

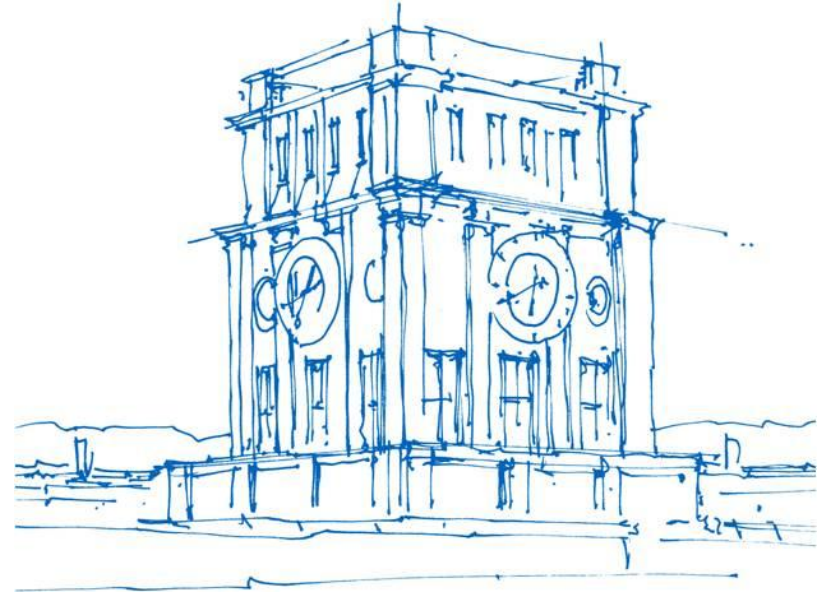
# Beyond Deep Learning: Selected Topics

Christian Tomani, Yuesong Shen

Technical University of Munich

Chair of Computer Vision and Artificial Intelligence

Garching, July. 7<sup>th</sup>, 2021



*Uhrenturm der TUM*

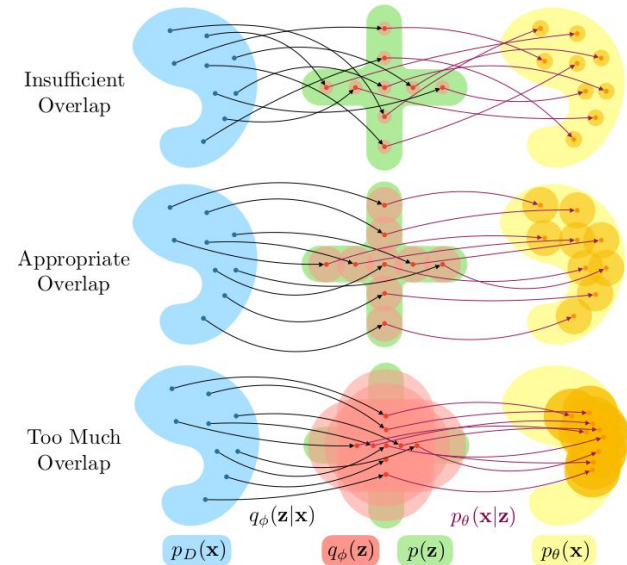
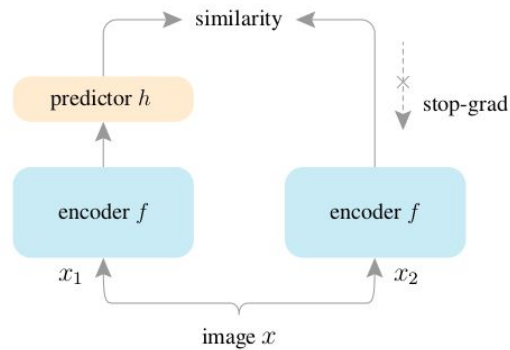
# Agenda

- 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

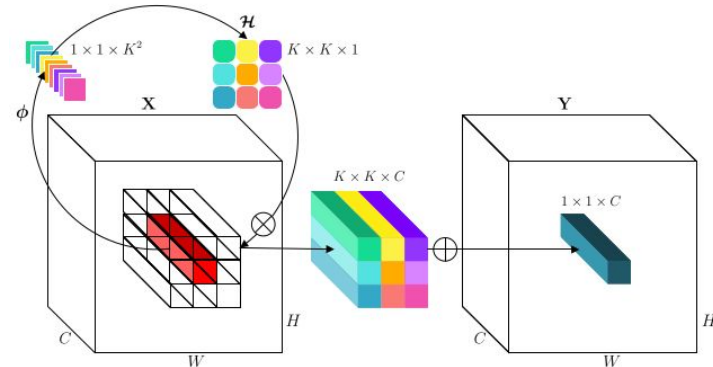
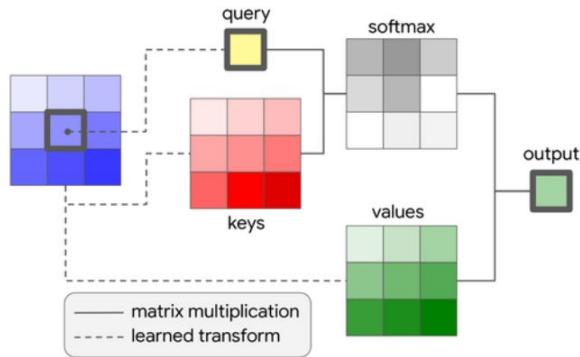


Original Images published in:

“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 Inference 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

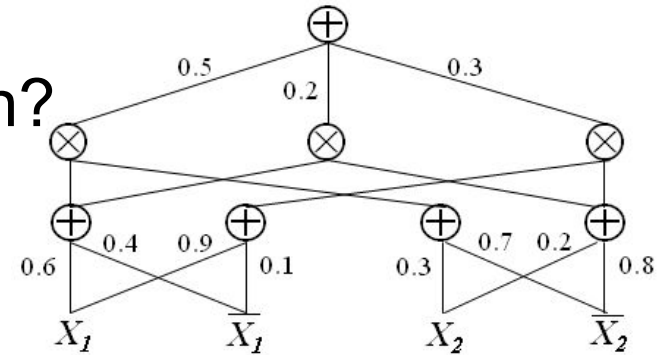
⇒ Why should we care about alternative ML models?

- 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
- ...

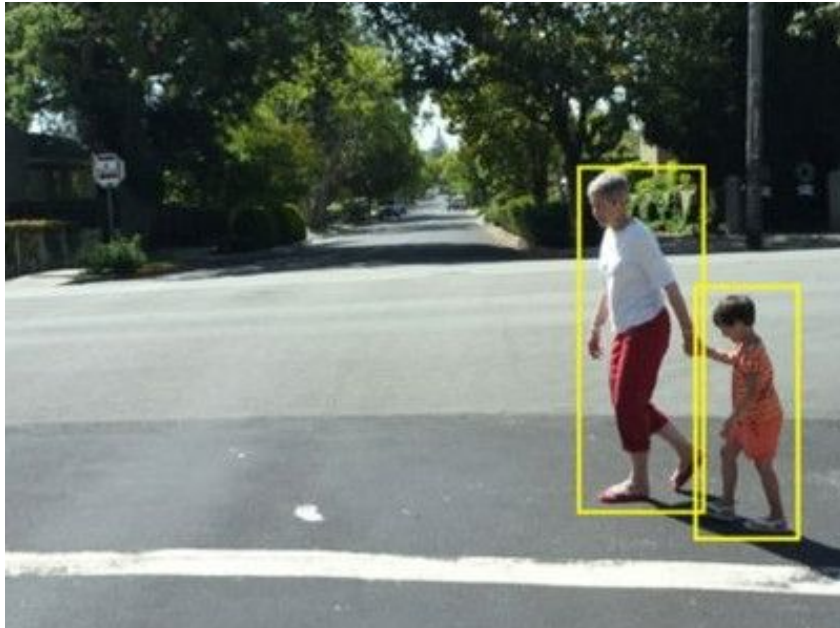


Original Image published in:  
“Sum-Product Networks: A New Deep Architecture, Poon and Domingos, 2011”



# Uncertainty Aware Models

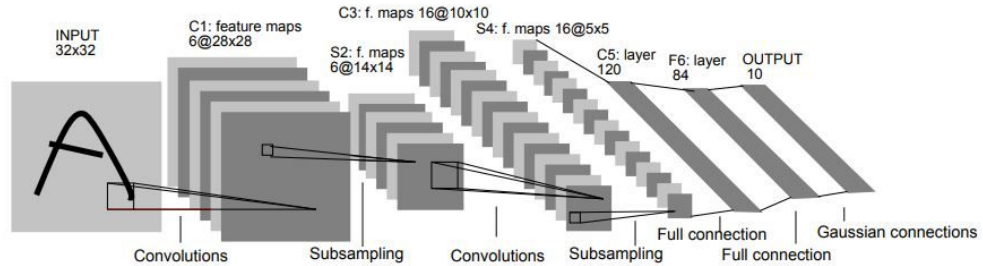
# Safety critical applications



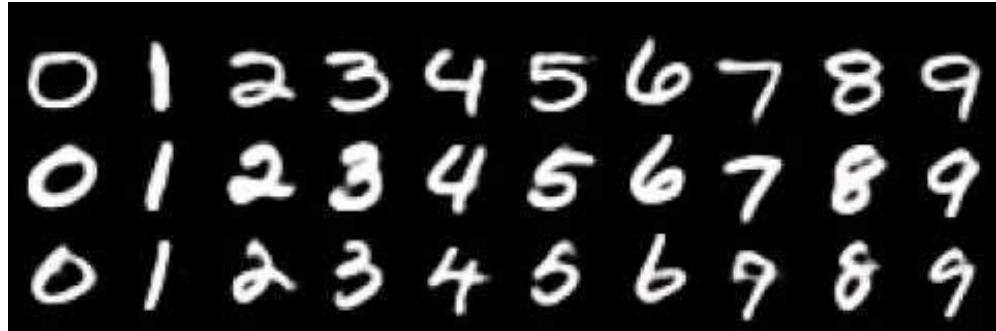
# The issue with Deep Learning - Can we trust the model?

## Setup

LeNet-5 Model with weight decay



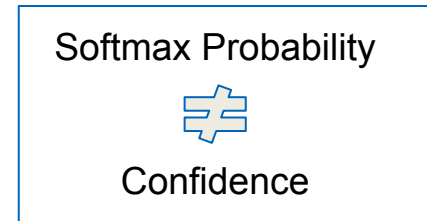
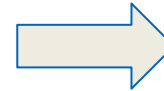
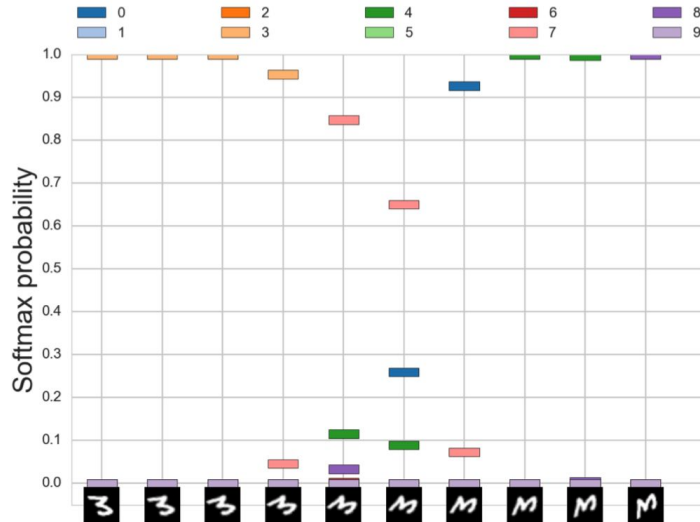
MNIST Dataset



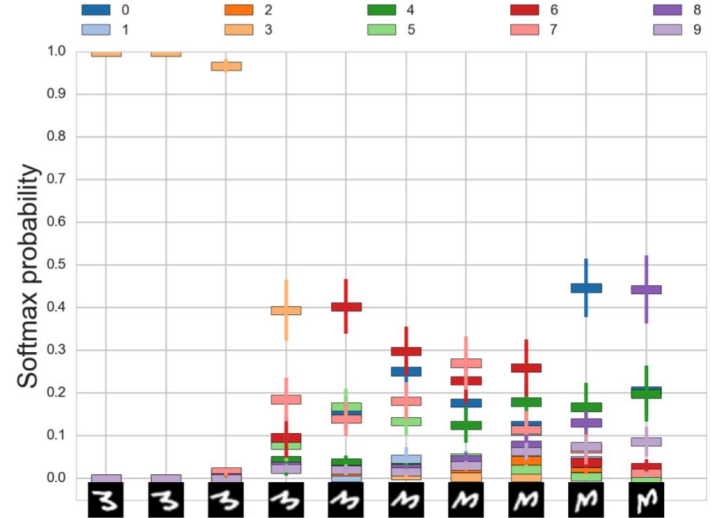
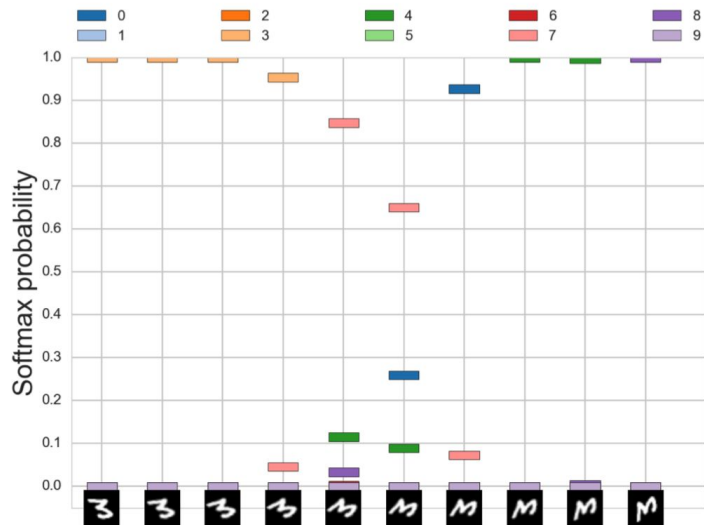
# The issue with Deep Learning - Can we trust the model?

## 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



# The issue with Deep Learning - Can we trust the model?



# Time Series and Sequence Models

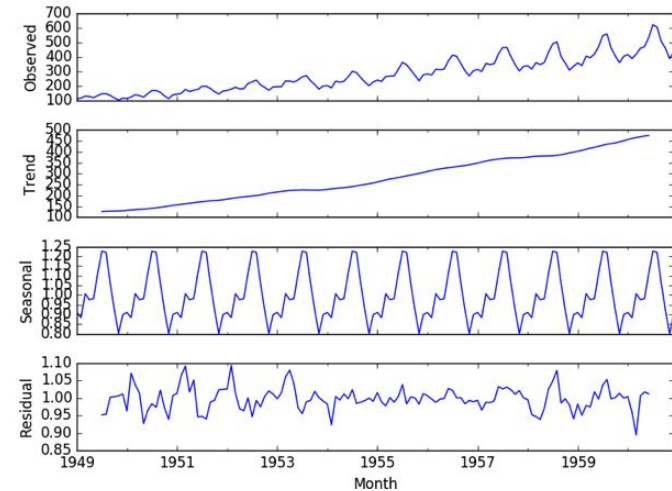
# Time Series Basics

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)



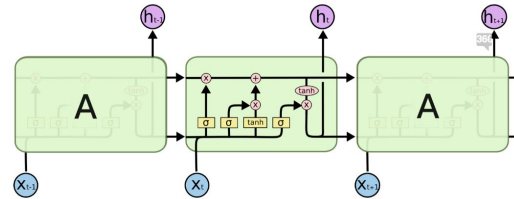
$$y_t = d_t + c_t + s_t + \epsilon_t$$

# Time Series Models

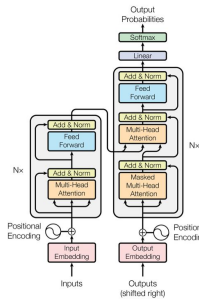
Autoregressive Model:

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

Long Short Term Memory Model (LSTM):

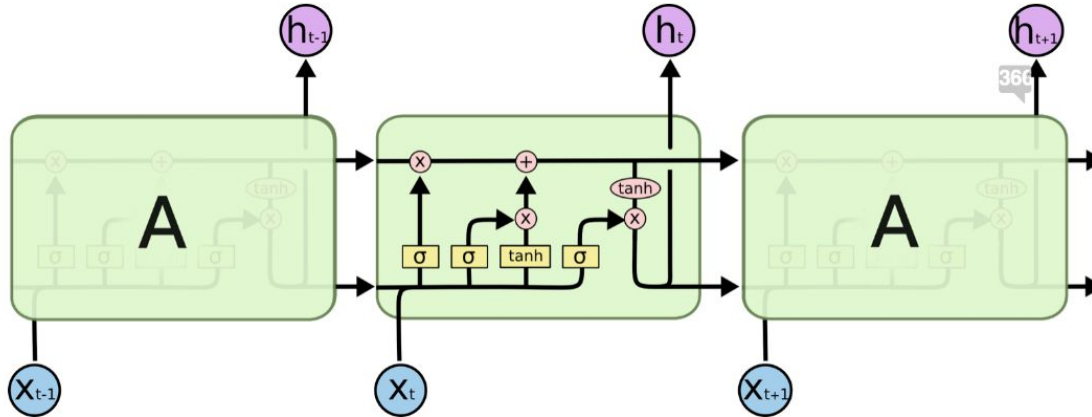


Transformer Models:

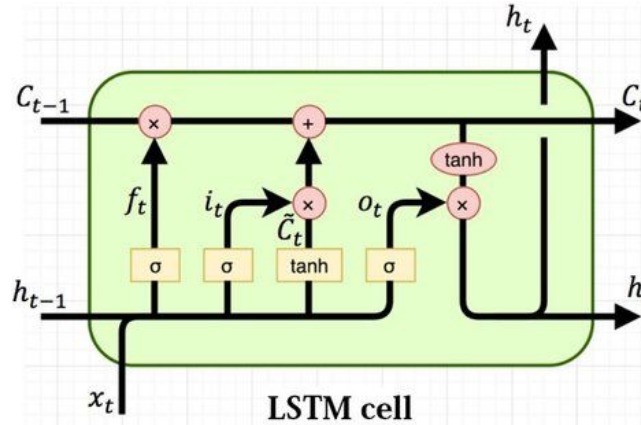




# Long Short Term Memory Model (LSTM)



# Long Short Time Model (LSTM)

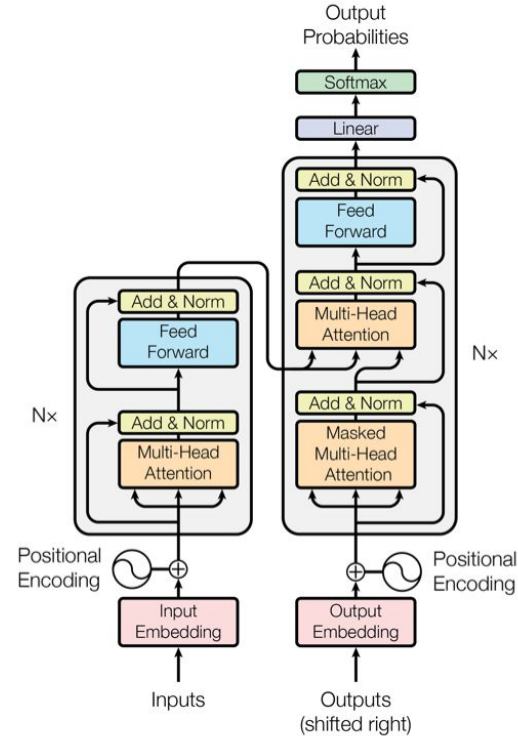


$$\begin{aligned}i_t &= \sigma(x_t U^i + h_{t-1} W^i) \\f_t &= \sigma(x_t U^f + h_{t-1} W^f) \\o_t &= \sigma(x_t U^o + h_{t-1} W^o) \\\tilde{C}_t &= \tanh(x_t U^g + h_{t-1} W^g) \\C_t &= \sigma(f_t * C_{t-1} + i_t * \tilde{C}_t) \\h_t &= \tanh(C_t) * o_t\end{aligned}$$

# Transformer Models

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

**Attention is all you need**  
**vs.**  
**Hopfield Networks is All You Need**



# Course logistics

# Course Organization

Course website: [https://vision.in.tum.de/teaching/ws2021/bdlstnc\\_ws2021](https://vision.in.tum.de/teaching/ws2021/bdlstnc_ws2021)

Course email: [bdlstnc-ws21@vision.in.tum.de](mailto: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 15<sup>th</sup> - 20<sup>th</sup>, 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](mailto:bdlstnc-ws21@vision.in.tum.de) **latest July 20<sup>th</sup>** 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?

