Interpretable and unsupervised phase classification



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General framework

SETUP: The parameter space of a physical system is sampled at a set of points $\{p_i\}$

• at each point p_i , samples $\{S_i\}$ that represent the system's state are generated

TASK: Automated construction of the phase diagram in an

- unsupervised way \Leftrightarrow without prior knowledge of phases
- interpretable way \Leftrightarrow without black-box models

IDEA: CALCULATE INDICATOR I(p) THAT HIGHLIGHTS PHASE BOUNDARIES

 $p_1 extsf{and} \{S_1\}$



Mean-based method

$$I(\boldsymbol{p}) = \sum_{i} \left\| \frac{\partial \bar{\boldsymbol{x}}}{\partial p_{i}} \right\| \approx \sum_{i} \frac{\left\| \bar{\boldsymbol{x}}(\boldsymbol{p} + \boldsymbol{e}_{i} \Delta p_{i}) - \bar{\boldsymbol{x}}(\boldsymbol{p} - \boldsymbol{e}_{i} \Delta p_{i}) \right\|}{2\Delta p_{i}},$$

where $\bar{x}(p)$ is the mean input at p

• representation $\mathcal{R}: S \to x$, HERE: correlation functions measuring square, axial, and diagonal correlations

Prediction-based method

$$I(\boldsymbol{p}) = \nabla_{\boldsymbol{p}} \cdot \boldsymbol{\delta} \boldsymbol{p} \approx \sum_{i} \frac{\delta p_{i}(\boldsymbol{p} + \boldsymbol{e}_{i} \Delta p_{i}) - \delta p_{i}(\boldsymbol{p} - \boldsymbol{e}_{i} \Delta p_{i})}{2\Delta p_{i}},$$

where $\delta p = \hat{p} - p$ is the deviation of prediction \hat{p} from underlying system parameter *p*

• predictive model $m : \boldsymbol{x} \to \hat{\boldsymbol{p}}$ trained on a mean-square-error loss function, HERE: deep neural network

Ground-state phase diagram of the Falicov-Kimball model

The Falicov-Kimball model describes mobile *d*- and localized *f*-particles on a lattice: $\hat{H} = -t \sum_{\langle ij \rangle} (\hat{d}_i^{\dagger} \hat{d}_j + \hat{d}_j^{\dagger} \hat{d}_i) + U \sum_i \hat{d}_i^{\dagger} \hat{d}_i \hat{f}_i^{\dagger} \hat{f}_i$







- simple analytical expression for indicator \Rightarrow directly interpretable
- relies on a highly expressive predictive model \Rightarrow *not* directly interpretable
- allows for direct physical insight into the revealed phases and phase transitions
- rendered interpretable via derivation of analytical expression for optimal indicator $I_{\text{opt}}(\boldsymbol{p})$ based on predictive model m_{opt} that minimizes loss function
- indicator measures magnitude of change in mean ordering across phase boundary
- indicator measures mean extent of neighbouring phases in parameter space

 \Rightarrow TWO DISTINCT APPROACHES THAT PROVIDE COMPLEMENTARY INSIGHTS INTO THE PHASE DIAGRAM

References	Contacts	Acknowledgments
[F. Schäfer and N. Lörch, Phy. Rev. E 99 , 062107 (2019)] [E. Greplova <i>et al.</i> , New J. Phys. 22 , 045003 (2020)] [J. Arnold <i>et al.</i> , Phys. Rev. Res. 3 , 033052 (2021)]	julian.arnold@unibas.ch frank.schaefer@unibas.ch	EXERCISENT SCIENCE FOUNDATION WISS NATIONAL SCIENCE FOUNDATION <i>Contemption</i> <i>Contemption</i> <i>Contemption</i> <i>Contemption</i> <i>Contemption</i> <i>Contemption</i>