



Bayesian inference for quantum sensing and model learning



Cristian Bonato, Quantum Photonics Lab,
Heriot-Watt University, Edinburgh (UK)
qpl.eps.hw.ac.uk

Collaboration



Cristian Bonato
(experimental physics)



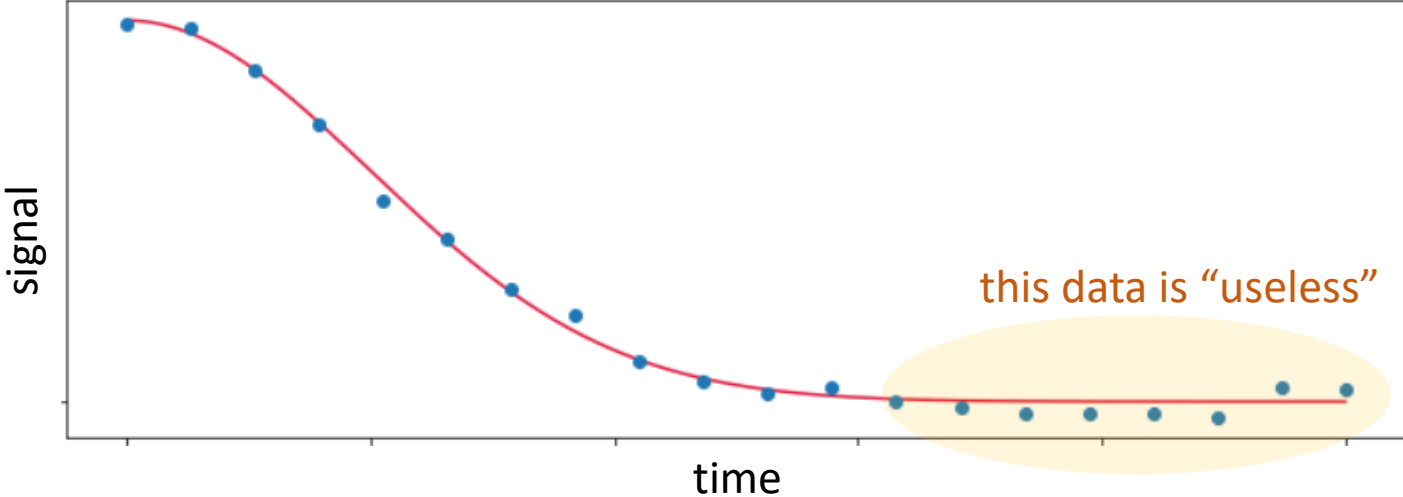
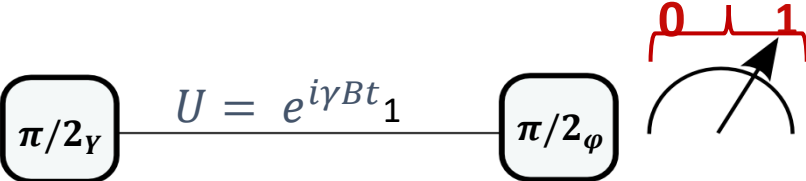
Erik Gauger
(theoretical physics)



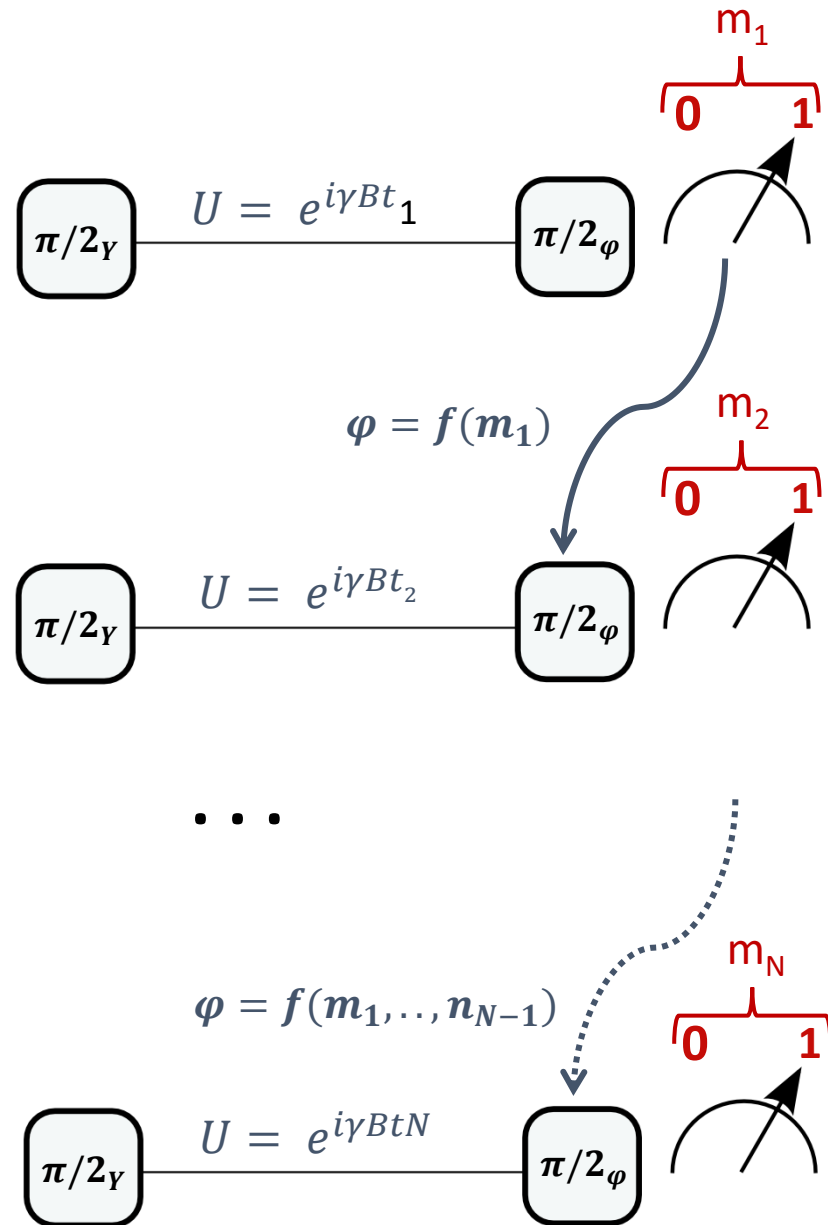
Yoann Altmann
(signal processing)

Standard way of taking data: sweep a parameter

For example, if you want to measure the loss of quantum coherence, you perform a sequence of Ramsey experiments, sweeping the delay time over a pre-determined range:



Adaptive quantum sensing experiments



Adaptive measurement: use information from earlier measurement outcomes to estimate the a quantity and optimise parameters for later measurements in real-time

Adaptive Bayesian experiment design

$$P(B|m) \propto P(m|B) P(B)$$

(1) Easily include **ALL information (imperfections, prior info, etc)** available

Ideal likelihood:

$$\Pr["0"] \sim 1 + \cos(\gamma B t + \varphi)$$

$\gamma = 28 \text{ MHz/mT}$



photon collection efficiency

dark counts

decoherence

$$P(\mu = 0|f_B) = \frac{(1 + F_0 - F_1)}{2} + \frac{(F_0 + F_1 - 1)}{2} e^{-(t/T_2^*)^2} \cos[2\pi f_B t + \vartheta]$$
$$P(\mu = 1|f_B) = 1 - P(\mu = 0|f_B)$$

(2) integrate **online adaptation**:

Current $P(B)$ can be used to optimise settings for next measurement

Our strategy is to maximise Fisher information:

Fisher information:

$$\mathcal{I}(\theta) = -\mathbb{E} \left[\frac{\partial^2}{\partial \theta^2} \log f(X; \theta) \middle| \theta \right]$$

Cramer-Rao bound:

$$\text{var}(\hat{\theta}) \geq \frac{1}{I(\theta)}$$

It's an asymptotic bound, but it works well for simple cases of single-peaked distributions

Summarising:

- (1) probability distribution $P_k(x)$,
(encodes your knowledge about x)
- (2) select value of k to make the most change to $P(x)$,
(we use Fisher information).
- (3) perform your measurement with optimal settings,
getting outcome m .
- (4) update $P_k(x)$ using Bayes rule, for outcome m

Our application: spin-based quantum sensors

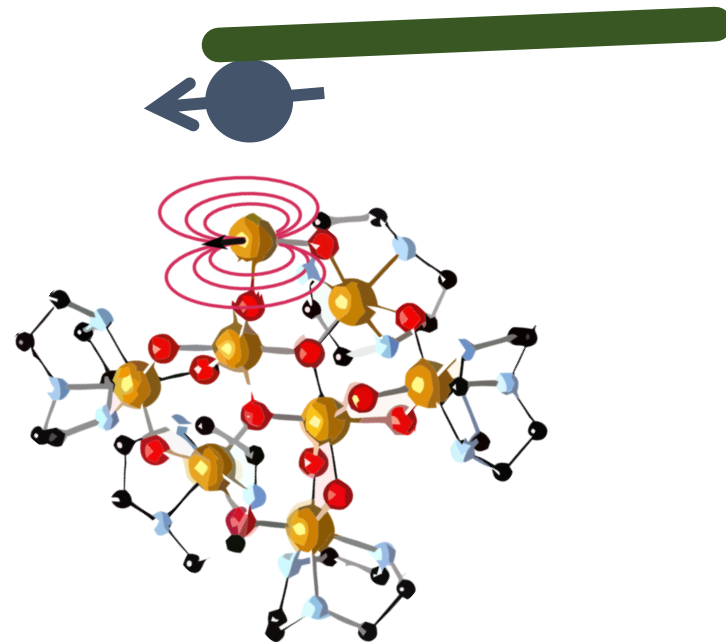
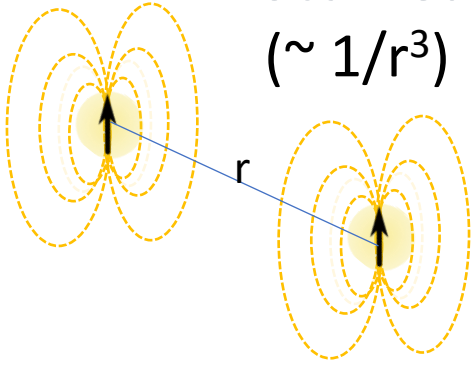
spins need to be **VERY** close to interact

For (arbitrary) interaction strength of 100 kHz:

- e-spin/e-spin, $r = 15 \text{ nm}$
- e-spin/ ^{13}C nuclear spin, $r = 1.2 \text{ nm}$

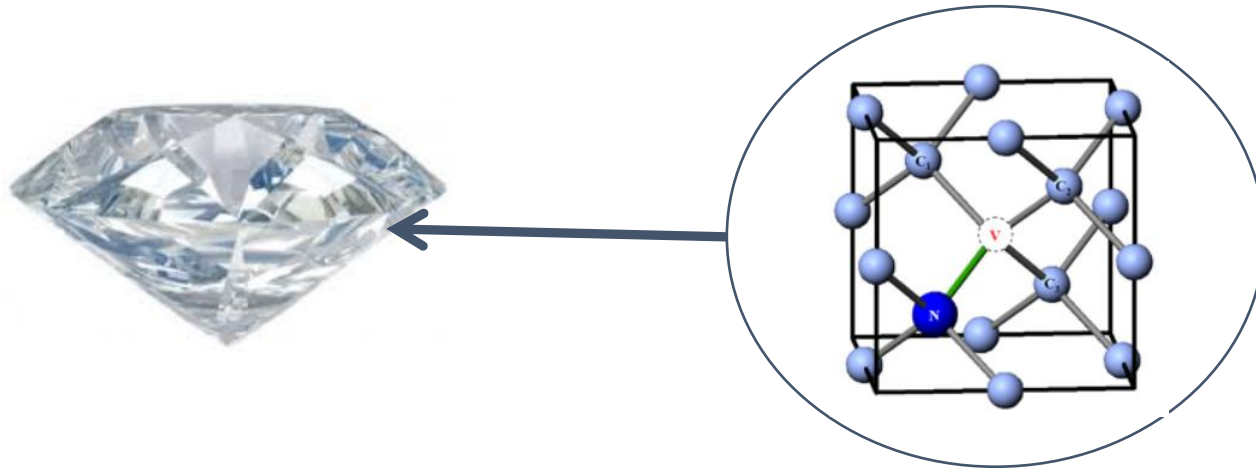
magnetic interaction is

'localized'
($\sim 1/r^3$)

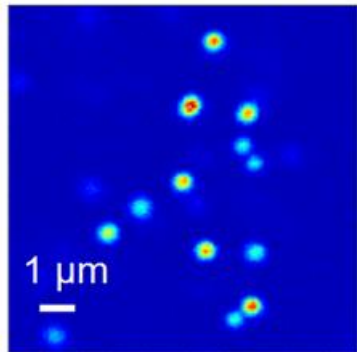


Since spins only interact when they are close by, one can achieve nanoscale spatial resolution!

Our system: nitrogen-vacancy (NV) centre in diamond

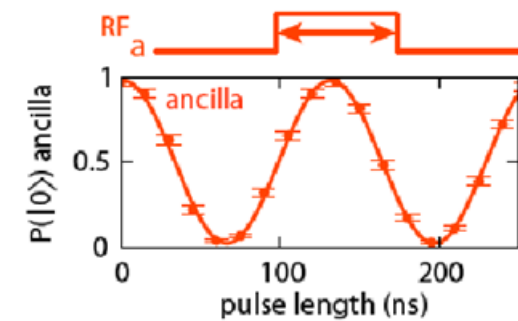
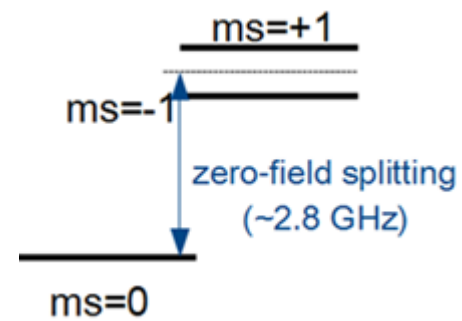


optically-active



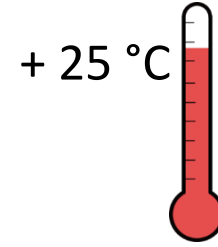
spin state can be read-out by a change in photoluminescence

paramagnetic ground state ($S=1$)

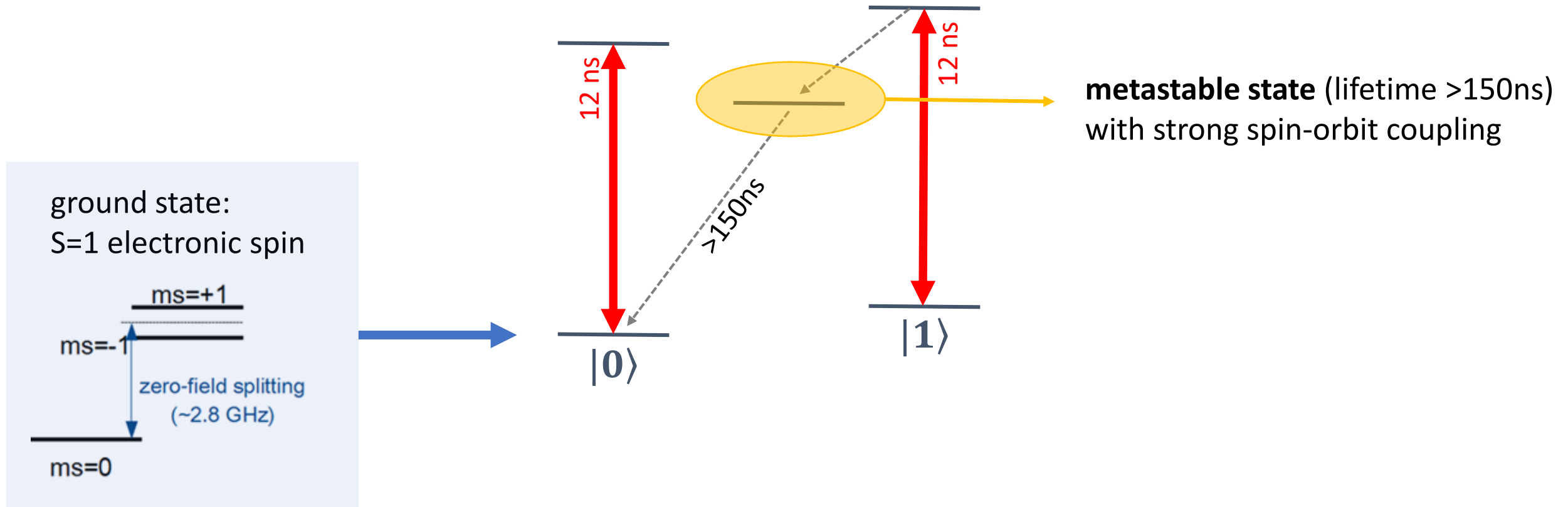


spin manipulation by microwave pulses

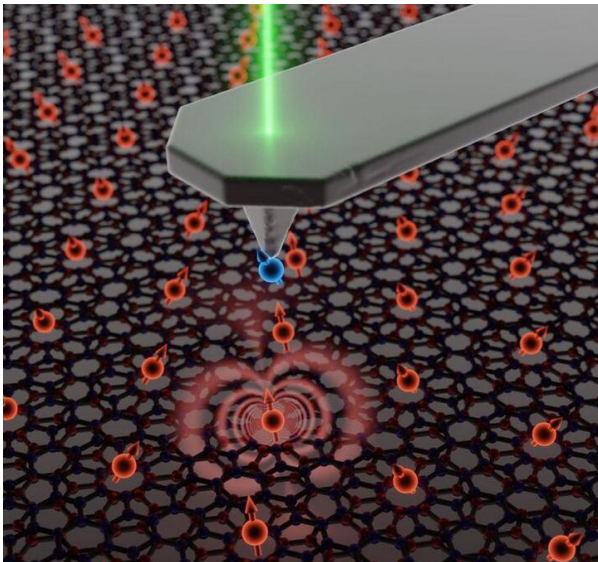
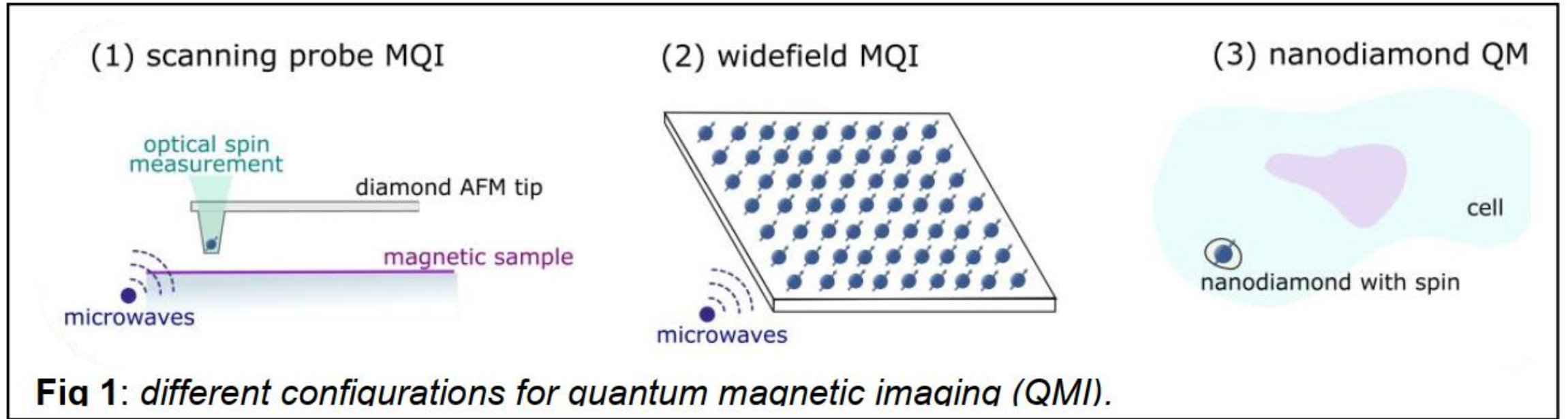
What's unique about the NV centre in diamond?



Electron spin can be polarised and readout at room temperature:



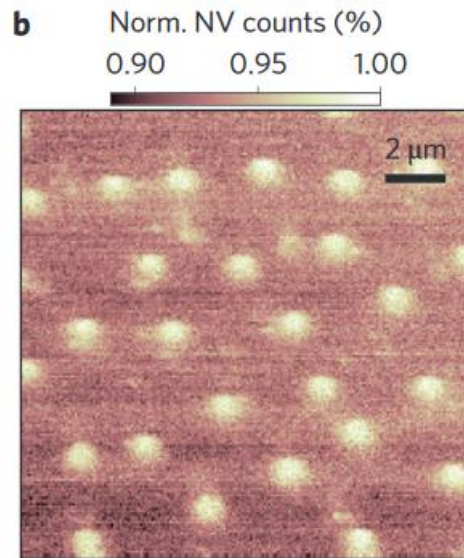
Quantum sensing modalities



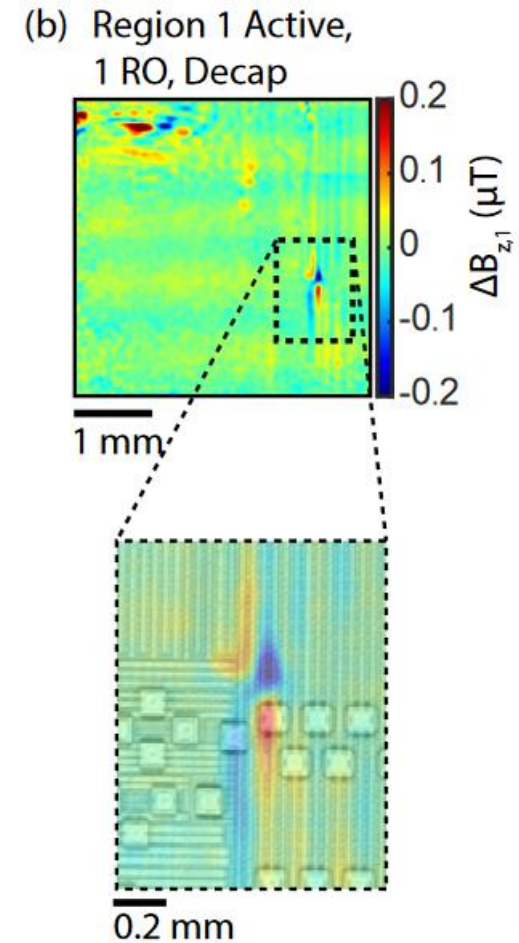
Heriot-Watt's ESRC Quantum Magnetometry facility,
DSTL project "Quantum magnetometry of complex 2D materials"

Nanoscale magnetic fields

Single spins are already being used as sensors in different fields:



Imaging vortices in superconductors
Nature Nanotech 11 (2016)



Imaging of currents in an electronic chip
Phys. Rev. Applied 14, 014097 (2020)

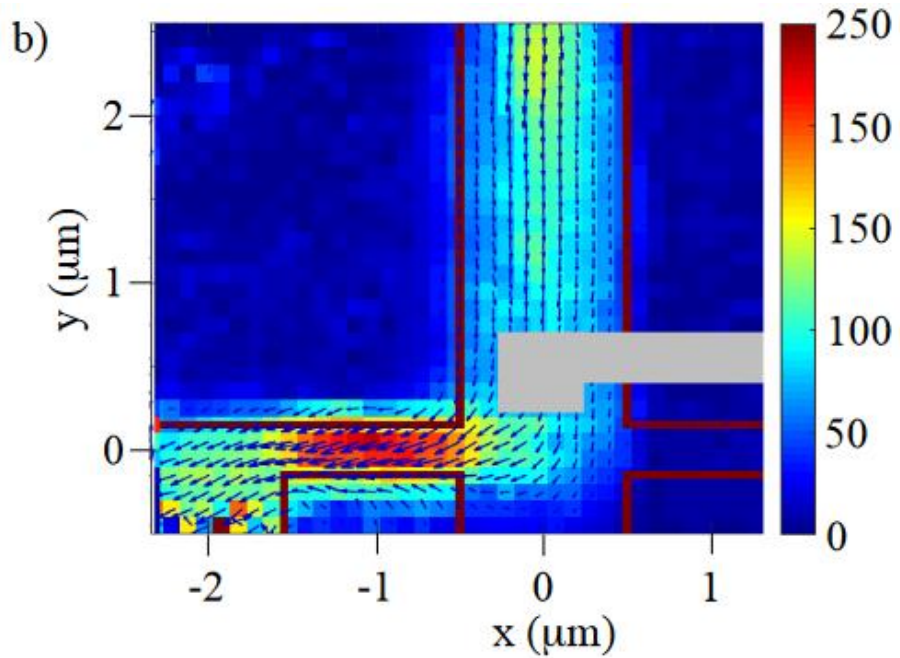
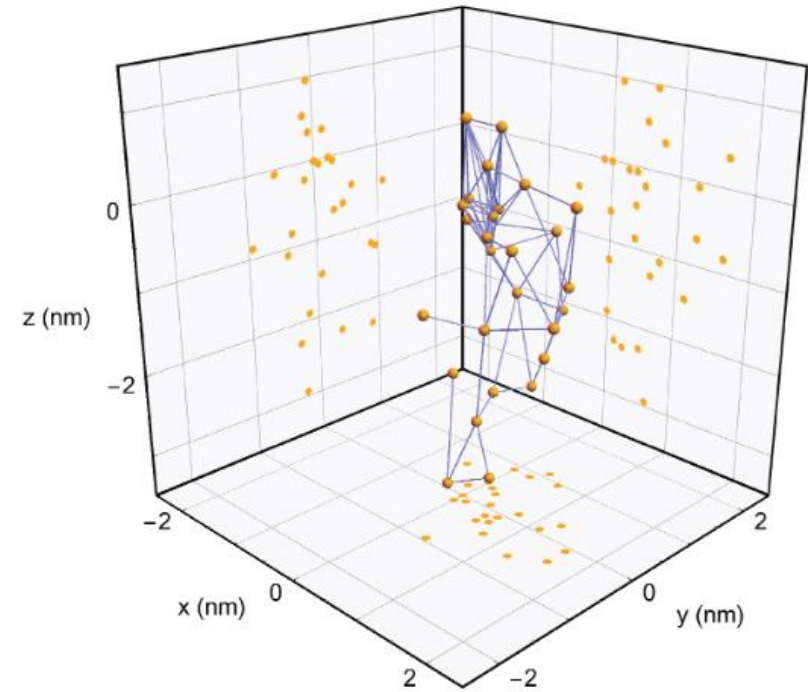


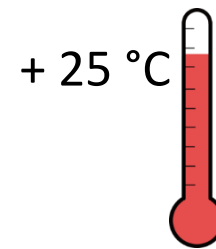
Image “viscous” flow of Dirac electron fluid in graphene
 Nature 583, 537 (2020)



Detection of 27 individual ¹³C nuclei in diamond
 Nature 576, 411 (2019)

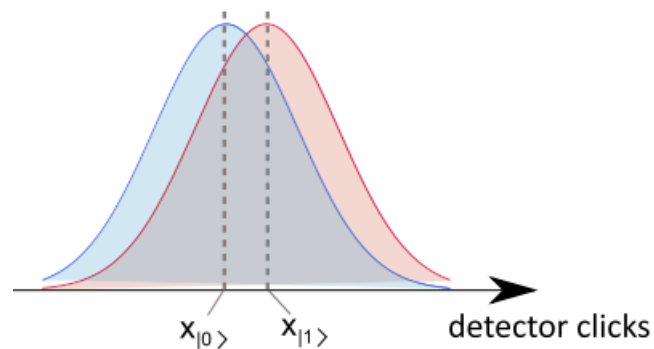
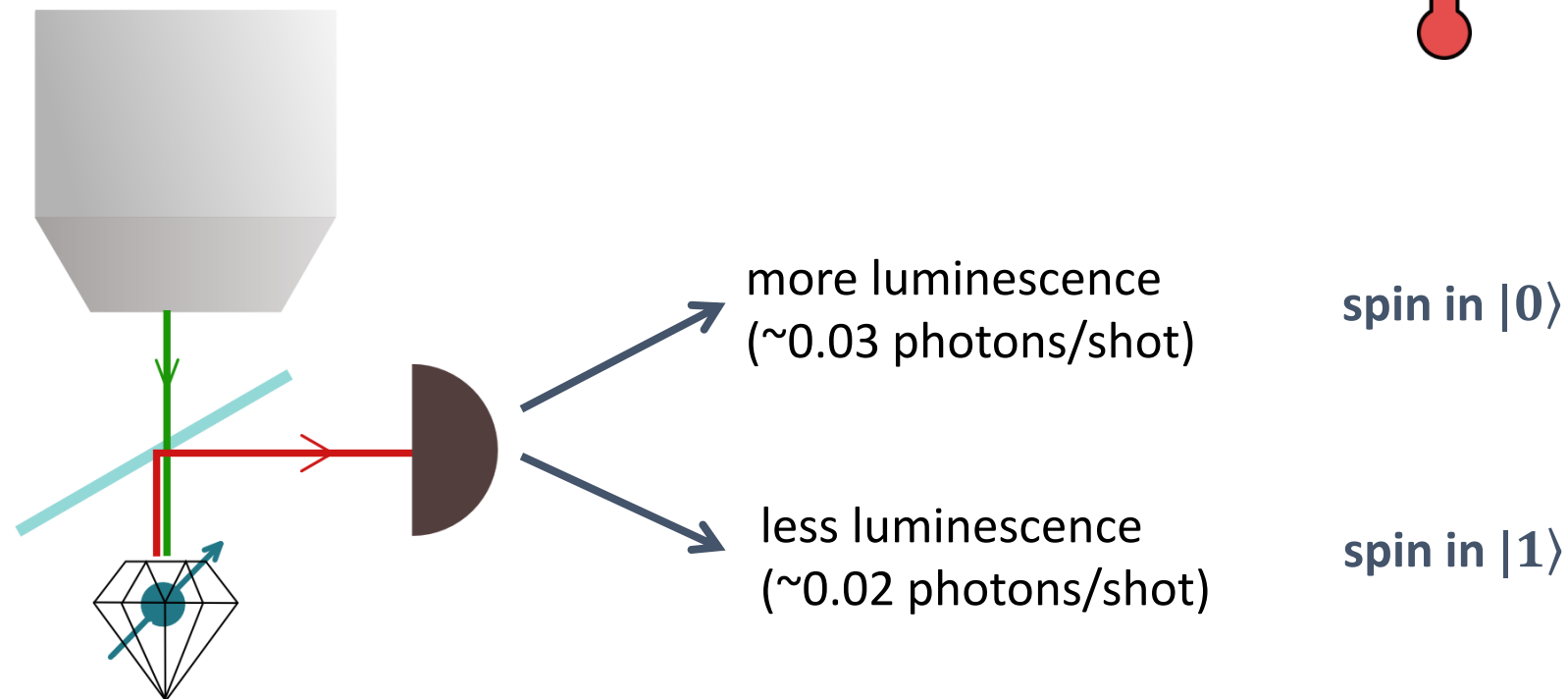
...just few examples from the tens of papers published every year

NV centres in diamond: room temperature readout



Recipe:

- shine green laser
- collect photoluminescence

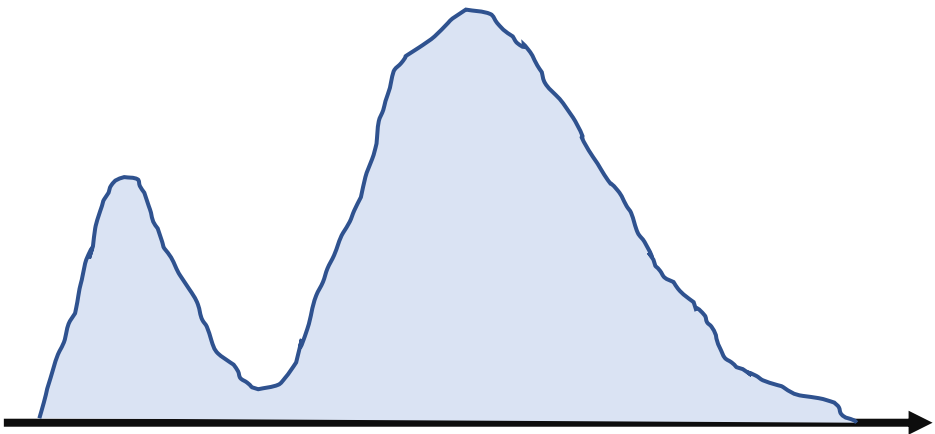


A single shot does not give us the spin info, we need to **repeat R (e.g. $R=10,000$) times**

Bayesian framework:

we update using “we detected r photons in R trials”

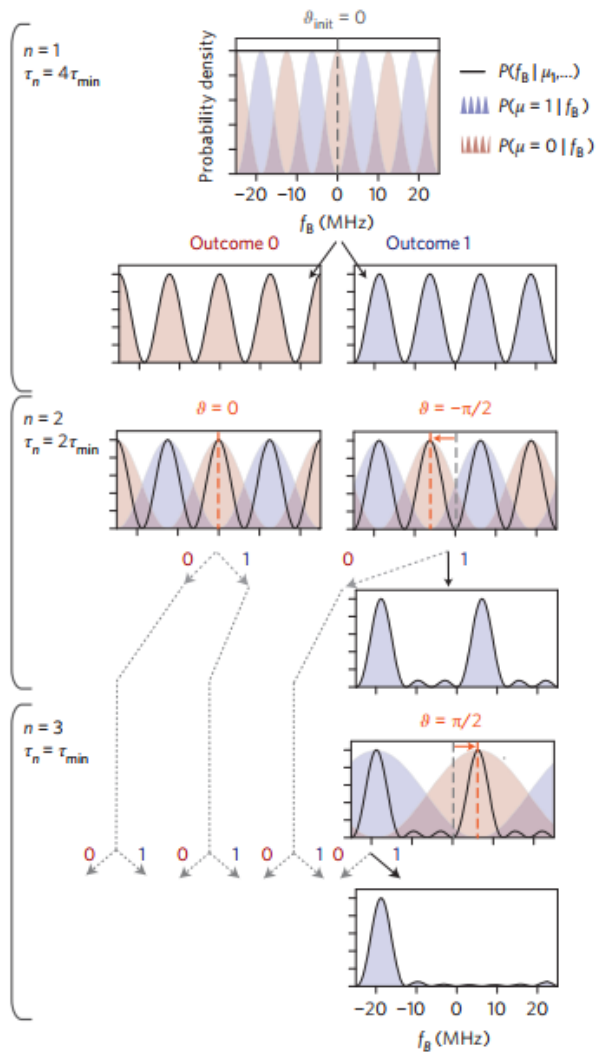
Implementation: how do you store/process the probability distribution?



discretise probability distribution $\{x_i\}$
(more obvious way: uniform discretization)

store $\{x_i\}$ in memory (not a big deal)

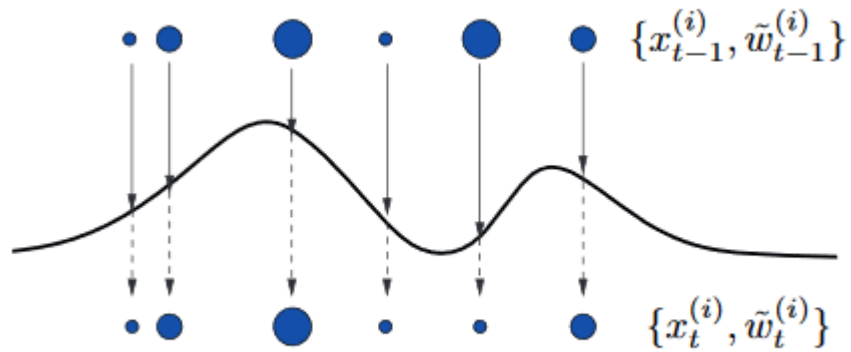
after each measurement, update all $\{x_i\}$
(complexity $O(N)$)



when you start, you know nothing
so you need a broad range

... as the measurement
progresses, there are low-
probability regions which are
useless, but still occupy
resources

Particle filtering (or sequential MonteCarlo)

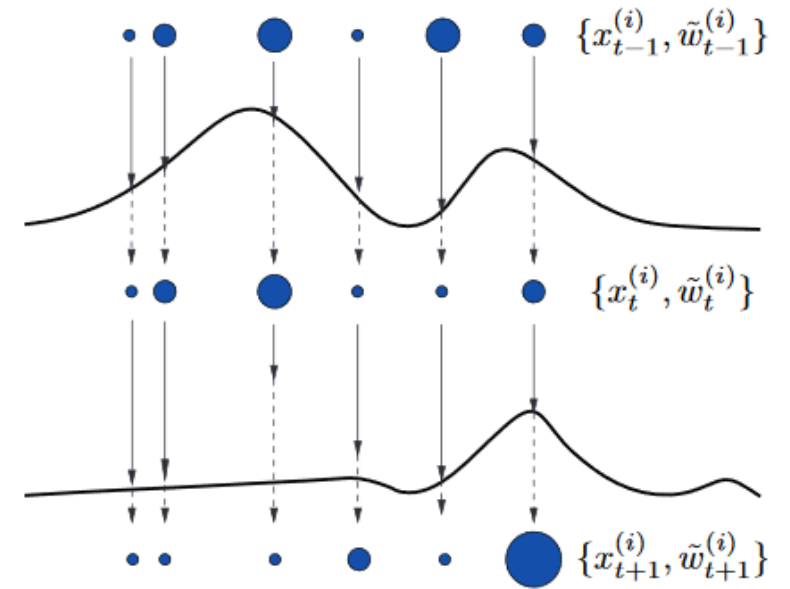


Adapted from (Doucet *et al.*, 2001)

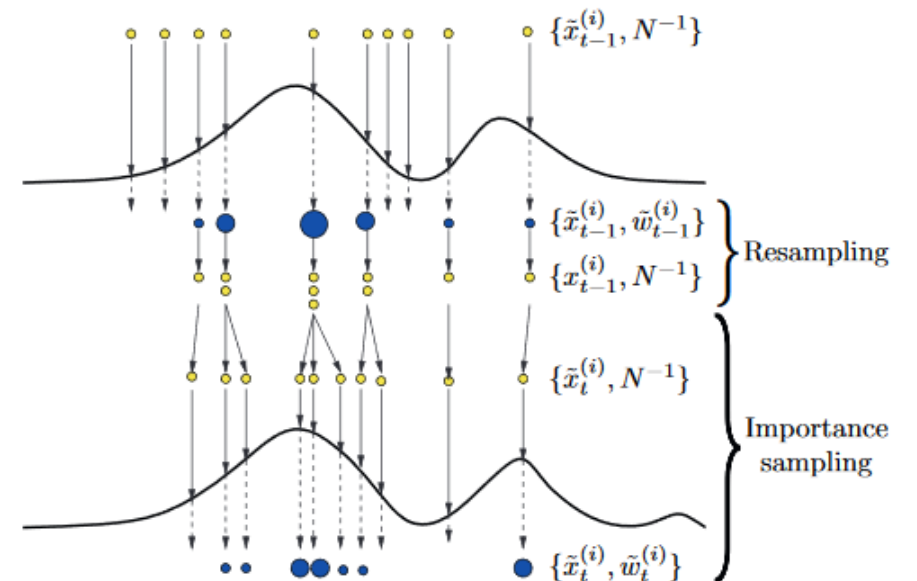
Used for quantum Hamiltonian learning by:

R Santagati et al, "Magnetic-Field Learning Using a Single Electronic Spin in Diamond with One-Photon Readout at Room Temperature", Phys Rev X (2019)

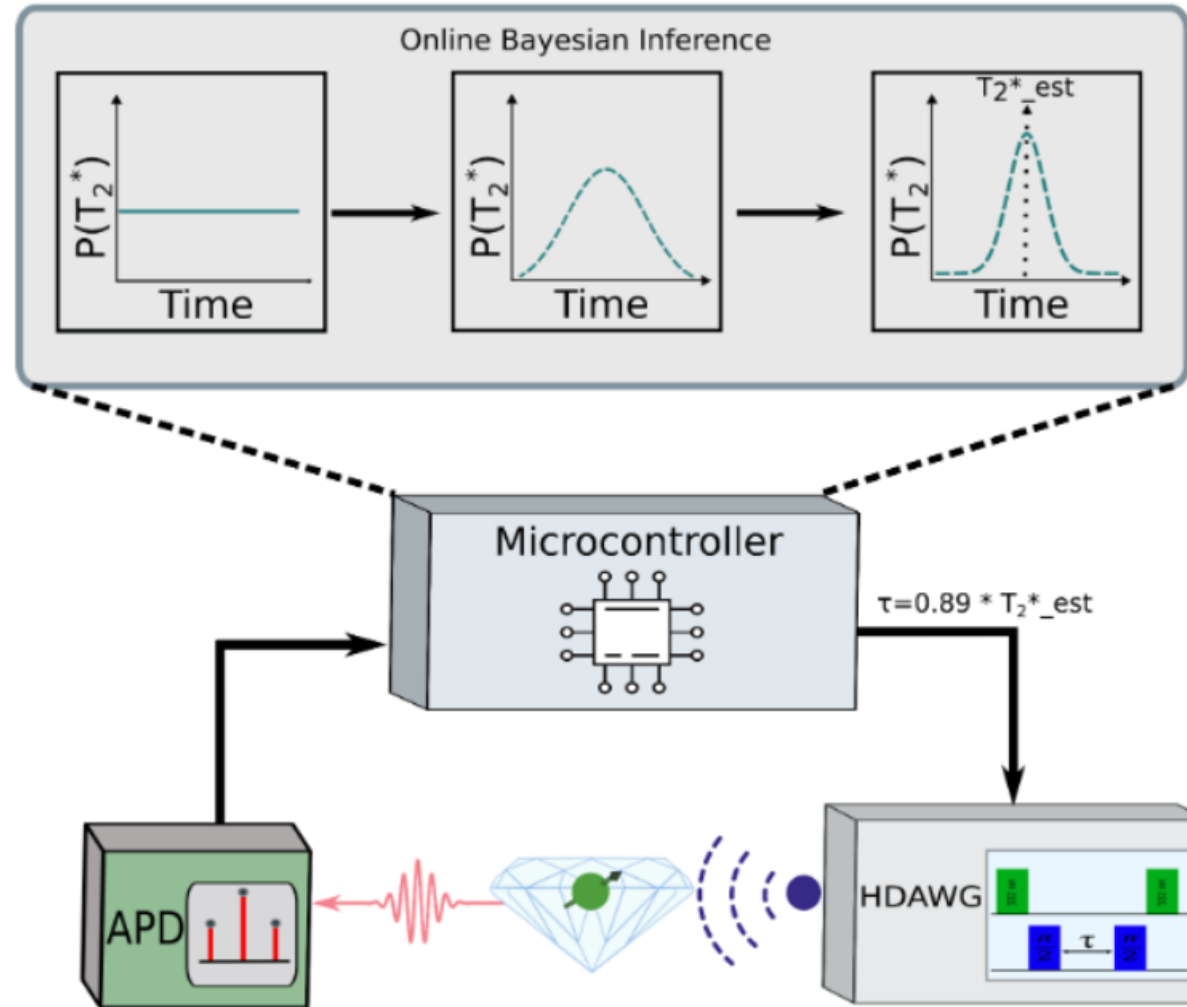
Bayesian update:



Re-sampling:



Experiment idea



Muhammad



Ben



Christiaan

Real-time Micro-controller: Adwin Pro II

AWG: Zurich Instruments HDAWG4

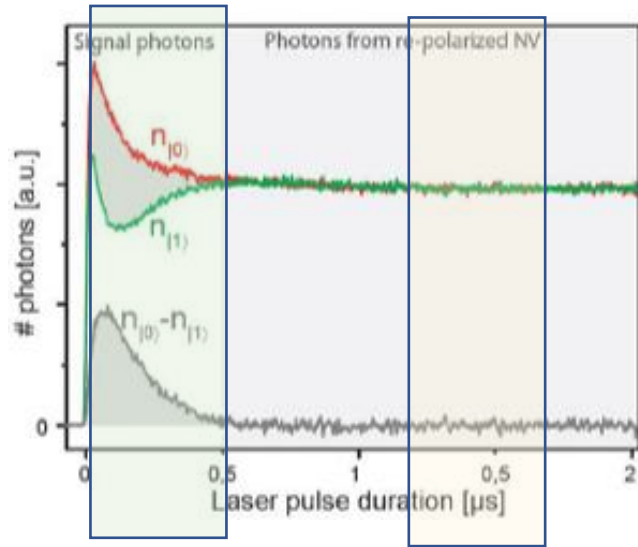
Real-time feedback loop duration: 50us

MJ Arshad et a, arxiv:2210.06103 (2022)

Electronics Detailed Schematic

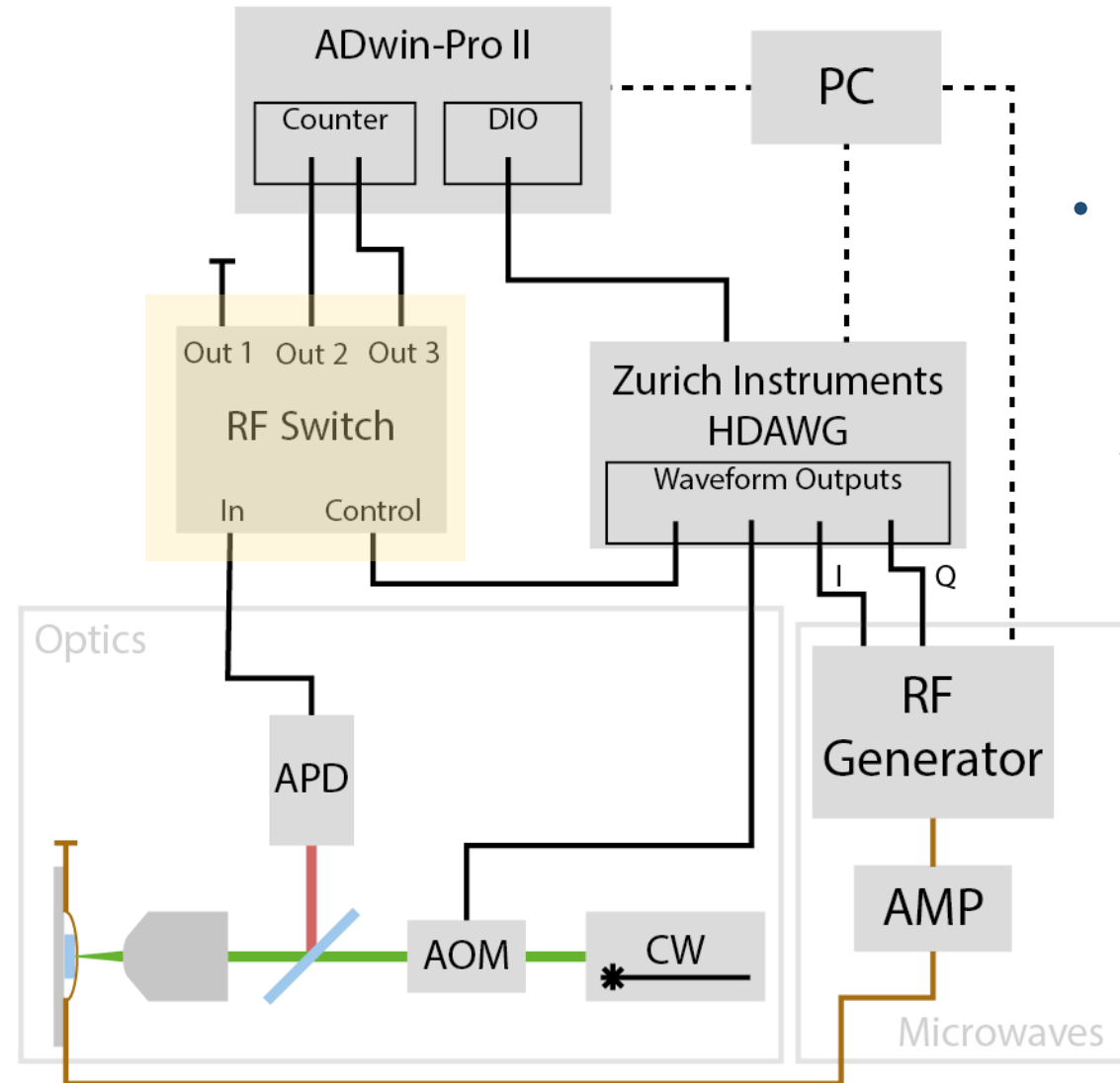
RF switch

Filters out signal and normalization in NV time-resolved PL:



Here we have a difference in photon count based on the spin state

Here we have no spin-related difference (we can use this to detect system drifts – “normalisation”)



- Adwin (**microcontroller**) initiates experiment, reads out photon counts and provides optimised parameters
- **ZI Arbitrary Waveform Generator** controls the experimental apparatus and routes count signals to ADwin counters

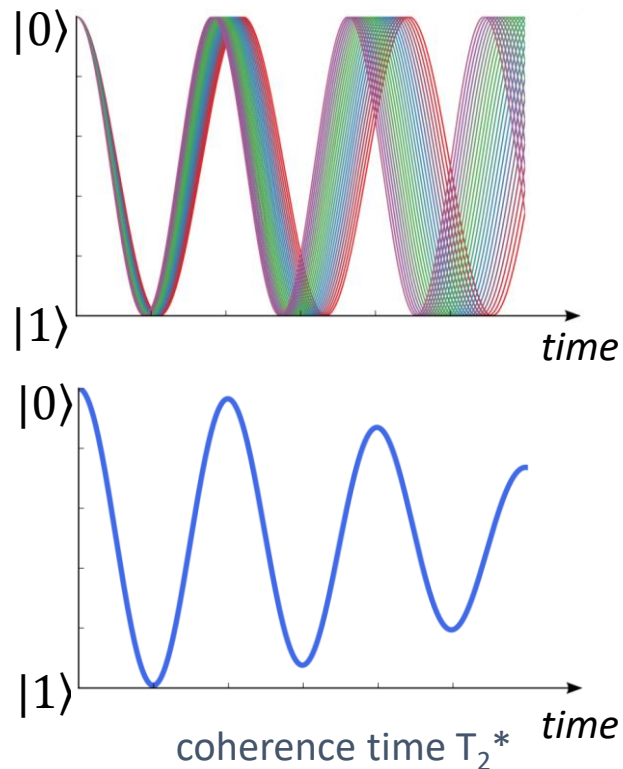
Feedback loop: 50-100 microseconds

Example: measuring loss of quantum coherence

Decoherence:

quantum systems lose their “*quantumness*” by interacting with the environment.

Example: fluctuations in magnetic field induce fluctuations in spin precession frequency



The loss of quantum coherence can be generally described as:

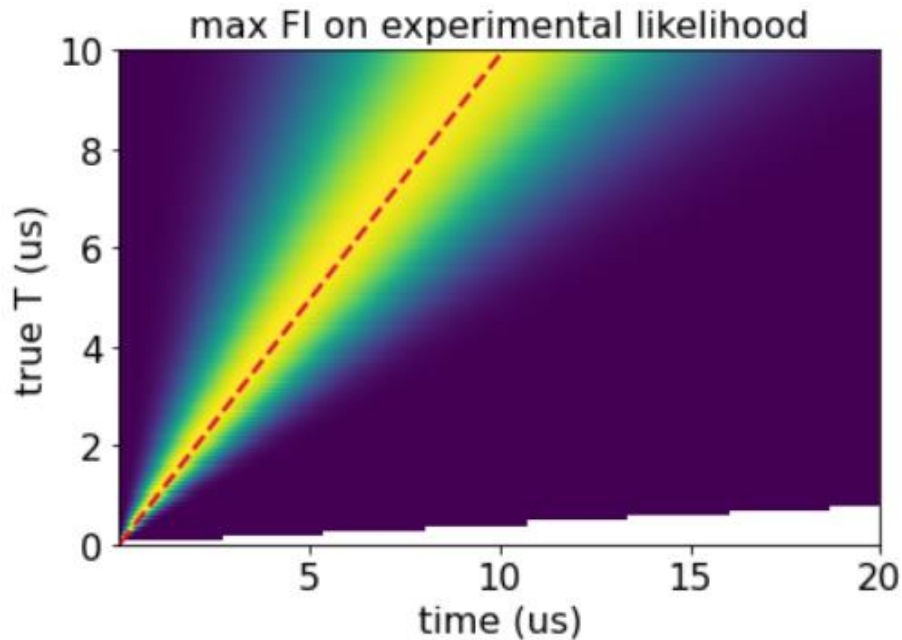
$$p(t) \propto \frac{1}{2} \left(1 - e^{-\chi(t)} \right)$$

$$\chi(t) \propto \left(\frac{t}{T_\chi} \right)^\beta$$

How do you adaptively choose best settings?

Our approach: simple “analytical” near-optimal max(FI)

(formula needs to be simple for adaptive choice to be fast so that
computations do not slow sensing down)



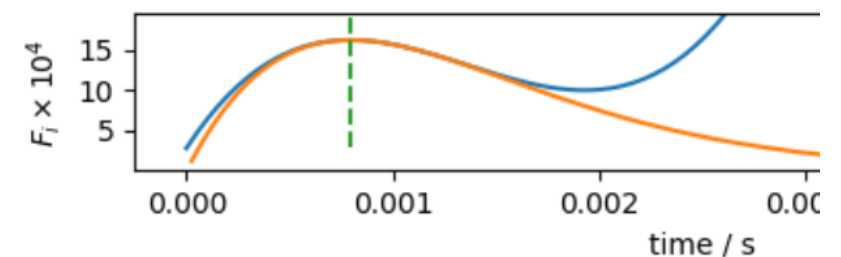
Fisher Information for T_1 :

$$F_i(t, T_1) = \frac{t^2}{T_1^4 \left(e^{\frac{2t}{T_1}} - 1 \right)}$$

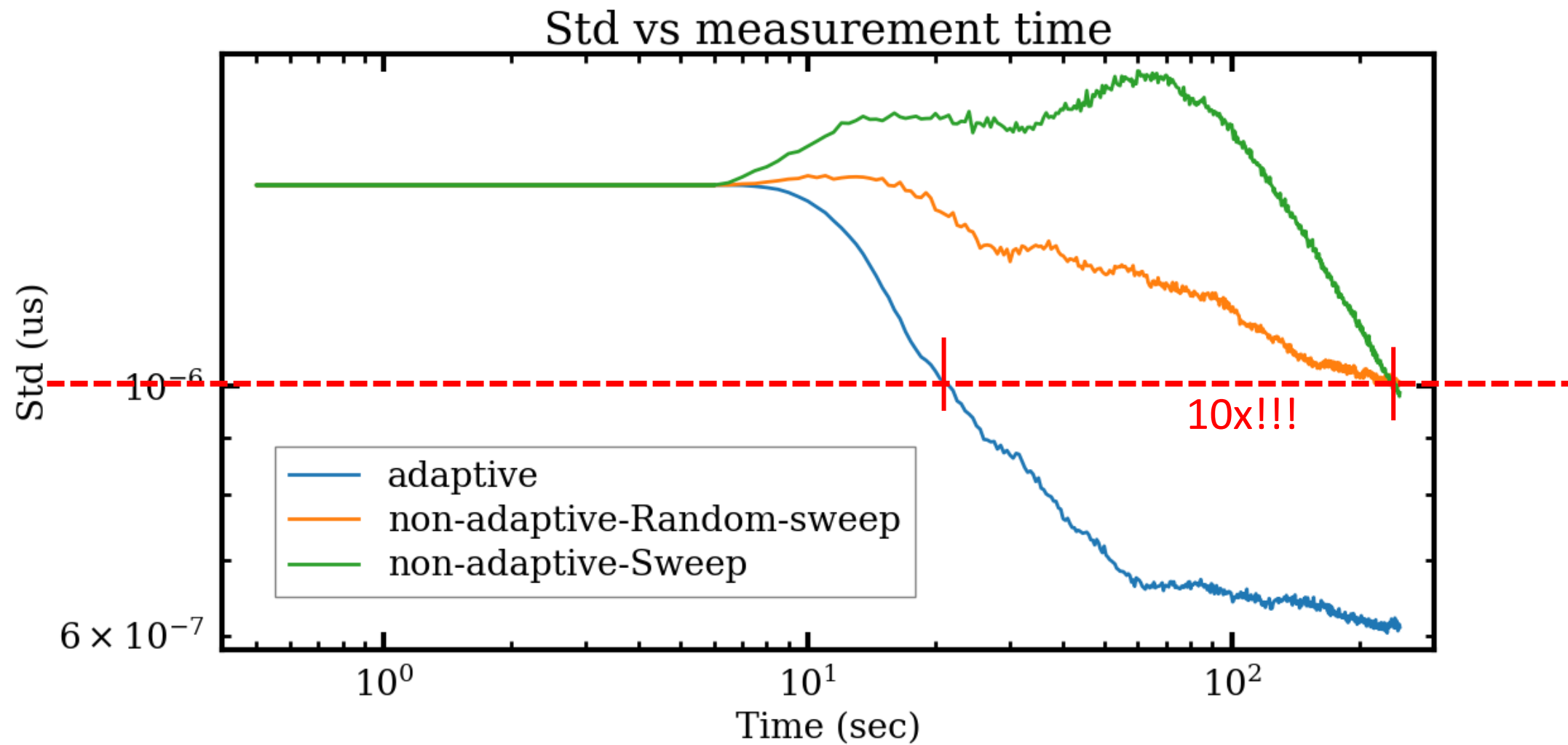
No analytical solution, Taylor expansion:

$$F_i(t, T_1) \approx \frac{0.028T_1^3 + 0.390T_1^2t - 0.347T_1t^2 + 0.085t^3}{T_1^5}$$

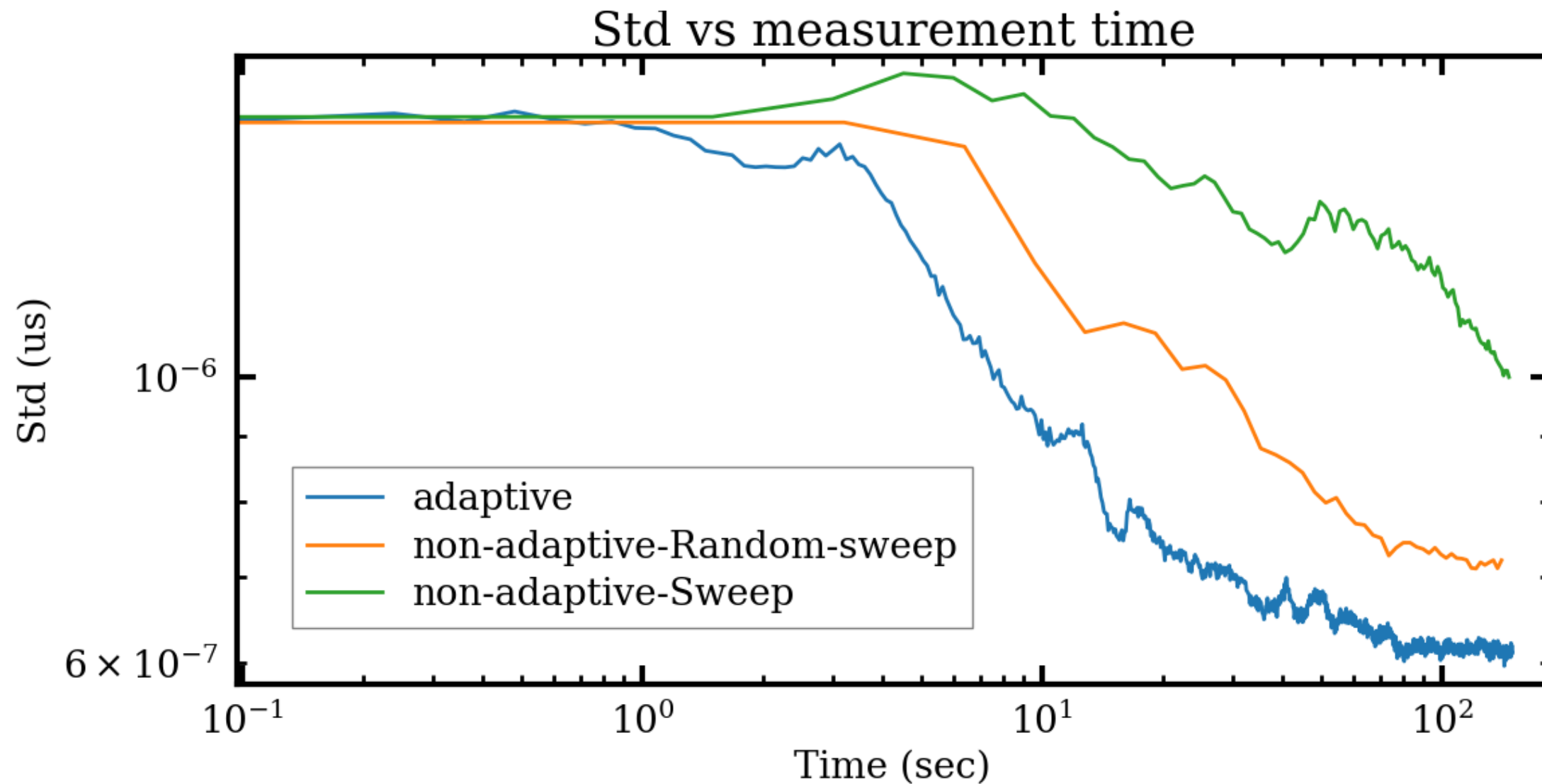
approximately: $t_{\text{opt}} \sim 0.8 * T_1_{\text{est}}$



Experimental T2* estimation (averaged-readout with R=10⁶ reps)



Experimental T2* estimation (averaged-readout with R=10⁵ reps)



What should we optimise when sensing time is not constant?

A longer measurement that yields the same sensitivity as a shorter one should be penalised!

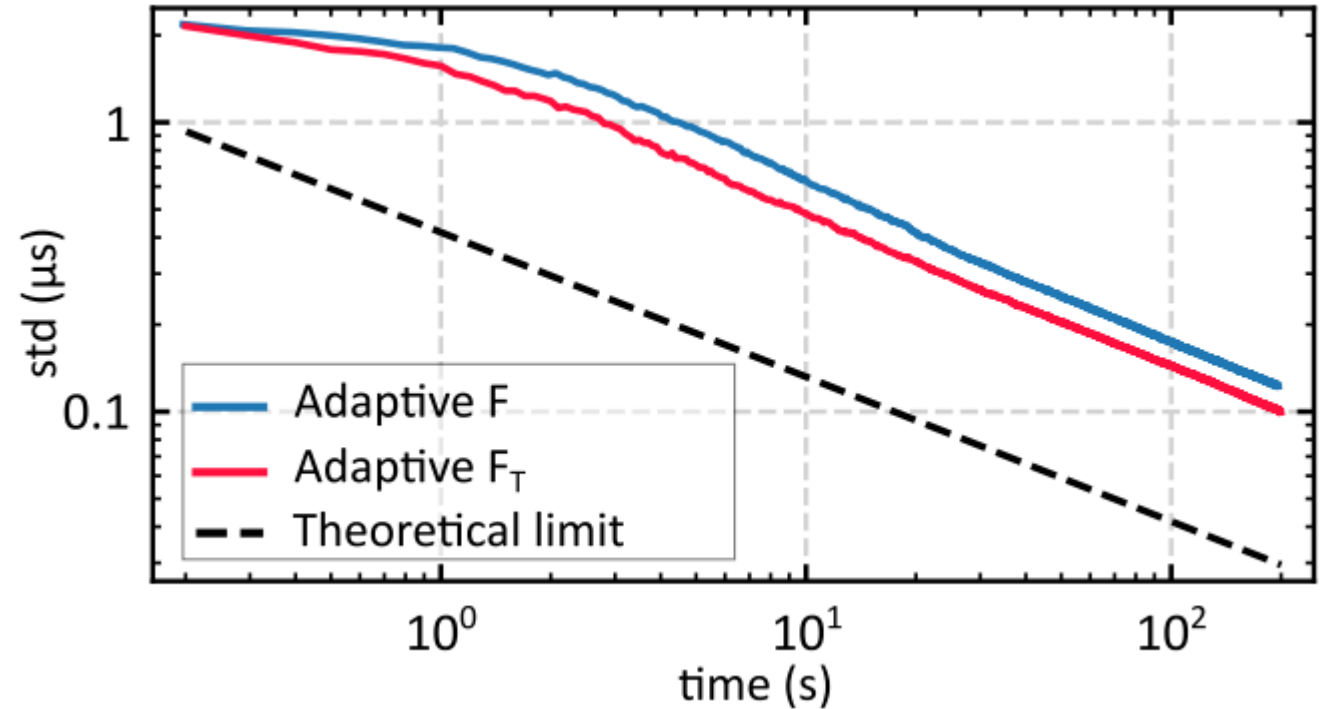
Instead of looking at variance, we can look at sensitivity, commonly defined as $\text{Var} * T$

From the Cramer-Rao bound:

$$\text{Var} * T > \frac{1 * T}{FI}$$

Instead of maximising FI , let's maximise:

$$F_T = F/T$$



Multi-parameter estimation

The loss of quantum coherence can be generally described as:

$$p(t) \propto \frac{1}{2} \left(1 - e^{-\chi(t)} \right)$$

$$\chi(t) \propto \left(\frac{t}{T_\chi} \right)^\beta$$

decay exponent provides information about the statistics of the noise acting on the spin sensors

Can we estimate β and T_χ simultaneously?

Multi-parameter estimation

Problem: the determinant of the Fisher information is zero!

Why are β and T_x correlated?

They are not. But with just one sensing time, they become correlated (one equation with two unknowns)

Solution: use two sensing times!

Multi-parameter estimation

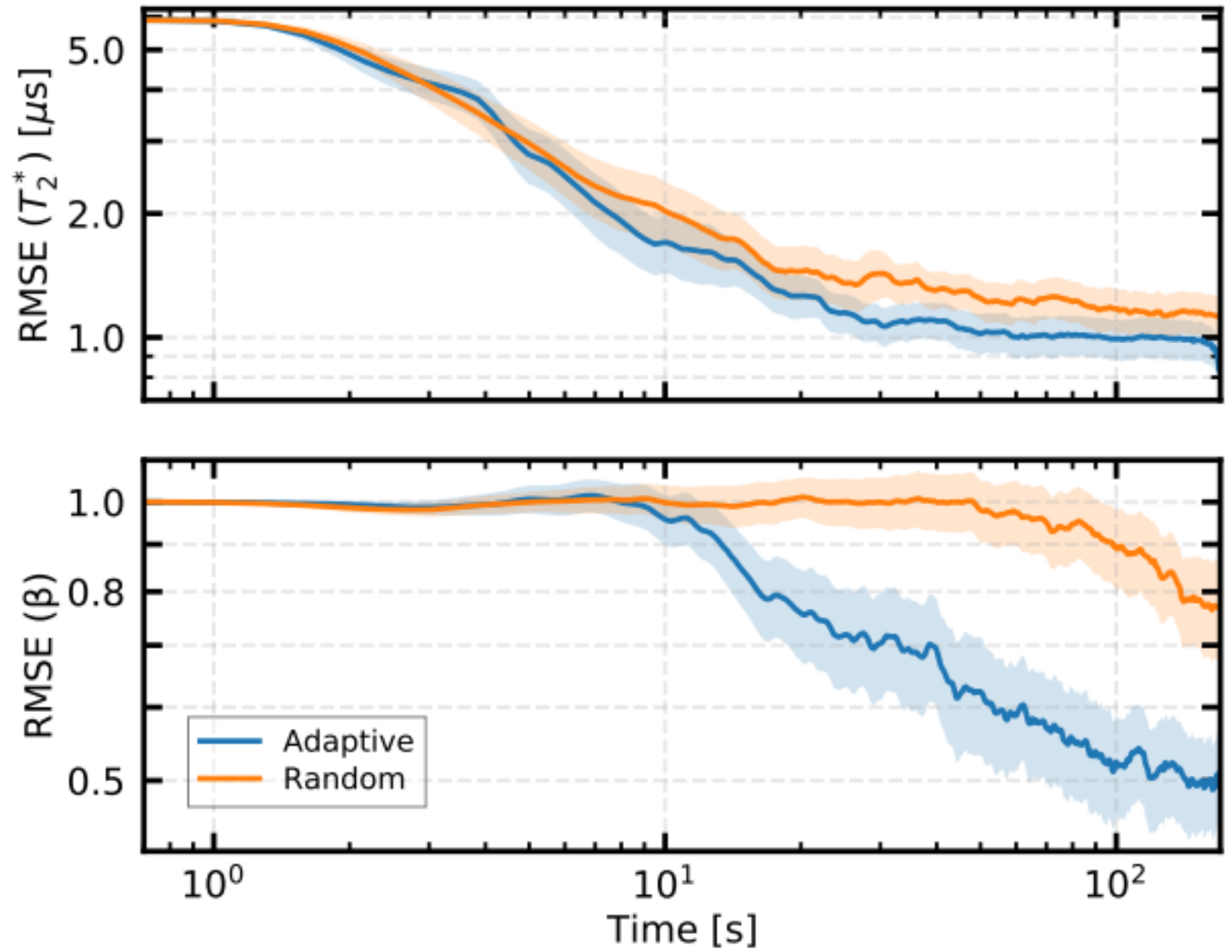
Determinant of the Fisher information matrix:

$$\det \hat{F}_B = \frac{N^2 \left(\frac{\tau_0}{T_\chi}\right)^{2N} \left(\frac{\tau_1}{T_\chi}\right)^{2N} \left(\log^2\left(\frac{\tau_0}{T_\chi}\right) - 2 \log\left(\frac{\tau_0}{T_\chi}\right) \log\left(\frac{\tau_1}{T_\chi}\right) + \log^2\left(\frac{\tau_1}{T_\chi}\right)\right)}{T_\chi^2 \left(-\exp\left[2\left(\frac{\tau_0}{T_\chi}\right)^N\right] - \exp\left[2\left(\frac{\tau_1}{T_\chi}\right)^N\right] + \exp\left[2\left(\frac{\tau_0}{T_\chi}\right)^N + 2\left(\frac{\tau_1}{T_\chi}\right)^N\right] + 1\right)}$$

Simple approximation for its maximum:

$$\tau_{1_{opt}} = \begin{cases} 0.313\tau_0 + 1.04\hat{T}_\chi, & \text{if } \tau_0 < 0.83\hat{T}_\chi \\ 0.7\tau_0, & \text{if } 0.83\hat{T}_\chi < \tau_0 < 0.96\hat{T}_\chi \\ 0.109\tau_0 + 0.55\hat{T}_\chi, & \text{if } 0.96\hat{T}_\chi < \tau_0 \end{cases}$$

Multi-parameter estimation



What do we need this for?

Decoherence of the central spin can give us information about the local environment

SCIENCE ADVANCES | RESEARCH ARTICLE

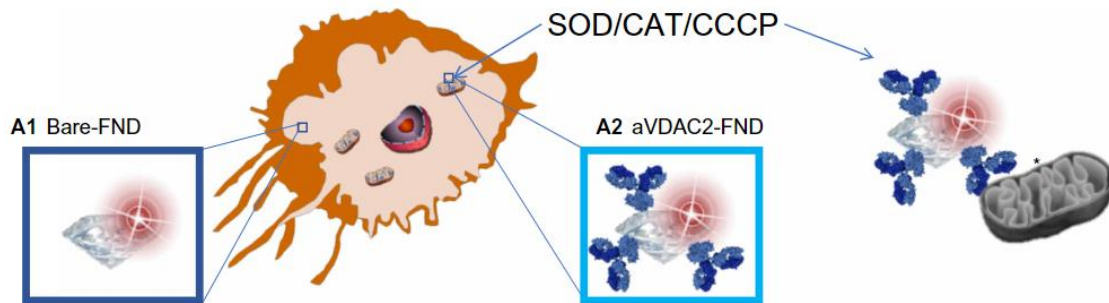
APPLIED PHYSICS

Quantum monitoring of cellular metabolic activities in single mitochondria

L. Nie^{1†}, A. C. Nusantara^{1†}, V. G. Damle¹, R. Sharmin¹, E. P. P. Evans¹, S. R. Hemelaar¹, K. J. van der Laan¹, R. Li¹, F. P. Perona Martinez¹, T. Vedelaar¹, M. Chipaux^{2*}, R. Schirhagl^{1*}

A Measurements in cells

B Measurements on organelles



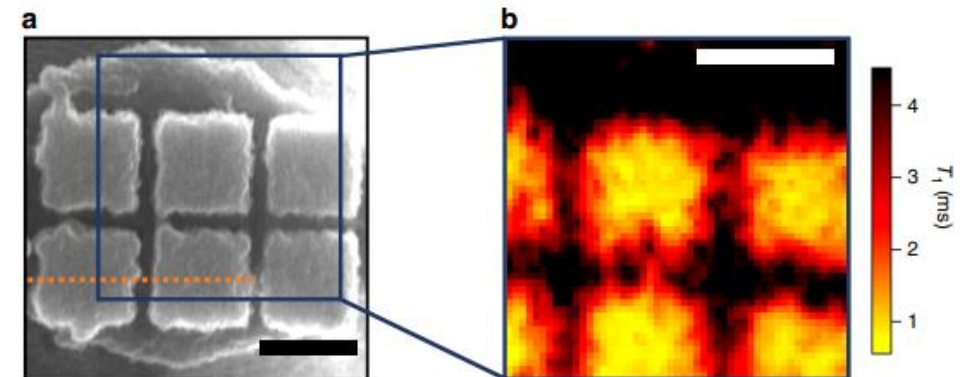
ARTICLE

DOI: 10.1038/s41467-018-04798-1

OPEN

Nanoscale electrical conductivity imaging using a nitrogen-vacancy center in diamond

Amila Ariyaratne¹, Dolev Bluvstein¹, Bryan A. Myers¹ & Ania C. Bleszynski Jayich¹



**What's the longer-term
vision for this?**

Our lab's goal: adaptive automated nanoscale magnetic resonance

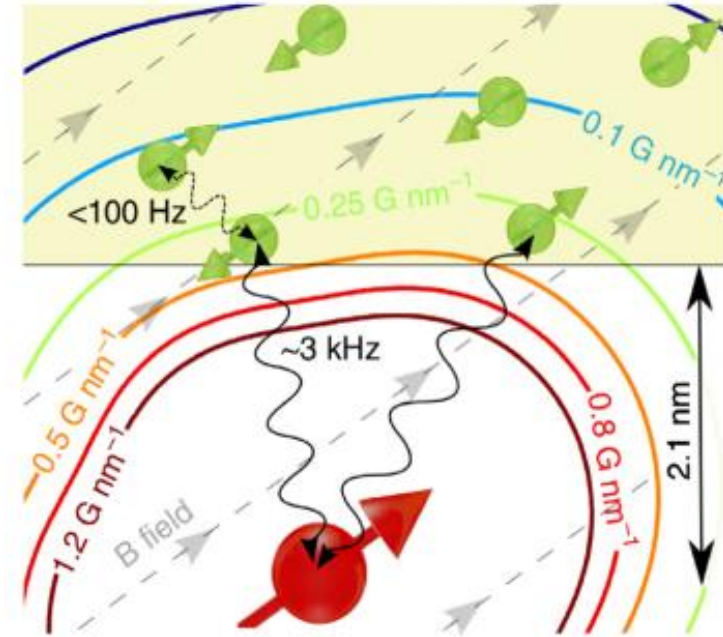
Detecting nuclear spins is important...



Current limits:

- volume $40 \mu\text{m}^3$
- number spins: $10^{13} \text{ Hz}^{1/2}$

Solution: go NANO!

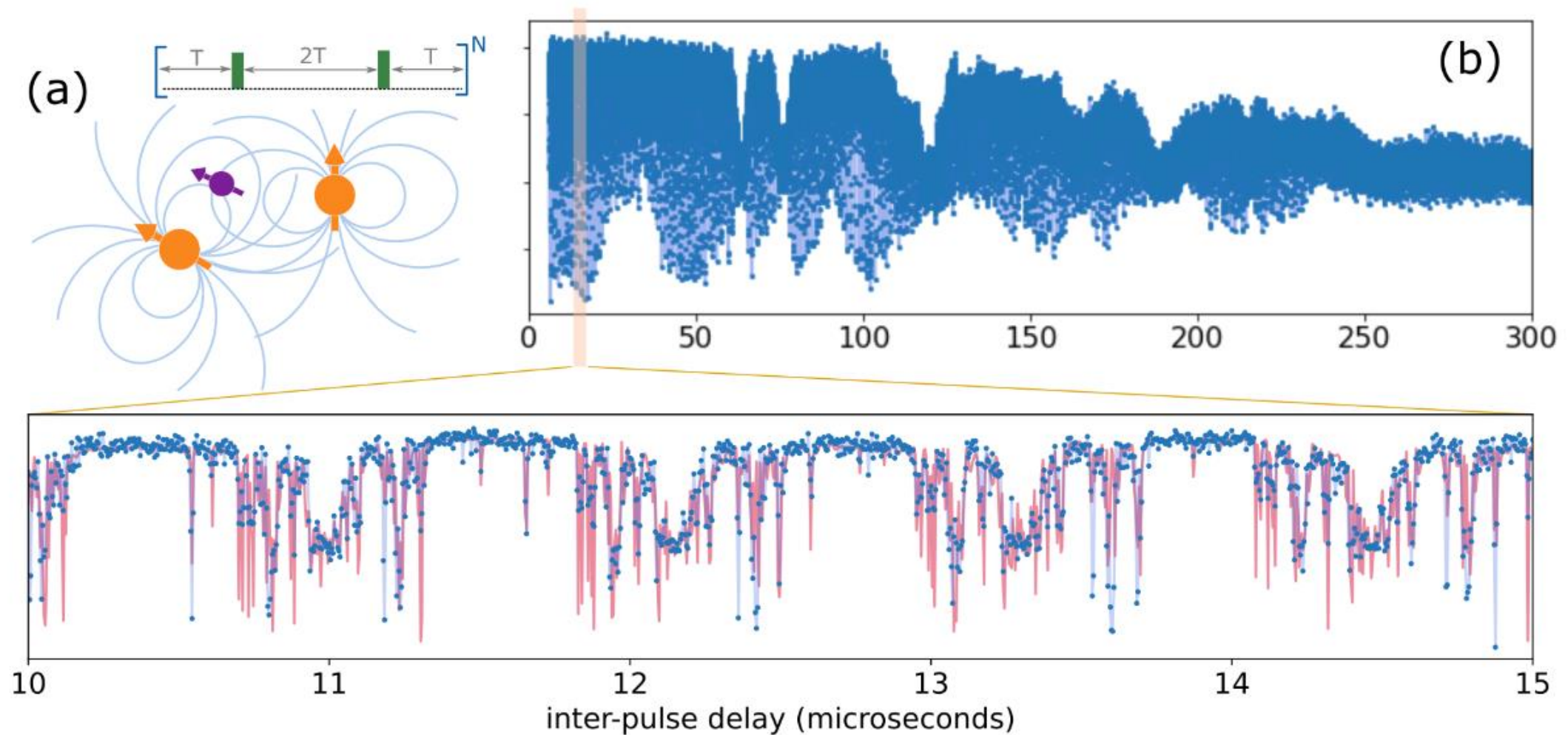


Use a single spin as **nearby** quantum sensor and detect nuclear spins by their dipolar coupling (statistical polarisation!)

See work from Taminiau (Delft), Degen (EH), Wrachtrup (Stuttgart)

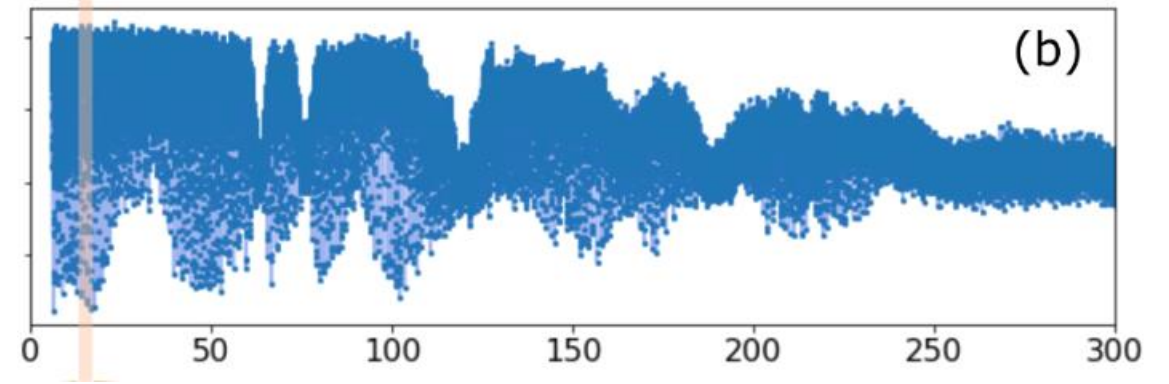
Our lab's goal: adaptive automated nanoscale magnetic resonance

The signal from many individual nuclear spins is complex, data acquisition is time-consuming:



(data from Taminiau group)

Our lab's goal: adaptive automated nanoscale magnetic resonance

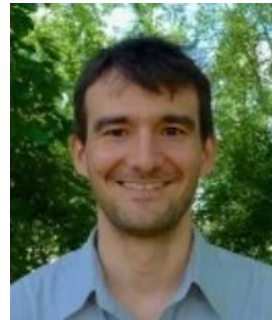


- (1) Can we adaptively optimise data taking for each point?
- (2) Can we adaptive take only the points that give more information?
- (3) How do we automatically fit the data and then link hyperfine values to position (need DFT prior)?

Automating physics: Learning models of quantum systems from data



Stewart Wallace



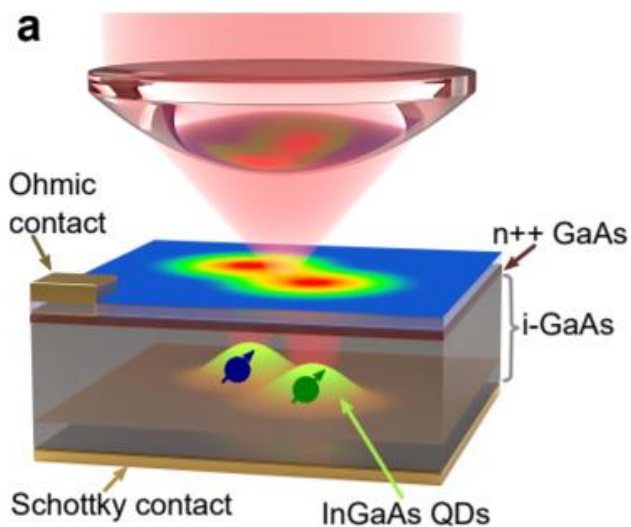
Erik Gauger
(open quantum
system theorist)



Yoann Altmann

Can we learn the model for two “cooperatively-emitting” quantum emitters?

Two quantum dots
brought into resonance:

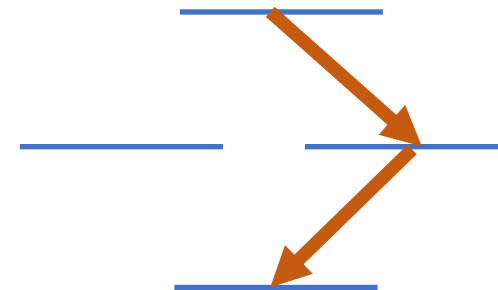


Data from Gerardot's group at HWU
Zhe Xian Koong, Science Adv (2022)

Independent emitters:

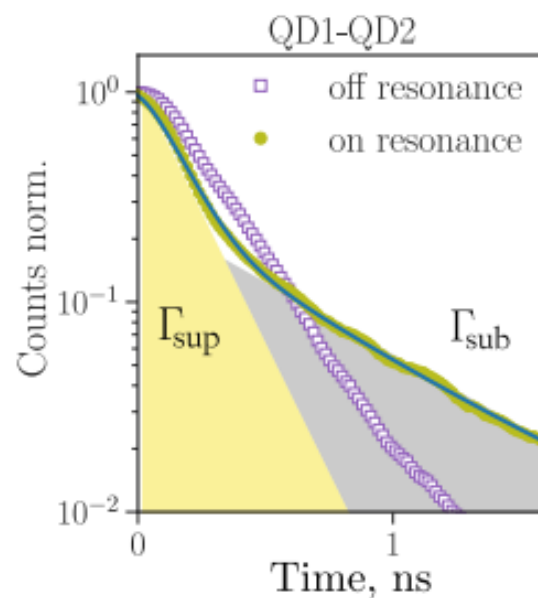


Super-radiance:

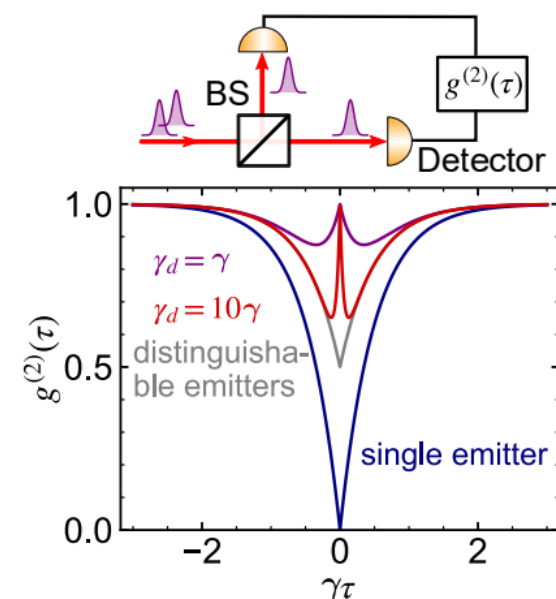


Signatures

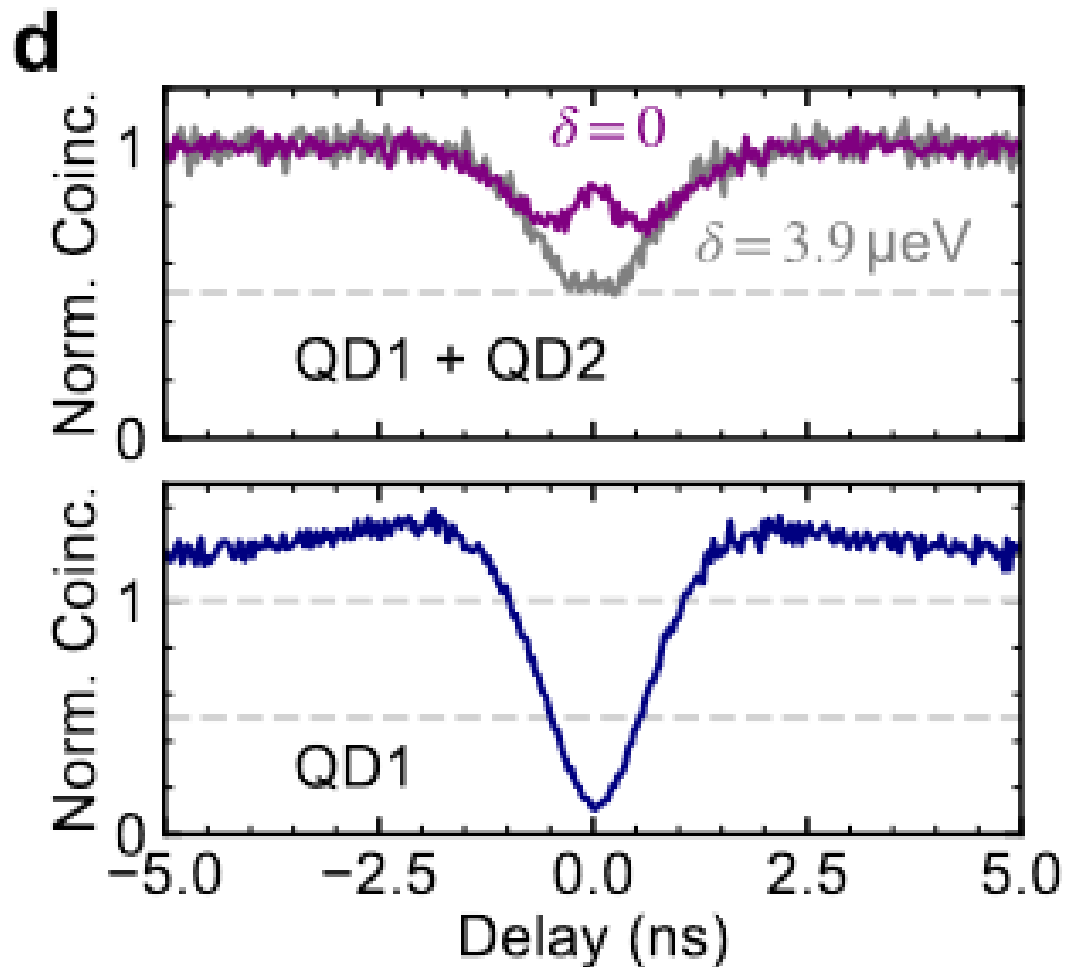
Lifetime:



Correlation ($g^{(2)}$):



Can we learn the model for two “cooperatively-emitting” quantum emitters?



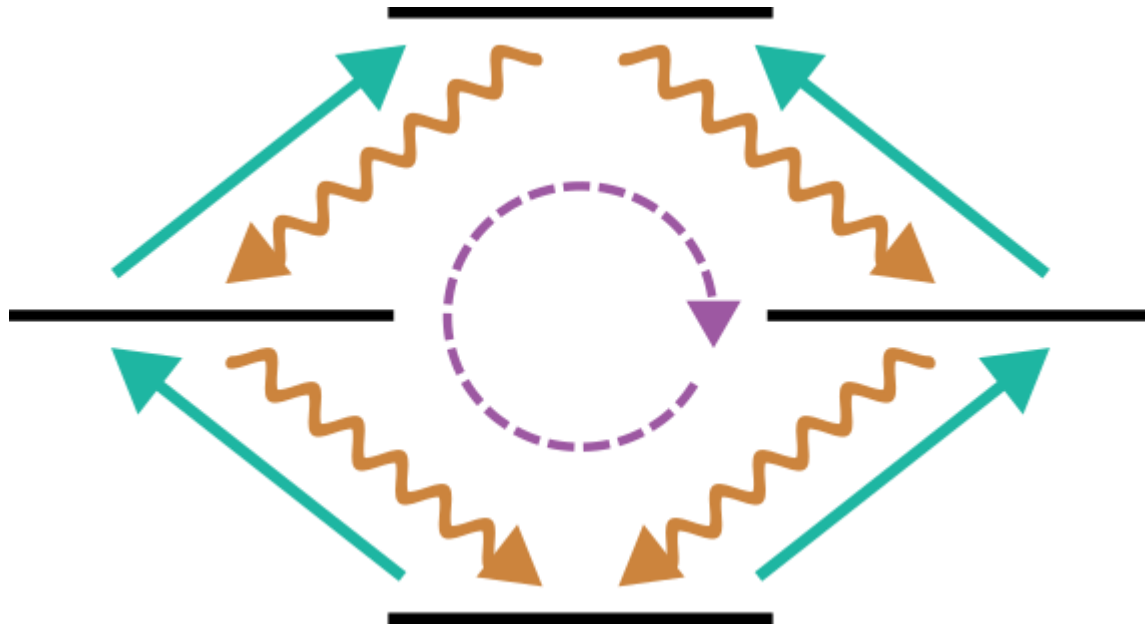
Experimental data:

- lifetime does not appear to be changed
- g_2 shows a small peak

What is going on?

Again, using Bayesian inference

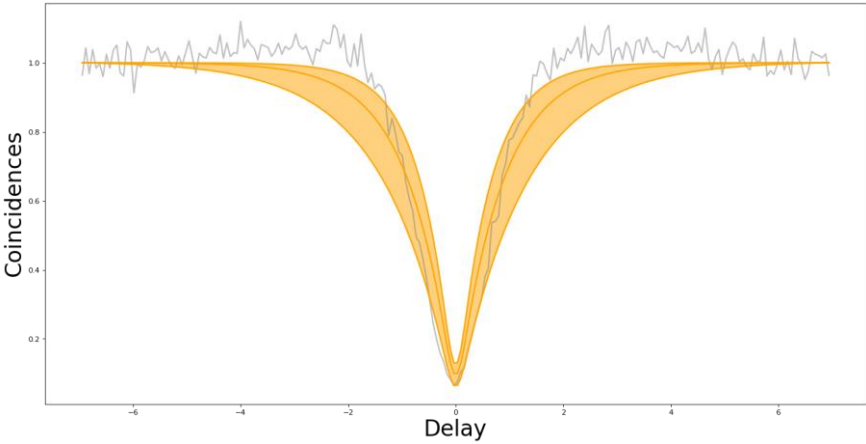
(just a more complex algorithm known as **Markov-chain MonteCarlo**)



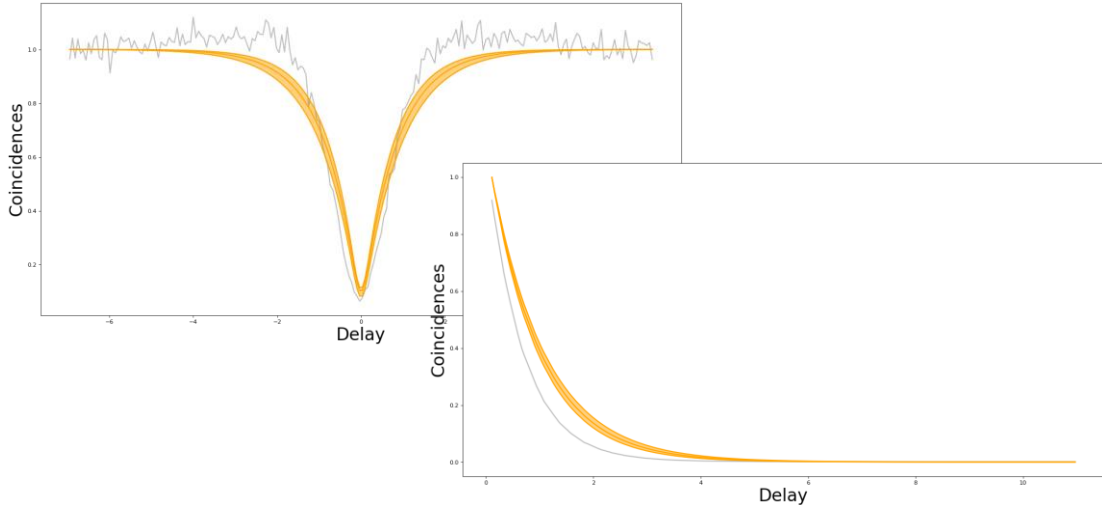
10 parameters = 9 rates + background

- method to sample a probability distribution
- a Markov-chain is used to walk across the parameters space
- every proposed move in parameters space can be accepted or rejected depending on how well it explains the data (Metropolis-Hastings algorithm)

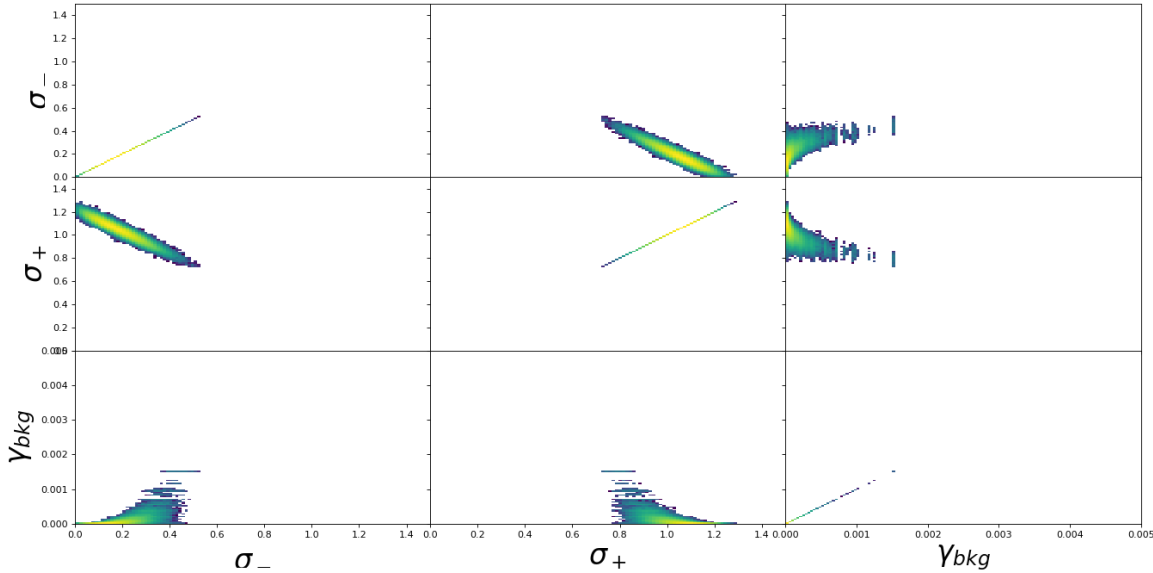
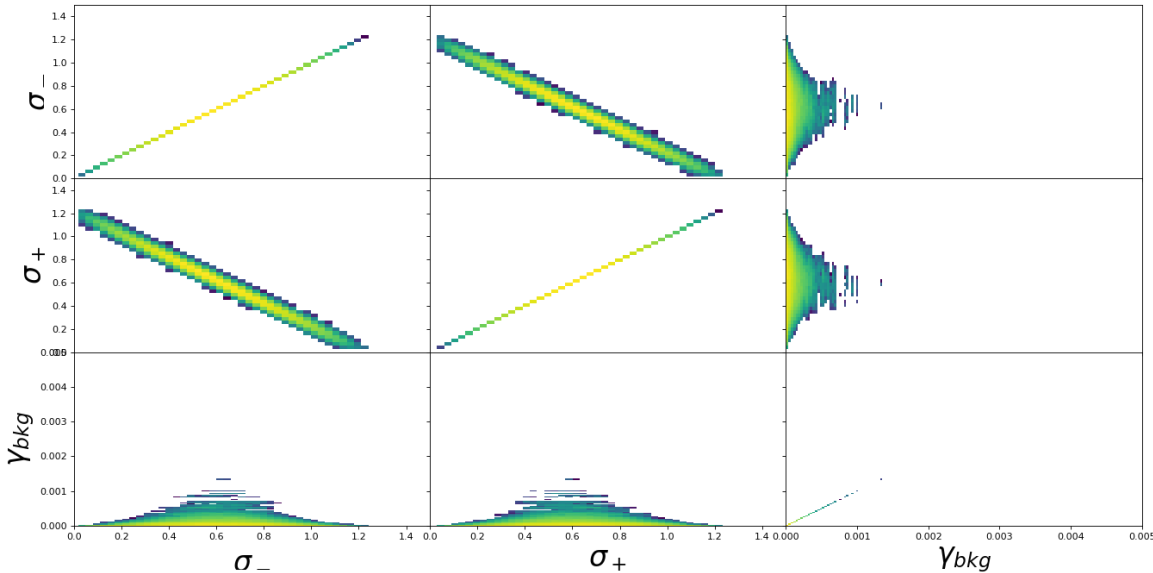
Single emitter estimation (3 parameters)



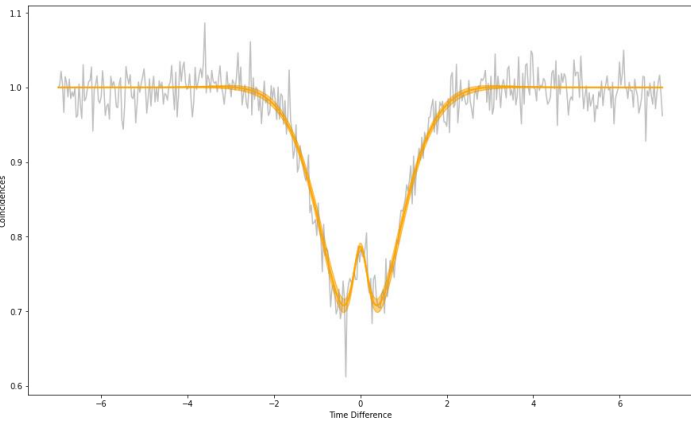
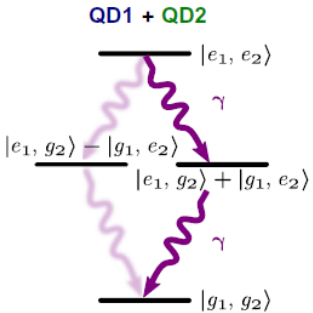
Sharing x per column, y per row



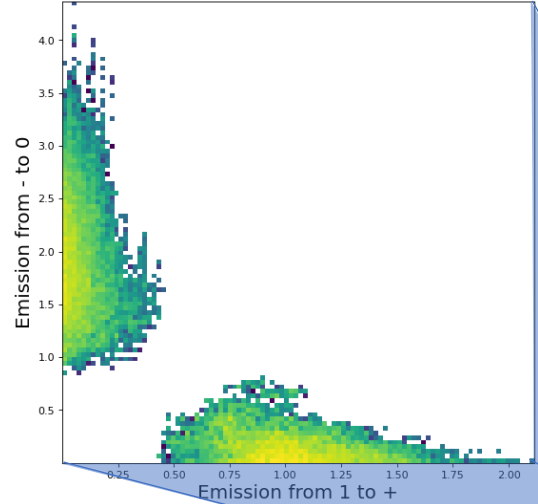
Sharing x per column, y per row



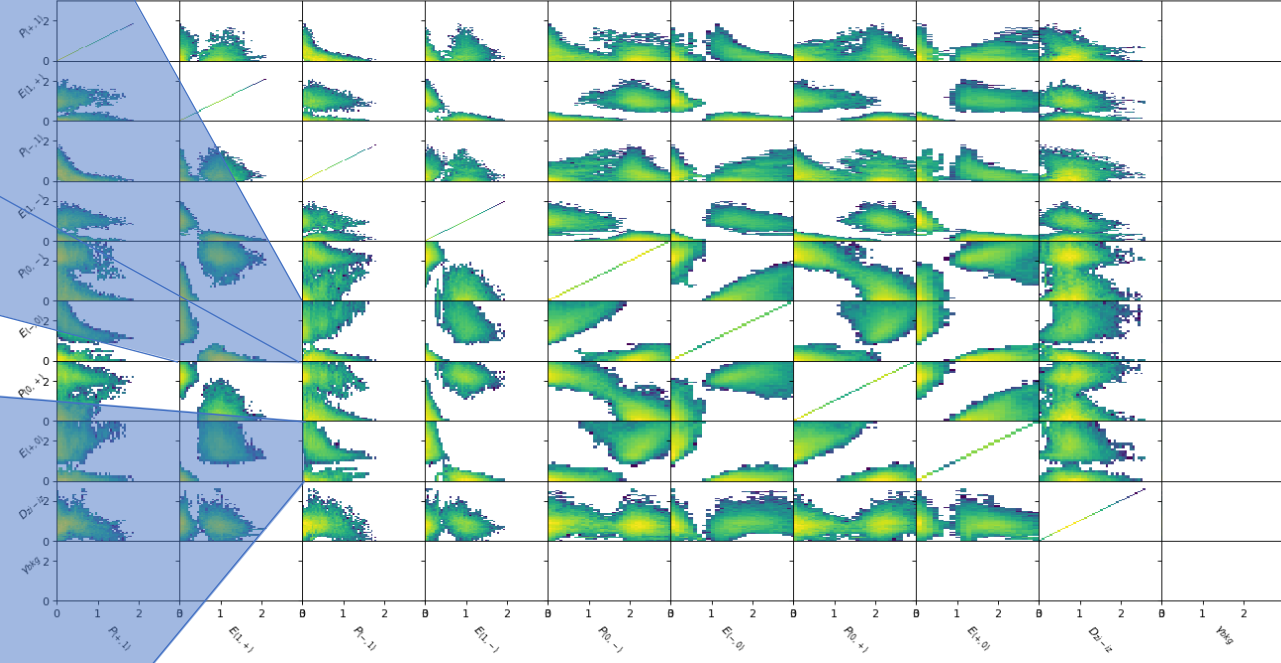
Two emitters estimation (10 parameters)



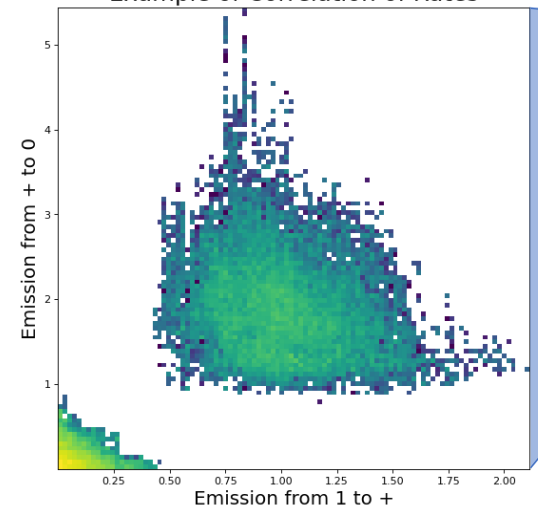
Example of Anti-Correlation of Rates



Cross Correlation of Rates



Example of Correlation of Rates



Can we learn a Lindblad master equation without making assumptions?

We are learning a differential equation of the form:

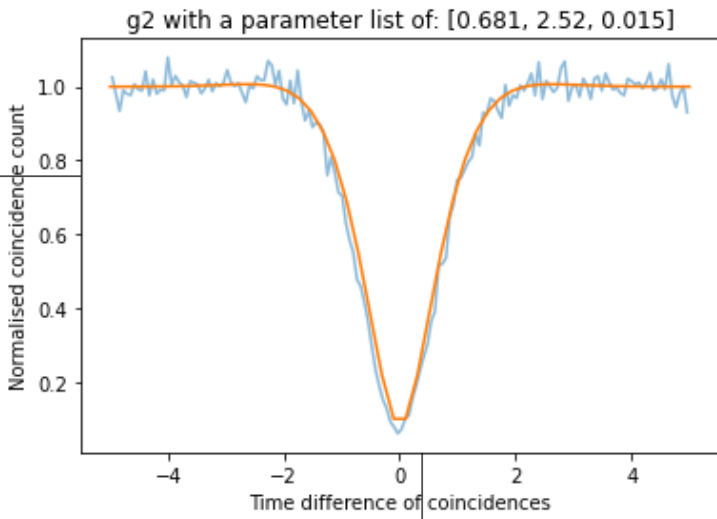
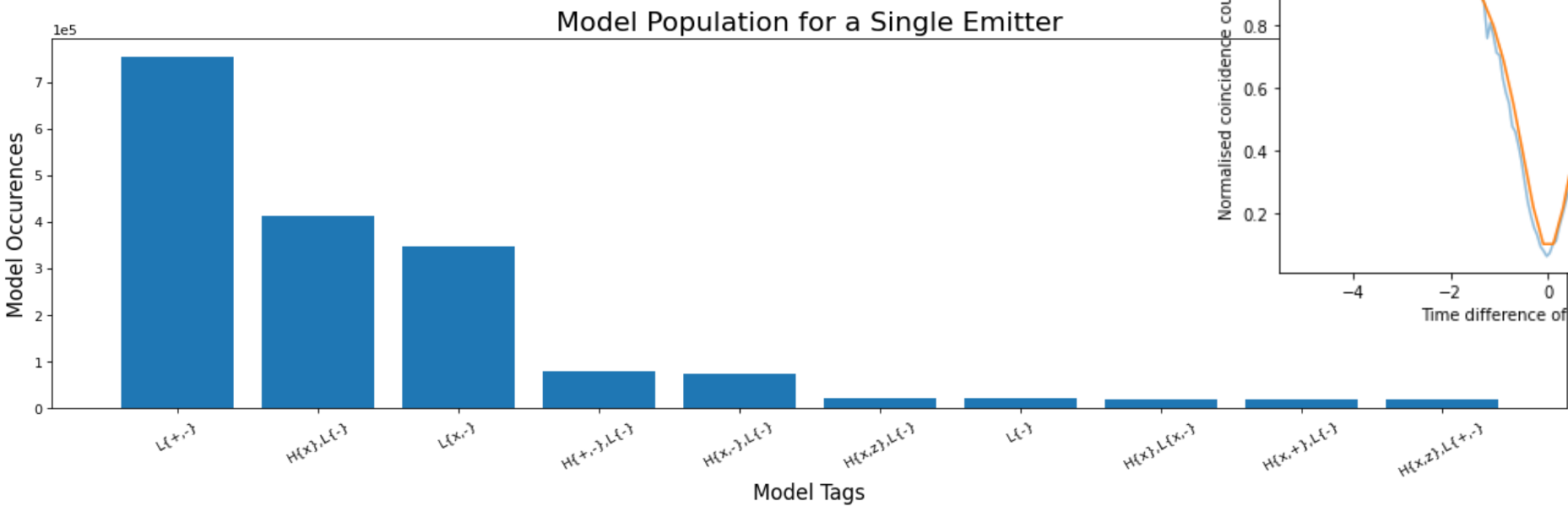
$$\dot{\rho} = -i[\hat{H}, \rho] + \sum_v (\hat{L}_v \rho \hat{L}_v^\dagger - \frac{1}{2} [\hat{L}_v^\dagger \hat{L}_v, \rho])$$

where the number of terms is unknown.

our approach:
reversible-jump MCMC

Can we learn a Lindblad master equation without making assumptions?

First results (showing goodness of fit for different models):



... work in progress ...

Can we learn a Lindblad master equation without making assumptions?

General problem:

The size of quantum systems scales exponentially with size!

N quantum levels \rightarrow matrix $2^N \times 2^N$

e.g. already 256 (complex) parameters with 4 levels

This problem can only be solved in a scalable way with a quantum computer!

To conclude:

(1) Self-optimising experiments

Considerable speed-up for long measurements (nano-MRI for NVs)

(2) “Machine learning” can help physics

We can use most sophisticated tools to help us do physics
(e.g. are there any alternative explanations for our data?)

(3) Capitalising on new instruments

“Programmable” AWGs (Zurich Instruments, Quantum Machines), or
directly FPGAs (for the brave)


(4) Other platforms?

This is obviously not restricted to NVs

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Review article

 Check for updates

Learning quantum systems

Valentin Gebhart^{1,2}, Raffaele Santagati³, Antonio Andrea Gentile⁴, Erik M. Gauger⁵, David Craig⁶, Natalia Ares⁷,
Leonardo Banchi^{8,9}, Florian Marquardt^{10,11}, Luca Pezzè¹²✉ & Cristian Bonato⁵✉

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qpl.eps.hw.ac.uk
c.bonato@hw.ac.uk



Muhammad
Junaid Arshad
(PDRA)



Ben Haylock
(PDRA)



Pasquale Cilibrizzi
(PDRA)

Quantum (Theory)



Erik Gauger



Hannah Scott
(PhD)



Stewart Wallace
(PhD)



Issam Belgacem
(PhD)



Nick Werren
(PDRA)



Malte Kroj
(intern)

Applied statistics



Yoann Altmann