



# FREE LOSSLESS IMAGE FORMAT

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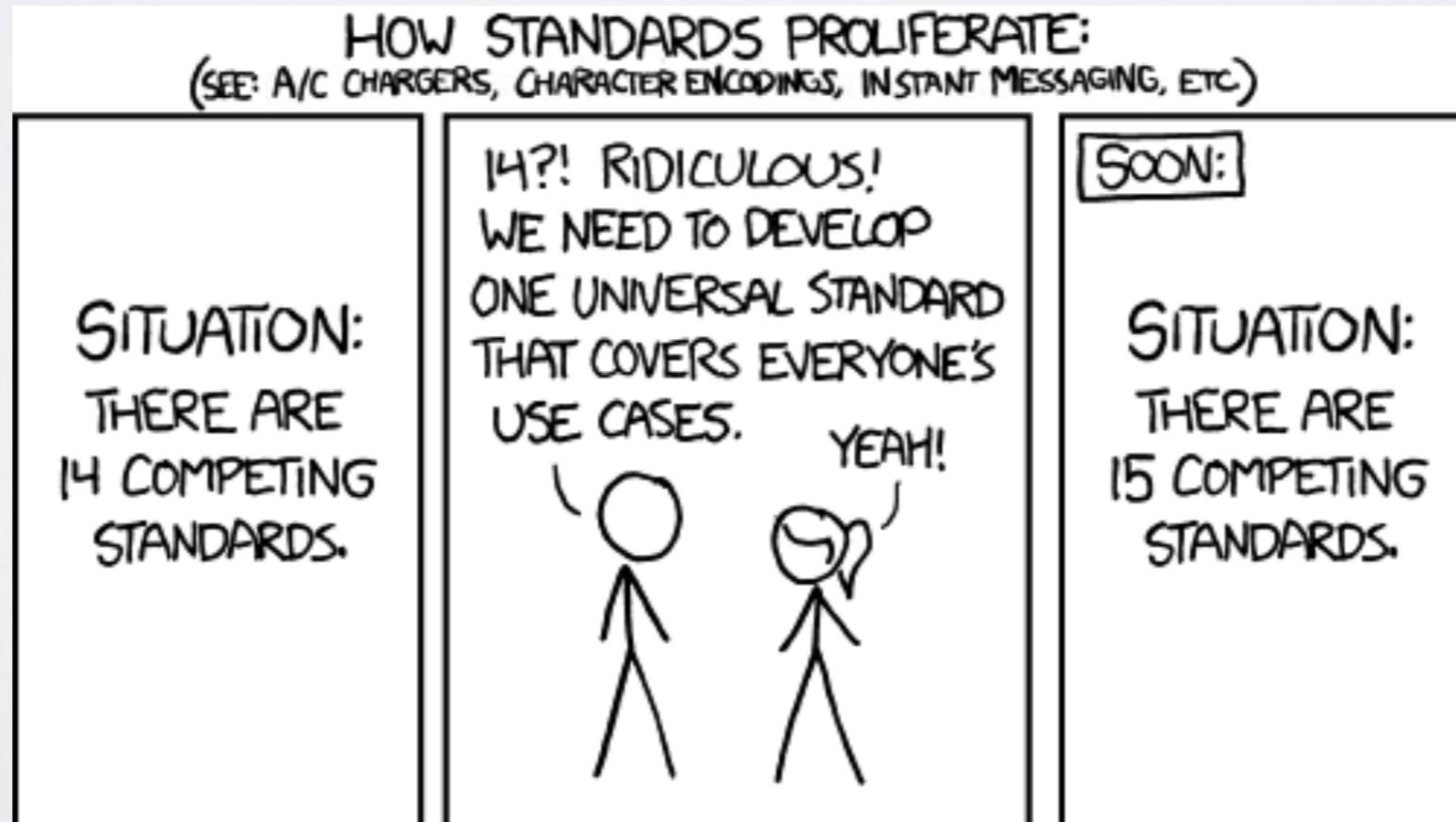
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Blockstream

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# DON'T WE HAVE ENOUGH IMAGE FORMATS ALREADY?

- JPEG, PNG, GIF, WebP, JPEG 2000, JPEG XR, JPEG-LS, JBIG(2), APNG, MNG, BPG, TIFF, BMP, TGA, PCX, PBM/PGM/PPM, PAM, ...
- Obligatory XKCD comic:



# YES, BUT...

- There are many kinds of images:  
photographs, medical images, diagrams, plots, maps,  
line art, paintings, comics, logos, game graphics,  
textures, rendered scenes, scanned documents,  
screenshots, ...



the FreeType Project

# EVERYTHING SUCKS AT SOMETHING

- None of the existing formats works well on *all* kinds of images.
  - JPEG / JP2 / JXR is great for photographs, but...
  - PNG / GIF is great for line art, but...
  - WebP: basically two totally different formats
    - Lossy WebP: somewhat better than (moz)JPEG
    - Lossless WebP: somewhat better than PNG
    - They are both .webp, but you still have to pick the format

GOAL: ONE FORMAT  
THAT COMPRESSES ALL IMAGES WELL

JIF



# EXPERIMENTAL RESULTS

Corpus (bit depth)	Lossless formats										JPEG*	
	FLIF	FLIF*	WebP	BPG	PNG	PNG*	JP2*	JXR	JLS	100%	90%	
Natural (photo)	[4] 8	1.002	<b>1.000</b>	1.234	1.318	1.480	2.108	1.253	1.676	1.242	1.054	0.302
	[4] 16	1.017	<b>1.000</b>	/	/	1.414	1.502	1.012	2.011	1.111	/	/
	[5] 8	1.032	<b>1.000</b>	1.099	1.163	1.429	1.664	1.097	1.248	1.500	1.017	0.302
	[6] 8	1.003	<b>1.000</b>	1.040	1.081	1.282	1.441	1.074	1.168	1.225	0.980	0.263
	[7] 8	1.032	<b>1.000</b>	1.098	1.178	1.388	1.680	1.117	1.267	1.305	1.023	0.275
	[8] 8	1.001	<b>1.000</b>	1.059	1.159	1.139	1.368	1.078	1.294	1.064	1.152	0.382
	[8] 12	1.009	<b>1.000</b>	/	1.854	2.053	2.378	2.895	5.023	2.954	/	/
Artificial	[9] 8	1.039	<b>1.000</b>	1.212	1.145	1.403	1.609	1.436	1.803	1.220	1.193	0.233
	[10] 8	<b>1.000</b>	1.095	1.371	1.649	1.880	2.478	4.191	7.619	3.572	5.058	2.322
	[11] 8	<b>1.000</b>	1.037	1.982	4.408	2.619	2.972	10.31	33.28	33.12	14.87	9.170
	[12] 8	1.106	1.184	<b>1.000</b>	2.184	1.298	1.674	3.144	3.886	2.995	3.186	1.155
	[13] 8	<b>1.000</b>	1.049	1.676	1.734	2.203	2.769	4.578	10.35	4.371	5.787	2.987

\* : Format supports progressive decoding (interlacing).

/ : Unsupported bit depth.

Numbers are scaled so the best (smallest) lossless format corresponds to 1.

**Fig. 4.** Compressed corpus sizes using various image formats.

# HOW DOES IT WORK?

- General outline: pretty traditional
  - Color transform
  - Spatial domain (no DCT/DWT transform)
  - Interlacing
  - Prediction
  - Entropy coding: MANIAC

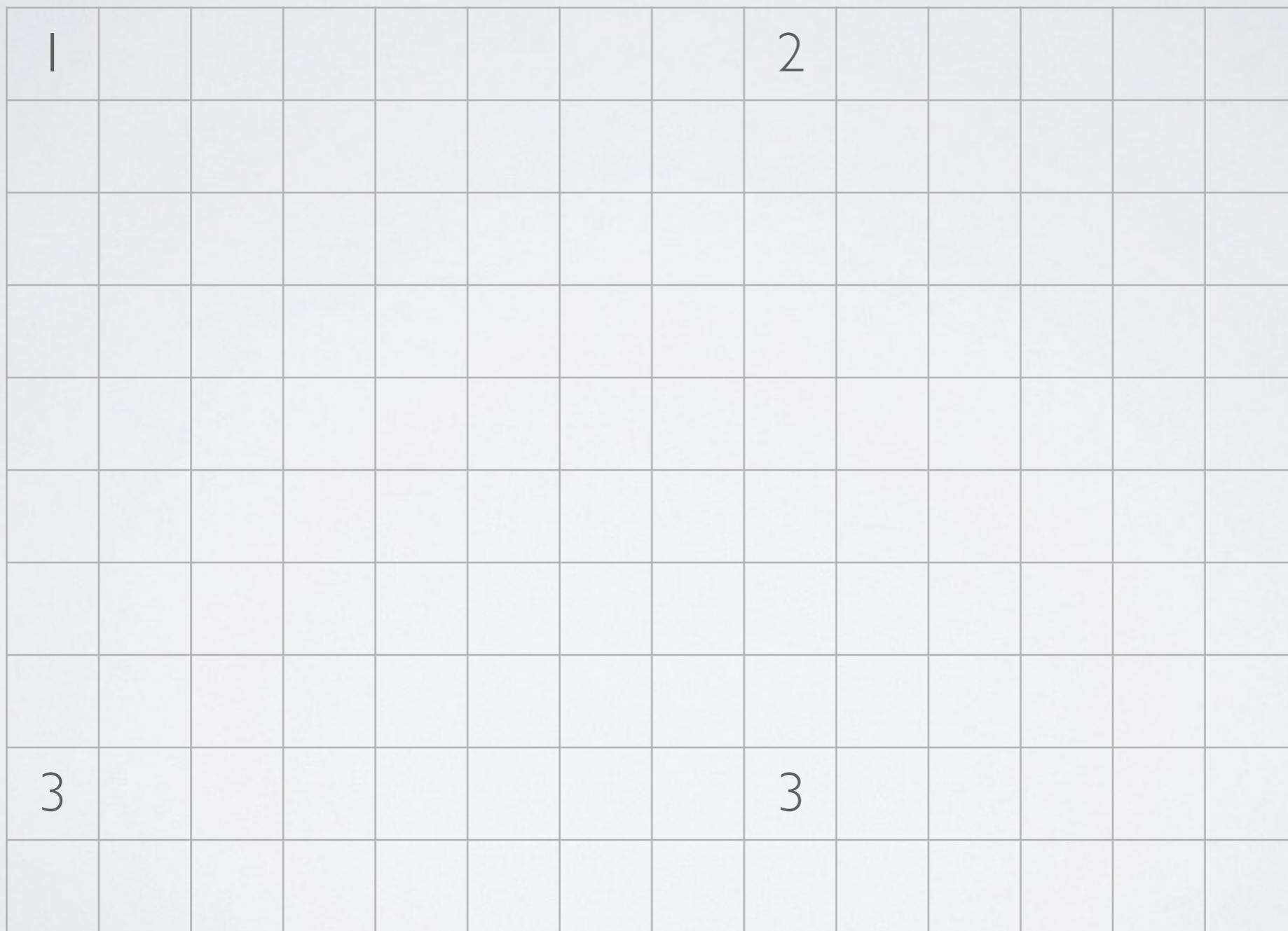
# COLOR TRANSFORM

- RGBA **channel compaction** to reduce effective bit depth if only a subset of the  $2^8$  or  $2^{16}$  possible values effectively occur in the image
- (compacted) **RGB**A to **YCoCg**A
  - Purple =  $(R+B)/2$ , Y =  $(P+G)/2$ , Co =  $R-B$ , Cg =  $G-P$   
Note: one extra bit for Co/Cg (signed values)
  - YCoCg is lossless and optional, can also use (permuted / green-subtracted) RGB
- If very sparse colors: **palette** (just like PNG/GIF), arbitrary palette size
- If relatively sparse colors: **color buckets**, a generalization of palette with ‘discrete’ and ‘continuous’ buckets to reduce the range of Y/Co/Cg given the value of nothing/Y/Y+Co

# INTERVAL COLOR RANGES

- Channel order: A, Y, Co, Cg
- To encode any color value, first compute the interval of ‘valid’ values based on known constraints
- E.g. if  $Y=0$ , then we know that  $-3 \leq Co \leq 3$
- Intervals are derived from YCoCg definition, color buckets, explicitly stored bounds

# INTERLACING: ADAM $\infty$



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1	6	4	6	2	6	4
5	6	5	6	5	6	5
3	6	4	6	3	6	4

# INTERLACING: ADAM $\infty$

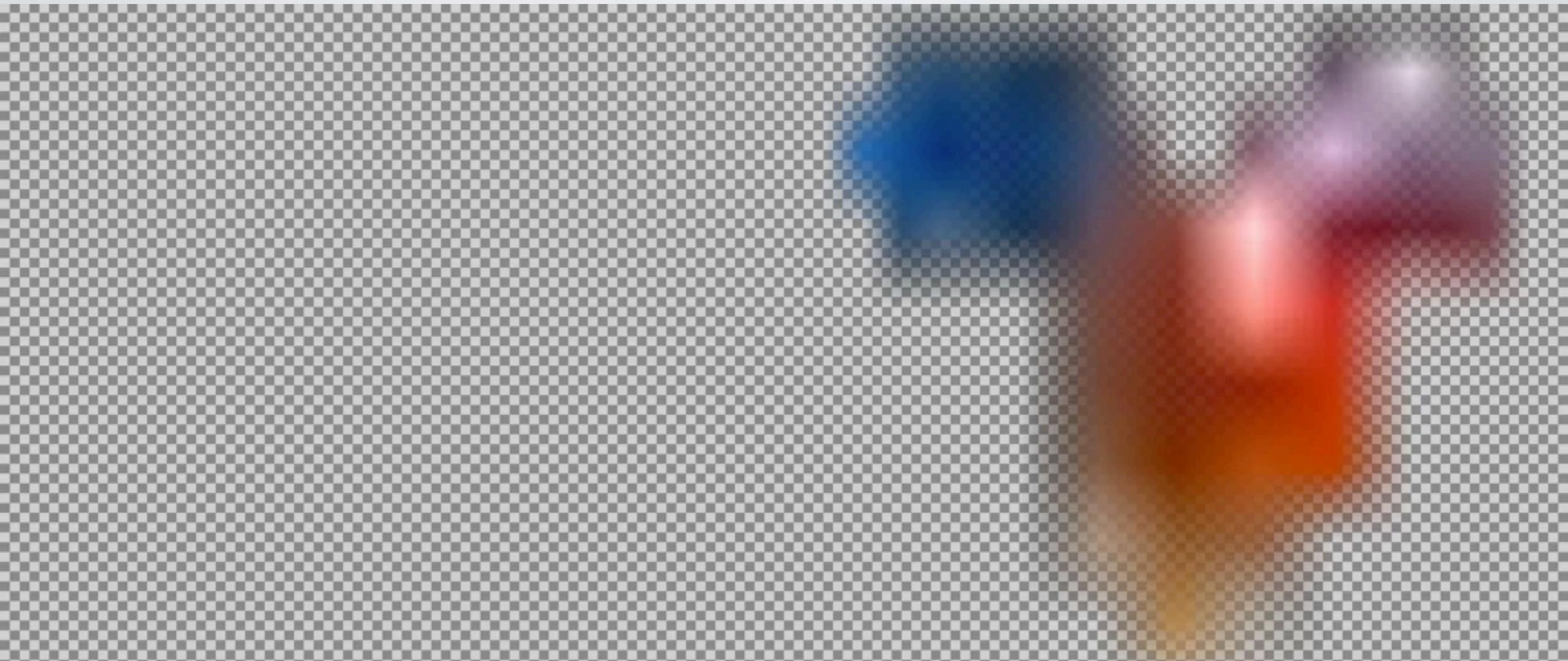
1		6		4		6		2		6		4
7		7		7		7		7		7		7
5		6		5		6		5		6		5
7		7		7		7		7		7		7
3		6		4		6		3		6		4

# INTERLACING: ADAM $\infty$

1	8	6	8	4	8	6	8	2	8	6	8	4	8
7	8	7	8	7	8	7	8	7	8	7	8	7	8
5	8	6	8	5	8	6	8	5	8	6	8	5	8
7	8	7	8	7	8	7	8	7	8	7	8	7	8
3	8	6	8	4	8	6	8	3	8	6	8	4	8

# INTERLACING: ADAM $\infty$

**ADAM7**    vs    **ADAM $\infty$**   
or rather: plain RGB                  vs              prioritized YCoCg



**PNG (Adam7)**  
**289924 bytes**  
**(.06%)**

**partial file**  
**200 bytes**

**FLIF**  
**158184 bytes**  
**(.12%)**

# PREDICTION

- Key difference with Adam7-PNG: interlacing is taken into account in the prediction/filtering

# PNG (ADAM7) PREDICTION

	8	6	8	4	8	6	8	2	8	6	8	4	8
7	8	7	8	7	8	7	8	7	8	7	8	7	8
5	8	6	8	5	8	6	?	5		6		5	
7		7		7		7		7		7		7	
3		6		4		6		3		6		4	

# FLIF PREDICTION

1	8	6	8	4	8	6	8	2	8	6	8	4	8
7	8	7	8	7	8	7	8	7	8	7	8	7	8
5	8	6	8	5	8	6	?	5		6		5	
7		7		7		7		7		7		7	
3		6		4		6		3		6		4	

# MANIAC ENTROPY CODING

The main “new thing” in FLIF



**M**eta-**A**daptive **N**ear-zero **I**nteger **A**rithmetic **C**oding

# MANIAC ENTROPY CODING

- **M**eta-**A**daptive **N**ear-zero **I**nteger **A**rithmetic **C**oding
- Base idea: CABAC (context-adaptive binary AC)
- Contexts are not static (i.e. one big fixed array) but dynamic (a tree which grows branches during encode/decode)
  - The tree structure is learned at encode time, encoded in the bitstream
  - Context model *itself* is specific to the image, not fixed by the format (so it is *meta*-adaptive)

# CONTEXT MODEL

- Problem: how many contexts?
  - Too few: cannot really capture the actual ‘context’ (contexts that behave differently get lumped together)
  - Too many: too few symbols per context (similar contexts get updated separately)

# CABAC

- Example context model: FFV1, “large model”
  - up to **5** properties: (TT-T), (LL-L), (L-TL), (TL-T), (T-TR)
  - Properties are **quantized**, and used to determine the AC context
  - Context are organized in an array (i.e. `context[11][11][5][5][5]`)
  - **Fixed** number of contexts
    - 666 in the “small model”
    - 7563 in the “large model”

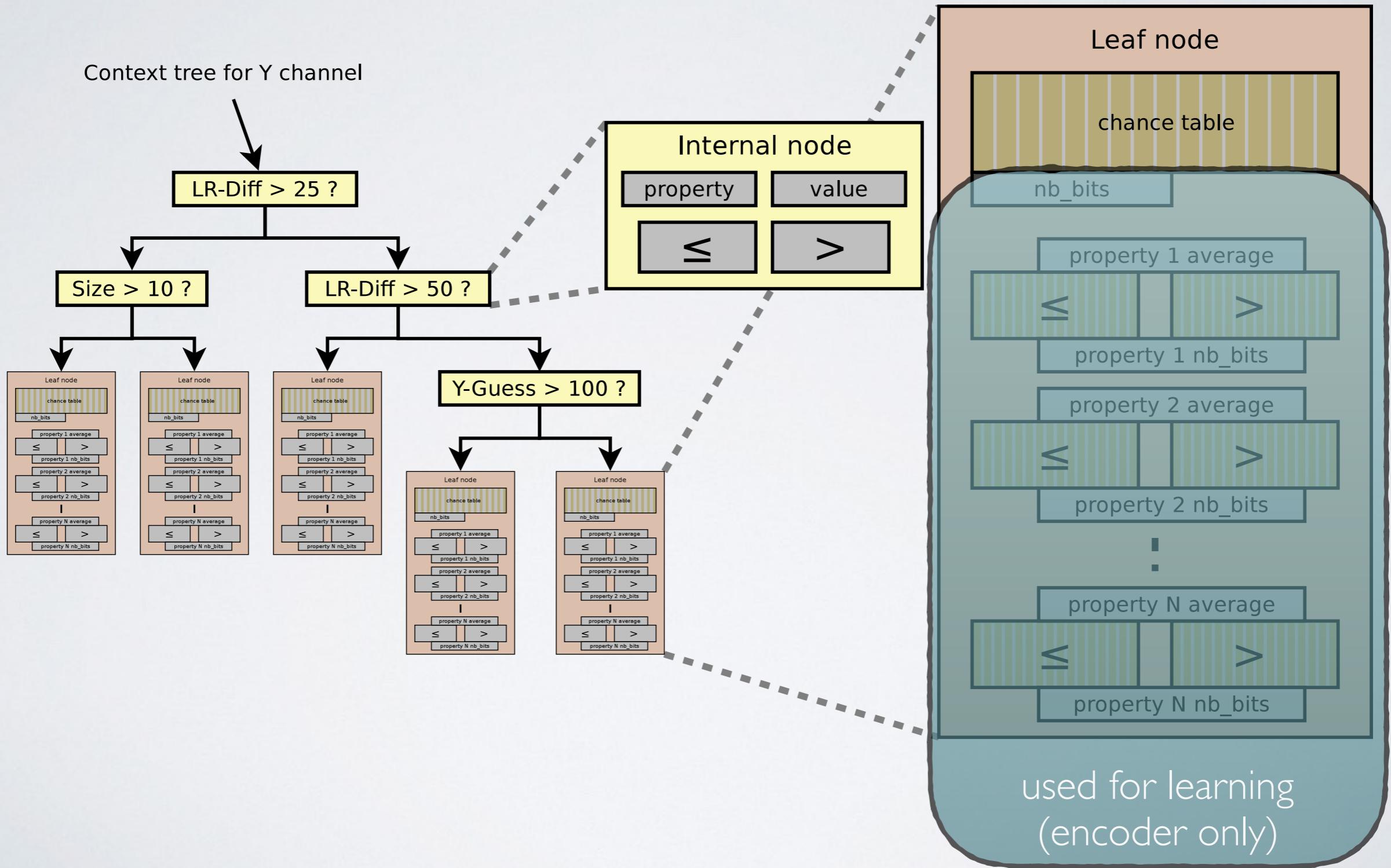
# MANIAC

- Example context model: FLIF
  - up to **11** properties: e.g.  $(TT-T)$ ,  $(LL-L)$ ,  $(L-(TL+BL)/2)$ ,  $(T-(TL+TR)/2)$ ,  $(B-(BL+BR)/2)$ ,  $(T-B)$ , the predictor: e.g.  $\text{median}((T+B)/2, T+L-TL, L+B-BL)$ , the median-index, the value of A, the value of Y, the “luma prediction miss”:  $(Y - (YT+YB)/2)$
  - Properties are **not quantized**, and used to determine the AC context
  - Contexts are organized in a dynamic structure (“MANIAC tree”)
  - **No fixed** number of contexts

# MANIAC TREE



# MANIAC TREE



# KEY INSIGHT

- Compression = Machine Learning
  - If you can (probabilistically) predict/classify, then you can compress
- Every ML technique is a potential entropy coder
  - MANIAC: decision trees

# ENTROPY CODING

	Huffman	LZW	DEFLATE (LZ + Huffman)	AC (pre-CABAC)	CABAC	MANIAC
Used in	JPEG	GIF	PNG, lossless WebP	JPEG-AC, JPEG 2000, VP8 (WebP)	H.264, FFV1, HEVC (BPG), VP9	FLIF
Global adaptive (initial chances can be tuned)	✓	✗	✓	✓	✓	✓
Local adaptive (chances can be updated)	✗	✓	✓	✓	✓	✓
Context-adaptive (chances per context)	✗	✗	✗	✗	✓	✓
Meta-adaptive (context model can be tuned)	✗	✗	✗ (lossless WebP: somewhat)	✗	✗	✓

# FLIF FEATURES

- Up to 16-bit RGBA, lossless (like PNG)  
A=0 pixels can have *undefined* RGB values (values not encoded), this is optional
- Interlaced (default) or non-interlaced
- Animation (with some inter-frame features: FrameShape, Lookback)
- Can store metadata (ICC color profile, Exif/XMP metadata)
- Rudimentary support for camera raw RGGB
- Poly-FLIF: javascript polyfill decoder

APNG: 962KB



50KB

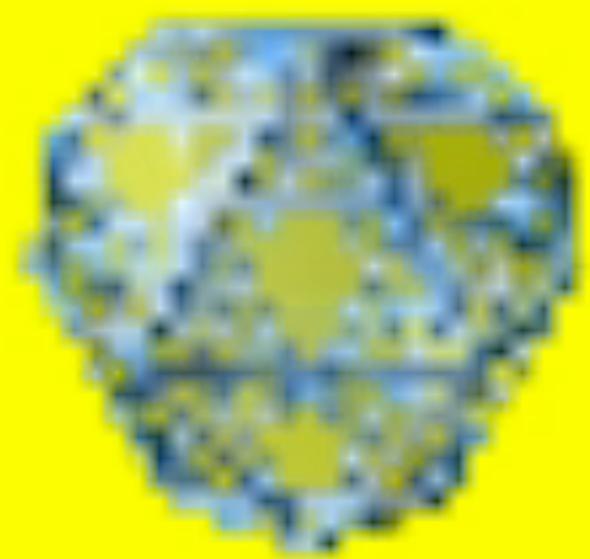
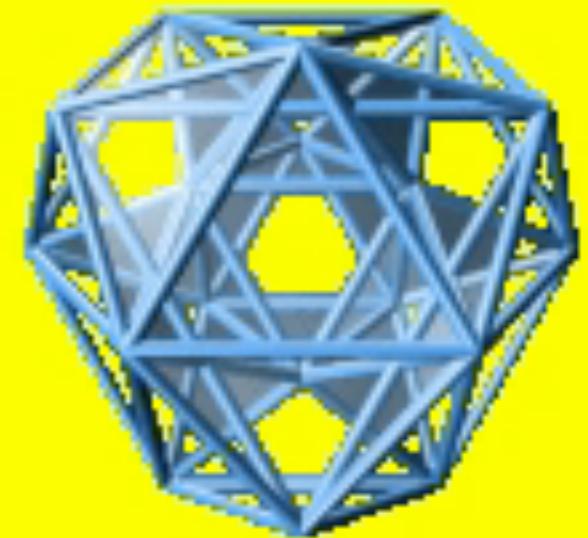


150KB



250KB

GIF: 436KB  
(256 colors, no full alpha)



FLIF: 526KB



Fully decoded  
APNG or FLIF

# LOSSY FLIF?

- Encoder can optionally modify the input pixels in such a way that the image compresses better
- This works surprisingly well!
  - Other lossless formats (PNG, lossless WebP) can also be used in a lossy way, but they typically don't even get anywhere near the lossy formats
- Plus: there's room for future improvement

# MOZJPEG

262,800 BYTES

DSSIM: 0.00134261

PSNR: 33.5447

VS

# PNG8

264,653 BYTES

DSSIM: 0.00639207

PSNR: 31.9077



# MOZJPEG

262,800 BYTES

DSSIM: 0.00134261

PSNR: 33.5447

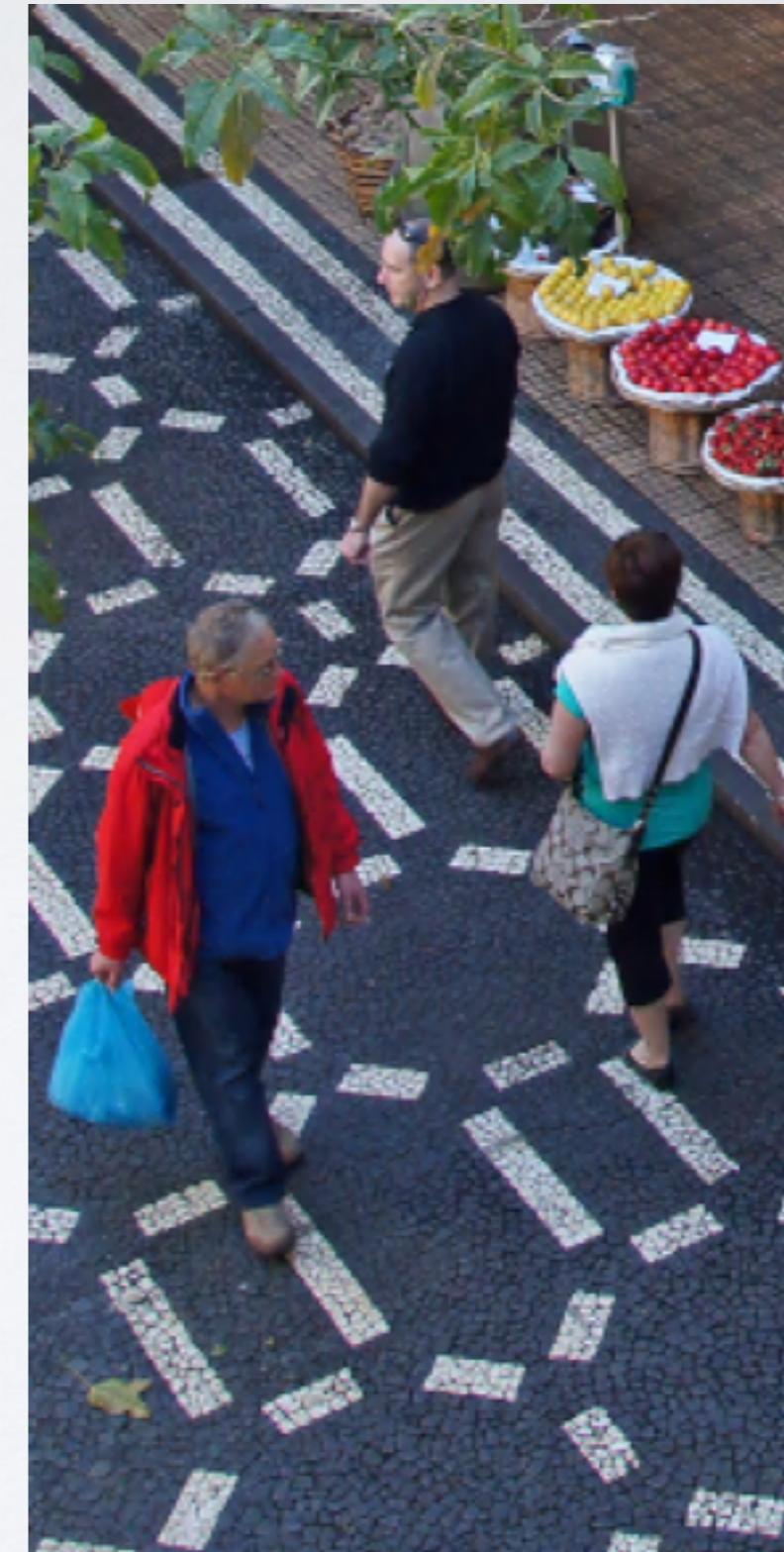
VS

# FLIF

248,225 BYTES

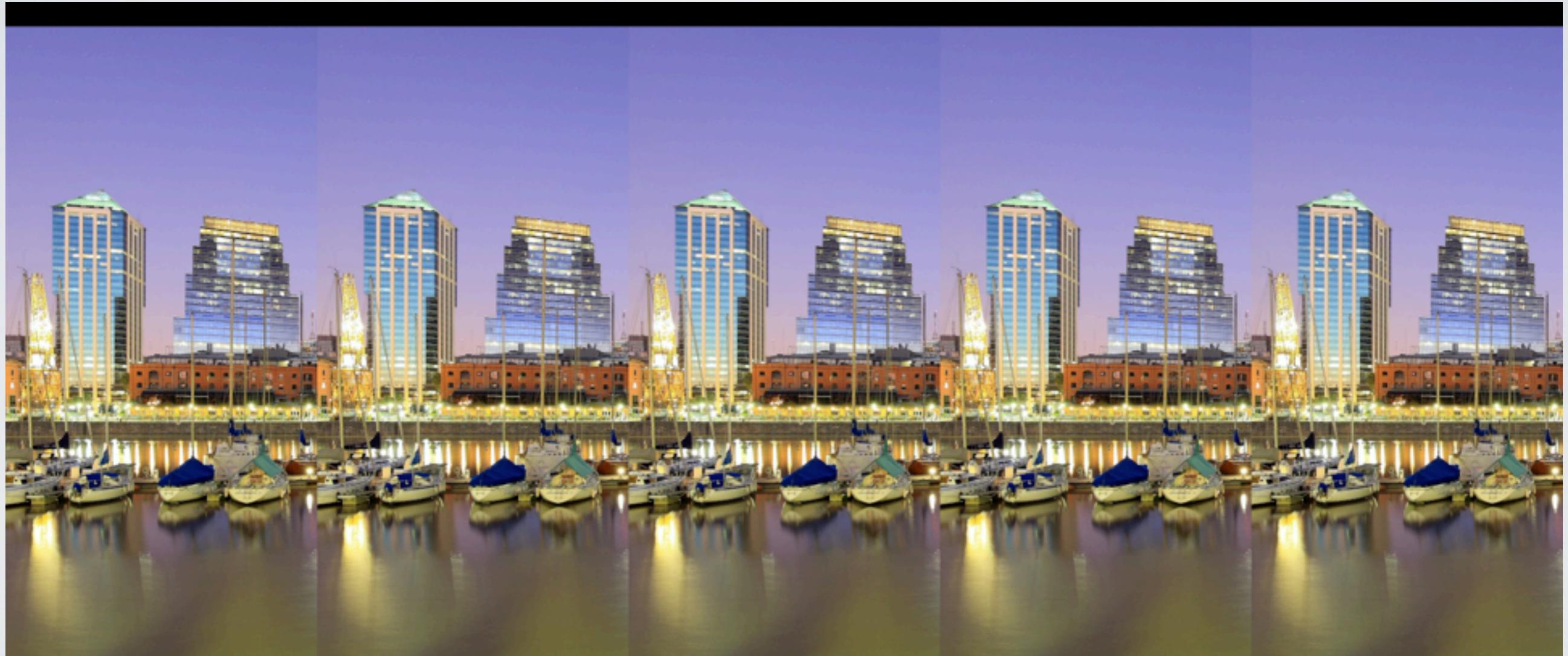
DSSIM: 0.00106984

PSNR: 37.2284



# DO WE STILL NEED LOSSY?

- Maybe we don't need (inherently) lossy **formats** anymore?
  - Lossy is still useful, but maybe lossy encoding to lossless target formats is good enough?



FLIF -Q100 PSNR: inf 403065 bytes	WebP q:100 PSNR: inf 404234 bytes	BPG q:0 PSNR: inf 495599 bytes	JPEG q:100 PSNR: 50.6423 410311 bytes	MozJPEG q:100 PSNR: 36.5992 216941 bytes
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0 generations (lossless)

# FUTURE DIRECTIONS

- Apply MANIAC to other formats / general-purpose compression
- Try MANIAC-style entropy coding based on other ML techniques (Neural nets, SVM, etc etc)
- Improve (decoding) performance
- Improve (lossless/lossy) compression

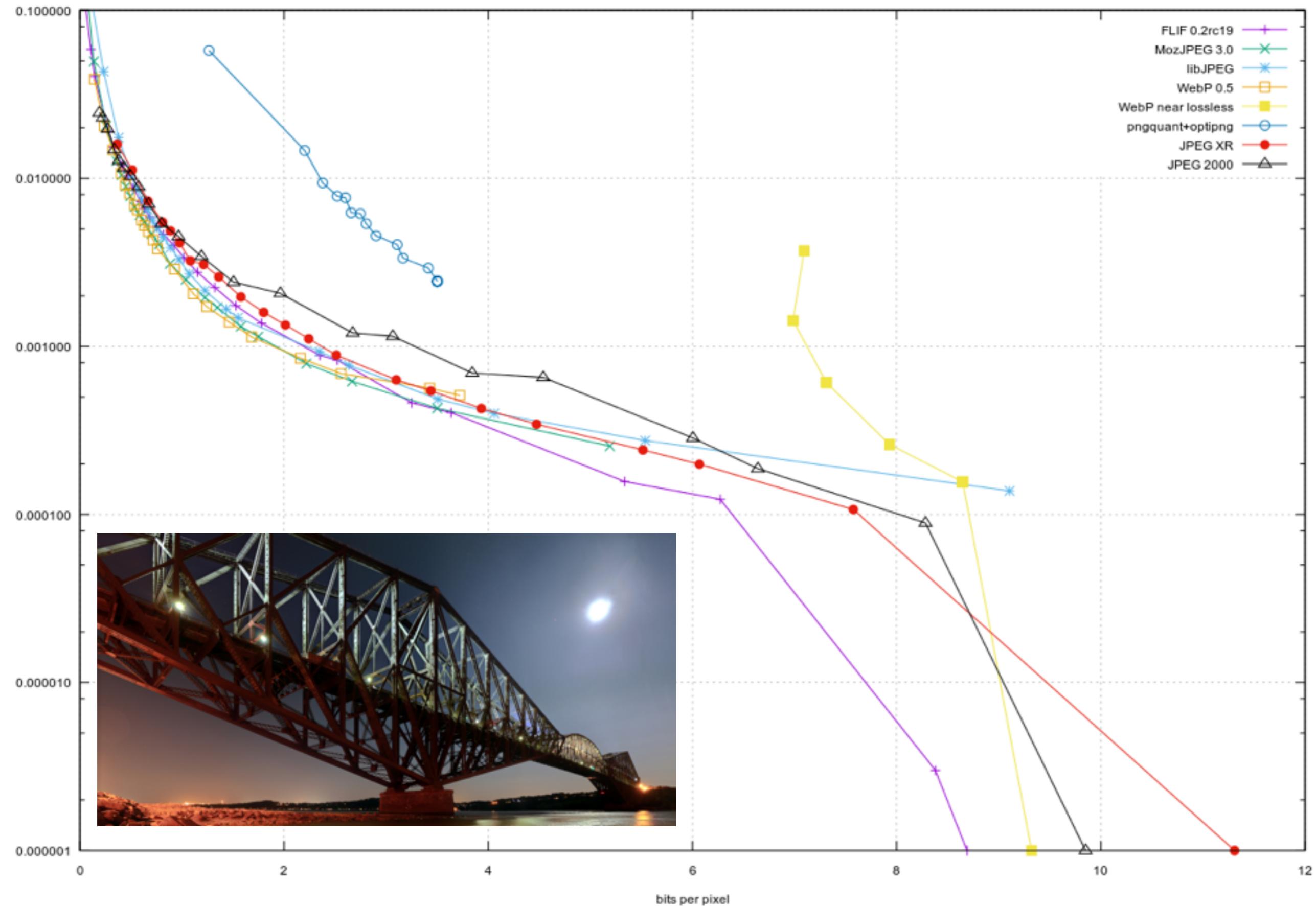
# QUESTIONS?

- Reference implementation of FLIF:  
<https://github.com/FLIF-hub/FLIF>
- FLIF home page: <http://flif.info/>
- Decoder license: Apache 2.0

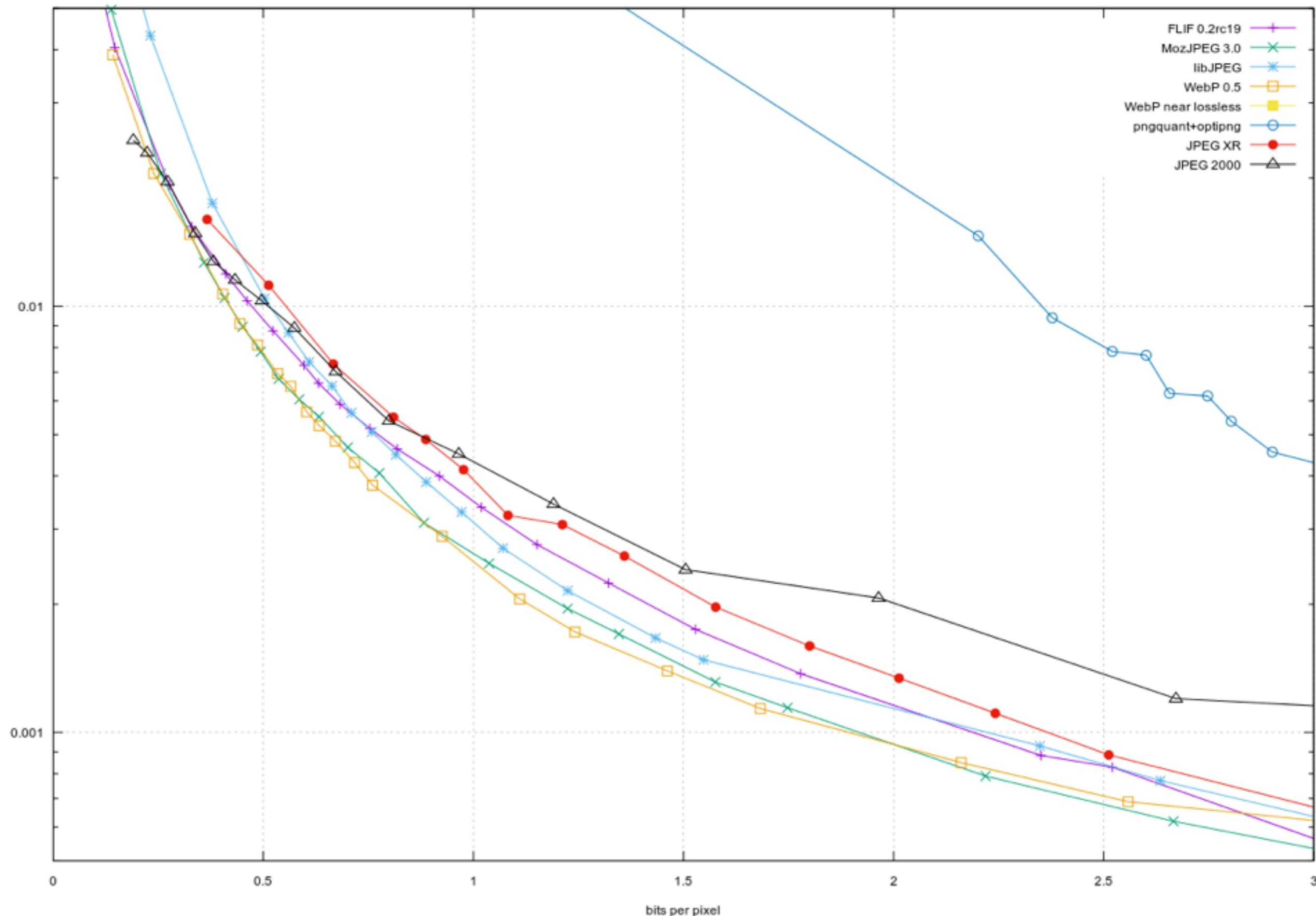


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Lossy image compression comparison, corpus: wikipedia-photos, image:



Lossy image compression comparison, corpus: wikipedia-photos, image:



Lossy image compression comparison, corpus: SMBC, image:

