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[CVPR 2026] Presentation

Block-based Learned Image Compression without Blocking Artifacts

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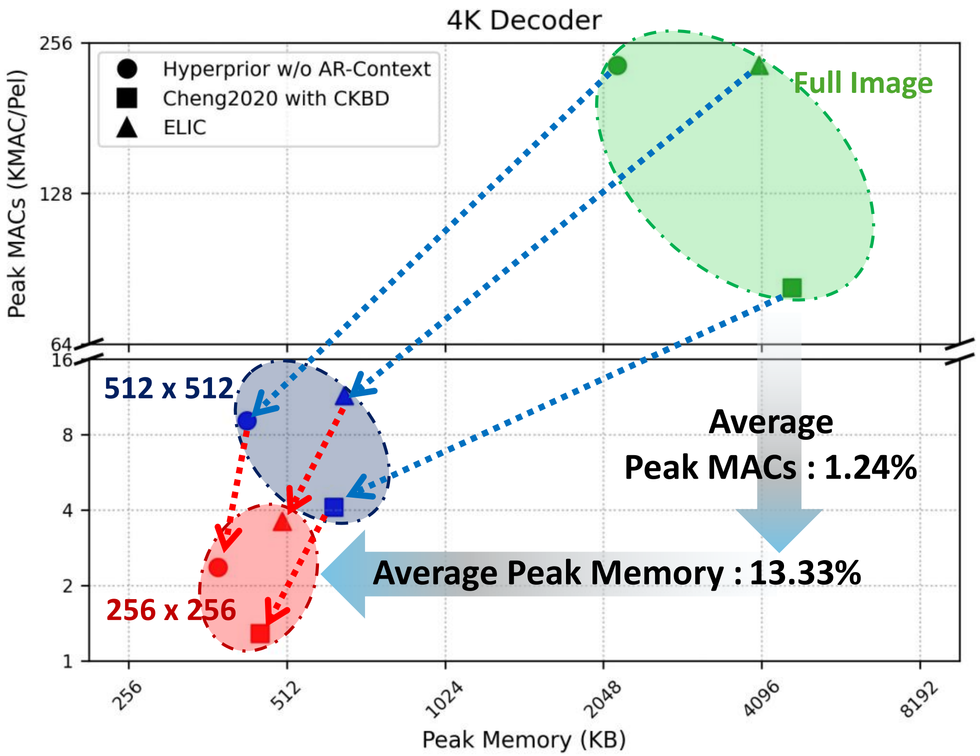
ToC

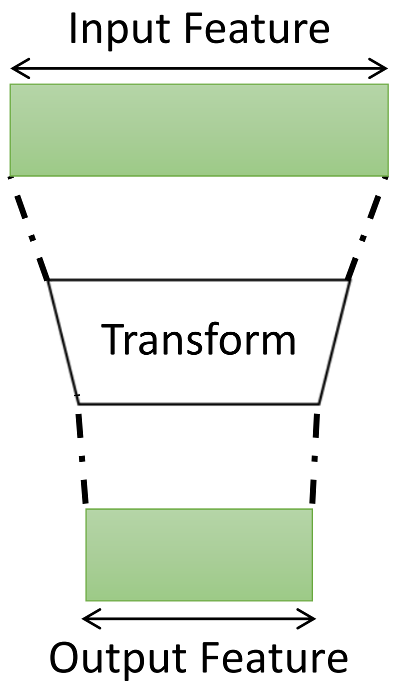
1. Introduction
2. Derivation of Minimal Overlap
3. Implementation Methodologies
4. Experimental Results

Introduction

[Sec. 1] Introduction

- **State-of-the-art learned image compression (LIC) models outperform traditional codecs.**
  - However, processing entire feature maps makes peak memory a practical bottleneck.
  - For high-resolution images, traditional codecs such as VVC and HEVC adopt block-based processing.

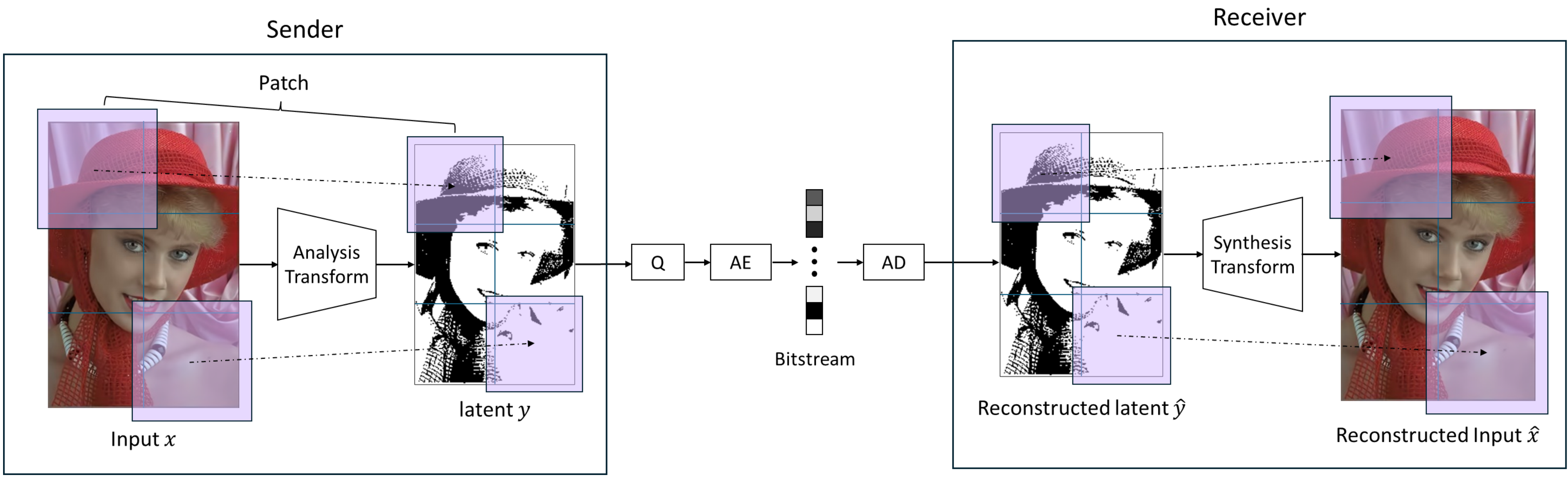




Full-image LIC

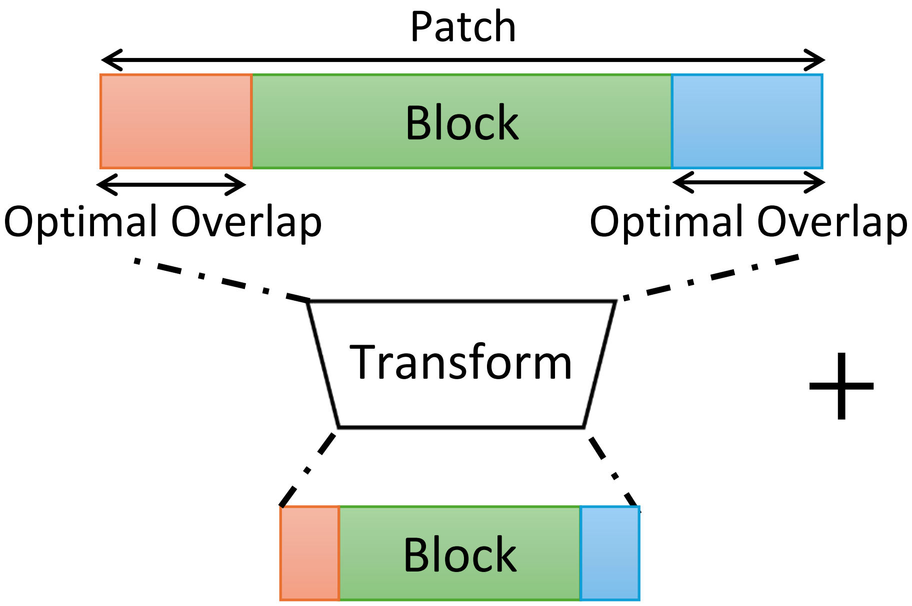
[Sec. 1] *Image Partitioning Strategies in LIC*

- **Patch-based LIC reduces these costs, yet empirical overlaps cannot guarantee artifact-free reconstruction.**
  - If the overlap is too small, insufficient boundary context causes artifacts.
  - If the overlap is too large, redundant processing increases memory and computation.



[Sec. 1] *Purpose of this study*

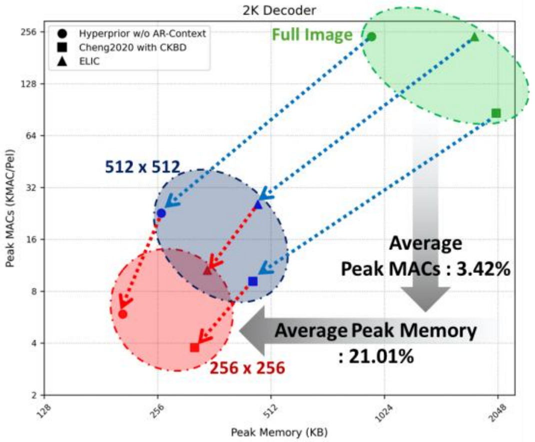
- **We mathematically derive the minimum overlap required to match Full-image LIC.**
  - We model layer-wise overlap propagation through recursive formulas.
- **Using the computed overlap, we apply several implementation techniques to practical LIC models.**
  - Our method achieves **identical BD-rate performance** to Full-image inference **without retraining process**.
  - It also significantly **reduces computational resources**.



Patch-based Coding

+ Proposed Implementation Methodologies =

Artifact-Free Reconstruction with no BD-rate loss



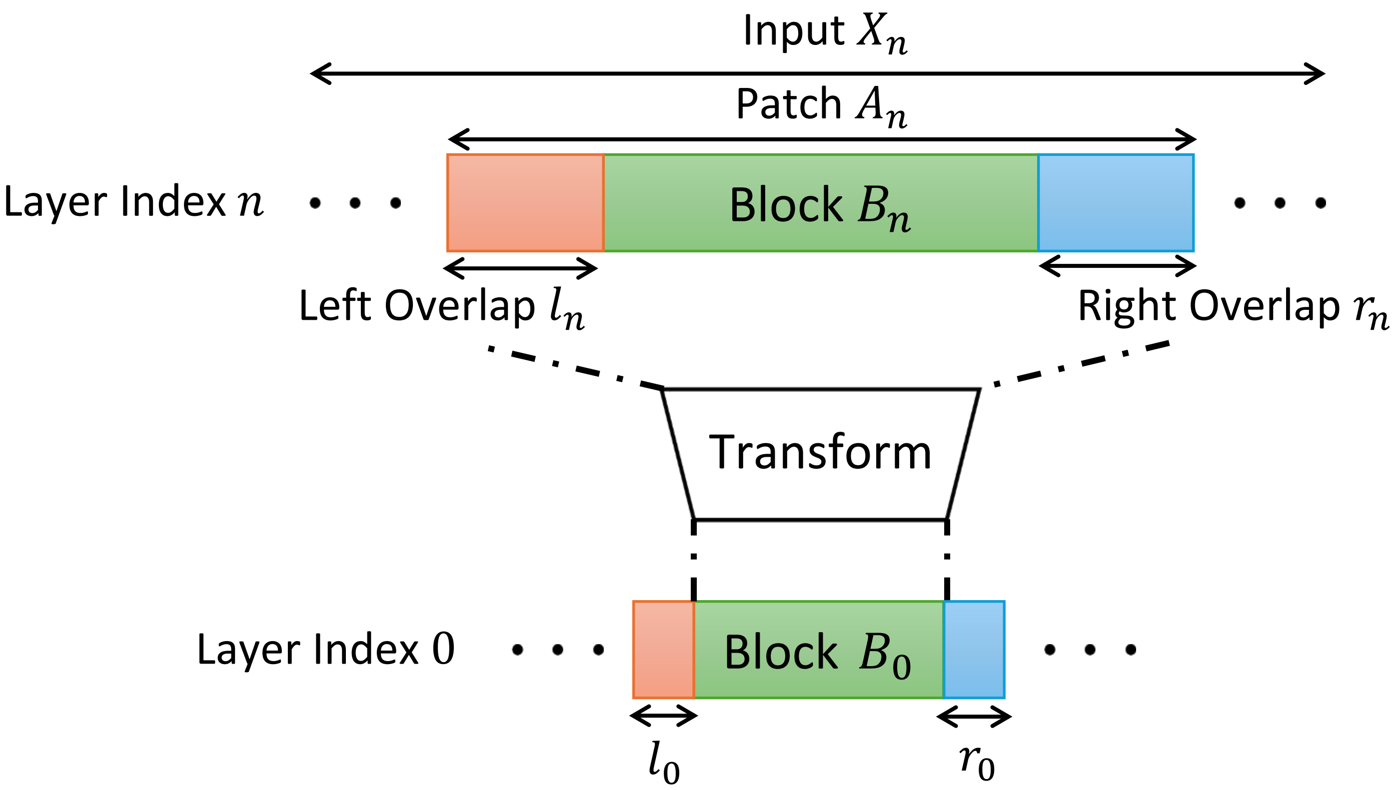
Peak Memory & Peak Computation Cost ⬇️

Derivation of Minimal Overlap

1. Notations
2. Minimal Overlap Calculation

[Sec. 2] *Notations*

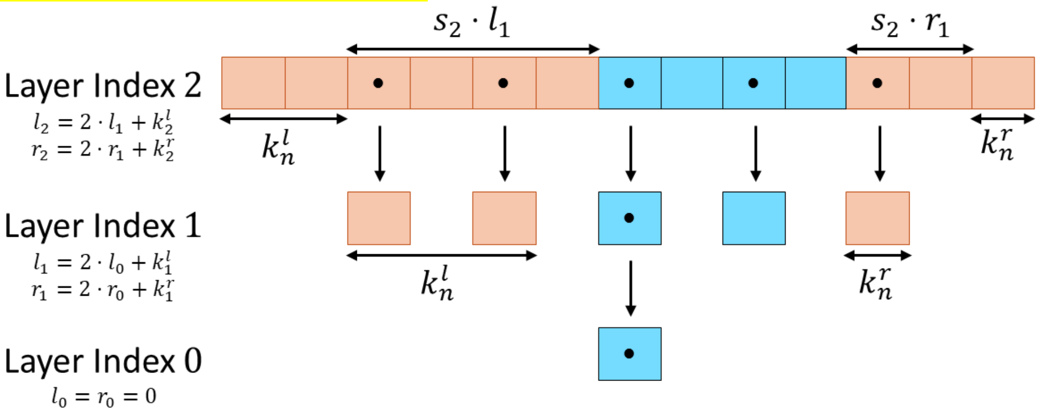
Symbol	Meaning
N	Total number of layers in the network
n	Layer index, where $n \in \{0,1,\dots,N\}$
X_n	Size of the entire feature map at layer n
B_n	Size of the patch at layer n
l_n, r_n	Sizes of the left and right overlaps at layer n
k_n	Kernel size at layer n
s_n	Stride at layer n



[Sec. 2] *Minimal Overlap Calculation*

Overlap Propagation Formula

- Required overlap is recursively computed layer by layer to match Full-image LIC.
  - ★ Key idea: precisely **measure the receptive support** required for convolution on block features.



Derivation example of the recursive formula for convolution

For Convolution,

- $l_n = s_{n-1} \cdot l_{n-1} + \left\lfloor \frac{k_n - 1}{2} \right\rfloor, r_n = s_{n-1} \cdot r_{n-1} + \max\{0, \left(k_n - 1 - \left\lfloor \frac{k-1}{2} \right\rfloor\right) - (s_n - 1)\}$

For Transposed Convolution,

- $l_{n-1} = s_n \cdot l_n - \left\lfloor \frac{k_n - 1}{2} \right\rfloor, r_{n-1} = s_n \cdot r_n - \left(k_n - 1 - \left\lfloor \frac{k_n - 1}{2} \right\rfloor\right) - (s_n - 1)$

See the paper for the detailed derivation and calculation method.

Implementation Methodologies

1. Handling Boundary Block
2. Handling Multi-Path Network

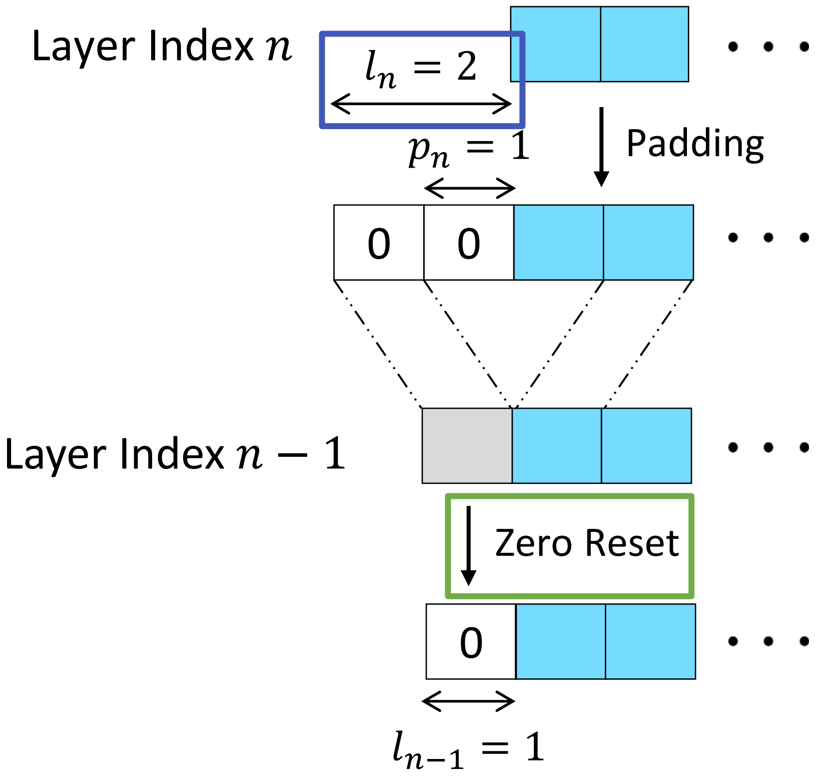
[Sec. 3] *Handling Boundary Block*

Problem

- Center and boundary blocks require different operations because neighboring data is not equally available.

Solution

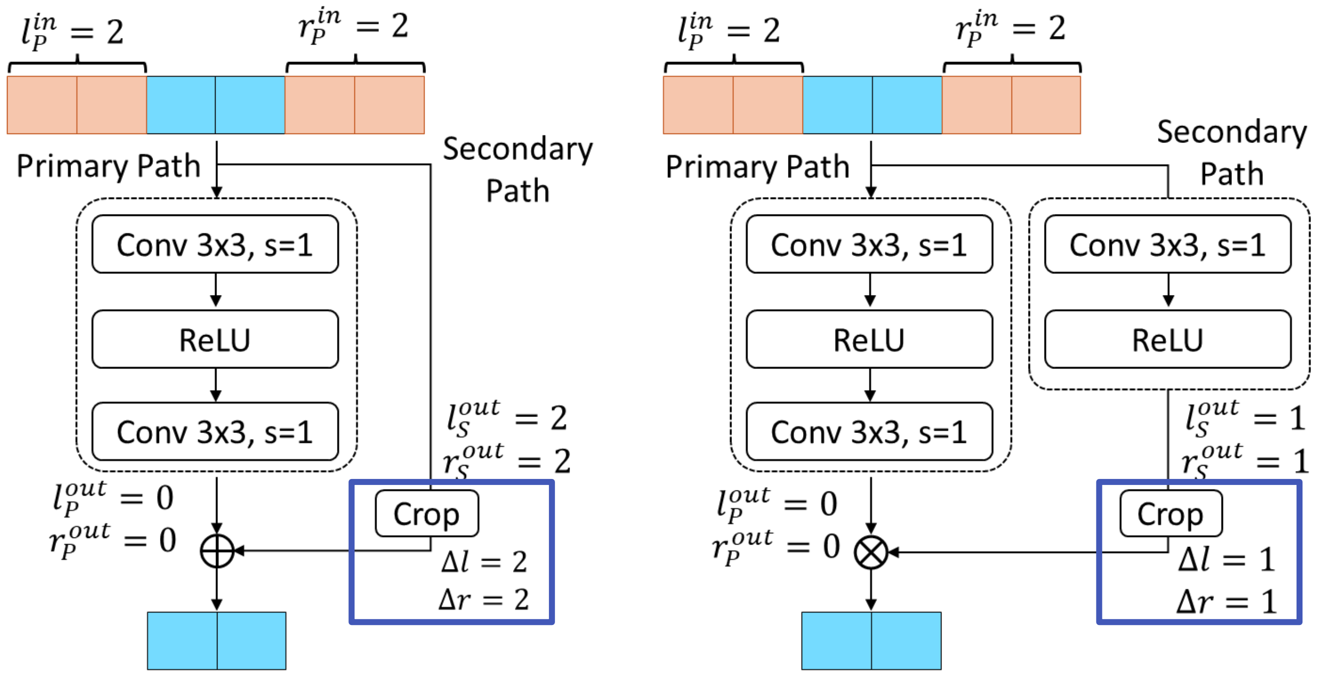
- Boundary blocks are **padded** to match center-block shapes, and **post-processing** preserves both simplicity and correctness.



Convolution for handling the left block
$k_n = 3, s_n = 1, B_n = 2, l_n = 2, r_n = 2$

[Sec. 3] *Handling Multi-Path Network*

- **Problem**
  - Multi-branch architectures, such as ResNet, may produce different feature sizes across paths before merging.
- **Solution**
  - Unnecessary overlap regions are **precisely cropped before merging** to align feature resolutions.



(a) Residual Network (b) Gating Network

- **See the paper for detail explanations.**

Ref : He, Kaiming, et al. "Deep residual learning for image recognition." Proceedings of the IEEE conference on computer vision and pattern recognition. 2016.

Experiment Result

1. **Experiment in Various LIC Models**

[Sec. 4] Experiment in Various LIC Models

Result (Minimal Overlap Validation)

- Anchor : Full-image inference
- Each overlap is reduced by one pixel from the computed value for the hyper encoder, hyper decoder, encoder, and decoder.
- This leads to a significant PSNR drop, a substantial Bpp increase and also introduces visible artifacts.

Transform	BD-rate (%)	BD-PSNR (dB)
h_a	+76.34	-2.99
h_s	+230.52	-5.91
g_a	–	-14.36
g_s	–	-20.31

BD-rate and BD-PSNR results with insufficient overlap on Hyperprior w/o AR-Context

Full image Inference

Encoder overlap reduced by 1 pixel

Decoder overlap reduced by 1 pixel

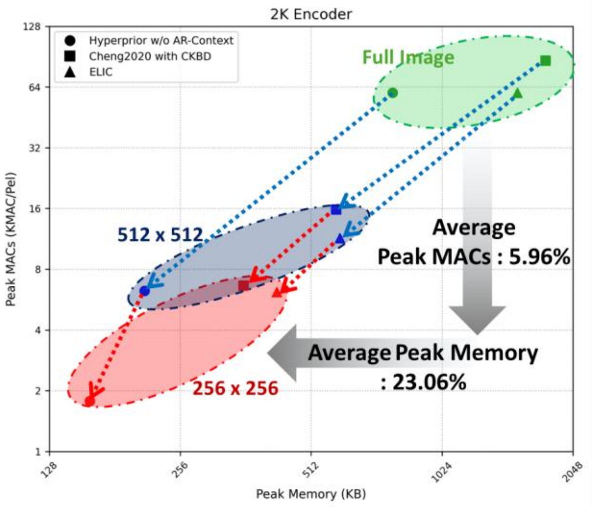
Ref : Johannes Ball´e, David Minnen, Saurabh Singh, Sung Jin Hwang, and Nick Johnston. Variational image compres sion with a scale hyperprior. In International Conference on Learning Representations (ICLR), 2018

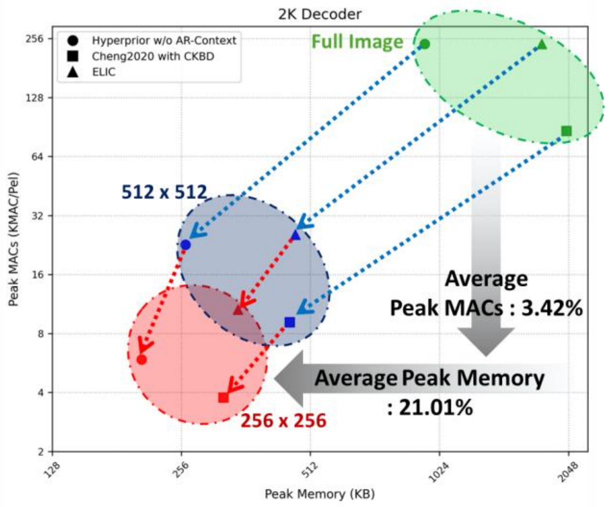
[Sec. 4] *Experiment in Various LIC Models (Cont'd)*

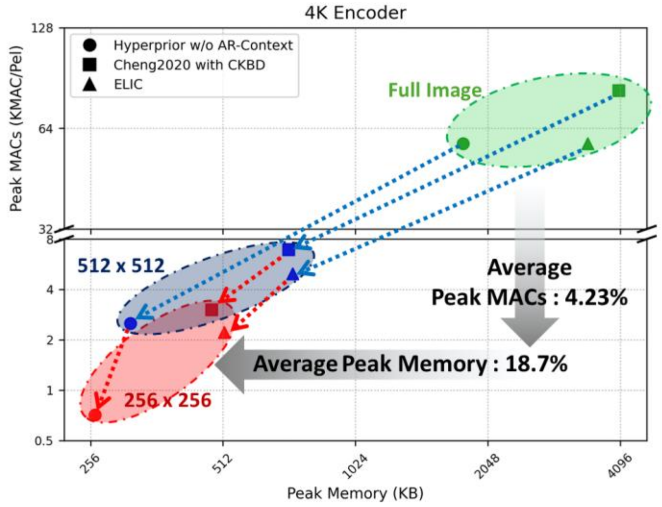
- **Result (BD-rate & Peak MACs / Peak Memory)**
  - Applying the computed overlap to the encoder, decoder, hyper encoder, and hyper decoder
    - ★ There is **negligible BD-rate loss** compared to full-image Inference.
    - ★ **Peak memory and peak computation are significantly reduced** across various resolutions.

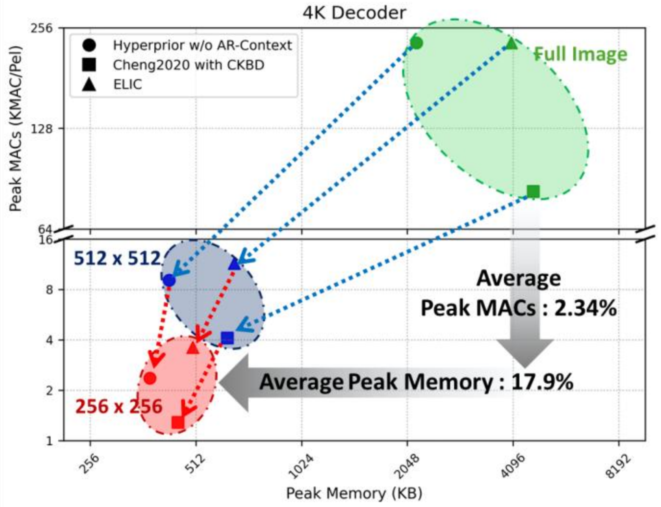
Resolution	Hyperprior w/o AR-Context	Hyperprior With CKBD	Cheng With CKBD	ELIC
2K	+0.0013%	+0.0021%	+0.0081%	-0.0000%
4K	+0.0022%	-0.0018%	-0.004%	+0.0050%

BD-rate comparison across LIC models at 2K and 4K resolutions









Conclusion

[Sec. 5] Conclusion

- We introduced a retraining-free block-based LIC framework that analytically derives minimal overlaps to match full-image inference.

- The proposed method achieves artifact-free reconstruction with no BD-rate loss, while substantially reducing peak memory and peak computational cost.

- This shows that high-resolution LIC can be performed efficiently through principled block-based processing, without modifying or retraining existing CNN-based models.

Q & A