Beyond Deep Learning: Selected Topics

Christian Tomani, Yuesong Shen

Technical University of Munich
Chair of Computer Vision and Artificial Intelligence
Garching, July 7th, 2021
Agenda

● What are the topics we will cover?
  ○ Layer and Architecture Designs
  ○ Alternatives to Neural Networks
  ○ Uncertainty Aware Models
  ○ Time Series and Sequence Models

● How is the course organized?

● How to apply?
Layer and Architecture Design
Self-supervised representation learning

- Learning without labels
- Learn “good” representation efficiently

Original Images published in:
“Exploring Simple Siamese Representation Learning, Chen and He, 2020”; “Disentangling Disentanglement in Variational Autoencoders, Mathieu et al., 2019”
Learning in vision beyond CNNs

- New trend in CNN-dominated vision domain: attention
- Best of both Convolution and self attention?

Original Images published in:
“Stand-Alone Self-Attention in Vision Models, Ramachandran et al., 2019”; “Involution: Inverting the Inherence of Convolution for Visual Recognition, Lee et al., 2021”
Alternatives to Neural Networks
Alternatives to Neural Networks: why?

Neural network is currently the “star model” in the machine learning community

Why should we care about alternative ML models?

- NN does not offer solution to all problems
- Alternative solutions for generative modeling, unsupervised learning, uncertainty estimation ...
- Offer inspirations for improving NN / combination
- Better appreciate the strong / weak points of NN
Alternatives to Neural Networks: which?

Some possible alternatives to neural network:

- (Deep) Gaussian process
- Deep belief network
- Deep Boltzmann machine
- Sigmoid belief network
- Sum-product network
- ...

Original Image published in:
“Sum-Product Networks: A New Deep Architecture, Poon and Domingos, 2011”
Uncertainty Aware Models
Safety critical applications
The issue with Deep Learning - Can we trust the model?

Setup

LeNet-5 Model with weight decay

MNIST Dataset

LeCun et al. - Gradient Based Learning Applied to Document Recognition, 1998
https://github.com/cazala/mnist
The issue with Deep Learning - Can we trust the model?

Vanilla LeNet-5 Model on MNIST

- Model is unreliable and not calibrated
- Gives totally wrong but highly confident predictions if data is perturbed
- Wrong predictions cannot be distinguished from correct ones

Christos Louizos - Multiplicative Normalizing Flows for Variational Bayesian Neural Networks, 2017
The issue with Deep Learning - Can we trust the model?
Time Series and Sequence Models
Time Series Basics

2 Types of time series:

- univariate time series
- multivariate time series

Decomposition of time series:

- $d_t$ trend component (deterministic)
- $c_t$ cyclical component (deterministic, periodic)
- $s_t$ seasonal component (deterministic, periodic)
- $\epsilon_t$ irregular component (stochastic, stationary)

$y_t = d_t + c_t + s_t + \epsilon_t$

Time Series Models

Autoregressive Model:

\[ X_t = c + \sum_{i=1}^{p} \varphi_i X_{t-i} + \varepsilon_t \]

Long Short Term Memory Model (LSTM):

Transformer Models:

https://colah.github.io/posts/2015-08-Understanding-LSTMs/
Vasvani et al.: Attention is all you need, 2017
Long Short Term Memory Model (LSTM)

https://colah.github.io/posts/2015-08-Understanding-LSTMs/
Long Short Time Model (LSTM)

\[
\begin{align*}
    i_t &= \sigma(x_t U^i + h_{t-1} W^i) \\
    f_t &= \sigma(x_t U^f + h_{t-1} W^f) \\
    o_t &= \sigma(x_t U^o + h_{t-1} W^o) \\
    \tilde{C}_t &= \tanh(x_t U^g + h_{t-1} W^g) \\
    C_t &= f_t \ast C_{t-1} + i_t \ast \tilde{C}_t \\
    h_t &= \tanh(C_t) \ast o_t
\end{align*}
\]
Transformer Models

- Encoder and decoder stacks
- Attention
- No recurrent neural network
- Applications:
  - Sequence modeling
  - Language translation
  - Text processing

\[
\text{Attention is all you need} \quad \text{vs.} \quad \text{Hopfield Networks is All You Need}
\]

Vasvani et al.: Attention is all you need, 2017
Course logistics
Course Organization

Course website: https://vision.in.tum.de/teaching/ws2021/bdlstnc_ws2021

Course email: bdlstnc-ws21@vision.in.tum.de

Course structure:

- Kick-Off Meeting with all the topics (default date: October 20th)
- Matching to the topics
- Read the papers and do a literature search and elaborate on the topic you are provided with
- Get optional help, if you did not understand the paper
- Send a first draft of the presentation and get optional feedback
- Presentations take place on January 18th-19th 2022
- Final report will be due after the presentations
Prerequisites

- Machine learning & deep learning knowledge:
  
  Basic ML concepts and ML/DL models

  **Min. Requirement**: passed one ML/DL related course (I2ML, I2DL, ADL4CV, PGM ...)

- Soft skills:
  
  Manage regular workflow and communicate with tutors efficiently

- We also value:
  
  - solid basis & interest for maths
  - prior experience with ML/DL projects
How to apply

1. Apply via the **TUM Matching system** (July 15th - 20th, 2021)
   ○ If you like our course, make sure to give it a high priority :)

2. **Send us an email** to show your interest and fulfillment of prerequisites
   ○ Crucial for us to give you a priority

   The email should be sent to **bdlstnc-ws21@vision.in.tum.de** latest July 20th with the title
   “[Application] <Firstname> <Lastname>” and contain
   ○ Filled information form (template on course website, rename to “firstname_lastname.xlsx”)
   ○ Transcript
   ○ CV
Thank you! Questions?