

NEURAL CRITICALITY METRIC FOR OBJECT DETECTION DEEP NEURAL NETWORKS



WE MAKE IDEAS HAPPEN

AGENDA

1	Introduction
2	„Why do we need a new safety-related evaluation metric?“
3	Definition of criticality for object detection
4	Experiment setup
5	Conclusion
6	Outlook

WHY DO WE NEED CRITICALITY

Original idea: What is the equivalent of SoftWare Criticality Analysis (SWCA) in ML domain?

SWCA: Actuator-to-sensor analysis of SWC-interfaces and their dependencies/criticalities

We can quantify the contribution of a neuron (weights and biases) to the decision process

Analysis can discover critical feature extractors, the abilities of which can be re-distributed over several layers

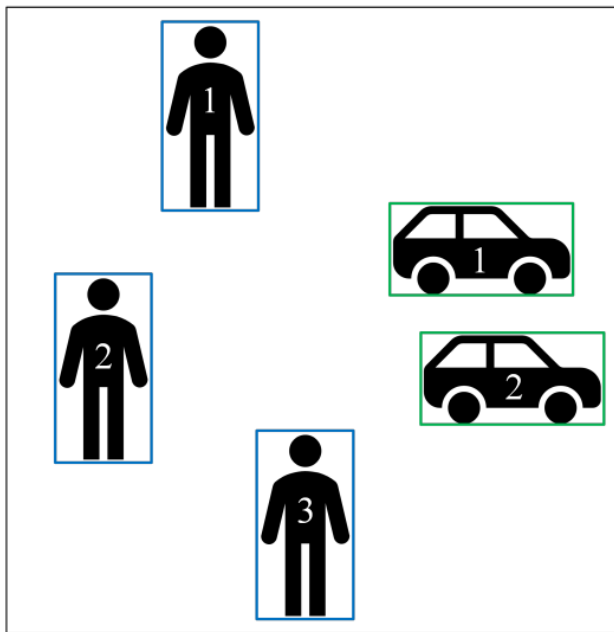
The analysis, as part of the development process minimizes the uncertainty of unknown-unsafe scenario -> SOTIF compliant

Increase the understanding and reliability of the system and can be used for any other CV task

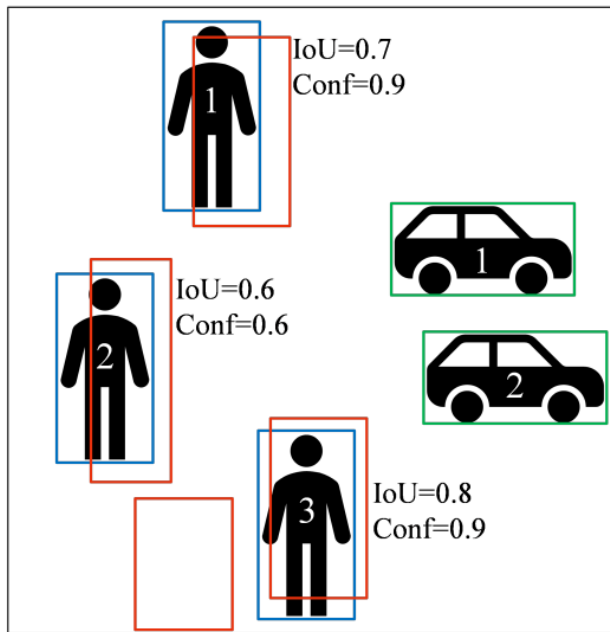
„To the best of our knowledge, there is no method, in the field of computer vision, that would evaluate and quantify the contribution of a neuron to the decision process of an arbitrary object detection DNN.”

HOW TO CALCULATE CRITICALITY

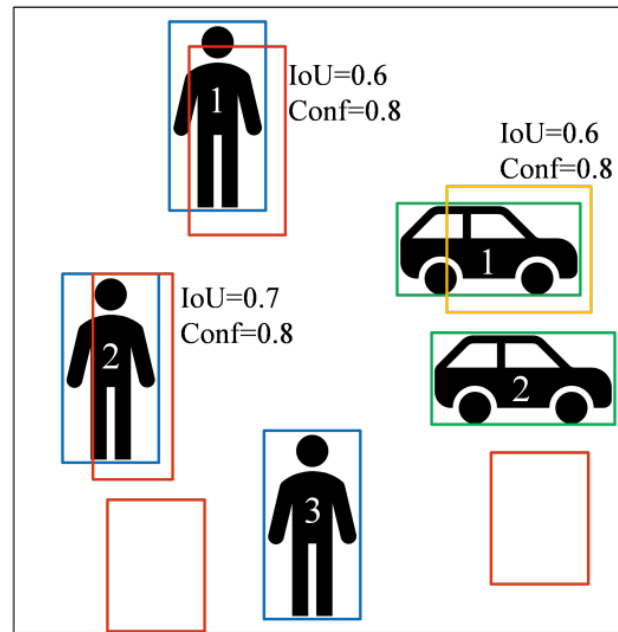
Original image with GT information



Original image with GT information and predictions generated by the unmasked DNN



Original image with GT information and predictions generated by the masked DNN



HOW TO CALCULATE CRITICALITY

	True Positive (TP)	False Negative (FN)	False positive (FP)
Reality	object present	object present	no object present
Prediction	object detected	no object detected	object detected

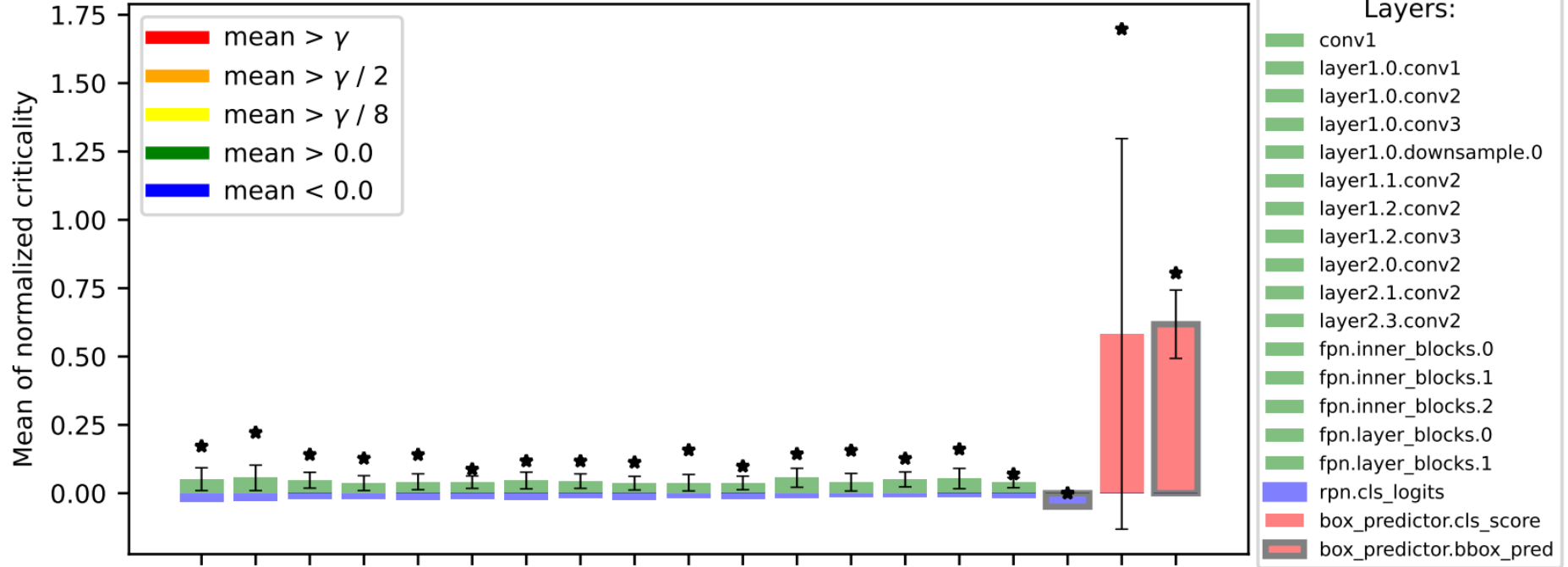
$$f_{cri,TP-FN,c_j}(CONF_{c_j}, IOU_{c_j}, CONF_{c_j,m}, IOU_{c_j,m}) = \frac{\sum_{i=1}^{n_{c_j}} ((conf_i - conf_{i,m}) + (iou_i - iou_{i,m}))}{n_{c_j}}$$

$$f_{cri,FP,c_j}(n_{FP,c_j}, n_{FP,c_j,m}) = \min\left(\frac{n_{FP,c_j,m} - n_{FP,c_j}}{n_{FP,c_j} + \epsilon}, 2\right), \text{ where } \epsilon = 10^{-6}$$

$$f_{cri,total,c_j} = f_{cri,TP-FN,c_j} + f_{cri,FP,c_j}$$

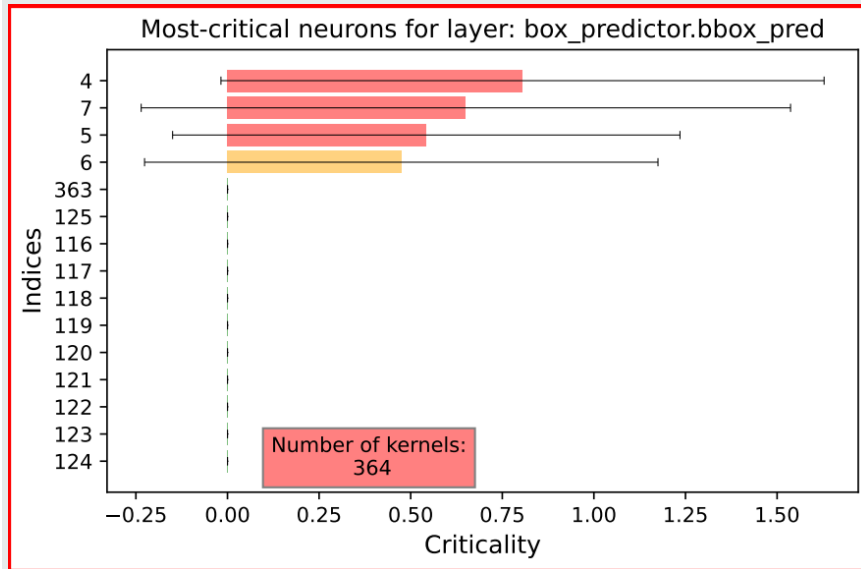
1) OVERALL MODELS' CRITICALITY

Layers' criticality for model fasterrcnn_resnet50_fpn and for class: person

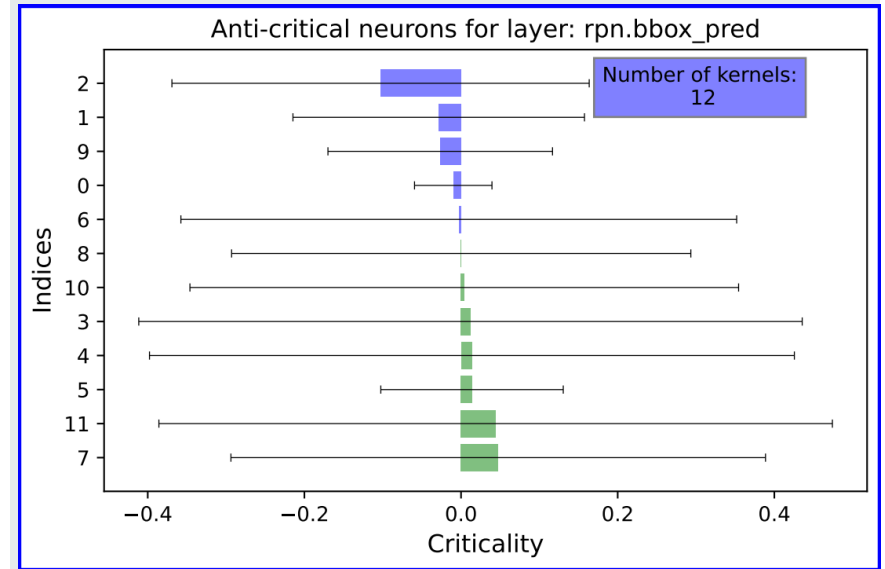


2) MOST CRITICAL AND ANTI-CRITICAL LAYERS

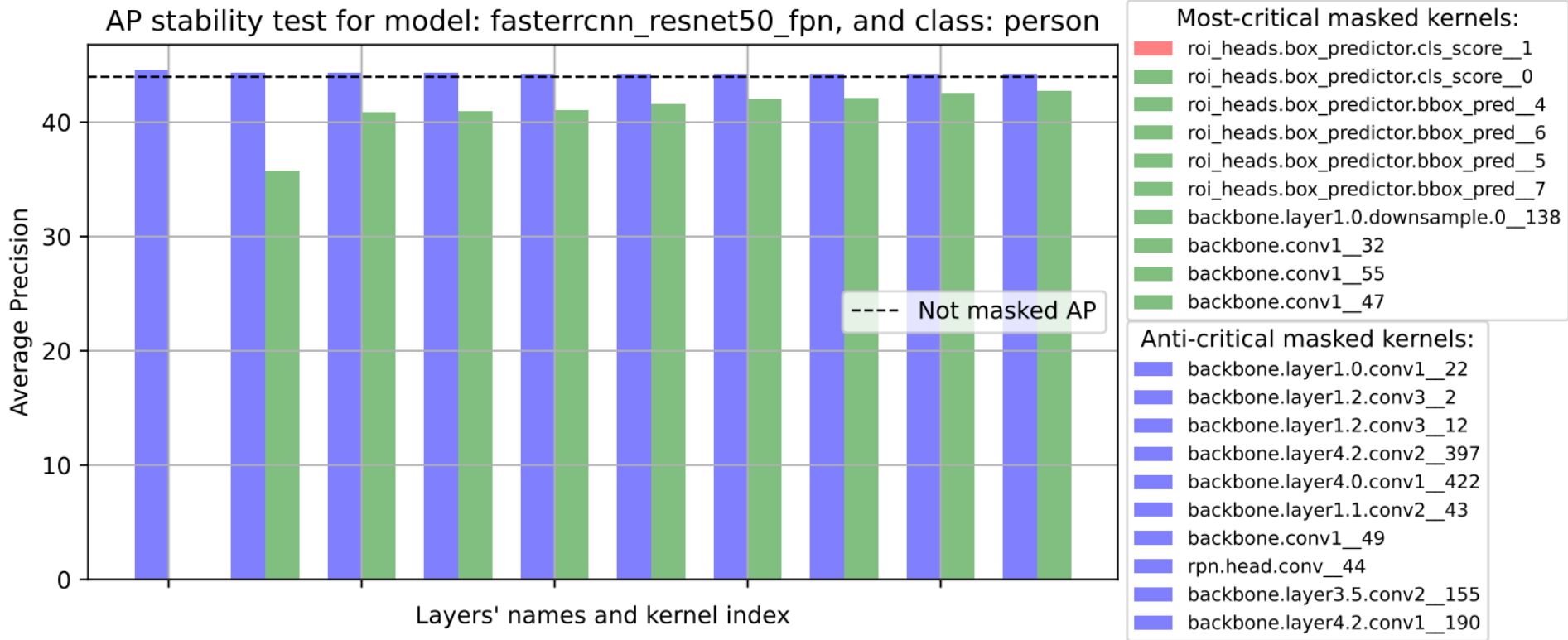
CRITICAL NEURONS



ANTI-CRITICAL NEURONS

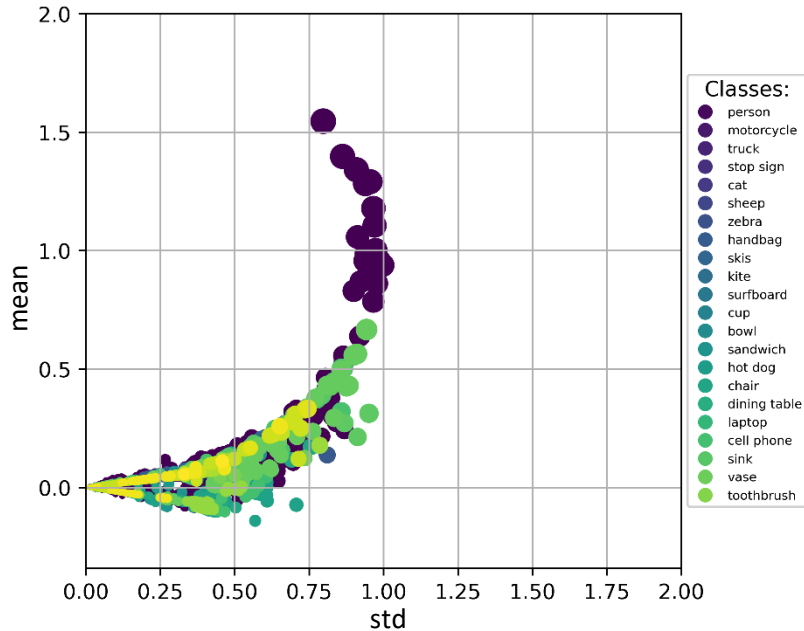


3) STABILITY TEST

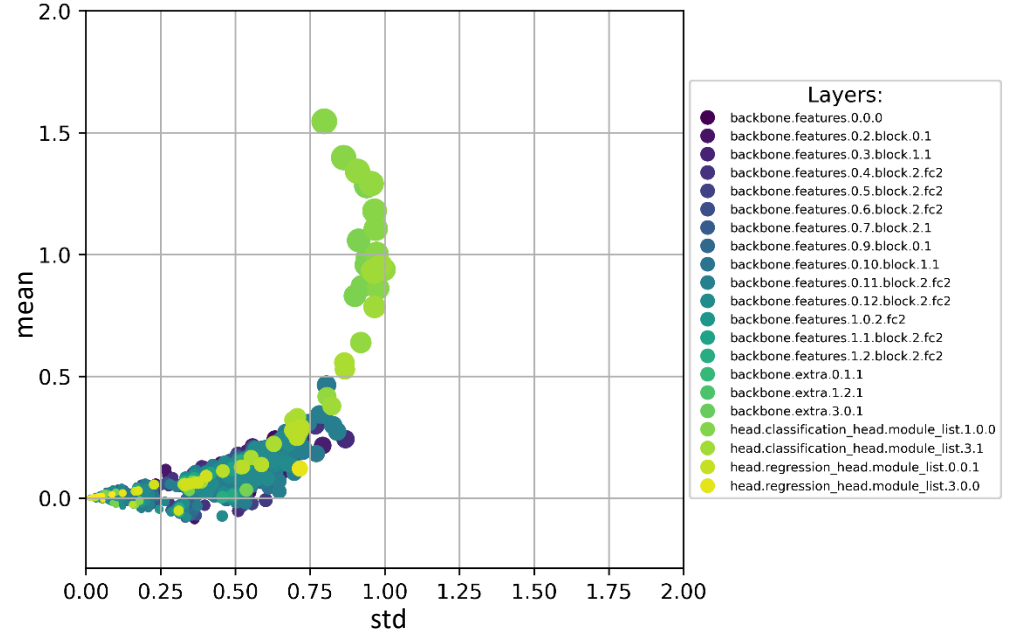


4) FURTHER ANALYSIS – CLUSTERED NEURONS (CLASSES/LAYERS)

CRITICALITY - CLASSES CLUSTERED



CRITICALITY - LAYERS CLUSTERED – CLASS: PERSON



CONCLUSION

	Number of neurons	Number of neurons $cri > 1.0$	$\ cr\ $ 'person'	AP 'person'	AP_{anti} 'person'	AP_{cri} 'person'
Faster R-CNN	31382	2	0.0295	43.97%	44.54%	0.07%
SSD	40244	33	0.0411	21.10%	21.16%	9.04%
YOLOv5	30781	1	0.0150	44.41%	45.07%	27.49%
DETR	80576	3	0.0490	20.34%	23.97%	0.65%

All analyzed models contain class-related critical neurons which can **prevent correct** object detection

Layers' MEAN criticality is a by-product of an inefficient or **non-present regularization** during the training

The explanation of anti-critical neurons is more complex and would require a deeper dive into **cross-classes correlation**

With this article we opened a space for a potential future work such as: evaluation and explanation of anti-critical neurons

From a functional safety point of view, the **optimal criticality** of the neurons within the layers should form a **uniform distribution**. How to achieve it?

OUTLOOK

INTEGRATION

- Incorporation of the criticality into training loss and backpropagation mechanism

FUNCTIONAL SAFETY

- Theoretical definition of a mapping to an ASIL

PRUNING CRITERION

- ✓ Neural Criticality as a potential network pruning metric

COMPUTATIONAL COST

- Minimize the computational costs and extend criticality to problem-specific parameters like distance to object or size of object

CONTACT



ARRK ENGINEERING GMBH

Frankfurter Ring 160
80807 München
Deutschland

www.arrk-engineering.com



Ing. Václav Diviš

Senior Expert Machine Learning ADAS
ADAS Department, ARRK Engineering

+49 157 5010 0497

vaclav.divis@arrk-engineering.com



Tobias Schuster, M.Sc.

Junior Test Architect
Siemens Technology

+49 171 1187456

tobias.schuster@siemens.com



Ing. Marek Hrzůz PhD.

Professor - UWB - Pilsen
DEPARTMENT OF CYBERNETICS

+420 37763 2555

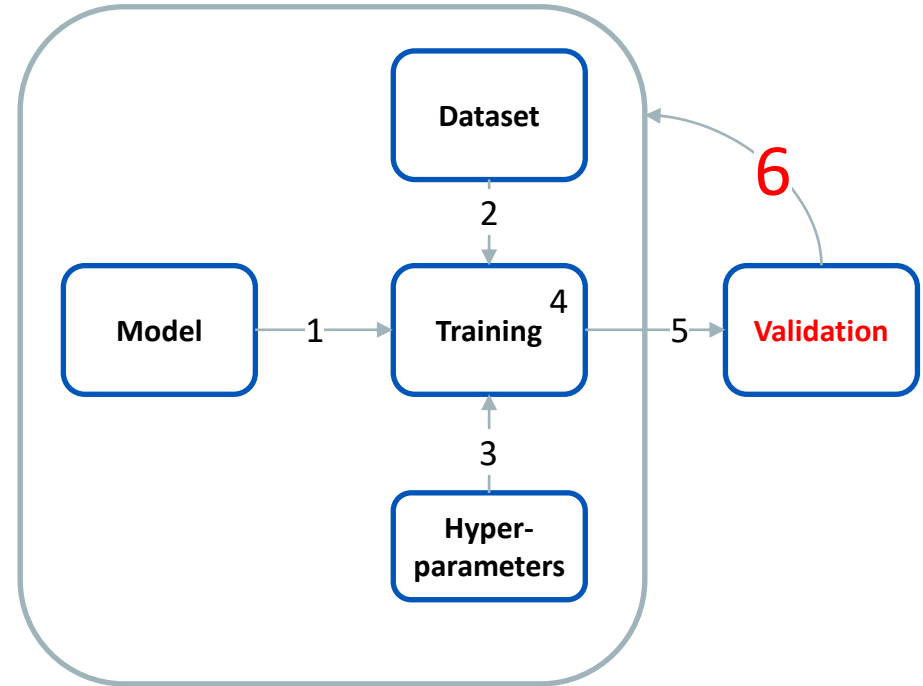
mhruz@ntis.zcu.cz

BACKUP

SIMPLIFIED ML TRAINING PROCESS

- **Data-driven supervised learning**
(object detection, classification, segmentation)

1. Define a model (SOTA Architecture)
2. Gather dataset (preprocess, data-augmentation)
3. Define initial training hyper-parameters
4. Setup a pipeline and start training
5. Validate the training results
6. **Evaluate results, update training setup, dataset and repeat the training**



ANALYSIS METHODOLOGY

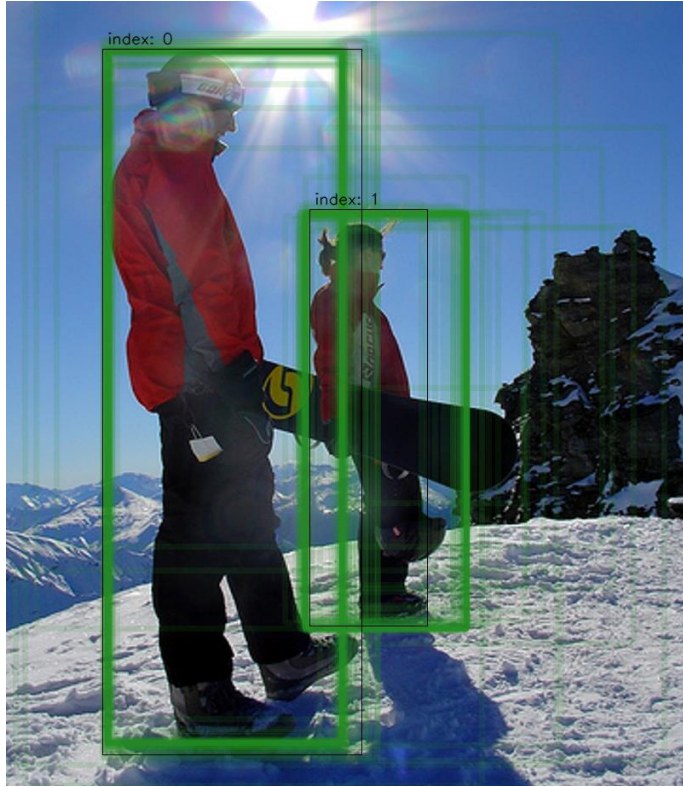
- Dataset: **COCO Dataset**
- Analysed Networks:
 - Two stage: **Faster R-CNN**
 - One stage: **YOLO, SSD**
 - Attention: **DETR**
- Process:
 - For each image and each neuron calculate criticality
 - Conduct a stability test to verify

```

for image  $d \in \mathcal{D}$  do
   $\mathcal{R}_{PR}, \mathcal{C}_{PR}, \mathcal{CONF}_{PR} = \text{predict}(DNN, d, \tau, \delta)$ 
  for every  $L$  in  $DNN$  do
    for every  $k$  in layer  $L$  do
       $DNN_{masked} = \text{mask\_neuron}(k)$ 
       $\mathcal{R}_{PR,m}, \mathcal{C}_{PR,m}, \mathcal{CONF}_{PR,m} = \text{predict}(DNN_{masked}, d, \tau, \delta)$ 
       $CONF, IOU, N_{FP} = \text{match}(\mathcal{R}_{PR}, \mathcal{C}_{PR}, \mathcal{CONF}_{PR}, \mathcal{R}_{GT}, \mathcal{C}_{GT}, \alpha)$ 
       $CONF_m, IOU_m, N_{FP,m} =$ 
         $\text{match}(\mathcal{R}_{PR,m}, \mathcal{C}_{PR,m}, \mathcal{CONF}_{PR,m}, \mathcal{R}_{GT}, \mathcal{C}_{GT}, \alpha)$ 
      for every  $c_j$  in  $\mathcal{C}$  do
         $f_{cri,total,c_j} =$ 
           $f_{cri,TP-FN,c_j}(CONF_{c_j}, IOU_{c_j}, CONF_{c_j,m}, IOU_{c_j,m}) +$ 
           $f_{cri,FP,c}(n_{FP,c_j}, n_{FP,c_j,m})$ 
       $DNN_{masked} = \text{unmask\_neuron}(k)$ 

```

4) FURTHER ANALYSIS - BB HEATMAP



Fußnote: ...

Quelle: ...