

embedded **VISION** SUMMIT 2018

Implementing and Improving Traditional Computer Vision Algorithms using DNN Techniques

- Introduction
- Mapping traditional vision to deep learning primitives
- Traditional vision to learning-based vision

Imagination: A global technology leader

A technology powerhouse for multimedia and communications IP

Developing innovative IP

- PowerVR GPU: leader in graphics & compute
- PowerVR Vision & AI: dedicated IP for vision & AI
- Enigma: connectivity and broadcast communications IP

Delivering exceptional service

- Enabling very fast time to market
- Enabling customers to leverage IP to maximise differentiation

Driving major markets

- Helping our partners to create successful solutions
- Influencing new and emerging opportunities
- Showcasing and proving our technology with real products

Products

- More than 10bn units shipped
- Over 3m per day
- Around 1.2bn in past year

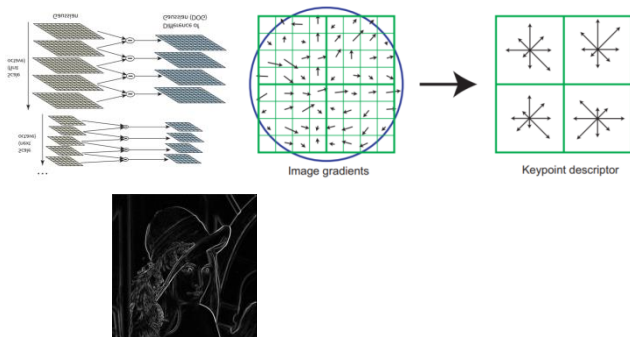
People

- HQ in UK
- >800 people world-wide
- >80% of staff are engineers

Introduction

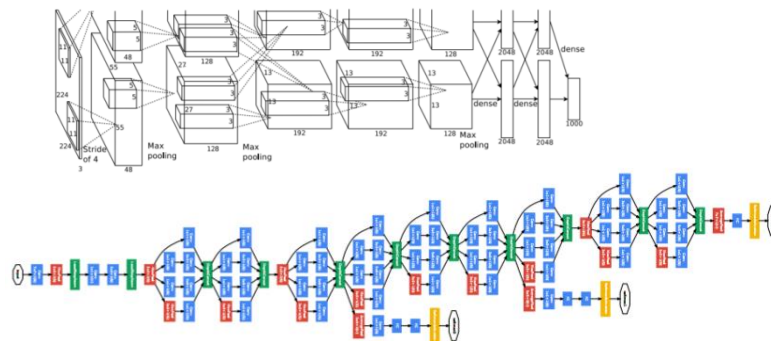
- Traditional vision -> deep learning
- Significant investment in traditional vision
 - Expect to move over to deep learning for some or all algorithms
- Choices today when designing or selecting silicon
 - Optimise for deep learning
 - Optimise for traditional vision
 - Increased cost to provide dedicated support for both
- Programmable solutions available do not 'solve' the problem
 - Still need to make a choice about priorities

Traditional Vision v Deep Learning



• Traditional Vision

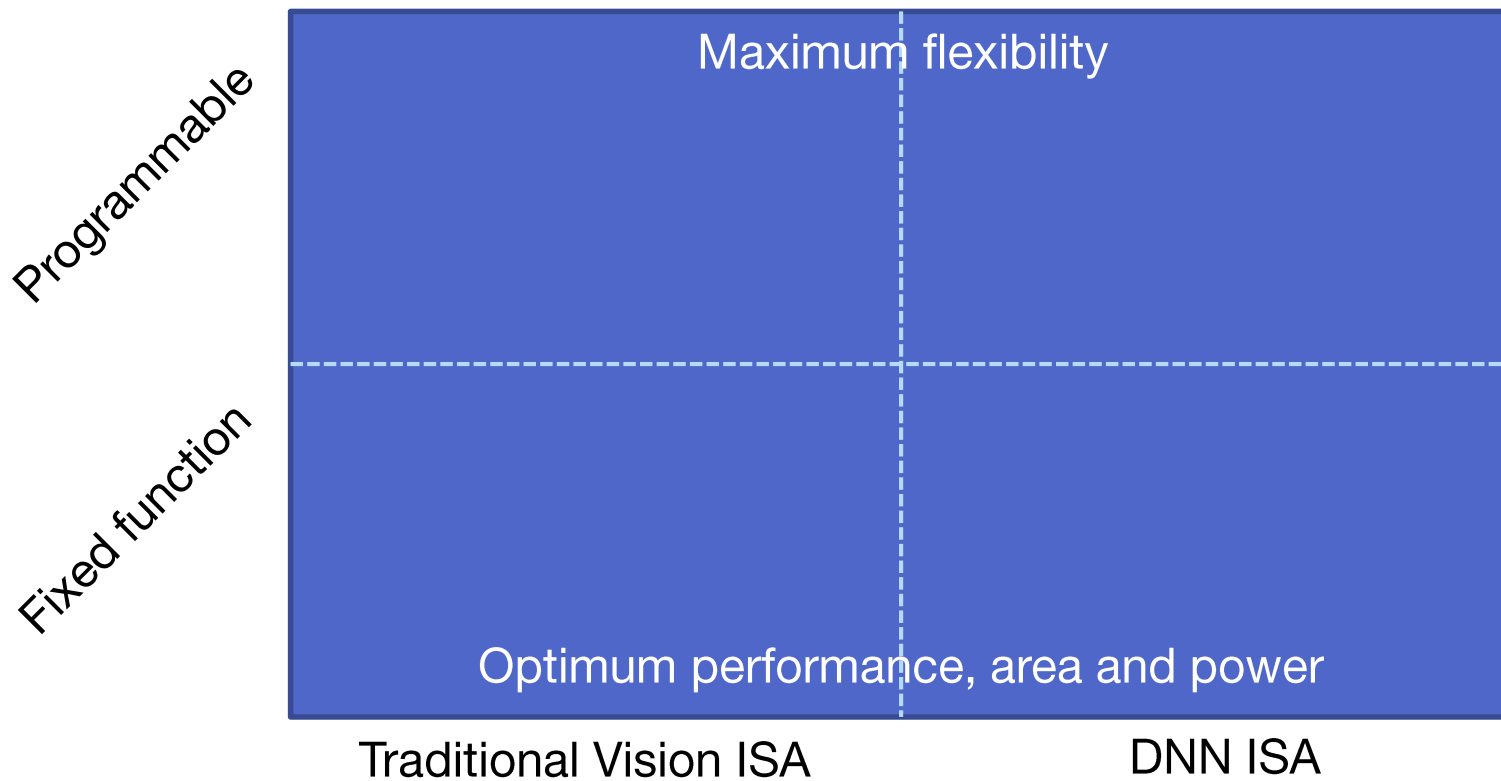
- > 30 years investment by industry
- Often good enough for specific tasks
- Proven, mature and understood
- Diverse set of primitive operations
 - Lots of algorithmic secret-sauce



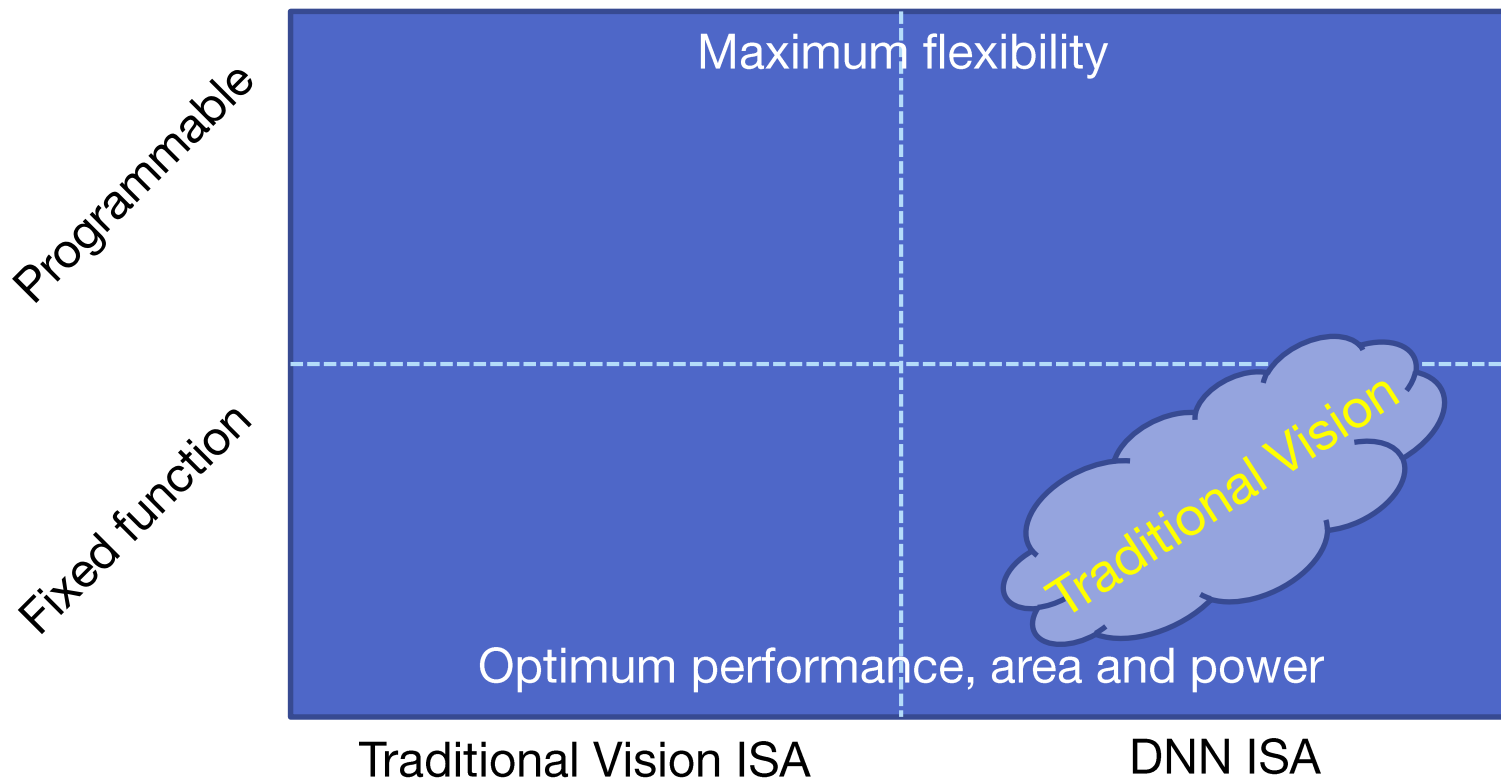
• Deep Learning

- Huge investment over past 3-4 years
- State-of-the-art for many tasks
- New model development takes investment
- Relatively small set of basic primitives
 - Although increasing

Processors for Embedded Vision



Processors for Embedded Vision

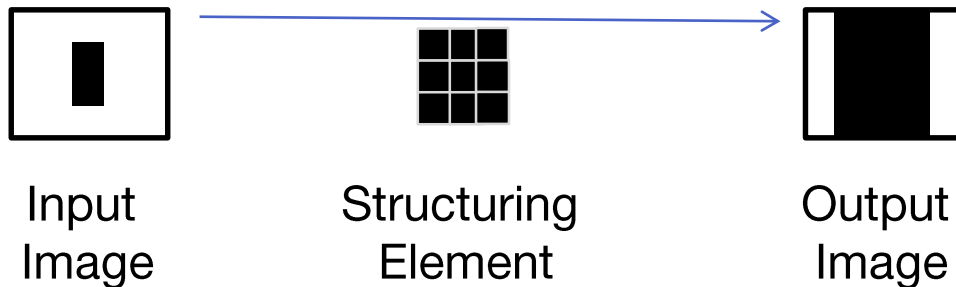


Deep Learning Primitives

- DNN primitives
 - Convolution
 - Deconvolution
 - Fully Connected
 - Activation
 - Pooling
 - Tensor Operations
 - Normalisation
- Supported by DNN processors
- Expressing traditional vision using DL primitives
 - Run on DNN processor

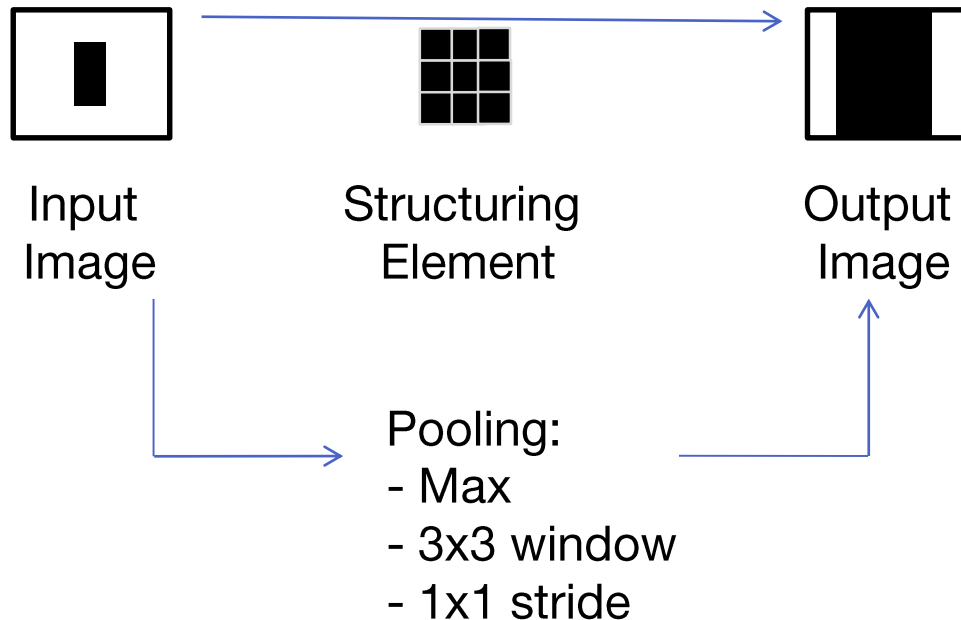
Mapping Traditional Vision to DNN Primitives

Binary Morphological Operator - Dilate



Mapping Traditional Vision to DNN Primitives

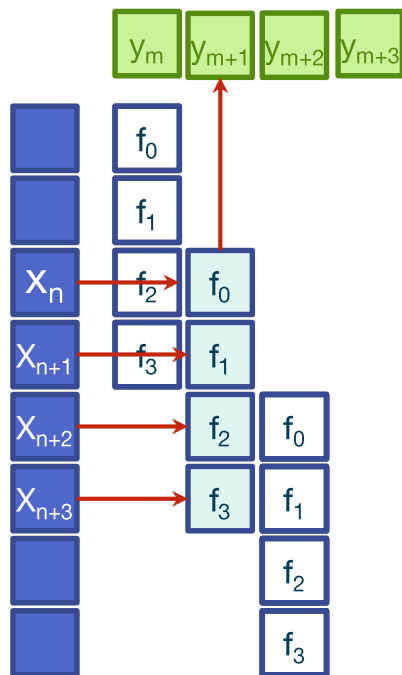
Binary Morphological Operator - Dilate



Mapping Traditional Vision to DNN Primitives

2x Bilinear Up-Scaling

- Make use of deconvolution primitives

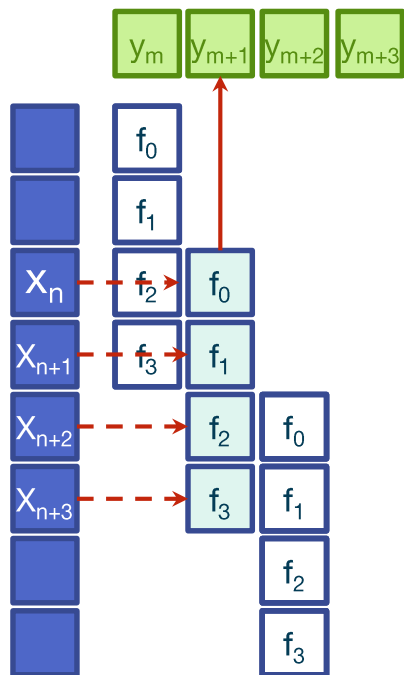


Convolution with stride = 2

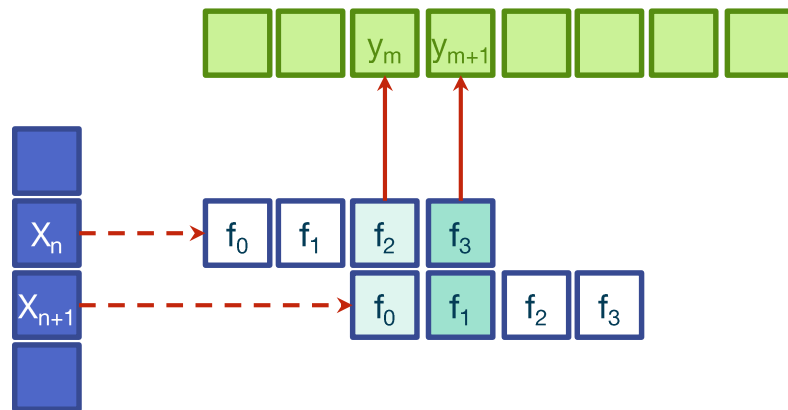
Mapping Traditional Vision to DNN Primitives

2x Bilinear Up-Scaling

- Make use of deconvolution primitive



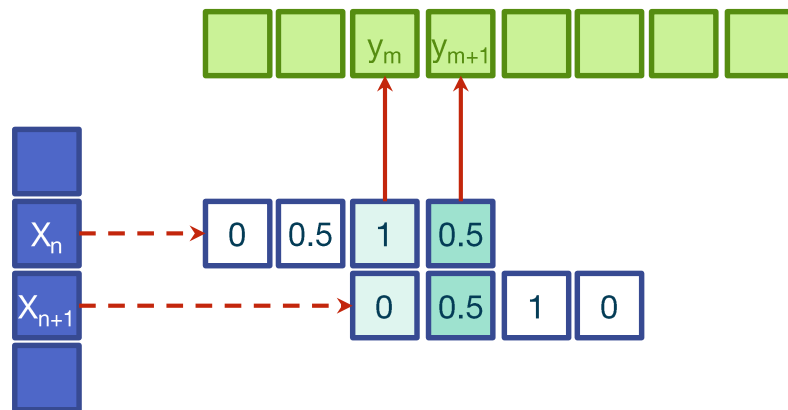
Deconvolution with scaling factor = 2



Mapping Traditional Vision to DNN Primitives

2x Bilinear Up-Scaling

Linear upscale with scaling factor = 2



Mapping Traditional Vision to DNN Primitives

2x Bilinear Up-Scaling

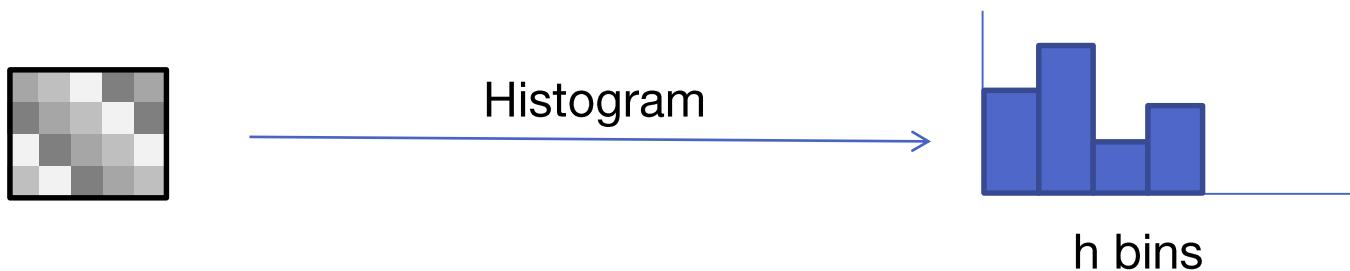
2D linear upsample filter with scaling factor = 2

0.25	0.5	0.25
0.5	1	0.5
0.25	0.5	0.25

0.25	0.25	0.5	0
0.25	0.25	0.5	0
0.5	0.5	1	0
0	0	0	0

Mapping Traditional Vision to DNN Primitives

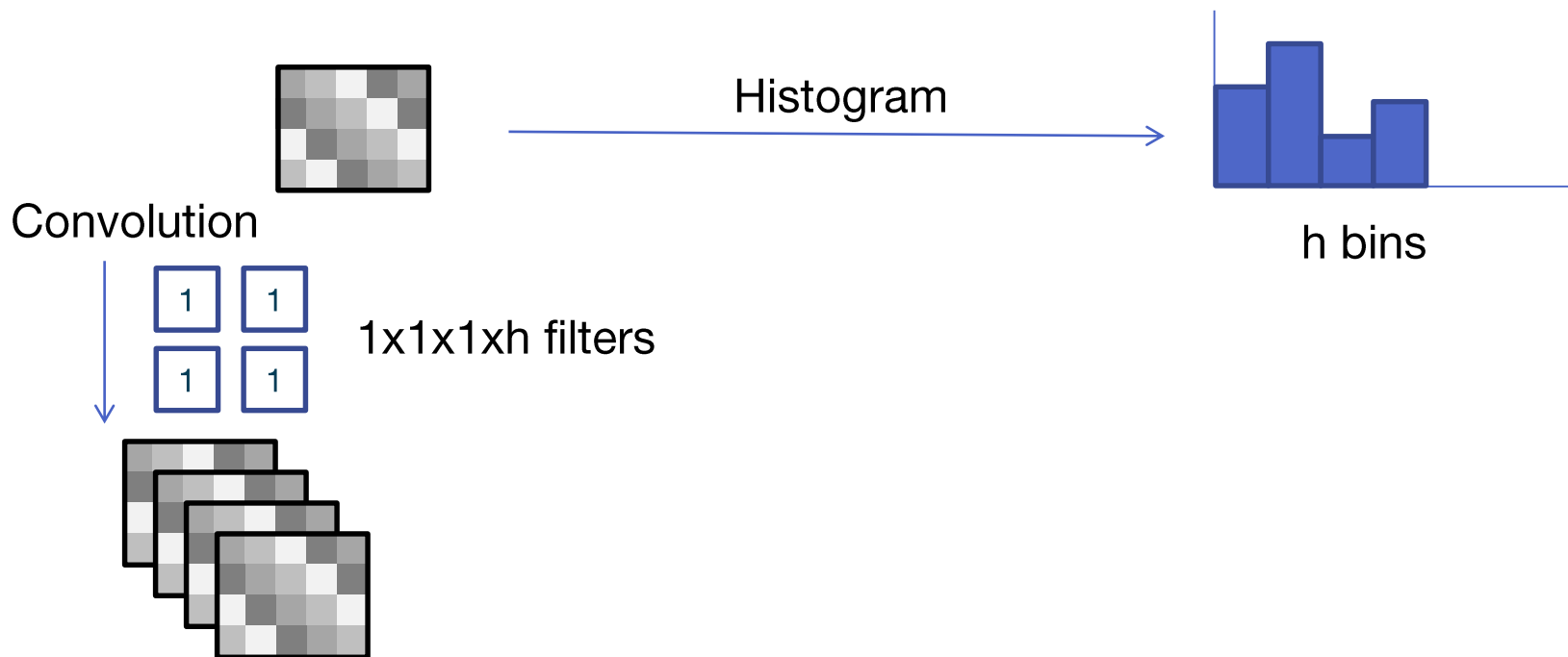
Histogram



Mapping Traditional Vision to DNN Primitives

Histogram

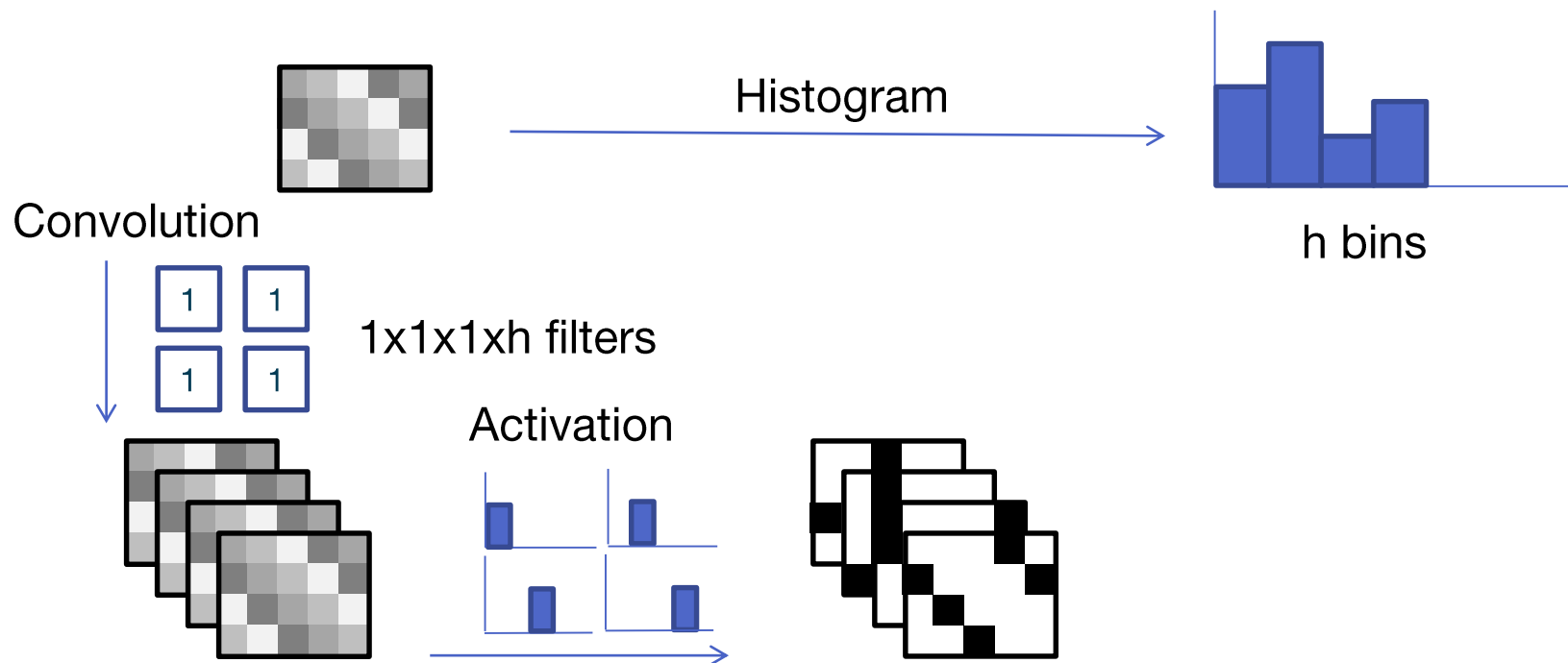
- Convolution, activation and pooling



Mapping Traditional Vision to DNN Primitives

Histogram

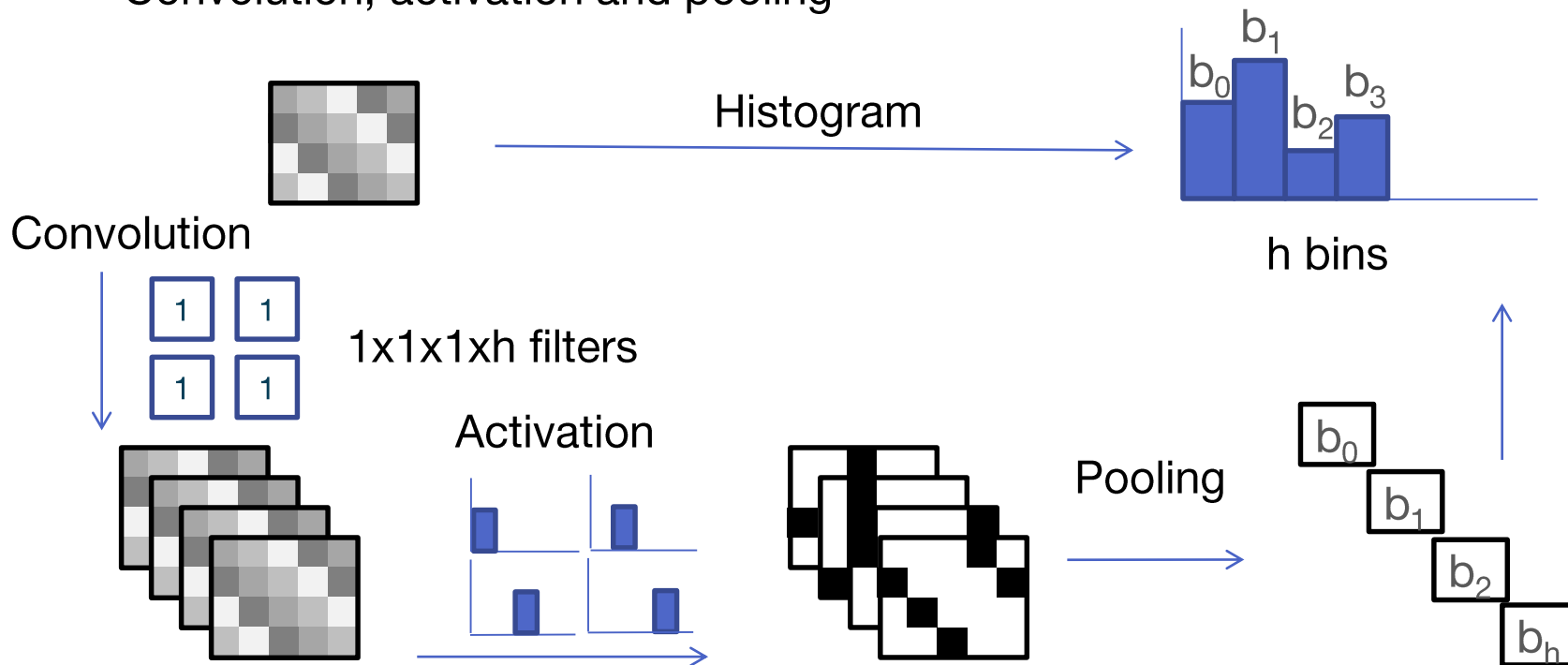
- Convolution, activation and pooling



Mapping Traditional Vision to DNN Primitives

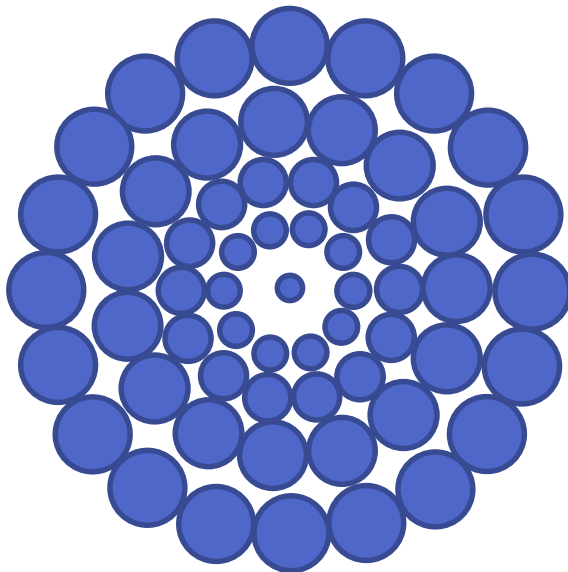
Histogram

- Convolution, activation and pooling



Mapping Traditional Vision to DNN Primitives

Feature Descriptor: Brisk



BRISK sampling positions

- Well-known & widely used binary image feature descriptor
- Good example of traditional vision
 - Hand designed, based on insights and intuition
- Defined 60 samples around feature point
- Set of 512 ‘short-distance’ pairs defined S

$$B = \{b_{ij}\}, b_{ij} = \begin{cases} 1, I(p_i) > I(p_j) \\ 0, \text{otherwise} \end{cases}$$

- Generates a 512D patch descriptor

Mapping Traditional Vision to DNN Primitives

Feature Descriptor: Brisk

- Express Brisk feature pairs as (sparse) matrix

$$\mathbf{D} = \text{sigmoid} \left(\begin{bmatrix} 1 & 0 & \dots & -1 & \dots & 0 \\ 0 & 1 & \dots & 0 & -1 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & \dots & 1 & 0 & \dots & -1 \end{bmatrix} \begin{bmatrix} \mathbf{I}(p_1) \\ \mathbf{I}(p_2) \\ \vdots \\ \mathbf{I}(p_{60}) \end{bmatrix} \right)$$

- Map to DNN primitives
 - Fully connected (matrix-vector multiply)
 - Activation

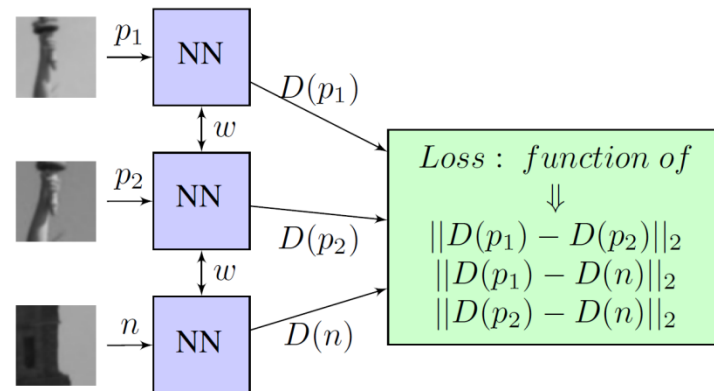
Learning a Feature Descriptor: Brisk

Learning a better descriptor

- Set up a trainable weight matrix

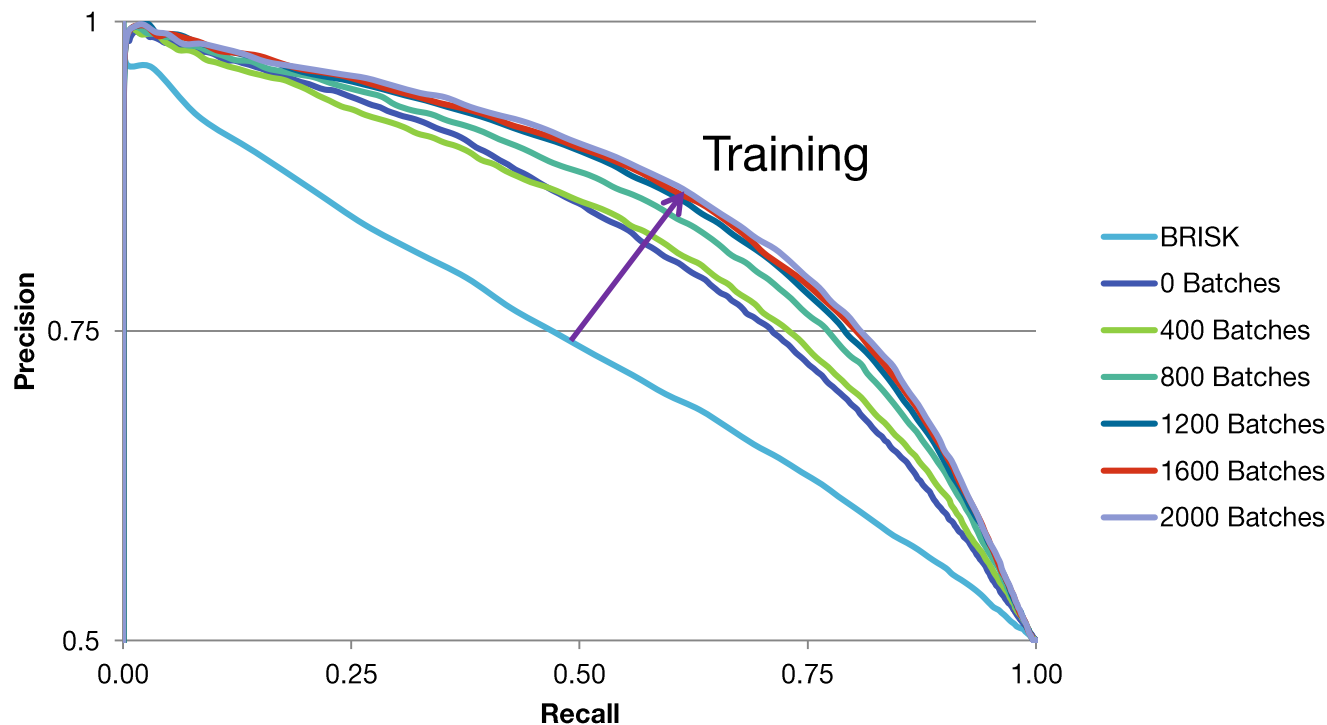
$$\mathbf{D} = \text{sigmoid} \left(\begin{bmatrix} \mathbf{w}_{1,1} & \cdots & \mathbf{w}_{1,60} \\ \vdots & \ddots & \vdots \\ \mathbf{w}_{512,1} & \cdots & \mathbf{w}_{512,60} \end{bmatrix} \begin{bmatrix} I(p_1) \\ I(p_2) \\ \vdots \\ I(p_{60}) \end{bmatrix} \right),$$

- Use triplet-loss to simultaneously
 - Maximise distance between different patches
 - Minimise distance between same patches
- Use HPatches dataset

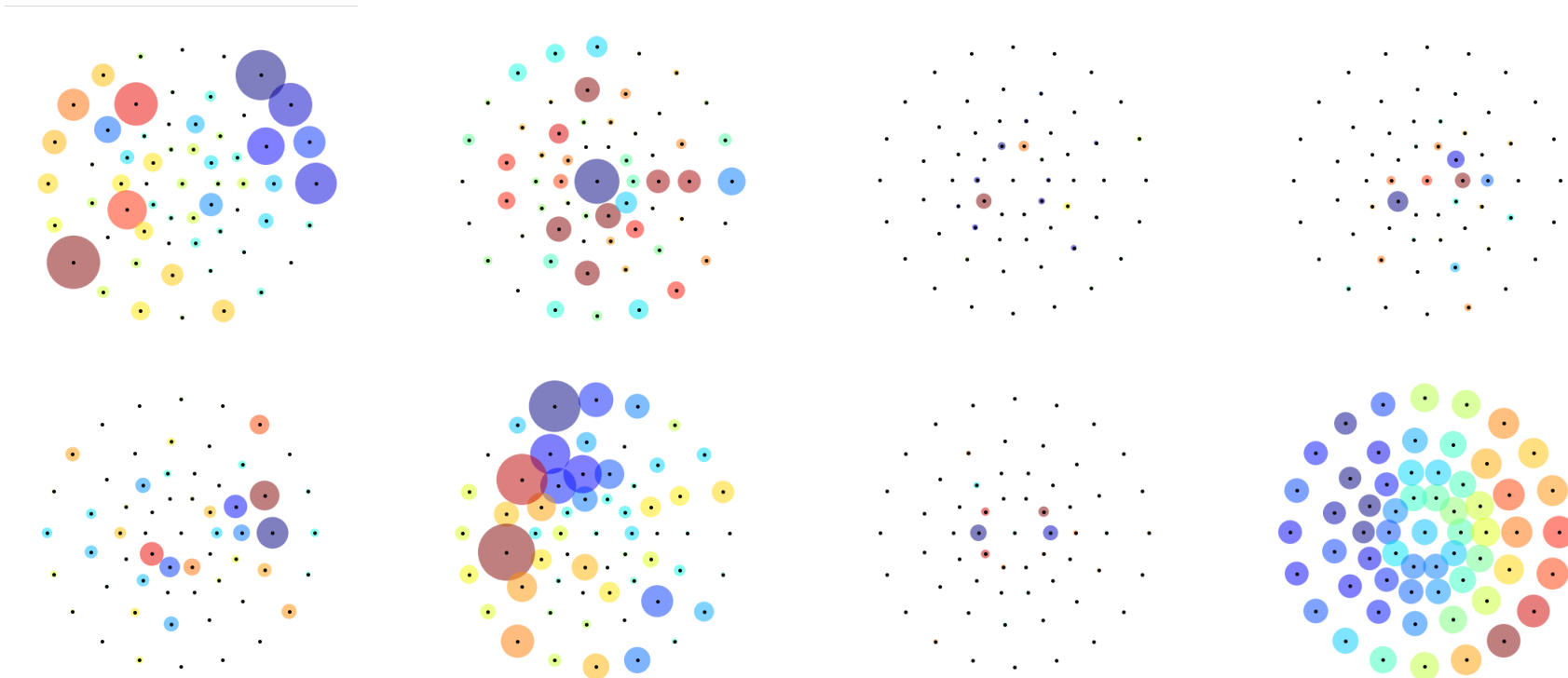


Feature Descriptor: Brisk

Results: HPatches (Easy)



Example learnt 'features'



Summary

- Deep learning defines a set of basic primitives
- Traditional computer vision can be enabled in a deep learning world by exploiting these primitives
- Traditional vision algorithms can then be used as a starting point for learning
 - Leverage existing investment
 - Provides a path to take incremental steps into learning

Resources

- PowerVR Blog
 - <https://www.imgtec.com/blog/>
- Traditional Vision
 - Computer Vision: Algorithms and Applications (Richard Szeliski)
 - <http://szeliski.org/Book/>
- Other Reading
 - <http://zbigatron.com/has-deep-learning-superseded-traditional-computer-vision-techniques/>