

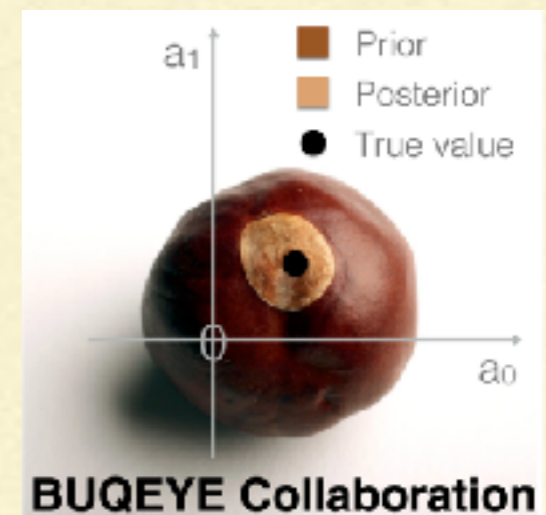
Using Bayesian methods to assess model uncertainty in nuclear physics



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RESEARCH SUPPORTED BY THE DOE OFFICE OF
SCIENCE, THE NNSA, AND THE NSF OAC

Nuclear Science model uncertainty

- Neutrinoless double beta decay
 - r-process: extrapolation to the dripline and beyond; ties in to other nuclear-structure issues
 - Heavy-ion Collisions: energy deposition; pre-hydrodynamic stage; conversion of hydrodynamic output to final-state particles
 - Different approaches to reaction dynamics (R-matrix, statistical models, global optical potentials, microscopic optical potentials, ...)
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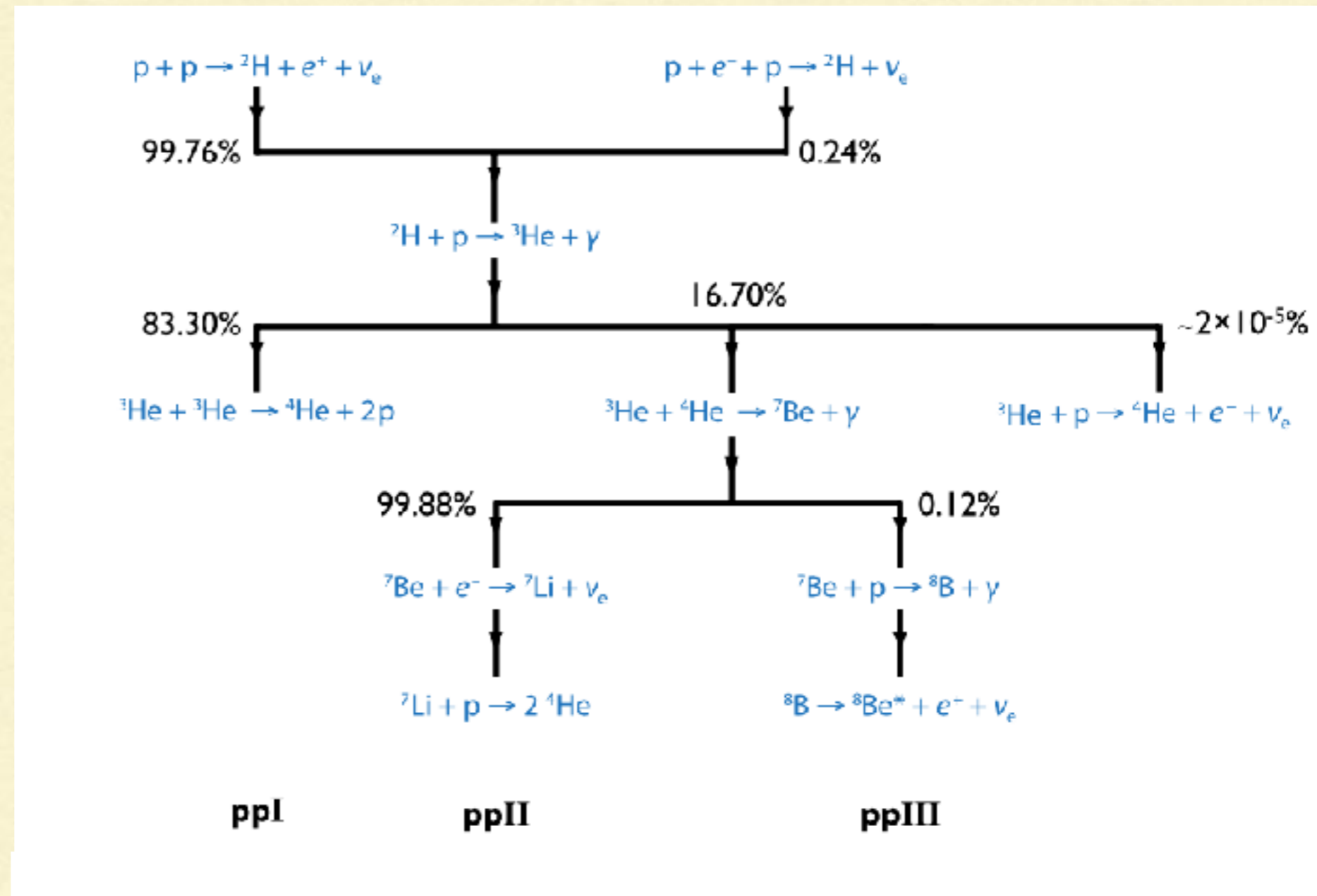
Outline

- ${}^3\text{He} + {}^4\text{He} \rightarrow {}^7\text{Be} + \gamma$ as an example of how to assess model uncertainty
 - How Halo Effective Field Theory can help
 - From S-factor data to Halo EFT parameters, and back
 - Halo EFT as a “super model”
 - Bayesian Model Averaging \rightarrow Bayesian Model Mixing
 - What is Bayesian Model Averaging?
 - An application: the overall prediction of EDFs for the neutron drip line
 - Toy-model test of BMA
 - The BAND Software Framework
-

Why is ${}^3\text{He}({}^4\text{He},\gamma)$ important?

Adelberger et al., Rev. Mod. Phys. 83, 195 (2011)

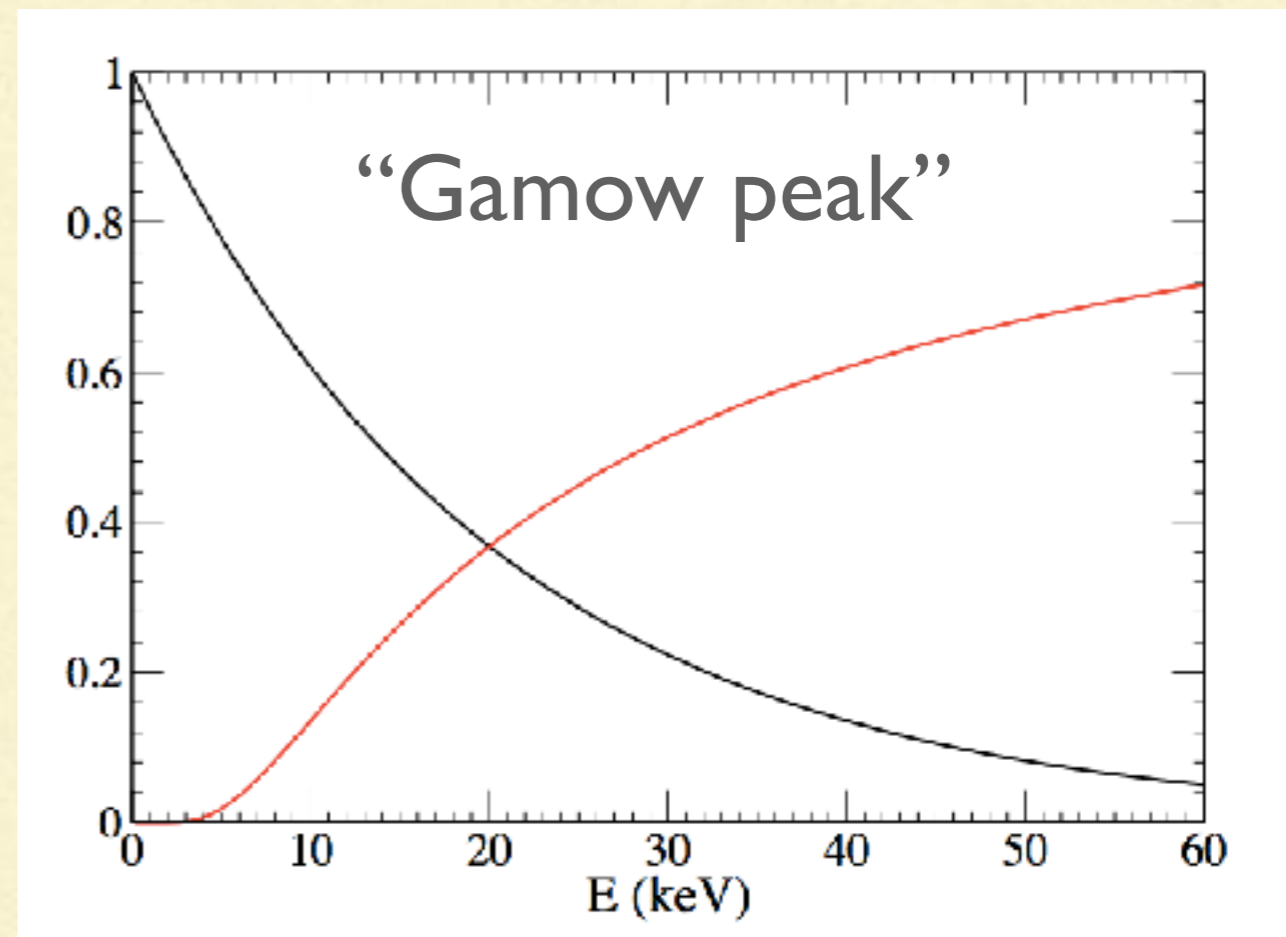
- Accurate knowledge of ${}^3\text{He}({}^4\text{He},\gamma)$ needed to reliably predict amount of ${}^7\text{Be}$ in the Sun
- Therefore key for prediction of ${}^8\text{B}$ solar neutrino flux
- BBN implications, but I will not discuss those here



This is an extrapolation problem

Thermonuclear reaction rate $\propto \langle v\sigma \rangle \propto \int_0^\infty dE \exp\left(-\frac{E}{k_B T}\right) E \sigma(E)$

$$\sigma(E) = \frac{S(E)}{E} \exp\left(-\pi Z_1 Z_2 \alpha_{\text{em}} \sqrt{\frac{m_R}{2E}}\right)$$

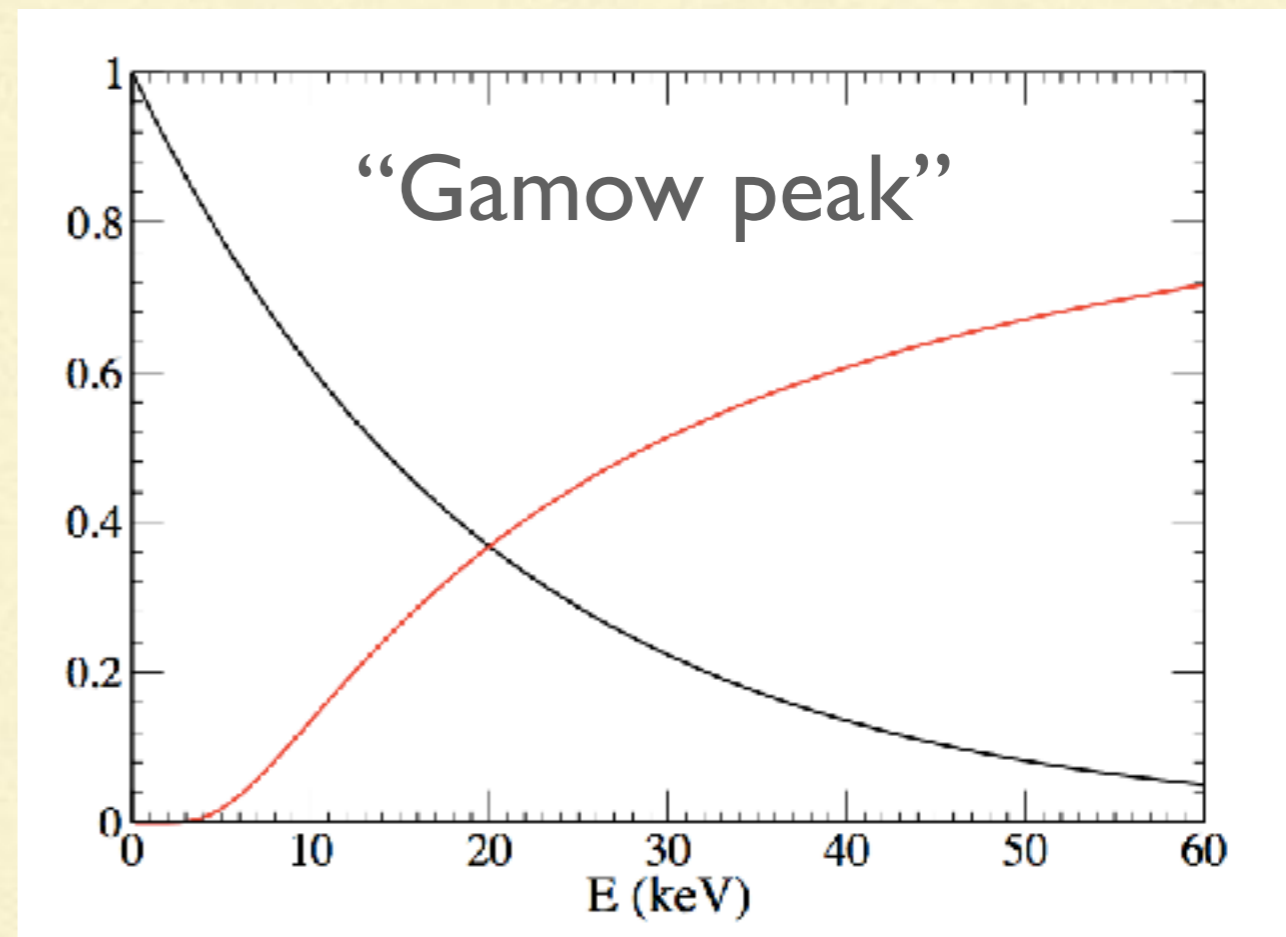


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- EI capture: ${}^3\text{He} + {}^4\text{He} \rightarrow {}^7\text{Be} + \gamma$
and ${}^7\text{Be} + \text{p} \rightarrow {}^8\text{B} + \gamma$
- Energies of relevance 20 keV

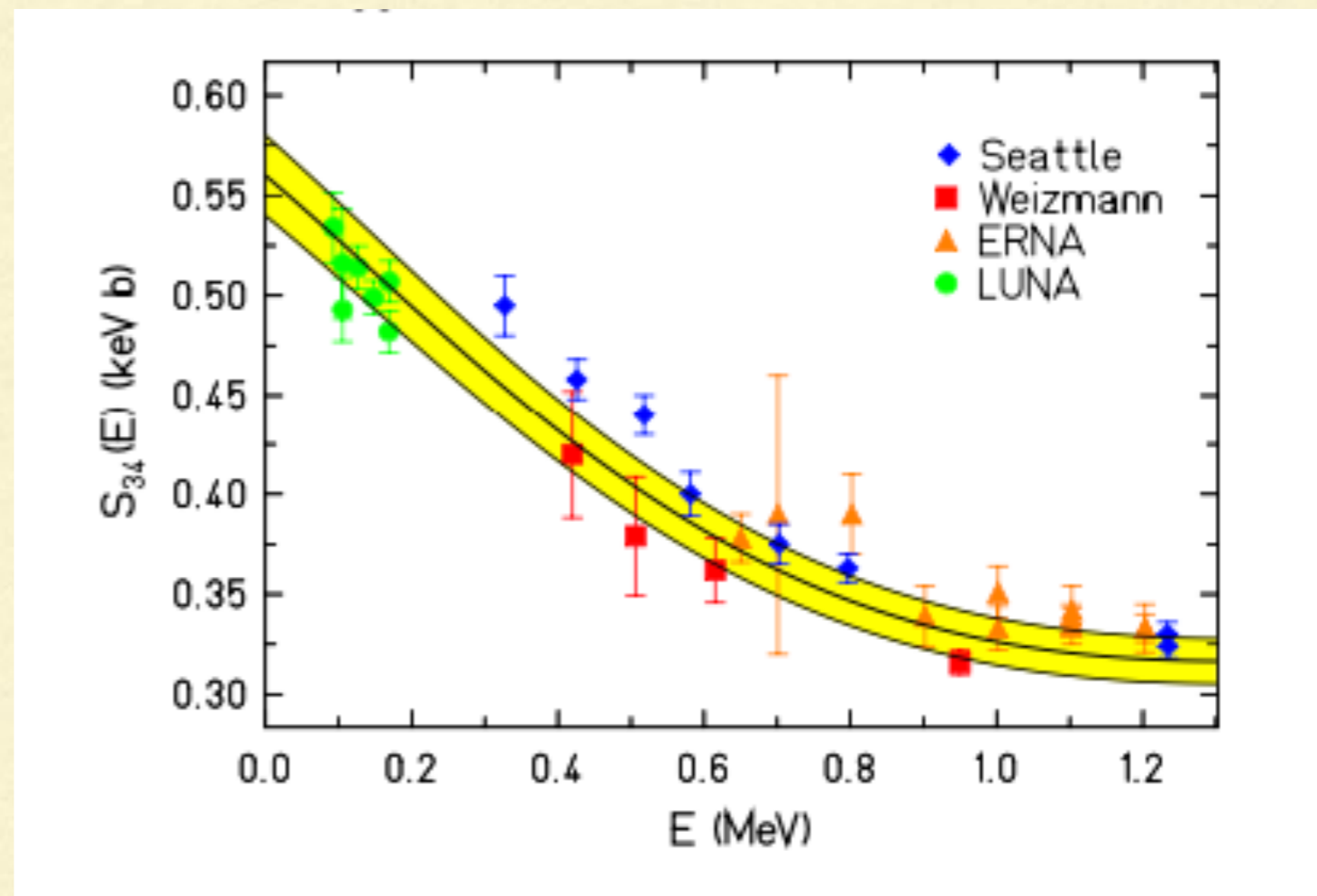


Building a good extrapolant

$\mathcal{M}(E)$ dominated by inter-nucleus separations outside $V(r)$

$$\mathcal{M}(E) \propto \int dr A_1 \exp(-\gamma_1 r) \left(1 + \frac{1}{\gamma_1 r} \right) r (\cot \delta(E) \sin(pr) + \cos(pr))$$

ANC



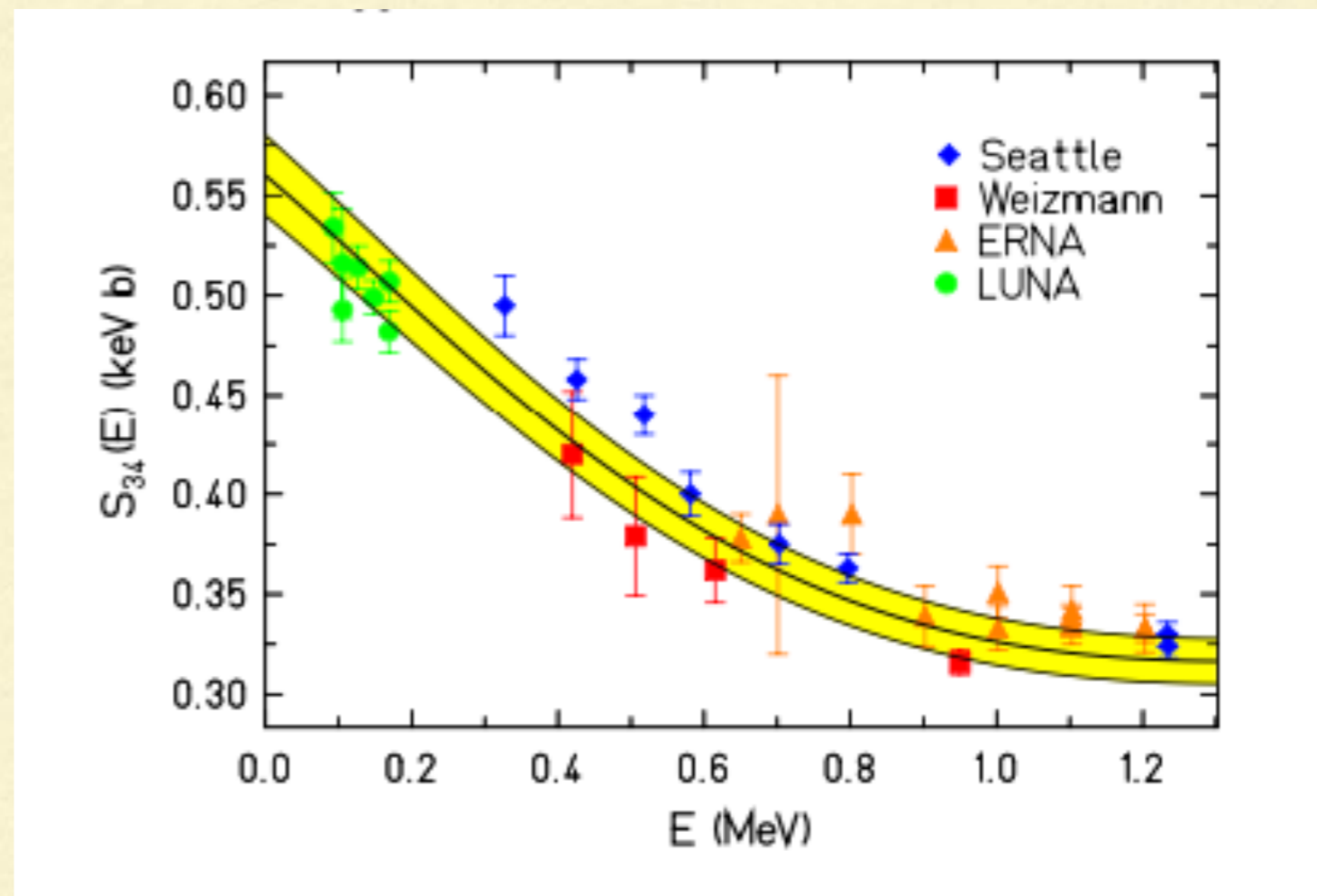
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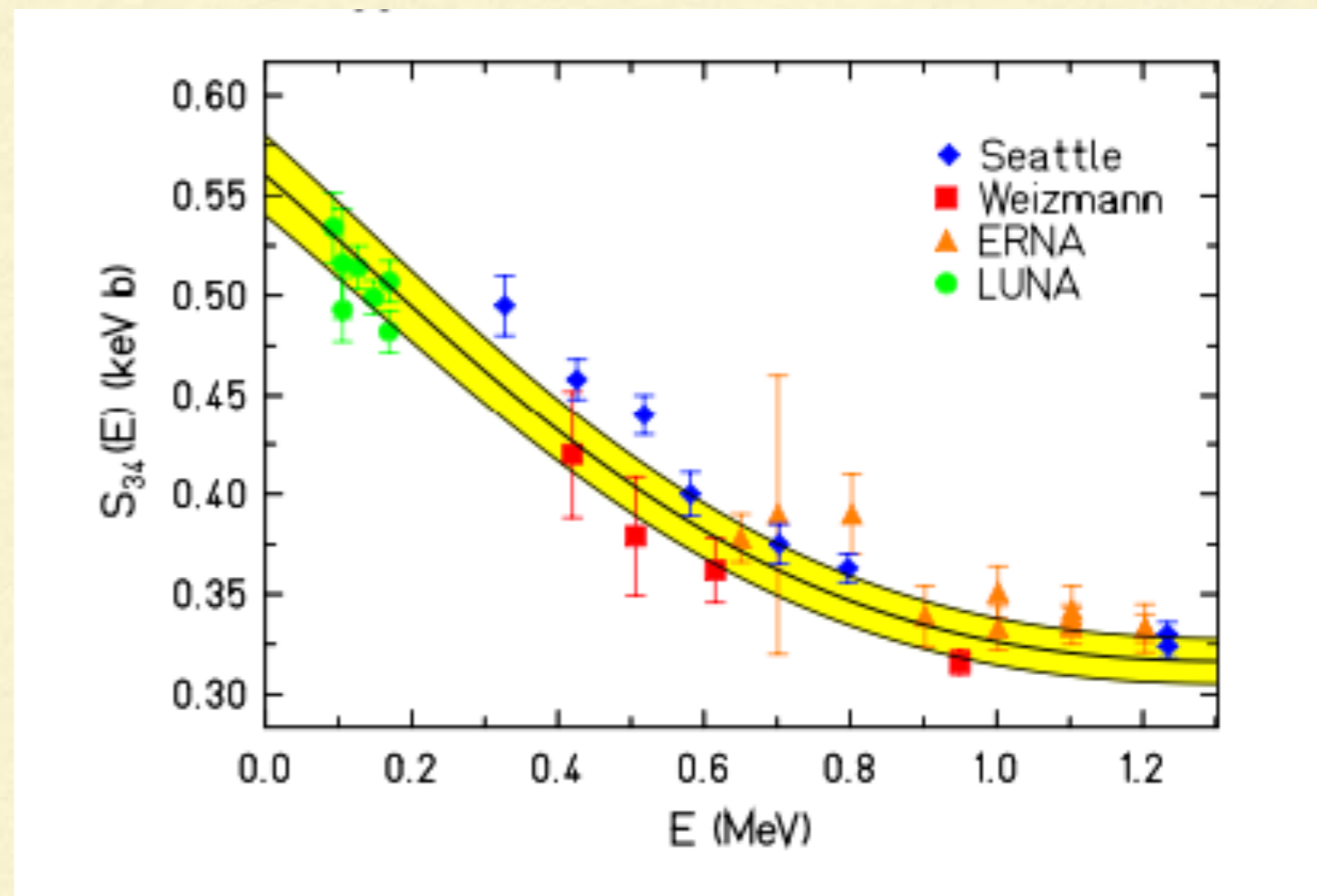
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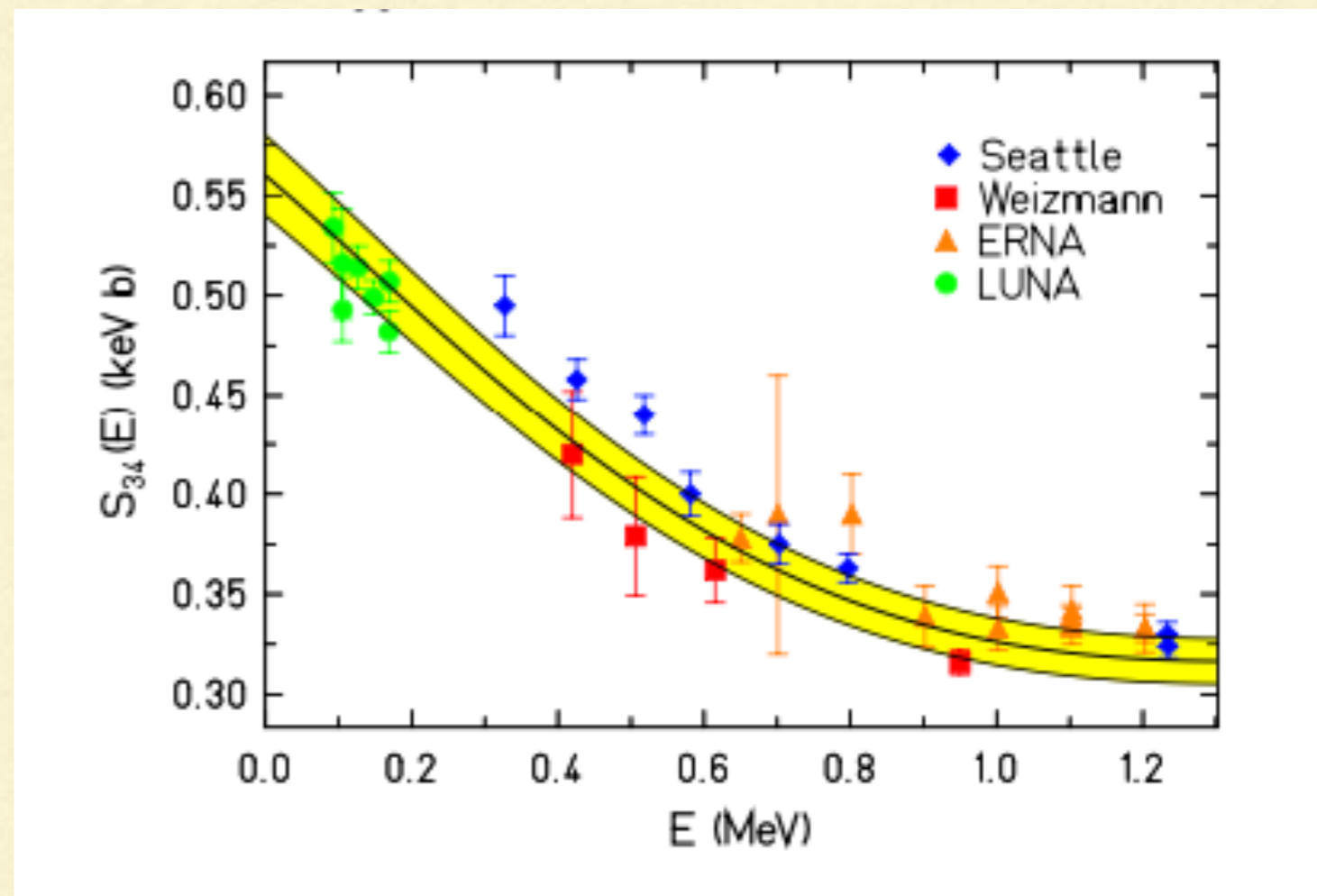
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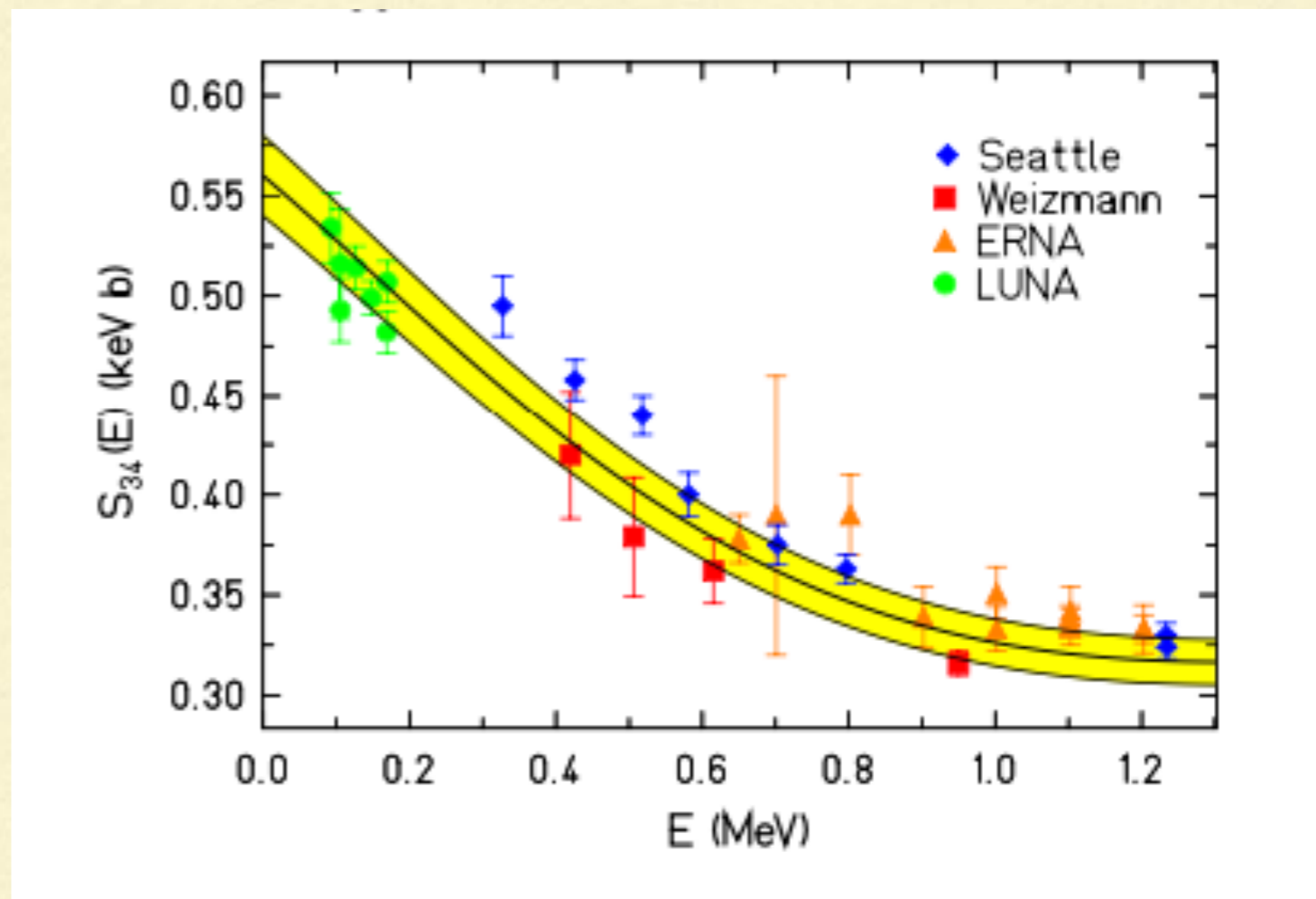
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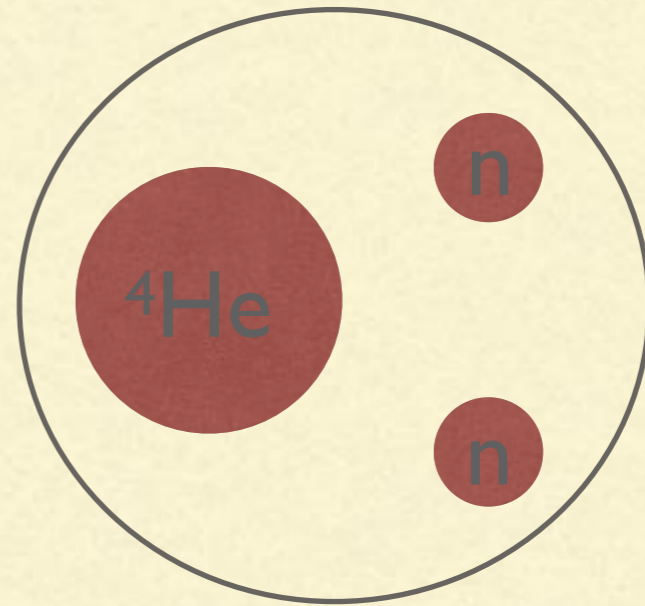
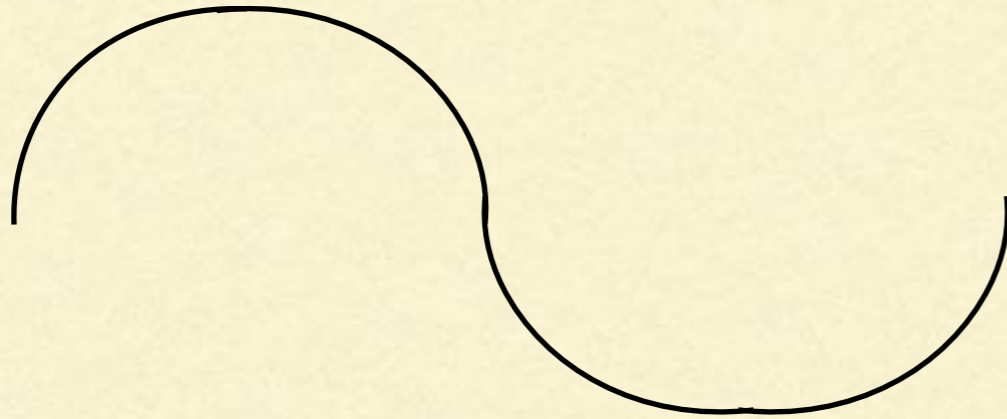
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- SFII: energy dependence taken from models, overall size adjusted to data



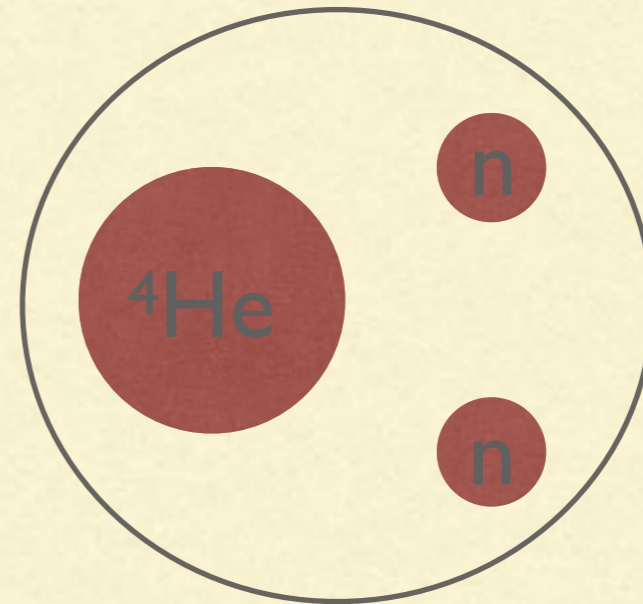
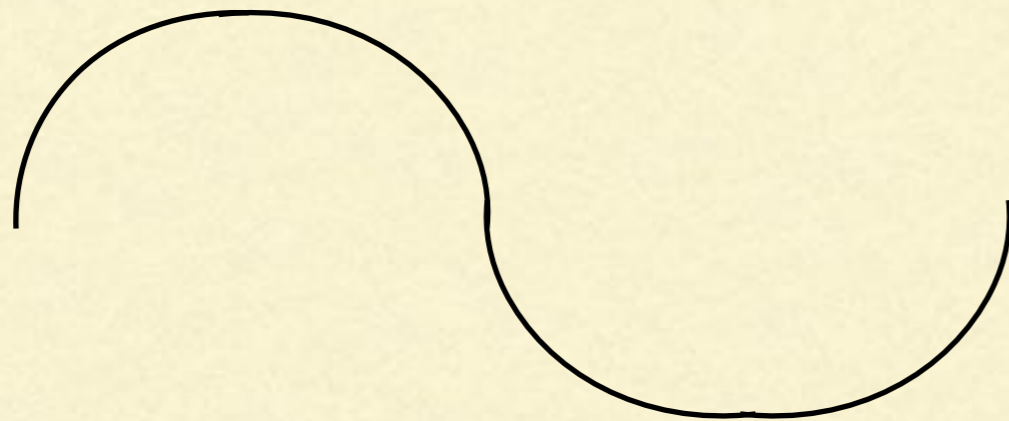
Halo EFT

$$\lambda \gg R_{\text{core}}; \lambda \lesssim R_{\text{halo}}$$



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- Define $R_{\text{halo}} = \langle r^2 \rangle^{1/2}$. Seek EFT expansion in $R_{\text{core}}/R_{\text{halo}}$. Valid for $\lambda \lesssim R_{\text{halo}}$
- Typically $R \equiv R_{\text{core}} \sim 2$ fm. And since $\langle r^2 \rangle$ is related to the neutron separation energy we are looking for systems with neutron separation energies less than 1 MeV
- By this definition the deuteron is the lightest halo nucleus, and the pionless EFT for few-nucleon systems is a specific case of halo EFT

Lagrangian: shallow S- and P-states

$$\begin{aligned}\mathcal{L} = & c^\dagger \left(i\partial_t + \frac{\nabla^2}{2M} \right) c + n^\dagger \left(i\partial_t + \frac{\nabla^2}{2m} \right) n \\ & + \sigma^\dagger \left[\eta_0 \left(i\partial_t + \frac{\nabla^2}{2M_{nc}} \right) + \Delta_0 \right] \sigma + \pi_j^\dagger \left[\eta_1 \left(i\partial_t + \frac{\nabla^2}{2M_{nc}} \right) + \Delta_1 \right] \pi_j \\ & - g_0 [\sigma n^\dagger c^\dagger + \sigma^\dagger n c] - \frac{g_1}{2} \left[\pi_j^\dagger (n i\overleftrightarrow{\nabla}_j c) + (c^\dagger i\overleftrightarrow{\nabla}_j n^\dagger) \pi_j \right] \\ & - \frac{g_1}{2} \frac{M - m}{M_{nc}} \left[\pi_j^\dagger i\overrightarrow{\nabla}_j (nc) - i\overleftrightarrow{\nabla}_j (n^\dagger c^\dagger) \pi_j \right] + \dots ,\end{aligned}$$

- c, n: “core”, “neutron” fields. c: boson, n: fermion.
 - σ, π_j : S-wave and P-wave fields
 - Minimal substitution generates leading EM couplings
 - Additional EM couplings at sub-leading order
-

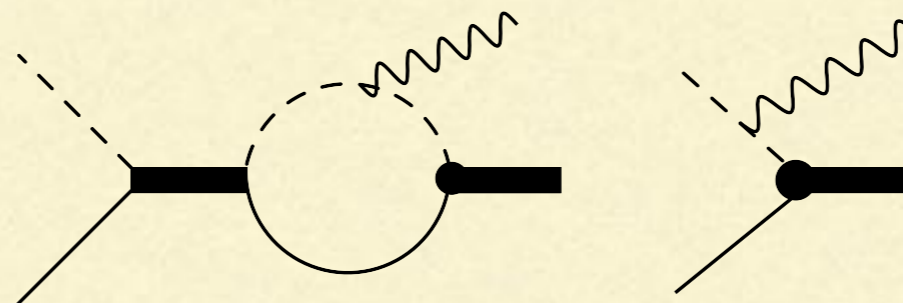
p-wave bound states and capture thereto

Hammer & DP, NPA (2011)

- At LO p-wave In halo described solely by its ANC and binding energy

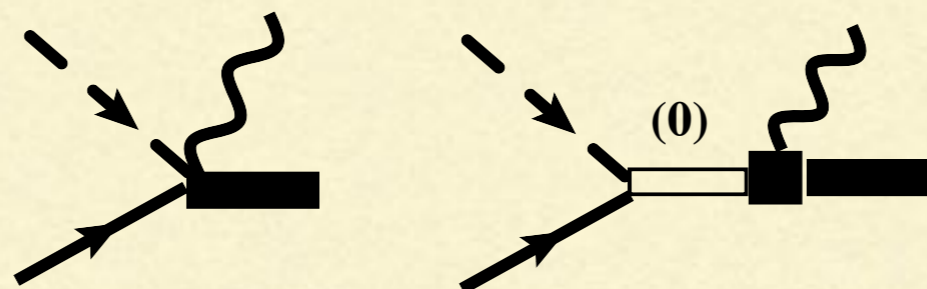
$$u_1(r) = A_1 \exp(-\gamma_1 r) \left(1 + \frac{1}{\gamma_1 r} \right) \quad \gamma_1 = \sqrt{2m_R B}$$

- Capture to the p-wave state proceeds via the one-body E1 operator: “external direct capture”



$$E1 \propto \int_0^\infty dr u_0(r) r u_1(r); \quad u_0(r) = 1 - \frac{r}{a}$$

- NLO: piece of the amplitude representing capture at short distances, represented by a contact operator \Rightarrow there is an LEC that must be fit



${}^3\text{He} + {}^4\text{He} \rightarrow {}^7\text{Be} + \gamma_{\text{EI}}$ at LO in Halo EFT

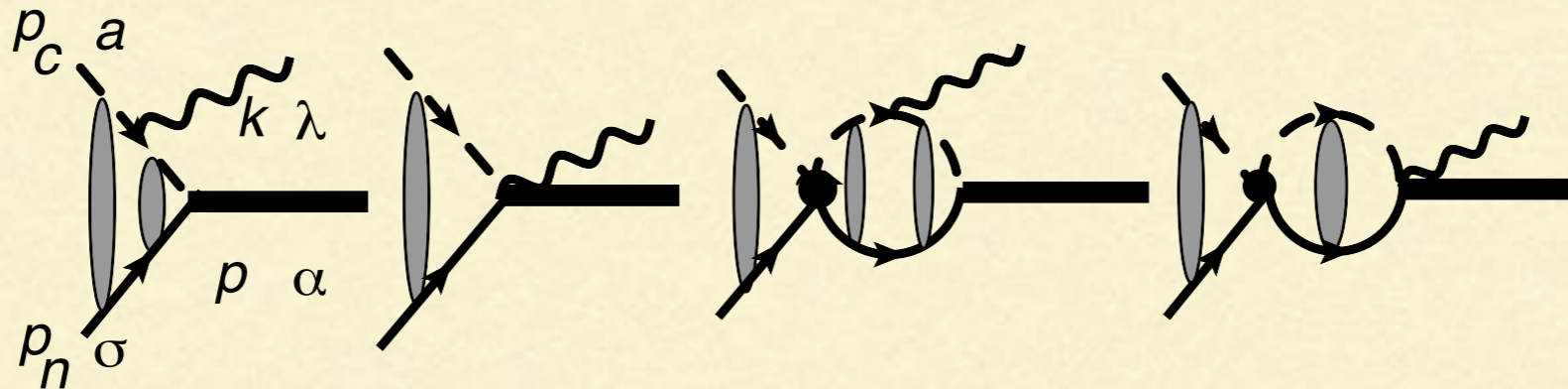
Zhang, Nollett, DP, *J. Phys. G* (2020); cf. Rupak, Higa, Vaghani, *EPJA* (2018)

- In this system $R_{\text{core}} \sim 1.5$ fm, $R_{\text{halo}} \sim 3$ fm

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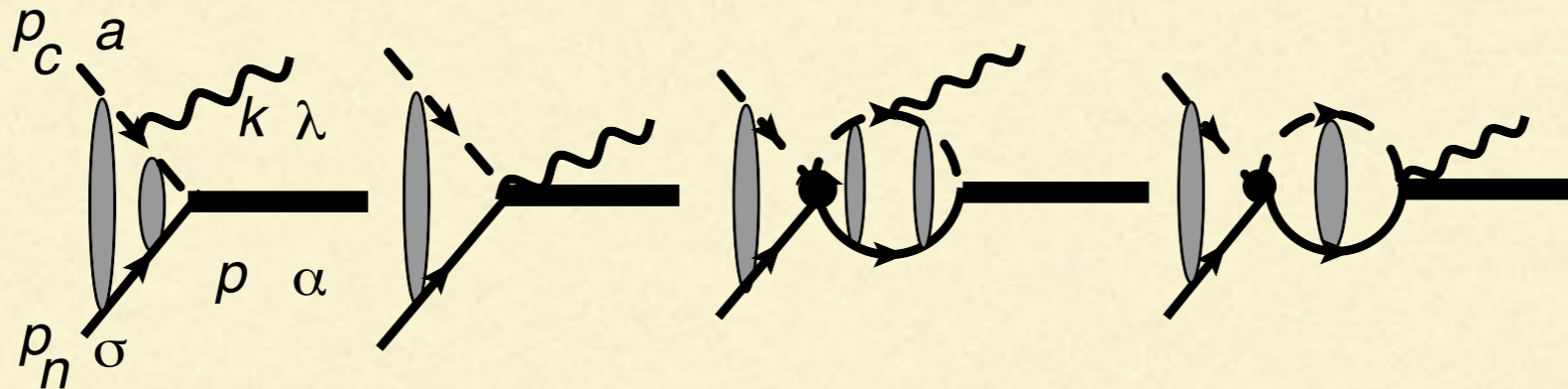
- In this system $R_{\text{core}} \sim 1.5$ fm, $R_{\text{halo}} \sim 3$ fm
- Also need to include Coulomb interactions non-perturbatively:
 $k_C = Q_c Q_n \alpha_{\text{EM}} M_R = 45$ MeV; $a \sim 10$ s of fm, both $\sim R_{\text{halo}}$



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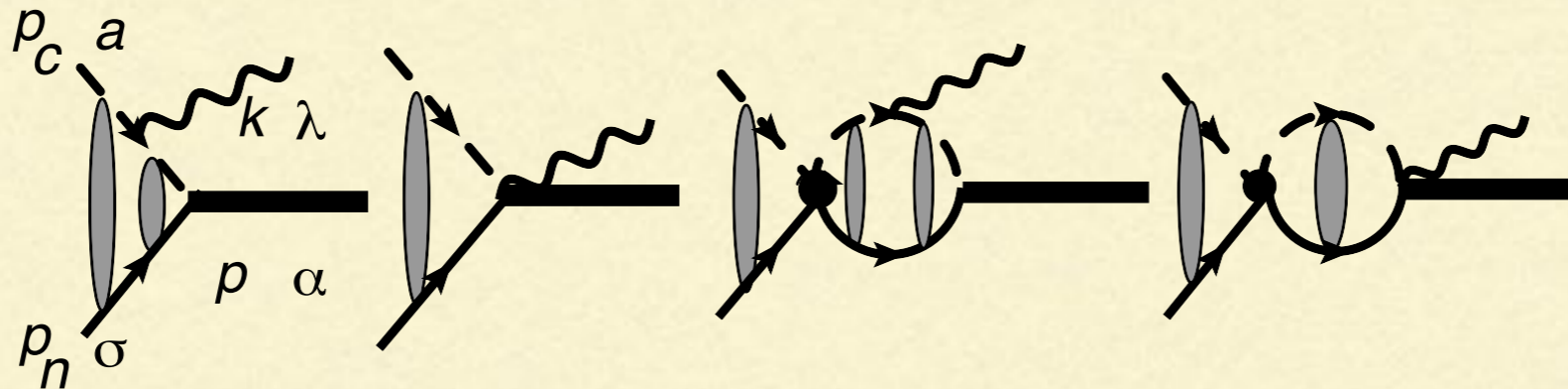


- Scattering wave functions are linear combinations of Coulomb wave functions F_0 and G_0 . Bound state wave function = the appropriate Whittaker function.

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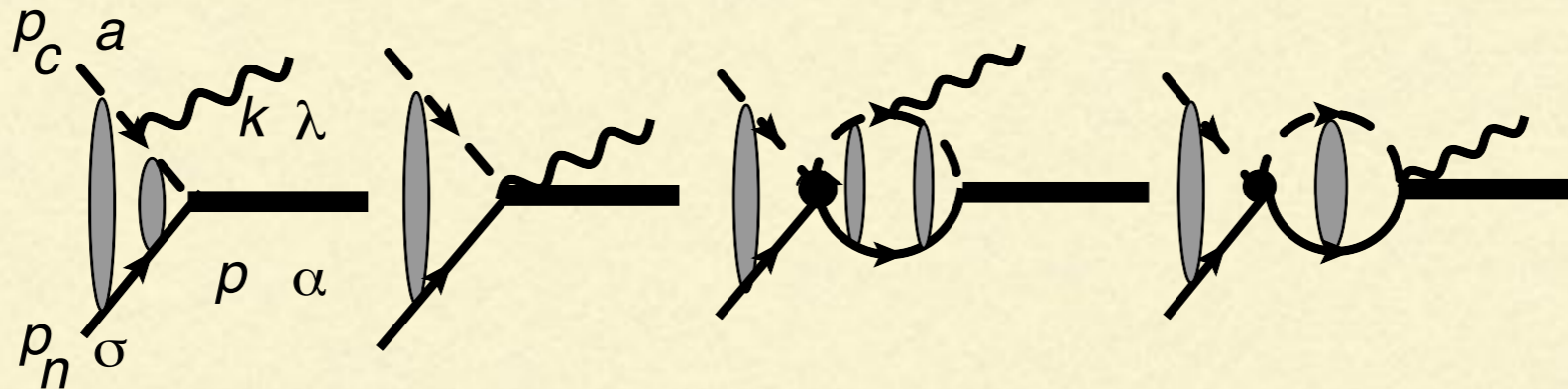
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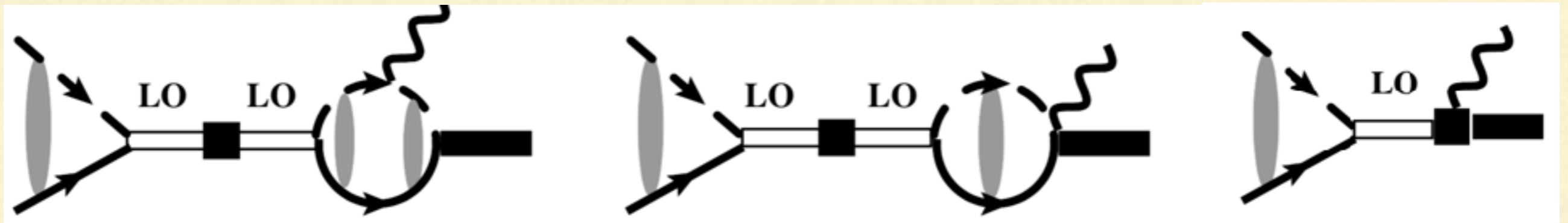
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- Can also predict capture to the excited $1/2^-$ in ${}^7\text{Be}$

Three parameters at leading order

Additional ingredients at NLO

Zhang, Nollett, DP, Phys. Lett. B751, 535 (2015), Phys. Rev. C (2018);
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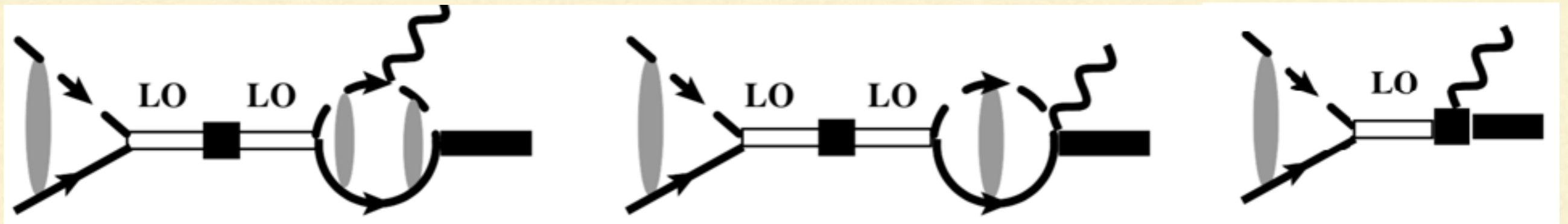
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Three more parameters at NLO

- Effective range (can add shape parameter which enters at N³LO)
- LECs associated with contact interaction, \bar{L} and \bar{L}_*
- Can also consider contact interaction for D-wave capture, \bar{L}_D (enters at N⁴LO)

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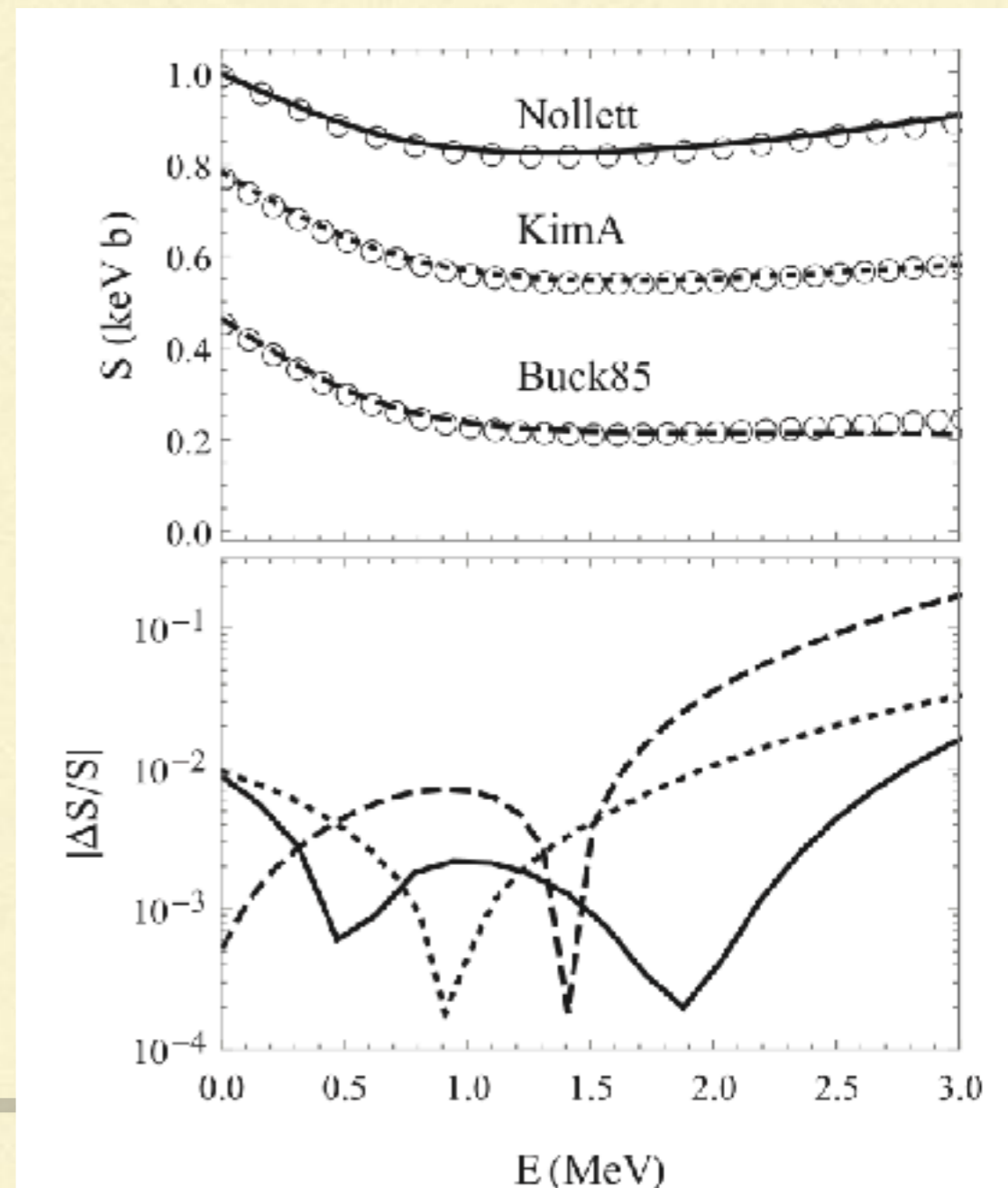
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- Halo EFT is the EFT of all the models used to extrapolate the cross section in “Solar Fusion II”: should reproduce them at NLO accuracy in validity region
- Differences are sub-% level between 0 and 1.5 MeV
- Parameters generally obey $a \sim 1/R_{\text{halo}}$, $r \sim R_{\text{core}}$, $L \sim R_{\text{core}}$; some large N4LO parameters

Table 1. EFT parameters obtained from partial-N4LO fits to models from the literature. Quantities are total ANC squared (C_T^2), the ratio of ES ANC squared to C_T^2 , the scattering length, effective range, and shape parameters as well as s-to-p-wave short-distance parameters, \bar{L} and \bar{L}_* and d-to-p-wave short-distance parameters \bar{L}_D and \bar{L}_{D*} . The last two rows are the binding energies of ${}^7\text{Be}$'s GS and ES.

	Buck85 [34]	KimA [36]	Nollett [13]
C_T^2 (fm $^{-1}$)	30.33	29.22	21.01
$R_{(P_{1/2})}$	0.4197	0.4192	0.4002
a_0 (fm)	36.97	18.27	29.48
r_0 (fm)	0.9726	0.9979	0.9723
\mathcal{P}_0 (fm 3)	-0.3688	-0.086 66	-0.5227
\bar{L}	0.9018	0.6434	0.9546
\bar{L}_*	0.9079	0.6334	0.9772
\bar{L}'	0.091 25	0.5311	0.2240
\bar{L}'_*	0.079 64	0.5465	0.2366
\bar{L}_D (fm 4)	-4.541	-1.950	0.5124
\bar{L}_{D*} (fm 4)	-4.844	-3.096	0.3444
B (MeV)	1.608	1.656	1.587
B_* (MeV)	1.163	1.192	1.158

Data for ${}^3\text{He} + {}^4\text{He} \rightarrow {}^7\text{Be} + \gamma_{\text{EI}}$

- 59 S-factor data below 2 MeV
 - Seattle (S)
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 - In general use activation data, to avoid photon emission asymmetry systematic; recoil data from Erna; prompt measurements from Notre Dame
 - Deal with CMEs by introducing six additional parameters, ξ_i
 - Plus 32 branching-ratio data: CMEs assumed absent there
-

Bayesian tools

Thomas Bayes (1701?-1761)



<http://www.bayesian-inference.com>

$$\text{pr}(A|B, I) = \frac{\text{pr}(B|A, I)\text{pr}(A|I)}{\text{pr}(B|I)}$$

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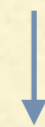


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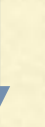
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Likelihood



Prior



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Posterior



Normalization

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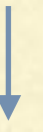
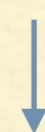
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Posterior



Normalization

Marginalization: $\text{pr}(x|\text{data}, I) = \int dy \text{pr}(x, y|\text{data}, I)$

Allows us to integrate out “nuisance” (e.g. higher-order) parameters

Building the pdf

- χ^2 needs to include cross-section and branching-ratio data

$$\chi^2 \equiv \sum_J^{N_{\text{exp}}} \left\{ \sum_{j=1}^{N_{s,J}} \frac{\left[(1 - \xi_J) S(\vec{g}; E_{Jj}) - D_{Jj} \right]^2}{\sigma_{Jj}^2} + \frac{\xi_J^2}{\sigma_{c,J}^2} \right\} + \sum_{l=1}^{N_{br}} \frac{\left[Br(\vec{g}; E_l) - \tilde{D}_l \right]^2}{\sigma_{br,l}^2}$$

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$$\chi^2 \equiv \sum_J^{N_{\text{exp}}} \left\{ \sum_{j=1}^{N_{s,J}} \frac{\left[(1 - \xi_J) S(\vec{g}; E_{Jj}) - D_{Jj} \right]^2}{\sigma_{Jj}^2} + \frac{\xi_J^2}{\sigma_{c,J}^2} \right\} + \sum_{l=1}^{N_{br}} \frac{\left[Br(\vec{g}; E_l) - \tilde{D}_l \right]^2}{\sigma_{br,l}^2}$$

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- Mild Bayesian priors:
 - Independent gaussian priors for ξ_i , centered at zero and with width=CME
 - Other EFT parameters, a , r , L , and two ANCs assigned flat priors, corresponding to natural ranges
 - Probability $e^{-\chi^2/2}$ sampled using Markov Chain Monte Carlo
-

${}^3\text{He}({}^4\text{He}, \gamma)$ results

Zhang, Nollett, DP, JPG (2020)
cf. Higa, Rupak, Vaghani, EPJA (2018)

${}^3\text{He}({}^4\text{He},\gamma)$ results

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- EI external direct capture to a shallow p-wave bound state
- Only one spin channel

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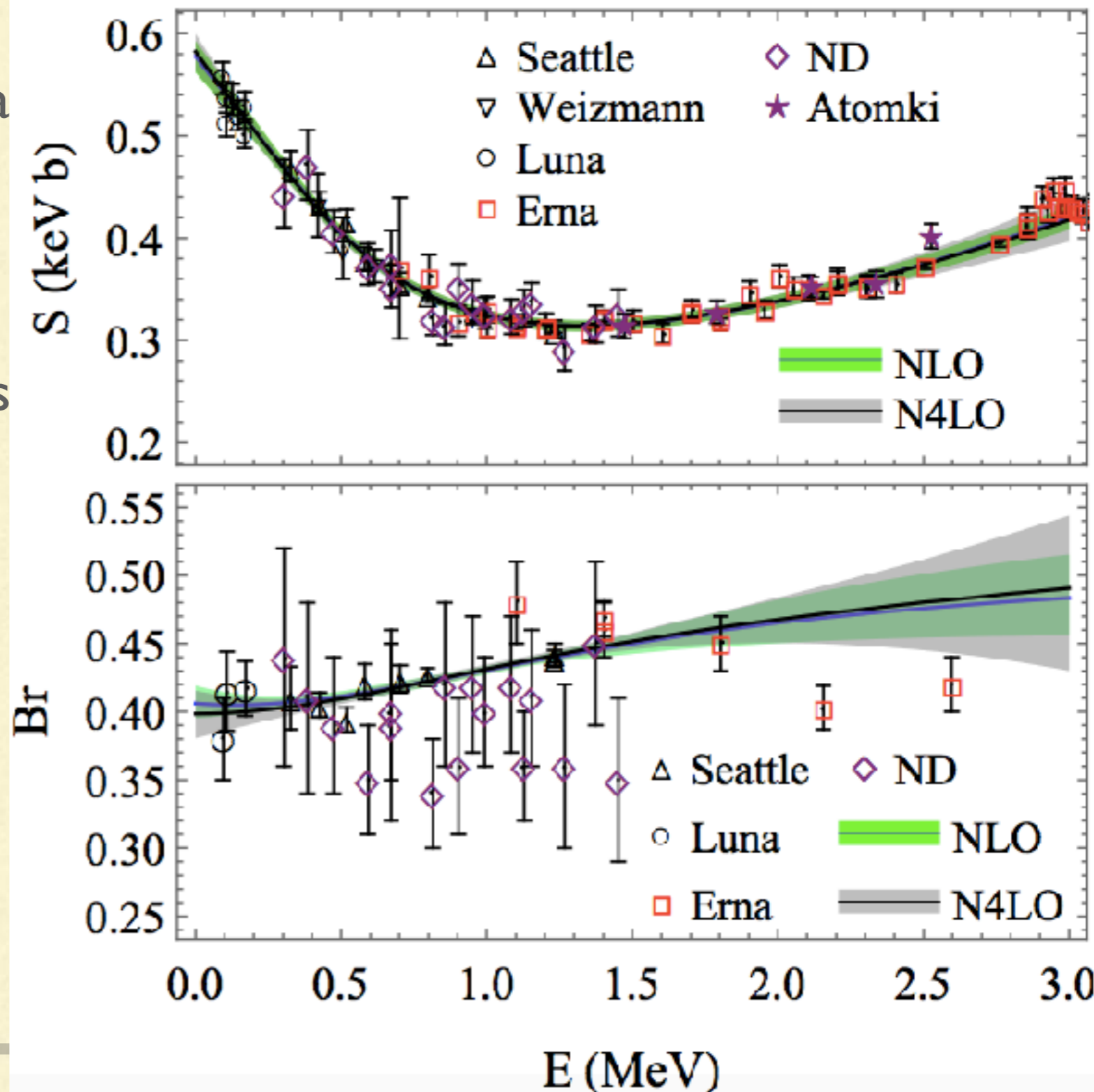
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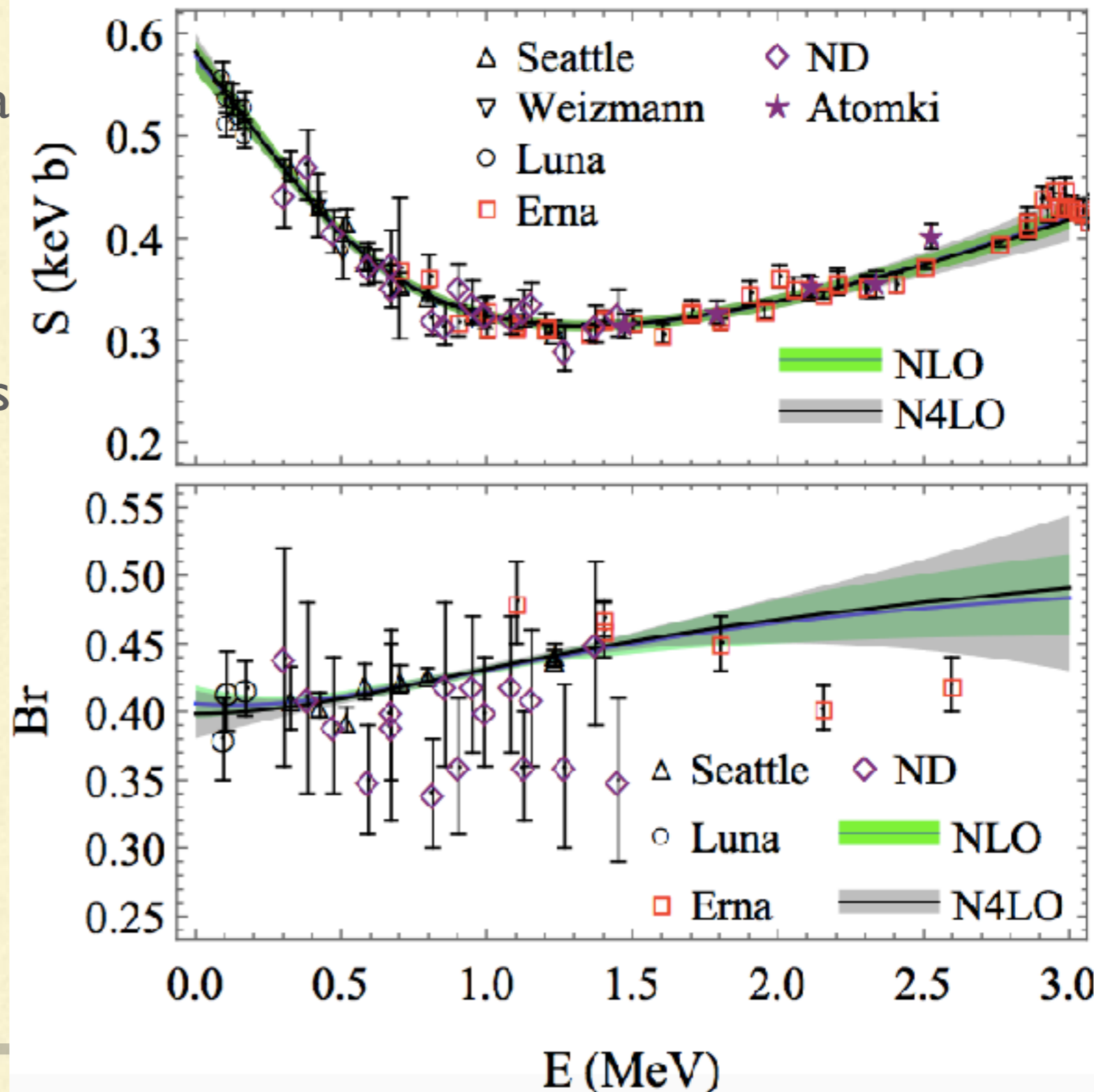
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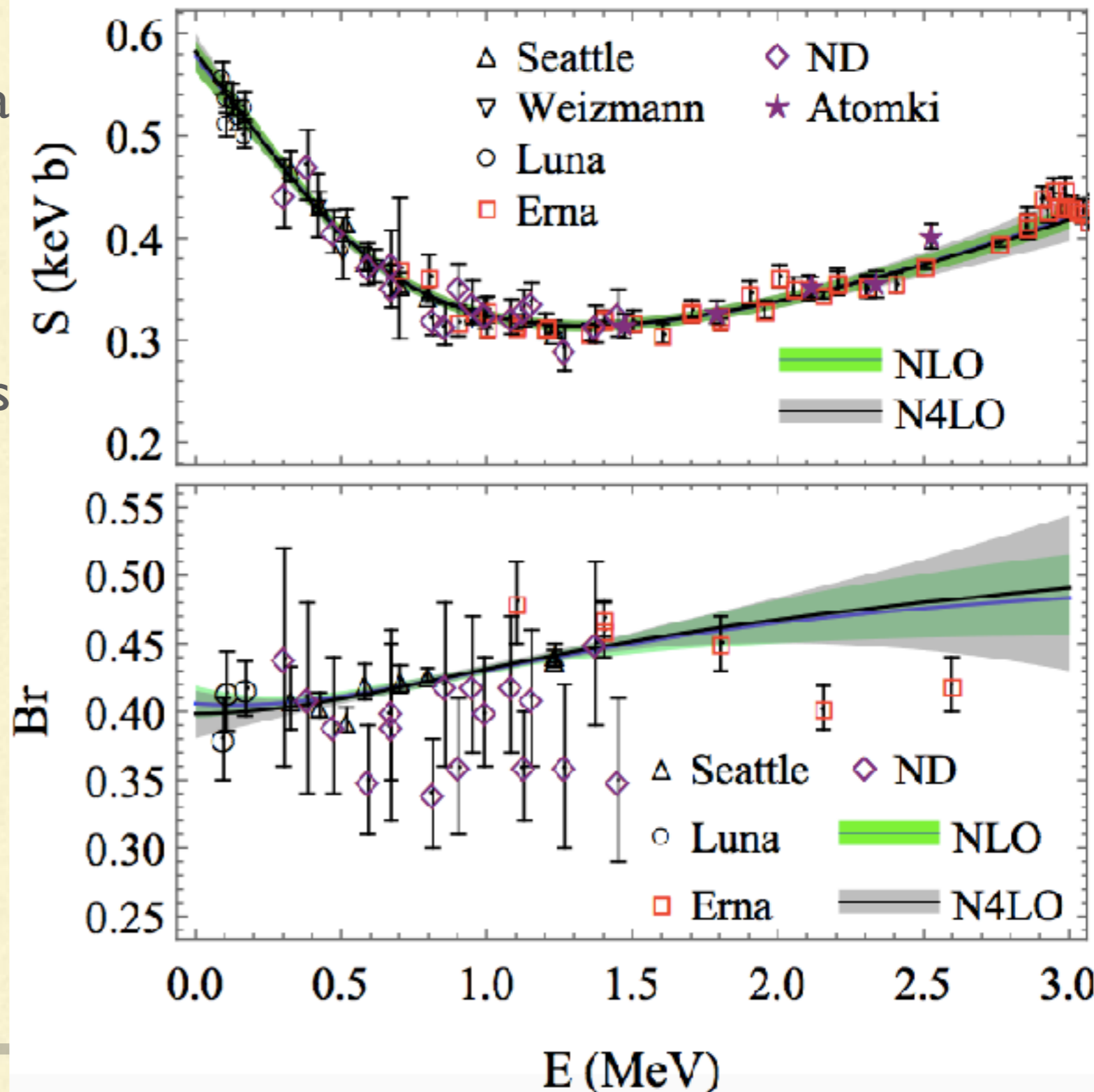
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- Distribution peaks at $\chi^2 = 82$



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- Bayesian evidence ratio $\cong 6$ for NLO cf. N⁴LO



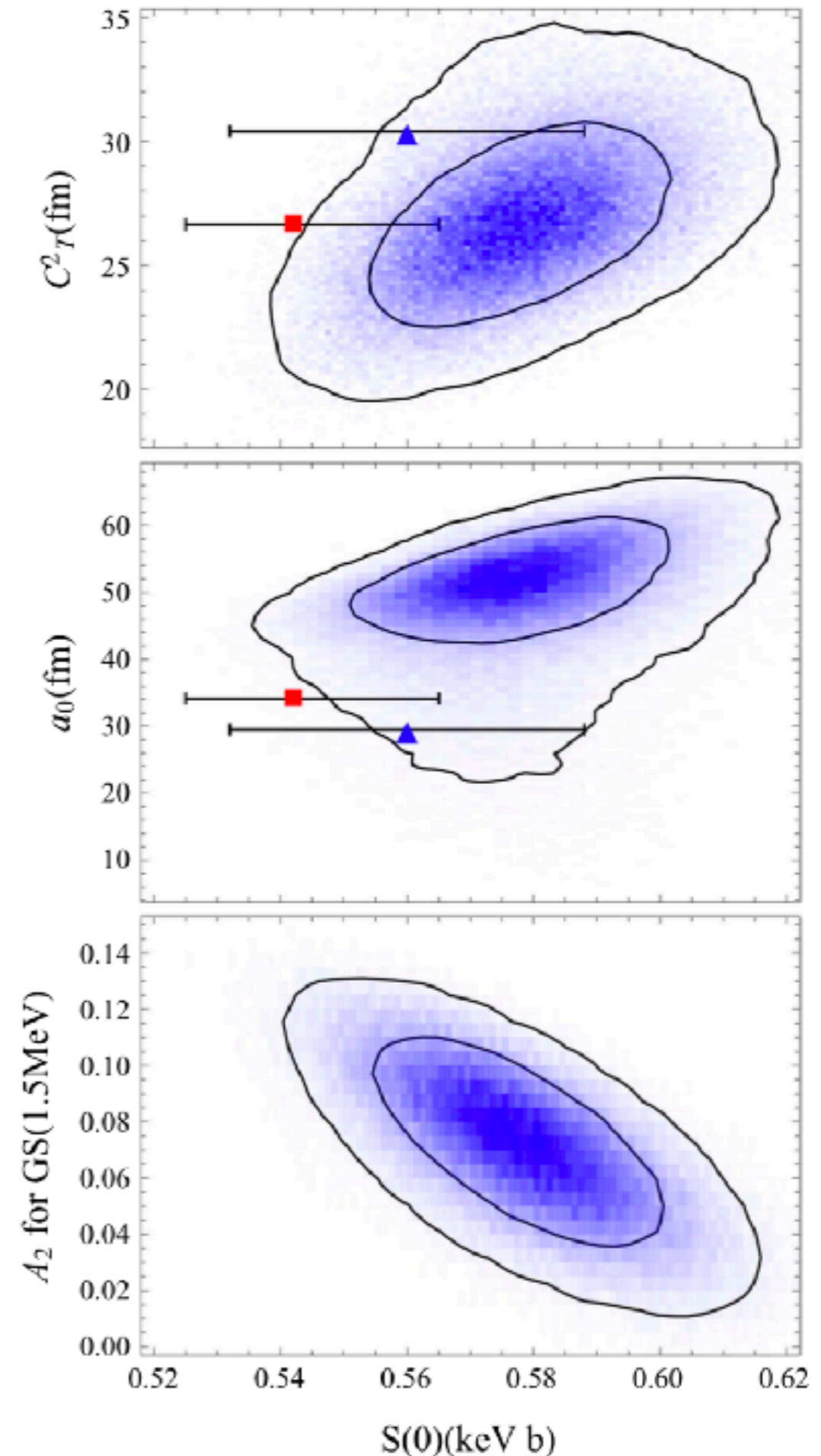
$S(0)$ and its correlants

$$S(0) = 0.578^{+0.015}_{-0.016} \text{ keV b}$$

cf. SFII: $S(0) = 0.56 \pm 0.03 \text{ keV b}$

$$Br(0) = 0.406^{+0.013}_{-0.011}$$

Mostly consistent with other analyses, but 1.5σ higher than that of deBoer et al.



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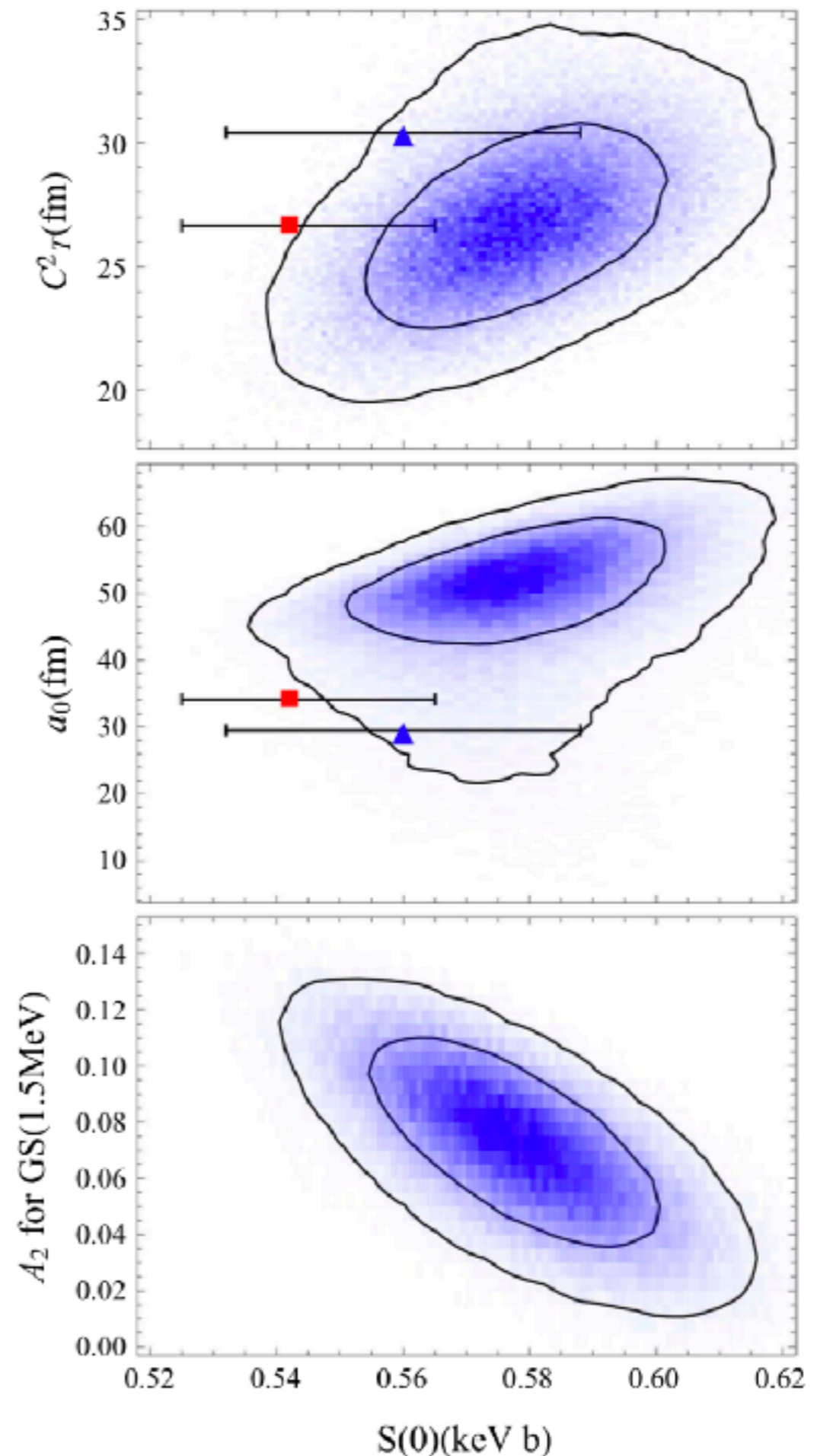
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How to tell difference?

1. Measure $P_2(\cos \Theta)$ dependence
2. Tight constraints on scattering parameters from capture data alone



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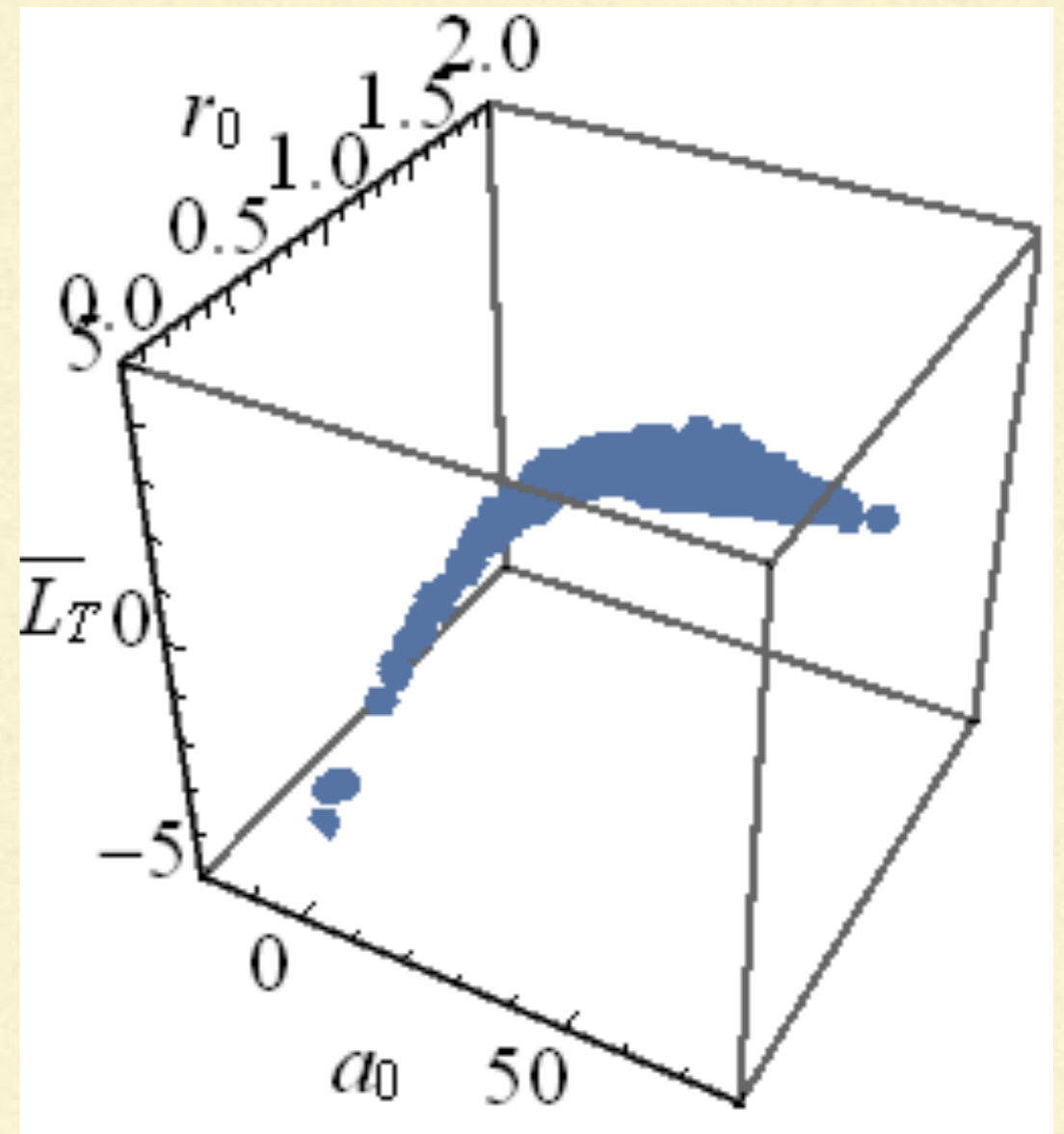
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Outline

- ${}^3\text{He} + {}^4\text{He} \rightarrow {}^7\text{Be} + \gamma$ as an example of how to assess model uncertainty
 - How Halo Effective Field Theory can help ✓
 - Halo EFT as a “super model” ✓
 - From S-factor data to Halo EFT parameters, and back ✓
 - Bayesian Model Averaging → Bayesian Model Mixing
 - What is Bayesian Model Averaging?
 - An application: the overall prediction of EDFs for the neutron drip line
 - Toy-model test of BMA
 - The BAND Software Framework
-

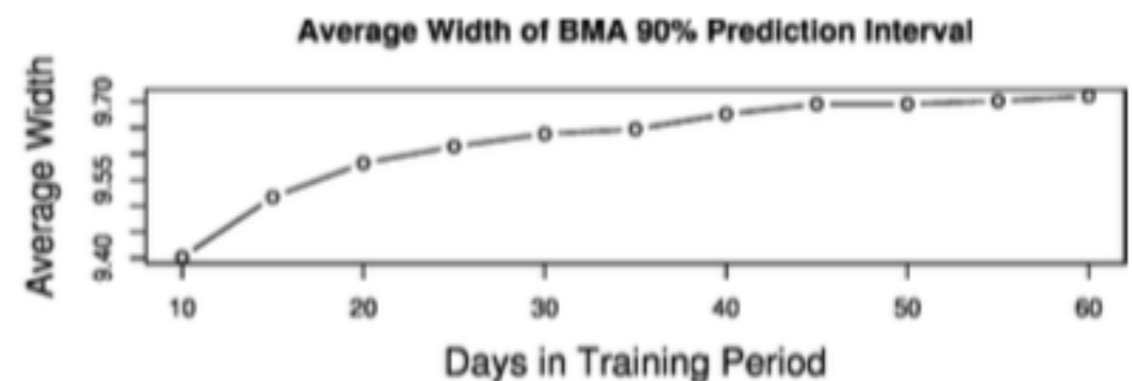
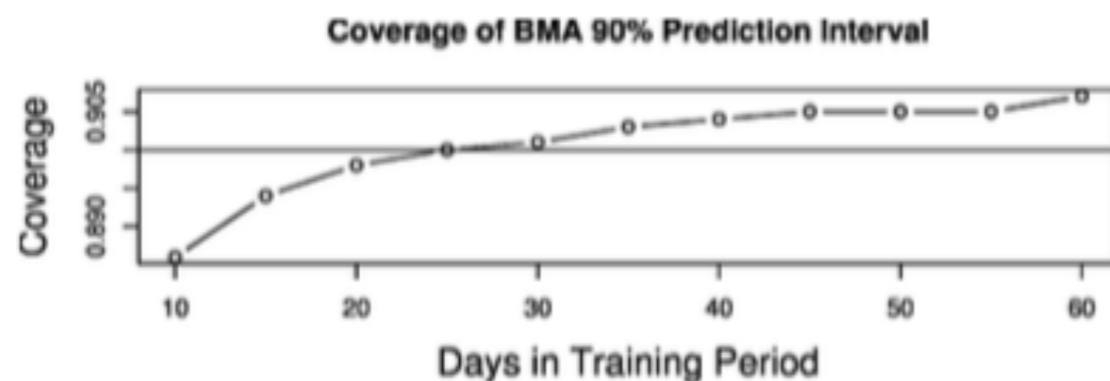
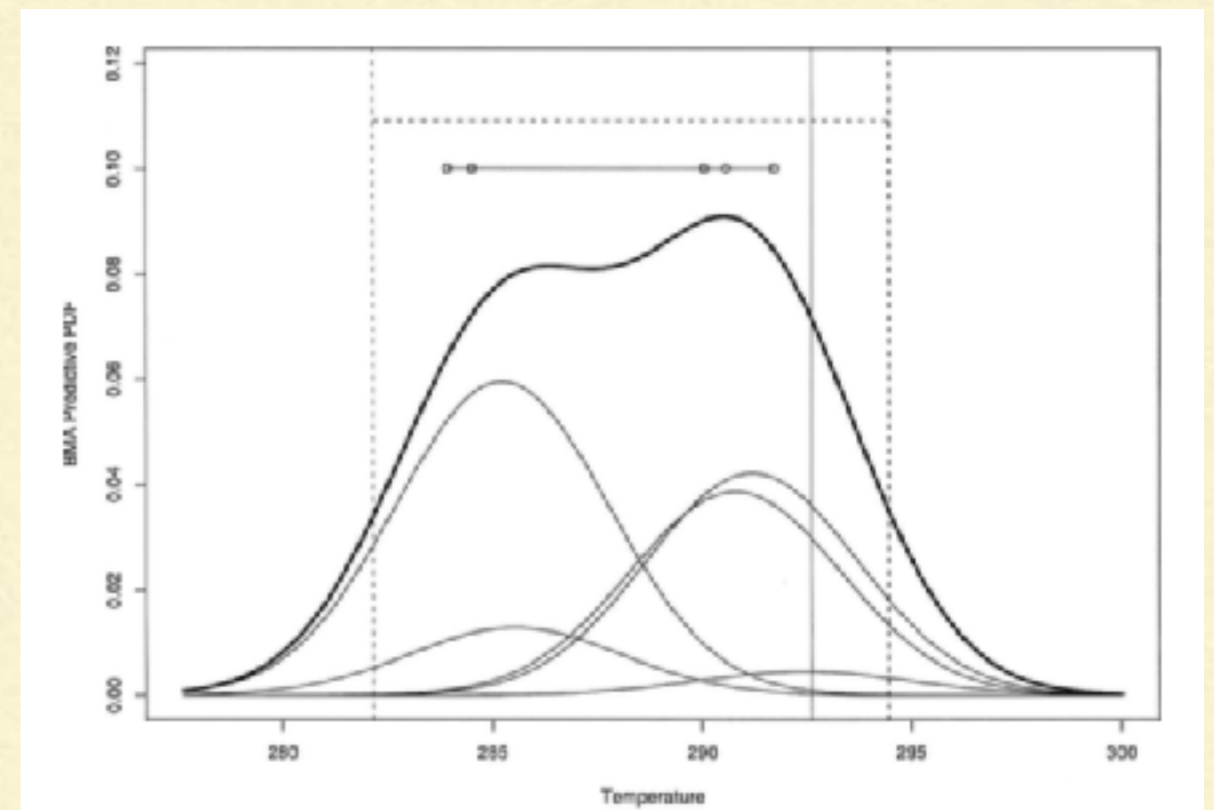
Bayesian Model Averaging

Bayesian Model Averaging:
marginalize over a discrete
set of models $\{M\}$

$$\text{pr}(Q | D, I) = \sum_M \text{pr}(Q | M, D, I) \text{pr}(M | D, I)$$

- Used in several other fields
- Improves central values and coverage properties in weather forecasting

Raftery et al. (2005)



Bayesian Model Averaging: some details

$$\text{pr}(Q | D, I) = \sum_M \text{pr}(Q | M, D, I) \text{pr}(M | D, I)$$

- Average over models, with weights given by “Bayesian model evidence”

$$\text{pr}(M | D, I) \propto \text{pr}(D | M, I) \text{pr}(M | I)$$

$$\text{pr}(D | M, I) = \int \text{pr}(D | \theta, M, I) \text{pr}(\theta | M, I) d\theta$$

- Requires computation of integral over parameter space: cannot be done using (standard) MCMC
 - If set of models $\{M\}$ includes true model BMA is guaranteed to converge to result from that model as more data acquired: \mathfrak{M} closed
 - If set of models $\{M\}$ does not include true model then BMA will converge to one with smallest KL divergence: \mathfrak{M} open
-

BMA+EDF: where is the neutron drip line?

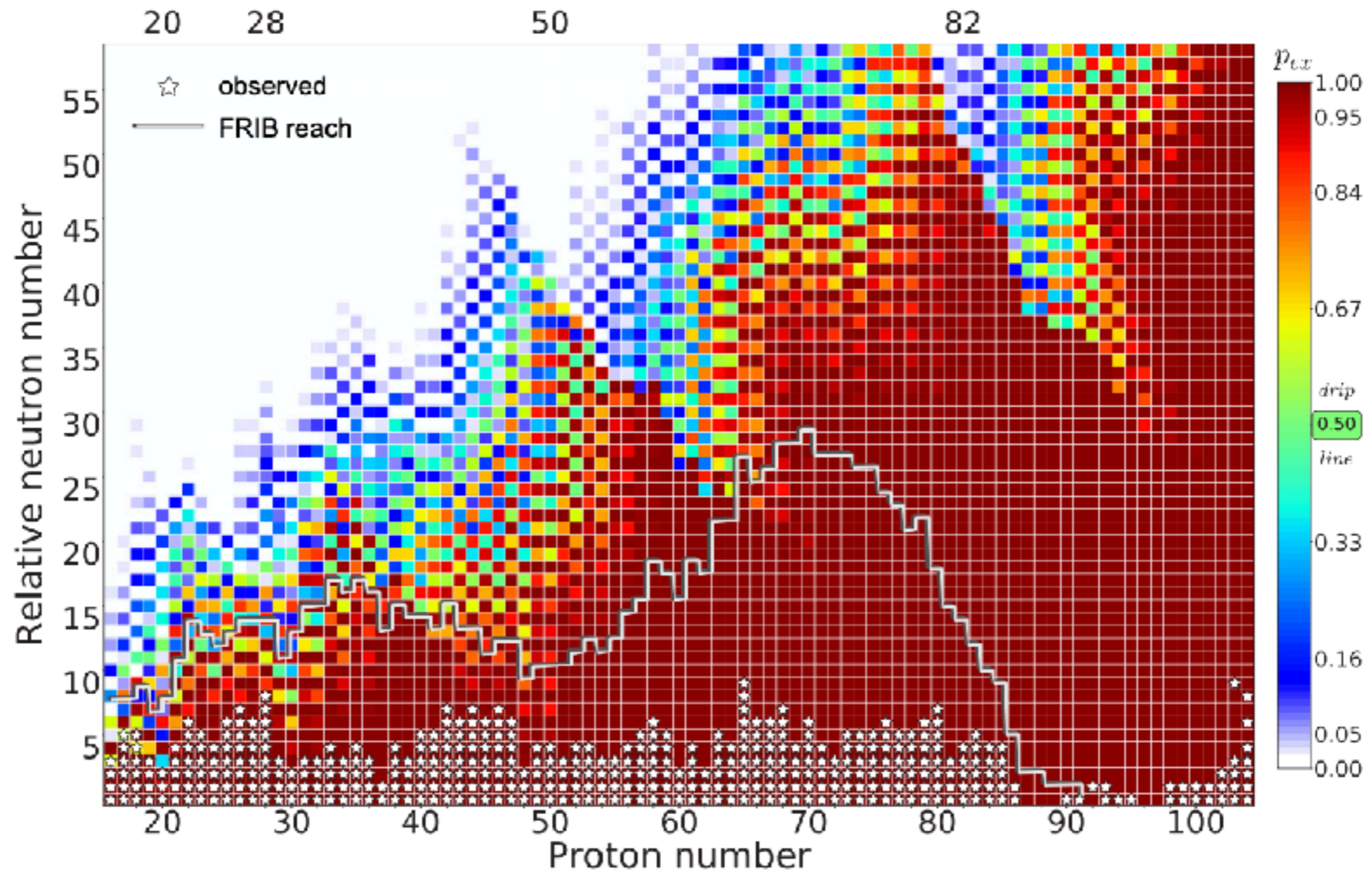
Neufcourt et al., PRL (2019); PRC (2020)

- Take 8 Skyrme EDFs: SkM*, SkP,SLy4, SV-min, UNEDF0, UNEDF1, and UNEDF2, as well as Gogny functional DIM and functional BCPM, and FRDM-2012 and Skyrme-HFB model HFB-24
- Each model augmented by Gaussian Process trained to AME2016+ dataset
- Mix models according to weights: $w_k(n) \propto p[S_{1n/2n}(x) > 0 | \mathcal{M}_k]$ for x one of the 254 neutron-rich nuclei with no neutron-separation energy measured

TABLE I. Model posterior weights obtained in the variants BMA(n) (4) and BMA(p) (5) of our BMA calculations. For compactness, the following abbreviations are used: UNEn = UNEDFn ($n = 0,1,2$) and FRDM = FRDM-2012.

BMA variant	SkM*	SkP	SLy4	SV-min	UNE0	UNE1	UNE2	BCPM	D1M	FRDM	HFB-24
BMA(n)	0.10	0.10	0.06	0.11	0.12	0.10	0.09	0.06	0.04	0.12	0.09
BMA(p)	0.00	0.03	0.08	0.05	0.04	0.14	0.12	0.04	0.16	0.17	0.17

Results



Toy model test for Bayesian methods

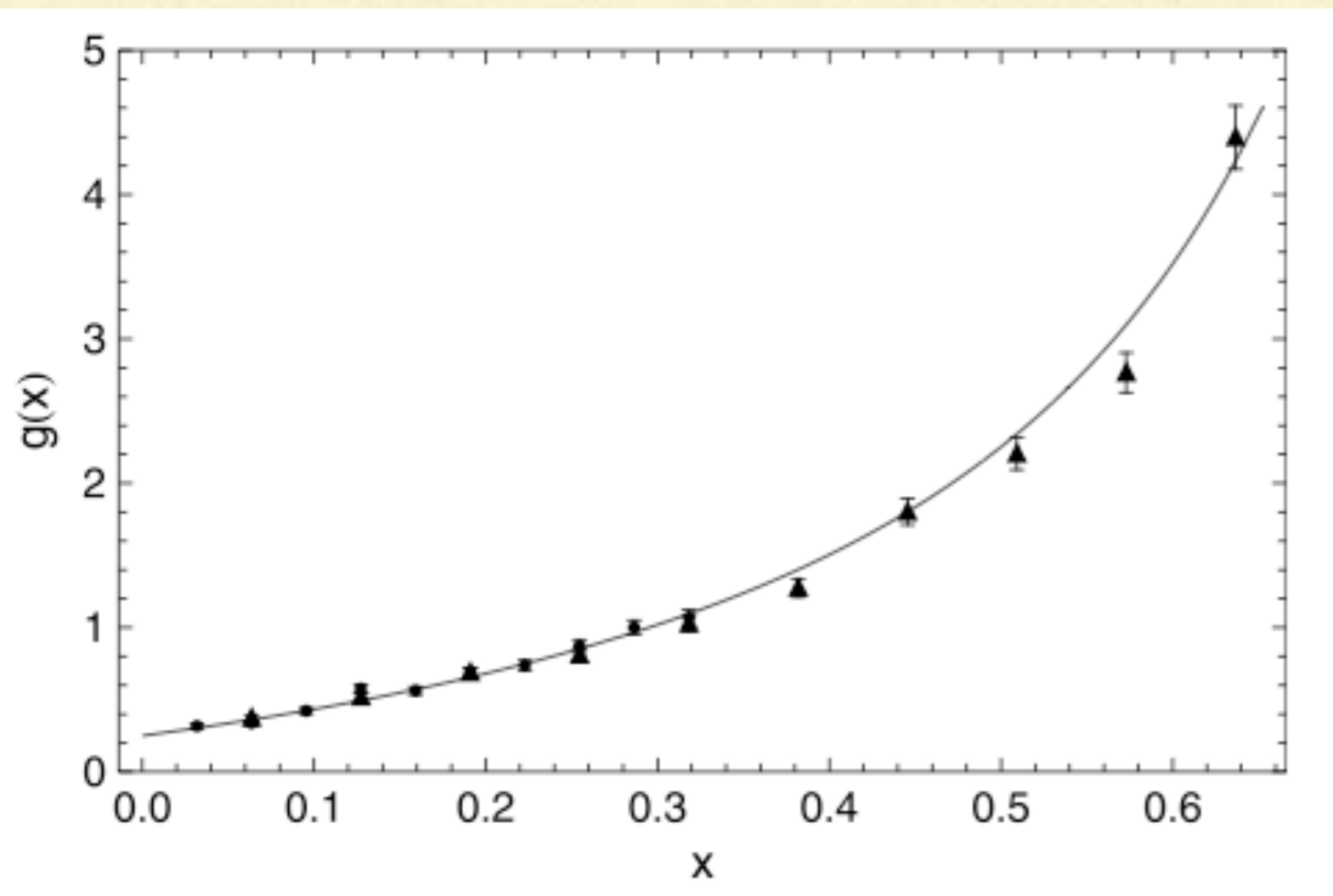
Schindler, DP, Ann. Phys., 2009; Wesolowski, Klcio, Furnstahl, DP, Thapaliya, JPG, 2016

- Given data $D=\{(d_k, \sigma_k):k=1, \dots, N\}$ taken at points x_k and a fit function $f(x; \mathbf{a})$ that depends on LECs $\mathbf{a}=\{a_0, a_1, a_2, \dots\}$, extrapolate to a target point that is either “near” or “far”
- BUT, be careful! f only describes data in a limited domain

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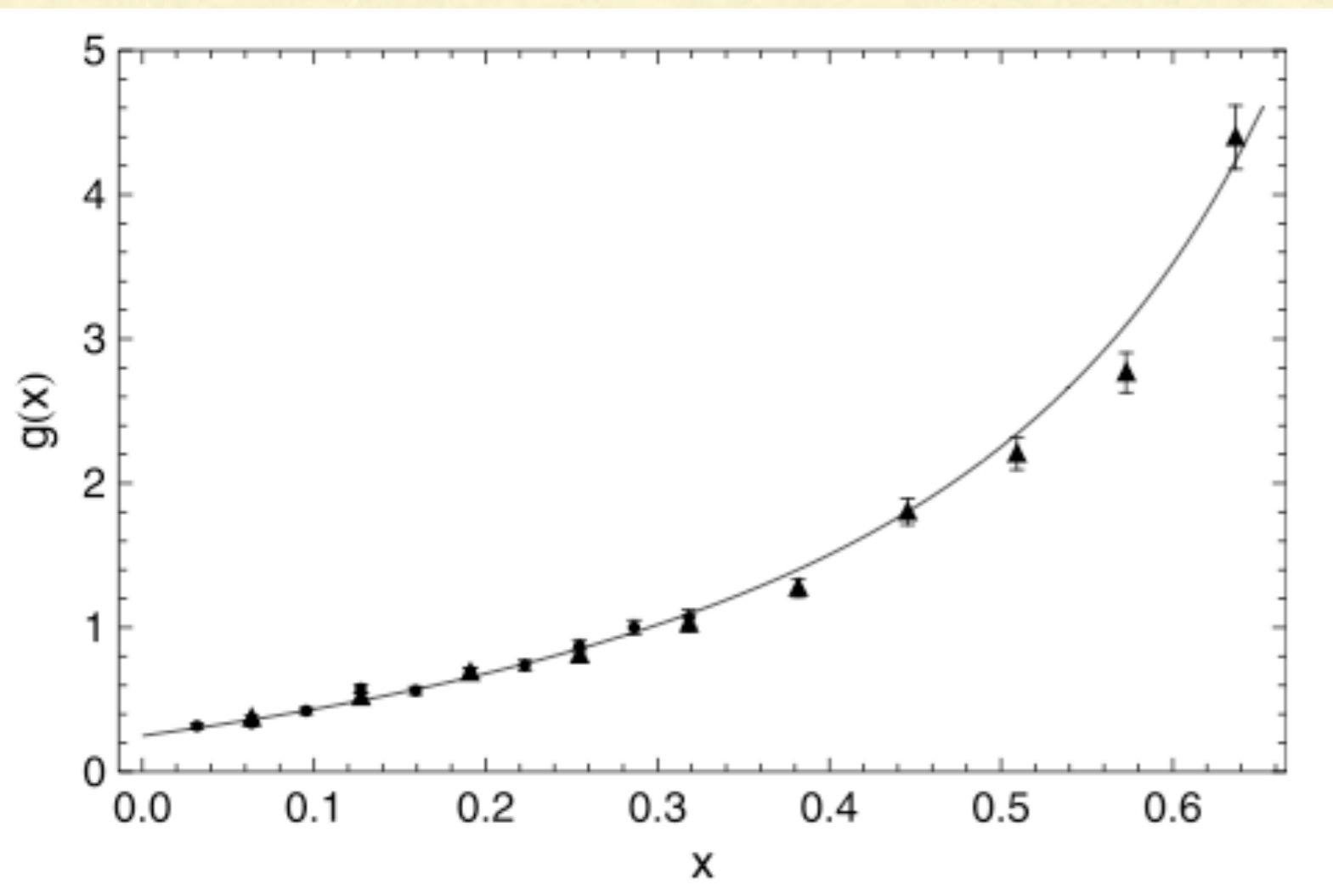
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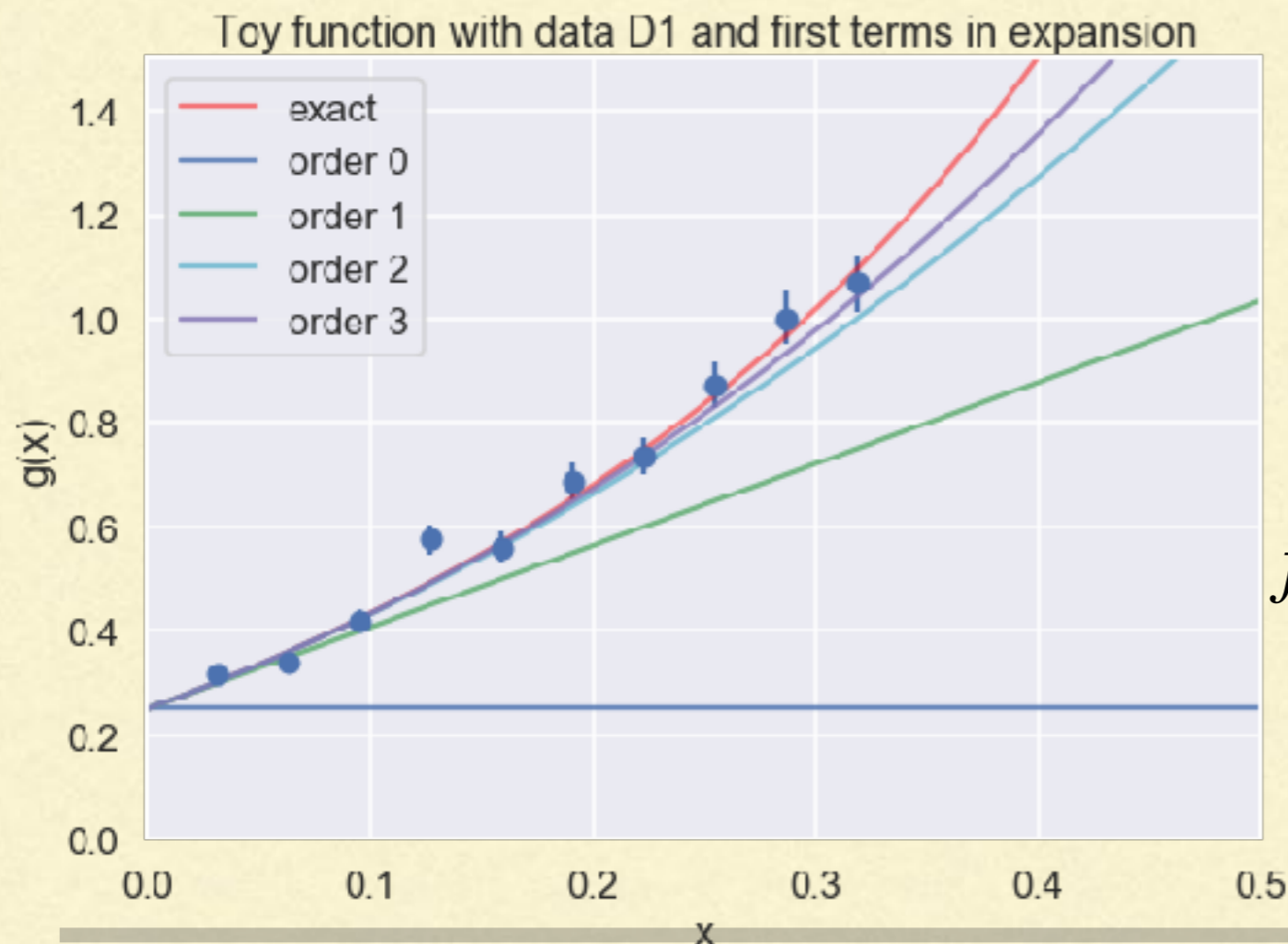


Toy example 1: data from
 $g(x) = (1/2 + \tan(\pi x/2))^2$

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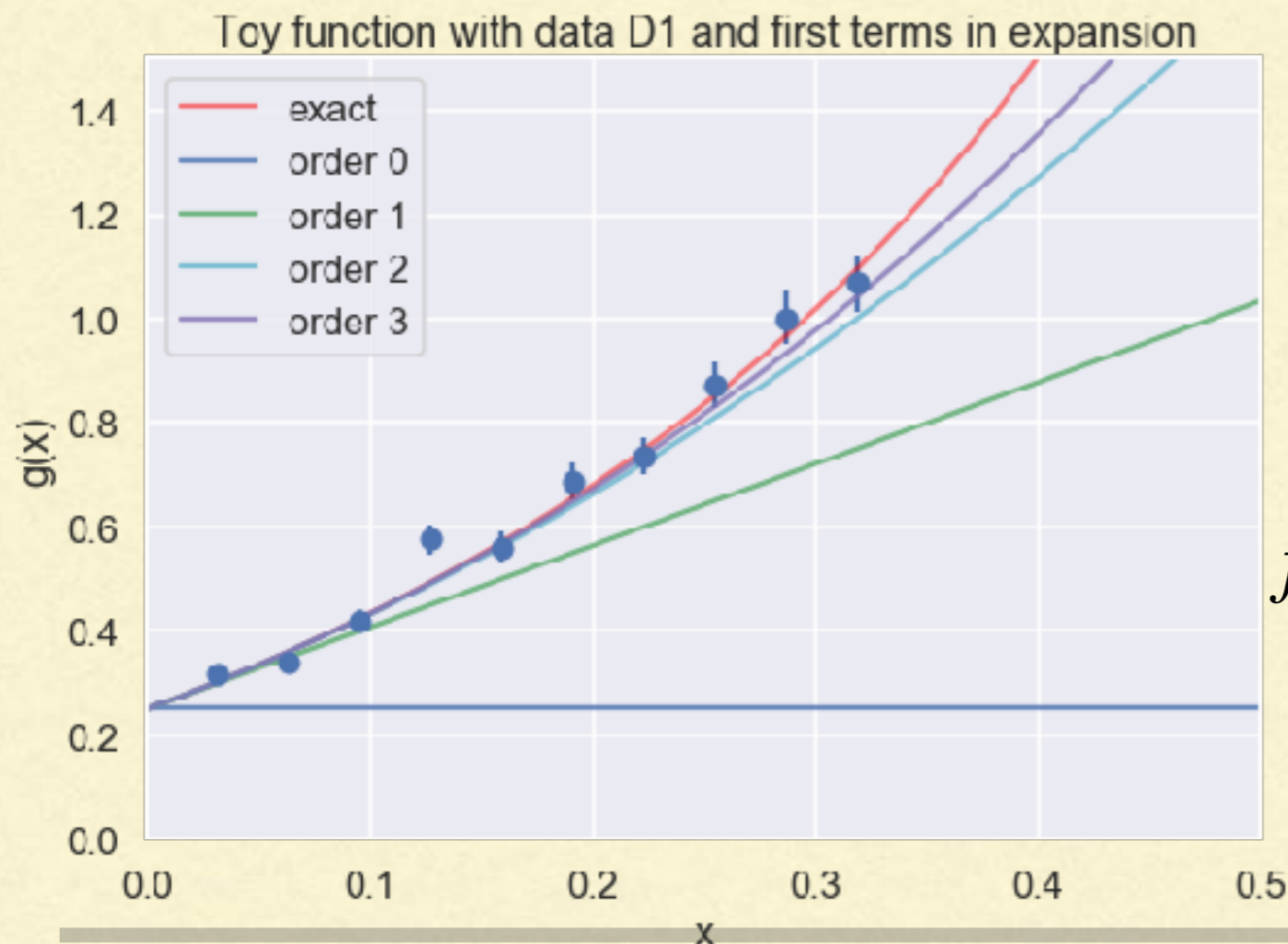
Fit function:

$$f(x) = a_0 + a_1x + a_2x^2 + \dots + a_Mx^M$$

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**What order should
we take for M?**

Coefficient extraction

Wesolowski, Furnstahl, Kleo, Phillips, Thapaliya, JPG (2016)

		Uniform prior				Gaussian prior			
k	k_{\max}	χ^2/dof	a_0	a_1	a_2	Evidence	a_0	a_1	a_2
0	0	67	0.48 ± 0.01			~ 0	0.48 ± 0.01		
1	1	2.2	0.20 ± 0.01	2.6 ± 0.1		6.0×10^2	0.20 ± 0.01	2.6 ± 0.1	
2	2	1.6	0.25 ± 0.02	1.6 ± 0.4	3.3 ± 1.3	3.3×10^3	0.25 ± 0.02	1.6 ± 0.4	3.1 ± 1
2	3	1.9	0.27 ± 0.04	1.0 ± 1	8.1 ± 8.0	2.9×10^3	0.25 ± 0.02	1.7 ± 0.5	3.0 ± 2
2	4	2.0	0.33 ± 0.07	-1.9 ± 3	45 ± 30	2.8×10^3	0.25 ± 0.02	1.7 ± 0.5	3.0 ± 2
2	5	1.4	0.57 ± 0.1	-15 ± 7	280 ± 100	2.8×10^3	0.25 ± 0.02	1.7 ± 0.5	3.0 ± 2
2	6	1.9	0.59 ± 0.3	-16 ± 20	310 ± 400	2.8×10^3	0.25 ± 0.02	1.7 ± 0.5	3.0 ± 2
True values			0.25	1.57	2.47		0.25	1.57	2.47

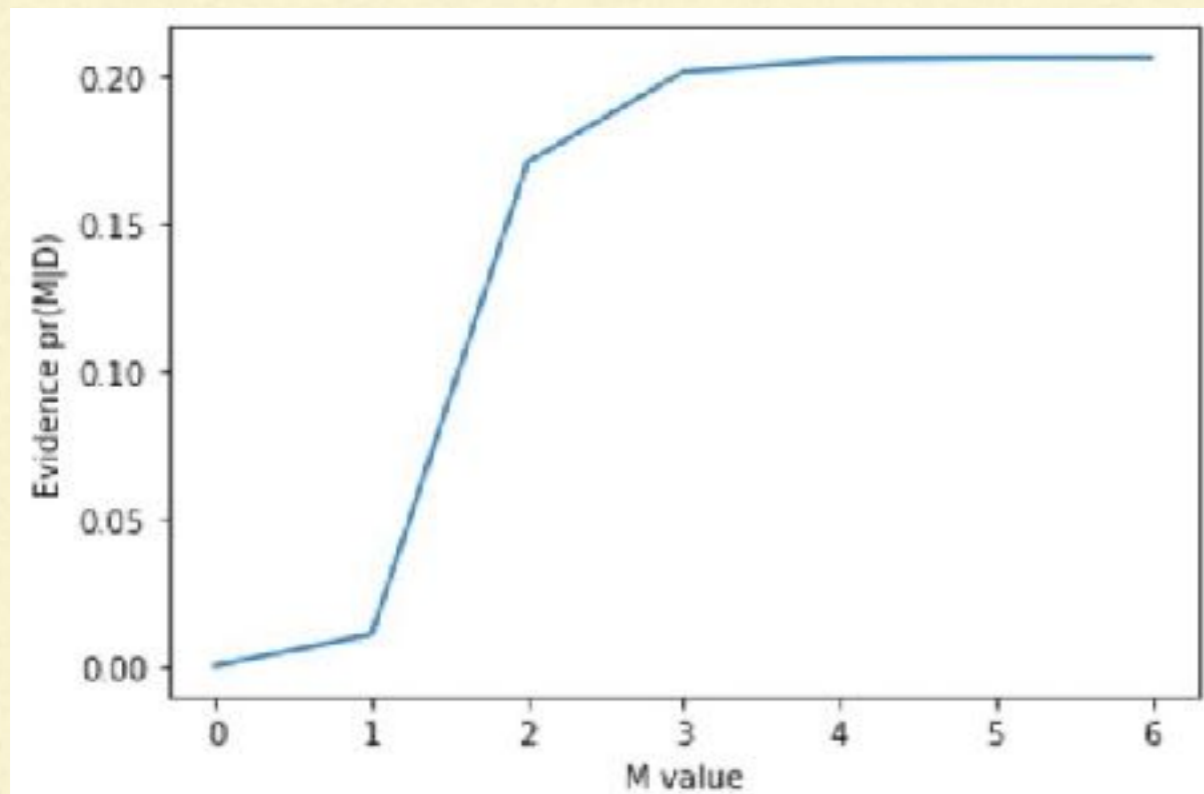
$$\bar{a}_{\text{fix}}=5$$

- Minimizing χ^2 = Least-squares fitting = Uniform prior
- Corresponds to not employing any additional information on the problem, beyond that provided by the data (including errors)
- Similar results up to $k=2$, not beyond

Model evidence & BMA

Connell, Billig, DP, JPG (2021)

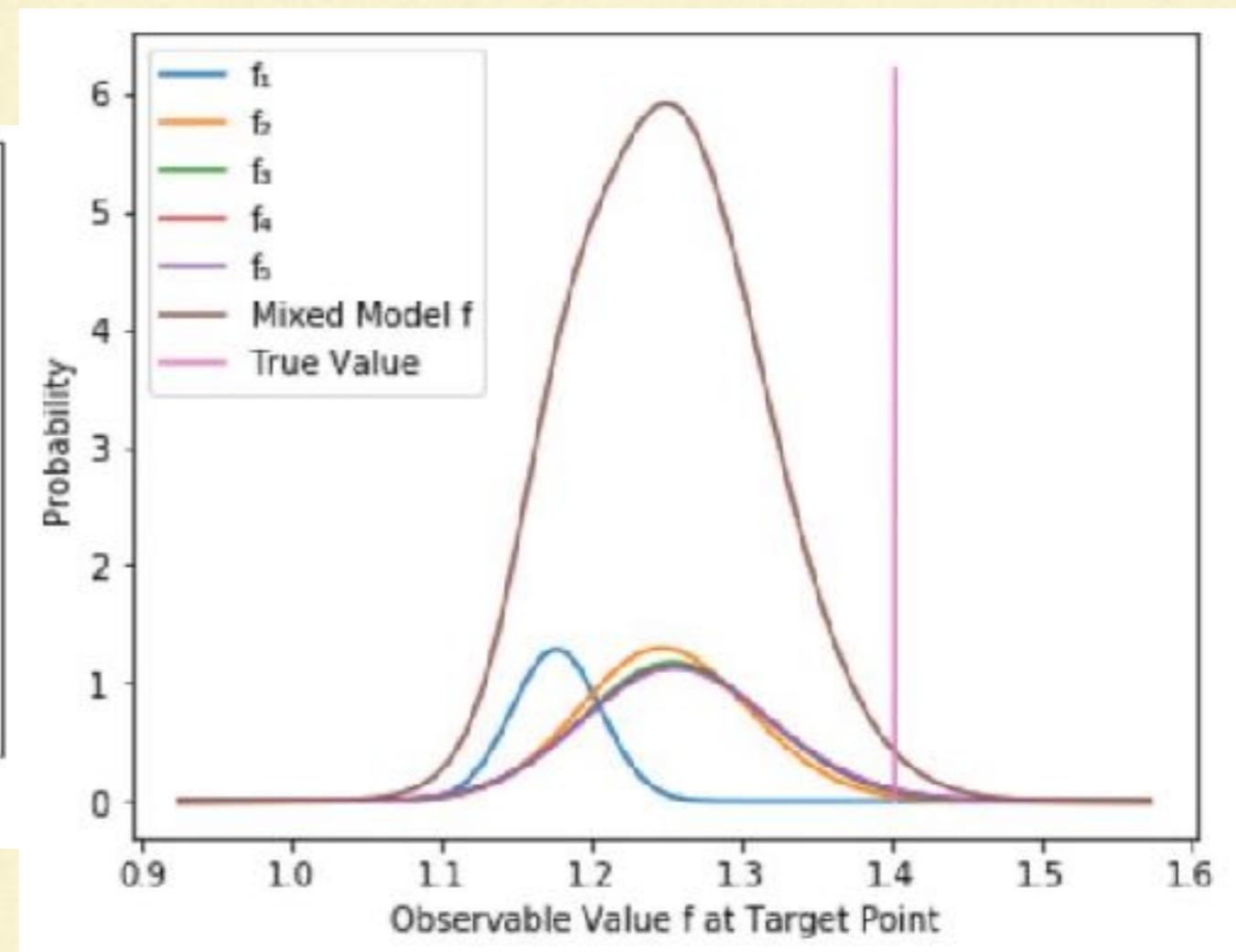
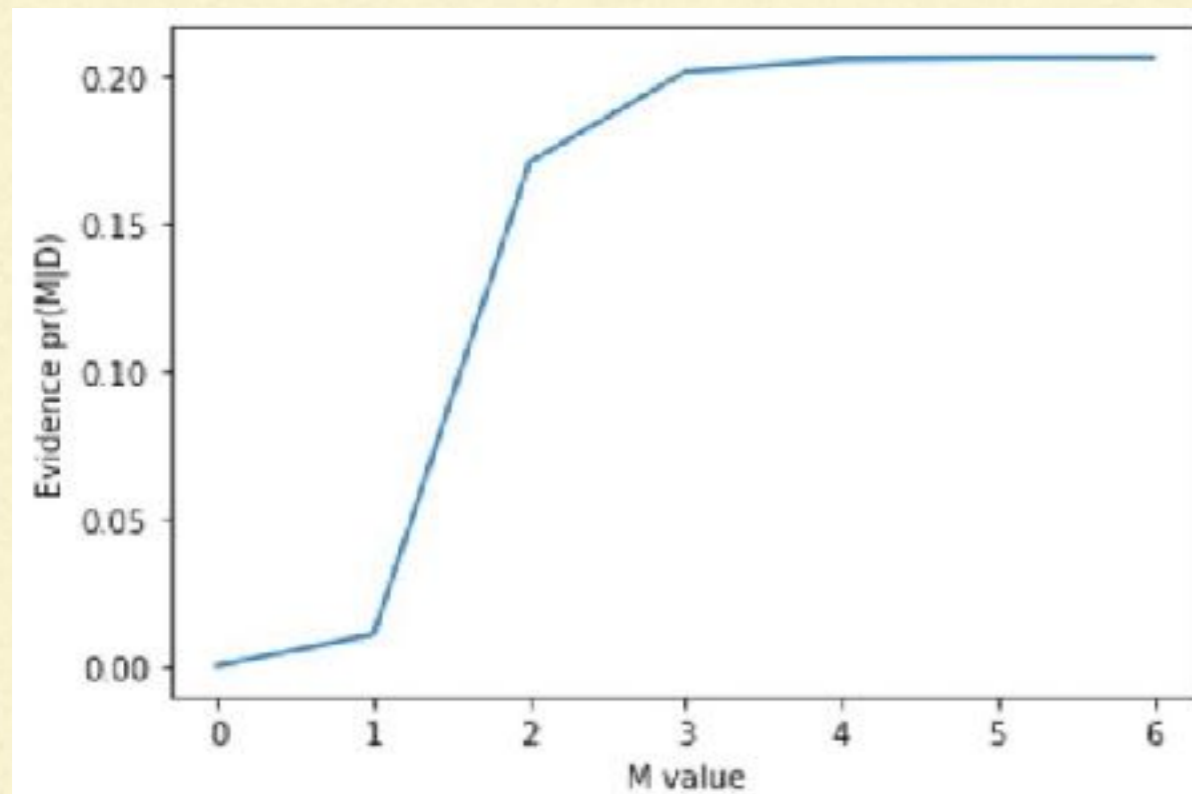
$$\text{pr}(f(x_t) | D) = \sum_M \text{pr}(f(x_t) | D, M) \text{pr}(M | D)$$



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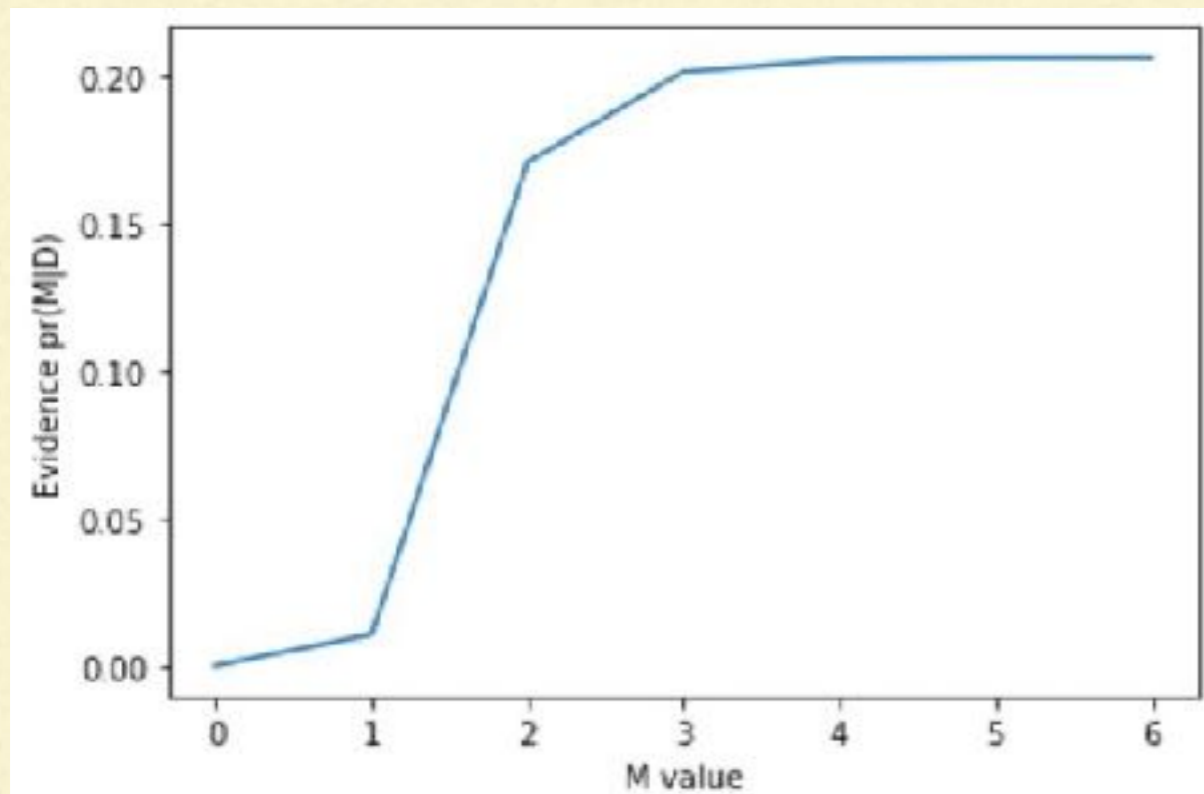
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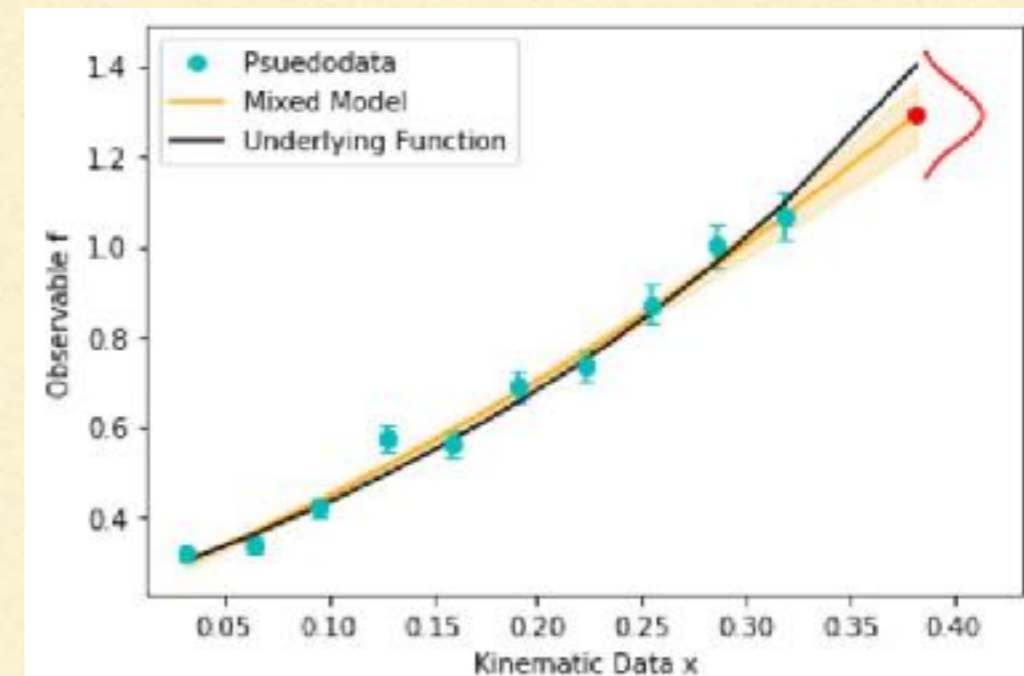
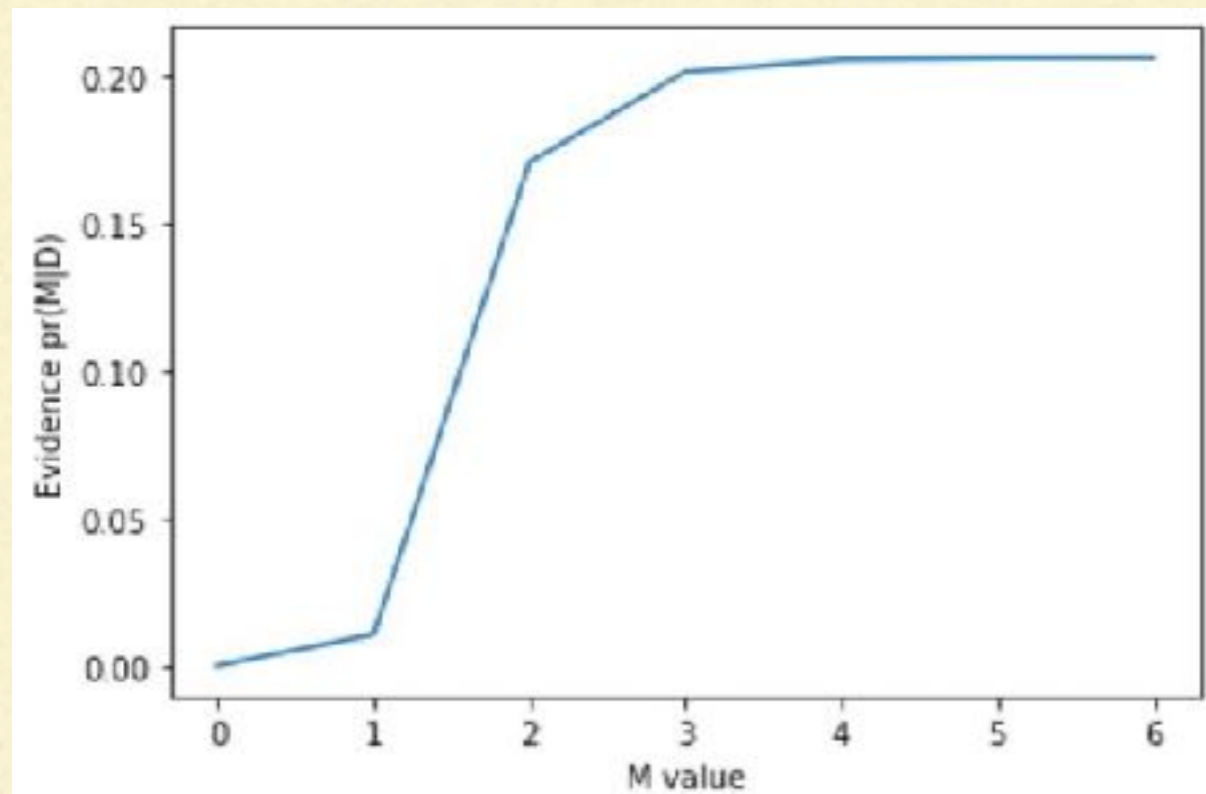
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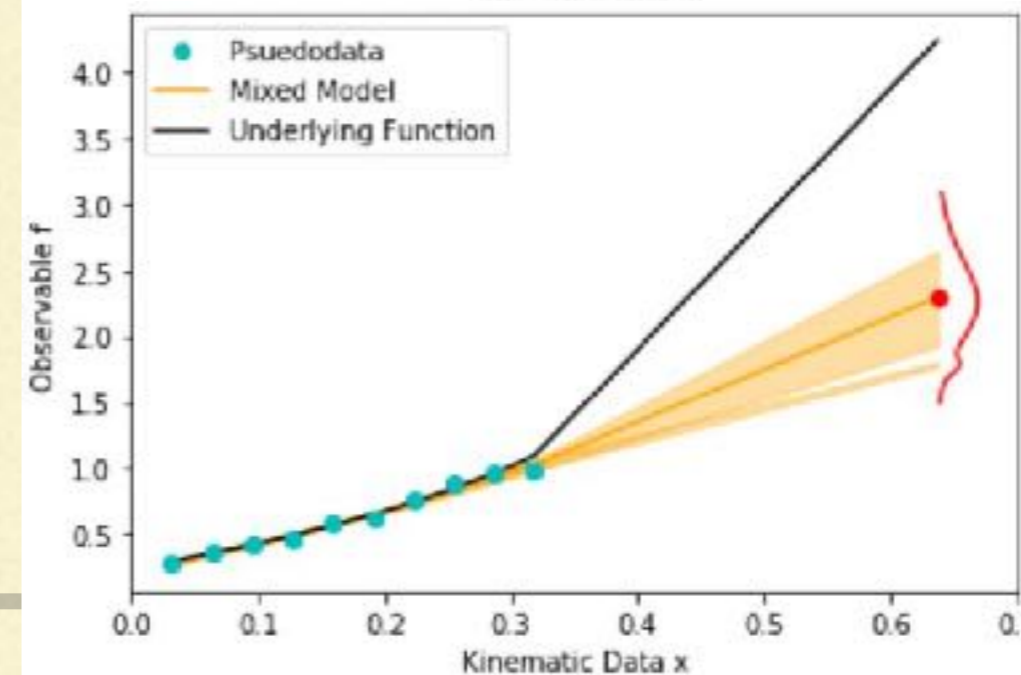
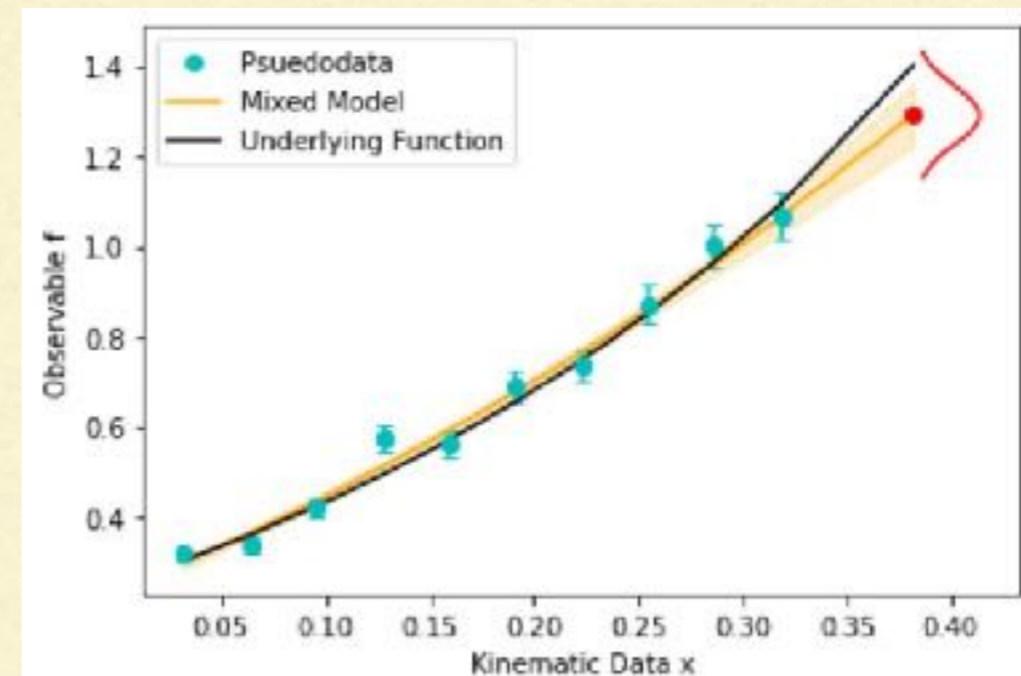
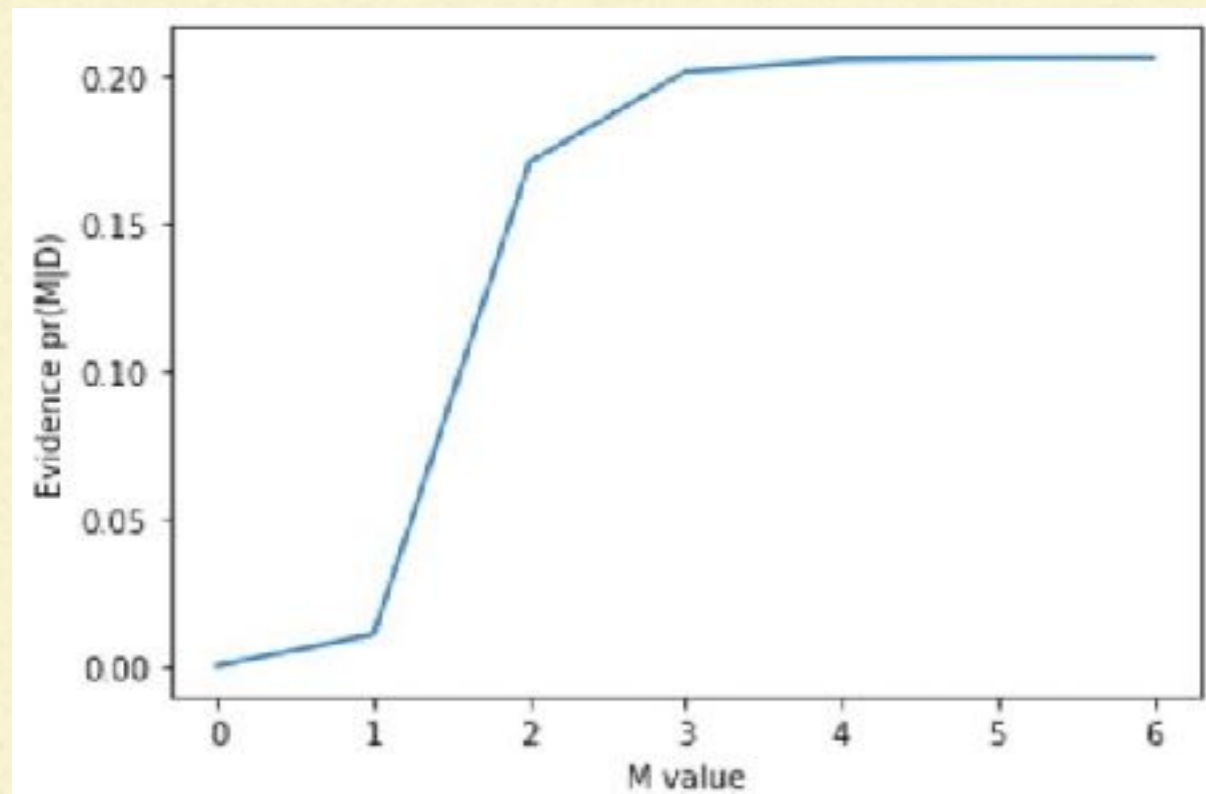
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Model evidence & BMA

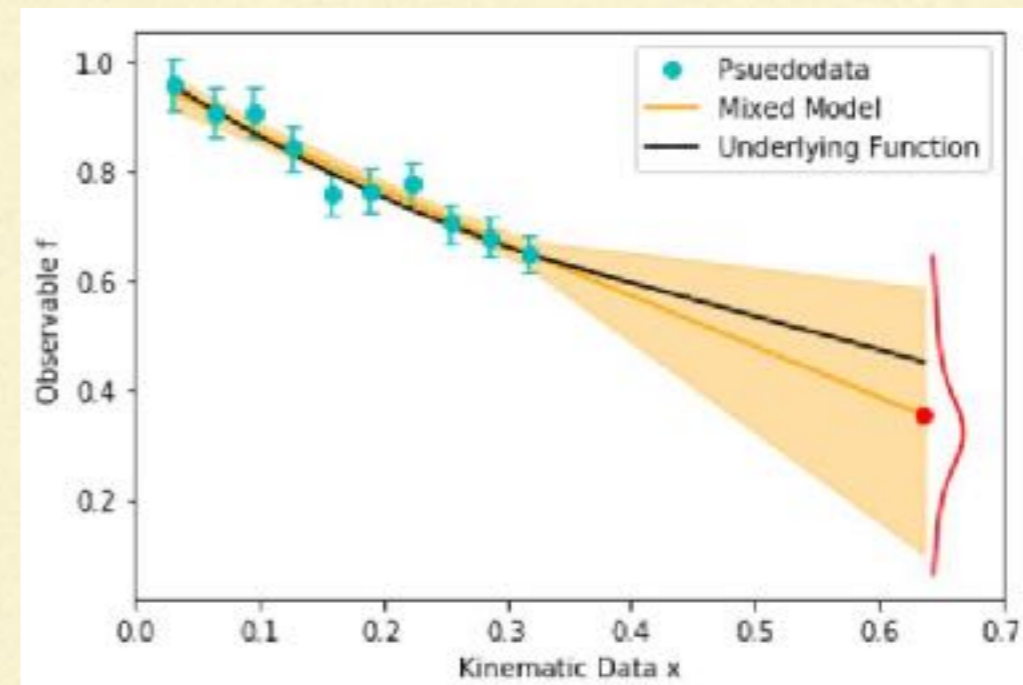
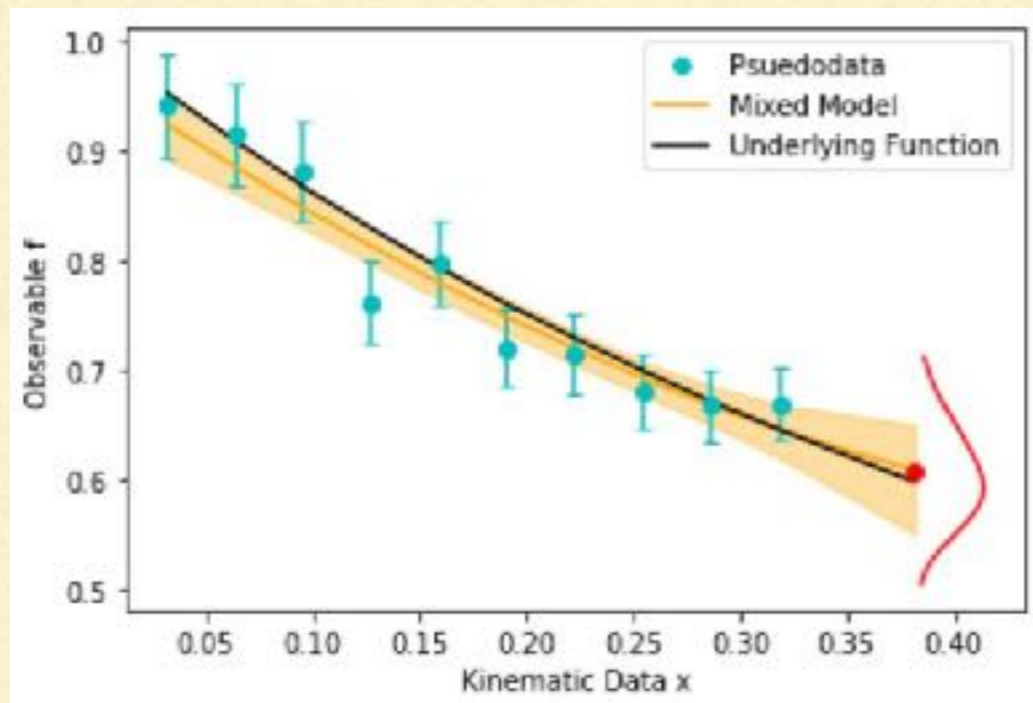
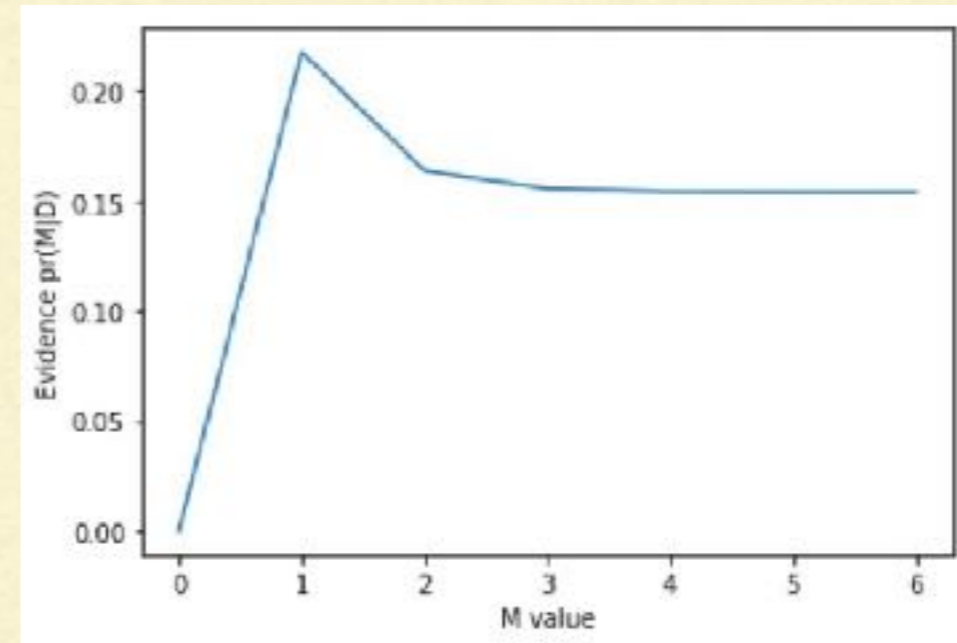
Connell, Billig, DP, JPG (2021)

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A more docile function

$$g_2(x) = \left(\frac{1.3}{1.3 + x} \right)^2$$



- Performance can be quantified using “Empirical Coverage Probability”

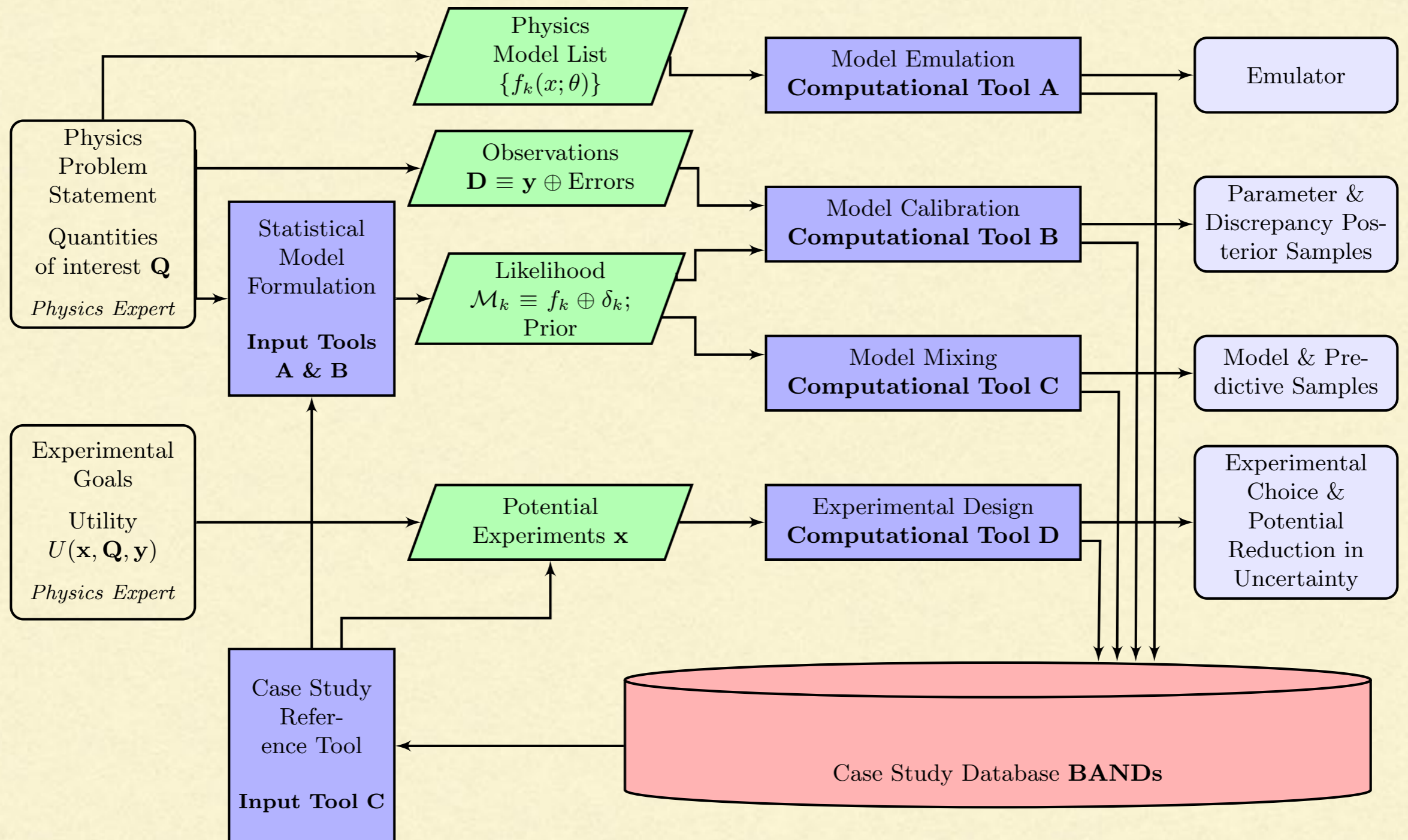
Conclusions from toy model

- In this case both situations are formally “open” but polynomials can describe the second case, so BMA works quite well. BMA extrapolate better than highest-order or highest-evidence model
- BMA not a panacea though: BMA does not help dire situation with $g_1(x)$ as we get close to singularity
- Could choose different weights: stacking uses LOO weights
- But one defect of BMA is that it uses weights based on global model performance. Could also consider locally-defined weights: “Local Bayesian Model Mixing”
- Locally-defined weights can leverage strengths of models in different regions, e.g., mixing expansions in g and $1/g$ could provide a result (with UQ!) that works well for all g



- Much progress on Uncertainty Quantification in Nuclear Physics in last few years
 - But still some inhibitions regarding use of Bayesian methods:
 - What prior should I choose?
 - Isn't MC sampling too computationally expensive a way to estimate the parameters I care about?
 - Difficult to assess model uncertainty
 - Proposal: use “Bayesian Model Mixing” to provide error bars that reflect full error bar for a nuclear-physics prediction, based on best available Nuclear Physics knowledge
 - Consistently calibrated and mixed nuclear-physics models can then be used for optimal design of experiments
-

The Framework



The Team I: Senior Investigators

- Ohio U., Daniel Phillips: Nuclear Physics (PI)
- Michigan State U., Witek Nazarewicz, Filomena Nunes, Scott Pratt: Physics; Taps Maiti, Frederi Viens: Statistics
- Northwestern U., Matthew Plumlee: Statistics, Stefan Wild: Computer Science
- Ohio State U., Dick Furnstahl, Uli Heinz: Physics, Matthew Pratola, Statistics

MICHIGAN STATE
UNIVERSITY



Northwestern
University



OHIO
UNIVERSITY



THE OHIO STATE
UNIVERSITY

The Team II: Students & Post-docs

Postdoctoral Researchers



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Ozge Surer

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Mookyong Son

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Michigan State University
email: sonmooky@msu.edu*



John Yannotty

*Department of Statistics,
The Ohio State University
email: yannotty.1@osu.edu*

Get on the BAND Wagon: A Bayesian Framework for Quantifying Model Uncertainties in Nuclear Dynamics

D. R. Phillips¹, R. J. Furnstahl², U. Heinz², T. Maiti³,
W. Nazarewicz⁴, F. M. Nunes¹, M. Plumlee^{5,6}, M. T. Pratola⁷,
S. Pratt⁴, F. G. Viens³, S. M. Wild^{6,8}

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²Department of Physics, The Ohio State University, Columbus, OH 43210, USA

³Department of Statistics and Probability, Michigan State University, East Lansing, Michigan 48824, USA

⁴Department of Physics and Astronomy and Facility for Rare Isotope Beams, Michigan State University, East Lansing, Michigan 48824, USA

⁵Department of Industrial Engineering and Management Sciences, Northwestern University, Evanston, Illinois 60208, USA

⁶NAISE, Northwestern University, Evanston, Illinois 60208, USA

⁷ Department of Statistics, The Ohio State University, Columbus, OH 43210, USA

⁸Mathematics and Computer Science Division, Argonne National Laboratory, Lemont, Illinois 60439, USA

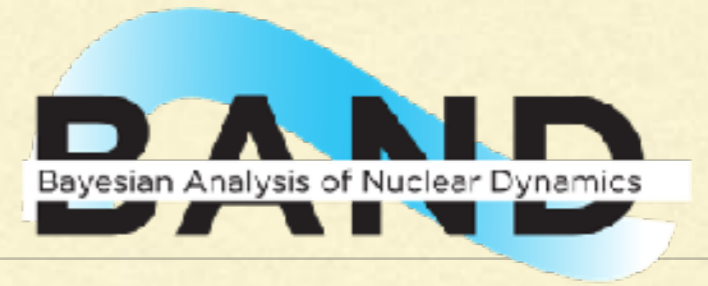
E-mail: phillid1@ohio.edu

15 December 2020

Abstract. We describe the Bayesian Analysis of Nuclear Dynamics (BAND) framework, a cyberinfrastructure that we are developing which will unify the treatment of nuclear models, experimental data, and associated uncertainties. We overview the statistical principles and nuclear-physics contexts underlying the BAND toolset, with an emphasis on Bayesian methodology's ability to leverage insight from multiple models. In order to facilitate understanding of these tools we provide a simple and accessible example of the BAND framework's application. Four case studies are presented to highlight how elements of the framework will enable progress on complex, far-ranging problems in nuclear physics. By collecting notation and terminology, providing illustrative examples, and giving an overview of the associated techniques, this paper aims to open paths through which the nuclear physics and statistics communities can contribute to and build upon the BAND framework.

“BANDifesto”,
J. Phys. G **48**,
072001 (2021)

Timeline



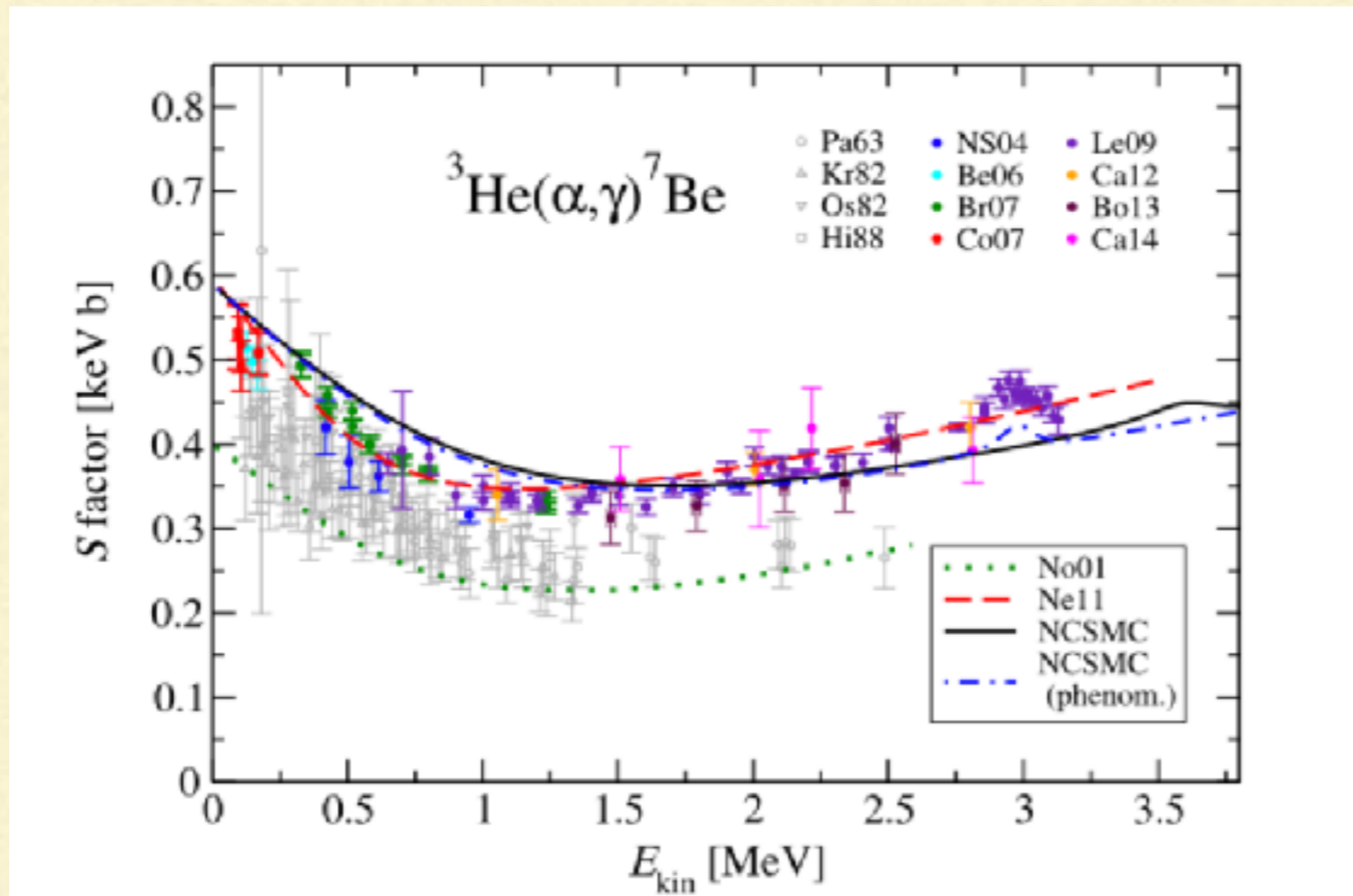
- Year 1: Release of BAND Manifesto; Nuclear-physics codes in repo
- Year 2: Version 1 demo released; POC demos for toy models
- Year 3: Version 2 framework released
- Years 4 & 5: Mature version of BAND Framework released with database; POC demos for experimental planning and forefront nuclear theory; tutorial & bootcamp; workshop for other disciplines
- Throughout: Roundtables with community, BAND camps, tutorials
- Collaboration & input welcomed

<https://bandframework.github.io/>

Ultimate goal is to build framework that is *generally useful*

Backup slides

Connecting to *ab initio* calculations



Dohet-Eraly et al., PLB (2016)

- ANC extracted from capture data: $C_{P1/2}^2 + C_{P3/2}^2 = 27 \pm 3 \text{ fm}^{-1}$
- Significant constraints on s-wave scattering parameters already from capture
- Short-distance parameter L_{E1} is smaller for data and for Nollett's *ab-initio* based calculation than for cluster models. Pauli principle?