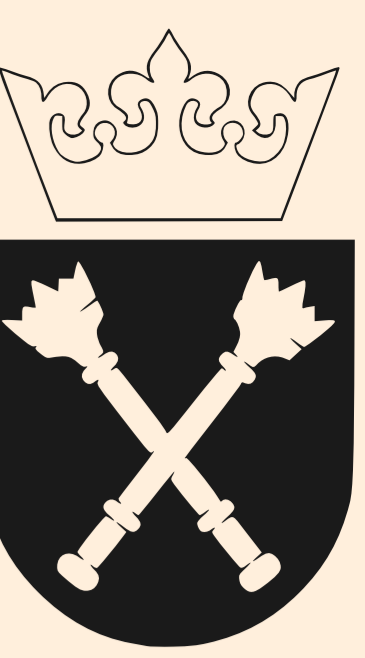


Machine classification for probe-based quantum thermometry



Fabício S. Luiz¹, A. de Oliveira Junior², Felipe F. Fanchini¹, Gabriel Landi³

Faculdade de Ciências, UNESP - Universidade Estadual Paulista, 17033-360 Bauru, São Paulo, Brazil¹

Faculty of Physics, Astronomy and Applied Computer Science, Jagiellonian University, 30-348 Krakow, Poland²

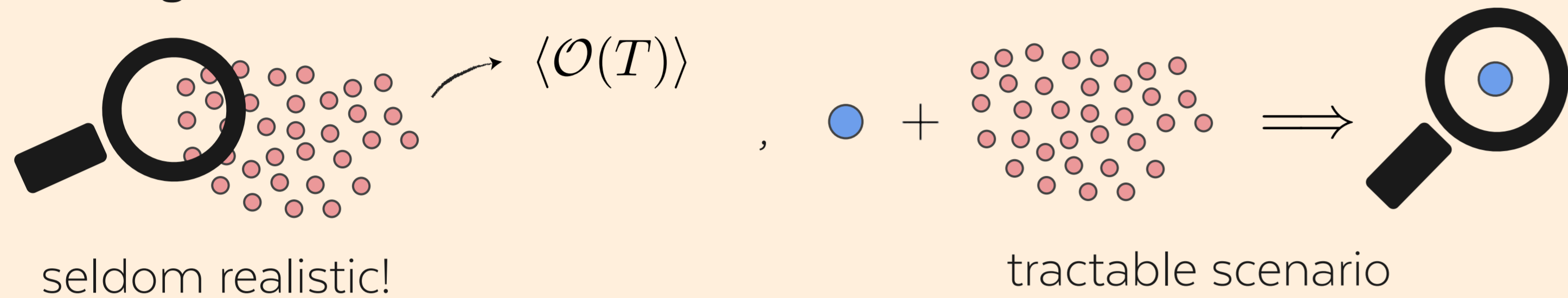
Instituto de Física da Universidade de São Paulo, 05314-970 São Paulo, Brazil³

Introduction

Motivation: Quantum thermometry is crucial for experimental applications. But known strategies are highly model-dependent.

This work: introduces machine classification for quantum thermometry and show that it provides reliable and entirely model-independent predictions.

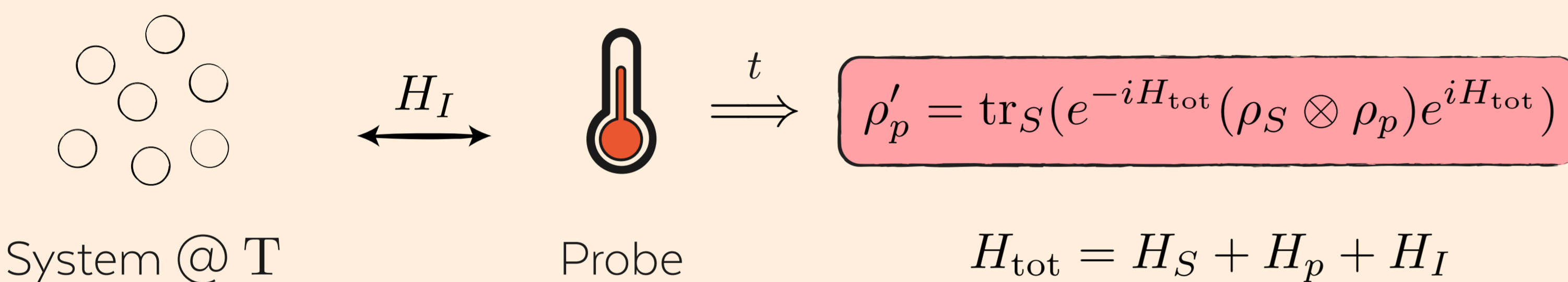
Setting the scene



Probe-based thermometry

The temperature of the system is estimated by **coupling it to a probe**, which is subsequently **measured**. The protocol can be summarised as follow:

1. Interaction



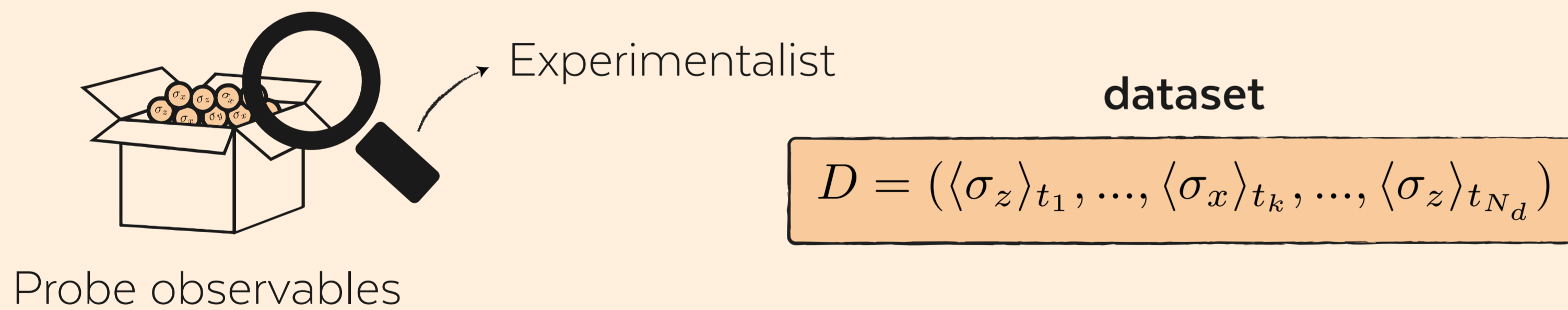
$$\rho_S = \frac{e^{-H_S/T}}{Z}$$

unknown

ρ_p

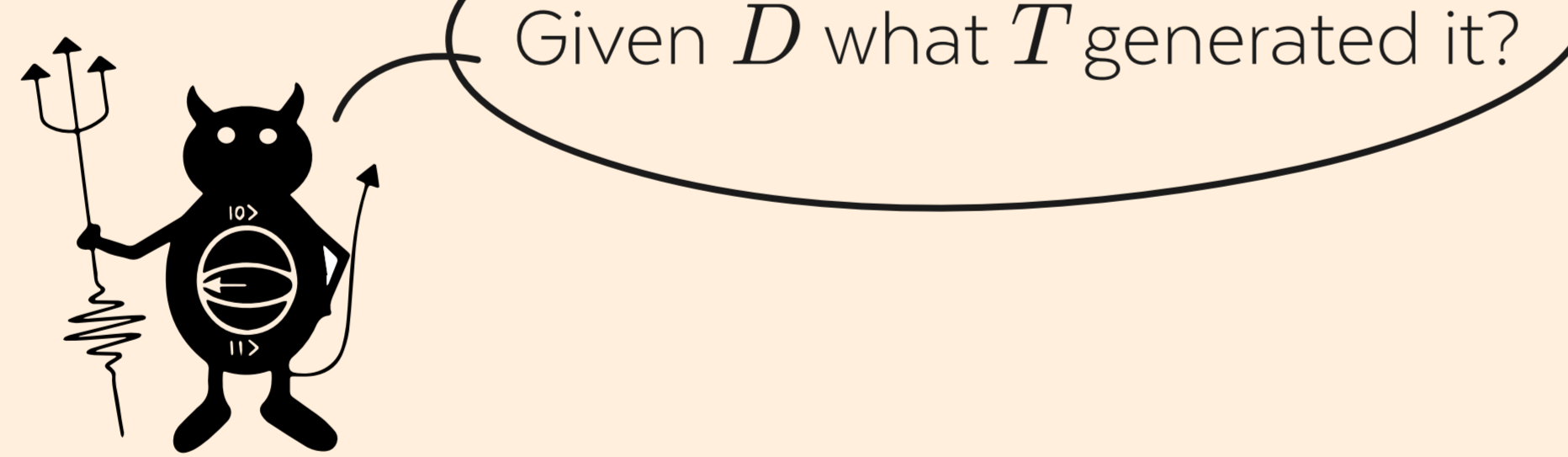
Impurities in **ultra-cold gases**, phonon occupation number of **trapped ions**, or a **mechanical resonator** represents a **prototypical example** of probe-based thermometry.

2. Measurement



3. Predictor

$$(D, T) \Rightarrow \hat{T}(D)$$



The k-nearest-neighbours (KNN) algorithm

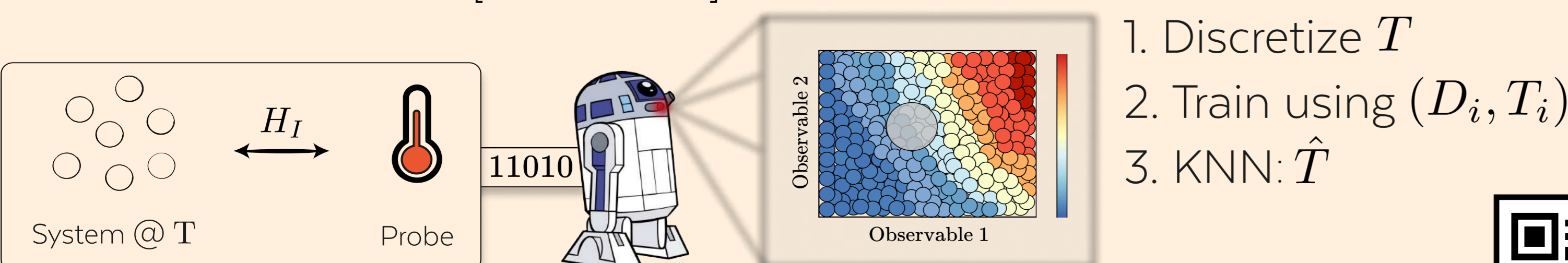
Classification is a **pattern recognition** method that can be employed as a concrete estimation strategy.

KNN in a nutshell

The green dot should be classified either as blue squares or red triangles. If $k = 3$ (solid circle) it is assigned to red triangles. However, if $k = 5$ (dashed circle), it is assigned to the blue squares.

Probe-based thermometry and machine classification

Prior information: $T \in [T_{\min}, T_{\max}]$



Data: **training (70%)** and **validation (30%)** sets.



Results

Jaynes-Cummings (JC) model - We illustrate the idea using the JC model. The probe is described by a qubit and the system by a bosonic mode. The total Hamiltonian is

$$H = \omega a^\dagger a + \frac{\Omega}{2} \sigma_z + \gamma (a^\dagger \sigma_- + a \sigma_+)$$

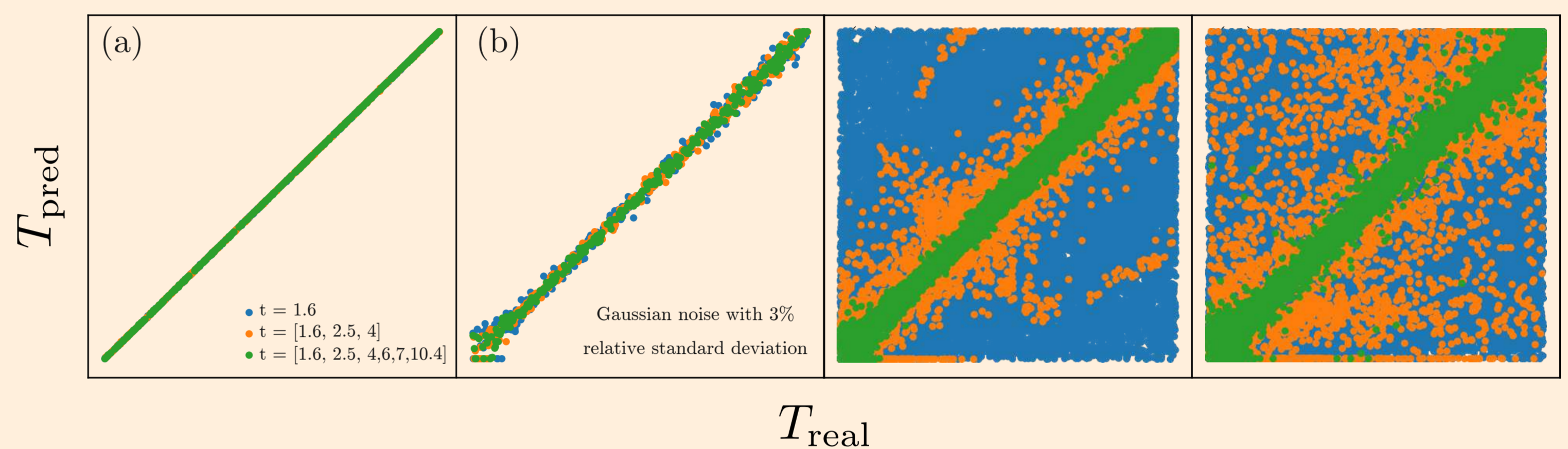
The probe is taken to be resonant with the system ($\Omega = \omega$) and start in the pure state:

$$|\psi_P\rangle = |+\rangle = \frac{1}{\sqrt{2}}(|0\rangle + |1\rangle)$$

Setting: $T \in [0.1, 2]$

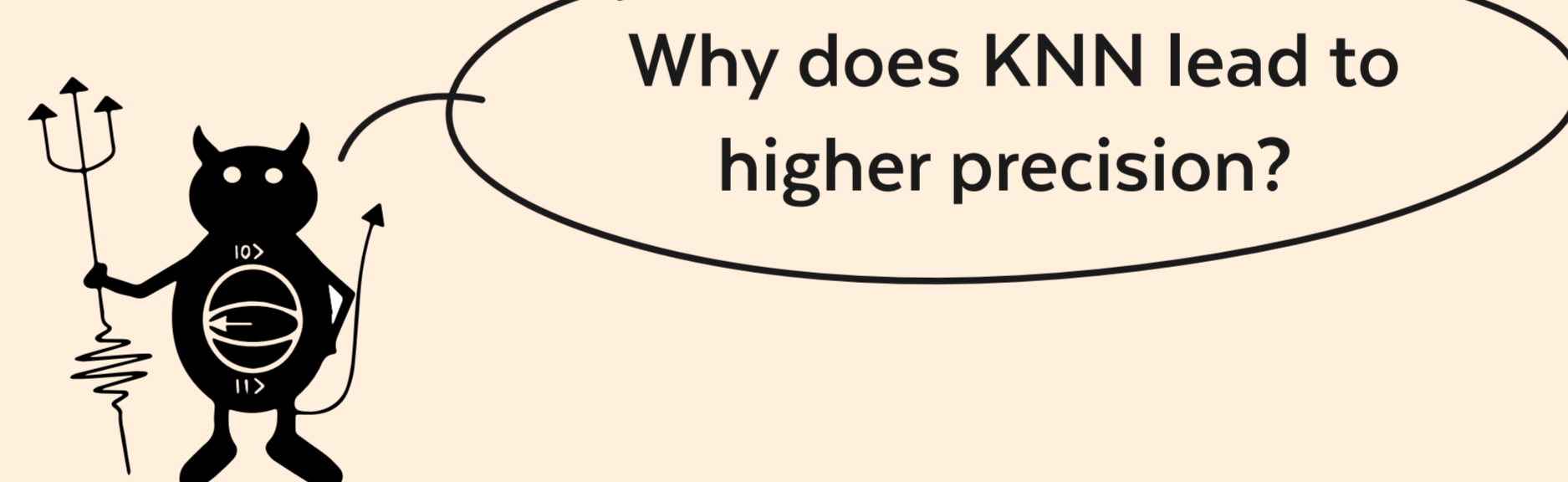
Free parameters: γ, T

Predicted vs real temperature for the validation set

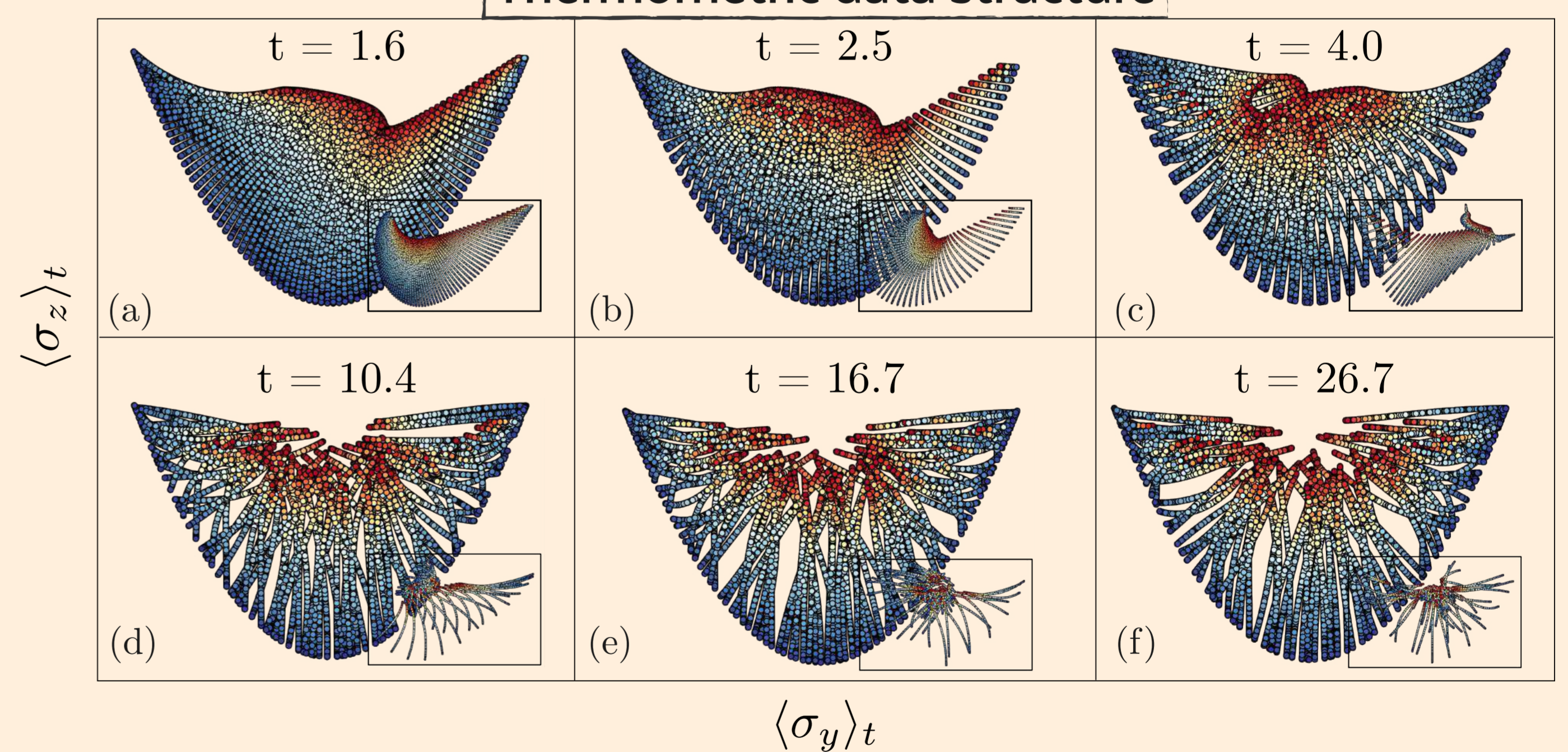


- (a) Using only data from $\langle \sigma_z \rangle_t$ with $\gamma = 1$.
- (b) Same, but with noise.
- (c) Similar to (b) but with $\gamma \in [0.1, 2]$.
- (d) Same, but using $\langle \sigma_y \rangle_t$ instead.
- (e) Net mean-squared error as function of the number of measurement times.

$$\text{MSE} = \frac{1}{N_{\text{val}}} \sum_{\text{val. set}} (T_{\text{pred}} - T_{\text{real}})^2$$



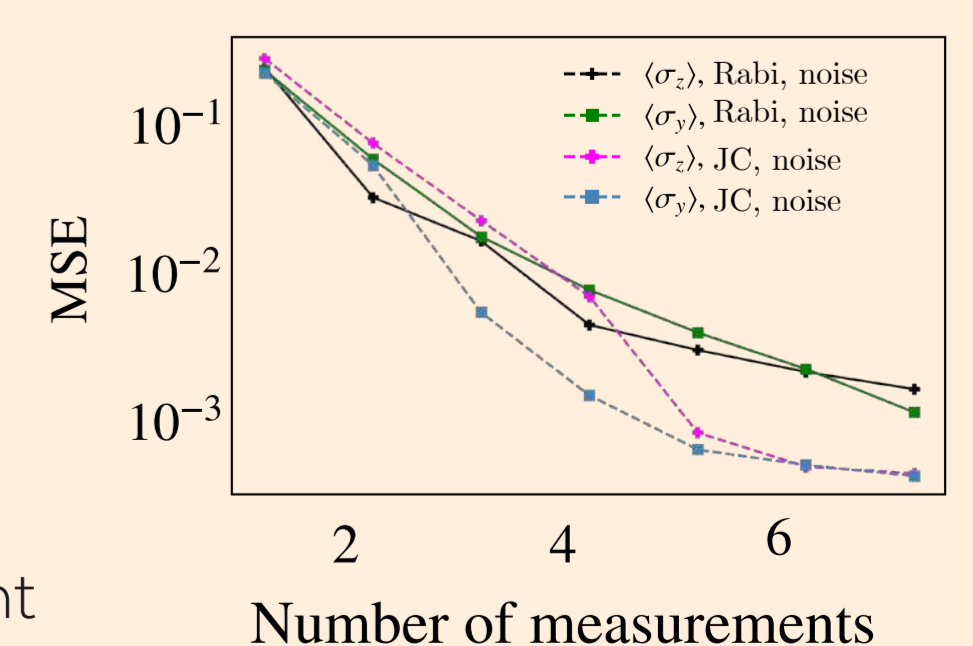
Thermometric data structure



The dataset is segmented into well-defined regions, e.g., the change from hot to cold regions is smooth.

(a)-(f) $\langle \sigma_z \rangle_t$ vs $\langle \sigma_y \rangle_t$ JC model at different times, for $T \in [0.1, 2]$ and $\gamma \in [0.1, 2]$. The colors represent the temperature of the corresponding data point. The insets are similar, but for the Rabi model instead.

We also have explored other systems, such as qudits and spin chains. Also, performed a variety of parameter choices: resonant vs non-resonant energy gaps, different probe states, and so on.



Classification is completely general and can be applied to any probe-based system. It can accept any observation as input data; it handles noise in the validation set and allows one to include uncertainties about the experiment concerning the system-probe dynamics. Classification may become a handy tool in experimental quantum thermometry as coherent quantum experiments, such as trapped ions and optomechanics, falls under this category.