Nondestructive Characterization of Cold Atomic Clouds with Machine Learning

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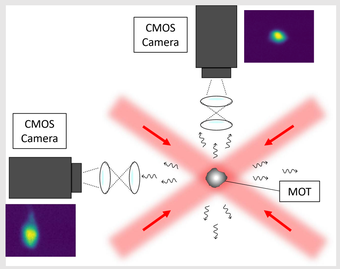
Abstract

We present machine learning techniques in conjunction with a varied dataset of laser cooled potassium-39 atoms in vapor fed magneto-optical traps for the prediction of physical parameters (i.e. number of atoms and temperature) of these atomic ensembles using only scattered light (fluorescence) images. The light emitted from fluorescing clouds provides structural information with known techniques to extract an estimate of atom number, but other internal properties, namely cloud temperature, are currently "hidden" until the trap is released and a free expansion image is captured, in turn destroying that instance of captured atoms. We collect a wide ranged and balanced dataset of approximately 5 x 10^3 unique parameter groups that have (potentially) captured atoms; the set spans cases of no discernable captured atoms to large dense groupings of atoms, and a variety of oddly shaped and sized atom clouds betwixt. The data is then distilled into meaningful images with systematic generation of labels, including a label for presence of a cloud in the image and quality of cloud fitting for trusted calculation of temperature and atom number. Several machine learning models with increasing complexity are then trained to predict the atom number and temperature using only the non-destructive images and labels, with no access to the free expansion images typically required for such characterization. Trained models include a single layer matrix multiplication, a deep fully connected network (FNN), and a convolutional neural network (CNN).

Background and Motivation

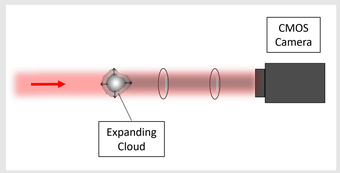
Magneto-Optical Trap (MOT): Capture technique using lasers and a quadrupole magnetic field for cooling and trapping neutral atoms from vapor.

Fluorescence Imaging



- ***Nondestructive technique***
- ***Can estimate atom number***
- ***One run of the experiment***

Absorption Imaging



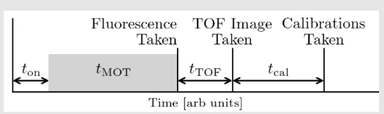
- ***Destructive technique (releases trap)***
- ***Can determine temperature and atom number***
- ***Multiple runs of the experiment***

Goal: Use machine learning models to **predict both temperature and atom number** using only the nondestructive **fluorescence images.**

Data Collection

Atomic Species: Potassium-39 (K^{39})

Experimental Shot Sequence



Images Generated

- A shot is one instance of the sequence; Five shots comprise a set (identical parameters)
- Full dataset contains **~ $6.8\ x\ 10^3$ experimental sets / $3.4\ x\ 10^4$ experimental shots**
- Each set has parameters varied to make unique clouds (and sometimes no cloud at all)

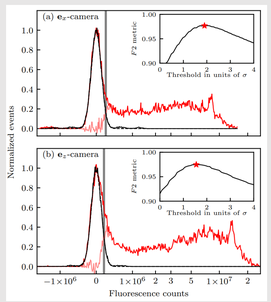
Table of Parameters Varied During Data Collection

Symbol	Label	Approximate range	Description
V_{cool}	Cooling_AOM_Volts	0.1 V to 1.5 V	Parameter: Voltage of the cooling laser beam's AOM. Controls the intensity of the cooling laser beam.
V_{rep}	Repump_AOM_Volts	0.4 V to 1.5 V	Parameter: Voltage of the repump laser beam's AOM. Controls the intensity of the repump laser beam.
f_{lock}	Cooling_Lock_Offset	85 MHz to 95 MHz	Parameter: Controls the frequency offset of the cooling laser with respect to the repump laser
f_{rep}	Repump_AOM_Freq	74 MHz to 94 MHz	Parameter: Controls the frequency offset of the repump laser beam compared to the repump laser source
I_{quad}	MOT_Quad_Amps	2 A to 40 A	Parameter: Current of the MOT quadrupole coils. Affects the strength of the magnetic field
t_{MOT}	MOT_Loading_Time	100 ms to 1 800 ms	Parameter: Duration of MOT loading time
t_{TOF}	TOF_Time	1 ms to 5 ms	Set variable: Time of flight

Generating Labels

MOT Thresholding in Fluorescence

Fluorescence images are labeled using counts in each image compared to a "No MOT" threshold for each camera.



Absorption Images and Fitting

Absorption images are labeled based on fits to 2D Gaussian functions. Fits are constrained to maintain density as they spread.

Each fit labels a set of shots with atom number, temperature, and reliability predictions. If the fit completely fails, the set is labeled invalid.

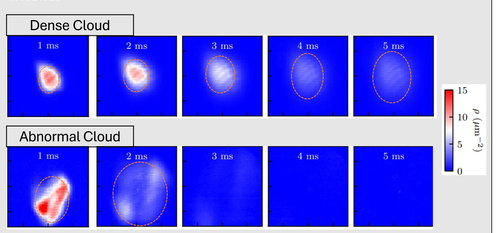


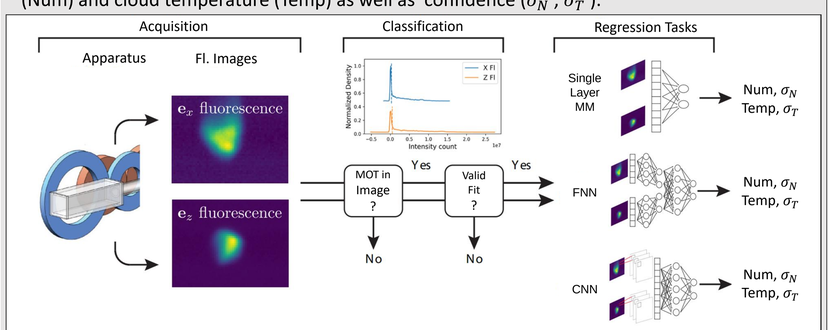
Table of Labels

Symbol	Label	Approximate range	Description
-	MOT	[true, false]	Label: indicates whether there is any identifiable fluorescence signal.
-	VALID_SET	[true, false]	Label: data for which the labels could not be assigned.
T	TEMP	0.5 mK to 30 mK	Label: Temperature
-	TEMP_REL	0.1 to 100	Label: Temperature reliability
N	NUM	8×10^6 to 2×10^8	Label: Number of atoms
-	NUM_REL	0.1 to 100	Label: Number reliability

Machine Learning

Operational Workflow of Machine Learning:

- ***Acquisition*** - Data is generated by the experiment and pre-processed into images
- ***Classification*** - A classifier model determines if a cloud is present and valid for prediction
- ***Regression Tasks*** - Trained machine learning models give predictions for the atom number (Num) and cloud temperature (Temp) as well as confidence (σ_N , σ_T).



Machine Learning Models

Single Layer Matrix Multiplication (MM)	Fully Connected Neural Network (FNN)	Convolutional Neural Network (CNN)
1D vector representations, and a linear transformation is applied	Fully connected layers with non-linear activation functions	Convolution matrices and then fed to fully connected layers

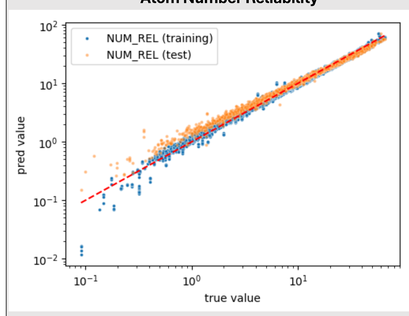
Results

Models are trained with a training set of ~ $2.3\ x\ 10^4$ images (or 90% of labeled data) and performance is evaluated with a test set of ~ $2.3\ x\ 10^3$ images (or 10% of labeled data).

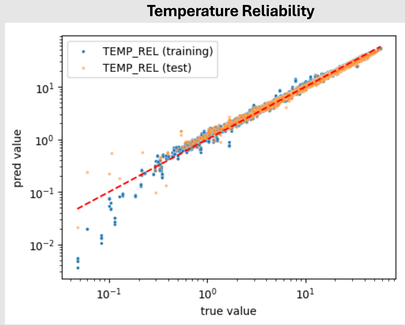
All models have shown ability to learn both temperature and atom number, but the CNN models have performed the best and proved most robust when data is augmented.

CNN Results (w/ Reliability)

Atom Number Reliability

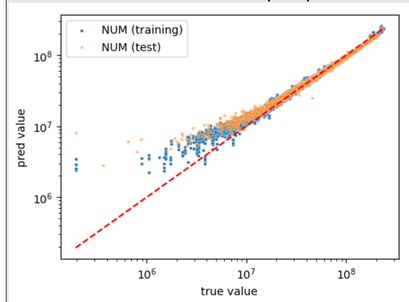


Temperature Reliability

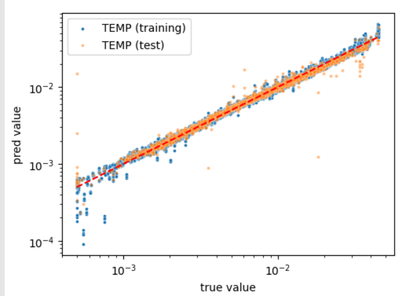


Notable Result: Temperature prediction can be achieved using machine learning models! The CNN result shown below for temperature prediction has an error of less than 8%.

Atom Number (CNN)



Temperature (CNN)



- More research is ongoing, including attempts to understand the models and what features they use in the fluorescence images to determine temperature.
- An instrument that can give predictions of temperature and atom number as clouds are loading in real time is in development.

References

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