ECE 5578 Multimedia Communication

Lec 06 - Arithmetic Coding II Context Models

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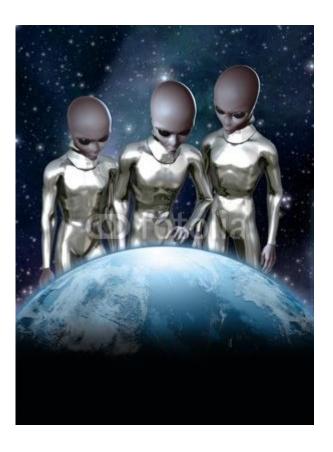


slides created with WPS Office Linux and EqualX LaTex equation editor

Outline

- ☐ Lecture 05 Re-Cap
- ☐ Context Adaptive Arithmetic Coding
 - PAQ
 - CABAC in H264
 - Context model in deep learning compression

Arithmetic Coding ReCAp



Aliens visit earth....



- ☐ Arithmetic coding:
 - Symbols $A = \{a_1, a_2, ..., a_n\}$, with prob= $\{p_1, p_2, ..., p_n\}$
 - For a sequence of symbol, $X=[x_1, x_2, ..., x_m]$ compute the sequence prob, P(X), the binary code is,

$$l(X) = \left\lceil \log \frac{1}{p(X)} \right\rceil + 1$$
 bits.

of the F(X) representation.

☐ Sequence prob based, more efficient than Huffman codes

Example - Arithmetic

☐ Encoding:

• pmf: [0.7, 0.1, 0.2], CDF: $F_x()=[0.7 0.8 1]$

```
LOW=0.0, HIGH=1.0; 0.2. Using while (not EOF) { partitions of the partition of the partition
```

- T(X)=(0.546+0.560)/2=0.553
- P(X) = 0.014; I(X) = 7 bits
- Code: $(0.553)_2 = 0.100011011$

$$l(X) = \left\lceil \log \frac{1}{p(X)} \right\rceil + 1 \text{ bits.}$$

Consider a three-letter alphabet $\mathcal{A} = \{a_1, a_2, a_3\}$ with $P(a_1) = 0.7$, $P(a_2) = 0.1$, and $P(a_3) = 0.2$. Using the mapping of Equation (4.1), $F_X(1) = 0.7$, $F_X(2) = 0.8$, and $F_X(3) = 1$. This partitions the unit interval as shown in Figure 4.1.

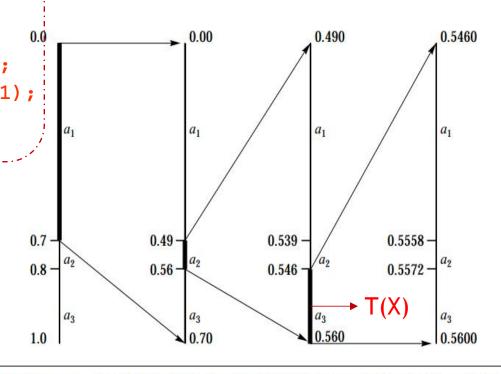


FIGURE 4. 1 Restricting the interval containing the tag for the input sequence $\{a_1, a_2, a_3, \ldots\}$.

Uniqueness and Efficiency

□ Prove the code is uniquely decodable (prefix free):

☐ Any code with prefix

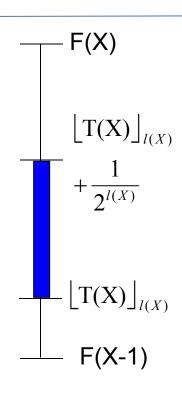
■Need to show that this is in [F(X-1), F(X)):

We already show
$$\left[T(X) \right]_{l(X)} \ge F(X-1)$$
.

Only need to show
$$F(X) - \lfloor T(X) \rfloor_{l(X)} > \frac{1}{2^{l(X)}}$$

$$F(X) - \lfloor T(X) \rfloor_{l(X)} > F(X) - T(X) = \frac{p(X)}{2} > \frac{1}{2^{l(X)}}$$

$$\lfloor T(X) \rfloor_{l(X)}$$
 is prefix free if $l(X) = \left| \log \frac{1}{p(X)} \right| + 1$ bits.



Uniqueness and Efficiency

□Efficiency of arithmetic code:

$$l(X_1^m) = \left\lceil \log \frac{1}{p(X_1^m)} \right\rceil + 1 \text{ bits.}$$
 $X_1^m : \{x_1, ..., x_m\}$

$$L = E\{p(X_1^m)l(X_1^m)\} = \sum P(X_1^m) \left(\left\lceil \log \frac{1}{p(X_1^m)} \right\rceil + 1 \right)$$

$$\leq \sum P(X_1^m) \left(\log \frac{1}{p(X_1^m)} + 1 + 1 \right) = H(X_1^m) + 2$$

l(X) is the bits to code a sequence $\{x_1, x_2, ..., x_m\}$.

Assume iid sequence, $H(X_1^m) = mH(X)$

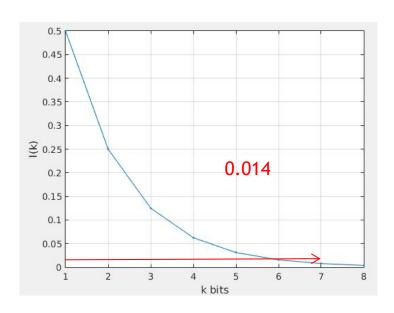
$$H(X) \le \frac{L}{m} \le H(X) + \frac{2}{m}$$

 $L/m \rightarrow H(X)$ for large m, stronger than prev results.

AC example

□ Take pmf=[0.7, 0.1, 0.2], F(1)=0.7, F(2)=0.8, F(3)=1, and seq: $X=\{a_1, a_2, a_3\}$

- p(X) = 0.5600 0.5460 = 0.014
- l(X) = 7 bits
- coding length: 8 bits/0.0039
- 0.0078/7bits not working



Consider a three-letter alphabet $\mathcal{A} = \{a_1, a_2, a_3\}$ with $P(a_1) = 0.7$, $P(a_2) = 0.1$, and $P(a_3) = 0.2$. Using the mapping of Equation (4.1), $F_X(1) = 0.7$, $F_X(2) = 0.8$, and $F_X(3) = 1$. This partitions the unit interval as shown in Figure 4.1.

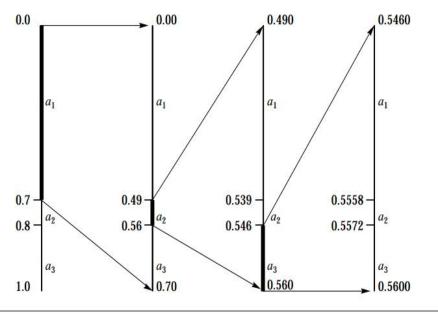


FIGURE 4. 1 Restricting the interval containing the tag for the input sequence $\{a_1, a_2, a_3, \ldots\}$.

 $L(k) = 0.5000 \quad 0.2500 \quad 0.1250 \quad 0.0625 \quad 0.0312 \quad 0.0156 \quad 0.0078 \quad 0.0039$

Encoding of Binary Arithmetic Coding

$$HIGH \leftarrow LOW + RANGE \times CDF(n)$$

 $LOW \leftarrow LOW + RANGE \times CDF(n-1)$

$$LOW = 0$$
, $HIGH = 1$

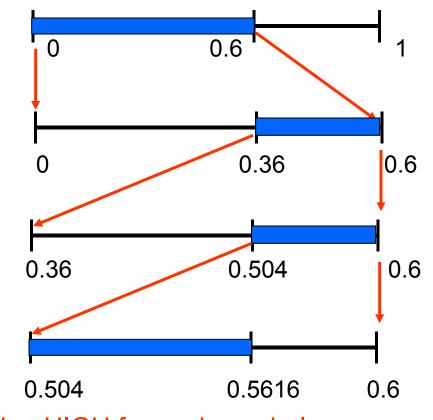
LOW = 0, HIGH = 0.6

LOW = 0.36, HIGH = 0.6

LOW = 0.504, HIGH = 0.6

LOW = 0.504, HIGH = 0.5616

Prob(0)=0.6. Sequence: 0110



Only need to update LOW or HIGH for each symbol.

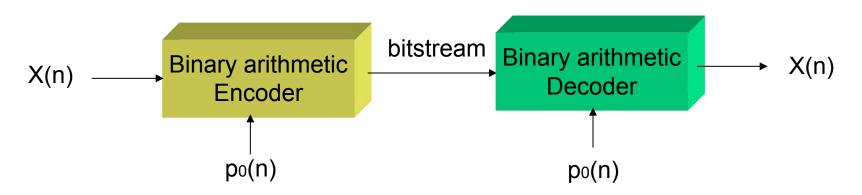
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Adaptive Arithmetic Coding

□Observation:

- The partition of [0, 1) can be different from symbol to symbol
- ☐ The bit stream can be decoded perfectly as long as both encoder and decoder are synchronized (use the same probability).
- □Only need to update the probabilities
- □Adaptive Huffman code:
 - Has to redesign the codebook each time
 - Time-consuming.



Example

- Binary sequence: 01111
- Initial counters for 0's and 1's:

$$C(0)=C(1)=1$$
.

→
$$P(0)=P(1)=0.5$$

After encoding 0: C(0)=2, C(1)=1.

$$\rightarrow$$
P(0)=2/3, P(1)=1/3

After encoding 01: C(0)=2, C(1)=2.

$$\rightarrow$$
P(0)=1/2, P(1)=1/2

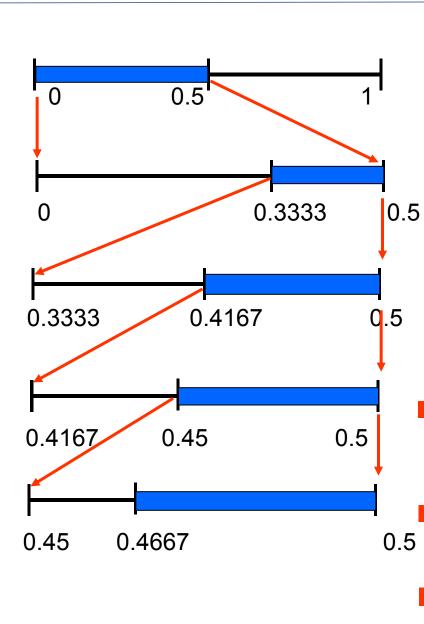
After encoding 011: C(0)=2, C(1)=3.

$$\rightarrow$$
P(0)=2/5, P(1)=3/5

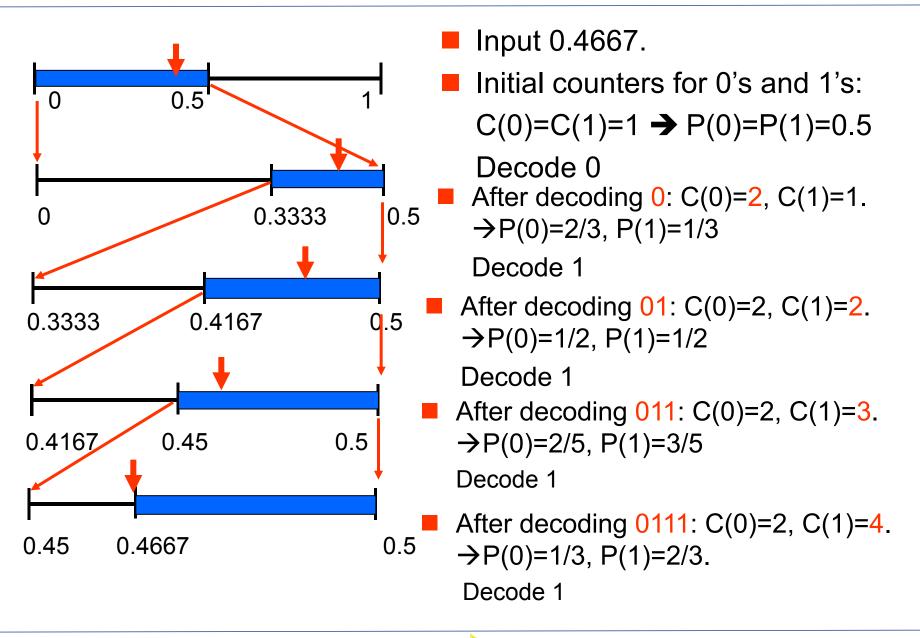
After encoding 0111: C(0)=2, C(1)=4.

$$\rightarrow$$
P(0)=1/3, P(1)=2/3.

Encode 0.4667.



Decoding - FIFO



Context-adaptive Arithmetic Coding

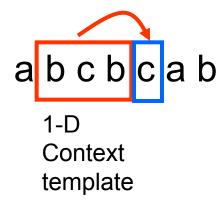
□ In many cases, a sample has strong correlation with its near neighbors.

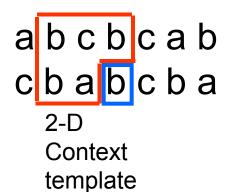
☐Idea:

 Collect conditional probability distribution of a symbol for given neighboring symbols (context):

$$P(x(n) | x(n-1), x(n-2), ... x(n-k))$$

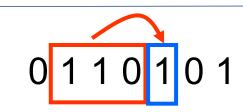
- Use this conditional probability to encode the next symbol
- More skewed probability distribution can be obtained (desired for arithmetic coding)





Example

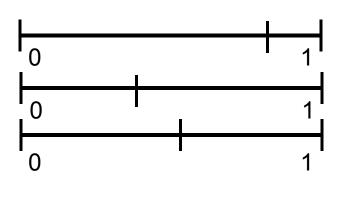
- \square Binary sequence: 0, 1
- Neighborhood (template) size: 3



 \rightarrow 2^3=8 possible combinations (contexts) of 3 neighbors (x(n-1), x(n-2), x(n-3)).

□Collect frequencies of 0's and 1's under each context

Context	C(0)	C(1)
(0, 0, 0)	9	2
(0, 0, 1)	3	6
(0, 1, 0)	10	10
(0, 1, 1)		
(1, 0, 0)	•••	•••
(1, 0, 1)	•••	
(1, 1, 0)		
(1, 1, 1)		



Each symbol is coded with the probability distribution associated with its context.

PAQ1 Algorithm

- ☐ Modeling large context of binary strings...
 - for an input string 0000001111..., maintain the count of 0 and 1
 - update prob of 1 as p(1)

```
If the training bit is y (0 or 1) then increment c_y (c_0 or c_1).
If c_{1-y} > 2, then set c_{1-y} = c_{1-y} / 2 + 1 (rounding down if odd).
```

- Then arithmetic coding with this updated p(1) as it moves along.
- At the decoder, this can be repeated as AC decode the FIFO way.

PAQ1 Implementation and Performance

- □ PAQ1 is implemented with a large window on binary strings
 - rotating 4 MB (222 character) buffer and an index of 1M (220) 3-byte pointers
 - indexed by a hash of the last 8 bytes with no collision resolution.
 - reuse 8byte-64bit context model in driving the AC

☐ Performance:

Program	Options	Туре	MB	14 files	Time	Concat.	Reuters
Original si	ze			3,141,622		3,141,622	28,329,337
COMPRESS		LZ78	<1	1,272,772	1.5	1,318,269	10,406,527
PKZIP 2.04e		LZ	0.4	1,032,290	1.5	1,033,217	8,334,457
GZIP 1.2.4	- 9	LZ77	<1	1,017,624	2	1,021,863	8,114,057
ACB	u	AC-s	<16	766,322	110	769,363	4,567,213
BOA 0.58b	-m15 -s	PPMZ-s	15	747,749	44	769,196	4,326,917
PPMD H	e -m64 -o16	PPMII	64	744,057	5	759,674	4,286,536
	e -m64 -o8	PPMII	64	746,316	5	762,843	3,850,243
SBC 0.910	c -m3 -b16	BWT	65	740,161	4.7	819,027	4,197,501
PPMONSTR H	e -m64 -o1	PPMII	64	719,922	13	736,899	4,465,502
	e -m64 -o8	PPMII	64	726,768	11	744,960	3,917,444
RK 1.02 b5	-mx3 -M64	PPMZ-s	64	707,144	44	750,744	4,404,256
	-mx3 -M64 -ft	PPMZ-s	64	717,384	44	750,744	4,207,960
RK 1.04	-mx3 -M64	PPMZ-s	64	712,188	36	755,872	3,978,800
	-mx3 -M64 -ft	PPMZ-s	64	730,100	39	755,876	3,857,780
PPMN 1.00b1	-M:50 -MT1 -09	PPM	50	716,297	23	748,588	3,934,032
PPMONSTR Ip	re -m64 -o128	PPMII	64	696,647	35	703,320	4,514,279
(3/3/02)	-m64 -o8	PPMII	64	704,914	30	707,581	3,781,287
DEC-SPLIT			<64	685,341		decompress)	-,,
DEC-SOLID			<64	680,558	W. C	decompress)	
PAQ1		NS-s	48	716,704	68.1	716,240	4,078,101

Larger Non-Binary Context Model - PAQ7

- \square Condition reduces entropy, $H(Y|X_1) > H(Y|X_1, X_2, ...)$
- \square How to model very large context (x1, x2,)?
 - Use a (shallow/deep) neural network to model context
 - Large window of 552 input nodes
 - 7 sets of 3080 hidden nodes

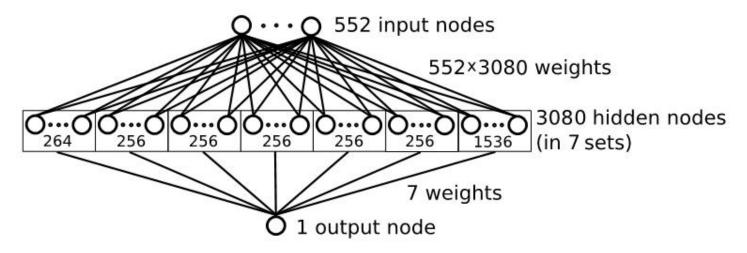
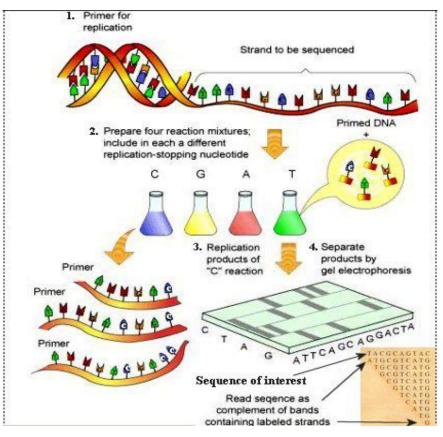


Figure 4: PAQ8 model mixer architecture.

Implementation with a matlab wrapper (thanks to Biren Kathriya): https://umkc.box.com/s/kg7blpc0jpaoctgauhhfyszz178a0pcy

PAQ 7 Performance in DNA compression

☐ Application to DNA sequence compression



It is sequence of 4 nitrogenous bases; GATCCTGAGCTAGG......

ATCGTT







Genome Data Compression

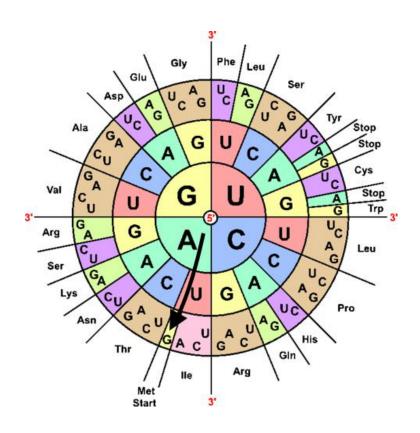
- ☐ Compress DNA seq for bioinformatics/precision medicine applications
 - represent in Codon Seq, 64 symbols as if English alphabeta
 - Then apply PAQ for compression (need retraining)

Codon:

A sequence of three nucleotides that together form a unit of genetic code in a DNA or RNA molecule.

So 4 symbols will make 4^3=64 codons.

Codon represents a total of 20 amino acids.



Performance

☐ SOTA performance

Dataset	Num ber of Sym bols	Number of bits after compression	Bit/symbol
NC_012920	1656 9	3990	0.2408
NC_0189127.	8847	2117	0.2393
NC_000016.1 0	8847	2043	0.2309

[□]Can be improved with a LSTM engine for PAQ's shallow neural network.

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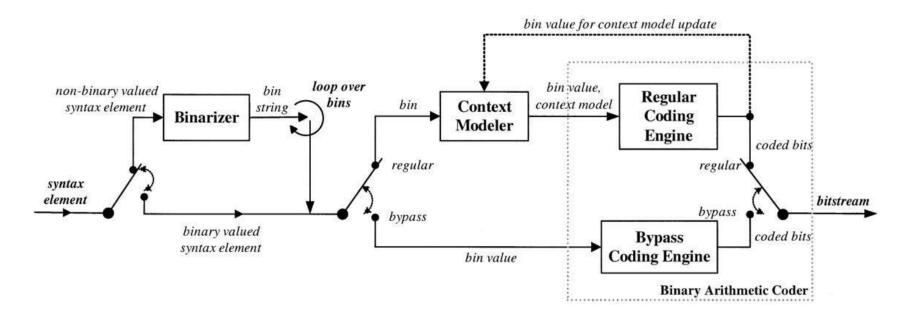
Basic framework of CABAC (1)

- CABAC: Content-Based Adaptive Binary Arithmetic Coding
 - Content-Based Adaptive: Adjust the possibility of each bin according to the context or previous coded bins
 - -Binary Arithmetic Coding: Arithmetic Coding based on 0 and 1

Basic framework of CABAC (2)

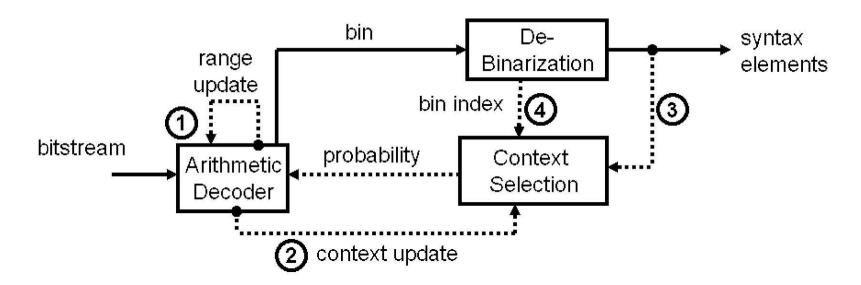
□CABAC Fraemwork

- Step 1: Binarization
- Step 2: Context model selection
- Step 3: Regular/Bypass coding engine
- Step 4: Context model update



Basic framework of CABAC (3)

- ☐ Context model
 - Step 1: Context model selection
 - Step 2: Arithmetic decoding
 - Step 3: Context model updating
 - Step 4: De-binarization



Binarization (1)

- ☐ Why Binarization? (One premise and two reasons)
 - Binarization is a lossless operation
 - Adaptive m-order (m>2) arithmetic coding is complex operation requiring at least two multiplications for each symbol to encode while binary arithmetic coding can be performed in a multiplication-free way
 - Binarization enables context modeling on a subsymbol level
 - MSB uses context model, eg. group id in Golomb
 - LSB uses bypass coding mode (no context)

Binarization (2)

- Basic binarization schemes (1)
 - Unary Binarization

n	Codeword	0 0 1
0	0	
1	10	0 0 1
2	110	10 0 1
3	1110	110
4	11110	1110
5	111110	1110

- Truncated Unary (TU) Binarization
 - If the max number S is 5 then 5 can be binarized as 11111, the 0 in the last is not needed

Binarization (3)

- Basic binarization schemes (2)
 - -Fix Length (FL) binarization
 - N is to the Lth power of 2: log2N
 - N is not to the Lth power of 2: example

- -Kth order Exp-Golomb Binarization (EGB)
 - A combination of unary binarization and fix length binarization
 - Refer to Prof. Li slides for more information

Binarization (4)

- Concatenation of basic binarization scheme
 - Coded block pattern: 4-bit FL prefix and a TU suffix with max number S equal to 2
 - -TU prefix and Kth order Exp-Golomb Binarization
 - Absolute motion vector difference: TU prefix with max value of 9 and 3-order Exp-Golomb
 - Transform coefficient levels: TU prefix with max value of 14 and 0-order Exp-Golomb

Binarization (5)

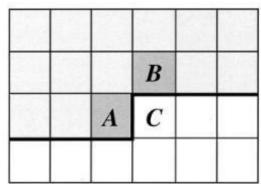
- After binarization, all the symbols are converted into bin string
 - Reference index 3: 111 (TU)
- For the binary symbol, the binarization process is ignored (skip flag)
- Then for each bin, we will choose a suitable context model and finish the arithmetic coding

Context modeling (1)

- What is context modeling
 - Context modeling is used to estimate an accurate possibility of each bin
 - Context
 - The coded results of the previous blocks
 - The coded results of the previous bins
 - The position of the current block
 - Different context models mean different possibilities for various bins

Context modeling (2)

- Context modeling type (1)
 - Just one context model to represent the possibility (maintain only one possibility distribution)
- Context modeling type (2)
 - the neighboring element to the left and on top of the current syntax element (3 possibility distributions
 - -Examples for Skip flag



Context modeling (3)

- Context modeling type (3)
 - The values of prior coded bins are used for the choice of a model for a given bin

- Context modeling type (4)
 - The position in the scanning path
 - The accumulated number of encoded levels

Context modeling (4)

- Context model initialization (initial possibility distribution)
 - Based on two parameters (Slice type and Quantization parameters)
 - The initialized context model is based on some training data
 - According to the AVS2 (audio video standard), the initialized context model will not lead to significant BD-rate difference

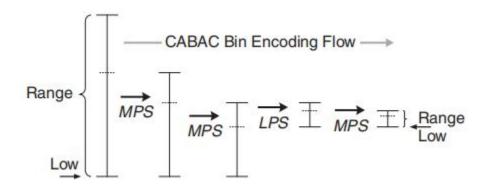
Arithmetic Coding (1)

- Arithmetic coding
 - Update the Low Bound and Range

Bin Arithmetic Coding (2)

Multiplication operation:

$$R_{LPS} = R \times P_{LPS}$$



MPS: Most Prob Symbol LPS: Least Prob Symbol

R: Range

 $P_{LPS} = 1 - P_{MPS}$

- Mult iplication is replaced with a lookup table implementation
- R is quantized with 4 values only when calculating the $R_{LP\,S}$
 - p_{LP S} is quantized with 64 values
 - A look-up table with 64 by 4 entries will be used to replace the multiplication operation

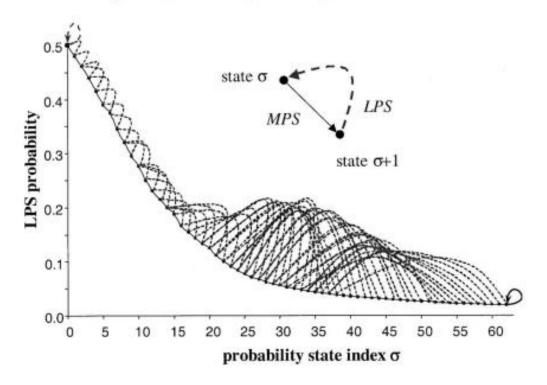
Arithmetic Coding (3)

- · R is quantized with 4 values
 - $-2^{8} \le R \le 2^{9}$ (corresponding to [0.5,1))
 - The 4 parts: [256, 320], [320, 384], [384, 448], [448, 512] (ρ =0,1,2,3)
 - Quantization: replaced using the median value of the zone: 288, 352, 416, 480
- P_{LPS} is quantized using 64 values $-P_{LPS}$ is within [0.01875, 0.5] $\alpha = (\frac{0.01875}{0.5})^{1/63}$
 - $-P_{\sigma} = \alpha \times P_{\sigma-1}$ (α is approximated as 0.95)

Arithmetic Coding (4)

☐ Prob update table

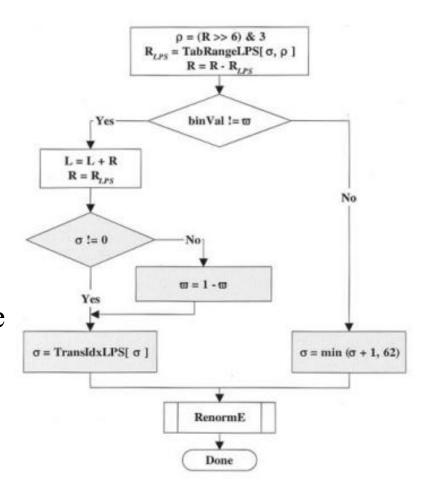
$$p_{\text{new}} = \begin{cases} \max(\alpha \cdot p_{\text{old}}, p_{62}), & \text{if a MPS occurs} \\ \alpha \cdot p_{\text{old}} + (1 - \alpha), & \text{if a LPS occurs} \end{cases}$$



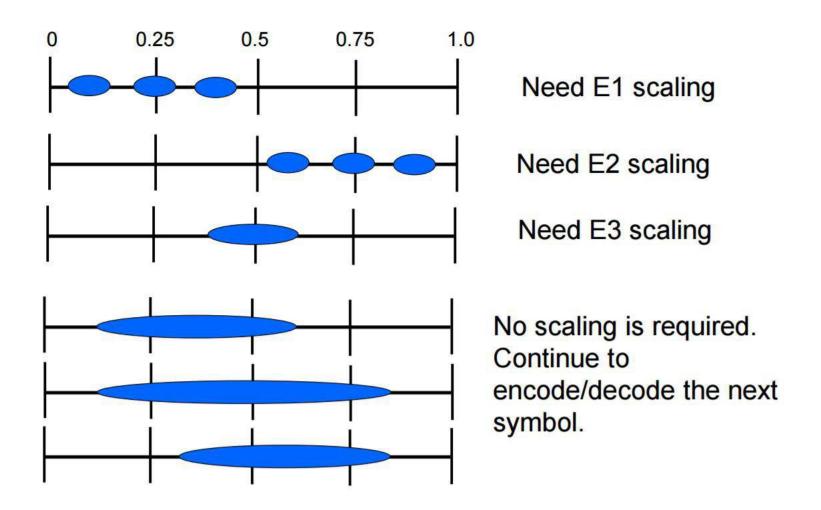
Arithmetic Coding (5)

☐ Encoding process

- Calculate R_{LPS}
 according to the look-up table
- If the current bin is MPS, update R and possibility model
- If the current bin is LPS, update R, Lower Bound, and possibility model
- Renorm Process is used to make sure R is in a suitable range (28 <= R < 29)
 - Refer to the three scalar operations in the slides provided by E1, E2, E3 conditions

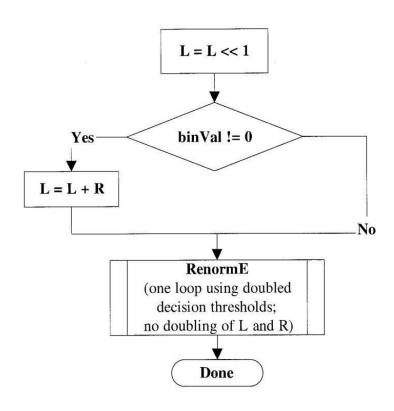


Scaling



Arithmetic coding - Bypass Logic

- Bypass coding (No need to update context model)
 - -Both the possibilities of LPS and MPS are 0.5



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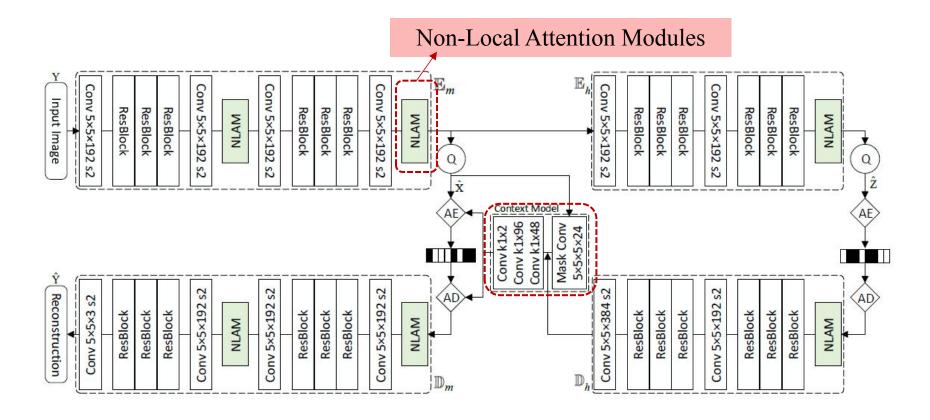
Neural Image Compression via Non-Local Attention Optimization and Improved Context Modeling Tong Chen, Zhan Ma, et.al.

https://arxiv.org/pdf/1904.09757.pdf

Introduction - NIC

□ A variational autoencoder with

- Non-local operations
- Attention mechanism
- Context model for spatial-channel correlations



Non-Local Attention Modules (NLAM)

□Non-local Network

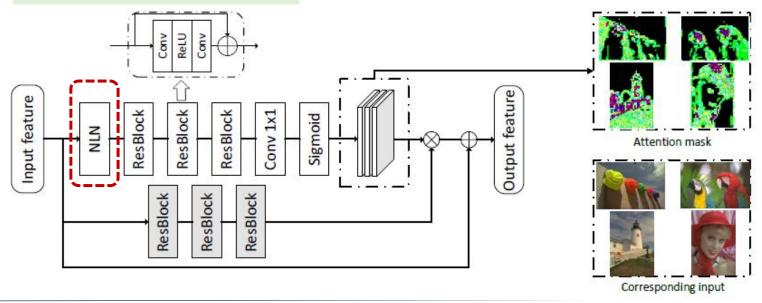
■ This NLN computes the output at *i*-th position, Y*i*, using a weighted average of the transformed feature values of input X, as below:

$$\mathbf{Y}_i = \frac{1}{C(\mathbf{X})} \sum_{\forall j} f(\mathbf{X}_i, \mathbf{X}_j) g(\mathbf{X}_j),$$
 (X and Y share the same size)

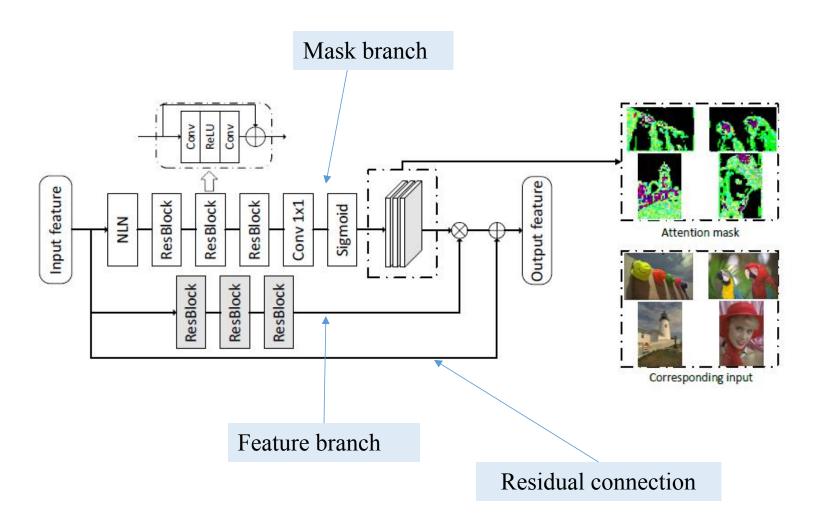
function f(.) computes the correlations between Xi and Xj

function g(.) derives the representation of the input at the position j

C(X) is a normalization factor: $C(X) = \sum_{\forall i} f(X_i, X_j)$



Non-Local Attention Modules (NLAM)



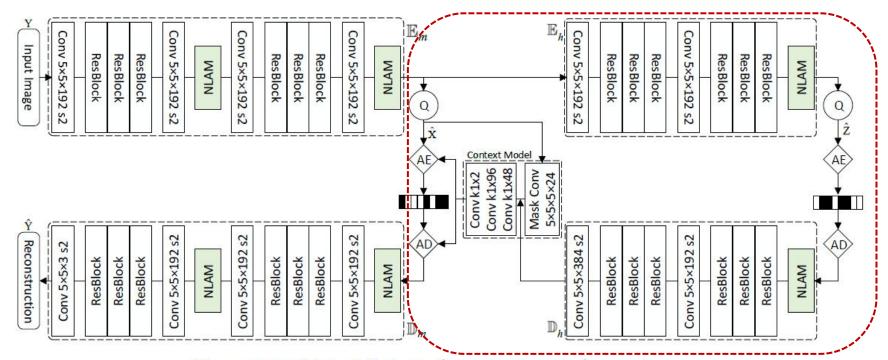
Non-Local Attention Modules (NLAM)



Fig. 2: Visualization of attention masks generated by NLAM. Brighter means more attention. Attention masks have the same size as latent features with several channels. Here channel 4 and 19 are picked to show the spatial and channel attention mechanism (values are in the range of (0,1)). Term "sum of attention" denotes the accumulated attention maps over all channels.

Conditional Entropy Rate Modeling

- ☐ Context Modeling Using Joint Autoregressive Spatial-Channel Neighbors and Hyperpriors
 - Local image neighbors usually present high correlations



For quantized latent features $\hat{\mathbf{x}}$, each element $\hat{\mathbf{x}}_i$ can be modeled as a conditional Gaussian distribution as:

Conditional Entropy Rate Modeling

- ☐ Context Modeling Using Joint Autoregressive Spatial-Channel Neighbors and Hyperpriors
 - Local image neighbors usually present high correlations

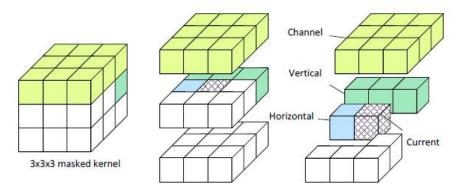
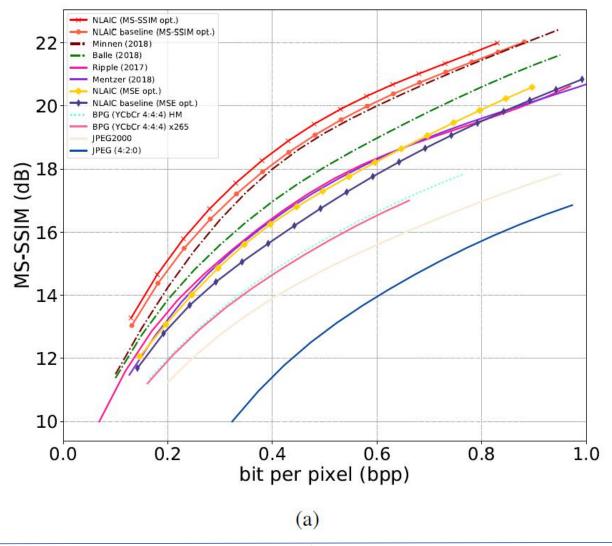


Fig. 3: **3D Masked Convolution.** A $3\times3\times3$ masked convolution exemplified for exploring contexts of spatial and channel neighbors jointly. Current pixel (in purple grid cube) is predicted by the causal/processed pixels (in yellow for neighbors from previous channel, green for vertical neighbors, and blue for horizontal neighbors) in a 3D space. Those unprocessed pixels (in white cube) and the current pixel are masked with zeros.

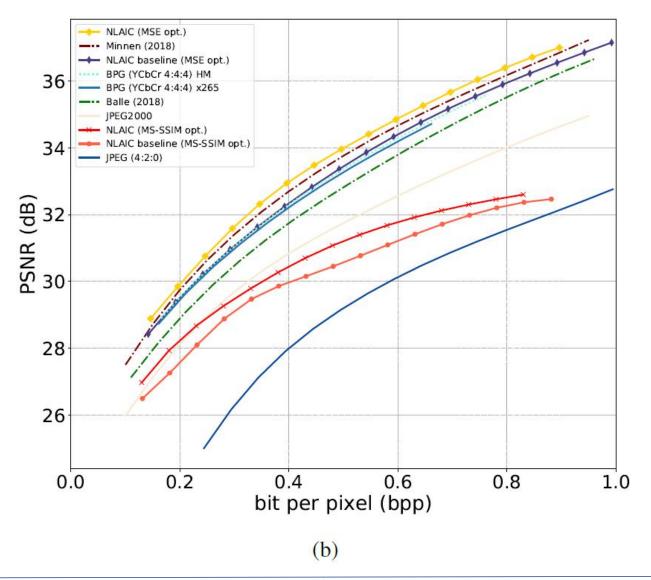
Experimental Results

☐ RD performance



Experimental Results

☐ RD performance



Experimental Results

☐ Subjective results



Fig. 8: Subjective Evaluation. Visual comparison among JPEG420, BPG444, NLAIC MSE opt., MS-SSIM opt. and the original image from left to right. Our method achieves the best visual quality containing more texture without blocky nor blurring artifacts.

Summary

- ☐ Adaptive Arithmetic Coding
 - AC can be adaptive by changing the prob of 1 and 0s
 - Simple solutions PAQ1
 - Shallow neural network solutions: PAQ6 and variations
 - H264 CABAC implementation
 - Context modeling in new learning based compression schemes