www.multicorewareinc.com

Targeting CNNs for Embedded Platforms

Anshu Arya, Solution Architect @ MulticoreWare

MULTICORE WARE

Company Introduction

- Founded 2009
- Core Competency: Heterogeneous Computing
- HQ: Silicon Valley
- Seven Location [US, China, India, and Taiwan]
- 225+ Employees

<table>
<tr><th colspan="2">BUSINESS UNITS</th></tr>
<tr><td>Machine Learning/Neural Networks</td><td rowspan="4">Performance Optimization Services</td></tr>
<tr><td>Image Processing [OpenCV]</td></tr>
<tr><td>Video Codecs [x265]</td></tr>
<tr><td>Compilers [LLVM, OpenCL]</td></tr>
</table>

Global Customers and Partners

ALTERA, AMD, ARM, Bright Visionary Technologies

cadence, Google, Imagination, Microsoft

Movidius, NVIDIA, PEGASYS, QUALCOMM

sorenson MEDIA, SYNOPSYS, telestream, XILINX

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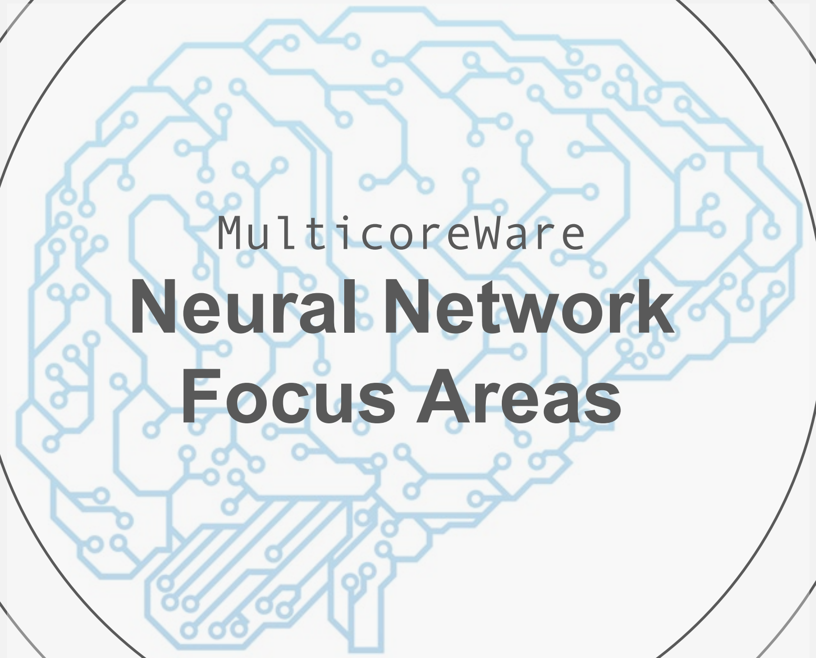
Neural Network Focus Areas



Automotive & ADAS

- Pedestrian Detection
- Vehicle Detection
- Traffic Sign Recognition

Video Quality

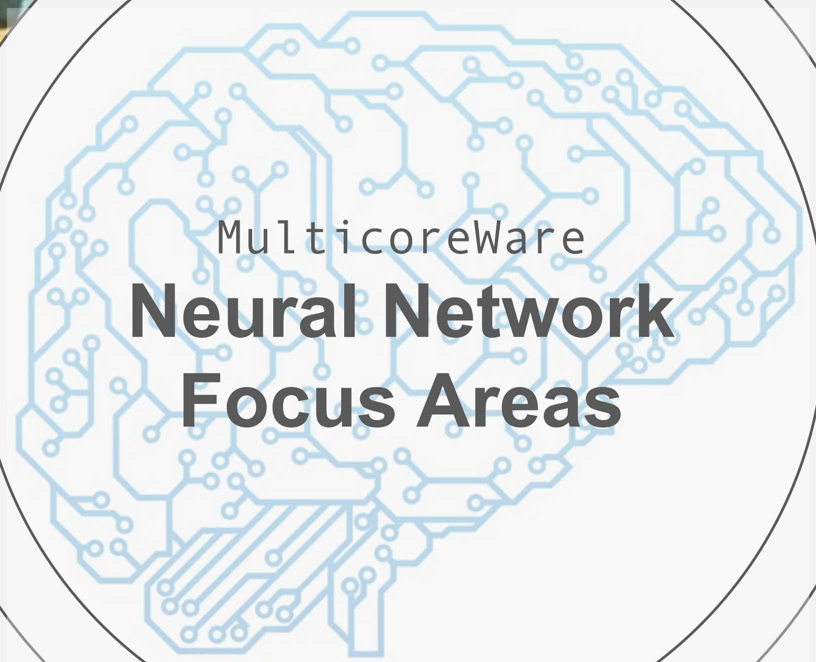
- Audio/Video Lip Sync
- Subtitle Sync
- Text ROI Detection

Action Detection

- Facial Expressions
- Sports Pose Detection

Other

- Medical Tool Recognition



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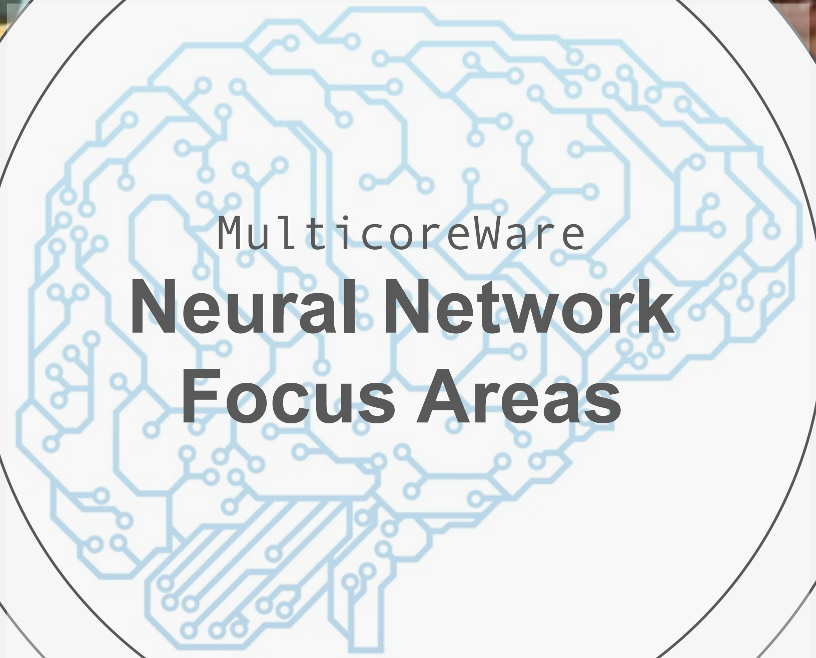

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Neural Network Focus Areas

Action Detection

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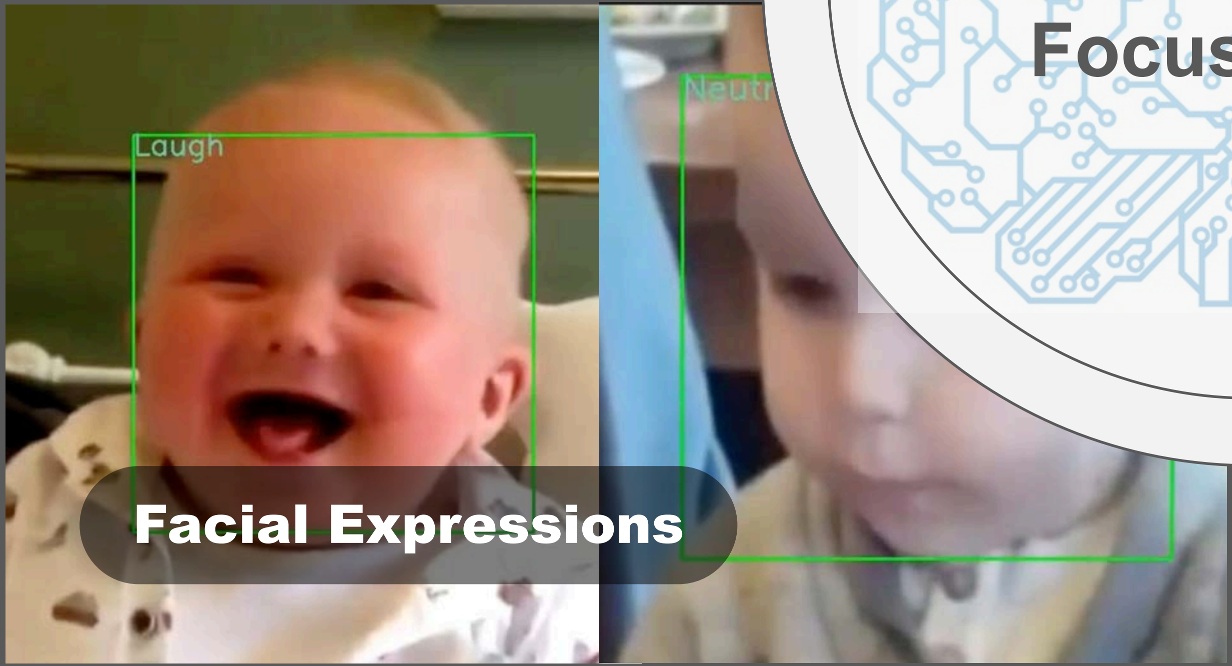

Other

- Medical Tool Recognition

[Neural Network Services]

Data Labeling

Curate and label image or video data for input into neural network training.

- In-house team of data labelers to perform any type of labeling task confidentially
- Proprietary machine-assisted labeling tool to increase productivity by an order of magnitude

Design & Training

Design a neural network architecture and train it using labeled data.

- Neural network architecture chosen to fit within constraints of target hardware platform
- Training is done on MulticoreWare GPU-accelerated workstations

Deployment & Upgrades

Integrate the neural network engine into your application and receive on-going upgrades.

- Build an application or integrate a neural network engine into your existing code
- Improve the accuracy of the neural network as you collect more training data

Platform Optimization

Iterate on the neural network architecture and perform hardware-specific optimizations.

- Performance and memory optimizations for target hardware platform
- Code rewrites using hardware intrinsics, assembly, RTL, OpenCL, CUDA, etc.

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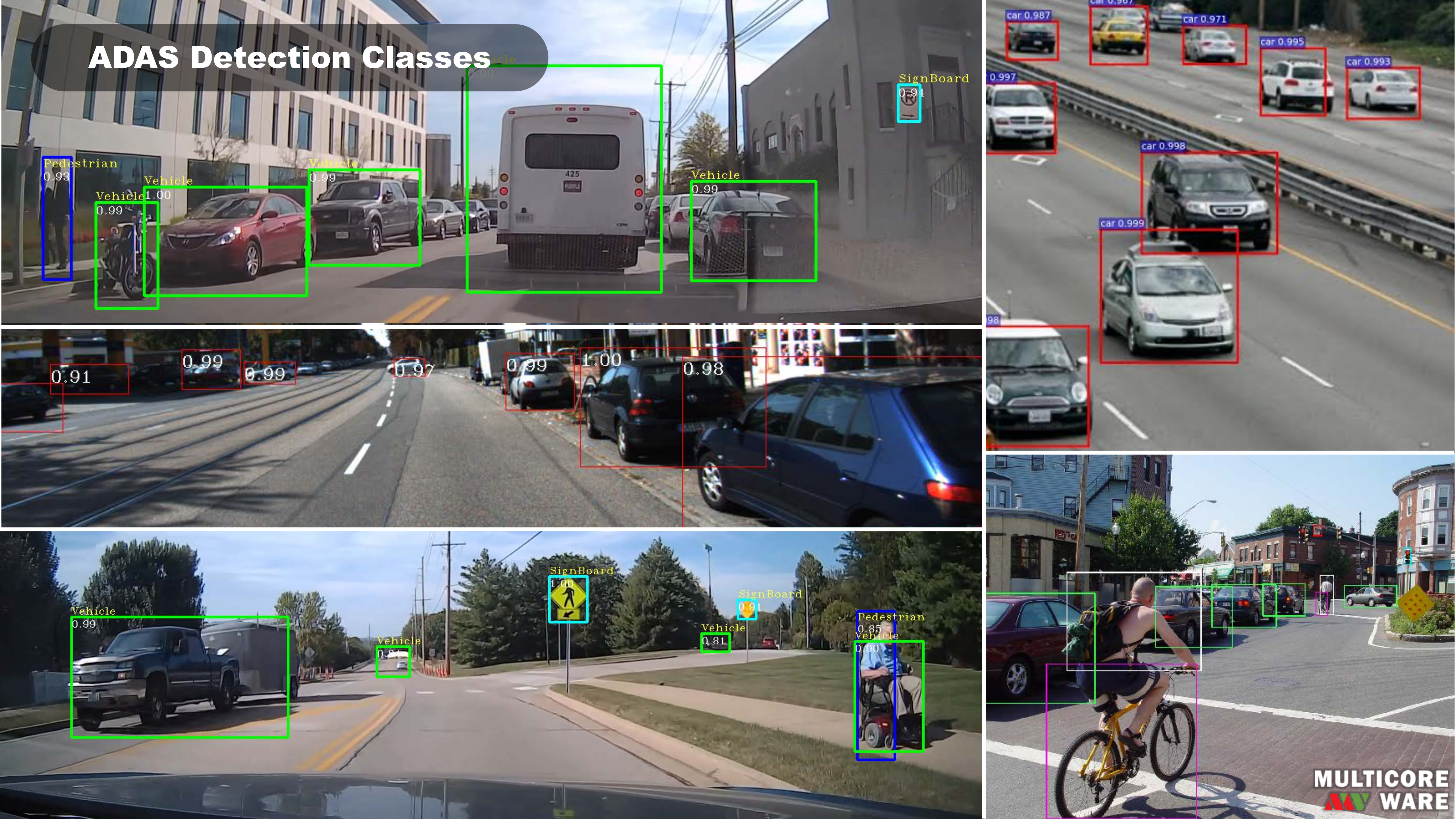
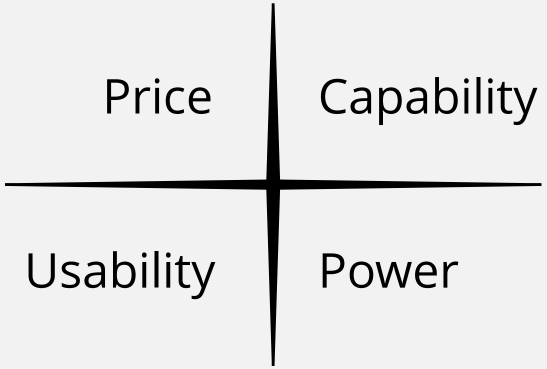
ADAS Detection Classes



[Mobile/Embedded Platforms]

What platform(s) will dominate?

- GPUs
- FPGAs
- Vision DSPs
- Custom ASICs



Current Examples

- NVIDIA Drive PX 2 & Xavier
- Xilinx Zynq UltraScale+
- Cadence VP5 & VP6
- Synopsys DesignWare EV6x
- MobileEye EyeQ 4

[Challenges for Embedded CNNs]

Performance / Power / Memory

- Need fast detection (not just classification)

Quality

- Predict accurate bounding boxes

[Challenges for Embedded CNNs]

Performance / Power / Memory

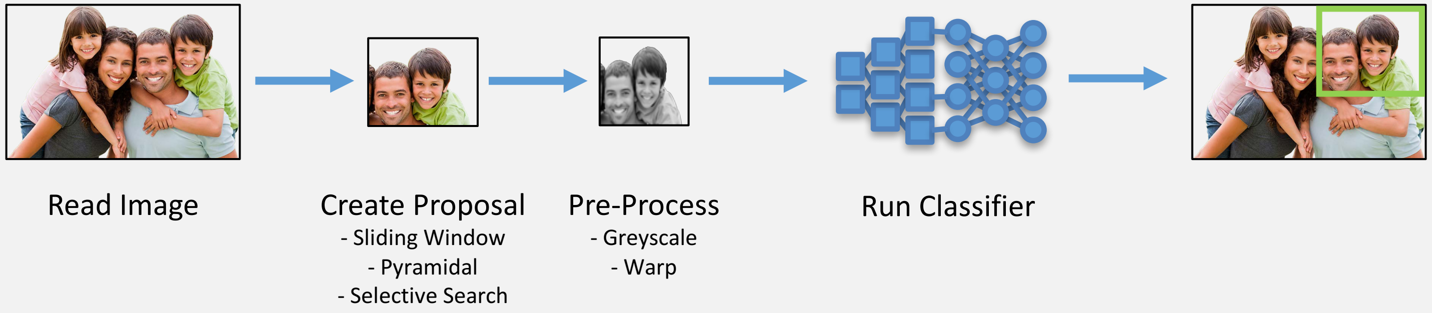
- Need fast detection (not just classification)
- Need “smaller” CNN architectures
  - Fewer parameters
  - Fewer operations
  - Lower intermediate memory usage

Quality

- Predict accurate bounding boxes
- General advice: use a network with as many parameters/layers as you can reliably train

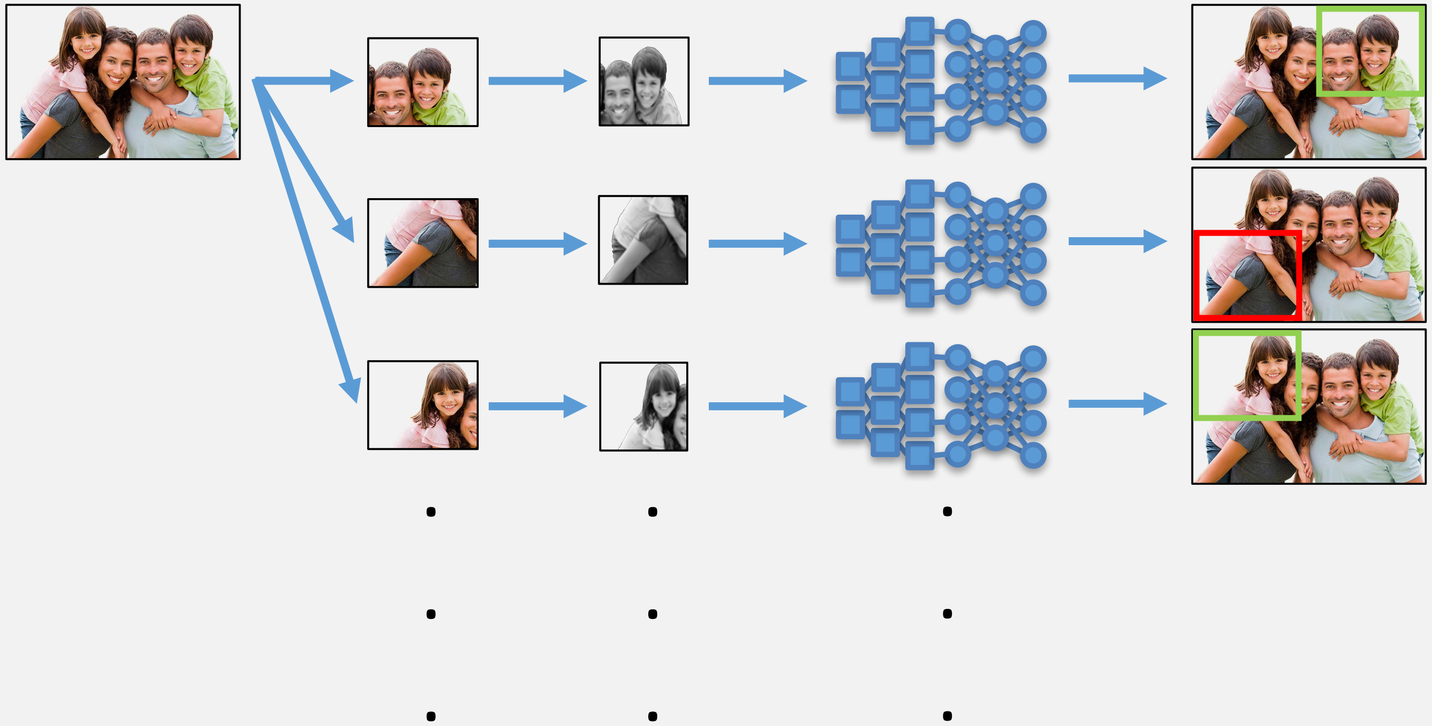
Need Fast Detection

[Typical Detection]



- Read image
- Create object proposals (e.g. Pyramidal, Sliding Window, etc.)
- <u>For each</u> proposal:
  - Crop from frame
  - Pre-process (e.g. warp)
  - Run CNN classifier
- Post-process (NMS)

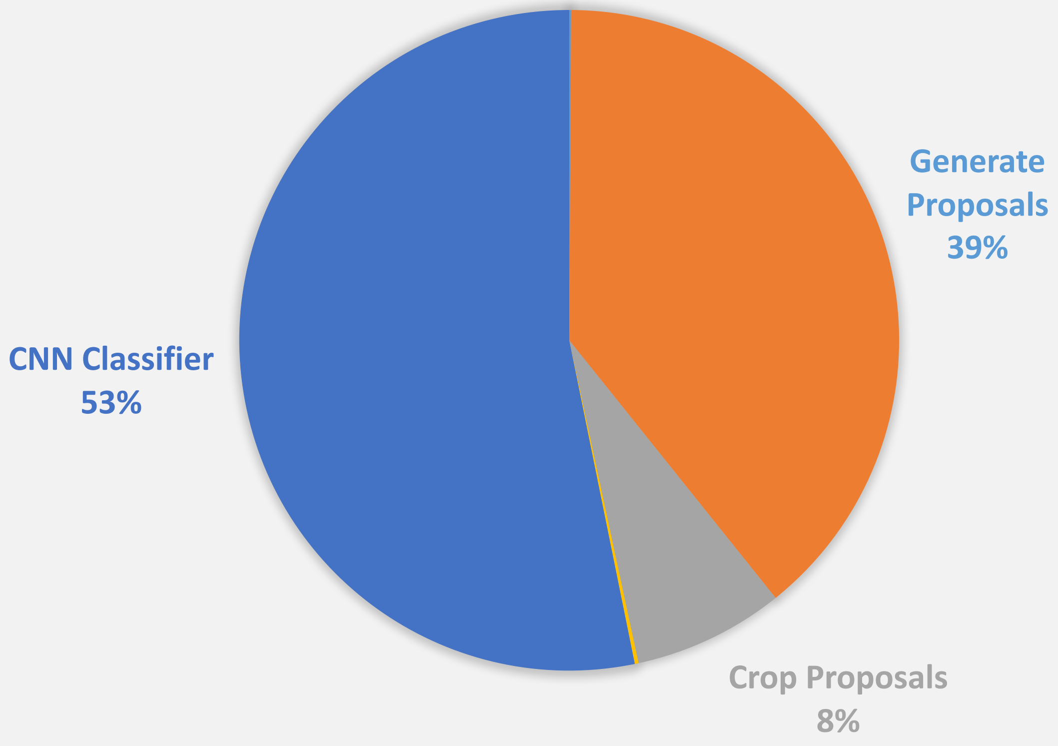
[Typical Detection]



[Typical Detection]

Potentially hundreds to thousands of proposals needed to get tight bounding boxes

[Typical Detection - Cycles]



[Fast Detection – “Fast R-CNN”]

- Change the pipeline
  - No need to run classifier on each proposal
  - Re-use convolution feature map across proposals
- Requires RoI Pooling layer
  - Extracts proposal features from full frame map
- Still need to generate proposals via Selective Search (SS)
  - Now even more limited by SS speed

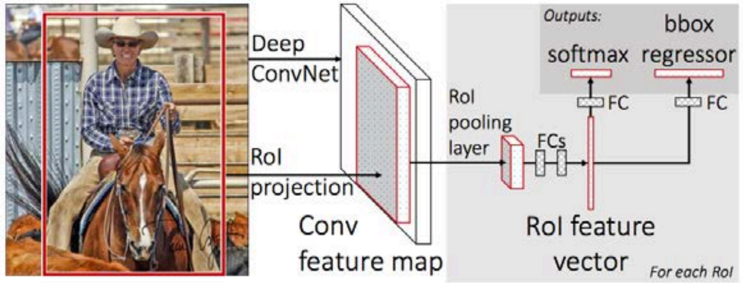


Figure 1. Fast R-CNN architecture. An input image and multiple regions of interest (RoIs) are input into a fully convolutional network. Each RoI is pooled into a fixed-size feature map and then mapped to a feature vector by fully connected layers (FCs). The network has two output vectors per RoI: softmax probabilities and per-class bounding-box regression offsets. The architecture is trained end-to-end with a multi-task loss.

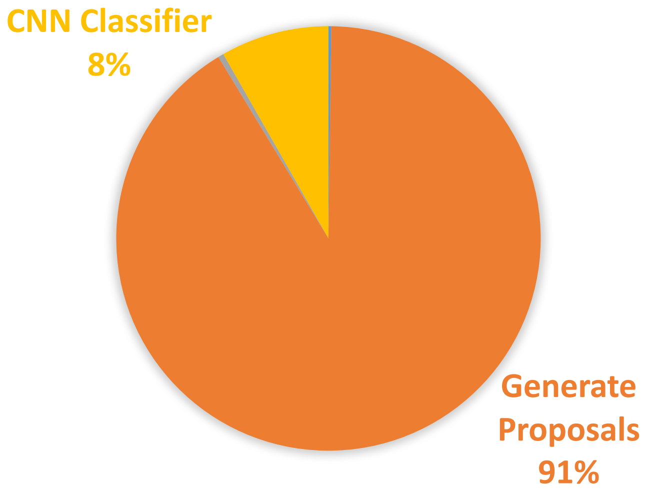


*Image from Girshick, “Fast R-CNN”

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[Fast Detection – "Faster R-CNN"]

- State-of-the-Art Localization + Classification
  - 26+ implementations by 2015 & 2016 ImageNet competitors
    - All winners use some variation
- Use a CNN to create proposals
  - RPN (region proposal network)
  - Re-use convolution feature map for localization & classification
  - Uses pre-defined "anchor" boxes to determine bounding box dimensions
- Must be trained in 4 stages
- Eliminates the need for prior object proposals
  - No more Selective Search or EdgeBoxes

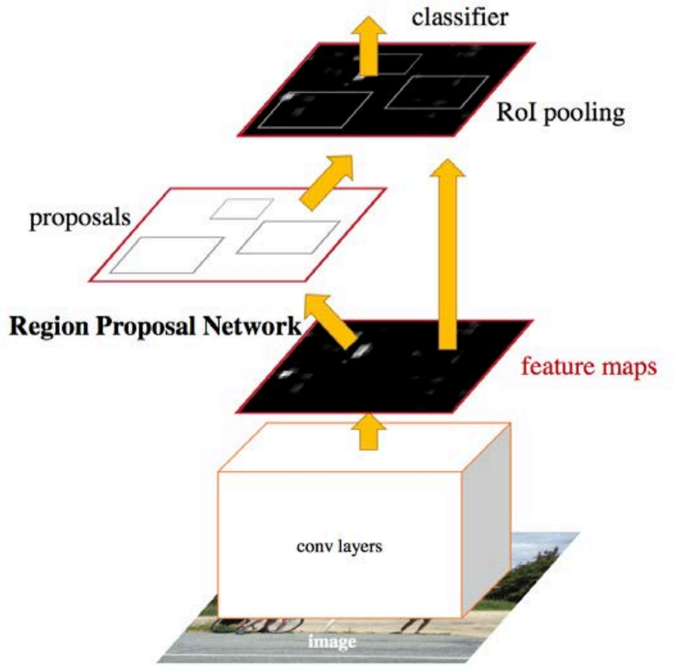

Figure 2: Faster R-CNN is a single, unified network for object detection. The RPN module serves as the 'attention' of this unified network.

*Image from Ren et al., "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks"

[Fast Detection – Pipeline Evolution]

Typical Detection

- Read image
- Create object proposals
- For each proposal:
  - Crop from frame
  - Pre-process
  - Run CNN classifier
- Post-process (NMS)

Fast R-CNN

- Read image
- Create object proposals
- ~~For each proposal:~~
  - ~~Crop from frame~~
  - ~~Pre-process~~
  - ~~Run CNN classifier~~
- Run CNN classifier
  - Take as input a list of proposals
  - Use RoI pooling layer
- Post-process (NMS)

Faster R-CNN

- Read image
- ~~Create object proposals~~
- Run CNN classifier
  - Take as input a list of proposals
  - Generate proposals using feature map and region proposal network
  - Re-use feature map for classification
- Post-process (NMS)

[Fast Detection – Fully Convolutional]

R-FCN

- Adopts RPN network from Faster-RCNN
- Replaces all fully-connected layers
- Inherits training difficulty of Faster-RCNN
- Comparable quality, but better inference speed
- Showed RPNs can outperform Selective-Search and EdgeBox proposals
- Can be integrated with existing network architectures

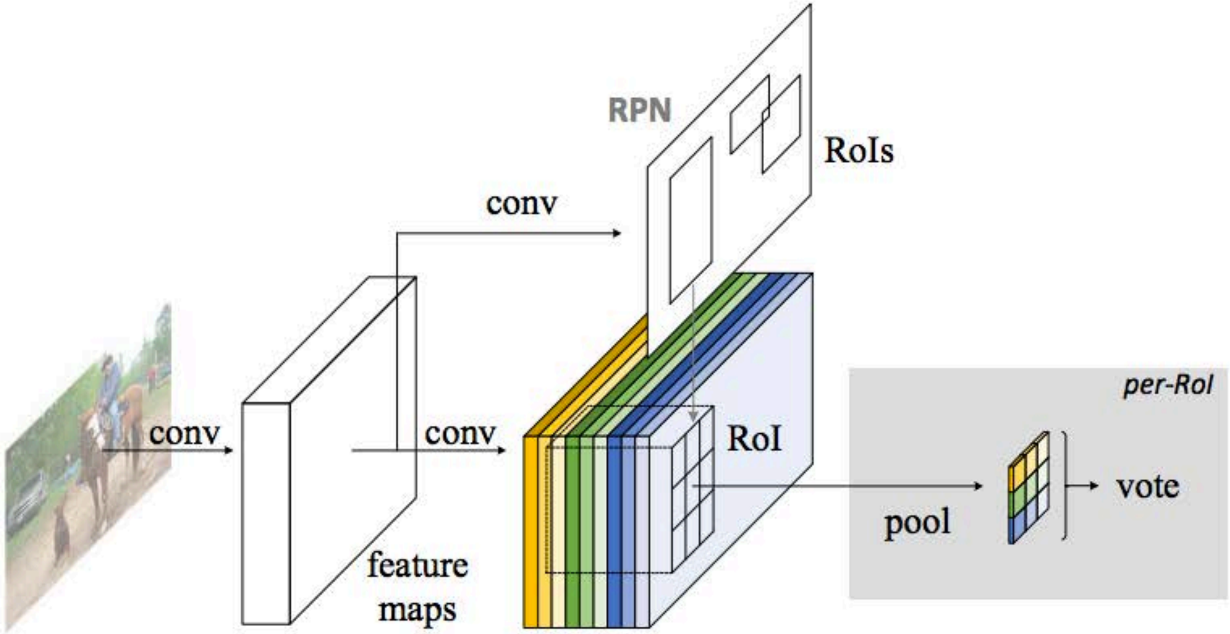

Figure 2: Overall architecture of R-FCN. A Region Proposal Network (RPN) [18] proposes candidate RoIs, which are then applied on the score maps. All learnable weight layers are convolutional and are computed on the entire image; the per-RoI computational cost is negligible.

*Image from Dai et al., “R-FCN: Object Detection via Region-based Fully Convolutional Networks”

[Even Faster Detection]

YOLO/YOLOv2

- No explicit region proposals or RPN
- v2 is fully-convolutional
- Uses k-means to determine best shapes for bounding boxes
- Multi-scale training allows trade-off for lower resolution input and speed vs. higher resolution and accuracy
- Has problems detecting small/overlapping objects

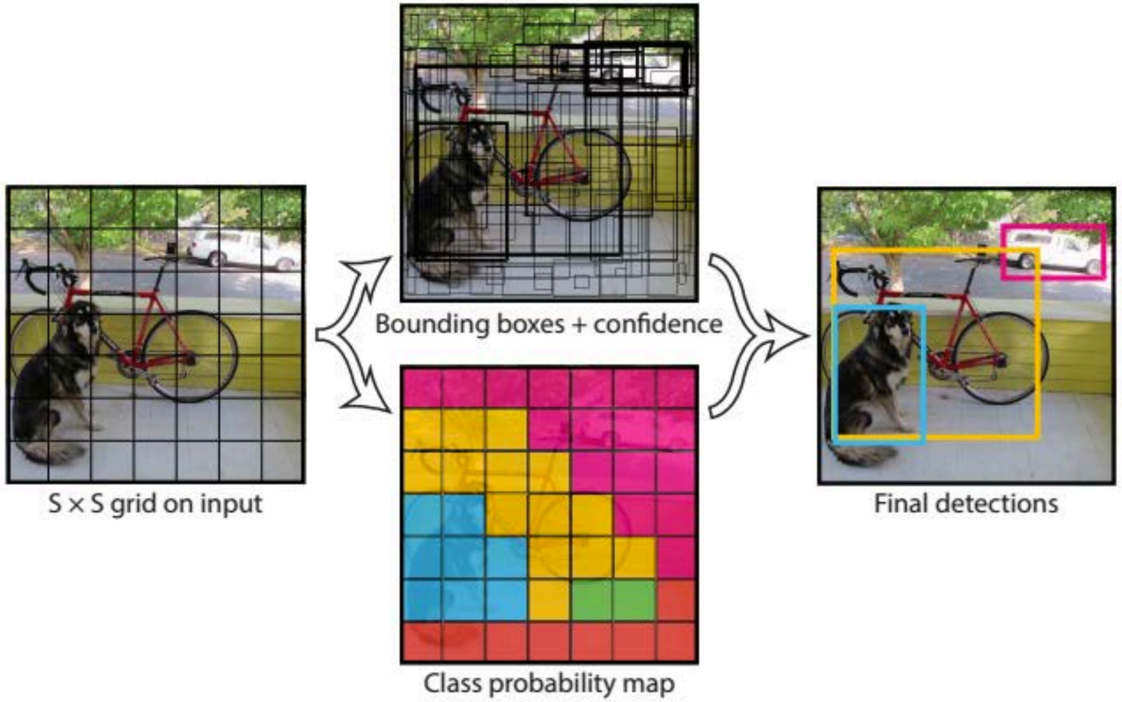

Figure 2: The Model. Our system models detection as a regression problem. It divides the image into an $S \times S$ grid and for each grid cell predicts B bounding boxes, confidence for those boxes, and C class probabilities. These predictions are encoded as an $S \times S \times (B * 5 + C)$ tensor.

*Image from Redmon et al., “You Only Look Once: Unified, Real-time Object Detection”

[Even Faster Detection]

SSD

- Adds convolutional layers to predict bounding boxes of various scales/aspect ratios
- Fully convolutional
- Performance & Quality > YOLO & < YOLOv2

SqueezeDet

- Uses "convdet" layers inspired by YOLO
- Uses anchor boxes inspired by Faster R-CNN, but uses k-means to improve them
- Fully convolutional
- Performance & Quality comparable to YOLOv2

YOLO/YOLOv2

Simultaneous Classification and Detection [FAST]

Faster R-CNN
R-FCN

Explicit Proposals [ACCURATE]

Need “Smaller” Architectures

“Don’t be a hero”

\- Sage advice from cs231, Andrej Karpathy

Top-Down Design

- Start with top architectures on ILSVRC

[CNN Architecture Design – What Already Works?]

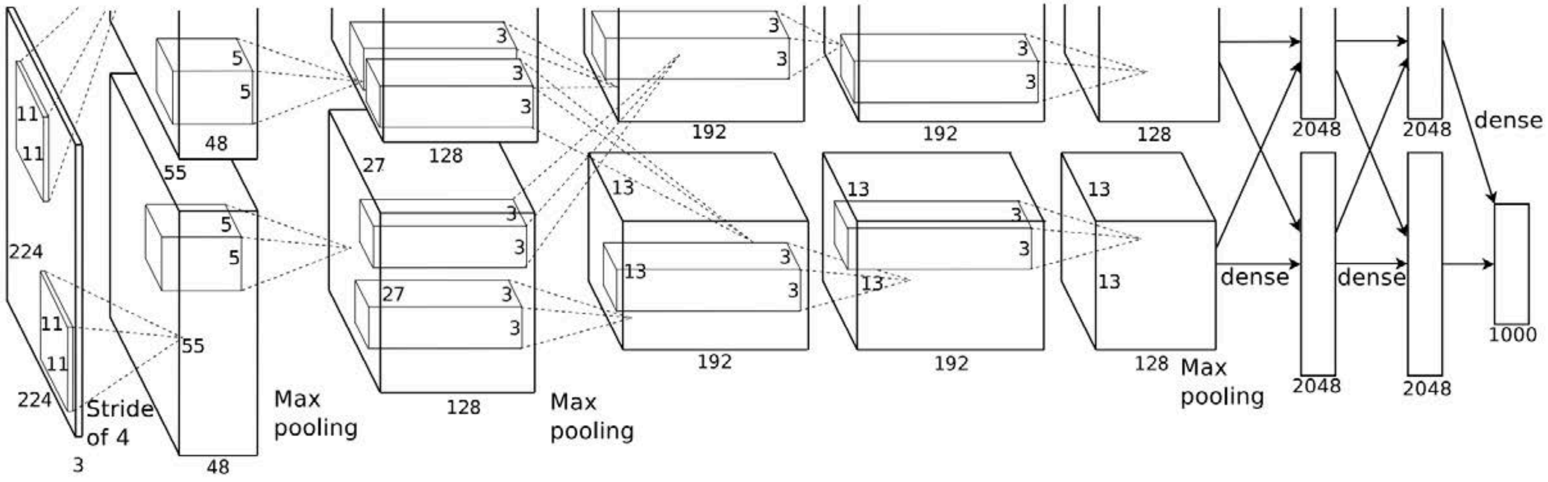

Figure 2: An illustration of the architecture of our CNN, explicitly showing the delineation of responsibilities between the two GPUs. One GPU runs the layer-parts at the top of the figure while the other runs the layer-parts at the bottom. The GPUs communicate only at certain layers. The network's input is 150,528-dimensional, and the number of neurons in the network's remaining layers is given by 253,440–186,624–64,896–64,896–43,264–4096–4096–1000.

Parameter	AlexNet Requirement	Available on Embedded
Weight Space	~250 MB	128 – 512 Kb
Operations for 30FPS VGA	~2400 GMAC/s	24 - 32 GMAC/s

Challenges:

- Reduce weight space ~400x
- Reduce compute by ~100x
- Retain high accuracy

Image attribution: Krizhevsky, et. al

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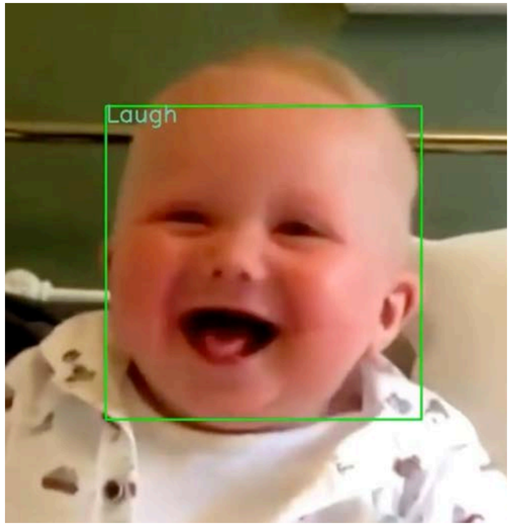
Top-Down Design

- Start with top architectures on ILSVRC
- “Shrink” it:
  - Remove layers (especially FC layers)
  - Reduce # of convolution filters
  - Decrease convolution filter size
  - Made easier if fewer detection classes

[CNN Architecture Design – Top Down]

Toy Example: Detecting Faces

- 1 class
- AlexNet is clearly overkill
- Similar accuracy with smaller network



Classifier	AlexNet Type	Shrunk Network
Weight Space	~250MB (500x)	<512Kb (1x)
Layers	10 (7 CV + 3 FC)	5 (3 CV + 2 FC)
Compute Time	640x	1x
Operations per input	832 MMACs	1.3 MMACs

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- Reduce until it fits into your target compute/memory constraints
- Structured approaches:
  - SVD
  - Pruning

Top-Down Design

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Bottom-Up Design

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Top-Down Design

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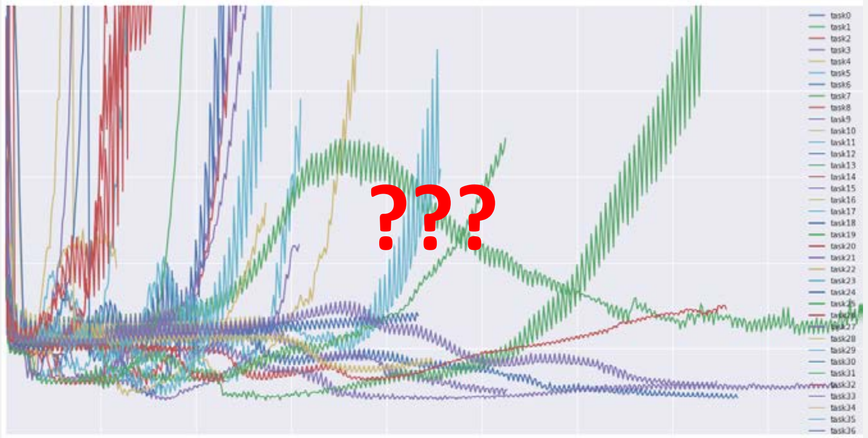
Bottom-Up Design

- Consider target hardware and its compute/memory constraints
- Assemble architecture layer-by-layer
- Use top ILSVRC architectures as a guideline
  - Mimic structure/layer patterns
  - Inception modules (Szegedy, et al.)
- Error-prone, could end up with something "untrainable", leave to the experts



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[CNN Architecture Design]

SqueezeNet

- Back-bone of “SqueezeDet”
- Fully convolutional
- “Fire Modules” use 1x1 convolutions to ”squeeze” a layer before feeding into a mixed 1x1 and 3x3 layer

Darknet-19

- Backbone of “YOLOv2”
- Fully convolutional
- Uses 1x1 convolutions to compress feature maps between 3x3 convolutions

Classifier	SqueezeNet-Type	Darknet-Type
Weight Space	4MB	100MB
Runtime Memory	100MB	500MB
Operations per input	3.6 GMACs	1.4 GMACs

[More To Do]

- Energy-Aware Pruning (Yang, et al.)
- Deep Compression (Han, et al.)
  - SqueezeNet shown to compress effectively
- Shortcut Connections (He, et al.)
  - DenseNets, Highway

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Progress

- Simultaneous classification and detection
- Pruning, 1x1 convolutions, Bottom-up design with hardware considered

[End]

Contact Me

Anshu Arya
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