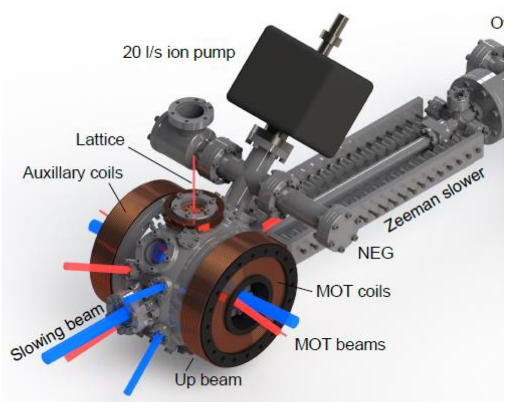
Machine Learning in QM experiments

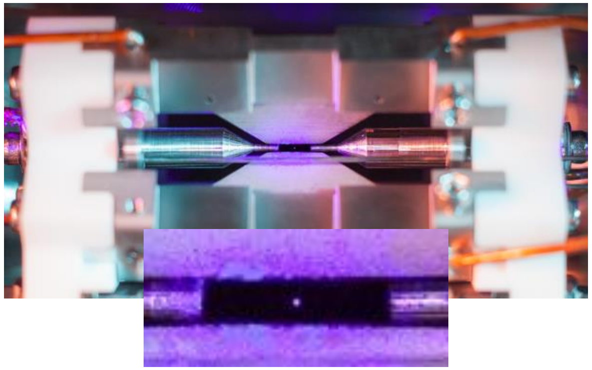
DR. ELLIOT BENTINE

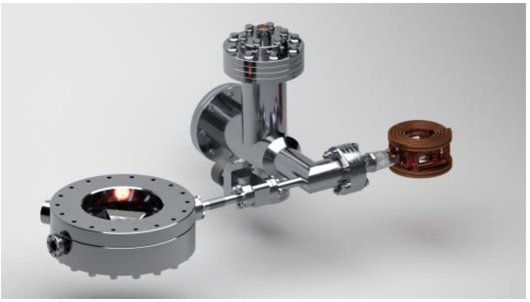
Aims of this talk

- Give an appreciation of the **complexity** of modern quantum mechanics experiments.
- Understand **why** they are well suited to machine learning techniques.
- Showcase examples where machine learning has been used to **optimise these experiments**.

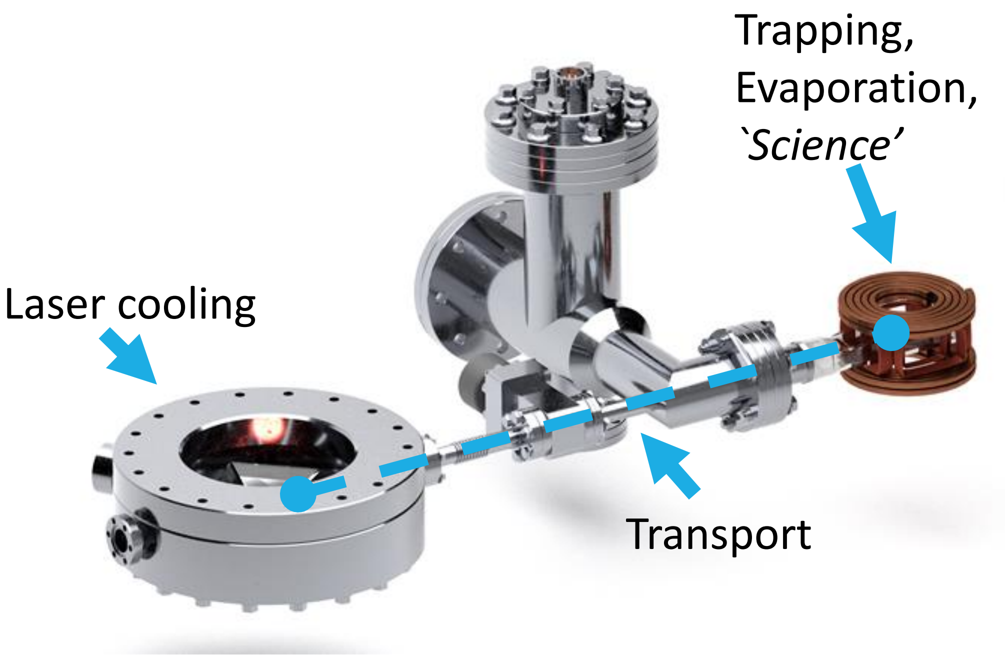
Why build these experiments?

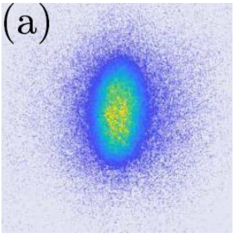


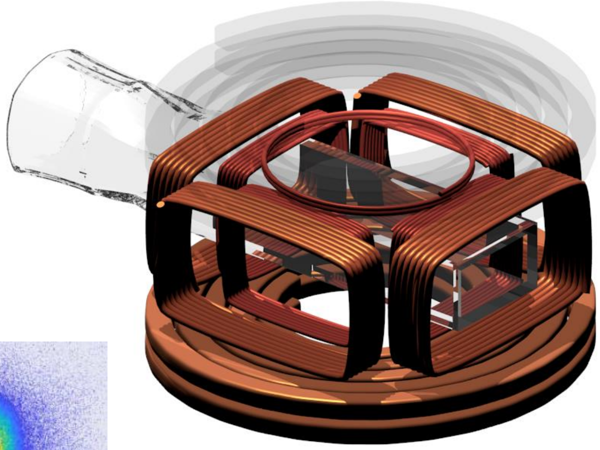




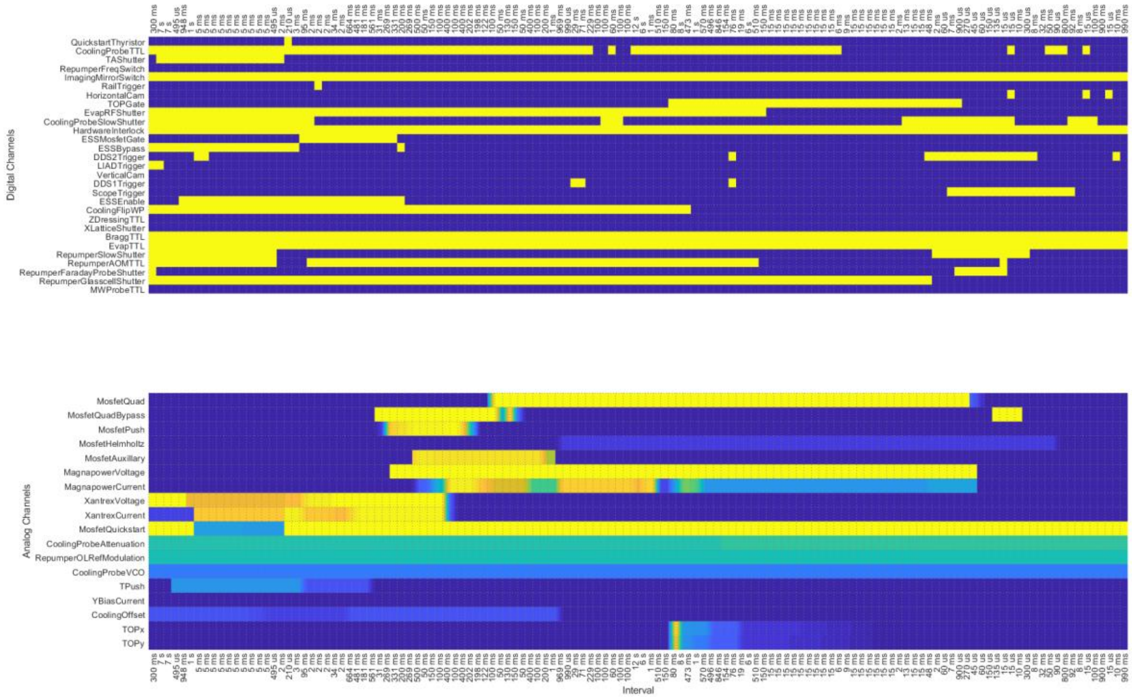
A typical apparatus







A typical sequence



- Large number of experimental parameters.
- Complex sequence in time-domain.
- **Vast** parameter space.
- …but **already computer controlled!**

Machine learning: optimisation

PRODUCING ULTRACOLD GASES

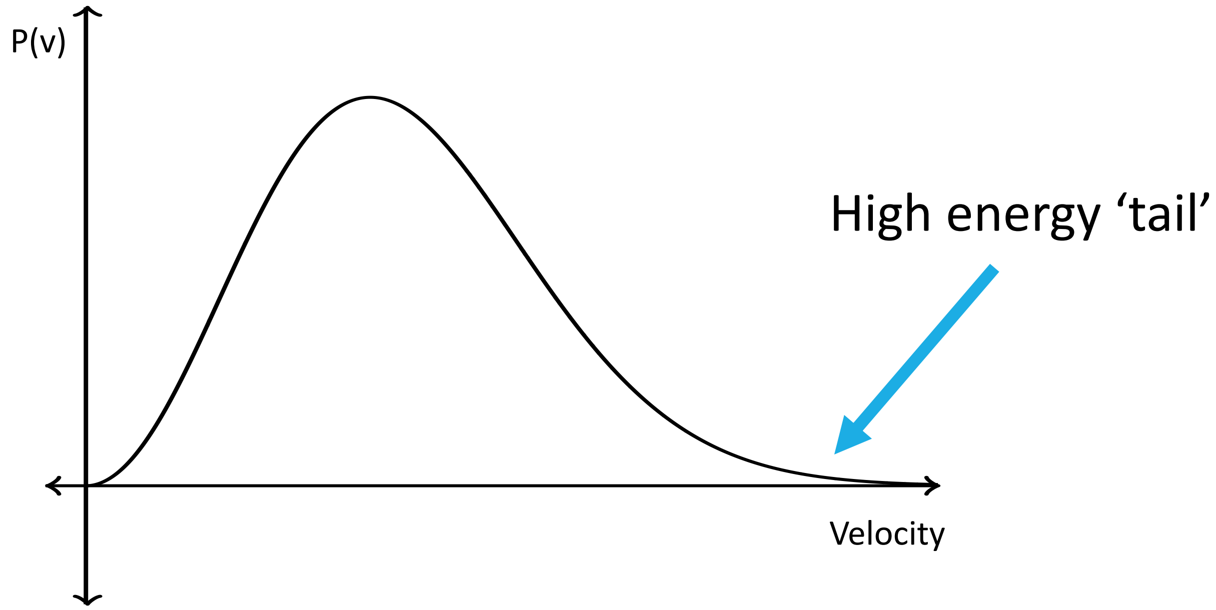
Why machine learning?

- Learner acquires an **intuitive understanding** of how an experiment behaves with no *a priori* model.
- **Unbiased**, led only by the data itself. May find counter-intuitive and unexpected solutions.
- **Patience:** Can meticulously and rigorously explore a parameter space, without distraction.
- Optimisation **frees experimentalists** to think about the physics.

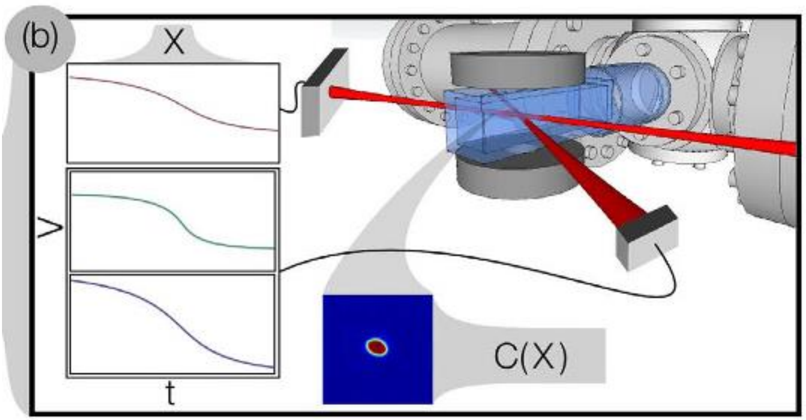
Two workhorse techniques:

- Evaporative cooling 
- Laser cooling 

Evaporative cooling

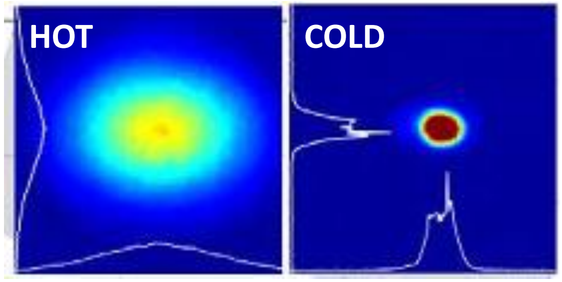


Optimisation of evaporative cooling



- Atoms confined through the dipole force.
- Trap formed by red-detuned laser beams.
- Trap depth proportional to the intensity of the laser beams.
  - Maximum here of ~70 uK
- Evaporative cooling by ramping the laser beam intensity.

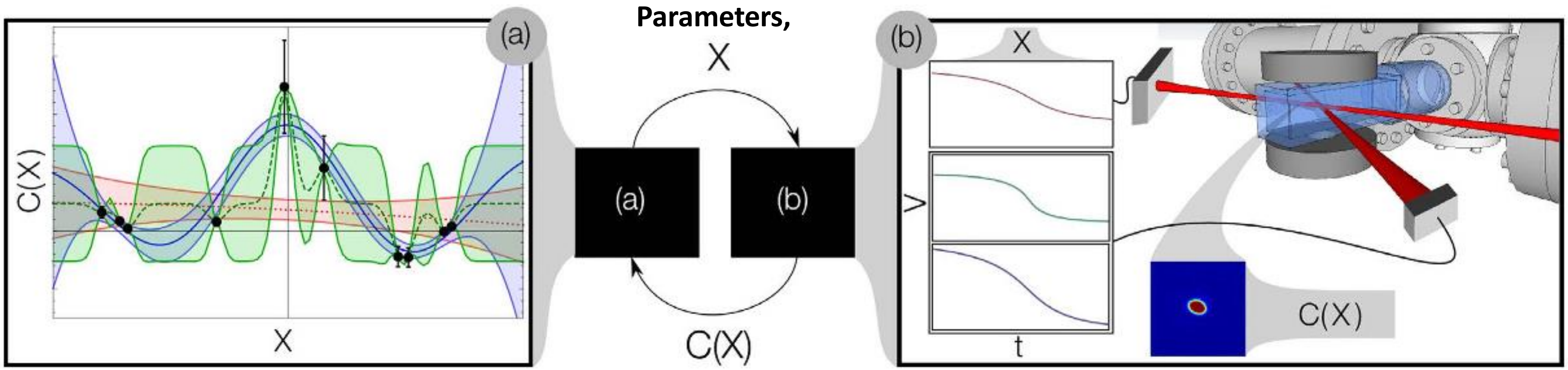
Measure temperature by imaging the atom distribution after time-of-flight
→ provides a means to measure performance



Optimisation of evaporative cooling

- Goal: Maximise phase space density at the end of evaporative cooling → produce colder, denser clouds
- Wigley et al model the experiment as a **Gaussian Process**.

Parameters,

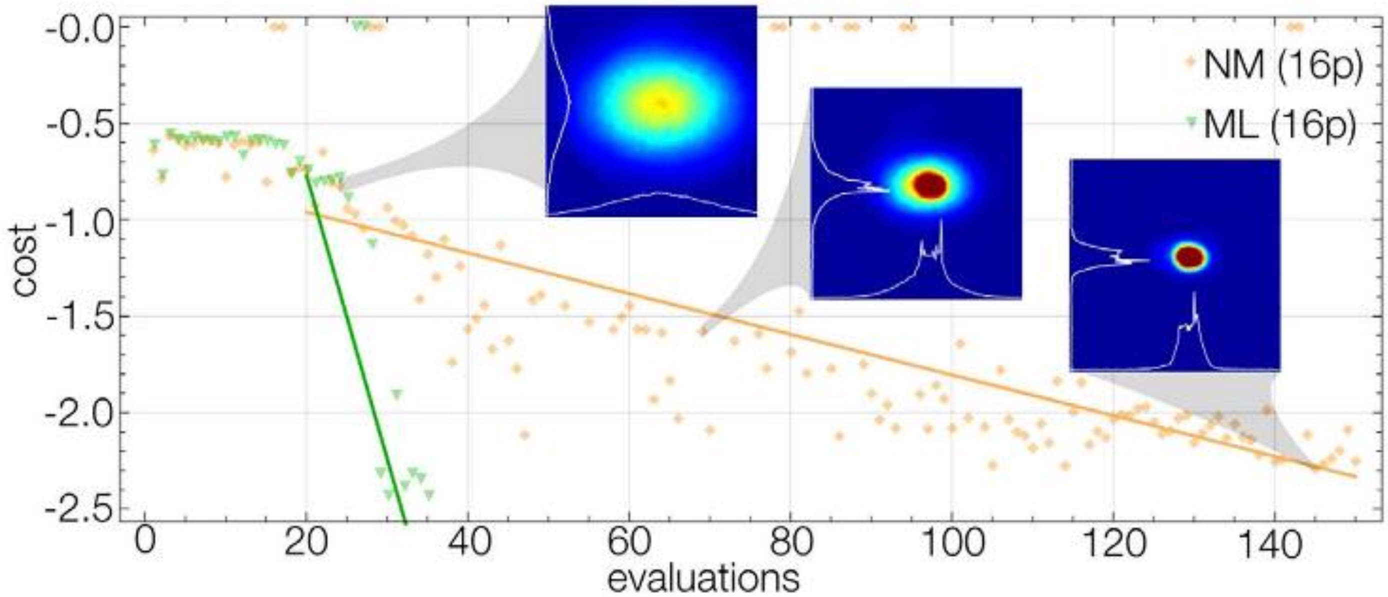


Gaussian Process
(Model of the experiment)

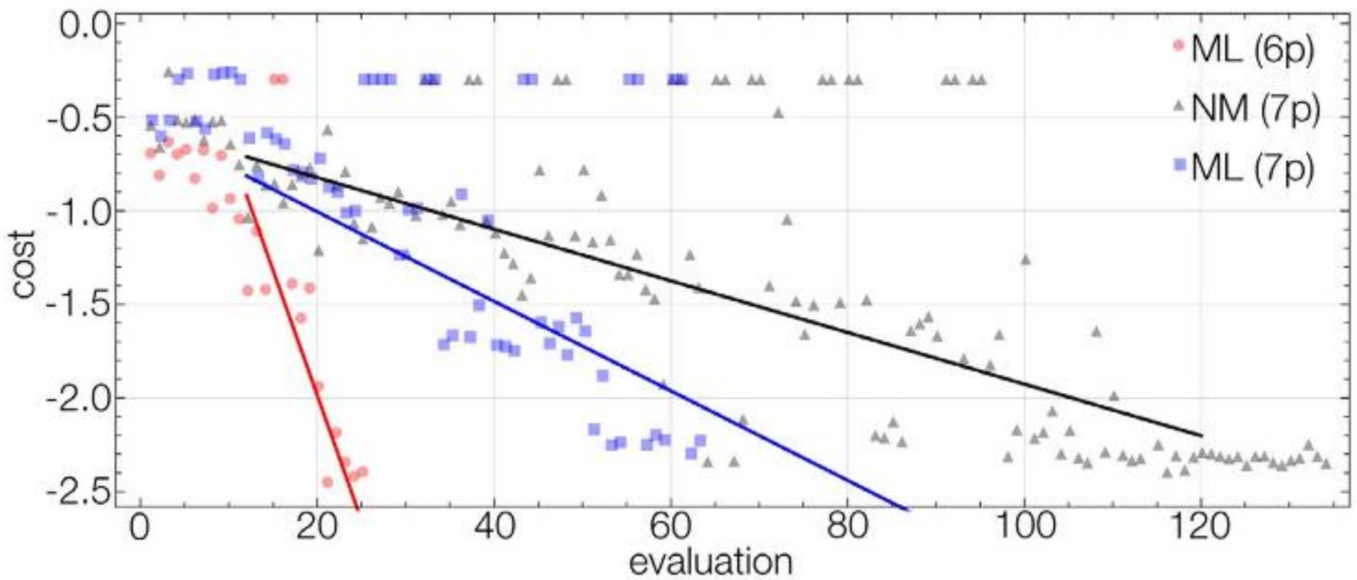
The cost function
Measure of performance

The experiment
(Driven by parameters X)

Optimisation of evaporative cooling

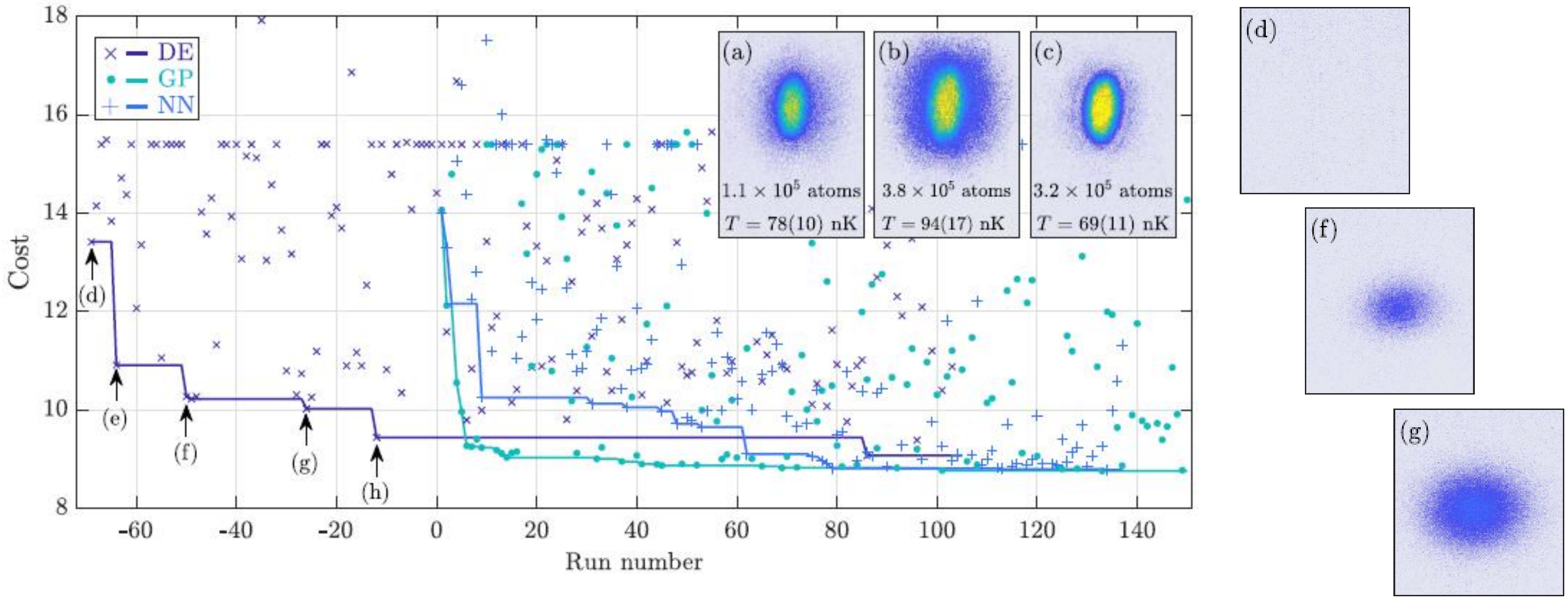


Optimisation of evaporative cooling

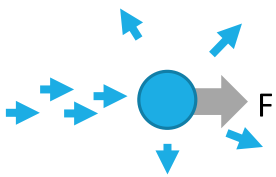


- Optimising using Gaussian Process gives **fast convergence** and allows the **most important parameters** to be determined.

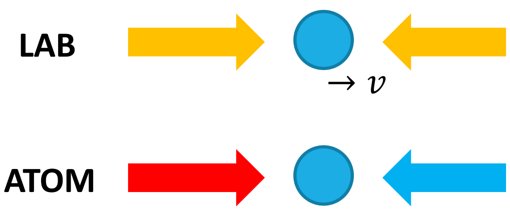
Benchmarking the Gaussian Process



Laser cooling

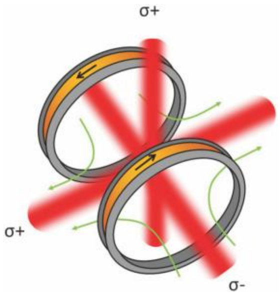


- Photons have momentum $\hbar k$.
- Absorption from a well-defined direction.
- Re-emission in a random direction.
- Net force applied.

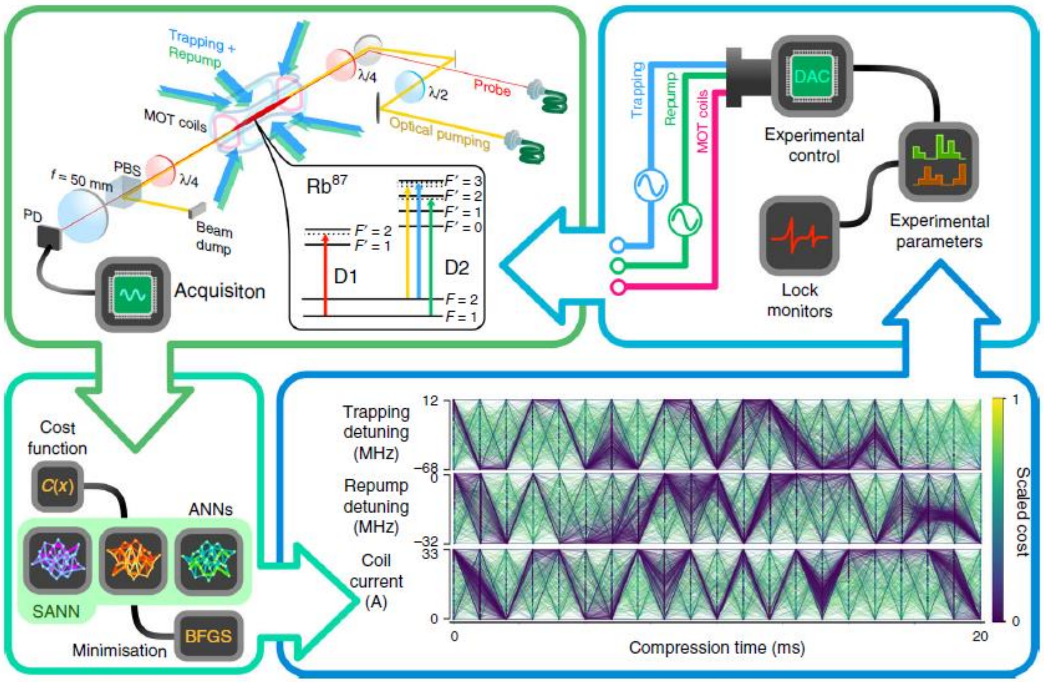


- Atoms scatter photons within a narrow range of frequencies.
- Use **doppler shift** to favour absorption from laser beam opposite to direction of travel.

- To make a trap, apply a magnetic field gradient.
- Detuning becomes spatially dependent through the **zeeman effect**.



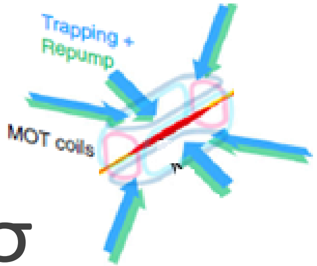
Optimisation of laser cooling



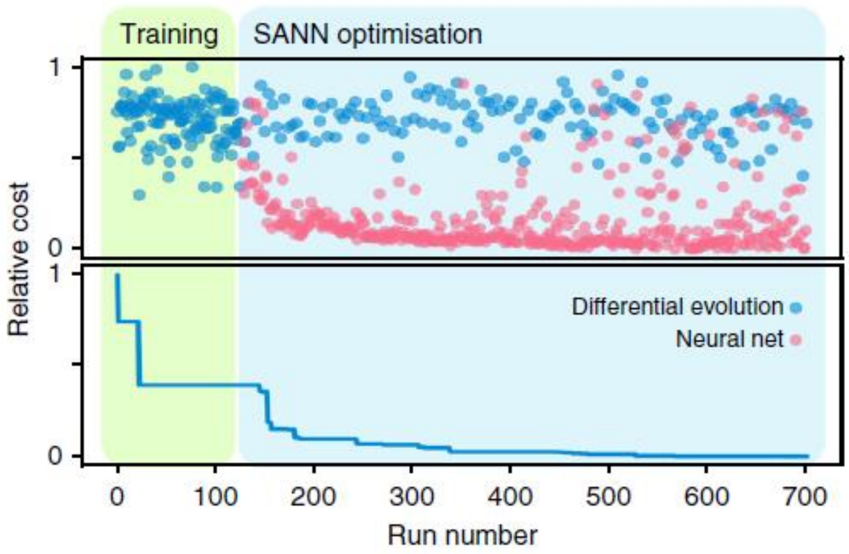
- 3 control variables:
  - Cooling light detuning
  - Repumping light detuning
  - Magnetic field gradient
- Separated into 21 time bins
- 21x3=63 total parameters

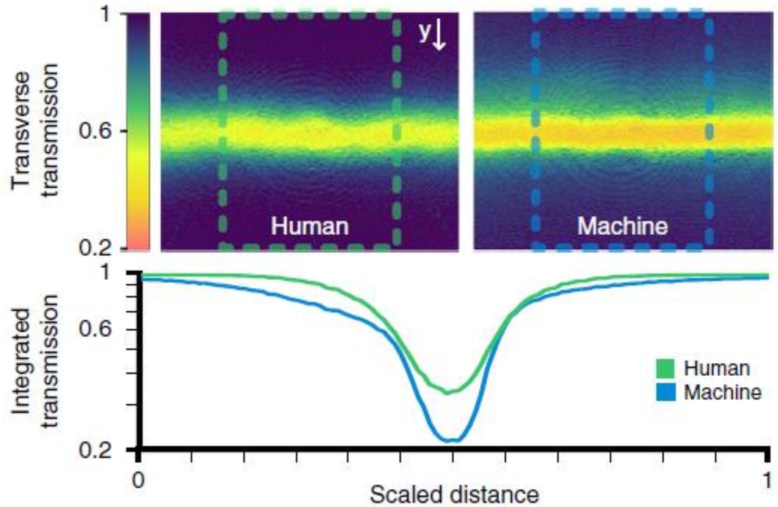
- Optimise **optical density**.
- Absorption through cloud measured using a photodiode.

- Use 3 Neural networks to model behaviour of experiment.



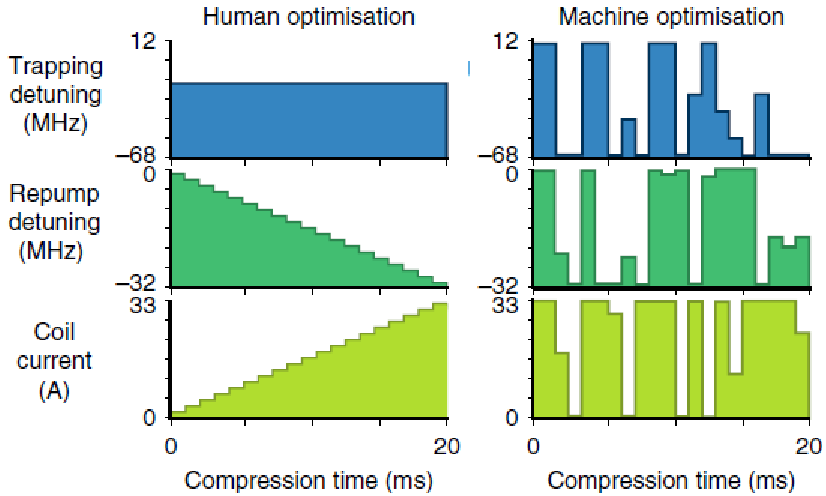
Optimisation of laser cooling

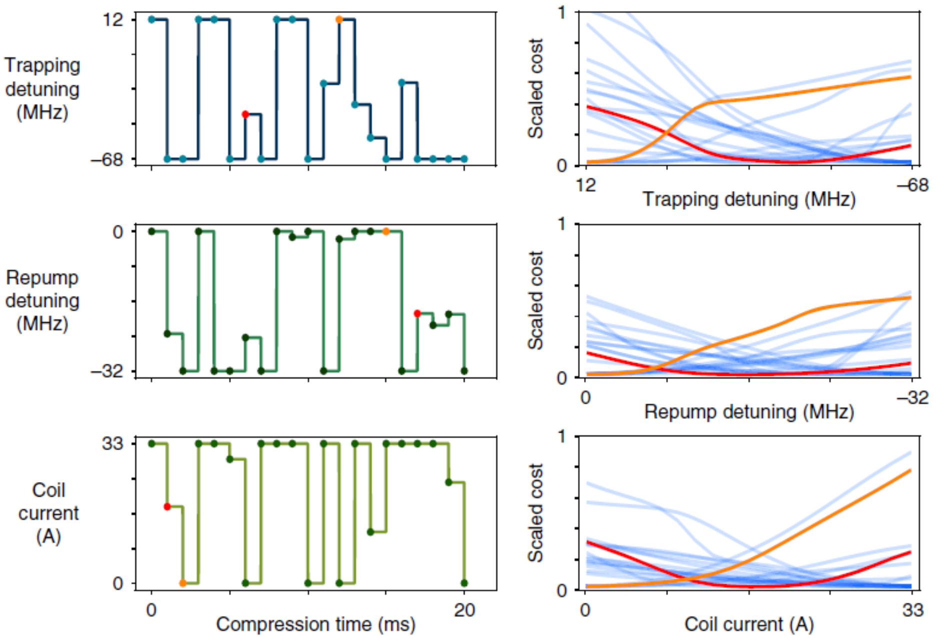




Optimisation of laser cooling

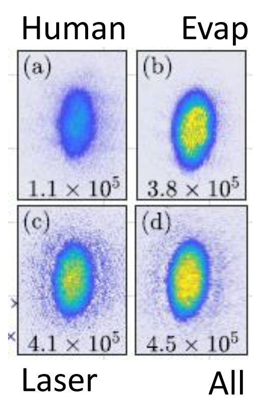
ML produces a better sequence, with entirely unpredicted features.

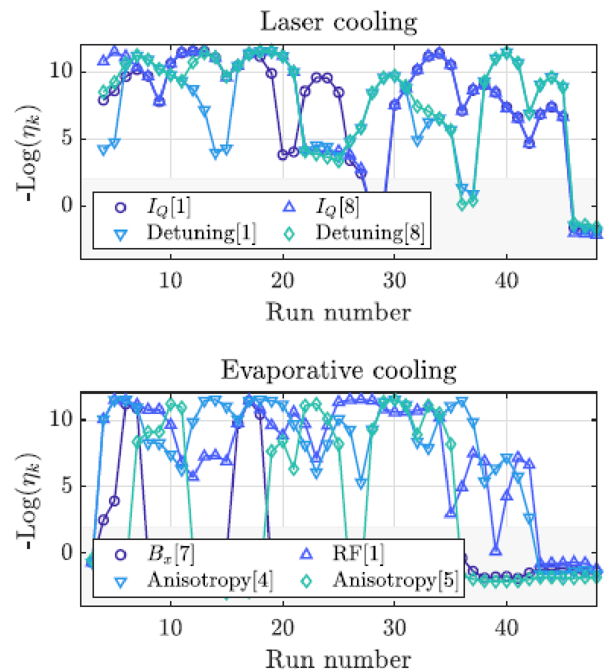




Multi-stage optimisation

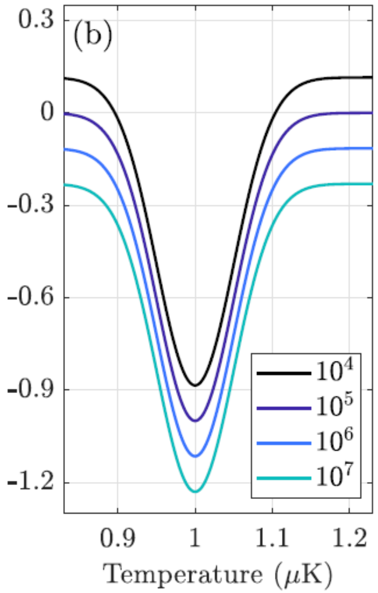
- We perform a full optimisation of all stages of our apparatus.
- First, use Gaussian Process to reduce the parameter space.
- Optimise most important parameters from each stage.

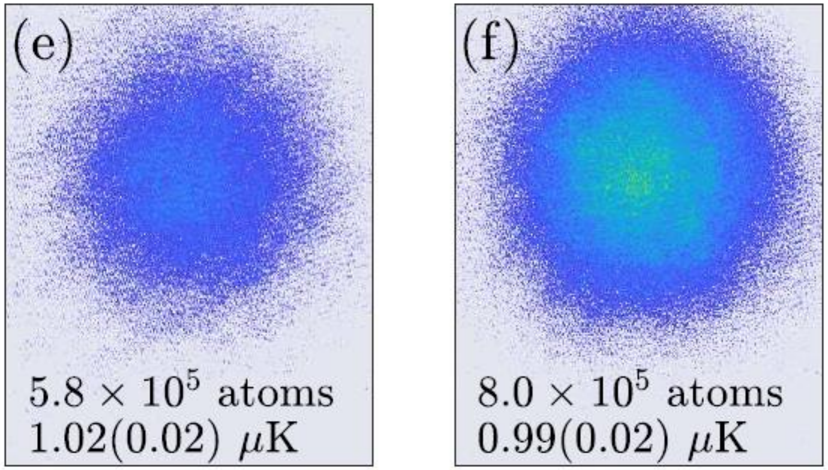




Tailoring the cost function

- Easily re-optimise for specific scenarios – just redefine the cost function to suit goal!



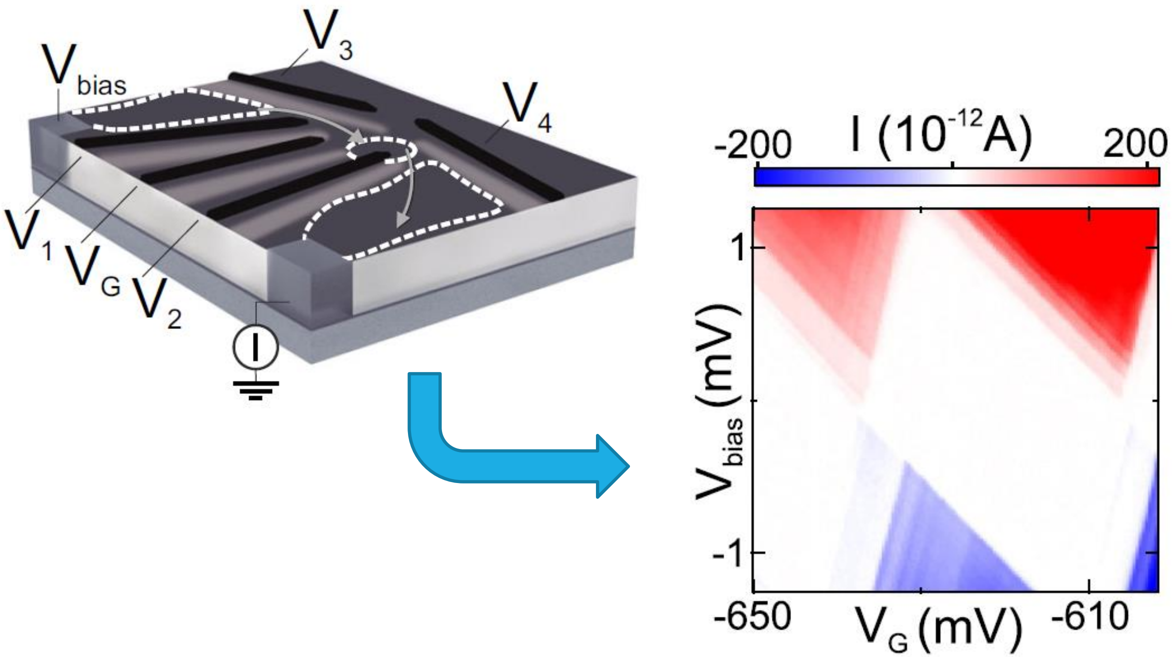


Here: maximise atom number at a desired temperature.

Machine learning: characterisation

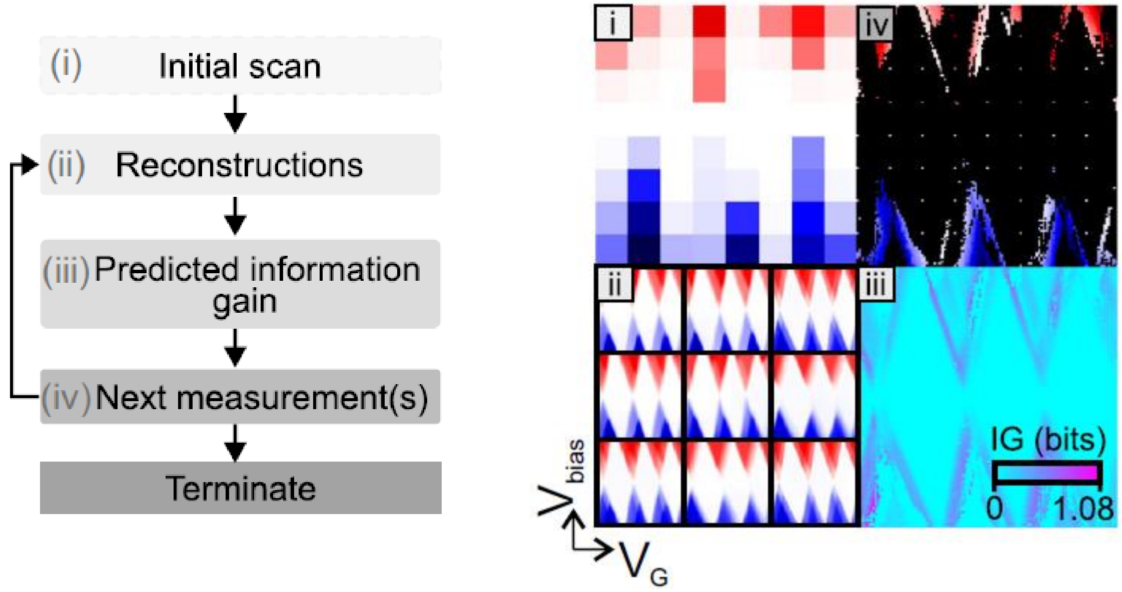
FAST AND EFFICIENT EVALUATION OF DEVICES

Efficiently Measuring a Quantum Device

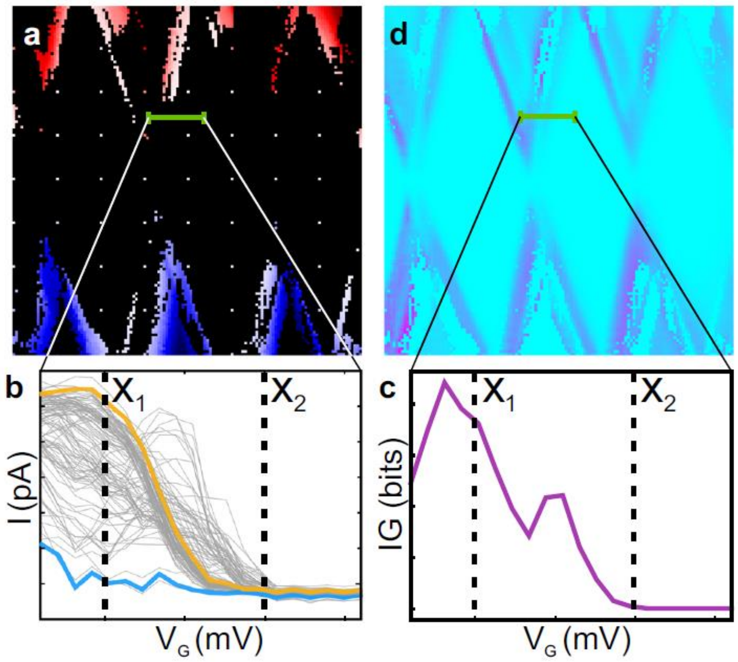


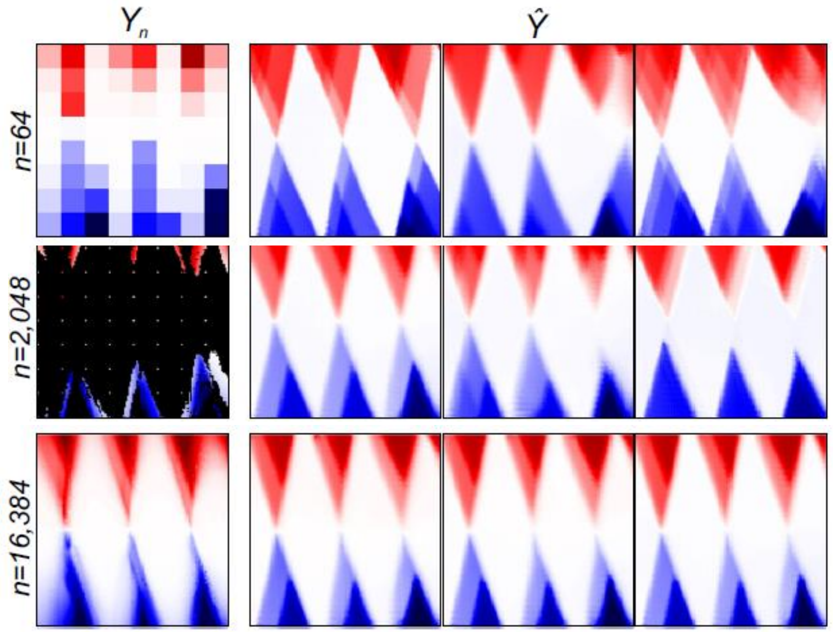
- Goal: to accurately characterise a quantum device with as few measurements as possible.
- Device characterised by measuring conductance for different electrode voltages.
- **What measurements should we make to extract the largest possible amount of information**?

Efficiently Measuring a Quantum Device



Efficiently Measuring a Quantum Device





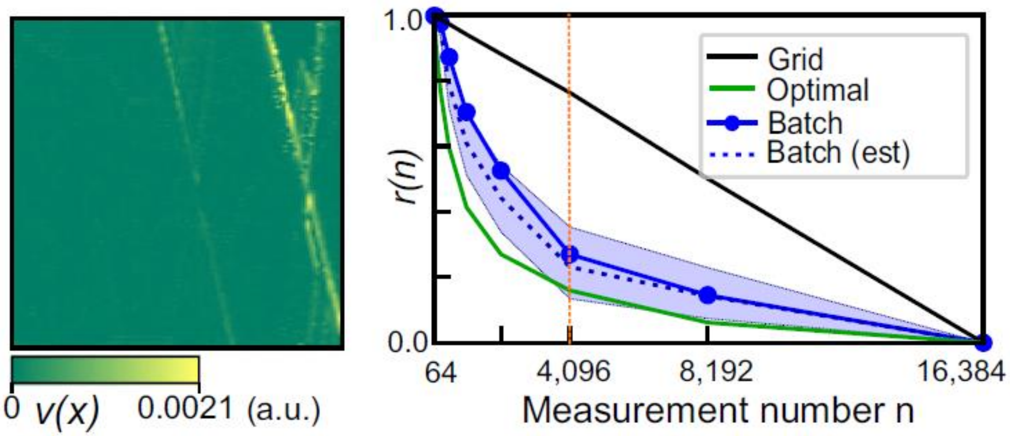
Efficiently Measuring a Quantum Device

- Define gradient:

$$v(x) = \sqrt{\left(\frac{\partial I(x)}{\partial V_G}\right)^2 + \left(\frac{\partial I(x)}{\partial V_{bias}}\right)^2}$$

Define information content:

$$r = 1 - \frac{\Sigma_m v(m)}{\Sigma\, v(m)}$$



The ML performance is close to optimal, it greatly outperforms a simple raster scan.

Conclusions

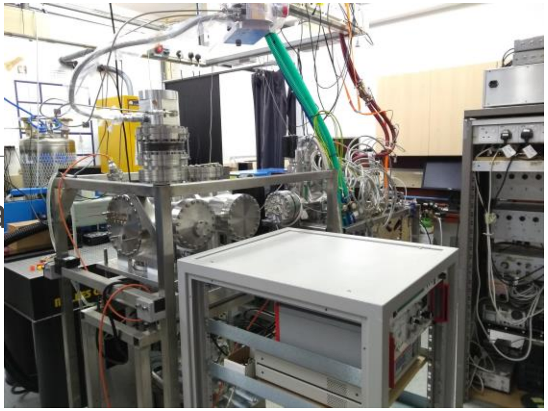
- Learner acquires an **intuitive understanding** of how an experiment behaves with no *a priori* model.
- **Unbiased**, led only by the data itself. May find counter-intuitive and unexpected solutions.
- **Patience:** Can meticulously and rigorously explore a parameter space, without distraction.
- Optimisation **frees experimentalists** to think about the physics.

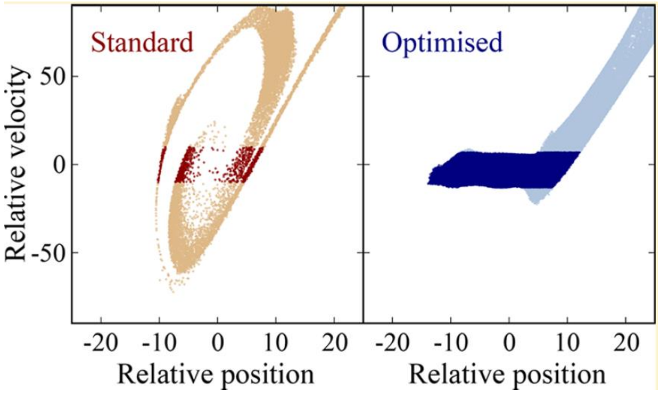
Thank you for listening

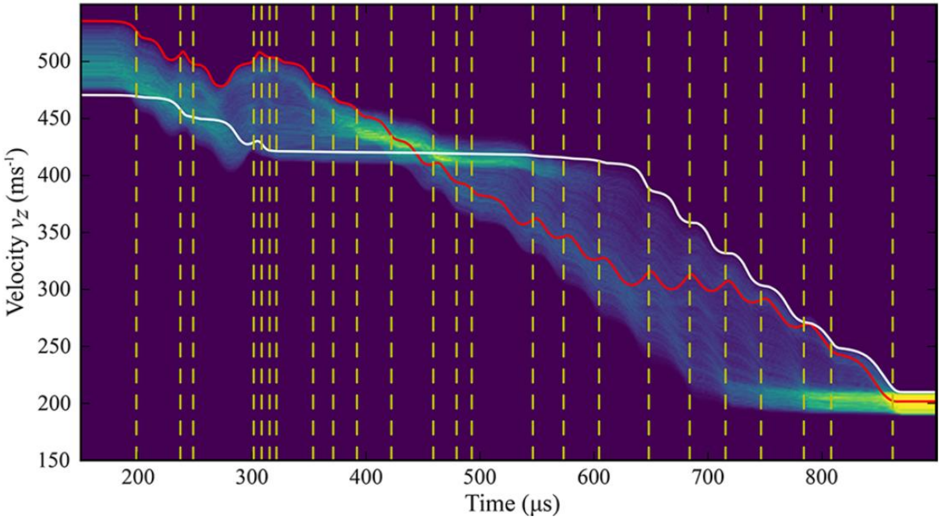
QUESTIONS

Zeeman Deceleration:

- Optimise the cooling of atoms using applied pulsed ma
- Evolutionary algorithm
- 60-fold increase in the flux of cooled atoms!







More detail on the cost function