# View Reviews

**Paper ID**
110

**Paper Title**
DRASIC: Distributed Recurrent Autoencoder for Scalable Image Compression

**Reviewer #1**

## Questions

**1. Choose your review score**
Accept as a paper

**Reviewer #2**

## Questions

**1. Choose your review score**
Strong accept as a paper

**3. Comments for the authors. Mandatory if score is "Weak accept as a paper" or less.**
The authors present a very nice paper on a highly relevant topic.
There appears to be two contributions in the paper. 1) scalable or layered image coding based on DNNs, 2) distributed image coding based on DNN.

The authors emphasise that the system can handle any correlation, which is quite significant, since this is where existing model based scheme often fails.
The results are quite convincing.
I am perhaps missing a bit of details on the binarization step.

**Reviewer #3**

## Questions

**1. Choose your review score**
Accept as a poster, not as a paper

**3. Comments for the authors. Mandatory if score is "Weak accept as a paper" or less.**
This work proposes an autoencoder scheme for distributed source coding. The proposed technique uses a recurrent convolutional neural network permitting scalable lossy coding. At each iteration, the quantized bottlneck encoded from the residuals is transmitted progressively reducing the distortion. The correlations between the separate sources are exploited and codes are designed by training the entire batch using autoencoders. As all source correlation information is implicitly embedded in the autoencoders, no source synchronization is required, and this appears to be one of the greatest advantages of the proposed scheme.

The proposed method uses different encoders and a joint decoder to satisfy the requirements of distributed coding and the Slepian-Wolf setting. Moreover, using a single encoder and a single decoder (trained on the pooled data) is described as joint-source coding and considered to be the approximation of the theoretical upper bound. It is shown that the distributed coding performs close to the joint coding. As the proposed methodology is

learned compression, it is assumed that the codecs are designed offline using a training set. Once the encoders and the decoder are learned, they are deployed for coding. In such a scenario, containing different encoders in each source coder or containing the same encoder copy in each source should not make a difference. In both cases, sources encode separately and satisfy Slepian-Wolf setting. Therefore, a copy of joint-source encoders in each source will still be considered as distributed coding. This argument makes the proposal irrelevant. A claim that the encoders cannot communicate, thus they should be trained separately would require an online training scheme, which is not implied in the manuscript. This issue appears to be a major drawback of the study.