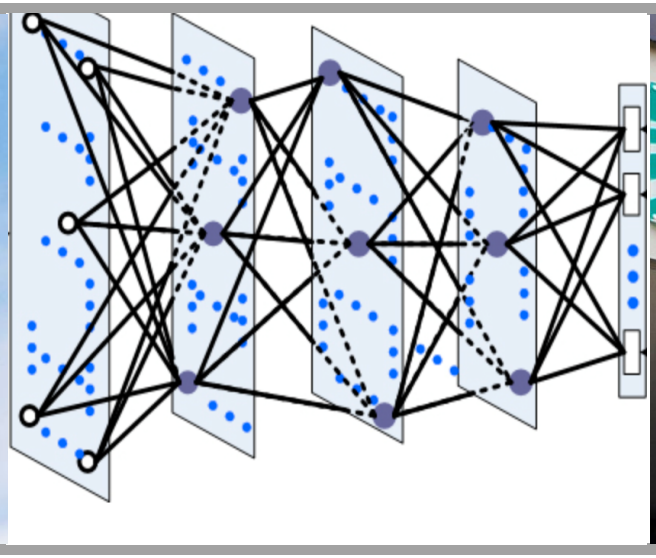
Fraunhofer
Heinrich Hertz Institute

Compression of Deep Neural Networks

Fraunhofer HHI, Machine Learning Group

Wojciech Samek



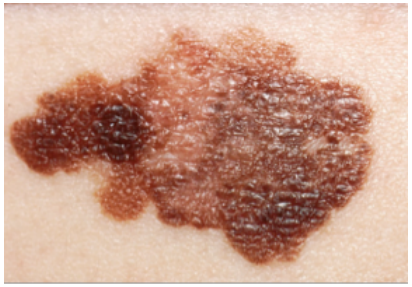
Record Performances with DNNs

AlphaGo beats Go human champ

Deep Net outperforms humans in image classification

IMAGENET

Dermatologist-level classification of skin cancer with Deep Nets



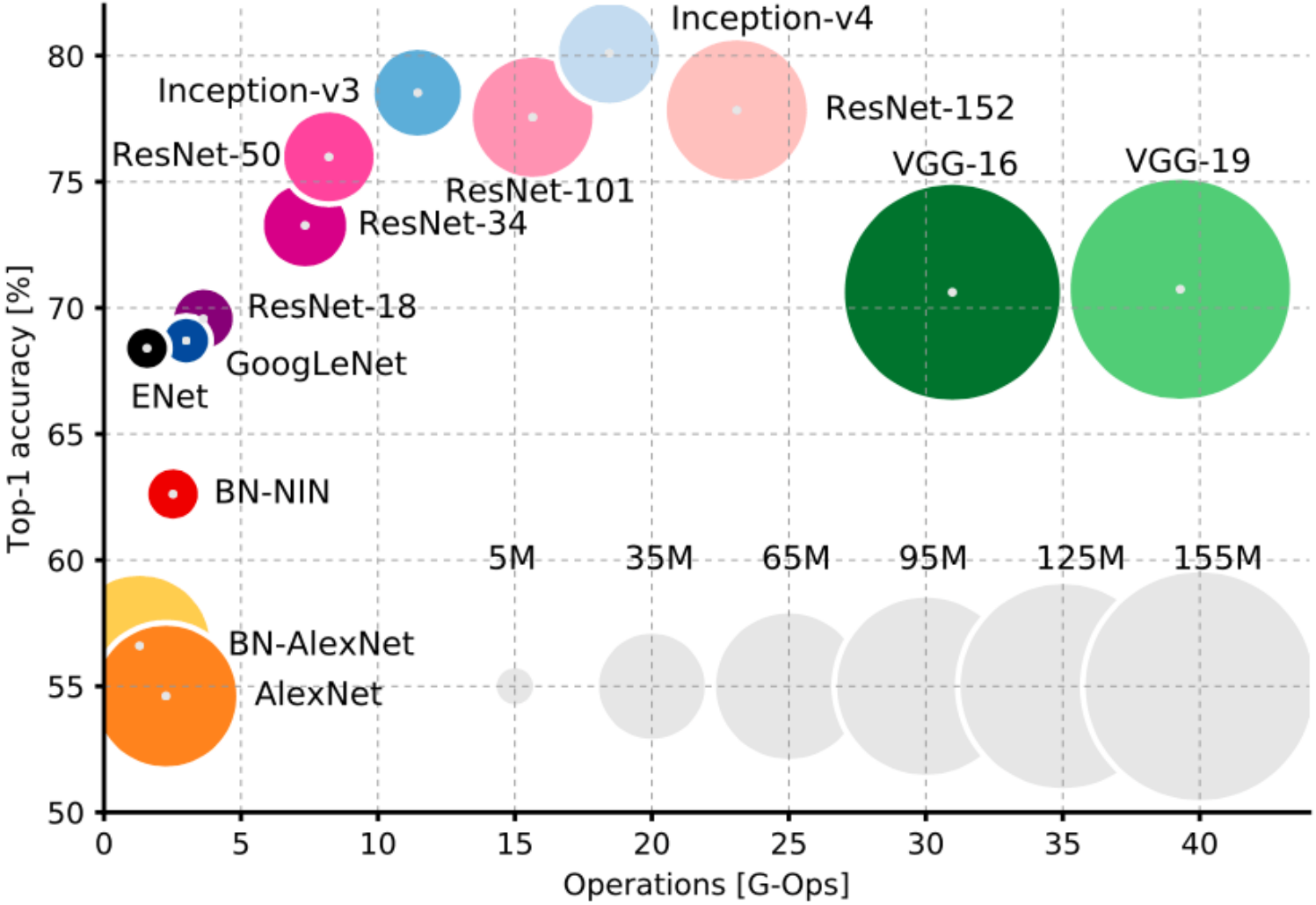
DeepStack beats professional poker players

Computer out-plays humans in "doom"

Revolutionizing Radiology with Deep Learning

Deep Net beats human at recognizing traffic signs

Complexity of DNN is Growing



Large Computational Resources Needed

Common carbon footprint benchmarks

in lbs of CO2 equivalent

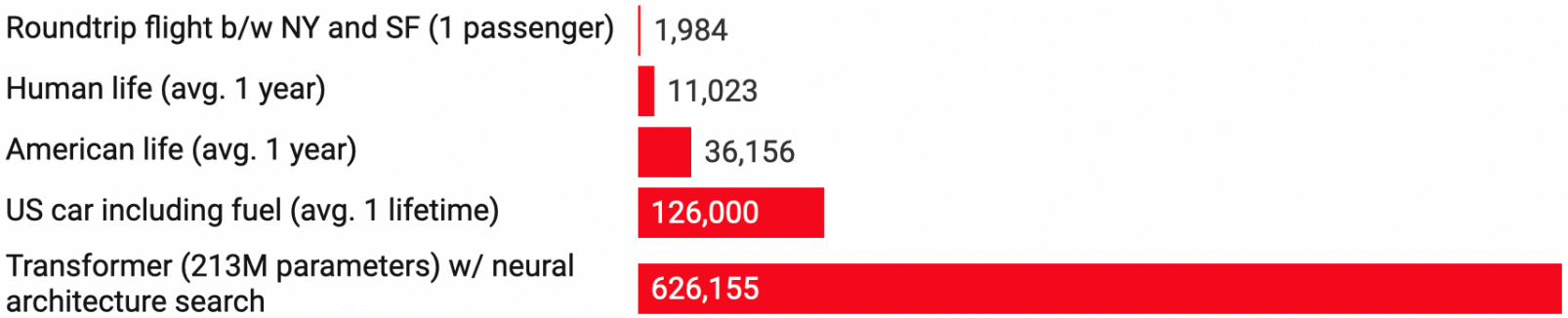


Chart: MIT Technology Review • Source: Strubell et al. • Created with Datawrapper

Large Computational Resources Needed

We need techniques to reduces the computational complexity
(i.e., storage, memory, energy, runtime)

Co

in lb

Rou

Hun

American life (avg. 1 year) 36,156

US car including fuel (avg. 1 lifetime) 126,000

Transformer (213M parameters) w/ neural architecture search 626,155

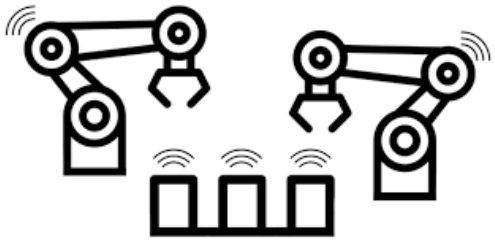
Chart: MIT Technology Review • Source: Strubell et al. • Created with Datawrapper

Processing at the “Edge”

On-device deep learning

Privacy-preserving

Latency constraints



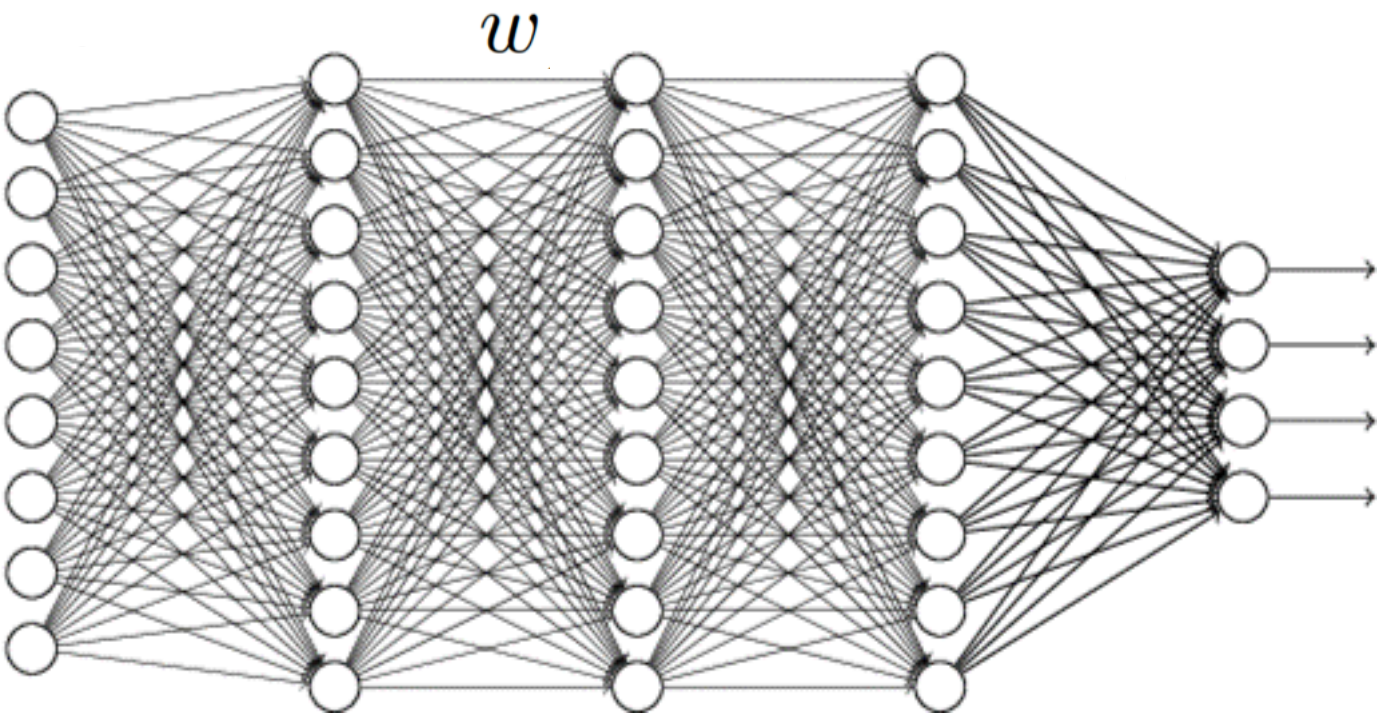
Outline of this talk

This talk will discuss how to reduce the complexity of DNNs by model compression and efficient representation.

Outline

1. Background
2. DeepCABAC
3. Compressed Entropy Row Format

Deep Neural Networks



$y' \sim P(y'|x, w)$

For instance, VGG16
- 16 weight layers
- 138 000 000 parameters
- 553 MB (uncompressed)

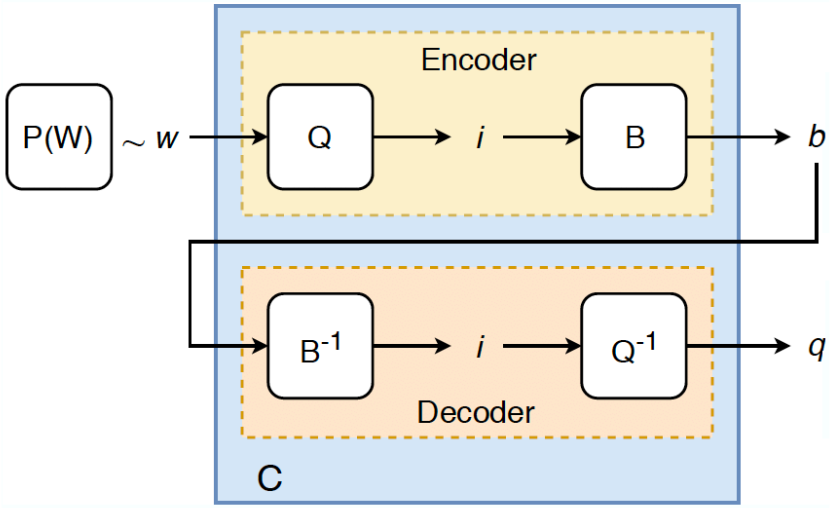
$(x, y) \in \mathbb{D}$

0
0
1
0

cross-entropy

DNN & Signal Compression

Assume B to be fix universal lossless code.

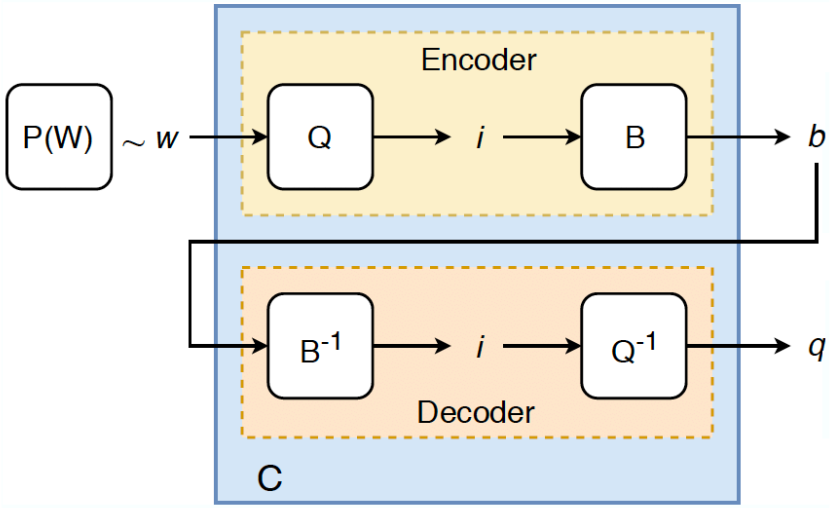


Signal compression
Distortion between elements
(e.g. pixel values)

$$\arg\min_{(Q,Q^{-1})} D(w_j, q_j) + \lambda L(b)$$

DNN & Signal Compression

Assume B to be fix universal lossless code.



Signal compression
Distortion between elements
(e.g. pixel values)

$$\underset{(Q,Q^{-1})}{\arg\min}\, D(w_j, q_j) + \lambda L(b)$$

Neural network compression
Distortion between function of elements
(e.g. prediction outputs)

$$\underset{(Q,Q^{-1})}{\arg\min}\, \mathcal{L}(y'', y') + \lambda L(b)$$

Neural Network Compression

$$(Q, Q^{-1})^* = \arg\min_{(Q,Q^{-1})} \sum_{(x,y)\in\mathbb{D}} \mathcal{L}(y'', y') + \lambda L_Q(b)$$

$y' \sim P(y'|x, w)$

0.1
0.05
0.85
0

$y'' \sim P(y''|x, q)$

0.05
0.1
0.8
0.05

Neural Network Compression

$$(Q, Q^{-1})^* = \arg\min_{(Q,Q^{-1})} \sum_{(x,y)\in\mathbb{D}} \mathcal{L}(y'', y') + \lambda L_Q(b)$$

$$(Q, Q^{-1})^* = \arg\min_{(Q,Q^{-1})} \sum_{(x,y)\in\mathbb{D}} D_{KL}(y''||y') + \lambda L_Q(b)$$

Use KL-divergence as distortion measure

Neural Network Compression

$$(Q, Q^{-1})^* = \arg\min_{(Q,Q^{-1})} \sum_{(x,y)\in\mathbb{D}} \mathcal{L}(y'', y') + \lambda L_Q(b)$$

$$\downarrow$$

$$(Q, Q^{-1})^* = \arg\min_{(Q,Q^{-1})} \sum_{(x,y)\in\mathbb{D}} D_{KL}(y''||y') + \lambda L_Q(b)$$

$$\downarrow$$

$$(Q, Q^{-1})^* = \min_{(Q,Q^{-1})} (q-w)F(q-w)^T + \lambda L_Q(b)$$

If the output distributions do not differ too much, we can approximate KL with the Fisher Information Matrix (FIM)

$$\mathbb{E}_{P_\mathbb{D}}[D_{KL}(y''||y')] = \delta w F \delta w^T + \mathcal{O}(\delta w^2)$$

with $\delta w = q - w$ and

$$F := \mathbb{E}_{P_\mathbb{D}}\mathbb{E}_{P(y'|x,w)}[\partial_w \log P(y'|x,w)(\partial_w \log P(y'|x,w))^T]$$

Neural Network Compression

$$(Q, Q^{-1})^* = \arg\min_{(Q,Q^{-1})} \sum_{(x,y)\in\mathbb{D}} \mathcal{L}(y'', y') + \lambda L_Q(b)$$

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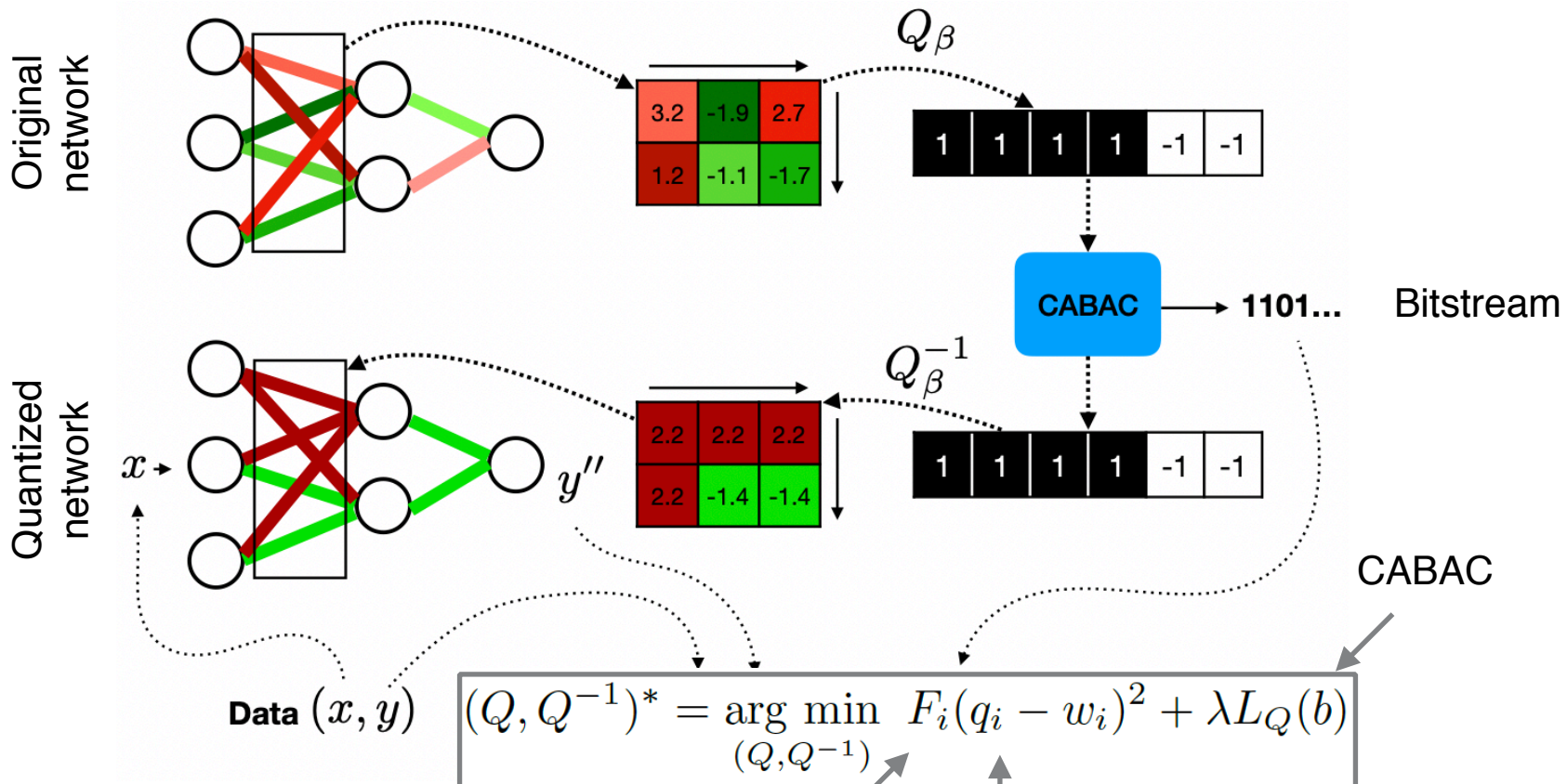
$$(Q, Q^{-1})^* = \min_{(Q,Q^{-1})} (q-w)F(q-w)^T + \lambda L_Q(b)$$

$$(Q, Q^{-1})^* = \arg\min_{(Q,Q^{-1})} F_i(q_i - w_i)^2 + \lambda L_Q(b)$$

Approximate FIM by only its diagonal elements

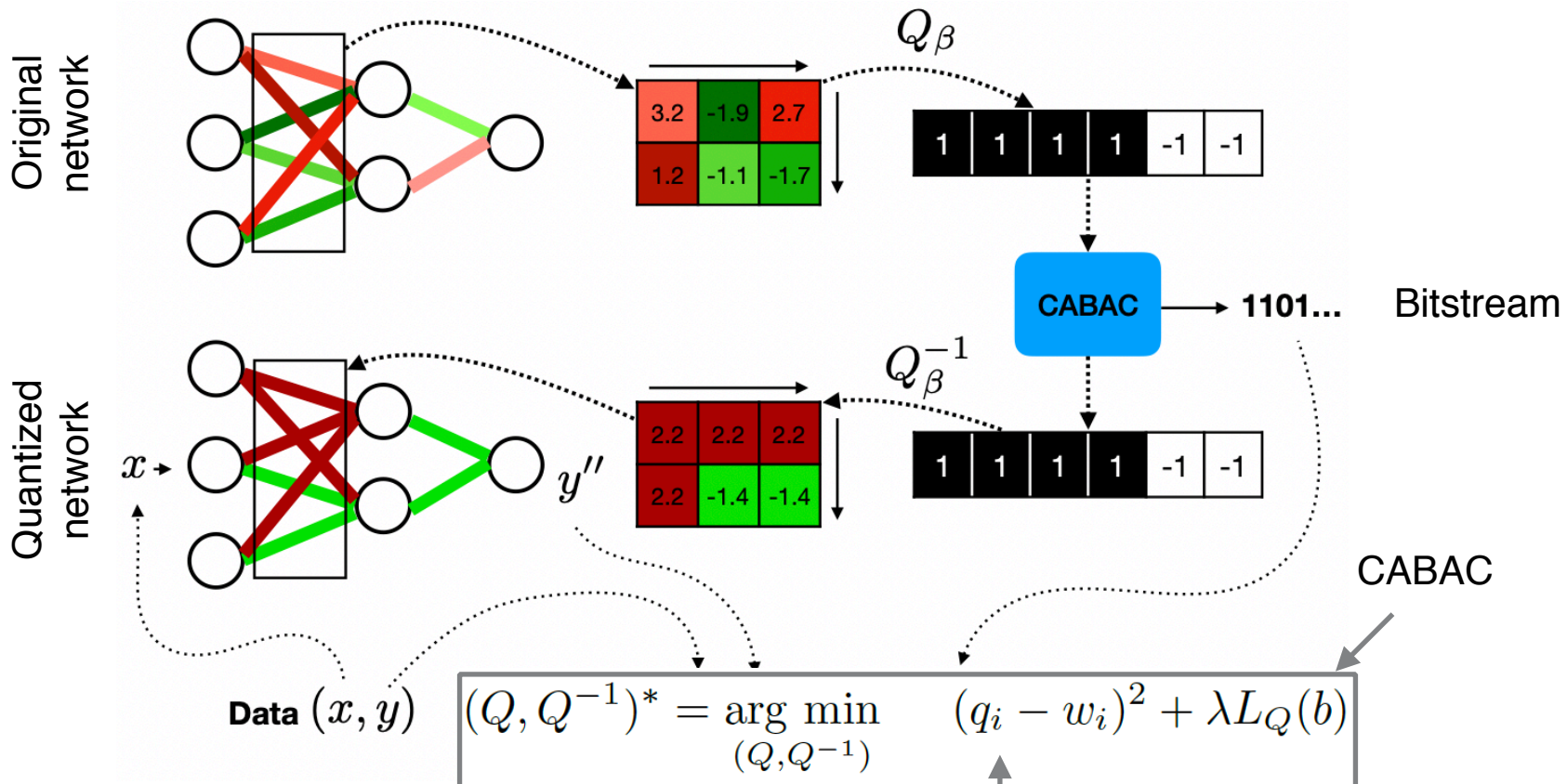
DeepCABAC



DeepCABAC-v1

[Wiedemann et al. 2019, arXiv:1907.11900]
[Wiedemann et al. 2019, ODML-CDNNR]
best paper award

DeepCABAC

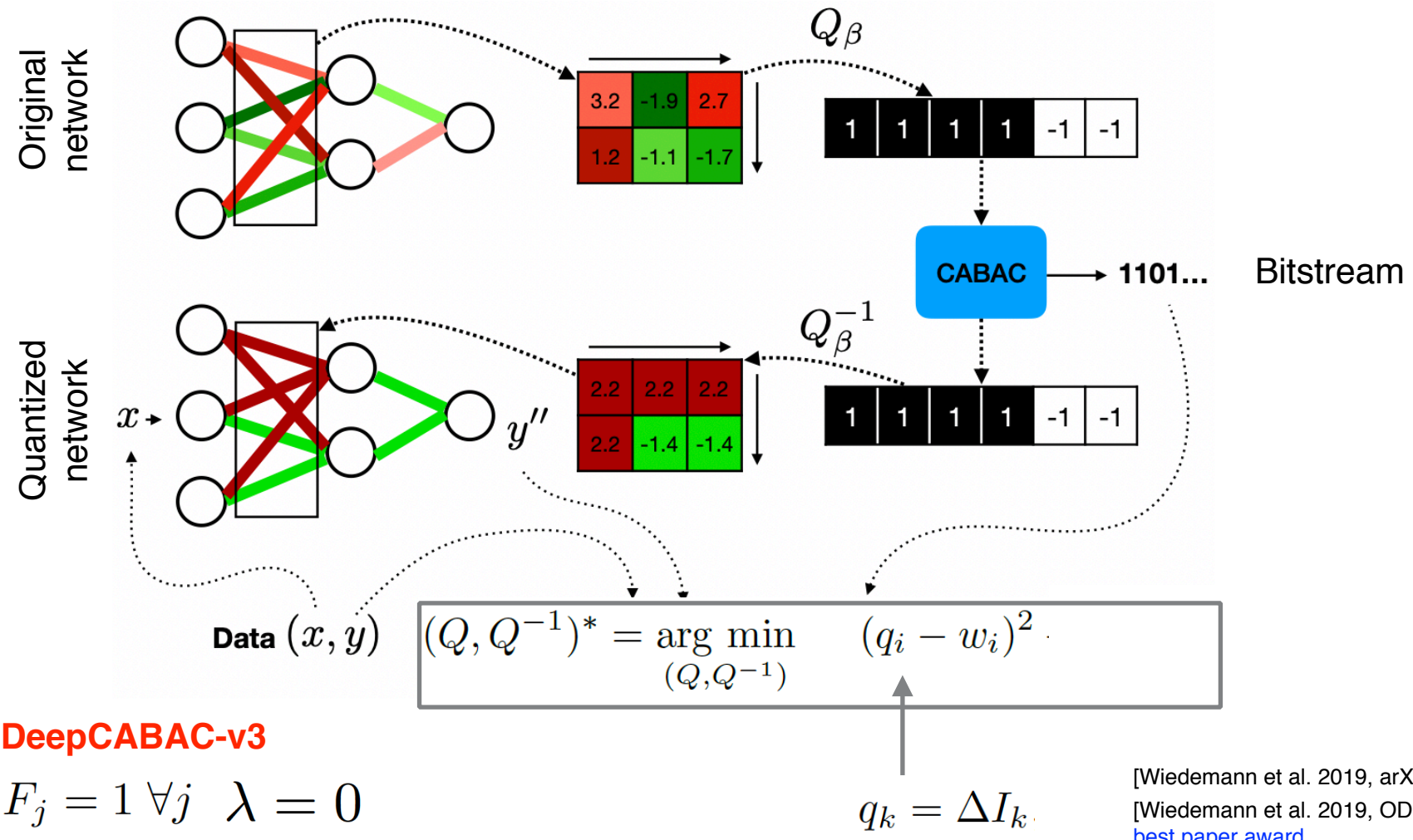


DeepCABAC-v2

$F_j = 1 \; \forall j$

[Wiedemann et al. 2019, arXiv:1907.11900]
[Wiedemann et al. 2019, ODML-CDNNR]
best paper award

DeepCABAC

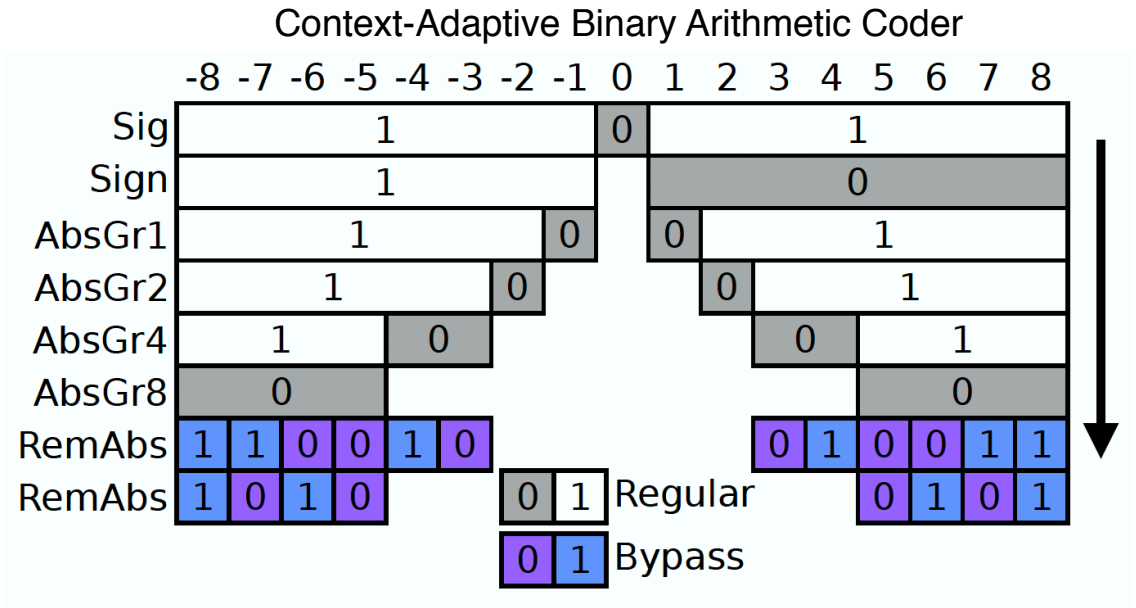


DeepCABAC-v3

$F_j = 1 \; \forall j \quad \lambda = 0$

[Wiedemann et al. 2019, arXiv:1907.11900]
[Wiedemann et al. 2019, ODML-CDNNR]
best paper award

Properties of CABAC



Examples

$1 \rightarrow 100$

$-4 \rightarrow 111101$

$7 \rightarrow 10111010$

Properties of CABAC

Binarization: represents each unique input value as a sequence of binary decisions.

Context modelling: probability model for each decision, which is updated on-the-fly by the local statistics of the data -> universality.

Arithmetic coding: arithmetic coding for each bit -> minimal redundancy + high efficiency

DeepCABAC Results

Sparse Models (sparsity [%])	Org. Acc. Top1 [%]	Os_size [MB]	DeepCABAC (acc. [%])
VGG16 (9.85)	69.43	553.43	**1.57** (69.43)
ResNet50 (74.12)	74.09	102.23	**4.74** (73.65)
Small-VGG16 (7.57)	91.35	60.01	**1.6** (91.00)
LeNet5 (1.90)	99.22	1.72	**0.72** (99.16)

DeepCABAC Results

Sparse Models (sparsity [%])	Org. Acc. Top1 [%]	Os_size [MB]	DeepCABAC (acc. [%])
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VGG16 **553.4MB** -> **8.7MB** at an acc. **69.43%**

ResNet50 **102.2MB**-> **4.85MB** at an acc. **73.65%**

Efficient Representations

Goal: Find a representation for the weight matrices of a neural network, which is:

1) efficient with regard to storage
2) efficient with regard to algorithm complexity of the dot product operation.

Matrix Formats

$$M = \begin{pmatrix} 0 & 3 & 0 & 2 & 4 & 0 & 0 & 2 & 3 & 4 & 0 & 4 \\ 4 & 4 & 0 & 0 & 0 & 4 & 0 & 0 & 4 & 4 & 0 & 4 \\ 4 & 0 & 3 & 4 & 0 & 0 & 0 & 4 & 0 & 2 & 0 & 0 \\ 0 & 0 & 0 & 4 & 4 & 4 & 0 & 3 & 4 & 4 & 0 & 0 \\ 0 & 4 & 4 & 0 & 0 & 4 & 0 & 4 & 0 & 0 & 0 & 0 \end{pmatrix}$$

Storage requirements: 60 entries

dense format

Scalar product (second row M, vector a):

- 24 load
- 12 multiply
- 11 add
- 1 write operations

$$4a_1 + 4a_2 + 0a_3 + 0a_4 + 0a_5 + 4a_6 + 0a_7 + 0a_8 + 4a_9 + 4a_{10} + 0a_{11} + 4a_{12}$$

Matrix Formats

$$
\begin{aligned}
W :& [3, 2, 4, 2, 3, 4, 4, 4, 4, 4, 4, 4, 4, 4, 3, \\
& 4, 4, 2, 4, 4, 4, 3, 4, 4, 4, 4, 4, 4] \\
colI :& [1, 3, 4, 7, 8, 9, 11, 0, 1, 5, 8, 9, 11, 0, \\
& 2, 3, 7, 9, 3, 4, 5, 7, 8, 9, 1, 2, 5, 7] \\
rowPtr :& [0, 7, 13, 18, 24, 28]
\end{aligned}
$$

sparse format

Storage requirements: 62 entries

Scalar product (second row M, vector a):

- 20 load
- 6 multiply
- 5 add
- 1 write operations

$$4a_1 + 4a_2 + 4a_6 + 4a_9 + 4a_{10} + 4a_{12}$$

Matrix Formats

$$\Omega : [0, 4, 3, 2]$$
$$colI : [4, 9, 11, 1, 8, 3, 7, 0, 1, 5, 8, 9, 11, 0, 3, 7, 2, 9, 3, 4, 5, 8, 9, 7, 1, 2, 5, 7]$$
$$\Omega Ptr : [0, 3, 5, 7, 13, 16, 17, 18, 23, 24, 28]$$
$$rowPtr : [0, 3, 4, 7, 9, 10]$$

CER format

Storage requirements: 49 entries

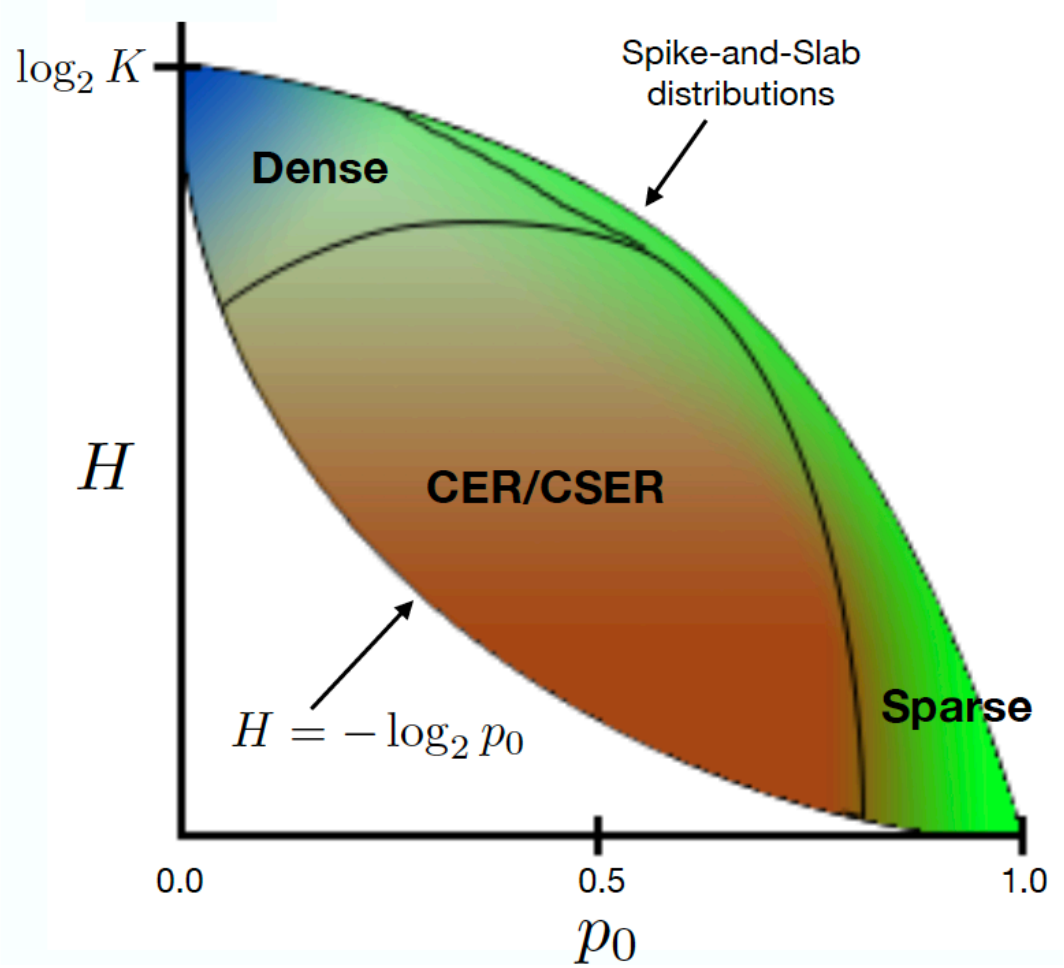
Scalar product (second row M, vector a):

- 17 load
- 1 multiply
- 5 add
- 1 write operations

$$4(a_1 + a_2 + a_6 + a_9 + a_{10} + a_{12})$$

[Wiedemann et al. 2019, IEEE TNNLS]

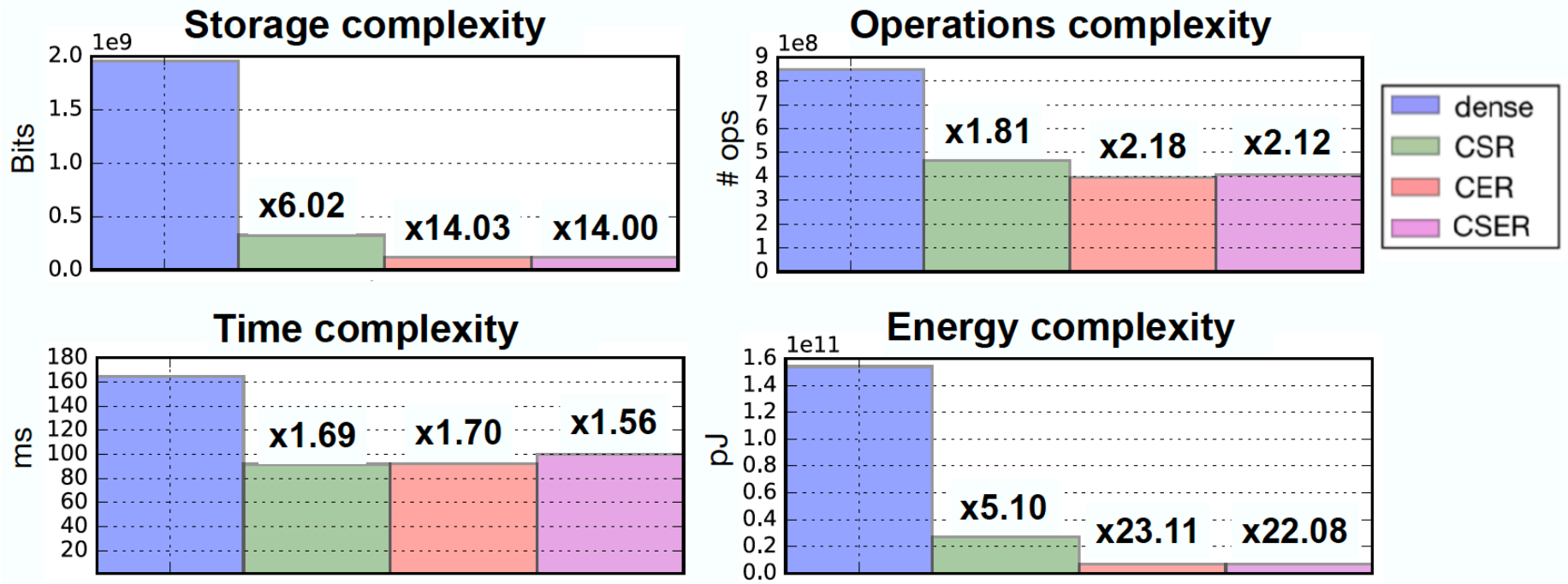
Storage efficiency



[Wiedemann et al. 2019, IEEE TNNLS]

Results

Compressed AlexNet after converting it's weight matrices into the different data structures.



[Wiedemann et al. 2019, IEEE TNNLS]

Thank you for your attention

Questions ???

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