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Computer Systems Laboratory

RECONFIGURING THE IMAGING PIPELINE FOR COMPUTER VISION

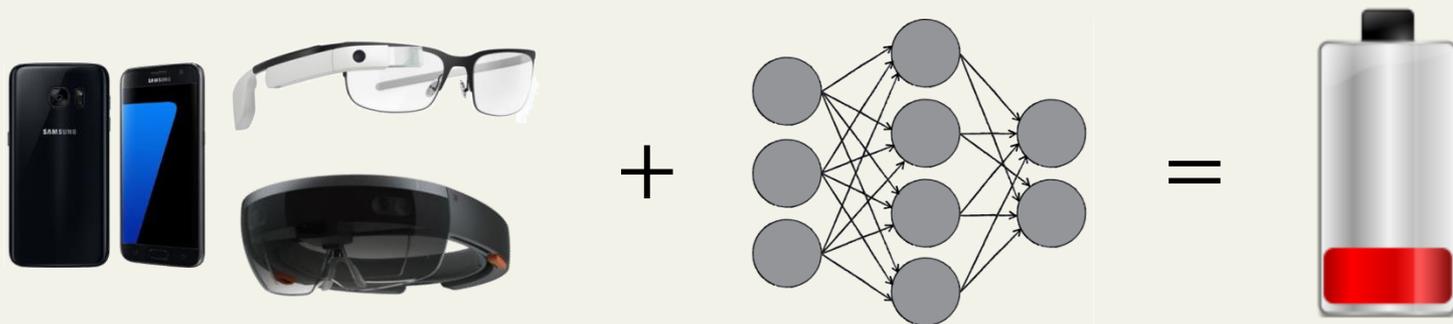
Mark Buckler, Suren Jayasuriya, Adrian Sampson

March 23, 2017

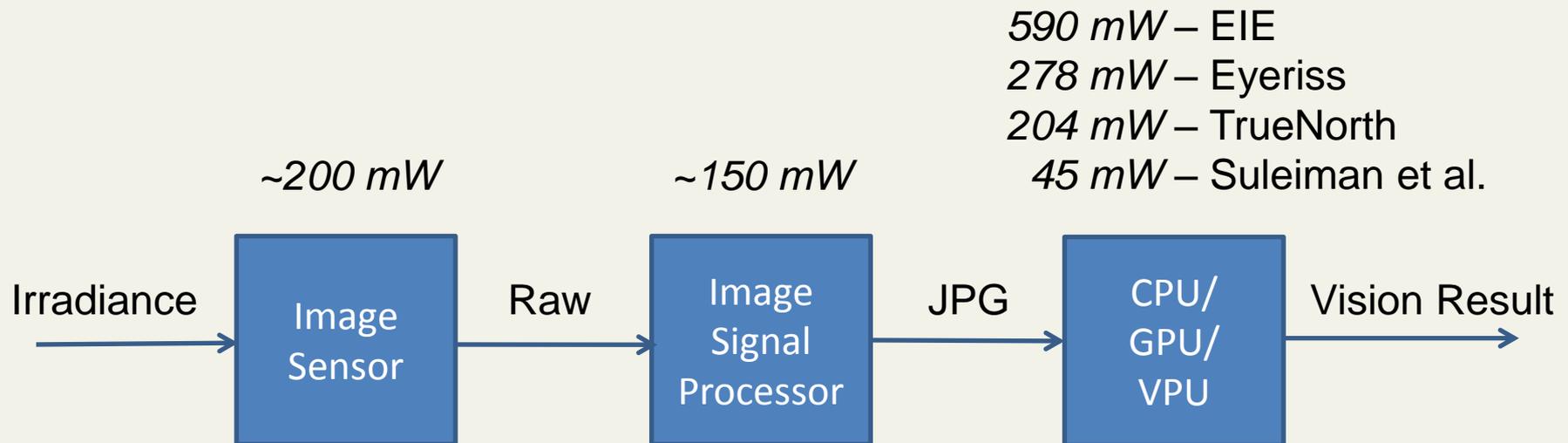


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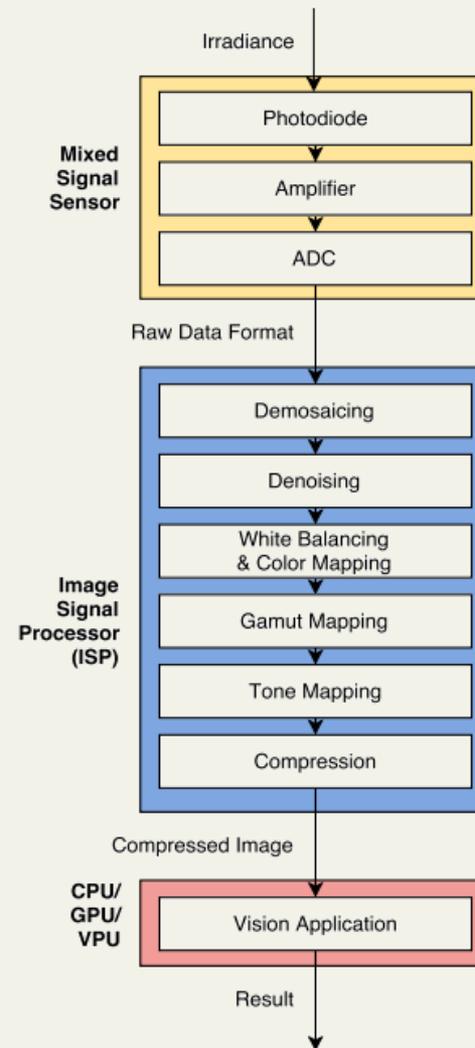
- **Deep learning has dramatically increased accuracy for computer vision tasks: face recognition, object detection, etc**
- **Deep learning and other computer vision applications drain the battery of embedded devices**



- Innovation in deep learning ASIC design continues to reduce the cost of embedded inference
- Modifications to the image sensor or ISP have been proposed, but their effect on vision algorithms is unknown



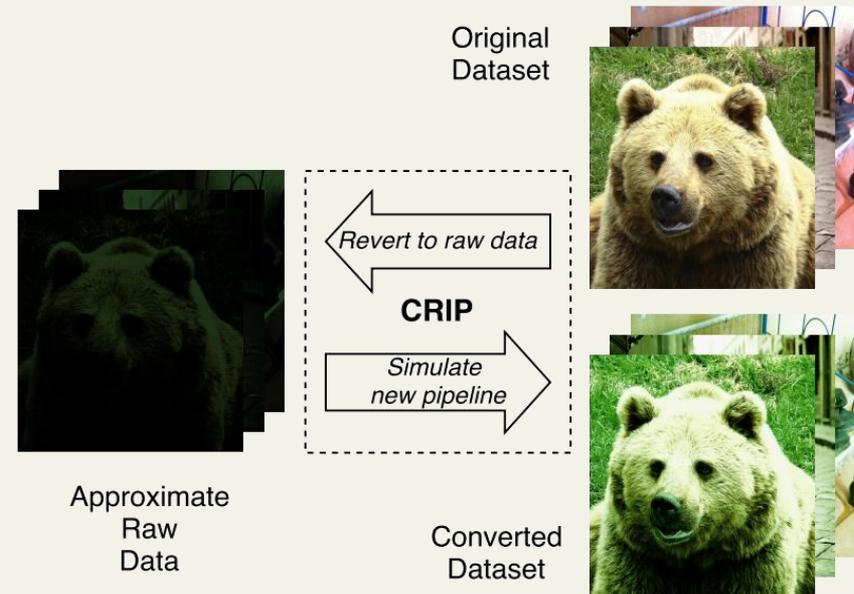
- *Step 1: Determine computer vision algorithms' sensitivity to sensor approximations and ISP stage removal*
- *Step 2: Use this information to design a configurable pipeline capable of capturing images for both humans and vision algorithms*



- Nearly all vision datasets consist of human readable images
- To train and test vision algorithms on data created by a modified pipeline, we need to convert these datasets

- *Configurable & Reversible Imaging Pipeline (CRIP)*

- Four stages adapted from Kim et al.'s reversible pipeline
- Image sensor noise model adapted from Chehdi et al.
- **Accurate:** <1% error
- **Fast:** CIFAR-10 in an hour

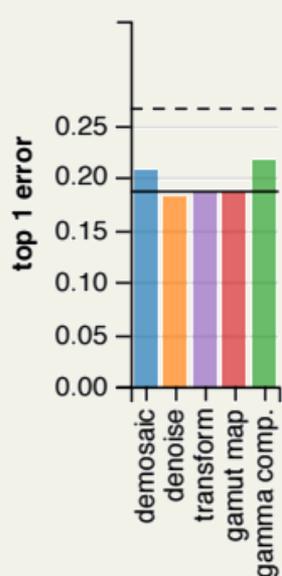


- A wide variety of computer vision algorithms were tested (including deep learning and traditional techniques)

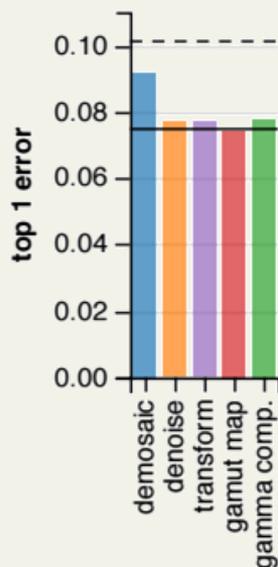
Algorithm	Dataset	Vision Task
3 Deep LeNet [30]	CIFAR-10 [29]	Obj. Classification
20 Deep ResNet [21]	CIFAR-10	Obj. Classification
44 Deep ResNet [21]	CIFAR-10	Obj. Classification
Faster R-CNN [38]	VOC-2007 [17]	Object Detection
OpenFace [1]	CASIA [46] and LFW [24]	Face Identification
OpenCV Farneback [26]	Middlebury [40]	Optical Flow
OpenCV SGBM [26]	Middlebury	Stereo Matching
OpenMVG SfM [35]	Strecha [42]	Structure from Motion



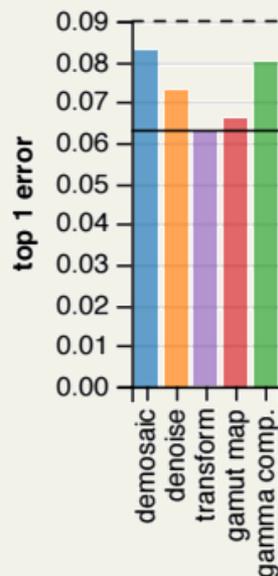
SENSITIVITY TO ISP STAGE REMOVAL



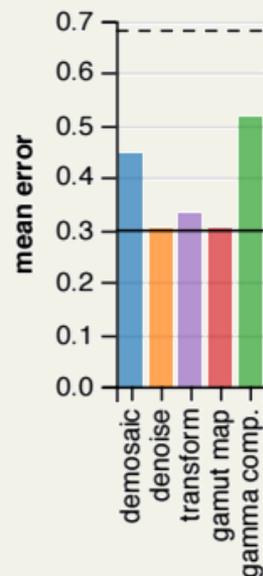
LeNet3



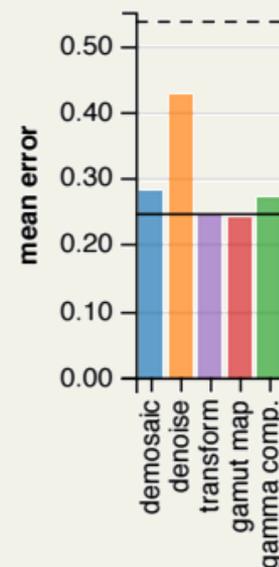
ResNet20



ResNet44



Farneback



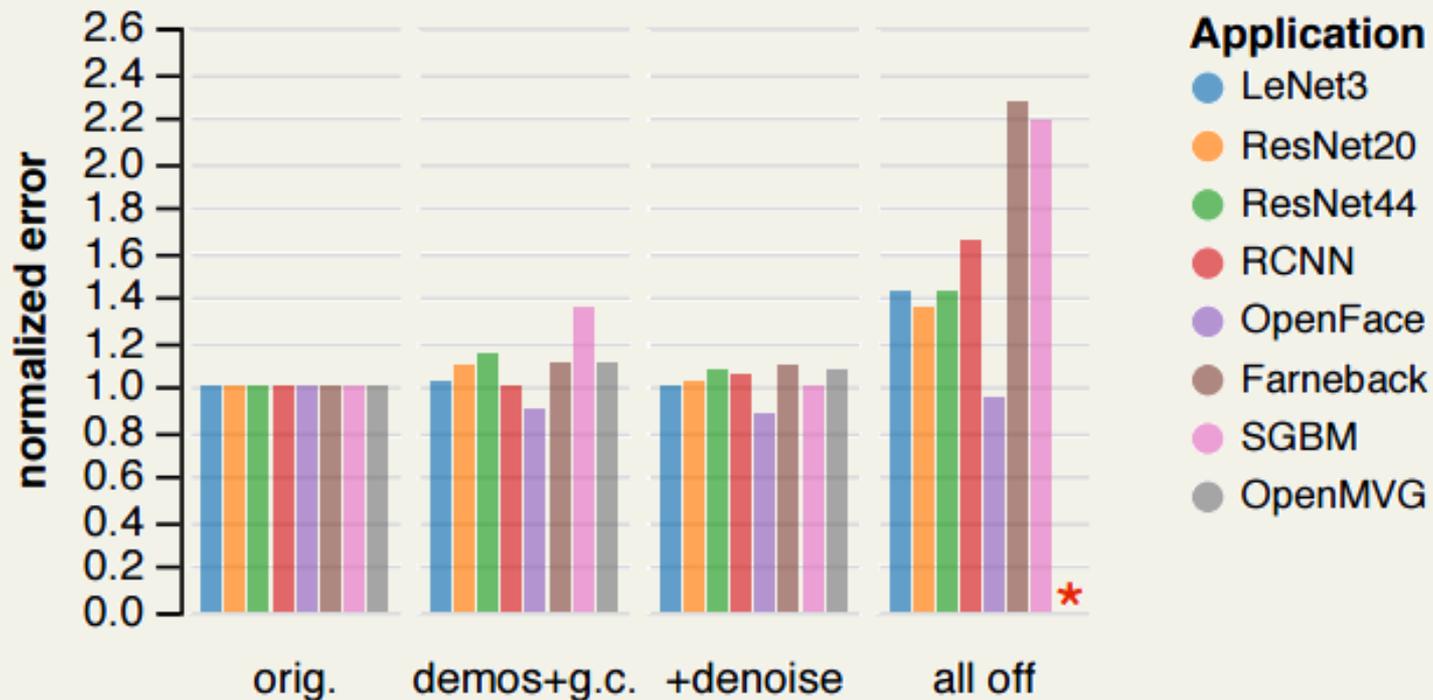
SGBM



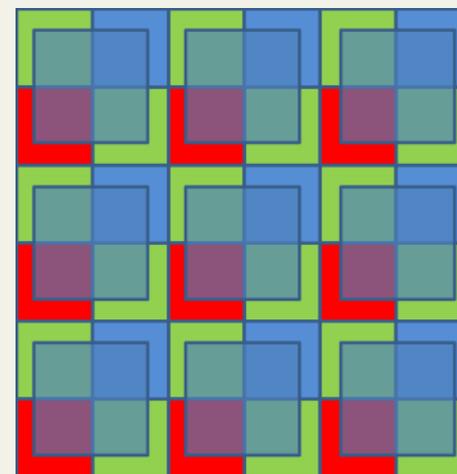
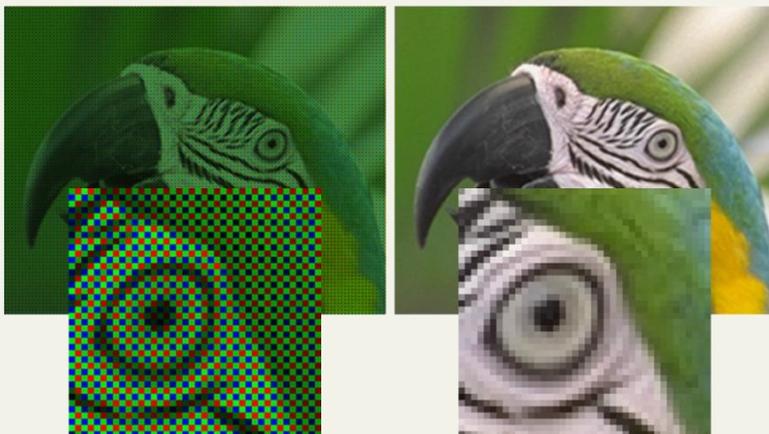
OpenMVG

PROPOSED ISP PIPELINE

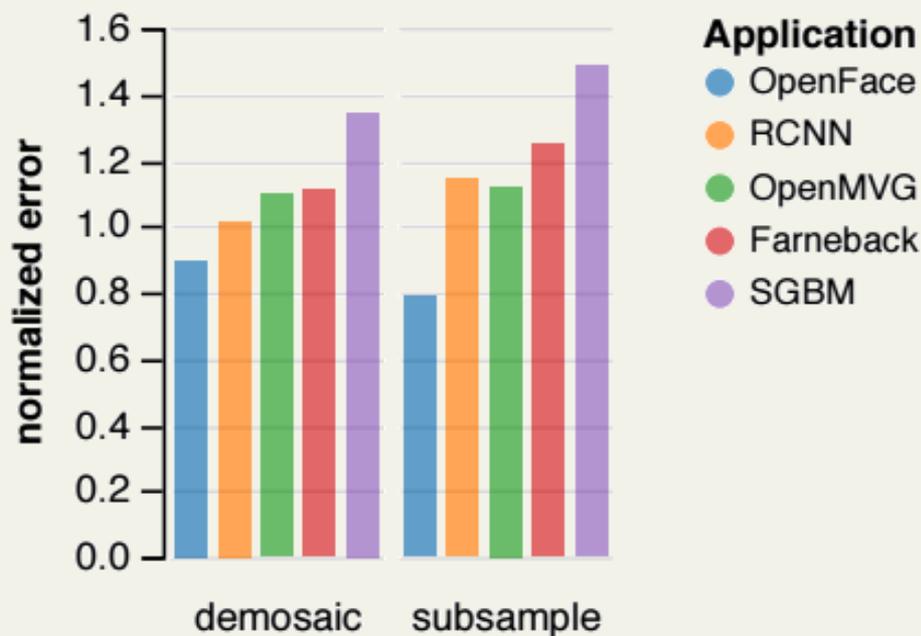
- Most only need demosaicing and gamma compression
- SGBM also needs denoising



- Demosaicing algorithms interpolate color values missing from the sensor's filter pattern
- **Mobile camera resolution \gg Network input resolution**
 - Why not subsample instead of demosaicing?

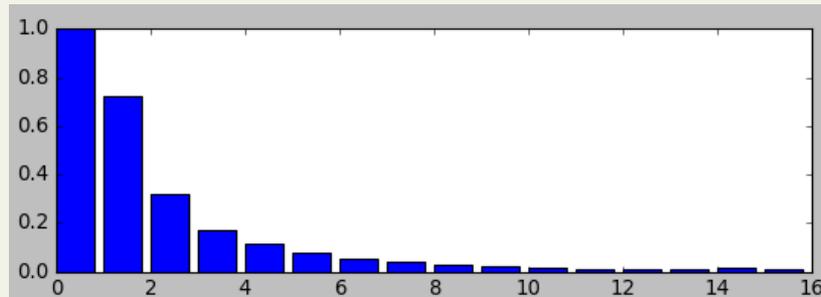


- Tests done with non-CIFAR-10 algorithms
- Tested pipeline contains only gamma compression

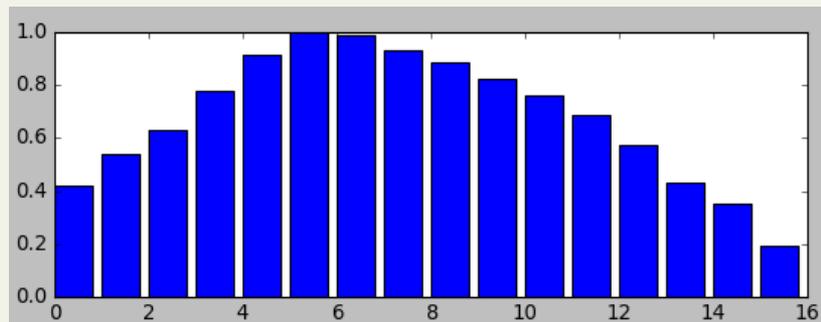


GAMMA COMPRESSION: CAN WE APPROXIMATE?

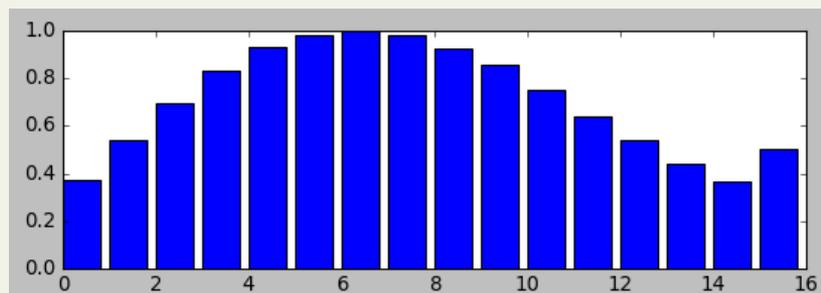
Raw data
(lognormal distribution)



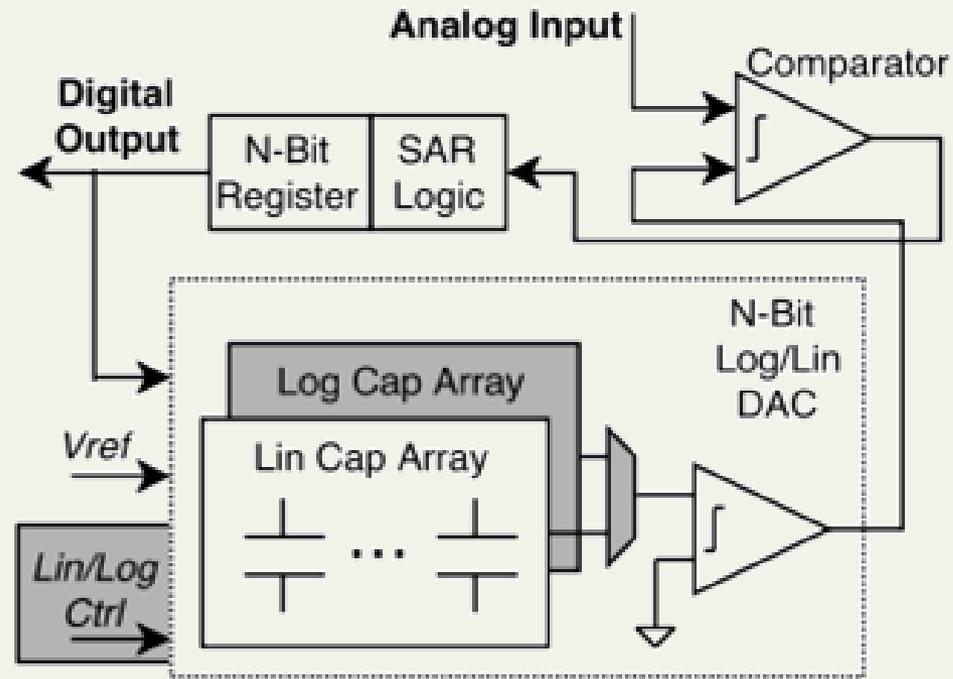
Tone mapped raw data
(normal distribution)



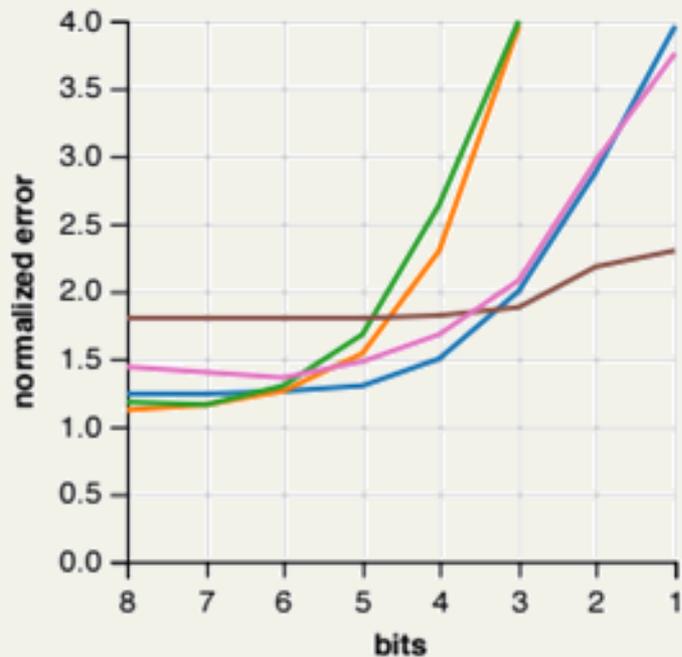
JPEG from standard pipeline
(normal distribution)



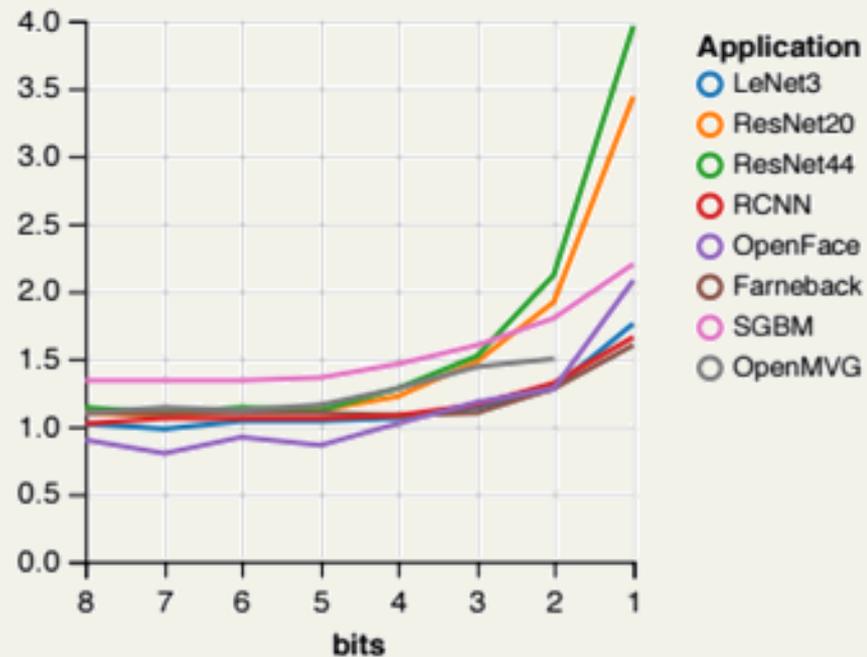
GAMMA COMPRESSION: CAN WE APPROXIMATE?



GAMMA COMPRESSION: USE A LOG ADC



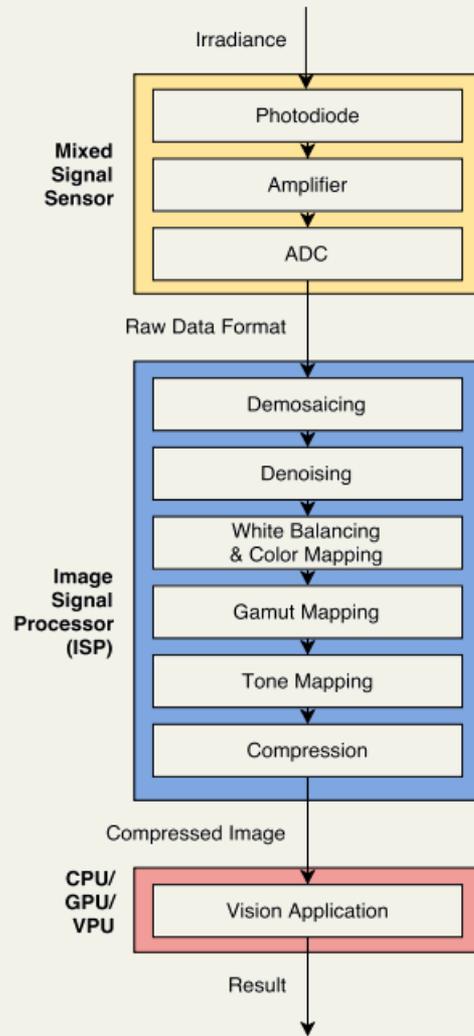
Linear
Quantization
Sweep



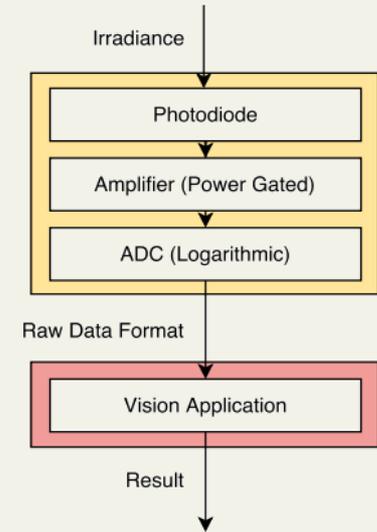
Logarithmic
Quantization
Sweep

- Application**
- LeNet3
 - ResNet20
 - ResNet44
 - RCNN
 - OpenFace
 - Farneback
 - SGBM
 - OpenMVG

Photography Mode



Vision Mode



1. All but one application needed only two ISP stages: *demosaicing and gamma compression*
2. Our image sensor can approximate the effects of demosaicing and gamma compression, *eliminating the need for the ISP*
3. Our image sensor can reduce its bitwidth from 12 to 5 by replacing linear ADC quantization with logarithmic quantization



- **Sensor: ~200 mW, ISP: ~150 mW, VPU: ~300mW**
- **Half of the sensor energy consumption can be saved by switching from 12 bits to 5 bits**
- **The entire ISP energy can be saved with power gating**
- **Our configurable vision mode can save ~40% of the total system power consumption!**

