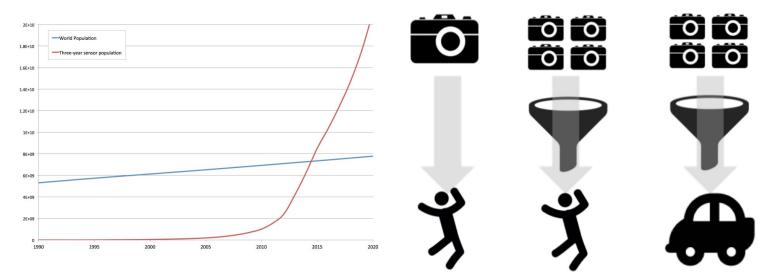
Smart Embedded Vision with Quantized Neural Networks

zsc@megvii.com



Why Smart Embedded Vision?



- Human Consumption
- Human Decision Making
- Autonomous Action





Challenges

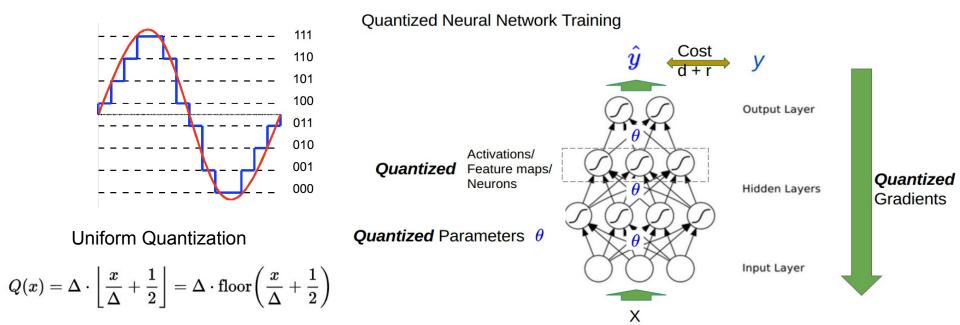
- Vast amount of computations
- Power Consumption and Cooling

	Full load (TDP Watts)	FLOPS	Source
ARM (Snapdragon 835)	4.5 (2 (CPU) + 2 (GPU) + 0.5)	< <u>0.06T (FP32),</u> 4+4 cores	3rd party
TX1 (module)	15	1T (FP16)	<u>NVidia</u>
FPGA (7030)	7.5 (5.8 (chip) + 1 (DDR) + 0.7(power))	0.9T (2w2f)	Face++



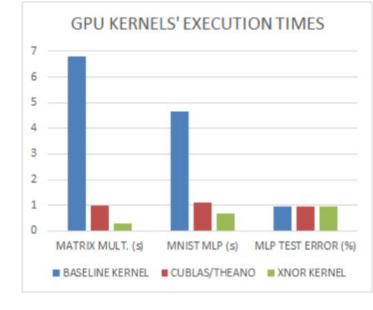
Quantized Neural Networks (QNNs)

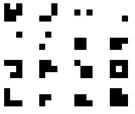
Parameters/Activations/Gradients are quantized to discrete values.



Impact of Quantization

- Pro
 - Can exploit bitwise operations for speeding up computations.
 - XNOR-popent kernel instead of multiply-add
 - Smaller storage size and memory footprint
- Con
 - Often less accurate in predictions, especially when bitwidth less than 4





3-by-3 filters in a QNN, the weights are 1-bit hence black and white.



QNN at Megvii (Face++)

- DoReFa-net https://arxiv.org/abs/1606.06160
 - Stochastic Quantization of Gradients for ImageNet
- Quantization of RNN https://arxiv.org/abs/1611.10176
- Quantization of FCN http://cn.arxiv.org/pdf/1612.00212v1
- Balanced Quantization https://arxiv.org/abs/1706.07145
 - State-of-the-art in 4-bit quantization of GoogleNet/ImageNet and RNN/PTB



DoReFa-Net: Training Low Bitwidth Convolutional Neural Networks with Low Bitwidth Gradients

- Uniform stochastic quantization of gradients
 - 6 bit for ImageNet, 4 bit for SVHN
- Simplified scaled binarization: only scalar
 - Forward and backward multiplies the bit matrices from different sides.
 - Using scalar binarization allows using bit operations
- Floating-point-free inference even when with BN
 - Comparison with floating point thresholds can be scaled to be comparison with integers
- Future work
 - BN requires FP computation during training
 - Require FP weights for accumulating gradients

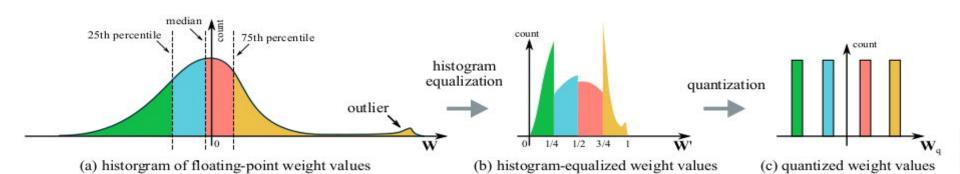


Effective Quantization Methods for Recurrent Neural Networks 2016 Balanced Quantization: An Effective and Efficient Approach to Quantized

-0.75 -0.50 -0.25 0.00 0.25 0.50 0.75

Neural Networks 2017

Model	weight-bits	activation-bits	balanced	PPW unbalanced	0.4 -
LSTM LSTM	2 2	2 3	152 142	164 155	0.1 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0
LSTM (Hubara et al., 2016a)	2	3		220	(a) floating point copy of weights in (b) imbalanced quantization (no equaliza-QNN after 60 epochs tion)
LSTM (Hubara et al., 2016a)	4	4		100	
					0.2 - 0.1 - 0.1 - 0.1 - 0.0



Training Bit Fully Convolutional Network for Fast

Semantic Segmentation 2016

bit-width (W / A)	mean IoU	Complexity - 64	
32 / 32	69.8%		
8/8	69.8%		
4/4	68.6%	16	
3/3	67.4%	9	
2/2	65.7%	4	
1/4	64.4%	4	
4/1	diverge	4	
1/2	62.8%	2	

Table 5: Results of different bit-width allocated to weight and activation on PASCAL VOC 2012 val set.

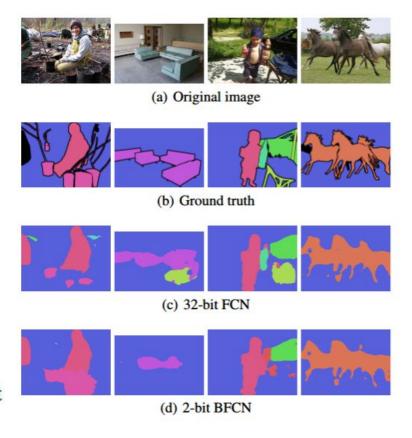
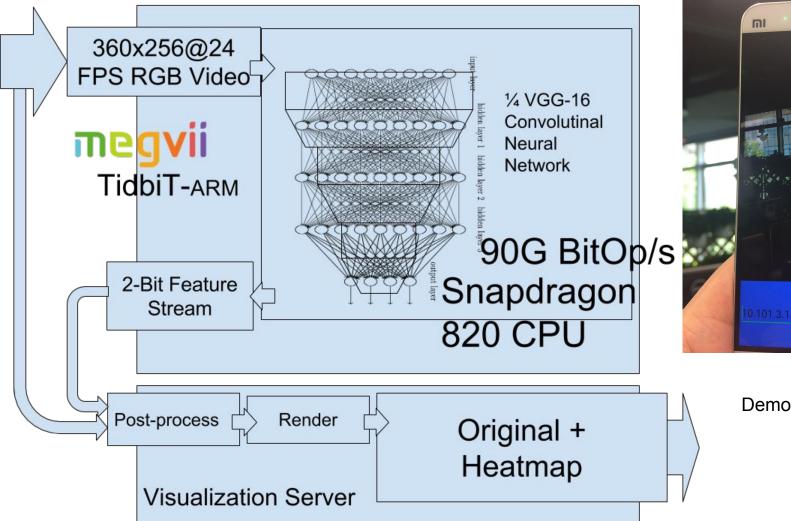
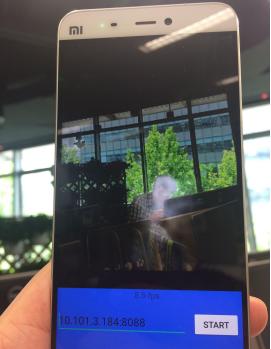


Figure 4: Examples on PASCAL VOC 2012.

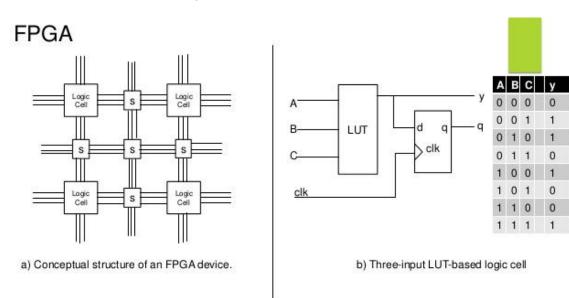


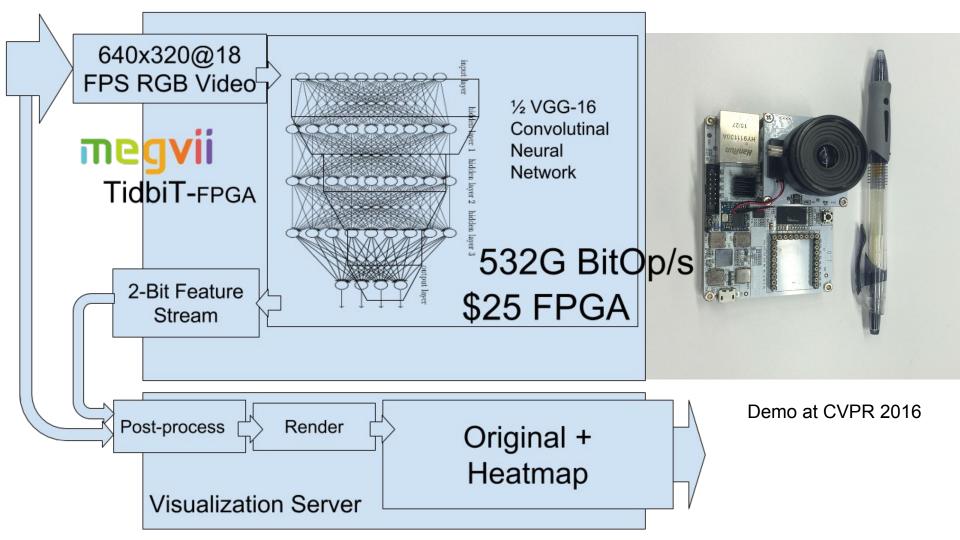


Demo at CVPR 2016

QNN on FPGA

- FPGA is made up of LUT's
- Bit-convolution kernel can be implemented by LUT





Smart Camera

- Benefits
 - Local processing
 - Low latency and high availability
 - High Frame Rate Conditional Capture
 - Less storage and bandwidth
 - High FPS = larger candidate set



Sort by Clearness



Sort by pose (frontal face)



Backup after this slide

zsc@megvii.com

job@megvii.com

