Errors in Effective Field Theory and Why They Matter

Jordan Melendez¹

November 1, 2020

¹The Ohio State University











Background

- A subset of nuclear theorists works on ab initio methods.
- Goal: predict all nuclear properties from basic assumptions

- A subset of nuclear theorists works on ab initio methods.
- Goal: predict all nuclear properties from basic assumptions
- Take protons & neutrons as given; predict everything else.
- Desire a connection to the more fundamental theory: quantum chromodynamics















- We've entered the precision era!
- $\bullet~\rightarrow$ It's time to worry about the details.
- Error bars aren't just for experimentalists...

Phys. Rev. A Editorial (April 2011)

Papers presenting the results of theoretical calculations are expected to include uncertainty estimates...

- If the authors claim high accuracy, or improvements on the accuracy of previous work.
- If the primary motivation for the paper is to make comparisons with present or future high precision experimental measurements.
- If the primary motivation is to provide interpolations or extrapolations of known experimental measurements.

Phys. Rev. A Editorial (April 2011)

Papers presenting the results of theoretical calculations are expected to include uncertainty estimates...

- If the authors claim high accuracy, or improvements on the accuracy of previous work.
- If the primary motivation for the paper is to make comparisons with present or future high precision experimental measurements.
- If the primary motivation is to provide interpolations or extrapolations of known experimental measurements.

This work makes novel contributions to uncertainty quantification methods for nuclear predictions.

Figure credit: Danielle Towne



Figure credit: Danielle Towne



The codes for all published work has been made publicly available \rightarrow reproducibility & extendability



Grav. force (short distances):

F = -mg



Grav. force (short distances):

F = -mg

Grav. force (large distances):

$$F = -\frac{GMm}{r^2}$$

The laws look quite different!



Grav. force (short distances):

F = -mg

Grav. force (large distances):

$$F = -\frac{GMm}{r^2}$$

The laws look quite different!

Connected via series expansion about radius of Earth R:

$$F \approx -mg + 2mg\left(\frac{r-R}{R}\right) - 3mg\left(\frac{r-R}{R}\right)^2 + \mathcal{O}\left[\left(\frac{r-R}{R}\right)^3\right]$$



Grav. force (short distances):

F = -mg

Grav. force (large distances):



The laws look quite different!

Can fit unknown parameters to data \Rightarrow inverse problem!

$$F \approx a_0 + a_1 \left(\frac{r-R}{R}\right) + a_2 \left(\frac{r-R}{R}\right)^2 + \mathcal{O}\left[\left(\frac{r-R}{R}\right)^3\right]$$



Grav. force (short distances):

F = -mg

Grav. force (large distances):



The laws look quite different!

Use prior info from physics:

$$F \approx mg\left\{a_0' + a_1'\left(\frac{r-R}{R}\right) + a_2'\left(\frac{r-R}{R}\right)^2 + \mathcal{O}\left[\left(\frac{r-R}{R}\right)^3\right]\right\}$$



Grav. force (short distances):

F = -mg

Grav. force (large distances):



The laws look quite different!

Propagate full uncertainty

$$F \approx mg \left\{ a_0' + a_1' \left(\frac{r-R}{R} \right) + a_2' \left(\frac{r-R}{R} \right)^2 + \mathcal{O}\left[\left(\frac{r-R}{R} \right)^3 \right] \right\}$$

• There is interesting physics at all scales



Predictions in Low-Energy Nuclear Physics

- There is interesting physics at all scales
- Fine details at one level of analysis do not affect the physics at a coarser level of analysis



Predictions in Low-Energy Nuclear Physics

- There is interesting physics at all scales
- Fine details at one level of analysis do not affect the physics at a coarser level of analysis
- Start simple \rightarrow add corrections to reach desired precision.



$$y_{\exp}(x) = y_{th}(x, \vec{a}) + \delta y_{th}(x) + \delta y_{\exp}(x)$$



$$\chi^{2} \text{ fit}$$

$$y_{\text{exp}}(x) = y_{\text{th}}(x, \overline{a}) + \delta y_{\text{exp}}$$



Full Prediction

$$y_{exp}(x) = \overline{y_{th}(x, \vec{a}) + \delta y_{th}(x)} + \delta y_{exp}$$

$$y_{\exp}(x) = y_{th}(x, \vec{a}) + \underbrace{\delta y_{th}(x)}_{Can we build this?}$$

Can we use it?

$$y_{\text{exp}}(x) = y_{\text{th}}(x, \vec{a}) + \underbrace{\delta y_{\text{th}}(x)}_{\text{Can we build this}} + \delta y_{\text{exp}}$$
Can we use it?

Takeaway info about our δy_{th} model:

Built in		Results in
Physics-based	\longleftrightarrow	Discovery
Energy degradation	\longleftrightarrow	E _{max} insensitivity
Correlations	\longleftrightarrow	Derivatives (& More!)
Smart priors	\longleftrightarrow	Easy & analytic!

•
$$V_{NN}(\vec{a}) = V_{LO} + V_{NLO} + \dots + V_{N^k LO} \Longrightarrow |$$
 Schrödinger Eq. $| \Longrightarrow y_k(x; \vec{a})$

Predictions 0 y_0 $^{-5}$ $^{-10}$ -15-20 0.00 0.25 0.50 0.75 1.00 х

{ <mark>y_0</mark> }

 $y_0 \rightarrow LO$

•
$$V_{NN}(\vec{a}) = V_{LO} + V_{NLO} + \dots + V_{N^k LO} \Longrightarrow |$$
 Schrödinger Eq. $| \Longrightarrow y_k(x; \vec{a})$

 $\{ \underline{y_0}, y_1 \}$



$$y_0 \rightarrow LO$$

 $y_1 \rightarrow NLC$

•
$$V_{NN}(\vec{a}) = V_{LO} + V_{NLO} + \dots + V_{N^k LO} \Longrightarrow |$$
 Schrödinger Eq. $| \Longrightarrow y_k(x; \vec{a})$

 $\{y_0, y_1, y_2\}$



$$y_0 \rightarrow LO$$

 $y_1 \rightarrow NLO$
 $y_2 \rightarrow N^2LO$

•
$$V_{NN}(\vec{a}) = V_{LO} + V_{NLO} + \dots + V_{N^k LO} \Longrightarrow |$$
 Schrödinger Eq. $| \Longrightarrow y_k(x; \vec{a})$

 $\{\underline{y_0}, \underline{y_1}, \underline{y_2}, \underline{y_3}\}$



$$y_0 \rightarrow LO$$

$$y_1 \rightarrow NLO$$

$$y_2 \rightarrow N^2LO$$

$$\vdots$$

$$y_k \rightarrow N^kLO$$
- $V_{NN}(\vec{a}) = V_{LO} + V_{NLO} + \dots + V_{N^k LO} \Longrightarrow$ Schrödinger Eq. $\Rightarrow y_k(x; \vec{a})$
- One can change variables for convenience/insight.

 $y_0 = y_0$



- $V_{NN}(\vec{a}) = V_{LO} + V_{NLO} + \dots + V_{N^k LO} \Longrightarrow$ Schrödinger Eq. $\Rightarrow y_k(x; \vec{a})$
- One can change variables for convenience/insight.

 $y_1 = y_0 + \Delta y_1$



- $V_{NN}(\vec{a}) = V_{LO} + V_{NLO} + \dots + V_{N^k LO} \Longrightarrow$ Schrödinger Eq. $\Rightarrow y_k(x; \vec{a})$
- One can change variables for convenience/insight.

 $y_2 = y_0 + \Delta y_1 + \Delta y_2$



- $V_{NN}(\vec{a}) = V_{LO} + V_{NLO} + \dots + V_{N^k LO} \Longrightarrow$ Schrödinger Eq. $\Rightarrow y_k(x; \vec{a})$
- One can change variables for convenience/insight.
- $\Delta y_n = y_{\text{ref}} c_n Q^n$

 $y_3 = y_0 + \Delta y_1 + \Delta y_2 + \Delta y_3$



- $V_{NN}(\vec{a}) = V_{LO} + V_{NLO} + \dots + V_{N^k LO} \Longrightarrow$ Schrödinger Eq. $\Rightarrow y_k(x; \vec{a})$
- One can change variables for convenience/insight.
- $\Delta y_n = y_{\text{ref}} c_n Q^n$

$$y_0 = y_{\rm ref} \left[\frac{c_0 Q^0}{2} \right]$$



- $V_{NN}(\vec{a}) = V_{LO} + V_{NLO} + \dots + V_{N^k LO} \Longrightarrow$ Schrödinger Eq. $\Rightarrow y_k(x; \vec{a})$
- One can change variables for convenience/insight.
- $\Delta y_n = y_{\text{ref}} c_n Q^n$

$$y_1 = y_{\text{ref}} \left[\frac{c_0}{Q} Q^0 + c_1 Q^1 \right]$$



- $V_{NN}(\vec{a}) = V_{LO} + V_{NLO} + \dots + V_{N^k LO} \Longrightarrow$ Schrödinger Eq. $\Rightarrow y_k(x; \vec{a})$
- One can change variables for convenience/insight.
- $\Delta y_n = y_{\text{ref}} c_n Q^n$

$$y_2 = y_{\text{ref}} \left[\frac{c_0 Q^0 + c_1 Q^1 + c_2 Q^2}{Q^2} \right]$$



- $V_{NN}(\vec{a}) = V_{LO} + V_{NLO} + \dots + V_{N^k LO} \Longrightarrow$ Schrödinger Eq. $\Rightarrow y_k(x; \vec{a})$
- One can change variables for convenience/insight.

•
$$\Delta y_n = y_{\text{ref}} c_n Q^n$$

 $y_3 = y_{\text{ref}} \left[c_0 Q^0 + c_1 Q^1 + c_2 Q^2 + c_3 Q^3 \right]$



Real Life

Coefficients from NN scattering look like our toy model!





Model Building



11

Model Building



11

Model Building



Gaussian Processes: How We Induct on the c_n

What are Gaussian processes?



Gaussian Processes: How We Induct on the c_n

What are Gaussian processes?

• An infinite dimensional generalization of the Gaussian distribution (??)



Gaussian Processes: How We Induct on the c_n

What are Gaussian processes?

- An infinite dimensional generalization of the Gaussian distribution (??)
- A popular machine learning tool for non-parametric regression



Quantifying Truncation Uncertainty

Inexpensive Prediction



Quantifying Truncation Uncertainty



Quantifying Truncation Uncertainty



Beyond Truncation Errors



Beyond Truncation Errors

$$y_3 = y_{\text{ref}} \left[\frac{c_0 Q^0 + c_1 Q^1 + c_2 Q^2 + c_3 Q^3}{c_1 Q^1 + c_2 Q^2 + c_3 Q^3} \right]$$



Beyond Truncation Errors

$$y_3 = y_{\text{ref}} \left[\frac{c_0 Q^0 + c_1 Q^1 + c_2 Q^2 + c_3 Q^3}{2} \right]$$



14



The Equation of State

An important bridge from the nucleon-nucleon interaction to neutron-rich matter



Saturation Properties

Using the Entem, Machleidt, and Nosyk potential with two momentum cutoffs:

 $\Lambda = 500 \, \text{MeV}$

 $\Lambda = 450 \, \text{MeV}$



17

- Correlated errors permit derivatives
- The first rigorous uncertainty propagation
- Furthermore, the convergence pattern of E/N is correlated with that of E/A.
- So the uncertainty in

 $S_2 = E/N - E/A$ is smaller than naively expected






























The truncation error model:

$$y_{\exp}(x) = y_{th}(x, \vec{a}) + \delta y_{th}(x) + \delta y_{\exp}(x)$$

With Bayes' theorem, leads to

$$pr(\vec{a} \mid y_{exp}) \propto pr(y_{exp} \mid \vec{a}) \times pr(\vec{a})$$
$$pr(y_{exp} \mid \vec{a}) = \mathcal{N}[y_k(\vec{a}), \Sigma_{exp} + \Sigma_{th}]$$

This can be sampled using MCMC for full uncertainty propagation

What You Get for Free: Max Energy Insensitivity

- y axis: posterior median $\pm 1\sigma$
- x axis: max energy of data in fit



What You Get for Free: Max Energy Insensitivity

- y axis: posterior median $\pm 1\sigma$
- x axis: max energy of data in fit
- Q, and hence $\delta y_{\rm th}$, grows with energy

$$\delta y_{\rm th} = y_{\rm ref} \sum_{n=k+1}^{k_{\rm max}} c_n Q^n$$

- This weights high energy data less!
- Stabilizes LEC fit as a function of E



What You Get for Free: Max Energy Insensitivity

- y axis: posterior median $\pm 1\sigma$
- x axis: max energy of data in fit
- Q, and hence $\delta y_{\rm th}$, grows with energy

$$\delta y_{\rm th} = y_{\rm ref} \sum_{n=k+1}^{k_{\rm max}} c_n Q^n$$

- This weights high energy data less!
- Stabilizes LEC fit as a function of E
- Correlation assumptions can lead to different results





- Nuclear polarizabilities: a fundamental property
- Can be probed by Compton scattering: light off nucleon





But Where to Measure?

- Beam time is not cheap...
- Experimental difficulties vary
- Theoretical difficulties vary
- How do we balance these constraints?
 - Plan effective experiments
 - Test theory



Prior Work

- Grießhammer et al. (2018) EPJA
- Chart shows sensitivity of χEFT diff. cross section at a range of energies and angles.
- Looked at sensitivities of theory to polarizabilities (think derivatives)
- Does not account for experimental hardships or theory uncertainty
- Cannot estimate the utility of any given experiment



0 50 100 150 200 250 300 photon energy (μ)ob [MeV]

 $d(d\sigma/d\Omega)/d\xi$ [nb/sr×inverse canonical units]

-0.65

-4.58 -6.78 -10.

Bayesian Experimental Design

- Includes experimental and correlated theory errors
- Includes symmetry constraints on the truncation error (0th, 1st, and 2nd derivatives)
- Can answer questions like:
 - Is extra precision worth the cost?
 - Measure one point well or multiple points less well?
 - What is the benefit of jointly constraining polarizabilities?



The Effect of EFT Errors



Is an Experiment Worth It?



Percent Decrease in Uncertainty



• Truncation and interpolation error informed by convergence pattern

- Truncation and interpolation error informed by convergence pattern
- Full error can be propagated, using physics insight

- Truncation and interpolation error informed by convergence pattern
- Full error can be propagated, using physics insight
- Permits learning of physical quantities, e.g., Λ_b

- Truncation and interpolation error informed by convergence pattern
- Full error can be propagated, using physics insight
- Permits learning of physical quantities, e.g., Λ_b

- Truncation and interpolation error informed by convergence pattern
- Full error can be propagated, using physics insight
- Permits learning of physical quantities, e.g., Λ_b

Implications

• To progress, science must

reason under uncertainty

- Truncation and interpolation error informed by convergence pattern
- Full error can be propagated, using physics insight
- Permits learning of physical quantities, e.g., Λ_b

Implications

- To progress, science must reason under uncertainty
- This work is important step for such reasoning in EFTs

- Truncation and interpolation error informed by convergence pattern
- Full error can be propagated, using physics insight
- Permits learning of physical quantities, e.g., Λ_b

Implications

- To progress, science must reason under uncertainty
- This work is important step for such reasoning in EFTs
- All code is publicly available

- Truncation and interpolation error informed by convergence pattern
- Full error can be propagated, using physics insight
- Permits learning of physical quantities, e.g., Λ_b

Implications

- To progress, science must reason under uncertainty
- This work is important step for such reasoning in EFTs
- All code is publicly available
- This promotes reproducibility and extendability

Thank you!



Uncorrelated Posteriors

Assumes that the variance of the c_n is independent at each point





Source: "The Signal and the Noise" by Nate Silver | Author: Randy Olson (randalolson.com / @randal_olson)











• Gaussian process correlations propagate via Σ_{th} matrix (computed once!)



- Gaussian process correlations propagate via Σ_{th} matrix (computed once!)
- Different correlation assumptions \rightarrow different results!

NN Scattering Errors (with Constraint)



NN Scattering Errors (with Constraint)



NN Scattering Errors (with Constraint)


Model Checking Diagnostics

Model Checking Diagnostics







- See Bastos & O'Hagan (2009) "Diagnostics for Gaussian Process Emulators"
- But we have multiple curves on which to test

Mahalanobis Distance

• Measures distance from mean, taking into account covariance structure

$$D_{MD}^2 = (y - m)^T \Sigma^{-1} (y - m)^2$$



https://blogs.sas.com/content/iml/2019/03/25/geomet multivariate-univariate-outliers.html

Mahalanobis Distance

• Measures distance from mean, taking into account covariance structure

$$D_{MD}^2 = (y-m)^T \Sigma^{-1} (y-m)$$

• Can decompose scalar D_{MD}^2 into a vector D_G using $\Sigma = GG^T$

$$D_G = G^{-1}(y-m)$$

 D_G can illuminate why some curves fail



https://blogs.sas.com/content/iml/2019/03/25/geomet multivariate-univariate-outliers.html

Mahalanobis Distance Toy Example



Mahalanobis Distance Toy Example





Mahalanobis Distance Toy Example







Mahalanobis Distance Real Example

EKM Semilocal ($R = 0.9 \,\text{fm}$). Total cross section



Mahalanobis Distance Real Example

EKM Semilocal ($R = 0.9 \,\text{fm}$). Total cross section



Mahalanobis Distance Real Example

EKM Semilocal ($R = 0.9 \,\text{fm}$). Total cross section





Credible Interval Diagnostics

