COMET

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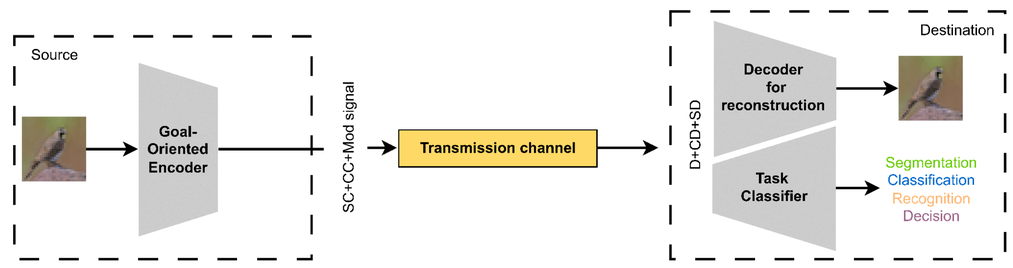
INTRODUCTION

Objectives of CoLearn/COMET: explore new compression methods for learning over compressed data. This is in line with current initiatives for novel compression standards, like JPEG AI and video coding for machine (VCM).

One of the main issues: how can we design new entropic coding techniques that allow the application of a learning task in the compressed domain, **without any partial decoding**? Usual entropy coding techniques (Huffman, arithmetic) indeed break the data structure.

In CoLearn, we demonstrate that using LDPC codes as entropy coders, together with GRU models, allows for image classification in the compressed domain.



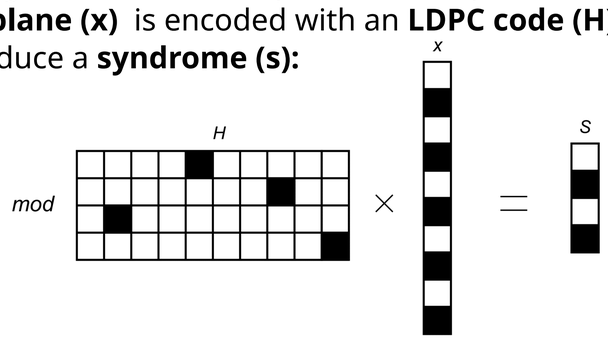
SC: Source Coding
CC: Channel Coding
Mod: Modulation

D: Demodulation
CD: Channel Decoding
SC: Source Decoding

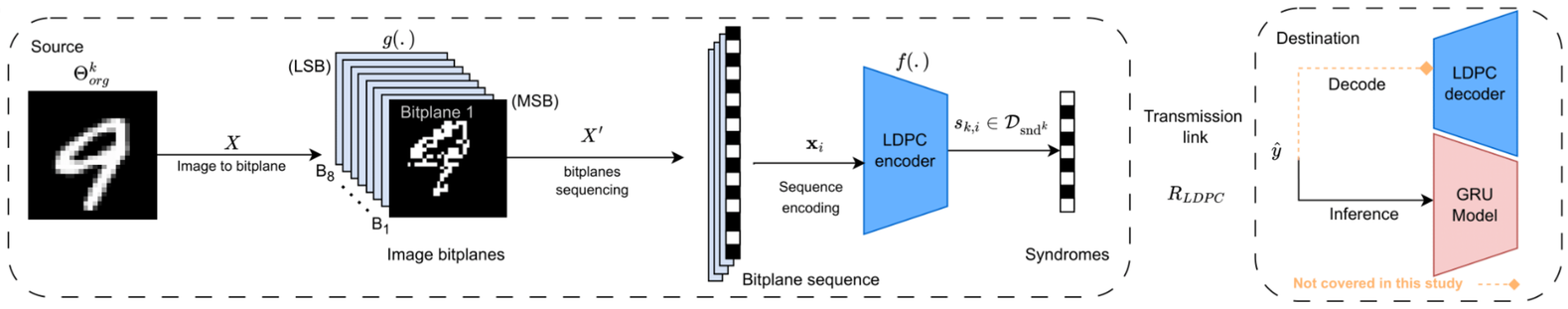
Encoding with LDPC codes

Key Idea: LDPC codes may better preserve the data structure than usual entropy coding techniques

Images are first decomposed into bitplanes, and each **bitplane (x)** is encoded with an **LDPC code (H)** to produce a **syndrome (s):**



Learning over LDPC-coded data



- We consider image compression with either LDPC codes alone, or DCT + quantization + LDPC codes
- We construct a dataset of syndromes and we train a learning model to classify the syndromes
- We consider a **lightweight GRU model** for learning, in accordance with recent works on Deep Learning for Maximum Likelihood decoding of channel codes

Numerical Results

With LDPC codes alone:

Dataset	Model	Without coding		On Original data (Setup1)		
		None	None MSB	Huff[1]	Arith[1]	LDPC
MNIST	**GRU12(proposed)**	0.9439	0.8842	-	-	0.8192
	GRU32(proposed)	0.9799	0.9154	-	-	0.8556
	UVGG11 [1]	0.9891	-	0.8323	0.6313	-
	URESNET18 [1]	0.9875	-	0.7450	0.5949	-
	FullyConn [2]	0.9200	-	-	-	-
Fashion -MNIST	**GRU12**	0.8616	0.8052	-	-	0.8166
	GRU32	0.8750	0.8314	-	-	0.8306
	UVGG11 [1]	0.9018	-	0.7634	0.6898	-
	URESNET18 [1]	0.8497	-	0.6862	0.6116	-
YCIFAR -10	**GRU12**	0.3127	0.3249	-	-	0.4070
	GRU32	0.3596	0.3560	-	-	0.4171
	UVGG11 [1]	0.5657	-	0.3606	0.2976	-
	URESNET18 [1]	0.3836	-	0.2591	0.2432	-
	FullyConn [2]	0.3800	-	-	-	-

With DCT + quantization + LDPC codes:

Dataset	Model	JPEG [1]	DCT -tr.[2]	J-L 8bp	J-L MSB	J-L MSB+1bp
MNIST	**GRU12(Proposed)**	-	-	0.9060	0.6548	0.8791
	GRU32(Proposed)	-	-	0.9237	0.6843	0.8849
	UVGG11 [1]	-	-	-	-	-
	URESNET18 [1]	-	-	-	-	-
	FullyConn [2]	-	0.90	-	-	-
Fashion -MNIST	**GRU12**	-	-	0.8332	0.5222	0.8325
	GRU32	-	-	0.8434	0.5395	0.8414
	UVGG11 [1]	-	-	-	-	-
	URESNET18 [1]	-	-	-	-	-
YCIFAR -10	**GRU12**	-	-	0.4234	0.1350	0.3537
	GRU32	-	-	0.4316	0.1403	0.3544
	UVGG11 [1]	0.3245	-	-	-	-
	URESNET18 [1]	-	-	-	-	-
	FullyConn [2]	-	0.30	-	-	-

Conclusions:
- Setup 1 is better in classifying coded images, with a 15% improvement for CIFAR-10 and 10% for Fashion-MNIST and MNIST.
- Setup 2 surpasses Setup 1 due to DCT's features.
- Learning on fewer bitplanes is possible, which allows better compression!
- Learning on the DCT coefficients sign biplane + the first bitplane gives results comparable to learning over original data
- The considers GRU models are of extremely low complexity, (70k weight vs. 80M weight for ResNet and VGG models over Huffman-coded data)

Objectives of the follow-up action

- In CoLearn and IoTAD-CEO, we have shown that **LDPC codes are also relevant for other learning tasks**: hypothesis testing, regression, clustering.
- we intend to consider an additional important learning task, that is **image retrieval over JPEG compressed data**
- Image retrieval consists of finding images, or parts of the images, similar to a request, in a dataset.

Working plan:
- Investigate image retrieval over JPEG-coded data, using LDPC codes as entropy codes
  - Identify relevant DL architectures adapted for this problem
- Develop a demonstrator in the form of a **universal JPEG coder** able to handle different learning tasks including classification, clustering, and image retrieval
- This demonstrator will be in the form of a Python code freely available on GitHub

References:
[1] Rémi Piau, Thomas Maugey, et Aline Roumy. Learning on entropy-coded images with CNN. 2023 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pages 1–5, 2023
[2] Ahcen Aliouat, Elsa Dupraz, Learning on JPEG-LDPC Compressed Images: Classifying with Syndromes, EUSIPCO 2024
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[5] Elsa Dupraz, K-means Algorithm over Compressed Binary Data, Data Compression Conference (DCC), Utah, United States, March 2018