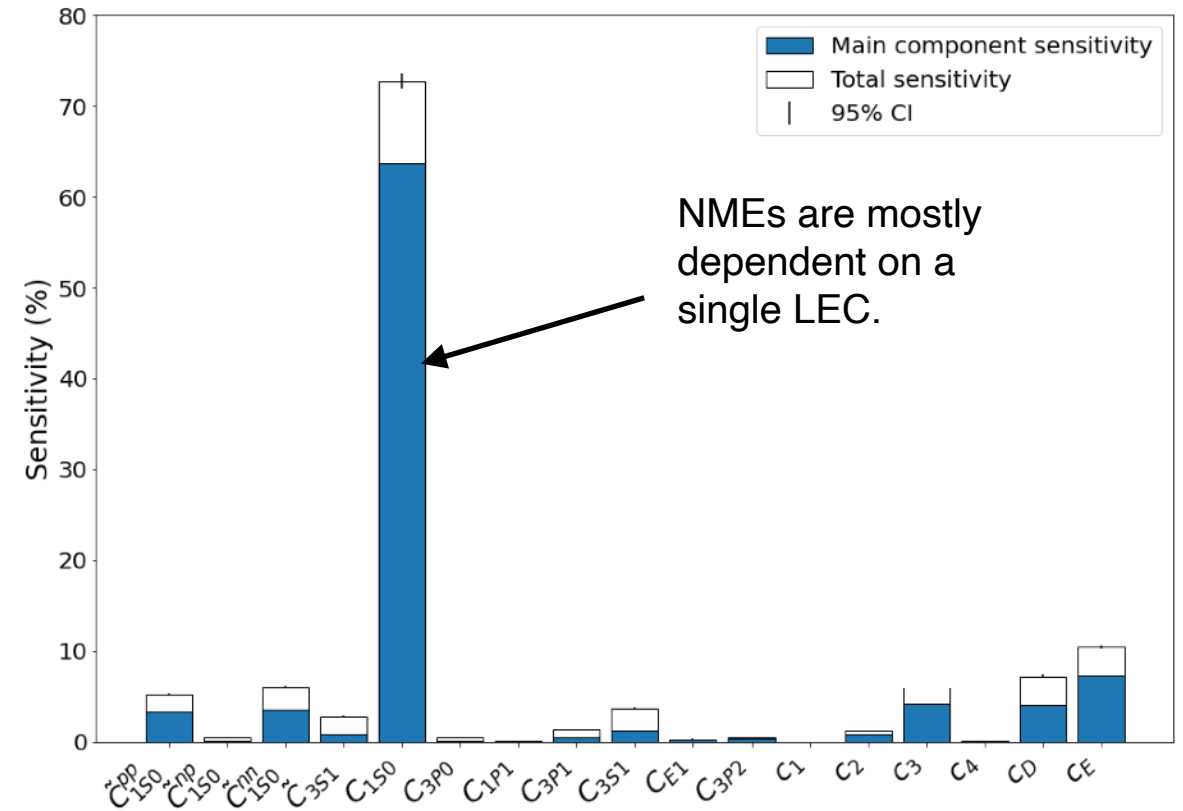


Root Mean Square
Error = 0.13

Ground state energies



$$M_L^{0\nu}$$



NMEs are mostly dependent on a single LEC.

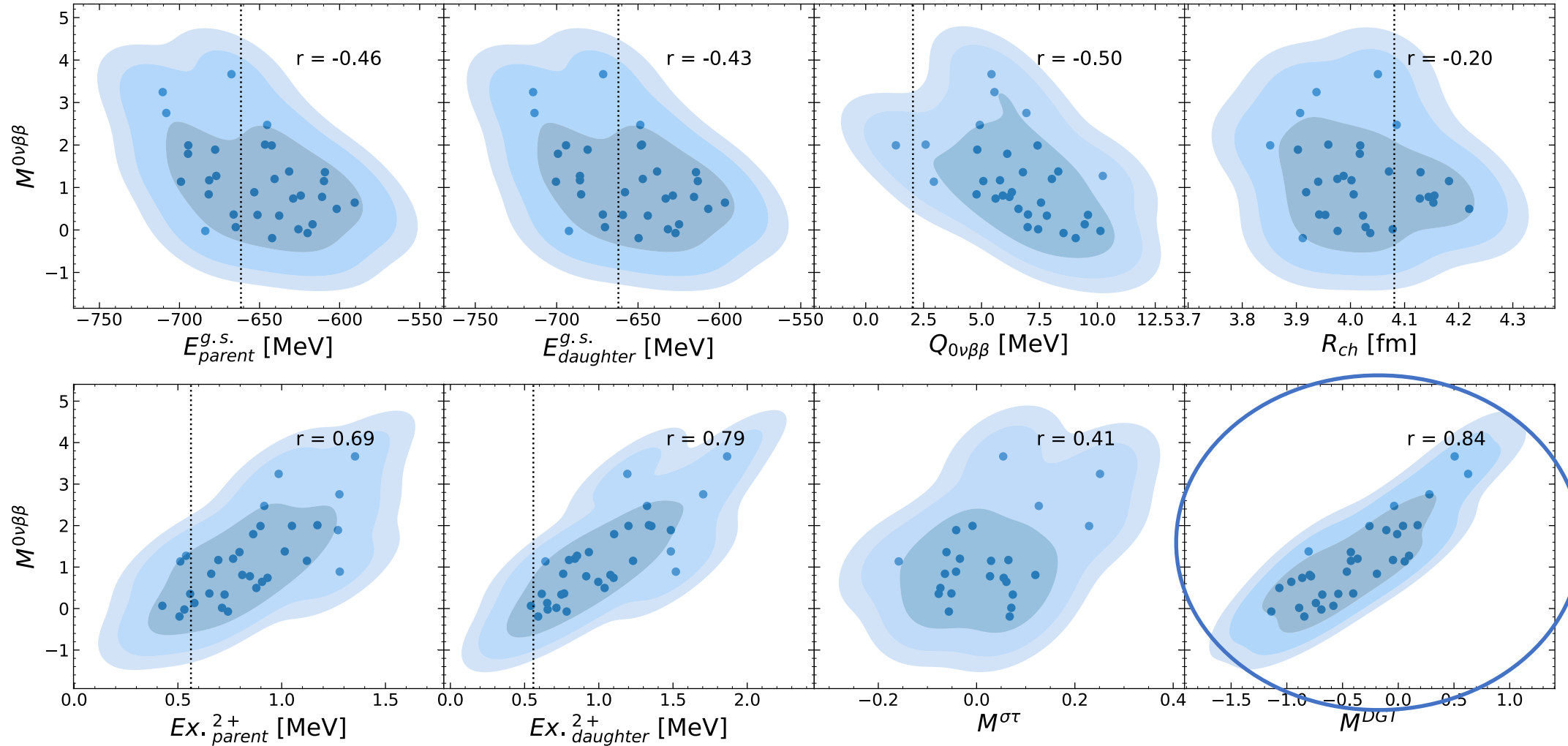


Consistent with results of Coupled Cluster and physics based emulator

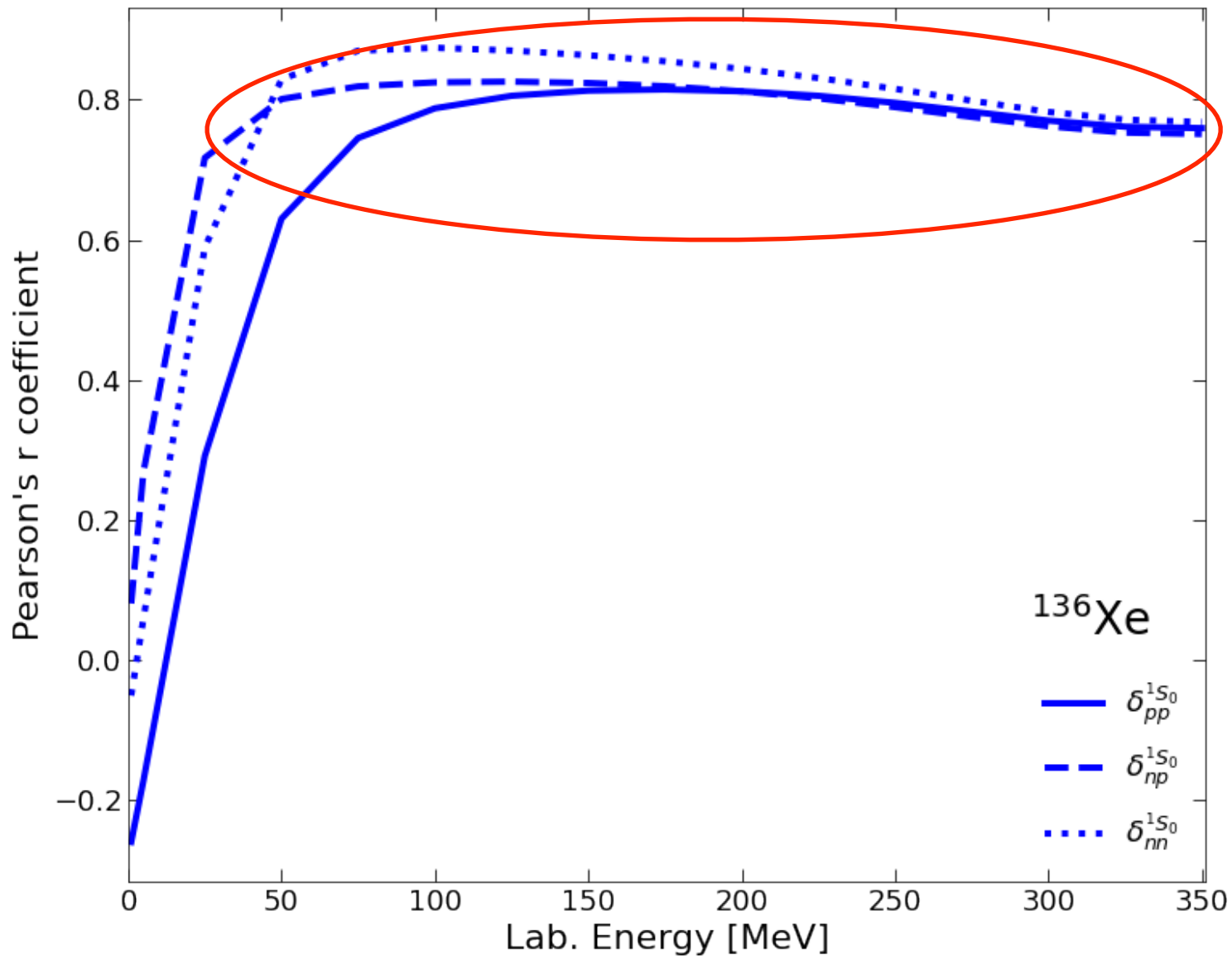
Belley, Pitcher et al. in prep.

Belley et al., arXiv:2210.05809

In ^{76}Ge :



Only correlation seen in multiple nuclei is with the unobserved double Gamow-Teller transition NME.



Strong correlation for energies > 50 MeV



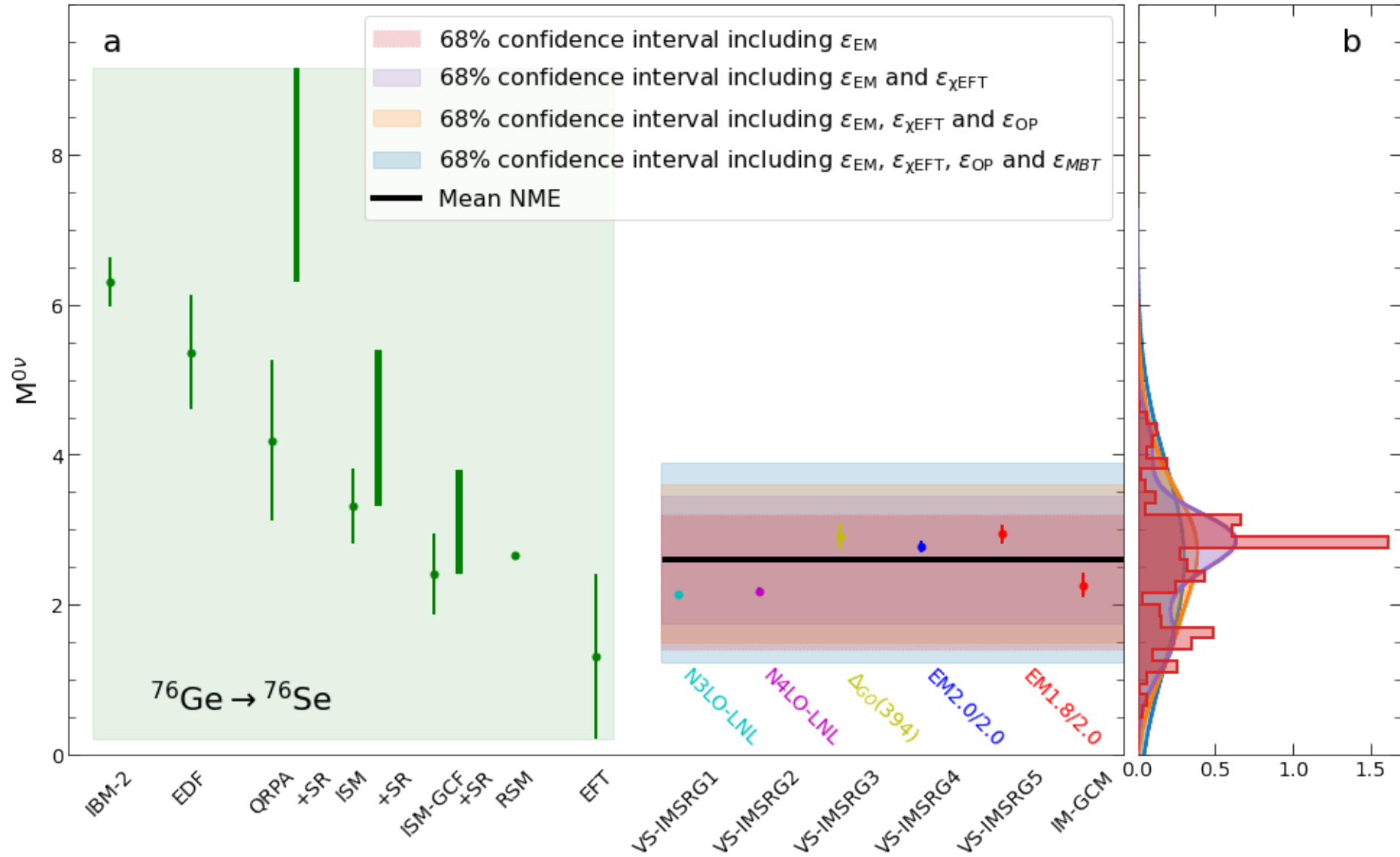
The size of matrix elements is mostly constrained by the interaction between the two nucleons that undergo the decay, given they are close enough from each other.

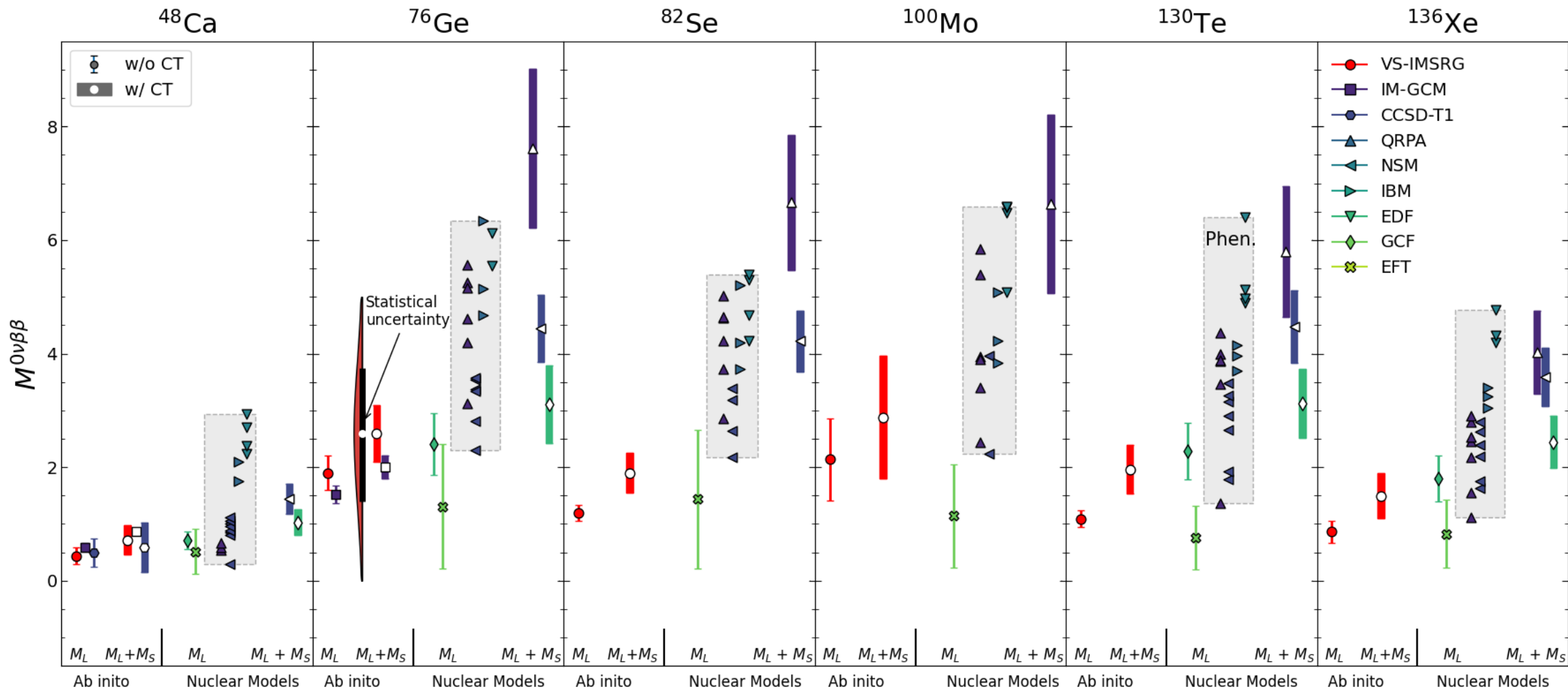
- Use 8188 “non-implausible” samples obtain by Jiang, W. G. et al. ([arXiv:2212.13216](https://arxiv.org/abs/2212.13216)).
- Many-body problem is “solved” with the MM-DGP.
- Consider all sources of uncertainties by taking:

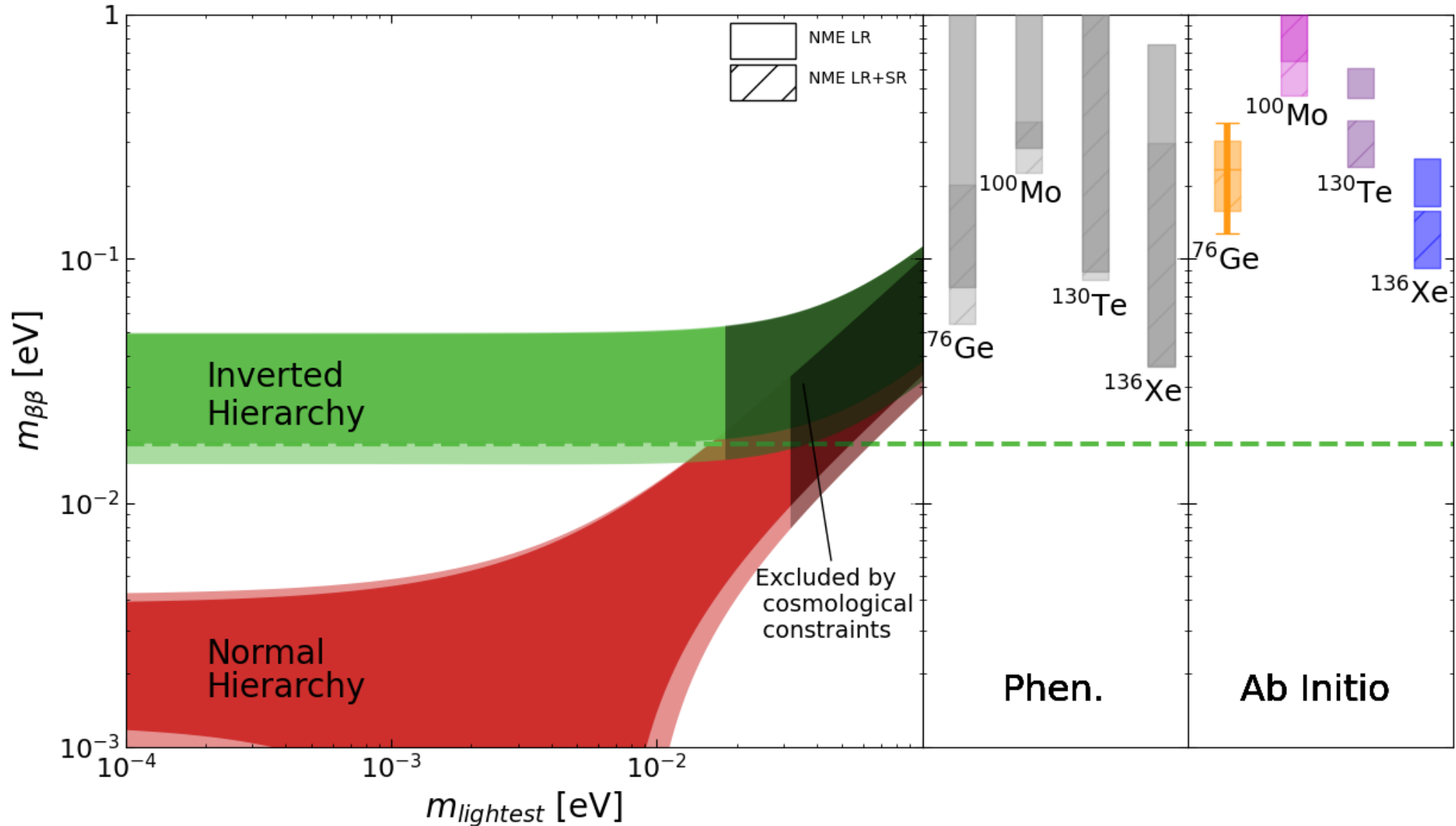
$$y = y_{MM-DGP} + \epsilon_{emulator} + \epsilon_{EFT} + \epsilon_{many-body} + \epsilon_{operator}$$

where the ϵ 's are the errors coming from different sources and are assumed to be normally distributed and independent.

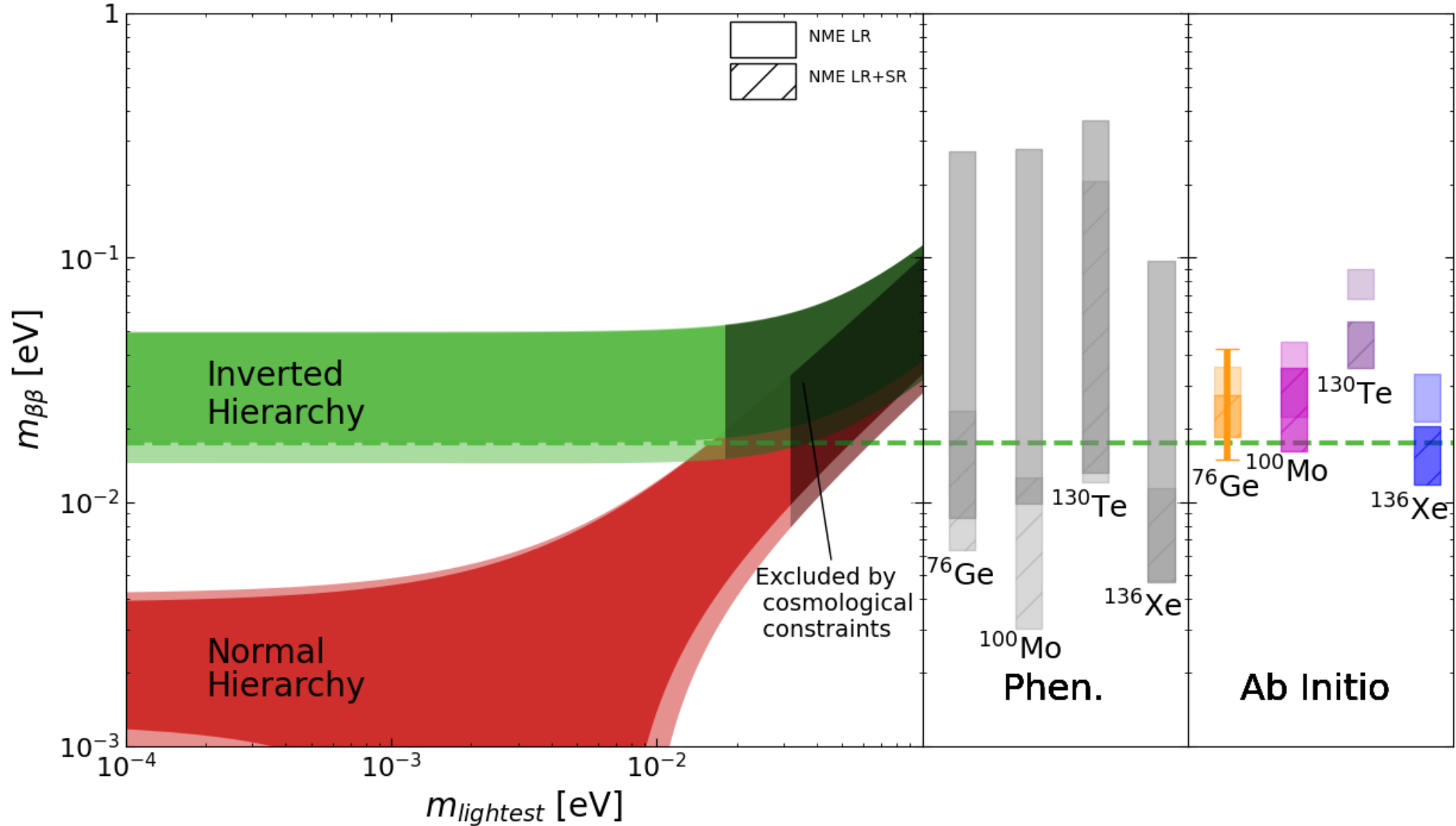
- Interactions are weighted by the 1S_0 neutron-proton phase shifts at 50 MeV and observables for mass $A=2-4, 16$.







Experimental limits: **GERDA (^{76}Ge)** Phys. Rev. Lett. 125, 252502, **CUPID-Mo (^{100}Mo)** Eur. Phys. J. C 82 11, 1033, **CUORE(^{130}Te)** Nature 604, 53–58 and **Kamland Zen (^{136}Xe)** Phys. Rev. Lett. 130, 051801.



Expected limits: **LEGEND (^{76}Ge)** arXiv:2107.11462, **CUPID (^{100}Mo)** arXiv:1907.09376, **SNO+ (^{130}Te)** arXiv:2104.11687 and **nEXO (^{136}Xe)** J. Phys. G 49 1, 015104.

Summary

1. Computed first ever ab initio NMEs of isotopes of experimental interest as a first step towards computing NMEs with reliable theoretical uncertainties.
2. Computed NMEs with multiple interactions for ^{48}Ca , ^{76}Ge , ^{82}Se , ^{100}Mo , ^{130}Te and ^{136}Xe .
3. Studied effects of the contact term on the NMEs.
4. Developed an emulator for the VS-IMSRG based on Gaussian Processes.
5. Obtained the first statistical uncertainty for the NMEs which includes all sources of errors in the calculation.



Questions?

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