Towards the smeared R-ratio with $N_f = 2+1+1$ highly improved staggered quarks

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Fermilab Lattice and MILC Collaboration

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Outline

- Introduction & Motivations
- Numerical setup
- Linear reconstruction methods
- Non-linear reconstruction methods
- Conclusions & Outlook

⇒ **Introduction & Motivations**

⋆ **Numerical setup**

⋆ **Linear reconstruction methods**

⋆ **Non-linear reconstruction methods**

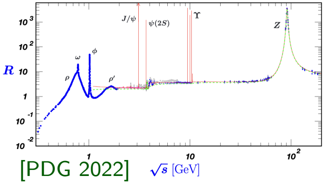
⋆ **Conclusions & Outlook**

THE (SMEARED) R-RATIO

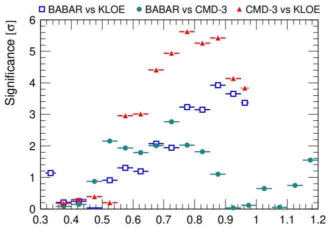
A prime example of (smeared) spectral density

Total cross-section $\sigma(e^+e^- \to \text{hadrons}) \propto R(s)$
[Cabibbo and Gatto 1961; Cabibbo et al. 1970]

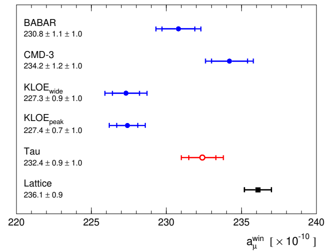
$$R(q^2)\left(q_\mu q_\nu - q^2\delta_{\mu\nu}\right)$$
$$\propto \langle 0|V_\mu^{\mathrm{EM}}(0)\delta^4\left(\mathbb{H}-q\right)V_\nu^{\mathrm{EM}}(0)|0\rangle$$
$$V_\mu^{\mathrm{EM}}(x) = \sum_f q_f\overline{\psi}(x)\gamma_\mu\psi(x)$$



[PDG 2022]



[Davier et al. 2024]



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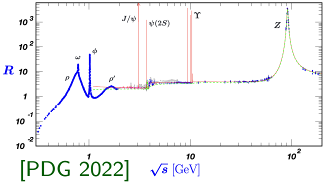
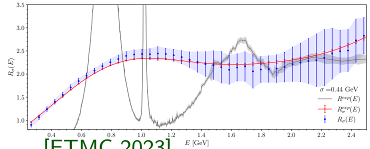


[PDG 2022]

In Lattice QCD we only measure $C(t) = \int_0^\infty d\omega\, \frac{R(\omega)}{12\pi^2}\omega^2 e^{-\omega t}$

- ⋆ **Inverse problem** $\Longleftarrow$
- ⋆ Only smeared ($\sigma > 0$) quantities

$$R_\sigma^{\rm g}(E) = \int_0^\infty d\omega\, R(\omega)\delta_\sigma^{\rm g}(\omega, E)$$
$$\delta_\sigma^{\rm g}(\omega, E) = e^{-\frac{(\omega-E)^2}{2\sigma^2}}/\sqrt{2\pi\sigma^2}$$



[ETMC 2023]

[Margari Fri 16:50]

$$C(t) = -\frac{1}{3}\sum_{k=1}^{3}\int d^3\vec{x}\,\langle V_k^{\mathrm{EM}}(t,\vec{x})\,V_k^{\mathrm{EM}}(0)\rangle = \int_0^\infty d\omega\,\frac{R(\omega)}{12\pi^2}\omega^2 e^{-\omega t}$$

$$= \int_0^\infty d\omega\, e^{-\omega t}\rho(\omega) \quad \stackrel{?}{\Longrightarrow} \quad \rho[\kappa] \equiv \int_0^\infty d\omega\,\rho(\omega)\kappa(\omega)$$

Many approaches are currently viable, including

- ⋆ Backus-Gilbert, HLT, Chebyshev polynomials, Gaussian processes
  [Hansen et al. 2017, HLT 2019, Bailas et al. 2020, Del Debbio et al. 2025]
- ⋆ Analyticity/causality–based [Fields, Abbott, Jay Mon 14:40–15:20]

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Staggered correlation functions also admit *oscillating* contributions

$$C(na) = \int_0^\infty d\omega\, e^{-\omega na}\rho(\omega) - (-1)^n\int_0^\infty d\omega\, e^{-\omega na}\rho_{\mathrm{osc}}(\omega)$$

Here:

1. Generalize methods to staggered correlation functions
2. Test reconstruction methods on mock data

   ⇒ reconstructions on real data with controlled systematic errors

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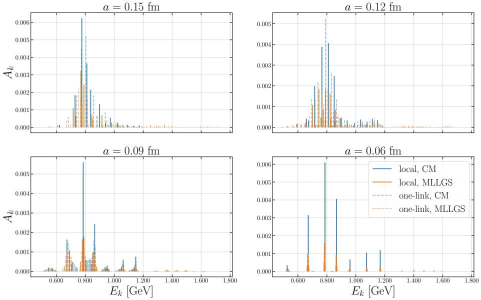
$$C(na) = \int_0^\infty d\omega\, \rho(\omega) e^{-\omega na} - (-1)^n \int_0^\infty d\omega\, \rho_{\text{osc}}(\omega) e^{-\omega na}$$
$$= \sum_k A_k e^{-E_k na} \qquad - (-1)^n \sum_k A_{k,\text{osc}} e^{-E_{k,\text{osc}} na}$$

a [fm]	L [fm]	$N_s^3 \times N_t$
0.15	5.00	$32^3 \times 48$
0.12	5.95	$48^3 \times 64$
0.09	5.70	$64^3 \times 96$
0.06	5.48	$96^3 \times 128$

Model light connected energies and amplitudes [Bazavov et al. 2025]

1. finite-volume effects
   $\rightarrow$ Chiral and MLLGS models
2. taste-breaking
   $\rightarrow$ local and one-link data
3. one oscillating state
   with $E_{1,\text{osc}} = 1.170$ GeV



Finite-volume *unsmeared* R-ratio

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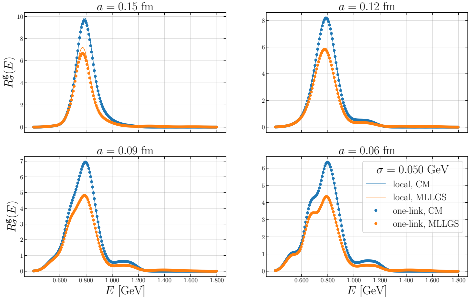

Finite-volume *smeared* R-ratio

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1. Standard linear reconstruction inversion strategies solve for

$$C(na) = \int_0^\infty d\omega\, \rho(\omega) b_n(\omega) \quad \Longrightarrow \quad \rho[\kappa] = \int_0^\infty d\omega\, \rho(\omega)\kappa(\omega)$$

   i. Approximated target smearing kernel: $\kappa(\omega) \approx \sum_n g_n b_n(\omega) = \overline{\kappa}(\omega)$

   ii. Approximated smeared spectral function: $\rho[\kappa] \approx \sum_n g_n C(na) = \rho[\overline{\kappa}]$

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2. Can be applied to even-odd staggered data [Stewart et al. Lattice 2024]

$$\begin{cases} C(2na) = \int_0^\infty d\omega\, \rho_{\text{even}}(\omega) b_{2n}(\omega)\,, & \rho_{\text{even}}(\omega) = \rho(\omega) + \rho_{\text{osc}}(\omega) \\ C((2n+1)a) = \int_0^\infty d\omega\, \rho_{\text{odd}}(\omega) b_{2n+1}(\omega)\,, & \rho_{\text{odd}}(\omega) = \rho(\omega) - \rho_{\text{osc}}(\omega) \end{cases}$$

$$\begin{aligned} \frac{1}{2}\left(\rho_{\text{even}}[\overline{\kappa}_{\text{even}}] + \rho_{\text{odd}}[\overline{\kappa}_{\text{odd}}]\right) &= \sum_n \left[g_{2n}^{\text{even}} C(2na) + g_{2n+1}^{\text{odd}} C((2n+1)a) \right] \\ &= \rho[\tfrac{1}{2}(\overline{\kappa}_{\text{even}} + \overline{\kappa}_{\text{odd}})] + \rho_{\text{osc}}[\tfrac{1}{2}(\overline{\kappa}_{\text{even}} - \overline{\kappa}_{\text{odd}})] \\ &= \rho[\overline{\kappa}] + \rho_{\text{osc}}[\overline{\kappa}_{\text{osc}}]\,, \quad \overline{\kappa}_{\text{osc}} \approx \kappa_{\text{osc}}(\omega) = 0 \end{aligned}$$

Reconstructing smeared observables

Linear reconstruction strategies applied to even-odd data

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3. Can we design strategies to directly target $\rho[\kappa]$ and $\rho_{\text{osc}}[\kappa_{\text{osc}} = 0]$?

1. Apply HLT inversion strategy [HLT 2019] to even-odd data

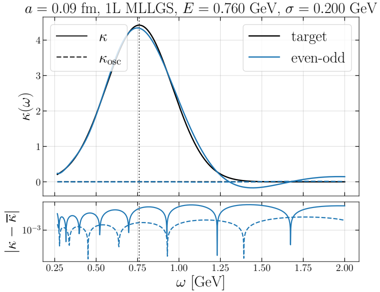
$$\kappa(\omega) \approx \sum_n g_n b_n(\omega) \equiv \overline{\kappa}(\omega)$$

$\Rightarrow$ g_n minimize $A[g] + \lambda B[g]$

$$A[g] = \int d\omega \, |\kappa(\omega) - \overline{\kappa}(\omega)|^2$$

$$B[g] = g^T B g \,, \quad B = \frac{A[0]}{C(a)^2} E^6 \, \mathrm{Cov}$$

$\Rightarrow$ Tune λ s.t. $A[g_\lambda] = 10 B[g_\lambda]$



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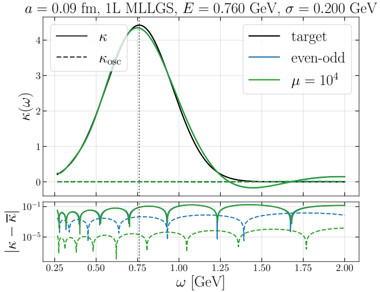


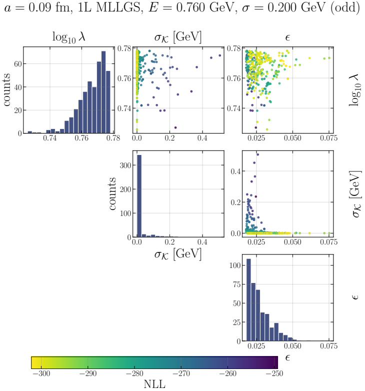
2. Implement dedicated staggered HLT strategy

$$\kappa(\omega) \approx \sum_n g_n b_n(\omega) \equiv \overline{\kappa}(\omega)\,, \quad \kappa_{\mathrm{osc}}(\omega) \approx \sum_n g_n (-1)^n b_n(\omega) \equiv \overline{\kappa}_{\mathrm{osc}}(\omega)$$

Define g_n to simultaneously target $\kappa(\omega)$ and $\kappa_{\mathrm{osc}}(\omega) = 0$ by minimizing

$$A[g] + \mu A_{\mathrm{osc}}[g] + \lambda B[g]\,, \quad A_{\mathrm{osc}}[g] = \int d\omega\, |\kappa_{\mathrm{osc}}(\omega) - \overline{\kappa}_{\mathrm{osc}}(\omega)|^2$$

1. Apply GP inversion strategy [Del Debbio et al. 2025] to even-odd data



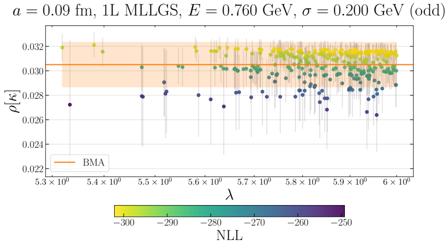
$\Rightarrow$ Take $\rho \sim \mathrm{GP}\left(\rho_\vartheta^{\text{prior}}, \mathcal{K}_\vartheta^{\text{prior}}\right)$

$\Rightarrow$ Infer $\rho \sim \mathrm{GP}\left(\rho_\vartheta^{\text{post}}, \mathcal{K}_\vartheta^{\text{post}}\right)$

e.g. $\mathcal{K}^{\text{prior}}(\omega, \omega') = \frac{e^{\alpha\omega'}}{\lambda}\delta^{\text{g}}_{\sigma_{\mathcal{K}}}(\omega, \omega')$

a. Fix ϑ by minimizing NLL

b. Marginalize (MC) w.r.t. ϑ $\Longleftarrow$



Gaussian Processes
Even-odd & staggered strategies

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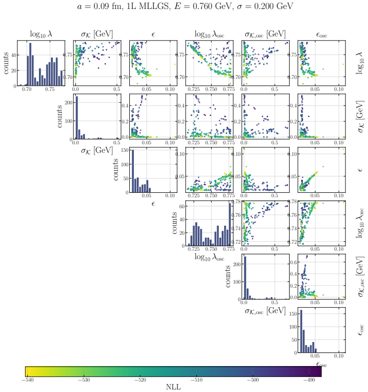

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2. Implement dedicated staggered GP strategy

$\Rightarrow$ Take $\rho \sim \mathrm{GP}\left(\rho_{\vartheta}^{\text{prior}}, \mathcal{K}_{\vartheta}^{\text{prior}}\right)$ and $\rho_{\text{osc}} \sim \mathrm{GP}\left(\rho_{\text{osc},\vartheta}^{\text{prior}}, \mathcal{K}_{\text{osc},\vartheta}^{\text{prior}}\right)$

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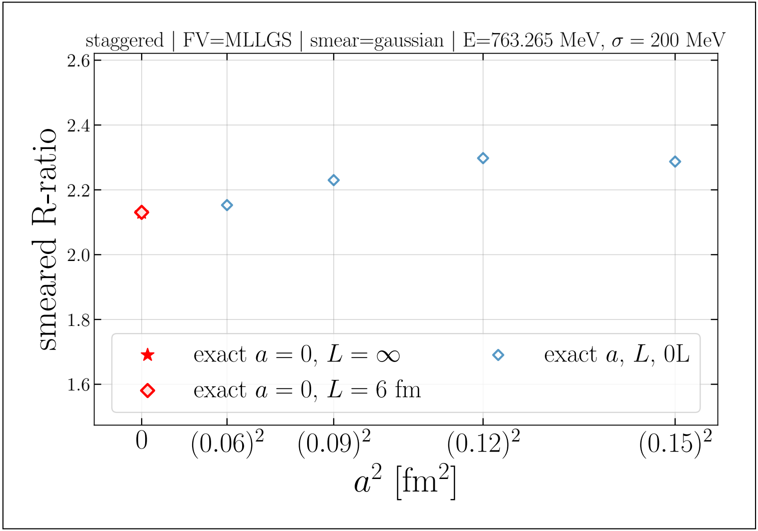
Analysis pipeline

Pointwise extraction (staggered)



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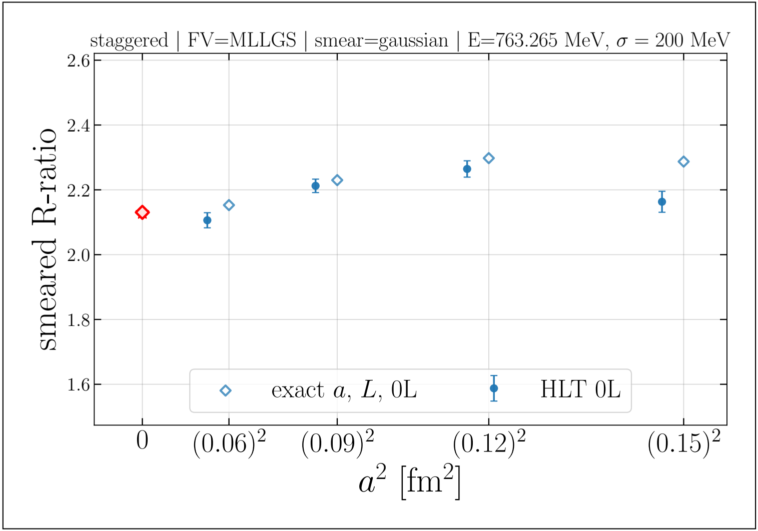

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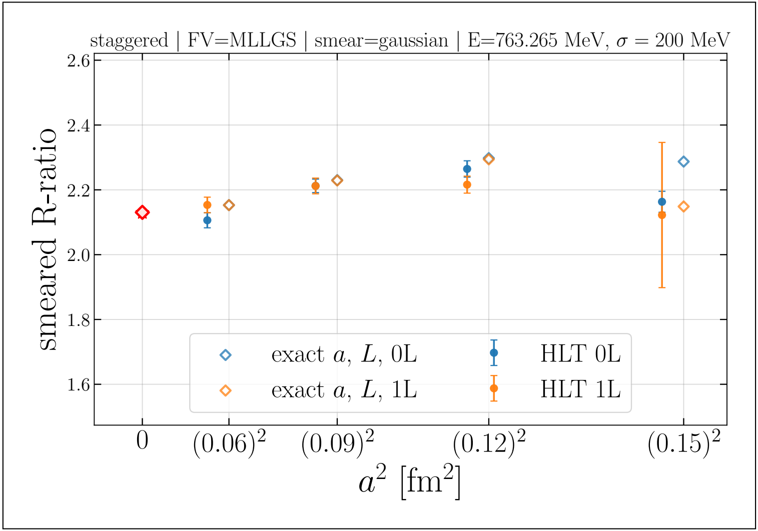

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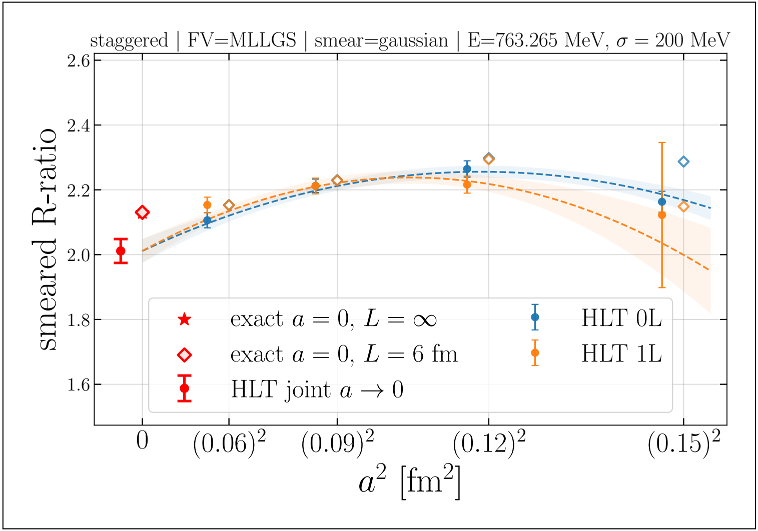

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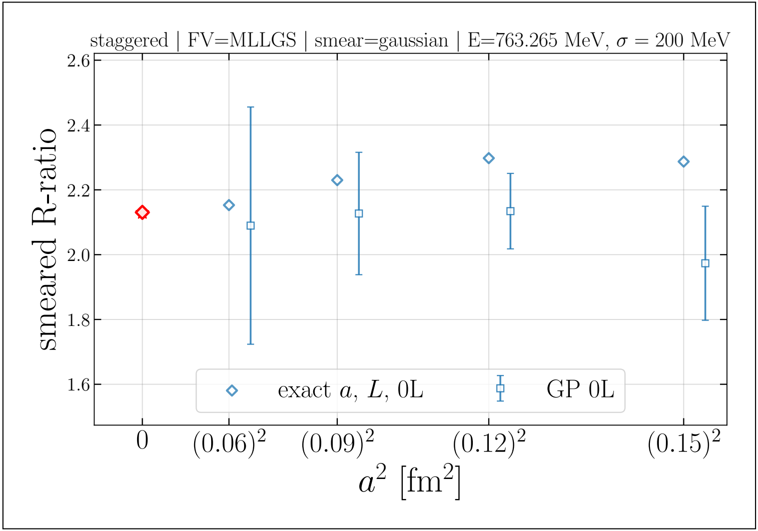

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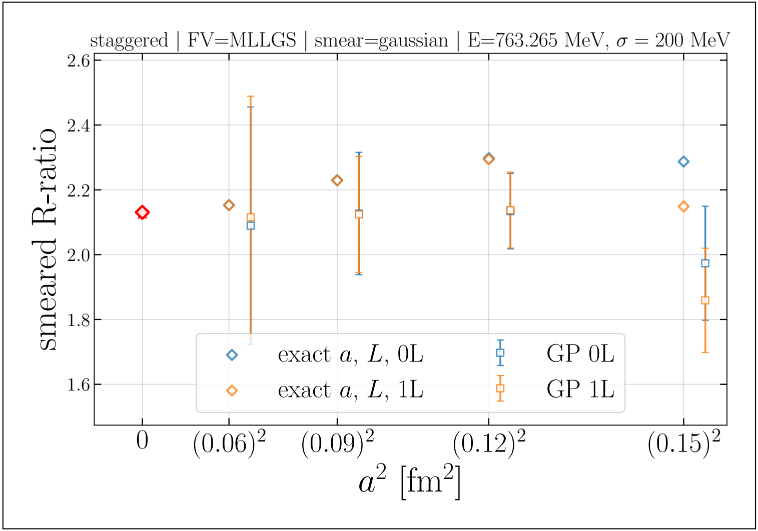

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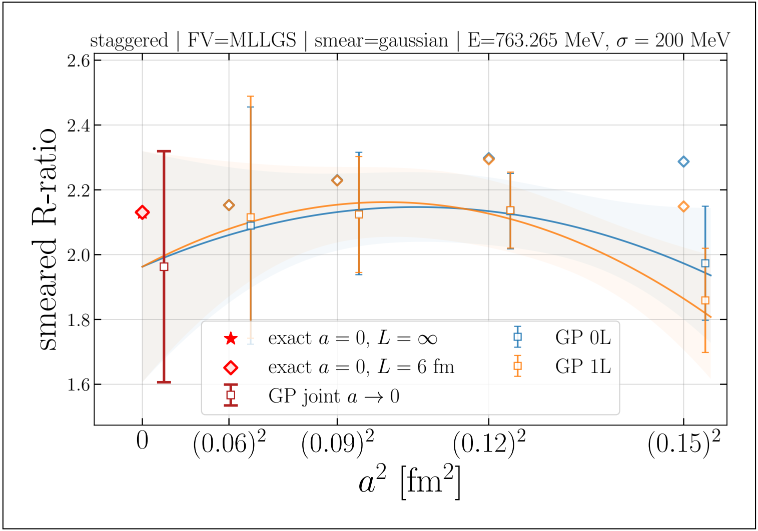

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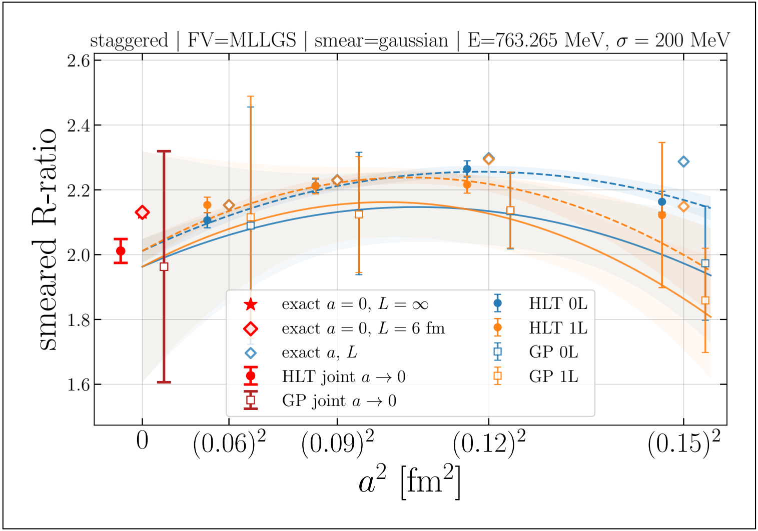

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1. Apply CB inversion strategy to even-odd data
   Fails if not modified, as $\rho_{\text{odd}} = \rho - \rho_{\text{osc}}$ is not necessarily positive
2. Implement dedicated staggered strategies

Primal problem i.e. computing upper/lower bounds on $\rho[\kappa]$

$$\max/\min_{\rho,\rho_{\text{osc}}} \int_0^\infty d\omega\, \rho(\omega)\kappa(\omega)$$

$$\text{s.t. } \rho(\omega) \geq 0\,,\ \rho_{\text{osc}}(\omega) \geq 0$$

$$\text{and } (C[\rho,\rho_{\text{osc}}] - C)^T \text{Cov}^{-1}(C[\rho,\rho_{\text{osc}}] - C) \leq \chi_0^2$$

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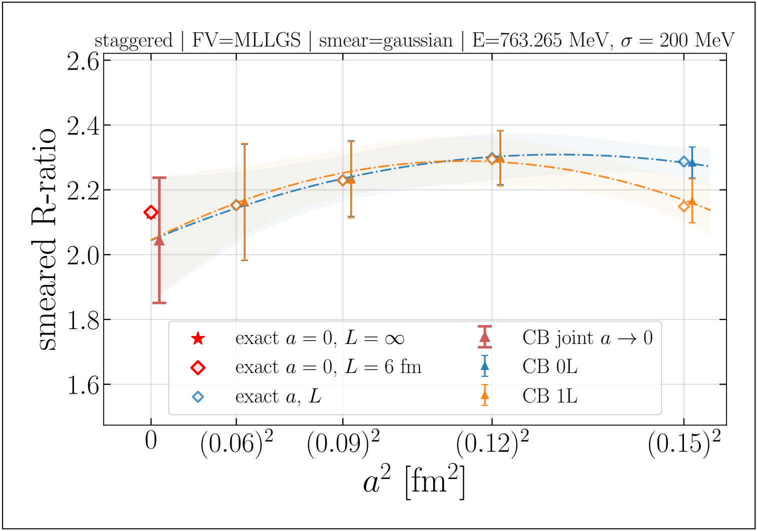
Dual problem i.e. computing upper/lower bounds on κ and $\kappa_{\text{osc}} = 0$

$$\max/\min_g\ g^T C - \chi_0\sqrt{g^T \text{Cov}\, g}$$
$$\text{s.t. } \kappa(\omega) - \sum_n g_n b_n(\omega) \lesseqgtr 0$$
$$\text{and } \kappa_{\text{osc}}(\omega) - \sum_n g_n (-1)^n b_n(\omega) \lesseqgtr 0$$

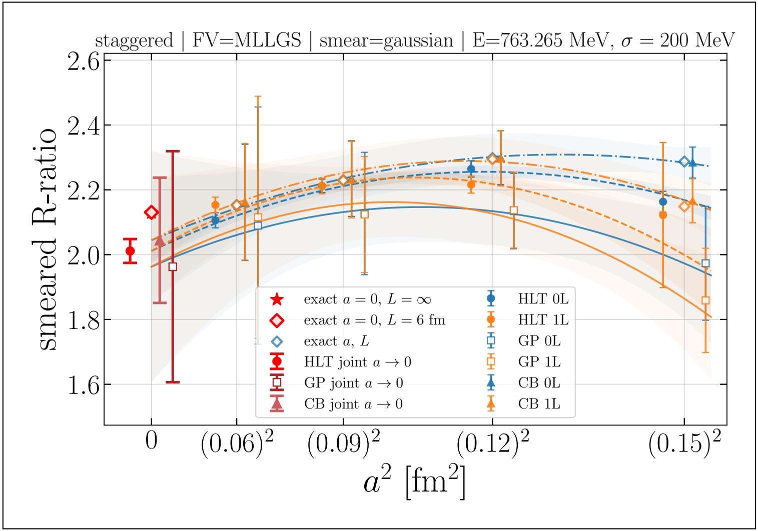
Analysis pipeline

Pointwise extraction (staggered #2)



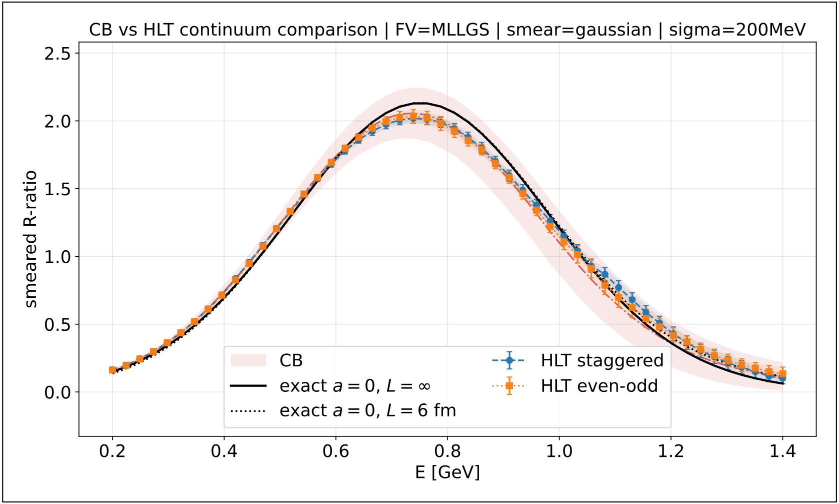
Analysis pipeline

Pointwise extraction (staggered #2)



Analysis pipeline

Energy scan



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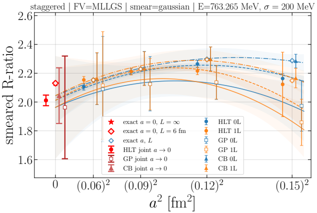
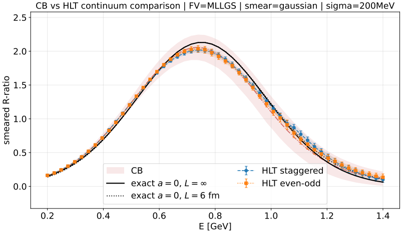
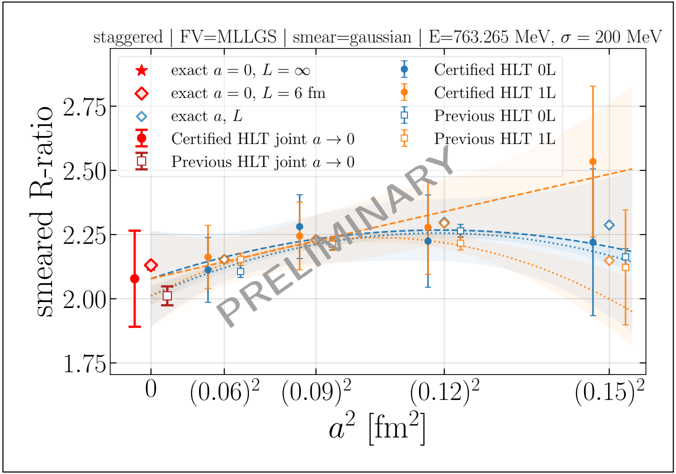
Conclusions





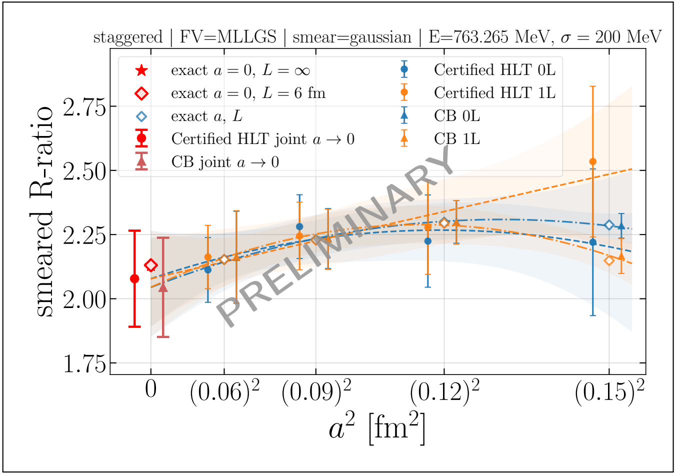
- Staggered correlation functions require dedicated methods
  - Linear methods: HLT and GP
  - Causal bootstrap: certified bounds for $\rho(\omega) \geq 0$
- Mock data with realistic FV and TB effects $\Rightarrow$ closure tests
- Interesting questions remain open
  - Matrix-valued $C(t)$ (variational, e.g. $\pi\pi$) [Abbott Mon 15:00]
  - Choice of smearing kernels [Jay Mon 15:20]
  - Finite-volume corrections [Bresciani Tue 15:00]
  - Continuum limit: at fixed t_{min} [MS and Toniolo Tue 14:00–14:20]

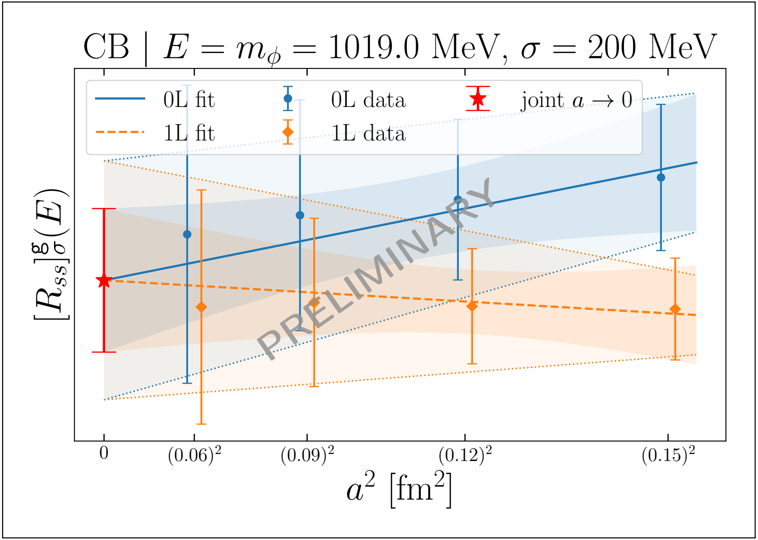
1. Linear methods only guarantee the reconstruction of $\rho[\overline{\kappa}]$
2. *Bound* $\rho[\kappa] - \rho[\overline{\kappa}] \leq \overline{\sigma}_{\text{syst}}[\rho[\kappa]]$ from $C(t)$ [Jay and MS 2026]
3. Tune λ balancing e.g. $\overline{\sigma}_{\text{syst}}[\rho[\kappa]] = \sigma_{\text{stat}}[\rho[\overline{\kappa}]]$

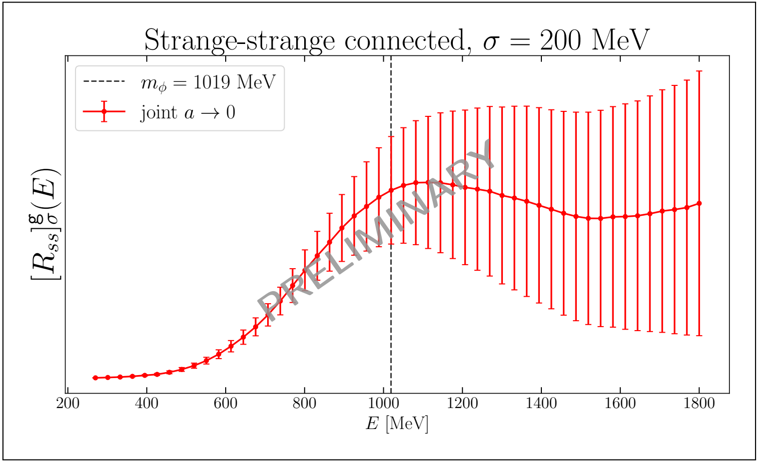


Certifying linear methods [Jay Mon 15:20]

1. Linear methods only guarantee the reconstruction of $\rho[\overline{\kappa}]$
2. *Bound* $\rho[\kappa] - \rho[\overline{\kappa}] \leq \overline{\sigma}_{\mathsf{syst}}[\rho[\kappa]]$ from $C(t)$ [Jay and MS 2026]
3. Tune λ balancing e.g. $\overline{\sigma}_{\mathsf{syst}}[\rho[\kappa]] = \sigma_{\mathsf{stat}}[\rho[\overline{\kappa}]]$




CB | $E = m_\phi = 1019.0$ MeV, $\sigma = 200$ MeV
0L fit
1L fit
0L data
1L data
joint $a \to 0$
PRELIMINARY
$[R_{ss}]^{g}_{\sigma}(E)$
0
$(0.06)^2$
$(0.09)^2$
$(0.12)^2$
$(0.15)^2$
a^2 [fm^2]

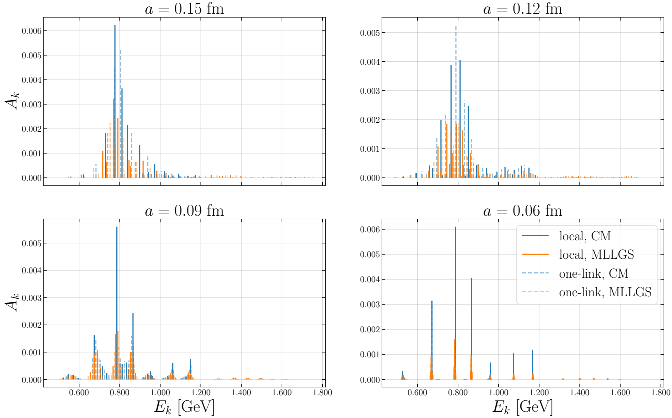


Thank you for your attention!

Backup slides

Closure tests
Ensembles

a [fm]	L [fm]	$N_s^3 \times N_t$	am	aM_Ω
0.15	5.00	$32^3 \times 48$	0.002426	1.3246(26)
0.12	5.95	$48^3 \times 64$	0.0001907	1.0494(17)
0.09	5.70	$64^3 \times 96$	0.0001326	0.75372(97)
0.06	5.48	$96^3 \times 128$	0.0008	0.4834(11)



Finite-volume *unsmeared* R-ratio

a [fm]	L [fm]	$N_s^3 \times N_t$	am	aM_Ω
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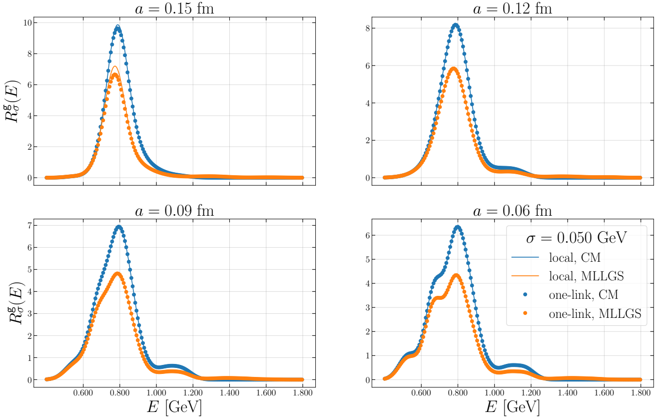
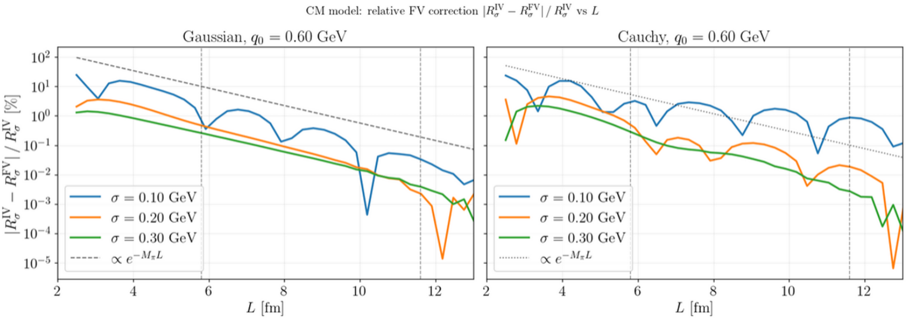
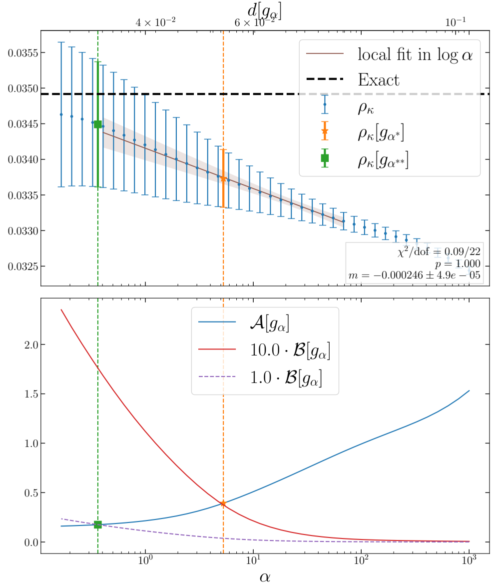


Finite-volume *smeared* R-ratio

Finite-volume effects

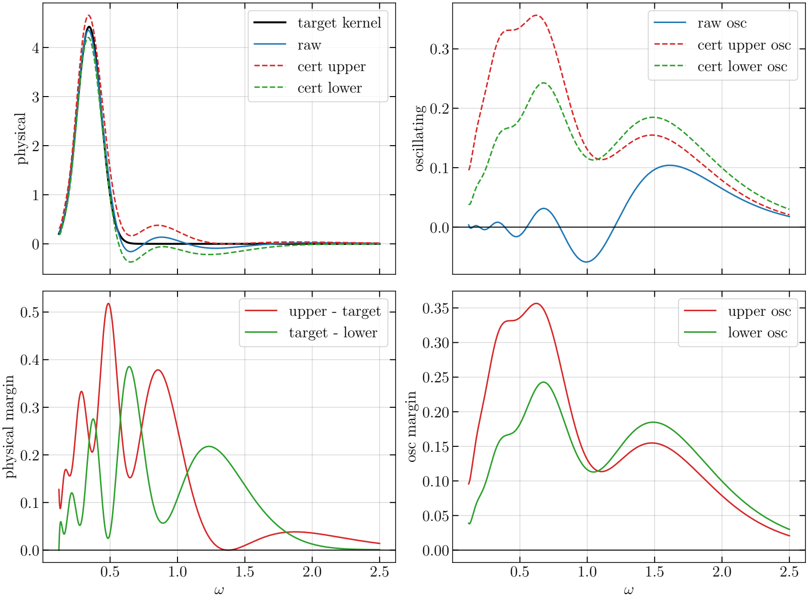


HLT STABILITY ANALYSIS
Tuning the regulator parameter



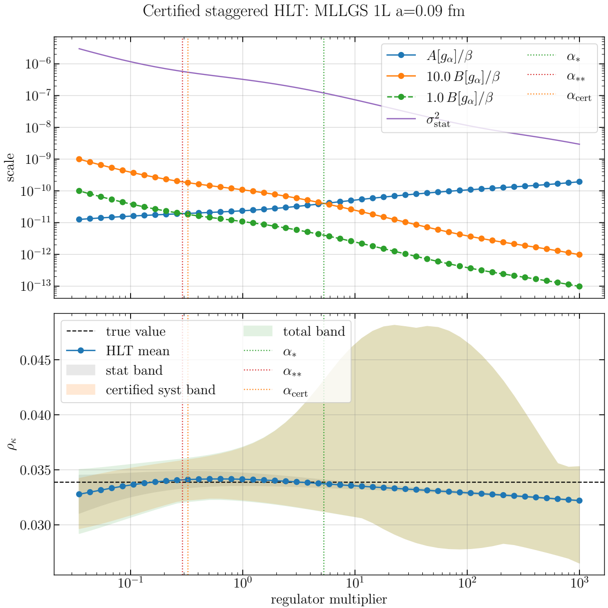
Certifying linear methods [Jay and MS 2026]

Computing upper and lower bounds on smearing kernels



Certifying linear methods [Jay and MS 2026]

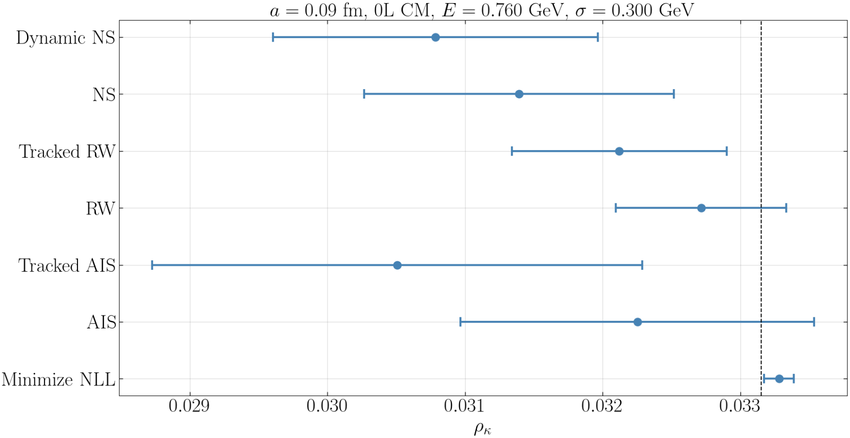
Tuning the regulator parameter



Gaussian Processes

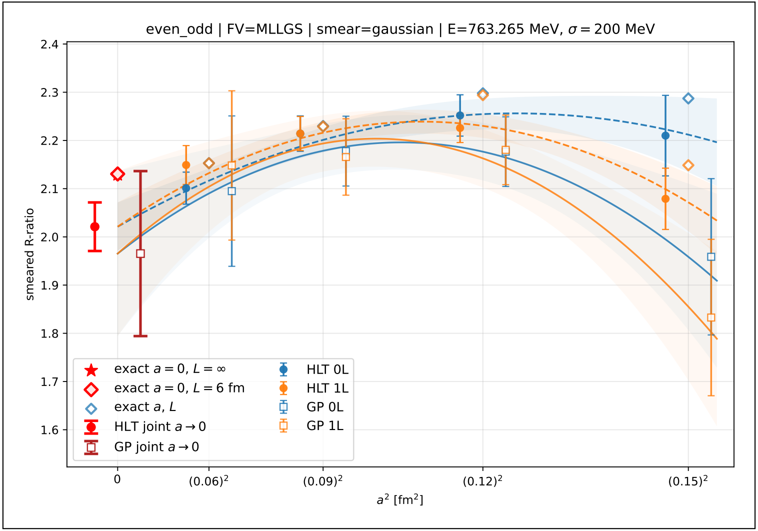
Sampling strategies

- ⋆ Nested Sampling (NS) [Skilling 2004; Skilling 2006]
- ⋆ Random walk (RW) MCMC
- ⋆ Affine-Invariant Sampling (AIS) [Goodman and Weare 2010]



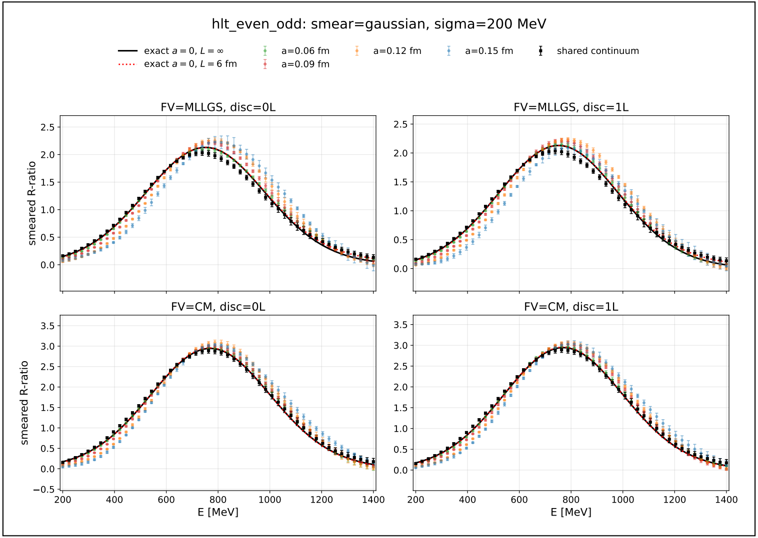
Analysis pipeline

Pointwise extraction (even-odd)



Analysis pipeline

HLT energy scan (even-odd)



Analysis pipeline
CB energy scan