### Efficient Semifield Convolutions

Peter Adema 14460165

Honours Thesis extension Credits: 6 EC

Bachelor  $Kunstmatige\ Intelligentie$ 



University of Amsterdam Faculty of Science Science Park 900 1098 XH Amsterdam

Supervisor Dr. ir. R. van den Boomgaard

Informatics Institute
Faculty of Science
University of Amsterdam
Science Park 900
1098 XH Amsterdam

Semester 2, 2024-2025

#### Abstract TODO

 ${\bf Acknowledgements} \ {\bf {\color{red}TODO}}$ 

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# Chapter 1 Introduction TODO

#### 1.1 Related work TODO

# Convolutional derivatives TODO

To perform semifield convolutions within the context of a deep-learning application, we must ensure that we can take the gradient with respect to our inputs in an efficient manner for all operations we seek to perform.

# CUDA semifield convolutions TODO

Armed with an understanding of the types of semifield convolutions where a gradient can be calculated in a reasonably efficient manner, we now turn to the task of efficiently implementing these operations as programs that can run on a (NVIDIA) GPU: CUDA kernels.

# PyTorch C++ Extensions TODO

Now that we have working implementations of semifield convolutions in the form of CUDA kernels, it is important to examine how these kernels can best be used within the context of a deep-learning model created with the PyTorch machine learning framework.

### Conclusions TODO

- 5.1 Findings TODO
- 5.2 Discussion TODO

- 5.3 Contributions TODO
- 5.4 Further research TODO
- 5.5 Reproducibility TODO
- 5.6 Ethics Maybe?

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### Bibliography

## Appendix