Colorization for Image Compression

Mohammad Haris Baig\textsuperscript{a},*  , Lorenzo Torresani\textsuperscript{a}

\textsuperscript{a}Hanover, New Hampshire. United States

Abstract

In this work we focus on the problem of colorization for image compression. Since color information occupies a large proportion of the total storage size of an image, a method that can predict accurate color from its grayscale version can produce dramatic reduction in image file size. But colorization for compression poses several challenges. First, while colorization for artistic purposes simply involves predicting plausible chroma, colorization for compression requires generating output colors that are as close as possible to the ground truth. Second, many objects in the real world exhibit multiple possible colors. Thus, to disambiguate the colorization problem some additional information must be stored to reproduce the true colors with good accuracy. To account for the multimodal color distribution of objects we propose a deep tree-structured network that generates multiple color hypotheses for every pixel from a grayscale picture (as opposed to a single color produced by most prior colorization approaches). We show how to leverage the multimodal output of our model to reproduce with high fidelity the true colors of an image by storing very little additional information. In the experiments we show that our proposed method outperforms traditional JPEG color coding by a large margin, producing colors that are nearly indistinguishable from the ground truth at the storage cost of just a few hundred bytes for high-resolution pictures!

Keywords: Colorization, Deep Learning, Image Compression.

1. Introduction

Learning to colorize grayscale images is an important task for three main reasons. First, in order to predict the appropriate chroma of objects in an image, a colorization model effectively learns to perform high level understanding from unlabeled color images. In other words, it learns to recognize the spatial extents and the prototypical colors of semantic segments in the picture. Since unlabeled photos are plentiful, colorization can be used as an unsupervised pretraining mechanism for subsequent supervised learning of high-level models for which labeled data may be scarce. Second, colorization can be useful for artistic pursuits by giving new life to grayscale vintage photos and old footage. Finally, colorization models can greatly help with image and video compression. Most objects cannot have all possible colors and by learning the plausible color space for each object we can more compactly encode the color information. In this work we focus predominantly on this last application of colorization, by learning parametric models of image colorization for image compression. We outline the challenges posed by colorization for image compression and propose a new deep architecture to overcome these hurdles.

Recent successful learning-based approaches \cite{2, 3} for automatic colorization operate under the regime of “zero cost,” i.e., they assume that the output color must be predicted from the input grayscale image without any additional storage expense. While this may be reasonable for generating artistic colorization automatically, it is not applicable for the purpose of image compression as many objects in the real world admit multiple plausible colors. The problem is exemplified in Table 7 where we report zero-cost colorization results for different methods as well as our approach. While some of the colors produced by these methods are realistic-looking, they are actually quite different from the ground truth (first column). In order to reproduce with high fidelity the true colors, we propose to store some additional information that helps to disambiguate between the choices (last column of Table 7).

To account for the multimodal color distribution of many objects we propose a convolutional neural network (CNN) that takes as input a grayscale photo and outputs $K$ plausible color values per image pixel, where $K$ is treated as a hyper-parameter defining the complexity of the model. The multiple outputs are produced by using a CNN structured in the form of a tree, with a single trunk splitting at a given depth into $K$ branches, each generating a candidate color per pixel. The trunk contains convolutional layers that compute shared features utilized by all branches, while each individual branch predicts a distinct plausible color mode for each pixel. We study how to use this architecture both in the zero-cost setting as well as for compression. In the zero-cost setting, we train the network to choose one of its $K$ candidates outputs at ev-
Table 1: We show visualizations generated by our proposed low-cost framework and JPEG color coding [1] (for JPEG we report the storage space required to compress only the color channels). Our approach, produces vibrant realistic looking images at only about 1/6th the storage requirements of JPEG. 

| Image | JPEG [1] | Our approach |
|-------|----------|--------------|
| ![Image](image1.png) | ![Image](image2.png) | ![Image](image3.png) |
| 1,207 bytes | 192 bytes | 338 bytes |
| ![Image](image4.png) | ![Image](image5.png) | ![Image](image6.png) |
| 1,104 bytes | 198 bytes | 383 bytes |
| ![Image](image7.png) | ![Image](image8.png) | ![Image](image9.png) |
| 1,170 bytes | 195 bytes | 279 bytes |
| ![Image](image10.png) | ![Image](image11.png) | ![Image](image12.png) |
| 1,207 bytes | 192 bytes | 338 bytes |

In summary, the contributions of our work are as follows:

1. We introduce a tree-structured network architecture that can produce multiple plausible colorization of an input grayscale picture.
2. We discuss how we can apply this model for zero-cost colorization, where the objective is to produce a single color hypothesis. We show that our approach is competitive with existing algorithms in this field.
3. We describe how we can leverage the multimodal output of our CNN to perform highly effective image color compression, which corresponds to the case of non-zero cost colorization. In this regime, we study approaches that can be used to generate varying trade-offs between color fidelity and image size.

2. Background

In order to understand the position of our work we begin with a discussion of the literature in the field in two parts. First we discuss existing "zero-cost" colorization approaches and how our proposed approach handles challenges of the zero-cost colorization task differently. Then,
we compare our approach to existing colorization for compression approaches and provide a brief overview of the benefits of our approach.

A recent trend in zero-cost colorization based approaches involves the use of deep learning to learn models from images annotated with class labels indicating the objects present in the photos, such as traditional datasets for image categorization. Examples of this category are the work of Dahl [4], Zhang et al. [2] Larson et al. [3] and Iizuka et al. [5]. These approaches learn features from grayscale images that are useful for producing colors. In contrast Cheng et al. [6] learn a network for colorization on top of existing feature descriptors. These methods leverage deep networks pretrained on the task of object categorization in one way or another. Only some of these methods [2, 3] handle multi-modality of image colors explicitly by predicting probability distributions over a quantized output space.

These modern parametric models are in contrast to the previously popular “color transfer” methods such as Charipat et al. [7] and the recently proposed framework of Desphande et al. [8]. Color transfer based methods work by finding color images similar in content to a grayscale testing input in a large database and transferring color from these reference images by using local features. Such approaches address the issue of multi-modality of color output by relying on finding example images in large databases with color distributions similar to the ground truth color image. An optional step in such methods is to use a color histogram (semantic class specific or from the ground truth) to explicitly match color distributions in the colorized output with those from the example images. In addition to these, approaches have also been proposed that use human annotation to identify color seeds or image regions. Chia et al. [9] use hand labeled image regions from gray scale images to search the internet for similar semantic content and to identify plausible colorizations. Levin et al.’s [10] original work also proposed the use of human labeling of color seeds which would be propagated to non-seed pixels for dense color output.

Our approach differs from existing “zero-cost” colorization approaches in our treatment multi-modality of colors of objects in the real world. We use a tree structured network which branches at the end to predict multiple color hypotheses per pixel. Our model is trained to reproduce exact color as opposed to “color classes” as was done by Larson et al. [3] and Zhang et al. [2]. Other learning based approaches [6, 5, 4] do not explicitly handle the multi-modality of color outputs. To produce a final zero-cost colorization we train a separate module to identify the most plausible coloring from the hypotheses as a secondary step.

We now discuss existing approaches to the colorization for compression problem. Some of the colorization for compression methods [11, 12] operate by storing the true colors of a small subset of pixels (the “seeds”) and then apply color propagation techniques [10] to extend color information to all the other pixels in the image. Egge et al. [13] propose a low-cost colorization method based on fitting a parametric regression model to each grayscale patch of the image to predict its colors. The parameters are stored and used at decoding time to generate the colors.

Our work differs from existing colorization for compression approaches in our approach’s ability to generate meaningful color hypotheses by an analysis of semantic content of the image as opposed to storing the exact color for a set of pixels.

The most similar method to our proposed work is the recent unpublished work of Larson et al. [3] in which the authors use a deep network to learn how to colorize images and also show that they can leverage ground truth color histogram information to improve their zero-cost results. Our work differs from this [3] method in two ways. First, we learn to model exact colors as opposed to predicting from one of the many choices in a quantized output space. Second, we train our model to produce multiple “equally likely” color hypotheses with our branched architecture which can later be ranked with a separate module for zero-cost colorization. Furthermore, we also show how to use the multiple outputs of our model with minimal ground truth information to solve the colorization for compression problem with substantial improvements over the color coding module of the most widely used image compression codec, jpeg [1].

3. Technical Approach

We adopt a two-step approach for image compression via colorization. First we use our proposed branched deep network to generate multiple color hypotheses per-pixel. Second, we specify how to compactly store the best hypothesis at a per-pixel level so as to produce low-cost colorization at inference time.

We start by formally defining our colorization problem. Colorization entails generating a color image from a grayscale image. We assume we are given a training set of $N$ examples, where $I_G^{(i)} \in \mathbb{R}^{H \times W}$ represents the grayscale version of the $i$-th training image and $I_C^{(i)} \in \mathbb{R}^{H \times W \times 2}$ contains its two color channels. Our task is to estimate $I_C^{(i)}$ from $I_G^{(i)}$.$I_C$ and $I_G$ can be represented in many different ways. Cheng et al. [6] make use of the YUV color space. Desphande et al. [8], Larson et al. [3], Zhang et al. [2] and Iizuka et al. [5] adopted the LAB color space. Since our work is geared towards image compression, we make use of the $YCbCr$ color space, which is more commonly used by image compression architectures.

We begin by considering a potential learning objective for our colorization task. The goal is to learn a model $F(\theta)$ parameterized by weights $\theta$ that can be used to predict the color channels associated with the grayscale input, i.e., such that $F(I_G; \theta) \approx I_C$. A seemingly natural choice for the learning objective is the sum of squared $L2$
In order to address the inherent ambiguity of colorization, we propose a network architecture that predicts $K$ color hypotheses per pixel. This is achieved by means of a CNN whose single trunk splits at a certain depth into $K$ distinct branches, each outputting a 2 channel color output per pixel. All layers, both in the trunk as well as in the $K$ branches, are fully convolutional. The rationale behind this architecture choice is that it allows us to express the multimodal plausible colors of many objects in the real world with a reduced number of parameters. Rather than training $K$ distinct networks, which would require a huge number of parameters and would have large computational cost, a single tree-structure network with a shared trunk (capturing common features) is parsimonious both in terms of storage as well in terms of training cost. Furthermore, a single optimization (as opposed to disjoint training of separate networks) assures that the $K$ branches will naturally diversify in order to cover the multimodality of the output. Figure 1 illustrates the proposed branched architecture.

The hyperparameter $K$ controls the complexity of our model. Its appropriate value depends on the number of color modes exhibited by most objects in the real world. The greater the value of $K$, the higher the number of color hypotheses that the model can express. But a higher value of $K$ also increases the number of parameters that must be learned. In the experiments we report empirical evaluations for various values of $K$.

The question is: how do we train this multi-output architecture given that for each training grayscale input $I_G^{(i)}$ we are only given one color version of it, its ground-truth color channels $I_C^{(i)}$? We assume that the color of each pixel in $I_C^{(i)}$ must be generated by one of the $K$ branches. But different pixels may be generated by different branches. In other words, the color of each pixel is generated independently from the others. During each iteration of training, for each image in the mini-batch we perform forward propagation through all branches to produce $K$ color values per pixel. Then, we assign to each pixel the branch that best approximates the color of that pixel. Finally, the backpropagation update for that pixel will only change the

distances between predicted color values and the ground truth, i.e.,

$$E(\theta) = \sum_{i=1}^{N} \sum_{(x,y)} ||F(I^{(i)}_G; \theta)|(x,y) - I^{(i)}_C|(x,y)||^2_2 \quad (1)$$

This objective guides the model to learn that only $I^{(i)}_C$ is the correct color estimate for a given input $I^{(i)}_G$. However, we know that this is not true based on our observation of the real world where many objects have multimodal color distributions. Our experiments suggest that a model trained with this objective learns to reproduce fairly well the colors of objects that have unique or characteristic chroma, such as the sky. But this model is reluctant to predict vibrant color hypothesis for objects that do not have a single prototypical chroma. In such cases the model avoids committing to a clear response and instead tends to predict an “average color” that has small L2 distance from most possible values. This phenomenon is clearly visible in the comparative analysis between different approaches shown in Table 7. The second column shows the results achieved with the system of by Dahl [4], which uses a model minimizing Eq. 1. This leads to "grayish" estimates on highly multimodal color regions such as clothing but predicts correct colors in regions showing little variance as can be seen in the almost correct reproduction of the sky and grass.

3.1. Learning Multiple Color Hypotheses with Branching

In order to address the inherent ambiguity of colorization, we propose a network architecture that predicts $K$ color hypotheses per pixel. This is achieved by means of a CNN whose single trunk splits at a certain depth into $K$ distinct branches, each outputting a 2 channel color

Figure 1: High-level illustration of our tree-structured network architecture. Each branch outputs one color value per pixel. This allows our model to produce $K$ hypotheses per pixel. The branch predictor estimates the best performing branch for every pixel. This can be used for zero-cost colorization, in the scenario where a single color output must be predicted.
branch assigned to the pixel. Thus, the loss optimized by our model is of the form:

$$
\hat{E}(\theta) = \sum_{i=1}^{N} \sum_{(x,y)} \min_{j=1,...,K} \|F_j(I_G^{(i)}; \theta) - I_C^{(i)}(x,y)\|_2^2
$$

(2)

where $F_j(I_G^{(i)}; \theta)$ represents the color output produced by the $j$-th branch in our network. Note that this training scheme allows us to learn models without manual assignment of pixels to branches. Although we update a single branch for every pixel, because every mini-batch contains several images, each consisting of many pixels, in practice we typically update all branches in every mini-batch iteration. A similar scheme of training was adopted by VonDrick et al. [14] to learn to anticipate multiple hypotheses of future actions from unlabeled video.

Note that while a single-branch architecture will tend to predict bland “average colors” for ambiguous regions (in an attempt to keep the L2 error low), our model will naturally exploit the multiple branches to produce a diverse set of color hypotheses representing distinct color interpretations of the objects. This can be seen in Table 2 where we visualize the color image produced by each branch. It can be noted that the branches generate diverse outputs covering multiple color hypotheses for the objects in the image.

### 3.2. Image Compression via Low-Cost Colorization Oracle

We now consider how to leverage our pretrained model for colorization to perform color compression. Note that in the compression regime we are allowed to store some additional information in order to reproduce the original color of the image. A simple solution is to store an index to the branch that best approximates the color at every pixel. This allows us to encode (approximately) the color of an image by storing $O(\log_2 K)$ bits per pixel in addition to the grayscale version of the image $I_G$. Then at decoding time, we pump the grayscale version of the image through the network to produce the $K$ color outputs and use the stored branch indices to select the appropriate branch for every pixel. In the context of compression, we see that the value of $K$ influences the storage required per pixel. With fewer branches we get improved compression as fewer bits are needed to store the branch index; but with a greater number of branches we get improved reconstruction capability.

We refer to the procedure of selecting the best branch per-pixel by looking at the ground truth as using an “oracle”. We note that the oracle encodes for each pixel the branch that best approximates the channels ($C_b$ and $C_r$) jointly. This is a design choice we made supported by experiments where we found that this strategy produces nearly the same error as when storing the best branch for each channel separately, but it allows us to save half of the information, thus producing a huge saving in storage.

As can be noted from the results in Figure 3 our oracle can approximate the true colors with low error, at the expense of a small additional storage.

### Compact Lossy Encoding of the Oracle

Table 2 shows in the second column the oracle encoding of the best branch for a few image examples. It can be observed that the oracle branch-index maps exhibit high spatial coherence. This happens because the best branch for nearby pixels is often the same branch. This suggests that in order to save storage, rather than saving the best branch index for every pixel, we can store the best branch index per-region or per-patch. Specifically, given a region, we store the index of the branch that yields the best color recon-

| Image | Oracle | Small | Large | Small | Large |
|-------|--------|-------|-------|-------|-------|
| ![Image](image1.png) | ![Oracle](oracle1.png) | ![Small](small1.png) | ![Large](large1.png) | ![Small](small1.png) | ![Large](large1.png) |
| ![Image](image2.png) | ![Oracle](oracle2.png) | ![Small](small2.png) | ![Large](large2.png) | ![Small](small2.png) | ![Large](large2.png) |

Table 2: The second column shows the oracle encoding in the form of a colormap of the branch indices. Columns 3-6 represent various approximations to the oracle encoding by exploiting region coherence, based on a subdivision of the image into cells (columns 3-4) or segments (columns 5-6). Above each encoding we state the size in bytes required to store the decisions with the choice of encoding.
Table 3: We show the output from each of the branches when presented with a grayscale input. As can be seen, the branches estimate various plausible colors for objects such as grass and sky within the image which reflect variations in these objects observed in the training set.

Table: GrayScale Input | Branch 1 | Branch 2 | Branch 3 | Branch 4 | Branch 5
---|---|---|---|---|---

struction with respect to the ground truth in that entire region (i.e., the branch yielding the lowest mean squared error (MSE) in the region). We consider two ways of defining regions for compression: (1) a subdivision of the image into a grid of fixed-size square cells and (2) a segmentation of the grayscale photo into superpixels using traditional bottom-up segmentation methods [15, 16]. Obviously, the higher the number of regions, the more accurate the encoding of the oracle will be.

Columns 3-6 of Table 2 show the effectiveness of these approaches in approximating the oracle encoding for various sized representations. Details about the grid subdivision and the segmentation methods used to partition the image into regions are provided in the experimental section.

Global Correction. We found experimentally that the color maps produced by our models can be dramatically improved by applying a global correction with respect to the ground truth color. The global correction corrects for a similarity transform (scale and translation) between the ground truth and the estimate. In a compression scenario, we can simply store these 4 global parameters (2 for each color channel) and use them to produce more accurate color reconstructions at decoding time.

3.3. Zero-Cost Colorization

Although we designed our model to operate in the scenario of image compression under the regime of low-cost colorization, we now show how to use it to perform zero-cost colorization. In zero-cost colorization we are asked to produce the most plausible color version of the input grayscale image \( I_G \). How can we do this with our multiple-output network? A simple solution would entail choosing arbitrarily one of the \( K \) color outputs \( F_j(I_G; \theta) \) for \( j = 1, \ldots, K \). A better strategy instead is to attempt to predict the best branch to use for each pixel, given that training was also done under this scheme. This is effectively a multi-class classification problem, where for each pixel \((x, y)\) of \( I_G \) we are asked to output the best branch label \( b(x, y) \in \{1, \ldots, K\} \).

To perform this branch prediction we add a separate component to the network outlined above. This component is illustrated in Figure 1. The prediction component takes as input the feature maps from the \( K \) branches and it is trained to predict a 1-hot vector encoding of the oracle. We train this additional component with the multinomial logistic loss per pixel.

4. Experiments

We evaluate our approaches for colorization of images on two datasets, CIFAR100 [17] and Imagenet [18]. CIFAR100 is small enough (50,000 training and 10,000 testing examples) that it allows us to test various incarnations of our models but at the same time it is diverse enough (containing examples from 100 classes) for the conclusions drawn to be meaningful. The downside of using CIFAR100 is that images are quite small (32 × 32) and span fewer classes. Thus it is difficult to tell how the results scale with respect to higher-resolution images and more varied content. We use the Imagenet [18] dataset as a more realistic benchmark where images are of higher resolution and span 1000 object classes.

We evaluate the ability of our models to estimate the ground truth chroma channels \( I_C \) given the intensity channel \( I_G \). To quantify reconstruction quality of the estimated chroma channels we measure the mean squared error (MSE) on the chroma space. Since the end objective is to get good quality output images in the RGB space, we also evaluate the PSNR metric (measured in dB) of our estimated color image on the RGB output space. For decisions pertaining to encoding, we also evaluate with respect to the MS-SSIM [19] metric which is known to have strong correlations with human perception of quality. Note that MSE is measuring error, thus the lower the better. Instead PSNR and MS-SSIM measure quality, thus the higher the better.
Tables A.8 and A.9 outline the architectures that were used to train our proposed model for estimating colors on the two datasets and also the details on how learning was performed.

4.1. Zero-Cost Colorization

We begin by assessing different design choices and hyperparameters of our model in the context of zero-cost colorization.

Branching Factor. We start by studying the impact of the branching factor in the context of a single color prediction (zero-cost colorization). To produce a single hypothesis from the multiple branches, here we use our trained branch predictor. On one hand, we expect that increasing the branching factor will allow our colorization model to better fit multimodal color hypotheses. But on the other hand having more branches makes life hard for the predictor which needs to select the best branch for every pixel to produce the final output. This interpretation is confirmed by the results listed in Table 3 which reports colorization performance of our models on the CIFAR100 testing set. The “Branch prediction accuracy” reports the percentage of times the method chooses the branch yielding the minimum error. It can be seen that when using only 1 branch the performance is poor despite no ambiguity in the selection of the branch. This model underfits the data, as it cannot represent multiple color modes. Conversely, a model with high branching factor (e.g., 7) does poorly because of the challenge posed by selecting the correct branch out of many. The best performance is obtained for a balanced trade-off between these two risks, achieved with an architecture of 5 branches.

Table 4: Understanding the role of branching for zero-cost colorization on the CIFAR100 dataset. Accuracy measures the percentage of correct branch predictions made. The 3,5,7 Branch networks are trained with the branch predictor.

| Architectures | MSE | PSNR | Branch prediction accuracy |
|---------------|-----|------|---------------------------|
| 1 Branch      | 219.02 | 23.72 | 100                        |
| 3 Branches    | 213.62 | 23.68 | 54.61                      |
| 5 Branches    | 210.85 | 23.94 | 56.62                      |
| 7 Branches    | 214.63 | 23.13 | 36.96                      |

Learning from Scratch vs Fine-Tuning. Colorization is a task that requires high level reasoning. While the results in Table 4 were obtained by training the network from scratch for the purpose of colorization, it is interesting to study whether performance can be boosted by fine tuning the model from a deep network trained for high level reasoning tasks (e.g., image classification).

Table 5 shows results on both CIFAR100 and ImageNet when learning from scratch (LFS) as well as when fine-tuning (FT) the weights of our model from a network pretrained on image categorization. When fine-tuning we initialize the trunk with the weight of the pretrained categorization model. Then we add to this component layers that perform upsampling for dense prediction and the K branches. The upsampling layers and the branches are initialized with random weights. Further details of the categorization pretraining procedure are given in Tables A.8 and A.9.

Whereas for single branch architectures, fine-tuning can help achieve better results, for the K-branch architectures proposed in this paper, the advantage of fine-tuning is minimal.

Table 5: Understanding the role of learning from scratch (LFS) vs fine tuning (FT) a pretrained categorization architecture for the purpose of zero-cost colorization.

| Architectures | MSE | PSNR |
|---------------|-----|------|
| CIFAR100      |     |      |
| 1 Branch-LFS  | 219.02 | 23.72 |
| 1 Branch-FT   | 192.44 | 24.19 |
| 5 Branch-LFS  | 210.85 | 23.94 |
| 5 Branch-FT   | 250.28 | 23.64 |
| Imagenet      |     |      |
| 5 Branch-LFS  | 232.64 | 23.13 |
| 5 Branch-FT   | 194.12 | 23.72 |

Comparison to the State-of-the-Art in Zero-Cost Colorization. We now perform a quantitative and qualitative comparison of our approach against various recently introduced methods for zero-cost colorization utilizing the large-scale ImageNet dataset. The training is performed on the entire Imagenet dataset and testing is done on the Imagenet-10k benchmark introduced by Larson et al.

Table 6 summarizes the quantitative results on the zero-cost colorization task. The first two rows corresponds to weak baselines intended to help us understand the difficulty of the colorization task on this benchmark. The first row shows performance obtained by predicting the constant average chroma irrespective of the input. The average is calculated per-pixel over the entire training set. The second row makes use of ground-truth class labels and outputs for each test image the per-pixels color average computed from the training examples belonging to the class of the input image. This baseline is useful as the colors in the image are strongly correlated to the category information.

Based on the two studies above, for this experiment we used a network with K = 5 branches fine-tuned from the pretrained categorization model of He et al. [20]. We can observe that, although zero-cost colorization is not the focus of our work, our model with branch prediction is actually outperforming the recent approaches of Dahl [4] and Zhang et al. [2], which were designed for this task. Our method is a close second behind Larson et al. [3].
Table 6: Evaluation of various approaches for zero-cost colorization on the Imagenet-10k benchmark proposed by Larson et al. [3]. The table evaluates the performance of the networks in their relative ability to reproduce the original color image from its grayscale version.

| Architectures | MSE | PSNR |
|---------------|-----|------|
| Per-Pixel Average Chroma Over all Classes | 225.34 | 22.78 |
| Class-Specific Per-Pixel Average Chroma | 198.70 | 23.26 |
| Dahl [4] | 199.17 | 22.88 |
| Larson et al. [3] | 154.69 | 24.80 |
| Zhang et al. [2] | 270.17 | 21.58 |
| Ours - 5 branches w/ branch predictor | 194.12 | 23.72 |

We now turn to a qualitative analysis of our results. In table 7 we show how different approaches perform when tasked with colorizing certain images. We can see that our zero-cost colorization with branch prediction is able to generate accurate colors for objects whose chroma is unambiguous (e.g., grass or road). In some cases it can produce plausible colors for objects that have multiple possible coloring although the plausible output may differ from the ground truth. For example ..... In the last column of the Table we show the output produced by our low-cost encoding scheme, which is able to approximate with high-fidelity the true colors for all objects contained in the example images. This illustrates the importance of adopting a non-zero cost framework if the intended objective is compression.

4.2. Low-Cost Colorization for Image Compression

In this subsection we study our approach in the regime of low-cost colorization for image compression.

Lossy Encoding of the Oracle. In order to reduce storage space, we proposed to perform region-based approximations of the oracle encoding. Figure 2 shows PSNR achieved for three different methods for defining regions: SLIC [16], QuickShift [15] and a regular grid. The first two are segmentation methods that take as input the intensity image \( I^{(i)} \) and subdivide it into segments according to low-level cues (similar grayscale intensity values in nearby pixels). The figure also shows the impact of varying the size of the regions. For the segmentation methods, the number of regions is varied by adjusting hyperparameters (region size and spatial regularization for SLIC and ratio of intensity to spatial localization, kernel size for computing similarity and maximum distance to search in for neighbors with Quickshift). We can see that SLIC tends to perform the best out of the three proposed methods. As we are performing compression, storing which of these three methods to use requires fairly low cost. Thus, we also denote on the figure an overall method "Combined" which selects the best of the three methods for a given encoding size. We note that the encoding the oracle without the region-based approximations would require a storage space of 4490 bytes. The oracle yields a PSNR of 30.89 (dB) Thus, overall the region-based encodings provide orders of magnitude savings in space at very little loss in quality.

Figure 2: We show how various methods for encoding the oracle in a lossy fashion perform with respect to each other. The combined curve shows the maximum benefit that can be achieved by using these three approaches in conjunction.

Trading-Off Size vs Quality for Image Compression. In this section we consider several schemes of colorization for image compression and their ability to generate different quality levels by varying the storage size. Training was done on the entire Imagenet dataset and testing was performed on the Imagenet-10k benchmark introduced by Larson et al. We include in this analysis both zero-cost and low-cost approaches. Note that while He et al. [12] and Cheng et al. [11] have also proposed methods for low-cost colorization, we are unable to include them in this comparison as neither code nor predictions have been released for these systems. We include JPEG compression applied to only the color channels. For our oracle encoding, we used DPCM (Differential pulse-code modulation) followed by Huffman encoding [21] in order to perform lossless compression. We also include results based on lossy encoding of the oracle using our image region decompositions (described in section 3.2). For all our models we used a 5-branch architecture fine tuned from the pretrained categorization network described in Appendix A.
Table 7: Qualitative comparison of the recently proposed deep architectures for image colorization with our zero-cost and low cost predictions.

| Original | 1 | 2 | 3 | Ours zero-cost | Ours low-cost |
|----------|---|---|---|----------------|---------------|

The curve denoted as “ours: low-cost” corresponds to a selection of the best candidate from the various lossy encoding schemes considered (SLIC, QuickShift, Grid). For this system, the size corresponding to the encoding of an image includes the bits needed for storing which lossy method is being used, its associated hyperparameter settings for generating regions of a certain size and global correction parameters in addition to the branch index for each region. We observe that our method is by far the best in the extremely low file-size regime. For the same quality,
it is several order of magnitude more compact than JPEG.

5. Future Work

In this paper we explored low-cost colorization for image compression using deep learning methods. The key idea behind our approach is the use of multi-branch architecture that allows us to represent the multi-modality of colors exhibited by many objects in the real world. Such architecture is well suited to be used in image compression scenarios: it is sufficient to store for each pixel a branch indicator denoting the best branch for the color output. We refer to this encoding as the oracle. We further improve on this scheme by presenting algorithms that leverage the spatial coherence of the oracle output to compactly approximate it via image subdivision. We demonstrate that the resulting system outperforms traditional JPEG color coding by a large margin, producing colors that are nearly indistinguishable from the ground truth at the storage cost of just a few hundred bytes for high-resolution pictures. Although our system was not designed to address the problem of zero-cost colorization (i.e., producing a single color hypothesis given a grayscale input without additional information being stored), our experiments indicate that our zero-cost variant is comparable to the best systems in this field. In the future we plan to investigate architectures that yield similar compression gains for images in the high-quality regime. We also intend to study reliable metrics for understanding the color reproduction problem. Finally, we are interested in using our colorization models learned from unlabeled images either as a pretraining mechanism or as an auxiliary task for high-level image understanding methods.

6. Acknowledgments

This work was funded in part by NSF CAREER award IIS-0952943 and NSF award CNS-120552. We gratefully acknowledge NVIDIA for the donation of GPUs used for portions of this work. We thank Karim Ahmed and Du Tran for numerous helpful discussions. We are also thankful to Larson et al. [3] for providing clarification about their work.

References

[1] G. K. Wallace, The jpeg still picture compression standard, Consumer Electronics, IEEE Transactions on 38 (1) (1992) 30–37.
[2] R. Zhang, P. Isola, A. A. Efros, Colorful image colorization, arXiv preprint arXiv:1603.08511.
[3] G. Larsson, M. Maire, G. Shakhnarovich, Learning representations for automatic colorization, arXiv preprint arXiv:1603.06066.
[4] Automatic colorization, http://tinyclouds.org/coloreize/accessed: 2016-05-13.
[5] S. Iizuka, E. Simo-Serra, H. Ishikawa, Let there be Color!: Joint End-to-end Learning of Global and Local Image Priors for Automatic Image Colorization with Simultaneous Classification, ACM Transactions on Graphics (Proc. of SIGGRAPH 2016) 35 (4).
[6] Z. Cheng, Q. Yang, B. Sheng, Deep colorization, in: The IEEE International Conference on Computer Vision (ICCV), 2015.
[7] G. Charpiat, M. Hofmann, B. Schölkopf, Automatic image colorization via multimodal predictions, in: Computer Vision–ECCV 2008, Springer, 2008, pp. 126–139.
[8] A. Deshpande, J. Rock, D. Forsyth, Learning large-scale automatic image colorization, in: ICCV, 2015.
[9] A. Y.-S. Chia, S. Zhuo, R. K. Gupta, Y.-W. Tai, S.-Y. Cho, P. Tan, S. Lin, Semantic colorization with internet images, in: ACM Transactions on Graphics (TOG), Vol. 30, ACM, 2011, p. 156.
[10] A. Levin, D. Lischinski, Y. Weiss, Colorization using optimization ACM Trans. Graph. 23 (3) (2004) 689–694. doi:10.1145/1015706.1015780 URL http://doi.acm.org/10.1145/1015706.1015780
[11] L. Cheng, S. Vishwanathan, Learning to compress images and videos, in: Proceedings of the 24th international conference on Machine learning, ACM, 2007, pp. 161–168.
[12] X. He, M. Ji, H. Bao, A unified active and semi-supervised learning framework for image compression, in: Computer Vision and Pattern Recognition, 2009. CVPR 2009. IEEE Conference on, IEEE, 2009, pp. 65–72.
[13] N. E. Egge, J.-M. Valin, Predicting chroma from luma with frequency domain intra prediction, in: IS&T/SPIE Electronic Imaging, International Society for Optics and Photonics, 2015, pp. 941008–941008.
[14] C. Vondrick, H. Pirsiavash, A. Torralba, Anticipating the future by watching unlabeled video, arXiv preprint arXiv:1504.08023.
[15] A. Vedaldi, S. Soatto, Quick shift and kernel methods for mode seeking, in: Computer vision–ECCV 2008, Springer, 2008, pp. 705–718.
[16] R. Achanta, A. Shaji, K. Smith, A. Lucchi, P. Fua, S. Susstrunk, Slic superpixels compared to state-of-the-art superpixel methods, Pattern Analysis and Machine Intelligence, IEEE Transactions on 34 (11) (2012) 2274–2282.
[17] A. Krizhevsky, G. Hinton, Learning multiple layers of features from tiny images (2009).
Appendix A. Network Architectures for models trained

We now describe the network architecture for the models that we used for colorization with our proposed zero-cost and low-cost framework. A block in the table indicates a combination of layers in the following order: convolution, batch normalization, scaling, reLU, convolution, batch normalization, scaling, elementwise addition with the previous layer indicated in the column for “Residual Connection” and a reLU for CIFAR100 architectures. A block in the Imagenet architecture refers to blocks as defined in the Resnet-50 architecture from He et al. [20]. “Block(2-9)” indicate that blocks 2 to 9 have the same parameters as indicated in the row. The numbers in the filter column following a Block indicate the number of filters used in each of the convolution layers for the block. We use identity projections. [20] to match the number of layers for performing element-wise addition when we have to connect layers with different number of output channels by a residual connection. The second number in the projection column indicates the stride used during the projection. “Block-Prev” refers to a residual connection from the previous block in a chain of Blocks. Branch-K refers to the K branched module and its filters represent the number of parameters in the convolution layers for each branch.

For all architectures we used the learning method proposed by Kingma and Ba. [22] with $\beta_1 = 0.9$ and $\beta_2 = 0.999$. We initialize all layers with the MSRA method for initialization as was proposed by He et al. [23]. The Colorization loss for training is described in equation 2.

Table A.8 shows the architecture of the model that was used to study how to train models with branching on the CIFAR100 dataset. The model was trained using the entire training set for CIFAR100 with mirroring for data augmentation with no cropping.

Training Details for CIFAR100 Arch. The model was trained for 40,000 iterations with a mini-batch size of 64 examples per each GPU using 2 GPUs. We start training with a learning rate of 0.001 and drop the learning rate twice during training by a factor of 10 (after 10,000 iterations and 20,000 iterations). For experiments on the role of learning from scratch vs fine tuning we used the vanilla pretrained network on the image categorization task that was trained by Ahmad et al. [24]. For zero-cost colorization our branch prediction module uses the feature maps from the first layer of each branch (16 feature maps each). The branch predictor produces a per-pixel output of 5 channels. This is followed by a softmax Loss.

Table A.9 describes the architecture used for colorization in our framework for the Imagenet experiments.

Training Details for Imagenet Arch. The model was trained for 120,000 iterations with a mini-batch size of 20 examples per GPU with 4 GPUs. We start training...
Table A.8: The architecture of our deep network for colorization of images on the CIFAR100 dataset.

| Layers         | Filters | Kernel | Stride | Batch Normalization | Scaling | ReLU | Residual | Connection | Projection |
|----------------|---------|--------|--------|--------------------|---------|------|----------|------------|------------|
| Conv-1         | 64      | 3      | 1      | Y                  |         | Y    | Y        | No         | No         |
| Block-1        | 64-64   | 3-3    | 1-1    | Y-Y                | Y-Y     | Y-N  |           | No         | No         |
| Block(2-9)     | 64-64   | 3-3    | 1-1    | Y-Y                | Y-Y     | Y-N  | Block-Prev | No         | 128-2      |
| Block-10       | 128-128 | 3-3    | 2-1    | Y-Y                | Y-Y     | Y-N  | Block-9   | 256-2      |
| Block(11-18)   | 128-128 | 3-3    | 1-1    | Y-Y                | Y-Y     | Y-N  | Block-Prev | No         | 256-2      |
| Block(20-29)   | 256-256 | 3-3    | 1-1    | Y-Y                | Y-Y     | Y-N  | Block-Prev | No         | No         |
| UpSample-1     | 256     | 4      | 2      | N                  | N       | N    | No        | No         | No         |
| Block-30       | 128     | 3      | 1      | Y                  | Y       | Y    | Block-18  | No         | No         |
| UpSample-2     | 128     | 4      | 2      | N                  | N       | N    | No        | No         | No         |
| Block-19       | 64      | 1      | 1      | Y                  | Y       | N    | Block-9   | No         | No         |
| Branch-5       | (16,2)  | Each   | 3-3    | Each              | N-N     | N-N  | Y-N      | -N N       | No         |
| Colorization Loss |       |        |        |                    |         |      |          |            |            |
| BranchPred     | 5       | 3      | 1      | N                  | N       | N    | N        | N          |            |
| Softmax Loss   |         |        |        |                    |         |      |          |            |            |

with a learning rate of 0.0005 and drop the learning rate twice during training by dividing it 5 (after 40,000 iterations and 80,000 iterations). We use a regularization of 0.0001 for all layers except for the output layers in the branches and the output of the branch prediction module. For the Branch Prediction module in Imagenet experiments we used the features from the layers "UpSample-4", "Conv-1" and "Block-3". The feature maps from "Conv-1" and "Block-3" were upsampled independently to match the resolution of the input grayscale image for dense prediction. The branch prediction module consisted of a convolution layer with 256 filters (kernel size 3) followed by batch normalization and scaling and a second convolution layer with 64 filters followed by batch normalization, scaling and a ReLU. This was followed by a convolution layer with 5 output channels per pixel trained with Softmax Loss. For experiments involving fine tuning of the base model we replicated the input grayscale image 3 times form a 3 channel input for the network.
Table A.9: The architecture of our deep network for colorization of images on Imagenet.

| Layers | Filters | Kernel | Stride | Batch Normalization | Scaling | ReLU | Residual Projection |
|--------|---------|--------|--------|---------------------|---------|------|--------------------|
| Conv-1 | 64      | 7      | 2      | Y                   | Y       | Y    | N                  |
| Pool-1 | 3       | 2      |        |                     |         |      |                    |
| Block-1 | 64-64-256 | 1-3-1 | 1-1-1 | Y-Y-Y               | Y-Y-Y   | Y-Y-N| Pool-1 256-1       |
| Block(2-3) | 64-64-256 | 1-3-1 | 1-1-1 | Y-Y-Y               | Y-Y-Y   | Y-Y-N| Block-Prev No      |
| Block-4 | 128-128-512 | 1-3-1 | 2-1-1 | Y-Y-Y               | Y-Y-Y   | Y-Y-N| Block-3 512-2      |
| Block(5-7) | 128-128-512 | 1-3-1 | 1-1-1 | Y-Y-Y               | Y-Y-Y   | Y-Y-N| Block-Prev No      |
| Block-8 | 256-256-1024 | 1-3-1 | 2-1-1 | Y-Y-Y               | Y-Y-Y   | Y-Y-N| Block-7 1024-2     |
| Block(9-13) | 256-256-1024 | 1-3-1 | 1-1-1 | Y-Y-Y               | Y-Y-Y   | Y-Y-N| Block-Prev No      |
| Block-14 | 512-512-2048 | 1-3-1 | 2-1-1 | Y-Y-Y               | Y-Y-Y   | Y-Y-N| Block-13 2048-2    |
| Block(15-16) | 512-512-2048 | 1-3-1 | 1-1-1 | Y-Y-Y               | Y-Y-Y   | Y-Y-N| Block-Prev No      |
| Block-17 | 1024     | 1      | 1      | Y                   | Y       | N    | No                 |
| UpSample-1 | 1024      | 4      | 2      | N                   | N       | N    | Block-13 No       |
| Block-18 | 512      | 1      | 1      | Y                   | Y       | N    | No                 |
| UpSample-2 | 512       | 4      | 2      | N                   | N       | N    | Block-7 No        |
| Block-19 | 256      | 1      | 1      | Y                   | Y       | N    | No                 |
| UpSample-3 | 256       | 4      | 2      | N                   | N       | N    | Block-3 No        |
| Block-20 | 64       | 1      | 1      | Y                   | Y       | N    | No                 |
| UpSample-3 | 64        | 4      | 2      | N                   | N       | N    | Conv-1 No         |
| Block-21 | 32       | 1      | 1      | Y                   | Y       | N    | No                 |
| UpSample-4 | 32        | 4      | 2      | N                   | N       | N    | No                 |
| Branch-5 | 2 Each   | 3 Each | 1 Each | N                   | N       | N    | No                 |
| Colorization Loss | | | | | | | |
| BranchPred | 5       | 3      | 1      | N                   | N       | N    | N                 |
| Softmax Loss | | | | | | | |

13