Aalto University School of Science Master's Programme in Life Science Technologies

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Probabilistic Precipitation Nowcasting using Bayesian Convolutional Neural Networks

Master's Thesis Espoo, July 20th, 2022

DRAFT! — May 24, 2022 — DRAFT!

Supervisor: Professor Arno Solin Advisor: Terhi Mäkinen D.Sc.

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ABSTRACT OF MASTER'S THESIS

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Espoo, July 20th, 2022

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Abbreviations and Acronyms

DL Deep learning

NWP Numerical Weather Prediction BNN Bayesian Neural Network

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Introduction

- Nowcasting precipitation is a societally important problem
- Disaster damage control, flash flood prevention, etc
- Predicting accurate short-term (0-6h) (nowcasts) weather forecasts is not feasible with NWP
- This is due to: Numerical stability not reached yet at time-scales such short. + computationally expensive
- Dedicated nowcasting systems / algorithms to the rescue
- Extrapolation / cell tracking based algorithms are traditional : fairly good results, but become worse quickly, in well less than an hour
- Recently, DL based precipitation nowcasting approaches have shown promising results delving into short-comings of traditional methods.

1.1 Problem statement

- accurate uncertainty quantification / probabilistic forecasts are necessary in order to quantify risk for real life-decision-making in meteorological crisis
- Current models: STEPS, LINDA have limited usefulness and are computationally expensive
- Also: No insight into the nature and validity of uncertainty
- Bayesian neural networks (BNN) provide a framework for forecast uncertainty estimation

- They have been proposed for use in problems where uncertainty quantification is primordial, such as autonomous vehicles and other risk-aware use cases, making them ideal candidates to tackle the current problem.
- In this work, we will approach the problem of making useful probabilistic precipitation nwocast by building an uncertainty-aware nowcasting deep neural network, turning a convolutional neural network into a BNN with stochastic variational inference.

1.2 Structure of the Thesis

The present work is organized as follows. Section two (II) contains background and a literature review on precipitation nowcasting and bayesian deep learning, aiming to familiarize the reader with essential concepts regarding the subject. Section three (III) describes the experimental details of the work performed, including the datasets used for training and verification, the models implemented, as well as verification methods and baselines.

- results
- discussion
- conclusions

Background

2.1	Precipitation	Nowcasting

- 2.1.1 Weather radars and radar products
- 2.1.2 Overview of weather forecast methods
- 2.1.3 Precipitation nowcasting: classical methods
- 2.1.4 Machine learning approaches to precipitation nowcasting

2.2 Bayesian deep learning

- 2.2.1 Learning probability distributions
- 2.2.2 Intractable integrals and ways to deal with them
- 2.2.2.1 MCMC based methods
- 2.2.2.2 Variational inference
- 2.2.2.3 Monte-Carlo dropout
- 2.2.3 Applications of bayesian deep learning
- 2.2.4 Predictive uncertainty estimation
- 2.2.4.1 Epistemic and aleatoric uncertainty

2.3 Probabilistic machine learning in atmospheric sciences

Materials and Methods

3.1	Datasets	and	data	selection
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- 3.2 Model
- 3.2.1 The baseline: RainNet
- 3.2.2 Our model: a bayesian extension to RainNet
- 3.3 verification methods
- 3.3.1 Baseline models for verification
- 3.3.1.1 Deterministic predictions
- 3.3.1.2 Probabilistic predictions
- 3.3.2 Prediction skill evaluation metrics
- 3.3.2.1 Deterministic evaluation metrics
- 3.3.2.2 Probabilistic evaluation metrics
- 3.3.3 Evaluation of nowcast predictive uncertainty
- 3.4 Experiments

Results

- 4.1 Case studies for nowcasts
- 4.1.1 Case study 1 : Large-scale Stratiform rain event
- 4.1.2 Case study 2 : Rapidly evolving convective rain event
- 4.2 Deterministic prediction skill (Metrics)
- 4.3 Probabilistic prediction skill (Metrics)
- 4.4 Uncertainty estimation
- 4.4.1 Uncertainties against leadtime
- 4.4.2 Uncertainties against rainfall intensity
- 4.4.3 Epistemic uncertainty against training parameters

Discussion

- 5.1 Goodness of results
- 5.2 Validity of results
- 5.3 What could we learn from uncertainty
- 5.4 What would have to be improved, potential problems in the study?
- 5.5 Directions for further work

Conclusions

Bibliography

Appendix A

First appendix

This is the first appendix. You could put some test images or verbose data in an appendix, if there is too much data to fit in the actual text nicely. For now, the Aalto logo variants are shown in Figure A.1.



(a) In English



(b) Suomeksi



(c) På svenska

Figure A.1: Aalto logo variants