

Sparse modeling approach to analytic continuation of imaginary-time data and quantum many-body calculations

Hiroshi SHINAOKA
Saitama University, JST

Acknowledgements

📌 Saitama University
N. Chikano

📌 University of Tokyo
K. Yoshimi
Arita's group

📌 Okayama University
J. Otsuki

📌 Tohoku University
M. Ozeki, T. Koretsune

📌 JAEA
Y. Nagai

📌 University of Michigan
Gull's group

📌 Rutgers University
K. Haule

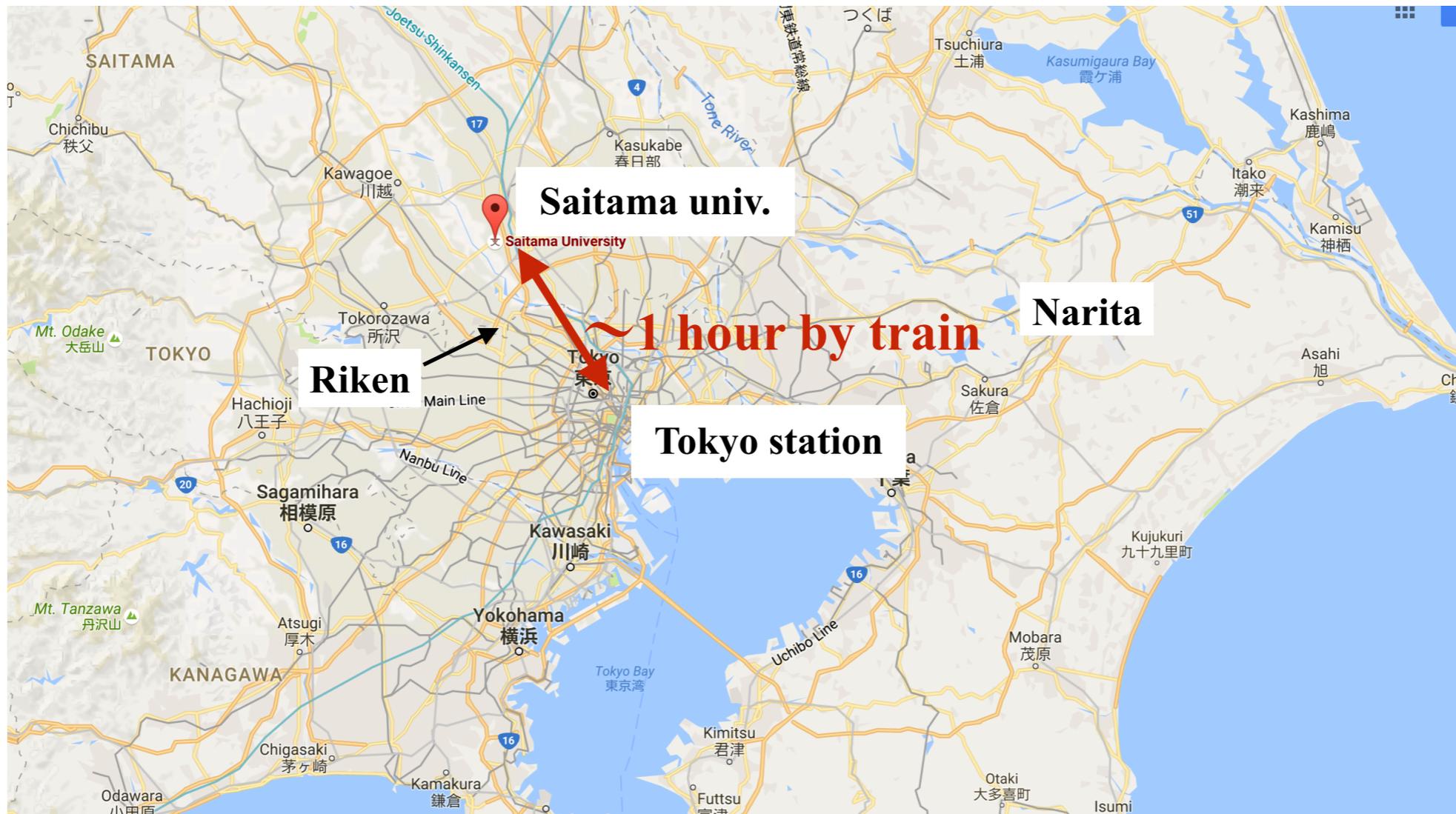
📌 TU Wien
Kuneš's group
Held's group

Self introduction

Developing first-principles method for correlated materials

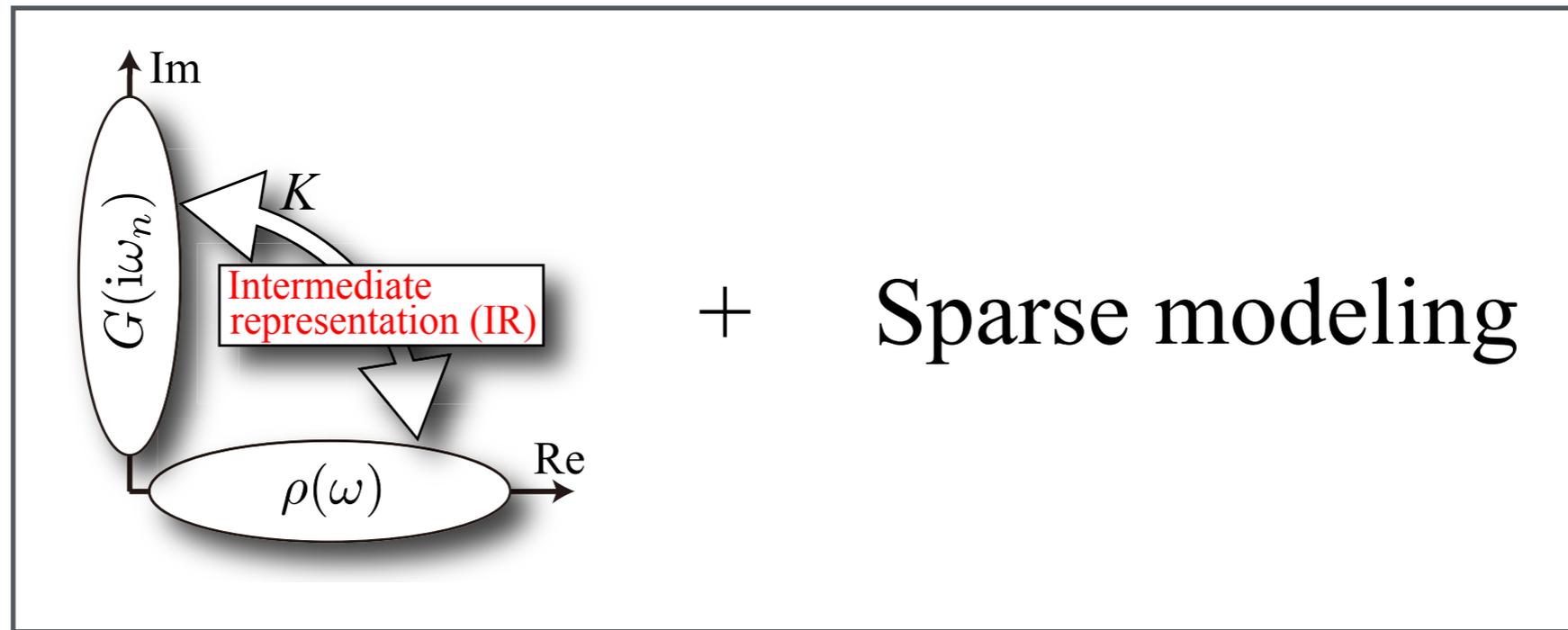
Continuous-time quantum Monte Carlo, dynamical mean-field theory

Post doc for three years in Switzerland (Prof. M. Troyer & Prof. P. Werner)

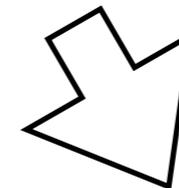
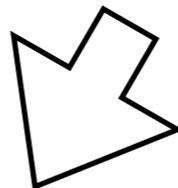


Prof. Kajita used to be an undergraduate student of our university long time ago.

Overview



+ Sparse modeling



Stable analytic continuation

Review: J. Otsuki, M. Ohzeki, **HS**, K. Yoshimi, JPSJ **89**, 012001 (2020)

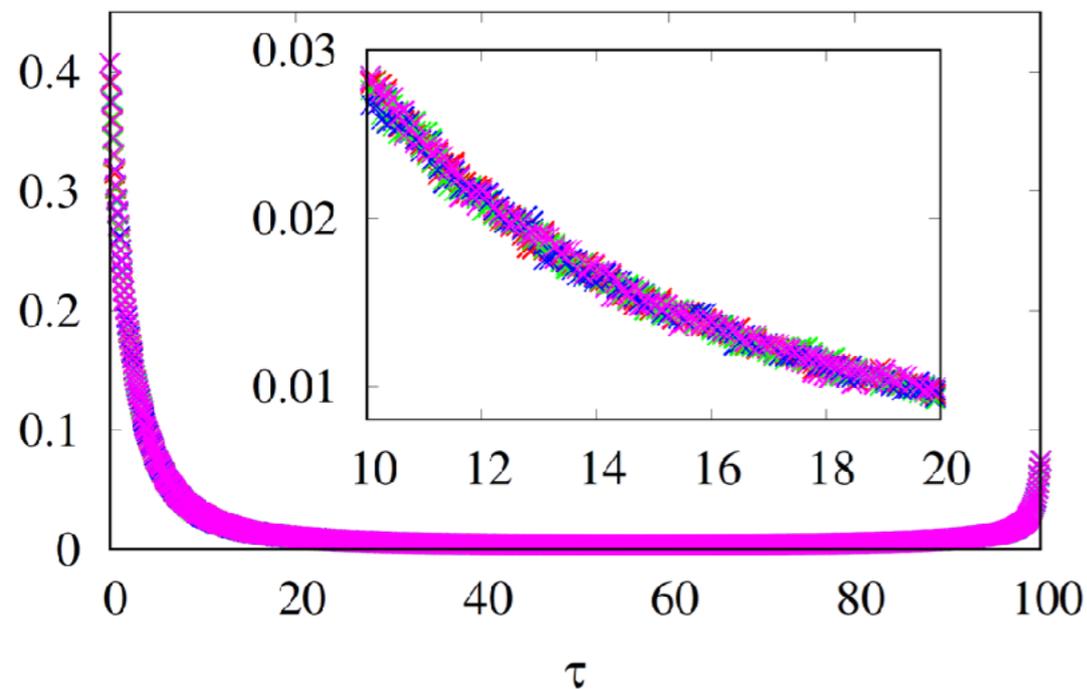
Efficient diagrammatic calculation

Review: **HS**, N. Chikano, E. Gull, J. Li, T. Nomoto, J. Otsuki, M. Wallerberger, T. Wang, K. Yoshimi, arXiv:2106.12685

Analytic continuation is sensitive to noise

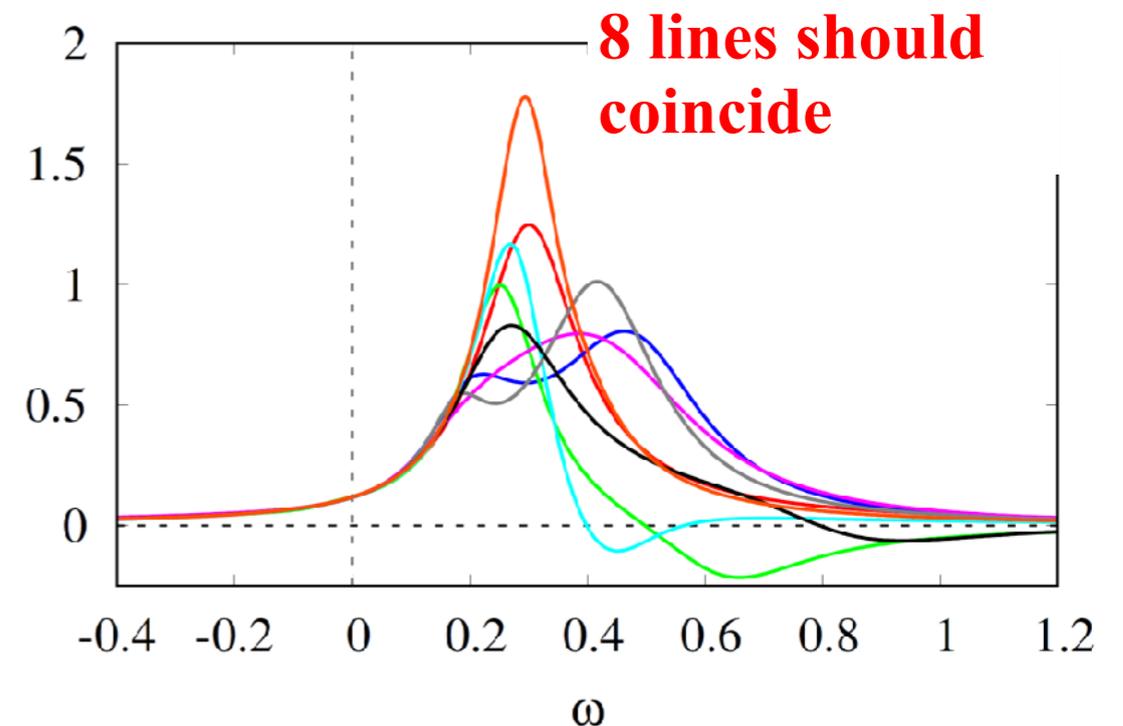


$G(\tau)$ **8-fold degenerate**
impurity Anderson model



Continuous-time QMC data

$\rho(\omega)$



Padé approximation

Vidberg, Serene, 1977

Many sophisticated methods: machine-learning method, stochastic methods, *etc.*

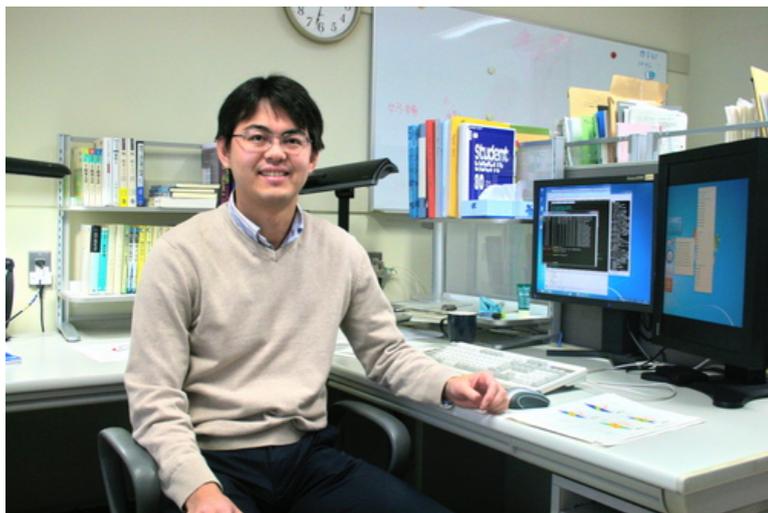
Question What information remains in imaginary-time data?
Can we extract the relevant information?

Sparse modeling of imaginary-time Green's functions

J. Otsuki, M. Ohzeki, H. Shinaoka, K. Yoshimi, PRE **95**, 061302(R) (2017)

Junya Otsuki

Tohoku univ. → Okayama univ.



Masayuki Ohzeki

Tohoku univ.



Kazuyoshi Yoshimi

Univ. Tokyo



Sparse modeling in data science

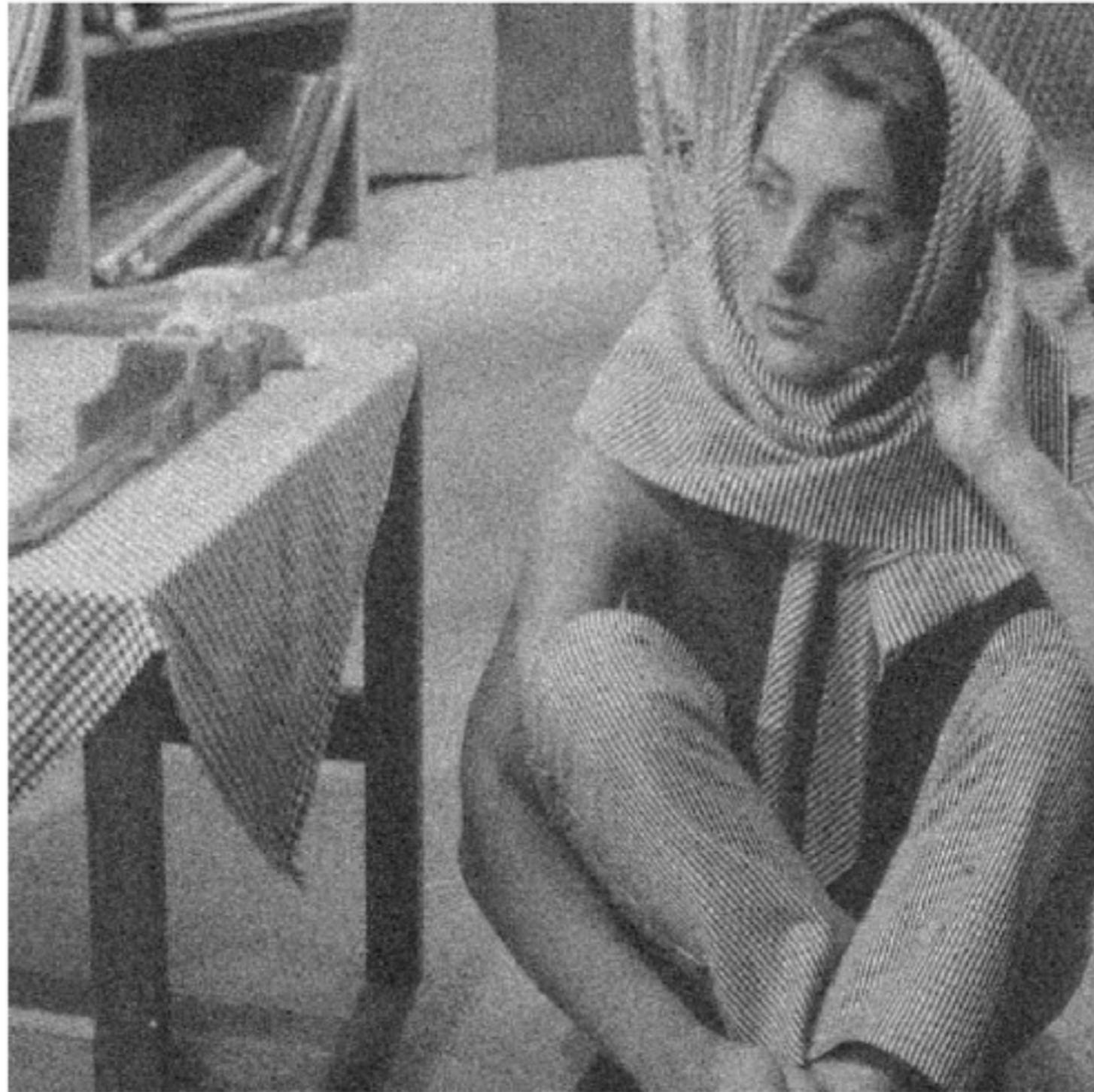


M. Elad and M. Aharon, IEEE Transactions on Image Processing **15**, 3736 (2006)

TACKLING THE REAL-TIME CHALLENGE IN STRONGLY CORRELATED SYSTEMS:
SPECTRAL PROPERTIES FROM EUCLIDEAN PATH INTEGRALS

Review1: JPSJ **89**, 012001 (2020)
Review2: arXiv:2106.12685

Sparse modeling in data science



Noise

M. Elad and M. Aharon, IEEE Transactions on Image Processing **15**, 3736 (2006)

[TACKLING THE REAL-TIME CHALLENGE IN STRONGLY CORRELATED SYSTEMS:
SPECTRAL PROPERTIES FROM EUCLIDEAN PATH INTEGRALS](#)

Review1: JPSJ **89**, 012001 (2020)
Review2: arXiv:2106.12685

Sparse modeling in data science



Denoised

M. Elad and M. Aharon, IEEE Transactions on Image Processing **15**, 3736 (2006)

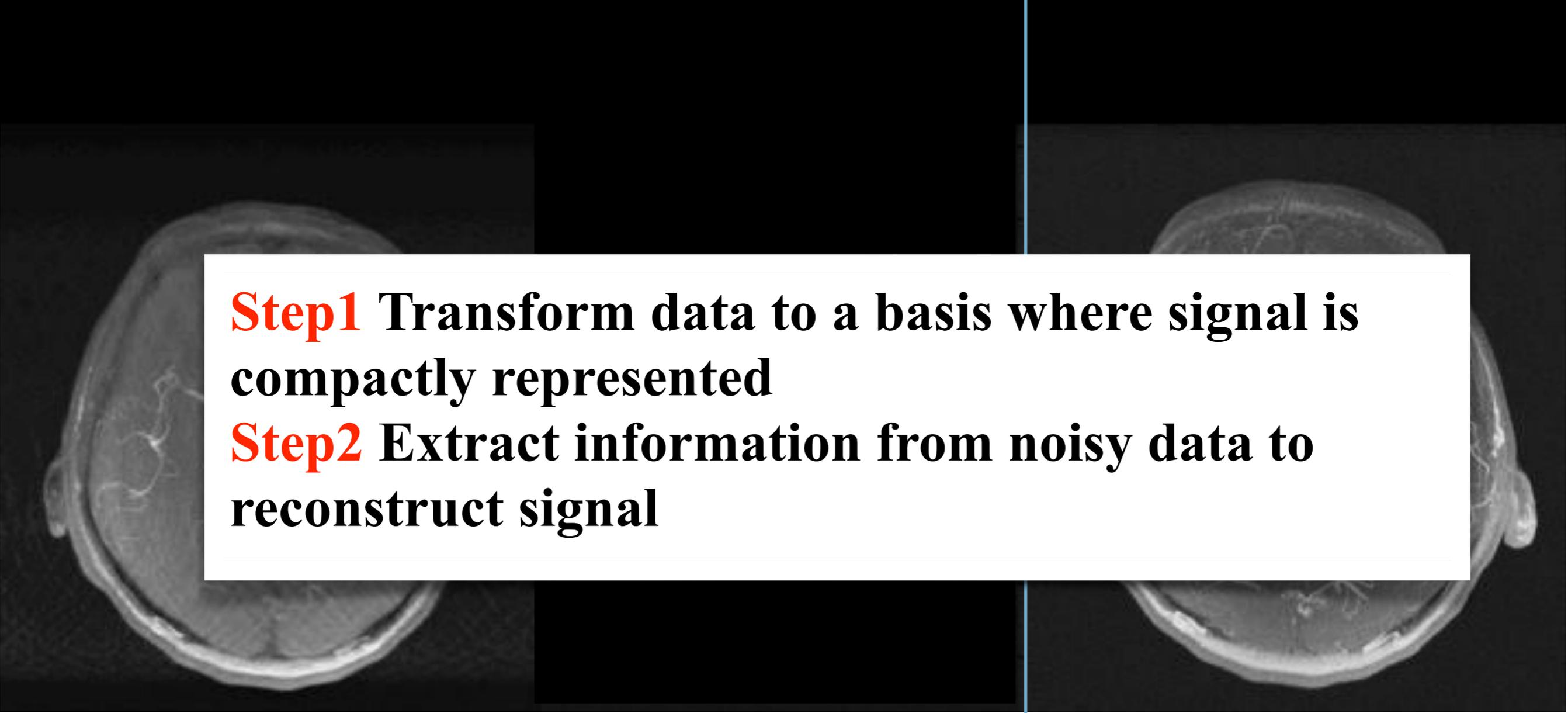
[TACKLING THE REAL-TIME CHALLENGE IN STRONGLY CORRELATED SYSTEMS:
SPECTRAL PROPERTIES FROM EUCLIDEAN PATH INTEGRALS](#)

Review1: JPSJ **89**, 012001 (2020)
Review2: arXiv:2106.12685

MRI

1/4 measurement time

Full measurement time



Step1 Transform data to a basis where signal is compactly represented

Step2 Extract information from noisy data to reconstruct signal



大関真之

<https://japan.zdnet.com/article/35074052/4/>

Step 1: basis transformation

Lehmann representation

$$G(\tau) = \int_{-\infty}^{\infty} d\omega K_{\pm}(\tau, \omega) \rho(\omega)$$

$$K_{\pm}(\tau, \omega) = \frac{e^{-\tau\omega}}{1 \pm e^{-\beta\omega}} \quad \text{Fermion (+), boson (-)}$$

$$G = K \rho$$

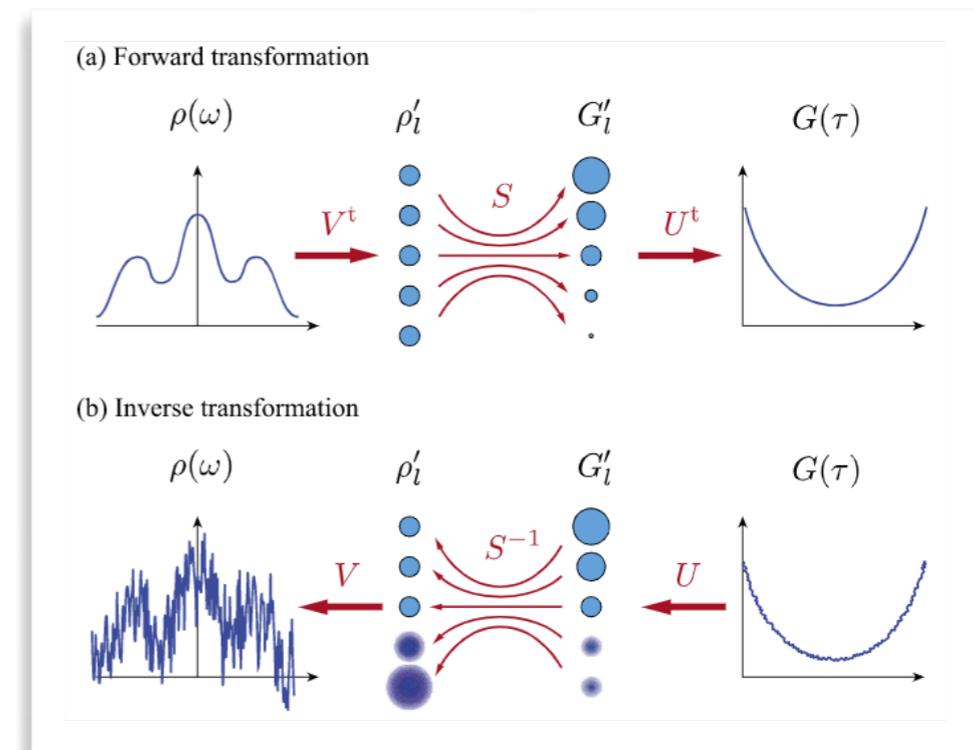
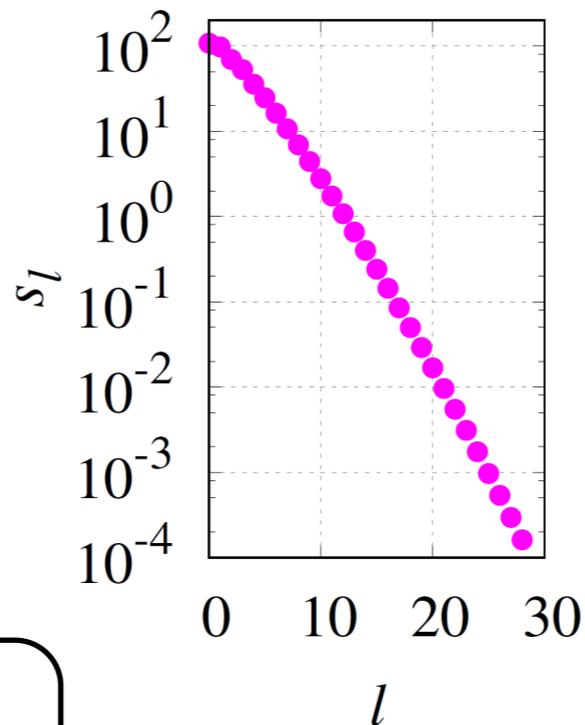
Discretization

Singular value decomposition (SVD)

$$K = U S V^t$$

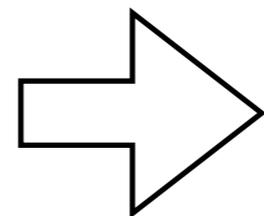
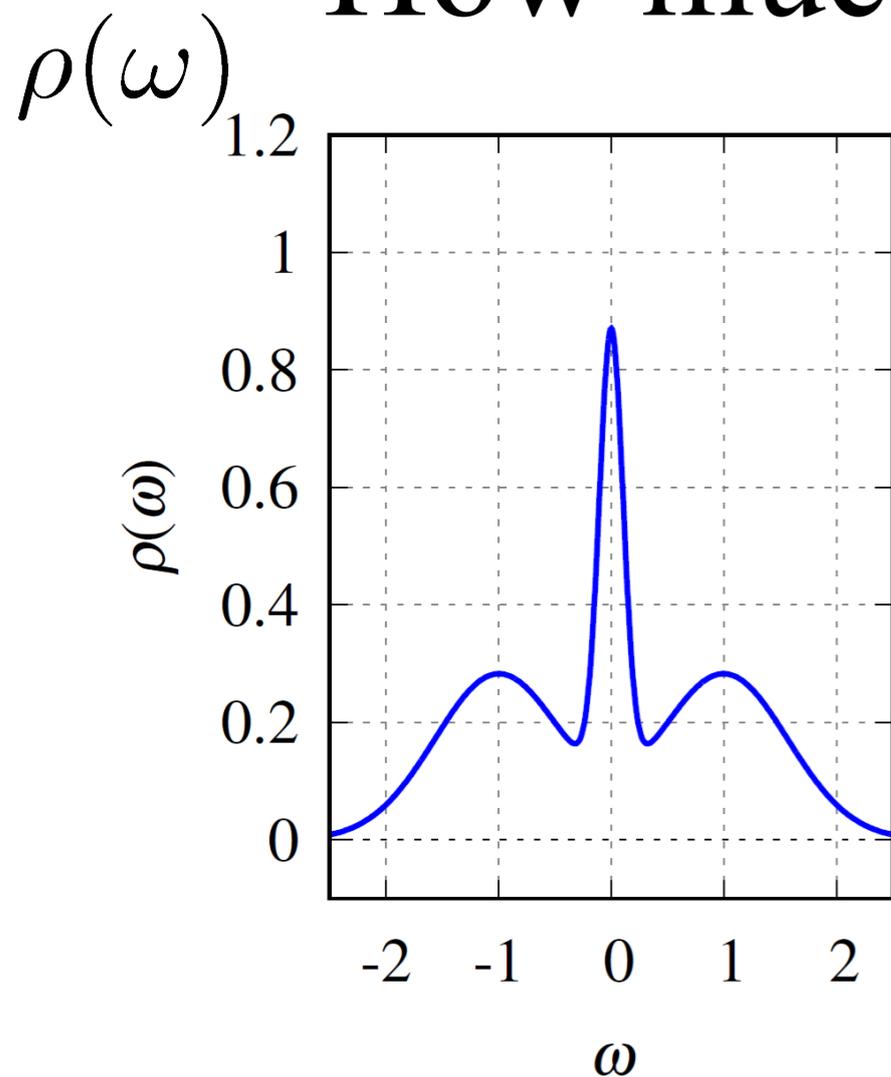
$$G' \equiv U^t G, \quad \rho' \equiv V^t \rho$$

$$G'_l = s_l \rho'_l$$

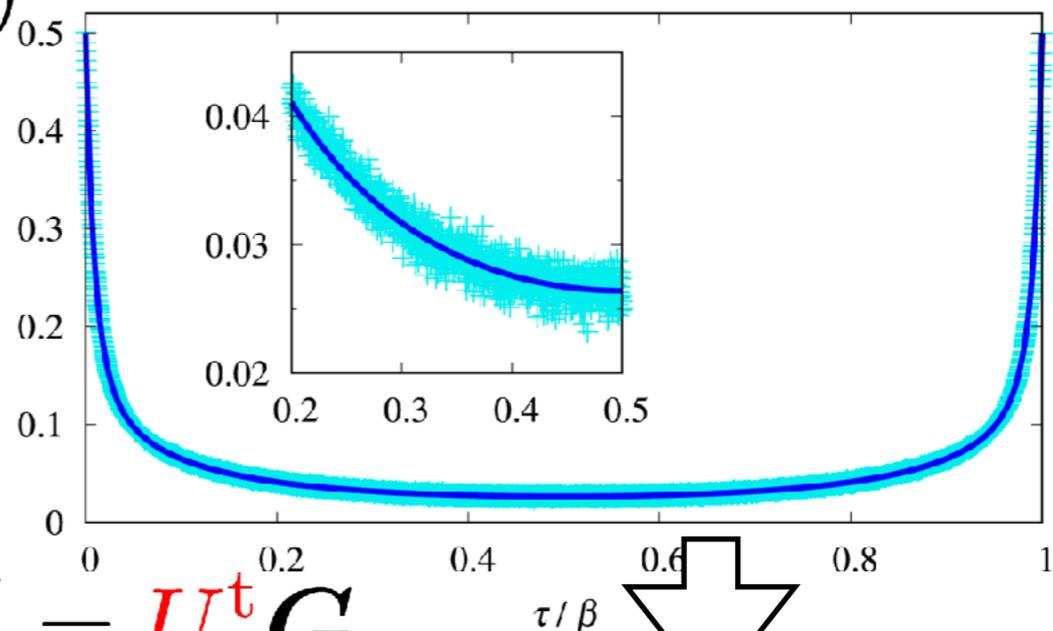


Information in G is carried by a few coefficients.

How much information is in $G(\tau)$?

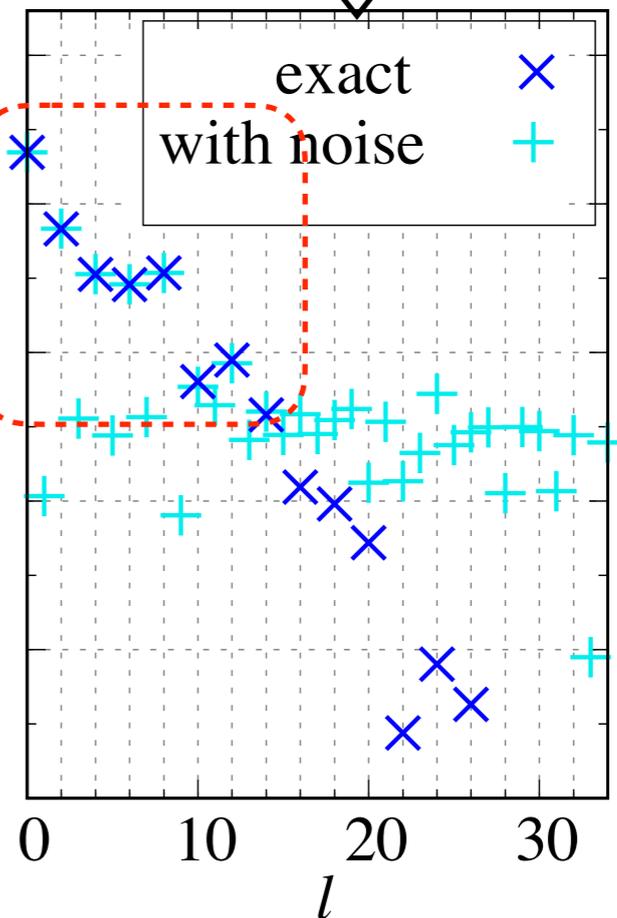
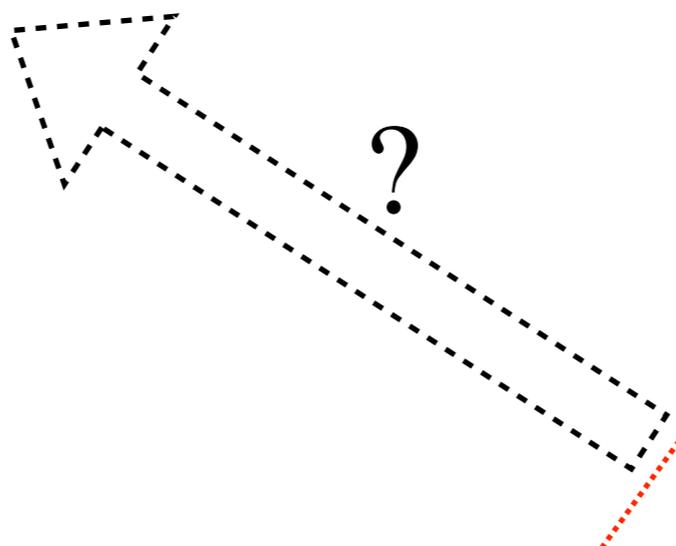
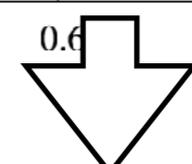


$G(\tau)$



$$G' = U^t G$$

τ/β



Only few components are intact.
Can we reconstruct the spectrum
from these data?

Step 2: extract signal

The least absolute shrinkage and selection operator (LASSO)

R. Tibshirani, Stat. Soc., Ser. B58, 267 (1996)

Minimize

$$\frac{1}{2} \left\| \underset{\substack{\uparrow \\ \text{Data fit}}}{\mathbf{G}' - S\boldsymbol{\rho}'} \right\|_2^2 + \lambda \|\boldsymbol{\rho}'\|_1$$

with

$$\begin{array}{l} \text{Positiveness} \\ \rho_i \geq 0, \end{array} \quad \begin{array}{l} \text{Sum rule} \\ \sum_i \rho_i = 1 \end{array}$$

Sparseness of solution

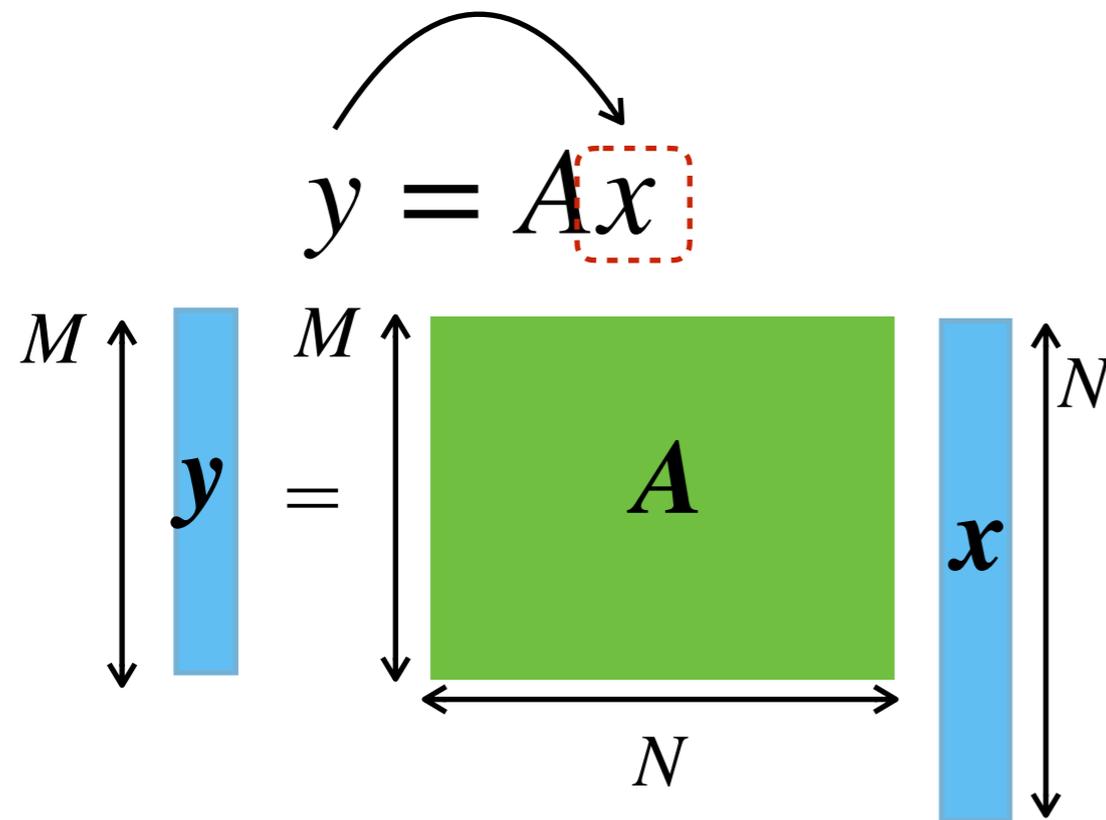
$$\|\boldsymbol{\rho}'\|_1 \equiv \sum_l |\rho'_l|$$

L1 regularization

- Convex optimization problem \rightarrow fast & stable
- No default model like Maximum entropy method
- λ can be optimized automatically.

Regularizing ill-conditioned inverse problem

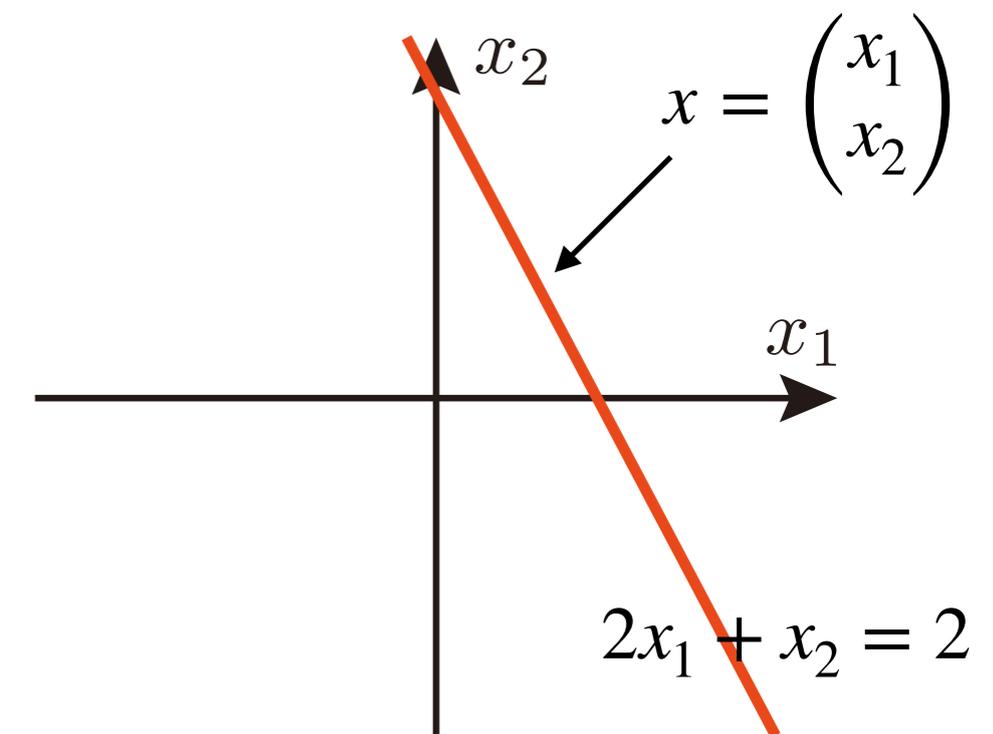
Ill-conditioned inverse problem for $M < N$



Example:

$$y = (2)$$

$$A = (2, 1)$$

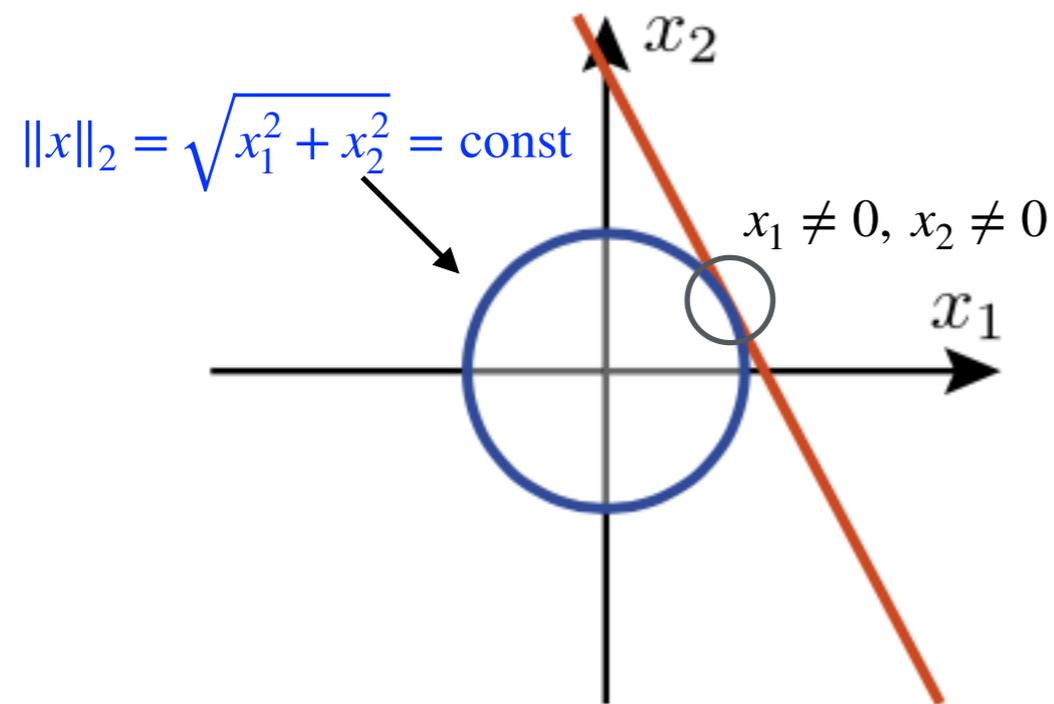


Select out a unique solution out of degenerate solutions \rightarrow Regularization

L1 vs L2 regularization

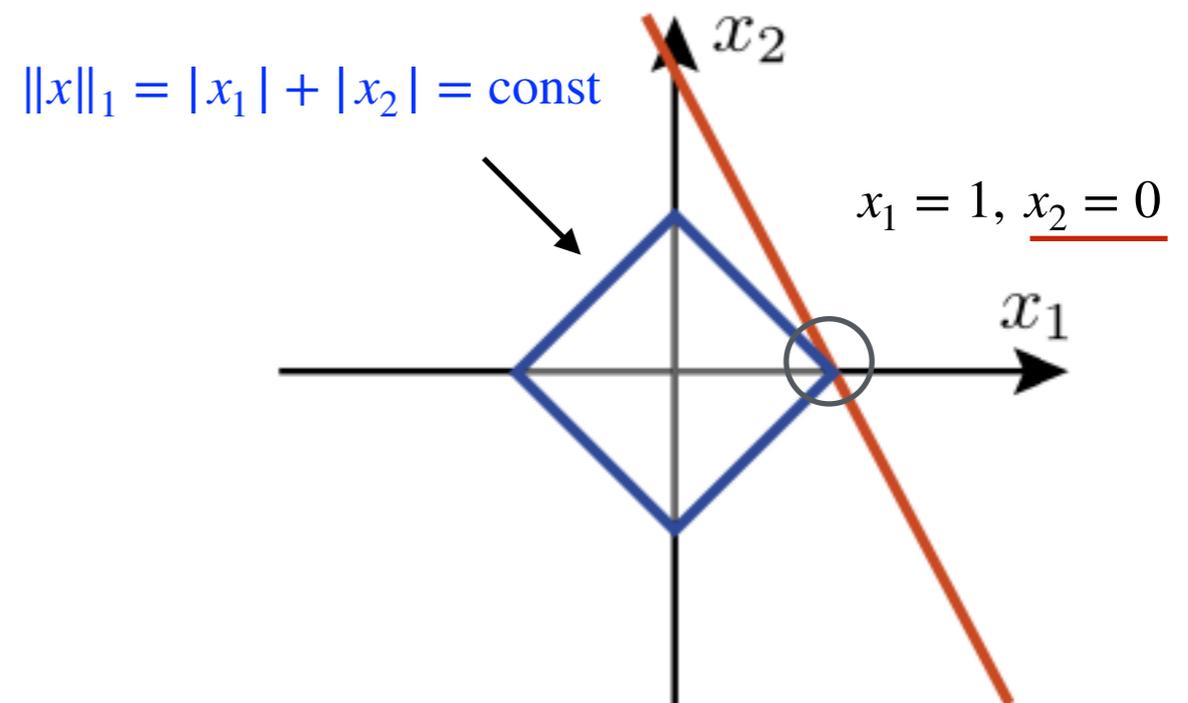
Let us adopt the solution minimizing L1/L2 norm of the solution...

L2 regularization



Known as Ridge/Tikhonov regularization

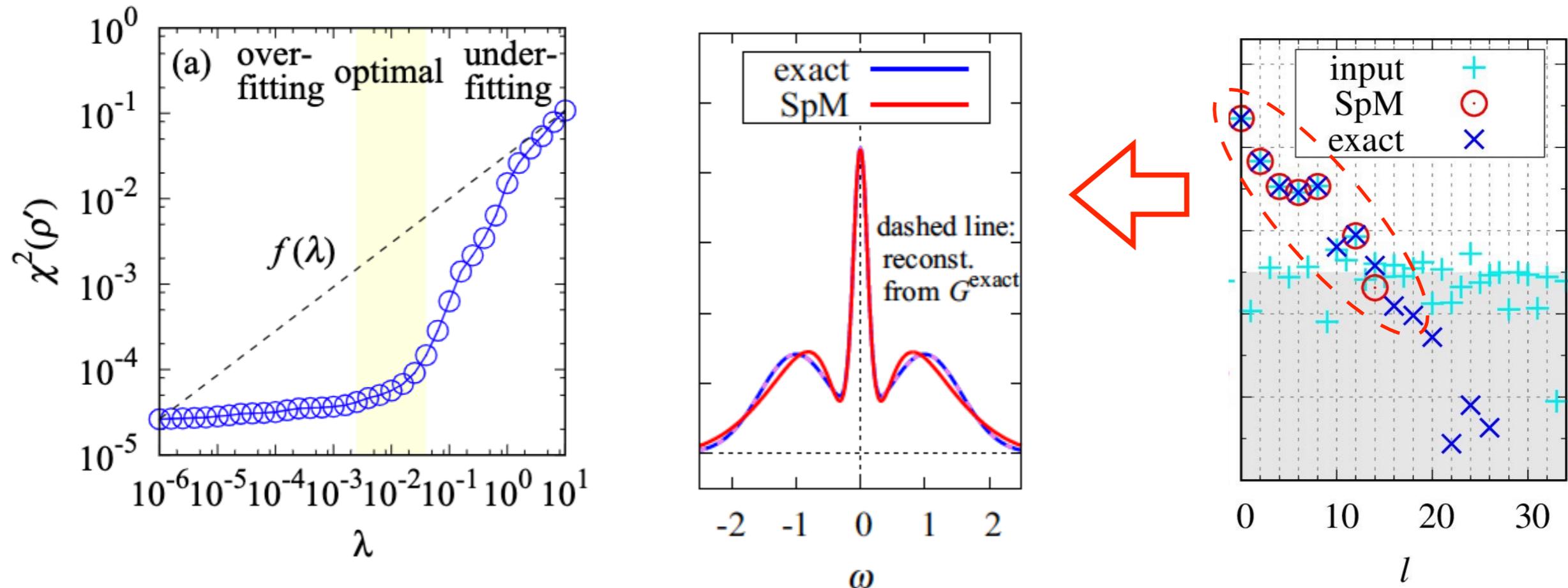
L1 regularization



In general, L1 regularization suppresses irrelevant parameters to exactly zero.

Step 2: extract signal

$$\text{Minimize } \frac{1}{2} \|G' - S\rho'\|_2^2 + \lambda \|\rho'\|_1$$



Relevant parameters are selected out automatically.

Possible extensions:

- Covariance
- Matrix-valued correlation functions

Open-source implementation

<https://github.com/SpM-lab/SpM>

SpM

Navigation

- [1. How to install](#)
- [2. Tutorials](#)
- [3. Algorithm](#)
- [4. Calculation flow](#)
- [5. Input files](#)
- [6. Output files](#)

Quick search

Welcome to SpM's documentation!

This is a documentation of Sparse Modeling (SpM) tool for analytical continuation.

What is SpM ?

A sparse-modeling tool for computing the spectral function from the imaginary-time Green function. It removes statistical errors in quantum Monte Carlo data, and performs a stable analytical continuation. The obtained spectral function fulfills the non-negativity and the sum rule. The computation is fast and free from tuning parameters.

License

This package is distributed under GNU General Public License version 3 (GPL v3).

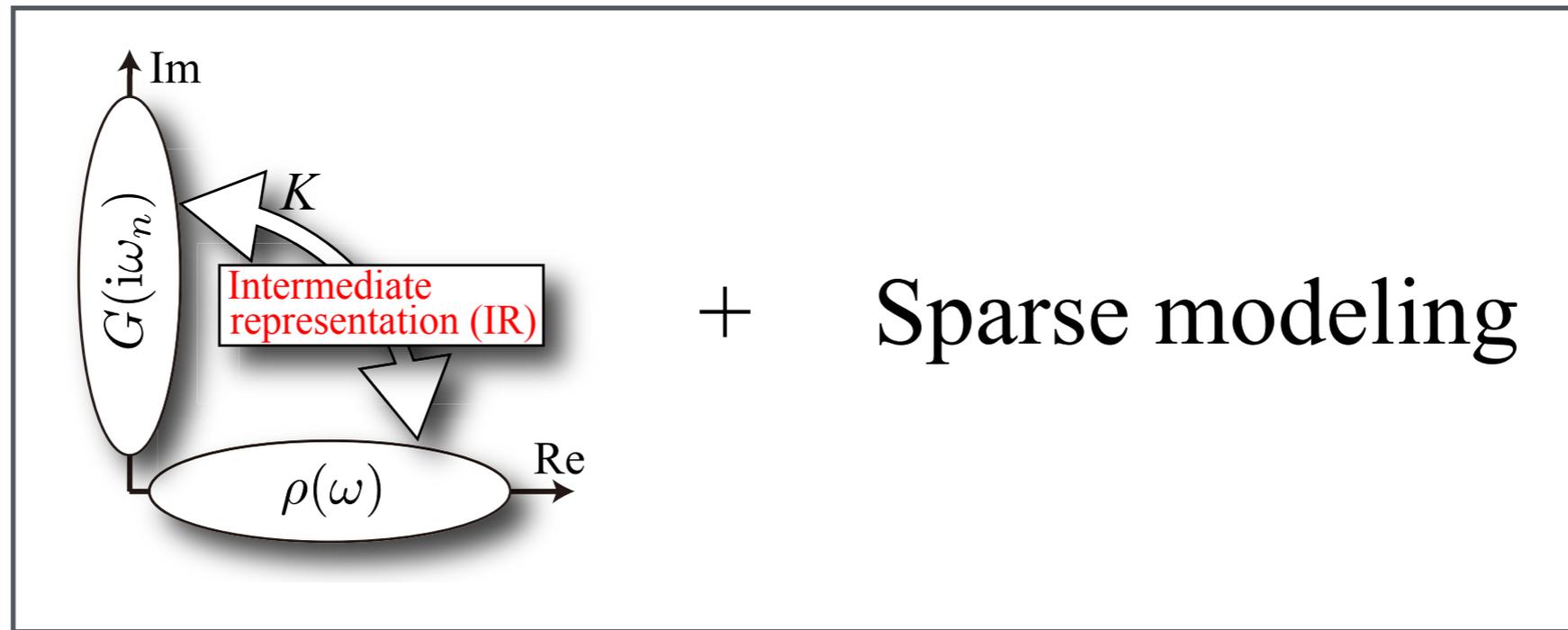
We kindly ask you to cite the article

J. Otsuki, M. Ohzeki, H. Shinaoka, K. Yoshimi, "Sparse modeling approach to analytical continuation of imaginary-time quantum Monte Carlo data" [Phys. Rev. E 95, 061302\(R\) \(2017\)](#).

in publications that includes results obtained using this package.

Version 2 will be released soon! (Improved stability for boson, improved determination of hyper parameter)

Overview



Stable analytic continuation

Review: J. Otsuki, M. Ohzeki, [HS](#), K. Yoshimi, JPSJ **89**, 012001 (2020)

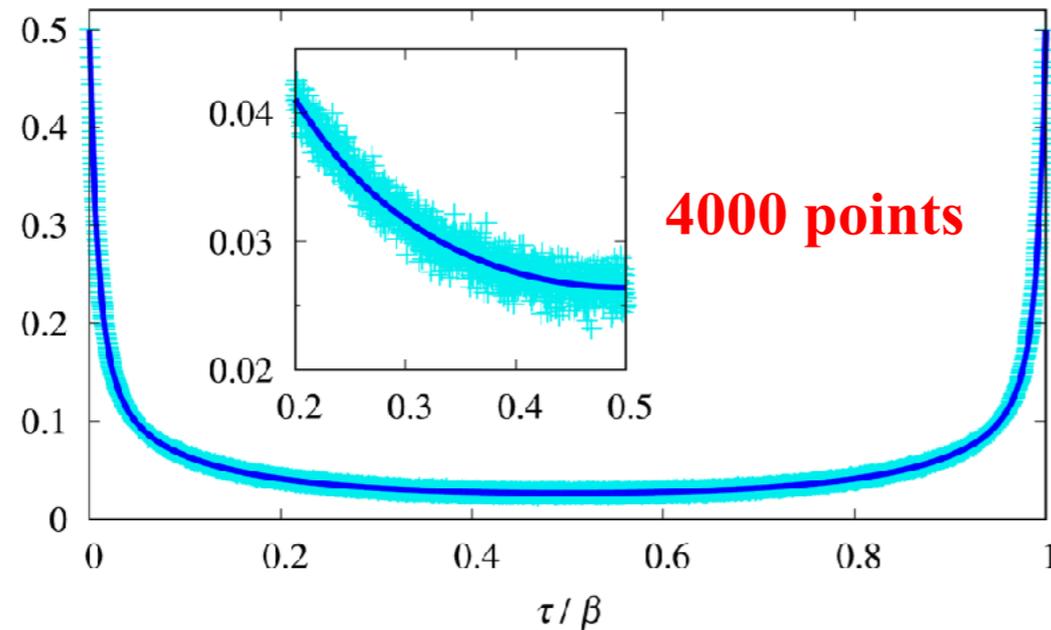
Efficient diagrammatic calculation

Review: [HS](#), N. Chikano, E. Gull, J. Li, T. Nomoto, J. Otsuki, M. Wallerberger, T. Wang, K. Yoshimi, arXiv:2106.12685

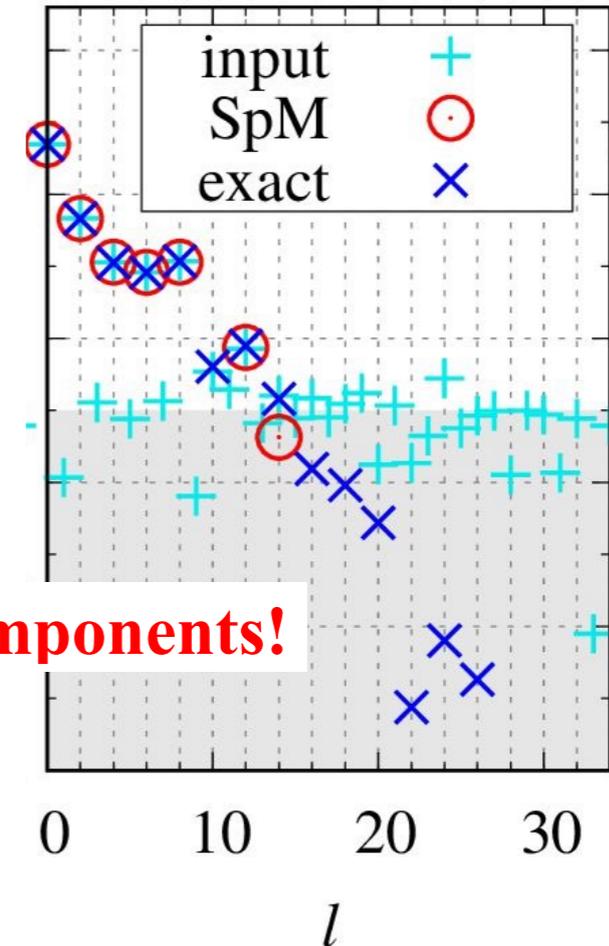
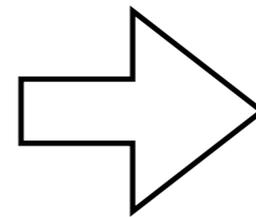
You saw that ...

$$G(\tau)$$

$$G' = U^t G$$



Transformation



- How the SVD basis functions look like?
- Can we use the compactness of the SVD basis in many-body calculations?

Intermediate representation (IR)

HS, J. Otsuki, M. Ohzeki, K. Yoshimi, PRB **96**, 035147 (2017)

HS, N. Chikano, E. Gull, J. Li, T. Nomoto, J. Otsuki, M. Wallerberger, T. Wang, K. Yoshimi, arXiv:2106.12685v1

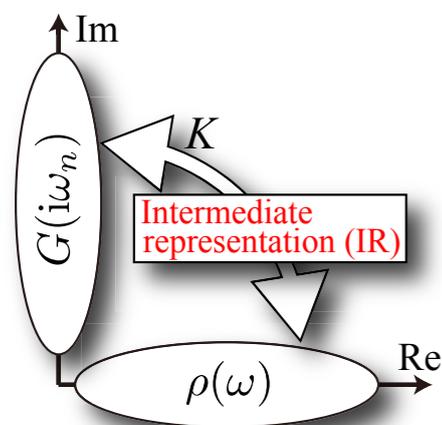
$$G(\tau) = \int_{-\omega_{\max}}^{\omega_{\max}} d\omega K^\alpha(\tau, \omega) \rho(\omega)$$

$\alpha = \text{F (fermion), B (boson)}$

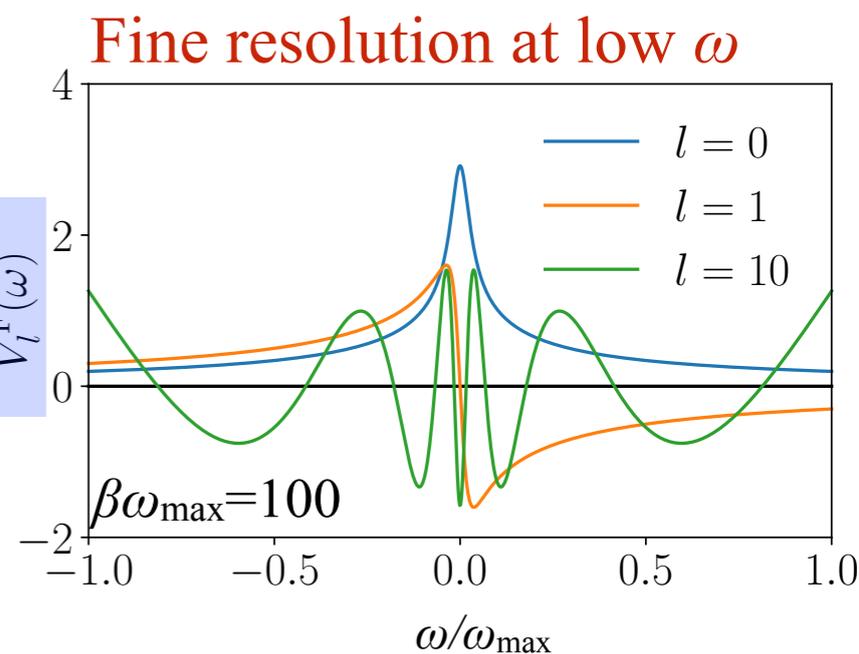
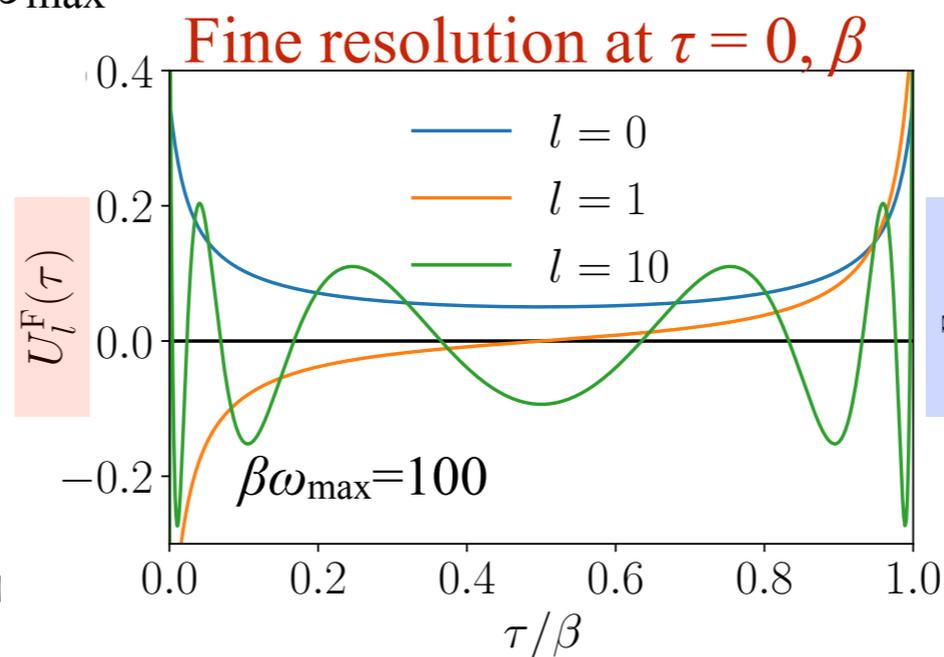
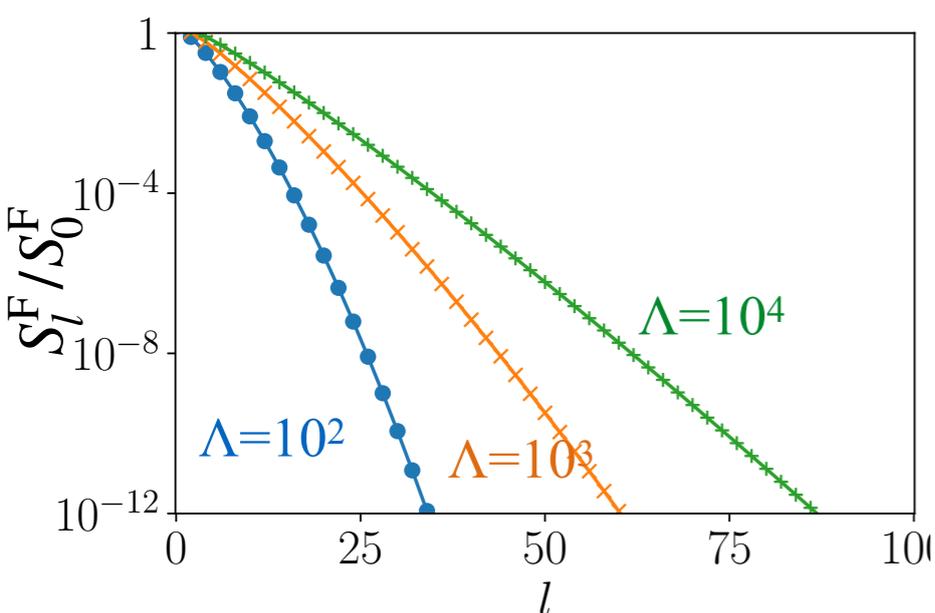
Singular value expansion

$$K^\alpha(\tau, \omega) = \sum_{l=0}^{\infty} S_l^\alpha U_l^\alpha(\tau) V_l^\alpha(\omega)$$

Singular values IR basis functions

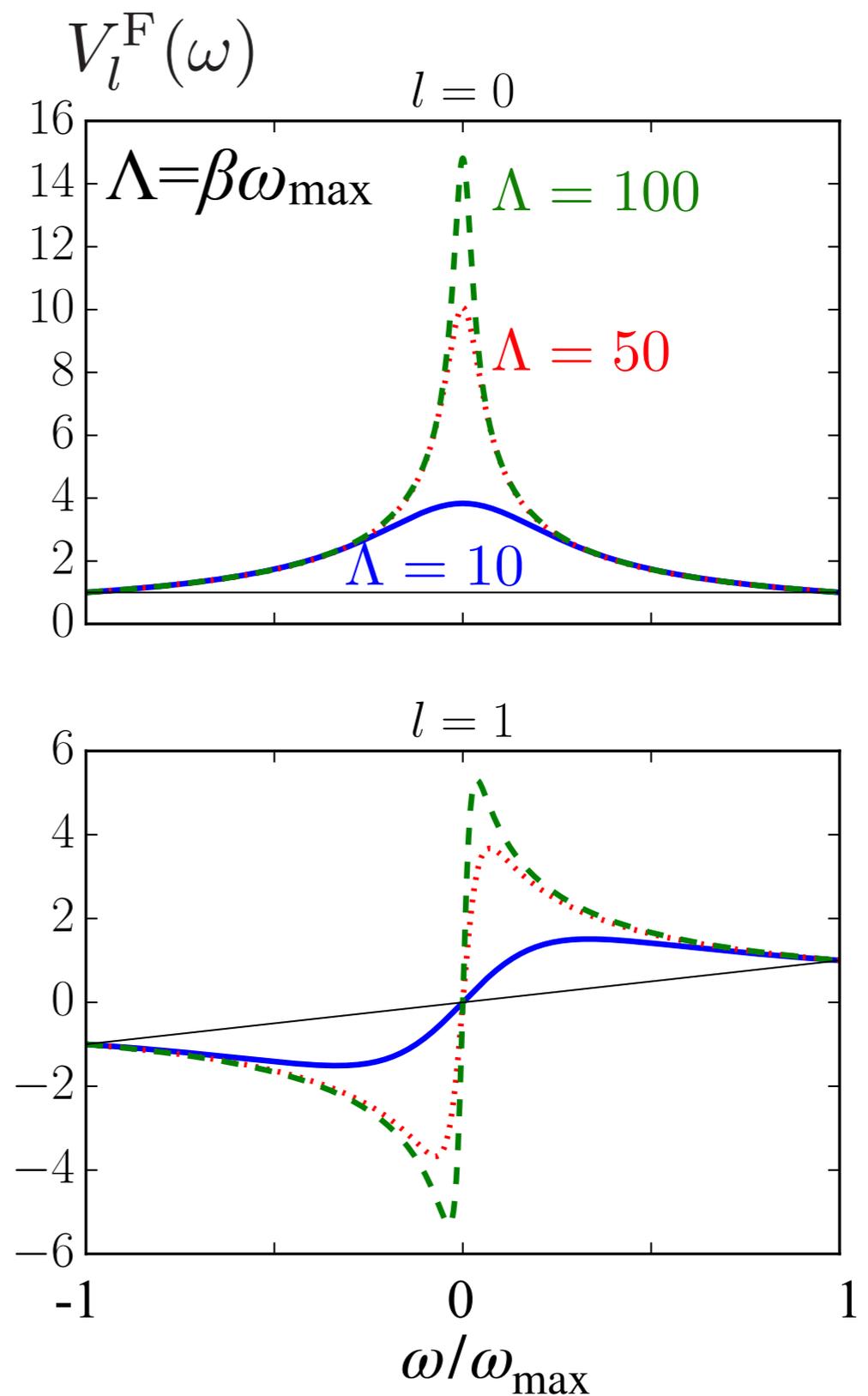
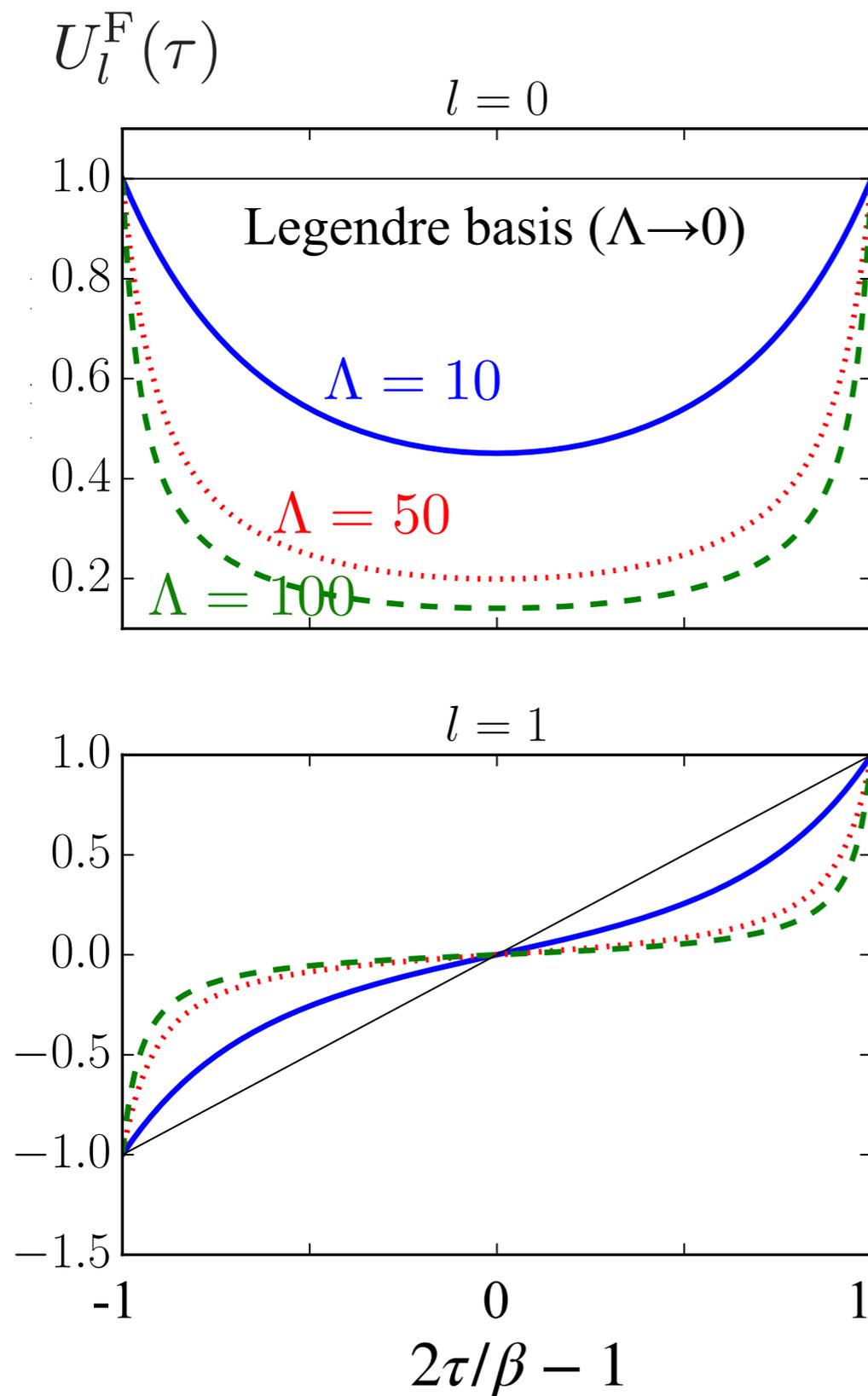


$$\Lambda \equiv \beta \omega_{\max}$$



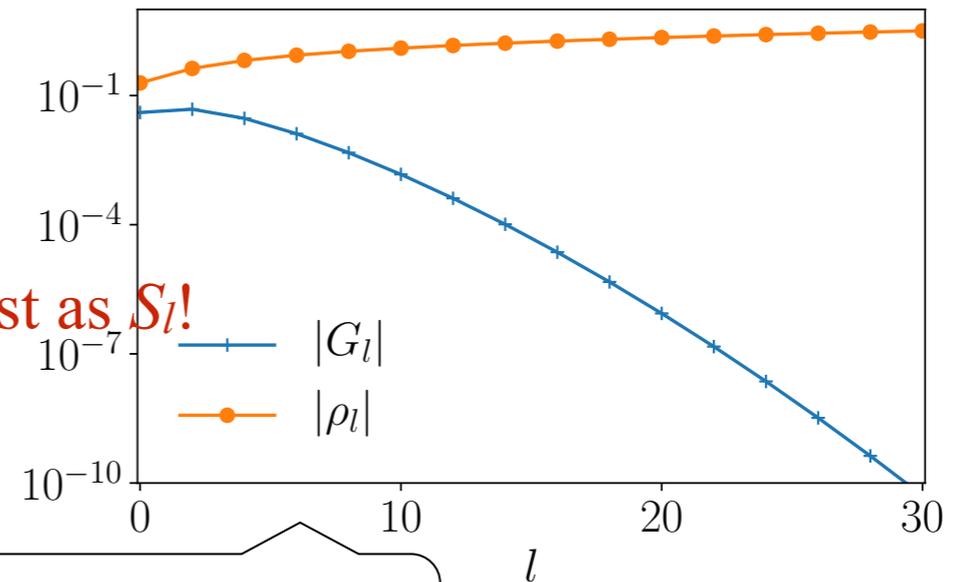
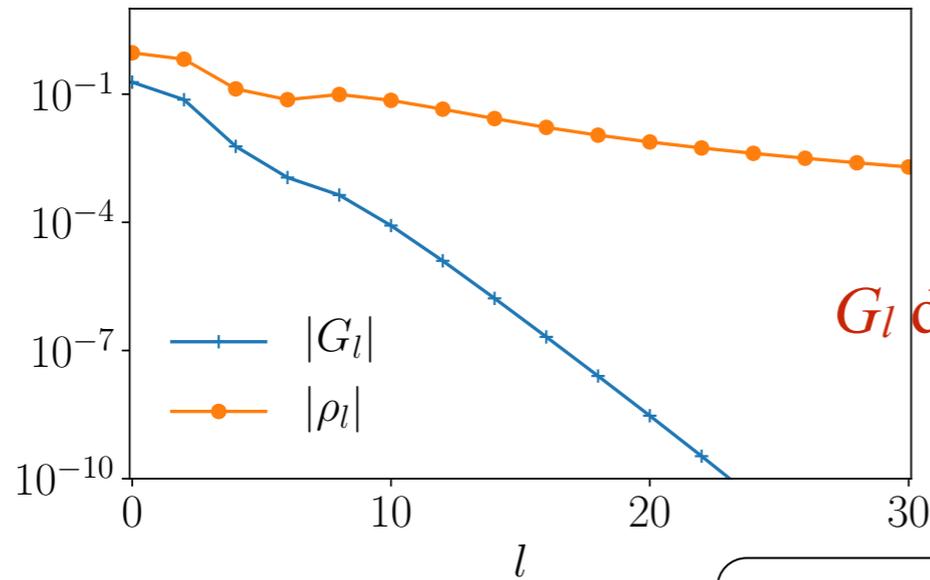
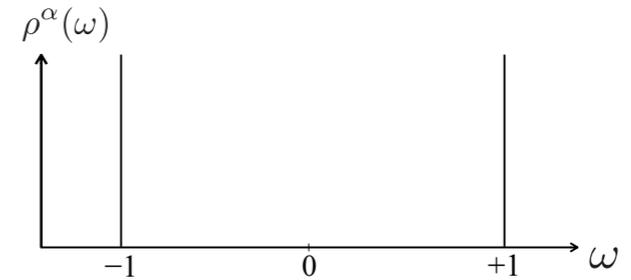
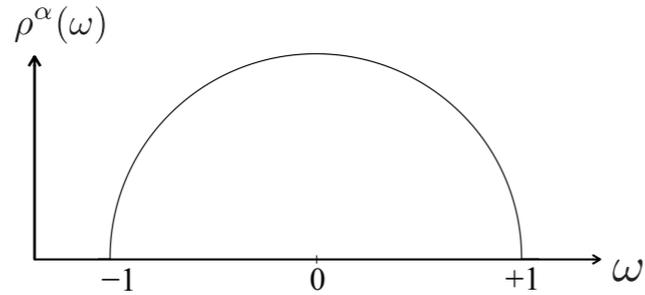
IR basis functions

$$\Lambda \equiv \beta\omega_{\max}$$

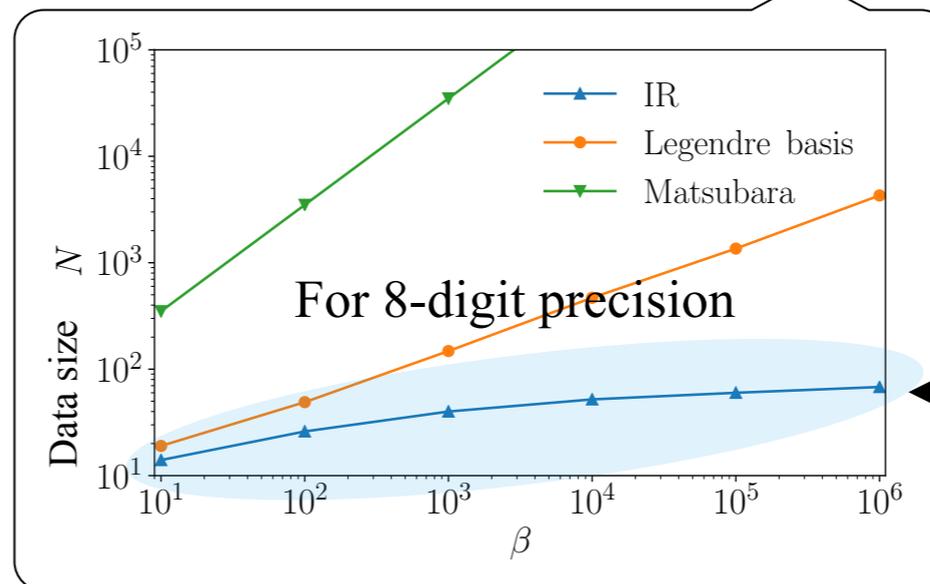


Compactness of IR

$$\omega_{\max} = 1, \beta = 100 \text{ (fermion)}$$



G_l decay as fast as S_l!



Most compact!

Open source software: irbasis

<https://github.com/SpM-lab/irbasis>

N. Chikano, K. Yoshimi, J. Otsuki, H. Shinaoka (2018) + M. Wallerberger (2019)

- Python and C++
- Step-by-step tutorial



Integral form

$$S_l^\alpha U_l^\alpha(\tau) = \int_{-\omega_{\max}}^{\omega_{\max}} d\omega K^\alpha(\tau, \omega) V_l^\alpha(\omega)$$

$$\Downarrow x \equiv 2\tau/\beta - 1, y \equiv \omega/\omega_{\max}$$

$$\underline{s_l^\alpha u_l^\alpha(x)} = \int_{-1}^1 dy \underline{k^\alpha(x, y) v_l^\alpha(y)} \quad x, y \in [-1, 1]$$

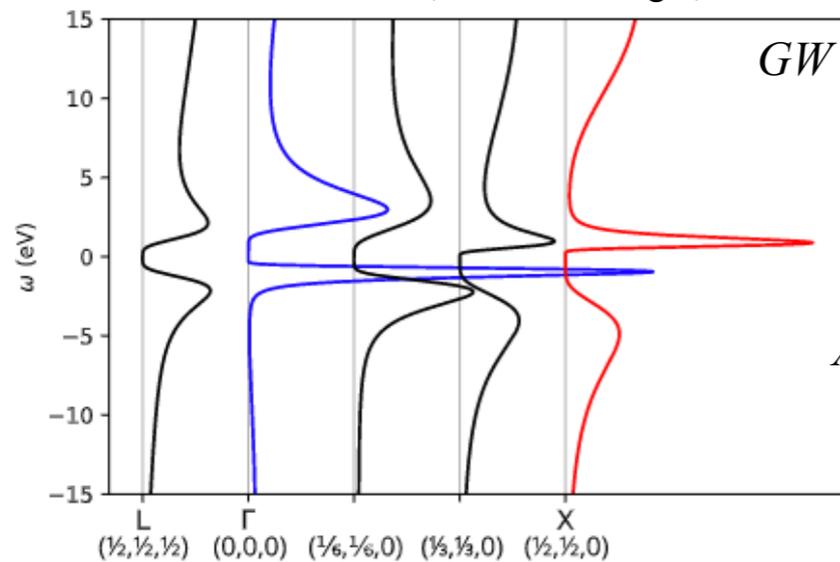
Precomputed data for $\Lambda=10, 10^2, \dots, 10^7$

Applications

Review: **HS** *et al.*, arXiv:2106.12685

Diagrammatic calculations for materials

J. Li, M. Wallerberger, C.-N. Yeh, N. Chikano, E. Gull, **HS**, PRB **101**, 035144 (2020)



GW calculations of silicon crystals

Ab initio calculations of superconducting materials

T. Wang, T. Nomoto, Y. Nomura, **HS**, J. Otsuki, T. Koretsune, and R. Arita, PRB **102**, 134503 (2020)

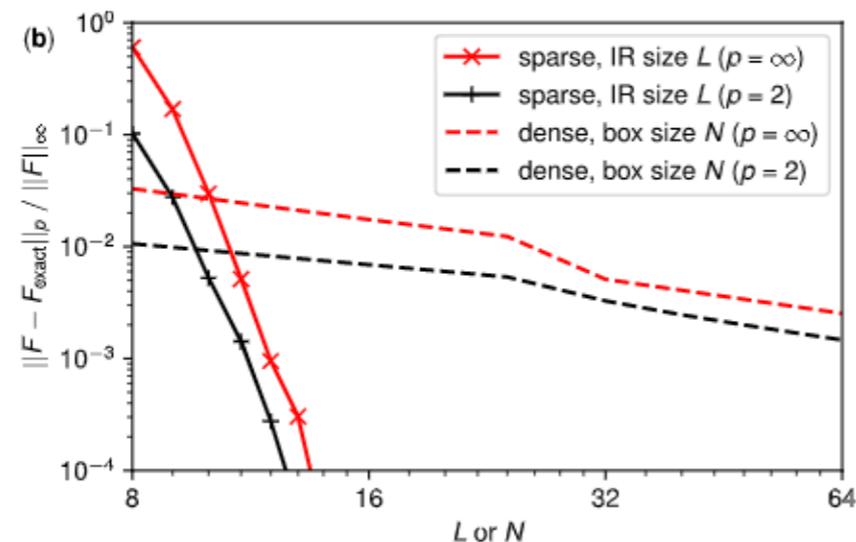
Denoiser

Y. Nagai and **HS**, JPSJ **88**, 064004 (2019)

Extension to two-particle quantities

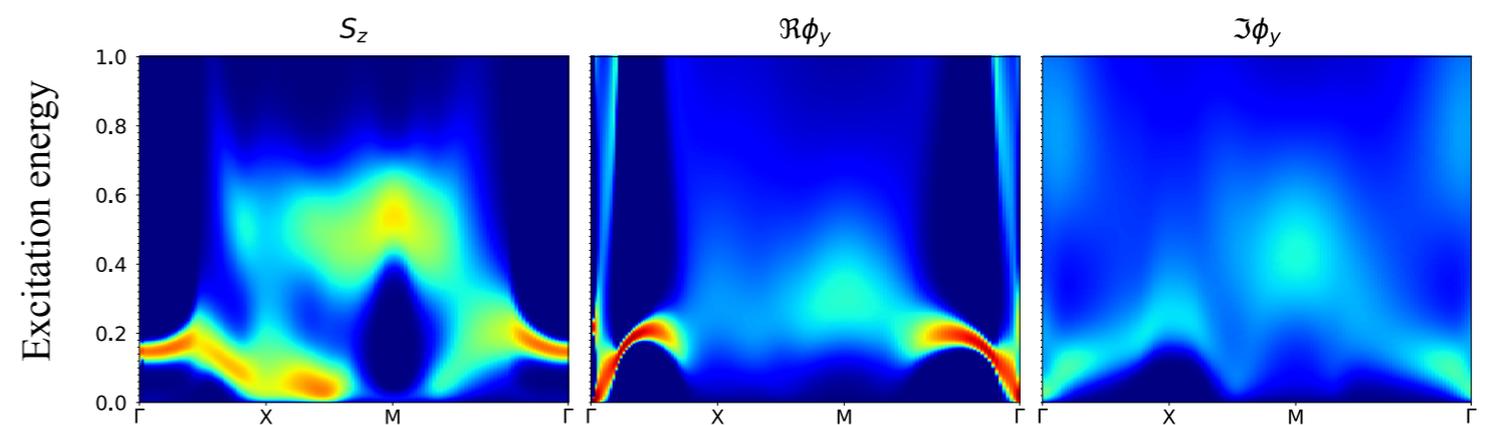
Bethe-Salpeter equation with exponential convergence

M. Wallerberger*, **HS***, A. Kauch, PRR **3**, 033168 (2021)

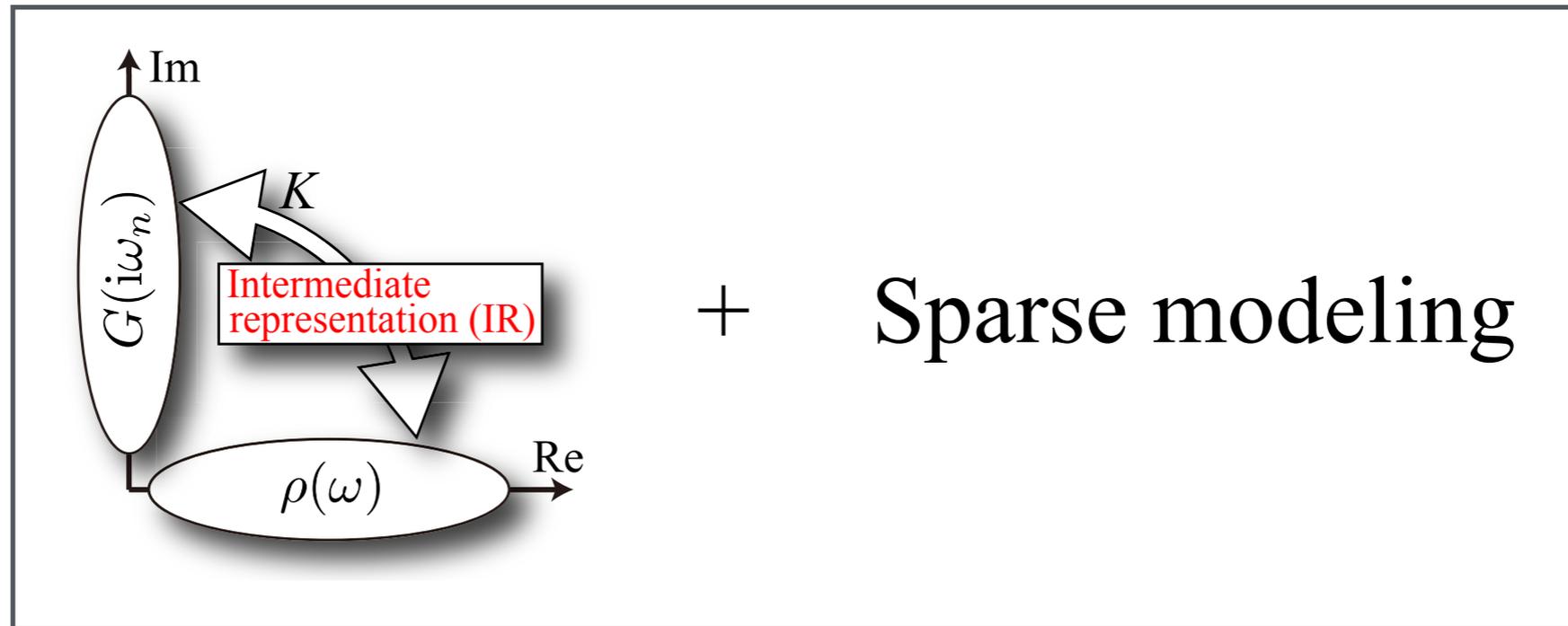


Dynamical spin-orbital susceptibility

HS *et al.*, SciPost **8**, 12 (2020)



Summary



Stable analytic continuation

Review: J. Otsuki, M. Ohzeki, **HS**, K. Yoshimi, JPSJ **89**, 012001 (2020)

Efficient diagrammatic calculation

Review: **HS**, N. Chikano, E. Gull, J. Li, T. Nomoto, J. Otsuki, M. Wallerberger, T. Wang, K. Yoshimi, arXiv:2106.12685

IR basis and sparse modeling may be combined with other techniques such as ML!
I am open to interdisciplinary research! h.shinaoka@gmail.com