NEUROMORPHIC AND AI RESEARCH AT BCAI

THOMAS PFEIL

MARCH 16TH 2021

NICE 2021

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Neuromorphic and AI research at BCAI
Outline

- Introduction to Bosch and BCAI
- Introduction to ULPEC
- Streaming rollouts
- Spiking neural networks for spatio-temporal data streams
- Iterative neural networks
- Highlights of deep learning research

Introducing Bosch
A worldwide leading IoT Company

77.7 billion €
company's sales in 2019

398,200
Bosch associates worldwide

around **440**
subsidiaries and regional companies in appr. 60 countries

6.1 billion €
invested in research and development in 2019

72,600
Bosch researcher and developer worldwide

130
research and development sites worldwide

Introducing Bosch
Four Business Sectors with increasing synergies

Mobility Solutions

46.8 billion €

- One of the world's largest suppliers of mobility solutions

Industrial Technology

7.5 billion €

- Leading in drive and control technology, packaging, and process technology

Energy & Building Technology

5.6 billion €

- One of the leading manufacturers of security & communication technology
- Leading manufacturer of energy-efficient heating products and hot-water solutions

Consumer Goods

17.8 billion €

- Leading supplier of power tools and accessories
- Leading supplier of household appliances

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Bosch Center for Artificial Intelligence (established 2017)

270 AI experts* at 7 locations

Business impact and achievements

185+ projects across all functions and divisions

EUR 13m internal revenue in 2019

EUR 80m savings through AI in 2019

264 invention reports

109 tier-1 publications

Established Bosch as **relevant AI player**

AI learning plattform

* status June 2020

Introducing the BCAI pillars

AI Consulting
Support project strategies

AI Enabling
Build up AI competence in Business units

AI Marketing
Promote Bosch AI internally and externally

AI Research
Gain best in class AI technology

AI Services
Drive commercialization

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BCAI focus on differentiating AI research

with 13 research fields to develop safe, robust and explainable AI methods

AI / ML

Deep Learning

- Robust & Explainable DL
- Robust & Safe DL
- Robust DL
- Generative & Embedded DL

Knowledge Representation

- Robust Learning with Structured Knowledge

Natural Language Processing

- Natural Language Processing & Semantic Reasoning

Reinforcement Learning (RL)

- RL & Planning
- RL & Optimization
- Environmental Understanding & Decision Making
- Information Theoretic RL
- Computational Methods for RL

Probabilistic Modeling

- Probabilistic Modeling for Design of Dynamic Experiments
- Probabilistic Modeling for Dynamical Systems

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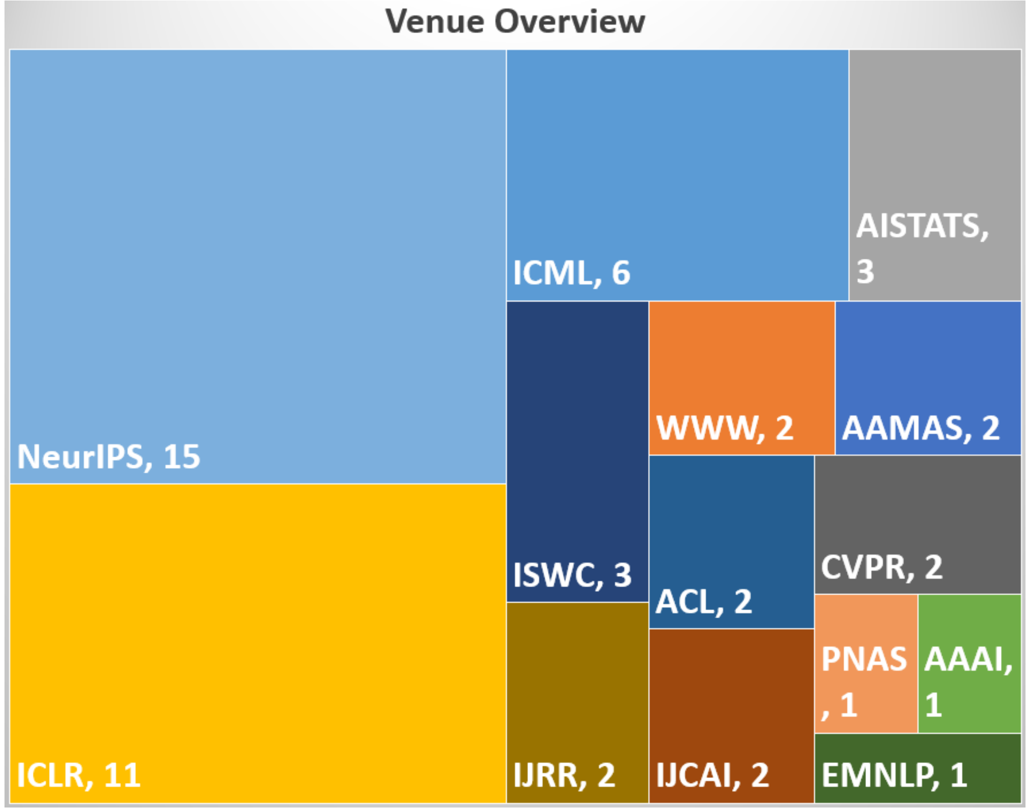
BCAI Research 2020
Key Statistics - Publications

- 151 Researchers worldwide
- 38 PhD Students
- 53 Tier-1 Publications in 2020
- NeurIPS, ICML, ICLR are main venues
- Since 2017 #1 European company in AI research
- In top 11 companies @NeurIPS ins past 3 years
- ~ 200 AI-related patent applications in 2020
  - Nr. 2 in European Patent Office ranking 2019



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Bosch increases activities in AI

> “
>
> ***By 2025, the aim is for all Bosch products to either contain AI or have been developed or manufactured with its help.***
>
> *Bosch vision towards AI*
>
> *Chairman of the Board of Management, Robert Bosch GmbH*

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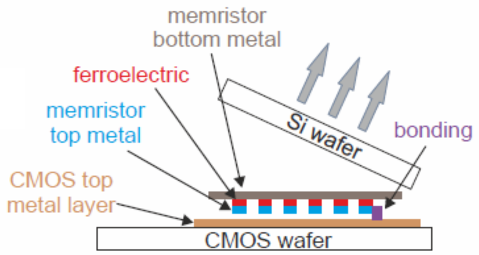
Neuromorphic and AI research at BCAI

(Ultra-Low Power Event-Based Camera)

Main goal

Build a smart microsystem that will exploit the benefits of event-based camera, spiking neural network and memristive technology.

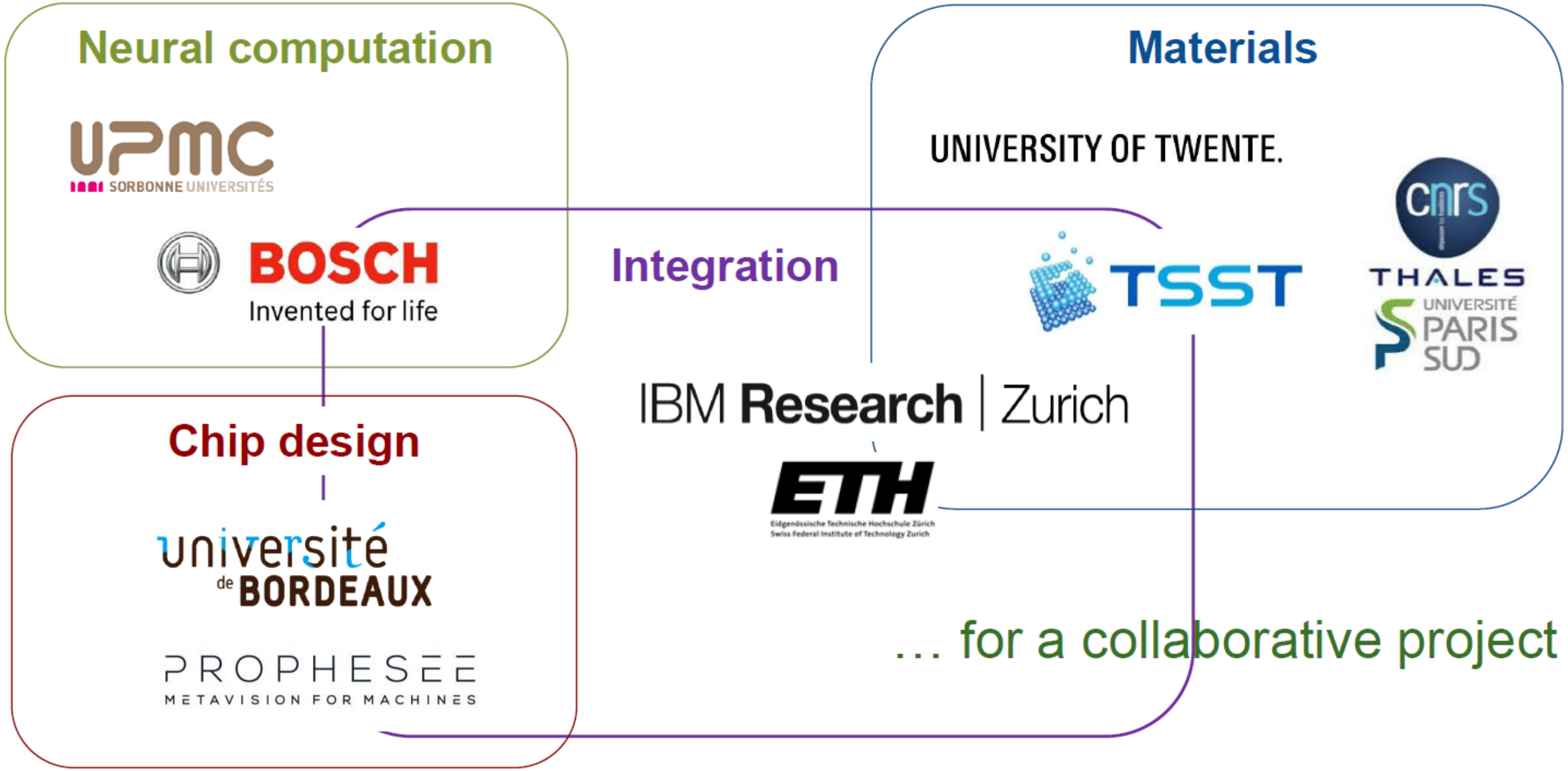


Intermediate goals

- Novel device technology to establish ferroelectric memristor technology on Si
- Advanced circuit design to implement a hardware neural network based on ferroelectric memristors
- Innovative integration technology to embed on SoC the optical sensor and the memristive neural network to achieve a compact and ultra-low power system.
- Smart algorithms to natively process the output of the event-based camera by a neural network

Neuromorphic and AI research at BCAI

ULPEC (Ultra-Low Power Event-Based Camera)



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Neuromorphic and AI research at BCAI

Deep Learning With Spiking Neurons: Opportunities and Challenges

REVIEW ARTICLE

Front. Neurosci., 25 October 2018 | https://doi.org/10.3389/fnins.2018.00774

Check for updates

Deep Learning With Spiking Neurons: Opportunities and Challenges

Michael Pfeiffer* and Thomas Pfeil

Bosch Center for Artificial Intelligence, Robert Bosch GmbH, Renningen, Germany

Spiking neural networks (SNNs) are inspired by information processing in biology, where sparse and asynchronous binary signals are communicated and processed in a massively parallel fashion. SNNs on neuromorphic hardware exhibit favorable properties such as low power consumption, fast inference, and event-driven information processing. This makes them interesting candidates for the efficient implementation of deep neural networks, the method of choice for many machine learning tasks. In this review, we address the opportunities that deep spiking networks offer and investigate in detail the challenges associated with training SNNs in a way that makes them competitive with conventional deep learning, but

- Opportunities
  - Sparse, asynchronous and binary signals are processed massively in parallel
  - On neuromorphic hardware: Low power, low latency, event-driven
  - Similarities between spiking neural networks and binary neural networks
- Challenges
  - Approaches for training
    - Conversion (of constrained networks)
    - Spiking variants of error backpropagation
    - Local learning rules like spike-timing dependent plasticity
  - High computational cost for training
    - Local on-chip learning
  - Datasets
    - Exploitation of temporal codes

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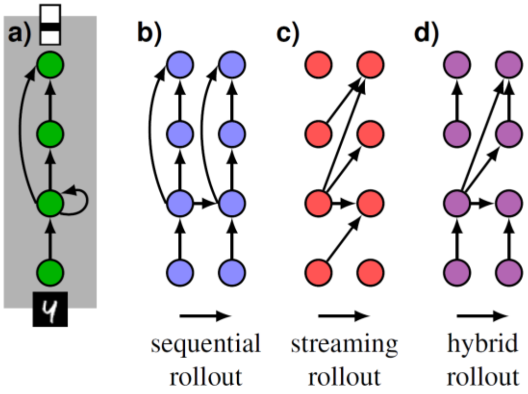
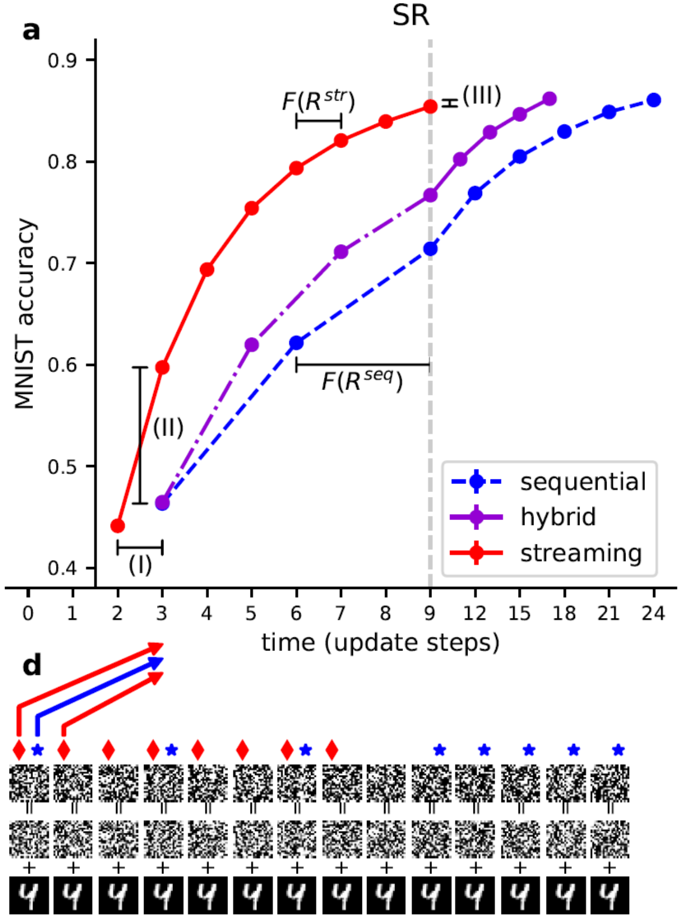
Fischer, Köhler, Pfeil
NIPS 2018

The streaming rollout of deep networks - towardsfully model-parallel execution

- Different rollouts for the same network



- Advantages of streaming rollouts
  - Fully model-parallel execution
  - Shorter response time (I)
  - Highest sampling and output frequency
  - Temporal integration via skip connections
  - Usually better early (II) and comparable late (III) performance



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SNNs for Efficient Sequence Processing

Kugele, Pfeil, Pfeiffer, Chicca
Front. Neurosci. 2020

Efficient Processing of Spatio-Temporal Data Streams With Spiking NNs

Goal

- Efficient classification on event streams

Foundation

- Streaming rollouts[1]
  - Execute an ANN with skip connections in an efficient way
- ANN-SNN conversion[2]
  - Convert trained ANNs to SNNs for efficient classification of static data (images)

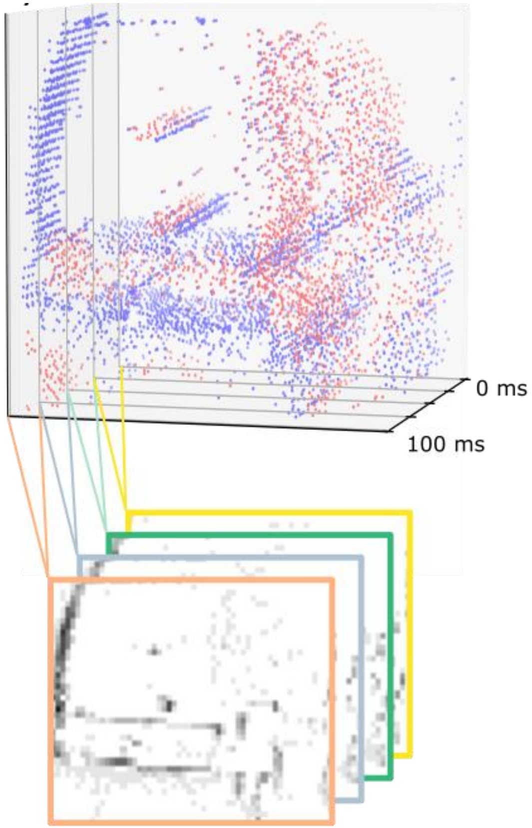
Result

- Convert ANNs with skip connections to SNNs for efficient classification of sequential data (frames)

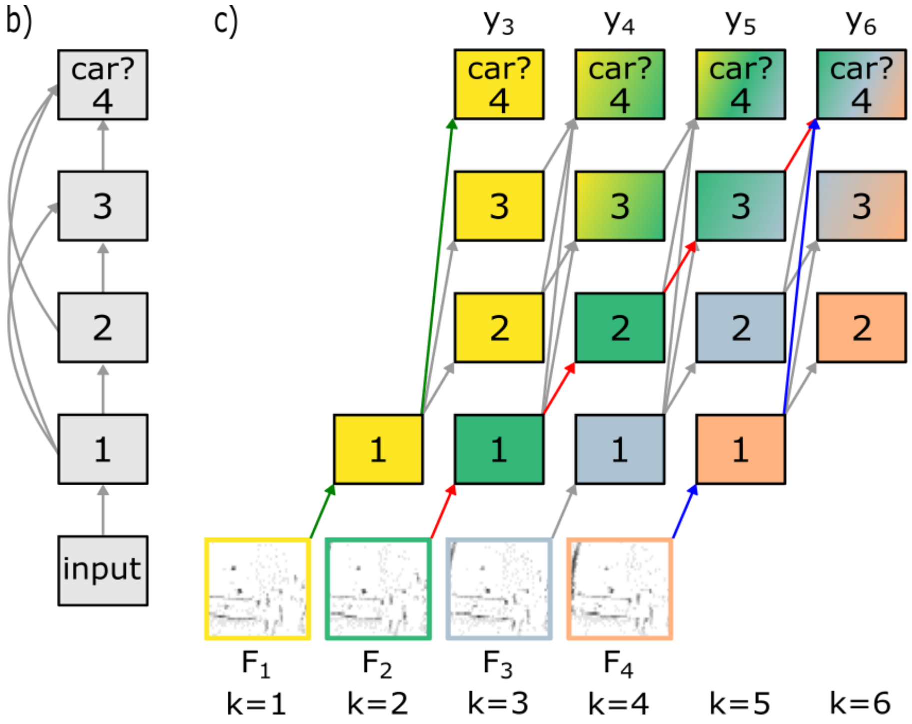
[1] Fischer, Köhler and Pfeil, *The streaming rollout of deep networks – towards fully model-parallel execution*, NeurIPS 2018

[2] Rueckauer, B., Lungu, I.-A., Hu, Y., Pfeiffer, M., and Liu, S.-C, *Conversion of continuous-valued deep networks to efficient event-driven networks for image classification,* Frontiers in Neuroscience 2017

SNNs for Efficient Sequence Processing
Approach: Transport information via delay



Network component structure



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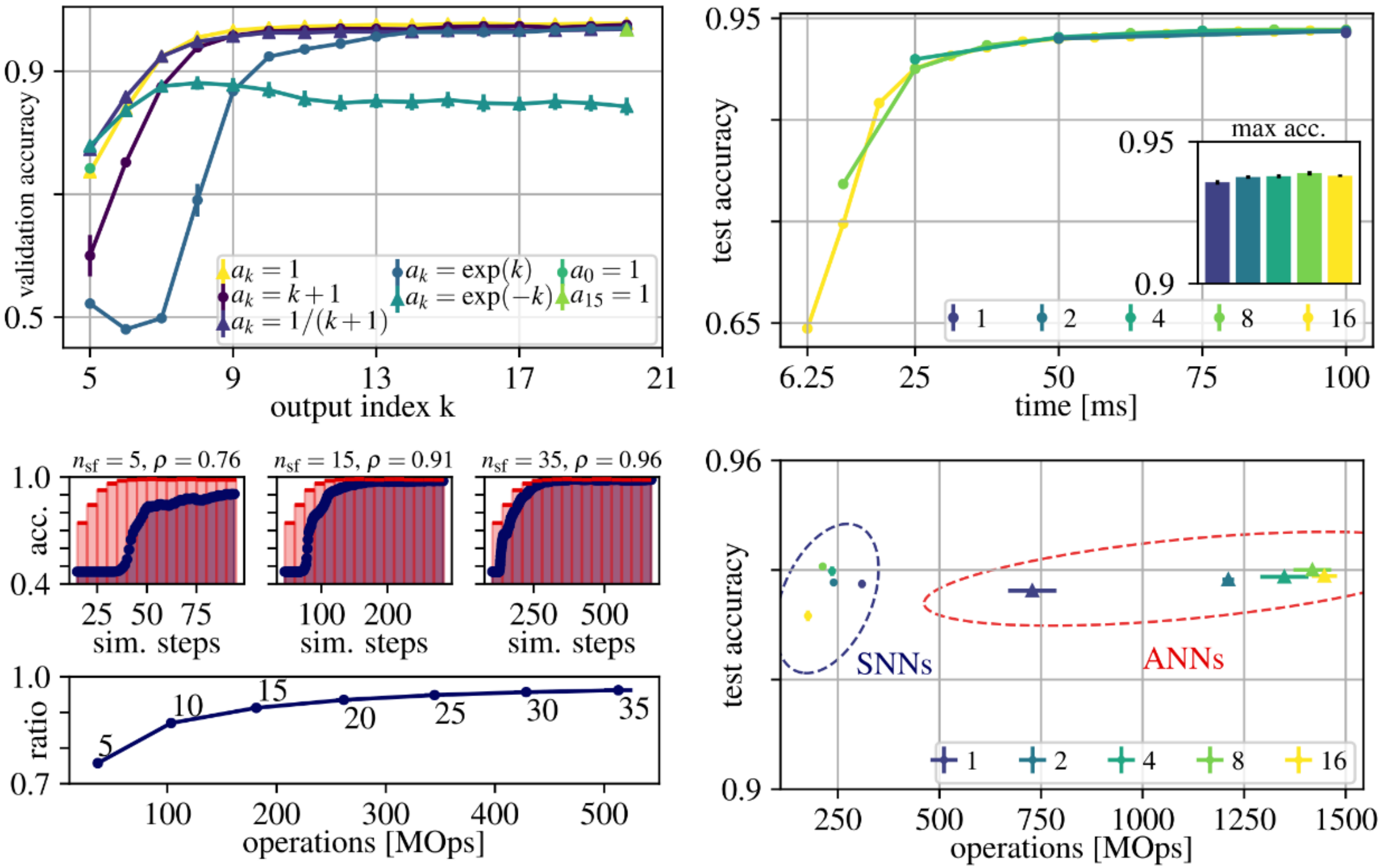
SNNs for Efficient Sequence Processing
ANN-SNN Conversion for sequential data



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SNNs for Efficient Sequence Processing
Results

- We always provide the most accurate model
- All our models have fewer parameters than other approaches
- SNNs always need fewer operations to reach approximately the same accuracy

N-CARS	acc.	# params	# ops [MOps]
HATS/linear SVM (Sironi et al., 2018)	90.2	-	-
Rec. U-Net+CNN (Rebecq et al., 2019)	91.0	$> 10^6$	-
ResNet-34 (Gehrig et al., 2019)	92.5	10^7	-
Streaming rollout ANN (**ours**)	94.00(±0.05)	10^5	1420(±47)
Converted SNN (**ours**)	**94.07**(±0.05)	10^5	212.9(±2.5)

N-MNIST	acc.	# params	# ops [MOps]
SNN with backprop (Lee et al., 2016)	98.66	$2 \cdot 10^6$	-
SNN with backprop (Wu et al., 2019)	99.53	$2 \cdot 10^6$	-
HATS/linear SVM (Sironi et al., 2018)	99.1	-	-
Rec. U-Net+CNN (Rebecq et al., 2019)	98.3	$> 10^6$	-
Streaming rollout ANN (**ours**)	**99.56**(±0.01)	$3 \cdot 10^5$	3500(±360)
Converted SNN (**ours**)	99.54(±0.01)	$3 \cdot 10^5$	460(±38)

DvsGesture	acc.	# params	# ops [MOps]
10 classes			
SNN on TrueNorth (Amir et al., 2017)	96.7	$1.5 \cdot 10^6$	-
SNN with backprop (Shrestha and Orchard, 2018)	93.64(±0.49)	-	-
PointNet-like ANN (Wang et al., 2019)	97.08	-	-
Streaming rollout ANN (**ours**)	**97.16**(±0.11)	$5 \cdot 10^5$	8150(±740)
Converted SNN (**ours**)	96.97(±0.17)	$5 \cdot 10^5$	651(±43)
11 classes			
SNN on TrueNorth (Amir et al., 2017)	94.59	$1.5 \cdot 10^6$	-
PointNet-like ANN (Wang et al., 2019)	95.32	-	-
Streaming rollout ANN (**ours**)	**95.68**(±0.32)	$8 \cdot 10^5$	15 000(±1000)
Converted SNN (**ours**)	95.56(±0.14)	$8 \cdot 10^5$	931(±24)

CIFAR10-DVS	acc.	# params	# ops [MOps]
HATS/linear SVM (Sironi et al., 2018)	52.4	-	-
SNN with backprop (Wu et al., 2019)	60.5	$2 \cdot 10^6$	-
Streaming rollout ANN (**ours**)	**66.75**(±0.22)	$5 \cdot 10^5$	8800(±1300)
Converted SNN (**ours**)	65.61(±0.20)	$5 \cdot 10^5$	1551(±65)

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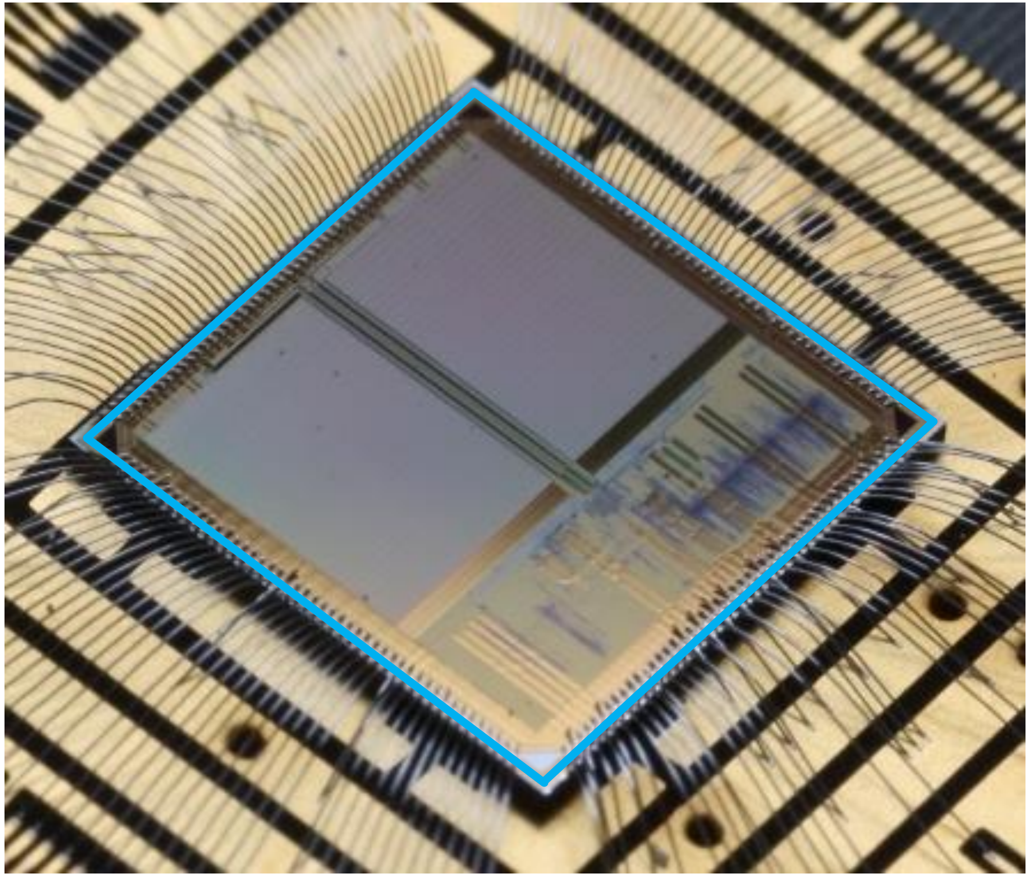
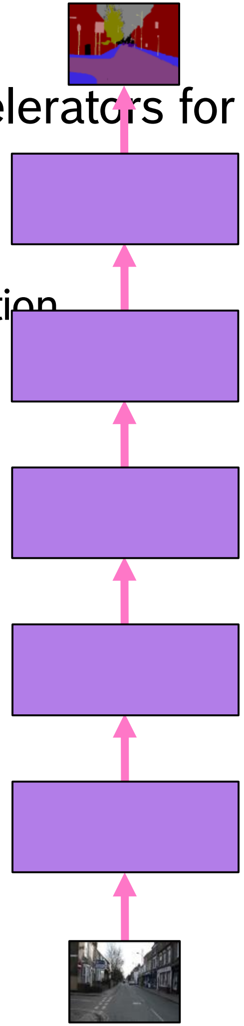
ItNet: Iterative Neural Networks
Motivation

Thomas Pfeil
preprint on arxiv.org



Source: www.kip.uni-heidelberg.de

- Novel hardware accelerators for deep neural networks
  - Massively parallel
  - In-memory computation
  - Advantages
    - High throughput
    - Low latency
    - Low power
  - Disadvantages
    - Area



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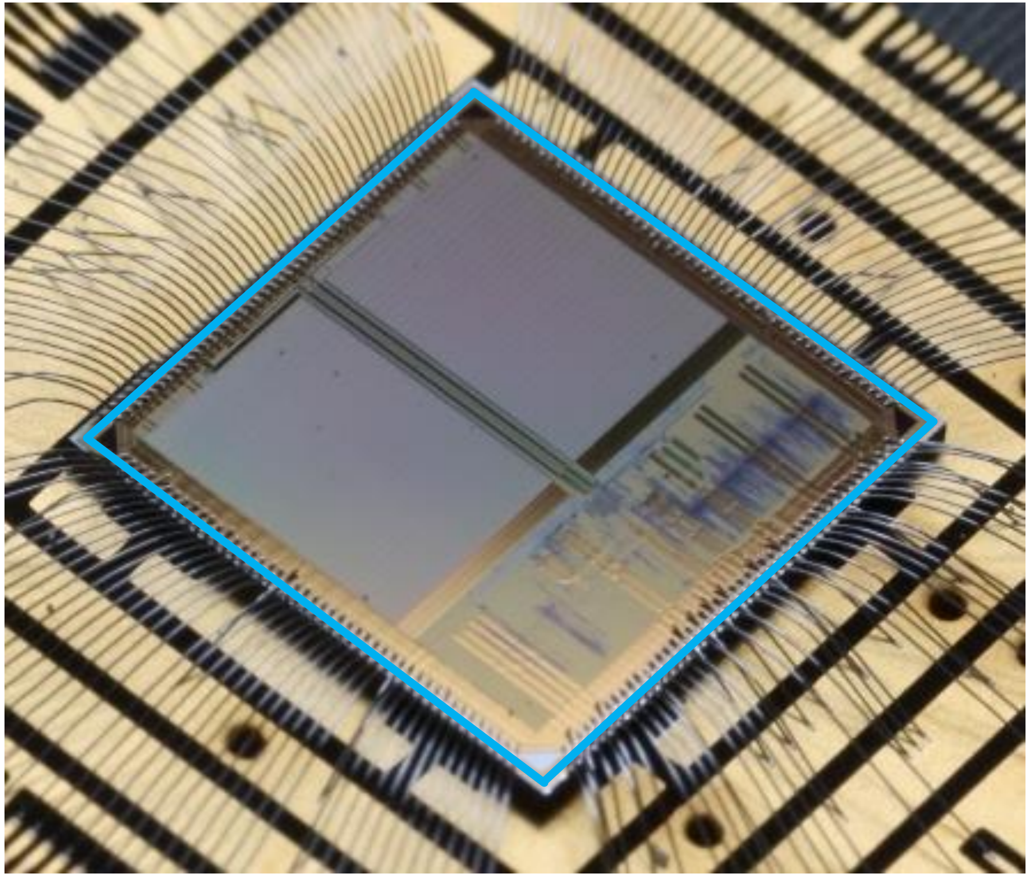

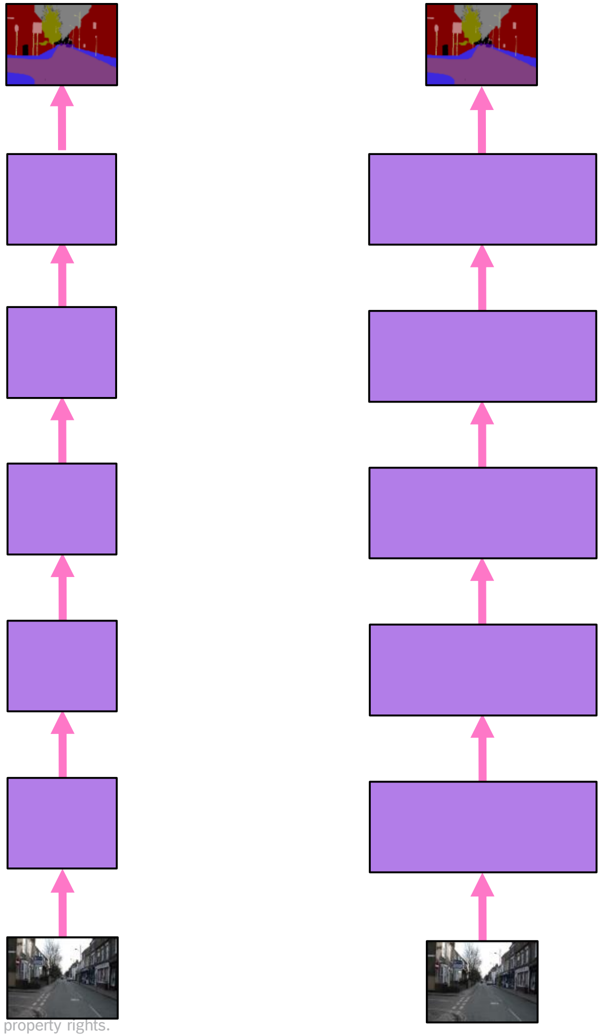

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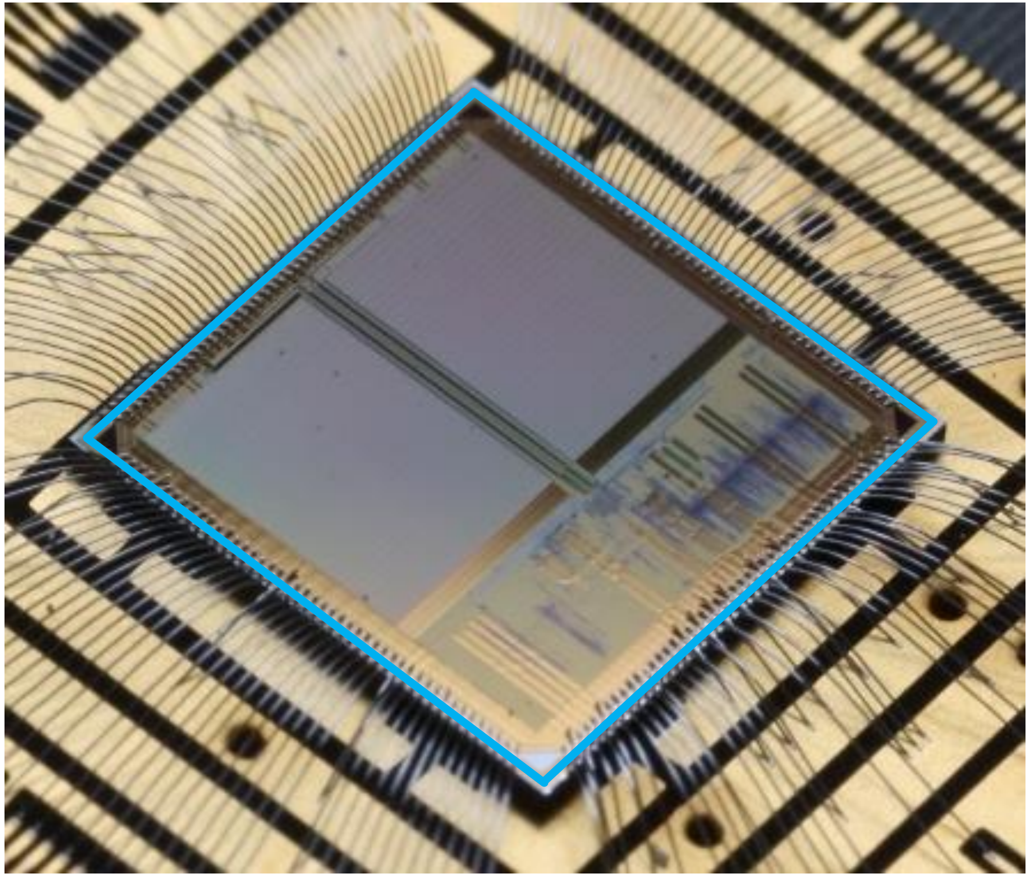

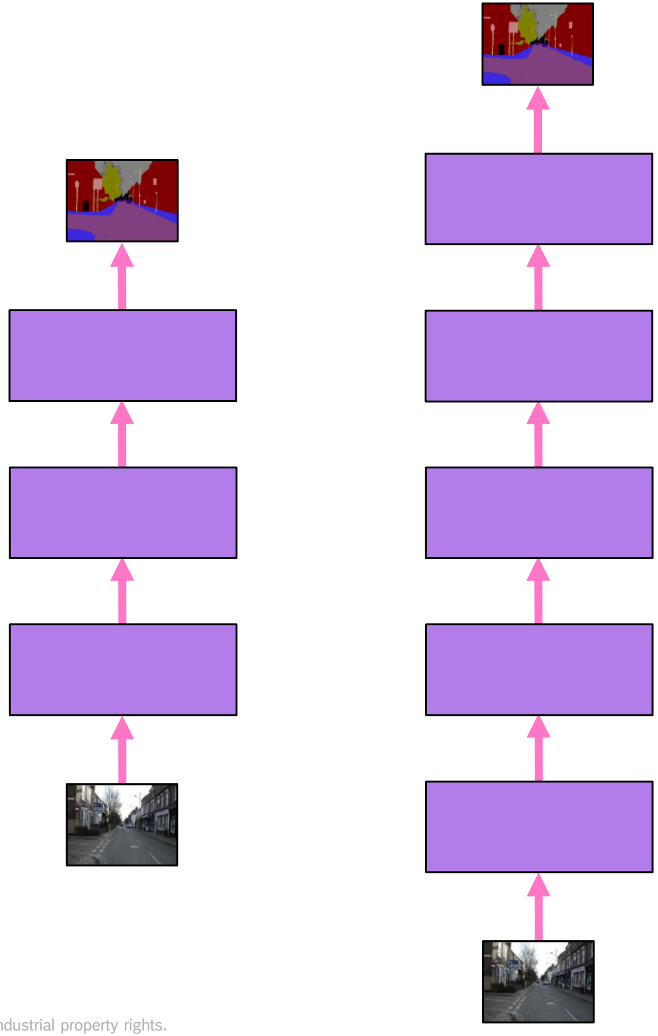

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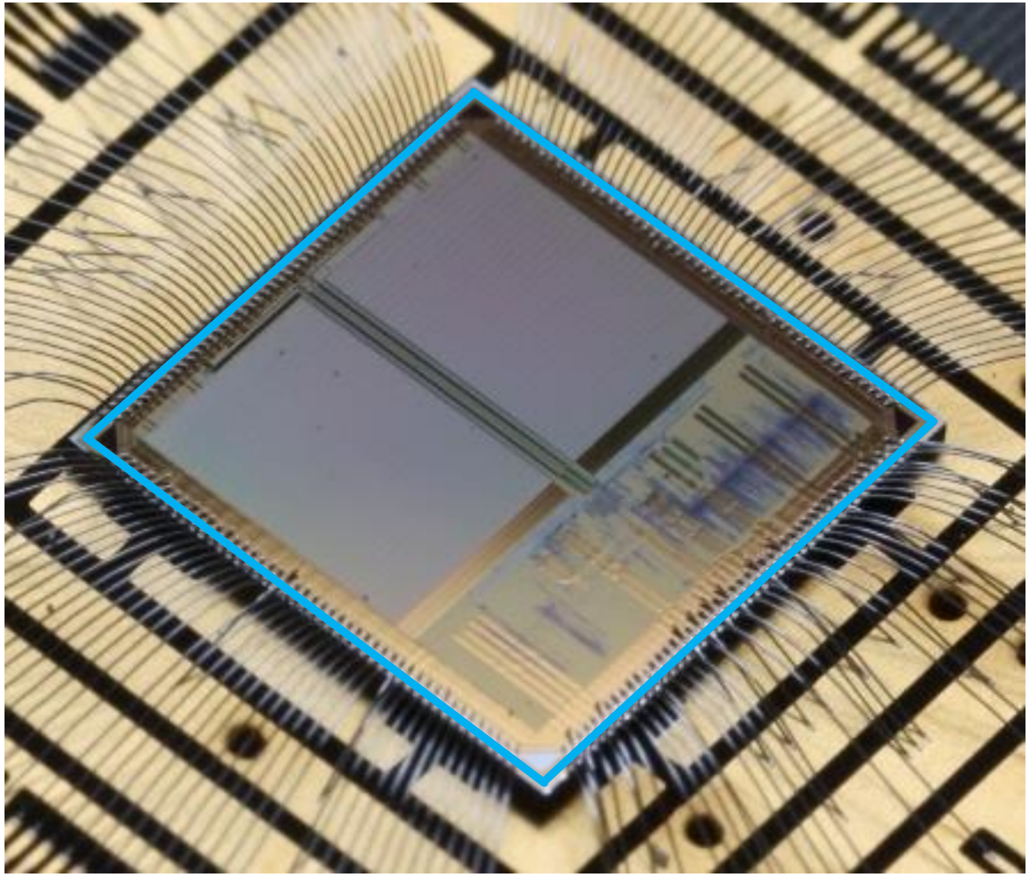

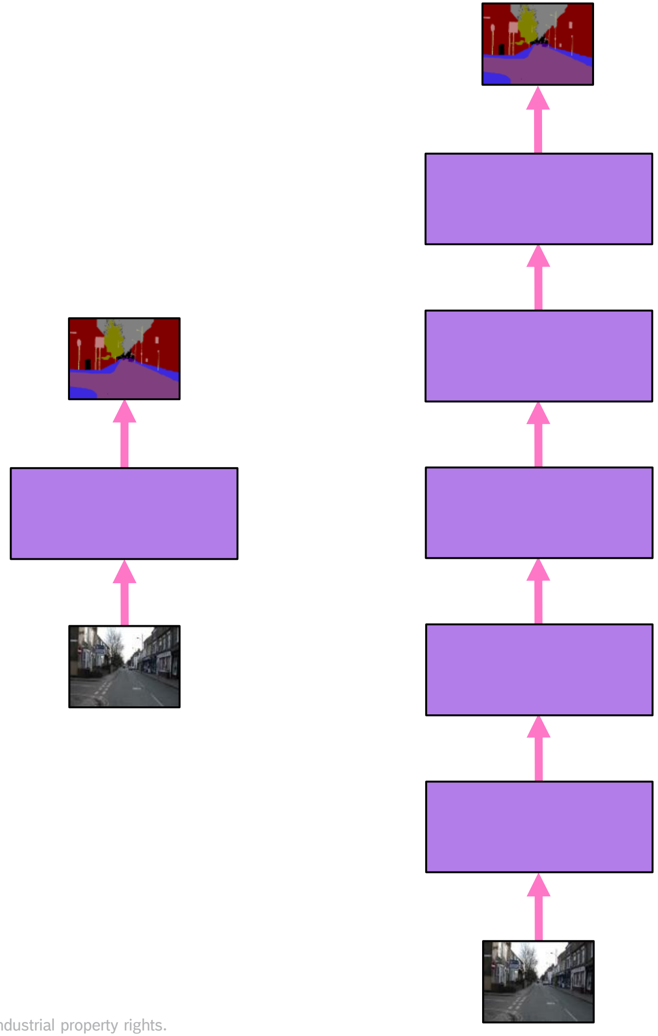

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ItNet: Iterative Neural Networks
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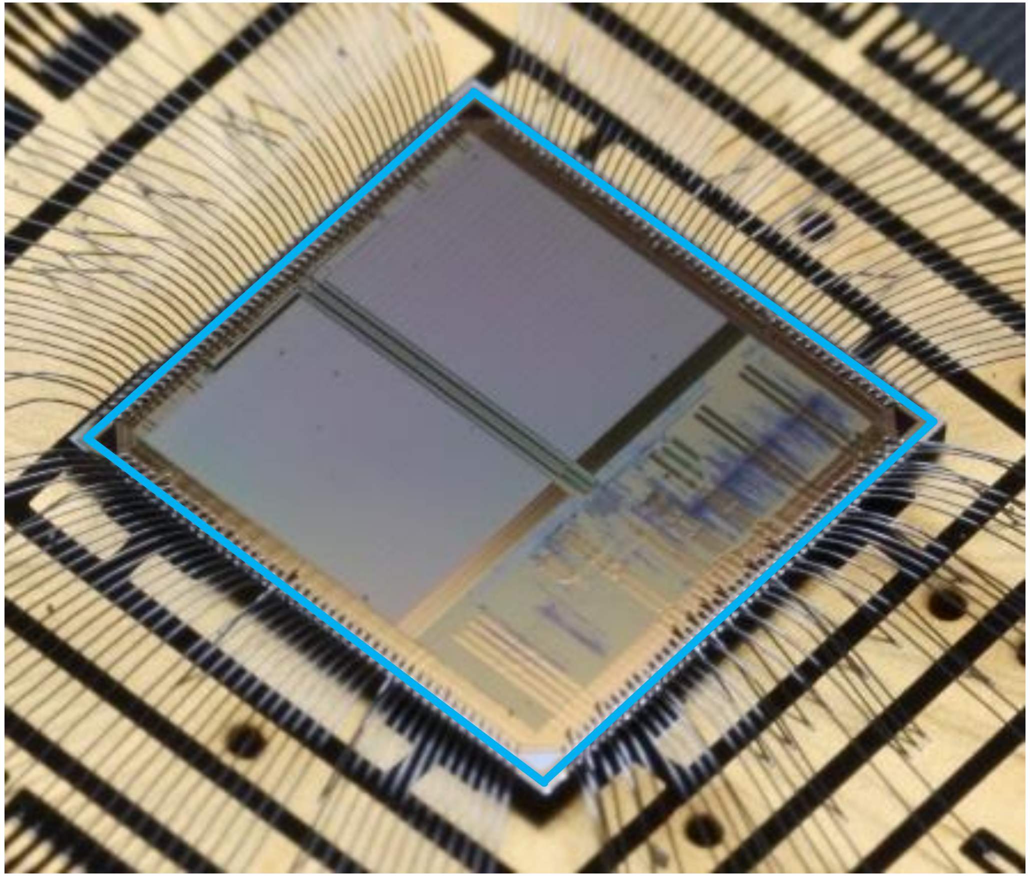

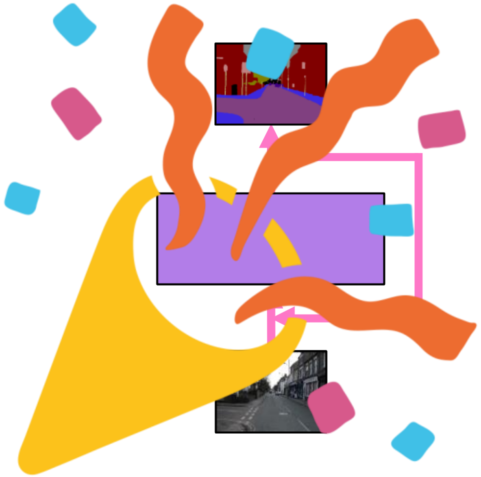

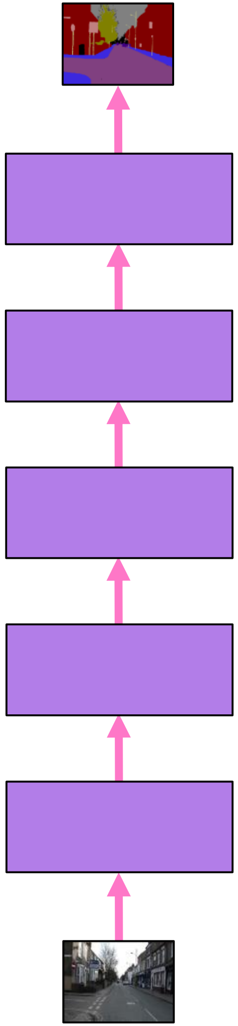

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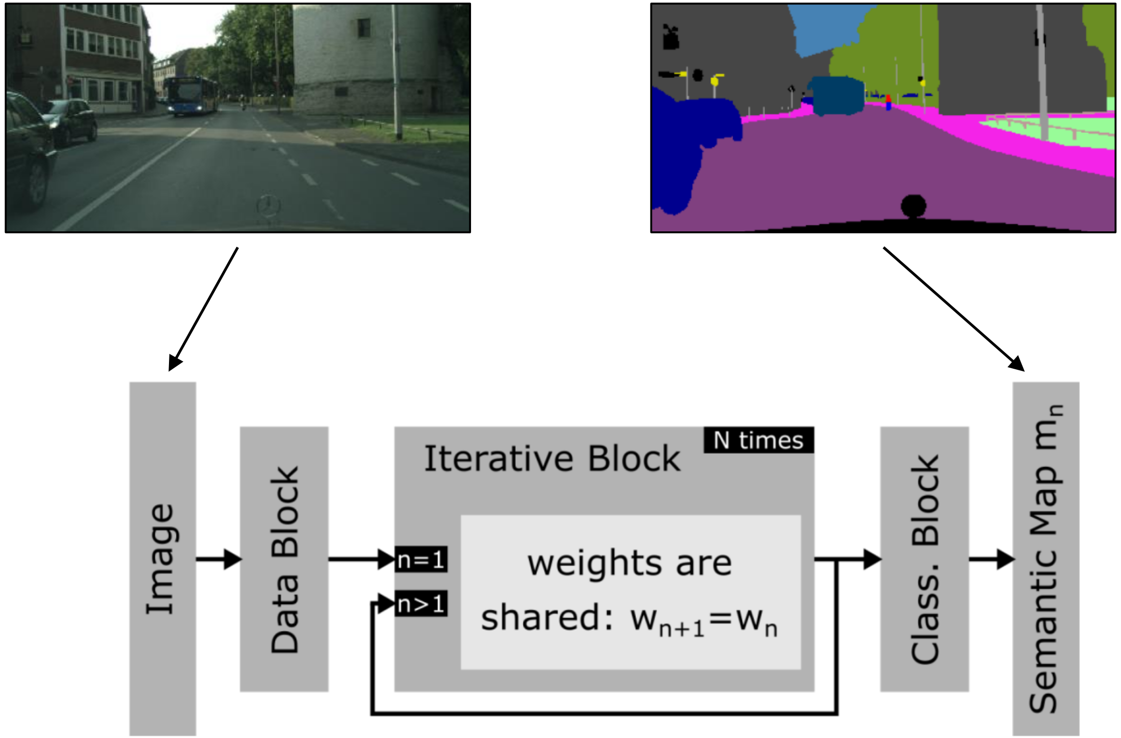
ItNet: Iterative Neural Networks
Task and network model

- Task
  - Semantic segmentation
    - Cityscapes dataset (2 mega pixels)
    - CamVid dataset
  - Target
    - Tiny graph
    - Few billion multiply accumulate operations
- Network model
  - Data block
    - Down-sampling (4-fold) and preparation for iterative block
  - Iterative block
    - Weight are shared between iteration
  - Classification block
    - Classification and up-sampling



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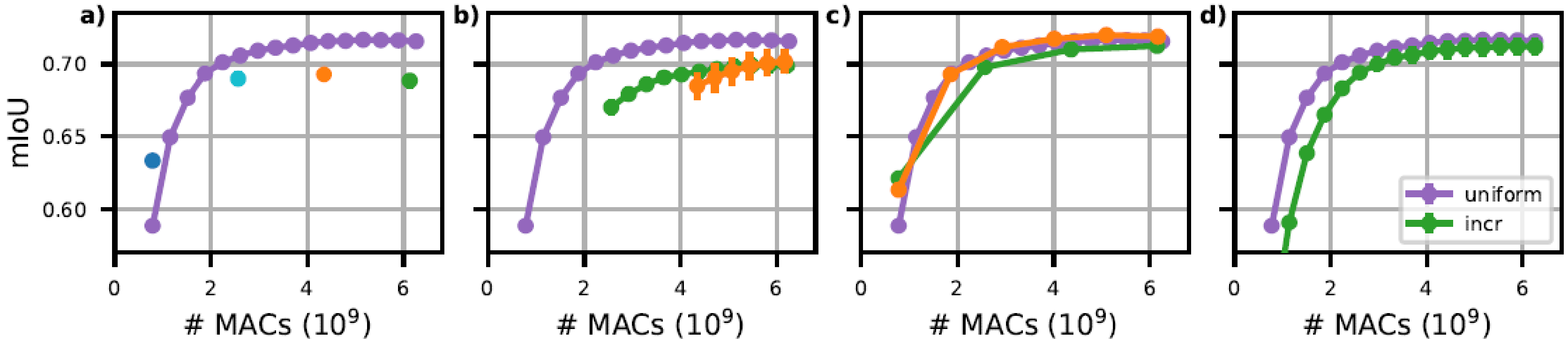
ItNet: Iterative Neural Networks
Network training with intermediate outputs

- Training with backpropagation using the loss function

$$\mathcal{L} = \sum_n \bar{a}_n c_n(\tilde{m}_n, m_n)$$

  with $\bar{a}_n$ the weight of the output n
- Application
  - Anytime prediction
  - Efficiently use limited computational budget

- Results
  - Early outputs improve accuracy of late outputs (a-d)
  - Thinned out outputs result in less constraints and, hence, higher accuracy (c)
  - Uniform weights are better than linearly increasing weights (d)



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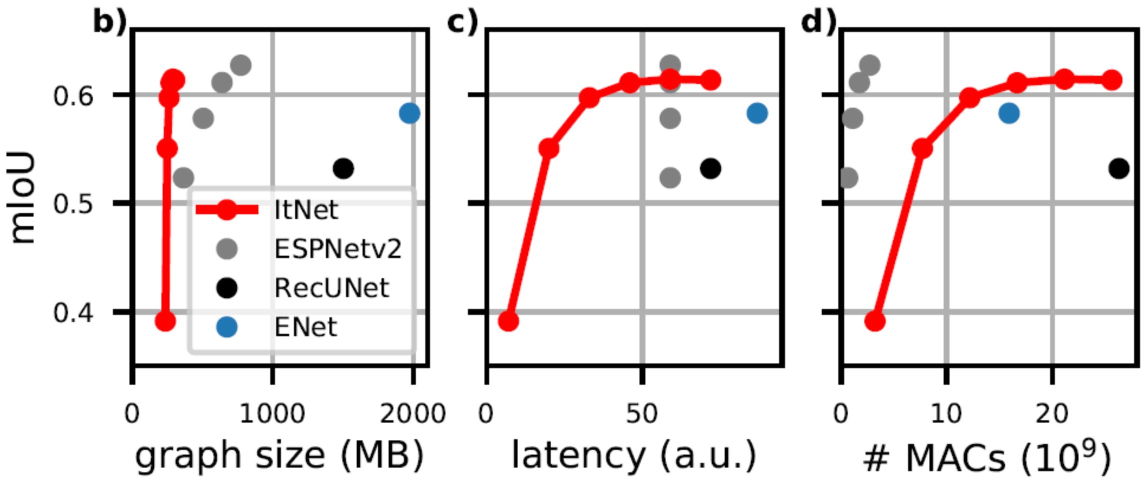
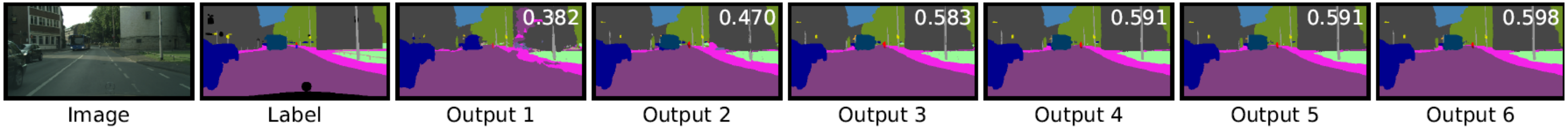
ItNet: Iterative Neural Networks
Results for the Cityscapes dataset

- Compared to the state-of-the-art in terms of MACs (ESPNetv2), ItNets
  - shrink the graph by a factor of 2 (b)
  - allow for anytime prediction with low latencies (c)
  - require 10 times more MACs (d)
- Training can be scaled by, e.g., “Multiscale Deep Equilibrium Models” (Bai, Koltun, Kolter at NeurIPS 2020)





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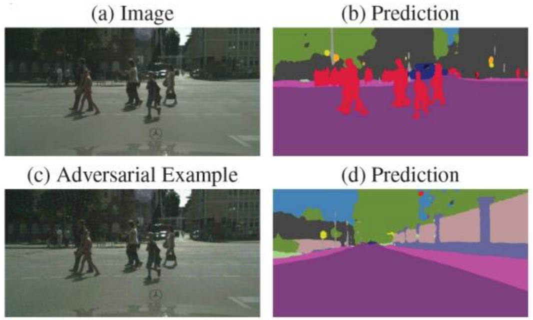
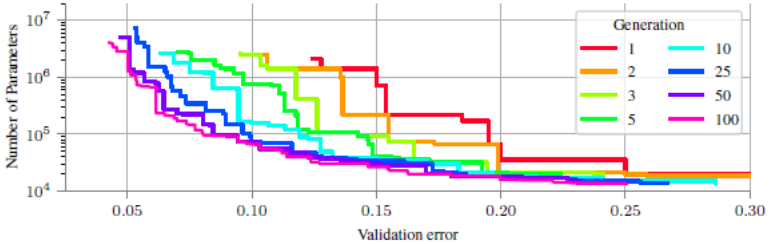
Neuromorphic and AI research at BCAI
Highlights of deep learning research at BCAI

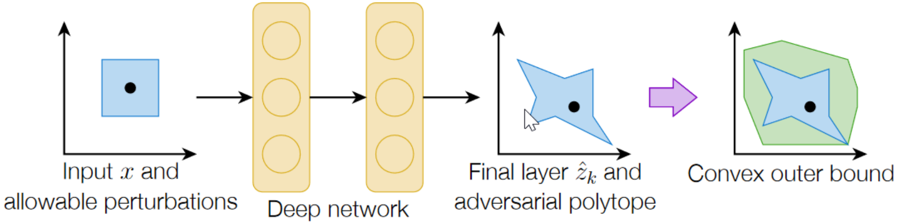
- Metzen, J. H., Mummadi, C. K., M., Brox, T., & Fischer, V.
  Universal adversarial perturbations against semantic image segmentation.
  ICCV 2017



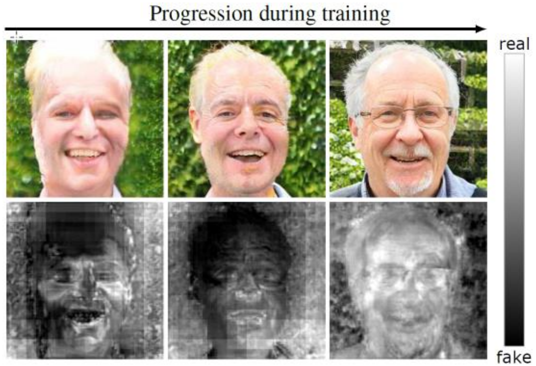
- Elsken, T., Metzen, J. H., & Hutter, F.
  Efficient Multi-Objective Neural Architecture Search via Lamarckian Evolution.
  ICLR 2018



- Wong, E., & Kolter, Z.
  Provable Defenses against Adversarial Examples via the Convex Outer Adversarial Polytope.
  ICML 2018



- Schönfeld, E., Schiele, B., & Khoreva, A.
  A U-Net Based Discriminator for Generative Adversarial Networks
  CVPR 2020



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References

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- Pfeil, T. (2021). ItNet: iterative neural networks with tiny graphs for accurate and efficient anytime prediction. *arXiv preprint arXiv:2101.08685*.

THANK YOU!