Machine Learning and Physics
Winter Semester 2023/2024

Exercise Sheet #8

Due: 09.01.2024 11h00

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General Regulations.

- Please hand in your solutions in groups of three people. A mix of attendees from different tutorials is fine. We will not correct submissions from single students.
- Your solutions to theoretical exercises can be either handwritten notes (scanned to `pdf`), typeset using LaTeX, or directly in the jupyter notebook using Markdown.
- For the practical exercises, the data and a skeleton for your jupyter notebook are available at `https://github.com/heidelberg-hepml/mlph2023-Exercises`. Always provide the (commented) python code as well as the output, and don't forget to explain/interpret the latter, we do not give points for code that does not run. Please hand in both the notebook (`.ipynb`) and an exported pdf. Combine your the pdfs from theoretical and notebook exercises into a single pdf.
- Submit all your files in the Übungsgruppenverwaltung, only once for your group of three. Please list all names and tutorial numbers to simplify things for us.

1 Anomaly Detection with Autoencoders

Disclaimer This is a special exercise where you can collect bonus points for the exam. It is organized like the previous exercises, i.e. you work in groups, get feedback on your submission and the results are discussed in the tutorials.

Conventional searches for New Physics at the LHC look for specific signals. They construct observables and constrain phase space regions to enhance sensitivity to this particular signal, making the analysis specific to assumptions about the signal. This bias can be reduced with unsupervised machine learning methods. In this exercise we will approach this task with autoencoders[1]. We recycle the top-tagging dataset for this application, and take one of the two jet classes to be the anomalous events.

(a) Construct an autoencoder network, consisting of two MLPs that act as the encoder and decoder. The encoder maps from the high-dimensional jet image onto a low-dimensional bottleneck space, whereas the encoder performs the reverse operation. (1 exam pts)

(b) Let top jets be the anomalous objects that we are searching for. In this setup, the autoencoder only sees QCD jets during training. Train the autoencoder on a MSE loss that compares the reconstructed jet image to the original jet image. (1 exam pts)

(c) The trained autoencoder can now be used to reconstruct QCD as well as top jets. Visualize both original and reconstructed jet images for the first 4 QCD jets and the first 4 top jets. Discuss your results. (1 exam pts)

(d) The MSE can be used as a test statistic to discriminate top jets from QCD jets. Visualize the pixel-wise MSE for the 8 jet images studied in the last part. Compute and plot the ROC curve of this test statistic. For which jet type does the reconstruction work better? (1 exam pts)

(e) On sheet 6 we concluded that training MLPs on images is not efficient. Repeat parts (a)-(d) with a CNN and discuss your results. *Hint:* For the decoder, you should use the `ConvTranspose2d` and `Upsample` layers instead of `Conv2d` and `MaxPool2d`. (1 exam pts)

(f) Lets flip the situation and let QCD jets be the anomaly. Repeat the previous steps for an autoencoder trained on top jets and test the sensitivity to QCD jets as anomalies. Explain your findings. (1 exam pts)

[1] `https://arxiv.org/pdf/1808.08979.pdf`