

# View Reviews

## Paper ID

493

## Paper Title

DRASIC: Distributed Recurrent Autoencoder for Scalable Image Compression

## Track Name

First Round Submission

## Reviewer #1

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### Questions

#### 1. PAPER SUMMARY What is the paper about? Please, be concise (2 to 3 sentences).

Authors propose a new architecture, Distributed Recurrent Autoencoder for Scalable Image Compression, for distributed image compression from a group of distributed data sources.

#### 2. PAPER STRENGTHS Please discuss, justifying your comments with the appropriate level of details, the strengths of the paper (i.e. novelty, theoretical approach and/or technical correctness, adequate evaluation, clarity, etc).

Authors use data-driven approach to learn the dependencies with the neural network parameters, and applied DSC to image compression. Experimental results show that their method is effective.

#### 3. PAPER WEAKNESSES Please discuss, justifying your comments with the appropriate level of details, the weaknesses of the paper (i.e. lack of novelty – given references to prior work-, lack of novelty, technical errors, or/and insufficient evaluation, etc). Note: If you think there is an error in the paper, please explain why it is an error.

It lack theoretical analysis about low complexity encoding problem.

#### 4. RECOMMENDATION

Strong Accept

#### 5. JUSTIFICATION Justify your recommendation based on the strengths and weaknesses. Please be considerate to the authors and provide constructive feedback.

I am not familiar with this topic, so I almost have no confident.

#### 6. REVISION OPTION - QUESTION ONE If not accepted in this first round, should the paper be invited to resubmit a revised version of the paper? It would then be considered by the same reviewers and area chair. REVISION PREFERRED. Paper is close and does not need significant improvements.

#### 7. REVISION OPTION - QUESTION TWO Please clearly indicate the issues that you feel should be addressed in a revised version such that the paper could potentially be considered for acceptance.

No problem should be addressed.

## Reviewer #2

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### Questions

#### 1. PAPER SUMMARY What is the paper about? Please, be concise (2 to 3 sentences).

Summary: The authors propose a scheme for distributed image compression from a group of distributed data sources. We also show that by training distributed encoders and joint decoders on correlated data sources, the performance of compression is much better than that by training codecs separately. They also tie their main approach with a information theory (Slepian-Wolf Theorem) in Distributed Source Coding (DSC). They compare with traditional codecs and a prior art in learnt image compression Toderici et al.

#### 2. PAPER STRENGTHS Please discuss, justifying your comments with the appropriate level of details, the strengths of the paper (i.e. novelty, theoretical approach and/or technical correctness, adequate evaluation,

**clarity, etc).**

Strengths:

1. Authors tackle a challenging and an important problem. Good to see the authors tie their main contribution (DRASIC) to information theory principals in DSC (specifically Slepian-Wolf Theorem).
2. Overall, the paper is well written and easy to follow (barring missing citations).
3. The authors do a good job in running various experiments showing that distributed encoders can perform as well as a single encoder trained with all data sources together.
4. The proposed DSC framework is data driven and not hand-engineered which makes it amenable to different data sources.
5. The results look promising.

**3. PAPER WEAKNESSES Please discuss, justifying your comments with the appropriate level of details, the weaknesses of the paper (i.e. lack of novelty – given references to prior work-, lack of novelty, technical errors, or/and insufficient evaluation, etc). Note: If you think there is an error in the paper, please explain why it is an error.**

Weaknesses:

1. Main issue with this paper is the lack of proper experiments and lack of comparisons with related prior art. The main idea is encouraging but based on the results presented right now I have no way of telling if its better or worse than current image compression state-of-the-art (Lee et al. [1]).
2. One of the main contribution might not be true (correct me if I am wrong), but [9] show that using different importance maps they use a single model to achieve different compression rates without tuning. How is this different from [9] see page 10?
3. I tried to piece together the finer aspects of implementation and I feel the authors do not provide enough implementation details for an independent researcher to replicate the work and results.
4. Lots of missing citations [1-7] see below. Citation [8] missing Line 201
5. Lines 163-170. The authors completely forget to mention GAN based image compression papers.
6. Approach/Implementation:
  - a. Missing ablation studies (see points 6, 7, 8)
  - b. Authors seem to have used tanh activation. Tanh has a tendency of saturating the gradients at -1 or 1 leaving dead neurons early in the training. Do the authors have a comment on this? Why not relu or leakyrelu? What's the reason behind tanh?
  - c. Why no BatchNormalization?
  - d. PixelUnshuffle vs ConvTranspose vs maxpool. Since the authors introduce a new block PixelUnshuffle, I expect to see more justification on performance. Just stating that PixelUnshuffle is non-parametric is not sufficient.
  - e. Line 312, How many iterations?
  - f. Line 460, how do a single decoder decipher an image from multiple sources. Authors say they concatenate codes in quantized space in a batch.
  - g. Is there a rate-distortion loss function? Is there an entropy model? What sort of arithmetic coding was used for measuring compression?
  - h. Use of masks for variable bit-rate allocation [2-3]. That is missing from typical approach for learnt image compression prior art. In the absence of variable bit-rate allocation, how do the models know which regions of the image to allocate more/less bits? Or is this module irrelevant for this task?
7. Experiments:
  - a. Section 4, Lines 483-520. Not clear. So 2 datasets (MSNIST and CIFAR10) were used and tested on Kodak? But the authors say 10 sources (line 540). Do the train and test data sources need to be same? What if we have different number of data sources in test?

- b. Do each source (encoder) have the same architecture shown in Fig.2?
- c. The results are only compared with traditional codecs (jpeg, jpeg2k, bpg) and 1 learnt codec (toderici et al). Toderici is circa 2015/2016, more comparisons are needed with latest sota. Based on these numbers it looks like DRASIC is inferior (in terms of psnr@bpp) to current sota. If so, why would anyone prefer DRASIC?

#### 4. RECOMMENDATION

Weak Reject

**5. JUSTIFICATION** Justify your recommendation based on the strengths and weaknesses. Please be considerate to the authors and provide constructive feedback.

While the work is very interesting and results encouraging, it needs more work to be accepted into WACV 2020. Please refer to Weaknesses section

**6. REVISION OPTION - QUESTION ONE** If not accepted in this first round, should the paper be invited to resubmit a revised version of the paper? It would then be considered by the same reviewers and area chair. UNDECIDED between revision/reject.

**7. REVISION OPTION - QUESTION TWO** Please clearly indicate the issues that you feel should be addressed in a revised version such that the paper could potentially be considered for acceptance.

I am open to revising my score provided questions asked in Weaknesses section are addressed.

Reviewer #5

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### Questions

**1. PAPER SUMMARY** What is the paper about? Please, be concise (2 to 3 sentences).

This paper is about the distributed source coding (DSC). The basic idea is to learn a encoder-decoder framework to approach the limit of the Slepian-Wolf and/or Wyner-Ziv theory.

**2. PAPER STRENGTHS** Please discuss, justifying your comments with the appropriate level of details, the strengths of the paper (i.e. novelty, theoretical approach and/or technical correctness, adequate evaluation, clarity, etc).

The idea of investigating DSC in the deep learning era is interesting and worth exploring.

**3. PAPER WEAKNESSES** Please discuss, justifying your comments with the appropriate level of details, the weaknesses of the paper (i.e. lack of novelty – given references to prior work-, lack of novelty, technical errors, or/and insufficient evaluation, etc). Note: If you think there is an error in the paper, please explain why it is an error.

Though the basic idea in this paper is reasonable, the experiment setting is inaccurate and misleading to be viewed as a DSC problem.

First, DSC is the coding of two or more dependent sources with separate encoders and joint decoder. However, all the experiments use statistically-independent images as input sources (sampling from the same dataset doesn't imply any statistical dependency!), which are unreasonable in DSC setting.

Second, joint decoding doesn't imply the joint training of one decoder and multiple encoders, instead, it means the decoder should process all the encoded sources jointly, rather than processing them one by one in this paper.

#### 4. RECOMMENDATION

Strong Reject

**5. JUSTIFICATION** Justify your recommendation based on the strengths and weaknesses. Please be considerate to the authors and provide constructive feedback.

Given the inaccurate experiment setting/problem formulation, the proposed method is actually not related to a DSC problem, consequently the conclusions drawn in this paper are meaningless.

**6. REVISION OPTION - QUESTION ONE** If not accepted in this first round, should the paper be invited to resubmit a revised version of the paper? It would then be considered by the same reviewers and area chair. REJECT Preferred. Authors will need to submit a SUBSTANTIALLY IMPROVED version for review.

**7. REVISION OPTION - QUESTION TWO** Please clearly indicate the issues that you feel should be addressed in a revised version such that the paper could potentially be considered for acceptance.

Please refer to 3. PAPER WEAKNESSES