KI DELTA LEARNING
Scalable AI for Automated Driving

Final Event | March 09, 2023

Interpretable Pruning

Saqib Bukhari

Topics

- Model Compression & Filter Pruning
  - SoTA in Filter Pruning
- Interpretable Pruning
  - Method Illustration
  - Results for classification and object detection

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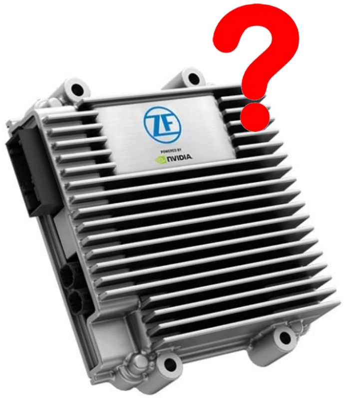
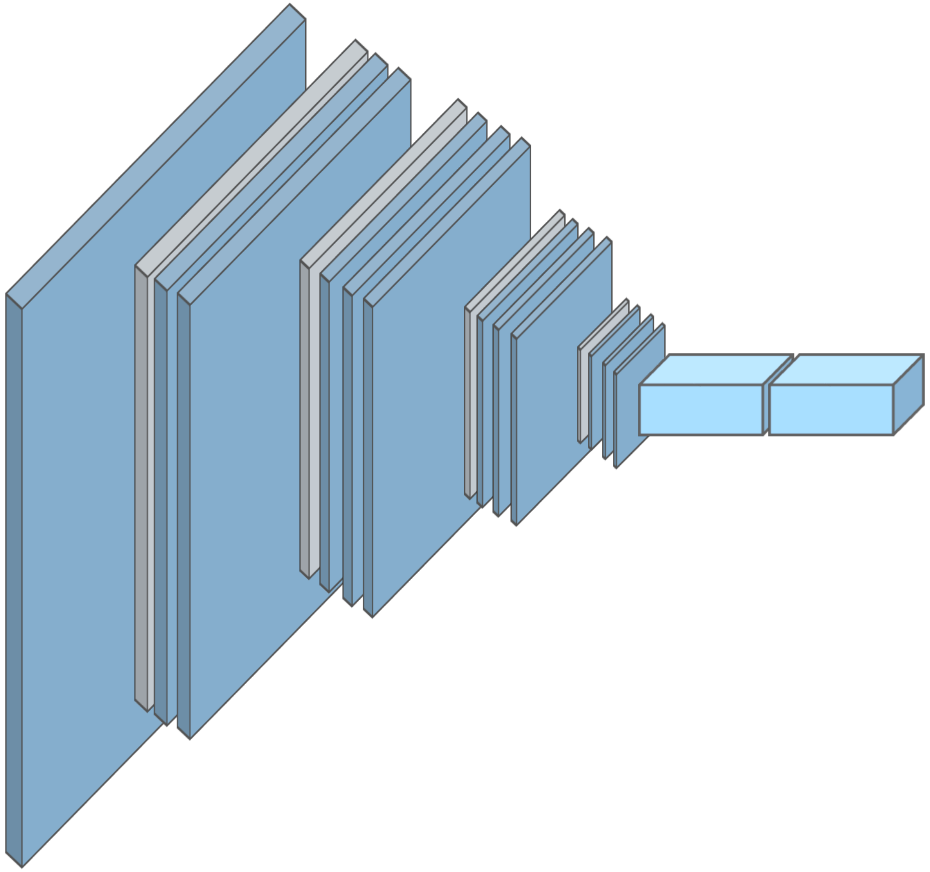
Model Compression: Pruning

Deep Neural Network (DNN) – Challenges and Limitations

- Deep Convolutional Neural Networks (CNNs) achieve superior performance but bring **expensive computation cost**



ZF Pro AI
(Embedded HW)

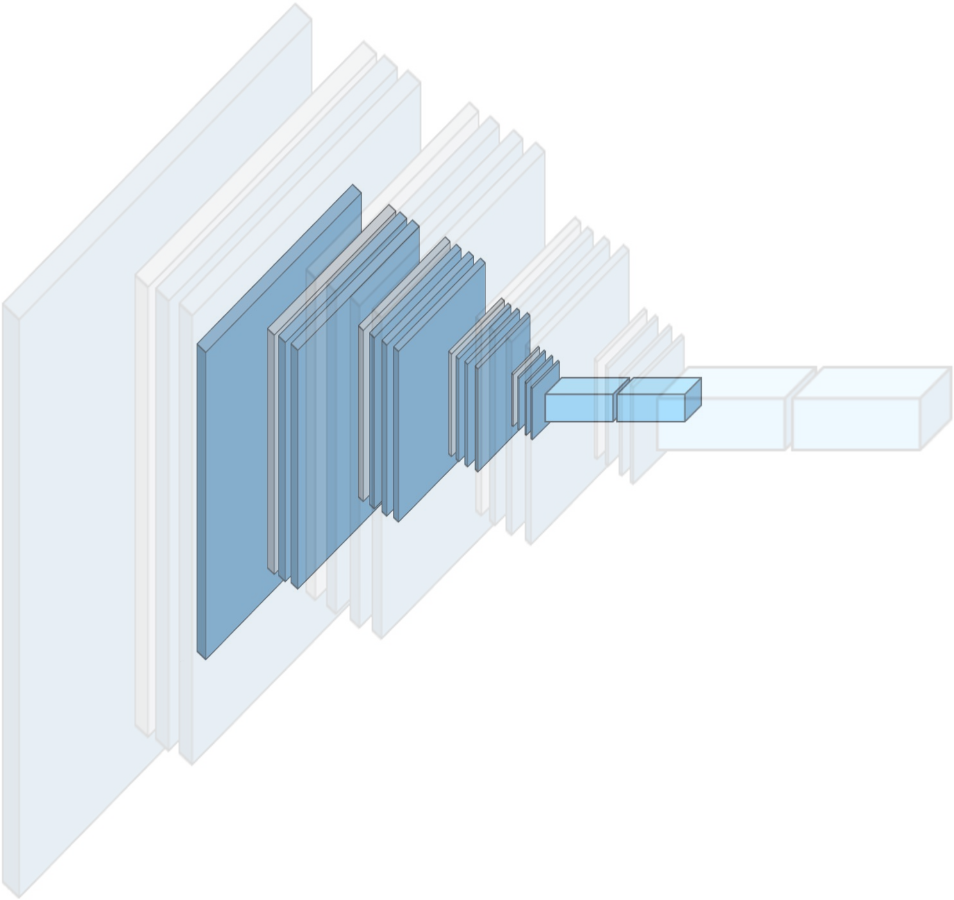


ZF Shuttle
(Autonomous People Mover)

Deep Neural Network (DNN) - Compression

- Reducing the size of a trained model

ZF Pro AI
(Embedded HW)



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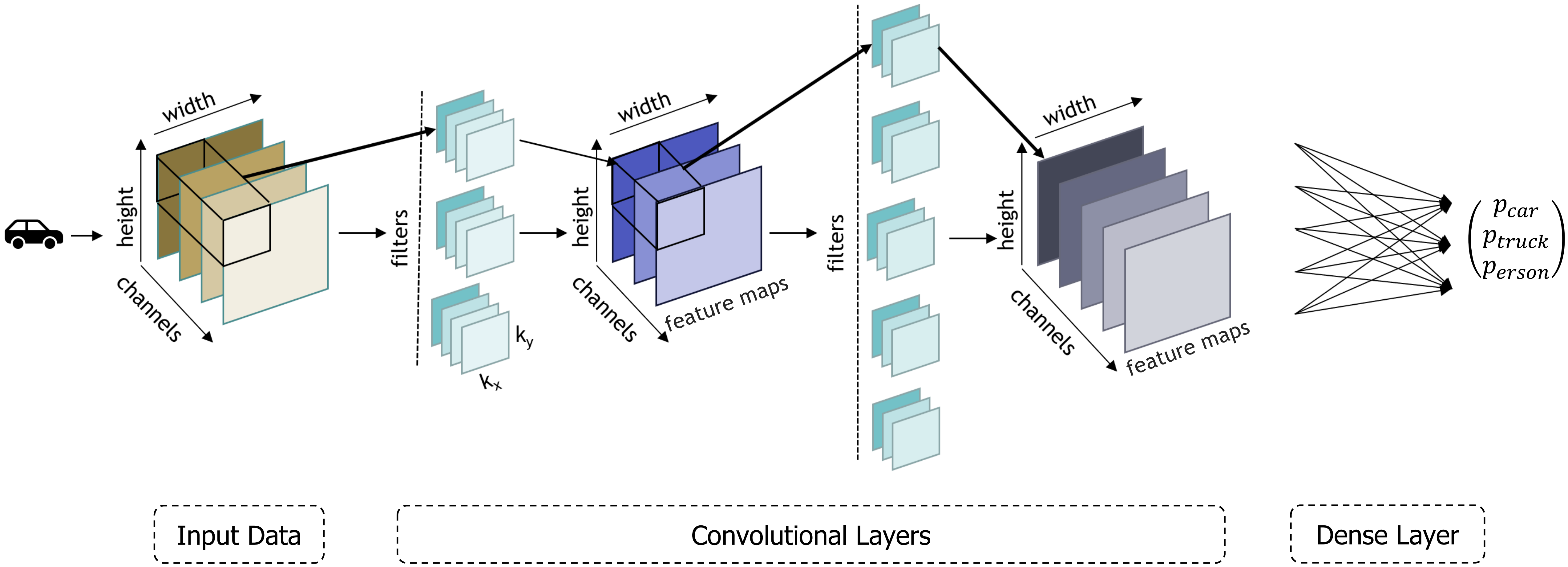
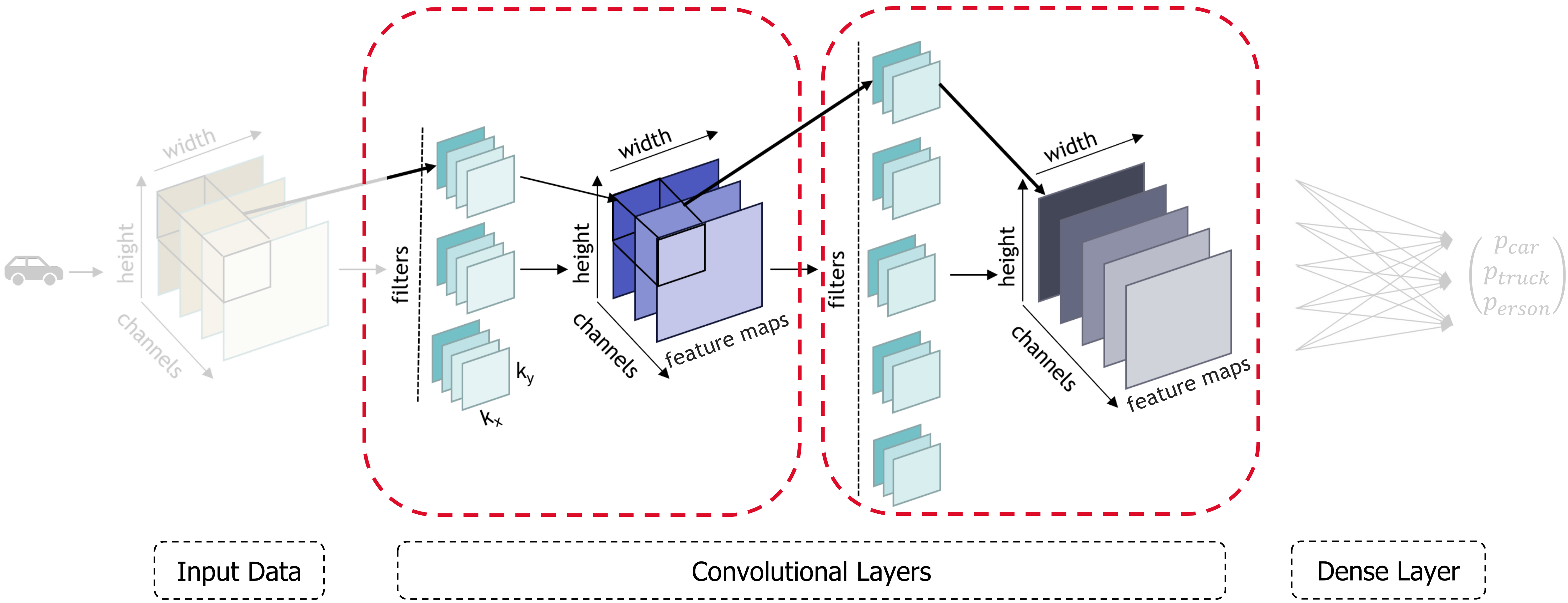
Convolutional Neural Networks – A Simple Model

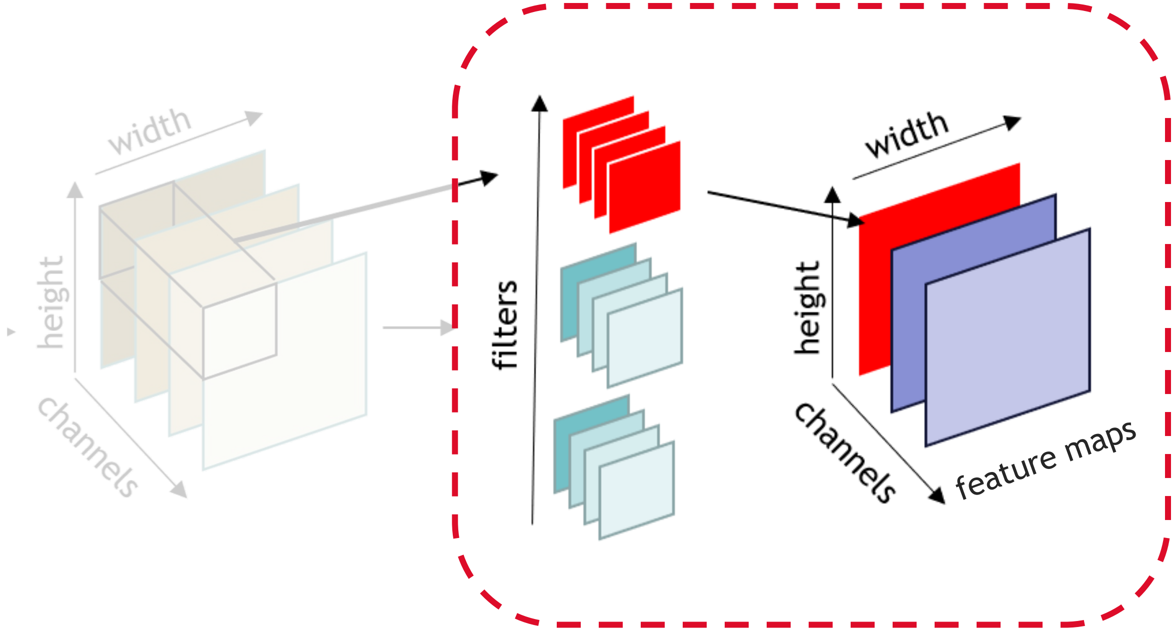


Model Compression on Convolutional Layers

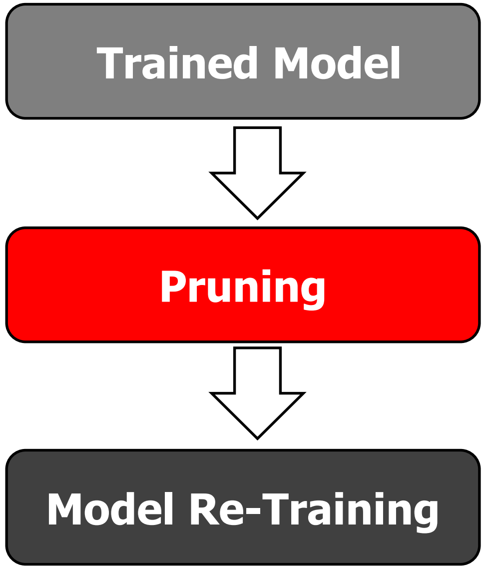


Filter Pruning

- Reduced the complexity of a CNN by removing less important filter kernels



Filter Pruning



A Pruning Process

SoTA Pruning Methods

L1 Norm [1]:

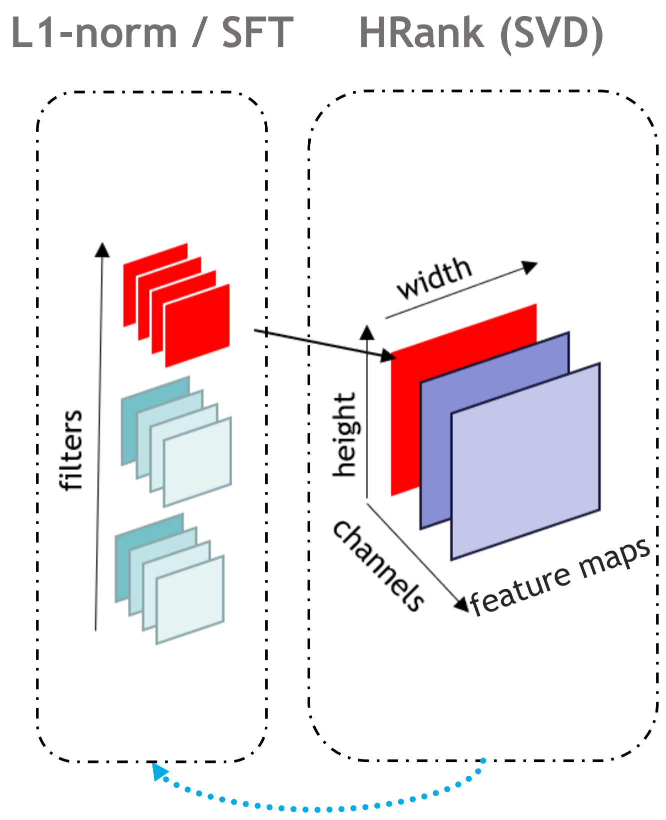
- Filter-Kernels Ranking with respect to the values of **L1-norm** $||F_{i,j}||$

Soft Filter Pruning (SFT) [2]:

- Filter-Kernels Ranking using L1-norm, but iterative pruning-&-retraining cycles

HRank Method [3]:

- Filer-Kernels ranking through the SVD values of corresponding Feature-Maps



[1] Li et al., Pruning filters for efficient convnets. arXiv preprint, 2016.
[2] He et al., Asymptotic soft filter pruning for deep convolutional neural networks. IEEE transactions on cybernetics, 2019.
[3] Lin et al., HRank: Filter pruning using highrank feature map. CVPR, 2020.

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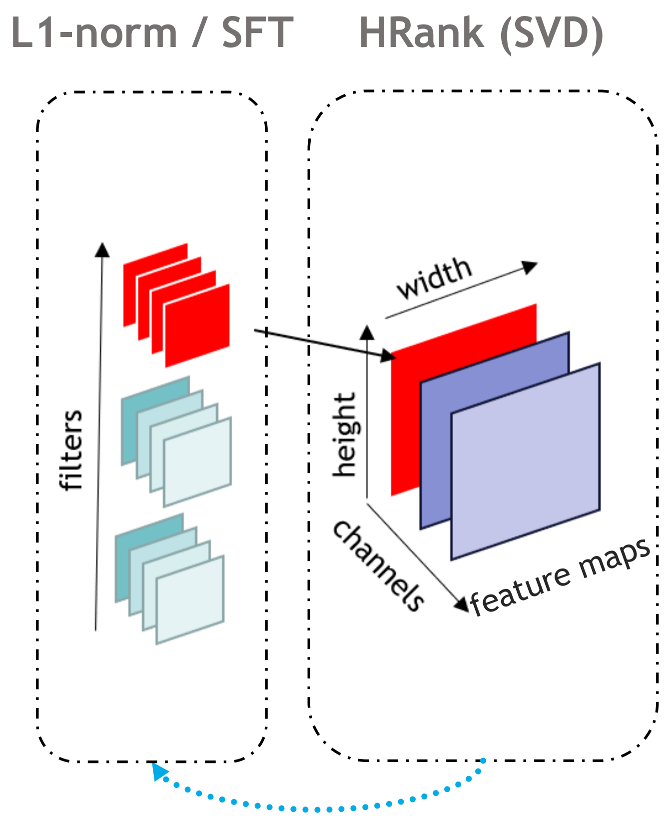

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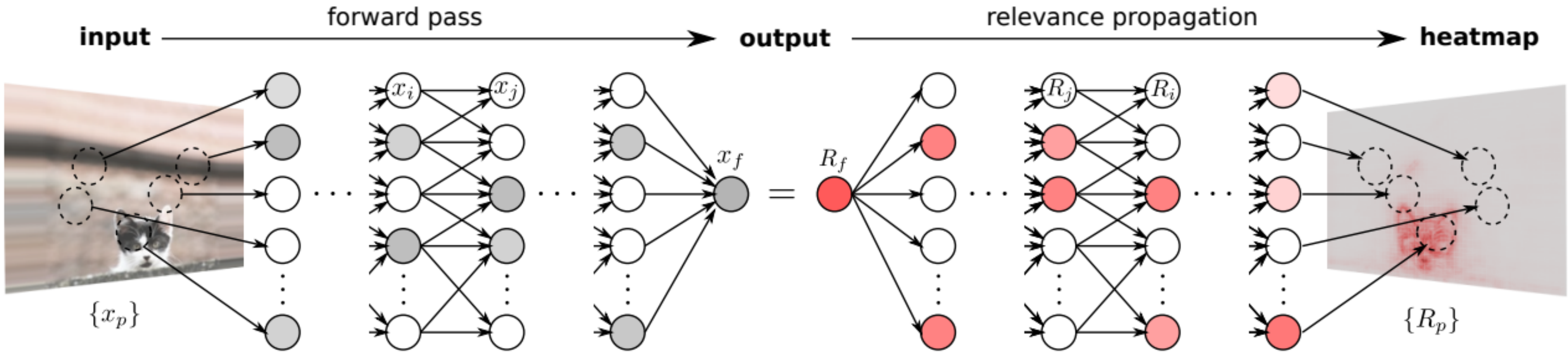
Interpretable Pruning

Motivation: DNN's Interpretation & Understanding

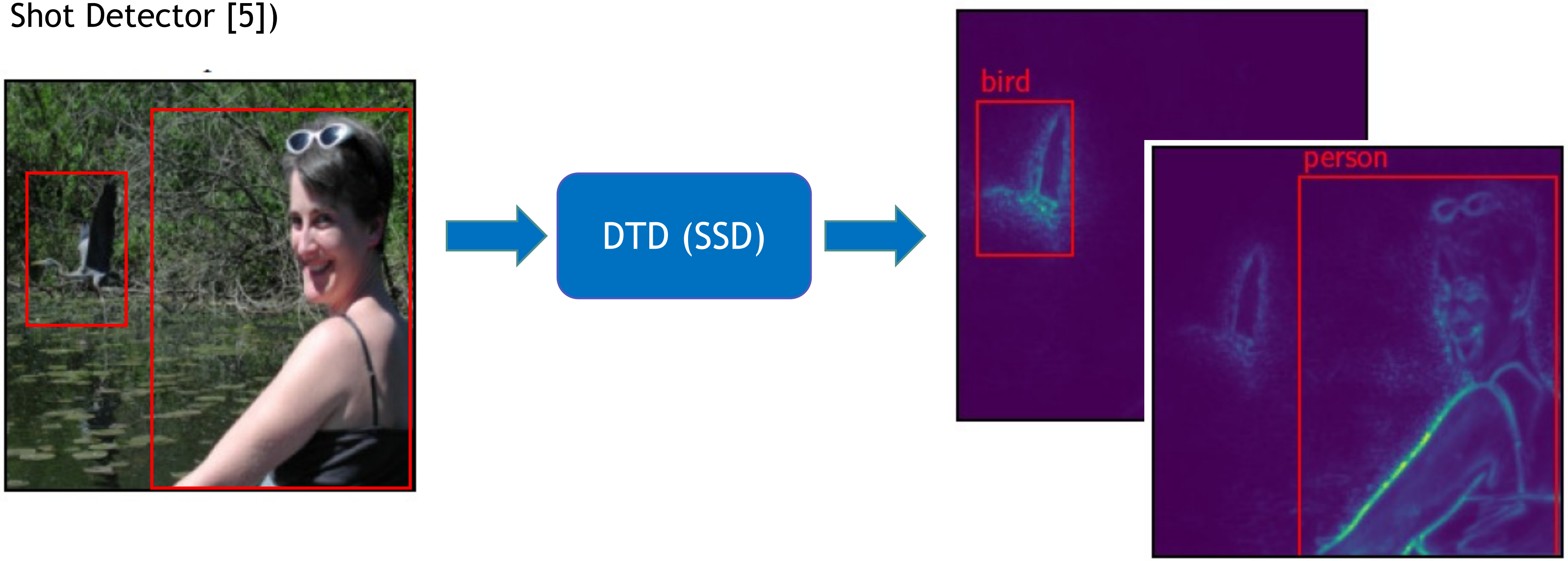
- DNNs act as a black box -> lack of transparency in interpreting results
- **Heatmaps:** SotA methods for interpreting DNNs
  - Deep Taylor Decomposition (DTD) for Image Classification [4]



[4] Montavon et al., Explaining nonlinear classification decisions with deep Taylor decomposition, Pattern Recognition, Volume 65, 2017.

Motivation: DNN’s Interpretation & Understanding

- A ZF’s contribution in KI-Absicherung Project: Adapted Deep Tailor Decomposition (DTD) for Object Detection (SSD: Single Shot Detector [5])



[5] Liu et al., SSD: Single Shot Multibox Detector. In European Conference on Computer Vision, 2016.

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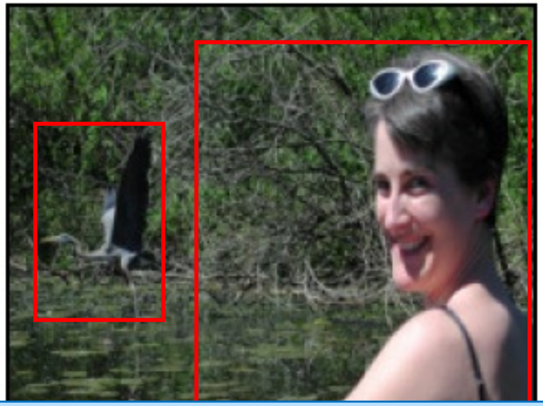
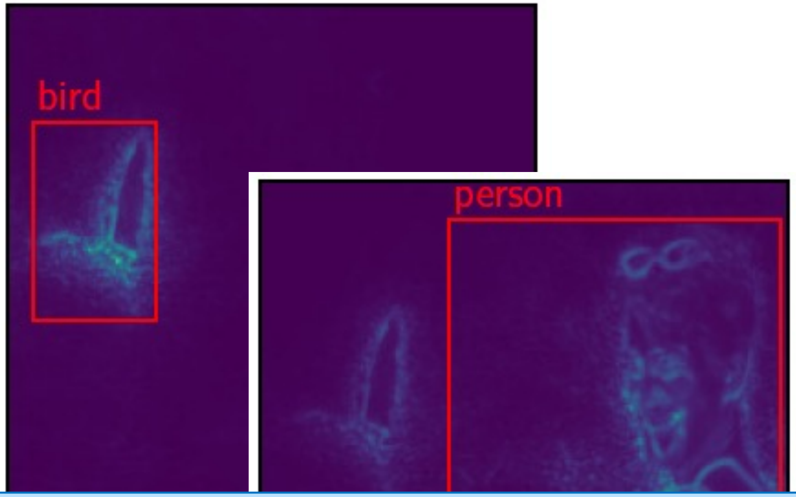


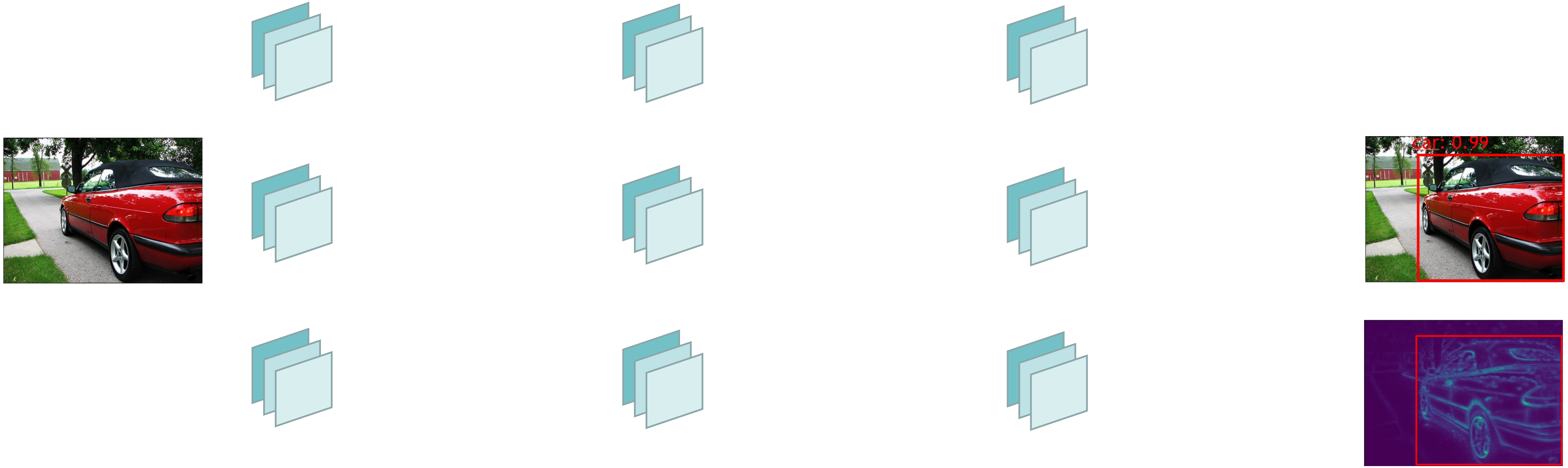
DTD (SSD)



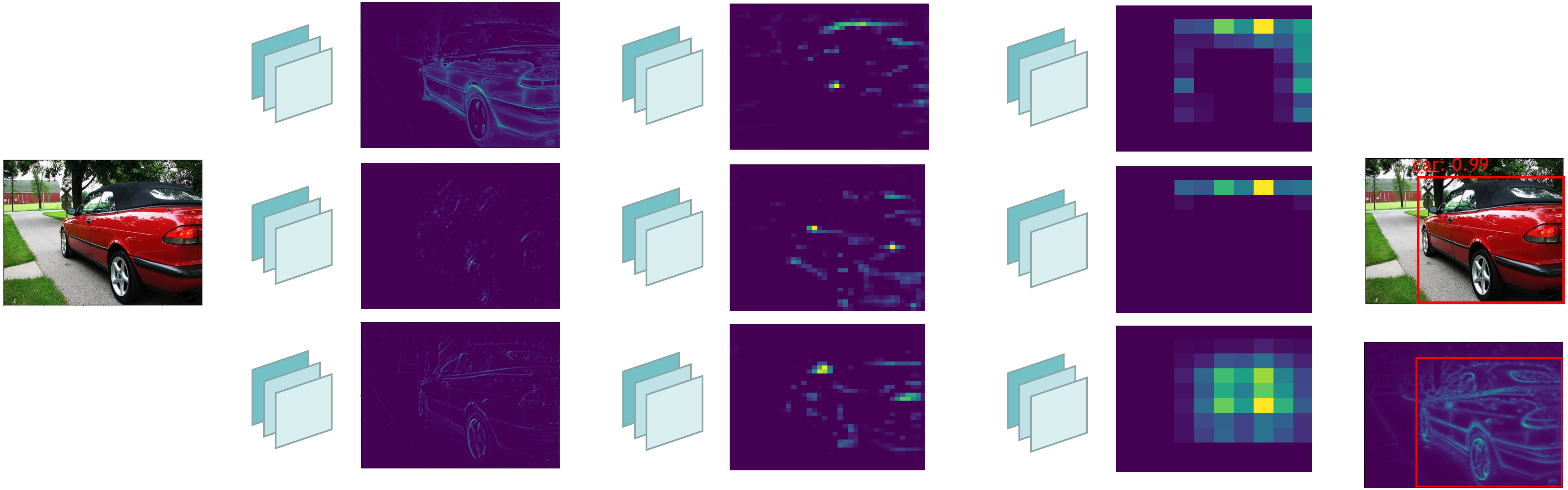
Main Contribution in KIDL

We use ***heatmaps*** *for* ***pruning*** *to improve* ***transparency*** *and* ***safety*** *aspects*

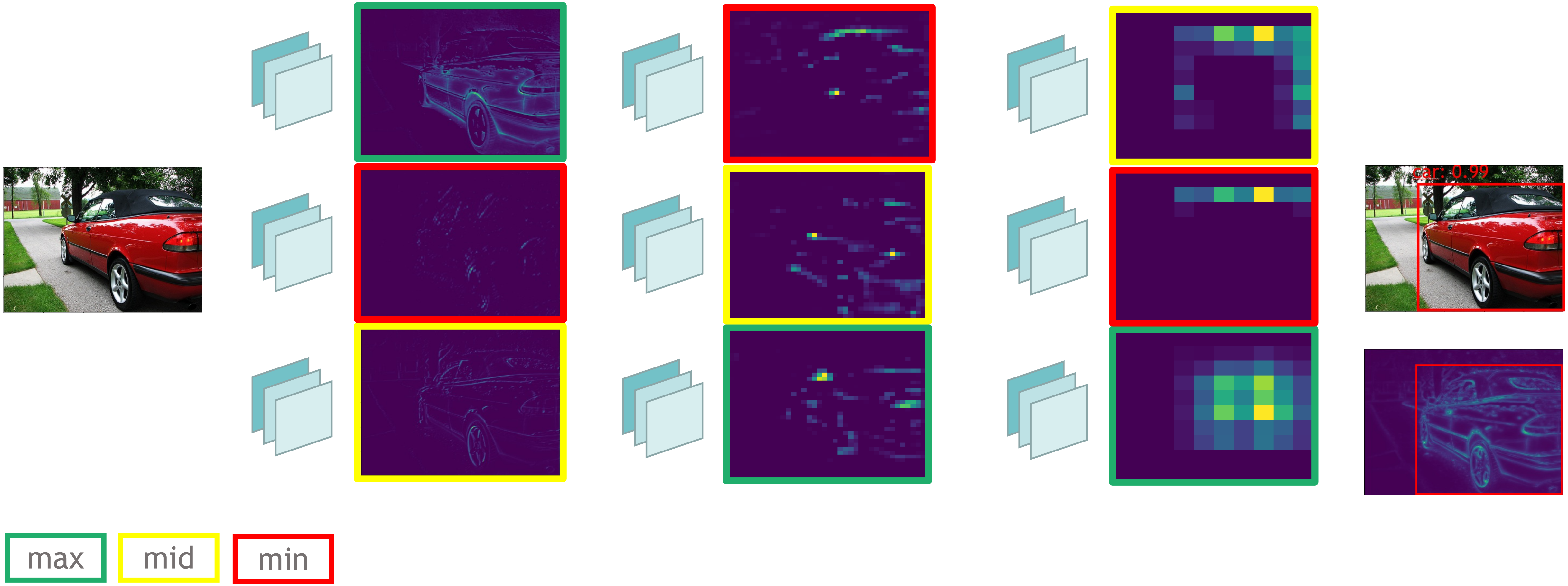
Illustration of Interpretable Pruning Method



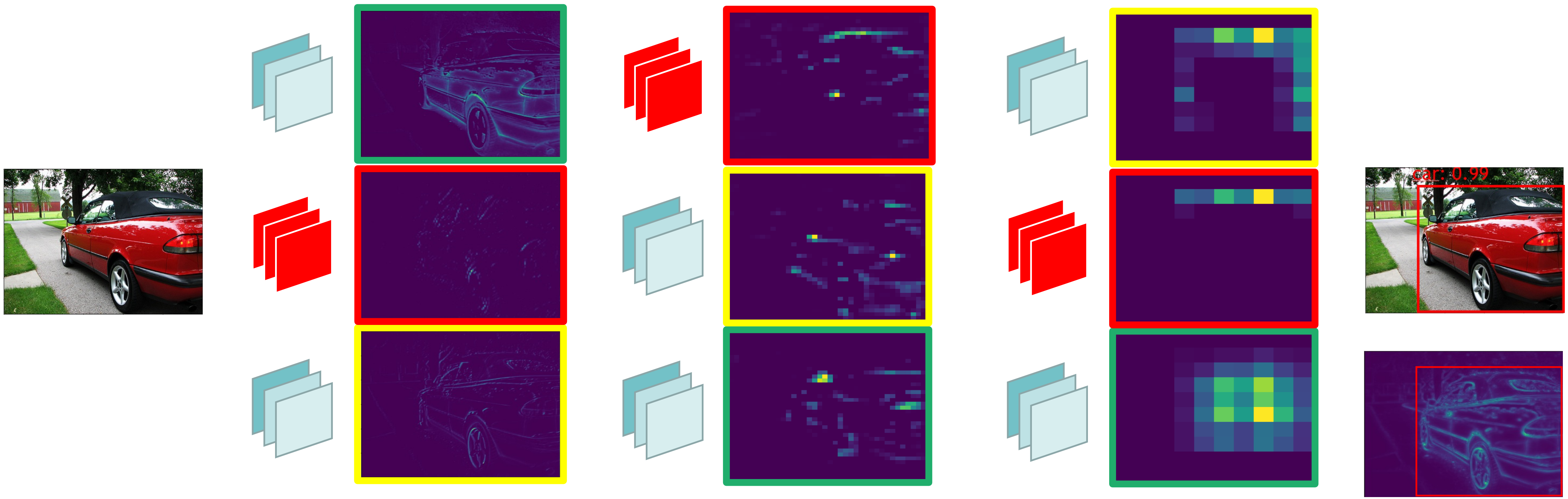
DTD Heatmaps for Filter Kernels



Layer-wise Heatmaps ordering through brightness



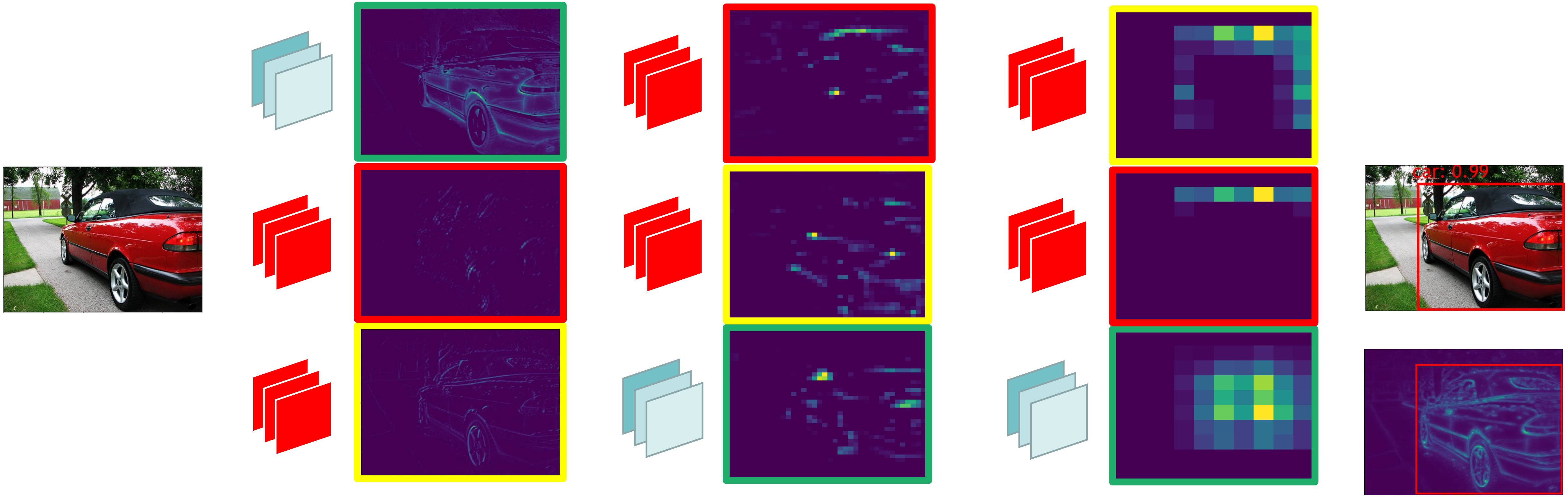
Removal of Filter Kernels Corresponding to low values



max mid min

33% Pruning Ratio (i.e. removing 3 out of total 9 filters)

Removal of Filter Kernels Corresponding to low values



66% Pruning Ratio (i.e. removing 6 out of total 9 filters)

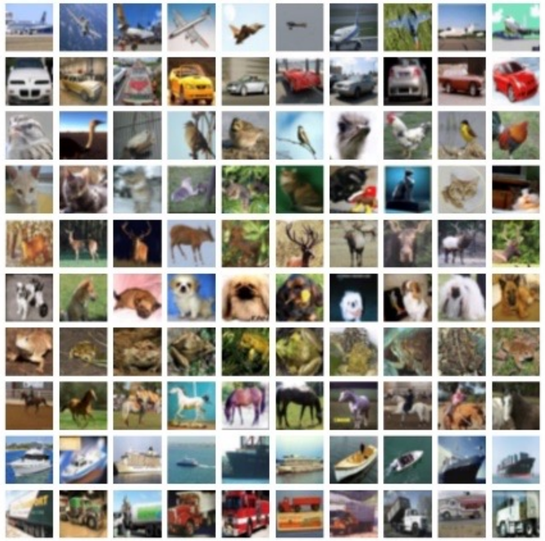
3

Results

Problem Domain: Image Classification

- **Model:** VGG16
- **Dataset:** CIFAR10 & CIFAR100
- **Pruning Methods:**
  - HRank
  - Interpretable Pruning

CIFAR10 & 100 Dataset

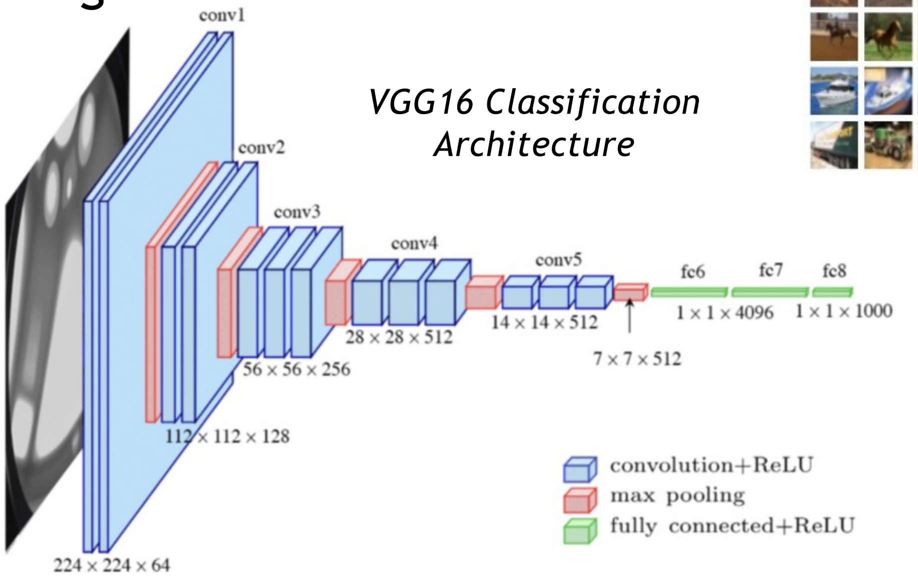


Classes:
airplane, automobile, bird, cat, deer, dog, frog, horse, ship, truck

Classes
beaver, dolphin, otter, seal, whale
aquarium fish, flatfish, ray, shark, trout
orchids, poppies, roses, sunflowers, tulips
bottles, bowls, cans, cups, plates
apples, mushrooms, oranges, pears, sweet peppers
clock, computer keyboard, lamp, telephone, television
bed, chair, couch, table, wardrobe
bee, beetle, butterfly, caterpillar, cockroach
bear, leopard, lion, tiger, wolf
bridge, castle, house, road, skyscraper
cloud, forest, mountain, plain, sea
camel, cattle, chimpanzee, elephant, kangaroo
fox, porcupine, possum, raccoon, skunk
crab, lobster, snail, spider, worm
baby, boy, girl, man, woman
crocodile, dinosaur, lizard, snake, turtle
hamster, mouse, rabbit, shrew, squirrel
maple, oak, palm, pine, willow
bicycle, bus, motorcycle, pickup truck, train
lawn-mower, rocket, streetcar, tank, tractor

https://www.cs.toronto.edu/~kriz/cifar.html

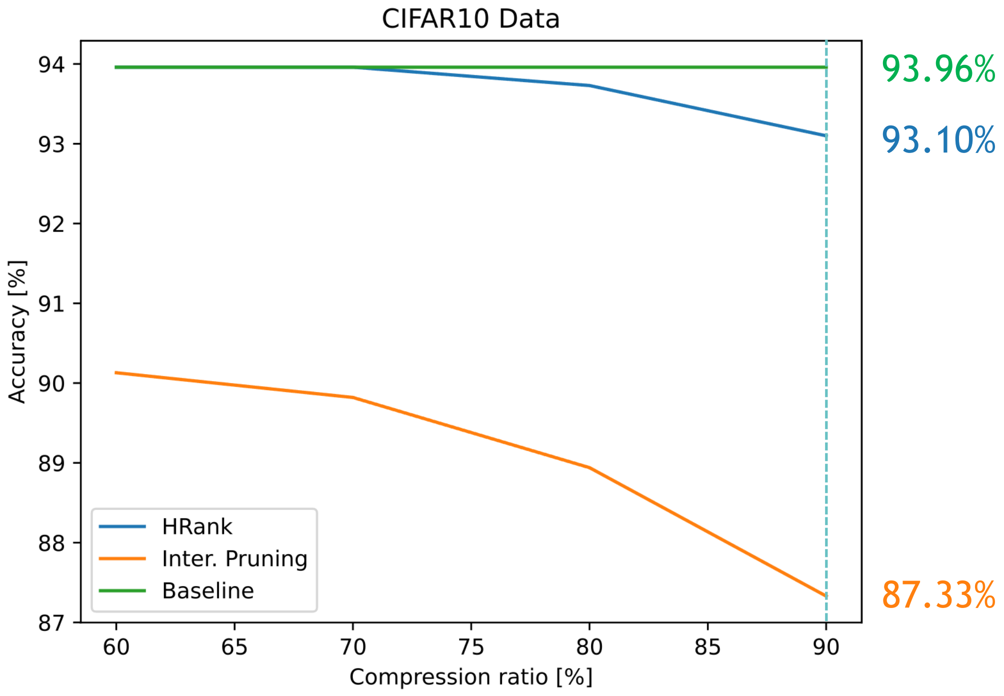
VGG16 Classification Architecture

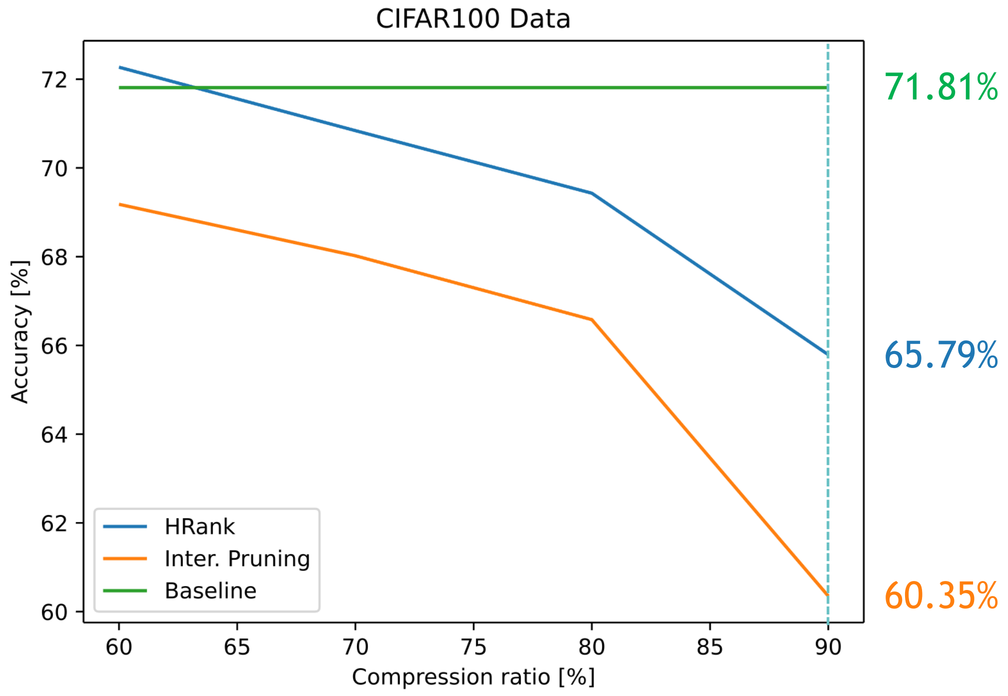


https://arxiv.org/abs/1409.1556v6

Results: Classification

- Comparing HRank with Interpretable Pruning





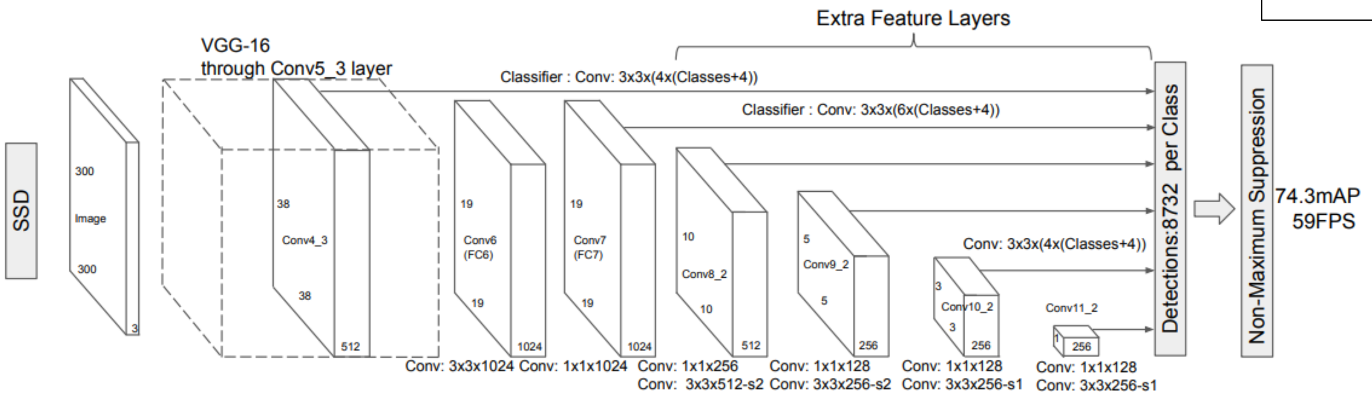
Problem Domain: Object Detection

- **Model:** Single Shot Detector (SSD)
- **Dataset:** PASCAL VOC 2007
- **Pruning Methods:**
  - HRank *(we extended it for object detection problem)*
  - Interpretable Pruning

PASCAL VOC 2007 Dataset

http://host.robots.ox.ac.uk/pascal/VOC/voc2007/

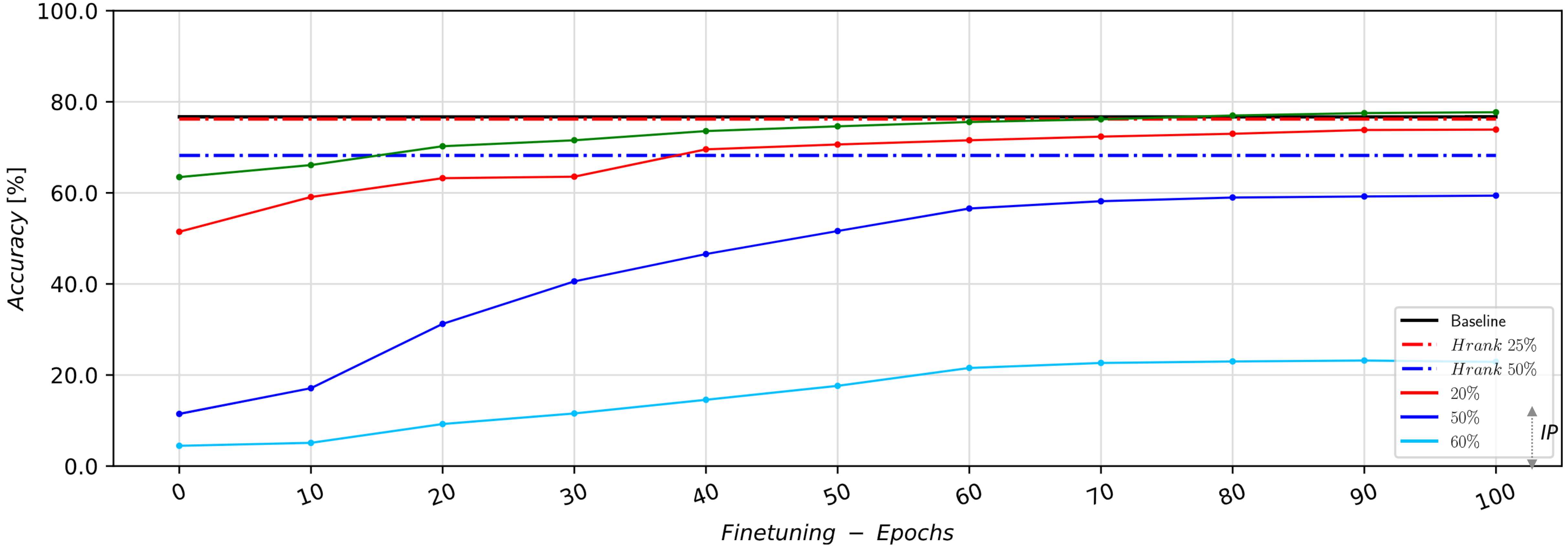
SSD - Object Detection & Classification Architecture



https://arxiv.org/abs/1409.1556

Results: Object Detection

- Comparing HRank with Interpretable Pruning (IP)



Summary & Conclusion

- Briefly presented the main concept of filter pruning process for model compression
- Introduced the approach of *Interpretable Pruning*
- Compared Interpretable Pruning with HRank (SoTA pruning technique) for image classification and object detection problems

- ***Interpretable Pruning results are comparable with HRank, and it makes the model compression process more transparent***

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KI FAMILIE

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Federal Ministry for Economic Affairs and Climate Action

on the basis of a decision by the German Bundestag

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