

DIRECT AND INDIRECT INVERSE-LAPLACE STRATEGIES FOR SPECTRAL RECONSTRUCTION

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SPECTRAL DENSITIES

Euclidean lattice correlators are related to spectral densities via **a Laplace transform**:

$$C(t) = \int_0^\infty dE e^{-Et} \rho(E)$$

At finite volume, the energy spectrum is discrete:

$$\rho(E) = \sum_n Z_n \delta(E - E_n) , \quad Z_n \equiv |\langle 0 | \mathcal{O} | n \rangle|^2$$

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Challenges

- The Laplace kernel **suppresses high-energy contributions** and makes **nearby states difficult to distinguish**.
- Lattice correlators contain only a **finite number of noisy Euclidean-time samples**.

Reconstructing the underlying spectral information is therefore a severely **ill-posed inverse problem**.

TWO RECONSTRUCTION STRATEGIES

1. Direct reconstruction

Reconstruct a regularized, finite-resolution spectral observable.

$$C(t) \longrightarrow \hat{\rho}_{\sigma}(E)$$

- The result depends on **the resolution kernel and regularization choice**.
- Improving resolution generally increases sensitivity to statistical noise.
- Localized structures or peaks may be identified afterward.

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2. Indirect spectral construction

Infer a finite-state representation over a selected Euclidean-time window.

$$C(t) \longrightarrow \left\{ \hat{E}_n, \hat{Z}_n \right\}_{n=1}^N \longrightarrow \hat{\rho}(E) = \sum_{n=1}^N \hat{Z}_n \delta(E - \hat{E}_n)$$

- The **extracted energies and weights** define an effective discrete spectral model.
- Performance depends on state separation, model order, and noise.
- A smeared spectrum can subsequently be obtained by convolution with a resolution kernel

INDIRECT STRATEGY

EXPONENTIAL-FITTING METHODS

Over a selected Euclidean-time window, approximate the correlator by a finite sum of exponentials:

$$C(t) \simeq \sum_{n=1}^N Z_n e^{-E_n t}, \quad Z_n \geq 0$$

Several approaches have been introduced, including Prony, matrix-pencil, Lanczos, and GEVP-based methods.

They exploit the **same finite-exponential spectral structure**, but differ in how they construct and truncate the reduced eigenvalue problem and control noise-induced modes. ^[1]

^[1] M. Fischer *et al.*, Eur. Phys. J. A **56**, 206 (2020)

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Reference indirect method in our benchmarks: Truncated Hankel Correlator method ^[2]

The THC method first constructs a **low-rank approximation of** the maximal correlator **Hankel matrix** by retaining its most significant modes.

A **Prony generalized eigenvalue problem** is then solved to extract approximations to the energy levels.

^[1] M. Fischer *et al.*, Eur. Phys. J. A **56**, 206 (2020)

^[2] J. Ostmeyer and C. Urbach, arXiv:2510.15500 (2025)

Z-RCNW: RATIONAL INITIALIZATION IN Z-SPACE

For equally spaced Euclidean times, $C_n \equiv C(n\Delta t) \simeq \sum_{k=1}^K Z_k q_k^n$, $q_k = e^{-E_k \Delta t}$

The finite z-transform is $G_N(z) \equiv \sum_{n=0}^{N-1} C_n z^{-n} \simeq \sum_{k=1}^K Z_k \frac{1 - (q_k/z)^N}{1 - q_k/z}$

For finite N , $G_N(z)$ is a polynomial in z^{-1} . RCNW (our version of rational approximation) fits a rational model to the sampled transform and retains poles satisfying

$$0 < q_k < 1, \quad E_k = -\frac{\log q_k}{\Delta t}$$

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Reconstruction workflow of z-RCNW:

$$C_n \xrightarrow{\text{finite } z\text{-transform}} G_N(z) \xrightarrow{\text{RCNW}} \{q_k\} \xrightarrow{E_k = -\log q_k / \Delta t} \{E_k\} \xrightarrow{\text{time-domain refinement}} \{E_k, Z_k\}$$

DIRECT STRATEGY

SMEARED SPECTRAL-DENSITY RECONSTRUCTION

Direct methods reconstruct a finite-resolution spectral observable rather than attempting to identify individual delta-function states:

$$\rho_{\sigma}(\omega) \equiv \int_0^{\infty} dE \Delta_{\sigma}(\omega, E) \rho(E) , \quad \hat{\rho}_{\sigma}(\omega) = \sum_t g_t(\omega) C(t)$$

- **Smearing stabilizes the inverse problem** by sacrificing pointwise spectral resolution.
- The achievable **resolution is limited** by the Euclidean-time range, statistical noise, and regularization.
- The reconstructed observable should therefore be interpreted together with its achieved resolution kernel.

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- The reconstructed observable should therefore be interpreted together with its achieved resolution kernel.

Reference direct method in our benchmark: Hansen–Lupo–Tantalo method ^[3]

HLT chooses a target smearing kernel in advance and determines the coefficients $g_t(\omega)$ that best reproduce it, while balancing kernel resolution against statistical uncertainty.

^[3] M. Hansen, A. Lupo and N. Tantalo, Phys. Rev. D 99, 094508 (2019).

ILDF: INVERSE-LAPLACE DOMAIN FITTING

First construct a regularized inverse-Laplace representation of the correlator and of a single trial exponential:

$$\mathbf{A}_{\text{data}} \equiv \mathcal{T}_\lambda[C] , \quad \mathbf{A}(E) \equiv \mathcal{T}_\lambda[e^{-Et}]$$

Fit $\mathbf{A}_{\text{data}}$ with a finite positive spectral model

$$\mathbf{A}_{\text{model}} = \sum_{k=1}^K Z_k \mathbf{A}(E_k) , \quad Z_k \geq 0$$

- Search and refine the energies by minimizing the transformed-domain residual.
- For fixed energies, determine the amplitudes by non-negative least squares.

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More about the method and its recent developments in the upcoming talks [**Di Renzo 9:40, Vidal Maxia 10:00**].

CONTROLLED BENCHMARKS

THREE CONTROLLED TOY MODELS

The exact correlators are generated from
$$C(t) = \sum_{k=1}^K Z_k e^{-E_k t}, \quad Z_k > 0, \quad t = 0, 1, \dots, 32$$

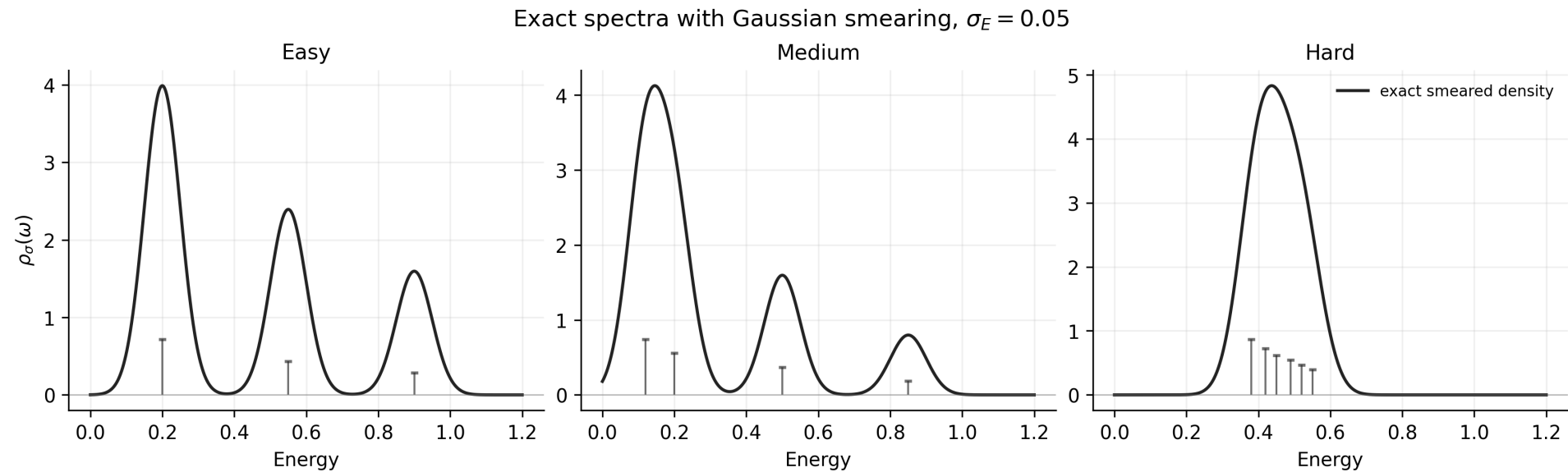
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Easy model: Three well-separated states, $\Delta E_{\min}^{\text{easy}} = 0.35$

Medium model: Nearby low-energy pair and weaker excited structures, $\Delta E_{\min}^{\text{medium}} = 0.08$

Hard model: Six crowded states, $\Delta E_{\min}^{\text{hard}} = 0.03$



COMMON BENCHMARK PROTOCOL

Apply 2 indirect methods: **THC** (GitHub implementation), **z-RCNW**
and 2 direct methods: **HLT** (GitHub implementation), **ILDF**

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Noise input

- The full-sample mean $C(t)$ is the central noisy correlator.
- **100 bootstrap means** are passed identically to THC, z-RCNW, and HLT.
- HLT regularization is selected once and held fixed across bootstrap replicas.

Finite-resolution diagnostic

$$\Delta_\rho(\sigma_E) = \int dE \left| \rho_{\sigma_E}^{\text{true}}(E) - \rho_{\sigma_E}^{\text{rec}}(E) \right|$$

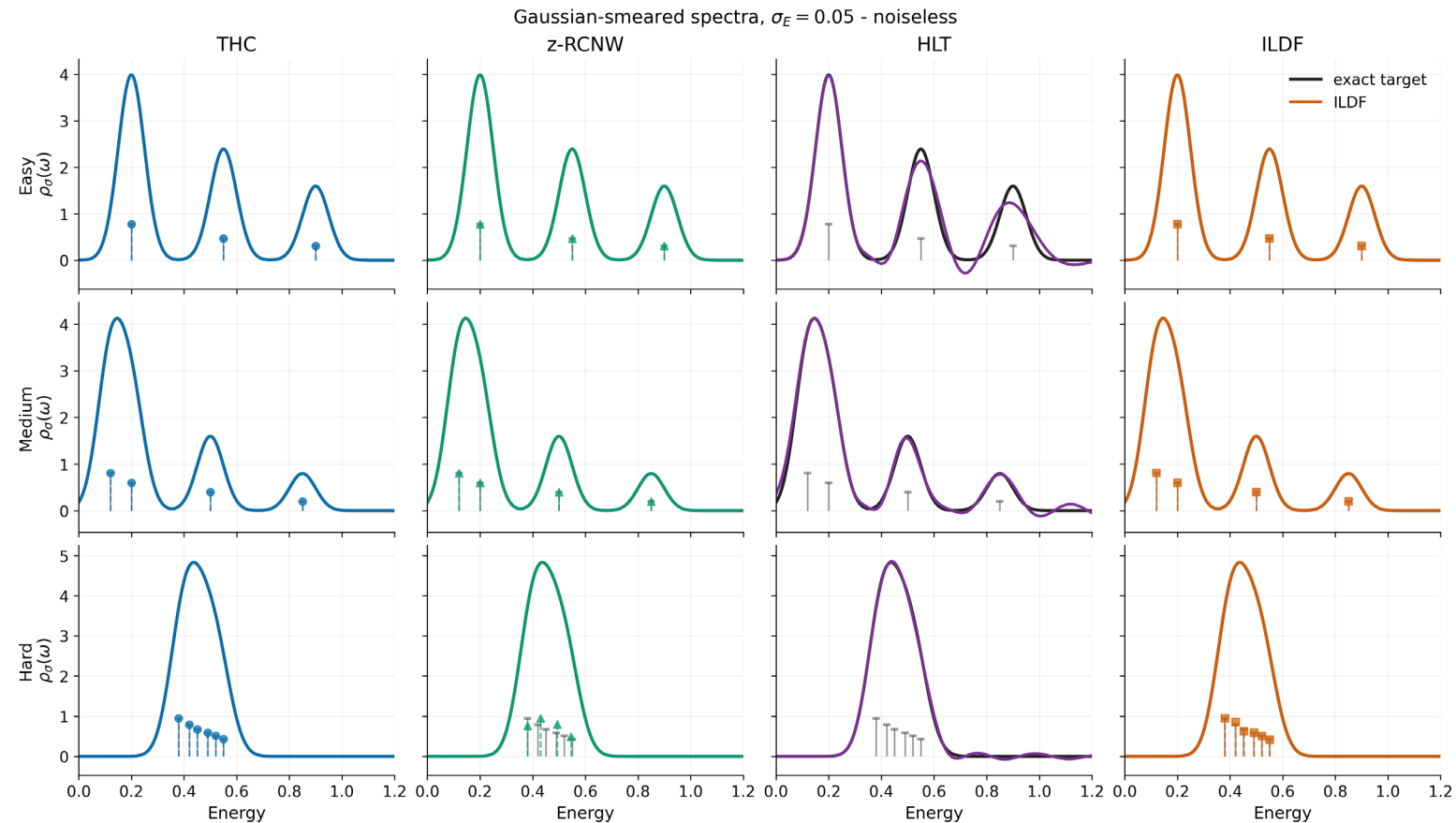
- All methods are compared after applying the same Gaussian resolution.
- HLT is evaluated only as a direct smeared-density reconstruction.

RECONSTRUCTION FROM NOISELESS DATA

Easy and medium: the expected states and smeared spectra are recovered.

Hard: some nearby levels merge or shift, yet the smeared spectrum remains well reconstructed.

HLT: evaluated only as a smeared-density method, with no discrete state count.



RECONSTRUCTION WITH 1% NOISE

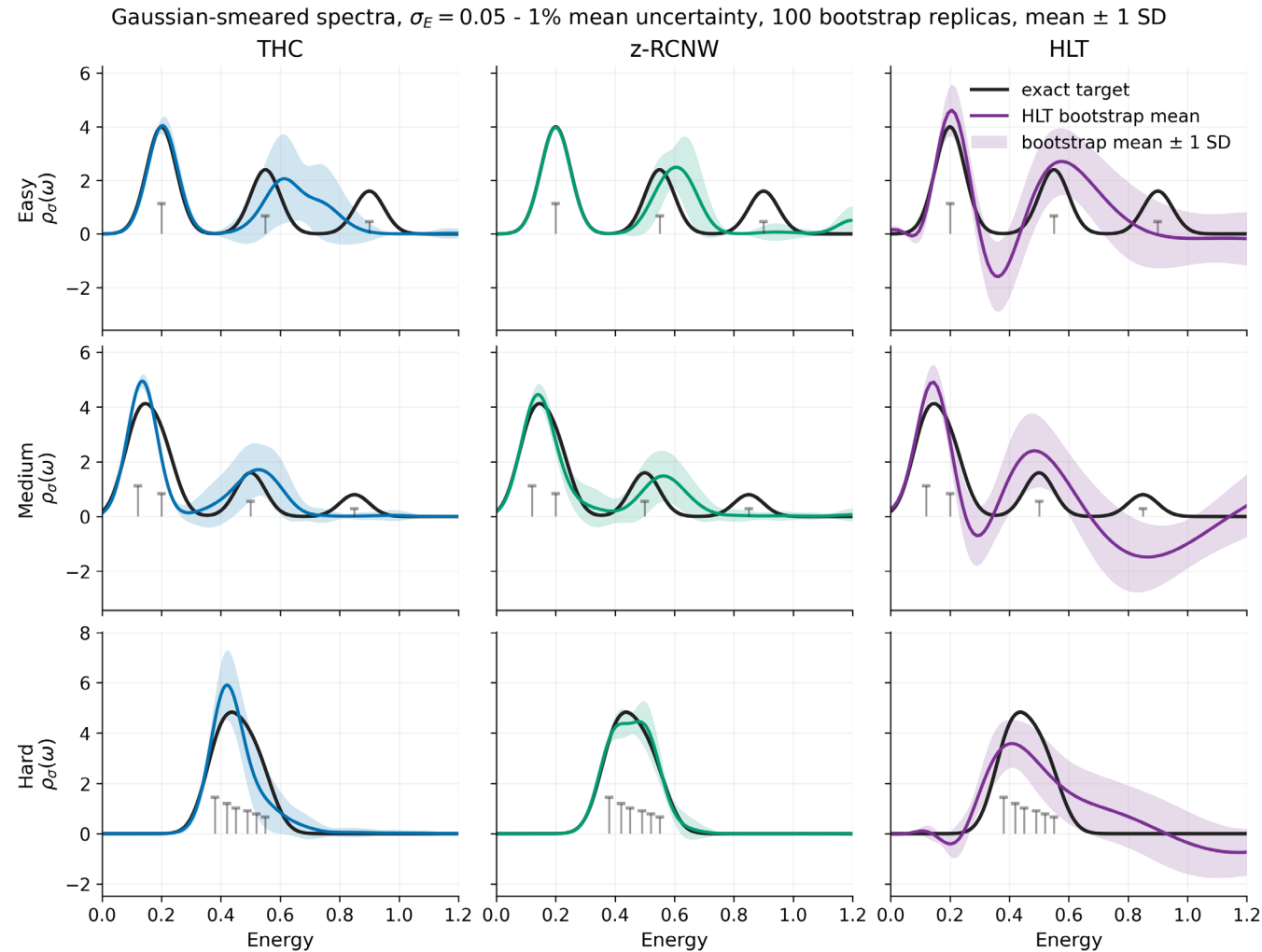
At 1% uncertainty on the correlator mean, the focus shifts to bootstrap stability and finite-resolution consistency.

THC: median of two effective states for all models.

z-RCNW: median of three states for easy and medium, and two for hard.

HLT: direct smeared-density estimate with broad bands

ILDF: no noisy-data analysis. Work in progress.



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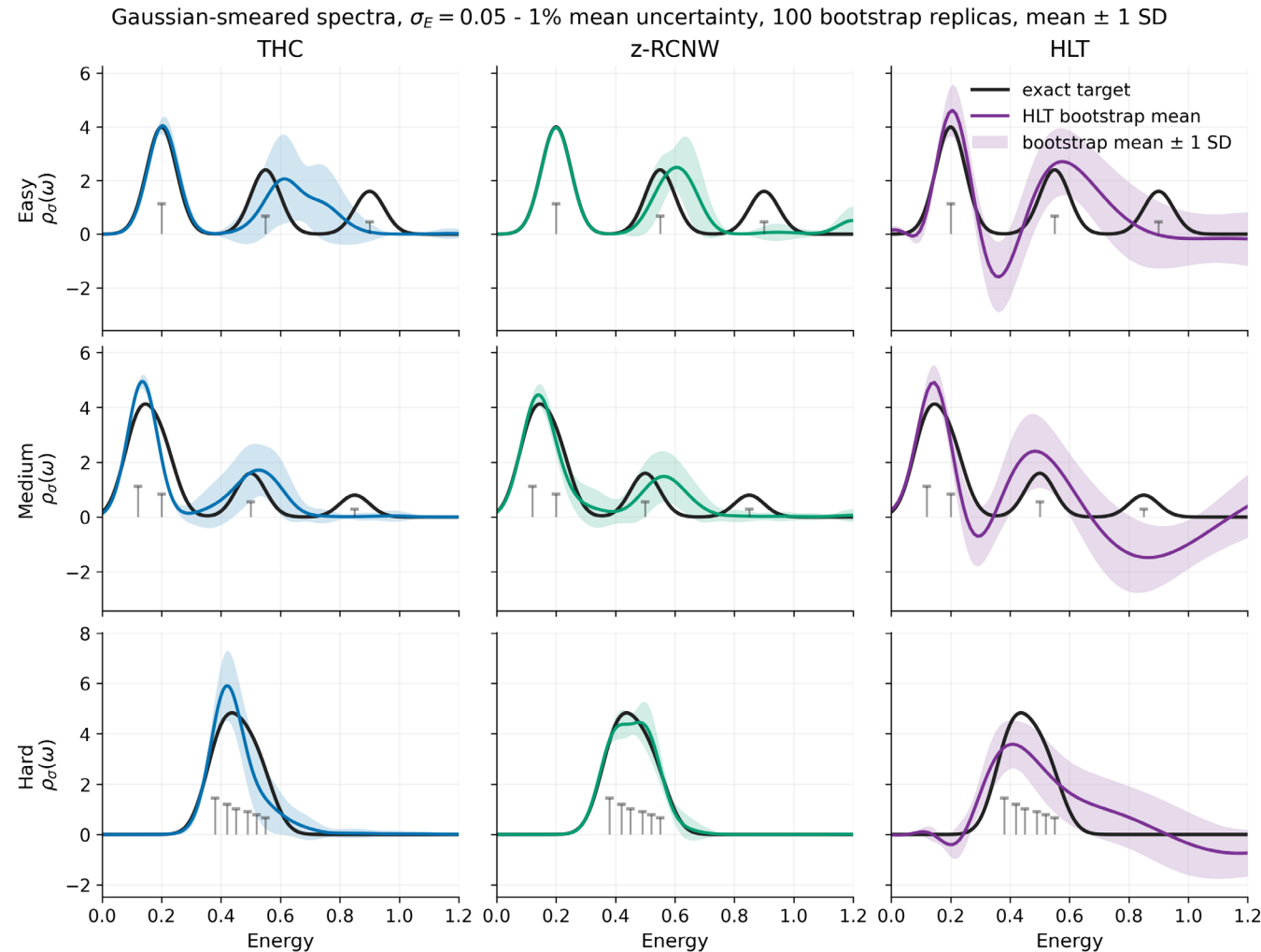
z-RCNW: median of three states for easy and medium, and two for hard.

HLT: direct smeared-density estimate with broad bands

ILDF: no noisy-data analysis. Work in progress.

Individual states may be unresolved, while **the smeared spectral structure remains reasonably reproduced.**

This provides a preliminary comparison of the direct and indirect strategies.



APPLICATION TO LATTICE-QCD DATA

NPLQCD DATA AND ANALYSIS SETUP

Dataset

Five NPLQCD correlator constructions corresponding to the five rows of Table I in Detmold et al.^[4]:

$$N, \quad NN (I = 1,1D), \quad NN (I = 0,1D), \quad NN (I = 1,3D), \quad NN (I = 0,10D).$$

Only z-RCNW analysis

- Data-derived windows: $t_{min} \in \{1,2,3,4\}$, $8 \leq N_t \leq 16$.
- Full delete-one-block jackknife with 327 replicas.
- Window selection and reconstruction are repeated in every replica.

^[4] W. Detmold et al., arXiv:2601.22273 (2026).

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Assessment

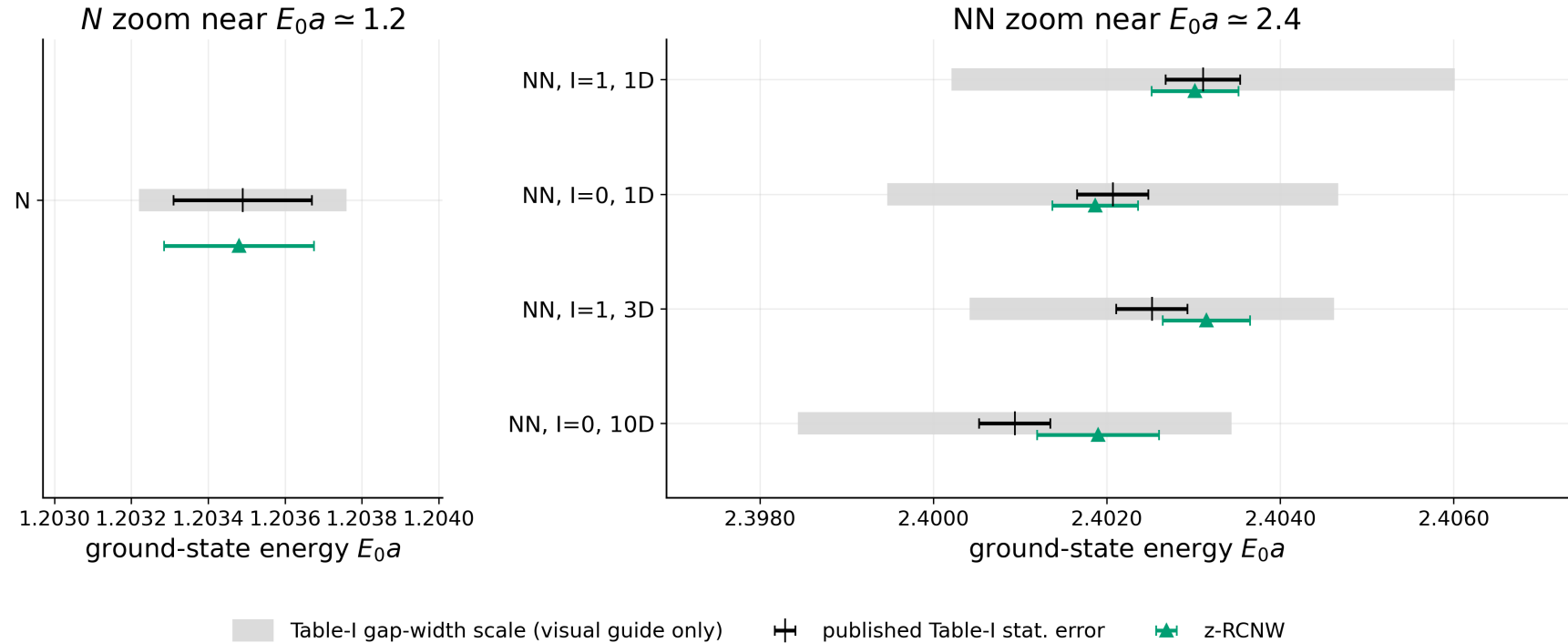
Lowest-energy consistency, correlator reconstruction, and stability under window and jackknife variations.

Reference: published block-Lanczos $E_0 a$ with statistical and bound widths.

^[4] W. Detmold et al., arXiv:2601.22273 (2026).

NPLQCD GROUND-STATE COMPARISON

z-RCNW Ground-State Energies with Full Delete-One Jackknife



- Stable ground-state extraction is obtained for all five NPLQCD correlator constructions.
- The lowest-energy level is recovered in all 327 delete-one-block jackknife replicas.
- The reconstructed ground-state energies agree with the published Lanczos estimates within $|\Delta(E_0a)| < 10^{-3}$

SUMMARY AND OUTLOOK

SUMMARY AND NEXT STEPS

Summary

- Direct methods recover smeared spectra; indirect methods recover effective states whose convolution reproduces the smeared structure.
- **Noiseless benchmark:** the expected structures are recovered for the easy and medium models. In the hard model, nearby levels may merge or shift into effective peaks, while the $\sigma_E = 0.05$ smeared spectrum remains well reproduced.
- **At 1% uncertainty on the correlator mean:** the recovered state count becomes unstable, but the finite-resolution spectral structure remains reasonably reconstructed.
- **NPLQCD data:** z-RCNW stably recovers the lowest-energy state in all five correlator constructions, consistently with the published Lanczos estimates.

Next steps

- Extend **ILDF to noisy correlators**, including bootstrap uncertainties and covariance weighting.
- Test the methods on additional published lattice-QCD datasets with different **channels, operators, volumes, and noise levels**.

THANK YOU

BACKUP: RCNW

Approximate sampled transform data by a compact rational model:

$$F(s_i) \simeq \hat{F}(s_i) = \sum_{j=1}^P \frac{r_j}{s_i - p_j}$$

For an inverse-Laplace representation with physical decaying modes,

$$p_j = -E_j < 0, \quad f(t) = \sum_{j=1}^P r_j e^{-E_j t}$$

Workflow

Padé initialization → noise-weighted residue fitting → pruning and clustering → pole position → Bayesian information
provide candidate pole configurations through regularized linear least-squares problem of poles refinement via variable projection criterion selection

BACKUP: BENCHMARK TABLES

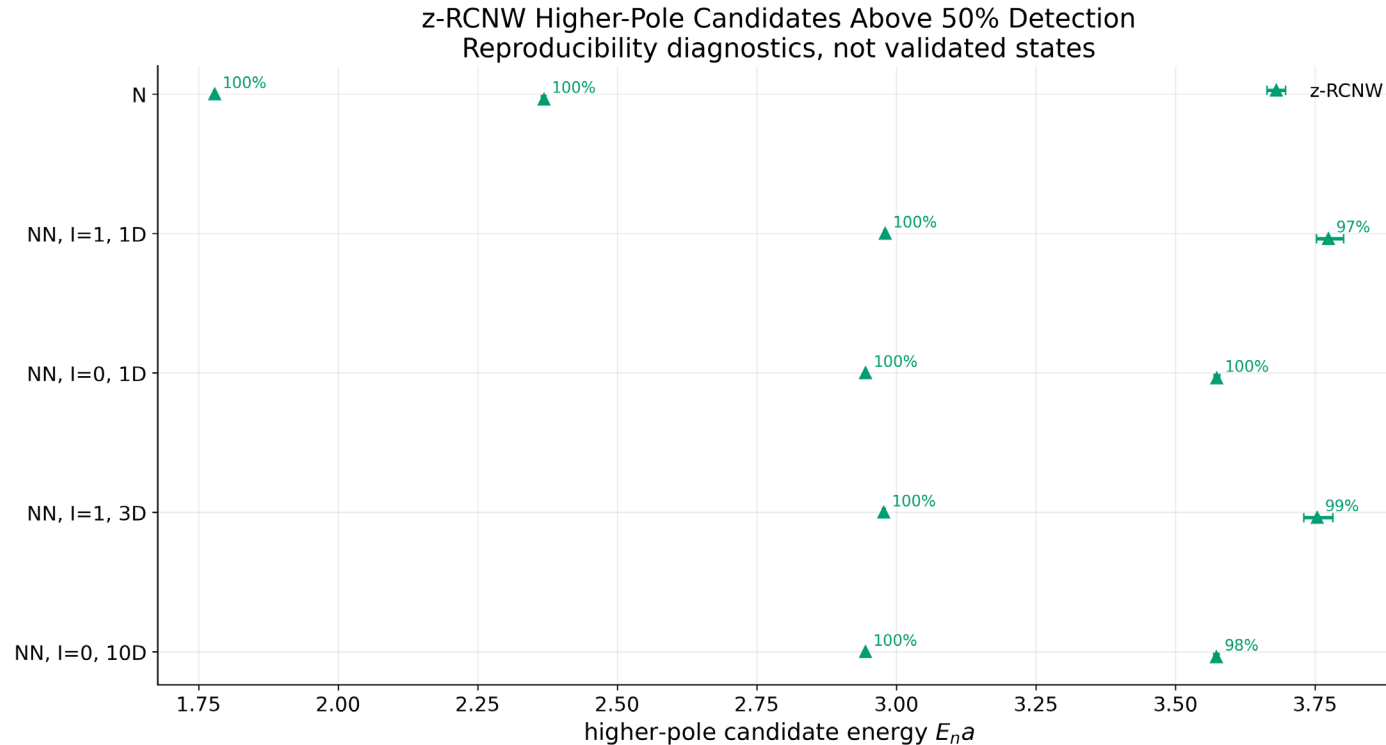
Noiseless:

model	THC	z-RCNW	HLT	ILDF
easy	7.633997e-13	3.473289e-14	1.337098e-01	3.514857e-06
medium	9.587402e-13	2.427791e-13	6.774389e-02	7.057580e-06
hard	9.147813e-08	7.182133e-04	3.821673e-02	7.076600e-05

Noisy:

model	THC	z-RCNW	HLT
easy	7.038183e-01	4.928502e-01	1.165325e+00
medium	5.451476e-01	4.976796e-01	1.245215e+00
hard	4.534850e-01	1.210823e-01	1.020680e+00

BACKUP: JACKKNIFE-STABLE HIGHER-POLE CANDIDATES



- Table I provides lowest-energy references only; no one-to-one higher-state reference exists for all five constructions.
- Candidates are retained when a compatible pole is detected in at least 50% of the 327 delete-one-block jackknife replicates; every candidate shown here is detected in 96.6%–100%.
- Horizontal intervals show the empirical 5th–95th percentile range; percentage labels give the detection fraction.
- Detection measures algorithmic reproducibility, not the probability that a candidate is a physical state.