Deep Learning application to Proton Radiography Analysis

Malo Marrec*, Adrien Descamps**

*MS&E Department, Stanford University

** Aeronautics and Astronautics Department, Stanford University

Motivation

- **What is Proton Radiography?**

When we radiate a target with a high intensity laser ($> 10^{20} W.cm^{-2}$), we generate plasmas that can be opaque to light. We use protons to analyze the internal structure of the plasmas ($\vec{E}$, $\vec{B}$ fields) and retrieve information (Magnitude, Orientation, ...)

- **How do we analyze experimental radiographs?**

That is a difficult task, as the relationship between radiographs and $\vec{E}$, $\vec{B}$ fields are highly non linear. In pratice, we guess a geometry for the fields, propagate the protons on this geometry and compare the simulated radiograph with the experimental one.

- **Couldn't we use Deep Learning to analyze them?**

We train a Neural Network to come up with an automatic procedure to extract information from radiographs.

- **Is there any related work?**

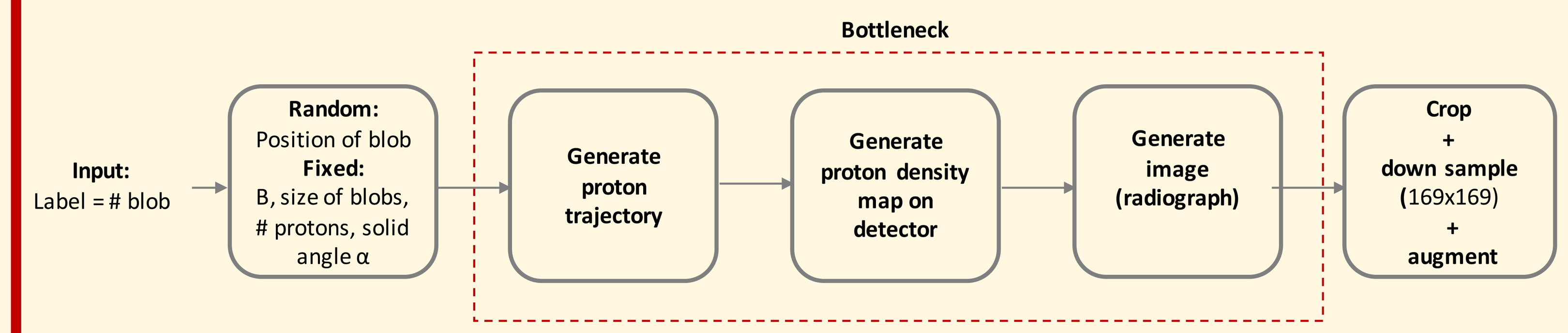
One paper* studied a simple geometry for $\vec{B}$ (Gaussian). Then they trained a FFNN to retrieve the parameters used for $\vec{B}$ (Amplitude, Mean, StD).

- **What is the task?**

We classify each radiographs based on the number of blobs used to describe $\vec{B}$.

* *Machine learning applied to proton radiography of high-energy-density plasmas*, Chen, Nicholas F. Y. and Kasim, Muhammad Firmansyah and Ceurvorst, Luke and Ratan, Naren and Sadler, James and Levy, Matthew C. and Trines, Raoul and Bingham, Robert and Norreys, Peter

Data Generation

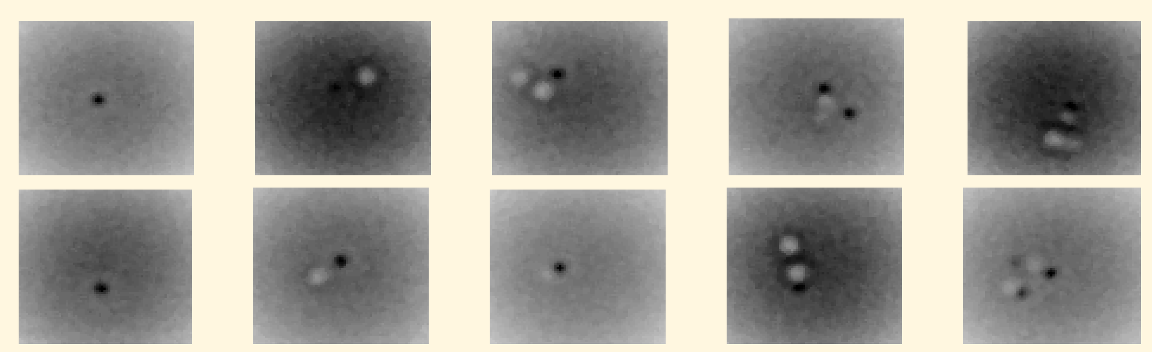


- **Why do we have to use simulated data?**

There is no way to access the ground truth from experimental radiographs as measuring magnetic fields is hard in practice. In addition to that, the number of real radiographs available is extremely limited.

- **Data generation is a bottleneck …**

Each radiograph takes ~1min to generate and may run into instability. The final training data set consists of ~ 11000 simulated radiographs (after data augmentation).

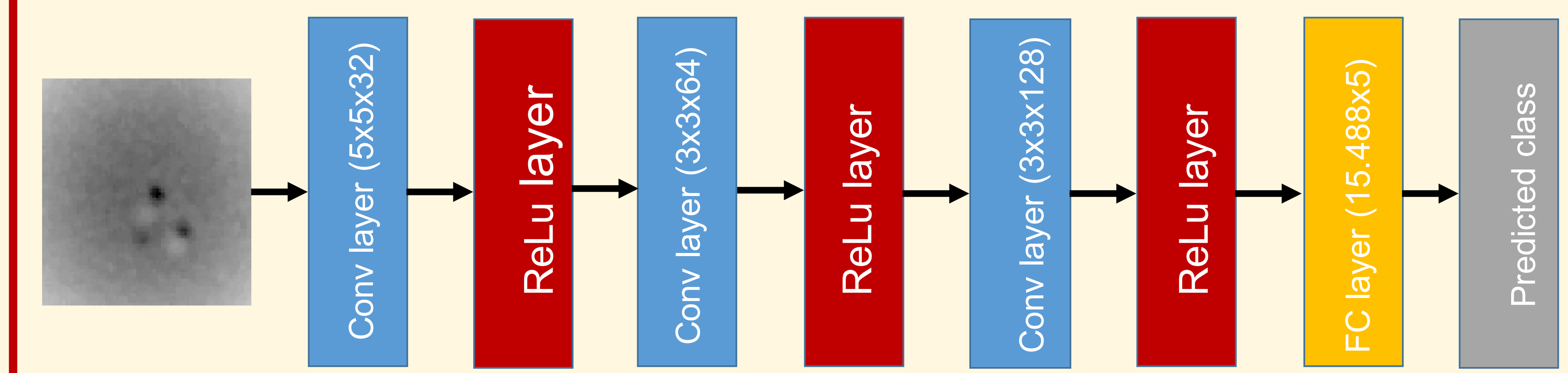


1 blob | 2 blobs | 3 blobs | 4 blobs | 5 blobs

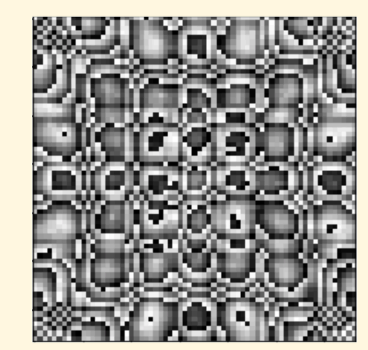
Training set: 8293
Validation set: 1382
Test set: 1382

Approach

- Task: Classify each radiograph based on the number of blobs used to describe $\vec{B}$ (# blobs ≤ 5)



- Cross entropy classifier
- Train on mean images for robustness



Training image after preprocessing

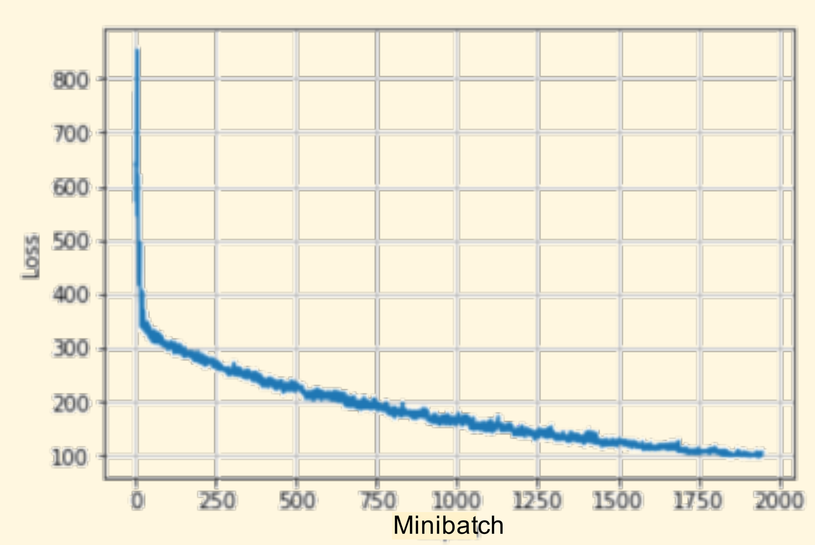
- Keep the number of parameters small (prevent overfitting on our "small" dataset)
- Increase training speed: resize images before training (169x169x3)

Experimental Results

Hyperparemeters/Model design:

- Loss choice (cross-entropy, hinge loss, L2 loss)
- Number of layers (adding more convolutional and Fully Connected layers seems to decrease performance)
- Batch normalization decreases performance on the final model
- Decay and Annealing rate at training time
- Size of convolutional layers
- Regularization strength
- Size of filters and strides

Due to the "small" dataset for this task , we achieve the best results with a simpler model (less parameters in the model).



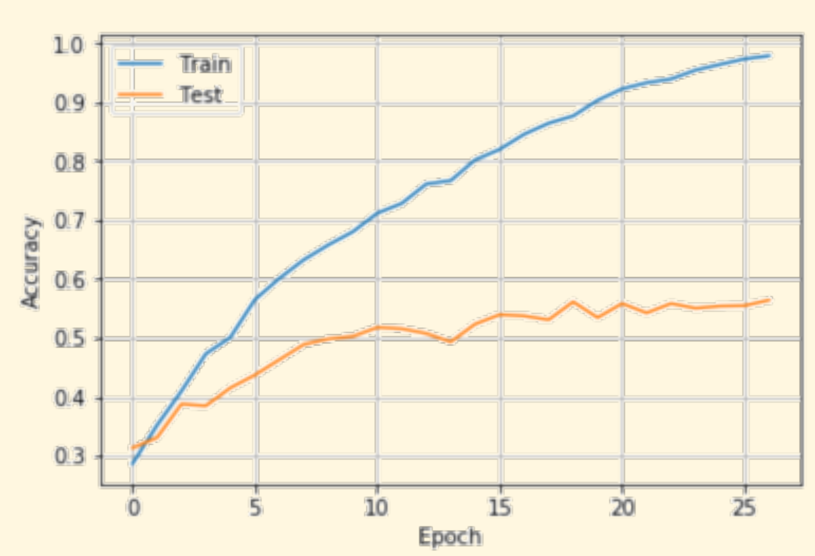


Image Size	Best Validation	Best Test
169x169	56.4%	54.8%
67x67	54.2%	54.1%

We achieve a much faster training by down sampling the data even more to get images of size 67x67 (down from the original size of 676x676 and the best training size of 169x169).

That comes at the expense of 2% points of validation accuracy. However it would be a path to explore if we had more data and needed to train faster or diminish the dataset size to fit it in memory.

Conclusion

- The classification task is difficult, there is no obvious relationship between a radiograph and its label for a human.
- More training points are needed to prevent overfitting and improve the accuracy.
- This project extended the previous work to the classification of more complex $\vec{B}$ fields.
- Application of Deep Learning on realistic radiographs generated from full simulation.
- The training phase was accelerated by reducing the size of the picture as the cost of 2% loss of accuracy on the validation set.

Aknowledgement

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