Google Research

Data Compression Conference

The Rate-Distortion-Accuracy Tradeoff: JPEG Case Study

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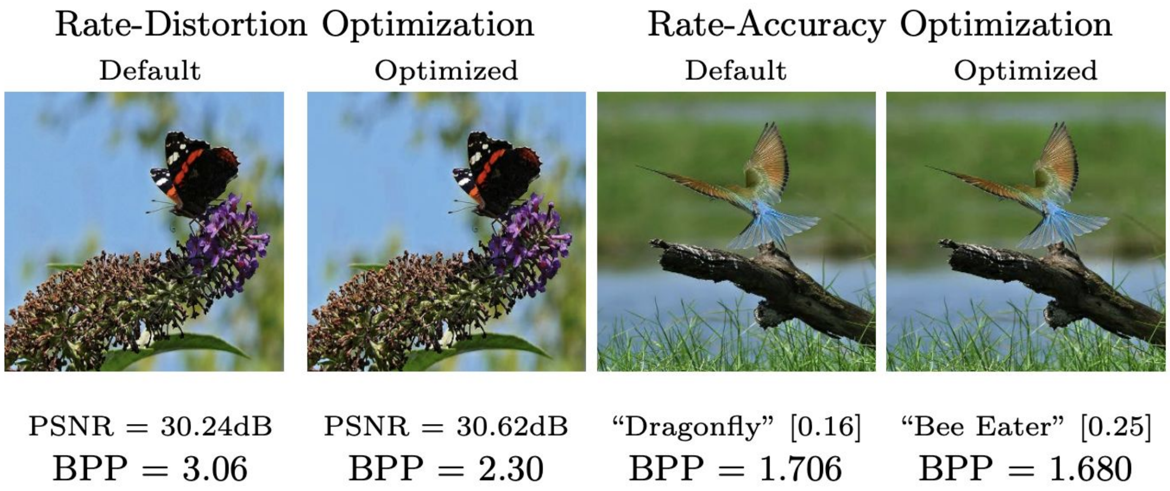
[1]Google Research

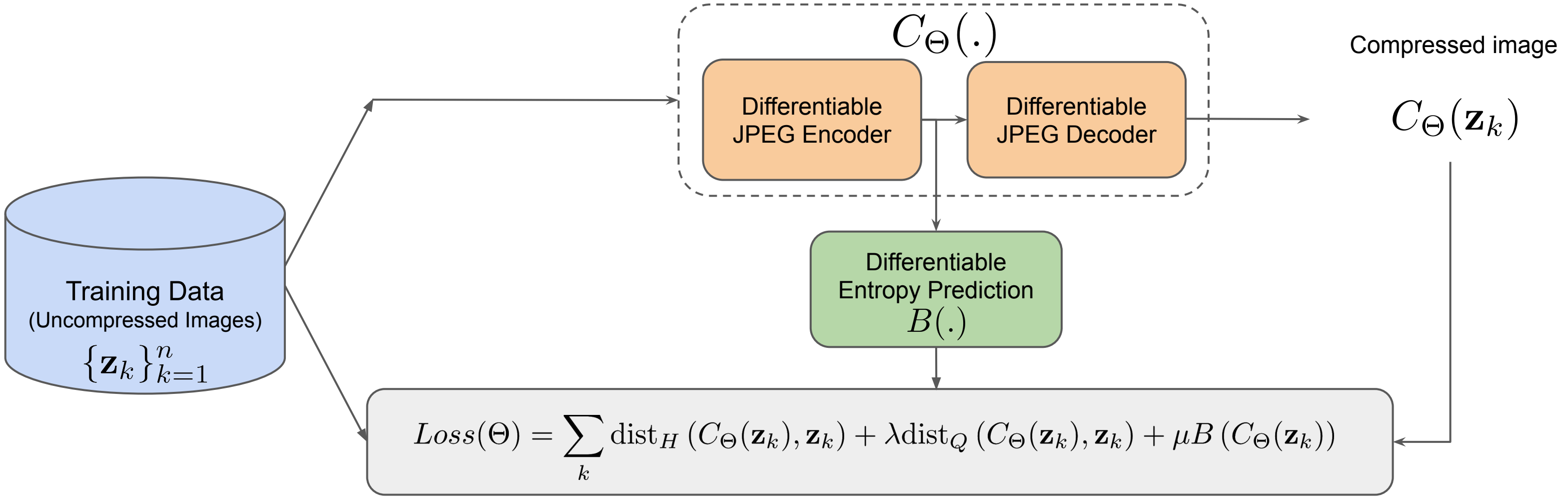
Paper Link

Overview



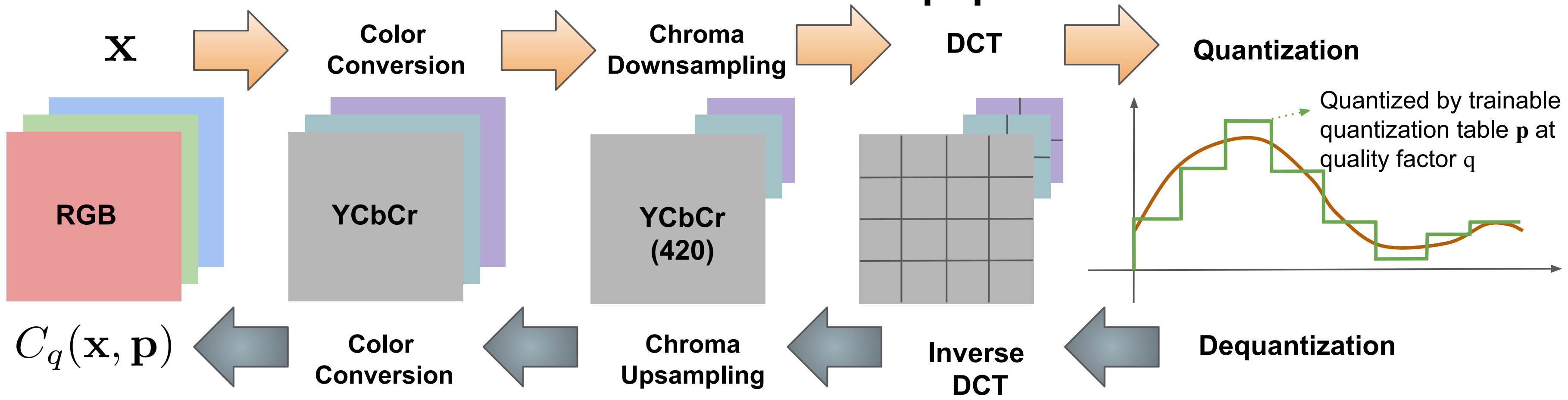
- A differentiable and unified framework for optimizing the JPEG quantization table for rate, distortion, and classification accuracy.

Method – Overview



- A unified and differentiable framework for optimizing the JPEG quantization table for both rate-distortion and rate-accuracy.

Method – Differentiable JPEG pipeline



Overview of the JPEG Compression Pipeline

JPEG pipeline:

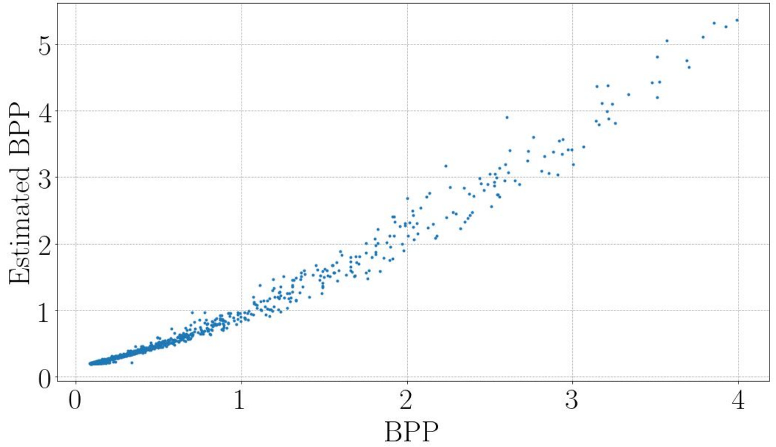
- Color conversion, Chroma down / up sampling, DCT are all differentiable.
- Quantization is approximated by *round*(x) - (x - *round*(x))^3[1].

[1] JPEG-resistant Adversarial Images, Shin, Richard, and Dawn Song, NeurIPS 2017 Workshop on Machine Learning and Computer Security.

Method – Differentiable Rate Estimation

$$B_q^l(\mathbf{x},\mathbf{p}) = \sum_{i=0}^{M}[E_{\theta^l_{DC}}(\mathbf{d}^l_{0,i} - \mathbf{d}^l_{0,i-1}) + \sum_{k=1}^{63} E_{\theta^l_{AC}}(\mathbf{d}^l_{k,i})],$$

- A differentiable entropy[2] model on the DCT coefficients.
- Separate rate model for Y/UV and DC/AC, since JPEG uses 4 huffman tables for each.
- DPCM (Differential Pulse Code Modulation) on the DC coefficients.



Estimated vs real JPEG compression rate

[2] Variational image compression with a scale hyperprior, Johannes Ballé, David Minnen, Saurabh Singh, Sung Jin Hwang, Nick Johnston, ICLR 2018

Method – Loss

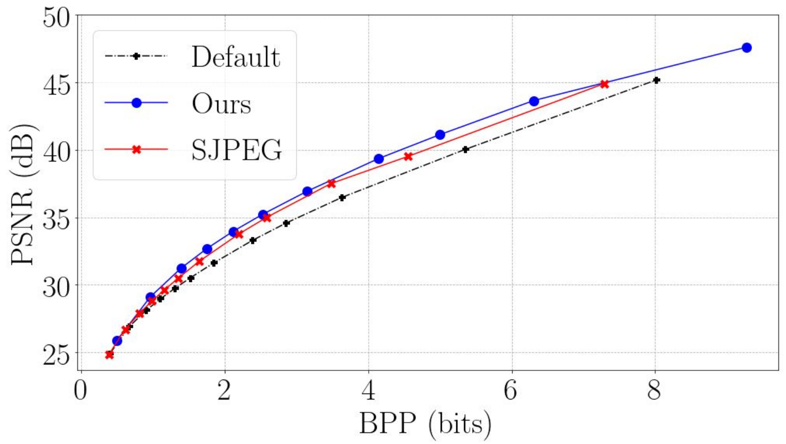
Training Loss:

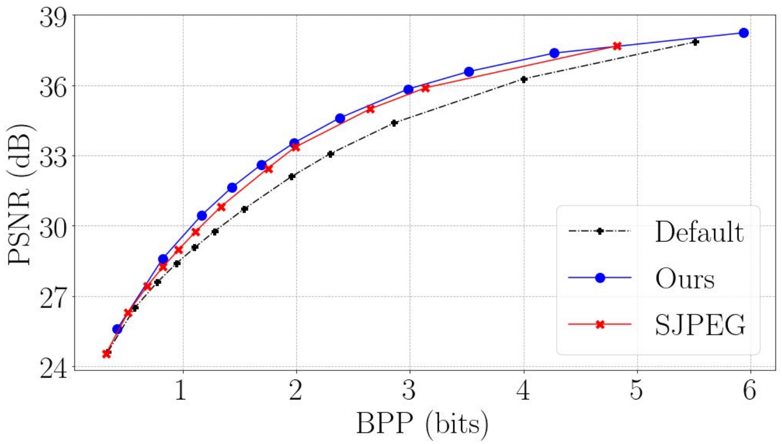
$$LOSS_{image}(\mathbf{p}) = c_r B_q(\mathbf{x}, \mathbf{p}) + c_d \left\| C_q(\mathbf{x}, \mathbf{p}) - \mathbf{x} \right\|_2^2 + c_c A \left[C_q(\mathbf{x}, \mathbf{p}), \mathbf{y} \right]$$

Components:

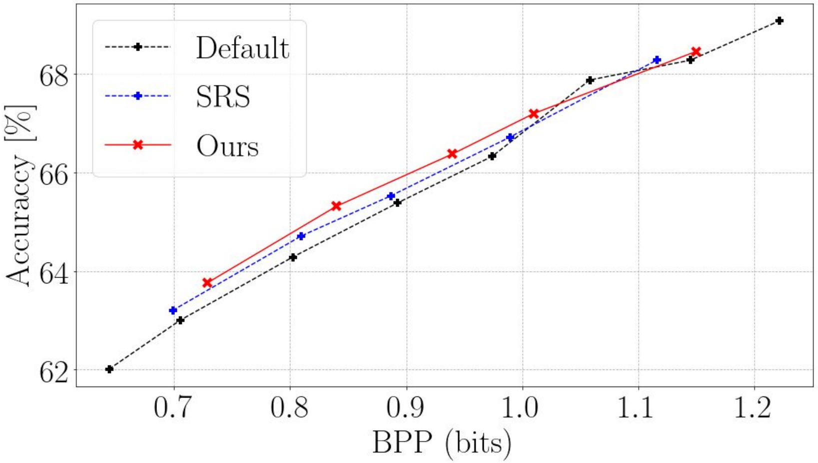
$B_q(\mathbf{x}, \mathbf{p})$	Differentiable rate estimator
$\left\| C_q(\mathbf{x}, \mathbf{p}) - \mathbf{x} \right\|_2^2$	L2 loss
$A \left[C_q(\mathbf{x}, \mathbf{p}), \mathbf{y} \right]$	Classification loss

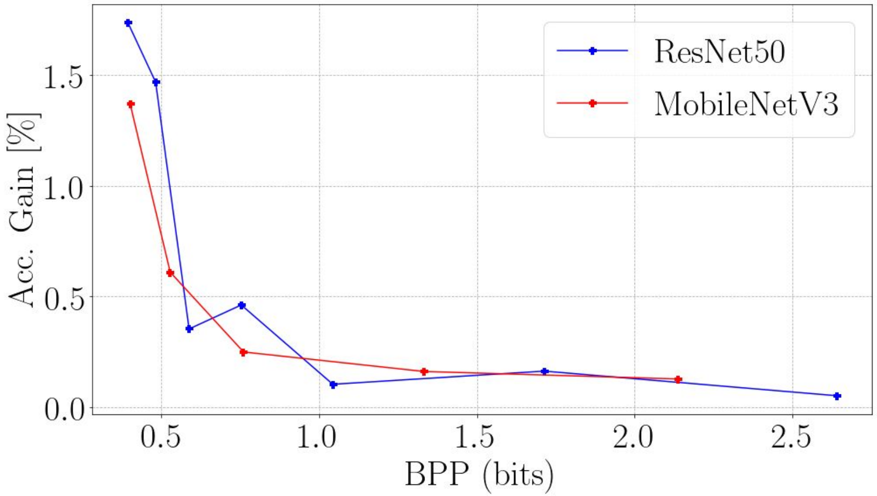
Results: Rate - Distortion





Results: Rate - Recognition





Quantization Tables

Luma

16	11	10	16	24	40	51	61
12	12	14	19	26	58	60	55
14	13	16	24	40	57	69	56
14	17	22	29	51	87	80	62
18	22	37	56	68	109	103	77
24	35	55	64	81	104	113	92
49	64	78	87	103	121	120	101
72	92	95	98	112	100	103	99

Chroma

17	18	24	47	99	99	99	99
18	21	26	66	99	99	99	99
24	26	56	99	99	99	99	99
47	66	99	99	99	99	99	99
99	99	99	99	99	99	99	99
99	99	99	99	99	99	99	99
99	99	99	99	99	99	99	99
99	99	99	99	99	99	99	99

Default Tables

Luma

16.0	15.3	14.8	15.4	16.2	18.0	19.1	20.0
15.5	15.1	15.2	15.6	16.3	19.9	19.8	18.9
15.4	15.1	15.3	16.1	17.8	19.5	20.6	18.7
15.2	15.4	15.8	16.4	18.8	22.7	21.5	19.2
15.4	15.7	17.4	19.3	20.4	24.9	23.9	20.6
15.9	17.0	19.1	19.8	21.5	23.9	24.6	22.0
18.6	20.0	21.3	22.0	23.6	25.4	25.0	22.7
21.0	22.8	22.9	22.9	24.2	22.6	22.7	22.1

Chroma

16.0	15.3	15.3	17.1	21.9	21.0	20.4	19.9
15.3	14.9	14.7	18.2	20.9	20.1	19.5	19.1
15.3	14.7	17.2	21.1	20.3	19.6	19.0	18.7
17.0	18.1	21.0	20.4	19.7	19.0	18.5	18.2
21.8	20.7	20.2	19.6	19.0	18.4	17.9	17.7
20.8	19.9	19.4	18.9	18.3	17.8	17.4	17.3
20.2	19.2	18.8	18.3	17.8	17.4	17.1	17.0
19.7	18.8	18.4	18.0	17.6	17.2	16.9	16.9

Learned Tables for Rate-Distortion