

CONDITIONAL AND RESIDUAL METHODS IN SCALABLE CODING FOR HUMANS AND MACHINES

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GOAL

We would like to **compose** the information required for tasks in a **scalable** fashion, in which base representations are **shared** among multiple tasks and only **incremental** amounts of information are required for more specific tasks.

CONTRIBUTIONS

- 1. Conditional and residual approaches in scalable image coding for humans and machines¹
- 2. Upper and lower baselines
- 3. Entropy model for conditional coding
- 4. Empirical results on semantic image segmentation and object detection

¹H. Choi and I. V. Bajić. "Scalable Image Coding for Humans and Machines". In: *IEEE TIP* 31 (2022), pp. 2739–2754.

RELATED WORK

- Dedicated and shared representations are concatenated and used as input for a target task
- · Results show considerable redundancy²

²E. Ozyilkan et al. "Learned Disentangled Latent Representations for Scalable Image Coding for Humans and Machines". In: *arXiv 2301.04183* (2023); Choi and Bajić, "Scalable Image Coding for Humans and Machines".

CONDITIONAL AND RESIDUAL APPROACHES

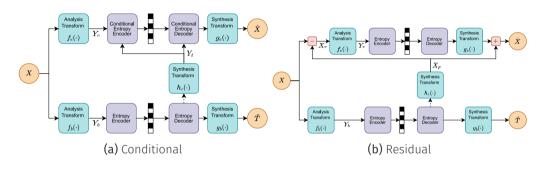


Figure 1: Overall architecture of the conditional and residual methods.

LOSSLESS BOUNDS FOR CONDITIONAL CODING

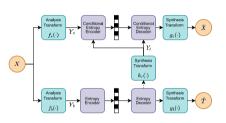
- We model $H(Y_b) + H(Y_c|Y_t)$
- · Lower bound:

$$H(Y_c) \le H(Y_b) + H(Y_c|Y_t). \tag{1}$$

- Tight when $H(Y_b) = I(Y_c; Y_t)$
- · Upper bound:

$$H(Y_b) + H(Y_c|Y_t) \le H(Y_b) + H(Y_c).$$
 (2)

• Tight when $I(Y_c; Y_t) = 0$

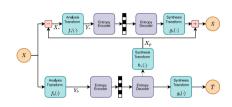


LOSSLESS BOUNDS FOR RESIDUAL CODING

Conditional coding is an upper bound of residual coding³:

$$H(X|X_p) \le H(X_r) = H(X|X_p) + I(X_p; X_r).$$
 (3)

 $I(X_p; X_r)$ acts as a penalty term.



³F. Brand, J. Seiler, and A. Kaup. "On Benefits and Challenges of Conditional Interframe Video Coding in Light of Information Theory". In: *PCS*. 2022, pp. 289–293.

BASELINES FOR SCALABLE CONDITIONAL AND RESIDUAL CODING

- · Rate-distortion bounds motivated by lossless bounds
- · Upper baseline Y_e generated without side information: $\hat{H}(Y_e) = R(D_{Y_e})$
- · Lower baseline as $\hat{H}(Y_b) + \hat{H}(Y_e)$
- Identical baselines for both approaches since $H(Y_c|Y_t) = H(Y_r)$ is easier to achieve

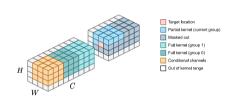
ENTROPY MODEL FOR CONDITIONAL CODING



Figure 2: Entropy model overview.

ENTROPY MODEL FOR CONDITIONAL CODING

- Model spatial-dimensional dependencies using an auto-regressive CNN
- Scaled residual connections and kernels sizes larger than 1 throughout
- Group channels with fixed size K and process them in parallel
- All reachable locations in the previous groups as context ⁴



⁴D. Minnen and S. Singh. "Channel-Wise Autoregressive Entropy Models for Learned Image Compression". In: *IEEE ICIP*. 2020, pp. 3339–3343.

LEARNABLE SCALABLE COMPRESSION

- · Small reconstruction penalty added to base layer RD objective:
 - · Allows reconstruction task to use more available information

$$\mathcal{L}_b = D_b + \lambda_b \hat{H}(Y_b) + \beta \mathbb{E}[d_e(\hat{h}_r(Y_b), X)]$$
 (4)

· Standard rate-distortion loss function for enhancement:

$$\mathcal{L}_{c} = D_{c} + \lambda_{e} \hat{H}(Y_{c}|Y_{t}), \qquad \qquad \mathcal{L}_{r} = D_{r} + \lambda_{r} \hat{H}(Y_{r})$$
 (5)

EXPERIMENTS

- · Semantic segmentation: Cityscapes; object detection: COCO 2017
- Train the base independently: $f_b(\cdot)$ and $g_b(\cdot)$ under various λ_b
- \cdot Pick single (good) base representation Y_b for conditional/residual setting
- · Upper baseline: reconstruction task with no side information
- · Lower baseline: upper baseline + base rate $\hat{H}(Y_b) + \hat{H}(Y_e)$

EXPERIMENTS

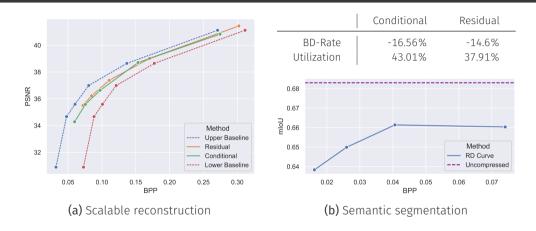


Figure 3: Rate-distortion curves for Cityscapes.

EXPERIMENTS

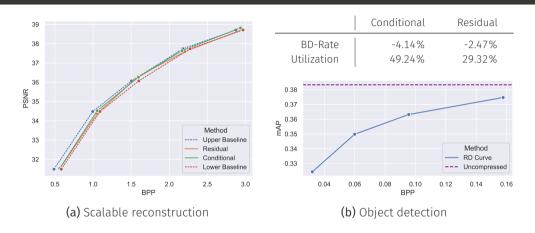


Figure 4: Rate-distortion curves for COCO.

CONCLUSION

- · Conditional and residual coding perform similarly using proposed design
- RD curves between presented baselines (operational bounds)
- Proposed conditional entropy model and small reconstruction penalty leads to improved utilization of side information

DERIVATIONS

Lossless lower bound:

$$H(Y_c) \le H(Y_c) + H(Y_t|Y_c) = H(Y_c, Y_t)$$

= $H(Y_t) + H(Y_c|Y_t) \le H(Y_b) + H(Y_c|Y_t).$ (6)

Lossless upper bound:

$$H(Y_b) + H(Y_c|Y_t) = H(Y_b) + H(Y_c) - I(Y_c; Y_t)$$

$$\leq H(Y_b) + H(Y_c). \tag{7}$$

Residual and conditional coding:

$$H(X|X_p) = H(X_r + X_p|X_p) = H(X_r|X_p)$$
 (8)

$$= H(X_r) - I(X_p; X_r) \le H(X_r) = H(X|X_p) + I(X_p; X_r). \tag{9}$$