Machine Learning at Edge

A. Afsharrad, E. Sharifian

A Literature Review

Supervisor: Dr. M. Maddah-Ali

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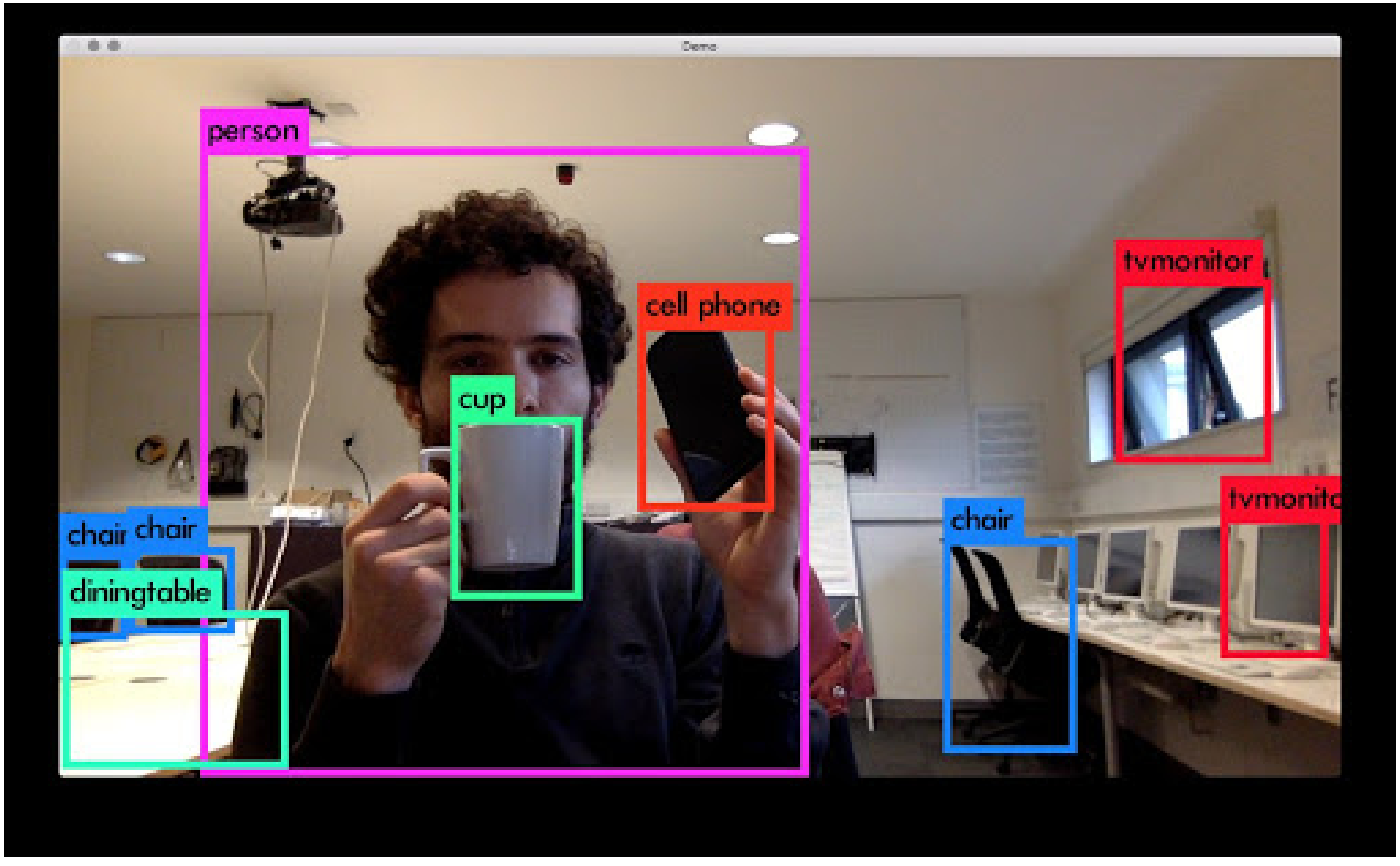
Overview

Introduction

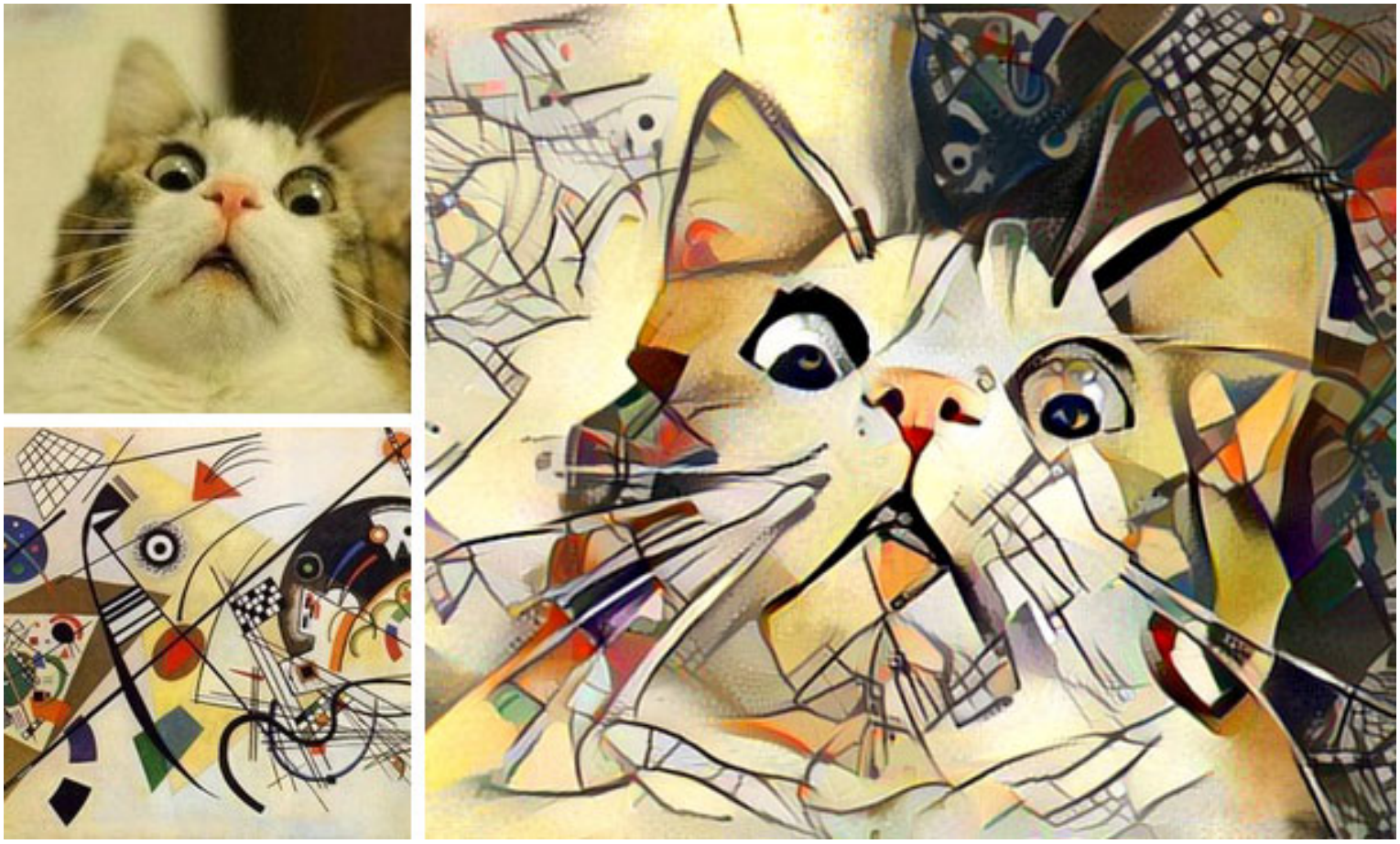
Motivation

Neural networks are everywhere.



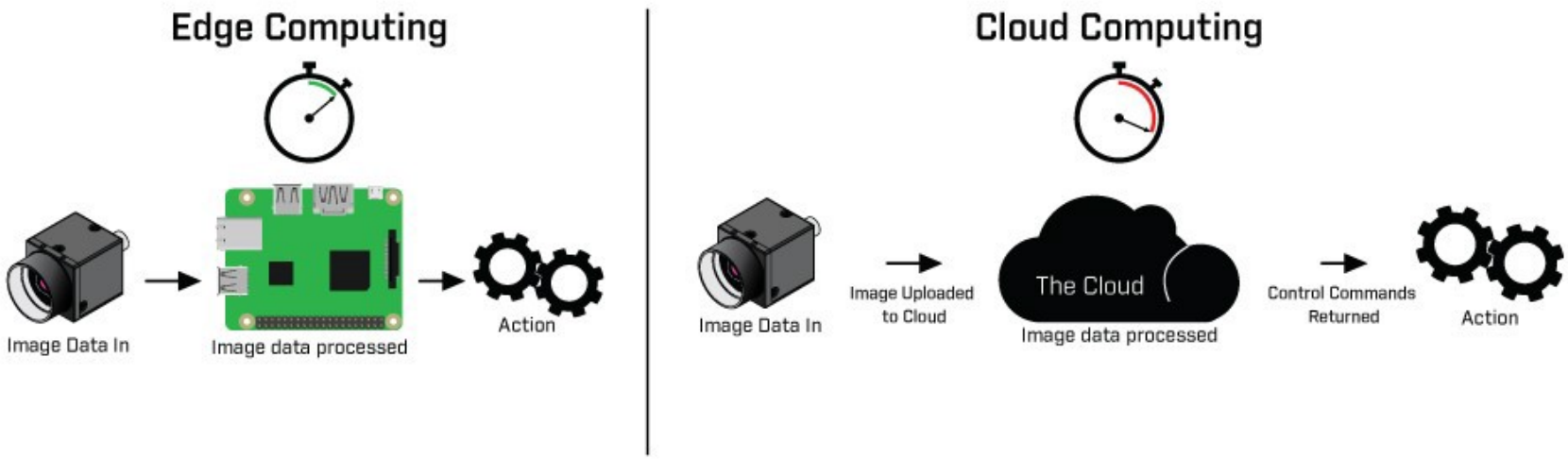
Motivation

Neural networks are everywhere.
Even in art!



Machine Learning at Edge

And implementing ML models on edge devices seems more important than before.

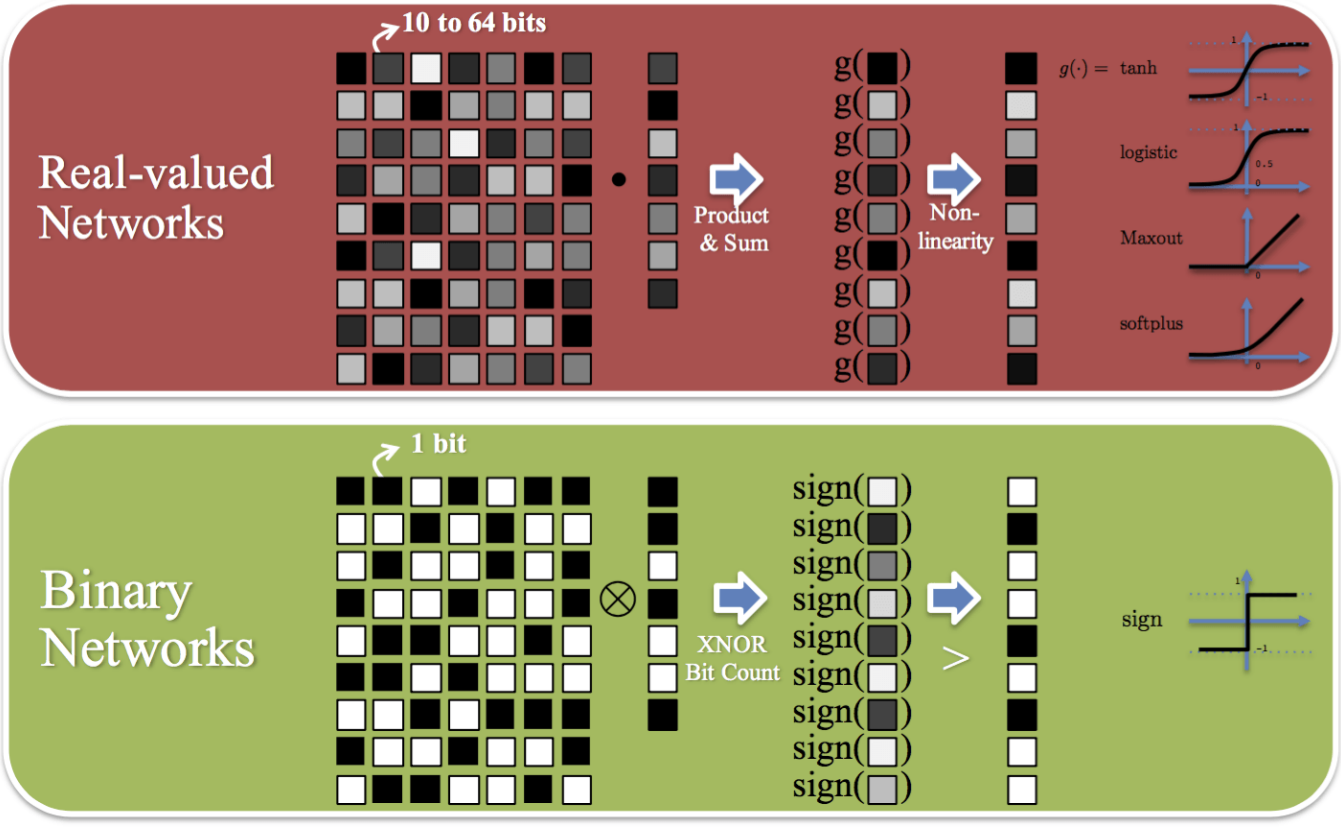


But the problem is the very limited resources available on edge devices.

General Ideas

Network Binarization

Idea: Replace network weights and/or inputs with binary values



Selected Paper: XNOR-Net

XNOR-Net: ImageNet Classification Using Binary Convolutional Neural Networks

Mohammad Rastegari[1(✉)], Vicente Ordonez[1], Joseph Redmon[2], and Ali Farhadi[1,2]

Key Idea: Approximate any vector $\mathbf{W} \in \mathbb{R}^n$ with $\alpha \in \mathbb{R}$ and $\mathbf{B} \in \{-1, +1\}^n$ as $\mathbf{W} = \alpha\mathbf{B}$.

Selected Paper: XNOR-Net – Methodology

Key Idea: Approximate any vector $\mathbf{W} \in \mathbb{R}^n$ with $\alpha \in \mathbb{R}$ and $\mathbf{B} \in \{-1, +1\}^n$ as $\mathbf{W} = \alpha\mathbf{B}$.

Method: Solve the following optimization problem

$$\alpha^*, \mathbf{B}^* = \text{argmin}_{\alpha,\mathbf{B}} \|\mathbf{W} - \alpha\mathbf{B}\|^2$$

Result:

$$\mathbf{B}^* = \text{Sign}(\mathbf{W}) \quad , \quad \alpha^* = \frac{1}{n}\|\mathbf{W}\|_{\ell_1}$$

Selected Paper: XNOR-Net – Results

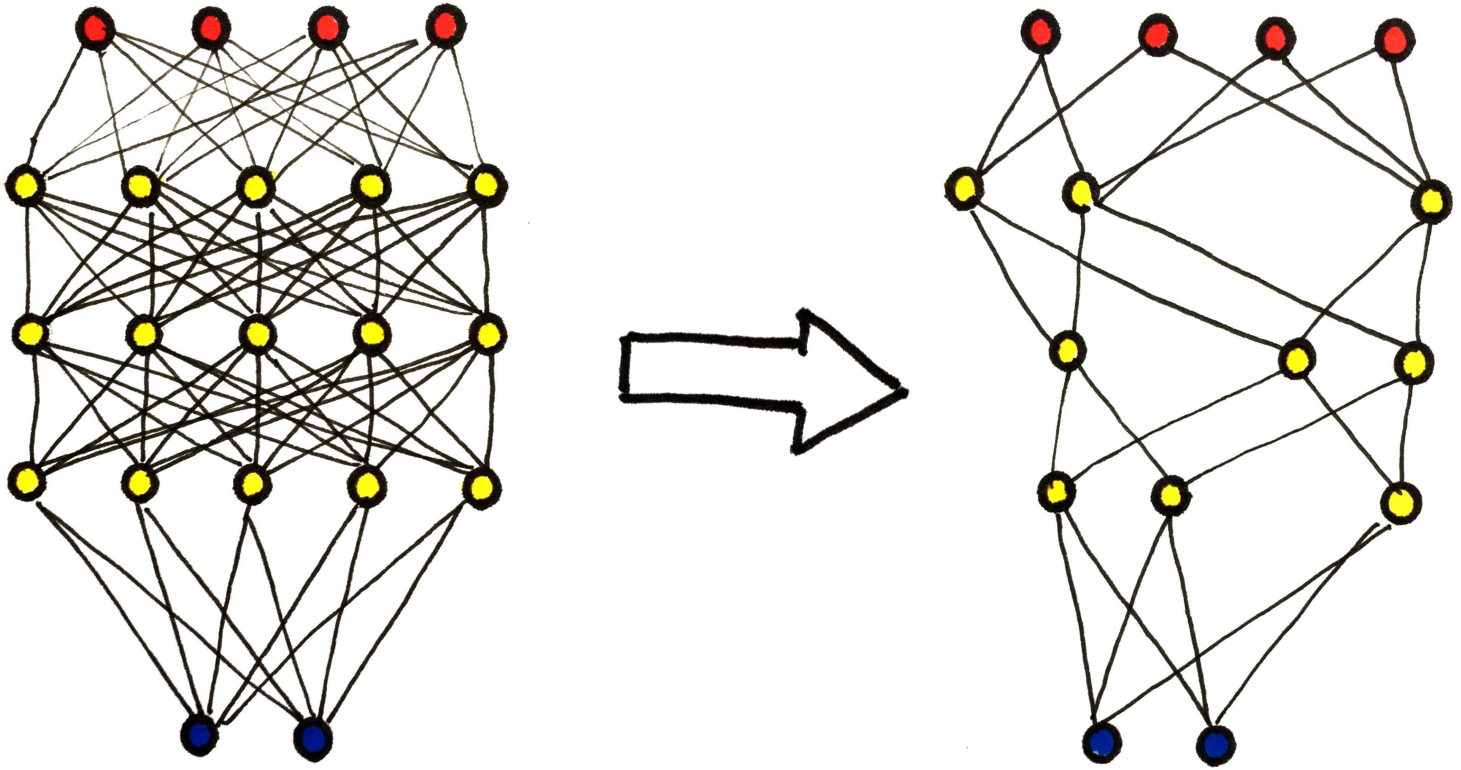
- $58\times$ faster convolution operations
- $32\times$ memory saving
- better than previous work, comparable to state-of-the-art:

Table 1. This table compares the final accuracies (Top1 - Top5) of the full precision network with our binary precision networks; Binary-Weight-Networks (BWN) and XNOR-Networks (XNOR-Net) and the competitor methods; BinaryConnect (BC) and BinaryNet (BNN).

Classification accuracy (%)									
Binary-weight				Binary-input-binary-weight				Full-precision	
BWN		BC [11]		XNOR-Net		BNN [11]		AlexNet [1]	
Top-1	Top-5	Top-1	Top-5	Top-1	Top-5	Top-1	Top-5	Top-1	Top-5
56.8	**79.4**	35.4	61.0	**44.2**	**69.2**	27.9	50.42	56.6	80.2

Network Pruning

Idea: Remove unimportant connections, filters, and layers from a network.



Selected Paper: An Entropy-based Pruning method

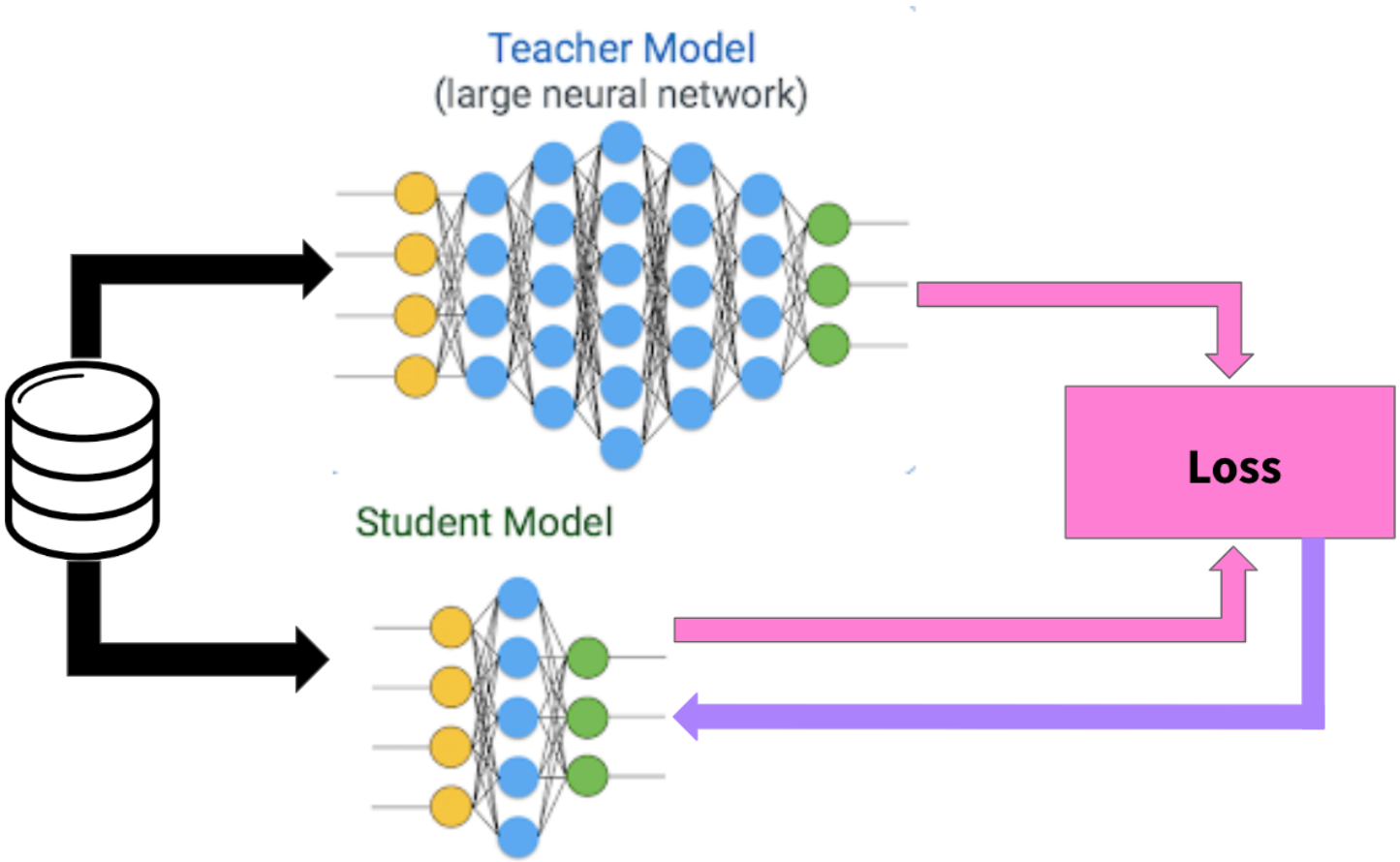
An Entropy-based Pruning Method for CNN Compression

Jian-Hao Luo Jianxin Wu
National Key Laboratory for Novel Software Technology
Nanjing University, China
{luojh, wujx}@lamda.nju.edu.cn

Key Idea: The importance of each filter is evaluated by the proposed entropy-based method first. Then several unimportant filters are discarded to get a smaller CNN model.

Knowledge Distillation

Idea: Transfer the knowledge from a cumbersome (teacher) network to a smaller (student) model for deployment.



Selected Paper: Distilling the Knowledge in a Neural Net

Distilling the Knowledge in a Neural Network

Geoffrey Hinton[*†]
Google Inc.
Mountain View
geoffhinton@google.com

Oriol Vinyals[†]
Google Inc.
Mountain View
vinyals@google.com

Jeff Dean
Google Inc.
Mountain View
jeff@google.com

Key Idea: After training a cumbersome neural network for a specific task, one can transfer the knowledge to a light-weight network which is more suitable for deployment.

Selected Paper: Distilling the Knowledge in a Neural Net

Key Idea: After training a cumbersome neural network for a specific task, one can transfer the knowledge to a light-weight network which is more suitable for deployment.

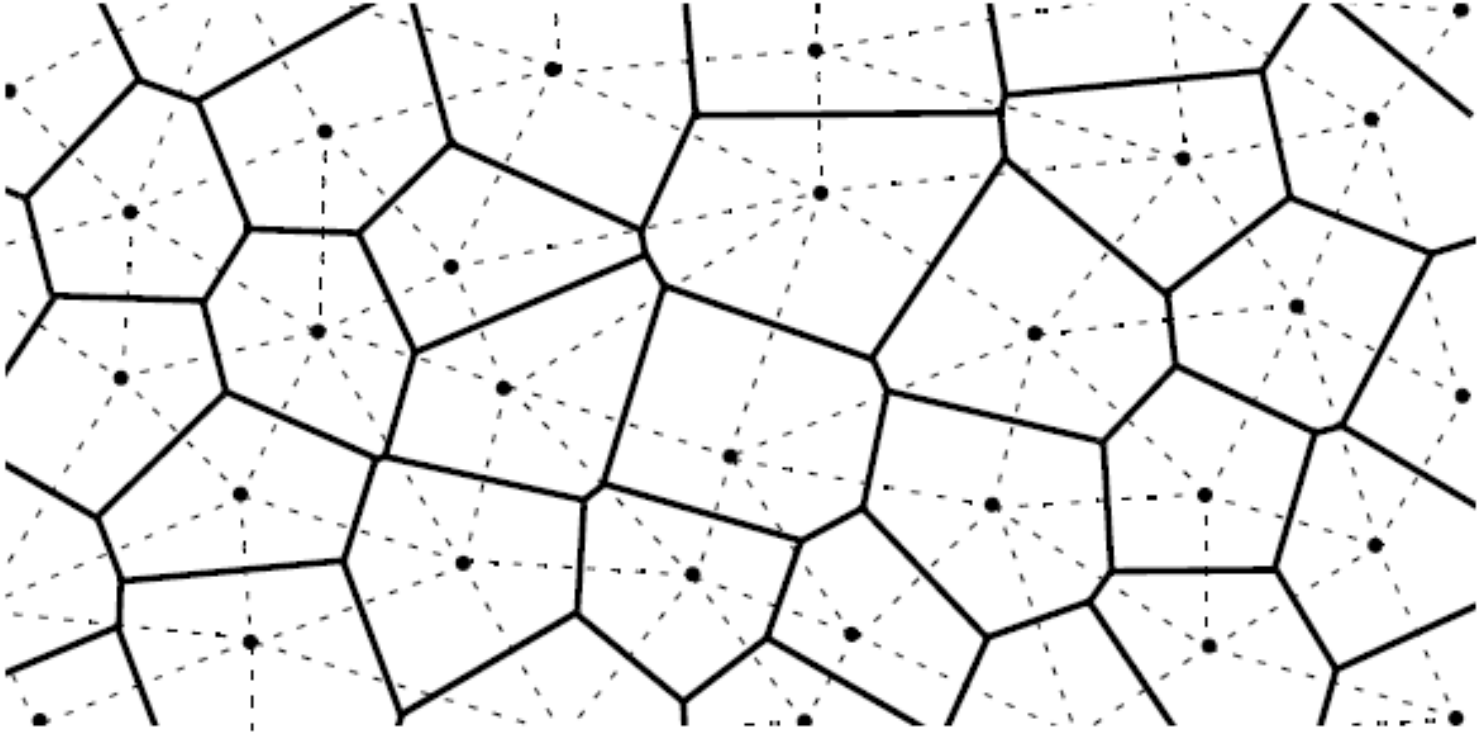
Method: Define the cost function for training the student model so that it would imitate the teacher.

Example: for a classification task with n classes:

- $\mathbf{p}, \mathbf{q} \in \mathbb{R}^n$ the probability vectors each model assigns to each class for a given sample
- Cost function $C = d(\mathbf{p}, \mathbf{q})$
  (d is a suitable metric for probability distributions)

Network Quantization

Idea: quantize each network parameter (or vector of parameters) as an element drawn from a finite set, i.e., the codebook, so as to discard the original value for model compression.



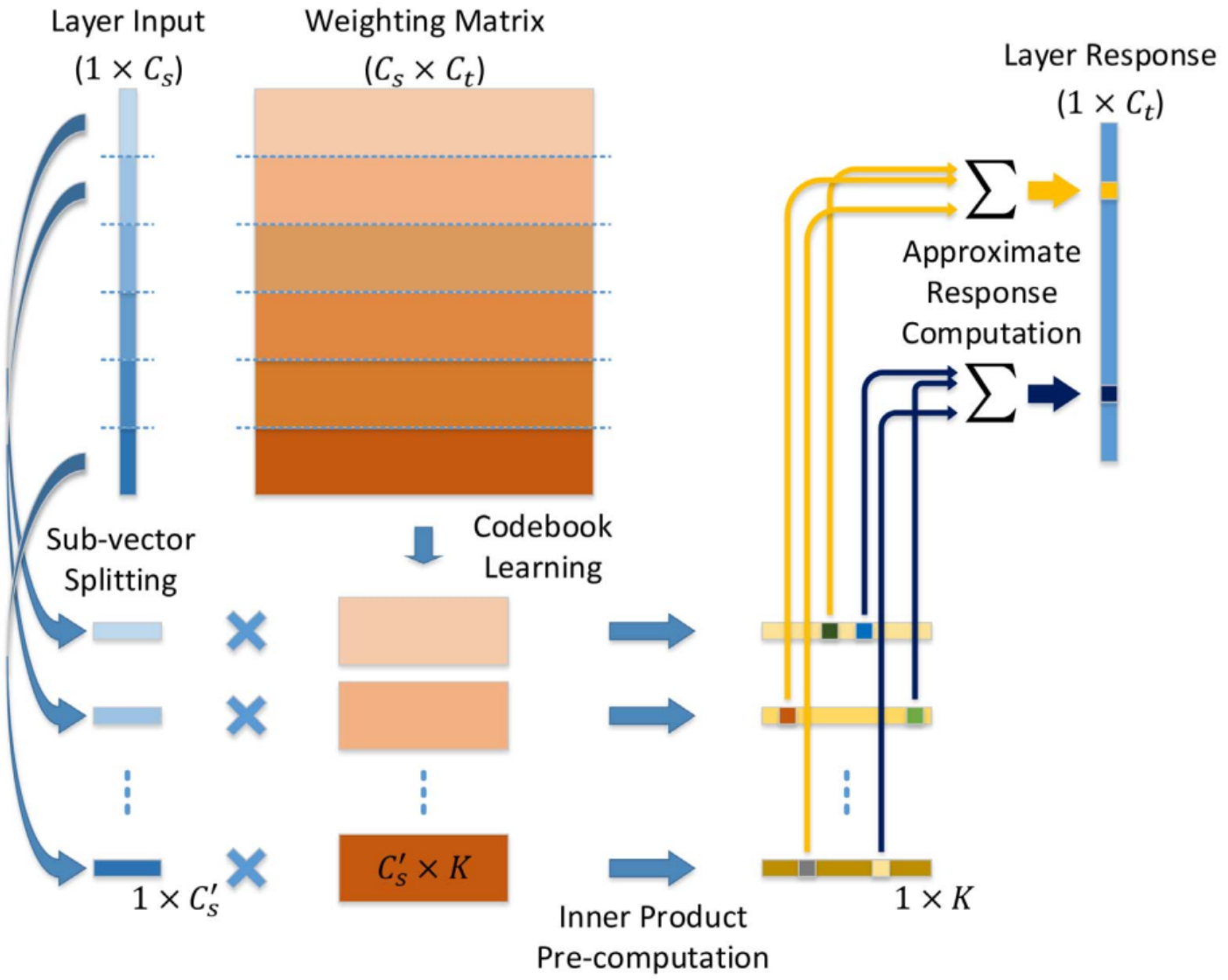
Selected Paper: Quantized CNN

Quantized CNN: A Unified Approach to Accelerate and Compress Convolutional Networks

Jian Cheng, Jiaxiang Wu, Cong Leng, Yuhang Wang, and Qinghao Hu

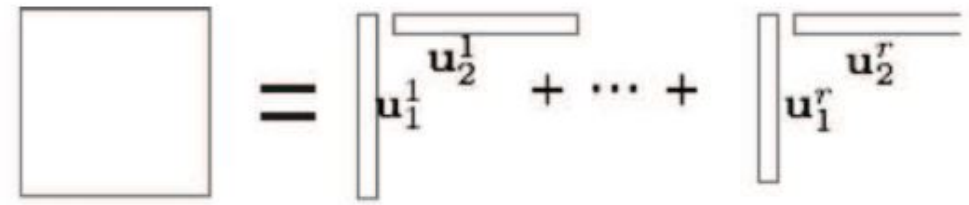
Key Idea: product quantization treats the feature space as the Cartesian product space composed by multiple subspaces. In each subspace, we learn a subcodebook.

quantization process

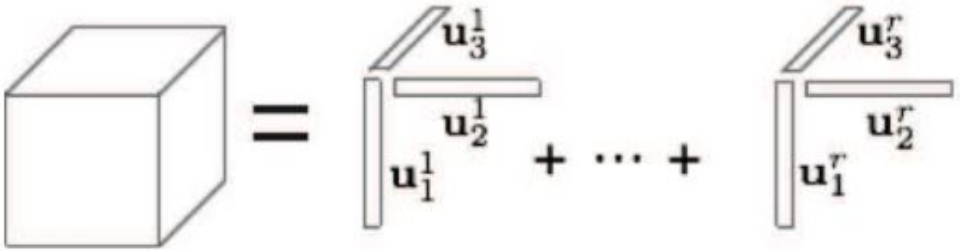


Low-Rank Approximation

Idea: Low-rank approximation for weight matrices or tensors.



$$\mathbf{A} = \sum_{j=1}^{r} \mathbf{u}_1^j \circ \mathbf{u}_2^j$$



$$\mathcal{A} = \sum_{j=1}^{r} \mathbf{u}_1^j \circ \mathbf{u}_2^j \circ \mathbf{u}_3^j$$

Modifying the Convolution Operation

Key Idea: use a variation of the classic convolution to achieve a smaller and/or faster network

Selected Paper: MobileNets

MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications

Andrew G. Howard Menglong Zhu Bo Chen Dmitry Kalenichenko
Weijun Wang Tobias Weyand Marco Andreetto Hartwig Adam

Google Inc.

{howarda,menglong,bochen,dkalenichenko,weijunw,weyand,anm,hadam}@google.com

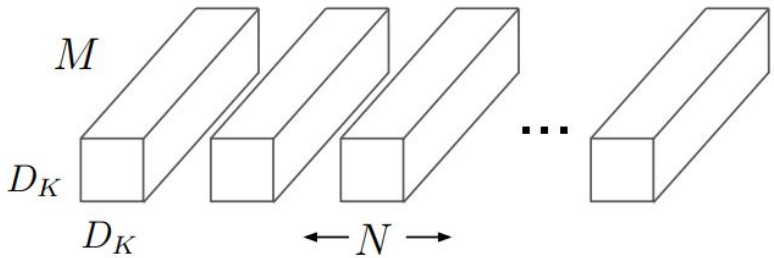
Modifying the Convolution Operation

Selected Paper: MobileNets

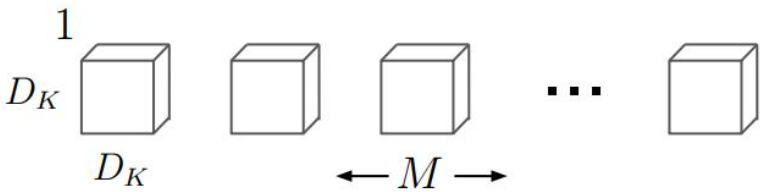
Method: use a depth-wise separable convolution

Result: a reduction computation factor of

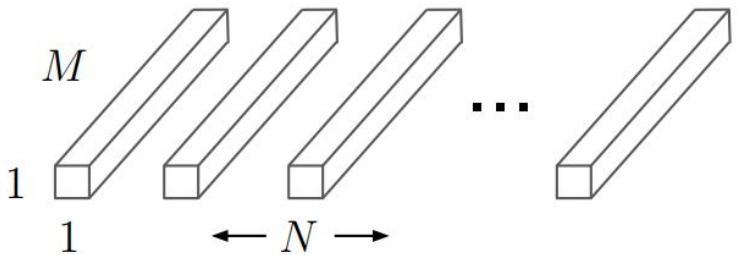
$$\frac{1}{N} + \frac{1}{D_K^2}$$



(a) Standard Convolution Filters



(b) Depthwise Convolutional Filters



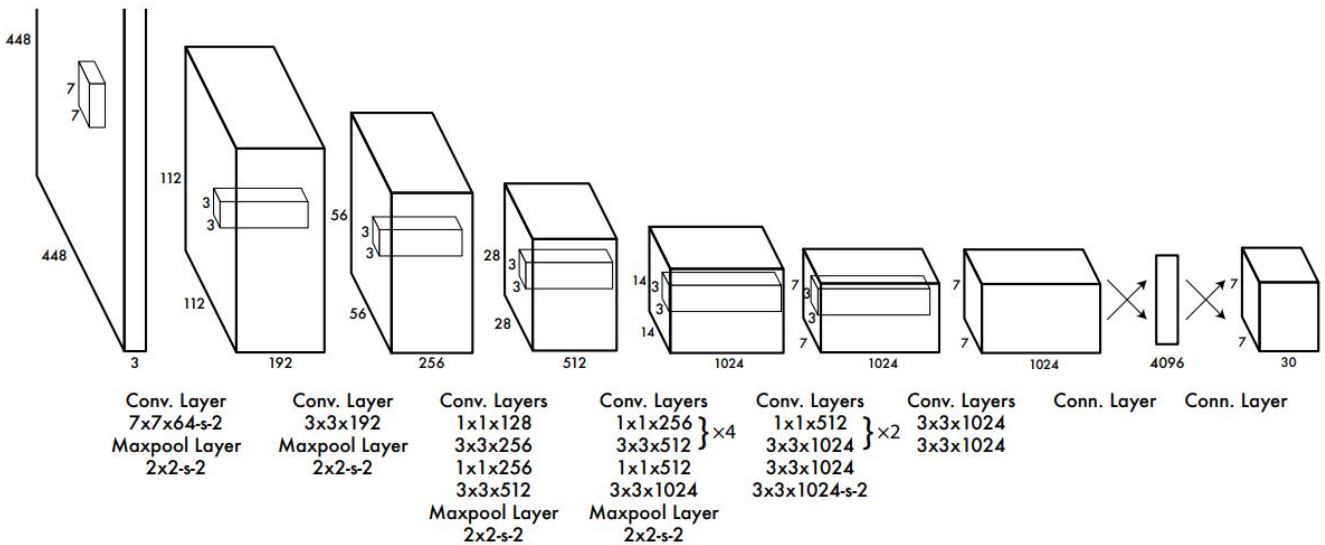
(c) 1×1 Convolutional Filters called Pointwise Convolution in the context of Depthwise Separable Convolution

Case Study: YOLO – a new approach to object detection

You Only Look Once:
Unified, Real-Time Object Detection

Joseph Redmon*, Santosh Divvala*†, Ross Girshick¶, Ali Farhadi*†
University of Washington*, Allen Institute for AI†, Facebook AI Research¶
http://pjreddie.com/yolo/

Key Idea: Determine the bounding boxes and the object types simultaneously using a single neural network.



Case Study: YOLO – a new approach to object detection

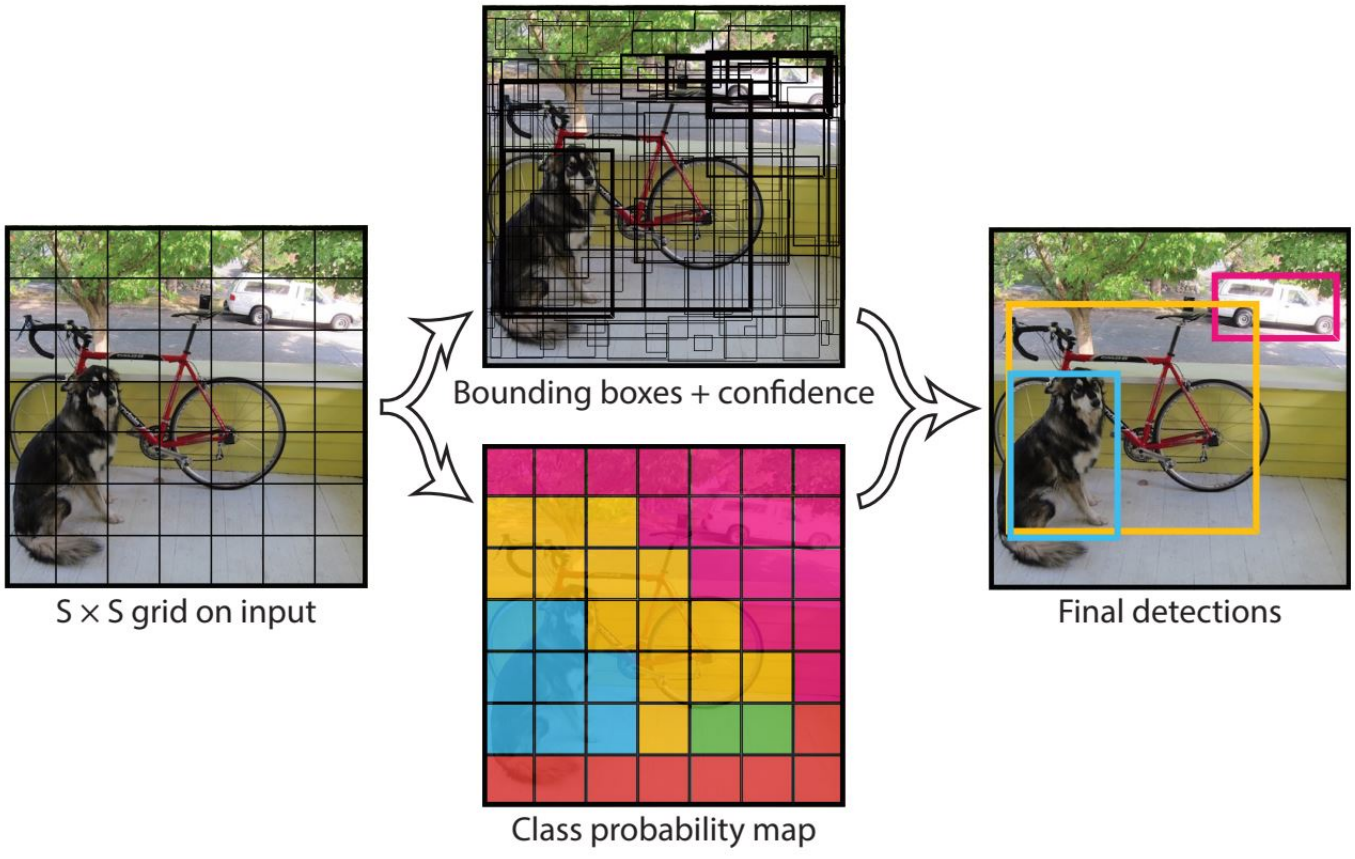


Figure: The system divides the image into an $S \times S$ grid and for each grid cell predicts B bounding boxes, confidence for those boxes, and C class probabilities.

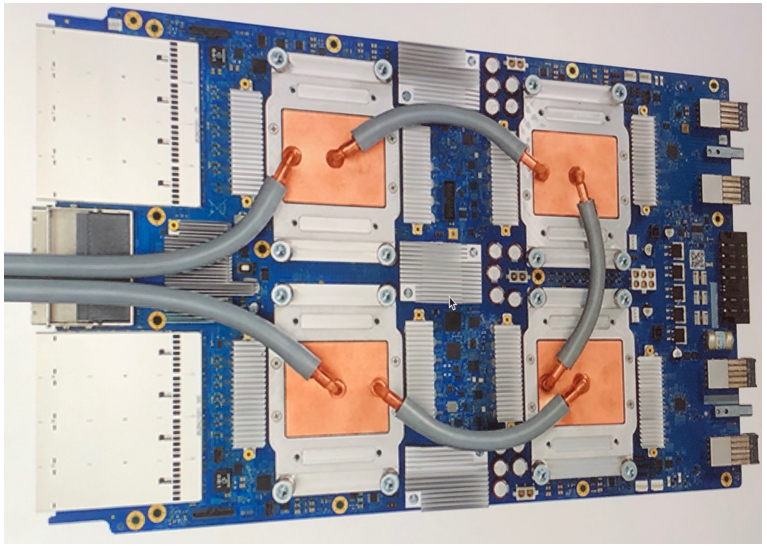
Products on the Market

Popular Edge Devices for Neural Nets

Edge device	GPU	CPU	ML software support
Coral SoM – Google	Vivante GC7000Lite	Quad ARM Cortex-A53 + Cortex-M4F	TensorFlow Lite, AutoML Vision Edge
Intel NCS2	Movidius Myriad X VPU (not GPU)		TensorFlow, Caffe, OpenVINO toolkit
Raspberry Pi 4	VideoCore VC6	Quad ARM Cortex-A72	TensorFlow, TensorFlow Lite
NVIDIA Jetson TX2	NVIDIA Pascal	Dual Denver 2 64-bit + quad ARM A57	TensorFlow, Caffe
RISC-V GAP8			TensorFlow
ARM Ethos N-77	8 NPUs in cluster, 64 NPUs in mesh		TensorFlow, TensorFlow Lite, Caffe2, PyTorch, MXNet, ONNX
ECM3531 A – Eta Compute	ARM Cortex-M3 + NXP CoolFlux DSP		TensorFlow, Caffe

Google TPU

- Tensor Processing Unit
- an AI application-specific integrated circuit developed by Google
- In January 2019, Google made the Edge TPU available to developers with a line of products under the **Coral** brand.



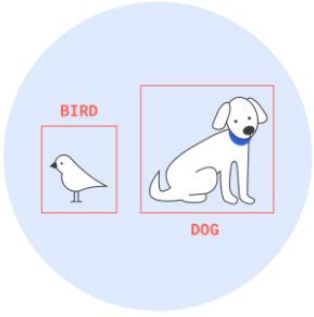
Google Coral

Coral is a complete toolkit to build products with local AI.

Google Coral

Coral is a complete toolkit to build products with local AI.

Solutions for on-device intelligence



Object detection

Draw a square around the location of various recognized objects in an image.

Pose estimation

Estimate the poses of people in an image by identifying various body joints.

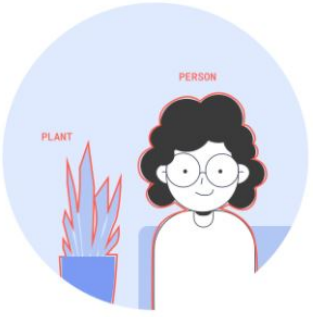


Image segmentation

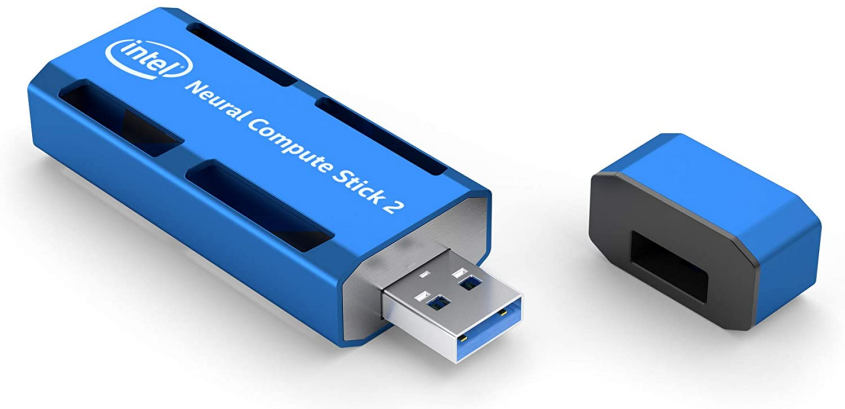
Identify various objects in an image and their location on a pixel-by-pixel basis.

Key phrase detection

Listen to audio samples and quickly recognize known words and phrases.

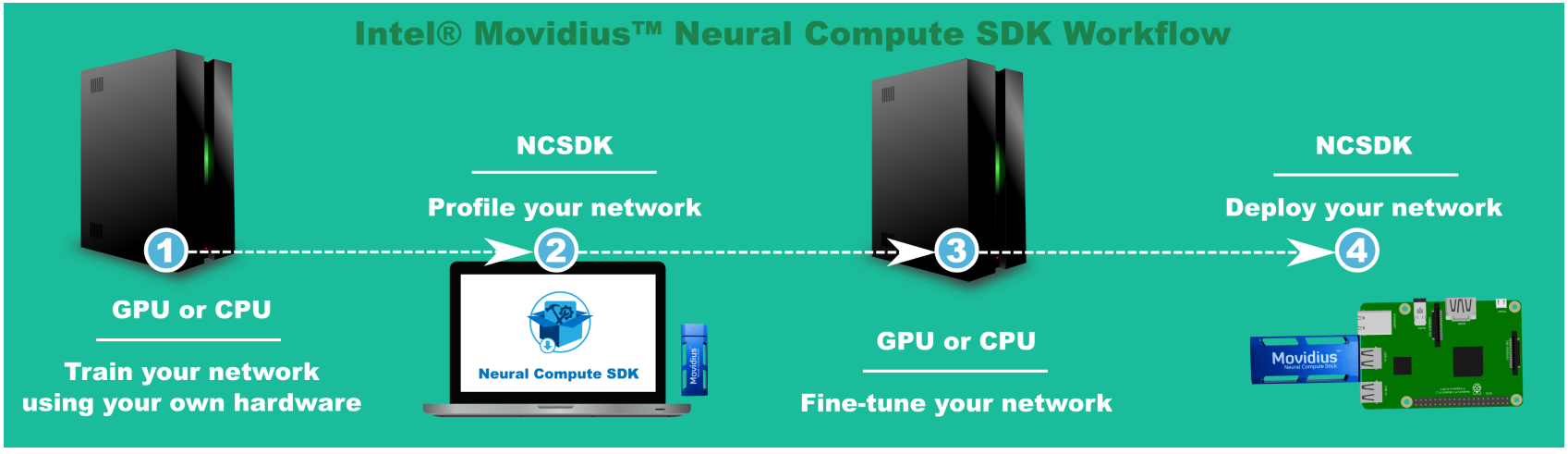
Intel Neural Compute Stick

- The Intel Neural Compute Stick (NCS) is a tiny fanless deep learning device that you can use to learn AI programming at the edge.
- Movidius Neural Compute Stick enables rapid prototyping, validation and deployment of Deep Neural Network (DNN) inference applications at the edge



Intel Neural Compute Stick – Workflow Schematic

The Intel Neural Compute Stick could pair with Raspberry Pi single board computer.



Xnor.ai

Xnor.ai: a company founded in 2016 and bought by Apple for $200M in 2020.

- brings state-of-the-art artificial intelligence to the edge
- Xnor's platform allows companies to run complex deep learning algorithms, formerly restricted to the cloud, locally on a range of devices including mobile phones, drones, and wearables.

Xnor.ai

COMPANY BACKGROUND

Professor Ali Farhadi and Dr. Mohammad Rastegari founded Xnor.ai based on their pioneering research developed at the Allen Institute for Artificial Intelligence in Seattle, WA

Publications

Xnor-Net: ImageNet classification using binary convolutional neural networks

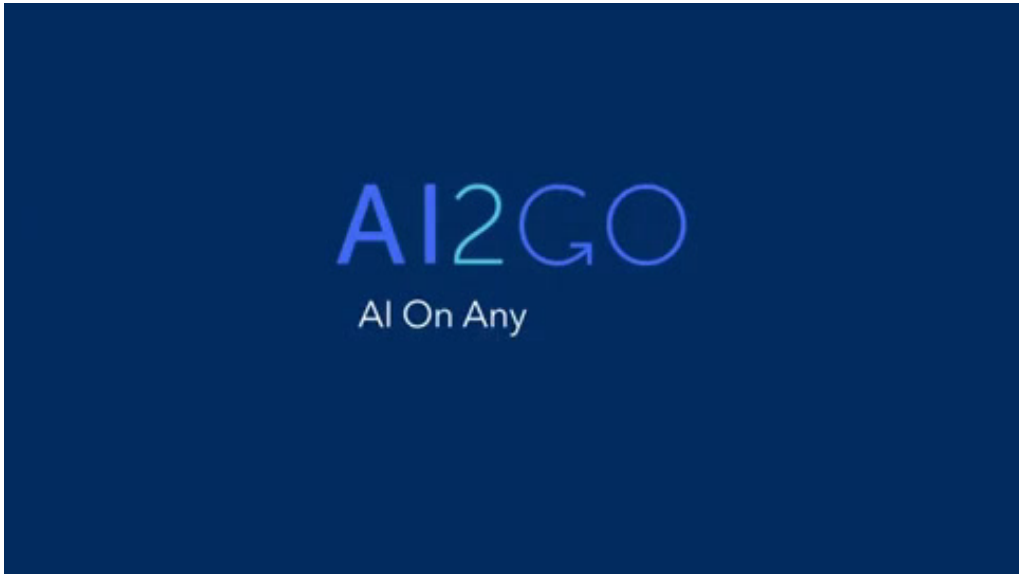
YOLO: A new approach to object detection

YOLO9000: A state-of-the-art, real-time object detection system capable of detecting over 9,000 object categories

Label Refinery: Improving state-of-the-art accuracy by iteratively updating ground truth labels

AI2GO

In 2019, Xnor released **AI2GO**, a do-it-yourself software platform for artificial intelligence.



A short introductory video:
`https://www.youtube.com/watch?v=jfAkV9JrErY`

AI2GO

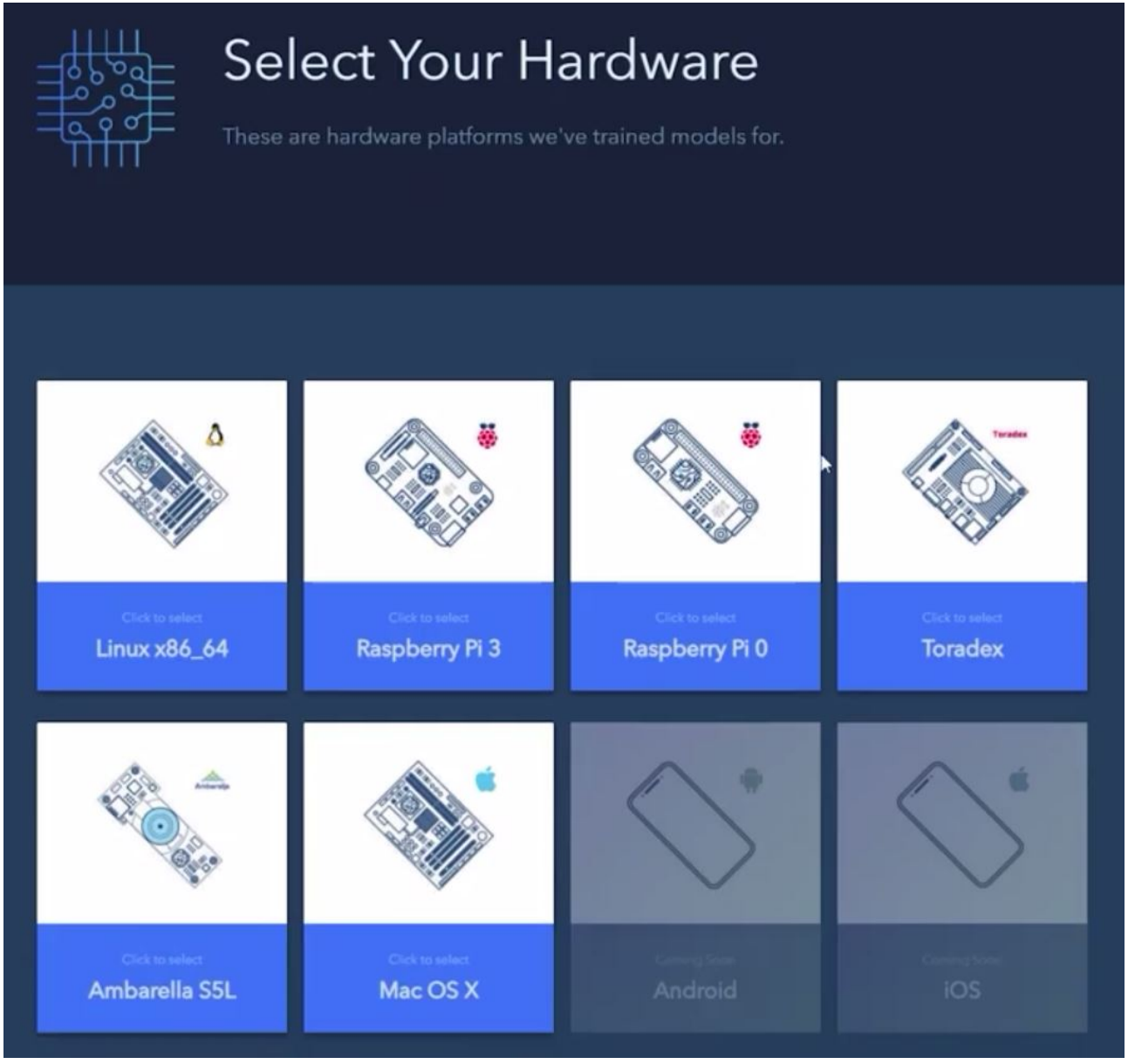
A slide from AI2GO introduction by Xnor.ai:

AI2GO

Introducing AI2GO, a first-of-its-kind developer platform for AI on any device

- Software SDK for embedded devices (C++, Python, Swift)
- Xnor Bundles (XB): modular, pre-trained AI models combined with optimized inference engine runtime and APIs
- Hundreds of Deep Learning models tuned for popular use cases and devices
- Build & deploy your AI solution with state-of-the-art accuracy on the most resource-constrained edge devices
- No learning curve, no special equipment needed

A journey through AI2GO website



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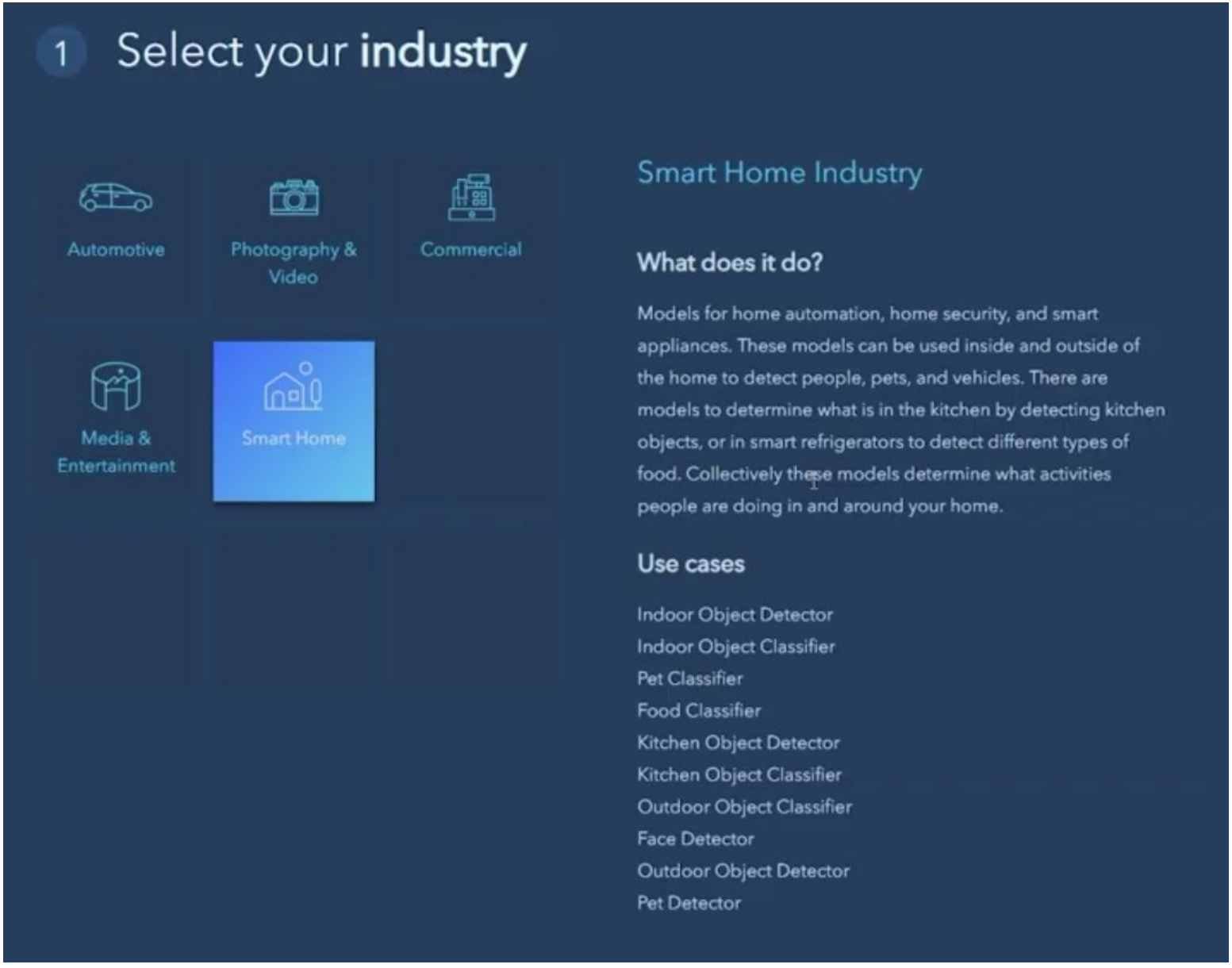

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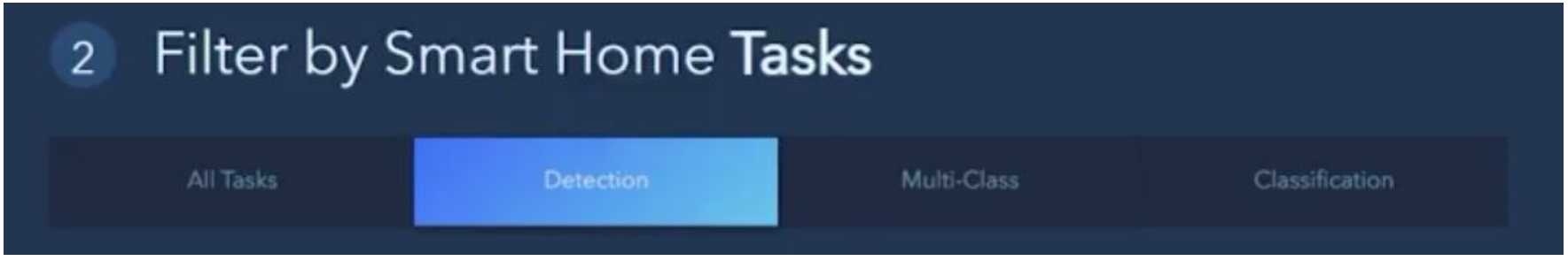

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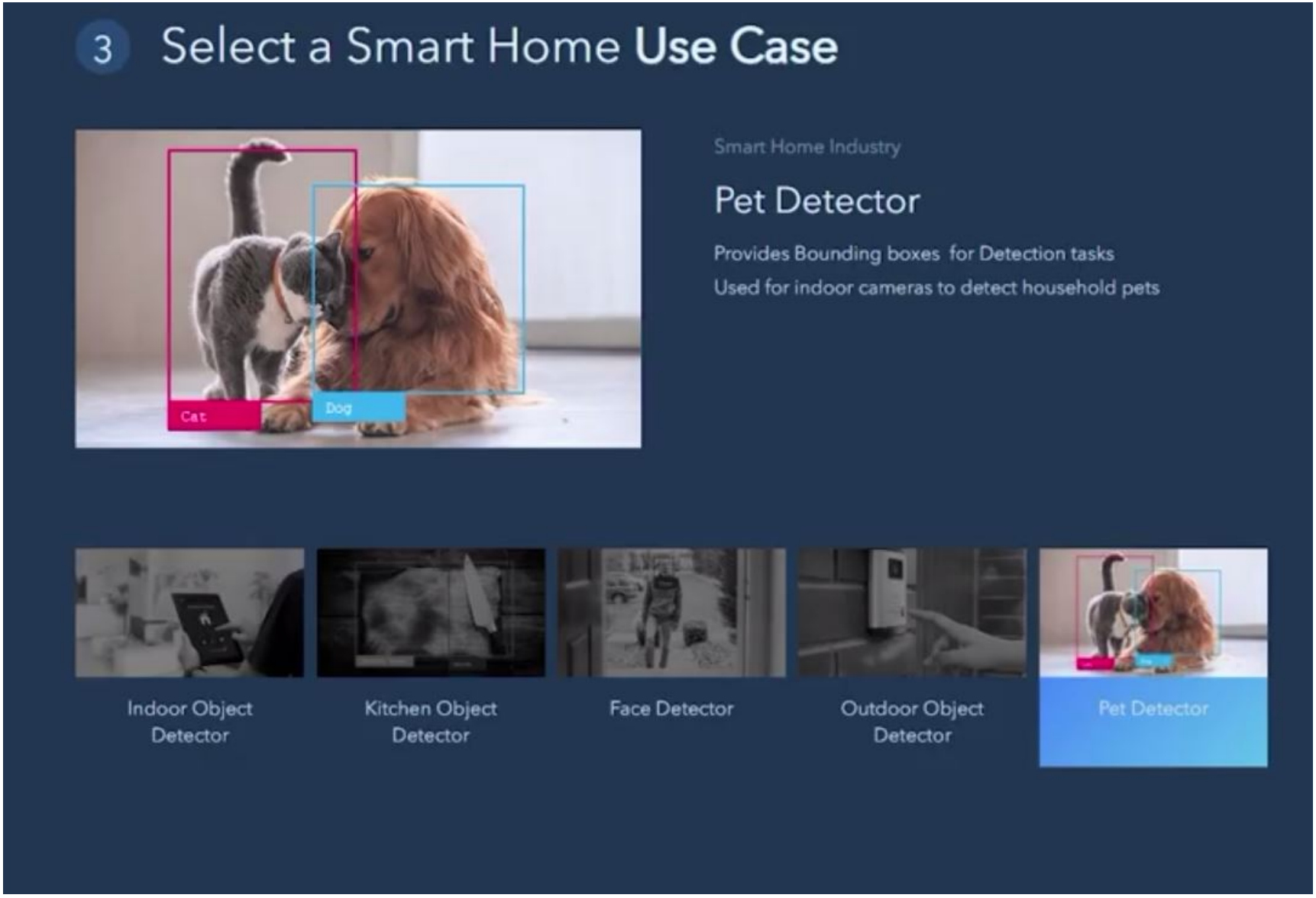

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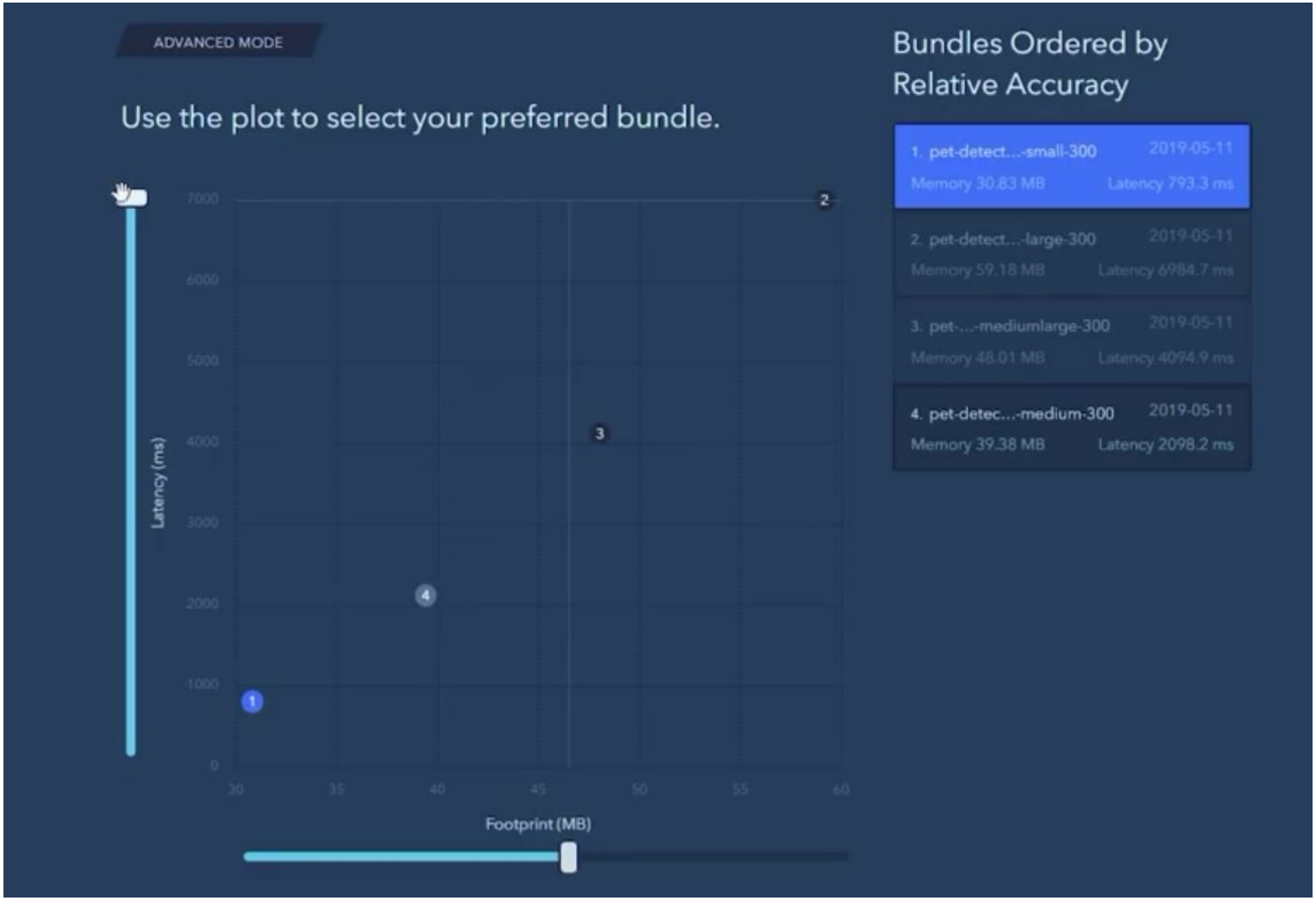

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