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Looking back at my bachelors thesis (about 2 years after I wrote it), there is no longer much I am proud of.

I choose my topic "Entwicklung eines Deep Learning Verfahrens zur Ladungsrekonstruktion mit dem Übergangsstrahlungsdetektor des AMS-Experiments"(German for "Development of a Deep Learning Method to reconstruct charges from the Transition radiation detector of the AMS experiment") because I did not know anything about deep learning, and I thought my bachelor thesis would be a great opportunity to learn about it.

And even though this worked quite well, everything else didn't go that well. I talk more about what I think went wrong and what I've learned from this [here](#).

I was working in the AMS group of my university, and my goal was to create a model, that could take in hits in the AMS TRD (Transition Radiation Detector) and try to reconstruct the (absolute value of the) charge of an input particle.

Ordinarily you can do this, by looking at the total energy deposition, which should be proportional to the square of the particle's charge.

This was not used in the group, mostly because other parts of AMS, like for example the RICH (Ring Image Cherenkov counter) detector is better suited for this task, and the TOF (Time Of Flight) detector is able to also get the sign of the particle's charge.

My task was now, to try to use the TRD data, to get a better charge reconstruction (using machine learning) than using Rutherford's formula.

Because of the abundance of measurements in this group, I was able to work on actual detector measurements, and thus tried to reconstruct the charge that the group generated from the whole of AMS from just the TRD.

The only limitation was, that I had to limit my model to charges between 1 and 8 electron charges (particles that are not charged leave no marks in a TRD).

This task is fairly limited for machine learning, since the input data is not (completely) translation invariant, which restricted me to use simple dense networks.

These might not be very fast to train, but the group had nearly infinite computational resources for their other analysis tasks, so this was not a problem. A more interesting question was the type of machine learning task: Since charges of incoming nuclei are quantized to integer multiples of electron charges, it seems to be appropriate to use a classification network, but since we prefer a particle of charge 9 to be identified as a particle of charge 8 than of a charge 2, using a regression task has also benefits.

I tried both to compare them later. Sadly this comparison is not so easy, since finding a clear loss function is not trivial (If you also take a look at my master thesis (or its [abstract](#)), there I write multiple subchapters on how I defined my loss function for a choice between 2 classes, and here I have 8 classes, that are also distributed drastically differently: While basically all particles have a low charge, those particles with a high charge are usually the most interesting).

I preferred the regression task, since even though a regression network allows for basically every charge, by training it on quantized outputs, you also get mostly quantized outputs, and the deviation from this quantized expectations is a good indication of the uncertainty of the classification (Even though it is not simply the uncertainty).

The fact that defining a loss function is not so trivial, also makes giving you final numbers here not so easy.

My network was able to reconstruct more than 99% of all expected particles correctly, but this is mostly a consequence of low charge particles being reconstructed better than high particles (even though in my training set each charge was represented the same).

For high particles, the accuracy never falls below 60% and most errors are only a few charges away. The average difference between the charge measured by AMS and by my network, amounts to about ± 0.25 which is considerably lower, than by just using Rutherford's formula, which resulted in an average difference of ± 0.4 .