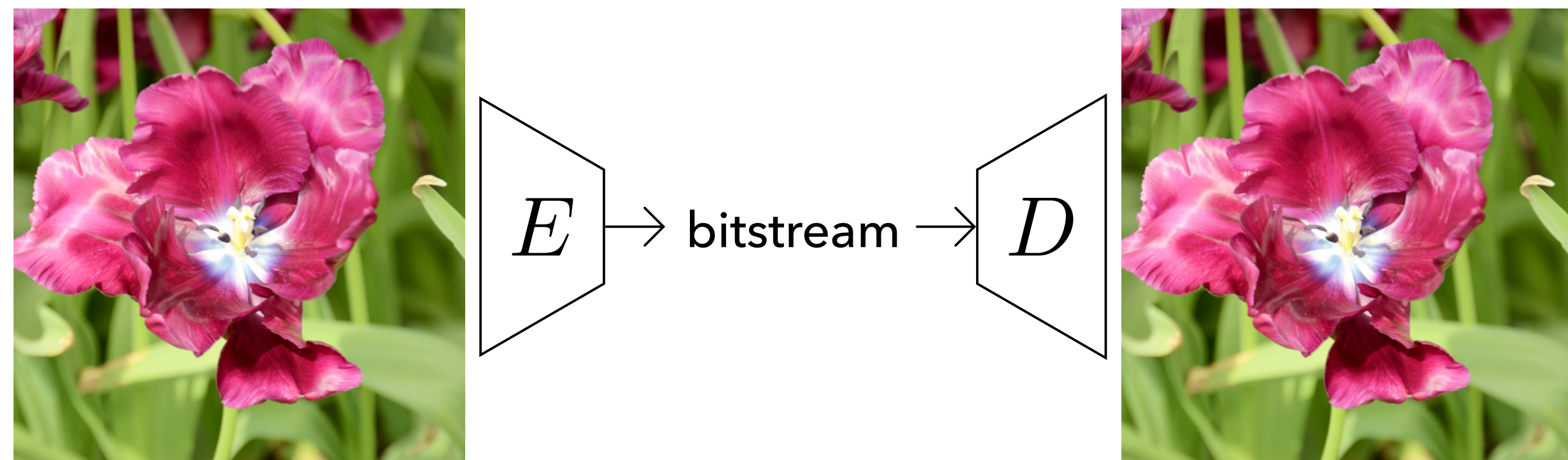


Practical Full Resolution Learned Lossless Image Compression

Fabian Mentzer, Eirikur Agustsson, Michael Tschannen, Radu Timofte, Luc Van Gool



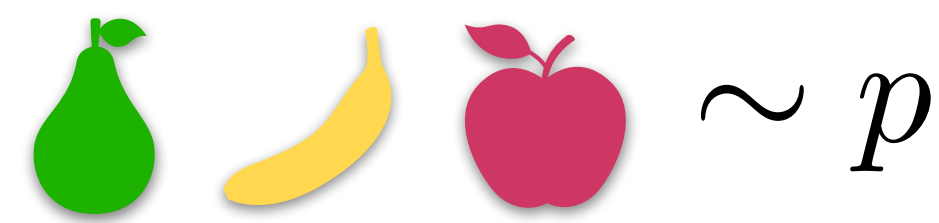
Overview



- **First Learned** Full-Resolution Lossless Image Compression
- **Smaller** than non-learned lossless codecs: PNG, JPEG2000, WebP
- Our probabilistic model is orders of magnitude **faster** than PixelCNN

Lossless Compression

Symbols Probability distribution



Symbol stream = message



i.i.d. $\sim p$
Entropy Coding:
 Arithmetic Coding
 Huffman Coding

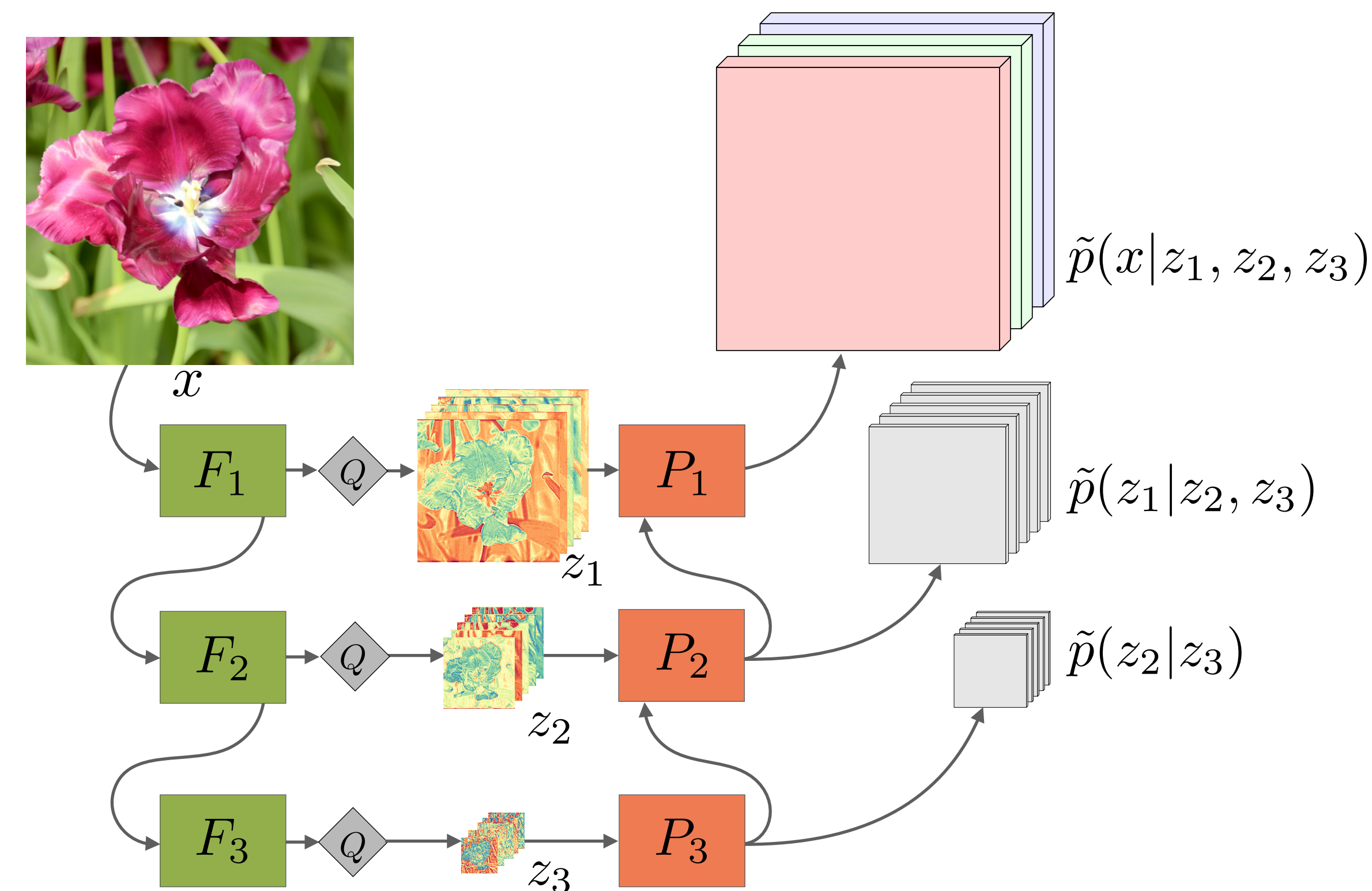
$p(\text{image})$ unknown
 → we learn a **model** \tilde{p}

Use pixels as symbols: not i.i.d.
 So we learn the joint:
 $\tilde{p}(x_1, x_2, \dots, x_N)$. **Must factorize!**

- minimize **Cross Entropy**
 $H(p, \tilde{p}) = \mathbb{E}_{x \sim p}[-\log \tilde{p}(x)]$
- ≡ minimize **-log likelihood** \tilde{p}
- ≡ minimize **bitcost when using** \tilde{p}

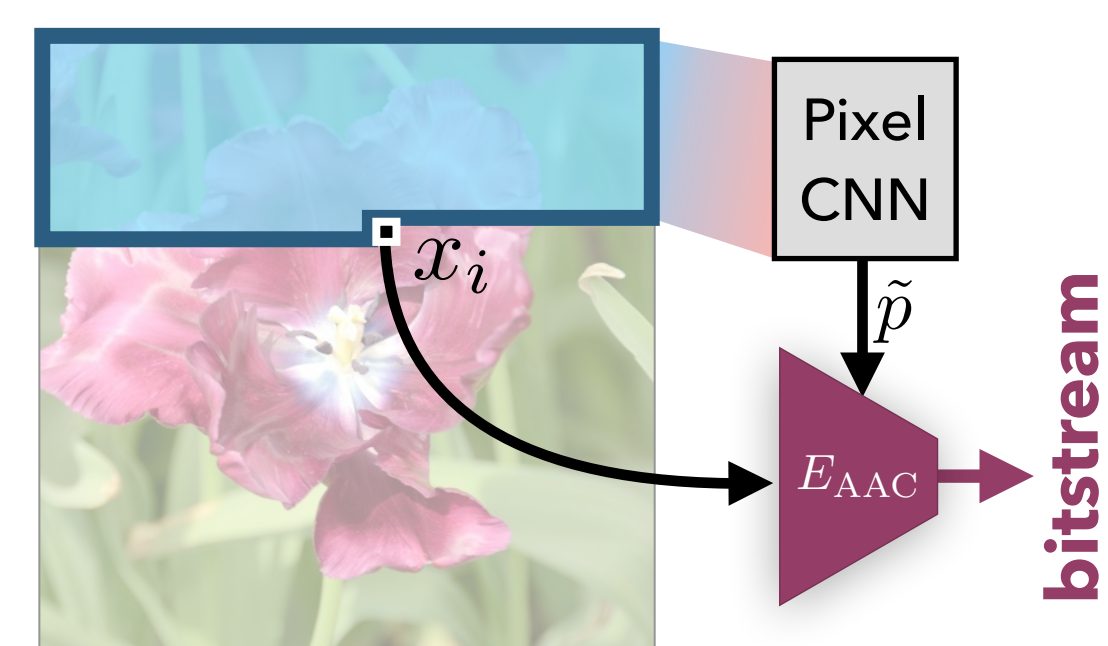
Our Method: L3C

Our **factorization**: $\tilde{p}(x) = \tilde{p}(x | z_1, z_2, z_3) \cdot \tilde{p}(z_1 | z_2, z_3) \cdot \tilde{p}(z_2 | z_3) \cdot \tilde{p}(z_3)$

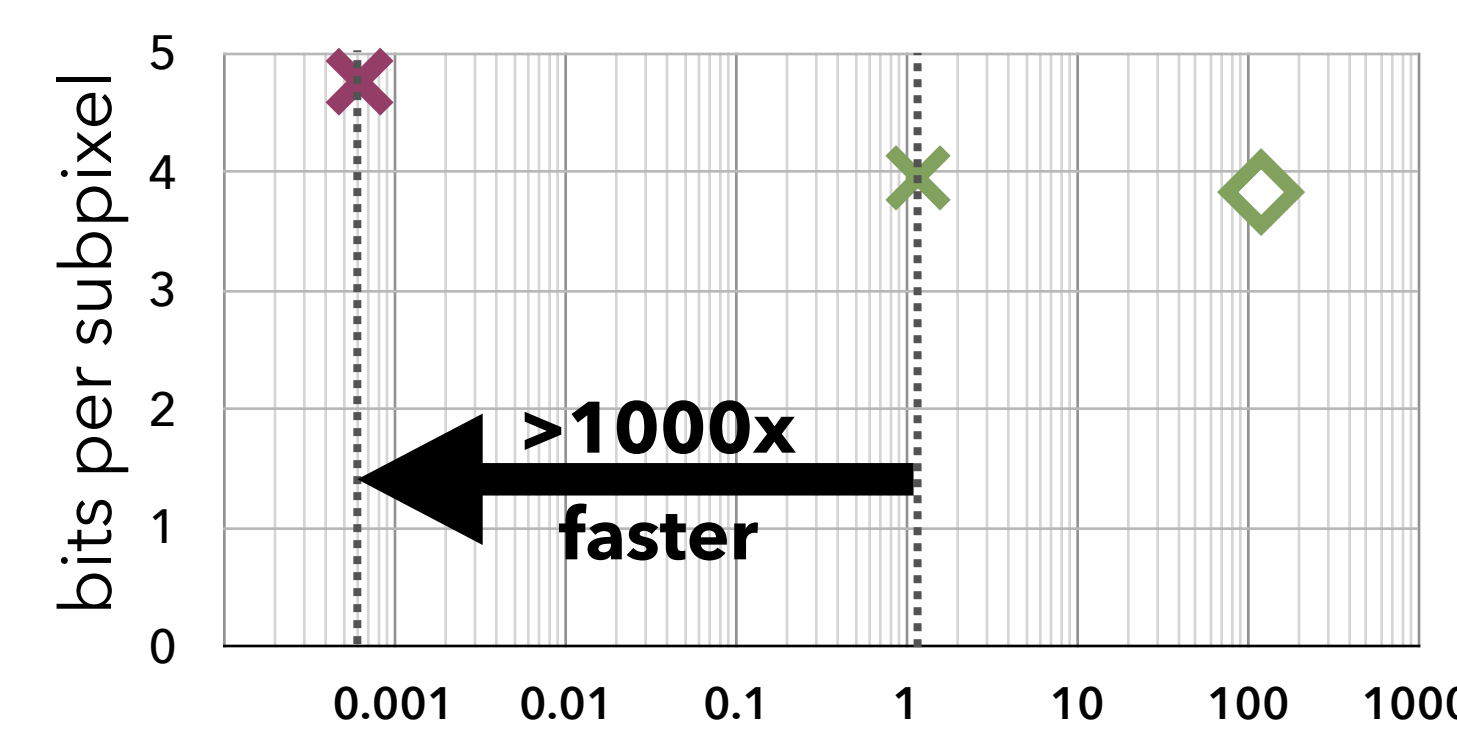


Using discretized mixture of logistics $p_m(z_{cuv}^{(s)} | f^{(s+1)}) = \sum_k \pi_{cuv}^k p_l(x_{cuv} | \mu_{cuv}^k, \sigma_{cuv}^k)$

L3C vs. PixelCNN

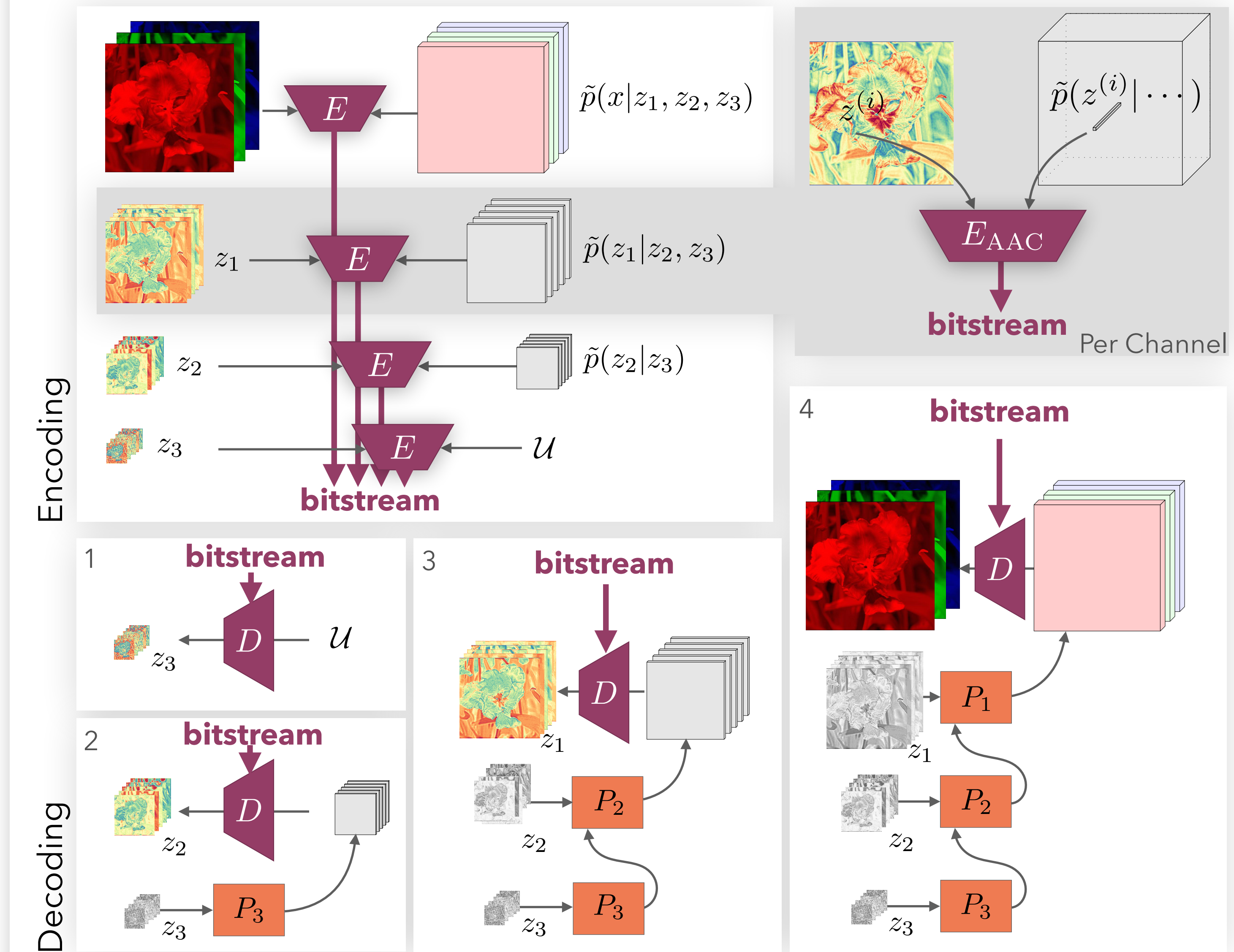


Their **factorization**:
 $\tilde{p}(x) = \prod_{i=1}^N \tilde{p}(x_i | x_1, \dots, x_{i-1})$
 Forward pass per pixel!

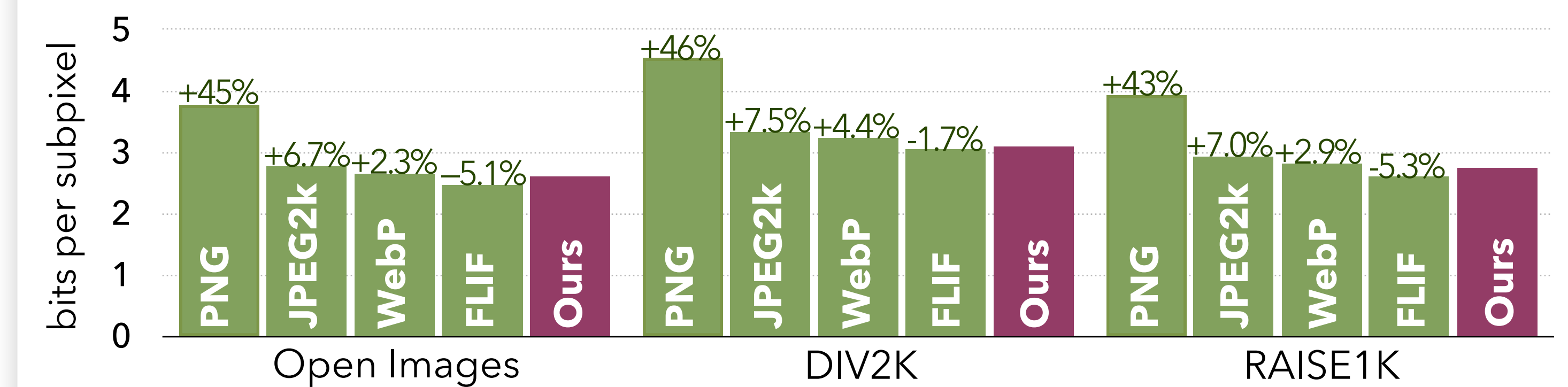


- ✖ Ours
- ✕ MS-PixelCNN
- ◇ original PixelCNN

Encoding Decoding Details



Results



Runtime on 512x512

Codec	Encoding [s]	Decoding [s]	GPU	CPU
Ours	0.242	0.374	✓	✓
FLIF	1.72	0.133		✓
WebP	0.157	0.0712		✓



Code Models

